Out[45]:

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
model											
Mazda RX4	21.0	6	160.0	110	3.90	2.620	16.46	0	1	4	4
Mazda RX4 Wag	21.0	6	160.0	110	3.90	2.875	17.02	0	1	4	4
Datsun 710	22.8	4	108.0	93	3.85	2.320	18.61	1	1	4	1
Hornet 4 Drive	21.4	6	258.0	110	3.08	3.215	19.44	1	0	3	1
Hornet Sportabout	18.7	8	360.0	175	3.15	3.440	17.02	0	0	3	2
Valiant	18.1	6	225.0	105	2.76	3.460	20.22	1	0	3	1
Duster 360	14.3	8	360.0	245	3.21	3.570	15.84	0	0	3	4
Merc 240D	24.4	4	146.7	62	3.69	3.190	20.00	1	0	4	2
Merc 230	22.8	4	140.8	95	3.92	3.150	22.90	1	0	4	2
Merc 280	19.2	6	167.6	123	3.92	3.440	18.30	1	0	4	4
Merc 280C	17.8	6	167.6	123	3.92	3.440	18.90	1	0	4	4
Merc 450SE	16.4	8	275.8	180	3.07	4.070	17.40	0	0	3	3
Merc 450SL	17.3	8	275.8	180	3.07	3.730	17.60	0	0	3	3
Merc 450SLC	15.2	8	275.8	180	3.07	3.780	18.00	0	0	3	3
Cadillac Fleetwood	10.4	8	472.0	205	2.93	5.250	17.98	0	0	3	4
Lincoln Continental	10.4	8	460.0	215	3.00	5.424	17.82	0	0	3	4
Chrysler Imperial	14.7	8	440.0	230	3.23	5.345	17.42	0	0	3	4
Fiat 128	32.4	4	78.7	66	4.08	2.200	19.47	1	1	4	1
Honda Civic	30.4	4	75.7	52	4.93	1.615	18.52	1	1	4	2
Toyota Corolla	33.9	4	71.1	65	4.22	1.835	19.90	1	1	4	1
Toyota Corona	21.5	4	120.1	97	3.70	2.465	20.01	1	0	3	1
Dodge Challenger	15.5	8	318.0	150	2.76	3.520	16.87	0	0	3	2
AMC Javelin	15.2	8	304.0	150	3.15	3.435	17.30	0	0	3	2
Camaro Z28	13.3	8	350.0	245	3.73	3.840	15.41	0	0	3	4
Pontiac Firebird	19.2	8	400.0	175	3.08	3.845	17.05	0	0	3	2
Fiat X1-9	27.3	4	79.0	66	4.08	1.935	18.90	1	1	4	1
Porsche 914-2	26.0	4	120.3	91	4.43	2.140	16.70	0	1	5	2
Lotus Europa	30.4	4	95.1	113	3.77	1.513	16.90	1	1	5	2
Ford Pantera L	15.8	8	351.0	264	4.22	3.170	14.50	0	1	5	4
Ferrari Dino	19.7	6	145.0	175	3.62	2.770	15.50	0	1	5	6
Maserati Bora	15.0	8	301.0	335	3.54	3.570	14.60	0	1	5	8
Volvo 142E	21.4	4	121.0	109	4.11	2.780	18.60	1	1	4	2

# In [3]: dat\_mtcars.info()

<class 'pandas.core.frame.DataFrame'>
Index: 32 entries, Mazda RX4 to Volvo 142E

Data columns (total 11 columns):

#	Column	Non-Null Count	Dtype
0	mpg	32 non-null	float64
1	cyl	32 non-null	int64
2	disp	32 non-null	float64
3	hp	32 non-null	int64
4	drat	32 non-null	float64
5	wt	32 non-null	float64
6	qsec	32 non-null	float64
7	VS	32 non-null	int64
8	am	32 non-null	int64
9	gear	32 non-null	int64
10	carb	32 non-null	int64

dtypes: float64(5), int64(6)

