Trajectory Analysis in Wide-Area Motion Imagery

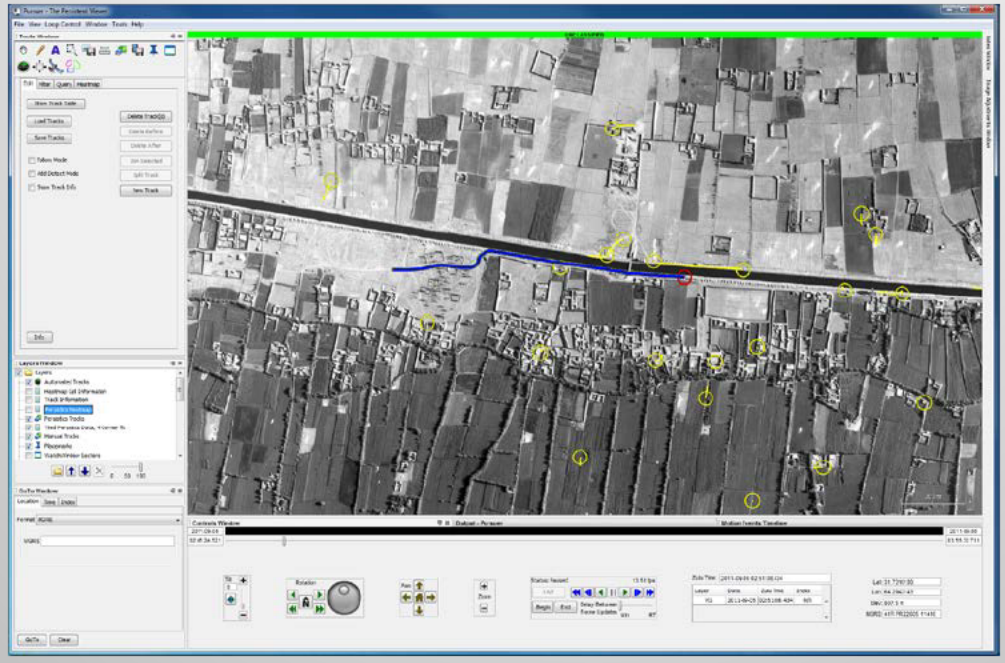
Kofi Boakye
Lawrence Livermore National Laboratory

Alex Zhao
Princeton University

LLNL-PRES-636917

This work performed under the auspices of the U.S. Department of Energy by Lawrence Livermore National Laboratory under Contract DE-AC52-07NA27344.

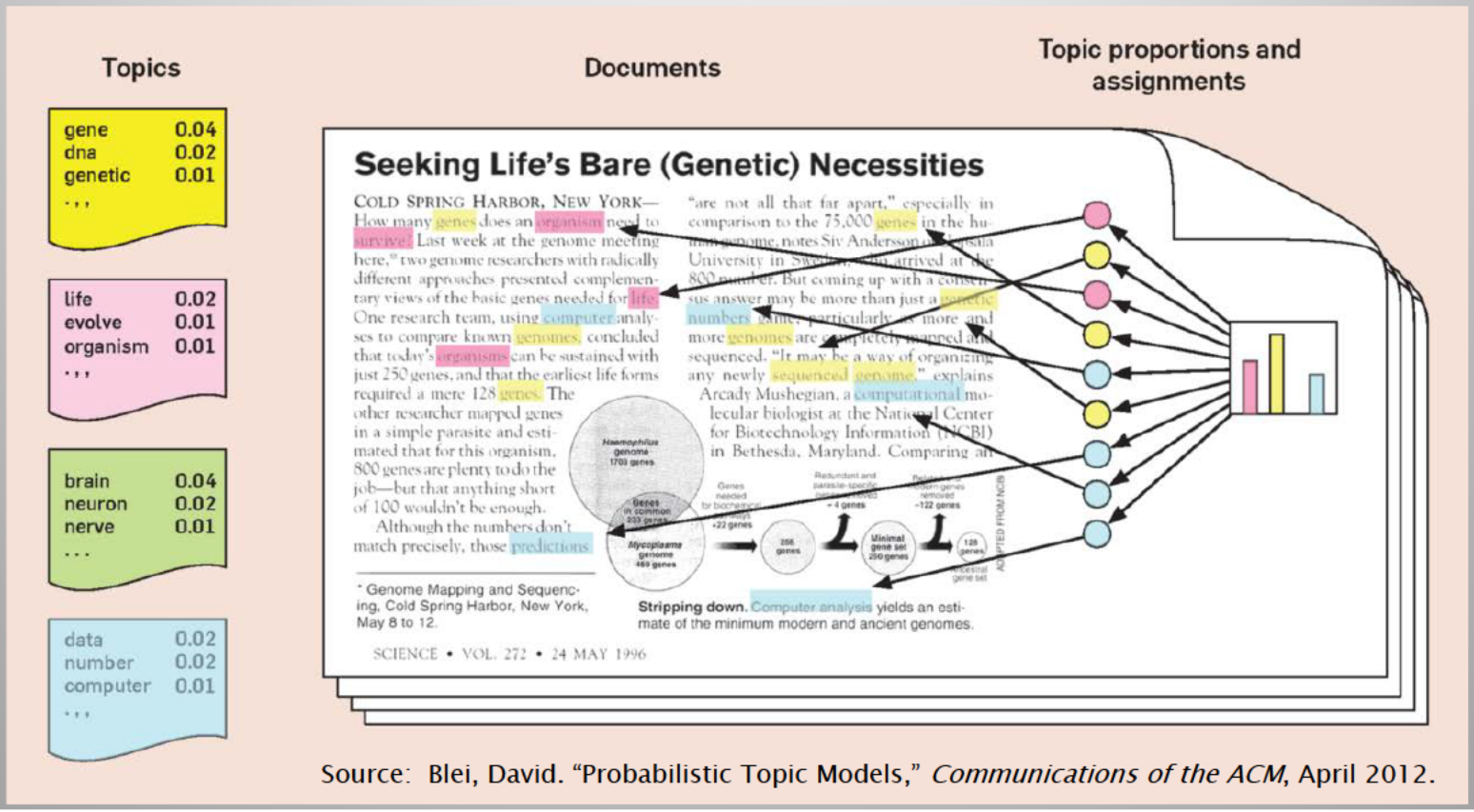
Introduction: WAMI Exploitation



- Exploitation of wide area motion imagery (WAMI) relies heavily on the analysis of mover trajectories
- Of particular interest are “anomalous” trajectories which may be indicative of potential threats

