Taxi Prediction In [1]: import numpy as np import pandas as pd import matplotlib.pyplot as plt import seaborn as sns import plotly.express as px import random import time import sklearn import statsmodels.api as sm import datetime from datetime import datetime, timedelta import scipy.stats from sklearn.linear model import ElasticNet, Lasso, LinearRegression, Ridge from sklearn.ensemble import RandomForestRegressor, ExtraTreesRegressorfrom sklearn.ensemble import GradientBoostingRegressor %matplotlib inline #sets the default autosave frequency in seconds **%autosave** 60 sns.set_style('dark') sns.set(font_scale=1.2) plt.rc('axes', labelsize=14) plt.rc('xtick', labelsize=12) plt.rc('ytick', labelsize=12) from sklearn.model_selection import cross_val_score, train_test_split, GridSearchCV, RandomizedSearchCV from sklearn.model_selection import cross_validate, KFold, RepeatedStratifiedKFold from sklearn.preprocessing import LabelEncoder, StandardScaler, MinMaxScaler, OneHotEncoder from sklearn.tree import export_graphviz, plot_tree from sklearn.metrics import confusion_matrix, classification_report, mean_absolute_error, mean_squared_error,r2 from sklearn.metrics import plot confusion matrix, plot precision recall curve, plot roc curve, accuracy score from sklearn.metrics import auc, f1_score, precision_score, recall_score, roc_auc_score import warnings warnings.filterwarnings('ignore') from pycaret.regression import * pd.set_option('display.max_columns', None) #pd.set option('display.max rows',100) pd.set option('display.width', 1000) pd.set_option('display.float_format','{:.2f}'.format) random.seed(0) np.random.seed(0) np.set_printoptions(suppress=True) Autosaving every 60 seconds **Exploratory Data Analysis** In [2]: df = pd.read_csv("week3.csv",parse_dates=['PickupTime','DropoffTime']) Vendor PickupTime DropoffTime Passengers Distance PickupLon PickupLat RateCode HeldFlag DropoffLon DropoffLat PayType 2015-12-01 2015-12-01 Credit 0 18.60 -73.78 40.64 JFK Ν -74.00 40.72 1 00:00:00 00:29:35 card 2015-12-04 2015-12-04 2 2 0.33 -73.98 40.76 Standard Ν -73.98 40.75 Cash 19:00:00 19:11:56 2015-12-04 2015-12-04 1 8.70 -73.87 40.77 Standard Ν -73.97 40.69 Cash 19:00:00 19:27:42 2015-12-04 2015-12-04 Credit 1.55 -73.98 40.75 Standard Ν -73.99 40.76 19:00:00 19:31:36 card 2015-12-04 2015-12-04 4 0.90 1 -73.99 40.76 Standard Ν -73.99 40.75 Dispute 19:00:00 19:17:47 2016-01-01 2015-12-31 Credit 31525 2 16.98 -73.78 40.64 JFK Ν -73.98 40.75 23:00:00 00:12:14 card 2015-12-31 2015-12-31 Credit 31526 1.40 -73.98 40.76 Ν -73.96 40.77 Standard 23:00:00 23:58:53 card 2015-12-31 2016-01-01 2 2 31527 1.44 -73.99 40.75 Standard Ν -74.01 40.74 Cash 23:00:00 00:02:57 2015-12-31 2015-12-31 Credit Standard 31528 0.10 -73.99 40.76 Ν -73.99 40.76 23:00:00 23:59:25 card 2015-12-31 2016-01-01 31529 1.50 -73.99 40.75 Standard -74.01 40.74 Cash 23:00:00 00:05:42 31530 rows × 22 columns In [4]: df.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 31530 entries, 0 to 31529 Data columns (total 22 columns): Column Non-Null Count Dtype 0 Vendor 31530 non-null int64 1 PickupTime 31530 non-null datetime64[ns] 31530 non-null datetime64[ns] 2 DropoffTime 31530 non-null Passengers int64 Distance 31530 non-null float64 31530 non-null float64 PickupLon 31530 non-null float64 PickupLat RateCode 31530 non-null object 8 HeldFlag 31530 non-null object 9 DropoffLon 31530 non-null float64 DropoffLat 31530 non-null float64 10 11 PayType 31530 non-null object 12 31530 non-null float64 13 ExtraCharge 31530 non-null float64 31530 non-null float64 14 Tax 31530 non-null float64 15 Tip 31530 non-null float64 16 Tolls 17 ImpSurcharge 31530 non-null float64 31530 non-null float64 18 TotalCharge 19 Duration 31530 non-null float64 AveSpeed 31530 non-null float64 31530 non-null object Location dtypes: datetime64[ns](2), float64(14), int64(2), object(4) memory usage: 5.3+ MB df.describe(include='all') Vendor PickupTime