End-to-End Video Classification with Knowledge Graphs

Fang Yuan, Zhe Wang, Jie Lin, Luis Fernando D’Haro, Kim Jung Jae, Zeng Zeng, Vijay Chandrasekhar

Fang Yuan, Zhe Wang, Jie Lin, Luis Fernando D’Haro, Kim Jung Jae, Zeng Zeng, Vijay Chandrasekhar

Abstract

Video understanding has attracted much research attention especially since the recent availability of large-scale video benchmarks. In this paper, we address the problem of multi-label video classification. We first observe that there exists a significant knowledge gap between how machines and humans learn. That is, while current machine learning approaches including deep neural networks largely focus on the representations of the given data, humans often look beyond the data at hand and leverage external knowledge to make better decisions. Towards narrowing the gap, we propose to incorporate external knowledge graphs into video classification. In particular, we unify traditional “knowledgeless” machine learning models and knowledge graphs in a novel end-to-end framework. The framework is flexible to work with most existing video classification algorithms including state-of-the-art deep models. Finally, we conduct extensive experiments on the largest public video dataset YouTube-8M. The results are promising across the board, improving mean average precision by up to 2.9%.

Introduction

Since the advent of neural networks and deep learning, major breakthroughs have been made in many artificial intelligence tasks ranging from computer vision to natural language processing. However, a significant knowledge gap still exist between machine and human intelligence. In particular, humans often relate to and make use of semantic knowledge outside of the task-specific data to make better decisions. On the other hand, most machine learning algorithms including state-of-the-art deep methods, only focus on the representation of the given data, without leveraging any external knowledge that could benefit the given task.

Consider the surfing man example in Figure 1(a). By only analyzing the pixels of the image (i.e., given data), it is difficult to conclude that the man is on a surfboard since most of it is obscured by the waves. However, given the knowledge that a man cannot stand freely on water and surfing is a typical sport at sea, it is straightforward to identify the surfboard in the picture. Note that the knowledge crucial to recognizing the surfboard is external to the raw data. Likewise, in the zoo example in Figure 1(b), with the knowledge that man-made structures containing polar bears are most likely zoos, the video can be correctly classified as zoo even though it is not evident from the appearance of the structure in the frames.

In this paper, we study the problem of video classification. In contrast to traditional “knowledgeless” models, we aim to design an end-to-end “knowledge-aware” framework that can integrate external knowledge into the learning process. The incorporation of knowledge is especially critical to large-scale video classification benchmarks such as the recently released YouTube-8M dataset (Abu-El-Haija et al. 2016), which presents two major challenges (Wang et al. 2017). First, videos can be very diverse in nature, with vastly different topics (e.g., sports, politics, entertainment, etc.) and genres (e.g., animation, documentary, etc.). Second, the class distributions are highly imbalanced, where majority of the classes have only very few instances. Such diversity and imbalance makes the classes not easily separable based only on features in the videos. Thus, external knowledge can play a vital role in complementing the video features to attain higher classification performance.

More formally, knowledge is often represented as a knowledge graph (Paulheim 2017), modeling each real-world concept as a node, and each semantic relationship between two concepts as an edge. A toy knowledge graph is illustrated in Figure 2. In particular, the relationships “person–on top of–surfboard” and “surfboard–found in–sea” are likely to reinforce the recognition of surfboard in Figure 1(a); similarly the relationship “polar bear–live in–zoo” could help with the classification of zoo in Figure 1(b). While knowledge graphs have already seen widespread use in fields such as Web search and social networks (Dong et al. 2014), it has not been integrated into visual tasks including video classification in a flexible and end-to-end fashion—Most existing knowledge-aware approaches are either specific to a particular task and model, or applying external knowledge as a decoupled after-thought, which we will elaborate in related work.

Towards knowledge-aware video classification, we make the following contributions in this paper.

• We propose to incorporate external knowledge graphs into video classification, bridging the gap in existing state-of-the-art approaches.
Figure 1: Bridging the knowledge gap between how humans and machines learn in visual tasks: (a) Recognition of an obscured surfboard in an image; (b) Classification of zoo where the raw pixels in the video frames do not clearly indicate a zoo.

Figure 2: Toy knowledge graph.

- We unify knowledge graphs and machine learning including deep neural networks in a novel end-to-end learning framework, which is flexible to work with most existing learning models.
- We conduct extensive experiments on the largest public video dataset YouTube-8M, outperforming state-of-the-art methods by up to 2.9% in mean average precision.

The remainder of this paper is organized as follows. First, we review related work. Next, we present the proposed approach, followed by experimental evaluation. Finally, we conclude our paper and lay out directions for future research.

