MSBA Practicum The City of Rochester Project

Team 13

William He, Xinyu Xing, Yichan Ang, Nam Vo, Yuqi Yang, and Suyao Xu

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Machine Learning Pipeline:

A pipeline process that produces machine-leaning models to predict the suitability of national restaurants or retailers in the Rochester area

Case Analysis Findings:

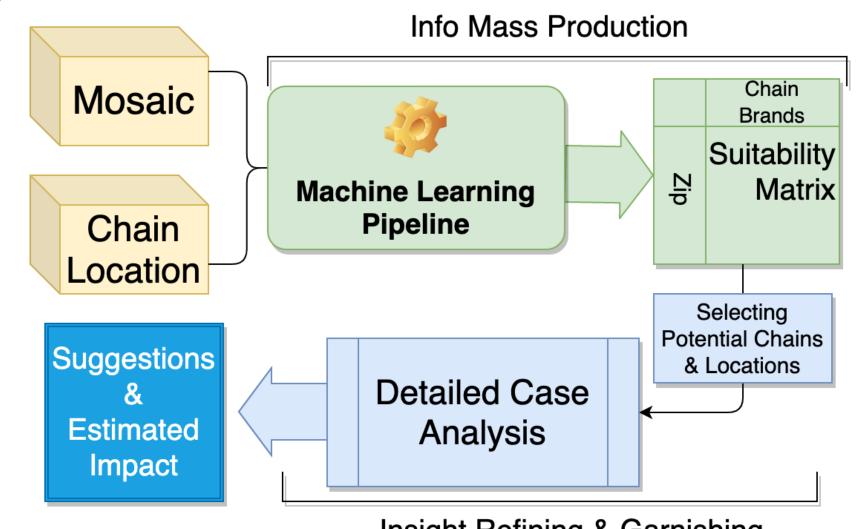
From the results produced by the pipeline, four top-tier brands are matched with area suggestions based on strategy and potential revenue analyses

Final Recommendation:

Financial outlook and recommended addresses for the four brands' hypothetical stores in Rochester, which can further facilitate investment decisions



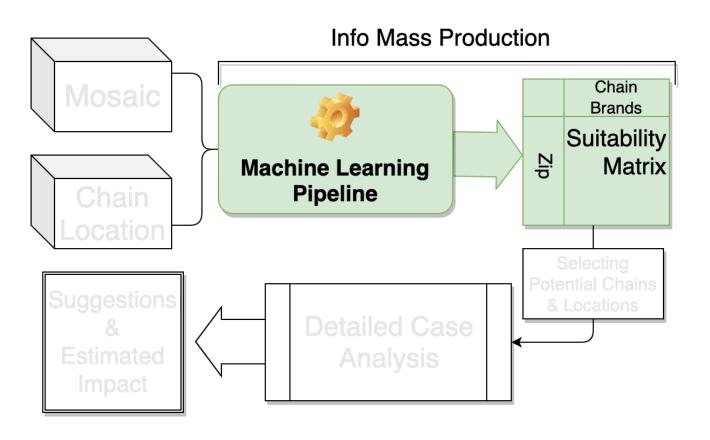
Project Overview



Insight Refining & Garnishing



Phase 1 – Machine Learning Pipeline



Goal

Build a model for each brand that predicts if each ROC zip location is suitable for that brand?

Process

1. Data Extraction

Extract Model-Ready Datasets

2. Resampling

Resample Datasets Based On Target

3. Model Tuning

Tune Model Using Hyper-Parameters



Pipeline – Data Extraction

Model-Ready Datasets

| ZipCode | IfStore | Mosaic Seg 1 | Mosaic Seg 2 | Mosaic Seg | Mosaic Seg 71 |
|---------|---------|--------------|--------------|------------------------|---------------|
| 10001 | 1 | 245 | 98 | | 13 |
| 10002 | 0 | 42 | 23 | | 6 |
| | Target | | Pr | e <mark>dictors</mark> | |



10 Datasets: One each for 9 picked brands from given data plus Shake Shack, which we scraped from its website.

| | ZipCode | IfStore | Mosaic Seg 1 | Mosaic Seg 2 | Mosaic Seg | Mosaic Seg 71 |
|--|---------|---------|--------------|--------------|------------|---------------|
| | 10001 | 0 | 245 | 98 | | 13 |
| | 10002 | 0 | 42 | 23 | | 6 |



Binary Target: To predict classification of ifSuitable, we turned count into binary ifStore.

