Scalable End-to-End Training of Knowledge Graph-Enhanced Aspect Embedding for Aspect Level Sentiment Analysis

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Abstract

Aspect level sentiment classification (ALSC) is a difficult problem with state of the art models showing less than 80% macro-F1 score on benchmark datasets. Existing models do not incorporate information on aspect-aspect relations in knowledge graphs (KGs), e.g. DBpedia. Two main challenges stem from inaccurate disambiguation of aspects to KG entities, and inability to learn aspect representations from the large KGs in a joint training with ALSC models. We propose a two-level global-local entity embedding scheme which allows efficient joint training of KG based aspect embeddings and ALSC models. A novel incorrect disambiguation detection technique addresses the problem of inaccuracy in aspect disambiguation. The proposed methods show a consistent improvement of 2.5 – 4.1 percentage points, over the recent BERT-based baselines.

1 Introduction

Aspect level sentiment classification (ALSC) is an important NLP task (Hu and Liu, 2004; Pontiki et al., 2014; Dong et al., 2014), where we design algorithms to predict the sentiment portrayed in a sentence towards an identified aspect phrase. Recently, models capturing aspect specific features, e.g. Transformation Network (TNet) (Li et al., 2018), which constructs aspect-specific embedding of context words, or BERT-based models (Devlin et al., 2019), which capture aspect specific representations of sentences have outperformed previous sequential prediction models. Other recent improvements include domain adaptation of BERT model (Rietzler et al., 2020), and incorporating entity relationships within the same sentence using graph convolutional networks (Zhao et al., 2020). However, existing ALSC methods do not explicitly utilize the relations between aspects, which could potentially lead to better performance.

We observe that many of the aspect phrases, e.g. Windows 8, Mozzarella, Taylor Swift, etc., are mentions of named entities appearing in knowledge graphs (KG) e.g. DBpedia, which encode various entity-entity relations. While some of the aspects may be unseen in the training data, their neighbors (related aspects) in the KG may be abundant. This information can be used to infer important signals from the context sentence, which in turn can help in the prediction of correct polarity. For example, in the sentence My laptop with Windows 7 crashed and I did not want Windows 8, the aspect Windows 7 has only 17 examples in the training data. The current state-of-the-art ALSC model (Rietzler et al., 2020) wrongly predicts the aspect sentiment as positive. However, its related aspects (1-hop neighbors in the DBpedia KG) have 209 training examples, which can lead to correct prediction of sentiment. Hence, in this paper, we propose to incorporate the KG relations into ALSC using network embedding techniques.

The main challenges in doing so are: (1) end-to-end training of ALSC models with KG embeddings is infeasible due to large scale of KGs, and (2) most scalable off-the-shelf named entity disambiguation techniques, e.g. wikifier (Brank et al., 2018) are highly inaccurate. While state of the art named entity disambiguation methods (Kar et al., 2018; Broscheit, 2019) are accurate, they still do not scale to the entire DBpedia KG. We solve the problem of learning aspect representations from large KGs using a two-level graph embedding technique: one corresponding to a higher level cluster graph, and another for subgraphs. These embeddings can be efficiently trained jointly along with ALSC models. The problem of inaccurate wikification (Brank et al., 2018) method for aspect disambiguation, is ameliorated by a novel probing function based detection of incorrect aspect disambiguations. Figure 1 shows the overall architecture of the proposed
Experimental results show that proposed methods improve the macro-F1 score and accuracy of state-of-the-art ALSC methods on three benchmark datasets by between 2.5% – 4.1%. We also demonstrate that the scarcity of training examples is indeed a factor for the inaccuracy of existing models. Finally, we also show that classification accuracy of wrongly disambiguated aspects improves significantly with the disambiguation correction method.

2 ALSC with Aspect Relation

In this section, we describe our approach for improving the performance of aspect level sentiment classification (ALSC) methods using semantic relations between aspects which can be extracted from Knowledge Graphs (KG), e.g. DBpedia. The key motivation behind our work is that certain aspects are not well represented by examples in the training set, but they have neighboring entities in the KG which have more examples. Hence, the semantic information learned from the neighboring aspect may be transferred to the current aspect through aspect embeddings. For example, in the sentence [However, I can refute that OSX is "FAST"], the aspect OSX has the corresponding DBpedia entity MacOS, which has only 7 examples in the training set. However, MacOS has a related entity Microsoft_Windows which has 37 examples. This leads to the existing BERT-based ALSC method (Rietzler et al., 2020) misclassifying this example as positive sentiment polarity based on the context word FAST (according to LIME (Ribeiro et al., 2016) explanation), whereas our method focusses on the context word refute and classifies the example correctly as negative sentiment polarity.

