

Unsupervised Semantic Action Discovery from Video Collections

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Abstract Human communication takes many forms, including speech, text and instructional videos. It typically has an underlying structure, with a starting point, ending, and certain objective steps between them. In this paper, we consider instructional videos where there are tens of millions of them on the Internet.

We propose a method for parsing a video into such semantic steps in an unsupervised way. Our method is capable of providing a semantic “storyline” of the video composed of its objective steps. We accomplish this using both visual and language cues in a joint generative model. Our method can also provide a textual description for each of the identified semantic steps and video segments. We evaluate our method on a large number of complex YouTube videos and show that our method discovers semantically correct instructions for a variety of tasks.¹

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1 Introduction

In the last decade, we have seen a significant democratization in the way we access and generate information. One of the major shifts has been in moving from expert-curated information sources into crowd-generated large scale knowledge bases such as Wikipedia(Wikipedia 2004). For example, the way we generate and access *cooking recipes* has been transformed substantially. Google Trends(Google 2016) indicates that in the year of 2005 number of Google searches for *cookbooks* were 1.56 times larger than the number of searches for *cooking videos*. In the year 2016, the number of searches for *cooking videos* is 8.6 times larger than that of *cookbooks*. This behavior is mostly due to the large volume of cooking videos available on the internet. In an era where an average user gets 2 million videos for the query *How to make a pancake?*, we need computer vision algorithms that can understand such information and represent it to the users in a compact form. Such algorithms are not only useful for humans to digest millions of videos but also useful for robots to learn concepts from online video collections in order to perform tasks.

Considering the intractability of supervised information in large-scale video collections, we believe the key to the unsupervised grounding is utilizing the structural assumptions. Human communication takes many forms, including language and videos. For instance, explaining “how-to” perform a certain task can be communicated via language (e.g., Do-It-Yourself books) as well as visual (e.g., instructional YouTube videos) information. Regardless of the form, such human-generated communication is generally structured and has a clear beginning, end, and a set of steps in between. Finding this hidden and objective steps of human communica-

tion is a critical step to understand large video collections.

Language and vision provide different, but correlating and complementary information. Challenge lies in that both video frames and language (from subtitles generated via Automatic Speech Recognition) are only a noisy, partial observation of the actions being performed. However, the complementary nature of language and vision gives the opportunity to understand the activities only from these partial observations. In this paper, we present a unified model, considering both of the modalities, in order to parse human activities into activity steps with no form of supervision other than requiring videos to be the same category (e.g., all cooking eggs, changing tires, etc.).

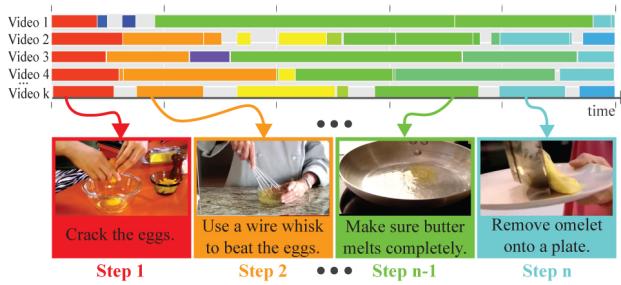


Fig. 1: Given a large video collection (frames and subtitles) of an instructional category (e.g., How to cook an ommelette?), we discover activity steps (e.g., crack the eggs). We also parse the videos based on the discovered steps.

The key idea in our approach is the observation that the large collection of videos, pertaining to the same activity class, typically include only a few objective activity steps, and the variability is the result of exponentially many ways of generating videos from activity steps through subset selection and time ordering. We study this construction based on the large-scale information available in YouTube in the form of instructional videos (e.g., “Making pancake”, “How to tie a bow tie”). Instructional videos have many desirable properties like the volume of the information and a well defined notion of activity step. However, the proposed parsing method is applicable to any type of videos as long as they are composed of a set of steps.

The output of our method can be seen as the semantic “storyline” of a rather long and complex video collection (see Fig. 1). This storyline provides what particular steps are taking place in the video collection, when they are occurring, and what their meaning is (*what-when-how*). This method also puts videos per-

forming the same overall task in common ground and capture their high-level relations.

In the proposed approach, given a collection of videos, we first generate a set of language and visual atoms. These atoms are the result of relating object proposals from each frame as well as detecting the frequent words from subtitles. We then employ a generative *beta process mixture model*, which identifies the activity steps shared among the videos of the same category based on a representation using learned atoms. Although we do not explicitly enforce these steps to be semantically meaningful, our results highly correlate with the semantic steps. In our method, we do neither use any spatial or temporal label on actions/steps nor any labels on object categories. We later learn a Markov language model to provide a textual description of the activity steps based on the language atoms it frequently uses.

We evaluate our approach on various settings. First of all, we collected a large-scale dataset of instructional videos from YouTube following the most frequently performed *how to* queries. Then, we evaluate temporal parsing quality per video and also a semantic clustering per category (how-to query). Second of all, we extensively analyze the contribution of each modality as well as the robustness against the language noise. Robustness against the language noise is a critical one since ASR always expected to have some errors. Moreover, results suggest that both language and vision is critical for semantic parsing. Finally, we discuss and present a novel robotics application. We start with a single query and generate a detailed physical plan to perform the task. We present a compelling simulation results suggesting that our algorithm has a great potential for robotics applications.

2 Related Work

Designing an artificial intelligence agent which can understand human generated videos have been topic of computer vision and robotics researchers for decades. Motivated by the application of surveillance, video summarization was one of the earliest methods which are related to our problem. The surveillance applications further motivated the activity and event recognition methods. With the help of the availability of larger datasets, researchers managed to train machine learning models which can detect certain events. Recently, the datasets have gotten larger and cross-modal enabling algorithms which can link vision with language. In the mean time, the focus of robotics community was on parsing recipes directly for manipulation. We list and discuss related works from each field in the following sections.

2.1 Video Summarization:

Summarizing an input video as a sequence of key frames (static) or video clips (dynamic) is useful for both multimedia search interfaces and retrieval purposes. Early works in the area are summarized in (Truong and Venkatesh 2007) and mostly focus on *choosing keyframes*.

Summarizing videos is particularly important for some specific domains like ego-centric videos and news reports as they are generally long in duration. There are many successful works (Lee et al 2012; Lu and Grauman 2013; Rui et al 2000); however, they mostly rely on characteristics specific to the domain.

Summarization is also applied to the large image collections by recovering the temporal ordering and visual similarity of images (Kim and Xing 2014), and by Gupta et al. (Gupta et al 2009) to videos in a supervised framework using action annotations. These collections are also used for key-frame selection (Khosla et al 2013) and further extended to video clip selection (Kim et al 2014; Potapov et al 2014). Unlike all of these methods which focus on forming a set of key frames/clips for a compact summary (which is not necessarily semantically meaningful), we provide a fresh approach to video summarization by performing it through semantic parsing on vision and language. However, regardless of this dissimilarity, we experimentally compare our method against them.

2.2 Modeling Visual and Language Information:

Learning the relationship between the visual and language data is a crucial problem due to its immense applications. Early methods (Barnard et al 2003) in this area focus on learning a common multi-modal space in order to jointly represent language and vision. They are further extended to learning higher level relations between object segments and words (Socher and Fei-Fei 2010). Similarly, Zitnick et al.(Zitnick et al 2013; Zitnick and Parikh 2013) used abstracted clip-arts to understand spatial relations of objects and their language correspondences. Kong et al. (Kong et al 2014) and Fidler et al. (Fidler et al 2013) both accomplished the task of learning spatial reasoning by only using the image captions. Relations extracted from image-caption pairs, are further used to help semantic parsing (Yu and Siskind 2013) and activity recognition (Motwani and Mooney 2012). Recent works also focus on automatic generation of image captions with underlying ideas ranging from finding similar images and transferring their captions (Ordonez et al 2011) to learning language models conditioned on the image features (Kiros et al 2014; Socher et al 2014; Farhadi et al 2010); their employed

approach to learning language models is typically either based on graphical models (Farhadi et al 2010) or neural networks (Socher et al 2014; Kiros et al 2014; Karpathy and Fei-Fei 2014).

All aforementioned methods are using supervised labels either as strong image-word pairs or weak image-caption pairs, while our method is fully unsupervised.

