Large-Scale Statistical Modelling of Motion Patterns: A Bayesian Nonparametric Approach

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Objective:

- Clustering of *indefinite* number of motion patterns from a *continuous* video stream in an *efficient* manner.

- Keywords:

  - ***Indefinite:*** The number of motion patterns are unknown apriori. Besides the number can change over time.

  - ***Efficient:*** Continuous video processing requires fast feature computation and bounded time incremental update.

Clustering with Dirichlet Process Mixture Model (DPMM):

- Probabilistic mixture model with Dirichlet Process prior.
- Model complexity (no. of components) grows with the data (*infinite mixture model*).
- Additionally, efficient sampling scheme is available with stick-breaking construction of Sethuraman, 1994.

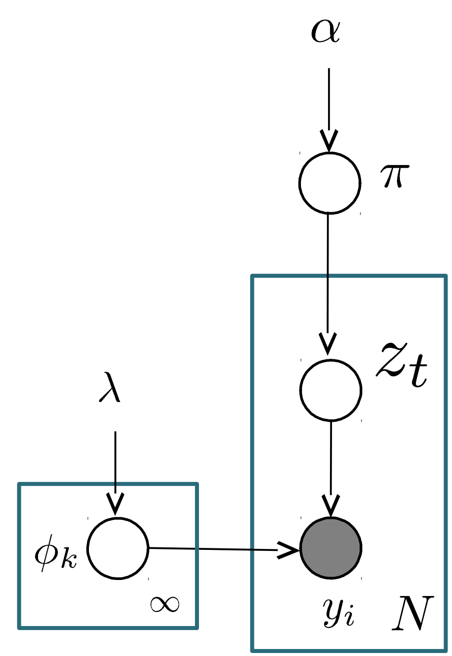
Addresses the issue with the unknown number of clusters!

Inference for DPMM: collapsed Gibbs sampling

- Sample z_t

$$p\left(z_t = k \mid \boldsymbol{z}_{-t}, y_{1:t}, \alpha, \lambda\right)$$

$$\propto \underbrace{p\left(z_t = k \mid \boldsymbol{z}_{-t}, \alpha\right)}_{\text{(1)Prior}} \underbrace{p\left(y_t \mid z_t = k, \boldsymbol{z}_{-t}, \boldsymbol{y}_{-t}, \lambda\right)}_{\text{(2)Predictive}}$$



Stick-breaking view of DPMM

(1)

$$p\left(z_t = k \mid \boldsymbol{z}_{-t}, \alpha\right) \propto \begin{cases} n_k^{-t} & \text{if } k \in \{1, \ldots, K\} \\ \alpha & \text{if } k = k_{\text{new}} \end{cases}$$

(2)

Computing predictive likelihood is easy when conjugate prior is used.

Incremental inference

- Decayed MCMC filtering
  - Concentrate sampling on the immediate past. Always convergent when decay function provides non-zero probability to the states at arbitrary past.
  - Constant time update since a fixed number of past states are re-sampled at each step.

- Our Improvement: *Cluster-sensitive Decayed MCMC (CSD-MCMC)*
  - Concentrate sampling on the immediate past as well as to the neighbouring clusters.
  - Still convergent and update takes constant time.

