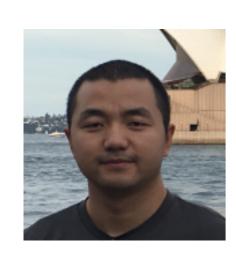








Efficient Nonmyopic Batch Active Search



Shali Jiang



Gustavo Malkomes



Matthew Abbott



Benjamin Moseley



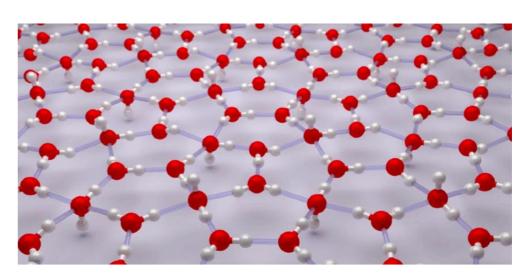
Roman Garnett

NeurIPS 2018

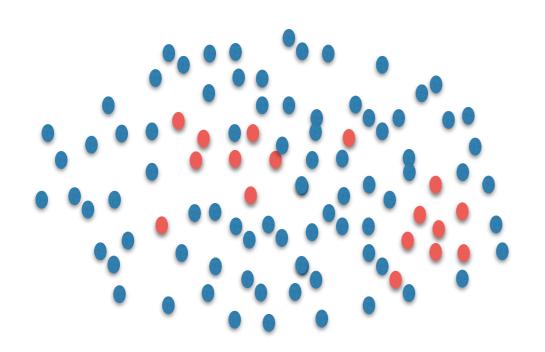
Many real problems involve searching for valuable items from a large pool of candidates in an iterative fashion

