```
import pandas as pd
import numpy as np
from google.colab import drive
drive.mount('/content/gdrive')
```

```
Drive already mounted at /content/gdrive; to attempt to forcibly remount, call drive.mount("/content/gdrive", force_remount=T
```

```
file = ('/content/gdrive/MyDrive/CS410_FinalProject/reading_habit.csv')
df = pd.read_csv(file)
df
```

	Age	Sex	Race	Marital status?	Education	Employement	Incomes	How books you du 12mor
0	66	Male	Refused	Divorced	College graduate	Retired	$20,000 to under $30,000	
1	46	Male	Native American/American Indian	Married	High school graduate	Employed full-time	Less than $10,000	
2	32	Male	Mixed race	Never been married	High school graduate	Employed full-time	Less than $10,000	
3	27	Male	Mixed race	Married	High school graduate	Employed full-time	$40,000 to under $50,000	
4	16	Female	Mixed race	Never been married	High school incomplete	Employed part-time	$10,000 to under $20,000	
...	...	...	...	...	...	...	...	
2827	18	Male	White	Never been married	High school graduate	Employed part-time	$75,000 to under $100,000	
2828	17	Male	White	Never been married	High school incomplete	Employed part-time	$30,000 to under $40,000	
2829	17	Female	White	Never been married	High school incomplete	Not employed for pay	9$100,000 to under $150,000	
2830	16	Male	White	Never been married	High school graduate	Not employed for pay	9$100,000 to under $150,000	
2831	16	Male	White	Never been married	Don't know	Not employed for pay	Refused	

2832 rows × 14 columns

```
from pathlib import Path
import os
# File Size
df_path =Path('/content/gdrive/MyDrive/CS410_FinalProject')/'reading_habit.csv'
print(f'File size: {os.path.getsize(df_path) / 1024:0.2f} KiB')
```

```
File size: 401.75 KiB
```

```
from pathlib import Path

# Finding the Format
def head(filepath, n=7):
    with filepath.open() as f:
        for _ in range(n):
```

```
            print(f.readline(), end='')
head(df_path)
```

```
Age,Sex,Race,Marital status?,Education,Employement,Incomes,How many books did you read during last 12months?,Read any printec
66,Male,Refused,Divorced,College graduate,Retired,"$20,000 to under $30,000",97,Yes,No,Yes,Purchased the book,No,Yes
46,Male,Native American/American Indian,Married,High school graduate,Employed full-time,"Less than $10,000",97,Yes,Yes,Yes,Pu
32,Male,Mixed race,Never been married,High school graduate,Employed full-time,"Less than $10,000",97,No,Yes,Yes,Borrowed the
27,Male,Mixed race,Married,High school graduate,Employed full-time,"$40,000 to under $50,000",97,Yes,No,Yes,Borrowed the bool
16,Female,Mixed race,Never been married,High school incomplete,Employed part-time,"$10,000 to under $20,000",97,Yes,Yes,No,Pu
55,Female,Asian or Pacific Islander,Divorced,"Some college, no 4-year degree",Have own business/self-employed,"$40,000 to unc
```

It is Delimited format since there is a comma that seperate the data values.

```
# File Encoding
import chardet
encoding = chardet.detect(df_path.read_bytes())['encoding']
print(f'File encoding: {encoding}')
```

```
File encoding: utf-8
```

```
# Granularity
print("Reading Habit shape:", df.shape)
```

```
Reading Habit shape: (2832, 14)
```

```
# Quality Check
df.isnull().sum()
```

```
Age                                                    0
Sex                                                    0
Race                                                   0
Marital status?                                        0
Education                                              0
Employement                                            0
Incomes                                                0
How many books did you read during last 12months?      0
Read any printed books during last 12months?         390
Read any audiobooks during last 12months?            390
Read any e-books during last 12months?               390
Last book you read, you…                             390
Do you happen to read any daily news or newspapers?    0
Do you happen to read any magazines or journals?       0
dtype: int64
```

```
# Scope of the education
df['Education'].value_counts().tail(10)
```

```
High school graduate                                        688
Some college, no 4-year degree                              651
College graduate                                            597
Post-graduate training/professional school after college    501
High school incomplete                                      263
Technical, trade or vocational school AFTER high school      66
None                                                         58
Don’t know                                                    8
Name: Education, dtype: int64
```

```
# Scope of the incomes
df['Incomes'].value_counts().tail(10)
```

```
$100,000 to under $150,000     530
$50,000 to under $75,000       394
$75,000 to under $100,000      316
Refused                        291
$30,000 to under $40,000       265
$20,000 to under $30,000       238
$10,000 to under $20,000       216
9$100,000 to under $150,000    212
$40,000 to under $50,000       207
Less than $10,000              163
Name: Incomes, dtype: int64
```

```
# Scope of the Employement
df['Employement'].value_counts().tail(10)
```

```
Employed full-time                 1238
Retired                             605
Not employed for pay                474
Employed part-time                  355
Disabled                             70
Have own business/self-employed      53
Student                              22
Other                                15
Name: Employement, dtype: int64
```

```
# Quality of Relationships between Age and Education
display(pd.crosstab(df['Age'], df['Education'])[:10])
```

