# Package 'atmopt'

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Type Package

Version 0.1.0

Title Analysis-of-Marginal-Tail-Means

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|---|
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| <b>Description</b> Provides functions for implementing the Analysis-of-marginal-Tail-Means (ATM) method, a robust optimization method for discrete black-box optimization. Technical details can be found in Mak and Wu (2018+) <arxiv:1712.03589>. This work was supported by USARO grant W911NF-17-1-0007.</arxiv:1712.03589> |
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atmopt-package

Analysis-of-marginal-Tail-Means

## **Description**

The 'atmopt' package provides functions for implementing the ATM optimization method in Mak and Wu (2018+) <arXiv:1712.03589>.

#### **Details**

Package: atmopt
Type: Package
Version: 1.0

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The 'atmopt' package provides functions for implementing the Analysis-of-marginal-Tail-Means (ATM) method in Mak and Wu (2018+). ATM is a robust method for discrete, black-box optimization, where function evaluations are expensive and limited.

#### Author(s)

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#### References

Mak, S. and Wu, C. F. J. (2018+). Analysis-of-marginal-Tail-Means (ATM): a robust method for discrete black-box optimization. Under review.

atm.addpts

Add new data for ATM

#### **Description**

atm. addpts adds new data into an ATM object.

## Usage

atm.addpts(atm.obj,des.new,obs.new)

atm.addpts 3

#### **Arguments**

atm.obj Current ATM object.

des.new Design matrix for new evaluations.

obs.new Observations for new evaluations.

#### **Examples**

}

```
## Not run:
# Example 1: detpep10exp (9-D)
nfact <- 9 #number of factors
ntimes <- floor(nfact/3) #number of "repeats" for detpep10exp
lev <- 4 #number of levels
nlev <- rep(lev,nfact) #number of levels for each factor</pre>
nelim <- 3 #number of level eliminations
fn <- function(xx){detpep10exp(xx,ntimes,nlev)} + objective to minimize (assumed expensive)
#initialize objects
# (predicts & removes levels based on tuned ATM percentages)
fit.atm <- atm.init(nfact,nlev)</pre>
#initialize sel.min object
# (predicts minimum using smallest observed value & removes levels with largest minima)
fit.min <- atm.init(nfact,nlev)</pre>
#Run for nelim eliminations:
res.atm <- rep(NA,nelim) #for ATM results
res.min <- rep(NA,nelim) #for sel.min results
for (i in 1:nelim){
  # ATM updates:
  new.des <- atm.nextpts(fit.atm) #get design points</pre>
  new.obs <- apply(new.des,1,fn) #sample function</pre>
  fit.atm <- atm.addpts(fit.atm,new.des,new.obs) #add data to object</pre>
  fit.atm <- atm.predict(fit.atm) #predict minimum setting</pre>
  idx.atm <- fit.atm$idx.opt</pre>
  res.atm[i] <- fn(idx.atm)</pre>
  fit.atm <- atm.remlev(fit.atm) #removes worst performing level</pre>
  # sel.min updates:
  new.des <- atm.nextpts(fit.min) #get design points</pre>
  new.obs <- apply(new.des,1,fn) #sample function</pre>
  fit.min <- atm.addpts(fit.min,new.des,new.obs) #add data to object</pre>
 fit.min <- atm.predict(fit.min, alphas=rep(0,nfact)) #find setting with smallest observation
  idx.min <- fit.min$idx.opt</pre>
  res.min[i] <- fn(idx.min)</pre>
  #check: min(fit.min$obs.all)
  fit.min <- atm.remlev(fit.min) #removes worst performing level</pre>
```

