Automatic Discovery of Novel Intents & Domains from Text Utterances

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Abstract

One of the primary tasks in Natural Language Understanding (NLU) is to recognize the intents as well as domains of users’ spoken and written language utterances. Most existing research formulates this as a supervised classification problem with a closed-world assumption, i.e. the domains or intents to be identified are pre-defined or known beforehand. Real-world applications however increasingly encounter dynamic, rapidly evolving environments with newly emerging intents and domains, about which no information is known during model training. We propose a novel framework, ADVIN, to automatically discover novel domains and intents from large volumes of unlabeled data. We first employ an open classification model to identify all utterances potentially consisting of a novel intent. Next, we build a knowledge transfer component with a pairwise margin loss function. It learns discriminative deep features to group together utterances and discover multiple latent intent categories within them in an unsupervised manner. We finally hierarchically link mutually related intents into domains, forming an intent-domain taxonomy. ADVIN significantly outperforms baselines on three benchmark datasets, and real user utterances from a commercial voice-powered agent.

1 Introduction

Numerous everyday gadgets like mobile phones or smart speaker devices consist of an NLU component to automatically understand the semantics of user requests. Comprehending the intent and/or domain (groups of mutually related intents) of users’ natural language utterances is a key task in these devices. Deep learning models have been proposed in the literature for intent detection in diversely expressed utterances, to avoid additional feature engineering (Bhargava et al., 2013; Kim et al., 2016; Liu and Lane, 2016; Sun et al., 2016; Zhang and Wang, 2016; Kim et al., 2017; Goo et al., 2018). But most models are supervised or semi-supervised, i.e. they require sufficient labeled data, and can only handle a fixed number of intents and domains seen during model training. However, user interactions with voice-powered agents generate large amounts of unlabeled conversational text. This data often contains newly emergent, unseen domains and intents not encountered by the learning models before. Expanding the capabilities of voice assistants to account for these new intents and domains would require expensive and time-consuming human labeling efforts each time a new skill, functionality or intent is to be added. Thus, it is crucial to be able to learn effectively from unlabeled text.

Zero shot techniques (Kumar et al., 2017; Xia et al., 2018) recognize intents for which no labeled training data is available. However, they require the number of the new intent types, and some prior knowledge about the new intents to be discovered to be available at test time. Such information may be unfeasible to obtain. Efforts have been made to break the closed-world assumption in computer vision (Scheirer et al., 2014; Bendale and Boult, 2015; Bendale and Boult, 2016; Fei and Liu, 2016) as well as in the NLU literature (Shu et al., 2017; Kim and Kim, 2018; Vedula et al., 2020; Lin and Xu, 2019). This is the paradigm of open world learning or open set recognition, that identifies instances with labels unseen during training. However, the task of discovering the actual latent categories in the instances identified as containing unseen labels is relatively under explored. (Shu et al., 2018) attempted this for image classification, but their model could not always outperform baselines. (Vedula et al., 2020) developed a sequence tagging approach to discover unseen intents in dialog. However, unlike our proposed
framework, their method (i) is restricted to intents containing an action or activity to be performed; (ii)
is customized for longer utterances containing additional background context such as customer support
conversations; and (iii) does not recognize an intent expressed in different ways semantically as the same
intent, or group related novel intents into novel domains. In this work, we attempt to bridge the gap
between detecting utterances belonging to new intents/domains and actually discovering a taxonomy of
those new intents/domains. Though we address the problem of novel user intent and domain discovery,
our technique can easily be applied to any open classification setting.

We propose a novel three-stage framework called ADVIN (Automatic Discovery of noVel Intents
and DomaiNs). It automatically discovers user intents and domains in massive, unlabeled text corpora,
without any prior knowledge about the intents or domains that the text may comprise of. Similar to an
open classification setting, our method first leverages a multi-layer transformer network, BERT [Devlin
et al., 2018], to determine if the text input is likely to contain a novel, unseen intent or not. In the next
step, ADVIN discovers the latent intent categories in the above identified input utterances in an unsupervised
manner, via a knowledge transfer component. Finally, ADVIN hierarchically links semantically related
groups of the newly discovered intents to form new domains. ADVIN is a generic algorithm and we
empirically demonstrate that it is equally effective across several task domains and fields. To summarize:

(i) We propose a novel, fully automated method, ADVIN, that jointly discovers newly emerging intents
as well as domains in unlabeled user utterances.

(ii) Unlike existing literature, ADVIN can generalize to diverse, open-world scenarios, and is independent
of the intents and domains that it has been trained upon.

(iii) We extensively evaluate ADVIN on public benchmark datasets and real-world data from a commercial
voice agent, and significantly outperform baselines across various empirical configurations.

