NamVien_STATS101A_FinalProject

December 5, 2024

1 UCLA STATS 101A Final Project

Professor: Vivian Lew
Teaching Assistant: Jialiang Geng
Student: Nam Vien
Date: Friday, June 14th, 2024

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import folium
from folium.plugins import HeatMap
from sklearn.feature_extraction import FeatureHasher
from sklearn.linear_model import LogisticRegression, LinearRegression, Lasso,␣
 ↪Ridge
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
 ↪mean_squared_error
from sklearn.model_selection import train_test_split, GridSearchCV, KFold
from xgboost import XGBRegressor, plot_importance
import lightgbm as lgb
import os
```

1.1 Data Exploratory Analysis

[2]:
```
# Read the data into the environment
data = pd.read_csv('uber_fare_prediction.csv')
```

[3]:
```
# Display the dimensions of the data frame
data.shape
```

[3]:
```
(200000, 8)
```

[4]:
```
# Display the names of the columns
data.columns
```

[4]:
```
Index(['key', 'fare_amount', 'pickup_datetime', 'pickup_longitude',
       'pickup_latitude', 'dropoff_longitude', 'dropoff_latitude',
       'passenger_count'],
      dtype='object')
```

[5]:
```
# Display the first 10 rows of the data
data.head(10)
```

[5]:
```
      key  fare_amount          pickup_datetime  pickup_longitude  \
0  26:21.0          4.5  2009-06-15 17:26:21 UTC        -73.844311
1  52:16.0         16.9  2010-01-05 16:52:16 UTC        -74.016048
2  35:00.0          5.7  2011-08-18 00:35:00 UTC        -73.982738
3  30:42.0          7.7  2012-04-21 04:30:42 UTC        -73.987130
4  51:00.0          5.3  2010-03-09 07:51:00 UTC        -73.968095
5  50:45.0         12.1  2011-01-06 09:50:45 UTC        -74.000964
6  35:00.0          7.5  2012-11-20 20:35:00 UTC        -73.980002
7  22:00.0         16.5  2012-01-04 17:22:00 UTC        -73.951300
8  10:00.0          9.0  2012-12-03 13:10:00 UTC        -74.006462
9  11:00.0          8.9  2009-09-02 01:11:00 UTC        -73.980658

   pickup_latitude  dropoff_longitude  dropoff_latitude  passenger_count
0        40.721319         -73.841610         40.712278                1
1        40.711303         -73.979268         40.782004                1
2        40.761270         -73.991242         40.750562                2
3        40.733143         -73.991567         40.758092                1
4        40.768008         -73.956655         40.783762                1
5        40.731630         -73.972892         40.758233                1
6        40.751662         -73.973802         40.764842                1
7        40.774138         -73.990095         40.751048                1
8        40.726713         -73.993078         40.731628                1
9        40.733873         -73.991540         40.758138                2
```

[6]:
```
# Get the summary information of the data
data.describe()
```

[6]:
```
         fare_amount  pickup_longitude  pickup_latitude  dropoff_longitude  \
count  200000.000000     200000.000000    200000.000000      199999.000000
mean       11.342877        -72.506121        39.922326         -72.518673
std         9.837855         11.608097        10.048947          10.724226
min       -44.900000       -736.550000     -3116.285383       -1251.195890
25%         6.000000        -73.992050        40.735007         -73.991295
50%         8.500000        -73.981743        40.752761         -73.980072
75%        12.500000        -73.967068        40.767127         -73.963508
max       500.000000       2140.601160      1703.092772          40.851027

