Improving Text Classification with Vectors of Reduced Precision*

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Abstract: This paper presents the analysis of the impact of a floating-point number precision reduction on the quality of text classification. The precision reduction of the vectors representing the data (e.g. TF–IDF representation in our case) allows for a decrease of computing time and memory footprint on dedicated hardware platforms. The impact of precision reduction on the classification quality was performed on 5 corpora, using 4 different classifiers. Also, dimensionality reduction was taken into account. Results indicate that the precision reduction improves classification accuracy for most cases (up to 25% of error reduction). In general, the reduction from 64 to 4 bits gives the best scores and ensures that the results will not be worse than with the full floating-point representation.

1 INTRODUCTION

Natural Language Processing (NLP), as well as Image Processing, is a part of Artificial Intelligence. Despite intensive research and huge recent progress in Deep Learning Techniques, applications of NLP have not reached a level that would allow a construction and a practical implementation of robots and machines operating like humans. Such human-level solutions would allow for seamless and smooth communication between machines and people. The future communication interfaces will allow to convey information directly to the machines processing units using natural language (Bengio et al., 2013)(Schmidhuber, 2015)(Kumar et al., 2015). This future vision, however, requires a substantial progress in both speech recognition and text processing domains. Applications of those two domains are in an essence very similar and share most of the processing flow. In our research (Karwatowski et al., 2015) we focus on text processing, but the proposed modules may also be employed in voice processing solutions.

NLP as a research and application field has been developed in a course of last few decades (Manning and Schütze, 1999)(Collobert et al., 2011)(Hermann et al., 2014)(Petrov et al., 2012). Three different models of the language representation have been established, namely Boolean Model, Vector Space Model (VSM) and Sparse Representation Model (Mikolov et al., 2013a). The latter model slowly becomes a standard for applications and systems using Natural Language Processing (Mikolov et al., 2013b). This is due to its superior performance, which in turn results from the fact that it mimics the language representation within a human brain (Hawkins and Blakeslee, 2004). It is worth noting that a language as such belongs to a human cognition domain. It was developed by humans to enable communication and was implemented with biological components in a neural fashion (Mountcastle, 1997). Therefore, pure ontological models of the language tend to be inferior to the biologically–inspired ones (Hawkins and George, 2006).

Representation of knowledge within a human brain is highly distributed, sparse and hierarchical (Hawkins and Blakeslee, 2004)(Mountcastle, 1997). Neural operations of cognition, which also involve language processing, are performed using single bit precision. Every bit of the information carries semantic meaning which reflects relationships between concepts acquired and stored within the brain. Inspired by this we decided to examine to what extent it is possible to implement such a bit processing scheme on a

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top of currently used models in NLP. We focused on the Vector Space Model (tf-idf) as one which is popular and widely used in various applications. However, the research results may also be transferred to the other models since all of them employ vector as a basic representation structure. The vectors are a collection of fixed or floating–point numbers which represent a certain dynamic range of a data representation. It turns out that the dynamic range, at least in the case of floating–point numbers, is too large and can accommodate much more information than necessary. Therefore, we decided to reduce the range to the extent that, on the one hand still preserves a required precision and on the other hand substantially decreases the number of bits. Precision reduction of vector representation may be perceived as way of concept generalization.

Precision reduction approach may not have significant performance impact on standard processors, as they typically operate on fixed data width, usually stored in IEEE–754 floating–point representation. Therefore, reduction to below standard width or, moreover, not byte aligned width, does not introduce notable speedup. The situation improves for single instruction, multiple data (SIMD) processors, like general–purpose computing on graphics processing units (GPGPU), or vector CPUs however data alignment is still required and speedup is only achieved through parallelism and reduction of clock cycles required to process given an amount of data. Real benefits of precision reduction can be observed on fully customizable platforms, such as field-programmable gate arrays (FPGA) (Wielgosz et al., 2013a)(Wielgosz et al., 2013b)(Wielgosz et al., 2012). They are not bound to any specific bitwidth or representation. Data may be stored in any integer bitwidth, which can also differ between consecutive processing stages. Narrower representation requires a less complicated circuit to execute calculations, which improves operating frequency. Switching to fixed point representation further reduces circuit complexity, thus increases operating frequency, which can also vary between processing stages. Data flow architecture can also be designed to process data in a parallel manner. A combination of aforementioned features makes FPGA a very interesting choice as a hardware platform. However, creating efficient design architecture and its implementation are not trivial and generate interesting research task. As authors of this paper already began work on the dedicated hardware platform and presented their initial results in (Karwatowski et al., 2017), we will not cover this topic. Still much effort needs to be put into FPGA implementation in order to utilize its potential in NLP tasks. Additionally, precision reduction can be perceived as an alternative method to SVD or PCA to achieve memory footprint reduction without drop in classification accuracy.

