Leveraging Knowledge Graphs for Zero-Shot Object-agnostic State Classification

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Abstract

We investigate the problem of Object State Classification (OSC) as a zero-shot learning problem. Specifically, we propose the first Object-agnostic State Classification (OaSC) method that infers the state of a certain object without relying on the knowledge or the estimation of the object class. In that direction, we capitalize on Knowledge Graphs (KGs) for structuring and organizing knowledge, which, in combination with visual information, enable the inference of the states of objects in object/state pairs that have not been encountered in the method's training set. A series of experiments investigate the performance of the proposed method in various settings, against several hypotheses and in comparison with state of the art approaches for object attribute classification. The experimental results demonstrate that the knowledge of an object class is not decisive for the prediction of its state. Moreover, the proposed OaSC method outperforms existing methods in all datasets and benchmarks by a great margin.

1. Introduction

Objects play a significant role in our daily lives, as we use them as tools and interact with them regularly. Objects may be in different states. The accurate recognition of such states is crucial because it determines the actions that can be performed with or upon it [16]. In the field of computer vision, object state classification (OSC) is important for inferring an object's functionality and is closely related to action recognition [39], object classification [11] and affordance learning [9].

Taking into consideration these observations, it could be argued that the research on state classification is disproportionately low, especially in comparison to the enormous effort that has been invested on the related field of object classification. However, this situation seems to change during the last few years and the number of works dedicated to this



Figure 1. The proposed method for Object-agnostic State Classification (OaSC) combines (a) structured knowledge on object states stemming from common-sense repositories with (b) visual information that relates the appearance of certain objects to their states. This combination enables the possibility to infer the state of objects that have never been presented to the training set.

problem keeps growing [13, 15, 22, 35].

In the context of visual recognition, states can be viewed as a distinct subset of attributes. Attributes typically refer to static visual properties of objects, such as color, shape, or texture. In contrast, states capture the dynamic aspects and represent the current condition or situation of an object. Attributes are typically defined based on visual properties that remain relatively stable across different contexts and appearances. In contrast, states are defined based on changes in appearance or context, which are more subtle and can be influenced by various factors. Thus, the accurate recognition of states requires to deal with challenges such as capturing and modeling the dynamic nature of visual information, identifying subtle changes in appearance, and accounting for contextual variations (see Figure 2).

In this work we investigate the OSC problem by focus-



Figure 2. State classification poses various unique challenges. Minor details can determine different states for an object (e.g., the open bottle in (a) is very similar in appearance to a closed one in (b)). States exhibit significant intra-class variability: different and visually distinct objects can share the same state (e.g., the closed object in (b) and the closed door in (c)). Lastly, states are applicable only to specific object categories: (i.e., a mug can have green or orange color (d), however the state "folded" does not apply to a mug (e)). However, in open-set or zero-shot settings, such constraints might not be known in advance.

ing on household objects studying the important variation of zero-shot-classification. To achieve this goal, we explore the potential of Knowledge Graphs (KGs), which are recognized as a powerful tool for structuring and organizing knowledge that can be applied to various fields, including zero-shot learning. We find that KGs are particularly useful for the OSC task because they offer a structured representation of the relationships among different entities and concepts, enabling the inference of relationships between unseen categories and known ones. As a result, knowledge graphs can enhance the accuracy and robustness of OSC models by providing a powerful tool for knowledge representation and inference.

Towards this end, we developed and extensively evaluated a novel zero-shot object-agnostic method $(OaSC)^1$ that does not depend on object classification (see Figure 1). To the best of our knowledge, this is the first zero-shot method that focuses on household objects states and does not rely on object classification. This aspect of our approach enables the recognition of states in classes of objects that are not known beforehand, a property that current zero-shot attribute classification does not support. Our contributions can be summarized as follows:

- We propose a novel zero-shot state classification method that outperforms existing state-of-the-art methods. Notably, our approach is object-agnostic, meaning that its performance does not rely on prior accurate object classification, resulting in greater robustness than other competing methods. To the best of our knowledge, our method is the first to exhibit this property.
- We conduct an extensive experimental evaluation of the proposed method in several datasets and in com-

parison with relevant state of the art methods. The obtained results exceed the state of the art by a great margin.

• We conduct an ablation study across various settings to evaluate the strengths and weaknesses of our method. This analysis provides valuable insights towards developing further improvements.

2. Related Work

State/Attribute Classification: The most generally accepted definition of "visual attributes" is that they are visual concepts which are detectable by machines and can be comprehended by humans [10]. The current approach for learning attributes is similar to that of object classes, where a convolutional neural network is trained with discriminative classifiers using annotated image datasets [34]. However, labeled attribute image datasets often lack the data scale found in object datasets, contain a limited number of generic attributes, or cover only a few specific categories [15, 19, 23, 28, 48]. The number of works focusing exclusively on state classification is limited [13]. Most of them are based on the same assumptions that are used for the task of attribute classification.

Zero-shot Object Classification: Zero-shot object classification has gained increasing attention in recent years due to its practical importance in real-world applications, where it is often difficult to obtain training data for all possible object classes [43]. A number of approaches have been proposed to address this problem, including semantic embeddingbased methods [40, 44], attribute-based methods [20], generative models [8, 44] and learning of a compatibility function between image and class embeddings [2]. Semantic embedding-based methods utilize a low-dimensional semantic space to represent objects and their attributes, and

¹The implementation code will be soon publicly available.

use this representation to map between seen and unseen object classes. Attribute-based methods leverage a set of attributes that describe object classes, and use these attributes to infer the class of an unseen object. Generative models generate samples of unseen object classes by synthesizing images that are similar to images of seen object classes. In addition to these approaches, recent work has also explored the use of knowledge graphs [17,27], which capture semantic relationships between objects and can be used to facilitate zero-shot learning. Prior methods in zero-shot learning have typically utilized predetermined attributes or pretrained embeddings, in contrast to our proposed approach which centers on acquiring class representations directly from the knowledge graph during the task.

Compositional Zero-shot Learning: Compositional Zero-Shot Learning (CZSL) aims to generalize to unseen combinations of object and state primitives by learning their compositionality from the training set. Two groups of CZSL approaches have been proposed: the first group models individual classifiers of states and objects or learns a hierarchical decomposition and composition of visual primitives [24,26,46], while the second group learns a joint compatibility function with respect to the image, the state, and the object by conditioning modular networks on each composition [3,29]. The work in [3] recently proposed learning the visual transformation through a causal graph, where the latent representations of primitives are independent of each other, as a way to achieve generalization in CZSL. The work in [21] presented a transformation framework consisting of two modules inspired by group theory that incorporates the principle of symmetry in attribute-object transformations. Mancini [23] utilizes a graph convolutional neural network to model the dependency between states, objects and their compositions, and estimates a feasibility score for each unseen composition to improve representations in open-world CZSL scenarios.

Graph Neural Networks: Graph Neural Networks have gained popularity due to their ability to learn node embeddings that reflect the structure of the graph [18]. These networks have shown significant improvements in downstream tasks, such as node classification and graph classification [14, 33, 37, 41]. In this work, we make use of the transformer graph convolutional networks which has been recently used in the context of zero-shot object classification [27]. Prior works have considered transformers as a method to learn meta-paths in heterogeneous graphs rather than as a neighborhood aggregation technique. Furthermore, graph neural networks have been applied to various applications, including fine-grained entity typing [45], text classification [47], reinforcement learning [1], and neural machine translation [5].

Leveraging common sense Knowledge Graphs: Com-

mon sense knowledge graphs have been extensively utilized in various tasks including transductive zero-shot text classification [50] and object classification [17, 43]. Previous works such as [6] and [7] have explored the application of common sense knowledge graphs in diverse settings. The notable work in [50] used ConceptNet for transductive zeroshot text classification as shallow features for class representation. Another related work [49] also utilized common sense knowledge graphs and graph neural networks for transductive zero-shot object classification. This approach learns to model seen-unseen relations with a graph neural network and requires knowledge of unseen classes during training, utilizing hand-crafted attributes. Drawing inspiration from [27] which proposed a novel GNN architecture capable of generating dense vector representations from ConceptNet, we further extend this approach in a novel context.

3. Methodology

Let O denote the set of objects, S denote the set of states, and I denote the set of images, which is partitioned into the training set I^T and the testing set I^U . Each image $i \in I$ contains an object $o \in O$ that is in a state $s \in S$. The goal of OSC is to predict the state label $s \in S$, given an object o appearing in an image $i \in I^U$ as input. In the zero-shot variation of OSC, the set of states in the testing images S^U is not a subset of the set of states in the training images S^S , i.e., there exists some states in the testing set that do not appear in the training set. It is important to note that although the set of object classes does not directly affect the task, its size is proportional to the complexity of the problem.

3.1. Overview

The proposed method draws inspiration from prior research on zero-shot object classification and leverages the potential of KGs and GNNs to classify previously unseen objects. The fundamental idea behind this approach is that the semantic information stored in the KG can be processed by the GNN and then used in conjunction with visual information from training images. This technique enables the model to generalize to new object classes by leveraging the semantic information encoded in the KG.

GNNs are designed by default to operate on graphstructured data, such as KGs [25]. KGs are typically represented as labeled multi-graphs, where nodes correspond to entities, and edges represent the relationships between them. GNNs process this graph by iteratively aggregating information from neighboring nodes, using neural networkbased operations.

At each iteration, a GNN receives a feature vector for each node in the graph, which is initially set to the node's embedding vector. Then, the GNN performs a message-



Figure 3. The pipeline of OaSC. Our method consists of four stages. In Stage 1, using as reference points the concepts of seen and unseen state classes (referring to state classes that appear and do not appear in the training set of images, respectively), a common-sense repository is queried in order for a KG to be created. In Stage 2, the KG is processed by a GNN, which computes embeddings for all state classes (both seen and unseen). These embeddings serve as the final layer of a pre-trained classifier (a CNN model). Moving to Stage 3, the classifier is re-trained (fine-tuned) using images that only contain seen classes, with the last layer of the classifier being fixed. Finally, in Stage 4, the fine-tuned classifier can be utilized for prediction, accepting images that include both types of state classes.

passing step, where it aggregates information from neighboring nodes, based on the edge weights and the features of the nodes. This message-passing operation can be formulated as a neural network layer, which applies a learnable function to the features of the neighboring nodes and returns an aggregated message for each node.

After the message-passing step, the GNN updates the node features by applying a learnable transformation that takes into account the original features of the node and the received messages from its neighbors. This updated feature vector is then passed to the next iteration of the messagepassing step. The process continues until a fixed number of epochs or convergence is achieved.

In the method that we are proposing, a GNN architecture is incorporated into the classifier that is for trained on seen classes. In particular, the last layer of the GNN is designed to have the same size as the last layer of the classifier. This enables the GNN to generate semantic embedding features that correspond to all classes, including both seen and unseen classes that will be encountered during the inference phase. Subsequently, the semantic embedding features replace the last layer of the classifier, while keeping this layer fixed. The body of the classifier is then fine-tuned with the training images to optimize the overall model for state recognition.

The graph neural network that we utilize is the Trans-

former Graph Convolutional network (Tr-GCN) [27] which is capable of combining input sets non-linearly by utilizing multilayer perceptrons and self-attention. Overall, we experimented with four different architectural frameworks. Further details are provided in subsection 4.3 and in the supplementary material. We leverage the aforementioned property of Tr-GCN to train a permutation invariant non-linear aggregator that captures the intricate structure of a common sense knowledge graph. Tr-GCN is an inductive model that learns node representations by aggregating local neighborhood features. This allows the learned model to make predictions on new graph structures without retraining, rendering it well-suited for zero-shot learning. It is worth noting that a similar network architecture has been effectively employed for zero-shot object classification [27].

3.2. The proposed OaSC pipeline

Overall, the proposed pipeline (see Figure 3) consists of four stages: (1) the creation of the KG, (2) the production of the semantic embeddings, (3) the fine-tuning of the classifier and, (4) the deployment of the fine-tuned classifier.

Construction of the KG (Stage 1): To create the KG we query a common sense repository. The goal is to offer a solution that can generalize, instead of having to create our own KG tailored to the entities at hand and the relationships

they have. The process begins by generating a set of nodes that correspond to the target state classes. Then, we query the repository for each of these nodes and add their neighbors to the knowledge graph if they meet specific criteria (see the ablation section for further information). We repeat this process for the newly added nodes until we reach a specified number of hops.

Building a KG in this manner offers a number of advantages in comparison to custom-made approaches. First, being more problem-agnostic this approach is more generic than hand-crafted methods, and allows the same KG to be used for different variations of the task at hand. Second, this property enables transfer learning since KGs can be reused in related problems. Moreover, their creation does not rely on expert knowledge which is expensive and timeconsuming. The trade-off is that KGs of this type are prone to the introduction of noisy information. Besides, the structured representation of relationships between entities and concepts that KGs provide can be leveraged to generate robust embeddings for zero-shot learning.

Computation of semantic embeddings (Stage 2): The KG that was created in the Stage 1 is passed to a GNN and processed in the manner described previously. The procedure results in the computation of semantic embeddings for all target state classes. These embeddings serve as the last layer of the CNN classifier that is utilized during Stages 3 and 4.

A critical aspect of this procedure involves calibrating the weights of the GNN in a manner that its predictions in the semantic space, i.e. semantic embeddings, are useful for the classifier deployed in the visual space during Stage 3 and 4. To accomplish this, we adopt an approach based on prior research [17, 27, 40] that involves learning the semantic class representations by minimizing the L2 distance between the learned class representations and the weights of a fully connected layer in a ResNet classifier pre-trained on the ILSVRC 2012 dataset [31].

Fine-tuning of the Classifier (Stage 3): The semantic embeddings that were computed in Stage 2 are incorporated in a classifier pre-trained on object classification that uses a ResNet backbone. Namely, they constitute the last layer of the network, i.e. the part which corresponds to the representations of the target classes that are used for the prediction. Consequently, the classifier is re-trained for the classification of the target state classes with the input images that are passed on containing solely states belonging to the training set (seen states). During this fine-tuning procedure the weights of the last layer of the classifier remain fixed so that the learned representations of Stage 2 can not be altered. As a consequence, the weights of the previous layers, which are not fixed, are updated in order to adapt to the "frozen" weights of the last layer.

Deployment (Stage 4): After the procedure of the fine-

tuning is completed, the classifier can be utilized for prediction. It should be noted that the classifier is suitable for the prediction of either only unseen classes, i.e. zero-shot classification, or both seen and unseen classes, i.e. generalized zero-shot classification.

4. Experimental Evaluation

Our study involves a sequence of experiments that entail comparing our approach to another SoA model, as well as conducting an extensive ablation study to investigate various aspects of the problem. Specifically, we aim at an in depth exploration of three Hypotheses. First, we examine the degree to which the KG contributes to the success of the OSC task. Second, we evaluate the impact of the GNN architecture on the method's overall performance. Additionally, we investigate whether knowledge of the object class has an effect on the performance of the OSC task. The previous hypotheses can be formulated as follows:

Hypothesis 1: The KG is beneficial to the task. Its impact depends primarily on the type of the knowledge it contains.

Hypothesis 2: The GNN architecture is crucial to the performance of the method.

Hypothesis 3: The knowledge of an object class is not decisive for the prediction of its state. Therefore, a method that is agnostic to the object class, can perform equally well to a method that relies on it.

4.1. Implementation and evaluation issues

Implementation details: The GNN was trained following the method outlined in Nayak et al. [27]. The model was trained for 1000 epochs on 950 randomly selected classes from the ILSVRC 2012 dataset [31], while the remaining 50 classes were held out for validation. The model with the lowest validation loss was chosen to generate the seen and unseen class embeddings using the graph. For the seen classes, the embeddings were frozen, and a pretrained ResNet101-backbone was fine-tuned on the individual datasets for 50 epochs using stochastic gradient descent with a learning rate of 0.0001 and momentum of 0.9.

Datasets: At present, there is a lack of datasets exclusively dedicated to object states, with the exception of the OSDD [13] which is a dataset tailored for state detection. Instead, existing attribute datasets include object states among their classes. To address this, we utilized two of the most widely used attribute datasets [15, 23] and extracted subsets that specifically relate to object states for use in our experimental evaluation. Regarding the OSDD, we extracted the bounding boxes of the original images in order to create images suitable for the OSC task. The complexity of each dataset can be assessed primarily by (a) the number of unseen state classes and (b) the average number of

Dataset	Train	Val	Test	Seen	Unseen	Objects	VOSC	TOSC	S\0
OSDD [13]	6,977	1,124	5,275	5	4	14	35	126	2.36
CGQA-states [23]	244	46	806	2	3	17	41	75	1.71
MIT-states [15]	170	34	274	2	3	14	20	70	1.57

Table 1. Dataset details. Train/Val/Test: Number of Training/Validation/Testing Images. Seen/Unseen: Number of seen/unseen State classes. Objects: Number of Object classes. VOSC/TOSC: Valid/Total Object-State combinations. S\O: Average number of states than an Object can be situated in.

Mathad Varsian		OSDD				CGQA-States				MIT-States			
	version	Seen	Unseen	HM	AUC	Seen	Unseen	HM	AUC	Seen	Unseen	HM	AUC
	00	84.2	18.2	14.0	6.7	93.2	45.7	33.9	24.7	97.8	55.5	37.5	30.6
AoP [26]	OW^\dagger	69.7	33.3	21.6	9.2	90.3	40.1	22.5	13.2	38.7	12.3	7.2	1.3
CW [†]	CW^\dagger	75.9	41.1	28.7	13.4	95.5	50.0	35.6	27.7	48.5	20.8	15.1	4.1
	00	31.2	39.8	23.8	9.2	96.7	13.0	14.0	6.2	99.8	20.7	20.7	10.3
LE+ [24]	OW^{\dagger}	71.6	14.3	20.8	6.5	76.7	11.1	9.5	3.0	63.6	14.6	20.3	7.1
CW^{\dagger}	CW^\dagger	68.6	31.7	34.5	16.9	93.5	16.1	16.1	8.1	99.4	20.5	19.4	10.0
00	00	85.5	67.2	38.5	27.5	99.0	17.1	16.5	8.5	99.2	9.5	17.2	8.9
TMN [29]	OW^\dagger	73.4	43.6	33.7	19.0	99.0	17.1	16.5	8.5	69.7	18.4	22.4	6.3
CW^{\dagger}	CW^\dagger	71.5	49.8	34.9	20.7	97.0	76.0	39.9	32.3	84.9	30.7	27.4	16.1
	00	83.2	36.7	28.3	16.3	98.5	66.4	34.3	27.2	97.3	29.1	29.6	17.3
SymNet [21]	OW^{\dagger}	77.7	14.0	21.1	7.5	94.0	7.1	13.2	6.1	79.3	17.2	10.2	5.1
CW^{\dagger}	77.7	59.4	44.2	31.1	95.5	27.4	39.4	24.4	96.9	27.5	26.8	15.7	
$\begin{tabular}{c} & OO\\ Compcos [23] & OW^{\dagger}\\ CW^{\dagger} \end{tabular}$	00	76.1	51.1	35.9	25.4	95.7	72.8	21.9	10.1	97.6	49.4	21.8	10.2
	OW^\dagger	79.9	3.7	30.1	22.1	86.8	42.8	7.7	3.4	97.3	29.1	28.3	16.9
	CW^\dagger	81.7	33.2	38.7	23.8	94.2	73.9	48.1	41.5	94.6	33.7	44.9	23.8
OaSC		86.5	64.2	45.6	35.4	97.1	68.6	43.0	35.0	85.7	69.6	52.7	40.9

Table 2. Aggregate results. Seen: Best Accuracy on seen classes. Unseen: Best accuracy on unseen classes. HM: Best harmonic mean. AUC: Area under curve for the pairs of accuracy for seen and unseen classes. OO: Object-Oracle version. OO: Open-World Vversion. CO: Closed-World version.

[†] Serves as external reference but is not considered a baseline due to violation of experiment assumption.

states per object class. The details for the three datasets are presented in Table 1.

Metrics: Our evaluation protocol follows the standard generalized zero-shot evaluation described in [30]: we calculate the Area Under the Curve (AUC) measuring the accuracy on both seen and unseen compositions at different operating points based on the bias term that is added to the scores of the unseen classes. The optimal zero-shot performance occurs when the bias term is positive, leading the classifier to prioritize the unseen labels. Conversely, the best seen performance is achieved with a negative bias term, which result in a focus on the seen labels. Additionally, we report the best harmonic mean (HM) which expresses balance between the seen and unseen accuracy, respectively.

Comparison with SoA methods: Given that there are currently no zero-shot state classifiers available, we resort to employing 5 state-of-the-art models [21,23,24,26,29] from the field of CZSL that deal with predicting both object and state labels and are, therefore, closely related to OSC. As these models are capable of producing state labels, they

can be used in the context of OSC without any modifications. We evaluate the performance of this approach on three different versions: closed world, open world, and object-oracle:

- Closed World (CW) version: the method is tasked with predicting only among the valid object-state pairs.
- **Open World (OW) version**: the method is tasked with predicting among all object-state pairs.
- **Object Oracle (OO) version**: all object labels are replaced with the generic term "object", allowing the method to solely predict the state label.

While the closed world version setting violates the zeroshot conditions since it assumes that the valid states for each object are known in advance, we include it as a baseline for comparison. Moreover, the open world version is less generic than our approach since it presupposes that the set of object labels to which the states corresponds is closed, i.e. the same during training and inference, whereas our method is totally agnostic to this parameter. In addition, both the closed and the open world versions of the models make use of the information corresponding to the object categories, something that violates the object-agnostic assumption. Therefore, the most fair comparison to our method is the object oracle version of the models. However, we report the results of the closed and open world version of each model as frames of reference.

4.2. Results

Table 2 summarizes the results of the evaluation for the three employed datasets. We report the performance of the version of our model that was selected by the ablation study described in the next version. It should be noted that this version of the model does not exhibit the best performance in all categories. The results indicate that under the Object Oracle version, our method clearly outperforms the competing methods in both metrics, namely AUC and HM, across all three datasets. Furthermore, our method achieves superior performance than the Closed-World setting of all the competing methods in most cases (it scores best 14 out of 15 cases, e.g. 5 competing models X 3 datasets, in the AUC metric and 13 out of 15 times in the HM metric, respectively). This attests to the robustness of our method, since the Closed-World setting makes use of additional information regarding the object classes and the valid object-state combinations. In the following, we refer only to the performance of the object oracle versions of the competing methods.

The largest performance margin in favor of our method is observed in the MIT-states dataset, with an increase of 10.3%/ for AUC and 15.2% for HM in comparison to the scores of the best performed competing method (AoP). In the case of the OSDD dataset, there is a difference of 7.9% for AUC and 7.1% for HM in favor of our method w.r.t. TMN method which is the competing method that performs best in this dataset. Finally, for the CGQA-States dataset a difference of 7.8% for AUC and for 8.7% HM is observed between our method and the SymNEt model which scores best among the competing methods in this setting.

The substantial margin by which our proposed objectagnostic OaSC method outperforms the competing objectbased method in every experiment supports strongly the **Hypothesis 3**, namely that that object information does not provide any advantages in the context of zero-shot OSC. Additionally, the behavior of the three versions of the competing models provides further insights regarding the problem. Specifically, the Open-World version performs very poorly, while the performance of the Object-Oracle version can be deemed only average, given the significantly smaller search space (i.e., set of states) in comparison to the search spaces of the Closed (i.e., set of valid object-state pairs) and Open (i.e., set of all object-state pairs) Worlds, respectively.

4.3. Ablation Study

We conducted a host of ablation experiments across several problem dimensions with the purpose of selecting the optimal parameters for our model and of investigating more thoroughly the three hypotheses stated previously. Specifically, we explored the impact of varying the GNN architecture, the KG source, the maximum number of hops used for KG creation, and the policy for including nodes in the KG. Due to space consideration, it is not possible to present the performance exhibited by every ablated model that was tested. Instead, we present aggregated means of all models across each of the ablated dimensions reporting the best harmonic mean and the AUC for each of the three datasets, respectively.

GNN architecture: We experiment with 4 different GNN architectures: GCN [18], R-GCN [32], LSTM [14] and Tr-GCN [27].The ablation results for the different architectures are presented in Table 3. We can see that the Tr-GCN framework outperforms the other frameworks in all datasets w.r.t. AUC metric. whereas it scores best w.r.t. HM metric in the OSSD and comes second in the two other datasets. The R-GCN framework exhibits the second-best performance, while the GCN framework comes in third and the LSTM framework exhibits the worst performance respectively. These findings are consistent with prior research in the domain of zero-shot object classification and substantiate **Hypothesis 2**.

KG source: We employed two KG sources, namely ConceptNet [36] and WordNet [12], and also experimented with combining information from both sources. Other sources such as Dbpedia [4] and WikiData [38] were also considered, but the necessary information for constructing a KG could not be obtained. Moreover, to assess more accurately the contribution of the KGs we include a ConceptNet-based model in which the target states classes were mapped to other unrelated state embeddings of the KG and a random model where the embeddings corresponding to the target state classes were generated by a random process.

Consulting the results in Table 4, we can observe that ConceptNet outperforms WordNet in all three datasets, while combining both sources results in performance gains for the HM metric in all three datasets and for the AUC metric in two of the datasets. The difference in favor of ConceptNet can be attributed to the difference between the type of information that each KG holds. Specifically, ConceptNet contains mainly common-sense knowledge and also includes some lexicographic information, in contrast to WordNet which contains only lexicographic information. Nonetheless, the fact that the best results are achieved by a model that uses both sources suggests that they may be complementary to each other. Taken together, these findings offer substantial support for **Hypothesis 1**.

Furthermore, we can see that the performance of the model using the random embeddings is very low, whereas the ConceptNet-based model using unrelated state embeddings achieves a clearly better performance which yet remains significantly lower than that of the other CN-based models. The distinction between these approaches can be attributed to the distribution of their embeddings: the former model employs a balanced and representative distribution enabled by GNN which permits the model to map the learned representations to the visual information of seen classes during the fine-tuning procedure. In contrast, the latter model has a completely random distribution which cannot be mapped to the semantic representations. The unrelated embeddings do not provide leverage for the recognition of unseen classes, thus resulting in the overall mediocre performance of the model.

Number of max hops: We experiment with a hop equal to 2 and to 3 for both KGs. The results are shown in the first two columns of Table 5. We can observe that no consistent pattern can be identified. The best average performance is achieved for the OSDD dataset at a hop count of 2, while best average performance is exhibited for the CGQA-State dataset at a hop count of 3. In the case of MIT-States, there is no clear winner, as hop 2 shows superior AUC and hop 3 exhibits superior HM. This suggests that introducing additional nodes beyond a certain limit may introduce noise, potentially impacting negatively overall performance in specific cases, as observed in the OSDD dataset. This outcome is consistent with the **Hypothesis 1**.

Node policy: We investigate two strategies for adding nodes to our knowledge graph: indiscriminate inclusion of all neighboring nodes and selective inclusion of only relevant nodes. To determine relevance in ConceptNet, we use the edge weight between the queried node and its neighbors as the inclusion criterion. In WordNet, we use the Wu-Palmer Similarity metric [42] between the two nodes. Additionally, in WordNet, we explore a hierarchical policy of accepting candidate nodes only if their ancestors belong to certain generic categories, such as attributes or objects.

From the results (as shown in the last two columns of Table 5) it is evident that adopting this policy leads to significant performance improvements across all three datasets. This finding complements the previous observation regarding the number of hops and further strengthens the notion that the presence of noisy nodes can have a detrimental effect on model performance. These results align with **Hypothesis 1**.

5. Summary

We proposed OaSC, a novel approach for the task of zero-shot state classification. Our model holds the great advantage of being object-agnostic, a property that renders it

Arch Dataset	LSTM	GCN	R-GCN	Tr-GCN
OSDD	39.0/25.7	40.0/27.0	42.9/29.9	43.2/30.3
CGQA-States	28.3/37.8	30.6/40.2	29.0 /38.1	28.2/ 38.5
MIT-States	47.7/30.7	50.7/34.3	53.7 /36.6	51.2/ 39.8

Table 3. Ablation results for the framework architecture. The first (second) value in each cell corresponds to the best HM (AUC).

KG Dataset	CN	WN	CN+WN	IE	RN
OSDD	43.5/30.5	32.6/18.5	45.4/34.7	19.4/9.3	8.2/3.1
CGQA-States	39.2/29.1	37.9/27.4	44.5/34.7	20.1/9.0	11.1/5.7
MIT-States	53.3/ 42.6	38.5/26.6	54.0 /42.1	33.8/22.1	18.6/13.0

Table 4. Ablation results for the KG source. The first (second) value in each cell corresponds to the best HM (AUC). CN: ConceptNet. WN: WordNet, WN+CN: Model based on both ConceptNet and WordNet. IE: ConceptNet-Based Model with irrelevant embeddings. RN: Model with random embeddings.

Hops/Policy Dataset	H2	Н3	NP	THR
OSDD	43.1/30.6	41.0/27.6	38.8/25.3	42.5/28.5
CGQA-States	30.3/39.5	31.4/41.0	25.9/36.0	29.8/39.5
MIT-States	52.3/ 36.9	54.8 /36.5	45.9/31.7	56.0/42.3

Table 5. Ablation results for the number of hops (column 1 and 2) and the threshold policy (column 3 and 4). The first (second) column refers to the average performance of models which are based on a KG with hop equal to 2 (3). The third (fourth) column refers to the average performance of models which are based on a KG created without (with) threshold policy. The first (second) value in each cell corresponds to the best HM (AUC).

more robust and generic than other methods which depend on object class classification. We evaluated our approach on three benchmark datasets ([13, 15, 23]). OaSC outperforms the competing SoA method and shows strong performance in all benchmark datasets. Moreover, an extensive ablation study evaluated several design options and shed light in important aspects of the object state estimation problem.

In terms of future directions, firstly, we aim to experiment with the tuning of the GNN by using a classifier pre-trained on attribute classes or object-attributes pairs instead of object classes. Secondly, we would like to examine whether the exclusive inclusion of nodes related to objects into KGs leads to better results. Overall, we consider that the zero-shot state classification in the objectagnostic setting is worth further investigation. We hope that our work will encourage future efforts towards this direction.

References

 Ashutosh Adhikari, Xingdi Yuan, Marc-Alexandre Côté, Mikuláš Zelinka, Marc-Antoine Rondeau, Romain Laroche, Pascal Poupart, Jian Tang, Adam Trischler, and Will Hamilton. Learning dynamic belief graphs to generalize on textbased games. Advances in Neural Information Processing Systems, 33:3045–3057, 2020. 3

- [2] Zeynep Akata, Scott Reed, Daniel Walter, Honglak Lee, and Bernt Schiele. Evaluation of output embeddings for fine-grained image classification. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 2927–2936, 2015. 2
- [3] Yuval Atzmon, Felix Kreuk, Uri Shalit, and Gal Chechik. A causal view of compositional zero-shot recognition. Advances in Neural Information Processing Systems, 33:1462– 1473, 2020. 3
- [4] Sören Auer, Christian Bizer, Georgi Kobilarov, Jens Lehmann, Richard Cyganiak, and Zachary Ives. Dbpedia: A nucleus for a web of open data. In *The Semantic Web:* 6th International Semantic Web Conference, 2nd Asian Semantic Web Conference, ISWC 2007+ ASWC 2007, Busan, Korea, November 11-15, 2007. Proceedings, pages 722–735. Springer, 2007. 7
- [5] Jasmijn Bastings, Ivan Titov, Wilker Aziz, Diego Marcheggiani, and Khalil Sima'an. Graph convolutional encoders for syntax-aware neural machine translation. *arXiv preprint arXiv:1704.04675*, 2017. 3
- [6] Chandra Bhagavatula, Ronan Le Bras, Chaitanya Malaviya, Keisuke Sakaguchi, Ari Holtzman, Hannah Rashkin, Doug Downey, Scott Wen-tau Yih, and Yejin Choi. Abductive commonsense reasoning. arXiv preprint arXiv:1908.05739, 2019. 3
- [7] Antoine Bosselut, Hannah Rashkin, Maarten Sap, Chaitanya Malaviya, Asli Celikyilmaz, and Yejin Choi. Comet: Commonsense transformers for automatic knowledge graph construction. arXiv preprint arXiv:1906.05317, 2019. 3
- [8] Soravit Changpinyo, Wei-Lun Chao, Boqing Gong, and Fei Sha. Synthesized classifiers for zero-shot learning. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 5327–5336, 2016. 2
- [9] Ching-Yao Chuang, Jiaman Li, Antonio Torralba, and Sanja Fidler. Learning to act properly: Predicting and explaining affordances from images. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 975–983, 2018. 1
- [10] Kun Duan, Devi Parikh, David Crandall, and Kristen Grauman. Discovering localized attributes for fine-grained recognition. In 2012 IEEE conference on computer vision and pattern recognition, pages 3474–3481. IEEE, 2012. 2
- [11] Ali Farhadi, Ian Endres, Derek Hoiem, and David Forsyth. Describing objects by their attributes. 2009 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2009, pages 1778–1785, 2009. 1
- [12] Christiane Fellbaum. Wordnet. In *Theory and applications of* ontology: computer applications, pages 231–243. Springer, 2010. 7
- [13] F. Gouidis, T. Patkos, A. Argyros, and D. Plexousakis. Detecting object states vs detecting objects: A new dataset and a quantitative experimental study. In *Proceedings of the 17th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISAPP)*, volume 5, pages 590–600, 2022. 1, 2, 5, 6, 8

- [14] Will Hamilton, Zhitao Ying, and Jure Leskovec. Inductive representation learning on large graphs. Advances in neural information processing systems, 30, 2017. 3, 7
- [15] Phillip Isola, Joseph J. Lim, and Edward H. Adelson. Discovering states and transformations in image collections. Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 07-12-June:1383–1391, 2015. 1, 2, 5, 6, 8
- [16] Lorenzo Jamone, Emre Ugur, Angelo Cangelosi, Luciano Fadiga, Alexandre Bernardino, Justus Piater, and José Santos-Victor. Affordances in psychology, neuroscience, and robotics: A survey. *IEEE Transactions on Cognitive and Developmental Systems*, 10(1):4–25, 2016. 1
- [17] Michael Kampffmeyer, Yinbo Chen, Xiaodan Liang, Hao Wang, Yujia Zhang, and Eric P. Xing. Rethinking knowledge graph propagation for zero-shot learning. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2019-June:11479–11488, 2019. 3, 5
- [18] Thomas N Kipf and Max Welling. Semi-supervised classification with graph convolutional networks. *arXiv preprint arXiv:1609.02907*, 2016. 3, 7
- [19] Christoph H Lampert, Hannes Nickisch, and Stefan Harmeling. Learning to detect unseen object classes by betweenclass attribute transfer. In 2009 IEEE conference on computer vision and pattern recognition, pages 951–958. IEEE, 2009. 2
- [20] Christoph H. Lampert, Hannes Nickisch, and Stefan Harmeling. Attribute-based classification for zero-shot visual object categorizationa. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 36(3):453–465, 2014. 2
- [21] Yong-Lu Li, Yue Xu, Xiaohan Mao, and Cewu Lu. Symmetry and group in attribute-object compositions. pages 11316– 11325, 2020. 3, 6
- [22] Yang Liu, Ping Wei, and Song-Chun Zhu. Jointly recognizing object fluents and tasks in egocentric videos. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 2924–2932, 2017. 1
- [23] Massimiliano Mancini, Muhammad Ferjad Naeem, Yongqin Xian, and Zeynep Akata. Learning Graph Embeddings for Open World Compositional Zero-Shot Learning. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 8828(c):1–15, 2022. 2, 3, 5, 6, 8
- [24] Ishan Misra, Abhinav Gupta, and Martial Hebert. From red wine to red tomato: Composition with context. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 1792–1801, 2017. 3, 6
- [25] Sebastian Monka, Lavdim Halilaj, and Achim Rettinger. A survey on visual transfer learning using knowledge graphs. *Semantic Web*, 13(3):477–510, 2022. 3
- [26] Tushar Nagarajan and Kristen Grauman. Attributes as operators: factorizing unseen attribute-object compositions. In *Proceedings of the European Conference on Computer Vi*sion (ECCV), pages 169–185, 2018. 3, 6
- [27] N. V. Nayak and S. H. Bach. Zero-shot learning with common sense knowledge graphs. *Transactions on Machine Learning Research (TMLR)*, 2022. 3, 4, 5, 7
- [28] Genevieve Patterson and James Hays. Coco attributes: Attributes for people, animals, and objects. In *Computer*

Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11-14, 2016, Proceedings, Part VI 14, pages 85–100. Springer, 2016. 2

- [29] Senthil Purushwalkam, Maximilian Nickel, Abhinav Gupta, and Marc'Aurelio Ranzato. Task-driven modular networks for zero-shot compositional learning. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 3593–3602, 2019. 3, 6
- [30] Senthil Purushwalkam, Maximilian Nickel, Abhinav Gupta, and Marc Aurelio Ranzato. Task-Driven Modular Networks for Zero-Shot Compositional Learning. pages 3593–3602.
- [31] Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, et al. Imagenet large scale visual recognition challenge. *International journal of computer vision*, 115:211–252, 2015. 5
- [32] Michael Schlichtkrull, Thomas N Kipf, Peter Bloem, Rianne Van Den Berg, Ivan Titov, and Max Welling. Modeling relational data with graph convolutional networks. In *The Semantic Web: 15th International Conference, ESWC 2018, Heraklion, Crete, Greece, June 3–7, 2018, Proceedings 15,* pages 593–607. Springer, 2018. 7
- [33] Chao Shang, Yun Tang, Jing Huang, Jinbo Bi, Xiaodong He, and Bowen Zhou. End-to-end structure-aware convolutional networks for knowledge base completion. In *Proceedings* of the AAAI conference on artificial intelligence, volume 33, pages 3060–3067, 2019. 3
- [34] Krishna Kumar Singh and Yong Jae Lee. End-to-end localization and ranking for relative attributes. In Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11-14, 2016, Proceedings, Part VI 14, pages 753–769. Springer, 2016. 2
- [35] Tomáš Souček, Jean-Baptiste Alayrac, Antoine Miech, Ivan Laptev, and Josef Sivic. Multi-Task Learning of Object State Changes from Uncurated Videos. 2022. 1
- [36] Robyn Speer, Joshua Chin, and Catherine Havasi. Conceptnet 5.5: An open multilingual graph of general knowledge. In *Proceedings of the AAAI conference on artificial intelligence*, volume 31, 2017. 7
- [37] Shikhar Vashishth, Soumya Sanyal, Vikram Nitin, and Partha Talukdar. Composition-based multi-relational graph convolutional networks. *arXiv preprint arXiv:1911.03082*, 2019. 3
- [38] Denny Vrandečić and Markus Krötzsch. Wikidata: a free collaborative knowledgebase. *Communications of the ACM*, 57(10):78–85, 2014. 7
- [39] Xiaolong Wang, Ali Farhadi, and Abhinav Gupta. Actions ~ Transformations. In Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, volume 2016-Decem, pages 2658–2667. IEEE, jun 2016. 1
- [40] Xiaolong Wang, Yufei Ye, and Abhinav Gupta. Zero-Shot Recognition via Semantic Embeddings and Knowledge Graphs. Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, pages 6857–6866, 2018. 2, 5

- [41] Felix Wu, Amauri Souza, Tianyi Zhang, Christopher Fifty, Tao Yu, and Kilian Weinberger. Simplifying graph convolutional networks. In *International conference on machine learning*, pages 6861–6871. PMLR, 2019. 3
- [42] Zhibiao Wu and Martha Palmer. Verb semantics and lexical selection. arXiv preprint cmp-lg/9406033, 1994. 8
- [43] Yongqin Xian, Christoph H Lampert, Bernt Schiele, and Zeynep Akata. Zero-shot learning—a comprehensive evaluation of the good, the bad and the ugly. *IEEE transactions* on pattern analysis and machine intelligence, 41(9):2251– 2265, 2018. 2, 3
- [44] Yongqin Xian, Tobias Lorenz, Bernt Schiele, and Zeynep Akata. Feature generating networks for zero-shot learning. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 5542–5551, 2018. 2
- [45] Wenhan Xiong, Jiawei Wu, Deren Lei, Mo Yu, Shiyu Chang, Xiaoxiao Guo, and William Yang Wang. Imposing labelrelational inductive bias for extremely fine-grained entity typing. arXiv preprint arXiv:1903.02591, 2019. 3
- [46] Muli Yang, Cheng Deng, Junchi Yan, Xianglong Liu, and Dacheng Tao. Learning unseen concepts via hierarchical decomposition and composition. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 10248–10256, 2020. 3
- [47] Liang Yao, Chengsheng Mao, and Yuan Luo. Graph convolutional networks for text classification. In *Proceedings* of the AAAI conference on artificial intelligence, volume 33, pages 7370–7377, 2019. 3
- [48] Aron Yu and Kristen Grauman. Semantic jitter: Dense supervision for visual comparisons via synthetic images. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 5570–5579, 2017. 2
- [49] Chenrui Zhang, Xiaoqing Lyu, and Zhi Tang. Tgg: Transferable graph generation for zero-shot and few-shot learning. In Proceedings of the 27th ACM International Conference on Multimedia, pages 1641–1649, 2019. 3
- [50] Jingqing Zhang, Piyawat Lertvittayakumjorn, and Yike Guo. Integrating semantic knowledge to tackle zero-shot text classification. arXiv preprint arXiv:1903.12626, 2019. 3