

Work in Lri

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Table des matières

| | | |
|-----------|---|-----------|
| 1 | 25/06/2019 : | 2 |
| 1.1 | DQN batch | 2 |
| 2 | Before 02/07/2019 : | 2 |
| 2.1 | DQN with(out) batch and Experimentation | 2 |
| 3 | 03/07/2019 : | 3 |
| 3.1 | DQN batch | 3 |
| 4 | 04/07/2019 : | 3 |
| 4.1 | Meeting in LINC'S | 3 |
| 5 | 05/07/2019 : | 4 |
| 5.1 | Experimental Work | 4 |
| 6 | 08/07/2019 : | 6 |
| 6.1 | Experimental Work(mean) | 6 |
| 7 | 15/07/2019 : | 10 |
| 7.1 | Start Semi-reel Data | 10 |
| 8 | 16/07/2019 : | 11 |
| 8.1 | Curves Semi-reel Data | 11 |
| 9 | 17/07/2019 : | 12 |
| 9.1 | X optimal outside Interval initial | 12 |
| 9.2 | For Article | 13 |
| 10 | 18/07/2019 : | 14 |
| 10.1 | Work on Paper | 14 |

1 25/06/2019 :

1.1 DQN batch

Coder DQN With Batch

I created a new version of DQN which trains the network with batch, rather than train the network with each simulation.

What it was :

Loop :

- simulate one time and get tuple $\langle s_t, r_t, s_{t+1} \rangle$
- set $y_t = r_t + \beta \min_a Q_t(s_{t+1}, a; w_t)$
- train the network by minimizing the loss with the input $= X = (F(s_t), G(a)), Y = y_t$

What I modified :

Loop :

- there is memory D and I simulate $n = (20)$ times, save the each tuple $\langle s_t, r_t, s_{t+1} \rangle$ in D
- sample a batch(=10) from D and calculate y for each tuple in the batch
- train the network by minimizing the loss of the batch

Comparison. With Time=2000(each time correspond to one simulation), K=5, and the cost of arm a is calculated by formula : $c(a) = 10 * (a + 1) + 55 * \theta_{true}[a]$ where $\theta_{true} = [0.9, 0.64013, 0.50242, 0.37156, 0.26535]$.

The regret/time of DQN without batch and UCB is 1.988 and 3.617 respectively.

Unfortunately, the DQN training with batch, it doesn't work. The problem is that when I trained the network, after several epochs, the output of network will be -inf. I have tried to use *Keras* to build the network and use *mean square error* as loss function, it doesn't work, the problem is when I trained the network, after several epochs, the output of network will be the same for any input.

2 Before 02/07/2019 :

2.1 DQN with(out) batch and Experimentation

Before 01/07

Before today, I have implemented Deep Q-Learning algorithm training with(out) batch, simple UCB. And I have gotten the results of executing UCB for 20 epochs, 30000 iterations, 100 resources. I have given a presentation of my work in Nokia.

01/07 - 02/07

- Rebuilt the **code** to separate the part of data and algorithm
- Added comments for every variable and function
- Wrote the **manual** for others can use my programme easily.

3 03/07/2019 :

3.1 DQN batch

Results of Experimentation for Ext with T=6000

The calculate of executing algorithm extension with T=6000, epochs=20, 100 resource has been finished, But the result of regret per T Figure 1 is very strange, I am executing on epoch more to find whether the result of regret is always strange or not.

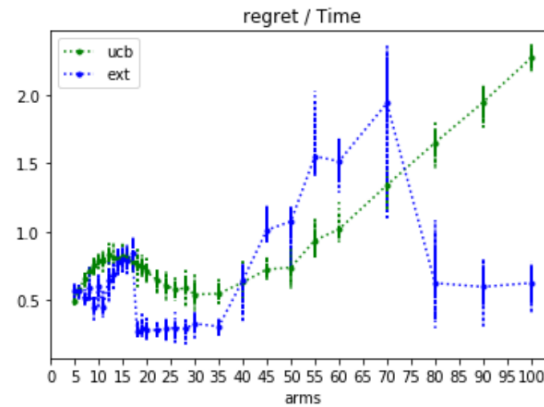


FIGURE 1 – Comparison of Ext and UCB with T=6000 epochs=20

Modified the Code and Re-execute the Program

I modified the number of T of every test(extract 10 resources) when I execute algorithm, and it is calculating.

