Improving Zero Shot Learning Baselines with Commonsense Knowledge

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Abstract

Zero shot learning — the problem of training and testing on a completely disjoint set of classes — relies greatly on its ability to transfer knowledge from train classes to test classes. Traditionally semantic embeddings consisting of human defined attributes (HA) or distributed word embeddings (DWE) are used to facilitate this transfer by improving the association between visual and semantic embeddings. In this paper, we take advantage of explicit relations between nodes defined in ConceptNet, a commonsense knowledge graph, to generate commonsense embeddings of the class labels by using a graph convolution network-based autoencoder. Our experiments performed on three standard benchmark datasets surpass the strong baselines when we fuse our commonsense embeddings with existing semantic embeddings i.e. HA and DWE.

1 Introduction

How does one recognize an instance of an object they have never seen before? Instinctively, the first step is to find any resemblance with familiar objects. Take the example of Fig. 1 — with the information “Olinguito has the shape of a Koala and the color of a Bear”, we can establish shape- and color-based associations between known animals (Bear and Koala) and the unknown one (Olinguito). Inspired by such analogies, we explore how we can discover and exploit such associations between classes in zero-shot learning (ZSL) — the problem of learning a visual classifier for a class with no training data.

In a traditional ZSL setup, a visual classifier trained on a certain set of classes, namely seen classes, is expected to perform reasonably well on a completely disjoint set of classes, namely unseen classes. The key idea in dealing with such a scenario is to utilize knowledge from the seen classes to characterize unseen classes (Norouzi et al., 2013). To this end, researchers often model the association between semantic embeddings of the classes and visual embeddings of the images. A high association score indicates a strong candidate class for the given image. During inference, each of the unseen class embeddings is paired with the visual embedding of the given image and fed to the association function. Typically, the class with the highest association score is selected as the predicted class. In literature, usually two types of semantic embeddings are used (Xian et al., 2017) — human-defined attributes (HA) and distributed word embeddings (DWE).

A number of approaches (Zhang et al., 2017; Kodirov et al., 2017; Kumar Verma et al., 2018) use human-defined visually identifiable attributes (HA) such as stripes, long neck, furry, spots to describe classes. But, these approaches are rather expensive as human annotation is involved.

On the other hand, distributed word embeddings (DWE), such as word2vec successfully model different semantic properties of a language as a result of it being trained on a large-scale textual corpus (Jiang et al., 2017; Kodirov et al., 2015; Qiao et al., 2017). The primary objective of learning such word embeddings is based on the distributional hypothesis that states that similar words tend to appear in similar context. Using this hypothesis, pretrained word embeddings encode semantic properties of
words. Nowadays, such embeddings are extensively used in many NLP tasks. However, these word embeddings are not trained on explicit knowledge representations to directly provide knowledge for an unseen word. These models can also struggle to find similarity between the words that never or rarely appear in each other’s context (see Table 2).

Returning to the example in Fig. 1, we can observe that external knowledge helps in finding an explicit relation between different classes by traversing through the paths between them in the graph. To elucidate this, consider the example in Fig. 2 — class ‘Aeroplane’ (seen class) is connected to class ‘Motorbike’ through ‘Motor racing’ (unseen class). In this example, the relations (in red) that connect the nodes (in yellow) on the path from aeroplane to motorbike are explicitly defined in ConceptNet (Speer et al., 2017). Such a relational knowledge-graph that contains relations among the words can efficiently model associations that can be very beneficial to the ZSL task by transferring knowledge from seen to unseen classes.

![Figure 2: An example of commonsense relations between Aeroplane and Motorbike in ConceptNet.](image)

Another benefit of using knowledge graphs for ZSL is that it can provide additional background information on the class labels, which in turn can improve the semantic embeddings. An illustration in Fig. 2 shows the background knowledge of aeroplane being represented with the nodes in magenta. For someone oblivious to an aeroplane, the shape and size of it is still imaginable through the associated background commonsense knowledge. For instance, aeroplane CapableOf fly or aeroplane HasContext wing are strong conceptual indicators to aeroplanes, but not to motorbikes. Naturally, the semantic embeddings, created from such knowledge graph, will be vastly different for an aeroplane as compared to that of a motorbike, leading to stronger association between the representation of the input image in Fig. 2 and aeroplane than motorbike. We therefore hypothesize that the improved semantic embeddings will lead to improved association of visual and semantic embeddings, resulting to correct class prediction during inference. We achieve this by fusing commonsense embeddings, extracted from ConceptNet, with the human-defined attributes (HA) and distributed word embeddings (DWE).

Commonsense knowledge broadly represents the large amount of small but well-known facts that we often take for granted (Andrich et al., 2009), and yet we regularly use to understand our surrounding context or to interpret or synthesize language. To leverage commonsense-knowledge, we employ ConceptNet (Speer et al., 2017), a large-scale knowledge graph that contains commonsense knowledge. We posit that using such commonsense knowledge is beneficial for our task, as compared to other knowledge graphs, such as WordNet which only contain relations like Isa, Synonymy, Hypernymy.

We first train a global (covering all possible classes as nodes) graph autoencoder on ConceptNet to learn inter-class associations. To this end, a graph convolutional network (GCN) is employed for relation prediction in the graph. The learnt node embeddings are used as the commonsense embeddings (CSE) of the corresponding class names. Further, we fuse this CSE with the semantic embeddings. We surmise that the obtained CSE encode associations between seen and unseen classes in the ZSL setup. Additionally, CSE should also encode key background information about the image class labels. To validate our claim, we use the CSE of the class labels to induce external commonsense knowledge in two different ZSL baselines. We observe noteworthy improvements in ZSL performance throughout our experiments across three different benchmark ZSL datasets.

The main contributions of this paper are—

- We encode the commonsense knowledge in ConceptNet using a graph convolutional network (GCN)-based autoencoder;
- We improve association between visual and semantic embeddings by fusing existing semantic embeddings (HA and DWE) with commonsense embeddings (CSE);
- We demonstrate effectiveness of CSE through extensive experiments and comparisons with two different ZSL baseline methods across three different datasets.

The rest of this paper is organized as follows:
§2 briefly reviews ZSL approaches related to this work; §3 provides task definition and the details of the two baselines that we use in this work; §4 describes our method; we report findings of our experiments and related discussions in §5; finally, §6 concludes this paper.

2 Related Work

Early works on zero-shot learning use human defined attributes (Farhadi et al., 2009; Lampert et al., 2009; Jayaraman and Grauman, 2014) to represent each class as a vector that denotes presence/absence of attributes. Direct mapping between image features and these class vectors is used to learn visual classifiers.

Another line of work use distributed word embeddings (DWE)s such as word2vec (Mikolov et al., 2013b) to represent each category. These are consecutively mapped to visual classifiers (Frome et al., 2013; Norouzi et al., 2013; Kodirov et al., 2015; Roy et al., 2018; Qiao et al., 2017). Frome et al. (2013) use convolutional neural network (CNN) and a transformation layer to train a mapping from image to word embeddings. Few recent works (Kodirov et al., 2015; Roy et al., 2018; Qiao et al., 2017) propose to reduce the gap between CNN image features and DWEs. Combination of attributes and distributed word embeddings are used in works such as (Akata et al., 2013; Zhang et al., 2017).

Our work is also related to recent approaches that use knowledge graphs to distill knowledge explicitly from knowledge representations (Salakhutdinov et al., 2011; Deng et al., 2014; Kampffmeyer et al., 2019; Wang et al., 2018). Many approaches exist in object recognition that use such approach. (Salakhutdinov et al., 2011) uses a hierarchical classification model that allows rare objects to borrow statistical strength from related objects that have many training examples.

Closest to our work is (Wang et al., 2018). Although our approach is similar to theirs, in that we both use Graph Convolution Network (GCN) to improve class embeddings, the way we use GCN is vastly different.

3 Background

3.1 Task Definition

In a ZSL setup, we have a set of training instances (in this case, these are images), \( X_{\text{train}} \), belonging to a set of classes \( \mathcal{Y}_{\text{seen}} \). We test on a set of images, \( X_{\text{test}} \) belonging to a set of classes \( \mathcal{Y}_{\text{unseen}} \). It is assumed that \( \mathcal{Y}_{\text{seen}} \cap \mathcal{Y}_{\text{unseen}} = \emptyset \). Ideally, for each \( x_i \in X_{\text{train}} \), we extract its visual embedding \( f(x_i) \in \mathbb{R}^m \) by passing it through a visual feature extractor such as a deep CNN (Simonyan and Zisserman, 2014). Each class \( y \in \mathcal{Y}_{\text{seen}}, \mathcal{Y}_{\text{unseen}} \) has a semantic embedding \( s_y \in \mathbb{R}^N \). \( s_y \) can be human defined attributes of the image class-label such as stripes, furry or distributed word embeddings of the image class (such as word2vec). In a standard ZSL training, we use \( \mathcal{Y}_{\text{seen}} \) class data to learn relation module relation between \( f(x); \forall x \in X_{\text{train}} \) and \( s_y; \forall y \in \mathcal{Y}_{\text{train}} \). During testing, we use the same relation module to find the corresponding \( \hat{y} \in \mathcal{Y}_{\text{unseen}} \) for a test image \( \tilde{x} \in X_{\text{test}} \).

3.2 Baseline Methods

We utilize the commonsense knowledge extracted from ConceptNet in two different strong ZSL baselines: 1) Deep Embedding ZSL; 2) Relation Network. Each of them consists of two main modules:

- **Semantic embedding module** encodes the semantic embedding of the image class-label embedding of the image. We refer to this module as the \( \Theta \) network.
- **Relation module** takes input from the semantic embedding module and visual embeddings. It aims to model the association between the semantic embedding of the image class-label and the visual/image embedding.

We describe the two baselines in more detail below.

3.2.1 Deep Embedding ZSL (DeZSL)

Following the work of Zhang et al. (2017), we jointly encode both image and semantic representations into a unified embedding space.

**Semantic embedding module:** The \( m \)-dimensional semantic embeddings of the class-label \( y \), namely \( s_y \), is fed to the semantic embedding module named the \( \Theta \) network, composed of two fully-connected (FC) layers with ReLU activation, for projection onto visual embedding space:

\[
\Theta_{\text{DeZSL}} = FC_{b}^{\text{ReLU}}(FC_{a}^{\text{ReLU}}) \tag{1}
\]

The output size of the \( FC_{b}^{\text{ReLU}} \) is kept equal to image feature dimension.

**Relation module:** The relation module tries to minimize distance between the image feature \( f(x_i) \)
We use a two-branch Relation Network following which later is sent to the relation module to model the association and relation between the image class-label and the image features.

### 3.2.2 Relation Network (RN)

We use a two-branch Relation Network following the work of (Sung et al., 2018) as our second baseline approach.

**Semantic embedding module**: It takes semantic representations of the image class-label $s_y$ as inputs, passes it to $\Theta$ and produces a representation which later is sent to the relation module to model the relation and association between the image class-label and the image features.

$$\Theta_{RN} = FC^{Relu}_c$$  \hspace{1cm} (4)

Finally we obtain $\Theta_{RN}(s_y)$ where $y \in \mathcal{Y}_{train}$

**Relation module**: Relation module of the RN takes concatenated image and semantic representations of the image class-label and passes them through a non-linear transformation using $FC^{Relu}_d$ layer to model the association and relation among these two different types of representations.

$$\Gamma(s_y, x) = FC^{Relu}_d(\Theta_{RN}(s_y) \oplus f(x))$$  \hspace{1cm} (5)

where $x \in X_{train}$, $f(x)$ represents visual features and $\oplus$ is the concatenation operation. In order to calculate a single score to measure the relation and association between the image class-label embeddings and the image features, $\Gamma(s_y, x)$ is fed to a FC layer of output size $M$ with sigmoid activation where $M$ is the number of unique image class-labels in the training data.

$$R(s_y, x) = FC_{sigmoid}(\Gamma(s_y, x))$$  \hspace{1cm} (6)

where $s_y$ is the set of all unique class-labels i.e., $s_{y_1}, s_{y_2}, s_{y_3}, ..., s_{y_M}$ in the training dataset.

Finally the model is trained using MSE loss using the following equation:

$$L = \frac{1}{N} \sum_{i=1}^{N} \|R(x_i, s_{y_i}) - 1(s_{y_i} == s_{y_j})\|^2$$  \hspace{1cm} (7)

**Inference**: For an unseen image $\bar{x}$, we find the nearest of all possible prototype $\Theta(s); \forall s \in \mathcal{Y}_{unseen}$ in visual embedding space, denoted as:

$$y = \arg \min \_y D(f(\bar{x}), \Theta_{DeZSL}(s_y))$$  \hspace{1cm} (3)

Here, $D$ is a distance function and $y \in \mathcal{Y}_{test}$.

We incorporate our commonsense knowledge embedding with attribute/semantic embeddings in each of the $\Theta$s to improve the existing semantic embedding (human defined attribute or word2vec embedding) $s_y$ in our experiments.

### 4 Method

Our method integrates commonsense knowledge extracted from ConceptNet, and leverages com-
We construct our class-aggregated graph from ConceptNet. In particular: a) We create a sub-graph of ConceptNet based on all seen-unseen classes (§4.1), and b) We train a graph-convolutional autoencoder model to learn CSE of the classes (§4.2).

Phase 2: After the graph autoencoder model is trained, a) We extract CSE for each of the classes from the graph (§4.3), and b) We feed the corresponding CSE into our ZSL framework (§3.2.1,§3.2.2).

We define each of these steps in detail below:

4.1 Phase 1: a) Class-Aggregated Commonsense Graph Construction

We construct our class-aggregated graph from ConceptNet (Speer et al., 2017). First, we introduce the following notation: ConceptNet graph is represented as a directed labeled graph $G = (V,E,R)$, with concepts/nodes $v_i \in V$ and labeled edges $(v_i, r_{ij}, v_j) \in E$, where $r_{ij} \in R$ is the relation type of the edge between $v_i$ and $v_j$. The concepts in ConceptNet are unigram words or n-gram phrases. For instance, a labelled edge from ConceptNet is (baking-oven, AtLocation, kitchen), where baking-oven and kitchen are concept nodes and AtLocation is the relation.

ConceptNet has approximately 34 million edges, from which we first extract a subset of edges based on the following heuristic. The seen and unseen class names are treated as the seeds that we use to filter ConceptNet into a sub-graph. In particular, we extract all the triplets from $G$ which are within the vicinity of radius 2 of any of those seed class names, resulting in a sub-graph $G' = (V', E', R')$, with approximately 500K edges.

4.2 Phase 1: b) Knowledge Graph Pre-training

To utilize $G'$ in our task, we first need to compute a representation of its nodes. We do this by training a graph autoencoder model to perform link prediction (a standard knowledge graph completion task). The model takes as input an incomplete set of edges $\hat{E}'$ from $E'$ in $G'$ and then assign scores to possible edges $(c_1, r, c_2)$, determining how likely are these edges to be in $E'$.

Following Schlichtkrull et al. (2018), our graph autoencoder model has two modules: a R-GCN entity encoder and a DistMult scoring decoder.

Encoder Module. We employ the Relational Graph Convolutional Network (R-GCN) encoder from Schlichtkrull et al. (2018) as our graph encoder network. The R-GCN transformation encodes concepts in a multi-relational graph and can be understood as a special case of a basic differentiable message passing (Gilmer et al., 2017). The power of this model comes from its ability to accumulate relational evidence in multiple inference steps from the local neighbourhood around a given concept. The neighborhood-based convolutional feature transformation process always ensures that distinct classes are connected to each other via latent concepts and influence each other to create enriched class-aggregated feature vectors.

Specifically, our encoder module consists of two R-GCN encoders stacked upon one another. This enables information flow from concepts that are within a distance of two hops. Extending this by the rule of associativity ($a \rightarrow b \rightarrow c$ and $c \leftarrow d \leftarrow e$) the model can capture a relatively long path relation ($a \rightarrow b \rightarrow c \leftarrow d \leftarrow e$). An alternate way to make the model capable of capturing long path relations would be to make the encoder module deeper. However, stacking more layers results in over-smoothing as node features eventually converge to the same value. Training deep GCN networks is thus very difficult and still an open research problem.

The initial concept feature vector $g_i$ is initialized randomly and thereafter transformed into the class-aggregated feature vector $h_i \in \mathbb{R}^{d'}$ using the two-step graph convolution process. The transformation process is detailed below:

$$f(x_i, l) = \sigma\left(\sum_{r \in R, j \in N'_i} c_{i,r} \frac{1}{N'_i} W_r^{(l)} x_j + W_0^{(l)} x_i\right)$$

$$h_i = h_i^{(2)} = f(h_i^{(1)}, 2) ; \quad h_i^{(1)} = f(g_i, 1)$$

where, $N'_i$ denotes the neighbouring concepts of concept $i$ under relation $r \in R$; $c_{i,r}$ is a problem specific normalization constant which can be set in advance, such that, $c_{i,r} = |N'_i|$, or can be learned in a gradient-based learning setup. $\sigma$ is an activation function such as ReLU, and $W_r^{(l)/2}$, $W_0^{(l)/2}$ are learnable parameters of the transformation.

This stack of transformations (Eq. (9)) effectively accumulates normalized sum of the local neighbourhood i.e. the neighbourhood information...
for each concept in the graph. The self connection ensures self-dependent feature transformation.

**Decoder Module.** DistMult factorization (Yang et al., 2014) is used to score a triplet \((c_i, r, c_j)\).

\[
s(c_i, r, c_j) = \sigma(h_{c_i}^T R_c h_{c_j})
\]

\(\sigma\) is the logistic sigmoid function; \(h_{c_i}, h_{c_j} \in \mathbb{R}^d\) are the R-GCN encoded feature vectors for concepts \(c_i, c_j\) from Eq. (9). Each relation \(r \in \mathcal{R}\) is also associated with a diagonal matrix \(R_r \in \mathbb{R}^{d \times d}\).

**Training.** We train our graph autoencoder model using negative sampling following Yang et al. (2014); Schlichtkrull et al. (2018). For triplets in \(\mathcal{E}'\) (positive samples), we create an equal number of negative samples by randomly corrupting the positive triplets. The corruption is performed by randomly modifying either one of the constituting relations or the concept.

The target label is set to \(y = 1/0\) for the positive/negative triplets. In this setup, the model is then trained with standard cross-entropy loss:

\[
\mathcal{L}_{\text{pos}} = -\frac{1}{2|\mathcal{E}'|} \sum_{(c_i, r, c_j) \in \mathcal{T}} (y \log s(c_i, r, c_j) + (1 - y) \log(1 - s(c_i, r, c_j)))
\]

Once we train the graph autoencoder model, it will inherently capture relevant information likely to be helpful in ZSL.

**4.3 Phase 2: Commonsense Embedding Extraction & ZSL**

The trained graph autoencoder model from Section 4.2, can now be used for the commonsense embedding extraction. For a particular class name \(C\), it is performed as follows:

1. First, we extract a subgraph from \(G'\), where we take all triplets which are within the vicinity of radius 2 of \(C\). We call this graph \(G'_C\).
2. We then make a forward pass of \(G'_C\) through the encoder of the pretrained graph autoencoder model. This results in feature vectors \(h_j\) for all unique nodes \(j\) in \(G'_C\).

3. Finally we take the feature vector \(h_C\) for node \(C\), to obtain the commonsense embedding \(CSE_C\) for class \(C\).

We hypothesize that since unseen classes will be connected to the seen classes through the inter-class associations in \(G'\), \(CSE_C\) will inherently capture relevant information likely to be helpful in ZSL.

**4.4 Fusion: Integrating Commonsense Embedding into the ZSL framework**

Once the commonsense embeddings for an image class-label are extracted, we need a mechanism to fuse these embeddings with the semantic embeddings that are used in the baselines. We carry out this using the following operations:

\[
\hat{s}_y = FC_{\text{Relu}}(s_y) \\
\tilde{c}_y = FC_{\text{Relu}}(CSE_y) \\
s'_{y} = \hat{s}_y \oplus \tilde{c}_y
\]

where \(s_y\) and \(CSE_y\) are the semantic and commonsense embeddings respectively. The output dimension of \(FC_{\text{Relu}}\) is set equal to the size of the visual feature embedding size in the case of DeZSL. Finally, \(s'_{y}\) is sent to the \(\Theta\) in both the baselines models– DeZSL and RN. This can be expressed using the equations:

\[
\Theta_{\text{DeZSL}}(s'_{y}) = FC_{h}^{\text{Relu}}(FC_{u}^{\text{Relu}}(s'_{y})) \\
\Theta_{\text{RN}}(s'_{y}) = FC_{c}^{\text{Relu}}(s'_{y})
\]

The outputs from \(\Theta_{\text{DeZSL}}(s'_{y})\) and \(\Theta_{\text{RN}}(s'_{y})\) are fed to respective relation module of both the baseline models (Eq. (7) and Eq. (5)) – DeZSL and RN for training.

Although the adopted fusion scheme is relatively simpler than the ones proposed in recent literature, we find it very effective. In this paper we focus only on efficacy of commonsense knowledge in ZSL rather than effectiveness of fusion methods.
Table 1: Description of the ZSL benchmark datasets used. Note: \( C_1 / C_2 \) - No. of seen/unseen classes

| Dataset   | #instances | \( C_1 / C_2 \) |
|-----------|------------|-----------------|
| AwA1 (Lampert et al., 2009) | 30475 | 40/10 |
| AwA2 (Xian et al., 2017)     | 37322 | 40/10 |
| aP&Y (Farhadi et al., 2009) | 15339 | 20/12 |

5 Experiments

5.1 Experimental Setup

We validate our commonsense embedding by performing experiments on three benchmark datasets on the task of ZSL. We choose two mid-sized datasets namely Animals with Attributes1 (AwA1) (Lampert et al., 2009) and Animals with Attributes2 (AwA2) (Xian et al., 2017). They share the same animal classes (such as horse, zebra, sheep, blue-whale etc.) but different images. aPascal & aYahoo (aP&Y) (Farhadi et al., 2009) is a small dataset containing image-classes from varied domains (such as dogs, aeroplane, jet-ski, potted-plant etc.). Details regarding these datasets are provided in Table 1.

We adopt GBU settings (Xian et al., 2017) commonly used in ZSL literature. We use ConceptNet 5.5 (Speer et al., 2017) in all our experiments.

5.2 Features Used

We use the following features in our ZSL baselines.

Visual Embedding: As used in (Xian et al., 2017; Zhang et al., 2017), our visual embeddings are 2048-dim top-layer pooling units of the 101-layered ResNet. It is pre-trained on ImageNet 1K (Deng et al., 2009) and not fine-tuned.

Semantic Embeddings: As discussed in the earlier sections, we use two different kinds of semantic embeddings:

- Distributed Word Embeddings (DWE): We use word2vec vectors pre-trained on part of Google News dataset (Mikolov et al., 2013a) to cast each class name into a 300-dimensional vector representation.

- Human Defined Attributes: Human defined attributes (such as furry, stripes) are 85 dimensional attribute vectors for AwA1 and AwA2. For aP&Y, we have 64 dimensional attribute vectors.

5.3 Implementation Details

In both the baselines, number of nodes in FC layers are chosen from — 512, 1024, 2048 and 4096 and are empirically determined using 10% data from the training set validation set. Both baselines are trained using ADAM optimizer (Kingma and Ba, 2014) with a learning rate of \( 10^{-5} \).

5.4 Model Variants and Baselines

In order to study the effect of commonsense knowledge, we look into the following variants:

- **HA**: Only using human defined attributes.
- **DWE**: Only constituting of word2vec DWEs.
- **HA+DWE**: Fusion of HA + DWE (as in Fig. 4).
- **HA+CSE**: We fuse human defined attributes with commonsense embedding.
- **DWE+CSE**: Word2vec is fused with commonsense embedding in order to compare against performance of DWE.
- **HA+DWE+CSE**: We fuse CSE with the fusion of HA and DWE for comparison with HA+DWE.
- **Wang et al. (2018)**: We compare our results with (Wang et al., 2018) as their approach is closest to ours. The purpose of this experiment is to check whether the existing knowledge graph-based approaches can produce results similar to ours. Wang et al. (2018) use a knowledge graph, NELL, and find the shortest path between each class pair in it. This process generates a sub-graph. They apply a GCN on this sub-graph to compute the node embeddings. As some of these nodes actually represent the classes in the dataset, they then feed these class embeddings into ZSL. We re-implemented their method by replacing NELL with ConceptNet. Note that the only similarity between Wang et al. (2018) and our work is that we both use graph convolution, but the methodologies and motivation are completely different. Wang et al. (2018) use GCN on a knowledge graph to transform initial pre-trained word embeddings and find an association among the transformed embeddings to visual embedding. However, we extract sub-graphs for all seen and unseen classes from the knowledge graph and pass them through a graph convolutional autoencoder model to extract a commonsense embedding. As such, our results are superior to Wang et al. (2018)’s as indicated in Table 4.

5.5 Evaluation Scheme

We follow conventional ZSL setting – training and testing classes are completely disjoint. This setting is standard for majority of ZSL works (Wang et al., 2019) including the original papers we formulate our baselines upon (Zhan et al., 2017; Sung et al., 2018). All experiments report top-1 accuracy.
monitor

Wherein, in the other two datasets the class labels are from only varied domains e.g., 'animal', 'statue', 'train'. We feed commonsense embedding (CSE) into two strong baseline models as discussed in §3.1. To do so, we fuse commonsense CSE with two different semantic embeddings 1) human defined attributes (HA); 2) word2vec (DWE). Experimental results showed that our knowledge graph encoding method achieved significant performance improvement over two strong baselines on three well-known datasets. We believe this happens because the underlying formulation of the trained GCN model. Our corresponding ZSL performance gain also corroborates with this. 

Effect of Commonsense Knowledge: We take a qualitative look at the effectiveness of commonsense knowledge in Table 2. Here, Column 1 indicates a pair of <seen, unseen> classes. Column 2 shows cosine similarity of their word2vec class embeddings. Column 3 reports association of these classes in commonsense graph. Although the pairs are not contextually similar as reflected in cosine similarity between their word2vec embeddings, they still have a path of associations between them. Even in cases of visually similar classes such as <Jetski, Motorbike> we see low cosine similarity of 0.45. Whereas in our commonsense graph, they have a direct relation ('relatedTo') – 'jet ski' relatedTo 'motorbike'. This ensures that commonsense embedding of 'Motorbike' can carry a great deal of information about the embedding of 'Jetski' because neighborhood message passing is the underlying formulation of the trained GCN model. Our corresponding ZSL performance gain can be seen that our proposed approach outperforms Wang et al. (2018) by a significant margin. It shows that our knowledge graph encoding method and its usage in the ZSL baselines are superior.

5.6 Results and Analysis

We feed commonsense embedding (CSE) into two strong baseline models as discussed in §3.1. To do so, we fuse commonsense CSE with two different semantic embeddings 1) human defined attributes (HA); 2) word2vec (DWE). Experimental results are shown in Table 3.

We observe a common trend of increase in ZSL recognition accuracies when CSE is fused with HA, DWE as well as HA+DWE. This demonstrates the role that commonsense knowledge can play in discovering meaningful associations between seen and unseen classes, which in turn facilitates knowledge transfer. We notice that the overall performance of the models on aP&Y is lesser compared to the other two datasets. We believe this happens because the seen and unseen class labels in the aP&Y dataset are from varied domains e.g., 'bird', 'statue', 'train'. Wherein, in the other two datasets the class labels are from only animal domain.

Comparison with WordNet: Can we replicate our performance with a knowledge graph that does not contain commonsense related information that we see in ConceptNet? Performances consistently drop by a large margin when WordNet is replaced with ConceptNet (Table 3).

Comparison with Wang et al. (2018): The results of this experiment are shown in Table 4. It can be seen that our proposed approach outperforms Wang et al. (2018) by a significant margin. It shows that our knowledge graph encoding method and its usage in the ZSL baselines are superior.

6 Conclusion

In this work, we built upon ConceptNet to extract commonsense embeddings to address the task of Zero Shot Learning (ZSL). To generate commonsense embeddings, we applied Graph Convolutional Network on the ConceptNet commonsense graph. Experimental results showed that our method achieved significant performance improvement over two strong baselines on three well known datasets.
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