

## Overview

- Explicitly detect visual bursts in an image at an early stage
- Aggregate bursty groups into meta-descriptors on database side
- Asymmetric scheme: do not aggregate on query side
- On par with state of the art, yet at much lower memory and query time

## Representation and matching

### Image representation

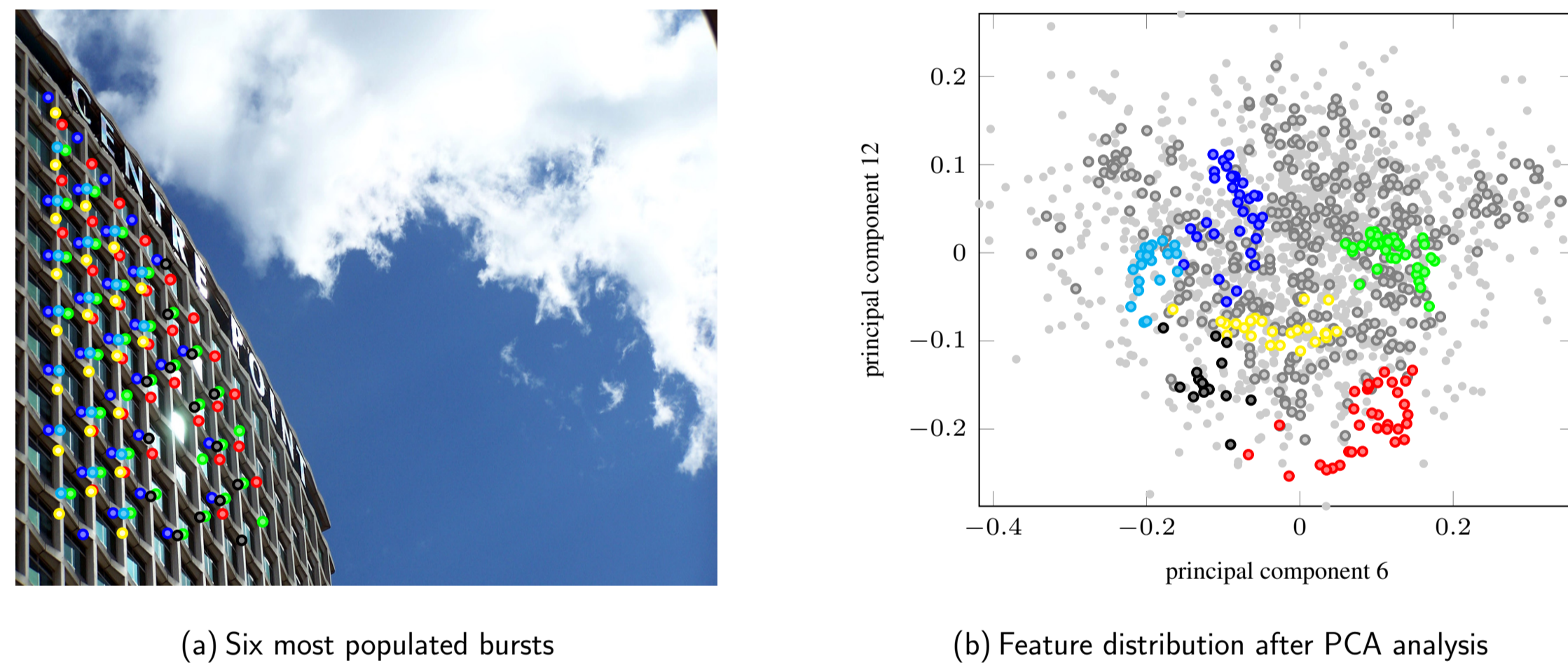
- $\mathcal{X}$ : set of  $d$ -dimensional local descriptors per image
- $\mathcal{C}$ : codebook of  $d$ -dimensional visual words or cells
- $\mathcal{X}_c$ : descriptors assigned to cell  $c \in \mathcal{C}$

### Similarity function

$$S(\mathcal{X}, \mathcal{Y}) = \nu(\mathcal{X}) \nu(\mathcal{Y}) \sum_{c \in \mathcal{C}} w_c M(\mathcal{X}_c, \mathcal{Y}_c)$$

