Multi-Label Zero-Shot Human Action Recognition via Joint Latent Embedding

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Abstract Human action recognition refers to automatic recognizing human actions from a video clip, which is one of the most challenging tasks in computer vision. Due to the fact that annotating video data is laborious and time-consuming, most of the existing works in human action recognition are limited to a number of small scale benchmark datasets where there are a small number of video clips associated with only a few human actions and a video clip often contains only a single action. In reality, however, there often exist multiple human actions in a video stream. Such a video stream is often weakly-annotated with a set of relevant human action labels at a global level rather than assigning each label to a specific video episode corresponding to a single action, which leads to a multi-label learning problem. Furthermore, there are a great number of meaningful human actions in reality but it would be extremely difficult, if not impossible, to collect/annotate video clips regarding all of various human actions, which leads to a zero-shot learning scenario. To the best of our knowledge, there is no work that has addressed all the above issues together in human action recognition. In this paper, we formulate a real-world human action recognition task as a multi-label zero-shot learning problem and propose a framework to tackle this problem. Our framework simultaneously tackles the issue of unknown temporal boundaries between different actions for multi-label learning and exploits the side information regarding the semantic relationship between different human actions for zero-shot learning. As a result, our framework leads to a joint latent embedding representation for multi-label zero-shot human action recognition. The joint latent embedding is learned with two component models by exploring temporal coherence underlying video data and the intrinsic relationship between visual and semantic domain. We evaluate our framework with different settings, including a novel data split scheme designed especially for evaluating multi-label zero-shot learning, on two weakly annotated multi-label human action datasets: Breakfast and Charades. The experimental results demonstrate the effectiveness of our framework in multi-label zero-shot human action recognition.

Keywords Human action recognition · Multi-label learning · Zero-shot learning · Joint latent embedding · Weakly supervised learning

1 Introduction

As one of the most challenging tasks in computer vision, human action recognition refers to automatic recognizing human actions conveyed in a video clip. In last two decades, human action recognition has been extensively studied. As there are many different human actions in reality, this task is generally formulated as a multi-class classification problem. To train a multi-class classifier for human action recognition, a great number of examples for each single action are required in the current setting. To collect such training examples, one needs to manually trim a video steam to ensure that there is only one human action appearing in a trimmed video episode. This annotation process is laborious and time-consuming and there is hence no large-scale dataset with “fine-grained” annotation for human action recognition. In contrast to ImageNet (Deng et al. 2009) for object recognition, where it consists of a total of 3.2 million cleanly labelled images spread over 5,247 categories, there are much fewer annotated video clips involving only a small number of human actions. For instance, HMDB51...
and UCF101 are among the most commonly used benchmark datasets in human action recognition, where there are 6,676 and 13,320 instances of only 51 and 101 different human actions, respectively. The limitation of human action datasets in such a scale has become an obstacle in developing a large-scale human action recognition system.

In a real scenario, a video clip often conveys multiple human actions corresponding to different concepts. Hence, a set of multiple action labels have to be used to characterize its complete semantics underlying human actions conveyed in this video clip. For example, video clips on YouTube are usually uploaded by users along with some descriptive terms that can be used to infer the human actions conveyed in those video clips, where descriptive terms may be viewed as a set of coherent labels that collectively characterize the semantics at a global level. Recently, a very large multi-label video dataset YouTube-8M (Abu-El-Haija et al. 2016) has been collected by Google Research. Although the dataset is not restricted to human action video clips, it paves a new way for various video analyses including human action recognition. One of essential video analysis problems on such a data set may be formulated as multi-label learning that predicts a set of labels associated to a given instance or a set of confidence scores corresponding to the candidate labels related to this instance. In multi-label learning, a training example often consists of an input instance and a set of labels associated with this instance at a global level (no need of explicitly associating each of those labels to a relevant object within this instance). While multi-label data are common in many domains and multi-label classification has been studied under different applications (Zhang and Zhou 2014), e.g., semantic image tagging, text categorization and gene functionality prediction, only few works focusing on multi-label human action recognition can be found in literature due to a lack of human action datasets annotated with multiple class labels. To fill in this gap, a dataset dubbed with Charades (Sigurdsson et al. 2016) was collected especially for multi-label human action recognition and made publicly available very recently. In addition, other datasets were also considered to be used in multi-label human action recognition although they were originally collected for different tasks. Thus, such data sets provide a proper test bed for multi-label human action recognition studies.

Multi-label human action recognition works on weakly labelled video data, i.e., the training data are annotated at the video level without exhaustively trimming and annotating multiple action episodes. While it is easier to collect such video clips associated with a set of labels at a global level than those with “fine-grained” annotation, it would be still very challenging to collect all the training examples due to the existence of many different human actions. Zero-shot learning (ZSL) provides an alternative solution to alleviate this problem. ZSL aims to recognize the instances belonging to novel classes which are not seen during training. It has been formally shown that a ZSL system trained on a dataset of finite classes could be used to predict infinite number of classes unseen during the learning (Zhang et al. 2016a). Under the ZSL framework, we merely need to collect and annotate training examples for a moderate set of training classes and expect that a large number of novel classes can be recognized via exploiting the semantic relationship between different human actions. To this end, a ZSL algorithm needs to transfer the knowledge regarding the relations between visual features and class label semantics learned from known or training classes to unseen or test classes. The knowledge transfer is enabled by modelling the semantic representations of different classes, which can be easily obtained from side information, e.g., descriptive texts, with a much less effort. Nevertheless, most of the existing ZSL methods were proposed to tackle single-label ZSL problems. Although some of those methods may be extended to multi-label scenarios, their effectiveness of different ZSL algorithms have not been extensively investigated in the multi-label learning scenarios. To the best of our knowledge, there exists no work in multi-label zero-shot human action recognition.

In this paper, we address the multi-label ZSL issue in the context of human action recognition. The training video data are weakly annotated so that the exact temporal-spatial locations of multiple human actions in a video clip are unknown. In addition, training examples are only available for training/known labels, a subset of the action label collection considered in the recognition stage. To address the multilabel ZSL problem in human action recognition, we propose a novel joint latent embedding (JLE) framework. The framework aims to learn a joint latent space from visual and semantic representations. In the learned joint space, visual and semantic representations of human actions are mapped into visual and semantic embedding, respectively. Then, the visual and semantic domains are related via the joint embedding space where any human actions in a considered action label collection can be recognized regardless of known or unseen classes during learning. In our framework, a visual model learns mapping visual representations of a video clip into latent visual embedding, and a semantic model learns mapping the semantic representations of human action labels into latent semantic embedding in the same joint embedding space. In the visual model, a long short-term memory (LSTM) network is employed to explore saliency of the multiple human actions conveyed in the weakly annotated multi-label video data, which plays a role in implicitly finding out a specific episode containing one of multiple human actions conveyed in a video clip. In the semantic model, a three-layer fully-connected neural network is employed to learn the latent semantic embedding so that the semantic gap between visual and semantic space can be bridged and the semantic relations between all different labels in a con-
sidered action collection can be well explored and modeled properly. During learning, both visual and semantic models are trained with our proposed alternate learning algorithm. For recognition, the trained visual and semantic models are used together to recognize a test video clip by measuring the distance between its visual embedding and the semantic embedding of all the labels.

Our main contributions in this paper are summarized as follows:

- By considering real scenarios, we formulate generic human action recognition as a multi-label zero-shot learning problem. To the best of our knowledge, our work presented in this paper is the first attempt to study human action recognition from a multi-label zero-shot perspective.
- To address the multi-label zero-shot issue arising from weakly annotated data for human action recognition, we propose a novel joint latent embedding framework consisting of visual and semantic embedding models. To train two embedding models effectively, we come up with a learning algorithm that alternately optimizes the parameters in two embedding models during learning.
- To test the performance of our proposed framework, we conduct a thorough evaluation via a comparative study on two benchmark multi-label human action datasets, Breakfast and Charades, with various evaluation metrics and different settings including a novel data split protocol simulating a real scenario of zero-shot human action recognition.

The rest of this paper is organized as follows. Section 2 reviews related works. Section 3 presents our framework for multi-label zero-shot human action recognition. Section 4 describes our experimental settings, and Section 5 reports the experimental results. The last section draws conclusions.

2 Related Work

In this section, we review the existing works relating to multi-label human action recognition, especially for those applicable to multi-label zero-shot learning scenarios. We also address the limitations of the existing works and make a connection between our work and those related works. As a result, we first overview existing multi-label classification methods and then focus on the existing works in multi-label ZSL learning despite the fact that none of such multi-label ZSL methods has been applied to human action recognition.

2.1 Multi-label Learning

In a real scenario, data that need to be characterized with multiple labels are often complicated but common in real world, e.g., web videos. In a human action video clip, multiple actions could happen simultaneously, e.g., sitting, eating and listening. In this scenario, no episode in such a video clip can be characterized by a single action label and a set of labels hence have to be collectively used to describe this video clip. Even though a video clip can be divided into several episodes corresponding to different human actions, the segmentation and annotation process could be difficult, tedious, laborious and time-consuming. In particular, semantic image segmentation and human action detection in video streams remain unsolved. As a result, multi-label learning is often formulated as a weakly supervised learning task that predicts a set of labels associated with an instance but does not address the issue in assigning each of labels in the set to a specific object within this instance. To tackle a weakly supervised multi-label learning problem, two different representation methods are used to characterize input data: instance-level and object-level representation. Instance-level representation is a holistic representation of an instance without considering objects containing in this instance, while object-level representation is an object-based representation that extracts potential objects from instances to form bag-of-object representations. Depending on the representation of input data, multi-label learning methods can be divided into two categories.

In multi-label learning, most of the existing methods (Guillaumin et al. 2009; Nam et al. 2014; Wang et al. 2016; Zhang et al. 2016b) work on an instance-based representation, a single feature vector holistically representing multiple objects within an instance. Recently, Fast0Tag (Zhang et al. 2016b) was proposed for multi-label image tagging by learning a mapping from visual space to a label space. An image containing multiple objects is represented by one aggregated visual representation. Alternatively, TagProp (Guillaumin et al. 2009) uses an adapted nearest neighbour model for multi-label learning in the visual space where each image of multiple objects is also represented by one feature vector. Wang et al. (2016) use a convolutional neural network (CNN) directly working on raw images of multiple objects to learn image-level deep visual representations for multi-label classification. Nam et al. (2014) use a deep neural network with a ranking loss in learning for large-scale multi-label text classification where an input document is represented with a feature vector. Although representing one instance with a single feature vector is straightforward and convenient, it might neglect the intrinsic relationship between multiple objects within an instance. Thus, a holistic instance-level representation might result in a catastrophic information loss, especially for long-term dependent and complex video data.

To overcome the weakness in neglecting the information regarding the intrinsic relationship between objects within an instance, researchers attempt to exploit such information
in their multi-label learning methods. Although it is difficult, the segmentation of multiple objects within an instance turns out to be beneficial to multi-label learning. One framework named multi-instance multi-label learning (MIML) (Zhou and Zhang 2007) demonstrates that multi-label learning can be fulfilled effectively if multiple objects within an instance have been explicitly separated or segmented even if no label is explicitly assigned to each of multiple objects within an instance during learning. In real applications, however, automatic semantic segmentation of objects in an instance is also challenging, and a manual segmentation process is laborious and time-consuming. Recently, some efforts have been made to explore object-based representations without using any explicit semantic object segmentation techniques, which seeks a synergy between the MIML and object-level representations. Gu et al. (2016) address this weakly supervised issue in multi-label human action detection with a two-stage solution. First, a set of potential objects or spatial-temporal volumes are generated and selected from a video instance with a set of handcrafted rules. Then the problem is transformed into a MIML problem which can be solved by those traditional multi-label learning algorithms under the MIML framework. A similar idea was also explored by Wei et al. (2016) and Tang et al. for multi-label image classification. However, the extraction of true positive objects from the original example is a very challenging yet non-trivial task, which critically determines the multi-label learning performance. To extract all the meaningful objects within an instance, a lot of candidate proposals have to be considered so that it might suffer from a high computational burden. Instead of using the MIML, Cabral et al. (2015) attempt to explore the information regarding multiple objects in instances via a matrix completion method. Their method works on the assumption that an instance may be represented by a linear combination of those object representations in this instance. Experimental results reported by Cabral et al. (2015) demonstrate the effectiveness of this method via an object-level bag-of-words image representation. However, it remains unknown whether this method is also applicable to other kinds of representations, such as those popular yet powerful deep representations.