2.3 Activity/Event Recognition:

The literature of activity recognition is broad. The closest techniques to ours are either supervised or focus on detecting a particular (and often short) action in a weakly/unsupervised manner. Also, a large body of action recognition methods are intended for trimmed video clips or remain limited to detecting very short actions (Kuehne et al 2011; Soomro et al 2012; Niebles et al 2010; Laptev et al 2008; Efros et al 2003; Ryoo and Aggarwal 2009). Even though some recent works attempted action recognition in untrimmed videos (Jiang et al 2014; Oneata et al 2014; Jain et al 2014), they are mostly fully supervised.

Additionally, several methods for localizing instances of actions in rather longer video sequences have been developed (Duchenne et al 2009; Hoai et al 2011; Laptev and Pérez 2007; Bojanowski et al 2014; Pirsavash and Ramanan 2014). Our work is different from those in terms of being multimodal, unsupervised, applicable to a video collection, and not limited to identifying pre-defined actions or the ones with short temporal spans. Also, the previous works on finding action primitives such as (Niebles et al 2010; Yao and Fei-Fei 2010; Jain et al 2013; Lan et al 2014b,a) are primarily limited to discovering atomic sub-actions, and therefore, fail to identify complex and high-level parts of a long video.

Recently, event recounting has attracted much interest and intends to identify the evidential segments for which a video belongs to a certain class (Sun and Nevatia 2014; Das et al 2013; Barbu et al 2012). Event recounting is a relatively new topic and the existing methods mostly employ a supervised approach. Also, their end goal is to identify what parts of a video are highly related to an event, and not parsing the video into semantic steps.

2.4 Recipe Understanding:

Following the interest in community generated recipes in the web, there have been many attempts to automatically process recipes. Recent methods on natural language processing (Malmaud et al 2014; Tenorth et al 2010) focus on semantic parsing of language recipes in

order to extract actions and the objects in the form of predicates. Tenorth et al.(Tenorth et al 2010) further process the predicates in order to form a complete logic plan. The aforementioned approaches focus only on the language modality and they are not applicable to the videos. The recent advances (Beetz et al 2011; Bollini et al 2011) in robotics use the parsed recipe in order to perform cooking tasks. They use supervised object detectors and report a successful autonomous experiment. In addition to the language based approaches, Malmaud et al.(Malmaud et al 2015) consider both language and vision modalities and propose a method to align an input video to a recipe. However, it can not extract the steps automatically and requires a ground truth recipe to align. On the contrary, our method uses both visual and language modalities and extracts the actions while autonomously discovering the steps. There is also an approach which generates multi-modal recipes from expert demonstrations (Grabler et al 2009). However, it is developed only for the domain of "teaching user interfaces" and are not applicable to videos.

In summary, three aspects differentiate this work from the majority of existing techniques: 1) discovering semantic steps from a video category, 2) being unsupervised, 3) adopting a multi-modal joint vision-language model for video parsing.

3 Problem Overview

Our algorithm takes an *how-to* sentence as an input query which we further use to download a large-collection of videos. We then learn a multi-modal dictionary using a novel hierarchical clustering approach. We finally use the learned dictionary in order to discover and localize activity steps. We visualize this process in Figure 2 with a toy example. The output of our algorithm is temporal parsing of each video as well as an id for each semantic activity step. In other words, we not only temporally segment each video, we also relate the occurrence of same activity over multiple videos with each other. We further visualize the output in Figure 1.

Atoms: Given a large video-collection composed of visual information as well as subtitles, our algorithm starts with learning a set of visual and language *atoms* which are further used for representing multimodal information (Section 4). These atoms are designed to be likely to correspond to the mid-level semantic concepts like actions and objects. In order to learn language *atoms*, we find frequently occurring salient words among the subtitles using tf-idf like approach. Learning visual atoms is slightly trickier due to the intra-cluster variability of visual concepts. We generate object proposals and

Table 1: Notation of the Paper

Learning Atoms	
I_t	t^{th} frame of the video
L_t	subtitle for t^{th} frame
$y_t = [y_t^v, y_t^l]$	feature representation of t^{th} frame
$x_{i,r}^p$	1 if i^{th} cluster has r^{th} proposal of i^{th} video, 0 o.w.
z_t	activity ID of frame t

Learning Activities - Beta Process HMM	
x_i^p	binary vector for p^{th} cluster
f_i^k	1 if i^{th} video has k^{th} activity O.o.w.
$\Theta_k = [\Theta_k^v, \Theta_k^l]$	emission prob. of k^{th} activity
$\eta_i^{k,k'}$	$P(z_{t+1} = k' z_t = k)$ for i^{th} vid
$\pi_i^{k,k'}$	$\eta_i^{k,k'} \times f_i^k \times f_i^{k'}$

jointly-cluster them into mid-level atoms to obtain visual atoms. We develop a hierarchical clustering algorithm for this purpose (Section 5).

Discovering Activities: After learning the atoms, we represent the multi-modal information in each frame based on the occurrence statistics of the atoms. Given the multi-modal representation of each frame, we discover set of temporal clusters occurring over multiple videos using a non-parametric Bayesian method (Section 6). We expect these clusters to correspond to the activity steps which construct the high level activities. Our empirical results confirms this as the resulting clusters significantly correlates with the semantic activity steps.

4 Multi-Modal Representation with Atoms

Finding the set of activity steps over large collection of videos having large visual varieties requires us to represent the semantic information in addition to the low-level visual cues. Hence, we find our language and visual atoms by using mid-level cues like object proposals and frequent words.

Learning Visual Atoms: In order to learn visual atoms, we create a large collection of object proposals by independently generating object proposals from each frame of each video. These proposals are generated using the Constrained Parametric Min-Cut (CPMC) (Carreira and Sminchisescu 2010) algorithm based on both appearance and motion cues. We note the k^{th} proposal of t^{th} frame of i^{th} video as $r_t^{(i),k}$. Moreover, we drop the video index (i) if it is clearly implied in the context.

In order to group this object proposals into mid-level visual atoms, we follow a clustering approach. Although any graph clustering approach (eg. Keysegments (Lee et al 2011)) can be applied for this, the joint

processing of a large video collection requires handling large visual variability among multiple videos. We propose a new method to jointly cluster object proposals over multiple videos in Section 5. Each cluster of object proposals correspond to a visual atom.

Learning Language Atoms: We define the language atoms as the salient words which occur more often than their ordinary rates based on the *tf-idf* measure. The *document* is defined as the concatenation of all subtitles of all frames of all videos in the collection as $D = \bigcup_{i \in N_C} \bigcup_{t \in T^{(i)}} L_t^i$. Then, we follow the classical tf-idf measure and use it as $tfidf(w, D) = f_{w,D} \times \log \left(1 + \frac{N}{n_w} \right)$ where w is the word we are computing the tf-idf score for, $f_{w,D}$ is the frequency of the word in the *document* D , N is the total number of video collections we are processing, and n_w is the number of video collections whose subtitle include the word w .

We sort words with their "tf-idf" values and choose the top K words as language atoms ($K = 100$ in our experiments). As an example, we show the language atoms learned for the category *making scrambled egg* in Figure 2

Representing Frames with Atoms: After learning the visual and language atoms, we represent each frame via the occurrence of atoms (binary histogram). Formally, the representation of the t^{th} frame of the i^{th} video is denoted as $\mathbf{y}_t^{(i)}$ and computed as $\mathbf{y}_t^{(i)} = [\mathbf{y}_t^{(i),1}, \mathbf{y}_t^{(i),v}]$ such that k^{th} entry of the $\mathbf{y}_t^{(i),1}$ is 1 if the subtitle of the frame has the k^{th} language atom and 0 otherwise. $\mathbf{y}_t^{(i),v}$ is also a binary vector similarly defined over visual atoms. We visualize the representation of a sample frame in the Figure 3.