Our method has 2 broad components: (1) disambiguating mentions of aspects (e.g. OSX) to entities from a KG (e.g. DBpedia entity MacOS), and representing them as an embedding vector, and (2) incorporation of the vector representation of the aspects into state of the art ALSC models, e.g. TNET and BERT, using end-to-end training. Figure 1 describes the overall architecture of our technique. Section 2.1 provides the problem formulation and background on existing ALSC techniques. Section 2.2 describes a two-level network embedding, which allows us to incorporate information from large KGs, into an efficient end-to-end training framework. Section 2.3 describes our techniques for learning ALSC models (modular and end-to-end training) using information from KG embeddings. Finally, section 2.4 describes a novel technique for detecting incorrectly disambiguated aspects from their BERT embeddings, which is then used for further improvement in ALSC prediction.

2.1 Background in ALSC

The task of aspect level sentiment classification (ALSC) is to determine the sentiment polarity $y \in \{P, N, O\}$ of an input sentence $w$ for an aspect phrase $w_t$, which is a part of the input sentence. Here, $P$, $N$, and $O$ correspond to positive negative and neutral sentiment respectively. ALSC models take representations of the context $w$, $\vec{x} = (x_1, ..., x_n)$, and that of the aspect $w_t$, $\vec{x}^t = (x_{t1}, ..., x_{tm})$ as inputs. Most state-of-the-art ALSC models, including TNET (Li et al., 2018), and BERT (Devlin et al., 2019) transform the context representation using an aspect representation.
to finally arrive at an aspect-specific representation for context words. Here, \( n \) denotes the length of the (context) sentence and \( m \) denotes the length of the aspect. We briefly describe the architectures of these methods.

TNet (Li et al., 2018) consists of three sequential modules (sets of layers): The first module is a Bi-LSTM layer which takes context embeddings \( \vec{x} \) and aspect (target) word embeddings \( \vec{x}_t \) corresponding to each example and outputs the contextualized representations \( \vec{h}_t^{(0)} = (h^{(0)}_1(\vec{x}), ..., h^{(0)}_m(\vec{x})) \) and \( \vec{h}_t = (h^t_1(\vec{x}^t), ..., h^t_m(\vec{x}^t)) \) respectively where \( h^{(0)}_i(x), h^t_i(x^t) \in \mathbb{R}^{2D_h} \), \( i \in \{1, ..., n\}, \, j \in \{1, ..., m\} \). The second module contains \( L \) layers of context preserving transformations (CPT) blocks. In each layer \( l \) the aspect representation is first transformed into aspect specific representation as \( r^l_i = \sum_{j=1}^m h^l_i \cdot \text{SoftMax}(h^{l,(1)}_i, h^{l,(2)}_i) \), then incorporated into context representation as \( \vec{h}^l_i = \text{FeedForward}(h^l_i, r^l_i) \), and finally passed into context preserving LF/AS block to get the output of next layer: \( h^{l,(i+1)}_i = \text{LF}/\text{AS}(h^{l,(1)}_i, h^{l,(2)}_i) \).

The third module uses convolution and pooling layers on position-aware encodings to produce a fixed dimensional vector \( z \).

BERT has been applied to ALSC by Rietzler et al. (2020) and Sun et al. (2019), where they model the sentiment classification task as a sequence-pair classification task. The input sentence (\( \vec{x} \)) and aspect phrase (\( \vec{x}_t \)) are encoded as [CLS] \( \vec{x} \) [SEP] \( \vec{x}_t \) [SEP]. The last layer hidden representation of CLS token \( h_{[CLS]} \in \mathbb{R}^{768} \) which is the aspect-aware representation of the input sequence, is used for the downstream classification task. The sentiment polarity distribution is predicted using a feedforward layer with softmax activation and trained using the cross-entropy loss. Recently, SDGCN-BERT (Zhao et al., 2020) has been proposed to capture sentiment dependencies between multiple aspects in a sentence using a graph convolution network. BERT-ADA (Rietzler et al., 2020) uses BERT domain-specific language model fine-tuning for ALSC and results in best accuracy on some benchmark datasets. In this paper we build on TNet, BERT, SDGCN-BERT, and BERT-ADA, to incorporate knowledge from KG. Next, we describe our framework for the scalable incorporation of KG information in ALSC.