Education Age	College graduate	Don't know	High school graduate	High school incomplete	None	Post-graduate training/professional school after college	Some college, no 4-year degree	Technical, trade or vocational school AFTER high school
16	0	1	3	59	5	0	0	0
17	0	0	7	61	0	0	0	0
18	0	0	35	15	1	0	8	0
19	0	0	19	1	0	0	14	0
20	1	0	7	1	1	0	24	0
21	2	0	10	3	0	0	23	1
22	7	0	10	3	1	4	19	1
23	8	0	12	1	0	3	17	0
24	12	0	7	0	0	5	8	2
25	15	0	11	0	1	3	8	0

```
# Rename long named feature
df.columns = df.columns.str.replace('How many books did you read during last 12months?', 'N_of_Books')
```

```
<ipython-input-13-2b786763cf3e>:2: FutureWarning: The default value of regex will change from True to False in a future vers:
  df.columns = df.columns.str.replace('How many books did you read during last 12months?', 'N_of_Books')
```

```
# Drop features that we are not interested in to answer our questions

new_df = df.drop(columns = ['Read any printed books during last 12months?', 'Read any audiobooks during last 12months?', 'Read any
                            'Last book you read, you…', 'Do you happen to read any daily news or newspapers?', 'Do you happen to r
```

```
new_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2832 entries, 0 to 2831
Data columns (total 8 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   Age              2832 non-null   int64
 1   Sex              2832 non-null   object
 2   Race             2832 non-null   object
 3   Marital status?  2832 non-null   object
 4   Education        2832 non-null   object
 5   Employement      2832 non-null   object
 6   Incomes          2832 non-null   object
 7   N_of_Books?      2832 non-null   int64
dtypes: int64(2), object(6)
memory usage: 177.1+ KB
```

```
new_df
```

	Age	Sex	Race	Marital status?	Education	Employement	Incomes	N_of_Books?
0	66	Male	Refused	Divorced	College graduate	Retired	$20,000 to under $30,000	97
1	46	Male	Native American/American Indian	Married	High school graduate	Employed full-time	Less than $10,000	97
2	32	Male	Mixed race	Never been married	High school graduate	Employed full-time	Less than $10,000	97
3	27	Male	Mixed race	Married	High school graduate	Employed full-time	$40,000 to under $50,000	97
4	16	Female	Mixed race	Never been married	High school incomplete	Employed part-time	$10,000 to under $20,000	97

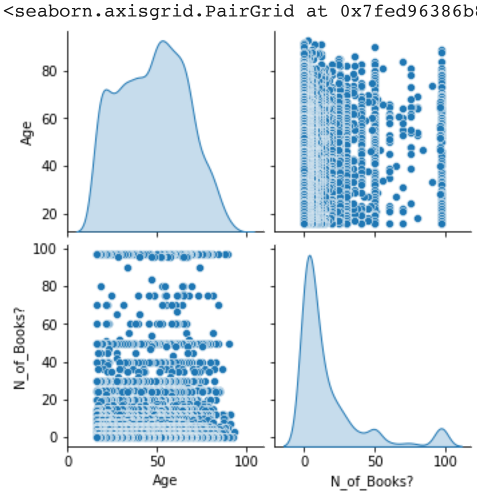
```
#new_df = new_df[new_df['Race'] == 'White']
#new_df
```

