Open-domain Topic Identification of Out-of-domain Utterances using Wikipedia

Alexandry Augustin* University of Southampton Southampton, UK aa7e14@soton.ac.uk Alexandros Papangelis* Amazon Alexa AI Sunnyvale, USA papangea@amazon.com

Margarita Kotti Toshiba Research Europe Cambridge, UK margarita.kotti@crl.toshiba.co.uk

Pavlos Vougiouklis[†] Huawei Technologies Edinburgh, UK pavlos.vougiouklis©huawei.com Jonathon Hare University of Southampton Southampton, UK jsh2@ecs.soton.ac.uk

Norbert Braunschweiler Toshiba Europe Limited Cambridge, UK norbert.braunschweiler@crl.toshiba.co.uk

Abstract

Users of spoken dialogue systems (SDS) expect high quality interactions across a wide range of diverse topics. However, the implementation of SDS capable of responding to every conceivable user utterance in an informative way is a challenging problem. Multi-domain SDS must necessarily identify and deal with out-of-domain (OOD) utterances to generate appropriate responses as users do not always know in advance what domains the SDS can handle. To address this problem, we extend the current state-of-the-art in multi-domain SDS by estimating the topic of OOD utterances using external knowledge representation from Wikipedia. Experimental results on real human-to-human dialogues showed that our approach does not degrade domain prediction performance when compared to the base model. But more significantly, our joint training achieves more accurate predictions of the nearest Wikipedia article by up to about 30% when compared to the benchmarks.

1 Introduction

Human-to-human dialogues are often composed of multiple sub-dialogues bridging a wide range of *topics*. In contrast, multi-domain spoken dialogue systems (SDS) are often designed to operate over a limited and static set of predefined topics called *domains* (e.g. hotel or restaurant booking) to improve on performance [26]. The limited domain coverage in multi-domain SDS has proven to

^{*}Work done while working at Toshiba Research Europe.

[†]Work done while working at University of Southampton.

be a challenge for inexperienced users as they do not necessarily know in advance what domains the SDS is able to handle efficiently. Such users may attempt to formulate utterances that cannot be handled by the SDS. These are referred to as out-of-domain (OOD) utterances. To illustrate the ubiquity of OOD, around 13% of utterances in the TourSG dataset used in the fourth edition of the Dialogue State Tracking Challenge³ (DSTC4) were OOD. For this reason, graceful handling of OOD utterances is crucial to provide robustness to SDS against unexpected user inputs while providing helpful responses.

A number of fallback strategies have been employed to generate responses to OOD utterances. They range from very simplistic answers such as "I do not understand. Could you please rephrase?" [38], to more sophisticated chatbots that generate responses to hold the users' attention [34, 9]. These approaches however do not always provide informative answers to the users. Some efforts have been devoted towards integrating large knowledge graphs to allow users more freedom in expressing their intents [35]. Other efforts have focused on leveraging large amount of unstructured data to extract answers (e.g. sentences or phrases), or to synthesise new answers [29]. In all of these scenarios, the identification of open-domain topics can be leveraged to provide informative responses to OOD utterances [19]. For example, access to the knowledge graph can be restricted only to areas relevant to the open-domain topic [41]. Similarly, keywords or keyphrases can be extracted from unstructured documents and used as answers based on the open-domain topic [12]. Finally, answers can be synthesised from entire or sections of documents which are topically relevant [32, 24].

Now, a growing body of research explores the use of topics to enable informative responses to OOD utterances in SDS [25, 3, 41, 18, 26, 23]. A simple way to identify such topics is to use approaches based on word [38] or phrase [6] matching. Alternatively, probabilistic topic modelling [5] offers another powerful, albeit more complex, strategy to identify open-domain topics [13, 19]. These methods however do not usually take advantage of the time-dependence between utterances in the dialogue history to improve on topic identification. Since utterances are often short (e.g. "thank you" or "yes"), one should account for long-term dependencies between utterances to provide context. Furthermore, topic models provide no guarantee that the topics inferred will be interpretable to humans [8]. This is particularly true when faced with short utterances as large amounts of data is required for these models to be accurate. Approaches based on recurrent architectures [15] have been proposed [20] to account for the time-dependency between utterances. In particular Kim et al. [20] used an LRCN-based approach [11, 17] to classify the domain of each utterance accounting for the dialogue history up to that particular utterance. The Kim et al. [20] method however only classify the domain and do not reveal new information on OOD utterances.