- $M$ : cell similarity function
- $w_c$ : visual word weighting e.g. idf
- $\nu(\mathcal{X}) = (\sum_{c \in \mathcal{C}} w_c M(\mathcal{X}_c, \mathcal{X}_c))^{-1/2}$ : normalization factor

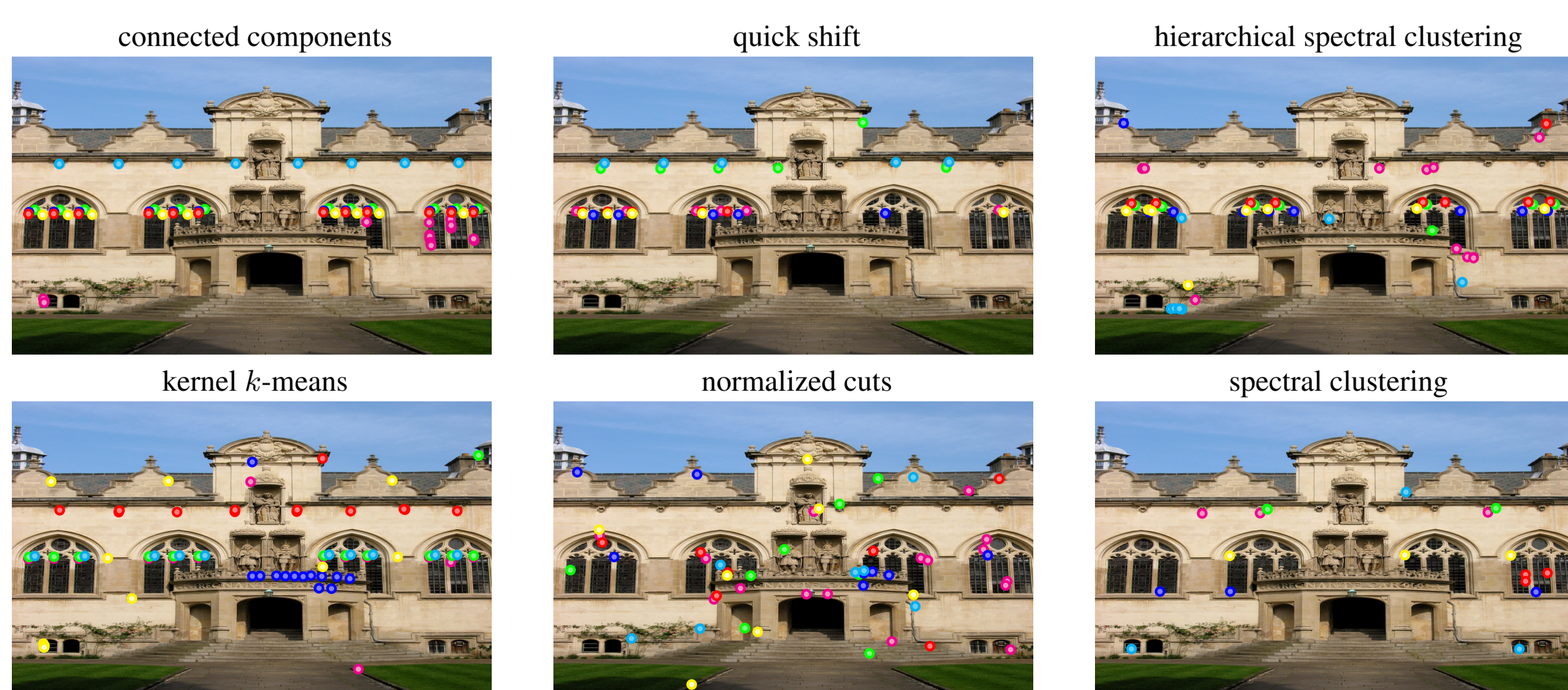
## What are visual bursts?