**Related Work**

Video understanding has been an active research area in computer vision. Significant progress has been made especially since the release of large-scale benchmarks such as Sports-1M (Karpathy et al. 2014), YFCC-100M (Thomee et al. 2015) and YouTube-8M (Abu-El-Haija et al. 2016).

The problem of video classification is usually addressed at frame or video levels. The deep bag-of-frames (DBoF) (Abu-El-Haija et al. 2016) is a typical frame-level approach, inspired by various classic bag-of-words representations (Laptev et al. 2008; Wang et al. 2009). It feeds frame-level features from randomly sampled input frames into a fully connected layer, whose parameters are shared across the input frames. Beyond a bag of frames, a video is naturally a temporal sequence of frames, which can be modeled using a recurrent neural network. Typically Long Short-Term Memory (LSTM) cells can be employed to capture long-term dependencies in the temporal dimension (Yue-Hei Ng et al. 2015). Furthermore, as an alternative to LSTM, Gated Recurrent Unit (GRU) often achieves comparable if not better performance (Chung et al. 2014; Chen et al. 2017). At video level, a fixed-length feature vector is often extracted from the frames through simple aggregation (which we call “aggregation of frame features” or AoFF). As such, standard classifiers including logistic regression and support vector machines can be adopted. In particular, the mixture of experts (MoE) (Jordan and Jacobs 1994) classifier has shown superior empirical performance on video-level representations (Abu-El-Haija et al. 2016). In this model, a binary classifier is trained for each class, which is composed of a set of “experts” or hidden states, and a softmax function is used to model the probability of selecting an expert. Apart from frame or video-level features directly extracted from the videos, there is also initial success in exploiting text features associated with the videos, such as the accompanied title and keywords in YouTube (Wang et al. 2017).

All of the above methods are knowledgeless in the sense that they do not exploit external knowledge. The use of external knowledge is emerging in some computer vision tasks, including image classification (Deng et al. 2014), motivation prediction (Vondrick et al. 2016), question answering (Wu et al. 2016), relationship extraction (Lu et al. 2016), as well as object detection (Fang et al. 2017). However, most of these works are task or model specific, and thus cannot be easily applied to different scenarios. While the recent work on object detection (Fang et al. 2017) can work with any detection models, their proposed approach is not end-to-end. Rather, it consists of two stages: in the first stage, object localizations and class probabilities are obtained using any existing model; in the second stage, the class probabilities are re-optimized based on a knowledge graph. In particular, the use of knowledge in the second stage is independent from the first stage, which means there is a lack of feedback mechanism for the knowledge to directly improve the parametrization of the existing model.

Finally, knowledge graph is a popular choice to represent external knowledge, for capturing both concepts and their pairwise relationships. The use of knowledge graphs have already demonstrated various degrees of success in machine learning applications including Web search and social media (Dong et al. 2014). Quite a number of large-scale

---

1http://cocodataset.org/
2https://www.youtube.com/
knowledge graphs are available commercially or in open source, which are generally constructed based on human curation (Lenat 1995), crowdsourcing (Liu and Singh 2004, Krishna et al. 2017), and distillation from semi-structured (Suchanek, Kasneci, and Weikum 2007; Auer et al. 2007) or unstructured data (Carlson et al. 2010; Fang and Chang 2011). The details of knowledge graph construction is beyond the scope of this work.

Proposed Approach

We describe our end-to-end knowledge-aware learning in this section, starting with some preliminaries, followed by our choice of knowledge representation, as well as the eventual knowledge-aware classification.

Preliminaries and notations

Consider a set of pre-defined class labels $L = \{1, 2, \ldots, L\}$ and a set of videos $d$. We address the multi-label classification problem for videos, where each video has one or more ground-truth labels which form a subset of $L$. We assume a supervised setting where some training videos with known ground-truth labels are available. Given a test video with hidden ground truth, the task is to estimate a series of probabilities $(p_1, p_2, \ldots, p_L)$ where $p_i$ represents the probability of label $i$ on the video. We can subsequently rank the labels in descending probability and take the top few as the final output.

In this work, we further assume a knowledge graph. Many off-the-shelf knowledge graphs (Paulheim 2017) exist for our purpose. A knowledge graph is formally a graph $G = (V, E)$: $V$ is a set of vertices and $E$ is a set of edges between the vertices. In the context of knowledge graph, each vertex represent a concept or class label and each edge represent a relationship between two concepts. A typical large-scale knowledge graph often contains millions or billions of concepts, and hundreds or thousands of different relationship types.

