```
In [1]: import numpy as np
    import pandas as pd
    import matplotlib.pyplot as plt
    import seaborn as sns
    from sklearn.datasets import load_diabetes
    from sklearn.model_selection import train_test_split
    from sklearn.linear_model import LinearRegression
    from sklearn.metrics import mean_squared_error, r2_score
    import plotly.express as px
```

In [2]: diabetes_data = load_diabetes()
diabetes_data

```
Out[2]: {'data': array([[ 0.03807591, 0.05068012, 0.06169621, ..., -0.00259226,
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                [-0.00188202, -0.04464164, -0.05147406, ..., -0.03949338,
                 -0.06833155, -0.09220405],
                                           0.04445121, ..., -0.00259226,
                [ 0.08529891, 0.05068012,
                  0.00286131, -0.02593034],
                [ 0.04170844,
                              0.05068012, -0.01590626, ..., -0.01107952,
                 -0.04688253,
                              0.01549073],
                                           0.03906215, ...,
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                                                             0.02655962,
                  0.04452873, -0.02593034],
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                                                                     61., 92.,
                                       75., 142., 155., 225.,
                259.,
                      53., 190., 142.,
                                                                59., 104., 182.,
                      52., 37., 170., 170., 61., 144., 52., 128.,
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                128.,
                      97., 160., 178., 48., 270., 202., 111.,
                150.,
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                200., 252., 113., 143.,
                                        51.,
                                              52., 210., 65., 141.,
                                                                      55., 134.,
                 42., 111., 98., 164., 48.,
                                              96., 90., 162., 150., 279.,
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                 94., 183., 66., 173., 72., 49., 64., 48., 178., 104., 132.,
                220.,
                      57.]),
         'frame': None,
         'DESCR': '.. _diabetes_dataset:\n\nDiabetes dataset\n------\n\n
```

'DESCR': '.. _diabetes_dataset:\n\nDiabetes dataset\n-----\n\n
Ten baseline variables, age, sex, body mass index, average blood\npressur
e, and six blood serum measurements were obtained for each of n =\n442 dia
betes patients, as well as the response of interest, a\nquantitative measu
re of disease progression one year after baseline.\n\n**Data Set Character

istics:**\n\n :Number of Instances: 442\n\n :Number of Attributes: First 10 columns are numeric predictive values\n\n :Target: Column 11 is a quan titative measure of disease progression one year after baseline\n\n :Attr ibute Information:\n - age age in years\n - bmi - sex\n body mass index\n - bp average blood pressure\n t - s1 c, total serum cholesterol\n - s2 ldl, low-density lipoproteins hdl, high-density lipoproteins\n - s3 - s4 ltg, possibly log of serum triglycer al cholesterol / HDL\n - s5 ides level\n - s6 glu, blood sugar level\n\nNote: Each of these 10 feature variables have been mean centered and scaled by the standard de viation times the square root of `n_samples` (i.e. the sum of squares of e ach column totals 1).\n\nSource URL:\nhttps://www4.stat.ncsu.edu/~boos/va r.select/diabetes.html\n\nFor more information see:\nBradley Efron, Trevor Hastie, Iain Johnstone and Robert Tibshirani (2004) "Least Angle Regressio n," Annals of Statistics (with discussion), 407-499.\n(https://web.stanfor d.edu/~hastie/Papers/LARS/LeastAngle 2002.pdf)\n',

```
'feature_names': ['age',
   'sex',
   'bmi',
   'bp',
   's1',
   's2',
   's3',
   's4',
   's5',
   's6'],
'data_filename': 'diabetes_data_raw.csv.gz',
'target_filename': 'diabetes_target.csv.gz',
'data_module': 'sklearn.datasets.data'}
```

In [3]: X = pd.DataFrame(diabetes_data.data, columns=diabetes_data.feature_names)
X

Out[3]:

	age	sex	bmi	bp	s1	s2	s3	s4	
0	0.038076	0.050680	0.061696	0.021872	-0.044223	-0.034821	-0.043401	-0.002592	0.
1	-0.001882	-0.044642	-0.051474	-0.026328	-0.008449	-0.019163	0.074412	-0.039493	-0.
2	0.085299	0.050680	0.044451	-0.005670	-0.045599	-0.034194	-0.032356	-0.002592	0.
3	-0.089063	-0.044642	-0.011595	-0.036656	0.012191	0.024991	-0.036038	0.034309	0.
4	0.005383	-0.044642	-0.036385	0.021872	0.003935	0.015596	0.008142	-0.002592	-0.
437	0.041708	0.050680	0.019662	0.059744	-0.005697	-0.002566	-0.028674	-0.002592	0.
438	-0.005515	0.050680	-0.015906	-0.067642	0.049341	0.079165	-0.028674	0.034309	-0.
439	0.041708	0.050680	-0.015906	0.017293	-0.037344	-0.013840	-0.024993	-0.011080	-0.
440	-0.045472	-0.044642	0.039062	0.001215	0.016318	0.015283	-0.028674	0.026560	0.
441	-0.045472	-0.044642	-0.073030	-0.081413	0.083740	0.027809	0.173816	-0.039493	-0.