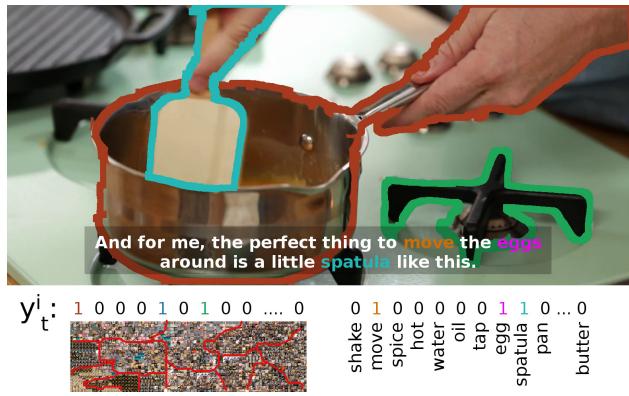


Fig. 3: Representation for a sample frame.
Three of the object proposals of sample frame are in the visual atoms and three of the words are in the language atoms.

5 Joint Clustering over Video Collection

Given a set of object proposals generated from "multiple videos", simply combining them into a single collection and clustering them into atoms is not desirable for two reasons: (1) semantic concepts have large visual differences among different videos and accurately clustering them into a single atom is hard, (2) atoms should contain object proposals from multiple videos in order to semantically relate the videos. In order to satisfy these requirements, we propose a joint extension to spectral clustering. Note that the purpose of this clustering is generating atoms where each clusters represents an atom.

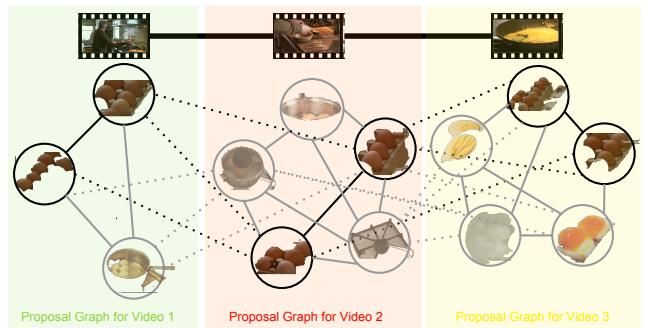


Fig. 4: Joint proposal clustering. Here, we show the $1^{st}NN$ video graph and $2^{nd}NN$ region graph. Each object proposal is linked to its two NNs from the video it belongs and two NNs from the videos it is neighbour of. Black nodes are the proposals selected as part of the cluster and the gray ones are not selected. Moreover, dashed lines are intra-video edges and solid ones are inter-video edges.

Basic Graph Clustering: Consider the set of object proposals extracted from a single video $\{r_t^k\}$, and a pairwise similarity metric $d(\cdot, \cdot)$ for them. We follow the single cluster graph partitioning (SCGP)(Olson et al 2005) approach to find the dominant cluster which maximizes the intra-cluster similarity:

$$\arg \max_{x_t^k} \frac{\sum_{(k_1, t_1), (k_2, t_2) \in K \times T} x_{t_1}^{k_1} x_{t_2}^{k_2} d(r_{t_1}^{k_1}, r_{t_2}^{k_2})}{\sum_{(k, t) \in K \times T} x_t^k} \quad (1)$$

where x_t^k is a binary variable which is 1 if r_t^k is included in the cluster, T is the number of frames and K is the number of clusters per frame. Adopting the vector form of the indicator variables as $\mathbf{x}_{tK+k} = x_t^k$ and the pairwise distance matrix as $\mathbf{A}_{t_1K+k_1, t_2K+k_2} = d(r_{t_1}^{k_1}, r_{t_2}^{k_2})$, equation (1) can be compactly written as $\arg \max_{\mathbf{x}} \frac{\mathbf{x}^T \mathbf{A} \mathbf{x}}{\mathbf{x}^T \mathbf{x}}$. This can be solved by finding the dominant eigenvector of \mathbf{x} after relaxing x_t^k to $[0, 1]$ (Olson

et al 2005; Perona and Freeman 1998). Upon finding the cluster, the members of the selected cluster are removed from the collection and the same algorithm is applied to find remaining clusters.

Joint Clustering: Our extension of the SCGP into multiple videos is based on the assumption that the key objects occur in most of the videos. Hence, we reformulate the problem by enforcing the homogeneity of the cluster over all videos.

We first create a kNN graph of the videos based on the distance between their textual descriptions. We use the χ^2 distance of the bag-of-words computed from the video description. We also create the kNN graph of object proposals in each video based on the pretrained "fc7" features of AlexNet(Krizhevsky et al 2012). This hierarchical graph structure is visualized in Figure 4 for 3 videos sample. After creating this graph, we impose both "inter-video" and "intra-video" similarity among the object proposals of each cluster. Main rationale behind this construction is having a separate notion of distance for inter-video and intra-video relations since the visual similarity decreases drastically for inter-video ones.

Given the intra-video distance matrices $\mathbf{A}^{(i)}$, the binary indicator vectors $\mathbf{x}^{(i)}$, and the inter-video distance matrices as $\mathbf{A}^{(i,j)}$, we define our optimization problem as;

$$\arg \max \sum_{i \in N} \frac{\mathbf{x}^{(i)T} \mathbf{A}^{(i)} \mathbf{x}^{(i)}}{\mathbf{x}^{(i)T} \mathbf{x}^{(i)}} + \sum_{i \in N} \sum_{j \in \mathcal{N}(i)} \frac{\mathbf{x}^{(i)T} \mathbf{A}^{(i,j)} \mathbf{x}^{(j)}}{\mathbf{x}^{(i)T} \mathbf{1} \mathbf{1}^T \mathbf{x}^{(j)}}, \quad (2)$$

where $\mathcal{N}(i)$ is the neighbours of the video i in the kNN graph, $\mathbf{1}$ is vector of ones and N is the number of videos.

Although we can not use the efficient eigen-decomposition approach from (Olson et al 2005; Perona and Freeman 1998) as a result of the modification, we can use Stochastic Gradient Descent as the cost function is quasi-convex when relaxed. We use the SGD with the following analytic gradient function:

$$\nabla_{\mathbf{x}^{(i)}} = \frac{2\mathbf{A}^{(i)} \mathbf{x}^{(i)} - 2\mathbf{x}^{(i)} r^{(i)}}{\mathbf{x}^{(i)T} \mathbf{x}^{(i)}} + \sum_{i \in N} \frac{\mathbf{A}^{i,j} \mathbf{x}^j - \mathbf{x}^{(j)T} \mathbf{1} r^{(i,j)}}{\mathbf{x}^{(i)T} \mathbf{1} \mathbf{1}^T \mathbf{x}^{(j)}}, \quad (3)$$

where $r^{(i)} = \frac{\mathbf{x}^{(i)T} \mathbf{A}^{(i)} \mathbf{x}^{(i)}}{\mathbf{x}^{(i)T} \mathbf{x}^{(i)}}$ and $r^{(i,j)} = \frac{\mathbf{x}^{(i)T} \mathbf{A}^{(i,j)} \mathbf{x}^{(j)}}{\mathbf{x}^{(i)T} \mathbf{1} \mathbf{1}^T \mathbf{x}^{(j)}}$

We iteratively use the method to find clusters, and stop after the $K = 20$ clusters are found as the remaining object proposals were deemed not relevant to the activity. Each cluster corresponds to a visual atom for our application.

In Figure 5, we visualize some of the atoms (i.e. clusters) we learned for the query *How to Hard Boil*

an Egg?. As apparent in the figure, the resulting atoms are highly correlated and correspond to semantic objects&concepts regardless of their significant intra-class variability.

6 Unsupervised Activity Representation

In this section, we explain our model for discovering the activity steps from a video collection given the language and visual atoms. The main idea behind this step is utilizing the repetitive nature of steps. In other words, although there are large number of videos in any chosen category, the underlying set of steps are very few. Hence, we tried to find smallest set of activities which can generate all the videos we crawl.

We note the extracted representation of the frame t of video i as $\mathbf{y}_t^{(i)}$. We model our algorithm based on activity steps and note the activity label of the t^{th} frame of the i^{th} video as $z_t^{(i)}$. We do not fix the the number of activities and use a non-parametric approach.

