

# Package ‘CBT’

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**Type** Package

**Title** Confidence Bound Target Algorithm

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**Description** The Confidence Bound Target (CBT) algorithm is designed for infinite arms bandit problem. It is shown that CBT algorithm achieves the regret lower bound for general reward distributions. Reference: Hock Peng Chan and Shouri Hu (2018) <[arXiv:1805.11793](#)>.

**License** GPL-2

**RoxygenNote** 6.0.1

**NeedsCompilation** no

**Repository** CRAN

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CBT	<i>Confidence Bound Target (CBT) Algorithm</i>
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### Description

CBT and Emp\_CBT provide simulation to infinite arms with Bernoulli Rewards. CBT assumes prior distribution in known whereas Emp\_CBT does not. Ana\_CBT performs analysis to real data.

**Usage**

```
CBT(n, prior, bn = log(log(n)), cn = log(log(n)))
Emp_CBT(n, prior, bn = log(log(n)), cn = log(log(n)))
Ana_CBT(n, data, bn = log(log(n)), cn = log(log(n)))
```

**Arguments**

n	total number of rewards.
prior	prior distribution on mean of the rewards. Currently available priors: "Uniform", "Sine" and "Cosine".
bn	bn should increase slowly to infinity with n.
cn	cn should increase slowly to infinity with n.
data	A matrix or dataframe. Each column is a population.

**Details**

If bn or cn are not specified they assume the default value of  $\log(\log(n))$ .  
The confidence bound for an arm with  $t$  observations is

$$L = \max(xbar/bn, xbar - cn * sigma/sqrt(t)),$$

where xbar and sigma are the mean and standard deviation of the rewards from that particular arm.  
CBT is a non-recalling algorithm. An arm is played until its confidence bound  $L$  drops below the target mean  $\mu_*$ , and it is not played after that.

If the prior distribution is unknown, we shall apply empirical CBT, in which the target mean  $\mu_*$  is replaced by  $S/n$ , with  $S$  the sum of rewards among all arms played at current stage. Unlike CBT however empirical CBT is a recalling algorithm which decides from among all arms which to play further, rather than to consider only the current arm.

**Value**

A list including elements

regret	cumulative regret generated by n rewards.
K	total number of experimented arms.

**Author(s)**

Hock Peng Chan and Shouri Hu

**References**

H.P. Chan and S. Hu (2018) Infinite Arms Bandit: Optimality via Confidence Bounds <arXiv:1805.11793>

**Examples**

```
R = 1000

cum_regret = numeric(R)
arms = numeric(R)

for(i in 1:R){
  result = CBT(n = 10000, prior = "Sine")
  cum_regret[i] = result$regret
  arms[i] = result$K
}

mean(cum_regret)
sd(cum_regret)/sqrt(R)
mean(arms)
sd(arms)/sqrt(R)
```

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