

Analysis of Utterance Embeddings and Clustering Methods Related to Intent Induction for Task-Oriented Dialogue

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Abstract

This paper investigates unsupervised approaches to overcome quintessential challenges in designing task-oriented dialog schema: assigning intent labels to each dialog turn (*intent clustering*) and generating a set of intents based on the intent clustering methods (*intent induction*). We postulate there are two salient factors for automatic induction of intents: (1) clustering algorithm for intent labeling and (2) user utterance embedding space. We compare existing off-the-shelf clustering models and embeddings based on DSTC11 evaluation. Our extensive experiments demonstrate that we should add two huge caveat that selection of utterance embedding and clustering method in intent induction task should be very careful. We also present that pretrained MiniLM with Agglomerative clustering shows significant improvement in NMI, ARI, F1, accuracy and example coverage in intent induction tasks. The source code for reimplement will be available at Github.

1 Introduction

Why Intent Induction? Humans are generalists. During a conversation, they listen to the other person’s utterance and naturally grasp which intent of the utterance is.

With the skyrocketing demand for conversational AI, however, the more user utterances a dialogue system encounters, the more unknown intents it does. Note that predefining user intent is expensive and it is impossible to annotate all the user intents.

Since provided user utterances are unlabeled, intent induction (Haponchyk et al., 2018; Perkins and Yang, 2019; Chatterjee and Sengupta, 2020; Zeng et al., 2021; Zhang et al., 2022) aims to discover unseen intents and consummates a tethered intent classifier.

Our Intuition. We postulate there are two salient factors for automatic induction of intents: (1) clustering algorithm for intent labeling (Cheung

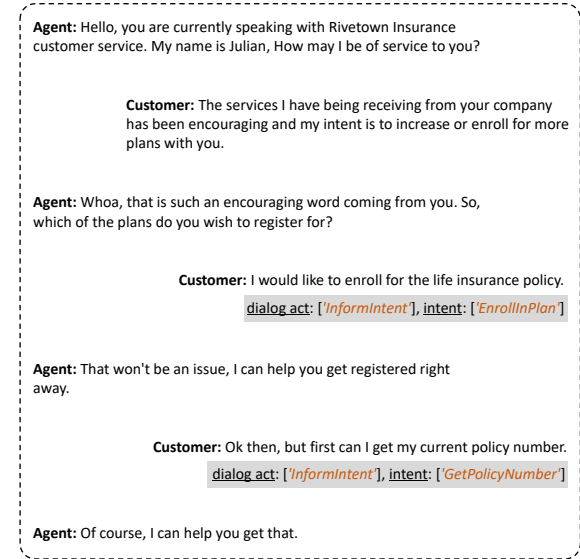


Figure 1: A sample segment of conversation transcript.

and Li, 2012; Hakkani-Tür et al., 2015; Padmasundari, 2018) and (2) user utterance embedding space (Wang et al., 2020; Song et al., 2020; Gao et al., 2021; Chuang et al., 2022; Nishikawa et al., 2022). Intuitively, for good intent induction, user utterances must be well represented in the embedding space, and good clustering algorithms must be employed to capture latent barycenters of user intent clusters to handle both predefined and unseen intents well.

In this paper, we analyze how the two key factors affect to user intent clustering and intent induction. Our extensive experiments with existing models demonstrate that pretrained MiniLM with Agglomerative clustering shows significant improvement in NMI, ARI, F1, accuracy and example coverage.

2 Task 1: Intent Clustering

2.1 Task Description.

A set of conversation transcripts are given as Figure 1, intent clustering model aims to (i) generate intent

Dataset	Domain	#Intents	#Utterances
DSTC11 _{dev}	insurance	22	66,875
DSTC11 _{test}	insurance	22	913

Table 1: Statistics of development dataset.

labels and (ii) align each utterance annotated with dialog act (i.e., "InformIntent").

Dataset. We conduct experiments on DSTC11 development dataset. It consists of 948 human-to-human conversation transcript with speaker role, utterance, dialog act, and intent. Testset is composed of 913 customer utterances and corresponding user intents. The dataset statistics are summarized in Table 1.

Metrics. We follow the same experimental metrics employed in the DSTC11 task proposal: Normalized mutual information (NMI), Adjusted rand index (ARI), Accuracy (ACC), Precision, Recall, F1 score, Intent example coverage, and the number of clusters (#K).

