Pricing & Social Influence

Data Intelligence Applications

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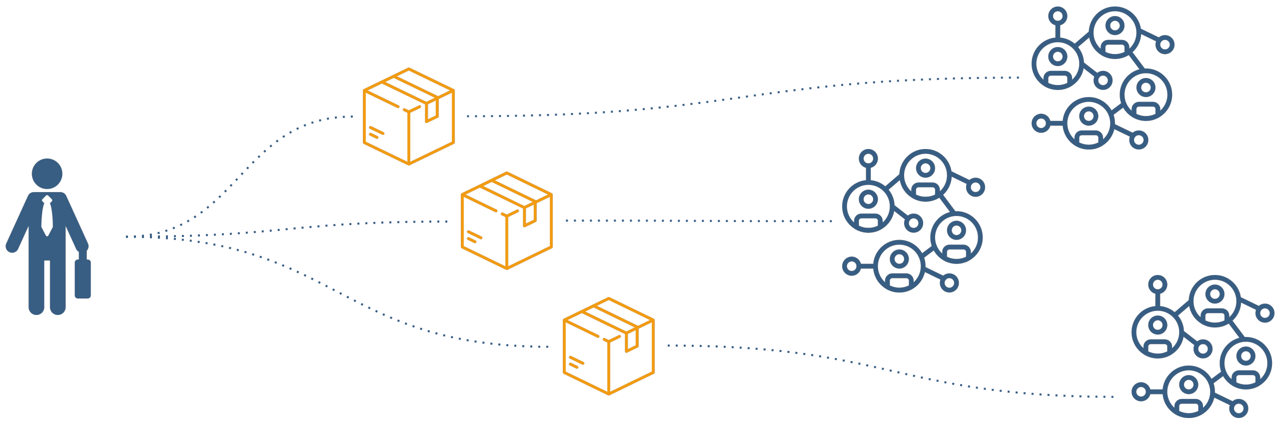
1. The problem

The goal is modeling a scenario in which a seller is pricing some products and spends a given budget on social networks to persuade more and more nodes to buy the products.



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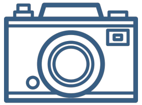
1. The products

Television

500, 690, 750, 850

Laptop

500, 690, 750, 850



Camera

500, 690, 750, 850

1. The features

Gender: Male/Female

Age: <18, 18-25, 26-34, 35-50, >50

Location: Africa, Asia, Europe, North America, South America, Australia

Interests: technology, sports, politics, science, economics, health

Authority: a node connected to many neighbors can be seen as an influencer

1. The social networks

Facebook

age

Twitter

interests

Instagram

authority

2. Greedy algorithm

`greedy_algorithm(graph, budget, k)`

Search the best set of seeds adding one at the time until we reach the budget

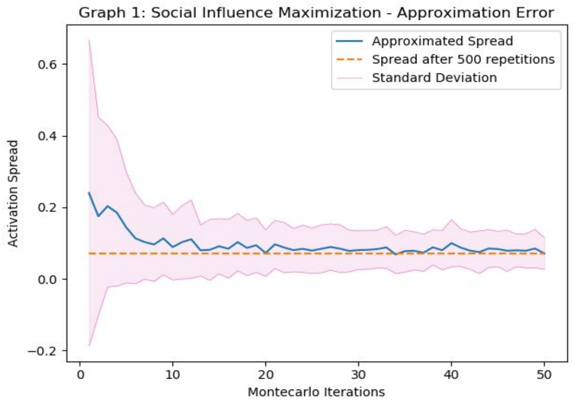
`montecarlo_sampling(seeds, max_repetitions)`

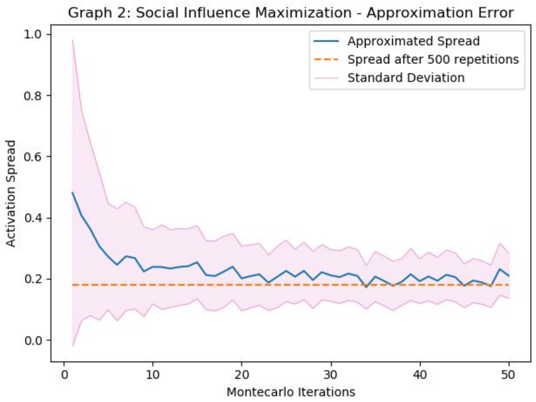
Given a set of seeds, evaluate the spread in the network through different simulations