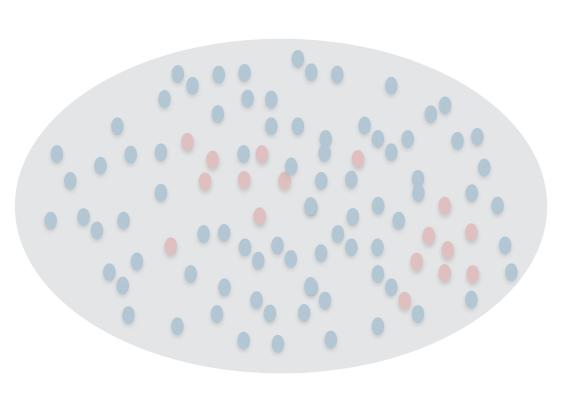


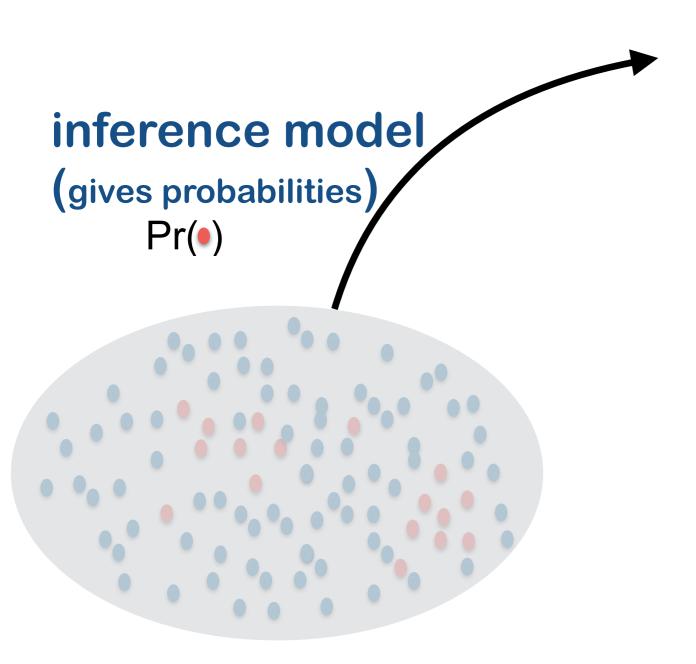
Drug discovery

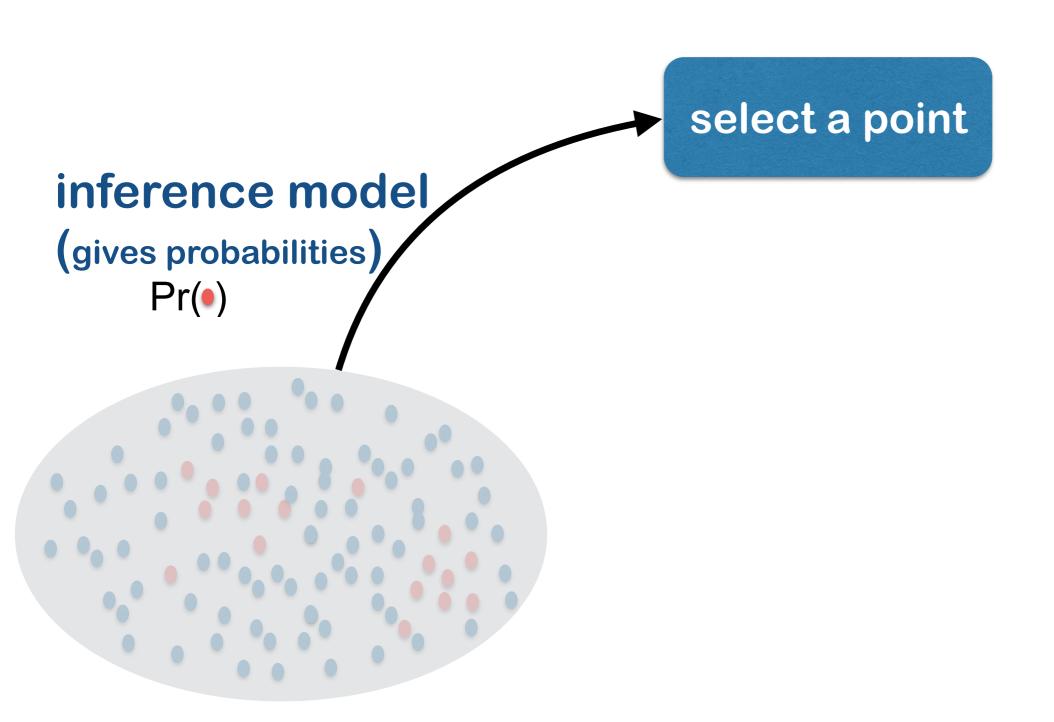


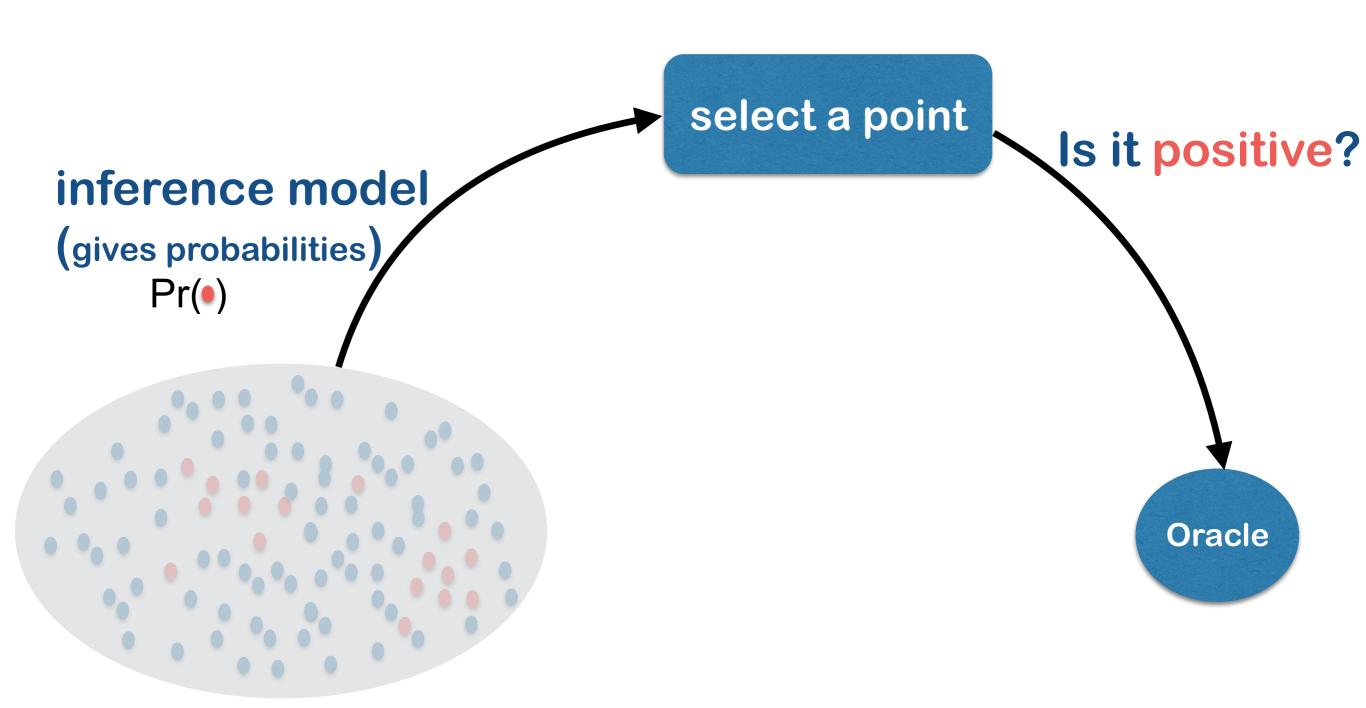