Addresses one aspect of the issue of efficiency

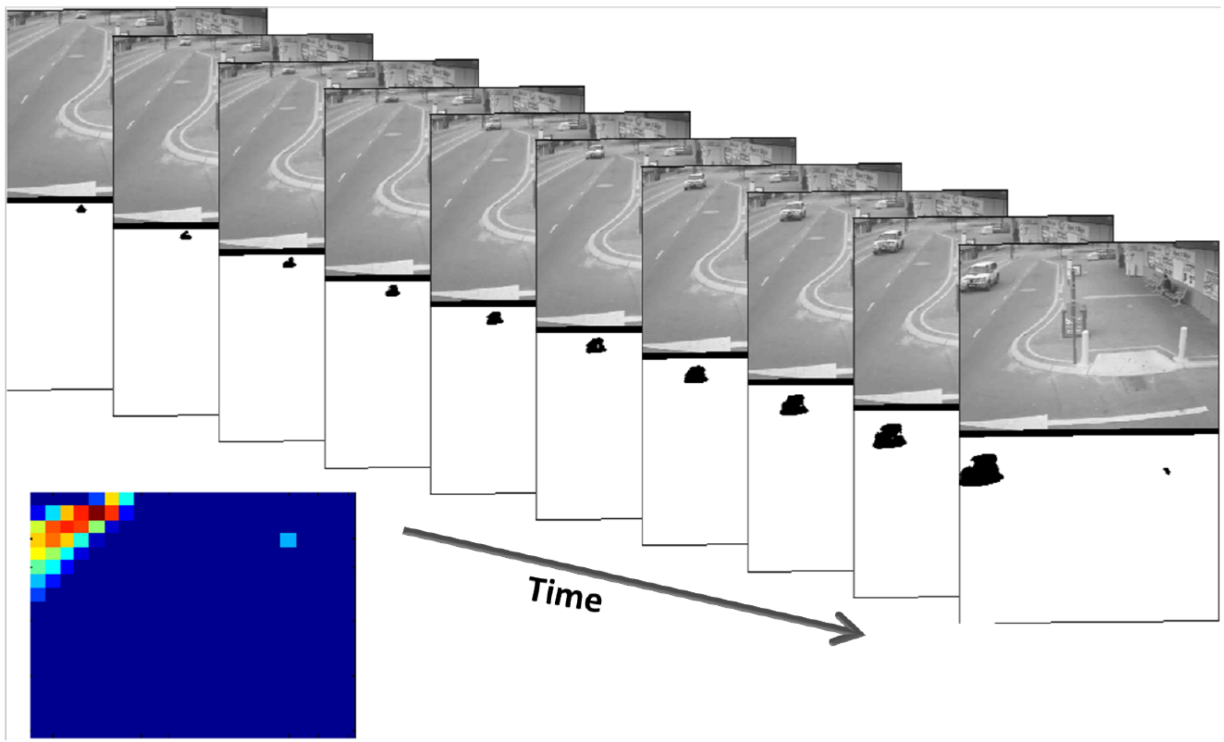
(fixed-cost incremental update)!

Fast feature computation

- Rank-1 constrained Robust PCA for background-foreground separation. Essentially, a robust version of temporal median filter and *fast!*
- Spatial histogram of foreground locations over a coarse grid (eg. 10x10) for each frame are added over a temporal window to create the feature.
    - Fast and simple representation of motions (approx. 10x faster than Optic Flow computation).
    - Robust to spurious motions.

Addresses the other aspect of the issue of efficiency!

Example of the motion feature:



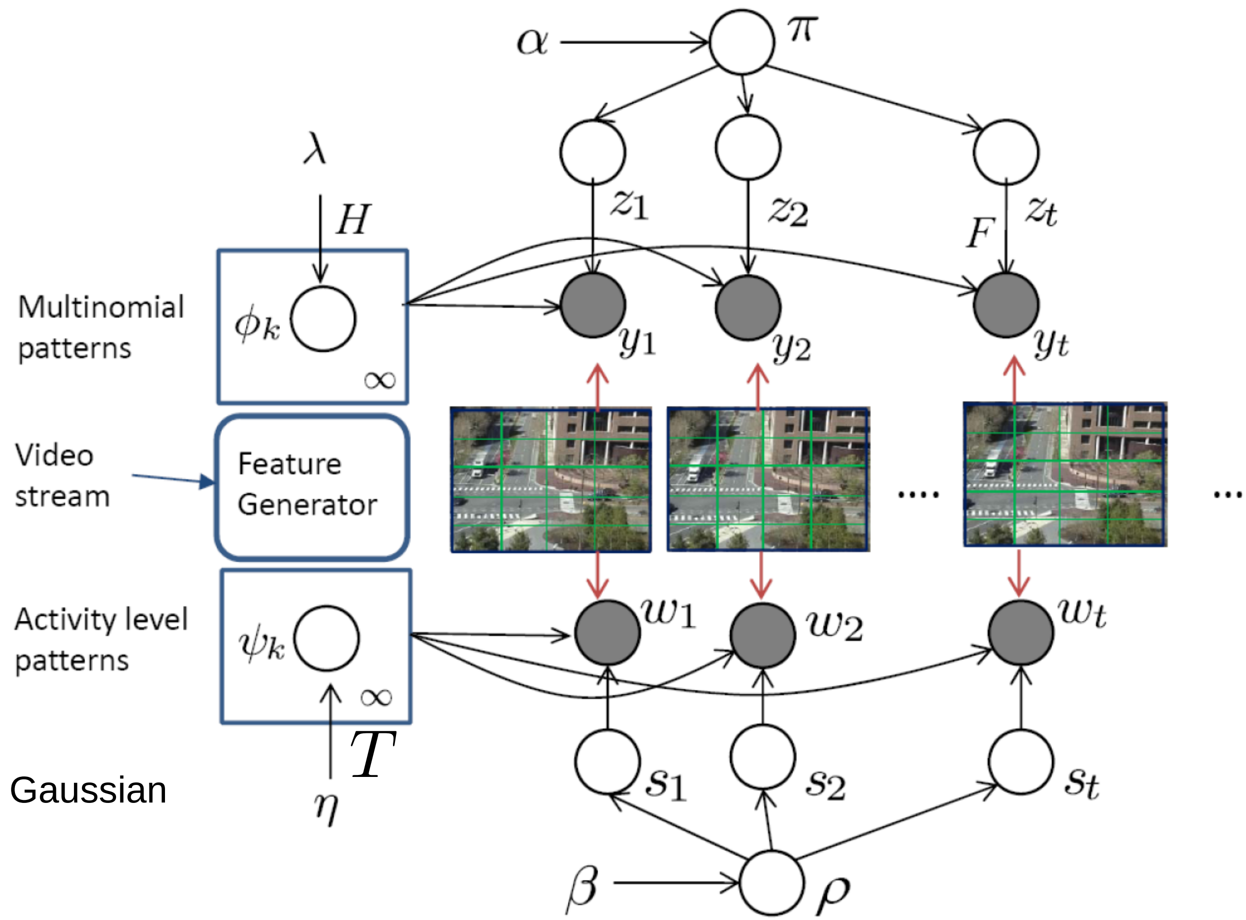
Model aspects: Motion Pattern + Motion Level

- We model motion pattern as samples from a mixture of Multinomial distributions.

- However, Multinomial has a normalization effect.

