

# Optimal Testing for Crowd Workers

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# Crowdsourcing

- Fun



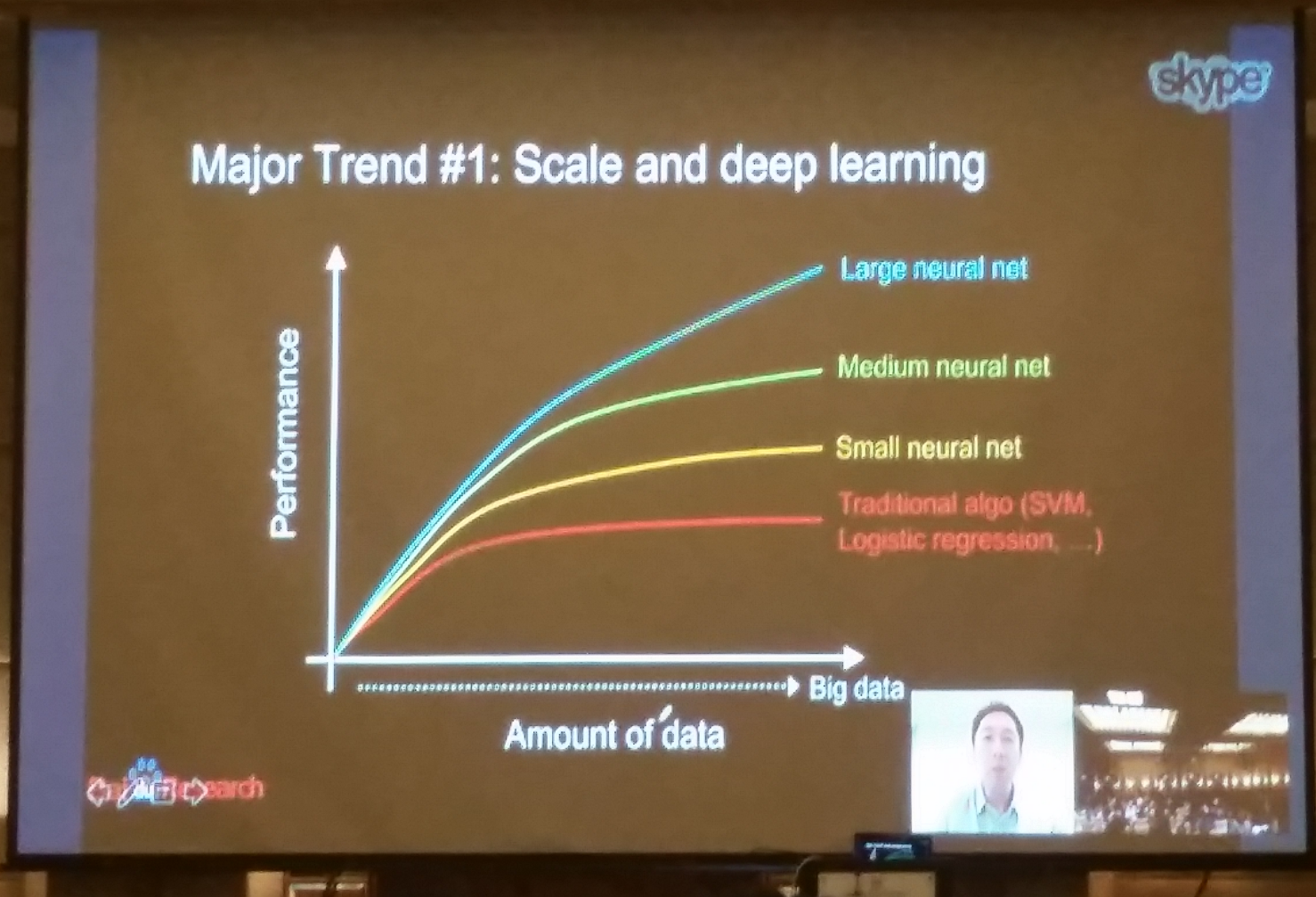
- Altruism



- Money



# Supervised learning



# Quality control

High quality



Low quality



# Quality control

High quality



?



Low quality



# Quality control in practice

- Gold question insertion
- Worker filtering

# Quality control in practice

- Gold question insertion      What fraction?
- Worker filtering      What accuracy?



# Quality control parameters

- Researchers (NLP relation extraction task)
  - 13% gold, 67% accuracy threshold [1]
  - 30% gold, 85% accuracy threshold [2]
  - 20% gold, 80% accuracy threshold [3]
- Industry
  - CrowdFlower: 20% gold, 80% accuracy threshold

[1] Angeli et al. 2014. In EMNLP.

[2] Gormley et al. 2010. In NAACL.

[3] Zhang et al. 2012. In ACL.



