

CS4246 Project 1

Depression Prediction

Team 01

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Abstract

For our experiment, we will use the GP model to measure and compute depression severity via audio recordings. We will also be discussing about the desirable properties of the GP model as well as the technical details such as the GP model requirements for the proposed application and modifications made to enhance performance. We will also include our experimental evaluations and procedure in this report.

Introduction

Depression is a worrying issue in modern times. If left unregulated, it can be detrimental both health and life. According to surveys, approximately 7.2% of the American household population suffered from depression between 2009-2012 [Laura A. Pratt and Debra J. Brody, 2014] and in 2013, there were 41,149 recorded cases of suicide [Jiaquan Xu et al., 2016].

Motivation and Hypothesis

The rationale of depression prediction is enable authorities to take appropriate actions if an area or individual is depressed. For example, suicide and crime are often linked to high depression and stress levels. The data can help authorities to monitor and mitigate crime in areas with marked as 'depressed'. In addition, annual health checks may include psychiatrist recommendations which is given to individuals who falls into the depression category.

Future Applications

The output is the level of depression an individual is currently experiencing, much like the PHQ-8 survey itself. This will enable both users and experts to gauge how depressed is an individual. If successful, the data collected can be contributed to the implementation of a depression calculator application. Instead of undergoing the standard Patient Health Questionnaire depression scale (PHQ-8), users will be able

to check their depression scale objectively with the app.

With the ability to monitor depressions, psychiatrist and experts can identify and offer consultation to those who needs it before it reaches unhealthy levels. The application may even incorporate these feature such that the nearest psychiatrist's number will be displayed if depression levels exceed a certain threshold. Similar to diet and workout applications, this app and the data collected will be able to help users plan their lifestyle as well as offer help to those in need.

Gaussian Process Regression Model

As all individuals have varying inherent stress management, the use of the GP model for depression prediction makes use of all samples and feature information to perform the prediction including training data with different or uneven sampling rates. From the mean and variance obtained from previous data, we are able to predict if an individual is depressed.

Qualitative Advantages

GP is exceptionally useful in this application as it enables us to perform prediction on various training data including outliers or those with irregular sampling rates. As our experiment is based on individuals and their personality, the data is therefore subjective for each individual. This helps in our attempt to verify our hypothesis of the correlation between human behaviour and depression.

One key advantage of GP is that it is able to give the confidence interval. Curve-fitting algorithms for interpolation of data do not accomodate well to noise, unlike GP as it can be optimized with the appropriate hyper-parameters and thus, allows a fine and precise trade-off between smoothing and fitting the data.

With GP, we can also obtain a probability distribution such as the predictive mean and variance. These properties have a significant role to play in estimating the depression levels. For instance, the mean could be use as the baseline for an average working-human mood. The variance here would give us a picture to how depressed is an individual or vice versa. These properties allows us to gauge the depression 'levels' as well as measure the accuracy of the correlation

between a subject's emotion and how depressed they are feeling.

Requirements

Aside from the audio recordings, our GP model makes use of the following:

1. **Energy**
The Energy feature of a sound refers to the loudness of the sound at various timeframes, hence it is obvious that energy of a sound is directly proportional to the amplitude of the soundwave. This shows that the higher the energy, the louder the sound is going to be.
2. **Mel Frequency Cepstral Coefficients (MFCC)**
Mel Frequency Cepstral (MFC) is a representation of short-term power spectrum of a sound, based on a linear cosine transform of a log power spectrum on a non-linear Mel scale of frequency. MFCC are the coefficients that form the MFC. The greatest benefit of using MFCC is that the scale approximates to the human's auditory system response more closely, hence it allows for a better representation of sound. In order to obtain MFCC, Fourier transform is performed on the sound signals.
3. **Magnitude Spectrum**
Magnitude spectrum can be produced by converting the input signal of an audio into frames. Fast Fourier Transform (FFT) is performed on each frame and this will form the Magnitude Spectrum.
4. **Zero-Crossing Rate**
Zero crossing rate is the rate of sign-changes along a signal. This feature is extremely useful in speech recognition and music information retrieval.