### Observation

- Not like text bursts: the descriptor space is continuous
- Bursts have arbitrary shape and overlap: unlikely to fit within codebook cells
- Possible sources: to structure in man-made scenes, texture in natural environments, multiple feature detector responses

## Burst detection example



## Feature kernel

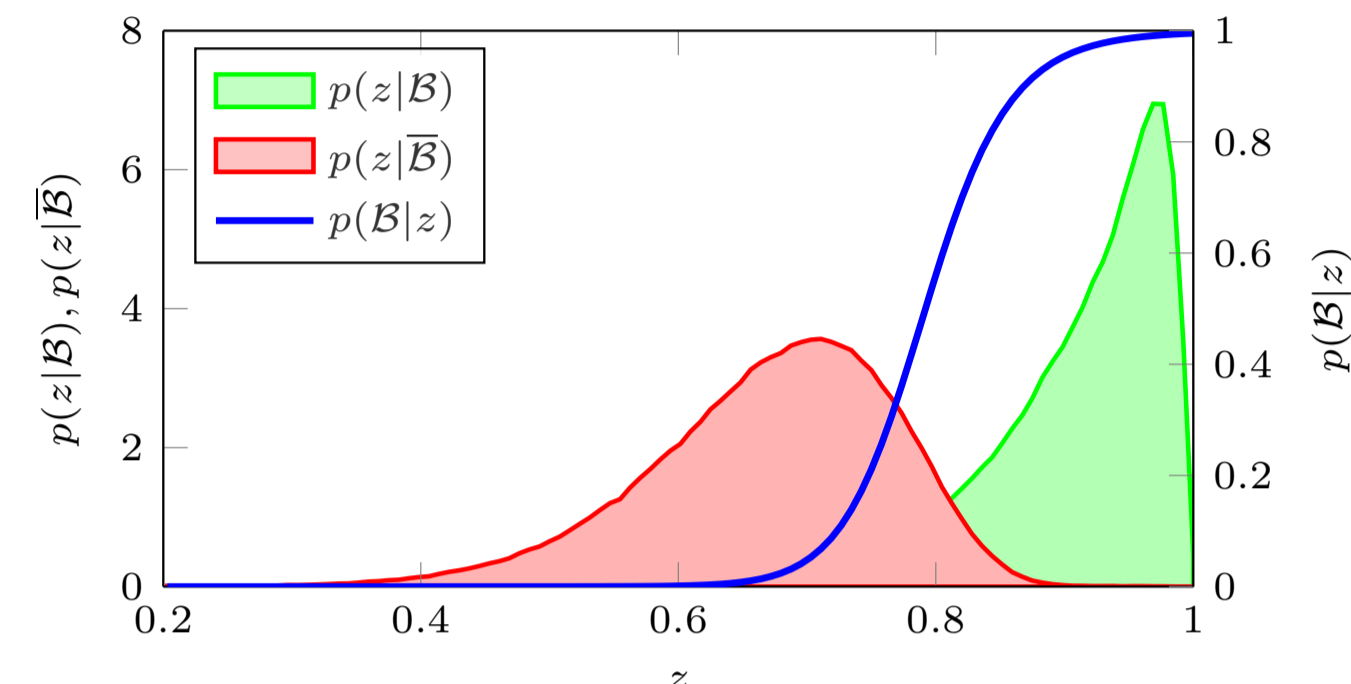
### Feature kernel $k$

$$k(f, g) = k_u(u_f, u_g) k_s(s_f, s_g) k_\theta(\theta_f, \theta_g)$$

- $f, g$ : local image features
- $u_f$ : local descriptor;  $s_f$ : scale;  $\theta_f$ : orientation

### Descriptor kernel $k_u$

- Generative binary classifier:



$$k_u(x, y) = \frac{p(\mathcal{B}|x, y)}{p(z|\mathcal{B})p(\mathcal{B}) + p(z|\bar{\mathcal{B}})p(\bar{\mathcal{B}})}$$

- $\mathcal{B}$ : pairs in the same burst
- $\bar{\mathcal{B}}$ : pairs not in the same burst

### Scale kernel $k_s$

- Gaussian:  $k_s(s, t) = \exp\left\{-\lambda \log^2\left(\frac{s}{t}\right)\right\}$

### Orientation kernel $k_\theta$

- von Mises:  $k_\theta(\theta, \phi) = \frac{e^{\kappa \cos(\theta - \phi)} - e^{-\kappa}}{2 \sinh(\kappa)}$

## Burst detection and aggregation

### Representation

- $\mathcal{F} = \{f_1, \dots, f_n\}$ : set of  $n$  local image features
- $K$ :  $n \times n$  affinity matrix with  $K_{ij} = k(f_i, f_j)$

### Burst detection

- Based on a kernel method, or operate on metric spaces
- Able to automatically determine (or to control with a parameter) the number of groups, such that non-matching features are not grouped
- The clear winner amongst all tested methods is connected component analysis