Against this background, we argue that a key research direction to enable informative responses to OOD utterances in SDS is the joint identification and tracking of both the domain and topic of each utterance to ensure robustness and accuracy in a wide range of dialogue settings [16]. In particular, when utterances fall into domains that the SDS can handle, they are dealt with efficiently. On the other hand, when utterances are OOD, an informative answer is still provided based on the topic identified. As such, we extend Kim et al. [20] to support open-domain topic tracking. We fit the model to real world human-to-human dialogues which have been manually labelled with the domain of each utterance and automatically labelled with the most relevant topic. Our method is based on the assumption that external encyclopedic knowledge from Wikipedia can be used to identify relevant topics for any given utterance. This assumption is common and has been employed in a number of prior related works [39, 37, 2, 7, 4]. Since Wikipedia is constructed and maintained collaboratively by a large number of volunteers, it provides huge amounts of encyclopedic knowledge. This enables the construction of a shared semantic space in which new and unseen utterances are mapped to the closest article in terms of semantic similarity.

In more detail, we make the following contributions to the state-of-art: (i) we define a new model that jointly learns, for the first time, both the domain and topic of each utterance, (ii) we empirically show that our approach generates comparable performance when identifying the domains when compared to the Kim et al. [20] model, and achieves up to about 30% improvement in accuracy against the benchmarks when predicting the topics, (iii) we show that the exclusion of previous utterances when training leads to suboptimal performance.

³http://www.colips.org/workshop/dstc4/

The remainder of this paper is organised as follows. We first introduce the Kim et al. [20] model in Section 2. We then detail our extension in Section 3. In Section 4, we present the results of our experimental evaluation. We conclude in Section 5.

2 Preliminaries

The Kim et al. [20] model takes as input an utterance and performs a classification of its domain accounting for the dialogue history up to that particular utterance. In more detail, the architecture is based on a long recurrent convolutional neural network (LRCN) [11, 17, 40], that is, a composition of a CNN [28] and an LSTM [15] (Figure 1). While CNN computes a fixed-size feature vector for each utterance, the LSTM captures the dependency in time between the feature vectors. More precisely, let $\mathcal{D} = \{(\mathbf{u}_t, \mathbf{x}_t) : 0 \leq t \leq |\mathcal{D}|\}$ be a dataset of utterance and domain pairs. The model takes as input an utterance $\mathbf{u}_t \in \mathbb{N}^N$ at time t where N is the number of words in the utterance. Each element of \mathbf{u}_t contains the index of a word in the vocabulary. An embedding layer [33] then map each discrete index to a continuous embedding vector resulting in a matrix $\mathbf{U}_t \in \mathbb{R}^{N \times K}$ where K is the embedding size. The embedding layer is shared across timesteps such that a given word contributes changes during training to the same embedding regardless of the timestep at which it appears. Furthermore, the word embeddings [33] to speed up the training [20]. The CNN used is based on the architecture proposed by Kim et al. [21] and takes as input the utterance \mathbf{U}_t . It performs a convolution over \mathbf{U}_t by sliding a set of filters of given height M and fixed width K (the same as width as the input) over the rows of \mathbf{U}_t . Each filter is applied to \mathbf{U}_t to generate a feature map \mathbf{v}_t . Each feature element $\mathbf{v}_{t,i}$ of a feature map is generated from a subregion $\mathbf{U}_{t,i:i+M-1} = \{U_{t,k} : \text{ for } i \leq k \leq i + M - 1\}$ of the input utterance from the *i*-th to the (i + M - 1)-th row such that

$$\mathbf{v}_{t,i} = f\left(\mathbf{W}\mathbf{U}_{t,i:i+M-1} + \mathbf{b}\right)$$

where f an activation function (e.g. ReLU or sigmoid). The weights $\mathbf{W} \in \mathbb{R}^{M \times K}$ and biases $\mathbf{b} \in \mathbb{R}^M$ of each filter are shared for all i. To capture the salient feature of each feature map, a global max-pooling is applied resulting in a scalar $m_t = \max(\mathbf{v}_t)$ for each filter. Since utterances at different time steps are likely to be of different lengths, global max-pooling is particularly suited as it guarantees that the output of the CNN will always stay the same regardless of the input size. The resulting scalar from the global max-pooling of each filter are then concatenated into a single feature vector \mathbf{m}_t . In turn, the utterance feature vector \mathbf{m}_t is presented as input to an LSTM which captures the dependency in time between the utterances via a hidden state vector $\mathbf{h}_t \in \mathbb{R}^H$ and a cell state vector $\mathbf{c}_t \in \mathbb{R}^H$. The hidden state \mathbf{h}_t of the LSTM is then presented to a dropout layer [14] to improve on training performance and generalisation. Finally, a feedforward layer is added to compute the domain classification scores over the D domains. These scores are then fed into a softmax layer that produces the predictive distributions over the domain such that