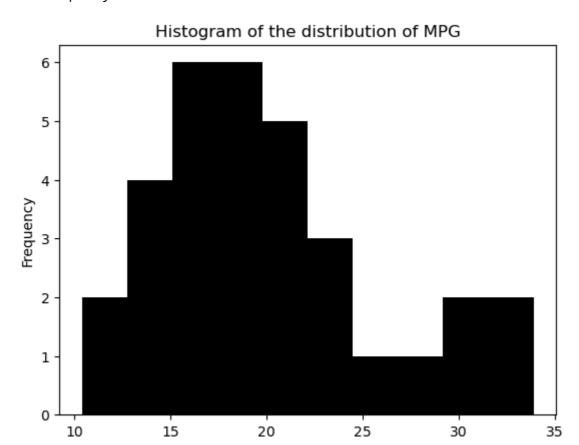
memory usage: 3.0+ KB

In [4]: | dat\_mtcars.describe()

## Out[4]:

	mpg	cyl	disp	hp	drat	wt	qsec	
count	32.000000	32.000000	32.000000	32.000000	32.000000	32.000000	32.000000	32.000
mean	20.090625	6.187500	230.721875	146.687500	3.596563	3.217250	17.848750	0.437
std	6.026948	1.785922	123.938694	68.562868	0.534679	0.978457	1.786943	0.504
min	10.400000	4.000000	71.100000	52.000000	2.760000	1.513000	14.500000	0.000
25%	15.425000	4.000000	120.825000	96.500000	3.080000	2.581250	16.892500	0.000
50%	19.200000	6.000000	196.300000	123.000000	3.695000	3.325000	17.710000	0.000
75%	22.800000	8.000000	326.000000	180.000000	3.920000	3.610000	18.900000	1.000
max	33.900000	8.000000	472.000000	335.000000	4.930000	5.424000	22.900000	1.000
50% 75%	19.200000 22.800000	6.000000 8.000000	196.300000 326.000000	123.000000 180.000000	3.695000 3.920000	3.325000 3.610000	17.710000 18.900000	0.000

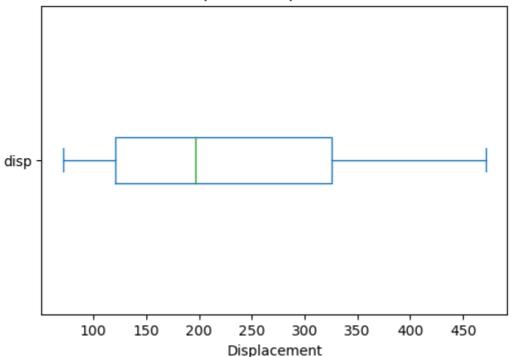
In [34]: # 1. Explore the distribution of fuel efficiency of the cars.
# Remember to label both the axes and put a title to the plot.
dat\_mtcars["mpg"].plot(kind = 'hist',x='mpg',y='frequency',bins=10, title="F



```
In [22]: dat_mtcars["mpg"].plot(kind="box")
Out[22]: <AxesSubplot:>
           35
                                                0
           30
           25
           20
           15
           10
                                              mpg
In [27]: # 2.1 Cars with best efficiency.
         max_mpg=dat_mtcars["mpg"].max()
         dat_mtcars[dat_mtcars["mpg"]==max_mpg]
Out[27]:
                       mpg cyl disp hp drat
                                                wt qsec vs am gear carb
                 model
          Toyota Corolla
                       33.9
                              4 71.1 65 4.22 1.835
                                                    19.9
In [26]:
         # 2.2 Cars with worst fuel efficiency.
         min_mpg=dat_mtcars["mpg"].min()
         dat_mtcars[dat_mtcars["mpg"]==min_mpg]
Out[26]:
                           mpg cyl
                                    disp
                                          hp drat
                                                     wt qsec vs am gear carb
                     model
           Cadillac Fleetwood
                           10.4
                                 8 472.0
                                         205 2.93 5.250 17.98
                                                                        3
                                                                             4
          Lincoln Continental
                           10.4
                                 8 460.0 215 3.00 5.424 17.82
                                                                        3
                                                                             4
In [18]:
         # Features like am, gearsw are numeric but binary features. They are used to
         # 3. How many cars are manual v/s automatic?
         dat_mtcars["am"].nunique()
         dat_mtcars["am"].value_counts()
Out[18]: 0
               19
               13
         Name: am, dtype: int64
```

```
In [38]:
         dat_mtcars=pd.read_csv("mtcars.csv")
In [39]:
         # 4. Car with the worst horsepower
         worst_hp_car = dat_mtcars[dat_mtcars['hp'] == dat_mtcars['hp'].min()][['mode
         print(f"Car with worst horsepower:\n{worst_hp_car}")
         Car with worst horsepower:
                   model hp
         18 Honda Civic 52
In [47]: # 5. Find 5 number summary and draw boxplot of displacement.
         disp_summary=dat_mtcars['disp'].describe()[['min','25%','50%','75%','max']]
         print(f"5 number summary of displacement:\n{disp_summary}")
         dat_mtcars['disp'].plot(kind='box', vert=False, figsize=(6, 4), title='Boxpl
         plt.xlabel("Displacement")
         plt.show()
         5 number summary of displacement:
                 71.100
         min
         25%
                120.825
         50%
                196.300
         75%
                326.000
                472,000
         max
         Name: disp, dtype: float64
```