Topic Modeling

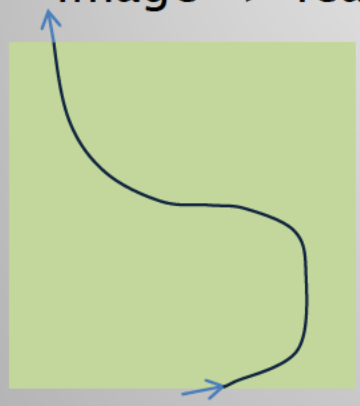
- Originally used to find the underlying topics within a text document to predict its meaning
- Utilize this approach to find the underlying structure within trajectories to establish "normalcy" and detect anomalies



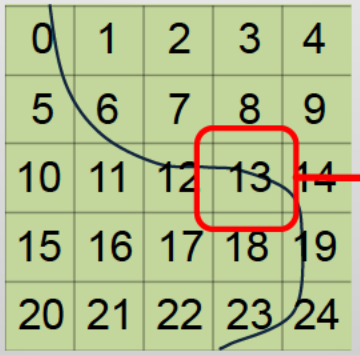
Source: Blei, David. "Probabilistic Topic Models," *Communications of the ACM*, April 2012.

Feature Vector

- Convert each trajectory into a feature vector; *bag-of-words* model
- Each trajectory has numerous *detects*, each detect is a word
  - Region is divided into cells (an index of <u>location</u>)
  - Each detect is moving in a specific <u>direction</u>
- A word corresponds to a particular location & direction
- image -> feature vector (i.e., a document vector)

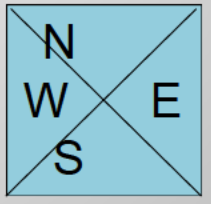


One trajectory in this scene



Divide region into cells

Zoom in on Cell 13



Each detect moving in one of 4 directions

Convert all detects in the trajectory into words

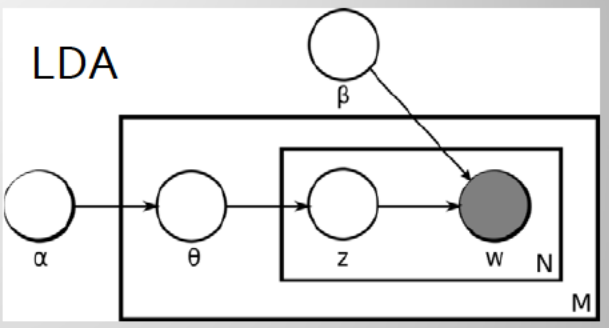
Word (Cell, Direction)	12 W	12 S	**13 E**	**13 N**	**13 W**	**13 S**	14 E	14 N
Frequency	0	0	0	1	7	0	0	2

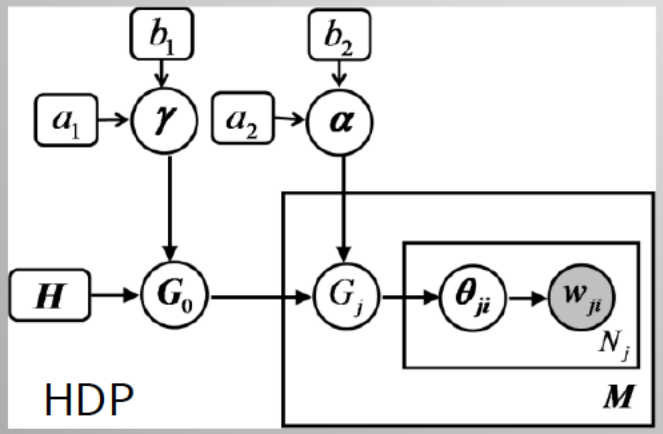
Feature vector for this trajectory
Note: There is a word for each possible location & direction.

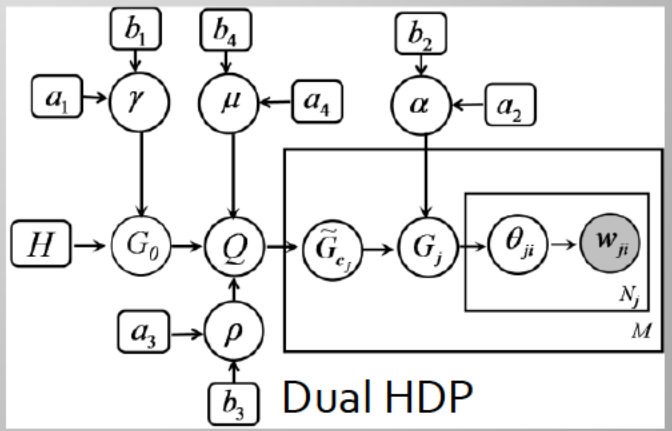
Approach

- Document = Trajectory Vector
- Topic = Semantic regions (e.g., right turn)
- Word = Location & Direction

1. Cluster Analysis
2. Latent Dirichlet Allocation
3. Hierarchical Dirichlet Process
4. Dual-Hierarchical Dirichlet Process







LDA: Blei, David. "Probabilistic Topic Models," *Communications of the ACM*, April 2012.
HDP: Wang et al. "Trajectory Analysis and Semantic Region Modeling Using a Nonparametric Bayesian Model," MIT-CSAIL, 2008.
Dual-HDP: *Ibid.*

Data Sets

Region	Tracks	Words
A	2,177	339,695
B	1,038	152,146
C	930	116,260
D	247	43,974

Cluster Analysis

- Algorithms:
  - K-Means
  - Hierarchical (Ward)
  - Mean Shift
  - Affinity Propagation
  - DBSCAN

