ADL^{TM}: A Topic Model for Discovery of Activities of Daily Living in a Smart Home

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Goals and Motivation

- To be able to automatically recognize activities of Daily Living

- Varied Applications in Improved daily living:
  - Assistive Applications for elderly people.
  - Monitor Actions for lifestyle change.

- Three Main Sources of Information:
  - Video Streams – Vision Community / Demonstration by Learning
  - Wearable Sensors – Vision Community (Deep Learning gaining popularity)
  - Environmental Sensors (Temperature sensors, pressure sensors, light switches etc.)
    - Cheap and Easy to Set up
    - Lesser Privacy Concerns.

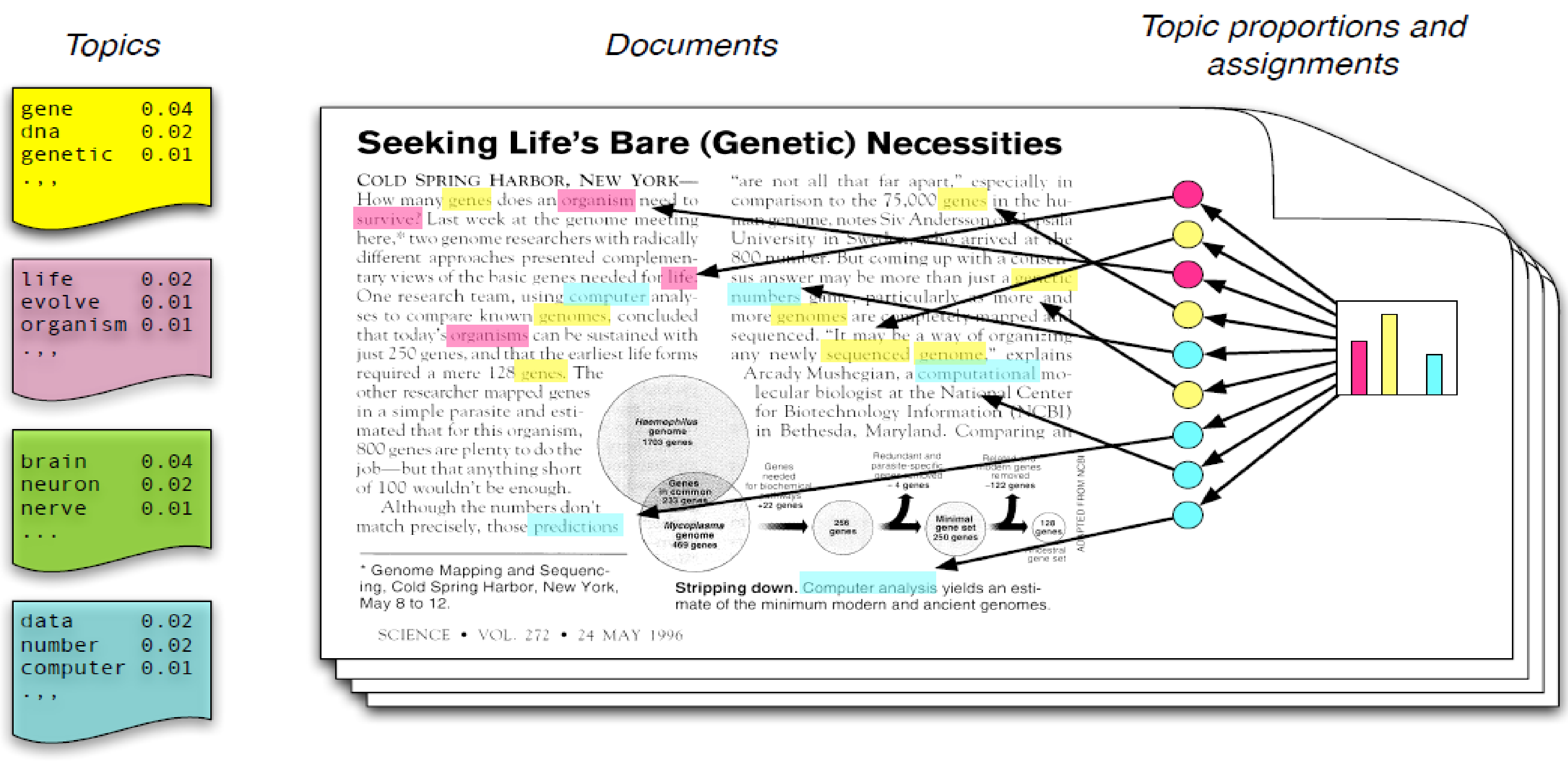
Activity Recognition is a Hard Problem

- Multiple Activities & Instances of the Same Activity Class
- Interleaved Activities
- Multiple Ways/Actions to Achieve Goals (Uncertainty)
- Difficult to Define Goals for Intentions (example : Cleaning)

