



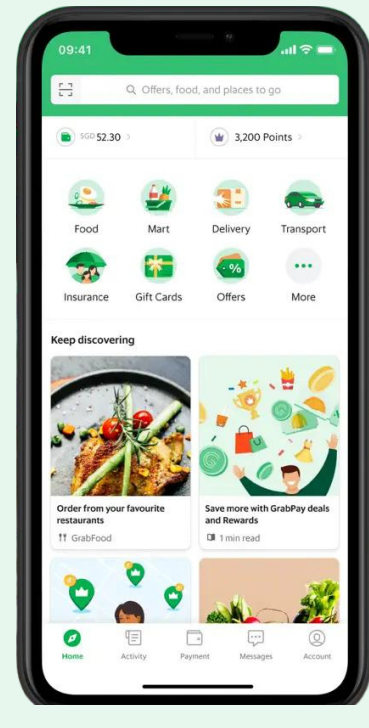
Cravings Can't Wait

Routing food deliveries under time uncertainty

By: Gabriel Afriat & Mariana Suarez
 Faculty Advisors: Professor D. Freund & Professor S. Graves
 Grab Advisors: Larry Lin & Yibo Ji

Overview

Problem Statement



- Company:** Southeast Asia superapp
- Scope:** GrabFood deliveries
- Current State:** Batching algorithm assigns drivers to routes containing one or more orders based on deterministic time estimates
- Limitation:** Does not take into account real-world travel time uncertainties

Goal

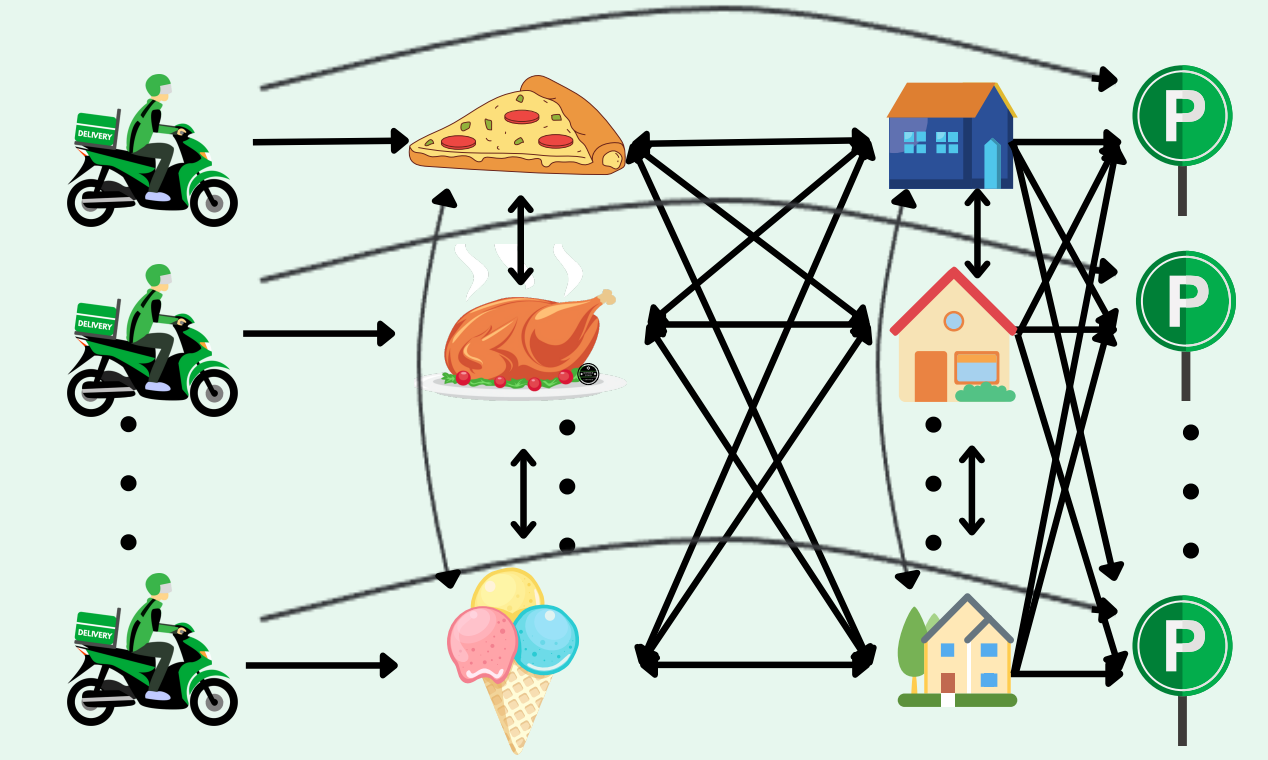
To add **robustness** (the consideration of uncertainty) to Grab's batching algorithm in order to **minimize delays**

Why It Matters?