Overall end-to-end framework

The overall framework of our proposed end-to-end learning with knowledge graphs is presented in Figure 3. Given an input video, we can first extract video and audio features from each frame. Note that in YouTube-8M, the pre-extracted video and audio features per frame consist of 1024 and 128 dimensions, respectively, as exemplified in the diagram. The frame-by-frame feature vectors are then fed into either frame or video-level models, to produce ultimate input into the classifier. As our main novelty, in addition to accounting for features from the video instance, our classifier further integrates a knowledge graph to narrow the knowledge gap between traditional machine learning and human intelligence. As such, in our running example, while the man-made structure is not clearly a zoo from the frame pixels, we are still able to predict it with the help of a knowledge graph, which reveals the strong semantic tie between polar bears and zoos.

The proposed framework embodies two advantages. First, it enables the incorporation of most existing video classification algorithms, including both deep and shallow models. Thus, our framework can be highly flexible, without being approach or task-specific. Second, the unification with knowledge graphs happens within an end-to-end framework, which means external knowledge can directly influence the feature-based models in a feedback loop through mechanisms such as backpropagation. In contrast, one recent approach for the related task of object recognition (Fang et al. 2017) also draws input from knowledge graphs. However, it is not end-to-end; it consists of two decoupled stages where external knowledge is independent of the feature-based model. Due to the lack of a feedback loop, their performance turns out to be unsatisfactory in video classification.

Knowledge representation

While external knowledge is commonly represented as graphs, knowledge graphs are inherently still symbolic and relational. Thus, quantifiable semantics must be further extracted to enable integration with machine learning models which typically operate over numerical representations. The notion of semantic consistency has been used (Fang et al. 2017) to quantify the strength of semantic ties between class labels. Generally two labels with high semantic consistency suggests that they are likely to show up in the same video. For instance, polar bear and zoo are two semantically consistent concepts, whereas polar bear and volcano have weak or no semantic consistency.

---

1 We use the terms concept and label interchangeably hereafter.
We can encode semantic consistency in an \( L \times L \) matrix \( S \), such that \( S_{ij} \) represents the semantic consistency between labels \( i \) and \( j \), \( \forall ij \in L^2 \). In particular, \( S_{ij} \) can be established based on the edges connecting the nodes representing labels \( i \) and \( j \) on the knowledge graph. Note that two nodes can be either directly connected by an edge (e.g., polar bear–zoo), or indirectly through a path of edges (e.g., person–surfing–sea), improving the generalization ability for concepts without any direct edge. There can also exists multiple paths between two labels for robustness. Intuitively, between two nodes on the knowledge graph, when there are more paths between two labels for robustness. Intuitively, between two nodes on the knowledge graph, when there are more paths and these paths are shorter, their semantic consistency is stronger.

Random walk with restart (Tong, Faloutsos, and Pan 2006) is a well-known method to realize the above intuition. Starting from one node representing label \( i \), we compute the probability \( R_{ij} \) of reaching another node representing label \( j \) through random walk. The higher probability \( R_{ij} \) implies that there are more and shorter paths from \( i \) to \( j \) and thus the semantic consistency \( S_{ij} \) is also higher. As \( R_{ij} \neq R_{ji} \) in general, but the semantic consistency matrix \( S \) should be symmetric in our context, we adopt the below definition follow the earlier work (Fang et al. 2017). We refer readers to existing work (Tong, Faloutsos, and Pan 2006; Fang, Chang, and Lauw 2013; Zhu et al. 2013) on the computation of random walk probabilities \( R_{ij} \).

\[
S_{ij} = S_{ji} = \sqrt{R_{ij} R_{ji}}
\]

It is worth noting that semantic consistency can also be defined based on the similarity of node embeddings, as enabled by recent representation learning approaches on graphs (Grover and Leskovec 2016; Bordes et al. 2013). However, our proposed approach is orthogonal to the computation of semantic consistency, which is beyond the scope of this paper.

Finally, for efficiency it is preferable to make the matrix \( S \) sparser, by only focusing on the largest semantic consistency. To this end, we consider the \( K \)-nearest neighbor (KNN) reduction for matrix \( S \). A pair of labels \( i \) and \( j \) are deemed KNN if \( S_{ij} \) is one of the largest \( K \) elements in the \( i \)-th row or \( j \)-th row of \( S \). Subsequently, we simply set \( S_{ij} = S_{ji} = 0 \) iff \( i \) and \( j \) are not KNN. The resulting matrix is much sparser, as it only encodes the strongest semantic consistency.

### Knowledge-aware classification

Consider any classifier with a cost function \( C \) and model parameters \( \Theta \). For a given video instance, we propose the following knowledge-aware cost function \( K \), where \( p_1, p_2, \ldots, p_L \) encode the label probabilities of the video and they are functions of \( \Theta \).

\[
K(\Theta) = C(\Theta) + \lambda \sqrt{\text{Tr}[p(D-S)p^T]} \quad (3)
\]

where \( D \) is a diagonal matrix such that \( D_{ii} = \sum_{j=1}^{L} S_{ij} \) and \( p = (p_1, p_2, \ldots, p_L) \) is a vector of label probabilities. Note that \( D - S \) is known as the Laplacian matrix. Using matrix computations, the dataflow graph is greatly simplified as illustrated in Figure 4(b) with batch size \( M = 1 \). The total number of nodes simply become bounded by \( O(M) \), improving the scalability significantly.

