Discovering Dynamic Topic Transitions in Topic Models

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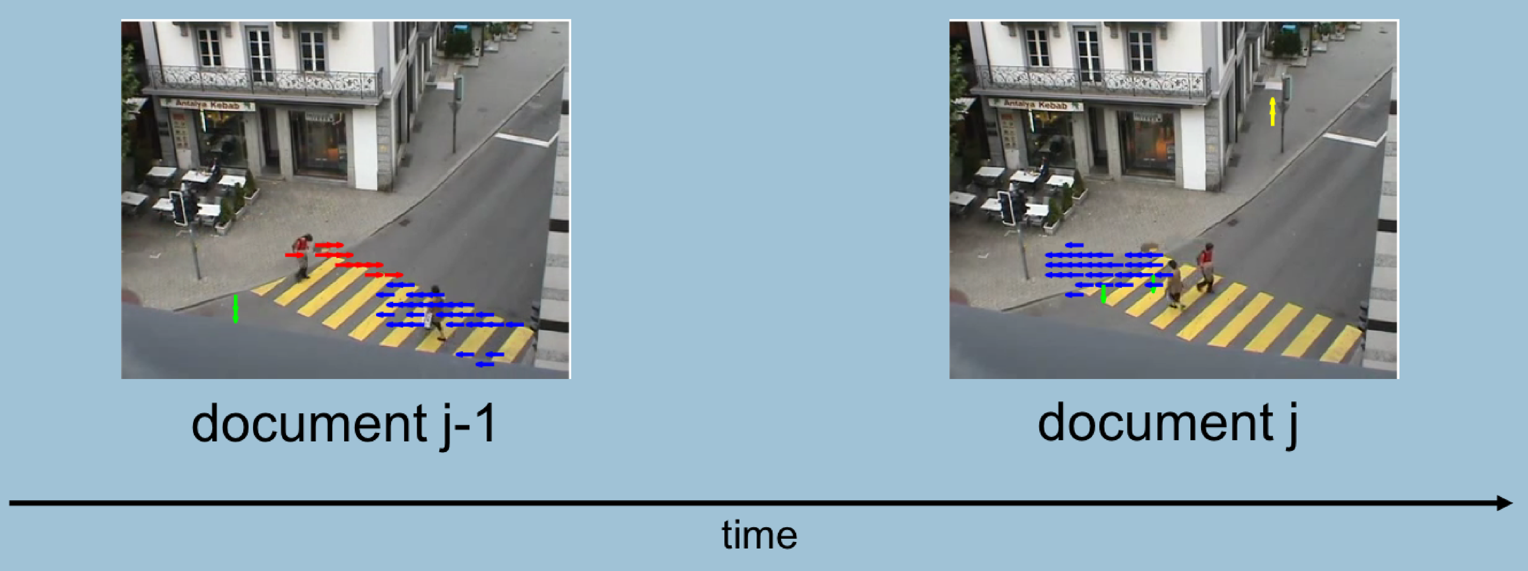
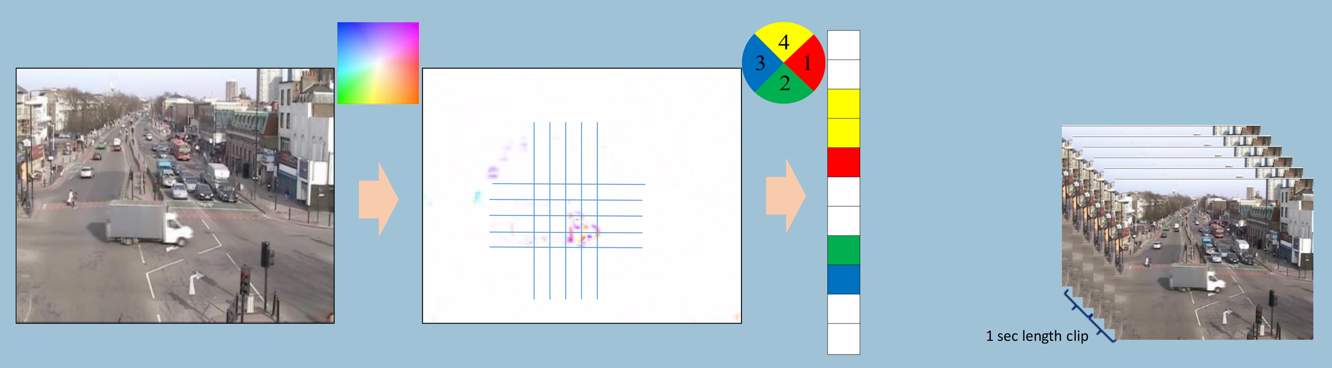
1. Motivation