# Problems

- How to set parameters?
- Static policy is sub-optimal
  - Heterogeneous workers
  - Non-stationary worker population

# Goal

Automatically insert gold questions to maximize **quality & quantity** of individual worker answers

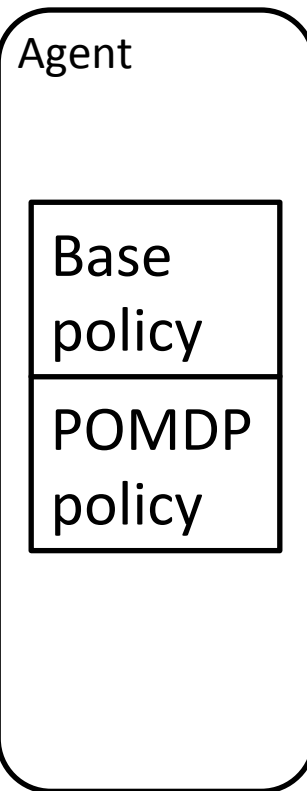
# Agent architecture



Give me answers  
above accuracy  $a^*$



Gold questions  
Base policy



# Agent architecture



Give me answers  
above accuracy  $a^*$



Gold questions  
Base policy



Agent

Base  
policy

POMDP  
policy

**Actions:**

Ask **test** question

Ask **work** question

**Replace** worker



Environment

**amazon**  
mechanical turk beta

Gold (test)  
questions



# Agent architecture



Give me answers  
above accuracy  $a^*$



Gold questions  
Base policy



Agent

Base  
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POMDP  
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Actions:

Ask **test** question

Ask **work** question

**Replace** worker



Observations:

**Correct** test answer

**Incorrect** test answer

Worker **leaves**



Environment

**amazon**  
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Gold (test)  
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# Agent architecture



Give me answers  
above accuracy  $a^*$

Gold questions  
Base policy

Reward:

$\begin{cases} 1 & \text{if correct **work** answer} \\ -\text{PENALTY} & \text{if incorrect **work** answer} \end{cases}$

Unobservable!

Agent

Base  
policy

POMDP  
policy

Actions:

Ask **test** question

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Replace worker

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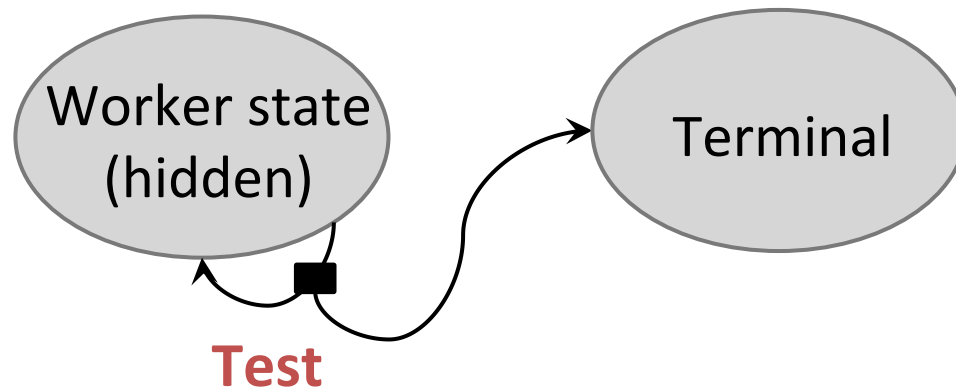


# Reinforcement learning

- Challenges
  - Unobservable rewards
  - Exploration should not upset workers
- Our approach
  - Explore with base policy (e.g., “test 20%”)
  - Exploit with learned POMDP policy



