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IMapBook Collaborative Discussions Classification

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Abstract

In this paper we explore natural language processing approaches that aim to classify replies from discussions into predefined categories. Classes range from content discussion, greeting, logistics to feedback, response and others.

Keywords

...

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Introduction

Natural language processing (NLP) is a field of research where artificial intelligence, computer science and linguistics meet. Text classification is one of the NLP applications. It is defined as the process of categorizing free text according to its content. In this project we will address the text classification of collaborative discussions in online chat. For testing data we will use conversations from IMapBook [1], a web-based technology that allows reading material to be intermingled with interactive discussion. IMapBook users have access to a chat and text box where they collaborate to formulate an answer to a given question. Each message in the testing data was manually annotated with some classes, based on the information in the message. The goal of our project is to build a classifier, that would annotate messages with these classes. Such classifier could then be implemented into this platform, and could help with keeping pupils focused on discussion about the book.

Related work

What can we do with natural language processing? We can find answers on specific questions, offensive language detection, chatbots, autocorrect and autocomplete,... The goal of our project is to classify messages (short text) from chat. Short texts compared to documents have less contextual informations, meaning they are more ambiguous, which poses a great challenge for short text classification. Examples of short texts are tweets, chat messages, reviews, search queries,...

The most used vector representations of words that capture well the semantic information are Word2Vec [2] and GloVe [3]. Both models learn vector of words from their co-occurrence information (how often they appear together in large text corpora) and are pre-trained. Word2Vec is algorithm that uses neural networks to produce word embeddings and it does not have explicit global information embedded in it by default. GloVe is an unsupervised algorithm and has a global co-occurrence matrix with an estimate of the probability that a certain word will appear together with other words.

There are also contextual embeddings such as ELMo and BERT. They assign each word a representation based on its context, thereby capturing uses of words across varied contexts and encoding knowledge that transfers across languages [4].

Data

Discussion dataset consists of 3 tabs. The first one includes (crew) chat data from pupils, that were discussing answers from books. Each row contains information about the course they were attending, book id, topic (question), bookclub, pseudonym (pupil ID), message content, code preliminary, message time, yes/no if message is the answer (all no), page (shows on which page the activity was shown, not relevant) and response number, which links us to the grading in third tab of dataset. Third tab has data about grading and final answer pupils submited. Data in second tab has the same format as the data in the first one. The only difference between these two is, that the second tab has only discussion data, where pupils answered directly and it doesn't include grades.

There is a total of 712 data in the dataset. We are interested in the code preliminary classes and there's 16 of them. As we can see from Figure 1 the distribution of classes is skewed, which might present additional challenges during model fitting. This can be especially problematic when the

distribution in the training set differs from the distribution seen in the real world. Luckily for us, training and testing sets will be constructed from the same data and will have similar distributions.

By far the most common class is content discussion, followed by response and logistics. The bottom half of the classes are practically non-existent.

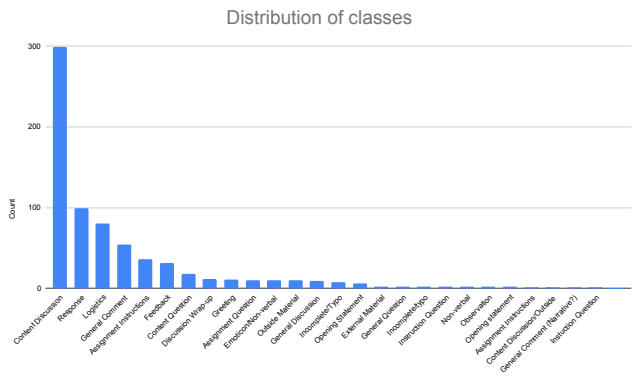

Figure 1. Distribution of classes in the provided dataset of collaborative discussions.

Data was collected from 6 different courses, with EDF6284 P2 having the highest number (229) of chat messages, and EDF6284 P1 with the lowest number with only 13 messages. 48 pupils participated. Figure 2 shows the most active users were edf-15 and edf-16 with 104 messages and the least active users were edf-01, pim-23, dig-06 and dig-07 with only 1 message.