Different Communities to Solve this Problem:

- Plan Recognition
  - Libraries of Plans
- Logic Programming (Hybrid, Ontologies etc)
  - Careful Domain Knowledge & Engineering
- Supervised Learning
  - Time Consuming & Error Prone Labelling
  - Unable to Recognize Unseen Activities.
- Unsupervised Learning
  - Lesser Accuracy on Datasets compared to Supervised Learning
  - Flexibility to Capture Exceptions in realistic scenarios

Topic Modelling, The Generative Model: David M. Blei, MLSS, September 2009,



- Each document is a random mixture of corpus-wide topics
- Each word is drawn from one of those topics

http://videolectures.net/site/normal_dl/tag=50740/mlss09uk_blei_tm.pdf

Sample Dataset and Definition of Words

- CASAS Project Datasets: Popular Datasets for Activity Recognition
- Unigrams and Bigram Words
- Documents are collection of Spatially Correlated words

Timestamp	Sensor	Reading	Activity
2013-04-01 00:04:09.340911	M007	ON	Sleep Begin
2013-04-01 00:04:10.485392	M007	OFF	
2013-04-01 00:56:31.879063	T106	24	
2013-04-01 01:13:53.616434	BATV104	3070	
...	...	...	
2013-04-01 02:45:47.215554	M006	OFF	Sleep End

Document Segmentation Algorithm : Contribution 1

- Change of Location is Strong Indication for Segmentation

- Threshold has a role to play in Segmentation Error

- Online Version is suggested to include second Threshold for Maximum duration of Document

Algorithm 1: Document Segmentation Algorithm

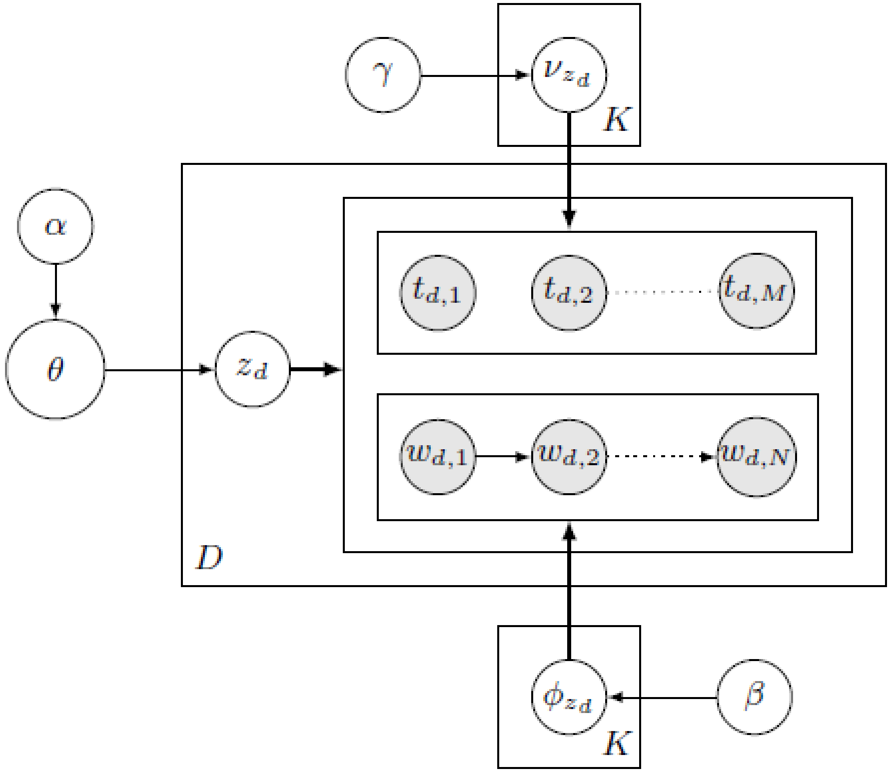
Input : L_s - the sequence of sensor locations, terminated with an extra 0, and all location IDs are non zero.
Input : t_{th} - time threshold
Output: $Docs$ - the list of start and stop indices of each document

```
Docs = ∅;
idx_start = 0;
idx_stop = idx_start;
while idx_stop < len(L_s) − 1 do
    id_l = L_s[idx_stop] ;
    idx_stop = idx_next − 1, where idx_next is the next index
      that satisfies L_s[idx_next] ≠ id_l;
    t_stop = timestamp of L_s[idx_stop];
    t_start = timestamp of L_s[idx_start];
    if t_stop − t_start > t_th then
        append (idx_start , idx_stop) into Docs;
        idx_start = idx_next ;
    end
    idx_stop = idx_next ;
end
return Docs;
```

