Youtube2Story: Unsupervised Joint-Representation of Instructional Videos

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Paper ID ****

Abstract

The ABSTRACT

1. Introduction

Leaning the instructions of a novel non-trivial task is both a challange and a necessity for both humans and autonomous systems. This necessity resulted in many community generated instruction collections [**?**, **?**] and expert curated recipe books[**?**, **?**]. However, this instructions are generally based on a language modality and explains a single way of performing the task although there are variety of ways. On the other hand, online video storage services are full of unstructured instructional videos[1] covering variety of ways, environment conditions and view angles. Although there have been many succesfull attempts in detecting activities from videos [**?**, **?**], structural representation of such a large and useful video collection is not possible. In this paper, we focus on joint semantic representation of YouTube videos as a response to a single query. We specficially study the unsupervised joint-detection of the activities from a collection of YouTube videos.

Understanding of the instructional videos, requires the careful processing of two complementary modaliities namely language and the vision. Luckily the target domain, YouTube videos, has unstructured subtitles as well. They are either generated by the content developer (5% of the time) or automatically generated by using the Automatic Speech Recognition (ASR) softwares. The main limitations of the existing activity detection literature for this problem is scalability and representation level. Existing approaches are mainly supervised and requires extensive training set which is not tractable in the scale of YouTube videos. Moreover, current activity detection research focuses on the low-level visual features. However, such videos in the wild have objects with completely different texture and shape characteristics from wide range of views. Instead, we focus on extracting high-level visual semantic representations and using salient words occuring among the videos.

We rely on the assumption that the videos collected as the response of a same instructional query, share similar activities performed by the similar objects. We start with the independent processing of the videos in order to create a large collection of visual object proposals and words. After the proposal generation, we jointly process the proposal collections and words to detect the visual objects and words which can be used to represent the unstructured information. Since we rely on high-level information instead of the low-level features, the resulting objects represent the semantic information instead of visual characteristic. By using the extracted objects, we compute the holistic representation of the multi-modal information in each frame.

Moving from frame-wise visual understading to activity understanding, requires the joint processing of all the videos with the temporal information. In order to exploit the temporal information, we model each video as a Hidden Markov Model using state space of activities. Since we assume that the videos share some of the activities and we have no supervision, we use a model based on *beta process mixture model*. Our model jointly learn the activities and detect them in the videos. Moreover, it does not require prior knowledge over the number of activities.

2. Related Work

Video Summarization Summarizing an input video as a sequence of keyframes (static) or as a sequence of video clips (dynamic) is useful for both multi-media search interfaces and retrieval purposes. Early works in the area are summarized in [27] and mostly focus on choosing key-frames for visualization. Idea of choosing key-frames is also extended by using the video tags by Hong et al[8] and using the spatio-temporal information by Gygli et al.[7].

Summarizing videos is crucial for ego-centric videos since the ego-centric videos are generally long in duration. There are many works which succesfully segment such videos in to a sequence of important shots [15, 16]; however, they mostly rely on specific features of ege-centric videos. Rui et al. [23] proposed another dynamic summarization method based on the excitement in the speech of the

[1] YouTube has 281.000 videos for *"How to tie a bow tie"*

reporter. Due to their domain specific designs, these algorithms are not applicable to the general instructional videos.

Same idea is also applied to the large image collecitons by recovering the temporal ordering and visual similarity of images [12]. This image colelctions are further used to choose important view points for video key-frame selection by Khosla et al.[10]. And further extended to video clip selection by Kim et al[11] and Potapov et al.[22]. Although they are different from our approach since they do not use any high-level semantic information or the language information, we experimentally compare our method with them.

Understanding Multi-Modal Information: Learning the relationship between the visual and language data is a crucial problem due to its immense multimedia applications. Early methods [1] in the area focus on learning a common multi-modal space in order to jointly represent language and vision. They are also extended to learning higher level relations between object segments and words [24]. Zitnick et al.[30, 29] used abstracted clip-arts to further understand spatial relations of objects and their language correspondences. Kong et al. [14] and Fidler et al. [5] both accomplished the same task by using the image captions only. Relations extracted from image-caption pairs, are further used to help semantic parsing [28] and activity recognition [20]. Recent works also focused on generating image captions automatically using the input image. These methods range from finding similar images and using their captions [21] to learning language modal conditioned on the image [13, 25, 4]. And the methods to learn language models vary from graphical models [4] to neural networks [25, 13, 9].

