Agenda

Adapting to the changing world

Introduction to reinforcement learning and contextual bandits

Personalizer overview

Apprentice mode

Making contextual bandits work in practice

Q&A

Microsoft

Making contextual bandits work in practice

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Debugging Learning Systems

How do you debug something that is expected to make mistakes?

Property Based Testing

Find something that is true in a correct system

Search for counterexamples

Property of Learning Algorithms

Performance of learned policy should not be too much worse than performance of best representable policy

Property of Learning Algorithms

<u>Performance</u> of learned policy should not be too much worse than <u>performance</u> of best representable policy

Evaluation

Evaluation is critical

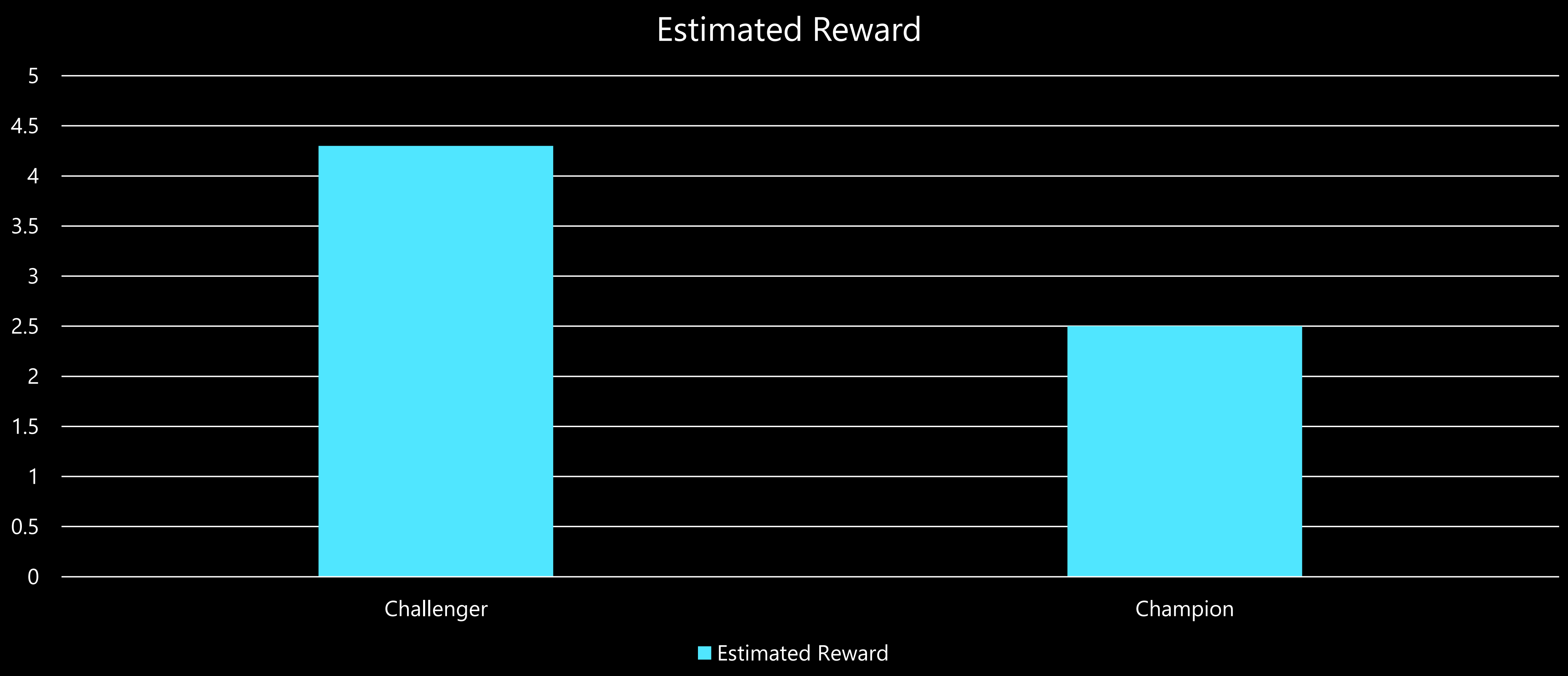
- Online evaluation is the gold standard
- Offline evaluation is critical for rapid iteration