2 Related Work

Intent detection has been successfully performed in the literature via machine learning based ap-
proaches [Tur et al., 2011; Jeong and Lee, 2008; Kim et al., 2016; Ravuri and Stoicke, 2015], as well as
deep learning models [Sun et al., 2016; Xia et al., 2018; Shivakumar et al., 2019; Castellucci et al., 2019;
Lin and Xu, 2019]. In recent years, intent detection has been jointly done with slot filling to improve
its performance [Xu and Sarikaya, 2013; Bhargava et al., 2013; Liu and Lane, 2016; Zhang and Wang,
2016; Kim et al., 2017; Goo et al., 2018; Wang et al., 2018]. However, the above approaches either require
sufficient labeled data for each domain and intent, or some prior knowledge about the new intents
to be discovered. ADVIN seeks to eliminate these restrictions.

Methods were proposed to recognize input texts belonging to novel domains [Kim and Kim, 2018]
and novel intents [Lin and Xu, 2019; Vedula et al., 2020]. However, unlike ADVIN, they do not jointly detect
both novel domains and novel intents, cannot detect the number of novel domains and intents, and do
not discover a taxonomy of the potential domain and intent types within user utterances. Deep clustering
networks [Hsu and Kira, 2015] and Bayesian non-parametric models [Dundar et al., 2012; Akova et al.,
2012] were proposed to identify mixture components or clusters in data. But unlike ADVIN, the clusters
identified cannot automatically be mapped to unique unseen categories. Our work is also different from
semi-supervised clustering techniques [Fu and Sigal, 2016; Akova et al., 2012; Yi et al., 2013; Yi et
al., 2013; Hsu and Kira, 2015], which lever small amounts of labeled data and require the classes to be
discovered to be known beforehand. Having said that, we show the gains achieved by a semi-supervised
version of ADVIN, in case prior knowledge is available about the novel intents (Table 6).

3 Our Framework ADVIN

Formally, we are given a corpus of training utterances $D_T$ labeled with $S$ seen intents, and a corpus
of unlabeled utterances $D_C$ consisting of $U$ novel intents such that $S \cap U = \emptyset$. We propose a three-stage
framework ADVIN that (i) classifies the incoming test utterance $x \in D_C$ with one of the $S = (s_1, ..., s_S)$
seen intent labels or as an unseen (novel) intent; (ii) for utterances $D_X$ predicted as having a novel intent,
it discovers the latent intents $U = (u_1, ..., u_U)$ present in them; and (iii) links together mutually related
novel intents discovered to form novel domains, and an intent-domain taxonomy.
3.1 Stage I: Detecting Instances with Novel Intents

We construct a two-step system to detect instances with novel intents, inspired by the success of models pre-trained on large unlabeled corpora, like GPT (Radford et al., 2018) and BERT (Devlin et al., 2018).

**Step I:** Prior open classification literature has modeled the problem of finding novel or unseen classes as an $(S + 1)$-class classification problem, with $S$ seen classes and an additional unseen class. Labeled training data is available for the seen classes, and an input instance is classed as unseen if it does not belong to any of the seen classes (Xu et al., 2019; Shu et al., 2018; Shu et al., 2017). In a similar vein, to classify utterances as containing a novel intent or not, we learn a BERT based multi-class classifier (Figure 1a). Given an input utterance $x$, it is converted into a sequence of tokens to be input to BERT. A special classification embedding $[CLS]$ is added as the first token. The output of BERT is an $n$-dimensional utterance encoding $(e_1, ..., e_n)$. A multi-class intent classification layer on top of BERT predicts the utterance intent based on the final hidden state $e_1$ of the $[CLS]$ token as:

$$y = \text{softmax}(We_1 + b)$$

where $W$ is a task-specific parameter weight matrix. We fine tune the parameters $\theta$ in different BERT layers with different learning rates as in (Howard and Ruder, 2018), as follows:

$$\theta_l^t = \theta_l^{t-1} - \eta_l^t \nabla_{\theta_l} J(\theta)$$

where $\eta_l$ and $\theta_l$ represent the learning rate and parameters respectively of the $l$-th BERT layer. $\nabla_{\theta_l} J(\theta)$ is the gradient with respect to the model’s objective function. We set the base learning rate to $\eta_l^1$ and use $\eta_l^{t-1} = \xi \cdot \eta_l^{t}$, where $\xi$ is a decay factor $\leq 1$. We fine-tune all BERT parameters as well as $W$ jointly by maximizing the log-probability of the correct intent label.