- Key to increase **user satisfaction**
- Vital to understand **trade-off** between time **efficiency** and order **delays**

Problem Architecture

Pick-up delivery vehicle routing problem



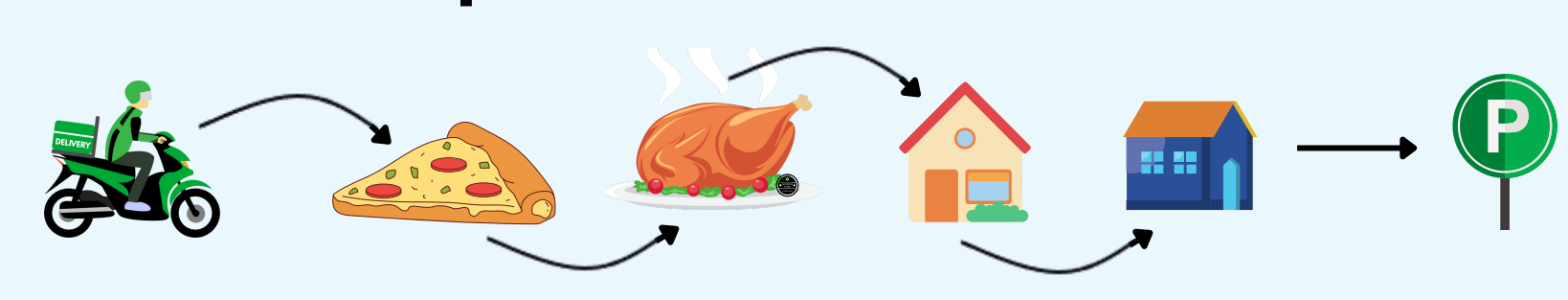
What Do We Need?

Data Input

- Travel times:** 100 historical times per arc
- Time windows:** lower and upper time bounds per pick-up and drop-off
- Vehicle capacity:** number of orders a driver can carry

Model Output

The path that each driver should take



Our Approach



Simplification

1. Clustering

Create a **distance metric** between orders to **group** nearby nodes and break down the problem into **smaller problems**



$$d_{o_1, o_2}^{temp} = \left\{ \begin{array}{l} \text{Distance between order 1 and order 2} \\ t_{P_1, P_2} + t_{P_2, D_1} + \dots \end{array} \right\}$$

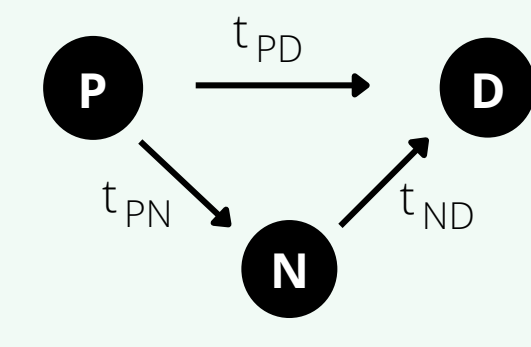
$$\min(\text{waiting}_{P_1, P_2}, \text{waiting}_{P_2, D_1}) + \dots$$

$$(+\infty) \mathbb{1}_{\text{infeasible_batching}}$$

Hierarchical clustering performed on $d_{o_1, o_2} = \min(d_{o_1, o_2}^{temp}, d_{o_2, o_1}^{temp})$

2. Graph Construction

Create a **smaller graph** that includes only **"most likely" arcs** based on cost metric



$$\text{cost}_{PN} = \left\{ \begin{array}{l} \text{Cost of the arc between pick-up } P \text{ and node } N \\ t_{PN} + t_{ND} + \dots \end{array} \right\}$$

$$\text{waiting}_{PN} + \dots$$

$$(+\infty) \mathbb{1}_{\text{infeasible_arc}}$$

Arcs (P,N) and (N,D) are only kept for the **best k neighbors N**

Similar metrics are defined for arc (N,D) and for arc (D,N)

Optimization

3. Optimization

Generate **solution path** for drivers by taking into account **time travel uncertainties**

