Statical Methods: Chi-Square, ANNOVA and Regression Analysis.

```
import warnings

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
import statsmodels.api as sm
import statsmodels.graphics.gofplots as gof
from scipy.stats import chi2_contingency, chisquare
from statsmodels.formula.api import ols
from statsmodels.stats import outliers_influence as sm_oi
from statsmodels.stats.anova import anova_lm

warnings.filterwarnings("ignore")
sns.set_theme("notebook", "whitegrid")
```

Custom Functions

```
def custom_statsmodel_OLS(_DF, *vars):
    """fitting OLS on specified independent and dependent variables- DF, dependent_var and ir
    # sm.add_constant
    try:
        LOS_COLS = [v for v in vars]
        _X = LOS_COLS[1:]
        _Y = LOS_COLS[0]
        xvars = sm.add_constant(_DF[_X])
        yvar = _DF[_Y]
        _model_spec = sm.OLS(yvar, xvars)
        return _model_spec
    except Exception as e:
        print(f"There is an error while creating a model spec due to:{e}")


def custom_model_preds(_model, _new_df):
    """Predictions on new data points"""
    _feat = sm.add_constant(_new_df)
    _pred = _model.predict(sm.add_constant(_feat))
    _df_pred = pd.DataFrame(_pred)
    _df_pred.columns = ["predicted_y"]
```

```
    return _df_pred


def custom_VIF(_MSPEC):
    """Custom function to get the VIF"""
    var_names = _MSPEC.exog_names
    X = _MSPEC.exog
    _limit = X.shape[1]
    try:
        vif_dict = {}
        for idx in range(_limit):
            vif = round(sm_oi.variance_inflation_factor(X, idx), 5)
            vif_dict[var_names[idx]] = vif
        _DF = pd.DataFrame([vif_dict]).T
        _DF.columns = ["VIF"]
        _DF = _DF.reset_index()
        df_sorted = _DF.iloc[1:].sort_values(by="VIF", ascending=False)
        ax = sns.barplot(x="index", y="VIF", data=df_sorted)
        # Add text labels to the top of each bar
        for bar in ax.containers[0]:
            ax.text(
                bar.get_x() + bar.get_width() / 2,
                bar.get_height(),
                int(bar.get_height()),
                ha="center",
                va="bottom",
            )
        ax.set_xlabel("FIELD")
        ax.set_ylabel("VIF")
        plt.xticks(rotation=45)
        plt.title("VIF")
        plt.tight_layout()
        plt.show()
    except Exception as e:
        pass


def custom_ols_qqplot(_resid):
    """Q-Q Plot of residuals"""
    gof.qqplot(_resid, line="s")
    plt.xlabel("Standard Normal Quantiles")
    plt.ylabel("Standardized Residuals")
```

```
    plt.title("Normal Q-Q plot")
    plt.show()


def custom_ols_res_vs_fitted(_fitted, _resid):
    """Fitted Vs Residuals Plot"""
    plt.scatter(_fitted, _resid)
    plt.axhline("0", color="r")
    plt.xlabel("Fitted Values")
    plt.ylabel("Residual")
    plt.title("Residual Vs Fitted")
```

Chi-Square and Annova- Cases

```
# Importing data
df_ecom = pd.read_excel(
    r"/Users/malleshamyamulla/Desktop/SSBBA/assignments/w4/data/ecom.xlsx"
)
df_smoke = pd.read_csv(
    r"/Users/malleshamyamulla/Desktop/SSBBA/assignments/w4/data/smoking.csv"
)
df_health = pd.read_excel(
    r"/Users/malleshamyamulla/Desktop/SSBBA/assignments/w4/data/HealthStats_SSBB.xlsx"
)
```

```
df_ecom.head()
```

	Gender	Age	Overall Use_Level	Amazon_Level	Flipkart_Level	Swiggy_Level	Zomato_Level	C
0	Male	34	Medium	High	Medium	Medium	Medium	L
1	Male	33	High	High	Low	Medium	Medium	M
2	Female	34	High	High	Low	Low	Low	M
3	Male	32	Low	Medium	Medium	Low	Medium	L
4	Female	40	Low	Low	Medium	Low	Low	L

```
df_health.head()
```

	Participant No.	Data Segment	Industry	Stress-Per	Stress-Pro	Activity_Level	Age	Sex
0	1	Group-1	ITES	Medium	High	High	30	F
1	2	Group-1	Mfg & Process	Low	High	Medium	40	M
2	3	Group-1	ITES	Medium	Medium	High	42	F
3	4	Group-1	ITES	Medium	Medium	High	34	M
4	5	Group-1	Mfg & Process	Low	Medium	High	31	M

```
df_ecom_sel = df_ecom[["Overall Use_Level", "Overall CS_Level"]]
```

Experiment 1

Hypothesis

```
Ho: There is no association between Overall Usage and Customer CS Score(Independent)
Ha: There is an association between Overall Usage and Customer CS Score(Dependent)
```

```
df_ecom_CT = (
    pd.crosstab(df_ecom_sel["Overall Use_Level"], df_ecom_sel["Overall CS_Level"])
    .reset_index()
    .drop(["Overall Use_Level"], axis=1)
)

CS_LVEL = df_ecom_CT.to_numpy()
```

```
_chi2, _pvalue, _ddof, _expected = chi2_contingency(CS_LVEL)
```

```
print(
    f"P-Value Caluclated is:{round(_pvalue,3)} which is lesser than to 0.05, hence we can re
)
```

```
P-Value Caluclated is:0.041 which is lesser than to 0.05, hence we can reject the null hypot
```

Experiment 2:

Hypothesis

```
Ho: There is no association between Maritual Status and Smoking
Ha: There is an association between Maritual Status and Smoking
```

Hypothesis

```
Ho: There is no association between Gender and Smoking
Ha: There is an association between Gender and Smoking
```

```
df_smoke_tidy = df_smoke[["marital_status", "smoke"]]
df_gender_tidy = df_smoke[["gender", "smoke"]]
df_smoke_CT = (
    pd.crosstab(df_smoke_tidy["marital_status"], df_smoke_tidy["smoke"])
    .reset_index()
    .drop(["marital_status"], axis=1)
)
df_gender_CT = (
    pd.crosstab(df_gender_tidy["gender"], df_gender_tidy["smoke"])
    .reset_index()
    .drop(["gender"], axis=1)
)
smoke_NUM = df_smoke_CT.to_numpy()
gender_NUM = df_gender_CT.to_numpy()
```

```
# ChiSquare ex1
_chi2, _pvalue, _ddof, _expected = chi2_contingency(smoke_NUM)
```

```
print(
    f"P-Value Caluclated is:{round(_pvalue,3)} which is lesser than to 0.05, hence we can rej
)
```

```
P-Value Caluclated is:0.0 which is lesser than to 0.05, hence we can reject the null hypothes
```

```
# ChiSquare ex2
_chi2, _pvalue, _ddof, _expected = chi2_contingency(gender_NUM)
```

```
print(
    f"P-Value Caluclated is:{round(_pvalue,3)} which is greater than to 0.05, hence we failed
)
```

```
P-Value Caluclated is:0.513 which is greater than to 0.05, hence we failed to reject the null
```

Experiment 3

Hypothesis

```
Ho: There is no association between Industry and HappyNess Index
Ha: There is an association between Industry and HappyNess Index
```

```python
df_health_CT = (
    pd.crosstab(df_health["Industry"], df_health["Happiness-Index-State"])
    .reset_index()
    .drop(["Industry"], axis=1)
)

health_NUM = df_health_CT.to_numpy()
```

```python
# ChiSquare ex2
_chi2, _pvalue, _ddof, _expected = chi2_contingency(health_NUM)
```

```python
print(
    f"P-Value Caluclated is:{round(_pvalue,3)} which is greater than to 0.05, hence we failed
)
```

```
P-Value Caluclated is:0.08 which is greater than to 0.05, hence we failed to reject the null
```

Conclusions

1) There is an association between Maritual Status and Smoking
2) There is no association between Gender and Smoking
3) There is no association between Industry and HappyNess Index

Experiment 4:

Hypothesis

```
Ho: The average age of all marital status are equal
Ha: The average age of all marital status are not equal
```

Hypothesis

```
Ho: The average age of all usage level customers are equal
Ha: The average age of all usage level customers are not equal
```

Hypothesis

```
Ho: The average BMI of All industry participants are equal
Ha: The average BMI of All industry participants are not equal
```

```
df_msage = df_smoke[["marital_status", "age"]]

# Define the model formula
model_1 = ols("age ~ marital_status", data=df_msage).fit()

# Perform ANOVA
anova_table_ex1 = anova_lm(model_1)

# Print ANOVA results
print(anova_table_ex1)
```

```
                    df          sum_sq       mean_sq           F         PR(>F)
marital_status     4.0   234048.777309  58512.194327  274.597439  7.189135e-182
Residual        1686.0   359258.847765    213.083540         NaN            NaN
```

```
print(
    f"P-Value Caluclated is:{round(anova_table_ex1['PR(>F)'][0],3)} which is lesser than to 0
)
```

```
P-Value Caluclated is:0.0 which is lesser than to 0.05, hence we can reject the null hypothes
```

```
df_cs = df_ecom[["Overall Use_Level", "Age"]]
df_cs.columns = ["usage", "age"]

# Define the model formula
model_2 = ols("age ~ usage", data=df_cs).fit()

# Perform ANOVA
anova_table_ex2 = anova_lm(model_2)

# Print ANOVA results
print(anova_table_ex2)
```

```
            df       sum_sq    mean_sq        F    PR(>F)
usage      2.0    23.580519  11.790260  0.17447  0.840748
Residual  30.0  2027.328571  67.577619      NaN       NaN
```

```
print(
    f"P-Value Caluclated is:{round(anova_table_ex2['PR(>F)'][0],3)} which is greater than to
)
```

```
P-Value Caluclated is:0.841 which is greater than to 0.05, hence we failed to reject the null
```

```
df_h = df_health[["Industry", "BMI"]]

# Define the model formula
model_3 = ols("BMI ~ Industry", data=df_h).fit()

# Perform ANOVA
anova_table_ex3 = anova_lm(model_3)

# Print ANOVA results
print(anova_table_ex3)
```

```
             df       sum_sq    mean_sq         F    PR(>F)
Industry    2.0   173.765060  86.882530  5.370873  0.005568
Residual  153.0  2475.021863  16.176613       NaN       NaN
```

```
print(
    f"P-Value Caluclated is:{round(anova_table_ex3['PR(>F)'][0],3)} which is lesser than to 0
)
```

```
P-Value Caluclated is:0.006 which is lesser than to 0.05, hence we reject the null hypothesis
```

Conclusions

1) The average age of all usage level customers are equal
2) The average age of all marital status are not equal
3) The average BMI of All industry participants are not equal

Linear Regression Analysis - Cases

Case 1: BikeShare

Data Importing and Data Preparation

```
df_dcbikes = pd.read_csv(
    r"/Users/malleshamyamulla/Desktop/SSBBA/assignments/w4/data/dcbikeshares.csv"
)
```

```
df_dcbikes.head()
```

	instant	dteday	season	yr	mnth	holiday	weekday	workingday	weathersit	temp	atemp
0	1	1/1/2011	1	0	1	0	6	0	2	0.344167	0.3636
1	2	1/2/2011	1	0	1	0	0	0	2	0.363478	0.3537
2	3	1/3/2011	1	0	1	0	1	1	1	0.196364	0.1894
3	4	1/4/2011	1	0	1	0	2	1	1	0.200000	0.2121
4	5	1/5/2011	1	0	1	0	3	1	1	0.226957	0.2292

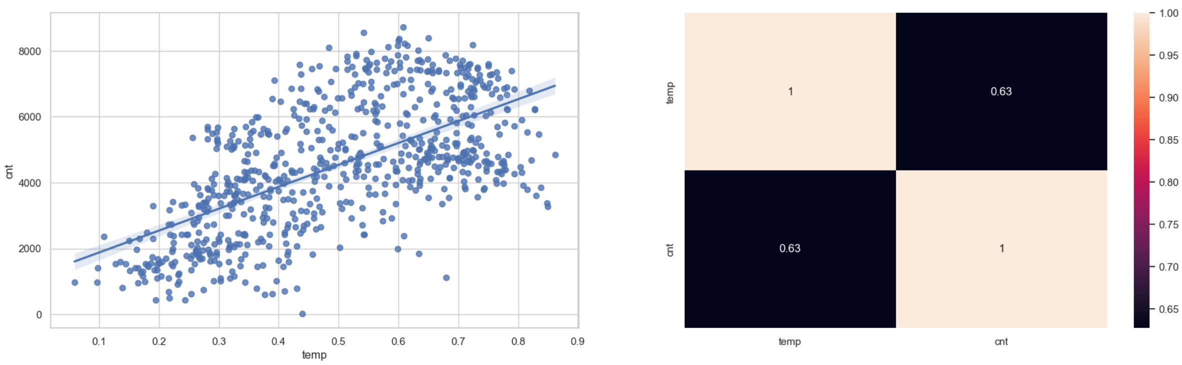
```
df_dcbikes_tidy = df_dcbikes[
    [
        "season",
        "holiday",
        "workingday",
        "weathersit",
        "temp",
        "atemp",
        "hum",
        "windspeed",
        "casual",
        "registered",
        "cnt",
    ]
]
```

```
df_dcbikes_tidy.head()
```

	season	holiday	workingday	weathersit	temp	atemp	hum	windspeed	casual	registe
0	1	0	0	2	0.344167	0.363625	0.805833	0.160446	331	654
1	1	0	0	2	0.363478	0.353739	0.696087	0.248539	131	670
2	1	0	1	1	0.196364	0.189405	0.437273	0.248309	120	1229
3	1	0	1	1	0.200000	0.212122	0.590435	0.160296	108	1454
4	1	0	1	1	0.226957	0.229270	0.436957	0.186900	82	1518

EDA 1: Visualize the distribution of daily bike rentals and temperature as well as the relationship between these two variables.

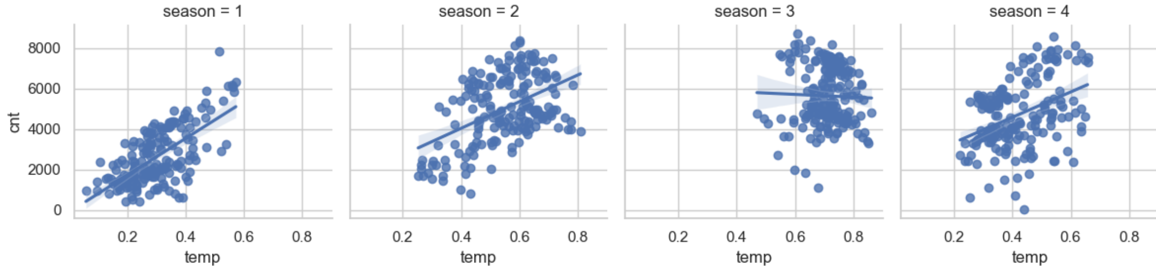
```
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(22, 6))
v1 = sns.regplot(x="temp", y="cnt", data=df_dcbikes_tidy, ax=ax1)
v2 = sns.heatmap(df_dcbikes_tidy[["temp", "cnt"]].corr(), annot=True, ax=ax2)
plt.show()
```



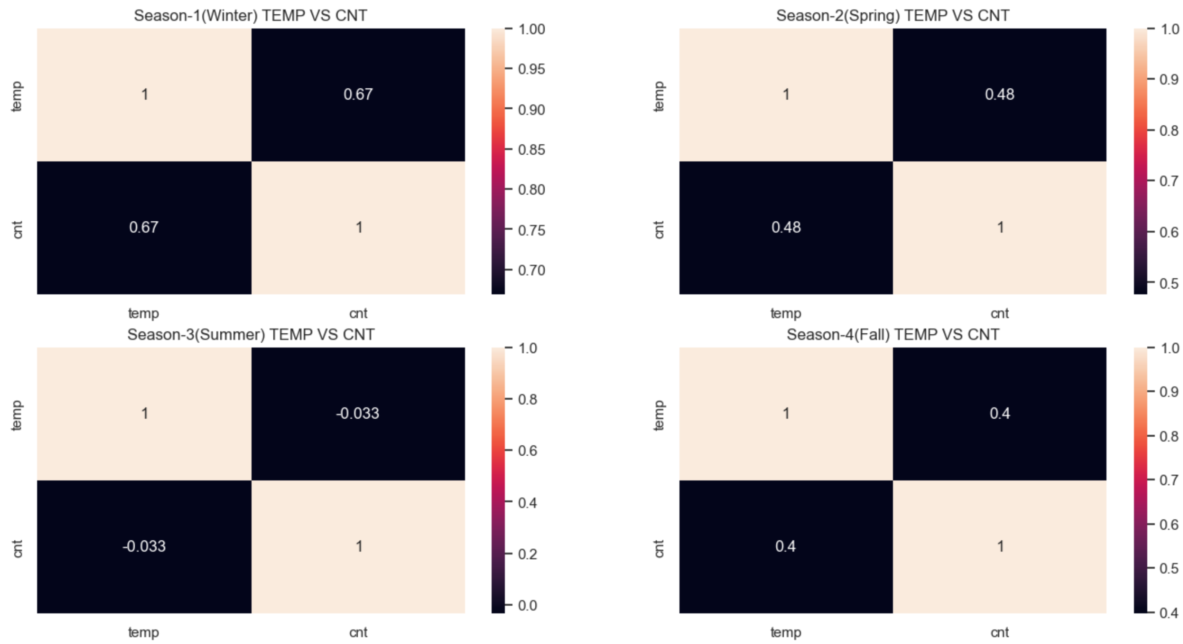
EDA2: Visualize the distribution of daily bike rentals and temperature per season

```
df_eda2 = df_dcbikes_tidy[["season", "temp", "cnt"]]
```

```
vis_season_grid = sns.FacetGrid(df_dcbikes_tidy, col="season")
vis_season_grid.map_dataframe(sns.regplot, x="temp", y="cnt")
vis_season_grid.add_legend()
plt.show()
```