All afforementioned methods are using supervised labels either as strong image-word pairs or weak image-caption pairs. On the other hand, our method is fully unsupervised.

Activity Detection/Recognition:

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 [18, 26] focus on semantic parsing of language recipes in order to extract actions and the objects in the form of predicates. Tenorth et al.[26] further process the predicates in order to form a complete logic plan. Mori et al.[19] 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. We have also seen recent advances [2, 3] in robotics which uses the parsed recipe in order to perform cooking tasks. They use supervised object detectors and report a succesfull autonomous cooking experiment. In addition to the language based approaches, Malmaud et al.[17] 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 recipe. There is also an approach which generates multi-modal recipes from expert demonstrations [6]. However, it is developed only for the domain of *teaching user interfaces* and are not applicable to the videos.

3. Method

In this section, we explain the high-level compenents of the method we develop to jointly represent multi-modal instructions. As shown in the Figure **??**, our proposed method consists of three major components; online query and filtering, frame-wise multi-modal representation and joint clustering to extract activities. **(1) Query subsystem:** Our system starts with querying the YouTube with an *How to* question for top 100 videos. The text descriptions of the returned videos are represented as bag-of-words and clustered to eliminate outliers. **(2) Framewise Representation:** In order to represent the frames of the returned videos, we process both the visual and language content of the videos. We extract the object proposals and jointly cluster them in order to detect the salient objects of the recipe. For the language descriptions, we use the top salient words of the courpus generated by concatenation of the all subtitles. We represent each frame in terms of the resulting salient objects and words. **(3) Unsupervised Activity Detection:** After describing each frame by using the salient objects and words, we apply a non-parametric Bayesian method in order to find the temporally consistent video clip clusters occuring over multiple videos. Our empirical results suggest that the resulting clusters mostly correspond to the activities. We now explain the details of the each sub-system in the following sections.

3.1. Semantic Multi-Modal Frame Representation

We represent the each frame of input videos as in terms of set of language and visual atoms. Language atoms are the salient words detected via ranking tf-idf like measure, and the visual atoms are found via clustering over object proposals which we extract from frames. We explain the details of finding the atoms and representing the frames in the subsequent sections.

3.1.1 Learning Language Atoms

In order to detect the salient words, we use tf-idf like measure. For each recipe, we concatanate all subtitles into a single term corpus. As a document corpus, we use all the

