Subword Semantic Hashing for Intent Classification on Small Datasets

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Abstract—In this paper, we introduce the use of Semantic Hashing as embedding for the task of Intent Classification and achieve state-of-the-art performance on three frequently used benchmarks. Intent Classification on a small dataset is a challenging task for data-hungry state-of-the-art Deep Learning based systems. Semantic Hashing is an attempt to overcome such a challenge and learn robust text classification. Current word embedding based methods [11], [13], [14] are dependent on vocabularies. One of the major drawbacks of such methods is out-of-vocabulary terms, especially when having small training datasets and using a wider vocabulary. This is the case in Intent Classification for chatbots, where typically small datasets are extracted from internet communication. Two problems arise with the use of internet communication. First, such datasets miss a lot of terms in the vocabulary to use word embeddings efficiently. Second, users frequently make spelling errors. Typically, the models for intent classification are not trained with spelling errors and it is difficult to think about ways in which users will make mistakes. Models depending on a word vocabulary will always face such a challenge. An ideal classifier should handle spelling errors inherently. With Semantic Hashing, we overcome these challenges and achieve state-of-the-art results on three datasets: Chatbot, Ask Ubuntu, and Web Applications [3]. Our benchmarks are available online.

Index Terms—Natural Language Processing, Intent Classification, Chatbots, Semantic Hashing, Machine Learning, State-of-the-art.

I. INTRODUCTION

State-of-the-art systems in many different classification tasks have their basis in deep neural networks [8]. This is, among other reasons, because of neural networks’ ability to efficiently learn the various features present in the classes. However, this ability also makes neural networks prone to overfitting on the training data. A wide variety of strategies are used to prevent this, but the most reliable way to prevent overfitting is to have a large amount of training data. This makes neural networks, deep networks in particular, unsuited for solving problems with small datasets.

With small datasets, it is often better to use less complex machine learning models. With less complex models however the feature learning of deep networks is lost. Without feature learning, the input features given to the model have a much larger impact on the model’s ability to learn. In this paper, we experiment with a new feature extraction model.

One field where datasets are often small is the intent classification for industries like CRMs, Chatbots, business process automation, customer support, and so on. Intent classification is the task of giving an input, usually a text, finding the intent behind the said text. For example, the intent behind the sentence Sugar causes teeth decay is to make you eat less sugar.

Since there are countless different intents that a text can have, labelling them is difficult and highly problem-specific. For example, political intents may have labels such as left-wing or right-wing while questions may have intents such as where to or how to. Because of this, most of the real-life intent classification datasets are small (below 100 examples per class).

In this paper, we introduce an effective method for providing features to an intent classifier and we evaluate it on the Chatbot, AskUbuntu, and WebApplication corpora [3]. A classifier trained on semantic hashing (semhash) features achieves state-of-the-art performance.

The three datasets on which the classifier has been evaluated were introduced in the paper Evaluating Natural Language Understanding Services for Conversational Question Answering Systems [3] as a baseline to test Natural Languages Understanding (NLU) services.

An NLU service is a toolkit or API which can train a natural language classifier. The idea is that a user without prior knowledge of machine learning can simply provide examples of the input and the expected output of a natural language processing system, and the NLU will train that system for them. An NLU trained on intent classification data is therefore also an intent classifier.

II. RELATED WORK

One of the essential parts of any deep learning based Natural Language Processing system is embeddings. Text quanta, when represented as dense learnable vectors (rather than sparse vectors), are called embeddings, which are trained with a
certain predefined objective. Post training, their purpose is to be used for feature extraction and representation of text in various Machine Learning tasks. One of the most popular forms of embedding is the Word Embedding, as pioneered by models such as Word2Vec [13] and GloVe [17].

Both of these embedding models are trained in an unsupervised fashion and are based on the distributional hypothesis: Words that occur near words have similar contextual meaning. These word embeddings were further improved by FastText [9] with the inclusion of character n-grams. N-grams inclusion allowed better approximations of out of vocabulary words. Further, state-of-the-art was improved by Allen Institute for AI with the introduction of Deep Contextualized Word Representations (ELMo) [18].

Words to Sentence Embedding involves averaging of a sentence’s word vectors, often referred to as the Bag of Word approach. This simple approach was further improved by the usage of Concatenated p-mean Embeddings [19] instead of a simple averaging. Quick thought-vectors [10] is another approach to learning unsupervised sentence embeddings. A vocabulary expansion scheme improved their results by handling unseen words during training. The training time is very high for quick-thought-vectors. Quick thought vectors [12] improved the training time by replacing the decoder with a classifier by following a discriminative approximation to the generation problem.

