
# Columbia University TRECVID-2006 High-Level Feature Extraction

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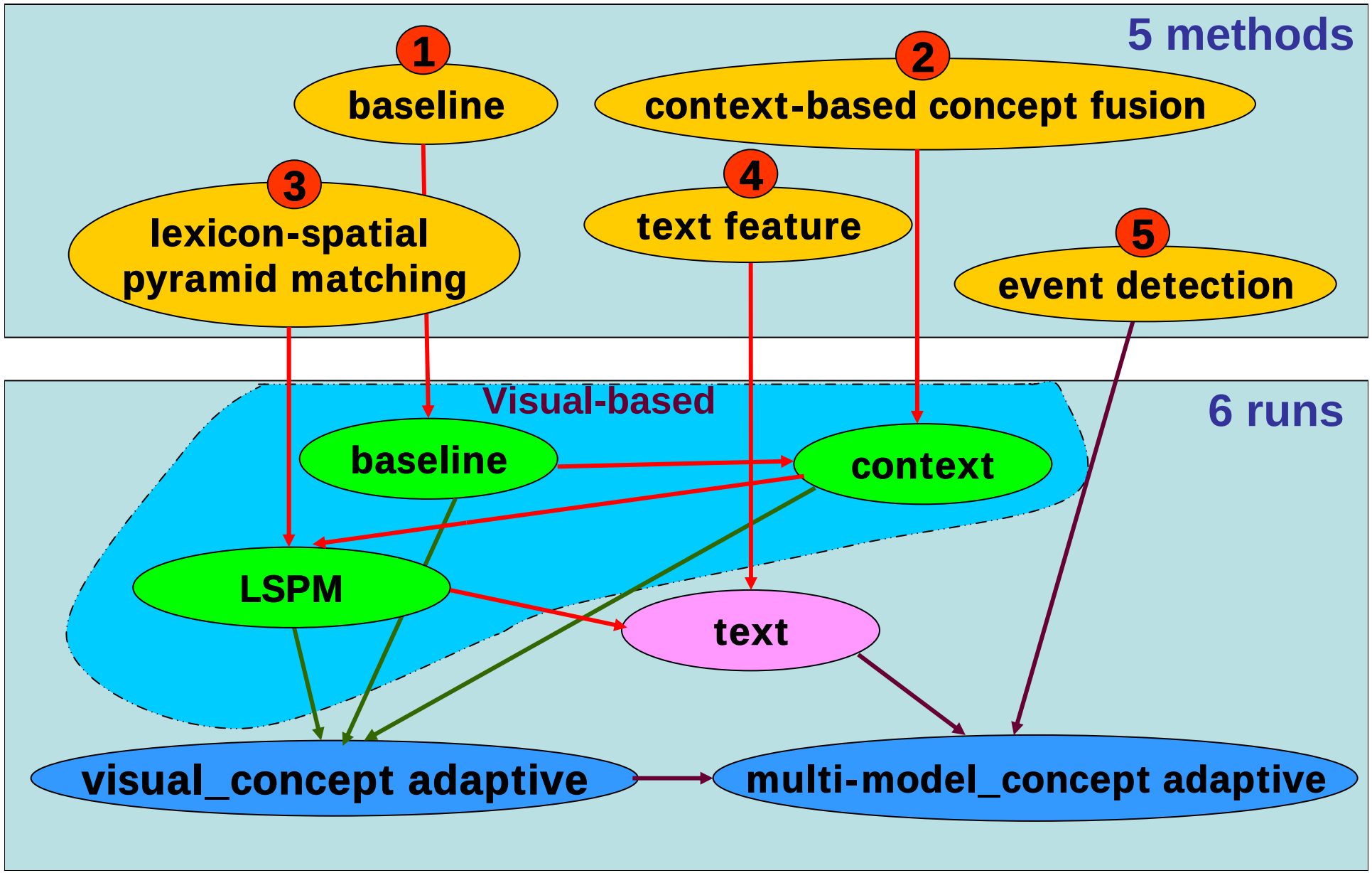
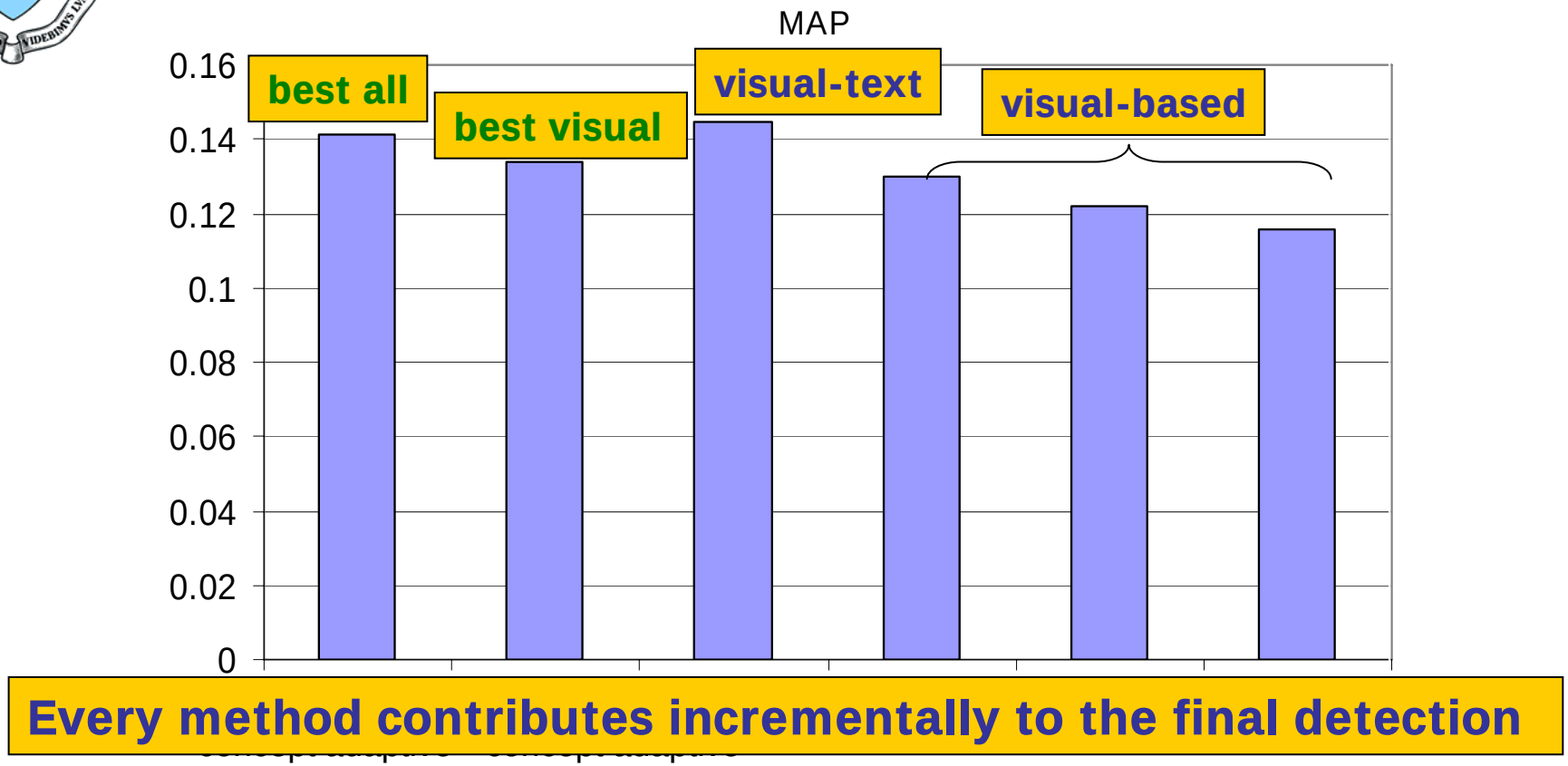
**http://www.ee.columbai.edu/dvmm**