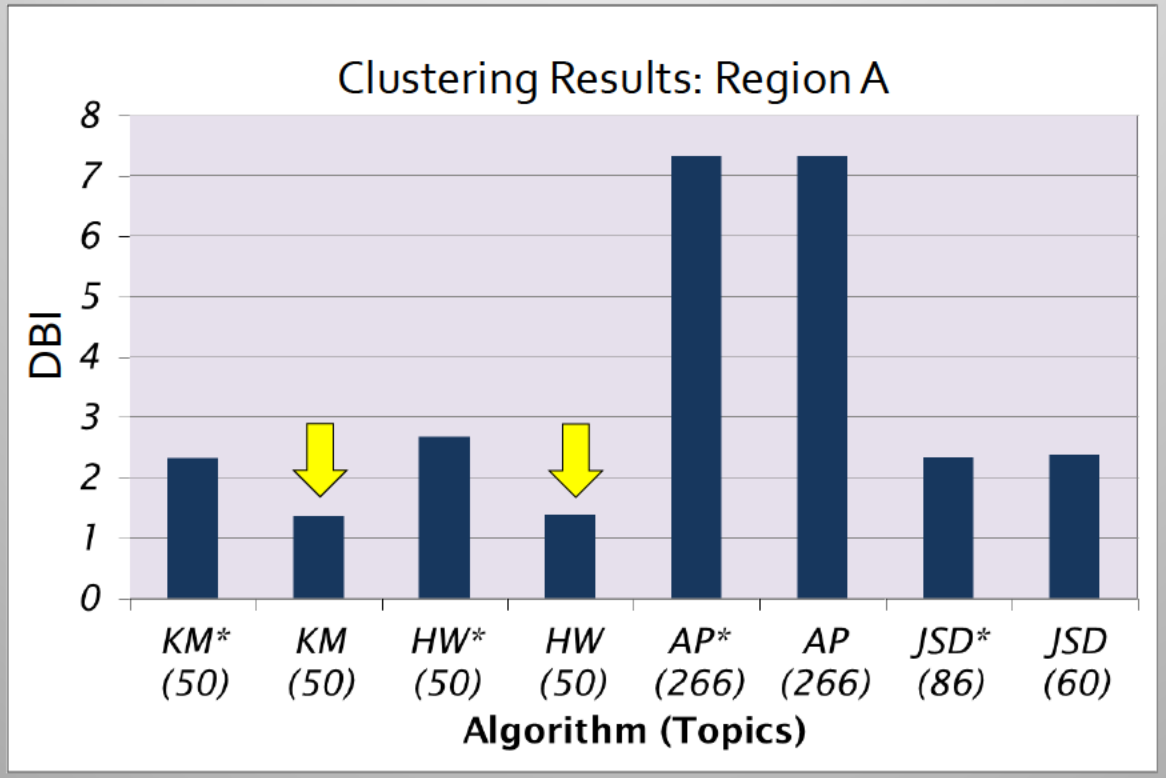
- "Natural" number of clusters determined through experimentation, confirmed by results from LDA

- (*) Feature vector weighting: tf*idf

Clustering Evaluation

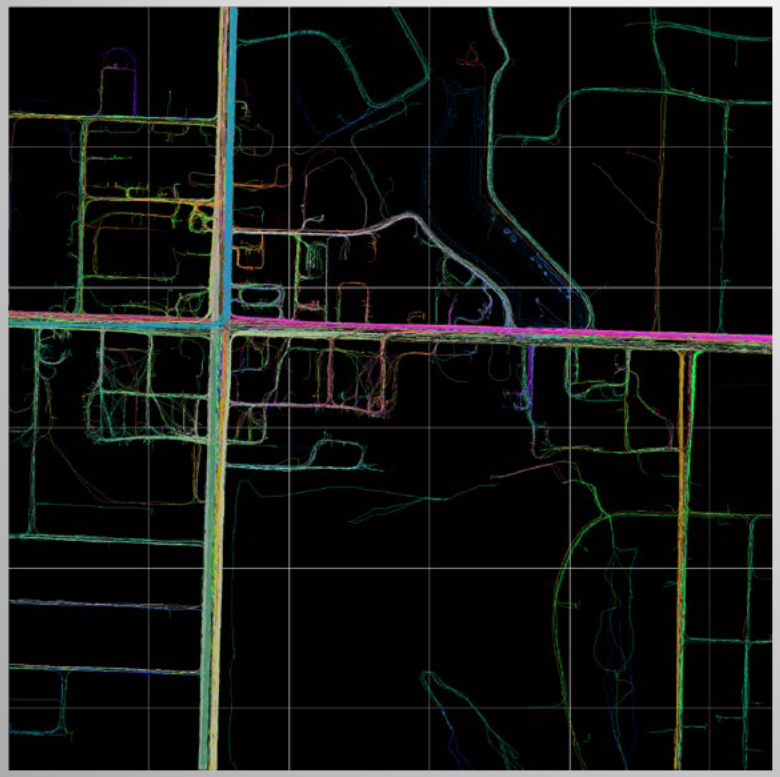
- Davies-Bouldin Index (DBI): calculates the "correctness" of a clustering algorithm

$$DB = \frac{1}{n}\sum_{i=1}^{n}\max_{i\neq j}\left(\frac{\sigma_i + \sigma_j}{d(c_i, c_j)}\right)$$