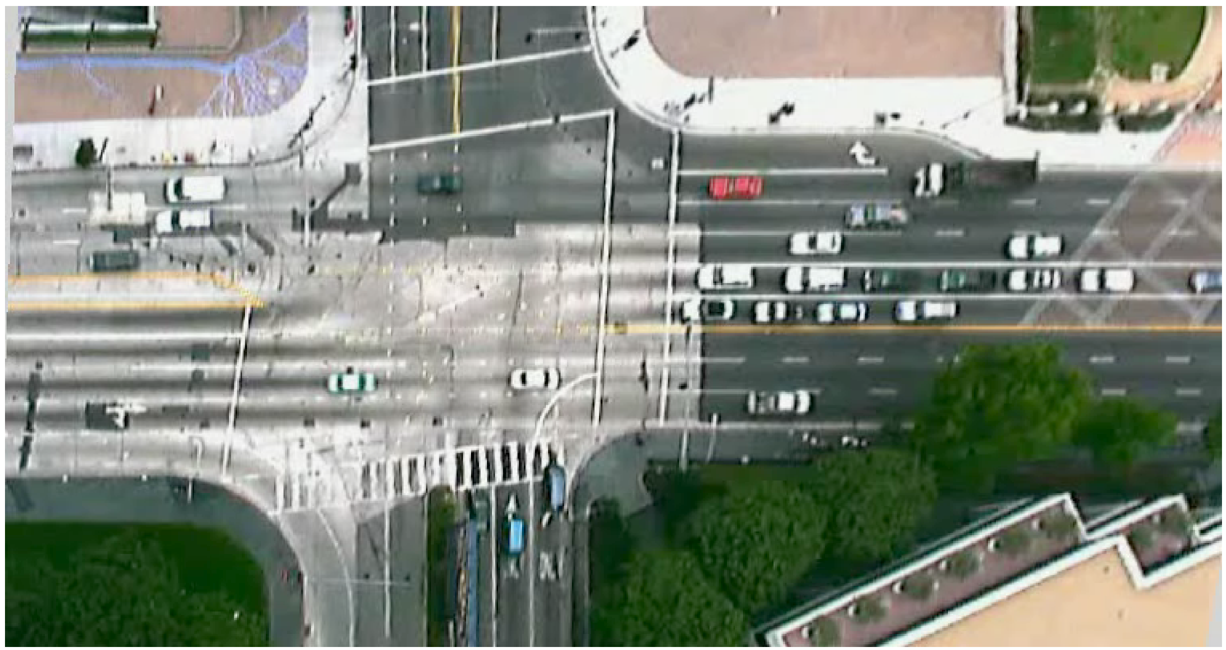
- Hence, a mixture of Gaussian distributions is used to model the activity level.

