Peeping into Food Delivery Platforms

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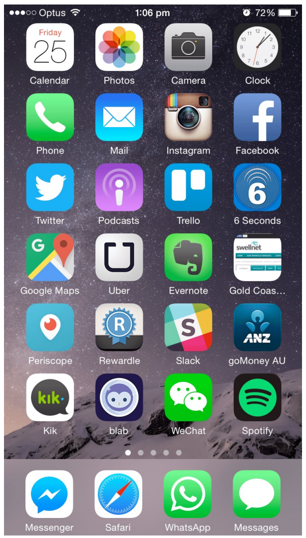
Computing and Society

Huge impact of computing systems on society today



New domains have emerged due to algorithmic innovations and advancements

- Social Media: Facebook, Twitter, WhatsApp
- Content Streaming: Youtube, Spotify
- Ecommerce: Amazon, Flipkart
- Sharing Economy: Uber, Airbnb, Ola

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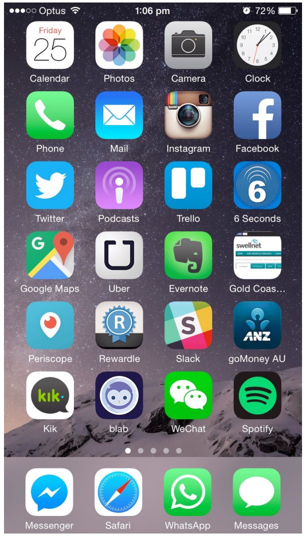

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- Social Media: Facebook, Twitter, WhatsApp
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- Ecommerce: Amazon, Flipkart
- Sharing Economy: Uber, Airbnb, Ola

Need to systematically understand potential issues with existing systems and develop solutions to mitigate the impact

Research Approach

Analysis

- Acquire large scale data from online systems
- Adopt proper quantification framework
- Identify trade-offs between different system objectives

Operationalization

- Formally interpret social desiderata in different algorithmic scenarios

Synthesis

- Design efficient mechanisms to incorporate different interpretations

FairFoody: Bringing in Fairness in Food Delivery

AAAI 2022

Gigs with Guarantees: Achieving Fair Wage for Food Delivery Workers

IJCAI 2022

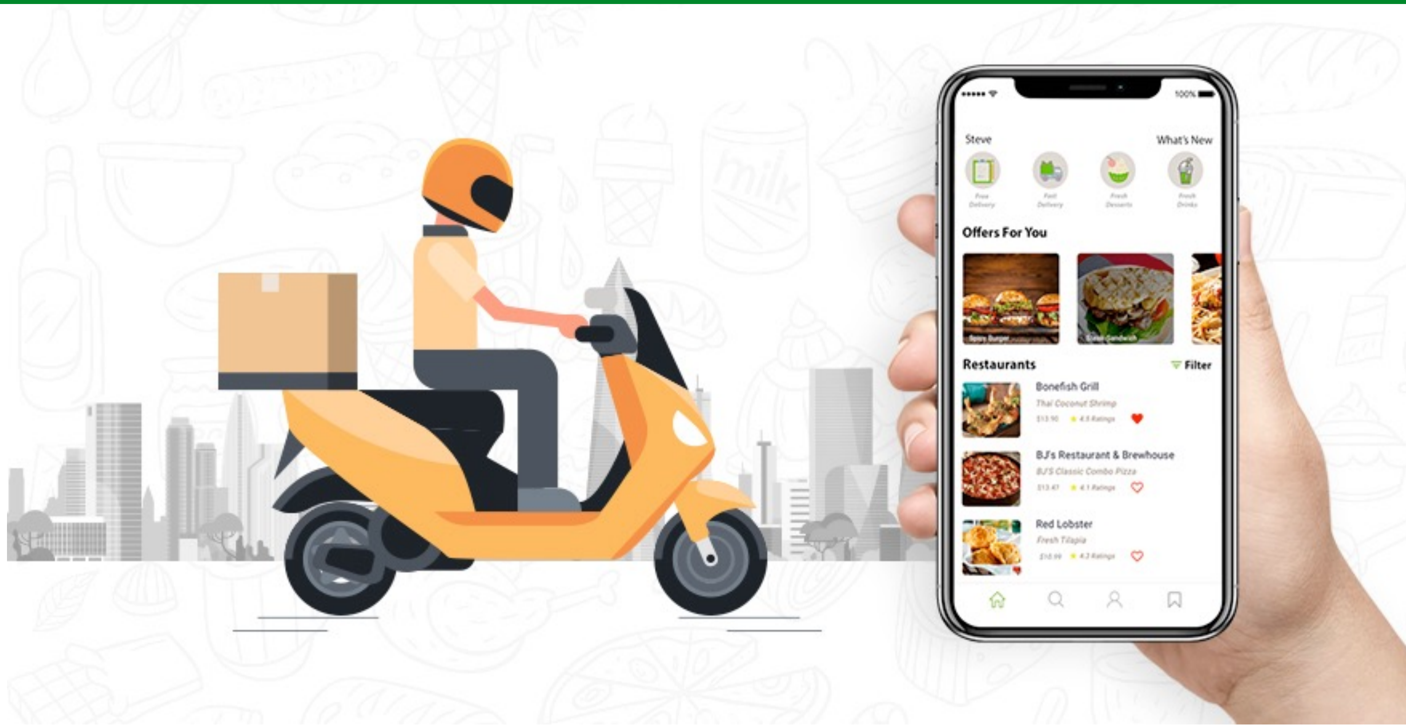
FairAssign: Stochastically Fair Driver Assignment in Gig Delivery Platforms

FAccT 2023

joint work with

Anjali Gupta, Daman Deep Singh, Rahul Yadav, Ashish Nair, Syamantak Das, Sayan Ranu and Amitabha Bagchi

Food Delivery Platforms



- Food delivery industry is now valued at $150 billion [McKinsey 2021]
- DoorDash and Zomato have launched mega-IPOs in recent years

What about the drivers in these platforms?

https://www.mckinsey.com/industries/technology-media-and-telecommunications/our-insights/ordering-in-the-rapid-evolution-of-food-delivery

Concerns about Drivers

Food delivery workers protest 'exploitation' on Twitter; companies deny charges

THE ECONOMIC TIMES

‘We are slaves to them’: Zomato, Swiggy delivery workers speak up against unfair practices

They are battling job insecurity, variable pay, low base pay, increasing fuel prices, and inconsistency in incentive payments.

newslaundry

Turkey’s food delivery couriers latest to strike amid economic crisis

AL-MONITOR

Dataset

- Data provided by a large food delivery service provider in India
- 18 days of food delivery data from three metropolitan cities
- Total 1.8 million orders
- Data consists of
  - Trajectories of the delivery vehicles
  - Road network of each city
  - Other metadata, e.g., food preparation time

City	# Rest-aurants	# Vehicles (avg./day)	# Orders (avg./day)	Food prep. time (avg. in min)
City A	2085	2454	23442	8.45
City B	6777	13429	159160	9.34
City C	8116	10608	112745	10.22

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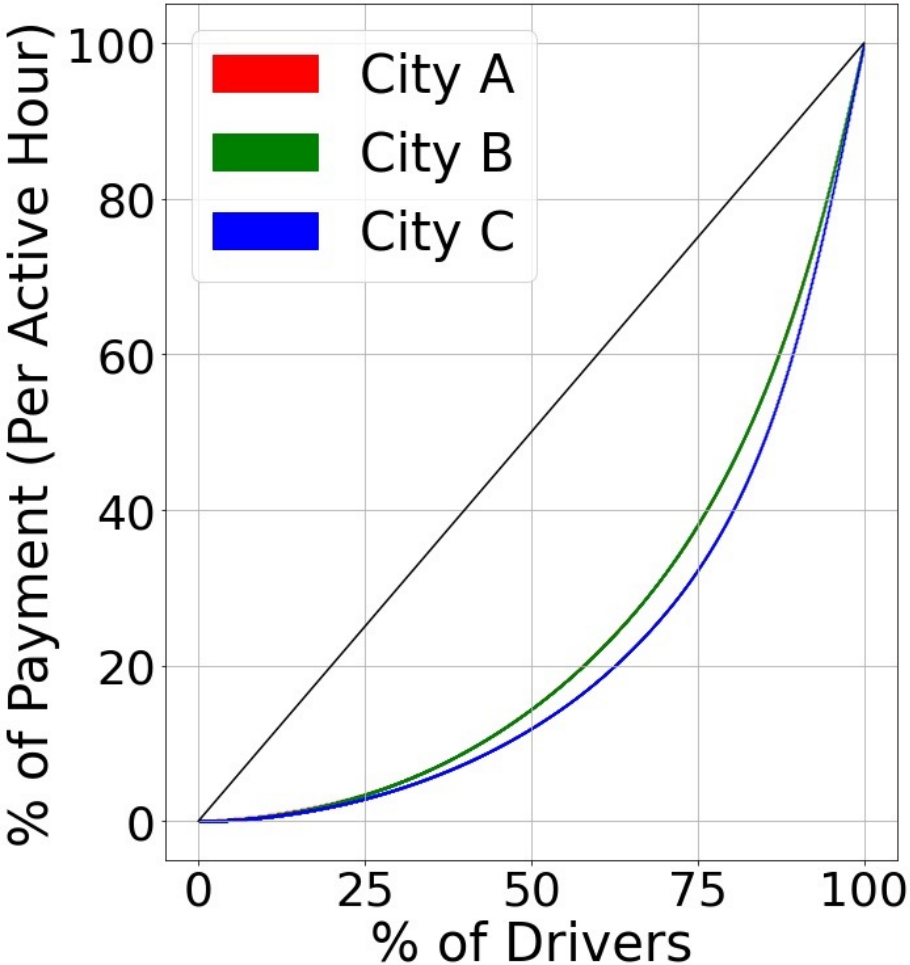
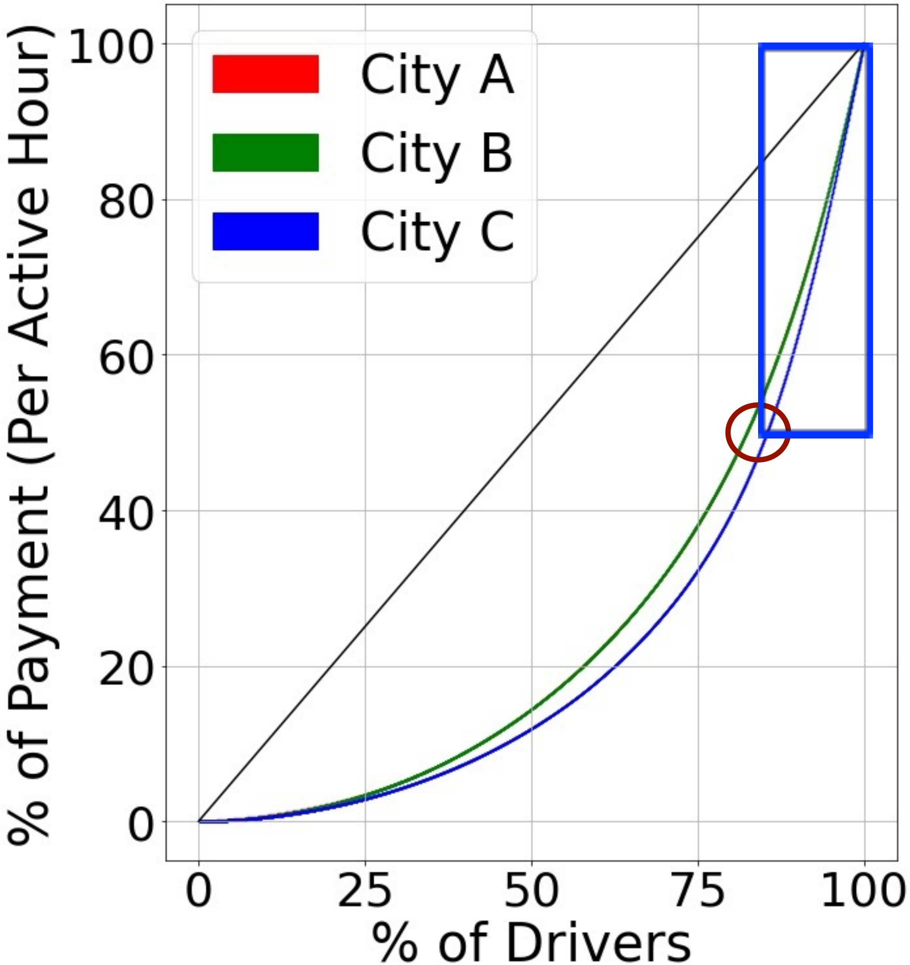
What is the distribution of driver income?

