## Task 2: Explain your analysis of the code. Make a detailed analysis that can also cover the following questions: (Submit the PDF of the Report)

## Code Analysis:

1. Program for understanding Overfitting and Underfitting
   Firstly, we import all the libraries needed. A true_fun is defined which is a cosine function. Then a random sample is taken and sorted and passed through the true_fun function. Then apply polynomial features and linear regression model to the data. Then pipeline the polynomial features and linear regression. Finally, evaluate the model using cross-validation. Plot the graphs for degree 1, degree 4, and degree 15 using MSE. The function is not sufficient to fit the training samples for degree 1, this is called underfitting. Degree 4 polynomial fits perfectly without underfitting or overfitting. When the degree increases, the model will overfit the training data by learning the noise of the training data. This is called overfitting.

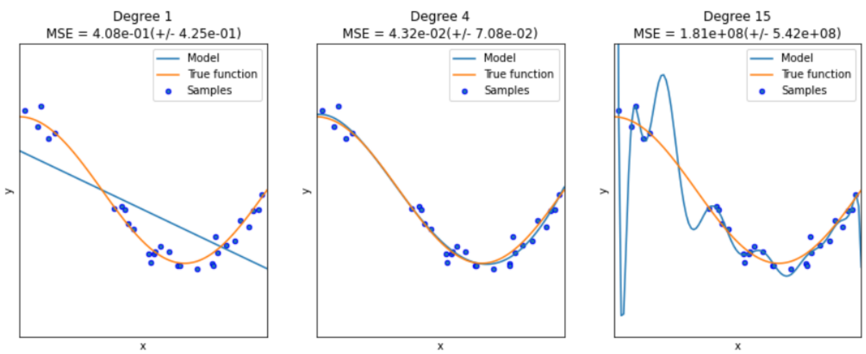
```
[2] import numpy as np
    import matplotlib.pyplot as plt
    from sklearn.pipeline import Pipeline
    from sklearn.preprocessing import PolynomialFeatures
    from sklearn.linear_model import LinearRegression
    from sklearn.model_selection import cross_val_score
```

```
[3] def true_fun(X):
        return np.cos(1.5 * np.pi * X)
```

```
[4] np.random.seed(0)

    n_samples = 30
    degrees = [1, 4, 15]

    X = np.sort(np.random.rand(n_samples))
    y = true_fun(X) + np.random.randn(n_samples) * 0.1
```

```
[5] plt.figure(figsize=(14, 5))
    for i in range(len(degrees)):
        ax = plt.subplot(1, len(degrees), i + 1)
        plt.setp(ax, xticks=(), yticks=())

        polynomial_features = PolynomialFeatures(degree=degrees[i], include_bias=False)
        linear_regression = LinearRegression()
        pipeline = Pipeline(
            [
                ("polynomial_features", polynomial_features),
                ("linear_regression", linear_regression),
            ]
        )
        pipeline.fit(X[:, np.newaxis], y)

        # Evaluate the models using crossvalidation
        scores = cross_val_score(
            pipeline, X[:, np.newaxis], y, scoring="neg_mean_squared_error", cv=10
        )

        X_test = np.linspace(0, 1, 100)
        plt.plot(X_test, pipeline.predict(X_test[:, np.newaxis]), label="Model")
        plt.plot(X_test, true_fun(X_test), label="True function")
        plt.scatter(X, y, edgecolor="b", s=20, label="Samples")
        plt.xlabel("x")
        plt.ylabel("y")
        plt.xlim((0, 1))
        plt.ylim((-2, 2))
        plt.legend(loc="best")
```

```
[5]     plt.title(
            "Degree {}\nMSE = {:.2e}(+/- {:.2e})".format(
                degrees[i], -scores.mean(), scores.std()
            )
        )
    plt.show()
```




