SIMVECS: Similarity-based Vectors for Utterance Representation in Conversational AI Systems

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Abstract

Conversational AI systems are gaining a lot of attention recently in both industrial and scientific domains, providing a natural way of interaction between customers and adaptive intelligent systems. A key requirement in these systems is the ability to efficiently parse user queries, understand the intent behind each query, and provide adequate responses to users. Therefore, many applications such as conversation bots and smart IoT devices have a natural language understanding (LU) service integrated within. One of the greatest challenges of language understanding services is efficient utterance (sentence) representation in vector space, which is an essential step for most ML tasks. In this paper, we propose a novel approach for generating vector space representations of conversational utterances using pair-wise similarity metrics. The proposed approach uses only a few corpora to tune the weights of the similarity metric without relying on external general purpose ontologies. Our experiments confirm that the generated vectors can improve the performance of LU services in unsupervised, semi-supervised and supervised learning tasks over state-of-the-art prior works.

1 Introduction

Challenges of conversational AI systems: Conversational AI systems empower virtual assistants in many applications such as conversation bots (also known as Chatbots) and smart IoT devices. Their ability to understand user spoken commands and identify the user’s intent(s) is one of their main benefits. However, this is a very challenging task due to the diversity of domains and languages they are required to support. For example, Microsoft LUIS\(^1\) currently supports 12 languages, whereas IBM Watson\(^2\) supports 10 languages in their language understanding services. Moreover, conversational text queries are often very short and sparse, which hinders conventional text representations such as Bag-of-words (BOW) from capturing adequate features of the utterance.

In LU services, a language understanding application is often represented as a group of intents and entities that serve a specific business application. For example, a restaurant application may define intents such as \textit{Order Food}, \textit{Show Menu} and \textit{Cancel Order}. The task of the language understanding service then is to classify newly received queries (utterances) into one (or more) of the defined intents.

Although many prior works were focused on constructing word-level vector representation such as (Mikolov et al., 2013) and (Pennington et al., 2014), generating an utterance-level vector representation is still a challenging task. Existing language modeling (LM) based approaches such as Para2Vec (Le and Mikolov, 2014) rely on deep neural networks to generate vector representations for the paragraph-level. However, these approaches are normally trained with an abundance of utterances to achieve the required performance, which is usually not present in the conversational text domain (Boyanov et al., 2017). Moreover, pre-trained vectors (i.e., vectors generated from an external corpus) provide the same vector representation for all domains (i.e. static). The desirable characteristic on the other hand is that for the same utterance to have different vector representations, and correspondingly, different intents, in different domains. Additionally, the current approaches make the embeddings more prone to bias towards the domain of the training data (Bolukbasi et al., 2016).

\(^1\)www.luis.ai/home

\(^2\)www.ibm.com/watson/
We propose a vector representation method, SIMVECS that generates dynamic utterance-level vector representations for different LU applications. With SIMVECS, each utterance is represented as a vector of similarity scores to a set of automatically identified “representative utterances” within the same application. This way the same utterance can have different representations depending on the application. As an example: the utterance "I want a large pizza" can be of type Order Food for a restaurant application, while the same utterance can be of type None (i.e., outlier) for a bus-tracking application. Therefore, application-determined vector representations are essential for capturing the semantics of utterances in LU services and hence accurate mapping to user-defined intents.

The following list represents our key contributions:

1. A novel approach to combine multiple similarity sub-metrics into one metric, automatically adjusting the weight for each sub-metric to the overall similarity score.
2. A novel approach for the vector representation of each utterance in a conversational AI system.
3. A semi-supervised algorithm for refining the vector representations based on user’s feedback.

The rest of the paper is organized as follows. Section 2 covers related work and separates our approach from existing solutions. Section 3 gives an overview of the main components in our proposed solution. Section 4 describes how we calculate the similarity scores between utterances and generate the vector representations. Sections 5, 6, and 7 evaluate the generated vectors in unsupervised, semi-supervised, and supervised learning tasks respectively and compares the performance of SIMVECS to several baselines.

