Machine Learning Engineer Nanodegree - Capstone Project

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I. Definition

Project Overview

As one gets older, an increasingly difficult awareness of our parent's mortality becomes a serious concern. Personally, my parents are both in their early 70's and according to a study[^1] done in **2015** by the **American Heart Association**, around **370,000** people die of heart attacks each year and is the **No. 1** cause of in the United States. In **2014**, around **356,500** people experienced heart attacks out of the hospital. Of that amount only **12%** survived due to emergency medical services intervention. Personally, I would not like my parents to be one the **88%** who suffered from a fatal heart attack and didn't survive due to the fact that there was no intervention by emergency medical services. According to the study, there is a prevalence of almost a *third* of the population at risk of *Heart Disease* leading to a *Heart Attack* as one approaches **80+** years of age. Having no personal experience in the Coronary Field of Medical research, it would be difficult for me to diagnose any potential warning signs, but with the advent of wearable technology, the mechanisms are in place to potentially aid in this early warning and detection of heart attacks. The majority of wearable technology today has the built-in ability to monitor heart rates. Therefore in this project, I proposed that this input data can be uploaded or sent to a **data ingestion pipeline** that this capable of interpreting, analyzing and detecting an the patterns that could be classified as symptoms of a heart attack.

Additionally, since one of the potential symptoms is the increase in heart rates. There are a number of potential factors that influence the increase in heart rate, but there are well published guidelines[^2] that can be used to determine anomalous patterns. If these anomalies occur, the the **data ingestion pipeline** could proactively determine if a heart attack is about to *or* has occurred and alert the appropriate emergency medical response. Thus proactively preventing a fatal or near-fatal heart attack. As an added benefit, the **pipeline** mechanism can be used to monitor patients who are in *Cardiac Rehabilitation*[^3].

Problem Statement

For this Project, I propose creating a classification pipeline that ingests heart-rate signal data (from a simulated wearable monitor) and classifies whether the subject is in a stressful situation that could lead to *Cardiac Unrest*. Additionally, in order to prevent a "cry-wolf" scenario or *false-positives*, the pipeline employs a consensus mechanism where three classifiers must all agree on the classification.

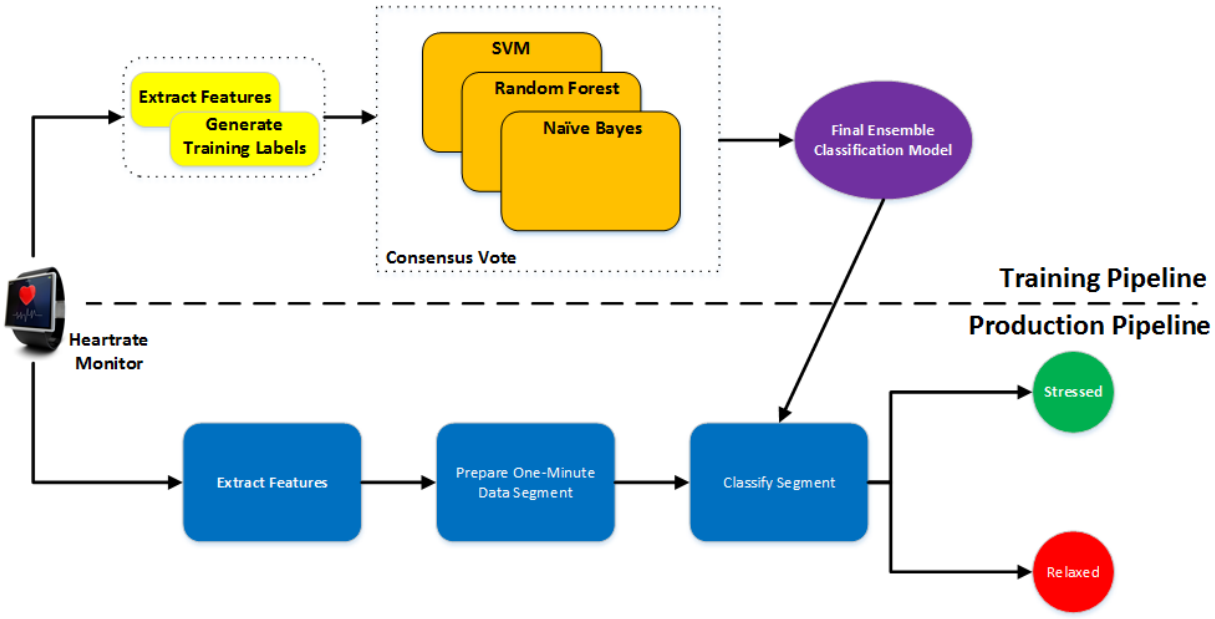


Figure 1: Training/Testing Pipeline

To address the scope of this project however, I propose training three separate supervised machine learning models by applying the following methodology to create the pipeline. Once created, the pipeline (see Figure 1.) will be used to test and deploy the models on a sample unseen data from the test subjects and hence predict their stress levels by following these steps:

1. Collect already filtered PPG [^4] signal data with symbolic peaks (and other features) have been collected for a one-minute time segment. Each one-minute time segment is considered an observation labeled with the class `relax` or `stress`. Additionally, separate the input data into two separate data sets. One for the observations and one for the labeled output.
2. Apply **Feature Extraction** and if needed, **normalization** and/or **standardization** techniques to preprocess the data.
3. Define three separate models to evaluate the the data.
   - Random Forest
   - Support Vector Machine (SVM)
   - Gaussian Naive Bayes
4. Apply the models and measure their performance on a completely **separate** and as yet **unseen** dataset. This dataset is exactly the same as the training dataset except it is has no `State` label.

Once created, the pipeline will be used to test and deploy the models on a sample unseen data from the new test subjects and hence predict their stress levels.

Metrics

Since the success criteria of the project is based on the overall probability of the observation belonging to either class (`stressed` or `relaxed`), each individual model as well as the overall weighted consensus model will be evaluated using the following metrics:

1. **Accuracy:** → The proportion of the total number of predictions that are "correct".
2. **Recall:** → The measure of completeness of the classifier. In other words, if the label is `stressed`, how well does the model predict that the subject is `stressed`. Basically, the ratio of the number of observations the model can correctly recall, to the number of all correct observations.

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative}$$

3. **Precision:** → The number of positive predictions divided by the total positive class values. So, precision is the ratio of a number of observations the model can correctly predict to a number of all observations the model can recall. In other words, it is how precise the model's recall is.

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive}$$

4. **F1 Score:** → If the models are good at *Recall*, that doesn't necessarily mean that they are good at *Precision*. The *F1 Score* is the balanced average of the the two. This balanced *F1 Score* is necessary as an overall performance metric due to the fact that if there is a misclassification that the subject is under stress, but isn't, then the emergency medical services are called out unnecessarily. If however, there is a misclassification that the subject isn't stressed, but actually is, then this could result in a fatality. Having the *F1 Score* will allow us to allocate more weight to *Precision* or *Recall*.

$$F1\ Score = \frac{2 \cdot Precision}{Precision + Recall}$$

II. Analysis

Data Exploration and Visualization

The dataset used for this Project was obtained as part of a *Proof of Concept (POC)* project in the **Dell IoT Solutions Lab** [^6] in Santa Clara, California, where a PPG [^4] Pulse sensor was used to measure Heart Rate Variability (HRV) [^7] reading, similar to those found on current wearables like the **Fitbit Charge 2** [^8]. The scope of the original POC is simply to verify if the data can be extracted and filtered to detect peaks in the PPG signal for a one

minute data segment. Four separate test subjects (between the ages of 68 and 76) were subjected to different stimuli to induce *stress* and *relaxing* scenarios. The one minute observations (**300** in total) are stored in a `data.csv` file. Each observation has **8** specific features of the PPG waveform, namely:

1. **Time** → Time Stamp of the observation.
2. **AVRR** → Average "normal" hert beats.
3. **AVHR** → Average total heart beats.
4. **SDRR** → Standard Deviation of "normal" heart beats.
5. **RMSRR** → Root Mean Squared of "normal" hear beats.
6. **ppNN50** → Proportion of NN50 (50 successive "normal" heart beats) divided by total number of "normal" heart beats.
7. **ppNN20** → Proportion of NN20 (20 successive "normal" heart beats) divided by total number of "normal" heart beats.
8. **State** → "Stressed" or "Relaxed".

