AutoData

November 21, 2025

1 Auto Dataset Analysis

This notebook analyzes the Auto dataset to investigate how vehicle characteristics relate to fuel efficiency (mpg).
We apply **simple linear regression** (Q8) and **multiple linear regression** (Q9), including diagnostic plots and transformations.

[1]:
```python
import pandas as pd
import statsmodels.api as sm
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

# Load Auto.csv (make sure it's in the same folder)
auto = pd.read_csv("/home/mlahkim15/ve/Auto/Auto.csv")

# Convert columns to numeric if necessary
auto['horsepower'] = pd.to_numeric(auto['horsepower'], errors='coerce')
auto = auto.dropna()  # drop rows with missing values

auto.head()
```

[1]:
```
    mpg  cylinders  displacement  horsepower  weight  acceleration  year  \
0  18.0          8         307.0       130.0    3504          12.0    70
1  15.0          8         350.0       165.0    3693          11.5    70
2  18.0          8         318.0       150.0    3436          11.0    70
3  16.0          8         304.0       150.0    3433          12.0    70
4  17.0          8         302.0       140.0    3449          10.5    70

   origin                       name
0       1  chevrolet chevelle malibu
1       1          buick skylark 320
2       1         plymouth satellite
3       1              amc rebel sst
4       1                ford torino
```

1.1 Question 8 — Simple Linear Regression

We model **mpg** as the response and **horsepower** as the predictor.

[2]:
```
# Simple linear regression
X = sm.add_constant(auto["horsepower"])
y = auto["mpg"]

model_simple = sm.OLS(y, X).fit()
model_simple.summary()
```

[2]:

Dep. Variable:	mpg	**R-squared:**	0.606
Model:	OLS	**Adj. R-squared:**	0.605
Method:	Least Squares	**F-statistic:**	599.7
Date:	Fri, 21 Nov 2025	**Prob (F-statistic):**	7.03e-81
Time:	10:22:31	**Log-Likelihood:**	-1178.7
No. Observations:	392	**AIC:**	2361.
Df Residuals:	390	**BIC:**	2369.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
const	39.9359	0.717	55.660	0.000	38.525	41.347
horsepower	-0.1578	0.006	-24.489	0.000	-0.171	-0.145

Omnibus:	16.432	**Durbin-Watson:**	0.920
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	17.305
Skew:	0.492	**Prob(JB):**	0.000175
Kurtosis:	3.299	**Cond. No.**	322.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

1.1.1 Interpretation

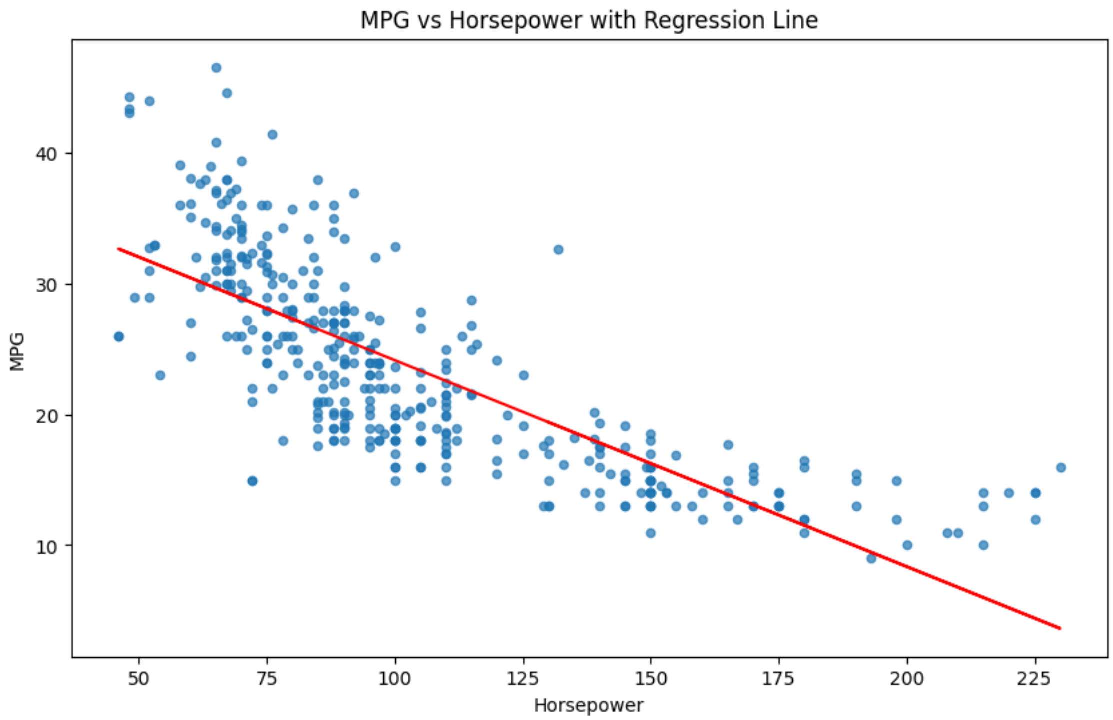
- **Relationship:** Strong negative relationship — higher horsepower → lower mpg.
- **Strength:** R^2 ~0.60 → 60% of mpg variation explained by horsepower.
- **Prediction:** For horsepower = 98, see below.

