A Simple But ***Quantifiable*** Approach to

# DYNAMIC PRICE PREDICTION WITH MULTI-SOURCE URBAN DATA

## in Ride-on-Demand Services

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# Outline

## A Brief Presentation of Our Work

**Background**

*-- Problem, Solution & Methodology*

**Multi-source Urban Datasets**

*-- RoD, Taxi, Public Transportation, POI, Weather*

**Basic Features**

**Composite Features**

**Model & Evaluation**

**Feature Contribution & Discussions**

### 01 RoD Service

Emerging transportation services with dynamic pricing -- Uber, Didi, Lyft, Shenzhou UCar, etc.

### 02 Dynamic Pricing

Trip fare = (dynamic) price multiplier * (fixed) normal price.

### 03 What We Do?

Based on a number of features extracted from fare estimation, calculate (or estimate, or predict) the price multiplier for this estimation.

### 04 What Data?

Multi-source urban datasets: RoD, Taxi, POI, weather, public transportation, etc.

**In Short...**

# Background

## Problem, Solution & Methodology

## PROBLEM

TAXI → Dynamic Pricing → UBER, 神州专车, •••

### Passenger's Worry

- price too high
- do I get a good price now?
- better price later or nearby?
- ...

### Industry & Policy Maker's Worry

- price manupulation?
- killing taxi/buses?
- fairness?
- ...

## SOLUTION

### Price Predicton

- What will be the price multiplier, given features?
- & the price multiplier later?
- & the price multiplier nearby?
- ...

**For Passenger:** SOLVED

**For Industry & Policy Maker:**

- price manipulation -- solved
- killing taxi/buses -- introduce features relevant to taxi and buses
- fairness -- all passengers now have the same guidance

## METHODOLOGY

✗ **Unveil the "secret algorithm"**

✓ **Learn from data, don't care the truth**

↓ **Model selection?**

✗ **Complex & non-linear models:**
**highly accurate, non-interpretable**

✓ **Linear models:**
**interpretable, hard to describe non-linear correlation between features.**

# But, How To Compensate for the Drawbacks of a Linear Model?

1. Have more features -- use multi-source urban datasets
2. Add non-linear terms -- construct composite features

# Multi-source Urban Datasets

| | |
|---|---|
| RoD Service | **Event-log data**: record the time, location, price multiplier, etc. for every fare estimation on the app. |
| Taxi Service | **Taxi GPS trajectories**: used to describe the traffic condition and taxi availability around given locations. |
| Public Transport. | **Distribution of lines/stations**: how many bus/metro lines/stations around given locations. |
| POI | **Number of POIs**: how many POIs of each categories are there around given locations. |
| Weather | **Weather**: the weather condition (temp, wind speed, humidity, pressure, etc.) around given locations. |

**Information about time, price, etc.**

**Information about location.**

# Feature Engineering

## Basic Features

| | |
|---|---|
| **RoD Service** 神州专车 | **Temporal**: hour-of-day, day-of-week, day-of-month, isHoliday, isWeekend, ...<br>**Price**: estimated trip fare, price multiplier, historical price multiplier, ... |
| **Taxi Service** | **Taxi availability**: number of full taxis, full taxi ratio, up/down count, ...<br>**Traffic condition**: average speed, variance of speed, ... |
| **Public Transport.** | **Public transport. availability**: number of bus/metro lines/stations nearby |
| **POI** | **Number of POIs**: the number of POIs of 14 different categories (i.e., restaurant, shopping, business, etc.) |
| **Weather** | **Weather**: temperature, wind speed, humidity, pressure, visibility, weather condition (e.g., 'rainy', 'sunny', 'sprinkler', ...), etc. |