Materials discovery

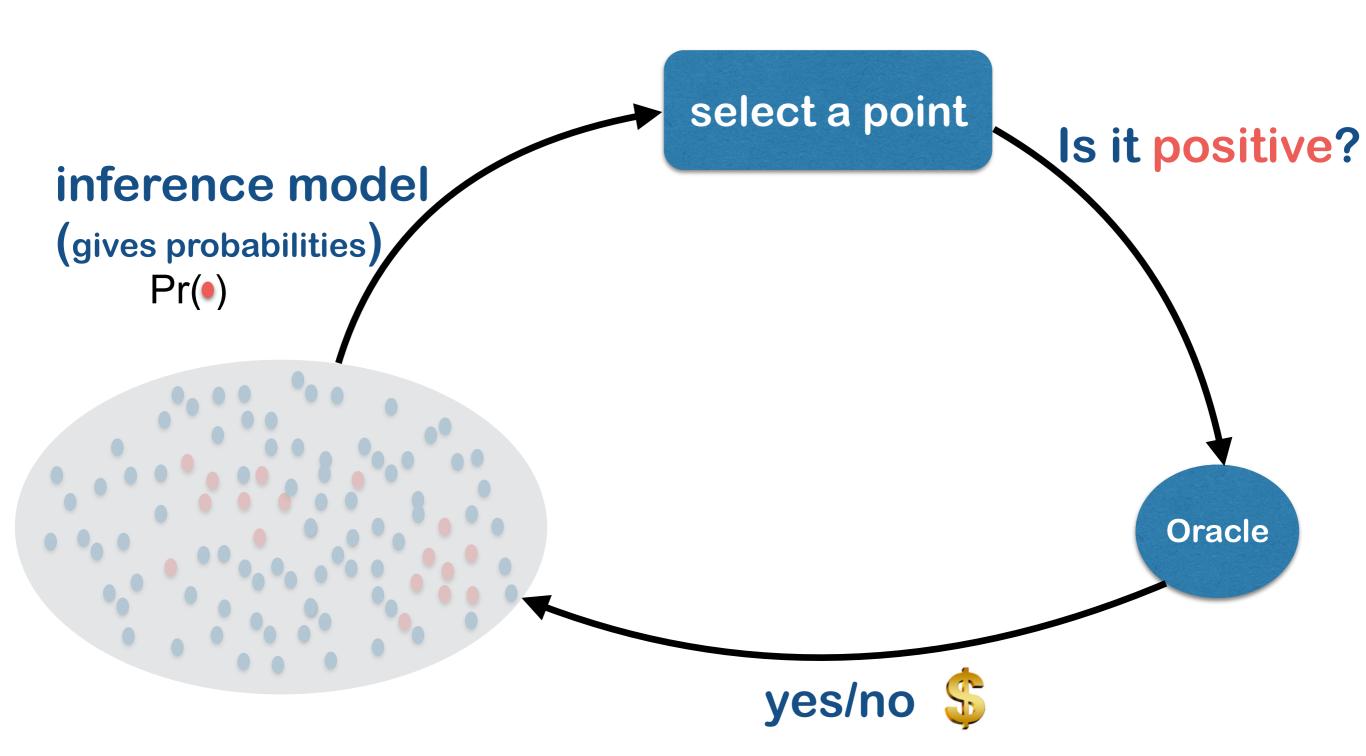


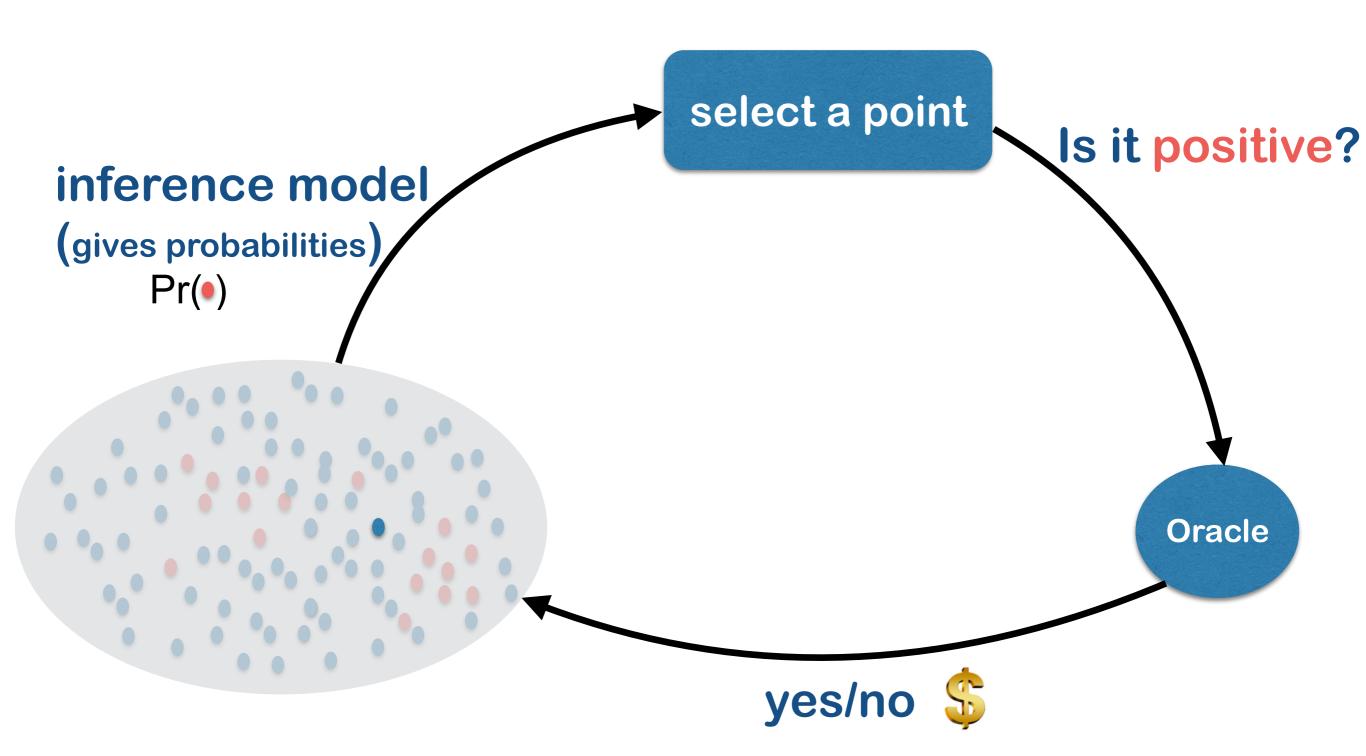


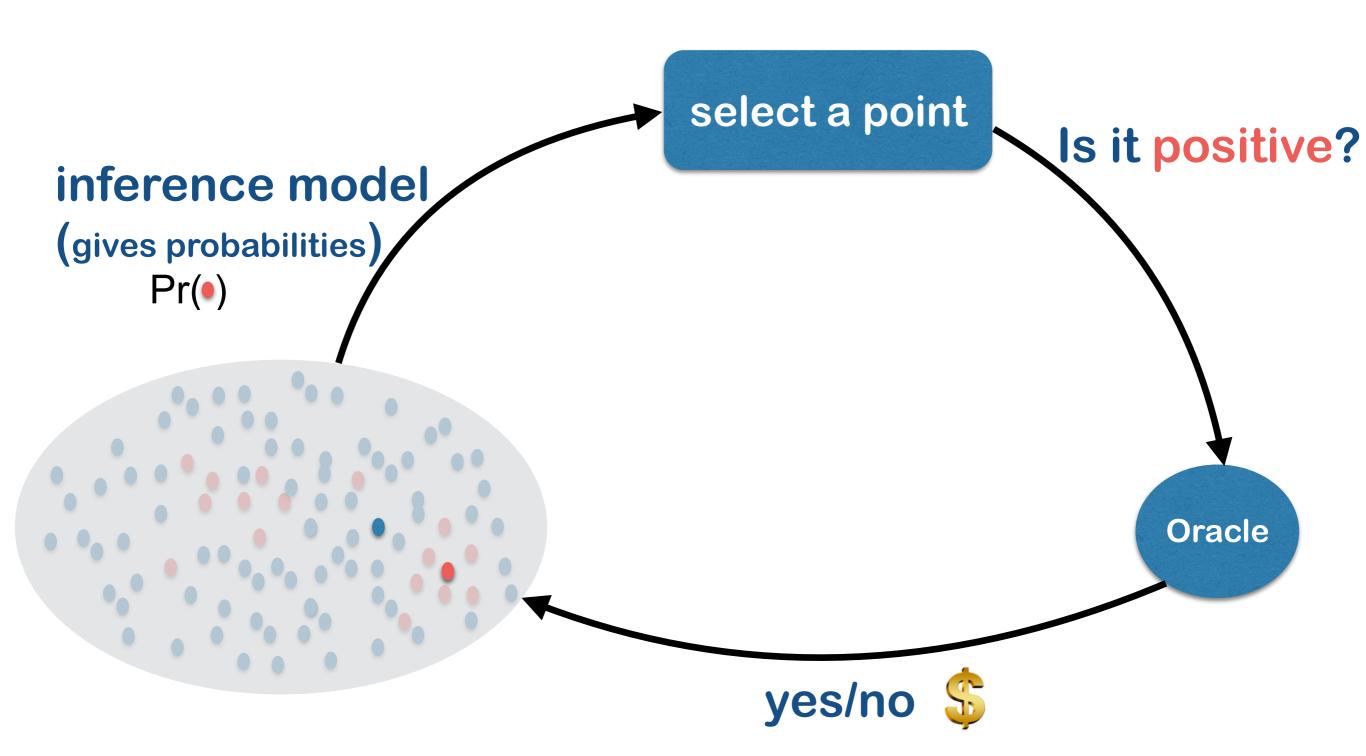


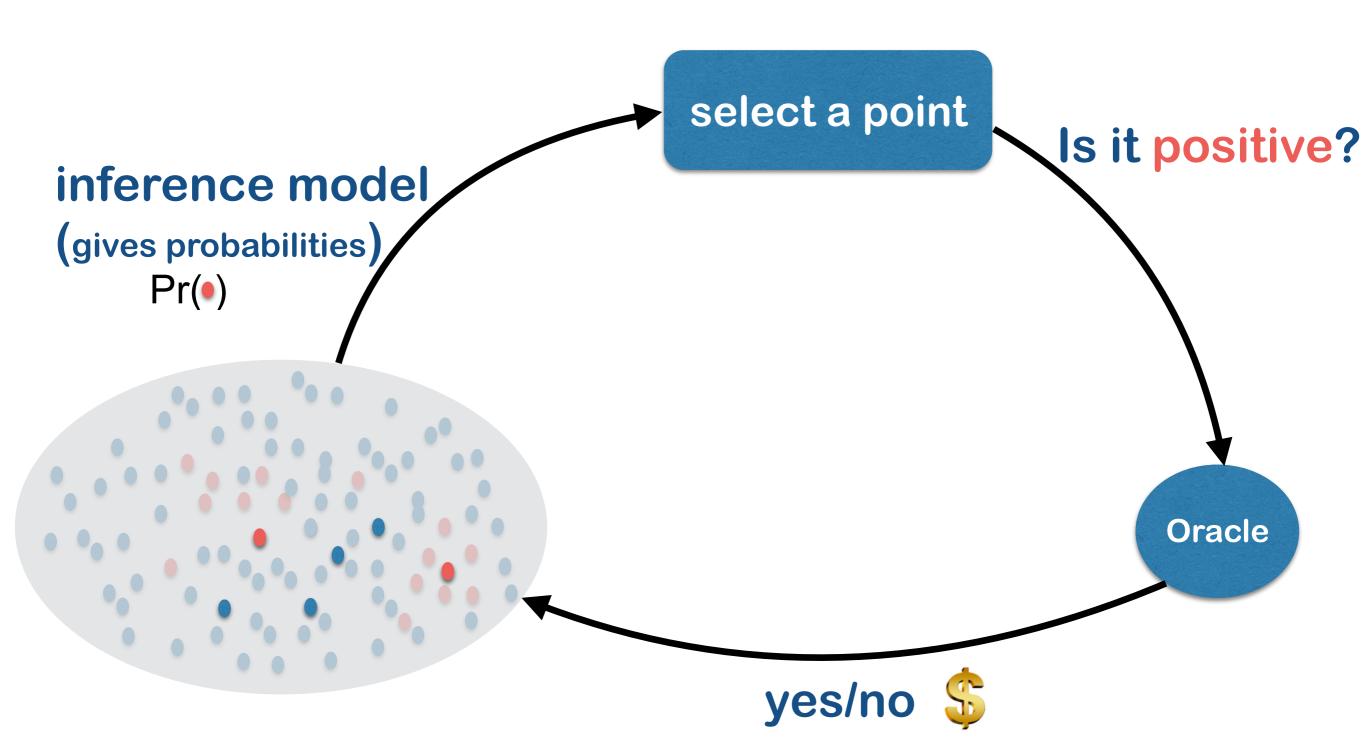


