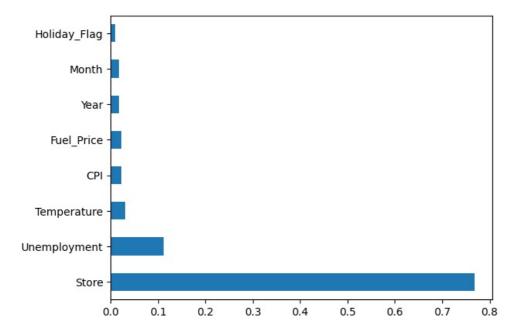
```
In [1]: # importing necessary liberary
         import numpy as np
         import pandas as pd
         import pymongo
         import sklearn
         import matplotlib.pyplot as plt
         import seaborn as sns
         %matplotlib inline
         import plotly.express as px
         import pickle
         from scipy import stats
In [2]: import warnings
         warnings.filterwarnings('ignore')
In [3]: csv_file_path = 'Walmart.csv'
         json file path ='Walmart.json'
         password='satish321'
         connection string=f'mongodb+srv://satishkandel198:{password}@cluster0.odylp4l.mongodb.net/?retryWrites=true&w=mid
         db name='WALMART'
         my_collection='preprocessed_data'
In [4]: # create a function that returns the database connection
         def get_connection(connection_string):
             try:
                 client=pymongo.MongoClient(connection_string)
                 return client
             except Exception as e:
                 return e
In [5]: # importing data from mongo db database into the pandas dataframe
         client=get_connection(connection_string)
         print(client)
         mydb=client[db name]
         collection=mydb[my_collection]
         curser=collection.find()
         # print(type(curser))
         df=pd.DataFrame(curser)
        MongoClient(host=['ac-ny1yb7u-shard-00-01.odylp4l.mongodb.net:27017', 'ac-ny1yb7u-shard-00-02.odylp4l.mongodb.ne
        t:27017', 'ac-nylyb7u-shard-00-00.odylp4l.mongodb.net:27017'], document class=dict, tz aware=False, connect=True
        , retrywrites=True, w='majority', authsource='admin', replicaset='atlas-vd77c7-shard-0', tls=True)
In [6]: df.drop('_id',axis=1,inplace=True)
In [7]: X = df.drop(['Weekly_Sales'],axis=1)
         y = df['Weekly Sales']
In [8]: ### Feature Importance
         from sklearn.ensemble import ExtraTreesRegressor
         import matplotlib.pyplot as plt
         model = ExtraTreesRegressor()
         model.fit(X,y)
Out[8]: v ExtraTreesRegressor
         ExtraTreesRegressor()
In [9]: print(model.feature_importances_)
        [0.76781639 0.00922275 0.03096975 0.021875
                                                     0.02261776 0.11214033
                   0.01753947 0.01781854]
        0.
In [10]: #plot graph of feature importances for better visualization
         feat importances = pd.Series(model.feature_importances_, index=X.columns)
         feat_importances.nlargest(8).plot(kind='barh')
```

plt.show()



