

# HW5\_Myunghee\_ID\_2446752777

March 27, 2019

## 1 HW5, Myunghee Lee (USC ID: 2446752777)

### 1. Multi-class and Multi-Label Classification Using Support Vector Machines

(a) Choose 70% of the data randomly as the training set.

```
In [1]: import pandas as pd
        from sklearn.model_selection import train_test_split # to divide training and test data

        df = pd.read_csv("Frogs_MFCCs.csv")
        print(df)
```

|    | MFCCs_ 1 | MFCCs_ 2 | MFCCs_ 3  | MFCCs_ 4  | MFCCs_ 5 | MFCCs_ 6 | MFCCs_ 7  | \ |
|----|----------|----------|-----------|-----------|----------|----------|-----------|---|
| 0  | 1.0      | 0.152936 | -0.105586 | 0.200722  | 0.317201 | 0.260764 | 0.100945  |   |
| 1  | 1.0      | 0.171534 | -0.098975 | 0.268425  | 0.338672 | 0.268353 | 0.060835  |   |
| 2  | 1.0      | 0.152317 | -0.082973 | 0.287128  | 0.276014 | 0.189867 | 0.008714  |   |
| 3  | 1.0      | 0.224392 | 0.118985  | 0.329432  | 0.372088 | 0.361005 | 0.015501  |   |
| 4  | 1.0      | 0.087817 | -0.068345 | 0.306967  | 0.330923 | 0.249144 | 0.006884  |   |
| 5  | 1.0      | 0.099704 | -0.033408 | 0.349895  | 0.344535 | 0.247569 | 0.022407  |   |
| 6  | 1.0      | 0.021676 | -0.062075 | 0.318229  | 0.380439 | 0.179043 | -0.041667 |   |
| 7  | 1.0      | 0.145130 | -0.033660 | 0.284166  | 0.279537 | 0.175211 | 0.005791  |   |
| 8  | 1.0      | 0.271326 | 0.027777  | 0.375738  | 0.385432 | 0.272457 | 0.098192  |   |
| 9  | 1.0      | 0.120565 | -0.107235 | 0.316555  | 0.364437 | 0.307757 | 0.025992  |   |
| 10 | 1.0      | 0.148539 | -0.096910 | 0.257523  | 0.260881 | 0.312603 | 0.134134  |   |
| 11 | 1.0      | 0.277948 | 0.091657  | 0.331656  | 0.307372 | 0.257359 | 0.065702  |   |
| 12 | 1.0      | 0.106109 | -0.025790 | 0.358875  | 0.297543 | 0.244335 | 0.016446  |   |
| 13 | 1.0      | 0.126523 | -0.040482 | 0.341129  | 0.381446 | 0.261154 | -0.017049 |   |
| 14 | 1.0      | 0.267687 | 0.099327  | 0.510454  | 0.511468 | 0.317788 | 0.067992  |   |
| 15 | 1.0      | 0.137623 | -0.085808 | 0.322446  | 0.344695 | 0.285642 | 0.056517  |   |
| 16 | 1.0      | 0.263944 | 0.090358  | 0.368888  | 0.356645 | 0.252806 | 0.063921  |   |
| 17 | 1.0      | 0.146299 | -0.075174 | 0.291935  | 0.367094 | 0.268947 | 0.054049  |   |
| 18 | 1.0      | 0.179298 | -0.038306 | 0.319636  | 0.383029 | 0.275313 | 0.099083  |   |
| 19 | 1.0      | 0.273218 | -0.234703 | -0.079620 | 0.159811 | 0.416406 | 0.368838  |   |
| 20 | 1.0      | 0.196429 | 0.009021  | 0.317772  | 0.293484 | 0.185684 | 0.044063  |   |
| 21 | 1.0      | 0.230999 | 0.135657  | 0.431966  | 0.403423 | 0.276571 | 0.060464  |   |
| 22 | 1.0      | 0.145109 | -0.035846 | 0.282707  | 0.291044 | 0.206862 | 0.048627  |   |
| 23 | 1.0      | 0.235682 | 0.029241  | 0.349117  | 0.355932 | 0.290697 | 0.081008  |   |

|      |     |           |           |           |           |          |           |
|------|-----|-----------|-----------|-----------|-----------|----------|-----------|
| 24   | 1.0 | 0.146944  | -0.009583 | 0.352534  | 0.313435  | 0.197599 | 0.015352  |
| 25   | 1.0 | 0.233512  | 0.067249  | 0.352310  | 0.316899  | 0.220584 | 0.044433  |
| 26   | 1.0 | 0.172672  | -0.037870 | 0.301100  | 0.303533  | 0.203767 | 0.017798  |
| 27   | 1.0 | 0.198494  | 0.078718  | 0.478231  | 0.425219  | 0.257916 | 0.049410  |
| 28   | 1.0 | 0.165998  | -0.004175 | 0.289963  | 0.295084  | 0.224001 | 0.085586  |
| 29   | 1.0 | 0.155225  | -0.063337 | 0.231699  | 0.284514  | 0.219596 | 0.038581  |
| ...  | ... | ...       | ...       | ...       | ...       | ...      | ...       |
| 7165 | 1.0 | 0.132365  | 0.503936  | 0.271392  | -0.042392 | 0.024487 | 0.080317  |
| 7166 | 1.0 | 0.165383  | 0.408082  | 0.270187  | 0.015300  | 0.019000 | 0.025284  |
| 7167 | 1.0 | 0.411916  | 0.322796  | 0.344183  | 0.333873  | 0.094867 | -0.230982 |
| 7168 | 1.0 | 0.404936  | 0.726247  | 0.167376  | -0.169260 | 0.112154 | 0.050805  |
| 7169 | 1.0 | 0.209224  | 0.625373  | 0.246565  | -0.108078 | 0.174846 | 0.100347  |
| 7170 | 1.0 | 0.242842  | 0.516606  | 0.263976  | -0.040676 | 0.052257 | 0.055201  |
| 7171 | 1.0 | 0.153789  | 0.522557  | 0.267617  | -0.043499 | 0.034436 | 0.081305  |
| 7172 | 1.0 | 0.266711  | 0.735734  | 0.233772  | -0.075867 | 0.140193 | 0.080212  |
| 7173 | 1.0 | 0.183156  | 0.506970  | 0.247162  | -0.048503 | 0.041090 | 0.093071  |
| 7174 | 1.0 | 0.197679  | 0.553775  | 0.269271  | -0.056261 | 0.062528 | 0.061367  |
| 7175 | 1.0 | -0.673025 | -0.279960 | 0.065945  | 0.086890  | 0.469024 | 0.088019  |
| 7176 | 1.0 | -0.574239 | -0.258302 | 0.007644  | 0.078566  | 0.402132 | 0.093501  |
| 7177 | 1.0 | -0.515567 | -0.219812 | 0.118473  | 0.106919  | 0.471155 | 0.121196  |
| 7178 | 1.0 | -0.614409 | -0.261315 | 0.051138  | 0.062119  | 0.501500 | 0.096506  |
| 7179 | 1.0 | -0.578837 | -0.331501 | 0.105921  | 0.089931  | 0.456617 | 0.079131  |
| 7180 | 1.0 | -0.528595 | -0.208051 | 0.103669  | 0.086537  | 0.408476 | 0.069610  |
| 7181 | 1.0 | -0.442139 | -0.328404 | 0.031452  | 0.056017  | 0.424856 | 0.073288  |
| 7182 | 1.0 | -0.616029 | -0.302357 | 0.063417  | 0.095671  | 0.439930 | 0.069414  |
| 7183 | 1.0 | -0.547168 | -0.266780 | 0.056115  | 0.048947  | 0.423631 | 0.081924  |
| 7184 | 1.0 | -0.520958 | -0.258779 | -0.070416 | -0.025129 | 0.447967 | 0.180033  |
| 7185 | 1.0 | -0.512794 | 0.056322  | 0.259677  | 0.030140  | 0.369783 | -0.117154 |
| 7186 | 1.0 | -0.591520 | -0.268901 | 0.050042  | 0.116960  | 0.444706 | 0.059268  |
| 7187 | 1.0 | -0.507564 | -0.249969 | 0.031781  | -0.079888 | 0.484274 | 0.125143  |
| 7188 | 1.0 | -0.512599 | -0.171956 | 0.325813  | 0.169600  | 0.421567 | -0.123749 |
| 7189 | 1.0 | -0.558546 | -0.238442 | 0.066527  | 0.123090  | 0.395953 | 0.066522  |
| 7190 | 1.0 | -0.554504 | -0.337717 | 0.035533  | 0.034511  | 0.443451 | 0.093889  |
| 7191 | 1.0 | -0.517273 | -0.370574 | 0.030673  | 0.068097  | 0.402890 | 0.096628  |
| 7192 | 1.0 | -0.582557 | -0.343237 | 0.029468  | 0.064179  | 0.385596 | 0.114905  |
| 7193 | 1.0 | -0.519497 | -0.307553 | -0.004922 | 0.072865  | 0.377131 | 0.086866  |
| 7194 | 1.0 | -0.508833 | -0.324106 | 0.062068  | 0.078211  | 0.397188 | 0.094596  |