Consequently, the paper addressed two main objectives:

- an examination of the precision reduction impact on the text classification results,
- proposition and practical verification of various popular classification methods with different grade of reduced precision,

The rest of the paper is organized as follows. Section 2 describe a procedure of precision reduction used in our experiments. Section 3 describes classification parameters of the employed classifiers. Experiments are presented in Section 4. Finally, we present our conclusions in Section 5.

2 PRECISION REDUCTION

Language models are usually very large multidimensional structures composed of vectors. The vectors contain IEEE–754 floating–point numbers which can be either stored in dense or sparse format for a sake of a storage space utilization reduction.

We reduce precision of each vector element given by Eq. 1:

$$S_{single} : \{\pm 2^{-126} \dots (2-2^{-23}) \times 2^{127}\}^{1\times n} \quad (1)$$

where S and n is a vector of IEEE–754 floating–point numbers and its dimension, respectively.

Generated TF–IDF coefficients are in IEEE–754 double floating–point format and their values span between 0 and 1. Therefore to map these values to desired fixed precision is enough to multiply them by the maximal value possible to encode with that precision:

1. $max\_value = 2^{bitwidth} - 1$
2. $for\ tf\_idf\ in\ database$:
3. $norm\_tf\_idf = ceil(tf\_idf * max\_value)$

after that we receive rounded values from a set:

$$\{0, \frac{1}{2^{bitwidth}} \dots, 1 - \frac{1}{2^{bitwidth}}, 1\}^{1\times n} \times 2^{bitwidth} - 1 \quad (2)$$

Back normalization to floating–point format is performed accordingly, only the value needs to be divided by maximal value.

1. $max\_value = 2^{bitwidth} - 1$
2. $for\ norm\_value\ in\ results$:

3. $value = norm\_value / max\_value$

The set values after normalization are represented by a following set:

$$\{0, \frac{1}{2^{bitwidth}} \ldots, 1 - \frac{1}{2^{bitwidth}}, 1\}^{1 \times n} \quad (3)$$

The reduction parameter *bitwidths* strongly affects performance results since it directly decides about a number of bits which are left for the vector elements representation. It is worth noting that it is possible to employ global dimensionality reduction techniques such as SVD along with the methods proposed in this paper. In this work, we consider the order of these operations (precision reduction before or after SVD) for the sake of the best final results.

3 CLASSIFICATION

In order to evaluate the influence of the precision reduction on the robustness of VSM model we employed them in the problem of multi-class (single-lable) text classification. We have chosen k–nearest neighbors algorithm (KNN), logistic regression (LR) and support vector machines (SVM) as the tested classifiers.KNN was used with cosine similarity metric and the number of neighbors $k \in \{1,5\}$. The algorithm does not require training, but the testing phase involves calculating similarity with every document. It also needs to store all the documents from the training corpus. As such it is not well suited for large corpora, which are much more popular in the recent years. In LR we applied L2 regularization. SVM was trained with hinge loss and linear kernel. Both execute iterative training and do not store documents for testing.

For macro–averaged objective the weights associated with classes were adjusted inversely proportional to class frequencies in the input data

$$w_c = \frac{\sum n_i}{n_c}, \quad (4)$$

where w_c is a weight associated with class c and n_i is a number of samples in class i.

4 EXPERIMENTS AND THE DISCUSSION

4.1 Experimental Setup

4 modules were developed in order to execute experiments:

- Term frequency–inverse document frequency was calculated on training data without setting any limit on the number of words.
- Precision reduction was performed on VSM representation of documents as described in 2, where b is the precision in bits.
- Singular value decomposition was used to reduce the dimensionality of data, where k is the number of components.
- 4 classifiers were used: k–nearest neighbors algorithm with cosine similarity metric for $k \in \{1,5\}$, logistic regression and support vector machines with linear kernel.