2 Related Work
2.1 Similarity metrics
Measuring the similarity between natural language sentences is crucial in many tasks such as: Question-answering systems (Achananuparp et al., 2008b) and information retrieval (Li et al., 2006; Zahran et al., 2015). Authors in (Achananuparp et al., 2008a) provide an evaluation for 14 different similarity metrics. The authors reported the best metric found was a composite between word-order and ontology-based similarity. However, the weights for how much each of the two sub-metrics contributes to the overall similarity metric is selected based on human intuition. Such selection becomes harder when several sub-metrics are considered and multiple domains have to be satisfied. We consider these weights as hyper-parameters and hence use an automated technique that applies Genetic-Algorithm (GA) (Mitchell, 1996) to find the optimal weights as it has been used in multiple hyper-parameter tuning tasks such as in (Friedrichs and Igel, 2005), (Lam et al., 2001), and (Mahgoub et al., 2017).

2.2 Vector Representation
One of the most common vector representation for both documents and sentences is the Bag-of-Words (BOW) model (Harris, 1954). In BOW, the sentence is represented as a binary vector that dominates the existence or absence of individual words (i.e. vocabulary) in that sentence. One of the major disadvantages of BOW representation is the loss of word order. Consequently, two sentences with totally different meaning can have very close representation just because they use similar vocabulary. A variation of the model is bag-of-ngrams (Mcnamee and Mayfield, 2004), which aims at preserving the word order. However, both representations are very sparse and generate vectors with very high dimensions. (Mikolov et al., 2013) proposed a technique that uses deep neural-networks to learn efficient representations for the word level. Although the trained vectors capture many semantic features, generating a sentence-level representation from individual words vectors is still a challenging task. One simple approach is to represent the sentence as weighted average of all the words in the document. However, this approach has the same weakness of not preserving the word order (Le and Mikolov, 2014). A recent approach proposed by (Le and Mikolov, 2014) generates both word-level and paragraph-level representations. However, the approach relies on training the network with a large corpus with billions of tokens, which is rarely available in the conversational text domain. Moreover, the generated vectors can still suffer from being biased by the train-
ing data domain and cannot generalize for differ-
ent domains. (Dai and Le, 2015) proposed an ap-
proach to improve the vector representations with
pre-trained recurrent neural networks. The pro-
posed approach showed significant improvement
over both BOW and Paragraph vectors. SIMVECS
uses only a few corpora to tune the weights of the
similarity metric without relying on external gen-
eral purpose ontologies.

3 Overview of SIMVECS

SIMVECS relies on pair-wise similarity metrics.
Each metric serves as a function that assigns sim-
ilarity (or distance) scores to a pair of utterances.
Many similarity metrics have been proposed in the
literature. Although we use only six, our solution
is generic and can incorporate any additional sim-
ilarity sub-metrics.

3.1 Similarity sub-metrics definition

The six similarity sub-metrics which SIMVECS
uses are:

(1) Unigrams: measures similarity based on the
inverse-document-frequency (IDF) scores of com-
mon unigrams. The resulting score is then normal-
ized by dividing over the sum of IDF scores of all
unique words in the two utterances:

\[
Sim_{uni}(U_i, U_j) = \sum_{w \in U_i \cap U_j} \frac{IDF[w]}{\sum_{w' \in U_i \cup U_j} IDF[w']}
\]

(2) Character N-grams: measures similarity based on the
overlapping character n-gram tokenization. We use an equation similar to the
unigram except that words (and their correspond-
ing IDF scores) are replaced by overlapping
character N-grams. We use tokens of size n=4
as recommended by literature (Menname and
Mayfield, 2004).

(3) Bigrams: similar to unigram except that it uses
tokens of two adjacent words. For each bigram,
we set the IDF score to be the max between the
two words in the token (presented as \(IDF_{bi}\)).

(4) Trigrams: similar to bigrams except that it
uses tokens of three adjacent words.

(5) Utterance Length: this captures the similarity
between a pair of utterances based on their num-er of tokens. Although this might be a dangerous
feature to rely on individually, it becomes very
useful in the domain of conversational text when
combined with other features. For example, Table.
1 shows the average utterance lengths per intent in
the WebApp corpus. We observe a large variance
in utterance lengths of different intents. This is
because one might need more tokens to specify
a complex intent such as booking a flight (which
requires lots of details) than simpler intents like
asking for help or canceling a request. We use the
following formula for utterance length similarity:

\[
Sim_{len}(U_i, U_j) = \frac{\min(\text{Length}(U_i), \text{Length}(U_j))}{\max(\text{Length}(U_i), \text{Length}(U_j))}
\]

(6) Word order: measures the normalized differ-
ence of word order between the two utterances.

\[
Sim_{wo}(U_i, U_j) = 1 - \frac{|r_i - r_j|}{|r_i + r_j|}
\]

where \(r_i\) and \(r_j\) are word order vectors (a vec-
or which represents the order of each word in
the utterance) of utterances \(U_i\) and \(U_j\) respectively.