For a pair of labels \( i \) and \( j \), if \( S_{ij} \) is large (i.e., the two labels have strong semantic consistency), minimizing the cost function would force \( p_i \) and \( p_j \) to become similar. That is, it is likely that they either both appear in the video, or both do not appear. In contrast, if \( S_{ij} \) is small (i.e., they are not semantically consistent), \( p_i \) and \( p_j \) become less constrained by the knowledge graph. Note that the two cost terms, on the features and knowledge graph respectively, are balanced through a hyperparameter \( \lambda \in (0, \infty) \).

While the above formulation is intuitive, it is not practical for implementation with standard libraries such as TensorFlow. In particular, TensorFlow operations are organized into a dataflow graph, as illustrated in Figure 4(a) for the pairwise computation in Equation (3) with \( L = 4 \) and batch size \( M = 1 \) (i.e., for a single video). Evidently, the dataflow graph would contain \( O(L^2 M) \) nodes, which is not scalable in terms of the time required to construct this graph, as well as the memory overhead incurred by storing the computation of all the intermediate nodes.

As such, we employ the Laplacian matrix transformation. It has been established (Weiss, Torralba, and Fergus 2009) that Equation (3) is equivalent to the following:

\[
K(\Theta) = C(\Theta) + \lambda \sqrt{\text{Tr}[p(D-S)p^T]} \quad (3)
\]

where \( D \) is a diagonal matrix such that \( D_{ii} = \sum_{j=1}^{L} S_{ij} \) and \( p = (p_1, p_2, \ldots, p_L) \) is a vector of label probabilities. Note that \( D - S \) is known as the Laplacian matrix. Using matrix computations, the dataflow graph is greatly simplified as illustrated in Figure 4(b) with batch size \( M = 1 \). The total number of nodes simply become bounded by \( O(M) \), improving the scalability significantly.

Provided that the original cost function \( C \) and \( p \) are differentiable (which are generally true), our knowledge-aware cost function is also differentiable, as follows. Thus, it can be optimized with the gradient descent algorithm.

\[
\frac{\partial K(\Theta)}{\partial \Theta} = \frac{\partial C(\Theta)}{\partial \Theta} + \lambda \frac{\sqrt{\text{Tr}[p(D-S)p^T]}}{\sqrt{\text{Tr}[p(D-S)p^T]}} \frac{\partial p}{\partial \Theta}
\]

\[
= \frac{\partial C(\Theta)}{\partial \Theta} + \lambda \frac{p(D-S)}{\sqrt{\text{Tr}[p(D-S)p^T]}} \frac{\partial p}{\partial \Theta}
\]
Empirical Evaluation
In this section, we conduct empirical evaluations on the largest public video classification benchmark to date, namely YouTube-8M. We compare the performance of our approach against state-of-the-art video classification models, and further investigate the impact of parameters on the performance, and finally present some case studies to illustrate the reasons that knowledge graphs can improve video classification.

Experimental setup
Data We use the YouTube-8M benchmark[^1] the largest public dataset for multi-label video classification. It contains over 7 million video instances and a diverse range of 4,716 classes (entities), with an average of 3.4 labels per video. Pre-extracted and compressed features at frame and video-levels are available, where the video and audio features have 1024 and 128 dimensions, respectively.

We employ the off-the-shelf knowledge graph ConceptNet[^5]. Following previous work (Fang et al. 2017), we only adopt its English subgraph, and remove self-loops and the so-called “negative” relationships (e.g., NotDesires, NotCapableOf, Antonym and DistinctFrom). After these filtering steps, we obtain a knowledge graph with 1.3 million concepts and 2.8 million relationships. To further compute semantic consistency, we set the random walk restarting probability to 0.15 as well.

To map the concepts in ConceptNet to class labels, we simply apply exact string matching. As a result, 1,867 labels that have a path to at least one other label are found in ConceptNet. To demonstrate the advantage of using knowledge graphs, we only consider these 1,867 class labels, which cover about 97% the videos. Furthermore, these labels account for almost 80% of all label frequency. We emphasize that obtaining better concept-class mapping for more coverage is not the focus of this paper, and the current mapping already include the majority of the video instances and label occurrences.

We use the given training set for training, and the given validation set for testing since the ground truth of the original test set is not known.

Evaluation metric For each test video, a ranked list of class labels is produced, and we consider up to top 20 predictions per video for the following evaluation metrics.

