Thresholding Bandits with Augmented UCB

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Overview

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- The rewards for each of the arms are identical and independent random variables drawn from distribution specific to the arm.
- The learner does not know the mean $r_i, \forall i \in A$ of the distribution or the variance σ_i^2.

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- The more we pull arm i the closer $\hat{r}_i$ gets to r_i.
- Due to the uncertainty in $\hat{r}_i$ we have to carefully conduct exploration.

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- **Condition:** This has to be achieved within T timesteps of exploration and this is termed as a fixed-budget problem.

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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:

$$\mathbb{E}[\mathcal{L}(T)] = \mathbb{P}\Big(\underbrace{\{S_\tau \cap \hat{S}_\tau^c \neq \emptyset\}}_{\textbf{Rejected good arms}} \cup \underbrace{\{\hat{S}_\tau \cap S_\tau^c \neq \emptyset\}}_{\textbf{Accepted bad arms}} \Big)$$

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- Higher the variance of reward distribution of the arms' $\Rightarrow$ harder the problem.

Applications

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- Selecting a small set of best workers (out of a very large pool of workers) whose productivity is above a threshold.
- 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 addresses an open problem discussed in Auer and Ortner (2010) of designing an algorithm that can eliminate arms based on variance estimates.
- We also define a new problem complexity which uses empirical variance estimates along with arm's mean for giving the theoretical bound.

The Upper Confidence Bound (UCB) Approach

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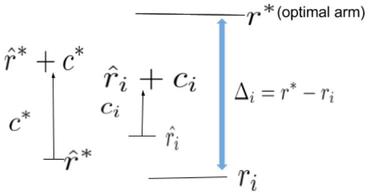
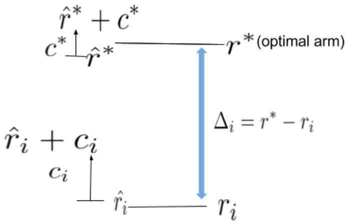
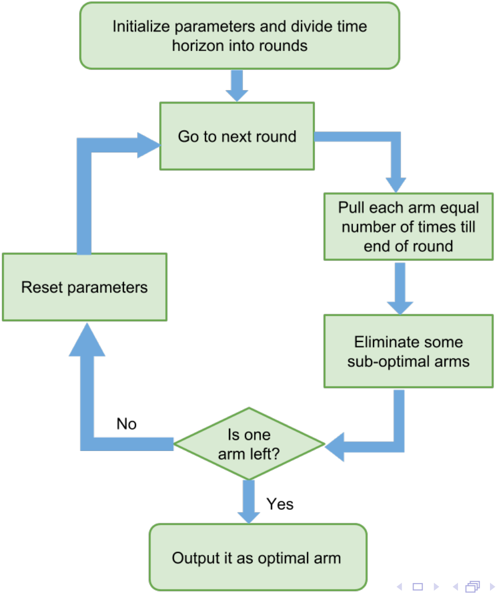
- c_i ensures that the arm i is properly explored and is gradually reduced with time as one pulls the arm i more.
- At every timestep pull arm $j \in \arg\max_{i \in A}\{\hat{r}_i + c_i\}$ and this will ensure that proper exploration is done.

The UCB Approach



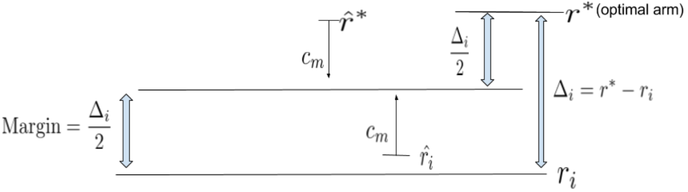


Approach of UCB-Improved (UCB-Imp)



Intuition of UCB-Improved (UCB-Imp)

Arm Elimination: $\hat{r}_i + c_m < \hat{r}_{max} - c_m$



APT Approach

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- This algorithm uses only mean estimation to find the S_τ.
- 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.