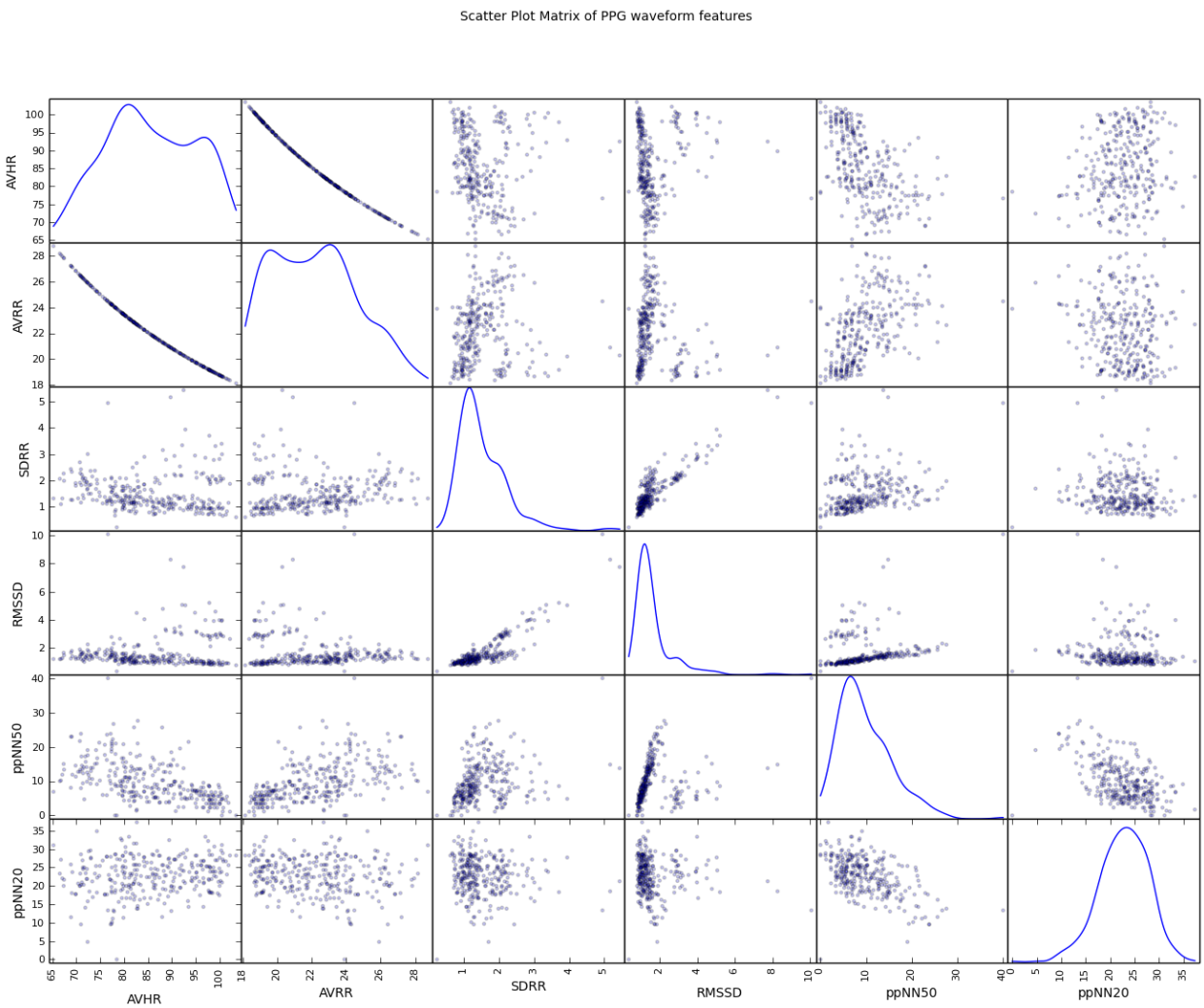
Table 1 shows a sample of the data.

	Time	AVHR	AVRR	SDRR	RMSSD	ppNN50	ppNN20	State
0	07:16:37 25-08-15	74.393829	25.203703	1.883951	1.710125	16.666666	22.222221	relax
1	07:17:32 25-08-15	74.949188	25.016949	1.408307	1.266273	10.169492	25.423729	relax
2	07:18:25 25-08-15	75.541191	24.820896	1.131969	1.154701	5.970149	26.865671	relax
3	07:19:19 25-08-15	79.637726	23.544117	1.772854	0.954174	7.352941	20.588236	relax
4	07:20:13 25-08-15	72.999283	25.685184	2.366614	1.504710	9.259259	29.629629	relax