.....



Pipeline – Resampling

We customized a resampling technique that prevents bias caused by one major problem using simple down-sampling.

No What-A-Burger



Brooklyn

Similar Demographics Difference caused by unobserved reasons*



Has What-A-Burger



Dallas

*Note: Distribution Strategy, What-A-Burger only sell in southern states



Pipeline – Resampling

We customized a resampling technique that random selects one nearby datapoint by zip location for each minority class point*

No What-A-Burger



Fort Worth

Eliminating Unobserved Influence

No Bias

Has What-A-Burger



Dallas

*Note: (ifStore = 1)



Pipeline – Model Tuning

Random Forest

Used Random Forest based on the nature of mass production and relatively high dimensionality

Hyperparameter Tuning

Models are tuned using a set of optimal parameters to optimize accuracy

Full Automation

Our pipeline, including tuning, is total automatized given the right data format

Tuning Example



| | Actual | | | | | | |
|-----------|--------------|--------------|----------|--|--|--|--|
| Predicted | | Not Suitable | Suitable | | | | |
| | Not Suitable | 40.56% | 3.27% | | | | |
| | Suitable | 9.44% | 46.73% | | | | |

87% Accuracy
High False Positive Rate
Low False Negative Rate



Pipeline Result – Suitability Matrix

Interpretation:

Model predicts 86% probability that Bahama Breeze is suitable in Zip Location 14610

Fully Expandable

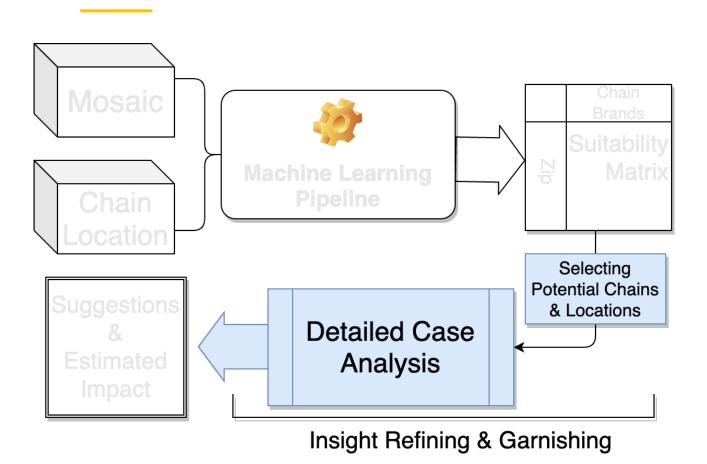
Our model pipeline works for every retailer or restaurant chain

| 14602 | 5% | 1% | 7% | 3% | 15% | 3% | 32% | 5% | 1% | 4% |
|-------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 14603 | 4% | 0% | 5% | 2% | 12% | 0% | 8% | 1% | 17% | 1% |
| 14604 | 39% | 9% | 72% | 19% | 49% | 36% | 66% | 43% | 13% | 57% |
| 14605 | 34% | 11% | 38% | 6% | 41% | 23% | 39% | 29% | 34% | 39% |
| 14606 | 54% | 34% | 28% | 14% | 36% | 24% | 21% | 19% | 61% | 53% |
| 14607 | 46% | 63% | 97% | 60% | 76% | 69% | 77% | 79% | 51% | 86% |
| 14608 | 31% | 23% | 83% | 34% | 49% | 60% | 59% | 63% | 38% | 73% |
| 14609 | 60% | 49% | 37% | 28% | 52% | 37% | 23% | 33% | 47% | 51% |
| 14610 | 71% | 86% | 93% | 90% | 65% | 89% | 75% | 89% | 43% | 85% |
| 14611 | 20% | 14% | 28% | 8% | 27% | 21% | 24% | 12% | 34% | 39% |
| 14612 | 69% | 56% | 26% | 47% | 68% | 27% | 12% | 59% | 36% | 37% |
| 14613 | 36% | 15% | 26% | 11% | 42% | 15% | 26% | 13% | 56% | 43% |
| 14614 | 12% | 1% | 22% | 2% | 15% | 4% | 32% | 5% | 4% | 10% |
| 14615 | 40% | 23% | 28% | 12% | 34% | 20% | 18% | 19% | 72% | 45% |
| 14616 | 53% | 35% | 20% | 21% | 51% | 19% | 16% | 16% | 46% | 31% |
| 14617 | 57% | 39% | 23% | 36% | 59% | 27% | 21% | 31% | 49% | 38% |
| 14618 | 74% | 96% | 63% | 80% | 68% | 92% | 72% | 93% | 33% | 88% |
| 14619 | 26% | 9% | 11% | 5% | 23% | 11% | 20% | 5% | 38% | 26% |
| 14620 | 41% | 78% | 79% | 51% | 64% | 72% | 62% | 74% | 53% | 86% |
| 14621 | 30% | 17% | 35% | 14% | 35% | 25% | 28% | 23% | 45% | 50% |
| 14622 | 28% | 20% | 20% | 18% | 26% | 13% | 13% | 11% | 20% | 23% |
| 14623 | 47% | 46% | 45% | 32% | 54% | 45% | 28% | 52% | 45% | 74% |
| 14624 | 65% | 47% | 17% | 35% | 63% | 18% | 4% | 43% | 43% | 32% |
| 14625 | 38% | 43% | 15% | 49% | 26% | 35% | 17% | 34% | 18% | 30% |
| 14626 | 73% | 46% | 17% | 37% | 66% | 19% | 6% | 44% | 40% | 36% |
| 14627 | 0% | 3% | 9% | 3% | 43% | 2% | 9% | 1% | 0% | 2% |
| 14692 | 3% | 6% | 6% | 7% | 15% | 5% | 21% | 7% | 4% | 9% |

