# Outlet Sales Forecasting With Ensemble Modeling

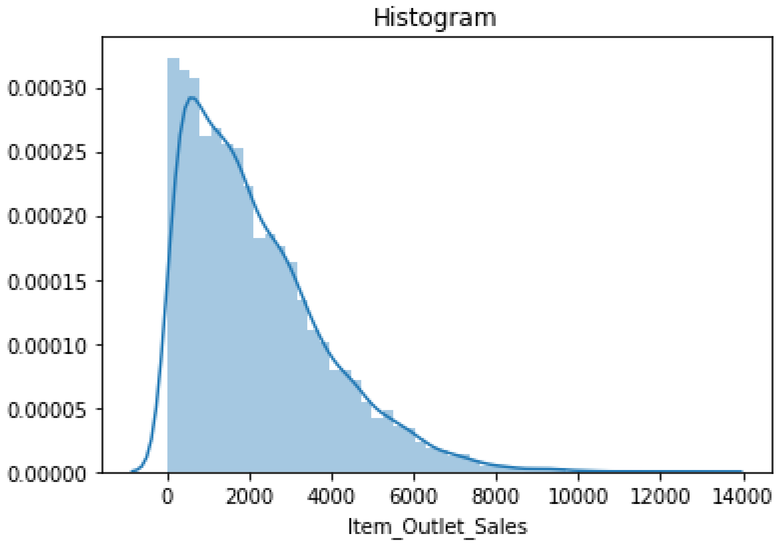
# CONTENTS

# EDA

## What is the target variable?

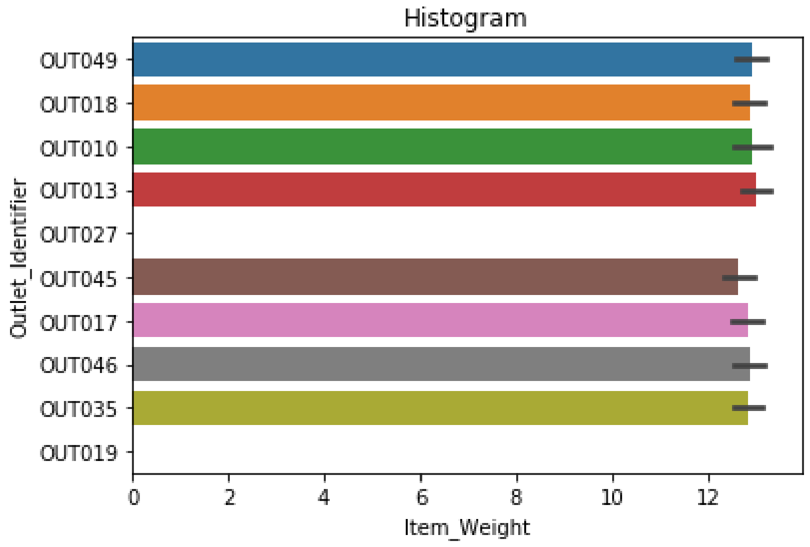
## And what are the features we have?

- From the descriptive analysis we could find out the distribution of target variables is not normalized.



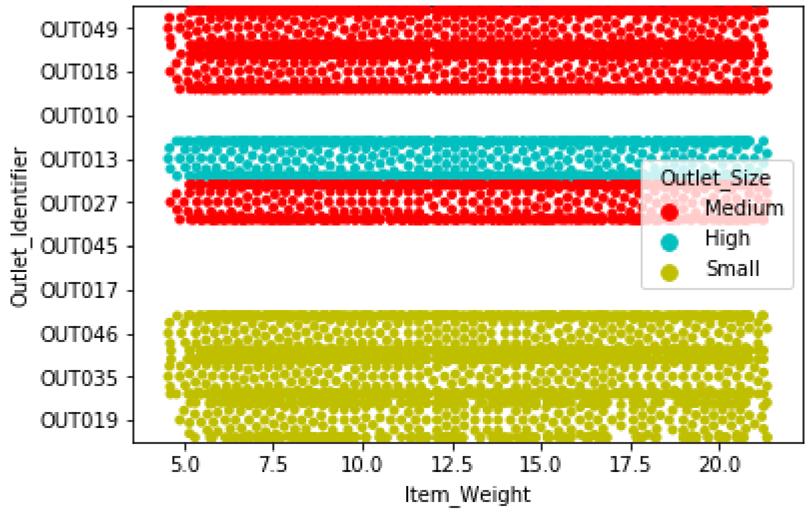
## Item Weight

The missing values in this feature are limited to Outlet ID : Out019 and Out027.



