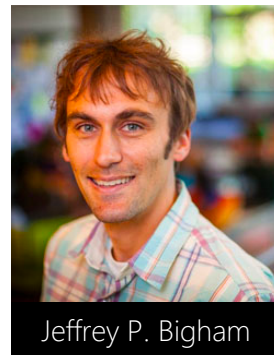
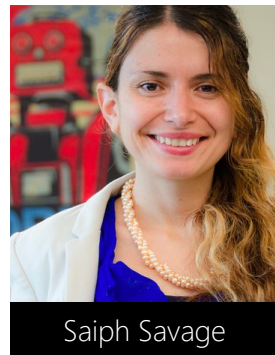
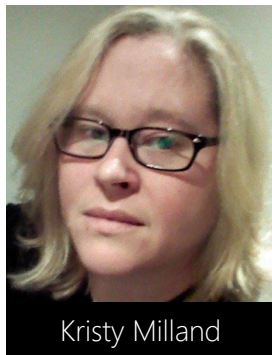
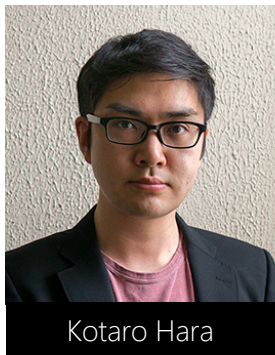


A Data-Driven Analysis of Workers' Earnings on Amazon Mechanical Turk

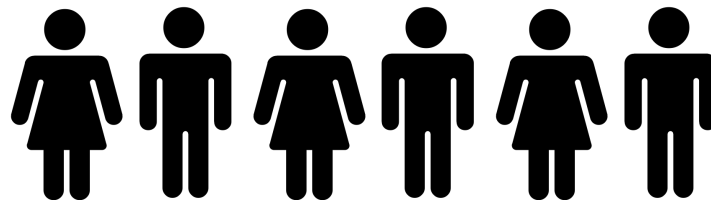
Kotaro Hara, Abigail Adams, Kristy Milland, Saiph Savage

Chris Callison-Burch, Jeffrey P. Bigham



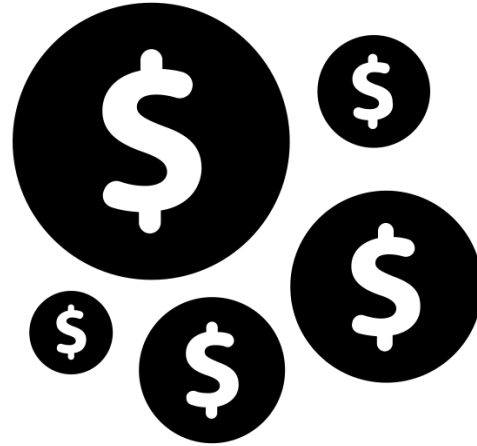
600k

online workers and counting



Online outsourcing
industry generated

\$2b

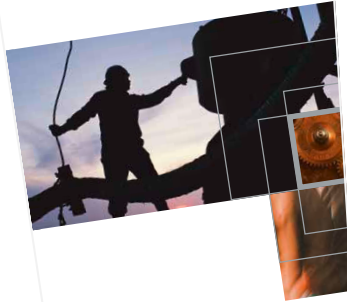




Are workers treated fairly? How does this new work style affect their lives?

Being A

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Xerox Research Centre Europe
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Incom
econ
from

Janine

ABSTRACT

We conducted an ethnomethodological analysis of publicly available content on Turker Nation, a general forum for Amazon Mechanical Turk (AMT) users. Using forum data we provide novel depth and detail on how the Turker Nation members operate as economic actors, working on which Requesters and jobs are worthwhile to them. We show some of the key ways Turker Nation functions as community and also look further into Turker-Requester relationships from the Turker perspective – considering practical, emotional and moral aspects. Finally, following Star and Strauss [25] we analyse Turking as a form of invisible work. We do this to illustrate practical and ethical issues relating to working with Turkers and AMT, and promote design directions to support Turkers and their relationships with Requesters.

Author Keywords

Ethnomethodology; content analysis; crowdsourcing; microtasking; Amazon Mechanical Turk; Turker Nation

ACM Classification Keywords

H.5.3 Group and Organizational Interfaces – Computer Supported Cooperative Work

General Terms

Human Factors

INTRODUCTION

The concept of crowdsourcing was originally coined by Jeff Howe of Wired Magazine as “the act of a community taking a function once performed by a single individual and outsourcing it to an undefined (and generally large) network of people in the form of an open call.” “undefined network of people” is the key to the article. We present the findings of an ethnomethodological analysis of posts and threads on a crowdsourcing site called Turker Nation¹. We have sought to understand the concerns, and relationships with requesters and jobs – as they are shown in their posts on the forum present them as faithfully as possible, in their own words.

Examining Crowdsourcing

Ali A.

{ali.a}

ABSTRACT

The internet is empowering the rise and other forms of on-demand labor. The design of objects, processes, and situations, but also the wider economic and cultural imaginaries of design as a social role. The paper illustrates the argument through the case of Turkopticon, an originally an activist tool for workers in Amazon Mechanical Turk (AMT), built by the authors and maintained since 2009. The paper analyzes public depictions of Turkopticon which cast designers as creative innovators and AMT workers as without agency or capacity to change their situation. We argue that designers' elevated status as workers in knowledge economies can have practical consequences for the politics of their design work. We explain the consequences of this status for Turkopticon and how we adapted our approach in response over the long term. We argue for analyses of power in design work that account for and develop counters to hegemonic beliefs and practices about design as high-status labor.

ACM Classification Keywords
H.5.3. Information Interfaces and Organization
Group and Organization Interaction

Author Keywords

Crowd work; gig work; on-demand labor

INTRODUCTION

The past decade has seen mediated labor. A framing components enables crowd of workers at scale [68], workers engage in work with little to no awareness but the very fact that we are read as designers at all?

For years, such labor was data annotation and user research. Designers are more than those who seek to move from relatively high rung in hierarchy. Designers are more than those who seek to move from relatively high rung in hierarchy.

Stories We Tell About Labor: Turkopticon and the Trouble with “Design”

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ABSTRACT

This paper argues that designers committed to advancing justice and other non-market values must attend not only to the design of objects, processes, and situations, but also to the wider economic and cultural imaginaries of design as a social role. The paper illustrates the argument through the case of Turkopticon, an originally an activist tool for workers in Amazon Mechanical Turk (AMT), built by the authors and maintained since 2009. The paper analyzes public depictions of Turkopticon which cast designers as creative innovators and AMT workers as without agency or capacity to change their situation. We argue that designers' elevated status as workers in knowledge economies can have practical consequences for the politics of their design work. We explain the consequences of this status for Turkopticon and how we adapted our approach in response over the long term. We argue for analyses of power in design work that account for and develop counters to hegemonic beliefs and practices about design as high-status labor.

Author Keywords

Activism; design, ethics, economics, social theory, critical design, human computation; Amazon Mechanical Turk

INTRODUCTION: THE POLITICS OF DESIGN IN KNOWLEDGE ECONOMIES

HCI works at the gap between technological possibility and human desires, conflicts, and labor. Some work to make things that make new kinds of relating possible. Others advocate for the making of things as a way of bringing people together to provoke and sustain democracies [9, 10, 21]. Environmental sustainability, socio-economic development, and pro-social reorganization of technological life, enliven international HCI communities. But what if the problem is not how we design in a highly unequal world, but the very fact that we are read as designers at all?

Designers are more than those who seek to move from relatively high rung in hierarchy. Designers are more than those who seek to move from relatively high rung in hierarchy.

projects. The World Bank, for example, cites design as an engine of “new value chains” in the face of global competition that drives existing commodity profit margins to zero [16]. Design is core to economic growth policies in Britain [21], China [49], and India [68]. American economic policy looks to hacking 3-D printing, STEAM (Science, Technology, Engineering, Arts, and Math) education to transform workers into citizens who can both generate new sources of financial value and improve material conditions for living.

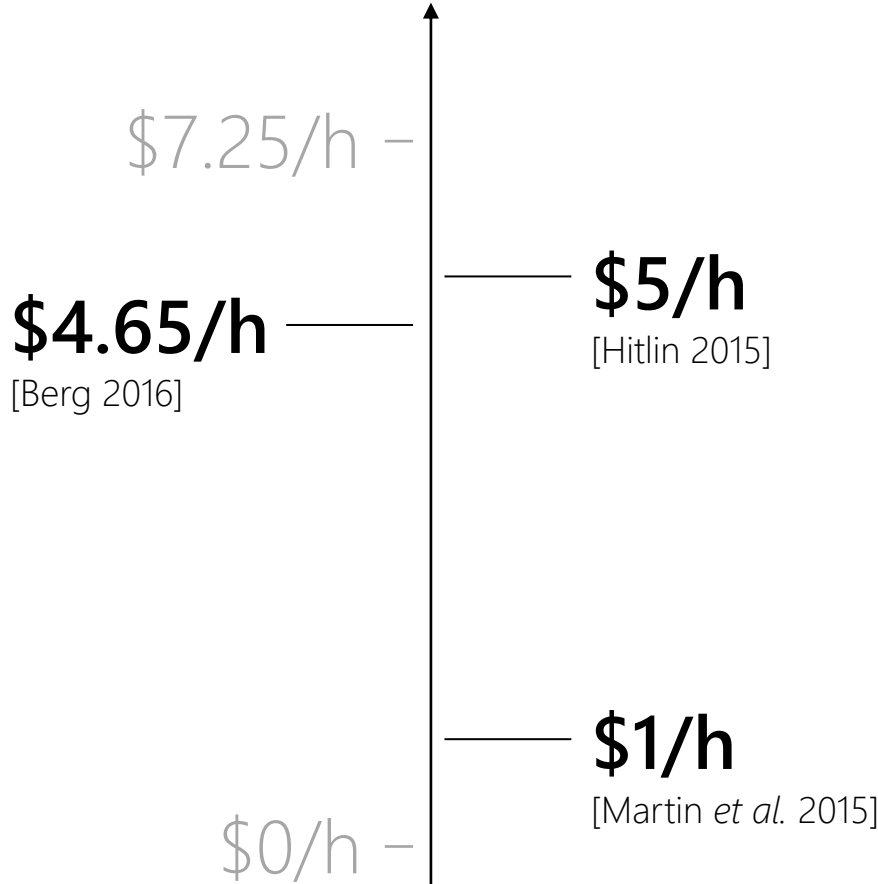
Within such a milieu, designers and HCI practitioners have a privileged place as a research community that self-consciously attempts to generate both the futures of pervasive technologies and methods for generating those futures. We are not simply Herbert Simon's designers in pursuit of preferred states [77, 111], but privileged economic actors. These stories of economic and social progress sustain us institutionally, but they also become complicities and liabilities for those who wish to redistribute power through design practice. We encountered these problems as designers of Turkopticon, an activist intervention into Amazon Mechanical Turk [see [45]]. In this paper, we explain how cultural and economic understandings of design shaped how broader publics interpreted our intervention, with problematic consequences for the workers the project sought to support. We describe the conflict between “design” as a cultural position to speak from and the projects' labor politics. We then describe how we expanded our tactics beyond design itself to sustain the projects' goals to improve digital microwork.

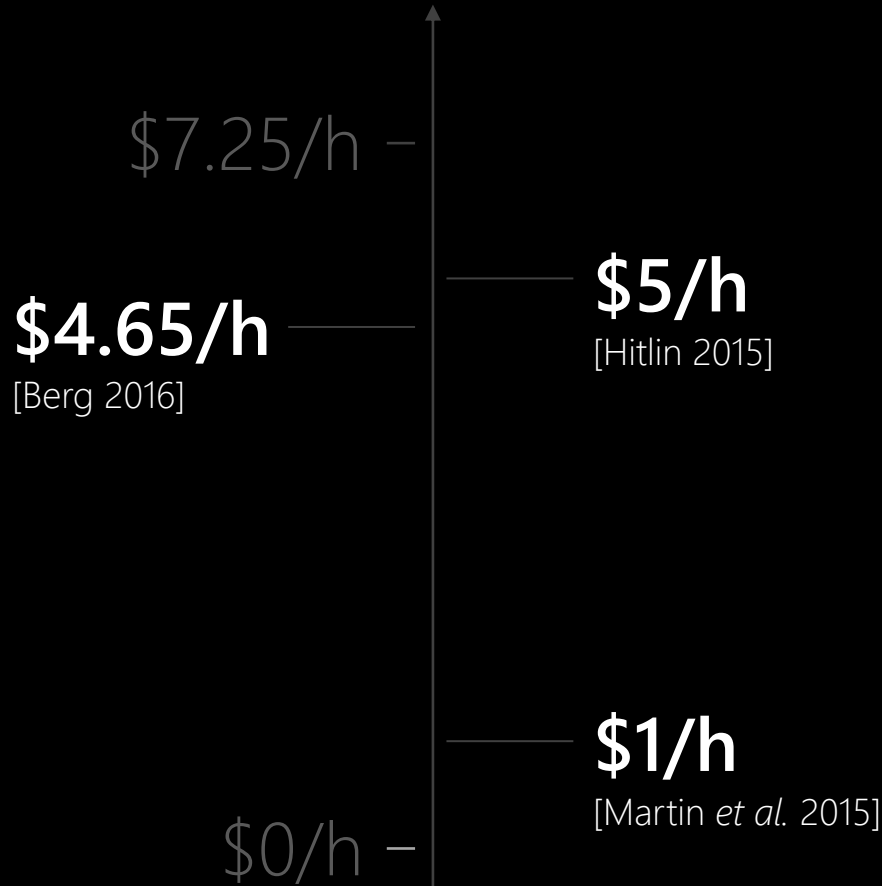
This paper contributes to HCI scholarship on design, systems development, and technology and policy innovation.