2. Overfitting (Printing accuracy at different steps)

Here make_classification function is used for problems with 10000 samples and 20 features. Dataset is split into training and testing data. A decision tree is used as a classifier, tree depth is adjusted. Test and training data are evaluated, and accuracies are printed at different depths. As the tree depth increases the performance increases, and the shallow trees have low performance. That is the reason the shallow trees do not overfit and extremely deeper trees overfit. As shown below, until depth 5 the accuracy of the test set increases, and later it decreases but the accuracy of the training sets increases until the maximum depth, this is called overfitting. This can be solved by decreasing the depth of the tree.

```
[6] # evaluate decision tree performance on train and test sets with different tree depths
    from sklearn.datasets import make_classification
    from sklearn.model_selection import train_test_split
    from sklearn.metrics import accuracy_score
    from sklearn.tree import DecisionTreeClassifier
    from matplotlib import pyplot
```

```
[65] # define dataset
     X, y = make_classification(n_samples=10000, n_features=20, n_informative=5, n_redundant=15, random_state=1)
     # summarize the dataset
     print(X.shape, y.shape)

     (10000, 20) (10000,)
```

```
# split into train test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)
# summarize the shape of the train and test sets
print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)

(7000, 20) (3000, 20) (7000,) (3000,)
```

```
[43] train_scores, test_scores = list(), list()

     # define the tree depths to evaluate
     values = [i for i in range(1, 31)]
```

```python
# evaluate a decision tree for each depth
for i in values:
    # configure the model
    model = DecisionTreeClassifier(max_depth=i)
    # fit model on the training dataset
    model.fit(X_train, y_train)
    # evaluate on the train dataset
    train_yhat = model.predict(X_train)
    train_acc = accuracy_score(y_train, train_yhat)
    train_scores.append(train_acc)
    # evaluate on the test dataset
    test_yhat = model.predict(X_test)
    test_acc = accuracy_score(y_test, test_yhat)
    test_scores.append(test_acc)
    # summarize progress
    print('>%d, train: %.3f, test: %.3f' % (i, train_acc, test_acc))
```

```
>1, train: 0.970, test: 0.970
>2, train: 0.974, test: 0.971
>3, train: 0.975, test: 0.972
>4, train: 0.976, test: 0.969
>5, train: 0.978, test: 0.970
>6, train: 0.980, test: 0.969
>7, train: 0.982, test: 0.967
>8, train: 0.983, test: 0.966
>9, train: 0.986, test: 0.965
>10, train: 0.987, test: 0.963
>11, train: 0.990, test: 0.962
>12, train: 0.992, test: 0.960
>13, train: 0.993, test: 0.962
>14, train: 0.994, test: 0.960
```


```
>14, train: 0.994, test: 0.960
```


```
>15, train: 0.995, test: 0.959
>16, train: 0.997, test: 0.959
>17, train: 0.997, test: 0.959
>18, train: 0.998, test: 0.957
>19, train: 0.999, test: 0.957
>20, train: 0.999, test: 0.956
>21, train: 1.000, test: 0.956
>22, train: 1.000, test: 0.956
>23, train: 1.000, test: 0.955
>24, train: 1.000, test: 0.955
>25, train: 1.000, test: 0.956
>26, train: 1.000, test: 0.957
>27, train: 1.000, test: 0.957
>28, train: 1.000, test: 0.956
>29, train: 1.000, test: 0.955
>30, train: 1.000, test: 0.955
```

3. Cross Validation

   Here, we are using dataset load_iris. We use cross-validation to evaluate overfitting and underfitting.

```python
[45] import numpy as np
     from sklearn.model_selection import train_test_split
     from sklearn import datasets
     from sklearn import svm

     X, y = datasets.load_iris(return_X_y=True)
     X.shape, y.shape
```

```
((150, 4), (150,))
```

Firstly, we use the basic method to compute the score using svm.

Basic method to compute score

```
[46] X_train, X_test, y_train, y_test = train_test_split(
         X, y, test_size=0.4, random_state=0)

     X_train.shape, y_train.shape

     X_test.shape, y_test.shape


     clf = svm.SVC(kernel='linear', C=1).fit(X_train, y_train)
     clf.score(X_test, y_test)
```

```
0.9666666666666667
```

Here, the accuracy is estimated by splitting the data, fitting the model, and evaluating the score 5 times. The score is calculated at each iteration.