# POMDP formulation



**Reward:** 0

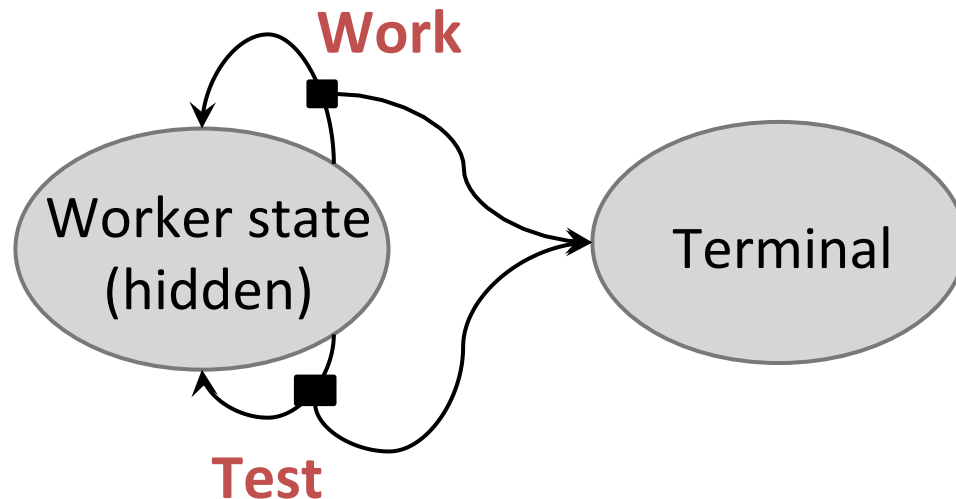
**Observation:** Correct / incorrect

# POMDP formulation

Set PENALTY s.t.  $\text{Reward} > 0$  iff  
worker accuracy  $> a^*$

**Reward:**  $P(\text{correct}) * 1 + (1 - P(\text{correct})) * (-\text{PENALTY})$

**Observation:** NULL



**Reward:** 0

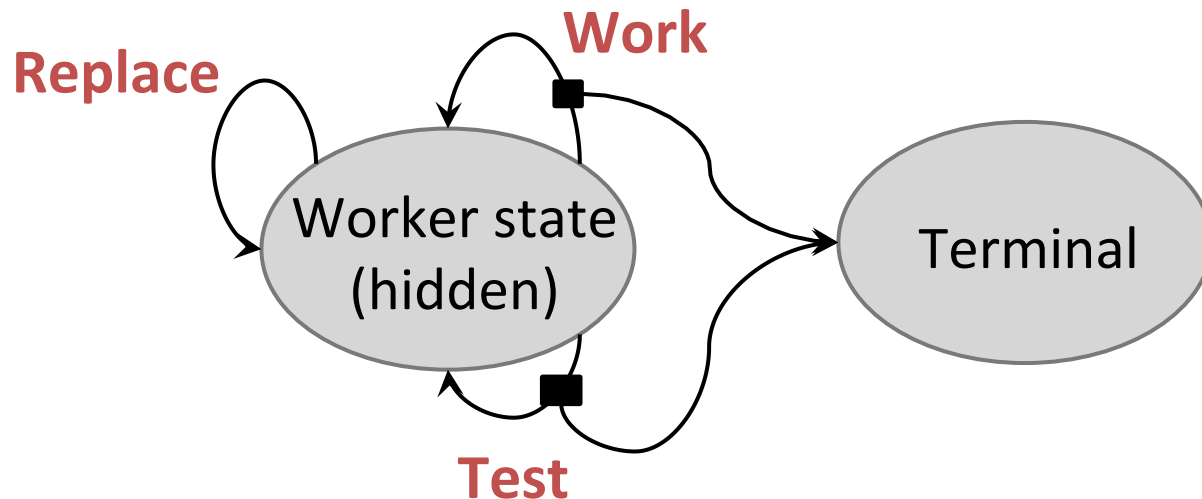
**Observation:** Correct / incorrect

# POMDP formulation

Set PENALTY s.t.  $\text{Reward} > 0$  iff  
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**Reward:**  $P(\text{correct}) * 1 + (1 - P(\text{correct})) * (-\text{PENALTY})$