Martin et al. 2014; Berg 2016; Irani and Silberman 2016; Alkhatib et al. 2017

COND

Workers earn a fraction of the
U.S. minimum wage (\$7.25/h)





These figures are **subjective data** based on workers' opinions on an online forum and survey responses

The lack of **reward and task duration data** has prevented us from objectively analysing workers' hourly wage



Crowd
Workers

3.8m
task records

Research Questions



How much are workers earning on Amazon Mechanical Turk?

What contributes to the low wage?

Do demographics affect earnings?

Research Questions



How much are workers earning on Amazon Mechanical Turk?

What contributes to the low wage?

Do demographics affect earnings?

Data

- N=2,676 workers
- Task description
 - title, keywords, description, task IDs, requester IDs, **reward (\$)**
- Task status
 - submitted vs. returned
 - **Timestamps (task start, task end, task return)**

Data

- N=2,676 workers
 - Task description
 - title, keywords, description, task IDs, requester IDs, **reward (\$)**
 - Task status
 - submitted vs. returned
 - **Timestamps (task start, task end, task return)**
- These pieces of information enable us to calculate hourly wage
- 

All HITs | HITs Available To You | HITs Assigned To You

Search for containing that pay at least \$ for which you are qualified

Timer: 00:00:00 of 5 minutes Want to work on this HIT? Want to see other HITs?

Total Earned: Unavailable
Total HITs Submitted: 0

Accept HIT

Skip HIT

Enter Postmark & Stamp Information for a Postcard

Requester: Cardcow

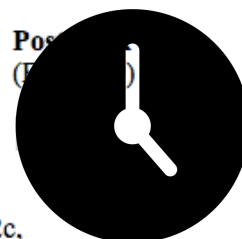
Reward: \$0.01 per HIT

HITs Available: 2

Duration: 5 minutes

Qualifications Required: Data Entry for Postcards has been granted

Enter Postmark & Stamp Information for this card



Postmark City:

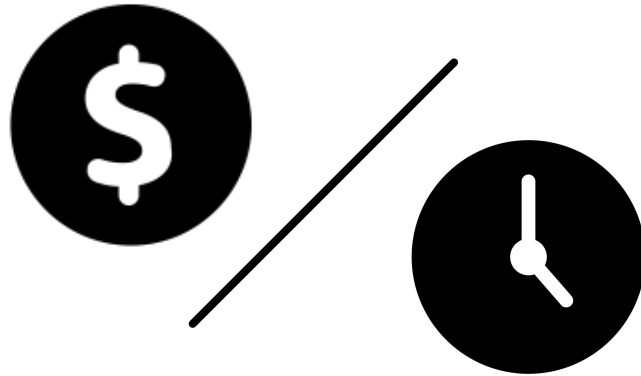
Postmark State:
(or Country)

Postmark Date:
(month & day)

(month & day)

Stamp: (Ex: 1c, 2c,
half penny)

Submit



Even with this data, it is surprisingly hard to get an accurate estimation of hourly wage

Hourly Wage Estimation (Naïve)



$$\text{Task Reward (\$)} / \text{Task Interval} = \text{Per-task Hourly Wage}$$

Hourly Wage Estimation (Naïve)



Worker

$$\frac{\sum \text{Task Reward (\$)}}{\sum \text{Task Interval}} = \text{Per-worker Hourly Wage}$$

Naïve method of calculating hourly wage

Hourly Wage Estimation (Naïve)



