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# CS 6780 Research Project: Multi-armed Bandits with Dependent Arms

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Bangrui Chen  
Saul Toscano Palmerin  
Zhengdi Shen

BC496@CORNELL.EDU  
ST684@CORNELL.EDU  
ZS267@CORNELL.EDU

## Abstract

In this paper, we studied the multi-armed bandits problem, where the reward of each arm linearly depends on a multi-variate random variable. We provided three heuristic algorithms based on the PEGE algorithm (*Paat Rusmevichientong, 2010*). We proved our first heuristic algorithm still has Bayes risk  $O(r\sqrt{T})$ . Numerical experiments suggest our new algorithms outperformed the PEGE algorithm as well as the Exponential Gradient algorithm.

## 1. Introduction

Exploration vs. Exploitation has been studied extensively under the framework of multi-armed bandits problem. The multi-armed bandits problem was first studied by Robbins (*Herbert, 1952*). The problem is trying to find the optimal policy so that we can pull arms sequentially in order to maximize the total expected reward. For the case each arm is independent, the Gittins Index (*Gittins, 1979*) provides an optimal policy for maximizing the expected reward. Further, Lai and Robbins (*Lai, 1985*) proved the regret under an arbitrary policy increases linearly with the number of arms. Most policies that assume independence require each arm to be tried at least once, which are impractical in settings involving many or infinite arms.

Since then, a lot of research has been focused on the dependent case. In (*Gabor Bartok, 2012*) and (*Chih-Chun Wang, 2004*), they studied the multi-bandit problem with side information. In (*Yasin Abbasi-Yadkori, 2009*) and (*Yasin Abbasi-Yadkori, 2011*), people consider the reward for each bandit is the inner product between an single unknown parameter and the bandit. In (*Paat Rusmevichientong, 2010*), they

modeled the expected reward of each arm linearly depends on a multivariate random variable. Furthermore in that paper, they showed that under arbitrary policy, the Bayes regret is  $O(r\sqrt{T})$  where  $r$  is the dimensional of the multivariate random variable. They also provided an simple Phased Exploration Greedy Exploitation (PEGE) algorithm that reaches the  $O(r\sqrt{T})$  regret bound.

Through PEGE reaches the optimal regret bound, it doesn't perform well in practice. In this project, we modified the PEGE algorithm and get three heuristic algorithms. We proved the first modified algorithm is still optimal in the sense their Bayes regret is still  $O(r\sqrt{T})$ . We perform numerical experiments using the Yelp academic data to compare our modified algorithms as well as the original PEGE algorithm. The results suggest our modified algorithm are much better. Further, we compare our modified algorithms with UCB and Exponential Gradient algorithm. Although UCB algorithm outperformed our new algorithms, it requires previous knowledge about the multivariate random variable, which is impossible for the "cold start" problems. Our newly modified performed better than other algorithms and doesn't require any previous knowledge.

There are lots of application for this problem. For instance, a newly registered user for a website with no background information will typically face a cold start problem. Same thing would happen to a investment company who wants to invest money into emerging industries. Furthermore, this problem is closely related to the recommender systems, which are a subclass of information filtering system that seek to predict the "rating" or "preference" that user would give to an item. In these applications, one natural question would be how can we quickly learn user's preference from their feedback? All of these problems can be modeled as a multi-armed bandit problem and our heuristic policies can be applied.

## 2. Problem Formulation

We have a finite set  $\mathcal{U}_r = \{\mathbf{u}_1, \dots, \mathbf{u}_m\} \subset \mathbb{R}^r$  that corresponds to the set of arms, where  $r \geq 2$ . For any time  $t = 1, 2, \dots, T$ , we are asked to pick one arm  $X_t$ . The reward  $Y_t$  of playing arm  $X_t \in \mathcal{U}_r$  in period  $t$  is given by

$$Y_t = \theta \cdot X_t + \epsilon_t,$$

where  $\epsilon_t \sim N(0, \sigma^2)$  is the measurement error with  $\sigma$  known. Here  $\theta$  is an unknown random vector, which is drawn from a multivariate normal distribution with mean  $\mu$  and variance  $\Sigma$ . We further assume  $\mu$  and  $\Sigma$  are known (In section 3, PEGE algorithm and our heuristic algorithms don't require  $\mu$  and  $\Sigma$  are known. However, UCB requires this information).

For a fixed time period  $T$ , the goal of this problem is to find a strategy  $\pi$  to maximize the following expression

$$E^\pi \left[ \sum_{t=1}^T Y_t \right]. \quad (1)$$

Or equivalently, we are trying to find a policy that can minimize the Bayes risk under  $\pi$ :

$$\text{Risk}(T, \pi) = E[\text{Regret}(\theta, T, \pi)], \quad (2)$$

where the cumulative regret is defined as the following:

$$\text{Regret}(\theta_0, T, \pi) = \sum_{t=1}^T E \left[ \max_{X \in \mathcal{U}_r} X \cdot \theta_0 - X_t \cdot \theta_0 \mid \theta = \theta_0 \right]. \quad (3)$$

## 3. PEGE

Theoretically this problem can be solved using stochastic dynamic programming, such as backward induction. However it usually suffers from the curse of dimensionality when the dimension of the arm, i.e.  $r$  is large. Thus, it is desirable to develop some computational feasible heuristic algorithms.

