Linkedin

Online Parameter Selection for Web-based Ranking via Bayesian Optimization

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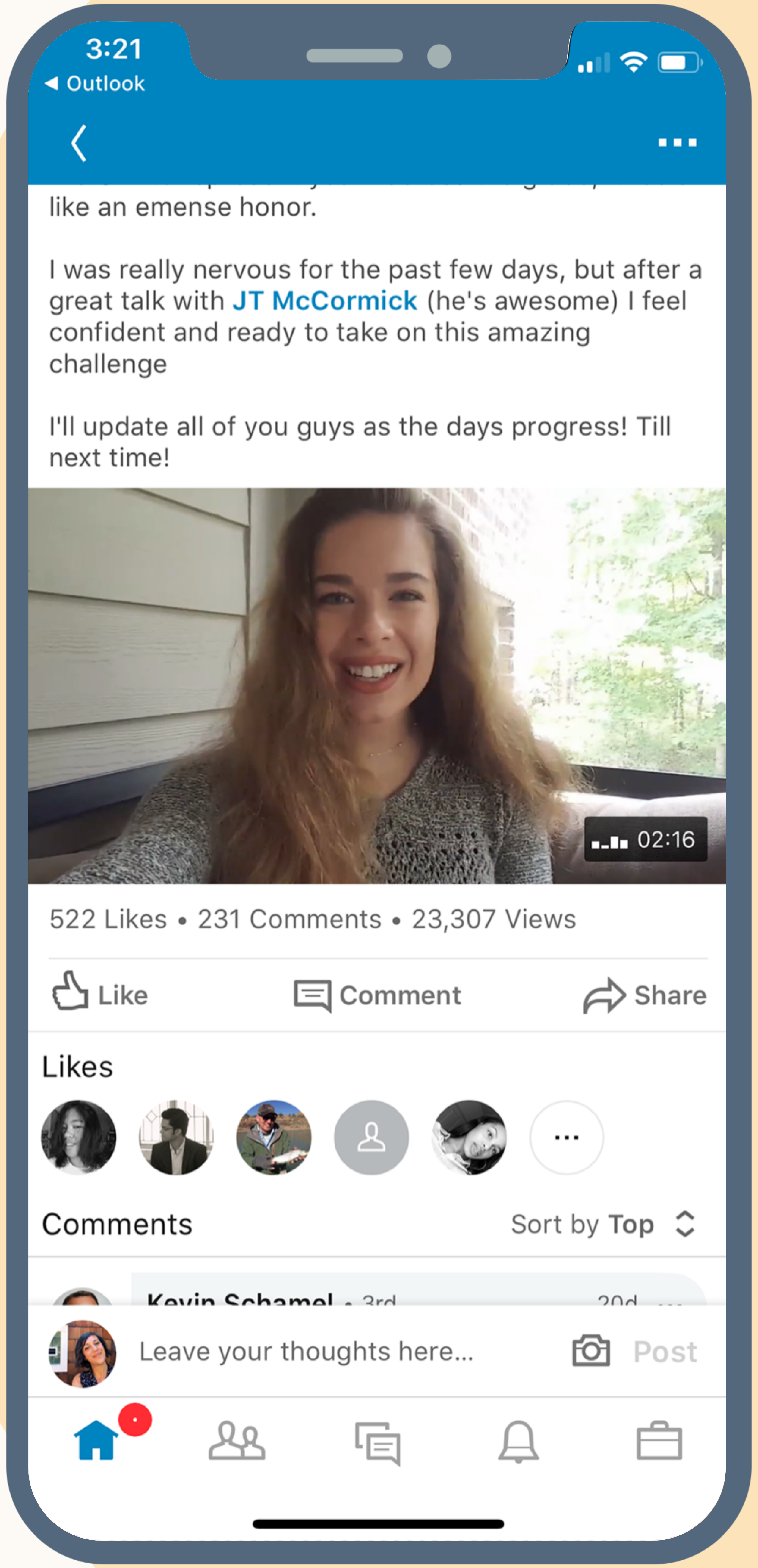
Agenda

1. Problem Setup
   LinkedIn Feed
2. Reformulation as a Black-Box Optimization
3. Explore-Exploit Algorithm
   Thompson Sampling
4. Infrastructure
5. Results

LinkedIn Feed

Mission: Enable Members to build an active professional community that advances their career.

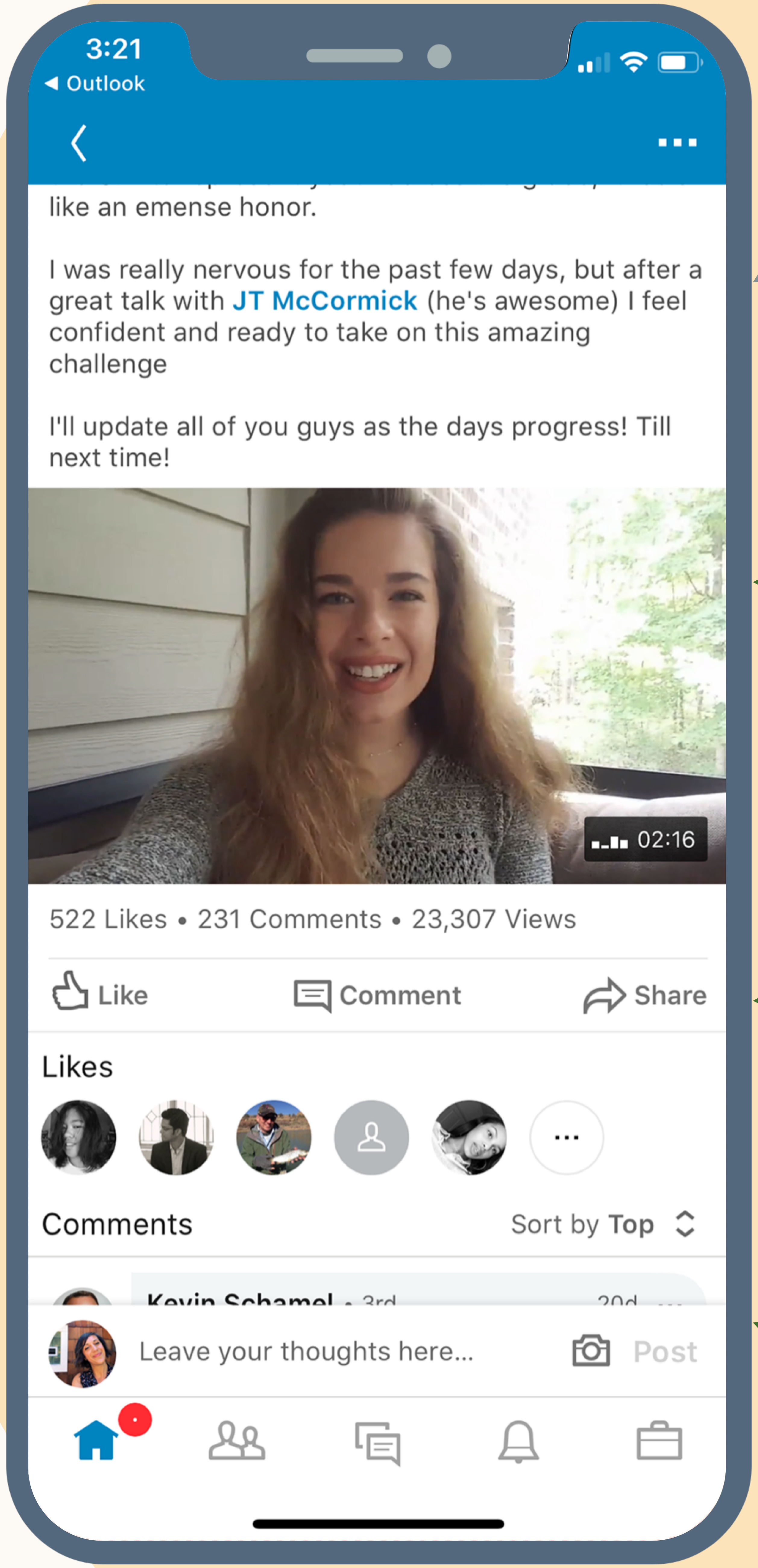


LinkedIn Feed

Mission: Enable Members to build an active professional community that advances their career.