Worker

The naïve method is prone to both
under- or over-estimate the hourly wage

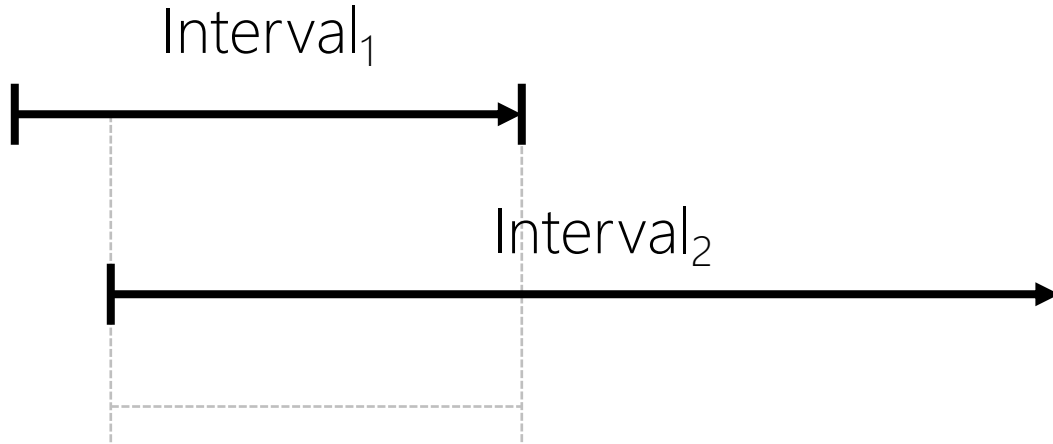
$\sum$ Task Interval

Naïve method of calculating hourly wage

Wage Under-estimation

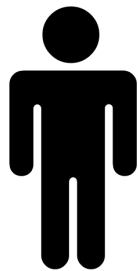


Worker

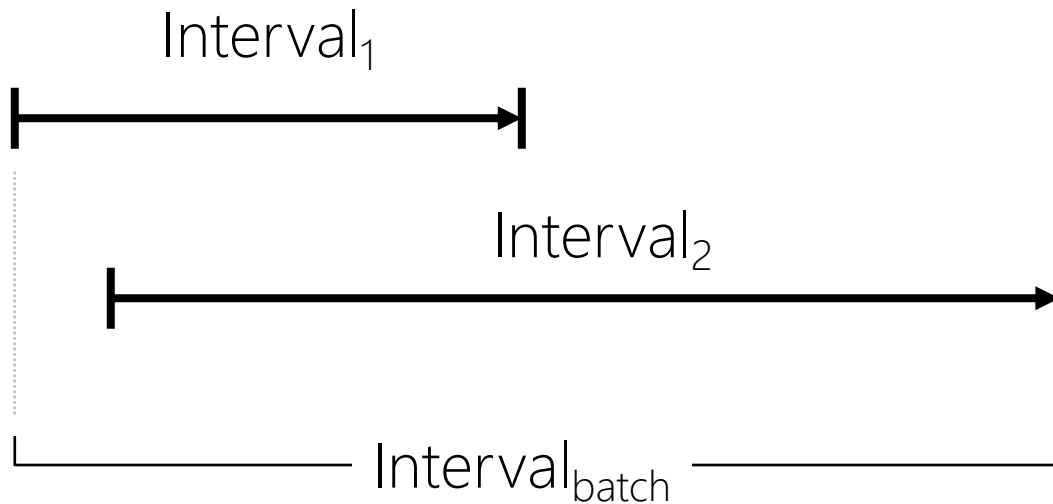


People can work on tasks concurrently

Wage Under-estimation

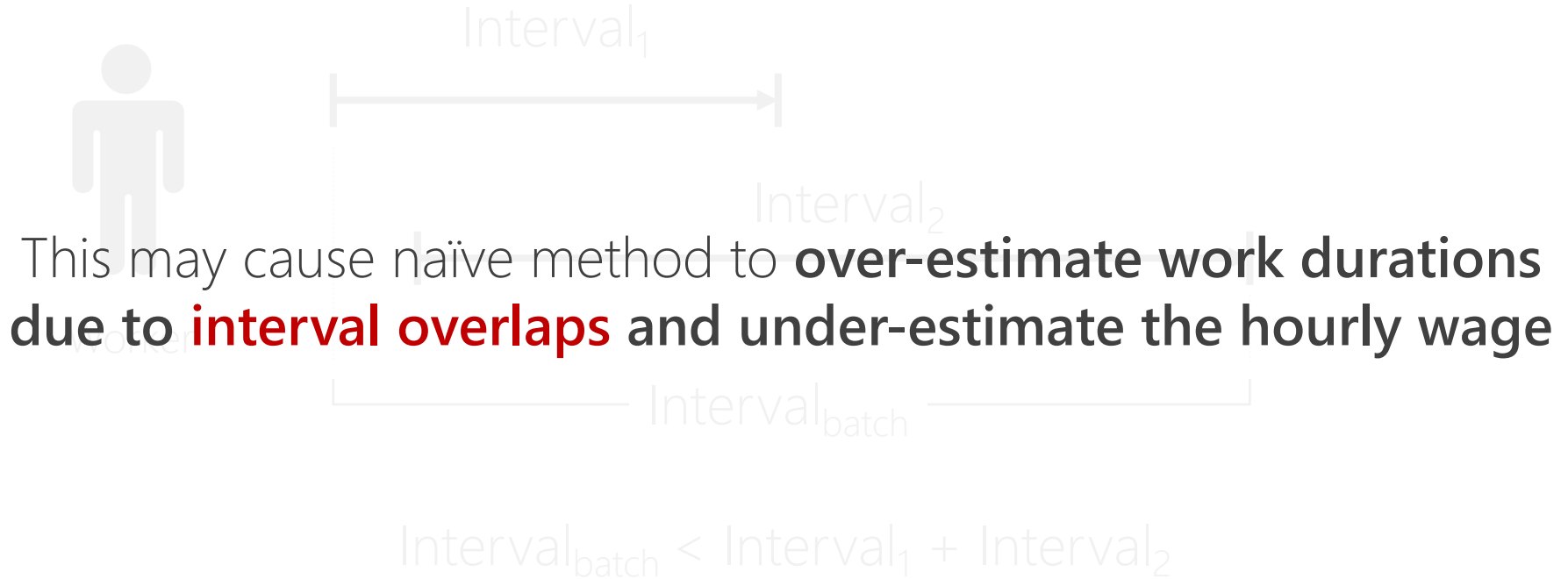


Worker

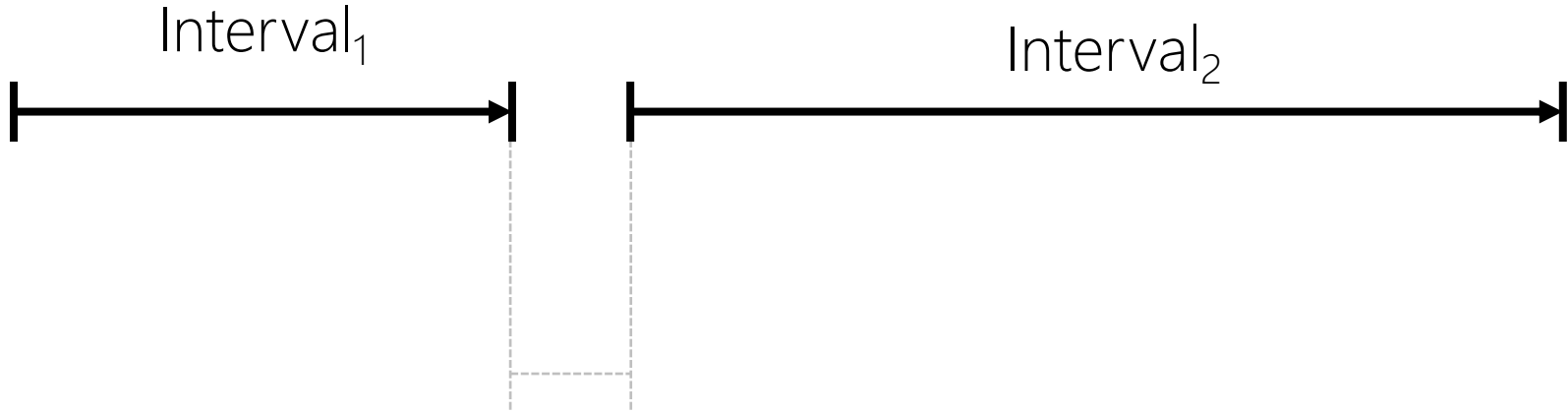


$$\text{Interval}_{\text{batch}} < \text{Interval}_1 + \text{Interval}_2$$

Wage Under-estimation

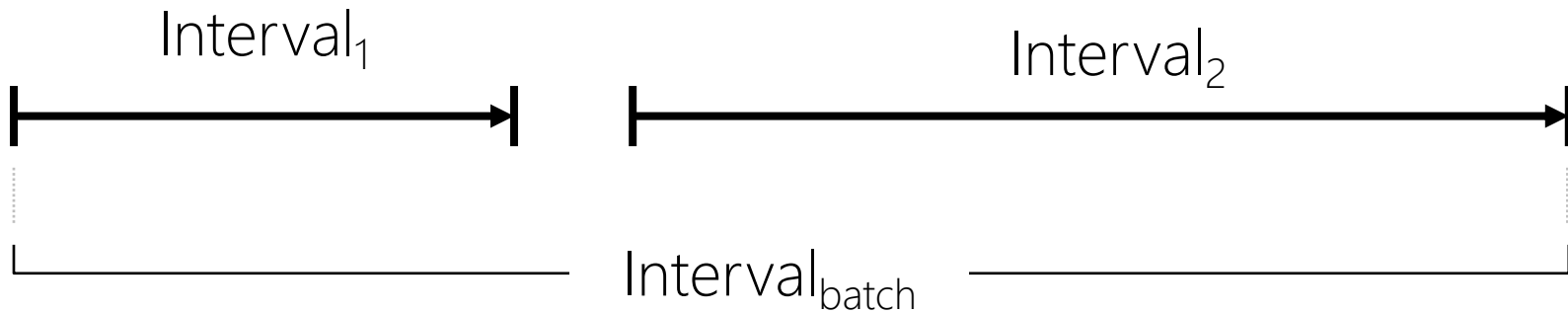


Wage Over-estimation



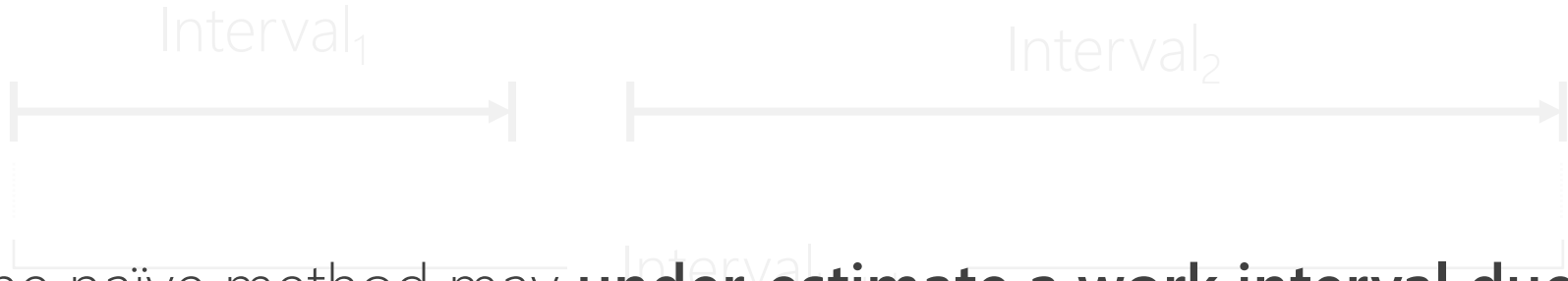
There could be a short gap between two tasks
(*e.g.*, time to search for a task)

Wage Over-estimation



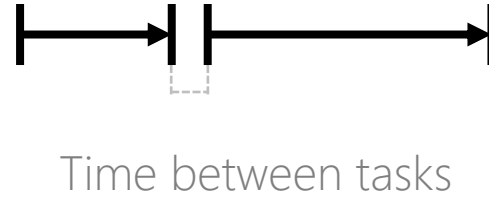
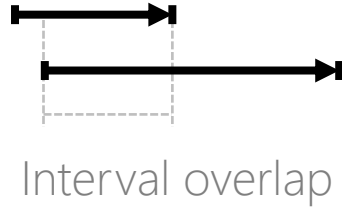
$$\text{Interval}_{\text{batch}} > \text{Interval}_1 + \text{Interval}_2$$

Wage Over-estimation



The naïve method may **under-estimate a work interval due to time between tasks** and **over-estimate the hourly wage**

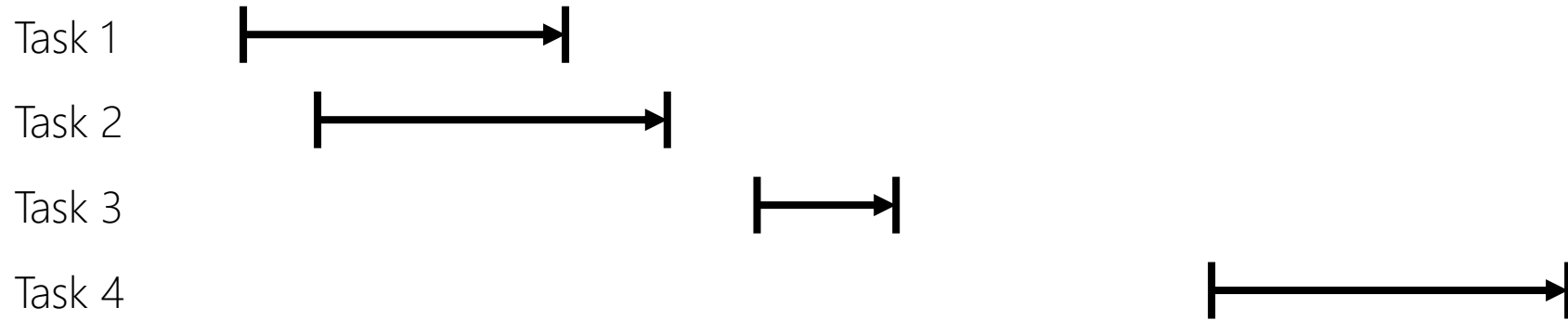
$$\text{Interval}_{\text{batch}} > \text{Interval}_1 + \text{Interval}_2$$



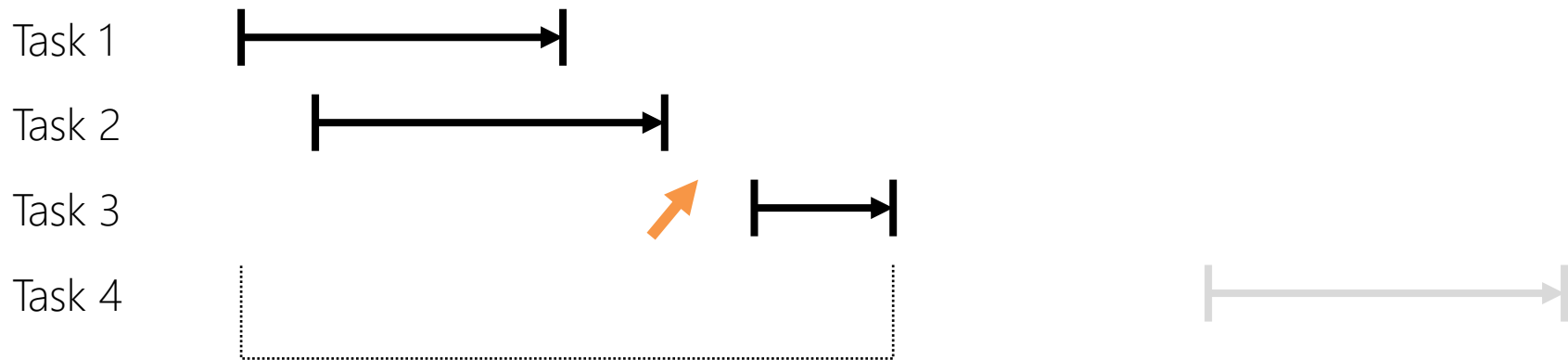
Wage over- and under-estimation may affect the accuracy of hourly wage calculation

To reduce the effects of interval overlaps and time between tasks, we used a **temporal clustering method** to compute hourly wage

Temporal Clustering

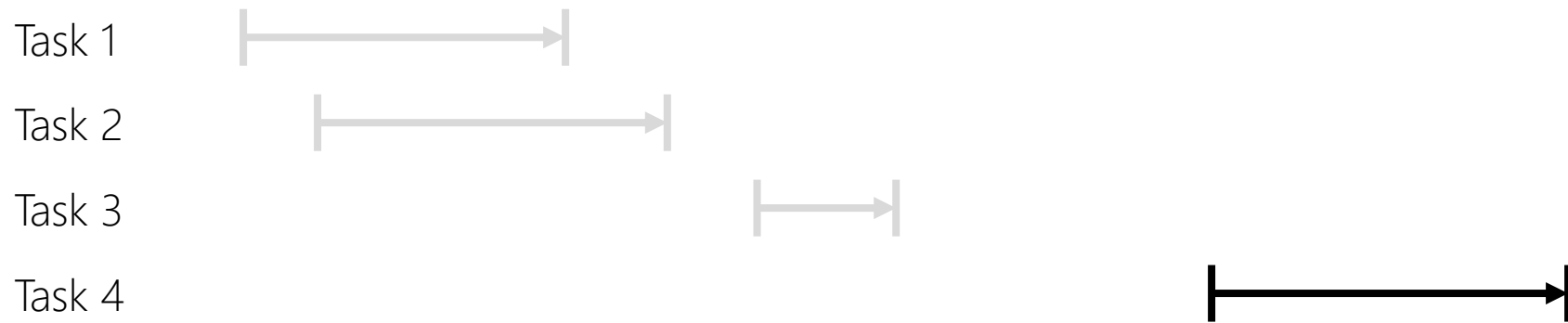


Temporal Clustering



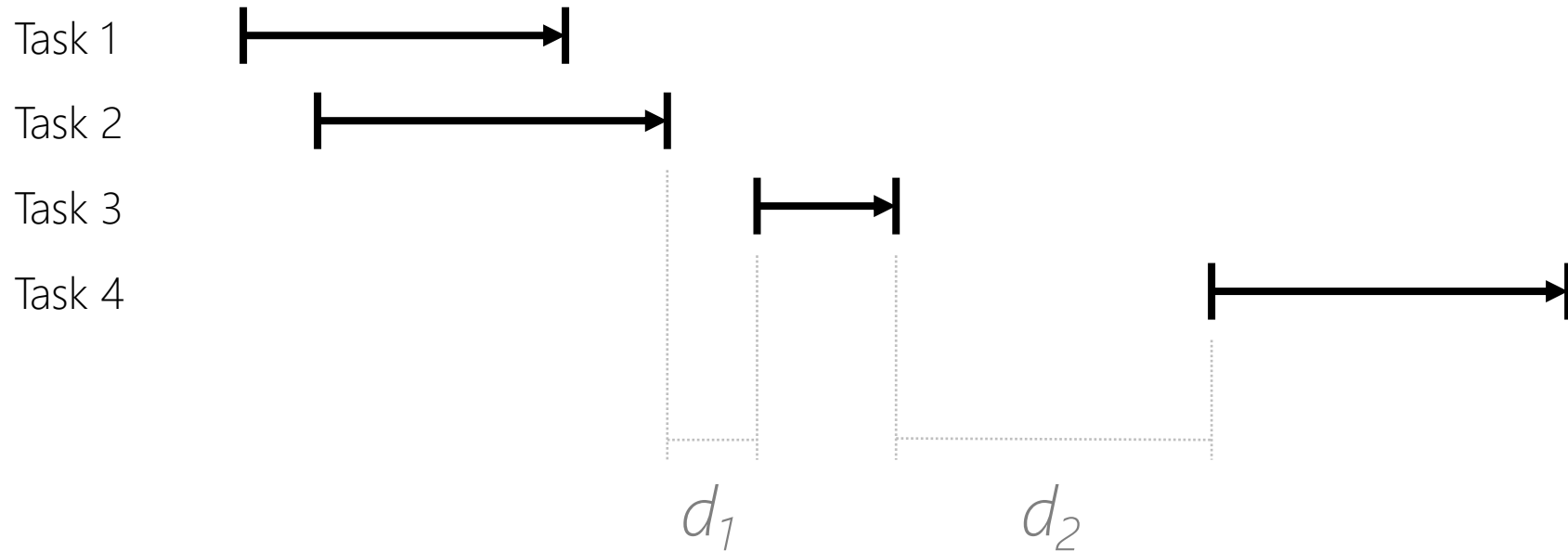
We want to cluster temporally close tasks together to ignore this **small gap**

