Thresholding Bandits with Augmented UCB

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Overview

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- The distributions for each of the arms are fixed throughout the time horizon denoted by T.

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- The above goal has to be achieved within T timesteps of exploration and this is termed as a fixed-budget problem.
- At the end of the given T timesteps the learner must recommend a set of arms which (according to it) are the arms having reward mean above τ.

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- Let $\hat{S}_\tau$ denote the recommendation of a learning algorithm after T time units of exploration, while $\hat{S}_\tau^c$ denotes its complement.
- The goal of the learning agent is to minimize the expected loss:

$$\begin{aligned}\mathbb{E}[\mathcal{L}(T)] &= \mathbb{P}\big(\{S_\tau \cap \hat{S}_\tau^c \neq \emptyset\} \cup \{\hat{S}_\tau \cap S_\tau^c \neq \emptyset\}\big) \\ &= 1 - \mathbb{P}\big(\{\hat{S}_\tau \cap S_\tau^c = \emptyset\}\big)\end{aligned}$$

Challenges in the TBP Settings

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- The higher the variance of the arms' the more difficult is to discriminate.

Some practical applications

- Selecting the best channels (out of several existing channels) for mobile communications in a very short duration whose qualities are above an acceptable threshold (see [Audibert and Bubeck(2010)]).

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- In anomaly detection and classification (see Locatelli et al. (2016)).

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- It is the first variance-based arm elimination algorithm for the considered TBP settings.
- It address an open problem discussed in [Auer and Ortner(2010)] of designing an algorithm that can eliminate arms based on variance estimates.
- It is the first algorithm on the larger pure exploration setting which uses empirical variance estimates along with arm elimination with a new problem complexity.

The UCB Approach

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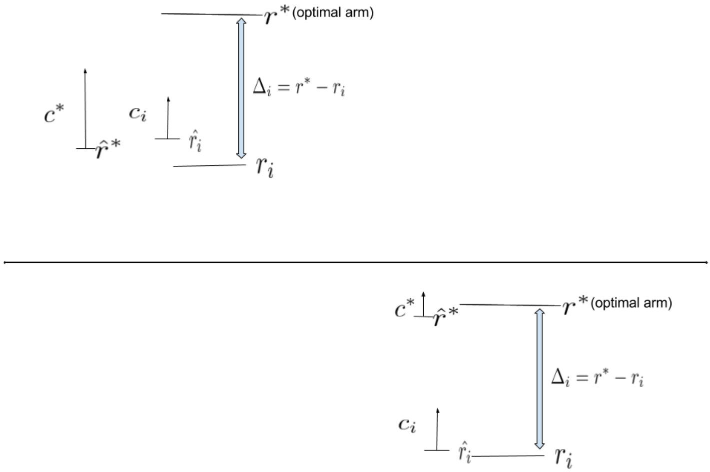
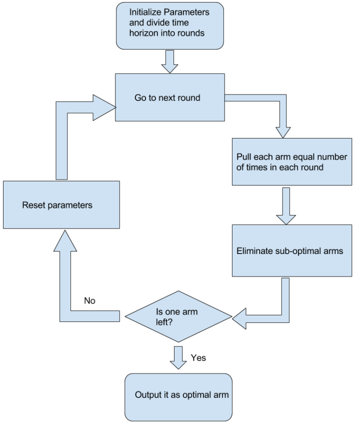
- c_i ensures that the arm i is properly explored and is gradually reduced with time as one pulls the arm i more.
- At every timestep pull arms that has the maximum value of $\hat{r}_i + c_i$ and this will ensure that proper exploration is done.

Figure: UCB Intuition



Approach of UCB-Improved (UCB-Imp)

Figure: UCB Imp Approach



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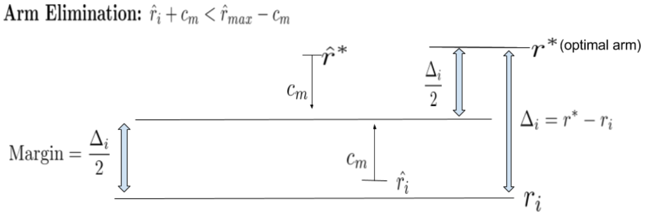

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- Theoretically they proved this algorithm to be almost optimal when only mean estimation is used as a metric of comparison.
- Empirically it outperformed other state-of-the-art algorithms which were modified to perform in the TBP setting.

