LEAR @ TrecVid MED 2012

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Outline

1. Low-level features: appearance, motion, audio
2. Feature encoding: Fisher vectors
3. High-level features: text
4. Fusion strategies
5. Experiments and results

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Appearance and audio features

Scale-invariant feature transform (SIFT, Lowe 2004):

- 21×21 patches at 4 pixel steps on 5 scales
- Every 60-th frame.

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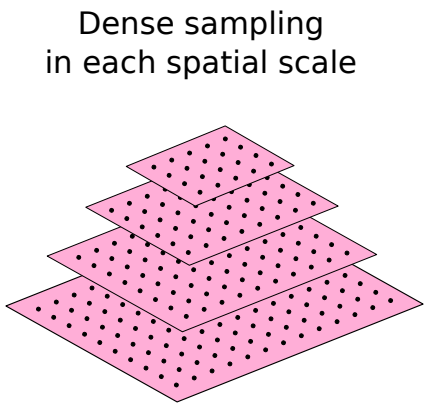
Mel-frequency cepstral coefficients (MFCC, Rabiner and Schafer 2007).

- Window of 25 ms and a step-size of 10 ms
- 39 coefficients: 12 MFCC and energy of the signal, first and second derivative
- Optionally: Speech/non-speech separation.

Motion features

Dense trajectories (Wang et al., 2011)

- Strong performance on many action recognition datasets: Hollywood2, Youtube, UCF Sports.
- Idea: MBH descriptors computed across short densely sampled trajectories.



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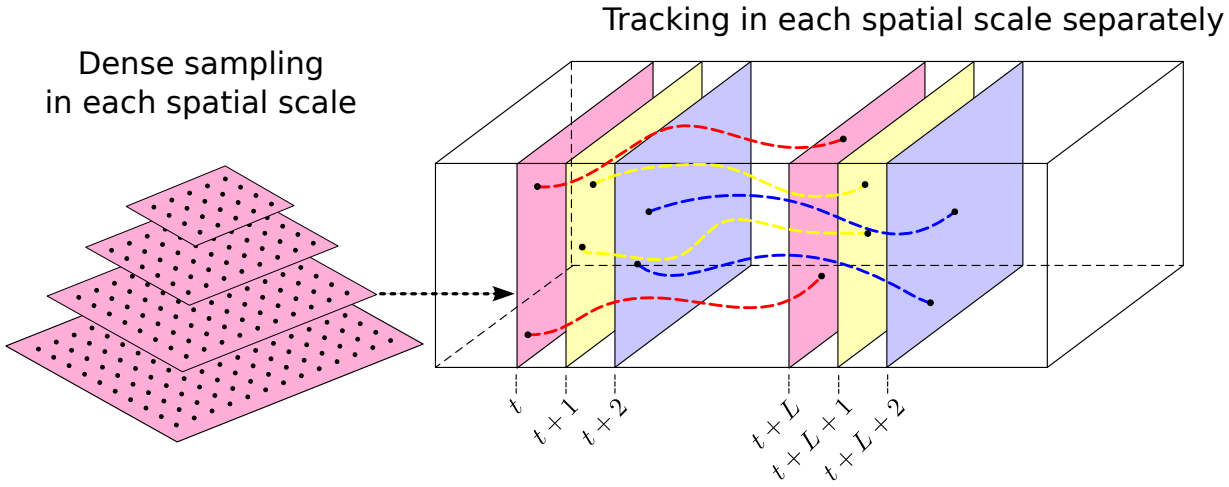

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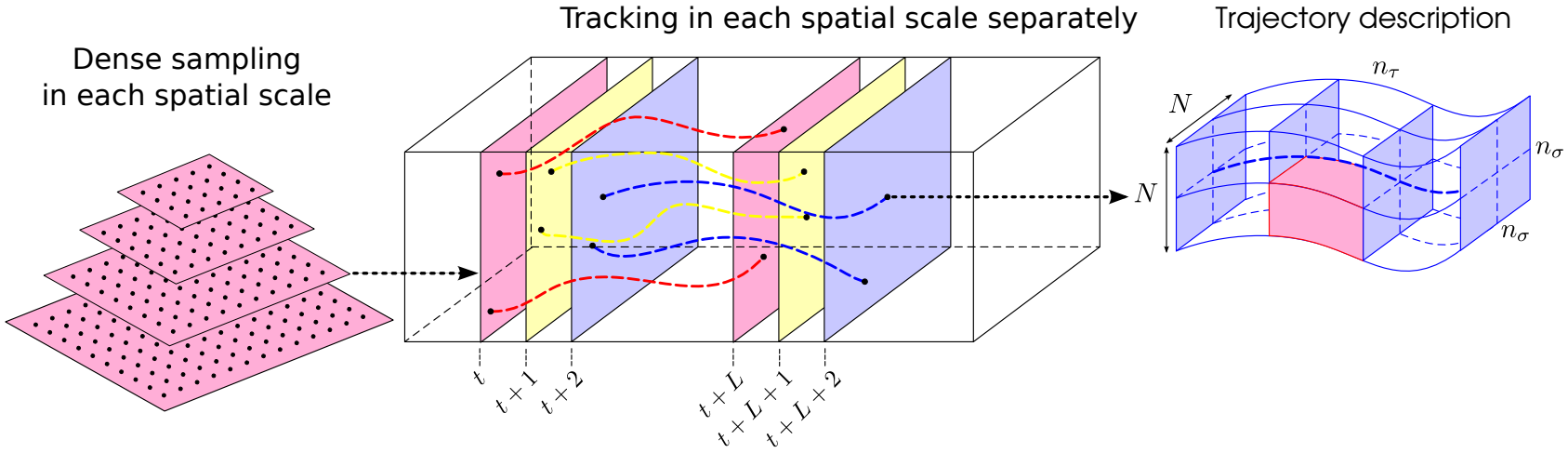