442 rows × 10 columns

```
In [4]: | y = pd.Series(diabetes_data.target, name='Diabetes Progression')
Out[4]: 0
               151.0
        1
                75.0
        2
               141.0
        3
               206.0
        4
               135.0
               . . .
        437
               178.0
        438
               104.0
        439
               132.0
        440
               220.0
        441
                57.0
        Name: Diabetes Progression, Length: 442, dtype: float64
In [5]: df = pd.concat([X, y], axis=1)
```

Out[5]:

	age	sex	bmi	bp	s1	s2	s3	s4	
0	0.038076	0.050680	0.061696	0.021872	-0.044223	-0.034821	-0.043401	-0.002592	0.
1	-0.001882	-0.044642	-0.051474	-0.026328	-0.008449	-0.019163	0.074412	-0.039493	-0.
2	0.085299	0.050680	0.044451	-0.005670	-0.045599	-0.034194	-0.032356	-0.002592	0.
3	-0.089063	-0.044642	-0.011595	-0.036656	0.012191	0.024991	-0.036038	0.034309	0.
4	0.005383	-0.044642	-0.036385	0.021872	0.003935	0.015596	0.008142	-0.002592	-0.
437	0.041708	0.050680	0.019662	0.059744	-0.005697	-0.002566	-0.028674	-0.002592	0.
438	-0.005515	0.050680	-0.015906	-0.067642	0.049341	0.079165	-0.028674	0.034309	-0.
439	0.041708	0.050680	-0.015906	0.017293	-0.037344	-0.013840	-0.024993	-0.011080	-0.
440	-0.045472	-0.044642	0.039062	0.001215	0.016318	0.015283	-0.028674	0.026560	0.
441	-0.045472	-0.044642	-0.073030	-0.081413	0.083740	0.027809	0.173816	-0.039493	-0.

442 rows × 11 columns

In [6]: print(df.describe())

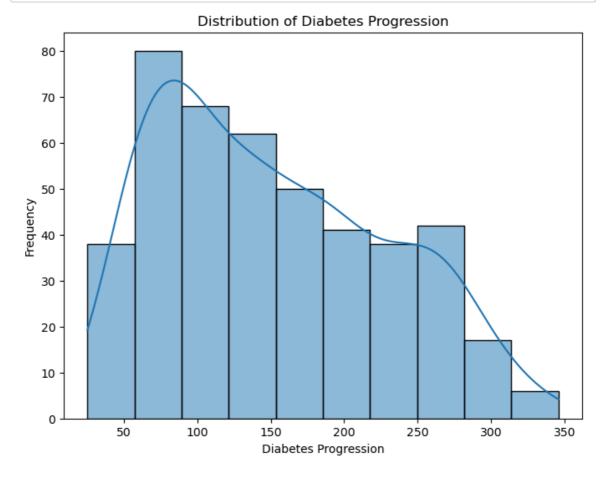
1 \	age	sex	bmi	bp	S
1 \ count	4.420000e+02	4.420000e+02	4.420000e+02	4.420000e+02	4.420000e+0
mean 7	-2.511817e-19	1.230790e-17	-2.245564e-16	-4.797570e-17	-1.381499e-1
std 2	4.761905e-02	4.761905e-02	4.761905e-02	4.761905e-02	4.761905e-0
min 1	-1.072256e-01	-4.464164e-02	-9.027530e-02	-1.123988e-01	-1.267807e-0
25% 2	-3.729927e-02	-4.464164e-02	-3.422907e-02	-3.665608e-02	-3.424784e-0
50% 3	5.383060e-03	-4.464164e-02	-7.283766e-03	-5.670422e-03	-4.320866e-0
75% 2	3.807591e-02	5.068012e-02	3.124802e-02	3.564379e-02	2.835801e-0
max 1	1.107267e-01	5.068012e-02	1.705552e-01	1.320436e-01	1.539137e-0
	s2	s3	s4	s5	S
6 \	32	33	34	33	3
count 2	4.420000e+02	4.420000e+02	4.420000e+02	4.420000e+02	4.420000e+0
mean 7	3.918434e-17	-5.777179e-18	-9.042540e-18	9.293722e-17	1.130318e-1
std 2	4.761905e-02	4.761905e-02	4.761905e-02	4.761905e-02	4.761905e-0
min 1	-1.156131e-01	-1.023071e-01	-7.639450e-02	-1.260971e-01	-1.377672e-0
25% 2	-3.035840e-02	-3.511716e-02	-3.949338e-02	-3.324559e-02	-3.317903e-0
50% 3	-3.819065e-03	-6.584468e-03	-2.592262e-03	-1.947171e-03	-1.077698e-0
75% 2	2.984439e-02	2.931150e-02	3.430886e-02	3.243232e-02	2.791705e-0
max 1	1.987880e-01	1.811791e-01	1.852344e-01	1.335973e-01	1.356118e-0
count	Diabetes Prog	gression 2.000000			
mean		2.133484			
std	77	7.093005			
min		5.000000			
25%		7.000000			
50% 75%		0.500000 1.500000			
1 5/0	21.				