Understand the Program of Stephan

I have understand the code of algorithms of LSE, LSE-BACKTRACK and how to execute the algorithms.

4 04/07/2019 :

4.1 Meeting in LINCS

Work in Nokia

Today, I have a meeting with Lorenzo and Johanne in LINCS, and we have discussed the graphs I should do :

- For artificial data, modify the 4 functions of simulation for the optimal x isn't always the same(0.5) and make it as a parameter.
- Execute the algorithms for artificial data and design graphs of regret and approximation.

5 05/07/2019 :

5.1 Experimental Work

Execute Algorithm and Draw Graphs

I have executed algorithms : ['lse', 'lse-backtrack', 'lse-weighted', 'without gradient', 'sgd'] using 3 sampling functions (Figure 2) : ['quadra', 'triangle', 'shark'] with $X_{opt} = 0.5$, Time=10000.

When I executed sgd, there was a problem and I implemented a classic sgd by sampling n times $x - d$ and get the mean reward r_{x-d} and sampling n times $x + d$ and get the mean reward r_{x+d} , then get $x_{new} = x + lr * \frac{r_{x+d} - r_{x-d}}{2*d}$.

— Sampling Functions.

X-axis represents the arms which are continuous from 0 to 1 and Y-axis represents the reward corresponding to each arm. The reward of X_{opt} is 1.

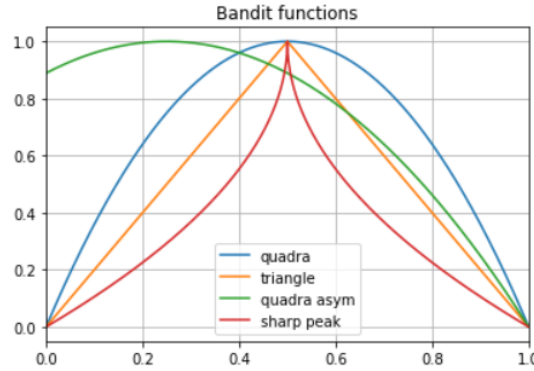


FIGURE 2 – 4 Sampling Functions

— Regret.

I have just executed the algorithms 1 time while X-axis represents time(each time sample 1 arm) and Y-axis represents cumulative regret.

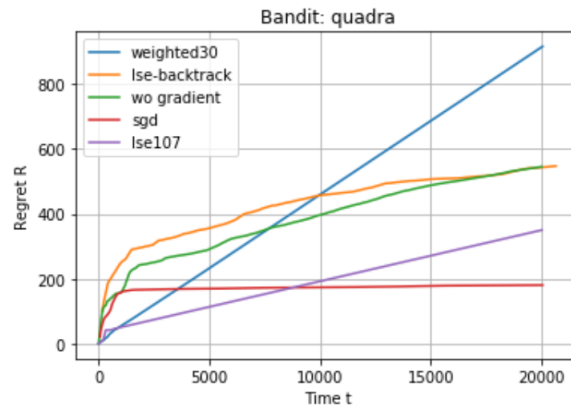


FIGURE 3 – 4 Sampling Functions

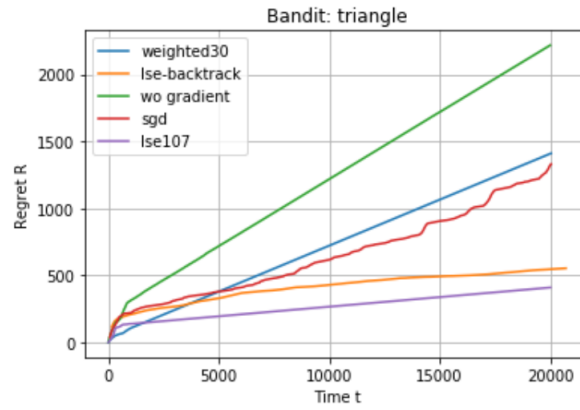


FIGURE 4 – 4 Sampling Functions

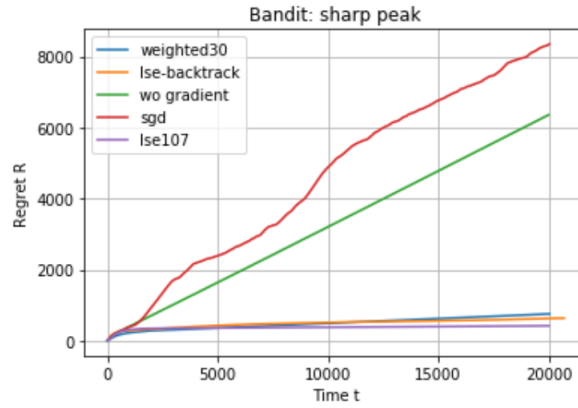


FIGURE 5 – 4 Sampling Functions

— Approximation.