Generative Process and Plate Notation:

Algorithm 2: Generative Processes of ADL[TM]

Draw a $\theta \sim Dir(\alpha)$;
for $d = 1$ *to* D **do**
  Draw a topic $\mathbf{z}_d \sim Multi(\theta)$;
  Draw a $\phi_{z_d} \sim Dir(\beta)$;
  Draw a $\nu_{z_d} \sim Dir(\gamma)$;
  for $n = 1$ *to* N **do**
    Draw a unigram $t_{d,n} | z_d \sim Mult(\nu_{z_d})$;
    if $n > 1$ **then**
      Draw a bigram $w_{d,n} | w_{d,n-1}, z_d \sim Mult(\phi_{z_d})$;
  end
end



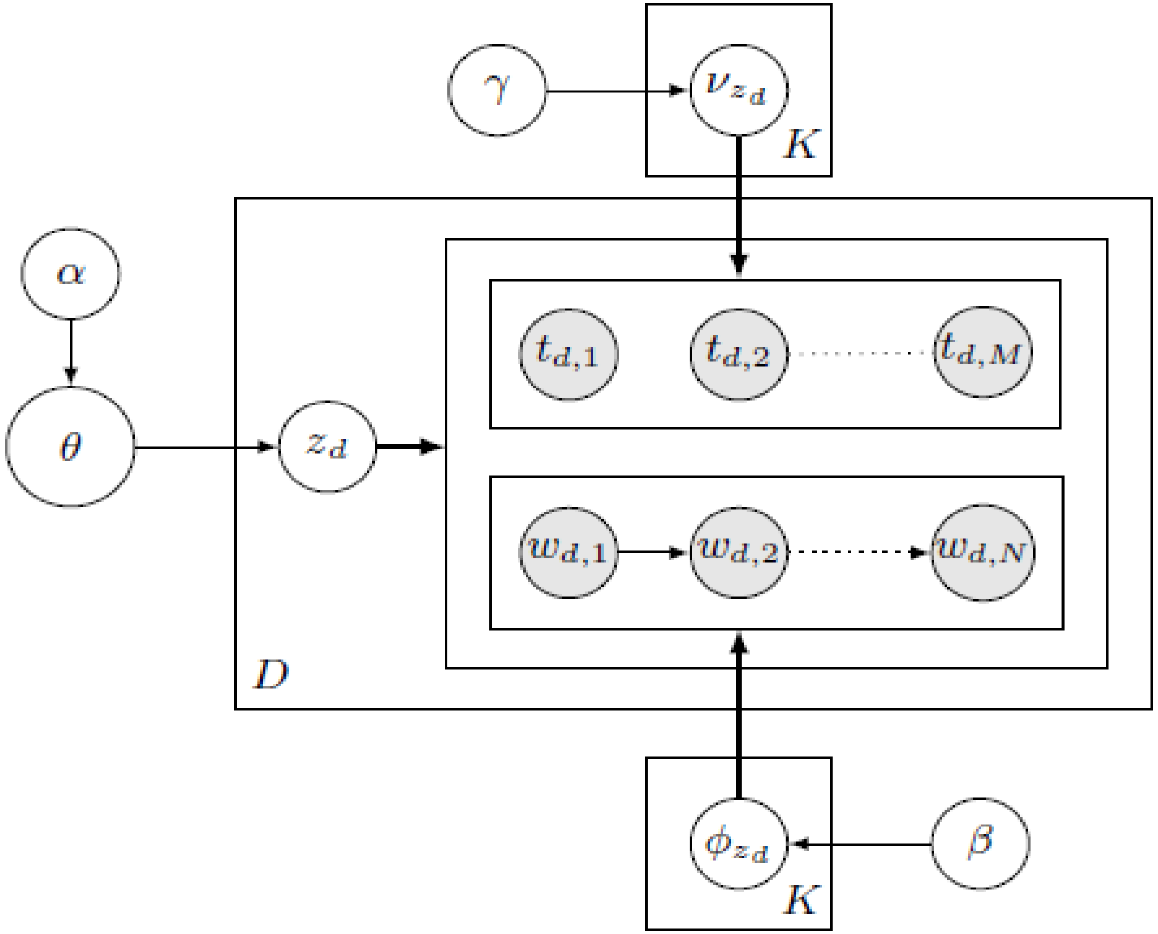
Difference between LDA and ADL

- Contribution 2:

- Topics drawn for documents rather than words

- Different Vocabularies for Unigram and Bigram Sequences