Table 1: First 5 Rows of Input Data

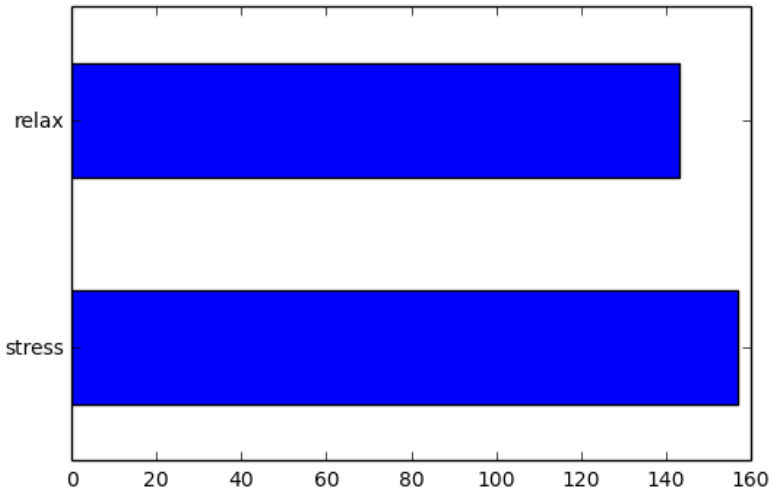
Since the features, shown in Table 1 are themselves, descriptive statistics of the original PPG waveform, describing them individually does not provide significant value. Therefore analyzing the relationship between them might provide better insight.

For instance, from the scatter plot matrix (Plot 1), it can be seen that there is a linear correlation between **RMSSD** and **SDRR** as well as **RMSSD** and **ppNN50**. However, the distribution of these features is **not** evenly spread and skewed to the **right**, with a significant number of outliers (especially the **RMSSD** variable). These factors could lead to high *bias* and low *variance* in the model. However there is a good spread and somewhat even distribution with **AVHR**, **AVRR** and **ppNN20** that may alleviate these issues.



Plot 1: Scatterplot Matrix of PPG Waveform Features

There are three concerns with the input dataset however. The *first* is that fact that it has only **300** observations, thus making it a relatively small data set. Based on this, the *second* is that we may not have an equal spread of labels. The *third* is the variables like **SDRR** and **RMSSD** show some extreme outliers and have different scales.



Plot 2: Stress and Relax Label Counts

As can be seen from Plot 2, there is a somewhat equal spread of labels for `stress` (**157**) and `realax` (**143**).

Algorithms and Techniques

The overarching problem that needs to be solved, is one of **classification**. In essence, when PPG waveform data is received and based on this input, can we predict that the subject is stressed or relaxed. There are a number of algorithms that provide this sort of classification, but for this project only three base classifieds have been selected. This is due to the fact that the end classification is time-sensitive. In other words, there is a trade-off between having the most optimal classification algorithm to determine the subjects state, but by the time the algorithm has determined the subjects state, it may be too late to effectively do anything with the classification data.

Additionally, since the chosen model is based on weighted probabilistic inference, the thee base classifiers that have been selected to be part of the ensemble must have easily fit into the goal. To this end, the following three algorithms have been selected:

1. **Gaussian Naive Bayes** → This algorithm is probabilistic in nature and even though it considers each of the features as independent contributors (ignoring some of the correlations already alluded to), it fits within the paradigm of the *Weighted Majority Rule* ensemble model. Additionally, this algorithm is an easy technique to implement and is robust in it's inference on many types of data.
2. **Support Vector Machine** → *SVM* has been selected due to it's ability to find the best separator for the data, ensuring a clean determination of what a data point's classification is.
3. **Random Forest** → The *Random Forest* algorithm has been selected because it does not have any of the characteristics that make it a fit for the final model. It is being used to hopefully balance out the ensemble and prevent any overfitting that the other models may cause.

The final classification is implemented using a **Weighted Majority Rule Ensemble Classifier**[^5], based on the probability of the time segment observation belonging to either class and using the following:

$$\hat{y} = \underset{i}{\operatorname{argmax}} \sum_{j=1}^{m} w_j \, p_{ij},$$

where wj is the weight that can be assigned to the j^{th} classifier.

Various techniques will be leveraged that address the three concerns highlighted in the **Data Exploration** section. To address the first two concerns, I propose leveraging the **k-fold cross validation** technique, where the process of training the algorithm is executed **10** times (10 Folds) where each fold is considered a unique set of training data. The advantage of this technique is that it can treat each test set uniquely, thus addressing the fact that the data set used is relatively small, and provide an average prediction result across the 10 folds. This process will be used for each of the three models discussed later. To ensure that there is not an **imbalance** of labels, we can verify the count of each label (as shown below).**However**, the third concern will not be addressed since the data are themselves statistical measurements of the original waveform. Scaling and normalizing the data to address outliers and scale may have a negative impact on the models capability to accurately predict the labels as it may overfit the data.

Benchmark

Since there isn't another comparable methodology for the proposed pipeline and hence there isn't a comparable model implementation to serve as a benchmark, the pipeline methodology will be compared to a simple **Logistic Regression**. The evaluation criteria will be leveraged to compare each individual model's performance as well as the final ensemble model's performance against the *Logistic Regression* baseline model.