2827	18	Male	White	married	graduate	Employed part-time	$100,000	0

```
from sklearn.preprocessing import OneHotEncoder, OrdinalEncoder
from sklearn.compose import make_column_transformer
from sklearn.pipeline import make_pipeline
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import GradientBoostingRegressor
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.metrics import mean_absolute_error, mean_squared_error
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import mean_absolute_error as mae
```

```
import seaborn as sns
# Pairplot for Numerical values in our dataset
sns.pairplot(data=df, diag_kind='kde')
```

```
<seaborn.axisgrid.PairGrid at 0x7fed96386b80>
```

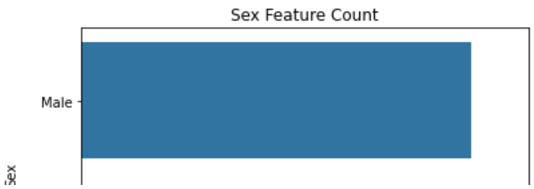


From the above plot:

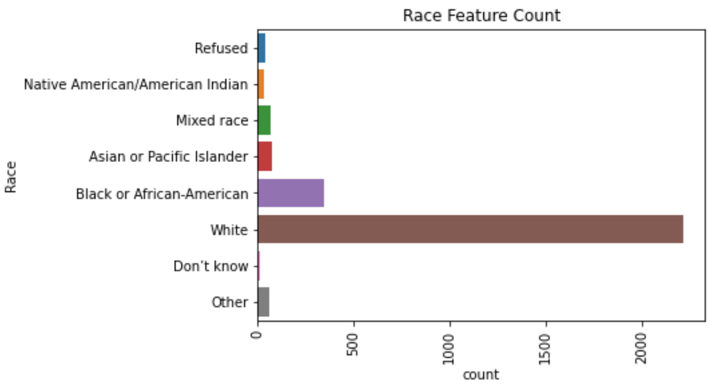
Age follows a normal distribution.

N_of_Books is skewed to the right.

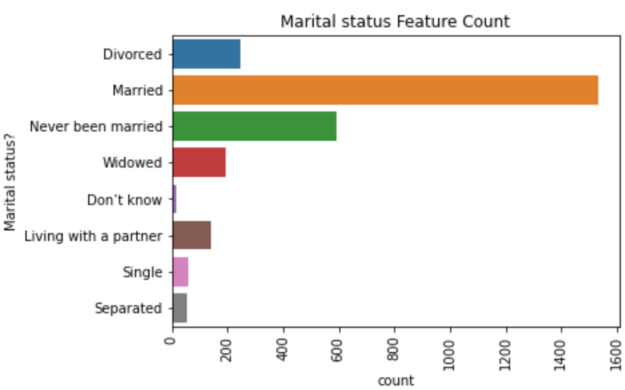
```
# Plotting Categorical Features
# Sex Feature
sns.countplot(y ='Sex', data = df)
plt.title("Sex Feature Count")
plt.show()
```



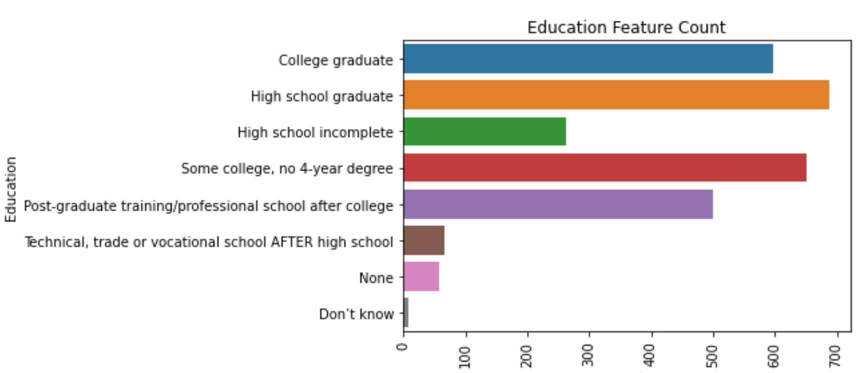

```
# Race Feature
plot = sns.countplot(y ='Race', data = df)
plot = plt.xticks(rotation='vertical')
plt.title("Race Feature Count")
plt.show()
```