Putting it all together

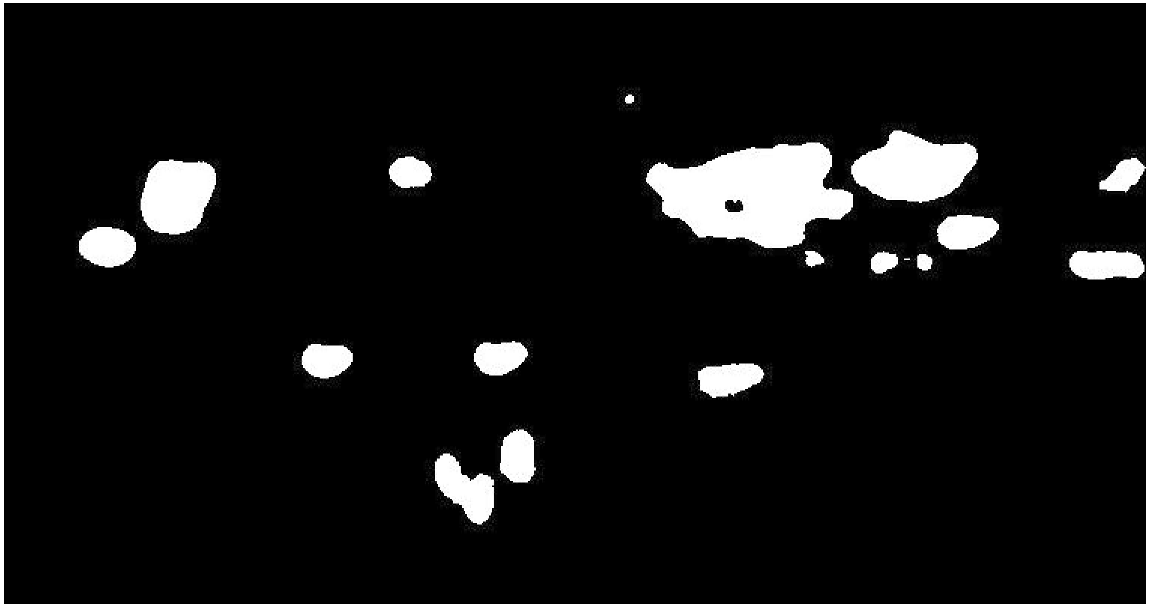


And the incremental inference is performed via CSD-MCMC

