Intent Mining from past conversations for Conversational Agent

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Abstract. Conversational systems are of primary interest in the AI community. Chatbots are increasingly being deployed to provide round-the-clock support and to increase customer engagement. Many of the commercial bot building frameworks follow a standard approach that requires one to build and train an intent model to recognize a user input. Intent models are trained in a supervised setting with a collection of textual utterance and intent label pairs. Gathering a substantial and wide coverage of training data for different intent is a bottleneck in the bot building process. Moreover, the cost of labeling a hundred to thousands of conversations with intent is a time consuming and laborious job. In this paper, we present an intent discovery framework that involves 4 primary steps: Extraction of textual utterances from a conversation using a pre-trained domain agnostic Dialog Act Classifier (Data Extraction), automatic clustering of similar user utterances (Clustering), manual annotation of clusters with an intent label (Labeling) and propagation of intent labels to the utterances from the previous step, which are not mapped to any cluster (Label Propagation); to generate intent training data from raw conversations. We have introduced a novel density-based clustering algorithm ITER-DBSCAN for unbalanced data clustering. Subject Matter Expert (Annotators with domain expertise) manually looks into the clustered user utterances and provides an intent label for discovery. We conducted user studies to evaluate the effectiveness of the trained intent model generated in terms of coverage of intents, accuracy and time saving concerning manual annotation. Although the system is developed for building an intent model for the conversational system, this framework can also be used for a short text clustering or as a labeling framework.

1 Introduction

In the past few years, there has been a growing community and business interest in conversational systems (chatbots primarily) and new approaches have been explored to model conversation. A key step towards designing a task-oriented conversational model is to identify and understand the intention from a user utterance. An intent in a conversational model maps semantically similar sentences to a high-level abstraction for a chatbot that can generate a similar response or a similar action. For example, “unable to log-in to the system”, “can not login”, “facing issue during sign-in” can be interpreted as intent login issue. The current crop of bot-building frameworks requires annotated data for building an Intent model. A collection of user utterances and expert provided intent labels is a type of supervised training mechanism, which is supported by many commercial chatbot building frameworks such as Microsoft Azure Bot Service [2], IBM Watson Assistant [1], Nuance Bot Framework [3] and it is well known that collecting high-quality training data with high coverage for each intent is difficult. The developers and domain experts typically consider past chat logs between human-human or human-computer as a valuable resource and carry out an extensive manual process of intent labeling. The process of intent discovery and training data creation by large manual and effort-intensive.

Collecting high quality data from past conversations has few challenges. First, intent classes are highly skewed; certain areas are discussed more often than others. For example, in an IT helpdesk scenario “login issue” is a common problem for many applications whereas “Application Crashing” may happen comparatively rarely. Collecting positive samples for rare classes of intent in a highly-skewed distribution is difficult. Second, for many industrial scenarios, the number of unknown intent categories may vary from hundred to thousands - making the task of actual conversation annotation very difficult. For expediency, domain experts often provide synthetic utterance samples for intent training in the bot frameworks and classifiers can not take full advantage of the previous chat logs.

In this work, we describe an Intent Mining framework that reduces the labeling effort significantly by using two sources of information - the metadata/short description about conversations and the conversations themselves (Refer to Table 1 for a sample conversation in the helpdesk scenario). In cases where raw conversations are presented without any metadata, we have experimented with different approaches to extract suitable description for representing the summary/short description of a conversation. We have discussed about feature engineering approaches, such as learning domain word embedding from the conversation data, converting textual description to feature vector using learned word embedding and also extracting domain independent user’s intent from conversations using a Dialog Act Classifier [10]. We have also experimented with pre-trained language model (Universal Sentence Encoder [5]) for sentence representation. We have used the textual descriptions to cluster conversations into unique groups, using a density-based clustering approach (discussed in section 3.2). Clusters are labeled to generate seed data for each intent. Features extracted from the labeled conversations along with intent labels are used to generate training data and train a statistical classifier. Unlabeled conversations are then labeled by the base classifier basis a cut-off confidence score of the model. The final training set can be used to train any supervised classification algorithm. We show that an intent model trained in this manner works with good efficacy and provides a good coverage of intents. We have also experimented and reported

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the accuracy of our algorithm on open source intent classification dataset and as well as on short text classification dataset.