346.000000

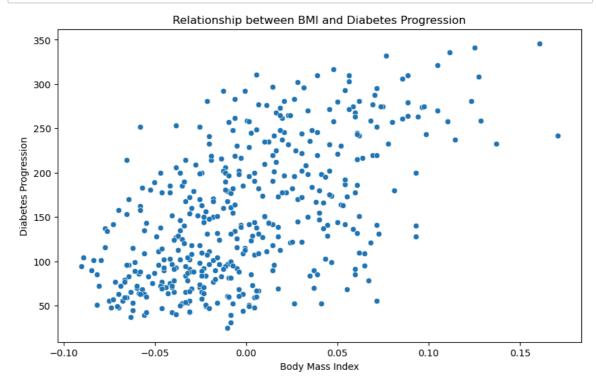
max

In [7]: print(df.isnull().sum()) 0 age 0 sex bmi 0 0 bp 0 s1 0 s2 s3 0 0 s4 s5 0 0 s6 Diabetes Progression dtype: int64

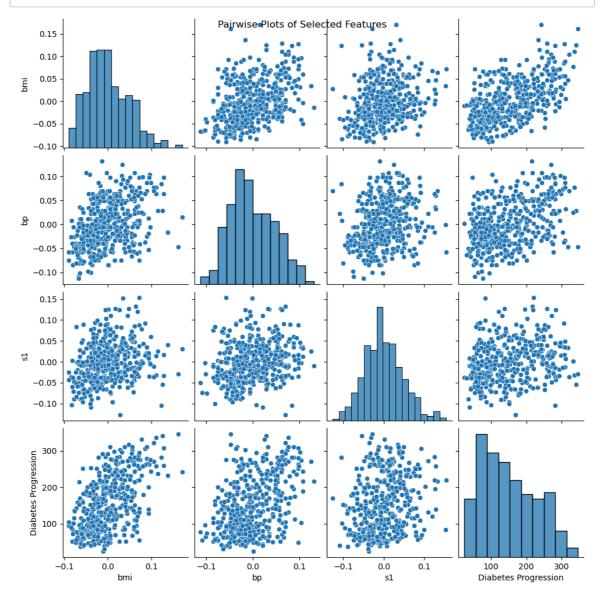
```
In [8]: plt.figure(figsize=(8, 6))
    sns.histplot(df['Diabetes Progression'], kde=True)
    plt.title('Distribution of Diabetes Progression')
    plt.xlabel('Diabetes Progression')
    plt.ylabel('Frequency')
    plt.show()
```



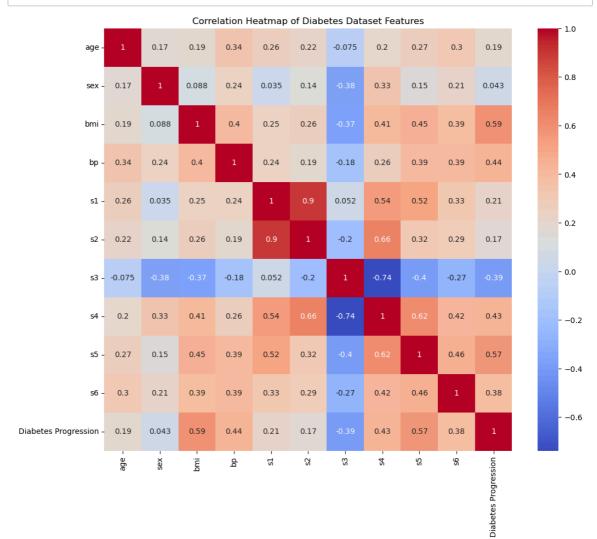
```
In [9]: plt.figure(figsize=(10, 6))
    sns.scatterplot(x='bmi', y='Diabetes Progression', data=df)
    plt.title('Relationship between BMI and Diabetes Progression')
    plt.xlabel('Body Mass Index')
    plt.ylabel('Diabetes Progression')
    plt.show()
```