Based on the feature importance diagram, only few features shows correlation with our target variable 'weekly\_sales'. So we are building our prediction model based on top 5 features.

```
In [11]:
           cols = ['Temperature', 'Fuel_Price', 'Unemployment', 'CPI', 'Store']
           X = df[cols]
In [12]: from sklearn.model selection import train test split
           X_{\text{train}}, X_{\text{test}}, y_{\text{train}}, y_{\text{test}} = \text{train\_test\_split}(X, y, \text{test\_size=0.3}, \text{random\_state=42})
In [13]: X_train
                 Temperature Fuel_Price Unemployment
Out[13]:
                                                                 CPI Store
                                -1.549656
             19
                     1.322736
                                                 0.018746 -1.549656
                                                                          1
            229
                     0.960343
                                -0.024970
                                                 0.043852 -0.024970
                                                                          2
           4127
                     0.771275
                                -1.371684
                                                 0.656712 -1.371684
                                                                         32
            668
                     0.547822
                                 0.552294
                                                 -1.639640
                                                            0.552294
                                                                          5
                                                                          2
            218
                     1.677391
                                 0.459041
                                                 0.043852 0.459041
           3772
                    -1.183390
                                 0.343959
                                                 0.642560
                                                           0.343959
                                                                         29
           5191
                    -2.058598
                                -0.410969
                                                 -1.756011 -0.410969
                                                                         40
           5226
                                -1.396596
                                                 -0.261484 -1.396596
                     -0.036025
                                                                         41
           5390
                     -0 565462
                                -0 702410
                                                 0.649886 -0.702410
                                                                         42
            860
                    -2.000763
                                -1.257179
                                                 0.714730 -1.257179
                                                                          7
          4143 rows × 5 columns
           from sklearn.compose import ColumnTransformer
           \begin{tabular}{ll} from & sklearn.preprocessing & import & OneHotEncoder \\ \end{tabular}
           transformer = ColumnTransformer(transformers=[('tf',OneHotEncoder(sparse=False),['Store'])],remainder='passthroi
In [15]: X train= transformer.fit transform(X train)
           X_test = transformer.transform(X_test)
In [16]: X_train[0:10]
Out[16]: array([[ 1.
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                   1.6211201 ,
                                0.93697939, 0.36608711, 0.93697939]])
In [17]: from sklearn.ensemble import RandomForestRegressor
In [18]: regressor=RandomForestRegressor()
         n estimators = [int(x) \text{ for } x \text{ in } np.linspace(start = 100, stop = 1200, num = 12)]
         print(n estimators)
        [100, 200, 300, 400, 500, 600, 700, 800, 900, 1000, 1100, 1200]
In [19]: #Randomized Search CV
         # Number of trees in random forest
         n estimators = [int(x) \text{ for } x \text{ in } np.linspace(start = 100, stop = 1200, num = 12)]
         # Number of features to consider at every split
         max features = ['auto', 'sqrt']
         # Maximum number of levels in tree
         \max_{x \in \mathbb{R}} depth = [int(x) \text{ for } x \text{ in } np.linspace(5, 30, num = 6)]
         # max depth.append(None)
         # Minimum number of samples required to split a node
         min samples split = [2, 5, 10, 15, 100]
         # Minimum number of samples required at each leaf node
         min_samples_leaf = [1, 2, 5, 10]
In [20]: # Create the random grid
         random_grid = {'n_estimators': n_estimators,
                          'max_features': max_features,
                         'max_depth': max_depth,
                         'min_samples_split': min_samples_split,
                         'min_samples_leaf': min_samples_leaf}
         print(random_grid)
        {'n_estimators': [100, 200, 300, 400, 500, 600, 700, 800, 900, 1000, 1100, 1200], 'max_features': ['auto', 'sqrt
'], 'max_depth': [5, 10, 15, 20, 25, 30], 'min_samples_split': [2, 5, 10, 15, 100], 'min_samples_leaf': [1, 2, 5]
        , 10]}
In [21]: from sklearn.model selection import RandomizedSearchCV
In [22]: # Use the random grid to search for best hyperparameters
         # First create the base model to tune
         rf = RandomForestRegressor()
In [23]: # Random search of parameters, using 3 fold cross validation,
         # search across 100 different combinations
         rf random = RandomizedSearchCV(estimator = rf, param distributions = random grid,scoring='neg mean squared erro
In [24]: rf random.fit(X train,y train)
        Fitting 5 folds for each of 10 candidates, totalling 50 fits
        [CV] END max depth=10, max features=sqrt, min samples leaf=5, min samples split=5, n estimators=900; total time=
        9.2s
        [CV] END max depth=10, max features=sqrt, min samples leaf=5, min samples split=5, n estimators=900; total time=
        9.5s
        [CV] END max depth=10, max features=sqrt, min samples leaf=5, min samples split=5, n estimators=900; total time=
        9.2s
        [CV] END max depth=10, max features=sqrt, min samples leaf=5, min samples split=5, n estimators=900; total time=
        10.7s
        [CV] END max depth=10, max features=sqrt, min samples leaf=5, min samples split=5, n estimators=900; total time=
        10.1s
        [CV] END max depth=15, max features=sqrt, min samples leaf=2, min samples split=10, n estimators=1100; total tim
        e = 15.9s
        [CV] END max depth=15, max features=sqrt, min samples leaf=2, min samples split=10, n estimators=1100; total tim
        e = 18.3s
        [CV] END max_depth=15, max_features=sqrt, min_samples_leaf=2, min_samples_split=10, n_estimators=1100; total tim
        e = 16.1s
        [CV] END max_depth=15, max_features=sqrt, min_samples_leaf=2, min_samples_split=10, n_estimators=1100; total tim
        e = 16.0s
        [CV] END max depth=15, max features=sqrt, min samples leaf=2, min samples split=10, n estimators=1100; total tim
        e = 15.7s
        [CV] END max depth=15, max features=auto, min samples leaf=5, min samples split=100, n estimators=300; total tim
             0.05
        [CV] END max depth=15, max features=auto, min samples leaf=5, min samples split=100, n estimators=300; total tim
             0.0s
        e=
        [CV] END max_depth=15, max_features=auto, min_samples_leaf=5, min_samples_split=100, n_estimators=300; total tim
             0.0s
        e=
        [CV] END max_depth=15, max_features=auto, min_samples_leaf=5, min_samples_split=100, n_estimators=300; total tim
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            0.0s
        [CV] END max_depth=15, max_features=auto, min_samples_leaf=5, min_samples_split=100, n_estimators=300; total tim
             0.0s
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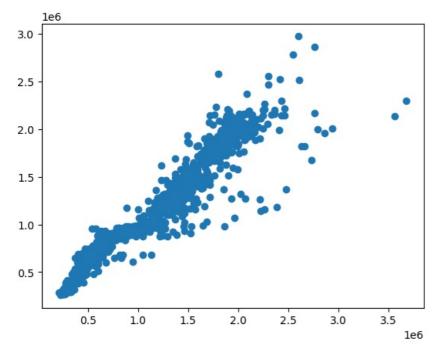
0.