Estimate the accuracy by splitting the data, computing the score 5 consecutive times (with different splits each time)

```
[47] from sklearn.model_selection import cross_val_score
     clf = svm.SVC(kernel='linear', C=1, random_state=42)
     scores = cross_val_score(clf, X, y, cv=5)
     scores
```

```
array([0.96666667, 1.        , 0.96666667, 0.96666667, 1.        ])
```

```
[48] print("%0.2f accuracy with a standard deviation of %0.2f" % (scores.mean(), scores.std()))
```

```
0.98 accuracy with a standard deviation of 0.02
```

Here, cross_val_score is used to cross-validate the score.

Using the different scoring parameter

```
[49] from sklearn import metrics

     scores = cross_val_score(clf, X, y, cv=5, scoring='f1_macro')
     scores
```

```
array([0.96658312, 1.        , 0.96658312, 0.96658312, 1.        ])
```

Here, the cross-validate iterator is used to calculate the score.

Calculate cross validation score by passing a cross validation iterator

```
[51] from sklearn.model_selection import ShuffleSplit
     n_samples = X.shape[0]
     cv = ShuffleSplit(n_splits=5, test_size=0.3, random_state=0)
     cross_val_score(clf, X, y, cv=cv)
```

```
array([0.97777778, 0.97777778, 1.        , 0.95555556, 1.        ])
```

Use an iterable yielding (train, test) splits as arrays of indices

```
[52] def custom_cv_2folds(X):
         n = X.shape[0]
         i = 1
         while i <= 2:
             idx = np.arange(n * (i - 1) / 2, n * i / 2, dtype=int)
             yield idx, idx
             i += 1

     custom_cv = custom_cv_2folds(X)
     cross_val_score(clf, X, y, cv=custom_cv)

     array([1.        , 0.97333333])
```

4. Different types of Cross validations: Below are a few cross-validation types.

   K-fold divides all the samples into k groups of samples(folds) of equal sizes. The prediction function is learned using k−1 folds, and the fold left out is used for testing.

K-fold

```
[77] import numpy as np
     from sklearn.model_selection import KFold

     kf = KFold(n_splits=2)
     for train, test in kf.split(X):
         print("%s %s" % (train, test))

     [ 75  76  77  78  79  80  81  82  83  84  85  86  87  88  89  90  91  92
       93  94  95  96  97  98  99 100 101 102 103 104 105 106 107 108 109 110
      111 112 113 114 115 116 117 118 119 120 121 122 123 124 125 126 127 128
      129 130 131 132 133 134 135 136 137 138 139 140 141 142 143 144 145 146
      147 148 149] [ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
      24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47
      48 49 50 51 52 53 54 55 56 57 58 59 60 61 62 63 64 65 66 67 68 69 70 71
      72 73 74]
     [ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
      24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47
      48 49 50 51 52 53 54 55 56 57 58 59 60 61 62 63 64 65 66 67 68 69 70 71
      72 73 74] [ 75  76  77  78  79  80  81  82  83  84  85  86  87  88  89  90  91  92
       93  94  95  96  97  98  99 100 101 102 103 104 105 106 107 108 109 110
      111 112 113 114 115 116 117 118 119 120 121 122 123 124 125 126 127 128
      129 130 131 132 133 134 135 136 137 138 139 140 141 142 143 144 145 146
      147 148 149]
```

Repeated K-fold repeats K-Fold n times. It can be used when one requires to run kfold, n times, producing different splits in each iteration.

