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Objects2action: Classifying and localizing actions without any video example

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Abstract

The goal of this paper is to recognize actions in video without the need for examples. Different from traditional zero-shot approaches we do not demand the design and specification of attribute classifiers and class-to-attribute mappings to allow for transfer from seen classes to unseen classes. Our key contribution is objects2action, a semantic word embedding that is spanned by a skip-gram model of thousands of object categories. Action labels are assigned to an object encoding of unseen video based on a convex combination of action and object affinities. Our semantic embedding has three main characteristics to accommodate for the specifics of actions. First, we propose a mechanism to exploit multiple-word descriptions of actions and objects. Second, we incorporate the automated selection of the most responsive objects per action. And finally, we demonstrate how to extend our zero-shot approach to the spatio-temporal localization of actions in video. Experiments on four action datasets demonstrate the potential of our approach.

1. Introduction

We aim for the recognition of actions such as blow dry hair and swing baseball in video without the need for examples. The common computer vision tactic in such a challenging setting is to predict the zero-shot test classes from disjunct train classes based on a (predefined) mutual relationship using class-to-attribute mappings [1, 8, 20, 32, 36]. Drawbacks of such approaches in the context of action recognition [24] are that attributes like ‘torso twist’ and ‘look-down’ are difficult to define and cumbersome to annotate. Moreover, current zero-shot approaches, be it for image categories or actions, assume that a large, and labeled, set of (action) train classes is available a priori to guide the knowledge transfer, but today’s action recognition practice is limited to at most hundred classes [16, 19, 35, 42]. Different from existing work, we propose zero-shot learning for action classification that does not require tailored definitions and annotation of action attributes, and not a single video or action annotation as prior knowledge.

We are inspired by recent progress in supervised video recognition, where several works successfully demonstrated the benefit of representations derived from deep convolutional neural networks for recognition of actions [14, 17, 39] and events [40, 49]. As these nets are typically pre-trained on images and object annotations from ImageNet [5], and consequently their final layer represent object category scores, these works reveal that object scores are well-suited for video recognition. Moreover, since these objects have a lingual correspondence derived from nouns in WordNet, they are a natural fit for semantic word embeddings [6, 9, 26, 29, 41]. As prior knowledge for our zero-shot action recognition we consider a semantic word embedding spanned by a large number of object class labels and their images from ImageNet, see Figure 1.

Our key contribution is objects2action, a semantic embedding to classify actions in videos without using any video data or action annotations as prior knowledge. Instead it relies on commonly available textual descriptions, images and annotations of objects.
ond, we incorporate the automated selection of the most re-
 sponsive objects per action. And finally, we demonstrate
our zero-shot approach to action classification and spatio-
temporal localization of actions.

Before going into detail, we will first connect our ap-
proach to related work on action recognition and zero-shot
recognition.

2. Related work

2.1. Action Recognition

The action classification literature offers a mature reper-
toire of elegant and reliable methods with good accuracy.
Many methods include sampling spatio-temporal descrip-
tors [7, 47], aggregating the descriptors in a global video
representation, such as versions of VLAD [12, 33] or Fisher
Vectors [34] followed by supervised classification with an
SVM. Inspired by the success of deep convolutional neural
networks in image classification [18], several recent works
have demonstrated the potential of learned video represen-
tations for action and event recognition [14, 17, 39, 40, 49].
All these deep representations are learned from thousands
of object annotations [5], and consequently, their final out-
put layer corresponds to object category responses indicat-
ing the promise of objects for action classification. We also
use a deep convolutional neural network to represent our
images and video as object category responses, but we do
not use any action annotations nor any training videos.

Action classification techniques have recently been ex-
tended to action localization [2, 13, 21, 30, 46] where in ad-
dition to the class, the location of the action in the video
is detected. To handle the huge search space that comes
with such precise localization, methods to efficiently sam-
plespienon action proposals [13, 30, 46] are combined with the
encodings and labeled examples used in action classification.
In contrast, we focus on the zero-shot case where there is
no labeled video data available for classification nor for lo-
calization. We are not aware of any other work on zero-shot
action localization.

2.2. Zero-Shot Recognition

The paradigm of zero-shot recognition became popular
with the seminal paper of Lampert et al. [20]. The idea is
that images can be represented by a vector of classification
scores from a set of known classes, and a semantic link can
be created from the known class to a novel class. Existing
zero-shot learning methods can be grouped based on the dif-
ferent ways of building these semantic links.

