Unsupervised Semantic Parsing of Video Collections

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Abstract

Human communication typically has an underlying structure. This is reflected in the fact that in many user generated videos, a starting point, ending, and certain objective steps between these two can be identified. In this paper, we propose a method for parsing a video into such semantic steps in an unsupervised way. The proposed method is capable of providing a semantic "storyline" of the video composed of its objective steps. We accomplish this utilizing both visual and language cues in a joint generative model. The proposed method can also provide a textual description for each of identified semantic steps and video segments. We evaluate this method on a large number of complex YouTube videos and show results of unprecedented quality for this intricate and impactful problem.

1. Introduction

Human communication takes many forms, including language and vision. For instance, explaining "how-to" perform a certain task can be communicated with language (e.g., Do-It-Yourself books) information as well as visual (e.g., instructional YouTube videos) information. Regardless of the form, such human-generated communication is generally structured and often has a clear beginning, end, and a set of steps in between. A typical and highly structured example is the description of an event or a procedure as the comprising steps can be clearly identified. Parsing such communication into its set of semantic steps is the key to understand human activities. With a large amount of instructional video collections, we present a method to ground and parse them into semantically meaningful actions.

The two modalities of language and vision often provide different, but correlating and complementary information. Challenge lies in that both video frames and language (from sub-titles or speech recognition[1]) are only a noisy, partial observation of the actions being performed. Moreover, the complementary nature of language and vision requires us to model them jointly. We present a unified model, learnt in a fully unsupervised manner, in order to jointly use these two modalities.

The key idea in our proposed model is to capture the underlying structure in activities, while accounting for the large intra-class variability (e.g., YouTube has 281.000 videos for *"How to tie a bow tie"*). We account for the intra-class variation by jointly learning the entire video collection instead of a single video. We evaluate our method on instructional videos (*e.g.*, "Making panckage", "How to tie a bow tie") as they typically have clear steps and provide concrete grounds for demonstrating a semantically meaningful parsing in a verifiable manner. In principle, 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 (see Fig. **??**). This storyline provides what particular steps are taking place in the video, when they are occurring, and what their semantic meaning is (*what-when-how*). This method is also capable of putting multiple videos performing the same overall task in common ground (i.e., the semantic steps space) and capture their high-level similarity, and therefore, provide a *categorical* storyline as well.

In our approach, given a video, we capture the visual properties of unsupervised object proposals from each frame as well as the frequencies of keywords from the subtitle. We then employ a generative *beta process mixture model*, which identifies the semantic steps shared among the videos of one category by clustering together the recurrent and co-occurring visual and textual cues. The model also identifies the text keywords which were deemed highly related to the semantic action of each steps. We later learn a HMM based language model to provide a textual description of the semantic steps based on the identified keywords.

This work is the first to provide a semantic storyline for a complex video collection. We are also the first to approach this problem in a multimodal (joint language and vision) manner. In addition, our method is capable of providing a caption describing the steps; our approach to captioning is fundamentally different from the majority of existing

[1]Subtitles, generated either via Automatic Speech Recognition (ASR) or by the user, are now available for most YouTube videos.

video/image-to-text work in two aspects: 1) the captions are generated in an unsupervised manner, 2) our captions are *descriptions* of the semantic steps, yet they are inferred from *narrations*. This is different from the existing captioning work as their reference data is also descriptive of the visual information, while the narration over videos often provides complementary information to the visuals and is not necessarily descriptive.

2. Related Work

Three key aspects differentiate this work from the majority of existing techniques for similar tasks: 1) capability of providing a semantic parsing of a video category leading to a compact storyline representation, 2) being unsupervised, 3) adopting a multi-modal joint vision-language model for video parsing. A thorough review of the related literature is provided below.

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 [56] and mostly focus on *choosing keyframes* for visualization. Keyframes are also improved by using the video tags by Hong et al. [19] and using the spatio-temporal information by Gygli et al. [17].

Summarizing videos is particularly important for egocentric videos as they are generally long in duration. There are many works which successfully segment such videos into a sequence of important shots [34, 36]; however, they mostly rely on characteristics specific to edge-centric videos, and therefore do not generalized to generic or instructional videos. For instance, Rui et al. [49] proposed a dynamic summarization method based on the excitement of the speech of the reporter.

Summarization is also applied to the large image collections by recovering the temporal ordering and visual similarity of images [26], and by Gputa et al. [16] to videos in a supervised framework using annotations of actions as well as partial spatial and temporal relationships among the actions. The image collections are also used to choose important view points for video key-frame selection by Khosla et al.[24] and further extended to video clip selection by Kim et al.[25], Potapov et al.[47]. Unlike all of these methods which mostly 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. Also, regardless of this dissimilarity, we experimentally compare our method against them.