### Repeated K-Fold

```
[78] import numpy as np
     from sklearn.model_selection import RepeatedKFold
     random_state = 12883823
     rkf = RepeatedKFold(n_splits=2, n_repeats=2, random_state=random_state)
     for train, test in rkf.split(X):
         print("%s %s" % (train, test))
```

```
[  2   4   5   7   8   9  12  13  14  15  16  18  19  20  27  28  29  30
  31  33  34  36  37  38  40  42  45  46  49  50  51  53  56  59  60  62
  63  68  69  73  74  75  78  80  84  86  87  88  89  91  95  96  97  98
  99 100 102 103 104 105 112 115 116 120 126 129 135 138 139 141 142 143
 144 145 147] [  0   1   3   6  10  11  17  21  22  23  24  25  26  32  35  39  41  43
  44  47  48  52  54  55  57  58  61  64  65  66  67  70  71  72  76  77
  79  81  82  83  85  90  92  93  94 101 106 107 108 109 110 111 113 114
 117 118 119 121 122 123 124 125 127 128 130 131 132 133 134 136 137 140
 146 148 149]
[  0   1   3   6  10  11  17  21  22  23  24  25  26  32  35  39  41  43
  44  47  48  52  54  55  57  58  61  64  65  66  67  70  71  72  76  77
  79  81  82  83  85  90  92  93  94 101 106 107 108 109 110 111 113 114
 117 118 119 121 122 123 124 125 127 128 130 131 132 133 134 136 137 140
 146 148 149] [  2   4   5   7   8   9  12  13  14  15  16  18  19  20  27  28  29  30
  31  33  34  36  37  38  40  42  45  46  49  50  51  53  56  59  60  62
  63  68  69  73  74  75  78  80  84  86  87  88  89  91  95  96  97  98
  99 100 102 103 104 105 112 115 116 120 126 129 135 138 139 141 142 143
 144 145 147]
```

In LOO, learning sets are created by taking all the samples leaving only one, which is the test set.

### Leave One Out (LOO)

```
[79] from sklearn.model_selection import LeaveOneOut

     loo = LeaveOneOut()
     for train, test in loo.split(X):
         print("%s %s" % (train, test))
```

```
  90  91  92  93  94  95  96  97  98  99 100 101 102 103 104 105 106 107
 108 109 110 111 112 113 114 115 116 117 118 119 120 121 122 123 124 125
 126 127 128 129 130 131 132 133 134 135 136 137 138 139 140 141 142 144
 145 146 147 148 149] [143]
[  0   1   2   3   4   5   6   7   8   9  10  11  12  13  14  15  16  17
  18  19  20  21  22  23  24  25  26  27  28  29  30  31  32  33  34  35
  36  37  38  39  40  41  42  43  44  45  46  47  48  49  50  51  52  53
  54  55  56  57  58  59  60  61  62  63  64  65  66  67  68  69  70  71
  72  73  74  75  76  77  78  79  80  81  82  83  84  85  86  87  88  89
  90  91  92  93  94  95  96  97  98  99 100 101 102 103 104 105 106 107
 108 109 110 111 112 113 114 115 116 117 118 119 120 121 122 123 124 125
 126 127 128 129 130 131 132 133 134 135 136 137 138 139 140 141 142 143
 145 146 147 148 149] [144]
[  0   1   2   3   4   5   6   7   8   9  10  11  12  13  14  15  16  17
  18  19  20  21  22  23  24  25  26  27  28  29  30  31  32  33  34  35
  36  37  38  39  40  41  42  43  44  45  46  47  48  49  50  51  52  53
  54  55  56  57  58  59  60  61  62  63  64  65  66  67  68  69  70  71
  72  73  74  75  76  77  78  79  80  81  82  83  84  85  86  87  88  89
  90  91  92  93  94  95  96  97  98  99 100 101 102 103 104 105 106 107
```

LPO creates all the possible training/test sets by removing p samples from the complete set. For n samples, this produces (np) train-test pairs.