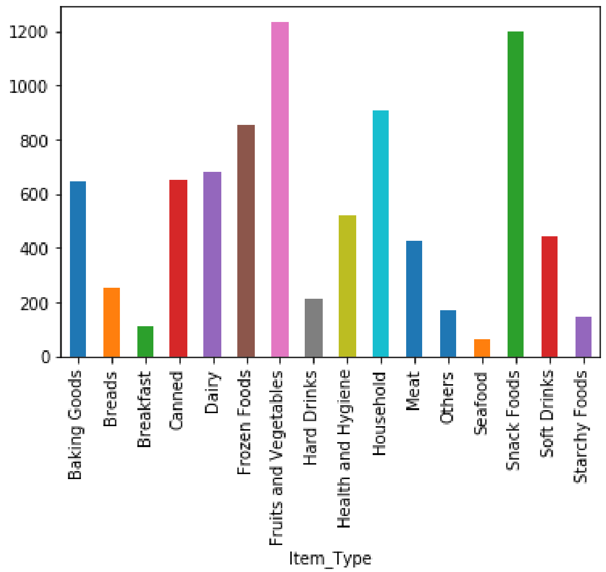

## Outlet Size

Outlet with ID Out010, Out017 and Out045 have missing values in this feature.



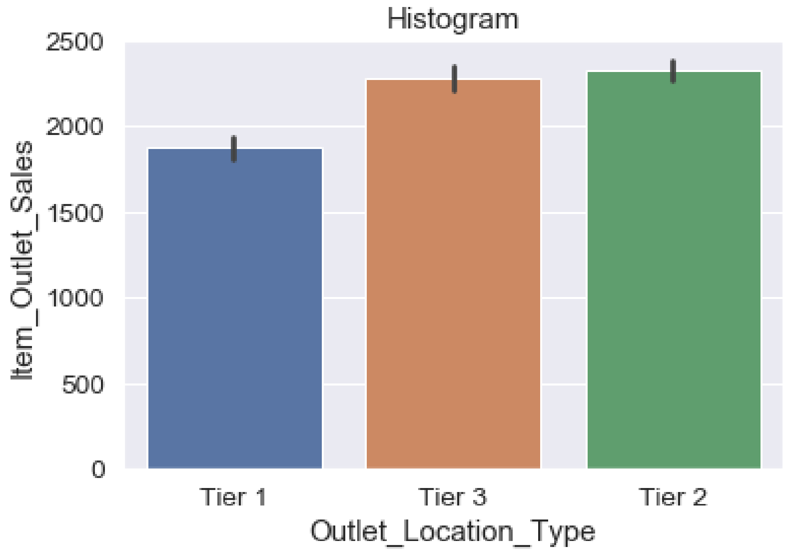
### Item Type

Different item types fall into different groups with regard to sales figure.



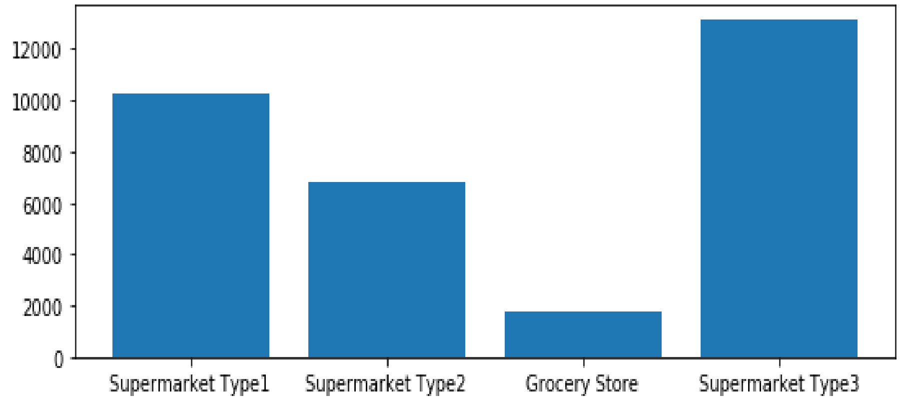

### Outlet Location

Location Tier 2 & 3 generally have higher sales than Tier 1.