A semantic link is commonly obtained by a human pro-
vided class-to-attribute mapping [1, 8, 20, 32], where for
each unseen class a description is given in terms of a set
of attributes. Attributes should allow to tell classes apart,
but should not be class specific, which makes finding good
attributes and designing class-to-attribute mappings a non-
trivial task. To overcome the need for human selection, at
least partially, Rohrbach et al. evaluate external sources for
defining the class-to-attribute mappings [36]. Typically,
attributes are domain specific, e.g. class and scene prop-
ties [20] or general visual concepts [23] learned from im-
ages, or action classes [37] and action attributes [24] learned
from videos. In our paper we exploit a diverse vocabulary
of object classes for grounding unseen classes. Such a setup
has successfully been used for action classification when
action labels are available [14]. In contrast, we have a zero-
shot setting and do not use any action nor video annotations.

Zero-shot video event recognition as evaluated in
TRECVID [31] offers meta-data in the form of a an event
kit containing the event name, a definition, and a precise
description in terms of salient concepts. Such meta-data
can cleverly be used for a class-to-attribute mapping based
on multi-modal concepts [11, 48], seed a sequence of mul-
timodal pseudo relevance feedback [15], or select relevant
tags from Flickr [3]. In contrast to these works, we do not
assume any availability of additional meta-data and only
rely on the action name.

To generalize zero-shot classification beyond attribute-
to-class mappings, Mensink et al. [25] explored various
metrics to measure co-occurrence of visual concepts for es-
establishing a semantic link between labels, and Froome
et al. [9] and Norouzi et al. [29] exploit semantic word em-
beddings for this link. We opt for the latter direction, and
also use a semantic word embedding [22, 26, 27] since this
is the most flexible solution, and allows for exploiting ob-
ject and action descriptions containing multiple words, such
as the WordNet synonyms and the subject, verb and object
triples to describe actions [10, 43] used in this paper.

3. Objects2action

In zero-shot classification the train classes \( \mathcal{Y} \) are dif-
ferent from the set of zero-shot test classes \( \mathcal{Z} \), such that
\( \mathcal{Y} \cap \mathcal{Z} = \emptyset \). For training samples \( \mathcal{X} \), a labeled dataset
\( \mathcal{D} = \{ \mathcal{X}, \mathcal{Y} \} \) is available, and the objective is to classify
a test sample as belonging to one of the test classes \( \mathcal{Z} \). Usu-
ally, test samples \( v \) are represented in terms of classification
scores for all train classes \( p_{vy} \forall y \in \mathcal{Y} \), and an affinity score
\( g_{yz} \) is defined to relate these train classes to the test classes.
Then the zero-shot prediction could be understood as a con-
 vex combination of known classifiers [1, 25, 29]:
\[
C(v) = \text{argmax}_z \sum_y p_{vy} g_{yz}. \tag{1}
\]

Often there is a clear relation between training classes
\( \mathcal{Y} \) and test classes \( \mathcal{Z} \), for example based on class-to-
attribute relations [1, 20] or all being nouns from the Im-
ageNet/Wordnet hierarchy [9, 29]. It is unclear, however,
how to proceed when train classes and test classes are semantically disjoint.

Our setup, see Figure 2, differs in two aspects to the standard zero-shot classification pipeline: i) our zero-shot test examples are videos \( \mathcal{V} \) to be classified in actions \( \mathcal{Z} \), while we have a train set \( \mathcal{D} \) with images \( \mathcal{X} \) labeled with objects \( \mathcal{Y} \) derived from ImageNet [5]. Therefore, we aim to transfer from the domain of images \( \mathcal{X} \) to the domain of videos \( \mathcal{V} \), and ii) we aim to translate objects semantics \( \mathcal{Y} \) to the semantics of actions \( \mathcal{Z} \).

**Object encoding** We encode a test video \( v \) by the classification scores to the \( m = |\mathcal{Y}| \) objects classes from the train set:

\[
p_v = [p(y_1|v), \ldots, p(y_m|v)]^T
\]

where the probability of an object class is given by a deep convolutional neural network trained from ImageNet [18], as recently became popular in the video recognition literature [14, 17, 39, 40, 49]. For a video \( v \) the probability \( p(y|v) \) is computed by averaging over the frame probabilities, where every \( 10^{th} \) frame is sampled. We exploit the semantics of in total 15,293 ImageNet object categories for which more than 100 examples are available.

We define the affinity between an object class \( y \) and action class \( z \) as:

\[
g_{yz} = s(y)^T s(z),
\]

where \( s(\cdot) \) is a semantic embedding of any class \( \mathcal{Z} \cup \mathcal{Y} \), and we use \( g_z = [s(y_1) \ldots s(y_m)]^T s(z) \) to represent the translation of action \( z \) in terms of objects \( \mathcal{Y} \). The semantic embedding function \( s \) is further detailed below.

### 3.1. Semantic embedding via Gaussian mixtures

The objective for a semantic embedding is to find a \( d \)-dimensional space, in which the distance between an object \( s(y) \) and an action \( s(z) \) is small, if and only if their classes \( y \) and \( z \) are found in similar (textual) context. For this we employ the skip-gram model of word2vec [26, 27] as semantic embedding function, which results in a look-up table for each word, corresponding to a \( d \)-dimensional vector.

Semantic word embeddings have been used for zero-shot object classification [29], but in our setting the key differences are i) that train and test classes come from different domains: objects in the train set and actions in the test set; and ii) both the objects and actions are described with a small description instead of a single word. In this section we describe two embedding techniques to exploit these multi-word descriptions to bridge the semantic gap between objects and actions.

**Average Word Vectors (AWV)** The first method to exploit multiple words is take the average vector of the embedded words [28]. The embedding \( s(c) \) of a multi-words description \( c \) is given by:

\[
s_A(c) = \frac{1}{|w|} \sum_{w \in c} s(w).
\]

This model combines words to form a single average word, as represented with a vector inside the word embedding. While effective, this cannot model any semantic relations that may exist between words. For example, the relations for the word *stroke*, in the sequence *stroke, swimming, water* is completely different than the word relations in the sequence *stroke, brain, ambulance*.

**Fisher Word Vectors (FWV)** To describe the precise meaning of distinct words we propose to aggregate the word embeddings using Fisher Vectors [38]. While these were originally designed for aggregating local image descriptors [38], they can be used for aggregating words as long as the *discrete* words are transformed into a *continuous* space [4]. In contrast to [4], where LSI is used to embed words into a continuous space, we employ the word embedding vectors of the skip-gram model. These vectors for each word are then analogous to local image descriptors and a class description is analogous to an image.

The advantage of the FWV model is that it uses an underlying generative model over the words. This generative model is modeling semantic topics within the word embedding. Where AWV models a single word, the FWV models a distribution over words. The *stroke* example could for example be assigned to two clear, distinct topics *infarct* and *swimming*. This word sense disambiguation leads to a more precise semantic grounding at the topic-level, as opposed to single word-level.

In the Fisher Vector, a document (i.e. a set of words) is described as the gradient of the log-likelihood of these
observations on an underlying probabilistic model. Following [38] we use a diagonal Gaussian Mixture Model with $k$ components as probabilistic model, which we learn on approximately $45K$ word embedding vectors from the 15K object classes in ImageNet.

The Fisher Vectors with respect to the mean $\mu_k$ and variance $\sigma_k$ of mixture component $k$ are given by:

$$G^c_{\mu_k} = \frac{1}{\sqrt{\pi_k}} \sum_{w \in c} \gamma_w(k) \left( \frac{s(w) - \mu_k}{\sigma_k} \right),$$  \hspace{1cm} (5)

$$G^c_{\sigma_k} = \frac{1}{\sqrt{2\pi_k}} \sum_{w \in c} \gamma_w(k) \left( \frac{(s(w) - \mu_k)^2}{\sigma_k^2} - 1 \right),$$  \hspace{1cm} (6)

where $\pi_k$ is the mixing weight, and $\gamma_w(k)$ denotes the responsibility of component $k$ and we use the closed-form approximation of the Fisher information matrix of [38]. The final Fisher Word Vector is the concatenation of the Fisher Vectors (Eq. (5) and Eq. (6)) for all components:

$$s_F(c) = [G^c_{\mu_1}, G^c_{\sigma_1}, \ldots, G^c_{\mu_k}, G^c_{\sigma_k}]^T.$$  \hspace{1cm} (7)

3.2. Sparse translations

The action representation $g_z$ represents the translation of the action to all objects in $V$. However, not all train objects are likely to contribute to a clear description of a specific action class. For example, consider the action class kayak. It makes sense to translate this action to objects such as kayak, water, and sea, with some related additional objects like surf-board, raft, and peddle. Likewise a similarity value with, e.g., dog or cat is unlikely to be beneficial for a clear detection, since it introduces clutter. We consider two sparsity metrics that operate on the action classes or the test video.