APT Algorithm

Algorithm 1 APT

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

Pull each arm once

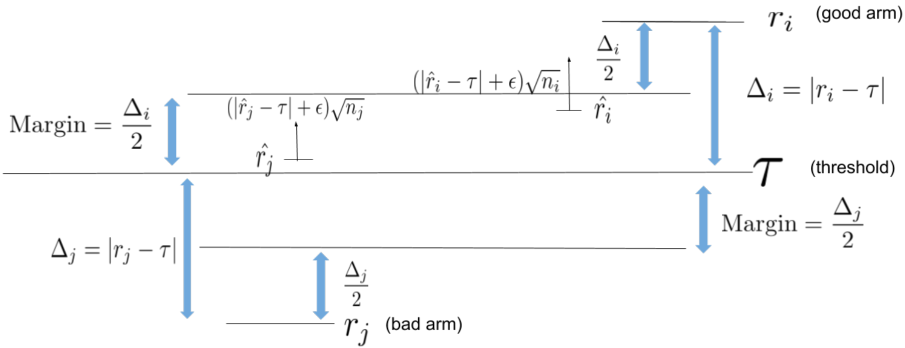
for $t = K + 1, .., T$ **do**

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.

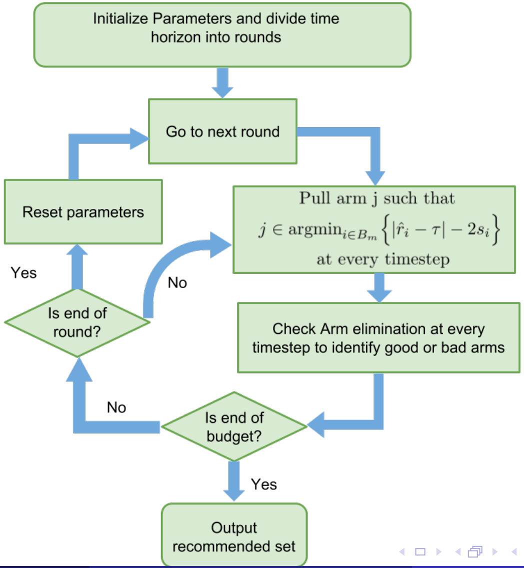
end for

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

Intuition of APT

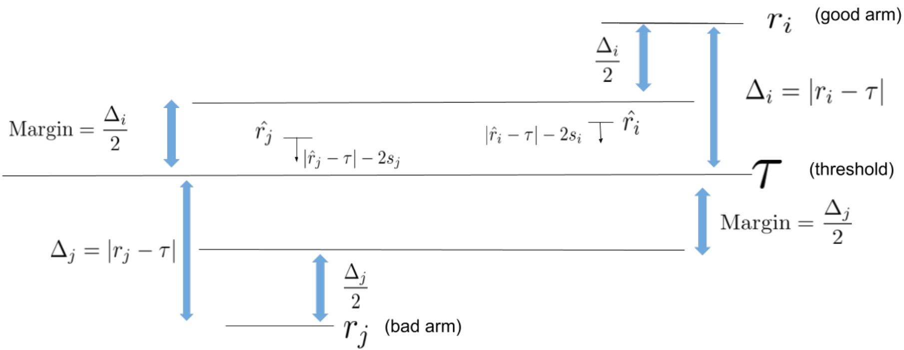


AugUCB algorithm



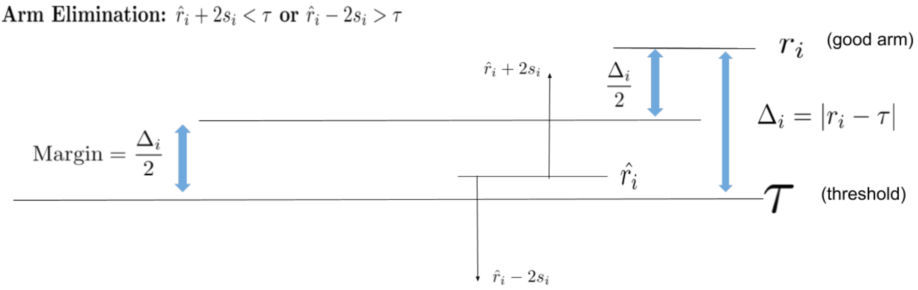
AugUCB algorithm (Intuition, Arm pulling)

- Like UCB-Imp, AugUCB also divides the time budget T into rounds.
- At every timestep we pull arm j s.t. $j \in \arg\min_{i \in B_m} \left\{ |\hat{r}_i - \tau| - 2s_i \right\}$ (like APT).