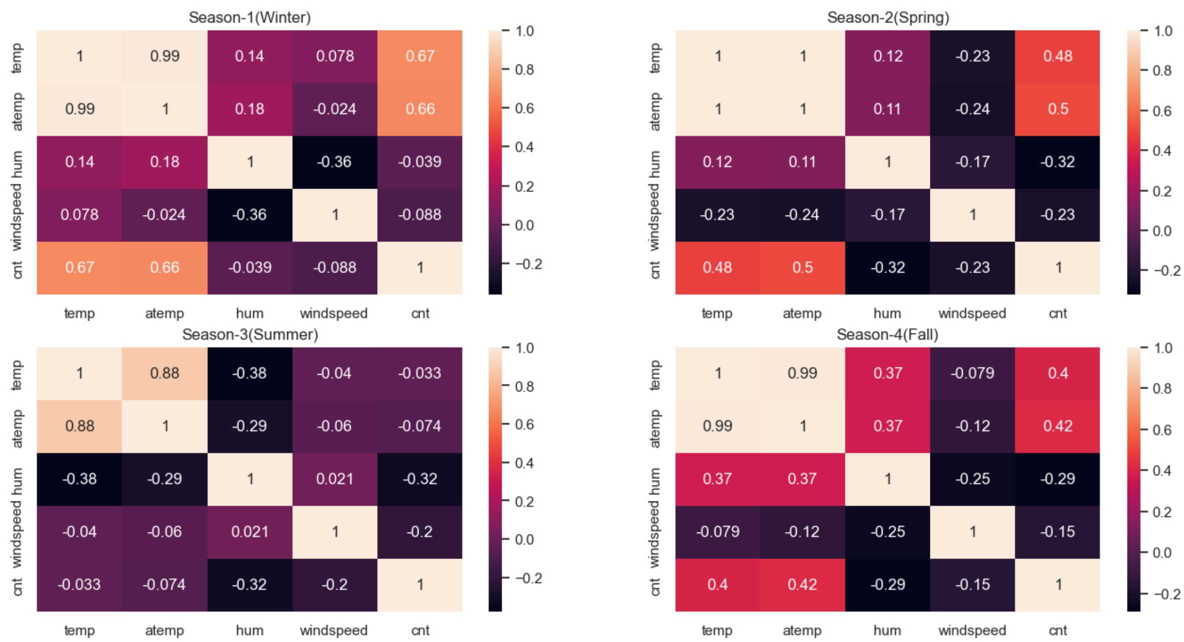



```python
fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(16, 8))
v1 = sns.heatmap(
    df_eda2.loc[df_eda2["season"] == 1, ["temp", "cnt"]].corr(),
    annot=True,
    ax=axes[0, 0],
)
v2 = sns.heatmap(
    df_eda2.loc[df_eda2["season"] == 2, ["temp", "cnt"]].corr(),
    annot=True,
    ax=axes[0, 1],
)
v3 = sns.heatmap(
    df_eda2.loc[df_eda2["season"] == 3, ["temp", "cnt"]].corr(),
    annot=True,
    ax=axes[1, 0],
)
v4 = sns.heatmap(
    df_eda2.loc[df_eda2["season"] == 4, ["temp", "cnt"]].corr(),
    annot=True,
    ax=axes[1, 1],
)
v1.set_title("Season-1(Winter) TEMP VS CNT")
v2.set_title("Season-2(Spring) TEMP VS CNT")
v3.set_title("Season-3(Summer) TEMP VS CNT")
v4.set_title("Season-4(Fall) TEMP VS CNT")
plt.show()
```




```python
fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(16, 8))
v1 = sns.heatmap(
    df_dcbikes_tidy.loc[
        df_dcbikes_tidy["season"] == 1, ["temp", "atemp", "hum", "windspeed", "cnt"]
    ].corr(),
    annot=True,
    ax=axes[0, 0],
)
v2 = sns.heatmap(
    df_dcbikes_tidy.loc[
        df_dcbikes_tidy["season"] == 2, ["temp", "atemp", "hum", "windspeed", "cnt"]
    ].corr(),
    annot=True,
    ax=axes[0, 1],
)
v3 = sns.heatmap(
    df_dcbikes_tidy.loc[
        df_dcbikes_tidy["season"] == 3, ["temp", "atemp", "hum", "windspeed", "cnt"]
    ].corr(),
    annot=True,
    ax=axes[1, 0],
)
v4 = sns.heatmap(
```

```
    df_dcbikes_tidy.loc[
        df_dcbikes_tidy["season"] == 4, ["temp", "atemp", "hum", "windspeed", "cnt"]
    ].corr(),
    annot=True,
    ax=axes[1, 1],
)
v1.set_title("Season-1(Winter)")
v2.set_title("Season-2(Spring)")
v3.set_title("Season-3(Summer)")
v4.set_title("Season-4(Fall)")
plt.show()
```



Regression Model

Experiment 1:One Numerical

Regression Equaltion: $bikecounts = \beta_0 + \beta_1 * temp + e$

```
OLS_M1 = custom_statsmodel_OLS(df_eda2, "cnt", "temp")
```

```
OLS_M1_fit = OLS_M1.fit()
```

```python
print(OLS_M1_fit.summary2())
```

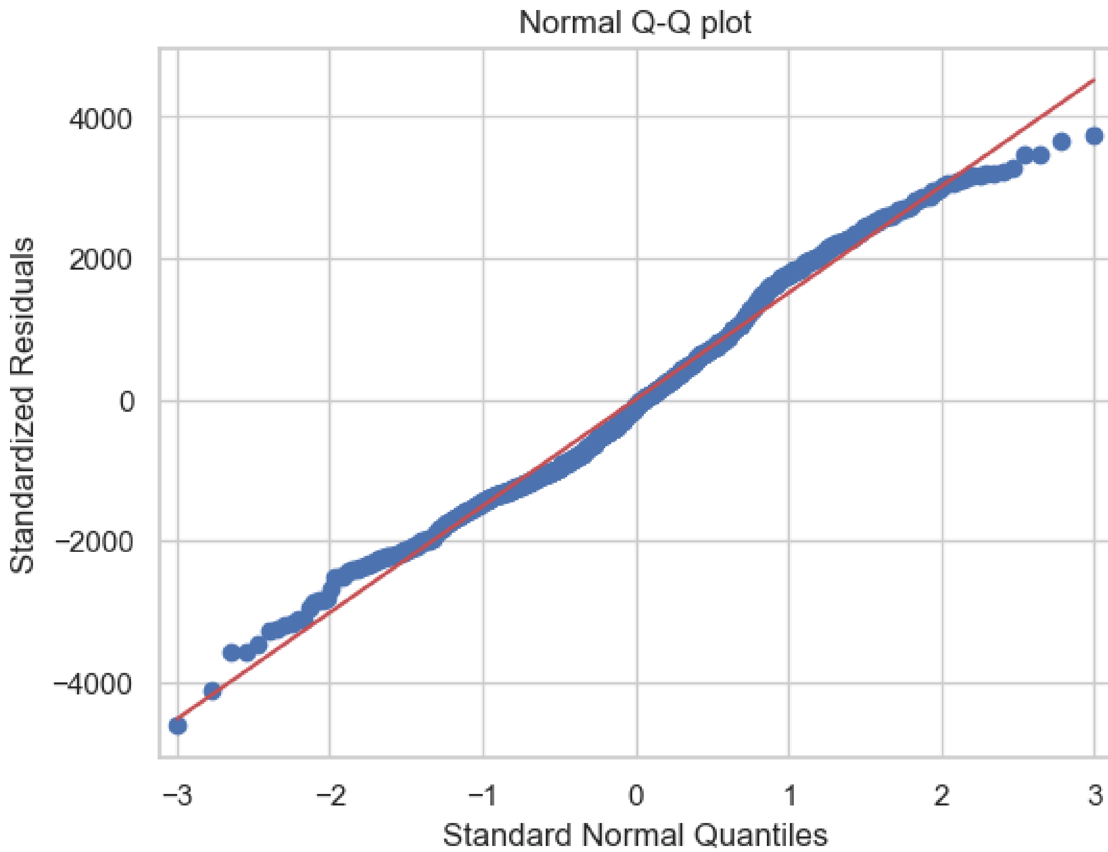
```
                 Results: Ordinary least squares
==================================================================
Model:              OLS              Adj. R-squared:     0.393
Dependent Variable: cnt              AIC:                12777.5357
Date:               2024-03-29 11:14 BIC:                12786.7245
No. Observations:   731              Log-Likelihood:     -6386.8
Df Model:           1                F-statistic:        473.5
Df Residuals:       729              Prob (F-statistic): 2.81e-81
R-squared:          0.394            Scale:              2.2783e+06
-------------------------------------------------------------------
            Coef.    Std.Err.     t     P>|t|     [0.025     0.975]
-------------------------------------------------------------------
const     1214.6421  161.1635   7.5367  0.0000   898.2421  1531.0421
temp      6640.7100  305.1880  21.7594  0.0000  6041.5577  7239.8623
------------------------------------------------------------------
Omnibus:              20.477       Durbin-Watson:          0.468
Prob(Omnibus):        0.000        Jarque-Bera (JB):       12.566
Skew:                 0.167        Prob(JB):               0.002
Kurtosis:             2.452        Condition No.:          7
==================================================================
Notes:
[1] Standard Errors assume that the covariance matrix of the errors
is correctly specified.
```

$\widehat{bikecounts} = 1214.64 + 6640.71 * \widehat{temp} + e$

Inferences:

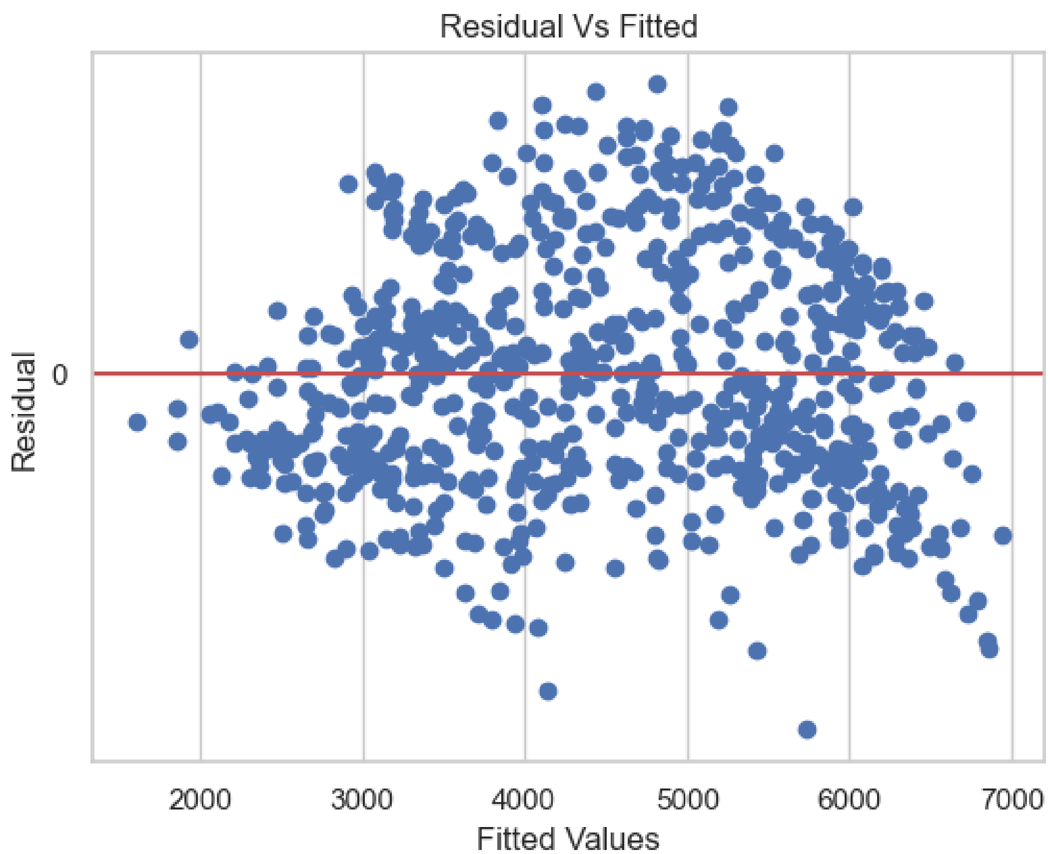
1. The p-value represents the probability of observing a slope as extreme or more extreme as the one we calculated in the sample, assuming there is truly no relationship between X and Y i.e null hypothesis. In our case p-value caluclated for temp is 0 hence we can reject the null in favor of alternate i.e there is a truly relationship between temp and counts.
2. For every increase of 1 unit in temperature, there is an associated increase of, on average, 6640 units of bike counts.
3. An average of bike counts 1214 when the temp is 0
4. The proportion of variability in the outcome variable i.e bike count explained by this model is about 0.39.

```
custom_ols_qqplot(OLS_M1_fit.resid)
```



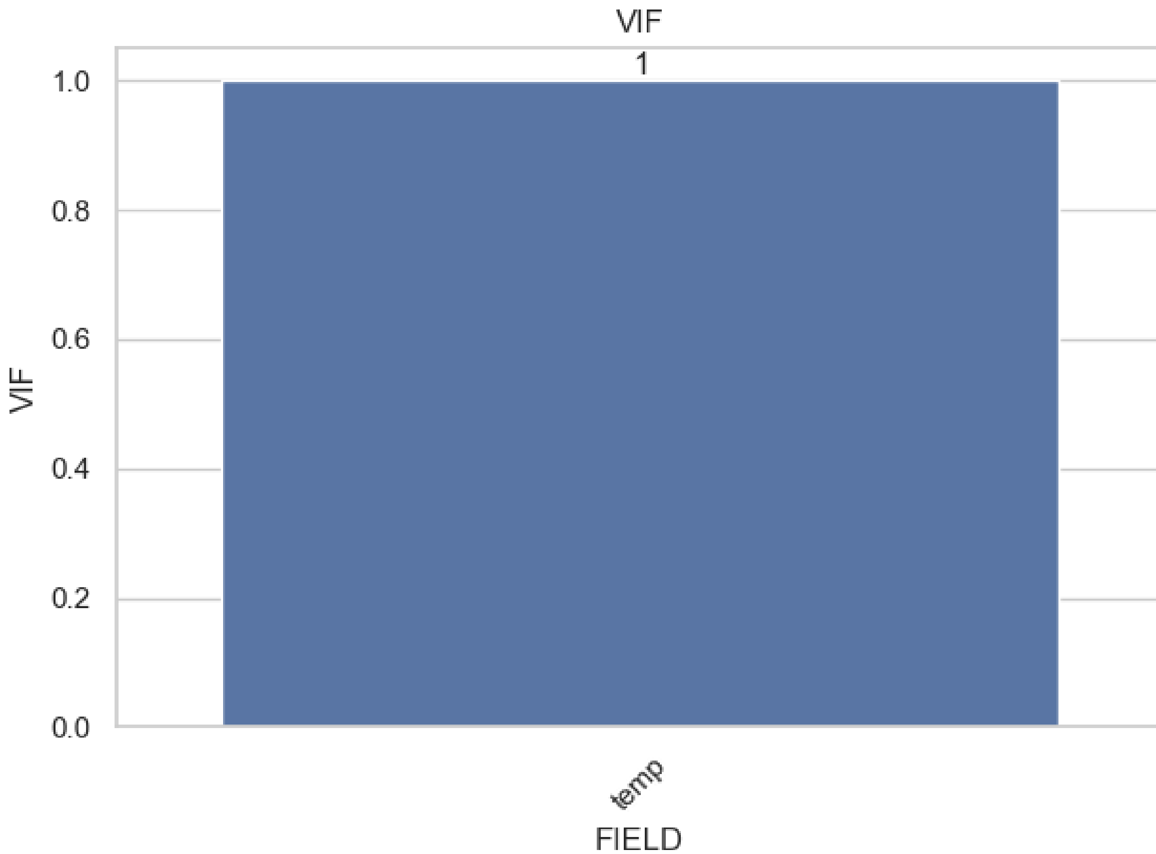
Comment: The Q-Q plot indicates that the residuals are approximately normally distributed.

```
custom_ols_res_vs_fitted(OLS_M1_fit.fittedvalues, OLS_M1_fit.resid)
```



Comment: The fitted vs. residual plot suggests a random scatter of residuals, with no apparent trends.

```
custom_VIF(OLS_M1)
```



Comment: The VIF suggests that temp might have a relatively low collinearity with other independent variables, making it a potentially good choice for exploration.

```
_new_df = pd.DataFrame({"temp": [0.35, 0.28, 0.34]})
custom_model_preds(OLS_M1_fit, _new_df)
```

	predicted_y
0	3538.890619
1	3074.040919
2	3472.483519

Experiment 2: One numerical and One Categorical

$bikecounts = \beta_0 + \beta_1 * temp + \beta_2 * season2 + \beta_1 * season3 + \beta_1 * season4 + e$

```python
df_eda2_encoded = pd.get_dummies(
    df_eda2, columns=["season"], dtype="int", drop_first=True
)
```

```python
OLS_M2 = custom_statsmodel_OLS(
    df_eda2_encoded, "cnt", "temp", "season_2", "season_3", "season_4"
)
```

```python
OLS_M2_fit = OLS_M2.fit()
```

```python
print(OLS_M2_fit.summary2())
```