Cluster Analysis: Example Results

Region A



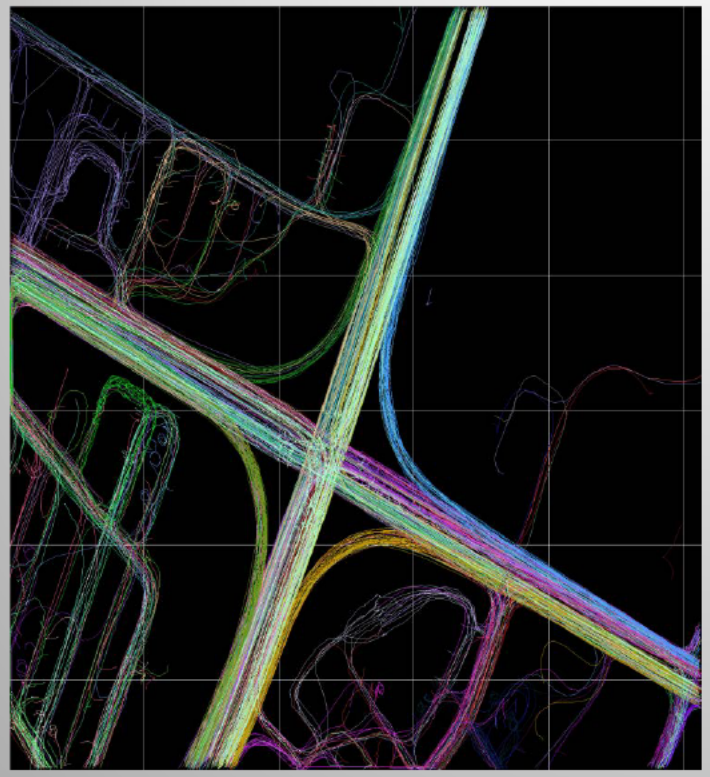
Clusters

Anomalies

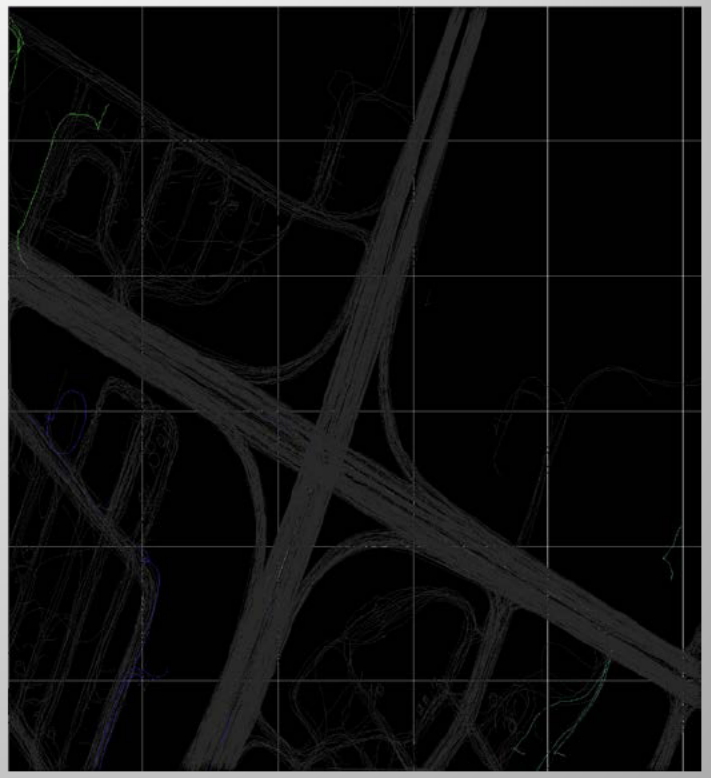
Hierarchical Ward (50 Clusters)

Cluster Analysis: Example Results

Region B



Clusters

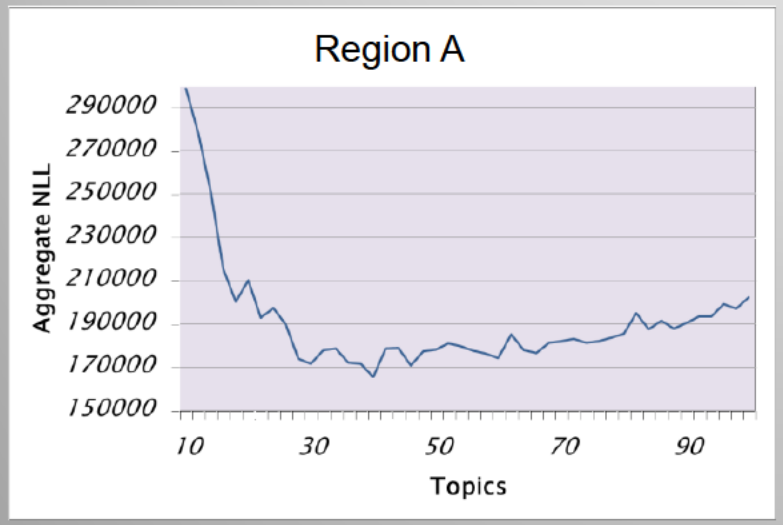


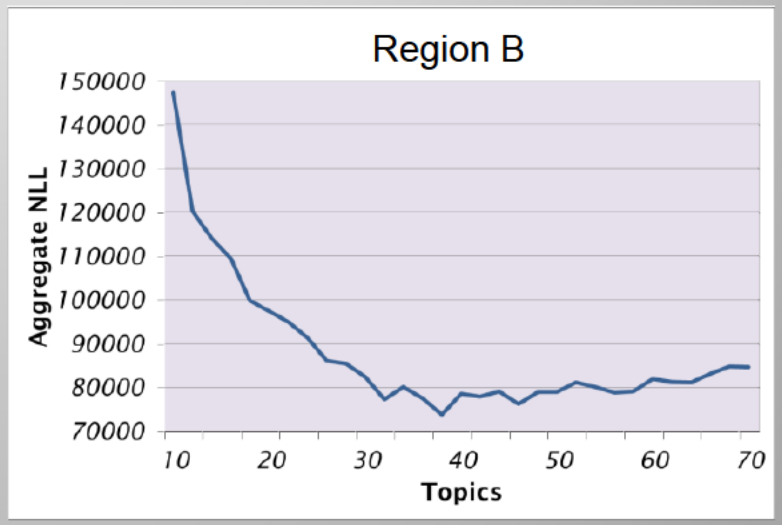
Anomalies

K-Means (40 Clusters)

Latent Dirichlet Allocation (LDA)

- Model fitted using Gibbs sampling approach
- Negative Log-Likelihood (NLL) calculated based on local (document) and global (corpus) topic distributions
  - Document (i.e., trajectory) NLL used as an indicator of anomalies
  - Corpus (i.e., collection of trajectories) NLL used to determine "natural" number of topics