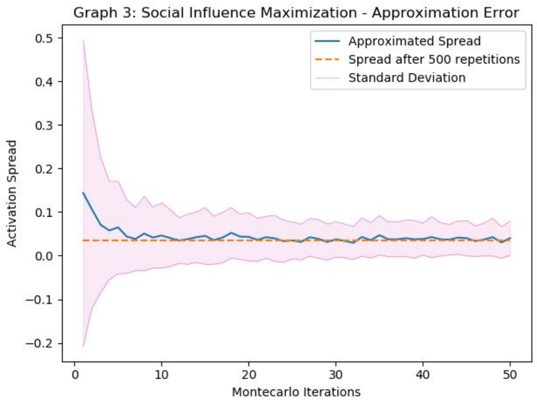
`approximation_error(graphs, budget, scale_factor, n_exp)`

Plot the result of running the greedy algorithm on the different networks

2. Greedy algorithm - Results







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3. Greedy algorithm over all networks

Now we want to perform jointly social influence in the three social networks

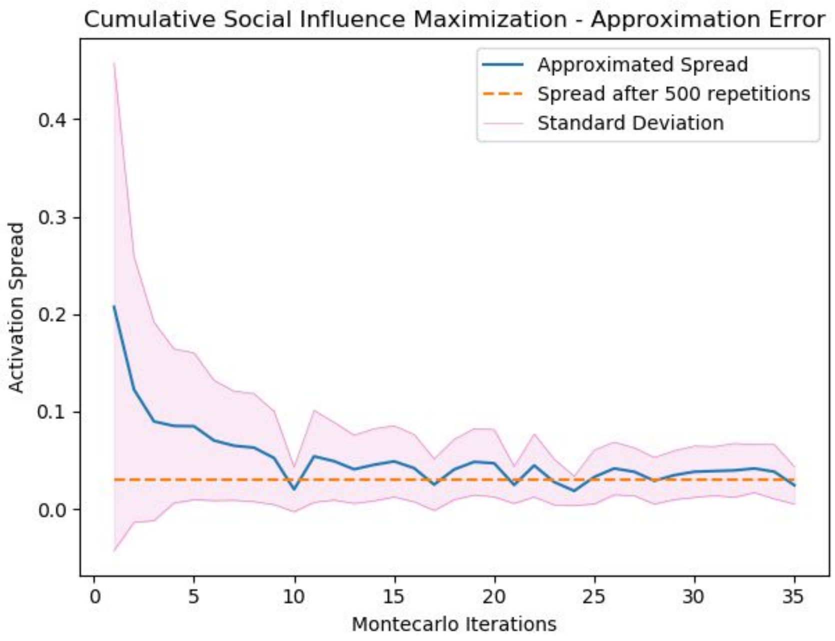
```
cumulative_greedy_algorithm(graphs, budget, k)
```

Until the budget is not finished, search in the different networks the seed that will provide the best marginal increase and add it to the set of seeds

```
cumulative_approximation_error(graphs, budget, scale_factor, n_exp)
```

Plot the results of running the cumulative greedy algorithm on the three social networks

3. Greedy algorithm over all networks - Results



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4. Unknown activation probabilities

We consider the adjacency matrix as the true values to which we want to converge

We model each edge as a Bernoulli variable and we define a Beta distribution over them