The primary contributions of the work can be summarized as below:

- The true class distribution of intents of the real world conversation data is unknown and may contain skewness. Our work presents an effort to automatically discover clusters without any prior knowledge about the intents.
- We have significantly reduced the labeling effort by forming coherent and pure clusters. Short nature of the descriptions makes it easier to visualize the grouped data and label the cluster.
- Our work also presents an approach to generate intent training data from raw conversations with novel clustering and feature extraction method. Intent training data generated from this approach is used for training an intent model. Trained intent model is then deployed with a live conversational system to measure the coverage and accuracy of the intents. We have also reported the coverage and accuracy on publicly available intent dataset and short text dataset.

Table 1. A sample conversation between a Customer (USER) and a Support Analyst (AGENT) along with Issue description added by Agent after the conversations in IT Support. The analyst is trying to solve a problem related to Microsoft Skype for Business Application.

| USER  | Hi, is there any way to enable skype recording. |
| USER  | Hello USER                                      |
| USER  | Hi                                             |
| AGENT | As I understand, you need recording service to be enabled for Skype for Business. |
| USER  | Yes correct.                                   |
| USER  | Did you check in “more” options?               |
| USER  | it is not there.                                |
| AGENT | It looks like you do not have recording option enabled for you. |
| AGENT | would you like to raise a request?             |
| AGENT | You can also raise a request on this WEB LINK  |
| USER  | Thanks. Can you raise it for me.               |
| USER  | Thanks. Sure. Is there anything i can assist you with? |

| Issue Description | User reported unable to record calls |

2 Related Work

Intent discovery and analysis is a fundamental step to build intelligent conversational agents. Intents are a sequence of words which are mapped to predefined categories to comprehend user request. Recent work points to two directions to build quality intent models. About re-using available chat log to bootstrap intent model building process [16][9][22][13]. The other is to allow domain experts to build an intent model by working on the model definition, labeling, and evaluation through user interfaces [24]. Our work is at the intersection of these two approaches, in the sense that we mine candidate clusters in an unsupervised way and then allow domain experts to review and label the clusters (Intent Discovery). The labels are then used to further refine and propagate to the entire dataset to create high-quality training data for each intent (Intent training data generation).

Gathering good quality labeled data for any machine learning process is expensive. There have been significant efforts to reduce labeling effort; including work on clustering, semi-supervised learning [8], active learning [21], transfer learning [9] and also recently proposed data programming frameworks [20][16]. Semi-supervised, Transfer learning and active learning requires seed training data for processing. Clustering is primarily used to collect the initial seed data. Most of the clustering algorithms fail to discover classes a highly skewed distribution. Our work overcomes these challenges to obtain labels on noisy data by applying a novel clustering algorithm for seed data collection and subsequently propagating labels to generate high quality training data.

Various works have been reported recently on using existing chat logs to build intent models. A transfer learning-based system has been proposed [23] to learn from low resource settings. Data programming based [15] systems provide an interface to write labeling function for labeled data generation. However, one underlying assumption of using these methods is that they all require the intents to be known beforehand. This pre-condition is very difficult to meet in real-world cases.

Clustering is also an active research area for pattern mining. A popular algorithm such as centroid based clustering algorithms (K-Means [14]), density-based algorithm (DBSCAN [7]), HDBSCAN [17]), are very useful in practical applications. Although K-Means is very fast and mostly used for clustering, it requires one to define the number of clusters as a parameter to the algorithm. Among the existing clustering approach, a density-based algorithm particularly DBSCAN (density-based spatial clustering with noise) and its variations, is more efficient for detecting clusters with arbitrary shapes from the noisy dataset where there is no prior knowledge about the number of clusters [8][13]. Many improved versions of this algorithm are also available (such as NG-DBSCAN [15]) to overcome the scalability issues of density-based clustering, but they fail to address the ineffectiveness of density-based approaches in sparse data setting.