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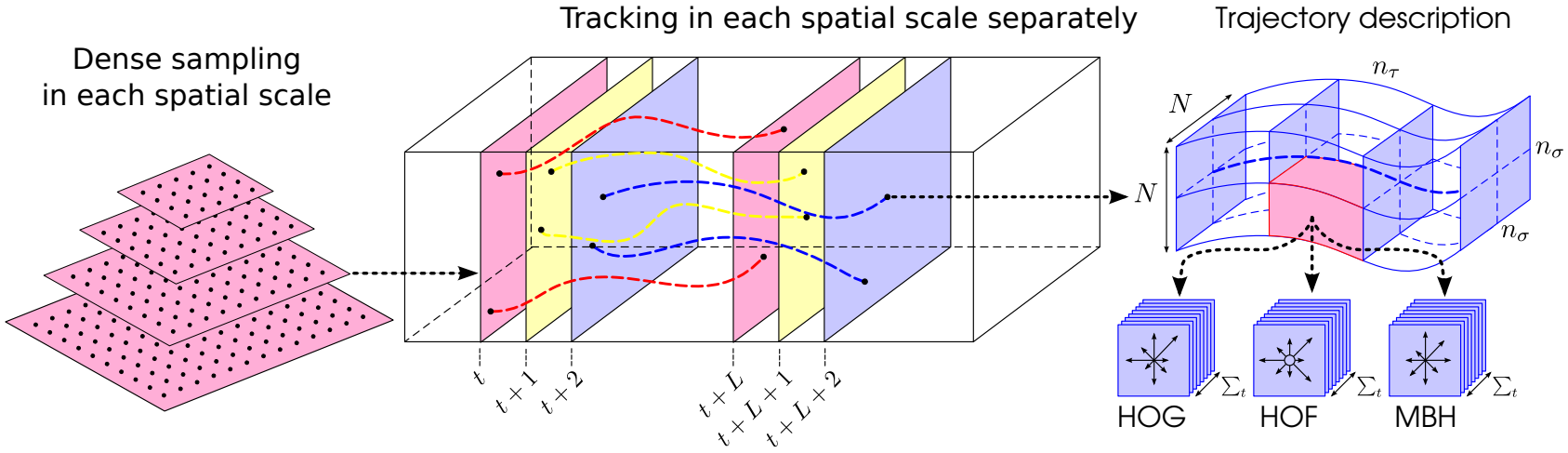