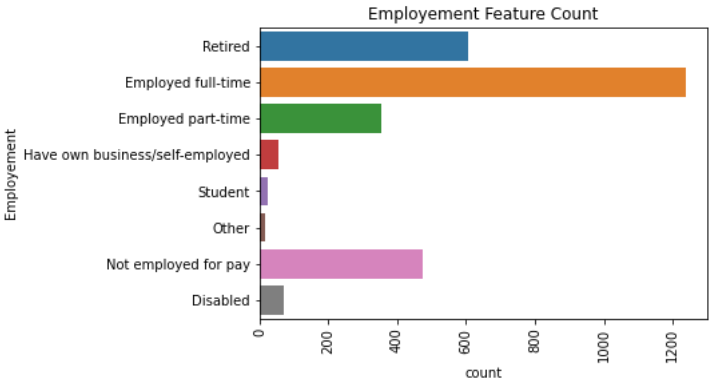

```
# Marital status? Feature
plot = sns.countplot(y ='Marital status?', data = df)
plot = plt.xticks(rotation='vertical')
plt.title("Marital status Feature Count")
plt.show()
```



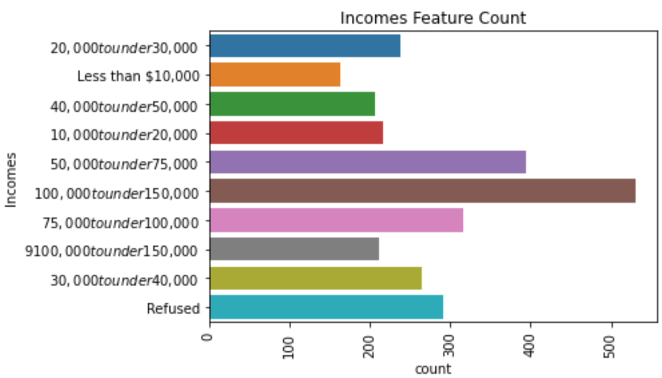

```
# Education Feature
plot = sns.countplot(y ='Education', data = df)
plot = plt.xticks(rotation='vertical')
plt.title("Education Feature Count")
plt.show()
```



```
# Employement Feature
plot = sns.countplot(y ='Employement', data = df)
plot = plt.xticks(rotation='vertical')
plt.title("Employement Feature Count")
plt.show()
```

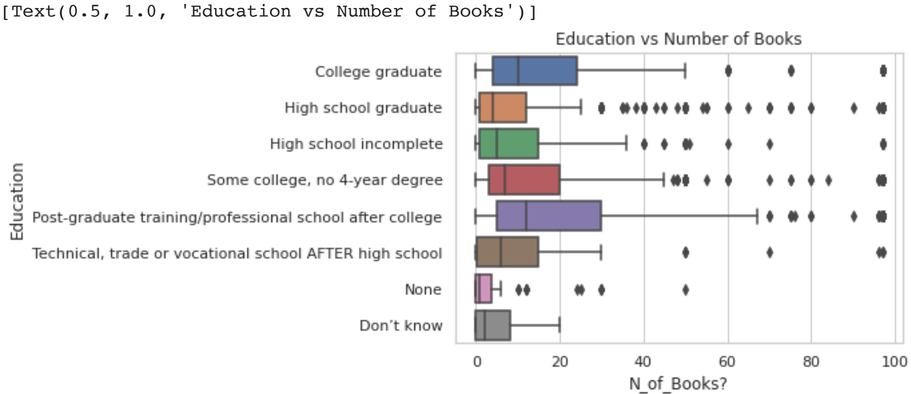



```
# Incomes Feature
plot = sns.countplot(y ='Incomes', data = df)
plot = plt.xticks(rotation='vertical')
plt.title("Incomes Feature Count")
plt.show()
```