NMI is used for measuring dependency between two different distributions:

$$NMI(X, Y) = \frac{\mathbb{I}(X; Y)}{\min(\mathbb{H}(X), \mathbb{H}(Y))} \quad (1)$$

, where X denote clustered labels, Y are reference labels, \mathbb{I} stands for mutual information, and \mathbb{H} is entropy.

ARI is a measure for computing similarities between clustered results and reference labels:

$$ARI(X, Y) = \frac{\sum_{ij} \binom{n_{ij}}{2} - [AB]/\binom{n}{2}}{\frac{1}{2}[A+B] - [AB]/\binom{n}{2}} \quad (2)$$

, where $A = \sum_i \binom{x_i}{2}$ and $B = \sum_j \binom{y_j}{2}$.

Both Precision and Recall measure many-to-one alignments from clustered labels to reference labels. F1 score is a harmonic mean between the precision and recall.

After performing a many-to-one alignment, Intent example coverage is determined as percent of examples whose reference has a corresponding predicted result.

2.2 Methods

Clustering Algorithm. Intent clustering focuses on assigning dialog intents to each dialog. K -means clustering (Lloyd, 1982), for example, regards a set of conversation transcript $\mathcal{T}_1, \dots, \mathcal{T}_m$. Each transcript \mathcal{T} consists of turn-level dialog acts, speaker's role whether it is Agent or Customer,

and dialog utterances $X_1, \dots, X_n \in \mathbb{R}^p$. K -means minimizes the following equation in the Euclidean embedding space:

$$\min_{\beta_1, \dots, \beta_K \in \mathbb{R}^d} \sum_{i=1}^n \min_{k \in [K]} \mu_{ik} \|X_i - \beta_k\|_2^2 \quad (3)$$

, where $\{\beta_k\}_{k=1}^K$ denotes centroid of each intent cluster, $[K] = 1, 2, \dots, K$, μ_{ik} is alignment factor. Equation 1 can be expressed as:

$$\min_{V_1, \dots, V_K} \left\{ \sum_{k=1}^K \sum_{i \in V_k} \mu_{ik} \|X_i - \beta_k\|_2^2 : \bigsqcup_{k=1}^K V_k = [n] \right\} \quad (4)$$

, where \sqcup stands for disjoint union, and $\{V_k\}_{k=1}^K$ is intent cluster, determined by Voronoi diagram in utterance embedding space.

Given initial intent centroids $\{\beta_k^1\}_{k=1}^K$, we assign each utterance embedding to its nearest centroid (a.k.a., Expectation step):

$$V_k^t = \{i \in [n] : \|X_i - \beta_k\|_2^2 \leq \|X_i - \beta_j\|_2^2, \} \quad (5)$$

, where $\forall j \in [K]$. Then, we update the location of centroids (a.k.a., Maximization step):

$$\beta_k^{t+1} = \frac{1}{|V_k^t|} \sum_{i \in V_k^t} X_i \quad (6)$$

We iterate equation 5 and equation 6 alternatively until equation 4 converges.

In this paper, we conduct experiments with K -means (Lloyd, 1982), BIRCH (Zhang et al., 1996), Agglomerative clustering (Steinbach et al., 2000), Spectral clustering (Yu and Shi, 2003), Bisecting K -means (Di and Gou, 2018), and Variational optimal transportation (VOT) (Mi et al., 2018).

Embeddings. User utterance should be represented in the embedding space which is able to capture universal and rich semantic information. MiniLM (Wang et al., 2020) is an effective task-agnostic distillation to compress transformer based language model. MPNet (Song et al., 2020) proposes permuted language model for dependency among predicted tokens and makes the model to see a full sentence and auxiliary position information. SimCSE (Gao et al., 2021) leverages a simple contrastive learning framework. DiffCSE (Chuang et al., 2022) learns the difference between the original sentence and stochastically masked sentence. EASE (Nishikawa et al., 2022) exploits sentence embedding via contrastive learning between the original sentence and its related entities.