|   | MFCCs_ 8  | MFCCs_ 9  | MFCCs_10 | ... | MFCCs_17  | MFCCs_18  | MFCCs_19  | \ |
|---|-----------|-----------|----------|-----|-----------|-----------|-----------|---|
| 0 | -0.150063 | -0.171128 | 0.124676 | ... | -0.108351 | -0.077623 | -0.009568 |   |
| 1 | -0.222475 | -0.207693 | 0.170883 | ... | -0.090974 | -0.056510 | -0.035303 |   |
| 2 | -0.242234 | -0.219153 | 0.232538 | ... | -0.050691 | -0.023590 | -0.066722 |   |
| 3 | -0.194347 | -0.098181 | 0.270375 | ... | -0.136009 | -0.177037 | -0.130498 |   |
| 4 | -0.265423 | -0.172700 | 0.266434 | ... | -0.048885 | -0.053074 | -0.088550 |   |
| 5 | -0.213767 | -0.127916 | 0.277353 | ... | -0.080487 | -0.130089 | -0.171478 |   |
| 6 | -0.252300 | -0.167117 | 0.220027 | ... | -0.046620 | -0.055146 | -0.085972 |   |
| 7 | -0.183329 | -0.158483 | 0.192567 | ... | -0.055978 | -0.048219 | -0.056637 |   |
| 8 | -0.173730 | -0.157857 | 0.207181 | ... | -0.120723 | -0.112607 | -0.156933 |   |

|      |           |           |           |     |           |           |           |
|------|-----------|-----------|-----------|-----|-----------|-----------|-----------|
| 9    | -0.294179 | -0.223236 | 0.268435  | ... | -0.051073 | -0.052568 | -0.111338 |
| 10   | -0.216262 | -0.189334 | 0.261960  | ... | -0.034082 | -0.120716 | -0.100800 |
| 11   | -0.191860 | -0.133537 | 0.220020  | ... | -0.119167 | -0.110900 | -0.112485 |
| 12   | -0.288733 | -0.146731 | 0.314207  | ... | -0.062939 | -0.071182 | -0.066827 |
| 13   | -0.294064 | -0.222278 | 0.282338  | ... | -0.071544 | -0.060630 | -0.067230 |
| 14   | -0.202826 | -0.142236 | 0.235510  | ... | -0.138830 | -0.139922 | -0.126448 |
| 15   | -0.314418 | -0.252324 | 0.288897  | ... | -0.058694 | -0.072913 | -0.064263 |
| 16   | -0.155007 | -0.137743 | 0.200262  | ... | -0.074168 | -0.083995 | -0.104413 |
| 17   | -0.242952 | -0.232617 | 0.235722  | ... | -0.051154 | -0.038580 | -0.022396 |
| 18   | -0.207998 | -0.219215 | 0.182845  | ... | -0.110969 | -0.105833 | -0.115237 |
| 19   | 0.016878  | -0.171288 | -0.115424 | ... | -0.253103 | -0.154244 | -0.002606 |
| 20   | -0.169936 | -0.121461 | 0.237437  | ... | -0.045409 | -0.067118 | -0.047625 |
| 21   | -0.192200 | -0.187348 | 0.180486  | ... | -0.163367 | -0.170739 | -0.169508 |
| 22   | -0.172111 | -0.115698 | 0.251256  | ... | -0.044077 | -0.067219 | -0.058514 |
| 23   | -0.193793 | -0.151462 | 0.212130  | ... | -0.158932 | -0.098565 | -0.078413 |
| 24   | -0.216492 | -0.133865 | 0.278309  | ... | -0.043595 | -0.052536 | -0.024106 |
| 25   | -0.172653 | -0.127641 | 0.190017  | ... | -0.105466 | -0.070941 | -0.085853 |
| 26   | -0.197260 | -0.124021 | 0.256757  | ... | -0.078277 | -0.023172 | 0.002809  |
| 27   | -0.146034 | -0.127461 | 0.170725  | ... | -0.172904 | -0.164822 | -0.152341 |
| 28   | -0.180608 | -0.169064 | 0.221722  | ... | -0.067536 | -0.084953 | -0.116397 |
| 29   | -0.183926 | -0.108442 | 0.245208  | ... | -0.072937 | -0.018316 | -0.034315 |
| ...  | ...       | ...       | ...       | ... | ...       | ...       | ...       |
| 7165 | 0.112706  | -0.071058 | -0.114414 | ... | -0.006677 | -0.070338 | 0.003964  |
| 7166 | 0.120438  | 0.042605  | -0.053960 | ... | 0.007785  | -0.002231 | 0.020593  |
| 7167 | 0.276750  | 0.232506  | -0.372219 | ... | 0.029924  | 0.031286  | -0.038367 |
| 7168 | 0.078670  | -0.243258 | -0.120933 | ... | 0.090483  | 0.126233  | 0.015162  |
| 7169 | 0.035056  | -0.149125 | -0.099348 | ... | -0.041610 | -0.039468 | 0.086045  |
| 7170 | 0.125361  | -0.023455 | -0.064192 | ... | 0.004518  | -0.013307 | -0.001609 |
| 7171 | 0.113272  | -0.034906 | -0.055563 | ... | -0.005648 | -0.028727 | 0.031281  |
| 7172 | 0.119675  | -0.038130 | -0.033289 | ... | -0.027436 | -0.007999 | 0.058854  |
| 7173 | 0.109081  | -0.049473 | -0.044991 | ... | -0.008959 | -0.034239 | 0.036489  |
| 7174 | 0.094837  | -0.047792 | -0.063015 | ... | 0.021719  | -0.041396 | -0.013619 |
| 7175 | -0.197498 | 0.031180  | 0.096919  | ... | 0.052054  | 0.114138  | 0.069353  |
| 7176 | -0.146350 | 0.040779  | 0.105841  | ... | 0.062850  | 0.038051  | 0.019184  |
| 7177 | -0.136494 | 0.027486  | 0.106110  | ... | 0.049024  | 0.109761  | 0.043604  |
| 7178 | -0.155093 | 0.035657  | 0.121933  | ... | 0.048454  | 0.072420  | 0.017823  |
| 7179 | -0.133406 | 0.056485  | 0.093265  | ... | 0.079075  | 0.125759  | 0.044132  |
| 7180 | -0.155217 | 0.080287  | 0.127136  | ... | 0.053063  | 0.085869  | 0.020705  |
| 7181 | -0.140148 | 0.043070  | 0.087675  | ... | 0.024943  | 0.068279  | 0.015953  |
| 7182 | -0.145534 | 0.031354  | 0.069073  | ... | 0.056971  | 0.037285  | 0.023818  |
| 7183 | -0.184252 | 0.024682  | 0.111803  | ... | 0.049831  | 0.115522  | 0.051333  |
| 7184 | -0.062297 | 0.032410  | -0.005379 | ... | 0.027392  | 0.019266  | -0.057772 |
| 7185 | -0.189292 | 0.248948  | 0.193566  | ... | 0.096589  | 0.255261  | 0.047039  |
| 7186 | -0.158389 | 0.066648  | 0.083924  | ... | 0.074444  | 0.117996  | 0.045522  |
| 7187 | -0.069555 | 0.114265  | 0.099647  | ... | 0.011524  | 0.111998  | 0.015886  |
| 7188 | -0.298284 | 0.089382  | 0.243902  | ... | 0.021225  | 0.157321  | 0.042847  |
| 7189 | -0.152216 | 0.078294  | 0.094184  | ... | 0.034202  | 0.040540  | -0.003755 |
| 7190 | -0.100753 | 0.037087  | 0.081075  | ... | 0.069430  | 0.071001  | 0.021591  |

