Analytic Methods for Optimizing Realtime Crowdsourcing



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Use queueing theory to understand and optimize performance of a paid, realtime crowdsourcing platform.

- Relationship between crowd size and response time
- Algorithm for optimizing crowd size & cost vs. response time
- Improvements to the platform: 500 millisecond feedback

Realtime Crowds

Answering visual questions for blind users

[Bigham et al. 2010]

What denomination is this bill?



Do you see picnic tables across the parking lot?



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Crowd-assisted photography

[Bernstein et al. 2011]

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Paid Crowdsourcing

Pay small amounts of money for short tasks

Amazon Mechanical Turk: Roughly five million tasks completed per year at 1-5¢ each [Ipeirotis 2010]

Label an image

Requester: Matt C. Reward: \$0.01

Transcribe short audio clip

Requester: Gordon L. Reward: \$0.04

Retainer Recruitment

Workers sign up in advance 1/2¢ per minute to remain on call Alert when the task is ready

Wait at most: 5 minutes Task: Click on the verbs in the paragraph

[Bernstein et al. 2011]

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alert()	
Start now!	OK

[Bernstein et al. 2011]

Retainer Recruitment

Workers sign up in advance 1/2¢ per minute to remain on call Alert when the task is ready

50% of workers return in two seconds, and 75% of workers return in three seconds.

[Bernstein et al. 2011]

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State of the Literature Realtime Crowds

- Recruit crowds in two seconds, execute traditional tasks (e.g., votes) in five seconds
- Maintain continuous control of remote interfaces
- Opportunities in deployable, intelligently reactive software

[Bigham et al. 2010, Bernstein et al. 2011, Lasecki et al. 2011]

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The Tradeoff

Missed tasks, non-realtime results



Extra retainer workers, extra cost



The Goal

Optimize the tradeoff between recruiting too many workers and dropping too many tasks.

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Budget-optimal crowdsourcing is possible in non-realtime scenarios

[Dai, Mausam and Weld 2010; Kamar, Hacker and Horvitz 2012; Karger, Oh, and Shah 2011]

1 Model 2 Optimization **3 Platform**

Queueing Theory

- Formal framework for stochastic arrival and service processes
- Basic idea: random task arrivals and random processing times for workers
- Quantify how long tasks will need to wait in line

Model Optimize Platform

Queueing theory for completion times: [Ipeirotis 2010]































- c c servers
- c max tasks in servers and queue



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Queueing Theory

M/M/c/c queue



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Modeling Retainer Recruitment

M/M/c/c queue

c workers, no waiting queue Task arrivals: Poisson process, rate λ Worker recruitment time: Poisson process, rate μ

M/M/c/c queue



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Crowc

M/M/c/c queue



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Crowc

Loss

c workers, no waiting queue Task arrivals: Poisson process, rate λ Worker recruitment time: Poisson process, rate μ Loss

row



c workers, no waiting queue Task arrivals: Poisson process, rate λ Worker recruitment time: Poisson process, rate μ

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Loss

All servers busy

c workers, no waiting queue Task arrivals: Poisson process, rate λ Worker recruitment time: Poisson process, rate μ

Loss



Loss



(rowd

Loss

P(i servers busy)



$P(i \text{ servers busy}) = \pi(i)$

row



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$P(i \text{ servers busy}) = \pi(i)$ P(all servers busy)

row



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$P(i \text{ servers busy}) = \pi(i)$ $P(\text{all servers busy}) = \pi(c)$

rowo



Model Predictions

- 1. Probability that all workers are busy: $\pi(c)$ \rightarrow the task has to wait for expected time $1/\mu$
- 2. Cost of keeping a retainer pool of size c
 - → cost depends on number of *idle* servers

Probability of Loss

- Draw on Erlang's Loss Formula from queueing theory: probability of a rejected request in an M/M/c/c queue
- Let ρ be the traffic intensity: $\rho = \lambda/\mu$ (roughly, the number of new tasks that will arrive in the time it takes to recruit a worker)

Probability of Loss

Erlang's Loss Formula says: $\pi(c) = P(c \text{ servers busy})$ $= \frac{\rho^c/c!}{\sum_{i=0}^c \rho^i/i!}$

Remarkably, this result makes no assumptions about the arrival distribution.