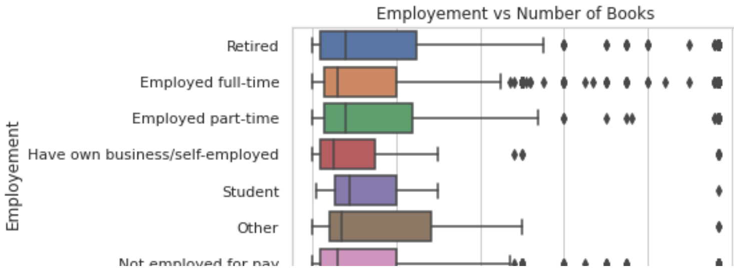

```
import seaborn
# plotting qualitative vs quantitative features using box plot
# (Education vs Number of Books) relationship visualization
seaborn.set(style="whitegrid")
seaborn.boxplot(y = 'Education', x = 'N_of_Books?', data = new_df).set(title='Education vs Number of Books')
```

```
[Text(0.5, 1.0, 'Education vs Number of Books')]
```



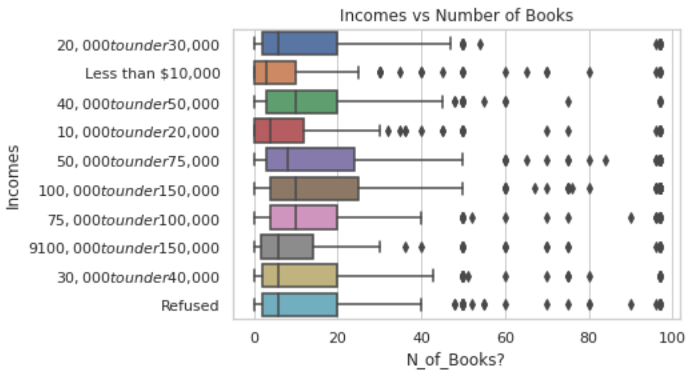

```
# (Employement vs Number of Books) relationship visualization
seaborn.boxplot(y = 'Employement', x = 'N_of_Books?', data = new_df).set(title='Employement vs Number of Books')
```

```
[Text(0.5, 1.0, 'Employement vs Number of Books')]
```



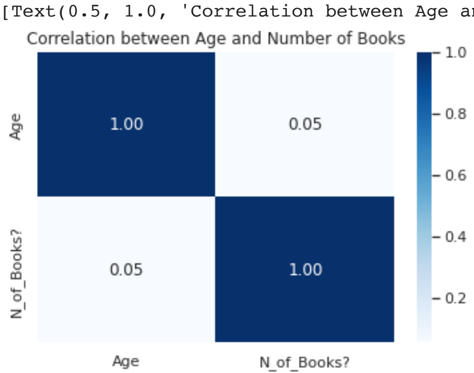

```
# (Incomes vs Number of Books) relationship visualization
seaborn.boxplot(y = 'Incomes', x = 'N_of_Books?', data = new_df).set(title='Incomes vs Number of Books')
```

```
[Text(0.5, 1.0, 'Incomes vs Number of Books')]
```




```
# The heatmap shows the correlation with numerical values. Numerical values in our dataset are two: AGe and Number of Books
import matplotlib.pyplot as plt
correlation = df.corr()
sns.heatmap(correlation, annot = True, fmt = '.2f', cmap = 'Blues').set(title='Correlation between Age and Number of Books')
```

```
[Text(0.5, 1.0, 'Correlation between Age and Number of Books')]
```



Correlation values range from -1 (negative correlation) to +1 (positive correlation), if the value is equal to zero, there is no correlation.