**Action sparsity** We propose to sparsify the representation $g_z$ by selecting the $T_z$ most responsive object classes to a given action class $z$. Formally, we redefine the action to object affinity as:

$$\hat{g}_z = [g_{z,y_1}, \delta(y_1, T_z), \ldots, g_{z,y_m}, \delta(y_m, T_z)]^T$$ \hspace{1cm} (8)

where $\delta(y_i, T_z)$ is an indicator function, returning 1 if class $y_i$ is among the top $T_z$ classes. In the same spirit, the objects could also have been selected based on their distance, considering only objects within an $\epsilon_z$ distance from $s(z)$. We opt for the selection of the top $T_z$ documents, since it is easier to define an a priori estimate of the value. Selecting $T_z$ objects for an action class $z$ means that we focus only on the object classes that are closer to the action classes in the semantic space.

**Video sparsity** Similarly, the video representation $p_v$ is, by design, a dense vector, where each entry contains the (small) probability $p(y|v)$, of the presence of train class $y$ in the video $v$. We follow [29] and use only the top $T_v$ most prominent objects present in the video:

$$\hat{p}_v = [p(y_1|v)\delta(y_1, T_v), \ldots, p(y_m|v)\delta(y_m, T_v)]^T$$ \hspace{1cm} (9)

where $\delta(y_i, T_v)$ is an indicator function, returning 1 if class $y_i$ is among the top $T_v$ classes. Increasing the sparsity, by considering only the top $T_v$ class predictions will reduce the effect of adding random noise by summing over a lot of unrelated classes with a low probability mass and is therefore likely to be beneficial for zero-shot classification.

The optimal values for both $T_z$ and $T_v$ are likely to depend on the datasets, the semantic representation and the specific action description. Therefore they are considered as hyper-parameters of the model. Typically, we would expect that $T_z \ll m$, e.g., the 50 most responsive object classes will suffice for representing the video and finding the best action to object description.

3.3. Zero-shot action localization

Objects2action is easily extendable to zero-shot localization of actions by exploiting recent advances in sampling spatio-temporal tube-proposals from videos [13, 30, 46]. Such proposals have shown to give a high localization recall with a modest set of proposals.

From a test video, a set $U$ of spatio-temporal tubes are sampled [13]. For each test video we simply select the maximum scoring tube proposal:

$$C(v) = \arg\max_{z \in Z, u \in U_v} \sum_y p_{uy} g_{yz},$$ \hspace{1cm} (10)

where $u$ denotes a spatio-temporal tube proposal, and $p_{uy}$ is the probability of the presence of object $y$ in region $u$.

For the spatio-temporal localization, a tube proposal contains a series of frames, each with a bounding-box indicating the spatial localization of the action. We feed just the pixels inside the bounding-box to the convolutional neural network to obtain the visual representation embedded in object labels. We will demonstrate the localization ability in the experiments.

4. Experiments

In this section, we employ the proposed object2action model on four recent action classification datasets. We first describe these datasets and the text corpus used. Second, we analyze the impact of applying the Fisher Word Vector over the baseline of the Average Word Vector for computing the affinity between objects and actions, and we evaluate the action and video sparsity parameters. Third, we report zero-shot classification results on the four datasets, and we compare against the traditional zero-shot setting where actions are used during training. Finally, we report performance of zero-shot spatio-temporal action localization.
4.1. Prior knowledge and Datasets

Our method is based on freely available resources which we use as prior knowledge for zero-shot action recognition. For the four action classification datasets used we only use the test set.

Prior knowledge We use two types of prior knowledge. First, we use deep convolutional neural network trained from ImageNet images with objects [18] as visual representation. Second, for the semantic embedding we train the skip-gram model of word2vec on the metadata (title, descriptions, and tags) of the YFCC100M dataset [44], this dataset contains about 100M Flickr images. Preliminary experiments showed that using visual metadata results in better performance than training on Wikipedia or Google-News data. We attribute this to the more visual descriptions used in the YFCC100M dataset, yielding a semantic embedding representing visual language and relations.