Heterogenous List:

- Shares from a member's connections
- Recommendations such as jobs, articles, courses, etc.
- Sponsored content or ads



Member Shares

Jobs

Articles

Ads

Important Metrics

Viral Actions (VA)

Members liked, shared or commented on an item

Job Applies (JA)

Members applied for a job

Engaged Feed Sessions (EFS)

Sessions where a member engaged with anything on feed.

Ranking Function

- m – Member, u - Item

$$S(m,u) \coloneqq P_{VA}(m,u) + \ x_{EFS}\ P_{EFS}(m,u) + x_{JA}\ P_{JA}(m,u)$$

- The weight vector $x = (x_{EFS}, x_{JA})$ controls the balance between the three business metrics: EFS, VA and JA.
- A Sample Business Strategy is

$$\begin{aligned}
&Maximize. \quad && VA(x) \\
&s.t. && EFS(x) > c_{EFS} \\
& && JA(x) > c_{JA}
\end{aligned}$$

Major Challenges

- The optimal value of x (tuning parameters) changes over time
- Example of changes
  - New content types are added
  - Score distribution changes (Feature drift, updated models, etc.)

- With every change engineers would manually find the optimal x
  - Run multiple A/B tests
- Not the best use of engineering time

Reformulation into a Black-Box Optimization Problem

Modeling The Metrics

- $Y_{i,j}^{k}(x) \in \{0,1\}$ denotes if the i-th member during the j-th session which was served by parameter x, did action k or not. Here k = VA, EFS or JA.
- We model this data as follows

$$Y_i^k \sim \text{Binomial}\left(n_i(x), \sigma\left(f_k(x)\right) \right)$$

where $n_i(x)$ is the total number of sessions of member i which was served by x and f_k is a latent function for the particular metric.

- Assume a Gaussian process prior on each of the latent function f_k .

Reformulation

We approximate each of the metrics as:

$$VA(x) = \sigma\left(f_{VA}(x)\right)$$
$$EFS(x) = \sigma\left(f_{EFS}(x)\right)$$
$$JA(x) = \sigma\left(f_{JA}(x)\right)$$

The original optimization problem can be written through this parametrization.

$$\begin{array}{ll} Maximize. & VA(x) \\ s.t. & EFS(x) > c_{EFS} \\ & JA(x) > c_{JA} \end{array} \Rightarrow \begin{array}{ll} Maximize & \sigma\left(f_{VA}(x)\right) \\ s.t. & \sigma\left(f_{EFS}(x)\right) > c_{EFS} \\ & \sigma\left(f_{JA}(x)\right) > c_{JA} \end{array} \Rightarrow \begin{array}{ll} Maximize & f(x) \\ x \in X & \end{array}$$

Benefit: The last problem can now be solved using techniques from the literature of Bayesian Optimization.

