



Forecasting Grocery Sales with Regression Models and Random Forests



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Introduction

- Finite supply
- Perishable



How to predict demand?

Corporacion Favorita

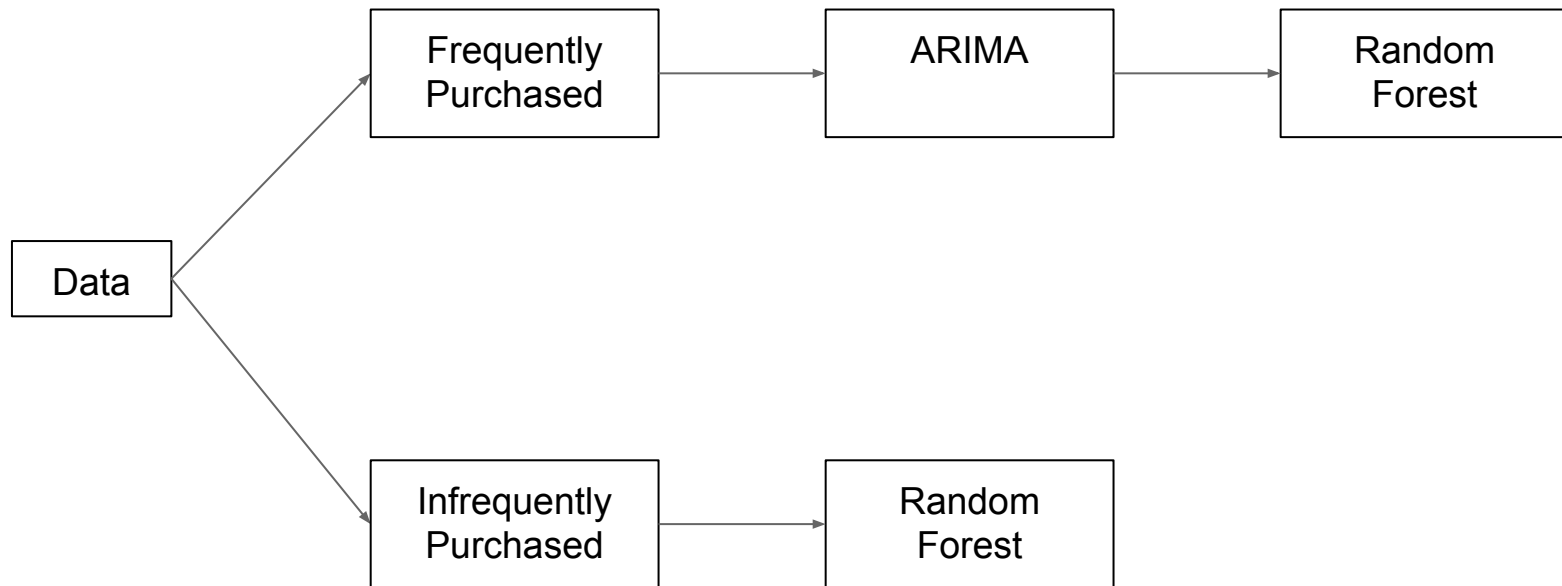
- 54 stores
- 200,000 items
- 125M transactions



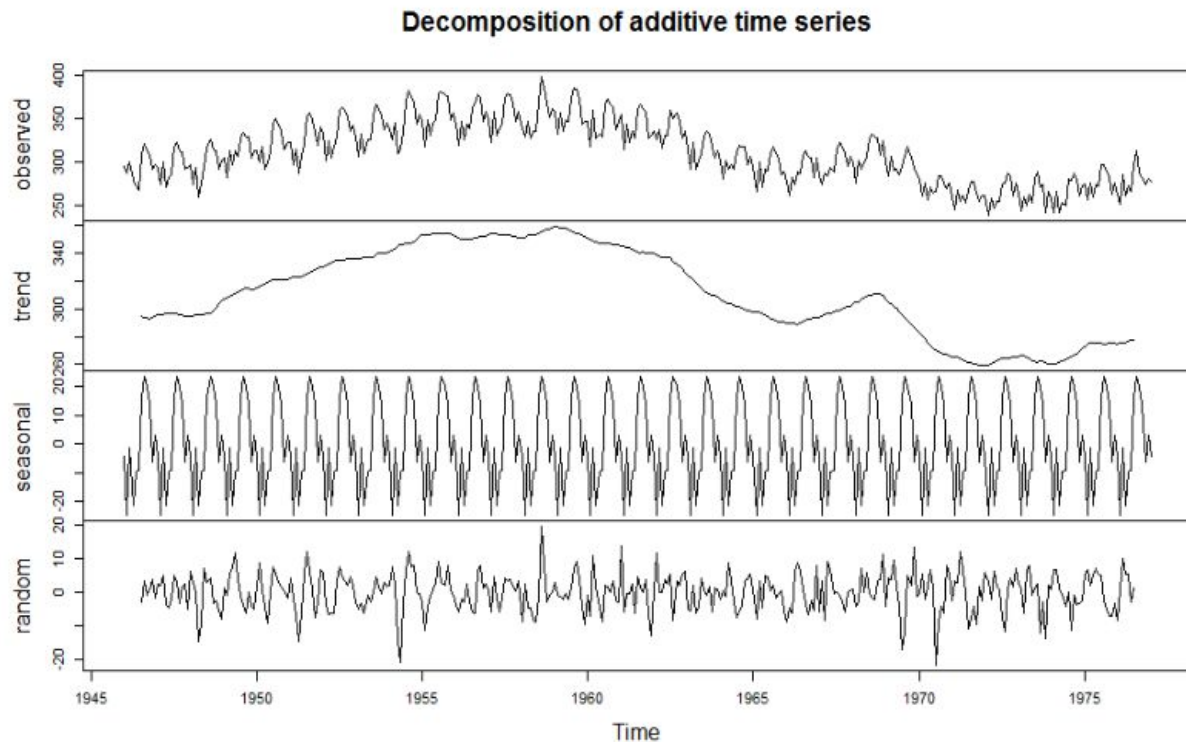
Datasets & Wrangling

- Items - type
- Stores - location, cluster
- Oil - date, price
- Train/Test Data - item number, store number, date → **sales**
 - Joined tables
 - Converted categorical to binary
 - Added numerical variable: days since payday