In our model, each activity step is represented over the atoms as the likelihood of including them. In other words, each activity step is a Bernoulli distribution over the visual and language atoms as $\theta_k = [\theta_k^l, \theta_k^v]$ such that m^{th} entry of the θ_k^l is the likelihood of observing m^{th} language atom in the frame of an activity k . Similarly, m^{th} entry of the θ_k^v represents the likelihood of seeing m^{th} visual atom. In other words, each frame's representation $\mathbf{y}_t^{(i)}$ is sampled from the distribution corresponding to its activity as $\mathbf{y}_t^{(i)} | z_t^{(i)} = k \sim Ber(\theta_k)$. As a prior over θ , we use its conjugate distribution – *Beta distribution* –.

Given the model above, we explain the generative model which links activity steps and frames in Section 6.1.

6.1 Beta Process Hidden Markov Model

For the understanding of the time-series information, Fox et al.(Fox et al 2014) proposed the Beta Process Hidden Markov Models (BP-HMM). In BP-HMM setting, each time-series exhibits a subset of available features. Similarly, in our setup each video exhibits a subset of activity steps.

Our model follows the construction of Fox et al.(Fox et al 2014) and differs in the choice of probability distributions since (Fox et al 2014) considers Gaussian observations whereas we adopt binary observations of atoms. In our model, each video i chooses a set of activity steps through an activity step vector $\mathbf{f}^{(i)}$ such that $f_k^{(i)}$ is 1 if i^{th} video has the activity step k , and 0 otherwise.

When the activity step vectors of all videos are concatenated, it becomes an activity step matrix \mathbf{F} such that i^{th} row of the \mathbf{F} is the activity step vector $\mathbf{f}^{(i)}$. Moreover, each activity step k also has a prior probability b_k and a distribution parameter θ_k which is the Bernoulli distribution as we explained in the Section 6.

In this setting, the activity step parameters θ_k and b_k follow the *beta process* as;

$$B|B_0, \gamma, \beta \sim \text{BP}(\beta, \gamma B_0), B = \sum_{k=1}^{\infty} b_k \delta_{\theta_k} \quad (4)$$

where B_0 and the b_k are determined by the underlying Poisson process (Griffiths and Ghahramani 2005) and the feature vector is determined as independent Bernoulli draws as $f_k^{(i)} \sim \text{Ber}(b_k)$. After marginalizing over the b_k and θ_k , this distribution is shown to be equivalent to Indian Buffet Process (IBP)(Griffiths and Ghahramani 2005). In the IBP analogy, each video is a customer and each activity step is a dish in the buffet. The first customer (video) chooses a Poisson(γ) unique dishes (activity steps). The following customer (video) i chooses previously sampled dish (activity step) k with probability $\frac{m_k}{i}$, proportional to the number of customers (m_k) chosen the dish k , and it also chooses Poisson($\frac{\gamma}{i}$) new dishes(activity steps). Here, γ controls the number of selected activities in each video and β promotes the activities getting shared by videos.

The above IBP construction represents the activity step discovery part of our method. In addition, we also need to model the video parsing over discovered steps. Moreover, we need to model this two steps jointly. We model the each video as an Hidden Markov Model (HMM) over the selected activity steps. Each frame has the hidden state –activity step– ($z_t^{(i)}$) and we observe the multi-modal frame representation $\mathbf{y}_t^{(i)}$. Since we model each activity step as a Bernoulli distribution, the emission probabilities follow the Bernoulli distribution as $p(\mathbf{y}_t^{(i)}|z_t^{(i)}) = \text{Ber}(\theta_{z_t^{(i)}})$.

For the transition probabilities of the HMM, we do not put any constraint and simply model it as any point from a probability simplex which can be sampled by drawing a set of Gamma random variables and normalizing them (Fox et al 2014). For each video i , a Gamma random variable is sampled for the transition between activity step j and activity step k if both of the activity steps are included by the video (i.e. if f_k^i and f_j^i are both 1). After sampling these random variables, we normalize them to make transition probabilities to sum up 1. This procedure can be represented formally as

$$\eta_{j,k}^{(i)} \sim \text{Gam}(\alpha + \kappa \delta_{j,k}, 1), \quad \pi_j^{(i)} = \frac{\eta_j^{(i)} \circ \mathbf{f}^{(i)}}{\sum_k \eta_{j,k}^{(i)} f_k^{(i)}} \quad (5)$$

Where κ is the persistence parameter promoting the self state transitions a.k.a. more coherent temporal boundaries, \circ is the element-wise product and $\pi_j^{(i)}$ is the transition probabilities in video i from activity step j to other steps. This model is also presented as a graphical model in Figure 6

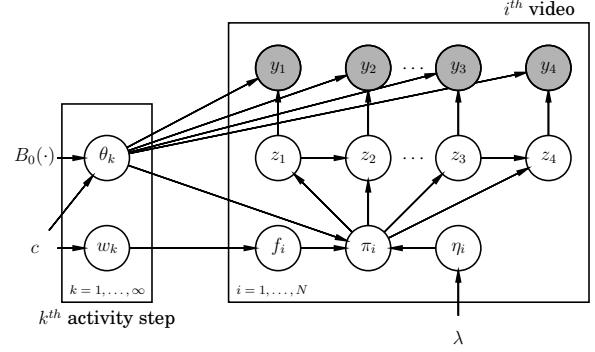


Fig. 6: Graphical model for BP-HMM: The left plate represent the activity steps and the right plate represent the videos. i.e. the left plate is for the activity step discovery and right plate is for parsing. See Section 6.1 for details.

6.2 Gibbs sampling for BP-HMM

We employ Markov Chain Monte Carlo (MCMC) method for learning and inference of the BP-HMM. We follow the exact sampler proposed by Fox et al.(Fox et al 2014). It marginalize over activity likelihoods w and activity assignments \mathbf{z} and samples the rest. MCMC procedure iteratively samples the conditional likelihood of activity matrix \mathbf{F} , activity parameters θ and transition weights η . We divide the explanation of this samplers into two sections, sampling the activities through activity matrix (\mathbf{F}) and activity parameters (θ), and sampling the HMM parameters η . Marginalization over activity assignments follows the efficient dynamic programming approach.

Sampling the Activities: Consider the binary activity inclusion matrix \mathbf{F} such that $F_{i,j}$ is 1 if the i^{th} video has the j^{th} activity. Following the sampler of Fox et al.(Fox et al 2014), we divide the sampling \mathbf{F} into two parts, namely, sampling the shared activities and sampling the novel activities. Sampling shared activities correspond the re-sampling of existing entries of \mathbf{F} . We simply iterate over each entry and propose a flip (i.e. if the i^{th} video has the j^{th} activity, we propose to flip it and not

to include j^{th} activity in the i^{th} video). We accept or reject this proposals following the Metropolis-Hastings rule.

In order to sample the novel activities, we follow the data-driven sampler (Hughes and Sudderth 2012). Consider the case in which we want to propose a novel activity by setting the $F_{i,j+1}$ to 0. In other words, we introduce a new activity ($j + 1^{th}$ activity) such that i^{th} video includes it. In order to sample the parameters θ_{j+1} of it, we first sample a temporal window W over the i^{th} video. This window is sampled by sampling the starting frame and the length of the window from a uniform distribution. Then, we sample the novel activity from *Beta distribution* as;

$$\theta_{k,n}|W \sim \text{Beta}(\alpha_n, \beta_n) \quad (6)$$

where $\theta_{k,n}$ is the n^{th} entry of θ_k , α_n is the number of frames in the window W which have the atom n , and β_n is the number of frames which do not have the atom n . We use *Beta distribution* because it is the conjugate prior of the *Bernoulli distribution* that we use to model activities.

Sampling the HMM Parameters: When the activities are defined via Θ and each video selects a subset of them via (\mathbf{F}) , we can compute the likelihood of each state assignment by using the dynamic programming given the transition probabilities η . By using the likelihoods, we sample the state assignments \mathbf{z} .

When the states are sampled, we can use the closed-form sampler derived in (Fox et al 2014). Fox et al.(Fox et al 2014) shows that the transition probabilities can be sampled through a *Dirichlet* random variable and scaling it with a *Gamma* random variable as;

$$\pi^{(i)} \sim Dir(\dots, N_{j,k}^{(i)} + \alpha + \delta_{j,k}\kappa, \dots) \quad (7)$$

followed by $\eta^{(i)} = \pi^{(i)} \times C^{(i)}$ such that $C^{(i)} \sim Gamma(K_+^{(i)}\lambda + \kappa, 1)$. Here, $N_{j,k}^{(i)}$ represents the number of transitions between state j and state k in the video i , α , λ and κ are hyperparameters which we learn with cross-validation, $\delta_{j,k}$ is 1 if $j = k$ and 0 o.w., and $K_+^{(i)}$ is the number of activities the i^{th} video has chosen.

