**1 INTRODUCTION**

Text classification is an important problem in Natural Language Processing (NLP). Real world use cases include spam filtering or e-mail categorization. It is a core component in more complex systems such as search and ranking. Recently, deep learning techniques based on neural networks have achieved state of the art results in various NLP applications. One of the main successes of deep learning is due to the effectiveness of recurrent networks for language modelling and their application to *speech recognition* and *machine translation* (*Mikolov, 2012*). However, in other cases including several text classification problems, it has been shown that deep networks do not convincingly beat the prior state of the art techniques (*Wang & Manning, 2012; Joulin et al., 2016*).

In spite of being (typically) orders of magnitude slower to train than traditional techniques based on n-grams, neural networks are often regarded as a promising alternative due to compact model sizes, in particular for character based models. This is important for applications that need to run on systems with limited memory such as smartphones. This paper specifically addresses the compromise between classification accuracy and the model size. We extend our previous work implemented in the fastText library 1. It is based on n-gram features, ***dimensionality reduction***, and a fast approximation of the softmax classifier (*Joulin et al., 2016*). We show that a few key ingredients, namely feature pruning, quantization, hashing, and retraining, allow us to produce text classification models with tiny size, often less than 100kB when trained on several popular datasets, without noticeably sacrificing accuracy or speed.

We plan to publish the code and scripts required to reproduce our results as an extension of the fastText library, thereby providing strong reproducible baselines for text classifiers that optimize the compromise between the model size and accuracy. We hope that this will help the engineering community to improve existing applications by using more efficient models.

This paper is organized as follows. *Section 2* introduces related work, *Section 3* describes our text classification model and explains how we drastically reduce the model size. *Section 4* shows the effectiveness of our approach in experiments on multiple text classification benchmarks.

**2 RELATED WORK**

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