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```
res.atm
res.min
#conclusion: ATM finds better solutions by learning & exploiting additive structure
# Example 2: camel6 (24-D)
nfact <- 24 #number of factors
ntimes <- floor(nfact/2.0) #number of "repeats" for camel6</pre>
lev <- 4
nlev <- rep(lev,nfact) #number of levels for each factor</pre>
nelim <- 3 #number of level eliminations
fn \leftarrow function(xx){camel6(xx,ntimes,nlev)} #objective to minimize (assumed expensive)
#initialize objects
# (predicts & removes levels based on tuned ATM percentages)
fit.atm <- atm.init(nfact,nlev)</pre>
#initialize sel.min object
# (predicts minimum using smallest observed value & removes levels with largest minima)
fit.min <- atm.init(nfact,nlev)</pre>
#Run for nelim eliminations:
res.atm <- rep(NA,nelim) #for ATM results
res.min <- rep(NA, nelim) #for sel.min results
for (i in 1:nelim){
 # ATM updates:
 new.des <- atm.nextpts(fit.atm) #get design points</pre>
 new.obs <- apply(new.des,1,fn) #sample function</pre>
 fit.atm <- atm.addpts(fit.atm,new.des,new.obs) #add data to object</pre>
 fit.atm <- atm.predict(fit.atm) #predict minimum setting</pre>
 idx.atm <- fit.atm$idx.opt</pre>
 res.atm[i] <- fn(idx.atm)</pre>
 fit.atm <- atm.remlev(fit.atm) #removes worst performing level</pre>
 # sel.min updates:
 new.des <- atm.nextpts(fit.min) #get design points</pre>
 new.obs <- apply(new.des,1,fn) #sample function</pre>
 fit.min <- atm.addpts(fit.min,new.des,new.obs) #add data to object</pre>
 fit.min <- atm.predict(fit.min, alphas=rep(0,nfact)) #find setting with smallest observation
 idx.min <- fit.min$idx.opt</pre>
 res.min[i] <- fn(idx.min)</pre>
 #check: min(fit.min$obs.all)
 fit.min <- atm.remlev(fit.min) #removes worst performing level</pre>
}
res atm
res.min
```

#conclusion: ATM finds better solutions by learning & exploiting additive structure

atm.init 5

```
## End(Not run)
```

atm.init

Initializing ATM object

## Description

atm. init initialize the ATM object to use for optimization.

## Usage

```
atm.init(nfact, nlev)
```

## Arguments

nfact Number of factors to optimize.

nlev A vector containing the number of levels for each factor.

## **Examples**

```
nfact <- 9 #number of factors
lev <- 4
nlev <- rep(lev,nfact) #number of levels for each factor
fit <- atm.init(nfact,nlev) #initialize ATM object</pre>
```

atm.nextpts

Computes new design points for ATM

## Description

atm. nextpts computes new design points to evaluate using a randomized orthogonal array (OA).

## Usage

```
atm.nextpts(atm.obj,reps=NULL)
```

## Arguments

atm.obj Current ATM object.

reps Number of desired replications for OA.

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```
# Example 1: detpep10exp (9-D)
nfact <- 9 #number of factors
ntimes <- floor(nfact/3) #number of "repeats" for detpep10exp</pre>
lev <- 4 #number of levels
nlev <- rep(lev,nfact) #number of levels for each factor</pre>
nelim <- 3 #number of level eliminations
fn < -function(xx){detpep10exp(xx,ntimes,nlev)} + function(xx){detpep10exp(xx,ntimes,nlev)} + function(xx){detpep10exp(xx){detpep10exp(xx){detpep10exp(xx){detpep10exp(xx){detpep10exp(xx){detpep10exp(xx){detpep10exp(xx){detpep10exp(xx){detpep10exp(xx){detpep10exp(xx){detpep10exp(xx){detpep10exp(xx){detpep10exp(xx){detpep10exp(xx){detpep10exp(xx){detpep10exp(xx){detpep10exp(xx){detpep10exp(xx){detpep10exp(xx){detpep10exp(xx){detpep10exp(xx){detpep10exp(xx){detpep10exp(xx){detpep10exp(xx){detpep10exp(xx){detpep10exp(xx){detpep10exp(xx){detpep10exp(xx){detpep10exp(xx){detpep10exp(xx){detpe
#initialize objects
# (predicts & removes levels based on tuned ATM percentages)
fit.atm <- atm.init(nfact,nlev)</pre>
#initialize sel.min object
# (predicts minimum using smallest observed value & removes levels with largest minima)
fit.min <- atm.init(nfact,nlev)</pre>
#Run for nelim eliminations:
res.atm <- rep(NA, nelim) #for ATM results
res.min <- rep(NA, nelim) #for sel.min results
for (i in 1:nelim){
   # ATM updates:
   new.des <- atm.nextpts(fit.atm) #get design points</pre>
   new.obs <- apply(new.des,1,fn) #sample function</pre>
   fit.atm <- atm.addpts(fit.atm,new.des,new.obs) #add data to object
   fit.atm <- atm.predict(fit.atm) #predict minimum setting</pre>
   idx.atm <- fit.atm$idx.opt</pre>
   res.atm[i] <- fn(idx.atm)</pre>
   fit.atm <- atm.remlev(fit.atm) #removes worst performing level</pre>
   # sel.min updates:
   new.des <- atm.nextpts(fit.min) #get design points</pre>
   new.obs <- apply(new.des,1,fn) #sample function</pre>
   fit.min <- atm.addpts(fit.min,new.des,new.obs) #add data to object</pre>
   fit.min <- atm.predict(fit.min, alphas=rep(0,nfact)) #find setting with smallest observation
   idx.min <- fit.min$idx.opt</pre>
   res.min[i] <- fn(idx.min)</pre>
   #check: min(fit.min$obs.all)
   fit.min <- atm.remlev(fit.min) #removes worst performing level</pre>
}
res.atm
res.min
#conclusion: ATM finds better solutions by learning & exploiting additive structure
# Example 2: camel6 (24-D)
```