Offline Evaluation

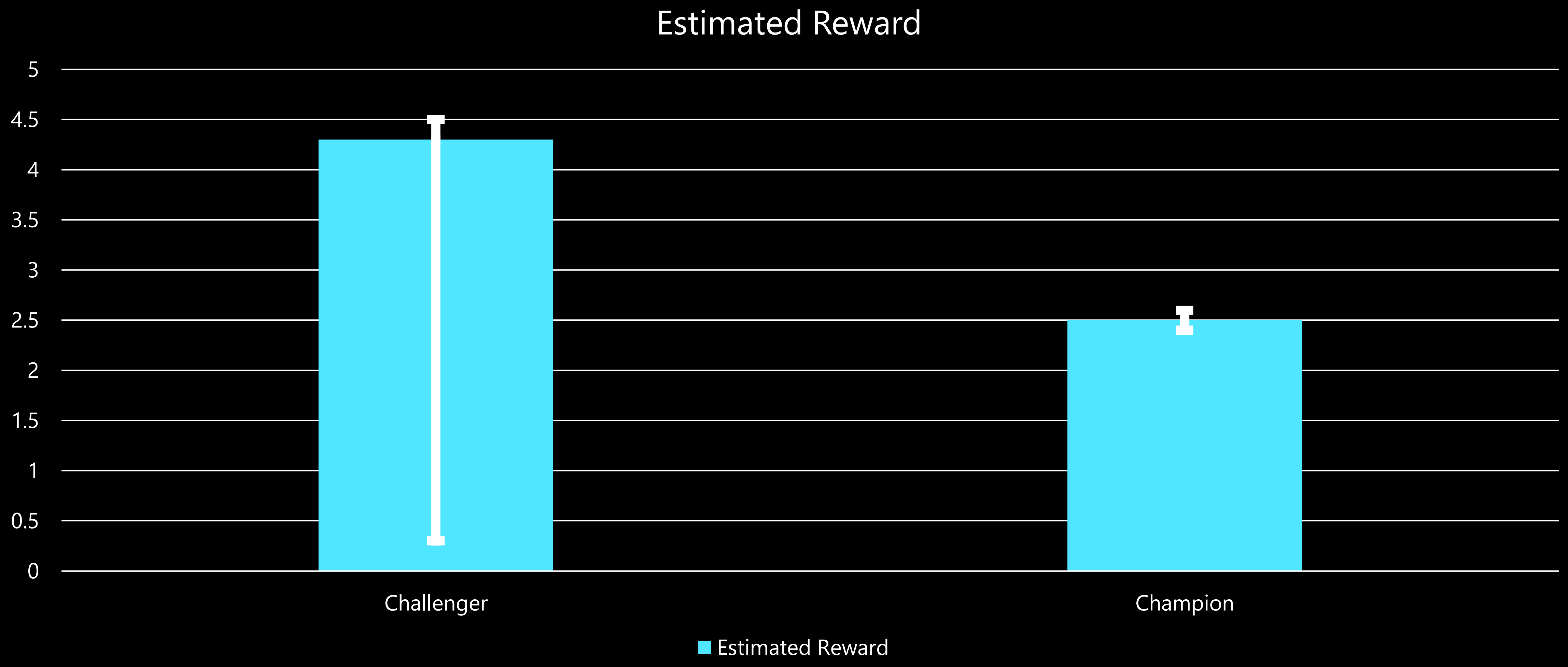
- Temporal: Respect time in train-test splits.
- CB: Must use a counterfactual estimator.
- Confidence Intervals: No point estimates ever!

Rant against point estimates

Which one is better?



How about now?