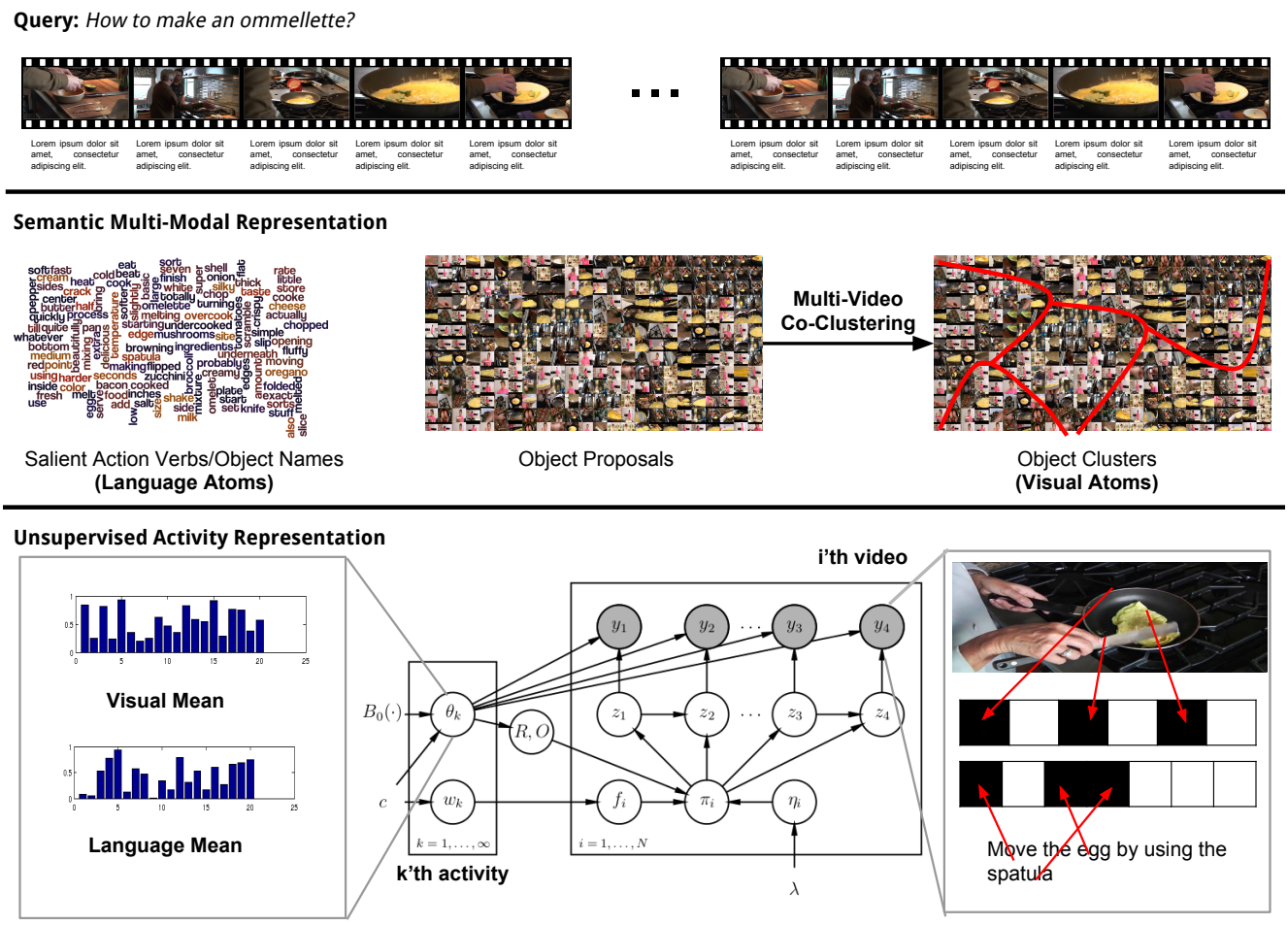


Figure 1: Components of our recipe understanding method. **Query:** We query the YouTube for top 100 *How To* videos and filter the outliers; **Framewise Representation:** We automatically extract object clusters and salient word in order to find multi-modal representation of each frame. **Unsupervised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

words extracted from all recipes. Moreover, we compute the tf-idf as $tfidf(w, d, D) = f_{w,d} \times \log \frac{N}{n_w}$ where w is the word, d is the corpus of the recipe, $f_{w,d}$ is the frequency of the word in the recipe, N is the total number of videos in all recipes and n_w is the number of videos whose subtitle include the word w. After computing the tf-idf, we sort all words with their tf-idf values and choose top K words as set of salient words (*We set* $K = 100$ *in our experiments*).

3.1.2 Learning Visual Atoms

In order to learn visual atoms, we initially generate object proposals from each frame of each videos. This proposals are generated by using apperance and motion cues via the Constrained Parametric Min-Cut (CPMC) [**?**] algorithm. We apply CPMC algorithm to each frame of the each video returned by the query independently and create a collection of region proposals. 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.

We follow the spectral graph clustering approach in order to group these regions into semantically meaningful objects similar to the KeySegments by Lee et al.[**?**]. Moreover, idea of clustering region proposals into semantic objects have been mostly utilizied for clusters generated by a single video and they fail to cluster objects having a large visual difference. Hence, we extend this work to spectral joint clustering of region proposals.