We observe from the heatmap that the age feature has positive/weak correlation with the N_of_Book feature.

```
# Define the upper and lower limit for the age outliers
upper_limit = new_df['Age'].quantile(0.99)
lower_limit = new_df['Age'].quantile(0.01)
print('Upper limit', upper_limit)
print('Lower limit',lower_limit)
```

```
Upper limit 85.0
Lower limit 16.0
```

```
# Filtering the outliers from age feature
new_df = new_df[(new_df['Age'] <= 85.0) & (new_df['Age'] >= 16.0)]
```

```
# Define the upper and lower limit for the Number of books outliers
upper_limit = new_df['N_of_Books?'].quantile(0.99)
lower_limit = new_df['N_of_Books?'].quantile(0.01)
print('Upper limit',upper_limit)
print('Lower limit',lower_limit)
```

```
Upper limit 97.0
Lower limit 0.0
```

```
# Filtering the outliers from Number of books feature
new_df = new_df[(new_df['N_of_Books?'] <= 97.0) & (new_df['N_of_Books?'] >= 0.0)]
```

```
# Instantiate OneHotEncoder
ohe = OneHotEncoder(sparse = False)
```

```
# Apply OneHotEncoder to the gender column
ohe.fit_transform(new_df[['Sex']])[:5]
```

```
array([[0., 1.],
       [0., 1.],
       [0., 1.],
       [0., 1.],
       [1., 0.]])
```

```
# Apply OneHotEncoder to the gender column
ohe.fit_transform(new_df[['Race']])[:5]
```

```
array([[0., 0., 0., 0., 0., 0., 1., 0.],
       [0., 0., 0., 0., 1., 0., 0., 0.],
       [0., 0., 0., 1., 0., 0., 0., 0.],
       [0., 0., 0., 1., 0., 0., 0., 0.],
       [0., 0., 0., 1., 0., 0., 0., 0.]])
```

```
# Apply OneHotEncoder to the gender column
ohe.fit_transform(new_df[['Marital status?']])[:5]
```

```
array([[1., 0., 0., 0., 0., 0., 0., 0.],
       [0., 0., 0., 1., 0., 0., 0., 0.],
       [0., 0., 0., 0., 1., 0., 0., 0.],
       [0., 0., 0., 1., 0., 0., 0., 0.],
       [0., 0., 0., 0., 1., 0., 0., 0.]])
```

```
# Apply OneHotEncoder to the gender column
ohe.fit_transform(new_df[['Employement']])[:5]
```

```
array([[0., 0., 0., 0., 0., 0., 1., 0.],
       [0., 1., 0., 0., 0., 0., 0., 0.],
       [0., 1., 0., 0., 0., 0., 0., 0.],
       [0., 1., 0., 0., 0., 0., 0., 0.],
       [0., 0., 1., 0., 0., 0., 0., 0.]])
```

```
# Unique values in the Education column
list(new_df['Education'].unique())
```

```
['College graduate',
 'High school graduate',
 'High school incomplete',
 'Some college, no 4-year degree',
 'Post-graduate training/professional school after college',
 'Technical, trade or vocational school AFTER high school',
 'None',
 'Don’t know']
```

```
# Specify the order for the level of education
education_categories = ['College graduate',
 'High school graduate',
 'High school incomplete',
 'Some college, no 4-year degree',
 'Post-graduate training/professional school after college',
 'Technical, trade or vocational school AFTER high school',
 'None',
 'Don’t know']
```

```
# Instantiate ordinal encoder
oe = OrdinalEncoder(categories = [education_categories])
```

```
# Apply ordinal encoder to Education column
oe.fit_transform(new_df[['Education']])[:10]
```

```
array([[0.],
       [1.],
       [1.],
       [1.],
       [2.],
       [3.],
       [3.],
       [0.],
       [4.],
       [1.]])
```

```
from sklearn.model_selection import train_test_split
from sklearn import preprocessing

# we dropped incomes feature because when we encoded it as a categorical/ordinal feature, we has an error due to typo error.
X = new_df.drop('Incomes', axis = 1)
Y = new_df["N_of_Books?"]
```

```
# Train test split
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.2, random_state = 42)

print("X_train shape: ", X_train.shape)
print("Y_train shape: ", Y_train.shape)
print("X_test shape: ", X_test.shape)
print("Y_test shape: ", Y_test.shape)
```

```
X_train shape:  (2243, 7)
Y_train shape:  (2243,)
X_test shape:  (561, 7)
Y_test shape:  (561,)
```

```
# Make column transformer which consists of OneHotEncoder and OrdincalEncoder
column_transform = make_column_transformer(
    (ohe, ['Sex', 'Race','Marital status?','Employement']),
    (oe, ['Education']))
```

```
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
```

```
# Instantiate pipeline with linear regression
lm = LinearRegression()
lm_pipeline = make_pipeline(column_transform, lm)
```

```
# Instantiate pipeline with gradient boosting
gbm = GradientBoostingRegressor()
gbm_pipeline = make_pipeline(column_transform, gbm)
```

```
# Instantiate pipeline with Decision Tree
dt = DecisionTreeRegressor()
dt_pipeline = make_pipeline(column_transform, dt)
```

```
# Fit pipeline to training set and make predictions on test set
lm_pipeline.fit(X_train, Y_train)
lm_predictions = lm_pipeline.predict(X_test)
print("First 5 LM predictions: ", list(lm_predictions[:5]))

gbm_pipeline.fit(X_train, Y_train)
gbm_predictions = gbm_pipeline.predict(X_test)
print("First 5 GBM predictions: ", list(gbm_predictions[:5]))

dt_pipeline.fit(X_train, Y_train)
dt_predictions = dt_pipeline.predict(X_test)
print("First 5 DT predictions: ", list(dt_predictions[:5]))
```

```
First 5 LM predictions:  [18.8125, 19.875, 11.65625, 7.53125, 20.15625]
First 5 GBM predictions:  [15.51783649561837, 22.448925065258695, 9.312678906344818, 1.480158929559059, 11.710230111880193]
First 5 DT predictions:  [14.066666666666666, 26.8125, 8.553846153846154, 10.0, 3.0]
```

```
# Compare the number of predictions with the size of test set
print("Number of LM predictions: ", len(lm_predictions))
print("Number of GBM predictions: ", len(gbm_predictions))
print("Number of DT predictions: ", len(dt_predictions))
print("Size of test set: ", len(Y_test))
```

```
Number of LM predictions:  561
Number of GBM predictions:  561
Number of DT predictions:  561
Size of test set:  561
```