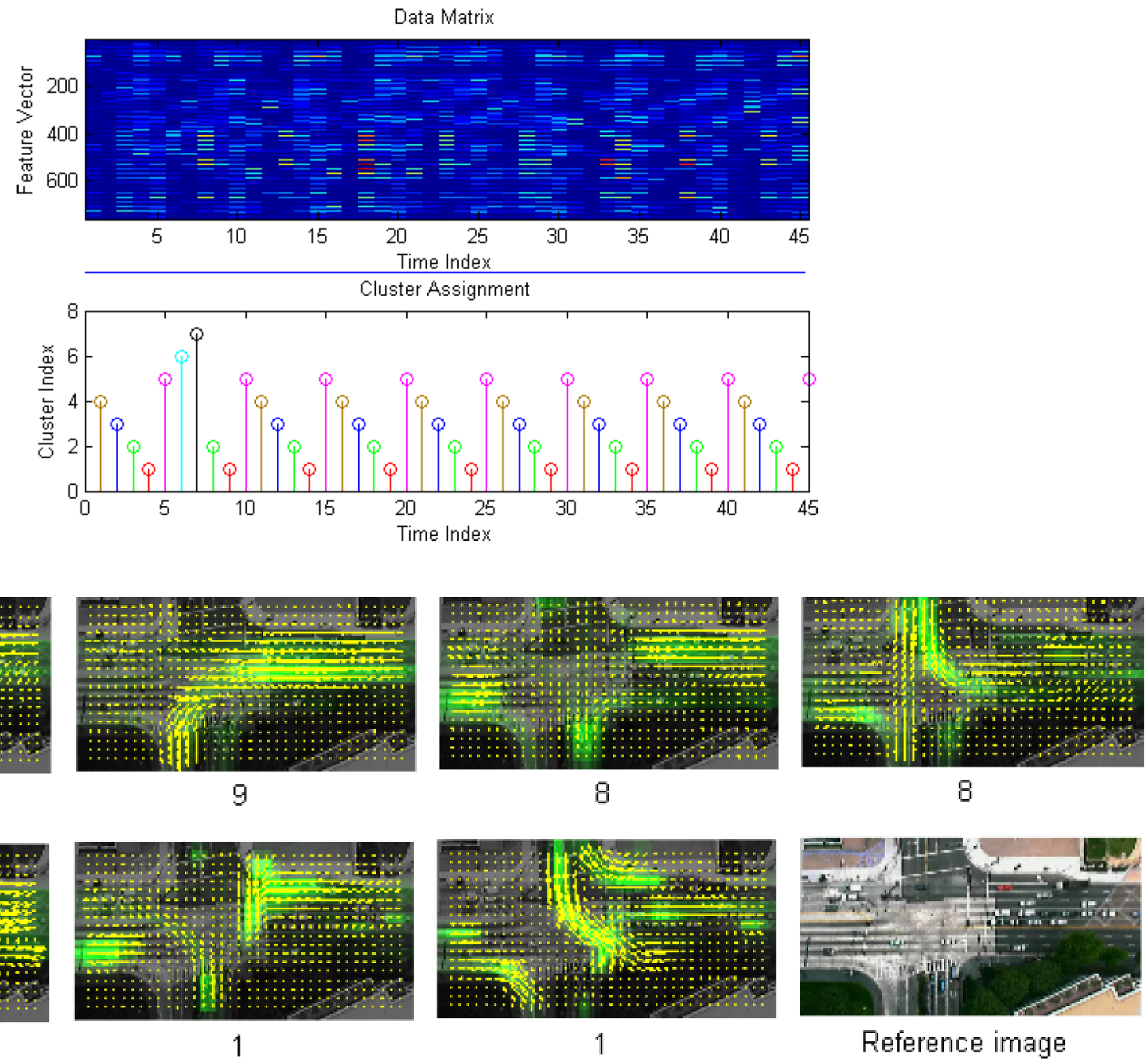
Result 1: Freeway intersection



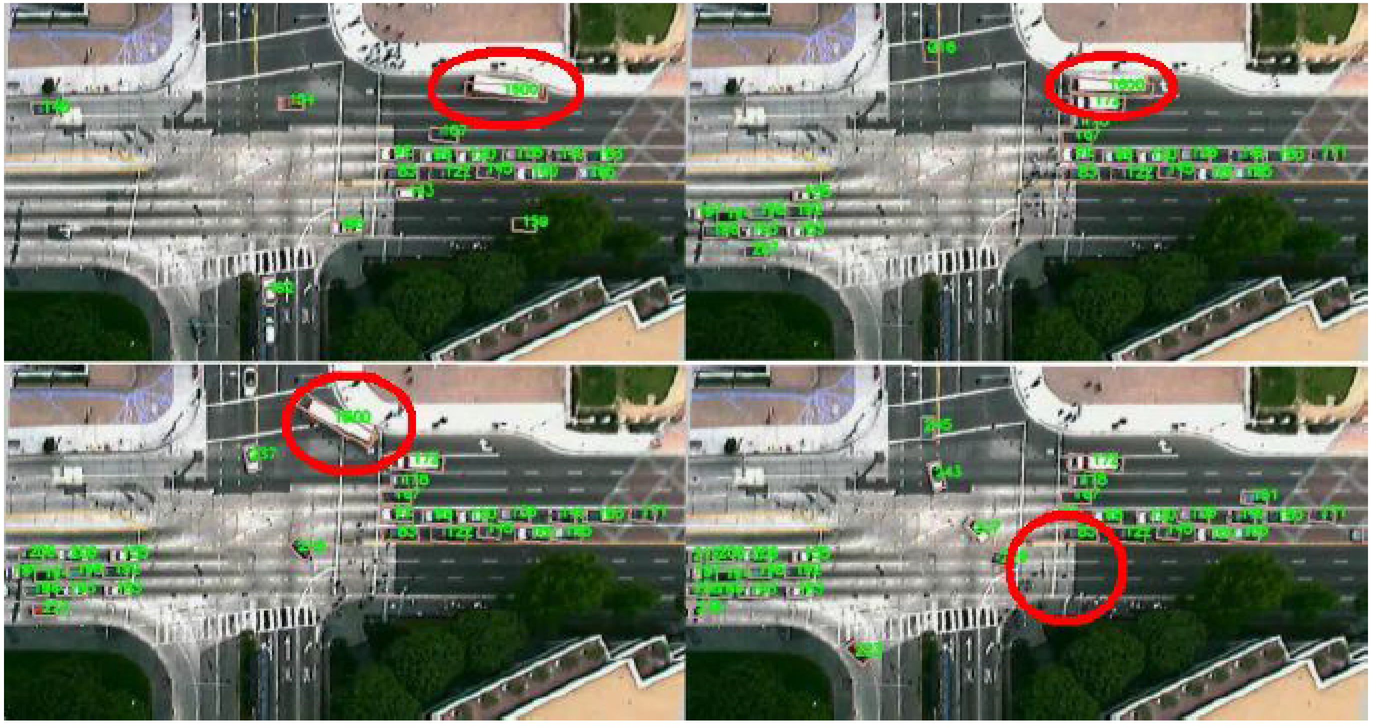
Freeway intersection: background extraction