```
[CV] END max depth=15, max features=auto, min samples leaf=5, min samples split=5, n estimators=400; total time=
        0.0s
        [CV] END max depth=15, max features=auto, min samples leaf=5, min samples split=5, n estimators=400; total time=
        0.0s
        [CV] END max depth=15, max features=auto, min samples leaf=5, min samples split=5, n estimators=400; total time=
        0.0s
        [CV] END max depth=15, max features=auto, min samples leaf=5, min samples split=5, n estimators=400; total time=
        0.0s
        [CV] END max depth=15, max features=auto, min samples leaf=5, min samples split=5, n estimators=400; total time=
        0.0s
        [CV] END max depth=20, max features=auto, min samples leaf=10, min samples split=5, n estimators=700; total time
            0.0s
        [CV] END max depth=20, max features=auto, min samples leaf=10, min samples split=5, n estimators=700; total time
            0.05
        [CV] END max depth=20, max features=auto, min samples leaf=10, min samples split=5, n estimators=700; total time
            0.05
        [CV] END max depth=20, max features=auto, min samples leaf=10, min samples split=5, n estimators=700; total time
            0.05
        [CV] END max depth=20, max features=auto, min samples leaf=10, min samples split=5, n estimators=700; total time
            0.0s
        [CV] END max depth=25, max features=sqrt, min samples leaf=1, min samples split=2, n estimators=1000; total time
        = 28.8s
        [CV] END max depth=25, max features=sqrt, min samples leaf=1, min samples split=2, n estimators=1000; total time
        = 28.7s
        [CV] END max depth=25, max features=sqrt, min samples leaf=1, min samples split=2, n estimators=1000; total time
        = 29.3s
        [CV] END max depth=25, max features=sqrt, min samples leaf=1, min samples split=2, n estimators=1000; total time
        = 28.5s
        [CV] END max depth=25, max features=sqrt, min samples leaf=1, min samples split=2, n estimators=1000; total time
        = 28.85
        [CV] END max depth=5, max features=sqrt, min samples leaf=10, min samples split=15, n estimators=1100; total tim
        e=
             7.0s
        [CV] END max depth=5, max features=sqrt, min samples leaf=10, min samples split=15, n estimators=1100; total tim
             7.85
        [CV] END max depth=5, max features=sqrt, min samples leaf=10, min samples split=15, n estimators=1100; total tim
        e=
             8.3s
        [CV] END max depth=5, max features=sqrt, min samples leaf=10, min samples split=15, n estimators=1100; total tim
        e=
             7.4s
        [CV] END max_depth=5, max_features=sqrt, min_samples_leaf=10, min_samples_split=15, n_estimators=1100; total tim
        e=
             8.3s
        [CV] END max depth=15, max features=sqrt, min samples leaf=1, min samples split=15, n estimators=300; total time
            4.5s
        [CV] END max depth=15, max features=sqrt, min samples leaf=1, min samples split=15, n estimators=300; total time
            4.35
        [CV] END max depth=15, max features=sqrt, min samples leaf=1, min samples split=15, n estimators=300; total time
            4.6s
        [CV] END max depth=15, max features=sqrt, min samples leaf=1, min samples split=15, n estimators=300; total time
            4.45
        [CV] END max depth=15, max features=sqrt, min samples leaf=1, min samples split=15, n estimators=300; total time
            5.1s
        [CV] END max depth=5, max features=sqrt, min samples leaf=2, min samples split=10, n estimators=700; total time=
        5.1s
        [CV] END max depth=5, max features=sqrt, min samples leaf=2, min samples split=10, n estimators=700; total time=
        5.1s
        [CV] END max depth=5, max features=sqrt, min samples leaf=2, min samples split=10, n estimators=700; total time=
        5.0s
        [CV] END max_depth=5, max_features=sqrt, min_samples_leaf=2, min_samples_split=10, n_estimators=700; total time=
        5.1s
        [CV] END max depth=5, max features=sqrt, min samples leaf=2, min samples split=10, n estimators=700; total time=
        5.85
        [CV] END max depth=20, max features=auto, min samples leaf=1, min samples split=15, n estimators=700; total time
            0.05
        [CV] END max depth=20, max features=auto, min samples leaf=1, min samples split=15, n estimators=700; total time
        [CV] END max depth=20, max features=auto, min samples leaf=1, min samples split=15, n estimators=700; total time
            0.0s
        [CV] END max_depth=20, max_features=auto, min_samples_leaf=1, min_samples_split=15, n_estimators=700; total time
            0.0s
        [CV] END max_depth=20, max_features=auto, min_samples_leaf=1, min_samples_split=15, n_estimators=700; total time
        = 0.0s
                   RandomizedSearchCV
Out[24]: -
          ▶ estimator: RandomForestRegressor
                ▶ RandomForestRegressor
```