Dual Model Pipeline



Time Series Forecasting

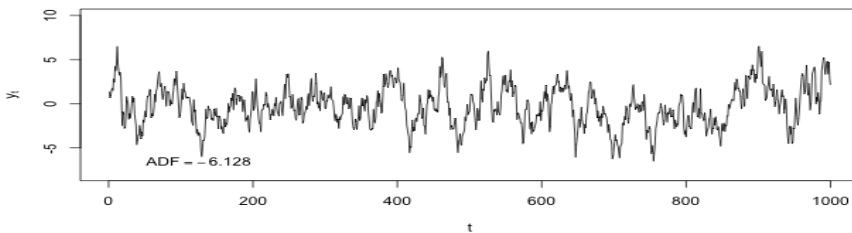


The ARIMA Model Equations

AR

$$Y_t = \alpha + \rho Y_{t-1} + e_t$$

I

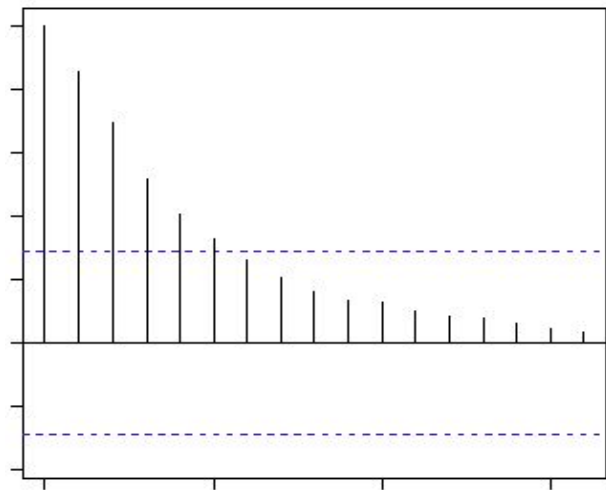


MA

$$Y_t = \alpha + \rho e_{t-1} + e_t$$

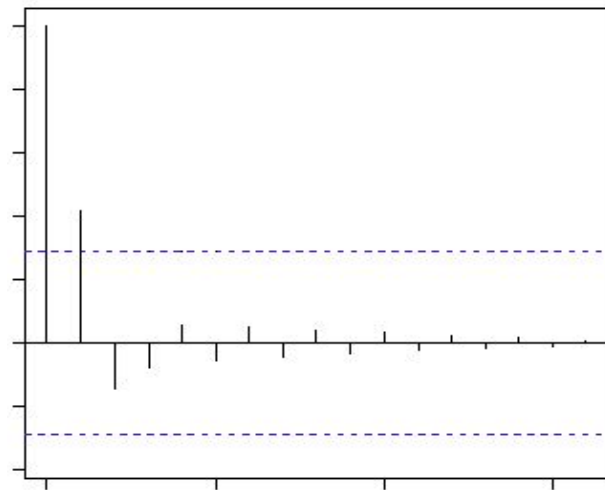
The ARIMA Model Choice

AR

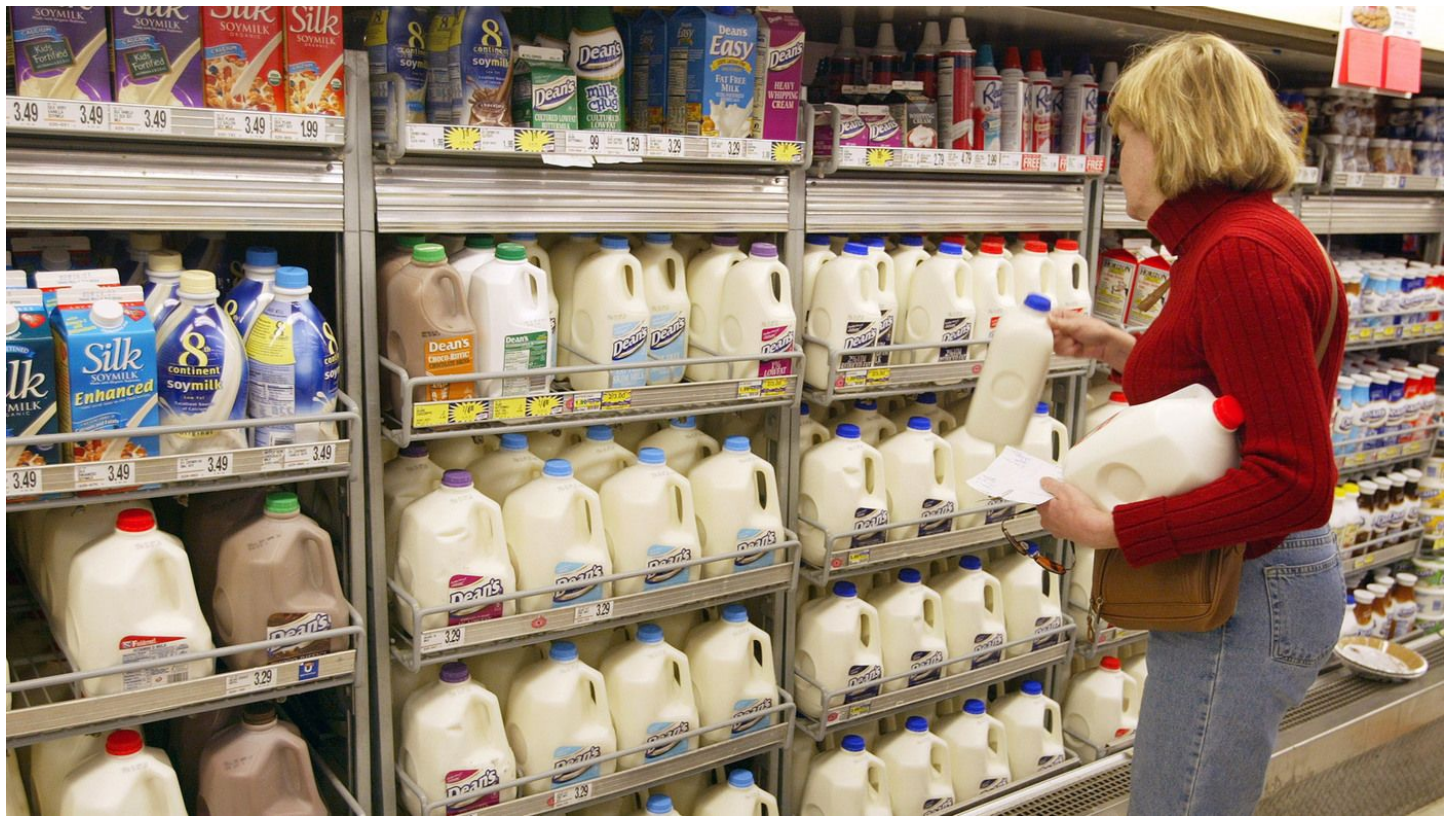


← ACF
Plots →

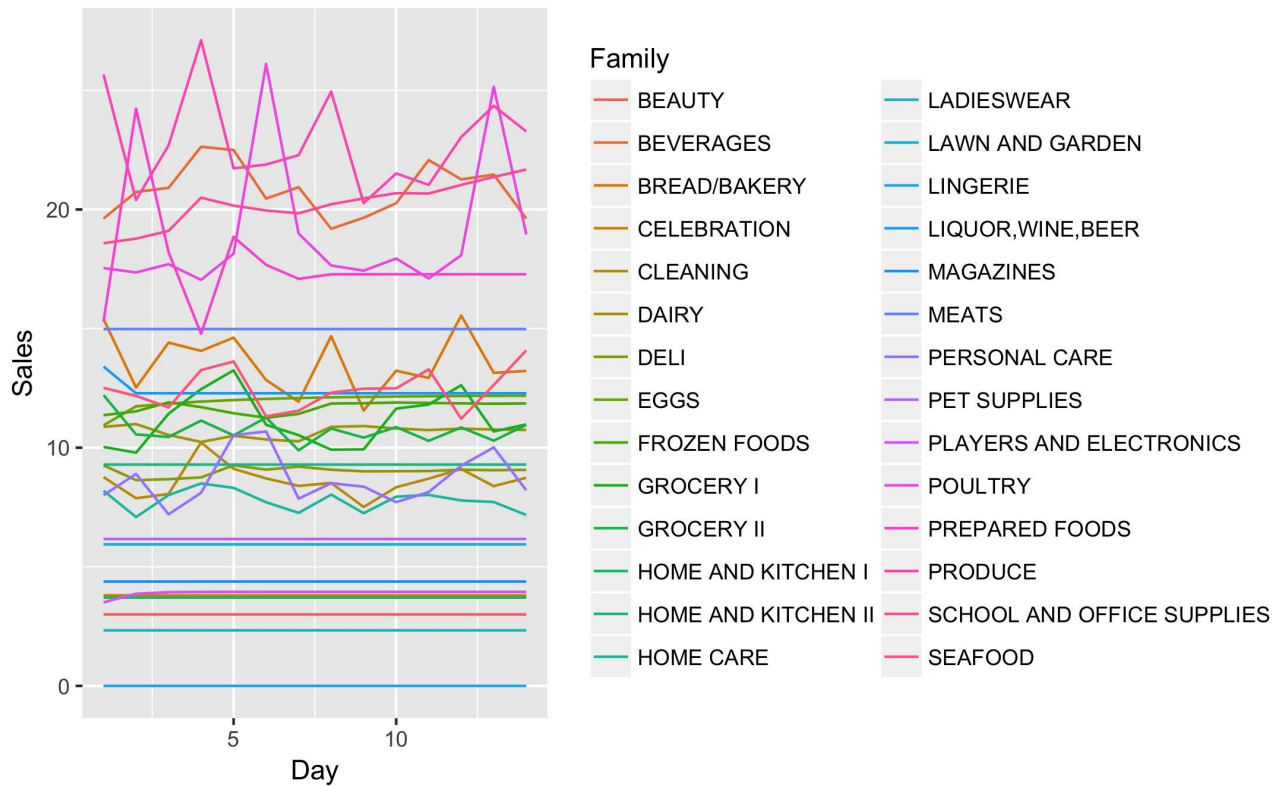
MA



Popularity



ARIMA Forecast



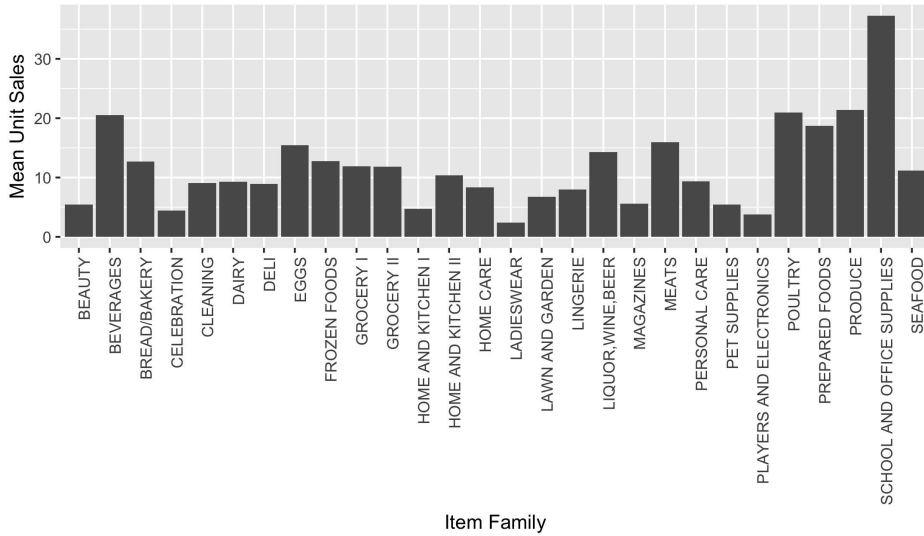
Random Forest Creation

Variables Included:

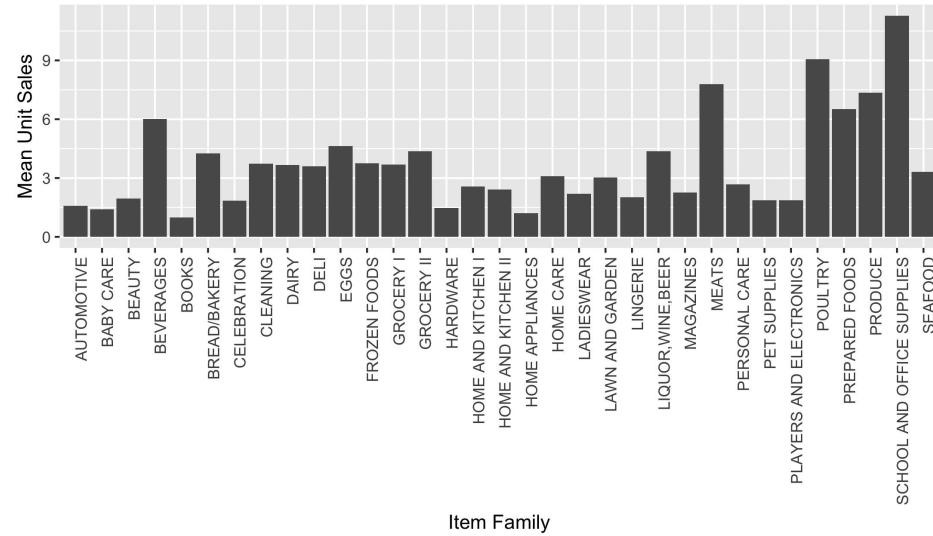
- Item Family
- Store City
- Store Cluster
- Store Type
- Day of Week
- Days Since Payday
- Popularity