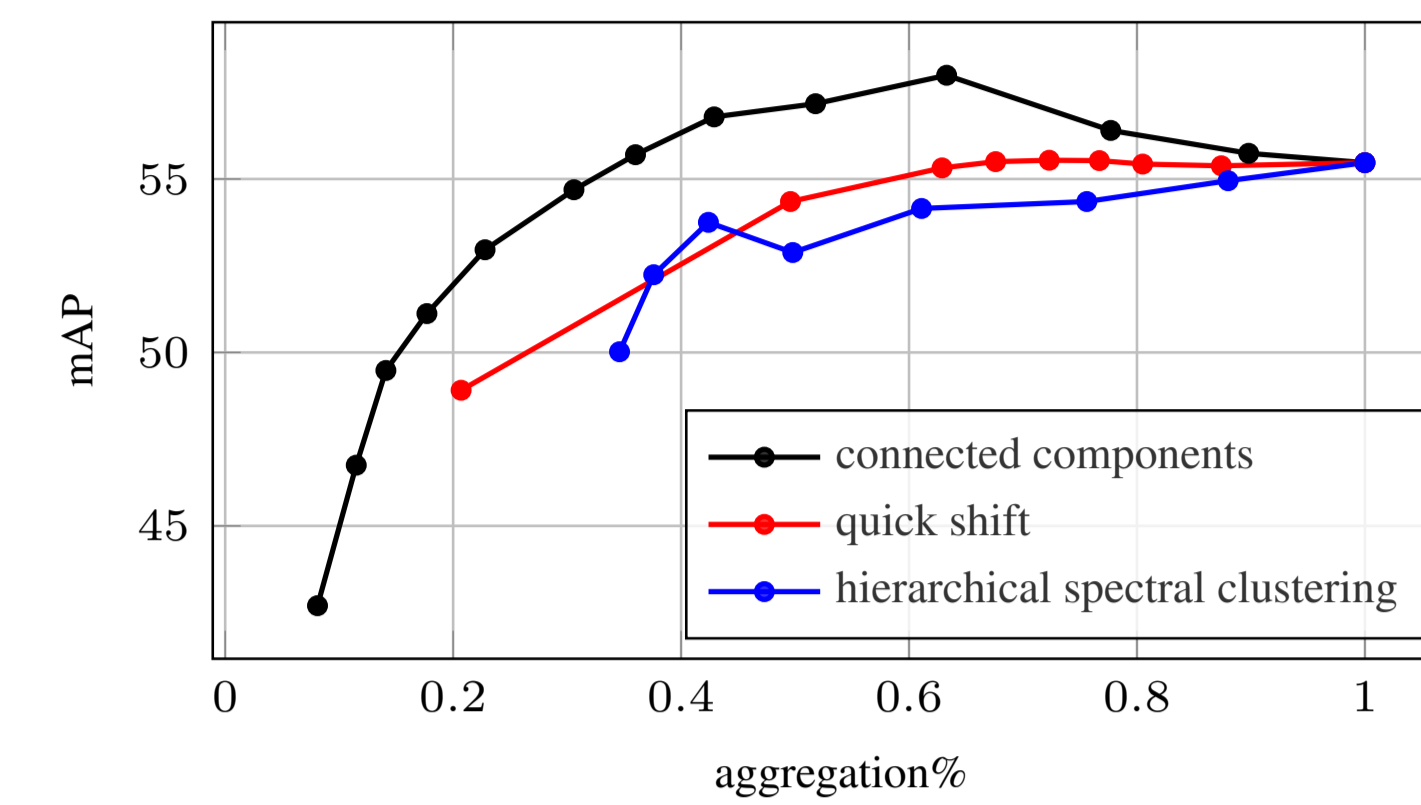
### Burst aggregation

- Take the average of the descriptors in each bursty group and  $\ell_2$ -normalize.