$$\mathbf{x}_t = \operatorname{softmax} \left(\mathbf{W}_{xh} \mathbf{h}_t + \mathbf{b}_x \right)$$

with weights $\mathbf{W}_{xh} \in \mathbb{R}^{D \times H}$ and bias $\mathbf{b}_x \in \mathbb{R}^D$. The output of the model at time t is the domain distribution \mathbf{x}_t associated with the current utterance \mathbf{u}_t . The model is trained using stochastic gradient descent in a supervised learning fashion, using a cross-entropy loss function between the ground truth domain $\hat{\mathbf{x}}_t$ (i.e. a one-hot vector) and the predicted domain distribution \mathbf{x}_t at each time-step t

$$H_{\theta_x} = -\sum_i \mathbf{x}_{t,i} \log \hat{\mathbf{x}}_{t,i} \tag{1}$$

where θ_x is the set of all weights and biases prior to \mathbf{x}_t . The benefit of this combined architecture is its ability to be trained end-to-end. That is, the CNN learns the input features that are relevant for the sequence labelling. However, such a model doesn't address open-domain topic tracking as is, due to the inherent limitation of classifying utterances into domains that have to be known a priori.

3 Joint Tracking

Our proposed model extends the one presented in the previous section to deal with settings where utterances are assigned to both domains and topics. To do so, in addition to learning the domain of each utterance, we also learn a continuous mapping of similarity between utterances and Wikipedia



Figure 1: LRCN architecture combining a CNN and an RNN for utterance classification and regression. During training, the model takes as input a set of utterances and outputs a domain and a topic embedding.

articles⁴ under a common semantic space. Specifically, our method consists of two main steps. In the first step, we automatically build a training set of utterance and Wikipedia article pairs. This is done offline prior to training our model. In the second step, we extend the structure of Kim et al. [20] to interpolate the mapping identified in the previous step to new and unseen utterances, taking into account the dialogue history up to that utterance.

More specifically, in the first step, we rank the most relevant Wikipedia articles to each training utterance. To perform the ranking, we use the term frequency inverse document frequency (TF-IDF) algorithm [31]. TF-IDF is a prevailing technique in information retrieval and suited to our setting for its simplicity given the large amount of Wikipedia articles considered. Words in an utterance with a high TF-IDF score imply a strong relationship with the Wikipedia article they appear in. Furthermore, independently of the ranking, we compute a document embedding for each Wikipedia article using the doc2vec algorithm [27]. Since doc2vec is applicable to texts of any length (although longer semantic units yield more accurate vectors), it can readily be used to compute the embeddings of the Wikipedia articles in our setting (hereafter referred to as *topic embeddings*). Let d_i be the topic embedding of the *i*-th article in the Wikipedia dataset \mathcal{D}_W computed from the doc2vec algorithm. The objective of doc2vec is to minimise the cross-entropy loss when predicting the missing word $w_{i,j}$ for all words *j* in each article $i \in \mathcal{D}_W$, that is minimising

$$-\log p(w_{i,j}|\cdots,w_{i,j-1},w_{i,j+1},\cdots,d_i).$$

The topic embeddings d_i are computed once, separately of our model. Now that we have both a ranking of Wikipedia articles per utterance, and a topic embedding for each article, we can associate a training target for each utterance in the training set. Each training target for an utterance consists of the topic embedding of the top matching article or the average top-k topic embeddings.

In the second step, we extend the Kim et al. [20] model to account for open-domain topics by performing a regression on the known target topic embeddings. This is achieved by using a fully connected feedforward layer linked to the output of the LSTM

$$\mathbf{y}_t = \mathbf{W}_{yh}\mathbf{h}_t + \mathbf{b}_y$$

with weights $\mathbf{W}_{yh} \in \mathbb{R}^{K \times H}$ and bias $\mathbf{b}_y \in \mathbb{R}^K$. Its role is to learn a mapping between the output of the LSTM and the target topic embeddings. In particular, the model learns to embed each utterance into the semantic space consisting of the topic embeddings constructed by the doc2vec algorithm (Figure 2). In such a semantic space, a continuous similarity measure (e.g. Euclidean distance or

⁴en.wikipedia.org



Figure 2: Illustration of a two-dimensional semantic space with associated convex Hull (shaded area) of the topic embeddings.

cosine similarity) is used to compute the distance between each utterance embedding and the closest topic embedding. When performing inference on unseen utterances, the solution lies within the convex Hull formed by topic embeddings in the training set (Figure 2). Given the set of all topic embeddings $S = \{d_i : \text{ for all } i \text{ in } |\mathcal{D}_W|\}$, the convex Hull is the intersection of all convex sets in S

$$C = \left\{ \sum_{j} \lambda_j d_j : \lambda_j \ge 0 \text{ for all } j \text{ and } \sum_{j} \lambda_j = 1 \right\}$$

Therefore, the extent of the training data defines the solution space for the topic embeddings.