2.2 Multi-label Zero-shot Learning

Zero-shot learning (ZSL) has attracted much attention in recent years and provides a promising technique for recognizing a large number of classes without the need of the training data concerning all the classes. Very recently, Zhang et al. (2016a) have formally shown that it is feasible to predict a collection of infinite unseen labels with a classifier learned on training data concerning only a number of labels in this collection or a subset of this collection, where multi-label ZSL is a special case in this so-called “infinite-label learning” paradigm. According to a taxonomy of ZSL (Wang and Chen 2017b), existing ZSL approaches are divided into three categories, namely, direct mapping (Akata et al. 2015; Fu and Huang 2010; Lampert et al. 2014; Xiao et al. 2015), model parameter transfer (Changpinyo et al. 2016; Mensink et al. 2014) and joint space learning (Wang and Chen 2017b; Zhang and Saligrama 2015). Although most existing works focus on single-label ZSL, efforts have been made to extend ZSL to multi-label learning scenarios (Fu et al. 2014; Mensink et al. 2014; Nam et al. 2015; Ren et al. 2015; Sandouk and Chen 2016b; Zhang et al. 2016b).

For direct mapping, it needs to learn a direct mapping from visual to semantic space for zero-shot recognition, which poses a challenge to multi-label ZSL. In single-label ZSL, a training example provides a visual-semantic representation pair used to learn a one-to-one direct mapping. In multi-label ZSL, however, one instance has to be associated with a set of multiple labels and the number of labels associated with different instances are various. As a label is represented with a semantic feature vector, e.g., a vector of attributes or a word vector, in a semantic space, it is no longer straightforward to learn a direct mapping from visual to semantic space in the context of multi-label ZSL. How to model complex semantics underlying a set of labels associated with an instance becomes a central issue in multi-label ZSL. To tackle this issue, most of existing works (Fu et al. 2014; Sandouk and Chen 2016b) make use of the composition properties of semantic representations such as word vectors by using the average of semantic representations of multiple labels to a collective semantic representation for a set of labels associated with the instance. Thus, a training example is formed with a pair of an instance-level visual representation and its corresponding collective semantic representation, which enables one to learning a direct mapping for multi-label ZSL. Apparently, such a collective representation cannot avoid information loss even though a contextualized semantic representation (Sandouk and Chen 2016b) was used. To alleviate the information loss problem in generating a collective semantic representation, Fast0Tag (Zhang et al. 2016b) introduces an alternative solution to collective semantic representations. In this method, each visual instance is mapped into a “principal direction” in the semantic space based on an assumption that there is always a direction for a multi-labelled instance in a semantic space, e.g., word vector space and all the labels relevant to this instance always have higher “ranking” values over irrelevant labels. In other words, we can always find a hyperplane to separate the relevant labels from the irrelevant ones for any multi-labelled instance. While this assumption holds for those datasets as demonstrated in their zero-shot image tagging work (Zhang et al. 2016b), it remains unclear for other datasets in different domain, e.g., human
action recognition, especially due to the existence of various semantic representations that lead to different semantic spaces. From a different perspective, Ren et al. (2015) suggest using an object-level visual presentation under the direct mapping framework for multi-label zero-shot object recognition. Before multi-label learning takes place, an image thus has to be semantically segmented into meaningful subregions and each subregion can be characterized by one label. As a result, their solution is actually a special case of the MIML (Zhou and Zhang 2007) and hence has to rely on sophisticated semantic segmentation techniques that remain unavailable up to date.

Like the works in extending direct mapping to multi-label ZSL, the model parameter transfer idea is also taken into account for multi-label ZSL. COSTA (Mensink et al. 2014) aims to estimate a model for each unseen label by a linear weighted combination of known-label models, e.g., support vector machines (SVMs). The combination coefficients are determined by label co-occurrences derived from either annotations of datasets in hand or external web sources. In COSTA, the models regarding each of known labels are trained independently by means of a one-vs-rest binary SVM classifier without considering the relation and coherence among labels assigned to a single object. Furthermore, COSTA only uses label co-occurrences to model the relatedness between a pair of labels but neglects the semantic of an individual label itself.

Among the three kinds of ZSL algorithms, those joint space learning methods (Frome et al. 2013; Lei Ba et al. 2015; Wang and Chen 2017b; Zhang et al. 2017; Zhang and Saligrama 2015; 2016) often yield more promising results in single-label ZSL. Apart from being used in ZSL, the joint space learning methodology has also been applied to traditional multi-label learning tasks (Gong et al. 2014; Weston et al. 2010) and led to favorable results. The main idea underlying joint space learning is learning a joint (common) latent representation space for both visual and semantic space to bridge the semantic gap. To the best of our knowledge, however, there is no extension of existing joint space learning methods to multi-label ZSL problems, to a great extent, due to the difficulty in modelling complex semantics underlying a set of labels describing an instance, as elucidated above regarding the direct-mapping. In this paper, we hence propose a novel approach to multi-label zero-shot human action recognition under the joint space learning framework by addressing those critical issues.

2.3 Semantic Representation

Regardless of different ZSL scenarios, modelling semantics underlying a collection of labels and their relatedness plays a critical role in knowledge transfer required by ZSL. Miscellaneous methods in semantics modelling and representations have been developed from different perspectives including attributes of labels, label embedding, co-occurrence of labels and concept embedding.

Attributes of labels are a semantic representation where a label is characterized by a list of attributes common to all the labels (Lampert et al. 2014). Label embedding refers to a class of approaches to embedding labels onto a semantic space where the semantic relatedness of labels are reflected (Mikolov et al. 2013). Label embedding is often carried out via learning on external textural resources. For example, the famous Word2Vec semantic embedding is obtained by training a skip-gram neural network on the large-scale corpora, e.g., Google News dataset (Mikolov et al. 2013). Such semantic representations are widely used in ZSL, e.g., (Fu et al. 2014; Ren et al. 2015; Wang and Chen 2017b; Zhang et al. 2016a;b). Unlike label embedding obtained with external resources, co-occurrence of labels is an approach to capturing the relatedness between different labels with the information on co-occurrence of labels or hierarchical relationship between labels in a given dataset used in ZSL, e.g., (Nam et al. 2015). Alternatively, the co-occurrence information on different class labels are also extracted from external resources for ZSL (Mensink et al. 2014). In particular, co-occurrence of labels allows for capturing the relatedness between labels jointly used to describe an instance. The label co-occurrence information may be incorporated into learning semantic embedding for a given dataset, e.g., (Nam et al. 2015). In concept embedding, the semantic meaning of a label is assumed to be polysemous depending on different labels (together treated its context of this target label) jointly used to describe an instance. Hence, the semantic meaning of a label under a specific context frames a concept. As a result, concept embedding (Sandouk and Chen 2016a) can be viewed as contextualized label embedding where a label may have multiple semantic representations in the embedding space if it is used with different labels in describing different instances. The concept embedding leads to a specific approach to multi-label ZSL (Sandouk and Chen 2016b). However, contextualized semantic representation learning suffers a high computational burden and is difficult to deal with a large-scale label collection. Our proposed framework for multi-label zero-shot human action action is generic so that all the semantic representations apart from concept embedding may be used directly in our proposed framework.

3 Model Description

In this section, we present a novel framework for multi-label zero-shot human action recognition. First, we overview the proposed framework along with our motivation. To make it self-contained, we then describe the LSTM unit, an important mechanism used in our framework for implicit saliency detection on video data. Next, we present a method for joint
3.1 Overview

Our proposed framework aims at multi-label zero-shot human action recognition. We formulate this problem as learning a mapping \( \phi: x \rightarrow \mathbb{R}^{|C|} \), where \( x \) is a visual input, e.g., a set of segment-level visual feature vectors extracted from a video clip, and \( y \in \mathbb{R}^{|C|} \) is a list of label-relatedness scores for \( x \) with respect to a action label collection, \( C = \{1, \cdots, |C|\} \), where \( C \) is further divided into two mutually exclusive label subsets corresponding to known (training) and unseen actions; i.e., \( C = C^T \cup C^U \) and \( C^T \cap C^U = \emptyset \). During learning the mapping \( \phi \), only training examples of labels in \( C = C^T \) are available. However, the learned mapping \( \phi \) is used to predict any actions in \( C \) including those unseen actions defined in \( C^U \) from a video clip.

To tackle the problem formulated above, we propose a joint latent embedding framework. Motivated by the joint space learning idea used in ZSL (Frome et al. 2013; Lei Ba et al. 2015; Wang and Chen 2017b; Zhang et al. 2017; Zhang and Saligrama 2015; 2016), we would tackle the knowledge transfer issue in a joint latent space where both visual and semantic representation embedding resides. By embedding visual and semantic representations into this latent space, we expect that semantic gap can be narrowed considerably and the semantic relatedness of known and unseen labels may be effectively explored and exploited in zero-shot recognition. Thus, our framework consists of two component models: visual and semantic models used to learn visual and semantic embedding as well as joint latent embedding for knowledge transfer, as illustrated in the left box of Figure 1.

For visual embedding, we encounter two major technical issues due to the nature of weakly annotated data: a) for a visual input, it remains unknown where an episode conveying an action, and b) it remains unclear which of those action labels describing a video clip is associated with a specific video episode. Nevertheless, a video clip is an ordered sequence of frames and we could explore the temporal coherence underlying a video clip to tackle two aforementioned technical issues. Motivated by recent works in video classification and activity recognition (Donahue et al. 2015; Ma et al. 2017; Yue-Hei Ng et al. 2015), we employ a long short-term memory (LSTM) (Hochreiter and Schmidhuber 1997) recurrent neural network layer to capture temporal
coherence underlying an action episode. Thus, the LSTM layer (c.f. Section 3.2) is first used to process a sequence of visual representations extracted from video segments. With the memorising and forgetting mechanism of LSTM units, we expect that the LSTM layer explores the temporal structure of human actions conveyed in a video sequence; the LSTM units would memorize the input segments until parsing an episode regarding a human action is completed and then forget all the previous input segments when an episode conveying another action starts. Thus, an implicit saliency detection is carried out where no action episode boundaries are explicitly specified. For visual embedding, we further employ two fully-connected layers, dense and visual embedding layers in Figure 1, to capture salient features on the temporal coherence representation yielded by the LSTM layer. While this specific visual model is used in our experiments, its capacity can be increased by adding more hidden layers if necessary. The score and averaging pool layers above the visual embedding layer are used for joint latent embedding learning as presented in Section 3.3. Thus, the visual model is a deep network of heterogeneous layers.

For semantic embedding, we employ a three-layer fully-connected neural network to carry out the semantic model. We expect that this learning model is capable of capturing the intricate semantic relatedness between different actions in a label collection of a moderate size, e.g. those datasets use in our experiments. In general, its capacity can be increased by adding more hidden layers if necessary. As a result, the neural network is fed with a specific semantic representation of action labels, e.g., word vectors and subsequently map them into the semantic embedding layer via a hidden layer, as shown in Figure 1. Likewise, the score and averaging pool layers above the semantic embedding layer are used for joint latent embedding learning. To explore the semantic relatedness between different labels in bridging the semantic gap between visual and semantic space, semantic embedding learning needs to exploit the information carried in training data, e.g., frequency of label co-occurrence in a training dataset (c.f. Section 3.3).

During the joint latent embedding learning, the visual and semantic models are coupled to form a joint latent embedding space. For learning, we propose a learning algorithm working alternately on two models for parameter estimation by promoting positive video-label pairs over negative ones. Thus, the visual model learns the visual embedding of a video example such that its corresponding relevant labels rank ahead of other irrelevant ones in terms of the relatedness scores estimated on the semantic latent space, $E^s$. Alternately, the semantic model learns the semantic embedding of action labels such that the relevant videos rank higher than the irrelevant ones in terms of relatedness scores calculated in the visual latent space, $E^v$. Once the learning is completed, the trained joint latent embedding model can be applied to a test video clip for human action recognition. As a result, the relatedness scores corresponding to all the known and unseen action labels in a label collection are achieved by using both visual and semantic models (c.f. Section 3.4), as illustrated in the right box of Figure 1.

3.2 Long Short Term Memory

As described previously, the LSTM layer plays a crucial role in tackling two technical issues arising from weakly annotated data for visual embedding in our proposed framework. Here, we briefly review the mechanism of an LSTM unit to facilitate understanding our framework.

As shown in Figure 2, an LSTM unit consists of a memory cell reserving the historic information at previous time steps. The output in time step $t$ is determined by the current input $x_t$ and the activation value in this memory cell. Three gates, input, output and forgetting gates, are used to control the information flow in the LSTM unit. The information flow in an LSTM unit (Graves 2013; Hochreiter and Schmidhuber 1997) is formulated as follows:

$$i_t = \sigma(W_ix_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i),$$

$$f_t = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f),$$

$$c_t = f_tc_{t-1} + i_t\tanh(W_{xc}x_t + W_{hc}h_{t-1} + b_c),$$

$$o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_{t} + b_o),$$

and

$$h_t = o_t\tanh(c_t),$$

where $\sigma(\cdot)$ and $\tanh(\cdot)$ are the sigmoid and the tangent hyperbolic functions, and $i$, $f$, $o$ refer to input, forget and output gates, respectively. $c$ is the cell state, representing the information stored in the cell, and $h$ is output of the LSTM unit or input receiving from the output of another LSTM unit.
unit retrospectivelly). $W$’s and $b$’s are weight matrices and bias vectors associated to different gates.

When LSTM units are used in a hidden layer as done in our framework, the dimension of hidden vector $h$ is determined by the number of LSTM units used in this hidden layer. Hence, it is a hyper-parameter that has to be tuned on a given dataset. The dimensions of weight matrices $W$ are thus determined by the dimensions of output vector $h$ and input $x$. The gates $i$, $f$, $o$ and the cell state $c$ are of the same dimension as that of $h$.

### 3.3 Joint Latent Embedding Learning

Now we present the joint latent embedding learning in our proposed framework. To facilitate our presentation, we summarize the notations used in this paper in Table 1.

| Notation | Description |
|----------|-------------|
| $D$, $D_T$ | training, test datasets |
| $|\cdot|$, $|\cdot|_1$ | cardinality of a set, $L_t$ norm of a vector |
| $C$, $C^T$, $C^i$ | label collection, training and unseen class label subsets |
| $E^v$, $E^s$ | visual and semantic embedding space |
| $x_{it}$ | visual representation for the $i$-th segment of the $t$-th example |
| $x_i$ | collection of all the segment-level visual representations of the $i$-th example |
| $s_c$ | semantic representation for the $c$-th label |
| $Y$ | binary target label matrix of training data set |
| $y_i$ | binary target label set of the $i$-th example, i.e., the $i$-th column of matrix $Y$ |
| $y_c$ | binary indicator vector of the $c$-th label appearing examples, i.e., the $c$-th row of matrix $Y$ |
| $E^v$, $e_i^v$ | visual embedding matrix and the column vector for the $i$-th video clip |
| $E^s$, $e_i^s$ | semantic embedding matrix and the column vector for the $i$-th label |
| $d_v$, $d_s$, $d_t$ | dimensions of visual, semantic, latent embedding space |
| $o_i$ | relatedness scores between the $c$-th label and all the candidate labels in visual model |
| $o_c$ | relatedness scores between the $c$-th label and all the training examples in semantic model |
| $\phi_v$, $\Theta_v$ | visual embedding function and parameters |
| $\phi_s$, $\Theta_s$ | semantic embedding function and parameters |
| $\phi = \{\phi_v, \phi_s\}$ | mapping function for multi-label zero-shot recognition |
| $C(\hat{x})$, $L(\hat{x})$ | the ground-truth label set of test instance $\hat{x}$, the ranking list of all the labels predicted for $\hat{x}$ in terms of the relatedness scores |
| $D^v$, $L^v$ | Set of test instances of which ground-truth label sets include the $c$-th label, the ranking list of all the test instances in terms of the relatedness scores for the $c$-th label |

### 3.3.1 General Description

Given a training set of $N$ annotated video clips, $D = \{x_i, y_i\}_{i=1}^N$, where $x_i$ is the visual input and $y_i \in \{0, 1\}^{|C^T|}$ is its binary target label vector in the $i$-th example; 0/1 element indicates the presence/absence of a specific action belonging to $c \in C^T$ in $x_i$.

For a video instance $x_i$ in $D$, we divide it evenly into $T$ segments$^1$, segment-level visual representations are extracted, which are collectively denoted by $\{x_{i1}, x_{i2}, \cdots, x_{iT}\}$. At the $t$-th time step, the segment representation $x_{it}$ is fed into a hidden LSTM layer and processed by this LSTM layer and two subsequent fully-connected layers of linear activation functions (c.f. Figure 1). The latent visual embedding of the $t$-th segment, $e_i^v$, is obtained as follows:

$$e_i^v = \phi_v(x_{it}; \Theta_v).$$

Here, $\phi_v$ is the visual embedding function implemented by the parametric visual model and $\Theta_v$ is a collective notation of all the parameters in this model, including weights and biases involved in this deep network.

Likewise, as depicted in Figure 1, the $c$-th label in a label collection is first represented by a specific semantic representation, $s_c$, that is fed to the semantic embedding function, $\phi_s$, implemented by the parametric semantic model of which all the parameters are denoted by $\Theta_s$ collectively. Thus, the semantic embedding, $e_i^s$, of the $c$-th label is:

$$e_i^c = \phi_s(s_c; \Theta_s).$$

A score layer is employed in each of the visual and the semantic models. In the visual model, the score layer takes the outputs of the visual embedding layer at all the time steps to yield the relatedness scores regarding all the labels for $x_i$ with a dot product between the visual embedding of each segment in $x_i$ and the semantic embedding of all the labels in a label collection:

$$o_{ic} = \langle e_i^v, E^v \rangle,$$

where $E^v \in \mathbb{R}^d \times |C^T|$ is a collective notation of the semantic embedding of all the labels. Here, $\langle a, B \rangle = a^T B$ is a vectorial notation of the dot product between a vector, $a$, and each column of a matrix, $B$. Then the relatedness scores between this video instance and different labels are achieved by averaging over the scores on all the segments of this video instance:

$$o_i = \frac{1}{T} \sum_{t=1}^T o_{it}.$$

Likewise, the relatedness scores between different video instances and the $c$-th label in the label collection, $o_c^i \in \mathbb{R}^{N \times 1}$.

---

$^1$ A segment refers to a volume of multiple consecutive frames.
is estimated in the same manner used in the visual model based on the visual embedding of those video instances and the semantic embedding of the c-th label. Thus, the i-th element of \( \mathbf{o}_c \), the relatedness score regarding the i-th visual instance is
\[
a^c_i = \frac{1}{T} \sum_{t=1}^T < \mathbf{e}^c_t, \mathbf{e}^c_t > .
\] (5)

For the joint latent embedding learning, we need to optimize the parameters in the visual and the semantic models with training data and proper loss functions (the technical details are presented in Section 3.3.2). Assume that \( l_c(\cdot, \cdot) \) and \( l_c(\cdot, \cdot) \) are two loss functions with respect to the visual and the semantic model, the joint latent embedding learning is boiled down to solving the following optimization problems:
\[
\Theta^*_v = \arg\min_{\Theta_v} \frac{1}{T} \sum_{t=1}^T l_c(\mathbf{o}_t, \mathbf{y}_t),
\] (6)
\[
\Theta^*_s = \arg\min_{\Theta_s} l_c(\mathbf{v}, \mathbf{y}^c).
\] (7)

Here, the binary indicator vector \( \mathbf{y}^c \) is a row vector in the target label matrix \( \mathbf{Y} \) of a training dataset, \( \mathcal{D} \), and non-zero elements in \( \mathbf{y}^c \) indicate that the c-th label appears in the target label sets of the corresponding training examples in \( \mathcal{D} \). The binary indicator vector \( \mathbf{y}_q \) is a column vector in \( \mathbf{Y} \), and non-zero elements in \( \mathbf{y}_q \) refers to those labels in the target label set associated with the i-th training example in \( \mathcal{D} \).

### 3.3.2 Loss Function

As described in Section 3.1, multi-label zero-shot learning needs to establish a mapping that outputs a label-relatedness score list for a video input where the scores of the relevant labels are higher than those of irrelevant ones. Motivated by the previous works (Burges et al. 2005; Zhang et al. 2016b), we develop regularized ranking-based loss functions for our joint latent embedding learning.

For the target label set expressed with binary indicators, \( \mathbf{y}_q \), in the i-th training example, \( (\mathbf{x}_t, \mathbf{y}_q) \), non-zero elements indicate the relevant labels and zero elements expresses the irrelevant labels to \( \mathbf{x}_t \). By converting this binary indicator representation, we can use non-zero elements in \( \mathbf{y}_q \) and \( 1 - \mathbf{y}_q \) to express the relevant and the irrelevant labels to \( \mathbf{x}_t \), respectively, where 1 is a vector where all the elements are one and it has the same dimension as that of \( \mathbf{y}_q \). Likewise, \( \mathbf{y}^c \), a binary indicator regarding whether the c-th action appears in training examples in \( \mathcal{D} \) is handled in the same manner. Thus, the relatedness scores of \( \mathbf{x}_t \) to its positive and negative labels, \( \mathbf{o}_c \), are achieved with Eqs. (2) and (3), and the relatedness scores of the c-th label to all the training examples, \( \mathbf{o}_c^* \), are calculated with Eqs. (1) and (5). Based on the above quantities, we can define our ranking-based loss functions, \( l_v(\mathbf{o}_t, \mathbf{y}_t) \) and \( l_s(\mathbf{o}_c^*, \mathbf{y}^c) \): no loss is exerted to an instance if all the positive labels rank ahead of the negative ones according to their relatedness scores. Otherwise, any violation of the expected ranking incurs a loss.

Formally, we define the loss function for visual embedding of \( \mathbf{x}_t \) as follows:
\[
l_v(\mathbf{o}_t, \mathbf{y}_t) = \omega_v \sum_{p \in \mathcal{C}_t} \sum_{q \in \mathcal{C}_t} \log \left( 1 + \exp \left( v(o_{tp}, o_{tq}, y_{tp}, y_{tq}) \right) \right),
\] (8)
where \( \omega_v = (\|\mathbf{y}_q\|_1 \cdot \|\mathbf{1} - \mathbf{y}_q\|_1)^{-1} \) normalizes this per-instance RankNet loss as specified in (Burges et al. 2005). The ranking loss incurred on two specific labels, \( p \) and \( q \), is
\[
v(o_{tp}, o_{tq}, y_{tp}, y_{tq}) = (1 - y_{tp}) o_{tp} - y_{tq} o_{tq}.
\] (9)

Intuitively, the loss function defined by Eqs. (8) and (9) is used to ensure ranking the relevant labels ahead of irrelevant ones when \( y_{tp} = 0 \) and \( y_{tq} = 1 \). During learning, the relatedness scores of the irrelevant labels will be decreased radically when \( y_{tp} = 0 \) and \( y_{tq} = 0 \), but the relatedness scores of relevant labels are increased considerably when \( y_{tp} = 1 \) and \( y_{tq} = 1 \).

