assignment6

April 26, 2024

[ ]:
```
from sklearn.datasets import load_diabetes
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
/home/oneautumleaf/.local/lib/python3.10/site-
packages/matplotlib/projections/__init__.py:63: UserWarning: Unable to import
Axes3D. This may be due to multiple versions of Matplotlib being installed (e.g.
as a system package and as a pip package). As a result, the 3D projection is not
available.
  warnings.warn("Unable to import Axes3D. This may be due to multiple versions
of "
```

1. Load the dataset

[ ]:
```
diabetes_data = load_diabetes()
```

[ ]:
```
df = pd.DataFrame(data=diabetes_data.data, columns=diabetes_data.feature_names)
df['progression'] = diabetes_data.target
```

[ ]:
```
df
```

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

           s4        s5        s6  progression
0   -0.002592  0.019907 -0.017646        151.0
1   -0.039493 -0.068332 -0.092204         75.0
```

```
2   -0.002592  0.002861 -0.025930        141.0
3    0.034309  0.022688 -0.009362        206.0
4   -0.002592 -0.031988 -0.046641        135.0
..        …         …         …          …
437 -0.002592  0.031193  0.007207        178.0
438  0.034309 -0.018114  0.044485        104.0
439 -0.011080 -0.046883  0.015491        132.0
440  0.026560  0.044529 -0.025930        220.0
441 -0.039493 -0.004222  0.003064         57.0

