Featureless: Bypassing Feature Extraction In Action Categorization

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What is Action Categorization?

Input Videos

Disregards tasks s.a. action segmentation, action localization.

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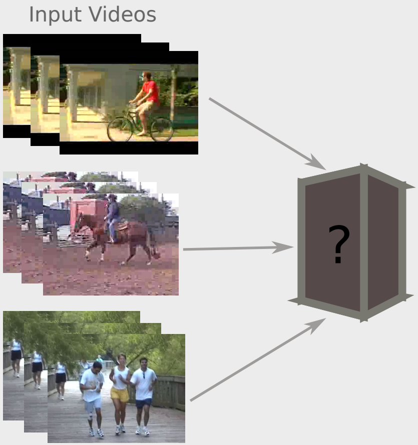

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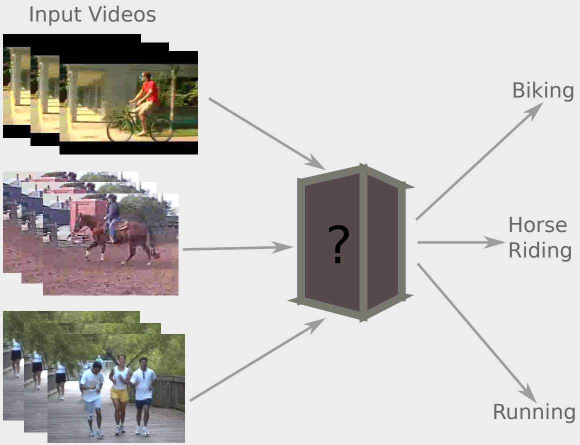

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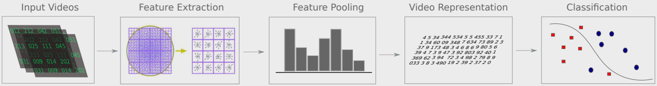
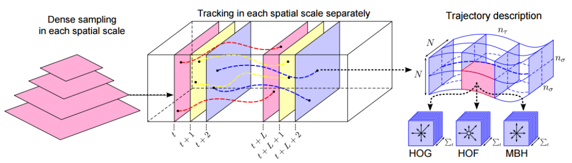
Standard Classic Approaches

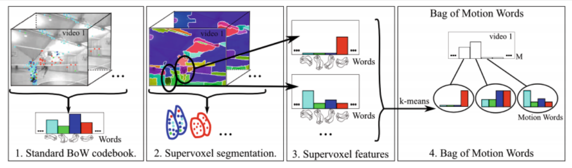


Variations of features over time:

H. Wang, ICCV, 2013.

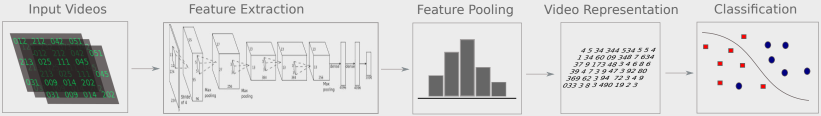


E. Taralova, ECCV, 2014.



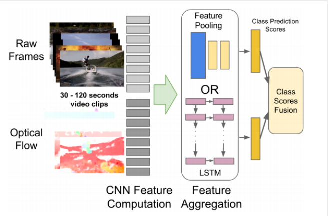
Problem: Feature extraction is slow and takes space to store.

Standard Deep Net Approaches

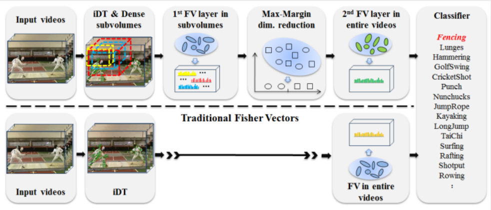


Variations of pooling over frames:

J Yue-Hei Ng, CVPR 2015.



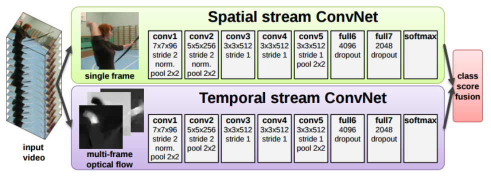
X. Peng, ECCV, 2014.



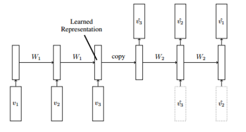
Problem: Still extracts features and aggregates them, but better features.

Deep Learning Approaches

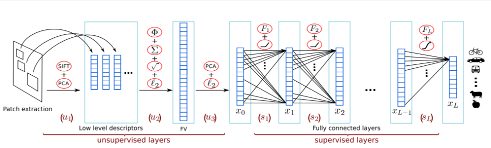
K Simonyan, NIPS 2014.