For the *Logistic Regression* baseline, the data is separated into **10** *Folds* of *Testing* and *Training* data to avoid over fitting and average out the final evaluation metrics across multiple trials since the data set are small. Additionally, since the `Time` variable has no impact on the model, it was removed.

The only preprocessing step involves performing **Feature Extraction**. For more details, see the **Data Preprocessing** section. The baseline scores are as follows:

```
Accuracy: 0.781535038932
Recall: 0.791666666667
Precision: 0.775215817321
F1 Score: 0.754255684256
```

Figure 2: Evaluation Metrics for the Logistical Regression Baseline Model

The initial benchmark evaluation metric for the *Logistic Regression* model is an **Accuracy** of **78.1%**. This is a fairly decent score considering no optimization or ensemble learning has been performed. Thus the *objective* of **Section III** below is to improve on this metric.

III. Methodology

Data Preprocessing

The *first* step in preprocessing the data for model fitting, is to perform **Feature Extraction**. *Feature Extraction* separates the incoming signal data from the heart rate monitor into two separate data sets. The first data set are the signal observations, while the second data set are the training labels associated with each observation. The *second* step is to further convert the labels into a binary integer value, demarcating:

- $0 \rightarrow$ **`relax`**
- $1 \rightarrow$ **`stress`**

Implementation

Once the data has been preprocessed, the three chosen classification models can be applied:

Note: Henceforth the following three models will be referred to as the *base* models.

Random Forest

The **Random Forest**[^9] classifier (an ensemble method itself) is used to cluster points of data into functional groups. When the data set is large and/or there are many variables it becomes difficult to cluster the data because not all variables can be taken into account, therefore the algorithm can also give a certain chance that a data point belongs in a certain group. Based on this, this classifier is selected as one of the methods due to the fact that the data set are relatively small.

To perform the classification, the algorithm clusters the data into groups and subgroups, or decision trees. At each split of the tree, variables are chosen at random as to whether the data points have a close relationship or not. The algorithm makes multiple trees to create a "forest", with each tree being different due to the fact that the decision split occurs on different variables. The classification is used to predict which tree in the forests makes the best classification of the label data.

Support Vector Machine (SVM)

The **SVM**[^10] is a classifier that tries to draw the *best* line to separate the classifications, in this case `stress` and `relax`. Since there can be multiple decision boundaries to correctly

separate the two classes, this model is implemented to find the best separation that maximizes the distance between all the data point in each classification.

Gaussian Naive Bayes

Since the overall objective for the final pipeline and *weighted majority rule* classifier is based on probability of an observation belonging to one one of the two classes, an obvious choice for the third classification method is the **Gaussian Naive Bayes**[^11] classifier as it is a simple probabilistic classifier based on applying *Bayes' theorem* with strong (or naive) independence assumptions between the features. In other words, a *Naive Bayes* classifier considers each feature to contribute independently to the final probability, regardless of any possible correlations between the features.

For the additional optimization techniques used with the three classifiers, see the next section, **Refinement**. To see the resultant evaluation metrics and how they compare with the *baseline* model's results, see **Section IV**.

Refinement

To refine the the above implementation, a number of model specific hyper parameters have been used to improve the overall performance above that of the default parameters. As a whole, the fact that the dataset is significantly small becomes apparent in that to get a better, more accurate fit, the original idea for a **10-Fold Cross Validation** has to be increased to **20 Folds**. The following highlights the individual hyper parameters tweaked for each model:

Random Forest Classifier

For the *Random Forest* classifier, the following hyper parameters are changed:

- **criterion** → The default setting to measure the quality of a split on a tree is the *Gini* impurity. Since *Gini* is intended for continuous attributes and *Entropy* is intended for attributes that occur in classes as in this case, `entropy` is used for the *criterion* parameter.[^12]
- **max_depth** → The maximum depth of each tree (vertical depth). This setting has been set to `4` as a higher depth will allow the model to learn relations that are specific to a particular data point and hence it could lead to overfitting.
- **min_samples_split** → The minimum amount of observations required in a node before it can be considered for splitting. This setting has been set to `4` as higher values prevent a model from learning relations that are too specific to a particular "tree".
- **min_samples_leaf** → The minimum amount of observations required in a terminal node (leaf node). This setting has been set to `5` which is one value higher then *min_samples_split* as this too controls overfitting.
- **max_features** → The number of features to consider while searching for the best split. This is set to `0.7` (or 70%), to avoid overfitting as the parameter is cross-validated with a 70/30 split.