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 [3] in this area focus on learning a common multimodal space in order to jointly represent language and vision. They are further extended to learning higher level relations between object segments and words [51]. Similarly, Zitnick et al.[60, 59] used abstracted clip-arts to understand spatial relations of objects and their language correspondences. Kong et al. [28] and Fidler et al. [12] 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 [58] and activity recognition [40]. Recent works also focus on automatic generation of image captions with underlying ideas ranging from finding similar images and transferring their captions [44] to learning language models conditioned on the image features [27, 52, 11]; their employed approach to learning language models is typically either based on graphical models [11] or neural networks [52, 27, 23].

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

Activity/Event Recognition: The literature of human action recognition is broad. The closes techniques to our problem are either supervised or focus on detecting a particular (and often short) action in a weakly or unsupervised manner. Also, a large body of action recognition methods are intended for trimmed videos clips or remain limited to detecting very short atomic actions [29, 53, 41, 32, 10, 50]. Even though some promising recent works attempted action recognition in untrimmed videos [22, 43, 21], they are primarily fully supervised.

Additionally, several method for localizing instances of actions in rather longer video sequences have been developed [9, 18, 33, 5, 46]. Our work is different from those in terms of being multimodal, unsupervised, applicable to a video collection, and not limited to identifying predefined actions or the ones with short temporal spans. Also, the previous works on finding action primitives such as [41, 57, 20, 31, 30] 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 [54, 8, 2]. 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.

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 [38, 55] focus on semantic parsing of language recipes in order to extract actions and the objects in the form of predicates. Tenorth et al.[55] further process the predicates in order to form a complete logic plan. Mori et al.[39] also learns the relations of the actions in terms of a flow graph with the help of a supervision. The aforementioned approaches focus only on the language modality and they are not applicable to the videos. The recent advances [4, 6] in robotics use the parsed recipe in order to perform cooking tasks. They use supervised object detectors and report a successful autonomous cooking experiment. In addition to the language based approaches, Malmaud et al.[37] 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/actions 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 constructing the objective steps (i.e., the recipe). There is also an approach which generates multi-modal recipes from expert demonstrations [14]. However, it is developed only for the domain of *teaching user interfaces* and are not applicable to the videos.

3. Overview

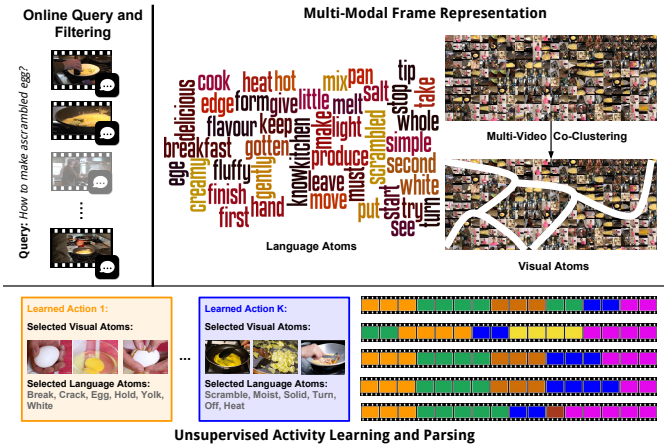


Figure 1: Components of our recipe understanding method. **Query:** We query the YouTube for top 100 *How To* videos and filter the outliers; **Framewise Representation:** We automatically extract object clusters and salient word in order to find multi-modal representation of each frame. **Unsupervised Activity Detection:** We jointly cluster videos in order to learn activities/steps related to the recipe.

In this section, we explain the high-level components of our method which we visualize in Figure 1. Our proposed method consists of three major components; **(1) Online query and filtering:** Our system starts with querying the YouTube with an *How to* question, and records the top 100 resulting videos. In order to detect the similarity of the videos quickly, we also process the text descriptions and eliminate outliers. **(2) Frame-wise multi-modal representation:** In order to semantically represent the spatio-temporal information in the videos, we process both the visual and language content of each video. We extract the region proposals and jointly cluster them to detect semantic visual objects. We also detect the salient words of the subtitles. Finally, we epresent the each frame in terms of the resulting objects and the salient words. **(3) Unsupervised joint clustering:** After describing the each frame by using both language and visual cues, we apply a non-parametric Bayesian method in order to find the temporally consistent clusters (collection of video clips) occurring over multiple videos. We expect these clusters to correspond to the actions which construct the high level activities. Moreover, our empirical results suggest that the resulting clusters significantly correlates with the fine-grained activities.

We now explain the details of the each sub-system in the following sections.

3.1. Video Collection and Outlier Detection

Our system starts with querying the YouTube for the recipe which we want to learn its actions. Although we explain how do we choose such queries in Section 4.1 in detail, any query starting with *How to* can be considered as an example. We collect the top 100 videos with their (automatically generated) captions. YouTube generates these captions by using an Automatic Speech Recognition (ASR) algorithm unless the user manually uploads them. After obtaining the corpus, we link similar videos to each other by creating a kNN video graph. As a distance metric, we use the χ^2-distance of bag-of-words extracted from the video descriptions. After the creating the graph, we compute the dominant video cluster by using the Single Cluster Graph Partitioning (SCGP)[42] and discards the remaining videos as outlier. As an example, in Figure 2 we visualize some of the discarded videos for various queries. As shown in the figure, they are outliers. However, our algorithm also have false positives *i.e.* some related videos are filtered. This does not couse a problem since we still have enough number of videos at the end thanks to the large-scale modelling.