- Mean average precision (MAP): the mean value of the areas under the precision-recall curve of each video.
- Hit ratio (HIT): the percentage of test videos with the top one prediction belonging to the ground truth.
- Global average precision (GAP): area under the precision-recall curve over a global list of predictions consisting of all the predictions of all videos.

Knowledgeless models Our framework is flexible to integrate knowledge graphs with different “knowledgeless” models (i.e., models without using external knowledge), including frame-level deep models and video-level models. Thus, we consider four different state-of-the-art baseline models, namely, AoFF, DBoF, LSTM and GRU. For the first three models (Abu-El-Haija et al. 2016), we use the implementation by Google[^7] for GRU (Miech, Laptev, and Sivic 2017), we use the implementation by Miech et al.[^8] More details of these models have been discussed in Related Work. To train the models, we adhere to the setup in the two studies, as follows.

- AoFF: learning rate 0.01, video-level model.
- DBoF: learning rate 0.01, 30 frames per video.
- LSTM: learning rate 1e-4, cell size 1024, all frames.
- GRU: learning rate 2e-4, cell size 1200, all frames.

Note that MoE classifier is used in all models, with 2 experts and 5 epochs. We further set a batch size of 1024 for AoFF and 128 for the other three models.

Knowledge-aware models We name our proposed end-to-end approach E2E. Each of the knowledgeless models (AoFF, DBoF, LSTM and GRU) can be coupled with knowledge graphs in our E2E framework. We use $K = 5$ for the KNN reduction of the semantic consistency matrix, and $\lambda = 0.01$ for the trade-off between feature-based cost and knowledge-based cost, which are generally robust values with stable performance. We will vary these hyperparameters to study their impact on the performance as well.

We also compare to a previous knowledge-aware method (Fang et al. 2017). This method is originally designed for object detection in images, which can be adapted for multi-label video classification as well. It involves two stages, where the first stage uses an existing knowledgeless model, and the second stage uses a knowledge graph to re-optimize the output from the first stage. Thus, the two stages are independent and their approach is not end-to-end. We name this method 2STG. We use $K = 5$ for KNN as well, and choose $\epsilon = 0.9$ which is found to be the best setting.

Comparison of performance
We first report the performance comparisons between the four knowledgeless models and their respective knowledge-aware counterparts. Specifically, for each knowledgeless model, we compare their results with those of both 2STG (previous work) and E2E (our approach). The results are summarized in Table[^9] Note that we are only interested in comparing the values in each column, instead of comparing across different knowledgeless models. Our approach E2E can achieve better performance every time, beating the respective knowledgeless model by up to 1.7% in MAP, 1.6% in HIT and 0.8% in GAP. In contrast, 2STG performs poorly as it is not an end-to-end model. While 2STG can outperform knowledgeless models for object detection on the Microsoft COCO (Lin et al. 2014) and PASCAL VOC (Everingham et al. 2010) datasets, the two datasets involve only a restricted set of 80 and 20 classes, respectively. In contrast,

[^1]: https://www.kaggle.com/c/youtube8m/data
[^5]: http://conceptnet.io/
[^7]: https://github.com/google/youtube-8m
[^8]: https://github.com/antoine77340/Youtube-8M-WILLOW
|        | AoFF | DBoF | LSTM | GRU |
|--------|------|------|------|-----|
|        | MAP  | HIT  | GAP  | MAP  | HIT  | GAP  | MAP  | HIT  | GAP  |
|        | 0.370| 0.846| 0.810| 0.279| 0.838| 0.800| 0.337| 0.856| 0.823|
| 2STG   | 0.364| 0.841| 0.804| 0.275| 0.838| 0.797| 0.331| 0.855| 0.819|
| E2E    | 0.384| 0.849| 0.817| 0.296| 0.854| 0.808| 0.340| 0.857| 0.824|
|        | (+1.4%)| (+0.3%)| (+0.7%)| (+1.7%)| (+1.6%)| (+0.3%)| (+0.3%)| (+0.1%)| (+0.1%)|

Table 1: Performance comparison between E2E and 2STG across four state-of-the-art knowledgeless methods. The first row records the performance of the knowledgeless models; the second row records the performance of 2STG that adopts the corresponding knowledgeless model in its first stage; the third row records the performance of E2E that couples with the corresponding knowledgeless model. Bold entries represent the best value in each column.

|        | AoFF | DBoF | LSTM | GRU |
|--------|------|------|------|-----|
|        | MAP  | HIT  | GAP  | MAP  | HIT  | GAP  | MAP  | HIT  | GAP  |
|        | 0.292| 0.828| 0.788| 0.211| 0.807| 0.757| 0.253| 0.819| 0.759|
| E2E    | 0.321| 0.829| 0.785| 0.232| 0.814| 0.767| 0.259| 0.826| 0.776|
|        | (+2.9%)| (+0.1%)| (-0.3%)| (+2.1%)| (+1.0%)| (+0.6%)| (+0.7%)| (+0.7%)| (+0.7%)|

Table 2: Performance advantage of E2E across four state-of-the-art knowledgeless methods using only 10% training data. The percentage improvements of E2E are bolded if they are greater than or equal to the corresponding values in Table 1.