- Markov Chain for Bigrams
  - (affects size of vocabulary for phi)



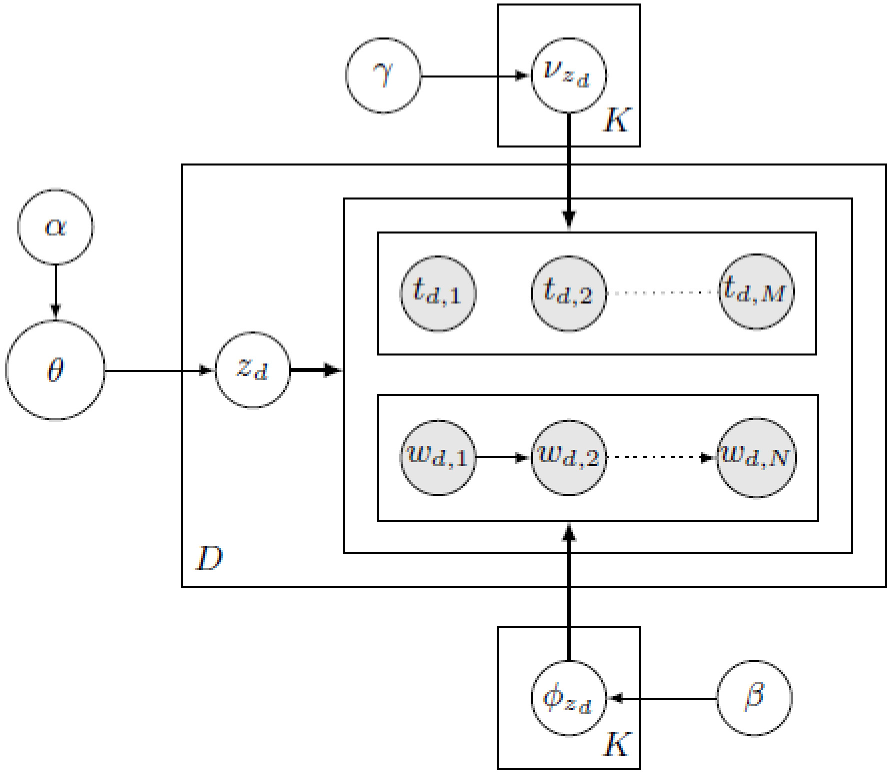
Gibbs Sampling of ADL

$$P(z_d|\mathbf{z}_{-d},\mathbf{w},\mathbf{t}) \propto P(z_d|\mathbf{z}_{-d})P(w_d|z_d,\mathbf{z}_{-d},\mathbf{w}_{-d}) \times P(t_d|z_d,\mathbf{z}_{-d},\mathbf{t}_{-d})$$

$$P(z_d = k|\mathbf{z}_{-d}) \propto C_k^- + \alpha$$

$$\begin{aligned} P(w_d|z_d = k,\mathbf{z}_{-d},\mathbf{w}_{-d}) &= \prod_{n=2}^{N} P(w_{d,n}|w_{d,n-1},z_d = k,\mathbf{z}_{-d},\mathbf{w}_{-d}) \\ &\propto \prod_{n=2}^{N}\left(\sum_{j=1}^{V}\frac{\sum_{i=1}^{V}(C_{w_{ijk}}^- + \beta)I(w_{d,n} = i)}{C_{w_{*ju}}^- + V\beta} I(w_{d,n-1} = j)\right) \end{aligned}$$