DropoffTime Passengers Distance PickupLon PickupLat RateCode HeldFlag DropoffLon DropoffLat PayTyr 31293 2 unique 744 NaN NaN NaN NaN NaN NaN 2015-12-07 2015-12-24 Crec top NaN NaN NaN NaN NaN Standard Ν NaN NaN 21:00:00 09:34:10 28611 31278 freq NaN 91 3 NaN NaN NaN NaN NaN NaN 1861 2015-12-01 2015-12-01 first NaN NaN NaN NaN NaN NaN NaN NaN NaN Na 00:00:00 00:06:38 2015-12-31 2016-01-01 last NaN NaN NaN NaN NaN NaN NaN NaN NaN Na 23:00:00 00:12:14 mean 1.54 NaN NaN 1.71 5.70 -73.94 40.74 NaN NaN -73.97 40.75 Na 0.50 0.04 0.04 std NaN NaN 1.33 6.02 0.08 NaN NaN 0.03 Na 1.00 0.03 40.64 min NaN NaN 1.00 -74.00 NaN NaN -74.19 40.57 Na 1.00 1.00 40.75 40.74 25% NaN NaN 1.19 -73.99 NaN NaN -73.99 Na **50**% 2.00 NaN NaN 1.00 40.75 -73.98 40.75 2.52 -73.98 NaN NaN Na **75**% 2.00 NaN NaN 2.00 9.51 -73.87 40.76 NaN NaN -73.97 40.76 Na 2.00 NaN 6.00 37.20 -73.78 40.77 -73.60 40.96 max NaN NaN NaN Na df.isnull().sum() Out[6]: Vendor 0 PickupTime 0 DropoffTime 0 Passengers 0 Distance 0 PickupLon 0 PickupLat 0 RateCode HeldFlag 0 DropoffLon 0 0 DropoffLat PayType Fare 0 ExtraCharge 0 0 Tax Tip Tolls 0 ImpSurcharge 0 TotalCharge 0 Duration 0 AveSpeed 0 Location 0 dtype: int64 df.shape (31530, 22) df.columns Out[8]: Index(['Vendor', 'PickupTime', 'DropoffTime', 'Passengers', 'Distance', 'PickupLon', 'PickupLat', 'RateCode', 'HeldFlag', 'DropoffLon', 'DropoffLat', 'PayType', 'Fare', 'ExtraCharge', 'Tax', 'Tip', 'Tolls', 'ImpSurcharg e', 'TotalCharge', 'Duration', 'AveSpeed', 'Location'], dtype='object') Choose Fare min USD8 and not more than USD31 In [9]: df.Fare.describe() Out[9]: count 31530.00 mean 20.41 std 15.87 2.50 min 25% 8.00 50% 13.00 75% 31.00 100.00 ${\tt max}$ Name: Fare, dtype: float64 df2 = df[df.Fare.between(8.00,31.00)]Vendor PickupTime DropoffTime Passengers Distance PickupLon PickupLat RateCode HeldFlag DropoffLon DropoffLat PayType 2015-12-04 2015-12-04 2 8.70 -73.87 40.77 Standard -73.97 40.69 Cash 19:00:00 19:27:42 2015-12-04 2015-12-04 Credit 1.55 -73.98 40.75 Standard -73.99 40.76 19:00:00 19:31:36 card 2015-12-04 2015-12-04 2 1 2.65 -73.99 40.75 Standard Ν -73.96 40.77 Cash 17:00:00 17:47:30 2015-12-04 2015-12-04 7 3 1.07 -73.98 40.76 Standard -73.98 40.77 Cash 17:00:00 17:35:36 2015-12-04 2015-12-04 8 1.68 -73.99 40.75 Standard -74.00 40.74 Cash 17:00:00 17:33:57 2015-12-31 2015-12-31 Credit 31508 1 6.70 -73.99 40.75 Standard Ν -73.95 40.82 23:00:00 23:42:01 card 2015-12-31 2015-12-31 31511 1.85 -73.98 40.75 Standard -74.01 40.74 Cash 23:00:00 23:34:11 2015-12-31 2015-12-31 31513 3 1.80 -73.99 40.75 Standard -73.98 40.76 Cash 23:00:00 23:46:07 2015-12-31 2015-12-31 31514 7.01 -73.99 40.76 Standard -73.96 40.70 Cash 23:00:00 23:58:48 2015-12-31 2015-12-31 31522 2 3.80 -73.99 40.75 Standard -73.99 40.72 Cash 23:00:00 23:55:40 16123 rows × 22 columns df2.reset index(inplace=True, drop=True) df2 Vendor PickupTime DropoffTime Passengers Distance PickupLon PickupLat RateCode HeldFlag DropoffLon DropoffLat PayType 2015-12-04 2015-12-04 0 8.70 -73.87 40.77 Standard -73.97 40.69 1 Ν Cash 19:00:00 19:27:42 2015-12-04 2015-12-04 Credit 1 1.55 -73.98 40.75 -73.99 40.76 Standard Ν 19:00:00 19:31:36 card 2015-12-04 2015-12-04 2 2 2.65 -73.99 -73.96 1 40.75 Standard Ν 40.77 Cash 17:00:00 17:47:30 2015-12-04 2015-12-04 3 3 1.07 -73.98 40.76 Standard Ν -73.98 40.77 Cash 17:00:00 17:35:36 2015-12-04 2015-12-04 4 -74.00 1 1.68 -73.99 40.75 Ν 40.74 Standard Cash 17:00:00 17:33:57 2015-12-31 2015-12-31 Credit 16118 6.70 -73.99 -73.95 40.82 40.75 Standard Ν 1 23:00:00 23:42:01 card 2015-12-31 2015-12-31 -73.98 16119 1.85 40.75 Ν -74.01 40.74 Cash Standard 23:00:00 23:34:11 2015-12-31 2015-12-31 3 Standard -73.98 16120 1.80 -73.99 40.75 Ν 40.76 Cash 23:00:00 23:46:07 2015-12-31 2015-12-31 16121 7.01 -73.99 40.76 -73.96 40.70 Cash Standard 23:00:00 23:58:48 2015-12-31 2015-12-31 16122 2 3.80 -73.99 40.75 Standard -73.99 40.72 Ν Cash 23:00:00 23:55:40 16123 rows × 22 columns df2["trip duration"] = df2['DropoffTime'] - df2['PickupTime'] In [14]: df2["trip duration"] = df2["trip duration"].dt.floor(freq="min") df2["trip_duration"] 0 days 00:27:00 0 days 00:31:00 0 days 00:47:00 3 0 days 00:35:00 0 days 00:33:00 16118 0 days 00:42:00 16119 0 days 00:34:00 16120 0 days 00:46:00 16121 0 days 00:58:00 16122 0 days 00:55:00 Name: trip duration, Length: 16123, dtype: timedelta64[ns] df2["trip_duration"] = df2["trip_duration"].astype('timedelta64[m]').astype('int') df2 Vendor PickupTime DropoffTime Passengers Distance PickupLon PickupLat RateCode HeldFlag DropoffLon DropoffLat PayType 2015-12-04 2015-12-04 0 8.70 -73.87 40.77 Standard -73.97 40.69 Cash 19:00:00 19:27:42 2015-12-04 2015-12-04 Credit 1.55 -73.98 40.75 Standard -73.99 40.76 19:00:00 19:31:36 card 2015-12-04 2015-12-04 2 2.65 -73.99 40.75 Standard -73.96 40.77 Cash 17:00:00 17:47:30 2015-12-04 2015-12-04 1.07 -73.98 40.76 Standard -73.98 40.77 Cash 17:00:00 17:35:36 2015-12-04 2015-12-04 1 1.68 -73.99 40.75 Standard -74.00 40.74 Cash 17:00:00 17:33:57 2015-12-31 2015-12-31 Credit 16118 6.70 -73.99 40.75 -73.95 40.82 Standard 23:00:00 23:42:01 card 2015-12-31 2015-12-31 16119 1.85 -73.98 40.75 Standard -74.01 40.74 Cash 23:00:00 23:34:11 2015-12-31 2015-12-31 16120 3 1.80 -73.99 40.75 Standard -73.98 40.76 Cash 23:00:00 23:46:07 2015-12-31 2015-12-31 16121 7.01 -73.99 40.76 Standard -73.96 40.70 Cash 23:00:00 23:58:48 2015-12-31 2015-12-31 16122 2 3.80 -73.99 40.75 Standard -73.99 40.72 Cash 23:00:00 23:55:40 16123 rows × 23 columns df2.describe() Out[18]: Vendor Passengers Distance PickupLon PickupLat DropoffLon DropoffLat Fare ExtraCharge Tip Tolls Im **count** 16123.00 16123.00 16123.00 16123.00 16123.00 16123.00 16123.00 16123.00 16123.00 16123.00 16123.00 16123.00 1.53 1.71 3.58 -73.96 40.75 -73.97 40.75 15.39 0.32 0.50 1.99 0.57 mean std 0.50 1.33 0.05 0.02 0.04 0.03 6.71 0.37 0.00 2.31 1.69 1.00 1.00 -74.00 40.64 -74.06 40.59 8.00 0.00 0.50 0.00 0.00 min 25% 1.00 1.59 -73.99 40.75 -73.99 40.73 10.00 0.00 0.50 0.00 0.00 50% 2.00 1.00 -73.99 40.75 -73.98 40.76 13.00 0.00 0.50 1.76 0.00 **75**% 2.00 2.00 4.78 -73.98 40.76 -73.96 40.77 19.50 0.50 0.50 3.09 0.00 max 2.00 6.00 22.10 -73.78 40.77 -73.68 40.92 31.00 0.50 40.00 11.08 In [19]: df2.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 16123 entries, 0 to 16122 Data columns (total 23 columns): Non-Null Count Dtype # Column _____ --- ----16123 non-null int64 Vendor 0 1 PickupTime 16123 non-null datetime64[ns] DropoffTime 16123 non-null datetime64[ns] 16123 non-null int64 Passengers 16123 non-null float64 Distance 16123 non-null float64 PickupLon 16123 non-null float64 PickupLat 7 RateCode 16123 non-null object 8 16123 non-null object HeldFlag 9 DropoffLon 16123 non-null float64 10 DropoffLat 16123 non-null float64 16123 non-null object PayType 11 16123 non-null float64 12 Fare 13 ExtraCharge 16123 non-null float64 16123 non-null float64 14 Tax 15 Tip 16123 non-null float64 16 Tolls 16123 non-null float64 17 ImpSurcharge 16123 non-null float64 TotalCharge 16123 non-null float64 16123 non-null float64 18 19 Duration 16123 non-null float64 20 AveSpeed 21 Location 16123 non-null object 22 trip duration 16123 non-null int32 dtypes: datetime64[ns](2), float64(14), int32(1), int64(2), object(4) memory usage: 2.8+ MB df2.PickupTime.min() Out[20]: Timestamp('2015-12-01 00:00:00') df2["month"] = pd.DatetimeIndex(df2['PickupTime']).month df2["day"] = pd.DatetimeIndex(df2['PickupTime']).day df2["dayofweek"] = pd.DatetimeIndex(df2['PickupTime']).dayofweek In [24]: df2["hour"] = pd.DatetimeIndex(df2['PickupTime']).hour Vendor PickupTime DropoffTime Passengers Distance PickupLon PickupLat RateCode HeldFlag DropoffLon DropoffLat PayType 2015-12-04 2015-12-04 -73.97 0 8.70 -73.87 40.77 Standard 40.69 Cash Ν 19:00:00 19:27:42 2015-12-04 2015-12-04 Credit 1.55 -73.98 40.75 Standard -73.99 40.76 19:00:00 19:31:36 card 2015-12-04 2015-12-04 1 