I have just executed the algorithms 1 time while X-axis represents time(each time sample 1 arm) and Y-axis represents $abs(x - X_{opt})$ where x is the arm sampled.

Problems

We can see the graphs to get that 'lse-backtrack' is worse than 'lse' which is unreasonable.

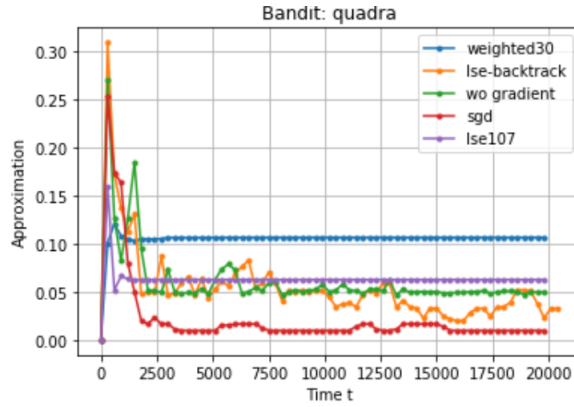


FIGURE 6 – 4 Sampling Functions

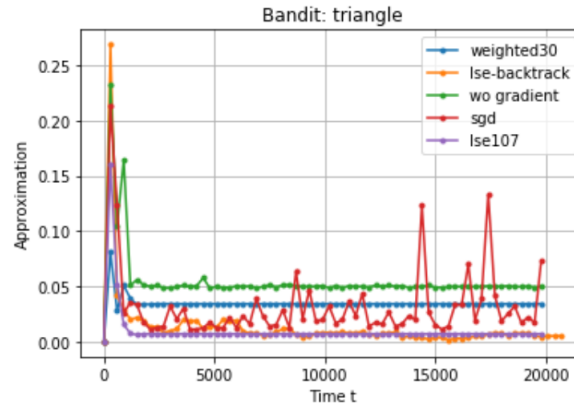


FIGURE 7 – 4 Sampling Functions

6 08/07/2019 :

6.1 Experimental Work(mean)

Solve Problems

- le 05/07 I encountered a problem which is that 'lse' is better than 'lse-backtrack', the reason is that the number of sampling isn't the same for the two algorithms, and for 'lse-backtrack' there are 6 points which needs more sampling for identify which point get max value.
So I tried the different number of sample for 'lse' and 'lse-backtrack'.
- For each algorithm, I execute $N(=30)$ times and calculate the mean to increase accuracy of results.

Results

I executed algorithms for $T=20000$, $x_{opt} = 0.5$ and $N = 30$.

