# **Predicting Car Stopping Distance**

The goal of this project is to predict a car's stopping distance by constructing a predictive model that will utilize the car's speed and the corresponding stopping distance.

Data

The source of the dataset is Ezekiel, M. (1930) Methods of Correlation Analysis. Wiley. They note the dataset is from the decade of the last century - the 1920's.

The dataset has two numerical attributes:

- speed speed of the car in mph
- · dist stopping distance in feet

```
In [ ]: #basic libraries
        import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns
        #train test split, grid search
        from sklearn.model_selection import train_test_split, GridSearchCV
        #regression models
        from sklearn.linear_model import LinearRegression
        from sklearn.preprocessing import PolynomialFeatures
        from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
        from sklearn.svm import SVR
        from sklearn.tree import DecisionTreeRegressor
        #evaluation
        import statsmodels.api as sm
        from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
In [ ]: #loading the data
        data = pd.read_csv('cars.csv', index_col=0)
```

### **Data Exploration and Visualization**

```
In []: #basic statistics
data.describe()
```

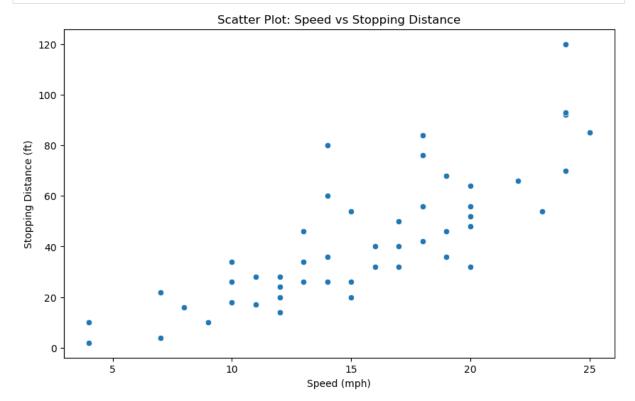
#### Out[]:

```
speed
                        dist
count 50.000000
                  50.000000
mean 15.400000
                  42.980000
       5.287644
                  25.769377
  std
 min
       4.000000
                   2.000000
 25%
      12.000000
                  26.000000
      15.000000
                  36.000000
      19.000000
                  56.000000
 max 25.000000 120.000000
```

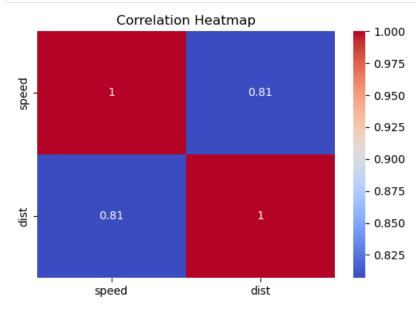
#### In [ ]: data.info()

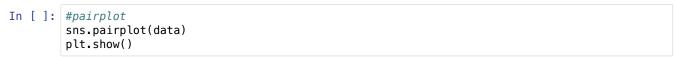
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 50 entries, 1 to 50
Data columns (total 2 columns):
# Column Non-Null Count Dtype
--- 0 speed 50 non-null int64
1 dist 50 non-null int64
dtypes: int64(2)
memory usage: 1.2 KB
```

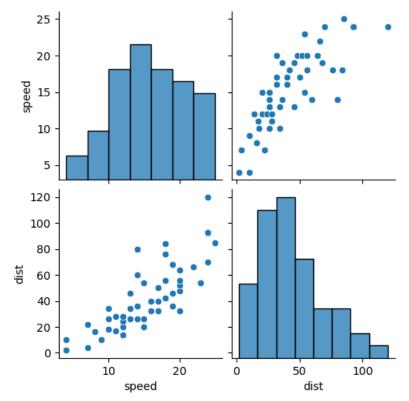
# In []: #speed and stopping distance scatter plot plt.figure(figsize=(10, 6)) sns.scatterplot(x='speed', y='dist', data=data) plt.title('Scatter Plot: Speed vs Stopping Distance') plt.xlabel('Speed (mph)') plt.ylabel('Stopping Distance (ft)') plt.show()



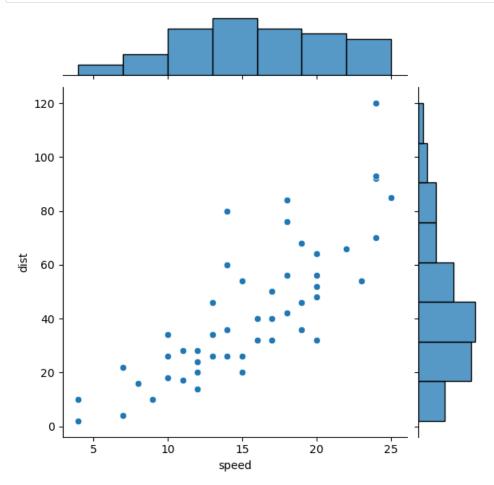
```
In []: #correlation
   plt.figure(figsize=(6, 4))
    sns.heatmap(data.corr(), annot=True, cmap='coolwarm')
   plt.title('Correlation Heatmap')
   plt.show()
```