N Srivastava, JMLR 2015.



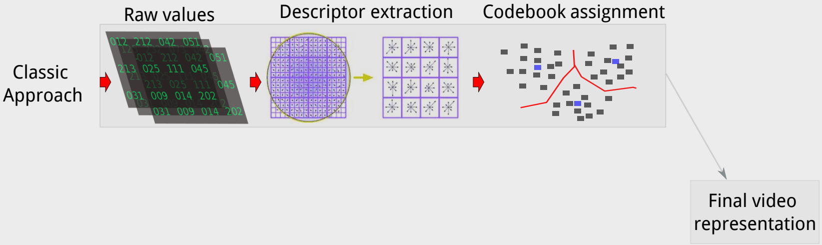
F. Perronnin, Florent, CVPR, 2015.



Slowly bridging the gap in performance.

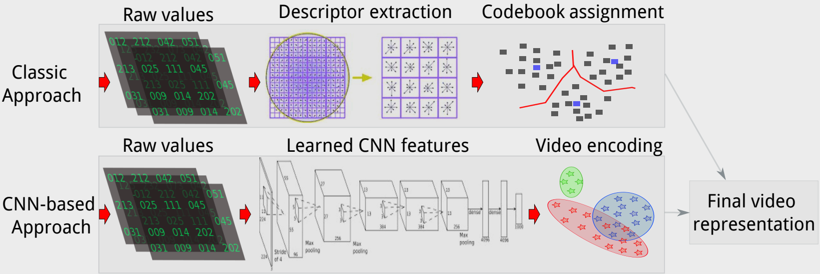
Is Feature Extraction Needed at Test-time?

- Classic: extract handcrafted features and use them in a video representation.



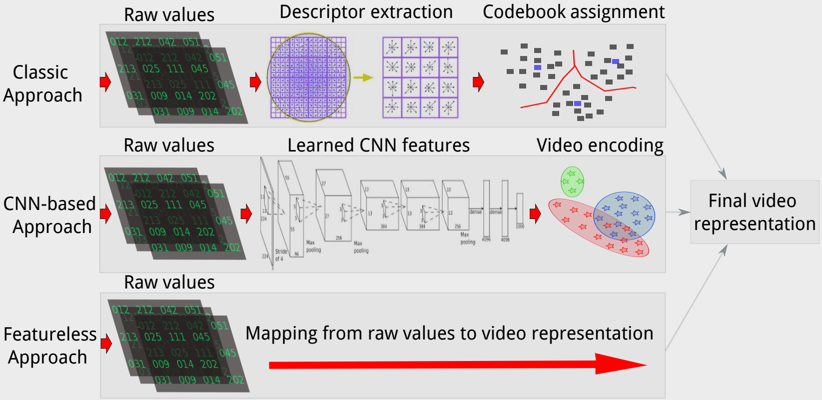
Is Feature Extraction Needed at Test-time?

- CNN-based: extract CNN features and use them in a video representation.



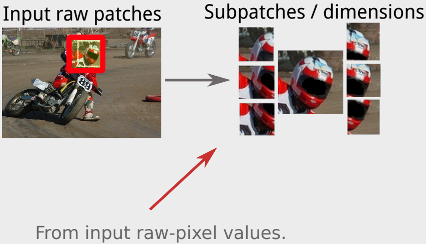
Is Feature Extraction Needed at Test-time?

- Featureless: predict codeword IDs and compute a first-order video representation.



How? — Featureless Boosting

Proof of concept: discard the features and learn their statistics instead.



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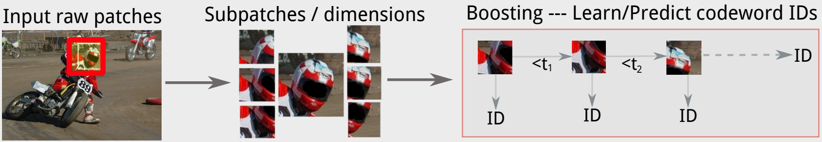

From input raw-pixels learn
a mapping to codeword ID-s.
(Time Efficient ---> so use Boosting)

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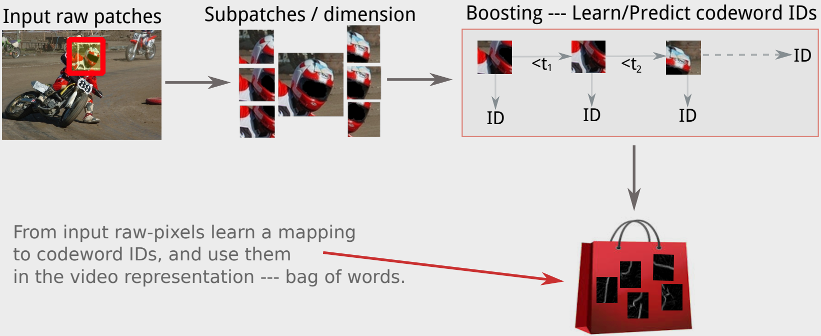