Zip_Code Baskin_Robbins Bahama_Breeze Capital_Grille Eddie_V Panda_Express Seasons_52 Shake_Shack Smashburger WhatABurger Yard_House



Phase 2 – Case Analysis



Goal

Further analyze selected results from pipeline to retrieve insights that can influence decision makers

Process

1. Select Top Zip Codes & Chains
Interpret the suitability matrix and select
potential combinations

2. Case-by-case Analysis

Conduct case-by-case analysis based on strategy and potential revenue



Case Analysis – Pipeline Result

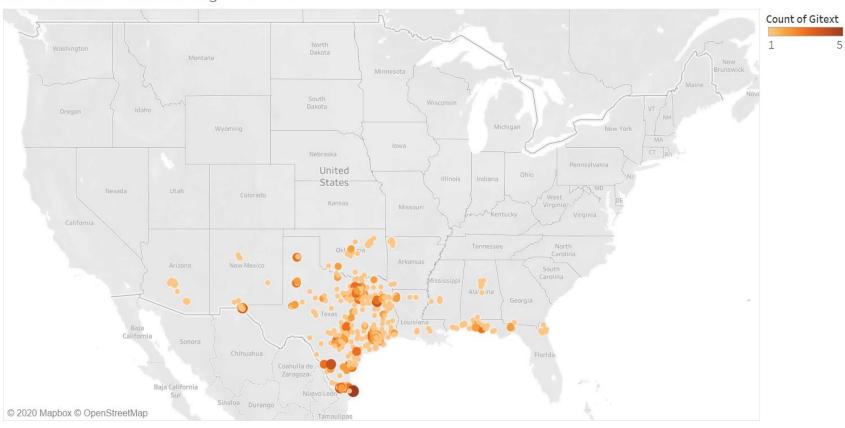
According to the suitability matrix, we selected the locations which have high suitability for the restaurant chains:

| Zipcode | BR paskin robbins | Bahama Breeze. ISLAND GRILLE | T H E CAPITAL G · R · I · L · L · E | Eddie V's | CHINESE KITCHE | Sqasom, | SHAKE SHACK* | SMASH BURGER | WHATABURGER | Yard House |
|---------|-------------------|------------------------------------|---------------------------------------|-----------|----------------|----------|--------------|-----------------|-------------|------------|
| 14607 | | | / | | V | | / | | | ~ |
| 14610 | | | / | | | | | | | |
| 14615 | | | | | | | | | V | |
| 14618 | | | | | | / | | / | | ~ |
| 14626 | | | | | | | | | | |



Case Analysis – Strategy Concern

Distribution of Whataburger in the US



What-A-burger's business strategy means it has **low probability** to settle in Rochester, although Rochester has high suitability.