![Figure 5](image-url)

**Figure 5:** Impact of parameters on the performance of E2E.

Impact of parameters

Next, we study the effect of parameters on the performance. There are two main parameters for E2E: the trade-off $\lambda$ between the feature-based and knowledge-based costs, and the choice of KNN for the semantic consistency matrix. For brevity we only present their impact on AoFF, as similar trends can be observed on other models.

In Figure 5(a), we vary $\lambda$ between $10^{-5}$ and $1000$, while fixing KNN at $K = 5$. Results show that the performance is generally stable for a wide range of $\lambda$ between $10^{-4}$ and $10$. The performance only deteriorates for very large values. Hence, it is robust to use $\lambda = 0.01$ in our experiments.

In Figure 5(b), we vary $K \in \{1, 2, 5, 10\}$ for the choice of KNN, while fixing $\lambda = 0.01$. When we use larger $K$, there is a slight increase in performance, especially in MAP, although the matrix $S$ becomes denser and results in lower efficiency. Generally, using $K = 5$ can achieve a good balance between accuracy and efficiency.

Result analysis

Finally, we conduct a more in-depth analysis of the results, using AoFF as the knowledgeless model. At an aggregate level, we observe better predictions for 24.9% of the videos after incorporating external knowledge with E2E, whereas we witness worse predictions for 8.9% of the videos. The remaining videos have no change in their predictions. Given that the number of videos with better results are almost three times of the videos with worse results, our approach E2E does bring in net benefits, consistent with the quantitative evaluation reported earlier.

We further zoom into some specific examples to understand the reasons behind the improvement. In Table [3] we illustrated 10 videos where knowledge graphs can help with...
In this paper, we studied the multi-label video classification problem. In particular, we observed the knowledge gap between machine and human intelligence. Towards bridging this gap, we proposed to utilize external knowledge graphs for video classification, unifying machine learning including deep neural networks with knowledge graphs in a novel end-to-end framework. Extensive experiments on the largest public benchmark YouTube-8M showed the superior performance of our approach, outperforming state-of-the-art knowledgeless models by up to 2.9% in MAP among other metrics. Finally, we analyzed some case studies to understand the scenarios in which knowledge graphs can or cannot help.

As future work, we plan to extract features from knowledge graphs and directly incorporate them into the deep neural networks. Moreover, it is also worth investigating how we can identify focus concepts that are related to the central theme of a video.

### Conclusion

| Ground truth | AoFF rank | E2E rank | Related concepts in the same video |
|--------------|-----------|----------|-----------------------------------|
| fashion      | 20        | 1 (↑19)  | hairstyle, bollywood, cosmetics   |
| origami      | 20+       | 1 (↑19+) | paper, toy                        |
| amusement park | 20+      | 1 (↑19+) | food, roller coaster, train       |
| disc jockey  | 5         | 2 (↑3)   | nightclub, dance, album, guitar   |
| food, drink  | 1, 5      | 1, 2 (↑3)| recipe, cocktail, juice, cooking, bartender, bottle |
| camera, photography | 4, 9 | 1 (↑3), 4 (↑5) | gadget, camera lens, smart phone |
| hunting, deer | 4, 20+    | 1 (↑3), 6 (↑14+) | forest, tree, plant, animal, weapon |
| vehicle, tool, drill | 2, 4, 20+ | 1 (↑1), 2 (↑2), 6 (↑14+) | car, metalworking |
| concert, lighting, festival | 2, 5, 16 | 1 (↑1), 2 (↑3), 8 (↑8) | dance, album, Ibiza |
| furniture, couch, bed, chair | 1, 3, 11, 20+ | 1, 2 (↑1), 6 (↑5), 4 (↑16+) | living room, home improvement, house, television |

Table 3: Example videos that knowledge graphs can help with learning. Each row describes a video, where “AoFF rank” and “E2E rank” columns indicate the rank position of the ground truth label in the output of AoFF and E2E, respectively; 20+ means the ground truth is not found in the top 20; ↑ indicates the number of positions moved up in E2E output as compared to AoFF; related concepts are listed if they have high semantic consistency with the ground truth and they are within top 20 of both AoFF and E2E.