Inequality in Driver Income



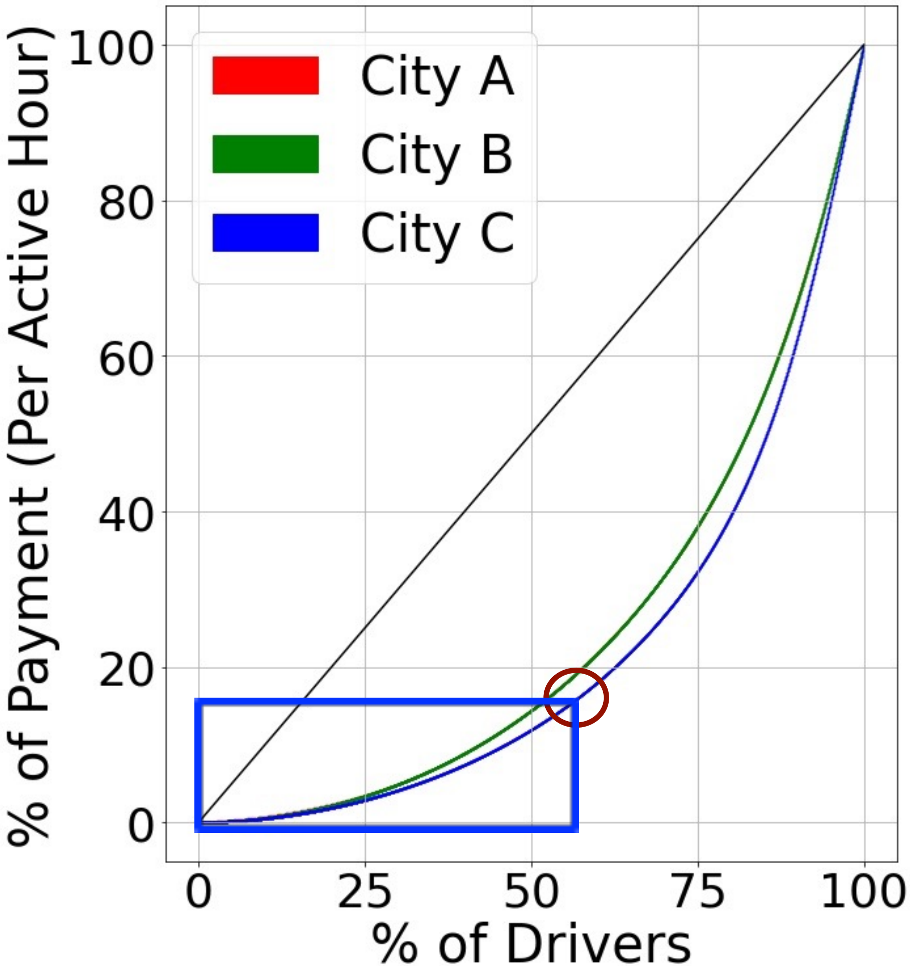
Lorenz Curve
Y-axis: Cumulative % of total income
X-axis: Cumulative % of the corresponding drivers

Inequality in Driver Income



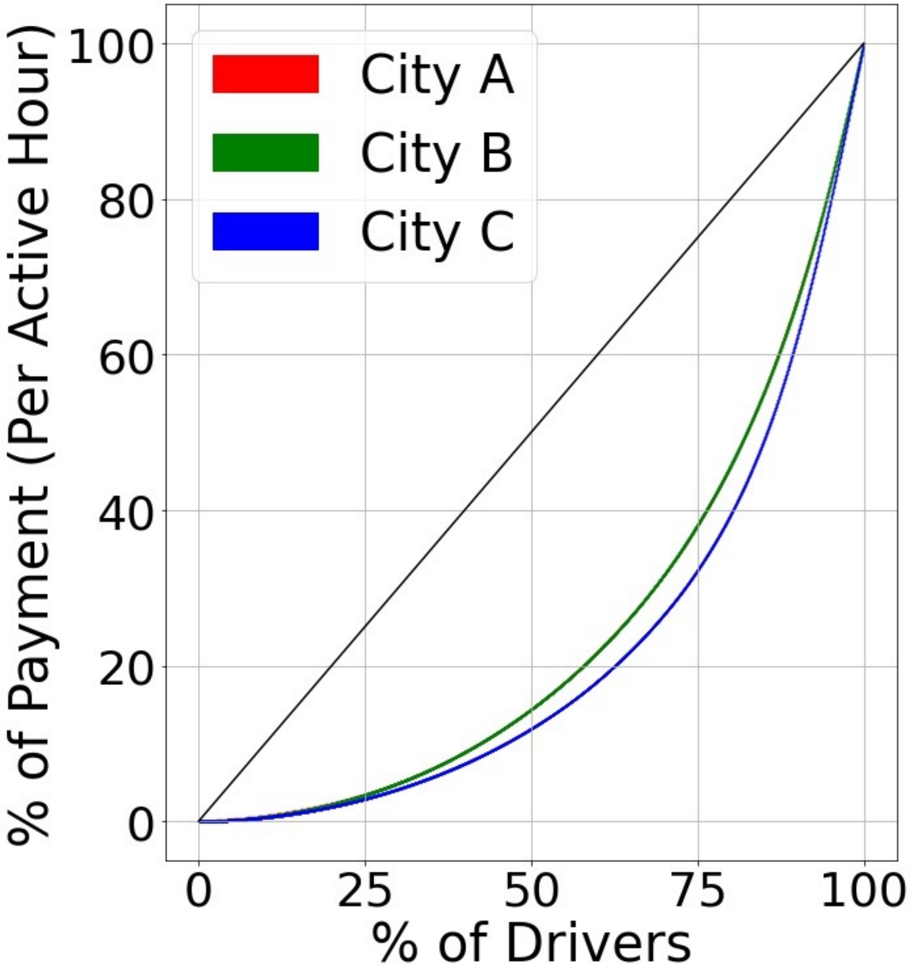
- Top 20% drivers earned more than 50% of total income

Inequality in Driver Income



- Bottom 60% didn't even get 20% of it

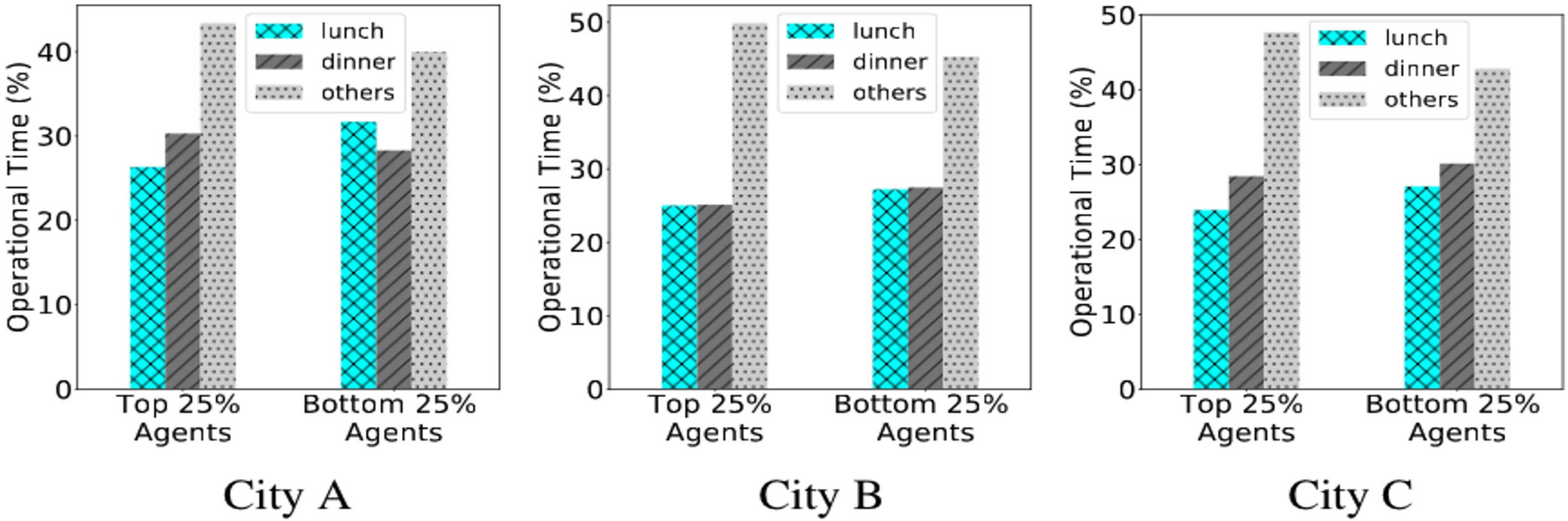
Inequality in Driver Income



- Top 20% drivers earned more than 50% of total income
- Bottom 60% did not get even 20% of it
- This is despite normalizing w.r.t. number of active hours

Is it due to the difference in operational periods?