[442 rows x 11 columns]
```

2. Exploratory Data Analysis

[ ]:
```
df.describe()
```

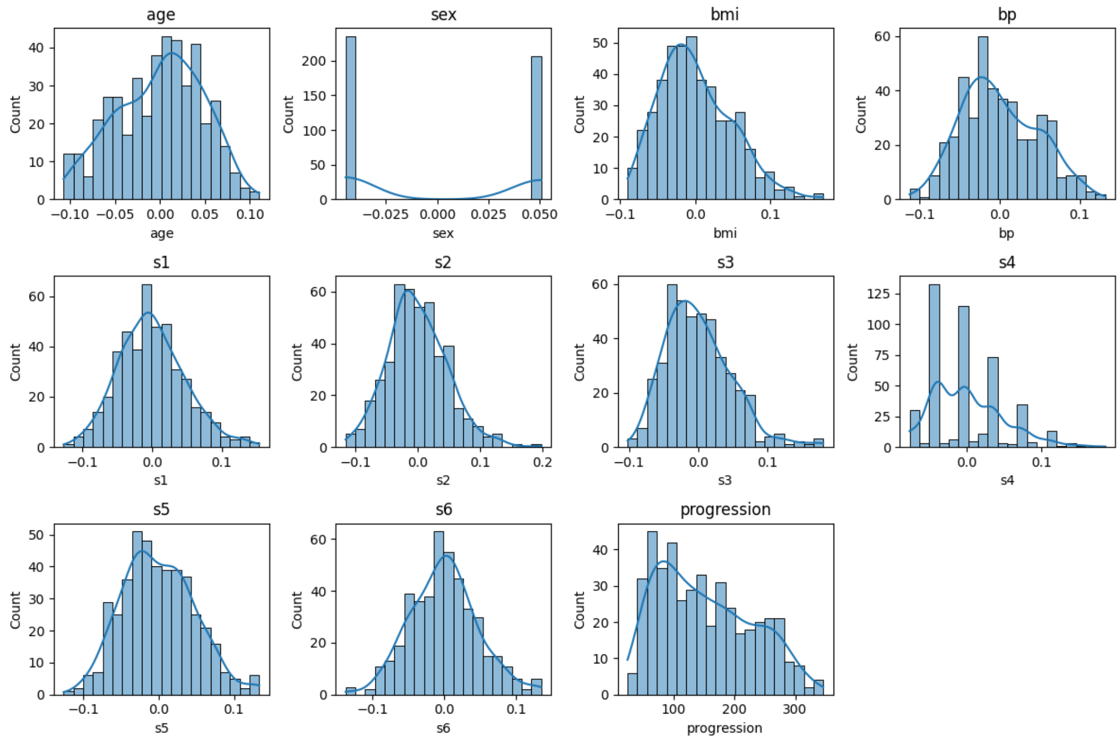
[ ]:

	age	sex	bmi	bp	s1
count	4.420000e+02	4.420000e+02	4.420000e+02	4.420000e+02	4.420000e+02
mean	-2.511817e-19	1.230790e-17	-2.245564e-16	-4.797570e-17	-1.381499e-17
std	4.761905e-02	4.761905e-02	4.761905e-02	4.761905e-02	4.761905e-02
min	-1.072256e-01	-4.464164e-02	-9.027530e-02	-1.123988e-01	-1.267807e-01
25%	-3.729927e-02	-4.464164e-02	-3.422907e-02	-3.665608e-02	-3.424784e-02
50%	5.383060e-03	-4.464164e-02	-7.283766e-03	-5.670422e-03	-4.320866e-03
75%	3.807591e-02	5.068012e-02	3.124802e-02	3.564379e-02	2.835801e-02
max	1.107267e-01	5.068012e-02	1.705552e-01	1.320436e-01	1.539137e-01

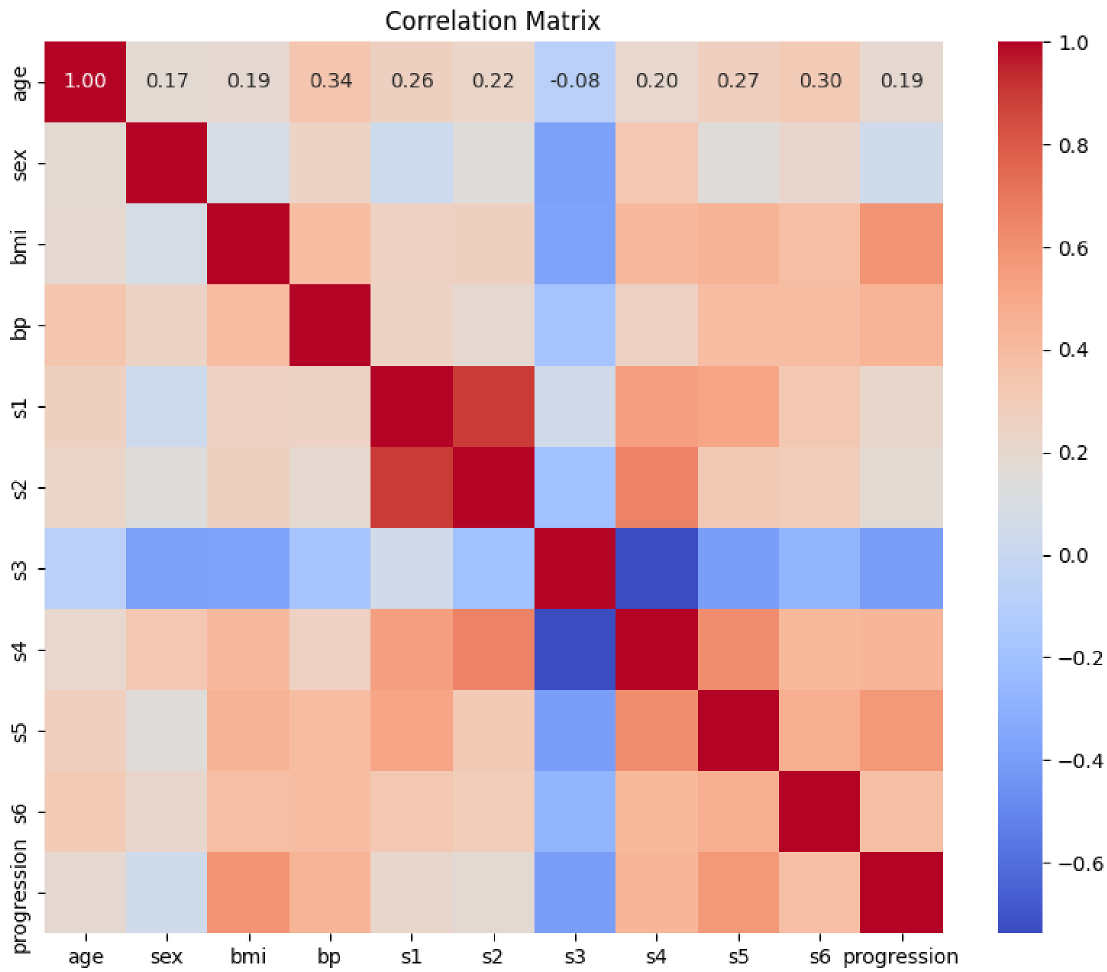
	s2	s3	s4	s5	s6
count	4.420000e+02	4.420000e+02	4.420000e+02	4.420000e+02	4.420000e+02
mean	3.918434e-17	-5.777179e-18	-9.042540e-18	9.293722e-17	1.130318e-17
std	4.761905e-02	4.761905e-02	4.761905e-02	4.761905e-02	4.761905e-02
min	-1.156131e-01	-1.023071e-01	-7.639450e-02	-1.260971e-01	-1.377672e-01
25%	-3.035840e-02	-3.511716e-02	-3.949338e-02	-3.324559e-02	-3.317903e-02
50%	-3.819065e-03	-6.584468e-03	-2.592262e-03	-1.947171e-03	-1.077698e-03
75%	2.984439e-02	2.931150e-02	3.430886e-02	3.243232e-02	2.791705e-02
max	1.987880e-01	1.811791e-01	1.852344e-01	1.335973e-01	1.356118e-01

	progression
count	442.000000
mean	152.133484
std	77.093005
min	25.000000
25%	87.000000
50%	140.500000
75%	211.500000
max	346.000000