UCF101 [42] This dataset contains 13,320 videos of 101 action classes. It has realistic action videos collected from YouTube and has large variations in camera motion, object appearance/scale, viewpoint, cluttered background, illumination conditions, etc. Evaluation is measured using average class accuracy, over the three provided test-splits with around 3,500 videos each.

THUMOS14 [16] This dataset has the same 101 action classes as in UCF101, but the videos have a longer duration and are temporally unconstrained. We evaluate on the testset containing 1,574 videos, using mean average precision (mAP) as evaluation measure.

HMDB51 [19] This dataset contains 51 action classes and 6,766 video clips extracted from various sources, ranging from YouTube to movies, and hence this dataset contains realistic actions. Evaluation is measured using average class accuracy, over the three provided test-splits with each 30 videos per class (1,530 videos per split).

UCF Sports [35] This dataset contains 150 videos of 10 action classes. The videos are from sports broadcasts capturing sport actions in dynamic and cluttered environments. Bounding box annotations are provided and this dataset is often used for spatio-temporal action localization. For evaluation we use the test split provided by [21] and performance is measured by average class accuracy.

<table>
<thead>
<tr>
<th>Embedding</th>
<th>Sparsity</th>
<th>Best accuracy</th>
<th>Accuracy at $T^s = 10, T^v = 100$</th>
</tr>
</thead>
<tbody>
<tr>
<td>AWV</td>
<td>Video</td>
<td>18.0%</td>
<td>17.5%</td>
</tr>
<tr>
<td></td>
<td>Action</td>
<td>22.7%</td>
<td>21.9%</td>
</tr>
<tr>
<td></td>
<td>Combine</td>
<td>22.7%</td>
<td>21.6%</td>
</tr>
<tr>
<td>FWV</td>
<td>Video</td>
<td>29.1%</td>
<td>29.0%</td>
</tr>
<tr>
<td></td>
<td>Action</td>
<td>30.8%</td>
<td>30.3%</td>
</tr>
<tr>
<td></td>
<td>Combine</td>
<td>30.8%</td>
<td>30.3%</td>
</tr>
</tbody>
</table>

Table 1. Evaluating AWV and FWV for object to class affinity, and comparing action and video sparsity on UCF101 dataset.

4.2. Properties of Objects2action

Semantic embedding We compare the AWV with the FWV as semantic embedding. For the FWV, we did a run of preliminary experiments to find suitable parameters for the number of components (varying $k = \{1, 2, 4, 8, 16, 32\}$), the partial derivatives used (weight, mean, and/or variance) and whether to use PCA or not. We found them all to perform rather similar in terms of classification accuracy. Considering a label has only a few words (1 to 4), we therefore fix $k = 2$, apply PCA to reduce dimensionality by a factor of 2, and to use only the partial derivatives w.r.t. the mean (conforming the results in [4]). Hence, the total dimensionality of FWV is $d$, equivalent to the dimensionality of AWV, which allows for a fair comparison. The two embeddings are compared in Table 1 and Figure 3 (left), and FWV clearly outperforms AWV in all the cases.

Sparsity parameters In Figure 3, we evaluate the action sparsity and video sparsity parameters. The left plot shows average accuracy versus $T^s$ and $T^v$. It is evident that
action sparsity, i.e., selecting most responsive object classes for a given action class leads to a better performance than video sparsity. The video sparsity (green lines) is more stable throughout and achieves best results in the range of 10 to 100 objects. Action sparsity is a bit sinuous, nevertheless it always performs better, independent of the type of embedding. Action sparsity is at its best in the range of selecting the 5 to 30 most related object classes. For the remaining experiments, we fix these parameters as $T_z = 10$ and $T_v = 100$.

We also consider the case when we apply sparsity on both video and actions (see the right plot). Applying sparsity on both sides does not improve performance, it is equivalent to the best action sparsity setting, showing that selecting the most prominent objects per action suffice for zero-shot action classification. Table 1 summarise the accuracies for the best and fixed choices of $T_z$ and $T_v$.