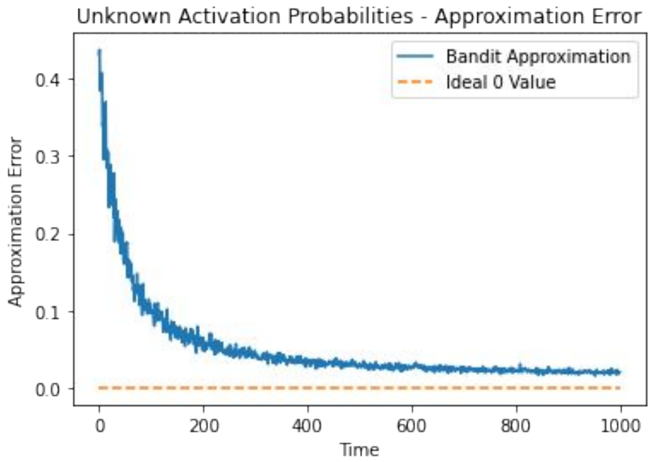
```
choose_seeds(graph, budget, epsilon, simulations)
```

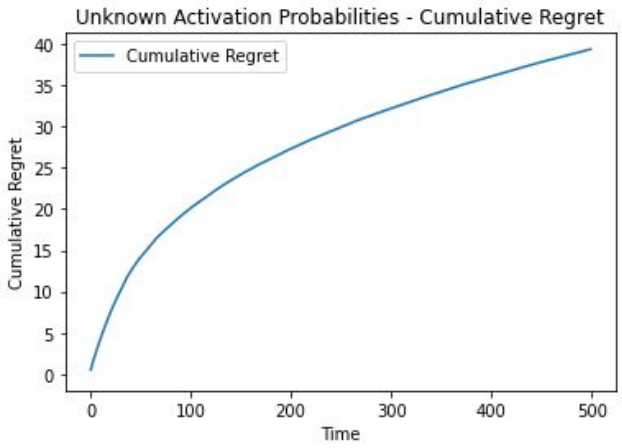
We use the greedy algorithm to select the set of seeds. The parameter epsilon allows to regulate the exploration/exploitation dilemma

```
influence_episode(seeds, true_graph.adj_matrix)
```

Collect a sample for each edge and observe which edges will activate, updating the Beta parameters

4. Unknown activation probabilities - Results





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5. Cumulative revenue maximization

We assume to have an unique seasonal phase and that the activations of the graph are known

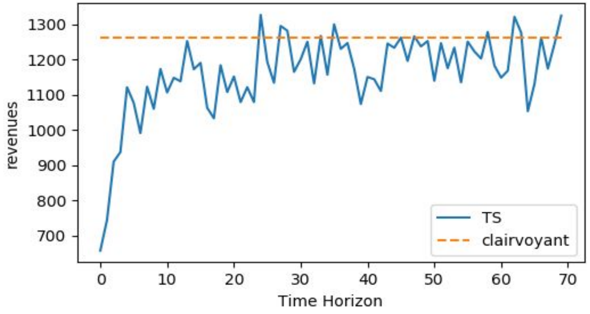
`TS_Learner(n_arms, arms)`

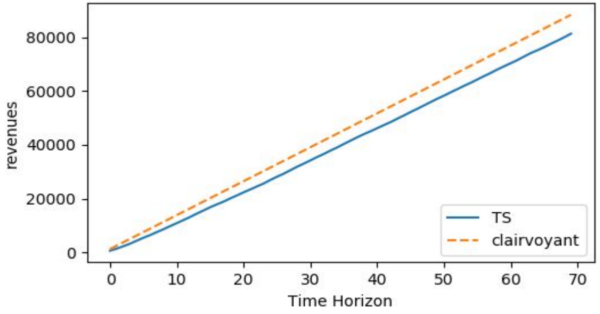
Builds a class to manage the Thompson Sampling operations: the choice of the arm to pull and, given the rewards, the update of the distributions.

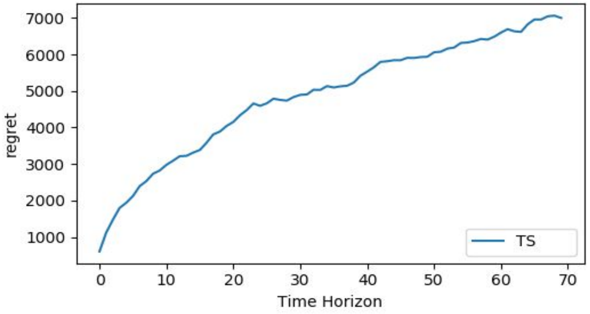
`Environment(n_arms, probabilities, horizon)`

Simulates the environment where the arms are: it gives the rewards based on the real probabilities for the event to occur.

