Large-Scale Unsupervised Understanding of Multi-Modal Recipes

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Unsupervised Learning of How to Perform a Task

We (humans & robots) are using recipe books since 9th century.

Humans

- ✔ Expert curated solution
- ✘ Generally a single recipe is available
- ✘ Lacks visual information
- ✘ Even if the visual information exists, only a single view with some important parts are occluded

Robots [1,2]

- ✘ Assume common sense knowledge
- ✘ Ambigous language
- ✘ Requires lots of supervision for (partially) succesfull operation.

[1] M. Bollini, J. Barry, and D. Rus, BakeBot: Baking Cookies with the PR2, IROS 2011

[2] M. Beetz, U. Klank, I. Kresse, A. Maldonado, L. Mosenlechner, D. Pangercic, T. Ruhr and M. Tenorth, Robotic Roommates Making Pancakes, Humanoids 2011

Community Driven Solution

YouTube already has large-scale, multi-modal recipes (eg 281,000 video with speech for how to tie a bow tie). For a given query,

- It has multiple ways of performing the task
- It has (automtically generated) language information.
- Videos cover variety of environment conditions, camera angles, close-up etc.

However,

- A typical human will not watch 281,000 videos.
- A robot needs a structured information.

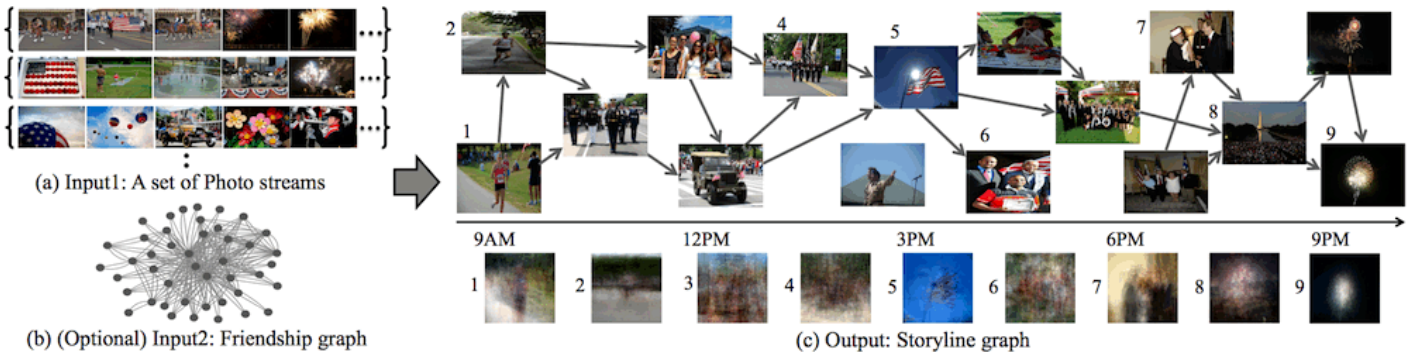
If we can automatically find the activities/steps, we can bring a structure to the videos and summarize 281,000 videos. Win-win scenario for both robots and humans.

Related Work

- Recipe Understanding
  - Cooking with Semantics [J Malmaud et al.]: Parsing text recipes and learning affordances
  - What's Cookin'? [J Malmaud et al.]: Matching a text recipe to the subtitles
  - BakeBot: Baking Cookies with the PR2 [M.Beetz et al.] Extracting a plan out of a recipe
- Multi-Modal Activity Detection/Recognition
  - Grounding Action Descriptions in Videos [M. Regneri]: Can visual data help semantic understanding of sentences?
  - Language Learning from Videos [H. Yu], YouTube2Text [S. Guadarrama], MPII Movie Description [A. Rohrbach]: Generating captions for video clips.

Related Work-2

- Video Summarization
  - Reconstructing Storyline Graphs [G. Kim]: Recovering the temporal dynamics of large photo collection.
  - Understanding Videos, Constructing Plots [A. Gupta]: Given activity labels, summarizing all videos as a graph.



Challanges-Noise

These are part of top 25 results when the query is How to make a milkshake?