Estimated Number of Topics
Using Aggregate NLL

LDA + Cluster Analysis

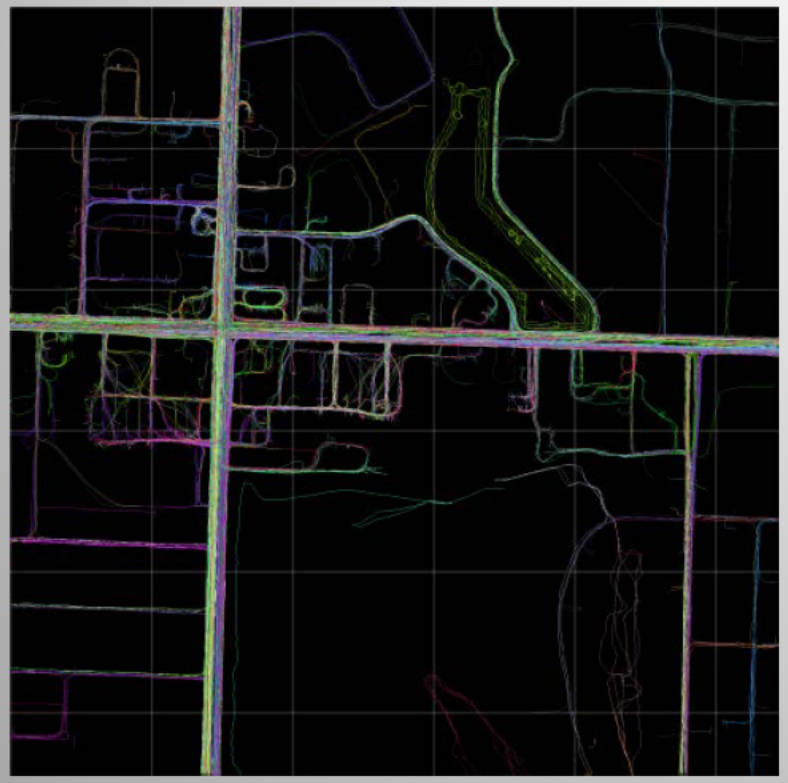
- *Jensen–Shannon divergence* used as a "distance" metric between trajectories
- Cluster trajectories based on topic distributions (rather than using feature vectors) using Affinity Propagation

$$JSD(P \parallel Q) = \frac{1}{2}D(P \parallel M) + \frac{1}{2}D(Q \parallel M)$$

$$D_{\mathrm{KL}}(P\|Q) = \sum_i P(i) \ln \frac{P(i)}{Q(i)}. \qquad M = \frac{1}{2}(P+Q)$$