```
In [ ]: #jointplot
sns.jointplot(x='speed', y='dist', data=data, kind='scatter')
plt.show()
```



# **Data Modeling**

```
In [ ]: #splitting the data into a train and test set
    X = data[['speed']]
    y = data['dist']
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

#### Fitting different regression models

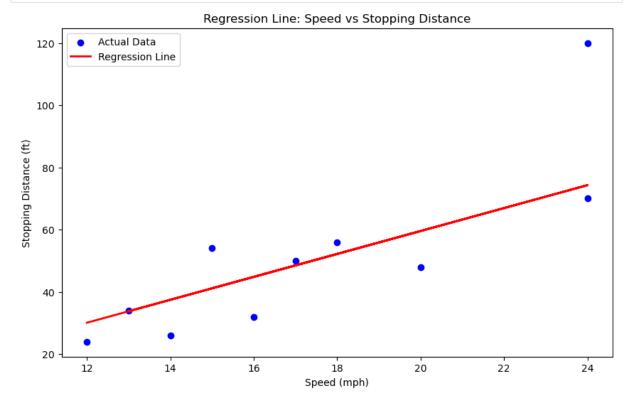
```
In [ ]: #fitting models
        #Linear Regression
        model_lr = LinearRegression()
        model_lr.fit(X_train, y_train)
        #Polynomial
        poly = PolynomialFeatures(degree=2)
        X_poly = poly.fit_transform(X_train)
        model_poly = LinearRegression()
        model_poly.fit(X_poly, y_train)
        #Random Forest
        model_rf = RandomForestRegressor(oob_score=True, random_state=42)
        param_grid_rf = {
            'n_estimators': [100, 200, 300],
            'max_depth': [None, 10, 20],
            'min_samples_split': [2, 5, 10]
        grid_rf = GridSearchCV(model_rf, param_grid_rf, cv=5)
        grid_rf.fit(X_train, y_train)
        #decicion tree
        model_dt = DecisionTreeRegressor(random_state=42)
        param_grid_dt = {
            'max_depth': [None, 5, 10, 15],
            'min_samples_split': [2, 5, 10]
        grid_dt = GridSearchCV(model_dt, param_grid_dt, cv=5)
        grid_dt.fit(X_train, y_train)
        #support vector machines
        model_svr = SVR(kernel='rbf')
        model_svr.fit(X_train, y_train)
        #gradient boost
        model_gb = GradientBoostingRegressor(random_state=42)
        param_grid_gb = {
            'n_estimators': [100, 200, 300],
            'max_depth': [3, 5, 7],
            'learning_rate': [0.01, 0.1, 0.2]
        grid_gb = GridSearchCV(model_gb, param_grid_gb, cv=5)
        grid_gb.fit(X_train, y_train)
Out[]: GridSearchCV(cv=5, estimator=GradientBoostingRegressor(random state=42),
                     param_grid={'learning_rate': [0.01, 0.1, 0.2],
                                  'max_depth': [3, 5, 7],
```

'n\_estimators': [100, 200, 300]})