### Boxplot of Displacement



3

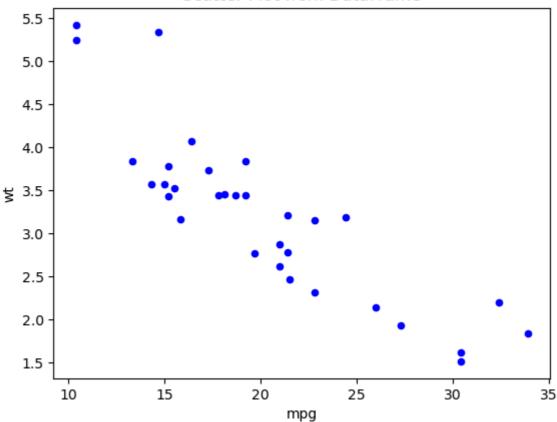
15

Lincoln Continental 5.424

```
# 7. Which is the car with the best qsec?
         best_qsec_car = dat_mtcars[dat_mtcars['qsec'] == dat_mtcars['qsec'].min()][[
         print(f"Car with best (fastest) qsec:\n{best_qsec_car}")
         Car with best (fastest) qsec:
                      model qsec
         28 Ford Pantera L 14.5
         # 8. What is average MPG for manual vs. automatic cars?
In [53]:
         dat_man= dat_mtcars[dat_mtcars["am"]==1]["mpg"] # Manual cars are marked as
         print("Average MPG of manual cars:",dat_man.mean())
         dat_auto= dat_mtcars[dat_mtcars["am"]==0]["mpg"]
         print("Average MPG of automatic cars:",dat_auto.mean())
         Average MPG of manual cars: 24.39230769230769
         Average MPG of automatic cars: 17.147368421052633
In [55]: # 9. Draw Side by Side box plot to understand the difference in fuel
         # efficience of Manual vs Automatic cars. Analyze and write about fuel
         # efficiency in each group (manual vs. automatic).
         dat_mtcars = pd.read_csv("mtcars.csv")
         fuel_efficiency_summary = dat_mtcars.groupby('am')['mpg'].describe()
         print("\nFuel Efficiency Summary (MPG) for Manual vs Automatic Cars:")
         print(fuel_efficiency_summary)
         manual_mpg_mean = dat_mtcars[dat_mtcars['am'] == 'Manual']['mpg'].mean()
         automatic_mpg_mean = dat_mtcars[dat_mtcars['am'] == 'Automatic']['mpg'].mear
         print("\nFuel Efficiency Analysis:")
         print(f"Manual Cars - Average MPG: {manual_mpg_mean:.2f}")
         print(f"Automatic Cars - Average MPG: {automatic_mpg_mean:.2f}")
         if manual_mpg_mean > automatic_mpg_mean:
             print("Manual cars tend to be more fuel efficient than Automatic cars.")
         else:
             print("Automatic cars tend to be more fuel efficient than Manual cars.")
         Fuel Efficiency Summary (MPG) for Manual vs Automatic Cars:
                                                 25%
                                                       50%
                                                             75%
             count
                         mean
                                    std
                                          min
                                                                   max
         am
              19.0 17.147368 3.833966 10.4 14.95 17.3 19.2
                                                                  24.4
              13.0 24.392308 6.166504 15.0 21.00 22.8 30.4 33.9
         Fuel Efficiency Analysis:
         Manual Cars - Average MPG: nan
         Automatic Cars - Average MPG: nan
         Automatic cars tend to be more fuel efficient than Manual cars.
```

```
In [56]: # 10. What is the relationship between the weight of the car and MPG?
    dat_x= dat_mtcars[["mpg","wt"]]
    dat_x= dat_x.reset_index(drop=True)
    dat_x.plot(kind='scatter', x='mpg', y='wt', color='blue',
    title='Scatter Plot from DataFrame')
```





```
In [58]: # 11. Categorize the cars based on the number of gears in the cars.
# How many cars are there in each type?
dat_mtcars = pd.read_csv("mtcars.csv")
gear_counts = dat_mtcars['gear'].value_counts()
print(f"Number of cars based on gear type:\n{gear_counts}")
```