       dropoff_latitude  passenger_count
count     199999.000000    200000.000000
```

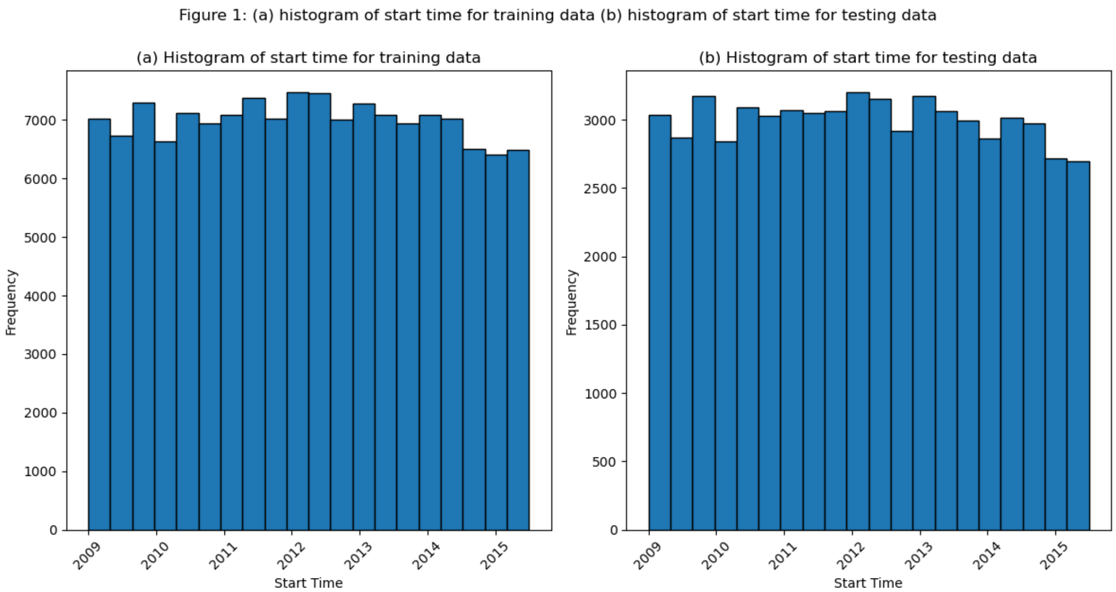
```
mean          39.925579          1.682445
std            6.751120          1.306730
min        -1189.615440          0.000000
25%           40.734092          1.000000
50%           40.753225          1.000000
75%           40.768070          2.000000
max          404.616667          6.000000
```

[7]:
```
# Check for missing values
data.isnull().sum()
```

[7]:
```
key                  0
fare_amount          0
pickup_datetime      0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    1
dropoff_latitude     1
passenger_count      0
dtype: int64
```

[8]:
```
# Draw plots to help understand the data

# Ensure the datetime column is in datetime format
data['pickup_datetime'] = pd.to_datetime(data['pickup_datetime'])

# Split the data into training (70%) and testing (30%) sets
train_data, test_data = train_test_split(data, test_size=0.3, random_state=42)

# Plot histogram for training data
plt.figure(figsize=(12, 6))

plt.subplot(1, 2, 1)
plt.hist(train_data['pickup_datetime'], bins=20, edgecolor='black')
plt.title('(a) Histogram of start time for training data')
plt.xlabel('Start Time')
plt.ylabel('Frequency')
plt.xticks(rotation=45)

# Plot histogram for testing data
plt.subplot(1, 2, 2)
plt.hist(test_data['pickup_datetime'], bins=20, edgecolor='black')
plt.title('(b) Histogram of start time for testing data')
plt.xlabel('Start Time')
plt.ylabel('Frequency')
plt.xticks(rotation=45)
```

```
plt.tight_layout()
plt.suptitle('Figure 1: (a) histogram of start time for training data (b)␣
↪histogram of start time for testing data', y=1.05)
plt.show()
```



[9]:
```
# Remove extreme outliers more effectively by focusing on realistic geographic␣
↪range (New York City)
data = data[(data['pickup_latitude'].between(40, 42)) &␣
↪(data['pickup_longitude'].between(-74, -72))]
data = data[(data['dropoff_latitude'].between(40, 42)) &␣
↪(data['dropoff_longitude'].between(-74, -72))]
```

[10]:
```
import folium
from folium.plugins import HeatMap

