Extracting value for Mileslife

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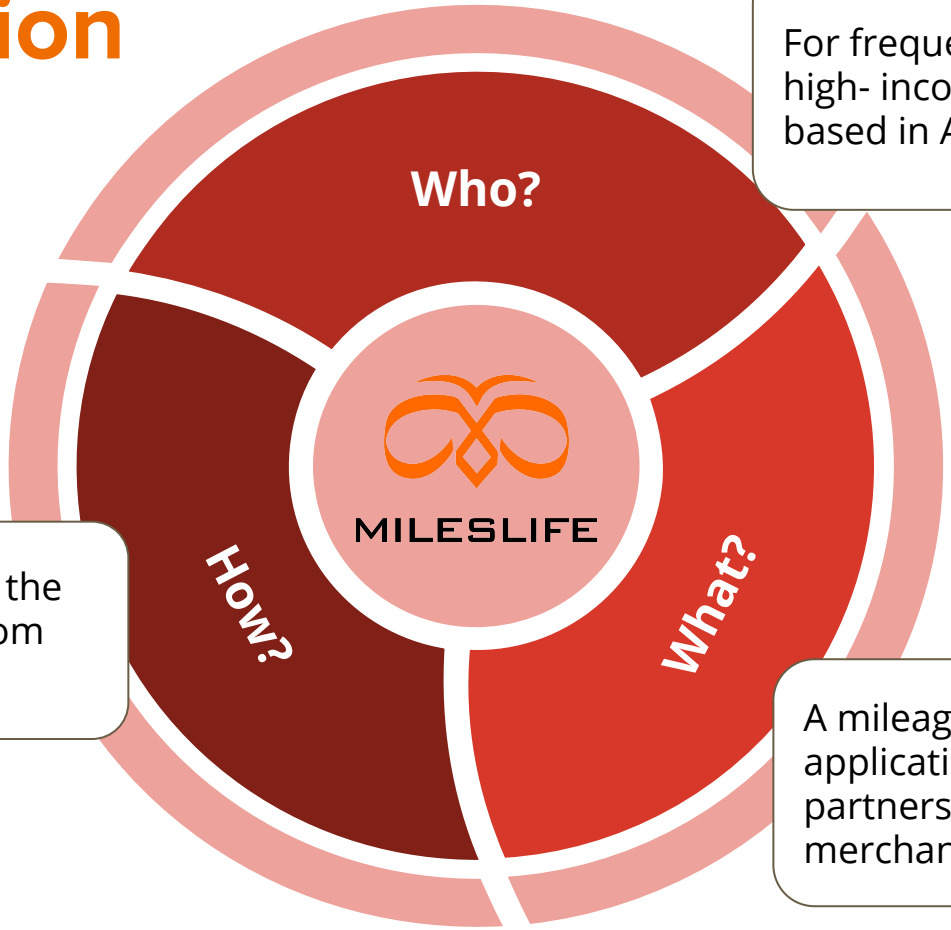
MILESLIFE

COLUMBIA UNIVERSITY
IN THE CITY OF NEW YORK

Introduction



For frequent flying, mid- to high- income professionals based in Asia

A mileage-earning loyalty mobile application linking over 16 airline partners worldwide to local merchant partners

Direct payment through the app, and commission from the transaction

The Process

The Problem	The Data	Visualization/ Modelling	Analysis	Insight
• Discussed with our client • Shortlisted problem statement • Extended problem statement	• Requested for a dataset with shortlisted variables • Cleaned and pre-processed the data	• Plot relationships of features to transaction frequency and commission paid • Heatmaps • Models	• Determined influential factors for merchant performance • Showed campaign effectiveness by zones	• Recommendations to improve campaign strategies • Predicting performance of F&B partners for better contractual terms

The Problem Statements

- Part 1: Assessing the quality of F&B merchant **partnerships**
  - **Not all partnerships are equal**
  - **Differential** commission slicing/ pricing
  - Historical **performance measure**: transaction frequency
  - Potential future performance measure: commission paid