Support Vector Machine (SVM)

For the *SVM* classifier, the following hyper parameter are changed:

- **kernel** → These are functions that transform low dimensional input space into higher dimensional space. In other words, convert non-separable problems into separable ones. This setting has been set to a `rbf` (Radial basis function) kernel since the data is not linearly separable.
- **gamma** → This parameter defines how "far" the influence for a single training example reaches, with low values meaning "far" and high values meaning "close". This parameter is required when using a `rbf` kernel and in this setting, the value is set to `0.01` so that the radius of the area of influence of the support vectors only includes the support vector itself.
- **C** → This parameter is also required when using the `rbf` kernel and is used as a trade-off for misclassification. This setting has been set to `1.0` which is relativley low due so as to reduce the complexity of the model and avoid overfitting.
- **probability** → This setting is set to `True` so that the score can be leveraged in the final *Majority Rule Ensemble* classifier, which is based on weighted probability.

Gaussian Naive Bayes

No hyper parameters have been applied to the *Gaussian Naive Bayes* classifier, as the `GaussianNB()` function from `sklearn` doesn't require any.

Majority Rule Ensemble Classifier

The *Majority Rule Ensemble* classifier takes a list of classifier objects, in this case, the three base models and provides the weighted average probability of each class (`stress` or `relax`), per sample. The only hyper parameter that can be applied to this classifier is the `weights` to assign to each of the individual classifiers. In this case the `weights` are set to `None` to give equal probability to each classifier. For more information on finding the optimal weights, see **Justification** in the next **Section**.

IV. Results

Model Evaluation and Validation

After training the models and cross validating them against the labeled data, we see the following results:

```
20-fold cross validation:

Scores for Random Forest

Accuracy: 0.824761904762
Recall: 0.742857142857
Precision: 0.797916666667
F1 Score: 0.755086163836
----------------------------------------

Scores for SVM

Accuracy: 0.810952380952
Recall: 0.734821428571
Precision: 0.782916666667
F1 Score: 0.741327700078
----------------------------------------

Scores for Naive Bayes

Accuracy: 0.813035714286
Recall: 0.797321428571
Precision: 0.75240981241
F1 Score: 0.764294625223
----------------------------------------

Scores for Ensemble (Equal Weights)

Accuracy: 0.822619047619
Recall: 0.791071428571
Precision: 0.768142968143
F1 Score: 0.771272184987
----------------------------------------
```

Figure 3: Evaluation Metric Results

As can be seen from the performance scores in Figure 3, the **Accuracy** scores for each are within the same range of each other, **81% - 82%**. This means that all three of the models had a relatively high proportion of all the predictions made, when compared to the label, were correct.

The models that have a higher **Recall** score, *Random Forest* and *SVM* are within the same range of **78% - 79%**. These also had a lower **Precision Score**, within a similar range of **73% - 74%**. On the other hand, the *Gaussian Naive Bayes* predictor has a higher **Precision Score** of 79%, but a lower **Recall**. As mentioned in **Section I**, having a higher *Recall* doesn't necessarily mean that the models are *Precise*. Therefore, looking at the **F1 Score**, a balanced average of *Precision* and *Recall*, we can clearly see that the models that have a higher *Accuracy* also have a higher *F1 Score*, in the range of **74% - 76%**.

As expected, the *Weighted Majority Rule* ensemble model performs the best as it is an accumulation of the other three base models. So by taking an equally weighted average of the performance of the underlying three models, we get an overall **Accuracy** of **82%** foe the ensemble model.

From these metrics, it seems that there is a *balance* when considering the ranges of performance values and how similar each individual classifiers metrics are when compared to the individual metric of the other classifiers. Thus, the models selected make good base predictors individually as well as when combined in the ensemble model.

Justification

Table 2 shows each of the models evaluation metrics, compared to the evaluation metrics from the benchmark.

	Metric:	benchmark	Random Forest	SVM	Naive Bayes	Ensemble (Equal Weights)
0	Accuracy	0.781535	0.824762	0.810952	0.813036	0.822619
1	Recall	0.775216	0.797917	0.782917	0.752410	0.768143
2	Precision	0.791667	0.742857	0.734821	0.797321	0.791071
3	F1 Score	0.754256	0.755086	0.741328	0.764295	0.771272

Table 2: Evaluation Metrics compared with Benchmark

As can be seen from Table 2, there is a significant improvement of all the evaluation metrics, from the base models and all the way to the ensemble model, when compared to the evaluation metrics from the *Logistic Regression* benchmark model. Except for, and has already noted, the *Random Forest* and *SVM*, which have a higher **Recall** than the benchmark model. The the *Naive Bayes* model has a lower **Recall** and thus "drags" the ensemble model's **Recall** down so that it too, it lower then the benchmark.