Models Evaluation:

Since our dataset has many outliers, we will use Mean Absolute Error and R2 to evaluate our models.

```
# Calculate mean absolute error and r squared
lm_mae = mean_absolute_error(lm_predictions, Y_test)
lm_r2 = r2_score(Y_test, lm_predictions)
print("Multiple Linear Regression (MAE): {:.2f}".format(round(lm_mae, 2)))
print("Multiple Linear Regression (r2): {:.2f}".format(round(lm_r2, 2)))
print("")


gbm_mae = mean_absolute_error(gbm_predictions, Y_test)
gbm_r2 = r2_score(Y_test, gbm_predictions)
print("Gradient Boosting Regressor (MAE): {:.2f}".format(round(gbm_mae, 2)))
print("Gradient Boosting Regressor (r2): {:.2f}".format(round(gbm_r2, 2)))
print("")


dt_mae = mean_absolute_error(dt_predictions, Y_test)
dt_r2 = r2_score(Y_test, dt_predictions)
print("Decision Tree Regressor (MAE): {:.2f}".format(round(dt_mae, 2)))
print("Decision Tree Regressor (r2): {:.2f}".format(round(dt_r2, 2)))
```

```
Multiple Linear Regression (MAE): 15.98
Multiple Linear Regression (r2): 0.03

Gradient Boosting Regressor (MAE): 15.67
Gradient Boosting Regressor (r2): 0.05

Decision Tree Regressor (MAE): 16.66
Decision Tree Regressor (r2): -0.13
```

For MAE:

This metric measures the difference between predictions and true value of the predictions.

For r2:

This metric compares the model predictions to the mean of our target. Values can range from negative infinity (very poor model) to 1 (perfectly predict the values).

Among the three models, Gradient boosting performs slightly better
(r2 =0.04) than multiple linear regression(r2 =0.03) and Decision tree (r2 = -0.30) models.

```
# Actual and Predicted Values
df_lm = pd.DataFrame({'Actual': Y_test, 'Predicted': lm_predictions})
df_lm[:7]
```

	Actual	Predicted
1098	12	18.81250

```
# Difference between actual and predicted values
df_lm['Difference'] = df_lm['Actual'] - df_lm['Predicted']
df_lm[:7]
```

	Actual	Predicted	Difference
1098	12	18.81250	-6.81250
1048	12	19.87500	-7.87500
1532	6	11.65625	-5.65625
2524	0	7.53125	-7.53125
1529	6	20.15625	-14.15625
699	20	23.09375	-3.09375
198	54	22.78125	31.21875