| Ground truth | AoFF top | E2E top | Other concepts in the same video |
|--------------|----------|---------|---------------------------------|
| telescope    | telescope | vehicle | camera, car, boat, bicycle, motorcycle |
| transistor   | transistor | vehicle | antenna, train, car |
| running, marathon | running, hiking | mountain, nature | climbing, walking, mountain pass, trail, lake |
| gardening, plant | plant, gardening | food, news program | tree, agriculture, cooking, television |
| banknote, money, dollar | banknote, dollar, money | paper, animation, guitar | manga, art, festival, musician |

Table 4: Example videos where knowledge graphs can hurt performance. Each row describes a video, where “AoFF top” and “E2E top” columns indicate the top prediction(s) of AoFF and E2E, respectively; other concepts are listed if they have high semantic consistency with the top prediction(s) of either AoFF or E2E, and they are within top 20 of both AoFF and E2E; bold entries are a group of concepts with strong mutual semantic consistency; likewise for italic entries.

Finally, we investigate some negative cases in Table 4 where knowledge graphs can hurt the performance. In these cases, E2E often makes overgeneralizations based on the related concepts. In these videos, there exist an overwhelm of concepts that are semantically consistent to the incorrect top predictions by E2E, whereas the concepts that are consistent with the ground truth are much fewer (e.g., #1 and #4) or even non-existent (e.g., #5). The root cause is that E2E treats each related concepts uniformly. However, in an ideal solution, we should only focus on the concepts related to the central theme of the video. We leave the study of such “focus” concepts as potential future work.
References

[Abu-El-Haija et al. 2016] Abu-El-Haija, S.; Kothari, N.; Lee, J.; Natsev, P.; Toderici, G.; Varadarajan, B.; and Vijayanarasimhan, S. 2016. Youtube-8m: A large-scale video classification benchmark. *arXiv preprint arXiv:1609.08675.*

[Auer et al. 2007] Auer, S.; Bizer, C.; Kobilarov, G.; Lehmann, J.; Cyganiak, R.; and Ives, Z. G. 2007. DBpedia: A nucleus for a web of open data. In *ISWC-ASWC*, 722–735.

[Bordes et al. 2013] Bordes, A.; Usunier, N.; Garcia-Duran, A.; Weston, J.; and Yakhnenko, O. 2013. Translating embeddings for modeling multi-relational data. In *NIPS*, 2787–2795. Curran Associates, Inc.

[Carlson et al. 2010] Carlson, A.; Betteridge, J.; Kisiel, B.; Settles, B.; Jr., E. R. H.; and Mitchell, T. M. 2010. Toward an architecture for never-ending language learning. In *AAAI*.

[Chen et al. 2017] Chen, S.; Wang, X.; Tang, Y.; Chen, X.; Wu, Z.; and Jiang, Y.-G. 2017. Aggregating frame-level features for large-scale video classification. *arXiv preprint arXiv:1707.00803.*

[Chung et al. 2014] Chung, J.; Gulcehre, C.; Cho, K.; and Bengio, Y. 2014. Empirical evaluation of gated recurrent neural networks on sequence modeling. *arXiv preprint arXiv:1412.3555.*

[Deng et al. 2014] Deng, J.; Ding, N.; Jia, Y.; Frome, A.; Murphy, K.; Bengio, S.; Li, Y.; Neven, H.; and Adam, H. 2014. Large-scale object classification using label relation graphs. In *ECCV, Part I*, 48–64.

[Dong et al. 2014] Dong, X.; Gabriilovich, E.; Heitz, G.; Horn, W.; Lao, N.; Murphy, K.; Strohmann, T.; Sun, S.; and Zhang, W. 2014. Knowledge vault: a Web-scale approach to probabilistic knowledge fusion. In *KDD*, 601–610.

[Everingham et al. 2010] Everingham, M.; Gool, L. J. V.; Williams, C. K. I.; Winn, J. M.; and Zisserman, A. 2010. The PASCAL visual object classes (VOC) challenge. *IJCV* 88(2):303–338.

[Fang and Chang 2011] Fang, Y., and Chang, K. C. 2011. Searching patterns for relation extraction over the web: re-discovering the pattern-relationship. In *WSDM*, 825–834.

[Fang et al. 2017] Fang, Y.; Kuan, K.; Lin, J.; Tan, C.; and Chandrasekar, V. 2017. Object detection meets knowledge graphs. In *IJCAI*, 1661–1667.

[Fang, Chang, and Lauw 2013] Fang, Y.; Chang, K. C.; and Lauw, H. W. 2013. RoundTripRank: Graph-based proximity with importance and specificity. In *ICDE*, 613–624.

[Grover and Leskovec 2016] Grover, A., and Leskovec, J. 2016. node2vec: Scalable feature learning for networks. In *KDD*, 855–864. ACM.