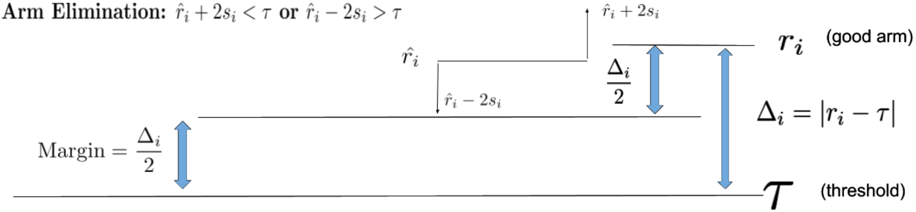
AugUCB algorithm (Intuition, Arm Elimination)

- We eliminate an arm when we are sure that $\hat{r}_i$ is close to r_i with high probability and hence identify it as good or bad arm.
- It's risky to eliminate an arm when $\hat{r}_i$ is inside *Margin*.
- Confidence interval s_i will make sure arm i is not eliminated while inside Margin with a high probability.

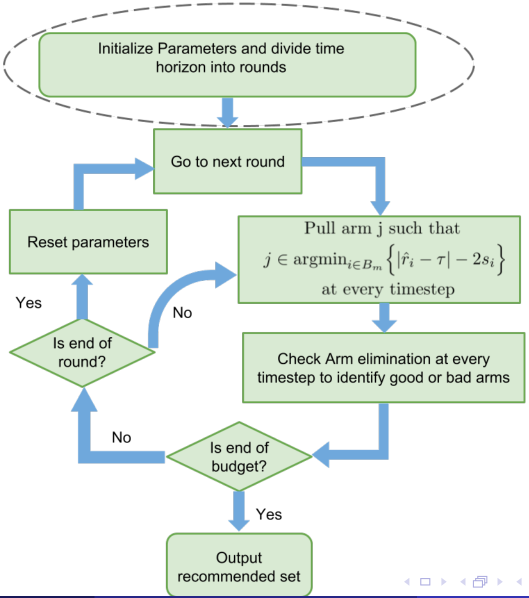


AugUCB algorithm (Intuition, Arm Elimination)

- Now we see that $\hat{r}_i$ has moved close to its true estimate r_i.
- We eliminate i and re-allocate the remaining budget to pull arms close to the threshold



AugUCB parameter initialization



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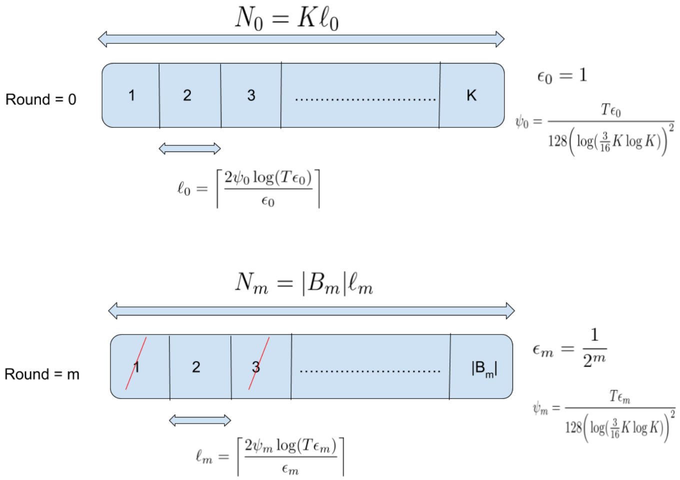
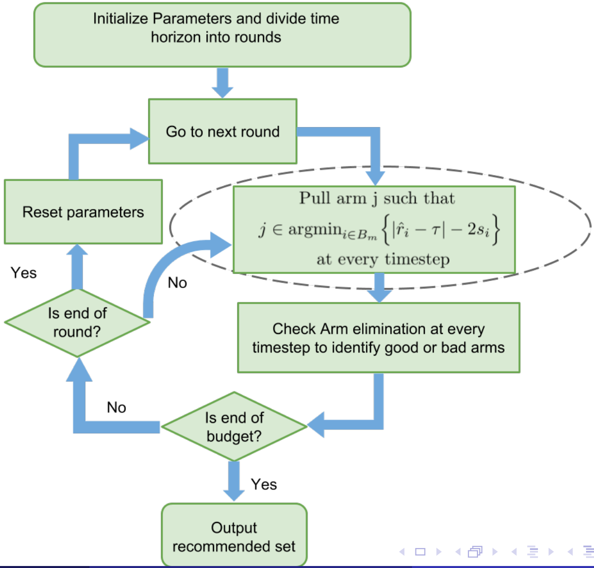