Operational Periods of Top & Bottom Earners

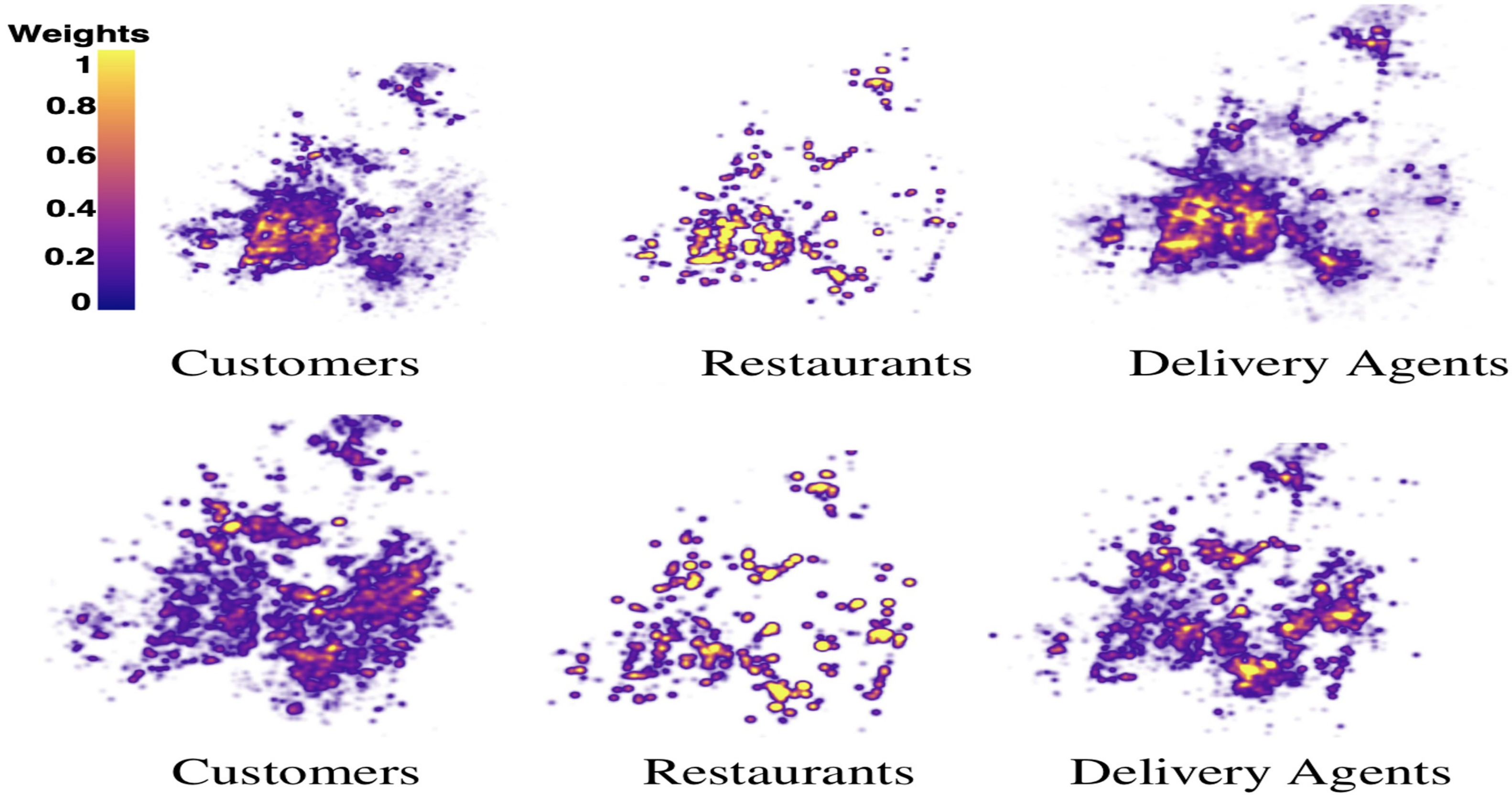


No noticeable difference in their activity patterns

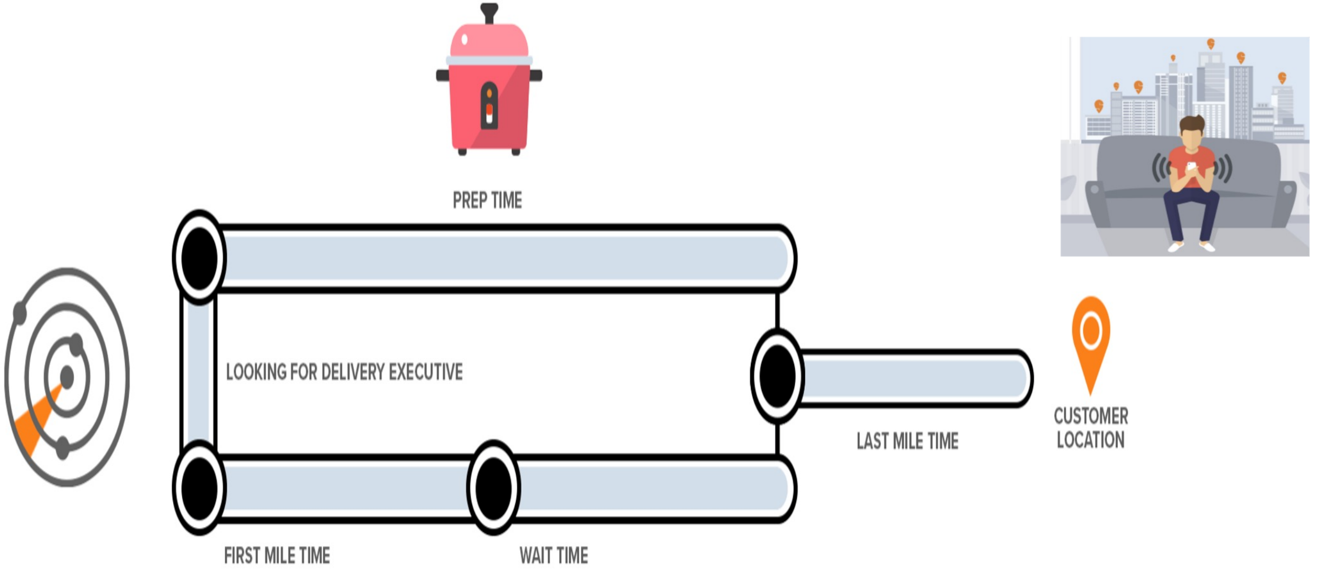
Difference in Catchment Zones

Top earners

Bottom earners



Formalizing Food Delivery Problem



Expected delivery time

$$EDT(o,v) = max(T_{(v,r)}^{FirstMile}, T_{o}^{Prep}) + T_{(r,c)}^{LastMile}$$

Formalizing Food Delivery Problem

A utilitarian objective would be to find an assignment A:

$$\underset{A \in \mathcal{A}}{\arg\min} \left\{ \frac{1}{|O|} \sum_{\forall o \in O} EDT(o, A(o)) \right\}$$

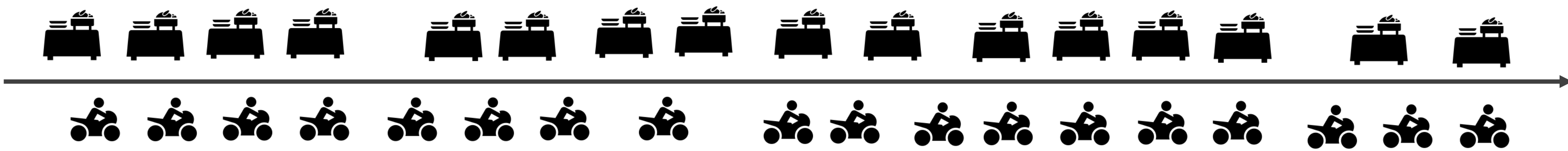
A greedy algorithm would assign the nearest driver to a restaurant subject to capacity constraints

FoodMatch, Joshi et al., ICDE 2021

How to think about fairness in such setting?

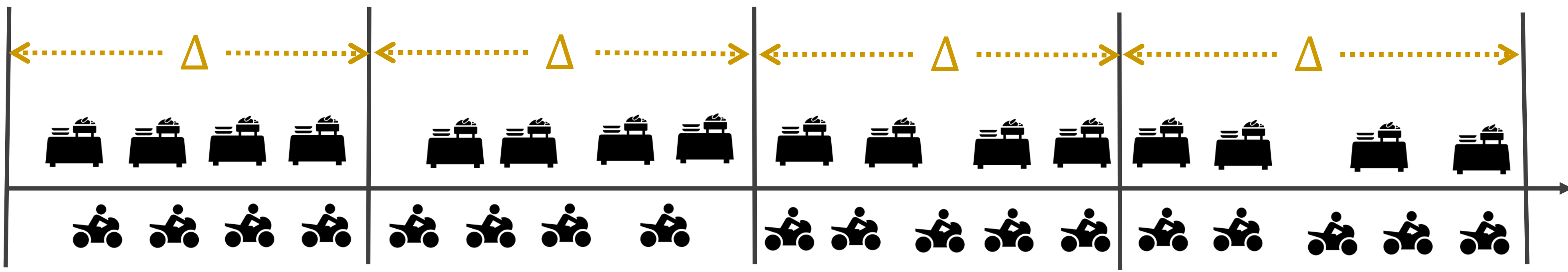
I. Streaming order data
II. Repeated matchings over time

Modeling a Food Delivery Platform



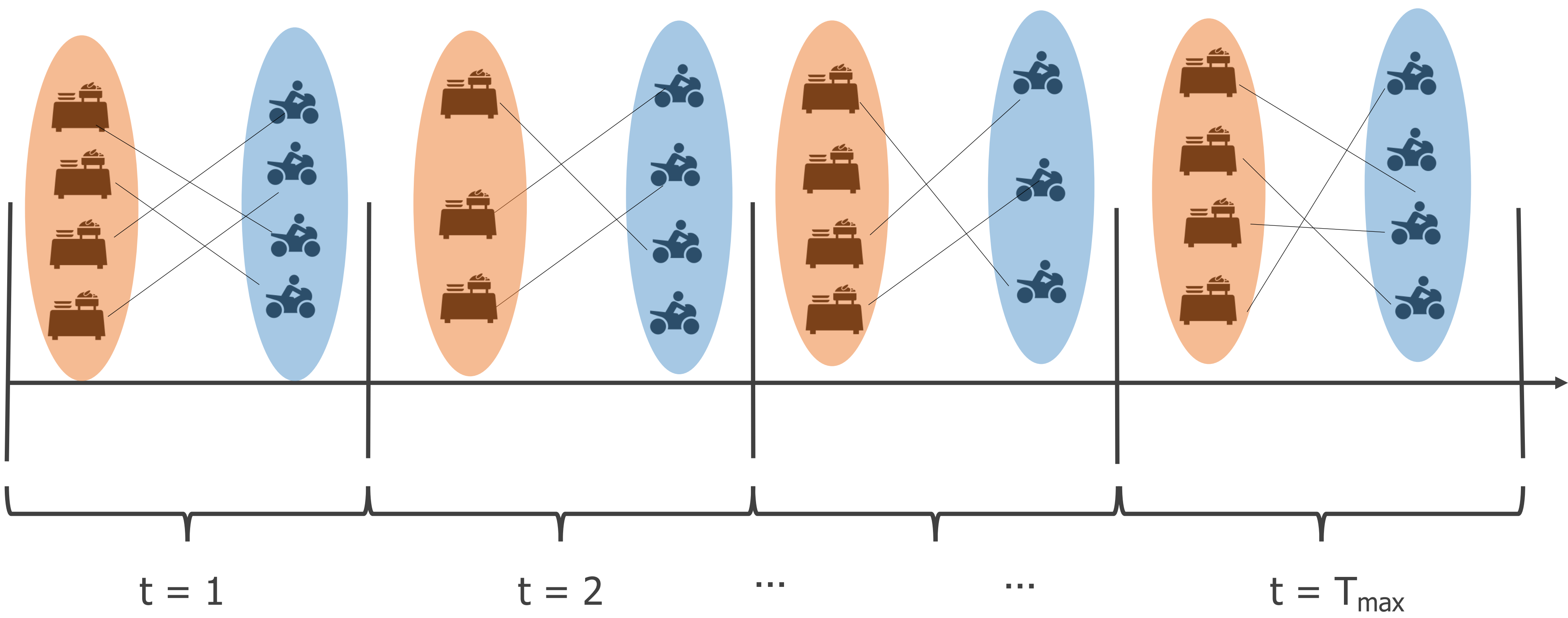
Platform produces a sequence of matches between drivers and orders over time

Modeling a Food Delivery Platform



Group incoming orders within a short period of time Δ to form matching rounds

Modeling a Food Delivery Platform



At every time window, match the orders and the drivers available to serve

Fairness of Repeated Matching

- Amortized Parity (Strict Egalitarianism)
  - Over time, sum of incomes of all drivers should be same
  - Platform collects all delivery charges and give fixed monthly payment to drivers
  - Difficult to achieve in Gig Economy

- Amortized Proportionality
  - Over time, sum of incomes of all drivers should be proportional to the amount of time they are active
  - Can also incorporate other criteria (vehicle type, rating, …)
  - Over time, similar drivers should receive similar income

Bringing Fairness in Food Delivery

An egalitarian objective:
Find the assignment A that minimizes the income gap

$$\arg\min_{A \in \mathcal{A}} \left\{ \max_{v \in \mathcal{V}} \{inc(v, 0, T_{max})\} - \min_{v \in \mathcal{V}} \{inc(v, 0, Tmax)\} \right\}$$

s.t. $EDT\big(o, A(o)\big) \leq SLA \quad \forall o \in O$

Time guarantee provided by the platform to a customer

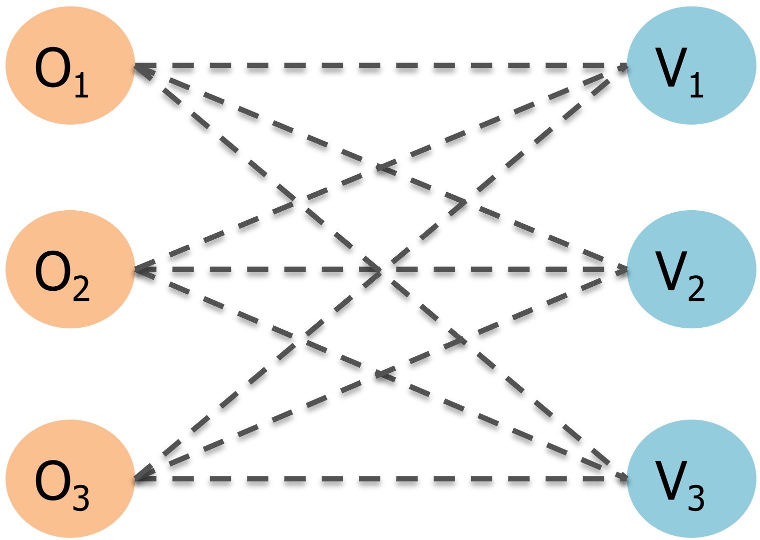
Normalized income of $\mathcal{V}$ in interval $[0, Tmax]$

It is a NP-Hard problem!