The reverse is true when it comes to **Precision**, where the *Naive Bayes* model's score is high when compared to the benchmark and thus "drives up" the ensemble model's score to be comparative to the benchmark model's score. The balanced average, **F1 Score**, for each of the three base models is relatively comparable to that of the benchmark model and thus helps "drive up" the ensemble model's **F1 Score** to be higher.

Of key import is the **Accuracy** scores. Each of the baseline models show a significant improvement over the benchmark model. The weighted average of these scores shows that the ensemble model too shows significant improvement over that of the benchmark model.

The critical point that Table **X** highlights is the fact that the objective of improving the overall scores of the benchmark model has been met. By leveraging different base models, their strengths and weaknesses (as can be see in the difference between **Precision** and **Recall** scores), and combining these into a final model that outperforms the benchmark.

Note: There is no difference in the preprocessing techniques for any of the models, highlighting that the performance gain is due to the models themselves as well as combining the weighted average in the ensemble model.

Although there is an overall balance between the individual model's metric as they are "rolled-up" into the final ensemble model, taking advantage of the fact that any "imbalance"

can be accounted for by applying weights to the base models. This is one of the key benefits of the *Weighted Majority Rule* ensemble model, as weights can be applied to accommodate any imbalance in the overall metrics of each base model. Until now, all of the base models have been treated equally and assigned an equal weight. Although the ensemble model's performance is an improvement, Table 2 highlights how certain metrics "drag drown" or "drive up" the performance of the ensemble model. To accommodate for this invariance, we choose the best weights to apply to individual base model.

Determining the best weights is accomplished by training each of the base models and calculating the best **Accuracy** score by weighting each model sequentially and then ordering the results highest to lowest, as shown below:

	Weight 1	Weight 2	Weight 3	Mean	Std
3	1.0	2.0	2.0	0.829524	0.205759
7	1.0	3.0	3.0	0.829524	0.205759
10	2.0	1.0	3.0	0.829524	0.205759
5	1.0	3.0	1.0	0.829286	0.197933
2	1.0	2.0	1.0	0.829286	0.196807

Table 3: Top 5 Weight Values

Table 3 shows the top 5 weight values, sorted by the highest **Accuracy** score and then further sorted by the **Standard Deviation** from that score. As can be seen, the best weights to apply are **1**, **2** and **2** to the the three base models. Table 4 shows the results of applying the weights to the ensemble model.

	Metric:	benchmark	Random Forest	SVM	Naive Bayes	Ensemble (Equal Weights)	Ensemble (Adjusted Weights)
0	Accuracy	0.781535	0.824762	0.810952	0.813036	0.822619	0.829524
1	Recall	0.775216	0.797917	0.782917	0.752410	0.768143	0.769658
2	Precision	0.791667	0.742857	0.734821	0.797321	0.791071	0.804464
3	F1 Score	0.754256	0.755086	0.741328	0.764295	0.771272	0.778276

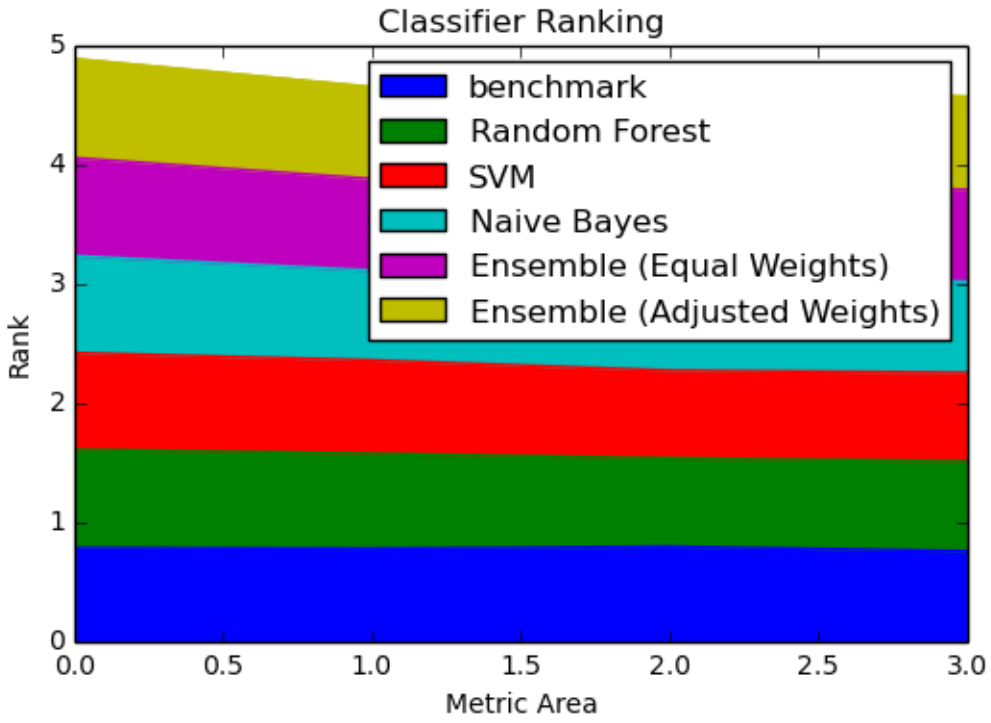
Table 4: Final Evaluation Metric Comparison