# Overview – 5 methods & 6 submitted runs



# Overview – performance




**Every method contributes incrementally to the final detection**

- context > baseline

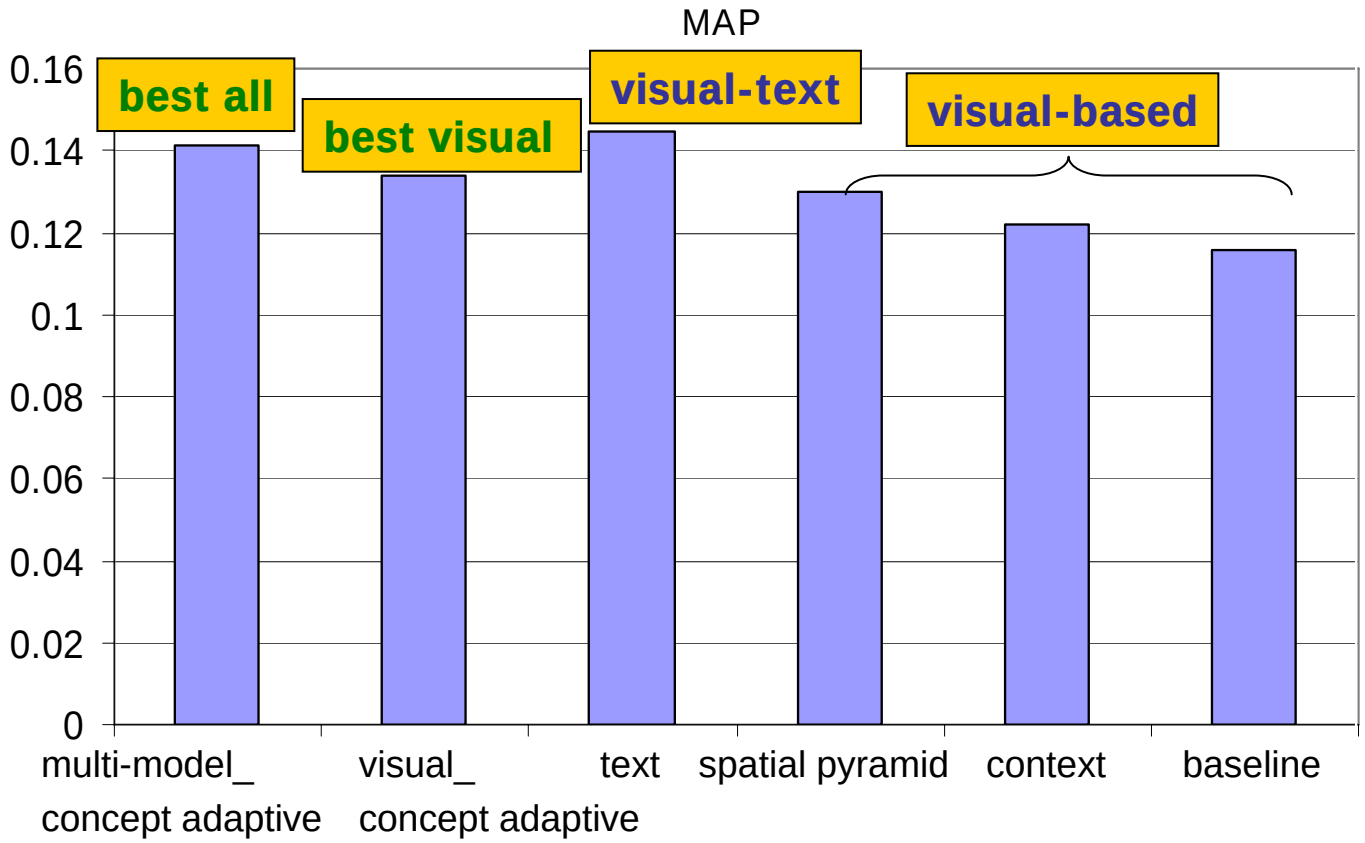
context-based concept fusion (**CBCF**) improves baseline