LDA: Example Results

Region A

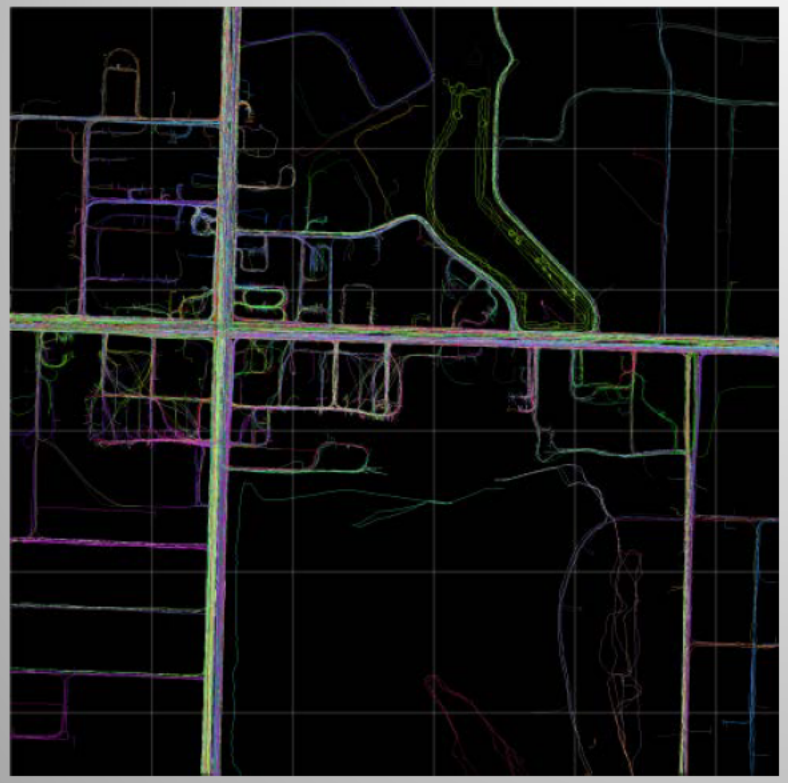


Clusters

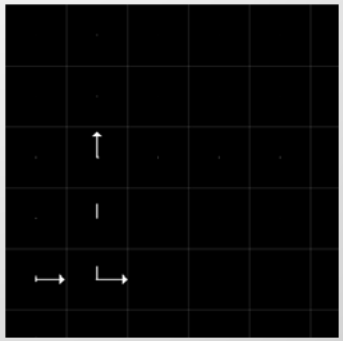
Anomalies

LDA: Example Results

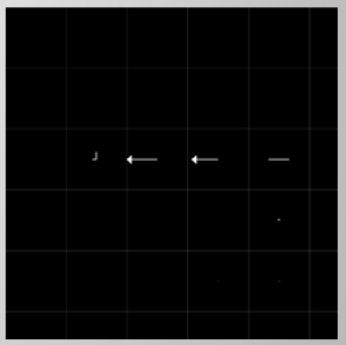
Region A



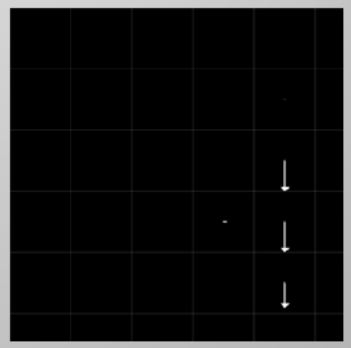
Clusters



Topic 0



Topic 13

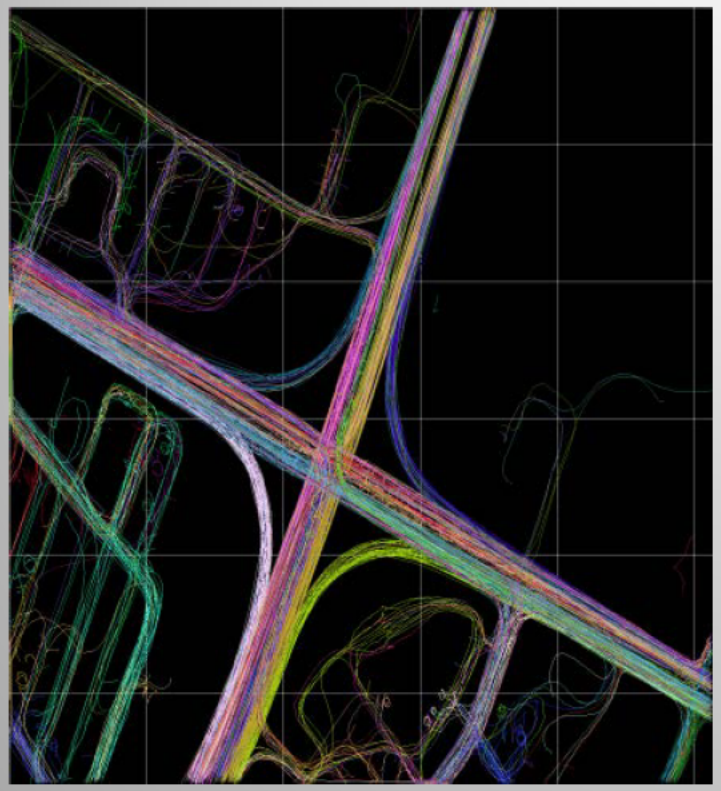


Topic 20

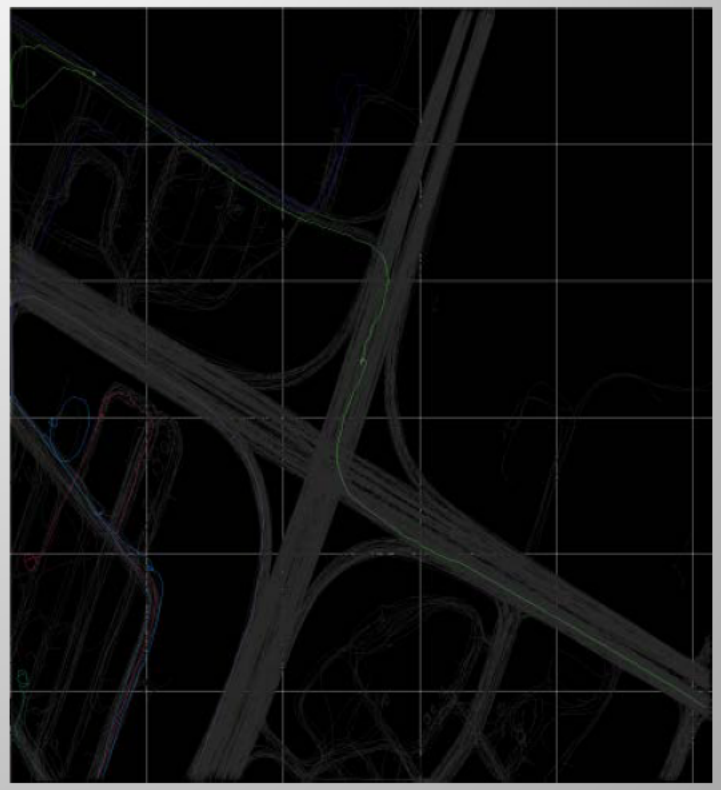
Topics

LDA: Example Results

Region B



