Large-scale visual recognition
Novel patch aggregation mechanisms

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CVPR tutorial on Large-Scale Visual Recognition

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Motivation

For large-scale visual recognition, we need image signatures which contain **fine-grained information**:

- in retrieval: the larger the dataset size, the higher the probability to find another similar but irrelevant image to a given query
- in classification: the larger the number of other classes, the higher the probability to find a class which is similar to any given class

BOV answer to the problem: increase visual vocabulary size

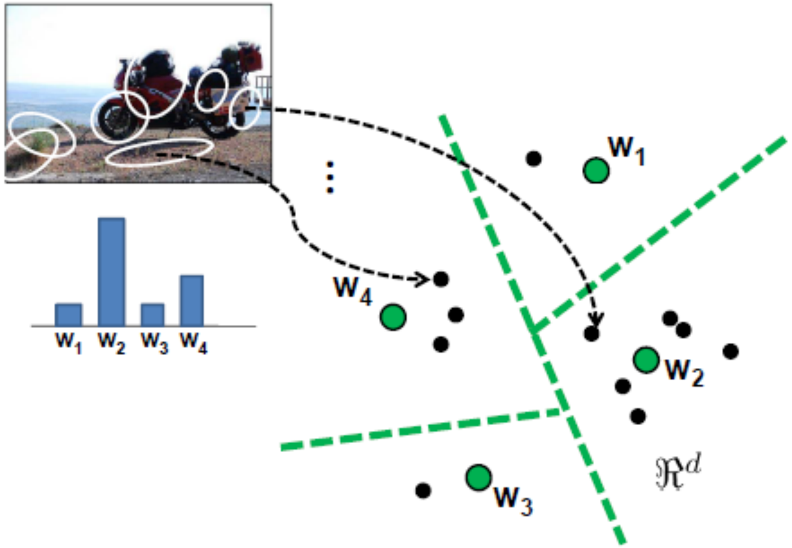
→ see previous part on scaling visual vocabularies

How to increase amount of information **without increasing the visual vocabulary size**?

Motivation

BOV is only about **counting** the number of local descriptors assigned to each Voronoi region

Why not including **other statistics**?



http://www.cs.utexas.edu/~grauman/courses/fall2009/papers/bag_of_visual_words.pdf

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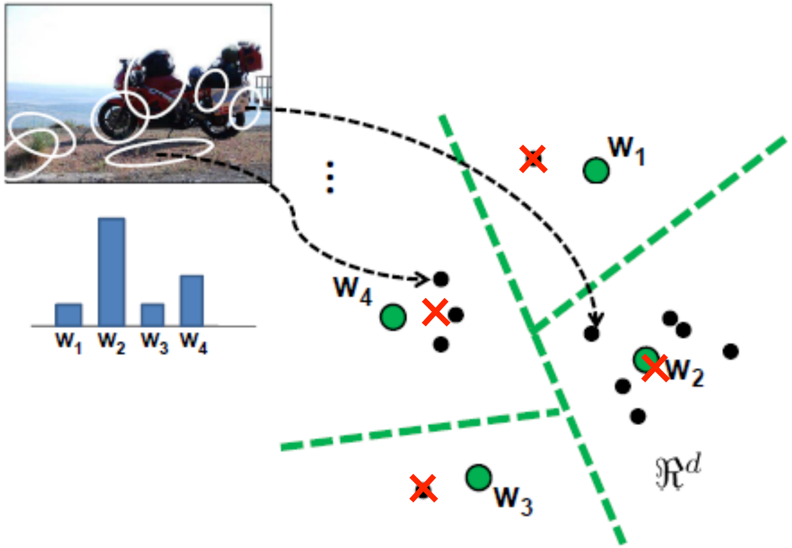
Why not including **other statistics**? For instance:

- mean of local descriptors ×



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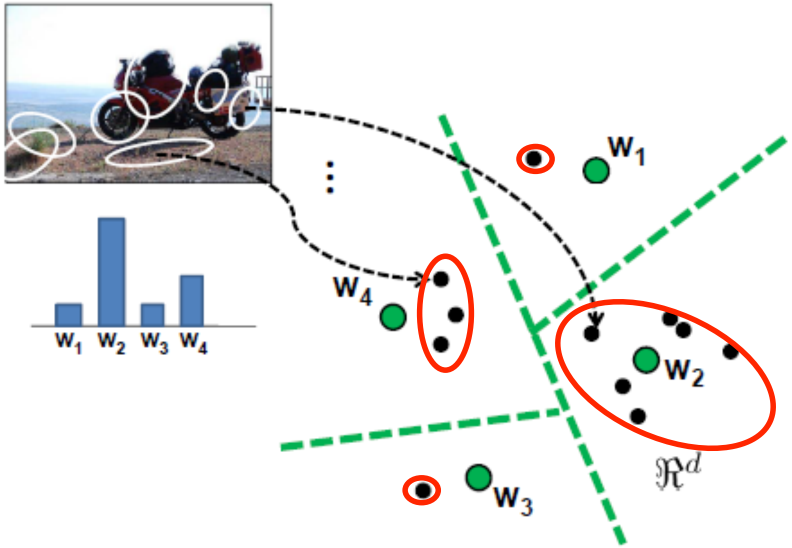
Motivation

BOV is only about **counting** the number of local descriptors assigned to each Voronoi region

Why not including **other statistics**? For instance:

- mean of local descriptors
- (co)variance of local descriptors



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Outline

A first example: the VLAD

The Fisher Vector

Other higher-order representations

Example results

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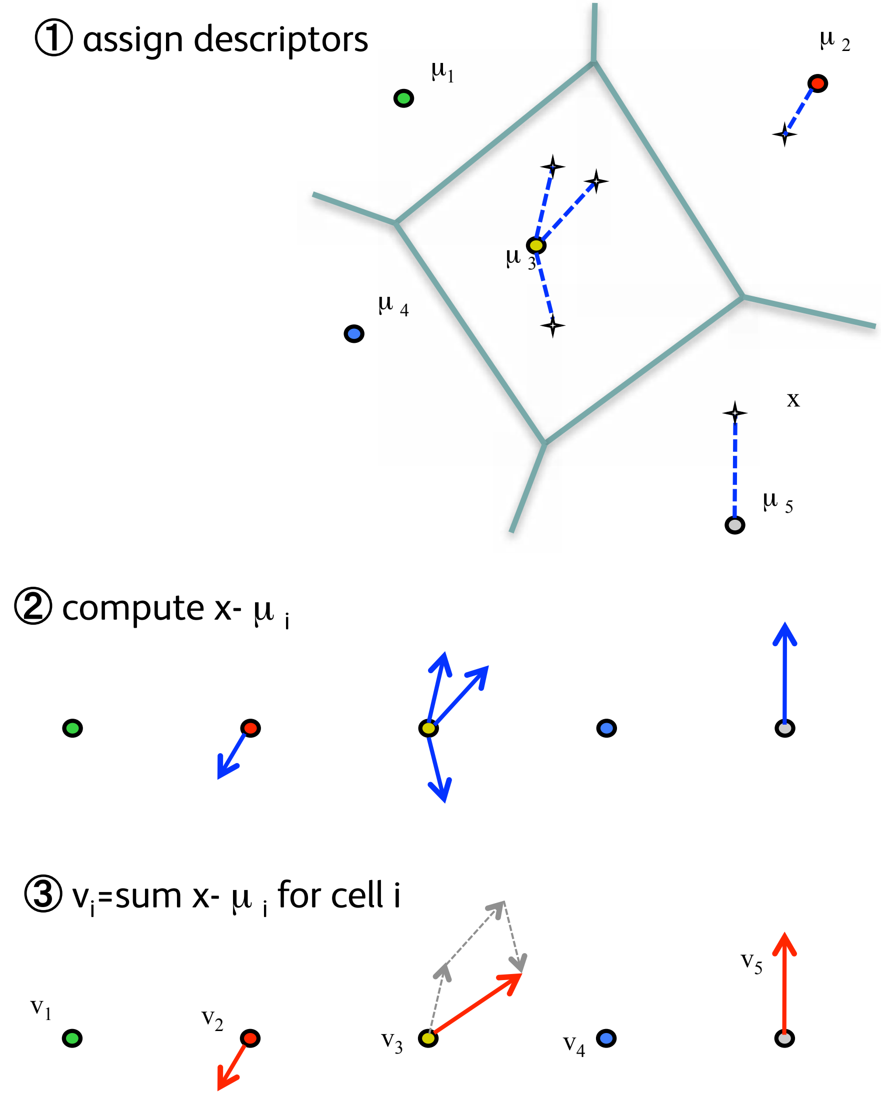
A first example: the VLAD