[3]:
```
new_value = pd.DataFrame({"const":[1], "horsepower":[98]})
pred_simple = model_simple.get_prediction(new_value).summary_frame(alpha=0.05)
pred_simple
```

[3]:
```
        mean   mean_se  mean_ci_lower  mean_ci_upper  obs_ci_lower  \
0  24.467077  0.251262      23.973079      24.961075     14.809396

   obs_ci_upper
0     34.124758
```

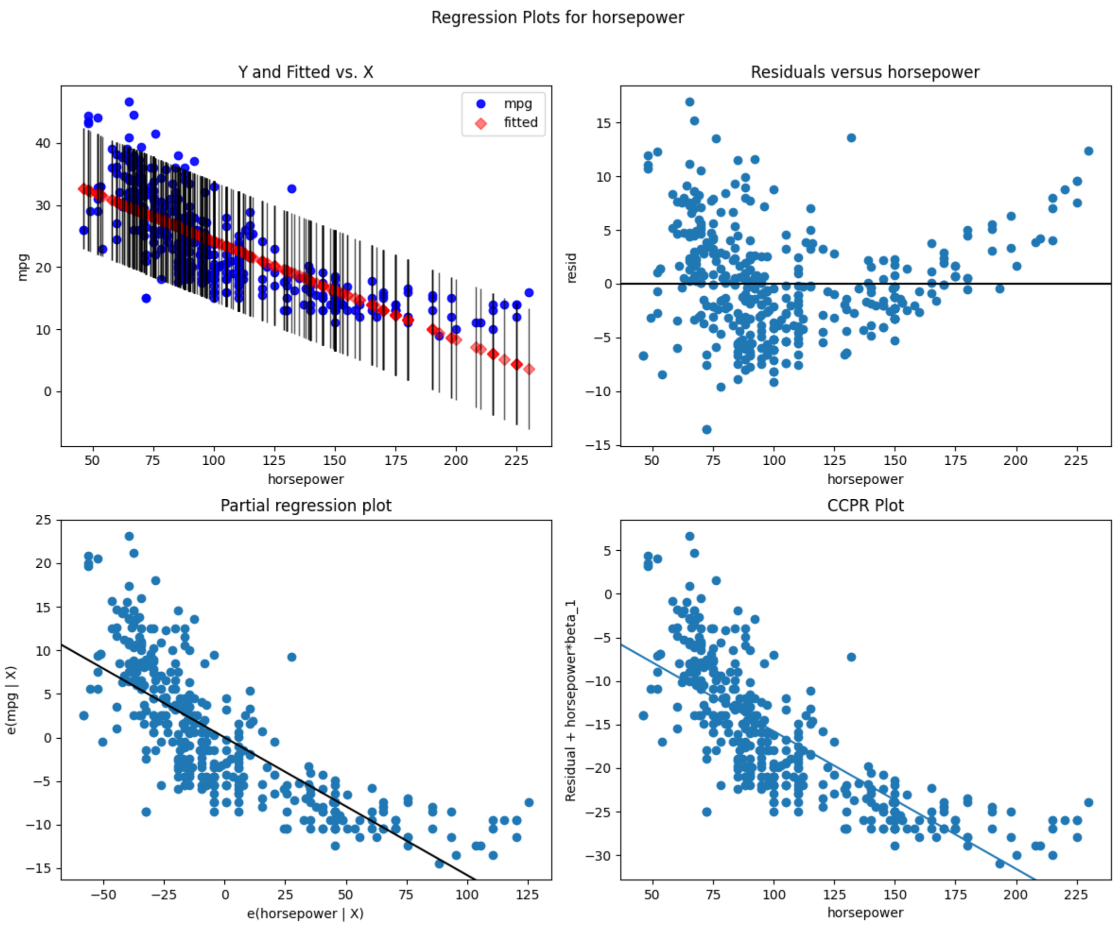
1.1.2 Scatter Plot with Regression Line

[4]:
```
fig, ax = plt.subplots(figsize=(10,6))
ax.scatter(auto["horsepower"], auto["mpg"], s=20, alpha=0.7)
ax.plot(auto["horsepower"], model_simple.predict(X), color='red')
ax.set_xlabel("Horsepower")
ax.set_ylabel("MPG")
ax.set_title("MPG vs Horsepower with Regression Line")
plt.show()
```



1.1.3 Diagnostic Plots for Simple Regression

[5]:
```
fig = plt.figure(figsize=(12,10))
sm.graphics.plot_regress_exog(model_simple, "horsepower", fig=fig)
plt.show()
```