Proposed a novel heuristic: FairFoody

FairFoody

Step 1: Create a complete bipartite graph between drivers & orders



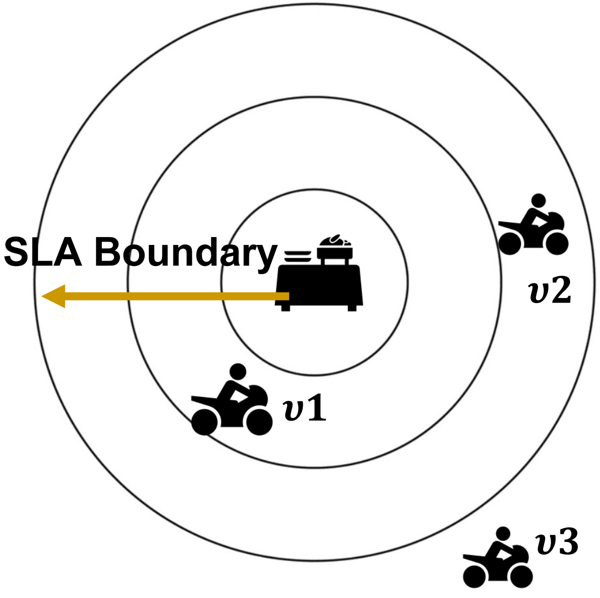
FairFoody

Step 2: Assign edge weights

A. Start from a restaurant location

B. Consider all nearby drivers till restaurant-driver distance forces EDT to exceed SLA

C. Edge weight at time-window l given by



$$w(v, o) = inc'(v, O, l) - \min_{v \in \mathcal{V}}\{inc(v, 0, l-1)\}$$

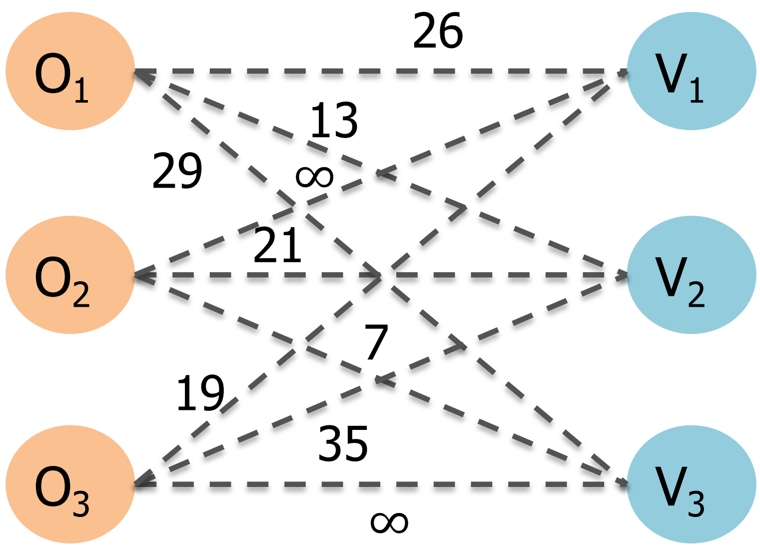
Future income gap of v w.r.t. to current lowest income

D. Drivers beyond this boundary are assigned an edge weight ≈ ∞

E. Repeat for all restaurants

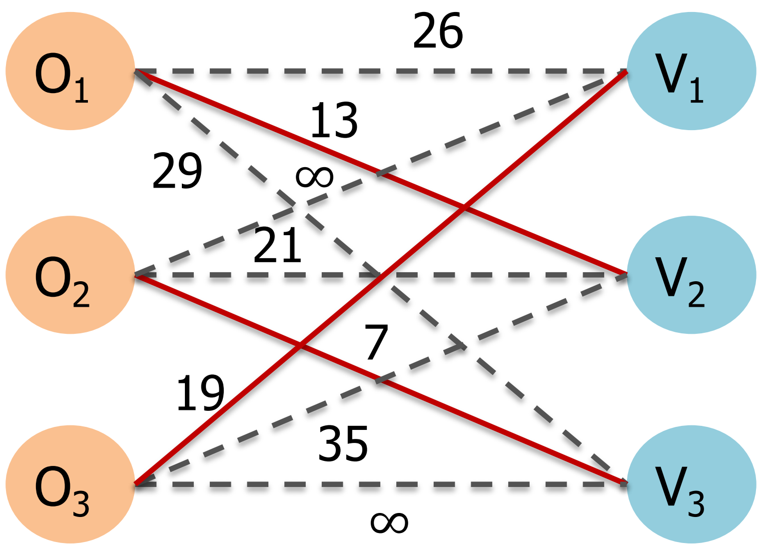
FairFoody

Step 3: Find the minimum cost matching in the graph



FairFoody

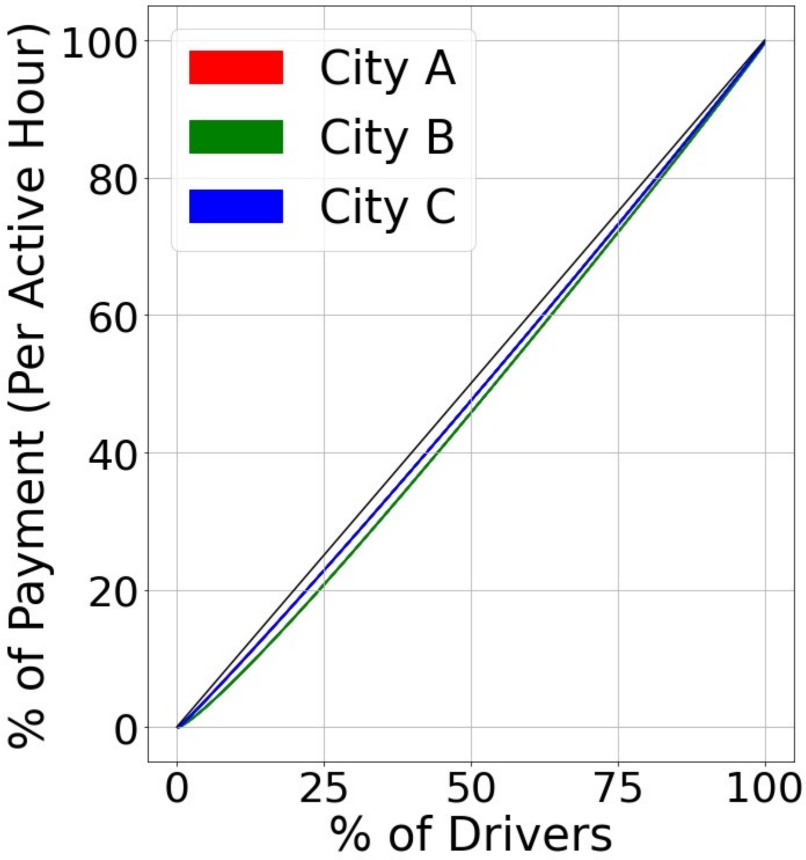
Step 3: Find the minimum cost matching in the graph



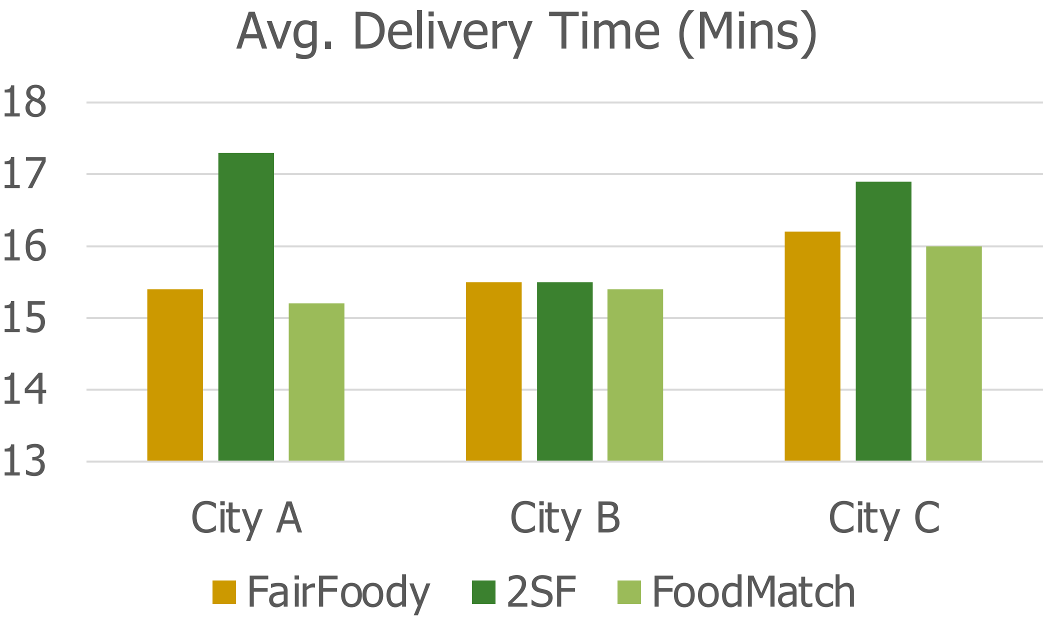
Used Hungarian (Kuhn-Munkres) algorithm: $O(\max(|O_a|, |V_a|)^3)$

Underlying idea: Prefer the lowest earning driver
from the eligible lot to assign an order

Effectiveness of FairFoody



Almost equal income distribution



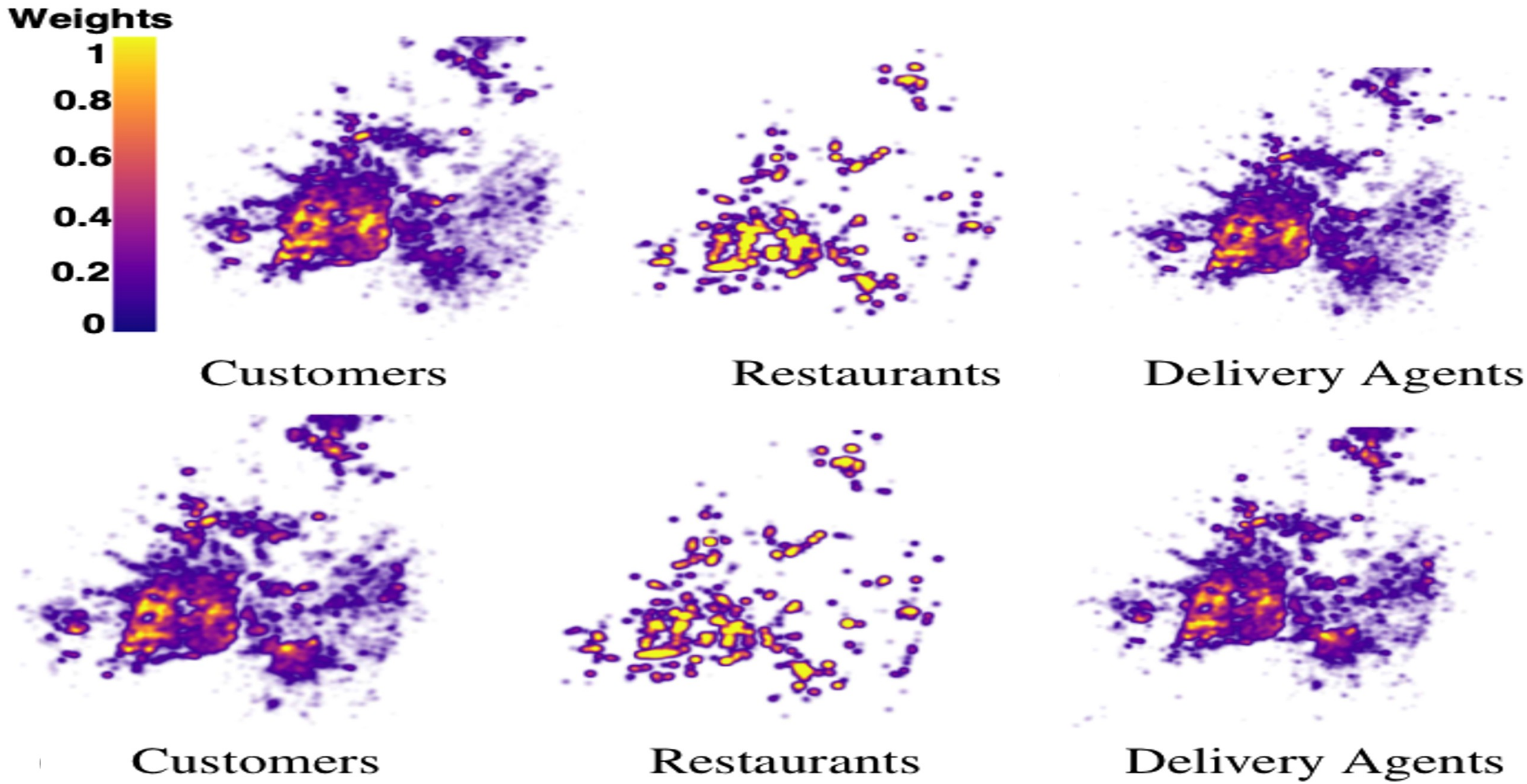
Minimal increase in delivery time

No SLA violation

Balanced Opportunity Distribution with FairFoody

Top 25%

Bottom 25%



Not All Roses

- To achieve fairness, FairFoody tends to send far-away drivers who can reach a restaurant before the food is prepared

  \+ Driver location becomes less important

  \- Higher delivery cost (who should bear? Platform? Customer?)