2.3 Important Machine Learning Methods

Machine learning is about using model to learn from existing data for some improvement or prediction. The following are some methods used in machine learning:

1. **k-nearest neighbors algorithm**
The k-Nearest Neighbors algorithm (or k-NN for short) is a non-parametric method used for classification and regression. K is the user defined constant which classifies the class of a vector data. The training examples are vectors in a multidimensional feature space, each with a class label. The classification process of this algorithm can be visualized as the graph below.
2. **Support Vector Machine (SVM)**
Support Vector Machine (SVM), with the help of the libsvm, a developed library for SVM. SVM is a type of linear classifier that aims at finding a unique solution in the form of an optimal hyperplane. This optimal hyperplane is defined as the one that maximizes the margins between the two classes. It will be positioned at equal distance between the closest points of each class and will create the largest possible corridor with no points from either classes inside. These closest points are on the border of the corridor and are called the support vectors.

3. Random Forest Regressor

Random Forest is an ensemble of decision trees, whereas a decision tree is trying to separate the data into different leaf nodes where the data points in each node have certain similarity. Each decision tree will predict a value and all of the values will be averaged. The average value would be the prediction result.

4. AdaBoost

AdaBoost is the short form of Adaptive Boost. The output of the other learning algorithms ('weak learners') is combined into a weighted sum that represents the final output of the boosted classifier. AdaBoost is adaptive in the sense that subsequent weak learners are tweaked in favor of those instances misclassified by previous classifiers. AdaBoost first finds out the classifier with the least errors, then focuses on those errors later by adding the weight to the outliers, then finds out another classifier with least errors again. The process is repeated till the end then all the classifiers will be combined to form a final classifier which will indicate the class of data. Therefore, AdaBoost is able to be sensitive to noisy data and outliers.

5. Naive Bayes

Naive Bayes is a prediction algorithm that uses Bayes rule in assumption that all naive Bayes classifiers assume that the value of a particular feature is independent of the value of any other feature, given the class variable. Naive Bayes multiplies all the possibilities of a particular event occurs, then gives the prediction of possibility that event. All the data are extracted from the dataset to represent the possibilities which are the number of times the particular event occurs in the dataset over the total number of events. Naive Bayes can produce great results if the features in the dataset are as independent as possible.

Technical Approach

Application of Gaussian Process model

Using Gaussian Process model as a machine learning model: When a person is depressed, no matter what time the person talks, we should also be able to determine the person is depressed according to the speech signal. And we assume that the speech signals extracted from different depressed people should be similar and thus is suitable to use Gaussian Process Model.

Some Famous Mathematical Formula

Euclidean Distance Euclidean Distance is used to find the distance between two points in an Euclidean Space. Euclidean Distance is defined as:

$$\|x - x'\| = \sqrt{(x_1 - x_1')^2 + (x_2 - x_2')^2 + \dots + (x_n - x_n')^2} \quad (1)$$

Squared Euclidean Distance It is just the squared of Euclidean Distance. Nothing special.

$$\|x - x'\|^2 = (x_1 - x_1')^2 + (x_2 - x_2')^2 + \dots + (x_n - x_n')^2 \quad (2)$$

Kernels

A general name for a function k of two arguments mapping a pair of inputs $x \in X, x' \in X$ into \mathbb{R} is a kernel. In other word, the similarity measure of all features is usually called kernel. This term arises in the theory of integral operators, where the operator T_k is defined as

$$(T_k f)(x) = \int_X k(x, x') f(x') d\mu(x'), \quad (3)$$

where μ denotes a measure. A real kernel is said to be symmetric if $k(x, x') = k(x', x)$; clearly covariance functions must be symmetric from the definition.

For a kernel to be used in Gaussian Process, one kernel must be positive semidefinite:

A real $n \times n$ matrix K which satisfies

$$Q(v) = v^T K v \geq 0, \forall v \in \mathbb{R}^n \quad (4)$$

is called positive semidefinite (PSD). If $Q(v) = 0$ only when $v = 0$ the matrix is positive definite. $Q(v)$ is called a quadratic form. A symmetric matrix is PSD if and only if all of its eigenvalues are non negative. A Gram matrix corresponding to a covariance function is PSD.