Temporal Clustering

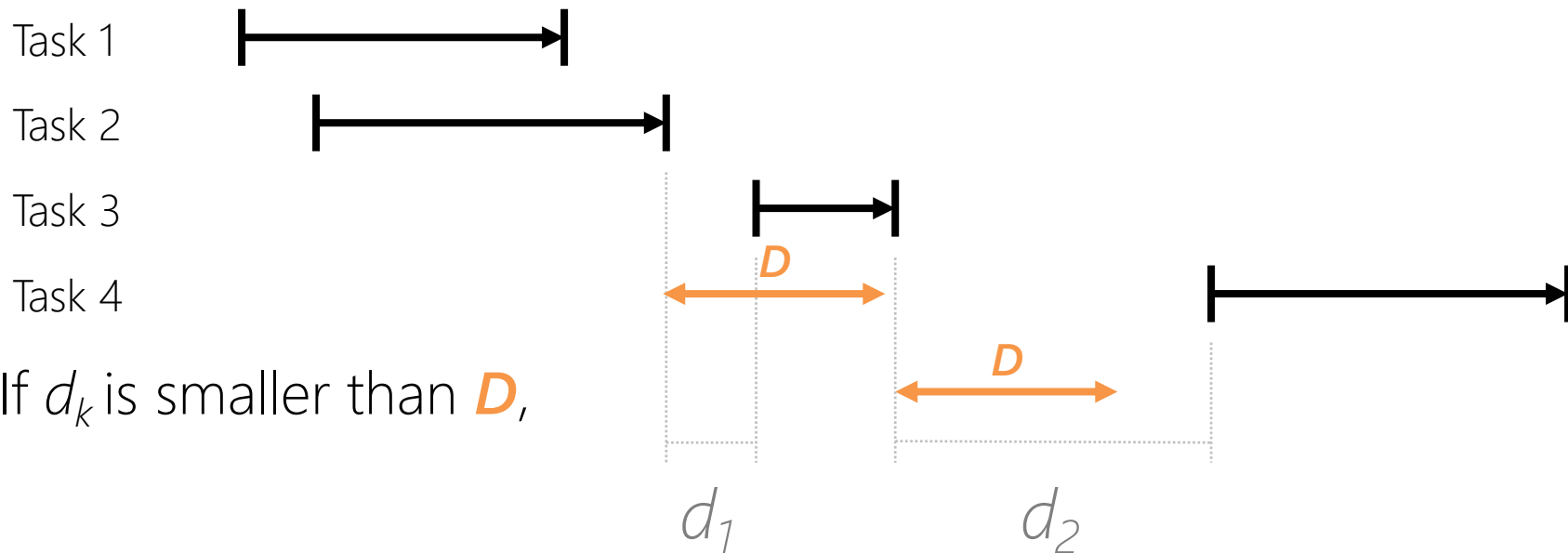


While keeping this isolated task disjoint

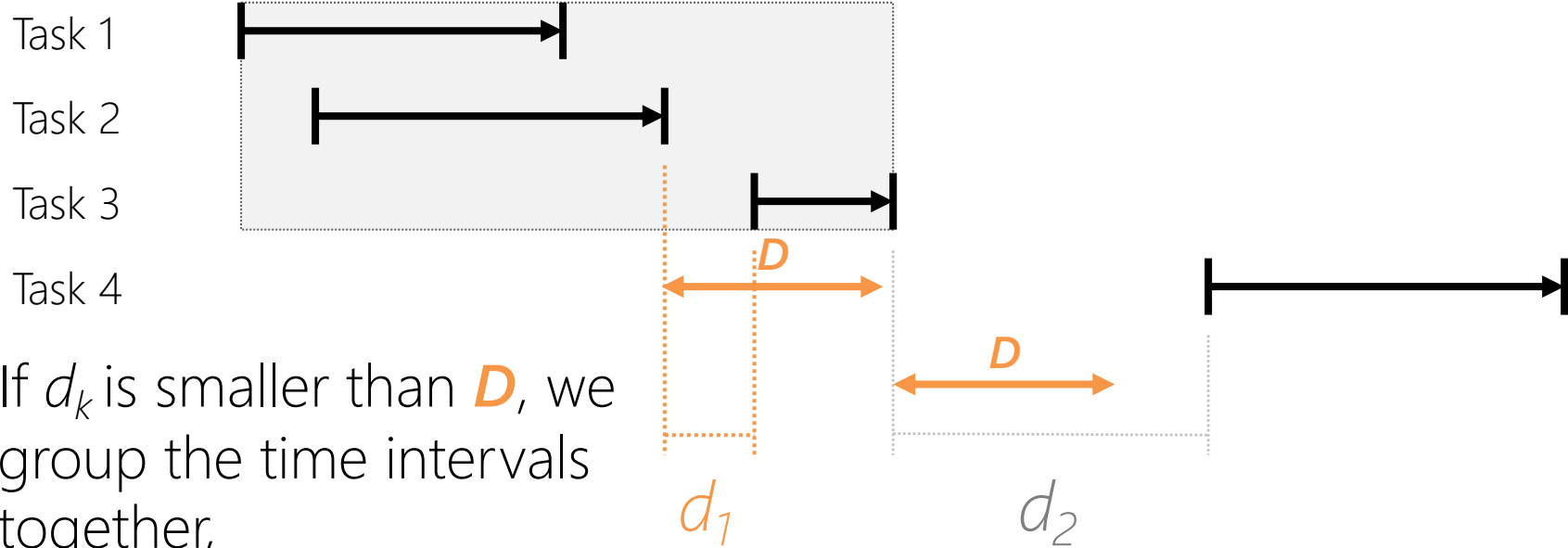
Temporal Clustering



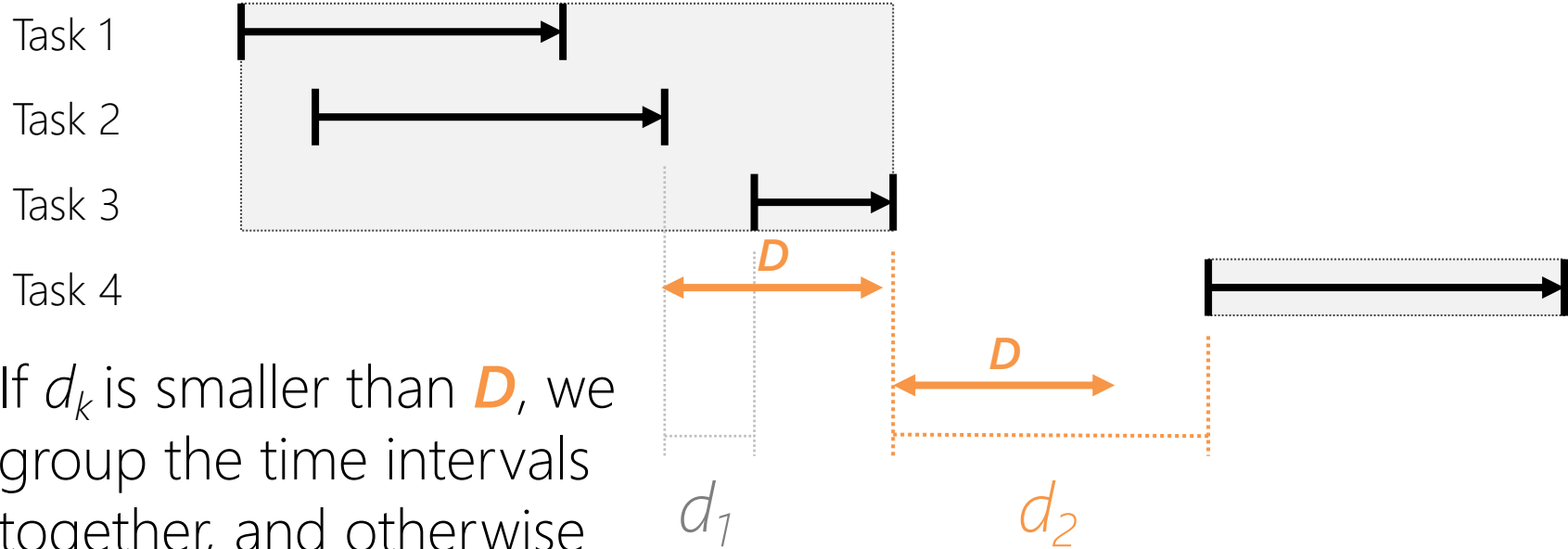
Temporal Clustering



Temporal Clustering

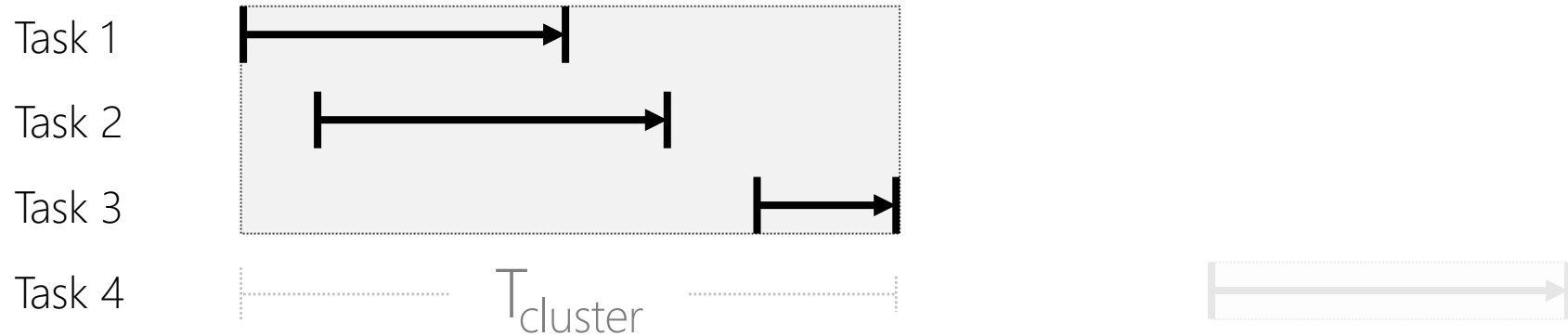


Temporal Clustering

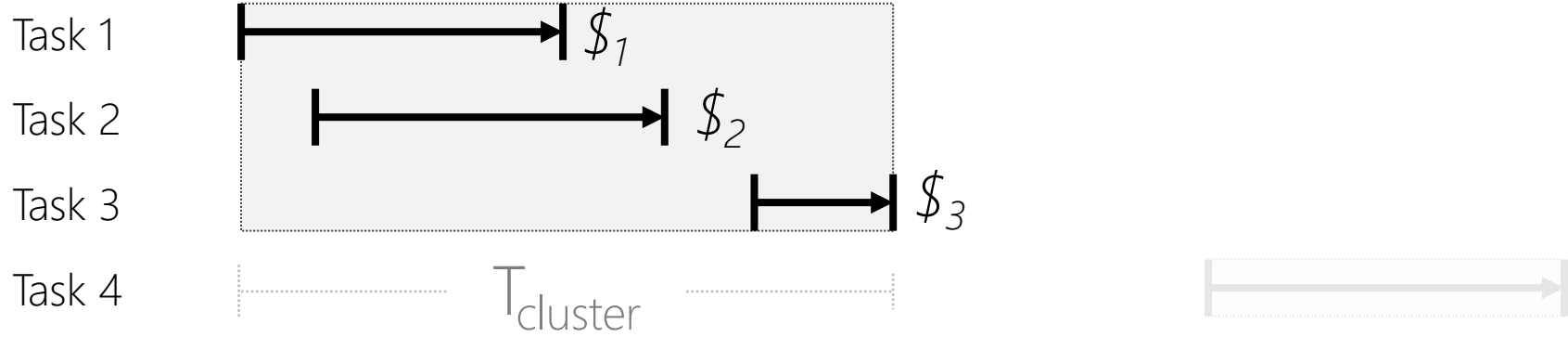


If d_k is smaller than D , we group the time intervals together, and otherwise keep them disjoint

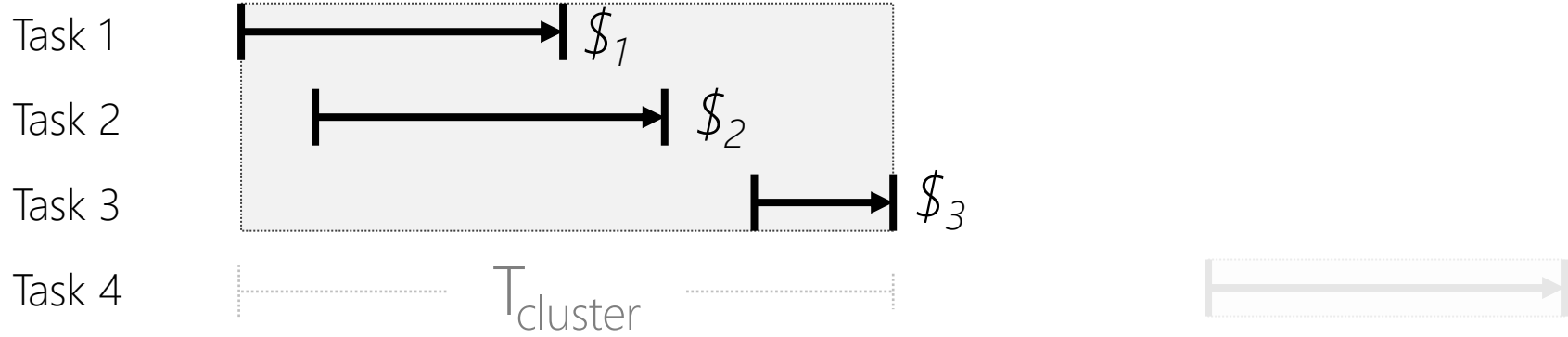
Temporal Clustering: Cluster-based Hourly Wage



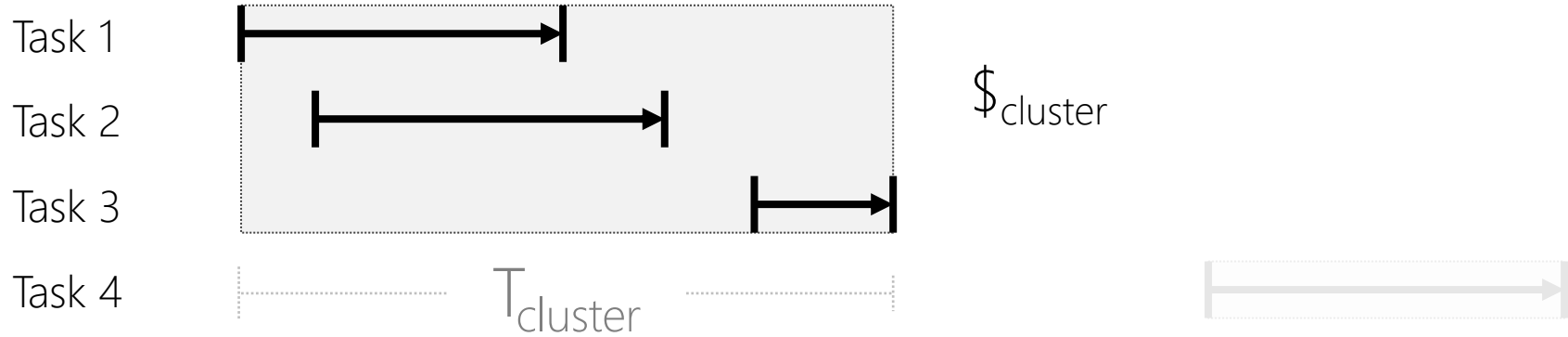
Temporal Clustering: Cluster-based Hourly Wage