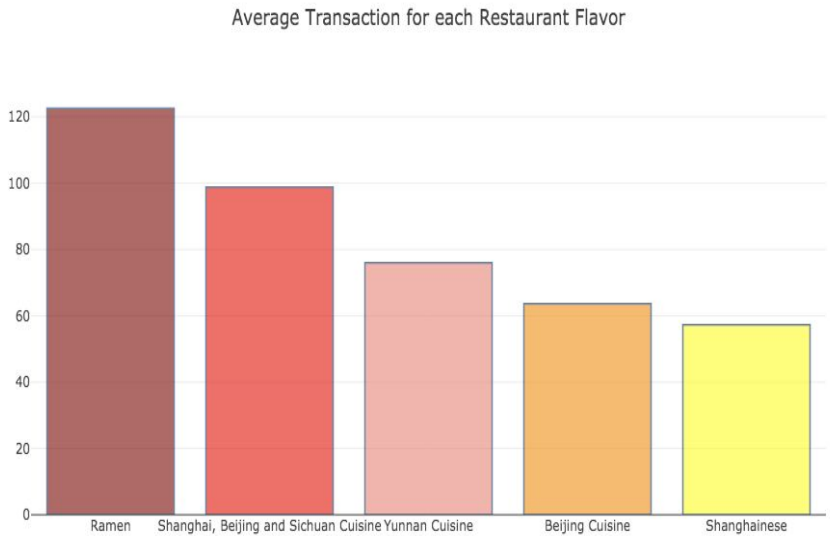
- Part 2: Evaluating the effectiveness of **campaigns**
  - **Type** of campaign (e.g. airline-specific, credit card-specific, festival-specific, restaurant-specific)
  - Performance of campaign by **different zones**
  - Sensitivity of **revenue** to campaigns

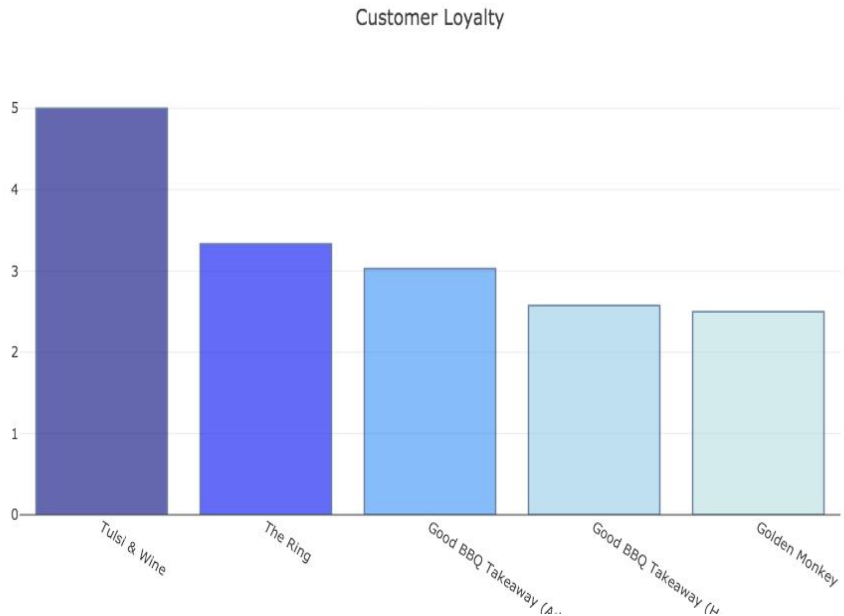
The Dataset

- Dataset: transaction data with 25 attributes x 160,000 rows
  - Restaurant-related: name, area, type of flavor
  - Campaign-related: name, promotion miles
  - Transaction-related: paid time, total price, commission for Mileslife
  - Focused on Hong Kong data: 15,200 rows

- Preprocessing :
  - Web-scraping to get exact location and address of each restaurant
  - Created ‘paid day of week’ and ‘paid hour ‘
  - Integrated a common campaign label for the same campaign in different languages
  - Encoded categorical variables for regression and created a categorical variable based on quantiles for pay_commission for classification

