Revisiting Rumour Stance Classification: Dealing with Imbalanced Data

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Abstract

Correctly classifying stances of replies can be significantly helpful for the automatic detection and classification of online rumours. One major challenge is that there are considerably more non-relevant replies (comments) than informative ones (supports and deniers), making the task highly imbalanced. In this paper we revisit the task of rumour stance classification, aiming to improve the performance over the informative minority classes. We experiment with traditional methods for imbalanced data treatment with feature- and BERT-based classifiers. Our models outperform all systems in RumourEval 2017 shared task and rank second in RumourEval 2019.

1 Introduction

A key step in the task of automatically analysing rumour veracity is to analyse the view of other users on a particular rumour (Procter et al., 2013), i.e. the stance of its replies. RumourEval 2017 and 2019 (Derczynski et al., 2017; Gorrell et al., 2019) are shared tasks that provide tree-structured conversation threads consisting of tweets directly or indirectly replying to a rumourous tweet and aim to label the stance of these replies towards the rumour (task A). Specifically, it is framed as a four-class classification problem: support, deny, query, and comment (SDQC). Supports and deniers are arguably the most informative stances for rumour verification (Mendoza et al., 2010), while comments are considered the least useful. However, the data for this task is highly imbalanced with supports and deniers corresponding, respectively, to 18% and 7% of instances in the RumourEval 2017, while comments are 66%.

Systems submitted for RumourEval 2017 task A, evaluated in terms of accuracy, have a high performance for the majority class (comments), whilst the minority classes are under-performed. Mama Edha (García Lozano et al., 2017) adjusts the weights of the four labels, while only correctly classifying 1% deniers and 37% supports. ECNU proposes a two-step classifier, however, only 1% of deniers and 28% of supports are accurately predicted (Wang et al., 2017). IITP over-samples the underrepresented classes (Singh et al., 2017), although only 12% deniers and 44% supports are recognised. The winner, Turing (Kochkina et al., 2017), is unable to identify any deniers in the test data. In RumourEval 2019, with macro-F1 as evaluation metric, eventAI (Li et al., 2019) (third place) achieves 55% and 79% of correct supports and deniers, respectively. Ranked first, BLCU NLP (Yang et al., 2019) increases the supports and deniers with external similar datasets. However, the expanded data is still skewed towards comments, and 38% supports and 51% deniers are accurately predicted. UPV (Ghanem et al., 2019) set different weights for each class, but 72% supports and 91% deniers are mis-classified. Despite GWU (Hamidian and Diab, 2019) designing a rule-based model to help predict the instances of minority classes, their system does not correctly classify any deniers. Other work (Zubiaga et al., 2018; Akhtar et al., 2018; Ma et al., 2018; Xuan and Xia, 2019) that also experiments with RumourEval or PHEME datasets does not consider imbalanced data approaches, and under-performs in support and deny classes.

In this paper, we experiment with well-known techniques for dealing with data imbalanced problems (e.g. SMOTE (Chawla et al., 2002)). We create feature-based models and a BERT-based model (Devlin...)

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1RumourEval 2019 dataset has a similar distribution: supports = 14%, deniers = 7% and comments = 72%.
et al., 2019). Results show that our models not only have higher performance for the minority classes but also have higher overall performance (in terms of macro-$F_1$ and geometric mean recall – GMR) than all systems submitted to RumourEval 2017 and all but one system submitted to RumourEval 2019.  

2 Resampling mechanisms and threshold-moving

Random under- or over-sampling (RUS or ROS)  RUS randomly discards samples in the majority class so that the class proportions can be balanced. Generally, it is computationally more efficient than over-sampling because it reduces the training data, although it may lead to under-fitting. ROS re-balances the class proportions through randomly replicating samples in the minority classes. However, these replications can increase the possibility of over-fitting (Prati et al., 2009).

Synthetic minority over-sampling technique (SMOTE)  is one of the most popular methods to over sample the minority class (Chawla et al., 2002). The mechanism is to artificially generate new samples based on $k$-nearest neighbours of each observation in the minority class. Although SMOTE also has other variants, such as Borderline-SMOTE (Han et al., 2005), we only experiment with the original SMOTE.

Adaptive synthetic (ADASYN) sampling approach (He et al., 2008) is another over-sampling method similar to SMOTE, where the new synthetic samples are also interpolated based on each observation’s $k$-nearest neighbours in the minority class. The main difference between SMOTE and ADASYN is the number of synthetic samples generated for each observation in the minority class. For SMOTE, it only depends on the required ratio of over-sampling, while in ADASYN, the number depends on the level of hardness of learning the data observation. ADASYN may focus too much on outliers, while SMOTE may associate outliers with inliers. Therefore, both of them could result in a sub-optimal decision.