### 2.2 Aspect Relation Incorporation from KG

Incorporating aspect relation from KG into ALSC models has two substeps: (1) Aspect to entity mapping and (2) Computation of entity embedding. The first step involves the identification of Wikipedia entities corresponding to an aspect word in a context. This problem is solved by named entity disambiguation (NED) or wikification. We use wikifier API (Brank et al., 2018) for this purpose. Note that, here we use a freely available and computationally efficient method for entity linking, at the cost of accuracy. We partially make up for the loss of accuracy in the posthoc disambiguation correction described in section 2.4.

For learning the entity embeddings (step 2), we use the popular GraphSAGE algorithm (Hamilton et al., 2017), which is applicable for both supervised and unsupervised tasks. The entity relation graph is generated using the DBpedia \(^1\) page links knowledge graph, where each vertex is an entity in the DBpedia KG, and an edge is a tuple of the form \(<\text{Sub}, \text{Pred}, \text{Obj} >\) where Sub and Obj are the subject and object entities, and Pred is the predicate relation between Sub and Obj. However, the whole DBpedia knowledge graph (KG) is too large (with \(~22\) million nodes and \(~173\) million edges) to embed using deep NRL techniques. Another alternative is to consider the subgraph \( G \) induced by entities present in the ALSC training dataset only. The problem with this subgraph is that it is disconnected. Hence, the similarity preserving embeddings of entities are only consistent within the connected components of \( G \). This may lead to two very different entities \( u \) and \( v \) accidentally ending up close to each other. In this section, we describe a two-level scalable network embedding technique that scales to DBpedia while avoiding the above-mentioned problems.

#### 2.2.1 Two-level Aspect Entity Embedding

The key idea behind two-level aspect embedding (representations) is to use two smaller graphs constructed from the large KG: (1) a cluster graph \( G_C(V_C, E_C, W_C) \): which captures the global connectivity structure between clusters of entities, and (2) the subgraph \( G_s(V_s, E_s) \) induced by aspects (entities) in the training dataset. Note that since the subgraph \( G_s \) can be disconnected, we need a combination of cluster graph embedding \( z_C(u) \), and subgraph embedding, \( z_s(u) \) for capturing the

\(^1\)https://wiki.dbpedia.org/downloads-2016-10
relations between aspect entity \( u \).

**Cluster graph embedding:** The weighted cluster graph \( G_C(V_C, E_C, W_C) \) is a compact representation of the KG where each vertex \( v \in V_C \) is a cluster of vertices (entities) of the knowledge graph \( G = (V, E) \). We use the Louvain hierarchical graph clustering (Blondel et al., 2008) algorithm for clustering the entire knowledge graph. Edge set \( E_C \) is calculated as: \((i, j) \in E_C, \forall i, j \in V_C\) if there is a connected pair of KG entities from clusters \( i \) and \( j \). The weight between clusters \( i \) and \( j \), \( W_C(i, j) \), is calculated as the fraction of actual edges between clusters \( i \) and \( j \) and the maximum edges possible between the two clusters, i.e., \( |i|\times|j| \), where \( |i| \) is the number of nodes present in cluster \( i \). We use a modified GraphSAGE embedding technique to construct the cluster embeddings \( z_C(i) \), \( i \in V_C \) of a weighted graph by optimizing the following graph based loss function:

\[
J_C(z_C(i)) = -\log(\sigma(z_C(i)^T z_C(j))) - Q \cdot E_{h \sim P_n(j)} \log(\sigma(-z_C(i)^T z_C(k)))
\]

where \( z_C(i) \) is the output representation of \( i \in V_C \), \( \sigma \) is the sigmoid function, \( j \in V_C \) is a cluster co-occurring with \( i \) on a fixed weighted random walk defined by \( W_C(i, j) \), \( P_n \) is the negative sampling distribution, \( Q \) is the number of negative samples, \( k \in V_C \) is a negative sample.