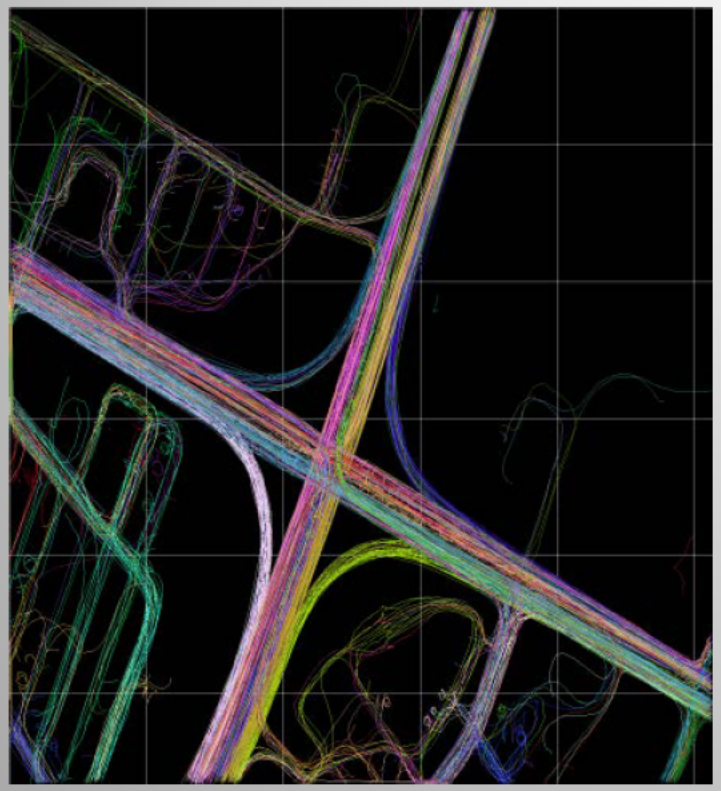
Clusters



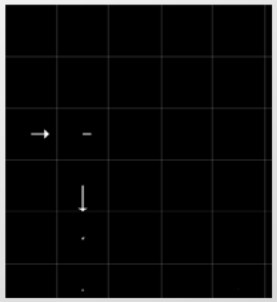
Anomalies

LDA: Example Results

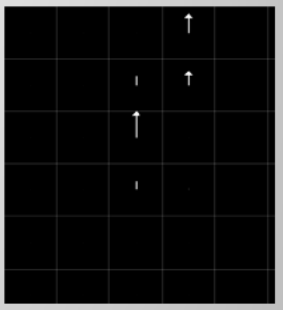
Region B



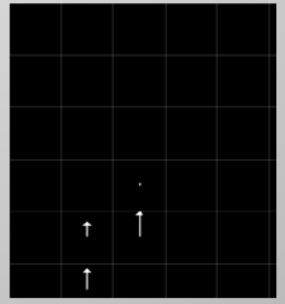
Clusters



Topic 3



Topic 6



Topic 16

Topics

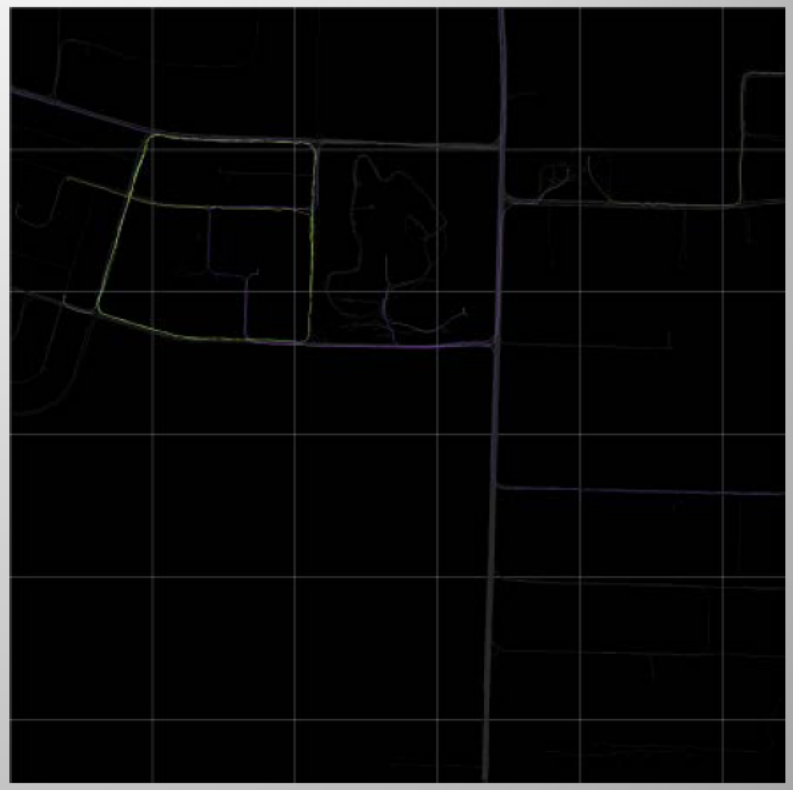
HDP

- Model fitted using Gibbs sampling approach
- Learns number of topics
- Computationally and space efficient