5. Cumulative revenue maximization - Results(1)







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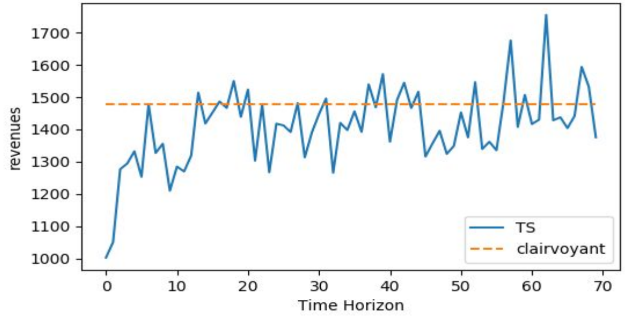
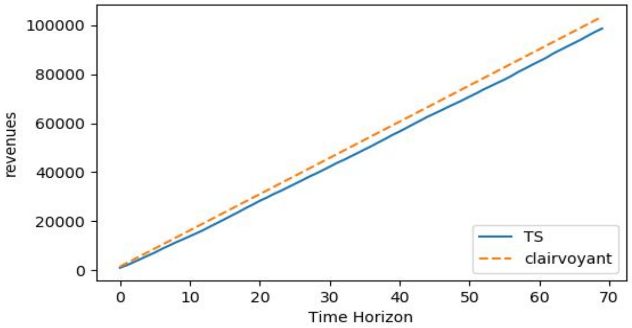
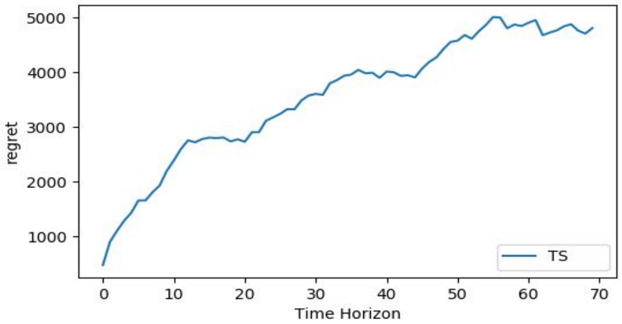
5. Cumulative revenue maximization - Results(2)







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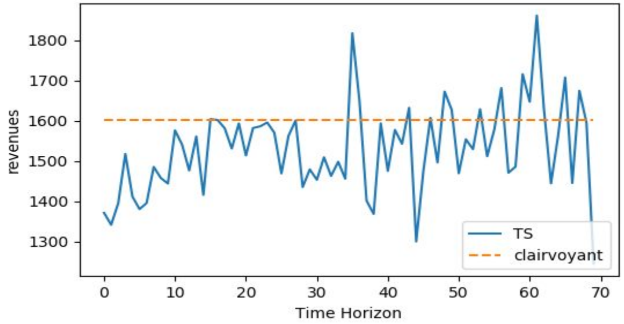
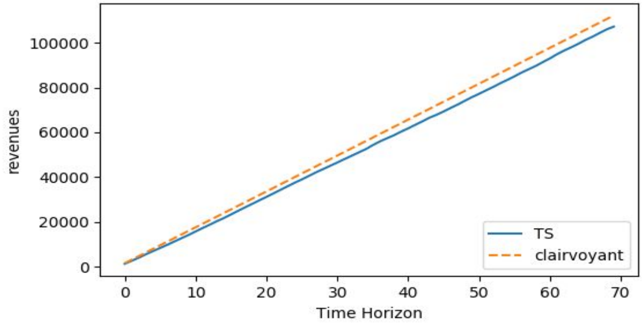
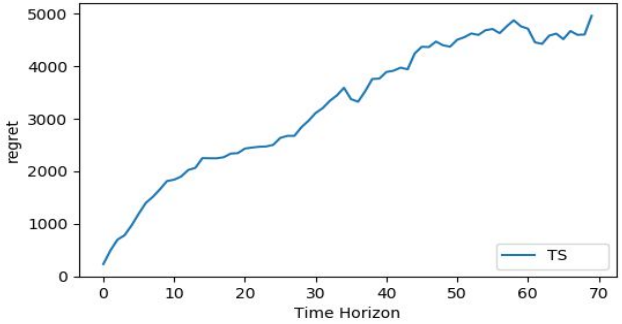
5. Cumulative revenue maximization - Results(3)