In (Paat Rusmevichientong, 2010), they proved the following theorem which gives a lower bound for the Bayes risk:

**Theorem 1. (Lower Bound)** Consider a bandit problem where the set of arms is the unit sphere in  $\mathbb{R}^r$ , and  $\epsilon_t$  has a standard normal distribution with mean 0 and variance one for all  $t$  and  $X_t$ . If  $\theta$  has a multivariate normal distribution with mean  $\mathbf{0}$  and covariance matrix  $\mathbf{I}_r/r$ , then for all policies  $\pi$  and every  $T \geq r^2$ ,

$$\text{Risk}(T, \pi) \geq 0.006r\sqrt{T}.$$

In their paper, they also provided a simple algorithm called Phased Exploration and Greedy Exploitation (PEGE) (Algorithm 1) that reaches the corresponding lower bound, i.e the bayes risk for PEGE is  $O(r\sqrt{T})$ . In order for the algorithm to work, it requires the following two assumptions:

**Assumption 1.** • There exists a positive constant  $\sigma_0$  such that for any  $r \geq 2$ ,  $\mathbf{u} \in \mathcal{U}_r$ ,  $t \geq 1$  and  $x \in \mathbb{R}$ , we have  $E[e^{x\epsilon_t}] \leq e^{\frac{x^2\sigma_0^2}{2}}$ .

• There exists positive constants  $\bar{u}$  and  $\lambda_0$  such that for any  $r \geq 2$ ,

$$\max_{\mathbf{u} \in \mathcal{U}_r} \|\mathbf{u}\| \leq \bar{u},$$

and the set of arms  $\mathcal{U}_r \subset \mathbb{R}^r$  has  $r$  linearly independent elements  $\mathbf{b}_1, \dots, \mathbf{b}_r$  such that  $\lambda_{\min}(\sum_{k=1}^r \mathbf{b}_k \mathbf{b}_k') \geq \lambda_0$ .

**Assumption 2.** We say that a set of arms  $\mathcal{U}_r$  satisfies the smooth best arm response with parameter  $J$  (SBAR( $J$ ), for short) condition if for any nonzero vector  $\mathbf{z} \in \mathbb{R}^r \setminus \{\mathbf{0}\}$ , there is a unique set best arm  $\mathbf{u}^*(\mathbf{z}) \in \mathcal{U}_r$  that gives the maximum expected reward, and for any two unit vectors  $\mathbf{z} \in \mathbb{R}^r$  and  $\mathbf{y} \in \mathbb{R}^r$  with  $\|\mathbf{z}\| = \|\mathbf{y}\| = 1$ , we have

$$\|\mathbf{u}^*(\mathbf{z}) - \mathbf{u}^*(\mathbf{y})\| \leq J\|\mathbf{z} - \mathbf{y}\|.$$

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**Algorithm 1** Phased Exploration and Greedy Exploitation

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**Description:** For each cycle  $c \geq 1$ , complete the following two phases:

1. **Exploration (r periods)** For  $k = 1, 2, \dots, r$ , play arm  $\mathbf{b}_k \in \mathcal{U}_r$  given in Assumption 1(b), and observe the reward  $Y^{b_k}(c)$ . Compute the OLS estimate  $\hat{\theta}(c) \in \mathbb{R}^r$ , given by

$$\begin{aligned} \hat{\theta}(c) &= \frac{1}{c} \left( \sum_{k=1}^r \mathbf{b}_k \mathbf{b}_k' \right)^{-1} \sum_{s=1}^c \sum_{k=1}^r \mathbf{b}_k Y^{b_k}(s) \\ &= \theta + \frac{1}{c} \left( \sum_{k=1}^r \mathbf{b}_k \mathbf{b}_k' \right)^{-1} \sum_{s=1}^c \sum_{k=1}^r \mathbf{b}_k \epsilon^{b_k}(s) \end{aligned}$$

where for any  $k$ ,  $Y^{b_k}(s)$ , and  $\epsilon^{b_k}(s)$  denote the observed reward and the error random variable associated with playing arm  $\mathbf{b}_k$  in cycle  $s$ .

2. **Exploitation (c periods)** Play the greedy arm  $\mathbf{G}(c) = \arg \max_{\mathbf{u} \in \mathcal{U}_r} \mathbf{u}' \hat{\theta}(c)$  for  $c$  periods.
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Under these two conditions, the Bayes risk for the PEGE algorithm is at most  $O(r\sqrt{T})$ .