To train the model, we first concatenate all the dialogue sessions with each other, and then slide a context window of length H across a fixed number of utterances. In other word, the input of the model at each timestep t consists of the set of utterances $U_{t-H:t}$ for $t \in \{1, \dots, |\mathcal{D}|\}$. This prevents the model's complexity (i.e. its number of parameters) being dependent on the shape of the dataset, and in particular to the maximum length of the sessions which may be large. We assess the loss using a squared error objective function between the predicted topic embedding \mathbf{y}_t and the ground truth topic target $\hat{\mathbf{y}}_t$

$$SE_{\theta_u} = ||\mathbf{y}_t - \hat{\mathbf{y}}_t||^2 \tag{2}$$

where θ_y is the set of all weights and biases prior to \mathbf{y}_t . The model is jointly optimised end-to-end using a multi-objective learning function, encompassing errors not only from the topic classification, but also errors from topic regression

$$\underset{\theta_x,\theta_y}{\arg\min \lambda_x H_{\theta_x} + \lambda_y SE_{\theta_y}} \tag{3}$$

where H_{θ_x} is given by Equation 1, SE_{θ_y} by Equation 2, and the weights $\lambda_x, \lambda_y \in \mathbb{R}$.

4 Experimental Evaluation

In this section we report our performance results on both domain and topic identification.

4.1 Dataset

Our experiments use a total of two datasets.

TourSG. This corpus (released as part of the DSTC4⁵ competition) is composed of 35 manually transcribed dialogue sessions between tour guides and tourists in Singapore. Each of the 31,034 utterances has been annotated with one of nine domains: ATTRACTION (39.2%), TRANSPORTA-TION (13%), OTHER (12.7%), FOOD (12.4%), ACCOMMODATION (11.3%), SHOPPING (5.7%), ITINERARY (2.3%), CLOSING (1.7%) and OPENING (1.6%). The dataset has a vocabulary size of

⁵http://www.colips.org/workshop/dstc4/

	Domain			Topic		
Utterance	Speaker	Actual	Predicted	Actual	Predicted	
Hi, good morning-	Guide	OPENING	OPENING	Hi convoys	Hi convoys	
#uh good afternoon.	Guide	OPENING	OPENING	Afternoon (disambiguation)	Phyllomacromia aureozona	
This is #uh tour guide one.	Guide	OPENING	OPENING	List of events at the Jacksonville	List of events at the Jacksonville	
				Coliseum	Coliseum	
Lynnette here.	Guide	OPENING	OPENING	Violin Concerto (Bernard Tan)	Udpura	
Yah.	Tourist	OPENING	FOOD	South Sea Tales (London	South Sea Tales (London	
				collection)	collection)	
Hi Lynnette this is participant	Tourist	OPENING	OPENING	Hi convoys	Bukit Nanas Monorail station	
number eleven.						
And can I have your name please?	Guide	OPENING	OPENING	Please	Phyllomacromia aureozona	
Yah.	Tourist	OPENING	SHOPPING	South Sea Tales (London	South Sea Tales (London	
				collection)	collection)	
Yah, this is participant number	Tourist	OPENING	ITINERARY	South Sea Tales (London	List of flag bearers for Singapore at	
eleven.				collection)	the Olym	
Okay, and how can I help you?	Guide	OPENING	OPENING	Okay (disambiguation)	Okay (disambiguation)	
Yah I'm planning to have #um- to	Tourist	ITINERARY	ITINERARY	South Sea Tales (London Uruguay (disambiguation)		
go around Asi				collection)		
And what attractions can I go in	Tourist	ATTRACTION	ATTRACTION	Outline of Singapore	Outline of Singapore	
Singapore?						
Okay.	Guide	ATTRACTION	ATTRACTION	Okay (disambiguation)	Okay (disambiguation)	
#Uh which part of the year are you	Guide	ITINERARY	FOOD	Planning cultures	European countries by electricity	
planning to					consumption	
#Um maybe this #um last week of	Tourist	ITINERARY	ITINERARY	Maybe	Stranger Things (disambiguation)	
May.						
This year.	Tourist	ITINERARY	OPENING	List of communes in Puerto Rico	1904 Philadelphia Phillies season	
Okay.	Guide	ITINERARY	ATTRACTION	Okay (disambiguation)	Okay (disambiguation)	

Table 1: Predictions from the jointly trained LRCN on a randomly selected dialogue session in the test set of the TourSG dataset.