A kernel is said to be positive semidefinite if

$$\int k(x, x') f(x) f(x') d\mu(x) d\mu(x') \geq 0, \forall f \in L_2(X, \mu) \quad (5)$$

Equivalently a kernel function which gives rise to PSD Gram matrices for any choice of n N and D is positive semidefinite.

The kernels that would be chosen as our kernel is shown below (The kernels are assumed to be defined on two samples $x = (x_1 x_2 x_3 \dots x_n)$ and $x' = (x'_1 x'_2 x'_3 \dots x'_n)$, represented as feature vectors in some input space):

1. Radial Basis Function (RBF)

The RBF kernel is defined as

$$K(x, x') = \exp\left(-\frac{\|x - x'\|^2}{2\sigma^2}\right) \quad (6)$$

$\|x - x'\|^2$ represents Squared Euclidean Distance And $\sigma > 0$ can either be a scalar (isotropic variant of the kernel) or a vector with the same number of dimensions as the inputs X (anisotropic variant of the kernel).

It is also known as the squared exponential kernel. This kernel is infinitely differentiable, which implies that GPs with this kernel as covariance function have mean square derivatives of all orders, and are thus very smooth.

2. Matern

The class of Matern kernels is a generalization of the

RBF and the absolute exponential kernel parameterized by an additional parameter ν . The smaller ν , the less smooth the approximated function is. For $\nu = \infty$, the kernel becomes equivalent to the RBF kernel and for $\nu = 0.5$ to the absolute exponential kernel. Important intermediate values are $\nu = 1.5$ (once differentiable functions) and $\nu = 2.5$ (twice differentiable functions).

3. Dot Product

The Dot Product kernel is non-stationary and can be obtained from linear regression by putting $N(0, 1)$ priors on the coefficients of x_d ($d = 1, \dots, D$) and a prior of $N(0, \sigma_0^2)$ on the bias. The Dot Product kernel is invariant to a rotation of the coordinates about the origin, but not translations. It is parameterized by a parameter σ_0^2 . For $\sigma_0^2 = 0$, the kernel is called the homogeneous linear kernel, otherwise it is inhomogeneous. The kernel is given by

$$K(x, x') = \sigma_0^2 + x \cdot x' \quad (7)$$

4. Constant Kernel

The constant Kernel just set the similar measures to be a constant. The kernel is given by:

$$k(x, x') = C \quad (8)$$

where C is a constant, $C \in \mathbb{R}$ and $C \geq 0$

5. Compound Kernel

Kernel which is composed of a set of other kernels.

6. Exp-Sine-Squared Kernel

The ExpSineSquared kernel allows modeling periodic functions. Therefore, it is also called Periodic Kernel. It is parameterized by a length-scale parameter, $l > 0$ and a periodicity parameter $p > 0$. The kernel given by:

$$k(x, x') = \exp\left(\frac{-2 \sin\left(\frac{\pi \|x - x'\|}{p}\right)}{l}\right)^2 \quad (9)$$

where $\|x - x'\|$ represents Euclidean Distance.

7. Rational Quadratic Kernel

The RationalQuadratic kernel can be seen as a scale mixture (an infinite sum) of RBF kernels with different characteristic length-scales. It is parameterized by a length-scale parameter $l > 0$ and a scale mixture parameter $\alpha > 0$. The kernel given by:

$$k(x, x') = \left(\frac{1 + \|x - x'\|^2}{2\alpha l^2}\right)^{-\alpha} \quad (10)$$

where $\|x - x'\|^2$ represents Squared Euclidean Distance

8. Linear Kernel

Linear Kernel is a simpler kernel which can run efficiently. However, its linearity assumption is its downside. The kernel is given by:

$$k(x, x') = x^T x' \quad (11)$$

9. White Kernel

The kernel is used to estimate the noise-level(δ) of the input. The kernel is given by:

$$if x == x', k(x, x') = \delta; \text{ else } 0 \quad (12)$$

10. OrnsteinUhlenbeck Kernel

The kernel is given by:

$$k(x, x') = \exp\left(\frac{-||x-x'||}{t}\right) \quad (13)$$

where $||x - x'||$ represents Euclidean Distance.