# Assuming the data has already been loaded and cleaned
# Extracting a subset of the data for heatmap plotting
data_train = data.sample(40000)

# Initialize the map centered around the mean of the pickup latitude and␣
↪longitude
m = folium.Map(location = [data_train.pickup_latitude.mean(), data_train.
↪pickup_longitude.mean()], zoom_start = 9)

# Prepare the data for the heatmap
heat_data = [[row['pickup_latitude'], row['pickup_longitude']] for index, row␣
↪in data_train.iterrows()]
```

```
# Add the heatmap layer to the map
HeatMap(heat_data).add_to(m)

# Save the map to an HTML file in the current working directory
output_file = 'heatmap_folium.html'
m.save(output_file)

print(f"Heatmap has been created and saved to {output_file}")

from IPython.display import IFrame

# Display the heatmap in Jupyter Notebook
IFrame(output_file, width = 600, height = 600)
```

```
Heatmap has been created and saved to heatmap_folium.html
```

[10]:

```
<IPython.lib.display.IFrame at 0x1691cd1d0>
```

[11]:

```
# Remove extreme outliers more effectively by focusing on realistic geographic␣
↪range (New York City)
data = data[(data['pickup_latitude'].between(40, 42)) &␣
↪(data['pickup_longitude'].between(-74, -72))]
data = data[(data['dropoff_latitude'].between(40, 42)) &␣
↪(data['dropoff_longitude'].between(-74, -72))]
```

[12]:

```
# Display the first few rows of the cleaned data
data.head(10)
```

[12]:

```
          key  fare_amount           pickup_datetime  pickup_longitude  \
0   26:21.0          4.5 2009-06-15 17:26:21+00:00        -73.844311
2   35:00.0          5.7 2011-08-18 00:35:00+00:00        -73.982738
3   30:42.0          7.7 2012-04-21 04:30:42+00:00        -73.987130
4   51:00.0          5.3 2010-03-09 07:51:00+00:00        -73.968095
6   35:00.0          7.5 2012-11-20 20:35:00+00:00        -73.980002
7   22:00.0         16.5 2012-01-04 17:22:00+00:00        -73.951300
9   11:00.0          8.9 2009-09-02 01:11:00+00:00        -73.980658
10  30:50.0          5.3 2012-04-08 07:30:50+00:00        -73.996335
12  04:03.0          4.1 2009-11-06 01:04:03+00:00        -73.991601
16  22:00.0         12.5 2014-02-19 07:22:00+00:00        -73.986430

    pickup_latitude  dropoff_longitude  dropoff_latitude  passenger_count
0         40.721319         -73.841610         40.712278                1
2         40.761270         -73.991242         40.750562                2
3         40.733143         -73.991567         40.758092                1
4         40.768008         -73.956655         40.783762                1
6         40.751662         -73.973802         40.764842                1
7         40.774138         -73.990095         40.751048                1
```

```
9          40.733873         -73.991540         40.758138                  2
10         40.737142         -73.980721         40.733559                  1
12         40.744712         -73.983081         40.744682                  2
16         40.760465         -73.988990         40.737075                  1
```

[13]:
```python
# Display summary statistics of the cleaned data
data.describe()
```

[13]:
```
         fare_amount  pickup_longitude  pickup_latitude  dropoff_longitude  \
count  150976.000000     150976.000000    150976.000000      150976.000000
mean       11.026938        -73.969078        40.755652         -73.967577
std         9.655898          0.039796         0.030285           0.038135
min       -44.900000        -74.000000        40.121653         -74.000000
25%         5.700000        -73.987497        40.743828         -73.986107
50%         8.100000        -73.978262        40.758294         -73.976638
75%        12.000000        -73.963847        40.771019         -73.960691
max       500.000000        -72.856968        41.650000         -72.854940