Given a codebook $\{\mu_i, i = 1 \dots N\}$,
e.g. learned with K-means, and a set of local descriptors $X = \{x_t, t = 1 \dots T\}$:

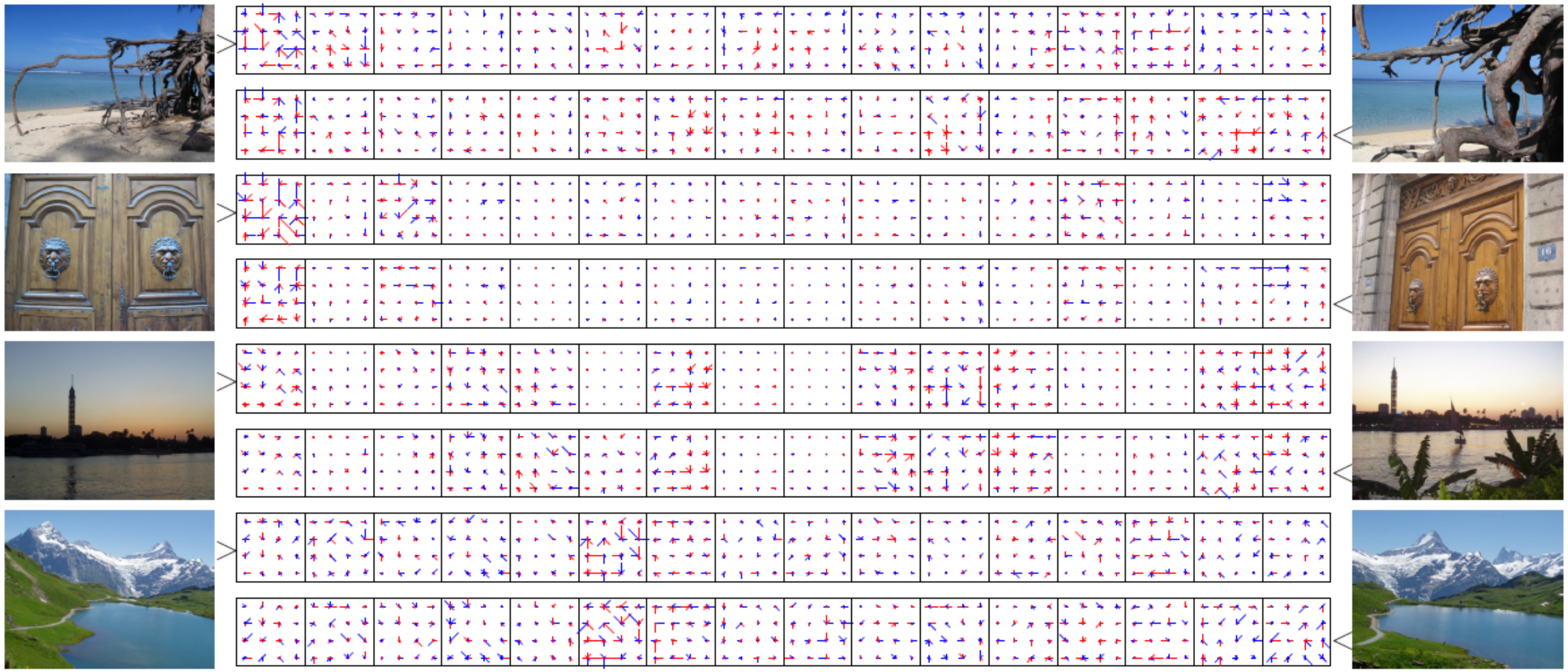
- ① assign: $\mathrm{NN}(x_t) = \arg\min_{\mu_i} ||x_t - \mu_i||$
- ②③ compute: $v_i = \sum_{x_t : \mathrm{NN}(x_t) = \mu_i} x_t - \mu_i$
- concatenate v_i's + ℓ_2 normalize



Jégou, Douze, Schmid and Pérez, "Aggregating local descriptors into a compact image representation", CVPR'10.

A first example: the VLAD

A graphical representation of $v_i = \sum_{x_t : \mathrm{NN}(x_t) = \mu_i} x_t - \mu_i$



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A first example: the VLAD

But in which sense is the VLAD optimal?