For our $(S + 1)$-class classification model described above, labeled training data $D_T$ is available for the $S$ seen intents. We use out-of-domain (OOD) intent detection datasets distinct from both $D_T$ and $D_C$, as training data for the $(S + 1)$-th ‘novel’ intent class. This OOD data comes from out-of-domain intent-labeled publicly available datasets (e.g. SNIPS (Coucke et al., 2018), ATIS (Dahl et al., 1994)). Since we use already annotated, publicly available intent labeled data as OOD data, we don’t require extra human annotation effort here. Note that while training, ADVIN only requires the information that the OOD intents do not overlap with those in $D_T$ or $D_C$, and not the actual intent labels of the OOD data. However, if the OOD data is annotated with $m$ intent classes, ADVIN can use this information by fragmenting the $(S + 1)$th class into $m$ classes, forming an $(S + m)$-class classification layer. Using $m$ classes may provide a better representation of the utterances likely to contain unseen intents (as shown in Section 4). An utterance classified into any of the $m$ classes is flagged as having a novel intent.

**Step II:** ADVIN employs an additional check as per the DOC algorithm (Shu et al., 2017). DOC learns statistical confidence thresholds for each seen intent class $s_i$. DOC thus captures instances that have been classified to one the $S$ seen intents with a low confidence. If the class-specific prediction probabilities for an input utterance are less than the thresholds learned for each seen intent $s_i$, that utterance is also classified as having a novel intent (see Figure 1a).
3.2 Stage II: Discovering Novel Intent Categories

The output of the previous step of ADVIN gives us all utterances \( D_X \) that potentially contain a newly emerging intent. The next step is to discover the actual latent intent categories \( U \) within \( X \). We use complete-linkage, agglomerative hierarchical clustering (Gowda and Krishna, 1978) to group together related utterances in \( D_X \), and find the potential novel intents \( U \).

**Knowledge Transfer Component:** Intuitively, humans seem to understand and categorize newly encountered objects based on the characteristics of similarities or differences that they learn from their prior knowledge of similar or comparable objects. We utilize a similar idea in order to learn the distance threshold \( \delta \) for hierarchical clustering. That is, we transfer the knowledge learned from clustering the utterances containing seen intents \( S \), to the utterances containing novel intents. First, we perform hierarchical clustering on the labeled training data utterances \( D_T \), using the seen intents as ground truth cluster labels. We obtain a distance value that maximizes the inter-intent distance between utterance clusters and minimizes the intra-intent distance within a cluster, by maximizing the F1 score of their clustering arrangement. In an ideal scenario, every obtained cluster \( L_i \) represents a single seen intent. We also assume that utterances in the training set \( D_T \) of seen intents, as well as those in the unlabeled corpus \( D_X \) of newly emerging unseen intents come from similar distributions. Our final step is then to transfer this distance threshold \( \delta \) learnt from the seen intent utterances, to hierarchically cluster utterances in \( D_X \) containing novel or unseen intents. The distance threshold \( \delta \) is defined as \( \max_{x \in L_i, x' \in L_j} f(Emb(x), Emb(x')) \) according to complete-linkage hierarchical clustering. Here, function \( f(.) \) quantifies the distance between the embeddings \( Emb(.) \) of an utterance pair \((x, x')\) belonging to clusters \( L_i \) and \( L_j \) respectively.

We now describe how we learn the distance function \( f \) between pairs of utterances.

**Learning Pairwise Utterance Distances for Clustering:** We learn a neural network model to obtain utterance embeddings \( Emb(.) \) for both the labeled corpus of seen intents \( (D_T) \) and the unlabeled utterances detected to have novel intents \( (D_X) \). To train this model (see Figure [15]), we create a training dataset from \( D_T \) comprising pairs of utterances \((x, x')\). Both \( x \) and \( x' \) contain a seen intent. For each \( x \), there are three possible choices for its paired utterance \( x' \): (i) \( x' \) containing the same domain and intent as \( x \), (ii) \( x' \) containing the same domain but different intent than \( x \), and (iii) \( x' \) containing a different domain and intent than \( x \). Thus, \( x' \in \{x^i, x^j, x^k\} \). These utterance pairs \((x, x')\) are fed as input to an EncoderNet, which consists of a BERT transformer block. We use the same learning rate decay strategy of fine-tuning the BERT layers as earlier. Representations \( E(x) \) and \( E(x') \) are learned by the second last BERT layer (Figure [15]). The next layer on top of the EncoderNet blocks uses a distance function \( d \) to compute pairwise representation distances, subject to the following bi-directional constraints: (i) the distance \( d(E(x), E(x^i)) \) between the representations of \( x \) and \( x^i \) should be less than \( d(E(x), E(x^j)) \); (ii) \( d(E(x), E(x^j)) \) between the representations of \( x \) and \( x^j \) should be less than \( d(E(x), E(x^k)) \); and (iii) the distance \( d(E(x), E(x^k)) \) between the representations of \( x \) and \( x^k \) should be less than the distance \( d(E(x), E(x^b)) \). These constraints utilize the semantic relationships between the utterance pairs containing different types of seen domains and seen intents. We then formulate a loss function \( \mathcal{L} \) to train our model, given by:

\[
\frac{1}{M} \sum_{i,j,k} \left\{ \max[0, m_1 + d(E(x), E(x^i)) - d(E(x), E(x^j))] + \alpha \max[0, m_2 + d(E(x), E(x^j)) - d(E(x), E(x^i))] \\
E(x^b)] + \beta \max[0, m_3 + d(E(x), E(x^j)) - d(E(x), E(x^k))] \right\}
\]

where \( m_1, m_2, m_3 \) are predefined margins, \( \alpha \) and \( \beta \) are predefined weighting scalars and \( M \) is the total number of utterance pairs \((x, x')\). We found such a loss formulation to outperform the popular contrastive loss (Hadsell et al., 2006) and triplet loss (Schroff et al., 2015) functions (Tables [3] and [4]). Next, a non-linear activation followed by a linear layer outputs embeddings \( Emb(x) \) and \( Emb(x^p) \) for the pair \((x, x^p)\). Finally, pairwise distances \( f(Emb(x), Emb(x^p)) \) are computed between all utterance pairs in this embedding space, to be given as input to hierarchical clustering. Note that we do not require any intent or domain labels for the unlabeled corpus \( D_X \) containing the unseen (novel) intents.
3.3 Stage III: Linking Related Novel Intents into Novel Domains

After hierarchical clustering, ADVIN discovers a set of novel emerging intents. We now aim to link together mutually related intents sharing the same broad functionality or the same semantic category into domains. Hierarchical clustering already gives us a provision to ‘merge’ together intents at the upper levels of the hierarchy based on distance. However, we find that using the domain labels available for the seen intents in a more direct manner leads to a better grouping of related novel intents into novel domains. We perform the following steps to link intents into domains, to create an intent-domain taxonomy:

(i) We assume that we have information regarding the domain of each seen intent in $S$. Assuming an ideal clustering in Section 3.2, each seen intent cluster $L_i$ will contain utterances belonging to a single seen intent $s_i \in S$. The domain label of cluster $L_i$ would be the domain of intent $s_i$ itself. However, $L_i$ may not be completely pure, i.e. it contains utterances with different seen intent labels. In such cases, we assign the domain label for $L_i$ as the domain of the intent of the majority of the utterances in $L_i$.

(ii) We next obtain a representation $Emb_L(L_i)$ for each seen and novel intent cluster $L_i$, as the average of the embeddings $Emb(x)$ (from Figure 1b) of all utterances $x \in L_i$.

(iii) Finally, we re-use our Knowledge Transfer component to cluster the representations $Emb_L(L_i)$ of the seen intent clusters $L_i$ themselves. This time we use the seen domains as ground truth cluster labels (instead of the seen intents as in Section 3.2). As earlier, we obtain a distance threshold $\delta$ that maximizes the F1 score with respect to the seen domains. We then transfer this threshold to perform hierarchical clustering of the novel (unseen) intent clusters.

Each cluster so obtained contains groups of related novel intents, representing novel domains. Thus, ADVIN creates a taxonomy of novel intents and domains from unlabeled user utterances.

4 Evaluation

4.1 Datasets and Experimental Setup

We test ADVIN on the real-world datasets of SNIPS (Coucke et al., 2018), ATIS (Dahl et al., 1994), Facebook’s task-oriented semantic parsing (FTOP) data (Gupta et al., 2018), and Internal NLU Data$^1$ from a commercial voice assistant. For evaluation on SNIPS, ATIS and the Internal data, we completely remove all utterances associated with certain random sets of intents and domains from the training and validation sets, detailed in Table 1. The FTOP dataset has intent types labeled as ‘unsupported’, so we simply remove all utterances belonging to these intents while training ADVIN. Treating these removed intent and domain categories as novel (unseen), we then assess the efficacy of ADVIN in discovering these intents and domains during the testing phase. ATIS dataset intents are about airline reservations and are relatively similar to each other, while the SNIPS dataset consists of relatively dissimilar intent types. Our empirical configurations therefore holistically exhibit the performance of ADVIN when the novel intents being discovered have varying degrees of similarity with each other (or with the existing ‘seen’ intents).