Consider topic modeling of dynamic data



Assumption:
Topics in the current document depend on topics from the previous document
Topics follow latent transitional rules

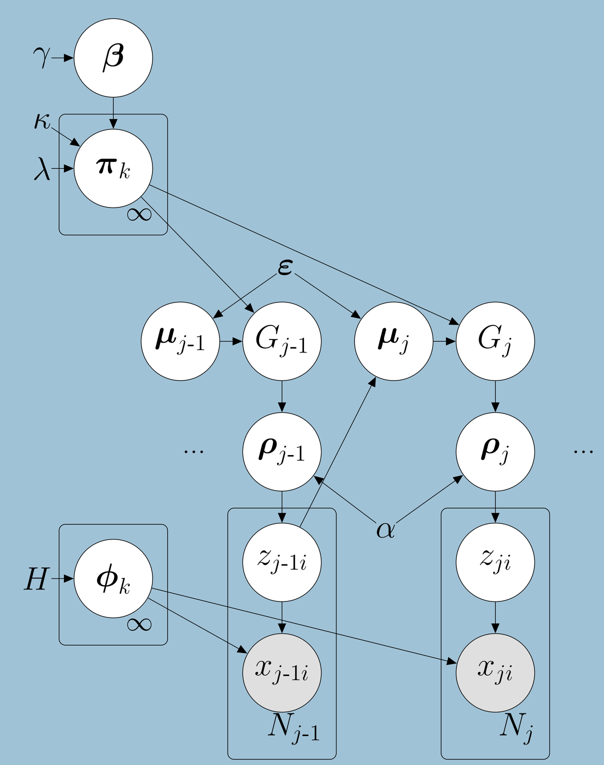
2. Visual features



(a) Visual word extraction (b) Visual documents

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. DP with HDP-HMM prior



Graph model for DP with HDP-HMM prior

Global topic probability

$$\boldsymbol{\beta}|\gamma \sim \mathrm{GEM}(\gamma)$$

Topic transition distributions

$$\boldsymbol{\pi}_k|\lambda, \kappa, \boldsymbol{\beta} \sim \mathrm{DP}\left(\lambda + \kappa, \frac{\lambda\boldsymbol{\beta} + \kappa\delta_k}{\lambda + \kappa}\right) \quad \forall k$$

Mixture weights for each document

$$\boldsymbol{\mu}_j|\mathcal{K}_{j-1}, \boldsymbol{\varepsilon} \sim Dir_{\mathcal{K}_{j-1}}(\boldsymbol{\varepsilon}) \quad \forall j$$

Base measure for each document

$$G_j = \sum_{k \in \mathcal{K}_{j-1}} \mu_{jk}\boldsymbol{\pi}_k \quad \forall j$$

Each document as a topic mixture

$$\boldsymbol{\rho}_j|\alpha, G_j \sim \mathrm{DP}(\alpha, G_j) \quad \forall j$$

Distribution over words for topic l

$$\boldsymbol{\phi}_l \sim H = Dir(\boldsymbol{\eta}) \quad \forall l$$

Topic and word assignments for each token

$$z_{ji}|\boldsymbol{\rho}_j \sim \boldsymbol{\rho}_j \quad \forall i, j$$

$$x_{ji}|z_{ji}, \{\boldsymbol{\phi}_l\}_{l=1}^{\infty} \sim F(\boldsymbol{\phi}_{z_{ji}}) = Mult(\boldsymbol{\phi}_{z_{ji}}) \quad \forall i, j$$

4. Inference

A novel **ancestor** Gibbs sampler is developed (based on CRF representation)