atm.predict 7

```
nfact <- 24 #number of factors
ntimes <- floor(nfact/2.0) #number of "repeats" for camel6</pre>
lev <- 4
nlev <- rep(lev,nfact) #number of levels for each factor</pre>
nelim <- 3 #number of level eliminations</pre>
fn <- function(xx){camel6(xx,ntimes,nlev)} #objective to minimize (assumed expensive)</pre>
#initialize objects
# (predicts & removes levels based on tuned ATM percentages)
fit.atm <- atm.init(nfact,nlev)</pre>
#initialize sel.min object
# (predicts minimum using smallest observed value & removes levels with largest minima)
fit.min <- atm.init(nfact,nlev)</pre>
#Run for nelim eliminations:
res.atm <- rep(NA,nelim) #for ATM results
res.min <- rep(NA,nelim) #for sel.min results
for (i in 1:nelim){
  # ATM updates:
  new.des <- atm.nextpts(fit.atm) #get design points</pre>
  new.obs <- apply(new.des,1,fn) #sample function</pre>
  fit.atm <- atm.addpts(fit.atm,new.des,new.obs) #add data to object</pre>
  fit.atm <- atm.predict(fit.atm) #predict minimum setting</pre>
  idx.atm <- fit.atm$idx.opt</pre>
  res.atm[i] <- fn(idx.atm)</pre>
  fit.atm <- atm.remlev(fit.atm) #removes worst performing level</pre>
  # sel.min updates:
  new.des <- atm.nextpts(fit.min) #get design points</pre>
  new.obs <- apply(new.des,1,fn) #sample function</pre>
  fit.min <- atm.addpts(fit.min,new.des,new.obs) #add data to object</pre>
 fit.min <- atm.predict(fit.min, alphas=rep(0,nfact)) #find setting with smallest observation
  idx.min <- fit.min$idx.opt</pre>
  res.min[i] <- fn(idx.min)</pre>
  #check: min(fit.min$obs.all)
  fit.min <- atm.remlev(fit.min) #removes worst performing level</pre>
}
res.atm
res.min
#conclusion: ATM finds better solutions by learning & exploiting additive structure
## End(Not run)
```

atm.predict

Predict the minimum setting for ATM

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#### **Description**

atm. init predicts the minimum setting for an ATM object.

#### Usage

```
atm.predict(atm.obj,alphas=NULL,ntimes=1,nsub=100,prob.am=0.5,prob.pw=1.0,reps=NULL)
```

#### **Arguments**

| atm.obj | Current ATM object.   |
|---------|---|
| alphas  | A p-vector for ATM percentiles. NULL if tuned from data.  |
| ntimes  | Number of resamples for tuning ATM percentages.   |
| nsub    | Number of candidate percentiles to consider.  |
| prob.am | In case of ties in percentage estimation, the probability of choosing marginal means (if optimal) for minimization. |
| prob.pw | In case of ties in percentage estimation, probability of picking-the-winner (if optimal) for minimization.          |
| reps    | Number of replications for internal OA in tuning ATM percentages.   |

```
## Not run:
# Example 1: detpep10exp (9-D)
nfact <- 9 #number of factors
ntimes <- floor(nfact/3) #number of "repeats" for detpep10exp</pre>
lev <- 4 #number of levels</pre>
nlev <- rep(lev,nfact) #number of levels for each factor</pre>
nelim <- 3 #number of level eliminations
fn <- function(xx){detpep10exp(xx,ntimes,nlev)} #objective to minimize (assumed expensive)</pre>
#initialize objects
# (predicts & removes levels based on tuned ATM percentages)
fit.atm <- atm.init(nfact,nlev)</pre>
#initialize sel.min object
# (predicts minimum using smallest observed value & removes levels with largest minima)
fit.min <- atm.init(nfact,nlev)</pre>
#Run for nelim eliminations:
res.atm <- rep(NA,nelim) #for ATM results</pre>
res.min <- rep(NA, nelim) #for sel.min results
for (i in 1:nelim){
 # ATM updates:
 new.des <- atm.nextpts(fit.atm) #get design points</pre>
 new.obs <- apply(new.des,1,fn) #sample function</pre>
 fit.atm <- atm.addpts(fit.atm,new.des,new.obs) #add data to object</pre>
 fit.atm <- atm.predict(fit.atm) #predict minimum setting</pre>
```