  \- Increased greenhouse emissions

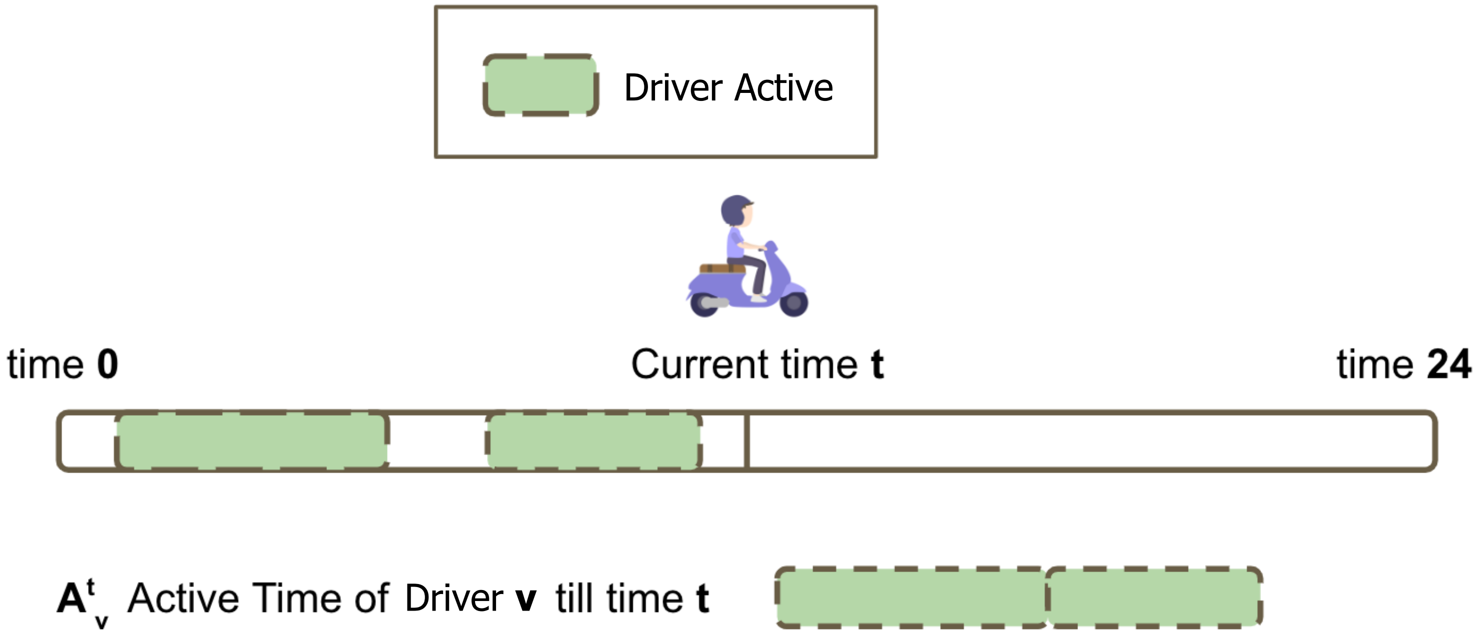
- Currently no Indian food delivery platform pay legal minimum wage even to drivers working 10+ hours a day [FairWork 2021]

- FairFoody does not explicitly guarantee legal minimum wage

Can we guarantee fair wage to the drivers without the associated pitfalls?

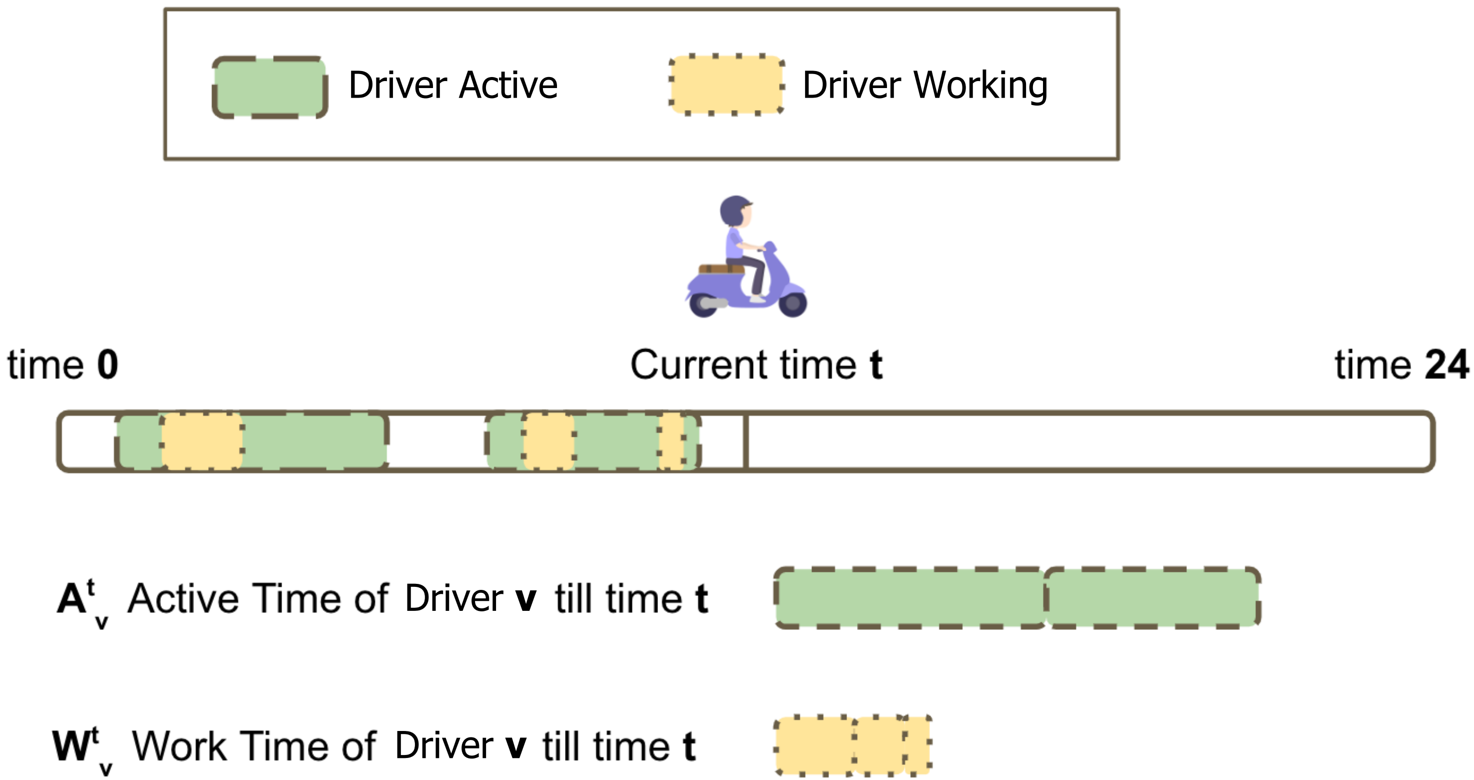
https://fair.work/wp-content/uploads/sites/17/2021/12/Fairwork-India-Report-2021.pdf

Active vs Working Times



A driver can be active/available for multiple shifts in a day

Active vs Working Times



A driver is working/earning money only when engaged in a delivery (not idly waiting for order assignment)

Minimum Wage Puzzle

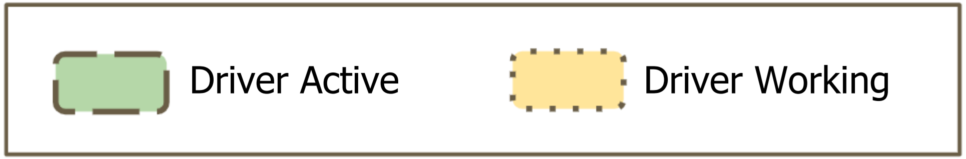
Driver Active   Driver Working

p: delivery payment per unit of time

Income earned by driver v: $\mathrm{inc}(v, 0, t) = p \times W^t{}_v$

Amount of actual work may not be sufficient for drivers to earn legal minimum wage

Our Proposal: Work Guarantee



p: delivery payment per unit of time

Income earned by driver v: $\mathrm{inc}(v, 0, t) = p \times {W^t}_v$ 

g_v: work guarantee (per active hour) to driver v

Promised income to driver v: $\Pr(v, 0, t) = p \times gv \times {A^t}_v$ 

Handout from the platform to driver v: $\max(0, \Pr(v, 0, t) - inc(v, 0, t))$

Platform must compensate drivers if enough work not given

Work4Food: Optimization Problem

Cost to platform: $\sum_{\forall v} \max\{inc(v), \Pr(v)\}$

Problem: Find allocation that minimizes cost to platform

$$\arg\min_{A \in \mathcal{A}} \sum_{v \in \mathcal{V}} max\{inc(v, 0, Tmax), \Pr(v, 0, Tmax)\}$$

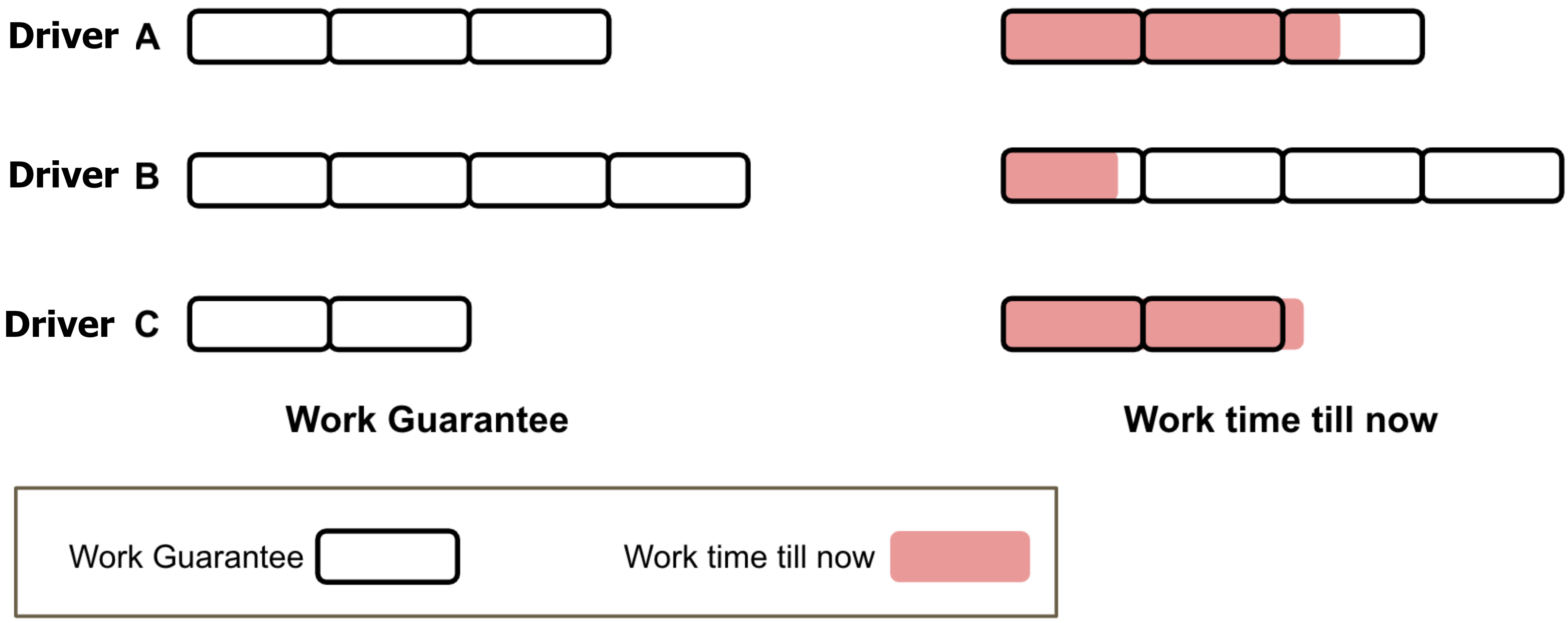
s.t. $EDT\big(o, A(o)\big) \leq SLA \quad \forall o \in O$

- Delivery time is a factor in the minimization function
- If a small set of drivers deliver most orders, cost increases since handouts increase.
- Hence, minimizing cost drives towards $inc(v, o, Tmax) = \Pr(v, o, Tmax)$
- Consequently, if $\Pr(v)$ is same for all drivers, $inc(v)$ tends to be same