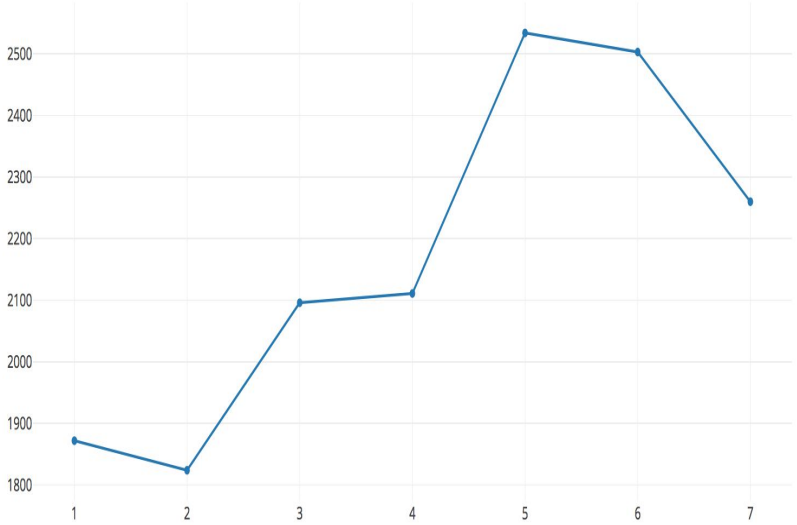
Restaurant Features



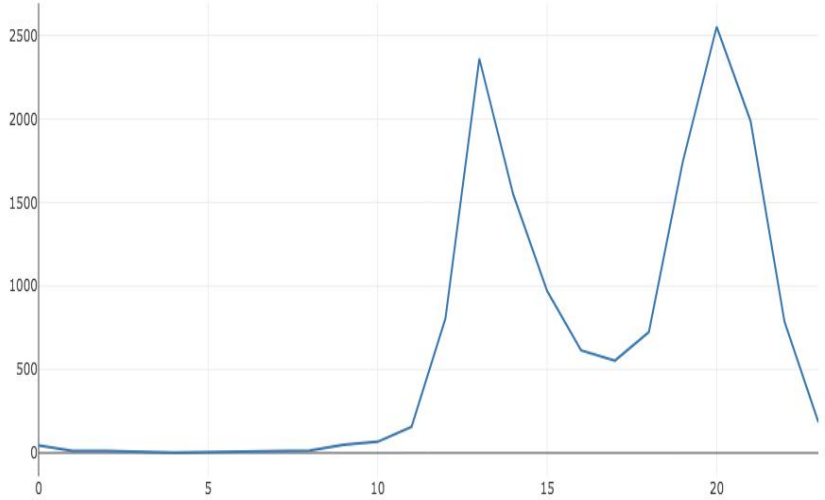


Paid Time

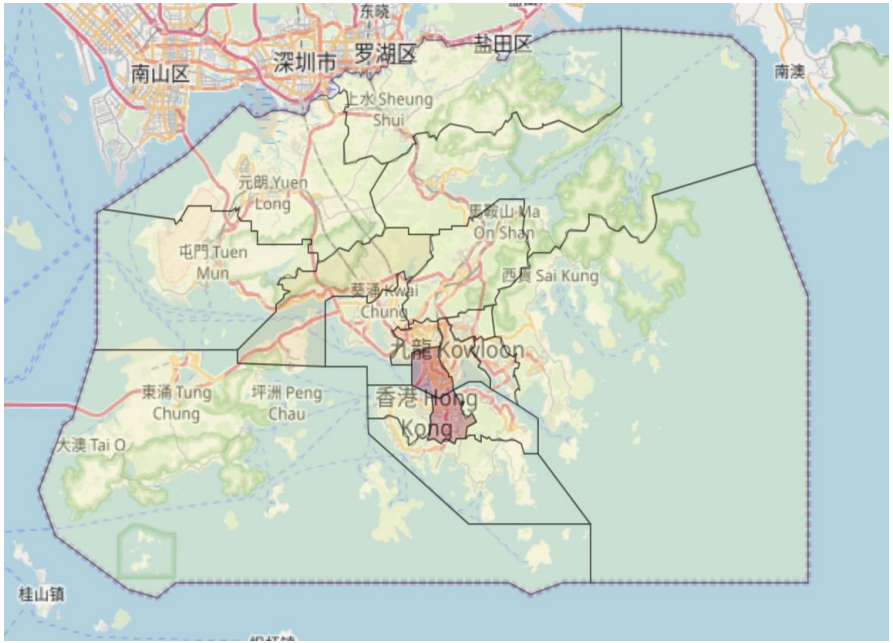
Paid day of the week



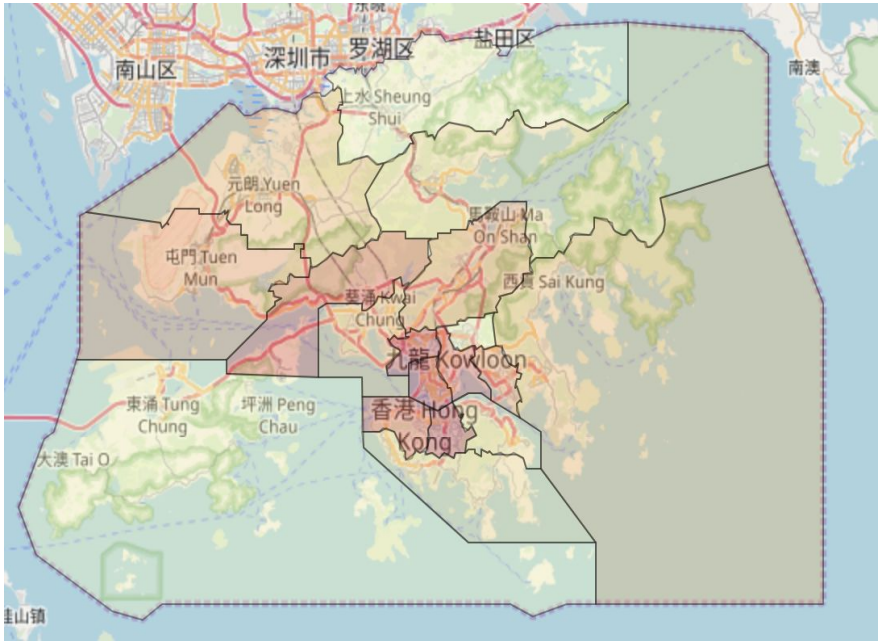
Paid hour of the day



Transaction Density in Hong Kong



By absolute number of transactions



By rank on number of transactions

Models and Evaluation

Model	Result	Measure
Linear Regression	695.16 **0.018**	Mean-squared Error
Decision Trees	69.9% **81.6%**	Accuracy
Random Forest	**77.6%**	Accuracy

- Feature engineering - include only relevant features
- Normalization and scaling
- Created a categorical variable for commission using quantiles as thresholds
- Result:
  a. Large improvement in Linear Regression after normalization
  b. Better accuracy after pruning the tree in Decision Trees
- Limited utility of predicting the amount of commission to assess quality of partnership