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6. Pricing with seasonal phases

15
november

01
december

25
december

15
january

1st season

BEFORE CHRISTMAS

2nd season

CHRISTMAS

3rd season

AFTER CHRISTMAS

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6. Pricing with seasonal phases

We consider now three different phases with abrupt transitions and we still assume to know the activation probabilities of the social networks

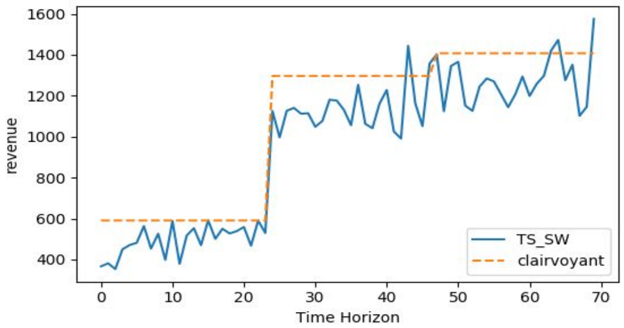
`SWTS_Learner(n_arms, arms, window_size, horizon)`

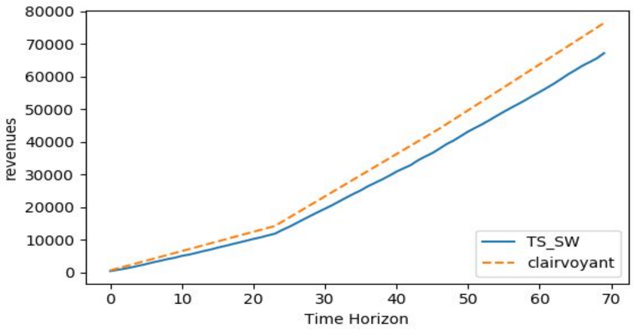
Builds the class to manage the operation of the Thompson Sampling with Sliding Window: the choice of the arm to pull and, given the rewards, the update of the distributions, taking into account only the rewards obtained inside the Sliding Window.

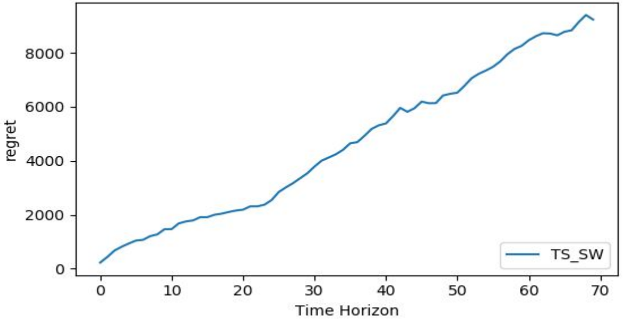
`Non_Stationary_Environment(n_arms, probabilities, horizon)`

Simulates the environment of the arms: it gives the rewards based on the real probabilities for the event to occur, taking into account the phase in that specific moment.