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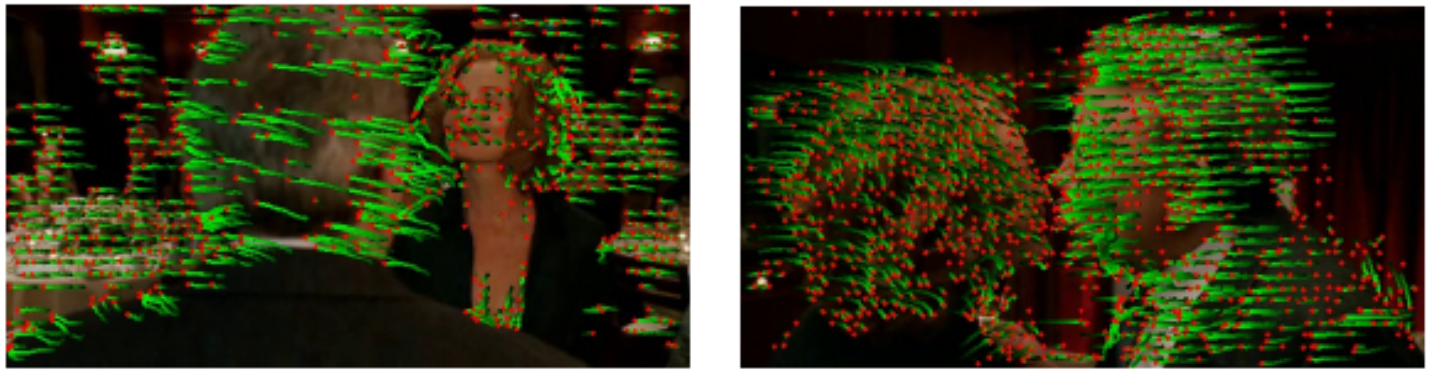
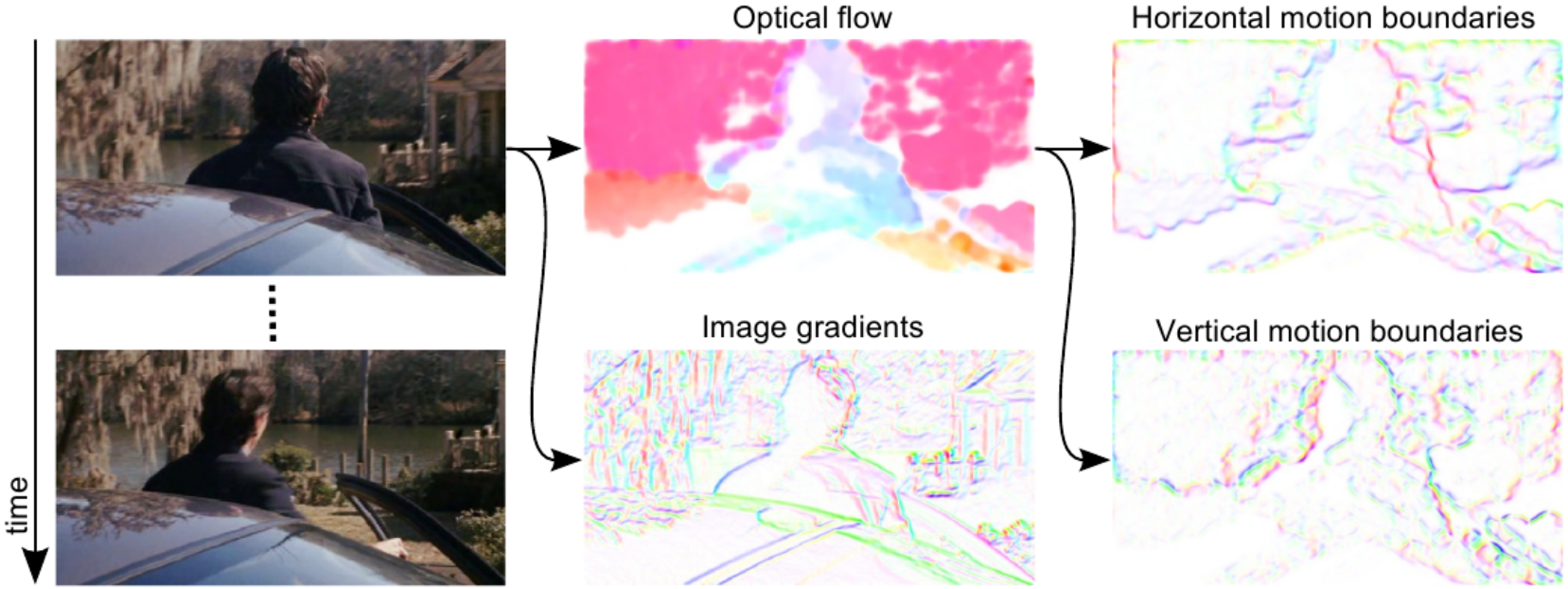
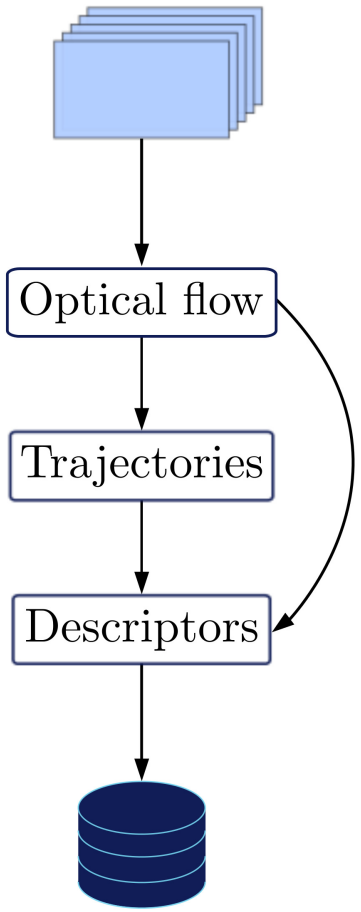




Video rescaling for dense trajectories

- Computationally expensive: cost scales linearly with the size of the video (time $\times$ resolution)