|      |           |          |          |     |          |          |           |
|------|-----------|----------|----------|-----|----------|----------|-----------|
| 7191 | -0.116460 | 0.063727 | 0.089034 | ... | 0.061127 | 0.068978 | 0.017745  |
| 7192 | -0.103317 | 0.070370 | 0.081317 | ... | 0.082474 | 0.077771 | -0.009688 |
| 7193 | -0.115799 | 0.056979 | 0.089316 | ... | 0.051796 | 0.069073 | 0.017963  |
| 7194 | -0.117672 | 0.058874 | 0.076180 | ... | 0.061455 | 0.072983 | -0.003980 |

|      | MFCCs_20  | MFCCs_21  | MFCCs_22  | Family          | Genus \   |
|------|-----------|-----------|-----------|-----------------|-----------|
| 0    | 0.057684  | 0.118680  | 0.014038  | Leptodactylidae | Adenomera |
| 1    | 0.020140  | 0.082263  | 0.029056  | Leptodactylidae | Adenomera |
| 2    | -0.025083 | 0.099108  | 0.077162  | Leptodactylidae | Adenomera |
| 3    | -0.054766 | -0.018691 | 0.023954  | Leptodactylidae | Adenomera |
| 4    | -0.031346 | 0.108610  | 0.079244  | Leptodactylidae | Adenomera |
| 5    | -0.071569 | 0.077643  | 0.064903  | Leptodactylidae | Adenomera |
| 6    | -0.009127 | 0.065630  | 0.044040  | Leptodactylidae | Adenomera |
| 7    | -0.022419 | 0.070085  | 0.021419  | Leptodactylidae | Adenomera |
| 8    | -0.118527 | -0.002471 | 0.002304  | Leptodactylidae | Adenomera |
| 9    | -0.040014 | 0.090204  | 0.088025  | Leptodactylidae | Adenomera |
| 10   | -0.001992 | 0.111462  | 0.103637  | Leptodactylidae | Adenomera |
| 11   | -0.053184 | 0.044291  | -0.011456 | Leptodactylidae | Adenomera |
| 12   | -0.028048 | 0.058353  | 0.064368  | Leptodactylidae | Adenomera |
| 13   | -0.038196 | 0.070127  | 0.048440  | Leptodactylidae | Adenomera |
| 14   | -0.067570 | 0.057888  | -0.011998 | Leptodactylidae | Adenomera |
| 15   | 0.022455  | 0.130752  | 0.074132  | Leptodactylidae | Adenomera |
| 16   | -0.071431 | 0.028842  | 0.019180  | Leptodactylidae | Adenomera |
| 17   | -0.018891 | 0.051480  | 0.031871  | Leptodactylidae | Adenomera |
| 18   | -0.012819 | 0.083194  | 0.052101  | Leptodactylidae | Adenomera |
| 19   | 0.092999  | 0.091724  | 0.003595  | Leptodactylidae | Adenomera |
| 20   | -0.005875 | 0.053107  | 0.030669  | Leptodactylidae | Adenomera |
| 21   | -0.112446 | 0.065072  | 0.050254  | Leptodactylidae | Adenomera |
| 22   | -0.001358 | 0.082058  | 0.045492  | Leptodactylidae | Adenomera |
| 23   | -0.043410 | 0.033478  | -0.006953 | Leptodactylidae | Adenomera |
| 24   | 0.016081  | 0.062506  | 0.042285  | Leptodactylidae | Adenomera |
| 25   | -0.025053 | 0.055194  | 0.003098  | Leptodactylidae | Adenomera |
| 26   | 0.009133  | 0.063916  | 0.047634  | Leptodactylidae | Adenomera |
| 27   | -0.068851 | 0.024412  | -0.009821 | Leptodactylidae | Adenomera |
| 28   | -0.008499 | 0.101151  | 0.022322  | Leptodactylidae | Adenomera |
| 29   | -0.029563 | 0.051715  | 0.023925  | Leptodactylidae | Adenomera |
| ...  | ...       | ...       | ...       | ...             | ...       |
| 7165 | 0.032534  | 0.002975  | 0.002724  | Hylidae         | Scinax    |
| 7166 | 0.014499  | 0.008208  | 0.018023  | Hylidae         | Scinax    |
| 7167 | -0.007837 | 0.102445  | 0.000755  | Hylidae         | Scinax    |
| 7168 | 0.059531  | 0.050905  | -0.026956 | Hylidae         | Scinax    |
| 7169 | 0.071944  | -0.021574 | 0.036031  | Hylidae         | Scinax    |
| 7170 | 0.022170  | 0.014327  | 0.003001  | Hylidae         | Scinax    |
| 7171 | 0.033687  | 0.005242  | 0.014982  | Hylidae         | Scinax    |
| 7172 | 0.008365  | 0.019086  | 0.090131  | Hylidae         | Scinax    |
| 7173 | 0.042205  | 0.003017  | 0.005602  | Hylidae         | Scinax    |
| 7174 | 0.010337  | 0.017903  | 0.022108  | Hylidae         | Scinax    |
| 7175 | 0.050519  | -0.069281 | -0.106642 | Hylidae         | Scinax    |