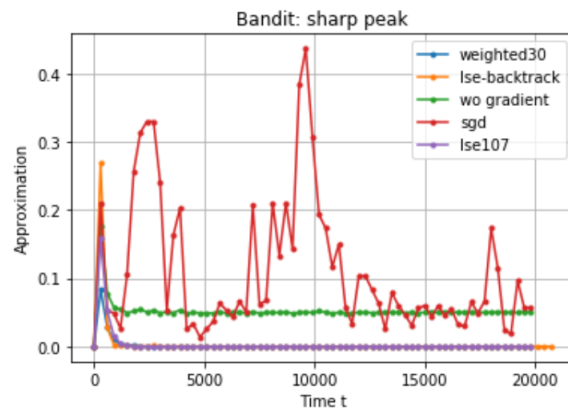


FIGURE 8 – 4 Sampling Functions

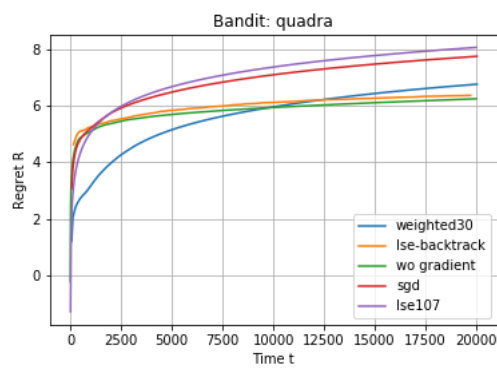


FIGURE 9 – 4 Sampling Functions

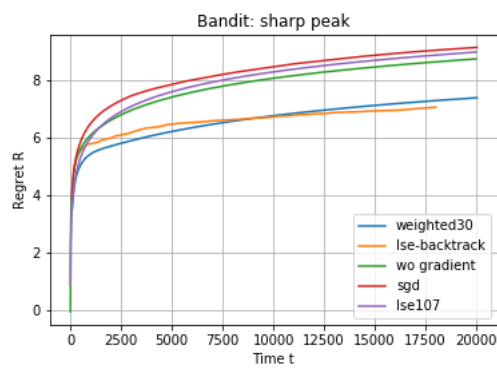


FIGURE 10 – 4 Sampling Functions

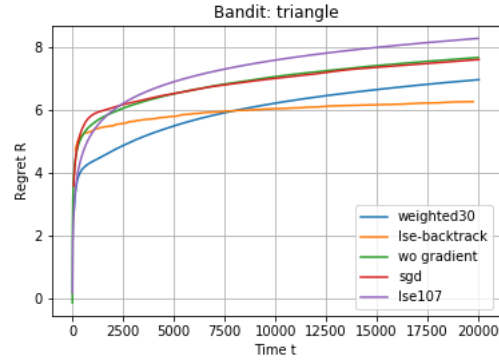


FIGURE 11 – 4 Sampling Functions

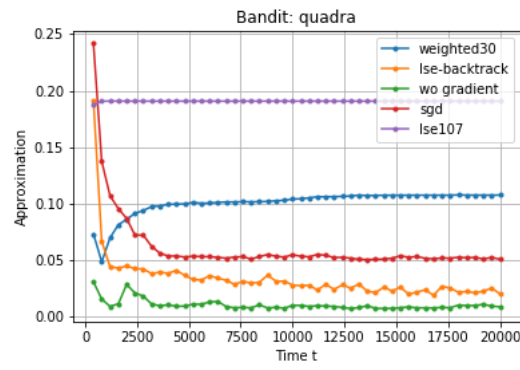


FIGURE 12 – 4 Sampling Functions

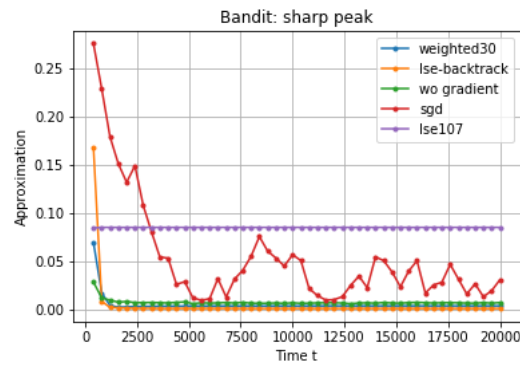


FIGURE 13 – 4 Sampling Functions

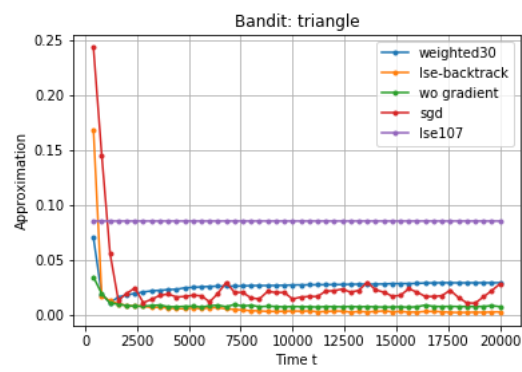


FIGURE 14 – 4 Sampling Functions

7 15/07/2019 :

7.1 Start Semi-reel Data

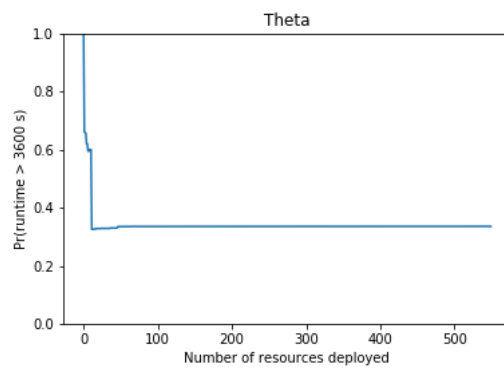
Study on Semi-real Data

There are 5 types of semi-real data proposed by Stephan, but it is necessary to find what represents arm x and what represents QoS.