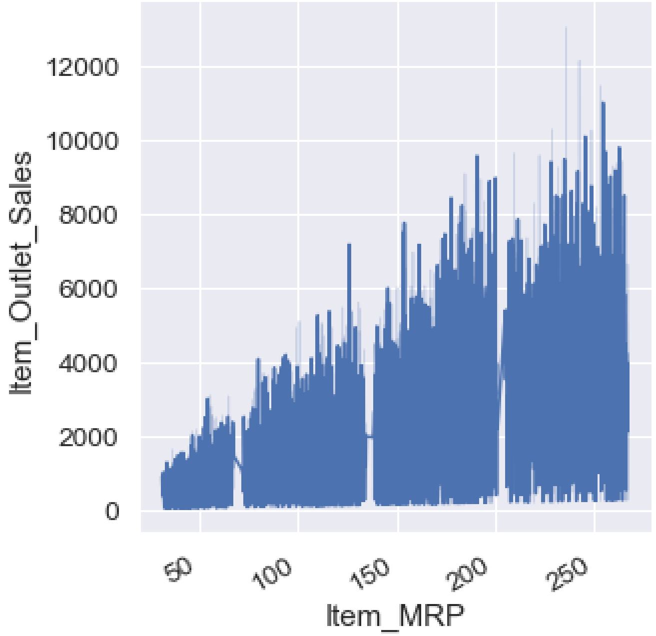
### Outlet Type

Grocery Store have a lot lower sales number than Supermarket.



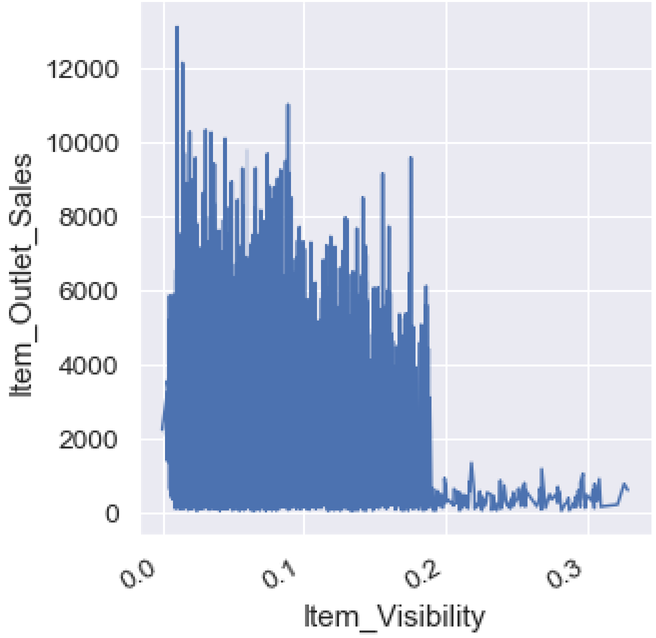

### Item MRP

Increasing of sales number demonstrated a gradual pattern with the growth of Item MRP in different levels.



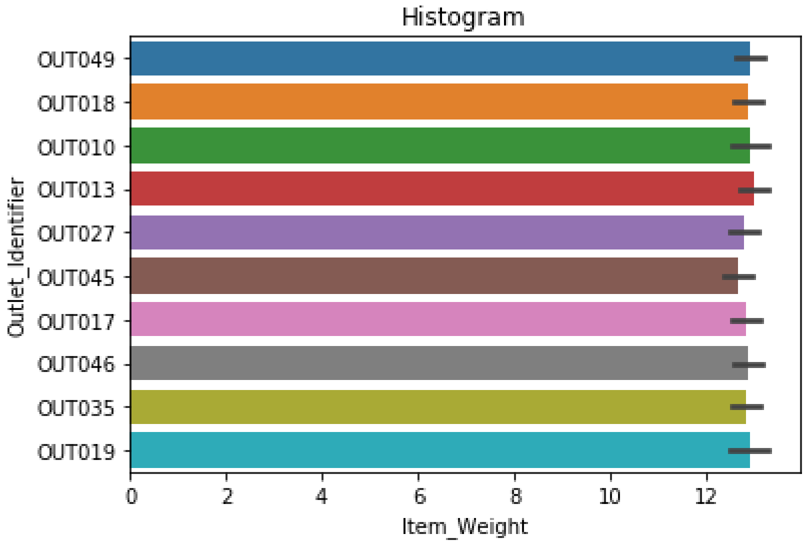
## Item Visibility

There are some spurious outliers in the Item visibility feature.