3.2 IDF scores calculation

The first 4 metrics (i.e. unigram, bigram, trigrams,
and character N-grams) rely on pre-calculated IDF
scores. All these IDF scores are pre-calculated
from a large corpus of conversational text gener-
ated from Cortana virtual assistant\(^3\). This corpus
contains 18M utterances that resembles conversa-
tions between a user and Cortana in different do-
 mains. With the calculated IDF scores, these sub-
metrics can be calculated and used to calculate a
composite similarity metric as follows:

\[
Sim_{comp}(U_i, U_j, \bar{W}) = \bar{W} \cdot \bar{Sim}\] = \begin{bmatrix}
Sim_{uni}(U_i, U_j) \\
Sim_{char}(U_i, U_j) \\
Sim_{bi}(U_i, U_j) \\
Sim_{tri}(U_i, U_j) \\
Sim_{len}(U_i, U_j) \\
Sim_{wo}(U_i, U_j)
\end{bmatrix}
\]

where \(W_i\)‘s are normalized weights which represen-
t the collaboration of each sub-similarity met-
ic to the overall metric. \(W_i\)‘s serve as hyper-
parameters that control the quality of the com-
posite similarity metric. The different sub-metrics
have different relative importances in detecting
similarities between utterances within the appli-
cation. Therefore, the weights should be tuned auto-
matically according to the LU application.

\(^3\)https://www.microsoft.com/en-us/cortana
3.3 Application-based weights tuning

In this section, we describe our method in tuning the weight \( W_i \) for every sub-metric in Eq. 4. First, we use 15 real-world applications from a popular language understanding service to serve as our training and testing data set. These applications represent different domains (e.g. restaurants, flight booking services, smart homes, etc.) and they are created by system admins. Therefore, they contain a user-defined label for every utterance, which serves as our ground truth. For every pair of utterances with the same label, we assign a similarity score of 1 (max similarity). Similarly, for every pair of utterances with different labels, we assign a similarity score of 0 (min similarity). Now the task of tuning the weights for the sub-metrics can be viewed as an optimization problem, which is given by the following formula:

\[
\bar{W}^* = \arg\min_W \sum_{i,j} \text{RMSE}(\text{Sim}_{gt}(U_i,U_j), \text{Sim}_{comp}(U_i,U_j, \bar{W}))
\]

(5)

Where \( \text{Sim}_{gt} \) is the ground truth similarity (either 0 or 1), \( \text{RMSE} \) is the root mean square error between the estimated similarity score and the ground truth. Therefore, the target of equation 5 is to find the vector of weights that minimizes the differences between the estimated similarity scores and the ground truth similarly provided by application users. We use genetic algorithms (GA) to find the best values of \( \bar{W}^* \). GA is a metaheuristic optimization algorithm that is inspired by biological evolution. It has the nice feature of balancing between exploration (a.k.a mutation) and exploitation (a.k.a crossover) of different solution candidates (a.k.a chromosome) in the search space (Črepinšek et al., 2013). GA is favorable in solving optimization problems which convexity is not known, since it does not rely on derivative information in finding good search directions (i.e. derivative-free). We used all pair-wise utterances from the 15 applications to train and validate our approach. Each candidate solution in GA simply represents a vector of weights in Eq. 4, and the fitness function is the resulting sum of \( \text{RMSE} \)s across all pairs of utterances (the lower the better). We perform 5-fold cross validation on the 15 applications and take the average of the best vectors of each fold. The resulting vector is then used for all subsequent experiments.

| Intents         | Avg. Tokens | Std. Tokens |
|-----------------|-------------|-------------|
| Change Password | 8.625       | 1.4         |
| Delete account  | 7.35        | 1.11        |
| Download video  | 7.0         | 0           |
| Export data     | 10.2        | 2.28        |

Table 1: Average number of tokens per utterance for the WebApp Corpora.

