Automated Essay Grading via Text Classification

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INTRODUCTION

Essays are considered by many researchers as the most useful tool to assess learning outcomes implying a) the ability to recall, organize and integrate ideas, b) the ability both to express oneself in writing and c) to supply more than identify interpretation and application of data. One of the difficulties of grading essays is represented by the perceived subjectivity of the grading process. Many researchers claim that the subjective nature of essay assessment leads to variation in grades awarded by different human assessors, which is perceived by students as a great source of unfairness. This issue may be faced through the adoption of tools for Automated Essay Grading (AEG). An AEG system would at least be consistent in the way it scores essays, and enormous cost and time savings could be achieved if the system can be shown to grade essays within the range of those awarded by human assessors. Moreover, an AEG system would be an extremely useful and valuable tool for distance learning students needing to practice self assessment on those topics that could not be easily covered via closed answer tests.

Page in (1996) introduced a distinction between grading essays for content and for style, where the former refers loosely to what an essay says, while the latter to “syntax and mechanics and diction and other aspects of the way it is said”. In the current literature on AEG systems papers reporting experiments with systems aimed to evaluate essays primarily for content or for style, are discussed. Furthermore, systems aimed to evaluate essays taking in account both aspects are reported too (Valenti et al., 2003).

Three different criteria have been discussed to measure the performance of AEG systems: accuracy of the results, multiple regression correlation and percentage of agreement between grades produced by the systems those assigned by human experts (Valenti et al., 2003).

This paper is aimed to discuss the design of an AEG system that we are developing at the Università Politecnica delle Marche. The system will be initially devoted to grade essays for content, and will be based on text classification techniques defined in the context of our research in Natural Language Processing (Cucchiarelli 2001, Velardi 2000).

Text Classification (TC) is the problem of assigning predefined categories to free text documents. The approach adopted relays on the Natural Language Processing (Cucchiarelli 2001, Velardi 2000).

FUNDAMENTALS OF TEXT CLASSIFICATION

Text Classification (TC) is the problem of assigning predefined categories to free text documents. Typically, the classifiers adopt two-phased machine learning algorithms: a training phase, in which the grading rules are acquired using various algorithms, and a testing phase, in which the rules gathered in the first step are used to determine the most probable grade for a particular essay.

Less informally, TC is the task of assigning documents to a set of predefined categories, and can be modelled as follows. Given a set of conceptual classes \( C = (c_1, c_2, \ldots, c_n) \) related to the topics of interest and a set of training documents \( D = (d_1, d_2, \ldots, d_m) \) each labelled according to the classes it belongs to, build a decision function \( f \) able to assign the correct classes to each document, i.e. \( f : D \mapsto \{2^n\} \).

The function \( f \) can be further applied to newly incoming documents, to classify them in one or more classes of \( C \).

According to the current research on this field, the design of a TC system consists of a set of subtasks, namely features design, features weighting, similarity estimation, inference and testing (Moschitti, 2003), that will be further discussed in this section.

Features Design

The training documents are usually represented as feature vectors, i.e. \( t \)-tuples of values \( X=(x_1, x_2, \ldots, x_n) \), being \( x_i \) the numeric value that feature \( j \) takes on for document \( X \). For example, if feature \( j \) is a word, \( x_i \) could be the value related to the frequency of \( j \) in \( X \). The selection of the \( n \) relevant features to be used in vectors definition has a strong influence on the classifier performances and is a very critical task. As words in the document are usually considered as basic unit of information, a sub-set of them (ignoring uninformative terms like articles, pronouns, adverbs known as stop words) are candidate as features. The set of candidate words are then normalized, through stemming (removing common suffixes from words) or lemmatisation (reducing each word to its base form).

Feature Weighting

Features could be more or less representative in documents. Roughly speaking, the higher in a document the frequency of a word is, the more it characterize the document itself; on the contrary, the wider the occurrence of a word in the entire set of training documents, the less its relevance for each single document. Many different schemes have been devised for the estimation of the weight \( x \) as for instance: \( \text{IDF} \cdot \text{TF} \) (Salton 1991), \( \log(\text{TF}) \cdot \text{IDF} \) (Inner et al. 1995) and \( \text{IWF} \) (Basilis et al. 1999) and different systems may benefit from the use of different weighting schemes.

Once the appropriate policy has been chosen, the weights for the class profile can be obtained. The class profile is a vector \( \mathbf{c} = (\mathbf{w}_1, \mathbf{w}_2, \ldots, \mathbf{w}_h) \), and the value of each element \( \mathbf{w}_j \) is the result of the evaluation of the relevance of feature \( j \) in the training set documents. Different policies can be applied to compute each \( \mathbf{w}_j \) from the simplest one:

\[
\mathbf{w}_j = \sum_{h \in T_j} \mathbf{w}_j^h
\]

that sums up the weights of feature \( j \) in all the training documents.
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These measures may be misleading when examined alone, so the use of documents correctly classified in recall is estimated by comparing the distance between human classification of the test set and the documents classified in the training set T (Rcut). Moreover, the value of the average number of classes valid for a generic document d can be used as a fixed threshold, estimated usually over the training set (Rcut); in this case, the first k ranked classes having positive value of $s_{id}$ are assigned to document d.

\[ s_{id} = \cos(c_i, d) = \sum_{j=1}^{k} w^i_j w^d_j \]

The above formula, computed for each class profile $c_i$, is the basis for the further classification of d over the classes in C.