- LSPM > context

lexicon-spatial pyramid matching (**LSPM**) further improves detection

- text > LSPM: text features improve visual

# Overview – performance




visual_concept adaptive > LSPM (also > context > baseline):

best of visual selection works

text > multi-model_concept adaptive:

best of all selection does not work well

probably due to over fitting of text tool


# Outline – New Algorithms

- Baseline
- Context-based concept fusion (CBCF)
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- Text features
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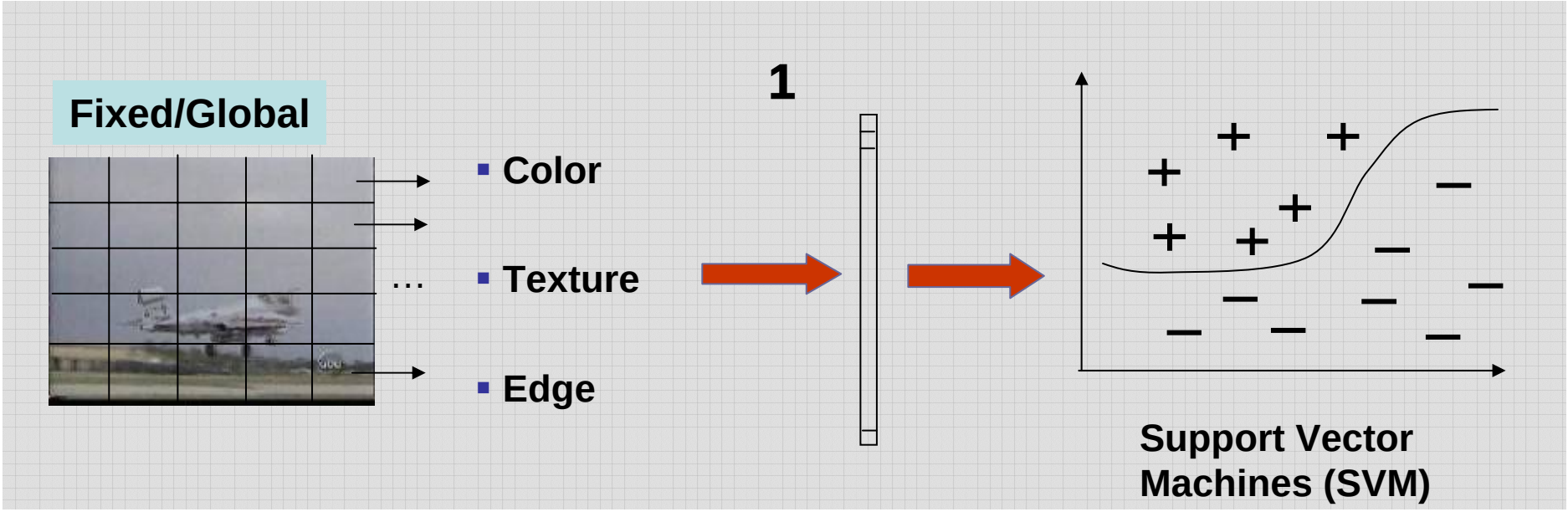
# Individual Methods: (1) Baseline