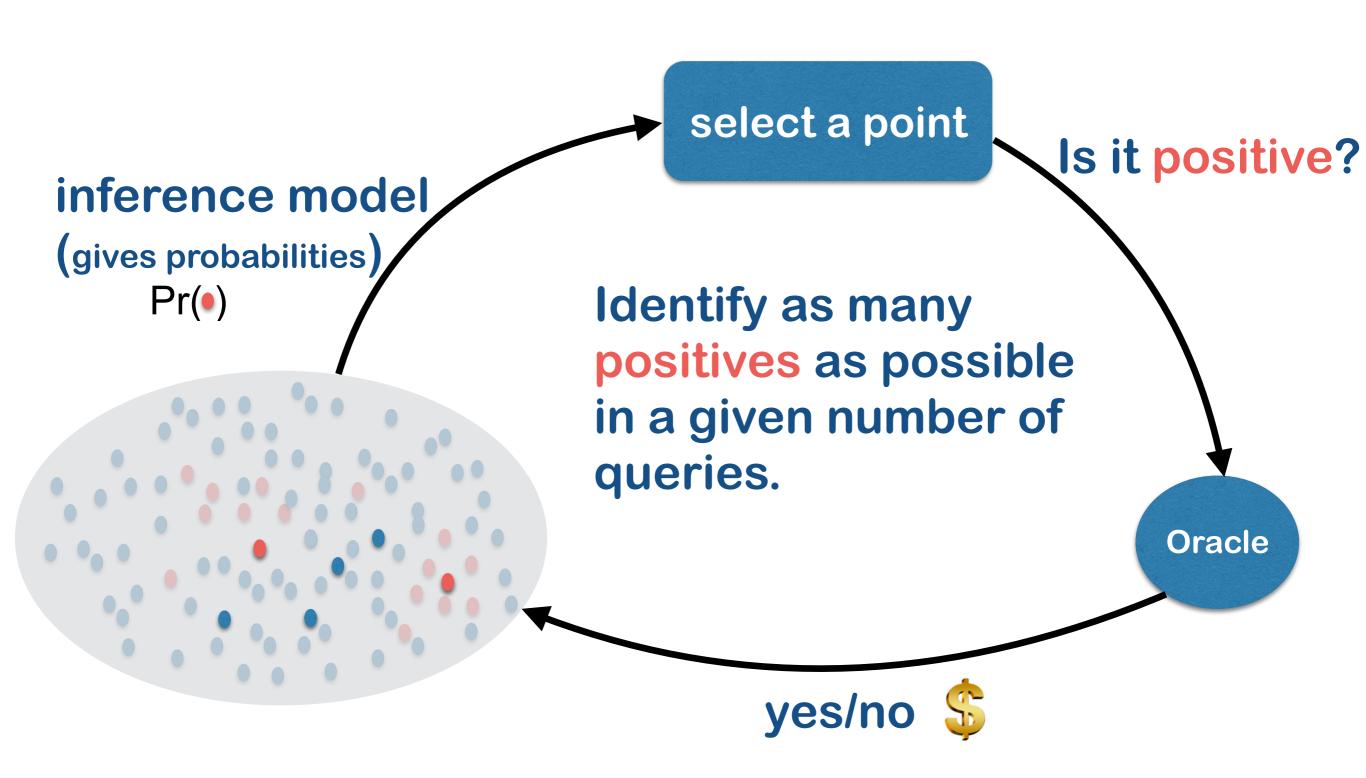


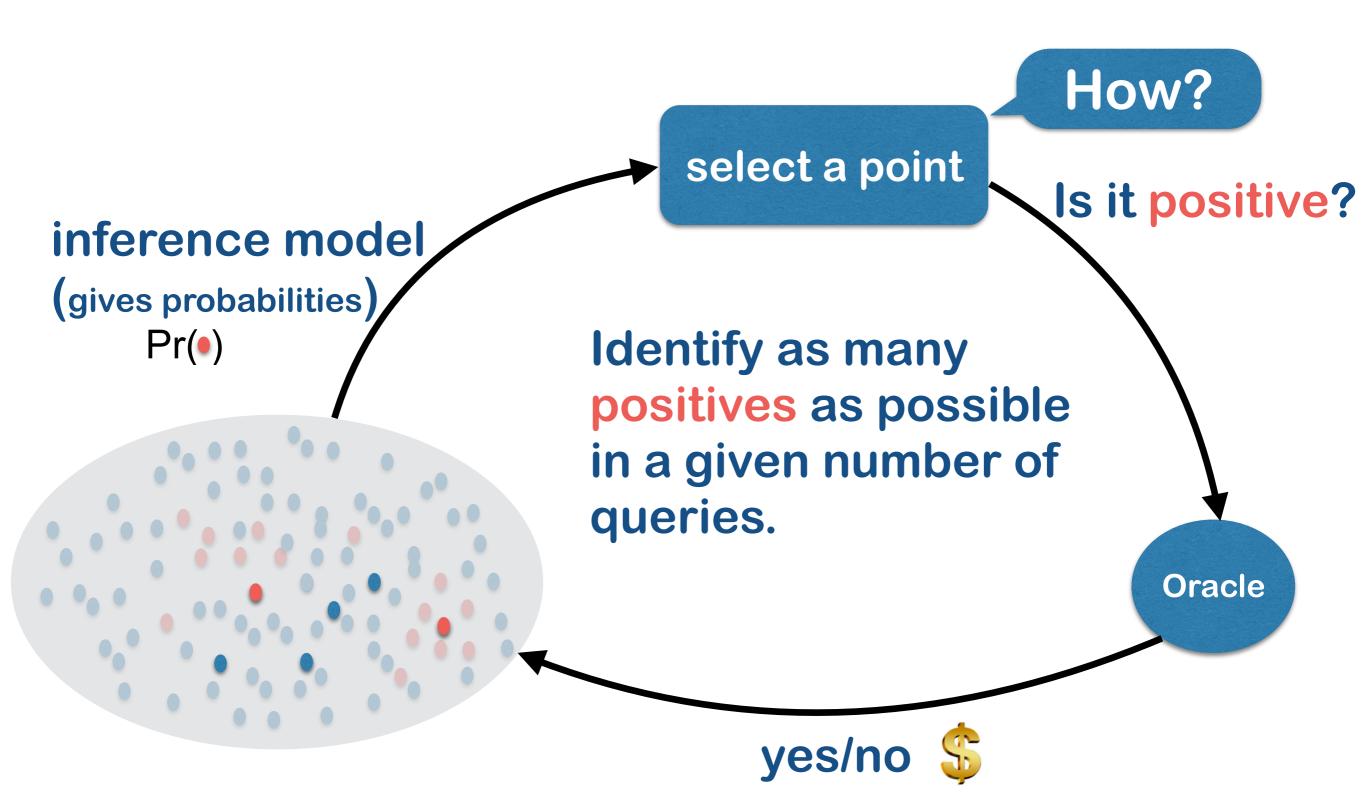


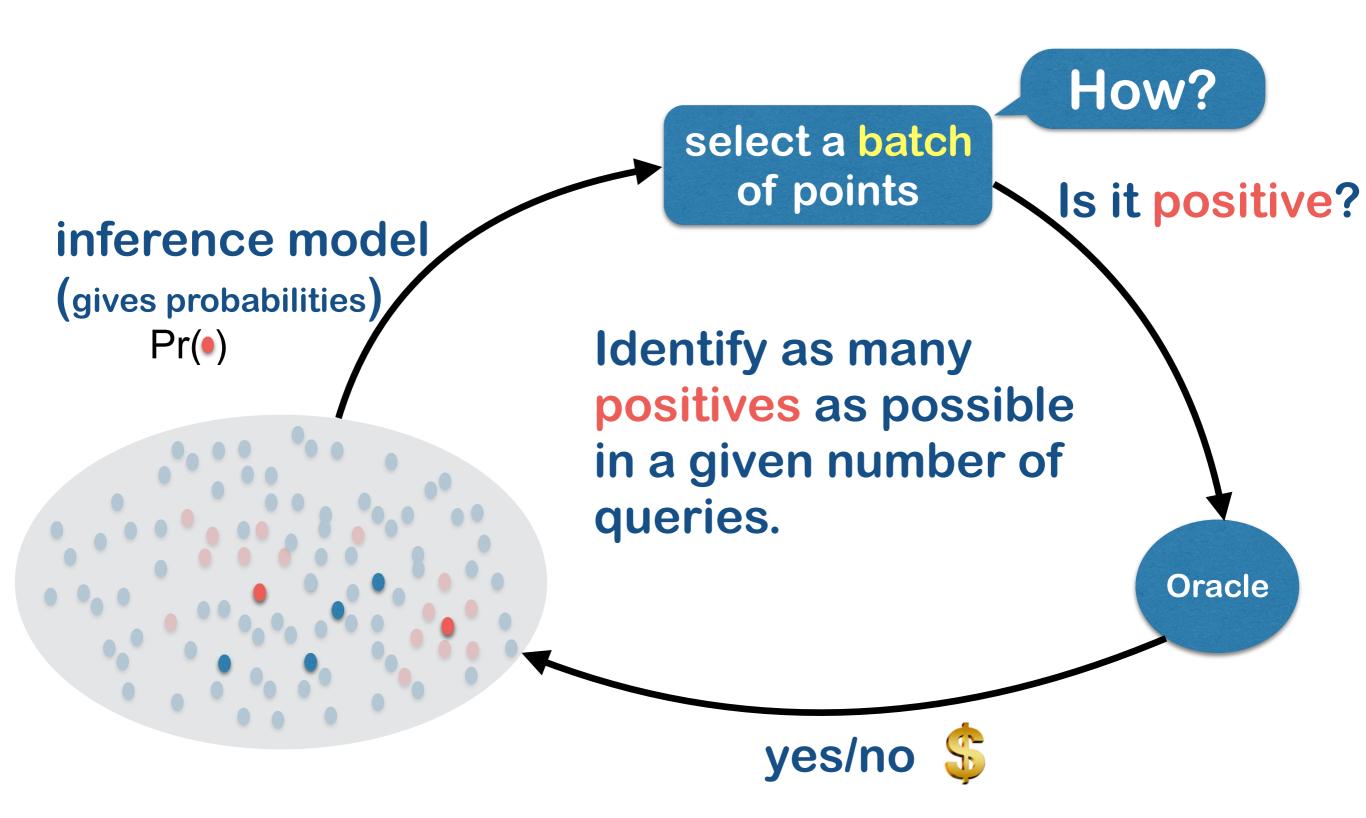












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How can we do better?

```
X^* = \underset{X}{\operatorname{arg\,max}} "[expected #positives in X]+
```

[expected #positives in future conditioned on X]".

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Assume conditional independence after X

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Efficient for sequential setting (batch size 1) (Jiang et al. (ICML 2017)).