AugUCB arm pull



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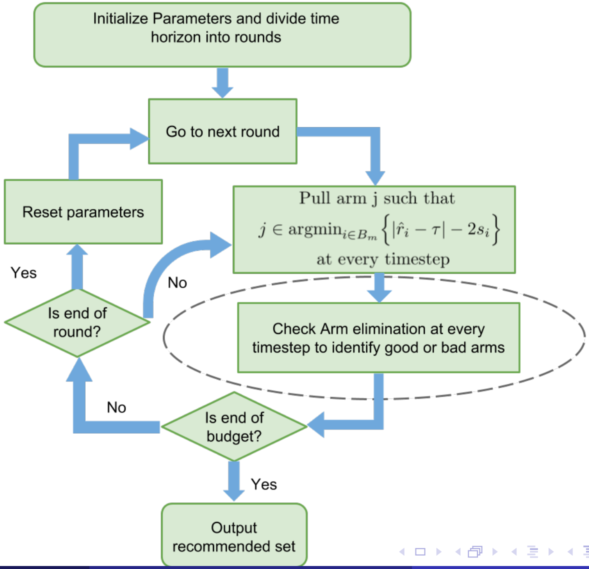
- s_i decreases with more n_i and ψ_m and ρ ensures that it decreases at a correct rate.
- Note that $\hat{v}_i$ estimated variance in s_i makes the algorithm pull the arm which shows more variance.

AugUCB arm elimination



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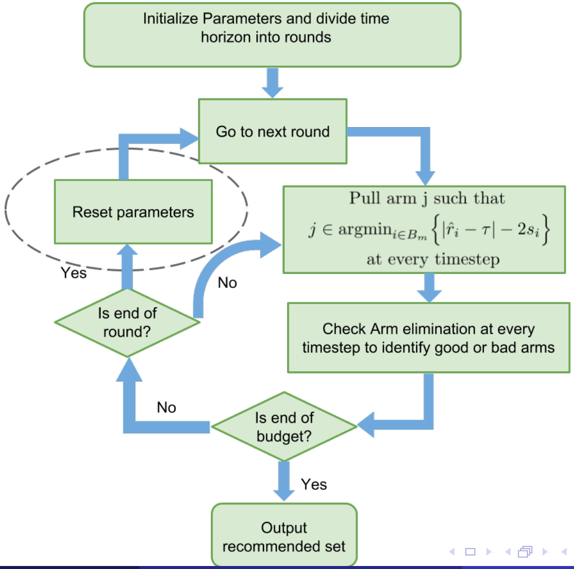
- It eliminates the arms which have been identified as good or bad arms (with a high probability) and re-allocates the remaining budget for surviving arms.

AugUCB parameter reset



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- Recalculate the length of next round on the number of surviving arms.

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- $H_{\sigma,1} = \sum_{i=1}^{K} \frac{\sigma_i + \sqrt{\sigma_i^2 + (16/3)\Delta_i}}{\Delta_i^2}$.
- $H_{\sigma,2} = \max_{i \in \mathcal{A}} \frac{i}{\tilde{\Delta}_{(i)}^2}$ where $\tilde{\Delta}_i^2 = \frac{\Delta_i^2}{\sigma_i + \sqrt{\sigma_i^2 + (16/3)\Delta_i}}$.
- From Audibert and Bubeck (2010) we can show $H_2 \leq H_1 \leq \log(2K) H_2$ and $H_{\sigma,2} \leq H_{\sigma,1} \leq \log(2K) H_{\sigma,2}$.

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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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- 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 and gaps (Δ_i) are very low we can say that $H_{\sigma,1} < H_1$.