### 4.3. Zero-shot action classification

In this section we employ the obtained parameters of Object2action, from the previous section, for zero-shot action classification on the test splits of all four datasets. We evaluate the benefit of using the FWV over AWV, and the effect of using sparsity (video sparsity, action sparsity or no sparsity at all). The results are provided in Table 2. We observe that the FWV always outperforms AWV, and that it is always beneficial to apply sparsity, and action sparsity with FWV performs the best. We also provide the supervised upper-bounds using the same video representation of object classification scores in Table 2. Here and for all the experiments, we power normalize ($\alpha = 0.5$) the video representations before applying $\ell_2$ normalization.

**Comparison to few-shot supervised learning** In this experiment we compare the zero-shot classifier against few-shot supervised learning, on the THUMOS14 dataset. For this we consider two types of video representation. The first representations, uses the state-of-the-art motion representation of [47], by encoding robust MBH descriptors along the improved trajectories [47] using Fisher Vectors. We follow the standard parameter cycle, by applying PCA, using a GMM with $K = 256$ Gaussians, employing power and $\ell_2$ normalization. The second representation uses the object scores $p_v$ of a video, here also we apply power and $\ell_2$ normalization. For both representations, we train one-vs-rest linear SVM classifiers and we average performance over 20 runs for every given number of train examples.

The results in mAP are shown in Figure 4. Interestingly, to perform better than our zero-shot classification, fully supervised classification setup requires 4 and 10 examples per class for object and motion representations respectively.

**Object transfer versus action transfer** We now experiment with the more conventional setup for zero-shot learning, where we have training data for some action classes, disjoint from the set of test action classes. We keep half of the classes of a given dataset as train labels and the other half as our zero-shot classes. The action classifiers are learned from odd (or even) numbered classes and videos from the even (or odd) numbered classes are tested.

We evaluate two types of approaches for action transfer, i.e., when training classes are also actions. The first method uses the provided action attributes for zero-shot classification with direct attribute prediction [20]. Since attributes are available only for UCF101, we experiment on this dataset.

<table>
<thead>
<tr>
<th>Embedding</th>
<th>Sparsity</th>
<th>UCF101</th>
<th>HMDB51</th>
<th>THUMOS14</th>
<th>UCF Sports</th>
</tr>
</thead>
<tbody>
<tr>
<td>AWV</td>
<td>None</td>
<td>16.7%</td>
<td>8.0%</td>
<td>4.4%</td>
<td>13.9%</td>
</tr>
<tr>
<td></td>
<td>Video</td>
<td>17.5%</td>
<td>7.7%</td>
<td>10.7%</td>
<td>13.9%</td>
</tr>
<tr>
<td></td>
<td>Action</td>
<td>21.9%</td>
<td>9.9%</td>
<td>19.9%</td>
<td>25.6%</td>
</tr>
<tr>
<td>FWV</td>
<td>None</td>
<td>28.7%</td>
<td>14.2%</td>
<td>25.9%</td>
<td>23.1%</td>
</tr>
<tr>
<td></td>
<td>Video</td>
<td>29.0%</td>
<td>14.5%</td>
<td>27.8%</td>
<td>23.1%</td>
</tr>
<tr>
<td></td>
<td>Action</td>
<td><strong>30.3%</strong></td>
<td><strong>15.6%</strong></td>
<td><strong>33.4%</strong></td>
<td><strong>26.4%</strong></td>
</tr>
</tbody>
</table>

Supervised: 63.9% 35.1% 56.3% 60.7%

Table 2. Evaluating semantic embeddings, action and video sparsity: Average accuracies (mAP for THUMOS14) for the four datasets. Action sparsity and FWV both boost the performance consistently. Supervised upper-bound using object scores as representation.

Figure 4. Our approach compared with the supervised classification with few examples per class: State-of-the-art object and motion representations respectively require 4 and 10 examples per class to catch up with our approach, which uses no example.
The train videos of the training classes are used to learn linear SVMs for the provided 115 attributes. The second method uses action labels embedded by FWV to compute affinity between train and test action labels. We use the same GMM with $k = 2$ components learned on ImageNet object labels. Here linear SVMs are learned for the training action classes. The results are reported for UCF101 and HMDB51 datasets. For both the above approaches for action transfer, we use MBH descriptors encoded by Fisher vectors for video representation. The results are reported in Table 3.