### Leave P Out (LPO)

```
from sklearn.model_selection import LeavePOut
lpo = LeavePOut(p=2)
for train, test in lpo.split(X):
  print("%s %s" % (train, test))
```

```
 146 147 148 149] [133 136]
[  0   1   2   3   4   5   6   7   8   9  10  11  12  13  14  15  16  17
  18  19  20  21  22  23  24  25  26  27  28  29  30  31  32  33  34  35
  36  37  38  39  40  41  42  43  44  45  46  47  48  49  50  51  52  53
  54  55  56  57  58  59  60  61  62  63  64  65  66  67  68  69  70  71
  72  73  74  75  76  77  78  79  80  81  82  83  84  85  86  87  88  89
  90  91  92  93  94  95  96  97  98  99 100 101 102 103 104 105 106 107
 108 109 110 111 112 113 114 115 116 117 118 119 120 121 122 123 124 125
 126 127 128 129 130 131 132 134 135 136 138 139 140 141 142 143 144 145
 146 147 148 149] [133 137]
[  0   1   2   3   4   5   6   7   8   9  10  11  12  13  14  15  16  17
  18  19  20  21  22  23  24  25  26  27  28  29  30  31  32  33  34  35
  36  37  38  39  40  41  42  43  44  45  46  47  48  49  50  51  52  53
  54  55  56  57  58  59  60  61  62  63  64  65  66  67  68  69  70  71
  72  73  74  75  76  77  78  79  80  81  82  83  84  85  86  87  88  89
  90  91  92  93  94  95  96  97  98  99 100 101 102 103 104 105 106 107
 108 109 110 111 112 113 114 115 116 117 118 119 120 121 122 123 124 125
 126 127 128 129 130 131 132 134 135 136 137 139 140 141 142 143 144 145
 146 147 148 149] [133 138]
[  0   1   2   3   4   5   6   7   8   9  10  11  12  13  14  15  16  17
  18  19  20  21  22  23  24  25  26  27  28  29  30  31  32  33  34  35
  36  37  38  39  40  41  42  43  44  45  46  47  48  49  50  51  52  53
```

Stratified k-fold is a variation of k-fold which returns stratified folds, each set contains approximately the same percentage of samples of each target class as the complete set.

### Stratified k-fold

```
[81] from sklearn.model_selection import StratifiedKFold, KFold
import numpy as np
skf = StratifiedKFold(n_splits=3)
print("Stratified k-fold")
for train, test in skf.split(X, y):
  print('train -  {}   |   test -  {}'.format(np.bincount(y[train]), np.bincount(y[test])))
print(" k-fold")
kf = KFold(n_splits=3)
for train, test in kf.split(X, y):
  print('train -  {}   |   test -  {}'.format(np.bincount(y[train]), np.bincount(y[test])))
```

```
Stratified k-fold
train -  [33 33 34]   |   test -  [17 17 16]
train -  [33 34 33]   |   test -  [17 16 17]
train -  [34 33 33]   |   test -  [16 17 17]
 k-fold
train -  [ 0 50 50]   |   test -  [50]
train -  [50  0 50]   |   test -  [ 0 50]
train -  [50 50]   |   test -  [ 0  0 50]
```

Stratified Shuffle Split is a variation of Shuffle Split, which returns stratified splits i.e., which creates splits by preserving the same percentage for each target class as in the complete set