11. Sum

Sum-kernel $k_1 + k_2$ of two kernels k_1 and k_2 .

Novel Modifications

Using Gaussian Process model to optimize the parameters of the ensemble of different machine learning model: The outcome of different machine learning model should be similar and thus is suitable to put inside Gaussian Process model.

Evaluation

In order to test our Gaussian Process model, we conducted tests on data obtained from Audio/Visual Emotion Challenge and Workshop(AVEC 2016) [Valstar et al., 2016]. The goal of AVEC is to weigh-in on the various approaches(visual, audio) used to recognize emotions under unambiguous conditions. AVEC 2016 provided 2 pieces of data as input: visual and auditory data. However, we would be reducing the scope of the experiment, limiting the experiment to only the auditory data. Two Sub-Challenges are listed in AVEC 2016. We are only interested in the Depression Classification Sub-Challenge, which requires participants to classify inputs by the PHQ-8 score.

Data

The depression data used in AVEC 2016 was obtained from the benchmarking database, the Distress Analysis Interview Corpus - Wizard of Oz(DAIC-WOZ). Data collected from DAIC-WOZ include audio and video recordings and the corresponding PHQ-8 score[CITE:27](0-24), which is a frequently used self-report scheme to access severity of depression[CITE]. Henceforth, we would need to pre-process the auditory data before we use it in our Gaussian Process Model. The data is pre-processed as described in the Section

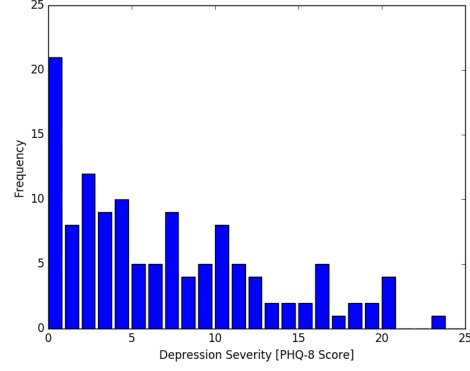


Figure 1: PHQ-8 scores' histogram of both training and development set

[REF]. The distribution of the depression severity scores in both training and development set is given in Figure 1. The data provided are split into 2 sets: training and development. A summary of the data is given in Table 1.

	Training	Development	All
n	95	31	126
μ	6.326	7.548	6.626
σ	5.597	6.690	5.909

Table 1: Summary of Datasets provided

Measure of Accuracy

AVEC 2016 provided a baseline classifier that consistently predicts the PHQ-8 score with $RMSE = 6.7418$ [CITE]. In order to provide a meaningful and consistent comparison to the baseline provided, we would be only using Root Mean Square Deviation Error(RMSE) to measure the error rate on both Training and Development datasets. RMSE(Equation 14) is a commonly used in machine learning communities to measure the differences between the values predicted by a model and the values actually observed.

$$RMSE = \sqrt{\frac{\sum_{t=1}^n (\hat{y}_t - y_t)^2}{n}} \quad (14)$$

[CITEDBLP:journals/corr/ValstarGSRLTSSC16]

Experimental Setup

We compared our Gaussian Model against commonly used machine learning algorithms. The list of algorithms and their hyperparameters are given in Table 2. The hyper-parameters are either determined by the defaults used in the popular machine learning library, Scikit Learn[CITE] or some reasonable values were used. Each machine learning algorithm is trained against the training set and thereafter tested against the development set using RMSE as the error metric. The process used is shown in Figure 2.

Algorithm	Hyper-parameters
K-Nearest Neighbors	x
Linear SVM	x
RBF SVM	x
Decision Tree	x
Random Forest	x
AdaBoost	x
Naive Bayes	x
Decision Tree	x

Table 2: List of Machine Learning Algorithms with their corresponding hyper-parameters

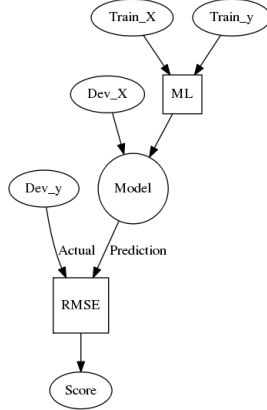


Figure 2: Experimental process

Results

The results of the experiment is shown in t

Algorithm	RMSE	
	Training	Development
K-Nearest Neighbors	x	x
Linear SVM	x	x
RBF SVM	x	x
Decision Tree	x	x
Random Forest	x	x
AdaBoost	x	x
Naive Bayes	x	x
Decision Tree	x	x
Gaussian Process	x	x

