Package ‘contextual’

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Type Package

Title Simulation and Analysis of Contextual Multi-Armed Bandit Policies

Version 0.9.8.1

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Description Facilitates the simulation and evaluation of context-free and contextual multi-Armed Bandit policies or algorithms to ease the implementation, evaluation, and dissemination of both existing and new bandit algorithms and policies.

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Encoding UTF-8

LazyData true

RoxygenNote 6.1.1

Imports R6 (>= 2.3.0), data.table, R.devices, foreach, doParallel, itertools, iterators, Formula, rjson

Suggests testthat, RCurl, splitstackshape, covr, knitr, here, rmarkdown, devtools, ggplot2, vdiffr

VignetteBuilder knitr

URL https://github.com/Nth-iteration-labs/contextual

BugReports https://github.com/Nth-iteration-labs/contextual/issues

NeedsCompilation no

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R topics documented:

`Agent` *Agent*

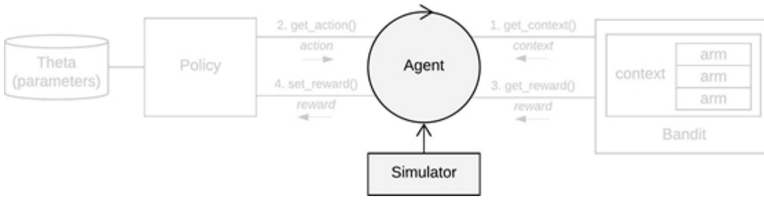
Description

Keeps track of one `Bandit` and `Policy` pair.

Details

Controls the running of one `Bandit` and `Policy` pair over $t = 1, \ldots, T$ looping over, consecutively, `bandit$get_context()`, `policy$get_action()`, `bandit$get_reward()` and `policy$set_reward()` for each time step `t`.

Schematic



Usage

```
agent <- Agent$new(policy, bandit, name=NULL, sparse = 0.0)
```

Arguments

`policy` `Policy` instance.

`bandit` `Bandit` instance.

`name` character; sets the name of the `Agent`. If `NULL` (default), `Agent` generates a name based on its `Policy` instance's name.

`sparse` numeric; artificially reduces the data size by setting a sparsity level for the current `Bandit` and `Policy` pair. When set to a value between `0.0` (default) and `1.0` only a fraction `sparse` of the `Bandit`'s data is randomly chosen to be available to improve the `Agent`'s `Policy` through `policy$set_reward`.

Methods

`new()` generates and instantializes a new `Agent` instance.

`do_step()` advances a simulation by one time step by consecutively calling `bandit$get_context()`, `policy$get_action()`, `bandit$get_reward()` and `policy$set_reward()`. Returns a list of lists containing `context`, `action`, `reward` and `theta`.

`set_t(t)` integer; sets the current time step to `t`.

`get_t()` returns current time step `t`.

See Also

Core contextual classes: `Bandit`, `Policy`, `Simulator`, `Agent`, `History`, `Plot`

Bandit subclass examples: `BasicBernoulliBandit`, `ContextualLogitBandit`, `OfflineReplayEvaluatorBandit`

Policy subclass examples: `EpsilonGreedyPolicy`, `ContextualLinTSPolicy`

Examples

```
## Not run:

  policy    <- EpsilonGreedyPolicy$new(epsilon = 0.1)
  bandit    <- BasicBernoulliBandit$new(weights = c(0.6, 0.1, 0.1))

  agent     <- Agent$new(policy, bandit, name = "E.G.", sparse = 0.5)
```

```
  history   <- Simulator$new(agents = agent,
                             horizon = 10,
                             simulations = 10)$run()

## End(Not run)
```

Bandit *Bandit: Superclass*

Description

Parent or superclass of all {contextual} Bandit subclasses.

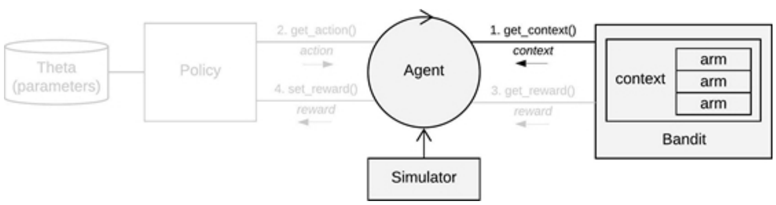
Details

In {contextual}, Bandits are responsible for the generation of (either synthetic or offline) contexts and rewards.

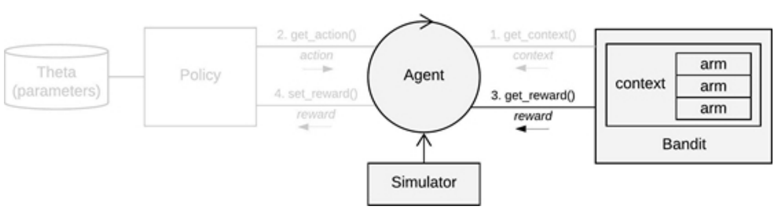
On initialisation, a Bandit subclass has to define the number of arms self$k and the number of contextual feature dimensions self$d.

For each $t = 1, \ldots,$ T a Bandit then generates a list containing current context in d x k dimensional matrix context$X, the number of arms in context$k and the number of features in context$d.

Note: in context-free scenario's, context$X can be omitted.



On receiving the index of a Policy-chosen arm through action$choice, Bandit is expected to return a named list containing at least reward$reward and, where computable, reward$optimal.



Usage

```
bandit <- Bandit$new()
```

Methods

`new()` generates and instantializes a new `Bandit` instance.

`get_context(t)` argument:

- `t`: integer, time step `t`.

returns a named `list` containing the current `d x k` dimensional matrix `context$X`, the number of arms `context$k` and the number of features `context$d`.

`get_reward(t, context, action)` arguments:

- `t`: integer, time step `t`.
- `context`: list, containing the current `context$X` (d x k context matrix), `context$k` (number of arms) and `context$d` (number of context features) (as set by `bandit`).
- `action`: list, containing `action$choice` (as set by `policy`).

returns a named `list` containing `reward$reward` and, where computable, `reward$optimal` (used by "oracle" policies and to calculate regret).

`post_initialization()` Called after class and seed initialisation, but before the start of the simulation. Set random values that remain available throughout the life of a `Bandit` here.

`generate_bandit_data()` Called after class and seed initialisation, but before the start of a simulation. Pregenerate `contexts` and `rewards` here.

See Also

Core contextual classes: `Bandit`, `Policy`, `Simulator`, `Agent`, `History`, `Plot`

Bandit subclass examples: `BasicBernoulliBandit`, `ContextualLogitBandit`, `OfflineReplayEvaluatorBandit`

Policy subclass examples: `EpsilonGreedyPolicy`, `ContextualLinTSPolicy`

`BasicBernoulliBandit` *Bandit: BasicBernoulliBandit*

Description

Context-free Bernoulli or Binary multi-armed bandit.

Details

Simulates `k` Bernoulli arms where each arm issues a reward of one with uniform probability `p`, and otherwise a reward of zero.

In a bandit scenario, this can be used to simulate a hit or miss event, such as if a user clicks on a headline, ad, or recommended product.

Usage

```
bandit <- BasicBernoulliBandit$new(weights)
```

Arguments

`weights` numeric vector; probability of reward values for each of the bandit's k arms

Methods

`new(weights)` generates and instantializes a new `BasicBernoulliBandit` instance.

`get_context(t)` argument:

- `t`: integer, time step `t`.

returns a named `list` containing the current `d x k` dimensional matrix `context$X`, the number of arms `context$k` and the number of features `context$d`.

`get_reward(t, context, action)` arguments:

- `t`: integer, time step `t`.
- `context`: list, containing the current `context$X` (d x k context matrix), `context$k` (number of arms) and `context$d` (number of context features) (as set by `bandit`).
- `action`: list, containing `action$choice` (as set by `policy`).

returns a named `list` containing `reward$reward` and, where computable, `reward$optimal` (used by "oracle" policies and to calculate regret).

See Also

Core contextual classes: `Bandit`, `Policy`, `Simulator`, `Agent`, `History`, `Plot`

Bandit subclass examples: `BasicBernoulliBandit`, `ContextualLogitBandit`, `OfflineReplayEvaluatorBandit`

Policy subclass examples: `EpsilonGreedyPolicy`, `ContextualLinTSPolicy`

Examples

```
## Not run:

horizon            <- 100
sims               <- 100

policy             <- EpsilonGreedyPolicy$new(epsilon = 0.1)

bandit             <- BasicBernoulliBandit$new(weights = c(0.6, 0.1, 0.1))
agent              <- Agent$new(policy,bandit)

history            <- Simulator$new(agent, horizon, sims)$run()

plot(history, type = "cumulative", regret = TRUE)


## End(Not run)
```

BasicGaussianBandit *Bandit: BasicGaussianBandit*

Description

Context-free Gaussian multi-armed bandit.

Details

Simulates `k` Gaussian arms where each arm models the reward as a normal distribution with provided mean `mu` and standard deviation `sigma`.

Usage

```
bandit <- BasicGaussianBandit$new(mu_per_arm, sigma_per_arm)
```

Arguments

`mu_per_arm` numeric vector; mean `mu` for each of the bandit's `k` arms

`sigma_per_arm` numeric vector; standard deviation of additive Gaussian noise for each of the bandit's `k` arms. Set to zero for no noise.

Methods

`new(mu_per_arm, sigma_per_arm)` generates and instantializes a new `BasicGaussianBandit` instance.

`get_context(t)` argument:

- `t`: integer, time step `t`.

returns a named `list` containing the current `d x k` dimensional matrix `context$X`, the number of arms `context$k` and the number of features `context$d`.

`get_reward(t, context, action)` arguments:

- `t`: integer, time step `t`.
- `context`: list, containing the current `context$X` (d x k context matrix), `context$k` (number of arms) and `context$d` (number of context features) (as set by `bandit`).
- `action`: list, containing `action$choice` (as set by `policy`).

returns a named `list` containing `reward$reward` and, where computable, `reward$optimal` (used by "oracle" policies and to calculate regret).

See Also

Core contextual classes: `Bandit`, `Policy`, `Simulator`, `Agent`, `History`, `Plot`

Bandit subclass examples: `BasicBernoulliBandit`, `ContextualLogitBandit`, `OfflineReplayEvaluatorBandit`

Policy subclass examples: `EpsilonGreedyPolicy`, `ContextualLinTSPolicy`

Examples

```
## Not run:

horizon            <- 100
sims               <- 100

policy             <- EpsilonGreedyPolicy$new(epsilon = 0.1)

bandit             <- BasicGaussianBandit$new(c(0,0,1), c(1,1,1))
agent              <- Agent$new(policy,bandit)

history            <- Simulator$new(agent, horizon, sims)$run()

plot(history, type = "cumulative", regret = TRUE)


## End(Not run)
```

BootstrapTSPolicy — *Policy: Thompson sampling with the online bootstrap*

Description

Bootstrap Thompson Sampling

Details

Bootstrap Thompson Sampling (BTS) is a heuristic method for solving bandit problems which modifies Thompson Sampling (see ThompsonSamplingPolicy) by replacing the posterior distribution used in Thompson sampling by a bootstrap distribution.

Usage

```
policy <- BootstrapTSPolicy(J = 100, a= 1, b = 1)

policy <- BootstrapTSPolicy(1000)
```

Arguments

`new(J = 100, a= 1, b = 1)` Generates a new `BootstrapTSPolicy` object. Arguments are defined in the Argument section above.

`set_parameters()` each policy needs to assign the parameters it wants to keep track of to list `self$theta_to_arms` that has to be defined in `set_parameters()`'s body. The parameters defined here can later be accessed by arm index in the following way: `theta[[index_of_arm]]$parameter_name`

`get_action(context)` here, a policy decides which arm to choose, based on the current values of its parameters and, potentially, the current context.

`set_reward(reward, context)` in `set_reward(reward, context)`, a policy updates its parameter values based on the reward received, and, potentially, the current context.

References

Eckles, D., & Kaptein, M. (2014). Thompson sampling with the online bootstrap. arXiv preprint arXiv:1410.4009.

Thompson, W. R. (1933). On the likelihood that one unknown probability exceeds another in view of the evidence of two samples. Biometrika, 25(3/4), 285-294.

See Also

Core contextual classes: `Bandit`, `Policy`, `Simulator`, `Agent`, `History`, `Plot`

Bandit subclass examples: `BasicBernoulliBandit`, `ContextualLogitBandit`, `OfflineReplayEvaluatorBandit`

Policy subclass examples: `EpsilonGreedyPolicy`, `ContextualLinTSPolicy`

`clipr` — *Clip vectors*

Description

Clips values to a mininum and maximum value. That is, all values below the lower clamp value and the upper clamp value become the lower/upper value specified

Usage

```
clipr(x, min, max)
```

Arguments

`x`	to be clipped vector
`min`	numeric. lowest value
`max`	numeric. highest value

`ContextualBernoulliBandit` — *Bandit: Naive Contextual Bernouilli Bandit*

Description

Contextual Bernoulli multi-armed bandit where at least one context feature is active at a time.

Usage

```
bandit <- ContextualBernoulliBandit$new(weights)
```

Arguments

`weights` numeric matrix; `d x k` matrix with probabilities of reward for `d` contextual features per `k` arms

Methods

`new(weights)` generates and initializes a new `ContextualBernoulliBandit` instance.

`get_context(t)` argument:

- `t`: integer, time step `t`.

returns a named `list` containing the current `d x k` dimensional matrix `context$X`, the number of arms `context$k` and the number of features `context$d`.

`get_reward(t, context, action)` arguments:

- `t`: integer, time step `t`.
- `context`: list, containing the current `context$X` (d x k context matrix), `context$k` (number of arms) and `context$d` (number of context features) (as set by `bandit`).
- `action`: list, containing `action$choice` (as set by `policy`).

returns a named `list` containing `reward$reward` and, where computable, `reward$optimal` (used by "oracle" policies and to calculate regret).

See Also

Core contextual classes: `Bandit`, `Policy`, `Simulator`, `Agent`, `History`, `Plot`

Bandit subclass examples: `ContextualBernoulliBandit`, `ContextualLogitBandit`, `OfflineReplayEvaluatorBandit`

Policy subclass examples: `EpsilonGreedyPolicy`, `ContextualLinTSPolicy`

Examples

```
## Not run:

horizon            <- 100
sims               <- 100

policy             <- EpsilonGreedyPolicy$new(epsilon = 0.1)

bandit             <- ContextualBernoulliBandit$new(weights = c(0.6, 0.1, 0.1))
agent              <- Agent$new(policy,bandit)

history            <- Simulator$new(agent, horizon, sims)$run()

plot(history, type = "cumulative", regret = TRUE)


## End(Not run)
```

ContextualBinaryBandit *Bandit: ContextualBinaryBandit*

Description

Contextual Bernoulli multi-armed bandit where at least one context feature is active at a time.

Usage

```
bandit <- ContextualBinaryBandit$new(weights)
```

Arguments

`weights` numeric matrix; `d x k` matrix with probabilities of reward for `d` contextual features per `k` arms

Methods

`new(weights)` generates and initializes a new `ContextualBinaryBandit` instance.

`get_context(t)` argument:

- `t`: integer, time step `t`.

returns a named `list` containing the current `d x k` dimensional matrix `context$X`, the number of arms `context$k` and the number of features `context$d`.

`get_reward(t, context, action)` arguments:

- `t`: integer, time step `t`.
- `context`: list, containing the current `context$X` (d x k context matrix), `context$k` (number of arms) and `context$d` (number of context features) (as set by `bandit`).
- `action`: list, containing `action$choice` (as set by `policy`).

returns a named `list` containing `reward$reward` and, where computable, `reward$optimal` (used by "oracle" policies and to calculate regret).

See Also

Core contextual classes: `Bandit`, `Policy`, `Simulator`, `Agent`, `History`, `Plot`

Bandit subclass examples: `ContextualBinaryBandit`, `ContextualLogitBandit`, `OfflineReplayEvaluatorBandit`

Policy subclass examples: `EpsilonGreedyPolicy`, `ContextualLinTSPolicy`

Examples

```
## Not run:

horizon            <- 100
sims               <- 100

policy             <- EpsilonGreedyPolicy$new(epsilon = 0.1)

bandit             <- ContextualBinaryBandit$new(weights = c(0.6, 0.1, 0.1))
agent              <- Agent$new(policy,bandit)

history            <- Simulator$new(agent, horizon, sims)$run()

plot(history, type = "cumulative", regret = TRUE)


## End(Not run)
```

ContextualEpochGreedyPolicy

Policy: A Time and Space Efficient Algorithm for Contextual Linear Bandits

---

Description

Policy: A Time and Space Efficient Algorithm for Contextual Linear Bandits

Usage

```
policy <- EpsilonGreedyPolicy(epsilon = 0.1)
```

See Also

Core contextual classes: `Bandit`, `Policy`, `Simulator`, `Agent`, `History`, `Plot`

Bandit subclass examples: `BasicBernoulliBandit`, `ContextualLogitBandit`, `OfflineReplayEvaluatorBandit`

Policy subclass examples: `EpsilonGreedyPolicy`, `ContextualLinTSPolicy`

ContextualEpsilonGreedyPolicy

Policy: ContextualEpsilonGreedyPolicy with unique linear models

---

Description

Policy: ContextualEpsilonGreedyPolicy with unique linear models

Usage

```
policy <- ContextualEpsilonGreedyPolicy(epsilon = 0.1)
```

Arguments

`epsilon` double, a positive real value R+

Parameters

`A` d*d identity matrix

`b` a zero vector of length d

Methods

`new(epsilon = 0.1)` Generates a new `ContextualEpsilonGreedyPolicy` object. Arguments are defined in the Argument section above.