**Theorem 2.** Suppose that assumption 1 holds and that the set  $\mathcal{U}_r$  satisfy the SBAR( $J$ ) condition. In addition, there exists a constant  $M > 0$  such that for every  $r \geq 2$  we have  $E[\|\theta\|] \leq M$  and  $E[1/\|Z\|] \leq M$ . Then, there exist a positive constant  $a_1$  that depends only on  $\sigma_0, \bar{u}, \lambda_0, J$  and  $M$ , such that for any  $T \geq r$ ,

$$\text{Risk}(T, \text{PEGE}) \leq a_1 r \sqrt{T}.$$

The proof of the theorem is first calculate the Bayes risk for the exploitation and exploration periods respectively and then add them together. In order to prove the above mentioned theorem, it requires the following two lemmas:

**Lemma 3.** Under Assumption 1, there exists a positive constant  $h_1$  that depends only on  $\sigma_0, \bar{u}$  and  $\lambda_0$  such that for any  $\mathbf{z} \in \mathbb{R}^r$  and  $c \geq 1$ ,

$$E \left[ \|\hat{\theta}(c) - \theta_0\|^2 | \theta = \theta_0 \right] \leq \frac{h_1 r}{c}. \quad (4)$$

**Lemma 4.** Suppose that Assumption 1 holds and the set  $\mathcal{U}_r$  satisfy the SBAR( $J$ ) condition. Then, there exists a positive constant  $h_2$  that depends only on  $\sigma_0, \bar{u}, \lambda_0$  and  $J$ , such that for any  $\mathbf{z} \in \mathbb{R}^r$  and  $c \geq 1$ ,

$$\begin{aligned} & E \left[ \max_{\mathbf{u} \in \mathcal{U}_r} \theta'_0(\mathbf{u} - \mathbf{G}(c)) | \theta = \theta_0 \right] \\ & \leq \frac{2}{\|\theta_0\|} E \left[ \|\hat{\theta}(c) - \theta_0\|^2 | \theta = \theta_0 \right] \leq \frac{2h_1 r}{c \|\theta_0\|} = \frac{h_2 r}{c \|\theta_0\|}. \end{aligned} \quad (5)$$

**Regret of PEGE** We analyse the convergence order of PEGE based on the above assumptions and lemmas:

In the  $k$ th step of an  $r$ -period exploration, we have the observation:

$$E \left[ \max_{X \in \mathcal{U}_r} X \cdot \theta_0 - \mathbf{b}_k \cdot \theta_0 | \theta = \theta_0 \right] \leq 2\bar{u} \cdot \|\theta_0\|$$

Suppose there are  $C$  cycles in the learning (the last cycle may not be completed), then the number of steps is

$$T \geq r(C-1) + C(C-1)/2. \quad (6)$$

Thus,  $C \leq \sqrt{2T}$  and the regret is bounded by the following expression:

$$\begin{aligned} \text{Regret}(\theta_0, T, \text{PEGE}) & \leq \sum_{c=1}^C \left[ 2\bar{u}\|\theta_0\| \cdot r + \frac{r h_2}{c \|\theta_0\|} \cdot c \right] \\ & = (2\bar{u}\|\theta_0\| + \frac{h_2}{\|\theta_0\|}) r C < \sqrt{2}(2\bar{u}\|\theta_0\| + \frac{h_2}{\|\theta_0\|}) r \sqrt{T}. \end{aligned} \quad (7)$$

Thus, we know the Bayes risk is at most  $O(r\sqrt{T})$ . Although PEGE algorithm reaches the theoretical Bayes risk lower bound, it doesn't perform well in practice. Thus, we proposed the following three modified PEGE algorithms which perform better in practice. One intuitive reason is for a small  $T$ , we do too many steps of exploration. Our heuristic policies focus on balancing the number of exploration and exploitation.

**Modification 1.** In the first modified algorithm, instead of doing  $c$  periods of exploitation in cycle  $c$ , we now do  $kc$  periods of exploitation, where  $k$  is a constant (Algorithm 2).

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#### Algorithm 2 PEGE Modified 1

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**Description:** For each cycle  $c \geq 1$ , complete the following two phases:

1. **Exploration ( $r$  periods)** For  $k = 1, 2, \dots, r$ , play arm  $\mathbf{b}_k \in \mathcal{U}_r$  given in Assumption 1(b), and observe the reward  $Y^{b_k}(c)$ . Compute the OLS estimate  $\hat{\theta}(c) \in \mathbb{R}^r$ , given by

$$\begin{aligned} \hat{\theta}(c) &= \frac{1}{c} \left( \sum_{k=1}^r \mathbf{b}_k \mathbf{b}_k' \right)^{-1} \sum_{s=1}^c \sum_{k=1}^r \mathbf{b}_k Y^{b_k}(s) \\ &= \mathbf{Z} + \frac{1}{c} \left( \sum_{k=1}^r \mathbf{b}_k \mathbf{b}_k' \right)^{-1} \sum_{s=1}^c \sum_{k=1}^r \mathbf{b}_k \epsilon^{b_k}(s) \end{aligned}$$

where for any  $k$ ,  $Y^{b_k}(s)$ , and  $\epsilon^{b_k}(s)$  denote the observed reward and the error random variable associated with playing arm  $\mathbf{b}_k$  in cycle  $s$ .