5 types :

— [Parallel Workloads Archive](#)

However, the data isn't suitable for us ??



— [Google Cluster Data](#)

This one is suitable for us Figure 15

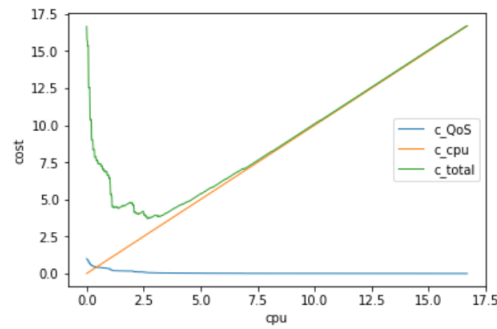


FIGURE 15 – Cost Google Cluster Data

— [Riiser](#) : mobile http streaming scenarios

This one is suitable for us Figure 16

— Call tests measurements

— Makram

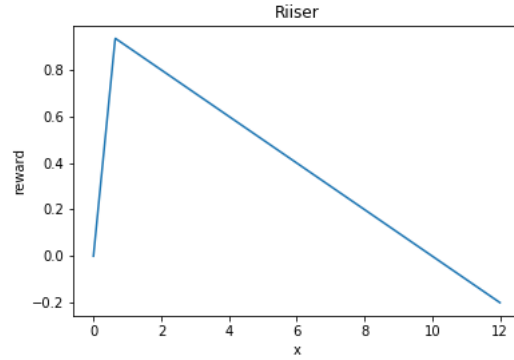


FIGURE 16 – Cost Google Cluster Data

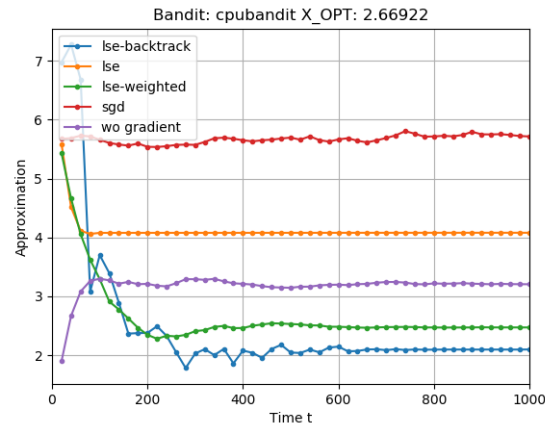
8 16/07/2019 :

8.1 Curves Semi-reel Data

Semi-real Data

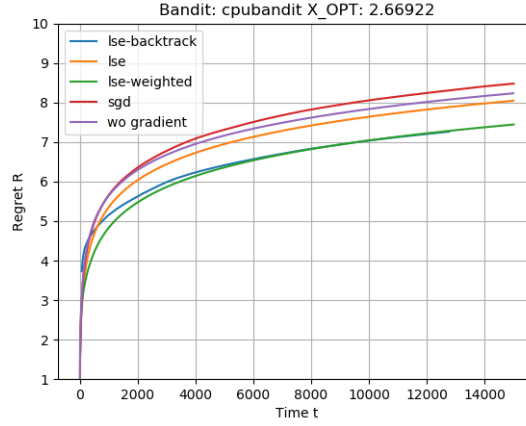
I executed the algorithms on semi-real data for $T = 15000$, rounds = 15, number of sampling = 9 :

— Approximation :



We can get that LSE-backtrack and LSE-weighted are much better than LSE, but they converge more slowlyl.

— Regret :



9 17/07/2019 :

9.1 X optimal outside Interval initial

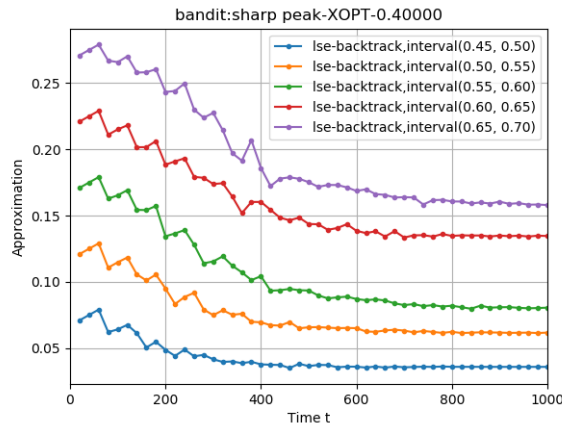
Execute LSE-BACKTRACK with different intervals