6. Pricing with seasonal phases - Results(1)







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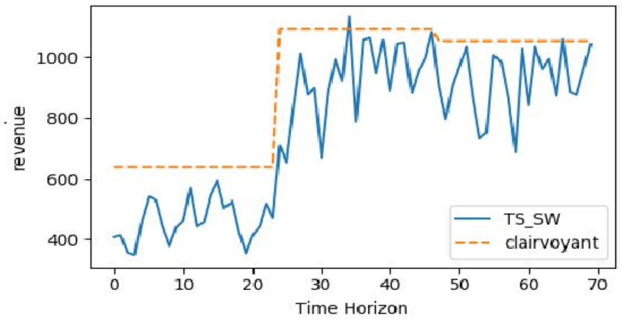
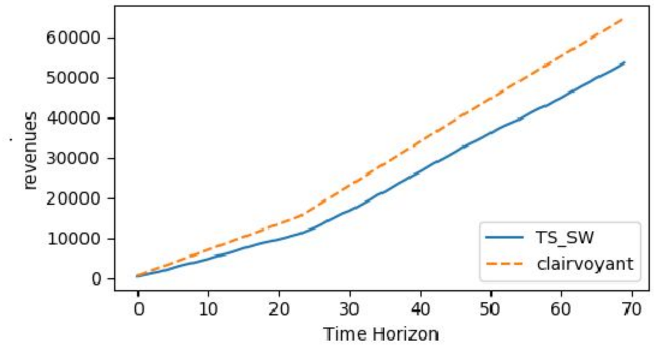
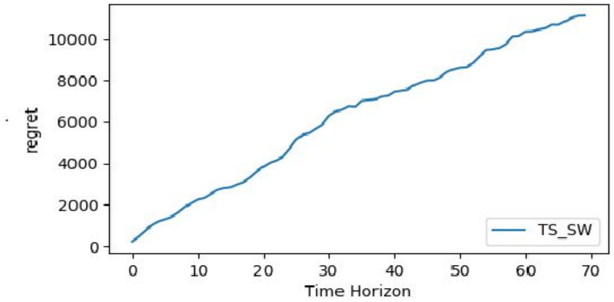
6. Pricing with seasonal phases - Results(2)







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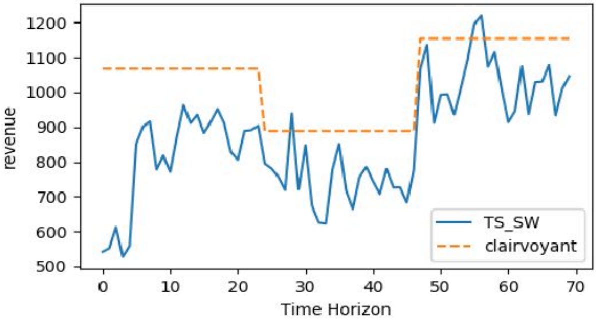
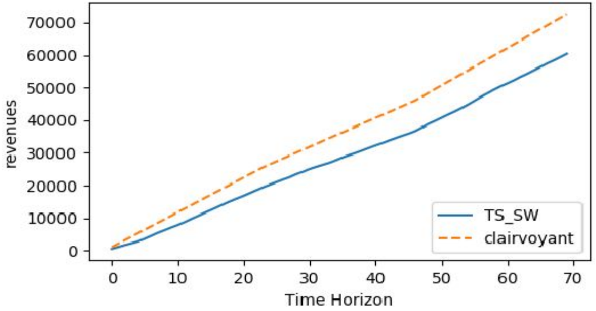
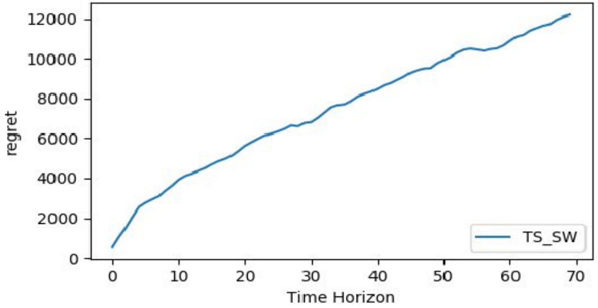
6. Pricing with seasonal phases - Results(3)