**Features Extracted from Single Dataset**

# Feature Engineering

## Composite Features

**Lack of non-linear terms**: how to describe correlations between features?

**Idea**: Adding product-form terms.

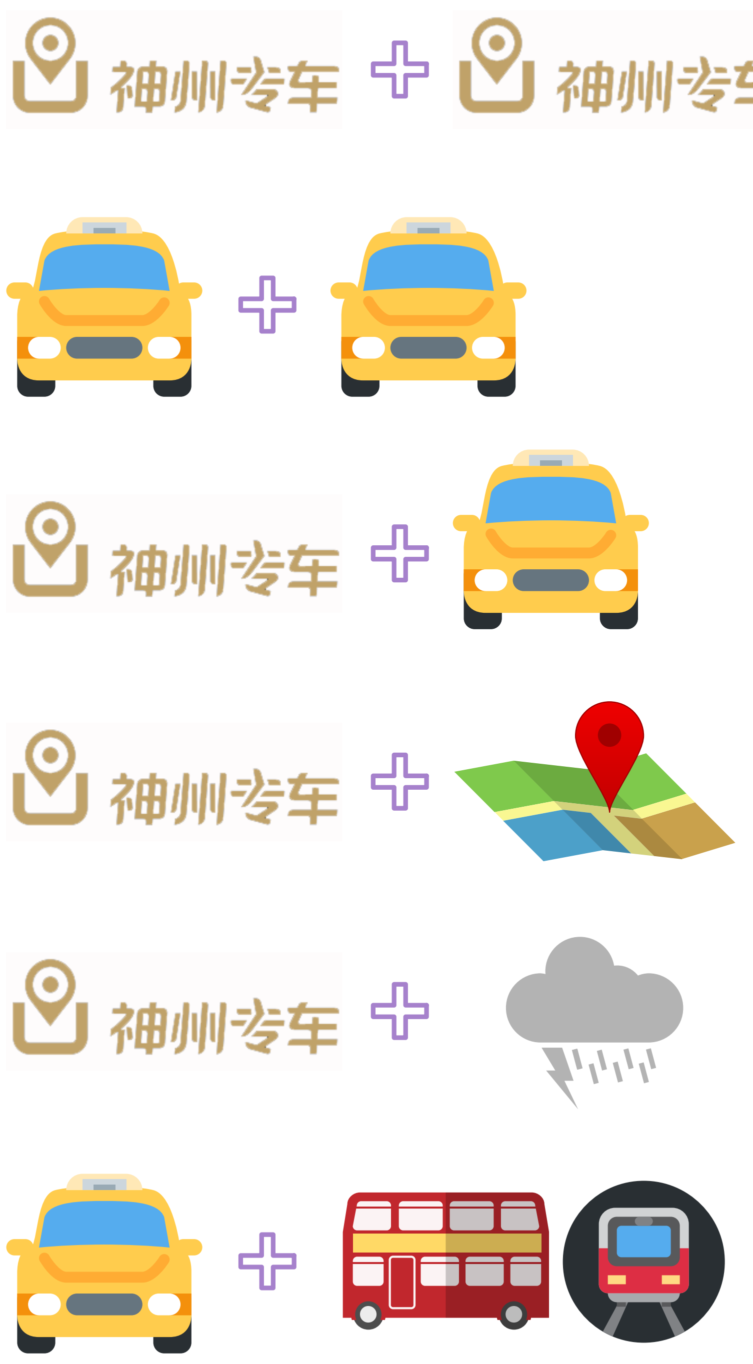
$$y = \omega_a x_a + \omega_b x_b + b$$

$$y = \omega_a x_a + \omega_b x_b + \omega_c x_a x_b + b$$

The linear model is transformed into a non-linear one, but still interpretable.

**Composite features**: combining basic features in product-form

**Examples of Combining Basic Features**




(day-of-week, hour-of-day)
(isWeekend, hour-of-day)...

(full taxi count, full taxi ratio)
(average speed, up count)...

(hour-of-day, full taxi ratio)
(historic price multiplier, full taxi ratio)...

(day-of-week, POI counts)
(hour-of-day, POI counts)...

(historic price multiplier, temperature)
(day-of-week, weather condition)...

(taxi count, bus station count)
(full taxi count, metro line count)...



Details of *normalization*, *generating product forms*, and *discussions* are omitted -- please refer to the paper.

# MODEL AND EVALUATION

## A Linear Regression Model

### What to Model?

- Given features describing a fare estimation, output the estimated or predicted price multiplier.
- As long as one can generate these features, the price multiplier could be estimated.

### How to Model?

- Simple linear regression model.
- Squared-error loss function: the difference between the predicted price multiplier and the ground truth;
- L1/L2 regularization: controls spasity and over-fitting;
- Spatio-temporal regularization: makes sure that the price multiplier does not change abruptly;
- Dimension of features: about 4000. Not very large as we don't combine more than 2 basic features together.

### Overall Results

- Use sMAPE as the evaluation metric;
- Have a very good prediction (with difference of price multiplier <= 0.1) in 81.17% cases;
- Using **composite features** reduces the sMAPE by 35.86%;
- Using **multi-source urban datasets** reduces the sMAPE by 25.17%;
- Tentatively, using a four-layer neural network could further reduce the sMAPE by 6.50%, and has a very good prediction in 85.68% cases. But neural network is not interpretable and quantifiable.

# FEATURE CONTRIBUTION

## Top-20 Features According to Absolute Weights

**Top datasets**

1. RoD Service
2. Weather
3. Taxi Service

**Top features (examples)**

- **historic price multipliers** (in the last 1, 2, 3 hours):
- --> with weights more than twice than others;
- --> basic and composite features;
- --> shows that prices are predictable.

- **weather**:
- --> higher temperature;
- --> when there is rain;
- --> quantifiable.

- **Competition between Taxi and RoD**:
- --> there is, but not that fierce;
- --> fewer taxis, higher prices;
- --> only obvious during evening rush;

**Public Transport.?**

- no strong influence on price multiplier: with weights far smaller than the top features.
- possible reasons: different customer bases --> needs further verification by other data.

**Influence of POI Features?**

- Again, no strong influence, with weights even smaller than public transportation.
- possible reasons: "POI counts" is not an accurate description; rather, the importance of POI should be addressed.

- **LBS checkin data:**
- --> more checkins, more important
- --> indeed increases weights by 20 times

- **TF-IDF of POI counts:**
- --> common POI categories get weights diminished.
- --> increases weights by at most 17.5 times

# THANK YOU FOR YOUR INTEREST!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