For comparison with our approach, the same setup of testing on odd or even numbered classes is repeated with the object labels. The training set is ImageNet objects, so no video example is used for training. Table 3 compares object transfer and action transfer for zero-shot classification. Object transfer leads to much better learning compared to both the methods for action transfer. The main reason for the inferior performance using actions is that there are not enough action labels or action attributes to describe the test classes, whereas from 15k objects there is a good chance to find a few related object classes.

**Zero-shot event retrieval** We further demonstrate our method on the related problem of zero-shot event retrieval. We evaluate on the TRECVID13 MED [31] testset for EK0 task. There are 20 event classes and about 27,000 videos in the testset. Instead of using the manually specified event kit containing the event name, a definition, and a precise description in terms of salient attributes, we only rely on the class label. In Table 4, we report mAP using event labels embedded by AWV and FWV. We also compare with the state-of-the-art approaches of Chen et al. [3] and Wu et al. [48] reporting their settings that are most similar to ours. They learn concept classifiers from images (from Flickr, Google) or YouTube video thumbnails, be it that they also use the complete event kit description. Using only the event labels, both of our semantic embeddings outperform these methods.

**Free-text action search** As a final illustration we show in Figure 6 qualitative results from free-text querying of action videos from the THUMOS14 testset. We used the whole dataset for querying, and searched for actions that are not contained in the 101 classes of THUMOS14. Results show that free-text querying offers a tool to explore a large collection of videos. Results are best when the query is close to one or a few existing action classes, for example “Dancing” retrieves results from “salsa-spin” and other dancing clips. Our method fails for the query “hit wicket”, although it does find cricket matches. Zero shot action recognition through an object embedding unlocks free text querying without using any kind of expensive video annotations.

### 4.4. Zero-shot action localization

In our final experiment, we aim to localize actions in videos, i.e., detect when and where an action of interest occurs. We evaluate on the UCF Sports dataset, following the latest convention to localize an action spatio-temporally as a sequence of bounding boxes [13,21,45]. For sampling the action proposal, we use the tubelets from [13] and compute object responses for each tubelet of a given video. We compare with the fully supervised localization using the object and motion representations described in Section 4.3. The top five detections are considered for each video after non-maximum suppression.
The three are compared in Figure 5, which plots area under the ROC (AUC) for varying overlap thresholds. We also show the results of another supervised method of Lan et al. [21]. It is interesting to see that for higher thresholds our approach performs better. Considering that we do not use any training example it is an encouraging result. There are other state-of-the-art methods [13, 14, 45] not shown in the figure to avoid clutter. These methods achieve performance comparable to or lesser than our supervised case.

For certain action classes many objects and scene from the context might not be present in the groundtruth tubelets. Still our approach finds enough object classes for recognizing the zero-shot classes in the tubelets, as we have large number of train classes. In contrast, finding atomic parts of actions such as ‘look-up’, ‘sit-down’, ‘lift-leg’ etc are difficult to collect or annotate. This is one of the most critical advantages we have with objects, that it is easier to find many object or scene categories.

5. Conclusion

We presented a method for zero shot action recognition without using any video examples. Expensive video annotations are completely avoided by using abundantly available object images and labels and a freely available text corpus to relate actions into an object embedding. In addition, we showed that modeling a distribution over embedded words with the Fisher Vector is beneficial to obtain a more precise sense of the unseen action class topic, as compared to a word embedding based on simple averaging. We explored sparsity both in the object embedding, as well as in the unseen action class, showing that sparsity is beneficial over mere feature-dimensionality.

We validate our approach on four action datasets and achieve promising results for action classification and localization. We also demonstrate our approach for action and event retrieval on THUMOS14 and TRECVID13 MED respectively. The most surprising aspect of our objects2action is that it can potentially find any action in video, without ever having seen the action before.

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References

[14] M. Jain, J. van Gemert, and C. Snoek. What do 15,000 object categories tell us about classifying and localizing actions? In CVPR, 2015, 1, 2, 3, 8
[40] C. Snoek et al. MediaMill at TRECVID 2013: Searching concepts, objects, instances and events in video. In TRECVID, 2013, 1, 2, 3
[49] Z. Xu, Y. Yang, and A. G. Hauptmann. A discriminative CNN video representation for event detection. In CVPR, 2015, 1, 2, 3