Although density-based clustering has limitations, it is a powerful tool for automatic data exploration and pattern mining. A key contribution of our work is to provide a better exploration strategy in unbalanced data settings. We search the feature space for different density clusters by adjusting the density definition of DBSCAN algorithm over iteration. This allows us to generate cluster with different densities and hence to find intents with low frequencies from the past chat log. Clusters are explicitly labeled by the expert to collect training data for the intent model. We apply this methodology in the publicly available intent classification dataset with highly skewed class distribution to understand the effectiveness of our clustering algorithm for intent discovery.

3 Methodology

In this section, we will describe the methods used for the Intent Mining framework.

3.1 Feature Engineering

The following methods are used for extracting features from the Natural language description and conversation data.

1. Word Embedding: Word Embedding such Word2Vec [18], Glove [19], are popular methods to maps words in a continu
ous vector space where similar words are mapped together. In our case, domain word embedding is learned from the natural language description and conversation data using the Word2Vec model. Sentences are extracted from the description and conversation data, which are pre-processed and tokenized for the Word2Vec model. The model essentially captures semantic and syntactic relationship in a continuous d-dimensional feature space, where d is dimension of the embedding. For example, words such as “sign-in”, “log-in”, “logging” are closer to each other in the embedding space.

2. **Average Embedding (AE)**: Average Embedding is a popular method to convert textual data into a numerical feature vector using word embedding. Tokens are extracted from the textual data using tokenization, which are converted to 2-d numerical feature vector where each row represents a token/word and each column represents a dimension of the word embedding. 2-d feature vector is converted into a 1-d feature representation by adding all the word vectors row wise, which are then normalized by the number of the token or the number of rows in the 2-d feature vector. The final 1-d vector represents the feature vector for a sentence/document that can be used for Machine Learning algorithms.

3. **Pre-Trained Sentence Embedding (USE)**: We have also used pre-trained sentence embedding (Universal Sentence Encoder [5]) without any fine-tuning for the downstream tasks to compare against average embedding method. Here, we passed each short description to the model[4] and extracted 1-d vector.

4. **Dialog Act Classifier**: Dialog Act Classifier [23] is crucial to Natural Language Understanding, as it provides a general representation of speaker’s intent, that is not bound to any particular dialog system. The correct interpretation of the intent behind a speaker’s utterance plays an important role in determining the success of the conversation. For example, consider this two utterances - “Book a flight for me” and “Can you book a flight”. The generic intent of the first utterance is a “Command” type and where the former is a “Question” type, and the domain dependent intent is same for both case, “book a flight”. Understanding different cues of the natural language helps to generate better response. For example, for the first utterance, the dialog system can generate more human-like response, “Sure. Please wait for few minutes as I start the booking process”, whereas for the second case it can be more straightforward as “Alright. Let me start the booking process.”

In the context of our work, we use ATIS Corpus [10]: the dataset contains textual conversations related to Air Travel Information System. Utterances in the conversations are tagged with dialog act types - “Information”, “Query”, “Command”, “Greetings”, “Confirmation-Affirmation”. Natural language based features such as part-of-speech of the tokens, bi-grams of part-of-speech are extracted from the utterances and a sequence based classifier (CRF [12]) is used to train a classifier. The following parameters are used for training the CRF model - a. training algorithm: lbfgs [20] (Gradient descent using the L-BFGS method), L2 regularization: 0.001 and the model is trained using python-crfsuite[7] trained model is used to tag utterances in dialog system. The trained model is tested with other domain conversations. Subsequently, top-3 user utterances of “Information” type as tagged by the DAC classifier are extracted for each conversation for label propagation step. This textual utterances are converted into feature representation by applying Term frequency-Inverse Document Frequency (TF-IDF) and Principal Component Analysis [11] (PCA) is applied to reduce the feature space of the TF-IDF representation.