Challanges-Visual Variety

Overview

Query: *How to make an ommellette?*

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Semantic Multi-Modal Representation

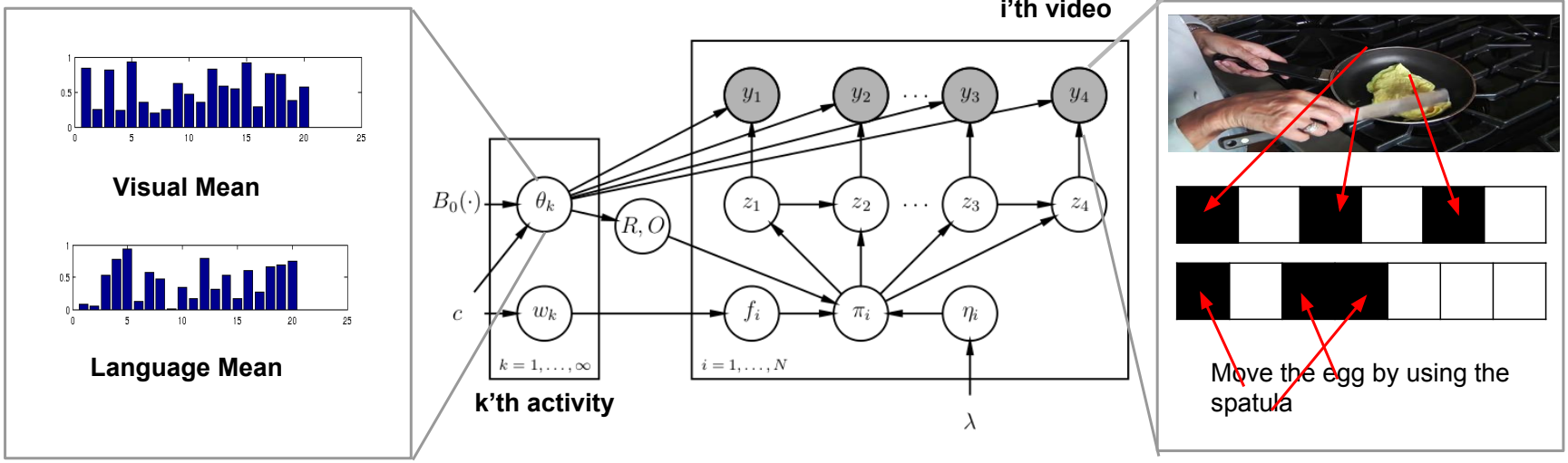
Salient Action Verbs/Object Names
(Language Atoms)

Object Proposals

Multi-Video Co-Clustering

Object Clusters
(Visual Atoms)

Unsupervised Activity Representation



Collecting Data

- For given a query, we download top 100 videos from YouTube.
- Each video has a language description (D_i), and we compute pairwise semantic distances by using Dice coefficients of n-grams ($n = 2$)
- We compute the normalized cut as thresholding the result of; ($A_{i,j} = d(D_i, D_j)$)

$$\arg\max_{x \in [0,1]^{100}} \frac{x^T A x}{x^T x}$$

- Resulting dominant cluster is used for the rest of the video.