       dropoff_latitude  passenger_count
count     150976.000000    150976.000000
mean          40.756510         1.677942
std            0.033011         1.306510
min           40.164927         0.000000
25%           40.743862         1.000000
50%           40.758524         1.000000
75%           40.772425         2.000000
max           41.543217         6.000000
```

[14]:
```python
# Check for missing values
data.isnull().sum()
```

[14]:
```
key                  0
fare_amount          0
pickup_datetime      0
pickup_longitude     0
pickup_latitude      0
dropoff_longitude    0
dropoff_latitude     0
passenger_count      0
dtype: int64
```

1.2 Feature Engineering

[15]:
```python
# Ensure the datetime column is in datetime format
data['pickup_datetime'] = pd.to_datetime(data['pickup_datetime'])

# Haversine Distance Calculation
```

```
def haversine(lat1, lon1, lat2, lon2):
    R = 6371  # Earth radius in kilometers
    lat1, lon1, lat2, lon2 = map(np.radians, [lat1, lon1, lat2, lon2])
    dlat = lat2 - lat1
    dlon = lon2 - lon1
    a = np.sin(dlat/2)**2 + np.cos(lat1) * np.cos(lat2) * np.sin(dlon/2)**2
    c = 2 * np.arcsin(np.sqrt(a))
    return R * c

data['distance'] = haversine(data['pickup_latitude'], data['pickup_longitude'],␣
 ↪data['dropoff_latitude'], data['dropoff_longitude'])

# Extract datetime features
data['year'] = data['pickup_datetime'].dt.year
data['month'] = data['pickup_datetime'].dt.month
data['day'] = data['pickup_datetime'].dt.day
data['hour'] = data['pickup_datetime'].dt.hour
data['day_of_week'] = data['pickup_datetime'].dt.dayofweek

# Encoding day of the week as an ordered categorical type with codes
data['day_of_week'] = data['day_of_week'].astype('category').cat.codes

# Drop only the datetime column as it's already been extracted into other␣
 ↪features
data = data.drop(columns=['pickup_datetime'])
```

[16]:
```
# Remove 'key' column, unnecessary for analysis and modeling.
data = data.drop(columns = ['key'])
```

1.3 Modeling and Evaluation

[17]:
```
# Split the data into predictors and the response
X = data.drop(columns = ['fare_amount'])
Y = data['fare_amount']
```

[18]:
```
# Split the data into training and testing sets
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.2,␣
 ↪random_state = 1)
```

[19]:
```
# Initialize, fit, and evaluate models
models = {
    'Linear Regression': LinearRegression(),
    'Lasso Regression': Lasso(alpha=1.0),
    'Ridge Regression': Ridge(alpha=1.0),
    'Decision Tree': DecisionTreeRegressor(random_state=42),
    'Random Forest': RandomForestRegressor(random_state=42, n_estimators=100),
    'Gradient Boosting': GradientBoostingRegressor(random_state=42),
```

```
    'XGBoost': XGBRegressor(objective='reg:squarederror', random_state=42),
    'LightGBM': lgb.LGBMRegressor(random_state=42, force_row_wise=True)
}