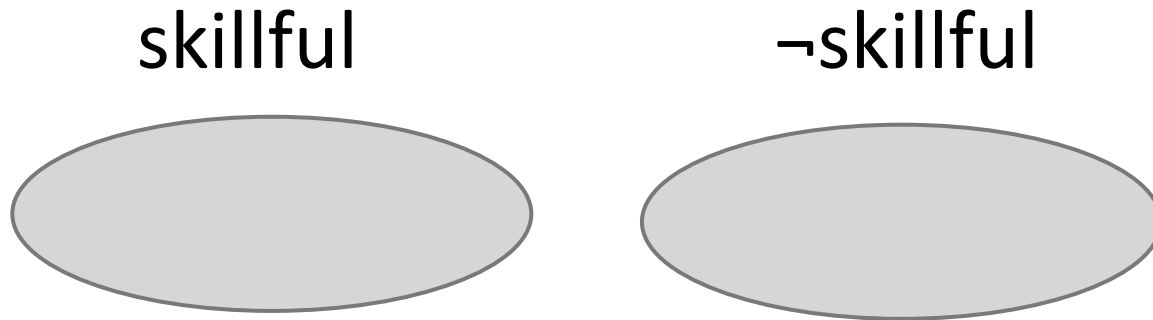
**Observation:** NULL



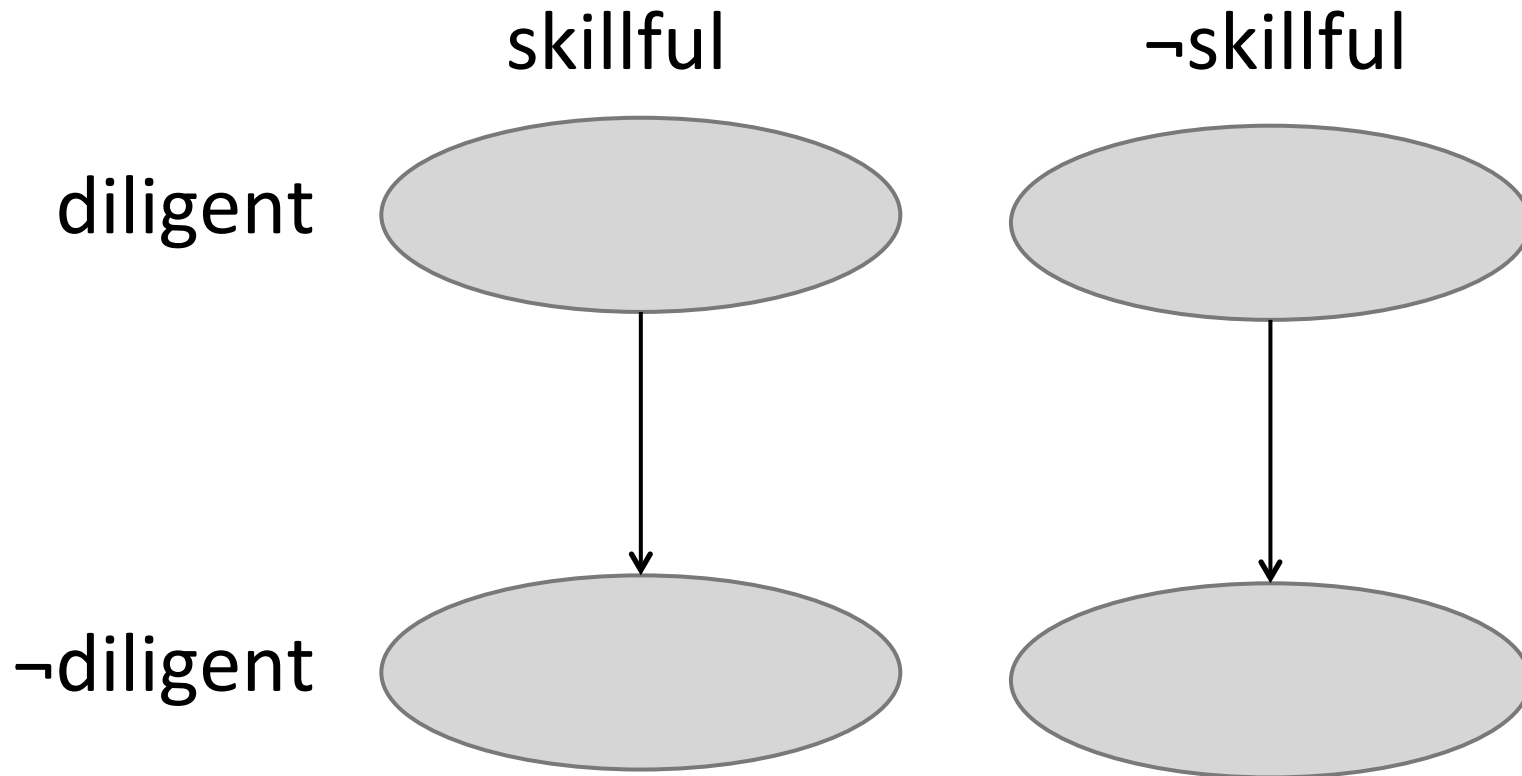
**Reward:** 0

**Observation:** Correct / incorrect

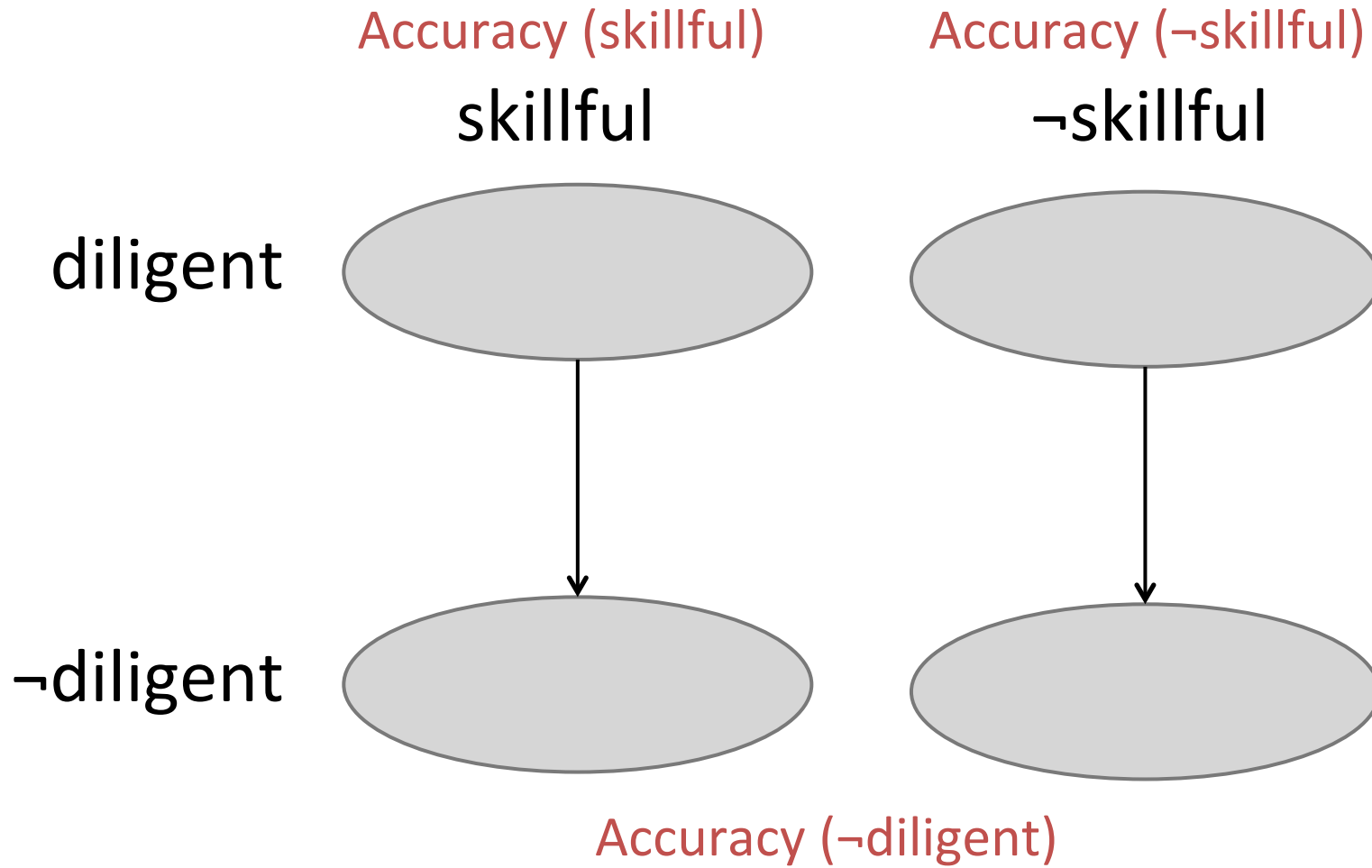
# Worker state transitions



# Worker state transitions



# Worker state transitions



# POMDP parameters to estimate

- Probability worker leaves
- Probability worker becomes  $\neg$ diligent
- Accuracy (skillful)
- Accuracy ( $\neg$ skillful)
- Accuracy ( $\neg$ diligent)
- Ratio of skillful to  $\neg$ skillful workers



