Store Sales Times Series Forecasting

Capstone Final Presentation
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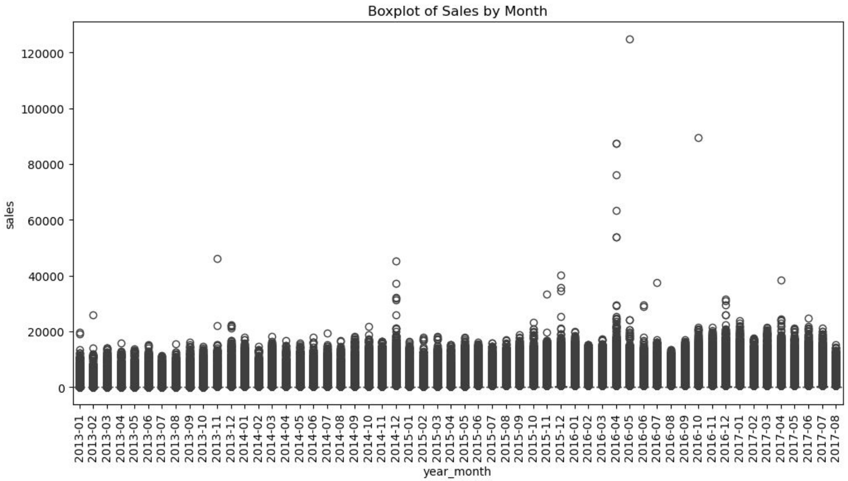
Introduction

Corporación La Favorita is one of Ecuador's largest corporations, operating across various industries.

This project focuses on analyzing historical daily sales data (2013-2017) from Corporación La Favorita.

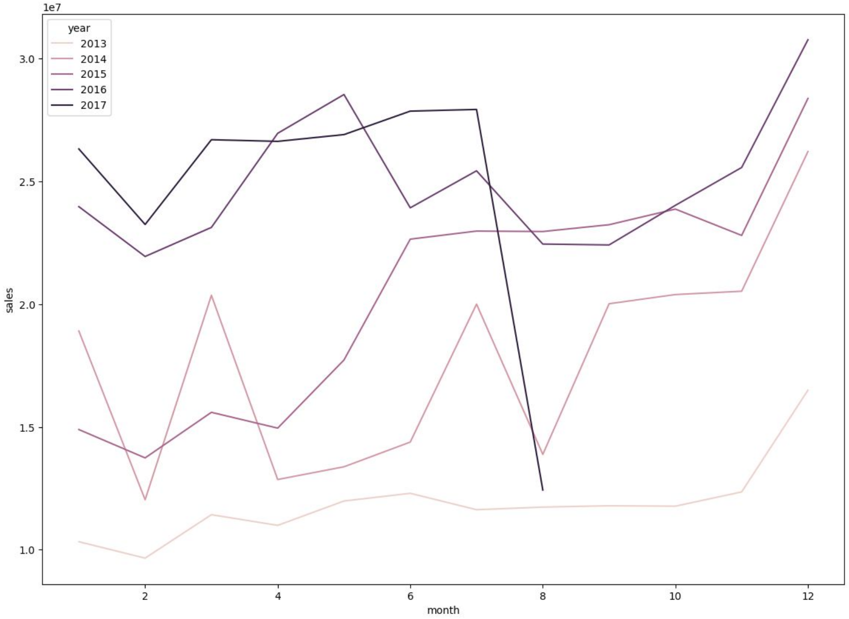
The goal is to build a predictive model to forecast future sales trends



