## Machine learning (Blended delivery) Assignment 2 (Autumn 2023)

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Problem specification:

```
b'edm' 4461
b'rap' 4339
b'pop' 4044
b'latin' 3748
b'rock' 3519
```

Name: playlist\_genre, dtype: int64

Based on the value counts for playlist\_genre it seems we are dealing with a multi-class classification problem with fairly balanced classes.

## **Dataset Exploration**

I began my analysis by exploring the dataset using python in jupyter notebook. The following are some methods I used when exploring the data.

```
num_rows = df.shape[0]
num_cols = df.shape[1]
datatypes = df.dtypes
missing_values = df.isnull().sum()
print(df.head(10))
print(df.tail(10))
num_duplicates = df.duplicated().sum()
df = df.drop_duplicates()
```

After dataset exploration it was determined there were no missing values and that the values in the dataset were coherent meaningful values based on the feature description. There were 1701 duplicates that were removed as they did not represent meaningful data. The features were all in the correct datatypes save 2 features, key and mode that were then changed to categorical data type as they represented only a few different categories. I then saved the updated data and uploaded it to weka where I made further changes to the data. I started by normalizing the features between 0 and 1 as this is required by some of the algorithms needed for this assignment such as KNN for example.

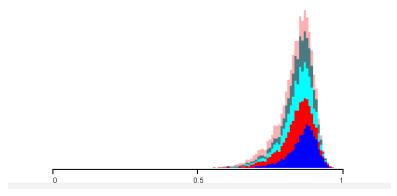


Fig 2. Represents a features scale after normalization

I then used the InterquartileRange and RemoveWithValues methods to remove outliers. However since this actually made performance on the algorithms worse I undid this. I also encoded the nominal features using one hot encoding using the NominalToBinary filter. This had a modest benefit for performance.

## **Beginning of questions 1.1 to 1.5**

## 1.1

## **Decision Tree Classifier**

- Accuracy: 49.23%. This shows a better performance compared to KNN, likely due to its capability to handle complex relationships between features.
- Kappa Statistic: 0.3634. A higher kappa statistic compared to KNN indicates a better agreement.
- F-Measure: Shows a better balance between precision and recall compared to KNN, especially for 'edm' and 'rock'.
- ROC and PRC Areas: Improved performance compared to KNN, indicating a better model fit.

## **Neural Network**

- Accuracy: 54.83%. The best among the three, suggesting that the Neural Network is more adept at capturing complex patterns.
- Kappa Statistic: 0.4338. This highest kappa statistic among the three indicates the best agreement between the predicted and actual classifications.
- F-Measure: Consistently higher across classes, indicating a balanced precision-recall trade-off.
- ROC and PRC Areas: Highest among the three models, indicating superior performance in class distinction.

## kNN (k=1)

K-Nearest Neighbors (k=1):

- Accuracy: 41.43%. This lower accuracy indicates that KNN with k=1 may be overly sensitive to noise in the dataset.
- Kappa Statistic: 0.2657. This value suggests a moderate agreement between the predicted and actual classifications, but it's lower compared to other classifiers.
- F-Measure for Each Class: Varied across classes, with 'rock' performing the best. This could indicate that some genres are more distinct than others.
- ROC and PRC Areas: Moderate performance, but it indicates that there's room for improvement, especially in distinguishing between classes.

```
== Stratified cross-validation ===
== Summary ===
Streetly Classified Instances 1170 51.5749 %
Scorrectly Classified Instances 10.2657
Scorrectly Classified Scorrec
```

## Conclusion

In conclusion, the Neural Network demonstrates the highest efficacy in classifying the genres in the given dataset, with superior performance across most metrics. This is followed by the Decision Tree and then KNN with k=1. The higher performance of the Neural Network can be attributed to its ability to model complex and non-linear relationships in the data. I feel it's also important to consider the model complexity and the computational resources required.

## Why did I pick the metrics I picked?

First I noted it was a multiclass classification problem with relatively balanced classes (shown in the problem specification on page 1 of this report). With that in mind.

**Accuracy** Fundamental to understanding the overall effectiveness of the model in classifying instances correctly.

**Kappa Statistic:** It provides insight into the agreement between the predicted and actual classifications, adjusting for the agreement that would be expected by chance.

**F-Measure:** As a harmonic mean of precision and recall, it is crucial in a balanced multiclass setting to understand how well the classifier is performing in terms of both false positives and false negatives.

**ROC and PRC Areas**: These provide a comprehensive view of the model's performance across different thresholds, which is particularly important in multiclass problems to evaluate the model's ability to distinguish between classes.

## 1.1 (second half of 1.1)

## **Majority vote**

## Average of probs

## **Maximum probs**

```
=== Stratified cross-validation ===
=== Stummary ===

Correctly classified Instances 8394 41.7384 %
Incorrectly classified Instances 11717 58.2616 %
Kappa statistic 0.2702
Mean absolute error 0.2428
Root mean squared error 7.6.0291 %
Root relative squared error 90.1783 %
Total Number of Instances 2011

=== Detailed Accuracy By Class ===

TP Rate FP Rate Precision Recall F-Measure MCC ROC Area FRC Area Class 0.494 0.159 0.464 0.494 0.474 0.320 0.813 0.607 b'edm'
0.493 0.117 0.536 0.493 0.514 0.388 0.895 0.636 b'tap'
0.260 0.202 0.244 0.260 0.252 0.056 0.637 0.266 b'pop'
0.339 0.158 0.333 0.329 0.326 0.169 0.709 0.371 b'latin'
0.514 0.092 0.524 0.514 0.527 0.431 0.896 0.649 b'rock'

Weighted Awg. 0.417 0.147 0.423 0.417 0.420 0.273 0.782 0.508

=== Confusion Matrix ===

a b c d e <-- classified as 2160 461 890 584 812 | a = b'edm'
558 2141 586 818 236 | b = b'rap'
544 491 1501 882 666 | c = b'pop'
579 711 910 1234 314 | d = b'latin'
413 189 775 334 1808 | e = b'rock'
```

## Analysis of the ensembles

- Majority Vote: Achieved 52.17% accuracy with a Kappa statistic of 0.4005. Notably better than KNN k=1, but slightly better than the Decision Tree and significantly underperformed compared to the Neural Network.
- Average of Probabilities: Recorded 50.28% accuracy with a Kappa statistic of 0.377.
   This was lower than the Majority Vote ensemble and also underperformed compared to the Neural Network, but still better than KNN k=1.
- Maximum Probability: Showed the lowest performance with 41.74% accuracy and a Kappa statistic of 0.2702, underperforming all individual classifiers.
- The Majority Vote ensemble provided a balanced output, slightly enhancing the Decision Tree's performance but not reaching the Neural Network's effectiveness.
- The Average of Probabilities method showed a decrease in performance compared to the Majority Vote, suggesting that averaging probabilities may dilute the effect of stronger classifiers.
- The Maximum Probability ensemble performed the worst, indicating that relying solely on the classifier with the highest confidence for each instance may not always yield the best results, especially if it overly trusts a weaker classifier.

## Why were there differences in performance of the combination rules?

## 1. Majority Voting:

Majority Vote tends to be a robust method as it requires a consensus among classifiers.
It works well when classifiers are diverse and make independent errors. However, its
performance is limited by the accuracy of the majority, which explains why it couldn't
surpass the Neural Network's performance.

## 2. Average of Probabilities:

This method considers the probability estimates from each classifier and averages them.
It is effective when classifiers are well-calibrated. However, in this case, it seems that
averaging diluted the impact of the stronger classifier (the Neural Network), leading to a
reduction in overall accuracy.

## 3. Maximum Probability:

• This rule selects the class with the maximum probability as predicted by any of the classifiers. It heavily relies on the confidence of individual classifiers and can be misled if a weak classifier is overly confident. This could explain its lowest performance, as it may have been overly influenced by the weaker KNN k=1 classifier.

## **Part 1.2**

#### **Decision Tree**

## 2 iterations

## 18 iterations (optimal)

For the decision tree classifier from 2 to 18 iterations (i.e 2,4,6,8.....) the performance was increasing i.e increasing accuracy from 45.95% to 54.1% and increasing kappa statistic from 0.32 to 0.42 and also increasing precision/ recall / F measure/ ROC /PRC . However the performance leveled off at 18 iterations and did not increase for 20 iterations.

## KNN k=1 (18 iterations)

```
=== Stratified cross-validation ===
=== Summary
Correctly Classified Instances
                                                      41.8925 %
Incorrectly Classified Instances
Kappa statistic
                                0.2721
0.2372
Mean absolute error
Root mean squared error
Relative absolute error
Root relative squared error 103.
                                     74.276
Relative absolute error
Total Number of Instances
=== Detailed Accuracy By Class ===
                TP Rate FP Rate Precision Recall F-Measure MCC
                                                                       ROC Area PRC Area Class
                0.471 0.314
                                                                      0.735 0.496
                                                                                          b'edm'
                                                                                          b'pop'
b'latin'
                0.267
                       0.206
                                 0.246
                                            0.267
                                                    0.256
                                                              0.059
                                                                       0.581
                                                                                 0.251
                                         0.267
0.336
0.515
0.419
                                                           0.059
0.174
0.439
0.276
                0.336
                               0.326
                                                    0.331
                                                                      0.645
                       0.159
                                                                                 0.322
                0.515
                       0.088
                                 0.553
                                                                       0.811
                                                                                 0.538
Weighted Avg. 0.419 0.147
                               0.427
                                                   0.422
                                                                      0.709
                                                                                 0.433
=== Confusion Matrix ===
                      e <-- classified as
a b c q e 2178 419 1019 552 293 | a = b'edm'
  996 433 1080 903 632 |
  585 666 921 1258 318 |
                           d = b'latin'
e = b'rock'
  422 178 748 357 1814 |
```

## KNN K=1, 20 iterations

```
orrectly Classified Instances
                                          8431
                                                                41.9223 %
incorrectly Classified Instances 11680
appa statistic
                                      0.2725
0.2371
lean absolute error
                                             0.4128
loot mean squared error
elative absolute error
elative absolute error
coot relative squared error
                                           103.2922 %
                                     20111
otal Number of Instances
=== Detailed Accuracy By Class ===
                  TP Rate FP Rate Precision Recall F-Measure MCC
                                                                                    ROC Area PRC Area Class
                                      0.456 0.488 0.472 0.315 0.737 0.552 0.482 0.515 0.394 0.777 0.246 0.268 0.256 0.059 0.583 0.328 0.338 0.332 0.177 0.647 0.553 0.515 0.534 0.439 0.812 0.428 0.419 0.423 0.277 0.711
                  0.488 0.166 0.456
0.482 0.107 0.552
                                                                                                0.551
                                                                                                            b'rap'
                  0.268 0.207
0.338 0.159
0.515 0.088
                                                                                                0.251
                                                                                                            b'pop'
                                                                                                0.539
Weighted Avg. 0.419 0.147 0.428
                                                                                               0.435
== Confusion Matrix ===
                             <-- classified as
2176 413 1024 553 295 | a = b'edm'
                                 b = b'rap'
 604 2091 629 792 223 |
                                 c = b'pop'
 988 438 1085 899 634 I
 583 668 919 1265 313 |
                                 d = b'latin'
 416 175 761 353 1814 |
```

KNN k=1 continued to show increased performance for higher numbers of iterations (i.e from 2,4,6,8.....etc) showing higher accuracy / F1 Measure/ precision / recall / kappa/ ROC/PRC statistic however this leveled off at 20 iterations and only increased by a tiny amount from 18

iterations suggesting a peak at 20 iterations. Accuracy at 20 iterations was only 0.02% higher than at 18 iterations and F1/Precision/Recall were similarly only 0.01% or less higher at 20 than 18 iterations.

## **Neural net (optimal 18 iterations)**

```
Time taken to build model: 719.38 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances 11293 56.1533 %

Hoofrectly Classified Instances 0818 43.8467 %

Kappa statistic Mean absolute error 0.231

Root mean squared error 0.3303

Relative absolute error 72.3399 %

Root relative squared error 84.6444 %

Total Number of Instances 2011

=== Detailed Accuracy By Class ===

TP Rate FP Rate Precision Recall F-Measure MCC ROC Area FRC Area Class 0.609 0.101 0.632 0.609 0.620 0.515 0.857 0.679 b'edm' 0.700 0.113 0.631 0.700 0.664 0.567 0.879 0.685 b'rap' 0.406 0.155 0.397 0.406 0.402 0.249 0.726 0.366 b'pop' 0.375 0.093 0.400 0.375 0.421 0.311 0.760 0.456 b'pop' 0.706 0.066 0.644 0.706 0.668 0.595 0.917 0.707 b'rock'

Weighted Avg. 0.562 0.111 0.556 0.562 0.557 0.448 0.828 0.581

=== Confusion Matrix ===

a b c d e <-- classified as 2718 416 820 270 237 | a = b'edm' 312 3039 334 522 132 | b = b'rap' 679 470 1643 534 718 | c = b'pop' 372 0.08 613 1407 348 | d = b'ltan' 470 1643 534 718 | c = b'pop' 372 0.08 613 1407 348 | d = b'ltan' 470 1643 534 718 | c = b'pop' 372 0.08 613 1407 348 | d = b'ltan' 470 1643 534 718 | c = b'pop' 372 0.08 613 13407 348 | d = b'ltan' 470 1643 534 718 | c = b'pop' 372 0.08 613 13407 348 | d = b'ltan' 472 132 | b = b'rap' 679 470 1643 534 718 | c = b'pop' 372 0.08 613 13407 348 | d = b'ltan' 472 132 | b = b'rap' 679 470 1643 534 718 | c = b'pop' 372 0.08 613 13407 348 | d = b'ltan' 472 132 | b = b'rap' 679 470 1643 534 718 | c = b'pop' 372 0.08 613 13407 348 | d = b'ltan' 472 132 | b = b'rap' 679 470 1643 534 718 | c = b'pop' 372 0.08 613 13407 348 | d = b'ltan' 472 | d = b'cok'
```

For the neural network, the performance continued to increase with increasing iterations (2,4,8,10....) i.e (accuracy/f1/precision/recall/kappa/ROC/PRC) for example accuracy is 2% higher at 18 iterations than the model made earlier. The performance leveled off at 18 iterations. At 20 iterations the performance was very slightly worse i.e less than 0.1% worse on accuracy/f1/precision/recall and 0.006 lower kappa statistic.

## 1.2 (second half of 1.2)

# Decision tree 18 iterations 70% Bag size

```
=== Stratified cross-validation ===
Correctly Classified Instances
Incorrectly Classified Instances
Kappa statistic 0.442
Mean absolute error 0.2279
Root mean squared error
                                             71.3532 %
Relative absolute error
 Root relative squared error
                                                    85.285 %
  == Detailed Accuracy By Class =
                                             0.629 0.641
0.632 0.713
0.349 0.305
0.455 0.371
                      0.305 0.143 0.349
                                                                       0.326
                                                                                      0.171
                                                                                                  0.676
                                                                                                               0.302
                                                                                                                            b'pop
                      0.371 0.102
                                                                        0.409
                                                                                      0.292
                                                                                                  0.741
                                                                                                               0.441
0.731 0.090
Weighted Avg. 0.555 0.112
=== Confusion Matrix ===
                                  <-- classified as
a b c d e <-- classified

280 364 699 330 208 | a = b'edm'

287 3093 328 467 164 | b = b'rap'

790 513 1235 693 813 | c = b'pop'

417 831 792 1392 316 | d = b'latin'

190 95 484 176 2574 | e = b'rock'
```

For the decision tree the performance was higher at 80% bag size compared to 100% with higher accuracy/ precision/ recall/ROC/PRC/ F measure and kappa statistic. I then tried for 60% and noticed performance was slightly worse. At 70% the performance was very marginally higher than at 60% and at 75% it was worse than 70% suggesting an optimum between 70% and 75%.

### KNN k=1 20 iterations

## 15% bag size

For KNN on the other hand the performance (accuracy/precision/recall/f1/kappa/ROC/PRC) continued to increase with smaller bag sizes until 15%. But then the performance went down somewhat for 10% indicating the optimal bag size is between 10 and 15%.

## Neural network 18 iterations (90% bag size)

```
=== Stratified cross-validation ===
=== Summary ===
Correctly Classified Instances
                                                                          55.9395 %
Incorrectly Classified Instances
                                                 0.4481
0.2313
Kappa statistic
Mean absolute error
Mean absolute error
Relative absolute error
Root relative squared error
Total Number of Instances
                                                     0.3389
                                                    84.8008 %
 === Detailed Accuracy By Class ===
                      TP Rate FP Rate Precision Recall F-Measure MCC
                                                                                                 ROC Area PRC Area Class
                     0.608
0.695
                                                                                                  0.854
                                 0.113
                                              0.627
                                                            0.695
                                                                       0.659
                                                                                     0.561
                                                                                                               0.682
                                                                                                                            b'rap'
                                            0.397 0.393 0.395 0.244 0.724 0.365
0.471 0.376 0.418 0.305 0.759 0.450
0.632 0.718 0.672 0.599 0.919 0.709
0.553 0.559 0.554 0.445 0.826 0.578
                                                                                                                             b'pop'
                      0.393 0.150
0.376 0.097
                                                                                                                            b'latin'
                       0.718
                                                                                                                          b'rock'
Weighted Avg. 0.559 0.111
 === Confusion Matrix ===
                               e <-- classified as
 2712 426 791 301 231 | a = b'edm'
331 3015 340 515 138 | b = b'rap'
  678 461 1590 573 742 | c = b'pop'
370 826 786 1408 358 | d = b'latin'
224 77 499 194 2525 | e = b'rock'
```

For the neural network performance was worse at 90% and even further worse at 80% and 70%....etc . Implying that the optimal bag size is between 90% and 100%

First before varying the subspace we need to find the optimal number of iterations for each of the algorithms again.

## **Decision tree**

After testing iterations in increasing order (2,4,6,8 etc) the accuracy and other benchmarks (f1 /precision/ recall / kappa /ROC/PRC) continued to increase till 20 and then leveled off at 20.

### KNN k=1

After testing iterations from 2 to 20 KNN also continued to increase but leveled off at 20 iterations for accuracy / f1/ precision /recall/kappa/ROC/PRC.

### **Neural network**

For the neural network performance (accuracy/f1/precision/recall/kappa/ROC/PRC) also continued to increase steadily with the number of iterations for the given subspace and continued to increase until 20 iterations where it leveled off.

# 1.3 second half : Varying the subspace size. KNN

For KNN k=1 when the number of features was lowered from 100% in iterations of 10% of the total the performance benchmarks continued to increase until they reached a peak at a subspace of about 40%. Further decreasing the subspace size caused the performance to get worse i.e lower accuracy/f1/precision/recall/kappa/ROC/PRC.

## KNN k=1 20 iterations subspace 40%

```
=== Stratified cross-validation ===
=== Summarv =--
Correctly Classified Instances 10037
Incorrectly Classified Instances 10074
Kappa statistic 0.
Kappa statistic 0.3715
Mean absolute error 0.259
Root mean squared error
Relative absolute error
                                                                             0.3713
81.0949 9

        Root mean squared error
        0.

        Relative absolute error
        81.

        Root relative squared error
        92.

        Total Number of Instances
        20111

                                                                                       92.9177 %
                                    TP Rate FP Rate Precision Recall F-Measure MCC
                                                                                                                                                                ROC Area PRC Area Class

    0.621
    0.152
    0.539
    0.621
    0.577
    0.447

    0.639
    0.121
    0.593
    0.639
    0.615
    0.505

    0.274
    0.156
    0.307
    0.274
    0.289
    0.123

                                                                                                                                                               0.786
0.838
0.586
                                                                                                                                                                                    0.530
0.586
0.251
                                                                                                                                                                                                          b'edm'
                                                                                          0.343 0.370
0.596 0.600
0.499 0.493
                                   0.343 0.118
                                                                      0.401
                                                                                                                                                                0.681
                                                                                                                                                                                      0.324
                                                                                                                                                                                                           b'latin'
 === Confusion Matrix ===
a b c d e <--classified as
2772 409 707 357 216 | a = b'edm'
414 2773 407 571 174 | b = b'rap'
1003 510 1108 725 698 | c = b'pop'
569 831 777 1286 285 | d = b'latin'
386 152 613 270 2098 | e = b'rock'
```

### **Decision tree**

For the decision tree the performance got worse at lower numbers of features and increased for higher numbers of features until it peaked at a subspace of around 70%. Further increasing it caused the performance benchmarks to worsen.

## Decision tree 20 iterations subspace 70%

## **Neural** net

The neural net performance on benchmarks (accuracy / f1 / precision / recall / kappa/ROC/PRC) worsened when subspace was lowered below 50% i.e 40%, 30% ... etc.

When it was increased from 50% the performance it continued to improve all the way till 100% (full set of features).

## Neural net, 20 iterations, subspace of 100% (full set)

### 1.4

### From the lectures....

Bagging is more beneficial for decision trees and possibly for KNN (k=1), as it helps reduce variance and overfitting.

Random SubSpacing could be more beneficial for decision trees, but less so for neural networks and KNN (k=1), due to their dependence on the full feature set for prediction accuracy.

## Finding the best strategy for each classifier

I used python to perform a grid search in order to find the optimum mix of subspace size, bag size and number of iterations.

## Here is the code I used to find the optimum for Decision tree

```
X_train = df.iloc[:, :-1].values
y_train = df.iloc[:, -1].values
tree = DecisionTreeClassifier()
bagging_tree = BaggingClassifier(base_estimator=tree)
param_grid_tree = {
    'max_samples': [0.2, 0.4, 0.6, 0.8, 1.0],
    'max_features': [0.2, 0.4, 0.6, 0.8, 1.0],
    'n_estimators': [2,4,6,8,10,12,14,16,18,20]}
grid_search_tree = GridSearchCV(bagging_tree, param_grid_tree, cv=5, n_jobs=-1, verbose=2)
grid_search_tree.fit(X_train, y_train)
```

## **Output**

Best parameters for Decision Tree: {'max\_features': 1.0, 'max\_samples': 0.4, 'n\_estimators': 20}

Best score for Decision Tree: 0.5570577459073283

## I then used the optimum to generate benchmarks for decision tree

## **Classification Report:**

	precisi	on re	ecall	f1-sc	ore s	suppo	rt
0	0.60		C.E.	0.6	1 1	161	
0	0.62	2 0.	65	0.64	+ 4	461	
1	0.45	5 0.	41	0.43	3 3	748	
2	0.35	5 0.	32	0.34	4	044	
3	0.68	5 0.	69	0.6	7 4	339	
4	0.66	o.	70	0.68	3	519	
accura	асу			0.56	20	111	
macro	avg	0.55	0.	55	0.55	20	111
weighted avg 0.		0.55	C	.56	0.55	20	)111

Cohen's Kappa: 0.4445369065318724

### Discussion

The findings align with the theoretical expectations, demonstrating the effectiveness of bagging in improving the Decision Tree's performance. The reliance on the full feature set (100% max features) also aligns with the expectation that Decision Trees can handle and benefit from more complex feature spaces.

## KNN K=1

## Similar code was used for KNN k=1

```
X_train = df.iloc[:, :-1].values
y_train = df.iloc[:, -1].values
knn = KNeighborsClassifier(n_neighbors=1)
bagging_knn = BaggingClassifier(base_estimator=knn)
param_grid_knn = {
    'max_samples': [0.2, 0.4, 0.6, 0.8, 1.0],
    'max_features': [0.2, 0.4, 0.6, 0.8, 1.0],
    'n_estimators': [2,4,5,8,10,12,14,16,18,20]}
grid_search_knn = GridSearchCV(bagging_knn, param_grid_knn, cv=5, n_jobs=-1, verbose=2)
grid_search_knn.fit(X_train, y_train)
```

## Output

Best parameters for kNN: {'max\_features': 0.6, 'max\_samples': 0.4, 'n\_estimators': 20}

Best score for kNN: 0.5006214638775821

## Classification Report KNN K=1

```
precision recall f1-score support
      0
                  0.65
                         0.64
                                4461
           0.62
      1
           0.45
                  0.40
                         0.42
                                3748
      2
          0.36
                  0.33
                         0.35
                                4044
      3
          0.66
                  0.70
                         0.68
                                4339
      4
          0.66
                  0.70
                         0.68
                                3519
  accuracy
                         0.56
                               20111
                      0.56
                             0.55
 macro avg
              0.55
                                   20111
weighted avg
               0.55
                      0.56
                              0.55
                                    20111
```

Cohen's Kappa: 0.4489736748565837

### **Discussion**

This result is somewhat in line with the theoretical expectations. While bagging was expected to be beneficial, the improvement in performance was not as significant as it was for the Decision Tree. The reduced feature set (60% max features) indicates some departure from the expectation that kNN relies heavily on the full feature set. This could be due to the specific nature of the dataset or the characteristics of kNN when k=1.

#### **Neural network**

```
X_train = df.iloc[:, :-1].values
y_train = df.iloc[:, -1].values
mlp = MLPClassifier(max_iter=1000)
bagging_mlp = BaggingClassifier(base_estimator=mlp)
param_grid_mlp = {
    'max_samples': [0.2, 0.4, 0.6, 0.8, 1.0],
    'max_features': [0.2, 0.4, 0.6, 0.8, 1.0],
    'n_estimators': [20]
}
grid_search_mlp = GridSearchCV(bagging_mlp, param_grid_mlp, cv=5, n_jobs=-1, verbose=2)
grid_search_mlp.fit(X_train, y_train)
```

Best parameters for MLP: {'max\_features': 1.0, 'max\_samples': 1.0, 'n\_estimators': 20} Best score for MLP: 0.5686300497520249

## **Discussion neural network**

These findings align well with the theoretical expectations. The reliance on the full feature set (100% max features) and the full sample set (100% max samples) fits in with the understanding that neural networks benefit from a more extensive data and feature space to model complex relationships effectively.

### 1.5

## **Linear regression**

```
Linear Regression Model

energy =

1.8559 * loudness +
0.1221 * liveness +
0.1162 * tempo +
-0.922

Time taken to build model: 0.04 seconds

=== Cross-validation ===
=== Summary ===

Correlation coefficient 0.6945
Mean absolute error 0.0998
Root mean squared error 0.1257
Relative absolute error 70.9086 %
Root relative squared error 71.9433 %
Total Number of Instances 20111
```

## energy =

```
1.8559 * loudness + 0.1221 * liveness + 0.1162 * tempo + -0.922
```

The linear regression model shows 'loudness' as the most influential predictor for 'energy', with a correlation coefficient of 0.6945 indicating a moderate positive relationship between the predictors and the target. The model has an MAE of 0.0998 and an RMSE of 0.1257, which suggests that predictions are relatively close to the actual values. However, the high relative errors (over 70%) imply that the model's performance is not vastly superior to a basic predictor based on the mean.

## **SGD**

```
energy =

1.8503 (normalized) loudness
+ 0.1169 (normalized) liveness
+ 0.1094 (normalized) tempo
- 0.9283

Time taken to build model: 0.65 seconds

=== Cross-validation ===
=== Summary ===

Correlation coefficient 0.6906
Mean absolute error 0.1008
Root mean squared error 0.1265
Relative absolute error 71.6253 %
Root relative squared error 72.4058 %
Total Number of Instances 20111
```

## energy =

- 1.8503 (normalized) loudness
- + 0.1169 (normalized) liveness
- + 0.1094 (normalized) tempo
- 0.9283

The SGD regression model indicates 'loudness' is the strongest predictor of 'energy'. The model also has moderate prediction accuracy (correlation coefficient of 0.6906). The MAE and RMSE values are low, showing close predictions to actual 'energy' levels, but relative errors over 70% suggest the model's predictions are not substantially better than a simple average based model.

## Comparison of Linear regression and SGD

Comparing the Linear Regression and SGD models, both identify 'loudness' as the primary influencing factor for predicting 'energy'. The Linear Regression model has a slightly higher correlation coefficient (0.6945 vs. 0.6906), suggesting it may fit the data marginally better than the SGD model. The MAE and RMSE are very close for both models, indicating similar predictive accuracy. However, both models exhibit high relative errors exceeding 70%, indicating that neither model is a significant improvement over a simple model that would predict the average 'energy' for all tracks. Overall, the performance of both models is comparable with no substantial differences in predictive accuracy.

### **END OF ASSIGNMENT 2**