4 Similarity-based utterance representation

We estimate all pair-wise similarity scores using Eq. 4 and store them in a matrix of size NxN where \( N \) is the number of utterances. We then apply Principal Component Analysis (PCA) (Wold et al., 1987) to reduce the dimensionality of this matrix. This pair-wise similarity matrix, \( \text{SimMatrix} \) for short, is then used to generate the vector representation for each utterance. Consider the example shown in Fig. 1. On the left hand, we show 10 utterances (selected from (Coucke et al., 2018)) and their corresponding intents. On the right hand, we show the corresponding \( \text{SimMatrix} \) (before we apply PCA). The resulting matrix is a symmetric matrix with all its diagonal values = 1, representing maximum similarity. Then we use PCA to reduce the number of columns, loosely speaking, creating a set of representative utterances in a data-driven manner. At this point, we use each row as the vector representation of the corresponding utterance. Thus, each representative utterance serves as a dimension in the vector space, allowing utterances with similar neighbors to have similar vector representations.

This approach has a number of advantages over conventional vector representations (such as BOW) and LM based techniques (such as Para2Vec) in the domain of conversational text understanding. The data collected by (Braun et al., 2017) shows that conversational text tends to be very short with an average of 7.8 tokens per utterance. Moreover, 80% of the collected utterances are shorter than 9 tokens. This makes BOW representation very sparse. Also for LM-based techniques, it is hard to learn efficient vector representations because of the shortness of the context sequences used for training. Another advantage of \( \text{SimVECS} \) is the easier detection of utterances that have no intent (i.e. the “None” intent utterances). As shown Fig. 1, the “None” intent utterances are expected to have similarity scores close to zero to
all other utterances, including other “None” utterrances. This makes them located closer to the origin in SIMVECS’s vector space and allows distance-based clustering techniques (such as K-means) to group “None” intent utterances in the same cluster. The second advantage is representative vector lengths: instead of using vectors of arbitrary lengths or length equal to the vocabulary size, we use vectors of length equal to the number of representative utterances in the given application. This can reduce the size of the generated vector representation significantly, especially when large vocabularies are used, while the LU application itself may have only a few tens or hundreds of utterances.

5 Unsupervised learning with conversational text

The problem of applying unsupervised learning techniques to text documents has been studied by many researchers in several domains such as (Beil et al., 2002), (Aggarwal and Zhai, 2012), and (Huang, 2008). The problem becomes more challenging with conversational text because of the shortness and the sparsity of the documents (Chen et al., 2011). We can categorize these techniques based on the input they need to perform clustering into two categories: 1) Techniques that require a vector representation for the data points, such as K-means and SVD. 2) Techniques that require a similarity (distance) function such as Affinity Propagation (Frey and Dueck, 2007) and DBSCAN (Ester et al., 1996). However, the second category still requires an efficient vector representation to estimate the distances between pairs of utterances. We evaluate the efficacy of SIMVECS generated vectors in the unsupervised learning task against several baselines. We vary the vector representation while the clustering algorithm itself remains the same. We show a comparison against the following techniques:

**Spherical K-means (Buchta et al., 2012):** This baseline uses BOW representation for the utterances and cosine-similarity as a distance function.

**LDA (Blei et al., 2003):** This baseline represents documents as probability distributions over latent topics. Documents with similar topic assignments are grouped together. Similar to K-means, it takes the number of latent topics (clusters) as an input. We set the number of topics to the number of intents in the corpus and then assign each utterance to the cluster with the maximum probability.

**LDA + K-means:** Here we use LDA’s latent topic distribution as a vector representation to the utterance. Then we apply K-means for clustering the utterances.

**Seq-Auto-encoder + K-means (Dai and Le, 2015):** A Neural-network based technique using recurrent language models. The network is trained on a large corpus of conversational text generated from the same Cortana corpus used for generating the IDF scores. Afterwards, the network is used to encode each utterance of the test data in a vector of length 1024. K-means is then used to cluster the utterances.

**Fast-text + K-means (Joulin et al., 2016):** Also a Neural-network based technique that incorporates several features such as BOW and N-gram features. The model generates word-level vectors which are averaged together to form sentence-level representations. We used English pre-trained word vectors⁴. These vectors are pre-trained with 16 billion tokens collected from Wikipedia 2017, UMBC webbase corpus and statmt.org news.