## Burst detection using connected components



## Experiments on VLAD

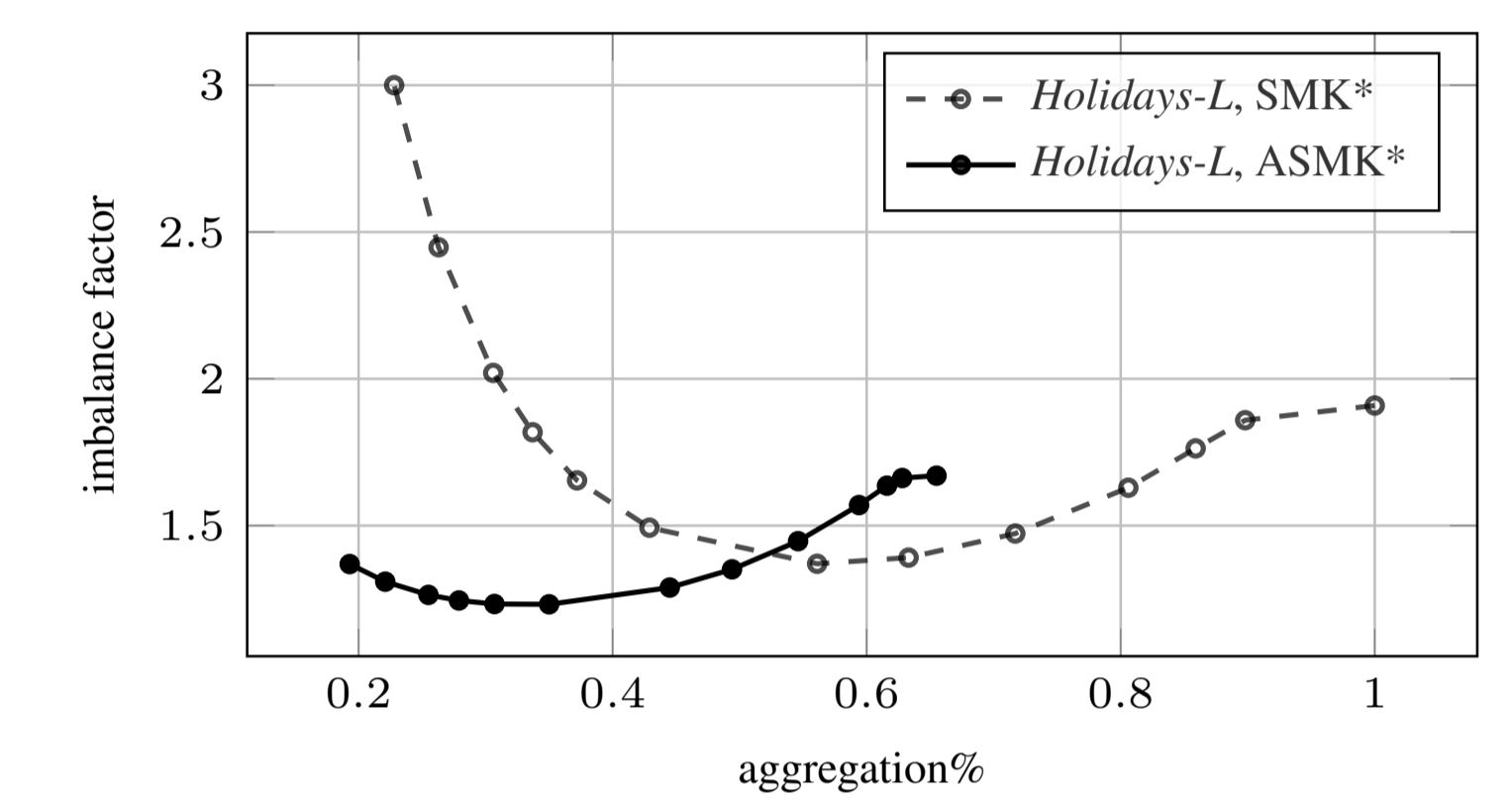
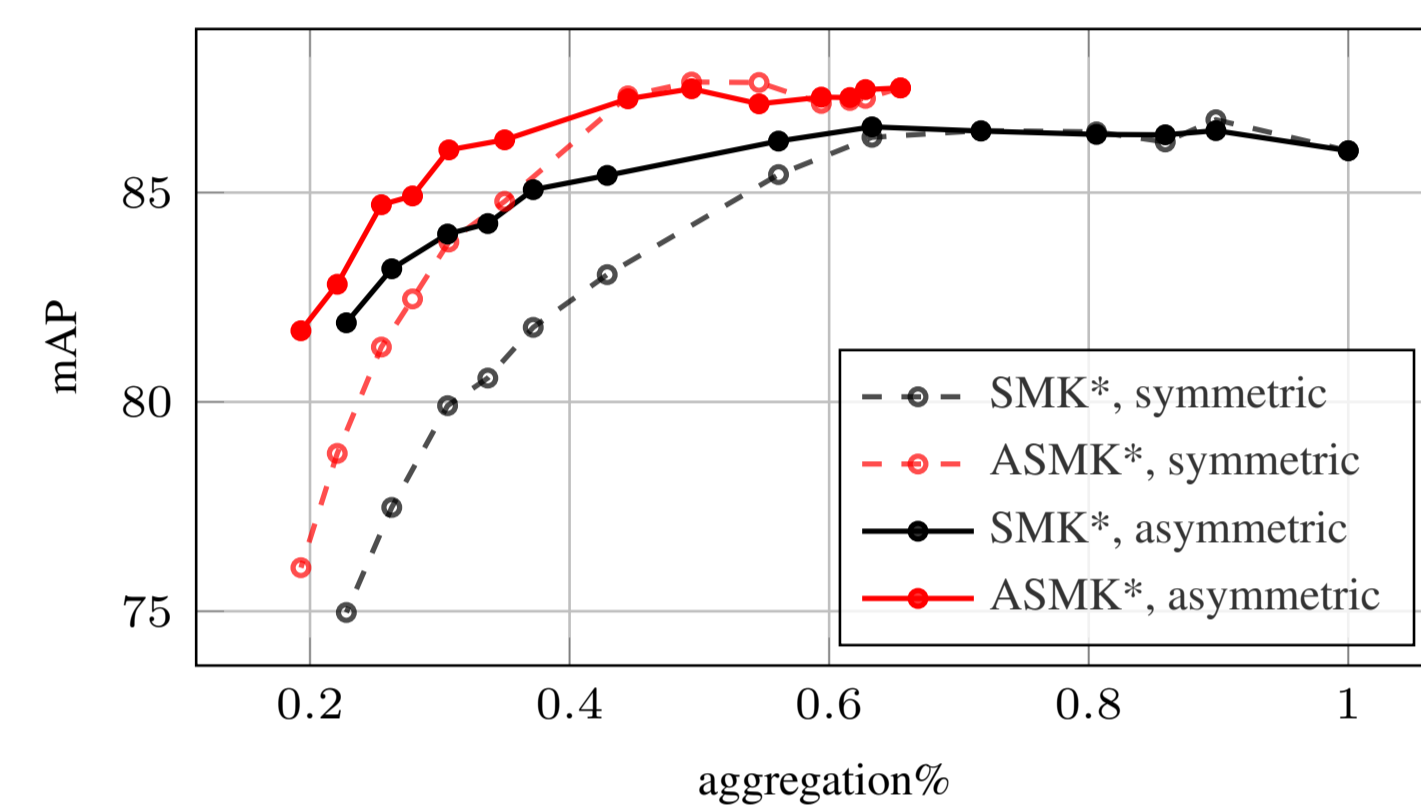