Table 3: RMSE results of the different machine learning algorithms

Conclusion

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Contributions

- **Antoine Charles Vincent Garcia:** Scripting the program, setting up machine learning libraries and running tests.
- **Chan Jun Wei:** Project technicalities such as problem formulation and modelling, mathematics and experiment planning.
- **Chen Tze Cheng:** Project technicalities such as problem formulation and modelling, mathematics and experiment planning.
- **Eric Ewe Yow Choong:** Documentation especially writing of the motivation, recording research findings and keeping track of requirements.
- **Han Liang Wee, Eric:** Scripting the program, setting up machine learning libraries and running tests.
- **Ho Wei Li:** Documentation especially writing up the motivation, recording research findings and keeping track of requirements.

References

- Jiaquan Xu, M.; Sheery L. Murphy, B.; Kenneth D. Kochanek, M.; and Brigham A. Bastian, B. 2016. Deaths: Final data for 2013. *National Vital Statistics Reports* Vol 64, No. 2.
- Laura A. Pratt, P., and Debra J. Brody, M. 2014. Depression in the u.s. household population 2009-2012. *NCHS Data Brief* No. 172.
- Valstar, M. F.; Gratch, J.; Schuller, B. W.; Ringeval, F.; Lalanne, D.; Torres, M.; Scherer, S.; Stratou, G.; Cowie, R.; and Pantic, M. 2016. AVEC 2016 - depression, mood, and emotion recognition workshop and challenge. *CoRR* abs/1605.01600.

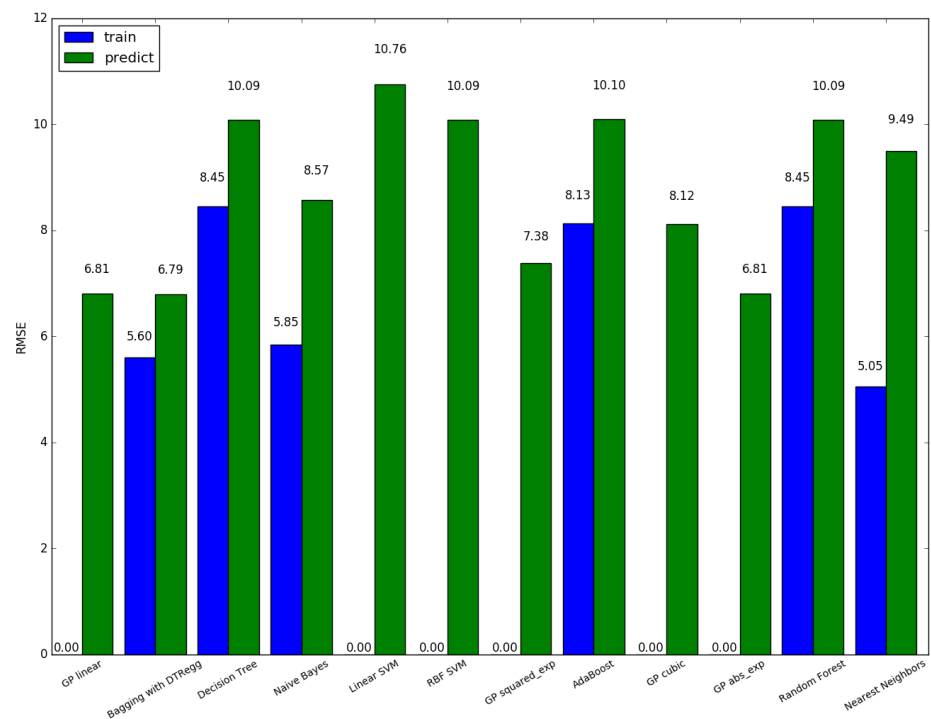


Figure 3: Chart showing RMSE(Training and Development) for the different classifiers