Could we add other (higher-order) statistics?

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The Fisher vector

Score function

Given a likelihood function u_λ with parameters λ, the **score function** of a given sample X is given by:

$$\boxed{G_\lambda^X = \nabla_\lambda \log u_\lambda(X)}$$

→ Fixed-length vector whose **dimensionality depends only on # parameters**.

Intuition: direction in which the parameters λ of the model should we modified to better fit the data.

The Fisher vector
Fisher information matrix

Fisher information matrix (FIM) or negative Hessian:

$$F_\lambda = E_{x \sim u_\lambda} \left[\nabla_\lambda \log u_\lambda(x) \nabla_\lambda \log u_\lambda(x)' \right]$$

Measure similarity between using the **Fisher Kernel (FK)**:

$$\boxed{K(X,Y) = G_\lambda^{X\prime} F_\lambda^{-1} G_\lambda^Y}$$

Jaakkola and Haussler, "Exploiting generative models in discriminative classifiers", NIPS'98.

$\longrightarrow$ can be interpreted as a score whitening

As the FIM, is PSD, it can be decomposed as: $F_\lambda^{-1} = L'_\lambda L_\lambda$

and the FK can be rewritten as a dot product between **Fisher Vectors** (FV):

$$\boxed{\mathcal{G}_\lambda^X \quad = \quad L_\lambda G_\lambda^X}$$

The Fisher vector
Application to images

$X = \{x_t, t = 1 \dots T\}$ is the set of T i.i.d. D-dim local descriptors (e.g. SIFT) extracted from an image:

$$\boxed{G_\lambda^X = \frac{1}{T}\sum_{t=1}^{T} \nabla_\lambda \log u_\lambda(x_t)}$$

→ **average pooling** is a direct consequence of independence assumption

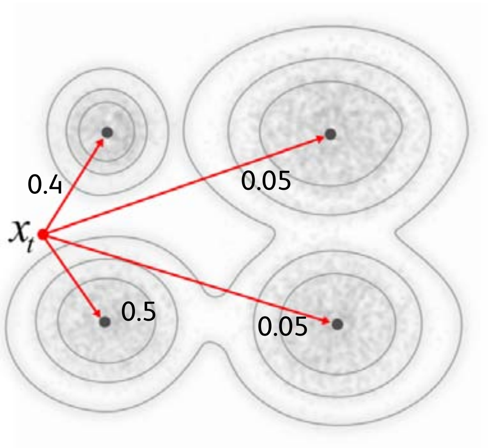
$u_\lambda(x) = \sum_{i=1}^{K} w_i u_i(x)$ is a Gaussian Mixture Model (GMM) with parameters $\lambda = \{w_i, \mu_i, \Sigma_i, i = 1 \dots N\}$ trained on a large set of local descriptors → a probabilistic **visual vocabulary**

Perronnin and Dance, "Fisher kernels on visual categories for image categorization", CVPR'07.

The Fisher vector

Relationship with the BOV

FV formulas:



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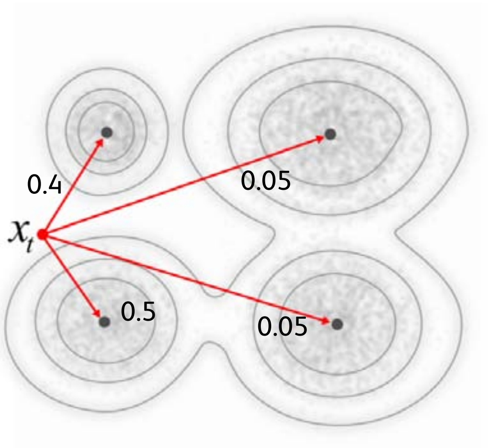
FV formulas:

- gradient wrt to w

$$\approx \boxed{\frac{1}{T}\sum_{t=1}^{T}\gamma_t(i)}$$

$\rightarrow$ **soft BOV**



$\gamma_t(i)$ = soft-assignment of patch t to Gaussian i

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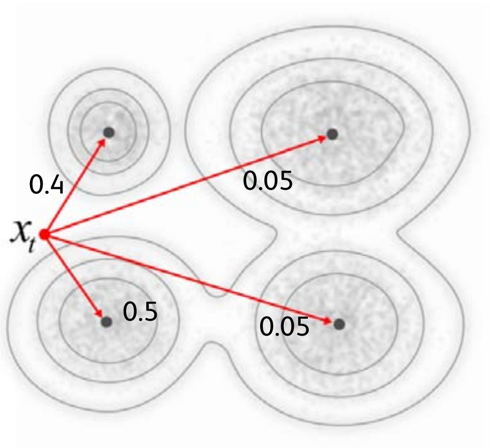