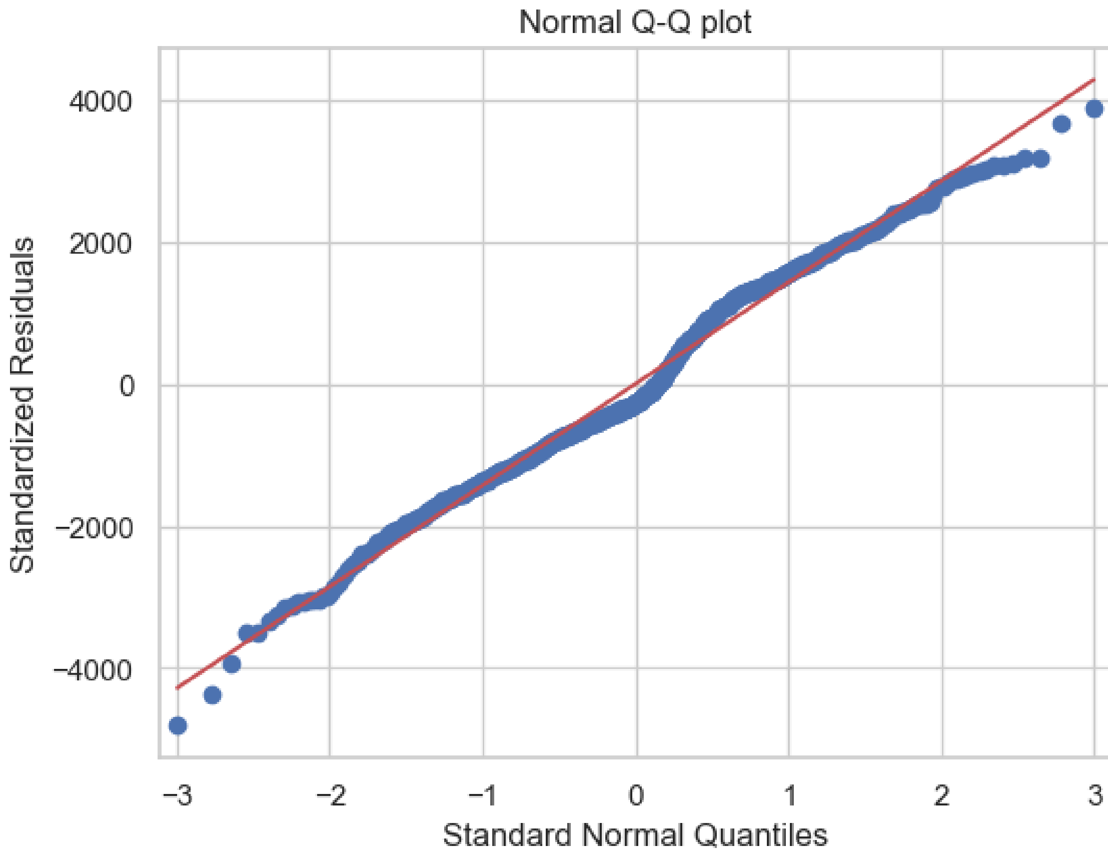
```
                  Results: Ordinary least squares
===================================================================
Model:              OLS              Adj. R-squared:     0.453
Dependent Variable: cnt              AIC:                12704.6549
Date:               2024-03-29 11:14 BIC:                12727.6269
No. Observations:   731              Log-Likelihood:     -6347.3
Df Model:           4                F-statistic:        152.0
Df Residuals:       726              Prob (F-statistic): 2.05e-94
R-squared:          0.456            Scale:              2.0537e+06
--------------------------------------------------------------------
             Coef.    Std.Err.     t      P>|t|     [0.025    0.975]
--------------------------------------------------------------------
const      745.7873  187.4757   3.9780  0.0001   377.7282  1113.8465
temp      6241.3453  518.1419  12.0456  0.0000  5224.1099  7258.5806
season_2   848.7236  197.0817   4.3065  0.0000   461.8056  1235.6416
season_3   490.1956  259.0055   1.8926  0.0588   -18.2936   998.6848
season_4  1342.8730  164.5878   8.1590  0.0000  1019.7482  1665.9978
-------------------------------------------------------------------
Omnibus:                7.571        Durbin-Watson:           0.523
Prob(Omnibus):          0.023        Jarque-Bera (JB):        5.112
Skew:                   0.011        Prob(JB):                0.078
Kurtosis:               2.591        Condition No.:           14
===================================================================
Notes:
[1] Standard Errors assume that the covariance matrix of the errors
is correctly specified.
```

$\widehat{bikecounts} = 745.7873 + 6241.34 * \widehat{temp} + 848.72 * \widehat{season}2 + 490.19 * \widehat{season}3 + 1342.87 * \widehat{season}4 + e$

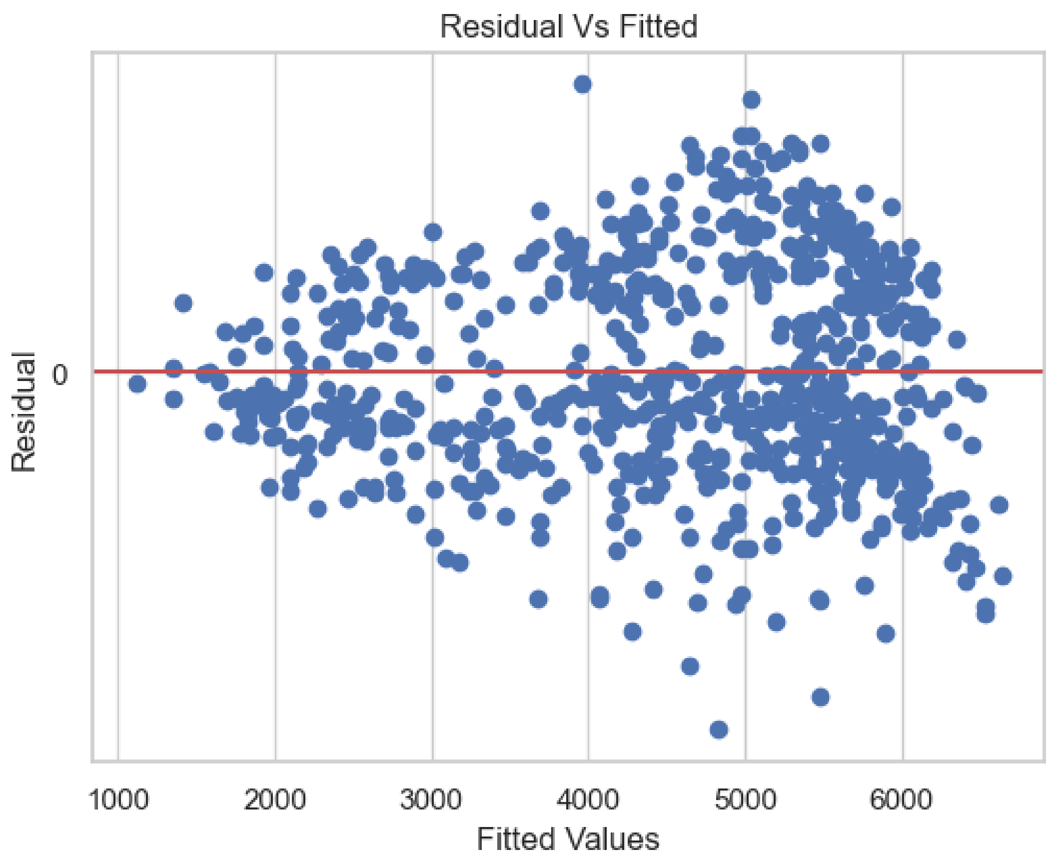
Inferences: 1. P-value caluclated - For temp is 0, we can reject the null in favor of alternate i.e there is a truly relationship between temp and counts. - For season_2 is 0.001, we can reject the null in favor of alternate i.e there is a truly relationship between Spring season and bike counts. - For season_3 is 0.05, we failed to reject the null i.e there is a truly no relationship between summer season and bike counts. - For season_4 is 0.0000, we can reject the null in favor of alternate i.e there is a truly relationship between Fall season and bike counts.

2. Taking into account all the other explanatory variables in our model, For every increase of 1 unit in temperature, there is an associated increase of, on average, 6241 units of bike counts.
3. Taking into account all the other explanatory variables in our model,
   - In 'Season2(Spring)' the average number of bike counts 848 units higher on average compared to the Season1(Winter).
   - In 'Season4(Fall)' the average number of bike counts 1342 units higher on average compared to the Season1(Winter).
4. An average of bike counts 745 when all the exploratory variables are zero
5. The proportion of variability in the outcome variable i.e bike count explained by this model is about 0.45.

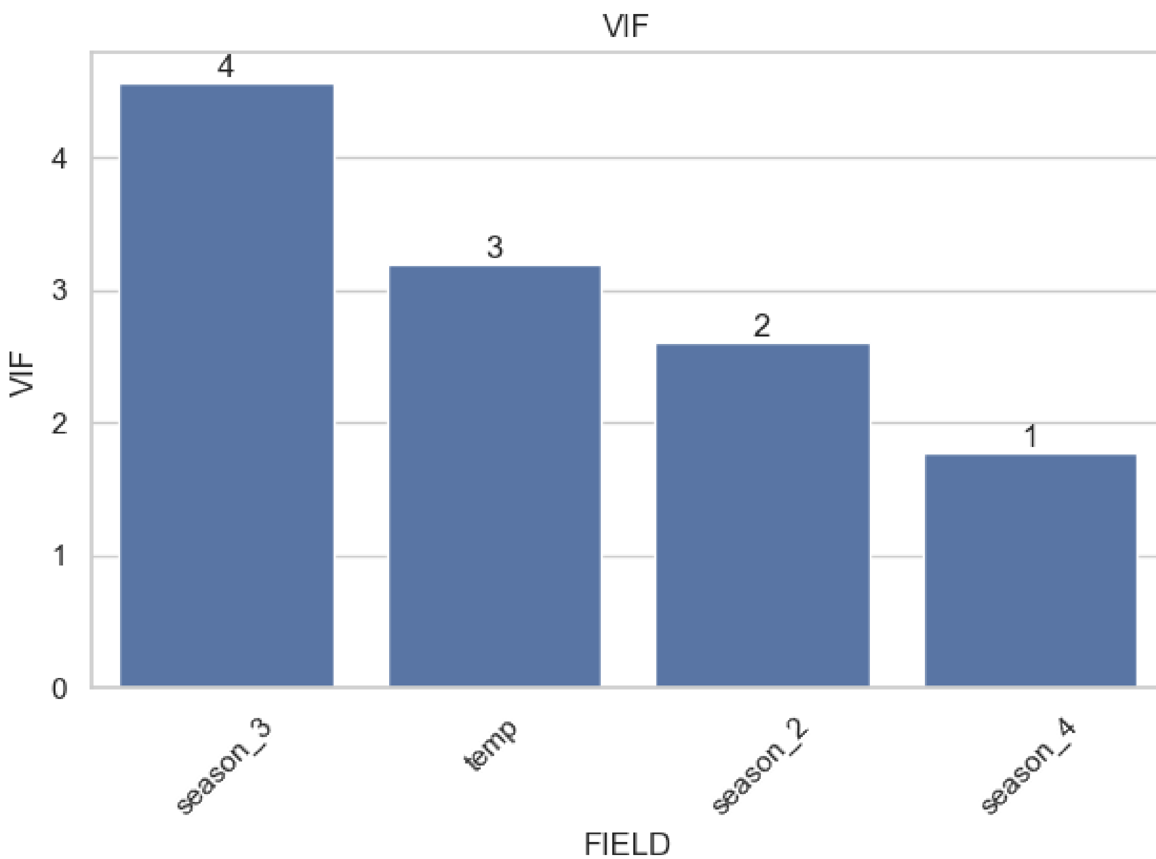
```
custom_ols_qqplot(OLS_M2_fit.resid)
```




```
custom_ols_res_vs_fitted(OLS_M2_fit.fittedvalues, OLS_M2_fit.resid)
```




```
custom_VIF(OLS_M2)
```




```
_new_df = df_eda2_encoded.loc[:10, ["temp", "season_2", "season_3", "season_4"]]
```

```
custom_model_preds(OLS_M2_fit, _new_df)
```

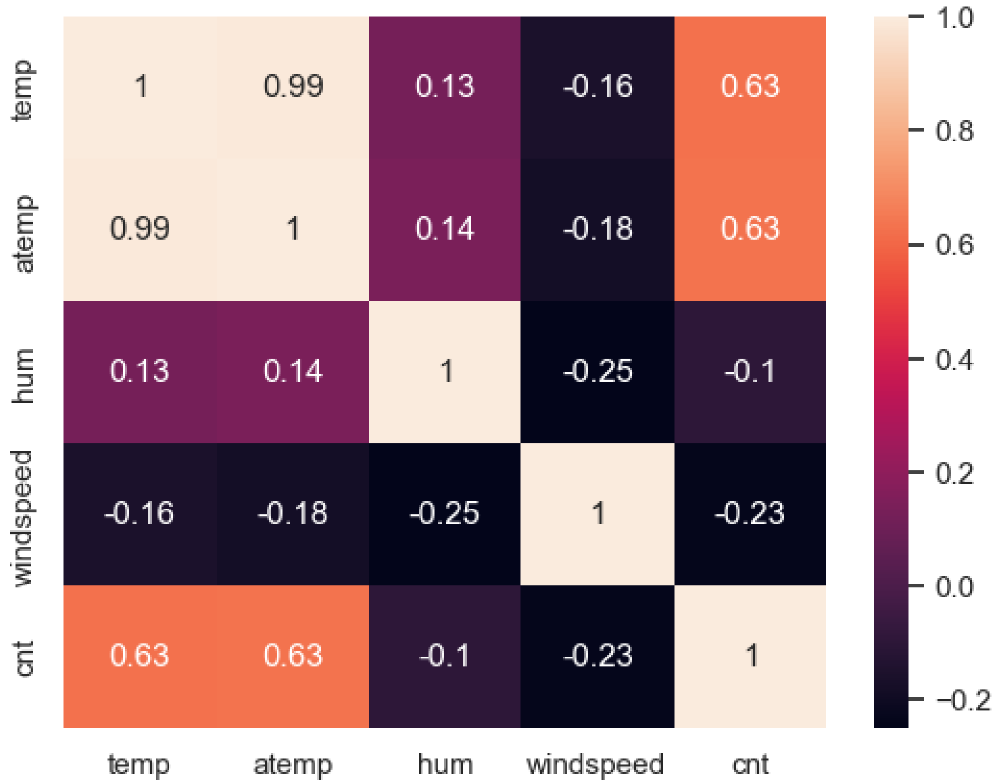
	predicted_y
0	2893.852416
1	3014.379035
2	1971.362862
3	1994.056394
4	2162.304338
5	2021.193763
6	1972.348995
7	1775.609309
8	1609.171355
9	1687.188171

	predicted_y
10	1801.142653

Experiment 3: More than one numerical: cnt = f(temp, atemp, hum, windspeed)

```
df_exp_3 = df_dcbikes_tidy[["temp", "atemp", "hum", "windspeed", "cnt"]]
```

```
sns.heatmap(df_exp_3.corr(), annot=True)
plt.show()
```




```
OLS_M3 = custom_statsmodel_OLS(df_exp_3, "cnt", "temp", "atemp", "hum", "windspeed")
```

```
OLS_M3_fit = OLS_M3.fit()
```

```python
print(OLS_M3_fit.summary2())
```

```
                  Results: Ordinary least squares
===================================================================
Model:              OLS              Adj. R-squared:     0.461
Dependent Variable: cnt              AIC:                12693.7344
Date:               2024-03-29 11:14 BIC:                12716.7065
No. Observations:   731              Log-Likelihood:     -6341.9
Df Model:           4                F-statistic:        157.0
Df Residuals:       726              Prob (F-statistic): 9.23e-97
R-squared:          0.464            Scale:              2.0232e+06
-------------------------------------------------------------------
            Coef.     Std.Err.    t    P>|t|    [0.025     0.975]
-------------------------------------------------------------------
const      3860.3685  355.3890 10.8624 0.0000  3162.6557  4558.0812
temp       2111.8136 2282.1976  0.9253 0.3551 -2368.6810  6592.3083
atemp      5139.1524 2576.9972  1.9942 0.0465    79.8964 10198.4085
hum       -3149.1098  383.9943 -8.2009 0.0000 -3902.9815 -2395.2380
windspeed -4528.6748  721.0854 -6.2804 0.0000 -5944.3362 -3113.0134
-------------------------------------------------------------------
Omnibus:                7.790       Durbin-Watson:          0.410
Prob(Omnibus):          0.020       Jarque-Bera (JB):       6.102
Skew:                   0.124       Prob(JB):               0.047
Kurtosis:               2.628       Condition No.:          91
===================================================================
Notes:
[1] Standard Errors assume that the covariance matrix of the errors
is correctly specified.
```

$\widehat{bikecounts} = 3860.36 + 2111.81 * \widehat{temp} + 5139 * \widehat{atemp} + (-3149.10) * \widehat{hum} + (-4528.67) * \widehat{windspeed} + e$

Inferences 1. P-value caluclated - For temp is 30, we failed to reject the null in favor of alternate i.e there is NO truly relationship between temp and counts. - For atemp is 0.04, we can reject the null in favor of alternate i.e there is a truly relationship between atemp and bike counts. - For hum is 0.05, we can reject the null i.e there is a truly relationship between humidity and bike counts. - For windspeed is 0.0000, we can reject the null in favor of alternate i.e there is a truly relationship between windspeed and bike counts.