5 variants of experiments were performed:

- TF–IDF and Classification,
- TF–IDF, Precision reduction (b) and Classification,
- TF–IDF, Precision reduction (b), SVD (k) and Classification,
- TF–IDF, SVD (k) and Classification,
- TF–IDF, SVD (k), Precision reduction (b) and Classification,

where $b \in \{16,8,7,6,5,4,3,2,1\}$ and $k \in \{100,200,300,400,500,1000\}$.

All results were obtained by taking an average of 5–fold cross–validation scores. Each datasets was randomly shuffled, partitioned into 5 subsets. The process of evaluation was repeated 5 times, with one subset used exactly once as testing data and the rest 4 as training data.

All experiments were performed in Python using scikit–learn (Pedregosa et al., 2011) library with default parameters. Calculations were performed on 64–bit floating point type with 4 cores of Intel Xeon E5–2680v3. Framework performing precision reduction is available at: `https://github.com/kwrobel-nlp/precision-reduction`. It determines what is the best number of bits for classification of specified corpus. Datasets used in this work are shared for reproducibility of results.

4.2 Datasets

Experiments were performed on multi–class (single–label) datasets. 5 datasets are publicly available:

- `webkb` - webpages collected from computer science departments,
- `r8` - Reuters articles with single label from R10 subcollection of Reuters-21578,
- `r52` - Reuters articles with single label from R90 subcollection of Reuters-21578,

Table 1: Volume of datasets: number of classes, number of documents, number of unique words, average length of documents in terms of number of words, smallest and largest class.

Dataset	webkb	r8	r52	20ng	cade
Classes	4	8	52	20	12
Documents	4199	7674	9100	18821	40983
Vocabulary	7770	17387	19241	70213	193997
Average number of words in document	909	390	418	851	913
Smallest class	504	51	3	628	625
Largest class	1641	3923	3923	999	8473
Average size of classes	1049	959	175	914	3415
Standard deviation of sizes of classes	408	1309	613	94	2451
Relative standard deviation of sizes of classes	0.39	1.36	3.51	0.10	0.72

- `20ng` - newsgroup messages,
- `cade` - webpages extracted from the CADÊ Web Directory.

All of them are pre–processed by (Cardoso-Cachopo, 2007):

- all letters turned to lowercase,
- one and two letters long words removed,
- stopwords removed,
- all words stemmed.

Multi–label datasets were transformed to single–label by removing samples with more than one class. Table 1 shows summary of corpora's main features. Corpora `webkb`, `r8`, `r52` and `20ng` are in English, `cade` is in Brazilian-Portuguese. `cade` is the largest dataset in terms of the number of documents, vocabulary and average length of documents. `20ng` is the most balanced (0.1 relative standard deviation), others are very skewed.

4.3 Quality Measure

The macro–averaged F1 score is used as a quality evaluation of the experiments' results presented in this paper. The precision and recall for corresponding classes are calculated as follows:

$$Precision(i) = \frac{tp_i}{tp_i + fp_i}, \quad (5)$$

$$Recall(i) = \frac{tp_i}{tp_i + fn_i}, \quad (6)$$

where tp_i is the number of items of class i that were classified as members of class i, fp_i is the number of items of class other than i that were wrongly classified as members of class i and fn_i is the number of items of class i wrongly classified as members of class other than i. The class' F1 score is computed as harmonic average of class precision and recall parameters.

The overall quality of the classification can be obtained by taking the unweighted average F1 scores for each class. It is given by the equation:

$$F1 = \frac{1}{c}\sum_i F1(i), \quad (7)$$

where c is the number of all classes. The F1 score value ranges from 0 to 1, with a higher value indicating a higher classification quality.

The error is defined as:

$$Error = 1 - F1. \quad (8)$$

The error reduction is defined as:

$$ErrorReduction = \frac{(Error_{ref} - Error_{new})}{Error_{ref}}, \quad (9)$$

where $Error_{ref}$ is a reference value of error and $Error_{new}$ is the new value of error.