The differences between actual and predicted values are high, which means our lm model is high in variance and not a strong model.

```
# Actual and Predicted Values
df_gbm = pd.DataFrame({'Actual': Y_test, 'Predicted': gbm_predictions})
df_gbm[:7]
```

	Actual	Predicted
1098	12	15.517836
1048	12	22.448925
1532	6	9.312679
2524	0	1.480159
1529	6	11.710230
699	20	26.049730
198	54	14.648265

```
# Difference between actual and predicted values
df_gbm['Difference'] = df_gbm['Actual'] - df_gbm['Predicted']
df_gbm[:7]
```

	Actual	Predicted	Difference
1098	12	15.517836	-3.517836
1048	12	22.448925	-10.448925
1532	6	9.312679	-3.312679
2524	0	1.480159	-1.480159
1529	6	11.710230	-5.710230
699	20	26.049730	-6.049730
198	54	14.648265	39.351735

The differences between actual and predicted values are high, which means our gbm model is high in variance and not a strong model.

```
# Actual and Predicted Values
df_dt = pd.DataFrame({'Actual': Y_test, 'Predicted': dt_predictions})
df_dt[:7]
```

	Actual	Predicted
1098	12	14.066667
1048	12	26.812500
1532	6	8.553846

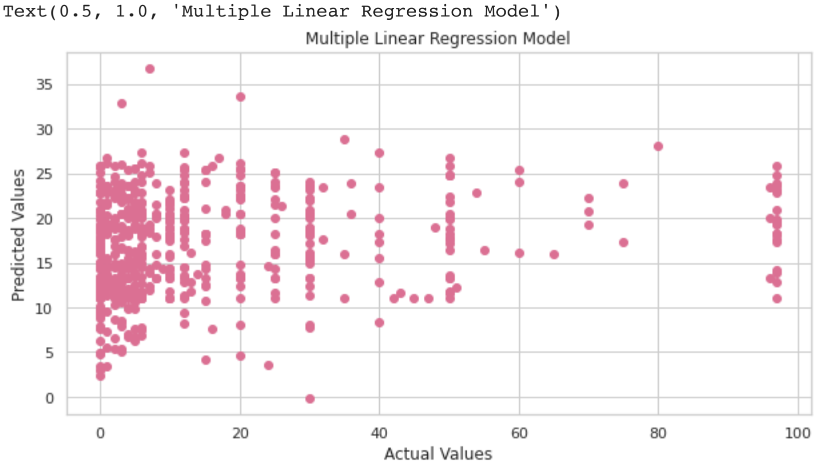
```
# Difference between actual and predicted values
df_dt['Difference'] = df_dt['Actual'] - df_dt['Predicted']
df_dt[:7]
```

	Actual	Predicted	Difference
1098	12	14.066667	-2.066667
1048	12	26.812500	-14.812500
1532	6	8.553846	-2.553846
2524	0	10.000000	-10.000000
1529	6	3.000000	3.000000
699	20	24.636364	-4.636364
198	54	15.000000	39.000000

The differences between actual and predicted values are high, which means our dt model is high in variance and not a strong model.

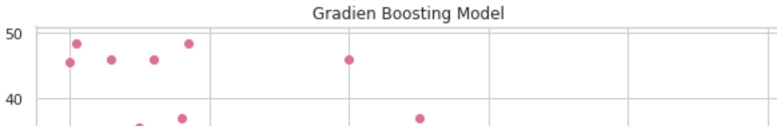
```
# Plotting our predictions
plt.figure(figsize=(10,5))
plt.scatter(Y_test, lm_predictions, c = 'palevioletred')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title("Multiple Linear Regression Model")
```

```
Text(0.5, 1.0, 'Multiple Linear Regression Model')
```




```
# Plotting our predictions
plt.figure(figsize=(10,5))
plt.scatter(Y_test, gbm_predictions, c = 'palevioletred')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title("Gradien Boosting Model")
```

```
Text(0.5, 1.0, 'Gradien Boosting Model')
```




```
# Plotting our predictions
plt.figure(figsize=(10,5))
plt.scatter(Y_test, dt_predictions, c = 'palevioletred')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title("Decision Tree Model")
```

```
Text(0.5, 1.0, 'Decision Tree Model')
```