$$\begin{aligned} P(t_d|z_d,\mathbf{z}_{-d},\mathbf{t}_{-d}) &= \prod_{n=1}^{M} P(t_{d,n}|z_d = k,\mathbf{z}_{-d},\mathbf{t}_{-d}) \\ &\propto \prod_{n=1}^{M}\left(\sum_{h=1}^{H}\frac{(C_{t_{hk}}^- + \gamma)}{(C_{t_{*k}}^- + H\gamma)} I(t_{d,n} = h)\right) \end{aligned}$$



Hyperparameters and Interpreting Counts

- Topic prior: alpha = 50/K
- Bigram and unigram priors: beta = 5/V, gamma = 5/H.

- Contribution 3: Interpretation of Counts

- Unigram counts are counted by term frequency
- Bigram counts are counted by document frequency (Avoid Self Transitions)

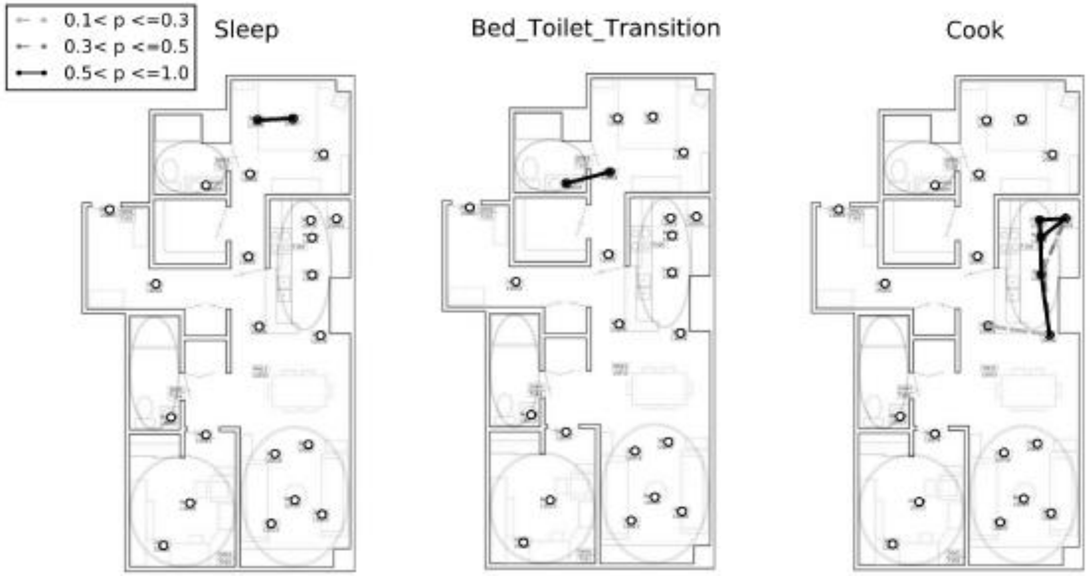
Evaluation

Dataset	# Activities	# Binary Sensors	Duration (days)	# Residents
hh122	32	24	30	1
hh120	32	24	64	1
milan	15	31	31	1+pet

Table 2: Properties of Datasets

	hh122	hh120	milan
Random topics	0.0798	0.0969	0.1193
BTM	0.1515	0.1988	0.3225
LDA	0.3268	0.3486	0.5634
ADL^{TM}	0.3362	0.4072	0.6190