To compare the results with other studies, micro–averaged accuracy is used. Micro–averaging does not take imbalance of classes into account.

$$Accuracy = \frac{\sum tp_i}{n}, \quad (10)$$

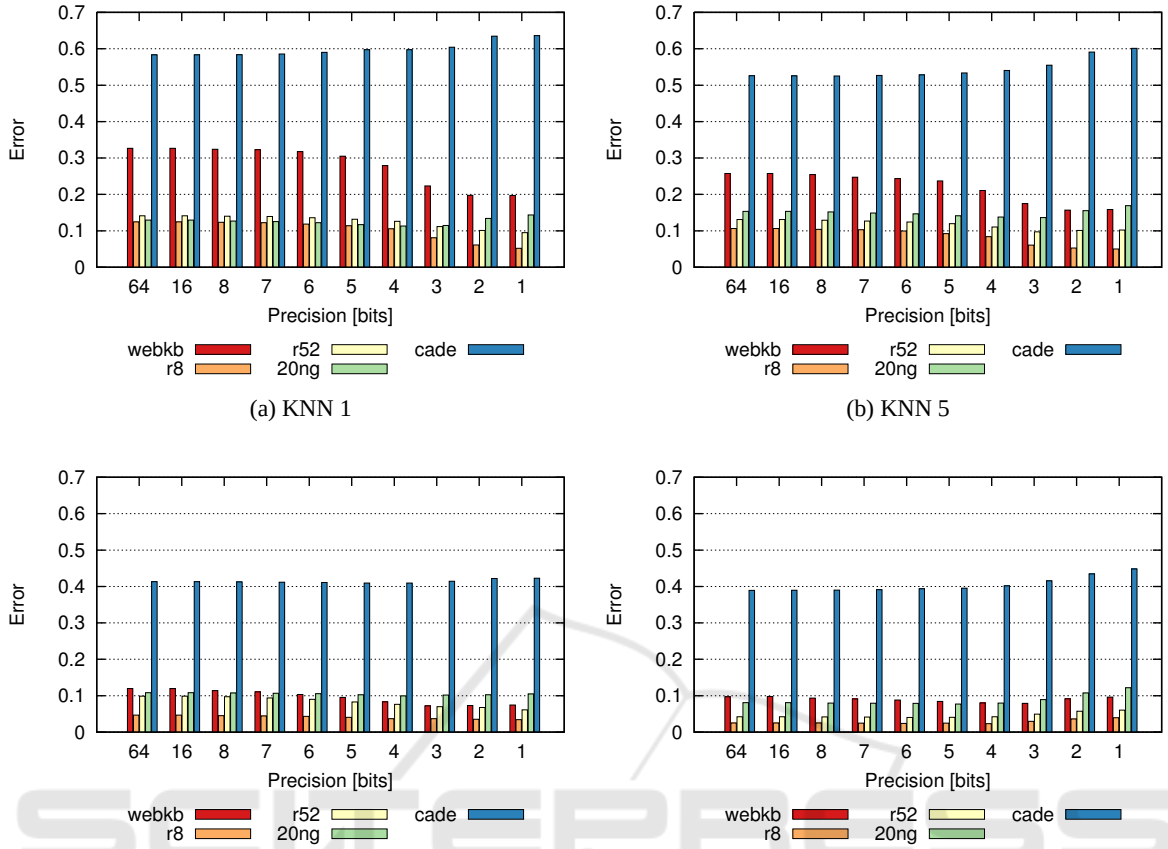
where n is a number of all training samples.

4.4 Results

Error values on the corpora for each classifier in function of precision bits are shown in Fig. 1. For every dataset logistic regression and SVM obtain smaller error than KNNs. LR and SVM are more powerful because they model inputs (i.e. terms) in relation to classes. Precision reduction with KNNs improves results on `webkb`, `r8` and `20ng` datasets. KNN 5 scores higher than KNN 1 on `webkb` and `cade`.

Fig. 2 shows averaged error reduction among the corpora for the classifiers. For SVM the precision reduction is the least beneficial. It can be observed that greater the complexity of the classifing algorithm, the bigger the drop in accuracy. For other classifiers macro–averaged errors decrease with the reduction of precision down to 3 bits. However, micro–averaged errors are the smallest for the precision of 1-3 bits. Four times reduction of precision from 64 bits to 16 bits does not change the classification results.

Fig. 3 shows averaged error reduction measure among the corpora for the classifiers with a precision



(a) KNN 1

(b) KNN 5

(c) Logistic Regression

(d) SVM

Figure 1: Error values of the classifiers on the corpora in function of precision bits.

reduction after SVD. The results indicate that introducing the precision reduction after SVD generates more errors in every case. These results prove that sparse distributed representation of vectors is more resistant for reduced precision than dense counterpart.