Average fusion of two SVM baseline classification results

Based on 3 visual features

- color moments over 5x5 fixed grid partitions
- Gabor texture
- edge direction histogram from the whole image




coarse local features, layout, and global appearance

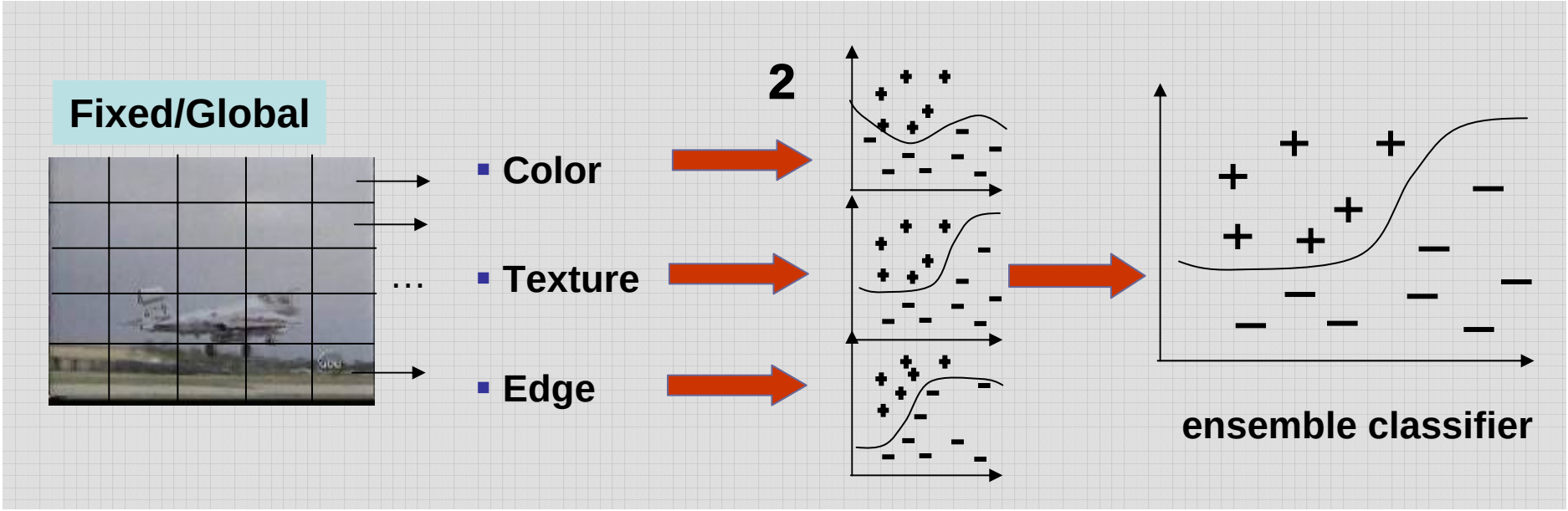
# Individual Methods: (1) Baseline

Average fusion of two SVM baseline classification results

Based on 3 visual fea

- color moments o
- Gabor texture
- edge direction histogram fro

**Features and models available for download soon!**




*Yanagawa et al., Tec. Rep., Columbia Univ., 2006 ,*
*http://www.ee.columbia.edu/dvmm/newPublication.htm*