2.65 -73.99 40.75 Standard Ν -73.96 40.77 Cash 17:00:00 17:47:30 2015-12-04 2015-12-04 1.07 -73.98 40.76 Standard -73.98 40.77 Cash 17:00:00 17:35:36 2015-12-04 2015-12-04 1.68 -73.99 40.75 Standard Ν -74.00 40.74 Cash 17:00:00 17:33:57 2015-12-31 2015-12-31 Credit 16118 -73.99 40.82 1 6.70 40.75 Standard Ν -73.95 23:00:00 23:42:01 card 2015-12-31 2015-12-31 16119 1.85 -73.98 40.75 Standard -74.01 40.74 Cash 23:00:00 23:34:11 2015-12-31 2015-12-31 16120 1.80 -73.99 40.75 Standard Ν -73.98 40.76 Cash 23:00:00 23:46:07 2015-12-31 2015-12-31 16121 7.01 -73.99 40.76 Standard -73.96 40.70 Cash 23:00:00 23:58:48 2015-12-31 2015-12-31 16122 2 3.80 -73.99 40.75 Standard Ν -73.99 40.72 Cash 23:00:00 23:55:40 16123 rows × 27 columns df3 = pd.read_csv("tripcounts.csv", parse_dates=['PickupTime']) PickupTime Location TripCount **0** 2015-01-01 00:00:00 Manhattan 22 **1** 2015-01-01 00:00:00 LaGuardia 2 2 2015-01-01 00:00:00 3 2015-01-01 01:00:00 Manhattan 10 4 2015-01-01 01:00:00 LaGuardia 0 **26212** 2015-12-31 22:00:00 LaGuardia 9 **26213** 2015-12-31 22:00:00 JFK 12 **26214** 2015-12-31 23:00:00 Manhattan 24 **26215** 2015-12-31 23:00:00 LaGuardia 7 **26216** 2015-12-31 23:00:00 JFK 26217 rows × 3 columns df3.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 26217 entries, 0 to 26216 Data columns (total 3 columns): # Column Non-Null Count Dtype O PickupTime 26217 non-null datetime64[ns] 26217 non-null object Location 2 TripCount 26217 non-null int64 dtypes: datetime64[ns](1), int64(1), object(1)memory usage: 614.6+ KB In [29]: df3["TripCount"].hist(bins=50, figsize=(20,10)) plt.suptitle('TripCount Feature Distribution', x=0.5, y=1.02, ha='center', fontsize=20) plt.tight layout() plt.show() **TripCount Feature Distribution** 2000 df3.boxplot(figsize=(20,10), by="Location") plt.suptitle('TripCount Feature Distribution', x=0.5, y=1.02, ha='center', fontsize=20) plt.xlabel("Location") plt.tight_layout() plt.show() **TripCount Feature Distribution** PickUpTime only in December month for merger df3["PickupTime"] = df3["PickupTime"].dt.strftime('%Y-%m-%d') df4 = df3[df3["PickupTime"].between(left='2015-12-01', right='2015-12-31')] PickupTime **Location TripCount** 23985 2015-12-01 Manhattan 14 23986 2015-12-01 LaGuardia 2 **23987** 2015-12-01 JFK 15 23988 2015-12-01 Manhattan **23989** 2015-12-01 LaGuardia 0 **26212** 2015-12-31 LaGuardia 9 **26213** 2015-12-31 **26214** 2015-12-31 Manhattan 24 **26215** 2015-12-31 LaGuardia 7 **26216** 2015-12-31 JFK 2232 rows × 3 columns df4.reset index(drop=True, inplace=True) In [34]: df4.head() Out[34]: **Location TripCount PickupTime 0** 2015-12-01 Manhattan 14 2015-12-01 2 LaGuardia 2 2015-12-01 JFK 15 2015-12-01 Manhattan 8 2015-12-01 LaGuardia 0 df4.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 2232 entries, 0 to 2231 Data columns (total 3 columns): # Column Non-Null Count Dtype PickupTime 2232 non-null object Location 2232 non-null TripCount 2232 non-null dtypes: int64(1), object(2) memory usage: 52.4+ KB df2["PickupTime"] = df2["PickupTime"].dt.strftime('%Y-%m-%d') df2.head() Vendor PickupTime DropoffTime Passengers Distance PickupLon PickupLat RateCode HeldFlag DropoffLon DropoffLat PayType 2015-12-04 1 2015-12-04 Standard -73.97 0 8.70 -73.87 40.77 40.69 Cash 25.! 19:27:42 2015-12-04 Credit -73.99 2 2015-12-04 1.55 -73.98 40.75 Standard 40.76 19:31:36 card 2015-12-04 2 2 2015-12-04 2.65 -73.99 40.75 -73.96 40.77 Standard Ν Cash 15.0 17:47:30 2015-12-04 3 2 2015-12-04 1.07 -73.98 40.76 -73.98 40.77 8.0 Standard Ν Cash 17:35:36 2015-12-04 2015-12-04 4 1 1.68 -73.99 40.75 Standard Ν -74.00 40.74 Cash 8.0 17:33:57 df2.columns Out[38]: Index(['Vendor', 'PickupTime', 'DropoffTime', 'Passengers', 'Distance', 'PickupLon', 'PickupLat', 'RateCode', 'HeldFlag', 'DropoffLon', 'DropoffLat', 'PayType', 'Fare', 'ExtraCharge', 'Tax', 'Tip', 'Tolls', 'ImpSurcharg e', 'TotalCharge', 'Duration', 'AveSpeed', 'Location', 'trip_duration', 'month', 