Optimizing the Profitability of Robo-Taxi Fleets

Andrey Aksyutkin, Alena Chan, Aksel Kretsinger-Walters, Blake Sisson

aa5499, ac5477, adk2164, mbs2246

Overview: Optimizing Robo-Taxi Fleets

Challenges:

- Predicting demand
- Minimizing wait times
- Setting competitive prices
- Recharging vehicles

Relevance:

- Emerging area
- Heavy company investment
- Active research and development

Data:

- Publicly available datasets to model
  - crowd behavior
  - weather conditions
  - seasonal effects
- Open simulation environments

Plan:

- Simulate robo-taxi fleet as MDP
- Develop RL algorithms to optimization fleet’s operation
- Evaluate against heuristic policies

Details

State

- Matrix of:
  - Vehicle location & battery level
  - Vehicle status
    - i.e. available, en route, occupied, charging
- Time/Day
- Weather conditions
- Ride Requests
- Environment
  - L_2 embeddable Graph (nodes & edges)

Reward

- Revenue from completed rides
- Penalty for long customer wait times
- Penalty of operation costs

Actions

- Move vehicle
  - Assign request to vehicle
  - Send vehicle to charging station
- Suggest price

Transitions

- Probabilistic customer acceptance / rejection (logistic func)
- Modify each car position, battery
- Modify each car usage status (occupied, en route, charging, etc)
  - Update corresponding requests
- Generate new requests

Implementation Outline

Phases (of increasing scope, complexity, dimensionality)

Phase I - optimal allocation of resources

Phase II - Simple pricing model

Phase III - Complex pricing model (weather, sporting events, global supply-demand imbalance)

Phase IV - Non-shortest route (traffic), charging stations

Phase V - multiple agents competing on price & allocation

Training Speedups & Model Architecture

- LLM feedback (set reasonable initial Q-values)
- Heuristic initial strategy
  - Nearest vehicle dispatch, price = cost * (1 + margin)
- Discretize training environment
- Neural Net to handle interpolation
- Manually compute intermediate & hard-to-costs
  - Customer satisfaction - credit assignment problem
  - Independent customer demand forecast
- Amortized rewards & costs

References

[1] U.S. Census Bureau. "LEHD Origin-Destination Employment Statistics (LODES). https://lehd.ces.census.gov/data/

[2] Waymo. "Waymo Open Dataset." https://waymo.com/open/

[3] Xiao, I. "Reinforcement Learning Project: CitiBike."
https://github.com/ianxxiao/reinforcement_learning_project/blob/master/Reports/Presentation_RL_citiBike_20180514.pdf

[3] Li, J., Li, X., & Wang, F. "Reinforcement Learning for Ridesharing: An Extended Survey." arXiv preprint arXiv:2102.11896, 2021.

[4] Lin, K., Zhou, M., Wang, J., & Li, L. (2018). *Efficient Large-Scale Fleet Management via Multi-Agent Deep Reinforcement Learning*. Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining (KDD 2018).

[5] Kim, H., & Kim, Y. (2020). Optimizing Large-Scale Fleet Management on a Road Network using Multi-Agent Deep Reinforcement Learning with Graph Neural Network. arXiv preprint arXiv:2011.06175.

[6] O'Mahony, E., & Shmoys, D. (2015). *Data Analysis and Optimization for (Citi)Bike Sharing*. Proceedings of the Twenty-Ninth AAAI Conference on Artificial Intelligence (AAAI 2015).

[7] Xu, Y., Zhang, R., Li, X., & Wang, F. (2021). *Towards More Efficient Shared Autonomous Mobility: A Learning-Based Fleet Repositioning Approach*. Proceedings of the AAAI Conference on Artificial Intelligence, 35(1), 1166-1174.