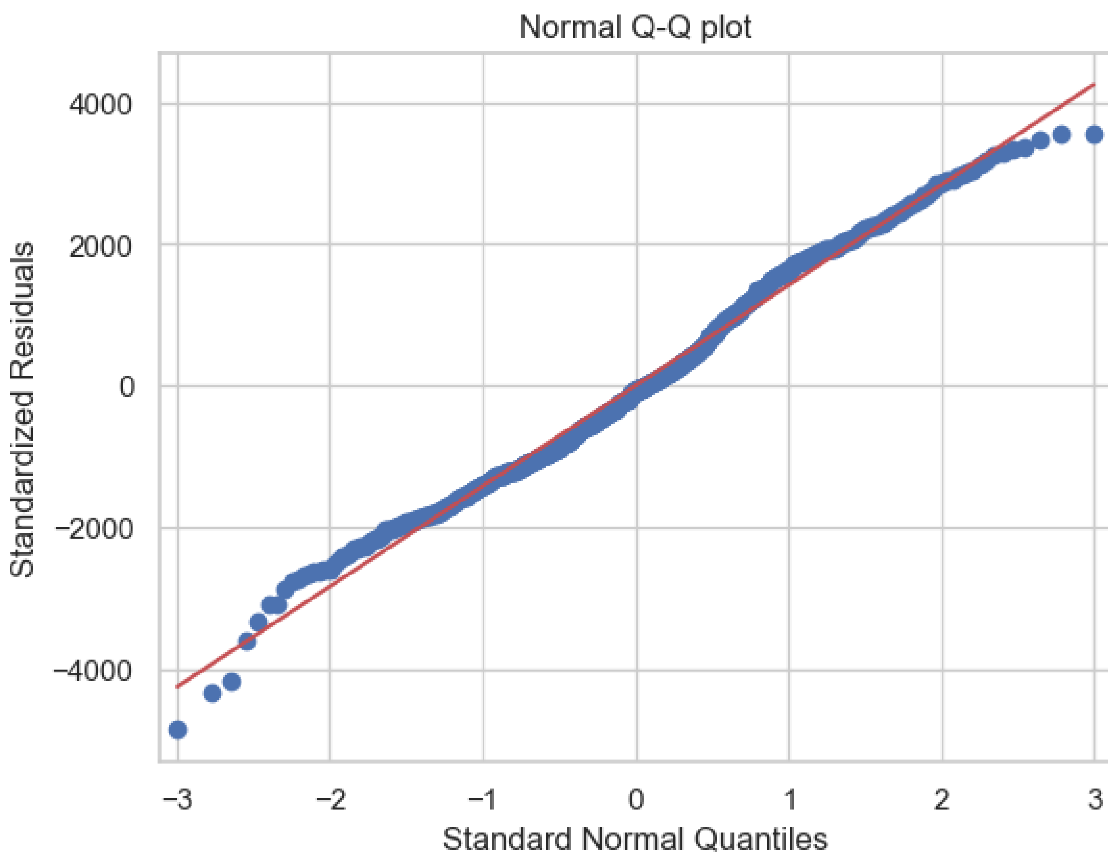
2. Taking into account all the other explanatory variables in our model,

    - for every increase of one unit in temperature, there is an associated increase of on average 2111 in bike counts.

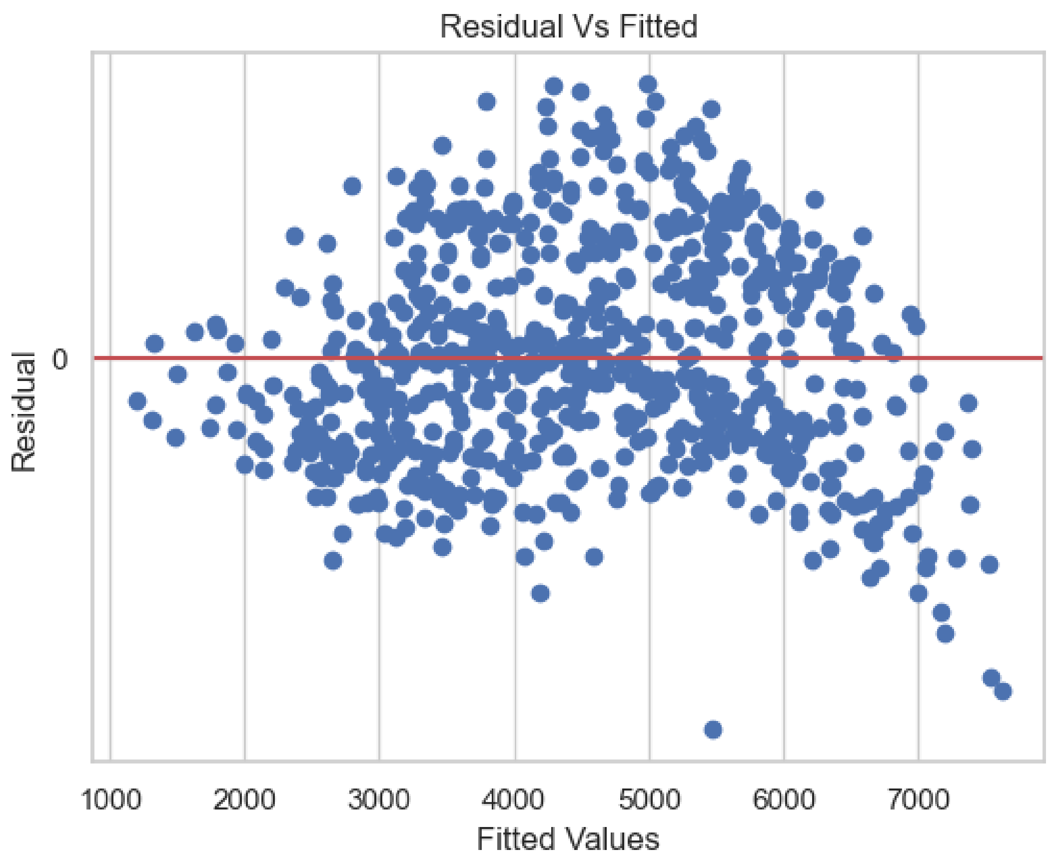
- for every increase of one unit in atemperature, there is an associated increase of on average 5139 in bike counts.
- for every increase of one unit in humidity, there is an associated decrease of on average 3149 in bike counts.
- for every increase of one unit in windpspeed, there is an associated decreased of on average 4528 in bike counts.

3. An average of bike counts 3860 when all the exploratory variables are zero
4. The proportion of variability in the outcome variable i.e bike count explained by this model is about 0.46.

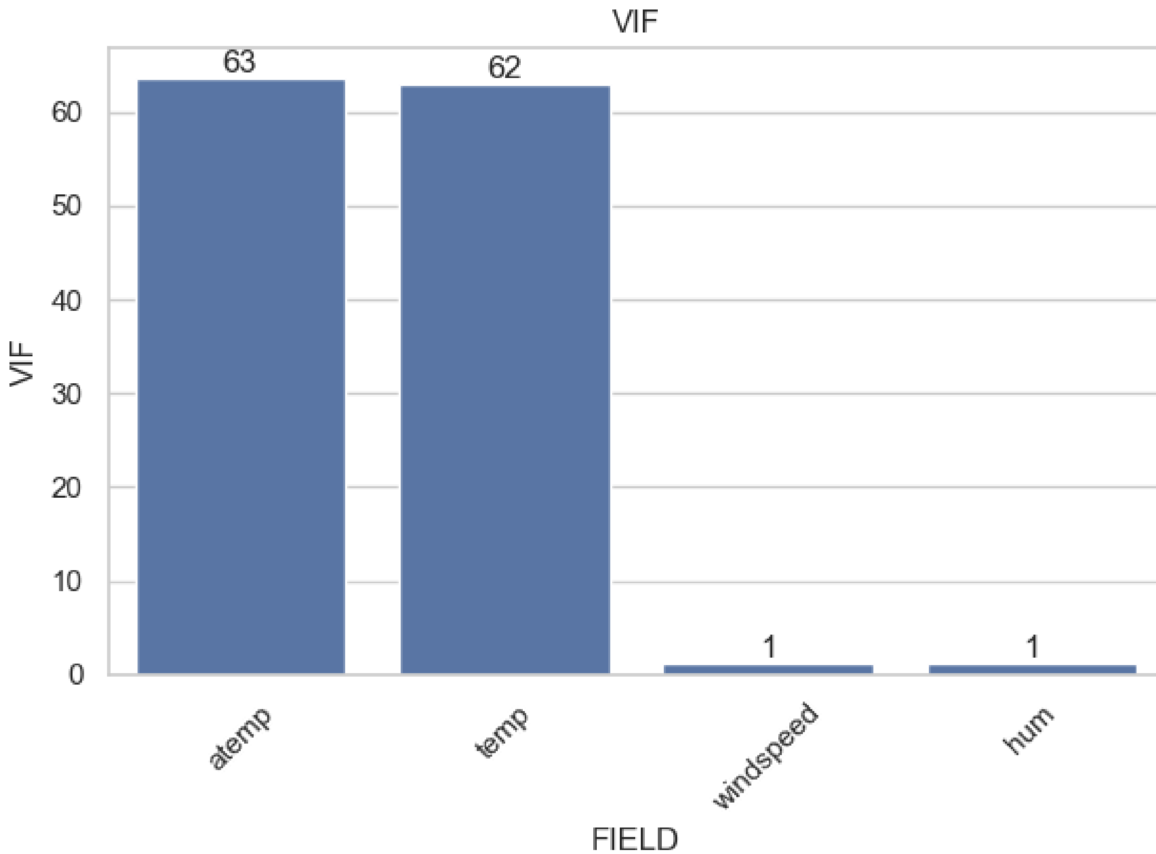
```
custom_ols_qqplot(OLS_M3_fit.resid)
```




```
custom_ols_res_vs_fitted(OLS_M3_fit.fittedvalues, OLS_M3_fit.resid)
```




```
custom_VIF(OLS_M3)
```



Case 2: Auto

Data Importing, Prep and EDA

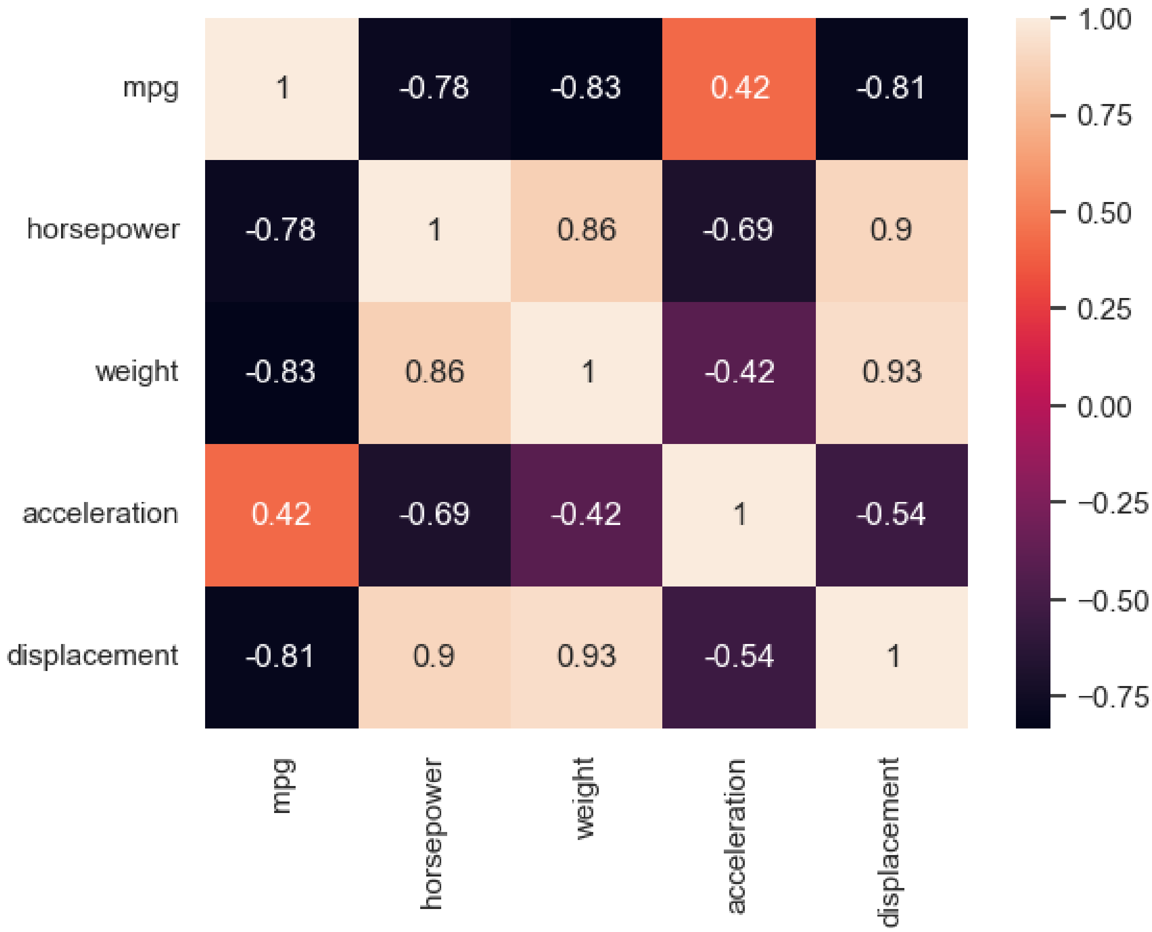
```
df_auto = pd.read_csv(
    r"/Users/malleshamyamulla/Desktop/SSBBA/assignments/w4/data/auto.csv"
)
```

```
df_auto.head()
```

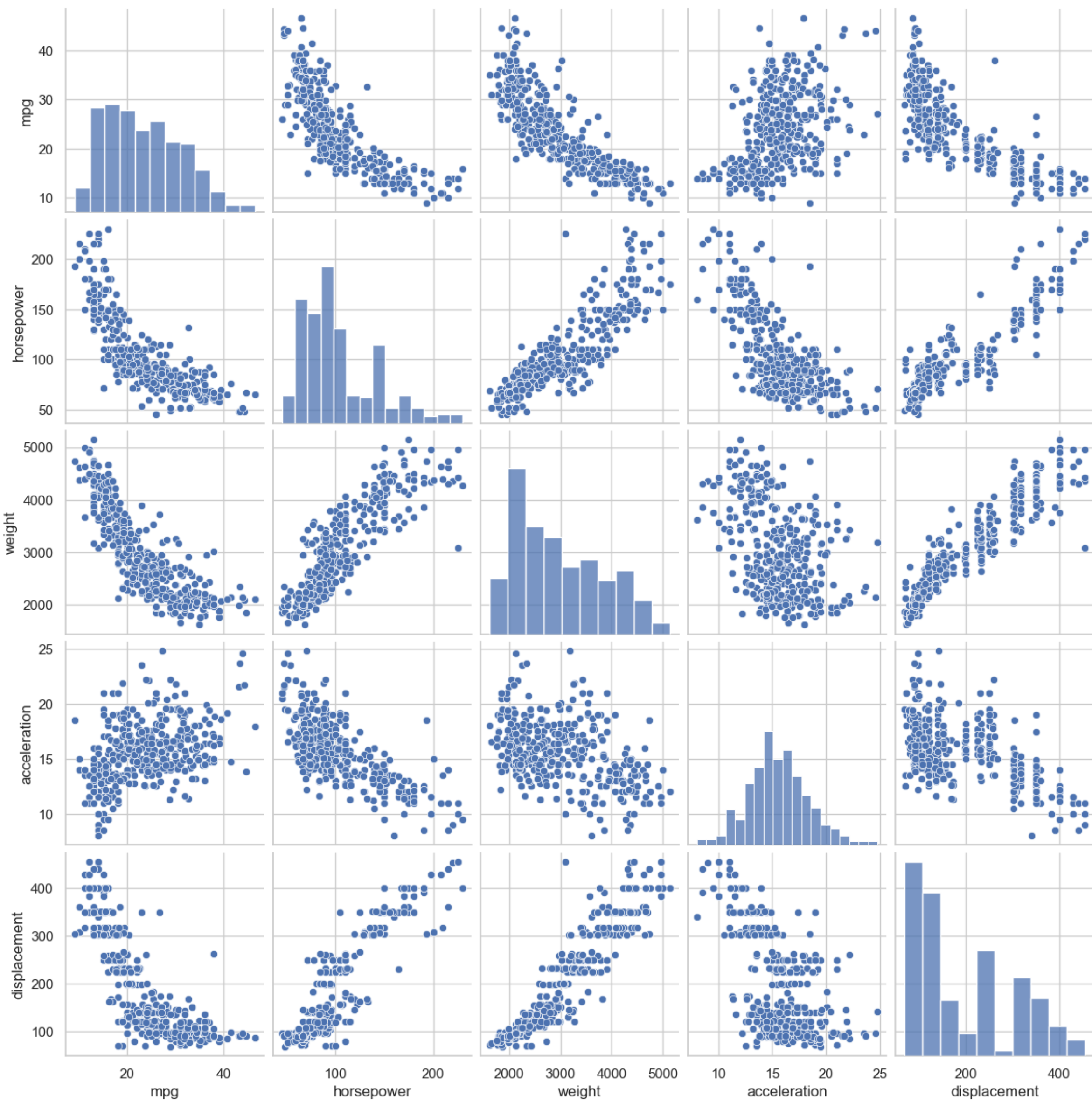
	mpg	cylinders	displacement	horsepower	weight	acceleration	year	origin
0	18.0	8	307.0	130	3504	12.0	70	1
1	15.0	8	350.0	165	3693	11.5	70	1
2	18.0	8	318.0	150	3436	11.0	70	1

	mpg	cylinders	displacement	horsepower	weight	acceleration	year	origin
3	16.0	8	304.0	150	3433	12.0	70	1
4	17.0	8	302.0	140	3449	10.5	70	1

```
sns.heatmap(
    df_auto[["mpg", "horsepower", "weight", "acceleration", "displacement"]].corr(),
    annot=True,
)
plt.show()
```




```
sns.pairplot(df_auto[["mpg", "horsepower", "weight", "acceleration", "displacement"]])
plt.show()
```



Regression Model

Experiment 1: One Numerical: mpg=f(horsepower)

```
SL1 = custom_statsmodel_OLS(df_auto, "mpg", "horsepower")
```

```
SL1_modelfit = SL1.fit()
```

```
print(SL1_modelfit.summary2())
```

