Anomaly Detection in Video with Bayesian Nonparametrics

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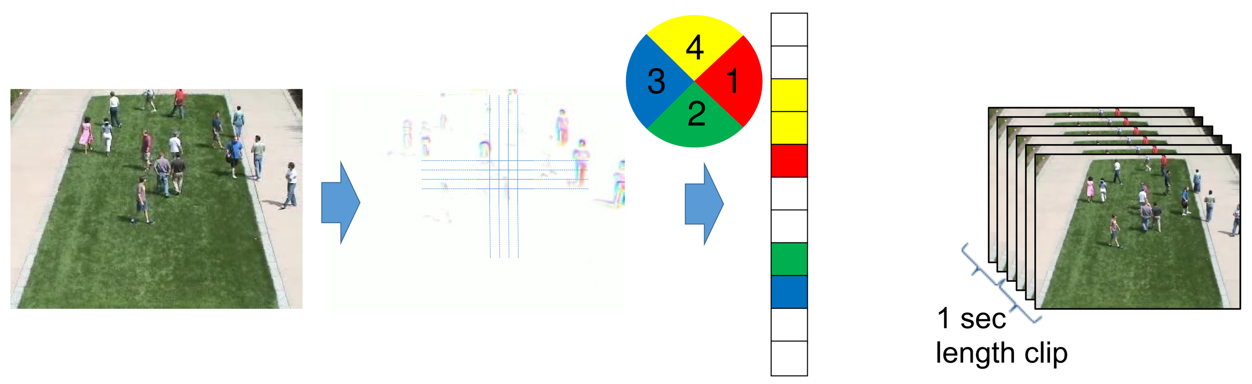
1. Introduction

- Advantages of topic modeling for anomaly detection: probabilistic framework, discovering typical activities in addition to normal/abnormal labeling, expandable
- Proposed:
  - novel dynamic Bayesian nonparametric topic model
  - batch and online Gibbs sampler for inference
  - abnormality measure

2. Visual Features



(a) Visual word extraction (b) Visual documents

Fig. 3: From an input frame an optical flow is calculated; the optical flow is averaged within the grid cells and quantised into four directions to get *visual words*; non-overlapping clips are treated as *documents*.

3. Hierarchical Dirichlet process

Word assignment to table (lower-level DP):