Temporal Clustering: Cluster-based Hourly Wage

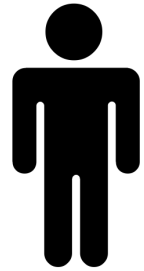


Temporal Clustering: Cluster-based Hourly Wage

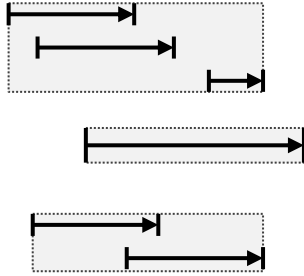


We define **per-cluster hourly wage** as $\$_{\text{cluster}} / T_{\text{cluster}}$

Temporal Clustering: Cluster-based Hourly Wage



Worker



$$\frac{\sum \text{Cluster Reward (\$)}}{\sum \text{Cluster Interval}} = \text{Per-worker Hourly Wage with Clustering}$$

Because different choice of D yield different sets of clusters, we use $D=0$ and $D=1$ minute and see their effects on cluster-based hourly wages

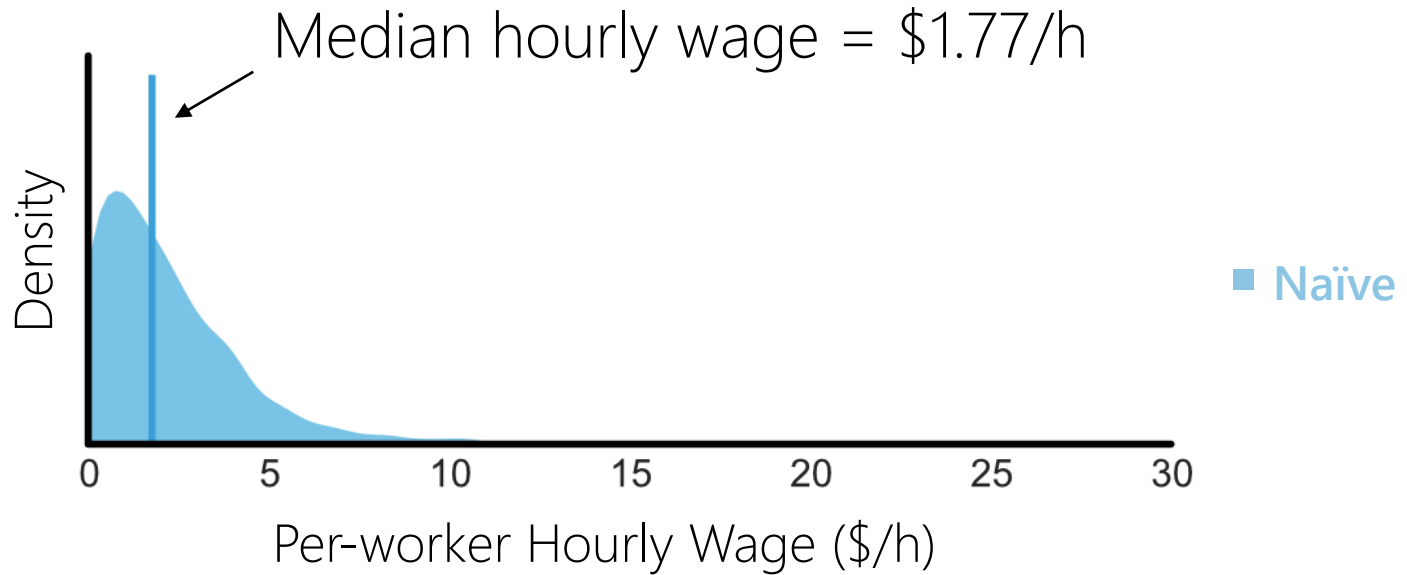
Worker Hourly Wage: Result (Naïve)



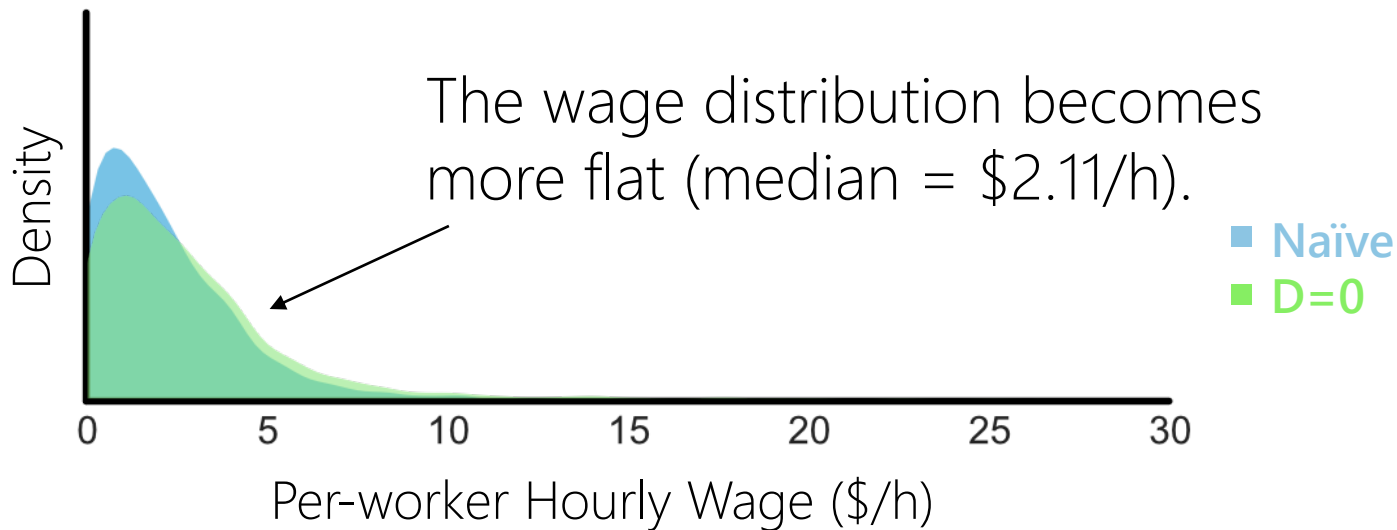
Worker Hourly Wage: Result (Naïve)



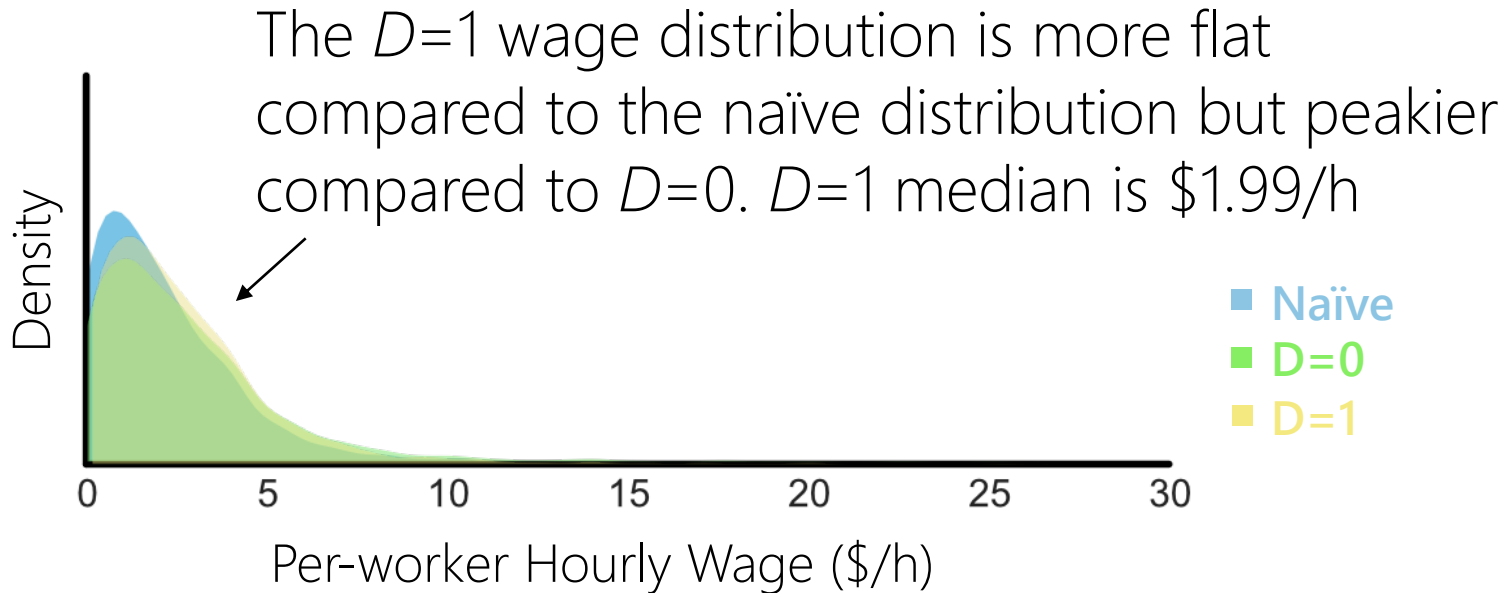
Worker Hourly Wage: Result (Naïve)



Worker Hourly Wage: Result (Clustered)



Worker Hourly Wage: Result (Clustered)



Worker Hourly Wage: Result

Median worker hourly wage is around **\$2/h**. Naïve estimation method under-estimates the hourly wage by approximately 12% (compared to $D=1$).



Per-worker Hourly Wage (\$/h)

Takeaway 1

The majority of workers on Amazon Mechanical Turk work with **hourly wage below \$2/h**

Research Questions



How much are workers earning on Amazon Mechanical Turk?

What contributes to the low wage?

Do demographics affect earnings?

Research Questions



How much are workers earning on Amazon Mechanical Turk?

What contributes to the low wage?

Do demographics affect earnings?

What contributes to the low wage?



Unpaid work



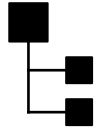
Low reward



Requesters



Qualifications



Task types

What contributes to the low wage?



Unpaid work



Low reward



Requesters



Qualifications



Task types

What contributes to the low wage?



Unpaid work



Low reward



Requesters



Qualifications



Task types

Being A Turker

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Neha Gupta

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ABSTRACT

We conducted an ethnomethodological analysis of publicly available content on Turker Nation, a general forum for Amazon Mechanical Turk (AMT) users. Using forum data we provide novel depth and detail on how the Turker Nation members operate as economic actors, working out which Requesters and jobs are worthwhile to them. We show some of the key ways Turker Nation functions as a community and also look further into Turker-Requester relationships from the Turker perspective – considering practical, emotional and moral aspects. Finally, following Star and Strauss [25] we analyse Turkling as a form of invisible work. We do this to illustrate practical and ethical issues relating to working with Turkers and AMT, and to promote design directions to support Turkers and their relationships with Requesters.

Author Keywords

Ethnomethodology; content analysis; crowdsourcing; microtasking; Amazon Mechanical Turk; Turker Nation.

ACM Classification Keywords

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INTRODUCTION

The concept of crowdsourcing was originally defined by Jeff Howe of Wired Magazine as “the act of a company or institution taking a function once performed by employees and outsourcing it to an undefined (and generally large) network of people in the form of an open call.” [8] This ‘undefined network of people’ is the key topic of this article. We present the findings of an ethnomethodological analysis of posts and threads on a crowdsourcing forum called Turker Nation¹. We have sought to understand members of the crowd – their reasoning practices, concerns, and relationships with requesters and each other – as they are shown in their posts on the forum. We seek to present them as faithfully as possible, in their own words, in

order to provide more definition to this network of people. We believe that this will be beneficial for researchers and businesses working within the crowdsourcing space.

Crowdsourcing encompasses multiple types of activity: invention, project work, creative activities, and microtasking. This latter is our focus here. The most well-known microtask platform is Amazon Mechanical Turk (AMT)², and the Turker Nation forum that we studied is dedicated to users of this platform. The basic philosophy of microtasking and AMT is to delegate tasks that are difficult for computers to do to a human workforce. This has been termed ‘artificial artificial intelligence’. Tasks like image tagging, duplicate recognition, translation, transcription, object classification, and content generation are common. ‘Requesters’ (the AMT term for people who have work to be completed) post multiple, similar jobs as Human Intelligence Tasks (HITs), which can then be taken up by registered ‘Turkers’ (Turkers termed ‘Providers’ by AMT) are the users completing the HITs, which typically take seconds or minutes paid at a few cents at a time.

For Amazon, the innovative idea was to have an efficient and cost effective way to curate and manage the quality of content on their vast databases (weeding out duplicates, vulgar content, etc.). While Amazon is still a big Requester, AMT has been deployed as a platform and connects a wide variety of Requesters with up to 500,000 Providers. However, Fort et al. [6] have performed an analysis on the available data and suggest that real number of active Turkers is between 15,059 and 42,912; and that 80% of the tasks are carried out by the 20% most active (3,011–8,582) Turkers. While these numbers are useful, the research community still has little deep qualitative knowledge about this workforce. Questions remain unanswered such as: how and what do they look for in jobs; what are their concerns; and how do they relate to requesters?

