CSC 558 Data Mining and Predictive Analytics II, Fall 2021 Parson's Answers

Dr. Dale E. Parson, Assignment 2, Classification of audio data samples from assignment 1 for predicting numeric white-noise amplification level for the signals' generators.[1] We will also investigate discretizing the white-noise target attribute (class) and other non-target attributes.

DUE By 11:59 PM on Thursday October 21, 2021 via D2L Assignment 2. The standard 10% per day deduction for late assignments applies.

There will be one in-class work session October 18 for this assignment. Start early and come prepared to ask questions. October 11 & 12 are holidays, and October 14 I will take my one personal day, so no Thursday office hour. I will hold my Wednesday 4-6 PM office hour on October 13 via Zoom as usual.

Download the following ZIP file via a web browser and unzip.

https://acad.kutztown.edu/~parson/whitenoise558fa2021.problem.zip

You can do all your work on a Kutztown PC or your home machine, no need for acad.

You will see the following files in this **whitenoise558fa2021** directory:

README.txt	Your answers to Q1 through Q20 below go here, in the required format.
csc558wn10Kfa2021.arff	The handout ARFF file for assignment 2, **wn** means white noise.

The following four files are from csc558wn10Kfa2021.arff without the five tnoign==0 instances.

csc558wnTrain100fa2021.arff	100 initial-order training instances from csc558wn10Kfa2021NoTid0.arff.
csc558wnTest9900fa2021.arff	9900 remaining initial-order test instances of csc558wn10Kfa2021NoTid0.arff.
csc558wnTrain100Rndfa2021.arff	100 random-order instances from csc558wn10Kfa2021NoTid0.arff.
csc558wnTest9900Rndfa2021.arff	9900 other random instances from csc558wn10Kfa2021NoTid0.arff.

ALL OF YOUR ANSWERS FOR Q1 through Q16 BELOW MUST GO INTO THE README.txt file supplied as part of assignment handout directory **whitenoise558fa2021**. You will lose an automatic 20% of the assignment if you do not adhere to this requirement.

1. Open **csc558wn10Kfa2021.arff** in Weka's Preprocess tab. This is the same dataset used for assignment 1, with AddExpression's derived attributes already in place, and with **tosc** and **tid** removed; tagged numeric attribute **tnoign**, which is the gain on the white-noise generator, is the class (a.k.a. target attribute) of assignment 2. Where assignment 1 had a nominal attribute as the class, this assignment has **tnoign** as a numeric class attribute.

Here are the attributes in csc558wn10Kfa2021.arff.

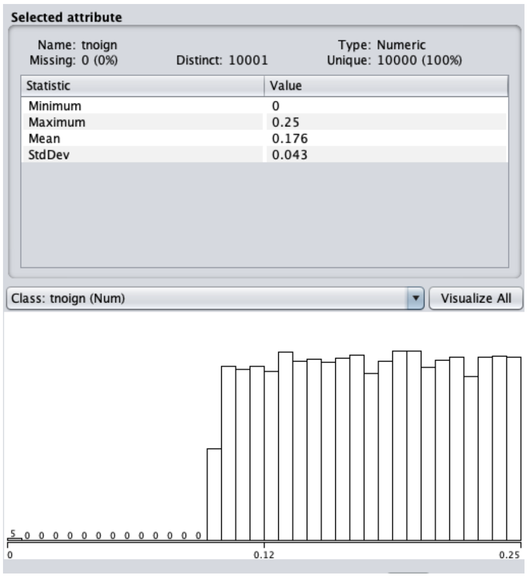
centroid	**Raw** spectral centroid extracted from the audio .wav file.
rms	**Raw** root-mean-squared measure of signal strength extracted from the audio .wav file.
roll25	**Raw** frequency where 25% of the energy rolls off, extracted from the audio .wav file.
roll50	**Raw** frequency where 50% of the energy rolls off, extracted from the audio .wav file.

[1] See Assn1AudioOverview http://faculty.kutztown.edu/parson/spring2020/CSC558Audio1_2020.html and in-class discussion on the Zoom archives.

roll75 **Raw** frequency where 75% of the energy rolls off, extracted from the audio .wav file.
amplbin1 through **amplbin19** Normalized amplitudes of 1st through 19th overtones of the fundamental. Filter **RemoveUseless** has removed **amplbin0** because of its constant value of 1.0.

Raw indicates an attribute that you normalized in assignment 1 to the reference fundamental frequency or amplitude. Attributes **centrfreq**, **roll25freq**, **roll50freq**, **roll75freq**, **nc**, **n25**, **n50**, **n75**, and **normrms** are Derived Attributes we created in assignment 1. Even though they are redundant with attributes from which they derive, they turn out to be useful for fine-tuning classifiers. We are keeping them for now. There are 34 attributes in the ARFF data of this assignment.

tnoign Target white noise signal gain passed to the audio generator in the range [0.0, 1.0]. Except for the five **tnoign**=0.0 samples that we will remove, the signal generator for this dataset generates **tnoign** in the range [0.1, 0.25). Note the Weka Preprocess statistics for **tnoign** below.



Selected attribute

Name: tnoign
Missing: 0 (0%)
Distinct: 10001
Type: Numeric
Unique: 10000 (100%)

Statistic	Value
Minimum	0
Maximum	0.25
Mean	0.176
StdDev	0.043

Figure 1: Class attribute tnoign in the handout dataset.

Since this assignment is about predicting white noise gain tagged as attribute **tnoign**, it is important to review the definition of white noise. As linked from Assn1AudioOverview, "White noise is a random signal having equal intensity at different frequencies, giving it a constant power spectral density…In discrete time, white noise is a discrete signal whose samples are regarded as a sequence of serially uncorrelated random variables with zero mean and finite variance.[2]" This white noise signal is distinct from the Sine, Triangle, Square, Sawtooth, and Pulse wave signals that were the focus of assignment 1, added into the composite signal with a random gain in the range [0.5, 0.75). The dataset of assignments 1 and 2 add white noise with a random gain in the range [0.1, 0.25) to each signal-record in the dataset, with 5 exceptions that you will remove in step 2 below. Compare the frequency domain plot of the noiseless 1000 Hz training sine wave of assignment 1[3] with the 1001 Hz sine wave with a **tnoign**= 0.139453694281 used as a noise-bearing training instance in assignment 1[4]. Both peak at about 1000 Hz, but the signal without white noise loses

[2] Wikipedia page on white noise https://en.wikipedia.org/wiki/White_noise , quotation checked for accuracy.
[3] http://faculty.kutztown.edu/parson/fall2021/lazy1_SinOsc_1000_0.9_0.0_0.FREQ.png
[4] http://faculty.kutztown.edu/parson/fall2021/lazy1_SinOsc_1001_0.500235007566_0.139453694281_615143.FREQ.png

most of its strength after that. The signal with **tnoign**= 0.139453694281 white noise falls off considerably less, maintaining an almost constant signal strength all the way to the Nyquist frequency of 22050 Hz. The contribution of white noise at each frequency is random and seemingly small, but the net contribution of white noise is to add signal strength evenly across the frequency spectrum. We are trying to determine that contribution based strictly on audio data in the WAV files in this assignment. Important points to note include the following.

- Most of the frequency spectrum in the range [0, 22050] Hz lies above the non-noise signal generation (sine, triangle, etc.) fundamental frequency of [100, 2000] Hz. White noise spans the [0, 22050] Hz range. While the non-sine waves contribute harmonics that push measures such as centroid and the rolloff frequencies higher than the fundamental frequency, white noise pushes these measures even further up the frequency spectrum because it spans the [0, 22050] Hz range.

- White noise contributes additional power beyond the non-noise signals across the wave + white noise signal. Attribute **rms** is the measure of power across the time-varying, time-domain signal. Unlike the normalized fundamental frequency of **amplbin0**, which represents only the strongest frequency component of a signal, **rms** integrates signal strength across the frequency spectrum.

The five **tnoign**=0.0 samples illustrated in Figure 1 are outliers in relation to the other 10,000 instances.

2. Use Weka's Unsupervised -> Instance -> RemoveWithValues Preprocess filter to remove the five outlying instances with **tnoign**=0.0. Use the attributeIndex to select tnoign, use the splitPoint to select a value for this attribute above which OR below which instances will be discarded, using invertSelection if necessary to change the direction of the split. Successful application of RemoveWithValues to tnoign results in 10,000 instances with tnoign in the range [0.1, 0.25), which is the range of white noise gain for the signal generator. **SAVE THIS 10000-INSTANCE DATASET INTO FILE csc558wn10Kfa2021NoTid0.arff**.

Q1: What is your exact RemoveWithValues command line from the top of Weka's Preprocess tab?

RemoveWithValues -S 1.0E-6 -C last -L first-last

3. Run Classify -> Functions -> LinearRegression using 10-fold cross-validation on this 10,000-instance dataset.

Q2: Paste the following measures into README.txt Q2. We will use Correlation coefficient as the primary measure of accuracy in this assignment.

Measures in blue use same approach of sorted amplitude-percentage-of-fundamental, frequency-multiple-of-fundamental (ampl1, freq1 … ampl32, freq32 of extractAudioFreqARFF.py) that performed consistently better than the handout data in Assignment 1 classification of waveform type. See https://faculty.kutztown.edu/parson/fall2021/csc558fa2021lazyassn1ANSWERS.pdf .

The bold black ones are the first 128 of 22,050 unsorted FFT bins, along with the mean of all 22,050 values, created by running extractAudioFreqARFF23Oct2021.py. I tried this approach because the blue **approach emphasizes the first 32 peaks of these FFT analyses, missing the white-noise average elevation of the troughs across the frequency spectrum. Adding the mean of all 22,050 FFT values improved accuracy slightly beyond just using the first 128 unsorted FFT bins. Compare for base elevation gain of tnoign**
http://faculty.kutztown.edu/parson/spring2020/lazy1_SinOsc_1000_0.9_0.0_0.FREQ.png
tnoign=0.0

http://faculty.kutztown.edu/parson/spring2020/lazy1_SinOsc_341_0.510394332522_0.249946792181_531147.FREQ.png tnoign=0.249946792181.

Correlation coefficient	0.7845
Mean absolute error	0.0208
Root mean squared error	0.0267
Relative absolute error	55.9807 %
Root relative squared error	62.0029 %
Total Number of Instances	10000

Correlation coefficient	0.2164
Mean absolute error	0.0359
Root mean squared error	0.042
Relative absolute error	96.4426 %
Root relative squared error	97.6888 %
Total Number of Instances	10000

Correlation coefficient	**0.9743**
Mean absolute error	**0.0071**
Root mean squared error	**0.0097**
Relative absolute error	**18.9487 %**
Root relative squared error	**22.6057 %**
Total Number of Instances	**10000**

Examine the Weka LinearRegression formula that starts out like this:

```
Linear Regression Model

tnoign =
      C.c * centroid +
      C.c * rms +
      …
     -0.4307
```

Q3: In terms of absolute value of the coefficients C.c, what are the top six, starting with the one with the highest magnitude in descending order? Include the ones with minus signs in front of them, using their magnitude (absolute value) to determine their ranking. Negative coefficients occur in one of two ways: a) the attribute being multiplied has a negative correlation with the target numeric attribute, which is still an informative correlation, or b) the negative coefficient is an adjustment for a positive coefficient elsewhere in the formula. The second case usually occurs for nominal non-target attributes that appear more than once in the formula. Do not use the constant, non-multiplier value at the end of the formula. Here is the first line of your answer; supply the other 5.

```
      9.1739 * rms +

      9.1739 * rms +
      0.4394 * centroid +
      0.392  * normrms +
      0.1893 * roll50 +
      0.1768 * amplbin19 +
     -0.1746 * roll25 +
 4.1211 * ampl29 +
 3.6207 * ampl32 +
 2.3383 * ampl30 +
-1.8375 * ampl31 +
-1.764  * ampl27 +
 1.6053 * ampl23 +
```

Weka rounds all of these coefficients to 0. We need to Normalize to see them.

Q4: Apply the unsupervised -> attribute -> Normalize preprocessing filter to all attributes using its default configuration parameters. With its default parameters Normalize adjusts each attribute except target **tnoign** to a value in the range [0.0, 1.0] using the formula **(value – min) / (max – min)** for the min and max of that attribute. Check several attributes to see the [0.0, 1.0] range and make sure tnoign has not been Normalized. Again run LinearRegression and paste the following measures into README.txt Q4:

```
Correlation coefficient                  0.7845
Mean absolute error                      0.0208
Root mean squared error                    0.0267
Relative absolute error                 55.9807 %
Root relative squared error               62.0029 %
Total Number of Instances                10000
```

```
Correlation coefficient                  0.2164
Mean absolute error                      0.0359
Root mean squared error                    0.042
Relative absolute error                 96.4426 %
Root relative squared error               97.6888 %
Total Number of Instances                10000
```

```
Correlation coefficient                  0.9743
Mean absolute error                      0.0071
Root mean squared error                    0.0097
Relative absolute error                 18.9487 %
Root relative squared error               22.6057 %
Total Number of Instances                10000
```

Q5: In terms of absolute value of the coefficients C.c for this Normalized LinearRegression model, what are the top six, starting with the one with the highest magnitude in descending order? Use the approach to coefficient absolute values that you used for Q3. List which attributes have been **Removed** from the top six, which have been **Added**, and which have been **Retained**.

```
-0.6034 * n50 +
 0.468  * n75 +
 0.3276 * n25 +
 0.1098 * centrfreq +
 0.1093 * centroid +
 0.1088 * rms +
```

Removed:	normrms, roll50, amplbin19, roll25
Added:	n50, n75, n25, centrfreq
Retained:	rms, centroid

0.2256 * freq7 +
0.2097 * **ampl29** +
-0.1991 * ampl9 +
0.1829 * ampl12 +
-0.18 * freq6 +
0.1573 * **ampl32** +
Removed ampl30, ampl31m ampl27, ampl23
Added freq7, ampl9, ampl12, freq6
Retained ampl29, ampl32

0.1304 * AVGFFT +
0.0237 * amplfft75 +
0.0218 * amplfft83 +
-0.0207 * amplfft1 +
0.0197 * amplfft39 +
0.0185 * amplfft20 +

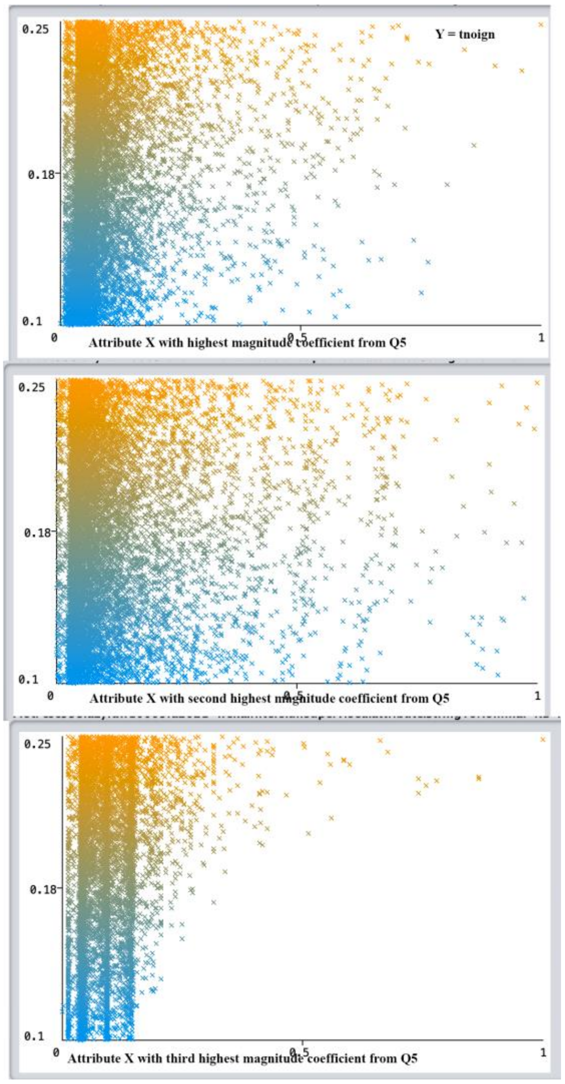


Figure 1

Figure 1 shows the non-target attribute with the highest magnitude LinearRegression coefficient along the X axis at the top plot from Weka's Visualize tab, the second highest magnitude coefficient in the middle, and the third highest magnitude coefficient at the bottom. The Y axis shows target attribute **tnoign**. The centers of their slopes are rather steep. A vertical slope would be useless because all values of **tnoign** would correlate with a single value of the non-target attribute. A horizontal slope would be useless because all values of the non-target attribute would correlate with a single value of **tnoign**. Use Weka's Visualize tab to see that most other attributes have much more scattered correlations of the non-target attributes to **tnoign**.

Q6: For some datasets Normalization to the range [0.0, 1.0] or some other fixed range addresses the problem of making some attributes appear more important in the LinearRegression formula than they are when interpreting the formula. Which attribute had the highest coefficient C.c in your answer to Q2 & Q3, and what happened to that attribute's importance in Normalized Q4 & Q5 relative to other attributes? Why was its coefficient C.c so very high in Q2 compared to Normalized Q4? (Hint: You probably need to execute Undo in the Preprocess tab to see its original range of min and max values to answer this question.)

The highest coefficient C.c in the answer to Q2 & Q3 was 9.1739 * rms +. It dropped to sixth place 0.1088 * rms + in Q4 & Q5. The numeric range of rms before Normalization was [0.006, 0.017], a very low range requiring substantial multiplication to make a contribution to the Q2 LinearRegression formula. Once it has been Normalized to the range [0.0, 1.0] it is no longer necessary to scale it up, since it matches the range of all other non-target attributes.

Q7: Re-Normalize if necessary to get Normalized non-target attributes. Continue using Normalized non-target attributes unless otherwise instructed. Run Classify -> Trees -> M5P model tree on this 10,000-instance Normalized dataset, and record the Results (not the Model) for Q7. How do the M5P Results (correlation coefficient and error measures) compare with those of LinearRegression for this Normalized dataset? Make sure to include M5P's Number of Rules measure, which is the number of leaf-linear-regression formulas in the M5P decision tree. (Note: If you executed Undo to discard Normalization in answering Q6, you will need to run the Normalize attribute filter now.)

```
Number of Rules : 135
Correlation coefficient              0.9143
Mean absolute error                  0.0129
Root mean squared error                0.0174
Relative absolute error             34.7104 %
Root relative squared error           40.5236 %
Total Number of Instances            10000
```

```
Number of Rules : 492
Correlation coefficient              0.8436
Mean absolute error                  0.0074
Root mean squared error                0.0265
Relative absolute error             19.9261 %
Root relative squared error           61.5375 %
Total Number of Instances            10000
```

Q8: Continue using the Normalized dataset. Run the instance-based (lazy) classifier IBk repeatedly with its default configuration parameters, increasing the KNN (number of nearest neighbors with **tnoign** values to be averaged together) parameter on each run until its performance begins to degrade, inspecting only correlation coefficient for its peak. If CC hits a plateau, keep going until it goes up or down. What lowest value of KNN gives the most accurate result in terms of correlation coefficient? Shows its Results.

KNN=10

```
Correlation coefficient            0.8742
Mean absolute error                0.0162
Root mean squared error              0.0215
Relative absolute error           43.5989 %
Root relative squared error         49.9213 %
Total Number of Instances          10000
```

KNN=11

```
Correlation coefficient            0.5848
Mean absolute error                0.0292
Root mean squared error              0.0384
Relative absolute error           78.4106 %
Root relative squared error         89.1891 %
Total Number of Instances          10000
```

KNN= 17 it keeps slowly going up, no time now, candidate for a batch file

```
Correlation coefficient            0.9754
Mean absolute error                0.0103
Root mean squared error              0.0127
Relative absolute error           27.778  %
Root relative squared error         29.4887 %
Total Number of Instances          10000
```

Q9: Run the instance-based (lazy) classifier IBk one more time with its KNN as determined in Q8, then run it again after changing the nearest neighbor search algorithm from LinearNNSearch to KDTree with default parameters, and run it again using BallTree instead of KDTree. What change in behavior or performance do you notice compared to using the default LinearNNSearch nearest neighbor search algorithm?

Builds take longer but model runs faster with KDTree and again with BallTree.

In preparation for the next steps, run Preprocess filter Unsupervised -> Attribute -> Discretize on the target attribute **tnoign**, making sure to set the **ignoreClass** configuration parameter to **true**, allowing the Filter to Discretize target attribute **tnoign** (the Last attribute). Leave the useEqualFrequency parameter at false, leave bins at 10, and check **tnoign** before and after using the filter to make sure its distribution histograms look similar, and that it is not numeric after discretization. Do NOT discretize any numeric attributes other than **tnoign**. Check in the Preprocess tab to make sure no other attributes are discretized.

Q10: Now, run Preprocess filter Unsupervised -> Attribute -> Discretize on all remaining attributes with useEqualFrequency parameter at the default false and bins at 10. Inspect some of them in the Preprocess tab. Run classifiers rule **OneR**, tree **J48**, **BayesNet**, and instance (lazy) classifier **IBk** with the KNN parameter found in Q8 and nearest neighbor search algorithm of KDTree, and give their Results as outlined below, preceding each Result with the name of its classifier.

OneR

```
Correctly Classified Instances       1929            19.29   %
Incorrectly Classified Instances     8071            80.71   %
Kappa statistic   0.1016
```

```
J48
Correctly Classified Instances       2501               25.01   %
Incorrectly Classified Instances     7499               74.99   %
Kappa statistic                         0.1668

BayesNet
Correctly Classified Instances       1886               18.86   %
Incorrectly Classified Instances     8114               81.14   %
Kappa statistic                         0.0986

IBk with the KNN parameter of 10
Correctly Classified Instances       2470               24.7    %
Incorrectly Classified Instances     7530               75.3    %
Kappa statistic                         0.1635

OneR
Correctly Classified Instances       1285               12.85   %
Incorrectly Classified Instances     8715               87.15   %
Kappa statistic                         0.0269

J48
Correctly Classified Instances       1324               13.24   %
Incorrectly Classified Instances     8676               86.76   %
Kappa statistic                         0.0361

BayesNet
Correctly Classified Instances       1175               11.75   %
Incorrectly Classified Instances     8825               88.25   %
Kappa statistic                         0.0197

IBk with KNN=11
Correctly Classified Instances       1309               13.09   %
Incorrectly Classified Instances     8691               86.91   %
Kappa statistic                         0.0352

OneR
Correctly Classified Instances       3852               38.52   %
Incorrectly Classified Instances     6148               61.48   %
Kappa statistic                         0.3159

AVGFFT rule
        '(-inf-0.1]'    -> '(-inf-0.11501]'
        '(0.1-0.2]'     -> '(0.11501-0.130008]'
        '(0.2-0.3]'     -> '(0.130008-0.145006]'
        '(0.3-0.4]'     -> '(0.160004-0.175001]'
        '(0.4-0.5]'     -> '(0.175001-0.189999]'
        '(0.5-0.6]'     -> '(0.189999-0.204997]'
        '(0.6-0.7]'     -> '(0.189999-0.204997]'
        '(0.7-0.8]'     -> '(0.234993-inf)'
        '(0.8-0.9]'     -> '(0.234993-inf)'
        '(0.9-inf)'     -> '(0.234993-inf)'
```

J48

```
Correctly Classified Instances       4705            47.05   %
Incorrectly Classified Instances     5295            52.95   %
Kappa statistic                    0.4116
```

BayesNet

```
Correctly Classified Instances       5043            50.43   %
Incorrectly Classified Instances     4957            49.57   %
Kappa statistic                    0.4491
```

IBk with KNN=17

```
Correctly Classified Instances       1433            14.33   %
Incorrectly Classified Instances     8567            85.67   %
Kappa statistic                    0.0499
```

Q11: Execute Preprocess -> Undo once, then check to make sure that only class **tnoign** is still Discretized. All other attributes except **tnoign** should be numeric. Now, run Preprocess filter **Supervised** -> Attribute -> Discretize on all remaining attributes (not **tnoign**). Inspect some of them in the Preprocess tab. Supervised Discretization attempts to correlate the non-target attribute bins with the target attribute ahead of classification model building. Run classifiers rule **OneR**, tree **J48**, **BayesNet**, and instance (lazy) classifier **IBk** with the KNN parameter found in Q8 and nearest neighbor search algorithm of KDTree, and give their Results as in Q10, preceding each Result with the name of its classifier. Which classifiers became BETTER as measured by Kappa when compared with Q10, and which became WORSE. Just write BETTER or WORSE or SAME behind their classifier names.

OneR WORSE or SAME

```
Correctly Classified Instances       1920            19.2    %
Incorrectly Classified Instances     8080            80.8    %
Kappa statistic                    0.101
```

J48 WORSE

```
Correctly Classified Instances       2011            20.11   %
Incorrectly Classified Instances     7989            79.89   %
Kappa statistic                    0.1124
```

BayesNet BETTER

```
Correctly Classified Instances       2002            20.02   %
Incorrectly Classified Instances     7998            79.98   %
Kappa statistic                    0.1118
```

IBk with the KNN parameter of 10 WORSE

```
Correctly Classified Instances       2153            21.53   %
Incorrectly Classified Instances     7847            78.47   %
Kappa statistic                    0.1284
```

OneR

```
Correctly Classified Instances       1780            17.8    %
Incorrectly Classified Instances     8220            82.2    %
Kappa statistic                    0.087
```

```
J48
Correctly Classified Instances        2001               20.01   %
Incorrectly Classified Instances      7999               79.99   %
Kappa statistic                          0.1114

BayesNet
Correctly Classified Instances        1890               18.9    %
Incorrectly Classified Instances      8110               81.1    %
Kappa statistic                          0.0973

IBk with the KNN parameter of 11
Correctly Classified Instances        2008               20.08   %
Incorrectly Classified Instances      7992               79.92   %
Kappa statistic                          0.1123
```

OneR

```
Correctly Classified Instances        4670               46.7    %
Incorrectly Classified Instances      5330               53.3    %
Kappa statistic                          0.407
```

AVGFFT:

```
	'(-inf-0.079226]'	-> '(-inf-0.11501]'
	'(0.079226-0.122959]'	-> '(0.11501-0.130008]'
	'(0.122959-0.160089]'	-> '(0.11501-0.130008]'
	'(0.160089-0.193093]'	-> '(0.130008-0.145006]'
	'(0.193093-0.239125]'	-> '(0.130008-0.145006]'
	'(0.239125-0.271473]'	-> '(0.145006-0.160004]'
	'(0.271473-0.312404]'	-> '(0.145006-0.160004]'
	'(0.312404-0.319145]'	-> '(0.145006-0.160004]'
	'(0.319145-0.356916]'	-> '(0.160004-0.175001]'
	'(0.356916-0.394196]'	-> '(0.160004-0.175001]'
	'(0.394196-0.400073]'	-> '(0.145006-0.160004]'
	'(0.400073-0.433844]'	-> '(0.175001-0.189999]'
	'(0.433844-0.47129]'	-> '(0.160004-0.175001]'
	'(0.47129-0.478431]'	-> '(0.160004-0.175001]'
	'(0.478431-0.520643]'	-> '(0.189999-0.204997]'
	'(0.520643-0.551228]'	-> '(0.189999-0.204997]'
	'(0.551228-0.582045]'	-> '(0.175001-0.189999]'
	'(0.582045-0.609358]'	-> '(0.204997-0.219995]'
	'(0.609358-0.627145]'	-> '(0.189999-0.204997]'
	'(0.627145-0.633593]'	-> '(0.189999-0.204997]'
	'(0.633593-0.6513]'	-> '(0.189999-0.204997]'
	'(0.6513-0.690092]'	-> '(0.219995-0.234993]'
	'(0.690092-0.709925]'	-> '(0.219995-0.234993]'
	'(0.709925-0.738432]'	-> '(0.234993-inf)'
	'(0.738432-0.769837]'	-> '(0.234993-inf)'
	'(0.769837-0.792624]'	-> '(0.234993-inf)'
	'(0.792624-0.825774]'	-> '(0.219995-0.234993]'
	'(0.825774-0.857932]'	-> '(0.234993-inf)'
	'(0.857932-0.916102]'	-> '(0.234993-inf)'
	'(0.916102-inf)'-> '(0.234993-inf)'
```

J48
Correctly Classified Instances 5248 52.48 %
Incorrectly Classified Instances 4752 47.52 %
Kappa statistic 0.4719

BayesNet
Correctly Classified Instances 6728 67.28 %
Incorrectly Classified Instances 3272 32.72 %
Kappa statistic 0.6364

IBk with the KNN parameter of 17
Correctly Classified Instances 1768 17.68 %
Incorrectly Classified Instances 8232 82.32 %
Kappa statistic 0.088

Q12: Execute Preprocess -> Undo once, then check to make sure that only class **tnoign** is still Discretized. All other attributes except **tnoign** should be numeric. Run classifiers rule **OneR**, tree **J48**, **BayesNet**, and instance (lazy) classifier **IBk** with the KNN parameter found in Q8 and nearest neighbor search algorithm of KDTree, and give their Results as before, preceding each Result with the name of its classifier. Which classifiers became BETTER as measured by Kappa when compared with **Q10**, and which became WORSE. Just write BETTER or WORSE or SAME behind their classifier names.

OneR WORSE
Correctly Classified Instances 1591 15.91 %
Incorrectly Classified Instances 8409 84.09 %
Kappa statistic 0.0657

J48 BETTER
Correctly Classified Instances 2902 29.02 %
Incorrectly Classified Instances 7098 70.98 %
Kappa statistic 0.2112

BayesNet BETTER
Correctly Classified Instances 1963 19.63 %
Incorrectly Classified Instances 8037 80.37 %
Kappa statistic 0.1075

IBk with the KNN parameter of 10 BETTER
Correctly Classified Instances 2896 28.96 %
Incorrectly Classified Instances 7104 71.04 %
Kappa statistic 0.2109

In general, increasing the resolution of the non-target attributes by keeping them numeric may help accuracy of prediction, since discretized non-target attributes only approximate the precision found in numeric non-target attributes. Unfortunately, precise numeric attributes may be harder for some classifiers to analyze. Bayesian analysis, for example, does its own discretization of numeric non-target attributes; this discretization may be better or worse than the Supervised Weka discretization filter at correlating non-target attributes to the target class.

OneR
Correctly Classified Instances 1706 17.06 %

```
Incorrectly Classified Instances     8294            82.94  %
Kappa statistic                      0.0783
```

J48

```
Correctly Classified Instances       1914            19.14  %
Incorrectly Classified Instances     8086            80.86  %
Kappa statistic                      0.1015
```

BayesNet

```
Correctly Classified Instances       1835            18.35  %
Incorrectly Classified Instances     8165            81.65  %
Kappa statistic                      0.0912
```

IBk with the KNN parameter of 11

```
Correctly Classified Instances       1817            18.17  %
Incorrectly Classified Instances     8183            81.83  %
Kappa statistic                      0.0925
```

OneR

```
Correctly Classified Instances       4257            42.57  %
Incorrectly Classified Instances     5743            57.43  %
Kappa statistic                      0.3616
```

J48

```
Correctly Classified Instances       5666            56.66  %
Incorrectly Classified Instances     4334            43.34  %
Kappa statistic                      0.5184
```

BayesNet

```
Correctly Classified Instances       6520            65.2   %
Incorrectly Classified Instances     3480            34.8   %
Kappa statistic                      0.6132
```

IBk with the KNN parameter of 17

```
Correctly Classified Instances       3764            37.64  %
Incorrectly Classified Instances     6236            62.36  %
Kappa statistic                      0.3072
```

Q13. All attributes numeric except **tnoign** should still be numeric and Normalized to the range [0.0, 1.0]. Try using ensemble meta-classifier **Bagging**, using your most accurate classifier (in terms of Kappa) configuration from Q12 as its base classifier. What base classifier did you select, and does it improve performance over Q12 in terms of Kappa by more than .02 of 1.0 of the non-bagged Result of Q12? Show your Result as before. All attributes except the target **tnoign** should be numeric at this point.

BASE CLASSIFIER USED: J48 SLIGHTLY BETTER, .258-.2109 = .0471, better than .02.

```
Correctly Classified Instances       3323            33.23  %
Incorrectly Classified Instances     6677            66.77  %
Kappa statistic                      0.258
```

BASE CLASSIFIER USED: J48 SLIGHTLY BETTER

```
Correctly Classified Instances       2125            21.25  %
```

```
Incorrectly Classified Instances      7875             78.75   %
Kappa statistic                          0.1249
```

Q14. Try using ensemble meta-classifier **AdaBoostM1**, using your most accurate classifier configuration form Q12 as its base classifier. What base classifier did you select, and does it improve performance over Q12 in terms of Kappa by more than .02 of 1.0 of the non-boosted Result of Q12? Show your Result as before. All attributes except the target **tnoign** should be numeric at this point.

BASE CLASSIFIER USED: J48 SLIGHTLY BETTER, .2558-.2109 = .0409, better than .02.

```
Correctly Classified Instances        3303             33.03   %
Incorrectly Classified Instances      6697             66.97   %
Kappa statistic                          0.2558
```

BASE CLASSIFIER USED: J48

```
Correctly Classified Instances        2079             20.79   %
Incorrectly Classified Instances      7921             79.21   %
Kappa statistic                          0.1198
```

Q15. Try using ensemble meta-classifier **RandomForest**, which uses RandomTree as its base classifier, running 100 RandomTrees by default. Does it improve performance over Q12 in terms of Kappa by more than .02 of 1.0 of the non-boosted Result of Q12? Show your Result as before. All attributes except the target **tnoign** should be Normalized numeric at this point.

.2752-.2109 = .0643, BETTER than .02.

```
Correctly Classified Instances        3478             34.78   %
Incorrectly Classified Instances      6522             65.22   %
Kappa statistic                          0.2752
```

```
Correctly Classified Instances        2256             22.56   %
Incorrectly Classified Instances      7744             77.44   %
Kappa statistic                          0.1396
```

Q16. What accounts for any performance improvements in terms of kappa in Q13 Q14 and Q15 over Q12 results?

Shuffling the training data for Bagging, boosting the misclassified instances for AdaBoost, integrating 100 alternative Random Trees for RandomForest.

For Q17 through Q20 I used the following bash shell script to create these files.

csc558wnTrain100fa2021.arff	100 initial training instances from csc558wn10Kfa2021NoTid0.arff.
csc558wnTest9900fa2021.arff	9900 remaining test instances from csc558wn10Kfa2021NoTid0.arff.
csc558wnTrain100Rndfa2021.arff	100 random-order instances from csc558wn10Kfa2021NoTid0.arff.
csc558wnTest9900Rndfa2021.arff	9900 other random instances from csc558wn10Kfa2021NoTid0.arff.

Bash script maker.sh. The non-SHUFFLED, non-Rnd instances are in original order.

```
echo "making 100 training instances in csc558wnTrain100fa2021.arff"
bash -c "echo '@relation csc558wnTrain100fa2021' >
csc558wnTrain100fa2021.arff"
bash -c "grep @ csc558wn10Kfa2021NoTid0.arff | grep -v  @relation >>
csc558wnTrain100fa2021.arff"
```

```
bash -c "grep ^[0-9] csc558wn10Kfa2021NoTid0.arff | head -100 >>
csc558wnTrain100fa2021.arff"
echo "making 9900 test instances in csc558wnTest9900fa2021.arff"
bash -c "echo '@relation csc558wnTest9900fa2021' >
csc558wnTest9900fa2021.arff"
bash -c "grep @ csc558wn10Kfa2021NoTid0.arff | grep -v  @relation >>
csc558wnTest9900fa2021.arff"
bash -c "grep ^[0-9] csc558wn10Kfa2021NoTid0.arff | tail -9900 >>
csc558wnTest9900fa2021.arff"
```

The SHUFFLED, Rnd instances are in random order

```
bash -c "grep ^[0-9] csc558wn10Kfa2021NoTid0.arff | sort --random-sort >
junk.txt"
echo "making 100 SHUFFLED training instances in
csc558wnTrain100Rndfa2021.arff"
bash -c "echo '@relation csc558wnTrain100Rndfa2021' >
csc558wnTrain100Rndfa2021.arff"
bash -c "grep @ csc558wn10Kfa2021NoTid0.arff | grep -v  @relation >>
csc558wnTrain100Rndfa2021.arff"
bash -c "head -100 < junk.txt >> csc558wnTrain100Rndfa2021.arff"
echo "making 9900 SHUFFLED test instances in csc558wnTest9900Rndfa2021.arff"
bash -c "echo '@relation csc558wnTest9900Rndfa2021' >
csc558wnTest9900Rndfa2021.arff"
bash -c "grep @ csc558wn10Kfa2021NoTid0.arff | grep -v  @relation >>
csc558wnTest9900Rndfa2021.arff"
bash -c "tail -9900 < junk.txt >> csc558wnTest9900Rndfa2021.arff
```

Q17. Load csc558wnTrain100fa2021.arff in the Preprocess tab as the training set, and set csc558wnTest9900fa2021.arff to be the supplied test set in the Classify tab. Do **NOT** Normalize or Discretize any attributes from Q17 through Q20. Run M5P and record its Results here. How many rules (linear formulas) does M5P generate?

```
Number of Rules : N
Correlation coefficient         ?
Mean absolute error             ?
Root mean squared error           ?
Relative absolute error        ? %
Root relative squared error       ? %
Total Number of Instances        9900
```

```
Number of Rules : 1
Correlation coefficient         0
Mean absolute error             0.0757
Root mean squared error           0.0868
Relative absolute error        100      %
Root relative squared error       100      %
Total Number of Instances        9900
```

Q18. Load csc558wnTrain100Rndfa2021.arff in the Preprocess tab as the training set, and set csc558wnTest9900Rndfa2021.arff to be the supplied test set in the Classify tab. Run M5P and record its Results here. How many rules (linear formulas) does M5P generate?

```
Number of Rules : 1
Correlation coefficient          0.6827
Mean absolute error              0.0248
Root mean squared error            0.0325
Relative absolute error         66.3996 %
Root relative squared error       75.3057 %
Total Number of Instances         9900
```

Q19. Before I removed **tosc** from your handout data, the instances were in the following order by **tosc** values. They remained in this order until my shell script randomized instance order in **`csc558wnTrain100Rndfa2021.arff`** and **`csc558wnTest9900Rndfa2021.arff`**. Note the five initial, 0-noise instances that you have deleted at the start of the current assignment in the above command output:

```
$ grep Osc csc558lazyraw10005sp2018.arff | cut -d, -f2 |uniq -c
      1 'PulseOsc'
      1 'SawOsc'
      1 'SinOsc'
      1 'SqrOsc'
      1 'TriOsc'
   2000 'PulseOsc'
   2000 'SawOsc'
   2000 'SinOsc'
   2000 'SqrOsc'
   2000 'TriOsc'
```

What accounts for the improvement in accuracy measures in going from Q17 to Q18? Note that before randomization, instances in file csc558wn10Kfa2021NoTid0.arff were in the same order as they are in the above csc558lazyraw10005sp2018.arff file.

Q17 is training on strictly on PulseOsc waveforms while Q18 has a better cross-section of the test data in the training date. Q17 is over-fit to PulseOsc waveforms.

Q20. Can you improve performance of M5P further by bagging it? Give Results showing improvement, or explain why this attempt at improvement fails. Make sure to use the randomized training and test files csc558wnTrain100Rndfa2021.arff and csc558wnTest9900Rndfa2021.arff of Q18, with M5P as the base classifier.

```
Correlation coefficient          0.7058 (BETTER THAN 0.6827)
Mean absolute error              0.0244
Root mean squared error            0.0307
Relative absolute error         65.4077 %
Root relative squared error       71.0967 %
Total Number of Instances         9900
```