3.2 Cluster & Label

DBSCAN is a density based clustering non-parametric algorithm, given a set of points, it groups points together that are closely packed (points with many nearby neighbors, high-density area) and marking as outliers points that lie alone in low-density regions (whose nearest neighbors are too far away). The primary advantages of density-based clustering one that a) it can automatically find clusters based on the definition of density, b) it can find clusters of arbitrary shape rather than being limited to “ball-shaped” ones. We propose a variation of this algorithm in our work and the primary motivation is driven by the following two research questions -

**Research Question 1**: How to automatically cluster short textual data without any background knowledge about the data distribution?

**Research Question 2**: How to automatically search for clusters with different densities without any assumption of number of classes?

DBSCAN is a popular density based clustering algorithm that searches for clusters broadly with two parameters - a. Maximum distance and b. Number of points. The algorithm groups near-by points based on the maximum allowed distance and the density constraint of the (number of points) algorithm determines where the group will be considered as noisy points or as a valid cluster. The search process is guided to find high density regions to form clusters, based on the parameter definition. But the algorithm has limitation in finding clusters with sparse densities.

Let, X be a set of points \{x_1, x_2, ..., x_i\} to be clustered and the distance between any two points is defined by \(D(\cdot, \cdot)\).

Let \(S(X)\) be a subset of \(X\). And, \(\|d - D(\text{p}, \text{o})\| = D(0, p)\) such that, \(i\) is the distance between point p and origin.

Let, \(\lambda(\cdot)\) be the cardinality of a set. Let, \(x_i, x_j\) be any two points from the set \(S(X)\), such that,

\[
\forall i, j \exists D(x_i, x_j) \leq d \quad (1)
\]

\[
\lambda(S(X)) \geq K \quad (2)
\]

Where, \(d\) is the maximum distance and \(K\) is the minimum number of points, according to the definition of DBSCAN.

We formulate that, there also exists a subset \(P(X)\) and let \(x_i, x_j\) be any two points in it. Then,
\[ \exists_{P(X)} \forall i, j D(x_i, x_j) \leq d + \delta d \quad (3) \]
\[ \gamma(P(X)) \geq K' \quad (4) \]

where \( K > K' \). We hypothesize in equation 3 and 4 i.e. less frequent classes in the dataset can be found by increasing the distance value constraint and reducing the minimum number points constraint for cluster discovery for unbalanced data distribution.

We have modified the DBSCAN algorithm, naming it ITER-DBSCAN, to work with datasets having imbalanced class distribution (Refer to Algorithm 1). The algorithm runs iteratively to search for clusters with high-density regions to low-density regions. The low-density region search is controlled by two parameters "max-distance" and "min-points". "max-distance" parameters controls what is maximum distance to consider two items belongs to same group and "min-points" controls what is minimum number of items in a group to qualify it as a cluster. We use cosine-distance for calculating distance between points.

Algorithm 1: ITER-DBSCAN

Input: A set of Textual utterances(data-points)

Parameters: featuretransformer, initial-min-distance, initial-number-of-points, delta-min-distance, delta-number-of-points, max-distance, min-points, max-iteration

Output: Data-points with cluster label

1. current-minimum-distance=initial-min-distance;
2. current-number-of-points=initial-number-of-points;
3. iteration=1;
4. while iter \( \leq \) max-iteration do
5.  \( \text{if current-minimum-distance == max-distance or current-number-of-points == min-points then} \)
6.     break;
7.  end
8.  /* compute feature representation of the data points with the featuretransformer method */
9.  feature-vector=featuretransformer(data-points);
10. Run DBSCAN Algorithm with current-minimum-distance, current-number-of-points and feature-vector;
11. set data-points with current-data-points;
12. current-minimum-distance = current-minimum-distance - delta-min-distance;
13. current-number-of-points = current-number-of-points - delta-number-of-points;
14. iteration = iteration + 1;
15. end