[Jordan and Jacobs 1994] Jordan, M. I., and Jacobs, R. A. 1994. Hierarchical mixtures of experts and the em algorithm. *Neural computation* 6(2):181–214.

[Karpathy et al. 2014] Karpathy, A.; Toderici, G.; Shetty, S.; Leung, T.; Sukthankar, R.; and Fei-Fei, L. 2014. Large-scale video classification with convolutional neural networks. In *CVPR*, 1725–1732.

[Krishna et al. 2017] Krishna, R.; Zhu, Y.; Groth, O.; Johnson, J.; Hata, K.; Kravitz, J.; Chen, S.; Kalantidis, Y.; Li, L.; Shamma, D. A.; Bernstein, M. S.; and Fei-Fei, L. 2017. Visual genome: Connecting language and vision using crowd-sourced dense image annotations. *IJCV* 123:32–73.

[Laptev et al. 2008] Laptev, I.; Marszalek, M.; Schmid, C.; and Rozenfeld, B. 2008. Learning realistic human actions from movies. In *CVPR*, 1–8. IEEE.

[Lenat 1995] Lenat, D. B. 1995. CYC: A large-scale investment in knowledge infrastructure. *Commun. ACM* 38(11):32–38.

[Lin et al. 2014] Lin, T.; Maire, M.; Belongie, S. J.; Hays, J.; Perona, P.; Ramanan, D.; Dollár, P.; and Zitnick, C. L. 2014. Microsoft COCO: common objects in context. In *ECCV, Part V*, 740–755.

[Liu and Singh 2004] Liu, H., and Singh, P. 2004. ConceptNet—a practical commonsense reasoning tool-kit. *BT Technology Journal* 22(4):211–226.

[Lu et al. 2016] Lu, C.; Krishna, R.; Bernstein, M. S.; and Li, F. 2016. Visual relationship detection with language priors. In *ECCV, Part I*, 852–869.

[Miech, Laptev, and Sivic 2017] Miech, A.; Laptev, I.; and Sivic, J. 2017. Learnable pooling with context gating for video classification. *arXiv preprint arXiv:1706.06905.*

[Paulheim 2017] Paulheim, H. 2017. Knowledge graph refinement: A survey of approaches and evaluation methods. *Semantic Web* 8(3):489–508.

[Suchanek, Kasneci, and Weikum 2007] Suchanek, F. M.; Kasneci, G.; and Weikum, G. 2007. YAGO: a core of semantic knowledge. In *WWW*, 697–706.

[Thomee et al. 2015] Thomee, B.; Shamma, D. A.; Friedland, G.; Elizalde, B.; Ni, K.; Poland, D.; Borth, D.; and Li, L.-J. 2015. The new data and new challenges in multimedia research. *arXiv preprint arXiv:1503.01817 (18).*

[Tong, Faloutsos, and Pan 2006] Tong, H.; Faloutsos, C.; and Pan, J. 2006. Fast random walk with restart and its applications. In *ICDM*, 613–622.

[Vondrick et al. 2016] Vondrick, C.; Oktay, D.; Pirsiavash, H.; and Torralba, A. 2016. Predicting motivations of actions by leveraging text. In *CVPR*, 2997–3005.

[Wang et al. 2009] Wang, H.; Ullah, M. M.; Klaser, A.; Laptev, I.; and Schmid, C. 2009. Evaluation of local spatio-temporal features for action recognition. In *BMVC*, 124–134. BMVA Press.

[Wang et al. 2017] Wang, Z.; Kuan, K.; Ravaut, M.; Manek, G.; Song, S.; Fang, Y.; Kim, S.; Chen, N.; Enriquez, L. F. D.; Tuan, L. A.; et al. 2017. Truly multi-modal youtube-8m video classification with video, audio, and text. *arXiv preprint arXiv:1706.05461.*

[Weiss, Torralba, and Fergus 2009] Weiss, Y.; Torralba, A.; and Fergus, R. 2009. Spectral hashing. In *NIPS*, 1753–1760.

[Wu et al. 2016] Wu, Q.; Wang, P.; Shen, C.; Dick, A. R.; and van den Hengel, A. 2016. Ask me anything: Free-form visual question answering based on knowledge from external sources. In *CVPR*, 4622–4630.
[Yue-Hei Ng et al. 2015] Yue-Hei Ng, J.; Hausknecht, M.; Vijayanarasimhan, S.; Vinyals, O.; Monga, R.; and Toderici, G. 2015. Beyond short snippets: Deep networks for video classification. In CVPR, 4694–4702.

[Zhu et al. 2013] Zhu, F.; Fang, Y.; Chang, K. C.; and Ying, J. 2013. Incremental and accuracy-aware personalized pagerank through scheduled approximation. PVLDB 6(6):481–492.