Clustering Method	<i>K</i> -means Clustering							
Metric	NMI	ARI	ACC	Precision	Recall	F1	Example Coverage	#K
EASE ^m _{ROBERTA}	33.4	14.2	28.0	28.0	69.0	39.9	43.9	5
EASE _{BERT}	36.1	18.1	35.3	36.8	58.9	45.3	53.5	8
EASE ^m _{BERT}	38.4	10.9	23.6	42.7	24.2	30.9	87.6	44
EASE _{ROBERTA}	45.8	25.4	40.0	43.7	60.7	50.9	65.6	12
DiffCSE ^{trans} _{BERT}	43.8	15.5	29.4	49.5	30.6	37.8	90.1	40
DiffCSE ^{sts} _{BERT}	46.6	16.9	29.9	50.4	30.8	38.2	89.9	43
DiffCSE ^{sts} _{ROBERTA}	53.9	29.0	45.1	57.2	46.8	51.5	91.1	30
DiffCSE ^{trans} _{ROBERTA}	55.0	23.1	35.7	60.6	35.7	44.9	96.7	50
SimCSE ^u _{BERT}	31.7	13.3	27.9	27.9	<u>65.0</u>	39.0	43.9	5
SimCSE ^u _{BERT+}	47.0	25.7	38.4	46.9	46.9	46.9	76.8	19
SimCSE ^u _{ROBERTA}	51.2	29.0	44.4	49.7	61.6	55.0	70.5	14
SimCSE _{BERT+}	53.0	27.8	39.8	55.0	42.2	47.8	91.0	31
SimCSE _{BERT}	53.1	24.4	39.0	60.5	39.5	47.8	96.3	44
SimCSE ^u _{ROBERTA+}	53.2	25.9	42.2	56.8	43.8	49.5	91.7	32
SimCSE _{ROBERTA}	56.6	28.8	42.7	60.8	43.3	50.6	91.3	36
SimCSE _{ROBERTA+}	56.8	28.9	41.3	62.5	41.6	49.9	98.4	42
Glove ^{avg}	30.5	7.0	20.6	34.6	22.2	27.0	92.2	50
MPNet	59.3	32.3	46.1	66.0	47.1	54.9	96.5	42
MiniLM _{L6}	59.3	35.7	52.6	62.2	54.9	58.4	92.4	28
MiniLM _{MULTIQA}	<u>61.7</u>	<u>38.2</u>	55.1	<u>66.6</u>	55.4	<u>60.5</u>	<u>98.8</u>	30
MiniLM _{L12}	63.1	38.9	<u>54.9</u>	68.0	54.9	60.8	100.0	31

Table 2: Clustering results on DSTC11 dataset. We employ *K*-means clustering algorithm to all utterance embeddings. *m* denotes multilingual model, *u* stands for unsupervised model, and + means large model.

2.3 Result Analysis

To analyze the effects of both embedding and clustering algorithm, We first heuristically fix the clustering algorithm and find the most meaningful embedding. Then, we opt for the most suitable clustering method based on the embedding.

Analysis of Embeddings. We show the experimental results for analyzing effect of embedding space in Table 4. We observe that EASE records poor performance in all metrics, followed by averaged Glove embedding which shows the worst result, though EASE is a large-scale model. Note that both entity-aware contrastive learning and multilingual setting cause performance degradation in dialog intent clustering task. The results for DiffCSE also shows that unsupervised contrastive learning between original utterance and edited utterance exacerbates model performance in both STS and Trans tasks. Despite the model size twice smaller than DiffCSE as shown in Table 3, SimCSE get comparable scores to MPNet, with similar model size. Note that MiniLM achieves remarkable per-

Method	DiffCSE	SimCSE	MPNet	MiniLM
# Param	250M	125M	110M	21.3M

Table 3: The number of parameters. Both DiffCSE and SimCSE denote RoBERTa_{base} model.

formances in both *L12* setting¹ and *MULTIQA* setting² in all metrics. These results demonstrate that (i) performance increases as the number of parameter decreases, which means excessively large embedding model leads to performance degradation, and (ii) the student network which is trained by the teacher’s self-attention distributions and guiding layer affects performance improvement.

Visualization. Figure 2 gives UMAP visualization of clustering results. Note that we employ UMAP, instead of t-SNE, because UMAP preserves more global structure than t-SNE. We observe that (b) - (e) vertically degenerated into