Intuition of APT

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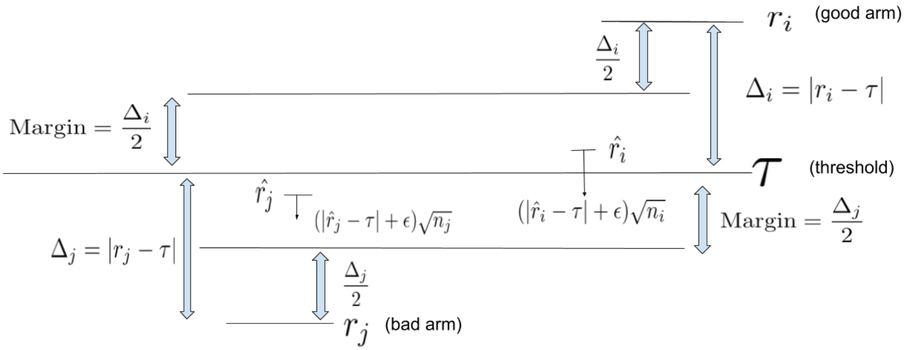


APT Algorithm

Algorithm 1 APT

Input: Time horizon T, threshold τ, tolerance factor $\epsilon \geq 0$

Pull each arm once

for $t = K + 1, .., T$ **do**

Pull arm $j \in \arg\min_{i \in A} \left\{ (|\hat{r}_i - \tau| + \epsilon) \sqrt{n_i} \right\}$ and observe the reward for arm j.

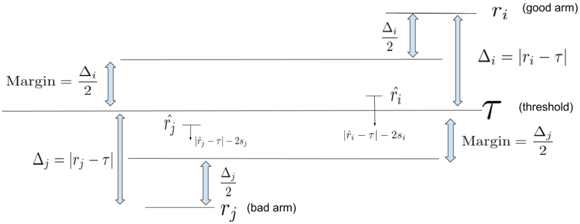
end for

Output: $\hat{S}_\tau = \{i : \hat{r}_i \geq \tau\}$.

AugUCB algorithm (Intuition, Arm pulling)

- We define $\Delta_i = |r_i - \tau|$.
- It is risky to eliminate arm i while $\hat{r}_i$ is inside *Margin*.
- Confidence interval s_i will make sure arm i is not eliminated while inside Margin with a high probability.

Figure: AugUCB Intuition (Arm pulling)



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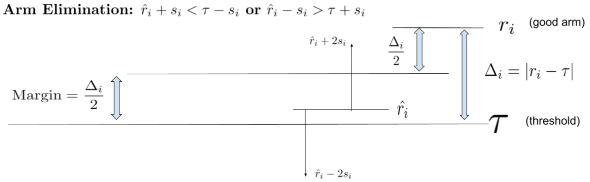

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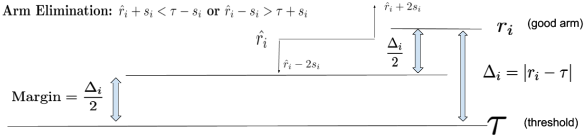

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- At every timestep now we run the arm elimination check to eliminate sub-optimal arms.
- At the end of the phase we reset the parameters.
- Note that the length of the phase, the exploration parameters and the confidence interval term $s_i = \sqrt{\frac{\rho\psi_m(\hat{v}_i+1)\log(T\epsilon_m)}{4n_i}}$ are set through detailed theoretical analysis.

AugUCB algorithm I

Input: Time budget T; parameter ρ; threshold τ
Initialization: $B_0 = \mathcal{A}$; $m = 0$; $\epsilon_0 = 1$;

$$M = \left\lfloor \frac{1}{2} \log_2 \frac{T}{e} \right\rfloor ; \quad \psi_0 = \frac{T\epsilon_0}{128\Big(\log(\frac{3}{16} K \log K)\Big)^2};$$

$$\ell_0 = \left\lceil \frac{2\psi_0 \log(T\epsilon_0)}{\epsilon_0} \right\rceil ; \quad N_0 = K\ell_0$$

Pull each arm once

for $t = K + 1, .., T$ **do**
  Pull arm $j \in \arg\min_{i \in B_m} \left\{ |\hat{r}_i - \tau| - 2s_i \right\}$
  for $i \in B_m$ **do**
    if $(\hat{r}_i + s_i < \tau - s_i)$ or $(\hat{r}_i - s_i > \tau + s_i)$ **then**
      $B_m \leftarrow B_m \backslash \{i\}$ (Arm deletion)
    end if

end for

if $t \geq N_m$ and $m \leq M$ **then**

Reset Parameters

$\epsilon_{m+1} \leftarrow \frac{\epsilon_m}{2}$

$B_{m+1} \leftarrow B_m$

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$\ell_{m+1} \leftarrow \left\lceil \frac{2\psi_{m+1}\log(T\epsilon_{m+1})}{\epsilon_{m+1}} \right\rceil$

$N_{m+1} \leftarrow t + |B_{m+1}|\ell_{m+1}$

$m \leftarrow m + 1$

end if

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- The relationship between H_1 and H_2 can be derived as,

$$H_2 \leq H_1 \leq \log(2K) H_2$$

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- For a variance aware algorithm we define $H_{\sigma,1}$ (as in Gabillon et al. (2011)) that incorporates reward variances into its expression as:

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- Finally, analogous to H_2, we introduce $H_{\sigma,2}$, such that $H_{\sigma,2} = \max_{i \in \mathcal{A}} \frac{i}{\tilde{\Delta}_{(i)}^2}$, where $\tilde{\Delta}_i^2 = \frac{\Delta_i^2}{\sigma_i + \sqrt{\sigma_i^2 + (16/3)\Delta_i}}$, $(\tilde{\Delta}_{(i)})$ is an increasing ordering of $(\tilde{\Delta}_i)$.