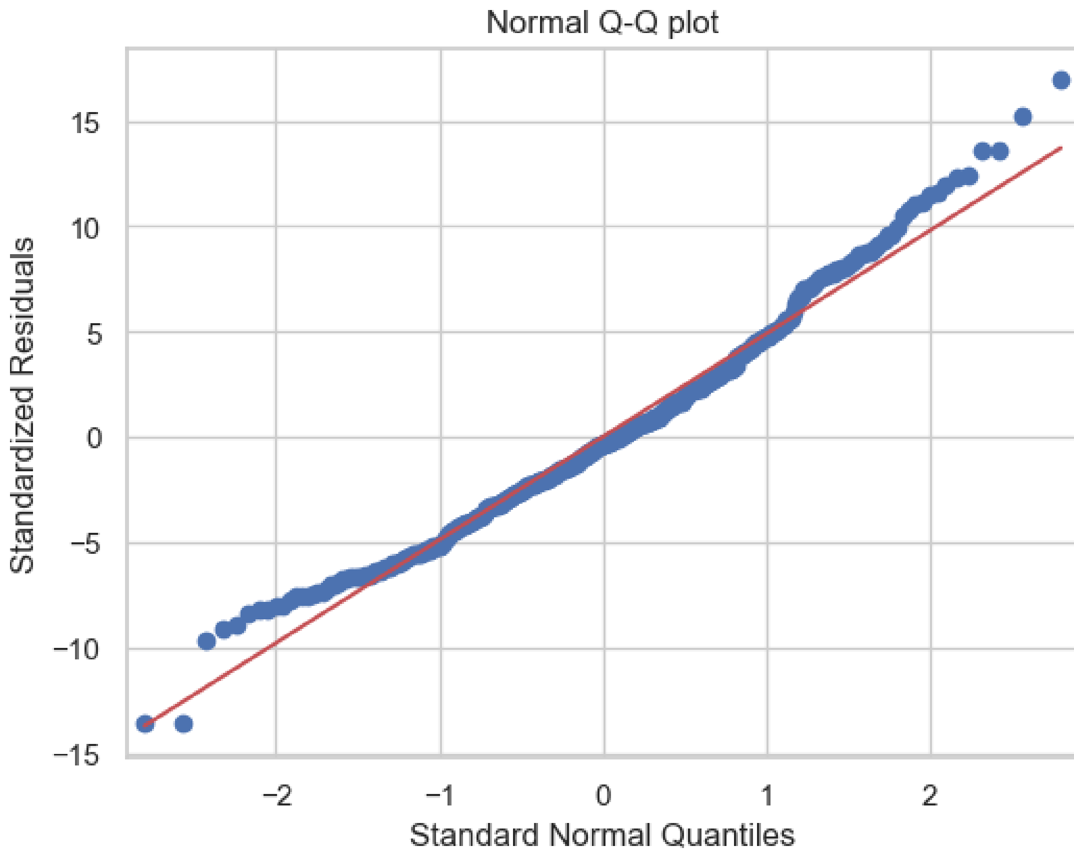
```
                 Results: Ordinary least squares
==================================================================
Model:              OLS              Adj. R-squared:     0.605
Dependent Variable: mpg              AIC:                2361.3237
Date:               2024-03-29 11:15 BIC:                2369.2662
No. Observations:   392              Log-Likelihood:     -1178.7
Df Model:           1                F-statistic:        599.7
Df Residuals:       390              Prob (F-statistic): 7.03e-81
R-squared:          0.606            Scale:              24.066
-------------------------------------------------------------------
               Coef.   Std.Err.     t      P>|t|    [0.025   0.975]
-------------------------------------------------------------------
const         39.9359    0.7175   55.6598  0.0000  38.5252  41.3465
horsepower    -0.1578    0.0064  -24.4891  0.0000  -0.1705  -0.1452
------------------------------------------------------------------
Omnibus:                16.432       Durbin-Watson:          0.920
Prob(Omnibus):          0.000        Jarque-Bera (JB):       17.305
Skew:                   0.492        Prob(JB):               0.000
Kurtosis:               3.299        Condition No.:          322
==================================================================
Notes:
[1] Standard Errors assume that the covariance matrix of the
errors is correctly specified.
```

$\hat{mpg} = 39.9359 + (-0.15) * \hat{horsepower} + e$

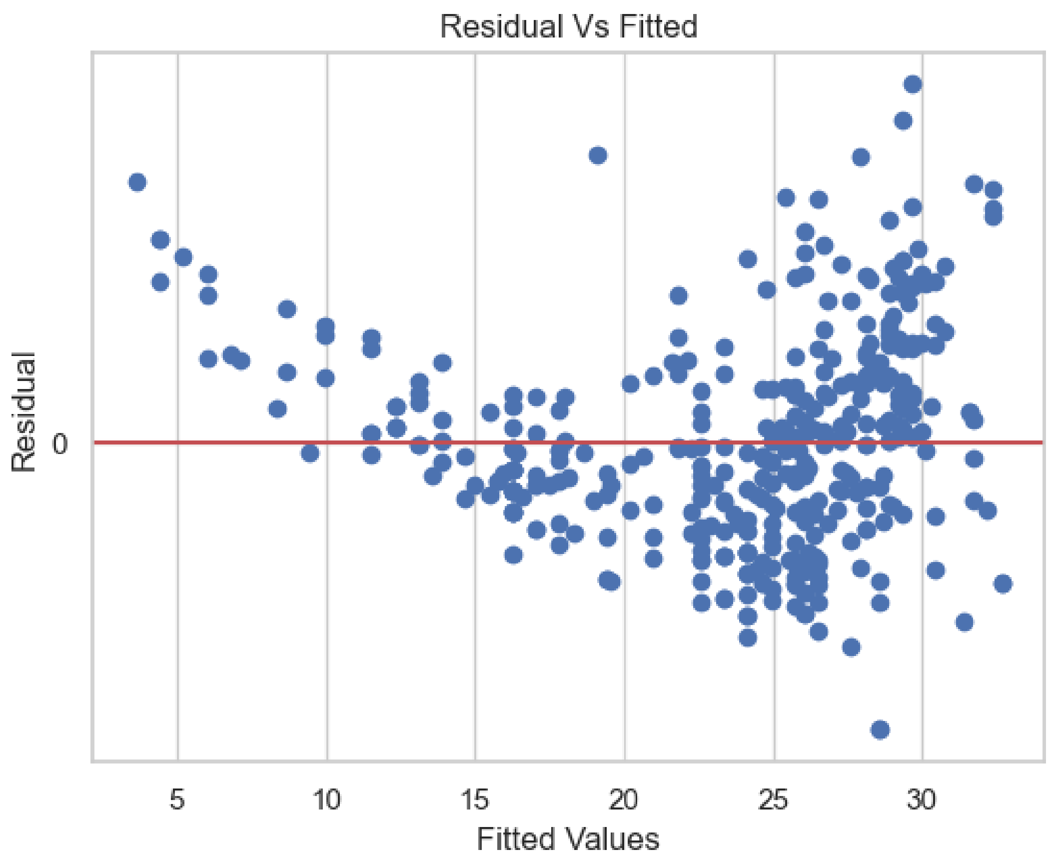
Inferences:

1. In our case p-value caluclated for HorsePower is 0 hence we can reject the null in favor of alternate i.e there is a truly relationship between Horsepower and MPG.
2. For every increase of 1 unit in HorsePower, there is an associated decrease of, on average, 0.15 units of MPG.
3. An average of MPG is 39 when the Horsepower is 0
4. The proportion of variability in the outcome variable i.e bike count explained by this model is about 0.60

```
custom_ols_qqplot(SL1_modelfit.resid)
```




```
custom_ols_res_vs_fitted(SL1_modelfit.fittedvalues, SL1_modelfit.resid)
```



Experiment2: two numericals: mpg=f(horsepower,acceleration)

```
SL2 = custom_statsmodel_OLS(df_auto, "mpg", "horsepower", "acceleration")
```

```
SL2_modelfit = SL2.fit()
```

```
print(SL2_modelfit.summary2())
```

```
                 Results: Ordinary least squares
==================================================================
Model:              OLS              Adj. R-squared:     0.628
Dependent Variable: mpg              AIC:                2338.2770
Date:               2024-03-29 11:15 BIC:                2350.1908
No. Observations:   392              Log-Likelihood:     -1166.1
```

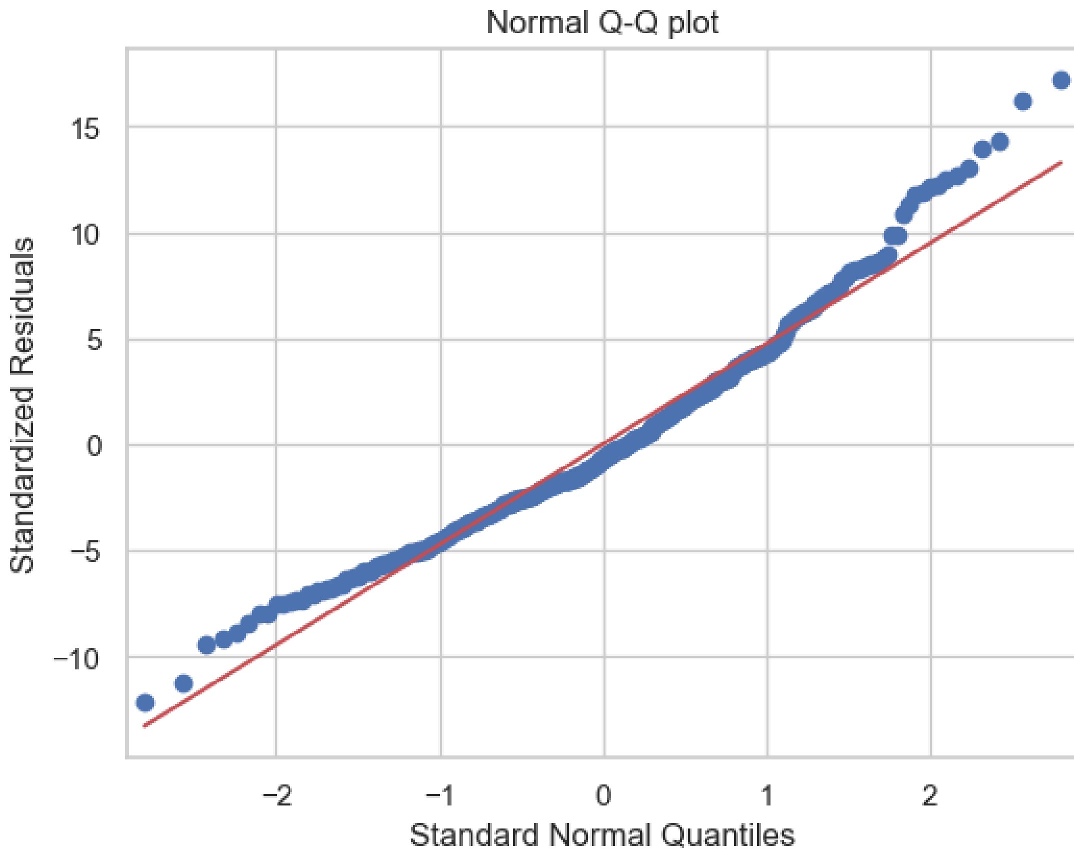
```
Df Model:           2                F-statistic:       331.7
Df Residuals:       389              Prob (F-statistic): 8.67e-85
R-squared:          0.630            Scale:             22.635
-------------------------------------------------------------------
               Coef.   Std.Err.     t      P>|t|    [0.025   0.975]
-------------------------------------------------------------------
const         52.5593    2.5870   20.3164  0.0000  47.4730  57.6457
horsepower    -0.1880    0.0086  -21.7883  0.0000  -0.2049  -0.1710
acceleration  -0.6098    0.1204   -5.0662  0.0000  -0.8464  -0.3731
------------------------------------------------------------------
Omnibus:              31.573      Durbin-Watson:         0.984
Prob(Omnibus):        0.000       Jarque-Bera (JB):      37.488
Skew:                 0.685       Prob(JB):              0.000
Kurtosis:             3.647       Condition No.:         1209
==================================================================
Notes:
[1] Standard Errors assume that the covariance matrix of the
errors is correctly specified.
[2] The condition number is large, 1.21e+03. This might indicate
that there are strong multicollinearity or other numerical
problems.
```

$\hat{mpg} = 52.5593 + (-0.18) * \widehat{horsepower} + (-0.60) * \widehat{acceleration} + e$

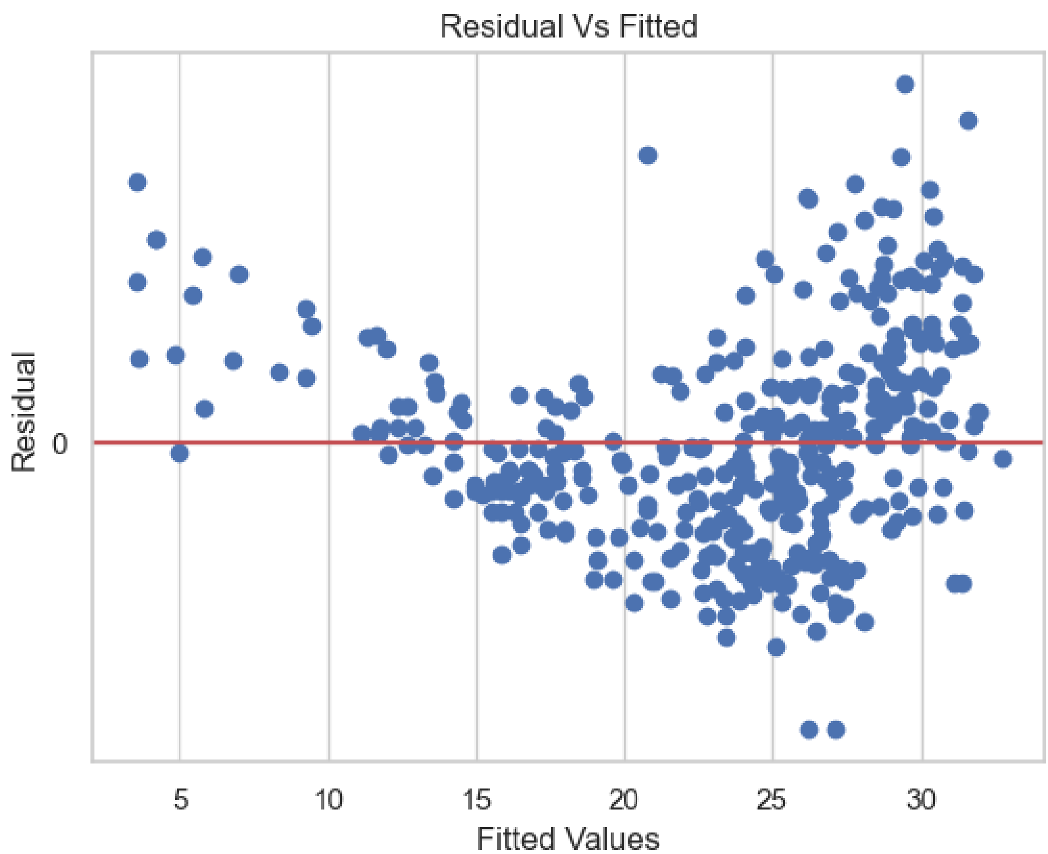
Inferences:

1. p-value caluclated
   - for HorsePower is 0 hence we can reject the null in favor of alternate i.e there is a truly relationship between Horsepower and MPG.
   - for Accelaration is 0 hence we can reject the null in favor of alternate i.e there is a truly relationship between Accelaration and MPG.
2. For every increase of 1 unit in HorsePower, there is an associated decrease of, on average, 0.18 units of MPG.
3. For every increase of 1 unit in Accelaration, there is an associated decrease of, on average, 0.6 units of MPG.
4. An average of MPG is 52 when the Horsepower is 0
5. The proportion of variability in the outcome variable i.e bike count explained by this model is about 0.62

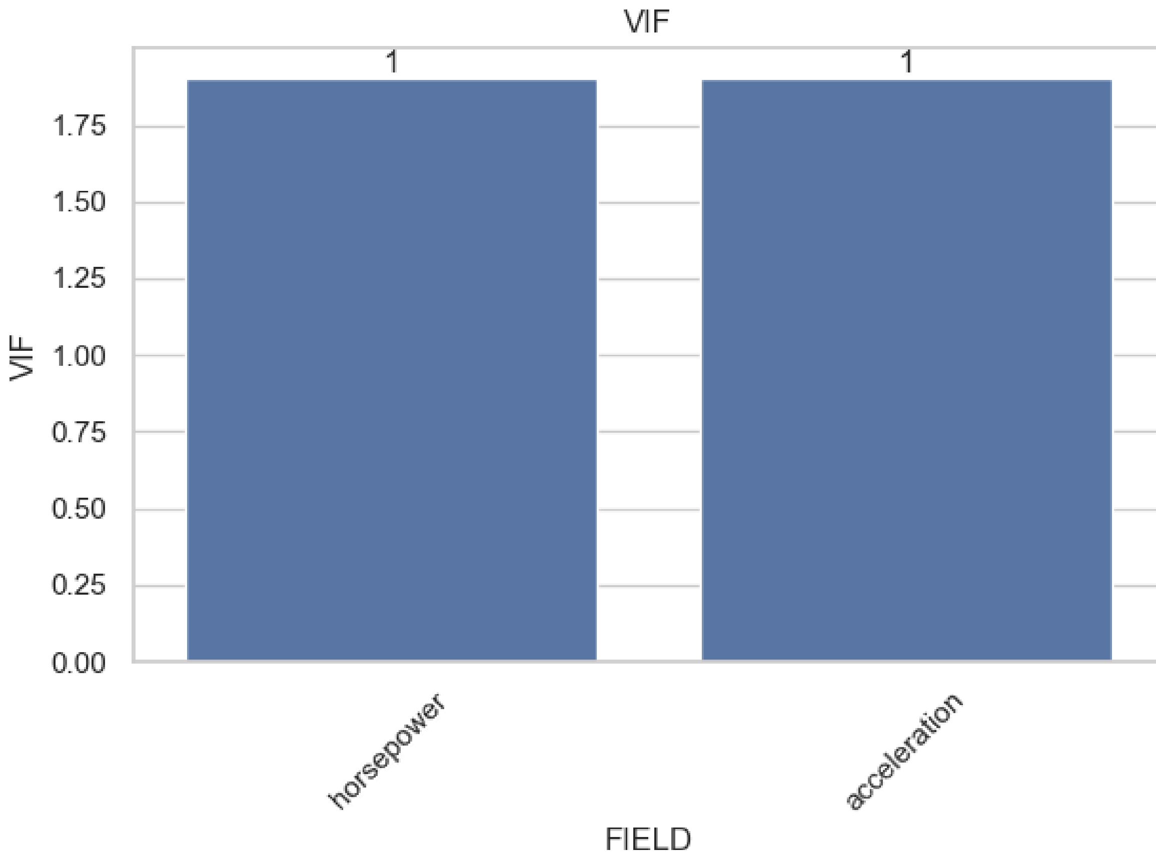
```
custom_ols_qqplot(SL2_modelfit.resid)
```




```
custom_ols_res_vs_fitted(SL2_modelfit.fittedvalues, SL1_modelfit.resid)
```




```
custom_VIF(SL2)
```