Parameters: ITER-DBSCAN parameters are described below,

- **data-points**: The primary input to the algorithm is a set of data-points (textual data) for clustering.
- **featuretransformer**: Transformer function to convert the textual data into feature vector.
- **initial-min-distance**: Initial distance value for creating cluster.
- **initial-number-of-points**: Initial number of points in a group for cluster validation.
- **delta-min-distance**: Single distance value is not enough to cluster sparse dataset, at each iteration the distance value is increased by delta-min-distance parameter to search for new cluster.
- **delta-number-of-points**: Minimum number of points parameter is decreased by delta-number-of-points parameter at each iteration for finding low-density clusters.
- **max-distance**: Iteration is terminated when the distance parameter reaches max-distance.
- **min-points**: Iteration is terminated when the minimum number of points for cluster creation reaches min-points.
- **max-iteration**: max-iteration is the maximum number of times algorithm runs for cluster search.

In the context of Intent Mining, we use the textual description as data-points and Average Embedding as a feature transformer. The algorithms automatically group similar textual description into groups and ask human labeler to provide a label. The labeling process is easier since the grouped textual data provides a understanding about the query/issue being reported. Clusters found by this approach are highly pure and coherent. Table 2 presents top-5 and below-5 frequency intent mined by analyzing conversations and Table 3 presents a cluster view containing similar textual descriptions related to Internal Skype for Business Application support (Refer Table 1 for sample conversation). Table 4 shows two clusters output where our algorithm can identify single and multiple intent clusters, where Cluster 1 is asking user for their username and Cluster 2 asking user for their username and email address.

Table 2. Intent distribution of conversations related to Skype for business, showing top-5 and below-5 intent frequency.

| Intent Class | Frequency |
|--------------|-----------|
| Enable Skype Phone Edition | 890 |
| Upgrade Issue | 640 |
| Login Issue | 628 |
| Frequently asking for password | 450 |
| Enable Recording | 398 |
| Installation Issue | 20 |
| Skype Performance Issue | 18 |
| Unable to join meetings | 13 |
| Followup on Open Ticket | 11 |
| Unable to contact external user | 7 |

Table 3. Cluster view: Similar textual descriptions are grouped together.

| Conversation Description | 
|--------------------------|
| Issue : user unable to save IM conversation in Lync |
| Skype- unable to auto save the conversation |
| Skype for Business: Unable to disable auto save conversations |
| skype: Im CONVERSATION save |
| Skype Auto Save issue |
| Skype for Business: User needs to save the conversation on skype |

3.3 Label Propagation

Our clustering approach provides a set of labeled conversation-intent pair and a set of unlabeled conversations, as the density based approach might not group all the data points. Now we discuss how intent labels are propagated to the unlabeled conversations.
Conversation are sequence of multiple utterances exchanged between two speakers, we extract up to top 3 user utterances providing “Information” or “Question” types of responses to agent using Dialog Act classifier (discussed in 3.1.3). The textual features are then pre-processed (tokenized, stop words removal) and converted to TF-IDF (Term frequency-Inverse document frequency) numerical representation. The TF-IDF features are compressed using PCA method to generate features for the conversations.

Labeled conversation features and intent pairs are then fitted to a statistical classifier using Logistic Regression\(^8\)\(^9\). The trained classifier is used to predict the labels of the unlabeled conversations. The final conversation and intent pair is generated based on the confidence threshold of the trained model.