Joint Proposal Clustering to Detect Visual Objects Since our proposals are generated from multiple videos, combining them into a single region collection and clustering it is not desired for two reaons; (1) the objects have large visual differences among different videos and accurately clustering them into a single object is hard, (2) objects clusters are desired to have region proposals from multiple videos in order to relate videos easily. Hence, we propose a joint version of the spectral region clustering algorithm.

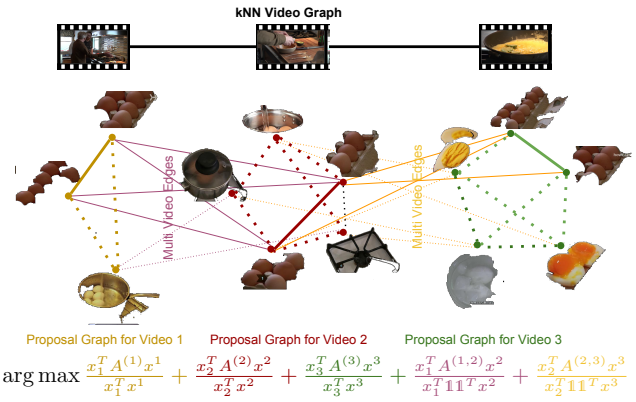


Figure 2: Visualization of the joint proposal clustering.

Here, we first explain the original spectral graph clustering algorithm and then extend it to our joint version. Consider set of region proposals extracted from a single video r_t^k, and a similarity metric $d(\cdot,\cdot)$ which assigns similarity between each region pair. We follow the Single Cluster Graph Partitioning (SCGP)[**?**] to find the dominant cluster which maximizes the inter-cluster similarity. In other words, we solve

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

Where, $x_t^{i,k}$ is a binary variable which is 1 if $r_t^{(i),k}$ is included in the cluster. Moreover, we drop the video index for clarity. 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 $\arg\max_{\mathbf{x}} \frac{\mathbf{x^T} A \mathbf{x}}{\mathbf{x^T x}}$ Moreover, it can be solved by computing the dominant eigenvector of $\mathbf{x}$ after relaxing it to $[0, 1]$ from binary [**?**, **?**]. After finding the maximum, the remaining clusters can be found by removing the selected region proposals from the collection, and re-aplying the same algorithm for the second dominant cluster.

Our extension of the SCGP into multiple videos is based on the assumption that the dominant objects occur in most of the videos. Hence, we re-formulate the problem by relating videos to each other. We start with creating the kNN graph of videos based on their language description similarities. Moreover, we also create the kNN graph of region proposals in each video. This hierarchical graph structure is visualized in Figure 2. After creating this graph, we impose the similarity of regions coming from each video as well as the similarity of regions coming from neighbour videos. Hence, given the pairwise distance matrix $\mathbf{A^{(i)}}$, 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;

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

where $\mathcal{N}(i)$ is the neighbours of the video i in the kNN graph and $\mathbb{1}$ is vector of ones. We visualize this optimization objective in Figure 2 for the case of 3 videos and 1-NN video graph, 2-NN region proposal graph.

After changing the optimization function, we can not use the efficient eigen-decomposition based approach from [**?**, **?**]; however, we can use stochastic gradient descent (SGD) since the cost function is quasi-convex when it is relaxed. Hence, we use SGD with the following gradient function;

$$\text{Some vector matrix multiplication} \quad (3)$$

In Figure 3, 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.

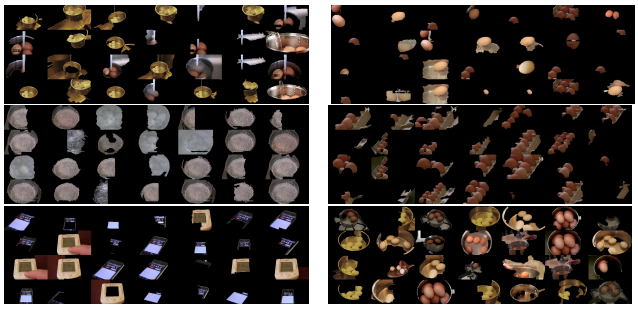


Figure 3: Randomly selected images of randomly selected clusters learned for *How to boil an egg?*

