The Value of Knowing Drivers' Opportunity Cost in Ride Hailing Systems

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Research Purpose

A ride hailing platform has knowledge about potential drivers' outside opportunities.

How is this knowledge beneficial? Can its value be quantified?

Understanding this is crucial for designing bonus programs and maintaining drivers' commitment towards the platform.

The Motivating Discrete Model

Imagine a city with many potential drivers, differing in their opportunity cost (OC).

Drivers choose whether to work for the platform based on expected revenue (rev.) rate.

The platform sets a matching policy subject to a pickup-time constraint.

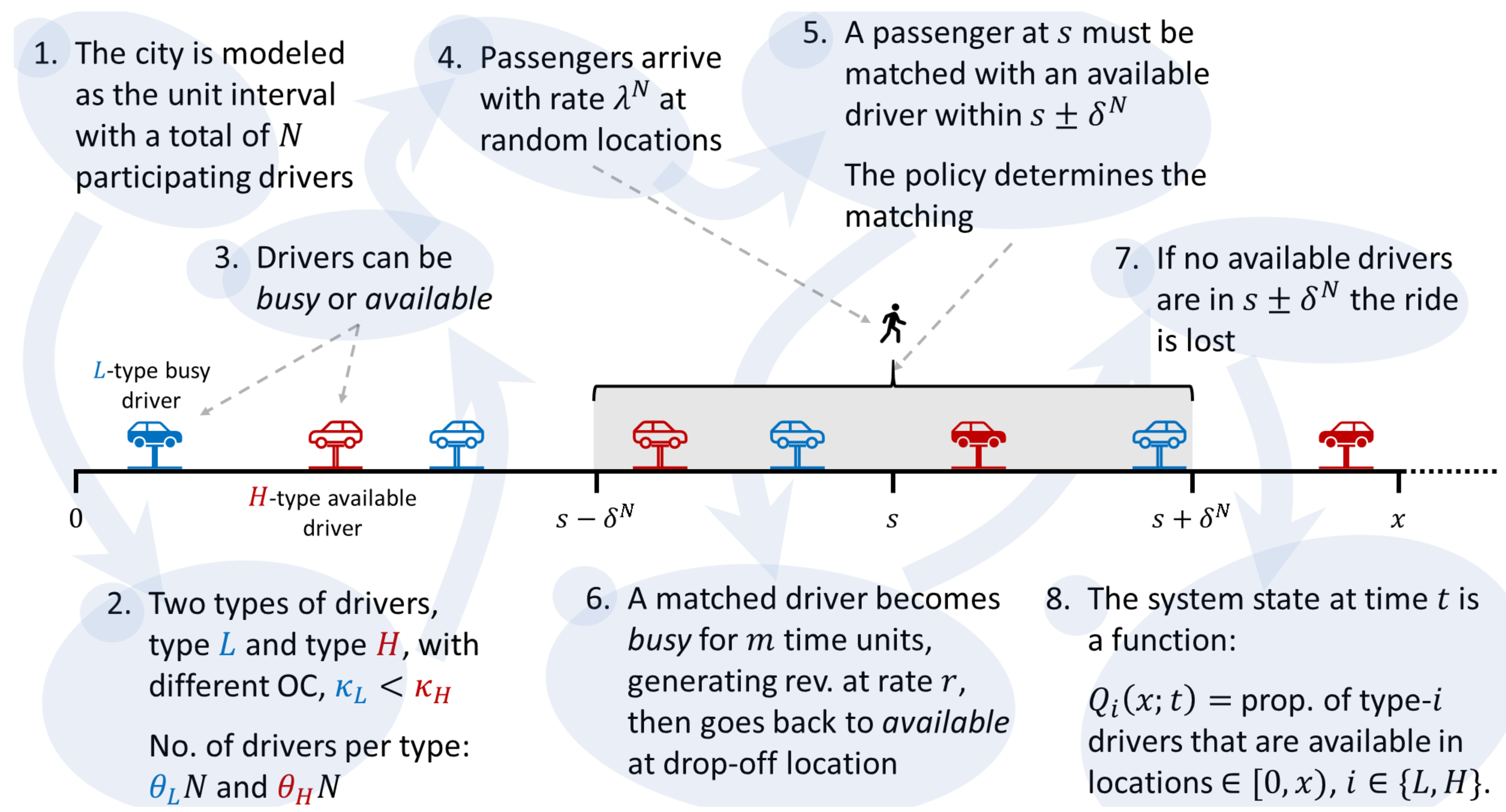

Fig 1. **Illustration of discrete model dynamics**

A passenger arriving at time t is matched with one close enough available driver whose score at time t is minimal. We consider two policies:

- ***MinRev*: Driver's score = accumulated rev. by time t**
- ***MinWeightRev*: Driver's score = accumulated rev. by time t divided by OC**

Which policy performs better in Equilibrium?