Table 3: FM Index of topics by different methods



(a) Sleep (b) Bed-to-Toilet (c) Cook

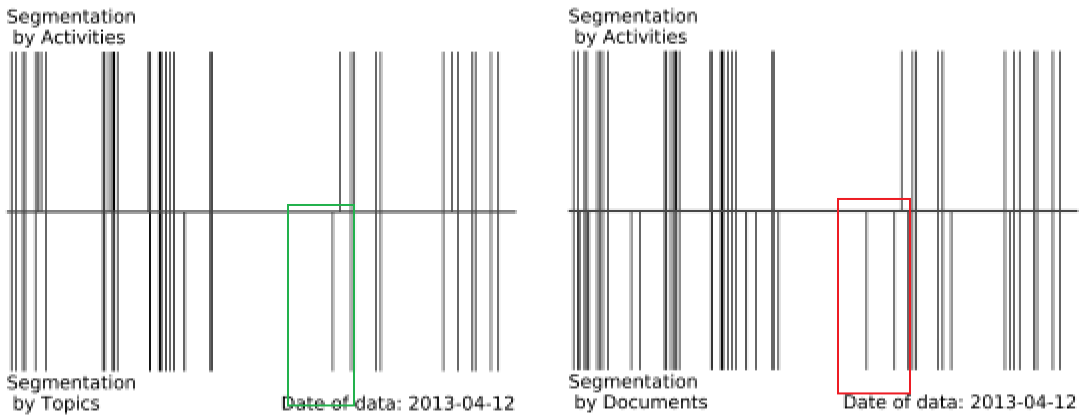
Segmentation and it's Metrics

Segmentation Error: Average Error over all Segments

$$Err_s = \frac{\sum_i^{D_s} E_i}{N_{dp}} \qquad E_i = N_i - \sum_{j=1}^{N_i} I(a_{ij} = m), \quad m = \underset{k}{\operatorname{argmax}}\left(\sum_{j=1}^{N_i} I(a_{ij} = k)\right)$$

Fragment Ratio: Average number of segments in one occurrence of an activity

$$R_{fr} = \frac{D_s}{D_a}$$



(a) Segmentation by topics and activities

(b) Segmentation by documents and activities

Segmentation Results

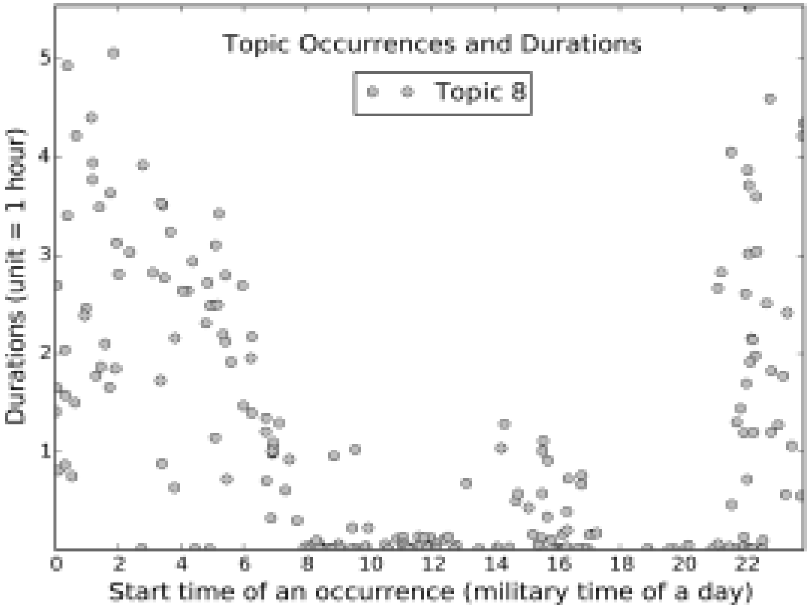
Effects of Threshold th:

- Smaller = higher fragment ratio + low segmentation error
- Larger = higher segmentation ratio + lower fragment error

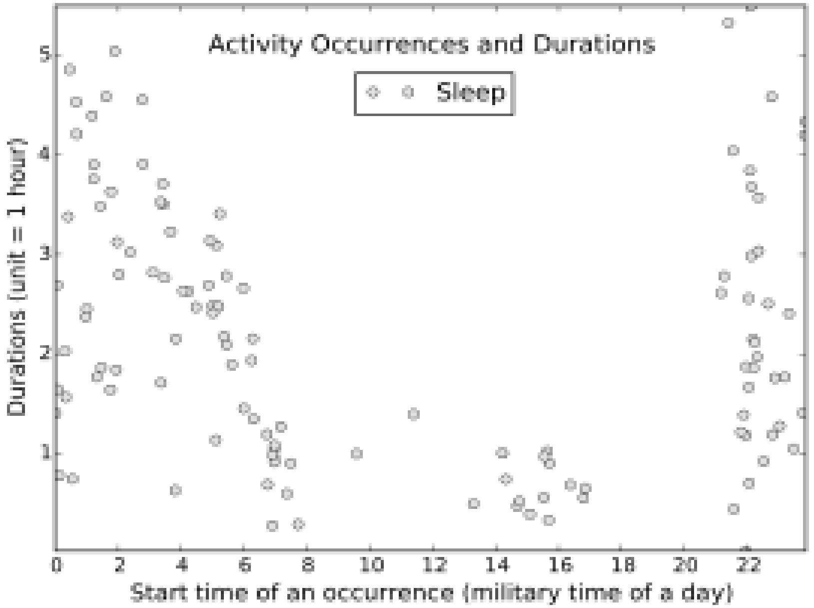
	hh122		hh120		milan	
	Err_s	R_{fr}	Err_s	R_{fr}	Err_s	R_{fr}
Documents	0.0197	1.596	0.0404	2.084	0.0342	1.563
LDA	0.0541	1.178	0.0531	1.554	0.0409	1.157
BTM	0.0619	1.174	0.0568	1.853	0.0428	1.394
ADL^{TM}	0.0512	1.102	0.0516	1.364	0.0406	1.149