Gibbs sampling for DP with HDP-HMM prior

Input: observed words $\mathbf{x}$, the number M of burn-in iterations

for $m = 1$ **to** M **do**
  Sample global topic probabilities $\boldsymbol{\beta}$;
  Sample topic transition probabilities $\boldsymbol{\pi}_k$, $\forall k$;
  Sample table assignments t_{ji} for each word, $\forall j, i$;
  Sample topic ancestor assignments k_{jt} for each table t, $\forall j, t$;
  Sample topic assignments z_{jt} for each table t, $\forall j, t$
end for

+ no complex dependences on future observations
+ truncation-free
+ linear time complexity

5. Topic structures learnt by the model

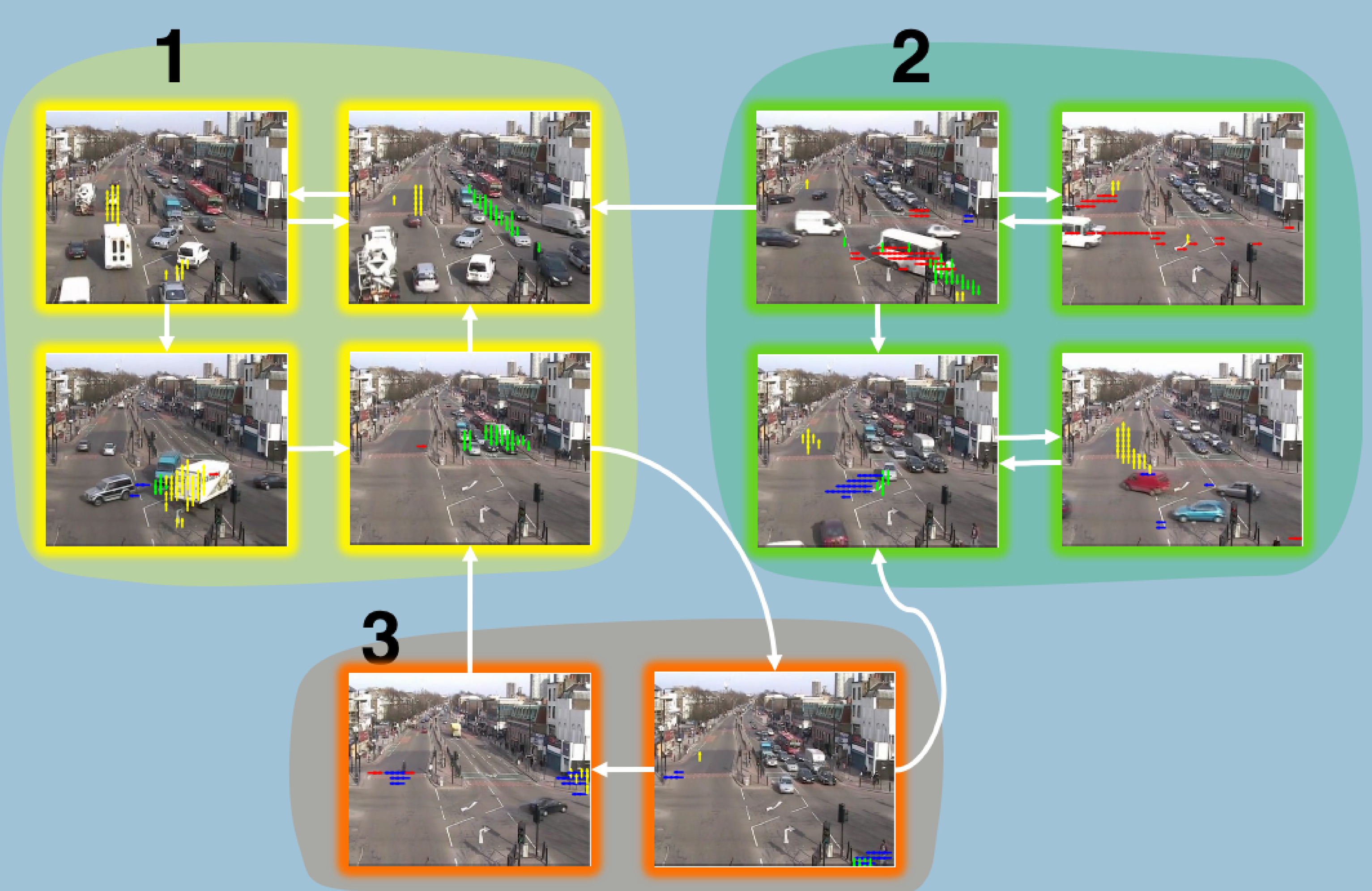


Diagram of learnt topic dynamics on the QMUL data

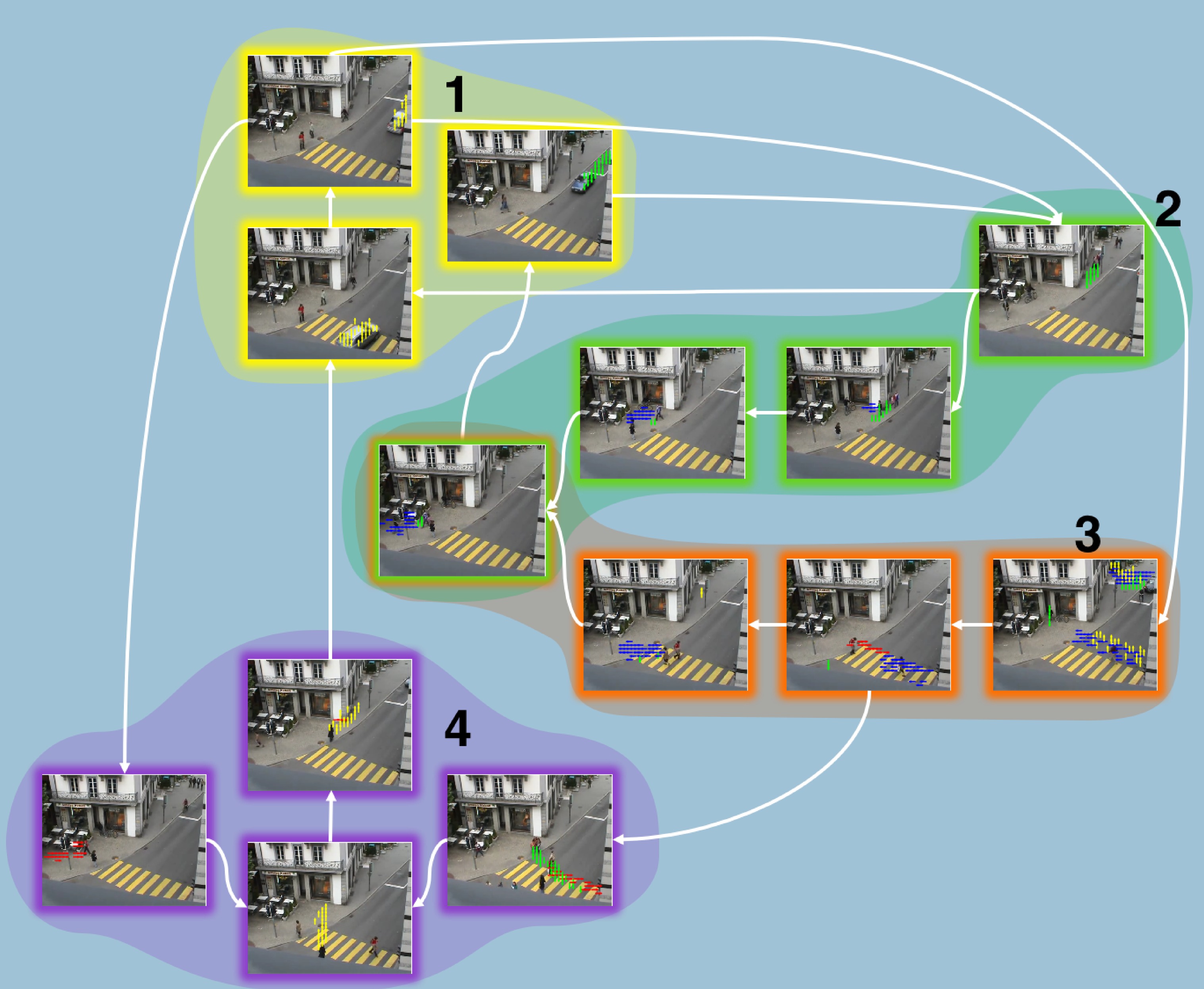
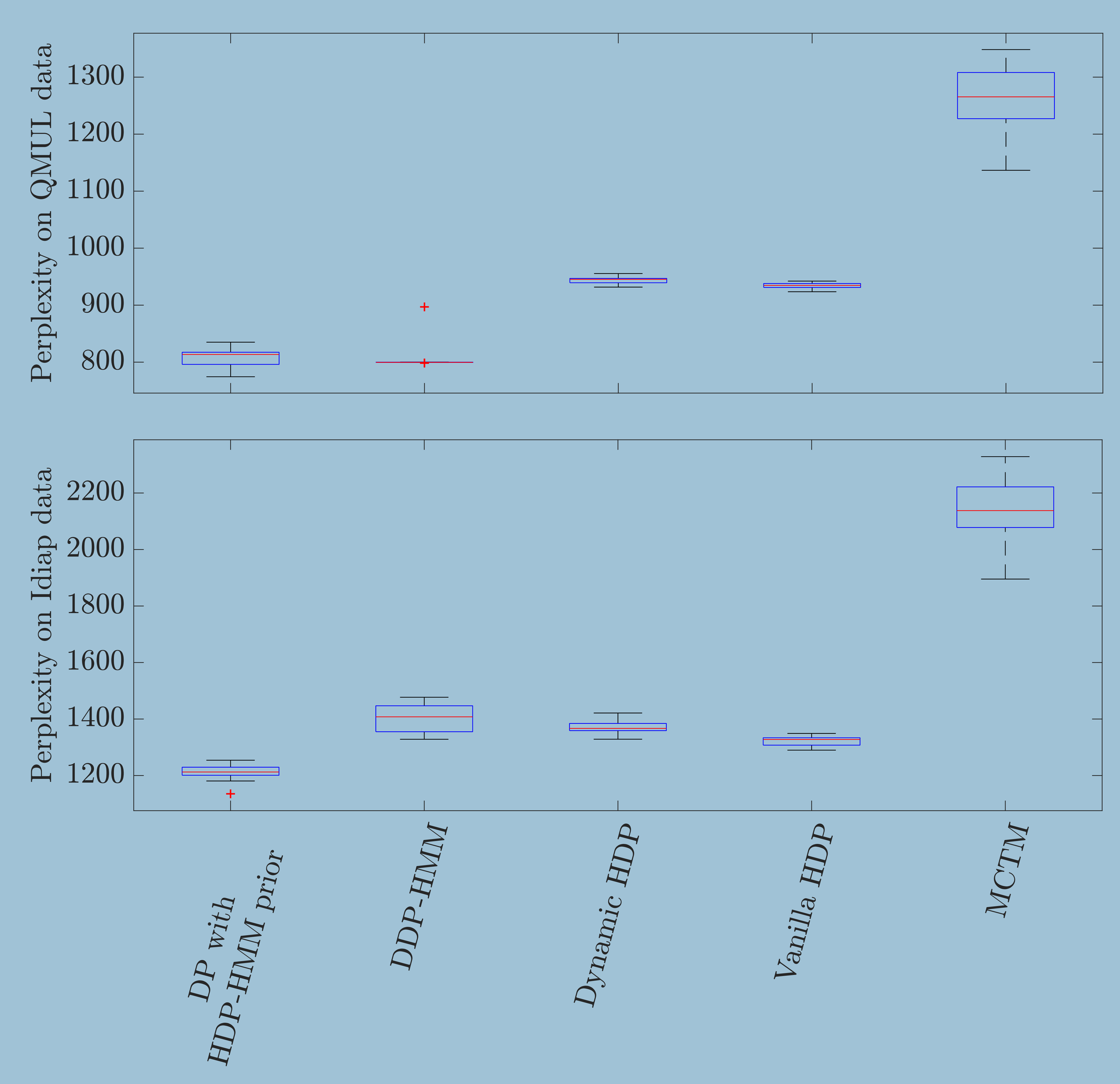


Diagram of learnt topic dynamics on the Idiap data

6. Quantitative comparison



Perplexity results

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