Figure 2: **Sample videos which our algorithm discards as an outlier for various queries.** First row include a video about a toy milkshake, a milkshake charm and a funny video about How to NOT make smoothie. Second row is a frozen yogurt recipe errornously labeled as *how to make a yougurt?*, an informative video about the danger of a fire while cooking and a cartoon about pancake. The final row is a neck-tie video errornously labeled as bow-tie, a song including the phrase *How to tell if a gold is real?* and a lamb cooking video mislabeled as *How to bake chicken?*

3.2. Semantic Multi-Modal Frame Representation

We represent each frame in terms of language and visual atoms. These atoms are the salient words and semantic objects which allows us to find representations, general enough to relate visually different frames of the same activity, and discrimanitive enough to distinguish different activities without supervision. We explain how to find them in the subsequent sections.

Learning Visual Atoms In order to learn visual atoms, we create a large collection of object proposals by independently generating region proposals from each frame of the each video. These proposals are generated by using the Constrained Parametric Min-Cut (CPMC) [7] algorithm by using both appearance and motion cues. We note the k^{th} region of t^{th} frame of i^{th} video as $r_t^{(i),k}$. Moreover, we drop the video index (i) if it is clear from the context.

In order to group this regioin proposals into sementically meaningful objects, we follow the spectral graph clustering approach similar to the Keysegments [35]. However, the joint processing of videos bring additional difficulties. Images of same objects coming from different videos have high visual diference. Moreover, basic clustering methods fail due to high inter-class variance. Hence, we propose a spectral joint clustering of region proposals over multiple videos in Section 3.3.

Learning Language Atoms We learn the language atoms as the salient words which occur more often than their ordinary rates based on *tf-idf* measure. We define the *document* 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, $f_{w,D}$ 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.

After computing the tf-idf, we sort all words with their tf-idf values and choose the top K words as set of salient words (*We set* $K = 100$ *in our experiments*).

We show below the top 50 salient words extracted for the query *How to hard boil an egg?*[2]. The resulting collection suggests that they correspond to the important objects, actions and adjectives which represent a semantic information occuring in multiple videos.

sort, place, water, egg, bottom, fresh, pot, crack, cold, cover, time, overcooking, hot, shell, stove, turn, cook, boil, break, pinch, salt, peel, lid, point, high, rules, perfectly, hard, smell, fast, soft, chill, ice, bowl, remove, aside, store, set, temperature, coagulates, yolk, drain, swirl, shake, white, roll, handle, surface, flat

Multi-Modal Representation of Frames After learning the objects and salient words, we represent each frame via the occurrence of salient words and objects. Formally, representation of the t^{th} frame of the i^{th} video is denoted as

[2] we include more results in the supplementary material

$\mathbf{y_t^{(i)}}$ and computed as $\mathbf{y_t^{(i)}} = [\mathbf{y_t^{(i),l}}, \mathbf{y_t^{(i),v}}]$ such that k^th entry of the $\mathbf{y_t^{(i),l}}$ is 1 if the subtitle of the frame has the k^{th} word and 0 otherwise. $\mathbf{y_t^{(i),v}}$ is also a binary vector similarly defined over objects. We visualize the representation of a sample state in the Figure 3.

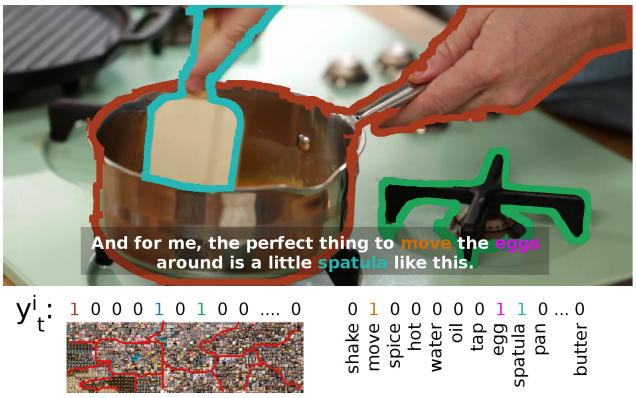


Figure 3: **Visualization of the representation of a sample frame.** 3 of the region proposals of the frame is included in the object clusters and 3 of the words in the subtitle of the frame is included in the salient word list.

3.3. Joint Region Proposal Clustering:

Given set of region proposals generated from multiple videos, combining them into a single collection and clustering them is not desired for two reasons; (1) objects have large visual differences among videos and accurately clustering them into a single cluster is hard, (2) clusters are desired to have region proposals from multiple videos in order to semantically relate videos. We propose a joint version of the spectral region clustering algorithm to satisfy these requirements.