Likewise, we define the loss function for semantic embedding of label \( c \) as follows:
\[
l_s(\mathbf{o}_c^*, \mathbf{y}^c) = \omega_c \sum_{p=1}^{\mathcal{D}} \sum_{q=1}^{\mathcal{D}} \log \left( 1 + \exp \left( s(o_{c_p}, o_{c_q}, y_{c_p}, y_{c_q}) \right) \right),
\] (10)
where \( \omega_c = (\|\mathbf{y}^c\|_1 \cdot \|\mathbf{1} - \mathbf{y}^c\|_1)^{-1} \) normalizes this per-class RankNet loss (Burges et al. 2005) and \( 1 \) is a vector where all the elements are one and it has the same dimension as that of \( \mathbf{y}^c \). The ranking loss incurred regarding two specific visual instances, \( p \) and \( q \), is
\[
s(o_{c_p}, o_{c_q}, y_{c_p}, y_{c_q}) = (1 - y_{c_p}) o_{c_p} - y_{c_q} o_{c_q}.
\] (11)

Intuitively, the loss function defined by Eqs. (10) and (11) is able to ensure that the video instances conveying the action of the c-th label are ranked above all those without this action when \( y_{c_p} = 0 \) and \( y_{c_q} = 1 \). Similarly, the video instances without action \( c \) tend to have small relatedness scores when \( y_{c_p} = 0 \) and \( y_{c_q} = 0 \), while the video instances having this action tend to have large relatedness scores when \( y_{c_p} = 1 \) and \( y_{c_q} = 1 \).

To understand the motivation behind our loss functions formulated in Eqs. (8)-(11), we would make the following remarks. Our loss functions have the nature of both cross-entropy and ranking-based losses. On the one hand, a cross-entropy loss tends to enlarge marching scores of its relevant labels and to diminish those of its irrelevant labels simultaneously for training examples during learning. To this
end, all the labels are considered independently and treated equally so that the less frequently used relevant labels might be overlooked during learning. On the other hand, a ranking-based loss generally makes use of pairwise constraints to exploring a relationship between labels associated with an instance explicitly. However, the relatedness scores in the ranking-based loss are not bounded and could hence vary across different examples. Thus, some “difficult” pairs of labels is likely to incur larger cost that predominates the overall loss, which could make the learning biased to those pairs of labels only. Furthermore, relatedness scores may vary in a large range for different examples in a training set even though proper ranking relationships among them are established. In this circumstance, the performance appears poor in terms of a label-centric evaluation metric, which will be described in Section 4.5. Thus, we tackle the above issues with the loss functions that seek the synergy between cross-entropy and ranking-based losses. In our loss functions, losses incurred by the irrelevant labels may predominate at the beginning of learning as there are much more irrelevant labels than relevant ones to a training example. However, minimizing this term allows for lowering relatedness scores for relevant and irrelevant labels considerably so that the loss functions gradually guide the learning to generate proper relatedness scores for relevant labels via the ranking-based loss. Thus, our proposed loss functions actually work on ranking-based constraints with the regularization via properly confining the magnitude of relatedness scores for relevant and irrelevant labels. Thus, our loss functions significantly distinguish from a ranking-based loss without the regularization such as the one used in Fast0Tag (Zhang et al. 2016b). Hence, we expect that our regularized ranking-based losses would lead to better generalization, which will be verified in our experiments.

### 3.3.3 Learning Algorithm

As formulated in Eqs. (6) and (7), learning is going to find the optimal parameters, $\Theta^v$ and $\Theta^s$, by minimizing two loss functions, $l_v(\mathbf{o}, \mathbf{y})$ and $l_s(\mathbf{o}', \mathbf{y}')$, defined in Eqs. (8) – (11). However, the relatedness scores required in $l_v(\mathbf{o}, \mathbf{y})$ regarding the visual model involve the output of the semantic model, $E^s$, and vice versa (c.f. Figure 1). Moreover, $l_v(\mathbf{o}, \mathbf{y})$ requires the relatedness scores between all the candidate labels and each of training examples, while $l_s(\mathbf{o}', \mathbf{y}')$ needs the relatedness scores between all the training examples and each of all the action labels in $C^v$. Thus, our optimization problems are very complex and unsolvable simultaneously with commonly used local search methods, e.g., gradient-descent based methods.

Motivated by the works dealing with similar optimization problems, e.g., (Jiang et al. 2017; Kavukcuoglu et al. 2010), we come up with an learning algorithm to train the visual and the semantic models alternately during learning. In our alternate learning strategy, our learning algorithm begins with randomly initializing the parameters in the semantic model and then use the initialized parameter to generate the initial semantic embedding. By using the initial semantic embedding in $l_v(\mathbf{o}, \mathbf{y})$, the visual model can be trained with a local search method such as the mini-batch stochastic gradient decent method. After one epoch, the current parameters in the visual model are frozen and used to generate the visual embedding for all the examples. In the same manner, By using the current visual embedding in $l_s(\mathbf{o}', \mathbf{y}')$, the semantic model is trained in the same manner. This alternate learning process carries on until a stopping condition is satisfied. The details of this alternate learning algorithm is described in Algorithm 1.

It is worth stating that two loss functions defined for visual and semantic model are related and the optimisation of one model would naturally promote the other towards its optimal solution. Hence, our alternative learning algorithms may converge after running finite epochs with the same properties held for similar methods (Jiang et al. 2017; Kavukcuoglu et al. 2010).

### 3.4 Multi-Label Zero-Shot Recognition

Once the joint latent embedding learning is completed, we obtain a mapping function: $\phi(\mathbf{x}, \mathbf{c}) = \{\phi_v(\mathbf{x}|\Theta^v), \phi_s(\mathbf{c}|\Theta^s)\}$ where $\phi_v(\mathbf{x}|\Theta^v)$ and $\phi_s(\mathbf{c}|\Theta^s)$ are the visual and the semantic embedding functions implemented by the trained visual and semantic models, respectively. Then, we can use this mapping function for multi-label zero-shot human action recognition.

---

**Algorithm 1 Joint Latent Embedding Learning**

**Input:** Randomly initialize parameters, $\Theta^v$ and $\Theta^s$, in the visual and the semantic models, respectively; extract the visual representations of training example, $\mathbf{x}_i$, $i = 1, \ldots, N$, and the semantic representations of all the training labels, $\mathbf{c}_i$, $\forall \mathbf{c} \in C^v$; input the target label matrix of the training set, $Y$; pre-set the dimensionality of joint latent embedding space, $d_s$.

**Output:** Optimal model parameters: $\Theta^v$ and $\Theta^s$.

1: Generate the initial semantic embedding $\phi_v(\mathbf{x}_i; \Theta^v)$, $\forall \mathbf{c} \in C^v$; $t \leftarrow 0$.

2: repeat

3: $t \leftarrow t + 1$;

4: $\Theta^v_t = \text{argmin}_{\Theta^v} \sum_{i=1}^{N} l_v(\mathbf{o}_i, \mathbf{y}_i)$ with the current semantic embedding for one epoch;

5: Generate the visual embedding with the current visual model, $\phi_v(\mathbf{x}_i; \Theta^v_t)$, $i = 1, \ldots, N$;

6: $\Theta^s_t = \text{argmin}_{\Theta^s} \sum_{\mathbf{c}\in C^v} l_s(\mathbf{o}_c^i, \mathbf{y}_c^i)$ with the current visual embedding for one epoch;

7: Generate the semantic embedding with the current semantic model $\phi_s(\mathbf{x}_i; \Theta^s_t)$, $\forall \mathbf{c} \in C^v$;

8: until Stopping condition is met.

9: $\Theta^v \leftarrow \Theta^v_t$ and $\Theta^s \leftarrow \Theta^s_t$. 

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For recognition, we first extract the semantic representations of all the labels, including both known and unseen labels, in a considered label collection: \( s_c, \forall c \in C; C = C^{Tr} \cup C^{Tl} \) and \( C^{Tr} \cap C^{Tl} = 0 \). By using the semantic embedding function, we achieve the semantic embedding of all the labels: \( \hat{e}_c = \phi_s(x_c|\Theta_s^r), \forall c \in C \). For a test video clip, we divide it into \( T \) segments and extract its segment-level representations collectively denoted by \( \hat{x} = \{\hat{x}_1, \hat{x}_2, \ldots, \hat{x}_T\} \). By feeding \( \hat{x} \) to the visual embedding function, we achieve its visual embedding: \( \hat{e}v = \phi_v(\hat{x}|\Theta_v^s) \). Thus, the relatedness scores between this test video clip and all the actions in the considered label collection \( C \), including known and unseen labels during learning, is achieved by

\[
\text{Score}(\hat{x}, c) = <\hat{e}_c, \hat{e}_c>, \quad \forall c \in C. \quad (12)
\]

Finally, we achieve a ranking action label list, \( L(\hat{x}) \), for this test video clip by sorting its relatedness scores measured against all the labels in \( C \) with Eq. (12):

\[
L(\hat{x}) = \{ c_i \}_{i=1}^{C}, \quad (13)
\]

where \( \forall c_i, c_j \in C \), \( \text{Score}(\hat{x}, c_i) \geq \text{Score}(\hat{x}, c_j) \) if \( i < j \).

4 Experimental Setting

In this section, we describe our experimental design and settings, including datasets, visual and semantic representations, model learning, evaluation scenarios and criteria used in our experiments. Moreover, we design a number of comparative experiments to exhibit the gain resulting from different components in our framework and to demonstrate the effectiveness of our framework by a comparison to several state-of-the-art multi-label ZSL methods that could be applied to human action recognition.

4.1 Datasets and Splits

We first describe datasets and their split settings used in our experiments for simulation of zero-shot scenarios.

4.1.1 Datasets

To evaluate our framework, we employ two publicly available video datasets: Breakfast (Kuehne et al. 2014) and Charades (Sigurdsson et al. 2016), in our experiments. In both datasets, at least two actions are involved in each video clip and the duration of each video clip is relatively long, which implies the temporal coherence information may be explored and exploited in human action recognition. Hence, both datasets are suitable to evaluate multi-label human action recognition. Below, we summarize the main aspects of two video datasets.

Breakfast: In this dataset (Kuehne et al. 2014), there are 1,989 video clips totally, where a video clip conveys several cooking actions. Totally, there are 49 cooking actions (excluding the “silence” label), such as ‘stirring’, ‘pouring milk’ and ‘opening_the_fridge’. Those actions are performed by 52 people in different kitchens. Although this dataset is not collected especially for multi-label human action recognition, we would use it as a proof-of-concept test bed.

Charades: This dataset (Sigurdsson et al. 2016) is collected from hundreds of people recording videos in their own home especially for video-based human activity analysis in daily lives. Hence, it is very challenging for multi-label human action recognition. In this dataset, there are 9,848 video clips involving 157 different human actions totally, acting out casual everyday activities. An average duration of video clips is around 30 seconds and an average number of actions involved in a video clip is 6.8. Those actions are performed by 267 people from three continents, and more than one person appear in over 15% of all the video clips. The raw video data (scaled to 480p) are used in our experiments, which are available from the Charades project page.

4.1.2 Dataset Splits

To simulate a zero-shot scenario, we need to split a dataset into training and test sets where a training set contains examples associated with only known classes while a test set has test instances involving at least one unseen class. Unlike single-label ZSL where a dataset is automatically split into training and test sets once unseen classes are specified, the dataset split issue in multi-label ZSL becomes much more complicated. In our experiments, we make two different split settings named instance-first and label-first split, respectively, as illustrated in Figure 3.