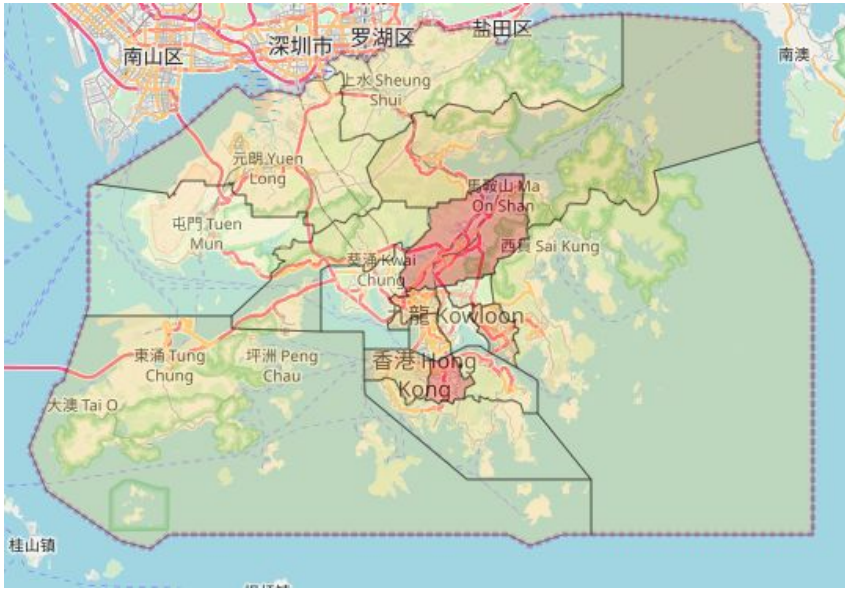
Analytics on Campaign Effectiveness

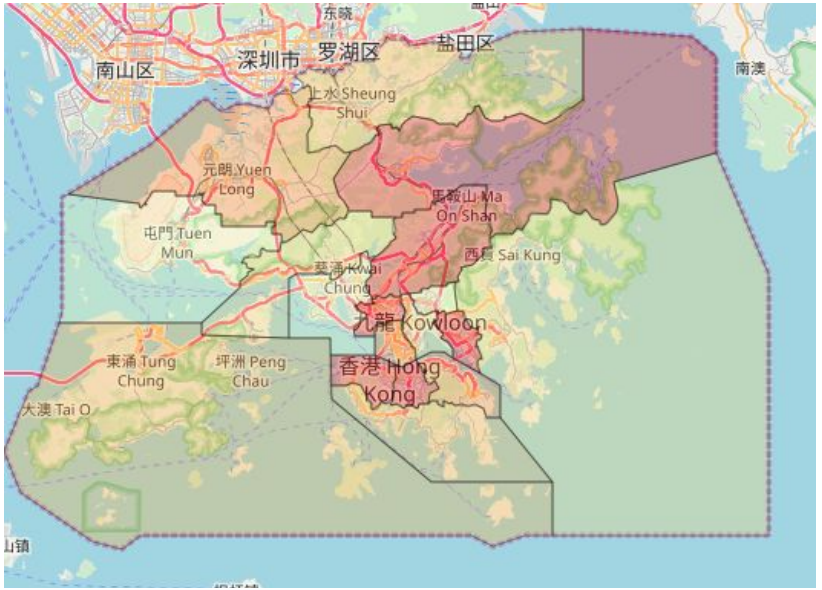
Methodology: A/B testing

1. Setting the objective function as revenue
2. Grouping transactions into different zones
3. Visualizing the result
4. Applying our analysis to more campaigns
5. Sensitiveness of revenue to changes in bonus miles multipliers

Analytics on Campaign Effectiveness

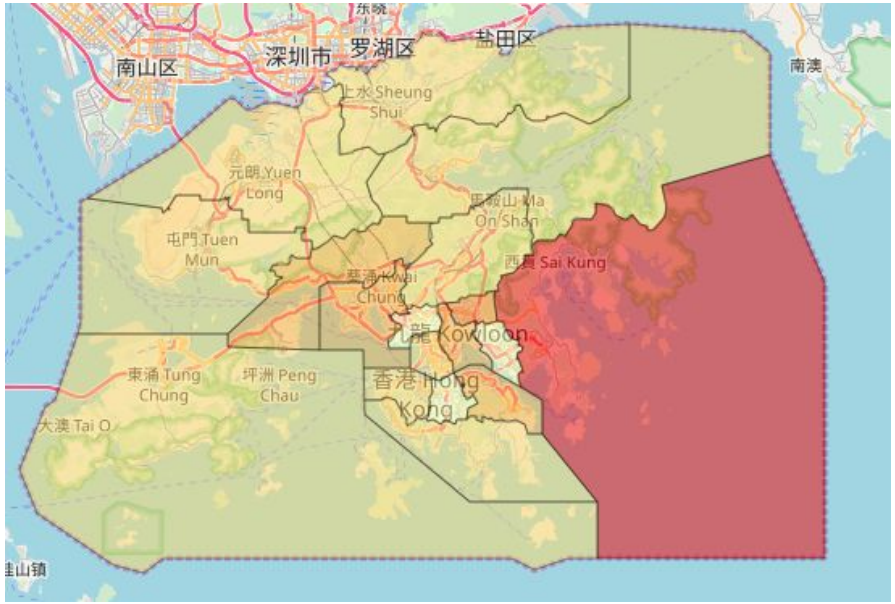
'September 3X ANA miles'





Analytics on Campaign Effectiveness

Sensitiveness to Bonus Miles Multiplier



Recommendations - Partnerships

Mileslife should:

1. **Scout Japanese ramen, Shanghai, Yunnan F&B partners** to suit the Asian palette
2. Favor existing partners with **good customer loyalty** such as Tulsi and Wine

Mileslife should not:

1. Solely assess potential partners on their **current metric alone**
2. **Overextend** partnerships with **Western restaurants**

Recommendations - Campaigns

Mileslife should:

1. **Focus on specific districts** in different campaigns
2. Implement more **festival- specific campaigns**
3. Increase the **bonus miles multiplier** by a greater magnitude for suburban areas

Mileslife should not:

1. **Arbitrarily target** districts with high transaction density
2. Provide **blanket multiplier** campaigns across all localities

Limitations and Further Improvements

- Dataset
  - **Limited timeframe** due to Mileslife Hong Kong starting in mid-2018
  - Unable to do **Difference-in-Difference analysis** for assessing campaigns with a single year's data
  - By **mid-2020**, there should be two annual revenue growth values for comparison

- Extension to a user-friendly interface for the client