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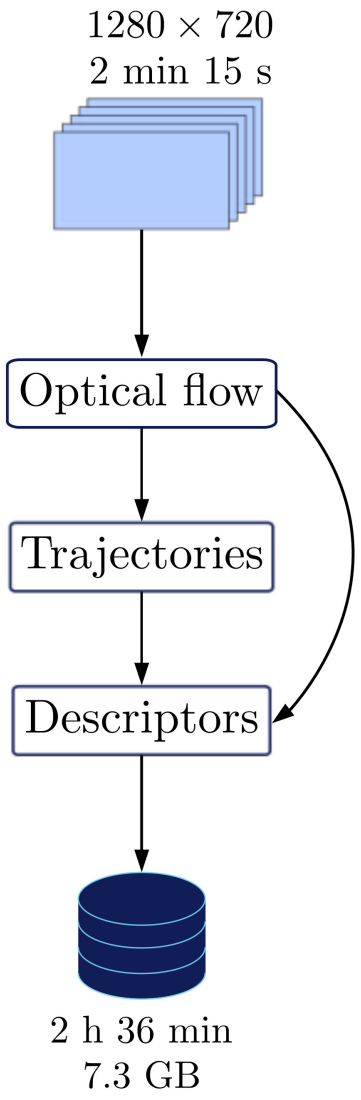

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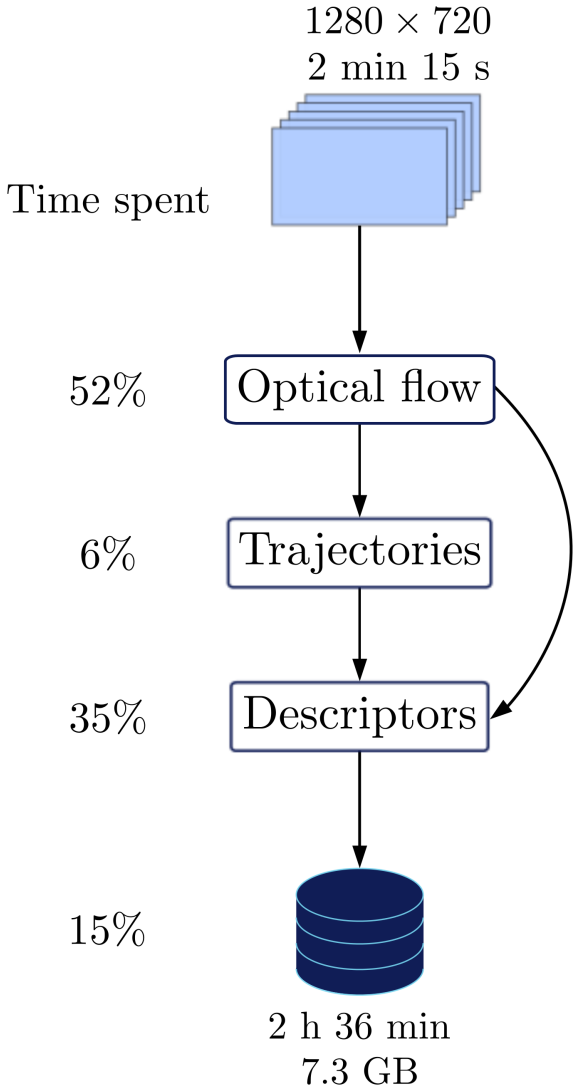

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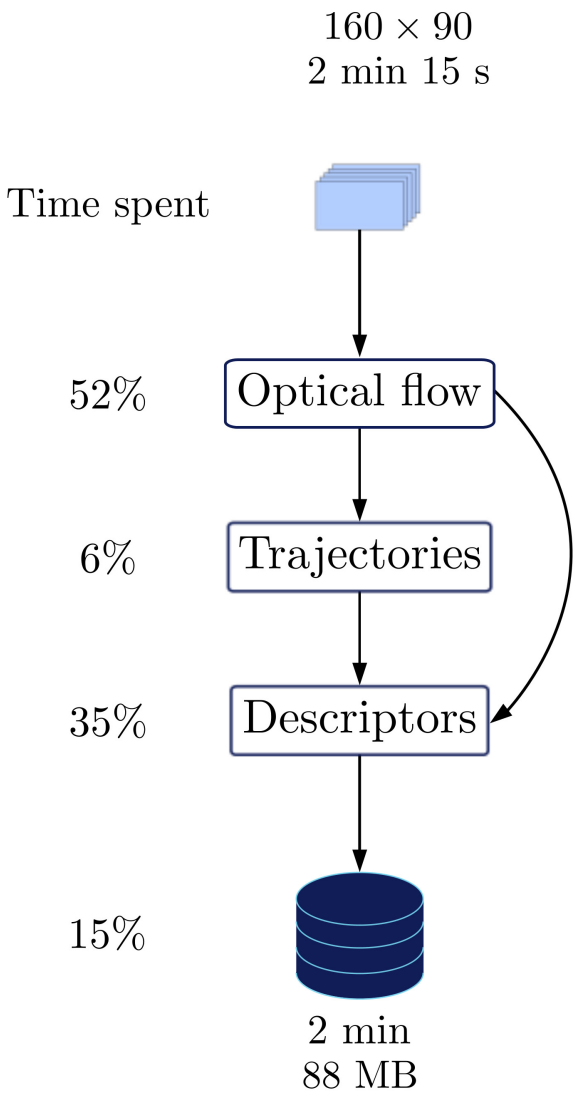