¹<https://huggingface.co/sentence-transformers/all-MiniLM-L12-v2>

²<https://huggingface.co/sentence-transformers/multi-qa-MiniLM-L6-cos-v1>

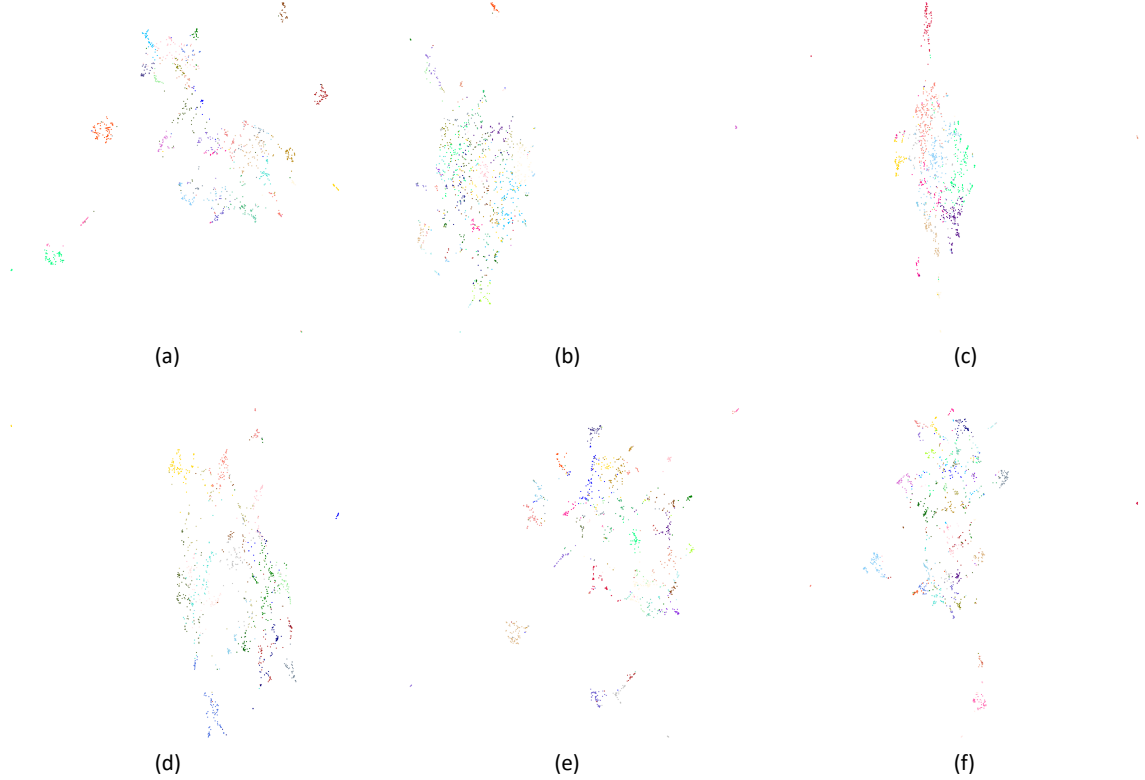


Figure 2: UMAP visualization of intent clustering results with different embeddings based on DSTC11 development dataset: (a) MiniLM, (b) Glove, (c) Ease-roberta, (d) DiffCSE-roberta, (e) SimCSE-roberta, and (f) MPNet. We apply K -means clustering algorithm to (a)-(e) experiments.

Utterance Embedding	MiniLM _{L12}							
Metric	NMI	ARI	ACC	Precision	Recall	F1	Example Coverage	#K
Bisect K -means	32.2	13.9	23.8	26.0	67.4	37.5	37.0	5
VOT	53.8	31.8	48.5	54.1	53.5	53.8	84.8	20
Spectral	57.6	<u>34.9</u>	51.3	58.8	56.1	<u>57.4</u>	82.9	24
Agglomerative	57.9	34.2	<u>51.8</u>	58.0	<u>55.4</u>	56.7	<u>88.6</u>	23
BIRCH	<u>59.9</u>	32.9	46.3	<u>64.6</u>	47.0	54.4	100.0	47
K -means	63.1	38.9	54.9	68.0	54.9	60.8	100.0	31

Table 4: Clustering results on DSTC11 dataset. We apply MiniLM_{L12} utterance embedding to all clustering methods.

the each embedding space while (a) is not. (a) also presents most well-clustered result while the other embeddings suffer from ill-clustered result and outliers.

Analysis of Clustering Methods. In Table 4, we observe that K -means method outperforms the other models, followed by BIRCH. Note that VOT records poor performance which means optimal transportation with the variational principle deteriorate the result in intent clustering task. Bisect K -means clustering algorithm calculate the point density and average density of all points to initialize cluster barycenters. However, K -means++ initializer shows much better performance, contributing

to the overall cluster inertia.

Visualization. Figure 3 gives UMAP visualization of clustering results with Voronoi diagram. The number of barycenters of Bisect K -means is five which means this ill-clustering model is not able to cover all latent user intents. Though BIRCH records compatible results to K -means, the number of predicted barycenters is too large compared to the number of reference K . It causes outlier barycenter problem that barycenter contains too little utterances and disrupts universal clustering representation. It also demonstrates that hierarchical process of BIRCH including remove outliers and cluster refining don’t have a substantial impact.