At the end of the Gibbs sampling, our algorithm ends with a set of activities each represented with respect to the discovered atoms i.e. $\Theta_1 \dots \Theta_k$ and label of each frame among the discovered activities $[1, \dots, k]$. Θ_i can be considered as a generative distribution of each discovered activity. In other words, if we want to sample a frame from activity i , we simply sample set of language and visual atoms from Θ_i . We perform this sampling in order to generate a language caption for each discovered activity as explained in Section A. We

also consistently visualize the results of discovery using story lines as shown in Figure 1. We assign a color code to each discovered activity and sample keyframes from 4 four different clips of same activity. We further generate a natural language description as well as display the temporal segmentation of each video as a colored timeline.

7 Experiments

In order to experiment the proposed method, we first collected a dataset (details in Section 7.1). We labelled small part of the dataset with frame-wise activity step labels and used it as an evaluation corpus. Neither the set of labels, nor the temporal boundaries are exposed to our algorithm since the set-up is completely unsupervised. We evaluate our algorithm against the several unsupervised clustering baselines and state-of-the-art algorithms from video summarization literature which are applicable.

7.1 Dataset

We use WikiHow(wik 2015) in order to obtain the top100 queries the internet users are interested in and choose the ones which are directly related to the physical world. Resulting queries are;

How to Bake Boneless Skinless Chicken, Make Jello Shots, Cook Steak, Bake Chicken Breast, Hard Boil an Egg, Make Yogurt, Make a Milkshake, Make Beef Jerky, Tie a Tie, Clean a Coffee Maker, Make Scrambled Eggs, Broil Steak, Cook an Omelet, Make Ice Cream, Make Pancakes, Remove Gum from Clothes, Unclog a Bathtub Drain

For each of the queries, we crawled YouTube and got the top 100 videos. We also downloaded the English subtitles if they exist. We further randomly choose 5 videos out of 100 per query. Although the choice was random, we discarded outlier videos at this stage and re-sampled without replacement to have 5 inlier evaluation video per query. Other than outlier removal, no human super vision is used to choose evaluation videos. Hence, we have total of 125 evaluation videos and 2375 unlabelled videos.

For each evaluation video, we asked an independent labeler to label them. The dataset is labeled by 5 independent labelers each annotating 5 categories. We asked labelers to label start and end frame of each activity step as well as the name of the step. We simply asked them the question *What are the activity steps and where does each of starts and end?*. All labelers are shown 5 wikiHow(?) video recipes with detailed steps before starting the annotation process as a baseline.

7.1.1 Outlier Video Removal

The video collection we obtain without any expert intervention might have outliers; since, our queries are typical daily activities and there are many cartoons, funny videos, and music videos about them. Hence, we have an automatic filtering stage. The key-idea behind the filtering algorithm is the fact that instructional videos have a distinguishable text descriptions when compared with outliers. To exploit this, we use a clustering algorithm to find the large cluster of instructional videos with no outlier. Given a large video collection, we use the graph we explain in Section 5 and compute the dominant video cluster by using the Single Cluster Graph Partitioning (Olson et al 2005) and discards the remaining videos as outlier. We represent each video as a bag-of-words of their textual description. In Figure 7, we visualize some of the discarded videos. Although our algorithm have false positives while detecting outliers, we always have enough number of videos (minimum 50) after the outlier detection thanks to the large-scale dataset.



Fig. 7: Sample videos which our algorithm discards as an outlier for various queries. A toy milkshake, a milkshake charm, a funny video about How to NOT make smoothie, a video about the danger of a fire, a cartoon video, a neck-tie video erroneously labeled as bow-tie, a song, and a lamb cooking mislabeled as chicken.

7.2 Qualitative Results

After independently running our algorithm on all categories, we discover activity steps and parse the videos according to discovered steps. We visualize some of these categories qualitatively in Figure 8 with the temporal parsing of evaluation videos as well as the ground truth parsing.

To visualize the content of each activity step, we display key-frames from different videos. We also train a 3rd order Markov language model(Shannon 2001) by using the subtitles. Moreover, we generate a caption for each activity step by sampling this model conditioned

on the θ_k^l . We explain the details of this process in the appendix.

As shown in the Figures 8a&8b, resulting steps are semantically meaningful. Moreover, the language captions are also quite informative hence we can conclude that there is enough language context within the subtitles in order to detect activities. On the other hand, some of the activity steps always occur together and our algorithm merges them into a single step while promoting sparsity.

7.3 Quantitative Results

We compare our algorithm with the following baselines.

Low-level features (LLF): In order to experiment the effect of learned atoms, we compare with low-level features. As features, we use the state-of-the-art Fisher vector representation of HOG, HOF and MBH features (Jiang et al 2014).

Single modality: To experiment the effect of multi-modal approach, we compare with single modality approach by only using the atoms of a single modality.

Hidden Markov Model (HMM): To experiment the effect of joint generative model, we compare our algorithm with an HMM. We use the Baum-Welch (Rabiner 1989) with cross-validation.

Kernel Temporal Segmentation(Potapov et al 2014): Kernel Temporal Segmentation (KTS) proposed by Potapov et al.(Potapov et al 2014) can detect the temporal boundaries of the events/activities in the video from a time series data without any supervision. It enforces a local similarity of each resultant segment.

Given parsing results and the ground truth, we evaluate both the quality of temporal segmentation and the activity step discovery. We base our evaluation on two widely used metrics; intersection over union (*IOU*) and mean average precision(*mAP*). **IOU** measures the quality of temporal segmentation and it is defined as; $\frac{1}{N} \sum_{i=1}^N \frac{\tau_i^* \cap \tau_i'}{\tau_i^* \cup \tau_i'}$ where N is the number of segments, τ_i^* is ground truth segment and τ_i' is the detected segment. **mAP** is defined per activity step and can be computed based on a precision-recall curve (Jiang et al 2014). In order to adopt these metrics into unsupervised setting, we use cluster similarity measure(*csm*)(Liao 2005) which enables us to use any metric in unsupervised setting. It chooses a matching of ground truth labels with predicted labels by searching over all matching and choosing the ones giving highest score. We use mAP_{csm} and IOU_{csm} as evaluation metrics.

Accuracy of the temporal parsing. We compute, and plot in Figure 9, the IOU_{cms} values for all competing algorithms and all categories. We also average over the categories and summarize the results in the Table 2. As the Figure 9 and Table 2 suggests, proposed method consistently outperforms the competing algorithms and its variations. One interesting observation is the importance of both modalities as a result of dramatic difference between the accuracy of our method and its single modal versions.

Moreover, the difference between our method and HMM is also significant. We believe this is due to the ill-posed definition of activities in HMM since the granularity of the activity steps is subjective. On the other hand, our method starts with the well-defined definition of finding set of steps which generate the entire collection. Hence, our algorithm do not suffer from granularity problem.

Coherency and accuracy of activity step discovery. Although IOU_{cms} successfully measures the accuracy of the temporal segmentation, it can not measure the quality of discovered activities. In other words, we also need to evaluate the consistency of the activity steps detected over multiple videos. For this, we use unsupervised version of mean average precision mAP_{cms} . We plot the mAP_{cms} values per category in Figure 10 and their average over categories in Table 2. As the Figure 10 and the Table 2 suggests, our proposed method outperforms all competing algorithms. One interesting observation is the significant difference between semantic and low-level features. Hence, the mid-level features are key for linking multiple videos.

Semantics of activity steps. In order to evaluate the role of semantics, we performed a subjective analysis. We concatenated the activity step labels in the ground-truth into a label collection. Then, we ask non-expert users to choose a label for each discovered activity for each algorithm. In other words, we replaced the maximization step with subjective labels. We designed our experiments in a way that each clip received annotations from 5 different users. We randomized the ordering of videos and algorithms during the subjective evaluation. Using the labels provided by subjects, we compute the mean average precision (mAP_{sem}).