6,035 words. The average length of an utterance is 9.25 ± 8.01 words, and the average length of a session is 887 ± 185 utterances.

Wikipedia. The pre-processing of our training data requires the Wikipedia dataset⁶. The dataset is composed of 4.5 million articles of the English Wikipedia, and has a vocabulary size of 2 million words. No other information from the dataset was used other than the title and the raw text content of each article.

4.2 Performance Metrics

The performance in identifying both domains and topics are assessed using standard multi-class classification measures. In particular, to identify the topics, we assess the models at recovering the Wikipedia articles identified by TF-IDF. That is, for each utterance in the test set we first compute its embeddings, and then we use the Euclidean distance to identify the nearest neighbouring topic embeddings from the Wikipedia articles. We label the learned embeddings as correctly classified if the nearest topic embedding matches with the one identified by TF-IDF, otherwise they are labelled as an incorrect classification.

4.3 Benchmarks

We compare performance against each component of our proposed architecture. The strength of each benchmark lies in the potential inclusion of the dialogue history and the mechanism by which the utterance features are calculated.

CNN. This benchmark does not take into account the dialogue history. It first computes the utterance features, and then performs classification and/or regression using a feedforward layer followed by a softmax layer for the classification, and a feedforward layer alone for the regression.

LSTM. This benchmark takes into account temporal dependencies between utterances. However, instead of taking as input the utterance features computed from the CNN, it uses pre-trained embeddings from the doc2vec algorithm.

Random. This benchmark assigns to each utterance a domain and a Wikipedia article at random with equal probabilities.

⁶https://en.wikipedia.org/wiki/Main_Page

Each benchmark is trained in three different configurations: domain classification only (D), topic regression only (T), and both⁷ (D+T).

4.4 Experimental Setting

To ensure generalisation and avoid a dependence of our model's parameters to the structure of the training dataset, we concatenate the 35 dialogues sessions of the TourSG dataset into a single contiguous sequence of 31,034 utterances. This enables us to use a context window of fixed size irrespective of the number and length of each dialogue session. For this reason, our approach is applicable to any dialogue dataset, provided a topic and a topic class are assigned to each utterance. It is worth noting that by concatenating the TourSG dataset, the context window will intermittently overlap with opening and closing utterances from adjacent dialogue sessions at training time. Although this consequence represents a small fraction of the training data, it may impact prediction performance of the opening and closing utterances at test time. One approach would be to pad each dialogue sessions by a small but fixed amount (depending of the context window's size) of missing values (i.e. NULL) prior to concatenation. For example, a context window of 10 utterances would require a padding of 9 missing values between each dialogue session.

As such, we unroll the LSTM for 20 timesteps which is a reasonable range for recurrent architectures to perform well [1]. We train the models in a supervised setting and divide our collection of 31,034 contiguous utterances into training (60%, i.e. 18,620 utterances), validation (20%, i.e. 6,207 utterances), and test sets (20%, i.e. 6,207 utterances). We further set the hidden state size of the LSTM to 300, the embedding size to 200, and the batch size to 5 utterances. We use 64 filters of height 1 and stride 1, with global max-pooling for the CNN. The CNN and LRCN are initialised with pre-trained GloVe⁸ word embeddings for faster convergence. We use the implementation of the doc2vec algorithm provided by the Gensim⁹ library to compute the pre-trained topic embeddings and utterance embeddings for the LSTM benchmark. Furthermore, we make use of PV-DM variant of the doc2vec algorithm as it has been shown to consistently perform better than PV-DBOW [27]. We exclude Wikipedia articles of less than 50 words due to the limitations of doc2vec with short-length documents [10]. We use the Gensim's implementation of the TF-IDF algorithm to map the utterances to the Wikipedia articles. After this mapping, we are left with 4,409 unique Wikipedia articles out of the 4.5 million initial candidates. We use the topic embedding of the top matching Wikipedia article (k = 1) as training target for each utterance. Finally, we set the dropout probability to 80%, and elect the Adam optimiser [22] with a learning rate to 0.001.