- gradient wrt to μ and σ

$$\boxed{\begin{aligned}\mathcal{G}_{\mu,i}^X &= \frac{1}{T\sqrt{w_i}}\sum_{t=1}^{T}\gamma_t(i)\left(\frac{x_t-\mu_i}{\sigma_i}\right)\\ \mathcal{G}_{\sigma,i}^X &= \frac{1}{T\sqrt{2w_i}}\sum_{t=1}^{T}\gamma_t(i)\left[\frac{(x_t-\mu_i)^2}{\sigma_i^2}-1\right]\end{aligned}}$$

$\gamma_t(i)$ = soft-assignment of patch t to Gaussian i

→ compared to BOV, include **higher-order statistics** (up to order 2)

Let us denote: D = feature dim, N = # Gaussians

- BOV = N-dim
- FV = 2DN-dim

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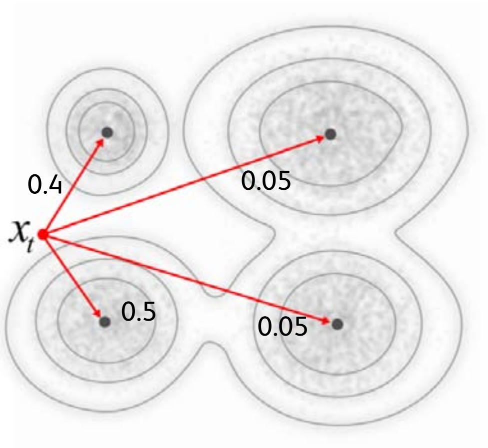

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$$\mathcal{G}^X_{\mu,i} = \frac{1}{T\sqrt{w_i}}\sum_{t=1}^{T}\gamma_t(i)\left(\frac{x_t-\mu_i}{\sigma_i}\right)$$

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$\gamma_t(i)$ = soft-assignment of patch t to Gaussian i

→ compared to BOV, include **higher-order statistics** (up to order 2)

→ FV **much higher-dim** than BOV for a **given visual vocabulary size**

→ FV **much faster to compute** than BOV for a **given feature dim**

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The Fisher vector

Dimensionality reduction on local descriptors

Perform PCA on local descriptors:

→ uncorrelated features are more consistent with diagonal assumption of covariance matrices in GMM

→ FK performs whitening and enhances low-energy (possibly noisy) dimensions

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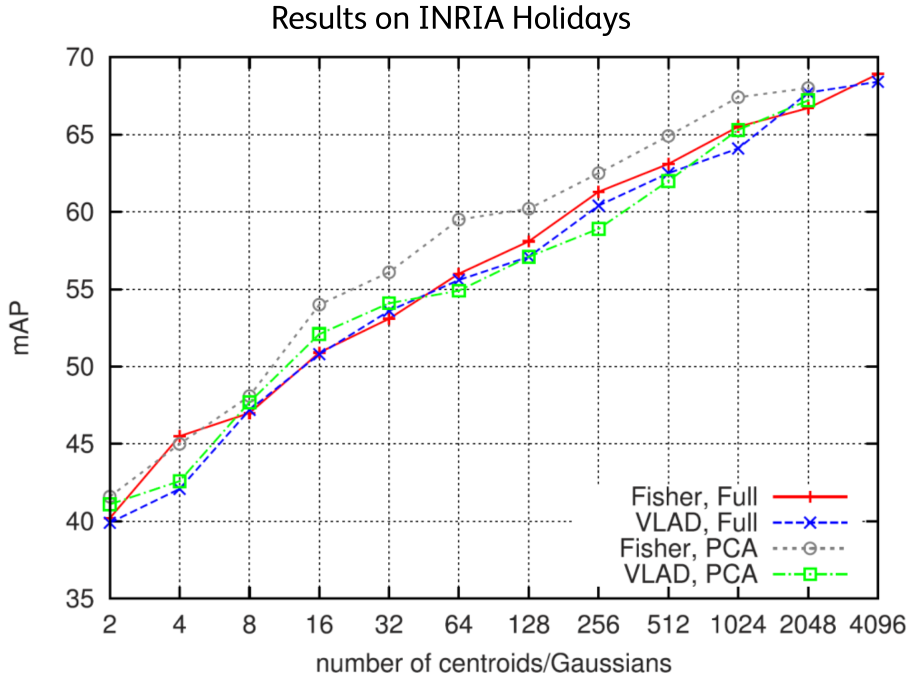