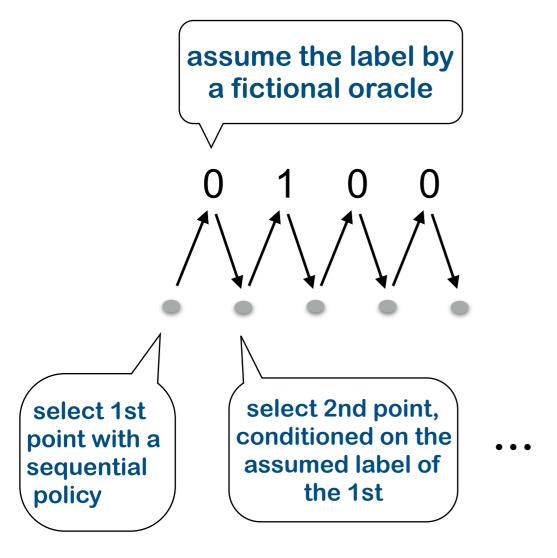
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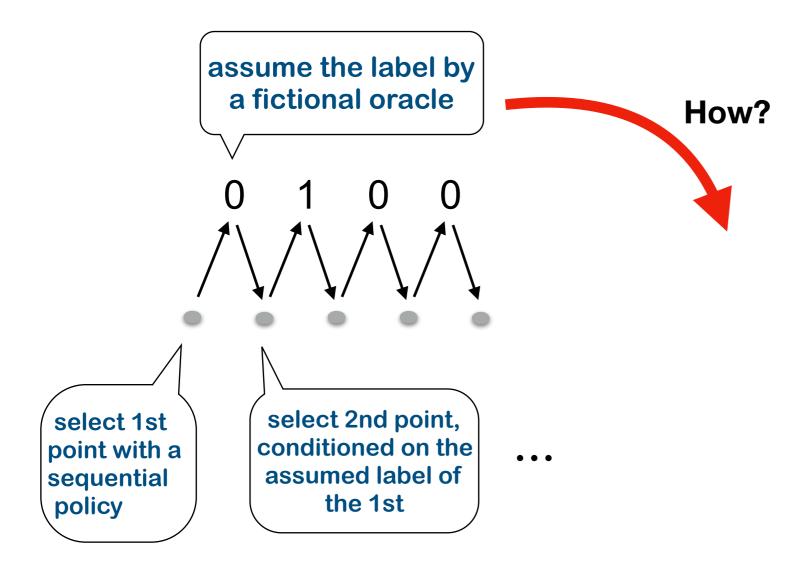
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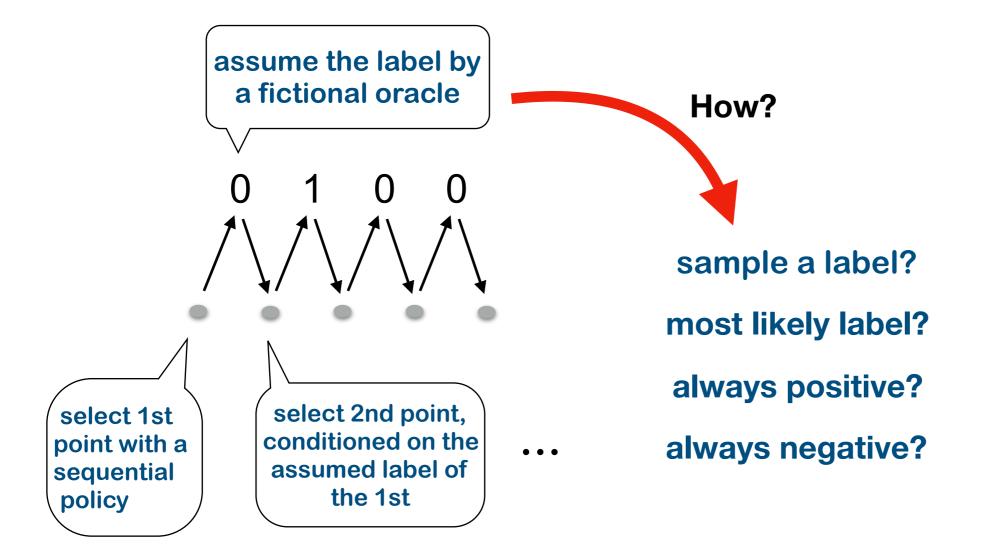
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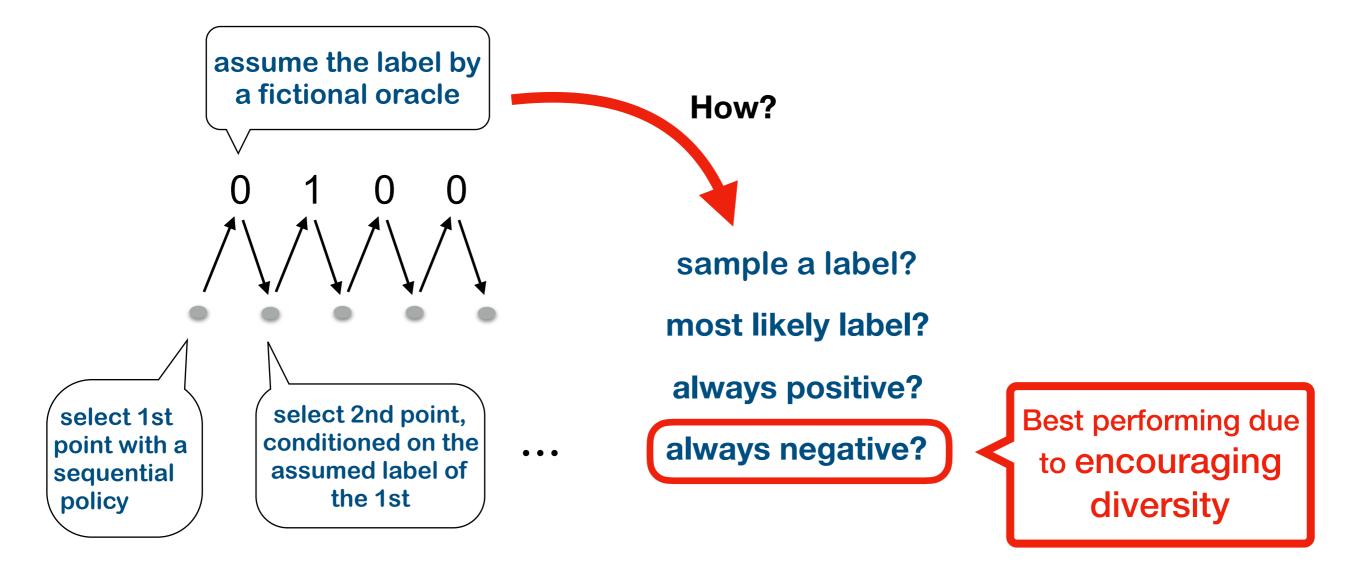
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Combinatorial search in batch setting → two approaches: greedy maximization and sequential simulation