LITERATURE REVIEW

To date much of the research on AMT takes the employers’ perspective, e.g. [14, 15, 17, 18], and this has in turn been highlighted [6, 16]. Silberman et al. [23] note that this mainstream research looks at how: “[to] motivate better, cheaper and faster worker performance [...] to get good

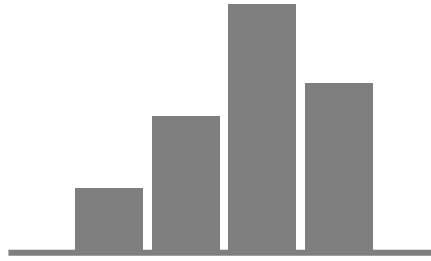
¹ <http://turkernation.com/forum.php>

² <http://www.mturk.com>

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CSCW ’13, February 23–27, 2013, San Antonio, Texas, USA.
Copyright 2013 ACM 978-1-4503-1331-5/13/02...\$15.00.

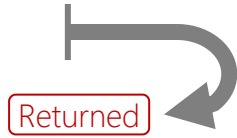
[...] aspects of turking [(working on Amazon Mechanical Turk)] like simply searching for jobs can take a considerable amount time. The time spent learning and searching are clear examples of invisible [(unpaid)] work that Turkers must engage in [...].

Martin et al., (2014) *Being a Turker*, CSCW 2014



The issue of unpaid work has been identified in prior work,
but **its effects are not quantified**

We quantify three types of unpaid work



Time spent on
returned tasks

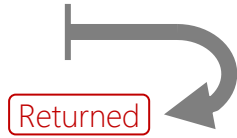


Time spent on
rejected tasks



Time
between tasks

We quantify three types of unpaid work



Time spent on
returned tasks



Time spent on
rejected tasks

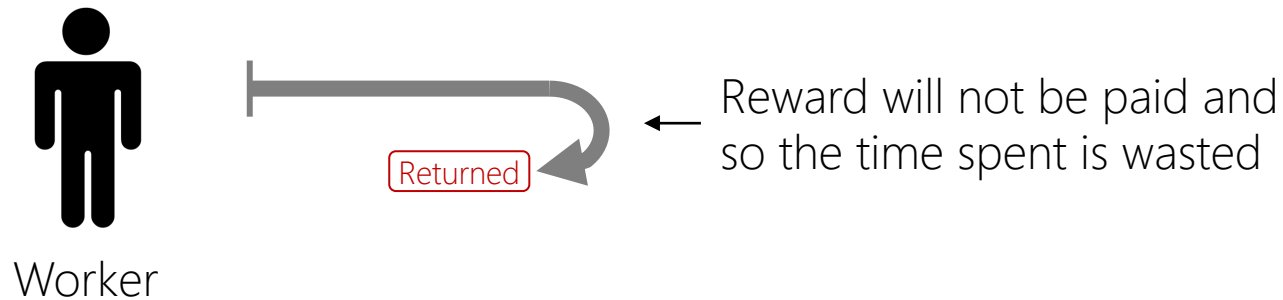


Time
between tasks

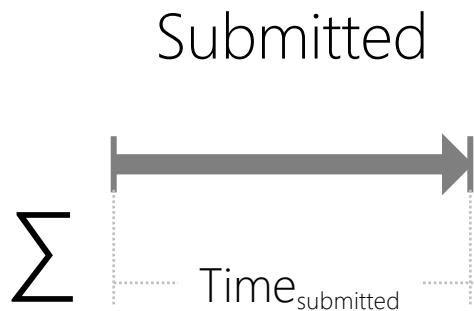
Task Submit and Return



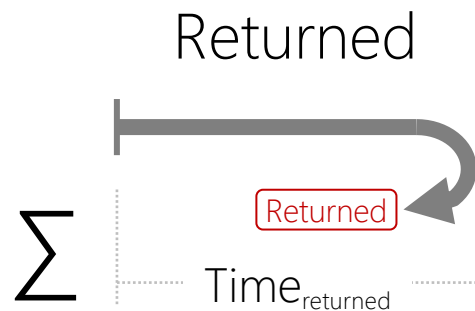
Task Submit and Return



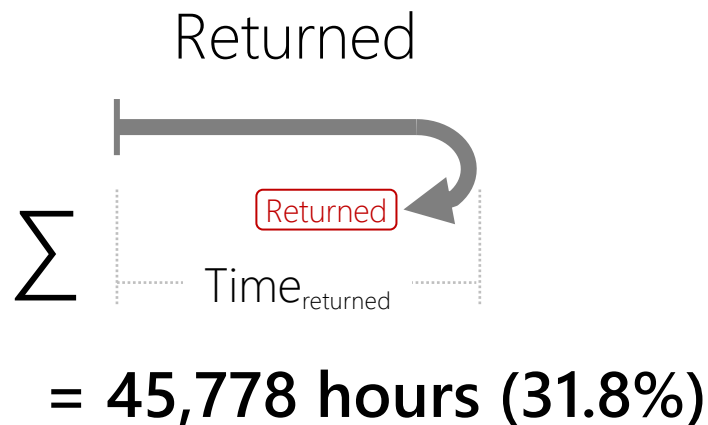
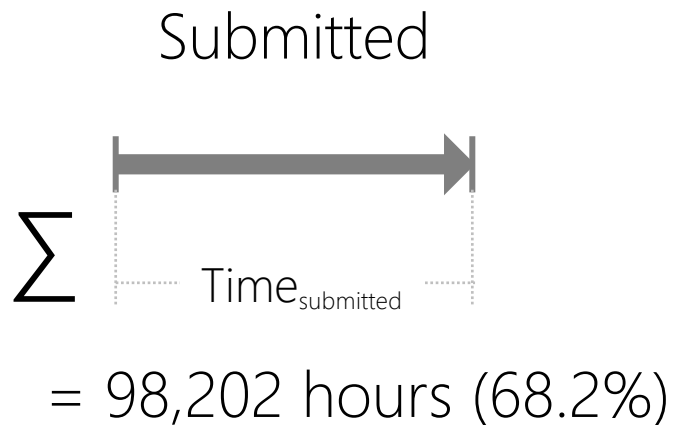
Time Spent on **Returned** Tasks



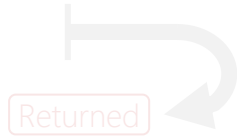
For all tasks from all workers



Time Spent on **Returned Tasks**: Result



We quantify three types of unpaid work



Time spent on
returned tasks

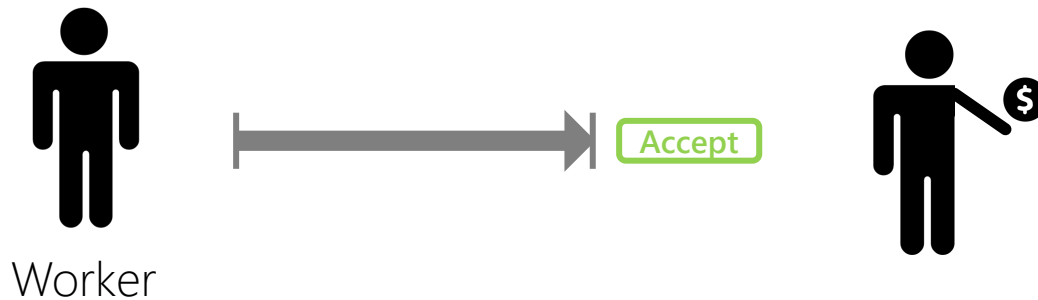


Time spent on
rejected tasks

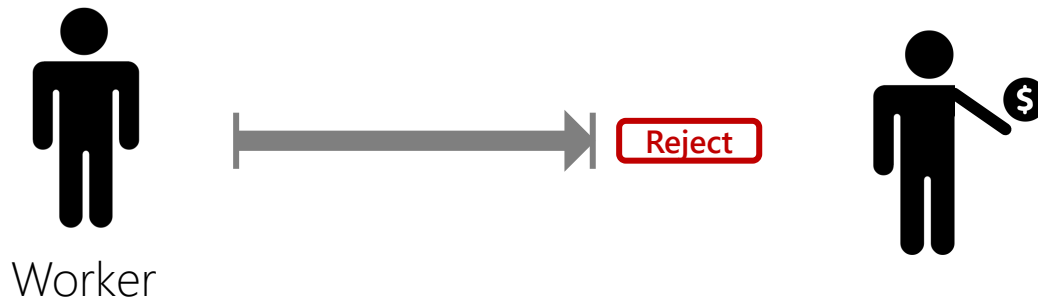


Time
between tasks

Task **Accept** and Reject

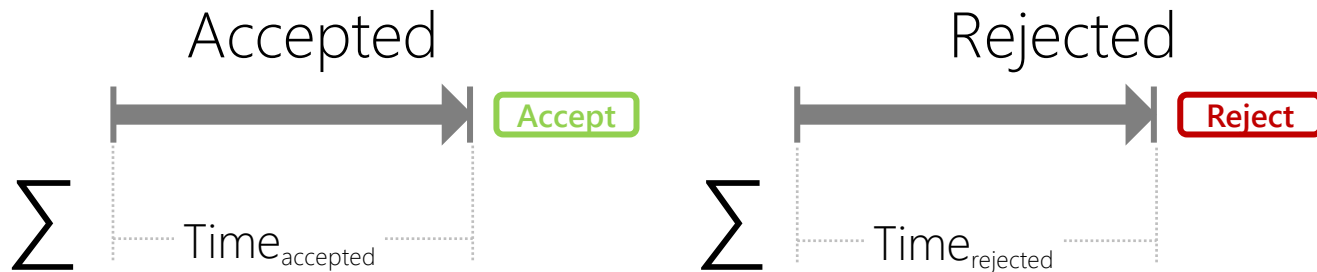


Task Accept and **Reject**



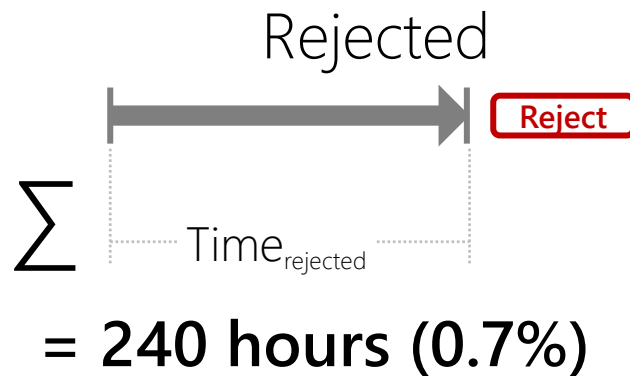
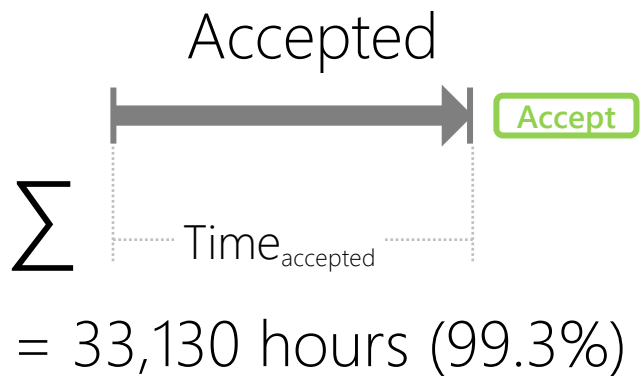
Time Spent on **Rejected Tasks**

We had data on task accept vs. reject status for 29.6% of the submitted tasks

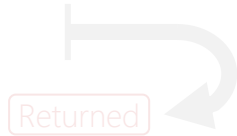


Time Spent on **Rejected Tasks: Result**

We had data on task accept vs. reject status for 29.6% of the submitted tasks



We quantify three types of unpaid work



Time spent on
returned tasks

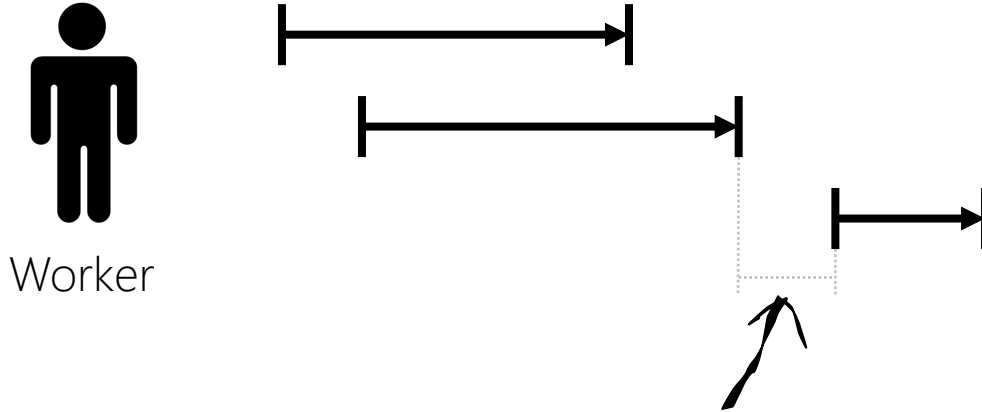


Time spent on
rejected tasks



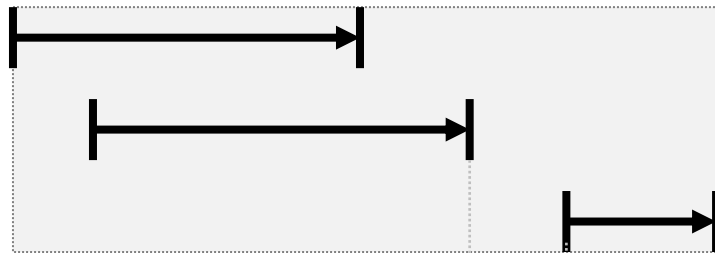
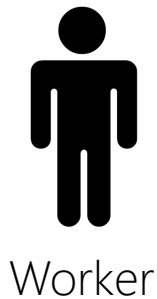
Time
between tasks