**Subgraph embedding:** The vertex set \( V_s \) of the entity-relation subgraph \( G_s(V_s, E_s) \) consists of all aspect entities extracted from instances in the training dataset, while the edge set \( E_s \) is the subset of induced edges from the original KG. We use the standard GraphSAGE embedding and loss function to construct the subgraph similarity embedding, \( z_s(u) \) for aspect entity \( u \). To preserve the local neighbourhood information as well as global graph structure in the knowledge graph, we use the concatenation of subgraph and cluster graph embeddings as our two-level entity embedding: \( z(u) = [z_C(i); z_s(u)] \), where \( u \in V_s \) and \( i \in V_C \) such that \( u \) is an entity in cluster \( i \). Figure 1 shows the methods for aspect disambiguation and two-level entity embedding on the left side in the overall scheme.

### 2.3 ALSC with entity relation learning

In this section, we incorporate the concatenated entity embedding proposed above into two state-of-the-art ALSC models: TNet and BERT (described in section 2.1). We propose two ways of incorporating the information contained in entity relations from KG into ALSC: (1) using static embeddings, and (2) by performing end-to-end learning. For incorporation of static embedding in TNet, the final entity embedding \( z(u) \) for entity \( u \) is concatenated with final layer CPT block output \( h(L) \) as \( h_{\text{concat}} = [h(L); z(u)] \) and this new aspect specific contextual representation \( h_{\text{concat}} \) is sent as input to the convolution layer module as described in section 2.1. The final layers and loss function is same as TNet. We call this model TNet-GS. We incorporate the entity embedding \( z(u) \) into BERT by concatenating it with representation of CLS token \( h_{[CLS]} \), as: \( h_{[CLS]} = [h_{[CLS]}; z(u)] \). Here \( h_{[CLS]} \) is the final aspect-specific sentence representation for an ALSC instance taken from domain specific BERT model (BERT-ADA) (Rietzler et al., 2020), and further fine-tuned on ALSC task. We call this model BERT-GS. We also incorporate the static entity embedding \( z(u) \) into SDGCN-BERT (Zhao et al., 2020), in an analogous way to train the SDGCN-BERT-GS model, through finetuning on ALSC.

**End-to-end learning:** Incorporation of GraphSAGE embeddings into ALSC models provide minor improvements to polarity prediction, since the aspect embeddings are not fine-tuned for the ALSC task. This is achieved with end-to-end training of the aspect embedding and ALSC models. The architecture of our end-to-end models are same as the models proposed with static embeddings above. Hence, for BERT based models, we calculate the final embeddings for a sentence and aspect pair as: \( h_{[CLS]} = [h_{[CLS]}; z(u)] \), where \( z(u) = [z_C(i); z_s(u)] \). For TNet-based models, \( h_{\text{concat}} = [h(L); z(u)] \). For both models, let \( L_{\text{ALSC}} \) denote the loss incurred from ALSC training, and \( L_{GS} \) be the loss incurred from GraphSAGE using the subgraph \( G_s = (V_s, E_s) \). We optimize the following loss for joint training:

\[
L_{\text{joint}}(\Theta_{\text{ALSC}}, \{z_s(u)\}) = \alpha_1 L_{\text{ALSC}} + \alpha_2 L_{GS}
\]

where, \( \Theta_{\text{ALSC}} \) are all the parameters from ALSC model, and \( \{z_s(u)\} \) are subgraph embeddings from \( G_s \). We minimize the above loss w.r.t. \( \Theta_{\text{ALSC}}, \{z_s(u)\} \), while keeping \( z_C(i) \) fixed to pre-learned GraphSAGE embeddings. We call the resulting models: BERT-GS-E, SDGCN-BERT-GS-E, and TNet-GS-E, for the base models BERT-ADA, SDGCN-BERT, and TNet, respectively.
2.4 Incorrect Disambiguation Detection