Both mAP_{cms} and mAP_{sem} metrics suggest that our method consistently outperforms the competing ones. There is only one recipe in which our method is outperformed by our baseline of no visual information. This is mostly because of the specific nature of the recipe *How to tie a tie?*. In such videos the notion of object is not useful since all videos use a single object -tie-.

Table 3: Semantic mean-average-precision mAP_{sem} . The results suggest that our algorithm outperforms all baselines. The results also suggest that both of the modalities are required for accurate parsing for video collections.

	HMM w/ LLF	HMM w/Sem	Ours w/ LLF	Ours w/o Vis	Ours w/o Lang	Our full
mAP_{sem}	6.44	24.83	7.28	28.93	14.83	39.01

The importance of each modality. As shown in Figure 9 and 10, performance significantly drops when any of the modalities is ignored consistently in all categories. Hence, the joint usage is necessary. One interesting observation is the fact that using only language information performed slightly better than using only visual information. We believe this is due to the less intra-class variance in the language modality (i.e. people use same words for same activities). However, it lacks many details(less complete) and more noisy than visual information. Hence these results validate the complementary nature of language and vision.

Generalization to generic structured videos. We experiment the applicability of our method beyond How-To videos by evaluating it on non-How-To categories. In Figure 11, we visualize the results for the videos retrieved using the query “Travel San Francisco”. The resulting clusters follow semantically meaningful activities and landmarks and show the applicability of our method beyond How-To queries. It is interesting to note that Chinatown and Clement St ended up in the same cluster. Considering the fact that Clement St is known for its Chinese food, this suggests that the discovered clusters are semantically meaningful.

Noise in the subtitles. We experiment and analyze the robustness to noise in subtitles. Handling noisy subtitles is an important requirement since the scale of large-video collections makes it intractable to transcribe all instructional videos. One study suggest that it would take 374k human-year effort to transcribe all youtube videos. Hence, we expect to have combination of automatic speech recognition(ASR) generated subtitles with user uploaded ones as an input to any unsupervised parsing algorithm.

We study the effect of noise, introduced by ASR, by evaluating our algorithm on three different video corpus. First, we only use the videos with user uploaded subtitles. Second, we only use the videos with ASR generated subtitles. Third, we use the entire dataset as

Table 2: Average of IOU_{cms} and mAP_{cms} over recipes. The results suggest that our algorithm outperforms all baselines. The results also suggest that both of the modalities as well as semantic representations of visual information are all required for successful parsing of video collections.

KTS (Potapov et al 2014)	KTS(Potapov et al 2014)	HMM	HMM	Ours	Ours	Ours	Our
w/ LLF	w/ Sem	w/ LLF	w/Sem	w/ LLF	w/o Vis	w/o Lang	full
IOU_{cms}	16.80	28.01	30.84	37.69	33.16	36.50	29.91
mAP_{cms}	n/a	n/a	9.35	32.30	11.33	30.50	19.50
							44.09

union of first two. The results are summarized in Table 4. Results indicates that noise-free subtitle improves the accuracy as expected. Moreover, the difference between the results obtained with full corpus and user uploaded subtitles corpus is very small when compared with ASR only corpus. Hence, our algorithm can fuse information from noisy and noise-free examples in order to compensate for errors in the ASR.

Table 4: Average of IOU_{cms} and mAP_{cms} over recipes with and without user uploaded subtitles. The results show that noise in the subtitles has an effect in the parsing accuracy. The results also indicate that our algorithm shows robustness to the noise since our accuracy results are comparable to the version using only user uploaded subtitles.

	IOU_{cms}	mAP_{cms}	mAP_{sem}
ASR only	47.61	39.13	33.27
User uploaded only	54.63	46.21	42.32
Combination	52.36	44.09	39.01

8 Grounding into Robotic Instructions

In this section, we demonstrate how we can apply our algorithm to the task of grounding recipe steps into robotic actions.

One of the most important applications of our algorithms is in robotics. In future, robots will need to perform many tasks upon user’s requests. We envision that the robots can use our video parser to first download a large video collection for a task and then parse it. For example, if a user asks to the robot *Please make ramen.*, the robot can download all videos returned from the query *How to make a ramen..* Robot can further parse the scene using any of the available RGB-D/RGB/Point Cloud segmentation algorithms (Koppula et al 2011; Ren et al 2012; Armeni et al 2016). Robot can use the

resulting segmentation in order to find the most similar recipe simply using the object categories that we output.

In order to demonstrate this application, we use a state of the art language grounding algorithm (Misra et al 2014, 2015) which converts the generated descriptions into robot actions based on the environment. Tell Me Dave algorithm of Misra et al (Misra et al 2014, 2015) uses a semantic simulator which encodes the common sense knowledge about the physical world. It takes the tuple of language, instructions and the environment as an input and outputs a series of robot actions to perform the task. In order to learn the transformation, it uses a large-scale game log of language instruction, environment and robot action tuples, and models them in terms of a graphical model. The environment is defined in terms of objects and their 3D positions, language is series of free-form English sentences describing each step and actions are low-level robot commands.

In our experimental setup, we choose two basic activities that Tell Me Dave can simulate; namely, *How to make a ramen?* and *How to make an affogato?*. We also chose a random environment for each query from Tell Me Dave environment dataset. We directly feed aforementioned how-to queries into YouTube and parse the resulting video collections. The resulting storylines are visualized in Figure 12.

In order to complete the loop until low-level robot commands, we then manually labelled the object categories our algorithm discovered. For example, if the category we discovered is mostly images of eggs, we labelled this category as *egg*.² Using these labels, our algorithm chose the video whose objects is a subset to the environment our robot lives in to make sure all objects of the recipe are accessible by the robot. Finally, we feed the environment and generated captions into the Tell Me Dave algorithm to obtain the physical plan robot needs to execute to perform each of the activity. We visualize each plan and the simulation in the Figure 12.

² This step can be automated using any object recognition algorithm (Russakovsky et al 2015).

Our results are shown in the Figure 12, demonstrating that our approach can be used for robotics applications with limited supervision. There were some errors in translation of video storyline steps to actual grounded steps. Example errors include turning on both of the knobs of the stove other than the single one. However, the resulting plans were still feasible in a way they can accomplish the required high-level task.

While a larger analysis and robotic experiments are outside the scope of this paper, with this demonstration we believe that our proposed method shows a feasible direction for robotics.

9 Conclusions

In this paper, we captured the underlying structure of human communication by jointly considering visual and language cues. We experimentally validate that given a large-video collection having subtitles, it is possible to discover activities without any supervision over activities or objects. Experimental evaluation also suggests the available noisy and incomplete information is powerful enough to not only discover activities but also describe them. We also demonstrated that the resulting discovered recipes are useful in robotics scenarios.

So; “is it possible to understand large-video collections without any supervision?”. Given video and speech information, the storylines we generate successfully summarize the large video collection. This compact representation of hundreds of videos is expected to be useful in designing user interfaces which users interact with instructional videos. We believe this is an important step in the direction of future video web-pages. Yet another very important question is “can machines understand large-video collections?”. Clearly, we needed a small amount of manual information and even used a method which is trained with human supervision in our robotic demonstration. Hence, it is too early to claim a success for machines watching large-collection of videos. On the other hand, the results are very promising and we believe algorithms which can convert a free-form input query into robot trajectories are a possible in near future. We also believe our algorithm is an important step in this ambitious target.

A Generation of Language Description

In this section, we explain how we generated the text description for the activity steps we discovered. We included these descriptions in Figure 8, 11&12 as well as in the supplementary videos.

In order to generate the descriptions, we simply used a Markov text generator. We collected all subtitles of all videos

we included in our dataset. After combining them, we trained a 3rd order Markov model by using the subtitles we downloaded. Main purpose of this training is learning the context dependent language model. Although this step can be accomplished by various of methods in the NLP literature, we choose Markov language model because of its simplicity. Indeed, this model is learned purely for visualization purposes and neither the activity step discovery nor the parsing algorithm uses this model.