Time **Between** Tasks

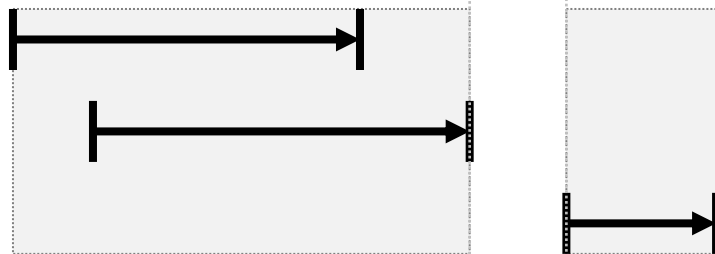


We want to know the effect of this small gap between tasks (e.g., task search time)

Time **Between** Tasks



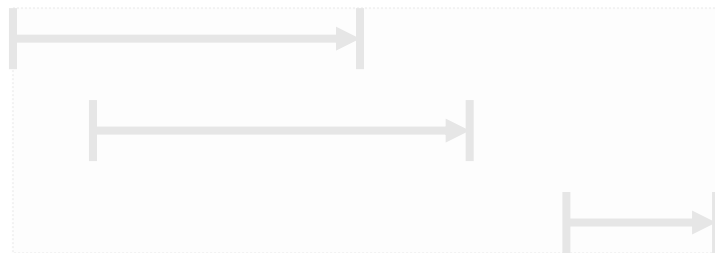
Clustering ($D=1\text{min}$)



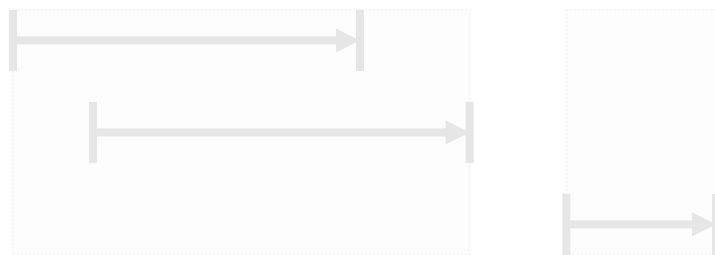
Clustering ($D=0\text{min}$)

$$\sum \Delta$$

Time **Between** Tasks: Result



Clustering ($D=1\text{min}$)

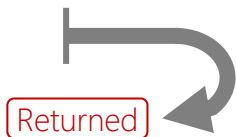


Clustering ($D=0\text{min}$)

$$\sum \Delta = 4,603 \text{ hours}$$

Result

45,778 hours
31.8% of work



240 hours
0.7% of work



4,603 hours
4.7% of work



Takeaway 2

Returning tasks has the biggest impact on the hourly wage. In fact, **31.8% of work time is wasted due to this unpaid work.**

What contributes to the low wage?



Unpaid work



Low reward



Requesters



Qualifications



Task types

What contributes to the low wage?



Unpaid work



Low reward



Requesters



Qualifications



Task types

< \$2/h

Workers are underpaid.

< \$2/h

Workers are underpaid. Is this because all requesters treat workers unfairly,

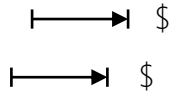
< \$2/h

Workers are underpaid. Is this because all requesters treat workers unfairly, or are there a small number of requesters who post many very low paid tasks?

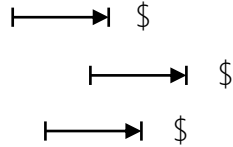
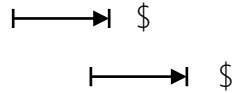


We investigated the distribution of **per-requester hourly payment**

Per-requester Hourly Payment

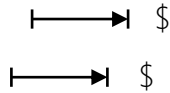


Requester

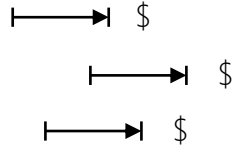
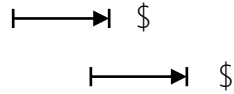


Workers

Per-requester Hourly Payment



Requester



Workers

Per-requester Hourly Payment



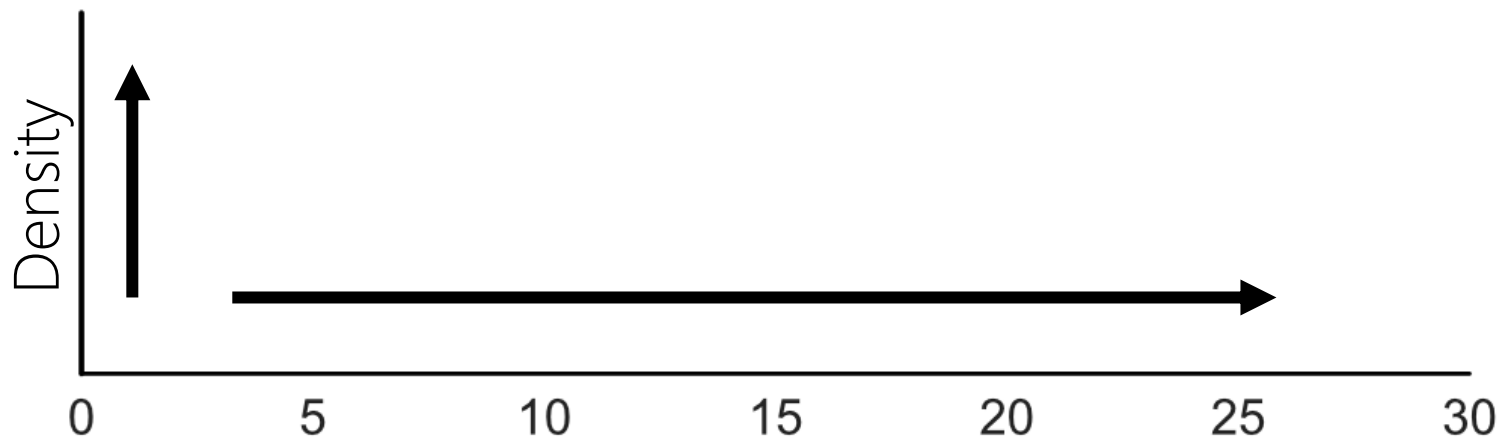
Requester



Workers

$$\frac{\sum \text{Task Payment (\$)}}{\sum \text{Task Interval}} = \text{Per-requester Hourly Payment}$$

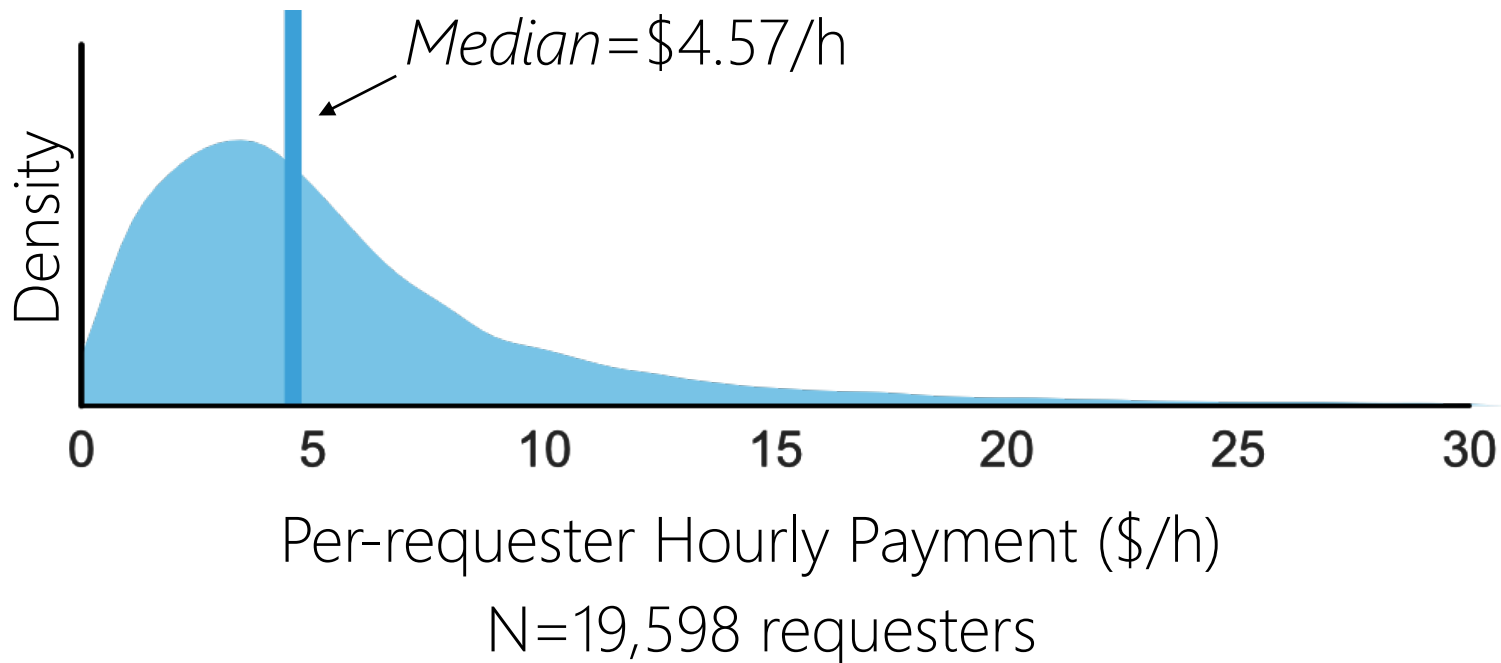
Per-requester Hourly Payment: Result



Per-requester Hourly Payment (\$/h)

N=19,598 requesters

Per-requester Hourly Payment: Result



Takeaway 3

About half of the requesters pay below \$5/h, which is below the U.S. federal minimum wage.

Research Questions



How much are workers earning on Amazon Mechanical Turk?

What contributes to the low wage?

Do demographics affect earnings?

Research Questions

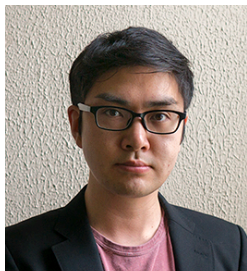


How much are workers earning on Amazon Mechanical Turk?

What contributes to the low wage?

Do demographics affect earnings?

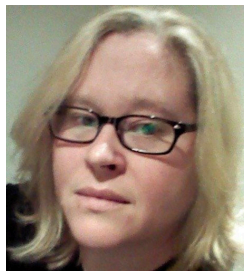
Worker Demographics and Earnings on Amazon Mechanical Turk: An Exploratory Analysis, Kotaro Hara, Abigail Adams, Kristy Milland, Saiph Savage, Benjamin V. Hanrahan, Chris Callison-Burch, Jeffrey P. Bigham



Kotaro Hara



Abigail Adams



Kristy Milland



Saiph Savage



Ben Hanrahan



Chris Callison-Burch



Jeffrey P. Bigham



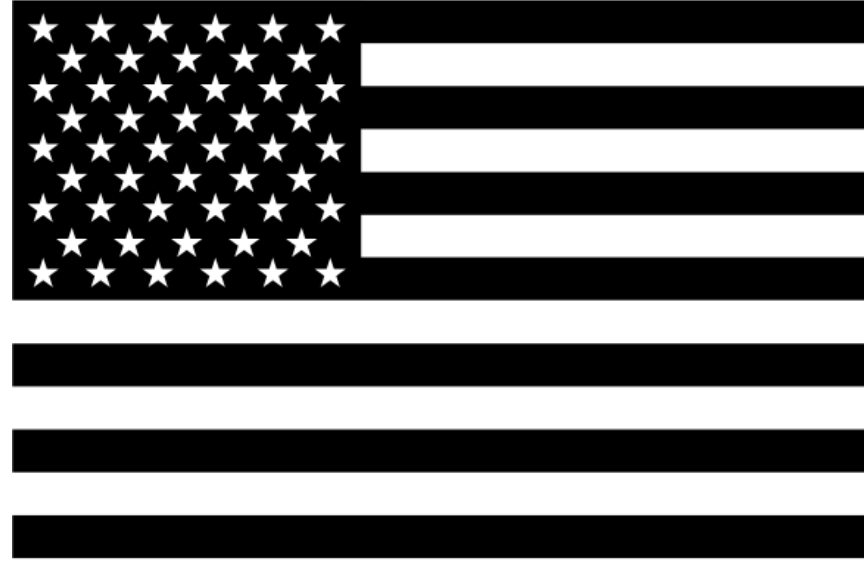
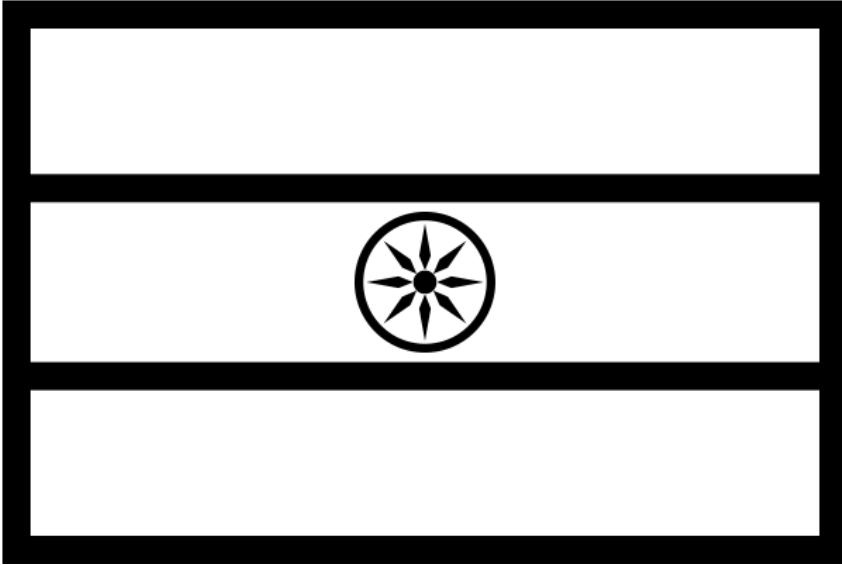
Research questions

Our prior work estimated that workers on Amazon Mechanical Turk earn approximately \$2/h. However, the lack of worker demographic information prevented us from asking questions like “is there an income gap between workers from different countries?” and “is there a difference in earnings between workers with and without disabilities?”

