Analytics Vidya Job A Thon- September 2021

Supplement Sales Prediction

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Problem Statement

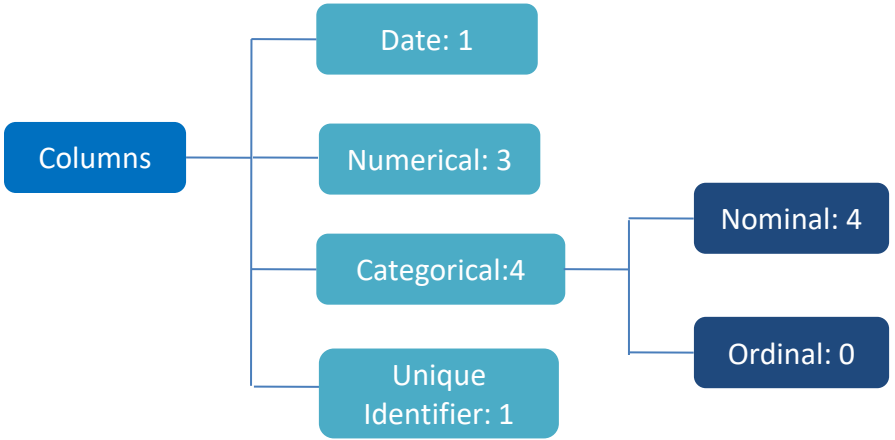
To predict the store sales for each store in the test set for the next two months.

Dataset Description

Train Data

Rows: 188340, Columns: 10
Y Variable: Sales

#	Column	Non-Null Count	Dtype
0	ID	188340 non-null	object
1	Store_id	188340 non-null	int64
2	Store_Type	188340 non-null	object
3	Location_Type	188340 non-null	object
4	Region_Code	188340 non-null	object
5	Date	188340 non-null	datetime64[ns]
6	Holiday	188340 non-null	int64
7	Discount	188340 non-null	object
8	#Order	188340 non-null	int64
9	Sales	188340 non-null	float64



Test Data

Rows: 22265, Columns: 8

#	Column	Non-Null Count	Dtype
0	ID	22265 non-null	object
1	Store_id	22265 non-null	int64
2	Store_Type	22265 non-null	object
3	Location_Type	22265 non-null	object
4	Region_Code	22265 non-null	object
5	Date	22265 non-null	datetime64[ns]
6	Holiday	22265 non-null	int64
7	Discount	22265 non-null	object

Steps in Building ML Model

1. **Reading Data**

2. **Data Preprocessing**
   - Handling Missing values
   - Handling Outliers
   - Check for Duplicates

3. **Exploratory Data Analysis**
   Analysing data to reveal hidden insights.

4. **Feature Engineering**
   - Generating New Features
   - Categorical Encodings

5. **Setting up Validation Strategy**
   - Splitting train and validation set based on date.

6. **Feature Scaling**
   MinMax Scaler

7. **Feature Selection**
   Since features in dataset were already less, hence feature selection is not performed.

8. **Model Building**

9. **Cross Validation**
   - To make model robust and reduce over fitting

Check for Missing Values

- No missing Values in Dataset

Train

```
# 0 missing values
train.isnull().sum()
```

```
ID                0
Store_id          0
Store_Type        0
Location_Type     0
Region_Code       0
Date              0
Holiday           0
Discount          0
#Order            0
Sales             0
dtype: int64
```

Test

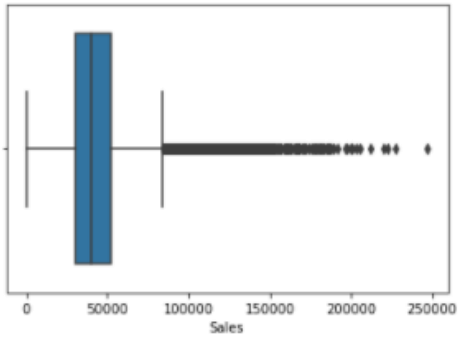
```
# 0 missing values
test.isnull().sum()
```

```
ID                0
Store_id          0
Store_Type        0
Location_Type     0
Region_Code       0
Date              0
Holiday           0
Discount          0
dtype: int64
```

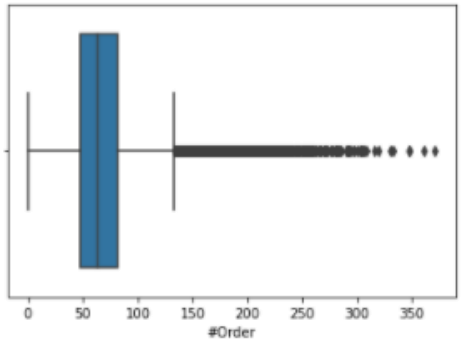
Handling Outliers

- Sales and Orders column contain outliers.
- 3.1% of Sales values are greater than upper whisker.
- 3.76% of Orders values are greater than upper whisker.
- Can't remove them since these data points reveal important information.
- Therefore, Trees and Ensemble techniques can be used for model building.

Sales



Orders



Check for Duplicated Rows

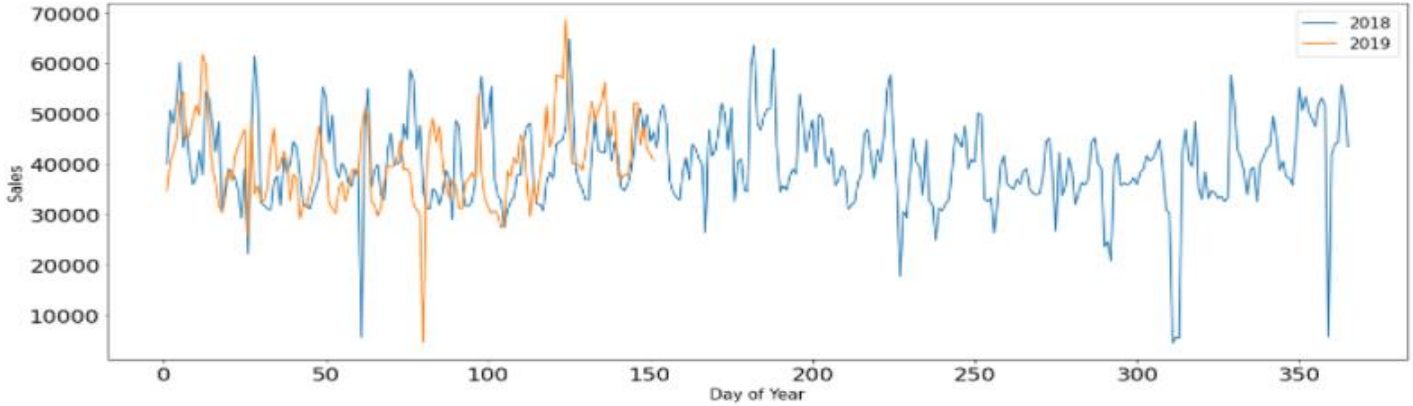
```
# 0 duplicates in train data.
train[train.duplicated()].shape[0]
```

```
0
```

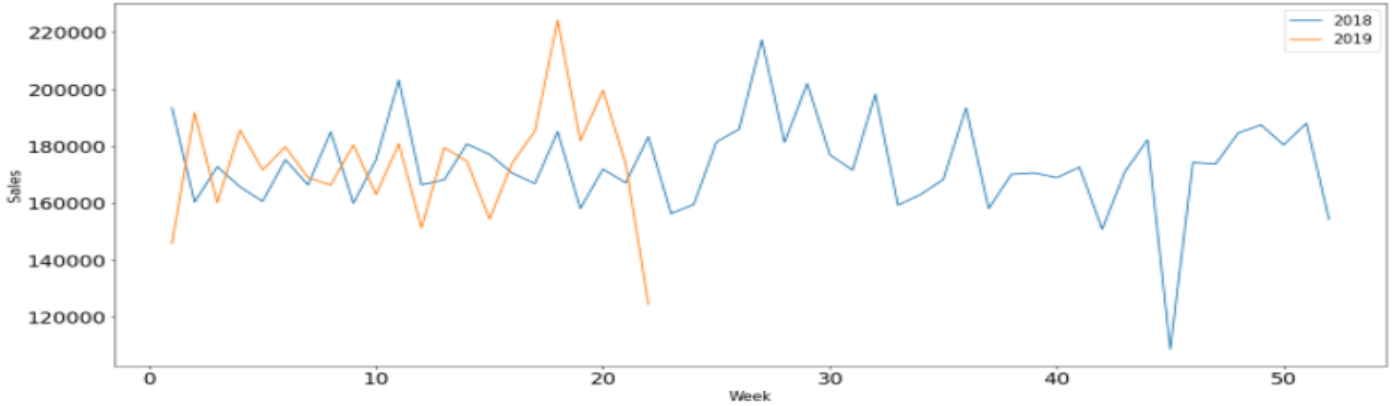
```
# 0 duplicates in test data.
test[test.duplicated()].shape[0]
```

```
0
```

Median Daily Sales



Median Weekly Sales



New Features

- Total Weekly Orders based on Store_type.
- Total weekends orders in every week of a month based on store_type.
- Total Weekly Orders based on Store_type & Location_Type.
- Total Weekend Orders based on Store_type & Location_Type.
- Total Weekly Orders by Store_id
- Total weekends orders in every week of a month based on Store_id.
- Avg Weekly Orders by Store_id
- Avg weekends orders in every week of a month based on Store_id.

store.

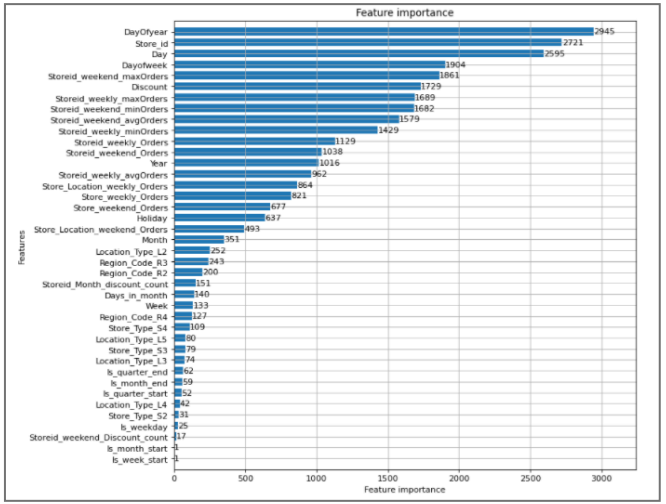
- Minimum Weekly Orders by Store_id
- Minimum weekends orders in every week of a month based on Store_id.
- Maximum Weekly Orders by Store_id
- Maximum weekends orders in every week of a month based on Store_id.
- Count of discounts offered by each store in every month
- Count of discounts on weekends of every week in a month for every store.

Feature Encoding

•One Hot Encoding for nominal categorical variables

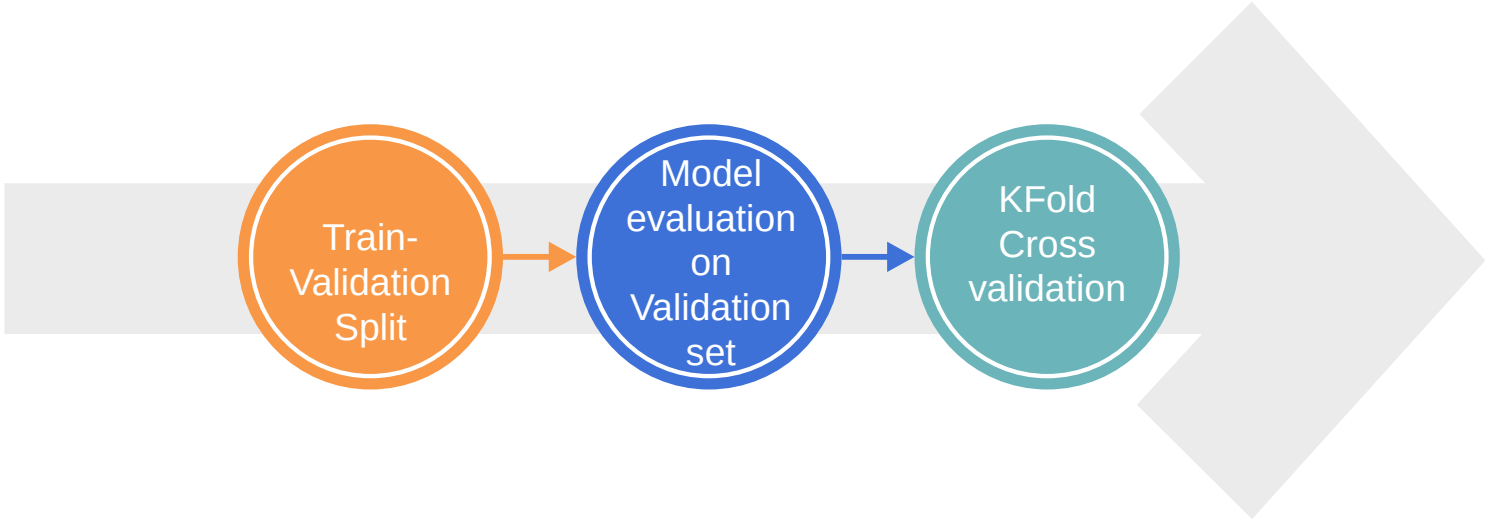
```
# One Hot Encoding
l = ['Store_Type','Location_Type','Region_Code']
tr_x = pd.get_dummies(tr_x, columns = l,drop_first=True)
val_x = pd.get_dummies(val_x, columns = l,drop_first=True)
test = pd.get_dummies(test, columns = l,drop_first=True)
```

Total Features after Feature Encoding & One Hot Encoding: 45



Min-Max Scaler for Numeric Columns

```
1  from sklearn.preprocessing import MinMaxScaler
2
3  scaler = MinMaxScaler()
4  scaler.fit(tr_x[numcols])
5  tr_x[numcols] = scaler.transform(tr_x[numcols])
6  val_x[numcols] = scaler.transform(val_x[numcols])
7  test[numcols] = scaler.transform(test[numcols])
```



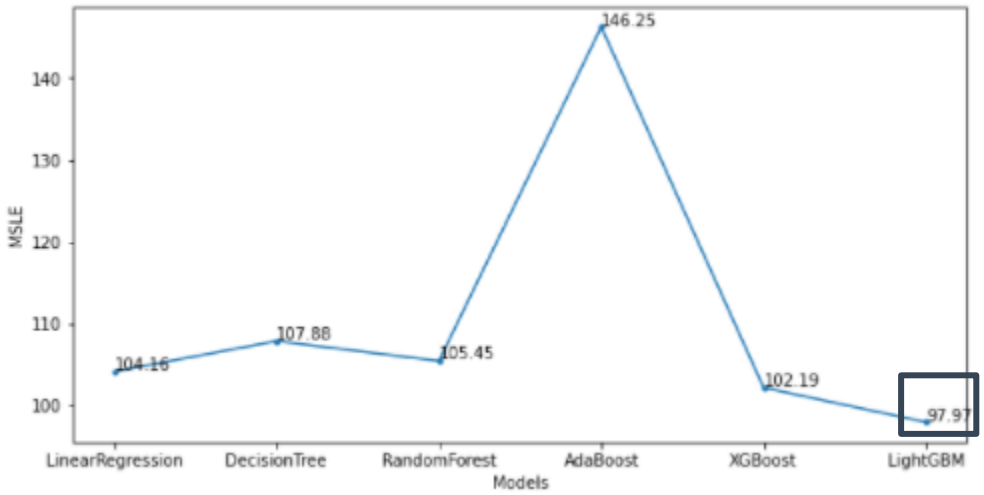
- Data Before 1st April 2019 : Train Set
- Data from 1st April 2019: Validation Set

Building models and tuning hyper parameters on train set and evaluating on validation set.

KFold cross validation on train set for final model evaluation.

Total Models Built: 6

Linear Regression | Decision Tree | Random Forest | AdaBoost | XgBoost | LightGBM



Best Performing model is LightGBM

	Models	MSLE
0	LinearRegression	104.159669
1	DecisionTree	107.875496
2	RandomForest	105.445846
3	AdaBoost	146.251692
4	XGBoost	102.185981
5	LightGBM	97.974466

-Being the lowest MSLE of 0.97, LightGBM Regressor model is selected among all other models.
- These scores are for the validation set and thus final scores are evaluated using Cross Validation.