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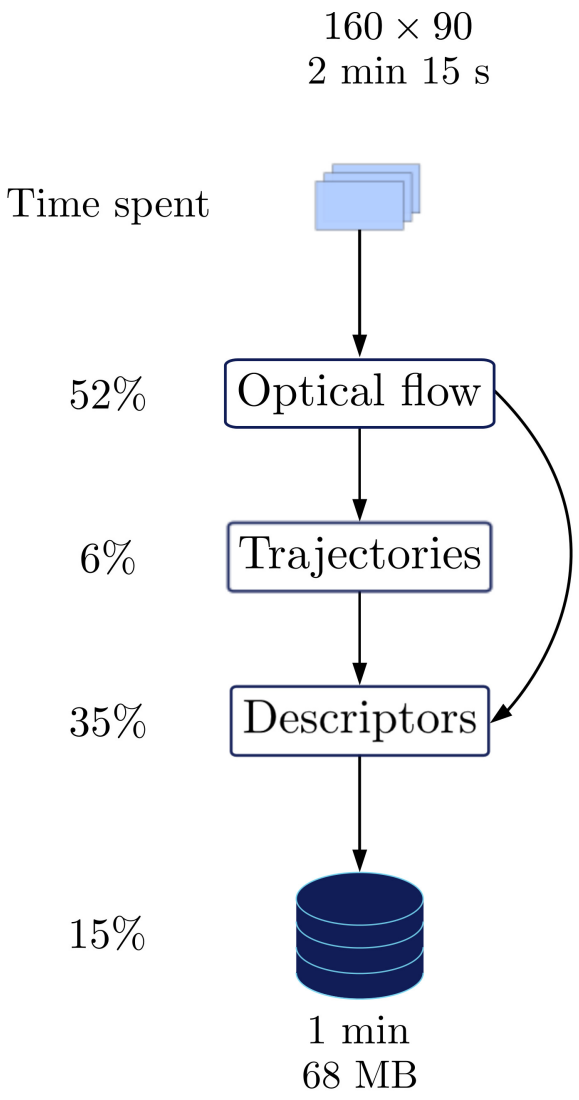

Video rescaling for dense trajectories

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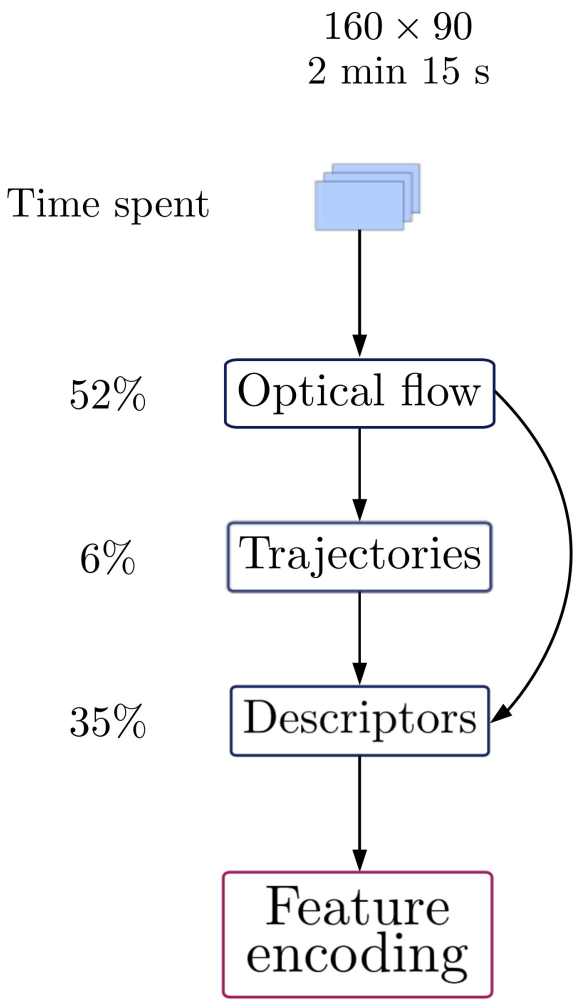
  - Process descriptors on-the-fly.



