

修士論文

Automatic Detection of Repressed Anger from Text Messages

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学籍番号 16906291

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論 文 要 旨

論文題目	Automatic Detection of Repressed Anger from Text Messages
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Contents

1	Classification Techniques	1
1.1	Fundamentals of Classification	1
1.2	Support Vector Machine	2
1.3	K-Nearest Neighbor	4
1.4	Neural Networks	4
	References	5
	Acronyms	6

List of Figures

1.1	Classification of animals. The image is extracted from Exploring Nature.	1
1.2	Classification as a task of mapping a set attributes x into its fitting class label y	2
1.3	hyperplane	4

List of Tables

Chapter 1

Classification Techniques

The aim of this chapter has two purposes. The first one, is to make an introduction of the basic concepts of classification, which is essential for the detection of repressed anger. The second one, is to explain how the algorithms used in this study work.

1.1 Fundamentals of Classification

According to [7], classification can be defined as the task of predicting an outcome from a given input. This outcome is produced by the process of mapping a group of characteristics present in the input to a certain category. In other words, it consists in assigning objects (the input) to one of several predefined classes (the outcome) [6]. Examples of classification can be found in everyday life, such as e-mail spam detection, news classifiers, Optical Character Recognition (OCR), animal kingdom classification (see Figure 1.1), among many others.

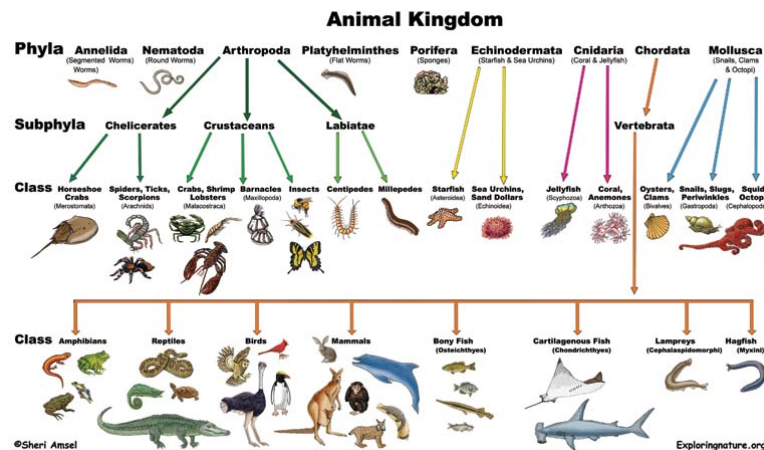


Figure 1.1: Classification of animals. The image is extracted from Exploring Nature.

The input data for a classification task is composed by a collection of records, the dataset. In the same time, each record, also known as an instance, is composed by a set attributes. From all these attributes there is one considered special, which is called the target attribute or the class label. The attribute set includes properties

of a vertebrate such as its body temperature, skin cover, method of reproduction, ability to fly, and ability to live in water. Although the attributes presented in Table 4.1 are mostly discrete, the attribute set can also contain continuous features. The class label, on the other hand, must be a discrete attribute. This is a key characteristic that distinguishes classification from regression, a predictive modeling task in which y is a continuous attribute. Regression techniques are covered in Appendix D. Table 4.1 shows a sample data set used for classifying vertebrates into one of the following categories: mammal, bird, fish, reptile, or amphibian.

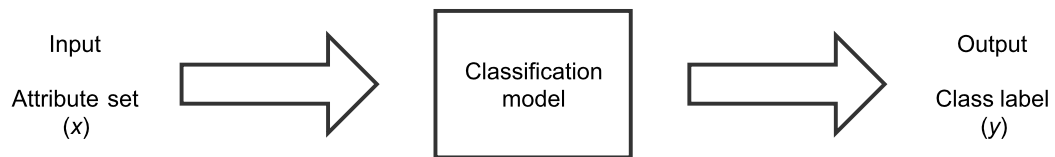


Figure 1.2: Classification as a task of mapping a set attributes x into its fitting class label y .

Definition (Classification). Classification is the task of learning a target function f that maps each attribute set x to one of the predefined class labels y .

The target function is also known informally as a classification model.

A classification model is useful for the following purposes:

- **Descriptive Modeling:** A classification model can serve as an explanatory tool to distinguish between objects of different classes.
- **Predictive Modeling:** A classification model can also be used to predict the class label of unknown records. As shown in Figure 1.2, a classification model can be treated as a black box that automatically assigns a class label when presented with the attribute set of an unknown record.

Classification techniques are most suited for predicting or describing data sets with binary or nominal categories. They are less effective for ordinal categories, because they do not consider the implicit order among the categories. Other forms of relationships, such as the subclass–superclass relationships among categories.