4.5 Results

Table 2 compares the performance of our model and the benchmarks when trained in the three different configurations: domain classification only, topic regression only, and both. We first observe that all models outperform the random benchmark by up to 20%. In particular, we observe that the challenge of predicting the correct Wikipedia article is so significant that the random benchmark is unable to recover any articles at all, achieving an accuracy, recall and precision of zero. Such a task is in effect equivalent to performing a multi-class classification with about four thousand alternatives (i.e. the number of unique Wikipedia articles in the training set) compared to the more manageable nine alternatives in the domain prediction problem. Furthermore, we note that the combined LRCN approach clearly outperforms each of its components in isolation across all training configurations. This confirms that the CNN is indeed learning useful utterance features, that in turn sees their dependencies in time successfully captured by the LSTM.

Table 3 shows the performance breakdown per domain of the LRCN when jointly trained, and trained on domains only. Table 1 depicts an example of our model's predictions (i.e. "Predicted domain" and "Predicted topic") for a randomly selected dialogue session in the test set. The "Actual domain" field refers to the annotated labels from the TourSG dataset. While "Actual topics" refers to the Wikipedia article identified by TF-IDF.

⁷Excluding the random benchmark.

⁸https://nlp.stanford.edu/projects/glove/

⁹https://radimrehurek.com/gensim/

	Domai	ns			Topics			
Models	А	F	Р	R	Â	F	Р	R
Random (D)	11.11	8.89	10.97	10.81	-	-	-	-
CNN (D)	50.17	47.61	56.48	50.17	-	-	-	-
LSTM (D)	35.28	34.31	34.89	35.28	-	-	-	-
LRCN (D)	51.44	50.78	52.25	51.44	-	-	-	-
Random (T)	-	-	-	-	0	0	0	0
CNN (T)	-	-	-	-	17.82	16.33	15.77	17.82
LSTM(T)	-	-	-	-	13.86	13.18	15.33	13.86
LRCN (T)	-	-	-	-	24.75	24.50	24.88	24.75
CNN (D+T)	51.09	48.26	57.43	51.09	18.81	17.19	16.04	18.81
LSTM(D+T)	38.51	36.52	37.16	38.51	19.80	18.38	18.05	19.80
LRCN (D+T)	50.28	49.49	50.71	50.28	30.69	30.24	31.55	30.69

Table 2: Performance comparison between our approach (i.e. LRCN (D+T)) and the benchmarks. The letter(s) in parentheses indicate if training has been performed on domain classification only (D), topic regression only (T), or both (D+T). The letters A, F, P, R stands for accuracy, F1-score, precision and recall respectively. The best performing models are highlighted in bold.

Domain	Model	А	F	Р	R
ACC	LRCN (D)	44.73	61.81	100.00	44.73
	LRCN (D+T)	38.97	56.08	100.00	38.97
ATTR	LRCN (D)	69.71	82.15	100.00	69.71
	LRCN (D+T)	69.37	81.92	100.00	69.37
CLOSE	LRCN (D)	50.52	67.12	100.00	50.52
	LRCN (D+T)	47.42	64.34	100.00	47.42
FOOD	LRCN (D)	46.01	63.02	100.00	46.01
	LRCN (D+T)	44.60	61.69	100.00	44.60
ITI	LRCN (D)	38.14	55.21	100.00	38.14
	LRCN (D+T)	28.81	44.74	100.00	28.81
OPEN	LRCN (D)	75.61	86.11	100.00	75.61
	LRCN (D+T)	69.51	82.01	100.00	69.51
OTHER	LRCN (D)	26.03	41.31	100.00	26.03
	LRCN (D+T)	25.39	40.49	100.00	25.39
SHOP	LRCN (D)	35.49	52.39	100.00	35.49
	LRCN (D+T)	32.76	49.36	100.00	32.76
TRSP	LRCN (D)	44.59	61.68	100.00	44.59
	LRCN (D+T)	45.98	63.00	100.00	45.98

Table 3: Classification performance breakdown per domain of the LRCN when trained jointly (D+T), and on domains only (D). The best performing settings are highlighted in bold.

5 Conclusion

We introduced a novel architecture that for the first time simultaneously tracks both the domain and the topic of each utterance in a dialogue session. Our key premises were that: (i) the handling of these two settings is essential to achieve both efficiency and accuracy in the response generated by downstream systems, and (ii) the title and content of Wikipedia articles are a reasonable proxy for the topic of an utterance. We showed experimentally on a real-world dataset that our approach of jointly training the LRCN generates comparable performance when identifying the domain than the components in isolation, but more significantly, it is up to about 30% more accurate when predicting the nearest Wikipedia article. As a future step, it would be beneficial to add a measure of uncertainty in the topic predictions to lessen the impact of prediction errors in downstream systems. Addressing this issue is challenging however as the large number of parameters in our approach prevents the direct use of Bayesian inference techniques [30, 36].