# Evaluate models using RMSE
rmse_scores = {}

for name, model in models.items():
    model.fit(X_train, Y_train)
    Y_pred = model.predict(X_test)
    rmse = np.sqrt(mean_squared_error(Y_test, Y_pred))
    rmse_scores[name] = rmse
    print(f"{name} RMSE: {rmse}")
```

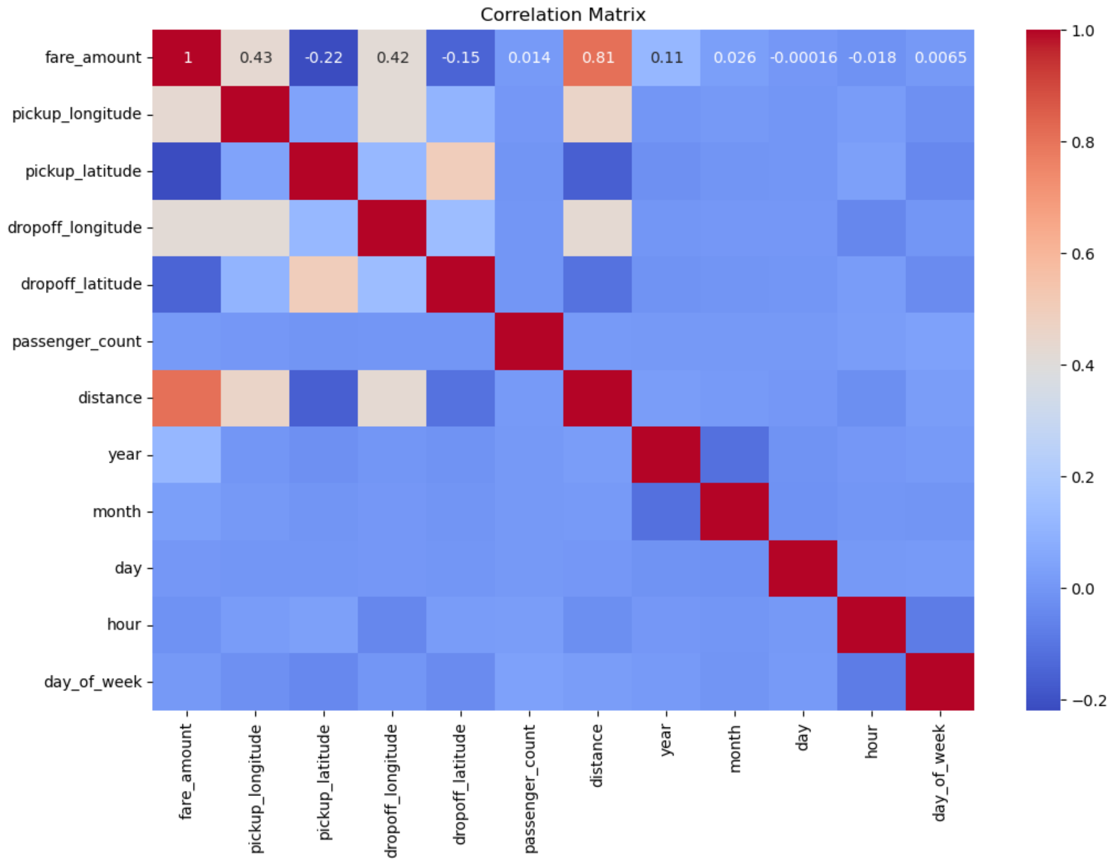
```
Linear Regression RMSE: 5.10819797622872
Lasso Regression RMSE: 5.310162425469536
Ridge Regression RMSE: 5.1079282654403055
Decision Tree RMSE: 6.317893535742014
Random Forest RMSE: 4.032109063597749
Gradient Boosting RMSE: 4.022892915420212
XGBoost RMSE: 3.8179084472423375
[LightGBM] [Info] Total Bins 1366
[LightGBM] [Info] Number of data points in the train set: 120780, number of used
features: 11
[LightGBM] [Info] Start training from score 11.033323
LightGBM RMSE: 3.7659650862175313
```

[20]:
```
# Identify the model with the lowest RMSE
best_model_name = min(rmse_scores, key = rmse_scores.get)
best_model_rmse = rmse_scores[best_model_name]
print(f"\nBest model is the {best_model_name} with lowest RMSE:␣
 ↪{best_model_rmse}")
```

```

Best model is the LightGBM with lowest RMSE: 3.7659650862175313
```

[21]:
```
# Correlation matrix
correlation_matrix = data.corr()
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()