As discussed in section 3.3, many of the misclassifications using models like BERT-GS, are due to incorrect disambiguation of aspect entities. In this section, we develop a scalable algorithm for identifying incorrect aspect disambiguations and mitigating their effect by setting the corresponding (modified) embedding to zero vector. We rely on the BERT aspect embedding vectors \( h_{[CLS]} \) (called \( h \) in this section for brevity) for the same. However, BERT embeddings encode many modalities of information including syntactic dependencies (Hewitt and Manning, 2019), semantic similarities, and entity relations (Reif et al., 2019). We propose to use a learned similarity function \( S_B(h_i, h_j) \) which captures the entity similarity between two BERT embeddings \( h_i \) and \( h_j \) of two entity mentions. Hence, following (Reif et al., 2019), we propose to use the following form of similarity function:

\[
S_B(h_i, h_j) = \sigma((B \cdot h_i)^T(B \cdot h_j))
\]

where, \( B \in \mathbb{R}^{\text{dim}_B \times \text{dim}_B} \) is a learned parameter. The parameter \( B \) can be thought of as a “probing function” (Reif et al., 2019), projecting BERT embedding \( h \) into a space which only distills out the entity relations.

Algorithm 1, describes the steps for learning the probing function parameter \( B \), which extracts entity relational similarities from BERT embeddings, and calculation of the modified embeddings. The key idea is: aspects which are close in graph embedding space should also have high similarity of BERT embeddings. The algorithm proceeds by constructing triplets \((i, j, k)\) of aspects where aspects \( i \) and \( j \) are close, but \( i \) and \( k \) are not close. It then learns \( B \) by minimizing the loss:

\[
\sum_{(i, j, k) \in \tau} (S_B(h_i, h_k) - \tilde{S}_B(h_i, h_j)).
\]

For each aspect \( i \), and for all it’s top \( n \) close aspects \( j \) and rest far away aspects \( k \), we modify it’s corresponding concatenated entity embedding as follows:

\[
z_{\text{mod}}(i) = \begin{cases} \{ \hat{0} \}^{\text{dim}_B}, & \text{if } S_B(h_i, h_j) - \tilde{S}_B(h_i, h_k) \geq 0 \\ z(i), & \text{otherwise} \end{cases}
\]

(2)

\( \{ \hat{0} \}^{\text{dim}_B} \) is the zero vector of dimension \( \text{dim}_B \).

We call ALSC models jointly (end-to-end) trained with these corrected embeddings as: BERT-GS-E[probe], SDGCN-BERT-GS-E[probe], and TNet-GS-E[probe], corresponding to base models BERT-ADA, SDGCN-BERT, and TNet.

3 Experiments

In this section, we report experimental results to empirically ascertain whether the proposed models indeed perform better than the existing state of the art methods.

3.1 Experimental Setup

Datasets and baselines: We evaluate our proposed models on the three benchmark datasets: LAPTOP and REST datasets from SemEval 2014 Task 4 sub-task 2 (Pontiki et al., 2014) which contains reviews from Laptop and Restaurant domain respectively and the TWITTER dataset (Dong et al., 2014) containing Twitter posts. For TNet-based models, we perform the same prepossessing procedure as done in (Li et al., 2018). We compare results of our proposed models with state-of-the-art methods reported in table 2.

Aspect disambiguation and KG Embedding: For each aspect in the dataset \( D \) mentioned above, we disambiguate its corresponding entity in the knowledge graph using the wikifier API (Brank et al., 2018). We use hierarchical Louvain graph clustering (Blondel et al., 2008) algorithm for clustering the KG and constructing the weighted cluster graph \( G_C(V_C, E_C, W_C) \) (ref section 2.2.1). Statistics of the knowledge graph and its corresponding cluster graph and sub-graphs are shown in Table 1. For training entity sub-graph and weighted cluster graph embedding, we use GraphSAGE mean as aggregate function. For training GraphSage (Hamil-
Table 1: Statistics of knowledge graph, weighted cluster graph and entity relation sub-graphs.

| Knowledge Graph Embedding | 
|---------------------------|
| #Edges | #Nodes | #Clusters | Max. inter-cluster degree |
| 173068197 | 22504204 | 606 | 341 |

| Sub-graph Embedding | 
|---------------------|
| Dataset | #Nodes | #Edges | Max. Node Degree |
| LAPTOP | 785 | 4477 | 107 |
| REST | 1031 | 7305 | 136 |
| TWITTER | 120 | 429 | 40 |

ton et al., 2017), we sample 25 nodes for layer 1 and 10 nodes for layer 2 using a random walk. The output hidden representation dimension is set as 50, and the number of negative samples $Q$ taken as 5. Default values are used for all other parameters.