```
[ ]: plt.figure(figsize=(12, 8))
     for i, column in enumerate(df.columns):
         plt.subplot(3, 4, i + 1)
         sns.histplot(df[column], bins=20, kde=True)
         plt.title(column)
     plt.tight_layout()
     plt.show()
```




```
[ ]: correlation_matrix = df.corr()
     plt.figure(figsize=(10, 8))
     sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f')
     plt.title('Correlation Matrix')
     plt.show()
```



3. Data Preprocessing

[ ]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
```

[ ]:
```
df.isna().sum(axis=0)
```

[ ]:
```
age             0
sex             0
bmi             0
bp              0
s1              0
s2              0
s3              0
s4              0
s5              0
s6              0
```

```
progression    0
dtype: int64
```

Since there are no null values, we don't need to impute any row

```
[ ]: X = df.drop('progression', axis=1)
     y = df['progression']
```

```
[ ]: # Split into train and test datasets
     X_train, X_test, y_train, y_test = train_test_split(
         X, y, test_size=0.2, random_state=42)
```

```
[ ]: scaler = StandardScaler()
     X_train_scaled = scaler.fit_transform(X_train)
     X_test_scaled = scaler.transform(X_test)
```

4. Model implementation

```
[ ]: from sklearn.tree import DecisionTreeRegressor
     from sklearn.ensemble import RandomForestRegressor
     from sklearn.metrics import mean_squared_error
```

```
[ ]: # Decision Tree Model
     decision_tree = DecisionTreeRegressor(random_state=42)
     decision_tree.fit(X_train_scaled, y_train)
```

```
[ ]: DecisionTreeRegressor(random_state=42)
```

```
[ ]: # Random Forest Model
     random_forest = RandomForestRegressor(n_estimators=100, random_state=42)
     random_forest.fit(X_train_scaled, y_train)
```

```
[ ]: RandomForestRegressor(random_state=42)
```

5. Model Evaluation

```
[ ]: # Predictions
     y_pred_decision_tree = decision_tree.predict(X_test_scaled)
     y_pred_random_forest = random_forest.predict(X_test_scaled)
```

```
[ ]: mse_decision_tree = mean_squared_error(y_test, y_pred_decision_tree)
     mse_random_forest = mean_squared_error(y_test, y_pred_random_forest)
```

```
[ ]: print(f"Mean Squared Error (Decision Tree): {mse_decision_tree}")
     print(f"Mean Squared Error (Random Forest): {mse_random_forest}")
```

```
Mean Squared Error (Decision Tree): 4887.0
Mean Squared Error (Random Forest): 2959.180561797753
```

6. Hyperparameter Tuning

[ ]:
```
X_scaled = scaler.transform(X)
```

[ ]:
```
from sklearn.model_selection import GridSearchCV
```

[ ]:
```
# Decision Tree

param_grid_decision_tree = {
    'max_depth': [None, 5, 10, 15],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

decision_tree = DecisionTreeRegressor(random_state=42)
grid_search_decision_tree = GridSearchCV(
    estimator=decision_tree, param_grid=param_grid_decision_tree,
    scoring='neg_mean_squared_error', cv=5, verbose=0, n_jobs=-1)

grid_search_decision_tree.fit(X_scaled, y)
```