Item Family

Effect of Item Family for Highly-Transacted Items

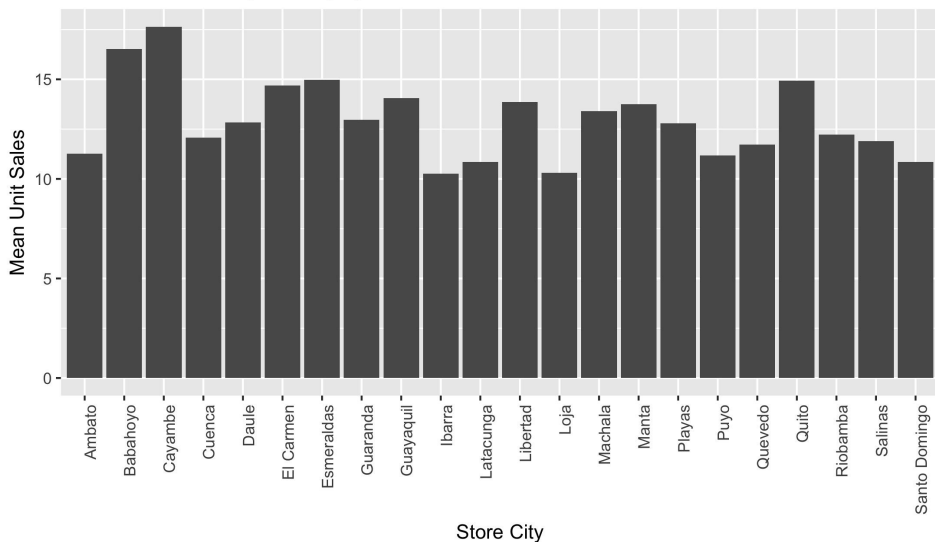


Effect of Item Family for Non-Highly-Transacted Items



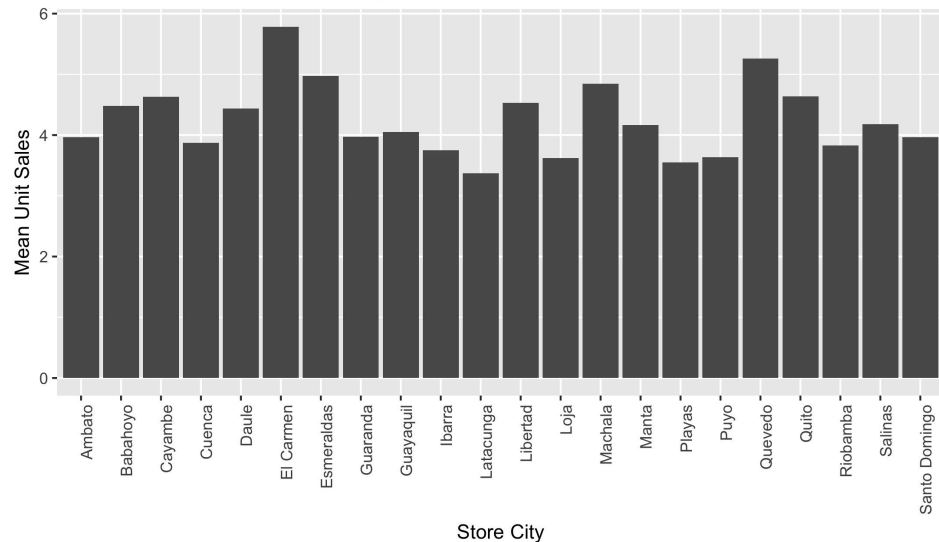
Store City

Effect of Store City for Highly-Transacted Items



Store City

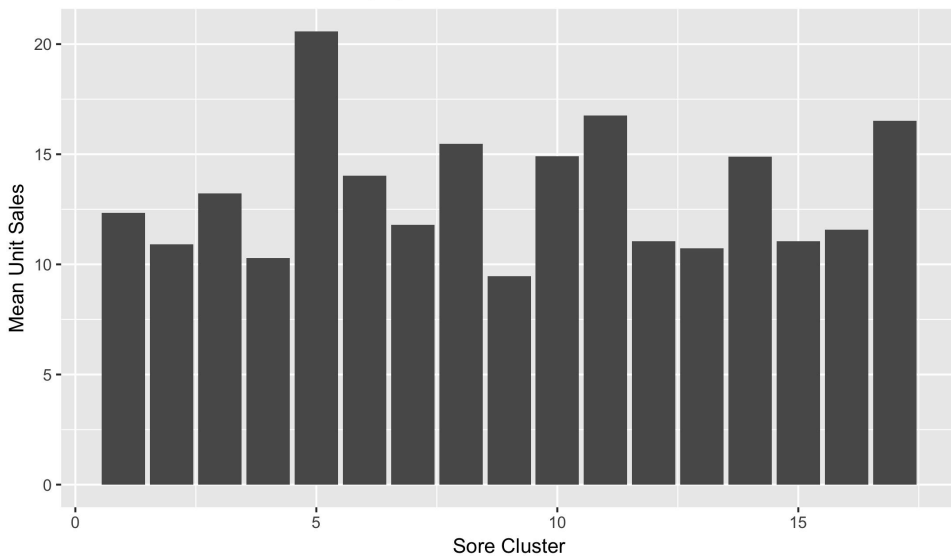
Effect of Store City for Non-Highly-Transacted Items