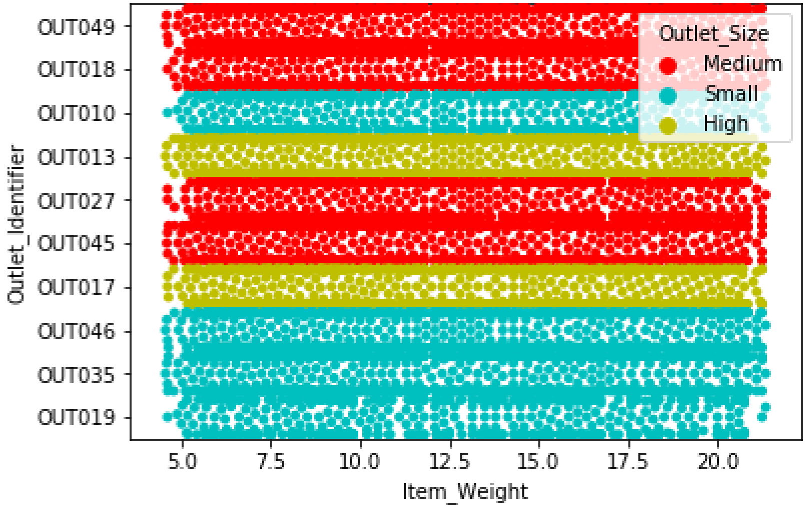
# Data Preprocessing

Data imputation for the Item Weight feature would be conducted based on The findings that only outlet with ID 019 and 027 have missing values, we randomly chose item weights from those two kinds of outlet to fill in as the actual item weight to minimize the effects of preexisting missing values.




Item Weight After Imputation

# Data Preprocessing

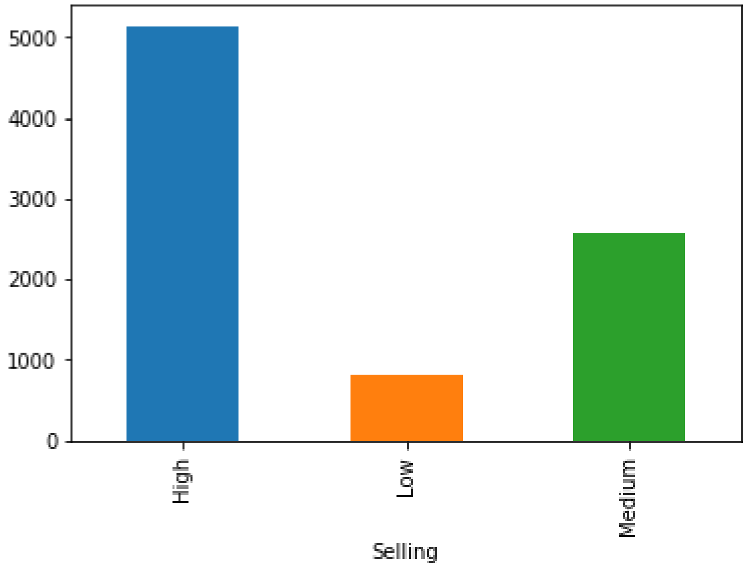



Outlet Size Scatterplot After Imputation.

Missing values for the categorical variables would be imputed based on the specific outlet ids and its corresponding Outlet Size and Item sales.
For example, We find out that Out010 corresponds to grocery store therefore the missing values for Outlet Size should be small.

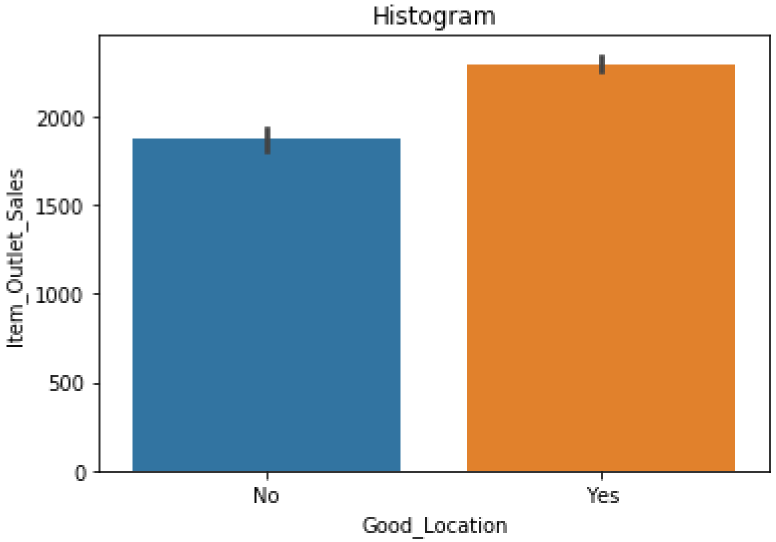
### Selling Level

Different Selling level are created to represent the difference in sales.