Instance-First Split

This is a commonly used data split setting in nearly all the existing multi-label ZSL works, e.g., (Mensink et al. 2014; Nam et al. 2015; Zhang et al. 2016b). In this setting, instances in a dataset are first split into training, validation and test subsets. The training and the validation subsets are used for parameter estimation and hyper-parameter tuning, the dimension of latent embedding space \( d_e \) and the number of iterations of Algorithm 1 for our model. The test set that may or may not involve unseen labels is reserved for performance evaluation. Then, we divide the action label collection into mutually exclusive known and unseen label sets. Before learning, any unseen labels in the target label set of an instance in the training and the validation subsets are removed as shown in the left plot of Figure 3. In other words, only known labels in the target label sets of an instance in those two datasets are used in learning. It is worth clarifying

\[ \text{http://allenai.org/plato/charades/} \]
Table 2 Information on two different data split settings.

| Dataset   | Split Method   | # Training Inst. | # Validation Inst. | # Test Inst. | # Known Labels | # Unseen Labels |
|-----------|----------------|------------------|--------------------|--------------|----------------|-----------------|
| Breakfast | Instance-first | 1196             | 126                | 667          | 39             | 10              |
|           | Label-first    | 1019/917/7823    | 200                | 770/872/966  | 39             | 10              |
| Charades  | Instance-first | 6385             | 1600               | 1863         | 117            | 40              |
|           | Label-first    | 4580/4176/3987   | 1000               | 4268/4672/4861 | 137           | 20              |

Human actions as unseen classes and the rest 117 human actions are hence known actions.

**Label-First Split**

Although the instance-first data split setting is widely used in multi-label ZSL, it suffers from a fundamental limitation. It is well known that multiple labels together could frame a specific concept and removing any label from this label cohort may lead to less accurate semantic meaning and biases in learning. Furthermore, the instance-first split allows for accessing to visual features of instances involved in unseen actions. To overcome this limitation, we propose a novel data split setting for multi-label ZSL named label-first split. In this new setting, all the labels in a label collection used in a dataset are first divided into two mutually exclusive subsets: known and unseen labels. Then, all the instances having any unseen labels are reserved for test and the rest instances of known labels only are further divided into two subsets for training and validation. Due to sparsity of training data, the validation in the label-first split also adopts the protocol used in multi-label learning (Zhang and Zhou 2014).

To split the Breakfast dataset with this setting, we randomly choose 10 labels for unseen labels and the rest 39 labels are designated as known labels accordingly. Hence, this dataset are naturally split into two sets for training and test. The training data are further divided for training and validation. For validation, we randomly choose 200 instances from the training data. Likewise, the Charades dataset is split by using 20 randomly chosen label for unseen labels. Thus, the remaining 137 labels become known labels. From the instances of known labels, we randomly choose 1,000 instance used for validation.

For reliability, we repeat our experiments on each dataset under each split setting for three trials. During a trial, training data given in the pre-split of each dataset are randomly divided into training and validation subsets with the instance-first split setting, and a known/unseen label split on each dataset is chosen randomly with the label-first split setting. For clarity, we summarize the data split information on two datasets in Table 2.

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3 All the data splits and source code used in our experiments are available on our project website: http://staff.cs.manchester.ac.uk/~kechen/MLZSHAR.
4.2 Visual and Semantic Representations

In our experiments, we use visual representations extracted with the existing C3D deep network (Tran et al. 2015) and word vectors as semantic representations (Mikolov et al. 2013).

As suggested by Tran et al. (2015), the C3D features are extracted for a segment of 16 frames with eight frames overlapping between two adjacent segments. Thus, a video clip is always divided into \( T \) segments with the following treatment: we simply pad the sequence of all zeros to short video clips and down-sample long video clips to ensure that each video clip can be divided into \( T \) segments. Then, \( T \) C3D feature vectors collectively form the features of this video clip. In our comparative study, we also convert \( T \) feature vectors into a holistic visual representation via averaging those \( T \) feature vectors. The use of such a holistic visual representation, we would demonstrate a performance gain benefiting from exploring/exploiting temporal coherence information underlying segments in a video clip. Based on a cross-validation experiment, we choose \( T = 300 \) for Breakfast and \( T = 20 \) for Charades. Although only C3D features are used in our experiments, it is worth mentioning that other kinds of visual representations, e.g., IDT features (Wang and Schmid 2013) and deep image features extracted on a frame basis, can also be used straightforwardly in our framework.

In our experiments, we adopt Word2Vec as our semantic representation. Word2Vec was trained with a skip-gram neural network on the Google News dataset of 100 billion words (Mikolov et al. 2013). As a result, one action label is represented by a 300-dimensional word vector. Although only 300-dimensional word vectors are used in our experiments, word vectors of different dimensionality may be used, and moreover, other semantic representations, e.g., attributes, can be used in our framework without any difficulty if available.

4.3 Model Learning

In our experiments, model learning is implemented on Keras (Chollet 2015), a high-level neural networks library, running on top of either TensorFlow or Theano. As we use two neural networks to carry out the visual and the semantic models (c.f. the left box in Figure 1), we need to decide the specific network architectures and relevant hyper-parameters on two datasets during the model learning. The optimal hyper-parameters are found by a grid-based search via a cross-validation procedure. The Adam (Kingma and Ba 2014), a stochastic optimisation method, is used for training our model with its default configuration.

The visual model takes an segment-level C3D representation of \( d_v = 4,096 \) features as input to the LSTM layer, where there are \( N_l \) LSTM units. To improve the generalization, we also apply the dropout procedure (Srivastava et al. 2014) to the LSTM layer where a dropout rate needs specifying. The output of LSTM units are fed to a fully connected dense layer of \( N_s \) neurons, and the output of this dense layer are further fed to the visual embedding layer of \( d_v \) neurons. During learning, there are no hyper-parameters involved in the score and the average pooling layer in the visual model.

As described in Section 3.1, the semantic model is carried out by a fully-connected three-layer feed-forward neural network. The word vectors of \( d_v = 300 \) dimensions are first input to a hidden layer of \( N_s \) \textit{ReLU} units (Nair and Hinton 2010). Subsequently, the output of this hidden layer are fed to the semantic embedding layer of \( d_v \) linear units. Note that for joint latent embedding learning, the dimension of the semantic embedding space is set to the same of the visual embedding space in our experiments. Likewise, there are no hyper-parameters involved in the score and the average pooling layer in the semantic model during learning.

4.4 Evaluation Scenarios

Multi-label zero-shot recognition is complex given the fact that a test instance may be associated with a label set including both known and unseen class labels. Thus, there are different evaluation scenarios in previous works (Sandouk and Chen 2016b; Zhang et al. 2016b); each focuses on a specific aspect. Following their settings (Sandouk and Chen 2016b; Zhang et al. 2016b), we evaluate our framework along with other learning models used in our comparative study described later on in this section in three different scenarios: **Known-action only**: In this setting, the performance is evaluated regarding only known (training) actions. This scenario boils down to the conventional supervised multi-label learning. In this circumstance, we no longer take any unseen action labels into account during test; for a test instance, its relatedness score ranking list contains only those regarding known action labels in \( C^T \) and any unseen action label in \( C^U \) in its ground-truth label set, if there is, will be removed such that the modified ground-truth set includes only known action labels in \( C^T \).

**Unseen-action only**: In this setting, the performance is evaluated regarding unseen (test) actions. This scenario boils down to a standard ZSL setting. In this situation, we no longer consider any known action labels; for a test instance, its relatedness score ranking list contains only those regarding unseen action labels in \( C^U \) and any known action label in \( C^T \) in its ground-truth label set, if there is, will be removed such that the modified ground-truth set includes only unseen action labels in \( C^U \).

**Generalized ZSL**: In this setting, the performance is evaluated regarding all the actions of which labels appearing in a label collection \( C \) without considering if an action label
is known or unseen during learning. This scenario has been named generalized ZSL in the machine learning community. In this situation, both known and unseen action labels are treated equally; for a test instance, its relatedness score ranking list contains those regarding all the action labels in $C$ and the evaluation is made against its ground-truth label set that could be a mixture of known and unseen labels. It is worth highlighting that the generalized ZSL setting is required by multi-label zero-shot human action recognition in a real application.

4.5 Evaluation Metrics

There are a variety of evaluation metrics for multi-label learning. Depending on the output of a multi-label learning system, the evaluation metrics are generally divided into two types: ranking-based and bipartition-based metrics (Nam et al. 2015; Sorower 2010). Ranking-based metrics work for the situation that a learning system yields a ranking list of continuous-valued relatedness scores on all the candidate labels. In contrast, bipartition-based metrics are used when a learning system produces only a binary indicator vector for all the candidate labels, where 0/1 element expresses the presence/absence. Since our model yields a ranking list of continuous-valued relatedness scores, we employ two commonly used ranking-based metrics for performance evaluation (Li et al. 2016; Mensink et al. 2014; Nam et al. 2015; Sorower 2010; Zhang et al. 2016b), Instance-centric Mean Average Precision (I-MAP) and Label-centric Mean Average Precision (L-MAP). In addition, we employ other metrics, precision, recall and $F_1$ score, which have also been used in the performance evaluation of multi-label learning (Gong et al. 2013; Zhang and Zhou 2014).

To facilitate our presentation, we first define the precision-at-$k$ (Manning et al. 2009) in a generic form:

$$P@k(A, B) = \frac{1}{k} |A \cap B[1, \cdots, k]|,$$

where $A$ is a ground-truth set, $B$ is a set of all the retrieved entities ranked in terms of relevance, and $B[1, \cdots, k]$ indicates top $k$ entities in $B$. Given a test dataset, $D_T = \{\hat{x}_i\}_{i=1}^{[D_T]}$, a learning model yields a label-based ranking list for a test instance, $\hat{x}_i \in D_T$, in terms of its relatedness scores to all the labels in $C$ (c.f. Eqs. (12) and (13)): $L(\hat{x}_i) = \{j \in [C] \mid \delta(c, C(\hat{x}_i)) = 1 \}$ if $c \in C(\hat{x}_i)$ and $\delta(c, C(\hat{x}_i)) = 0$ otherwise.

While I-MAP measures the accuracy in terms of test instances, L-MAP is used to evaluate the performance from a different perspective in light of candidate labels. Given a specific label $c \in C$, a model predicts the relatedness scores against the action specified by the $c$-th label for all the test instances in $D_T$. Hence, we can achieve an instance-based ranking list for the $c$-th label, $L^c = \{\hat{x}_j \}_{j=1}^{[D_T]}$, in terms of their relatedness scores against the $c$-th label where $\forall \hat{x}_p, \hat{x}_q \in D_T$, $\text{Score}(\hat{x}_p, c) \geq \text{Score}(\hat{x}_q, c)$ if $p < q$. Let $D^c$ denote the collection of those test instances of which their ground-truth label sets indeed include the $c$-th label. Thus, the L-MAP over a test dataset, $D_T$, is defined by

$$\text{L-MAP} = \frac{1}{|C|} \sum_{c=1}^{[C]} \frac{\sum_{i=1}^{[D_T]} P@i(D^c, L^c)}{|D^c|},$$

where $\delta(c, C(\hat{x}_i)) = 1$ if $c \in C(\hat{x}_i)$ and $\delta(c, C(\hat{x}_i)) = 0$ otherwise.

For the comparative study, we evaluate each of different models on three evaluation scenarios with evaluation metrics described in Sections 4.4 and 4.5 under the exactly same conditions, including visual and semantic representations.
4.6.1 Baseline Models

To investigate the roles played by different component mechanisms employed in our framework, we design four baseline models, random guess of scores, non-recurrent connection, without semantic embedding and randomized label representation, by manipulating our framework with different purposes described as follows:

Random guess of scores (RGS): This is a general baseline that provides a lowest performance bound used for a reference to improvement made by a learning model. In our work, we randomly generate relatedness scores of all the candidate labels for a test instance. Then the performance of this baseline model is evaluated based on the random guess of scores. For reliability, we repeat the RGS process 100 times in our experiments and the statistics of the RGS performance including mean and standard error of mean are reported.