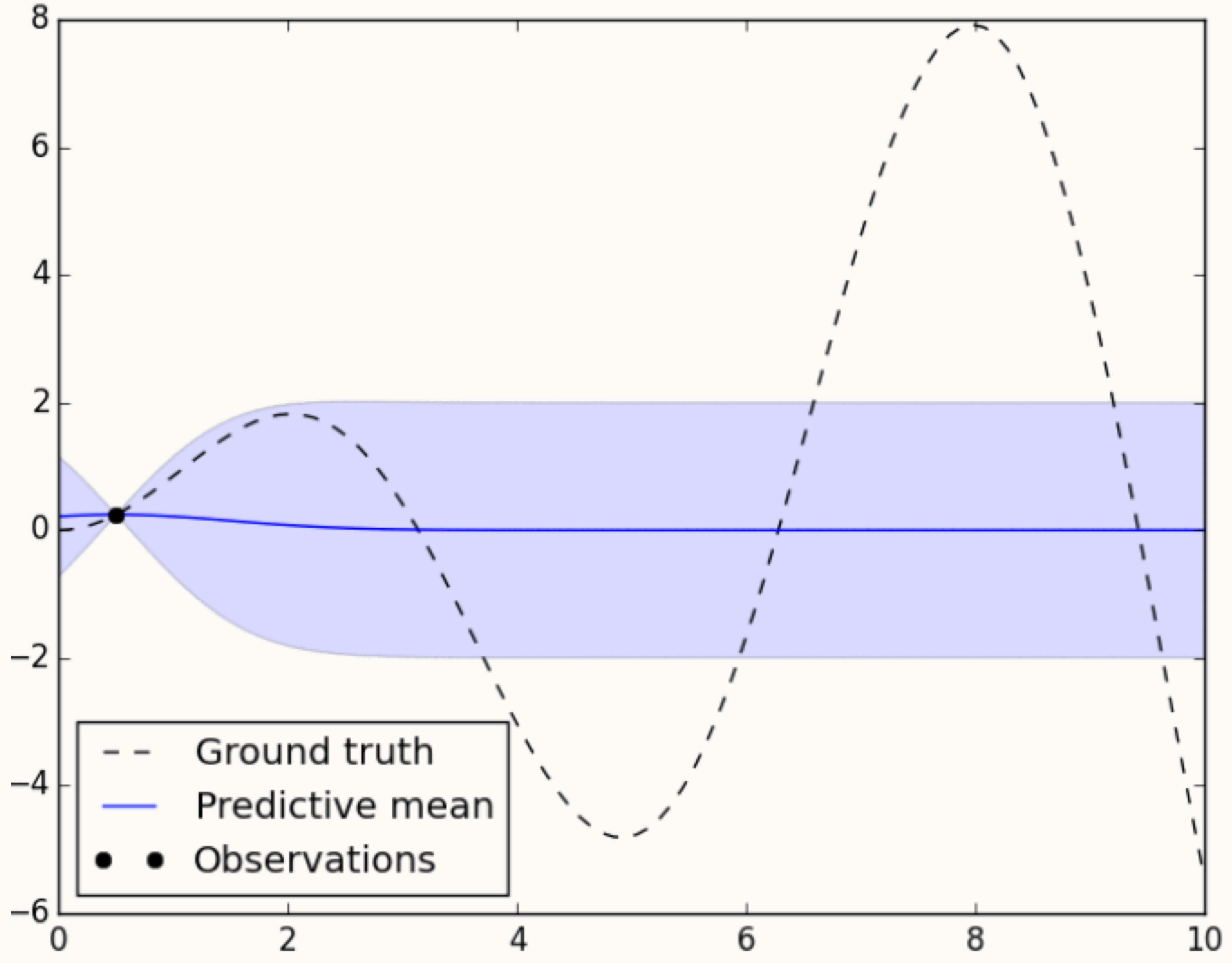
Explore-Exploit Algorithms

Bayesian Optimization

A Quick Crash Course

- Explore-Exploit scheme to solve

$$\underset{x \in X}{Maximize} \quad f(x)$$



Bayesian Optimization

A Quick Crash Course

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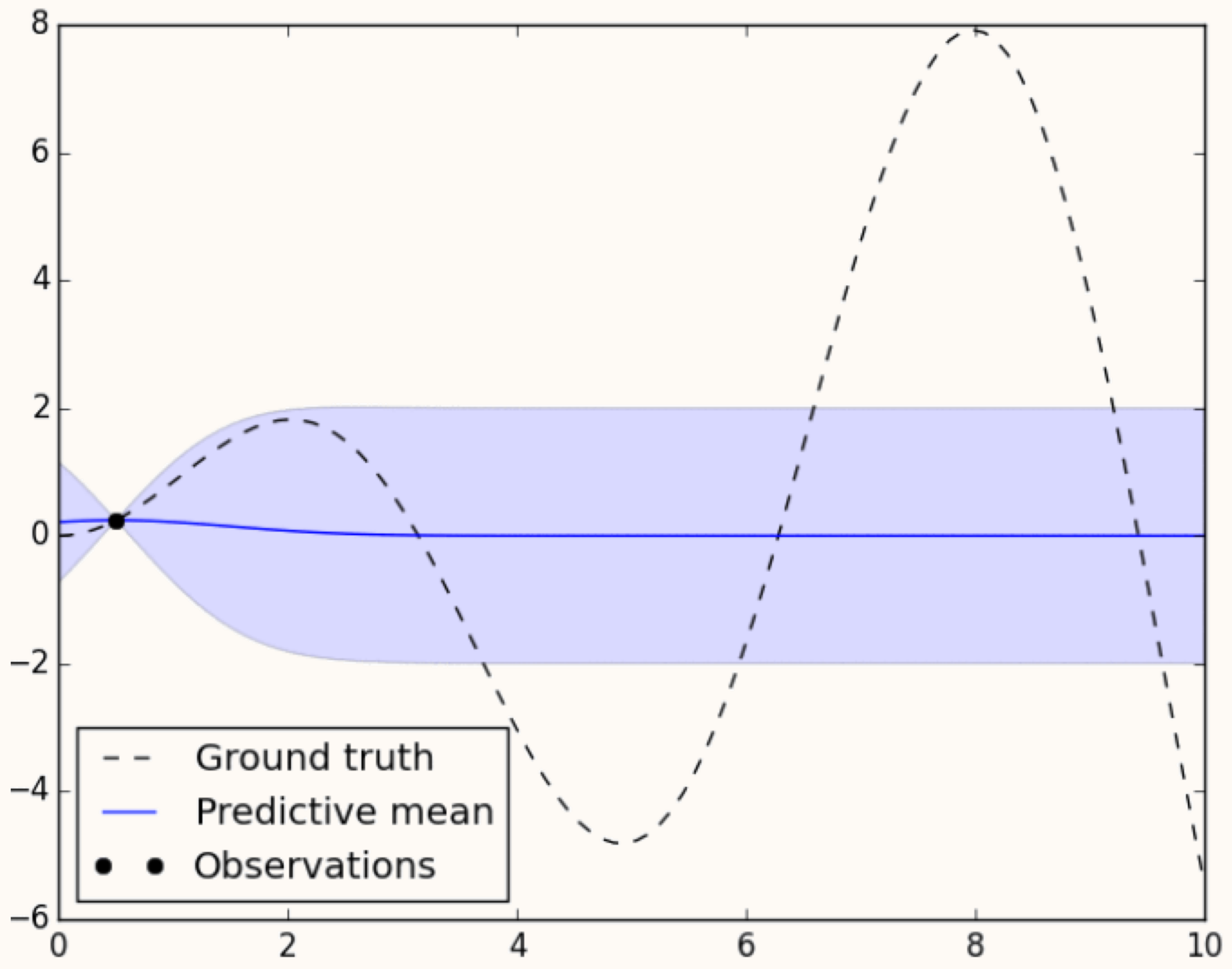
$$\underset{x \in X}{Maximize} \quad f(x)$$

- Assume a Gaussian Process prior on $f(x)$.
- Start with uniform sample get $(x, f(x))$
- Estimate the mean function and covariance kernel



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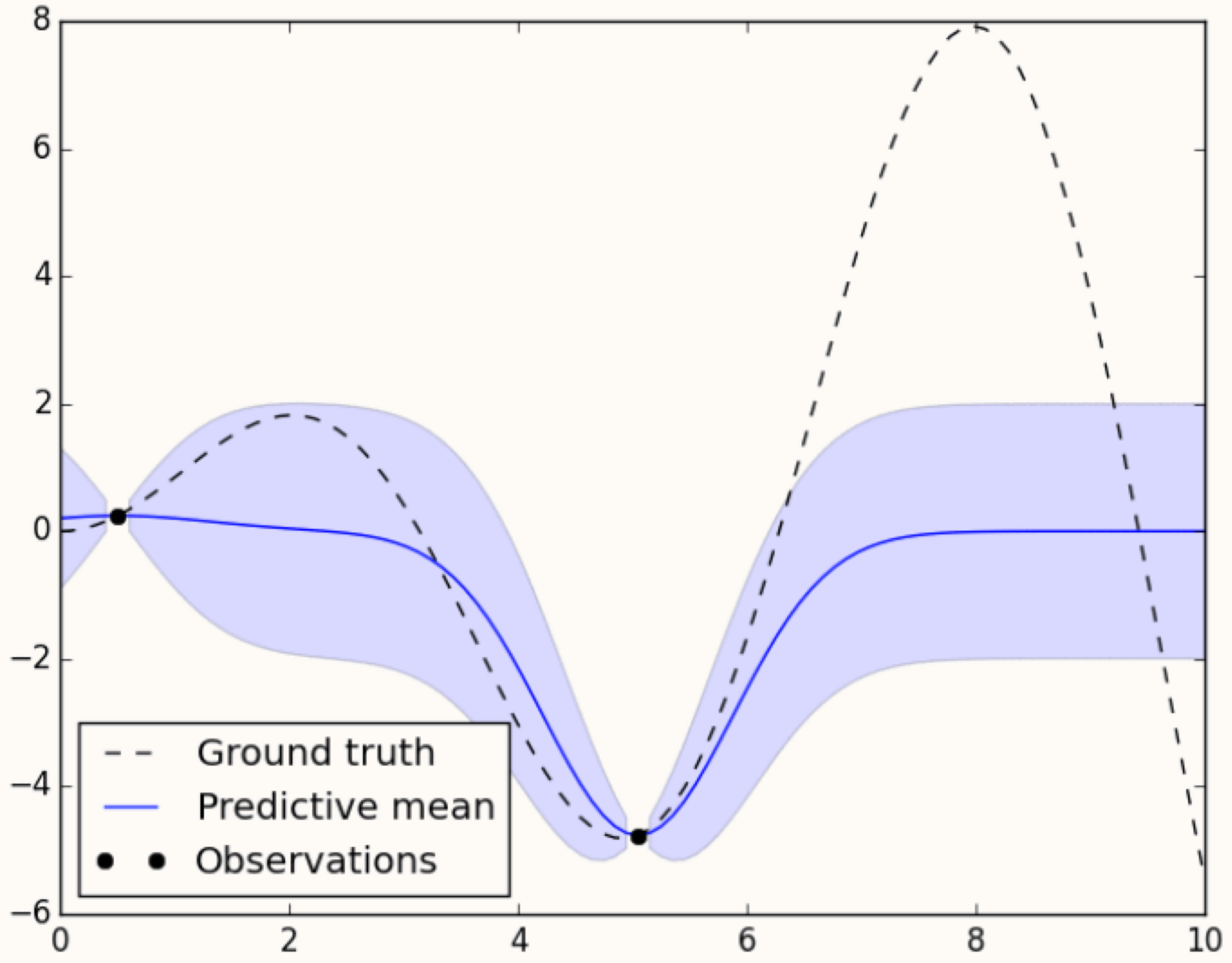
- Draw the next sample x which maximizes an *"acquisition function"* or predictive posterior.
- Continue the process.