How? — Featureless Boosting

We train the real version of the multiclass Adaboost [J. Zhu, 2009]:

1. *Initialize the observation weights* $w_i = 1/n,\ i = 1, 2, \ldots, n$.
2. *For* $m = 1$ *to* M*:*
   (a) *Fit a classifier* $T^{(m)}(\boldsymbol{x})$ *to the training data using weights* w_i.
   (b) *Obtain the weighted class probability estimates*
   $$p_k^{(m)}(\boldsymbol{x}) = \mathrm{Prob}_w(c = k|\boldsymbol{x}),\ k = 1, \ldots, K.$$
   (c) *Set*
   $$h_k^{(m)}(\boldsymbol{x}) \leftarrow (K-1)\left(\log p_k^{(m)}(\boldsymbol{x}) - \frac{1}{K}\sum_{k'} \log p_{k'}^{(m)}(\boldsymbol{x})\right),\ k = 1, \ldots, K.$$
   (d) *Set*
   $$w_i \leftarrow w_i \cdot \exp\left(-\frac{K-1}{K}\boldsymbol{y}_i^{\mathsf{T}} \log \boldsymbol{p}^{(m)}(\boldsymbol{x}_i)\right),\ i = 1, \ldots, n.$$
   (e) *Re-normalize* w_i.
3. *Output*
$$C(\boldsymbol{x}) = \arg\max_k \sum_{m=1}^{M} h_k^{(m)}(\boldsymbol{x}).$$

Training data are patch dimensions, labels are codeword IDs.

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Multiclass decision trees with probabilistic output.

How? — Featureless Boosting

We train the real version of the multiclass Adaboost [J. Zhu, 2009]:

Decision boundary weighted in each leaf by the sample weight:

$$p_k^m(\mathbf{x}_i) = \frac{\sum_{i\in\mathcal{L}} w_i(y_i^k = 1)}{\sum_{i\in\mathcal{L}} w_i}$$

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(d) Set

Weight updates.

$$w_i \leftarrow w_i \cdot \exp\left(-\frac{K-1}{K}\boldsymbol{y}_i^{\mathsf{T}} \log \boldsymbol{p}^{(m)}(\boldsymbol{x}_i)\right),\ i = 1, \ldots, n.$$

(e) Re-normalize w_i.

3. Output

$$C(\boldsymbol{x}) = \arg\max_k \sum_{m=1}^{M} h_k^{(m)}(\boldsymbol{x}).$$

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Predicted codeword ID for the input patch.

How? — Featureless Multiclass Waldboost

- Can we make it even faster?

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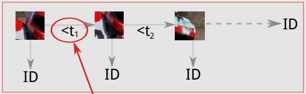
- Can we make it even faster?
- Early stopping — Waldboost [J. Sochman, CVPR, 2005].



If the prediction is below a threshold continue, else stop.

How? — Featureless Multiclass Waldboost

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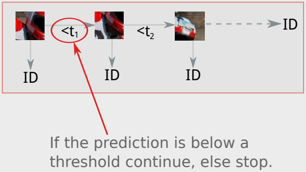

- But Waldboost finds stopping thresholds for 2-class Adaboost only.

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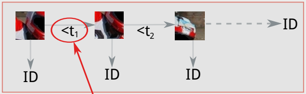


If the prediction is below a
threshold continue, else stop.

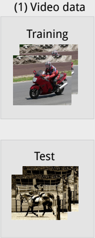
- But Waldboost finds stopping thresholds for 2-class Adaboost only.
- Train on unused training data a **stopping decision tree** that gets as input the prediction of the strong classifier up to now.

$$\max_k \left(\mathrm{Stop}_k^{M'} \left(\sum_{m=1}^{M' \leq M} s_k^m(\bar{\mathbf{x}}_i) \right) \right) \geq \alpha$$

The strong classifier
prediction up to M.

A-to-Z Featureless Approach

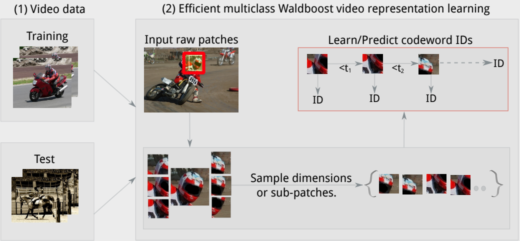
- Get a set of training videos and test videos.