In equilibrium (eq.) : Each driver participates iff it's profitable to them (compared to OC).

In this example (Fig 2), *MinWeightRev* attracts ×2 more drivers in eq. relative to *MinRev*, and increases the matching rate by roughly ×2.

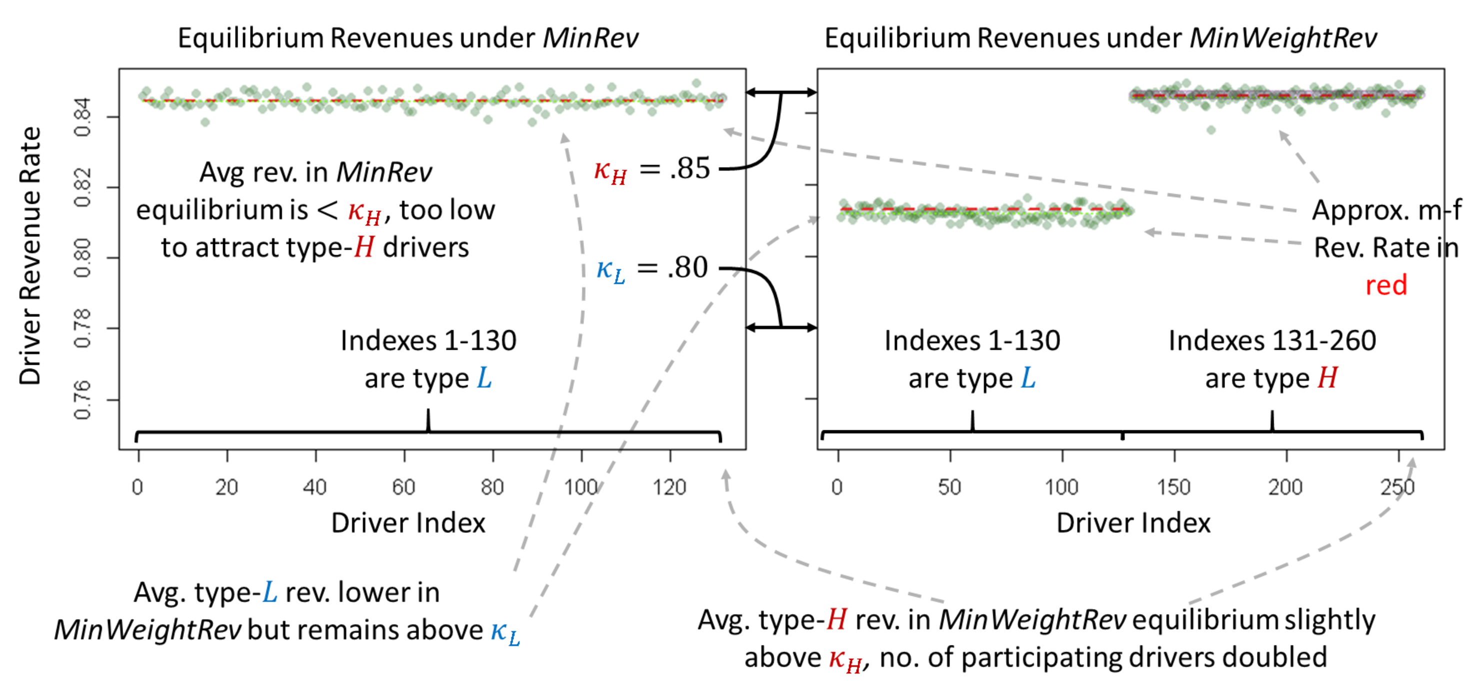

Fig 2. **Left: 130 drivers working in eq. under *MinRev*, all are type L**
Right: 260 drivers working in eq. under *MinWeightRev*, 130 of each type.
Approximated (mean field) rev. rate in both panels is shown in red.