3.2. Multi-Modal Representation via Learned Atoms

4. Unsupervised Activity Representation

Here we explain the generative model which we use in order to jointly learn the activities from videos. We start with explaining the basic notation we use in the model. We denote the t^{th} frame of the i^{th} video as I_t^i and its subtitle as

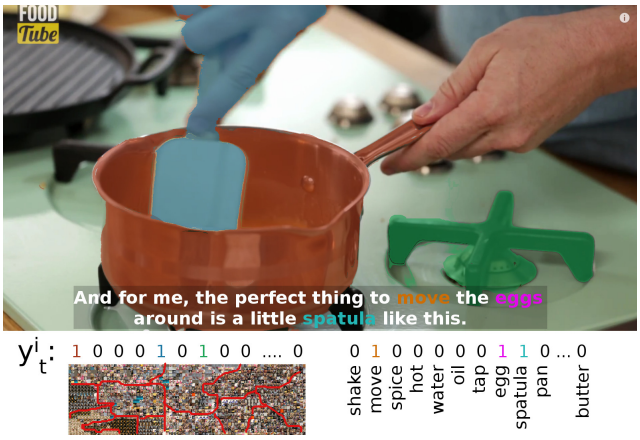


Figure 4: Visualziation of the representation of the Frame.

L^i_t. Moreover, we note the extracted frame representation as y^i_t. We model our algorithm based on activities and the note the activity of the t^{th} frame of the i^{th} video as z^i_t. Since our model is non-parametric, number of activities are not fixed and $z^i_t \in \mathcal{N}$.

Frame: Representation of each frame is computed as the occurence vector over the detected language and visual atoms. Formally, frame y^i_t is represented as $y^i_t = [y^{i,l}_t, y^{i,v}_t]$ such that k^th entry of the $y^{i,l}_t$ is 1 if the frame as language atom k and 0 otherwise. $y^{i,l}_t$ is also a binary vector similarly defined over visual atoms. We consider y^i_t as the observed variable and consider the underlying activity label as the hidden state z^i_t. A sample state is visualized in the Figure 4.

Activity: We represent each activity as a Bernoulli distribution over the visual and language atoms. In other words, each frame's representation y^i_t is sampled from its activity distribution as $y^i_t | z^i_t = k \sim Ber(\Theta_k)$. For the sake of clarity, we sample the Θ from its conjugate distribution *Beta distribution*.

In the following sections, we exlpain how these models can be jointly learned and inferred by using the Beta Process Hidden Markov Models. s

4.1. Beta Process Hidden Markov Model

For joint understanding of the time-series information, Fox et al.[**?**] proposed the Beta Process Hidden Markov Models (BP-HMM) using the Indian Buffet Process[**?**] of time-series sequences over features. It assumes that there exist a set of features(activities in our case) which can explain the behaviour of all time-series data (all videos in our case). Each time-series data exhibits a subset of available features. This setup is similar to Hughes et al.[**?**]. However, we differ in the choices of the underlying distributions since we based our model on semantic multi-modal information.

In our model, each video i chooses a set of activities through a activity vector $\mathbf{f^i}$ such that f^i_k is 1 if i^th video has activity k, 0 otherwise. When the feature vectors of all videos in the courpus is concatanated, 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 an activity frequency b_k and a distribution parameter Θ_k. Distribution parameter Θ_k is the Bernoulli distribution as explain in the Section 4. Moreover, its base distribution (B_0) is *Beta random variable* since it is the conjugate of Bernoulli. Moreover, in this setting, the activity paremeters Θ_k and b_k follow the *beta process* as;