`set_parameters()` each policy needs to assign the parameters it wants to keep track of to list `self$theta_to_arms` that has to be defined in `set_parameters()`'s body. The parameters defined here can later be accessed by arm index in the following way: `theta[[index_of_arm]]$parameter_name`

`get_action(context)` here, a policy decides which arm to choose, based on the current values of its parameters and, potentially, the current context.

`set_reward(reward, context)` in `set_reward(reward, context)`, a policy updates its parameter values based on the reward received, and, potentially, the current context.

See Also

Core contextual classes: `Bandit`, `Policy`, `Simulator`, `Agent`, `History`, `Plot`

Bandit subclass examples: `BasicBernoulliBandit`, `ContextualLogitBandit`, `OfflineReplayEvaluatorBandit`

Policy subclass examples: `EpsilonGreedyPolicy`, `ContextualLinTSPolicy`

`ContextualHybridBandit`

Bandit: ContextualHybridBandit

Description

TODO: Optimization.

Details

Extension of `ContextualLogitBandit` modeling hybrid rewards with a combination of unique (or "disjoint") and shared contextual features.

Usage

```
bandit <- ContextualHybridBandit$new(k, shared_features, unique_features, sigma = 1.0)
```

Arguments

`k` integer; number of bandit arms

`shared_features` integer; number of shared features

`unique_features` integer; number of unique/disjoint features

`sigma` integer; standard deviation of additive Gaussian noise

Methods

`new(k, shared_features, unique_features, sigma = 1.0)` generates and instantializes a new `ContextualHybridBandit` instance.

`get_context(t)` argument:

- `t`: integer, time step `t`.

returns a named `list` containing the current `d x k` dimensional matrix `context$X`, the number of arms `context$k` and the number of features `context$d`.

`get_reward(t, context, action)` arguments:

- `t`: integer, time step `t`.
- `context`: list, containing the current `context$X` (d x k context matrix), `context$k` (number of arms) and `context$d` (number of context features) (as set by `bandit`).
- `action`: list, containing `action$choice` (as set by `policy`).

returns a named `list` containing `reward$reward` and, where computable, `reward$optimal` (used by "oracle" policies and to calculate regret).

`post_initialization()` initializes `d x k` beta matrix.

See Also

Core contextual classes: `Bandit`, `Policy`, `Simulator`, `Agent`, `History`, `Plot`

Bandit subclass examples: `BasicBernoulliBandit`, `ContextualLogitBandit`, `OfflineReplayEvaluatorBandit`

Policy subclass examples: `EpsilonGreedyPolicy`, `ContextualLinTSPolicy`

Examples

```
## Not run:

horizon       <- 800L
simulations   <- 100L

bandit      <- ContextualHybridBandit$new(k = 100, shared_features = 10, unique_features = 2)

agents        <- list(Agent$new(ContextualLinTSPolicy$new(0.1), bandit),
                      Agent$new(EpsilonGreedyPolicy$new(0.1), bandit),
                      Agent$new(LinUCBGeneralPolicy$new(0.6), bandit),
                      Agent$new(ContextualEpochGreedyPolicy$new(8), bandit),
```

```
                     Agent$new(LinUCBHybridOptimizedPolicy$new(0.6), bandit),
                     Agent$new(LinUCBDisjointOptimizedPolicy$new(0.6), bandit))

simulation     <- Simulator$new(agents, horizon, simulations)
history        <- simulation$run()

plot(history, type = "cumulative", regret = FALSE, rate = TRUE, legend_position = "bottomright")

## End(Not run)
```

ContextualLinearBandit

Bandit: ContextualLinearBandit

Description

Samples data from linearly parameterized arms.

Details

The reward for context X and arm j is given by X^T beta_j, for some latent set of parameters beta_j : j = 1, ..., k. The beta's are sampled uniformly at random, the contexts are Gaussian, and sigma-noise is added to the rewards.

Usage

```
bandit <- ContextualLinearBandit$new(k, d, sigma = 0.1, binary_rewards = FALSE)
```

Arguments

`k` integer; number of bandit arms

`d` integer; number of contextual features

`sigma` numeric; standard deviation of the additive noise. Set to zero for no noise. Default is `0.1`

`binary_rewards` logical; when set to `FALSE` (default) ContextualLinearBandit generates Gaussian rewards. When set to `TRUE`, rewards are binary (0/1).

Methods

`new(k, d, sigma = 0.1, binary_rewards = FALSE)` generates and instantializes a new `ContextualLinearBandit` instance.

`get_context(t)` argument:

- `t`: integer, time step `t`.

returns a named `list` containing the current `d x k` dimensional matrix `context$X`, the number of arms `context$k` and the number of features `context$d`.

`get_reward(t, context, action)` arguments:

- t: integer, time step t.
- context: list, containing the current context$X (d x k context matrix), context$k (number of arms) and context$d (number of context features) (as set by bandit).
- action: list, containing action$choice (as set by policy).

returns a named list containing reward$reward and, where computable, reward$optimal (used by "oracle" policies and to calculate regret).

post_initialization() initializes d x k beta matrix.

References

Riquelme, C., Tucker, G., & Snoek, J. (2018). Deep Bayesian Bandits Showdown: An Empirical Comparison of Bayesian Deep Networks for Thompson Sampling. arXiv preprint arXiv:1802.09127.

Implementation follows https://github.com/tensorflow/models/tree/master/research/deep_contextual_bandits

See Also

Core contextual classes: Bandit, Policy, Simulator, Agent, History, Plot

Bandit subclass examples: BasicBernoulliBandit, ContextualLogitBandit, OfflineReplayEvaluatorBandit

Policy subclass examples: EpsilonGreedyPolicy, ContextualLinTSPolicy

Examples

```
## Not run:

horizon       <- 800L
simulations   <- 30L

bandit        <- ContextualLinearBandit$new(k = 5, d = 5)

agents        <- list(Agent$new(EpsilonGreedyPolicy$new(0.1), bandit),
                      Agent$new(LinUCBDisjointOptimizedPolicy$new(0.6), bandit))

simulation     <- Simulator$new(agents, horizon, simulations)
history        <- simulation$run()

plot(history, type = "cumulative", regret = FALSE, rate = TRUE, legend_position = "right")

## End(Not run)
```

ContextualLinTSPolicy *Policy: Linear Thompson Sampling with unique linear models*

Description

ContextualLinTSPolicy implements Thompson Sampling with Linear Payoffs, following Agrawal and Goyal (2011). Thompson Sampling with Linear Payoffs is a contextual Thompson Sampling multi-armed bandit Policy which assumes the underlying relationship between rewards and contexts are linear. Check the reference for more details.

Usage

```
policy <- ContextualLinTSPolicy$new(v = 0.2)
```

Arguments

v double, a positive real value R+; Hyper-parameter for adjusting the variance of posterior gaussian distribution.

Methods

`new(v)` instantiates a new `ContextualLinTSPolicy` instance. Arguments defined in the Arguments section above.

`set_parameters(context_params)` initialization of policy parameters, utilising `context_params$k` (number of arms) and `context_params$d` (number of context features).

`get_action(t,context)` selects an arm based on `self$theta` and `context`, returning the index of the selected arm in `action$choice`. The context argument consists of a list with `context$k` (number of arms), `context$d` (number of features), and the feature matrix `context$X` with dimensions $d \times k$.

`set_reward(t, context, action, reward)` updates parameter list `theta` in accordance with the current `reward$reward`, `action$choice` and the feature matrix `context$X` with dimensions $d \times k$. Returns the updated `theta`.

References

Shipra Agrawal, and Navin Goyal. "Thompson Sampling for Contextual Bandits with Linear Payoffs." Advances in Neural Information Processing Systems 24. 2011.

See Also

Core contextual classes: `Bandit`, `Policy`, `Simulator`, `Agent`, `History`, `Plot`

Bandit subclass examples: `BasicBernoulliBandit`, `ContextualLogitBandit`, `OfflineReplayEvaluatorBandit`

Policy subclass examples: `EpsilonGreedyPolicy`, `ContextualLinTSPolicy`

Examples

```
## Not run:

horizon       <- 100L
simulations   <- 100L

bandit        <- ContextualLinearBandit$new(k = 4, d = 3, sigma = 0.3)

agents        <- list(Agent$new(EpsilonGreedyPolicy$new(0.1), bandit, "EGreedy"),
                   Agent$new(ContextualLinTSPolicyPolicy$new(0.1), bandit, "LinTSPolicy"))

simulation     <- Simulator$new(agents, horizon, simulations, do_parallel = TRUE)
```

```
history        <- simulation$run()

plot(history, type = "cumulative", rate = FALSE, legend_position = "topleft")


## End(Not run)
```

ContextualLogitBandit *Bandit: ContextualLogitBandit*

Description

Samples data from a basic logistic regression model.

Details

ContextualLogitBandit linear predictors are generated from the dot product of a random `d` dimensional normal weight vector and uniform random `d x k` dimensional context matrices with equal weights per arm. This product is then inverse-logit transformed to generate `k` dimensional binary (0/1) reward vectors by randomly sampling from a Bernoulli distribution.

Usage

```
bandit <- ContextualLogitBandit$new(k, d, intercept = TRUE)
```

Arguments

`k` integer; number of bandit arms

`d` integer; number of contextual features

`intercept` logical; if TRUE (default) it adds a constant (1.0) dimension to each context X at the end.

Methods

`new(k, d, intercept = TRUE)` generates and instantializes a new `ContextualLogitBandit` instance.

`get_context(t)` argument:

- `t`: integer, time step `t`.

returns a named `list` containing the current `d x k` dimensional matrix `context$X`, the number of arms `context$k` and the number of features `context$d`.

`get_reward(t, context, action)` arguments:

- `t`: integer, time step `t`.
- `context`: list, containing the current `context$X` (d x k context matrix), `context$k` (number of arms) and `context$d` (number of context features) (as set by `bandit`).
- `action`: list, containing `action$choice` (as set by `policy`).

returns a named `list` containing `reward$reward` and, where computable, `reward$optimal` (used by "oracle" policies and to calculate regret).

`post_initialization()` initializes `d x k` beta matrix.

See Also

Core contextual classes: Bandit, Policy, Simulator, Agent, History, Plot

Bandit subclass examples: BasicBernoulliBandit, ContextualLogitBandit, OfflineReplayEvaluatorBandit

Policy subclass examples: EpsilonGreedyPolicy, ContextualLinTSPolicy

Examples

```
## Not run:

horizon       <- 800L
simulations   <- 30L

bandit        <- ContextualLogitBandit$new(k = 5, d = 5, intercept = TRUE)

agents        <- list(Agent$new(ContextualLinTSPolicy$new(0.1), bandit),
                      Agent$new(EpsilonGreedyPolicy$new(0.1), bandit),
                      Agent$new(LinUCBGeneralPolicy$new(0.6), bandit),
                      Agent$new(ContextualEpochGreedyPolicy$new(8), bandit),
                      Agent$new(LinUCBHybridOptimizedPolicy$new(0.6), bandit),
                      Agent$new(LinUCBDisjointOptimizedPolicy$new(0.6), bandit))

simulation     <- Simulator$new(agents, horizon, simulations)
history        <- simulation$run()

plot(history, type = "cumulative", regret = FALSE,
              rate = TRUE, legend_position = "right")

## End(Not run)
```

ContextualLogitBTSPolicy

Policy: ContextualLogitBTSPolicy

Description

Policy: ContextualLogitBTSPolicy

Usage

```
policy <- ContextualLogitBTSPolicy()
```

See Also

Core contextual classes: Bandit, Policy, Simulator, Agent, History, Plot

Bandit subclass examples: BasicBernoulliBandit, ContextualLogitBandit, OfflineReplayEvaluatorBandit

Policy subclass examples: EpsilonGreedyPolicy, ContextualLinTSPolicy

ContextualPrecachingBandit

Bandit: ContextualPrecachingBandit

Description

Illustrates precaching of contexts and rewards.

Details

TODO: Fix "attempt to select more than one element in integerOneIndex"

Contextual extension of BasicBernoulliBandit.

Contextual extension of BasicBernoulliBandit where a user specified `d x k` dimensional matrix takes the place of BasicBernoulliBandit `k` dimensional probability vector. Here, each row `d` represents a feature with `k` reward probability values per arm.

For every `t`, `ContextualPrecachingBandit` randomly samples from its `d` features/rows at random, yielding a binary `context` matrix representing sampled (all 1 rows) and unsampled (all 0) features/rows. Next, `ContextualPrecachingBandit` generates `rewards` contingent on either sum or mean (default) probabilities of each arm/column over all of the sampled features/rows.

Usage

```
bandit <- ContextualPrecachingBandit$new(weights)
```

Arguments

`weights` numeric matrix; `d x k` dimensional matrix where each row `d` represents a feature with `k` reward probability values per arm.

Methods

`new(weights)` generates and instantializes a new `ContextualPrecachingBandit` instance.

`get_context(t)` argument:

- `t`: integer, time step `t`.

returns a named `list` containing the current `d x k` dimensional matrix `context$X`, the number of arms `context$k` and the number of features `context$d`.

`get_reward(t, context, action)` arguments:

- `t`: integer, time step `t`.
- `context`: list, containing the current `context$X` (d x k context matrix), `context$k` (number of arms) and `context$d` (number of context features) (as set by `bandit`).
- `action`: list, containing `action$choice` (as set by `policy`).

returns a named `list` containing `reward$reward` and, where computable, `reward$optimal` (used by "oracle" policies and to calculate regret).

`generate_bandit_data()` helper function called before `Simulator` starts iterating over all time steps `t` in T. Pregenerates `contexts` and `rewards`.

See Also

Core contextual classes: Bandit, Policy, Simulator, Agent, History, Plot

Bandit subclass examples: BasicBernoulliBandit, ContextualLogitBandit, OfflineReplayEvaluatorBandit

Policy subclass examples: EpsilonGreedyPolicy, ContextualLinTSPolicy

Examples

```
## Not run:

horizon            <- 100L
simulations        <- 100L

# rows represent features, columns represent arms:

context_weights    <- matrix(  c(0.4, 0.2, 0.4,
                                 0.3, 0.4, 0.3,
                                 0.1, 0.8, 0.1),  nrow = 3, ncol = 3, byrow = TRUE)

bandit             <- ContextualPrecachingBandit$new(weights)

agents             <- list( Agent$new(EpsilonGreedyPolicy$new(0.1), bandit),
                            Agent$new(LinUCBDisjointOptimizedPolicy$new(0.6), bandit))

simulation         <- Simulator$new(agents, horizon, simulations)
history            <- simulation$run()

plot(history, type = "cumulative")


## End(Not run)
```

ContextualTSProbitPolicy *Policy: ContextualTSProbitPolicy*

Description

Makes use of BOPR, ergo only use binary indepependent variables.

Usage

```
policy <- ContextualTSProbitPolicy()
```

See Also

Core contextual classes: Bandit, Policy, Simulator, Agent, History, Plot

Bandit subclass examples: BasicBernoulliBandit, ContextualLogitBandit, OfflineReplayEvaluatorBandit

Policy subclass examples: EpsilonGreedyPolicy, ContextualLinTSPolicy

`ContextualWheelBandit` *Bandit: ContextualWheelBandit*

Description

Samples from Wheel bandit game.

Details

The Wheel bandit game offers an artificial problem where the need for exploration is smoothly parameterized through exploration parameter `delta`.

In the game, contexts are sampled uniformly at random from a unit circle divided into one central and four edge areas for a total of `k = 5` possible actions. The central area offers a random normal sampled reward independent of the context, in contrast to the outer areas which offer a random normal sampled reward dependent on a `d = 2` dimensional context.

For more information, see https://arxiv.org/abs/1802.09127.

Usage

```
bandit <- ContextualWheelBandit$new(delta, mean_v, std_v, mu_large, std_large)
```

Arguments

`delta` numeric; exploration parameter: high reward in one region if norm above delta.

`mean_v` numeric vector; mean reward for each action if context norm is below delta.

`std_v` numeric vector; gaussian reward sd for each action if context norm is below delta.

`mu_large` numeric; mean reward for optimal action if context norm is above delta.

`std_large` numeric; standard deviation of the reward for optimal action if context norm is above delta.

Methods

`new(delta, mean_v, std_v, mu_large, std_large)` generates and instantializes a new `ContextualWheelBandit` instance.

`get_context(t)` argument:

- `t`: integer, time step `t`.

returns a named `list` containing the current `d x k` dimensional matrix `context$X`, the number of arms `context$k` and the number of features `context$d`.

`get_reward(t, context, action)` arguments:

- `t`: integer, time step `t`.
- `context`: list, containing the current `context$X` (d x k context matrix), `context$k` (number of arms) and `context$d` (number of context features) (as set by `bandit`).
- `action`: list, containing `action$choice` (as set by `policy`).

returns a named `list` containing `reward$reward` and, where computable, `reward$optimal` (used by "oracle" policies and to calculate regret).

References

Riquelme, C., Tucker, G., & Snoek, J. (2018). Deep Bayesian Bandits Showdown: An Empirical Comparison of Bayesian Deep Networks for Thompson Sampling. arXiv preprint arXiv:1802.09127.