SMOTE + Edited Nearest Neighbors (ENN) (SMOTEENN)  is a hybrid resampling method that combines over-sampling and under-sampling (Batista et al., 2004). Generally, it can achieve better performance than solely using SMOTE. In this method, firstly, the minority class is over-sampled by SMOTE. Then ENN will examine both majority and minority class and remove the data samples that are mis-classified by their three-nearest neighbours, which works as a data cleaning method.

Threshold-moving (TM) (Maloof, 2003; Sheng and Ling, 2006) usually does not change the original class proportions. The classifier is trained with the imbalanced data, but the decision threshold that transforms the output probability into class label is changed. For example, we usually set 0.5 for a balanced binary classification. As there is no closed-form expression for a threshold that can maximise macro-$F_1$ (Lipton et al., 2014), we set the threshold according to the class proportions, which has been proved to maximise macro accuracy based on two assumptions: (1) the class proportion of the test set is similar to that of the training set, and (2) the prior of a class is equivalent to its proportion in the training set (Collell et al., 2018). Therefore, our process for threshold moving is: (1) compute the output probability $P_k$ for class $k$ and (2) assign the class with highest $P_k/a_k$, $a_k = \text{num}_k/\text{num}_\text{total}$, in which $\text{num}_k$ is the number of class $k$ in the training set, and $\text{num}_\text{total}$ is the total number of the training set.

3 Experiments and Results

3.1 Experimental setup

Techniques presented in Section 2 are explored in two types of classification models. We use implementations of resampling methods from the imbalanced-learn python toolkit (Lemaître et al., 2017).

Feature-based classifiers  Our feature-based approach is an adaptation of (Aker et al., 2017). We use Twitter-based features like number of re-tweets, presence of URLs and hashtags, number of followers for the user, among others. These features are then concatenated with a word vector representation for the tweets, using a pre-trained Twitter GloVe embedding model (Pennington et al., 2014). We train Random Forest (RF), Multi-Layer Perceptron (MLP) and Logistic Regression with stochastic gradient descent (LR–SGD) models using the scikit-learn python toolkit (Pedregosa et al., 2011).

2Our implementation is available at https://github.com/YLi999/RumorStanceClassification
Average GMR and standard deviations

|      | NT       | RUS      | ROS      | SMOTE    | ADASYN   | SMOTEEN  | TM       |
|------|----------|----------|----------|----------|----------|----------|----------|
| RF   | 0.000 ± 0.000 | 0.513 ± 0.025 | 0.454 ± 0.039 | 0.229 ± 0.242 | 0.000 ± 0.000 | 0.037 ± 0.079 | 0.457 ± 0.040 |
| MLP  | 0.357 ± 0.139 | 0.541 ± 0.046 | 0.428 ± 0.154 | 0.442 ± 0.078 | 0.494 ± 0.057 | 0.477 ± 0.035 | 0.508 ± 0.036 |
| LR-SGD | 0.000 ± 0.000 | 0.519 ± 0.076 | 0.149 ± 0.195 | 0.234 ± 0.162 | 0.110 ± 0.178 | 0.230 ± 0.178 | 0.409 ± 0.067 |
| BERT | 0.482 ± 0.057 | 0.622 ± 0.027 | 0.442 ± 0.056 | -         | -        | -        | 0.626 ± 0.028 |

Table 1: GMR and macro-$F_1$ on RumourEval 2017 development set. Best results overall are in bold. Best result for each approach are underlined.

BERT-based classifier (BERT) We employ the pre-trained BERT-base-uncased model (Devlin et al., 2018) with 12 transformer layers, hidden unit size of 768, 12 attention heads, and 110M parameters. The inputs are the texts of a rumourous tweet and a reply tweet, and we fine tune for three epochs with a batch size of 16, using the ktrain (Maya, 2020) toolkit. During training, we apply the 1 cycle policy (Smith, 2018), and search the optimal learning rate among $10^{-5}$, $4 	imes 10^{-5}$, $3 	imes 10^{-5}$, and $2 	imes 10^{-5}$. Since ROS, RUS and TM can be directly applied to raw text, we only apply BERT with these three methods.

Evaluation For evaluation we use macro-$F_1$ and GMR. Macro-$F_1$ is the arithmetic mean between the $F_1$-score $F_{1,c}$ of each class $c$: $\text{macro-$F_1$} = \frac{\sum_{c=1}^{C} F_{1,c}}{C}$ and is commonly applied in the evaluation of imbalanced binary classification. However, for multi-class problems, it is not robust to poor performance of the minority classes. GMR is denoted as $\sqrt{\prod_{c=1}^{C} R_c}$, in which $R_c$ is the recall of class $c$. False negatives may be more relevant than false positives in an imbalanced problem, therefore, it is important to assess models using recall-based metrics. Combining GMR with macro-$F_1$ for evaluation can avoid choosing a model with high macro-$F_1$ but actually with low recall for the minority classes.