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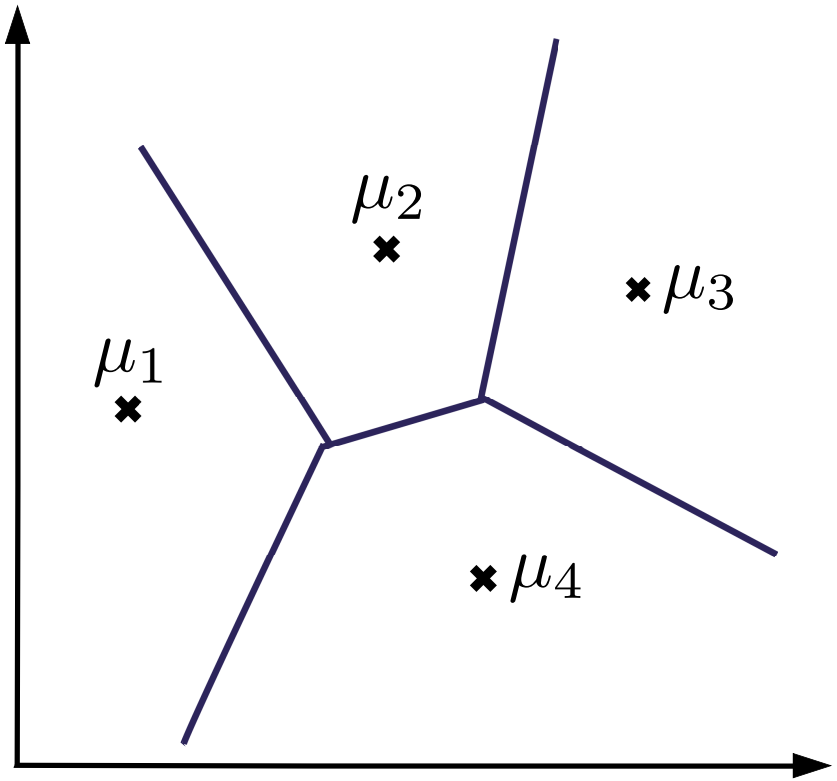

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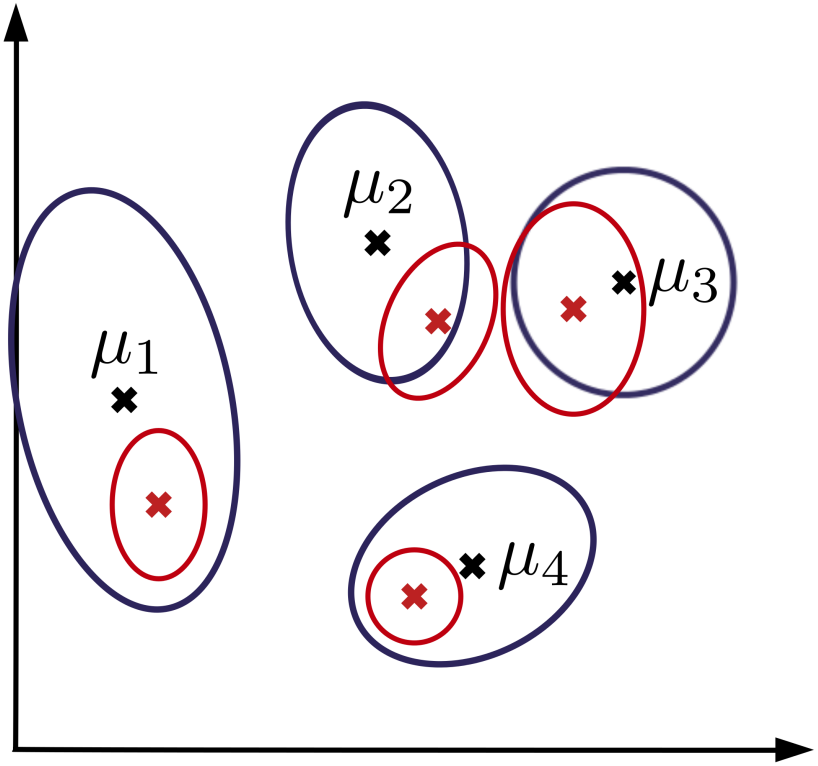