#### **Model Evaluation**

```
In [ ]: #evaluation instances
        y_pred_lr = model_lr.predict(X_test)
        mse_lr = mean_squared_error(y_test, y_pred_lr)
        r2_lr = r2_score(y_test, y_pred_lr)
        X_poly_test = poly.transform(X_test)
        y_pred_poly = model_poly.predict(X_poly_test)
        mse_poly = mean_squared_error(y_test, y_pred_poly)
        r2_poly = r2_score(y_test, y_pred_poly)
        y_pred_rf = grid_rf.predict(X_test)
        mse_rf = mean_squared_error(y_test, y_pred_rf)
        r2_rf = r2_score(y_test, y_pred_rf)
        y_pred_svr = model_svr.predict(X_test)
        mse_svr = mean_squared_error(y_test, y_pred_svr)
        r2_svr = r2_score(y_test, y_pred_svr)
        y_pred_gb = grid_gb.predict(X_test)
        mse_gb = mean_squared_error(y_test, y_pred_gb)
        r2_gb = r2_score(y_test, y_pred_gb)
        y_pred_dt = grid_dt.predict(X_test)
        mse_dt = mean_squared_error(y_test, y_pred_dt)
        r2_dt = r2_score(y_test, y_pred_dt)
```

# In []: #linreg regression line and actual data points plt.figure(figsize=(10, 6)) plt.scatter(X\_test, y\_test, color='blue', label='Actual Data') plt.plot(X\_test, y\_pred\_lr, color='red', linewidth=2, label='Regression Line') plt.title('Regression Line: Speed vs Stopping Distance') plt.xlabel('Speed (mph)') plt.ylabel('Stopping Distance (ft)') plt.legend() plt.show()



```
In []: #evaluation dataframe
models = ['Linear Regression', 'Polynomial Regression', 'Random Forest', 'SVR', 'Gradient
Boosting', 'Decision Tree']
y_preds = [y_pred_lr, y_pred_poly, y_pred_rf, y_pred_svr, y_pred_gb, y_pred_dt]
mse_scores = [mse_lr, mse_poly, mse_rf, mse_svr, mse_gb, mse_dt]
r2_scores = [r2_lr, r2_poly, r2_rf, r2_svr, r2_gb, r2_dt]

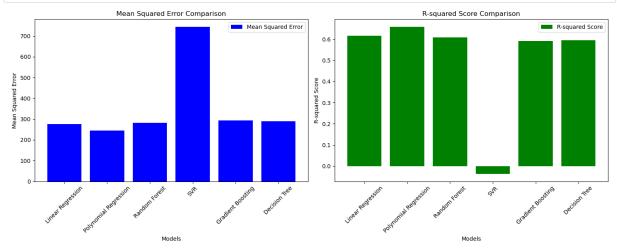
# Create a DataFrame to store the evaluation scores
evaluation_df = pd.DataFrame({
    'Model': models,
    'Mean Squared Error (MSE)': mse_scores,
    'R-squared (R2) Score': r2_scores
})
evaluation_df
```

#### Out[]:

	Model	Mean Squared Error (MSE)	R-squared (R2) Score
0	Linear Regression	275.428983	0.615773
1	Polynomial Regression	244.521644	0.658890
2	Random Forest	281.244514	0.607661
3	SVR	743.360370	-0.036996
4	Gradient Boosting	293.433486	0.590657
5	Decision Tree	290.146785	0.595242

## **Model Comparison and Visualizations**

```
In [ ]: #plotting MSE and R2
         plt.figure(figsize=(15, 6))
         plt.subplot(1, 2, 1)
         plt.bar(models, mse_scores, color='blue', label='Mean Squared Error')
plt.title('Mean Squared Error Comparison')
         plt.xlabel('Models')
         plt.ylabel('Mean Squared Error')
         plt.xticks(rotation=45)
         plt.legend()
         #R2
         plt.subplot(1, 2, 2)
         plt.bar(models, r2_scores, color='green', label='R-squared Score')
         plt.title('R-squared Score Comparison')
         plt.xlabel('Models')
         plt.ylabel('R-squared Score')
         plt.xticks(rotation=45)
         plt.legend()
         plt.tight_layout()
         plt.show()
```