Problem Statement

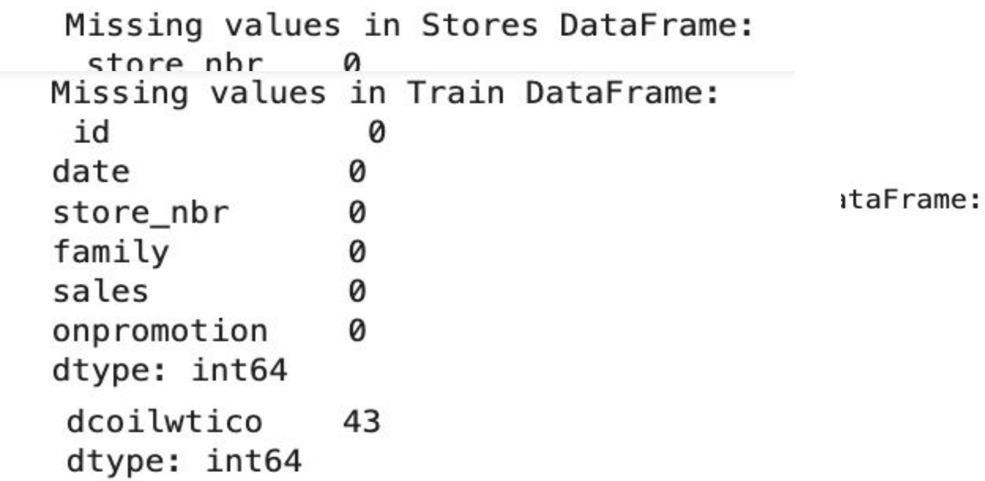
Can we accurately predict future sales trends using large volumes of historical data?

Test: developing and evaluating Time Series Model to analyze forecast sales trends from 2013 to 2017.



Data Overview

- train.csv: Historical sales data
- test.csv: Test data for sales
- oil.csv: Daily oil prices
- holidays_events.csv: Holidays and events metadata
- stores.csv: Store information



```
Missing values in Stores DataFrame:
 store_nbr     0
```

```
Missing values in Train DataFrame:
 id             0
date           0
store_nbr      0
family         0
sales          0
onpromotion    0
dtype: int64
```

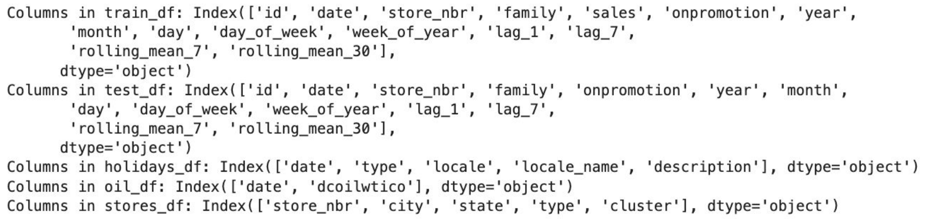
```
ataFrame:
```

```
 dcoilwtico    43
 dtype: int64
```

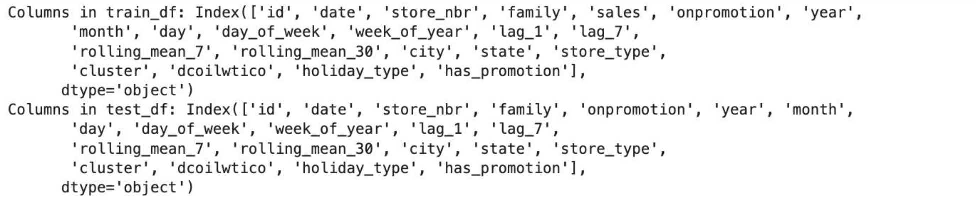
Data Reshaping and Wrangling

The raw data files included columns with varying formats and inconsistencies such as: missing oil prices, holidays_df date format, or unnecessary columns.