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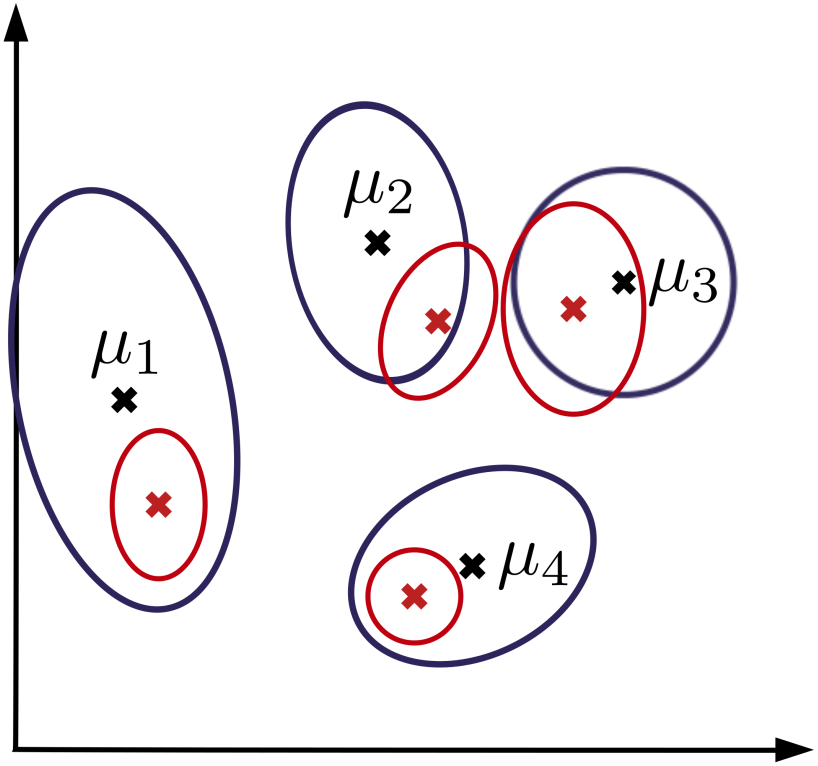
- FV size: $K + 2KD$
  - K: number of Gaussians
  - D: descriptor dimension.



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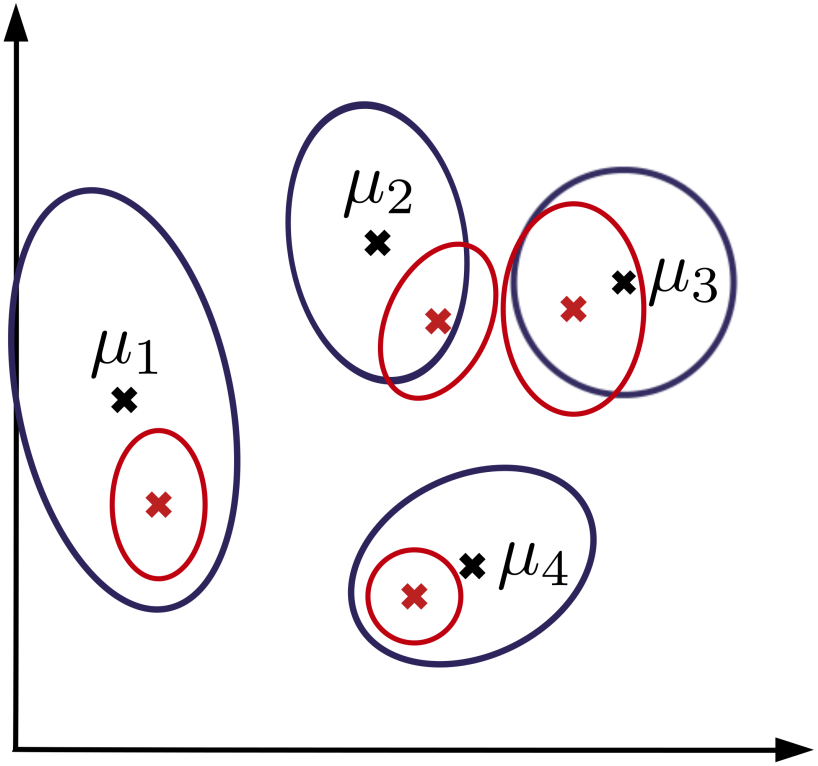
- Normalization:
  - zero mean, unit variance
  - signed square-rooting
  - ℓ_2 normalization.



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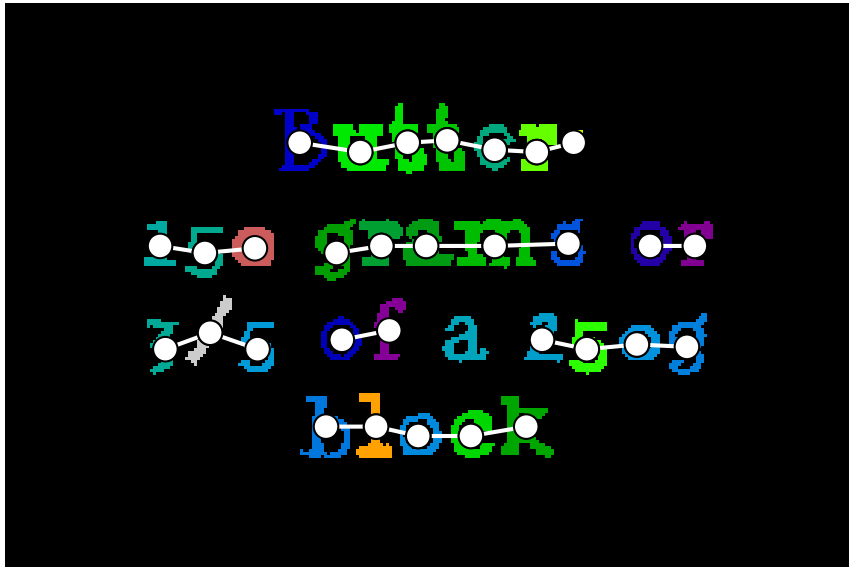