Experiment3: More than 2 numericals: mpg=f("horsepower", "weight", "acceleration", "displacement")

```
SL3 = custom_statsmodel_OLS(
    df_auto, "mpg", "horsepower", "weight", "acceleration", "displacement"
)
```

```
SL3_modelfit = SL3.fit()
```

```
print(SL3_modelfit.summary2())
```

```
                  Results: Ordinary least squares
==================================================================
Model:              OLS              Adj. R-squared:     0.704
```

```
Dependent Variable: mpg              AIC:                2251.1955
Date:               2024-03-29 11:15 BIC:                2271.0518
No. Observations:   392              Log-Likelihood:     -1120.6
Df Model:           4                F-statistic:        233.4
Df Residuals:       387              Prob (F-statistic): 9.63e-102
R-squared:          0.707            Scale:              18.035
-------------------------------------------------------------------
                Coef.   Std.Err.     t     P>|t|    [0.025   0.975]
-------------------------------------------------------------------
const          45.2511    2.4560  18.4244  0.0000  40.4223  50.0800
horsepower     -0.0436    0.0166  -2.6312  0.0088  -0.0762  -0.0110
weight         -0.0053    0.0008  -6.5123  0.0000  -0.0069  -0.0037
acceleration   -0.0231    0.1256  -0.1843  0.8539  -0.2701   0.2238
displacement   -0.0060    0.0067  -0.8944  0.3717  -0.0192   0.0072
------------------------------------------------------------------
Omnibus:              38.359       Durbin-Watson:          0.861
Prob(Omnibus):        0.000        Jarque-Bera (JB):       51.333
Skew:                 0.715        Prob(JB):               0.000
Kurtosis:             4.049        Condition No.:          35594
==================================================================
Notes:
[1] Standard Errors assume that the covariance matrix of the
errors is correctly specified.
[2] The condition number is large, 3.56e+04. This might indicate
that there are strong multicollinearity or other numerical
problems.
```

$\widehat{mpg} = 45.2511 + (-0.04) * \widehat{horsepower} + (0.0053) * \widehat{weight} + (0.0231) * \widehat{acceleration} + (-0.0060) * \widehat{displacement} + e$

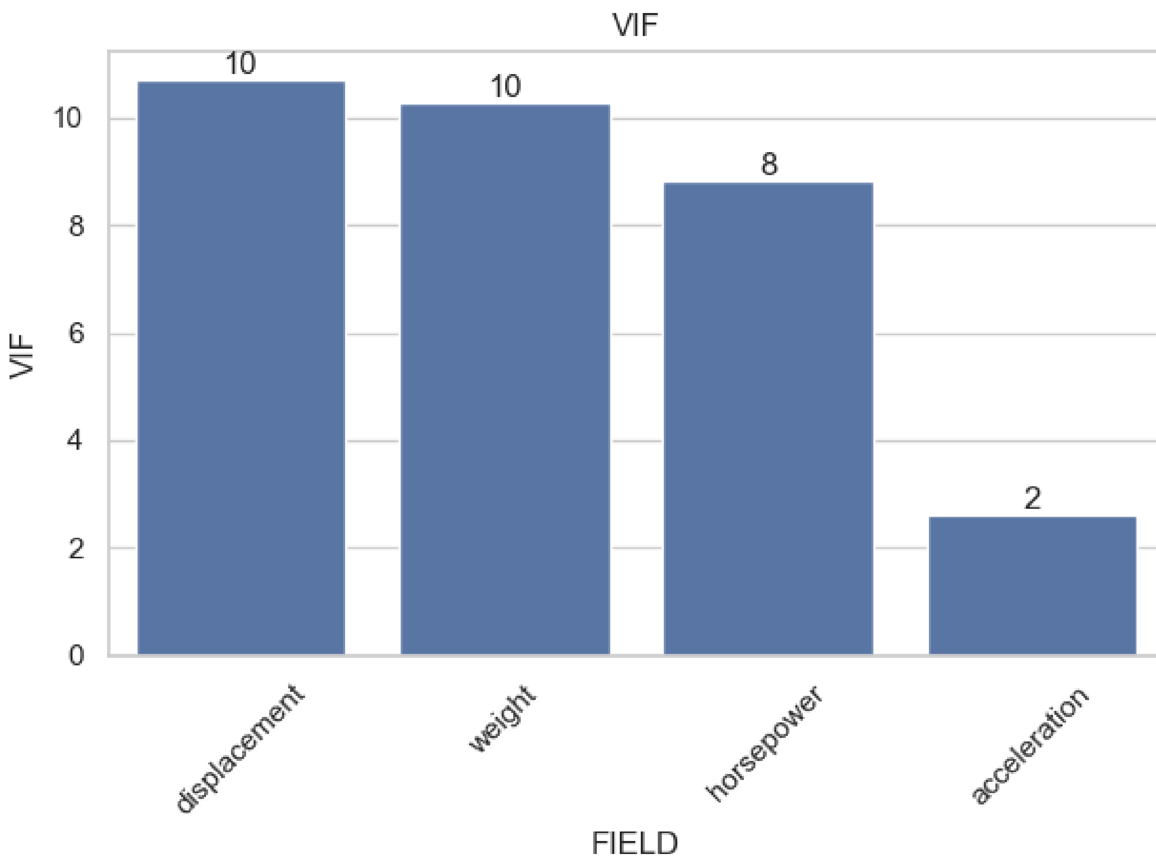
Inferences:

1. p-value caluclated

   - for HorsePower is 0 hence we can reject the null in favor of alternate i.e there is a truly relationship between Horsepower and MPG.
   - for Weight is 0 hence we can reject the null in favor of alternate i.e there is a truly relationship between Weight and MPG.
   - for Accelaration is 0.85 we fail to reject the null i.e there is NO truly relationship between Accelaration and MPG.
   - for Displacement is 0.37 we fail to reject the null i.e there is NO truly relationship between Displacement and MPG.

2. For every increase of 1 unit in HorsePower, there is an associated decrease of, on average, 0.04 units of MPG.
3. For every increase of 1 unit in weight, there is an associated decrease of, on average, 0.005 units of MPG.
4. An average of MPG is 45.25 when the Horsepower is 0
5. The proportion of variability in the outcome variable i.e bike count explained by this model is about 0.704

```
custom_VIF(SL3)
```



Case 3: CarSeats

Data Importing and Prep

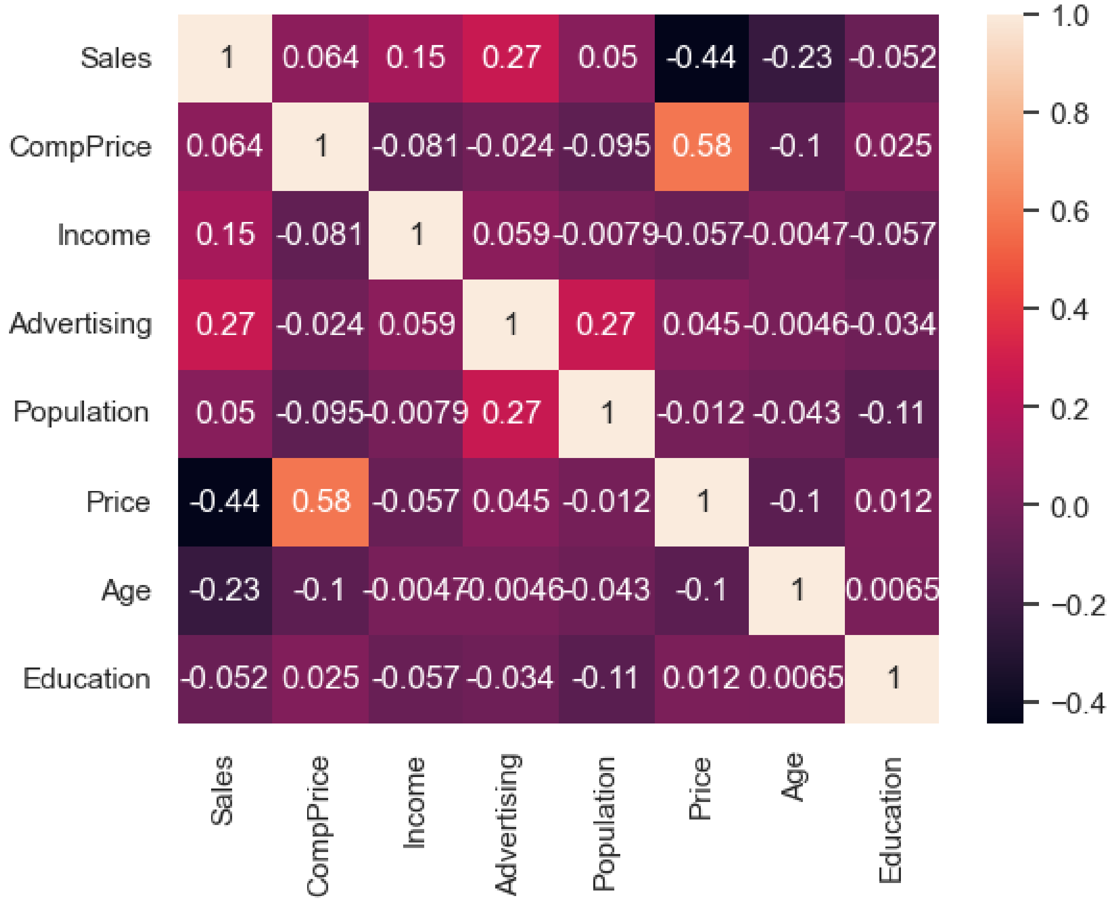
```
df_carseats = pd.read_csv(
    r"/Users/malleshamyamulla/Desktop/SSBBA/assignments/w4/data/carseats.csv"
)
```

```
df_carseats = pd.get_dummies(
    df_carseats, columns=["ShelveLoc", "Urban", "US"], dtype="int", drop_first=True
)
```

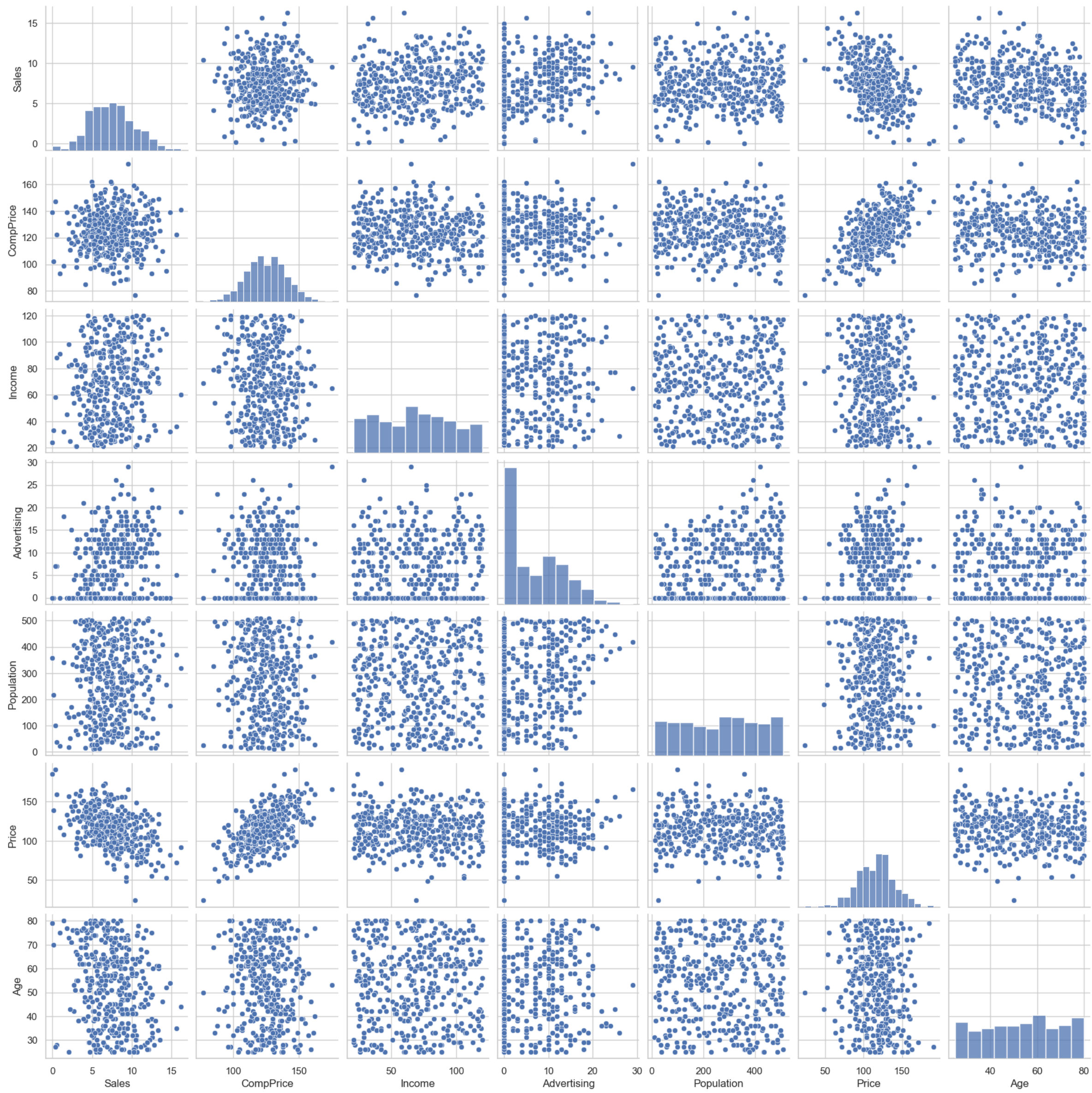
```
df_carseats.head()
```

	Sales	CompPrice	Income	Advertising	Population	Price	Age	Education	ShelveLoc_Good	Sh
0	9.50	138	73	11	276	120	42	17	0	0
1	11.22	111	48	16	260	83	65	10	1	0
2	10.06	113	35	10	269	80	59	12	0	1
3	7.40	117	100	4	466	97	55	14	0	1
4	4.15	141	64	3	340	128	38	13	0	0

```
sns.heatmap(
    df_carseats[
        [
            "Sales",
            "CompPrice",
            "Income",
            "Advertising",
            "Population",
            "Price",
            "Age",
            "Education",
        ]
    ].corr(),
    annot=True,
)
plt.show()
```




```
sns.pairplot(
    df_carseats[
        ["Sales", "CompPrice", "Income", "Advertising", "Population", "Price", "Age"]
    ]
)
plt.show()
```



Regression Model

Experiment 1: More than 1 Numericals:
Sales=f("CompPrice","Income","Advertising","Population","Price","Age","Education")

```
car_SL1 = custom_statsmodel_OLS(
    df_carseats,
```

```python
    "Sales",
    "CompPrice",
    "Income",
    "Advertising",
    "Population",
    "Price",
    "Age",
    "Education",
)
```

```python
car_SL1_fit = car_SL1.fit()
```

```python
print(car_SL1_fit.summary2())
```

```
                 Results: Ordinary least squares
==================================================================
Model:              OLS              Adj. R-squared:     0.533
Dependent Variable: Sales            AIC:                1668.6475
Date:               2024-03-29 11:15 BIC:                1700.5792
No. Observations:   400              Log-Likelihood:     -826.32
Df Model:           7                F-statistic:        66.18
Df Residuals:       392              Prob (F-statistic): 1.41e-62
R-squared:          0.542            Scale:              3.7208
-------------------------------------------------------------------
               Coef.   Std.Err.    t      P>|t|    [0.025   0.975]
-------------------------------------------------------------------
const          7.7077    1.1176   6.8965  0.0000   5.5104   9.9050
CompPrice      0.0939    0.0078  11.9797  0.0000   0.0785   0.1093
Income         0.0129    0.0035   3.7034  0.0002   0.0060   0.0197
Advertising    0.1309    0.0151   8.6539  0.0000   0.1011   0.1606
Population    -0.0001    0.0007  -0.1802  0.8571  -0.0015   0.0012
Price         -0.0925    0.0051 -18.3137  0.0000  -0.1025  -0.0826
Age           -0.0450    0.0060  -7.4854  0.0000  -0.0568  -0.0332
Education     -0.0400    0.0371  -1.0770  0.2821  -0.1130   0.0330
------------------------------------------------------------------
Omnibus:                8.263        Durbin-Watson:           1.969
Prob(Omnibus):          0.016        Jarque-Bera (JB):        7.705
Skew:                   0.288        Prob(JB):                0.021
Kurtosis:               2.639        Condition No.:           4049
==================================================================
Notes:
```

```
[1] Standard Errors assume that the covariance matrix of the
errors is correctly specified.
[2] The condition number is large, 4.05e+03. This might indicate
that there are strong multicollinearity or other numerical
problems.
```

Inferences 1. P-value caluclated - For CompPrice is 0.00, we can reject the null in favor of alternate i.e there is a truly relationship between ComPrice and Sales. - For Income is 0.00, we can reject the null in favor of alternate i.e there is a truly relationship between Income and Sales. - For Advertising is 0.0002, we can reject the null i.e there is a truly relationship between Advertising and Sales. - For Price is 0.00, we can reject the null i.e there is a truly relationship between Price and Sales. - For Age is 0.00, we can reject the null i.e there is a truly relationship between Age and Sales. - For Education is 0.28, we fail to reject the null i.e there is NO truly relationship between Education and Sales. - For Population is 0.85, we fail to reject the null i.e there is NO truly relationship between Population and Sales.