'day', 'dayofweek', 'hour'], d type='object') df2.drop(['Vendor','DropoffTime','PickupLon', 'PickupLat', 'RateCode', 'HeldFlag', 'DropoffLon', 'DropoffLat', 'PayType', 'Fare', 'ExtraCharge', 'Tax', 'Tip', 'Tolls', 'ImpSurcharge', 'Duration', 'Location'], axis=1, inplace=True) In [40]: df2.sort values("PickupTime") Out[40]: PickupTime Passengers Distance TotalCharge AveSpeed trip_duration month day dayofweek hour 1445 2015-12-01 1 6.51 21.80 19.91 29 12 12 1515 2015-12-01 1.00 8.80 5.89 56 12 14 71 1514 2015-12-01 1 9.09 42.41 21.54 12 1 1 14 1513 2015-12-01 0.99 14.04 3.78 12 14 2 3.20 24.36 73 1512 2015-12-01 6.49 12 1 1 14 15794 2015-12-31 3 4 0.82 8.80 4.45 43 12 31 12 15793 2015-12-31 3.05 15.38 14.52 12 31 12 15792 2015-12-31 1 1.87 8.80 15.37 27 12 31 3 12 15760 2015-12-31 8.70 39.99 25.53 70 12 31 10 2 3 23 **16122** 2015-12-31 3.80 15.80 15.87 55 12 31 16123 rows × 10 columns In [41]: df2 = df2.sort values("PickupTime") In [42]: df2.reset_index(inplace=True, drop=True) In [43]: df2 Out[43]: PickupTime Passengers Distance TotalCharge AveSpeed trip_duration month day dayofweek hour 2015-12-01 1 6.51 21.80 19.91 29 12 1 12 2015-12-01 8.80 5.89 12 2015-12-01 1 9.09 42.41 21.54 71 12 14 2015-12-01 0.99 14.04 3.78 61 12 2015-12-01 2 3.20 24.36 6.49 73 12 1 1 14 8.80 16119 2015-12-31 3 3.05 15.38 14.52 34 31 12 12 2015-12-31 3 1 1.87 8.80 15.37 27 12 12 16120 31 16121 2015-12-31 8.70 39.99 25.53 70 12 31 3 10 2 3 16122 2015-12-31 3.80 15.80 55 23 15.87 12 31 16123 rows × 10 columns In [44]: #Handling Redundancy/Duplicates in Joins df5 = pd.merge(df2,df4.drop duplicates(subset='PickupTime'),how='left',on='PickupTime') In [45]: df5 Out[45]: PickupTime Passengers Distance TotalCharge AveSpeed trip_duration month day dayofweek hour **Location TripCount** 2015-12-01 1 6.51 21.80 19.91 29 12 1 12 Manhattan 14 1 2015-12-01 1.00 8.80 5.89 56 12 1 14 Manhattan 14 2015-12-01 1 9.09 42.41 21.54 71 12 1 1 14 Manhattan 14 2015-12-01 2 0.99 14.04 3.78 61 12 1 Manhattan 14 2015-12-01 2 73 3.20 24.36 6.49 12 1 1 14 Manhattan 14 16118 2015-12-31 0.82 8.80 4 4.45 43 12 31 3 12 Manhattan 37 3.05 16119 2015-12-31 3 15.38 14.52 34 12 31 3 12 Manhattan 37 16120 2015-12-31 1 1.87 8.80 15.37 27 12 31 3 12 Manhattan 37 39.99 16121 2015-12-31 8.70 25.53 70 12 31 3 Manhattan 37 2015-12-31 2 15.80 55 3 37 16122 3.80 15.87 12 31 Manhattan 16123 rows × 12 columns **Data Visualization Univariate Data Exploration** In [46]: df5.hist(bins=50, figsize=(20,10)) plt.suptitle('Histogram Feature Distribution', x=0.5, y=1.02, ha='center', fontsize=20) plt.tight layout() plt.show() Histogram Feature Distribution Distance Passengers TotalCharge 10000 8000 1500 1000 1000 4000 2000 15000 1000 600 750 10000 200 60 11.8 2000 In [47]: df5.boxplot(figsize=(20,10)) plt.suptitle('BoxPlots Feature Distribution', x=0.5, y=1.02, ha='center', fontsize=20) plt.tight layout() plt.show() **BoxPlots Feature Distribution** Correlation In [48]: df5.corr() Out[48]: Passengers Distance TotalCharge AveSpeed trip_duration month day dayofweek hour TripCount **Passengers** 1.00 0.02 0.02 0.01 0.01 NaN 0.02 0.03 0.01 0.02 0.02 0.91 0.07 0.04 0.04 Distance 1.00 0.83 0.16 NaN -0.00 0.02 0.91 1.00 0.24 0.09 -0.01 **TotalCharge** 0.63 NaN 0.01 0.01 AveSpeed 0.01 0.83 0.63 1.00 -0.02 NaN 0.13 0.06 -0.01 -0.01 0.01 0.16 0.24 -0.02 1.00 -0.03 0.01 0.03 0.01 trip_duration NaN month NaN 0.02 0.07 0.01 -0.03 1.00 -0.04 0.01 0.02 0.13 NaN 0.03 0.04 0.01 -0.04 -0.02 dayofweek 0.06 0.01 NaN 1.00 0.65 hour 0.01 0.04 0.09 -0.01 0.03 NaN 0.01 -0.02 1.00 -0.06 0.02 -0.00 -0.01 -0.01 0.01 0.02 0.65 -0.06 1.00 **TripCount** NaN In [49]: df5.corr()["TripCount"].sort values()