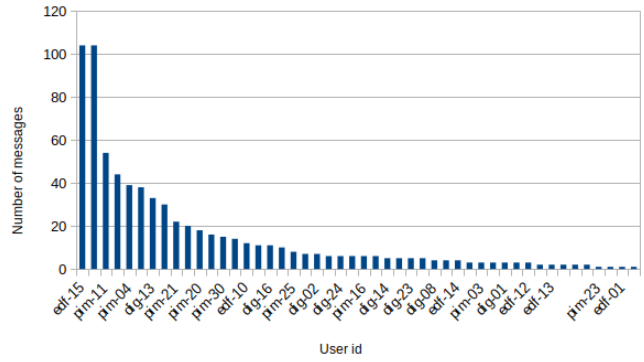

Figure 2. User activity: number of messages users sent in chat

Preprocessing

Since there were a few target classes with only one or two representatives, we decided to group them with the most appropriate classes. Having a class with a single representative does not make a lot of sense, since you can not evaluate the performance of the model. Considering that we use 4-fold stratified cross validation for the model evaluation, we wanted each class to have at least four representatives to simplify model training. Accounting for classes not present in the dataset would make training much more tedious without added benefits. Additionally, it seems that messages were inconsistently and somewhat carelessly annotated, and one could argue for many cases the another class would be more appropriate. Such as a message

- :)

that was tagged as a *Response* instead of an *Emoticon/Non-verbal*. Or the message

- /add

which was tagged as an *Assignment Question* instead of an *Incomplete/Typo*. Additionally, observe the following two messages.

- to mask, or not to mask. to eat, or not to eat. indoors, outdoors. out of state visitors.
- The man who moves a mountain begins by carrying away small stones.

They both fit in the context of the surrounding discussion similarly and sound alike. The first example was labeled as *General discussion*, and the second as *General comment*.

In the following paragraphs we try to justify some out of choices for grouping.

For example, the class *Observation* has only 2 representatives. We joined it with the *Feedback* class. Let us first look at a few messages from the *Feedback* class to get the general feel of how the replies sound:

- Oooo I like that idea of how he might send her to the arena and then tell her which is behind each door.
- Flipping a coin may not be the worst idea, honestly!
- That's a creative idea!

Now we can compare them with two examples of the *Observation* class:

- It feels collaborative in a way that the previous discussion was not, for me.
- I think this is turning into a message board...

We observe that examples annotated as *Observation* do sound like *Feedback*, so the joining makes sense.

Next let us take a look at a few examples of messages annotated as *Outside material*

- https://www.army.mil/article/125327/Army_designing_next_generation_protective_mask/
- Perhaps the stands they sit on can be made into mosaics like Gaudi's parks in Spain.

Comparing the with the two *External material*, we notice that one could use either of the two label for some of these replies.

- This isn't directly in the article, ...
- ...but Teresa made me also think that one way to invest in our future is to recruit, support, and mentor designers from marginalized communities with perspectives most mainstream designers don't have.

We decided to map the two examples from the *External material* to the *Outside material* class.

In total we grouped 11 classes, but most were due to typos, for example joining *Opening statement* and *Opening Statement*, or *Non-verbal* and *Emoticon/Non-verbal*, or *General Comment (Narrative?)* and *General Comment*. In the end we were left with 15 distinct classes.

Methods

In this section we present a few methods which we explored in our task of classifying messages.

TF-IDF

TF-IDF stands for *Term frequency - Inverse document frequency* and is a statistical measure that evaluates how relevant a word is for a specific messages in a collection of messages. It is frequently used for information retrieval tasks. We will use it to vectorize messages and feed them to other models, such as *Logistic regression*.

TF-IDF is calculated by multiplying two quantities

$$tf-idf(w,m,D) = tf(w,m) \cdot idf(w,D). \tag{1}$$

Where $tf(w,m)$ is the frequency of the word w in the message m, calculated as the number of o times the word occurs in the message, divided by the number of all words in the message. And $idf(w,D)$ is an inverse document frequency of the word w in the set of all messages denoted as D. It measures how much information the word provides. It is calculated as

$$idf(w,D) = \log \frac{|D|}{|\{m \in D : w \in m\}|}, \tag{2}$$

where $|D|$ is the number of documents or messages, and the denominator represents the number of messages where the word w appears.

Logistic regression

Since we are trying to predict multiple classes, we will actually use the multi-class version of *Logistic regression* also known as *Softmax regression*.

It is a generalized linear model that assumes a logit link function and a categorical distribution of the dependent variable. Specifically, for a single data point (x,y) it assumes the distribution

$$p(y = j \,|\, X = x) = \sigma(\theta_j^\top x) \tag{3}$$

$$= \frac{e^{\theta_j^\top x}}{\sum_{i=1}^{M} e^{\theta_i^\top x}} \tag{4}$$

where σ is the softmax function, also known as the inverse of the logit link function, and θ_i are the model parameters. We assume that x_0 is always equal to 1, and M is the number of classes. Using the maximum likelihood estimation or maximum aposteriori estimation and assuming data points are independent and identically distributed, we arrive at the categorical cross-entropy loss function, which can be minimized by multiple optimization algorithms.