Number of cars based on gear type:

3 15

4 12

5 5

Name: gear, dtype: int64

In [60]: # 12. What is the relationship between fuel efficiency and the number
# of gears in the car?
# Analyze the relationship between fuel efficiency and the number of gears.
gear\_mpg\_relation = dat\_mtcars.groupby('gear')['mpg'].mean()
print(f"Average MPG for each gear type:\n{gear\_mpg\_relation}")
print('''\nAnalysis:\nHigher gear cars generally tend to have lower or simil
efficiency compared to lower gear cars, depending on the engine
performance and aerodynamics.''')

Average MPG for each gear type:

gear

3 16.106667

4 24.533333

5 21.380000

Name: mpg, dtype: float64

### Analysis:

Higher gear cars generally tend to have lower or similar fuel efficiency compared to lower gear cars, depending on the engine performance and aerodynamics.

In [62]: # 13. Explain the relationship between horse power and number of # cylinders in the car.

hp\_cyl\_relation = dat\_mtcars.groupby('cyl')['hp'].mean()
print(f"Average Horsepower for each Cylinder type:\n{hp\_cyl\_relation}")
print('''\nAnalysis:\nCars with more cylinders have higher horsepower since
generally have larger engines capable of producing more power.''')

Average Horsepower for each Cylinder type:

cyl

4 82.636364

6 122.285714

8 209.214286

Name: hp, dtype: float64

#### Analysis:

Cars with more cylinders have higher horsepower since they generally have larger engines capable of producing more power.

In [63]: # 14. Explain the relationship between displacement and gross horse power.
 disp\_hp\_relation = dat\_mtcars[['disp', 'hp']].corr()
 print(f"Correlation between Displacement and Horsepower:\n{disp\_hp\_relation}
 print('''\nAnalysis:\nLarger displacement engines usually generate more powe
 this can also lead to increased fuel consumption.''')