Non-recurrent connection (NRC): In our framework, a LSTM layer of recurrent connections is employed to capture temporal coherence underlying sequential video data in the visual embedding learning. To examine the role played by the LSTM layer, we replace the recurrent connected layer with a fully connected layer without recurrent connections and keep all other components in our framework unchanged. By this setting, our model is converted into a baseline model named non-recurrent connection. During learning, obviously, this baseline model no longer explicitly makes use of the temporal dependency information underlying sequential segments in a video clip. Algorithm 1 is used directly for parameter estimation.

Without semantic embedding (WSE): In our framework, there is a semantic model for semantic embedding with the motivation that the use of a joint latent embedding space narrows the semantic gap between visual and semantic domains and the zero-shot recognition should be done in the joint latent embedding space. However, some existing works, e.g., Fast0Tag (Zhang et al. 2016b), do not learn a semantic embedding and the zero-shot recognition takes place directly in the semantic space. To examine the effectiveness of our semantic embedding, we come up with a baseline model named without semantic embedding by removing the semantic model from our framework. Thus, the original semantic representations are used to replace the semantic embedding representations, \( E' \), required by score layer of the visual model in our framework, which is amount to mapping the visual space directly onto the original semantic space. As this baseline model has only the visual model, the learning becomes simpler; i.e., solving the optimal problem formulated in Eq. (6) based on the original semantic representations. Thus, the The Adam (Kingma and Ba 2014) is used for parameter estimation.

It is worth clarifying that this baseline model is similar to Fast0Tag (Zhang et al. 2016b) apart from an LSTM-based visual embedding model used in our framework while a feed-forward neural network without recurrent connections is employed by Fast0Tag for visual embedding.

Randomized label representation (RLR): One of the most important issues in ZSL is exploring/exploiting the side information conveyed in the semantic domain. As our framework works for multi-label zero-shot recognition, we would investigate whether the semantic relatedness information encoded in the semantic embedding, inherited from the original semantic representations, is effectively used in knowledge transfer. To this end, we design another baseline model named randomized label representation by replacing the word vector of a label with a vector of the same dimensionality that is generated randomly and normalized with the \( l_2 \) norm to ensure that it has the same range as that of the word vector. Apparently, the semantic relatedness information no longer exists in such randomized label representations. For parameter estimation, Algorithm 1 is used directly via replacing the semantic representations of labels with the randomized label representations in training data.

4.6.2 State-of-the-Art Methods

Although, to the best of our knowledge, there exists no work in multi-label zero-shot human action recognition, we notice that there are a few multi-label ZSL algorithms. In our comparative study, we adopt and extend those multi-label ZSL algorithms for human action recognition for a thorough evaluation of our proposed framework. Below, we briefly describe those multi-label ZSL algorithms used in our experiments.

Direct Semantic Prediction (DSP): DSP is a well-known baseline model used in previous works for multi-label ZSL, e.g., (Sandouk and Chen 2016b). DSP is derived from direct attribute prediction originally proposed for single-label ZSL (Lampert et al. 2014). The idea behind DSP is learning a mapping function \( \phi : X \rightarrow S \) from visual to semantic space directly for ZSL. By using the composition property of word vectors, given a multi-labelled video clip, we use the mean word vector achieved by averaging those word vectors of the labels associated with this video clip to be its semantic representation. Thus, the multi-label ZSL problem is boiled down to single-label ZSL. In our experiments, we employ support vector regressor models to learn the mapping function \( \phi (\cdot) \). Given a test instance \( \hat{x} \), the learned \( \phi (\cdot) \) is used to predict its compositional semantic representation \( \hat{s} = \phi (\hat{x}) \), then the prediction scores regarding different labels are estimated by measuring distances between the predictions and the word vectors of all the labels in a label collection \( C \): \( \text{Score}(\hat{s}, c) = \langle \hat{s}, s_c \rangle, \forall c \in C \), which leads to a label-based
Convex combination of Semantic Embedding (ConSE): ConSE is a ZSL algorithm proposed by Norouzi et al. (2014), which can be naturally applied to multi-label ZSL. As same as formulated in DSP, ConSE also learns a mapping to predict a compositional semantic representation from the visual representation of a given video clip. Instead of learning a direct mapping function as DSP does, however, ConSE learns the conditional probabilities, \( P(c|x) \) for \( \forall c \in C^T \), regarding all the known actions with training data. For recognition, the compositional or collective semantic representation of a test instance \( \hat{x} \) is estimated by a convex combination of the semantic representations of top-5 known actions of the highest conditional probabilities. The combination weights are the \( l_2 \) normalized conditional probabilities of those top-5 known actions: \( \hat{c} = \sum_{c \in C^T} P(c|x) \hat{x} \). Thus, the prediction scores regarding all the labels in an action label collection \( C \) are \( \text{Score}(\hat{c}, \hat{x}) = \langle \hat{x}, \hat{x}, \hat{x} \rangle \), \( \forall c \in C \), which leads to a label-based ranking list, \( L(\hat{x}) \).

COSTA: COSTA is a method proposed by Mensink et al. (2014) especially for multi-label zero-shot classification. In this method, multi-label classification is converted into a number of binary classification problems via a one-vs-rest setting. \( |C^T| \) linear binary SVMs are trained based on the examples regarding \( |C^T| \) known actions. Then the parameters of the SVM for an unseen label \( c \in C^U \) is estimated by a weighted combination of the parameters of \( |C^T| \) trained SVMs corresponding to known actions: \( w_c = \sum_{k=1}^{C^T} \alpha_k \beta_{ck} w_k \). Here, \( w_k \) is the parameters of the SVM regarding the \( k \)-th label in \( C^T \) and \( \alpha_k \) is a combination coefficient regarding the importance of this SVM achieved via learning. \( \beta_{ck} = \exp(-d_{ck})/\sum_{j=1}^{C^T} \exp(-d_{ck}) \), which is a factor indicating the relatedness between an unseen label, \( c \in C^U \), and a known label, \( k \in C^T \), and \( d_{ck} \) is the semantic distance between labels \( c \) and \( k \) measured via their word vectors. Thus, the SVM with the parameters \( w_c \) can be used to predict the unseen label \( c \) for a given test instance. Note that our experimental results not reported in this paper due to the limited space suggest that learning \( \alpha_k \) is not only time consuming but also yields the poorer performance than that where all \( |C^T| \) SVMs are treated equally; i.e., \( \alpha_k = 1 \) for \( k = 1, \ldots, |C^T| \). Later on, we only report the best performance under this setting.

Fast0Tag: Fast0Tag is one of the latest state-of-the-art methods proposed for multi-label image tagging and multi-label ZSL. (Zhang et al. 2016b). The main idea behind Fast0Tag is learning a mapping function \( \phi : X \rightarrow S \) from visual to semantic space for multi-label zero-shot tagging and recognition. Unlike DSP, a ranking-based loss function, RankNet, is used to train a deep network to carry out \( \phi(\cdot) \) so that for an video clip, its relevant labels should be ranked ahead of those irrelevant ones. For recognition, the mapping function yields the predicted semantic representation, \( \phi(\hat{x}) \), for a test instance, \( \hat{x} \). Then, we can achieve the relatedness scores to all the labels in an action label collection and the label-based ranking list as same as done in DSP and ConSE. In our experiments, we strictly follow the same settings suggested by Zhang et al. (2016b).

Fast0Tag+: Our work presented in this paper suggests that the use of learned semantic embedding leads to better performance than the use of the original semantic representations directly. To further investigate this idea, we make an extension of Fast0Tag by incorporating our semantic model into the Fast0Tag model and name our extension Fast0Tag+. As a result, Fast0Tag+ has an architecture resembling ours (c.f. the left box of Fig.1), where the visual model is carried out by the original Fast0Tag architecture while the semantic model is the same as ours presented in Section 3. The original ranking-base loss functions in Fast0Tag are used and our alternate learning algorithm described in Algorithm 1 is used for parameter estimation. For recognition, the same procedure presented in Section 3.4 is used for a given test instance. Here, we argue that this extension would provide further evidence in examining the effectiveness of semantic embedding learning.

In our comparative study, the optimal hyper-parameters involved in baseline and state-of-the-art learning models are sought during their learning with the same cross-validation procedure as described in Section 4.3. Moreover, five state-of-the-art methods described above and ours are extendible to multi-label recognition straightforwardly; i.e., all the actions are known in advance and their training examples are available during learning. Thus, we also report the multi-label recognition performance, which not only extends our comparative study in a wider scope but also provides a benchmark to see how much the performance of each method is degraded in a zero-shot circumstance.

5 Experimental Results

In this section, we report the detailed experimental results in different settings and exemplify some typical test instances via visual inspection.

5.1 Results on Optimal Hyper-parameters

As described in Section 4.3, we employ a grid-based search procedure via cross-validation to find out the optimal hyper-parameters in terms of the I-MAP performance (c.f. Section 4.5). In our experiments, we seek an optimal value from a set of candidate hyper-parameters involved in different learning models as follows:

Network architecture: The optimal architecture of neural networks in a model used in our experiments is investigated by tuning different number of neurons in each hid-
### Table 3: Optimal hyper-parameter values of different learning models found by random search.

**Notation:** IFS – Instance-First Split; LFS – Label-First Split; V – Visual model; S – Semantic model; lr – learning rate; e – soft-margin and percentage of support vectors in SVM/SVR.

$N_1 \rightarrow N_2 \rightarrow d_e$ indicates a neural network architecture where $N_1$ (dropout rate) is the number of neurons in the first hidden layer and dropout rate used in learning; $N_2$ is the number of hidden neurons in the second hidden layer; and $d_e$ is the number of neurons in the latent embedding layer.

| Dataset | Data Split | Model | 1 | 2 | 3 |
|---------|------------|-------|---|---|---|
| NRC | IFS | V: $lr = 1e^{-4}$;4096(0.5) → 1024 → 500 | S: $lr = 1e^{-6}$;500 → 500 | S: $lr = 1e^{-4}$;2048(0.5) → 1024 → 500 | S: $lr = 1e^{-4}$;1024(0.5) → 1024 → 500 |
| WSE | IFS | V: $lr = 1e^{-4}$;4096(0.5) → 1024 | S: $lr = 1e^{-6}$;500 → 500 | S: $lr = 1e^{-6}$;600 → 500 | S: $lr = 1e^{-6}$;700 → 500 |
| RLR | IFS | V: $lr = 1e^{-4}$;4096(0.5) → 1024 → 500 | S: $lr = 1e^{-6}$;500 → 500 | S: $lr = 1e^{-4}$;2048(0.5) → 1024 → 500 | S: $lr = 1e^{-4}$;1024(0.5) → 1024 → 500 |

| LFS | Breakfast | IFS | V: $lr = 1e^{-4}$;4096(0.5) → 1024 → 500 | S: $lr = 1e^{-6}$;500 → 500 | S: $lr = 1e^{-6}$;600 → 500 |
| COSTA | V: $lr = 1e^{-4}$;4096(0.5) → 1024 | S: $lr = 1e^{-6}$;500 → 500 | S: $lr = 1e^{-6}$;600 → 500 | S: $lr = 1e^{-6}$;700 → 500 |
| ConSE | V: $lr = 1e^{-4}$;4096(0.5) → 1024 | S: $lr = 1e^{-6}$;500 → 500 | S: $lr = 1e^{-6}$;600 → 500 | S: $lr = 1e^{-6}$;700 → 500 |
| COSTA | V: $lr = 1e^{-4}$;4096(0.5) → 1024 | S: $lr = 1e^{-6}$;500 → 500 | S: $lr = 1e^{-6}$;600 → 500 | S: $lr = 1e^{-6}$;700 → 500 |
| ConSE+ | V: $lr = 1e^{-4}$;4096(0.5) → 1024 | S: $lr = 1e^{-6}$;500 → 500 | S: $lr = 1e^{-6}$;600 → 500 | S: $lr = 1e^{-6}$;700 → 500 |
| COSTA | V: $lr = 1e^{-4}$;4096(0.5) → 1024 | S: $lr = 1e^{-6}$;500 → 500 | S: $lr = 1e^{-6}$;600 → 500 | S: $lr = 1e^{-6}$;700 → 500 |
| ConSE+ | V: $lr = 1e^{-4}$;4096(0.5) → 1024 | S: $lr = 1e^{-6}$;500 → 500 | S: $lr = 1e^{-6}$;600 → 500 | S: $lr = 1e^{-6}$;700 → 500 |
| COSTA | V: $lr = 1e^{-4}$;4096(0.5) → 1024 | S: $lr = 1e^{-6}$;500 → 500 | S: $lr = 1e^{-6}$;600 → 500 | S: $lr = 1e^{-6}$;700 → 500 |