**Hyperparameters:** We used the English uncased BERT-Base model (Devlin et al., 2018) in all steps of ADVIN. It has 12 transformer layers, 768 hidden states, and 12 self-attention heads. We kept the dropout probability at 0.1 and used the Adam optimizer (Kingma and Ba, 2014) with parameters $\beta_1 = 0.9$ and $\beta_2 = 0.999$. We used slanted triangular learning rates (Howard and Ruder, 2018) for BERT with the base learning rate at $2e^{-5}$, and warm-up proportion at 0.1. We empirically set the batch size to 64, and the number of training epochs to 8 for detecting instances with novel intents, and 15 for discovering the latent intent categories. To learn pairwise distances between utterances for clustering, we set $\alpha = \beta = 1$, and $m_1 = m_2 = m_3 = 0.05$. While discovering novel intent categories (Section 3.2), we used cosine similarity as the function $d(. , \cdot)$ while computing $d(E(x), E(x^p))$, and euclidean distance as the function $f(\cdot, \cdot)$ while computing $f(Emb(x), Emb(x^p))$.

4.2 Baselines and Evaluation Metrics

We designate the first step of our proposed approach of detecting utterances with novel intents as “ADVIN (m-unseen + DOC)”, and compare it with the following state-of-the-art approaches in Table 2:

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$^1$Customer utterances from a voice-powered virtual assistant, whose name we omit for the double-blind review purpose.
Table 1: Evaluating ADVIN on discovering novel intents and domains removed during training

| Dataset | Sets of intents removed from training data for evaluation | # of data samples | Vocab size | Avg. text len. |
|---------|----------------------------------------------------------|-------------------|------------|---------------|
| SNIPS   | Set 1: Weather, Restaurant; Set 2: AddToPlaylist, Ratebook | 13.8K             | 10.9K      | 9.05          |
| ATIS    | Set 1: airline, meal, airfare, day-name, distance; Set 2: flight-time, flight-no, flight, aircraft, ground-service | 5.87K             | 0.87K      | 11.2          |
| FTOP    | Set 1: unsupported, unsupported-event, unsupported-navigation, unintelligible | 44.78K            | 16.69K     | 8.93          |
| Internal | Set 1: Weather, Calendar, Todos; Set 2: Bookings&Reservations, Sports, Local Search, Video, General Media; Set 3: Recipe, Music, Shopping, Communication | 3.16M             | 26.7K      | 3.72          |
| NLU     | Set 1: Weather, Calendar, Todos; Set 2: Bookings&Reservations, Sports, Local Search, Video, General Media; Set 3: Recipe, Music, Shopping, Communication; Set 4: Global, Knowledge | 3.16M             | 26.7K      | 3.72          |

Table 2: F1-score of various approaches for detecting if an utterance contains a novel intent or not.

| Approach | SNIPS | ATIS | FTOP | Internal Dataset |
|----------|-------|------|------|------------------|
| DOC (Shu et al., 2017) | 0.73 | 0.69 | 0.71 | 0.76 |
| IntentCapsNet (Xia et al., 2018) | 0.81 | 0.77 | 0.75 | 0.8 |
| LOF-LMCL (Lin and Xu, 2019) | 0.79 | 0.73 | 0.68 | 0.74 |
| ADVIN (1-unseen) | 0.76 | 0.73 | 0.68 | 0.72 |
| ADVIN (1-unseen+DOC) | 0.85 | 0.81 | 0.73 | 0.8 |
| ADVIN (m-unseen) | 0.78 | 0.75 | 0.75 | 0.8 |
| ADVIN (m-unseen+DOC) | 0.9 | 0.87 | 0.78 | 0.84 |

(i) **DOC** (Shu et al., 2017): uses a CNN with a 1-vs-rest sigmoid layer on top. It tightens the sigmoid decision boundary by learning class-specific confidence thresholds to detect novel intents.

(ii) **IntentCapsNet** (Xia et al., 2018): uses capsule neural networks in a zero shot setting to discover newly emerging intents.

(iii) **LOF-LMCL** (Lin and Xu, 2019): uses local outlier detection on top of a Bi-LSTM trained with a large margin cosine loss to classify seen and unseen intents.

(iv) **ADVIN (1-unseen)/ADVIN (1-unseen + DOC)**: variants of ADVIN using an $(S+1)$-class classification model (Section 3.1), with and without the additional check per the DOC heuristic.

(v) **ADVIN (m-unseen)**: ADVIN’s $(S+1)$-th class split into $m$ novel classes, without the DOC heuristic.