**SIMVECS+ K-means:** K-means applied to our similarity-based vectors.

To make the comparison fair, K-means algorithm with the same number of clusters (K*) is used for all techniques (Except LDA). Here K* is the number of intents in the corpora. For LDA, we set number of latent topics to be also K*.

5.1 Dataset description

We use the conversational text dataset presented in (Braun et al., 2017)⁵. The dataset represents a collection of three corpora, two corpora were extracted from StackExchange (Ask Ubuntu & WebApp), while the third one was extracted from a Telegram chatbot. **Combined** is a corpus that combines the intents of all three. Table 2 shows the number of intents, number of utterances, and number of tokens for each corpus in the dataset.

| Corpora   | # Intents | # Utterances | # Tokens |
|-----------|-----------|--------------|----------|
| AskUbuntu | 5         | 162          | 1289     |
| Chatbot   | 2         | 200          | 1539     |
| WebApp    | 8         | 89           | 717      |
| Combined  | 15        | 451          | 3545     |

Table 2: Conversational text corpora details.

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⁴https://fasttext.cc/docs/en/english-vectors.html
⁵The dataset is publicly available and can be obtained here: https://github.com/sebischair/NLU-Evaluation-Corpora
In this section, we show the efficacy of SămVēCS's vector representations and compare to other baseline techniques. We collected both positive and negative scores for each utterance. We omit NMI scores for space reasons as it shows the same trend as purity. As shown in Table 3, SămVēCS shows 6% better performance (in terms of Purity) in comparison to other baseline except in one corpus. Chatbot. The reason is that Fast-text through supervised learning tasks. One of the main tasks is to improve their performance during operation and also to improve clustering efficiency without losing important types of utterances. Fig. 2 shows an example of two groups of utterances that can be clustered at different levels of granularity based on their similarity. This behavior is highlighted in the poor performance of Fast-text in all other corpora compared to SămVēCS.

### 6 Semi-Supervised learning with conversational text

In this section, we evaluate the efficacy of SămVēCS's vector representations in semi-supervised learning tasks. One of the main tasks is to improve their performance during operation and also to improve clustering efficiency without losing important types of utterances. Fig. 2 shows an example of two groups of utterances that can be clustered at different levels of granularity based on their similarity. This behavior is highlighted in the poor performance of Fast-text in all other corpora compared to SămVēCS.

#### 5.2 Unsupervised learning results

In this section, we show the efficacy of SămVēCS's vector representations and compare to other baseline techniques. We collected both positive and negative scores for each utterance. We omit NMI scores for space reasons as it shows the same trend as purity. As shown in Table 3, SămVēCS shows 6% better performance (in terms of Purity) in comparison to other baseline except in one corpus. Chatbot. The reason is that Fast-text through supervised learning tasks. One of the main tasks is to improve their performance during operation and also to improve clustering efficiency without losing important types of utterances. Fig. 2 shows an example of two groups of utterances that can be clustered at different levels of granularity based on their similarity. This behavior is highlighted in the poor performance of Fast-text in all other corpora compared to SămVēCS.

#### Figure 1: An example showing extracting the vector representation for each utterance. The table on the left shows 10 utterances (examples) for 5 different intents, whereas the table on the right shows the corresponding SămVēCS's vector representations for the 10 utterances. Each row (or column) is then used as the vector representation for the corresponding utterance.

| Intent | Utterance | ID |
|--------|-----------|----|
| None   | Please look up the painting, Beyond Iconic: Photographer Dennis Stock. | U1 |
| None   | Please look up the painting, Beyond Iconic: The Case Against Christianity, album. | U2 |
| None   | Please look up the painting, Beyond Iconic: Photographer Dennis Stock, The Case Against Christianity, album. | U3 |
| None   | Please look up the painting, Beyond Iconic: Photographer Dennis Stock, The Case Against Christianity, album. | U4 |
| None   | Please look up the painting, Beyond Iconic: Photographer Dennis Stock, The Case Against Christianity, album. | U5 |
| None   | Please look up the painting, Beyond Iconic: Photographer Dennis Stock, The Case Against Christianity, album. | U6 |
| None   | Please look up the painting, Beyond Iconic: Photographer Dennis Stock, The Case Against Christianity, album. | U7 |
| None   | Please look up the painting, Beyond Iconic: Photographer Dennis Stock, The Case Against Christianity, album. | U8 |
| None   | Please look up the painting, Beyond Iconic: Photographer Dennis Stock, The Case Against Christianity, album. | U9 |
| None   | Please look up the painting, Beyond Iconic: Photographer Dennis Stock, The Case Against Christianity, album. | U10 |