Stratified Shuffle split

```
[87] from sklearn.model_selection import StratifiedShuffleSplit
sss = StratifiedShuffleSplit(n_splits=5, test_size=0.5, random_state=0)
sss.get_n_splits(X, y)
print(sss)

StratifiedShuffleSplit(n_splits=5, random_state=0)
for train_index, test_index in sss.split(X, y):
  print("TRAIN:", train_index, "TEST:", test_index)
  X_train, X_test = X[train_index], X[test_index]
  y_train, y_test = y[train_index], y[test_index]
```

```
StratifiedShuffleSplit(n_splits=5, random_state=0, test_size=0.5,
            train_size=None)
TRAIN: [ 16  69  15   4  78 138 111  10  93  45  74  58 106  22  56  28 107  27
  94  72  66  33 143  87  96 115  73  84  26 126  11  91 128 105  79  48
   7 148  31 119  59 124  38  57  95 101  83 137 112  52  92  30  63  42
  14 108 125 122 141  32 140  35  76  41   2  18 146 135 127 116  80  29
 104  82  34] TEST: [139  65 145   6 129  25  85  23 118  64  17 121  71  39  67  36 131 149
  24   0  89   8 136 110 132 147 117   9 130  75 134 144  97 114  19  43
  49  21  50  86  37  20  61  81   5 123  44  99  77 102  98   3 142  40
  88  60  12 103  53 109  90 133  70 100  13  47  54   1  51  68 113  62
 120  46  55]
```

```
[87] TRAIN: [  7  10 141   6  94  31 113 140 108  11 128  96 149 110  98   4 101  44
   5   2 144 102 112  86  41  20  59 118 148 115  99 132  88  57 105 103
  83  45 138  62  74  81  52  13 114  67  40  47  82  33 106  38  18 135
  63  75  79  37  55  72  70 111  95 142  15  64 121  19  91  42  26 126
  12   1  69] TEST: [120  78  29  46  58 134 125  25  53  48  51 104 146 123  54 131   9  68
  35 139  50  43 147 145  73 130  32   3  77 127  24 109  16  87  71  56
  93   0 124  14  23  66 100  27  89 137  76  17 133 116  34 136   8  22
  36  30  39  60 122  65 129  28  97  85 119  21  92 117  80  90  49 143
  84 107  61]
TRAIN: [131  76 116 145 114  18   4  95  52  61  94  87  29 103 142   9   0  65
  45  46  81 121  88  44  24  32  28  56 122  89  71  90  77  72 115  60
  78  85  49  58  41 129  91 117 127  69 107  99 113  11  33  74 119  34
 105 147 102   3 101  30 111 100 106 109   2  19  23  51  40 143  15  97
  20  38 123] TEST: [130  17 125 124  53  43  62  86  79  80  31 137  55  36  42  64 141   8
   5  82  98  84  10 134  83   7 135  27  50  48  12 132  35  16 133 139
  59 140 136  63  93  73 148 108   1 138 110  66  68  21 128  96  70  13
  26  92 126  39  54  22  75  37 149  67   6 118  25  57 104 144 120  47
 112 146  14]
TRAIN: [138 137 136 139  82  64  27  21   3  99   9  33  30 149 100  72  47 145
  50  40  96  79  97 140 109 134   7 142  92 133 112  58  45  42 131  32
   4  66  60 118 110  95  10  13  75  12  38  57  44  77  41  20  83  51
  81 130  73 101 117  18  28  91  89  62 125  68 106 148 143  78  36  34
 120 108   2] TEST: [ 23 123  26   1  37 102  15 113  25  90  31 124 147  22 111 105  71  86
 146  56 128  24  69  88 126 121 122  61   0  43  87 141 144 119  19 127
  49  17  65   5  46  85 135  76  16  67  52  14 103  11   6  55  93  94
 116  53  74  70  84 104 115  39 132 129  54  63  35  48 114  80  29   8
  98 107  59]
TRAIN: [ 65  30  56  92 131  37 149  49  57  38  99 125  19  24 134  55   1  68
 115 109  81  36 146 108  35 132 128   6  48  54  59  14  43  88 114  22
  26  73  84   3  85 121  47  72 100 138  82 130  39 106 141 140  76 113
 139  78 111  93 101  10  21  44  41 148  58  15  89 133  80  61 137  75
   2  18  97] TEST: [ 31 126  33  71 145 102   7  29  60  40  45  74 123  51  50 136  96 144
```

5. Validation Curve

The influence of a single hyperparameter on the training score and the validation score is used to find out if the estimator is overfitting or underfitting for some hyperparameter values. If the training score and the validation score are both low, the estimator will be underfitting. If the training score is high and the validation score is low, the estimator is overfitting.

Here, the train and test data CSV files are trained using a random forest classifier and data is fit, then used to draw a validation curve.

[58]
```python
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt

from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import cross_val_score, learning_curve, validation_curve
```

[59]
```python
df_train = pd.read_csv('train.csv')
df_test = pd.read_csv('test.csv')
df_comb = df_train.append(df_test)

X = pd.DataFrame()
```

[60]
```python
def encode_sex(x):
    return 1 if x == 'female' else 0

def family_size(x):
    size = x.SibSp + x.Parch
    return 4 if size > 3 else size

X['Sex'] = df_comb.Sex.map(encode_sex)
X['Pclass'] = df_comb.Pclass
X['FamilySize'] = df_comb.apply(family_size, axis=1)
```