atm.predict 9

```
idx.atm <- fit.atm$idx.opt</pre>
 res.atm[i] <- fn(idx.atm)</pre>
 fit.atm <- atm.remlev(fit.atm) #removes worst performing level</pre>
 # sel.min updates:
 new.des <- atm.nextpts(fit.min) #get design points</pre>
 new.obs <- apply(new.des,1,fn) #sample function</pre>
 fit.min <- atm.addpts(fit.min,new.des,new.obs) #add data to object</pre>
 fit.min <- atm.predict(fit.min, alphas=rep(0,nfact)) #find setting with smallest observation
 idx.min <- fit.min$idx.opt</pre>
 res.min[i] <- fn(idx.min)</pre>
 #check: min(fit.min$obs.all)
 fit.min <- atm.remlev(fit.min) #removes worst performing level</pre>
}
res.atm
res.min
#conclusion: ATM finds better solutions by learning & exploiting additive structure
# Example 2: camel6 (24-D)
nfact <- 24 #number of factors
ntimes <- floor(nfact/2.0) #number of "repeats" for camel6</pre>
lev <- 4
nlev <- rep(lev,nfact) #number of levels for each factor</pre>
nelim <- 3 #number of level eliminations</pre>
fn \leftarrow function(xx)\{camel6(xx,ntimes,nlev)\}\ #objective to minimize (assumed expensive)
#initialize objects
# (predicts & removes levels based on tuned ATM percentages)
fit.atm <- atm.init(nfact,nlev)</pre>
#initialize sel.min object
# (predicts minimum using smallest observed value & removes levels with largest minima)
fit.min <- atm.init(nfact,nlev)</pre>
#Run for nelim eliminations:
res.atm <- rep(NA,nelim) #for ATM results
res.min <- rep(NA, nelim) #for sel.min results
for (i in 1:nelim){
 # ATM updates:
 new.des <- atm.nextpts(fit.atm) #get design points</pre>
 new.obs <- apply(new.des,1,fn) #sample function</pre>
 fit.atm <- atm.addpts(fit.atm,new.des,new.obs) #add data to object</pre>
 fit.atm <- atm.predict(fit.atm) #predict minimum setting</pre>
 idx.atm <- fit.atm$idx.opt</pre>
 res.atm[i] <- fn(idx.atm)</pre>
 fit.atm <- atm.remlev(fit.atm) #removes worst performing level</pre>
 # sel.min updates:
```

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```
new.des <- atm.nextpts(fit.min) #get design points
new.obs <- apply(new.des,1,fn) #sample function
fit.min <- atm.addpts(fit.min,new.des,new.obs) #add data to object
fit.min <- atm.predict(fit.min, alphas=rep(0,nfact)) #find setting with smallest observation
idx.min <- fit.min$idx.opt
res.min[i] <- fn(idx.min)
#check: min(fit.min$obs.all)
fit.min <- atm.remlev(fit.min) #removes worst performing level
}
res.atm
res.atm
res.min
#conclusion: ATM finds better solutions by learning & exploiting additive structure
## End(Not run)</pre>
```

atm.remlev

Removing worst levels for ATM

#### **Description**

atm. remlev removes the worst (i.e., highest) levels from each factor in ATM.

#### Usage

```
atm.remlev(atm.obj)
```

#### **Arguments**

atm.obj

Current ATM object.

atm.remlev 11