### 3.4 Approaches for Description extraction form Conversation

In industrial service desk scenario, the metadata or description about the conversation is added later by the service agent after the issue is resolved and might not available in many cases. In this section, we describe two methods to extract textual descriptions from the raw conversation logs which can then be fed into our clustering model -

- The agent answering to the service call always clarifies the intent with the user. Therefore, we can extract all the question asked by the Agent during the conversation with Dialog Act Classifier model and apply our clustering and label propagation approach to find different set of questions asked by the agent. A special type of questions asked by the agent is “intent clarification” to clarify the intent. For example - “As i understand you need recording service to be enabled for Skype for Business” (Refer to Table 1) where Agent clarifies the request with the request with user. We can extract this sentence for Short description of the conversation.

- We can also extract top-3 user utterances of “Information” or “Question” type using Dialog Act Classifier model. This utterance set can be also used for representing a short description about the conversation. This design choice is made from the observation that the user informs about their queries in the top few messages and DAC model filters some of the top noisy utterances (such as greetings and command type). COMMAND type utterance removal is a special case, since in our conversation dataset users do not command agents for help rather it is more of a request. But in other scenario, we might need to add COMMAND type utterances for representing short description of the conversation.

### 4 Internal Case Study

We have conducted an experimental study of this approach with our internal IT support dataset, a sample conversation is described in Table 1 consists of human-human conversation along with issue description representing an abstract summary of the conversation. We have extracted around 5094 conversations related to service issues pertaining “Microsoft Skype for Business” and 8503 support conversations related to “Microsoft Outlook” application. ITER-DBSCAN algorithm on this two dataset of size 5k+ and 8k+ conversations is able to cluster 70.9 and 72.8 percent of the data. ITER-DBSCAN parameters are optimized only to cluster 65-80 percent of the total data samples. Resulting clusters were manually reviewed and annotated by domain experts. The resulting labeled dataset is used to build intent models for this two application. The clustering result is presented in Table 4.

Table 4. Cluster View: Automatic Single & Multi Intent Identification

| Cluster 1 | Cluster 2 |
|-----------|-----------|
| **What is your user name?** | **please tell me your username and email address** |
| **Can you please tell me your username?** | **what is your username and email address?** |
| **May i know your username?** | **May i know your username and email address** |
| **Sorry to hear that, please help me with your username** | **Can you please tell me your username and email id**

Our clustering approach reduced labeling effort from 5k+ conversations labeling to 169 clusters labeling. Two domain expert participated for the cluster annotation and validation. One domain expert able to annotate 169 clusters in a single day, whereas other domain expert validated the annotation quality of the other domain expert. Annotating 5k+ conversations based on this evaluation would take 5000/169 = 30 days (approx.) by a SME. Hence, we conclude that our approach can reduces months of manual effort to few days. We deployed the intent model for “Skype for Business” with live conversational agent to test the efficacy and coverage of the intent model due to the unavailability ground truth data of 5k+ conversations. Around 80 users participated from different countries for evaluating the model and 1k+ conversations are collected during this pilot phase. Evaluation statistics are presented in Table 6. Table 6 shows the the model accuracy in terms of 1 turn and 3 turn percent accuracy. 1 turn represents the accuracy of the intent model where the intent is identified correctly in the first response generated by the bot (and validated by users) and 3 turn accuracy shows the accuracy where intent is identified at max 3 attempts/turns. We have also reported the number of new intents identified during this evaluation process. It is observed during the field pilot, i.e. the 3 turn accuracy remains below 95 percent since the model is evaluated with out of domain queries as well.

### 5 Experiments with Public Dataset

We have evaluated our clustering approach with publicly available intent classification dataset and short text classification dataset. We have used number of intents discovered and accuracy as a score to benchmark against other published results.