Data from the multiple files provided needed merging for consistency and analysis.



```
Columns in train_df: Index(['id', 'date', 'store_nbr', 'family', 'sales', 'onpromotion', 'year',
       'month', 'day', 'day_of_week', 'week_of_year', 'lag_1', 'lag_7',
       'rolling_mean_7', 'rolling_mean_30'],
      dtype='object')
Columns in test_df: Index(['id', 'date', 'store_nbr', 'family', 'onpromotion', 'year', 'month',
       'day', 'day_of_week', 'week_of_year', 'lag_1', 'lag_7',
       'rolling_mean_7', 'rolling_mean_30'],
      dtype='object')
Columns in holidays_df: Index(['date', 'type', 'locale', 'locale_name', 'description'], dtype='object')
Columns in oil_df: Index(['date', 'dcoilwtico'], dtype='object')
Columns in stores_df: Index(['store_nbr', 'city', 'state', 'type', 'cluster'], dtype='object')
```



```
Columns in train_df: Index(['id', 'date', 'store_nbr', 'family', 'sales', 'onpromotion', 'year',
       'month', 'day', 'day_of_week', 'week_of_year', 'lag_1', 'lag_7',
       'rolling_mean_7', 'rolling_mean_30', 'city', 'state', 'store_type',
       'cluster', 'dcoilwtico', 'holiday_type', 'has_promotion'],
      dtype='object')
Columns in test_df: Index(['id', 'date', 'store_nbr', 'family', 'onpromotion', 'year', 'month',
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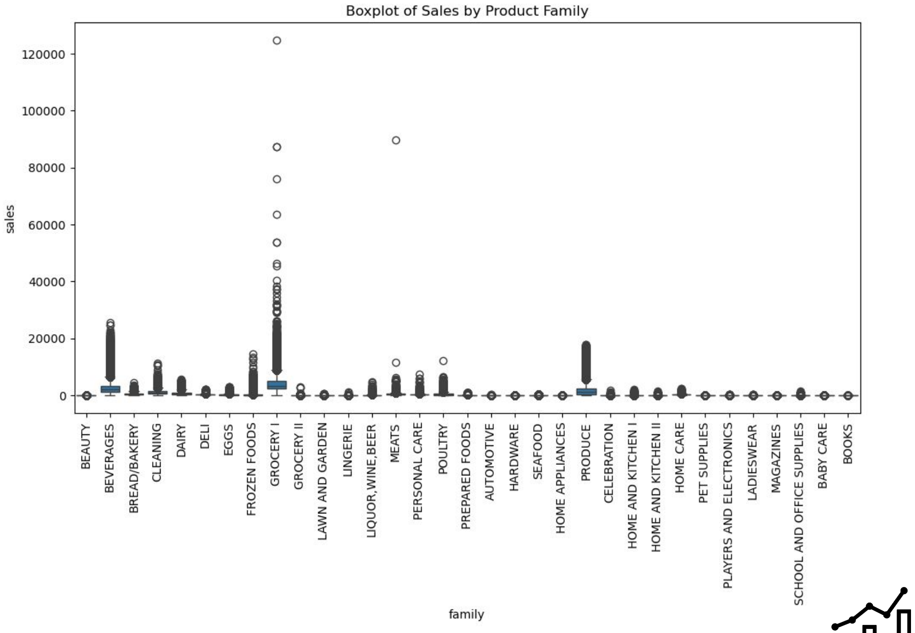
       'cluster', 'dcoilwtico', 'holiday_type', 'has_promotion'],
      dtype='object')
```

Exploratory Data Analysis (EDA)

Analyzed the distribution of sales across different product families to identify trends and outliers.

Grocery I and Produce, have significantly higher sales and exhibit notable outliers

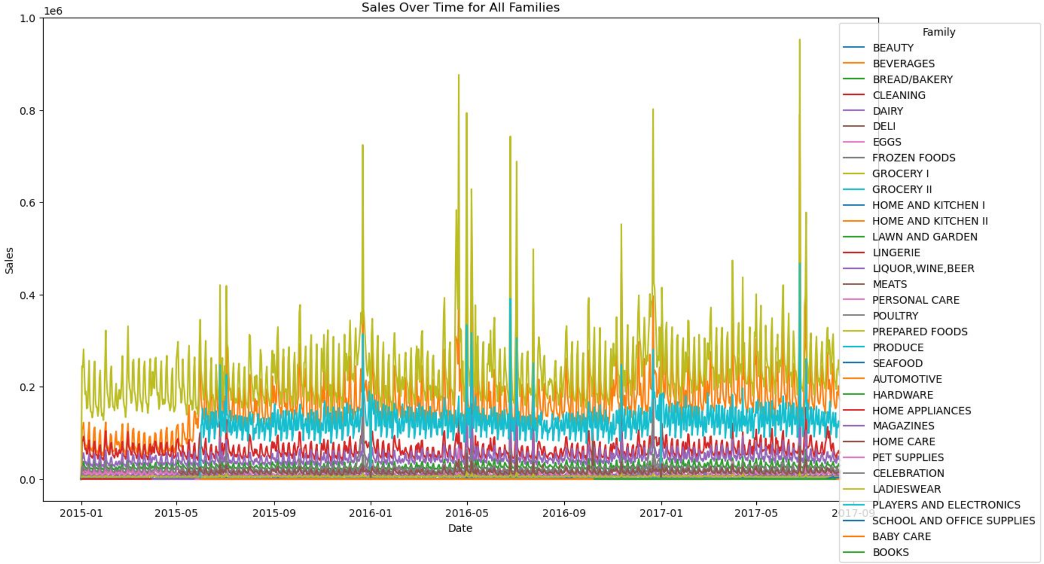
The EDA will guide the model-building process, as families may require separate handling or more detailed feature engineering.



Feature Selection

Grouped data by 'date' and 'family' to handle product categories separately and check that eac family had its trends.

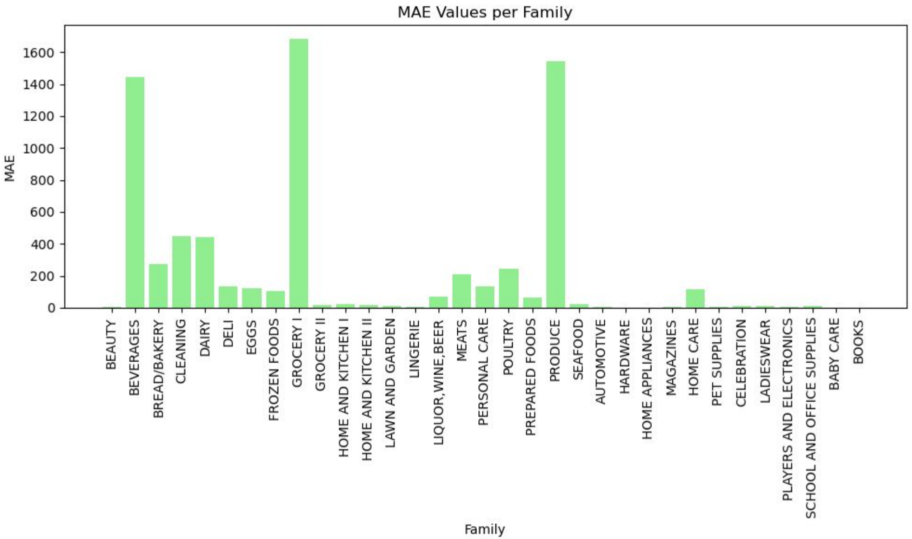
Ended up removing the years 2013-2014 for lighter load on model building.



Model Training

The model was trained on the following features:

- Differenced sales data (first-order differencing of the sales)
- Family type (each family of products was modeled individually)
- Time series structure (date components were implicitly captured in the sales sequence, though not as explicit features like year or month)