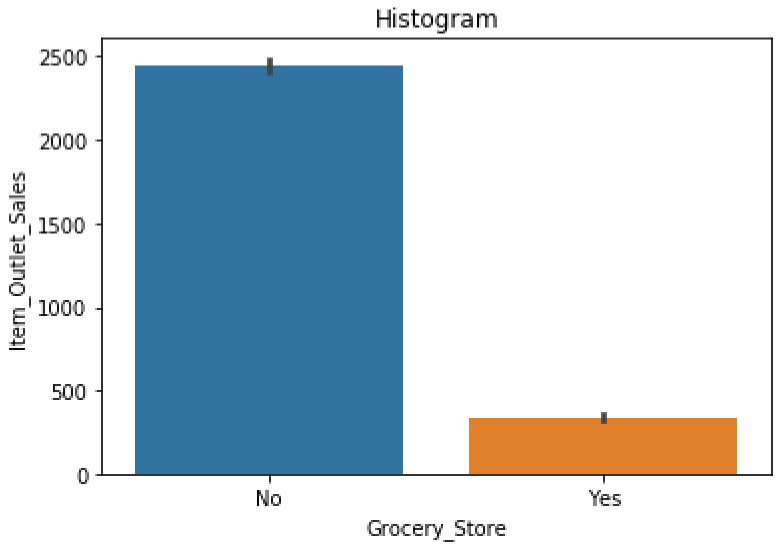

### Location Level

Location levels are applied to show the sales gap between outlets in various locations.



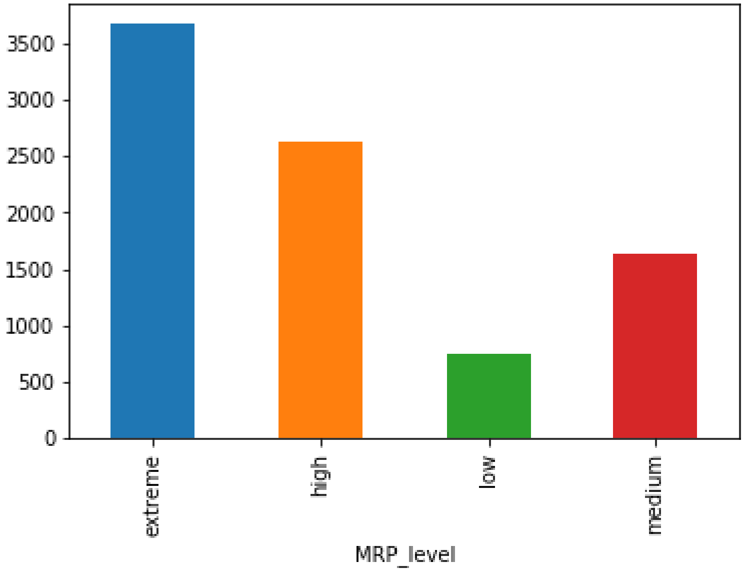
### Outlet level

Sales gap between Supermarket and Grocery Store was shown in this feature.



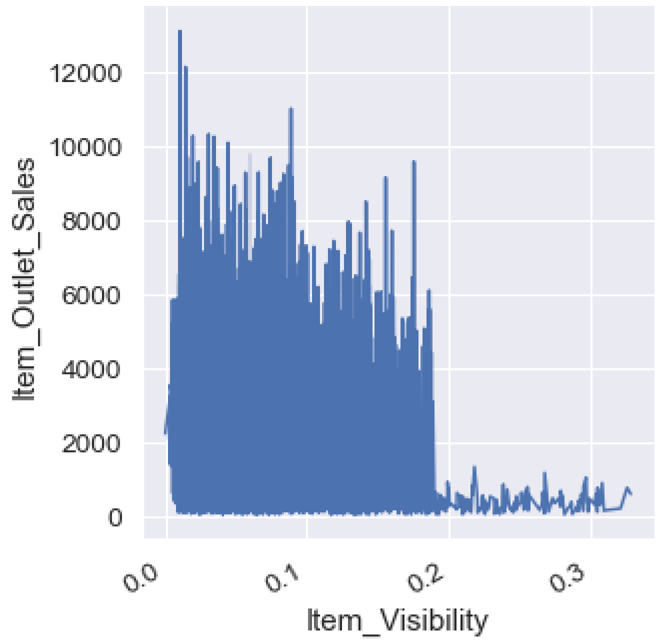

### MRP Level

Gradual pattern in sales growth regarding MRP level were reflected in this feature.