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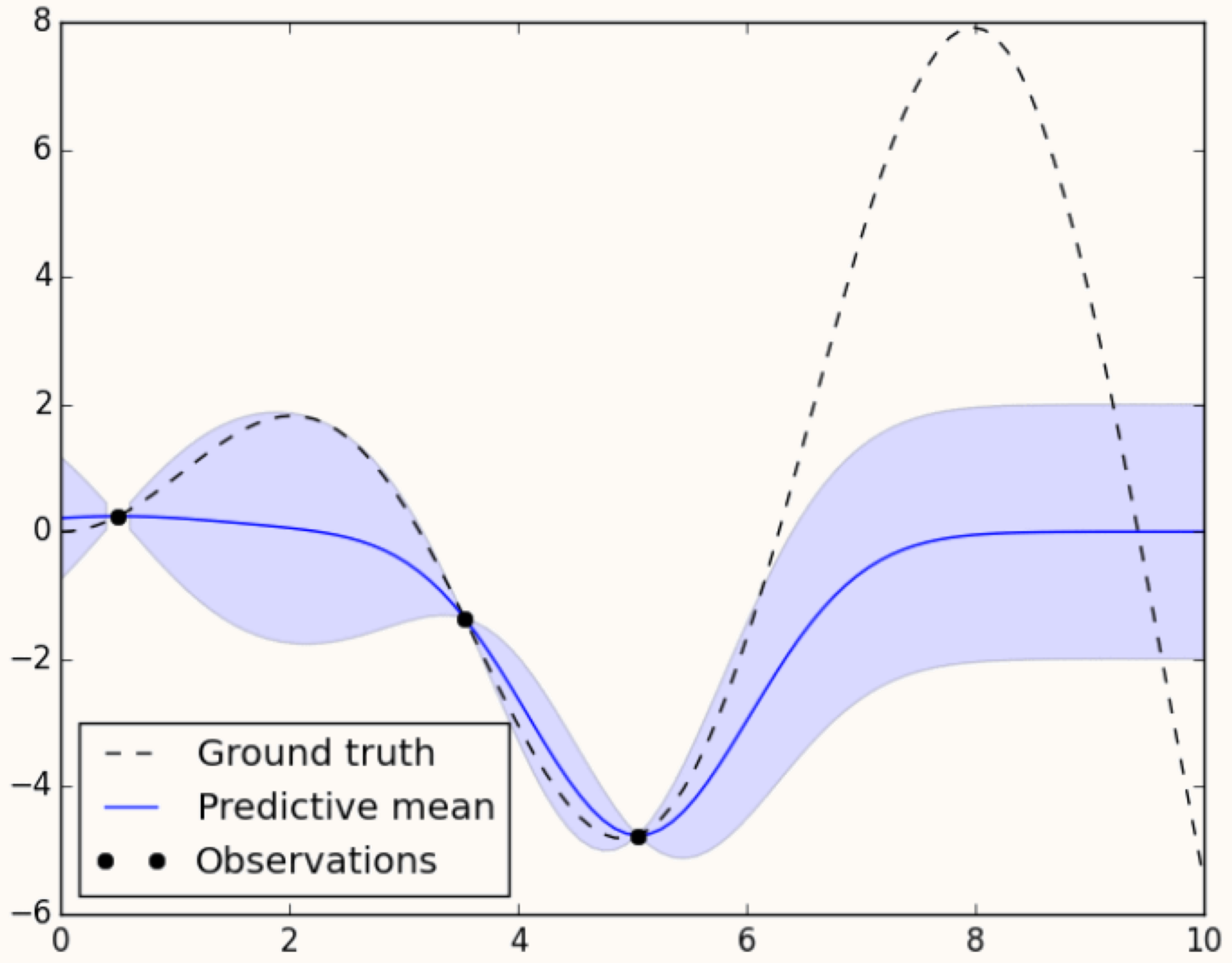

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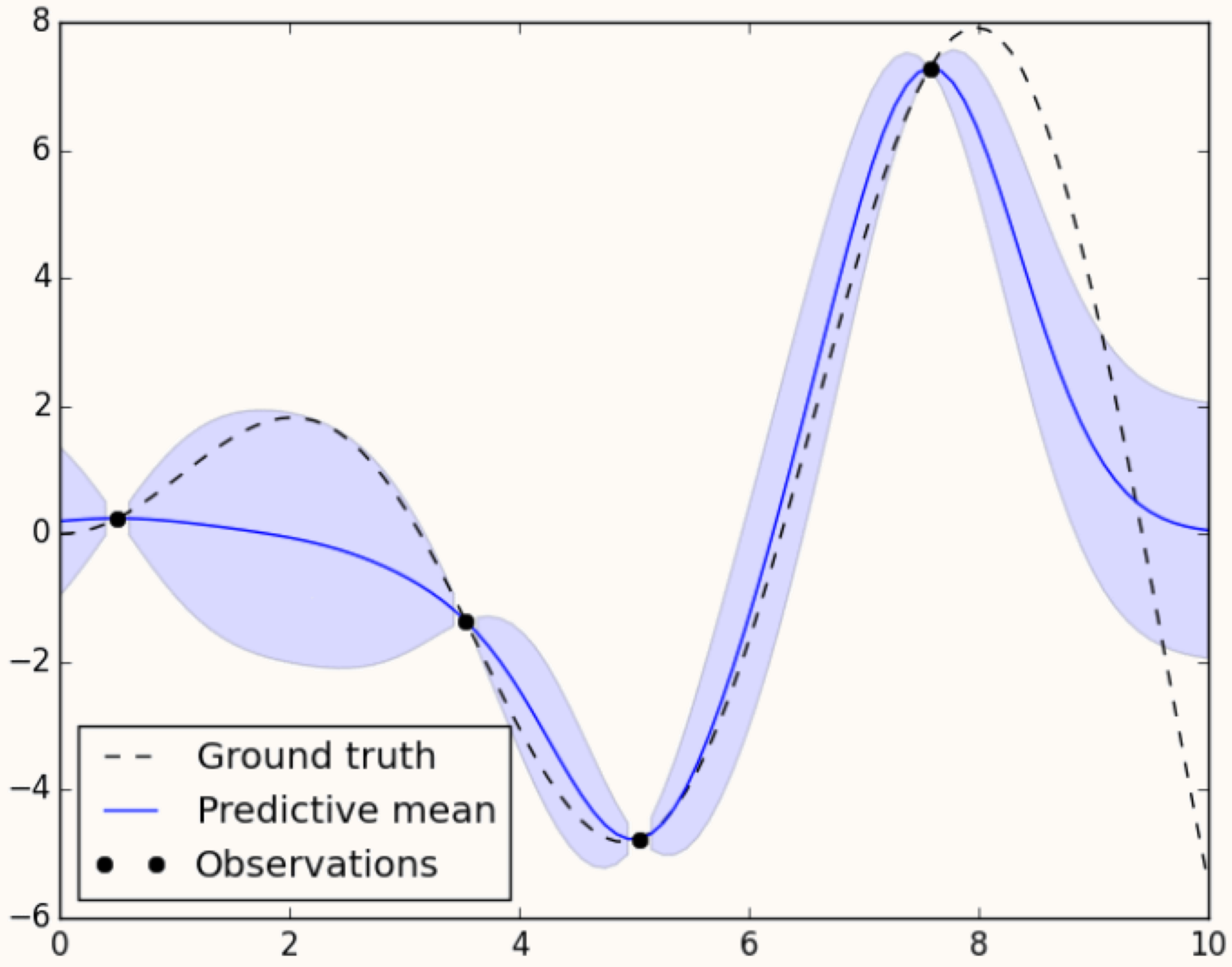