Fig. 4 presents F1 measure for 3 variants: TF–IDF, TF–IDF with the best precision reduction and TF–IDF with the best SVD. Precision reduction gives better or similar results as applying SVD except for KNNs on `r8`. k–nearest neighbors algorithm with precision reduction gives similar results as raw logistic regression on `r8`, `r52`, and `20ng` datasets. In the raw form SVM has the best results for the English datasets.

Fig. 5 presents comparison of F1 score on variant TF–IDF with SVD with and without precision reduction before SVD. Precision reduction before SVD has always positive impact, especially seen on `webkb` dataset.

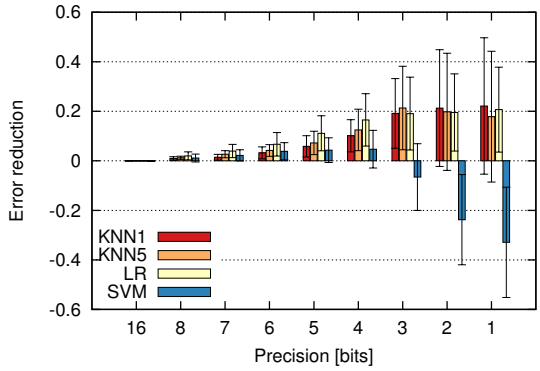
Table 2 shows overall macro–averaged F1 scores for every classifier on each corpus. The best results are obtained by logistic regression and SVM. Classification of `cade` is the most difficult task, the best classifier has only 55% of F1 measure.

Table 2: Macro–averaged F1 in 5-fold cross-validation scheme for each corpus and each classifier.

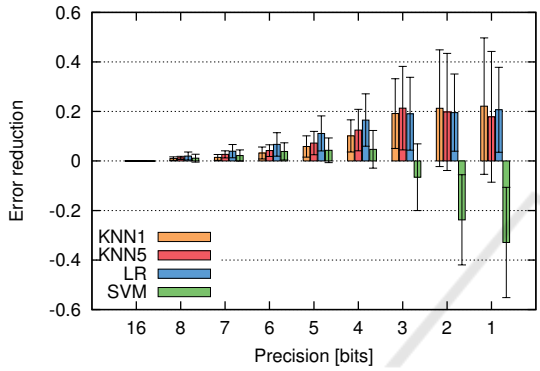
	webkb	r8	r52	20ng	cade
KNN 1	76.54	87.47	70.76	88.56	37.17
KNN 5	80.33	86.80	66.00	86.21	42.96
Logistic Regression	**92.44**	93.41	81.88	90.04	**55.25**
Linear SVM	91.17	**94.48**	**84.02**	**92.04**	52.67

Table 3 shows overall micro–averaged accuracy for every classifier on each corpus compared with the results of SVM from (Cardoso-Cachopo, 2007) and SVM with random search from (Puurula, 2012). Our SVM with precision reduction is superior on 4 datasets: `webkb`, `r52`, `20ng` and `cade`.

SVD is the most time consuming phase in training in comparison to classification. However, it can reduce time of testing. Time of testing using KNNs is higher than other classifiers, because it is proportional to number of documents. Time of precision reduction is negligible.



(a) Macro–averaged



(b) Micro–averaged

Figure 2: Average and standard deviation of error reduction among the corpora for the classifiers in function of precision bits.

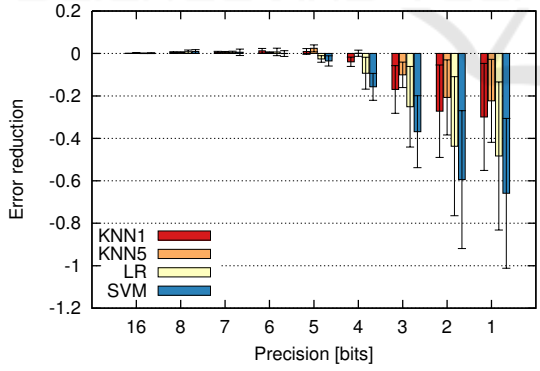


Figure 3: Average and standard deviation of error reduction among the corpora for the classifiers in function of precision bits for the variant with a precision reduction after SVD.