GloVe

GloVe [3] stands for *global vectors for word representation* and is an approach to non-contextual word embedding that aims to capture semantic relationship between words in their embeddings. First a global co-occurrence of words is constructed, based on a large text corpus, where the element in the i-th row and j-th column is the probability P_{ij} that word j occurs in the context of the word i. The probabilities are simply estimated from the text as normalized counts of co-occurences that sum to one for each word. This probability can be written as

$$P_{ij} = \frac{X_{ij}}{X_i}, \tag{5}$$

where X_{ij} is the count of co-occurence and X_i is the count of word i.

GloVe model then tries to model the relationship in the following way

$$\log X_{ik} = w_i^\top \tilde{w}_k + b_i + \tilde{b}_k, \tag{6}$$

where b_i and $\tilde{b}_k$ are biases, w_i is the embedding of the word i, and $\tilde{w}_k$ is a separate context embedding of the word k.

From this goal the weighted least squares cost function is constructed and optimized. Luckily the co-occurence matrix is very sparse, which makes its construction and this optimization feasible.

BERT

BERT (Bidirectional Encoder Representations from Transformers) is a Transformer based technique for natural language processing developed by Google. The Transformer is a model that uses mechanism of weighing the influence of different parts of the input data. There are two steps in the framework: pre-training and fine-tuning. During pre-training, the model is trained on unlabeled data over different pre-training tasks. For fine-tuning, the model is first initialized with the pre-trained parameters, and all of the parameters are fine-tuned using labeled data from the downstream tasks. Each downstream task has separate fine-tuned models, even though they are initialized with the same pre-trained parameters [5].

Results

Preliminary results are shown in Table 1. We used *negative log loss*, *f1 macro* and *accuracy* to measure each the model's performance. At the moment a simple *tf-idf* and *logistic*

regression model worked best. We have to point out that up until now it was the only model that also took collaborative responses if there were any into account where predicting the class.

model	neg_log_loss	accuracy	f1_macro
majority	-18.358	0.468	0.043
tf-idf-logreg	-1.244	0.666	0.419
glove	-8.493	0.631	0.343

Table 1. Classification metrics obtained with 4-fold cross validation.

BERT

We used pretrained model *bert − base − uncased*, that was trained on lower-cased English text. It uses 12 layers, hidden size=768, number of self-attention heads=12 and total parameters of 110M. For the beginning, we tested how epochs affects our results, for values in range from 3 to 12. Figure 3 shows how it affected accuracy and f1 values. For training our model we used dropout rate 0.2, 100 cnn filters, 256 dnn units and 15 output classes.

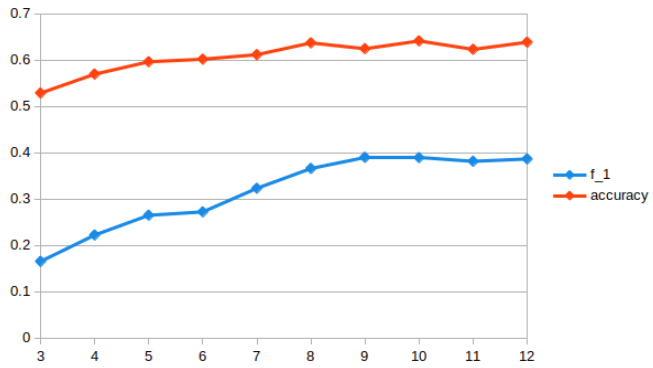

Figure 3. BERT accuracy and F1 values for different epochs.

We got the best results at epoch=8, where accuracy and F1 were the highest. The speed of training and evaluating increases linearly with increasing epoch, as we can see on Figure 4

Moving forward

We plan to fine tune and optimize the existing models. And we will try to improve their performance by taking additional data into account, be it collaborative responses, or user ids, or information regarding book club. It is surprising that for now a simple *logistic regression* and *tf-idf* based model has demonstrated the best performance. Although since messages are very short, and there is not a lot of data, simple models tend to work well, and complicated models with hundreds of thousands of trainable parameters tend to quickly overfit. We would be interested to know what performance using which models the other groups were able to achieve.

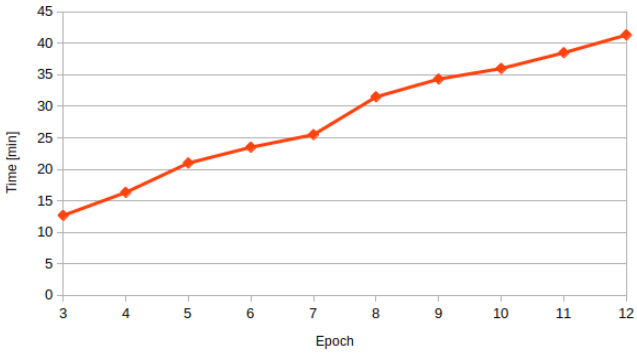

Figure 4. BERT time for training and evaluation in minutes.

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