We first explain the original spectral graph clustering algorithm and then extend it to joint clustering. Consider the set of region proposals extracted from a single video $\{r_t^k\}$, and a similarity metric $d(\cdot,\cdot)$ between any region proposal pair. We follow the single cluster graph partitioning (SCGP)[42] approach to find the dominant cluster which maximizes the inter-cluster similarity. In other words, we solve

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

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. When we use the vector form of the indicator variables as $\mathbf{x_{tK+k}} = x_t^k$ and the pairwise distance matrix as $\mathbf{A}_{t_1K+k_1,t_2K+k_2} = d(r_{t_1}^{k_1}, r_{t_2}^{k_2})$, this equation can be compactly written as $\arg\max_{\mathbf{x}} \frac{\mathbf{x^T}A\mathbf{x}}{\mathbf{x^T}\mathbf{x}}$

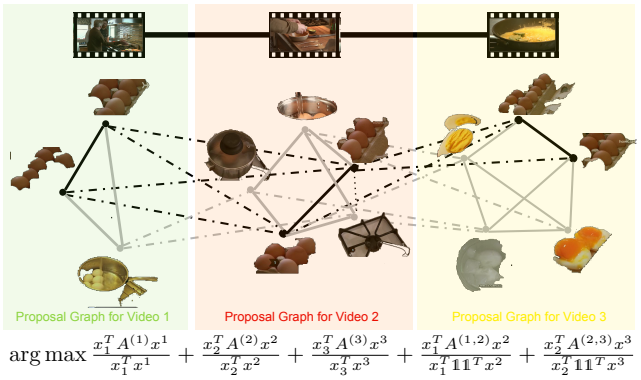


Figure 4: **Visualization of the joint proposal clustering.** Here, we show the 1NN video graph and 2NN region graph. Each region proposal is linked to its 2 nearest neighbours from the video it belongs and 2 nearest neighbours from the videos it is neighbour of. THIS NEED WORK

Moreover, it can be solved by finding the dominant eigenvector of $\mathbf{x}$ after relaxing x_t^k to $[0,1]$ [42, 45]. After finding the maximum, the remaining clusters can be found by removing the selected region proposals from the collection, and re-applying the same algorithm for the second dominant cluster.

Our extension of the SCGP into multiple videos is based on the assumption that the important objects of recipes occur in most of the videos. Hence, we re-formulate the problem by relating videos to each other. We use the kNN graph of the videos which we used for the outlier detection as explained in the Section 3.1. Moreover, we also create the kNN graph of region proposals in each video. This hierarchical graph structure is also visualized in Figure 4 for 3 videos example. After creating this graph, we choose region proposals for a cluster from each video seperately. Moreover, we impose both inter-video and intra-video similarity of chosen proposals. Main rationale behind is having seperate notion of similarity for inter-video and intra-video clusters since their visual similarity decreases drastically for intra-video case.

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

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

where $\mathcal{N}(i)$ is the neighbours of the video i in the kNN graph, $\mathbb{1}$ is vector of ones and N is the number of videos. We visualize this optimization objective in Figure 4 for the case of 3 videos.

Although we can not use the efficient eigen-

decomposition based approach from [42, 45] due to the modified cost function, we can use Stochastic Gradient Descent (SGD) since the cost function is quasi-convex when it is relaxed. We use the SGD with the following analytic gradient function;

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

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

After finding the dominant cluster by optimizing the cost function, we remove the selected cluster and re-apply the same algorithm to find the next dominant cluster. After finding $K = 20$ clusters, we discard the remaining region proposals. In Figure 5, we visualize some of the clusters which our algorithm generated after applied on the videos returned by the query *How to Hard Boil an Egg*. As shown the figure, the resulting clusters are highly correlated and correspond to semantic objects&concepts.

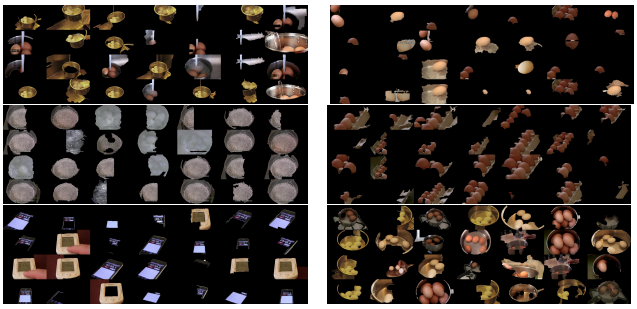


Figure 5: Randomly selected images of randomly selected clusters learned for *How to hard boil an egg?*

3.4. Unsupervised Activity Representation

In this section, we explain the generative model which we use in order to jointly learn the activities from videos. We start with explaining the notation. As we already defined in the previous sections, we note the extracted frame representation of the frame t of video i as $\mathbf{y_t^{(i)}}$. Moreover, we model our algorithm based on activities and the note the activity of the t^{th} frame of the i^{th} video as $z_t^{(i)}$. Since our model is non-parametric, the number of activities are not fixed *i.e.* $z_t^{(i)} \in \mathcal{N}$.