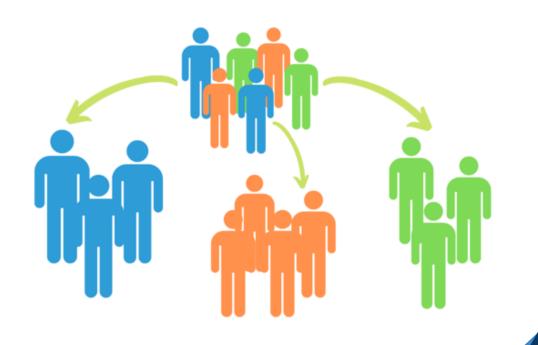


Reason

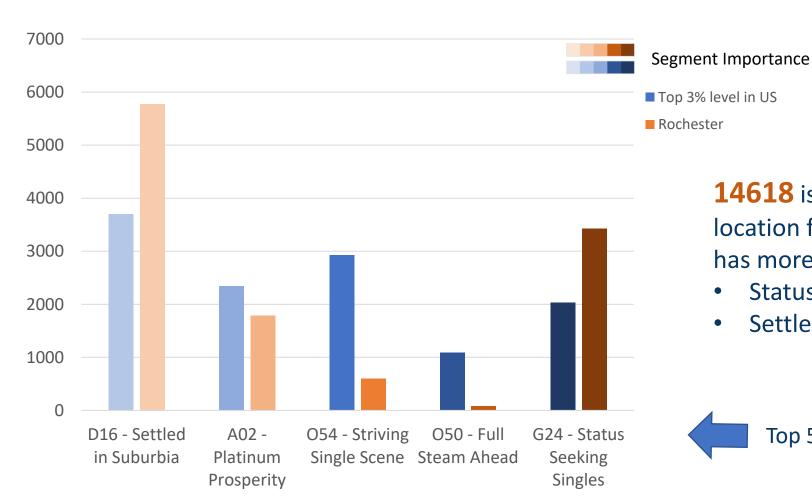
To verify the targeted location can bring satisfiable revenue, we need to make sure it has **ample potential customers**.

Method

Explore segments which have **high** correlation with the number of each restaurant brand.







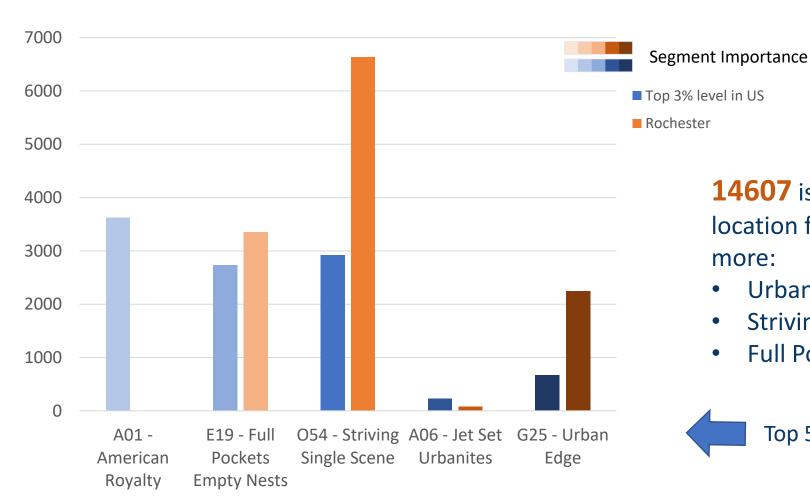


14618 is a standout profitable location for Bahama Breeze, since it has more:

- **Status Seeking Singles**
- Settled in Suburbia







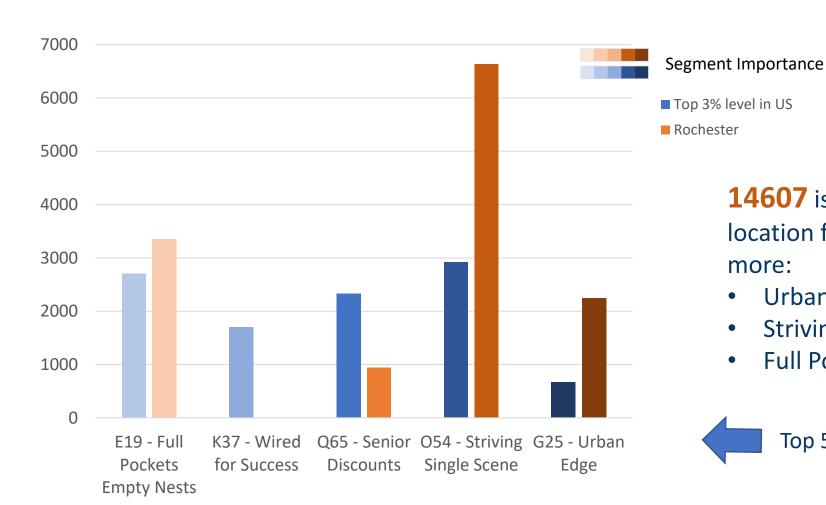


14607 is a standout profitable location for Capital Grille, since it has more:

- **Urban Edge**
- Striving Single Scene
- **Full Pockets Empty Nests**







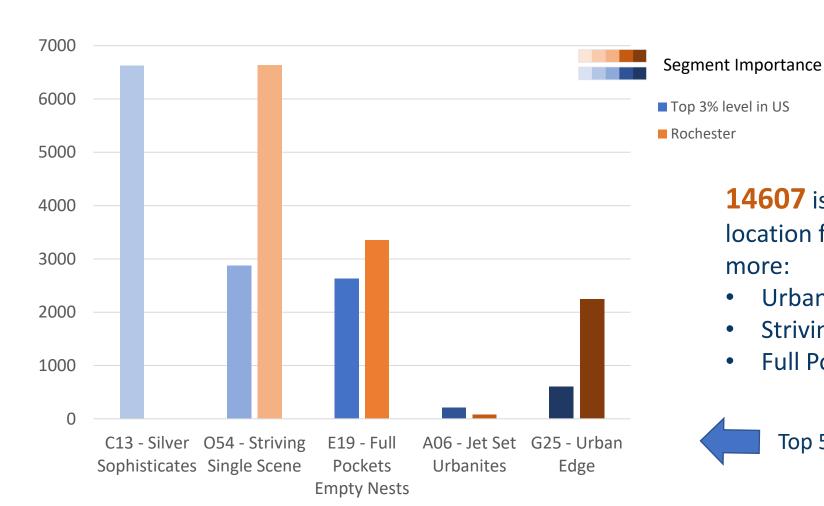


14607 is a standout profitable location for Yard House, since it has more:

- **Urban Edge**
- Striving Single Scene
- **Full Pockets Empty Nests**









14607 is a standout profitable location for Shake Shack, since it has more:

- **Urban Edge**
- Striving Single Scene
- Full Pockets Empty Nests





Case Analysis Result

| | _ | |
|-------|-------|-----------------|
| Docto | urant | Chain |
| RESIA | шаш | UHAIII |
| | MIMIL | U IIUIII |

Suitable Location



Yard House

14607



Shake Shack

14607



The Capital Grille

14607

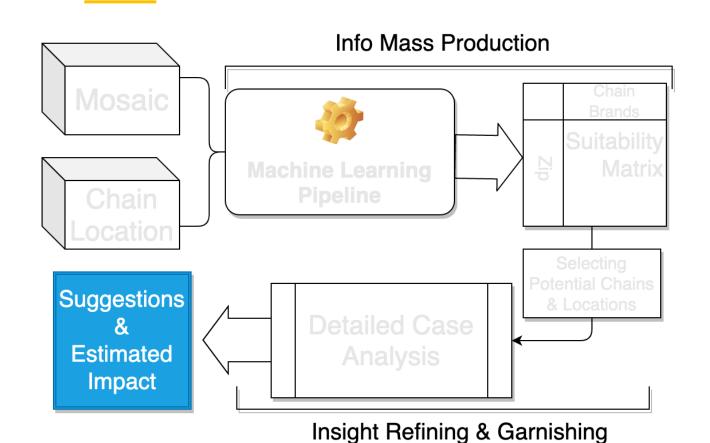


Bahama Breeze

14618



Final Recommendation



Goal

Summarize our findings and provide our own recommended findings that the City of R can use to influence decision-makers



Final Recommendation – Financials

- Revenue Forecast Achieve average
- Cost Forecast Lower than average

Server salary (per hour)



Rent (per square feet per year)





Final Recommendation – Financials

| | Revenue | Cost | Annual Profit | Initial Cost | Break-Even Point | Num of Employees |
|-------------------|-------------|-------------|---------------|--------------|---------------------|---------------------|
| Yard House | \$7,343,373 | \$6,625,033 | \$718,339 | \$2,096,775 | 2.9 yrs | 10 |
| Capital Grille | \$8,389,090 | \$7,568,458 | \$820,633 | \$2,395,362 | 2.9 yrs | 11 |
| Bahama Breeze | \$5,869,047 | \$5,294,928 | \$574,118 | \$1,675,807 | 2.9 yrs | 11 |
| Shake Shack | \$3,196,338 | \$3,059,274 | \$138,091 | \$296,680 | 2.1 yrs | 20 |









Final Recommendation – Store Address





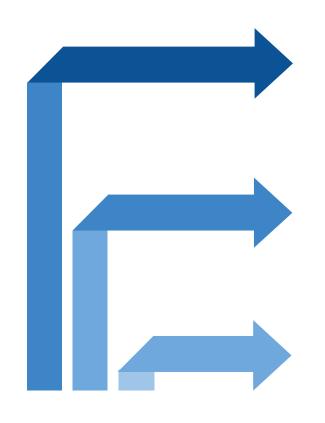
Possible Addresses

All recommended locations are owned by City of Rochester – Allow flexibility of rent decided by the city.

*Note: 250 Science Pkwy is technically in 14620 but is only a few blocks away from 14618.



Consolidated Recommendations



ML Pipeline

- Used to find potential locations for 10 brands
- Recommend applying this pipeline to any interested businesses

Case Analysis Findings

- Found four top-tier brands with optimal ROC locations
- The City can use our findings to persuade chains restaurants' decision makers or conduct further research

Financials & Addresses

- The most direct evidences to the decision makers
- Recommend the City to present these evidences to the chains' decision makers

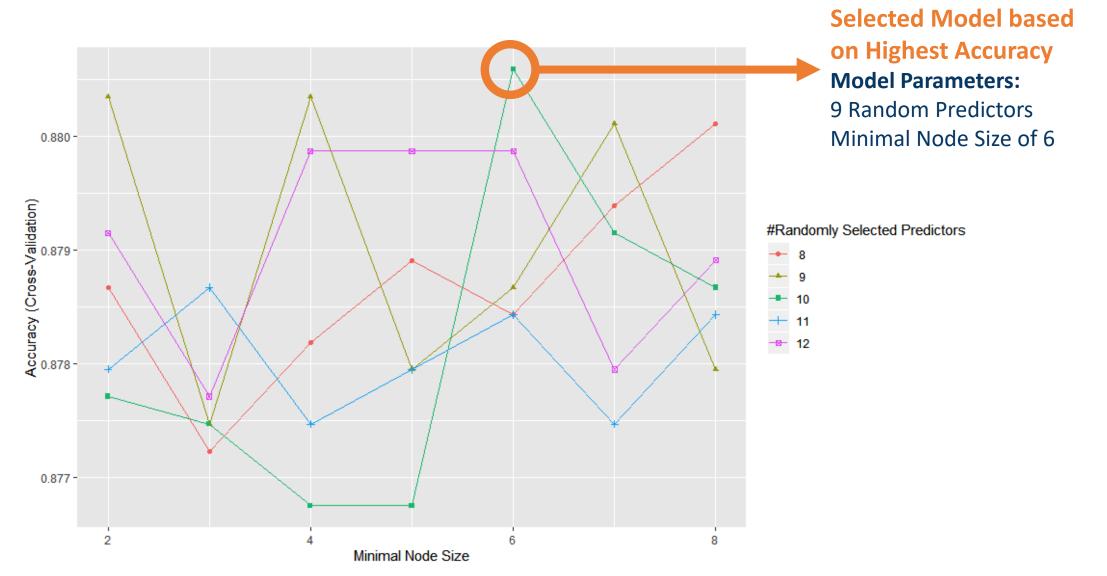
Lastly...

We hope the City of Rochester can use our project results to convince the restaurant decision-makers to invest in the local communities.



Thank you!







Current:

- Binary Classification
- Predict if a location is suitable?

Explained in the slides.



Original Design:

- Integer Regression
- Predict the degree of suitability.

Due to the problem with the distribution of restaurants count (the target), we have to use zero-inflated poisson regression to fit the model properly. However, we don't have enough data points to complete model fitting.