HDP: Example Results

Region D

Clusters

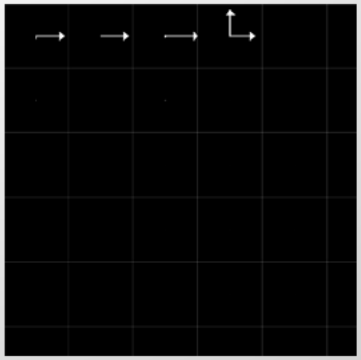


Anomalies

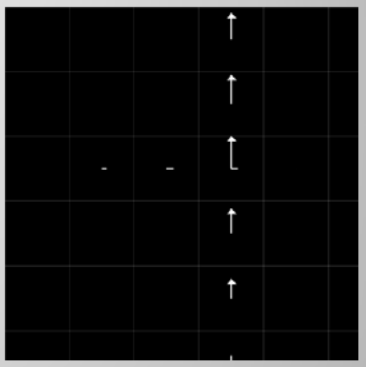
HDP: Example Results

Region D

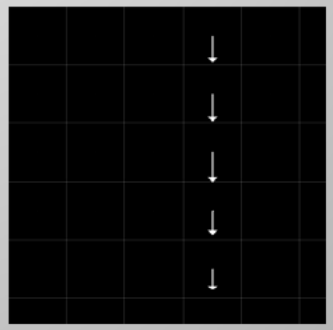
Clusters



Topic 0



Topic 1



Topic 3

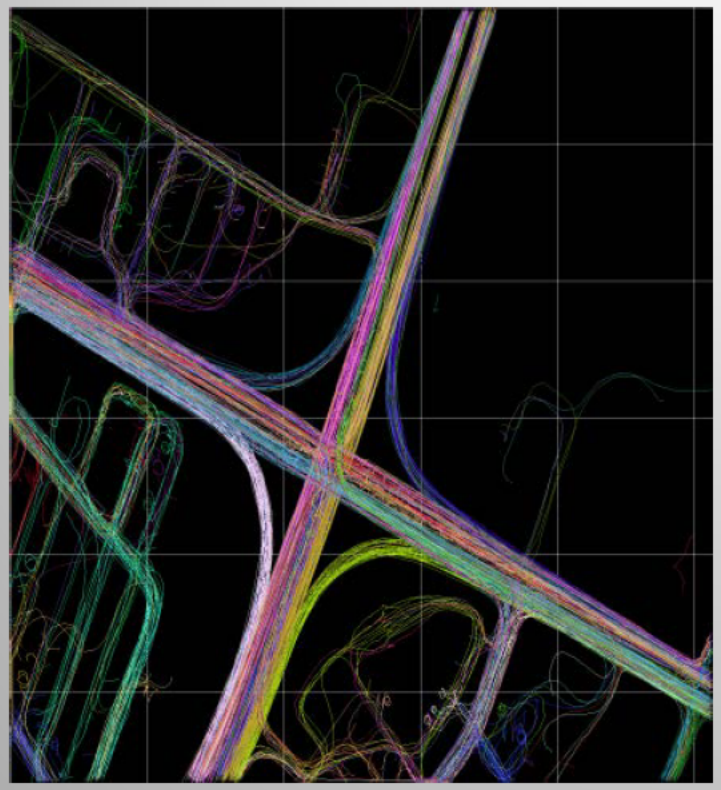
Topics

Dual-HDP

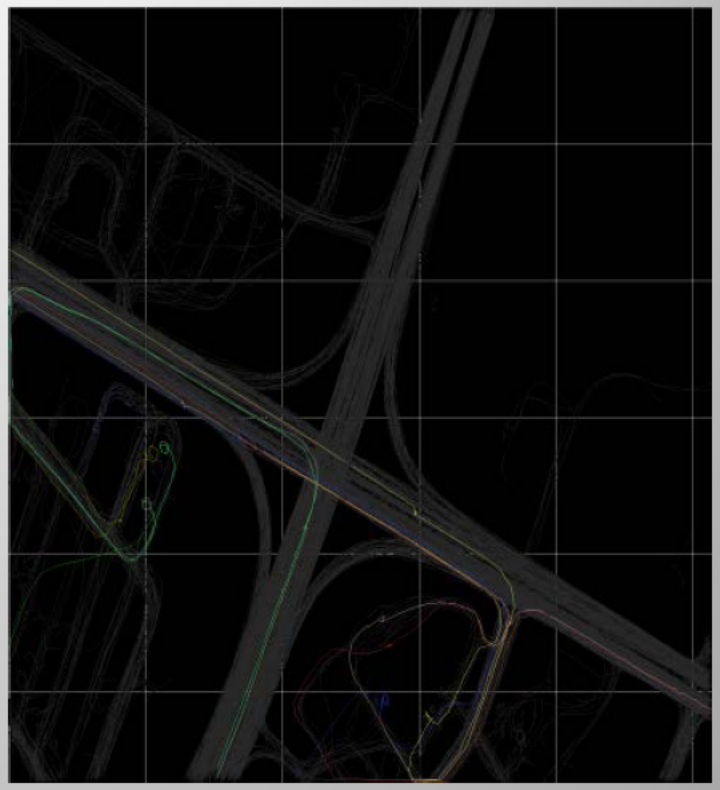
- Model fitted using Gibbs sampling approach
- Co-clusters both words and documents
- Learns number of topics
- Computationally and space efficient

Dual-HDP: Example Results

Region B



Clusters



Anomalies

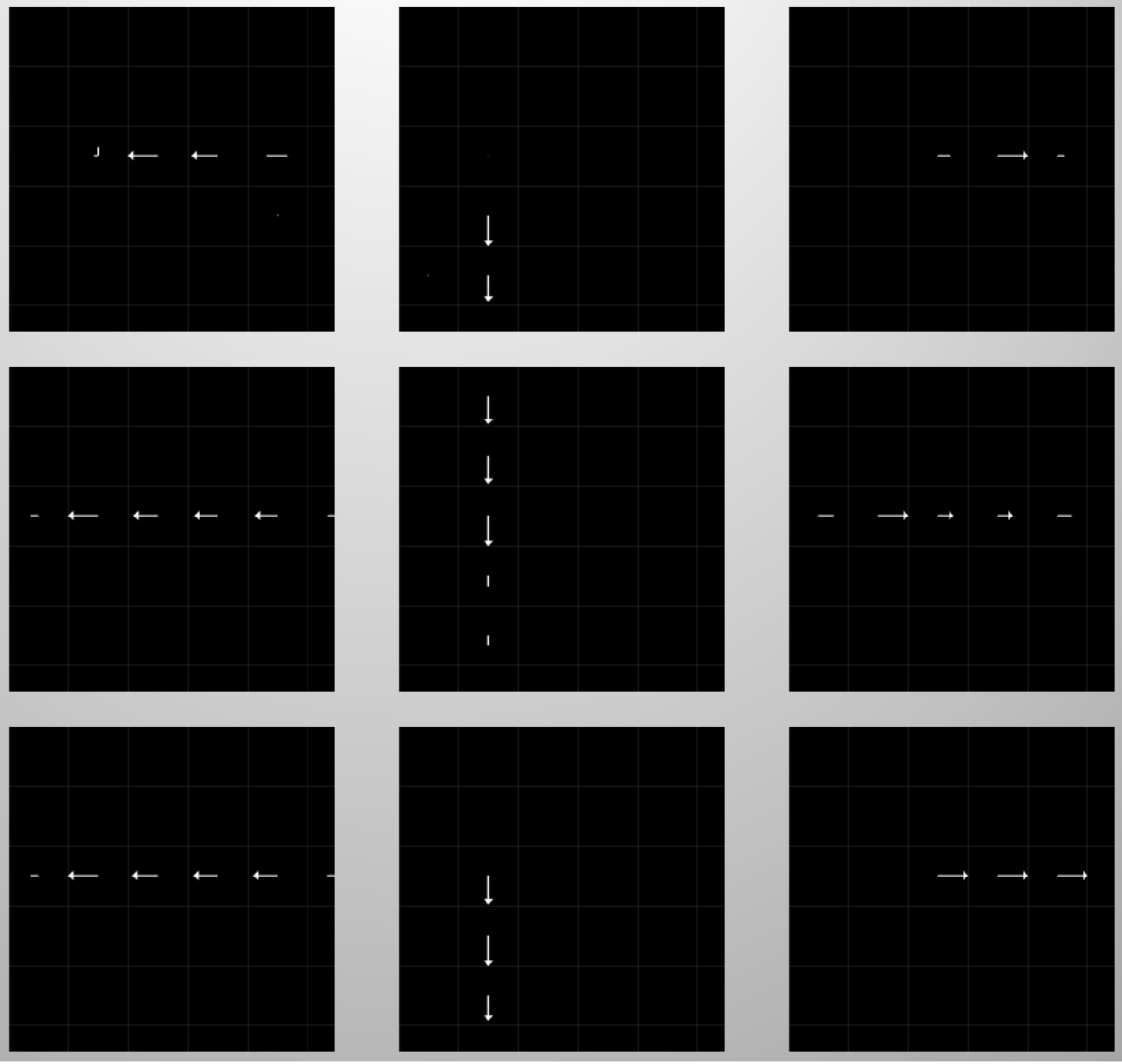
Topics: LDA / HDP / Dual-HDP

Region A

LDA

HDP

Dual-HDP



Anomalies: LDA / HDP / Dual-HDP

Region A

Anomalies: LDA / HDP / Dual-HDP

Region A

Anomalies: LDA / HDP / Dual-HDP

Region A

Number of Topics: LDA / HDP / Dual-HDP

Region	LDA (NLL)	HDP	Dual-HDP
A	50	20	34
B	40	15	30
C	40	21	36
D	35	15	20

Conclusion

- Topic modeling can be a useful tool for trajectory analysis
  → Achieves more consistent clusters and anomalies than simple clustering
  → Obtains meaningful topics related to motion patterns

- HDP and Dual-HDP more consistently detect anomalies
  → Topics less "fragmented" than LDA

Future Directions

- More sophisticated representations of a "word"
  → Smaller cells, more directions
  → Dictionary learning

- Spurious track detection for automated tracker output

- Performance optimization
  → Variational Bayesian methods