We model each activity as 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 represents the likelihood of seeing m^{th} language word in the frame having activity k. Similarly, m^{th} entry of the θ_k^v represents the likelihood of seeing m^{th} object. In other words, each frame's representation $\mathbf{y_t^{(i)}}$ is sampled from its activity distribution 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* –.

In the following sections, we first explain the generative model which links activities and frames. Then, we explain how this model can be jointly learned and inferred by using the combination of Gibbs sampling and Metropolis-Hasting samplers.

3.4.1 Beta Process Hidden Markov Model

For joint understanding of the time-series information, Fox et al.[13] proposed the Beta Process Hidden Markov Models (BP-HMM). It relies on the set of features(activities in our case) which can explain the behaviour of all time-series data (all videos in our case). In BP-HMM setting, each time-series data exhibits a subset of available features.

In our model, each video i chooses a set of activities through an activity vector $\mathbf{f^{(i)}}$ such that $f_k^{(i)}$ is 1 if i^th video has activity k, it is 0 otherwise. When the activity vectors of all videos are concatenated, it becomes an activity matrix $\mathbf{F}$ such that i^th row of the $\mathbf{F}$ is the activity vector $\mathbf{f^{(i)}}$. Moreover, each feature k also has a prior probability b_k and a distribution parameter θ_k. Distribution parameter θ_k is the Bernoulli distribution as explained in the Section 3.4. Moreover, its base distribution (B_0) is the *Beta random variable*. In this setting, the activity parameters θ_k and b_k follow the *beta process* as;

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

where B_0 and the b_k are determined by the underlying Poisson process [15] and the feature vector is determined as independent Bernoulli draws as $f_k^{(i)} \sim Ber(b_k)$. After marginalizing over the b_k and θ_k, this distribution is shown to be equivalent to Indian Buffet Process [15]. Where videos are customers and activities are dishes in the buffet. The first video chooses a Poisson(γ) unique dishes. The following video i chooses previously sampled activity k with probability $\frac{m_k}{i}$, proportional to the number of videos (m_k) chosen the activity k, and it also chooses Poisson($\frac{\gamma}{i}$) new activities. Here, γ controls the number of selected activities in each video and β controls the likelihood of the features getting shared by multiple videos.

After each video chooses a subset of activities, we model the videos as an Hidden Markov Model (HMM) over the selected activities. Each frame has the hidden state activity id($z_t^{(i)}$) and we observe the binary representation $\mathbf{y_t^{(i)}}$. Since we model each activity as a Bernoulli distribution, the emission probabilities follow the Bernoulli distribution as $p(\mathbf{y_t^{(i)}}|z_t^{(i)}) = Ber(\theta_{z_t^{(i)}})$. Following the construction of the Fox et al.[13], we sample the transition probabilities from a normalized Gamma distribution. For each video

i, we sample a Gamma random variable for the transition between activity j and activity k if both of the activities 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 have proper transition probabilities. This procedure can be represented formally as

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

Where κ is the persistence parameter promoting the self state transitions to have more coherent temporal boundaries, $\circ$ is the element-wise product and π_j^i is the transition probabilities in video i from state j to all states in the form of a vector. This model is also presented as a graphical model in Figure 6

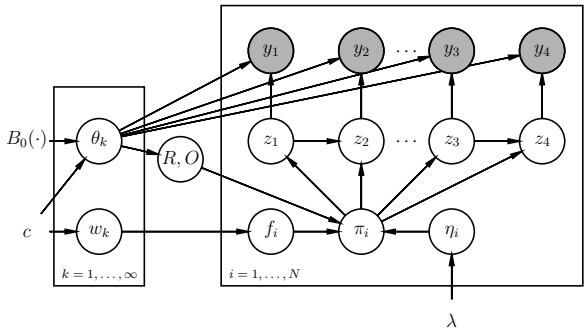


Figure 6: **Graphical model for BP-HMM:** The left plate represent the set of activities and right plate represent the set of videos. Each video choose a subset of activities through $\mathbf{f}^{(\mathbf{i})}$ and transition probabilities between them. After the features are selected, the marginal model of the each video becomes an Hidden Markov Model. *See the text for the details.*

3.4.2 Gibbs sampling for BP-HMM

We employ Markov Chain Monte Carlo (MCMC) method for learning and inference of the BP-HMM. We base our algorithms on the MCMC procedure proposed by Fox et al.[13]. Our sampling procedure composed of iterative sampling of activity assignments ($\mathbf{f}^{(\mathbf{i})}$) from the current activity means $\theta_{\mathbf{k}}$, state assignments $z_t^{(i)}$ and observations $y_k^{(i)}$, and HMM parameters η,π,$\theta_{\mathbf{k}}$ from the selected activities $\mathbf{f}^{(\mathbf{i})}$. We give the details of the sampler in the supplementary material.