Implementation follows https://github.com/tensorflow/models/tree/master/research/deep_contextual_bandits

See Also

Core contextual classes: Bandit, Policy, Simulator, Agent, History, Plot

Bandit subclass examples: BasicBernoulliBandit, ContextualLogitBandit, OfflineReplayEvaluatorBandit

Policy subclass examples: EpsilonGreedyPolicy, ContextualLinTSPolicy

Examples

```
## Not run:

horizon       <- 1000L
simulations   <- 10L

delta         <- 0.95
num_actions   <- 5
context_dim   <- 2
mean_v        <- c(1.0, 1.0, 1.0, 1.0, 1.2)
std_v         <- c(0.05, 0.05, 0.05, 0.05, 0.05)
mu_large      <- 50
std_large     <- 0.01

bandit        <- ContextualWheelBandit$new(delta, mean_v, std_v, mu_large, std_large)
agents        <- list(Agent$new(UCB1Policy$new(), bandit),
                      Agent$new(LinUCBDisjointOptimizedPolicy$new(0.6), bandit))

simulation     <- Simulator$new(agents, horizon, simulations)
history        <- simulation$run()

plot(history, type = "cumulative", regret = FALSE, rate = TRUE, legend_position = "bottomright")

## End(Not run)
```

ContinuumBandit *Bandit: ContinuumBandit*

Description

A function based continuum multi-armed bandit where arms are chosen from a subset of the real line and the mean rewards are assumed to be a continuous function of the arms.

Usage

```
bandit <- ContinuumBandit$new(FUN)
```

Arguments

FUN continuous function.

Methods

`new(FUN)` generates and instantializes a new `ContinuumBandit` instance.

`get_context(t)` argument:

- `t`: integer, time step `t`.

returns a named `list` containing the current `d x k` dimensional matrix `context$X`, the number of arms `context$k` and the number of features `context$d`.

`get_reward(t, context, action)` arguments:

- `t`: integer, time step `t`.
- `context`: list, containing the current `context$X` (d x k context matrix), `context$k` (number of arms) and `context$d` (number of context features) (as set by `bandit`).
- `action`: list, containing `action$choice` (as set by `policy`).

returns a named `list` containing `reward$reward` and, where computable, `reward$optimal` (used by "oracle" policies and to calculate regret).

See Also

Core contextual classes: `Bandit`, `Policy`, `Simulator`, `Agent`, `History`, `Plot`

Bandit subclass examples: `BasicBernoulliBandit`, `ContextualLogitBandit`, `OfflineReplayEvaluatorBandit`

Policy subclass examples: `EpsilonGreedyPolicy`, `ContextualLinTSPolicy`

Examples

```
## Not run:

horizon            <- 1500
simulations        <- 100

continuous_arms  <- function(x) {
  -0.1*(x - 5) ^ 2 + 3.5  + rnorm(length(x),0,0.4)
}

int_time    <- 100
amplitude   <- 0.2
learn_rate  <- 0.3
omega       <- 2*pi/int_time
x0_start    <- 2.0

policy             <- LifPolicy$new(int_time, amplitude, learn_rate, omega, x0_start)

bandit             <- ContinuumBandit$new(FUN = continuous_arms)

agent              <- Agent$new(policy,bandit)

history            <- Simulator$new(     agents = agent,
```

```
                                          horizon = horizon,
                                          simulations = simulations,
                                          save_theta = TRUE              )$run()

plot(history, type = "average", regret = FALSE)

## End(Not run)
```

`data_table_factors_to_numeric` *Convert all factor columns in data.table to numeric*

Description

Convert all factor columns in data.table to numeric

Usage

```
data_table_factors_to_numeric(dt)
```

Arguments

dt	a data.table

Value

the data.table with column factors converted to numeric

`dec<-` *Decrement*

Description

`dec<-` decrements x by value. Equivalent to `x <- x - value.`

Usage

```
dec(x) <- value
```

Arguments

x	object to be decremented
value	value by which x will be modified

Examples

```
x <- 6:10
dec(x) <- 5
x
```

EpsilonFirstPolicy *Policy: Epsilon First*

Description

EpsilonFirstPolicy implements a "naive" policy where a pure exploration phase is followed by a pure exploitation phase.

Details

Exploration happens within the first epsilon * N time steps. During this time, at each time step t, EpsilonFirstPolicy selects an arm at random.

Exploitation happens in the following (1-epsilon) * N steps, selecting the best arm up until epsilon * N for either the remaining N trials or horizon T.

In case of a tie in the exploitation phase, EpsilonFirstPolicy randomly selects and arm.

Usage

```
policy <- EpsilonFirstPolicy(epsilon = 0.1, N = 1000, time_steps = NULL)
```

Arguments

epsilon numeric; value in the closed interval (0,1] that sets the number of time steps to explore through epsilon * N.

N integer; positive integer which sets the number of time steps to explore through epsilon * N.

time_steps integer; positive integer which sets the number of time steps to explore - can be used instead of epsilon and N.

Methods

new(epsilon = 0.1, N = 1000, time_steps = NULL) Generates a new EpsilonFirstPolicy object. Arguments are defined in the Argument section above.

set_parameters() each policy needs to assign the parameters it wants to keep track of to list self$theta_to_arms that has to be defined in set_parameters()'s body. The parameters defined here can later be accessed by arm index in the following way: theta[[index_of_arm]]$parameter_name

get_action(context) here, a policy decides which arm to choose, based on the current values of its parameters and, potentially, the current context.

set_reward(reward, context) in set_reward(reward, context), a policy updates its parameter values based on the reward received, and, potentially, the current context.

References

Gittins, J., Glazebrook, K., & Weber, R. (2011). Multi-armed bandit allocation indices. John Wiley & Sons. (Original work published 1989)

Sutton, R. S. (1996). Generalization in reinforcement learning: Successful examples using sparse coarse coding. In Advances in neural information processing systems (pp. 1038-1044).

Strehl, A., & Littman, M. (2004). Exploration via model based interval estimation. In International Conference on Machine Learning, number Icml.

See Also

Core contextual classes: `Bandit`, `Policy`, `Simulator`, `Agent`, `History`, `Plot`

Bandit subclass examples: `BasicBernoulliBandit`, `ContextualLogitBandit`, `OfflineReplayEvaluatorBandit`

Policy subclass examples: `EpsilonGreedyPolicy`, `ContextualLinTSPolicy`

Examples

```
horizon            <- 100L
simulations        <- 100L
weights            <- c(0.9, 0.1, 0.1)

policy             <- EpsilonFirstPolicy$new(time_steps = 50)
bandit             <- BasicBernoulliBandit$new(weights = weights)
agent              <- Agent$new(policy, bandit)

history          <- Simulator$new(agent, horizon, simulations, do_parallel = FALSE)$run()

plot(history, type = "cumulative")
plot(history, type = "arms")
```

`EpsilonGreedyPolicy` *Policy: Epsilon Greedy*

Description

`EpsilonGreedyPolicy` chooses an arm at random (explores) with probability `epsilon`, otherwise it greedily chooses (exploits) the arm with the highest estimated reward.

Usage

```
policy <- EpsilonGreedyPolicy(epsilon = 0.1)
```

Arguments

`epsilon` numeric; value in the closed interval `(0,1]` indicating the probablilty with which arms are selected at random (explored). Otherwise, `EpsilonGreedyPolicy` chooses the best arm (exploits) with a probability of `1 - epsilon`

`name` character string specifying this policy. `name` is, among others, saved to the History log and displayed in summaries and plots.

Methods

`new(epsilon = 0.1)` Generates a new `EpsilonGreedyPolicy` object. Arguments are defined in the Argument section above.

`set_parameters()` each policy needs to assign the parameters it wants to keep track of to list `self$theta_to_arms` that has to be defined in `set_parameters()`'s body. The parameters defined here can later be accessed by arm index in the following way: `theta[[index_of_arm]]$parameter_name`

`get_action(context)` here, a policy decides which arm to choose, based on the current values of its parameters and, potentially, the current context.

`set_reward(reward, context)` in `set_reward(reward, context)`, a policy updates its parameter values based on the reward received, and, potentially, the current context.

References

Gittins, J., Glazebrook, K., & Weber, R. (2011). Multi-armed bandit allocation indices. John Wiley & Sons. (Original work published 1989)

Sutton, R. S. (1996). Generalization in reinforcement learning: Successful examples using sparse coarse coding. In Advances in neural information processing systems (pp. 1038-1044).

Strehl, A., & Littman, M. (2004). Exploration via model based interval estimation. In International Conference on Machine Learning, number Icml.

Yue, Y., Broder, J., Kleinberg, R., & Joachims, T. (2012). The k-armed dueling bandits problem. Journal of Computer and System Sciences, 78(5), 1538-1556.

See Also

Core contextual classes: `Bandit`, `Policy`, `Simulator`, `Agent`, `History`, `Plot`

Bandit subclass examples: `BasicBernoulliBandit`, `ContextualLogitBandit`, `OfflineReplayEvaluatorBandit`

Policy subclass examples: `EpsilonGreedyPolicy`, `ContextualLinTSPolicy`

Examples

```
horizon            <- 100L
simulations        <- 100L
weights          <- c(0.9, 0.1, 0.1)

policy             <- EpsilonGreedyPolicy$new(epsilon = 0.1)
bandit             <- BasicBernoulliBandit$new(weights = weights)
```

```
agent              <- Agent$new(policy, bandit)

history          <- Simulator$new(agent, horizon, simulations, do_parallel = FALSE)$run()

plot(history, type = "cumulative")

plot(history, type = "arms")
```

Exp3Policy *Policy: Exp3*

Description

In Exp3Policy, "Exp3" stands for "Exponential-weight algorithm for Exploration and Exploitation". It makes use of a distribution over probabilities that is is a mixture of a uniform distribution and a distribution which assigns to each action a probability mass exponential in the estimated cumulative reward for that action.

Usage

```
policy <- Exp3Policy(gamma = 0.1)
```

Arguments

gamma double, value in the closed interval (0,1], controls the exploration - often referred to as the learning rate

name character string specifying this policy. name is, among others, saved to the History log and displayed in summaries and plots.

Methods

new(gamma = 0.1) Generates a new Exp3Policy object. Arguments are defined in the Argument section above.

set_parameters() each policy needs to assign the parameters it wants to keep track of to list self$theta_to_arms that has to be defined in set_parameters()'s body. The parameters defined here can later be accessed by arm index in the following way: theta[[index_of_arm]]$parameter_name

get_action(context) here, a policy decides which arm to choose, based on the current values of its parameters and, potentially, the current context.

set_reward(reward, context) in set_reward(reward, context), a policy updates its parameter values based on the reward received, and, potentially, the current context.

References

Auer, P., Cesa-Bianchi, N., Freund, Y., & Schapire, R. E. (2002). The nonstochastic multi-armed bandit problem. SIAM journal on computing, 32(1), 48-77. Strehl, A., & Littman, M. (2004). Exploration via model based interval estimation. In International Conference on Machine Learning, number Icml.

Strehl, A., & Littman, M. (2004). Exploration via model based interval estimation. In International Conference on Machine Learning, number Icml.

See Also

Core contextual classes: `Bandit`, `Policy`, `Simulator`, `Agent`, `History`, `Plot`

Bandit subclass examples: `BasicBernoulliBandit`, `ContextualLogitBandit`, `OfflineReplayEvaluatorBandit`

Policy subclass examples: `EpsilonGreedyPolicy`, `ContextualLinTSPolicy`

Examples

```
horizon            <- 100L
simulations        <- 100L
weights          <- c(0.9, 0.1, 0.1)

policy             <- Exp3Policy$new(gamma = 0.1)
bandit             <- BasicBernoulliBandit$new(weights = weights)
agent              <- Agent$new(policy, bandit)

history          <- Simulator$new(agent, horizon, simulations, do_parallel = FALSE)$run()

plot(history, type = "cumulative")

plot(history, type = "arms")
```

`FixedPolicy` *Policy: Fixed Arm*

Description

`FixedPolicy` implements a "naive" policy which always chooses a prespecified arm.

Usage

```
policy <- FixedPolicy(fixed_arm = 1)
```

Arguments

`fixed_arm` numeric; index of the arm that will be chosen for each time step.

Methods

`new()` Generates a new `FixedPolicy` object. Arguments are defined in the Argument section above.

`set_parameters()` each policy needs to assign the parameters it wants to keep track of to list `self$theta_to_arms` that has to be defined in `set_parameters()`'s body. The parameters defined here can later be accessed by arm index in the following way: `theta[[index_of_arm]]$parameter_name`

`get_action(context)` here, a policy decides which arm to choose, based on the current values of its parameters and, potentially, the current context.

`set_reward(reward, context)` in `set_reward(reward, context)`, a policy updates its parameter values based on the reward received, and, potentially, the current context.

See Also

Core contextual classes: `Bandit`, `Policy`, `Simulator`, `Agent`, `History`, `Plot`

Bandit subclass examples: `BasicBernoulliBandit`, `ContextualLogitBandit`, `OfflineReplayEvaluatorBandit`

Policy subclass examples: `EpsilonGreedyPolicy`, `ContextualLinTSPolicy`

`formatted_difftime` *Format difftime objects*

Description

Format difftime objects

Usage

```
formatted_difftime(x)
```

Arguments

`x`	difftime object

Value

string "days, h:mm:ss.ms"

get_arm_context *Return context vector of an arm*

Description

Given d x k matrix or d dimensional vector X, returns a vector with arm's context.

Usage

```
get_arm_context(context, arm, select_features = NULL,
  prepend_arm_vector = FALSE)
```

Arguments

`context`	a context list containing a d x k Matrix or d dimensional context vector X, the number of features d and number of arms k.
`arm`	index of arm.
`select_features`	indices of to be returned features.
`prepend_arm_vector`	prepend a one-hot-encoded arm vector to the returned context vector. That is, when k = 5 arms, and the to be returned arm vector is arm 3, prepend c(0,0,1,0,0)

Value

Vector that represents context related to an arm

get_full_context *Get full context matrix over all arms*

Description

Given matrix or d dimensional vector X, number of arms k and number of features d returns a matrix with d x k context matrix

Usage

```
get_full_context(context, select_features = NULL,
  prepend_arm_matrix = FALSE)
```

Arguments

`context` a context list containing a d x k Matrix or d dimensional context vector X, the number of features d and number of arms k.

`select_features` indices of to be returned feature rows.b

`prepend_arm_matrix` prepend a diagonal arm matrix to the returned context vector. That is, when k = 5 arms, prepend diag(5) to the top of the matrix.

Value

A d x k context Matrix

GittinsBrezziLaiPolicy

Policy: Gittins Approximation algorithm for choosing arms in a MAB problem.

Description

`GittinsBrezziLaiPolicy` Algorithm based on Brezzi and Lai (2002) "Optimal learning and experimentation in bandit problems."

Details

The algorithm provides an approximation of the Gittins index, by specifying a closed-form expression, which is a function of the discount factor, and the number of successes and failures associated with each arm.

Usage

```
policy <- GittinsBrezziLaiPolicy$new(discount=0.95, prior=NULL)
```

Arguments

`discount` numeric; discount factor

`prior` numeric matrix; prior beliefs over Bernoulli parameters governing each arm. Beliefs are specified by Beta distribution with two parameters (alpha,beta) where alpha = number of success, beta = number of failures. Matrix is of arms times two (alpha / beta) dimensions

Methods

`new(discount=0.95, prior=NULL)` Generates and initializes a new `Policy` object.

`get_action(t, context)` arguments:

- `t`: integer, time step `t`.

- `context`: list, containing the current `context$X` (d x k context matrix), `context$k` (number of arms) and `context$d` (number of context features)

computes which arm to play based on the current values in named list `theta` and the current `context`. Returns a named list containing `action$choice`, which holds the index of the arm to play.

`set_reward(t, context, action, reward)` arguments:

- `t`: integer, time step `t`.
- `context`: list, containing the current `context$X` (d x k context matrix), `context$k` (number of arms) and `context$d` (number of context features) (as set by `bandit`).
- `action`: list, containing `action$choice` (as set by `policy`).
- `reward`: list, containing `reward$reward` and, if available, `reward$optimal` (as set by `bandit`).

utilizes the above arguments to update and return the set of parameters in list `theta`.

`set_parameters()` Helper function, called during a Policy's initialisation, assigns the values it finds in list `self$theta_to_arms` to each of the Policy's k arms. The parameters defined here can then be accessed by arm index in the following way: `theta[[index_of_arm]]$parameter_name`.

References

Brezzi, M., & Lai, T. L. (2002). Optimal learning and experimentation in bandit problems. Journal of Economic Dynamics and Control, 27(1), 87-108.

Implementation follows https://github.com/elarry/bandit-algorithms-simulated

See Also

Core contextual classes: `Bandit`, `Policy`, `Simulator`, `Agent`, `History`, `Plot`

Bandit subclass examples: `BasicBernoulliBandit`, `ContextualLogitBandit`, `OfflineReplayEvaluatorBandit`

Policy subclass examples: `EpsilonGreedyPolicy`, `ContextualLinTSPolicy`

`GradientPolicy` *Policy: Gradient*

Description

`GradientPolicy` is a SoftMax type algorithm, based on Sutton & Barton (2018).

Usage

```
policy <- GradientPolicy(alpha = 0.1)
```

Arguments

`alpha = 0.1` double, temperature parameter alpha specifies how many arms we can explore. When alpha is high, all arms are explored equally, when alpha is low, arms offering higher rewards will be chosen.

Methods

`new(epsilon = 0.1)` Generates a new `GradientPolicy` object. Arguments are defined in the Argument section above.