Demographic Survey

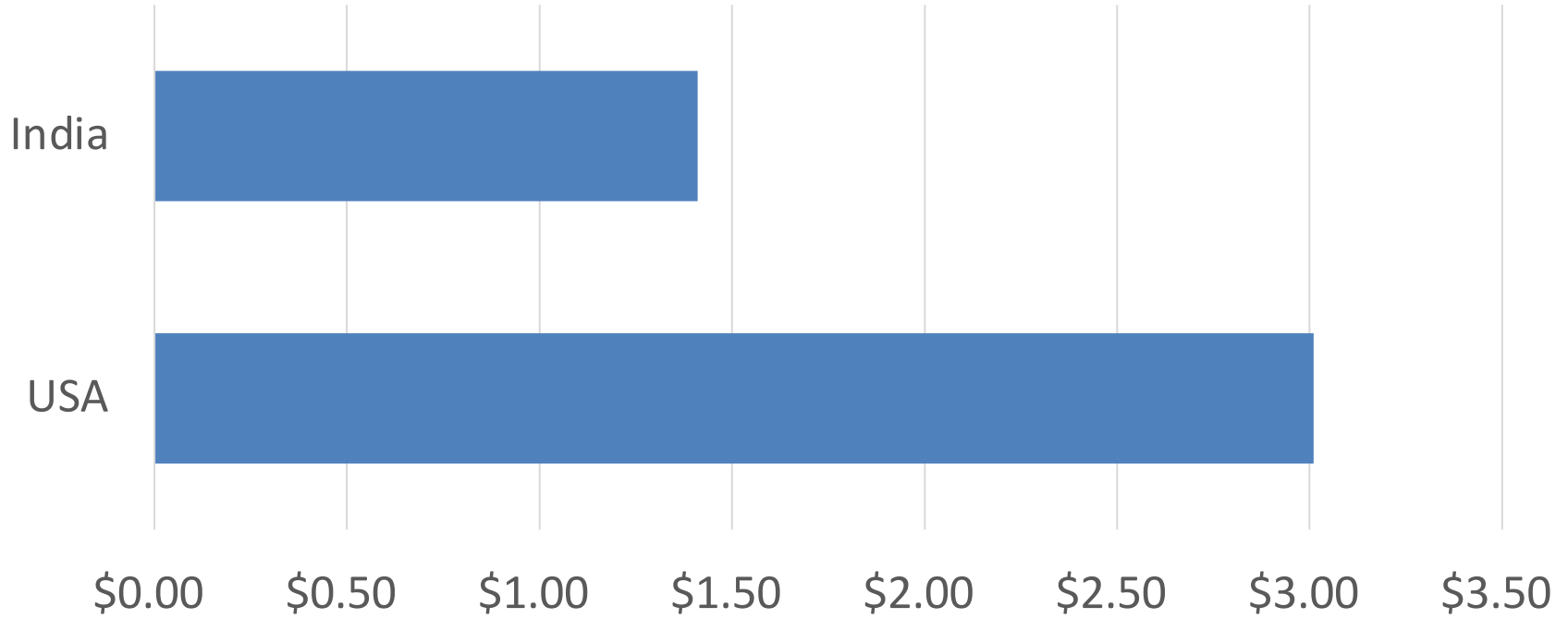
We gathered demographic information of **N=1,238** crowd workers who previously used the Crowd Workers plugin via an online survey posted on Amazon Mechanical Turk. The survey asked the **country of residence, gender, disability/health condition**. We combined this with the data gathers from the Crowd Workers plugin to calculate median hourly wage of each survey respondent.

Respondents

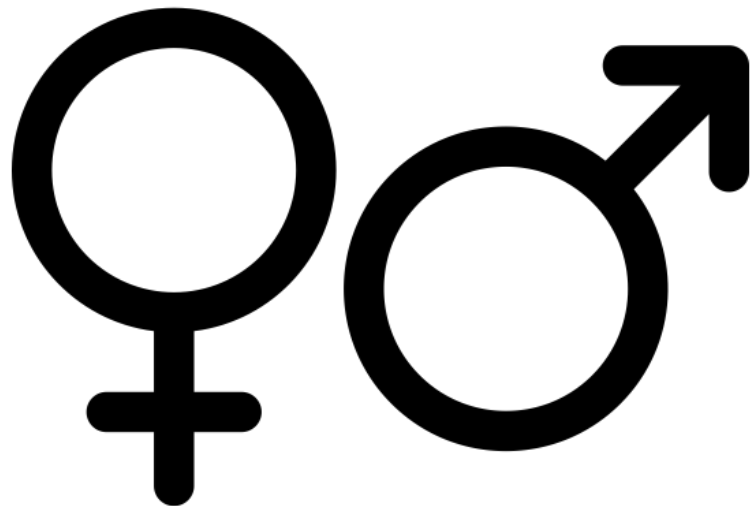


- US: 815, India: 298, Other: 125

Earnings by Country



Respondents



- 622 female
- 616 male

Earnings by Gender (USA)



Earnings by Gender (India)



Respondents



- 270 with disabilities or health conditions affecting work

Disability or Health Problem (USA)



Disability or Health Problem (India)



Takeaway 4

Women make less money than men, India-based workers make less than US-based workers, workers with health problems make less than workers without health problems.

The Gender Wage Gap in an Online Labour Market: The Cost of Interruptions

Abigail Adams-Prassl, Kotaro Hara, Kristy Milland, Saiph Savage,
Chris Callison-Burch, Jeffrey P. Bigham

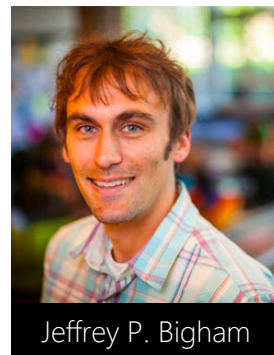
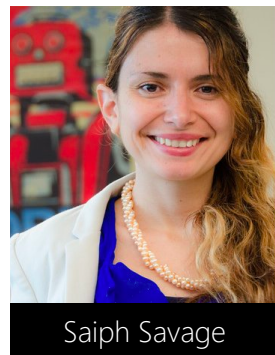
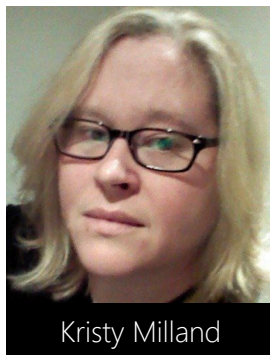
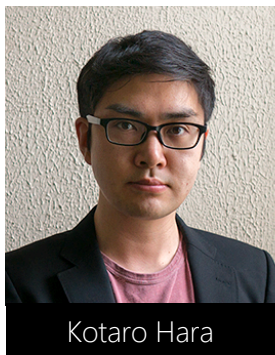
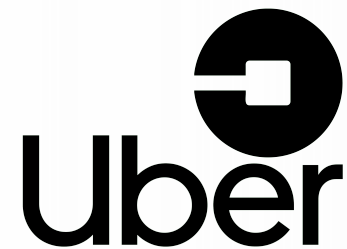
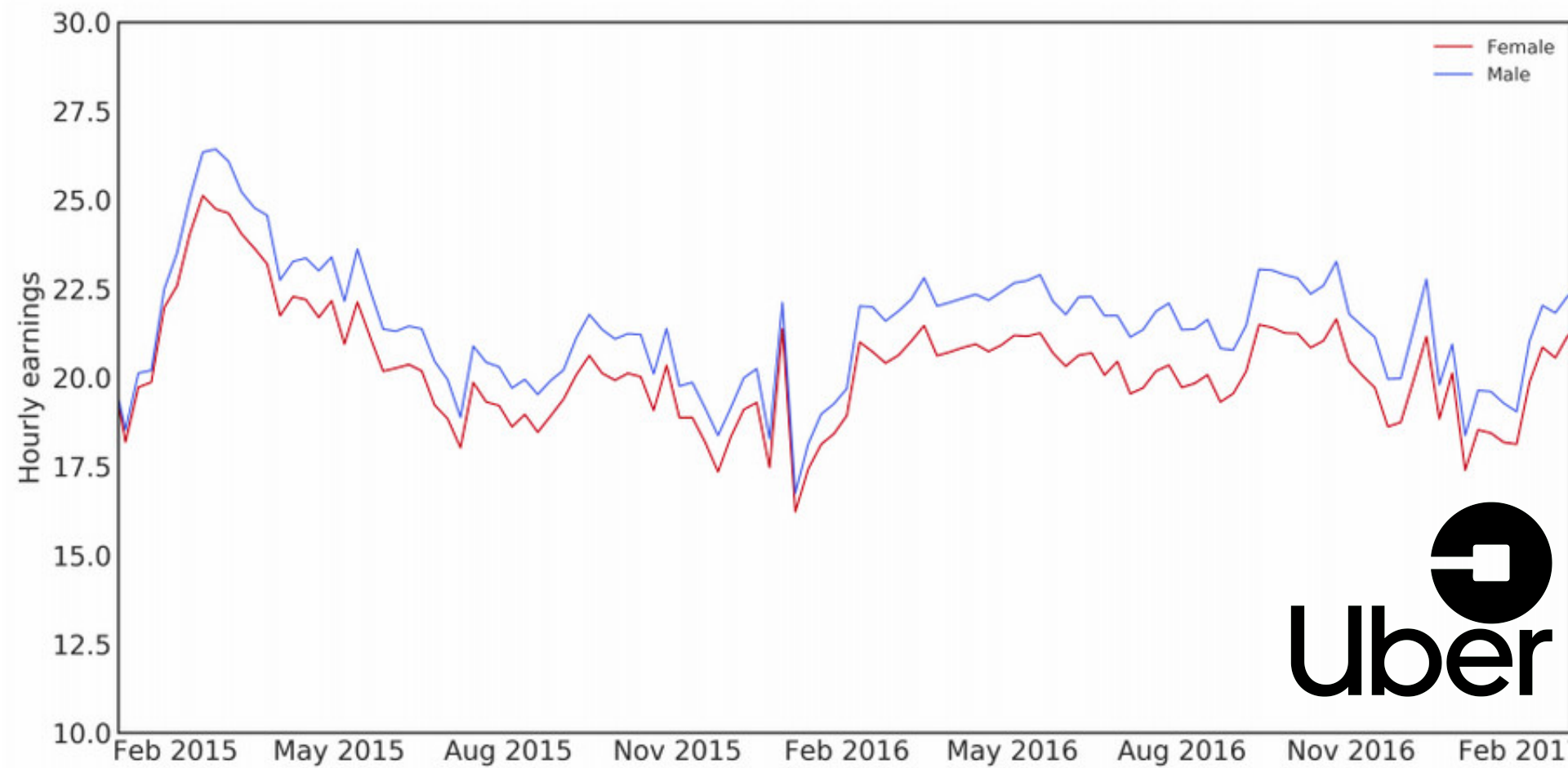


Figure 1: Average hourly earnings, US



Mturk Earnings by Gender (USA)



Why do women earn less than men?

Is there discrimination in the platform?

No, MTurk is gender blind.

Do women have less experience on MTurk?

No.

Do women select different tasks than men?

No.

Why do women earn less than men?

Women earn 20% less per hour on average.

Half of this gap is explained by differences in the scheduling of work.

Women have more fragmented work patterns with consequences for their task completion speed.

Mothers versus others?

The wage gap is concentrated amongst women with young children, who also report that domestic responsibilities affect their ability to plan and complete work online.

Takeaways

< \$2/h

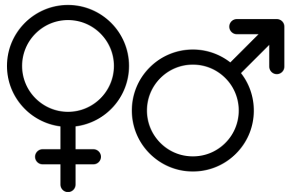
Crowd workers are underpaid and they often earn below \$2/h



Unpaid work, particularly returning tasks has a large impact on the hourly wage



Majority of the requesters reward workers below \$5/h



Women make less money than men even on online platforms

Discussion and Future Work

- Could we create **tools for workers** to make it easier to search for tasks that give them good wage, avoid tasks that are not completable, and find requesters fair wage?
- Could we create **technologies for requesters** to help them pay fairly?