### Performance on Holidays-L + Flickr 100k

aggregation%	1.000	0.764	0.638	0.556
$k = 16$	41.3	42.7	44.1	45.0
$k = 64$	46.3	47.5	48.3	48.8

- Holidays-L**: Holidays dataset, 6.6M features
- aggregation%: ratio of aggregated to original features averaged over the dataset

## Experiments on SMK\*/ASMK\*



### Performance on Holidays-L, Oxford + Flickr 100k

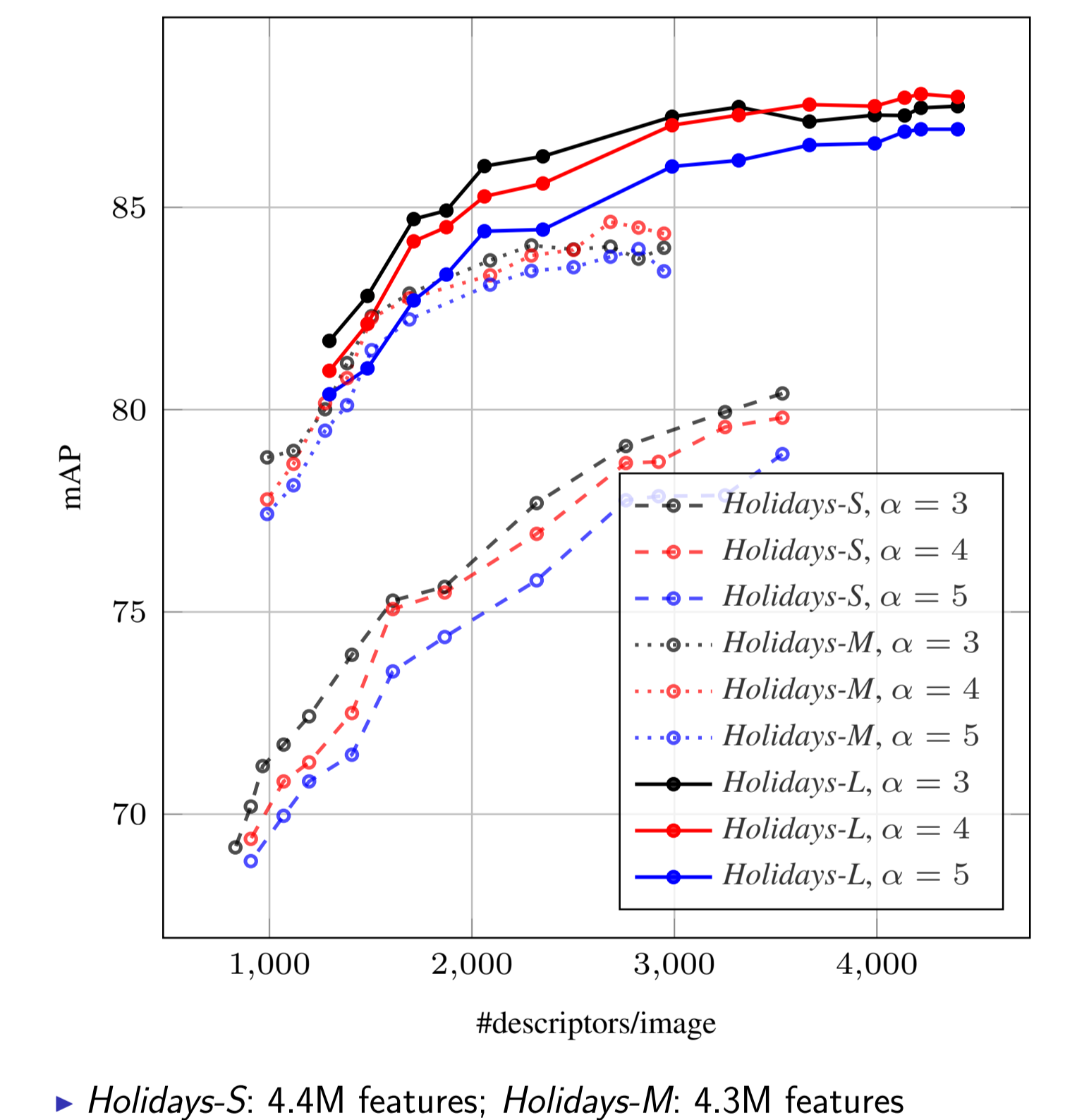
Dataset	Holidays-L 101k			Oxford 105k		
aggregation%	0.65	0.52	0.28	0.90	0.76	0.55
mAP	85.1	84.5	77.6	68.9	68.9	63.6

- Vocabulary size: 65k; first column is the baseline

### Comparison to state of the art

Dataset	MA	Hol.	Paris	Oxf.
BoW [27]	-	-	-	40.3
BoW [27]	✓	-	-	49.3
BoW [24]	-	-	-	55.8
Fine vocab. [22]	-	74.9	74.9	74.2
Multi-index [3]	✓	-	69.6	70.3
HE [15]	-	74.5	-	51.7
HE [15]	✓	77.5	-	56.1
AHE+burst [12]	-	79.4	-	66.0
AHE+burst [12]	✓	81.9	-	69.8
Query ad. [30]	-	81.4	70.3	73.9
Query ad. [30]	✓	82.1	73.6	78.0
aggregation%	-	78%	86%	89%
ASMK* [37]	-	80.0	74.4	76.4
ASMK* [37]	✓	81.0	77.0	80.4
This work	✓	<b>88.1</b>	<b>77.5</b>	<b>81.3</b>

### Memory efficiency performance on Holidays



## Size distribution of burst groups