Nominal Travel times for each arc is assumed to be known in advance

$$\min_{x, S} \sum_{k \in K} S_{3n+k, k}$$

such that

$$\sum_{k \in K} \sum_{j \in P \cup D} x_{i,j,k} = 1 \quad \forall i \in P$$

$$\sum_{j \in V} x_{i,j,k} - \sum_{j \in V} x_{j,n+i,k} = 0 \quad \forall k \in K, \forall i \in P$$

$$\sum_{j \in P \cup \{3n+k\}} x_{2n+k,j,k} = 1 \quad \forall k \in K$$

$$\sum_{i \in D \cup \{2n+k\}} x_{i,3n+k,k} = 1 \quad \forall k \in K$$

$$\sum_{i \in V} x_{i,j,k} - \sum_{j \in V} x_{j,i,k} = 0 \quad \forall k \in K, \forall j \in N$$

$$S_{i,k} + t_{i,j} - M_{i,j}^{(S)}(1 - x_{i,j,k}) \leq S_{j,k}$$

$$a_i \leq S_{i,k} \leq b_i$$

$$S_{i,k} \leq S_{n+i,k}$$

$$L_{i,k} + 1 - M^{(L)}(1 - x_{i,j,k}) \leq L_{j,k}$$

$$L_{i,k} - 1 - M^{(L)}(1 - x_{i,j,k}) \leq L_{j,k}$$

$$L_{i,k} \leq C$$

$$L_{2n+k,k} = L_{3n+k,k} = 0$$

$$x_{i,j,k} \in \{0, 1\}$$

$$S_{i,k} \geq 0$$

$$L_{i,k} \geq 0$$

Robust
Time constraint **verified for any time in a given uncertainty set**

$$S_{i,k} + t_{i,j}^{(\gamma)} - M_{i,j}^{(S,RC)}(1 - x_{i,j,k}) \leq S_{j,k}$$

$$\forall k \in K, \forall (i,j) \in A, \forall t_{i,j}^{(\gamma)} \in \mathcal{T}_{i,j}(\gamma)$$

where hyperparameter γ measures the size of the uncertainty set and therefore the level of robustness

Distributionally Robust
Time constraints **verified in expectation for any probability distribution** in a given ambiguity set

$$\sum_{i \in I_{\text{training}}} p_{i,j}^{(0)} (S_{i,k} + t_{i,j}^{(0)} - M_{i,j}^{(S,RC)}(1 - x_{i,j,k}) - S_{j,k}) \leq 0,$$

$$\forall k \in K, \forall (i,j) \in A, \forall (p_{i,j})_{i \in I_{\text{training}}} \in \mathcal{P}_{i,j}(\rho)$$

where hyperparameter ρ measures the size of the ambiguity set and therefore the level of robustness

4. Warm Start

Improve solution **quality** by providing the solver with an initial solution (here the **unbatched solution**)

5. Reducing the Dual Gap

Increase **confidence** in solution quality and facilitate the search for a better solution during **branch and bound** by experimenting with **5 formulations**

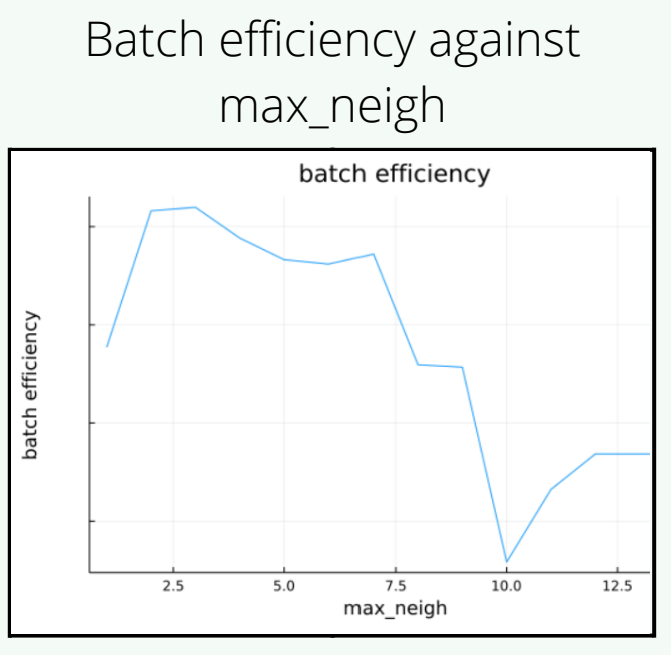


6. Fine-tuning

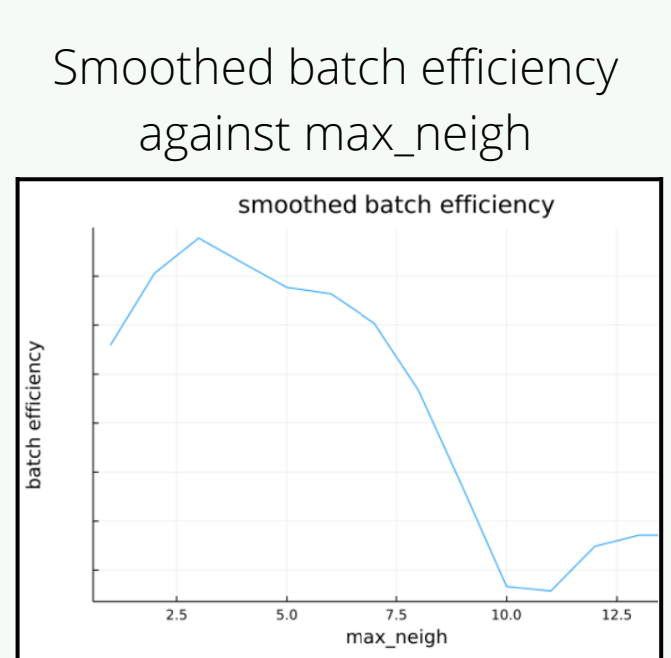
Identify **best combination** of **hyperparameters** for the **clustering, graph construction, and optimization** to improve performance across models