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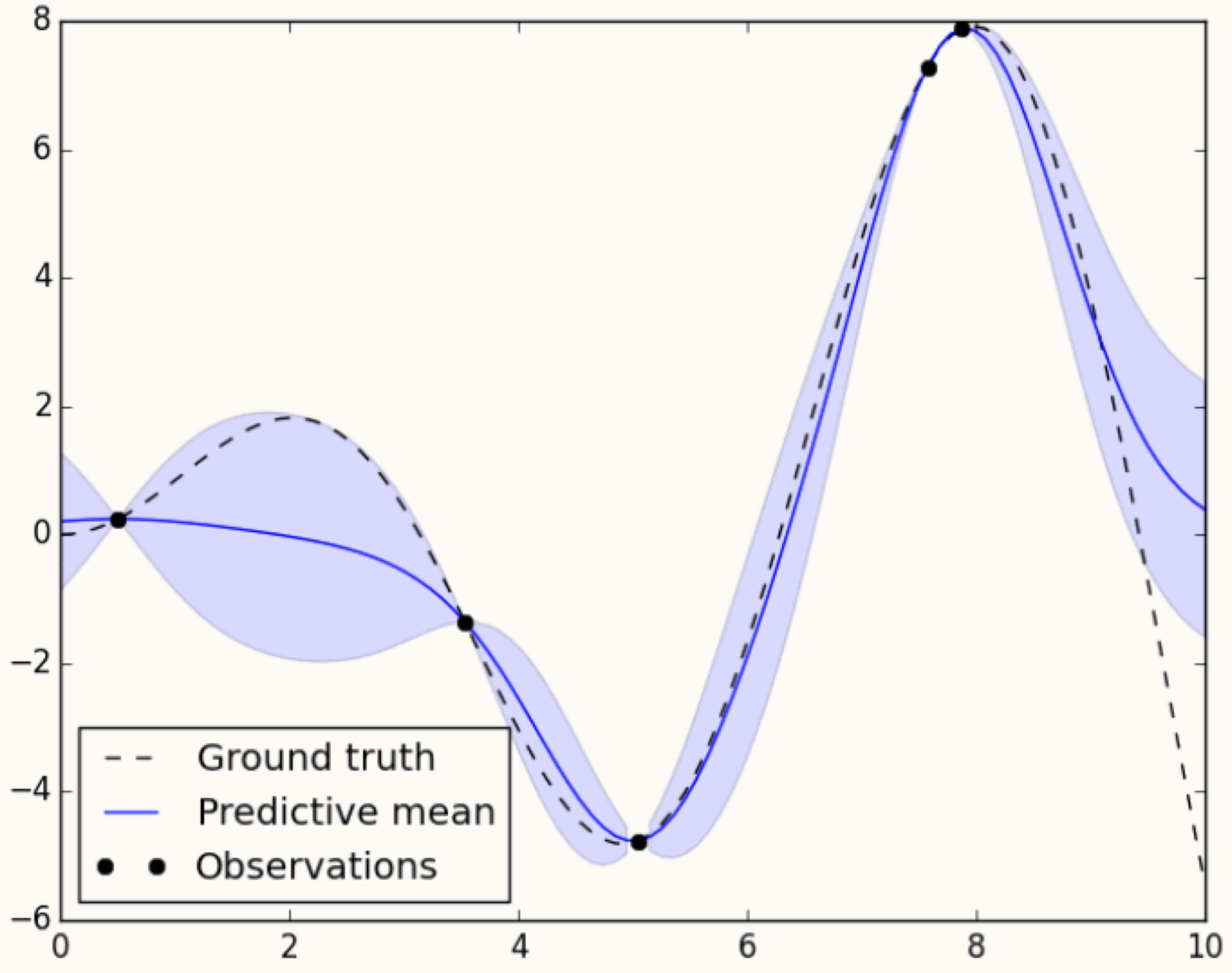


Thompson Sampling

- Consider a Gaussian Process Prior on each f_k, where k is VA, EFS or JA
- Observe the data $(x, f_k(x))$
- Obtain the posterior of each f_k which is another Gaussian Process
- Sample from the posterior distribution and generate samples for the overall objective function.
- We get the next distribution of hyperparameters by maximizing the sampled objectives (over a grid of QMC points).
- Continue this process till convergence.

$$
\begin{aligned}
&Maximize \quad \sigma\left(f_{VA}(x)\right) \\
&s.t. \quad \sigma\left(f_{EFS}(x)\right) > c_{EFS} \\
&\qquad \sigma\left(f_{JA}(x)\right) > c_{JA}
\end{aligned}
$$

Infrastructure

Overall System Architecture

Offline System

The heart of the product

Tracking

- All member activities are tracked with the parameter of interest.
- ETL into HDFS for easy consumption

Utility Evaluation

- Using the tracking data we generate $(x, f_k(x))$ for each function k.
- The data is kept in appropriate schema that is problem agnostic.

Bayesian Optimization

- The data and the problem specifications are input to this.
- Using the data, we first estimate each of the posterior distributions of the latent functions.
- Sample from those distributions to get distribution of the parameter x which maximizes the objective.

The Parameter Store and Online Serving

- The Bayesian Optimization library generates
  - A set of potential candidates for trying in the next round $(x_1, x_2, \dots, x_n)$
  - A probability of how likely each point is the true maximizer $(p_1, p_2, \dots, p_n)$ such that $\sum_{i=1}^{n} p_i = 1$

- To serve members with the above distribution, each **`memberId`** is mapped to [0,1] using a hashing function $\boldsymbol{h}$. For example, if

$$\sum_{i=1}^{k} p_i < h(Kinjal) \leq \sum_{i=1}^{k+1} p_i$$

  Then my feed is served with parameter x_{k+1}

- The parameter store (depending on use-case) can contain
  - `<parameterValue, probability>` i.e. (x_i, p_i) or
  - `<memberId, parameterValue>`

Online System

Serving hundreds of millions of users

Parameter Sampling

- For each member m visiting LinkedIn,
- Depending on the parameter store, we either evaluate `<m, parameterValue>`
- Or we directly call the store to retrieve `<m, parameterValue>`

Online Serving

- Depending on the parameter value that is retrieved (say x), the member's full feed is scored according to the ranking function and served