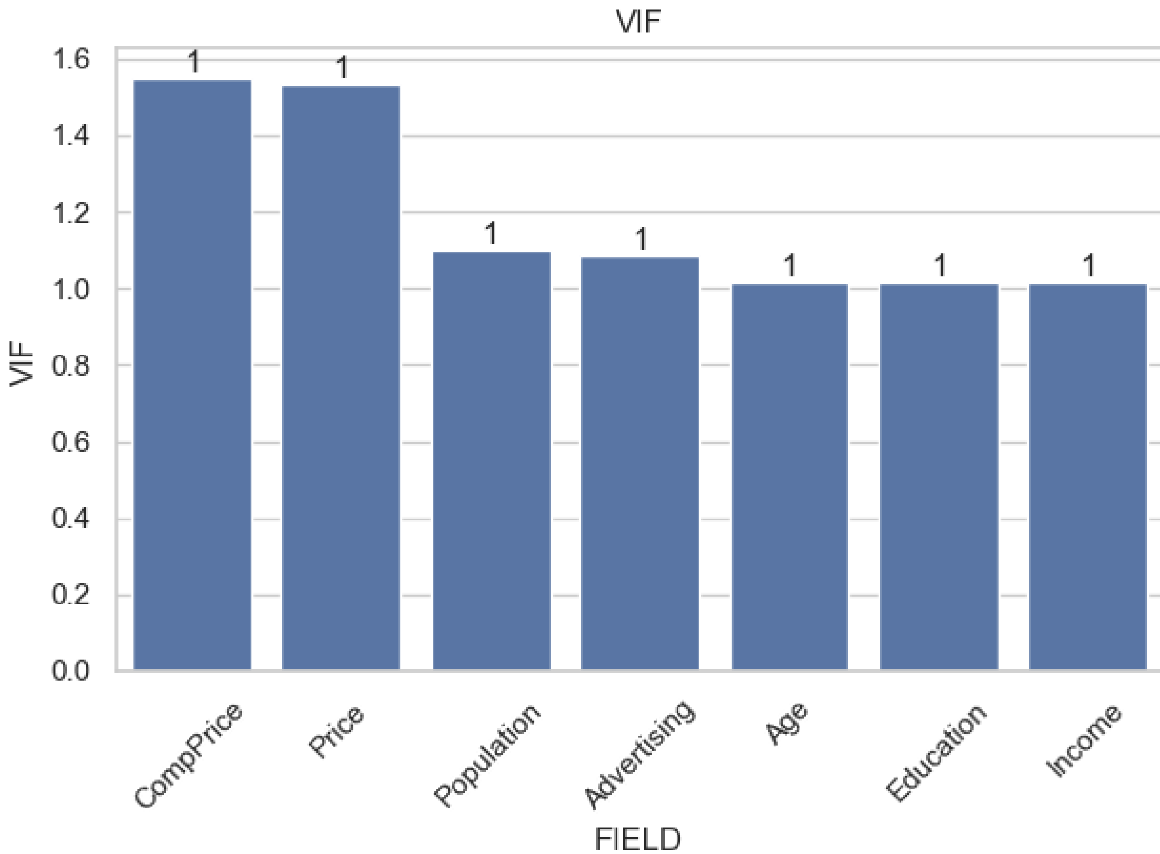
2. Taking into account all the other explanatory variables in our model,

    - for every increase of one unit in CompPrice, there is an associated increase of on average 0.09 in Sales
    - for every increase of one unit in Income, there is an associated increase of on average 0.01 in Sales
    - for every increase of one unit in Advertising, there is an associated increase of on average 0.13 in Sales.
    - for every increase of one unit in Price, there is an associated decreased of on average 0.09 in Sales.
    - for every increase of one unit in Age, there is an associated decreased of on average 0.04 in Sales.

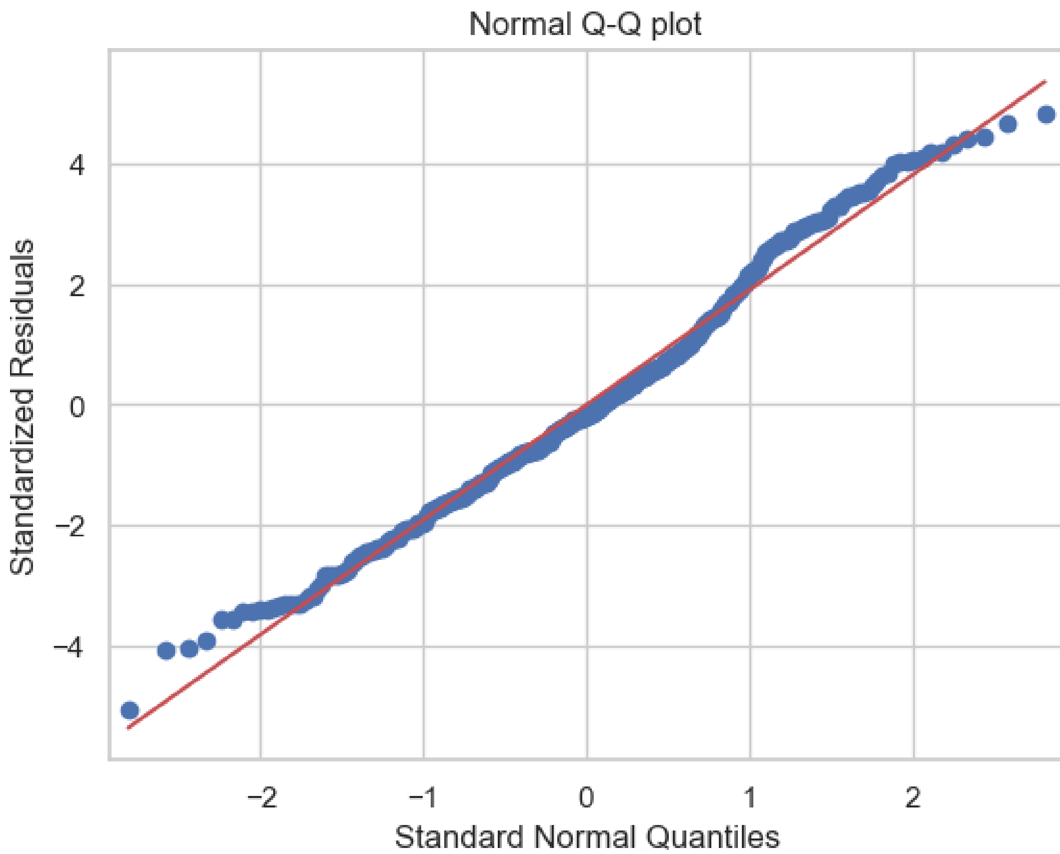
3. An average of Sales 7.7 when all the exploratory variables are zero

4. The proportion of variability in the outcome variable i.e bike count explained by this model is about 0.53

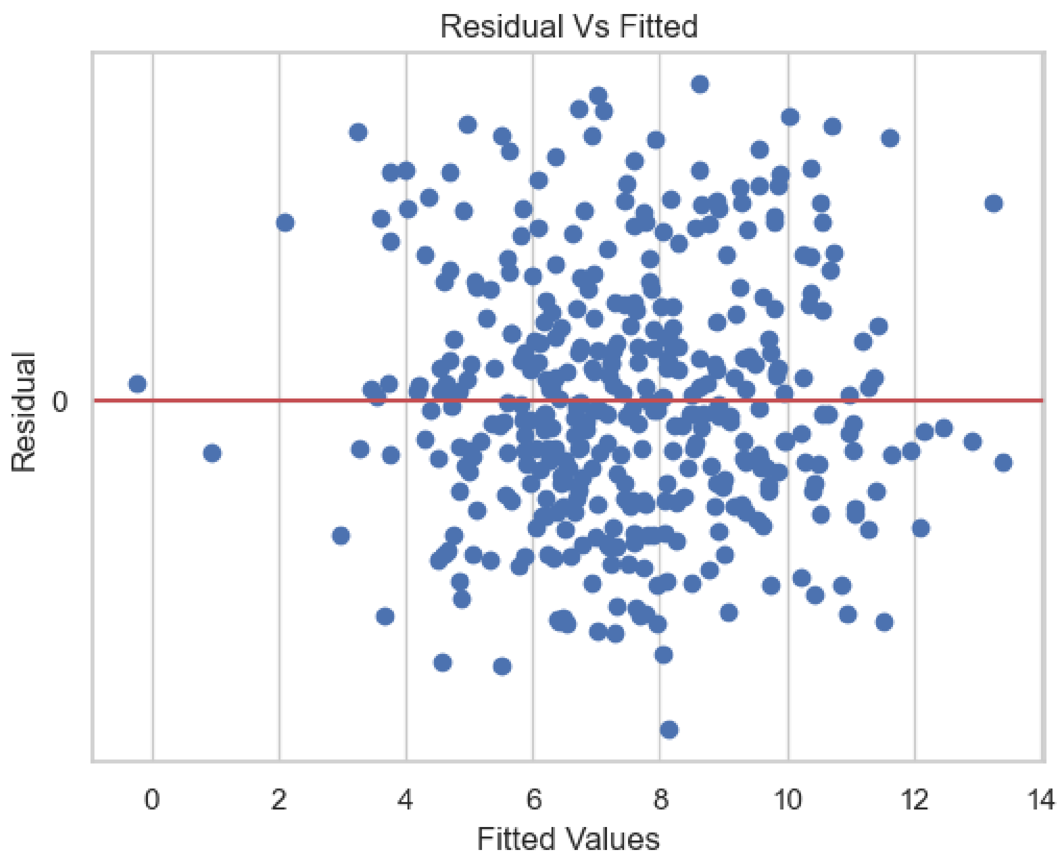
```
custom_VIF(car_SL1)
```




```
custom_ols_qqplot(car_SL1_fit.resid)
```




```
custom_ols_res_vs_fitted(car_SL1_fit.fittedvalues, car_SL1_fit.resid)
```



Experiment 2: More than 1 Numericals and Categorical:
Sales=f("CompPrice","Income","Advertising","Population","Price","Age","Education","ShelveLoc_Good

```
car_SL2 = custom_statsmodel_OLS(
    df_carseats,
    "Sales",
    "CompPrice",
    "Income",
    "Advertising",
    "Population",
    "Price",
    "Age",
    "Education",
    "ShelveLoc_Good",
    "ShelveLoc_Medium",
```

```python
    "Urban_Yes",
    "US_Yes",
)
```

```python
car_SL2_fit = car_SL2.fit()
```

```python
print(car_SL2_fit.summary2())
```

```
                 Results: Ordinary least squares
==================================================================
Model:              OLS              Adj. R-squared:     0.870
Dependent Variable: Sales            AIC:                1161.9744
Date:               2024-03-29 11:15 BIC:                1209.8719
No. Observations:   400              Log-Likelihood:     -568.99
Df Model:           11               F-statistic:        243.4
Df Residuals:       388              Prob (F-statistic): 1.60e-166
R-squared:          0.873            Scale:              1.0382
------------------------------------------------------------------
                   Coef.  Std.Err.    t     P>|t|   [0.025  0.975]
------------------------------------------------------------------
const              5.6606   0.6034   9.3805 0.0000  4.4742  6.8471
CompPrice          0.0928   0.0041  22.3778 0.0000  0.0847  0.1010
Income             0.0158   0.0018   8.5647 0.0000  0.0122  0.0194
Advertising        0.1231   0.0111  11.0660 0.0000  0.1012  0.1450
Population         0.0002   0.0004   0.5611 0.5750 -0.0005  0.0009
Price             -0.0954   0.0027 -35.7002 0.0000 -0.1006 -0.0901
Age               -0.0460   0.0032 -14.4718 0.0000 -0.0523 -0.0398
Education         -0.0211   0.0197  -1.0700 0.2853 -0.0599  0.0177
ShelveLoc_Good     4.8502   0.1531  31.6778 0.0000  4.5492  5.1512
ShelveLoc_Medium   1.9567   0.1261  15.5165 0.0000  1.7088  2.2047
Urban_Yes          0.1229   0.1130   1.0877 0.2774 -0.0992  0.3450
US_Yes            -0.1841   0.1498  -1.2286 0.2200 -0.4787  0.1105
------------------------------------------------------------------
Omnibus:               0.811        Durbin-Watson:           2.013
Prob(Omnibus):         0.667        Jarque-Bera (JB):        0.765
Skew:                  0.107        Prob(JB):                0.682
Kurtosis:              2.994        Condition No.:           4146
==================================================================
Notes:
[1] Standard Errors assume that the covariance matrix of the
errors is correctly specified.
```

```
[2] The condition number is large, 4.15e+03. This might indicate
that there are strong multicollinearity or other numerical
problems.
```

Inferences 1. P-value caluclated - For CompPrice is 0.00, we can reject the null in favor of alternate i.e there is a truly relationship between ComPrice and Sales. - For Income is 0.00, we can reject the null in favor of alternate i.e there is a truly relationship between Income and Sales. - For Advertising is 0.00, we can reject the null i.e there is a truly relationship between Advertising and Sales. - For Price is 0.00, we can reject the null i.e there is a truly relationship between Price and Sales. - For Age is 0.00, we can reject the null i.e there is a truly relationship between Age and Sales. - For Education is 0.28, we fail to reject the null i.e there is NO truly relationship between Education and Sales. - For Population is 0.85, we fail to reject the null i.e there is NO truly relationship between Population and Sales. - For Uran Yes, we fail to reject the null i.e there is NO truly relationship between Urban and Sales. - For US Yes, we fail to reject the null i.e there is NO truly relationship between US and Sales.

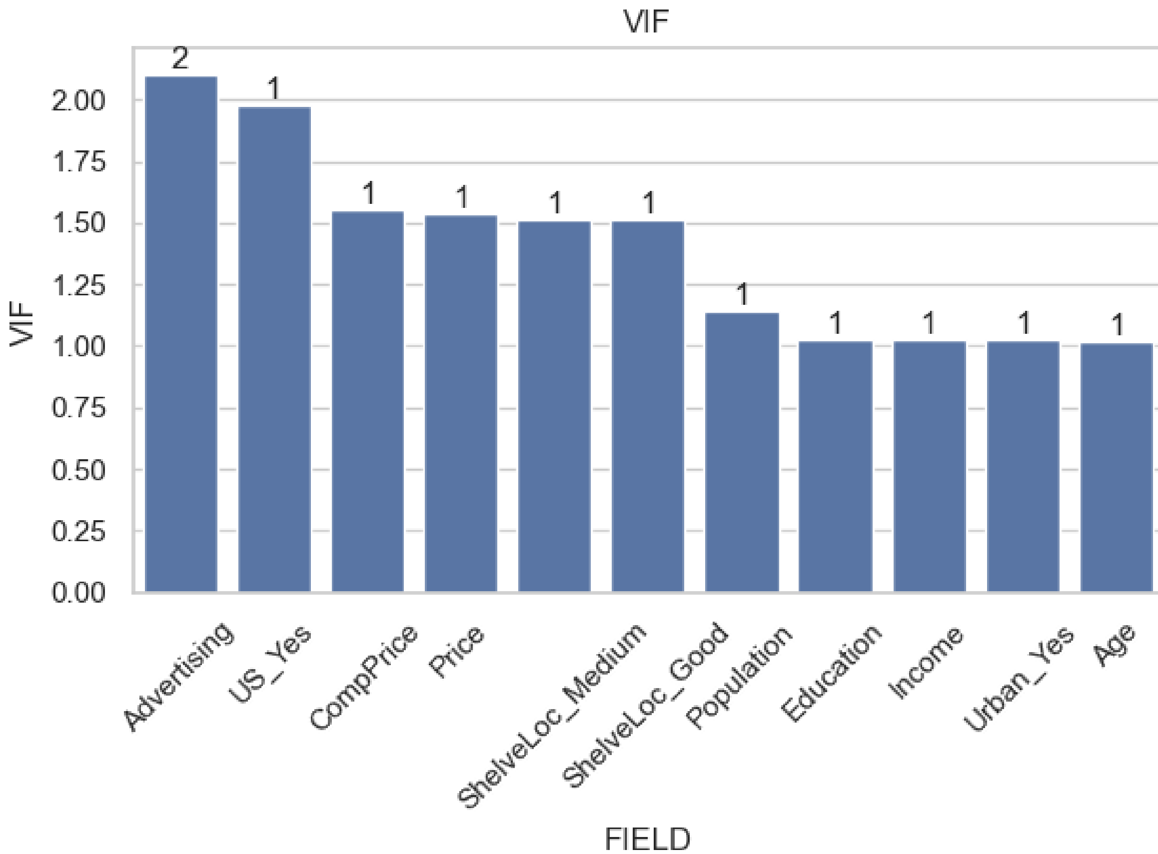
2. Taking into account all the other explanatory variables in our model,

    - for every increase of one unit in CompPrice, there is an associated increase of on average 0.09 in Sales
    - for every increase of one unit in Income, there is an associated increase of on average 0.01 in Sales
    - for every increase of one unit in Advertising, there is an associated increase of on average 0.12 in Sales.
    - for every increase of one unit in Price, there is an associated decreased of on average 0.09 in Sales.
    - for every increase of one unit in Age, there is an associated decreased of on average 0.04 in Sales.
    - For ShelveLoc_Good the average number of Sales 4.85 units higher on average compared to the ShelveLoc_Bad
    - For ShelveLoc_Medium the average number of Sales 1.95 units higher on average compared to the ShelveLoc_Bad