#### **Additional Statistics**

```
In [ ]: #linear regression
        mae_lr = mean_absolute_error(y_test, y_pred_lr)
        rmse_lr = np.sqrt(mean_squared_error(y_test, y_pred_lr))
        #random forest
        y_pred_rf_train = grid_rf.predict(X_train)
        oob_error_rf = 1 - grid_rf.best_estimator_.oob_score_
        #gradient boosting
        y_pred_gb_train = grid_gb.predict(X_train) # Predictions on the training set for learnin
        g curve
        train_errors_gb = [mean_squared_error(y_train, y_pred) for y_pred in grid_gb.best_estimat
        or_.staged_predict(X_train)]
        validation_errors_gb = [mean_squared_error(y_test, y_pred) for y_pred in grid_gb.best_est
        imator_.staged_predict(X_test)]
        #some general metrics
        adjusted_r2_lr = 1 - (1 - r2_lr) * (len(y_test) - 1) / (len(y_test) - X_test.shape[1] -
        1)
        mpe_lr = np.mean((y_test - y_pred_lr) / y_test) * 100
        mape_lr = np.mean(np.abs((y_test - y_pred_lr) / y_test)) * 100
        #displaying additional statistics
        print("Linear Regression Additional Statistics:")
        print(f'Mean Absolute Error (MAE): {mae_lr:.2f}')
        print(f'Root Mean Squared Error (RMSE): {rmse_lr:.2f}')
        print(f'Adjusted R-squared: {adjusted_r2_lr:.2f}')
        print(f'Mean Percentage Error (MPE): {mpe_lr:.2f}%')
        print(f'Mean Absolute Percentage Error (MAPE): {mape_lr:.2f}%')
        print("\nRandom Forest Additional Statistics:")
        print(f'Out-of-Bag (00B) Error: {oob_error_rf:.4f}')
        print("\nGradient Boosting Additional Statistics:")
        print(f'Learning Curve - Train Errors: {train_errors_gb}')
        print(f'Learning Curve - Validation Errors: {validation_errors_gb}')
```

Linear Regression Additional Statistics: Mean Absolute Error (MAE): 11.03 Root Mean Squared Error (RMSE): 16.60 Adjusted R-squared: 0.57 Mean Percentage Error (MPE): -6.77% Mean Absolute Percentage Error (MAPE): 21.21%