| LFS | Charades | IFS | V: $lr = 1e^{-4}$;4096(0.5) → 1024 → 500 | S: $lr = 1e^{-6}$;500 → 500 | S: $lr = 1e^{-6}$;600 → 500 |
| COSTA | V: $lr = 1e^{-4}$;4096(0.5) → 1024 | S: $lr = 1e^{-6}$;500 → 500 | S: $lr = 1e^{-6}$;600 → 500 | S: $lr = 1e^{-6}$;700 → 500 |
| ConSE | V: $lr = 1e^{-4}$;4096(0.5) → 1024 | S: $lr = 1e^{-6}$;500 → 500 | S: $lr = 1e^{-6}$;600 → 500 | S: $lr = 1e^{-6}$;700 → 500 |
| COSTA | V: $lr = 1e^{-4}$;4096(0.5) → 1024 | S: $lr = 1e^{-6}$;500 → 500 | S: $lr = 1e^{-6}$;600 → 500 | S: $lr = 1e^{-6}$;700 → 500 |
| ConSE+ | V: $lr = 1e^{-4}$;4096(0.5) → 1024 | S: $lr = 1e^{-6}$;500 → 500 | S: $lr = 1e^{-6}$;600 → 500 | S: $lr = 1e^{-6}$;700 → 500 |
| COSTA | V: $lr = 1e^{-4}$;4096(0.5) → 1024 | S: $lr = 1e^{-6}$;500 → 500 | S: $lr = 1e^{-6}$;600 → 500 | S: $lr = 1e^{-6}$;700 → 500 |

In our proposed model, there are totally four structural hyper-parameters. The number of hidden units in the LSTM layer is selected from the candidate set, $N_1 = 256, 512, 1024$. In the visual model, the number of neurons in the hidden layer above the LSTM layer is investigated with $N_2 = 1024, 2048$. In the semantic model, the number of neurons in the first hidden layer in the semantic model is chosen from $N_1 = 300, 500, 700$. As a critical hyper-parameter in our algorithm, the dimension of latent embedding space $d_e$, the number of neurons in the visual/semantic embedding layers, is investigated by setting the candidate values, $d_e = 200, 500, 800$. For the non-recurrent baseline model, the number of neurons in the first hidden layer replacing the LSTM layer is chosen from $N_1 = 1024, 2048, 4096$. For FastSE and FastSE+, the number of neurons in the first and the second hidden layers are selected from $N_1 = 2048, 4096, 8092$ and $N_2 = 1024, 2048$, respectively.
Learning rate: For all the neural networks in the proposed model, the baseline and the state-of-the-art models, candidate learning rates are to be \{1e-2, 1e-4\} for the visual model and \{1e-4, 1e-6\} for the semantic model, respectively.

Number of epochs: Learning is stopped when the I-MAP performance on a validation set is no longer improved within the last 10 epochs. The optimal model chosen is the one that yields the highest value of I-MAP on the validation set.

Dropout rate: The dropout rate used in the first layer of a neural model during learning is selected from (0.0, 0.5).

SVM hyper-parameters: In our comparative study, ConSE (Norouzi et al. 2014) and COSTA (Mensink et al. 2014) employ a linear SVM for classification and DSP (Lampert et al. 2014) uses a linear SVR for regression. In our experiments, an optimal soft-margin value C is sought from C = 0.01, 1, 100. For SVR, the percentage of support vectors is always set to \(\varepsilon = 0.1\) as suggested in literature.

As a result, the resultant optimal hyper-parameter values in different experimental settings are summarized in Table 3.

### 5.2 Results on Comparison to Baseline Models

Table 4 summarizes all the results yielded by four baseline models described in Section 4.6.1 and our full model described in Section 3.3. The experimental results are reported based on two different split data settings described in Section 4.1.2, instance-first split (IFS) and label-first split (LFS), under three different evaluation scenarios described in Section 4.4; i.e., generalized ZSL, known-action only and unseen-action only scenarios. For reliability, we report the mean and standard error of the mean (SEM) of results (\(k = 5\) used in evaluation metrics) over three randomly generated known/unknown label splits for each evaluation scenario.

For the IFS setting, it is observed from Table 4 that all the baseline models and ours perform significantly better than the RGS, a random guess model, on both datasets regardless of evaluation scenarios apart from the RLR model under the unseen-action only scenario. Due to a lack of knowledge transfer in a random label representation, the zero-shot performance of the RLR is expected. Overall, our full model outperforms all the baseline models on both datasets in the generalized ZSL scenario regardless of evaluation metrics and in the unseen-action only scenario in terms of precision, recall and \(F_1\) although the WSE performs better on Breakfast in this scenario in terms of L-MAP and I-MAP. In the known-action only scenario, the WSE and ours yield the best performance on Breakfast in general. This result implies that the necessity of semantic embedding learning depends on the complexity of semantics underlying the actions involved in a specific dataset. Although there are 49 human actions involved in Breakfast, all the video clips simply record the cooking processes of 10 dishes (Kuehne et al. 2014). Thus, multiple action labels regarding video clips on
Breakfast are already well characterized by relevant word vectors, the raw semantic representation used in our experiments. Hence, the semantic embedding learning does not lead to any gain due to the simplicity of semantics underlying those cooking actions. In contrast, the performance of the WSE and our full model on Charades lends evidence to support the semantic embedding learning in the presence of complex semantics underlying actions given the fact that the semantic embedding learning leads to a gain over the WSE on this data set in the known-action only scenario. We also observe that the RLR leads to the best performance on Charades in the known-action only scenario where the performance of our full model is slightly worse than that of the RLR. This result suggests that a label representation is not critically important for known actions in multi-label learning. Nevertheless, the performance in the unseen-action only and the generalized ZSL scenarios clearly indicate the importance of a action label semantic representation for knowledge transfer required by ZSL. It is also evident from Table 4 that our full model always outperforms the NRC where there are no recurrent connections. Thus, the comparison to the baseline models clearly suggest that the performance gain is brought by the use of an LSTM layer in the visual model and the semantic embedding learning fulfilled in the semantic model.

For the LFS setting, results shown in Table 4 suggest that all the baseline models perform significantly better than a random guess. Overall, our full model outperforms those baseline models on Charades in the generalized ZSL and the unseen-action only scenarios. However, our full model slightly under-performs the WSE in the generalized ZSL and the known-action only scenarios for the same reason as stated earlier for the results under the IFS setting. Also, the RLR the NRC generally performs better on Charades in the known-action only scenario and on Breakfast in the unseen-action only scenario, respectively. These results reveal that the recurrent layer used in the visual model and the semantic embedding learning in the semantic model are not sufficient in generalizing for capturing temporal coherence underlying an episode conveying an unseen action and exploring the intrinsic semantic relatedness between known and unseen actions due to insufficient training data in the LFS setting as described below.

In general, results in Table 4 reveal that all the models in question behave differently on two different data split settings. The performance of a model on the LFS setting is generally worse than that on the IFS setting. On Breakfast, there are the same number of unseen labels but the recognition performance on the LFS is much lower than that on the IFS. On Charades, the performance in the LFS is also inferior to that in the IFS despite the fact that the number of unseen actions in the LFS is a half of that in the IFS. This observation suggests that the LFS setting, which is closer to a real application, is more challenging than the IFS setting, which has been widely used in existing methods in literature. With a closer look at our experimental protocol, we notice that there are more training examples in the IFS than those in the LFS (c.f., Table 4.1.2). More critically, training examples contain the instances associated with unseen labels in the IFS though the relevant unseen labels to such an instance are not used in learning. Note that those known and unseen labels are linked by not only their semantic representations but also the label co-occurrences in training examples. For example, we know that actions “pour_cereal” and “stir_cereal” are closely related in the semantic space and have high probability of co-occurrences. Suppose those two actions fall into known and unseen action categories. In the IFS, any test instance with confidently high score for “pour_cereal” could lead to a high score for “stir_cereal”. Thanks to the label co-occurrences, “stir_cereal” could be easily recognized despite being an unseen action. In contrast, it is unlikely that in the LFS the label-occurrence property is exploited since a video clip containing the “pour_cereal” action would be excluded from the training data if it happens to contain the unseen action “stir_cereal”.

In summary, the comparison to the elaborated baseline models facilitates the understanding of different components employed in our proposed multi-label zero-shot human action recognition framework. By comparison to four baseline models, our full model generally leads to favorable results on two datasets measured with different evaluation metrics in all three evaluation scenarios, although the experimental results also reveal the limitation of components used in our full model to be studied in our future research.

5.3 Results on Comparison to State-of-the-Art Methods

Table 5 summarizes the experimental results of the comparative study described in Section 4.6.2. Multi-label ZSL performance of five different methods (including Fast0Tag+, an extension of Fast0Tag made by ourselves) with the reference to a random guess is reported to be compared with our proposed framework. Again, all the experiments are conducted with two different data split settings and evaluated under three evaluation scenarios, as described in Section 5.2. For reliability, we report the mean and the SEM of results ($k = 5$ used in evaluation metrics) over three randomly generated known/unseen label splits for each evaluation scenario.

For the IFS setting, it is seen from Table 5 that all the models perform better than random guess in most of evaluation scenarios. However, DSP and ConSE result in the poorer performance than random guess in the unseen-action only scenario on Breakfast in terms of some specific metric, e.g., I-MAP. Overall, DSP and ConSE under-perform other methods considerably in terms of all five evaluation metrics.
under all three evaluation scenarios. Such results demonstrate that simply combining semantic representations of co-occurred multiple labels into one collective representation leads to catastrophic loss of semantic information, which is mainly responsible for the poor performance of DSP and ConSE in multi-label recognition. Fast0Tag generally outperforms COSTA on two datasets in terms of most of evaluation metrics. While COSTA learns a classifier for each label separately without considering a relationship among co-occurred labels, taking into account such a relationship in Fast0Tag accounts for its better performance. By incorporating the semantic embedding learning into Fast0Tag, Fast0Tag+, our extension of Fast0Tag, constantly improves the performance of its original version in all the circumstances on two datasets in general. Once again, this result lends us evidence to justify the necessity of semantic embedding learning used in our framework for zero-shot multi-label ZSL. In contrast, our model generally outperforms all five models significantly in terms of five evaluation metrics under different evaluation scenarios on two datasets, as highlighted with bold-font in Table 5. By comparing our model to Fast0Tag+, we see three main differences between them as follows: visual representations, network architectures for the visual model and loss functions. Regarding visual representations, our model uses the segment-based visual features for an instance while Fast0Tag+ employs an instance-level holistic visual representation. For network architectures, we employ an LSTM layer with recurrent connections to capture temporal coherence among segments of a video clip while Fast0Tag+ simply uses a feed-forward network. As described in Section 3.3.2, we propose an alternative loss function to that in Fast0Tag+. Thus, those differences together leverage our performance gain over Fast0Tag+, which yet again lends us evidence to support our proposed framework.