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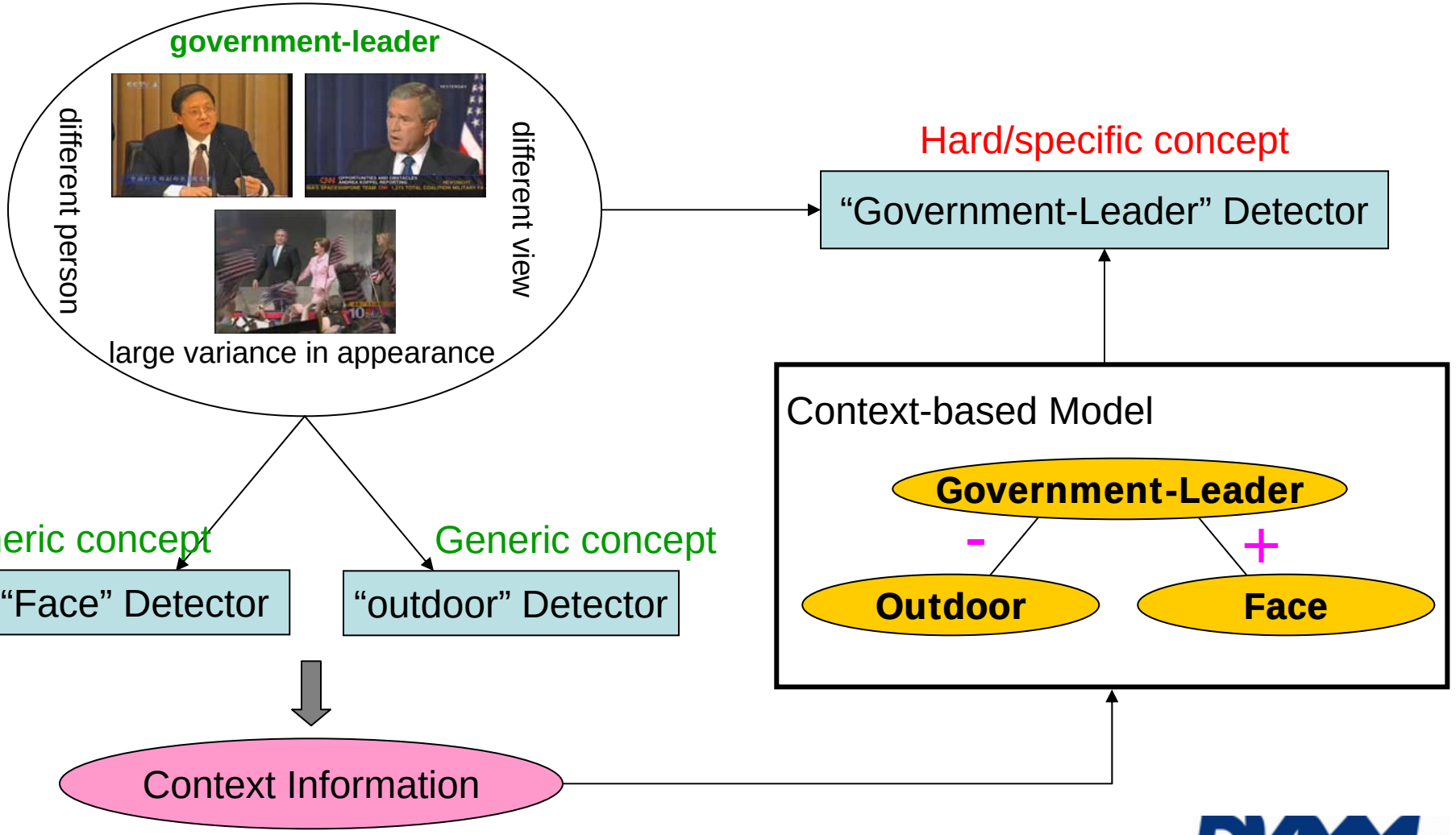
# Individual Methods: (2) CBCF

## Background on Context Fusion



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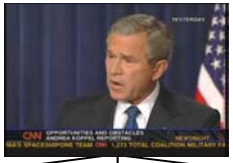
# Individual Methods: (2) CBCF

## Formulation



**outdoor detector** | **government-leader detector** | **face detector**

$P(\text{outdoor}|\text{image})$ $P(\text{government-leader}|\text{image})$ $P(\text{face}|\text{image})$

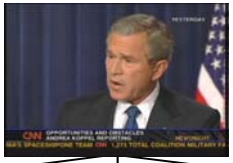
**context-based model**

(Naphade et al 2002)

$\tilde{P}(\text{outdoor}|\text{image})$ $\tilde{P}(\text{government-leader}|\text{image})$ $\tilde{P}(\text{face}|\text{image})$

# Individual Methods: (2) CBCF

Our approach: Discriminative + Generative



$I$

$C_1$ $C_2$ $C_3$

**outdoor detector** | **government-leader detector** | **face detector**

$P(\text{outdoor}|\text{image})$ $x_1$ $P(\text{government-leader}|\text{image})$ $x_2$ $P(\text{face}|\text{image})$ $x_3$