**Inference**

A decision function is usually applied over the similarity scores $s_{id}$ to assign an incoming document to one or several target classes. This is carried out by defining a threshold $s_0$ so that only the documents having $s_{id} > s_0$ are classified in $c_i$. Different strategies can be used to define $s_0$ (Yang, 1999). A value of threshold $s_0$ can be assigned to each class in C, as a probabilistic measure related to the risk of a document missclassification in a class (Scut), or to the probability $\text{prob}(c_i | T)$ of documents classified in $c_i$ in the training set T (Rcut). Moreover, the value $k$ of the average number of classes valid for a generic document d can be used as a fixed threshold, estimated usually over the training set (Rcut); in this case, the first k ranked classes having positive value of $s_{id}$ are assigned to document d.

**Testing**

The accuracy of the classification process defined by the previous steps is then evaluated over a test set of pre-labelled documents, disjoint by that used for training (training set). The correctness of classification is estimated by comparing the distance between human classification (given by the documents labels in the test set, usually assigned by human experts), and the output of the inference phase. Different scores can be used for this estimation (Yang, 1999). They range from the classic recall and precision, (respectively, the ratio between the number of correctly classified instances in $c_i$ by the system and the documents classified in $c_i$ by human judges, and the ratio between the number of domains correctly classified in $c_i$ by the system and all the documents it is assigned to $c_i$), to more complex ones like $F_1$ (that balances in a single measure recall and precision) or Break Even Point (the measure of classification performance when recall and precision have the same value). Some of these measures may be misleading when examined alone, so the use of multiple scores is a common practice.

**FROM TEXT CLASSIFICATION TO ESSAY GRADING**

Essay grading is a task that may be accomplished by considering at least two aspects: the style of the essay and its content. Our research is not concerned with the evaluation of style, even if we strongly believe that a system for automated essay grading must cope with this aspect. Currently, the efforts are concentrating on the definition of a general methodology to grade the content of an essay by using TC techniques.

The basic idea is to consider an essay as a document to be classified in one or more classes, each being an expression of a different grade, in a ranging running from ‘excellent’ to ‘poor’. Given the characteristics of TC techniques defined in the previous section, by focusing the representation of a single document on the relevant words it contains, this approach promises to be well suited for grading essays in domains characterized by a specific terminology, as expression of the surface appearance of relevant domain concepts. Under these circumstances, some relevant parameters used in grading by human expert, such as completeness, correctness and use of proper terminology, are evaluated by analysing essay terms. Presence or absence of terminological elements, along with their frequencies in text, is the basis for grading each single essay. TC systems use the same metric to grade an essay with respect to a set of grading classes’ profiles. Roughly speaking, the $c_i$ profile obtained in the training phase defines the number of domain terms used in documents belonging to the class (through features with $W^i_j \neq 0$) and the relevance of these terms (through the values of $W^i_j$), so modelling the human definition of grading classes on a terminological perspective.

In order to conduct some experiments a corpus of essays is needed. The term corpus has been used to designate a body of natural language data which can be used as a basis for linguistic research (Leech, 1997). Currently, the term has been applied to a body of language text that exist in electronic format. According to the discussion regarding the principles underlying the TC techniques, our AEG is based on a training phase, in which the grading rules are acquired using various algorithms, and a testing phase, in which the rules gathered in the first step are used to determine the most probable grade for a particular essay. As we started our research, we tried to find out a public domain corpus of essays already marked by human graders. The difficulty of obtaining a test bed has been outlined by other authors (Larkey, 2003; Christie, 2003). This is the reason why we decided to start the construction of an ad-hoc corpus that contains essays taken from the summative assessment of a course in Economics for Business Management that is offered at our University. The essays are written in Italian, and their content has been graded by a human grader considering, as main parameters, the use of proper terminology, the completeness and the correctness, along with other minor aspects. The grades range from A to E. Thus, the corpus is constituted by a collection of essays handed by the students and is annotated with some additional information including a reference to the question asked, the name of the grader, the grade assigned, the date of the test and the topic covered.

The TC model we adopted has been developed in partnership with the Linguistic Computing Group at the Dipartimento di Informatica, Università di Roma “La Sapienza”, and is based on the following approach:

**Sub-task** | **Solution adopted**
--- | ---
Feature Design | Lemmatisation of essays words.
Feature Weighting | Filtering of predefined class of stop word.
Similarity Estimation | Use of IDF $\times$ TF as weight algorithm.
Inference | Extraction of class profiles through Rocchio’s formula.
Testing | Use of the cosine operator.

**FINAL REMARKS**

This paper presents the overview of an automated approach to the problem of grading essays for content, via Text Classification. All the modules implementing the different subtasks that need to be performed to automatically classify text documents have been already implemented. Our effort is currently focused in linking together the various modules in order to obtain a system that may be used to support essay grading. At the same time, the construction of the corpus is in progress, and in the near future we should be able to perform some preliminary experiments.

As long as the performances of the system are to some extent comparable to those of the human grader, we have a number of issues to cover, including to a) identify some metrics for the assessment of the style of the essays, b) compare the performances of our system with those claimed by other authors (Valenti, 2003), c) extend the size of the corpus and identify some techniques for keeping in account multiple grades assigned by different human graders to the same essay.

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