Jégou, Perronnin, Douze, Sánchez, Pérez and Schmid, “Aggregating local descriptors into compact codes”, TPAMI’11.

The Fisher vector
Normalization: TF-IDF effect

Assuming that the x_t's are iid drawn from a distribution p, we have:

$$G_\lambda^X = \frac{1}{T}\sum_{t=1}^{T} \nabla_\lambda \log u_\lambda(x_t) \approx \nabla_\lambda E_{x\sim p} \log u_\lambda(x) = \nabla_\lambda \int_x p(x) \log u_\lambda(x) dx.$$

If we assume that p is a mixture of image-dependent and image-independent information:

$$p(x) = \omega q(x) + (1-\omega) u_\lambda(x)$$

Then we have:

$$G_\lambda^X \approx \omega \nabla_\lambda \int_x q(x) \log u_\lambda(x) dx + (1-\omega) \underbrace{\nabla_\lambda \int_x u_\lambda(x) \log u_\lambda(x) dx}_{\approx 0 \text{ (MLE)}}$$

→The FV depends only (approximately) on image-specific content (**TF-IDF**)

→ ℓ_2 normalization removes dependence on ω

Perronnin, Sánchez and Mensink, "Improving the Fisher kernel for large-scale image classification", ECCV'10.

The Fisher vector

Normalization: variance stabilization

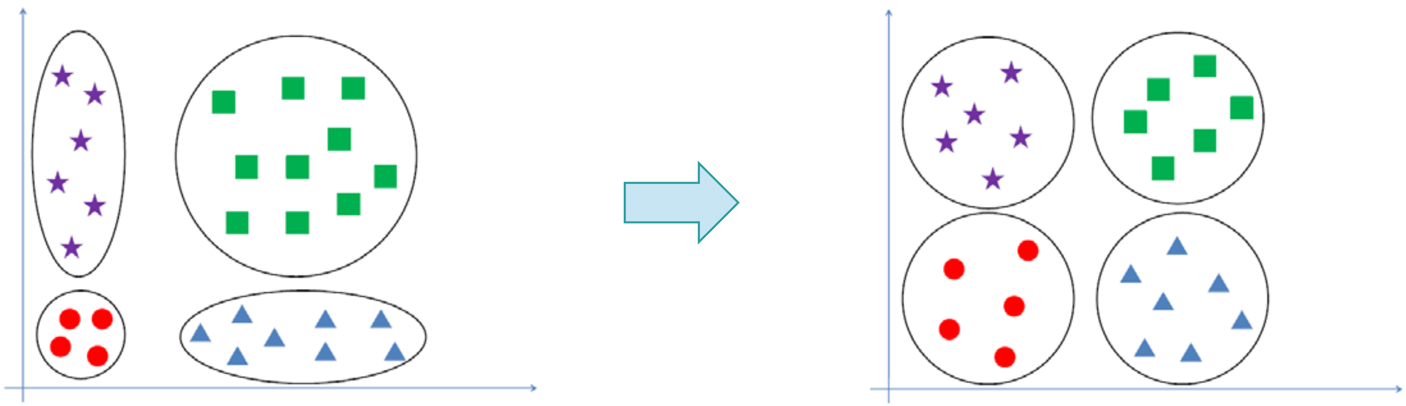
FVs can be (approximately) viewed as emissions of a compound Poisson: a sum of N iid random variables with N~Poisson.
☹ variance depends on mean

Jégou, Perronnin, Douze, Sánchez, Pérez and Schmid, "Aggregating local descriptors into compact codes", TPAMI'11.

→ **Variance stabilizing transforms** of the form:

$$\boxed{f(z) = \text{sign}(z)|z|^{\alpha} \text{ with } 0 \leq \alpha \leq 1}$$ (with α=0.5 by default)

can be used on the FV (or the VLAD).