-0.06 Out[49]: hour -0.01 AveSpeed -0.01 TotalCharge Distance -0.00 trip duration 0.01 0.02 Passengers 0.02 dayofweek 0.65 TripCount 1.00 month NaN Name: TripCount, dtype: float64 plt.figure(figsize=(16,9)) sns.heatmap(df5.corr(),cmap="coolwarm",annot=True,fmt='.2f',linewidths=2) plt.title("", fontsize=20) plt.show() 1.00 Passengers Distance 0.02 1.00 0.91 -0.00 8.0 1.00 0.63 0.24 TotalCharge 0.01 0.63 1.00 -0.01 AveSpeed 0.6 trip_duration 0.01 0.24 1.00 month 0.4 1.00 -0.04 -0.03 0.04 -0.04 1.00 dayofweek 0.65 0.2 -0.02 1.00 -0.06 hour -0.06 0.65 1.00 TripCount Passengers TotalCharge AveSpeed trip_duration dayofweek TripCount **Data Preprocessing Drop unwanted features** df5.columns Out[51]: Index(['PickupTime', 'Passengers', 'Distance', 'TotalCharge', 'AveSpeed', 'trip duration', 'month', 'day', 'day ofweek', 'hour', 'Location', 'TripCount'], dtype='object') df5.drop(['PickupTime', 'month', 'Location'], axis=1, inplace=True) df5 Passengers Distance TotalCharge AveSpeed trip_duration day dayofweek hour TripCount 0 6.51 21.80 19.91 29 12 14 1.00 8.80 5.89 56 14 14 9.09 42.41 21.54 71 14 14 0.99 14.04 3.78 2 3.20 24.36 6.49 73 14 14 16118 4 0.82 8.80 4.45 43 31 3 12 37 16119 3 3.05 15.38 14.52 12 37 31 16120 1 1.87 8.80 15.37 27 31 3 12 37 16121 8.70 39.99 25.53 10 37 70 2 3 37 16122 3.80 15.80 15.87 55 31 23 16123 rows × 9 columns **Treat Missing Values** In [54]: df5.isnull().sum() Out[54]: Passengers Distance TotalCharge AveSpeed trip_duration 0 day dayofweek 0 hour TripCount dtype: int64 **Treat Duplicate Values** df5.duplicated(keep='first').sum() Out[55]: 0 **Treat Data Types** df5.info() <class 'pandas.core.frame.DataFrame'> Int64Index: 16123 entries, 0 to 16122 Data columns (total 9 columns): Non-Null Count Dtype # Column 0 Passengers 16123 non-null int64 1 Distance 16123 non-null float64 TotalCharge 16123 non-null float64
AveSpeed 16123 non-null float64
trip_duration 16123 non-null int32
day 16123 non-null int64
dayofweek 16123 non-null int64 16123 non-null int64 hour 8 TripCount 16123 non-null int64 dtypes: float64(3), int32(1), int64(5) memory usage: 1.2 MB Create and save processed dataset #df5.to_csv("train2.csv",index=False) df5.shape Out[58]: (16123, 9) **Train Test Split** In [59]: X = df5.iloc[:,:8]y = df5.iloc[:,8]X.values, y.values Out[60]: (array([[1. , 6.51, 21.8 , ..., 1. , 1. , 12.], [1. , 1. , 8.8 , ..., 1. , 1. , 14.], [1., 9.09, 42.41, ..., 1., 1., 14.], [1. , 1.87, 8.8 , ..., 31. , 3. , 12.], [1. , 8.7 , 39.99, ..., 31. , 3. , 10.], [2. , 3.8 , 15.8 , ..., 31. , 3. , 23.]] array([14, 14, 14, ..., 37, 37, 37], dtype=int64)) In [61]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0) X_train.shape, X_test.shape, y_train.shape, y_test.shape Out[62]: ((12898, 8), (3225, 8), (12898,), (3225,)) **Feature Scaling** X train Passengers Distance TotalCharge AveSpeed trip_duration day dayofweek hour 15344 8.16 39.84 18.34 2 20 1 56 30 9228 2 1.78 11.16 13.46 39 17 0 13106 1 1.40 12.25 8.26 51 26 5 23 12415 3.60 17.16 16.12 23 1 3 9091 1.18 8.80 6.78 25 17 13 13123 3 3.20 11.80 20.35 9 26 5 10 3264 3.92 20.80 8.77 18 9845 2 1.65 12.80 5.93 19 5 35 20 10799 10.30 44.19 23.75 20 17 5 5 2732 1.29 12.30 5.64 50 20 12898 rows × 8 columns In [64]: scaler = StandardScaler() X_train_scaled = scaler.fit_transform(X_train) X_test_scaled = scaler.transform(X_test) In [67]: X_train_scaled Out[67]: array([[-0.53436466, 1.6951792, 2.26092482, ..., 1.60454256, -0.43213072, 0.9375585], [0.21454715, -0.66007444, -0.85358371, ..., 0.15876683, 0.07986836, -2.39972024], [-0.53436466, -0.80035601, -0.73521501, ..., 1.15968849, 1.10386653, 1.43815031], [0.21454715, -0.70806551, -0.67548768, ..., 0.38119386,1.10386653, 0.9375585], [0.21454715, 2.4851859, 1.61586561, 0.43696669], 2.73331367, ..., 0.49240738, [-0.53436466, -0.84096383, -0.72978525, ..., -1.17579539,1.10386653, 0.9375585]]) X_test_scaled Out[68]: array([[-0.53436466, -0.72652361, -0.59404133, ..., -0.50851428, 0.59186745, -0.56421694], [0.21454715, -0.84096383, -1.05557066, ..., 1.04847497, 0.59186745, 1.10442244], [-0.53436466, -0.6896074, -0.45829741, ..., -1.62064947, -0.9441298, 0.60383063], [-0.53436466, -0.4681102, -0.67548768, ..., -1.17579539,1.10386653, -2.06599237], [2.46128256, -0.33152025, -0.72978525, ..., 