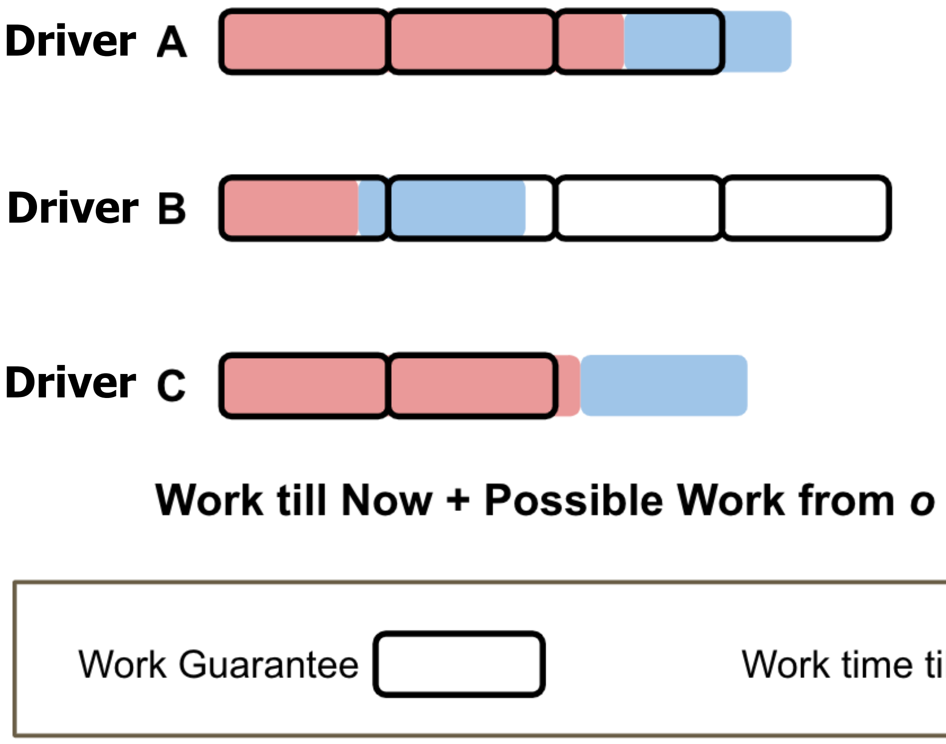
This problem is also NP-Hard

Use bipartite matching heuristic like FairFoody

Order Matching Example



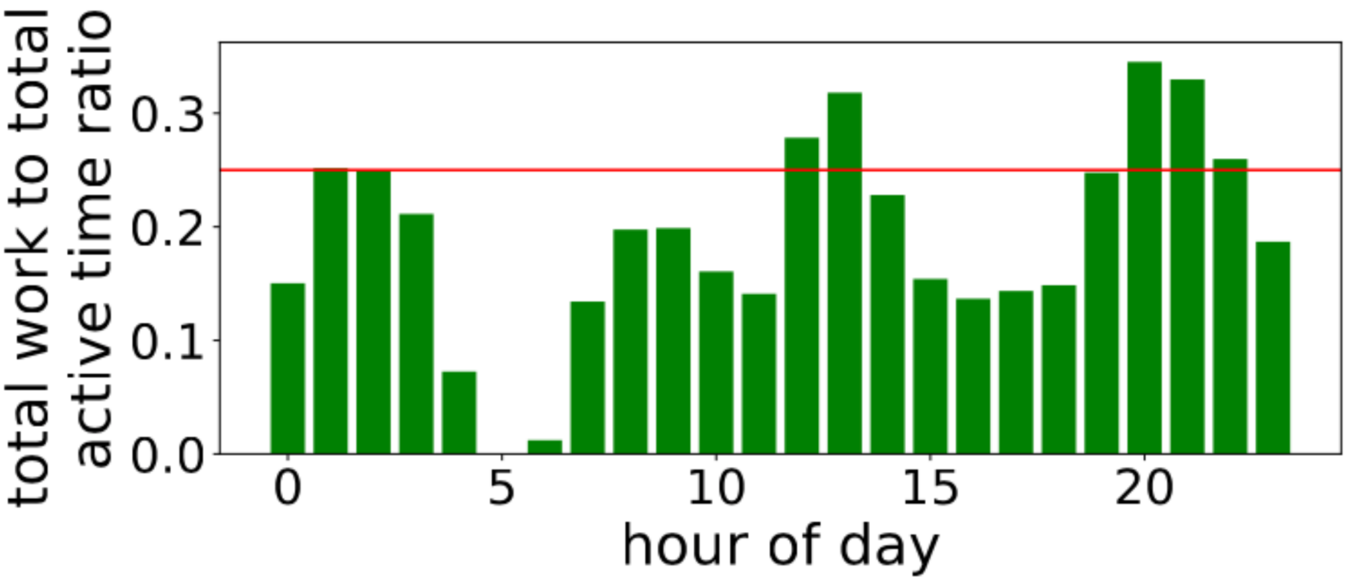
Order Matching Example



Allotting order o to A or C would increase total cost to the platform.

Optimal choice is to allot the order to B which minimizes the platform cost while ensuring B can achieve minimum pay.

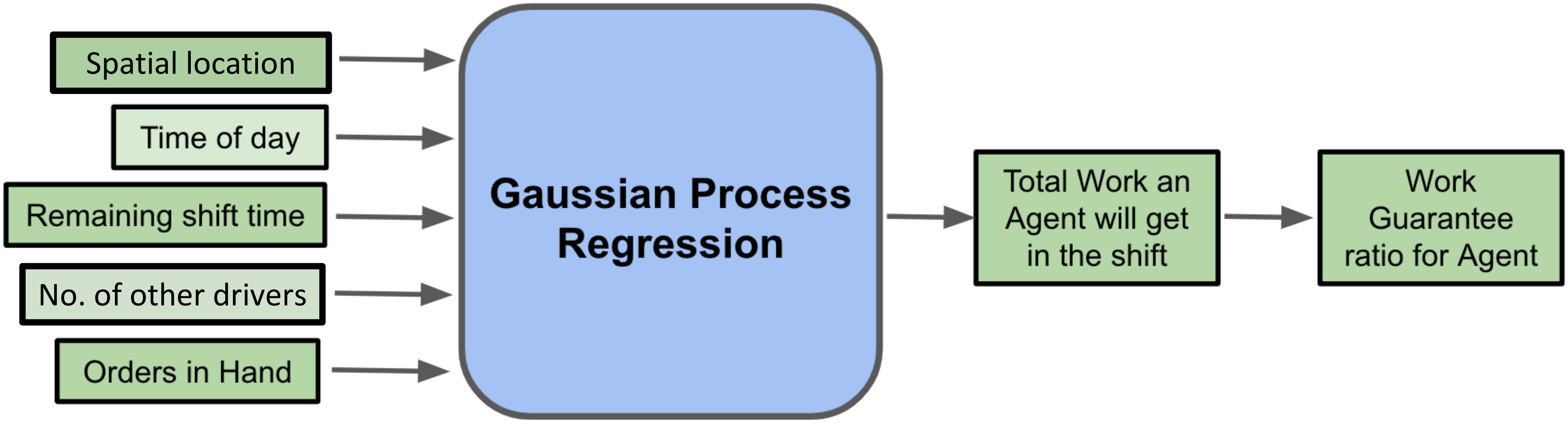
Estimating Work Guarantee for Each Driver



The amount of work available per driver can be different at different times of the day and at different locations

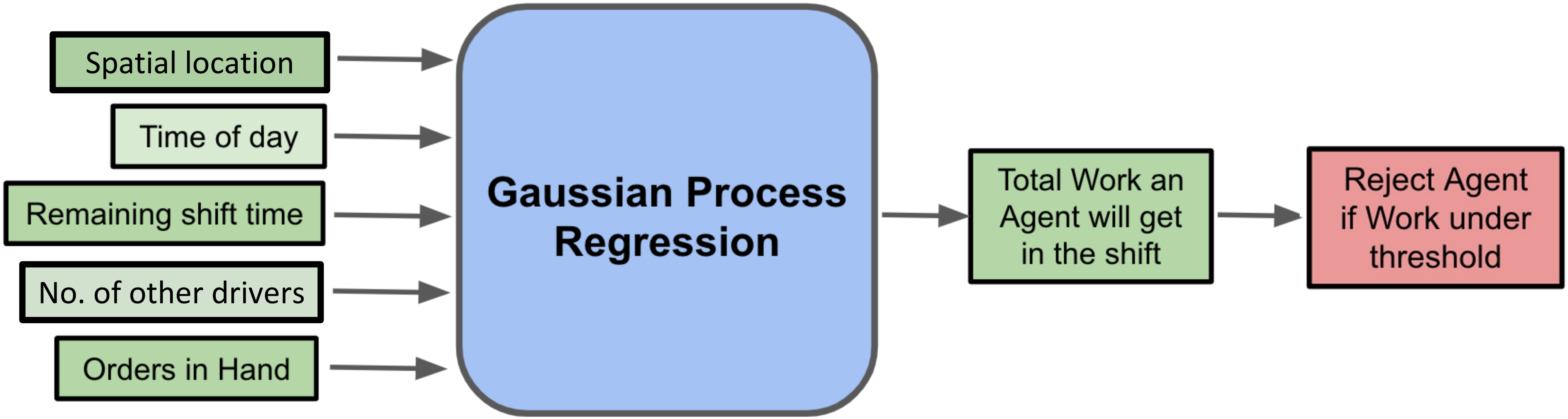
Need to consider the demand-supply dynamics

Estimating Work Guarantee for Each Driver



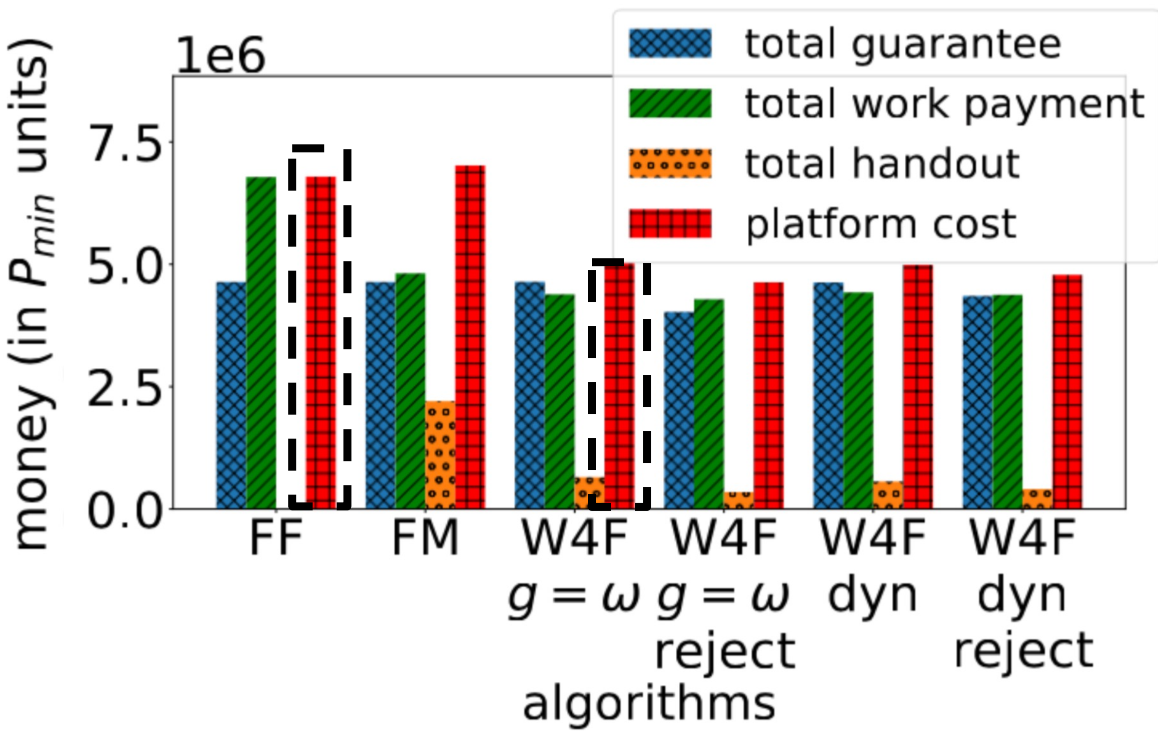
Personalized guarantee based on location and other factors