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

where B_0 and the b_k are determined by the underlying poisson process [**?**] and the feature vector is determined as independent Bernoulli draws as $f^i_k \sim Ber(b_k)$. After marginilizing over the b_k and Θ_k, this distribution is shown to be equivalent to Indian Buffet Process [**?**]. 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 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 active features 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 videos. Each frame has the hidden state activity id(z^i_t) and we observe the binary representation y^i_t. Since we model each activity as a Bernoulli distribution, the emmition probabilities follow the Bernoulli distribution as $p(y^i_t | z^i_t) = Ber(\Theta_{z^i_t})$. Following the construction of the Fox et al.[**?**], 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 (if f^i_k and f^i_j are both 1). After sampling these random variables, we normalize them to have proper transition probabilities. This procedure can be represented formally as

$$\eta^i_{j,k} \sim Gam(\alpha + \kappa\delta_{j,k}, 1), \quad \pi^i_j = \frac{\eta^i_j \circ f^i}{\sum_k \eta^i_{j,k} f^i_k} \qquad (5)$$

Where κ is the persistence parameter promoting self state transitions to have more coherent temporal bounderies, $\circ$ is the element-wise product and π^i_j 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 5

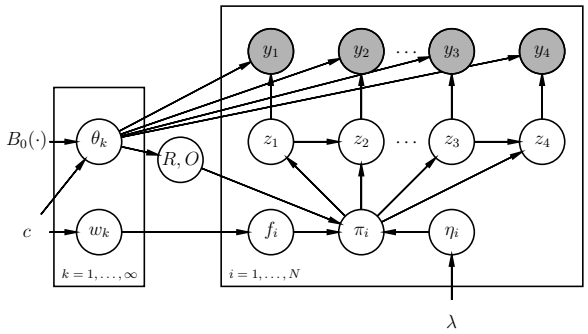


Figure 5: **Graphical model for BP-HMM:**Some explanation.

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.[**?**]. It marginilizes over blah and blah and sample blah and blah. For faster convergence, we also utilize a series of data driven samplers. Here we only discuss the proposed data driven samplers and move the details of the remainin samplers to the Supplementary Material.

Data-Driven Sampler1

Data-Driven Sampler2

5. Experiments

5.1. Dataset

We collected blah blah videos from YouTube and did blah blah... All numbers etc. These are recipes, 5 of them are evaluation set and labelled temporally and labels are matched.

5.2. Baselines

We compare against BP-HMM-O with local feauters and HMM with Semantic Features, HMM with local features, HMM with CNN feautes...

5.3. Qualitative Results

5.4. Accuracy over Activity Detection

5.5. Accuracy over Activity Learning

6. Discussions and Conclusions

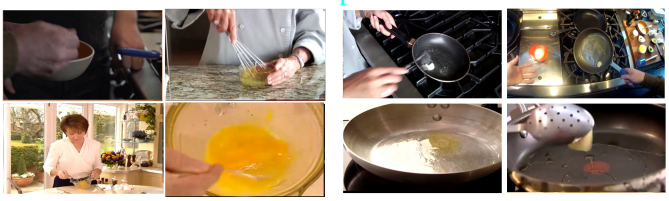
Discuss which recipes worked and why. Discuss the importance of semantic representation, scaling features and multi-modality.

(a) Ground Truth Activity Labels

(b) Activity Labels extracted by Our Method

Crack the eggs one at a time into a bowl.

Remove the omelette onto a plate.



You can either use a fork or wire whisk to beat the eggs into a bowl.

Eggs cook quickly, so make sure the pan gets very hot first; the butter melt completely.

(c) Sample images and the automatically generated captions for some of the clusters.

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Table 1: Notation of the Paper

$y_t = [y_t^v, y_t^l]$	feature representation of t^{th} frame	I_t	t^{th} frame of the video	$x_{i,r}^p$	1 if p^{th} cluster has r^{th} proposal of i^{th} video
x^p	binary vector for p^{th} cluster	L_t	subtitle for t^{th} frame	$O^{k,k'}$	1 if $\#(z_t = k, z_{t'}) = k') = 0 \forall \quad t \leq t'$
$\Theta_k = [\Theta_k^v, \Theta_k^l]$	emmition prob. of k^{th} activity	z_t	activity ID of frame t	f_i^k	1 if i^{th} video has k^{th} activity $0 o.w.$
$\eta_i^{k,k'}$	$P(z_{t+1} = k' \| z_t = k)$ for i^{th} vid	$\pi_i^{k,k'}$	$\eta_i^{k,k'} \times f_i^k \times f_i^{k'}$		

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