|      |           |           |           |         |        |
|------|-----------|-----------|-----------|---------|--------|
| 7176 | 0.027745  | -0.109677 | -0.131287 | Hylidae | Scinax |
| 7177 | 0.047369  | -0.018168 | -0.085380 | Hylidae | Scinax |
| 7178 | -0.021418 | -0.094280 | -0.091600 | Hylidae | Scinax |
| 7179 | 0.017652  | -0.077831 | -0.132563 | Hylidae | Scinax |
| 7180 | 0.009959  | -0.072003 | -0.121693 | Hylidae | Scinax |
| 7181 | 0.058530  | -0.009746 | -0.080940 | Hylidae | Scinax |
| 7182 | 0.042104  | -0.035603 | -0.097343 | Hylidae | Scinax |
| 7183 | 0.019697  | -0.061764 | -0.078648 | Hylidae | Scinax |
| 7184 | 0.037710  | 0.047717  | 0.001436  | Hylidae | Scinax |
| 7185 | -0.016643 | -0.046598 | -0.055862 | Hylidae | Scinax |
| 7186 | 0.050734  | -0.034757 | -0.085131 | Hylidae | Scinax |
| 7187 | 0.008636  | -0.021933 | -0.069692 | Hylidae | Scinax |
| 7188 | 0.006852  | 0.005439  | -0.013693 | Hylidae | Scinax |
| 7189 | 0.036059  | -0.031853 | -0.090206 | Hylidae | Scinax |
| 7190 | 0.052449  | -0.021860 | -0.079860 | Hylidae | Scinax |
| 7191 | 0.046461  | -0.015418 | -0.101892 | Hylidae | Scinax |
| 7192 | 0.027834  | -0.000531 | -0.080425 | Hylidae | Scinax |
| 7193 | 0.041803  | -0.027911 | -0.096895 | Hylidae | Scinax |
| 7194 | 0.031560  | -0.029355 | -0.087910 | Hylidae | Scinax |

|    | Species        | RecordID |
|----|----------------|----------|
| 0  | AdenomeraAndre | 1        |
| 1  | AdenomeraAndre | 1        |
| 2  | AdenomeraAndre | 1        |
| 3  | AdenomeraAndre | 1        |
| 4  | AdenomeraAndre | 1        |
| 5  | AdenomeraAndre | 1        |
| 6  | AdenomeraAndre | 1        |
| 7  | AdenomeraAndre | 1        |
| 8  | AdenomeraAndre | 1        |
| 9  | AdenomeraAndre | 1        |
| 10 | AdenomeraAndre | 1        |
| 11 | AdenomeraAndre | 1        |
| 12 | AdenomeraAndre | 1        |
| 13 | AdenomeraAndre | 1        |
| 14 | AdenomeraAndre | 1        |
| 15 | AdenomeraAndre | 1        |
| 16 | AdenomeraAndre | 1        |
| 17 | AdenomeraAndre | 1        |
| 18 | AdenomeraAndre | 1        |
| 19 | AdenomeraAndre | 1        |
| 20 | AdenomeraAndre | 1        |
| 21 | AdenomeraAndre | 1        |
| 22 | AdenomeraAndre | 1        |
| 23 | AdenomeraAndre | 1        |
| 24 | AdenomeraAndre | 1        |
| 25 | AdenomeraAndre | 1        |
| 26 | AdenomeraAndre | 1        |

|      |                |     |
|------|----------------|-----|
| 27   | AdenomeraAndre | 1   |
| 28   | AdenomeraAndre | 1   |
| 29   | AdenomeraAndre | 1   |
| ...  | ...            | ... |
| 7165 | ScinaxRuber    | 59  |
| 7166 | ScinaxRuber    | 59  |
| 7167 | ScinaxRuber    | 59  |
| 7168 | ScinaxRuber    | 59  |
| 7169 | ScinaxRuber    | 59  |
| 7170 | ScinaxRuber    | 59  |
| 7171 | ScinaxRuber    | 59  |
| 7172 | ScinaxRuber    | 59  |
| 7173 | ScinaxRuber    | 59  |
| 7174 | ScinaxRuber    | 59  |
| 7175 | ScinaxRuber    | 60  |
| 7176 | ScinaxRuber    | 60  |
| 7177 | ScinaxRuber    | 60  |
| 7178 | ScinaxRuber    | 60  |
| 7179 | ScinaxRuber    | 60  |
| 7180 | ScinaxRuber    | 60  |
| 7181 | ScinaxRuber    | 60  |
| 7182 | ScinaxRuber    | 60  |
| 7183 | ScinaxRuber    | 60  |
| 7184 | ScinaxRuber    | 60  |
| 7185 | ScinaxRuber    | 60  |
| 7186 | ScinaxRuber    | 60  |
| 7187 | ScinaxRuber    | 60  |
| 7188 | ScinaxRuber    | 60  |
| 7189 | ScinaxRuber    | 60  |
| 7190 | ScinaxRuber    | 60  |
| 7191 | ScinaxRuber    | 60  |
| 7192 | ScinaxRuber    | 60  |
| 7193 | ScinaxRuber    | 60  |
| 7194 | ScinaxRuber    | 60  |

[7195 rows x 26 columns]

```
In [2]: X = df.loc[:, :'MFCCs_22'] # independent variables
        labels = df.loc[:, 'Family'] # lables: Family, Genus, and Species

        # Choose 70% of the data randomly as the training set
        X_train, X_test, labels_train, labels_test = train_test_split(X, labels, test_size=0.3

        # 1. Family
        y1_train = labels_train.loc[:, 'Family']
        y1_test = labels_test.loc[:, 'Family']
```

```
# 2. Genus
y2_train = labels_train.loc[:, 'Genus']
y2_test = labels_test.loc[:, 'Genus']

# 3. Species
y3_train = labels_train.loc[:, 'Species']
y3_test = labels_test.loc[:, 'Species']
```

1. (b) Each instance has three labels: Families, Genus, and Species. Each of the labels has multiple classes. We wish to solve a multi-class and multi-label problem. One of the most important approaches to multi-class classification is to train a classifier for each label. We first try this approach:
  - i. Research exact match and hamming score/ loss methods for evaluating multilabel classification and use them in evaluating the classifiers in this problem.

(Answer) Exact match is the percentage of instances having all their labels classified correctly. Hamming score is the fraction of correctly classified labels to the total number of labels.

Hamming loss is the fraction of wrongly classified labels to the total number of labels. Thus, hamming score is '1-Hamming loss.'

1. (b) ii. Train a SVM for each of the labels, using Gaussian kernels and one versus all classifiers. Determine the weight of the SVM penalty and the width of the Gaussian Kernel using 10 fold cross validation. You are welcome to try to solve the problem with both standardized 2 and raw attributes and report the results.

```
In [3]: from sklearn.svm import SVC
        from sklearn.model_selection import GridSearchCV
        import numpy as np

        # decision_function_shape='ovr': one versus rest
        # kernel='rbf': Gaussian kernel
        clf = SVC(kernel='rbf', decision_function_shape='ovr')

        # C: the weight of the SVM penalty
        # gamma: the width of the Gaussian Kernel
        C_range = np.logspace(-2, 2, 5) # 0.01, 0.1, 1, 10, 100
        gamma_range = np.logspace(-2, 2, 5)
        param_grid = dict(gamma=gamma_range, C=C_range)
        # 10 fold cross validation
        grid = GridSearchCV(clf, param_grid=param_grid, cv=10)

In [4]: # 1. Family (raw data)
        # Determine C and gamma by 10 fold CV
        grid.fit(X_train, y1_train)
        print(grid.best_params_, grid.best_score_)
```

```
{'C': 10.0, 'gamma': 1.0} 0.9912629070691025
```

```
In [5]: C=grid.best_params_['C']
        gamma=grid.best_params_['gamma']
        clf = SVC(C=C, gamma=gamma, kernel='rbf', decision_function_shape='ovr')
        clf.fit(X_train, y1_train)
        print("train accuaracy: %0.4f" % clf.score(X_train, y1_train))
        print("test accuaracy: %0.4f" % clf.score(X_test, y1_test))
```

```
train accuaracy: 0.9986
test accuaracy: 0.9893
```

```
In [6]: from sklearn.metrics import hamming_loss

        y1_pred = clf.predict(X_test)
        h1 = hamming_loss(y1_test, y1_pred)
        print(h1) # the fraction of wrong labels for Family
```

```
0.010653080129689671
```

```
In [7]: # 2. Genus (raw data)
        # Determine C and gamma by 10 fold CV
        grid.fit(X_train, y2_train)
        print(grid.best_params_, grid.best_score_)
```

```
{'C': 10.0, 'gamma': 1.0} 0.9892772041302621
```

```
In [8]: C=grid.best_params_['C']
        gamma=grid.best_params_['gamma']
        clf = SVC(C=C, gamma=gamma, kernel='rbf', decision_function_shape='ovr')
        clf.fit(X_train, y2_train)
        print("train accuaracy: %0.4f" % clf.score(X_train, y2_train))
        print("test accuaracy: %0.4f" % clf.score(X_test, y2_test))
```

```
train accuaracy: 0.9990
test accuaracy: 0.9889
```

```
In [9]: y2_pred = clf.predict(X_test)
        h2 = hamming_loss(y2_test, y2_pred)
        print(h2) # the fraction of wrong labels for Genus
```

```
0.0111162575266327
```

```
In [10]: # 3. Species (raw data)
         # Determine C and gamma by 10 fold CV
         grid.fit(X_train, y3_train)
         print(grid.best_params_, grid.best_score_)
```



```
{'C': 10.0, 'gamma': 1.0} 0.9882843526608419
```

```
In [11]: C=grid.best_params_['C']
gamma=grid.best_params_['gamma']
clf = SVC(C=C, gamma=gamma, kernel='rbf', decision_function_shape='ovr')
clf.fit(X_train, y3_train)
print("train accuracy: %0.4f" % clf.score(X_train, y3_train))
print("test accuracy: %0.4f" % clf.score(X_test, y3_test))
```

```
train accuracy: 0.9988
```

```
test accuracy: 0.9893
```

```
In [12]: y3_pred = clf.predict(X_test)
h3 = hamming_loss(y3_test, y3_pred)
print(h3) # the fraction of wrong labels for Species
```

```
0.010653080129689671
```

```
In [13]: # exact match
# the percentage of instances having all their labels classified correctly
```

```
count = 0
for i in range(len(y1_test)):
    if y1_pred[i]==y1_test.iloc[i] and \
        y2_pred[i]==y2_test.iloc[i] and \
        y3_pred[i]==y3_test.iloc[i]:
        count += 1
```

```
e =(count*100)/len(y1_test) # exact math
h=(h1+h2+h3)/3 # hamming loss
```

```
print("exact match: %0.3f" % e, "%")
print("hamming loss: %0.3f" % h)
```

```
exact match: 98.518 %
```

```
hamming loss: 0.011
```

```
In [14]: # standardization
from sklearn.preprocessing import StandardScaler
```

```
scX_train = StandardScaler().fit_transform(X_train)
scX_test = StandardScaler().fit_transform(X_test)
```

```
In [15]: # 1. Family (standardized data)
# Determine C and gamma by 10 fold CV
grid.fit(scX_train, y1_train)
print(grid.best_params_, grid.best_score_)
```

```
{'C': 10.0, 'gamma': 0.1} 0.9900714853057982
```

```
In [17]: C=grid.best_params_['C']
        gamma=grid.best_params_['gamma']
        clf = SVC(C=C, gamma=gamma, kernel='rbf', decision_function_shape='ovr')
        clf.fit(scX_train, y1_train)
        print("train accuaracy: %0.4f" % clf.score(scX_train, y1_train))
        print("test accuaracy: %0.4f" % clf.score(scX_test, y1_test))
```

```
train accuaracy: 1.0000
```

```
test accuaracy: 0.9903
```

```
In [18]: y1_pred = clf.predict(scX_test)
        h1 = hamming_loss(y1_test, y1_pred)
        print(h1) # the fraction of wrong labels for Family
```

```
0.009726725335803613
```

```
In [19]: # 2. Genus (standardized data)
        # Determine C and gamma by 10 fold CV
        grid.fit(scX_train, y2_train)
        print(grid.best_params_, grid.best_score_)
```

```
{'C': 10.0, 'gamma': 0.01} 0.988482922954726
```

```
In [20]: C=grid.best_params_['C']
        gamma=grid.best_params_['gamma']
        clf = SVC(C=C, gamma=gamma, kernel='rbf', decision_function_shape='ovr')
        clf.fit(scX_train, y2_train)
        print("train accuaracy: %0.4f" % clf.score(scX_train, y2_train))
        print("test accuaracy: %0.4f" % clf.score(scX_test, y2_test))
```

```
train accuaracy: 0.9958
```

```
test accuaracy: 0.9852
```

```
In [21]: y2_pred = clf.predict(scX_test)
        h2 = hamming_loss(y2_test, y2_pred)
        print(h2) # the fraction of wrong labels for Genus
```

```
0.014821676702176934
```

```
In [22]: # 3. Species (standardized data)
        # Determine C and gamma by 10 fold CV
        grid.fit(scX_train, y3_train)
        print(grid.best_params_, grid.best_score_)
```

```
{'C': 10.0, 'gamma': 0.01} 0.9882843526608419
```

```
In [24]: C=grid.best_params_['C']
        gamma=grid.best_params_['gamma']
        clf = SVC(C=C, gamma=gamma, kernel='rbf', decision_function_shape='ovr')
        clf.fit(scX_train, y3_train)
        print("train accuaracy: %0.4f" % clf.score(scX_train, y3_train))
        print("test accuaracy: %0.4f" % clf.score(scX_test, y3_test))
```

```
train accuaracy: 0.9968
```

```
test accuaracy: 0.9889
```

```
In [25]: y3_pred = clf.predict(scX_test)
        h3 = hamming_loss(y3_test, y3_pred)
        print(h3) # the fraction of wrong labels for Species
```

```
0.0111162575266327
```

```
In [26]: # exact match
```

```
count = 0
for i in range(len(y1_test)):
    if y1_pred[i]==y1_test.iloc[i] and \
        y2_pred[i]==y2_test.iloc[i] and \
        y3_pred[i]==y3_test.iloc[i]:
        count += 1
```

```
e =(count*100)/len(y1_test) # exact math
h=(h1+h2+h3)/3 # hamming loss
```

```
print("exact match: %0.3f" % e, "%")
print("hamming loss: %0.3f" % h)
```

```
exact match: 97.869 %
```

```
hamming loss: 0.012
```

(Answer of 1. (b) ii) 1. raw data

exact match: 98.518 %

hamming loss: 0.011

2. standardized data

exact match: 97.869 %

hamming loss: 0.012

The performance of the raw data is slightly better than that of the standardized data.

1. (b) iii. Repeat 1(b)ii with L1-penalized SVMs.<sup>3</sup> Remember to standardize<sup>4</sup> the attributes. Determine the weight of the SVM penalty using 10 fold cross validation.

```
In [27]: from sklearn.svm import LinearSVC
```

```
clf = LinearSVC(penalty='l1', multi_class='ovr', dual=False)
C_range = np.logspace(-2, 5, 8) # 10^-2, 10^-1, 1, 10, ...10^5
param_grid = dict(C=C_range)
```

```
grid = GridSearchCV(clf, param_grid=param_grid, cv=10)
```

```
In [28]: # 1. Family (L1-penalized SVM)
# Determine C by 10 fold CV
grid.fit(scX_train, y1_train)
print(grid.best_params_, grid.best_score_)
```

```
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"the number of iterations.", ConvergenceWarning)
```

[illegible]



```
"the number of iterations.", ConvergenceWarning)
```

```
In [29]: clf = LinearSVC(C=grid.best_params_['C'], penalty='l1', multi_class='ovr', dual=False)
         clf.fit(scX_train, y1_train)
         print("train accuaracy: %0.4f" % clf.score(scX_train, y1_train))
         print("test accuaracy: %0.4f" % clf.score(scX_test, y1_test))
```

```
train accuaracy: 0.9432
test accuaracy: 0.9264
```

```
C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib
"the number of iterations.", ConvergenceWarning)
```

```
In [30]: y1_pred = clf.predict(scX_test)
         h1 = hamming_loss(y1_test, y1_pred)
         print(h1)
```

```
0.07364520611394164
```

```
In [31]: # 2. Genus (L1-penalized SVM)
         # Determine C by 10 fold CV
         grid.fit(scX_train, y2_train)
         print(grid.best_params_, grid.best_score_)
```

```
C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib
"the number of iterations.", ConvergenceWarning)
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"the number of iterations.", ConvergenceWarning)
C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib
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[illegible]



[illegible]

```

    "the number of iterations.", ConvergenceWarning)
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    "the number of iterations.", ConvergenceWarning)
C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib
    "the number of iterations.", ConvergenceWarning)
C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib
    "the number of iterations.", ConvergenceWarning)

```

```
{'C': 10.0} 0.9547259729944401
```

```

C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib
    "the number of iterations.", ConvergenceWarning)

```

```

In [32]: clf = LinearSVC(C=grid.best_params_['C'], penalty='l1', multi_class='ovr', dual=False)
        clf.fit(scX_train, y2_train)
        print("train accuaracy: %0.4f" % clf.score(scX_train, y2_train))
        print("test accuaracy: %0.4f" % clf.score(scX_test, y2_test))

```

```

train accuaracy: 0.9585
test accuaracy: 0.9416

```

```

C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib
    "the number of iterations.", ConvergenceWarning)

```

```

In [33]: y2_pred = clf.predict(scX_test)
        h2 = hamming_loss(y2_test, y2_pred)
        print(h2)

```

```
0.058360352014821676
```

```

In [34]: # 3. Species (L1-penalized SVM)
        # Determine C by 10 fold CV
        grid.fit(scX_train, y3_train)
        print(grid.best_params_, grid.best_score_)

```

```

C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib
    "the number of iterations.", ConvergenceWarning)
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    "the number of iterations.", ConvergenceWarning)
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    "the number of iterations.", ConvergenceWarning)

```

[illegible]

[illegible]

```

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    "the number of iterations.", ConvergenceWarning)
C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib
    "the number of iterations.", ConvergenceWarning)

```

```
{'C': 1.0} 0.9618745035742653
```

```

C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib
    "the number of iterations.", ConvergenceWarning)

```

```

In [35]: clf = LinearSVC(C=grid.best_params_['C'], penalty='l1', multi_class='ovr', dual=False)
        clf.fit(scX_train, y3_train)
        print("train accuaracy: %0.4f" % clf.score(scX_train, y3_train))
        print("test accuaracy: %0.4f" % clf.score(scX_test, y3_test))

```

```
train accuaracy: 0.9658
```

```
test accuaracy: 0.9467
```

```

C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib
    "the number of iterations.", ConvergenceWarning)

```

```

In [36]: y3_pred = clf.predict(scX_test)
        h3 = hamming_loss(y3_test, y3_pred)
        print(h3)

```

```
0.053265400648448355
```

```

In [37]: # exact match

count = 0
for i in range(len(y1_test)):
    if y1_pred[i]==y1_test.iloc[i] and \
        y2_pred[i]==y2_test.iloc[i] and \
        y3_pred[i]==y3_test.iloc[i]:
        count += 1

e =(count*100)/len(y1_test) # exact math
h=(h1+h2+h3)/3 # hamming loss

print("exact match: %0.3f" % e, "%")
print("hamming loss: %0.3f" % h)

exact match: 89.764 %
hamming loss: 0.062

```

1. (b) iv. Repeat 1(b)iii by using SMOTE or any other method you know to remedy class imbalance. Report your conclusions about the classifiers you trained.

```

In [38]: # making string classes to numerical classes for smote
from sklearn.preprocessing import LabelEncoder

# converting training label
lb1 = LabelEncoder().fit_transform(y1_train)
lb2 = LabelEncoder().fit_transform(y2_train)
lb3 = LabelEncoder().fit_transform(y3_train)
# converting test label
te1 = LabelEncoder().fit_transform(y1_test)
te2 = LabelEncoder().fit_transform(y2_test)
te3 = LabelEncoder().fit_transform(y3_test)

In [39]: # smote
from imblearn.over_sampling import SMOTE

X1_smote, y1_smote = SMOTE().fit_resample(scX_train, lb1)
X2_smote, y2_smote = SMOTE().fit_resample(scX_train, lb2)
X3_smote, y3_smote = SMOTE().fit_resample(scX_train, lb3)

In [40]: # 1. Family (L1-penalized SVM)
# Determine C by 10 fold CV
grid.fit(X1_smote, y1_smote)
print(grid.best_params_, grid.best_score_)

```

C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib  
 "the number of iterations.", ConvergenceWarning)  
 C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib

[illegible]

[illegible]





```
In [41]: clf = LinearSVC(C=grid.best_params_['C'], penalty='l1', multi_class='ovr', dual=False)
        clf.fit(X1_smote, y1_smote)
        print("train accuaracy: %0.4f" % clf.score(X1_smote, y1_smote))
        print("test accuaracy: %0.4f" % clf.score(scX_test, te1))
```

train accuaracy: 0.9532

test accuaracy: 0.9097

C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib  
"the number of iterations.", ConvergenceWarning)

```
In [42]: y1_pred = clf.predict(scX_test)
        h1 = hamming_loss(te1, y1_pred)
        print(h1)
```

0.09031959240389069

```
In [43]: # 2. Genus (L1-penalized SVM)
        # Determine C by 10 fold CV
        grid.fit(X2_smote, y2_smote)
        print(grid.best_params_, grid.best_score_)
```

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"the number of iterations.", ConvergenceWarning)

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"the number of iterations.", ConvergenceWarning)

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"the number of iterations.", ConvergenceWarning)

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"the number of iterations.", ConvergenceWarning)

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"the number of iterations.", ConvergenceWarning)

C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib  
"the number of iterations.", ConvergenceWarning)

C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib  
"the number of iterations.", ConvergenceWarning)

C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib  
"the number of iterations.", ConvergenceWarning)

C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib  
"the number of iterations.", ConvergenceWarning)

C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib  
"the number of iterations.", ConvergenceWarning)

C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib  
"the number of iterations.", ConvergenceWarning)

C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib  
"the number of iterations.", ConvergenceWarning)

[illegible]

[illegible]

```

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    "the number of iterations.", ConvergenceWarning)
C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib
    "the number of iterations.", ConvergenceWarning)
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    "the number of iterations.", ConvergenceWarning)
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    "the number of iterations.", ConvergenceWarning)
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    "the number of iterations.", ConvergenceWarning)
C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib
    "the number of iterations.", ConvergenceWarning)
C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib
    "the number of iterations.", ConvergenceWarning)
C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib
    "the number of iterations.", ConvergenceWarning)
C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib
    "the number of iterations.", ConvergenceWarning)
C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib
    "the number of iterations.", ConvergenceWarning)
C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib
    "the number of iterations.", ConvergenceWarning)

```

```
{'C': 100.0} 0.9573676928398478
```

```

C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib
    "the number of iterations.", ConvergenceWarning)

```

```

In [44]: clf = LinearSVC(C=grid.best_params_['C'], penalty='l1', multi_class='ovr', dual=False)
         clf.fit(X2_smote, y2_smote)
         print("train accuaracy: %0.4f" % clf.score(X2_smote, y2_smote))
         print("test accuaracy: %0.4f" % clf.score(scX_test, te2))

```

```
train accuaracy: 0.9584
```

```
test accuaracy: 0.9078
```

```

C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib
    "the number of iterations.", ConvergenceWarning)

```

```

In [45]: y2_pred = clf.predict(scX_test)
         h2 = hamming_loss(te2, y2_pred)
         print(h2)

```

```
0.0921723019916628
```

```
In [46]: # 3. Species (L1-penalized SVM)
# Determine C by 10 fold CV
grid.fit(X3_smote, y3_smote)
print(grid.best_params_, grid.best_score_)
```

[illegible]

[illegible]



```

    "the number of iterations.", ConvergenceWarning)
C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib
    "the number of iterations.", ConvergenceWarning)
C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib
    "the number of iterations.", ConvergenceWarning)
C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib
    "the number of iterations.", ConvergenceWarning)
C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib
    "the number of iterations.", ConvergenceWarning)

```

```
{'C': 10.0} 0.9617502054231717
```

```

C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib
    "the number of iterations.", ConvergenceWarning)

```

```

In [48]: clf = LinearSVC(C=grid.best_params_['C'], penalty='l1', multi_class='ovr', dual=False)
        clf.fit(X3_smote, y3_smote)
        print("train accuaracy: %0.4f" % clf.score(X3_smote, y3_smote))
        print("test accuaracy: %0.4f" % clf.score(scX_test, te3))

```

```
train accuaracy: 0.9625
```

```
test accuaracy: 0.9546
```

```

C:\Users\Myunghee\Anaconda3\lib\site-packages\sklearn\svm\base.py:922: ConvergenceWarning: Lib
    "the number of iterations.", ConvergenceWarning)

```

```

In [49]: y3_pred = clf.predict(scX_test)
        h3 = hamming_loss(te3, y3_pred)
        print(h3)

```

```
0.04539138490041686
```

```
In [50]: # exact match
```

```

count = 0
for i in range(len(y1_test)):
    if y1_pred[i]==te1[i] and \
        y2_pred[i]==te2[i] and \
        y3_pred[i]==te3[i]:
        count += 1

h=(h1+h2+h3)/3
e =(count*100)/len(y1_test)
print("hamming loss: %0.3f" % h)
print("exact match: %0.3f" % e, "%")

```

```
hamming loss: 0.076
exact match: 85.410 %
```

## 2. K-Means Clustering on a Multi-Class and Multi-Label Data Set Monte-Carlo Simulation:

Perform the following procedures 50 times, and report the average and standard deviation of the 50 Hamming Distances that you calculate.

- (a) Use k-means clustering on the whole Anuran Calls (MFCCs) Data Set (do not split the data into train and test, as we are not performing supervised learning in this exercise). Choose  $k \in \{1, 2, \dots, 50\}$  automatically based on one of the methods provided in the slides (CH or Gap Statistics or scree plots or Silhouettes) or any other method you know.

```
In [51]: from sklearn.cluster import KMeans
         from sklearn.metrics import silhouette_score
         # calinski_harabaz_score (CH index)

         # selecting K among {1, 2, ..., 50}
         def Kmeans_k (X):
             dic = dict()
             for i in range(49):
                 k = i+2
                 kmeans = KMeans(n_clusters=k).fit(X)
                 labels= kmeans.labels_

                 s_avg = silhouette_score(X, labels)
                 dic[k]=s_avg
             k_select=pd.DataFrame(dic, index=['s_avg']).T
             k_select = k_select.sort_values(by=['s_avg'], ascending = False)
             K = k_select.iloc[0].name
             return K

In [53]: K = Kmeans_k(X)
         print(K)
```

4

2. (b) In each cluster, determine which family is the majority by reading the true labels. Repeat for genus and species.
- (c) Now for each cluster you have a majority label triplet (family, genus, species). Calculate the average Hamming distance, Hamming score, and Hamming loss<sup>5</sup> between the true labels and the labels assigned by clusters.

```
In [54]: # making string classes to numerical classes
         family = df.loc[:, 'Family']
         genus = df.loc[:, 'Genus']
```

```

species = df.loc[:, 'Species']
l1=LabelEncoder().fit(family)
l2=LabelEncoder().fit(genus)
l3=LabelEncoder().fit(species)
label1 = l1.transform(family)
label2 = l2.transform(genus)
label3 = l3.transform(species)

```

In [57]: tot\_table=dict()

```

# repeating 50 times K-means clustering (K=4)
for i in range(50):
    kmeans = KMeans(n_clusters=K).fit(X)
    labels= kmeans.labels_
    cl_table = pd.DataFrame(labels, columns=['cluster'])
    cl_table.insert(1,"family", label1)
    cl_table.insert(2,"genus", label2)
    cl_table.insert(3,"species", label3)
    cl_table = cl_table.sort_values(by=['cluster'])

    clust=cl_table.iloc[:,0]
    c = np.bincount(clust) # counting # of each cluster

    # splitting data according to clusters
    clust0=cl_table.iloc[:c[0],:] # cluster 0
    clust1=cl_table.iloc[c[0]:c[0]+c[1],:] # cluster 1
    clust2=cl_table.iloc[c[0]+c[1]:c[0]+c[1]+c[2],:] # cluster 2
    clust3=cl_table.iloc[c[0]+c[1]+c[2]:,:] # cluster 3

    dic_class=dict()
    dic_loss=dict()

    # each cluster with a majority label triplet(family, genus, species)
    for j in range(3):
        c0=np.bincount(clust0.iloc[:,j+1])
        c1=np.bincount(clust1.iloc[:,j+1])
        c2=np.bincount(clust2.iloc[:,j+1])
        c3=np.bincount(clust3.iloc[:,j+1])
        m0=np.argmax(c0) # majority label of cluster 0
        m1=np.argmax(c1) # majority label of cluster 1
        m2=np.argmax(c2) # majority label of cluster 2
        m3=np.argmax(c3) # majority label of cluster 3

        dic_class[j+1]=m0, m1, m2, m3
        # the # of wrongly assigned labels
        dic_loss[j+1]=len(clust)-(c0[m0]+c1[m1]+c2[m2]+c3[m3])

    # assigned family labels list for each cluster

```

```

fam=l1.inverse_transform(dic_class[1])
# assigned genus labels list for each cluster
gen=l2.inverse_transform(dic_class[2])
# assigned species labels list for each cluster
spe=l3.inverse_transform(dic_class[3])

# hamming loss
HL=(dic_loss[1]+dic_loss[2]+dic_loss[3])/(len(clust)*3)

# each 50 iteration, family, genus, species labels for each cluster
# and hamming loss
tot_table[i]=fam, gen, spe, HL

```

```

In [64]: # answers of 2. (b) and (c)
         T=pd.DataFrame(tot_table)
         print(T)

```

```

                                0  \
0  [Hylidae, Leptodactylidae, Dendrobatidae, Hyli...
1      [Hypsiboas, Adenomera, Ameerega, Hypsiboas]
2  [HypsiboasCinerascens, AdenomeraHylaedactylus,...
3                                0.222423

                                1  \
0  [Dendrobatidae, Hylidae, Hylidae, Leptodactyli...
1      [Ameerega, Hypsiboas, Hypsiboas, Adenomera]
2  [Ameeregatrivittata, HypsiboasCinerascens, Hyp...
3                                0.222423

                                2  \
0  [Hylidae, Leptodactylidae, Dendrobatidae, Hyli...
1      [Hypsiboas, Adenomera, Ameerega, Hypsiboas]
2  [HypsiboasCinerascens, AdenomeraHylaedactylus,...
3                                0.222423

                                3  \
0  [Leptodactylidae, Dendrobatidae, Hylidae, Hyli...
1      [Adenomera, Ameerega, Hypsiboas, Hypsiboas]
2  [AdenomeraHylaedactylus, Ameeregatrivittata, H...
3                                0.221913

                                4  \
0  [Leptodactylidae, Hylidae, Dendrobatidae, Hyli...
1      [Adenomera, Hypsiboas, Ameerega, Hypsiboas]
2  [AdenomeraHylaedactylus, HypsiboasCordobae, Am...
3                                0.221774

                                5  \

```

0 [Leptodactylidae, Hylidae, Dendrobatidae, Hyli...  
1 [Adenomera, Hypsiboas, Ameerega, Hypsiboas]  
2 [AdenomeraHylaedactylus, HypsiboasCinerascens,...  
3 0.222423

6 \

0 [Leptodactylidae, Hylidae, Dendrobatidae, Hyli...  
1 [Adenomera, Hypsiboas, Ameerega, Hypsiboas]  
2 [AdenomeraHylaedactylus, HypsiboasCordobae, Am...  
3 0.222423

7 \

0 [Leptodactylidae, Dendrobatidae, Hylidae, Hyli...  
1 [Adenomera, Ameerega, Hypsiboas, Hypsiboas]  
2 [AdenomeraHylaedactylus, Ameeregatrivittata, H...  
3 0.222423

8 \

0 [Leptodactylidae, Dendrobatidae, Hylidae, Hyli...  
1 [Adenomera, Ameerega, Hypsiboas, Hypsiboas]  
2 [AdenomeraHylaedactylus, Ameeregatrivittata, H...  
3 0.222423

9 ... \

0 [Hylidae, Leptodactylidae, Dendrobatidae, Hyli...  
1 [Hypsiboas, Adenomera, Ameerega, Hypsiboas]  
2 [HypsiboasCinerascens, AdenomeraHylaedactylus,...  
3 0.222423

40 \

0 [Hylidae, Leptodactylidae, Hylidae, Dendrobati...  
1 [Hypsiboas, Adenomera, Hypsiboas, Ameerega]  
2 [HypsiboasCordobae, AdenomeraHylaedactylus, Hy...  
3 0.222423

41 \

0 [Dendrobatidae, Hylidae, Leptodactylidae, Hyli...  
1 [Ameerega, Hypsiboas, Adenomera, Hypsiboas]  
2 [Ameeregatrivittata, HypsiboasCordobae, Adenom...  
3 0.222423

42 \

0 [Hylidae, Leptodactylidae, Leptodactylidae, Hy...  
1 [Hypsiboas, Adenomera, Adenomera, Hypsiboas]  
2 [HypsiboasCordobae, AdenomeraHylaedactylus, Ad...  
3 0.245263

43 \

```

0 [Leptodactylidae, Hylidae, Hylidae, Dendrobati...
1     [Adenomera, Hypsiboas, Hypsiboas, Ameerega]
2 [AdenomeraHylaedactylus, HypsiboasCinerascens,...
3                                     0.222284

44 \
0 [Dendrobatidae, Hylidae, Leptodactylidae, Hyli...
1     [Ameerega, Hypsiboas, Adenomera, Hypsiboas]
2 [Ameeregatrivittata, HypsiboasCordobae, Adenom...
3                                     0.222423

45 \
0 [Leptodactylidae, Hylidae, Leptodactylidae, Hy...
1     [Adenomera, Hypsiboas, Adenomera, Hypsiboas]
2 [AdenomeraHylaedactylus, HypsiboasCordobae, Ad...
3                                     0.245263

46 \
0 [Dendrobatidae, Hylidae, Hylidae, Leptodactyli...
1     [Ameerega, Hypsiboas, Hypsiboas, Adenomera]
2 [Ameeregatrivittata, HypsiboasCordobae, Hypsib...
3                                     0.222423

47 \
0 [Leptodactylidae, Leptodactylidae, Hylidae, Hy...
1     [Adenomera, Adenomera, Hypsiboas, Hypsiboas]
2 [AdenomeraAndre, AdenomeraHylaedactylus, Hyspi...
3                                     0.233727

48 \
0 [Leptodactylidae, Hylidae, Hylidae, Dendrobati...
1     [Adenomera, Hypsiboas, Hypsiboas, Ameerega]
2 [AdenomeraHylaedactylus, HypsiboasCinerascens,...
3                                     0.222284

49
0 [Hylidae, Leptodactylidae, Dendrobatidae, Hyli...
1     [Hypsiboas, Adenomera, Ameerega, Hypsiboas]
2 [HypsiboasCordobae, AdenomeraHylaedactylus, Am...
3                                     0.222423

```

[4 rows x 50 columns]

Report the average and standard deviation of the 50 Hamming Distances that you calculate.  
 (Answer) Hamming score is the fraction of correctly classified labels to the total number of labels.

Hamming loss is the fraction of wrongly classified labels to the total number of labels. Thus,

hamming score is '1-Hamming loss.'

Hamming distance is the fraction of wrongly classified labels to the total number of samples. Thus, hamming distance is "Hamming loss X 'the number of labels(in this case: 3).'

Hamming score and hamming distance can be easily calculated from hamming loss, so I calculated only hamming loss in this HW.

```
In [65]: import statistics
```

```
    m = statistics.mean(T.iloc[3, :])  
    s = np.std(T.iloc[3, :])  
  
    print("avearge: %.3f" % m)  
    print("standard deviation: %.3f" % s)
```

```
avearge: 0.225
```

```
standard deviation: 0.007
```