[ ]:
```
GridSearchCV(cv=5, estimator=DecisionTreeRegressor(random_state=42), n_jobs=-1,
             param_grid={'max_depth': [None, 5, 10, 15],
                         'min_samples_leaf': [1, 2, 4],
                         'min_samples_split': [2, 5, 10]},
             scoring='neg_mean_squared_error')
```

[ ]:
```
best_params_decision_tree = grid_search_decision_tree.best_params_
print(f"Best Hyperparameters (Decision Tree): {best_params_decision_tree}")
```

```
Best Hyperparameters (Decision Tree): {'max_depth': 5, 'min_samples_leaf': 4,
'min_samples_split': 10}
```

[ ]:
```
best_model_decision_tree = grid_search_decision_tree.best_estimator_
y_pred_decision_tree = best_model_decision_tree.predict(X_test_scaled)
mse_decision_tree = mean_squared_error(y_test, y_pred_decision_tree)
print(f"Mean Square Error (Decision Tree): {mse_decision_tree}")
```

```
Mean Square Error (Decision Tree): 2096.5001361256
```

[ ]:
```
# Random Forest

param_grid_random_forest = {
    'n_estimators': [50, 100, 200],
    'max_depth': [None, 5, 10, 15],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}
```

```python
random_forest = RandomForestRegressor(random_state=42)

grid_search_random_forest = GridSearchCV(estimator=random_forest,␣
↪param_grid=param_grid_random_forest,
                                         scoring='neg_mean_squared_error',␣
↪cv=5, verbose=0, n_jobs=-1)

grid_search_random_forest.fit(X_scaled, y)
```

[ ]:
```
GridSearchCV(cv=5, estimator=RandomForestRegressor(random_state=42), n_jobs=-1,
             param_grid={'max_depth': [None, 5, 10, 15],
                         'min_samples_leaf': [1, 2, 4],
                         'min_samples_split': [2, 5, 10],
                         'n_estimators': [50, 100, 200]},
             scoring='neg_mean_squared_error')
```

[ ]:
```python
best_params_random_forest = grid_search_random_forest.best_params_
print("\nBest Hyperparameters (Random Forest):", best_params_random_forest)
```

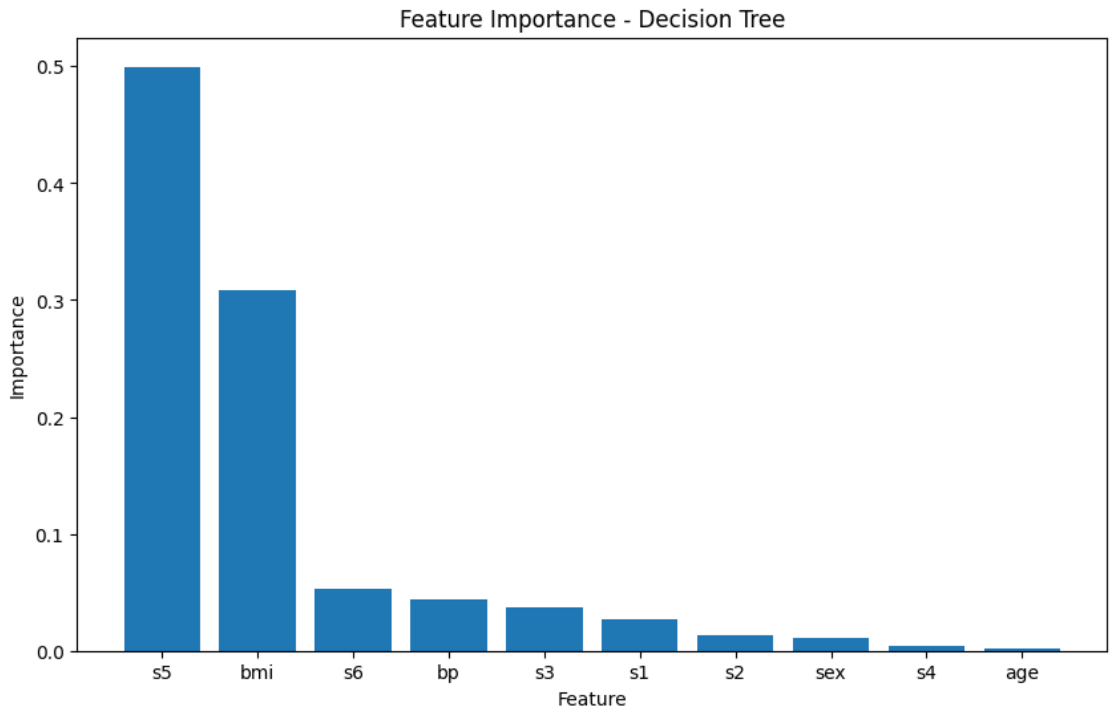
```
Best Hyperparameters (Random Forest): {'max_depth': 10, 'min_samples_leaf': 4,
'min_samples_split': 10, 'n_estimators': 200}
```