`set_parameters()` each policy needs to assign the parameters it wants to keep track of to list `self$theta_to_arms` that has to be defined in `set_parameters()`'s body. The parameters defined here can later be accessed by arm index in the following way: `theta[[index_of_arm]]$parameter_name`

`get_action(context)` here, a policy decides which arm to choose, based on the current values of its parameters and, potentially, the current context.

`set_reward(reward, context)` in `set_reward(reward, context)`, a policy updates its parameter values based on the reward received, and, potentially, the current context.

References

Kuleshov, V., & Precup, D. (2014). Algorithms for multi-armed bandit problems. arXiv preprint arXiv:1402.6028.

Cesa-Bianchi, N., Gentile, C., Lugosi, G., & Neu, G. (2017). Boltzmann exploration done right. In Advances in Neural Information Processing Systems (pp. 6284-6293).

See Also

Core contextual classes: Bandit, Policy, Simulator, Agent, History, Plot

Bandit subclass examples: BasicBernoulliBandit, ContextualLogitBandit, OfflineReplayEvaluatorBandit

Policy subclass examples: EpsilonGreedyPolicy, ContextualLinTSPolicy

Examples

```
horizon            <- 100L
simulations        <- 100L
weights            <- c(0.9, 0.1, 0.1)

policy             <- GradientPolicy$new(alpha = 0.1)
bandit             <- BasicBernoulliBandit$new(weights = weights)
agent              <- Agent$new(policy, bandit)

history          <- Simulator$new(agent, horizon, simulations, do_parallel = FALSE)$run()

plot(history, type = "cumulative")

plot(history, type = "arms")
```

`History` *History*

Description

The R6 class `History` keeps a log of all `Simulator` interactions in its internal `data.table`. It also provides basic data summaries, and can save or load simulation log data files.

Usage

```
History <- History$new(n = 1, save_context = FALSE, save_theta = FALSE)
```

Arguments

`n` `integer`. The number of rows, to be preallocated during initialization.

`save_context` `logical`. Save context matrix `X` when writing simulation data?

`save_theta` `logical`. Save parameter lists `theta` when writing simulation data?

Methods

`reset()` Resets a `History` instance to its original initialisation values.

`insert(index, t, action, reward, agent_name, simulation_index, context_value = NA, theta_value = NA`
Saves one row of simulation data. Is generally not called directly, but from a Simulator instance.

`save(filename = NA)` Writes the `History` log file in its default data.table format, with `filename` as the name of the file which the data is to be written to.

`load = function(filename, interval = 0)` Reads a `History` log file in its default `data.table` format, with `filename` as the name of the file which the data are to be read from. If `interval` is larger than 0, every `interval` of data is read instead of the full data file. This can be of use with (a first) analysis of very large data files.

`get_data_frame()` Returns the `History` log as a `data.frame`.

`set_data_frame(df, auto_stats = TRUE)` Sets the `History` log with the data in `data.frame` `dt`. Recalculates cumulative statistics when auto_stats is TRUE.

`get_data_table()` Returns the `History` log as a `data.table`.

`set_data_table(dt, auto_stats = TRUE)` Sets the `History` log with the data in `data.table` `dt`. Recalculates cumulative statistics when auto_stats is TRUE.

`clear_data_table()` Clear `History`'s internal `data.table` log.

`save_csv(filename = NA)` Saves History data to csv file.

`extract_theta(limit_agents, parameter, arm, tail = NULL)` Extract theta parameter from theta list for `limit_agents`, where `parameter` sets the to be retrieved parameter or vector of parameters in theta, `arm` is the relevant integer index of the arm or vector of arms of interest, and the optional `tail` selects the last elements in the list. Returns a vector, matrix or array with the selected theta values.

`print_data()` Prints a summary of the `History` log.

`update_statistics()` Updates cumulative statistics.

`get_agent_list()` Retrieve list of agents in History.

`get_agent_count()` Retrieve number of agents in History.

`get_simulation_count()` Retrieve number of simulations in History.

`get_arm_choice_percentage(limit_agents)` Retrieve list of percentage arms chosen per agent for `limit_agents`.

`get_meta_data()` Retrieve History meta data.

`set_meta_datan(key, value, group = "sim", agent_name = NULL)` Set History meta data.

`get_cumulative_data(limit_agents = NULL, limit_cols = NULL, interval = 1, cum_average = FALSE))` Retrieve cumulative statistics data.

`get_cumulative_result(limit_agents = NULL, limit_cols = NULL, interval = 1, cum_average = FALSE))` Retrieve cumulative statistics data point.

`save_theta_json(filename = "theta.json"))` Save theta in JSON format to a file. Warning: the theta log, and therefor the file, can get very large very fast.

`get_theta(limit_agent, to_numeric_matrix = FALSE)` Retrieve an agent's simplified data.table version of the theta log. If to_numeric is TRUE, the data.table will be converted to a numeric matrix.

`data` Active binding, read access to History's internal data.table.

`cumulative` Active binding, read access to cumulative data by name through $ accessor.

`meta` Active binding, read access to meta data by name through $ accessor.

See Also

Core contextual classes: `Bandit`, `Policy`, `Simulator`, `Agent`, `History`, `Plot`

Bandit subclass examples: `BasicBernoulliBandit`, `ContextualLogitBandit`, `OfflineReplayEvaluatorBandit`

Policy subclass examples: `EpsilonGreedyPolicy`, `ContextualLinTSPolicy`

Examples

```
## Not run:

  policy    <- EpsilonGreedyPolicy$new(epsilon = 0.1)
  bandit    <- BasicBernoulliBandit$new(weights = c(0.6, 0.1, 0.1))

  agent     <- Agent$new(policy, bandit, name = "E.G.", sparse = 0.5)

  history   <- Simulator$new(agents = agent,
                             horizon = 10,
                             simulations = 10)$run()

  summary(history)

  plot(history)
```

```
dt <- history$get_data_table()

df <- history$get_data_frame()

print(history$cumulative$E.G.$cum_regret_sd)

print(history$cumulative$E.G.$cum_regret)

## End(Not run)
```

`inc<-` *Increment*

Description

`inc<-` increments x by value. Equivalent to `x <- x + value`.

Usage

```
inc(x) <- value
```

Arguments

`x`	object to be incremented
`value`	value by which x will be modified

Examples

```
x <- 1:5
inc(x) <- 5
x
```

`ind` *On-the-fly indicator function for use in formulae*

Description

On-the-fly indicator function for use in formulae

Usage

```
ind(cond)
```

Arguments

`cond`	a logical condition to be evaluated

Value

a binary (0/1) coded variable indicating whether the condition is true

---

inv — *Inverse from Choleski (or QR) Decomposition.*

Description

Invert a symmetric, positive definite square matrix from its Choleski decomposition.

Usage

```
inv(M)
```

Arguments

`M`	matrix

Examples

```
inv(cbind(1, 1:3, c(1,3,7)))
```

---

invgamma — *The Inverse Gamma Distribution*

Description

Density, distribution function, quantile function and random generation for the inverse gamma distribution.

Usage

```
dinvgamma(x, shape, rate = 1, scale = 1/rate, log = FALSE)

pinvgamma(q, shape, rate = 1, scale = 1/rate, lower.tail = TRUE,
  log.p = FALSE)

qinvgamma(p, shape, rate = 1, scale = 1/rate, lower.tail = TRUE,
  log.p = FALSE)

rinvgamma(n, shape, rate = 1, scale = 1/rate)
```

Arguments

`x, q`	vector of quantiles.
`shape`	inverse gamma shape parameter
`rate`	inverse gamma rate parameter
`scale`	alternative to rate; scale = 1/rate
`log, log.p`	logical; if TRUE, probabilities p are given as log(p).
`lower.tail`	logical; if TRUE (default), probabilities are P(X <= x) otherwise, P(X > x).
`p`	vector of probabilities.
`n`	number of observations. If length(n) > 1, the length is taken to be the number required.

Details

The inverse gamma distribution with parameters shape and rate has density *f(x) = rate^shape/Gamma(shape) x^(-1-shape) e^(-rate/x)* it is the inverse of the standard gamma parameterization in R.

The functions (d/p/q/r)invgamma simply wrap those of the standard (d/p/q/r)gamma R implementation, so look at, say, `dgamma` for details.

Examples

```
s <- seq(0, 5, .01)
plot(s, dinvgamma(s, 7, 10), type = 'l')

f <- function(x) dinvgamma(x, 7, 10)
q <- 2
integrate(f, 0, q)
(p <- pinvgamma(q, 7, 10))
qinvgamma(p, 7, 10) # = q
mean(rinvgamma(1e5, 7, 10) <= q)
```

`invlogit` *Inverse Logit Function*

Description

Given a numeric object return the inverse logit of the values.

Usage

```
invlogit(x)
```

Arguments

`x`	A numeric object.

Value

An object of the same type as x containing the inverse logits of the input values.

`is_rstudio` *Check if in RStudio*

Description

Detects whether R is open in RStudio.

Usage

```
is_rstudio()
```

Value

A `logical` value that indicates whether R is open in RStudio.

Examples

```
is_rstudio()
```

`LifPolicy` *Policy: Continuum Bandit Policy with Lock-in Feedback*

Description

The continuum type Lock-in Feedback (LiF) policy is based on an approach used in physics and engineering, where, if a physical variable y depends on the value of a well controllable physical variable x, the search for argmax x f(x) can be solved via what is nowadays considered as standard electronics. This approach relies on the possibility of making the variable x oscillate at a fixed frequency and to look at the response of the dependent variable y at the very same frequency by means of a lock-in amplifier. The method is particularly suitable when y is immersed in a high noise level, where other more direct methods would fail. Furthermore, should the entire curve shift (or, in other words, if argmax x f(x) changes in time, also known as concept drift), the circuit will automatically adjust to the new situation and quickly reveal the new maximum position. This approach is widely used in a very large number of applications, both in industry and research, and is the basis for the Lock-in Feedback (LiF) method.

Details

In this, Lock in feedback goes through the following steps, again and again:

- Oscillate a controllable independent variable X around a set value at a fixed pace.
- Apply the Lock-in amplifier algorithm.to obtain values of the amplitude if the outcome variable Y at the pace you set at step 1.
- Is the amplitude of this variable zero? Congratulations, you have reached lock-in! That is, you have found the optimal value of Y at the current value of X. Still, this optimal value might shift over time, so move to step 1 and repeat the process to make sure we maintain lock-in.
- Is the amplitude less than, or greater than zero? Then move the set value around which we are oscillating our independent variable X up or down on the basis of the outcome.

Now move to step 1 and repeat..

Usage

```
b <- LifPolicy$new(inttime,amplitude,learnrate,omega,x0_start)
```

References

Kaptein, M. C., Van Emden, R., & Iannuzzi, D. (2016). Tracking the decoy: maximizing the decoy effect through sequential experimentation. Palgrave Communications, 2, 16082.

See Also

Core contextual classes: `Bandit`, `Policy`, `Simulator`, `Agent`, `History`, `Plot`

Bandit subclass examples: `BasicBernoulliBandit`, `ContextualLogitBandit`, `OfflineReplayEvaluatorBandit`

Policy subclass examples: `EpsilonGreedyPolicy`, `ContextualLinTSPolicy`

`LinUCBDisjointOptimizedPolicy`

Policy: LinUCB with unique linear models

Description

Each time step t, `LinUCBDisjointPolicy` runs a linear regression per arm that produces coefficients for each context feature d. Next, `LinUCBDisjointPolicy` observes the new context, and generates a predicted payoff or reward together with a confidence interval for each available arm. It then proceeds to choose the arm with the highest upper confidence bound.

Usage

```
policy <- LinUCBDisjointOptimizedPolicy(alpha = 1.0)
```

Arguments

`alpha` double, a positive real value R+; Hyper-parameter adjusting the balance between exploration and exploitation.

`name` character string specifying this policy. `name` is, among others, saved to the History log and displayed in summaries and plots.

Parameters

`A` d*d identity matrix

`b` a zero vector of length d

Methods

`new(alpha = 1)` Generates a new `LinUCBDisjointOptimizedPolicy` object. Arguments are defined in the Argument section above.

`set_parameters()` each policy needs to assign the parameters it wants to keep track of to list `self$theta_to_arms` that has to be defined in `set_parameters()`'s body. The parameters defined here can later be accessed by arm index in the following way: `theta[[index_of_arm]]$parameter_name`

`get_action(context)` here, a policy decides which arm to choose, based on the current values of its parameters and, potentially, the current context.

`set_reward(reward, context)` in `set_reward(reward, context)`, a policy updates its parameter values based on the reward received, and, potentially, the current context.

References

Li, L., Chu, W., Langford, J., & Schapire, R. E. (2010, April). A contextual-bandit approach to personalized news article recommendation. In Proceedings of the 19th international conference on World wide web (pp. 661-670). ACM.

See Also

Core contextual classes: `Bandit`, `Policy`, `Simulator`, `Agent`, `History`, `Plot`

Bandit subclass examples: `BasicBernoulliBandit`, `ContextualLogitBandit`, `OfflineReplayEvaluatorBandit`

Policy subclass examples: `EpsilonGreedyPolicy`, `ContextualLinTSPolicy`

`LinUCBDisjointPolicy` *Policy: LinUCB with unique linear models*

Description

Each time step t, `LinUCBDisjointPolicy` runs a linear regression per arm that produces coefficients for each context feature `d`. Next, `LinUCBDisjointPolicy` observes the new context, and generates a predicted payoff or reward together with a confidence interval for each available arm. It then proceeds to choose the arm with the highest upper confidence bound.

Usage

```
policy <- LinUCBDisjointPolicy(alpha = 1.0)
```

Arguments

`alpha` double, a positive real value R+; Hyper-parameter adjusting the balance between exploration and exploitation.

`name` character string specifying this policy. `name` is, among others, saved to the History log and displayed in summaries and plots.

Parameters

`A` d*d identity matrix

`b` a zero vector of length d

Methods

`new(alpha = 1)` Generates a new `LinUCBDisjointPolicy` object. Arguments are defined in the Argument section above.

`set_parameters()` each policy needs to assign the parameters it wants to keep track of to list `self$theta_to_arms` that has to be defined in `set_parameters()`'s body. The parameters defined here can later be accessed by arm index in the following way: `theta[[index_of_arm]]$parameter_name`

`get_action(context)` here, a policy decides which arm to choose, based on the current values of its parameters and, potentially, the current context.

`set_reward(reward, context)` in `set_reward(reward, context)`, a policy updates its parameter values based on the reward received, and, potentially, the current context.

References

Li, L., Chu, W., Langford, J., & Schapire, R. E. (2010, April). A contextual-bandit approach to personalized news article recommendation. In Proceedings of the 19th international conference on World wide web (pp. 661-670). ACM.

See Also

Core contextual classes: Bandit, Policy, Simulator, Agent, History, Plot

Bandit subclass examples: BasicBernoulliBandit, ContextualLogitBandit, OfflineReplayEvaluatorBandit

Policy subclass examples: EpsilonGreedyPolicy, ContextualLinTSPolicy

---

LinUCBGeneralPolicy *Policy: LinUCB with unique linear models*

Description

Algorithm 1 LinUCB with unique linear models A Contextual-Bandit Approach to Personalized News Article Recommendation

Details

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Each time step t, `LinUCBGeneralPolicy` runs a linear regression per arm that produces coefficients for each context feature d. It then observes the new context, and generates a predicted payoff or reward together with a confidence interval for each available arm. It then proceeds to choose the arm with the highest upper confidence bound.

Usage

```
policy <- LinUCBGeneralPolicy(alpha = 1.0)
```

Arguments

`alpha` double, a positive real value R+; Hyper-parameter adjusting the balance between exploration and exploitation.

`name` character string specifying this policy. `name` is, among others, saved to the History log and displayed in summaries and plots.

Parameters

`A` d*d identity matrix

`b` a zero vector of length d

Methods

`new(alpha = 1)` Generates a new `LinUCBGeneralPolicy` object. Arguments are defined in the Argument section above.

`set_parameters()` each policy needs to assign the parameters it wants to keep track of to list `self$theta_to_arms` that has to be defined in `set_parameters()`'s body. The parameters defined here can later be accessed by arm index in the following way: `theta[[index_of_arm]]$parameter_name` `get_action(context)` here, a policy decides which arm to choose, based on the current values of its parameters and, potentially, the current context.

`set_reward(reward, context)` in `set_reward(reward, context)`, a policy updates its parameter values based on the reward received, and, potentially, the current context.

References

Li, L., Chu, W., Langford, J., & Schapire, R. E. (2010, April). A contextual-bandit approach to personalized news article recommendation. In Proceedings of the 19th international conference on World wide web (pp. 661-670). ACM.

See Also

Core contextual classes: `Bandit`, `Policy`, `Simulator`, `Agent`, `History`, `Plot`

Bandit subclass examples: `BasicBernoulliBandit`, `ContextualLogitBandit`, `OfflineReplayEvaluatorBandit`

Policy subclass examples: `EpsilonGreedyPolicy`, `ContextualLinTSPolicy`

`LinUCBHybridOptimizedPolicy`

Policy: LinUCB with hybrid linear models

Description

Each time step t, `LinUCBHybridOptimizedPolicy` runs a linear regression per arm that produces coefficients for each context feature `d`. Next, it observes the new context, and generates a predicted payoff or reward together with a confidence interval for each available arm. It then proceeds to choose the arm with the highest upper confidence bound.

Usage

```
policy <- LinUCBHybridOptimizedPolicy(alpha = 1.0)
```

Arguments

`alpha` double, a positive real value R+; Hyper-parameter adjusting the balance between exploration and exploitation.

`name` character string specifying this policy. `name` is, among others, saved to the History log and displayed in summaries and plots.

Parameters

`A` d*d identity matrix

`b` a zero vector of length d

Methods

`new(alpha = 1)` Generates a new `LinUCBHybridOptimizedPolicy` object. Arguments are defined in the Argument section above.

`set_parameters()` each policy needs to assign the parameters it wants to keep track of to list `self$theta_to_arms` that has to be defined in `set_parameters()`'s body. The parameters defined here can later be accessed by arm index in the following way: `theta[[index_of_arm]]$parameter_name`

`get_action(context)` here, a policy decides which arm to choose, based on the current values of its parameters and, potentially, the current context.

`set_reward(reward, context)` in `set_reward(reward, context)`, a policy updates its parameter values based on the reward received, and, potentially, the current context.

References

Li, L., Chu, W., Langford, J., & Schapire, R. E. (2010, April). A contextual-bandit approach to personalized news article recommendation. In Proceedings of the 19th international conference on World wide web (pp. 661-670). ACM.

See Also

Core contextual classes: `Bandit`, `Policy`, `Simulator`, `Agent`, `History`, `Plot`

Bandit subclass examples: `BasicBernoulliBandit`, `ContextualLogitBandit`, `OfflineReplayEvaluatorBandit`

Policy subclass examples: `EpsilonGreedyPolicy`, `ContextualLinTSPolicy`

`LinUCBHybridPolicy` *Policy: LinUCB with hybrid linear models*

Description

Each time step t, `LinUCBHybridOptimizedPolicy` runs a linear regression per arm that produces coefficients for each context feature d. Next, it observes the new context, and generates a predicted payoff or reward together with a confidence interval for each available arm. It then proceeds to choose the arm with the highest upper confidence bound.

Usage

```
policy <- LinUCBHybridPolicy(alpha = 1.0)
```

Arguments

`alpha` double, a positive real value R+; Hyper-parameter adjusting the balance between exploration and exploitation.

`name` character string specifying this policy. `name` is, among others, saved to the History log and displayed in summaries and plots.

Parameters

A d*d identity matrix

b a zero vector of length d

Methods

`new(alpha = 1)` Generates a new `LinUCBHybridPolicy` object. Arguments are defined in the Argument section above.

`set_parameters()` each policy needs to assign the parameters it wants to keep track of to list `self$theta_to_arms` that has to be defined in `set_parameters()`'s body. The parameters defined here can later be accessed by arm index in the following way: `theta[[index_of_arm]]$parameter_name`

`get_action(context)` here, a policy decides which arm to choose, based on the current values of its parameters and, potentially, the current context.

`set_reward(reward, context)` in `set_reward(reward, context)`, a policy updates its parameter values based on the reward received, and, potentially, the current context.

References

Li, L., Chu, W., Langford, J., & Schapire, R. E. (2010, April). A contextual-bandit approach to personalized news article recommendation. In Proceedings of the 19th international conference on World wide web (pp. 661-670). ACM.

See Also

Core contextual classes: `Bandit`, `Policy`, `Simulator`, `Agent`, `History`, `Plot`

Bandit subclass examples: `BasicBernoulliBandit`, `ContextualLogitBandit`, `OfflineReplayEvaluatorBandit`

Policy subclass examples: `EpsilonGreedyPolicy`, `ContextualLinTSPolicy`

---

mvrnorm — *Simulate from a Multivariate Normal Distribution*

Description

Produces one or more samples from the specified multivariate normal distribution.

Usage

```
mvrnorm(n, mu, sigma)
```

Arguments

`n`	the number of samples required.
`mu`	a vector giving the means of the variables.
`sigma`	a positive-definite symmetric matrix specifying the covariance matrix of the variables.

Value

If `n = 1` a vector of the same length as `mu`, otherwise an `n` by `length(mu)` matrix with one sample in each row.

OfflineBootstrappedReplayBandit

Bandit: Offline Bootstrapped Replay

Description

Policy for the evaluation of policies with offline data through replay with bootstrapping.

Details

The key assumption of the method is that that the original logging policy chose i.i.d. arms uniformly at random.

Take care: if the original logging policy does not change over trials, data may be used more efficiently via propensity scoring (Langford et al., 2008; Strehl et al., 2011) and related techniques like doubly robust estimation (Dudik et al., 2011).

Usage

```
bandit <- OfflineBootstrappedReplayBandit(formula,
                                           data, k = NULL, d = NULL,
                                           unique = NULL, shared = NULL,
                                         randomize = TRUE, replacement = TRUE,
                                           jitter = TRUE, arm_multiply = TRUE)
```

Arguments

`formula` formula (required). Format: `y.context ~ z.choice | x1.context + x2.xontext + ...` By default, adds an intercept to the context model. Exclude the intercept, by adding "0" or "-1" to the list of contextual features, as in: `y.context ~ z.choice | x1.context + x2.xontext -1`

`data` data.table or data.frame; offline data source (required)

`k` integer; number of arms (optional). Optionally used to reformat the formula defined x.context vector as a `k x d` matrix. When making use of such matrix formatted contexts, you need to define custom intercept(s) when and where needed in data.table or data.frame.

`d` integer; number of contextual features (optional) Optionally used to reformat the formula defined x.context vector as a `k x d` matrix. When making use of such matrix formatted contexts, you need to define custom intercept(s) when and where needed in data.table or data.frame.

`randomize` logical; randomize rows of data stream per simulation (optional, default: TRUE)

`replacement` logical; sample with replacement (optional, default: TRUE)

`replacement` logical; add jitter to contextual features (optional, default: TRUE)

`arm_multiply` logical; multiply the horizon by the number of arms (optional, default: TRUE)

`unique` integer vector; index of disjoint features (optional)

`shared` integer vector; index of shared features (optional)

Methods

`new(formula, data, k = NULL, d = NULL, unique = NULL, shared = NULL, randomize = TRUE, replacement`
: generates and instantializes a new `OfflineBootstrappedReplayBandit` instance.

`get_context(t)` argument:

- `t`: integer, time step `t`.

returns a named `list` containing the current `d x k` dimensional matrix `context$X`, the number of arms `context$k` and the number of features `context$d`.

`get_reward(t, context, action)` arguments:

- `t`: integer, time step `t`.
- `context`: list, containing the current `context$X` (d x k context matrix), `context$k` (number of arms) and `context$d` (number of context features) (as set by `bandit`).
- `action`: list, containing `action$choice` (as set by `policy`).

returns a named `list` containing `reward$reward` and, where computable, `reward$optimal` (used by "oracle" policies and to calculate regret).

`post_initialization()` Randomize offline data by shuffling the offline data.table before the start of each individual simulation when self$randomize is TRUE (default)

References

Mary, J., Preux, P., & Nicol, O. (2014, January). Improving offline evaluation of contextual bandit algorithms via bootstrapping techniques. In International Conference on Machine Learning (pp. 172-180).

See Also

Core contextual classes: `Bandit`, `Policy`, `Simulator`, `Agent`, `History`, `Plot`

Bandit subclass examples: `BasicBernoulliBandit`, `ContextualLogitBandit`, `OfflineBootstrappedReplayBandit`

Policy subclass examples: `EpsilonGreedyPolicy`, `ContextualLinTSPolicy`

Examples

```
## Not run:

library(contextual)
library(data.table)

# Import personalization data-set

url         <- "http://d1ie9wlkzugsxr.cloudfront.net/data_cmab_basic/dataset.txt"
datafile    <- fread(url)

simulations <- 1
horizon     <- nrow(datafile)

bandit     <- OfflineReplayEvaluatorBandit$new(formula = V2 ~ V1 | . - V1, data = datafile)

# Define agents.
```

```
agents     <- list(Agent$new(LinUCBDisjointOptimizedPolicy$new(0.01), bandit, "alpha = 0.01"),
                  Agent$new(LinUCBDisjointOptimizedPolicy$new(0.05), bandit, "alpha = 0.05"),
                  Agent$new(LinUCBDisjointOptimizedPolicy$new(0.1),  bandit, "alpha = 0.1"),
                  Agent$new(LinUCBDisjointOptimizedPolicy$new(1.0),  bandit, "alpha = 1.0"))

# Initialize the simulation.

simulation  <- Simulator$new(agents = agents, simulations = simulations, horizon = horizon,
                             do_parallel = FALSE, save_context = TRUE)

# Run the simulation.
sim  <- simulation$run()

# plot the results
plot(sim, type = "cumulative", regret = FALSE, rate = TRUE,
     legend_position = "bottomright", ylim = c(0,1))



## End(Not run)
```

OfflineDirectMethodBandit
Bandit: Offline Direct Methods

Description

Policy for the evaluation of policies with offline data with modeled rewards per arm.

Usage

```
bandit <- OfflineDirectMethodBandit(formula,
                                     data, k = NULL, d = NULL,
                                     unique = NULL, shared = NULL,
                                     randomize = TRUE)
```

Arguments

`formula` formula (required). Format: `y.context ~ z.choice | x1.context + x2.xontext + ... | r1.reward + r2.r`
Here, r1.reward to rk.reward represent regression based precalculated rewards per arm. Adds an intercept to the context model by default. Exclude the intercept, by adding "0" or "-1" to the list of contextual features, as in: `y.context ~ z.choice | x1.context + x2.xontext -1`

`data` data.table or data.frame; offline data source (required)

`k` integer; number of arms (optional). Optionally used to reformat the formula defined x.context vector as a `k x d` matrix. When making use of such matrix formatted contexts, you need to define custom intercept(s) when and where needed in data.table or data.frame.

`d` integer; number of contextual features (optional) Optionally used to reformat the formula defined x.context vector as a `k x d` matrix. When making use of such matrix formatted contexts, you need to define custom intercept(s) when and where needed in data.table or data.frame.

`randomize` logical; randomize rows of data stream per simulation (optional, default: TRUE)

`replacement` logical; sample with replacement (optional, default: FALSE)

`replacement` logical; add jitter to contextual features (optional, default: FALSE)

`unique` integer vector; index of disjoint features (optional)

`shared` integer vector; index of shared features (optional)

Methods

`new(formula, data, k = NULL, d = NULL, unique = NULL, shared = NULL, randomize = TRUE)` generates and instantializes a new `OfflineDirectMethodBandit` instance.

`get_context(t)` argument:

- `t`: integer, time step `t`.

returns a named `list` containing the current `d x k` dimensional matrix `context$X`, the number of arms `context$k` and the number of features `context$d`.

`get_reward(t, context, action)` arguments:

- `t`: integer, time step `t`.
- `context`: list, containing the current `context$X` (d x k context matrix), `context$k` (number of arms) and `context$d` (number of context features) (as set by `bandit`).
- `action`: list, containing `action$choice` (as set by `policy`).

returns a named `list` containing `reward$reward` and, where computable, `reward$optimal` (used by "oracle" policies and to calculate regret).

`post_initialization()` Randomize offline data by shuffling the offline data.table before the start of each individual simulation when self$randomize is TRUE (default)

References

Agarwal, Alekh, et al. "Taming the monster: A fast and simple algorithm for contextual bandits." International Conference on Machine Learning. 2014.

See Also

Core contextual classes: Bandit, Policy, Simulator, Agent, History, Plot

Bandit subclass examples: BasicBernoulliBandit, ContextualLogitBandit, OfflineDirectMethodBandit

Policy subclass examples: EpsilonGreedyPolicy, ContextualLinTSPolicy

Examples

```
## Not run:

library(contextual)
library(data.table)

# Import myocardial infection dataset

url        <- "http://d1ie9wlkzugsxr.cloudfront.net/data_propensity/myocardial_propensity.csv"
data         <- fread(url)
```

```
simulations  <- 50
horizon      <- nrow(data)

# arms always start at 1
data$trt     <- data$trt + 1

# turn death into alive, making it a reward
data$alive   <- abs(data$death - 1)

# Run regression per arm, predict outcomes, and save results, a column per arm

f                <- alive ~ age + male + risk + severity

model_f          <- function(arm) glm(f, data=data[trt==arm],
                                      family=binomial(link="logit"),
                                      y=FALSE, model=FALSE)
arms             <- sort(unique(data$trt))
model_arms       <- lapply(arms, FUN = model_f)

predict_arm      <- function(model) predict(model, data, type = "response")
r_data           <- lapply(model_arms, FUN = predict_arm)
r_data           <- do.call(cbind, r_data)
colnames(r_data) <- paste0("R", (1:max(arms)))

# Bind data and model predictions

data             <- cbind(data,r_data)

# Define Bandit

f               <- alive ~ trt | age + male + risk + severity | R1 + R2  # y ~ z | x | r

bandit           <- OfflineDirectMethodBandit$new(formula = f, data = data)

# Define agents.
agents      <- list(Agent$new(LinUCBDisjointOptimizedPolicy$new(0.2), bandit, "LinUCB"),
                    Agent$new(FixedPolicy$new(1), bandit, "Arm1"),
                    Agent$new(FixedPolicy$new(2), bandit, "Arm2"))

# Initialize the simulation.

simulation  <- Simulator$new(agents = agents, simulations = simulations, horizon = horizon)

# Run the simulation.
sim  <- simulation$run()

# plot the results
plot(sim, type = "cumulative", regret = FALSE, rate = TRUE, legend_position = "bottomright")
plot(sim, type = "arms", limit_agents = "LinUCB", legend_position = "topright")b


## End(Not run)
```

OfflineDoublyRobustBandit

Bandit: Offline Doubly Robust

Description

Bandit for the doubly robust evaluation of policies with offline data.

Usage

```
bandit <- OfflineDoublyRobustBandit(formula,
                                    data, k = NULL, d = NULL,
                                    unique = NULL, shared = NULL,
                                    inverted = FALSE, randomize = TRUE)
```

Arguments

`formula` formula (required). Format: `y.context ~ z.choice | x1.context + x2.xontext + ... | r1.reward + r2.r`
Here, r1.reward to rk.reward represent regression based precalculated rewards per arm. When leaving out p.propensity, Doubly Robust Bandit uses marginal prob per arm for propensities: Adds an intercept to the context model by default. Exclude the intercept, by adding "0" or "-1" to the list of contextual features, as in: `y.context ~ z.choice | x1.context + x2.xontext -1`

`data` data.table or data.frame; offline data source (required)

`k` integer; number of arms (optional). Optionally used to reformat the formula defined x.context vector as a `k x d` matrix. When making use of such matrix formatted contexts, you need to define custom intercept(s) when and where needed in data.table or data.frame.

`d` integer; number of contextual features (optional) Optionally used to reformat the formula defined x.context vector as a `k x d` matrix. When making use of such matrix formatted contexts, you need to define custom intercept(s) when and where needed in data.table or data.frame.

`randomize` logical; randomize rows of data stream per simulation (optional, default: TRUE)

`replacement` logical; sample with replacement (optional, default: FALSE)

`jitter` logical; add jitter to contextual features (optional, default: FALSE)

`unique` integer vector; index of disjoint features (optional)

`shared` integer vector; index of shared features (optional)

`inverted` logical; have the propensities been inverted (1/p) or not (p)?

`threshold` float (0,1); Lower threshold or Tau on propensity score values. Smaller Tau makes for less biased estimates with more variance, and vice versa. For more information, see paper by Strehl at all (2010). Values between 0.01 and 0.05 are known to work well.

Methods

`new(formula, data, k = NULL, d = NULL, unique = NULL, shared = NULL, randomize = TRUE)`
generates and instantializes a new `OfflineDoublyRobustBandit` instance.

`get_context(t)` argument:

- `t`: integer, time step `t`.

returns a named `list` containing the current `d x k` dimensional matrix `context$X`, the number of arms `context$k` and the number of features `context$d`.

`get_reward(t, context, action)` arguments:

- `t`: integer, time step `t`.
- `context`: list, containing the current `context$X` (d x k context matrix), `context$k` (number of arms) and `context$d` (number of context features) (as set by `bandit`).
- `action`: list, containing `action$choice` (as set by `policy`).

returns a named `list` containing `reward$reward` and, where computable, `reward$optimal` (used by "oracle" policies and to calculate regret).

`post_initialization()` Randomize offline data by shuffling the offline data.table before the start of each individual simulation when self$randomize is TRUE (default)

References

Dudík, Miroslav, John Langford, and Lihong Li. "Doubly robust policy evaluation and learning." arXiv preprint arXiv:1103.4601 (2011).

Agarwal, Alekh, et al. "Taming the monster: A fast and simple algorithm for contextual bandits." International Conference on Machine Learning. 2014.

Strehl, Alex, et al. "Learning from logged implicit exploration data." Advances in Neural Information Processing Systems. 2010.