**ALSC and probing function training**: For training of TNet-based models, we use the same set of hyperparameters as described in (Li et al., 2018). For training of BERT-based models, we use the procedure suggested in Rietzler et al. (2020), for both pre-training and fine-tuning. For end-to-end training of ALSC with entity embedding generation, we use Adam optimizer with a learning rate of $3 \cdot 10^{-5}$, batch size of 512 for GraphSAGE-based entity embedding generation and 32 for ALSC task, number of epochs as 7. All the other hyper-parameters in GraphSAGE based entity embedding generation and ALSC task follow the same values in individual training. For training of the probing function $B$, we use Adam optimizer with a learning rate of $1 \cdot 10^{-5}$, the batch size of 128, the number of epochs as 100, the probe dimension $\text{dim}_B$ as 100, and the regularization rate as 0.01.

### 3.2 Comparison of ALSC Models

Table 2 reports all baseline and proposed models’ performance, using two standard metrics: macro-accuracy (ACC) and macro-F1 score (Macro-F1). We observe that BERT-GS-E[probe] outperforms all the other models on the REST and TWITTER dataset, and SDGCN-BERT-GS-E[probe] outperforms all the other models for the LAPTOP dataset, in terms of both Accuracy and Macro-Averaged F1 scores. Hence, we can conclude that representation of relations between aspect entities helps in training better ALSC models. The improvement in the performance by the proposed BERT-GS-E[probe] and SDGCN-BERT-GS-E[probe] models over other BERT-based baseline models imply that the DBpedia knowledge graph encodes information which supplements the information contained in BERT embeddings of the aspect terms. We also note that BERT based baseline models, e.g. BERT-ADA, perform better than other models, e.g. TNET, as they utilize the context-sensitive word embeddings fine-tuned on domain-related datasets.

### Figure 2: Effect of number of training datapoints

**Effect of training data scarcity**: Figure 2 reports the accuracy of the baseline model (BERT-ADA, blue bar) and the proposed model (green bar), for all test aspects in the LAPTOP dataset. The test aspects are bucketed according to their training data counts, and the bars report average accuracy for all aspects in the buckets. We can see that for aspects that have 0 – 20 training points, the proposed method outperforms the baseline. Hence, we conclude that for aspects with a low number of training data points, the proposed method improves the performance of ALSC by borrowing information from nearby aspects in the KG. The red line shows the number of test data points for each of the buckets. We find that a large fraction of test aspects have fewer than 20 training data points.

### Error Analysis

**Table 3** shows the confusion matrices of predictions of TNet-GS-E[probe] and BERT-GS-E[probe] w.r.t. their respective baseline models on the three datasets. The top-left and bottom-right values report the number of correctly classified or misclassified examples by both methods in each sub-matrix. We can see that the proposed models do not induce any new errors which were not present in the respective baselines. Finally, we see that we bottom left entries in each table that report the new corrects (examples classified wrongly by existing methods but are classified correctly by the proposed methods) are much higher. Thus, we conclude that the new technique is an improvement over the old methods.

### Anecdotal examples

Table 5 illustrates a few examples misclassified by BERT-ADA and correctly
Table 2: Experiment results on various datasets(%). The marker * refers to p-value <0.01 when comparing with respective baselines. % in bracket of best performing models implies overall gain wrt. its’ baselines.