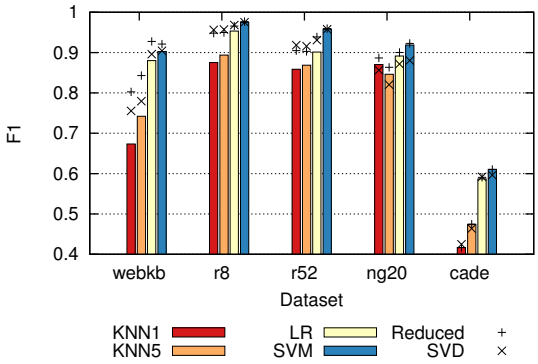


Figure 4: F1 of the classifiers on the corpora with only TF–IDF, TF–IDF with the best precision reduction and TF–IDF with the best SVD.

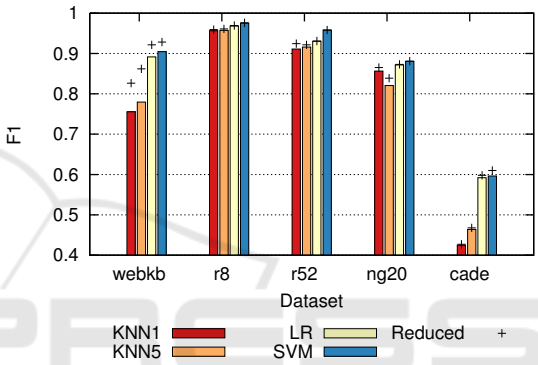


Figure 5: F1 of the classifiers on the corpora with TF–IDF with the best precision reduction and SVD compared to TF–IDF with SVD.

5 CONCLUSIONS AND FUTURE WORK

The conducted experiments show that it is beneficial to the perform precision reduction on the term–document representations. However, it is unclear what number of bits gives the best results for the specific corpus. For some corpora, a precision reduction to 1 bit is possible without loss of accuracy. On the other hand it is safe to reduce the number of bits from 64 to 4, which usually improves the quality of the obtained results and never leads to their degradation. As

Table 3: Micro–averaged accuracy in 5-fold cross-validation scheme for each corpus and each classifier compared to another system. SVM results are from (Cardoso-Cachopo, 2007) and SVM with random search is from (Pu-urula, 2012).

	webkb	r8	r52	20ng	cade
KNN 1	80.28	94.81	90.49	88.67	41.67
KNN 5	84.30	94.99	90.28	86.36	47.47
Logistic Regression	92.78	96.57	93.89	90.04	59.07
Linear SVM	92.11	97.69	95.96	92.27	61.07
Best	**92.78**	97.69	**95.96**	**92.27**	**61.07**
SVM	86.97	97.08	95.08	91.53	53.57
SVM with random search	92.69	**97.90**	95.37	84.39	60.69

such, precision reduction seems the be very promising result, especially combined with FPGA implementation, which should lead to significant computation speed-up and memory footprint reduction.

The precision reduction is also a good alternative to dimensionality reduction by SVD. It can lead to better accuracy. This feature is specially important for scenarios with very large vocabularies and document data sets. If SVD is still considered, the precision reduction should be applied before SVD, not in opposite order. It should be also observed that focusing on micro–averaged objective allows for stronger reduction than in macro-averaged measures. It should be noticed that reduced precision in more complex algorithms leads to higher probability of drop in accuracy because the error of data representation is propagated through longer computational path. Therefore KNN gives the highest gain in accuracy after precision reduction.

The approach developed and described in this paper enables porting NLP and VSM–based solutions to FPGA or embeded devices with reduced memory capacity or reduced precision arithmetic. This is done through reduction of the model memory footprint which results from low-bit vector representation. It is worth noting that the reduced memory occupation also affect the performance of the system, especially the response latency which is critical in embedded systems. Smaller vectors mean less computations which in turn leads to lower energy consumption. Further analysis will concentrate on datasets structures and theirs impact on reduction ability and simulations with other quantized vector space models (e.g. log tf, boolean).

Nowadays neural networks are one of the most popular machine learning tools used to solve NLP problems. Our further research will be focused on testing precision reduction on distributional representations, which are typically used as inputs to neural networks. It is not uncommon that neural networks have millions of parameters (e.g. Alexnet, Resnet 152, Inception Resnet) – the reduction of precision of the vector weights is an interesting direction of research, which will be pursued in our future work. Comparative studies on compressed deep learning models and reduced VSM representations with machine learning model presented in this article can show which method need less storage and be run in less number of cycles without significant drop in performance.

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