Always use confidence intervals

- Previous slide is typical in CBs but not supervised learning
- Challenger policy has better point estimate due to optimization, but
- Variance of CB estimate is higher for challenger policy.
- Tip: optimize lower bound with VW via `--cb_dro`

Bootstrap: Easy way to get CIs on (almost) anything

```
from numpy.random import choice as rc
from numpy import quantile
# resample testSet and compute estimate
samples = [ evaluate(rc(testSet, size=len(testSet)))
            for _ in range(100)
          ]
# get empirical quantiles from resampling
ninetyPctCI = quantile(testSet, q=[0.05, 0.95])
```

Property of Learning Algorithms

Performance of learned policy should not be too much worse than performance of best representable policy

I don’t know the performance of the best representable policy

Baseline

- A representable policy which you know is not very good.
- “not much worse than the best” implies “beat the baseline”.
- Example: choose an action uniformly at random.

Representable (?)

- To beat a baseline you must be able to mimic the baseline.
- Frequent fail: baseline has access to more information.
- Example: “Personalizer baseline”.

How to represent any baseline

- Use the prediction of the baseline as input to the new system.
- Performance jump → representation issue
- Performance the same → some other problem

Property of Learning Algorithms

Performance of learned policy should not be <u>too much worse</u> than performance of best representable policy

How much data is required for success?

How much data: theory answer

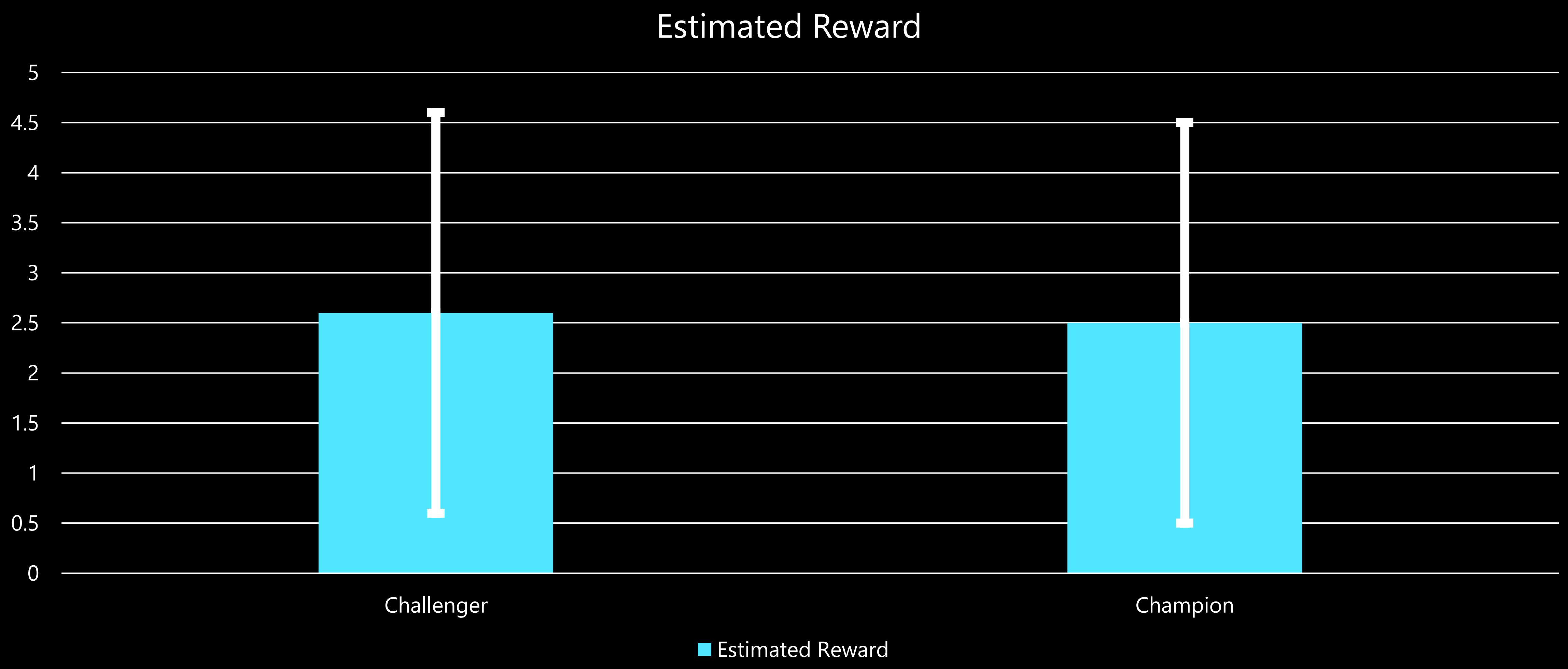
- More actions → more data required
- More reward variance → more data required
- Smaller lift → more data required

Do I have a bug or not enough data?