In [10]: sns.pairplot(df[['bmi', 'bp', 's1', 'Diabetes Progression']])
 plt.suptitle('Pairwise Plots of Selected Features')
 plt.show()



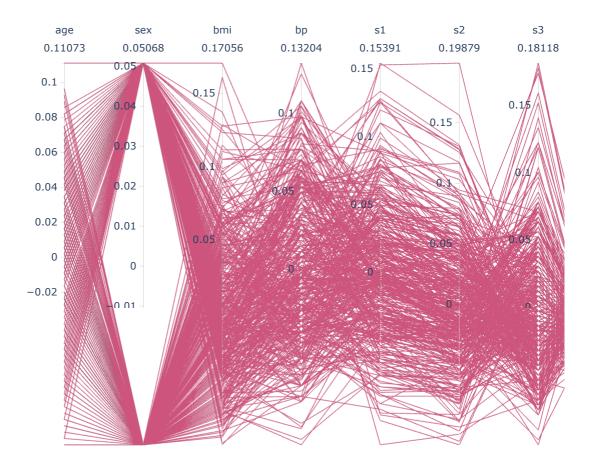
In [11]: plt.figure(figsize=(12, 10))
 correlation_matrix = df.corr()
 sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
 plt.title('Correlation Heatmap of Diabetes Dataset Features')
 plt.show()



```
In [12]: fig = px.parallel_coordinates(df, color='Diabetes Progression',
                                       dimensions=['age', 'sex', 'bmi', 'bp', 's1',
                                       color_continuous_scale=px.colors.diverging.Te
                                       color_continuous_midpoint=np.average(df['Diabe
         fig.show()
```

C:\Users\Aditya Kudva\anaconda3\Lib\site-packages\plotly\express_core.py: 279: FutureWarning: iteritems is deprecated and will be removed in a futur e version. Use .items instead.

dims = [



```
X_train, X_test, y_train, y_test = train_test_split(df[['bmi']], df['Diabet
In [13]:
         model = LinearRegression()
         model.fit(X_train, y_train)
```

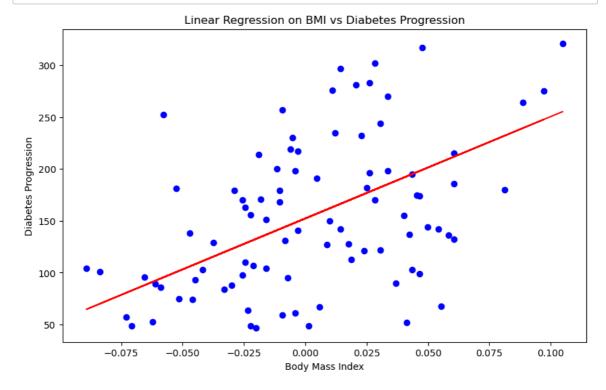
Out[13]:

▼ LinearRegression LinearRegression()

```
In [14]: y_pred = model.predict(X_test)
print('Mean Squared Error:', mean_squared_error(y_test, y_pred))
print('Coefficient of Determination:', r2_score(y_test, y_pred))
```

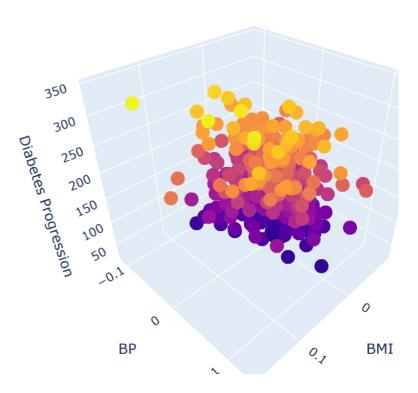
Mean Squared Error: 4150.6801893299835 Coefficient of Determination: 0.19057346847560142