```
# (predicts minimum using smallest observed value & removes levels with largest minima)
fit.min <- atm.init(nfact,nlev)</pre>
#Run for nelim eliminations:
res.atm <- rep(NA,nelim) #for ATM results</pre>
res.min <- rep(NA,nelim) #for sel.min results</pre>
for (i in 1:nelim){
 # ATM updates:
 new.des <- atm.nextpts(fit.atm) #get design points</pre>
 new.obs <- apply(new.des,1,fn) #sample function</pre>
 fit.atm <- atm.addpts(fit.atm,new.des,new.obs) #add data to object</pre>
 fit.atm <- atm.predict(fit.atm) #predict minimum setting</pre>
 idx.atm <- fit.atm$idx.opt</pre>
 res.atm[i] <- fn(idx.atm)</pre>
 fit.atm <- atm.remlev(fit.atm) #removes worst performing level</pre>
 # sel.min updates:
 new.des <- atm.nextpts(fit.min) #get design points</pre>
 new.obs <- apply(new.des,1,fn) #sample function</pre>
 fit.min <- atm.addpts(fit.min,new.des,new.obs) #add data to object</pre>
 fit.min <- atm.predict(fit.min, alphas=rep(0,nfact)) #find setting with smallest observation
 idx.min <- fit.min$idx.opt</pre>
 res.min[i] <- fn(idx.min)</pre>
 #check: min(fit.min$obs.all)
 fit.min <- atm.remlev(fit.min) #removes worst performing level</pre>
}
res.atm
res.min
#conclusion: ATM finds better solutions by learning & exploiting additive structure
# Example 2: camel6 (24-D)
nfact <- 24 #number of factors
ntimes <- floor(nfact/2.0) #number of "repeats" for camel6</pre>
lev <- 4
nlev <- rep(lev,nfact) #number of levels for each factor</pre>
nelim <- 3 #number of level eliminations
fn <- function(xx){camel6(xx,ntimes,nlev)} #objective to minimize (assumed expensive)</pre>
#initialize objects
# (predicts & removes levels based on tuned ATM percentages)
fit.atm <- atm.init(nfact,nlev)</pre>
#initialize sel.min object
# (predicts minimum using smallest observed value & removes levels with largest minima)
fit.min <- atm.init(nfact,nlev)</pre>
#Run for nelim eliminations:
res.atm <- rep(NA, nelim) #for ATM results
```

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```
res.min <- rep(NA, nelim) #for sel.min results
for (i in 1:nelim){
  # ATM updates:
  new.des <- atm.nextpts(fit.atm) #get design points</pre>
  new.obs <- apply(new.des,1,fn) #sample function</pre>
  fit.atm <- atm.addpts(fit.atm,new.des,new.obs) #add data to object</pre>
  fit.atm <- atm.predict(fit.atm) #predict minimum setting</pre>
  idx.atm <- fit.atm$idx.opt</pre>
  res.atm[i] <- fn(idx.atm)</pre>
  fit.atm <- atm.remlev(fit.atm) #removes worst performing level</pre>
  # sel.min updates:
  new.des <- atm.nextpts(fit.min) #get design points</pre>
  new.obs <- apply(new.des,1,fn) #sample function</pre>
  fit.min <- atm.addpts(fit.min,new.des,new.obs) #add data to object</pre>
 fit.min <- atm.predict(fit.min, alphas=rep(0,nfact)) #find setting with smallest observation
  idx.min <- fit.min$idx.opt</pre>
  res.min[i] <- fn(idx.min)</pre>
  #check: min(fit.min$obs.all)
  fit.min <- atm.remlev(fit.min) #removes worst performing level</pre>
}
res.atm
res.min
#conclusion: ATM finds better solutions by learning & exploiting additive structure
## End(Not run)
```

camel6

Six-hump discrete test function

#### **Description**

A discrete test function constructed from the six-hump camel function in Ali et al. (2005).

#### Usage

```
camel6(xx,ntimes,nlev)
```

#### **Arguments**

A *p*-vector for input factors.

ntimes Number of duplications for the function (base function is 2D).

nlev A p-vector corresponding to the number of levels for each factor(discretized on

equally-spaced intervals).

detpep10exp

## **Examples**

```
xx <- c(1,2,1,2,1,2) #input factors nlev <- rep(4,length(xx)) #number of levels for each factor ntimes <- length(xx)/2 #base function is in 2D, so duplicate 3 times camel6(xx,ntimes,nlev)
```

detpep10exp

DetPep10Exp discrete test function

## **Description**

A discrete test function constructed from the modified exponential function in Dette and Pepelyshev (2010).

#### Usage

```
detpep10exp(xx,ntimes,nlev)
```

## Arguments

A *p*-vector for input factors.

ntimes Number of duplications for the function (base function is 3D).

nlev A p-vector corresponding to the number of levels for each factor(discretized on

equally-spaced intervals).

```
xx <- c(1,2,1,2,1,2) #input factors nlev <- rep(4,length(xx)) #number of levels for each factor ntimes <- length(xx)/3 #base function is in 2D, so duplicate 2 times detpep10exp(xx,ntimes,nlev)
```

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