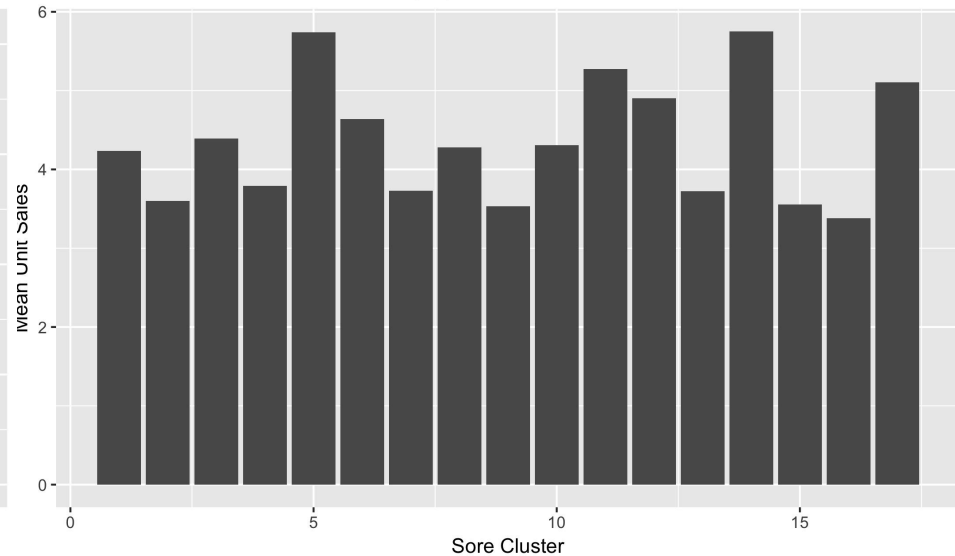
Store City

Store Cluster

Effect of Store Cluster for Highly-Transacted Items

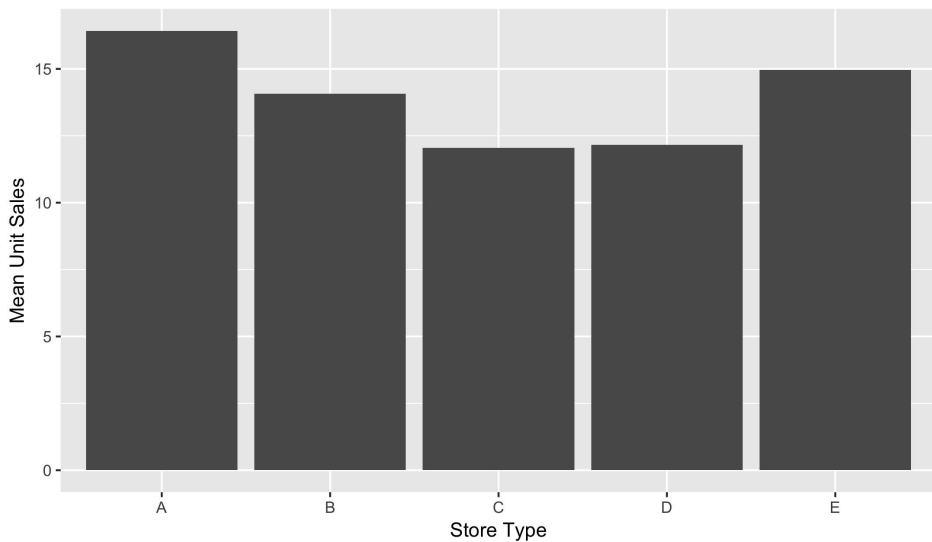


Effect of Store Cluster for Non-Highly-Transacted Items

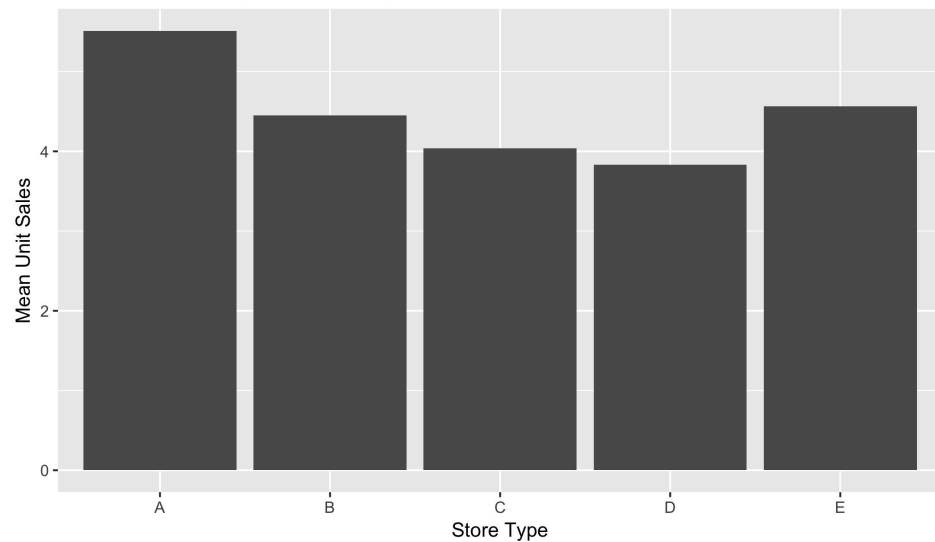


Store Type