4. Experiments

In order to experiment the proposed method, we first collected a dataset guided by the human preferences captured via the statistics of a popular online recipe collection –wikiHow [1]–. After collecting the dataset, we labelled small part of the dataset with frame-wise activity labels and used the resulting set as an evaluation corpus. Neither the set of labels, nor the temporal boundaries are exposed to the competing algorithm since the set-up is completely unsupervised. We experiment our algorithm against the set of unsupervised clustering baselines and state-of-the-art algorithms from video summarization literature which are applicable. In the rest of this section, we first explain the dataset we collected and labelled in detail. Then, we explain the method which we compare our method against. After explaining the metrics we use, we give both qualitative and quantitative results. Due to the space limitation, we defer some of the results to the supplementary material.

4.1. Dataset

We guide our data collection effort with human preferences based on wikiHow [1] statistics. After obtaining the top100 queries people interested in wikiHow, we chose top25 ones which are directly related to the physical world and objects. We ignore the queries like *How to get over a break up?* and *How to write a resignation Letter?*. Resulting 25 queries are;

How to*Bake Boneless Skinless Chicken, Cook Steak in a Frying Pan, Make Jello Shots, Tell if Gold Is Real, Bake Chicken Breast, Hard Boil an Egg, Make Pancakes, Tie a Bow Tie Broil Steak, Make a Grilled Cheese Sandwich, Make Scrambled Eggs, Tie a Tie, Clean a Coffee Maker, Make a Milkshake, Make Yogurt, Unclog a Bathtub Drain, Cook an Omelet, Make a Smoothie, Poach an Egg, Cook Lobster Tails, Make Beef Jerky, Remove Gum from Clothes, Cook Ribs in the Oven, Make Ice Cream, Tell if an Egg is Bad*

For each of the recipe, we queried YouTube and crawled the top 100 videos. We also downloaded the English subtitles if they exist. For evaluation set, we choose 5 videos out of 100 per query. Hence, we have total of 125 evaluation videos and 2375 unlabelled videos. We label the start and end frames of fine-grained activities (*i.e.* steps of the recipe) as well as their labels. We also release the collected dataset at `http://anonymous.edu/MMRecipe`.

4.2. Implementation Details

Aligning Clusters: While comparing the results of our algorithm with the ground truth, we have an alignment problem. Our algorithm generates arbitrary IDs for clusters and the cluster IDs are not necessarily matching the ground truth IDs since the method is unsupervised. For example, we can name the activity 1 of ground truth as activity 3 although their content is same. So, we apply an alignment procedure and choose the alignment of cluster IDs which maximizes the intersection over union with the ground truth. We apply this method to all competing algorithms for fairness.

4.3. Qualitative Results

In this section, we visualize some of the results of our recipe understanding method. After running our algorithm independently on all 25 recipes according to the details we explain in Section 4.2, we obtain set of clusters which correspond to the activities. These clusters have set of objects and words; moreover, we also have video clips from multiple videos corresponding to activities. We visualize some of the recipes qualitatively in Figure 7a and 7b. We show the temporal segmentation of 5 evaluation videos as well as the segmentation we compute. Moreover, we also color code the clusters to visualize how well the semantic activities are learned.

To visualize the content of each cluster, we display informative frames from different videos. We also train a 3rd order Markov language model[**?**] by using the subtitles covered by the cluster. Moreover, we generate a caption for each cluster by sampling this model conditioned on the θ_k^l. We explain the details of this process in supplementary material since it is orthogonal to the algorithm and only included for qualitative analysis of language information.

As shown in the Figures 7a&7b, resulting clusters are semantically meaningful and correspond to the real activities. 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 activities in the ground truth are not detected by our algorithm and they got merged into other clusters because they generally occur only in a very few videos.

4.4. Quantitative Results

4.4.1 Baselines

We compare our algorithm with the following baselines in the following sections.

HMM with semantic features: In order to experiment the importance of joint processing of the videos, we compare our algorithm with independent temporally coherent clustering of each video. We are using Hidden Markov Models with Baum-Welch algorithm[48] as a clustering method and choose the number of clusters with cross-validation.

BP-HMM with low-level features: In order to experiment the importance of defining objects, we also train our algorithm without using extracted object. We simply temporally over-segment the video and represent each segment by using state of the art low-level features from the activity detection literature [**?**]. We are using dense trajectory features for this purpose.

Kernel Temporal Segmentation[47]: Kernel Temporal Segmentation (KTS) proposed by Potapov et al.[47] 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.