1.38211553, -1.45612888, 0.10323881], [-0.53436466, 0.03395014, -0.51259498, ..., 1.71575608, 0.07986836, 1.10442244]]) **Model Training Using PyCaret** from pycaret.regression import * exp_reg = setup(data = df5, target = 'TripCount', session_id=0, normalize=True, train_size = 0.8, numeric_features=['Passengers', 'trip_duration']) Description Value 0 session_id TripCount 1 Target 2 Original Data (16123, 9)Missing Values 3 False 4 7 Numeric Features **Categorical Features** 5 1 6 **Ordinal Features** False 7 **High Cardinality Features** False 8 **High Cardinality Method** None 9 Transformed Train Set (12898, 14) 10 Transformed Test Set (3225, 14)Shuffle Train-Test 11 True 12 Stratify Train-Test False 13 Fold Generator KFold 14 Fold Number 10 15 **CPU Jobs** -1 16 Use GPU False 17 Log Experiment False 18 Experiment Name reg-default-name 19 USI 72bb 20 Imputation Type simple Iterative Imputation Iteration 21 None 22 Numeric Imputer mean Iterative Imputation Numeric Model 23 None 24 Categorical Imputer constant 25 Iterative Imputation Categorical Model None 26 **Unknown Categoricals Handling** least_frequent Normalize 27 True Normalize Method 28 zscore 29 Transformation False 30 Transformation Method None **PCA** 31 False 32 PCA Method None 33 **PCA Components** None 34 Ignore Low Variance False 35 Combine Rare Levels False Rare Level Threshold 36 None **Numeric Binning** 37 False 38 Remove Outliers False **Outliers Threshold** 39 None Remove Multicollinearity 40 False Multicollinearity Threshold 41 None Remove Perfect Collinearity 42 True 43 Clustering False 44 Clustering Iteration None 45 **Polynomial Features** False Polynomial Degree 46 None **Trignometry Features** 47 False 48 Polynomial Threshold None 49 **Group Features** False 50 Feature Selection False Feature Selection Method 51 classic 52 Features Selection Threshold None 53 Feature Interaction False 54 Feature Ratio False 55 Interaction Threshold None 56 Transform Target False Transform Target Method 57 compare_models(exclude=['omp','br','ard','par','ransac','tr','huber','kr','ada','mlp','xgboost','lightgbm'],fol Model MAE MSE RMSE R2 RMSLE MAPE TT (Sec) 0.0000 1.0000 0.0000 0.0000 0.0000 0.0000 0.0300 dt **Decision Tree Regressor** 1.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.6700 Random Forest Regressor 0.0143 1.0000 0.0000 0.3300 Extra Trees Regressor 0.0012 0.0002 0.0006 0.2526 0.9993 0.0119 0.0099 0.6380 **Gradient Boosting Regressor** 0.1999 0.0641 K Neighbors Regressor 1.2292 7.4005 2.7193 0.9150 0.1186 0.0613 0.1100 knn 0.2525 4.7568 35.7548 5.9787 0.5896 0.2802 1.1400 lr Linear Regression 4.7573 35.7548 5.9787 0.5896 0.2526 0.0140 ridge Ridge Regression 0.2802 Least Angle Regression 4.7568 35.7548 5.9787 0.5896 0.2802 0.2525 0.0160 7.2695 73.5511 8.5757 0.1557 0.4035 0.4177 0.0160 lasso Lasso Regression 0.4280 0.0140 en Elastic Net 75.9660 8.7154 0.1280 0.4095 llar Lasso Least Angle Regression 8.0209 87.1459 9.3348 -0.0004 0.4341 0.4594 0.0140 0.4594 **dummy** Dummy Regressor 8.0209 87.1459 9.3348 -0.0004 0.0140 0.4341 Out[71]: DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=None, max_features=None, max_leaf_nodes=None, min_impurity_decrease=0.0, min_impurity_split=None, min_samples_leaf=1, min_samples_split=2, min_weight_fraction_leaf=0.0, presort='deprecated', random_state=0, splitter='best') model_selected = create_model('gbr') MAE MSE RMSE **R2 RMSLE MAPE 0** 0.2004 0.0635 0.2521 0.9993 0.0124 0.0103 **1** 0.2116 0.0699 0.2644 0.9992 0.0124 0.0104 **2** 0.1990 0.0635 0.2520 0.9993 0.0111 0.0095 **3** 0.2467 0.0929 0.3048 0.9990 0.0139 0.0119 **4** 0.2498 0.1055 0.3249 0.9988 0.0158 0.0127 **5** 0.2336 0.0787 0.2806 0.9991 0.0130 0.0115 **6** 0.1989 0.0628 0.2506 0.9993 0.0128 0.0104 **7** 0.2326 0.0851 0.2917 0.9990 0.0139 0.0117 **8** 0.2344 0.0899 0.2998 0.9990 0.0133 0.0112 **9** 0.2175 0.0690 0.2627 0.9992 0.0118 0.0106 