Supervised learning approach did not seem intuitive for embeddings until InferSent [5] used the Stanford Natural Language Inference (SNLI) Corpus [2] to train a classifier. MILA/MSRs General Purpose Sentence Representation [21] further extended the supervised approach by encoding multiple aspects of the same sentence. Googles Universal Sentence Encoder [4] uses its transformer network to train over a variety of datasets and then use the same model for a variety of tasks.

III. DATASETS

Three different data corpora have been used for our evaluation and benchmarks: the Chatbot Corpus (Chabot), the Ask Ubuntu Corpus (AskUbuntu), and the Web Applications Corpus (WebApplication). The Chatbot corpus consists of questions written to a Telegram chatbot. The chatbot was used to answer questions regarding the public transport of Munich. The AskUbuntu and WebApplication corpora are questions and answers from StackExchange. All three corpora have predefined training and test splits. The corpora are available on GitHub under the Creative Commons CC BY-SA 3.0 license.2

A. The Chatbot Corpus

The Chatbot Corpus consists of two different intents (Departure Time and Find Connection) with a total of 206 questions. The corpus also has five different entity types (StationStart, StationDest, Criterion, Vehicle, Line) which have not been used in our benchmarks as we only focused on Intent Classification. The language of the samples present is English.

However, the train station names used are in German which is evident from German vowels usage (ü,ö,ü,ß). The data is further split in Train and Test datasets as shown in Table I.

| Intent                  | Train | Test |
|-------------------------|-------|------|
| Departure Time          | 43    | 35   |
| Find Connection         | 57    | 71   |

B. The AskUbuntu Corpus

AskUbuntu consists of five Intents (Make Update, Setup Printer, Shutdown Computer, Software Recommendation, and None). The dataset contains 190 samples that have been extracted from the AskUbuntu platform. Only questions with the highest scores and most were extracted. For mapping the correct Intent to these question, Amazon Mechanical Turk was used.

In addition to the questions and their labelled intent, the corpus also includes several other features: The author of the question, the URL for the page it was taken from, entities, the answer, and the author of the answer. However, none of these has been used for the benchmarks.

Table II shows the data distribution of AskUbuntu Corpus.

| Intent                  | Train | Test |
|-------------------------|-------|------|
| Make Update             | 10    | 37   |
| Setup Printer           | 10    | 13   |
| Shutdown Computer       | 13    | 14   |
| Software Recommendation | 17    | 40   |
| None                    | 3     | 5    |

C. The Web Applications Corpus

The WebApplication corpus has the same features and was prepared in the same way as AskUbuntu. The corpus consists of 100 samples and eight Intents (Change Password, Delete Account, Download Video, Export Data, Filter Spam, Find Alternative, Sync Accounts, and None). The data distribution is shown in Table III.

| Intent                  | Train | Test |
|-------------------------|-------|------|
| Change Password         | 2     | 6    |
| Delete Account          | 7     | 10   |
| Download Video          | 1     | 0    |
| Export Data             | 2     | 3    |
| Filter Spam             | 6     | 14   |
| Find Alternative        | 7     | 16   |
| Sync Accounts           | 3     | 6    |
| None                    | 2     | 4    |

2https://github.com/sebischair/NLU-Evaluation-Corpora
IV. METHODOLOGY

A. Semantic Hashing

Our method for semantic hashing is inspired by the Deep Semantic Similarity Model [20]. In that work, the authors propose a way to hash tokens in an input sentence so that the model will depend on a hash value rather than on tokens. This method also reduces hash collisions.

Our method extracts sub-word tokens (i.e. parts of words) from sentences as features. These features are then vectorized before being processed by a classifier for training or prediction. In that way, our method can be viewed as a featurizer and together with a vectorizer it can be used as an alternative to embeddings. A description of our method is as follows:

Given an input text $T$, e.g., "I have a flying disk", split it into a list of words $t_i$. The output of the split should look like, ["I", "have", "a", "flying", "disk"]. Pass each word into a pre-hashing function $H(t_i)$ to generate sub-tokens $t'_i$, where $j$ is the index of the sub-tokens. E.g., $H(\text{have}) = [\#ha, hav, ave, ve\#]$. $H(t_i)$ first adds a # at the beginning and at the end of each word and then extracts trigrams from it. These trigrams are the sub-tokens $t'_i$. This procedure is described in Algorithm 1.

$H(t_i)$ can then be applied to the entire corpus to generate sub-tokens. These sub-tokens are then used to create a Vector Space Model (VSM). This VSM should be used to extract features for a given input text. In other words, this VSM acts as a hashing function for an input text sequence.