3. An average of Sales 5.6 when all the exploratory variables are zero

4. The proportion of variability in the outcome variable i.e bike count explained by this model is about 0.87

```
custom_VIF(car_SL2)
```



Case 4: BodyFat

Data Importing and Prep

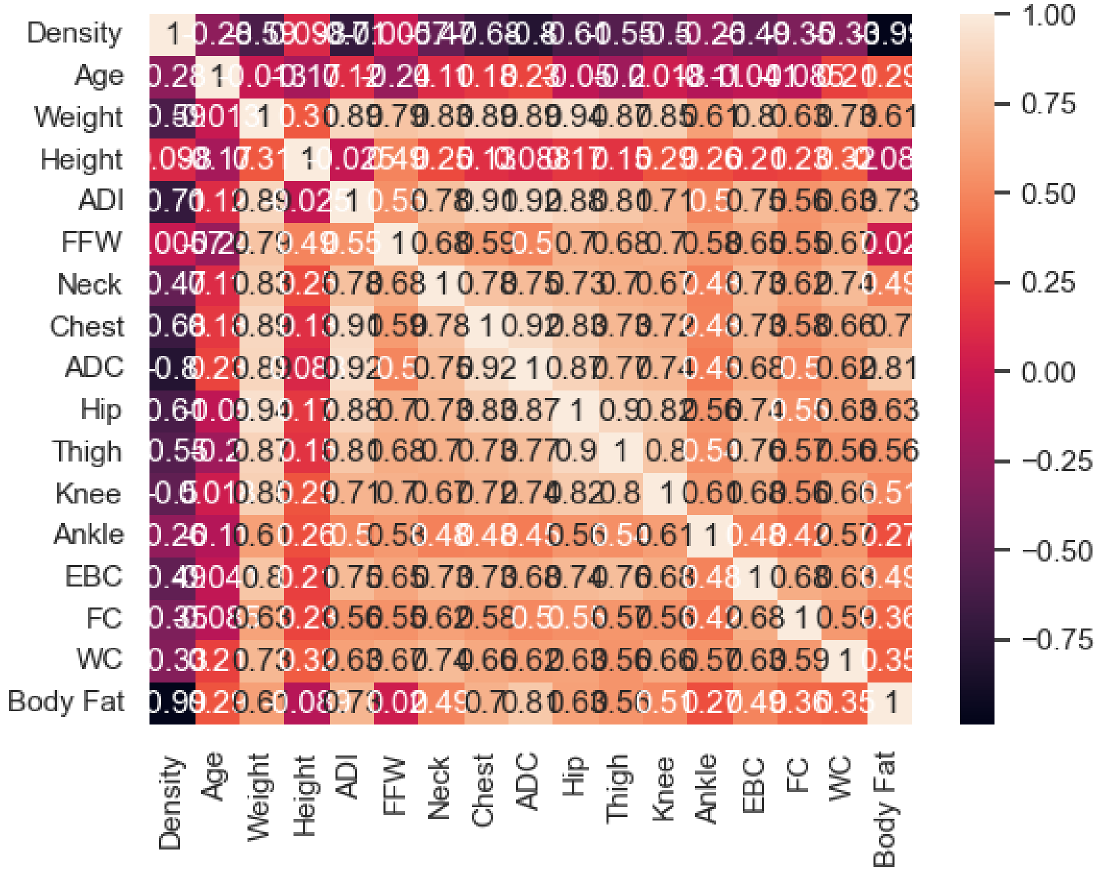
```
df_bodyfat = pd.read_csv(
    r"/Users/malleshamyamulla/Desktop/SSBBA/assignments/w4/data/bodyfat.csv"
)
```

```
df_bodyfat.head()
```

	Density	Age	Weight	Height	ADI	FFW	Neck	Chest	ADC	Hip	Thigh	Knee	Ankle	El
0	1.0708	23	154.25	67.75	23.7	134.9	36.2	93.1	85.2	94.5	59.0	37.3	21.9	32
1	1.0853	22	173.25	72.25	23.4	161.3	38.5	93.6	83.0	98.7	58.7	37.3	23.4	30
2	1.0414	22	154.00	66.25	24.7	116.0	34.0	95.8	87.9	99.2	59.6	38.9	24.0	28

	Density	Age	Weight	Height	ADI	FFW	Neck	Chest	ADC	Hip	Thigh	Knee	Ankle	E
3	1.0751	26	184.75	72.25	24.9	164.7	37.4	101.8	86.4	101.2	60.1	37.3	22.8	32
4	1.0340	24	184.25	71.25	25.6	133.1	34.4	97.3	100.0	101.9	63.2	42.2	24.0	32

```
sns.heatmap(df_bodyfat.corr(), annot=True)
plt.show()
```



Regression Model

Experiment 1:

```
body_fat_SL = custom_statsmodel_OLS(
    df_bodyfat,
```

```
    "Body Fat",
    "Density",
    "Age",
    "Weight",
    "Height",
    "ADI",
    "FFW",
    "Neck",
    "Chest",
    "ADC",
    "Hip",
    "Thigh",
    "Knee",
    "Ankle",
    "EBC",
    "FC",
    "WC",
)
```

```
body_fat_SL_fit = body_fat_SL.fit()
```

```
print(body_fat_SL_fit.summary2())
```

```
                 Results: Ordinary least squares
==================================================================
Model:              OLS              Adj. R-squared:     0.986
Dependent Variable: Body Fat         AIC:                680.7642
Date:               2024-03-29 11:15 BIC:                740.7645
No. Observations:   252              Log-Likelihood:     -323.38
Df Model:           16               F-statistic:        1138.
Df Residuals:       235              Prob (F-statistic): 1.62e-212
R-squared:          0.987            Scale:              0.81750
------------------------------------------------------------------
              Coef.   Std.Err.    t     P>|t|    [0.025    0.975]
------------------------------------------------------------------
const        253.2587  15.2445  16.6132 0.0000  223.2255  283.2920
Density     -234.0972  13.1352 -17.8221 0.0000 -259.9750 -208.2193
Age            0.0057   0.0068   0.8377 0.4030   -0.0077    0.0192
Weight         0.1594   0.0164   9.7451 0.0000    0.1272    0.1916
Height         0.0125   0.0235   0.5314 0.5956   -0.0339    0.0589
ADI           -0.2339   0.0645  -3.6260 0.0004   -0.3610   -0.1068
```

```
FFW           -0.2301   0.0183 -12.5450 0.0000   -0.2662   -0.1939
Neck           0.0199   0.0499   0.3990 0.6903   -0.0785    0.1183
Chest          0.0688   0.0224   3.0749 0.0024    0.0247    0.1128
ADC            0.0238   0.0234   1.0183 0.3096   -0.0223    0.0699
Hip            0.0191   0.0312   0.6125 0.5408   -0.0424    0.0806
Thigh          0.0691   0.0313   2.2055 0.0284    0.0074    0.1309
Knee           0.0116   0.0522   0.2230 0.8237   -0.0911    0.1144
Ankle          0.0033   0.0475   0.0705 0.9438   -0.0902    0.0969
EBC           -0.0030   0.0367  -0.0805 0.9359   -0.0752    0.0693
FC             0.0987   0.0425   2.3232 0.0210    0.0150    0.1824
WC             0.1632   0.1152   1.4165 0.1580   -0.0638    0.3902
-------------------------------------------------------------------
Omnibus:              249.344      Durbin-Watson:         1.872
Prob(Omnibus):        0.000        Jarque-Bera (JB):      25144.989
Skew:                 3.415        Prob(JB):              0.000
Kurtosis:             51.457       Condition No.:         110523
===================================================================
Notes:
[1] Standard Errors assume that the covariance matrix of the
errors is correctly specified.
[2] The condition number is large, 1.11e+05. This might indicate
that there are strong multicollinearity or other numerical
problems.
```

Inferences 1. P-value caluclated - For Density is 0.00, we can reject the null in favor of alternate i.e there is a truly relationship between Density and Body Fat - For Weight is 0.00, we can reject the null in favor of alternate i.e there is a truly relationship between Weight and Body Fat - For ADI is 0.00, we can reject the null in favor of alternate i.e there is a truly relationship between ADI and Body Fat - For Chest is 0.00, we can reject the null in favor of alternate i.e there is a truly relationship between Chest and Body Fat - For Density is 0.00, we can reject the null in favor of alternate i.e there is a truly relationship between Density and Body Fat - For Thigh is 0.02, we can reject the null in favor of alternate i.e there is a truly relationship between Thigh and Body Fat - For the independent variables: Age,Height,Neck,ADC,Hip,Knee,Ankle,EBC,and WC are having more p-value i.e >0.05, hence we failed to raject the null i.e there is NO true relationship between these variabels and body fat

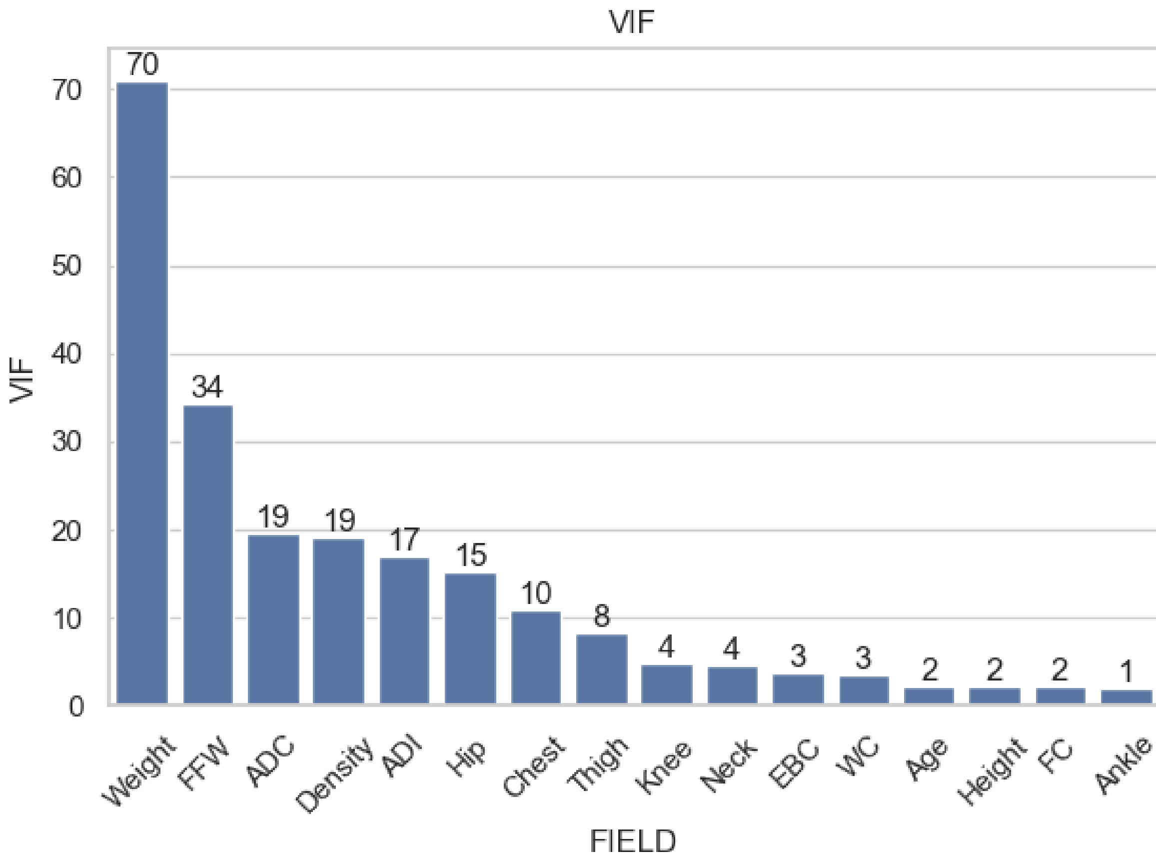
2. Taking into account all the other explanatory variables in our model,

   - for every increase of one unit in Weight, there is an associated increase of on average 0.15 in Body Fat

3. An average of Body Fat 253 when all the exploratory variables are zero

4. The proportion of variability in the outcome variable i.e bike count explained by this model is about 0.98

```
custom_VIF(body_fat_SL)
```




```
df_bodyfat_sel = df_bodyfat[
    ["Knee", "Neck", "EBC", "WC", "Age", "Height", "FC", "Ankle", "Body Fat"]
]
```

```
body_fat_SL_2 = custom_statsmodel_OLS(
    df_bodyfat_sel,
    "Body Fat",
    "Knee",
    "Neck",
    "EBC",
    "WC",
```

```python
    "Age",
    "Height",
    "FC",
    "Ankle",
)
```

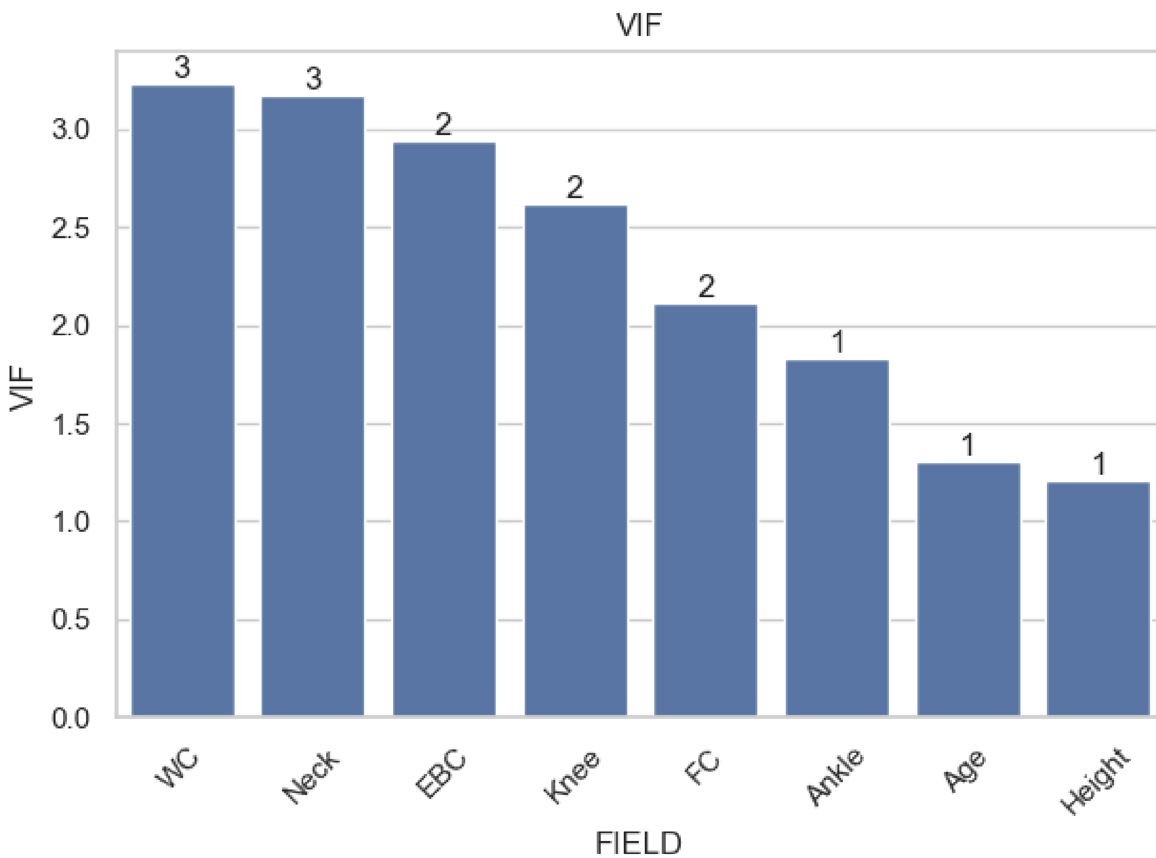
```python
body_fat_SL_2_fit = body_fat_SL_2.fit()
```

```python
print(body_fat_SL_2_fit.summary2())
```

```
                 Results: Ordinary least squares
==================================================================
Model:               OLS              Adj. R-squared:     0.442
Dependent Variable: Body Fat          AIC:                1609.1443
Date:               2024-03-29 11:15 BIC:                1640.9092
No. Observations:   252               Log-Likelihood:     -795.57
Df Model:           8                 F-statistic:        25.83
Df Residuals:       243               Prob (F-statistic): 1.05e-28
R-squared:          0.460             Scale:              33.534
--------------------------------------------------------------------
          Coef.    Std.Err.     t      P>|t|     [0.025     0.975]
--------------------------------------------------------------------
const    -23.6281    9.1181   -2.5913  0.0101  -41.5887   -5.6674
Knee       1.1799    0.2454    4.8071  0.0000    0.6964    1.6634
Neck       0.7565    0.2681    2.8217  0.0052    0.2284    1.2846
EBC        0.6198    0.2074    2.9889  0.0031    0.2113    1.0282
WC        -2.4084    0.7041   -3.4207  0.0007   -3.7953   -1.0215
Age        0.1878    0.0331    5.6709  0.0000    0.1226    0.2531
Height    -0.3859    0.1099   -3.5119  0.0005   -0.6023   -0.1694
FC         0.2852    0.2632    1.0835  0.2797   -0.2333    0.8037
Ankle      0.1151    0.2918    0.3944  0.6936   -0.4596    0.6898
--------------------------------------------------------------------
Omnibus:              0.516        Durbin-Watson:           1.798
Prob(Omnibus):        0.773        Jarque-Bera (JB):        0.553
Skew:                 0.108        Prob(JB):                0.758
Kurtosis:             2.921        Condition No.:           2811
==================================================================
Notes:
[1] Standard Errors assume that the covariance matrix of the
errors is correctly specified.
[2] The condition number is large, 2.81e+03. This might indicate
```

```
that there are strong multicollinearity or other numerical
problems.
```

```
custom_VIF(body_fat_SL_2)
```



END