Applications

- dataset hh122 compression
  - 129936 to 2792 data points.
- Detection of Sleep Patterns
  - Average duration: 7.02 hours)



(a) Distribution of Topic 8



(b) Distribution of “Sleep”

Applications : Continued

- Combination with Other Distributions
  - (Use of Sleep + Restroom)
- Subtopic Clustering
  - K-means with K explicitly = 3
  - Columns don't sum to 1
- Detection of Outliers
  - Deploy z-scores on duration of data-points

Timestamp	Sensor	Reading	Location
2013-04-27 18:29:28.187573	MA011	ON	Kitchen
2013-04-27 18:29:29.339714	MA011	OFF	Kitchen
2013-04-27 20:47:55.930002	M010	ON	Kitchen
2013-04-27 20:47:57.065529	M010	OFF	Kitchen

Sub-Topic	Cook Breakfast	Wash Breakfast Dishes	Cook Lunch	Wash Lunch Dishes	Cook Dinner	Wash Dinner Dishes
0	0.985	0.904	0	0	0	0
1	0	0	0	0	0.969	0.979
2	0	0.041	0.960	0.983	0	0

Answers to Questions

1) What do the authors claim is the contribution of the paper?

- Segmentation Algorithms (Document Generation + Topic Segmentation)
- ADL outperforms LDA and BTM (Novel Unsupervised Approach, powerful topic model)

2) What is the actual contribution of the paper?

- Segmentation Algorithms:
  - Document Generation due to spatial correlation
  - Don't give many details on criterion to segment/integrate topics from documents

- ADL outperforms LDA and BTM
  - Not Novel with respect to LDA (Use Case of LDA/hierarchical Bayesian inference)
  - Topic Distribution for Documents - insight into the domain
  - Interpretation of Counts in Unigram and Bigrams - insight into approximation for domain
  - Markov Chain for Bigrams

- Detailed Evaluation in terms of Applicability (example, Detect outliers for instance)

Answers to Questions : Continued

3) Are the results of the paper replicable?

May be not (No source code – probably proprietary work) :

- Document Segmentation Algorithm given (threshold calculation is not)

4) Are there significant technical faults in the paper or open cases that are not addressed?

Not Any Significant faults but some Strong Assumptions and minor issues

Assumption 1: Environmental Sensors reflect actions of humans and their Activities.

Assumption 2: Evaluation for 1 resident

Minor issue: 50 iterations for gibbs Sampling

Answers to Questions : Continued

5) What is the next incremental step in this research?

- Simultaneously Categorizing by Spatial and Temporal Dimensions
- Online Variational Inference Algorithm (Standard LDA)
- Prior knowledge for hyperparameters: alpha, beta and gamma
- Semi-Supervised Learning
- Correlations in topics introduced in the model

Answers to Questions : Continued

6) What is the next long term step in this research program?

Future Systems are to follow Complex, hybrid Architectures

- Evaluate formally (Quantitively and qualitatively) the true advantage of this against other methods (Deep Learning? Extend in Bayesian Nonparametrics?)

- Reason about motions of Humans, properties of objects (Fall Back to Video Streams)
  - Privacy-Preserving Human Activity Recognition from Extreme Low Resolution:
    Michael S. Ryoo 1;2, Brandon Rothrock, Charles Fleming, Hyeon Jong Yang (AAAI 2017)

Questions and Discussion