Random Forest Additional Statistics: Out-of-Bag (00B) Error: 0.3785

Gradient Boosting Additional Statistics: Learning Curve - Train Errors: [602.5176744999999, 593.5896804023646, 584.839353387272, 5 76.2631578797798, 567.857628662887, 559.6193694774099, 551.5450516497241, 543.63141274680 91, 535.8752552580622, 528.2734453033414, 520.8229113667195, 513.5206430554364, 506.36368 988354786, 499.3491600797797, 492.4742194191067, 485.73609007758114, 479.1320495099518, 4 72.65942934961834, 466.31561433047546, 460.0980412302136, 454.00419783464696, 448.0316219 22652, 442.17790027130593, 436.44066768082155, 430.81760601888766, 425.3064432840264, 41 9.90495268758895, 414.6109517540205, 409.4223014390301, 404.3369052653079, 399.3527084754 429, 394.46769720169624, 389.67989765229703, 384.98737531393095, 380.38823417009826, 375. 8806159350279, 371.46269930283546, 367.1326992116236, 362.8888661222269, 358.729485311309 13, 354.6528761785287, 350.6573915674906, 346.7414171002121, 342.8974481149634, 338.56330 3262721, 334.3154078930382, 330.6830281336423, 326.58520347630355, 322.5689255296458, 31 9.1360186755885, 315.2613670043186, 311.463820901307, 308.2189743869377, 304.555090983658 2, 300.96411886010407, 297.4446070818086, 294.4317630424823, 291.0358932017795, 287.70760 117090674, 284.85874112385875, 281.6471488798278, 278.4994673214532, 275.80524025905123, 272.7677110309575, 269.7906286345029, 267.2422258869935, 264.3691204164917, 261.553189744 8527, 259.14231333997526, 256.42453490729224, 253.76084026541963, 251.47967313767768, 24 8.90863666146873, 246.38876381113636, 244.22994175252342, 241.79754466454014, 239.4135522 7860777, 237.37013752891548, 235.06873232094313, 232.8131250766095, 230.87858145740665, 2 28.70094980387694, 226.56665302025255, 224.64811355782822, 222.58769597193776, 220.568280 6960066, 218.7480529957871, 216.79740500946065, 215.04142583465463, 213.15707761537297, 2 11.31022792565494, 209.64257116322443, 207.63123686185222, 205.65992811307729, 203.944871 38823828, 202.04634082438102, 200.18559101874445, 198.3618701342401, 196.57444129533738, 194.82258229032882, 193.10558527951986, 191.61253079283082, 190.25089856243804, 188.62264 080771132, 187.02678538230367, 185.64014154068832, 184.37450406441866, 182.8029632467968 8, 181.26269609144575, 179.9190137790307, 178.43568937528386, 176.98188312717156, 175.557 00762339671, 174.16048714214693, 172.7917574184741, 171.45026541630236, 170.2791807511720 8, 169.2540321810393, 167.98184115263246, 166.73496672569092, 165.6469007512894, 164.4458 308294549, 163.2686621990649, 162.11491922441968, 160.98413573496987, 159.87585483696012, 158.9083977994606, 158.0608529634801, 157.04690494531872, 156.01593701181213, 155.1161805 835638, 154.32946083612185, 153.35162975976914, 152.3932575218358, 151.55712287013552, 15 0.63393319679352, 149.72911499795106, 148.84230268126552, 147.93212371465452, 147.1715669 225582, 146.2917401660947, 145.46653161483368, 144.6183403558278, 143.9106925126208, 143. 09073999031338, 142.28710452319987, 141.6156342898104, 140.83873457056657, 140.1339027297 3257, 139.38434673277513, 138.75888621486575, 138.03422795367314, 137.431013375641, 136.7 3039616508444, 136.04372123701805, 135.47122380396166, 134.80723847979453, 134.2037519553 7397, 133.56250479602323, 133.0482192913906, 132.42719267234344, 131.8639784522224, 131.2 641687972416, 130.67629535439494, 130.20311765940303, 129.63375248860748, 129.17667918471 3, 128.62521328751683, 128.12450962226035, 127.59182994266389, 127.16501235102726, 126.64 903986847489, 126.14333523832536, 125.7368997030912, 125.24704400712373, 124.801682373137 17, 124.3284652193, 123.94882626037084, 123.49040502431299, 123.12360408672143, 122.67949 466746325, 122.24422302564831, 121.93077679633775, 121.50828948150256, 121.2051304278121 5, 120.79502869067987, 120.46709480870227, 120.06975324358805, 119.78598506848763, 119.40 02548375624, 119.03490072858581, 118.76443065803039, 118.39671762034268, 118.135077207069 53, 117.77806826871517, 117.52496150448903, 117.19135942948105, 116.91670776660828, 116.5 8011528542268, 116.25022099461266] Learning Curve - Validation Errors: [815.4540733034722, 803.2233951121406, 791.2339412242 88, 779.4809329382002, 767.9596864317089, 756.6656108762523, 745.5942065884494, 734.74106 32184332, 724.1018579742147, 713.6723538813635, 703.4483980772975, 693.4259201394963, 68 3.6009304469633, 673.9695185742748, 664.5278517175667, 655.2721731518229, 646.19880071884 9, 637.3041253453092, 628.5846095902409, 620.0367862214509, 611.6572568202248, 603.442690 4137832, 595.3898221349322, 587.495451908372, 579.756443163127, 572.1697215705804, 564.73 2273807607, 557.4411463442999, 550.2934442558031, 543.2863300577759, 536.417022565008, 52 9.6827957727381, 523.0809777602122, 516.6089496160475, 510.2641443849649, 504.04404603546 357, 497.94618844802505, 491.9681544234357, 486.1075747108259, 480.36212705503857, 474.72