[ ]:
```python
best_model_random_forest = grid_search_random_forest.best_estimator_
y_pred_random_forest = best_model_random_forest.predict(X_test_scaled)

mse_random_forest = mean_squared_error(y_test, y_pred_random_forest)
print("Mean Squared Error (Random Forest):", mse_random_forest)
```

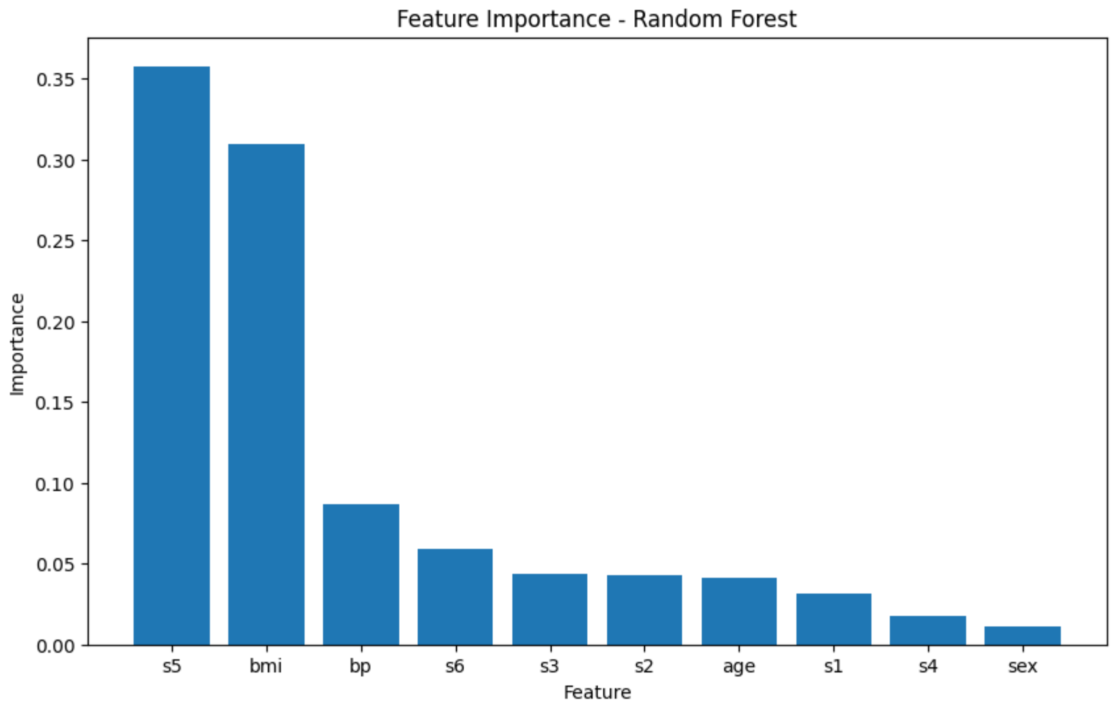
```
Mean Squared Error (Random Forest): 1248.4540709614996
```

7. Visualization

[ ]:
```python
feature_importances = best_model_decision_tree.feature_importances_
sorted_indices = feature_importances.argsort()[::-1]
feature_names = X.columns

plt.figure(figsize=(10, 6))
plt.bar(range(X.shape[1]), feature_importances[sorted_indices], align='center')
plt.xticks(range(X.shape[1]), [feature_names[i]
           for i in sorted_indices])

plt.xlabel('Feature')
plt.ylabel('Importance')
plt.title('Feature Importance - Decision Tree')
plt.show()
```



[ ]:
```
feature_importances = best_model_random_forest.feature_importances_
sorted_indices = feature_importances.argsort()[::-1]
feature_names = X.columns

plt.figure(figsize=(10, 6))
plt.bar(range(X.shape[1]), feature_importances[sorted_indices], align='center')
plt.xticks(range(X.shape[1]), [feature_names[i]
           for i in sorted_indices])

plt.xlabel('Feature')
plt.ylabel('Importance')
plt.title('Feature Importance - Random Forest')
plt.show()
```



[ ]:

[ ]:

[ ]:
```
import numpy as np
import matplotlib.pyplot as plt
```

```
/home/oneautumleaf/.local/lib/python3.10/site-
packages/matplotlib/projections/__init__.py:63: UserWarning: Unable to import
Axes3D. This may be due to multiple versions of Matplotlib being installed (e.g.
as a system package and as a pip package). As a result, the 3D projection is not
available.
  warnings.warn("Unable to import Axes3D. This may be due to multiple versions
of "
```

[ ]:
```
x = np.arange(-10, 10, .1)
y = 1 / (1 + np.exp(-x))
```

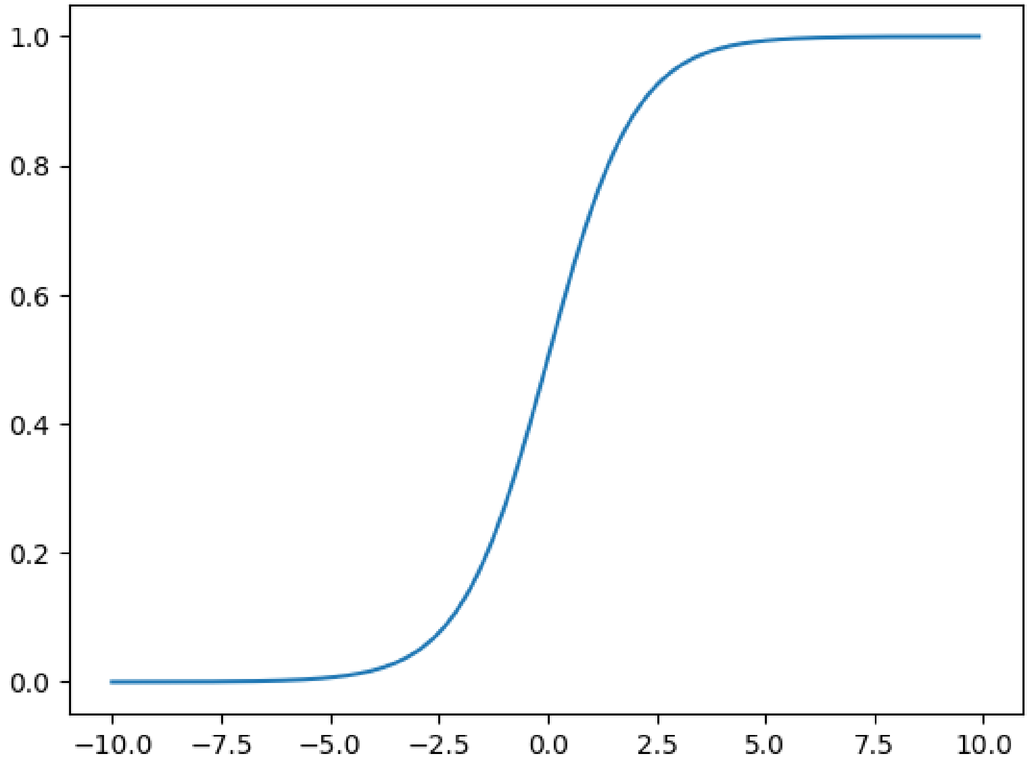
[ ]:
```
x
```

[ ]:
```
array([-1.00000000e+01, -9.90000000e+00, -9.80000000e+00, -9.70000000e+00,
       -9.60000000e+00, -9.50000000e+00, -9.40000000e+00, -9.30000000e+00,
       -9.20000000e+00, -9.10000000e+00, -9.00000000e+00, -8.90000000e+00,
       -8.80000000e+00, -8.70000000e+00, -8.60000000e+00, -8.50000000e+00,
```

```
-8.40000000e+00, -8.30000000e+00, -8.20000000e+00, -8.10000000e+00,
-8.00000000e+00, -7.90000000e+00, -7.80000000e+00, -7.70000000e+00,
-7.60000000e+00, -7.50000000e+00, -7.40000000e+00, -7.30000000e+00,
-7.20000000e+00, -7.10000000e+00, -7.00000000e+00, -6.90000000e+00,
-6.80000000e+00, -6.70000000e+00, -6.60000000e+00, -6.50000000e+00,
-6.40000000e+00, -6.30000000e+00, -6.20000000e+00, -6.10000000e+00,
-6.00000000e+00, -5.90000000e+00, -5.80000000e+00, -5.70000000e+00,
-5.60000000e+00, -5.50000000e+00, -5.40000000e+00, -5.30000000e+00,
-5.20000000e+00, -5.10000000e+00, -5.00000000e+00, -4.90000000e+00,
-4.80000000e+00, -4.70000000e+00, -4.60000000e+00, -4.50000000e+00,
-4.40000000e+00, -4.30000000e+00, -4.20000000e+00, -4.10000000e+00,
-4.00000000e+00, -3.90000000e+00, -3.80000000e+00, -3.70000000e+00,
-3.60000000e+00, -3.50000000e+00, -3.40000000e+00, -3.30000000e+00,
-3.20000000e+00, -3.10000000e+00, -3.00000000e+00, -2.90000000e+00,
-2.80000000e+00, -2.70000000e+00, -2.60000000e+00, -2.50000000e+00,
-2.40000000e+00, -2.30000000e+00, -2.20000000e+00, -2.10000000e+00,
-2.00000000e+00, -1.90000000e+00, -1.80000000e+00, -1.70000000e+00,