2. **Exploitation ( $kc$  periods)** Play the greedy arm  $\mathbf{G}(c) = \arg \max_{v \in \mathcal{U}_r} \mathbf{v}' \hat{\theta}(c)$  for  $kc$  periods.
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**Regret of Modification 1:** In this case, we modify the regret bound in equation (6), (7), and get

$$T \geq r(C-1) + kC(C-1)/2. \quad (8)$$

When  $k < 2r$ ,  $C \leq \sqrt{\frac{2T}{k}}$ . Therefore

$$\begin{aligned} \text{Regret}(\theta_0, T, \text{PEGE1}) & \leq (2\bar{u}\|\theta_0\| + k \frac{h_2}{\|\theta_0\|}) r C \\ & \leq \sqrt{2}(2\bar{u}\|\theta_0\|/\sqrt{k} + \sqrt{k} \frac{h_2}{\|\theta_0\|}) r \sqrt{T}. \end{aligned} \quad (9)$$

A suitable  $k$  which minimises this upper bound is

$$k^* = \frac{2\bar{u}\|\theta_0\|^2}{h_2}.$$

However, since we do not know  $\|\theta_0\|$  in advance, we need to estimate it base on the prior distribution of  $\theta$

and may also adjust our estimation adaptively based on the results we get in each step. If we don't have any previous information, we could choose a  $k$  based on  $T$  so that the ratio between the exploitation steps and the exploration steps are relatively large, for instance:

$$\frac{kC(C-1)}{r(C-1)} = \frac{kC}{r} \geq 0.8.$$

**Moditication 2.** One intuitive idea is to choose the number of exploitation steps adaptively based on the previous exploration. However, the following theorem says that this is impossible.

**Theorem 5.** *We can get an estimation of  $E[\|\hat{\theta}(c) - \theta_0\|^2 | \theta = \theta_0]$  better than (4), which is:*

$$E[\|\hat{\theta}(c) - \theta_0\|^2 | \theta = \theta_0] = \frac{1}{c} \text{tr}(\Sigma) \quad (10)$$

Here  $\Sigma = \sigma^2(B^T B)^{-1}$ , for which  $B = (\mathbf{b}_1, \dots, \mathbf{b}_r)$ . And conditional on the results of explorations in the first  $c$  cycles, we cannot get a better estimation than that.

*Proof.* To be brief, we introduce notations

$$W(c) = \left( \sum_{k=1}^r \mathbf{b}_k \mathbf{b}_k' \right)^{-1} \sum_{k=1}^r \mathbf{b}_k \epsilon^{\mathbf{b}_k}(c),$$

$$Z(c) = \left( \sum_{k=1}^r \mathbf{b}_k \mathbf{b}_k' \right)^{-1} \sum_{k=1}^r \mathbf{b}_k Y^{\mathbf{b}_k}(c).$$

It is easy to find that  $W(1), \dots, W(c) \stackrel{i.i.d.}{\sim} \mathcal{N}(\vec{0}, \Sigma)$ . Then,

$$\hat{\theta}(c) - \theta_0 = \frac{1}{c} \sum_{s=1}^c W(s)$$

$$E[\|\hat{\theta}(c) - \theta_0\|^2 | \theta = \theta_0] = \frac{1}{c^2} \sum_{s=1}^c E[\|W(s)\|^2] = \frac{1}{c} \text{tr}(\Sigma)$$

At  $c$ th cycle, conditional on  $Z(1), \dots, Z(c)$  (we will use  $Z(1, \dots, c)$  later), which are observable, we have

$$\begin{aligned} W(1) - W(2) &= Z(1) - Z(2) \\ W(1) - W(3) &= Z(1) - Z(3) \\ \dots &\dots \\ W(1) - W(c) &= Z(1) - Z(c) \end{aligned}$$

We can represent the relations by matrices:

$$A\vec{W} = \vec{Z}$$

$$A = \begin{pmatrix} 1 & -1 & 0 & \dots & 0 \\ 1 & 0 & -1 & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots \\ 1 & 0 & 0 & \dots & -1 \end{pmatrix}$$

$$\vec{W} = \begin{pmatrix} W'(1) \\ W'(2) \\ \dots \\ W'(c) \end{pmatrix}, \quad \vec{Z} = \begin{pmatrix} Z'(1) - Z'(2) \\ Z'(1) - Z'(3) \\ \dots \\ Z'(1) - Z'(c) \end{pmatrix}$$

The dimension of  $A$  is  $(c-1)$  by  $c$ . Using QR decomposition, we can get  $A = LQ$ , where  $L$  is  $(c-1)$  by  $c$  lower triangular matrix,  $Q$  is  $c$  by  $c$  orthogonal matrix. Let  $V = Q\vec{W}$ . Then

$$LV = \vec{Z}, \quad \vec{W} = Q'V$$

Further, we assume

$$L = (\tilde{L}, \vec{0}), \quad V = \begin{pmatrix} \tilde{V} \\ \vec{v}_c \end{pmatrix}, \quad Q = \begin{pmatrix} \tilde{Q} \\ \vec{q}_c \end{pmatrix},$$

where  $\tilde{L}$  is  $(c-1) \times (c-1)$  invertible matrix,  $\tilde{V}$  is  $(c-1) \times r$  matrix,  $\tilde{Q}$  is  $(c-1) \times c$  matrix,  $\vec{0}$  is  $c-1$  dimensional column vector,  $\vec{v}_c$  is  $r$  dimensional row vector, and  $\vec{q}_c$  is  $c$  dimensional row vector. Then

$$\vec{Z} = LV = \tilde{L}\tilde{V} \Rightarrow \tilde{V} = \tilde{L}^{-1}\vec{Z}.$$

$$\vec{W} = Q'V = \tilde{Q}'\tilde{V} + \vec{q}_c'\vec{v}_c = \tilde{Q}'\tilde{L}^{-1}\vec{Z} + \vec{q}_c'\vec{v}_c$$

Since  $\vec{v}_c$  is independent of  $\tilde{V}$ , conditional on all the results in the explorations, the distribution of  $\vec{v}_c$  is still  $\mathcal{N}(\vec{0}, \Sigma)$ .

Let  $\vec{1} = (1, 1, \dots, 1)'$ . Notice that

$$O = A\vec{1} = \tilde{L}\tilde{Q}\vec{1} \Rightarrow \tilde{Q}\vec{1} = O.$$

Since  $\vec{q}_c$  is orthogonal to each row of  $\tilde{Q}$ , we claim that  $\vec{q}_c = \frac{1}{\sqrt{c}}\vec{1}'$ .

Suppose we use

$$\hat{\theta}(c) = \left( \sum_{k=1}^r \mathbf{b}_k \mathbf{b}_k' \right)^{-1} \sum_{s=1}^c w_s \sum_{k=1}^r \mathbf{b}_k Y^{\mathbf{b}_k}(s) = \theta_0 + \sum_{s=1}^c w_s W(s)$$

as the estimator of  $\theta_0$  in the  $c$ th cycle, where  $\sum_{s=1}^c w_s = 1$ . Let  $\vec{w} = (w_1, \dots, w_c)'$ . Conditional on  $Z(1), \dots, Z(c)$ ,

$$\begin{aligned} E[\|\hat{\theta}(c) - \theta_0\|^2 | Z(1, \dots, c), \theta = \theta_0] \\ &= E[\vec{w}'\vec{W}\vec{W}'\vec{w} | Z(1, \dots, c), \theta = \theta_0] \\ &= \vec{w}' \left( \tilde{Q}'\tilde{L}^{-1}\vec{Z}\vec{Z}'\tilde{L}^{-1}\tilde{Q} + \text{tr}(\Sigma)\vec{q}_c'\vec{q}_c \right) \vec{w} \\ &:= \vec{w}' \left( \tilde{Q}'\tilde{L}^{-1}\vec{Z}\vec{Z}'\tilde{L}^{-1}\tilde{Q} \right) \vec{w} + \frac{\text{tr}(\Sigma)}{c} (\vec{w}'\vec{1})^2 \\ &= \|\vec{Z}'\tilde{L}^{-1}\tilde{Q}\vec{w}\|^2 + \text{tr}(\Sigma)/c \\ &\geq \text{tr}(\Sigma)/c \end{aligned}$$

When  $\vec{w} = \frac{1}{c}\vec{1}$ , the equality holds.

Therefore, we cannot get a better estimation than (10).  $\square$

Thus, in the second modification, we stop the exploration when we think we have already got a good estimation of  $\theta_0$ .

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**Algorithm 3** PEGE Modified 2
 

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**Description:**

1. If  $\|\hat{\theta}(c) - \hat{\theta}(c-1)\|^2 \leq \epsilon(T, \sigma)$ , go to step 2. Else, do step 1.(a) and 1.(b).
- 1.(a) **Exploration (r periods)** For  $k = 1, 2, \dots, r$ , play arm  $\mathbf{b}_k \in \mathcal{U}_r$  given in Assumption 1(b), and observe the reward  $Y^{b_k}(c)$ . Compute the OLS estimate  $\hat{\theta}(c) \in \mathbb{R}^r$ , given by

$$\begin{aligned}\hat{\theta}(c) &= \frac{1}{c} \left( \sum_{k=1}^r \mathbf{b}_k \mathbf{b}_k' \right)^{-1} \sum_{s=1}^c \sum_{k=1}^r \mathbf{b}_k Y^{b_k}(s) \\ &= \theta + \frac{1}{c} \left( \sum_{k=1}^r \mathbf{b}_k \mathbf{b}_k' \right)^{-1} \sum_{s=1}^c \sum_{k=1}^r \mathbf{b}_k \epsilon^{b_k}(s)\end{aligned}$$

where for any  $k$ ,  $Y^{b_k}(s)$ , and  $\epsilon^{b_k}(s)$  denote the observed reward and the error random variable associated with playing arm  $\mathbf{b}_k$  in cycle  $s$ .

- 1.(b) **Exploitation (c periods)** Play the greedy arm  $\mathbf{G}(c) = \arg \max_{v \in \mathcal{U}^r} \mathbf{v}' \hat{\theta}(c)$  for  $c$  periods in the  $c_{th}$  cycle.
  2. Play the greedy arm  $\mathbf{G}(c) = \arg \max_{v \in \mathcal{U}^r} \mathbf{v}' \hat{\theta}(c)$  thereafter.
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In the first step, there is an  $\epsilon(T, \sigma)$  we need to choose. In our numerical experiments, it turns out  $\epsilon(T, \sigma)$  is not sensitive to  $T$ . Though we couldn't prove this is a  $O(r\sqrt{T})$  algorithm, it outperformed PEGE algorithm.

**Modification 3.** In the third modified algorithm, it further modified the second algorithm: during the exploitation period, it also updates the ordinary least estimate each time (Algorithm 4).

**Regret of Modification 3:** We want to show Algorithm 4 has smaller Bayes Risk than Algorithm 3. Since during the exploration periods, it will play the same arms as in algorithm 3, we just need to show the regret during the exploitation periods is smaller than the regret of algorithm 3. If we denote  $\hat{\theta}(c, t)$  as the OLS estimator of  $\theta$  during the  $t_{th}$  exploitation period

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**Algorithm 4** PEGE Modified 3
 

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**Description:**

1. If  $\|\hat{\theta}(c) - \hat{\theta}(c-1)\|^2 \leq \epsilon(T)$ , go to step 2. Else, do step 1.(a) and 1.(b).
  - 1.(a) **Exploration (r periods)** For  $k = 1, 2, \dots, r$ , play arm  $\mathbf{b}_k \in \mathcal{U}_r$  given in Assumption 1(b), and observe the reward  $Y^{b_k}(c)$ . Compute the OLS estimate  $\hat{\theta}(c) \in \mathbb{R}^r$ .
  - 1.(b) **Exploitation (c periods)** Play the greedy arm  $\mathbf{G}(c) = \arg \max_{v \in \mathcal{U}^r} \mathbf{v}' \hat{\theta}(c)$  for  $c$  periods in the  $c_{th}$  cycle. Update  $\hat{\theta}$  each time.
  2. Play the greedy arm  $\mathbf{G}(c) = \arg \max_{v \in \mathcal{U}^r} \mathbf{v}' \hat{\theta}(c)$  thereafter. Update  $\hat{\theta}$  each time.
- 

in the  $c_{th}$  cycle, then to show algorithm 4 has smaller regret during exploitation is equivalent to show

$$E[\|\hat{\theta}(c, t) - \theta_0\|^2 | \theta = \theta_0] < E[\|\hat{\theta}(c) - \theta_0\|^2 | \theta = \theta_0]. \quad (11)$$

**Lemma 6.** Suppose  $X_1$  is a  $n_1 \times k$  matrix and  $X_2$  is a  $n_2 \times k$  matrix, then

$$\text{Trace}(X_1^T X_1 + X_2^T X_2) < \text{Trace}(X_1^T X_1).$$

*Proof.* Denote  $A = X_1^T X_1$ , then use the Woodbury matrix identity, we get

$$\begin{aligned}(X_1^T X_1 + X_2^T X_2)^{-1} \\ = A^{-1} - A^{-1} X_2^T (I + X_2 X_2^T)^{-1} X_2 A^{-1}\end{aligned}$$

Thus,  $\text{Trace}(X_1^T X_1 + X_2^T X_2) < \text{Trace}(X_1^T X_1)$  is equivalent to show  $\text{Trace}(A^{-1} X_2^T (I + X_2 X_2^T)^{-1} X_2 A^{-1}) > 0$ . However, it is easy to see that  $A^{-1} X_2^T (I + X_2 X_2^T)^{-1} X_2 A^{-1}$  is a positive semidefinite matrix which means all of the eigenvalue is greater or equal to 0. Thus, our lemma holds.  $\square$

**Theorem 7.** The Algorithm 4 has smaller bayes risk than Algorithm 3.

*Proof.* As we discussed before, we just need to show (11) holds true. Since we assume  $\epsilon \sim N(0, \sigma^2)$ , thus the OLS estimator  $\hat{\beta}$  of  $Y = X\beta + \epsilon$  follows a normal distribution  $\hat{\beta} \sim N(\beta, \sigma^2(X^T X)^{-1})$ . Thus  $E[\|\hat{\beta} - \beta\|^2] = \sigma^2 \text{Trace}(X^T X)^{-1}$ . If we denote  $X(c, t)$  is the  $X$  vector for the  $\theta(\hat{c}, t)$  and  $X(c)$  is the  $X$  vector for the  $\theta(\hat{c})$ , then  $X(c, t)$  contains more rows than  $X(c)$ . Based on our previous lemma, we know (11) holds true.  $\square$

## 4. UCB and EXP3

Besides the PEGE algorithm, there are two other well known algorithms for this problem, which are Exponential Gradient algorithm and the upper confidence bound algorithm. These are two different types of algorithms, UCB requires previous information about  $\theta$  which is impossible for the “cold start” problems. However, due to the previous information, it usually performs very well in most cases. Exponential Gradient (EXP3) is a randomized algorithm and doesn’t require any previous information. However, when the number of arms are large, it usually doesn’t perform very well.