4.4.2 Metrics

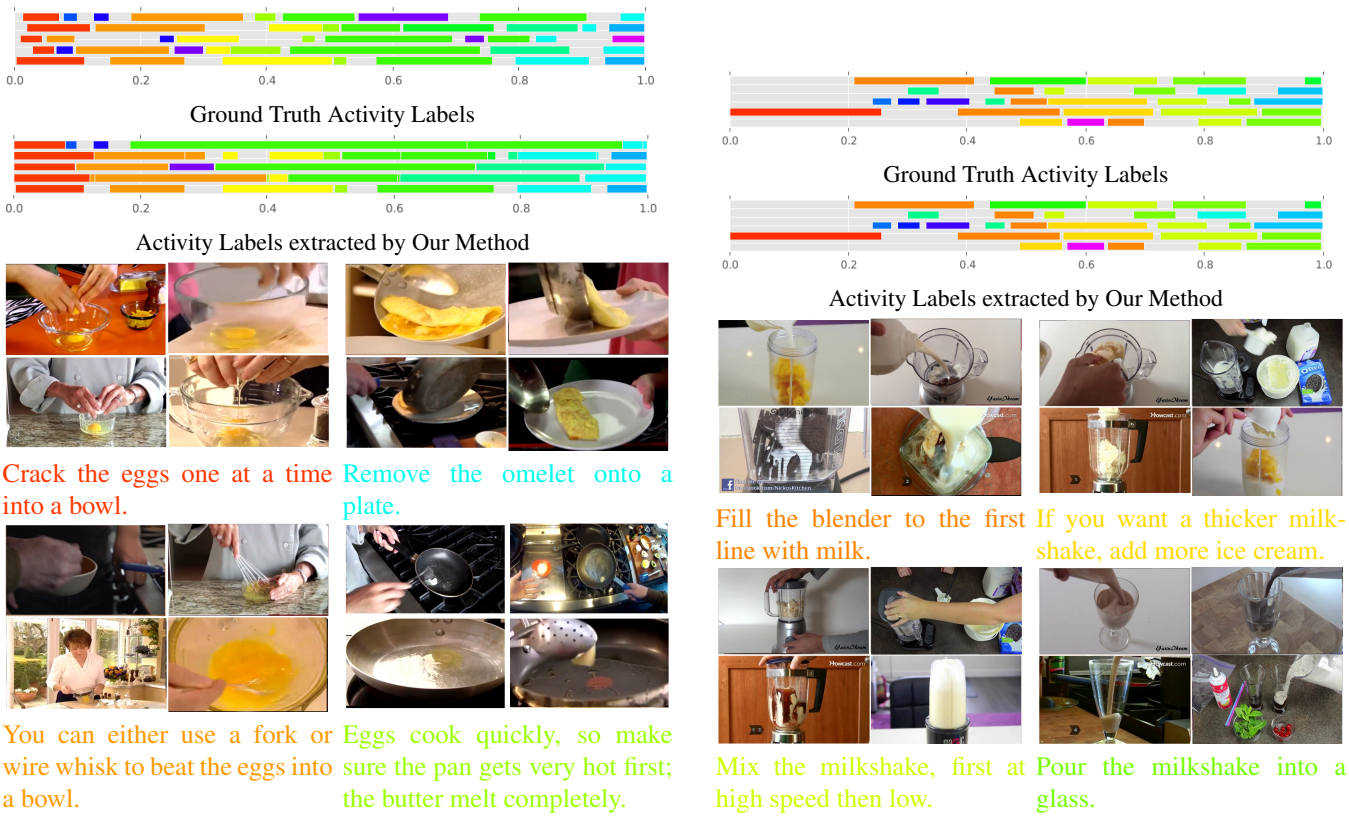
Maximum Intersection over Union (IOU_{max}): In order to evaluate the accuracy of the temporal segmentation of the activities, we use intersection-over-union(IOU). For N ground truth temporal activity segments ($\tau_i^\star, \quad i \in N$), N' computed segments ($\tau_i', \quad i \in N'$) and matching function $m(\cdot)$ such that i^{th} ground truth segment is matched to $m(i)^{th}$ computed segment, we define IOU as $IOU = \frac{1}{N}\sum_{i=1}^{N} \frac{\tau_i^\star \cap \tau'_{m(i)}}{\tau_i^\star \cup \tau'_{m(i)}}$. Since the matching function is unknown in the supervised setting, we use the maximum intersection-over-union while doing exhaustive search over all matchings as; $IOU_{max} = \max_{m(\cdot)} \frac{1}{N}\sum_{i=1}^{N} \frac{\tau_i^\star \cap \tau'_{m(i)}}{\tau_i^\star \cup \tau'_{m(i)}}$

Maximum Average Precision (AP_{max}): Since the IOU_{max} is computed per video, it does not capture the accuracy of the detected activities over multiple videos. Hence, we also evaluate maximum average precision. Given matching function $m(\cdot)$, we compute the mean of average precision over recipes. Note that this metric is defined over all the videos in the recipe and can only be high if the the same activities from multiple videos clustered into a single activity.

4.4.3 Results

We discuss the quantitative and qualitative results in the light of the following questions.