Balancing Driver-Order Dynamics



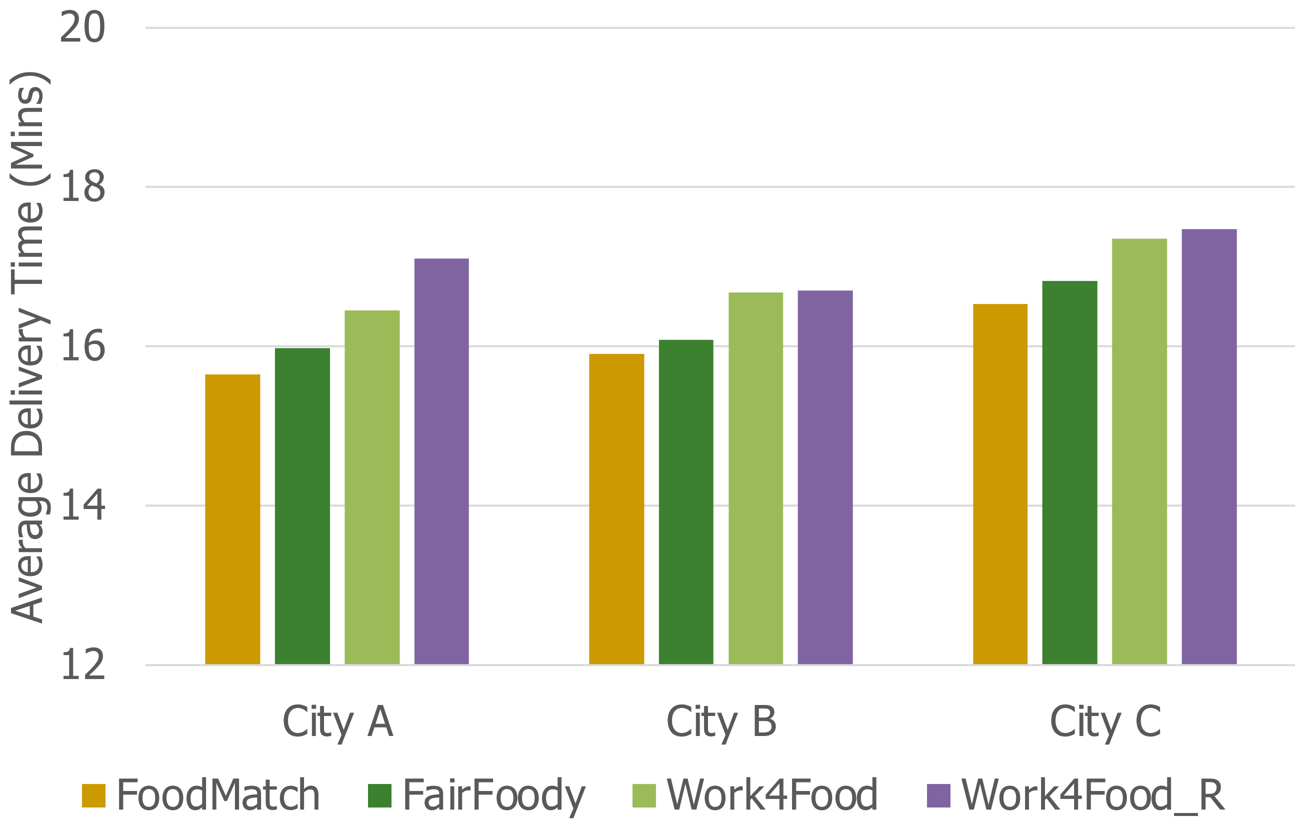
Platform can deny onboarding if enough work not available

Cost to Platform



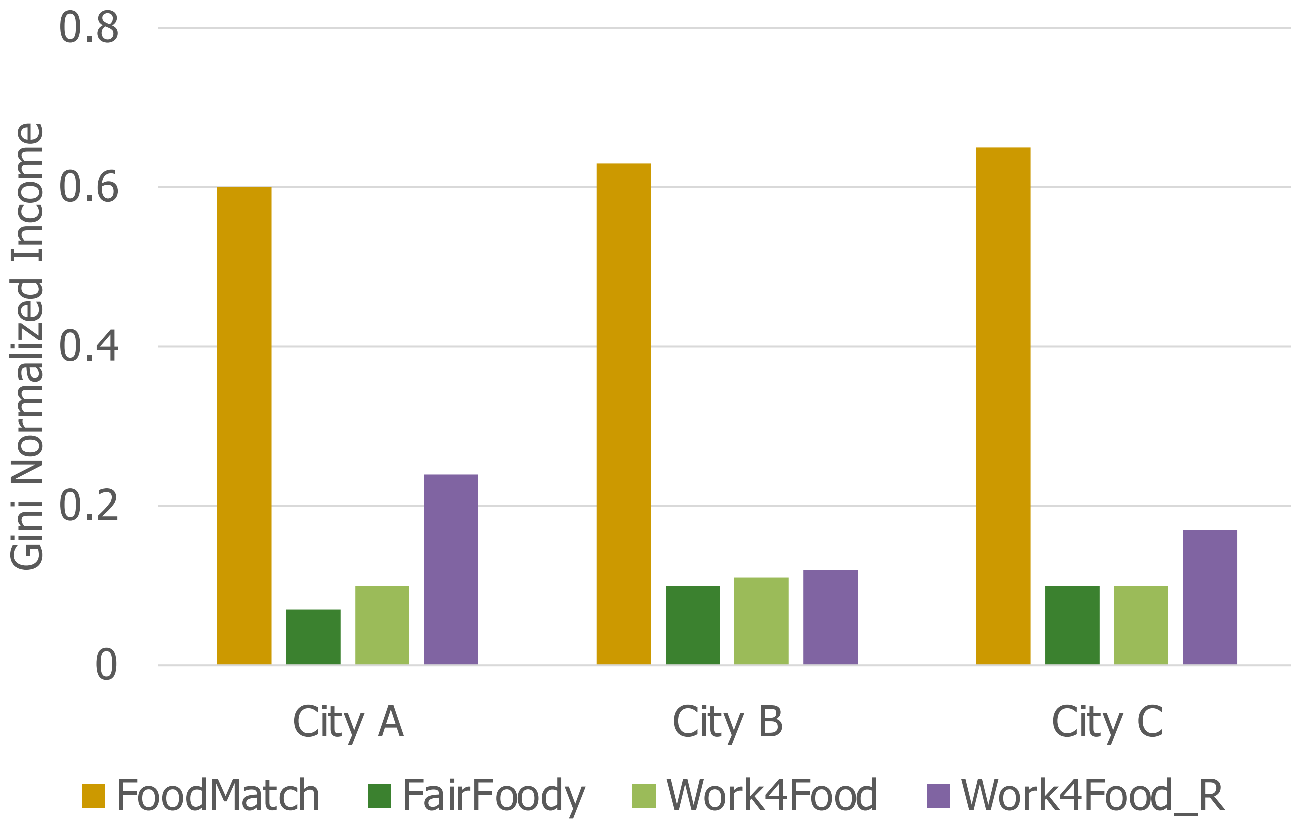
The platform cost of Work4Food while providing income guarantees is up to 25% lower than FairFoody

Efficacy of Work4Food



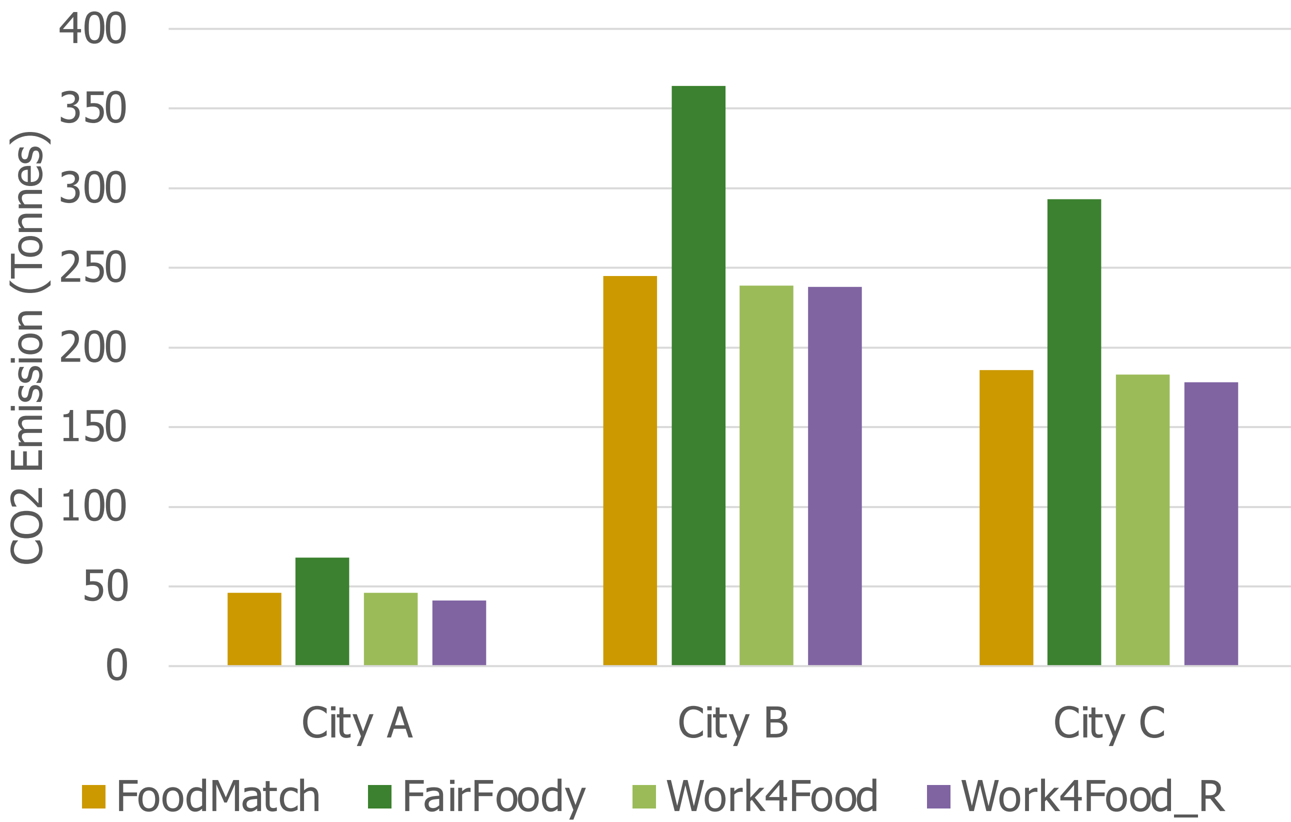
Small increase in average delivery time

Efficacy of Work4Food



Work4Food w/o rejection has comparably fair distribution of income as FairFoody

Efficacy of Work4Food



No excess emissions to improve driver income and income distribution

Summary

- FairFoody is the first algorithm to ensure fair distribution of work opportunities, yet falls short of guaranteeing legal minimum wage
- Work4Food works towards that direction by predicting future demand and onboards drivers only if it can provide guaranteed minimum wage
- If there is not enough order, the platform would have to compensate the drivers
- Algorithm tries to reduce the platform cost while assigning orders

Going Forward

In FairFoody or Work4Food, there is no consultation with the actual stakeholders being impacted – the drivers

We conduct in-person interviews with 30 drivers in two cities to gather their perception about what a fair distribution of income should look like

Without it, there is risk of top-down techno-solutionism!

Develop a fair zone assignment algorithm FairAssign that adheres to the fairness perceptions

Point of View of the Stakeholders

Q. Does the work-shift start at the same location every day?

- Nearest market area in the assigned zone
- Fixed zone is assigned by the platform at the time of joining

Q. How many hours of service / number of shifts?

- 3-4 work-shifts of 4 hours each chosen one day before

Q. Awareness about any income/order-assignment disparity between drivers operating in different zones?

- Aware about drivers operating in nearby areas
- Mostly unaware about other areas
- May depend on market area

Point of View of the Stakeholders

Q. Willingness to go to other zones if there is a chance of getting more orders given that the inter-zone travel is compensated?