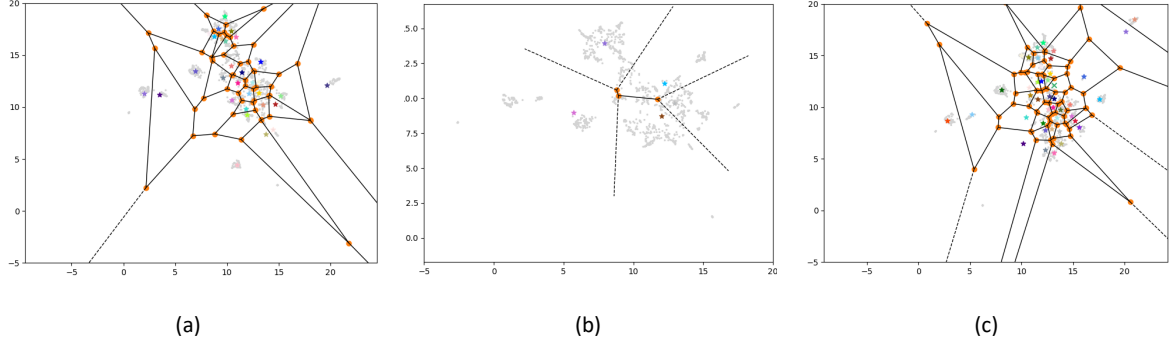


Figure 3: Voronoi diagram visualization of intent clustering results with different clustering algorithms based on DSTC11 development dataset: (a) K -means, (b) Bisect K -means, and (c) BIRCH. We apply MiniLM_{L12} user utterance embedding to (a)-(c) experiments. * stands for barycenter of each cluster and x represents outlier barycenter with fewer than five utterances.

Clustering Method	K -means Clustering							
Metric	NMI	ARI	ACC	Precision	Recall	F1	Example Coverage	#K
EASE _{BERT} ^m	27.0	12.3	23.9	24.1	72.9	36.2	26.4	5
EASE _{BERT}	53.1	25.6	42.8	50.2	57.4	53.5	80.0	26
EASE _{ROBERTA} ^m	59.6	41.8	53.7	57.8	68.8	62.8	86.0	34
EASE _{ROBERTA}	60.5	50.7	52.7	55.8	70.0	62.1	83.1	28
DiffCSE _{BERT} ^{trans}	21.0	11.5	23.3	23.7	<u>77.5</u>	36.3	32.5	6
DiffCSE _{BERT} ^{sts}	49.6	22.3	40.2	46.1	58.4	51.5	93.2	31
DiffCSE _{ROBERTA} ^{sts}	65.4	42.3	53.7	59.4	65.9	62.5	89.8	31
DiffCSE _{ROBERTA} ^{trans}	65.4	53.3	57.6	63.1	71.1	66.8	<u>90.0</u>	28
SimCSE _{BERT} ^u +	33.1	19.1	28.0	28.0	<u>77.5</u>	41.2	33.4	5
SimCSE _{BERT} ^u	58.3	29.6	46.4	58.5	59.1	58.8	83.1	32
SimCSE _{BERT} +	59.4	29.1	47.0	54.2	60.5	57.2	86.2	30
SimCSE _{ROBERTA}	61.4	34.3	47.1	54.3	62.0	57.9	80.3	29
SimCSE _{BERT}	62.7	37.3	52.6	63.4	59.8	61.6	89.6	34
SimCSE _{ROBERTA} ^u +	67.8	51.1	57.7	64.2	70.2	67.1	86.4	32
SimCSE _{ROBERTA} ^u	68.6	48.0	54.7	65.6	71.2	68.3	86.1	31
SimCSE _{ROBERTA} +	69.2	38.7	52.1	62.4	70.0	66.0	93.8	32
Glove ^{avg}	35.0	18.8	29.1	36.3	51.2	42.4	77.0	29
MPNet	72.8	41.6	60.2	65.6	76.3	70.6	86.5	26
MiniLM _{L12}	73.2	47.1	57.1	<u>66.0</u>	72.2	69.0	83.1	25
MiniLM _{L6}	<u>74.7</u>	<u>52.8</u>	<u>61.2</u>	70.5	74.9	<u>72.7</u>	83.4	25
MiniLM _{MULTIQA}	77.4	54.5	63.2	70.5	79.1	74.6	80.0	24

Table 5: Intent induction results on DSTC11 dataset. We employ K -means clustering algorithm to all utterance embeddings. *m* denotes multilingual model, *u* stands for unsupervised model, and + means large model.