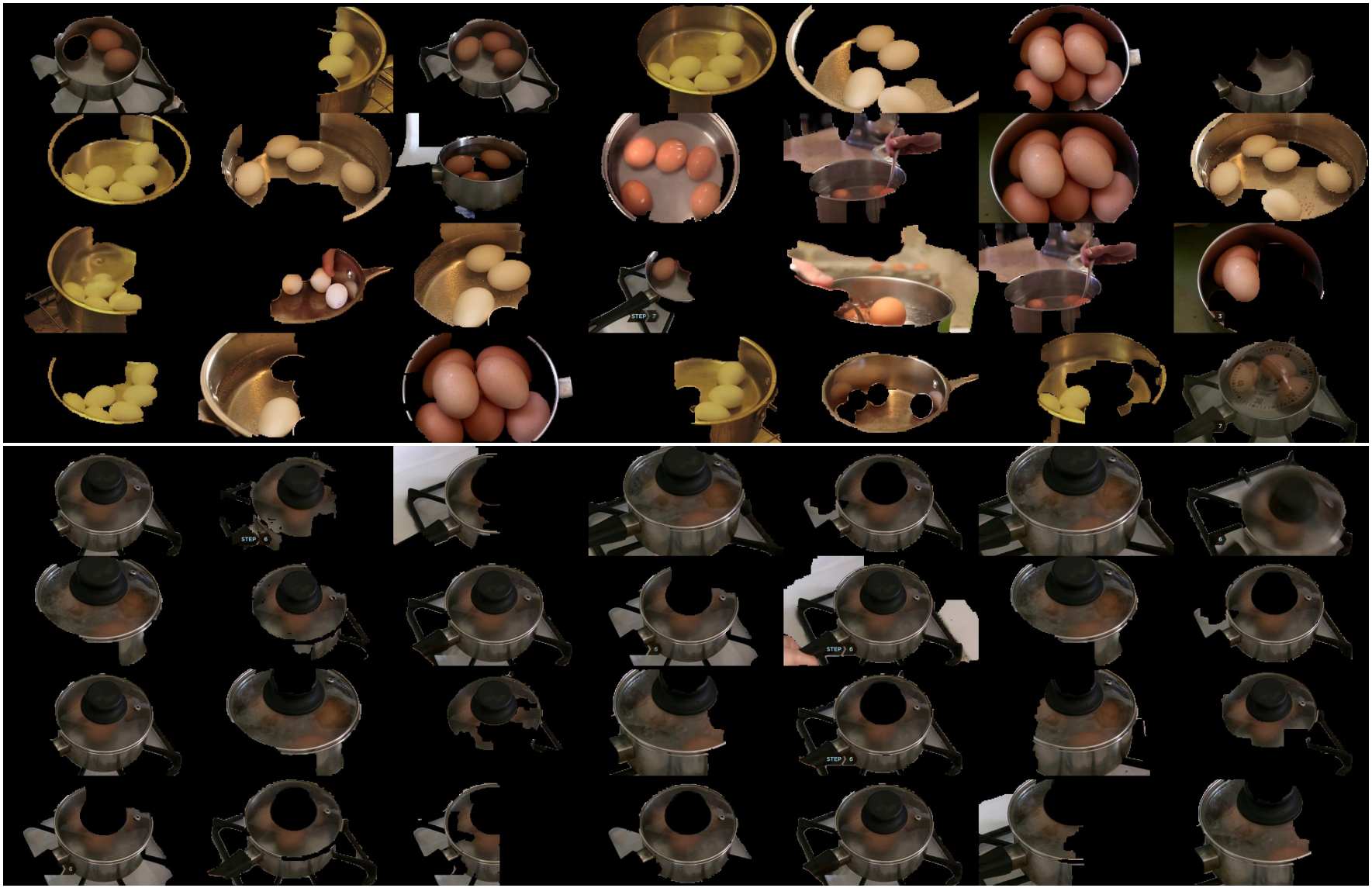
Finding Objects

- We generate object proposals $(P_i^1, \ldots, P_i^R)$ for each frame (t) of each video (i).
- We cluster the proposals in order to find objects; let's say $x_{i,r}^p$ is 1 if p^{th} cluster, has r^{th} proposal of i^{th} video.
- We define the clustering problem as (A is pairwise distance matrix with fc7 AlexNet features)

