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## Predicting Private Market Twin Cities Rents

**Final Presentation** 



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## Today's Discussion

#### **Given Scope** Final Project Scope

**Brief overview of the project definition process** 

#### Dashboard

□ A walkthrough, use case of the rental prediction dashboard

#### **D** Model Review

**Data quality, model selection, model validation** 

#### **Deployment**

Hosting the dashboard and transferring the tool

#### Potential Future Work

**General Refreshing the data, adding features** 

### Appendix



## How project scope has evolved over time





# How we're helping HousingLink and advocates achieve their mission

#### Solution

- Aggregation of multiple private and public data sources to create:
  - Historical rents for location of interest
  - Predicted rents for next 3-year period
- Interactive dashboard with multiple visualizations
   for different analyses and geographies

• Focus on maintenance (e.g., updating with future data)



## Predictions are built from user and fixed inputs







# How we're helping HousingLink and advocates achieve their mission

#### Solution

- Aggregation of multiple private and public data sources to create:
  - Historical rents for location of interest
  - **Predicted rents** for next 3-year period
- Interactive dashboard with multiple visualizations for different analyses and geographies

• Focus on maintenance (e.g., updating with future data)

#### Benefits

- Rent prices can inform policy discussions and investment decisions
- Robust & accurate 3-year predictions
- A centralized dataset to explore further





## **Dashboard Demonstration**





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## Understanding the Process



The process is sequential as each stage relies on the last to produce robust results







We hypothesized education, population, macroeconomics and investment drive rents





# Of those influential factors we collected these variables as proxies

Variable Name	Source
Average Annual Household Income	American Community Survey
Percent Bachelor's Attained	American Community Survey
Population Growth Rate	American Community Survey
Weighted Median Rent	HousingLink
Subsidized Units at Different AMI Levels	HousingLink
Annual Residential Permit Value (\$)	Metropolitan Council
Annual Non Residential Permit Value (\$)	Metropolitan Council
Small Area Housing Estimates	Metropolitan Council
U3 Unemployment Rate	St. Louis Federal Reserve
S&P 500 Index Value	St. Louis Federal Reserve





# We collected, cleaned and then aggregated the data from the tract level







# We tested 4 different learning models across 7 different geographies to find the best model





# Support vector regression minimizes error across different geographic levels

Supervised Learning Model	Avg. Difference from Actual
Baseline	\$143.88 <b>24% better than baseline</b>
Lasso Regression	\$138.13
K-Nearest Neighbors Regression	\$129.53
Random Forest Regression	\$121.51 <b>10% better than next best</b> learning model
Support Vector Regression	\$110.22



# Rent and education give the most predictive power while keeping the model simple

Variable Name	Source
Average Annual Household Income	American Community Survey
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Weighted Median Rent	HousingLink
Subsidized Units at Different AMI Levels	HousingLink
Annual Residential Permit Value (\$)	Metropolitan Council
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### Model performance in Longfellow illustrates potential future accuracy





### Downtown illustrates that predictions are not linear extrapolation







# Our dashboard is driven by R Studio and hosted by R Shiny





### Benefits

Free tier, 25 hours per month

Fast, responsive performance

Refresh without altering code

User metrics and system up time

The opportunity to increase resources and available hours at any time



# The tool works because each step is carefully built off the last





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## Final Logistics and Next Steps

## **Deployment Plan**





## Possible future enhancements

Enhancement	Difficulty
Refresh data with 2018 values	Moderate
Handle 2020 census tract redefinitions	High
Allow users to export data from dashboard	Moderate
Embed the app within a website	Moderate
Explore causal relationship between affordable housing and market units in relation to rent further	High



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## Thank You

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# Appendix

## How does a simple predictive model work?

We fit a line on the values of education and rent that we have observed

This gives us slopes or "effects" for the values

education = \$200 "for every 1% increase in education rent increases by 200 \* 1% dollars"

rent = \$1.2 "for every \$1 increase in previous rent, future rent
increases by \$1.2"

When we get an unseen data point e.g. education = 90% and rent = \$800 we just multiply each value by its slope and add them together:

200 \* (0.9) + 1.2 \* (800) = \$1,140 (prediction)





## Dashboard User Guide [Video]

A brief walkthrough of the dashboard and its features

#### https://youtu.be/9Rix05p2n9c



HousingLink Rent Predictor User Guide