Probability of Loss



Expected Waiting Time

 $P(c \ servers \ busy) \times (expected \ recruitment \ time)$

$$= \pi(c) \frac{1}{\mu} \\ = \frac{\rho^{c}/c!}{\sum_{i=0}^{c} \rho^{i}/i!} \frac{1}{\mu}$$

How much do we pay in steady-state?

Depends on how many workers are usually waiting on retainer.

Probability of *i* busy servers in an M/M/c/c queue is a more general version of Erlang's Loss Formula:

$$\pi(i) = \frac{\rho^{i}/i!}{\sum_{i=0}^{c} \rho^{i}/i!}$$

Derive the expected number of busy workers:

$$E[i] = \rho[1 - \pi(c)]$$

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Derive the expected number of busy workers:

$$E[i] = \rho[1 - \pi(c)]$$

Total cost is the number of *idle* workers:

$$c - \rho [1 - \pi(c)]$$





Size of retainer pool

Cost goes down when $c < \rho$, but performance suffers.

Optimal Retainer Size

- Size of retainer pool is typically the only value that requesters can manipulate
- Minimize costs by keeping the retainer pool small while keeping $\pi(c)$ low

Model Optimize

Optimal Retainer Size Based on Maximum Miss Probability

Given a maximum desired probability of a miss p_{max} :

Minimize c subject to $\pi(c) \leq p_{max}$



Expected payments per unit time

Cost vs. probability of waiting

Optimal Retainer Size Based on Maximum Miss Probability

Given a maximum desired probability of a miss p_{max} :

Minimize c subject to $\pi(c) \leq p_{max}$



Expected payments per unit time

Cost vs. probability of waiting
Optimal Retainer Size Based on Joint Cost

If the "pizza delivery" property holds: we can quantify the cost of loss





Size of retainer pool

Improving the Retainer Model

Subscriptions Shared Pools Predictive Recruitment

Model Optimize Platform

1

2

3

Retainer Subscriptions

- Proposal: increase μ by allowing workers to subscribe to realtime tasks
- Instead of posting to the global task list, the platform sends a message to subscribers
- Change crowdsourcing from a *pull* model to a *push* model

- Sharing one global retainer pool across requesters improves performance
- Intuition: Most workers are padding for unlikely runs of arrivals)



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- Through approximation, individual pools: $\pi(c) \approx \sqrt{2\pi c} \left(e^{-\rho} (e\rho/c)^c \right)$
- Shared pools across k requesters: $\pi(c) \approx \sqrt{2\pi kc} \left(e^{-\rho} (e\rho/c)^c \right)^k$
- Loss rate declines exponentially with the number of bundled retainer pools

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Cost dramatically decreases as you combine retainers: k dollars to log(k) dollars

Global Retainer Routing

- Not every worker in a global retainer pool is good at every task
- If we assigned each worker to any task they could do, some tasks would starve

Global Retainer Routing

- We want to maintain a buffer of workers to respond to all kinds of tasks
- A linear programming technique can balance the traffic intensities across all tasks

- Predictive Recruitment: notify workers
 before the task arrives
- Recall workers in expectation of having a task by the time they arrive 2–3 seconds later

Formative Study, N=373 tasks

- 3¢ for 3-minute retainer task: whack-a-mole
- 'Loading...' screen for randomly-selected time [0, 20] seconds after worker returns
- Click on randomly-placed mole

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Results

• Median time to mouse move: 0.50 seconds



• Standard retainer model (start timer @ alert): median mouse move in 1.36 seconds

Discussion

- Empirics: Can deployed crowdsourcing platforms support lots of realtime tasks?
- Theory: Crowds as queueing systems
- Reputation: median response time, overall response rate

Use queueing theory to understand and optimize performance of a paid, realtime crowdsourcing platform.

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MIT HUMAN-COMPUTER INTERACTION

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