After the model is learned, we need to generate a text description for each discovered activity. Since each discovered activity is represented as Bernoulli random variable, we have likelihood for each language atom. Our description generation strategy is sampling a large collection of descriptions and ranking them for their closeness to the discovered activities. We compute this closeness with the parameters of the Bernoulli random variable. Formally, given large-set of sampled descriptions $\{S_i\}_{i \in [1, K]}$, we rank them using the weights of the Bernoulli random variable as;

$$r_i = \frac{\sum_j [S_i^j = w^j] \theta^j}{\sum_j [S_i^j = w^j] 1}$$

Here, $[.]$ is an indicator function, S_i^j is the j^{th} word of i^{th} description, w^j is the j^{th} word and θ^j is the j^{th} entry of the activity description. We simply choose the description having largest rank.

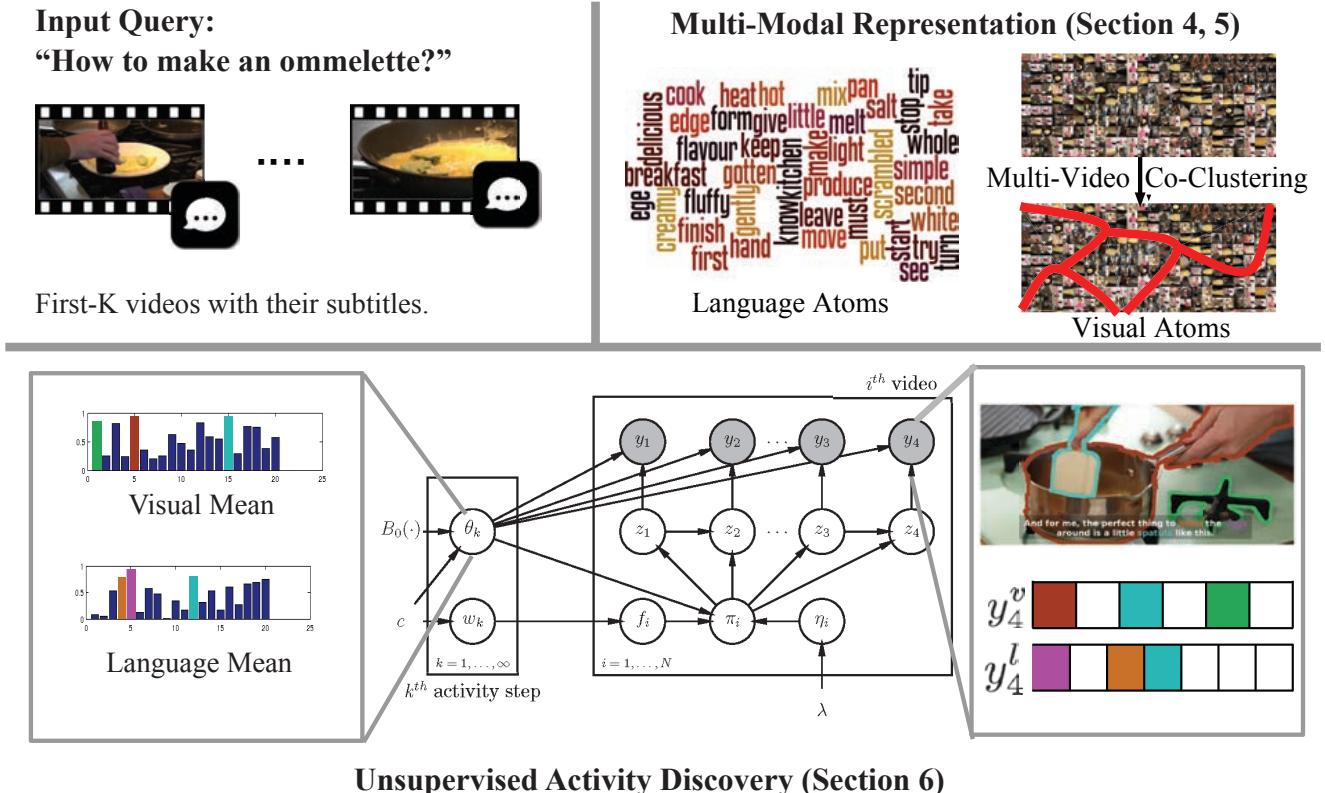


Fig. 2: Summary of our method. We start with a single natural language query like *how to make an omelette* and then we crawl the top K videos returned by this query from YouTube. We learn a multi-modal dictionary composed of salient words and object proposals. Rest of the algorithm represents frames and activities in terms of the learned dictionary. For example, in the bottom figure, colors represent such atoms and both activity descriptions Θ and frame representations y_t are defined in terms of these atoms. (see Fig 1 for output)

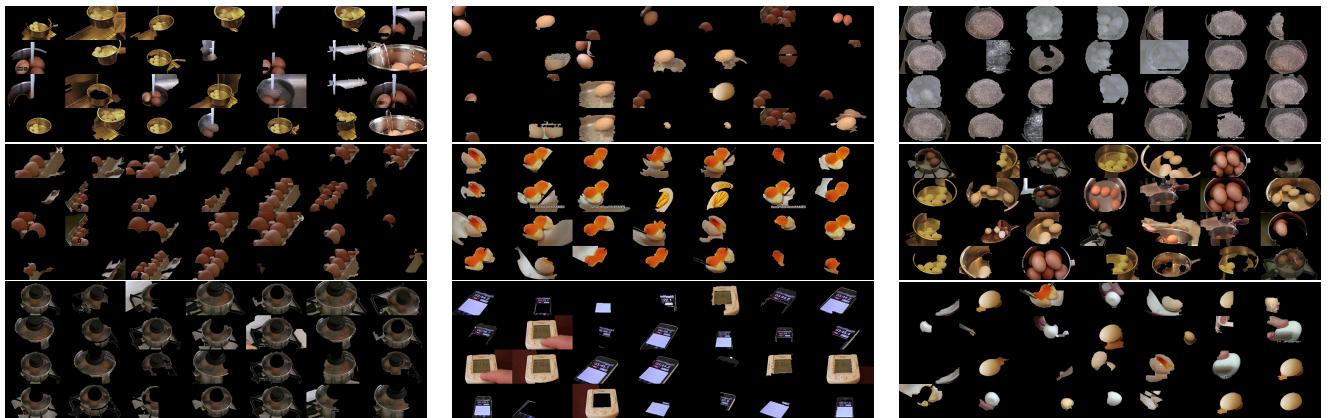


Fig. 5: Randomly selected images of four randomly selected clusters learned for *How to hard boil an egg?* Please note that the objects in the same cluster is not only coming from a single video but discovered over multiple videos. Hence, this stage helps in linking videos with each other. Resulting clusters are semantically accurate since they typically belong to a single semantic concept like water filling the pot.