I executed algorithm 'LSE-BACKTRACK' with parameters :

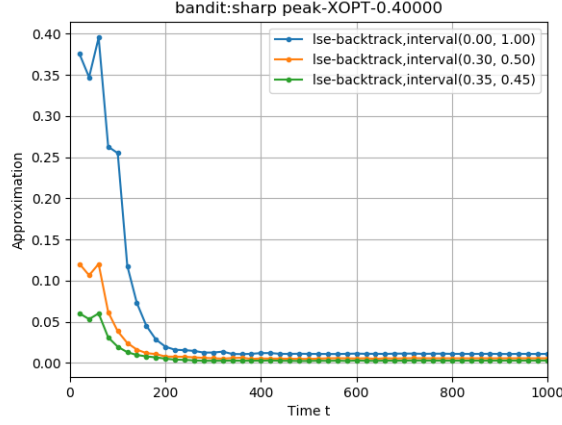
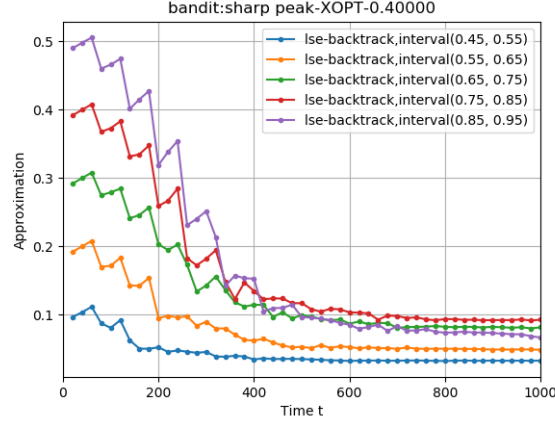
- curve 'Sharp Peak'
- $X_{opt} = 0.4$
- $T = 10000$
- epochs = 80 (execute algo 80 times and then calculate mean value)
- number of sampling = 10

For intervals initial :

- intervals = [(0.45,0.5), (0.5,0.55), (0.55,0.60), (0.6,0.65),(0.65,0.7)] : Figure ??



- intervals = [(0.45,0.55), (0.55,0.65), (0.65,0.75), (0.75,0.85),(0.85,0.95)] : Figure ??
- intervals = [(0,1),(0.3,0.5),(0.35,0.45)] Figure : ??



9.2 For Article

Sub Conclusion

For Artificial Data

- There are 3 types of functions for representing θ : 'quadra', 'sharp peak', 'triangle' : Figure 17.
- When also samples arm x , we use Normal distribution to add noise in the reward return to algo : $\text{Norm}(\text{mean} : \theta(x), \text{standard deviation} : 0.2 + \theta(x)/1.2)$ where $\theta(x)$ is calculated by function in Figure 17.
- For LSE, LSE-backtrack, LSE-weighted, we should define number of sampling(NS). We have executed algorithms by setting NS from 8 to 20.
- To avoid contingency, we have use rounds from 10 to 80(ex. execute 80 times for each algorithm and calculate the mean value).
- For function 'Sharp Peak', $X_{opt} = 0.4$, $T = 15000$, rounds = 80, number of sampling = 10, the curves of approximation and regret :Figure 20 21
- Intervals. To test the performance of LSE-backtrack, it is necessary to set the interval initial (x_i, x_j) where $x_i < x_j \wedge x_{opt} \notin [x_i, x_j]$

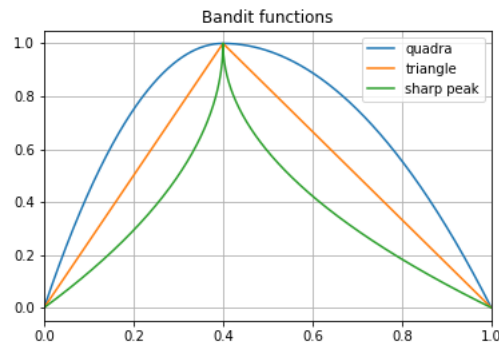


FIGURE 17 – Bandit functions $X_{OPT}=0.4$

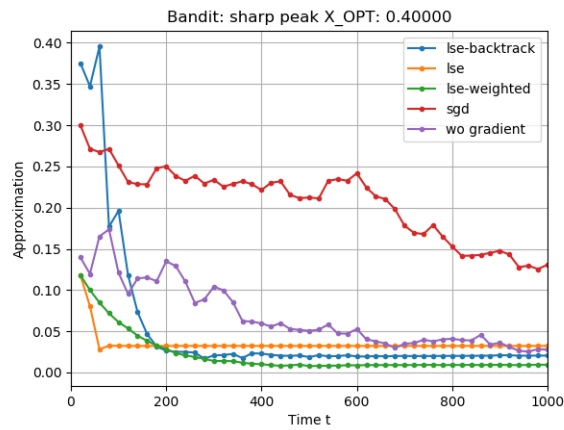


FIGURE 18 – Approximation $X_{OPT} = 0.4$

10 18/07/2019 :