```
Out[25]: {'n_estimators': 1000,
           'min_samples_split': 2,
           'min_samples_leaf': 1,
           'max_features': 'sqrt',
           'max_depth': 25}
In [26]: rf_random.best_score_
Out[26]:
          -33661033192.138744
In [27]: predictions=rf_random.predict(X_test)
          sns.distplot(y_test-predictions)
Out[27]: <Axes: xlabel='Weekly_Sales', ylabel='Density'>
           4.0
           3.5
           3.0
           2.5
           2.0
           1.5
           1.0
           0.5
           0.0
                          -0.5
                                       0.0
                                                    0.5
                                                                1.0
                                                                            1.5
              -1.0
                                          Weekly_Sales
                                                                              1e6
```

```
In [28]: plt.scatter(y_test,predictions)
```

Out[28]: <matplotlib.collections.PathCollection at 0x14df3898a10>



```
In [29]: # open a file, where you ant to store the data
file = open('random_forest_reg_model.pkl', 'wb')

# dump information to that file
pickle.dump(rf_random, file)
```

## **Predictive Modelling**

## Regression Metrics

- 1. MSE
- 2. MAE
- 3. R2 SCORE
- 4. RMSE
- 5. Median ABsolute Erro
- 6. Predictions Error Rate
- 7. Almost Correct Predictions Error Rate

pickle.dump(rf\_random, file3)

```
In [30]: from sklearn.linear_model import LinearRegression,Lasso,Ridge,ElasticNet
         from sklearn.metrics import mean_squared_error,mean_absolute_error,r2_score
         from sklearn.ensemble import RandomForestRegressor
         from sklearn.model_selection import cross_val_score
In [31]: def pred_model(model,X_train,Y_train,X_test,Y_test):
             c = model()
             c.fit(X_train,Y_train)
             y pred = c.predict(X test)
             print(model)
             print(f'MSE: {mean_squared_error(Y_test,y_pred)}')
             print(f'MAE: {mean_absolute_error(Y_test,y_pred)}')
             print(f'R2 : {r2_score(Y_test,y_pred)}')
In [32]: pred model(LinearRegression, X train, y train, X test, y test)
        <class 'sklearn.linear model. base.LinearRegression'>
        MSE: 24537082970.468002
        MAE: 92687.48701013514
        R2: 0.921969093387086
In [33]: pred model(Lasso,X train,y train,X test,y test)
        <class 'sklearn.linear_model._coordinate_descent.Lasso'>
        MSE: 24519218417.064873
        MAE: 92641.42299834719
        R2: 0.9220259048385515
In [34]: pred_model(Ridge,X_train,y_train,X_test,y_test)
        <class 'sklearn.linear_model._ridge.Ridge'>
        MSE: 24465201092.79901
        MAE: 92192.13197227362
        R2: 0.9221976864961487
In [35]: pred model(RandomForestRegressor, X train, Y train, X test, y test)
        <class 'sklearn.ensemble. forest.RandomForestRegressor'>
        MSE: 21788372573.71725
        MAE: 78718.38447460583
        R2 : 0.9307103265863603
In [36]: pred model(ElasticNet, X train, y train, X test, y test)
        <class 'sklearn.linear model. coordinate descent.ElasticNet'>
        MSE: 287521684428.2407
        MAE: 448797.8752374798
        R2: 0.08564609192500638
In [37]: c = LinearRegression()
         c.fit(X train,y train)
         y_pred = c.predict(X_test)
In [38]: # open a file, where you ant to store the data
         file1 = open('Linear_regression_model.pkl', 'wb')
         # dump information to that file
         pickle.dump(c, file1)
In [39]: # open a file, where you ant to store the data
         file2 = open('Lasso_regression_model.pkl', 'wb')
         # dump information to that file
         pickle.dump(rf random, file2)
In [40]: # open a file, where you ant to store the data
         file3 = open('elasticnet_model.pkl', 'wb')
         # dump information to that file
```

