

**COMSATS University Islamabad,
Lahore Campus**



Assignment-4

Course Title: Introduction to Data Science
Course Code: CSC461

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Group: IV

Semester: 6th

Program Name: Bachelor of Computer Science

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Q1: Provide responses to the following questions about the dataset.

1. How many instances does the dataset contain?

There are 80 instances in the data set. As we can see, after running it shows 80 rows.

```
In [5]: df = pd.read_csv(r'C:\Users\hp\Downloads\gender-prediction.csv')
print(df)
```

	height	weight	beard	hair_length	shoe_size	scarf	eye_color	gender
0	71	176	yes	short	44	no	black	male
1	68	165	no	bald	41	no	black	male
2	62	132	no	medium	37	yes	blue	female
3	65	138	no	long	38	no	gray	female
4	70	197	yes	medium	43	no	gray	male
..
75	65	99	no	short	39	yes	green	female
76	61	98	no	short	37	no	brown	female
77	67	119	yes	short	40	no	black	male
78	70	190	yes	medium	43	no	gray	male
79	62	142	yes	long	37	no	blue	female

[80 rows x 8 columns]

2. How many input attributes does the dataset contain?

There are 7 input attributes:

- height
- weight
- beard
- hair_length
- shoe_size
- scarf
- eye_color

3. How many possible values does the output attribute have?

There are two possible values of output attribute “gender”, which are:

- Male
- Female

These are encoded as 0 and 1

4. How many input attributes are categorical?

There are four categorical input attributes:

- beard
- hair_length
- scarf
- eye_color

5. What is the class ratio (male vs female) in the dataset?

There are 46 male and 34 female and the ratio of male vs female is 23:17.

Q2: Apply Random Forest, Support Vector Machines, and Multilayer Perceptron classification algorithms (using Python) on the gender prediction dataset with standard train/test split ratio and answer the following questions.

1. How many instances are incorrectly classified?

In Random Forest classifier:

```
model_cm = metrics.confusion_matrix(Y_test, prediction)
print("The confusion matrix is:\n",model_cm)
```

The confusion matrix is:

```
[[10  0]
 [ 0 17]]
```

There are zero incorrect classified instances.

In **Support Vector machine**:

```
: model_cm = metrics.confusion_matrix(Y_test, prediction)
print("The confusion matrix is:\n",model_cm)
```

The confusion matrix is:

```
[[ 7  3]
 [ 3 14]]
```

There are six incorrect classified instances.

In **Multilayer Perceptron classification**:

```
In [35]: model_cm = metrics.confusion_matrix(Y_test, prediction)
print("The confusion matrix is:\n",model_cm)
```

The confusion matrix is:

```
[[ 0 11]
 [ 0 16]]
```

There are eleven incorrect classified instances.

2. **Rerun the experiment using train/test split ratio of 80/20. Do you see any change in the results? Explain.**

Yes, there are changes in the experiment:

Random Forest:

67/33					80/20				
Confusion Matrix:					Confusion Matrix:				
[[10 0]					[[6 0]				
[0 17]]					[0 10]]				
Classification Report:					Classification Matrix:				
	precision	recall	f1-score	support		precision	recall	f1-score	support
0	1.00	1.00	1.00	10	0	1.00	1.00	1.00	6
1	1.00	1.00	1.00	17	1	1.00	1.00	1.00	10
accuracy			1.00	27	accuracy			1.00	16
macro avg	1.00	1.00	1.00	27	macro avg	1.00	1.00	1.00	16
weighted avg	1.00	1.00	1.00	27	weighted avg	1.00	1.00	1.00	16

SVC:

67/33	80/20
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Confusion Matrix: [[7 3] [3 14]]	Confusion Matrix: [[4 2] [1 9]]																																																												
Classification Report: <table><tr><td></td><td>precision</td><td>recall</td><td>f1-score</td><td>support</td></tr><tr><td>0</td><td>0.70</td><td>0.70</td><td>0.70</td><td>10</td></tr><tr><td>1</td><td>0.82</td><td>0.82</td><td>0.82</td><td>17</td></tr><tr><td>accuracy</td><td></td><td></td><td>0.78</td><td>27</td></tr><tr><td>macro avg</td><td>0.76</td><td>0.76</td><td>0.76</td><td>27</td></tr><tr><td>weighted avg</td><td>0.78</td><td>0.78</td><td>0.78</td><td>27</td></tr></table>		precision	recall	f1-score	support	0	0.70	0.70	0.70	10	1	0.82	0.82	0.82	17	accuracy			0.78	27	macro avg	0.76	0.76	0.76	27	weighted avg	0.78	0.78	0.78	27	Classification Report: <table><tr><td></td><td>precision</td><td>recall</td><td>f1-score</td><td>support</td></tr><tr><td>0</td><td>0.80</td><td>0.67</td><td>0.73</td><td>6</td></tr><tr><td>1</td><td>0.82</td><td>0.90</td><td>0.86</td><td>10</td></tr><tr><td>accuracy</td><td></td><td></td><td>0.81</td><td>16</td></tr><tr><td>macro avg</td><td>0.81</td><td>0.78</td><td>0.79</td><td>16</td></tr><tr><td>weighted avg</td><td>0.81</td><td>0.81</td><td>0.81</td><td>16</td></tr></table>		precision	recall	f1-score	support	0	0.80	0.67	0.73	6	1	0.82	0.90	0.86	10	accuracy			0.81	16	macro avg	0.81	0.78	0.79	16	weighted avg	0.81	0.81	0.81	16
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MLP:

67/33					80/20				
Confusion Matrix: [[8 4] [0 15]]					Confusion Matrix: [[6 0] [0 10]]				
Classification Report:					Classification Report:				
	precision	recall	f1-score	support		precision	recall	f1-score	support
0	1.00	0.67	0.80	12	0	1.00	1.00	1.00	6
1	0.79	1.00	0.88	15	1	1.00	1.00	1.00	10
accuracy			0.85	27	accuracy			1.00	16
macro avg	0.89	0.83	0.84	27	macro avg	1.00	1.00	1.00	16
weighted avg	0.88	0.85	0.85	27	weighted avg	1.00	1.00	1.00	16

3. Name 2 attributes that you believe are the most “powerful” in the prediction task. Explain why?

According to me, beard and scarf are the most powerful instances. Because if Beard= yes, then gender = male, and if scarf=yes, then gender=female. There are no instance in which Beard= yes, then gender = female and if scarf=yes, then gender=male.

4. Try to exclude these 2 attribute(s) from the dataset. Rerun the experiment (using 80/20 train/test split), did you find any change in the results? Explain.

No, there is no change.

Random Forest:

Before	After
Confusion Matrix: <pre>[[6 0] [0 10]]</pre>	Confusion Matrix: <pre>[[6 0] [0 10]]</pre>

Classification Report:					Classification Report:				
	precision	recall	f1-score	support		precision	recall	f1-score	support
0	1.00	1.00	1.00	6	0	1.00	1.00	1.00	6
1	1.00	1.00	1.00	10	1	1.00	1.00	1.00	10
accuracy			1.00	16	accuracy			1.00	16
macro avg	1.00	1.00	1.00	16	macro avg	1.00	1.00	1.00	16
weighted avg	1.00	1.00	1.00	16	weighted avg	1.00	1.00	1.00	16

SVC:

Before					After				
Confusion Matrix: <pre>[[4 2] [1 9]]</pre>					Confusion Matrix: <pre>[[4 2] [1 9]]</pre>				
Classification Report:					Classification Report:				
	precision	recall	f1-score	support		precision	recall	f1-score	support
0	0.80	0.67	0.73	6	0	0.80	0.67	0.73	6
1	0.82	0.90	0.86	10	1	0.82	0.90	0.86	10
accuracy			0.81	16	accuracy			0.81	16
macro avg	0.81	0.78	0.79	16	macro avg	0.81	0.78	0.79	16
weighted avg	0.81	0.81	0.81	16	weighted avg	0.81	0.81	0.81	16

MLP:

Before					After				
Confusion Matrix: <pre>[[6 0] [0 10]]</pre>					Confusion Matrix: <pre>[[6 0] [0 10]]</pre>				
Classification Report					Classification Report:				
	precision	recall	f1-score	support		precision	recall	f1-score	support
0	1.00	1.00	1.00	6	0	1.00	1.00	1.00	6
1	1.00	1.00	1.00	10	1	1.00	1.00	1.00	10
accuracy			1.00	16	accuracy			1.00	16
macro avg	1.00	1.00	1.00	16	macro avg	1.00	1.00	1.00	16
weighted avg	1.00	1.00	1.00	16	weighted avg	1.00	1.00	1.00	16

Q3: Apply Decision Tree Classifier classification algorithm (using Python) on the gender prediction dataset with Monte Carlo cross-validation and Leave P-Out cross-validation. Report F1 score for both cross-validation strategies.

Note: You are free to choose any parameter values for both cross-validation strategies, however, you have to provide these values in your submission document.

(On Notebook)

Q4: Add 5 sample instances into the dataset (you can ask your friends/relatives/sibling for the data). Rerun the ML experiment (using Python) by training the model using Gaussian Naïve Bayes

classification algorithm and all the instances from the gender prediction dataset. Evaluate the trained model using the newly added test instances. Report accuracy, precision, and recall scores.

Note: You have to add the test instances in your assignment submission document

```
In [144]: model_cm = metrics.confusion_matrix(Y_test, prediction)
print("The confusion matrix is:\n",model_cm)
```

```
The confusion matrix is:
[[10  1]
 [ 0 18]]
```

```
In [145]: model_cl_rep = metrics.classification_report(Y_test, prediction)
print(model_cl_rep)
```

	precision	recall	f1-score	support
0	1.00	0.91	0.95	11
1	0.95	1.00	0.97	18
accuracy			0.97	29
macro avg	0.97	0.95	0.96	29
weighted avg	0.97	0.97	0.97	29

```
In [147]: model_acc = accuracy_score(Y_test, prediction)*100
print("Accuracy score of the model is:",model_acc)
```

```
Accuracy score of the model is: 96.55172413793103
```