3 Task 2: Intent Induction

3.1 Task Description

Unlike the Task 1, intent induction takes different transcripts which annotated only speaker’s role and intent label. The goal of intent induction is to create a set of intents and match them to each utterance, without access to the ground-truth dialog acts.

Experimental Settings. We follow the experimental protocol in Task 1: We use DSTC11 dataset as shown in Table 1, exploit same clustering algorithms and utterance embeddings, evaluate methods using NMI, ARI, Accuracy, F1, and Example coverage. We did extensive experiments on 8 NVIDIA GeForce TITAN GPUs. The batch size are selected based on available GPU memory. We employ the

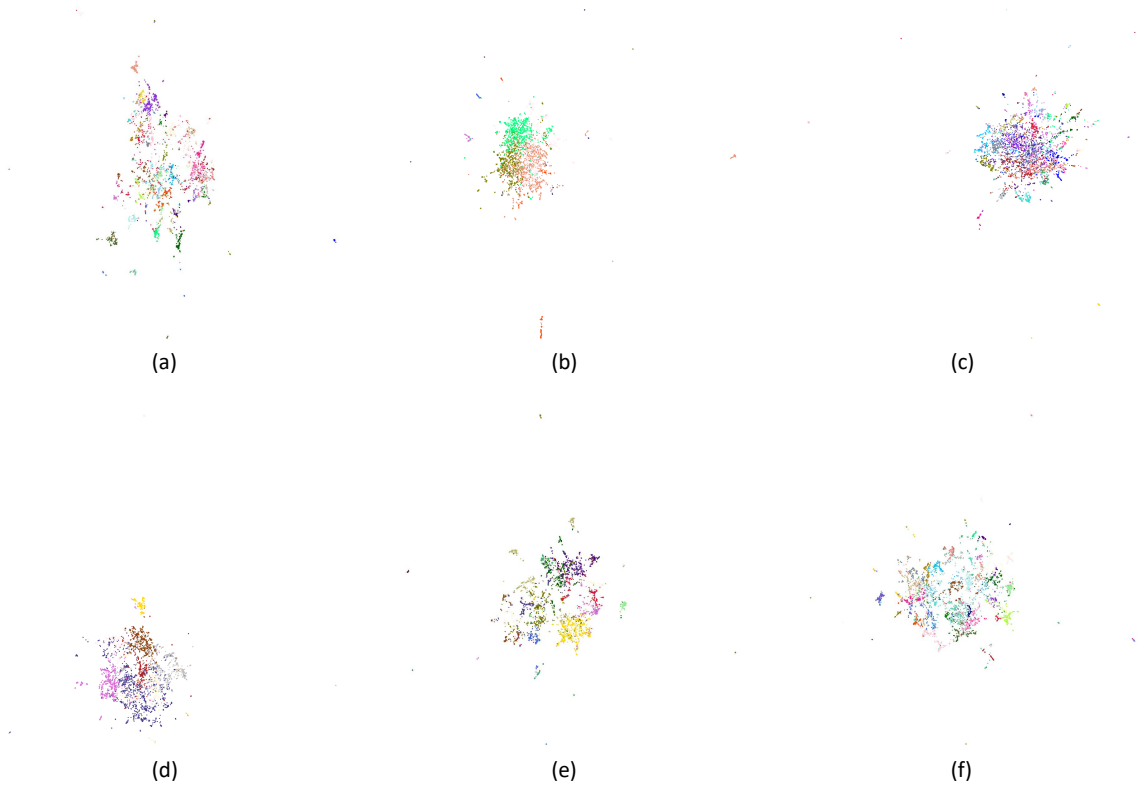


Figure 4: UMAP visualization of intent induction results with different embeddings based on DSTC11 development dataset: (a) MiniLM, (b) Glove, (c) Ease-roberta, (d) DiffCSE-roberta, (e) SimCSE-roberta, and (f) MPNet. We apply Agglomerative clustering algorithm to (a)-(e) experiments.

Utterance Embedding	MiniLM _{MULTIQA}							
Metric	NMI	ARI	ACC	Precision	Recall	F1	Example Coverage	#K
Bisect K -means	72.3	55.7	57.4	63.0	<u>81.2</u>	70.9	76.8	27
VOT	75.3	50.6	60.0	71.9	72.3	72.1	93.4	33
Spectral	75.0	51.7	59.0	67.7	75.9	71.6	86.3	23
K -means	77.4	54.5	63.2	70.5	79.1	74.6	80.0	24
BIRCH	<u>79.5</u>	<u>62.8</u>	68.1	<u>71.9</u>	84.6	<u>77.7</u>	<u>89.9</u>	24
Agglomerative	81.0	64.2	<u>66.5</u>	75.5	80.6	78.0	86.2	25

Table 6: Intent induction results on DSTC11 dataset. We apply MiniLM_{MULTIQA} utterance embedding to all clustering methods.

provided automatic dialog act predictions.