Correlation between Displacement and Horsepower:

disp hp disp 1.000000 0.790949 hp 0.790949 1.000000

#### Analysis:

Larger displacement engines usually generate more power, but this can also lead to increased fuel consumption.

```
In [66]: # 15. Which car would I pick if I am looking for high speed as well as
         # good fuel efficiency?
         dat_mtcars['performance_score'] = dat_mtcars['mpg'] / dat_mtcars['qsec']
         best_car = dat_mtcars.loc[dat_mtcars['performance_score'].idxmax(), ['model'
         'qsec']]
         print(f"Best car for high speed and good fuel efficiency:\n{best_car}")
         Best car for high speed and good fuel efficiency:
         model Lotus Europa
         mpg
                          30.4
                          16.9
         qsec
         Name: 27, dtype: object
In [1]: '''
         Question 2:
         For the CEREALS dataset, answer the specified questions with summarization
         and effective visuals.
         import pandas as pd
         df1 = pd.read_excel("Cereals.xls")
         df1.replace(-1, pd.NA, inplace=True)
         df1.to_csv("Cleaned_Cereals.csv", index=False)
         df=pd.read_csv("Cleaned_Cereals.csv")
         numeric_cols = ['rating', 'fiber', 'sugars', 'protein', 'calories']
         df[numeric_cols] = df[numeric_cols].apply(pd.to_numeric,errors='coerce')
 In [2]: # 1. How many unique cereal brands are there?
         unique_brands = df['name'].nunique()
         print("Unique cereal brands:", unique_brands)
         Unique cereal brands: 76
 In [3]: # 2. Number of cereals per manufacturer
         cereals_per_manufacturer = df['mfr'].value_counts()
         print(f"Cereals per manufacturer:\n{cereals per manufacturer}")
         Cereals per manufacturer:
         K
              23
         G
              22
         Ρ
               9
         Q
              8
         R
               8
               5
         N
               1
         Name: mfr, dtype: int64
 In [4]: # 3. Count of hot vs cold cereals
         cereal_types = df['type'].value_counts()
         print(f"Count of hot vs cold cereals:\n{cereal types}")
         Count of hot vs cold cereals:
         C 73
               3
         Name: type, dtype: int64
```

```
# 4. Best and worst cereal based on rating
In [5]:
        best_cereal = df.loc[df['rating'].idxmax(), ['name', 'rating']]
        worst_cereal = df.loc[df['rating'].idxmin(), ['name', 'rating']]
        print(f"Best cereal:\n{best_cereal}")
        print(f"Worst cereal:\n{worst_cereal}")
        Best cereal:
        name
                  All-Bran_with_Extra_Fiber
        rating
                                  93.704912
        Name: 2, dtype: object
        Worst cereal:
                  Cap'n'Crunch
        name
        rating
                     18.042851
        Name: 9, dtype: object
In [6]: # 5. Compare ratings for hot vs cold cereals
        avg_rating_by_type = df.groupby('type')['rating'].mean()
        print(f"Average rating for hot vs cold cereals:\n{avg_rating_by_type}")
        Average rating for hot vs cold cereals:
        type
             41.734838
        C
             56.737708
        Name: rating, dtype: float64
In [7]: # 6. Cereals with highest fiber and lowest sugar
        df_cleaned = df[df['sugars'] >= 0]
        highest_fiber = df_cleaned.loc[df_cleaned['fiber'].idxmax(), ['name', 'fiber']
        lowest_sugar = df_cleaned[df_cleaned['sugars'] == df_cleaned['sugars'].min()
        print(f"Cereal with highest fiber:\n{highest fiber}")
        print(f"\nCereal(s) with lowest sugar:\n{lowest_sugar}")
        Cereal with highest fiber:
        name
                 All-Bran_with_Extra_Fiber
        fiber
                                       14.0
        Name: 2, dtype: object
        Cereal(s) with lowest sugar:
                                       sugars
            All-Bran_with_Extra_Fiber
        2
                                           0.0
        19
               Cream_of_Wheat_(Quick)
                                           0.0
        53
                          Puffed_Rice
                                           0.0
        54
                         Puffed Wheat
                                          0.0
        62
                       Shredded_Wheat
                                          0.0
        63
               Shredded_Wheat_'n'Bran
                                          0.0
        64 Shredded_Wheat_spoon_size
                                          0.0
```

```
# 7. Cereals with more than 3 grams of protein
         high_protein_cereals = df[df['protein'] > 3][['name', 'protein']]
         print("\nCereals with more than 3 grams of protein:")
         print(high_protein_cereals)