1.2 Support Vector Machine

There are four main advantages: Firstly it has a regularisation parameter, which makes the user think about avoiding over-fitting. Secondly it uses the kernel trick, so you can build in expert knowledge about the problem via engineering the kernel. Thirdly an SVM is defined by a convex optimisation problem (no local minima) for which there are efficient methods (e.g. SMO). Lastly, it is an approximation to a bound on the test error rate, and there is a substantial body of theory behind it which suggests it should be a good idea. The disadvantages are that the theory only really

covers the determination of the parameters for a given value of the regularisation and kernel parameters and choice of kernel. In a way the SVM moves the problem of over-fitting from optimising the parameters to model selection. Sadly kernel models can be quite sensitive to over-fitting the model selection criterion [3]

SVMs are a new promising non-linear, non-parametric classification technique, which already showed good results in the medical diagnostics, optical character recognition, electric load forecasting and other fields.

Suitable for binary classification tasks.

The advantages of the SVM technique can be summarised as follows [1]:

1. By introducing the kernel, SVMs gain flexibility in the choice of the form of the threshold separating solvent from insolvent companies, which needs not be linear and even needs not have the same functional form for all data, since its function is non-parametric and operates locally. As a consequence they can work with financial ratios, which show a non-monotone relation to the score and to the probability of default, or which are non-linearly dependent, and this without needing any specific work on each non-monotone variable.
2. Since the kernel implicitly contains a non-linear transformation, no assumptions about the functional form of the transformation, which makes data linearly separable, is necessary. The transformation occurs implicitly on a robust theoretical basis and human expertise judgement beforehand is not needed.
3. SVMs provide a good out-of-sample generalization, if the parameters C and r (in the case of a Gaussian kernel) are appropriately chosen. This means that, by choosing an appropriate generalization grade, SVMs can be robust, even when the training sample has some bias
4. SVMs deliver a unique solution, since the optimality problem is convex. This is an advantage compared to Neural Networks, which have multiple solutions associated with local minima and for this reason may not be robust over different samples.
5. With the choice of an appropriate kernel, such as the Gaussian kernel, one can put more stress on the similarity between companies, because the more similar the financial structure of two companies is, the higher is the value of the kernel. Thus when classifying a new company, the values of its financial ratios are compared with the ones of the support vectors of the training sample which are more similar to this new company. This company is then classified according to with which group it has the greatest similarity.

Furthermore, $K(\mathbf{x}_i, \mathbf{x}_j) \equiv \phi(\mathbf{x}_i)^T \phi(\mathbf{x}_j)$ is called the kernel function. four basic kernels [5]:

- **Linear:** $K(\mathbf{x}_i, \mathbf{x}_j) = \mathbf{x}_i^T \mathbf{x}_j$.

- **Polynomial:** $K(\mathbf{x}_i, \mathbf{x}_j) = (\gamma \mathbf{x}_i^T \mathbf{x}_j + r)^d, \gamma > 0$.
- **Radial Basis Function (RBF):** $K(\mathbf{x}_i, \mathbf{x}_j) = \exp(-\gamma \|\mathbf{x}_i - \mathbf{x}_j\|^2), \gamma > 0$.
- **Sigmoid:** $K(\mathbf{x}_i, \mathbf{x}_j) = \tanh(\gamma \mathbf{x}_i^T \mathbf{x}_j + r)$.

Here, γ , r , and d are kernel parameters.

Support vector machines (SVM) were originally designed for binary classification [4].

solving multi-class SVM in one step: “all-together” methods: [25], [27] and [7]. We then compare their performance with three methods based on binary classifications: “one-against-all,” “one-against-one,” and DAGSVM [23]. Our experiments indicate that the “one-against-one” and DAG methods are more suitable for practical use than the other methods.

asdasdasd [2]

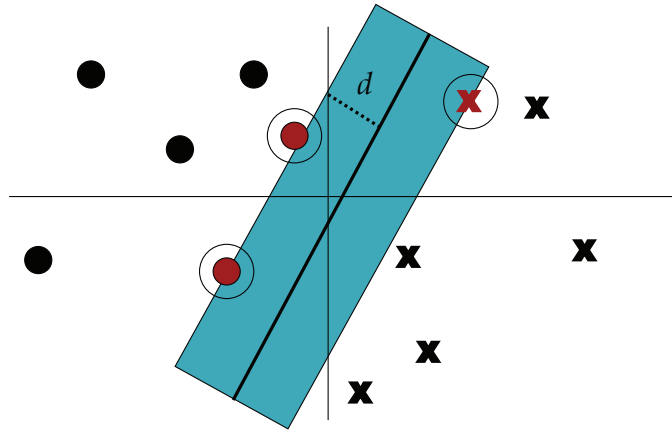


Figure 1.3: hyperplane

1.3 K-Nearest Neighbor

1.4 Neural Networks

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Acronyms

OCR Optical Character Recognition. 1