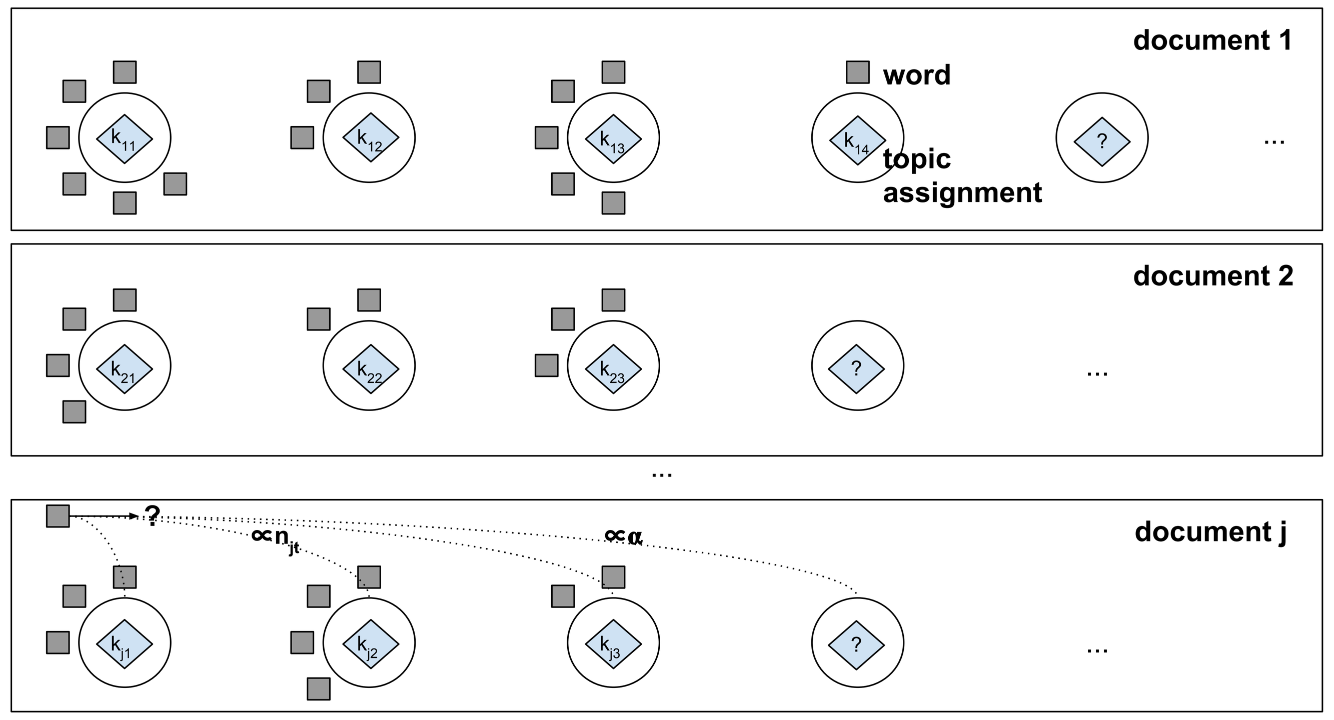


Fig. 1: Word level Chinese Restaurants

— n_{jt} is the number of words assigned to the table t in the document j,

— α is the parameter of the lower-level DP

$$p(t_{ji} = t | t_{j1}, \ldots, t_{ji-1}, \alpha) = \begin{cases} \dfrac{n_{jt}}{i-1+\alpha}, & \text{if } t = 1 : m_{j\cdot}; \\ \dfrac{\alpha}{i-1+\alpha}, & \text{if } t = t^{\text{new}} \end{cases} \quad (1)$$

Topic assignment for table (upper-level DP):

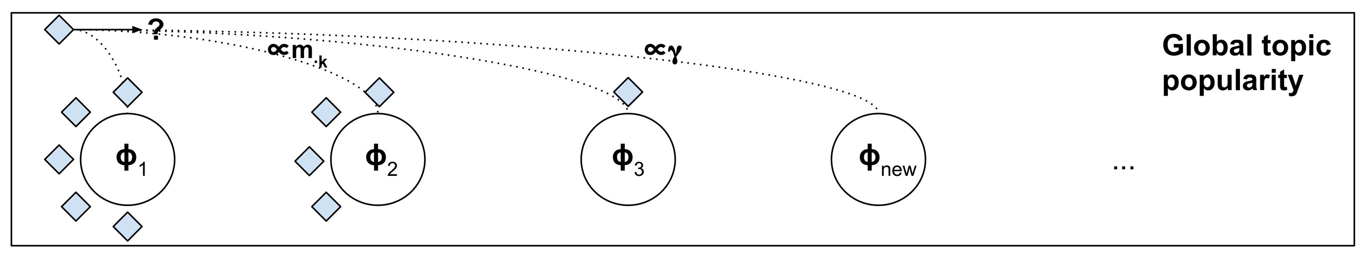


Fig. 2: Topic level Chinese Restaurant for the HDP

— $m_{\cdot k}$ is the number of tables having the topic k among all the documents,

— γ is the parameter of the upper-level DP

$$p(k_{jt^{\text{new}}} = k | k_{11}, \ldots, k_{jt-1}, \gamma) = \begin{cases} \dfrac{m_{\cdot k}}{m_{\cdot\cdot} + \gamma}, & \text{if } k = 1 : K; \\ \dfrac{\gamma}{m_{\cdot\cdot} + \gamma}, & \text{if } k = k^{\text{new}} \end{cases} \quad (2)$$

4. Dynamic Hierarchical Dirichlet Process

Word to table assignment remains the same (Figure 1 and Eq. (1)).