0.2225 0.0781 0.2783 0.9991 0.0130 **SD** 0.0185 0.0140 0.0247 0.0002 0.0012 0.0009 print(model_selected) ${\tt GradientBoostingRegressor(alpha=0.9, ccp_alpha=0.0, criterion="friedman_mse", ccp_alpha=0.0, criterion="friedman_mse", cop_alpha=0.0, criterion="friedman_mse", criterion="friedm$ init=None, learning_rate=0.1, loss='ls', max_depth=3, max_features=None, max_leaf_nodes=None, min_impurity_decrease=0.0, min_impurity_split=None, min_samples_leaf=1, min_samples_split=2, min weight fraction leaf=0.0, n estimators=100, n iter no change=None, presort='deprecated', random_state=0, subsample=1.0, tol=0.0001, validation_fraction=0.1, verbose=0, warm_start=False) In [74]: plot model (model selected) Residuals for GradientBoostingRegressor Model Train $R^2 = 0.999$ 40 Test $R^2 = 0.999$ 0.2 0.2 0 Residuals 0 0 -0.2 -0.2 0 -0.4-0.40 -0.6 -0.6 5 30 35 1000 Predicted Value Distribution plot_model(model_selected, plot = 'error') Prediction Error for GradientBoostingRegressor best fit identity $R^2 = 0.999$ 35 30 25 20 15 10 5 15 20 25 30 35 40 plot_model(model_selected, plot='feature') Feature Importance Plot day dayofweek_0 dayofweek_1 dayofweek_2 dayofweek_4 dayofweek_6 dayofweek_5 dayofweek 3 hour AveSpeed 0.00 0.05 0.10 0.20 0.25 0.30 0.35 Variable Importance **Using Regression or Classification Models** reg model = GradientBoostingRegressor() reg_model.fit(X_train_scaled,y_train) Out[78]: GradientBoostingRegressor(alpha=0.9, ccp_alpha=0.0, criterion='friedman mse', init=None, learning_rate=0.1, loss='ls', max_depth=3, max features=None, max leaf nodes=None, min_impurity_decrease=0.0, min_impurity_split=None, min samples leaf=1, min samples split=2, min_weight_fraction_leaf=0.0, n_estimators=100, n_iter_no_change=None, presort='deprecated', random state=None, subsample=1.0, tol=0.0001, validation fraction=0.1, verbose=0, warm start=False) y_pred = reg_model.predict(X_test_scaled) y pred Out[80]: array([37.08322843, 20.02907741, 13.81554489, ..., 24.40743378, 24.67452898, 36.79374546]) **Model Evaluation** mse = mean_squared_error(y_test,y_pred) mse Out[81]: 0.1080166158851585 rmse = np.sqrt(mse) rmse Out[82]: 0.3286588137950335 r2score = r2_score(y_test,y_pred) r2score Out[83]: 0.9987575637140792 In [84]: fig, ax = plt.subplots(figsize=(10,8))sns.regplot(x=y_test, y=y_pred, ax=ax) plt.title("Plot to compare actual vs predicted", fontsize=20) plt.ylabel("Predicted") plt.xlabel("Actual") plt.show() Plot to compare actual vs predicted 40 35 30 Predicted 15 10 Actual **Plot Feature Importances** reg_model.feature_importances_ [0. , 0. , 0. , 0. 0. 0.38300571, 0.61699429, 0. , 0. , 0. Out[85]: array([0.]) feat importances = pd.Series(reg_model.feature_importances_, index=X.columns) In [87]: feat_importances Out[87]: Passengers 0.00 Distance 0.00 0.00 TotalCharge 0.00 AveSpeed trip_duration 0.00 day 0.38 dayofweek 0.62 hour 0.00 dtype: float64 feat importances.nlargest(10).plot(kind='barh', figsize=(10,10)) plt.title('Feature Importances') plt.show() Feature Importances Passengers TotalCharge trip_duration Distance AveSpeed dayofweek 0.1 0.2 0.3 0.4 0.5 0.6 **Cross-Validation** cv = cross val score(reg model, X, y, cv=5, verbose=1, scoring='neg root mean squared error') [Parallel(n jobs=1)]: Using backend SequentialBackend with 1 concurrent workers. [Parallel(n_jobs=1)]: Done 5 out of 5 | elapsed: cv.mean() Out[90]: -6.323263197229591 Model Application, Results, and Analysis test_data = pd.DataFrame([10,3,30.00,20.0,10,5,6,12]).T test data 7 **0** 10.00 3.00 30.00 20.00 10.00 5.00 6.00 12.00 trip_count_prediction = reg_model.predict(test_data) In [94]: trip_count_prediction Out[94]: array([32.79617035]) Using Gradient Boosting Regressor, the model was able to acheive less than 4.9 RMSE score. We found out day and day of week is most important for taxi trip counts. Therefore deployment of taxi fleets must be targeted on customers who need them on special days or day of the week.