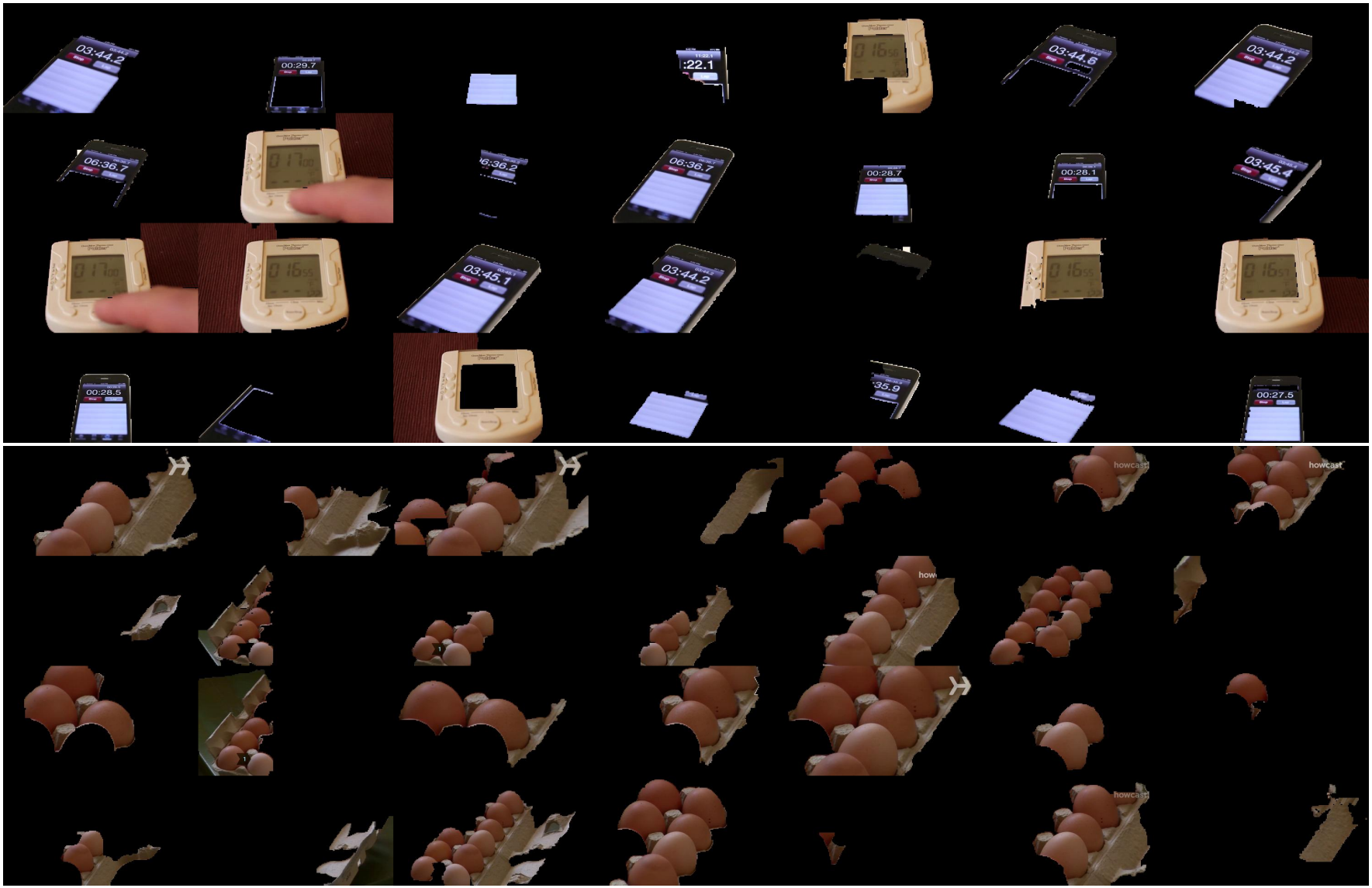
$$\arg\max_x \sum_i \frac{x_{i,.}^T A_i x_{i,.}}{x_{i,.}^T x_{i,.}} + \sum_i \sum_{j \in \mathcal{N}_k(i)} \frac{x_{i,.}^T A_{ij} x_{j,.}}{x_{i,.}^T \mathbb{1}\mathbb{1}^T x_{j,.}}$$

- This maximum of this function is a cut over proposals which all videos agree on and has maximum normalized total similarity within cluster.
- This function is quasi-convex and can be maximized by using sub-gradient method.