#### Table 1: Similarity matrix of utterances

| Utterance | U1 | U2 | U3 | U4 | U5 | U6 | U7 | U8 | U9 | U10 |
|-----------|----|----|----|----|----|----|----|----|----|-----|
| U1 | 1.00 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 |
| U2 | 0.03 | 1.00 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 |
| U3 | 0.03 | 0.03 | 1.00 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 |
| U4 | 0.03 | 0.03 | 0.03 | 1.00 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 |
| U5 | 0.03 | 0.03 | 0.03 | 0.03 | 1.00 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 |
| U6 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 1.00 | 0.03 | 0.03 | 0.03 | 0.03 |
| U7 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 1.00 | 0.03 | 0.03 | 0.03 |
| U8 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 1.00 | 0.03 | 0.03 |
| U9 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 1.00 | 0.03 |
| U10 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 1.00 |
criteria. Moreover, it is not known which criteria is to be used by the clustering algorithm without user feedback. Therefore, semi-supervised learning is typically used in directing SimVECS to the correct context-sensitive clustering. In this section, we evaluate the ability of SimVECS in a semi-supervised learning mode, compared to several baselines.

In semi-supervised clustering, few data points are labeled and used as constraints to the clustering technique. These constraints are of the form “Must-Link” and “Cannot-Link” for pairs of data points. A “Must-Link” constraint arises when the user indicates that two utterances belong to the same intent, while a “Cannot-Link” constraint is when the user indicates two utterances as belonging to different intents. We propose a simple algorithm to refine SimVECS vectors based on the provided constraints: Whenever a “Must-Link” constraint is provided for a pair of points, we collapse their 2 vectors into one vector in the space. This is achieved by taking the max value of each entry of the corresponding indexes. Thus, the resulting vector is closer to neighbors of both points, shrinking the distances between neighbors of both utterances. Moreover, because each feature (dimension) in the space is a representative utterance, after the collapsing of two utterances, we perform PCA to come up with the new dimensions after the user is done with the labeling.

On the other hand, whenever a “Cannot-Link” constraint is provided, the similarity score between the two utterances is set to zero in the corresponding entry in SimMatrix. This increases the distance between the two points and transitively, between the neighbors of these two points.

To evaluate the efficiency of the resulting vectors, we vary the amount of user-labeled data points and estimate the corresponding clustering purity scores. As shown in Fig. 3, semi-supervised learning can significantly improve the performance of the clustering algorithm. We compare the performance of SimVECS to BOW, Seq-Auto-encoder, and Fast-text. We use constrained K-means (COP-Kmeans) (Wagstaff et al., 2001) as the semi-supervised learner for SimVECS as well as all baseline techniques. We see that SimVECS achieves its maximum gain against other techniques when the proportion of labeled data is small. This is very useful in our problem as it reduces the labeling effort required from the user side to assist the clustering algorithm. The results show improvements over all three baselines, while the difference between the approaches shrinks with more labeled data points as expected. Also we notice that with few labeled data points (from 10% to 30%), Seq-Auto-encoder and Fast-text representations are performing better than BOW. However, with more labeled data points (≥ 50%), BOW starts to perform better. The reason is that with more labeled data points, the training examples (constraints) start to cover most of the expressions that can be used for a particular intent.

### 7 Supervised learning with conversational text

Supervised learning is critical to language understanding services in order to identify both intents and entities in new utterances coming in the stream. We compare the performance of intent classifiers when SimVECS is used against BOW, Seq-auto-encoders, and Fast-text vector representations. For all corpora, a linear SVM classifier is trained per intent in one-vs-all fashion. For each intent, the utterances that belong to that intent represent the positive class, whereas all other utterances represent the negative class. We apply 5-fold cross validation and calculate the average F1-Score across all runs. Fig. 4 shows the improvement in F1-Score with both variants over baseline.