See Also

Core contextual classes: `Bandit`, `Policy`, `Simulator`, `Agent`, `History`, `Plot`

Bandit subclass examples: `BasicBernoulliBandit`, `ContextualLogitBandit`, `OfflineDoublyRobustBandit`

Policy subclass examples: `EpsilonGreedyPolicy`, `ContextualLinTSPolicy`

Examples

```
## Not run:

library(contextual)
ibrary(data.table)

# Import myocardial infection dataset

url  <- "http://d1ie9wlkzugsxr.cloudfront.net/data_propensity/myocardial_propensity.csv"
data            <- fread(url)

simulations     <- 300
horizon         <- nrow(data)

# arms always start at 1
data$trt        <- data$trt + 1

# turn death into alive, making it a reward
```

```
data$alive      <- abs(data$death - 1)

# Run regression per arm, predict outcomes, and save results, a column per arm

f                <- alive ~ age + risk + severity

model_f          <- function(arm) glm(f, data=data[trt==arm],
                                  family=binomial(link="logit"),
                                  y=FALSE, model=FALSE)
arms             <- sort(unique(data$trt))
model_arms       <- lapply(arms, FUN = model_f)

predict_arm      <- function(model) predict(model, data, type = "response")
r_data           <- lapply(model_arms, FUN = predict_arm)
r_data           <- do.call(cbind, r_data)
colnames(r_data) <- paste0("r", (1:max(arms)))

# Bind data and model predictions

data             <- cbind(data,r_data)

m     <- glm(I(trt-1) ~ age + risk + severity, data=data, family=binomial(link="logit"))
data$p <-predict(m, type = "response")

f          <- alive ~ trt | age + risk + severity | r1 + r2 | p

bandit     <- OfflineDoublyRobustBandit$new(formula = f, data = data)

# Define agents.
agents      <- list(Agent$new(LinUCBDisjointOptimizedPolicy$new(0.2), bandit, "LinUCB"),
                    Agent$new(FixedPolicy$new(1), bandit, "Arm1"),
                    Agent$new(FixedPolicy$new(2), bandit, "Arm2"))

# Initialize the simulation.

simulation  <- Simulator$new(agents = agents, simulations = simulations, horizon = horizon)

# Run the simulation.
sim  <- simulation$run()

# plot the results
plot(sim, type = "cumulative", regret = FALSE, rate = TRUE, legend_position = "bottomright")

plot(sim, type = "arms", limit_agents = "LinUCB")


## End(Not run)
```

OfflineLookupReplayEvaluatorBandit

Bandit: Offline Replay with lookup tables

Description

Alternative interface for replay style bandit.

Details

TODO: Needs to be documented more fully.

Usage

```
bandit <- OfflineLookupReplayEvaluatorBandit(offline_data, k, shared_lookup = NULL, unique_lookup =
  unique_col = NULL, unique = NULL, shared = NULL, randomize = TRUE)
```

Arguments

`offline_data` data.table; offline data source (required)

`k` integer; number of arms (required)

`d` integer; number of contextual features (required)

`randomize` logical; randomize rows of data stream per simulation (optional, default: TRUE)

`unique` integer vector; index of disjoint features (optional)

`shared` integer vector; index of shared features (optional)

Methods

`new(offline_data, k, shared_lookup = NULL, unique_lookup = NULL, unique_col = NULL, unique = NULL,`
generates and instantializes a new `OfflineLookupReplayEvaluatorBandit` instance.

`get_context(t)` argument:

- `t`: integer, time step `t`.

returns a named `list` containing the current `d x k` dimensional matrix `context$X`, the number of arms `context$k` and the number of features `context$d`.

`get_reward(t, context, action)` arguments:

- `t`: integer, time step `t`.
- `context`: list, containing the current `context$X` (d x k context matrix), `context$k` (number of arms) and `context$d` (number of context features) (as set by `bandit`).
- `action`: list, containing `action$choice` (as set by `policy`).

returns a named `list` containing `reward$reward` and, where computable, `reward$optimal` (used by "oracle" policies and to calculate regret).

`post_initialization()` Randomize offline data by shuffling the offline data.table before the start of each individual simulation when self$randomize is TRUE (default)

References

Agrawal, R. (1995). The continuum-armed bandit problem. SIAM journal on control and optimization, 33(6), 1926-1951.

See Also

Core contextual classes: Bandit, Policy, Simulator, Agent, History, Plot

Bandit subclass examples: BasicBernoulliBandit, ContextualLogitBandit, OfflineLookupReplayEvaluatorBandit

Policy subclass examples: EpsilonGreedyPolicy, ContextualLinTSPolicy

Examples

```
## Not run:

library(contextual)
library(data.table)
library(splitstackshape)
library(RCurl)

# Import MovieLens ml-10M

# Info: https://d1ie9wlkzugsxr.cloudfront.net/data_movielens/ml-10M/README.html

movies_dat     <- "http://d1ie9wlkzugsxr.cloudfront.net/data_movielens/ml-10M/movies.dat"
ratings_dat    <- "http://d1ie9wlkzugsxr.cloudfront.net/data_movielens/ml-10M/ratings.dat"

movies_dat      <- readLines(movies_dat)
movies_dat      <- gsub( "::", "~", movies_dat )
movies_dat      <- paste0(movies_dat, collapse = "\n")
movies_dat      <- fread(movies_dat, sep = "~", quote="")
setnames(movies_dat, c("V1", "V2", "V3"), c("MovieID", "Name", "Type"))
movies_dat     <- splitstackshape::cSplit_e(movies_dat, "Type", sep = "|", type = "character",
                                             fill = 0, drop = TRUE)
movies_dat[[3]] <- NULL

ratings_dat     <- RCurl::getURL(ratings_dat)
ratings_dat     <- readLines(textConnection(ratings_dat))
ratings_dat     <- gsub( "::", "~", ratings_dat )
ratings_dat     <- paste0(ratings_dat, collapse = "\n")
ratings_dat     <- fread(ratings_dat, sep = "~", quote="")
setnames(ratings_dat, c("V1", "V2", "V3", "V4"), c("UserID", "MovieID", "Rating", "Timestamp"))

all_movies      <- ratings_dat[movies_dat, on=c(MovieID = "MovieID")]

all_movies      <- na.omit(all_movies,cols=c("MovieID", "UserID"))

rm(movies_dat,ratings_dat)

all_movies[, UserID   := as.numeric(as.factor(UserID))]

count_movies    <- all_movies[,.(MovieCount = .N), by = MovieID]
top_50          <- as.vector(count_movies[order(-MovieCount)][1:50]$MovieID)
not_50        <- as.vector(count_movies[order(-MovieCount)][51:nrow(count_movies)]$MovieID)

top_50_movies   <- all_movies[MovieID %in% top_50]
```

```
# Create feature lookup tables - to speed up, MovieID and UserID are
# ordered and lined up with the (dt/matrix) default index.

# Arm features

# MovieID of top 50 ordered from 1 to N:
top_50_movies[, MovieID   := as.numeric(as.factor(MovieID))]
arm_features    <- top_50_movies[,head(.SD, 1),by = MovieID][,c(1,6:24)]
setorder(arm_features,MovieID)

# User features

# Count of categories for non-top-50 movies normalized per user
user_features   <- all_movies[MovieID %in% not_50]
user_features[, c("MovieID", "Rating", "Timestamp", "Name"):=NULL]
user_features   <- user_features[, lapply(.SD, sum, na.rm=TRUE), by=UserID ]
user_features[, total  := rowSums(.SD, na.rm = TRUE), .SDcols = 2:20]
user_features[, 2:20 := lapply(.SD, function(x) x/total), .SDcols = 2:20]
user_features$total <- NULL

# Add users that were not in the set of non-top-50 movies (4 in 10m dataset)
all_users <- as.data.table(unique(all_movies$UserID))
user_features <- user_features[all_users, on=c(UserID = "V1")]
user_features[is.na(user_features)] <- 0

setorder(user_features,UserID)

rm(all_movies, not_50, top_50, count_movies)

# Contextual format

top_50_movies[, t := .I]
top_50_movies[, sim := 1]
top_50_movies[, agent := "Offline"]
top_50_movies[, choice := MovieID]
top_50_movies[, reward := ifelse(Rating <= 4, 0, 1)]

setorder(top_50_movies,Timestamp,Name)


# Run simulation

simulations <- 1
horizon     <- nrow(top_50_movies)

bandit      <- OfflineLookupReplayEvaluatorBandit$new(top_50_movies,
                                                       k             = 50,
                                                       unique_col    = "UserID",
                                                       shared_lookup = arm_features,
                                                       unique_lookup = user_features)
agents      <-
  list(Agent$new(ThompsonSamplingPolicy$new(), bandit, "Thompson"),
       Agent$new(UCB1Policy$new(), bandit, "UCB1"),
```

```
        Agent$new(RandomPolicy$new(), bandit, "Random"),
        Agent$new(LinUCBHybridOptimizedPolicy$new(0.9), bandit, "LinUCB Hyb 0.9"),
        Agent$new(LinUCBDisjointOptimizedPolicy$new(2.1), bandit, "LinUCB Dis 2.1"))

simulation  <-
  Simulator$new(
    agents          = agents,
    simulations     = simulations,
    horizon         = horizon
  )

results  <- simulation$run()

plot(results, type = "cumulative", regret = FALSE,
     rate = TRUE, legend_position = "topleft")



## End(Not run)
```

`OfflinePropensityWeightingBandit`

Bandit: Offline Propensity Weighted Replay

Description

Policy for the evaluation of policies with offline data through replay with propensity weighting.

Usage

```
bandit <- OfflinePropensityWeightingBandit(formula,
                                            data, k = NULL, d = NULL,
                                            unique = NULL, shared = NULL,
                                         randomize = TRUE, replacement = TRUE,
                                           jitter = TRUE, arm_multiply = TRUE,
                                            inverted = FALSE)
```

Arguments

`formula` formula (required). Format: `y.context ~ z.choice | x1.context + x2.xontext + ... | p.propensity` Wh
leaving out p.propensity, Doubly Robust Bandit uses marginal prob per arm for propensities: By default, adds an intercept to the context model. Exclude the intercept, by adding "0" or "-1" to the list of contextual features, as in: `y.context ~ z.choice | x1.context + x2.xontext -1 | p.propensity`

`data` data.table or data.frame; offline data source (required)

`k` integer; number of arms (optional). Optionally used to reformat the formula defined x.context vector as a `k x d` matrix. When making use of such matrix formatted contexts, you need to define custom intercept(s) when and where needed in data.table or data.frame.

`d` integer; number of contextual features (optional) Optionally used to reformat the formula defined x.context vector as a `k x d` matrix. When making use of such matrix formatted contexts, you need to define custom intercept(s) when and where needed in data.table or data.frame.

`randomize` logical; randomize rows of data stream per simulation (optional, default: TRUE)

`replacement` logical; sample with replacement (optional, default: TRUE)

`jitter` logical; add jitter to contextual features (optional, default: TRUE)

`arm_multiply` logical; multiply the horizon by the number of arms (optional, default: TRUE)

`inverted` logical; have the propensity scores been weighted (optional, default: FALSE)

`threshold` float (0,1); Lower threshold or Tau on propensity score values. Smaller Tau makes for less biased estimates with more variance, and vice versa. For more information, see paper by Strehl at all (2010). Values between 0.01 and 0.05 are known to work well.

`unique` integer vector; index of disjoint features (optional)

`shared` integer vector; index of shared features (optional)

Methods

`new(formula, data, k = NULL, d = NULL, unique = NULL, shared = NULL, randomize = TRUE, replacement`
generates and instantializes a new `OfflinePropensityWeightingBandit` instance.

`get_context(t)` argument:

- `t`: integer, time step `t`.

returns a named `list` containing the current `d x k` dimensional matrix `context$X`, the number of arms `context$k` and the number of features `context$d`.

`get_reward(t, context, action)` arguments:

- `t`: integer, time step `t`.
- `context`: list, containing the current `context$X` (d x k context matrix), `context$k` (number of arms) and `context$d` (number of context features) (as set by `bandit`).
- `action`: list, containing `action$choice` (as set by `policy`).

returns a named `list` containing `reward$reward` and, where computable, `reward$optimal` (used by "oracle" policies and to calculate regret).

`post_initialization()` Randomize offline data by shuffling the offline data.table before the start of each individual simulation when self$randomize is TRUE (default)

References

Agarwal, Alekh, et al. "Taming the monster: A fast and simple algorithm for contextual bandits." International Conference on Machine Learning. 2014.

Strehl, Alex, et al. "Learning from logged implicit exploration data." Advances in Neural Information Processing Systems. 2010.

See Also

Core contextual classes: `Bandit`, `Policy`, `Simulator`, `Agent`, `History`, `Plot`

Bandit subclass examples: `BasicBernoulliBandit`, `ContextualLogitBandit`, `OfflinePropensityWeightingBandit`

Policy subclass examples: `EpsilonGreedyPolicy`, `ContextualLinTSPolicy`

Examples

```
## Not run:

library(contextual)
ibrary(data.table)

# Import myocardial infection dataset

url  <- "http://d1ie9wlkzugsxr.cloudfront.net/data_propensity/myocardial_propensity.csv"
data            <- fread(url)

simulations     <- 3000
horizon         <- nrow(data)

# arms always start at 1
data$trt        <- data$trt + 1

# turn death into alive, making it a reward
data$alive      <- abs(data$death - 1)

# calculate propensity weights

m      <- glm(I(trt-1) ~ age + risk + severity, data=data, family=binomial(link="logit"))
data$p <-predict(m, type = "response")

# run bandit - if you leave out p, Propensity Bandit uses marginal prob per arm for propensities:
# table(private$z)/length(private$z)

f          <- alive ~ trt | age + risk + severity | p

bandit     <- OfflinePropensityWeightingBandit$new(formula = f, data = data)

# Define agents.
agents      <- list(Agent$new(LinUCBDisjointOptimizedPolicy$new(0.2), bandit, "LinUCB"))

# Initialize the simulation.

simulation  <- Simulator$new(agents = agents, simulations = simulations, horizon = horizon)

# Run the simulation.
sim  <- simulation$run()

# plot the results
plot(sim, type = "cumulative", regret = FALSE, rate = TRUE, legend_position = "bottomright")


## End(Not run)
```

`OfflineReplayEvaluatorBandit`

Bandit: Offline Replay

Description

Policy for the evaluation of policies with offline data through replay.

Details

The key assumption of the method is that that the original logging policy chose i.i.d. arms uniformly at random.

Take care: if the original logging policy does not change over trials, data may be used more efficiently via propensity scoring (Langford et al., 2008; Strehl et al., 2011) and related techniques like doubly robust estimation (Dudik et al., 2011).

Usage

```
bandit <- OfflineReplayEvaluatorBandit(formula,
                                        data, k = NULL, d = NULL,
                                        unique = NULL, shared = NULL,
                                       randomize = TRUE, replacement = FALSE,
                                        jitter = FALSE)
```

Arguments

`formula` formula (required). Format: `y.context ~ z.choice | x1.context + x2.xontext + ...` By default, adds an intercept to the context model. Exclude the intercept, by adding "0" or "-1" to the list of contextual features, as in: `y.context ~ z.choice | x1.context + x2.xontext -1`

`data` data.table or data.frame; offline data source (required)

`k` integer; number of arms (optional). Optionally used to reformat the formula defined x.context vector as a `k x d` matrix. When making use of such matrix formatted contexts, you need to define custom intercept(s) when and where needed in data.table or data.frame.

`d` integer; number of contextual features (optional) Optionally used to reformat the formula defined x.context vector as a `k x d` matrix. When making use of such matrix formatted contexts, you need to define custom intercept(s) when and where needed in data.table or data.frame.

`randomize` logical; randomize rows of data stream per simulation (optional, default: TRUE)

`replacement` logical; sample with replacement (optional, default: FALSE)

`replacement` logical; add jitter to contextual features (optional, default: FALSE)

`unique` integer vector; index of disjoint features (optional)

`shared` integer vector; index of shared features (optional)

Methods

`new(formula, data, k = NULL, d = NULL, unique = NULL, shared = NULL, randomize = TRUE, replacement` generates and instantializes a new `OfflineReplayEvaluatorBandit` instance.

`get_context(t)` argument:

- `t`: integer, time step `t`.

returns a named `list` containing the current `d x k` dimensional matrix `context$X`, the number of arms `context$k` and the number of features `context$d`.

`get_reward(t, context, action)` arguments:

- `t`: integer, time step `t`.
- `context`: list, containing the current `context$X` (d x k context matrix), `context$k` (number of arms) and `context$d` (number of context features) (as set by `bandit`).
- `action`: list, containing `action$choice` (as set by `policy`).

returns a named `list` containing `reward$reward` and, where computable, `reward$optimal` (used by "oracle" policies and to calculate regret).

`post_initialization()` Randomize offline data by shuffling the offline data.table before the start of each individual simulation when self$randomize is TRUE (default)

References

Li, Lihong, Chu, Wei, Langford, John, and Wang, Xuanhui. Unbiased offline evaluation of contextual-bandit-based news article recommendation algorithms. In King, Irwin, Nejdl, Wolfgang, and Li, Hang (eds.), Proc. Web Search and Data Mining (WSDM), pp. 297–306. ACM, 2011. ISBN 978-1-4503-0493-1.