For the LFS setting, experimental results suggest that most of the models in question have similar behavior to that in the IFS setting, as shown in Table 5. Once again, DSP and ConSE generally perform worse than other models and even under-perform random guess on Charades in

| Data Split | Evaluation Scenario | Model | ROC | L-MAP | T-MAP | Recall | Charades | $ \gamma$ |
|------------|---------------------|-------|-----|-------|-------|--------|----------|--------|
| GZSL       | DSPLAMer et al. 2014| ConSe/Norouzi et al. 2014 | COSTA/Mensi et al. 2014 | Fast0Tag+ (Zhang et al. 2016b) | Ours |
| Breakfast  | 14                  | 30    | 5   | 33    | 8     |        |          |        |
| IFS        | KnownA              | DSPLAMer et al. 2014 | ConSe/Norouzi et al. 2014 | COSTA/Mensi et al. 2014 | Fast0Tag+ (Zhang et al. 2016b) | Ours |
| UnseenA    | DSPLAMer et al. 2014 | ConSe/Norouzi et al. 2014 | COSTA/Mensi et al. 2014 | Fast0Tag+ (Zhang et al. 2016b) | Ours |
| GZSL       | DSPLAMer et al. 2014 | ConSe/Norouzi et al. 2014 | COSTA/Mensi et al. 2014 | Fast0Tag+ (Zhang et al. 2016b) | Ours |
| LFS        | KnownA              | DSPLAMer et al. 2014 | ConSe/Norouzi et al. 2014 | COSTA/Mensi et al. 2014 | Fast0Tag+ (Zhang et al. 2016b) | Ours |
| UnseenA    | DSPLAMer et al. 2014 | ConSe/Norouzi et al. 2014 | COSTA/Mensi et al. 2014 | Fast0Tag+ (Zhang et al. 2016b) | Ours |
the unseen-action only scenario. While COSTA yields better performance than DSP and ConSE overall, it generally under-performs Fast0Tag, Fast0Tag+ and ours in all three evaluation scenarios. Nevertheless, overall, our model does not perform better than Fast0Tag+ in the unseen-action only scenario although it outperforms Fast0Tag in the generalized ZSL and the known-action scenarios. As described in Section 5.2, the LFS setting is more challenging than the IFS setting and some salient visual features on test instances corresponding to unseen actions could completely miss in training examples. In this case, the use of a segment-level based visual representation and an LSTM layer in the visual model may not be able to generalize well due to a lack of training examples. Although such a result does not sufficiently favor the use of a segment-level based visual representation and an LSTM layer in the visual model in the presence of limited training data, it is no doubt that introducing a semantic model to Fast0Tag leverages the performance gain. Once again, experimental results here along with those compared to the baseline models under our LFS setting reveals a training data sparsity issue that has to be addressed in any future multi-label zero-shot human action recognition study.

Furthermore, Table 6 shows the experimental results in conventional multi-label human action recognition, i.e., all the actions are known in learning. In this circumstance, only the IFS setting is applicable. Hence, we use the same IFS setting as described in Section 4.1.2 but, unlike what has been done for simulating a zero-shot scenario, do not reserve any actions. Also we use the same procedure as done for zero-shot learning to search for optimal hyper-parameters for five models and ours and repeat the experiments on the same data split as the IFS setting for three trials with different parameter initialization. As a result, we report the mean and the standard deviation (std) of three-trial results yielded by different methods. It is evident from Table 6 that our model performs the best in conventional multi-label recognition on both datasets. To see the degraded performance in a zero-shot scenario, we can compare the performance in the generalized ZSL evaluation scenario under the IFS setting, as shown in Table 5, to that reported in Table 6. By such a comparison, it is seen that the zero-shot performance of our model drops with a narrow margin (approximately less than 10% overall in terms of five different evaluation metrics). Given the fact that 10 out of 49 and 40 out of 157 human actions are reserved as unseen labels on Breakfast and Charades, respectively, this comparison on experimental results suggests that our proposed framework yields the promising performance for multi-label zero-shot human action recognition, which is close to the performance in multi-label human action recognition. Experimental results shown in Table 6 also suggest that other state-of-the-art methods behave similarly to ours in general. However, we also observe an unusual phenomenon from their performance; i.e., by a comparison to the generalized ZSL performance reported in Table 5, DSP always yields slightly better performance in multi-label recognition than that in the generalized ZSL scenario regardless of evaluation metrics on Breakfast and so do Fast0Tag and Fast0Tag+ in terms of L-MAP. By a closer look at the dataset and results in two experiments as well as our analysis, we find that at least two factors account for this unusual phenomenon: a) co-occurred labels associated with most of video clips on Breakfast are redundant in light of semantics, and b) the single collective semantic representation of co-occurred multiple labels used in DSP is insensitive to missing of few co-occurred labels due to the label information redundancy and the information loss resulting from the averaging operation in forming the single representation. Thus, we reckon that this phenomenon is rather specific to the nature of this dataset and the ZSL setting where there are only a small number of unseen labels.

In summary, our comparative study suggests that our proposed framework yields the favorable results and outperforms the existing state-of-the-art methods in general although it does not always perform better than Fast0Tag+, an extension of Fast0Tag made by ourselves. Also our experimental results demonstrate challenges in multi-label ZSL via our novel LFS setting especially when training data are less correlated to test instances associated with unseen classes in both semantic and visual domains.

5.4 Visual Inspection

In general, visual inspection provides a manner that helps us understand the behavior of a method intuitively. To gain an intuitive insight into the multi-label zero-shot human ac-
**Fig. 4** A test video clip in the IFS setting and the top-5 labels predicted by different methods. Its ground-truth labels are *take_bowl, crack_egg, put_egg2plate, take_plate, stir_egg, pour_egg2pan, stir_fry_egg, add_salt_pepper, butter_pan*.

**Fig. 5** A test video clip in the IFS setting and the top-5 labels predicted by different methods. Its ground-truth labels are *cut_orange, squeeze_orange, pour_juice, take_glass*.

**Fig. 6** A test video clip in the IFS setting and the top-5 labels predicted by different methods. Its ground-truth labels are *cut_orange, squeeze_orange, pour_juice*.

For the IFS setting, Figures 4-6 illustrate three typical results yielded by different methods. Figure 4 exemplifies the success of our model, where all the top-5 labels predicted by our model are the ground-truth actions including one unseen action and no other methods can match the performance of our model. This exemplified test instance suggests that the use of an LSTM layer in our visual model facilitates the recognition of distinctive actions in a video clip. Figure 5 reveals further insights into the performance of different methods and highlights the robustness of our model in handling unseen actions.

In our future work, we aim to further improve the accuracy of action recognition by exploring more effective feature extraction techniques and leveraging additional data sources. This will enable our model to better capture the temporal dynamics of human actions and achieve higher performance across a variety of video datasets.
reveals a test instance on which all other methods outperform ours. By comparing those labels predicted by our model to the ground truth, we can see that some predicted labels are semantically correlated to the ground truth, e.g., cut_fruit vs. cut_orange and put_fruit2bowl vs. pour_juice. This test instance demonstrates the limitation of our model in capturing the fine features in visual domain to be associated to the accurate semantic description in semantic domain when there exist many similar actions in a targeted application. Figure 6 shows a test instance where all the methods fail to have any ground-truth labels in their top-5 predicted labels. Our visual inspection on this test instance reveals that non-trivial objects pertaining to different actions are concentrated in a small region located in top-right of frames in this video clip. Thus, it is extremely difficult to capture the useful information in visual domain, which poses a challenge to existing human action recognition techniques. Three test instances illustrated in Figures 4-6 also provide some insight as to how other methods work. For instance, ConSE is more likely to yield the labels regarding frequently used words in a human action domain. It is evident that ConSE predicts 4 out of the top-5 labels pertaining to different actions taken on “egg” for the instance shown in Figure 4 and all five “pour” actions commonly taken in kitchen for the instance shown in Figure 6. This limitation is due to the fact that ConSE uses a single collective semantic representation resulting from averaging the semantic representations of multiple co-occurred labels, which favors those frequently used word vectors but diminishes the opportunity of finding out infrequently used word vectors in prediction.

Experimental results reported in Tables 4 and 5 suggest that all the models including ours generally perform worse under the LFS setting than under the IFS setting. On the one hand, the LFS setting results in a training data sparsity issue in contrast to the IFS setting. To see this issue, let us take the first split on Breakfast as an example. In this split shown in Table 2, there are 1,196 and 1,019 training examples in the IFS and the LFS setting, respectively. However, the number of training examples pertaining to specific known actions is significantly different in two split settings due to different data split protocols described in Section 4.1.2. For example, there are 330, 217, 254, 109 and 156 training examples with specific target labels, e.g., crack_egg, put_egg2plate, take_plate, stir_egg, and add_salt_pepper. To see this issue, let us take the first split on Breakfast as an example. In this split shown in Table 2, there are 1,196 and 1,019 training examples in the IFS and the LFS setting, respectively. However, the number of training examples pertaining to specific known actions is significantly different in two split settings due to different data split protocols described in Section 4.1.2. For example, there are 330, 217, 254, 109 and 156 training examples with specific target labels, e.g., crack_egg, put_egg2plate, take_plate, stir_egg, and add_salt_pepper.
in two data split settings, as shown in Figure 7. It is evident that 4 out of the top-5 action labels predicted by our model are the ground truth and all other models can predict some of ground-truth actions correctly under the IFS setting. In contrast, however, none of the models correctly predicts more than one ground-truth action for this exactly same test instance under the LFS setting. The visual inspection on this test instance clearly demonstrates the distinction between two data split settings, where visual features associated with unseen actions are available in the IFS setting but unavailable in the LFS setting, and the training data sparsity issue in the LFS setting, which poses a big challenge to not only ours but also all the existing multi-label ZSL methods.

6 Concluding Remarks

In this paper, we have formulated human action recognition as a multi-label zero-shot learning problem and provide an effective solution by proposing a novel framework via joint latent embedding learning. To carry out our framework, we employ a neural network of the heterogeneous architecture for visual embedding, where an LSTM layer is used to facilitate capturing temporal coherence information underlying different actions from weakly annotated video data. Also, we advocate the use of semantic embedding learning to facilitate bridging the semantic gap and effective knowledge transfer, which is implemented by a feed-forward neural network. All the above contributions have been thoroughly verified via our comparative study with various well-motivated settings. Experimental results on two benchmark multi-label human action datasets suggest that our proposed framework generally outperforms not only the baseline systems but also several state-of-the-art multi-label ZSL approaches in all the different test scenarios.

Although we have demonstrated favorable results on two benchmark datasets in comparison to state-of-the-art approaches, our observations on the performance of all the approaches used in our comparative study including ours suggest that the existing multi-label ZSL techniques are not ready for a real application; in particular, the performance becomes even worse under the label-first split setting corresponding to a real scenario that an action recognition system is deployed. Nevertheless, our experiment results including visual inspection provide insightful information for improving our proposed framework. In our ongoing work, we would address issues arising from our experiments and observations with proper techniques. To address the training data sparsity issue revealed in our experiments, we would develop unsupervised learning algorithms to discover salient yet intrinsic visual features from unlabeled video clips and further incorporate proper temporal constraints into our loss functions to better capture temporal coherence. Moreover, we would introduce attention mechanisms to our model for improving implicit salient feature extraction of different actions involved in a video clip during the visual embedding learning. Also, we would employ alternative semantic representations developed by ourselves (Wang and Chen 2017a), which encode the semantic relatedness between action labels more accurately, in the semantic embedding learning to facilitate knowledge transfer.

While our framework is proposed especially for multi-label zero-shot human action recognition, we would highlight that it is directly applicable to multi-label human action recognition without modification as demonstrated in our experiments. Also, our framework is easy to adapt for tackling various multi-label ZSL problems in different domains. For example, we can apply our framework to miscellaneous multi-label zero-shot classification tasks on temporal or sequential data, e.g., acoustic event classification, straightforward as well as multi-label zero-shot learning tasks on static data, e.g., object recognition, by replacing a neural network of the heterogeneous architecture with a neural network of only feed-forward connections in the visual model. Thus, we are going to explore such extensions and applications in our future work.

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