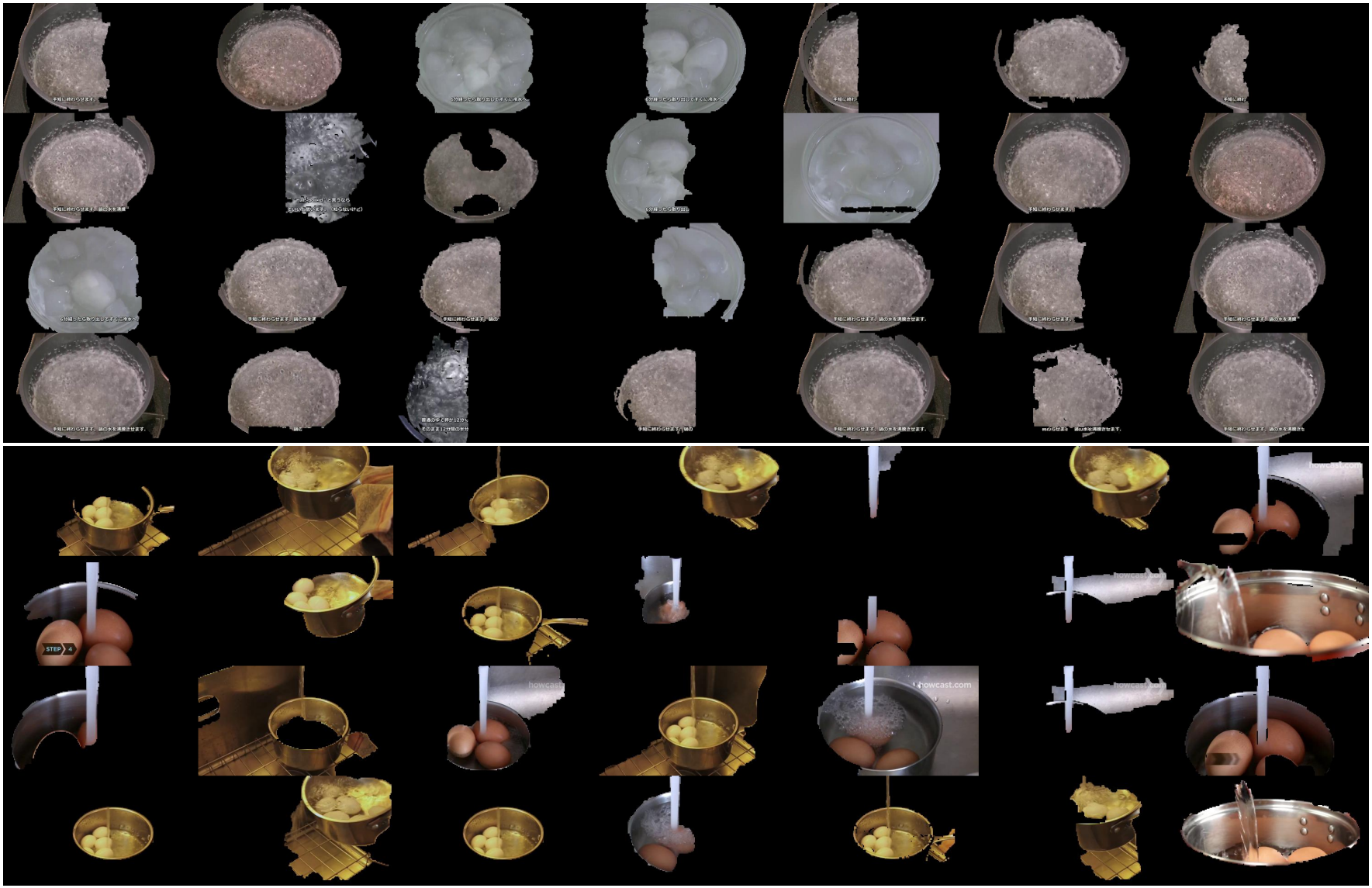
Some Visual Objects



Some Visual Objects-2



Some Visual Objects-3



Finding Salient Words

- We concatanate all subtitles and compute the frequency of each word (f_t).
- For each selected word, we compute the frequency of each word in NYTimes corpus (f_d).
- We choose the K most frequent words with property $f_t > f_d$.