Topic assignment for table (upper-level DP):

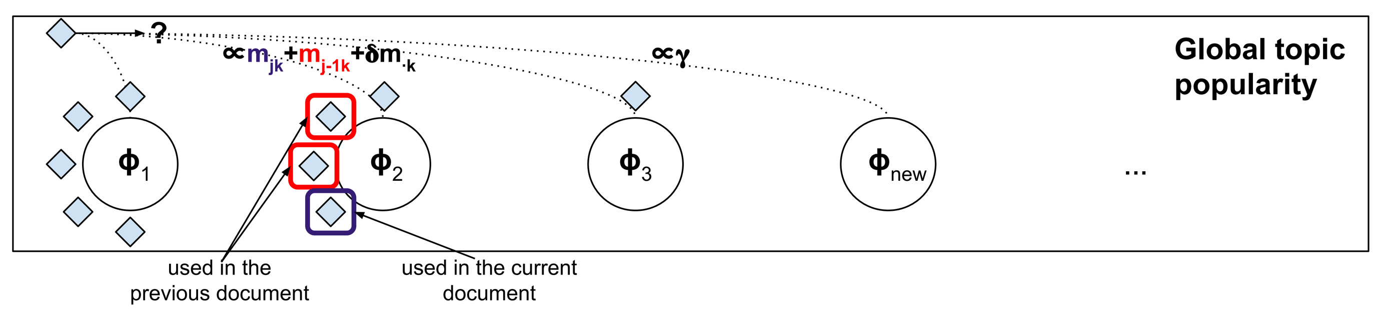


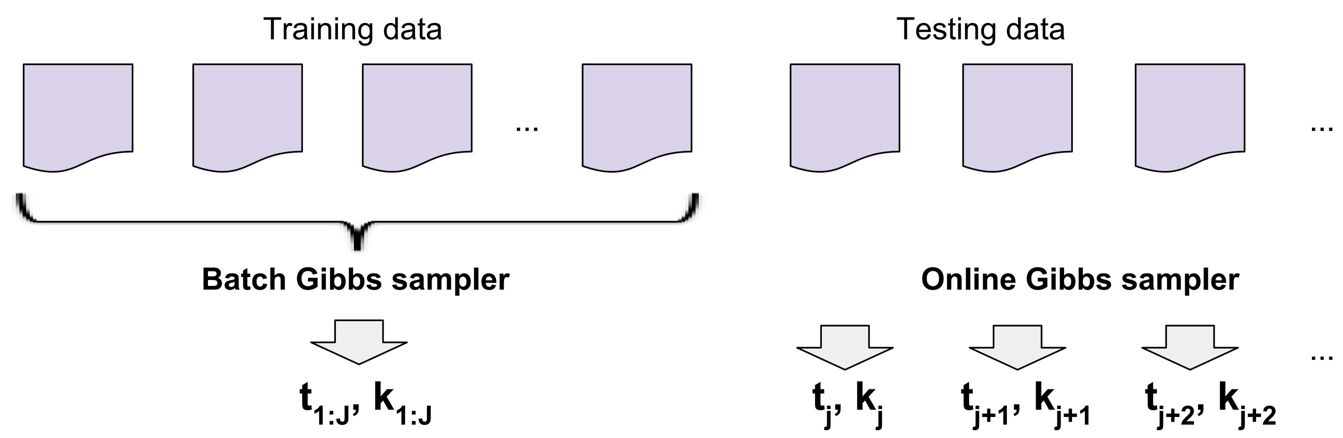
Fig. 4: Topic level Chinese Restaurant for the dynamic HDP

— m_{jk} and m_{j-1k} is the number of tables having the topic k in the current and previous documents respectively,

— δ is the parameter of the dynamic HDP, governing the influence of the old topics

$$p(k_{jt} = k | k_{11}, \ldots, k_{jt-1}, \gamma) = \begin{cases} \dfrac{m_{jk} + m_{j-1k} + \delta m_{\cdot k}}{m_{j\cdot} + m_{j-1\cdot} + \delta m_{\cdot\cdot} + \gamma}, & \text{if } k = 1 : K; \\ \dfrac{\gamma}{m_{j\cdot} + m_{j-1\cdot} + \delta m_{\cdot\cdot} + \gamma}, & \text{it } k = k^{\text{new}} \end{cases} \quad (3)$$