The Mean Field Model

We analyze two mean field (m.f.) systems, one for each policy, corresponding to a large market of drivers ($N \to \infty$)

The formulation builds on the intuition that when N and t are large:

- **Drivers' scaled locations along the city form a Spatial Poisson process (Fig 3)**
- **Long-run revenue rates of all drivers coincide under *MinRev* (Fig 4), and the same holds for all drivers of the same type under *MinWeightRev.***

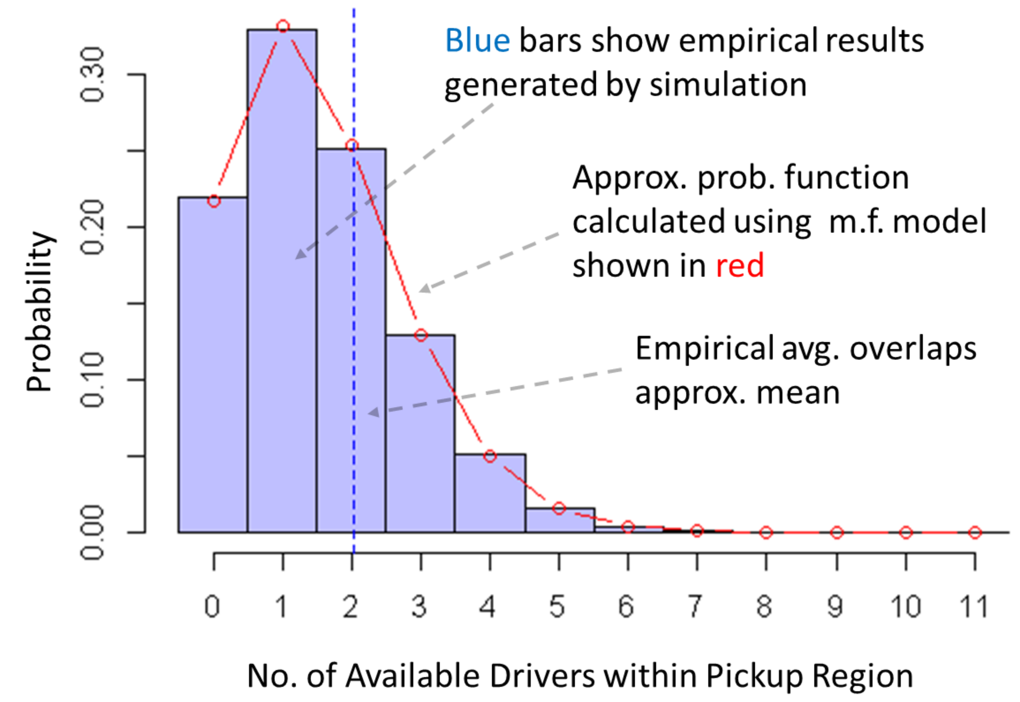

Fig 3. **The distribution of no. of available drivers per passenger's surrounding is well-approximated by Poisson, $N = 200$.**