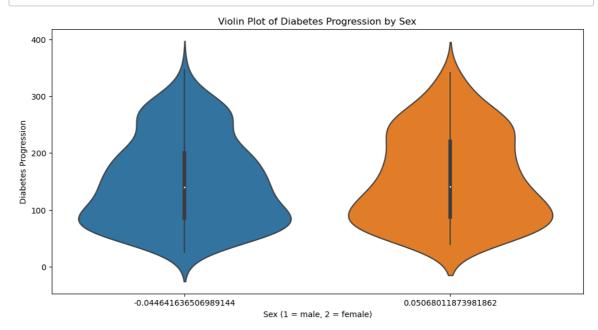
```
In [15]: plt.figure(figsize=(10, 6))
    plt.scatter(X_test, y_test, color='blue')
    plt.plot(X_test, y_pred, color='red')
    plt.title('Linear Regression on BMI vs Diabetes Progression')
    plt.xlabel('Body Mass Index')
    plt.ylabel('Diabetes Progression')
    plt.show()
```



In [16]: import plotly.express as px

3D Scatter Plot of BMI, BP, and Diabetes Progression



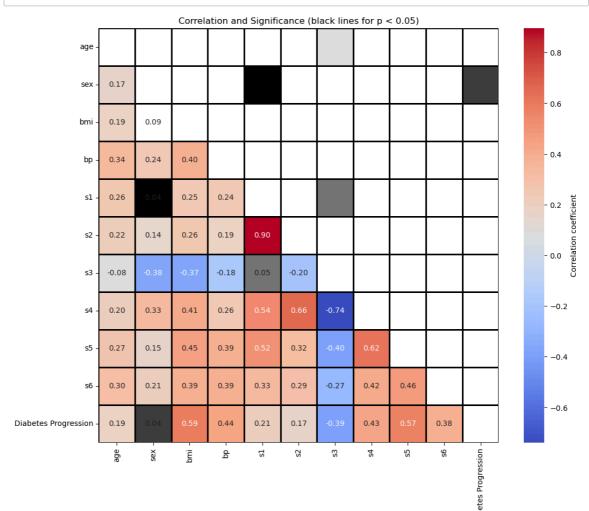


```
In [19]: from scipy.stats import pearsonr

In [20]: corr = df.corr()
    pval = pd.DataFrame([[pearsonr(df[col], df[col2])[1] for col2 in df.columns

In [21]: mask = np.triu(np.ones_like(corr, dtype=bool))
    corr[mask] = np.nan
```

In [22]: plt.figure(figsize=(12, 10))
 sns.heatmap(corr, annot=True, fmt=".2f", cmap='coolwarm', cbar_kws={'label'
 sns.heatmap(pval, mask=pval < 0.05, annot=False, cbar=False, cmap='binary',
 plt.title('Correlation and Significance (black lines for p < 0.05)')
 plt.show()</pre>

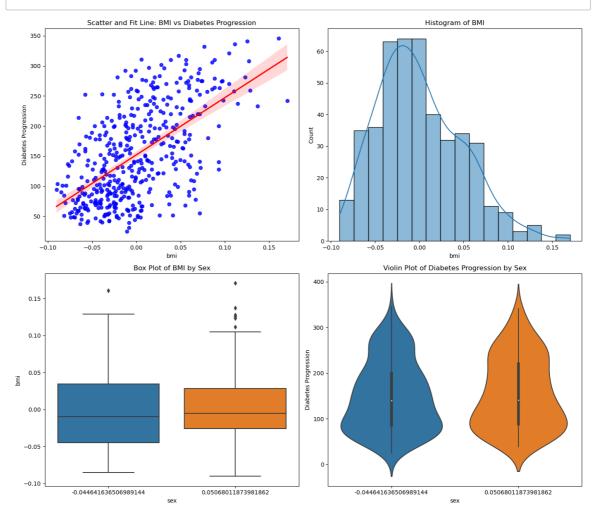


```
In [28]: fig, axes = plt.subplots(2, 2, figsize=(14, 12))
    sns.regplot(ax=axes[0, 0], x='bmi', y='Diabetes Progression', data=df, colo
    axes[0, 0].set_title('Scatter and Fit Line: BMI vs Diabetes Progression')

    sns.histplot(ax=axes[0, 1], data=df, x='bmi', kde=True)
    axes[0, 1].set_title('Histogram of BMI')

    sns.boxplot(ax=axes[1, 0], x='sex', y='bmi', data=df)
    axes[1, 0].set_title('Box Plot of BMI by Sex')

    sns.violinplot(ax=axes[1, 1], x='sex', y='Diabetes Progression', data=df)
    axes[1, 1].set_title('Violin Plot of Diabetes Progression by Sex')
    plt.tight_layout()
    plt.show()
```



In []: