

gender-recognition

May 19, 2022

1 Gender Recognition by Voice Machine Learning SVM

```
[2]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from plotly.offline import init_notebook_mode, iplot
init_notebook_mode(connected=True)
```

1.0.1 Reading Data

```
[3]: df=pd.read_csv("voice.csv")
```

```
[4]: df.sample(5)
```

```
[4]:
```

	meanfreq	sd	median	Q25	Q75	IQR	skew	\
1841	0.179750	0.034082	0.174082	0.167790	0.187016	0.019226	4.997551	
2522	0.203236	0.038226	0.195420	0.182460	0.231912	0.049452	2.764458	
558	0.111337	0.075083	0.095585	0.047542	0.172154	0.124611	1.792152	
2471	0.151091	0.066940	0.147940	0.099045	0.212299	0.113254	1.047134	
1122	0.186150	0.055903	0.189562	0.142044	0.235547	0.093504	0.851722	

	kurt	sp.ent	sfm	...	centroid	meanfun	minfun	\
1841	34.136764	0.800227	0.223223	...	0.179750	0.164371	0.015702	
2522	13.374830	0.870564	0.240827	...	0.203236	0.168331	0.046921	
558	8.022700	0.962835	0.735872	...	0.111337	0.084689	0.015671	
2471	6.083770	0.970128	0.725125	...	0.151091	0.179934	0.048436	
1122	2.900995	0.924422	0.444776	...	0.186150	0.128891	0.047291	

	maxfun	meandom	mindom	maxdom	dfrange	modindx	label
1841	0.225352	0.898828	0.164062	6.625000	6.460938	0.139258	female
2522	0.277457	1.474051	0.023438	8.039062	8.015625	0.136739	female
558	0.192771	0.195312	0.007812	0.734375	0.726562	0.247909	male
2471	0.279070	1.493304	0.023438	7.804688	7.781250	0.103473	female
1122	0.275862	1.298564	0.023438	8.929688	8.906250	0.165461	male

[5 rows x 21 columns]

```
[5]: df.info()
```

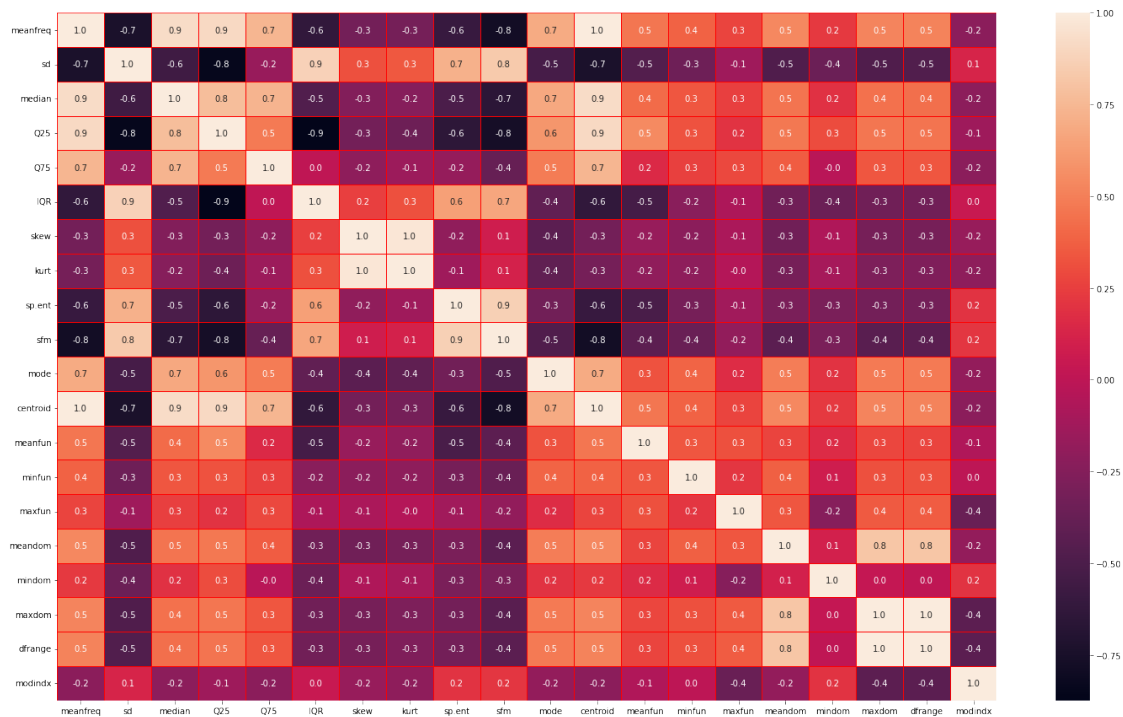
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3168 entries, 0 to 3167
Data columns (total 21 columns):
#   Column      Non-Null Count  Dtype
---  -
0   meanfreq    3168 non-null   float64
1   sd          3168 non-null   float64
2   median      3168 non-null   float64
3   Q25         3168 non-null   float64
4   Q75         3168 non-null   float64
5   IQR         3168 non-null   float64
6   skew        3168 non-null   float64
7   kurt        3168 non-null   float64
8   sp.ent      3168 non-null   float64
9   sfm         3168 non-null   float64
10  mode        3168 non-null   float64
11  centroid    3168 non-null   float64
12  meanfun     3168 non-null   float64
13  minfun      3168 non-null   float64
14  maxfun      3168 non-null   float64
15  meandom     3168 non-null   float64
16  mindom      3168 non-null   float64
17  maxdom      3168 non-null   float64
18  dfrange     3168 non-null   float64
19  modindx     3168 non-null   float64
20  label       3168 non-null   object
dtypes: float64(20), object(1)
memory usage: 519.9+ KB
```

2 Seaborn - Heatmap

2.0.1 Relationship between columns

- 01 -> Direct proportion
- 00 -> No relationship
- -1 -> Inverse proportion

```
[7]: f,ax = plt.subplots(figsize=(25, 15))
sns.heatmap(df.corr(), annot=True, linewidths=0.5, linecolor="red", fmt= '.
↪1f',ax=ax)
plt.show()
```



3 Separating Features and Labels

```
[8]: X=df.iloc[:, :-1]
X.head()
```

```
[8]:
```

	meanfreq	sd	median	Q25	Q75	IQR	skew \
0	0.059781	0.064241	0.032027	0.015071	0.090193	0.075122	12.863462
1	0.066009	0.067310	0.040229	0.019414	0.092666	0.073252	22.423285
2	0.077316	0.083829	0.036718	0.008701	0.131908	0.123207	30.757155
3	0.151228	0.072111	0.158011	0.096582	0.207955	0.111374	1.232831
4	0.135120	0.079146	0.124656	0.078720	0.206045	0.127325	1.101174

	kurt	sp.ent	sfm	mode	centroid	meanfun	minfun \
0	274.402906	0.893369	0.491918	0.000000	0.059781	0.084279	0.015702
1	634.613855	0.892193	0.513724	0.000000	0.066009	0.107937	0.015826
2	1024.927705	0.846389	0.478905	0.000000	0.077316	0.098706	0.015656
3	4.177296	0.963322	0.727232	0.083878	0.151228	0.088965	0.017798
4	4.333713	0.971955	0.783568	0.104261	0.135120	0.106398	0.016931

	maxfun	meandom	mindom	maxdom	dfrange	modindx
0	0.275862	0.007812	0.007812	0.007812	0.000000	0.000000
1	0.250000	0.009014	0.007812	0.054688	0.046875	0.052632
2	0.271186	0.007990	0.007812	0.015625	0.007812	0.046512

```
3  0.250000  0.201497  0.007812  0.562500  0.554688  0.247119
4  0.266667  0.712812  0.007812  5.484375  5.476562  0.208274
```

4 Converting String Value To int Type for Labels

4.0.1 Encode label category

- Male -> 1
- Female -> 0

```
[9]: df.label.unique()
```

```
[9]: array(['male', 'female'], dtype=object)
```

```
[10]: from sklearn.preprocessing import LabelEncoder
      y=df.iloc[:,-1]

      encoder = LabelEncoder()
      y = encoder.fit_transform(y)
      print(y)
```

```
[1 1 1 ... 0 0 0]
```

5 Data Standardisation

```
[11]: from sklearn.preprocessing import StandardScaler
      scaler = StandardScaler()
      scaler.fit(X)
      X = scaler.transform(X)
```

6 Splitting Dataset into Training Set and Testing Set

```
[12]: from sklearn.model_selection import train_test_split
      X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
      ↪random_state=1)
```

7 Build SVM Model with Default Hyperparameter