# Lasso regularization
lasso = Lasso(alpha=0.1)
lasso.fit(X_train, Y_train)
lasso_coefficients = pd.DataFrame({'Feature': X_train.columns, 'Coefficient':␣
 ↪lasso.coef_})
```

```
print('Lasso regularization')
print(lasso_coefficients[lasso_coefficients['Coefficient'] != 0])
```

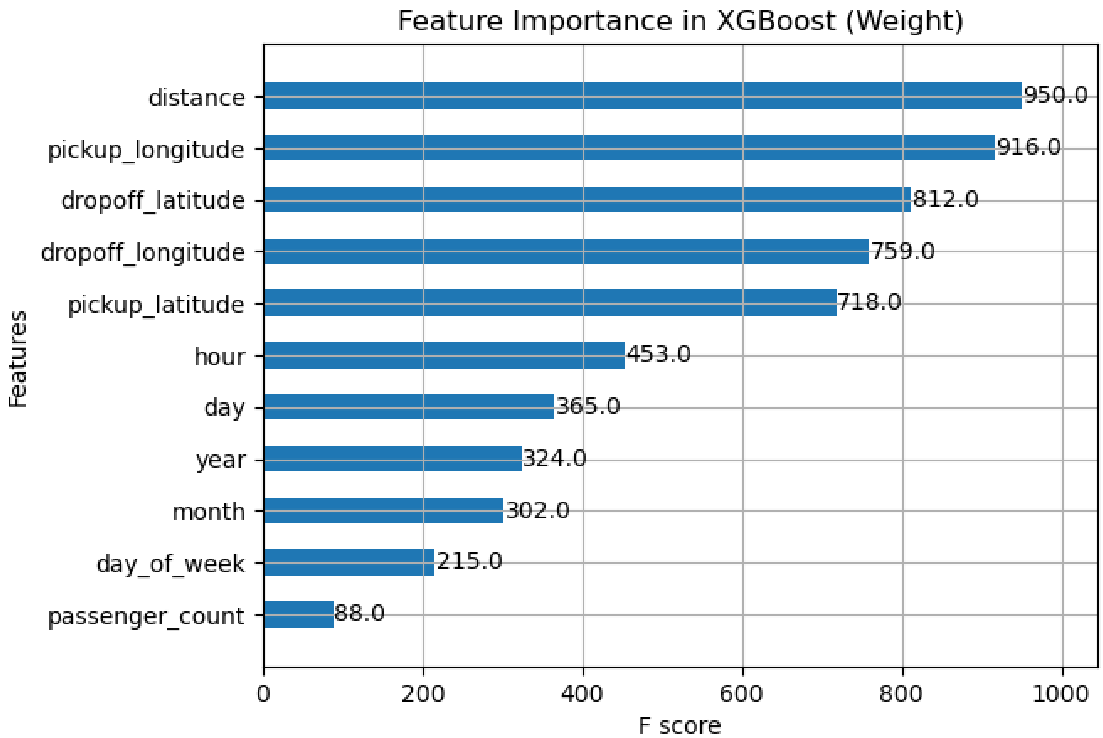