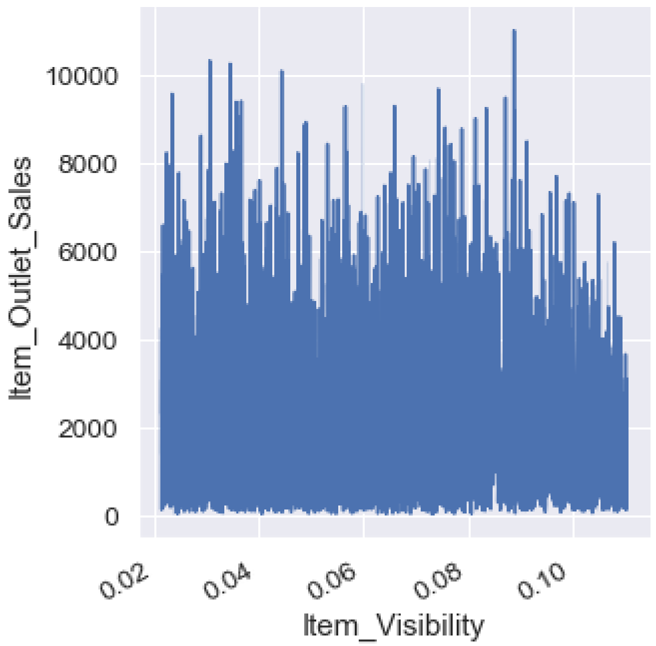
### Item Visibility

We decided to apply winsorization to the feature. Set a limit to the extreme values to reduce the effects of spurious outliers.



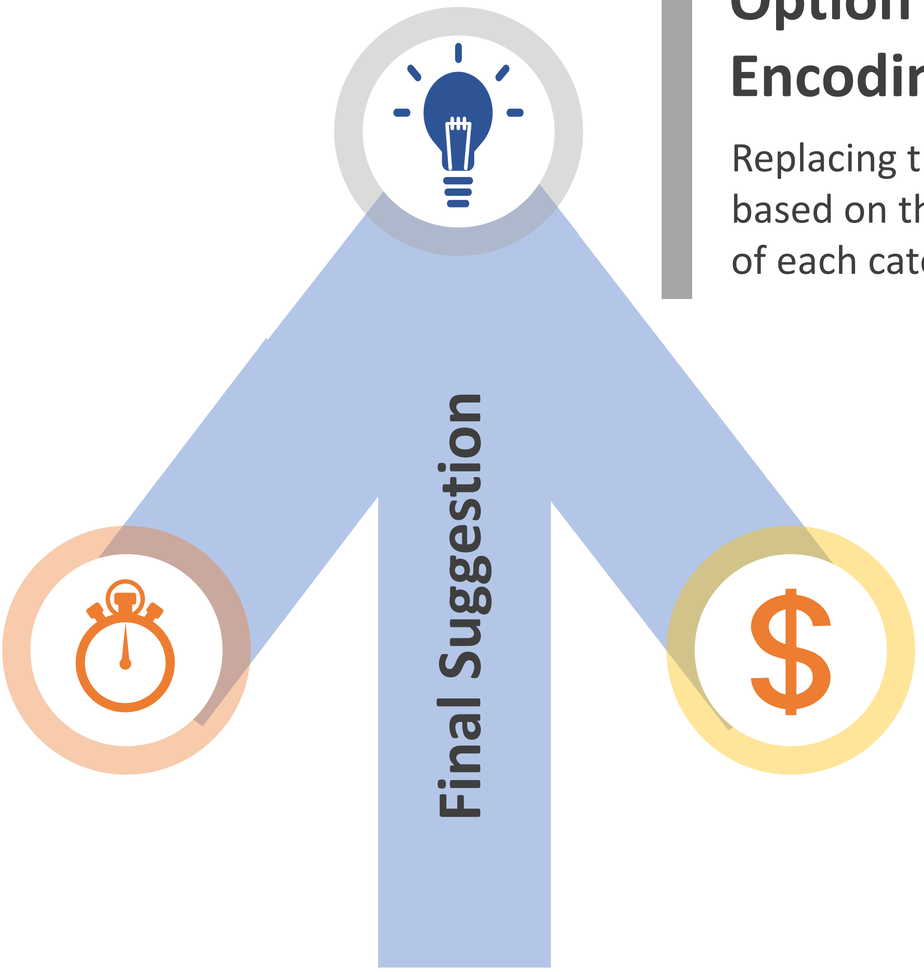

### After Winsorization

The extreme values has successfully been transformed within the range and the feature looks fine.



# Feature Engineering

## Encoding




### Option A(Target Encoding)

Replacing the categorical feature based on the target mean value of each category.