Effect of Store Type for Highly-Transacted Items

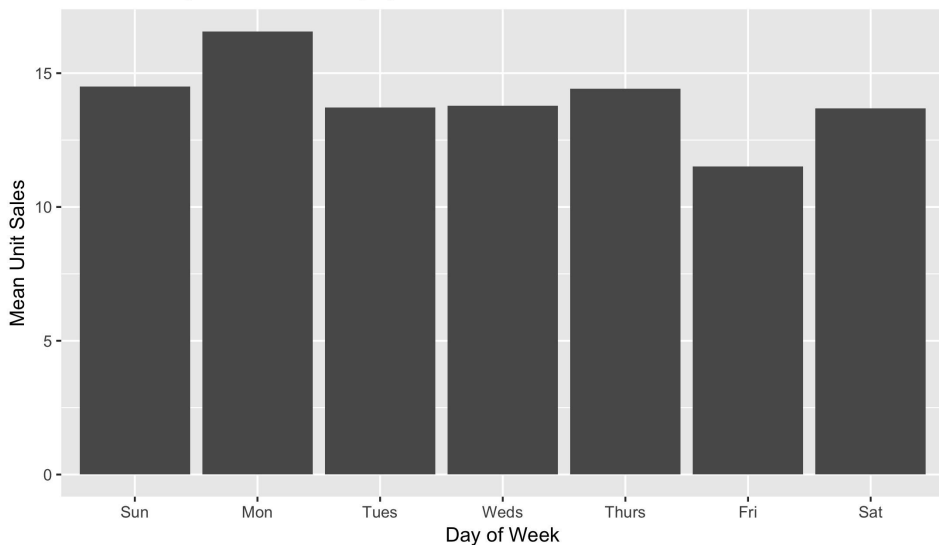


Effect of Store Type for Non-Highly-Transacted Items

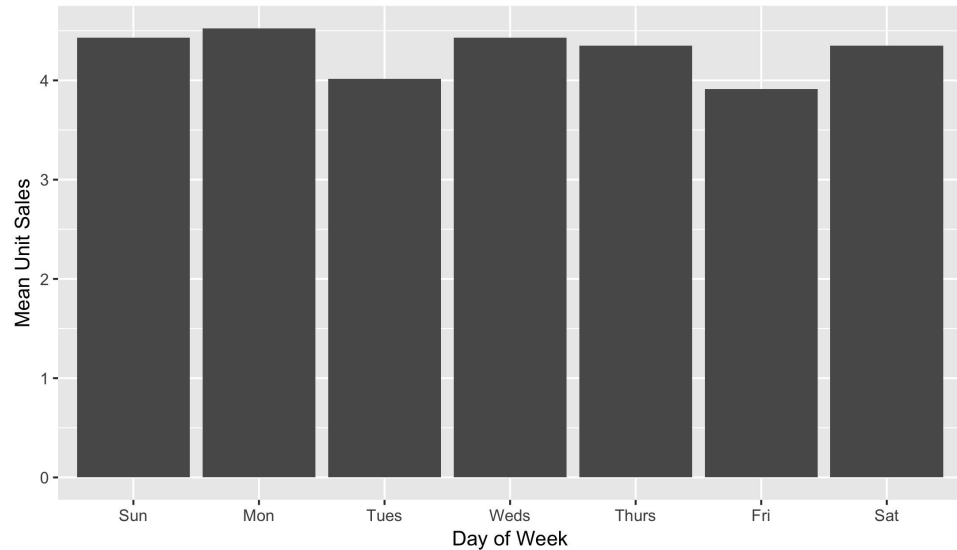


Day of Week

Effect of Day of Week for Highly-Transacted Items

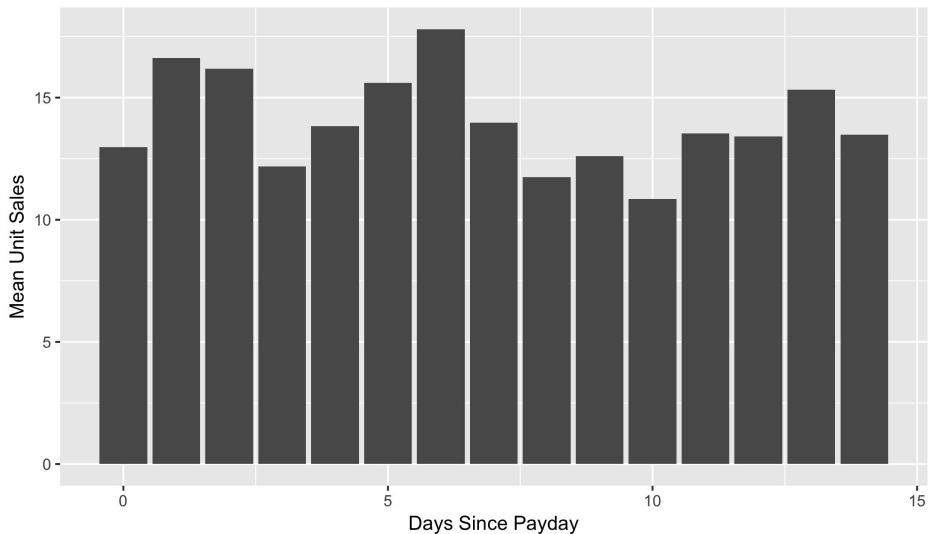