See Also

Core contextual classes: `Bandit`, `Policy`, `Simulator`, `Agent`, `History`, `Plot`

Bandit subclass examples: `BasicBernoulliBandit`, `ContextualLogitBandit`, `OfflineReplayEvaluatorBandit`

Policy subclass examples: `EpsilonGreedyPolicy`, `ContextualLinTSPolicy`

Examples

```
## Not run:

url  <- "http://d1ie9wlkzugsxr.cloudfront.net/data_irecsys_CARSKit/Movie_DePaulMovie/ratings.csv"
data <- fread(url, stringsAsFactors=TRUE)

# Convert data

data        <- contextual::one_hot(data, cols = c("Time","Location","Companion"),
                                         sparsifyNAs = TRUE)
data[, itemid := as.numeric(itemid)]
data[, rating := ifelse(rating <= 3, 0, 1)]

# Set simulation parameters.
simulations <- 10  # here, "simulations" represents the number of boostrap samples
horizon     <- nrow(data)

# Initiate Replay bandit with 10 arms and 100 context dimensions
log_S       <- data
formula     <- formula("rating ~ itemid | Time_Weekday + Time_Weekend + Location_Cinema +
                       Location_Home + Companion_Alone + Companion_Family + Companion_Partner")
bandit      <- OfflineReplayEvaluatorBandit$new(formula = formula, data = data)

# Define agents.
agents      <-
```

```
  list(Agent$new(RandomPolicy$new(), bandit, "Random"),
       Agent$new(EpsilonGreedyPolicy$new(0.03), bandit, "EGreedy 0.05"),
       Agent$new(ThompsonSamplingPolicy$new(), bandit, "ThompsonSampling"),
       Agent$new(LinUCBDisjointOptimizedPolicy$new(0.37), bandit, "LinUCB 0.37"))

# Initialize the simulation.
simulation  <-
  Simulator$new(
    agents           = agents,
    simulations      = simulations,
    horizon          = horizon
  )

# Run the simulation.
# Takes about 5 minutes: bootstrapbandit loops
# for arms x horizon x simulations (times nr of agents).

sim  <- simulation$run()

# plot the results
plot(sim, type = "cumulative", regret = FALSE, rate = TRUE,
     legend_position = "topleft", ylim=c(0.48,0.87))


## End(Not run)
```

`ones_in_zeroes` *A vector of zeroes and ones*

Description

A vector of zeroes and ones

Usage

```
ones_in_zeroes(vector_length, index_of_one)
```

Arguments

`vector_length`	How long will the vector be?
`index_of_one`	Where to insert the one?

Value

Vector of zeroes with one(s) at given index position(s) one_hot *One Hot Encoding of data.table columns*

Description

One-Hot-Encode unordered factor columns of a data.table mltools. From ben519's "mltools" package.

Usage

```
one_hot(dt, cols = "auto", sparsifyNAs = FALSE, naCols = FALSE,
  dropCols = TRUE, dropUnusedLevels = FALSE)
```

Arguments

dt	A data.table
cols	Which column(s) should be one-hot-encoded? DEFAULT = "auto" encodes all unordered factor columns.
sparsifyNAs	Should NAs be converted to 0s?
naCols	Should columns be generated to indicate the present of NAs? Will only apply to factor columns with at least one NA
dropCols	Should the resulting data.table exclude the original columns which are one-hot-encoded?
dropUnusedLevels	Should columns of all 0s be generated for unused factor levels?

Details

One-hot-encoding converts an unordered categorical vector (i.e. a factor) to multiple binarized vectors where each binary vector of 1s and 0s indicates the presence of a class (i.e. level) of the of the original vector.

Examples

```
library(data.table)

dt <- data.table(
  ID = 1:4,
  color = factor(c("red", NA, "blue", "blue"), levels=c("blue", "green", "red"))
)

one_hot(dt)
one_hot(dt, sparsifyNAs=TRUE)
one_hot(dt, naCols=TRUE)
one_hot(dt, dropCols=FALSE)
one_hot(dt, dropUnusedLevels=TRUE)
```

OraclePolicy *Policy: Oracle*

Description

OraclePolicy is a also known as a "cheating" or "godlike" policy, as it knows the reward probabilities at all times, and will always play the optimal arm. It is often used as a baseline to compare other policies to.

Usage

```
policy <- OraclePolicy()
```

Arguments

name character string specifying this policy. name is, among others, saved to the History log and displayed in summaries and plots.

Methods

new() Generates a new OraclePolicy object. Arguments are defined in the Argument section above.

set_parameters() each policy needs to assign the parameters it wants to keep track of to list self$theta_to_arms that has to be defined in set_parameters()'s body. The parameters defined here can later be accessed by arm index in the following way: theta[[index_of_arm]]$parameter_name

get_action(context) here, a policy decides which arm to choose, based on the current values of its parameters and, potentially, the current context.

set_reward(reward, context) in set_reward(reward, context), a policy updates its parameter values based on the reward received, and, potentially, the current context.

References

Gittins, J., Glazebrook, K., & Weber, R. (2011). Multi-armed bandit allocation indices. John Wiley & Sons. (Original work published 1989)

See Also

Core contextual classes: Bandit, Policy, Simulator, Agent, History, Plot

Bandit subclass examples: BasicBernoulliBandit, ContextualLogitBandit, OfflineReplayEvaluatorBandit

Policy subclass examples: EpsilonGreedyPolicy, ContextualLinTSPolicy

Plot *Plot*

Description

Generates plots from `History` data.

Details

Usually not instantiated directly but invoked by calling the generic `plot(h)`, where `h` is an `History` class instance.

Usage

```
Plot <- Plot$new()
```

Methods

`cumulative(history,...)` Plots cumulative regret or reward (depending on parameter regret=TRUE/FALSE) over time.

`average(history,...)` Plots average regret or reward (depending on parameter regret=TRUE/FALSE) over time.

`arms(history),...` Plot the percentage of simulations per time step each arm was chosen over time. If multiple agents have been run, plots only the first agent.

Plot method arguments

`type (character, "cumulative")` Can be either "cumulative" (default), "average", or "arms". Sets the plot method when Plot() is called through R's generic plot() function. Methods are descrived in the Methods section above.

`regret (logical, TRUE)` Plot policy regret (default, TRUE) or reward (FALSE)?

`rate (logical, TRUE)` If rate is TRUE, the rate of regret or reward is plotted.

`limit_agents (list , NULL)` Limit plotted agents to the agents in the list.

`limit_context (integer vector , NULL)` Only plots data of context(s) where vector equals 1 in as.vector(context), excludes where 0 or unspecified.

`no_par (logical, FALSE)` If no_par is TRUE, Plot() does not set or adjust plotting parameters itself. This makes it possible to set custom plotting parameters through R's par() function.

`legend (logical, TRUE)` Shows the legend when TRUE (default).

`legend_title (character , NULL)` Sets a custom legend title.

`legend_labels (character list , NULL)` Sets legend labels to custom values as specified in list.

`legend_border (logical , NULL)` When TRUE, the legend is borderless.

`legend_position` (character , "topleft") a single keyword from the list "bottomright", "bottom", "bottomleft", "left", "topleft", "top", "topright", "right" and "center". This places the legend on the inside of the plot frame at the given location.

`xlim` (c(integer,integer), NULL) Sets x-axis limits.

`ylim` (c(integer,integer), NULL) Sets y-axis limits.

`log` (character , "") A character string which contains "x" if the x axis is to be logarithmic, "y" if the y axis is to be logarithmic and "xy" or "yx" if both axes are to be logarithmic.

`use_colors` (logical, TRUE) If use_colors is FALSE, plots will be in grayscale. Otherwise, plots will make use of a color palette (default).

`disp` (character, NULL) When disp (for "dispersion measure") is set to either 'var','sd' or 'ci', the variance, standard deviation, or 95

`plot_only_disp` (logical, FALSE) When TRUE and disp is either 'var','sd' or 'ci', plot only dispersion measure.

`traces` (logical , FALSE) Plot traces of independent simulations (default is FALSE).

`traces_max` (integer , 100) The number of trace lines.

`traces_alpha` (numeric , 0.3) Opacity of the trace lines. Default is 0.3 - that is, an opacity of 30

`smooth` (logical , FALSE) Smooth the plot (default is FALSE)

`interval` (integer, NULL) Plot only every t

`cum_average` (logical , FALSE) Calculates moving average from cum_reward or cum_regret with step size `interval`.

`color_step` (integer, 1) When > 1, the plot cycles through `nr_agents/color_step` colors.

`lty_step` (integer, 1) When > 1, the plot cycles through `nr_agents/lty_step` line types.

`lwd` (integer, 1) Line width.

See Also

Core contextual classes: Bandit, Policy, Simulator, Agent, History, Plot

Bandit subclass examples: BasicBernoulliBandit, ContextualLogitBandit, OfflineReplayEvaluatorBandit

Policy subclass examples: EpsilonGreedyPolicy, ContextualLinTSPolicy

Examples

```
## Not run:

bandit <- ContextualPrecachingBandit$new(weights = c(0.9, 0.1, 0.1))

agents <- list(Agent$new(RandomPolicy$new(), bandit),
               Agent$new(OraclePolicy$new(), bandit),
               Agent$new(ThompsonSamplingPolicy$new(1.0, 1.0), bandit),
               Agent$new(Exp3Policy$new(0.1), bandit),
               Agent$new(GittinsBrezziLaiPolicy$new(), bandit),
               Agent$new(UCB1Policy$new(), bandit))

history <- Simulator$new(agents, horizon = 100, simulations = 1000)$run()
```

```
par(mfrow = c(3, 2), mar = c(1, 4, 2, 1), cex=1.3)

plot(history, type = "cumulative", use_colors = FALSE, no_par = TRUE, legend_border = FALSE,
     limit_agents = c("GittinsBrezziLai", "UCB1","ThompsonSampling"))

plot(history, type = "cumulative", regret = FALSE, legend = FALSE,
     limit_agents = c("UCB1"), traces = TRUE, no_par = TRUE)

plot(history, type = "cumulative", regret = FALSE, rate = TRUE, disp = "sd",
     limit_agents = c("Exp3", "ThompsonSampling"),
     legend_position = "bottomright", no_par = TRUE)

plot(history, type = "cumulative", rate = TRUE, plot_only_disp = TRUE,
     disp = "var", smooth = TRUE, limit_agents = c("UCB1", "GittinsBrezziLai"),
    legend_position = "bottomleft", no_par = TRUE)

plot(history, type = "average", disp = "ci", regret = FALSE, interval = 10,
     smooth = TRUE, legend_position = "bottomright", no_par = TRUE, legend = FALSE)

plot(history, limit_agents = c("ThompsonSampling"), type = "arms",
     interval = 20, no_par = TRUE)


## End(Not run)
```

`plot.history` *Plot Method for Contextual History*

Description

plot.history, a method for the plot generic. It is designed for a quick look at History data.

Usage

```
## S3 method for class 'History'
plot(x, ...)
```

Arguments

`x`	A `History` object.
`...`	Further plotting parameters.

See Also

Core contextual classes: `Simulator`, `Agent`, `History`, `Plot`

Bandit classes: `Bandit`, `BasicBernoulliBandit`, `OfflineReplayEvaluatorBandit`, `ContextualLogitBandit`

Policy *Policy: Superclass*

Description

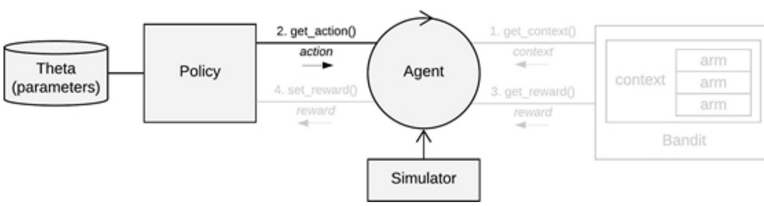
Parent or superclass of all `{contextual}` `Policy` subclasses.

Details

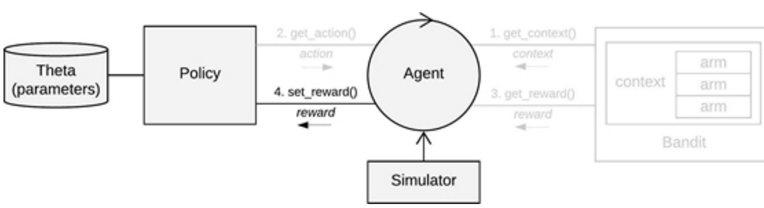
On every t = 1, . . . , T, a policy receives `d` dimensional feature vector or `d x k` dimensional matrix `context$X*`, the current number of `Bandit` arms in `context$k`, and the current number of contextual features in `context$d`.

To make sure a policy supports both contextual feature vectors and matrices in `context$X`, it is suggested any contextual policy makes use of **contextual**'s `get_arm_context(context, arm)` utility function to obtain the current context for a particular arm, and `get_full_context(context)` where a policy makes direct use of a `d x k` context matrix.

It has to compute which of the `k` `Bandit` arms to pull by taking into account this contextual information plus the policy's current parameter values stored in the named list `theta`. On selecting an arm, the policy then returns its index as `action$choice`.



On pulling a `Bandit` arm the policy receives a `Bandit` reward through `reward$reward`. In combination with the current `context$X*` and `action$choice`, this reward can then be used to update to the policy's parameters as stored in list `theta`.



* Note: in context-free scenario's, `context$X` can be omitted.

Usage

```
policy <- Policy$new()
```

Methods

`new()` Generates and initializes a new `Policy` object.

`get_action(t, context)` arguments:

- t: integer, time step t.
- context: list, containing the current context$X (d x k context matrix), context$k (number of arms) and context$d (number of context features)

computes which arm to play based on the current values in named list theta and the current context. Returns a named list containing action$choice, which holds the index of the arm to play.

set_reward(t, context, action, reward) arguments:

- t: integer, time step t.
- context: list, containing the current context$X (d x k context matrix), context$k (number of arms) and context$d (number of context features) (as set by bandit).
- action: list, containing action$choice (as set by policy).
- reward: list, containing reward$reward and, if available, reward$optimal (as set by bandit).

utilizes the above arguments to update and return the set of parameters in list theta.

set_parameters() Helper function, called during a Policy's initialisation, assigns the values it finds in list self$theta_to_arms to each of the Policy's k arms. The parameters defined here can then be accessed by arm index in the following way: theta[[index_of_arm]]$parameter_name.

See Also

Core contextual classes: Bandit, Policy, Simulator, Agent, History, Plot

Bandit subclass examples: BasicBernoulliBandit, ContextualLogitBandit, OfflineReplayEvaluatorBandit

Policy subclass examples: EpsilonGreedyPolicy, ContextualLinTSPolicy

---

print.history — *Print Method for Contextual History*

Description

print.history, a method for the print generic. It is designed for a quick look at History data.

Usage

```
## S3 method for class 'History'
print(x, ...)
```

Arguments

x	A History object.
...	Further plotting parameters.

See Also

Core contextual classes: Simulator, Agent, History, Plot

Bandit classes: Bandit, BasicBernoulliBandit, OfflineReplayEvaluatorBandit, ContextualLogitBandit

prob_winner *Binomial Win Probability*

Description

Function to compute probability that each arm is the winner, given simulated posterior results.

Usage

```
prob_winner(post)
```

Arguments

post	Simulated results from the posterior, as provided by sim_post()

Value

Probabilities each arm is the winner.

Author(s)

Thomas Lotze and Markus Loecher

Examples

```
x <- c(10,20,30,50)
n <- c(100,102,120,130)
betaPost <- sim_post(x,n)
pw <- prob_winner(betaPost)
```

RandomPolicy *Policy: Random*

Description

`RandomPolicy` always explores, choosing arms uniformly at random. In that respect, `RandomPolicy` is the mirror image of a pure greedy policy, which would always seek to exploit.

Usage

```
policy <- RandomPolicy(name = "RandomPolicy")
```

Arguments

name character string specifying this policy. name is, among others, saved to the History log and displayed in summaries and plots.

Methods

new() Generates a new RandomPolicy object. Arguments are defined in the Argument section above.

set_parameters() each policy needs to assign the parameters it wants to keep track of to list self$theta_to_arms that has to be defined in set_parameters()'s body. The parameters defined here can later be accessed by arm index in the following way: theta[[index_of_arm]]$parameter_name

get_action(context) here, a policy decides which arm to choose, based on the current values of its parameters and, potentially, the current context.

set_reward(reward, context) in set_reward(reward, context), a policy updates its parameter values based on the reward received, and, potentially, the current context.

References

Gittins, J., Glazebrook, K., & Weber, R. (2011). Multi-armed bandit allocation indices. John Wiley & Sons. (Original work published 1989)

See Also

Core contextual classes: Bandit, Policy, Simulator, Agent, History, Plot

Bandit subclass examples: BasicBernoulliBandit, ContextualLogitBandit, OfflineReplayEvaluatorBandit

Policy subclass examples: EpsilonGreedyPolicy, ContextualLinTSPolicy

Examples

```
horizon            <- 100L
simulations        <- 100L
weights            <- c(0.9, 0.1, 0.1)

policy             <- RandomPolicy$new()
bandit             <- BasicBernoulliBandit$new(weights = weights)
agent              <- Agent$new(policy, bandit)

history           <- Simulator$new(agent, horizon, simulations, do_parallel = FALSE)$run()

plot(history, type = "arms")
```

sample_one_of — *Sample one element from vector or list*

Description

Takes one sample from a vector or list. Does not throw an error for zero length lists.

Usage

```
sample_one_of(x)
```

Arguments

`x`	A vector of one or more elements from which to choose

Value

One value, drawn from x.

set_external — *Change Default Graphing Device from RStudio*

Description

Checks to see if the user is in RStudio. If so, then it changes the device to a popup window.

Usage

```
set_external(ext = TRUE, width = 10, height = 6)
```

Arguments

`ext`	A `logical` indicating whether to plot in a popup or within the RStudio UI.
`width`	Width in pixels of the popup window
`height`	Height in pixels of the popup window

Details

Depending on the operating system, the default drivers attempted to be used are:

OS X: quartz()

Linux: x11()

Windows: windows()

Note, this setting is not permanent. Thus, the behavioral change will last until the end of the session.

Also, the active graphing environment will be killed. As a result, any graphs that are open will be deleted.