**Intent Classification Dataset\(^6\)** The dataset \(^7\) is perfectly suitable for evaluating our clustering algorithm as the class distribution is highly-skewed. This dataset contains sample utterance with intent label. We have converted these utterances into numerical representation using pre-trained Glove word embedding model and then averaging the word embedding of a utterance. Along with that, we have also used Universal Sentence Encoder (USE) to represent the utterances into fixed sized numerical representation for comparison. Clusters are labeled based on the majority samples of the class the group belongs to. Figure 1 describes the class distribution of the Ask Ubuntu corpus. Figure 2 describes the class distribution of the Web Application Corpus. See Table 1 consists of human-human conversation along with issue description representing an abstract summary of the conversation. We have extracted around 5094 conversations related to service issues pertaining “Microsoft Skype for Business” and 8503 support conversations related to “Microsoft Outlook” application. ITER-DBSCAN algorithm on this two dataset of size 5k+ and 8k+ conversations is able to cluster 70.9 and 72.8 percent of the data. ITER-DBSCAN parameters are optimized only to cluster 65-80 percent of the total data samples. Resulting clusters were manually reviewed and annotated by domain experts. The resulting labeled dataset is used to build intent models for this two application. The clustering result is presented in Table 4.

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7. Better parameter search might generate less number of clusters, but since the dataset is un-annotated, data size to cluster count ration is reasonable for labeling.  
8. https://github.com/sebischair/NLU-Evaluation-Corpora  
9. http://nlp.stanford.edu/data/glove.6B.zip
We divide the total dataset size into a 80 percent training data and 20 percent testing data set. 80 percent of the data is used to cluster similar utterances into distinct group, each distinct group is labeled based on the majority class of the group. Labeled data generated from this step is further used to train a statistical classifier (Logistic Regression). The trained classifier is then used on 20 percentage of the hold-out set to measure the testing accuracy.

Ask Ubuntu corpus is another open-source intent identification corpus. Total number of available samples are 162 belongs to 4 classes. The initial dataset is divided into 80 percentage for training and validation of the intent model and 20 percent of held out data kept for testing the intent model. The clustering algorithm able to discover all the intent classes presents in the dataset. Clusters are labeled based on the majority of the samples of the group. Resulting training data is used to train a statistical classifier (Logistic Regression). Trained classifier is then used to predict the labels of the hold-out 20 percentage of the dataset, best testing accuracy reported by the classifier is 98.4.

Web Application corpus is another source of utterance and intent class annotated dataset with highly skewed class distribution. Total number of available samples are 83 belongs to 7 classes. Initial dataset is divided into 80 percentage for training and validation and 20 percentage of data kept for testing the intent model. Our clustering algorithm able to find 5 intent classes among 7 classes, since our algorithm are restricted to search for clusters with density more than 3. Generated training samples are used to train a classifier and the resultant classifier is used to predict the labels of the 20 percent of the held out dataset. Best testing accuracy reported by the classifier is 94.2.

ITER-DBSCAN parameters for the AskUbuntu and WebApplication corpus is described below, the parameters are optimized to maximize the percentage of points clustered -

- For AskUbuntu Corpus, we have used following parameters while using Average Embedding(AE) & Universal Sentence Encoder(USE): -
  - AE: Initial Distance: 0.09, Initial Sample Count: 10, Delta distance: 0.01, Delta minimum samples: 1, Minimum Samples: 2, Maximum Distance: 0.52, Iteration: 10.
  - USE: Initial Distance: 0.31, Initial Sample Count: 12, Delta distance: 0.01, Delta minimum samples: 1, Minimum Samples: 2, Maximum Distance: 0.20, Iteration: 10.

- For Web Application Corpus, we have used following parameters while using Average Embedding(AE) & Universal Sentence Encoder(USE): -
  - AE: Initial Distance: 0.11, Initial Sample Count: 12, Delta distance: 0.01, Delta minimum samples: 1, Minimum Samples: 2, Maximum Distance: 0.20, Iteration: 10.
  - USE: Initial Distance: 0.29, Initial Sample Count: 12, Delta distance: 0.01, Delta minimum samples: 1, Minimum Samples: 2, Maximum Distance: 0.6, Iteration: 10.