Effect of Day of Week for Non-Highly-Transacted Items

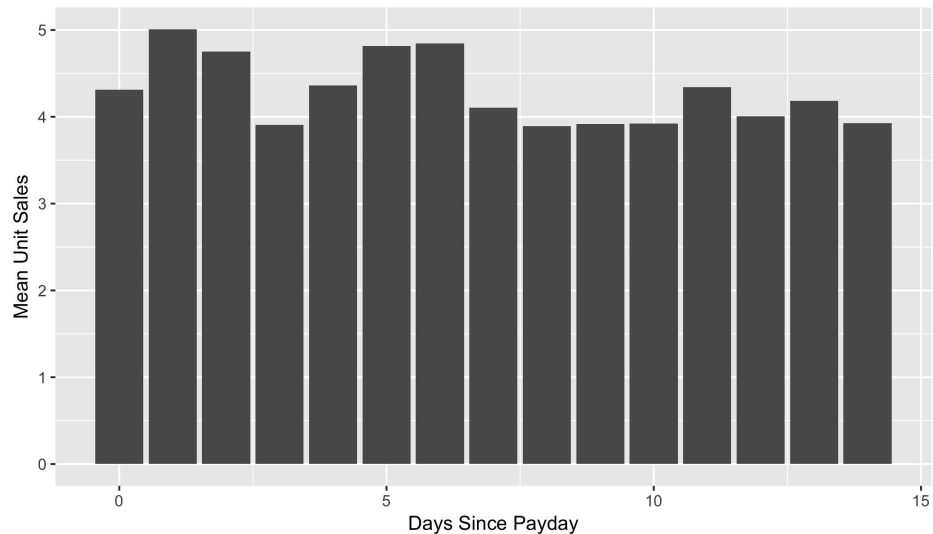


Days Since Payday

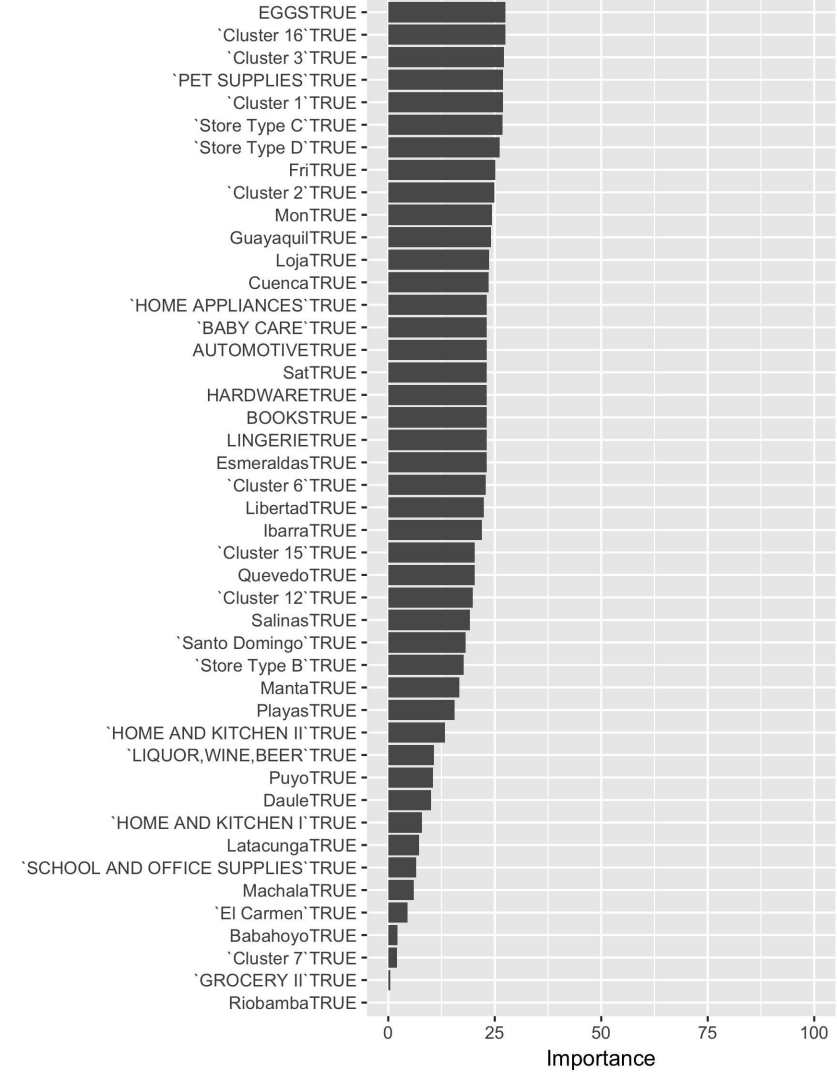
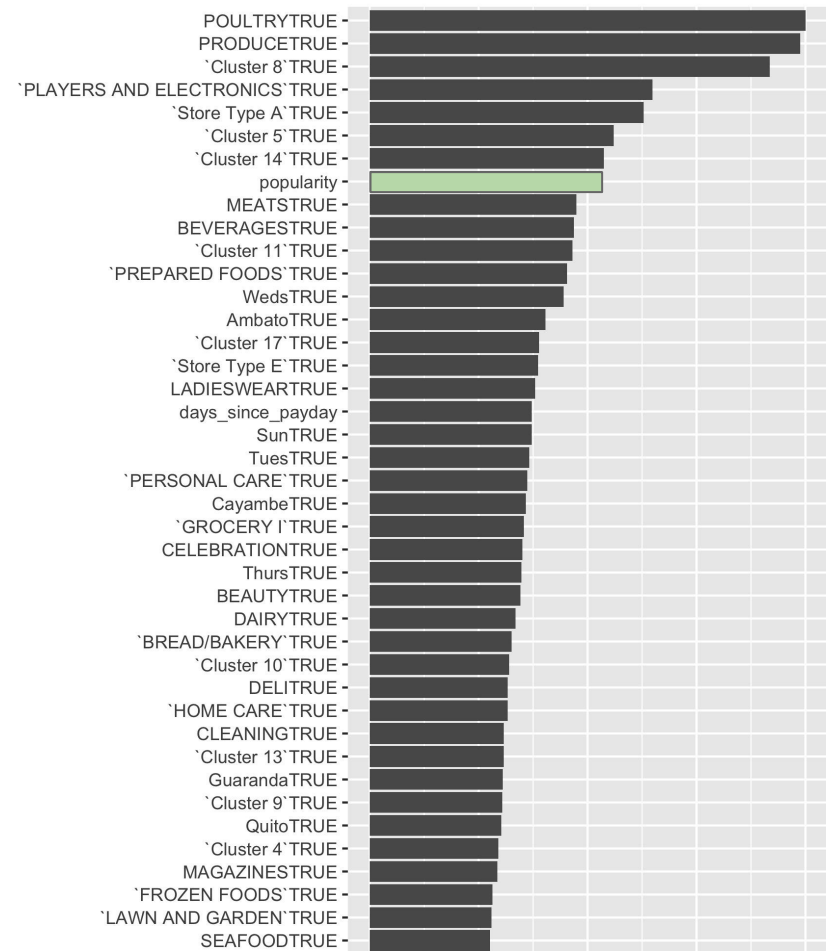
Effect of Days Since Payday for Highly-Transacted Items