As can be seen, the *Weighted Majority Rule* ensemble model, with the weight refinement takes into consideration some of the "unbalanced" metrics of the base models to show an overall improvement in the **Accuracy** score to **82.9%**.

V. Conclusion

Free-Form Visualization

Plot 3 shows where all of the models rank, from lowest to highest and the relative area of their cumulative evaluation metrics.



Plot 3: Classifier Ranking

Plot 3 shows the **scaled** cumulative performance metrics (*X* axis) and how these contribute to the overall ranking of the classifier in relation to the other models. As can seen (from the *Y* axis), the the models are ranked as follows from lowest to highest:

1. *Logistic Regression* (benchmark).
2. *Random Forest.*
3. *SVM*.
4. *Gaussian Naive Bayes*.
5. *Weighted Majority Rule* ensemble model with equal weights.
6. *Weighted Majority Rule* ensemble model with adjusted weights.

Reflection

In conclusion the project highlights a concept of a pipeline that can be leveraged to determine if a subject is suffering a heart attack and hence take appropriate action. To accomplish this the project has detailed the performance of three individual classifiers as

well as the performance when these models are combined. By applying weights based on the individual model's performance a weighted ensemble model has been selected for the final classifier.

So how well does the final classifier predict the classification on new, previously unseen iputs?

After training each of the individual models, a set of new data comprising of **10** unseen observations from the PPG waveform is used to determine how well the final model can correctly predicts whether the test subject's "state" is `stress` or `relax`.

Table 5 shows the predicted value of the final model against the actual (`truth`) label of the data.

Note: The same data preprocessing tasks have been applied to the new, unseen data set.

	Truth	Ensemble (Adjusted Weights)
0	1	0
1	0	0
2	0	0
3	0	0
4	1	0
5	0	0
6	1	0
7	0	0
8	1	0
9	0	0

Table 5: Prediction Results for Unseen Data

It is the final objective of this project to re-apply the resulting models to the overall pipeline and then avail the pipeline to a set of new test subjects to hopefully provide a viable prototype that can preemptively warn of potential heart attacks. If one considers that peoples lives are in essence at stake and if there is a misclassification that the subject isn't stressed, but actually is, then this could result in a fatality.

Table 5 shows the original, `truth` prediction of the new, unseen data. The subsequent column show the prediction of the *Weighted Majority Rule* ensemble model, the chosen classifier in this project. As can be seen, it only classifies **60%** of the observations correctly. This final classification accuracy must reflect this **urgency** and hence be higher. So based on the final classification results shown in the project, it is evident that there is more work to be done so as to improve on the accuracy of all the classifiers. **60%** is simply **not good enough!**

Improvement

So Even though there is a gradual improvement from each individual model to the *Majority Rule* ensemble classifier then further by improving the weights, the overall **Accuracy** score is not, in my opinion, high enough and Table 5 highlights this concern. To this end, further testing on other classification models, like a *Neural Network*, needs to be investigated.

Note: I'm personally not familiar with the intricacies of *Neural Networks*, but it is my hope that the classifier will find patterns in the PPG waveform that can be leveraged to make a higher prediction score.

The *Neural Network* will be compiled into a sequence of layers. There is not a set methodology to determine exactly how many layers (or the width of each layer) will be needed, only through a process of trial and error can this be determined. It is hoped that the final networks captures the structure of the problem by introducing non-linearity, such that the final output becomes more linearly separable. A similar methodology as to how the final ensemble model was chosen in this project, will also be applied to the *Neural Network*, where different activation functions (**relu**, **sigmoid**, **tanh** or **softmax**) will be weighted to see just how they capture the non-linearity. Backpropogation will help determine that. The final output layer will have two neurons to predict the class (`stress` or `relax`) probability.

One added benefit of using a *Neural Network* (if the accuracy score improves) is that it is easier to capture and save the model and apply it to the incoming PPG waveform data for the final production pipeline. It is my sincere hope that further testing and model evaluation will improve the overall predictive quality of the pipeline, to hopefully save lives.

VI. References

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