3.2 Models assessment

For this experiment, we consider RumourEval 2017 data only. We run each experiment 10 times to model variability and test on the development set. As baselines, we also train systems without any imbalanced data treatment (NT). Table 1 shows average and standard deviation of GMR and macro-$F_1$. Although BERT in the NT case shows the highest macro-$F_1 = 0.584$, BERT with TM (macro-$F_1 = 0.540$) is still a better system, since it has the highest GMR = 0.626 and performs significantly better for supports and denies. When using feature-based classifiers, RUS leads to better models than the other approaches for both macro-$F_1$ and GMR. The feature-based training data is high dimensional, which may harm the performance of resampling methods that are based on k-nearest neighbours. Systems with GMR = 0 are the worst case, since they could not correctly classify any denies in any of the 10 iterations (e.g. RF with ADASYN). Other systems, such as LR-SGD with SMOTE, fail to correctly predict any denies most of the time in 10 experiments, and consequently have high standard deviation of GMR (larger than 0.1). When using BERT, both RUS and TM result in a relatively good prediction on the minority classes, while TM perform better on the comments – the macro-$F_1$ of BERT with TM is larger than that of BERT with RUS, although their GMRs are almost the same. TM works well with our neural models, BERT and MLP, which can provide good estimation of posterior probabilities. Finally, this analysis highlights the necessity of using both GMR and macro-$F_1$ for evaluation. Some systems with high macro-$F_1$ have low GMR, such as MLP with ADASYN (macro-$F_1 = 0.531$, GMR = 0.494).

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3Since RumourEval 2019 has Reddit data, it is not possible to use the same level of metadata available for tweets in this dataset, which justify our focus only on RumourEval 2017 data for model selection.
Table 2: Comparison with selected systems from RumourEval 2017.

| Model                  | GMR  | macro-F1 |
|------------------------|------|----------|
| BERT-TM(ensemble)      | 0.635| 0.536    |
| BERT-TM(single)        | 0.626| 0.513    |
| FBE-RUS                | 0.618| 0.484    |
| BERT-NT(single)        | 0.403| 0.516    |
| NileTMRG               | 0.363| 0.452    |
| ECNU                   | 0.214| 0.467    |
| Turing                 | 0.000| 0.434    |

Table 3: Comparison with selected systems from RumourEval 2019.

| Model      | GMR  | macro-F1 |
|------------|------|----------|
| eventAI    | 0.726| 0.578    |
| BERT-TM(single) | 0.618| 0.561    |
| BERT-TM(ensemble) | 0.605| 0.571    |
| BLCU NLP   | 0.571| 0.619    |
| BUT-FIT    | 0.519| 0.607    |

Figure 1: Confusion matrix for proposed models and selected systems for RumourEval 2017

Figure 2: Confusion matrix for proposed models and selected systems for RumourEval 2019

3.3 Comparison with RumourEval submitted systems

As BERT with TM (BERT-TM(single)) is the best model on RumourEval 2017 development set, we further test it on both RumourEval 2017 and 2019 test sets, and compare it with the submitted systems. We also implement an ensemble of the three feature-based models (RF, MLP and LR-SGD) with RUS (FBE-RUS), and a bagging ensemble of BERT-TM(single) (Collell et al., 2018) – BERT-TM(ensemble). The process of training BERT-TM(ensemble) is: (1) generate $n$ training sets with simple bootstrap sampling; (2) fine-tune $n$ BERT base classifiers; (3) compute the average of $n$ probabilistic predictions for each class; and, (4) perform TM. Similar to BERT-TM(single), the threshold is set according to the class proportion of training data. The optimal number of the base classifiers $n$ is determined by the performance on development data ($n = 15$ in our case). We also present results for BERT without TM (BERT-NT(single)) on RumourEval 2017 test set.

For RumourEval 2017, we compare our models with Turing, ECNU, and NileTMRG (Enayet and El-Beltagy, 2017) (Table 2). BERT-TM(single), BERT-TM(ensemble), and FBE-RUS outperform other systems, showing similar performance for supports and denies. After applying TM on the output of BERT-NT(BERT-TM(single)), the performance on the minority classes is significantly enhanced (Figure 1). For RumourEval 2019, our models are compared with BLCU NLP, BUT-FIT (Fajcik et al., 2019), and eventAI (Table 3), outperforming BLCU NLP and BUT-FIT on supports and denies (Figure 2). Although eventAI performs better than our models, some details about its architecture are not provided in the paper and the code is not publicly available.

4 Conclusion and future work

We experiment with traditional imbalanced data techniques for the task of rumour stance classification and show that: (i) our models are capable of outperforming all systems in RumourEval 2017 and all but one system in RumourEval 2019 in terms of both macro-$F1$ and GMR scores, and (ii) a more in-depth evaluation is needed in order to correctly assess this task. Further improvements may be achieved by employing model-based imbalanced data techniques (e.g. by setting different weights for each class during training), which is left as future work.
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