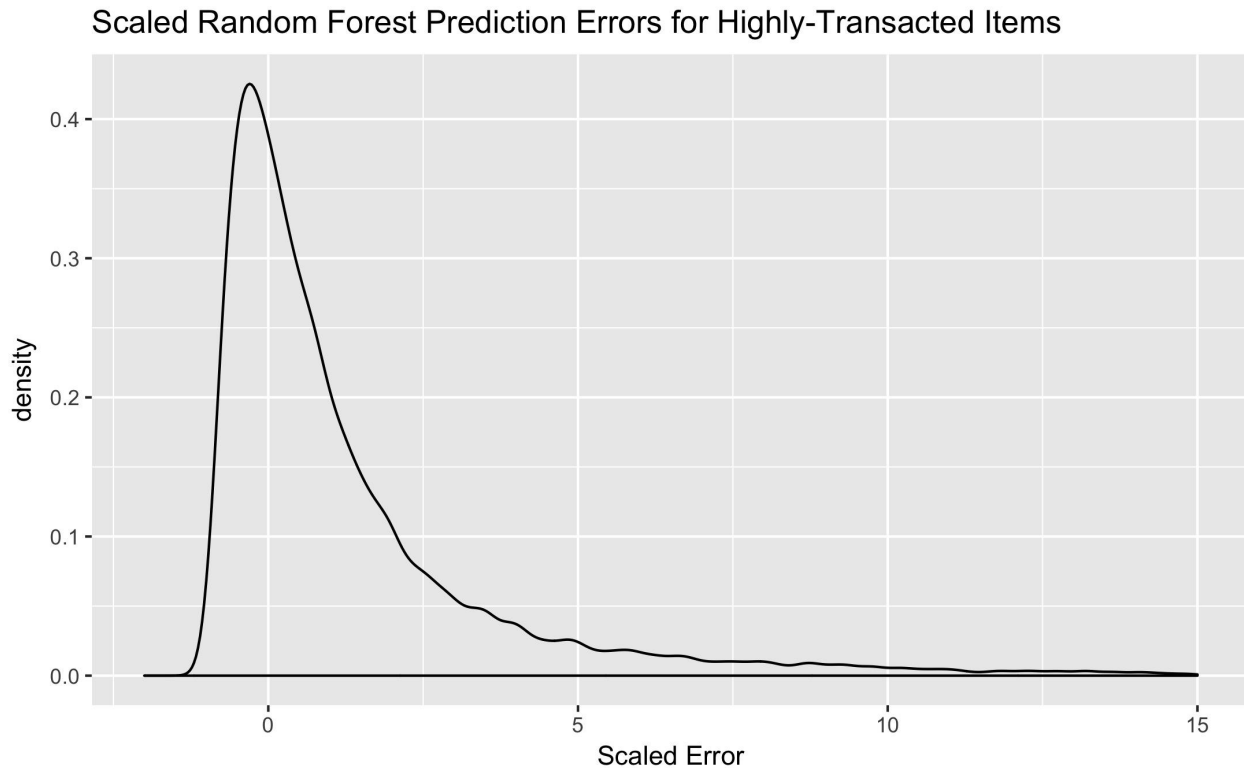
Effect of Days Since Payday for Non-Highly-Transacted Items












Results: Variable Importance



Results - Prediction Errors



Results: Kaggle

933	▼ 153	Matheus Facure		1.294
934	▼ 153	Yosuke Abe		1.295
935	▼ 153	rjuer		1.295
936	▼ 153	Jeffrie		1.295
937	▼ 153	Anjukan Kathirgamanathan		1.299
938	▼ 153	mhaulrich		1.303
939	new	Victor de Fefontnouvelle		1.307
940	▼ 106	Magic Logic		1.309
941	▼ 154	tomgrek		1.310

1036 Teams Total

Potential Improvements

- **0.25% of training set used**
- Add data for no sales
- Incorporate other datasets
 - Holiday
 - Weather
 - Economy