[61]
```python
fare_median = df_train.groupby(['Sex', 'Pclass']).Fare.median()
fare_median.name = 'FareMedian'

age_mean = df_train.groupby(['Sex', 'Pclass']).Age.mean()
age_mean.name = 'AgeMean'

def join(df, stat):
    return pd.merge(df, stat.to_frame(), left_on=['Sex', 'Pclass'], right_index=True, how='left')

X['Fare'] = df_comb.Fare.fillna(join(df_comb, fare_median).FareMedian)
X['Age'] = df_comb.Age.fillna(join(df_comb, age_mean).AgeMean)
```

[62]
```python
def quantiles(series, num):
    return pd.qcut(series, num, retbins=True)[1]

def discretize(series, bins):
    return pd.cut(series, bins, labels=range(len(bins)-1), include_lowest=True)

X['Fare'] = discretize(X.Fare, quantiles(df_comb.Fare, 10))
X['Age'] = discretize(X.Age, quantiles(df_comb.Age, 10))
```

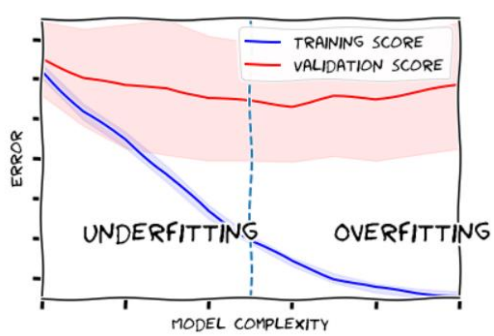
[31]
```python
X_train = X.iloc[:df_train.shape[0]]
X_test = X.iloc[df_train.shape[0]:]

y_train = df_train.Survived
```

[33]
```python
clf_1 = RandomForestClassifier(n_estimators=100, bootstrap=True, random_state=0)
clf_1.fit(X_train, y_train)
# Number of folds for cross validation
num_folds = 7
```

```python
[34] def plot_curve(ticks, train_scores, test_scores):
         train_scores_mean = -1 * np.mean(train_scores, axis=1)
         train_scores_std = -1 * np.std(train_scores, axis=1)
         test_scores_mean = -1 * np.mean(test_scores, axis=1)
         test_scores_std = -1 * np.std(test_scores, axis=1)

         plt.figure()
         plt.fill_between(ticks,
                          train_scores_mean - train_scores_std,
                          train_scores_mean + train_scores_std, alpha=0.1, color="b")
         plt.fill_between(ticks,
                          test_scores_mean - test_scores_std,
                          test_scores_mean + test_scores_std, alpha=0.1, color="r")
         plt.plot(ticks, train_scores_mean, 'b-', label='Training score')
         plt.plot(ticks, test_scores_mean, 'r-', label='Validation score')
         plt.legend(fancybox=True, facecolor='w')

         return plt.gca()
```

```python
[35] def plot_validation_curve(clf, X, y, param_name, param_range, scoring='roc_auc'):
         plt.xkcd()
         ax = plot_curve(param_range, *validation_curve(clf, X, y, cv=num_folds,
                                                        scoring=scoring,
                                                        param_name=param_name,
                                                        param_range=param_range, n_jobs=-1))
         ax.set_title('')
         ax.set_xticklabels([])
         ax.set_yticklabels([])
         ax.set_xlim(2,12)
         ax.set_ylim(-0.97, -0.83)
         ax.set_ylabel('Error')
         ax.set_xlabel('Model complexity')
         ax.text(9, -0.94, 'Overfitting', fontsize=22)
         ax.text(3, -0.94, 'Underfitting', fontsize=22)
         ax.axvline(7, ls='--')
         plt.tight_layout()
```

```python
[36] plot_validation_curve(clf_1, X_train, y_train, param_name='max_depth', param_range=range(2,13))
```