Algorithm 1 Subword Semantic Hashing

\begin{verbatim}
Texts ← collection of texts
Create set sub-tokens
Create list examples
for text T in Texts do
    Create list example
    tokens ← split T into words.
    for token t in tokens do
        t ← "#" + t + "#"
        for j in length(t)−2 do
            Add t[j:j+2] to set sub-tokens
            Append t[j:j+2] to list example
        end for
    end for
    Append example to list examples
end for
return (sub-tokens, examples)
\end{verbatim}

B. Preprocessing and Data Augmentation

The dataset have been preprocessed by changing all letters to lower case, replacing pronouns by ‘-PRON-’, and removing all special characters except stop characters.

Dataset distribution between classes have been analyzed and less sampled classes have been oversampled by adding more augmented sentences to these classes. In the final training set, each class had an equal number of training samples for all three datasets.

The extra samples have been augmented with a dictionary-based synonym replacement of nouns and verbs chosen randomly. This helped in getting new variations in the training dataset. However, it did not take the spelling errors into account. Dictionary replacement have been done using WordNet [7].

A stratified K-fold cross-validation have been performed on train dataset to obtain the training and validation split. The number of splits value was kept as 5.

C. Vectorization

The preprocessed text needs to be represented in the form of fixed sized numerical feature vectors to provide as an input to the classifier. The Bag of Words approach or in our case Bag of n-gram semhash tokens approach is used to form a matrix with rows depicting the documents and columns depicting the semhash tokens occurring in the corpus of documents. The sparse term frequency based vector for the corpus consisted of frequently occurring yet uninformative semhash tokens like ‘#a#’, ‘#th’, ‘he#’ and so on. A measure of inverse-document frequency was added to balance the occurrence of rarer yet informative semhash tokens defined as:

$$\text{idf}(t) = \log \frac{1+n}{1+df(t)} + 1$$

where $n$ is the total number of documents in the corpus and $df(t)$ is the number of documents in the corpus that contain the token $t$.

The inverse document frequency $idf(t)$ is multiplied by the term-frequency $tf(t,d)$ as obtained above to get the final term frequency - inverse document frequency vector, tf-idf(t,d).

$$\text{tf-idf}(t,d) = tf(t,d) \ast idf(t)$$

Finally, the obtained vector is normalized by the Euclidean norm to get the final vector $v_{final}$:

$$v_{final} = \frac{v}{||v||}$$

where,

$$||v|| = \sqrt{v_1^2 + v_2^2 + ... + v_n^2}$$

NOTE: On the Chatbot, AskUbuntu, and WebApplication corpora the document term in the above paragraph refers to one text sentence and corpus symbolizes the entire training set. The terms document and corpus are used for the consistency of explanation.

D. Intent Classification

A classifier for intents can be trained on the vectorized VSM generated by Algorithm 1. This classifier could be any classifier, like Support Vector Machines (SVM), Multi-Layer Perceptron (MLP), Convolutional Neural Network (CNN), etc.

The experiments in this paper have been carried out with a number of classifiers, namely Ridge Classifier, K-Nearest Neighbors (KNN) Classifier, Multilayer Perceptron, Passive
Aggressive Classifier, Random Forest Classifier, Linear Support Vector Classifier (SVC), Stochastic Gradient Descent (SGD) Classifier, Nearest Centroid, Multinomial Naive Bayes (NB), Bernoulli Naive Bayes, K-means. The classifiers have been provided by scikit-learn library [16].

Default parameters as provided by scikit-learn library have been used for Ridge, Passive Aggressive, Linear SVC, Nearest Centroid, Multinomial NB, Bernoulli NB, and K-means classifiers. Grid search has been used to find the best hyperparameters for MLP, Random Forest, SGD and KNN classifiers. Grid search was performed with 5-fold cross-validation on the training set and only the model with the best average validation score was applied to the test set. A prior value based on the class distribution was used for the Naive Bayes Classifiers. The results achieved are comparable to the state-of-the-art results for all the three corpora. To further improve the results, data augmentation was used as mentioned in the previous section.

### E. Evaluation

As for performance measure, we use the micro F1-score for each dataset. For the overall performance on all datasets, we took the weighted average. For the individual datasets, this is the same as calculating the accuracy. The overall micro F1-score is calculated by finding summing the total number of true positives (tp), false positives (fp), and false negatives (fn) for all test sets. From that, we calculate the precision and the recall from which the F1-score is derived.

\[
\text{precision} = \frac{tp}{tp + fp} \quad \text{recall} = \frac{tp}{tp + fn}
\]

\[
\text{F1-score} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}
\]

To alleviate the issue of random initialization we perform 10 runs per experiment and average the performance over the runs. Note that the best performance from an individual run is even higher.