The first stage of discovering utterances with novel intents (Section 3.1) is evaluated using the standard F1-score metric. For evaluating the next two stages of discovering the actual intent categories in the user utterances and linking the newly discovered intents into domains (Sections 3.2 and 3.3), we designate our proposed method as “ADVIN (pair+hier)”, i.e. using distances between embeddings learned via our pairwise margin loss function as input to hierarchical clustering. As per our knowledge, work in the literature only detects if text utterances contain novel intents or not, and does not identify the actual, latent intent categories in unlabeled text. Therefore, we compare ADVIN with its own variant baselines:

(i) **ADVIN (clf+hier)**: uses the representation learned by the 2nd to last BERT layer of our classification model in Figure 1a as input to hierarchical clustering.

(ii) **ADVIN (triplet+hier)**: uses embeddings learned by a triplet network (Schroff et al., 2015) as input to hierarchical clustering. The inputs to the network are utterance triplets $(x, x^-, x^+)$. $x$ and $x^+$ contain the same domain and intent, and different domain and intent as utterance $x$ respectively.

(iii) **ADVIN (ProdLDA)**: uses a neural topic modeling method ProdLDA (Srivastava and Sutton, 2017) to discover novel intent categories, instead of clustering. ProdLDA requires the number of topics as input, so we give it the number of clusters output by “ADVIN (pair+hier)”.

(iv) **ADVIN (pair+RCC)**: uses embeddings learned via our pairwise loss function as input to the Robust Continuous Clustering algorithm (RCC) (Shah and Koltun, 2017), instead of hierarchical clustering.

Ground truth intent and domain labels are available for the various experimental data Sets we used for evaluation (Table 1). We thus use the following standard clustering metrics to evaluate the novel intents and domains discovered: (i) Comparing the number of discovered intents and domains to the ground
Table 3: Discovering the latent intent types for utterances with novel intents. ‘#int.’ shows the number of discovered intents, ‘GT’ denotes the true number of intents, and ‘Pur.’ denotes cluster purity.

| Approach          | SNIPS Set 1 (GT = 2) | SNIPS Set 2 (GT = 2) | FTOP Set 1 (GT = 4) |
|-------------------|----------------------|----------------------|---------------------|
|                   | #int. | NMI | Pur. | F1   | #int. | NMI | Pur. | F1   | #int. | NMI | Pur. | F1   |
| ADVIN (clf+hier)  | 3     | 0.78 | 0.9  | 0.76 | 3     | 0.7 | 0.8  | 0.69 | 24    | 0.4 | 0.56 | 0.38 |
| ADVIN (triplet+hier) | 4     | 0.71 | 0.81 | 0.69 | 5     | 0.65 | 0.76 | 0.66 | 48    | 0.36 | 0.51 | 0.35 |
| ADVIN (ProdLDA)   | NA    | 0.71 | 0.84 | 0.72 | NA    | 0.66 | 0.79 | 0.68 | NA    | 0.42 | 0.53 | 0.38 |
| ADVIN (pair+RCC)  | 3     | 0.79 | 0.9  | 0.77 | 3     | 0.7 | 0.8  | 0.7  | 30    | 0.5 | 0.63 | 0.41 |
| ADVIN (pair+hier) | 3     | 0.8  | 0.92 | 0.78 | 3     | 0.72 | 0.83 | 0.71 | 19    | 0.46 | 0.61 | 0.51 |

Table 4: Discovering the actual, latent novel intents and novel domains of input utterances. For Internal Data Sets 1 and 2, the first two columns show the number of new intents (#int.) and new domains (#dom.) discovered respectively. ‘GT (d, i)’ denotes the true number of domains d and intents i.

| Approach          | Internal Data Set 1 (GT = 3, 22) | Internal Data Set 2 (GT = 5, 53) |
|-------------------|-----------------------------------|-----------------------------------|
|                   | # int. | # dom. | NMI | Pur. | F1 | # int. | # dom. | NMI | Pur. | F1 |
| ADVIN (clf+hier)  | 108    | 35     | 0.53 | 0.69 | 0.48 | 178    | 71     | 0.41 | 0.64 | 0.36 |
| ADVIN (triplet+hier) | 206   | 51     | 0.52 | 0.63 | 0.41 | 205    | 65     | 0.33 | 0.61 | 0.31 |
| ADVIN (ProdLDA)   | NA    | NA     | 0.56 | 0.7  | 0.55 | NA     | NA     | 0.4  | 0.69 | 0.42 |
| ADVIN (pair+RCC)  | 91    | 40     | 0.55 | 0.73 | 0.52 | 188    | 57     | 0.5  | 0.74 | 0.5  |
| ADVIN (pair+hier) | 74    | 29     | 0.6  | 0.75 | 0.6  | 167    | 36     | 0.57 | 0.75 | 0.55 |

4.3 Results

Baseline Comparison: Table 2 shows the F1-score of various approaches, on classifying an intent as novel or not on different datasets with different dataset configurations. We observe that our approach using an (S + m)-class classifier during training and the DOC heuristic, “ADVIN (m-unseen+DOC)”, outperforms all baselines on all datasets by at least 6% F1 score points. ADVIN also outperforms the zero shot IntentCapsNet model (that uses relevant information available beforehand about the new test intents to be discovered), without using any prior knowledge about the novel intents or domains.