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$$H_{\sigma,2} \leq H_{\sigma,1} \leq \log(2K) H_{\sigma,2}.$$

- Note that H_1, H_2 and $H_{\sigma,1}, H_{\sigma,2}$ are not directly comparable to each other except in a special case when variances are very low we can say that $H_{\sigma,1} < H_1$.

Expected Loss of AugUCB

Theorem

For $K \geq 4$ and $\rho = 1/3$, the expected loss of the AugUCB algorithm is given by,

$$\mathbb{E}[\mathcal{L}(T)] \leq 2KT \exp\left(-\frac{T}{4096 \log(K \log K) H_{\sigma,2}}\right).$$

Table: AugUCB vs. State of the art

Algorithm	Upper Bound on Expected Loss
AugUCB	$\exp\left(-\frac{T}{4096 \log(K \log K) H_{\sigma,2}} + \log(2KT)\right)$
UCBEV	$\exp\left(-\frac{1}{512}\frac{T-2K}{H_{\sigma,1}} + \log(6KT)\right)$
APT	$\exp\left(-\frac{T}{64 H_1} + 2\log((\log(T)+1)K)\right)$
CSAR	$\exp\left(-\frac{T-K}{72\log(K) H_{CSAR,2}} + 2\log(K)\right)$

Concentration Bounds

- Let $X_1, ..., X_n$ be random variables with common support $[0, 1]$ and such that $E[X_t | X_1, ..., X_{t-1}] = r_i$. Let $\hat{r}_i = \dfrac{X_1 +, ..., +X_n}{n}$. Then for all $c \geq 0$,

$$\mathbb{P}\{\hat{r}_i \geq r_i + c\} \leq \exp\left(-2c^2 n\right)$$
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- Along with the above information if we know that $\mathrm{Var}[X_t|X_1, ..., X_{t-1}] = \sigma_i^2$ then Bernstein inequality gives us,

$$\mathbb{P}\{\hat{r}_i \geq r_i + c\} \leq \exp\left(-\frac{c^2 n}{2\sigma_i^2 + \frac{2c}{3}}\right)$$
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- We bound the arm-elimination probability by Bernstein inequality (as in Audibert et al. (2009)) rather that the Chernoff-Hoeffding bounds (used in UCB-Imp).
- In the second module,we define a favourable event that will yield an upper bound on the expected loss and use union bound and module-1 (on the arm elimination probability) to derive the result through a series of simplifications.

Finally, experiment!!!

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- APT, AugUCB, CSAR, UA do not require access to H_1 or $H_{\sigma,1}$.
- UCBE, UCBEV, CSAR and UA come from the pure exploration lineage and are modified suitably to perform in TBP setting.

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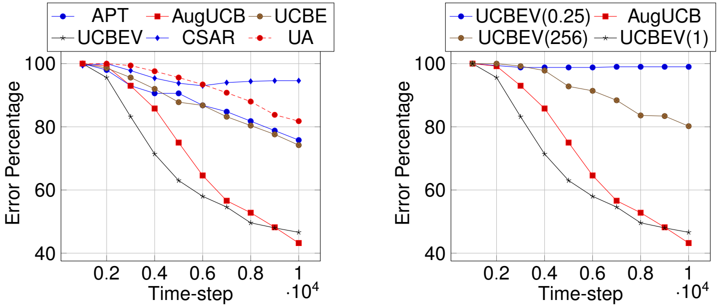
- The first 10 arms partitioned into two groups; the respective means are $r_{1:5} = 0.45$, $r_{6:10} = 0.55$.
- The means of arms $i = 11 : 100$ are chosen same as $r_{11:100} = 0.4$.
- Variances are set as $\sigma^2_{1:5} = 0.3$ and $\sigma^2_{6:10} = 0.8$; $\sigma^2_{11:100}$ are independently and uniformly chosen in the interval $[0.2, 0.3]$.

Experimental Result



(a) Expt-1: Two Group Setting (Advance)

(b) Expt-2: Two Group Setting (Advance)

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- Further studies are required to establish a lower bound on the expected loss of AugUCB.
- A more detailed analysis of the non-uniform arm selection and parameter selection is also required.

Future direction in MS

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- Termed as Efficient UCBV, we are preparing for submission for AAAI 2018.
- I am going to INRIA, SequeL Lab, Lille, France for a three month internship starting from 1st September under Dr. Odalric Maillard.

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Any Questions?

References I

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Thank You