6. ROC

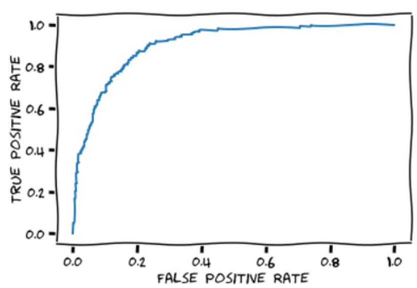
The two main metrics of true positive rate and two negative rates are visualized using a ROC.
Data is fetched from the GitHub URL; a logical regression model is used, and data is fit. The metrics are defined, and the ROC curve is drawn. If the curve touches the top left corner of the plot, the model is considered better at classifying the data into categories.

```
[37] import pandas as pd
     import numpy as np
     from sklearn.model_selection import train_test_split
     from sklearn.linear_model import LogisticRegression
     from sklearn import metrics
     import matplotlib.pyplot as plt
```

```
[38] #import dataset from CSV file on Github
     url = "https://raw.githubusercontent.com/Statology/Python-Guides/main/default.csv"
     data = pd.read_csv(url)

     #define the predictor variables and the response variable
     X = data[['student', 'balance', 'income']]
     y = data['default']

     #split the dataset into training (70%) and testing (30%) sets
     X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.3,random_state=0)

     #instantiate the model
     log_regression = LogisticRegression()

     #fit the model using the training data
     log_regression.fit(X_train,y_train)
```

```
LogisticRegression()
```

```
[39] #define metrics
     y_pred_proba = log_regression.predict_proba(X_test)[::,1]
     fpr, tpr, _ = metrics.roc_curve(y_test,  y_pred_proba)

     #create ROC curve
     plt.plot(fpr,tpr)
     plt.ylabel('True Positive Rate')
     plt.xlabel('False Positive Rate')
     plt.show()
```




1) According to you, why do overfitting and underfitting occur, and how resolve them? What is the difference between them?

When the model tries to capture the relation between the input and target values very efficiently leading to the memorization of the data, the model does not perform well on the testing data but performs well on the training data.

When the model performs poorly on training data, it is called underfitting. This is because the model is unable to capture the relationship between the input examples and the target values.

There are a few common ways to control the overfitting of data i.e., by Adding more data, data augmentation, regularization, and removing features from the data. In the code, we have regulated the depth of the decision tree to control overfitting. Or for the KNN classifier, we can change the neighbor number to control overfitting.

The underfitting problem can be solved by increasing the model complexity, reducing regularization, and adding features to training data.

A model that is under fitted will have high training and high testing error while an overfit model will have extremely low training error but a high testing error.

2) What kind of pattern did you analyze in the Train and Test score while running the code of overfitting?

   Test and training data are evaluated, and accuracies are printed at different depths. As the tree depth increases the performance increases, and the shallow trees have low performance. That is the reason why the shallow trees do not overfit and extremely deeper trees overfit, until depth 5 the accuracy of the test set increases, and later it decreases but the accuracy of the training sets increases until the maximum depth, this is called overfitting. This can be solved by decreasing the depth of the tree.

3) What is cross-validation, and what did you analyze in a different type of validation that you performed?

   To avoid overfitting, sometimes available data is divided into three parts training, testing, and validation data, as the size of the samples used for learning decreases, the results depend on a particular random pair of training and validation data, to solve this problem cross-validation is used.

   - K-fold divides all the samples into k groups of samples(folds) of equal sizes. The prediction function is learned using k−1 folds, and the fold left out is used for testing.
   - Repeated K-fold repeats K-Fold n times. It can be used when one requires to run kfold, n times, producing different splits in each iteration.
   - In LOO, learning sets are created by taking all the samples leaving only one, which is the test set.
   - LPO creates all the possible training/test sets by removing p samples from the complete set. For n samples, this produces (np) train-test pairs.
   - Stratified k-fold is a variation of k-fold which returns stratified folds, each set contains the same percentage of samples of each target class as the complete set.
   - Stratified Shuffle Split is a variation of Shuffle Split, which returns stratified splits i.e., which creates splits by preserving the same percentage for each target class as in the complete set.

4) Explain the analysis from generated ROC and validation curve and what they represent?

   Validation Curve:

To estimate the generalization accurately we must compute the score on another test set. If the training score and the validation score are both low, the estimator will be underfitting. If the training score is high and the validation score is low, the estimator is overfitting and otherwise, it is working very well. A low training score and a high validation score are usually not possible.

ROC Curve:

The two main metrics, true positive rate, and true negative rates are visualized using a ROC. If the curve touches the top left corner of the plot, the model is considered better at classifying the data into categories.