A-to-Z Featureless Approach

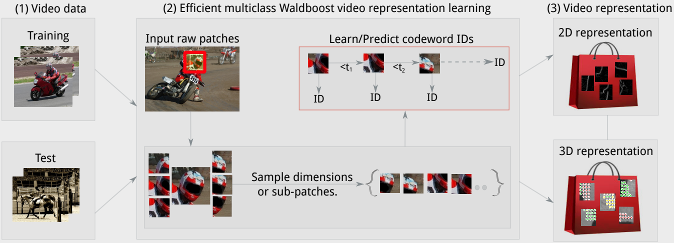
During:

- training: extract (patch, codeword-ID) pairs;
- testing: only patches and predict codeword-IDs in the multiclass Waldboost.



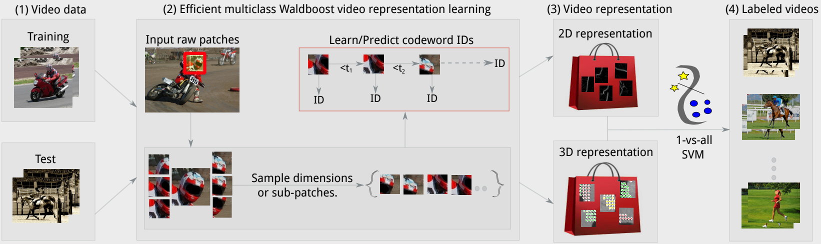
A-to-Z Featureless Approach

- Compute a video representation with the predicted codeword-IDs.



A-to-Z Featureless Approach

- Use the video representation for action categorization.



Experimental Evaluation

Experimental Setup:

- UCF11 dataset. [J. Liu, CVPR, 2009]
- Codebook with K-means over 100 K descriptors.
- Gray-scale patches of 24x24 dimensions.
- 1000 weak classifiers, trained on 24 random dimensions.
- Stopping threshold α set to .97.

Experimental Evaluation

Waldboost word prediction versus other learning algorithms

- Setup:
  - 100 dimensional codebook.
  - HOG descriptors for codebook construction.
- Results:

	Linear SVM	Adaboost	Waldboost
MAP	16%	41%	**41**%
Time/frame	15.00 sec	4.00 sec	0.60 sec

Experimental Evaluation

Learning versus feature extraction

- Setup:
  - 100 dimensional codebook for HOG, HOF.
  - 1000 dimensional codebook for $3D$-HOF.
  - $3D$-HOG descriptors over 8 frames.
- Results:

	HOG		HOF	
	BOW	Waldboost	BOW	Waldboost
MAP	**44%**	41%	**37%**	32%

$3D$ HOF		
BOW	Waldboost	BOW & Waldboost
45%	36%	**50%**

Experimental Evaluation

Learning featureless and codebookless representations

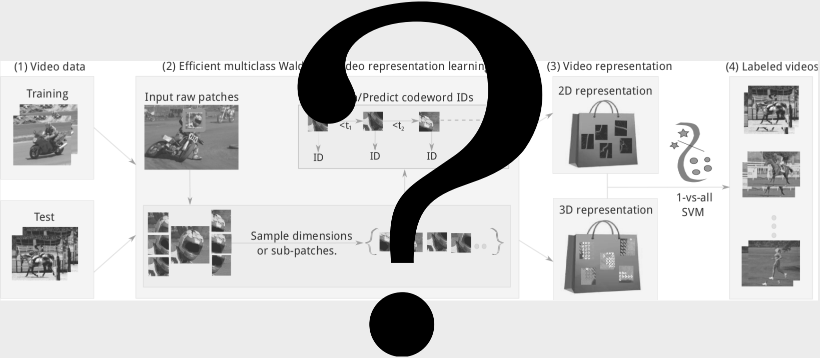
- Setup:
  - From the 100 K patches each is considered to be a data center.
  - Only ≈ 100 patches have test-time patches assigned to them.
- Results:

	BOW	Codebookless	
		Adaboost	Waldboost
MAP	44%	41%	37%

Conclusions

- Present a proof of concept showing that we can bypass feature extraction.
- Still obtain comparable performance with the representation we learn from.
- To this end, a straightforward Waldboost multiclass approach is proposed.
- Finally, we consider both featureless and codebookless representations.

Thank you


(1) Video data
Training
Test
Input raw patches
ID
ID
ID
Sample dimensions
or sub-patches.
(3) Video representation
2D representation
3D representation
1-vs-all
SVM
(4) Labeled videos