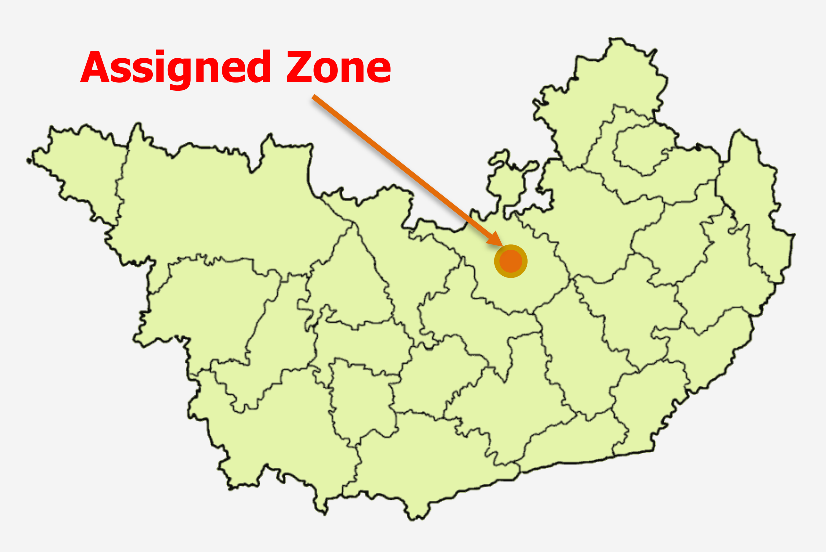
- Only to nearby known markets and zones
- Fear of losing orders while getting familiar with unknown market areas

Q. Do good ratings lead to more orders?

- Yes

Picture Emerging from Driver Interviews

- Static zoning maintained by platforms (logistic reasons)
- Reluctance to visit faraway, unknown zones
- Preference to *nearby zones* and areas (Spatial Stability is desirable)
- Locally rooted notions of fairness (Unaware and uncaring towards other zones)



Key Issues

- **Zoning** (Preferred by Platforms and Drivers)
- **Static Assignment** (Might lead to Income Disparity)

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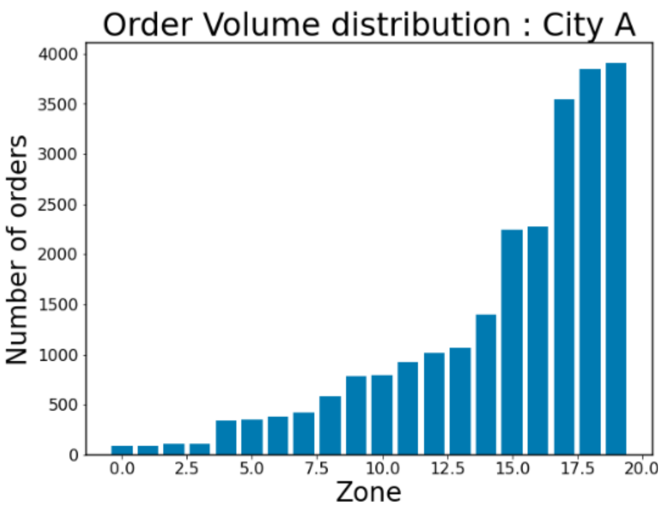
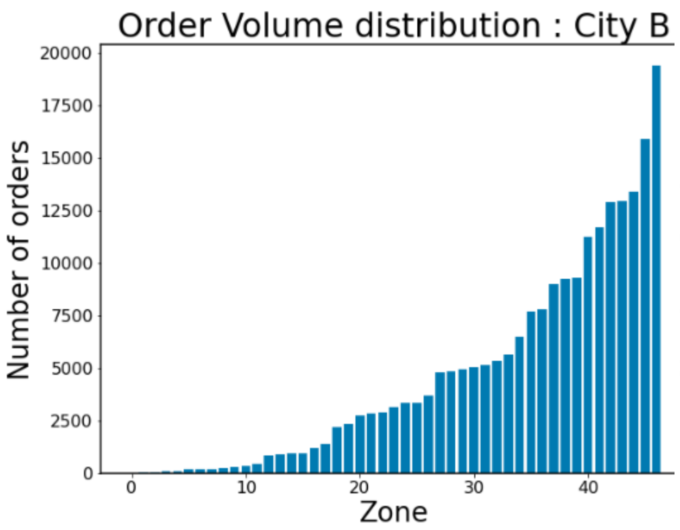
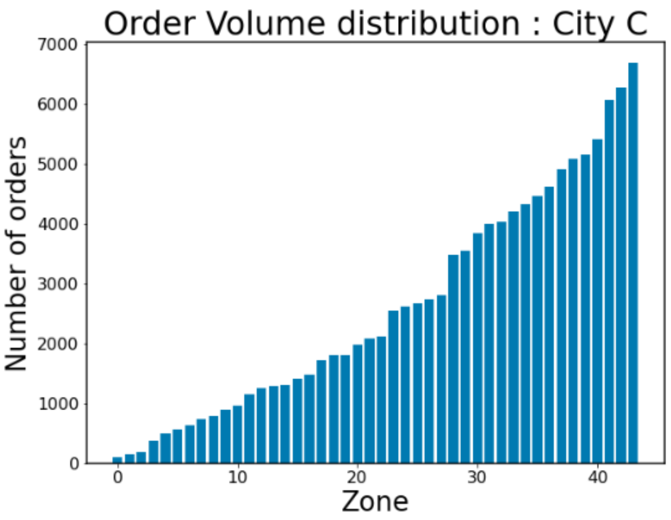






Solution

- ✔ Zoning (Preferred by Platforms and Drivers)
- ✖ Static Assignment (Might lead to Income Disparity)

➡ **Dynamic Assignment to Zones !**

Dynamic Assignment

- **Proposal:** Dynamic assignment of drivers to nearby delivery zones can lead to a reduction in the spatial inequality.

How to design a "Fair" and "Dynamic" assignment algorithm?

Dynamic Assignment

- **Proposal:** Dynamic assignment of drivers to nearby delivery zones can lead to a reduction in the spatial inequality.

- A two-stage dynamic assignment framework:
  - **Phase 1:**

    For each driver, find a probability distribution over the set of preferred zones. Modeled as a Linear Program.
  - **Phase 2:**

    Sample from the distribution daily to determine the actual zone assignment

Phase 1: Objective

Objective:

$$\min \sum_{v \in V} \sum_{c \in C} x_{vc} d(v, c)^2$$

$$\text{s.t.} \sum_{c \in C} x_{vc} = 1, \ \forall v \in V$$

- x_{vc} denotes the probability that driver 'v' is assigned to zone 'c'.
- Essentially, we minimize the expected L2-norm cost between the drivers and the zones.

Phase 1: Notion of Fairness

Fairness Constraint: $D_{\mathrm{TV}}(\vec{x}_{v_1} \,||\, \vec{x}_{v_2}) \leq \mathcal{F}(v_1, v_2), \ \forall v_1, v_2 \in V$

- Individual Fairness -- similar drivers should be treated similarly
- Similarity measure $\mathcal{F}$ between the drivers need to be defined.
- Can be based on the drivers features such as home address, rating, age, gender, date of joining the platform, etc.
- Total Variation Distance D_{TV} is a divergence measure.

$$D_{\mathrm{TV}}(P||Q) = \frac{1}{2} \sum_{x \in \mathcal{X}} |P(x) - Q(x)|$$

Phase 1: Capacity Captures Demand

Capacity Constraints:

$$\sum_{v \in V} x_{vc} \geq \ell(c),\ \forall c \in C$$

$$\sum_{v \in V} x_{vc} \leq u(c),\ \forall c \in C$$

- The capacity of each zone is the number of drivers needed for it to be operational (can be computed using historical data).
- $\ell(c)$ and $u(c)$ denote the minimum and maximum capacity for c.

Phase 1: Generating Probability Distributions

Phase-1: Fair-LP

Fairness Constraints

$$\textsc{Fair-LP}\,(\mathcal{I}) : \min \sum_{v \in V} \sum_{c \in C} x_{vc} d(v, c)^2$$

$$\text{s.t. } \sum_{c \in C} x_{vc} = 1, \; \forall v \in V$$

$$\boxed{D_{\mathrm{TV}}(\vec{x}_{v_1} || \vec{x}_{v_2}) \leq \mathcal{F}(v_1, v_2), \; \forall v_1, v_2 \in V}$$

$$0 \leq x_{vc} \leq 1, \; \forall v \in V, c \in C$$

$$\boxed{\begin{aligned} &\sum_{v \in V} x_{vc} \geq \ell(c), \; \forall c \in C \\ &\sum_{v \in V} x_{vc} \leq u(c), \; \forall c \in C \end{aligned}}$$

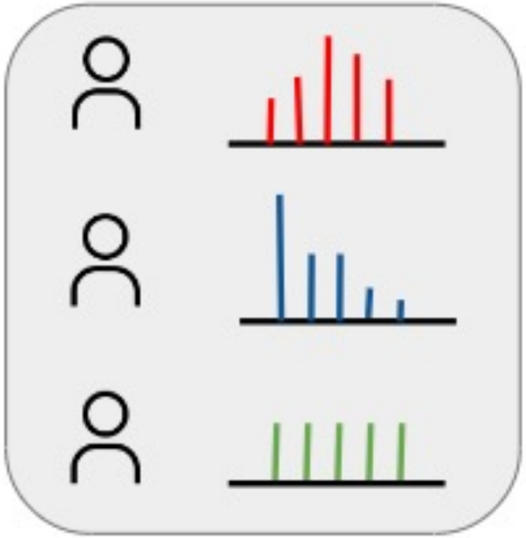
Capacity Constraints

Phase 2: Sampling / Rounding

- Sample from the probability distributions to realize the assignment
- Independent sampling may violate capacity constraints.
- Use **Randomized Dependent Rounding*** algorithm for sampling to ensure that the capacity constraints are not violated on sampling.

* Dependent rounding and its applications to approximation algorithms [Gandhi et al 2006]

FairAssign: Stochastically Fair Assignment



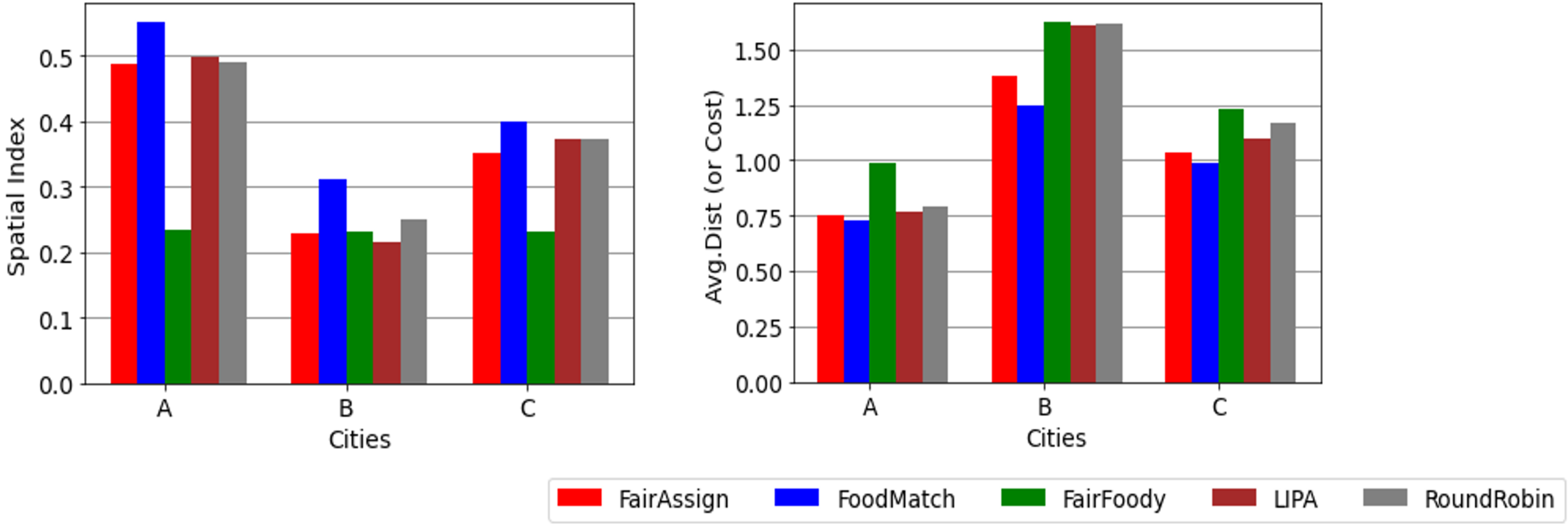
Driver	Day 1	Day 2	Day 3	...
	3	2	3	...
	1	1	1	...
	1	2	3	...

Phase-1: Get distributions

Phase-2: Sample from the distributions daily to realize the assignment

Why Stochastically Fair? Because the fairness guarantees only hold in expectation

Results: Cost-Fairness trade-off



Better cost-fairness trade-off compared to FairFoody

Summary

- FairAssign can achieve a good cost-fairness trade-off while accommodating the drivers' opinion in the algorithm design
- It can consider driver specific characteristics like ratings, active time while still having a comparable trade-off
- Can be easily extended to other domains like e-groceries, e-commerce logistics, or e-pharmacies

Research Papers to Read

I. FairFoody: Bringing in Fairness in Food Delivery. Anjali Gupta, Rahul Yadav, Ashish Nair, Abhijnan Chakraborty, Sayan Ranu, and Amitabha Bagchi. In *36th AAAI Conference on Artificial Intelligence (AAAI)*, Virtual, February 2022.

II. Gigs with Guarantees: Achieving Fair Wage for Food Delivery Workers. Ashish Nair, Rahul Yadav, Anjali Gupta, Abhijnan Chakraborty, Sayan Ranu and Amitabha Bagchi. In *31st International Joint Conference on Artificial Intelligence (IJCAI)*, Vienna, Austria, July 2022.

III. FairAssign: Stochastically Fair Driver Assignment in Gig Delivery Platforms. Daman Deep Singh, Syamantak Das and Abhijnan Chakraborty. In *6th ACM Conference on Fairness, Accountability, and Transparency (FAccT)*, Chicago, USA, June 2023.

Thank You