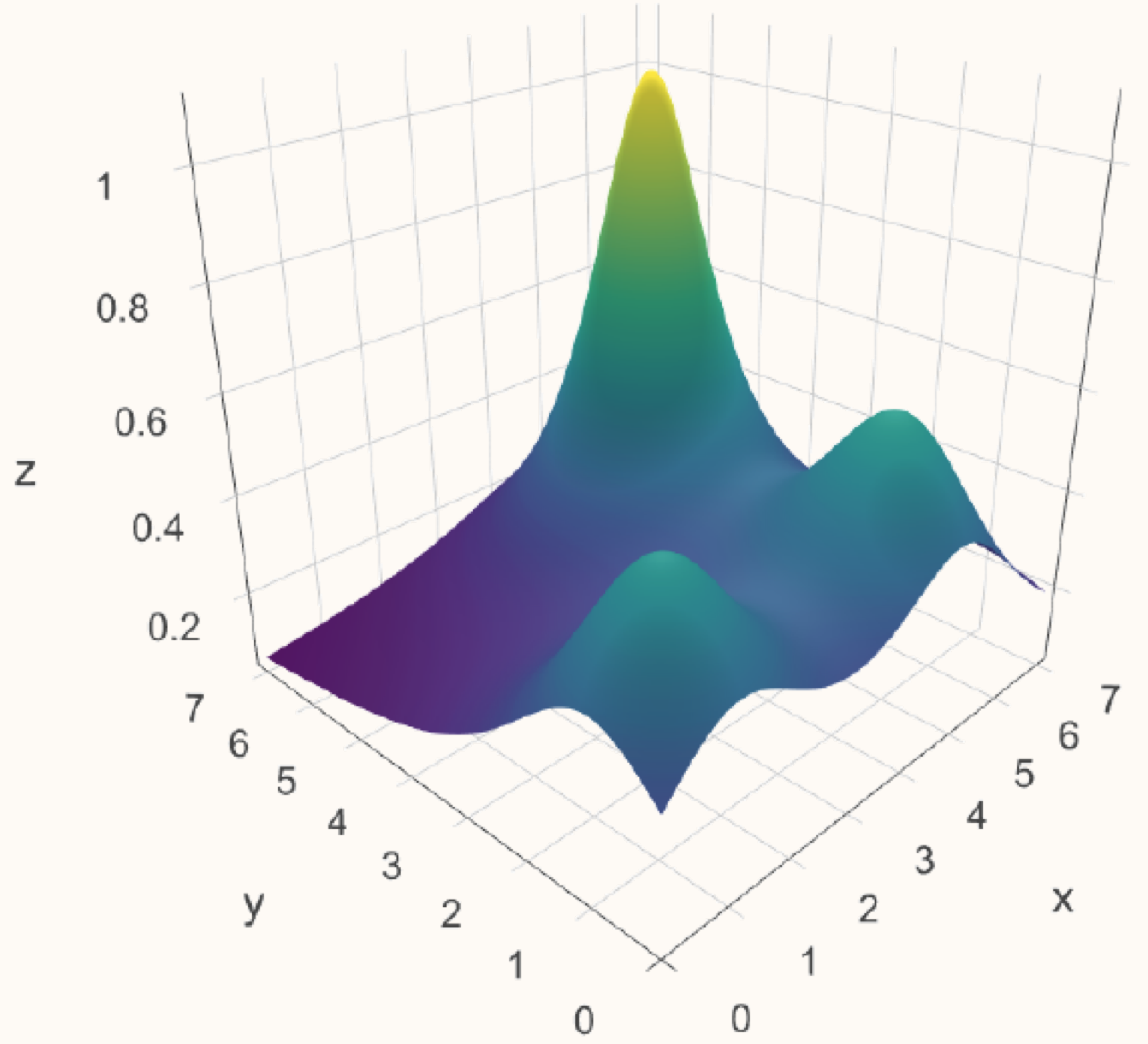
$$S(m,u) := P_{VA}(m,u) + x_{EFS}\, P_{EFS}(m,u) + x_{JA}\, P_{JA}(m,u)$$

Practical Design Considerations

- Consistency in user experience.
  - Randomize at member level instead of session level.
- Offline Flow Frequency
  - Batch computation where we collect data for an hour and run the offline flow each hour to update the sampling distribution.
- Assume $(f_{VA}, f_{EFS}, f_{JA})$ to be Independent
  - Works well in our setup. Joint modeling might reduce variance.
- Choice of Business Constraint Thresholds.
  - Chosen to allow for a small drop.

Results

Simulation Results



(a) Trimodal Shekel Function

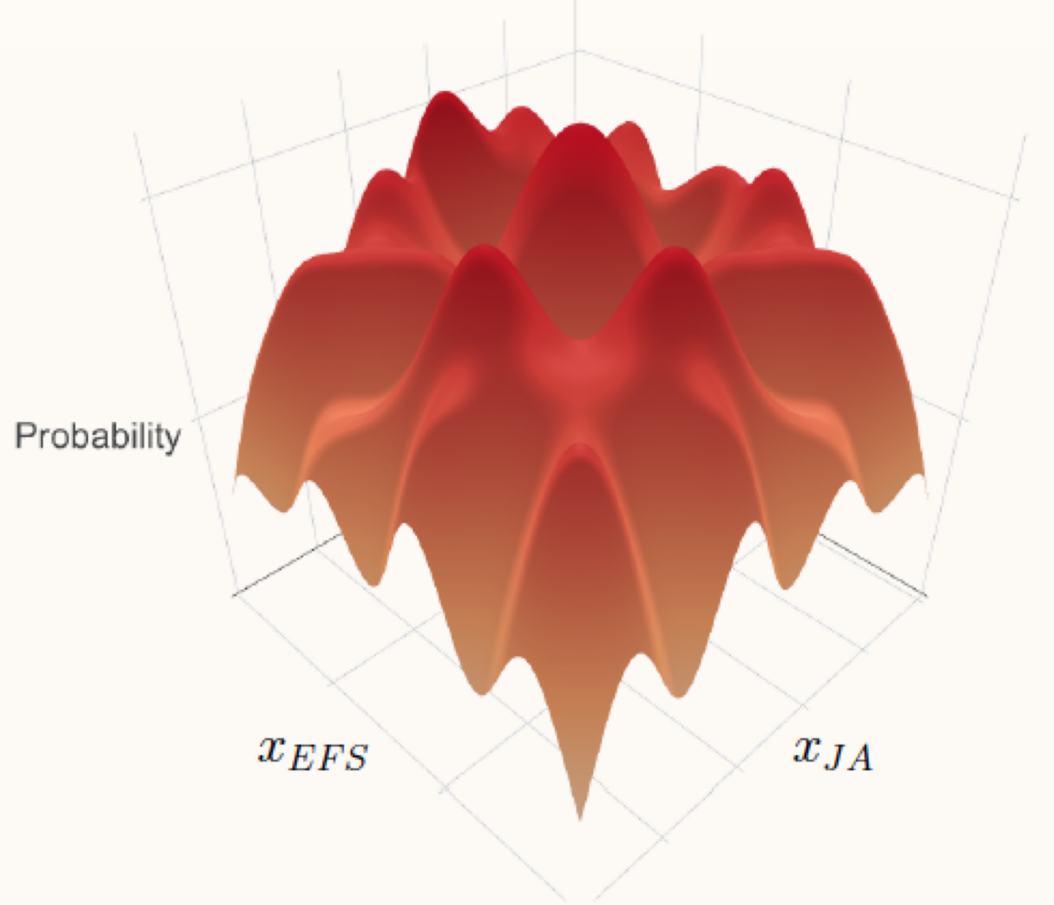
(b) Decay of log relative square error

Online A/B Testing Results

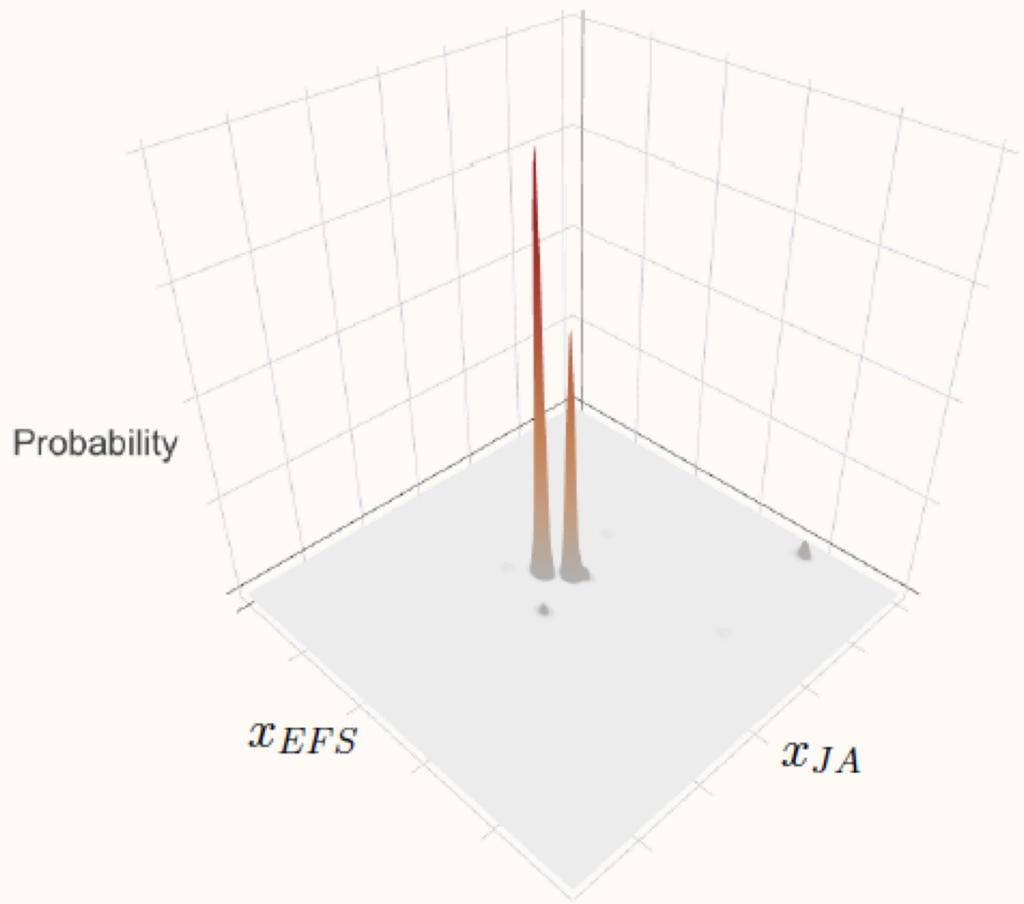
Table 1: Online A/B results for Online Parameter Selection in LinkedIn Feed Ranking