A direct fine-tuning would be **very long**.

For the **graph construction** parameter "max_neigh", we note the **close to concave** nature of the batch efficiency evolution with this parameter.

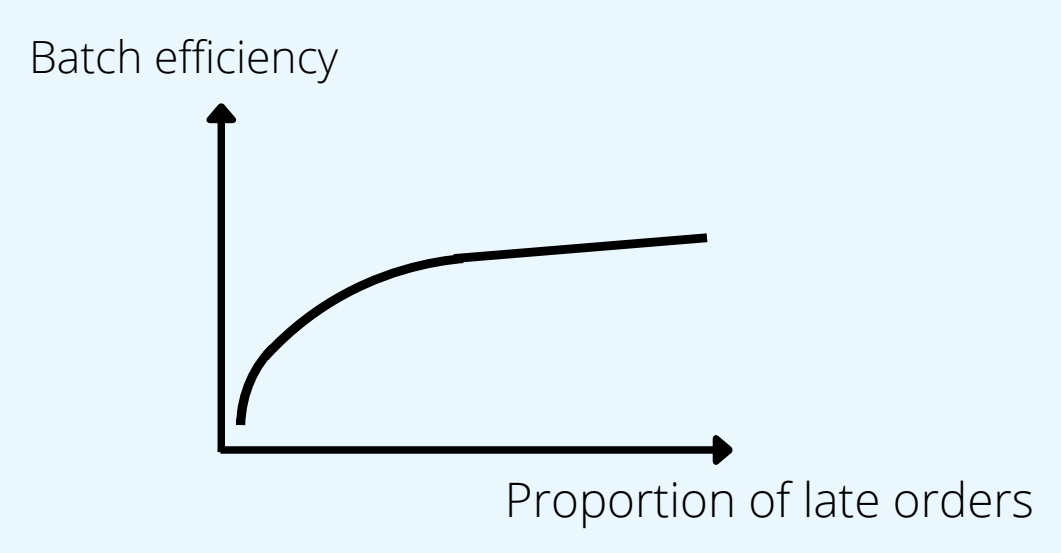


We **smooth** the curve to make it more concave and then we proceed to a **gradient ascent** via **dichotomy**.



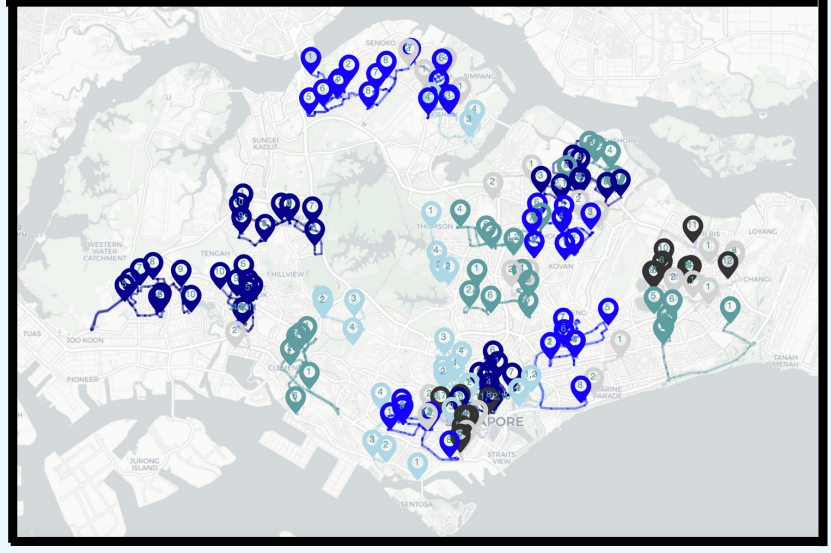
Results

1 Trade-off between time efficiency and order delays



2 Develop robust algorithms that improve Grab's operations

- ↓16%** Maximum proportion of late orders
- ↓70%** Maximum delay
- ↓11%** Batch efficiency



Key Takeaway
By including real-world uncertainty of driver routing times in delivery algorithms, we are able to reduce the number of delayed orders and improve food delivery operations.