```
[13]: from sklearn.svm import SVC
      from sklearn import metrics
      svc=SVC() #Default hyperparameters
      svc.fit(X_train,y_train)
      y_pred=svc.predict(X_test)
```

8 Accuracy Score

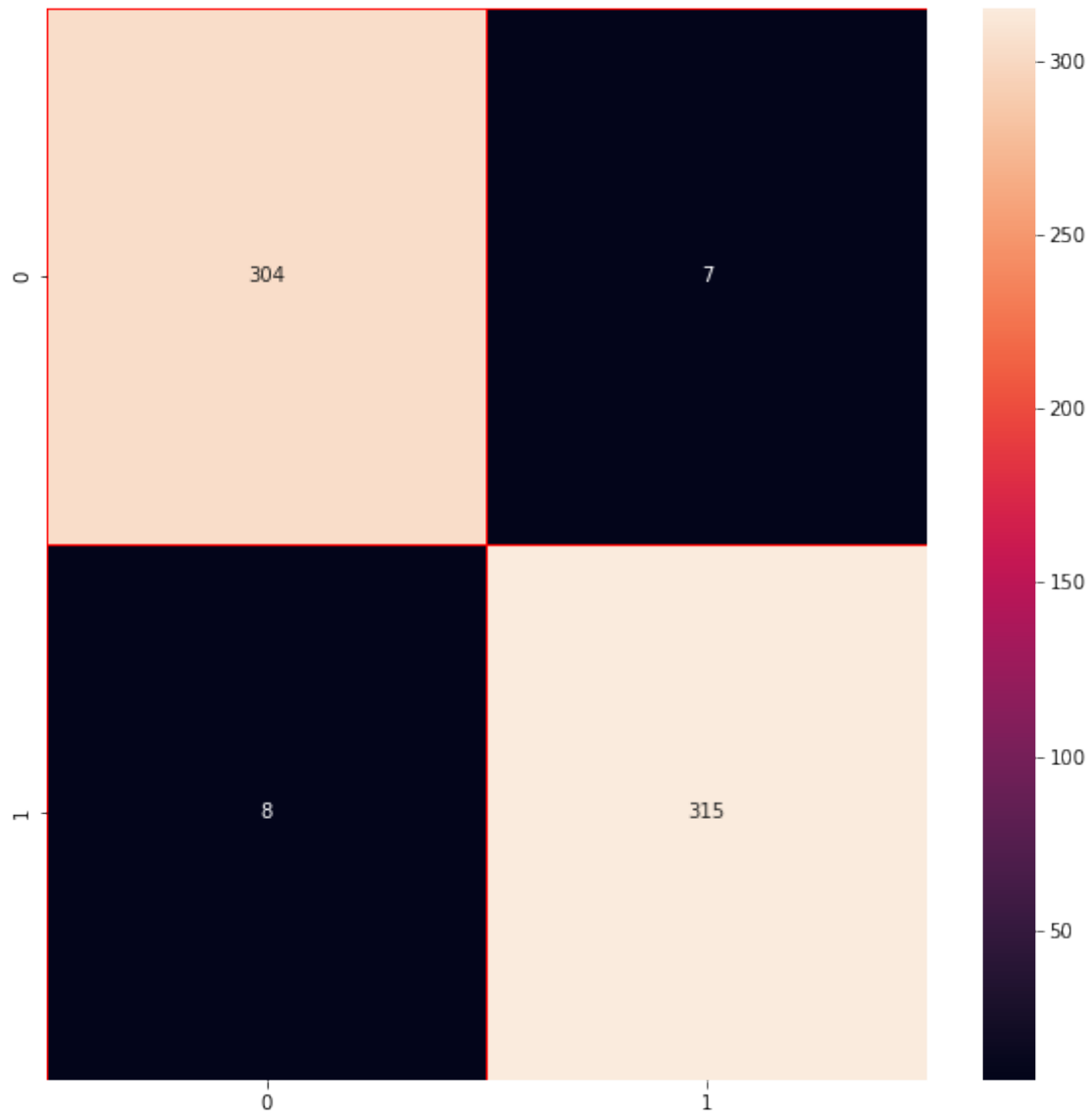
```
[14]: print('Accuracy Score:')  
      print(metrics.accuracy_score(y_test,y_pred))
```

Accuracy Score:
0.9763406940063092

9 Confusion Matrix with Seaborn - Heatmap

- Male -> 1
- Female -> 0

```
[15]: from sklearn.metrics import confusion_matrix  
      cm = confusion_matrix(y_test, y_pred)  
      f,ax = plt.subplots(figsize=(10, 10))  
      sns.heatmap(cm, annot=True, linewidths=0.5, linecolor="red", fmt= '.0f',ax=ax)  
      plt.show()  
      plt.savefig('ConfusionMatrix.png')
```



<Figure size 432x288 with 0 Axes>

10 F1 Score

```
[16]: from sklearn.metrics import f1_score
f1_score = f1_score(y_test, y_pred)
print("F1 Score:")
print(f1_score)
```

F1 Score:
0.9767441860465117

11 Thank You

If you have any suggestion or advice or feedback, I will be very appreciated to hear them.

[]: