University of St Andrews

Machine Learning

CS5014

Classification

Author:
150008022

April 16, 2019

Goal

The goal of this practical is to analyse a dataset in order to produce a classification model that can make predictions based on a set of inputs.

Contents

1 Loading Data

To load the data, the paths to the relevant files are supplied as arguments to the *__main__.py* script. The *pandas* module was used to load the file contents into *DataFrames*.

A test set was isolated from the original data using an 80%-20% split. Stratification was used to ensure that all classes were represented in the training data. Since the dataset was originally grouped by output class, the order of the samples were shuffled. This would avoid the later model being trained on several similiar instances in a row, which can have an affect on some algorithms performance.

2 Cleaning Data

When originally loading the CSV files the parameter to raise an exception on missing or extra columns was included, and so it could be assumed that all rows had the same number of columns. The dtype=**float** argument was also passed when loading the data to ensure that each column contained the expected numerical data. Any rows containing empty or NaN values were dropped from the dataset.

3 Data Visualisation and Analysis

The input CSV was understood to have the structure shown in figure 1. Each value is either the mean, minimum, or maximum reading from 100 radar pulses for a single component of a channel. Each channel is comprised of 256 components.

The mean, min, and max values were plotted for each channel for each sensor. The plots of the means of each channel for the book and plastic case objects are shown in figures 2 and 3 respectively. The difference between the resulting signals from the two objects are very clear.

In the binary dataset, the minimum and maximum components observed all followed a similiar shape as the average, but the book class did contain one severe outlier in two plots. The full plots are included in the submission under `plots/binarybook.png` and `plots/binaryplasticcase`, in which the plot of the minimum components in channel one and the maximum components

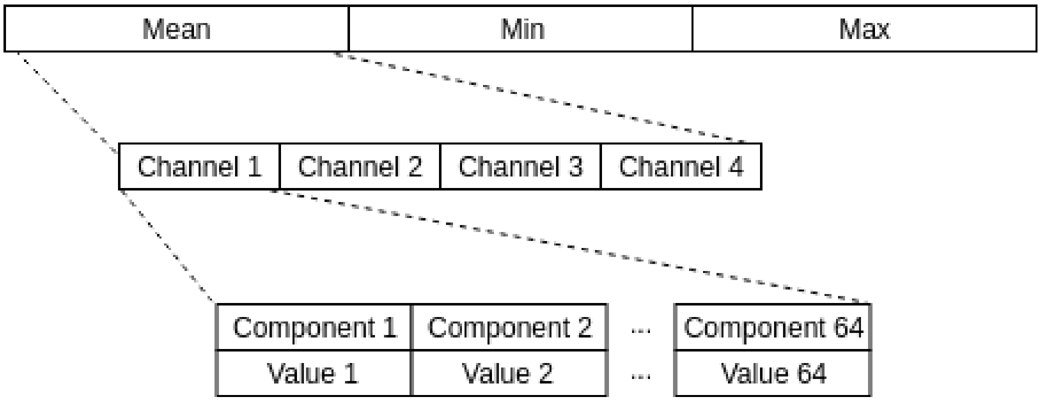


Figure 1: The structure of each row of the CSV file which is repeated for minimum and maximum values.

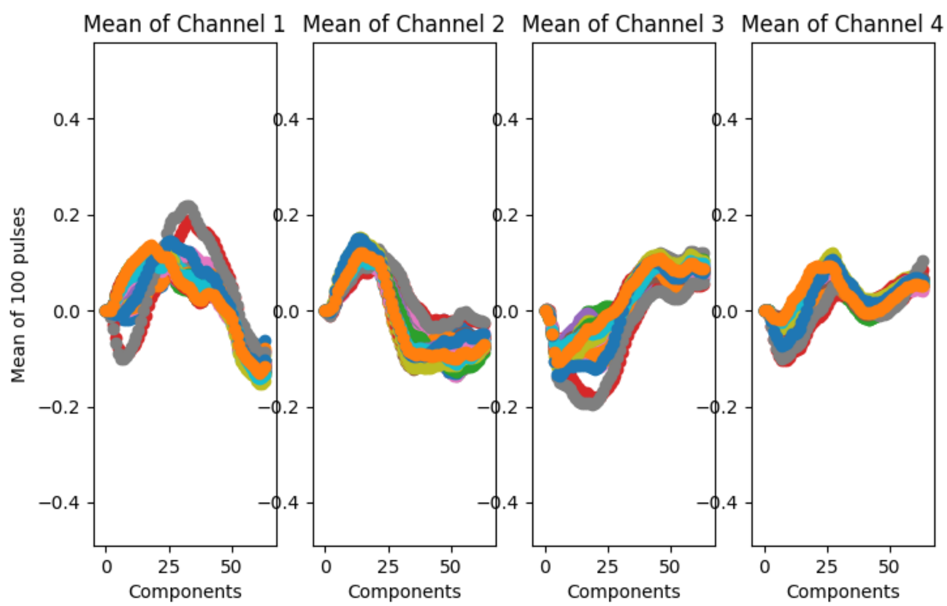


Figure 2: Mean of each channel measured for the book

in channel three both include one row of outliers. Since the average did not deviate from other components for that class, it seemed fair to say that these maximum and minimum readings were outliers. Instead of removing them and risking producing a biased model, the row was left in the data set. A

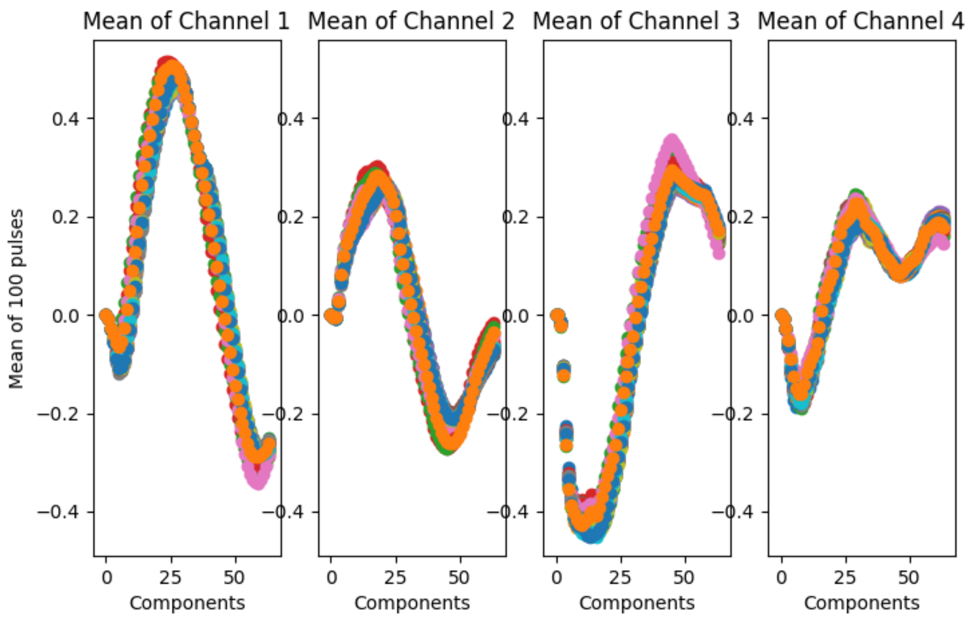


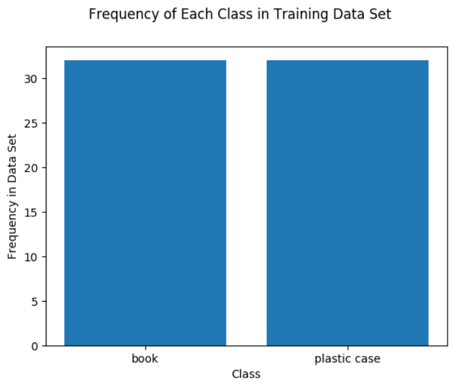
Figure 3: Mean of each channel measured for the plastic case

real world application of the sensor would likely involve noise, and so it made sense to train the model to be able to cope with anomalies. The existence of these outliers was however noted when choosing a cost function however in order to try and minimise their affect.

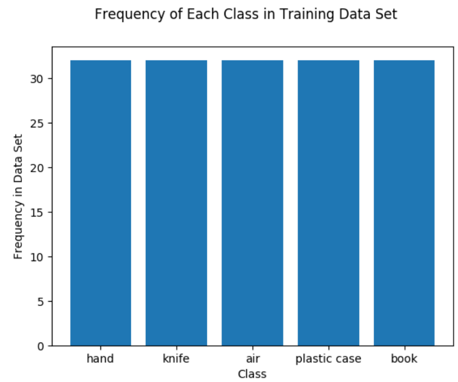
The same plots were made for the multiclass dataset, and from this it was clear that each material produced very different results, with varying levels of consistency. For example, the data aquired when the radar sensor was applied to a human hand varied wildly, whilst the readings for the plastic cover were a very clear sinusoidal shape. These plots can be found in `plots/multiclass*`.

Since the radar signature was determined by the reflection of the radar pulses on the surface and interior structure of each object, the resulting plots were understandable. For example, the plastic case shows a very consistent pattern likely due to the fact that it is composed of a single material in a uniform structure, whilst the human hand produces a very chaotic signature since it is composed of many different materials, especially fluids in motion.

The training data set was shown not be skewed by plotting the distribution of each class (figure4). The equal distribution of each class meant that



(a) Binary



(b) Multiclass

Figure 4: Frequencies of each class in the binary and multiclass training data sets

cross validation of a classifier that always guesses the same class will have a ratio of correct predictions inversely proportional to number of classes in the training data set.

All data from the feature set had values between -1 and 1, and from the plots of all classes it was noticed that the different classes had different global minumum and maximums for each channel. For example, the components of samples for air did not surpass 0.1, 0.25 for books, 0.5 for plastic case, and 0.75 to 1 for hand and knife. Based on this and the fact that there were no outliers and the values were evenly distributed, normalisation was used over standardisation. Plotting the normalised data and comparing it to the plots of the original data reinforced this decision, as the shape and scale of the resulting plots had been maintained.

4 Feature Selection

The large number of features available in the dataset makes computation of any model more expensive. In order to have an effective classifier, there should be at least five examples of each combination of values from each feature in the training data [1], which our dataset is unable to provide. Therefore a reduction of the feature set was considered necessary.

The visualisations of the training data showed that each class had very different levels of variation between each sample, and this variation could be used to identify a class. However our model would need to identify the class based on a single sample, and so this variation could not be relied on.

It was observed that the plots of each channel for the mean, minumum, and average were very similiar for each sample within a class. For this reason, all components were dropped except those based on the average of 100 pulses.

Principal component analysis (PCA) was then used to further reduce the number of features. PCA works by projecting the data onto the hyperplane that retains the most of the original variance in the dataset. By producing vectors that map and combine the original features to another set, PCA concentrates as much information into the first principle component, and then as much of whatever remains into the second component, and so on. Since the mapping combines features, the resulting components do not have any real meaning, though the original data can be recovered from the resulting principal components.

Initially, to try and understand PCA a plot of the first two principals components was produced (Figure 5. The first two principal components alone accounted for 82% of the original variance.

To show how variance changes as the number of principal components increases, the explained variance ratios were also plotted against the number of dimensions in figure 6. The return on increasing dimensions becomes miniscule after 20 dimensions. For the actual model, the PCA was configured to select the number of components that would retain 95% of the original variance. This reduced the feature set from 256 to 6.

The PCA used method requires loading the entire dataset into memory. Alternative methods exists such as incremental PCA and random PCA that can be used for online and batched learning.

5 Model Selection and Training

Multiclass classifcation can be implemented using binary classifiers through two methods, one-vs-one and one-vs-all. One-vs-all involves training an individual classifier per class, and each classifier is only able to state if the input represents its class or not. Since the training data used has an equal distribution of each class, each classifier would be trained on skewed data with far more negatives than positives as demonstrated in figure 7. This method would require as many classifiers as there are classes [2].

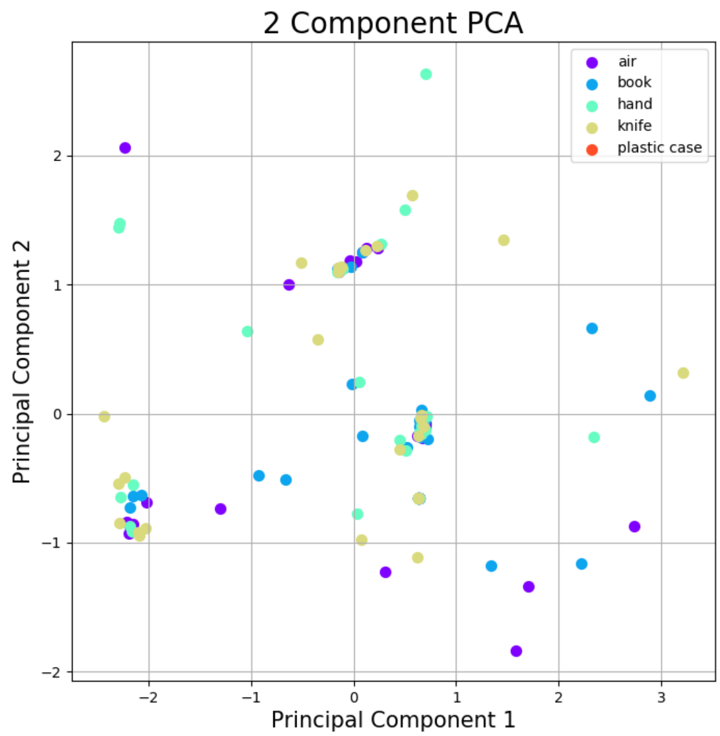


Figure 5: The first two principal components, coloured according to their class.

A one-vs-one classifier requires a classifier exists for each pair of classes. Each classifier will predict a value from the two classes it was trained to identify, and the resulting prediction will be the class that was chosen by the most classifiers. This method requires $n(n-1)^2$ classifiers, where n is the number of classes.

There also exist dedicated multiclass classifiers with different advantages and implementations.

Since the RadarCat [3] technology is intended to be able to allow users to identify and catalogue various every day objects, both the one-vs-one and one-vs-all approaches would involve a large number of classifiers being trained. Therefore an approach that required fewer classifiers would probably be preferred.

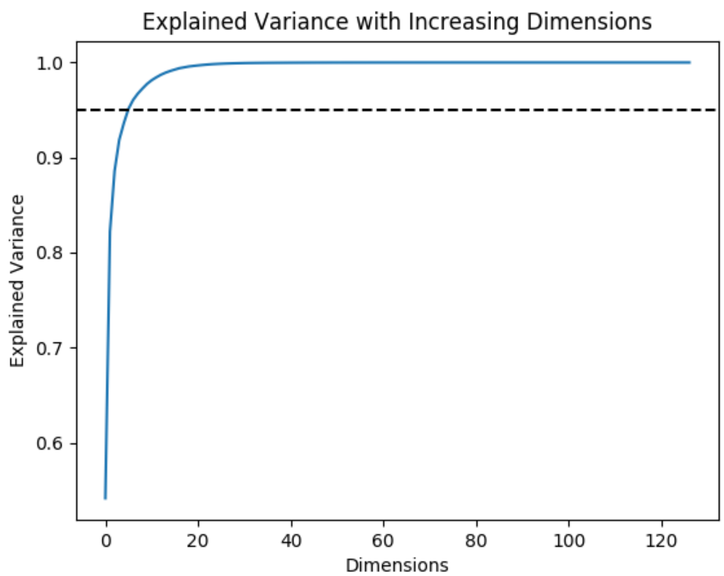


Figure 6: The elbow curve of explained variance that results from increasing the number of dimensions.

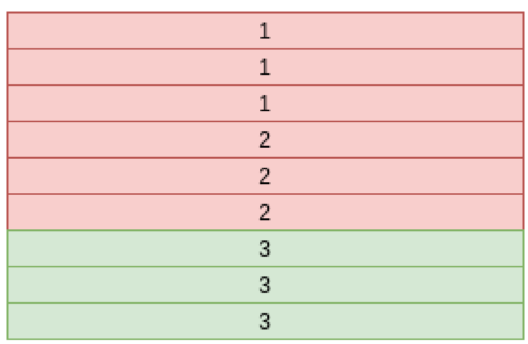


Figure 7: Distribution of negative and positive samples for a classifier trained to identify either class ’3’ or ’not 3’ when each class is equally represented

On the other hand, the Soli [4] technology used by RadarCat was designed with the intention of recognising hand gestures, and so being able to generalise well when trained on fewer classes would likely be favoured in that case (i.e. handling many variations of the same hand gesture).

Another possible solution that could reduce the number of classifiers needed as the number of classes grow is to create a hierarchy of classifiers. Each node has an "is-a" relationship with its parent in the tree, and prediction involves starting with a very generic classifier, and gradually getting more specific. [5] for example used such classifier to identify the musical genre of an audio clip using a heirachical structure. Though it performed similiarly to a flat classifier approach, it would be easier to include new classes. This would be useful for the RadarCat use case as the number of objects it is used to identify grows.

The ability to provide online learning (or at least batch learning) would also be useful, as user feedback could provide a method for crowdsourcing samples for further supervised learning. Crowdsourced data collection for producing data for supervised learning has famously been applied by projects such as reCAPTCHA [6], and a similiar method could be used by RadarCat to improve its error rate.

With the previous information in mind (and for the sake of evaluation and comparison), an inherently multiclass method (Random Forest) and a one-vs-all method (Linear Support Vector Machine) were chosen for the first and second models respectively.

5.1 Model 1: Random Forest Classifier

The random forest classifier was chosen due to its robustness when dealing with noisy data, which would definitely be present in real world applications [7]. The number of classifiers would not grow with the number of classes, though training would be slower. Especially so in this case due to the high number of dimensions involved.

5.2 Model 2: Linear Support Vector Machine

One-vs-all was implemented using SGDClassifier

6 Evaluation and Comparison

7 Discussion

References

[1] Sergios Theodoridis and Konstantinos Koutroumbas. *Pattern Recognition, Fourth Edition*. Academic Press, Inc., Orlando, FL, USA, 4th edition, 2008.

[2] Aurlien Gron. *Hands-On Machine Learning with Scikit-Learn, Keras, and Tensorflow*. O'Reilly Media, 2018.

[3] Hui-Shyong Yeo, Gergely Flamich, Patrick Schrempf, David Harris-Birtill, and Aaron Quigley. Radarcat: Radar categorization for input & interaction. pages 833–841, 10 2016.

[4] Jaime Lien, Nicholas Gillian, M Emre Karagozler, Patrick Amihood, Carsten Schwesig, Erik Olson, Hakim Raja, and Ivan Poupyrev. Soli: Ubiquitous gesture sensing with millimeter wave radar. *ACM Transactions on Graphics*, 35:1–19, 07 2016.

[5] Juan José Burred. A hierarchical music genre classifier based on user-defined taxonomies. 01 2005.

[6] Google. Introducing recaptcha v3: the new way to stop bots. 10 2018.

[7] Leo Breiman. Random forests. *Mach. Learn.*, 45(1):5–32, October 2001.