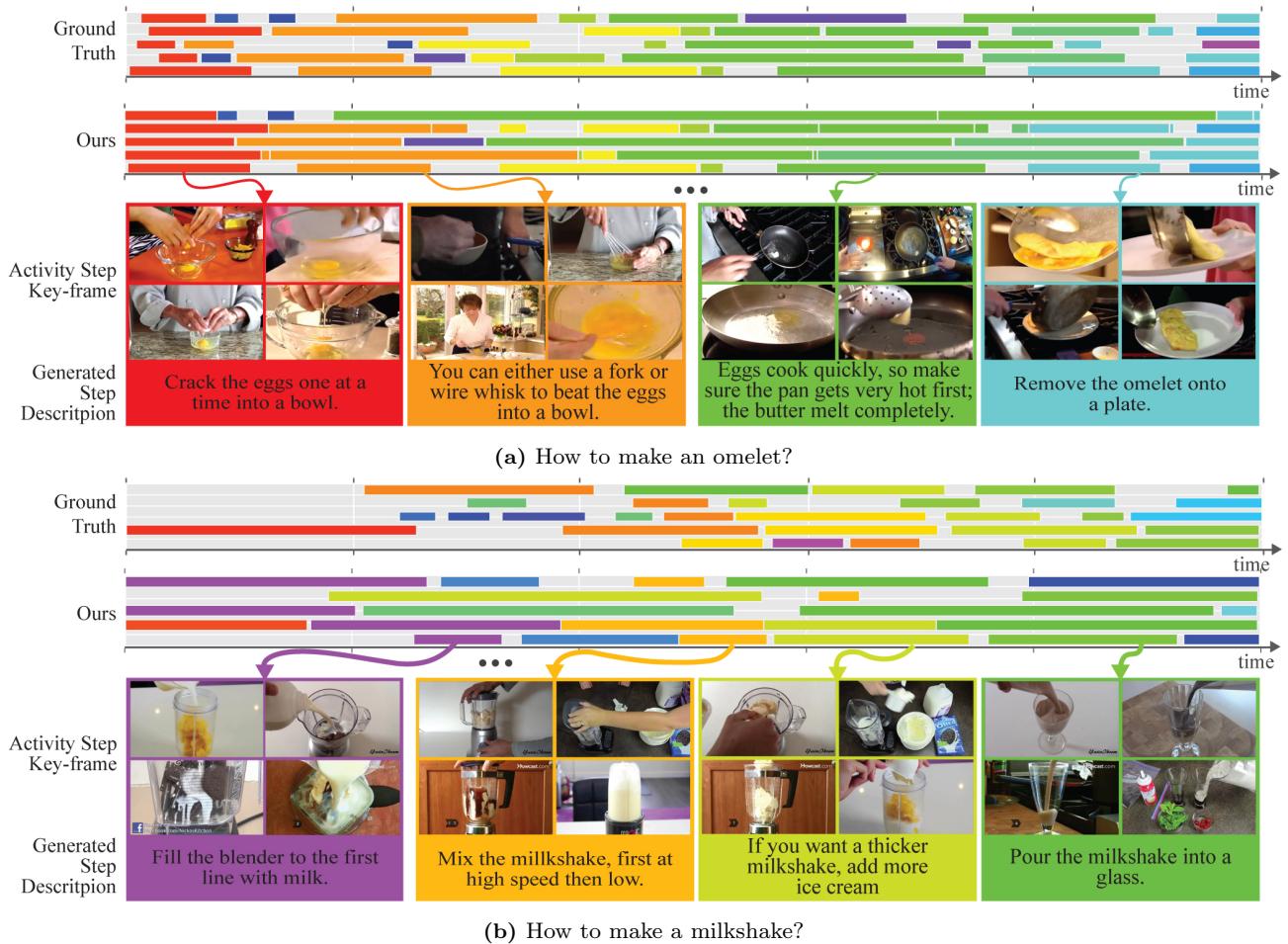


Fig. 8: Video storylines for queries *How to make an omelet?* and *How to make a milkshake?*
Temporal segmentation of the videos and ground truth segmentation. We also color code the activity steps we discovered and visualize their key-frames and the automatically generated captions. *Best viewed in color.*

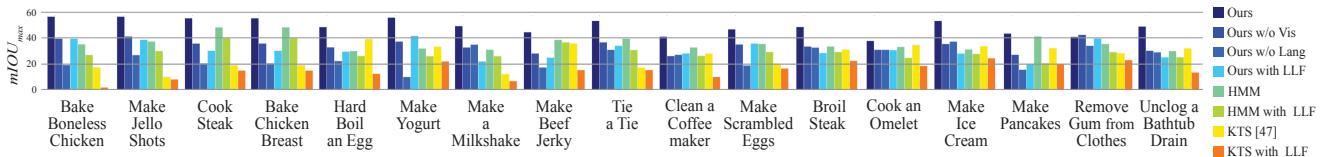


Fig. 9: $mIoU_{max}$ values for all categories, for all competing algorithms. Results suggest that our algorithm is outperforming all other baselines. It also suggests that the visual information is contributing more than language for temporal intersection over union. This is rather expected since people tend to talk about things they did and will do; hence, language is expected to have low localization accuracy.

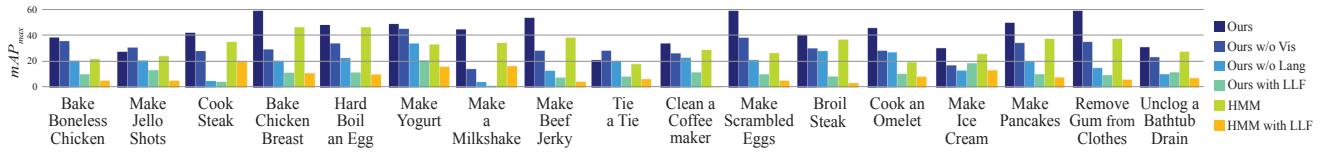
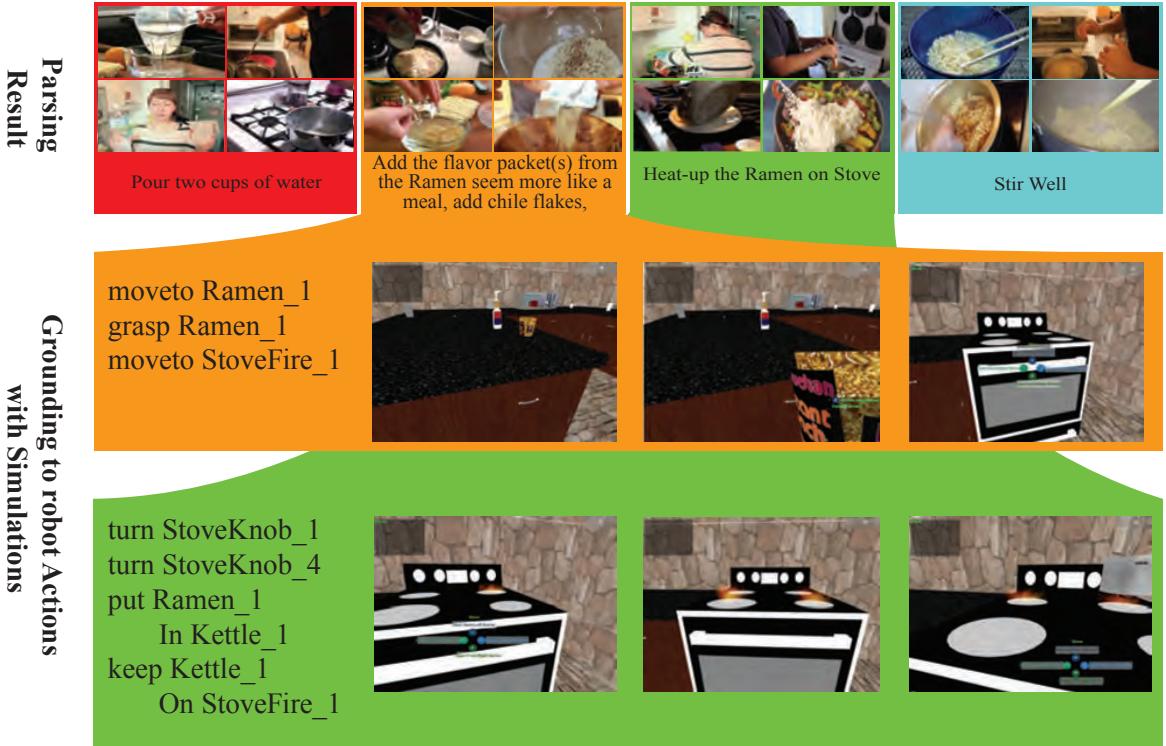


Fig. 10: AP_{max} values for all categories, for all competing algorithms. Results suggest that our algorithm is outperforming all other baselines in most of the cases. The failure cases included recipes like *How to tie a tie?* which is rather expected since a video about tying a tie only includes a tie in the scene which is not informative enough to distinguish steps. The results also suggest that language contributes more than visual information for average precision, which is also rather expected since same step has very high visual variance and generally referred by using same or similar words.



Fig. 11: Qualitative results for parsing ‘Travel San Francisco’ category. The results suggest that our algorithm can generalize categories beyond instructional videos. For example, travel videos can also be parsed using our method.

Input Query: *How to make ramen?*



Input Query: *How to make affogato?*



Fig. 12: Demonstration on robotic grounding. We considered two queries by the user: *How to make a ramen?* and *How to make an affogato?*. Given the result by our video parsing system, we find the grounded instruction for each recipe step. Top row shows the results as a storyline from our video parser, and the bottom row shows the robotic simulator and an actual robotic demonstration respectively. During this demonstration, we manually label each object category and fully automate rest of the task. In order to simulate/and implement the resulting steps on robots, we simply used the publicly available simulator/source code distributed by Tell Me Dave (Misra et al 2014, 2015)

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