An Ensemble method for Content Selection for Data-to-text Generation

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Abstract
We present a novel approach for automatic report generation from time-series data, in the context of student feedback generation. Our proposed methodology treats content selection as a multi-label classification (MLC) problem, which takes as input time-series data (students’ learning data) and outputs a summary of these data (feedback). Unlike previous work, this method considers all data simultaneously using ensembles of classifiers, and therefore, it achieves higher accuracy and F-score compared to meaningful baselines.

1 Introduction
Summarisation of time-series data refers to the task of automatically generating text from variables whose values change over time. We consider the task of automatically generating feedback summaries for students describing their semester-long performance during the lab of a Computer Science module. There have been 9 learning factors identified which contribute to students’ learning: (1) marks, (2) hours studied, (3) understandability, (4) difficulty, (5) deadlines, (6) health issues, (7) personal issues, (8) lectures attended and (9) revision (Gkatzia et al., 2013).

Gkatzia et al.’s analysis (2013) showed that there are 4 ways to refer to a learning factor:
1. <trend>: describing the trend,
2. <weeks>: describing what happened at every time stamp,
3. <average>: mentioning the average, or
4. <other>: making another general statement.

The task of content selection for feedback generation can be formulated as a classification task as follows: given a set of 9 learning factors, select the content that is most appropriate to be included in a summary. Content is represented by templates.

A template is defined as a quadruple consisting of an id, a factor, a reference type (trend, weeks, average, other) and surface text.

Overall, for all factors there are 29 different templates. There are two decisions that need to be made: (1) whether to talk about a factor and (2) in which way to refer to it. Instead of dealing with this task in a hierarchical way, where the algorithm will first decide whether to talk about a factor and then will decide how to refer to it, our proposed model treats both steps jointly. The proposed method reduces the decision workload by deciding either in which way to talk about a factor, or not to talk about a factor at all.

2 Multi-label Classification
Classification is concerned with the identification of a category \( l \) from a set of disjoint categories \( L \) (with \(|L| > 1\)) that an instance belongs to, given the characteristics of the instance. If \(|L| = 2\), then the learning task is called binary classification, for example a task where a classifier is trained to asso-
Associate e-mails with either spam or not (i.e., 1 or 0, and hence binary). If $|L| > 2$, then the learning task is called multi-class classification, for example a task where the classifier can associate a running area as good, bad or ok. In Multi-label classification (MLC), the instances are associated with a set of labels $Y \subseteq L$ (Tsoumakas et al., 2010). For example, a newspaper article can be classified into health, science, economy, politics, culture etc. A specific news article concerning the breakthrough of the Ebola cure can be classified into both of the categories health and science. In the same way, students’ data can be assigned labels that describe them, i.e. each label corresponds to a template. The set of chosen templates can then form a feedback summary. One set of factor values can result in various sets of templates as interpreted by the different experts, i.e. a single student can receive different feedback from different lecturers. A multi-label classifier is able to make decisions for all templates simultaneously and capture these differences. The RAndom k-labELsets (RAkEL) (Tsoumakas et al., 2010) is proposed for tackling content selection. RAkEL is based on Label Powerset (LP), a problem transformation method that uses ensembles of classifiers. LP benefits from taking into consideration label correlations, but does not perform well when trained with few examples (Tsoumakas et al., 2010), as in our case (37 instances). RAkEL overcomes this limitation by constructing a set of LP classifiers, which are trained with different random subsets of the set of labels.

3 Evaluation

We compare our approach to four meaningful baselines: DT (Decision Trees) (no history): 29 classifiers were trained, each one responsible for each template. No history is taken into account (see Figure 1). DT (with predicted history): 29 classifiers were also trained, but this time the input included the previous decisions made by the previous classifiers (i.e. the history) as well as the set of time-series data in order to emulate the dependencies in the dataset (see Figure 2). Majority-class: It labels each instance with the most frequent template. DT (with real history): A modification of the previous approach but the real, expert values were used in the model for history rather than the predicted ones.

3 Results and Conclusions

MLC - RAkEL (Gkatzia et al., 2014) achieves higher accuracy, precision, recall and F-score compared to (1) DT (no history), where each template is predicted from a separate classifier independently, (2) DT (with predicted history), where the decision of the previous template is taken into account in the next decision, similar to Classifier Chains, and (3) a Majority-class baseline. This method is powerful due to its ability to take into account data correlations (Gkatzia et al., 2014). Multi-label classification should be used when the data to be summarised need to be considered simultaneously and/or when there are limited data available, for example, in student feedback generation, the lectures a student attended is highly correlated with his/her understandability ($r = 0.6$).
References

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