3.2 Result Analysis

Analysis of Embeddings. Table 5 demonstrates that MiniLM-based utterance embedding can improve induction performance for user intents. Unlike the Task 1, MiniLM_{MULTIQA} outperforms the other methods, followed by MiniLM_{L6}³. It represents that MiniLM with 6 layers and 384 hidden size can learn universal utterance representation and capture meaningful information. Though the

³<https://huggingface.co/sentence-transformers/all-MiniLM-L6-v2>

performance tends to increase as the size of each embedding model increases, we observe that larger models do not always perform better. Note that DiffCSE_{BERT}^{trans} and EASE_{BERT}^m record high recall because the number of clusters K is disastrously low. We observe that it dampens overall model performance.

As shown in both Task 1 and Task 2 results, (i) entity-aware contrastive learning, (ii) multilingual setting, (iii) contrastive learning between the original utterance and edited utterance are ultimately not the optimal choice to improve intent induction performance.

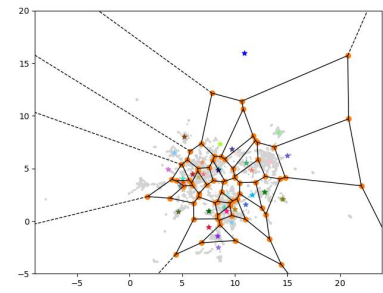
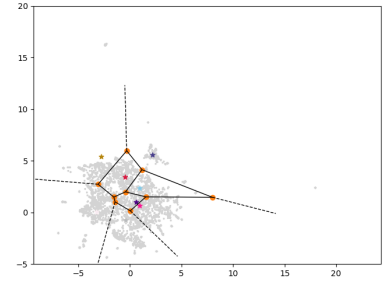
Method	Voronoi Diagram	Examples	Label
Agglomerative + MiniLM		Would it be on like any of my other bills?	34
		Oh okay. Where at on the bill. I'm looking now.	
		Okay. When will I see that in my bill?	
		Hi I am calling because I received a wrong bill.	
		Thank you. How much will this make my bill go up?	
		Yeah, so exactly how does this work? Do I just send a bill or what?	
Agglomerative + DiffCSE		Would it be on like any of my other bills?	5
		Oh okay. Where at on the bill. I'm looking now.	2
		Okay. When will I see that in my bill?	7
		Hi I am calling because I received a wrong bill.	6
		Thank you. How much will this make my bill go up?	0
		Yeah, so exactly how does this work? Do I just send a bill or what?	1
		crap! Well what can I do now? Can I make the payment and have the same policy that I had before?	4

Figure 5: Qualitative result on DSTC11 dataset comparing MiniLM-based and DiffCSE-based models. We fix the clustering model as Agglomerative clustering in this experiment.

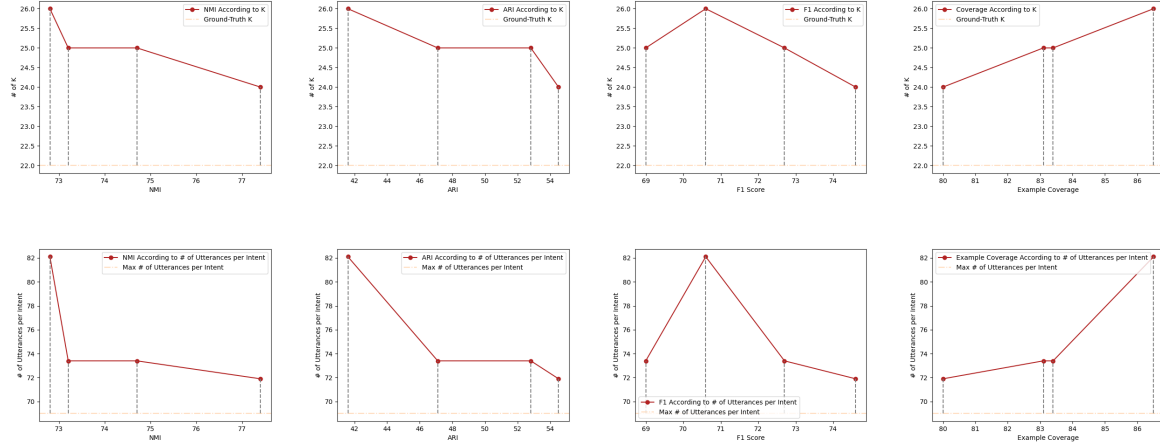


Figure 6: Quantitative results on DSTC11 dataset related to NMI, ARI, F1 score, and Example coverage. We analyze using four results with the best performance introduced in Table 5.