5. Inference



6. Anomaly detection procedure

Abnormality measure = predictive likelihood:

$$p(\mathbf{x}_j | \mathbf{x}_{1:j-1}) = \left(\sum_{\mathbf{t}_{1:j}, \mathbf{k}_{1:j}} \frac{p(\mathbf{t}_{1:j}, \mathbf{k}_{1:j} | \mathbf{x}_j, \mathbf{x}_{1:j-1})}{p(\mathbf{x}_j | \mathbf{t}_{1:j}, \mathbf{k}_{1:j}, \mathbf{x}_{1:j-1})} \right)^{-1} \approx \left(\frac{1}{S} \sum_{s=1}^{S} \frac{1}{p(\mathbf{x}_j | \mathbf{t}^s_{1:j}, \mathbf{k}^s_{1:j}, \mathbf{x}_{1:j-1})} \right) \quad (4)$$

— S is the number of the posterior samples,

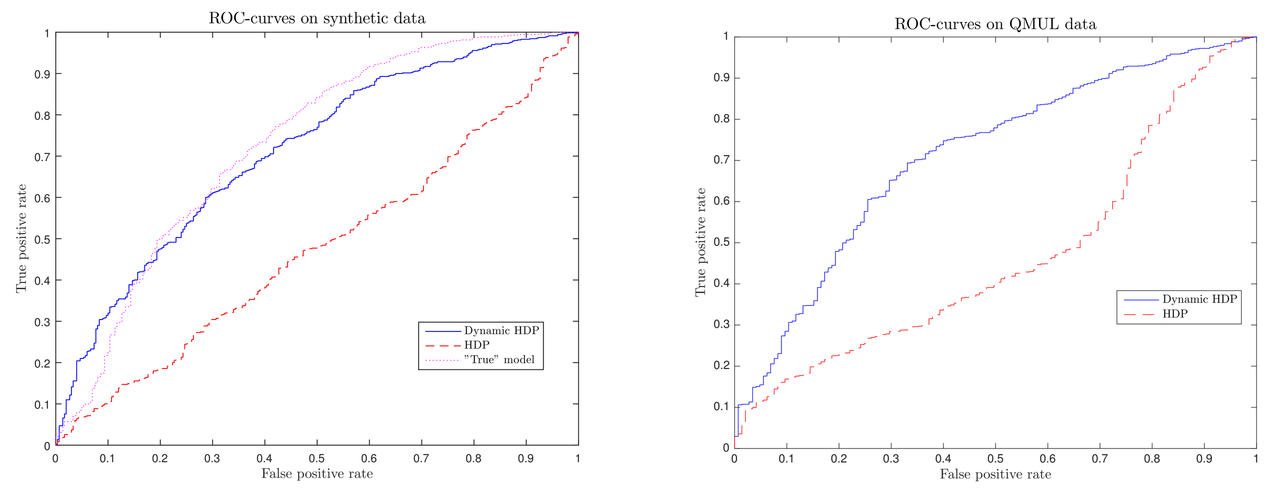
— $\mathbf{t}^s_{1:j}$ and $\mathbf{k}^s_{1:j}$ are from the s-th posterior sample obtained by the Gibbs sampler

7. Numerical experiments

The proposed method is compared with the one, based on the conventional HDP model, both on synthetic and real data.

(a) Normal motion sample (b) Jay-walking (c) Driving wrong direction (d) Disruption in traffic flow

Fig. 6: QMUL-junction real dataset snapshots: normal motion and three abnormal examples.



Synthetic data QMUL-junction real data

Fig. 7: ROC-curves for anomaly detection. For the synthetic data there is also the ROC-curve for the "true" model, i.e. the model with the true topics $\boldsymbol{\phi}_k$ and the true table and topic assignments $\mathbf{t}$ and $\mathbf{k}$. This model represents the one that can perfectly restore all the latent variables.

8. Conclusions

A novel Bayesian nonparametric dynamic topic model is proposed. Empirical results prove consideration of dynamics in topic modeling improves anomaly detection performance.

Future work includes further dynamics development and anomaly localisation.