# Experiments

- Existing datasets from Mechanical Turk: LinWiki, LinTag, [1] and Rajpal [2]
- Desired accuracy  $a^* = 0.85$

[1] Lin et al. 2012. In AAIL.

[2] Rajpal et al. 2015. In ICML workshop.

# Task: Named Entity Linking

“Only two states -- Vermont and **Washington** -- this year joined five others requiring private employers to grant leaves of absence to employees with newborn or adopted infants.”

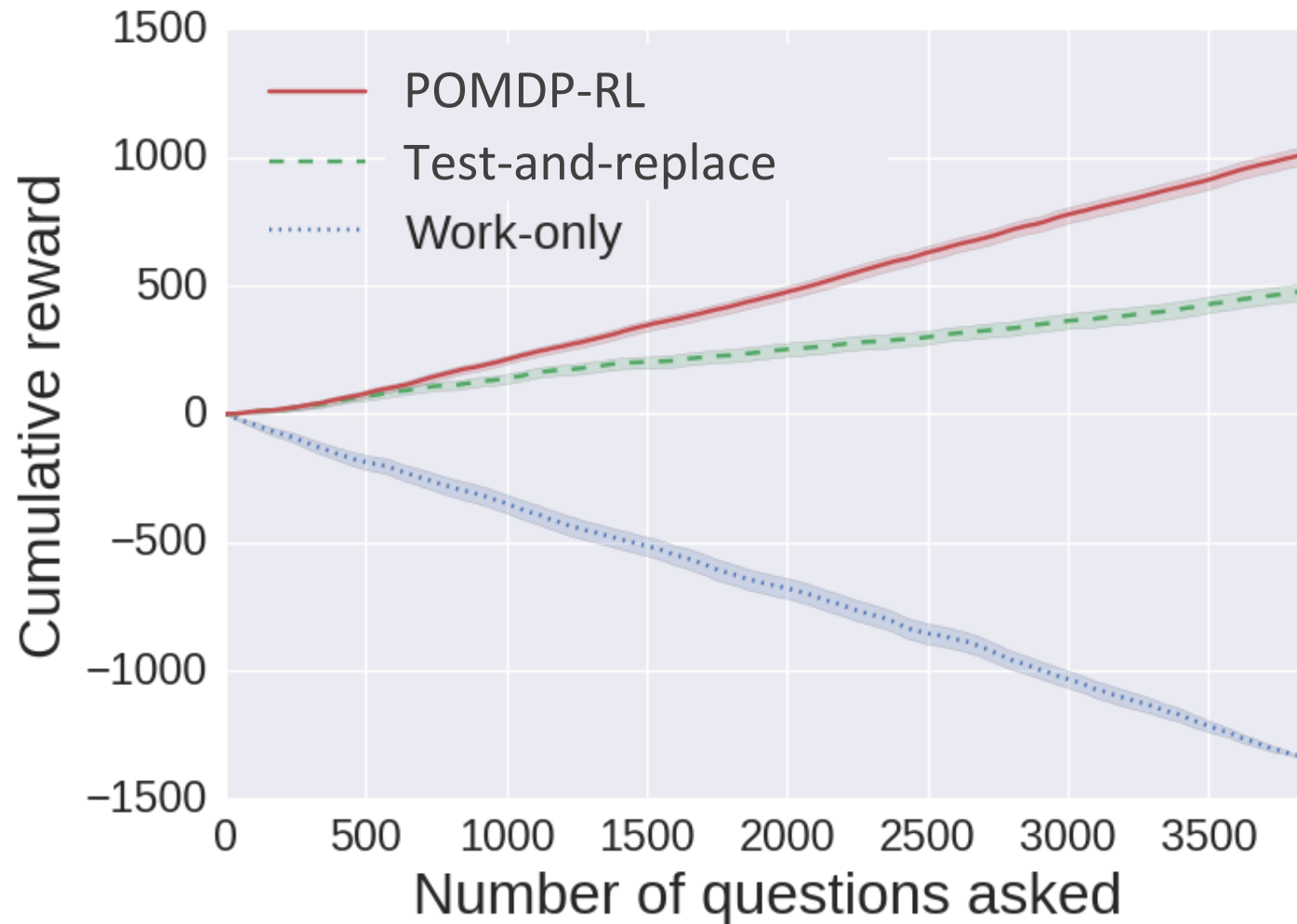
- ☐ Washington, D.C.
- ☒ Washington (state)