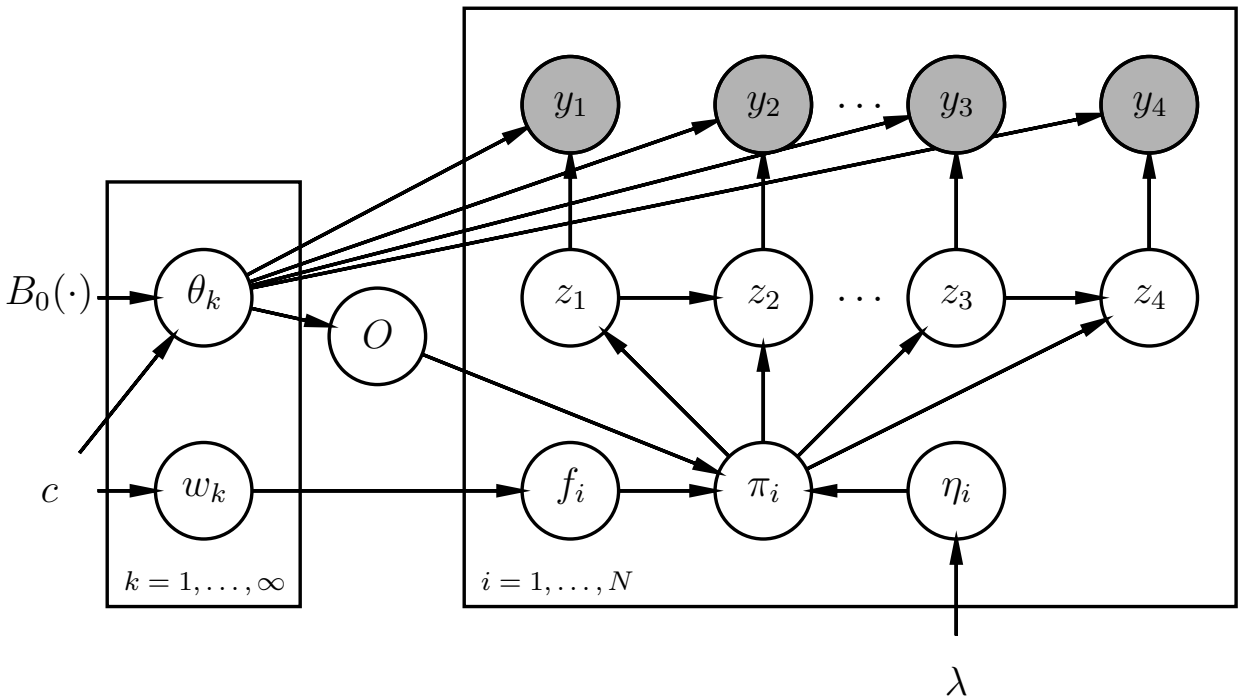
Salient Words

First 50 salient words:

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

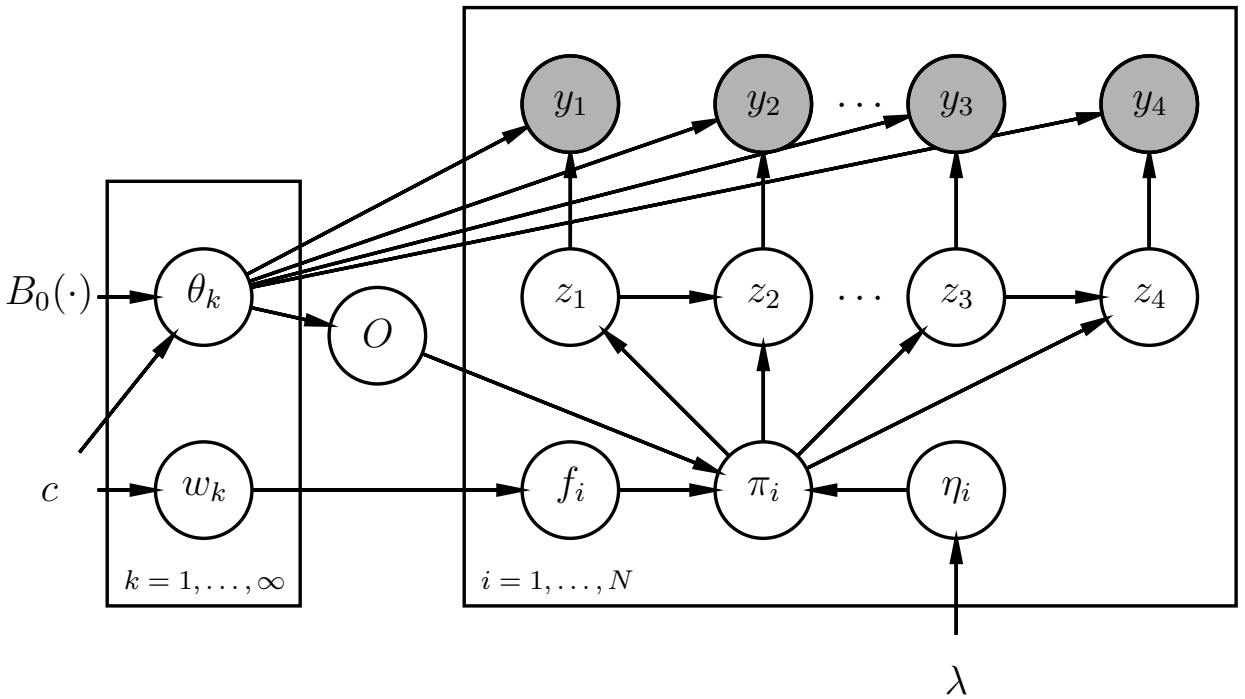
Learning Recipes

- Each activity (θ_k) is represented as Binomial r.v. over visual objects and Drichlet r.v. over language words.
- Each video choose set of activities (f_i) with likelihoods (w_k) following the Indian Buffet Process.



Learning Recipes - 2

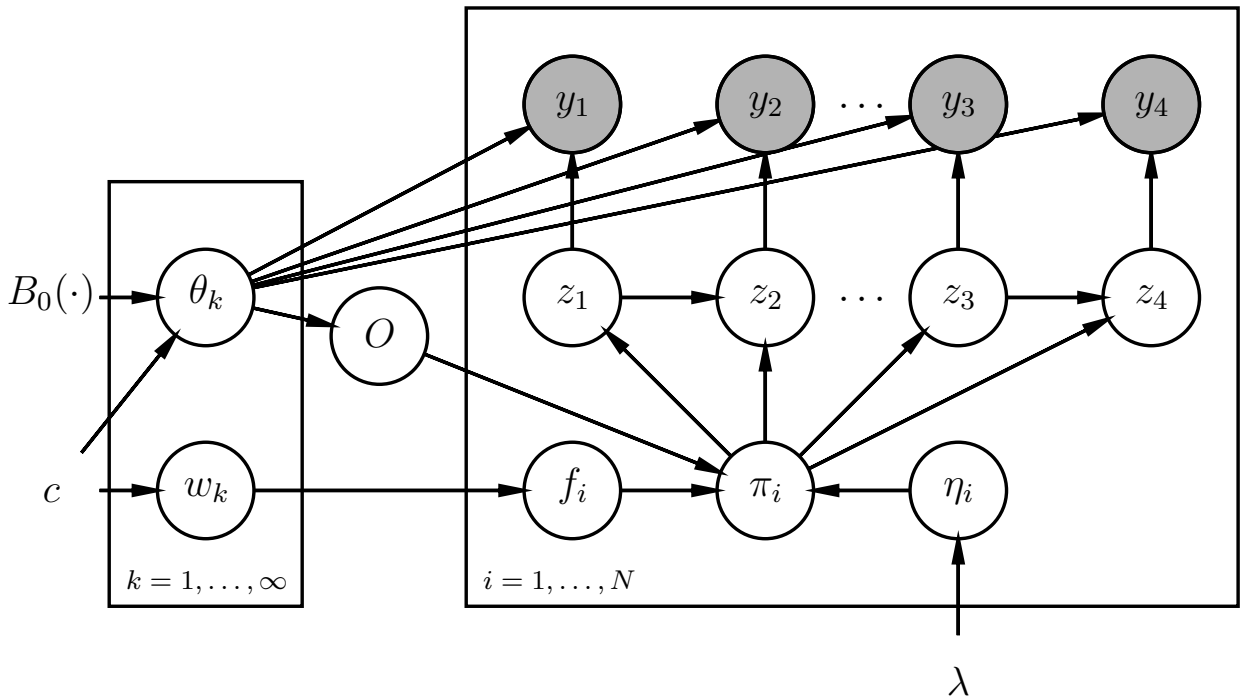
- Some activities impose time ordering via O e.g. activity 1 is always after activity 2 if $O_{1,2} = 1$.
- Activities have prior transition probabilities ($\eta_i^{m,n}$ is the transition prob from activity m to n, $\eta_i^{m,\cdot}$ follows a Drichlet r.v.



Learning Recipes - 3

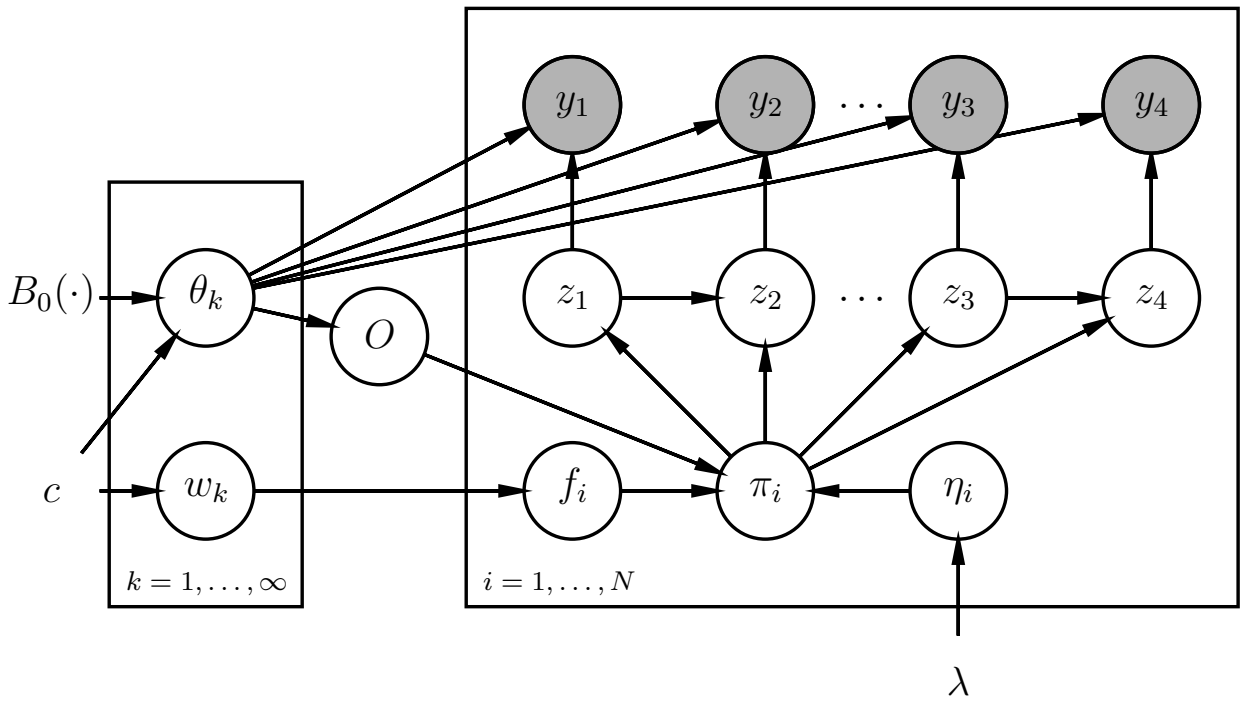
- Transition probabilities(π_i) is normalized version of prior transition probabilities obeying selected activities and time orderings.

$$\pi_i = \frac{f_i \otimes \eta_i \otimes O_{\cdot,i}}{\| f_i \otimes \eta_i \otimes O_{\cdot,i} \|}, \qquad \otimes \text{is elementwise product}$$



Learning Recipes - 4

- We represent each frame (y_i) as binary vector of occurance of visual objects and bag of language words.
- z_t is the activity of frame t and it follows an HMM.



Learning

- We use Metropolis–Hastings sampler for binary random variables and Gibbs sampler for the rest.
- Time ordering matrix and IBP is sampled via data driven manner (details omitted).

Preliminary Results

- We crawl the top 50 queries from the WikiHow.com and manually choose 25 out of them.
- For each query, we download 100 videos (total of 2500 videos, average length 7min, 80% have ASR subtitles)
- For each recipe, we have 5 evaluation videos with temporal activity labels as well as the activity names.
- We run the full model for 95 videos with no label and test in the remaining 5. For the test set, we do not sample the activities.
- We compute average intersection-over-union for the temporal segmentation (best over all matchings).

KMeans with Correct Number of States	20.74%
HMM with Correct Number of States	24.25%
Our Method	54.68%

Discussion

- Preliminary results suggest that the weak signal in the subtitles is powerful enough to recover activities.This can be used to scale-up activity detection algorithms.
- Activities are computed by using a generative model in other words we can have multiple/none activity in the same time.
- Integration of a recipe book is still an open problem and possibly a future work.

Dataset

(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 Omelette, 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