         Cereals with more than 3 grams of protein:
                                              name protein
         1
                                          All-Bran
         2
                         All-Bran_with_Extra_Fiber
                                                         4
         10
                                         Cheerios
         40
                                             Life
                                                         4
         42
                                             Maypo
                                                         4
         43
             Muesli_Raisins,_Dates,_&_Almonds
                                                         4
         44 Muesli_Raisins,_Peaches,_&_Pecans
                                Quaker_Oat_Squares
                                                         4
         55
         56
                                    Quaker_Oatmeal
                                                         5
         66
                                         Special_K
                                                         6
 In [9]:
         # 8. Tabulate cereals by display shelf
         display_shelf_counts = df['shelf'].value_counts()
         print("\nCereals by display shelf:")
         print(display_shelf_counts)
         Cereals by display shelf:
              35
         2
              21
              20
         Name: shelf, dtype: int64
In [10]: # 9. Sugar content variation across brands
         sugar_by_brand = df.groupby('mfr')['sugars'].mean()
         print("\nAverage sugar content per manufacturer:")
         print(sugar by brand)
         Average sugar content per manufacturer:
         mfr
         Α
              3.000000
              7.954545
         G
             7.565217
         Κ
         Ν
             1.000000
         Ρ
             8.777778
         Q
            6.142857
             6.125000
         Name: sugars, dtype: float64
```

```
In [11]: # 10. Average calories in cereals per manufacturer
         avg_calories_per_mfr = df.groupby('mfr')['calories'].mean()
         print("\nAverage calories per manufacturer:")
         print(avg_calories_per_mfr)
         Average calories per manufacturer:
         mfr
         Α
              100.000000
         G
              111.363636
         K
             108.695652
              90.000000
         N
         Р
              108.888889
              95.000000
         Q
             115.000000
         Name: calories, dtype: float64
In [12]: # 11. Average nutritional content across all cereals
         avg_nutritional_content = df[['calories', 'sugars', 'protein',
         'fiber']].mean()
         print("\nAverage nutritional content across all cereals:")
         print(avg_nutritional_content)
         Average nutritional content across all cereals:
         calories 107.368421
                      7.040000
         sugars
                      2.526316
         protein
         fiber
                       2.048684
         dtype: float64
In [13]: # 12. Relationship between sugar and calories
         sugar_calories_corr = df[['sugars', 'calories']].corr()
         print("\nCorrelation between sugar and calories:")
         print(sugar calories corr)
         Correlation between sugar and calories:
                     sugars calories
         sugars
                   1.000000 0.574758
         calories 0.574758 1.000000
In [14]: # 13. Compare sugar content in high vs low rated cereals
         median_rating = df['rating'].median()
         high_rated_cereals = df[df['rating'] >= median_rating]['sugars'].mean()
         low_rated_cereals = df[df['rating'] < median_rating]['sugars'].mean()</pre>
         print("\nAverage sugar content in high vs low rated cereals:")
         print("High rated cereals:", high_rated_cereals)
         print("Low rated cereals:", low_rated_cereals)
         Average sugar content in high vs low rated cereals:
```

Average sugar content in high vs low rated cereals: High rated cereals: 3.78378378378388

Low rated cereals: 10.210526315789474

```
In [15]: # 14. Do healthy cereals have higher ratings?
healthy_cereals = df[(df['fiber'] > 3) & (df['sugars'] < 5)]
healthy_cereal_avg_rating = healthy_cereals['rating'].mean()
print("\nAverage rating for healthy cereals:",
healthy_cereal_avg_rating)</pre>
```

Average rating for healthy cereals: 84.0889305

```
In [16]: # 15. Relationship between rating and display shelf
    rating_by_shelf = df.groupby('shelf')['rating'].mean()
    print("\nAverage rating by display shelf:")
    print(rating_by_shelf)
```

Average rating by display shelf: shelf
1 46.145439
2 34.972827
3 44.557662
Name: rating, dtype: float64