953526293725, 469.2075682882813, 463.79403933479597, 459.03796810712794, 454.192687064269 5, 449.4583748363975, 444.9956031850662, 440.4624884906868, 436.0338471372227, 431.847194 9856065, 427.6079528222332, 423.467058029367, 419.540349921038, 415.5777373045744, 411.70 769457711276, 407.9282424588826, 404.3234652391339, 400.7083507436495, 397.1784891573076, 393.79955454395486, 390.4243593656057, 387.1293831750009, 383.96305625806656, 380.8136338 731865, 377.7396830751378, 374.7735024107613, 371.83651918883254, 368.9705304018911, 366. 1927627109368, 363.4556512704019, 360.7853120206283, 358.18490954343406, 355.635824796012 86, 353.14953043772783, 350.71609078922154, 348.34386851701396, 346.0306816359023, 343.75 44100144504, 341.54852783315886, 339.39813998797996, 337.26981359992794, 335.22035417006 2, 333.22304983757857, 331.39418721987903, 329.48930699625663, 327.6334716055565, 325.893 65882040926, 324.12509724056633, 322.46442703494506, 320.779769743717, 319.1394527546493 7, 317.59133440143563, 316.2599572976127, 314.9712509344142, 313.49257459862963, 312.2856 978680401, 311.11858393533583, 309.9902840613296, 308.899869961339, 307.84643338239573, 3 06.82908568902644, 305.61198510972804, 304.42842133803526, 303.5093514143708, 302.6232382 9449895, 301.53349621009625, 300.46250778357, 299.734847602034, 299.03514127824496, 298.1 2669319630703, 297.4810673584458, 296.86140716681916, 296.2670647281465, 295.697406353992 73, 295.15181226497396, 294.629676300981, 293.8879070384465, 293.07291708320014, 292.6169 3394468523, 292.1822520243546, 291.52773123738257, 291.13481710531335, 290.7616261502259, 290.4076468390407, 290.0723790086052, 289.75533362752776, 289.21933999954655, 288.5903332 52008, 288.2686748829274, 288.0208374087342, 287.5550541889462, 286.99115826841046, 286.7 9085616886744, 286.60541975949167, 286.2034247312078, 286.04758417957004, 285.90543739673 99, 285.77660595129976, 285.7461699109772, 285.4160379365505, 285.41298339724335, 285.325 7774785258, 285.3478792278552, 285.06959441494064, 285.1164947902494, 285.17540953432456, 284.9329217723656, 285.0147906100988, 284.96719392349866, 285.07012820488455, 284.8720186 236062, 284.99566496834086, 284.8179704692564, 284.9612895677708, 285.1138505477103, 284. 96525252073474, 285.2684781341407, 285.3043893981035, 285.61876312529773, 285.45891770651 43, 285.7849490809457, 285.849446496081, 286.1852062491285, 286.52517538776567, 286.40250 254501063, 286.7524607705087, 286.6439550791102, 287.003295081684, 287.10999069355773, 28 7.47683777001913, 287.394868585129, 287.7699443456419, 288.14776903054207, 288.0829880742 2733, 288.46823032162877, 288.60964822643723, 289.0004907270212, 288.95825840415375, 289. 35552441147354, 289.32371301823457, 289.7269401410368, 290.13171950487657, 289.9583078034 0714, 290.3694688991508, 290.2077399776789, 290.624850926916, 290.62726778107066, 291.048 83217111706, 290.90920370343366, 291.3359068681746, 291.639097936047, 291.51635422814286, 291.94904708019396, 291.8359359972502, 292.2728040269813, 292.16891915314045, 292.4944044 684464, 292.5458479980315, 292.9897974611398, 293.4334861162174]

#### Out[]:

	Metric	Linear Regression	Random Forest
0	Mean Absolute Error (MAE)	11.031431	=
1	Root Mean Squared Error (RMSE)	16.596053	-
2	Adjusted R-squared	0.567745	-
3	Mean Percentage Error (MPE)	-6.767803	-
4	Mean Absolute Percentage Error (MAPE)	21.213804	-
5	Out-of-Bag (OOB) Error	-	0.378481

```
In []: #using statsmodel to display linreg coefficients, and p-values
    X = sm.add_constant(X)

#fitting the model
model = sm.OLS(y, X).fit()

#getting values
coefficients_lr = model.params
p_values = model.pvalues

#dataframe with values
coeff_pval_df = pd.DataFrame({
    'Coefficient': coefficients_lr,
    'P-value': p_values
})

print('Linear Regression:')
coeff_pval_df
```

Linear Regression:

#### Out[]:

	Coefficient	P-value
const	-17.579095	1.231882e-02
speed	3.932409	1.489836e-12