### Option B (Label-Encoding)

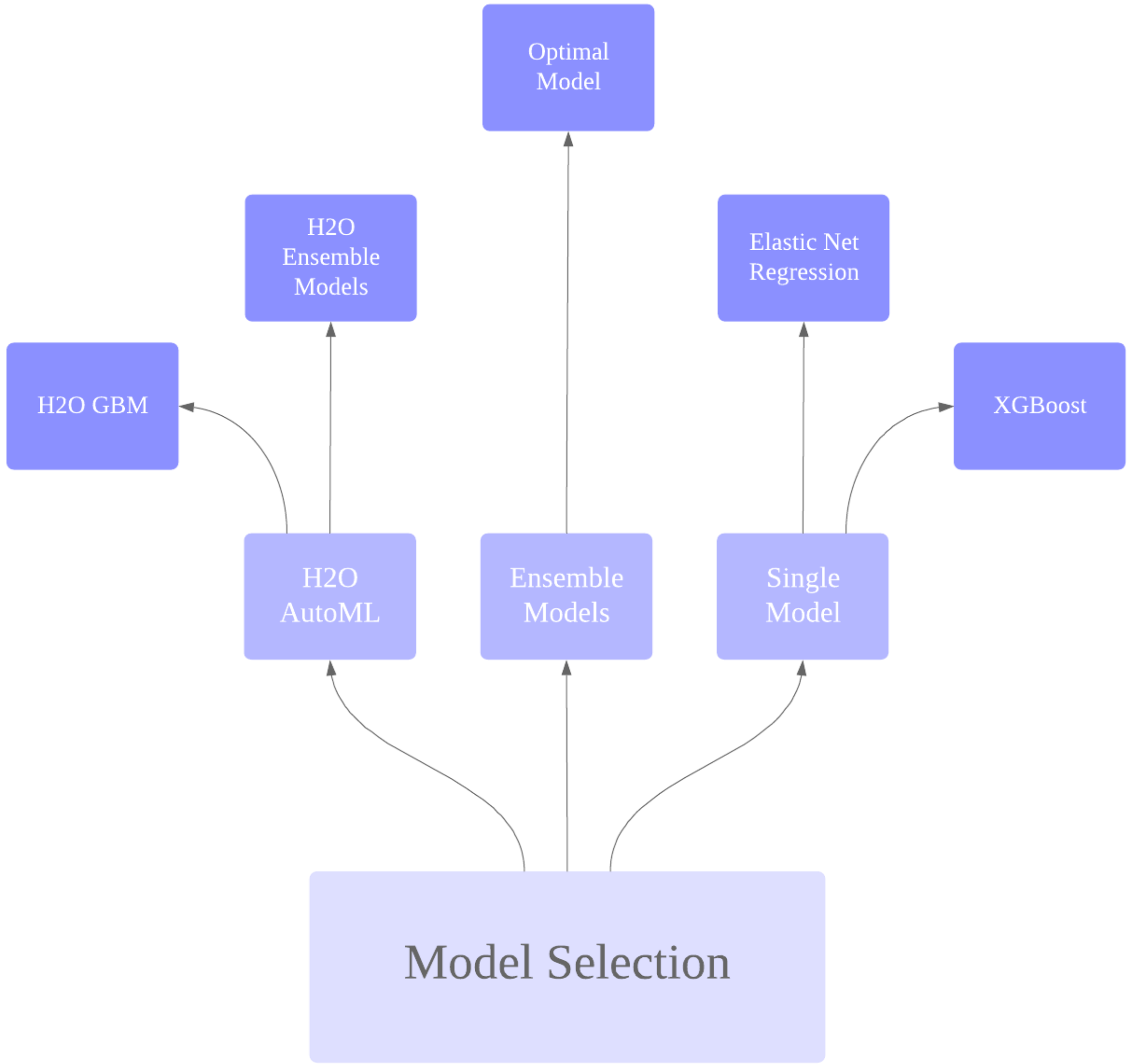
Convert categorical features into numerical features based on the feature’s ordinary sequence

### Option C(One-Hot Encoding)

Encode each categorical feature by creating a new binary column.