### 4.1. Upper Confidence Bound Algorithms

Upper confidence bound algorithms (UCB) are widely used in multiarmed bandit problems because these algorithms usually have good empirical performance. However, they are not as fast as other methods like the EXP3 algorithm, and this may be a problem when the number of stages is very big.

UCB algorithms follow two steps. First, at time  $t$ , for each arm  $u$  we compute a upper confidence bound  $U_t(u)$ . Then, at time  $t$  we choose the arm  $u^*$  such that  $u^* \in \arg \max_u U_t(u)$ , i.e.  $u^*$  has the maximal upper confidence bound.

In our project, we start supposing that  $\theta \sim N(\mu_0, \Sigma_0)$  where  $\mu_0$  and  $\Sigma_0$  are computed using the available data. We have that  $\theta \sim N(\mu_t, \Sigma_t)$  at step  $t+1$ , where  $\mu_t, \Sigma_t$  are the paramaters of the posterior distribution of  $\theta$  after we have seen  $x_1, y_1, \dots, x_t, y_t$ . Specifically,

$$\begin{aligned}\mu_t &= \Sigma_t \left( \Sigma_0^{-1} \mu_0 + \frac{1}{\sigma^2} X_t^T y \right) \\ &= \Sigma_t \left( \Sigma_{t-1}^{-1} \mu_{t-1} + \frac{1}{\sigma^2} x_t y_t \right) \\ \Sigma_t^{-1} &= \Sigma_0^{-1} + \frac{1}{\sigma^2} X_t^T X_t = \Sigma_t^{-1} + \frac{1}{\sigma^2} x_t x_t^T\end{aligned}$$

where

$$X_t = \begin{pmatrix} x_1^t \\ \vdots \\ x_t^t \end{pmatrix}.$$

Consequently an upper bound of the .95–confidence interval of the distribution of  $y(u)$  is

$$E_{\mu_t, \Sigma_t} [x^{(u)} \cdot \theta] + 1.96 \sqrt{\text{Var}_{\mu_t, \Sigma_t} (x^{(u)} \cdot \theta)}$$

and then we will choose the arm  $u^* = \arg \max_u \left( E_{\mu_t, \Sigma_t} [x^{(u)} \cdot \theta] + 1.96 \sqrt{\text{Var}_{\mu_t, \Sigma_t} (x^{(u)} \cdot \theta)} \right)$  at step  $t+1$ . In terms of our example, the arms are

restaurants and the vector  $x^{(u)}$  is a binary vector that represents the categories of the restaurant  $u$ .

### 4.2. Exponentiated Gradient Algorithm for Bandit Setting (EXP3)

This is a randomized algorithm. It keeps a vector of probabilities for each of the arms, and it chooses an arm according to this vector. The weight of the arm chosen is increased when the loss is small and decreased when the loss is high. Specifically, the algorithm is

1. Given  $\gamma \in [0, 1]$ , initialize the weights  $w_u(1) = 1$  for each arm  $u$ .
2. At each step  $t$ :
  - (a) Set  $p_u(t) = (1 - \gamma) \frac{w_u(t)}{\sum_j w_j(t)} + \frac{\gamma}{K}$  for each arm  $u$ .
  - (b) Draw the arm  $u_t$  choosen according to the distribution  $p_{u_t}(t)$ .
  - (c) Observe the loss  $y_{u_t}(t)$ .
  - (d) Set  $w_{u_t}(t+1) = w_{u_t}(t) \exp\left(\gamma \frac{y_{u_t}(t)}{p_{u_t}(t)m}\right)$ , and  $w_j(t+1) = w_j(t)$  for all other arms.

This algorithm is usually fast, but if there are too many arms, the weights may be zero in most of the cases.

## 5. Numerical Experiment

In this simulation, we use the yelp academic dataset. The goal of this simulation is to find the favorite restaurant categories for a new user. There are 4596 restaurants in the dataset and each restaurant belongs to one or multiple categories. We first find the top twenty categories that has most restaurants, which are Pizza, Sandwiches, Food etc, and use those 20 categories as our feature. For each restaurant, if it belongs to certain category, then the corresponding element of its feature vector is 1 and 0 otherwise. So the feature vector of each restaurant is a 20 dimensional binary vector.