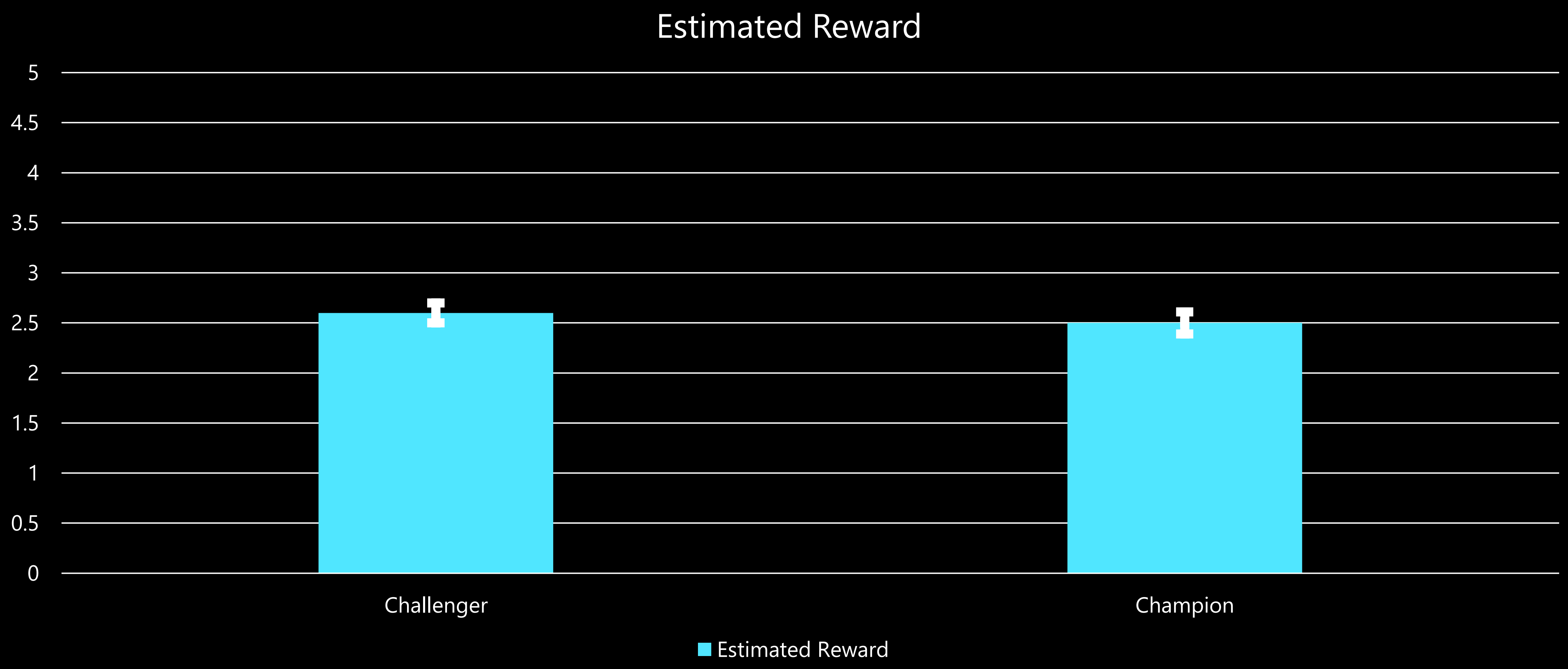
How much data: practical answer

- Confidence intervals are your friend.

You may need more data if you see this …



More data will not help if you see this …



Summary

Get the evaluation correct

Always use confidence intervals

Define baselines you can beat

Recap

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