### V. Results and Analysis

The performance of our method is evaluated on the test dataset on all three corpora. Specifically, we evaluate accuracy per dataset, the mean accuracy of all three datasets, and the overall micro-F1 score on all three datasets.

The performance is compared against the results on various NLU services and open source NLU platforms in the market: Botfuel, Dialogflow, Luis, Watson, Rasa, Recast, and Snips. In addition, we compare the performance against a recently published classifier dubbed TildeCNN [1]. Results for Dialogflow, Watson, Rasa, and Luis comes from [3] which have benchmarked the initial results. [6] reproduced the results for Watson, Rasa, Dialogflow and Luis and compared it with Snips platform. Finally, the result comparison table was extended by [15] with the inclusion of Recast, a bot building platform and Botfuel, an NLP classification service.

Table IV shows the comparisons of the evaluation. Our results are presented in two rows. Our Avg. shows the performance of the best single classifier, i.e. the classifier with achieves the best average performance (average of all three datasets). Our Best shows the performance of the best classifier for each dataset (still averaged over 10 runs).

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The best classifiers for each dataset appear in table V. The accuracy of all classifiers on Chatbot, AskUbuntu, and WebApplication can be found in Tables VI, VII, and VIII respectively.

A noteworthy result of the tests is that all the tested classifiers have extremely low (less than $10^{-3}$) variance between runs.

Another important result is that several classifiers managed to perfectly predict the classes of the Chatbot test set during some of the 10 runs. The best classifier on Chatbot, Passive Aggressive Classifier, managed this feat 7 out of the 10 runs. We achieved state-of-the-art results on all three corpora and outperformed the previous state-of-the-art on AskUbuntu corpus as well as the average and overall performance on all three datasets.

The preprocessing, featurizing, and training of the data is in the order of seconds. Even more impressive is the inference time which is in the order of milliseconds. The training and test times for the different classifiers on the three datasets can be found in Tables VI, VII, and VIII. The times in these tables are the training time on the entire training set and the test time on the entire test set. Preprocessing and featurizing times for each dataset can be found in table IX.
Preprocessing refers to the process of loading, oversampling, and making synonyms replacements on the dataset. Featureizing refers to extracting the trigrams according to Algorithm 1 and vectorizing. Unfortunately, there is no data available for training and testing time for other NLU services and hence no comparison can be made.

VI. DISCUSSION AND FUTURE WORK

The micro F1-score of the three big companies (Dialogflow, Luis, and Watson) vary a lot on the three corpora, showing a lot of difference in the approach used by these companies. One interesting thing to note is that the results are comparable to the start-ups: Recast, and Botfuel, as well as, the open source platforms, like Snips and Rasa. This shows that this field of AI is rather new for everyone and there is no clear domination by the giants in the field.

From our results, we can tell that our method is accurate, versatile, stable, and fast. Our method performs well on all three corpora and achieves the best results on average, which shows good potential for the method. Additionally, the method can achieve high accuracy with a wide variety of classifiers proving its versatility. The extremely low variance of performance across all the tested classifiers suggests that the method is stable. The quick training of the model allows the user to select the classifier that best suits the problem at hand. The whole solution if integrated into a conversational service will act in real time.

In future work, semhash needs to be tested and to be benchmarked on more datasets to assess the domain independence of the method. Furthermore, semhash should be compared with other feature extraction methods to determine where semhash is the preferred choice.

| TABLE VI |

PERFORMANCE OF ALL CLASSIFIERS ON CHATBOT

| Classifier | Avg. Acc | Train time | Test time |
|------------|----------|------------|-----------|
| Ridge Classifier | 0.99 | 0.03 s | 2.5 ms |
| RNN Classifier | 0.94 | 1.36 s | 66.4 ms |
| MNP | 0.99 | 37.21 s | 5.5 ms |
| Passive Aggressive | 0.796 | 0.06 s | 3.0 ms |
| Random Forest | 0.93 | 2.03 s | 7.2 ms |
| Linear SVC | 0.99 | 0.01 s | 1.5 ms |
| SGD Classifier | 0.99 | 0.07 s | 3.5 ms |
| Nearest Centroid | 0.99 | 0.07 s | 3.5 ms |
| Multinomial NB | 0.99 | 0.01 s | 8.6 ms |
| Bernoulli NB | 0.99 | 0.24 s | 5.2 ms |
| K-means | 0.04 | 0.02 s | 7.4 ms |

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