Examples

```
## Not run:

# Turn on external graphs
external_graphs()

# Turn off external graphs
external_graphs(F)

## End(Not run)
```

`sherman_morrisson` *Sherman-Morrisson inverse*

Description

Sherman-Morrisson inverse

Usage

```
sherman_morrisson(inv, x)
```

Arguments

`inv`	to be updated inverse matrix
`x`	column vector to update inv with

`Simulator` *Simulator*

Description

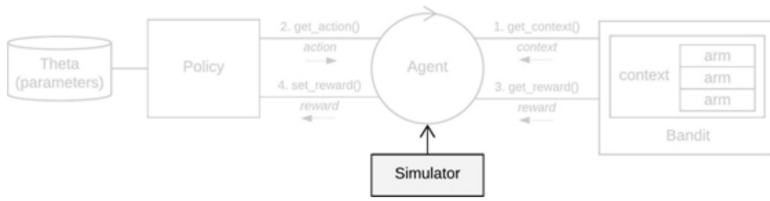
The entry point of any **contextual** simulation.

Details

A Simulator takes, at a minimum, one or more `Agent` instances, a horizon (the length of an individual simulation, $t = 1, \ldots, T$) and the number of simulations (How many times to repeat each simulation over $t = 1, \ldots, T$, with a new seed on each repeat*).

It then runs all simulations (in parallel by default), keeping a log of all `Policy` and `Bandit` interactions in a `History` instance.

* Note: to be able to fairly evaluate and compare each agent's performance, and to make sure that simulations are replicable, for each separate agent, seeds are set equally and deterministically for each agent over all `horizon x simulations` time steps.



Usage

```
simulator <- Simulator$new(agents,
                           horizon = 100L,
                           simulations = 100L,
                           save_interval = 1,
                           save_context = FALSE,
                           save_theta = FALSE,
                           do_parallel = TRUE,
                           worker_max = NULL,
                           t_over_sims = FALSE,
                           set_seed = 0,
                           progress_file = FALSE,
                           include_packages = NULL)
```

Arguments

`agents` An `Agent` instance or a `list` of `Agent` instances.

`horizon` `integer`. The number of pulls or time steps to run each agent, where $t = 1, \ldots, T$.

`simulations` `integer`. How many times to repeat each agent's simulation over $t = 1, \ldots, T$, with a new seed on each repeat (itself deterministically derived from set_seed).

`save_interval` `integer`. Write data to historyonly every `save_interval` time steps. Default is 1.

`save_context` `logical`. Save the context matrices `X` to the History log during a simulation?

`save_theta` `logical`. Save the parameter list `theta` to the History log during a simulation?

`do_parallel` `logical`. Run `Simulator` processes in parallel?

`worker_max` `integer`. Specifies how many parallel workers are to be used. If unspecified, the amount of workers defaults to `max(workers_available)-1`.

`t_over_sims` `logical`. Of use to, among others, offline Bandits. If `t_over_sims` is set to `TRUE`, the current `Simulator` iterates over all rows in a data set for each repeated simulation. If `FALSE`, it splits the data into `simulations` parts, and a different subset of the data for each repeat of an agent's simulation.

`set_seed` `integer`. Sets the seed of R's random number generator for the current `Simulator`.

`progress_file` `logical`. If `TRUE`, `Simulator` writes `workers_progress.log`, `agents_progress.log` and `parallel.log` files to the current working directory, allowing you to keep track of respectively `workers`, `agents`, and potential errors when running a `Simulator` in parallel mode.

`log_interval` `integer`. Sets the log write interval. Default every 1000 time steps.

include_packages List. List of packages that (one of) the policies depend on. If a Policy requires an R package to be loaded, this option can be used to load that package on each of the workers. Ignored if do_parallel is FALSE.

chunk_multiplier integer By default, simulations are equally divided over available workers, and every worker saves its simulation results to a local history file which is then aggregated. Depending on workload, network bandwith, memory size and other variables it can sometimes be useful to break these workloads into smaller chunks. This can be done by setting the chunk_multiplier to some integer value, where the number of chunks will total chunk_multiplier x number_of_workers.

Methods

reset() Resets a Simulator instance to its original initialisation values.

run() Runs a Simulator instance.

history Active binding, read access to Simulator's History instance.

See Also

Core contextual classes: Bandit, Policy, Simulator, Agent, History, Plot

Bandit subclass examples: BasicBernoulliBandit, ContextualLogitBandit, OfflineReplayEvaluatorBandit

Policy subclass examples: EpsilonGreedyPolicy, ContextualLinTSPolicy

Examples

```
## Not run:

  policy    <- EpsilonGreedyPolicy$new(epsilon = 0.1)
  bandit    <- BasicBernoulliBandit$new(weights = c(0.6, 0.1, 0.1))
  agent     <- Agent$new(policy, bandit, name = "E.G.", sparse = 0.5)

  history   <- Simulator$new(agents = agent,
                             horizon = 10,
                             simulations = 10)$run()

  summary(history)

  plot(history)

  dt <- history$get_data_table()

  df <- history$get_data_frame()

  print(history$cumulative$E.G.$cum_regret_sd)

  print(history$cumulative$E.G.$cum_regret)


## End(Not run)
```

sim_post *Binomial Posterior Simulator*

Description

Simulates the posterior distribution of the Bayesian probabilities for each arm being the best binomial bandit.

Usage

```
sim_post(x, n, alpha = 1, beta = 1, ndraws = 5000)
```

Arguments

x	Vector of the number of successes per arm.
n	Vector of the number of trials per arm.
alpha	Shape parameter alpha for the prior beta distribution.
beta	Shape parameter beta for the prior beta distribution.
ndraws	Number of random draws from the posterior.

Value

Matrix of bayesian probabilities for each arm being the best binomial bandit

Author(s)

Thomas Lotze and Markus Loecher

Examples

```
x <- c(10,20,30,50)
n <- c(100,102,120,130)
sp <- sim_post(x,n)
```

`SoftmaxPolicy` *Policy: Softmax*

Description

`SoftmaxPolicy` is very similar to Exp3Policy, but selects an arm based on the probability from the Boltmann distribution. It makes use of a temperature parameter tau, which specifies how many arms we can explore. When tau is high, all arms are explored equally, when tau is low, arms offering higher rewards will be chosen.

Usage

```
policy <- SoftmaxPolicy(tau = 0.1)
```

Arguments

`tau = 0.1` double, temperature parameter tau specifies how many arms we can explore. When tau is high, all arms are explored equally, when tau is low, arms offering higher rewards will be chosen.

Methods

`new(epsilon = 0.1)` Generates a new `SoftmaxPolicy` object. Arguments are defined in the Argument section above.

`set_parameters()` each policy needs to assign the parameters it wants to keep track of to list `self$theta_to_arms` that has to be defined in `set_parameters()`'s body. The parameters defined here can later be accessed by arm index in the following way: `theta[[index_of_arm]]$parameter_name`

`get_action(context)` here, a policy decides which arm to choose, based on the current values of its parameters and, potentially, the current context.

`set_reward(reward, context)` in `set_reward(reward, context)`, a policy updates its parameter values based on the reward received, and, potentially, the current context.

References

Kuleshov, V., & Precup, D. (2014). Algorithms for multi-armed bandit problems. arXiv preprint arXiv:1402.6028.

Cesa-Bianchi, N., Gentile, C., Lugosi, G., & Neu, G. (2017). Boltzmann exploration done right. In Advances in Neural Information Processing Systems (pp. 6284-6293).

See Also

Core contextual classes: `Bandit`, `Policy`, `Simulator`, `Agent`, `History`, `Plot`

Bandit subclass examples: `BasicBernoulliBandit`, `ContextualLogitBandit`, `OfflineReplayEvaluatorBandit`

Policy subclass examples: `EpsilonGreedyPolicy`, `ContextualLinTSPolicy`

Examples

```
horizon            <- 100L
simulations        <- 100L
weights          <- c(0.9, 0.1, 0.1)

policy             <- SoftmaxPolicy$new(tau = 0.1)
bandit             <- BasicBernoulliBandit$new(weights = weights)
agent              <- Agent$new(policy, bandit)

history          <- Simulator$new(agent, horizon, simulations, do_parallel = FALSE)$run()

plot(history, type = "cumulative")

plot(history, type = "arms")
```

---

summary.history — *Summary Method for Contextual History*

Description

summary.history, a method for the summary generic. It is designed for a quick summary of History data.

Usage

```
## S3 method for class 'History'
summary(object, ...)
```

Arguments

object	A History object.
...	Further summary parameters.

See Also

Core contextual classes: Bandit, Policy, Simulator, Agent, History, Plot

Bandit subclass examples: BasicBernoulliBandit, ContextualLogitBandit, OfflineReplayEvaluatorBandit

Policy subclass examples: EpsilonGreedyPolicy, ContextualLinTSPolicy

sum_of — *Sum of list*

Description

Returns the sum of the values of the elements of a list `x`.

Usage

```
sum_of(x)
```

Arguments

`x`	List

Details

If there is a tie, and equal_is_random is TRUE, the index of one of the tied maxima is returned at random. Otherwise, the value with the lowest index is returned.

Examples

```
theta = list(par_one = list(1,2,3), par_two = list(2,3,4))
sum_of(theta$par_one)
```

ThompsonSamplingPolicy — *Policy: Thompson Sampling*

Description

`ThompsonSamplingPolicy` works by maintaining a prior on the the mean rewards of its arms. In this, it follows a beta-binomial model with parameters alpha and beta, sampling values for each arm from its prior and picking the arm with the highest value. When an arm is pulled and a Bernoulli reward is observed, it modifies the prior based on the reward. This procedure is repeated for the next arm pull.

Usage

```
policy <- ThompsonSamplingPolicy(alpha = 1, beta = 1)
```

Arguments

`alpha` integer, a natural number N>0 - first parameter of the Beta distribution

`beta` integer, a natural number N>0 - second parameter of the Beta distribution

Methods

`new(alpha = 1, beta = 1)` Generates a new `ThompsonSamplingPolicy` object. Arguments are defined in the Argument section above.

`set_parameters()` each policy needs to assign the parameters it wants to keep track of to list `self$theta_to_arms` that has to be defined in `set_parameters()`'s body. The parameters defined here can later be accessed by arm index in the following way: `theta[[index_of_arm]]$parameter_name`

`get_action(context)` here, a policy decides which arm to choose, based on the current values of its parameters and, potentially, the current context.

`set_reward(reward, context)` in `set_reward(reward, context)`, a policy updates its parameter values based on the reward received, and, potentially, the current context.

References

Thompson, W. R. (1933). On the likelihood that one unknown probability exceeds another in view of the evidence of two samples. Biometrika, 25(3/4), 285-294.

Chapelle, O., & Li, L. (2011). An empirical evaluation of thompson sampling. In Advances in neural information processing systems (pp. 2249-2257).

Agrawal, S., & Goyal, N. (2013, February). Thompson sampling for contextual bandits with linear payoffs. In International Conference on Machine Learning (pp. 127-135).b

See Also

Core contextual classes: `Bandit`, `Policy`, `Simulator`, `Agent`, `History`, `Plot`

Bandit subclass examples: `BasicBernoulliBandit`, `ContextualLogitBandit`, `OfflineReplayEvaluatorBandit`

Policy subclass examples: `EpsilonGreedyPolicy`, `ContextualLinTSPolicy`

Examples

```
horizon            <- 100L
simulations        <- 100L
weights            <- c(0.9, 0.1, 0.1)

policy             <- ThompsonSamplingPolicy$new(alpha = 1, beta = 1)
bandit             <- BasicBernoulliBandit$new(weights = weights)
agent              <- Agent$new(policy, bandit)

history          <- Simulator$new(agent, horizon, simulations, do_parallel = FALSE)$run()

plot(history, type = "cumulative")
```

UCB1Policy *Policy: UCB1*

Description

UCB policy for bounded bandits with a Chernoff-Hoeffding Bound

Details

`UCB1Policy` constructs an optimistic estimate in the form of an Upper Confidence Bound to create an estimate of the expected payoff of each action, and picks the action with the highest estimate. If the guess is wrong, the optimistic guess quickly decreases, till another action has the higher estimate.

Usage

```
policy <- UCB1Policy()
```

Methods

`new()` Generates a new `UCB1Policy` object.

`set_parameters()` each policy needs to assign the parameters it wants to keep track of to list `self$theta_to_arms` that has to be defined in `set_parameters()`'s body. The parameters defined here can later be accessed by arm index in the following way: `theta[[index_of_arm]]$parameter_name`

`get_action(context)` here, a policy decides which arm to choose, based on the current values of its parameters and, potentially, the current context.

`set_reward(reward, context)` in `set_reward(reward, context)`, a policy updates its parameter values based on the reward received, and, potentially, the current context.

References

Lai, T. L., & Robbins, H. (1985). Asymptotically efficient adaptive allocation rules. Advances in applied mathematics, 6(1), 4-22.

See Also

Core contextual classes: `Bandit`, `Policy`, `Simulator`, `Agent`, `History`, `Plot`

Bandit subclass examples: `BasicBernoulliBandit`, `ContextualLogitBandit`, `OfflineReplayEvaluatorBandit`

Policy subclass examples: `EpsilonGreedyPolicy`, `ContextualLinTSPolicy`

Examples

```
## Not run:

horizon            <- 100L
simulations        <- 100L
weights            <- c(0.9, 0.1, 0.1)

policy             <- UCB1Policy$new()
bandit             <- BasicBernoulliBandit$new(weights = weights)
agent              <- Agent$new(policy, bandit)

history          <- Simulator$new(agent, horizon, simulations, do_parallel = FALSE)$run()

plot(history, type = "cumulative")

plot(history, type = "arms")


## End(Not run)
```

UCB2Policy — *Policy: UCB2*

Description

UCB policy for bounded bandits with plays divided in epochs.

Details

`UCB2Policy` constructs an optimistic estimate in the form of an Upper Confidence Bound to create an estimate of the expected payoff of each action, and picks the action with the highest estimate. If the guess is wrong, the optimistic guess quickly decreases, till another action has the higher estimate.

Usage

```
policy <- UCB2Policy(alpha = 0.1)
```

Arguments

`alpha` numeric; Tuning parameter in the interval `(0,1)`

Methods

`new(alpha = 0.1)` Generates a new `UCB2Policy` object.

`set_parameters()` each policy needs to assign the parameters it wants to keep track of to list `self$theta_to_arms` that has to be defined in `set_parameters()`'s body. The parameters defined here can later be accessed by arm index in the following way: `theta[[index_of_arm]]$parameter_name` `get_action(context)` here, a policy decides which arm to choose, based on the current values of its parameters and, potentially, the current context.

`set_reward(reward, context)` in `set_reward(reward, context)`, a policy updates its parameter values based on the reward received, and, potentially, the current context.

References

Auer, P., Cesa-Bianchi, N., & Fischer, P. (2002). Finite-time analysis of the multiarmed bandit problem. Machine learning, 47(2-3), 235-256.

See Also

Core contextual classes: `Bandit`, `Policy`, `Simulator`, `Agent`, `History`, `Plot`

Bandit subclass examples: `BasicBernoulliBandit`, `ContextualLogitBandit`, `OfflineReplayEvaluatorBandit`

Policy subclass examples: `EpsilonGreedyPolicy`, `ContextualLinTSPolicy`

Examples

```
horizon            <- 100L
simulations        <- 100L
weights          <- c(0.9, 0.1, 0.1)

policy             <- UCB2Policy$new()
bandit             <- BasicBernoulliBandit$new(weights = weights)
agent              <- Agent$new(policy, bandit)

history          <- Simulator$new(agent, horizon, simulations, do_parallel = FALSE)$run()

plot(history, type = "cumulative")

plot(history, type = "arms")
```

`value_remaining` *Potential Value Remaining*

Description

Compute "value_remaining" in arms not currently best in binomial bandits

Usage

```
value_remaining(x, n, alpha = 1, beta = 1, ndraws = 10000)
```

Arguments

x	Vector of the number of successes per arm.
n	Vector of the number of trials per arm.
alpha	Shape parameter alpha for the prior beta distribution.
beta	Shape parameter beta for the prior beta distribution.
ndraws	Number of random draws from the posterior.

Value

Value_remaining distribution; the distribution of improvement amounts that another arm might have over the current best arm.

Author(s)

Thomas Lotze and Markus Loecher

Examples

```
x <- c(10,20,30,80)
n <- c(100,102,120,240)
vr <- value_remaining(x, n)
hist(vr)

# "potential value" remaining in the experiment
potential_value <- quantile(vr, 0.95)
```

---

var_welford *Welford's variance*

Description

Welford described a method for 'robust' one-pass computation of the standard deviation. By 'robust', we mean robust to round-off caused by a large shift in the mean.

Usage

```
var_welford(z)
```

Arguments

z	vector

Value

variance

which_max_list — *Get maximum value in list*

Description

Returns the index of the maximum value in list x.

Usage

```
which_max_list(x, equal_is_random = TRUE)
```

Arguments

x	vector of values
equal_is_random	boolean

Details

If there is a tie and equal_is_random is TRUE, the index of one of the tied maxima is returned at random.

If equal_is_random is FALSE, the maximum with the lowest index number is returned.

Examples

```
theta = list(par_one = list(1,2,3), par_two = list(2,3,4))
which_max_list(theta$par_one)
```

which_max_tied — *Get maximum value randomly breaking ties*

Description

Returns the index of the maximum value in vector vec.

Usage

```
which_max_tied(x, equal_is_random = TRUE)
```

Arguments

x	vector of values
equal_is_random	boolean

Details

If there is a tie, and equal_is_random is TRUE, the index of one of the tied maxima is returned at random. Otherwise, the value with the lowest index is returned.

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