References

- D. Bahdanau, K. Cho, and Y. Bengio. Neural machine translation by jointly learning to align and translate. *arXiv preprint arXiv:1409.0473*, 2014.
- [2] S. Banerjee, K. Ramanathan, and A. Gupta. Clustering short texts using wikipedia. In Proceedings of the 30th annual international ACM SIGIR conference on Research and development in information retrieval, page 787, Amsterdam, The Netherlands, 2007. ACM Press.
- [3] J. Bang, S. Han, K. Lee, and G. G. Lee. Open-domain personalized dialog system using user-interested topics in system responses. In *Automatic Speech Recognition and Understanding* (ASRU), 2015 IEEE Workshop On, pages 771–776. IEEE, 2015.
- [4] S. Bhatia, J. H. Lau, and T. Baldwin. Automatic labelling of topics with neural embeddings. *arXiv preprint arXiv:1612.05340*, 2016.
- [5] D. M. Blei. Probabilistic topic models. Communications of the ACM, 55(4):77-84, 2012.
- [6] M. Boros and P. Heisterkamp. Linguistic Phrase Spotting in a Simple Application Spoken Dialogue System. page 4, 1999.
- [7] A. Breuing and I. Wachsmuth. Let's Talk Topically with Artificial Agents! Providing Agents with Humanlike Topic Awareness in Everyday Dialog Situations. In *Proceedings of the* 4th International Conference on Agents and Artificial Intelligence, pages 62–71, Vilamoura, Algarve, Portugal, 2012. SciTePress - Science and and Technology Publications.
- [8] J. Chang, S. Gerrish, C. Wang, J. L. Boyd-Graber, and D. M. Blei. Reading tea leaves: How humans interpret topic models. In *Advances in neural information processing systems*, pages 288–296, 2009.
- [9] F. Charras, G. D. Duplessis, V. Letard, A.-L. Ligozat, and S. Rosset. Comparing Systemresponse Retrieval Models for Open-domain and Casual Conversational Agent. page 13, 2018.
- [10] C. De Boom, S. Van Canneyt, S. Bohez, T. Demeester, and B. Dhoedt. Learning Semantic Similarity for Very Short Texts. 2015 IEEE International Conference on Data Mining Workshop, pages 1229–1234, Nov. 2015. arXiv: 1512.00765.
- [11] J. Donahue, L. A. Hendricks, M. Rohrbach, S. Venugopalan, S. Guadarrama, K. Saenko, and T. Darrell. Long-Term Recurrent Convolutional Networks for Visual Recognition and Description. 39(4):677–691, 2017.
- [12] E. Frank, G. W. Paynter, I. H. Witten, and C. G. Nevill-Manning. Domain-Speci c Keyphrase Extraction. page 6, 1999.
- [13] F. Guo, A. Metallinou, C. Khatri, A. Raju, A. Venkatesh, and A. Ram. Topic-based Evaluation for Conversational Bots. arXiv:1801.03622 [cs], Jan. 2018. arXiv: 1801.03622.
- [14] G. E. Hinton, N. Srivastava, A. Krizhevsky, I. Sutskever, and R. R. Salakhutdinov. Improving neural networks by preventing co-adaptation of feature detectors. 2012.
- [15] S. Hochreiter and J. Schmidhuber. Long short-term memory. 9(8):1735–1780, 1997.
- [16] K. Jokinen, A. Kerminen, M. Kaipainen, T. Jauhiainen, G. Wilcock, M. Turunen, J. Hakulinen, J. Kuusisto, and K. Lagus. Adaptive dialogue systems - interaction with interact. In *Proceedings* of the 3rd SIGdial workshop on Discourse and dialogue -, volume 2, pages 64–73, Philadelphia, Pennsylvania, 2002. Association for Computational Linguistics.
- [17] A. Karpathy and L. Fei-Fei. Deep visual-semantic alignments for generating image descriptions. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 3128–3137, 2015.
- [18] T. Kawahara, I. R. Lane, T. Matsui, and S. Nakamura. Topic classification and verification modeling for out-of-domain utterance detection. In *Eighth International Conference on Spoken Language Processing*, 2004.
- [19] C. Khatri, R. Goel, B. Hedayatnia, A. Metanillou, A. Venkatesh, R. Gabriel, and A. Mandal. Contextual Topic Modeling For Dialog Systems. arXiv:1810.08135 [cs], Oct. 2018. arXiv: 1810.08135.
- [20] S. Kim, R. Banchs, and H. Li. Exploring convolutional and recurrent neural networks in sequential labelling for dialogue topic tracking. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, volume 1, 2016.