| Model | LAPTOP | REST | TWITTER |
|-------|--------|------|---------|
|       | ACC    | Macro-F1 | ACC | Macro-F1 | ACC | Macro-F1 |
| Implemented baselines | | | | | | |
| TNet (Li et al., 2018) | 76.33 | 71.27 | 79.64 | 70.20 | 78.17 | 77.17 |
| TNet-ATT (Tang et al., 2019) | 77.62 | 73.84 | 81.53 | 72.90 | 78.61 | 77.72 |
| BERT-base (Devlin et al., 2019) | 77.69 | 72.60 | 84.92 | 76.93 | 78.81 | 77.94 |
| SDGCN-BERT (Zhao et al., 2020) | 81.35 | 78.34 | 83.57 | 76.47 | 78.54 | 77.72 |
| BERT-ADA (Rietzler et al., 2020) | 80.25 | 75.77 | 87.89 | 81.05 | 78.90 | 77.97 |
| Proposed methods | | | | | | |
| TNet-GS | | | 77.89 | ⋆ | 72.96 | ⋆ | 82.31 | ⋆ | 72.97 | ⋆ | 79.68 | ⋆ | 78.83 |
| TNet-GS-E | | | 78.80 | ⋆ | 73.87 | ⋆ | 83.40 | ⋆ | 73.91 | ⋆ | 80.52 | ⋆ | 79.79 |
| TNet-GS-E [probe] | | | 80.09 | ⋆ | 75.11 | ⋆ | 84.64 | ⋆ | 75.17 | ⋆ | 81.64 | ⋆ | 80.84 |
| BERT-GS | | | 80.87 | ⋆ | 76.13 | ⋆ | 88.21 | ⋆ | 81.45 | ⋆ | 79.92 | ⋆ | 80.15 |
| BERT-GS-E | | | 81.73 | ⋆ | 77.07 | ⋆ | 89.38 | ⋆ | 82.47 | ⋆ | 80.91 | ⋆ | 81.21 |
| BERT-GS-E [probe] | | | 82.91 | ⋆ | 78.31 | ⋆ | 90.62 | ⋆ | 83.81 | ⋆ | 82.08 | ⋆ | 81.21 |
| SDGCN-BERT-GS | | | 81.82 | ⋆ | 78.75 | ⋆ | 84.64 | ⋆ | 77.34 | ⋆ | 79.06 | ⋆ | 78.36 |
| SDGCN-BERT-GS-E | | | 82.37 | ⋆ | 79.21 | ⋆ | 85.27 | ⋆ | 78.07 | ⋆ | 79.67 | ⋆ | 78.89 |
| SDGCN-BERT-GS-E [probe] | | | 83.62 | ⋆ | 80.43 | ⋆ | 86.61 | ⋆ | 79.37 | ⋆ | 80.86 | ⋆ | 80.03 |

(+3.11%) (+3.40%) (+4.03%) (+4.15%)

Table 3: Confusion matrices of predictions of TNet-GS-E [probe] vs TNet and BERT-GS-E [probe] vs BERT-ADA w.r.t. correct and incorrect classification.

| Prediction | LAPTOP | REST | TWITTER | BERT-ADA |
|------------|--------|------|---------|----------|
| Correct    | 487    | 127  | 512     | 0        |
| Incorrect  | 24     | 17   | 109     |          |
| Correct    | 892    | 0    | 984     | 0        |
| Incorrect  | 56     | 31   | 105     |          |
| Correct    | 541    | 0    | 547     | 0        |
| Incorrect  | 24     | 127  | 22      | 124      |

Table 4: Fraction of incorrectly predicted examples in disambiguation categories.

| Disambiguation | BERT-GS     | BERT-GS-E |
|----------------|-------------|-----------|
| 'Unknown'      | 8 / 10      | 13 / 14   |
| Incorrect      | 49 / 53     | 82 / 87   |
| Correct        | 65 / 575    | 37 / 1019 |
| LAPTOP         |             |           |
| REST           |             |           |
| TWITTER        |             |           |
| 'Correct'      | 2 / 2       | 14 / 14   |
| disamb.        | 124 / 676   |           |
| BERT-GS-E [probe] |             |           |
| LAPTOP         | 6 / 10      | 10 / 14   |
| REST           | 41 / 53     | 65 / 87   |
| TWITTER        | 0 / 2       | 0 / 14    |
| Correct        | 124 / 676   |           |

3.3 Incorrect Disambiguation Detection

In this section, we demonstrate the effectiveness of our probing function for incorrect disambiguation detection. We categorized the aspects into 3 categories based on the disambiguation by wikifier: (1) unknown where there was no entity found, (2) correct disambiguation where the disambiguated aspect was mapped to the correct entity, and (3) incorrect disambiguation where the disambiguated aspect was mapped to an incorrect entity, based on manual annotation. Table 4 shows the number of incorrectly labeled examples (by the ALSC model) in each disambiguation category out of the total number of examples in that category (#Incorrect/#Total). We see that compared to BERT-GS and BERT-GS-E, BERT-GS-E [probe] has significantly fewer incorrect classifications for the unknown and incorrect disambiguation categories. For the correct disambiguation category, all methods have the similar fraction of misclassification, which is much lower than the other two
Table 5: Examples of mistakes by BERT-ADA which were correctly predicted by BERT-GS-E[probe]. Red and green backgrounds indicate LIME (Ribeiro et al., 2016) explanations for BERT-ADA and BERT-GS-E[probe].

| Category | Sentence                                                                                   | BERT-ADA | BERT-GS-E[probe] |
|----------|--------------------------------------------------------------------------------------------|----------|------------------|
| LAPTOP   | However, I can refuse that [OSX]_NEG is "FAST".                                            | POS      | NEG              |
|          | From the speed to the multi touch gestures this operating system beats [Windows]_NEG, easily.| POS      | NEG              |
|          | I used Windows XP, Windows Vista, and [Windows 7]_NEG, extensively.                          | POS      | NEU              |
| REST     | How pretentious and inappropriate for MJ Grill to claim that it provides power [lunch]_NEG| POS      | NEG              |
|          | and dinners!                                                                               |          |                  |
|          | *Anywhere else, the [prices]_POS would be 3x as high!*                                     | NEG      | POS              |
|          | A beautiful atmosphere, perfect for [drinks]_NEU and/or appetizers.                         | POS      | NEU              |
| TWITTER  | sorry but i had it with [Gaga]_POS, its old fashion what she does, come with a new are     | NEG      | POS              |
|          | ... -LRB- YouTube -RRB.                                                                   |          |                  |
|          | noobus Turns out [Snoop Dogg]_NEG is actually pretty funny.                                 | POS      | NEG              |
|          | just got hold of an [Ipod]_NEU . . it will be fun learning how to use it on the bus trip to| POS      | NEU              |
|          | canberra this monday                                                                       |          |                  |

Figure 3: Percentage of correct / incorrect detection of disambiguation

Figure 3 reports the percentage incorrect disambiguations which were detected correctly (left bar), and the correct disambiguations which were marked incorrectly (right bar) by the probing scheme. It can be seen that more than 80% of incorrectly disambiguated examples have been correctly detected, and less than 5% of correctly disambiguated examples have been wrongly flagged. Hence, we conclude that our incorrect disambiguation detection method shows excellent performance, while also being highly scalable.

4 Related Work

ALSC with Graph Embedding: (Majumder et al., 2018) uses memory networks generate aspect representations influences by other aspects in the same sentence. (Zhang et al., 2019a) uses aspect-specific GCN, and (Liang et al., 2020) uses an “interactive” dependency graph to capture the relations between aspect in a sentence. (Tang et al., 2020) also encodes information in dependency graph using a transformer-like network. However, none of the above methods can be used at a scale where we can apply it to a knowledge graph like DBpedia. (Xu et al., 2020),(Jiang et al., 2020) focus on determining aspect specific opinion spans. In addition to the models described in section 2.1, neural network models such as Memory Networks (Tang et al., 2016; Wang et al., 2018; Chen et al., 2017), LSTM-based models (Wang et al., 2016; Ma et al., 2017; Zhang and Liu, 2017), and Capsule Networks (Du et al., 2019) have also been explored for ALSC.

Knowledge in BERT representations. Reif et al. (2019) measures the word sense similarities using a semantic probe on word embeddings. Hewitt and Manning (2019) shows that contextual word embedding incorporates syntactic informations. Broscheit (2019) investigates entity knowledge in BERT embedding. (Poerner et al., 2020; Peters et al., 2019; Zhang et al., 2019b) propose a promising line of schemes for incorporating entity knowledge in KGs into BERT embeddings. However end-to-end training with these methods has to take entire KG into account, and is expected to be computationally expensive.

5 Conclusions

In this paper, we present a scalable technique for incorporating aspect relations from large knowledge graphs, into state of the art deep learning based ALSC models. Experimental results show
consistent and significant improvements in ALSC performance on all benchmark datasets.

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