```
Lasso regularization
        Feature  Coefficient
5      distance     2.013642
6          year     0.490917
7         month     0.066718
9          hour     0.003669
10  day_of_week    -0.030181
```

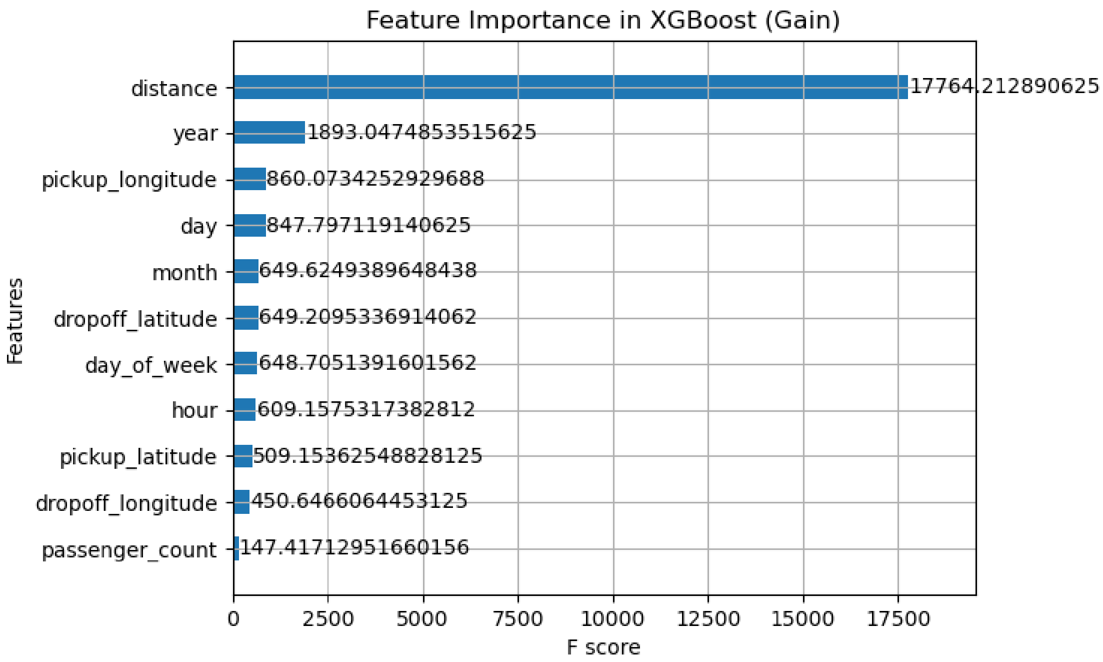
[22]:
```
# Fit the XGBoost model
xgb_model = XGBRegressor(objective='reg:squarederror', random_state=42)
xgb_model.fit(X_train, Y_train)

# Plot the feature importances for XGBoost model using 'weight'
plt.figure(figsize=(10, 6))
plot_importance(xgb_model, importance_type='weight', height=0.5)
plt.title('Feature Importance in XGBoost (Weight)')
plt.show()
```

```python
# If you want to plot using 'gain' as well, you can do it similarly
plt.figure(figsize=(10, 6))
plot_importance(xgb_model, importance_type='gain', height=0.5)
plt.title('Feature Importance in XGBoost (Gain)')
plt.show()
```

```
<Figure size 1000x600 with 0 Axes>
```




```
<Figure size 1000x600 with 0 Axes>
```



[23]:
```
# Define important features based on the analysis
important_features = ['distance', 'year', 'pickup_longitude',␣
 ↪'dropoff_latitude', 'pickup_latitude', 'dropoff_longitude', 'day', 'hour',␣
 ↪'month']

# Model with all features
lgb_model_all = lgb.LGBMRegressor(random_state=42, force_row_wise=True)
lgb_model_all.fit(X_train, Y_train)
Y_pred_all = lgb_model_all.predict(X_test)
rmse_all = np.sqrt(mean_squared_error(Y_test, Y_pred_all))
print(f"LightGBM with all features RMSE: {rmse_all}")

# Model with selected important features
X_train_imp = X_train[important_features]
X_test_imp = X_test[important_features]

lgb_model_imp = lgb.LGBMRegressor(random_state=42, force_row_wise=True)
lgb_model_imp.fit(X_train_imp, Y_train)
Y_pred_imp = lgb_model_imp.predict(X_test_imp)
rmse_imp = np.sqrt(mean_squared_error(Y_test, Y_pred_imp))
print(f"LightGBM with important features RMSE: {rmse_imp}")

# Compare the results
print(f"\nRMSE with all features: {rmse_all}")
print(f"RMSE with important features: {rmse_imp}")
```