Visualization. We present UMAP visualization of intent induction results with different utterance embeddings (Figure 4). It corroborates that MiniLM-based intent induction can provide wider and well-separated results preserving its meaningful embedding space.

Analysis of Clustering Methods. In Table 6, we show the results of intent induction comparing models that clustering algorithms. Unlike the results in Task 1, Agglomerative clustering and BIRCH outperform the other baselines. Agglomerative clustering starts with the utterances as indi-

vidual clusters and merge them if they have similar intents. Experiment cogently demonstrates that the approach exploiting MiniLM_{MULTIQA} and Agglomerative clustering achieves state-of-the-art results among the other methods in intent induction task.

3.3 Qualitative Results

Figure 5 shows qualitative result for intent induction on DSTC11 dataset. We generate user intent labels using two different model. We observe that Agglomerative clustering on MiniLM utterance embedding can classify bill-related utterances well. However, Agglomerative clustering on DiffCSE

utterance embedding is not able to discern user intent well and amalgamate completely different user utterances into a single intent cluster. Note that all cluster have bill-related user utterances which means it is an ill-clustered result. We conclude that user utterance embedding is one of the most important factors affecting performance, and we should add a huge caveat that selection of utterance embedding in intent induction task should be very careful. Further analyzing how to leverage an embedding model is an interesting direction of future work.

3.4 Quantitative Results

We conduct quantitative experiments to analyze (i) the correlation between the number of induced clusters and performance, and (ii) the correlation between the number of utterances per intent and performance (Figure 6). Note that maximum number of sample utterances aligned to an intent is limited to 50. First, We observe that NMI and ARI increase as the number of induced clusters approaches the reference K. We also notice that Example coverage decreases as the number of induced clusters go toward the reference K. We evince that there is a trade-off relationship between NMI, ARI and Example coverage. Second, the correlation between the number of utterances per intent and performance shows the same pattern as the correlation between the number of induced clusters and performance.

4 Conclusion

The conclusion of this paper is threefold:

- We empirically demonstrate that we should add two huge caveat that selection of utterance embedding and clustering method in intent induction task should be very careful.
- We also present that pretrained MiniLM with Agglomerative clustering shows significant improvement in NMI, ARI, F1, accuracy and example coverage in intent induction tasks.
- We evince that there is a trade-off relationship between NMI, ARI and Example coverage.

5 Discussion and Future Work

In clustering, broadly, there are three categories of methods: (i) Barycenter-based formulation, (ii) Density-based formulation, and (iii) Distance-based formulation. In this paper, we mainly dealt

with barycenter-based methods. Indeed, K -means clustering method, for instance, theoretically produce the same result as barycenter-based formulation and distance-based formulation in Euclidean embedding space:

$$\sum_{i,j=1}^n \|X_i - X_j\|_2^2 = 2n \sum_{i=1}^n \|X_i - \beta\|_2^2 \quad (7)$$

, where $\beta = \frac{1}{n} \sum_{i=1}^n X_i$. Besides, barycenter-based K -means in Euclidean space can circumvent the problem frequently caused by the location of barycenter in different measure space (e.g., Wasserstein space (Zhuang et al., 2022)):

$$\begin{aligned} \sum_{i=1}^n \|X - X_i\|_2^2 &= n\|X - \beta\|_2^2 + \sum_{i=1}^n \|X - X_i\|_2^2 \\ &\geq n\|X - \beta\|_2^2 \end{aligned} \quad (8)$$

However, K -means clustering in Euclidean space often lose salient geometric information of dataset, due to its formulation. In the same vein, though we didn't add experimental result of Density-based formulation to the table, the performance was disastrous. DBSCAN (Ester et al., 1996), for example, recorded 7.7 NMI, 0.0 ARI, 16.1 Accuracy, 27.6 F1 score, and 41.0 Example coverage in intent clustering task. Therefore, both clustering in different measure space and clustering using embedding density should be investigated. Further analyzing how to leverage an embedding model is also an interesting direction of future work.

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