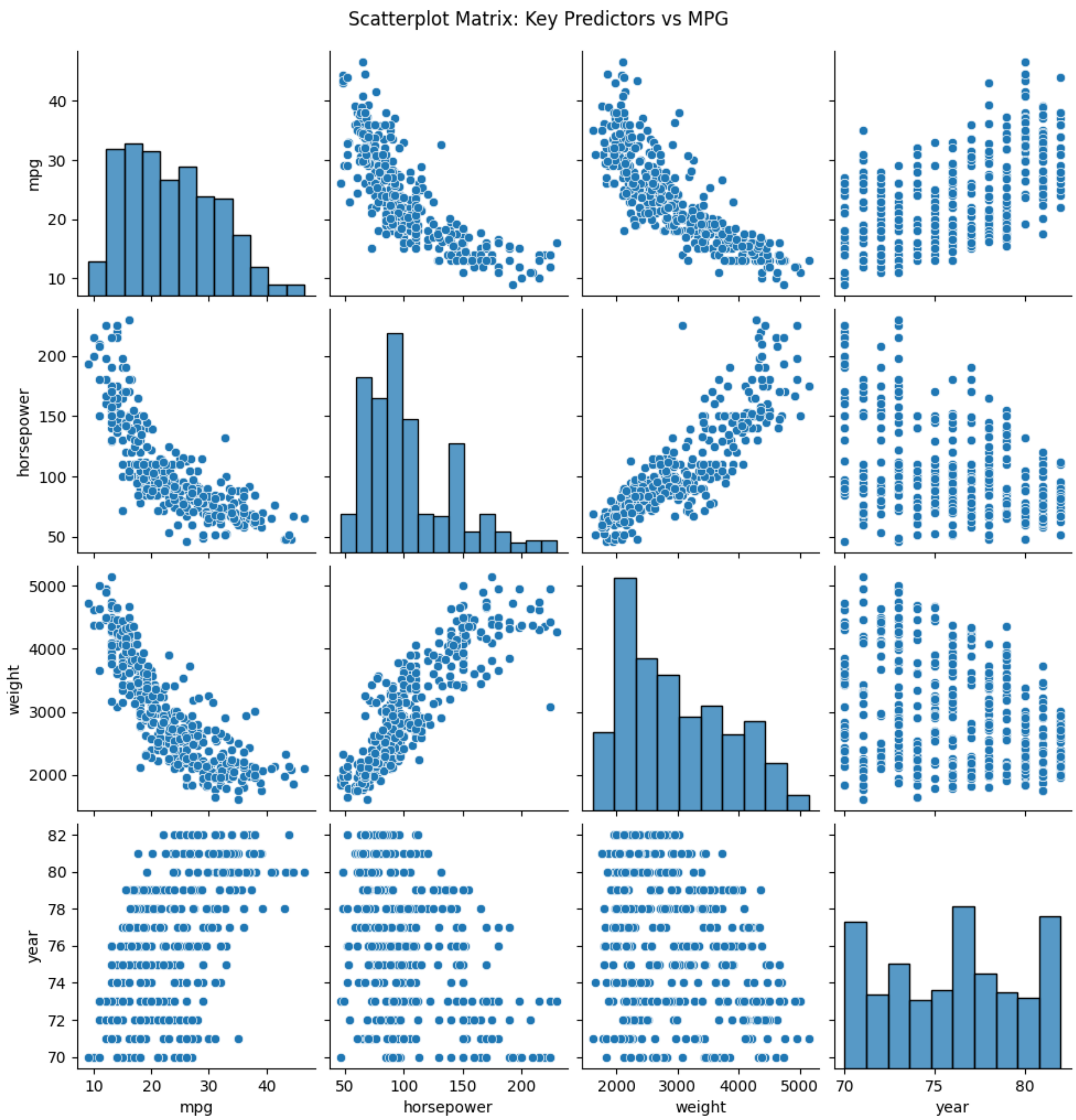


1.2 Question 9 — Multiple Linear Regression

We now include **all other variables (except name)** to predict mpg.
We also explore correlations, interactions, and transformations.

[10]:
```
# Convert horsepower to numeric (some values may be '?')
auto['horsepower'] = pd.to_numeric(auto['horsepower'], errors='coerce')

# Drop rows with missing values
auto = auto.dropna()

# Create numeric-only dataframe (drop 'name' column)
auto_numeric = auto.drop(columns=['name'])

# Select key variables for scatterplot matrix
subset = ["mpg", "horsepower", "weight", "year"]

# Create the scatterplot matrix
```

```
sns.pairplot(auto_numeric[subset], height=2.5)
plt.suptitle("Scatterplot Matrix: Key Predictors vs MPG", y=1.02)
plt.show()
```



1.2.1 Multiple Linear Regression

[ ]:
```
# Multiple regression
X_multi = auto_numeric.drop(columns=['mpg'])
X_multi = sm.add_constant(X_multi)
y_multi = auto_numeric['mpg']
```

```python
model_multi = sm.OLS(y_multi, X_multi).fit()
model_multi.summary()
```

1.2.2 Interpretation of Multiple Regression

- **Relationship:** The overall F-test and p-values indicate that predictors collectively explain mpg.

- **Significant predictors:** Weight, horsepower, year, etc. (check p-values < 0.05).

- **Coefficient of year:** Positive → newer cars tend to have higher mpg, all else equal.

[ ]:
```python
# Diagnostic plots for multiple regression
fig = plt.figure(figsize=(12,10))
sm.graphics.plot_regress_exog(model_multi, "weight", fig=fig)
plt.show()
```

1.2.3 Interactions & Transformations

We can try interactions (e.g., horsepower*weight) or transformations (log, sqrt, squared) to improve the model.