-1.60000000e+00, -1.50000000e+00, -1.40000000e+00, -1.30000000e+00,
-1.20000000e+00, -1.10000000e+00, -1.00000000e+00, -9.00000000e-01,
-8.00000000e-01, -7.00000000e-01, -6.00000000e-01, -5.00000000e-01,
-4.00000000e-01, -3.00000000e-01, -2.00000000e-01, -1.00000000e-01,
-3.55271368e-14,  1.00000000e-01,  2.00000000e-01,  3.00000000e-01,
 4.00000000e-01,  5.00000000e-01,  6.00000000e-01,  7.00000000e-01,
 8.00000000e-01,  9.00000000e-01,  1.00000000e+00,  1.10000000e+00,
 1.20000000e+00,  1.30000000e+00,  1.40000000e+00,  1.50000000e+00,
 1.60000000e+00,  1.70000000e+00,  1.80000000e+00,  1.90000000e+00,
 2.00000000e+00,  2.10000000e+00,  2.20000000e+00,  2.30000000e+00,
 2.40000000e+00,  2.50000000e+00,  2.60000000e+00,  2.70000000e+00,
 2.80000000e+00,  2.90000000e+00,  3.00000000e+00,  3.10000000e+00,
 3.20000000e+00,  3.30000000e+00,  3.40000000e+00,  3.50000000e+00,
 3.60000000e+00,  3.70000000e+00,  3.80000000e+00,  3.90000000e+00,
 4.00000000e+00,  4.10000000e+00,  4.20000000e+00,  4.30000000e+00,
 4.40000000e+00,  4.50000000e+00,  4.60000000e+00,  4.70000000e+00,
 4.80000000e+00,  4.90000000e+00,  5.00000000e+00,  5.10000000e+00,
 5.20000000e+00,  5.30000000e+00,  5.40000000e+00,  5.50000000e+00,
 5.60000000e+00,  5.70000000e+00,  5.80000000e+00,  5.90000000e+00,
 6.00000000e+00,  6.10000000e+00,  6.20000000e+00,  6.30000000e+00,
 6.40000000e+00,  6.50000000e+00,  6.60000000e+00,  6.70000000e+00,
 6.80000000e+00,  6.90000000e+00,  7.00000000e+00,  7.10000000e+00,
 7.20000000e+00,  7.30000000e+00,  7.40000000e+00,  7.50000000e+00,
 7.60000000e+00,  7.70000000e+00,  7.80000000e+00,  7.90000000e+00,
 8.00000000e+00,  8.10000000e+00,  8.20000000e+00,  8.30000000e+00,
 8.40000000e+00,  8.50000000e+00,  8.60000000e+00,  8.70000000e+00,
 8.80000000e+00,  8.90000000e+00,  9.00000000e+00,  9.10000000e+00,
 9.20000000e+00,  9.30000000e+00,  9.40000000e+00,  9.50000000e+00,
 9.60000000e+00,  9.70000000e+00,  9.80000000e+00,  9.90000000e+00])
```

[ ]:
```
plt.plot(x, y)
```

[ ]: [<matplotlib.lines.Line2D at 0x73d8669c48e0>]



[ ]:
```

```