# Model Building Iteration





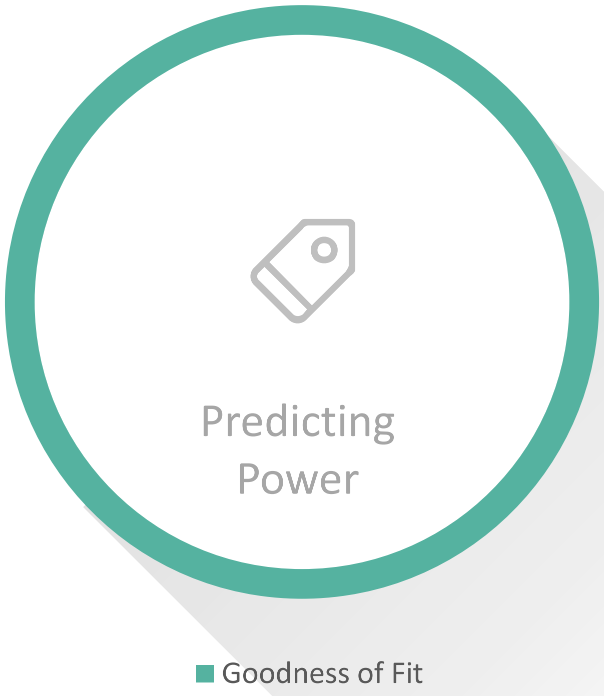
# Optimal Model

```
lr = LinearRegression()
svr_lin = SVR(kernel='linear')
ridge = Ridge(random_state=1)
lasso = Lasso(random_state=1)
reg = xgb.XGBRegressor()
svr_rbf = SVR(kernel='rbf')
regressors = [svr_lin, lr, ridge,lasso,reg]
stregr = StackingRegressor(regressors=regressors,
                           meta_regressor=svr_rbf)

params = {'lasso__alpha': [0.1, 0.5, 1.0],
          'ridge__alpha': [0.1, 0.5, 1.0],
          'svr__C': [0.1, 0.5, 1.0],
          #'reg__max_depth':[3,4,5],
          #'reg__n_estimators':[10,20,30],
          #'reg__learning_rate':[0.1,0.3,0.5],
           'meta-svr__C': [0.1, 1.0, 5.0],
           'meta-svr__gamma': [0.1, 1.0, 5.0]}

bestmodel4 = RandomizedSearchCV(estimator=stregr,
                               param_distributions=params,
                               cv=5,
                               n_iter=10,n_jobs=-1,random_state=1,scoring='r2')
bestmodel4.fit(train_x, train_y1)
```

Notebook Display

# Model Validation






75.65 %

We used cross-validation to evaluate our model since test.csv did not provide the label. Our model finally achieved a **75.65%** goodness of fit score($R^2$) with an RMSE of 1.76. Although it is not our ultimate performance since parameter tuning is not finished due to time limit and complexity, it still indicated that our model performed well.

```
stregr.predict(train_x)
print("Mean Squared Error: %.4f"
      % np.mean((stregr.predict(train_x) - train_y1) ** 2))
print('Variance Score: %.4f' % stregr.score(train_x, train_y1))
```

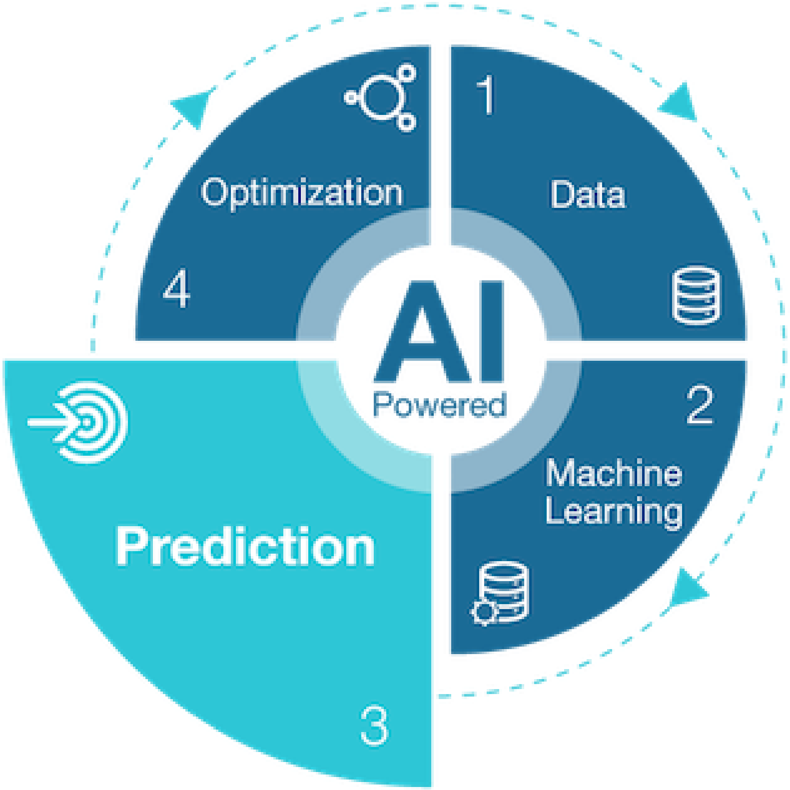
```
Mean Squared Error: 3.1240
Variance Score: 0.7565
```

```
np.sqrt(mean_squared_error(train_y1, stregr.predict(train_x)))
```

```
1.767470448092271
```

# Prediction & Future Improvement






## Further Improvement:

- Impute the missing values for Item weight based on the relationship with other column values.
- Customized feature encoding for every categorical variable.
- Parameter tuning for the final ensemble model.

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# THANK YOU

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