Metric	Lift (%) vs Control $\boldsymbol{x}_{c_1}$	Lift (%) vs Control $\boldsymbol{x}_{c_2}$
Viral Actions	+3.3%	+1.2%
Engaged Feed Sessions	-0.8%	0%
Job Applies	+12.8%	+6.4%

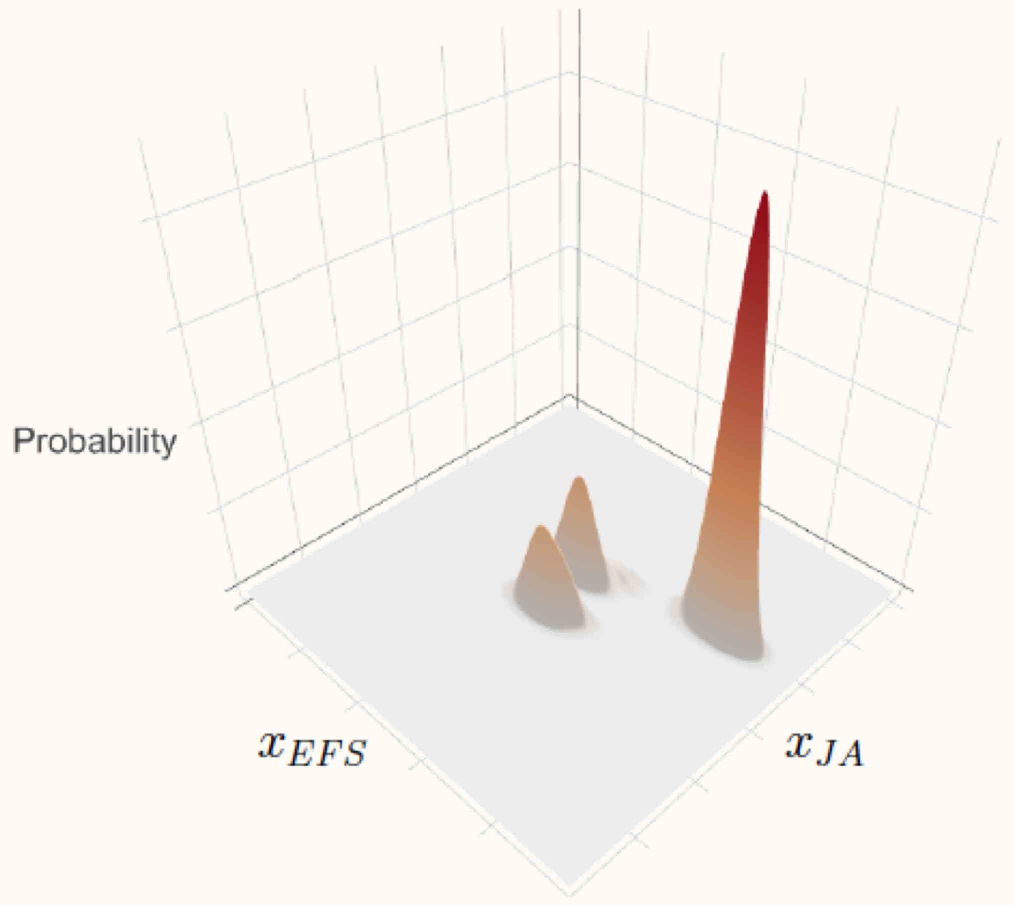
Online Convergence Plots



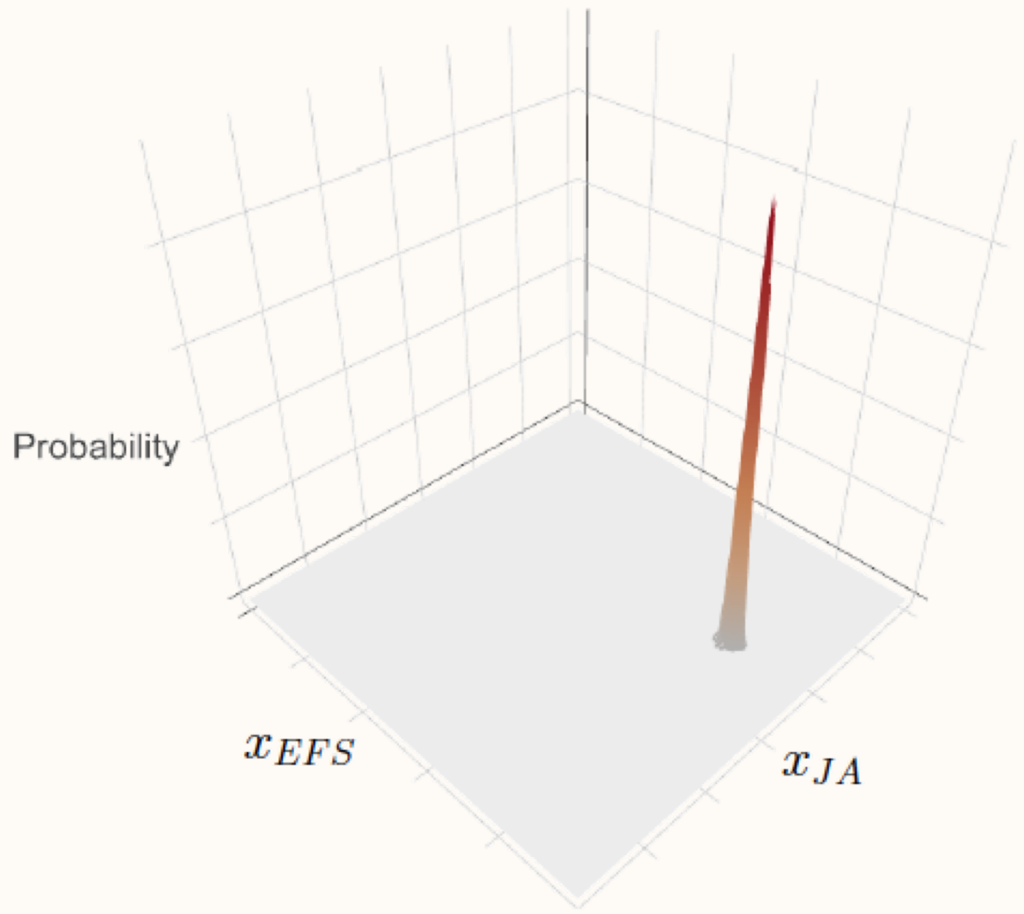
(a) Iteration = 10



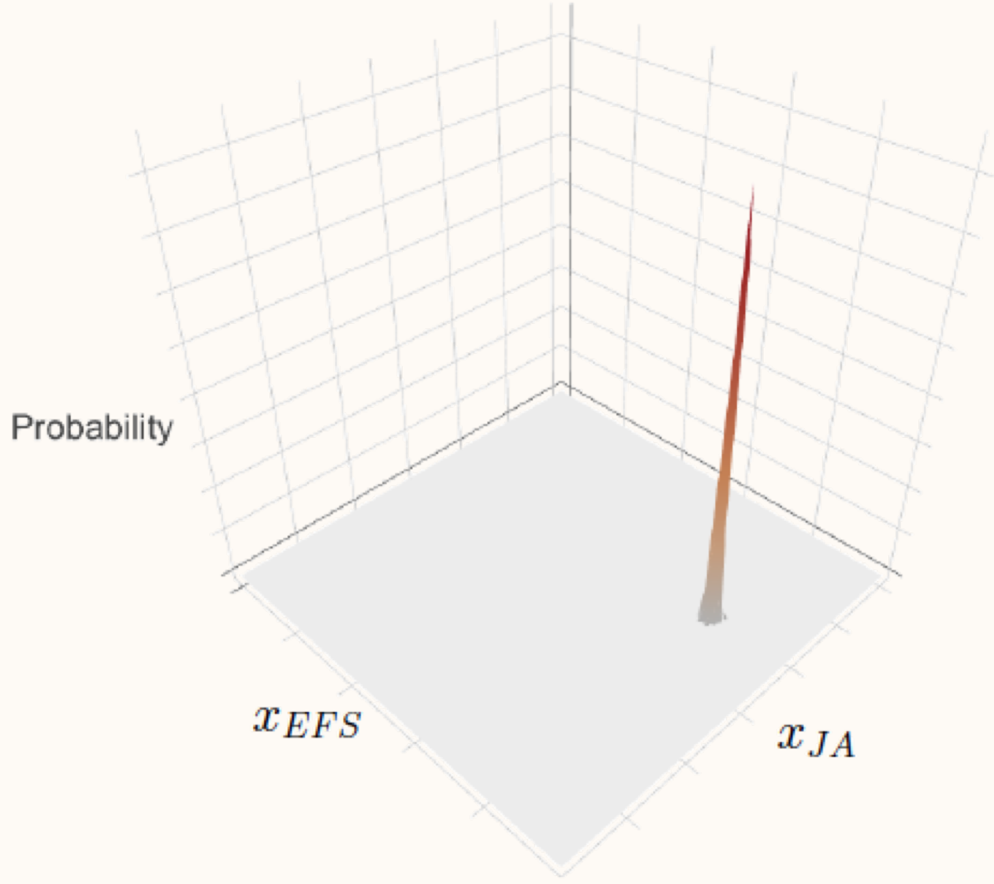
(b) Iteration = 15



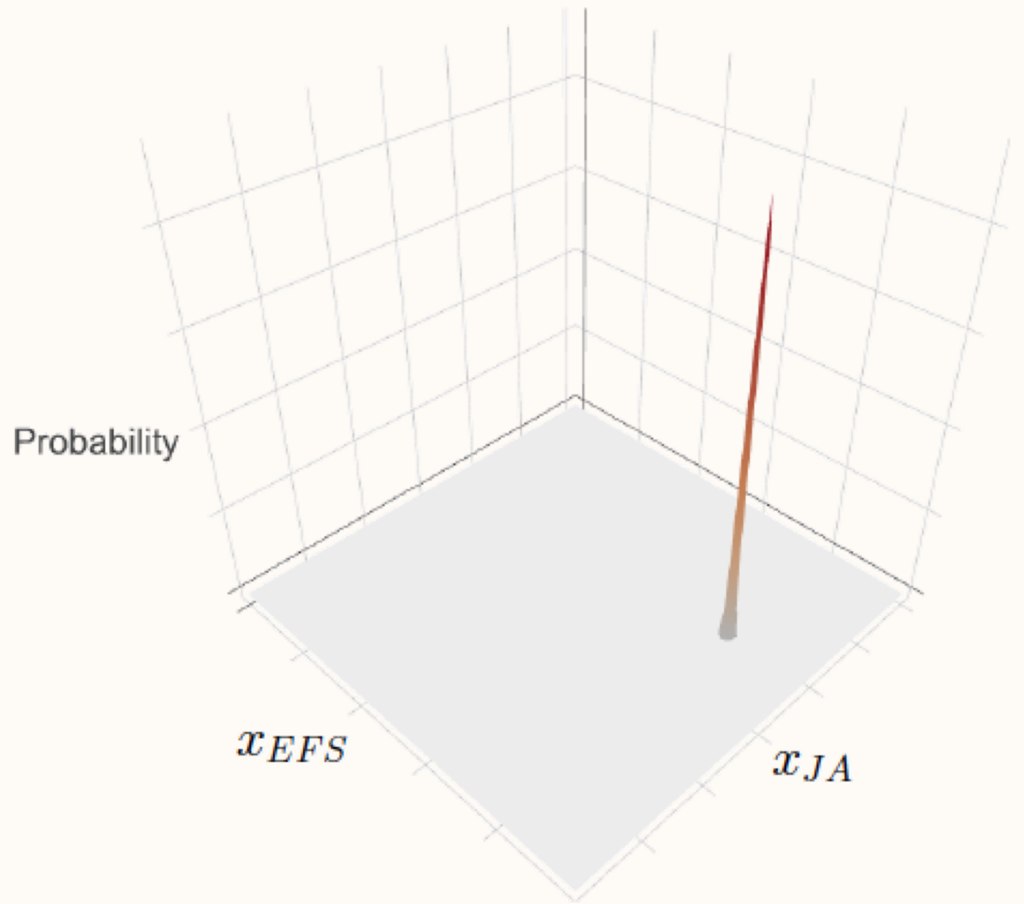
(c) Iteration = 20



(d) Iteration = 25



(e) Iteration = 30



(f) Iteration = 35

Key Takeaways

- Removes the human in the loop: Fully automatic process to find the optimal parameters.
- Drastically improves developer productivity.
- Can scale to multiple competing metrics.
- Very easy onboarding infra for multiple vertical teams. Currently used by Ads, Feed, Notifications, PYMK, etc.
- Future Direction
  - Add on other Explore-Exploit algorithms.
  - Move from Black-Box to Grey-Box optimizations
  - Create a dependent structure on different utilities to better model the variance.
  - Automatically identify the primary metric by understanding the models better.

Thank you

Linked in

Appendix – Library API

- Problem Specifications


```
{
  "treatmentModels":["treatmentModel-1"],
  "controlModel":"controlModel-1",
  "exploreNumIterations":"6",
  "params":[
      {
        "fieldName":"threshold",
        "parameterInfo":{
          "searchRange":{
            "low":"0.17",
            "high":"0.24"
          },
          "dataType":"Float"
        }
      }
    ]
  },
```

Appendix – Library API

- Objective and Constraints

```
"Objective":{
  "objectiveType":"max",
  "objectiveParts":[
    {
      "utilityName":"ClickRate",
      "ColumnNames":[
        "clickCount",
        "impressedCount"
      ],
      "distribution":"gaussian"
    }
  ]
},
```

```
"Constraints":[
  {
    "utilityName":"SendsByGenerated",
    "ColumnNames":[
      "sentCount",
      "generatedCount"
    ],
    "distribution":"gaussian",
    "upperBound":{
      "multiplier":"Inf"
    },
    "lowerBound":{
      "multiplier":"1.0"
    }
  }
]
}
}
```