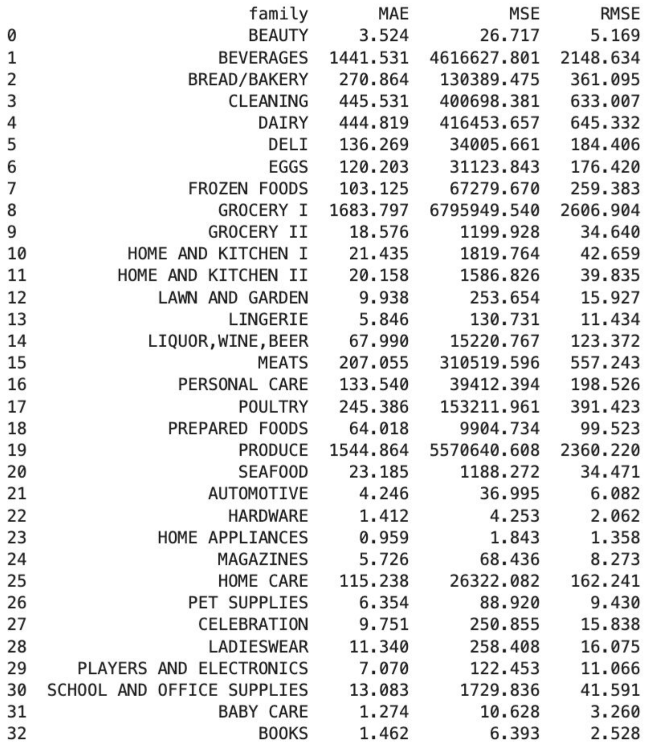


Model Evaluation

The ARIMA model performs well in predicting sales for categories with relatively stable demand, such as AUTOMOTIVE and HARDWARE.

For families like BEVERAGES and GROCERY I, large errors suggest that additional external factors or a more complex model may be needed for better accuracy.

Families in the middle range, such as CLEANING and FROZEN FOODS, show room for improvement but are reasonably well-captured by the model



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                       family       MAE          MSE      RMSE
0                      BEAUTY     3.524       26.717     5.169
1                   BEVERAGES  1441.531  4616627.801  2148.634
2                BREAD/BAKERY   270.864   130389.475   361.095
3                    CLEANING   445.531   400698.381   633.007
4                       DAIRY   444.819   416453.657   645.332
5                        DELI   136.269    34005.661   184.406
6                        EGGS   120.203    31123.843   176.420
7                FROZEN FOODS   103.125    67279.670   259.383
8                   GROCERY I  1683.797  6795949.540  2606.904
9                  GROCERY II    18.576     1199.928    34.640
10         HOME AND KITCHEN I    21.435     1819.764    42.659
11        HOME AND KITCHEN II    20.158     1586.826    39.835
12            LAWN AND GARDEN     9.938      253.654    15.927
13                   LINGERIE     5.846      130.731    11.434
14           LIQUOR,WINE,BEER    67.990    15220.767   123.372
15                      MEATS   207.055   310519.596   557.243
16              PERSONAL CARE   133.540    39412.394   198.526
17                    POULTRY   245.386   153211.961   391.423
18             PREPARED FOODS    64.018     9904.734    99.523
19                    PRODUCE  1544.864  5570640.608  2360.220
20                    SEAFOOD    23.185     1188.272    34.471
21                 AUTOMOTIVE     4.246       36.995     6.082
22                   HARDWARE     1.412        4.253     2.062
23            HOME APPLIANCES     0.959        1.843     1.358
24                  MAGAZINES     5.726       68.436     8.273
25                  HOME CARE   115.238    26322.082   162.241
26               PET SUPPLIES     6.354       88.920     9.430
27                CELEBRATION     9.751      250.855    15.838
28                 LADIESWEAR    11.340      258.408    16.075
29    PLAYERS AND ELECTRONICS     7.070      122.453    11.066
30 SCHOOL AND OFFICE SUPPLIES    13.083     1729.836    41.591
31                  BABY CARE     1.274       10.628     3.260
32                      BOOKS     1.462        6.393     2.528
```

Future Work/Recommendations

Several families like FROZEN FOODS, BREAD/BAKERY, CLEANING have moderate error values (e.g., RMSE between 200 and 600), suggesting there is still room for improvement.

BEVERAGES and GROCERY I show the highest errors across MAE, MSE, and RMSE, but they also have the most outliers, also suggesting room for improvement.

Overall there is still room for model improvement some personal suggestions are:

- modeling with more dates
- removing only the earthquake dates (as they caused a lot of outliers)
- incorporating more variables that capture more trends (holidays/events/promotions)