Tables 3 and 4 show the performance of different approaches in discovering intent categories for the utterances containing novel intents as predicted in Table 2. We observe that our proposed approach “(ADVIN + pair+hier)” using distances learned via our pairwise loss training method along with hierarchical clustering outperforms the rest of the baselines. The learned intent-clusters have a purity value more than 80% for the SNIPS dataset. Purity decreases to 61% for FTOP, primarily because semantically diverse utterances have been given the same ground truth intent label of ‘unsupported’ or ‘unsupported-event’. The ‘NA’ value for “ADVIN (ProdLDA)” in the column ‘# int.’ denotes that the ProdLDA algorithm by design does not output the number of new intents discovered. It takes this as input in the form of the number of topics. We observe similar empirical trends as above on ATIS Sets 1 and 2, and Internal NLU Data Sets 3 and 4. In the interests of space, we do not present these results.

Our technique discovers 1.5-4.5 times more novel intents than present in the ground truth, as seen from the ‘# int.’ columns in Tables 3 and 4. To investigate this further, we use t-SNE [Maaten and Hinton, 2008] to visualize the embeddings learned by training our proposed ADVIN method, for the utterances belonging to the ‘unsupported’ intent category of the FTOP dataset. In Figure ??, each color represents a different novel intent category discovered. We also show the most frequent utterance words present in each newly emergent intent. We observe that ‘Unsupported’ has been split up by ADVIN into 7 finer-grained, semantically sensible novel intents. For instance, the utterances “What city has the
snow sleds, ice skating, rink
art, museum, event, sunday
movie, theater, tickets, mall
thanksgiving, christmas, family dinner
brunch, restaurant, pizza, food truck, menu
birthday, party, reunion, wedding, christening, graduation
nightclub, concert, game, friday, saturday

Figure 2: (a) Visualizing embeddings learned by ADVIN for novel intents discovered within the ‘unsupported’ FTOP category. The figure also shows the varying F1 score averaged across (b) number of OOD intent classes and (c) number of labeled OOD instances, given as training data for Stage I.

Table 5: Evaluating ADVIN’s prediction of utterance pairs containing the same novel intent or not. Columns show F1 scores w.r.t using (i) user study and (ii) dataset-provided annotations as ground truth.

| Approach            | FTOP: F1 user study(F1 Dataset) | Internal: F1 user study(F1 Dataset) |
|---------------------|---------------------------------|-------------------------------------|
| ADVIN (clf+hier)    | 0.66 (0.6)                      | 0.6 (0.68)                          |
| ADVIN (triplet+hier)| 0.6 (0.57)                      | 0.55 (0.61)                         |
| ADVIN (ProdLDA)     | 0.65 (0.56)                     | 0.54 (0.61)                         |
| ADVIN (pair+RCC)    | 0.64 (0.6)                      | 0.56 (0.64)                         |
| ADVIN (pair+hier)   | 0.7 (0.61)                      | 0.61 (0.71)                         |

most traffic in the US” and “Family friendly bars near me”, from the ‘unsupported’ intent category, have been separated by ADVIN into different intent categories. Figure ?? also explains the lower performance values in Table 3 for the FTOP dataset. We thus find that ADVIN largely learns semantically appropriate, discriminative representations for the newly emerging intents (also echoed by our user study in Table 5).

Effect of OOD training data: We analyze the effect of the labeled OOD instances given as training input to Stage I (detecting utterances with novel intents) of ADVIN. Figures 2b and ?? show that the performances of both Stage I (Section 3.1) and II (Section 3.2) of ADVIN improve with increase in the number of (i) OOD intent classes, and (ii) OOD training data examples; up to a particular threshold ‘m’ for the Internal NLU Data Set I. Increasing ‘m’ beyond this value leads to a performance drop. We also observe that the presence of finer-grained labeled utterances (e.g. the intent labels of ATIS) in the OOD data has a higher performance impact, than the coarser-grained intent labels (e.g. FTOP intents). We find similar trends for the other datasets also, but do not present them due to space constraints.