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→ Reduce impact of bursty visual elements

Jégou, Douze, Schmid, "On the burstiness of visual elements", ICCV'09.

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Other higher-order representations

Revisiting the VLAD

But in which sense is the VLAD optimal?

Could we add other (higher-order) statistics?

Jégou, Douze, Schmid and Pérez, “Aggregating local descriptors into a compact image representation”, CVPR’10.

Other higher-order representations
Revisiting the VLAD

But in which sense is the VLAD optimal?

→ The VLAD can be viewed as a non-probabilistic version of the FV:

- gradient with respect to mean only
- replace GMM clustering by k-means

$$\mathcal{G}^X_{\mu,i} = \frac{1}{T\sqrt{w_i}} \sum_{t=1}^{T} \gamma_t(i) \left(\frac{x_t - \mu_i}{\sigma_i} \right) \qquad \rightarrow \qquad v_i = \sum_{x_t : \mathrm{NN}(x_t) = \mu_i} x_t - \mu_i$$

Could we add other (higher-order) statistics?

→ extension of the VLAD to include 2nd order statistics: VLAT

Picard and Gosselin, "Improving image similarity with vectors of locally aggregated tensors", ICIP '11.

Other higher-order representations
Super-Vector (SV) coding

$f : \mathbb{R}^D \rightarrow \mathbb{R}$ is Lipschitz smooth if $\forall (x, y) \in \mathbb{R}^D \times \mathbb{R}^D$:

$$|f(x) - f(y) - \nabla f(y)'(x - y)| \leq \frac{\beta}{2}||x - y||^2$$

Given a codebook $\{\mu_i, i = 1 \dots N\}$ and a patch x_t we have:

$$f(x_t) \approx f(\mu_i) + \nabla f(\mu_i)'(x_t - \mu_i) = w' \varphi_{SV}(x_t)$$

with $\varphi_{SV}(x_t) = \left[0, \dots, 0, \overbrace{s, (x_t - \mu_i)}^{(D+1) \text{ non-zero dim}}, 0, \dots, 0 \right]$

and $w = \left[0, \dots, 0, \frac{f(\mu_i)}{s}, \nabla f(\mu_i), 0, \dots, 0 \right]$ (to be learned)

Zhou, Yu, Zhang and Huang, "Image classification using super-vector coding of local image descriptors", ECCV'10.

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Average pooling → **SV ≈ BOV + VLAD**

Bound in Lipschitz smooth inequality provides argument for k-means.

Zhou, Yu, Zhang and Huang, “Image classification using super-vector coding of local image descriptors”, ECCV’10.
See also: Ladický and Torr, “Locally linear support vector machines”, ICML’11.

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Examples
Retrieval

Example on Holidays:

From: Jégou, Perronnin, Douze, Sánchez, Pérez and Schmid, "Aggregating local descriptors into compact codes", TPAMI'11.

Descriptor	K	D	Holidays (mAP)					
			$D' = D$	$\rightarrow D'$=2048	$\rightarrow D'$=512	$\rightarrow D'$=128	$\rightarrow D'$=64	$\rightarrow D'$=32
BOW	1 000	1 000	40.1		43.5	44.4	43.4	40.8
	20 000	20 000	43.7	41.8	44.9	45.2	44.4	41.8
Fisher (μ)	16	1 024	54.0		54.6	52.3	49.9	46.6
	64	4 096	59.5	60.7	61.0	56.5	52.0	48.0
	256	16 384	62.5	62.6	57.0	53.8	50.6	48.6
VLAD	16	1 024	52.0		52.7	52.6	50.5	47.7
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→ second order statistics are not essential for retrieval

→ even for the same feature dim, the FV/VLAD can beat the BOV

→ soft assignment + whitening of FV helps when number of Gaussians ↑

→ after dim-reduction however, the FV and VLAD perform similarly

Examples
Classification

Example on PASCAL VOC 2007:

From: Chatfield, Lempitsky, Vedaldi and Zisserman, “The devil is in the details: an evaluation of recent feature encoding methods”, BMVC’11.

	Feature dim	mAP
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LLC	25K	57.27
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→ including 2nd order information is important for classification

Packages

The INRIA package:

http://lear.inrialpes.fr/src/inria_fisher/

The Oxford package (soon to be released):

http://www.robots.ox.ac.uk/~vgg/research/encoding_eval/

Questions?