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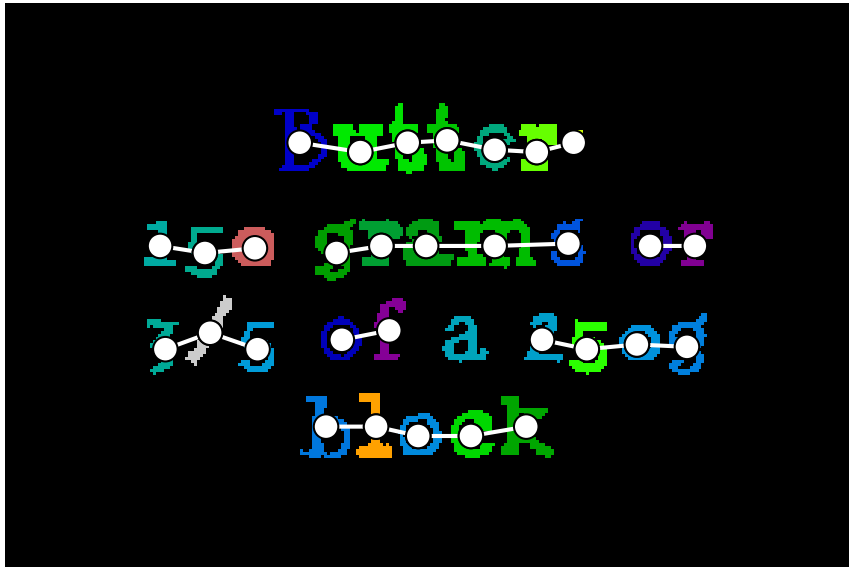
Video representation:

- Bag-of-words.



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- Early fusion: concatenate feature vectors.
  - Sum of kernels.
- Late fusion: linear combination of scores.
  - Learn classifiers for each channel
  - Learn weights using grid-search or logistic regression.

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MinNDC error on the TrecVid '11 data

- Best result in 2011 by BBN-Viser team (Natarajan et al., 2012).

Channel	birthday party	changing vehicle tire	flash mob gathering	unstuck vehicle	grooming an animal	making a sandwich	parade	parkour	repairing an appliance	sewing project	Average
Best 2011	0.45	0.47	0.28	0.38	0.62	0.57	0.45	0.31	0.38	0.57	0.45

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SIFT	0.71	0.63	0.40	0.45	0.75	0.69	0.71	0.57	0.61	0.77	0.63

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MFCC	0.65	0.93	0.70	0.77	0.96	0.94	0.80	0.94	0.55	0.82	0.81

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OCR	0.95	0.94	0.91	0.99	0.93	0.85	0.95	1.00	0.68	0.88	0.91

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MBH+SIFT	0.62	0.54	0.26	0.37	0.67	0.62	0.44	0.22	0.46	0.60	0.48

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$\cdots$+MFCC	0.49	0.48	0.26	0.38	0.59	0.65	0.41	0.21	0.35	0.52	0.43

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Our submissions

	Actual NDC			
Run	Features	Late fusion	PreSpec	AdHoc
`c-LFdnsmall`	small	grid search	0.544	0.711
`c-LFjrlrsmall`	small	logistic regression	0.536	0.749
`p-LFdnbig`	big	grid search	0.516	0.559
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Modality	Descriptor	small		big	
		dim	× RT	dim	× RT
Motion	MBH	33k	2.4	131k	3.0
Image	SIFT	16k	2.5	66k	6.6
Audio	MFCC	40k	0.2	81k	0.2
Text	OCR	200k	1.4	200k	1.4
Total		289k	6.5	478k	11.2

RT: single CPU computation × real time.

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Computation on MED test set: $4,000$ h video $\times 11.2/400$ CPUs ≈ 4 days.

Conclusions

Excellent results while being compact:

- Small set of low-level features: MBH, SIFT, MFCC
- High-dimensional FV encoding
- One type of high level features: OCR
- Linear classifiers + late fusion.

Code for MBH, SIFT and Fisher vectors available at
`http://lear.inrialpes.fr/software/`

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