**observation**

**Conditional Random Field** (Jiang, Chang, et al ICIP 2006)

**outdoor** **airplane** **office**

**updated posteriors**

$\tilde{P}(\text{outdoor}|\text{image})$ $\tilde{P}(\text{government-leader}|\text{image})$ $\tilde{P}(\text{face}|\text{image})$

$p(y_1 = 1 | \mathbf{X})$ $p(y_2 = 1 | \mathbf{X})$ $p(y_3 = 1 | \mathbf{X})$



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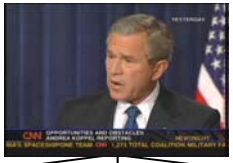
# Individual Methods: (2) CBCF

Our approach: Discriminative + Generative



$I$

$C_1$ **outdoor detector**

$C_2$ **government-leader detector**

$C_3$ **face detector**

$P(\text{outdoor}|\text{image})$ $x_1$

$P(\text{government-leader}|\text{image})$ $x_2$

$P(\text{face}|\text{image})$ $x_3$

**observation**

**Conditional Random Field**

**min** $J = -\prod_{I}\prod_{C_i} p(y_i = 1|\mathbf{X})^{(1+y_i)/2}\, p(y_i = -1|\mathbf{X})^{(1-y_i)/2}$

**iteratively minimized by boosting**

**updated posteriors**

$\tilde{P}(\text{outdoor}|\text{image})$ $p(y_1 = 1|\mathbf{X})$

$\tilde{P}(\text{government-leader}|\text{image})$ $p(y_2 = 1|\mathbf{X})$

$\tilde{P}(\text{face}|\text{image})$ $p(y_3 = 1|\mathbf{X})$



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# Individual Methods: (2) CBCF

**During each it**

**two**

**pt:**

**1. Using input**

**min** $J = -\prod_i p(y_i = 1 \mid \mathbf{x})^{(1+y_i)/2} p(y_i = -1 \mid \mathbf{x})^{(1-y_i)/2}$

**2. Using**

**ration t-1**

**iteratively**

**Classifier 2 keeps updating through iteration**
**And captures inter-conceptual influences**

**Without classifier 2, Traditional AdaBoost**

# Individual Methods: (2) CBCF

## Database & lexicon for context

- Predefined lexicon to provide context

  -- 374 concepts from LSCOM ontology (**observation**)
  *airplane, building, car, boat, person, outdoor, sports, etc*