- [21] Y. Kim. Convolutional neural networks for sentence classification. 2014.
- [22] D. Kingma and J. Ba. Adam: A method for stochastic optimization. 2014.
- [23] K. Komatani, S. Ikeda, T. Ogata, and H. G. Okuno. Managing out-of-grammar utterances by topic estimation with domain extensibility in multi-domain spoken dialogue systems. 50(10):863–870, 2008-10.
- [24] K. Krishna and B. V. Srinivasan. Generating Topic-Oriented Summaries Using Neural Attention. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 1697–1705, New Orleans, Louisiana, 2018. Association for Computational Linguistics.
- [25] K. Lagus and J. Kuusisto. Topic identification in natural language dialogues using neural networks. In *Proceedings of the 3rd SIGdial workshop on Discourse and dialogue -*, volume 2, pages 95–102, Philadelphia, Pennsylvania, 2002. Association for Computational Linguistics.
- [26] I. Lane, T. Kawahara, T. Matsui, and S. Nakamura. Out-of-Domain Utterance Detection Using Classification Confidences of Multiple Topics. 15(1):150–161, 2007.
- [27] Q. V. Le and T. Mikolov. Distributed Representations of Sentences and Documents. In *ICML*, volume 14, pages 1188–1196, 2014.
- [28] Y. LeCun, P. Haffner, L. Bottou, and Y. Bengio. Object Recognition with Gradient-Based Learning. In Shape, Contour and Grouping in Computer Vision, pages 319–. Springer-Verlag, 1999.
- [29] R. Lowe, N. Pow, L. Charlin, J. Pineau, and I. V. Serban. Incorporating Unstructured Textual Knowledge Sources into Neural Dialogue Systems. page 7, 2015.
- [30] D. J. C. MacKay. A Practical Bayesian Framework for Backprop Networks. page 11, 1992.
- [31] C. D. Manning, P. Raghavan, and H. Schutze. *Introduction to information retrieval*. Cambridge University Press, New York, 2008.
- [32] K. R. McKeown, J. L. Klavans, V. Hatzivassiloglou, R. Barzilay, and E. Eskin. Towards Multidocument Summarization by Reformulation: Progress and Prospects. In *Proceedings of the 16th National Conference of the American Association for Artificial Intelligence*, pages 453– 460, 1999.
- [33] T. Mikolov, K. Chen, G. Corrado, and J. Dean. Efficient estimation of word representations in vector space. 2013.
- [34] I. Papaioannou and O. Lemon. Combining Chat and Task-Based Multimodal Dialogue for More Engaging HRI: A Scalable Method Using Reinforcement Learning. pages 365–366. ACM Press, 2017.
- [35] A. Papangelis, P. Papadakos, M. Kotti, Y. Stylianou, Y. Tzitzikas, and D. Plexousakis. LD-SDS: Towards an Expressive Spoken Dialogue System based on Linked-Data. 2017.
- [36] T. Pearce, M. Zaki, A. Brintrup, N. Anastassacos, and A. Neely. Uncertainty in Neural Networks: Bayesian Ensembling. arXiv:1810.05546 [cs, stat], Oct. 2018. arXiv: 1810.05546.
- [37] P. Schonhofen. Identifying Document Topics Using the Wikipedia Category Network. In Proceedings of the International Conference on Web Intelligence, pages 456–462, Hong Kong, China, Dec. 2006. IEEE.
- [38] S. Ultes, L. M. Rojas Barahona, P.-H. Su, D. Vandyke, D. Kim, I. Casanueva, P. Budzianowski, N. Mrksic, T.-H. Wen, M. Gasic, and S. Young. PyDial: A Multi-domain Statistical Dialogue System Toolkit. In *Proceedings of ACL 2017, System Demonstrations*, pages 73–78, Vancouver, Canada, 2017. Association for Computational Linguistics.
- [39] A. W. v. d. Vaart. Asymptotic Statistics (Cambridge Series in Statistical and Probabilistic Mathematics). Cambridge University Press, 2000.
- [40] P. Vougiouklis, J. Hare, and E. Simperl. A neural network approach for knowledge-driven response generation. In *Proceedings of the 26th International Conference on Computational Linguistics: Technical Papers*, pages 3370–3380, 2016.
- [41] U. Waltinger, A. Breuing, and I. Wachsmuth. Interfacing virtual agents with collaborative knowledge: Open domain question answering using wikipedia-based topic models. In *IJCAI*, pages 1896–1902, 2011.