Expected Loss of AugUCB

Theorem

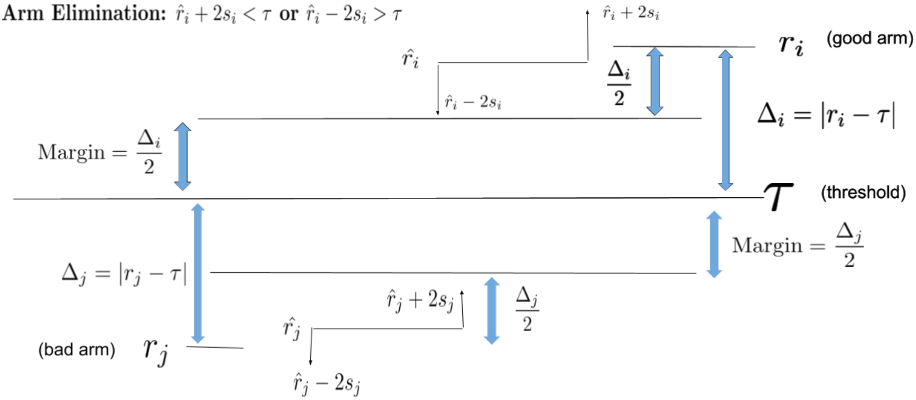
For $K \geq 4$ and $\rho = 1/3$, the expected loss of the AugUCB algorithm is given by,

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

Table: AugUCB vs. State of the art

Algorithm	Upper Bound on Expected Loss	Oracle
AugUCB	$\exp\left(-\frac{T}{4096 \log(K \log K) H_{\sigma,2}} + \log(2KT)\right)$	No
UCBEV	$\exp\left(-\frac{1}{512}\frac{T-2K}{H_{\sigma,1}} + \log(6KT)\right)$	Yes
APT	$\exp\left(-\frac{T}{64H_1} + 2\log((\log(T)+1)K)\right)$	No
UCBE	$\exp\left(-\frac{T-K}{18H_1} - 2\log(\log(T)K\right)$	Yes

Sketch of the proof



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- By access we mean that an oracle supplies them the H_1 or $H_{\sigma,1}$. They do not have access to individual means and variances.
- APT, AugUCB, UA do not require access to H_1 or $H_{\sigma,1}$.

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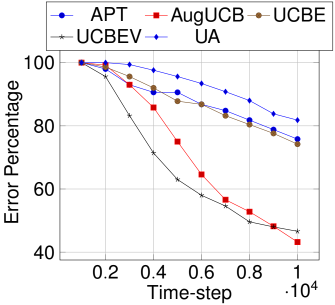
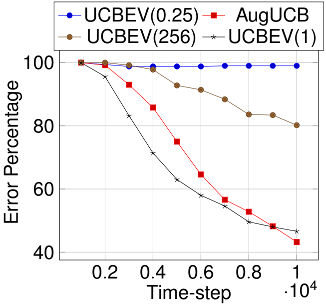
- The first 10 arms partitioned into two groups; the respective means are $r_{1:5} = 0.45$, $r_{6:10} = 0.55$.
- The means of arms $i = 11 : 100$ are chosen same as $r_{11:100} = 0.4$.
- Variances are set as $\sigma^2_{1:5} = 0.3$ and $\sigma^2_{6:10} = 0.8$; $\sigma^2_{11:100}$ are independently and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

Experimental Results

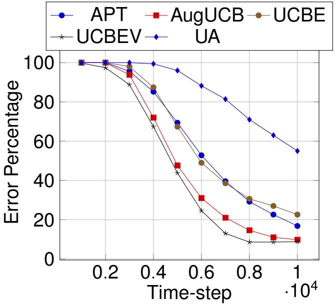


(a) Expt-1: Two Group Setting (Advance)

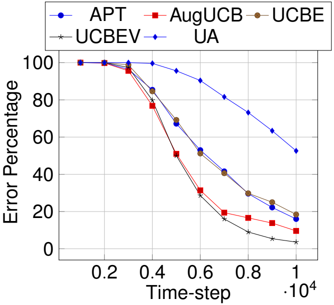


(b) Expt-2: Two Group Setting (Advance)

Experimental Results



(c) Expt-1: Arithmetic Progression (Gaussian)



(d) Expt-2: Geometric Progression (Gaussian)

Conclusion

- We proposed the AugUCB algorithm for the fixed budget TBP which uses variance estimation and arm elimination to give an improved theoretical and experimental guarantees than APT.
- This work has been accepted in the proceedings of IJCAI 2017. I thank my collaborator Dr. K.P. Naveen and both my guides for guiding me through this work. I also thank Dr. L. A. Prashanth for illuminating discussions on several areas of bandits.

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- A more detailed analysis of the non-uniform arm selection and parameter selection is also required.

Thank You