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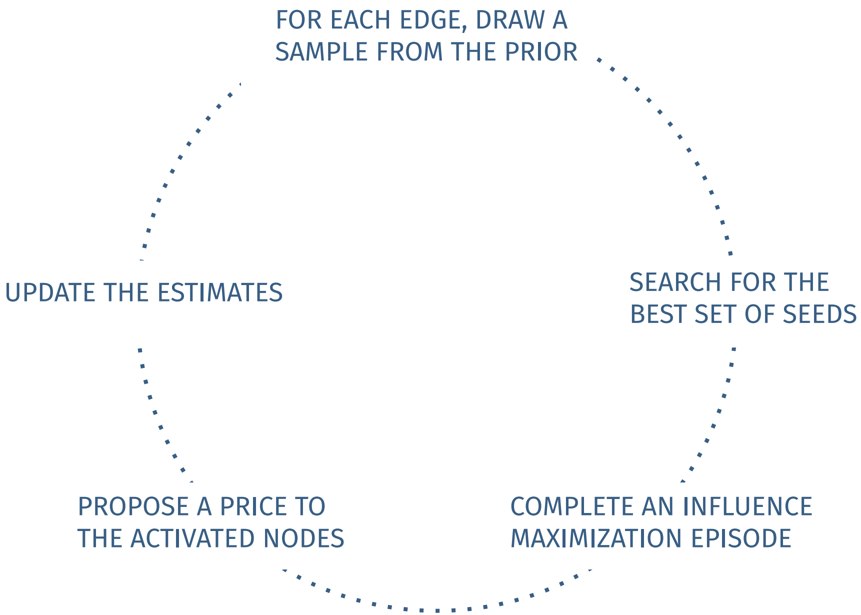
7. Pricing and social influence learning

Now we cannot consider the activation probabilities as known a priori

The seller needs to learn both the activation probabilities and the conversion rate curves simultaneously



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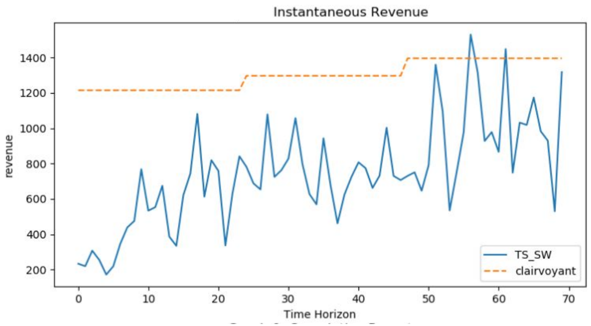
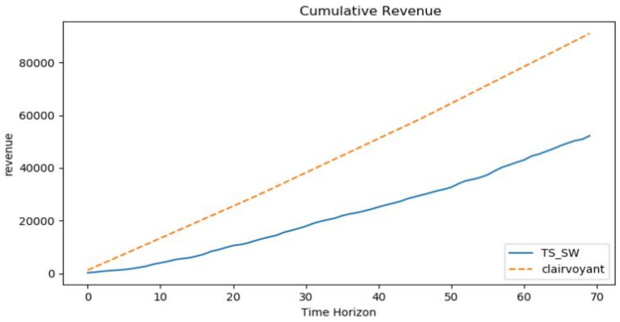
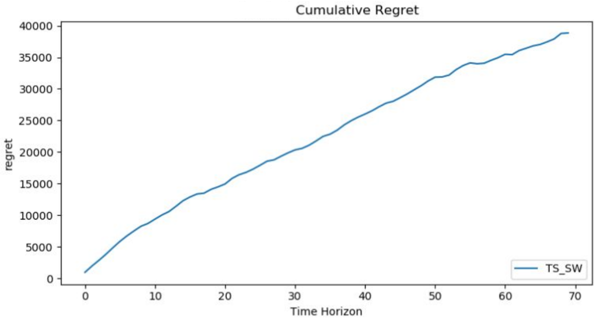
7. Pricing and social influence learning - Results(1)