For each historical user, we calculated his user preference vector based on his rating and the restaurants’ feature vectors that he rated using ridge regression (since there are not too many ratings, ordinary linear regression doesn’t work here due to singularity). Then we calculated the sample mean and the sample variance of all users’ preference vector and denote them as  $(\mu, \Sigma)$ . We further assume that for each user’s preference vector  $\theta \sim N(\mu, \Sigma)$  and generate new user from this distribution.



In our numerical examples, the reward function when the restaurant  $i$  is chosen is defined as

$$x_i \cdot \theta + \epsilon$$

where  $\epsilon \sim N(0, 0.8)$ ,  $\theta$  is the user's preference vector and  $x_i$  is the feature vector of the restaurant  $i$ .

In our first example, we compared the PEGE and our three heuristic algorithms. It can be seen that all of our heuristic algorithms outperform the PEGE algorithm and the third modification performs the best. However, since the third modification needs updating the OLS estimate every time, it is much slower than Algorithm 3. Algorithm 3 is the fastest algorithm among these four since it only updates OLS for few steps.

In our second example, we use the EXP3 algorithm with  $\gamma = 0.5$ . The time horizon is 1000, and we simulated 100 user's preference vectors. In Figure 2, we can see that the reward is little and our PEGE algorithms are much better. Thus, EXP3 doesn't perform well when the number of arms are large.

In our third example, we use the UCB algorithm described in the previous section. The time horizon is 1000, and we simulated 100 user's preference vectors. In Figure 3, we can see that its performance is much better than the performance of EXP3 algorithm and it outperformed our heuristic algorithms. However, UCB algorithms is much slower and requires previous information about the multivariate random variable.

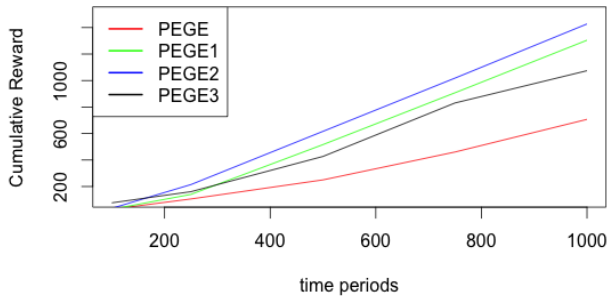


Figure 1. Comparison of different PEGE algorithms

## 6. Conclusion

In this paper, we studied the linearly parameterized bandits problem, where the reward of each arm linearly depends on a multivariate random variable. In (Paat Rusmevichientong, 2010), it provided a simple algorithm PEGE which reaches the optimal Bayes

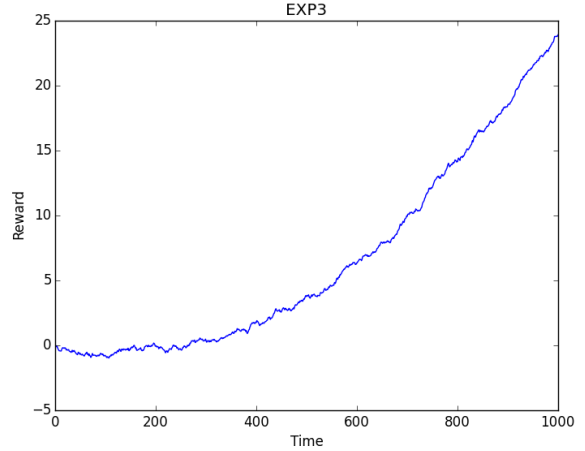


Figure 2. EXP3 algorithm.

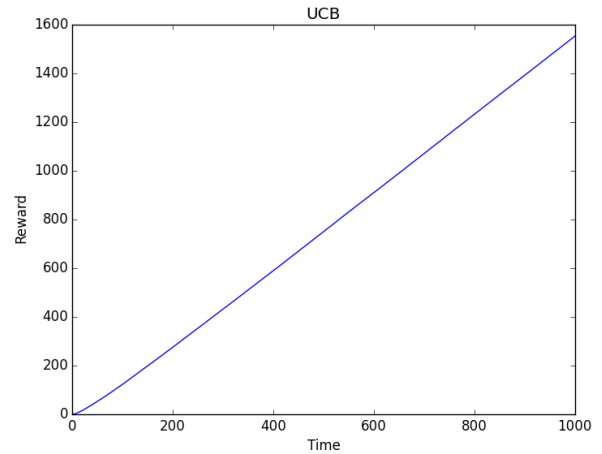


Figure 3. UCB algorithm.

regret bound  $O(r\sqrt{T})$ . However, the PEGE algorithm doesn't perform well in practice, since it does the same number of exploitation steps regardless the exploration result. We provided three new PEGE algorithms which balance the number of exploration and exploitation better. We proved that our first heuristic algorithm still has Bayes risk  $O(r\sqrt{T})$ . Further, we compared our modified algorithms with PEGE as well as UCB and EXP using the Yelp academic dataset. Though UCB performs the best (almost optimal) among these algorithms, it requires a lot of previous information. Our new algorithms which outperformed the PEGE and EXP3 don't depend on the previous information and could be applied to the "cold start" problems.

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