Linking Intents to form Domains: There is no domain information available for the SNIPS, ATIS and FTOP data. Hence, we only evaluate the performance of linking intents into domains on the Internal dataset. The column of ‘# dom.’ in Table 4 for Internal Data Sets 1 and 2 shows the number of newly discovered domains by ADVIN after linking mutually related newly discovered intents. As earlier, ADVIN obtains a finer-grained grouping of novel intents into novel domains. It finds 2-3 times more number of domains than the dataset annotations. On further inspection, we found that the domains for the Internal datasets have been created by collating intents satisfying common business goals or customer needs, and are less geared towards semantics. Contrarily, ADVIN focuses on the semantic meaning of the utterances and performs a more fine-grained categorization of newly emerging intents into domains. This leads to
Table 6: ADVIN discovering new intent categories for unlabeled utterances with novel intents, using limited supervision as pairwise constraints. Parentheses show original results without using supervision.

| Dataset             | # intents | NMI   | Purity | F1 score  |
|---------------------|-----------|-------|--------|-----------|
| SNIPS Set 1         | 2 (3)     | 0.82 (0.8) | 0.94 (0.92) | 0.85 (0.78) |
| ATIS Set 1          | 12 (13)   | 0.74 (0.72) | 0.77 (0.73) | 0.75 (0.72) |
| FTOP Set 1          | 17 (19)   | 0.5 (0.46)  | 0.64 (0.61)  | 0.54 (0.51)  |
| Internal Data Set 1 | 45 (56)   | 0.65 (0.61) | 0.75 (0.71) | 0.65 (0.62) |
| Internal Data Set 2 | 82 (92)   | 0.58 (0.54) | 0.7 (0.69)   | 0.61 (0.58)  |

a slight discord between the domains uncovered by ADVIN, and the domain annotations in the dataset. Such an over estimation of the number of novel intents or domains is often acceptable in a practical setting, since the granularity of domains and intents learned by ADVIN can be easily ‘coarsened’ by merging together certain novel intents or domains, based on downstream requirements. One way to do this is by soliciting human feedback (see Table 6).

User Study: To compare the intent and/or domain labels provided with the datasets and human perception of novel intents and domains while evaluating ADVIN, we conduct a user study on the FTOP and Internal datasets. We recruit crowd workers on Amazon Mechanical Turk for the FTOP data and employees familiar with the Internal Dataset for this purpose. We provide a set of random utterance pairs predicted as having novel intents to the annotators, and ask them to indicate whether the pair is likely to belong to the same intent category or not. For both datasets we compute the F1-score in Table 5, by comparing the output of ADVIN with that of the human annotators, for 2500 FTOP utterance pairs (inter-annotator agreement Cohen’s $\kappa = 0.78$) and 1100 Internal dataset utterance pairs (Cohen’s $\kappa = 0.9$). We observe that ‘ADVIN (pair+hier)’ trained with the pairwise margin loss and hierarchical clustering significantly outperforms all baselines by at least 5% on both datasets with respect to human evaluation.

Introducing Limited Supervision: There is often some partial supervision or background knowledge already known to humans or provided by domain experts, regarding the unlabeled user utterances. Utilizing this can enhance the quality of the novel intents and domains discovered by ADVIN. Therefore, we test ADVIN in a semi-supervised setting, instead of the unsupervised hierarchical clustering, where we provide limited prior knowledge in the form of two types of pairwise constraints: (i) must-link, for the utterances that must belong to the same novel intent category, and (ii) cannot-link, for the utterances that cannot contain the same novel intent. We incorporate the constraints during hierarchical clustering by modifying the learned distance values between the utterance pairs. We show in Table 6 the performance of ADVIN, while randomly selecting 3 groups of 4 utterances each for the must-link and cannot-link constraints. Thus, supervision is provided for < 25 utterances. We observe a 2-8% gain across various metrics and datasets. This experiment demonstrates that ADVIN can be easily extended to a semi-supervised setting, and minimal supervision if available, can significantly improve the quality of the discovered intents and domains over an unsupervised setting.

5 Conclusion

We propose a novel and flexible multi-stage framework, ADVIN, to discover newly emerging, unknown intents and domains in large volumes of unlabeled text data. We first identify all input utterances likely to contain a novel intent. We next develop a network that learns discriminative deep features by maximizing inter-intent variance and minimize intra-intent variance between utterance pairs. We then transfer knowledge learned from intents seen during training to the unlabeled data containing novel intents. Finally, we hierarchically link mutually related intents into domains, to obtain a taxonomy of newly discovered intents and domains. We extensively evaluate ADVIN on three public benchmark datasets and real user utterances from a commercial dialog agent, and achieve state-of-the-art results across various empirical configurations. In future, we plan to (i) extend our proposed framework to handle input utterances consisting of multiple intents and/or domains per utterance; and (ii) use additional knowledge to better
model human-perceived latent intents and domains.

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