Submit

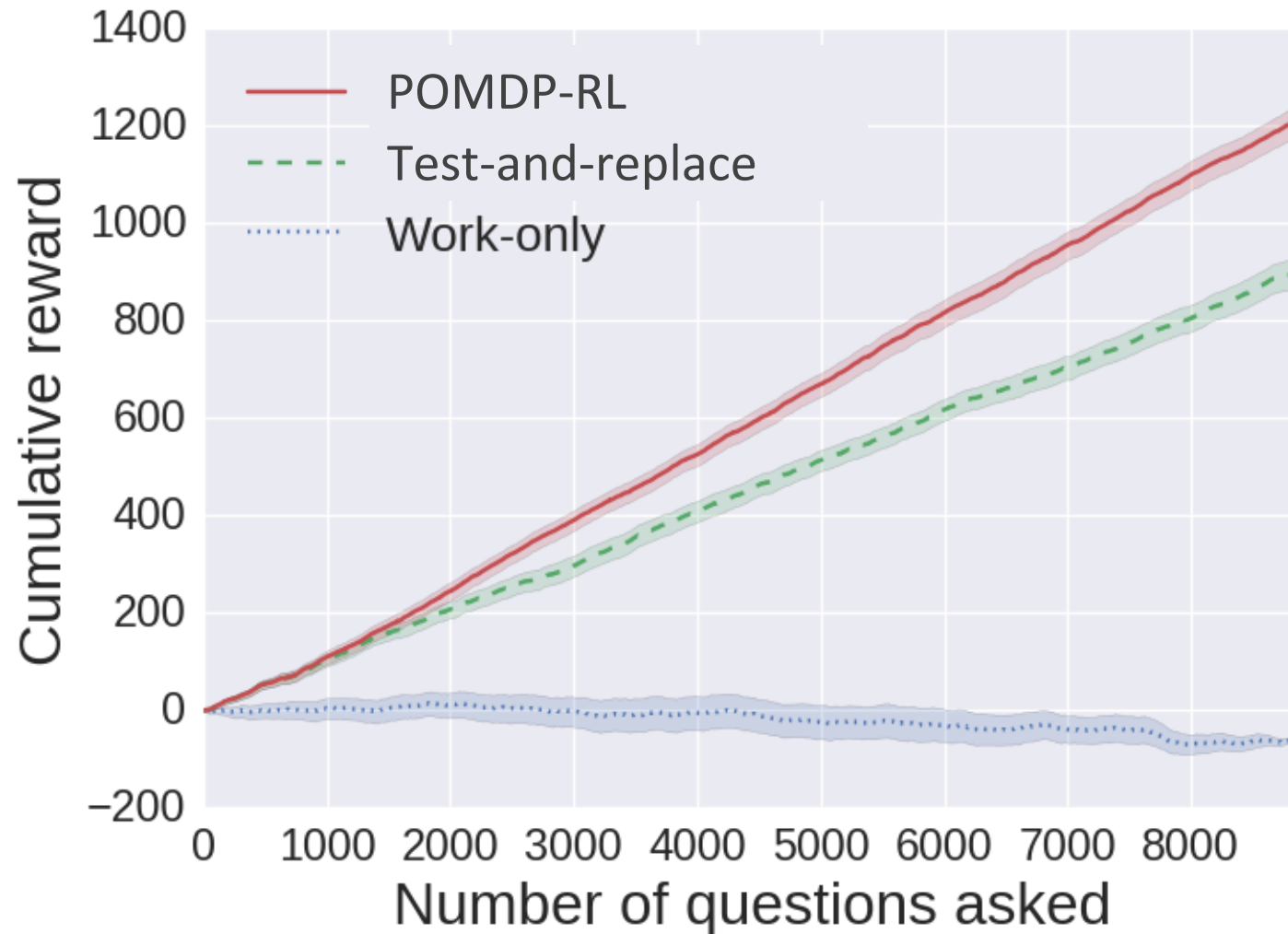
# Policies

- Work-only
- Test-and-replace
  - Test 20%
  - Replace if accuracy  $< 0.85$
- POMDP-RL
  - Base policy: Test-and-replace (above)
  - Exploration budget: 20 workers