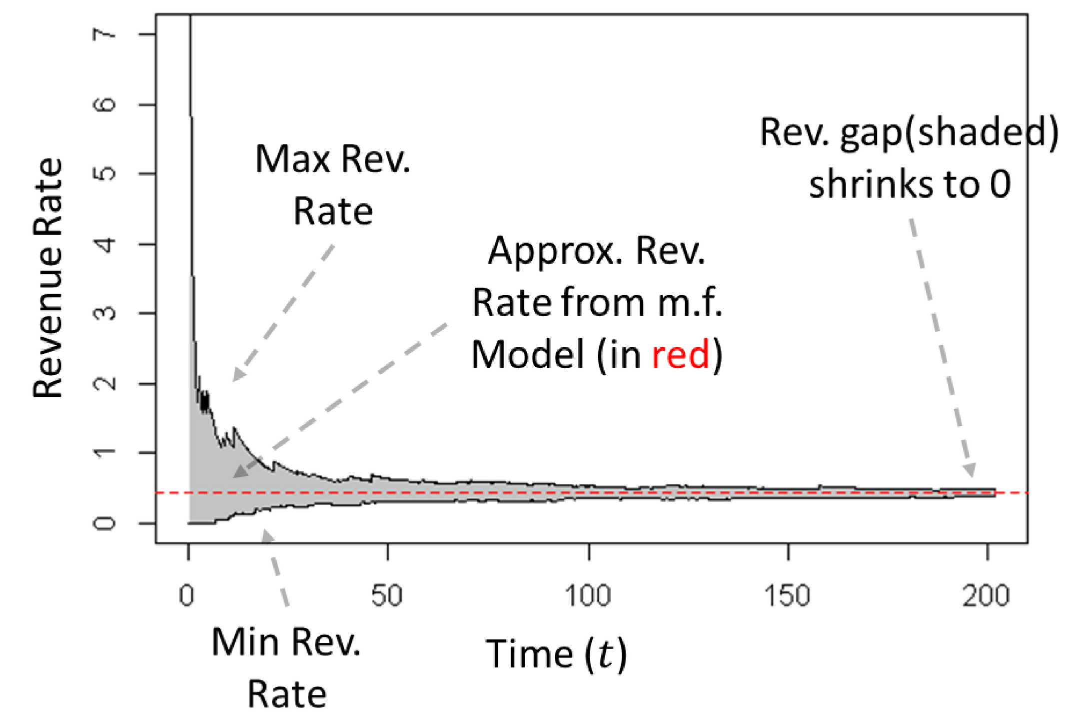

Fig 4. **The difference between maximal and the minimal revenue rates among drivers approaches 0 as $t \to \infty$, $N = 200$.**

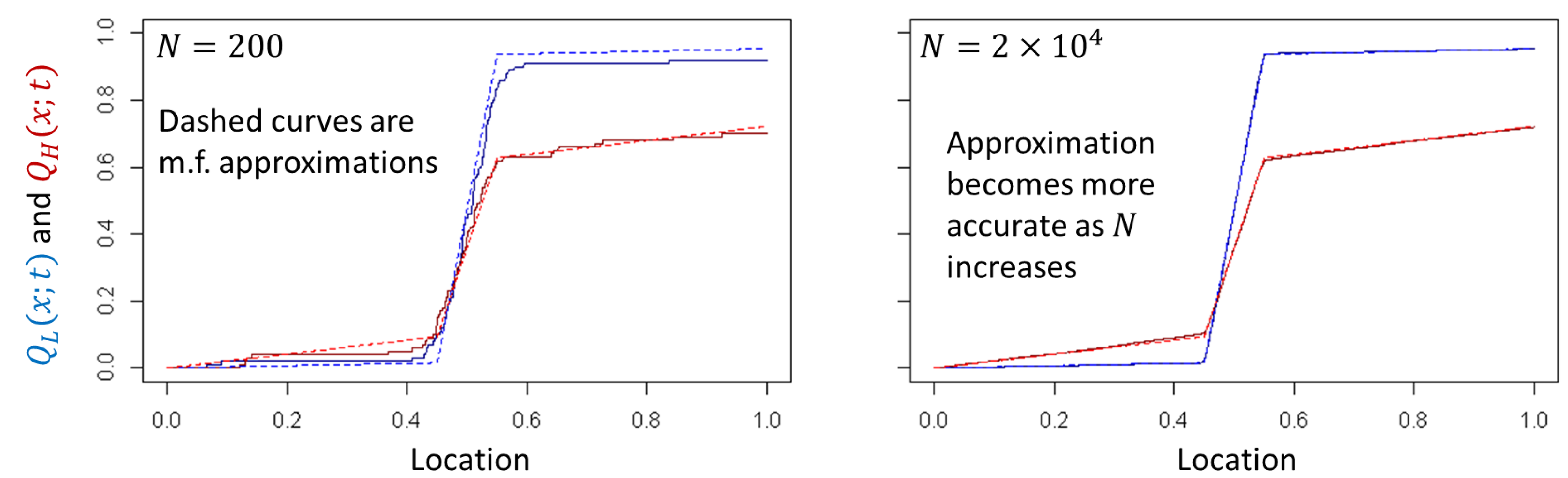

Fig 5. **Simulated system state (solid) vs. m.f. solution (dashed), for fixed t, with 2 different values of N. Type L in blue, type H in red.**

Key Findings – Improvement Bounds

Equilibrium participation profile of drivers is unique for each policy.

- ***MinWeightRev* eq. is always better than *MinRev* eq. in terms of drivers' participation rates and effective matching rate.**
- ***MinWeightRev* increases eq. total participation by up to ×2 relative to *MinRev*.**
- ***MinWeightRev* improves eq. matching rate by up to ×2 relative to *MinRev*.**

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Related Work:

Afeche, P., Liu, Z., & Maglaras, C. (2018). Ride-hailing networks with strategic drivers: The impact of platform control capabilities on performance. *Columbia Business School Research Paper*

Banerjee, S., Kanoria, Y., & Qian, P. (2018). State dependent control of closed queueing networks with application to ride-hailing. *arXiv preprint*

Braverman, A., Dai, J. G., Liu, X., & Ying, L. (2019). Empty-car routing in ridesharing systems. *Operations Research*