Check p-values for significance and whether plots look better.

[ ]:
```python
# Example: interaction between horsepower and weight
X_inter = auto_numeric.copy()
X_inter['hp_weight'] = X_inter['horsepower'] * X_inter['weight']
X_inter = sm.add_constant(X_inter.drop(columns=['mpg']))
y_inter = auto_numeric['mpg']

model_inter = sm.OLS(y_inter, X_inter).fit()
model_inter.summary()
```

1.2.4 Example Transformation

- Try log or squared transformations to see if model fit improves:
- log(horsepower), sqrt(weight), weight^2, etc.

[ ]:
```python
X_trans = auto_numeric.copy()
X_trans['log_horsepower'] = np.log(X_trans['horsepower'])
X_trans['weight_squared'] = X_trans['weight'] ** 2

X_trans = sm.add_constant(X_trans.drop(columns=['mpg']))
y_trans = auto_numeric['mpg']

model_trans = sm.OLS(y_trans, X_trans).fit()
model_trans.summary()
```

1.2.5 Conclusion

- **Simple regression:** mpg decreases as horsepower increases.
- **Multiple regression:** multiple variables (weight, year, horsepower) significantly affect mpg.
- **Interactions & transformations:** can improve model fit, but must be interpreted carefully.
- **Diagnostics:** always check residuals, leverage, and spread to ensure reliable predictions.

1.2.6 Reflective Summary

Working through this analysis helped me understand how vehicle characteristics like horsepower, weight, and year influence fuel efficiency. I learned how to interpret regression coefficients, evaluate model fit using diagnostic plots, and explore improvements through interactions and transformations. This project also strengthened my skills in presenting data analysis clearly in a professional blog format.