```
[LightGBM] [Info] Total Bins 1366
[LightGBM] [Info] Number of data points in the train set: 120780, number of used
features: 11
[LightGBM] [Info] Start training from score 11.033323
LightGBM with all features RMSE: 3.7659650862175313
[LightGBM] [Info] Total Bins 1352
[LightGBM] [Info] Number of data points in the train set: 120780, number of used
features: 9
[LightGBM] [Info] Start training from score 11.033323
LightGBM with important features RMSE: 3.7520658929993775

RMSE with all features: 3.7659650862175313
RMSE with important features: 3.7520658929993775
```

1.4 Prediction

[24]:

```python
# Retrain the best model on the full dataset and make final predictions
best_model = models[best_model_name]
best_model.fit(X_train_imp, Y_train)
Y_pred_best = best_model.predict(X_test_imp)

# Save the final predictions of the best model
final_predictions = pd.DataFrame({'actual_fare': Y_test, 'predicted_fare':␣
↪Y_pred_best})
final_predictions['predicted_fare'] = final_predictions['predicted_fare'].
↪round(1)

final_save_path = os.path.join('predictions.csv')
final_predictions.to_csv(final_save_path, index = False)
print(f"Final predictions saved to {final_save_path}")

# Load and display the saved final predictions CSV file to verify
final_predictions_loaded = pd.read_csv(final_save_path)
print(final_predictions_loaded.head(10))
```

```
[LightGBM] [Info] Total Bins 1352
[LightGBM] [Info] Number of data points in the train set: 120780, number of used
features: 9
[LightGBM] [Info] Start training from score 11.033323
Final predictions saved to predictions.csv
   actual_fare  predicted_fare
0         10.5             9.9
1          5.0             4.9
2         12.5            10.7
3          3.7             5.0
4          8.5             6.4
5         10.1             9.6
6         20.0            18.0
```

```
7           4.9              5.0
8          16.0             18.5
9           7.5              7.3
```

1.5 Optional: Hyperparameter Tuning

[25]:
```python
# Define the best parameters from Grid Search
best_params = {'learning_rate': 0.05, 'max_depth': 20, 'min_child_samples': 30,␣
 ↪'n_estimators': 300, 'num_leaves': 70}

# Initialize and train the final LightGBM model with the best parameters
final_model = lgb.LGBMRegressor(**best_params, random_state=42,␣
 ↪force_row_wise=True)
final_model.fit(X_train, Y_train)

# Make predictions on the test data
Y_pred_test = final_model.predict(X_test)

# Calculate RMSE on the test data
test_rmse = np.sqrt(mean_squared_error(Y_test, Y_pred_test))
print(f"Test RMSE: {test_rmse}")

# Save the final predictions
final_predictions = pd.DataFrame({'actual_fare': Y_test, 'predicted_fare':␣
 ↪Y_pred_test})
final_predictions['predicted_fare'] = final_predictions['predicted_fare'].
 ↪round(1)

# Define the save path (local path)
final_save_path = os.path.join('final_fare_predictions.csv')
final_predictions.to_csv(final_save_path, index=False)
print(f"Final predictions saved to {final_save_path}\n")

# Load and display the saved final predictions CSV file to verify
final_predictions_loaded = pd.read_csv(final_save_path)
print(final_predictions_loaded.head(10))
```

```
[LightGBM] [Info] Total Bins 1366
[LightGBM] [Info] Number of data points in the train set: 120780, number of used
features: 11
[LightGBM] [Info] Start training from score 11.033323
Test RMSE: 3.7173970237236516
Final predictions saved to final_fare_predictions.csv

   actual_fare  predicted_fare
0         10.5             9.9
1          5.0             4.8
2         12.5            11.3
```

3	3.7	5.4
4	8.5	6.1
5	10.1	10.1
6	20.0	18.5
7	4.9	5.2
8	16.0	18.8
9	7.5	7.1