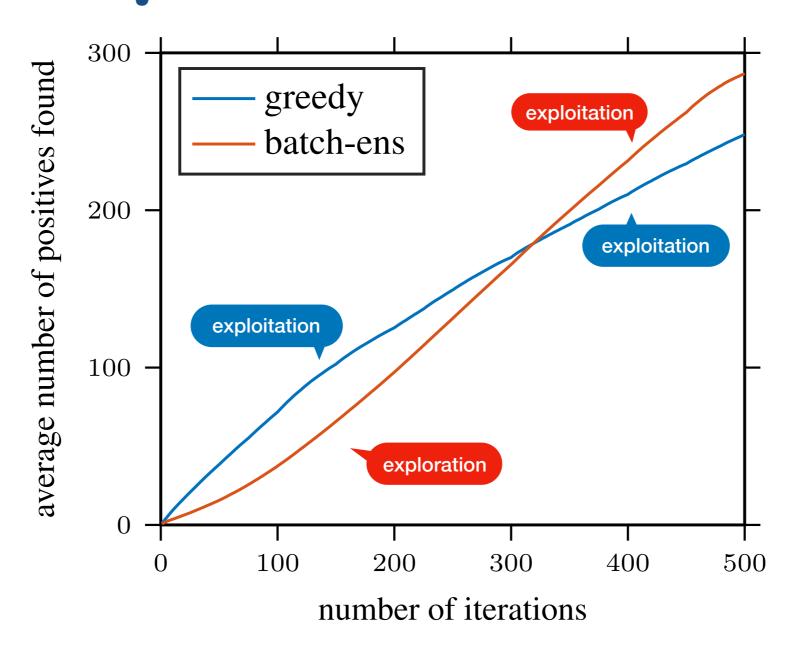








Empirical results



Averaged over 1600 experiments (10 drug discovery datasets, 8 batch sizes, and 20 repetitions each)

T=20

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every point is chosen after observing the outcomes of all previous points!

(1 point / iter) * (20 iters) b=1

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(1 point / iter) * (20 iters)

(5 points / iter) * (4 iters)

b=5







points are chosen without observing the outcomes of previously added points in this batch

T=20

every point is chosen after observing the outcomes of all previous points!

(1 point / iter) * (20 iters)
$$b=1$$

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Less adaptive decisions could lead to worse performance!

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Less adaptive decisions could lead to worse performance!

But how much worse?

points are chosen without observing the outcomes of previously added points in this batch

Adaptivity gap

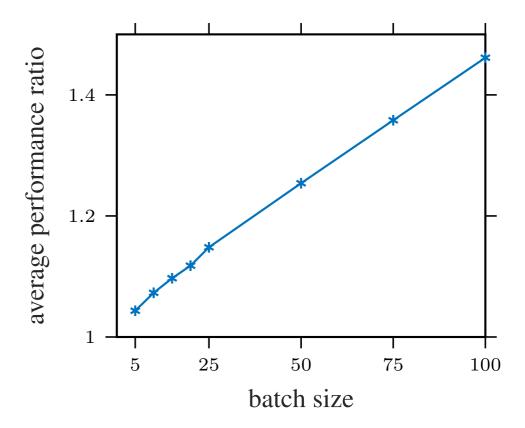
We prove that the performance ratio between optimal sequential and batch policies is at least linear in the batch size!

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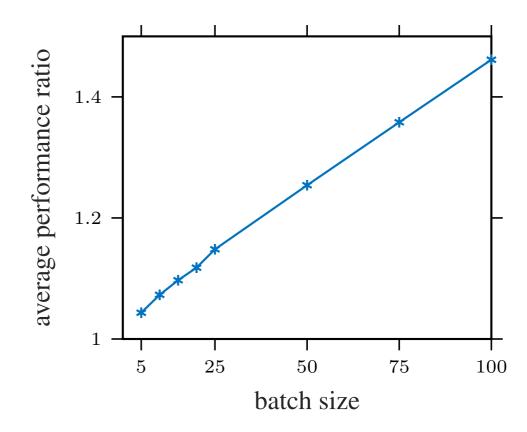
matching empirical results

Adaptivity gap

We prove that the performance ratio between optimal sequential and batch policies is at least linear in the batch size!

$$\frac{\text{OPT}_1}{\text{OPT}_b} = \Omega\left(\frac{b}{\log T}\right)$$

This insight could help us choose the batch size in cases where we have many options.



matching empirical results









Thanks for your attention! Poster: #131



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NeurIPS 2018