![Figure 1. Class Statistics of Web Application Corpus](image1.png)

![Figure 2. Class Statistics of Ask Ubuntu Corpus](image2.png)
Short text classification Dataset\cite{10}: We have also evaluated our approach on publicly available Stack Overflow dataset \cite{23}. For this dataset, textual descriptions contains more than 40 words for each document, average embedding was not giving good results. Hence, we have used TF-IDF (Term frequency- Inverse document frequency) for converting textual data into numerical features and features are compressed into 200-dimensions using PCA (Principal component Analysis algorithm). The dataset is equally distributed among 20 classes. The dataset is then divided into 80-20 for training and testing. We have used our clustering algorithm to cluster the textual data and labeling is done based on the majority sample of the class the cluster represents. Our algorithm automatically finds all the classes without any knowledge about the underlying distribution about the classes. In Table 7 we presents the the testing accuracy on the 20 percent held out dataset.

We have also used Universal Sentence Encoder for feature representation and reported the results in Table 7.

We have used following parameters while using Term-Frequency+ Principal Component Analysis(TF-Idf+PCA) & Universal Sentence Encoder(USE): -

- TF-Idf+PCA: Initial Distance: 0.16, Initial Sample Count: 70, Delta distance: 0.01, Delta minimum samples: 1, Minimum Samples: 2, Maximum Distance: 0.50, Iteration: 30.
- USE: Initial Distance: 0.32, Initial Sample Count: 50, Delta distance: 0.01, Delta minimum samples: 1, Minimum Samples: 2, Maximum Distance: 0.6, Iteration: 30.

We further extended this to compare against other reported baseline and presents the results In Table 8 \cite{23}. Table 8 compares the clustering accuracy on 20k dataset with K-Means algorithm with two different features (Term frequency and Term frequency- Inverse document frequency), DBSCAN with Term frequency-Inverse document frequency feature and Short text Clustering using Convolutional neural network (STCC) with class distribution information. In the first case K-Means algorithm is executed with 20 clusters with two different feature set and resultant clusters are annotated based on the majority of the samples. Classes discovered from the clustering step is compared against the original class information and the accuracy is reported in Table 8. Similarly DBSCAN and STCC is evaluated and the accuracy is presented in Table 8. Using our methodology, we first cluster all the 20k points and the clusters are annotated based on the majority of the samples. A percentage of data points clustered from the clustering step is used to train a statistical classifier (Logistic Regression) and used to predict labels of the noisy points from the clustering step. Resultant class label is then compared against the original class information and reported in terms of mean and variance of the accuracy.

Our clustering and label propagation step able to achieve very high accuracy on the Stack overflow dataset from the previously reported results.

From the results, we have concluded that better sentence representation (such as Universal sentence encoder) provides much more better results than average embedding of word vectors. While working with domain dataset with lots of domain terms, average embedding can also be used for short text clustering.

6 Conclusion and Feature Work

In this work, we have presented a framework that can cluster similar textual data using a simple average embedding method and as well as better sentence representation method (Universal sentence Encoder) for imbalanced class identification. We have also presented a feature extraction method using Dialog Act Classification model to extract data from a conversation for intent discovery and label propagation. We demonstrated our result with internal Microsoft application IT support conversational data and few publicly available intent classification and short text classification datasets.

In future, we would like to work towards making this algorithm more scalable to work large dataset. We would also like to investigate the application of this algorithm in general purpose clustering based application such as Knowledge graph generation by automatically clustering entities, and in other areas of data mining as well.

Table 8. Accuracy comparison on Stack Overflow Data

| Method       | Accuracy      |
|--------------|---------------|
| K-Means(TF)  | 20.31±3.15    |
| K-Means(TF-IDF) | 20.31±3.15  |
| DBSCAN       | 37.17±1.72    |
| STCC \cite{23} | 51.14±2.80    |
| TSTER-DBSCAN | 82.45±2.45    |

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