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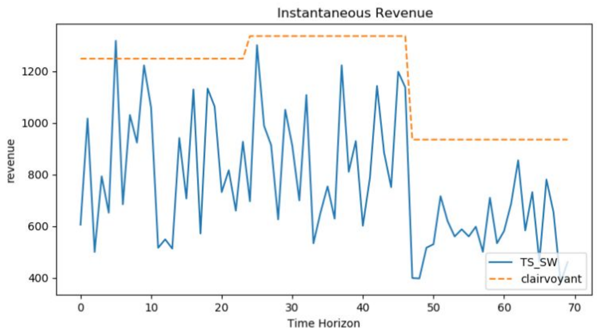
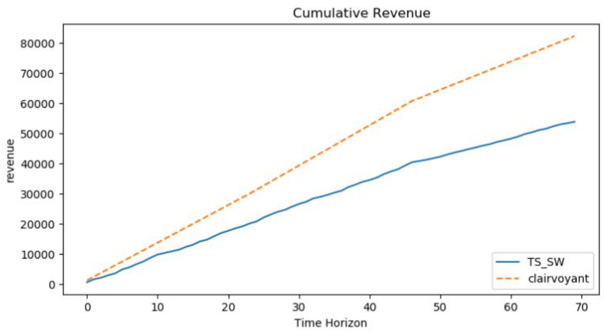
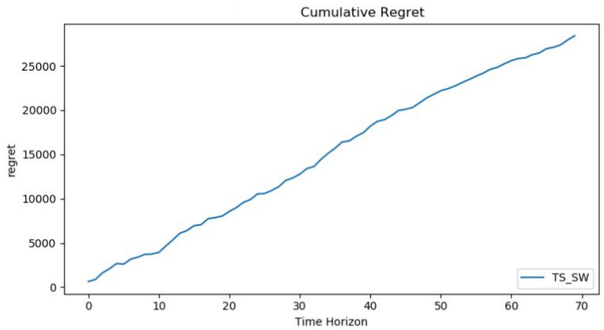
7. Pricing and social influence learning - Results(2)







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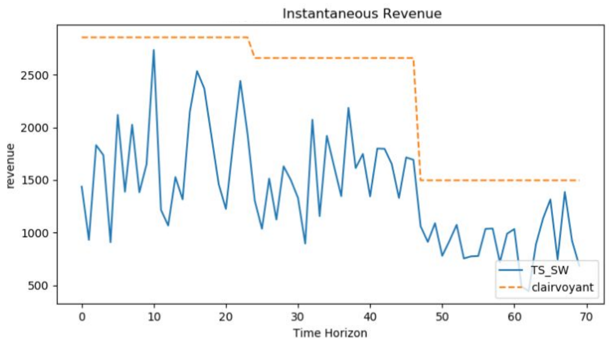
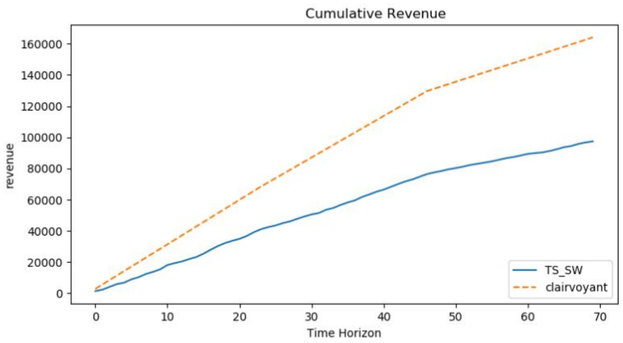
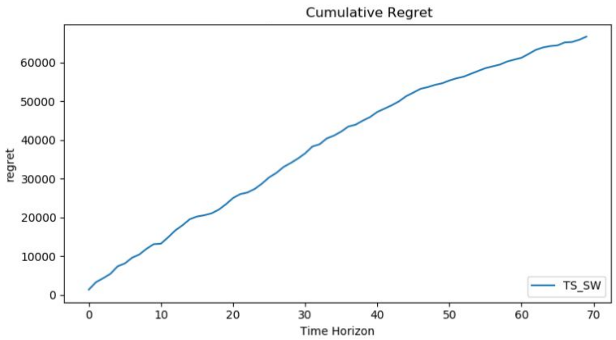
7. Pricing and social influence learning - Results(3)







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