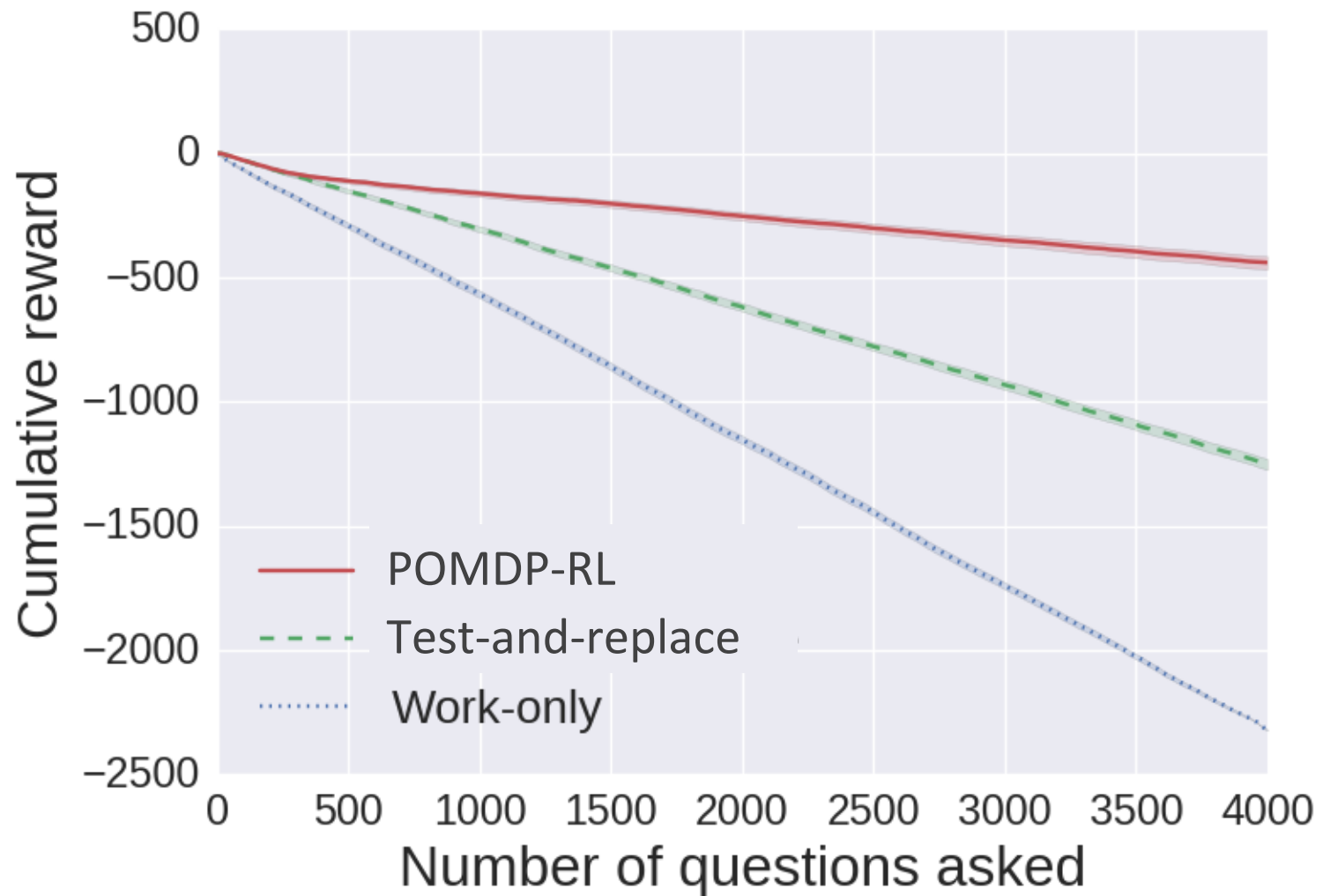
# LinWiki dataset



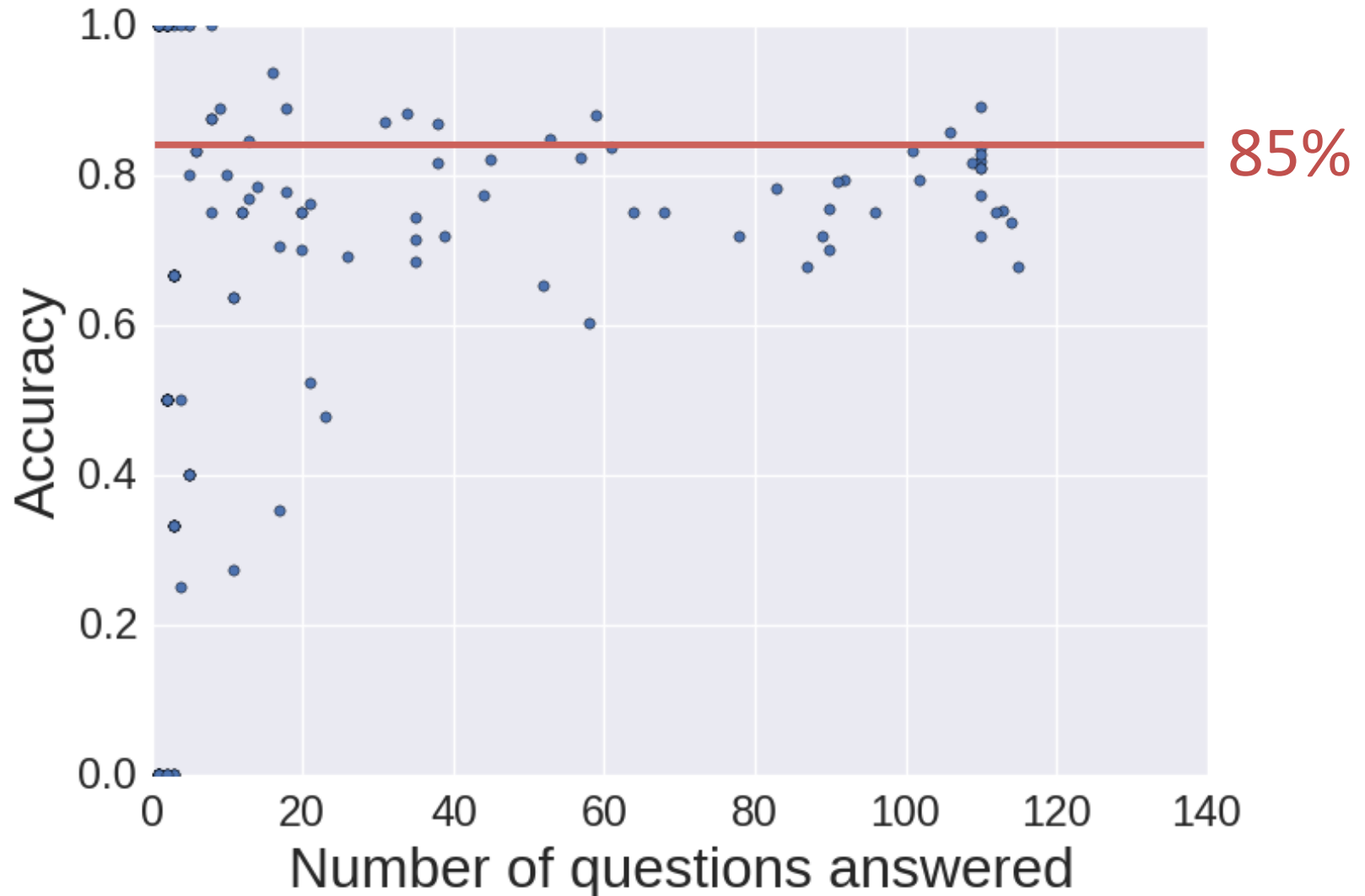
# Rajpal dataset



# LinTag dataset



# LinTag worker qualities





# Related work

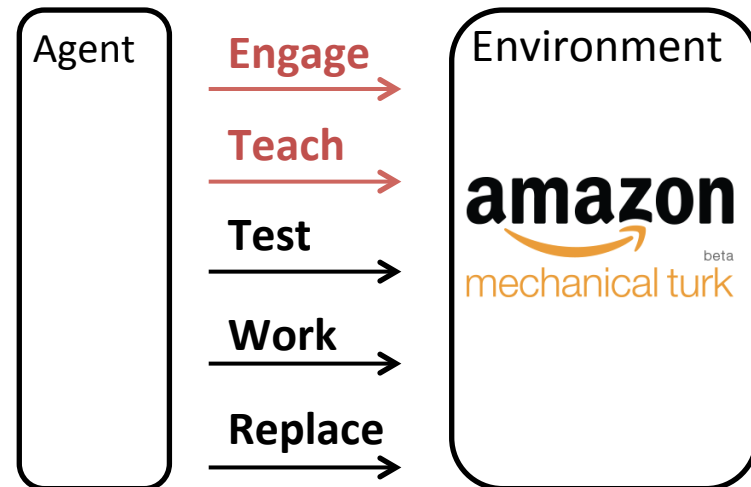
- Reinforcement learning in educational games  
[Mandel et al. AAMAS '14, AAI '15, '16]
- Task-centric control for crowdsourcing quality  
[Dai et al. AAI '10, '13; Kamar et al. AAMAS '12; Lin et al. AAI '12; Bragg et al. HCOMP '13]
- Worker-centric control for crowdsourcing engagement [Kobren et al. '15, Yin & Chen '15]

# Summary

- Problem: automatically insert gold questions to maximize quality & quantity of crowd work
- POMDP-based reinforcement learning algorithm
- Robust to parameter variations (see paper)
- Up to 111% more reward than common policies
- Code available online

# Future directions

- Subjective tasks
- Multiple answers per question
- Worker training [1] & engagement



[1] Bragg et al. 2015. In ICML workshop.

# Thanks!

- **Support:** NSF, ONR, WRF/Cable Professorship, Google, Bloomberg
- **Data:** Chris Lin, Shreya Rajpal, Karan Goel, workers on Mechanical Turk
- **Code:**  
<https://crowdlab.cs.washington.edu/optimal-training-and-testing-for-crowd-workers>



Give me answers  
above accuracy  $a^*$