10.1 Work on Paper

Modify LSE-weighted in Paper

Execute for Google cluster data

I have executed algorithms for Google cluster data for more rounds to achieve that the

11 19/07/2019 :

11.1 Work in LINCS

- Meeting with Lorenzo.
- Try more different intervals for LSE-backtrack. I have tried :

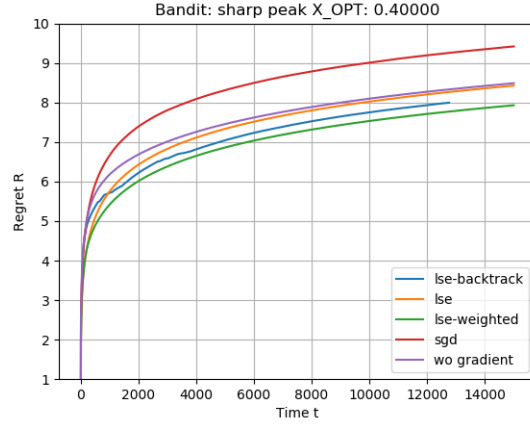


FIGURE 19 – Regret $X_{OPT}=0.4$

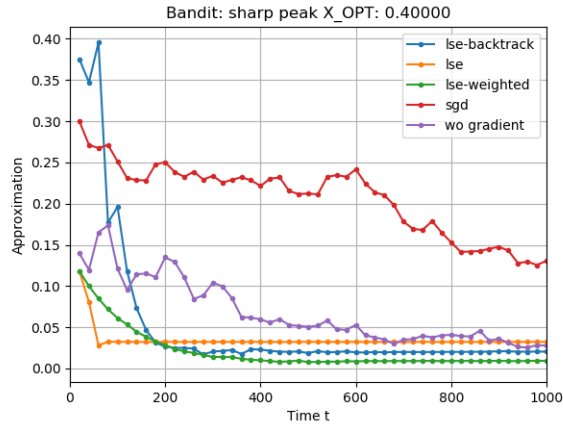


FIGURE 20 – Approximation $X_{OPT} = 0.4$

$\text{intervals1} = [(0.4, 0.45), (0.45, 0.5), (0.5, 0.55), (0.55, 0.6), (0.6, 0.65)]$
 $\text{intervals2} = [(0.45, 0.55), (0.55, 0.65), (0.65, 0.75), (0.75, 0.85), (0.85, 0.95)]$
 $\text{intervals3} = [(0.45, 0.65), (0.55, 0.75), (0.65, 0.85), (0.75, 0.95)]$
 $\text{intervals4} = [(0.45, 0.75), (0.5, 0.8), (0.55, 0.85), (0.6, 0.9), (0.65, 0.95)]$
 $\text{intervals5} = [(0.45, 0.85), (0.5, 0.9), (0.55, 0.95)]$

- For a interval, try different number of simple for LSE-backtrack. I have tried number of simple : 10, 20, \dots , 100

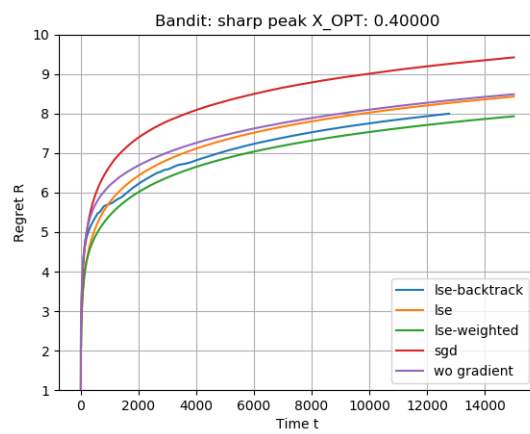


FIGURE 21 – Regret $X_{OPT}=0.4$