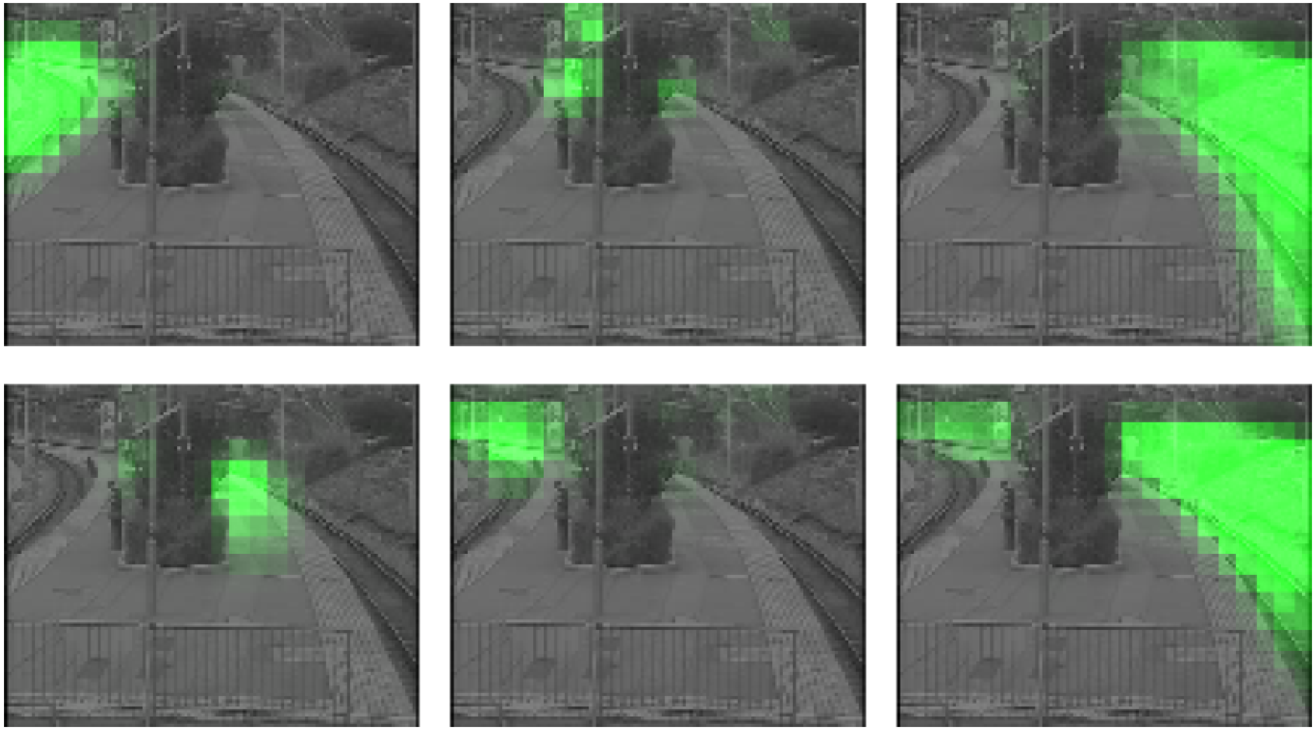
Freeway intersection motion patterns



Anomalous events corresponding to the singleton clusters



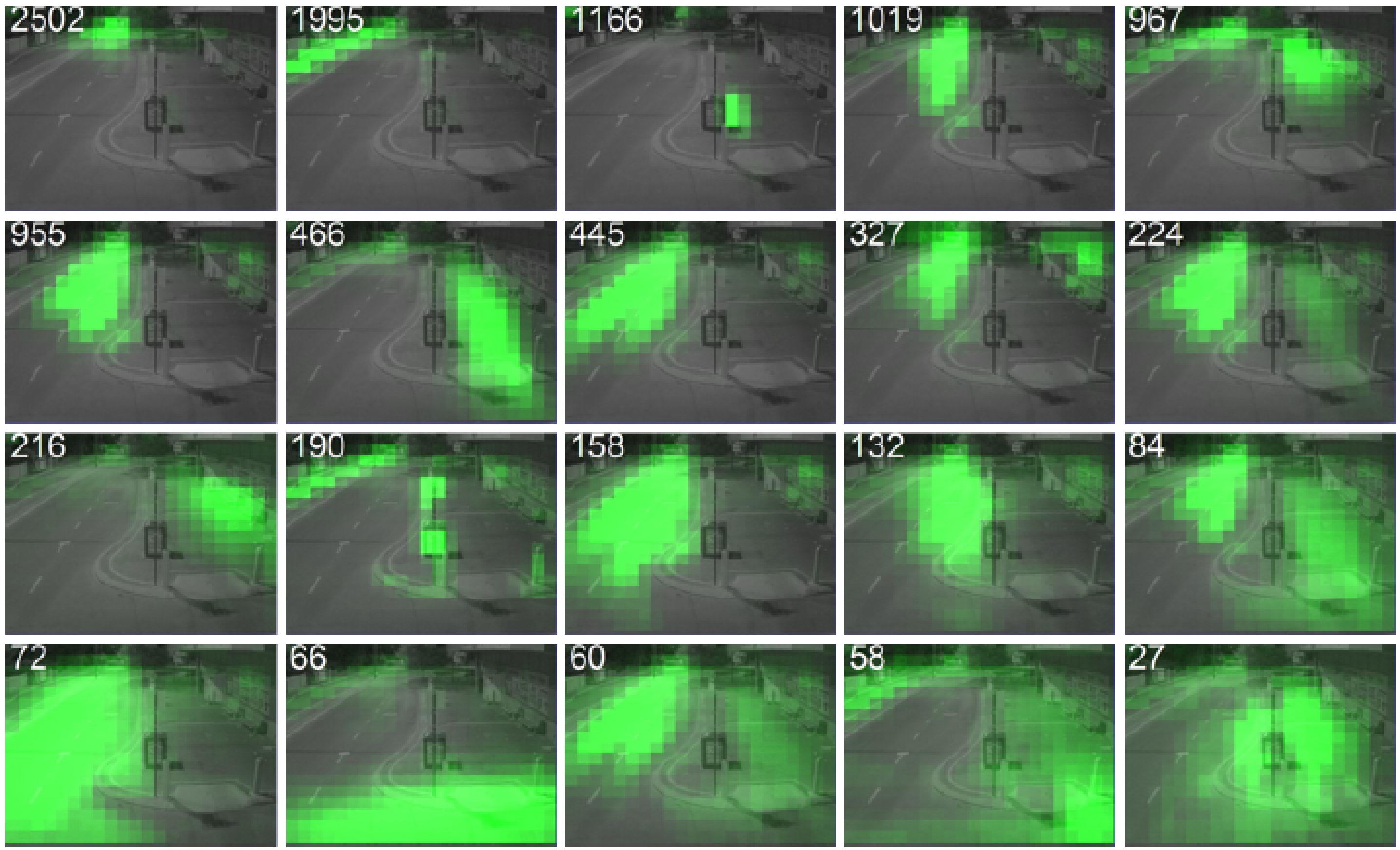
Train station video motion patterns



Train station anomalous events corresponding to cluster size <5

Event type	# events
Loitering, riding bike on the platform etc.	16
People near the edge of the platform.	2
People walking on the railway tracks	2
Technicians checking the camera.	1

Result 3: Street surveillance video (140 hours)



Summary

- We proposed a joint (pattern + activity level) mixture model framework to analyse motion patterns from fixed surveillance cameras.
- Bayesian non-parametric framework is used to scale up model complexity with streaming data.
- We proposed a novel motion feature which is fast to compute.
- We proposed a novel Cluster-Sensitive Decayed MCMC sampling technique for fixed-cost incremental inference.
- We validate our model on large real world surveillance videos.

Thank you!