| Corpora                | Combined | AskUbuntu | Chatbot | WebApplications | Average |
|------------------------|----------|-----------|---------|-----------------|---------|
| Spherical Kmeans       | 61%      | 63%       | 61%     | 64%             | 62%     |
| LDA                    | 46%      | 59%       | 61%     | 35%             | 50%     |
| LDA+Kmeans             | 55%      | 67%       | 62%     | 54%             | 59%     |
| Seq-Auto-encoder+Kmeans| 65%      | 64%       | 62%     | 57%             | 62%     |
| Fast-Text+Kmeans       | 53%      | 56%       | 94%     | 49%             | 63%     |
| SimVECS+Kmeans         | 71%      | 83%       | 61%     | 76%             | 73%     |

Table 3: Purity scores for SimVECS vs several baselines
Figure 2: Example of clustering with different levels of granularity. Without user feedback, it is not clear whether the clustering algorithm should put all the utterances in the same cluster (Get Weather) or split them into two separate clusters (Is Worm & Weather Update).

Table 1: Example of clustering with different levels of granularity.

| Is Warm                          | Weather Update               |
|---------------------------------|------------------------------|
| Will it get warmer, in Holy Cross Wilderness | What's the weather in Waretown, Lebanon |
| Will it be warmer, in five years, in Slogm, Kansas       | What's the weather like in Saint Regis Falls, ND |
| Will it be warm, in Powersville, Guam, 23 hours from now | Tell me the weather forecast for Carmichaels, Gambia, at one am |

Figure 3: Improvement on clusters Purity using SIMVECS with COP-Kmeans vs several baselines.

Techniques. An improvement of 29% is observed over Fast-text representation, whereas an improvement of 13% over Seq-Auto-encoder representation is observed. SIMVECS is only slightly better than BOW (3% improvement on average). Additionally, we introduce a variant of SIMVECS that doesn’t use the automatically tuned weights shown in Eq. 4. Instead, we concatenate all 6 similarity sub-metrics with all other utterances into one vector and use the resulting vector as the utterance representation (called Expanded-SIMVECS). Notice that this approach generates vector representations of size 6X compared to SIMVECS. We notice that using SIMVECS with our pre-trained weights is achieving better results than Expanded-SIMVECS across all corpora. The reason is that as Expanded-SIMVECS increases the number of dimensions, it also increases the sparsity of the space and hence requires more training data, which is known as "the curse of dimensionality" (Poggio et al., 2017). We also notice that the performance gain is proportional to the number of intents in the corpus. The peak gains of 8%, 25%, and 48% over BOW, Seq-Auto-encoder, and Fast-text respectively are observed with "Combined" corpora (which combines the 15 intents in all three corpora).

8 Background

In this section, we give the formulas used to estimate our evaluation metrics: Purity (Manning et al.) and F1-Score (Sasaki et al., 2007).

8.1 Purity:

is evaluated by the given formula:

\[
Purity = \frac{1}{N} \sum_{i=1}^{k} \frac{\text{Max}_{j}|C_{i} \cap t_{j}|}{N}
\]

(6)

Where N is the number of data points, k is the number of clusters, \( C_{i} \) is a generated cluster, and \( t_{j} \) is the intent which represents the majority in \( C_{i} \).

8.2 F1-Score:

is evaluated by the given formula:

\[
F_{1} = 2 \cdot \frac{P \times R}{P + R}
\]

(7)

Where P is the precision, and R is the recall.
9 Discussion

One of the practical challenges in implementing SIMVECS can be the size of the SimMatrix, particularly when the number of utterances grows very large. Currently, this is not a critical issue for current LU services as they tend to limit the number of utterances per application to a few thousands. But the maximum number of supported utterances is expected to grow in the future. For example, IBM Watson currently limits the number of utterances to 25,000 per workspace (application) whereas Microsoft LUIS limits the number of utterances to 15,000 per application. One approach to improve the scalability of SIMVECS is by constraining further the number of dimensions of the vector space thus reducing the memory requirements for storing SimMatrix. For reducing the computational time, multi-threading can be used to calculate similarity scores between different pairs of utterances concurrently and hence speedup the matrix construction process.

10 Conclusion

This paper introduces SIMVECS, a similarity-based vector representation technique designed to overcome prior work limitations in the field of conversational AI. We discussed the main challenges in vector representation for conversational AI applications and how SIMVECS overcomes these challenges. Through evaluation on different corpora and for different learning tasks, we showed the efficacy of vector representations generated by SIMVECS over several baselines.

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