Are the activities detected accurately? In this section, we discuss the results presented in Figure 8. Maximum-IOU captures the accuracy of the temporal segmentation of the videos. Since the ground-truth segmentation is the semantic one, high IOU_{max} requires both finding temporal activity boundaries and extracting correct activity definition. As shown in the Figure 8, proposed method consistently outperforms the competing algorithms. One interesting observation is the dramatic difference between the accuracy of HMM and our method. We believe this is the result of joint processing of multiple videos. HMM assumes all videos are generated from same set of activities with fixed transition probabilities and can not captures the inter-class variance. On the other hand, our algorithm is robust to inter-class variations since we are also modelling inclusion of activities for each video. Moreover, the segmentation problem is ill-posed since the granularity of the activities are subjective. Imposing the activity inclusion model brings an additional constraint to the problem and makes the problem well-posed as finding the set of small number of activities which can construct the any video within the context of the recipe. In other words, the segmentation problem becomes



(a) How to make an omelet?

(b) How to make a milkshake?

Figure 7: Temporal segmentation of the videos by our method and ground truth segmentation. We also color code the learned activity labels and visualize sample frames and the automatically generated captions for some of them. *Best viewed in color.*

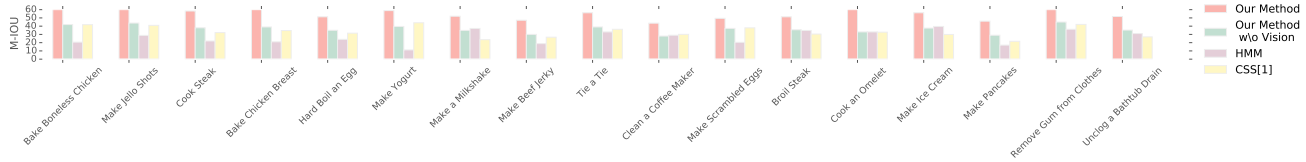


Figure 8: IOU_{max} values for all recipes, for all competing algorithms.

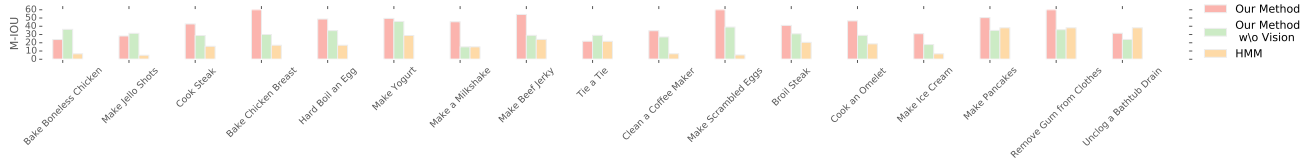


Figure 9: AP_{max} values for all recipes, for all competing algorithms.

learning the small dictionary of activities which is complete for the space of the recipe.

Here, we also include the average over the recipes

Are the same activities in different videos linked to each other? Although IOU_{max} successfully measures the accuracy of the detected activities, it can not measure the

Table 1: Average of IOU_{max} and mAP_{max} over recipes.

	KTS [47] w/ LLF	KTS[47] w/ Sem	HMM w/ LLF	HMM w/Sem	Ours w/ LLF	Ours w/o Vis	Ours w/o Lang	Our full
IOU_{max}		26.91		33.16		36.58	57.63	
mAP_{max}	n/a	n/a		18.9		30.50		43.20

Table 2: Semantic mean-average-precision mAP_{sem} computed based on subjective evaluation.

	HMM w/ LLF	HMM w/Sem	Ours w/ LLF	Ours w/o Vis	Ours w/o Lang	Our full
mAP_{sem}		11.79		29.83		39.01

matching activities over different videos. Therefore, we are using mAP_{max} for measuring the accuracy of matching different activities over multiple videos. mAP_{max} is defined for each activity class and requires the algorithms to produce activity labels consistent with the ground truth.

In order to further evaluate the role of semantics, we performed a subjective analysis in order to remove the maximization. Since, we have an evaluation set -ground truth activity labels-, we concatenated them into a label collection. Then, we collected the outputs of our algorithm, HMM and the variations of our algorithm to non-expert users and ask them to choose a label. In other words, we replaced the maximization with subjective labelling. We designed our experiments in a way that each clip received annotations from 5 different users. Moreover, we randomized the ordering of videos and algorithms during the subjective evaluation. We compute the mean average precision and call it mAP_{sem}. We also only used 5 random recipes out of 25.

How important is each modality? In order to experiment the importance of using both language and vision modalities, we compare our method with a self-baseline of using a single modality. As shown in Figure 8 and 9, our method significantly outperforms both of the baselines consistently in all recipes. Hence, we need to use both modalities. This result is expected because visual cues are good at separating different activities within the same video since the visual appearance is not changing much. However, language does not help much since there is too much background information other than the actual activity. On the other hand, language is good at relating activities from different videos since there is not much inter-class variation and it is easy to detect these variations caused by synonyms etc. thanks to the strong structure of the language modality.

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