- Independent detector

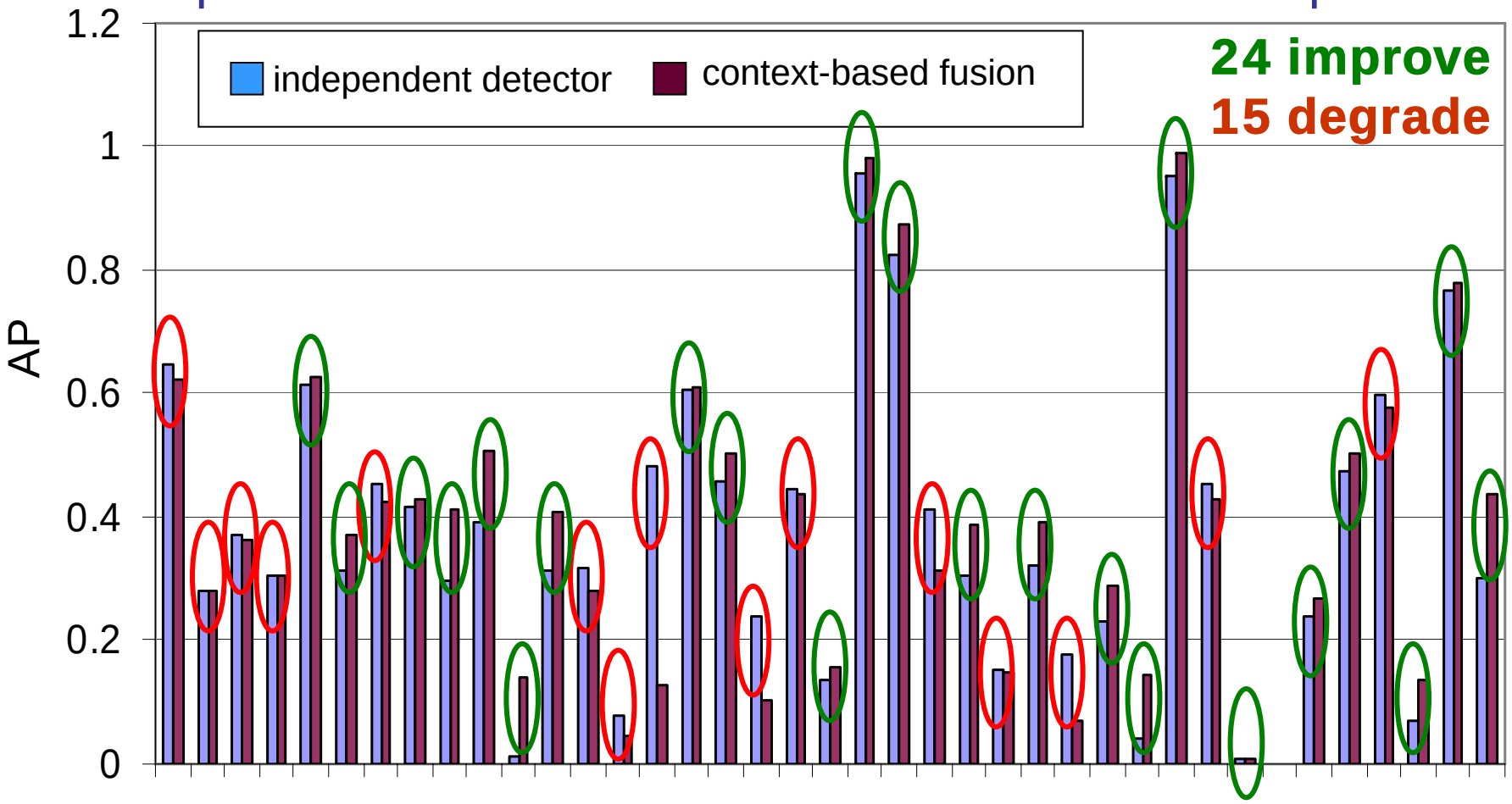
  -- our baseline

- Test concepts

  -- the 39 concepts defined by NIST (**update posteriors**)

# Individual Methods: (2) CBCF

experimental results over TRECVID 2005 development set



# Selective Application of Context

- Not every concept classification benefits from context-based fusion

  Consistent with previous context-based fusion:

  IBM: no more than 8 out of 17 concepts gained performance
  *[Amir et al., TRECVID Workshop, 2003]*

  Mediamill: 80 out of 101 concepts
  *[Snoek et al., TRECVID Workshop, 2005]*

- Is there a way to predict when it works?

# Predict When Context Helps

## Why CBCF may not help every concept ?

- Complex inter-conceptual relationships vs. limited training samples
- Strong classifiers may suffer from fusion with weak context

Avoid using CBCF for $C_i$ if $C_i$ is strong and with weak context

Use CBCF for concept $C_i$ if $C_i$ is weak or with strong context

$I(C_i;C_j)$ -- mutual information between $C_i$ and $C_j$

$E(C_i)$ -- error rate of independent detector for $C_i$

$$\frac{\sum_{C_j, j\neq i} I(C_j;C_i)E(C_j)}{\sum_{C_j, j\neq i} I(C_j;C_i)} < \beta$$

**Strong context**

or

$$E(C_i) > \lambda$$

**weak concept**

# Predict When Context Helps

Change parameters to predict different number of concepts

| # predicted | # concept improved | precision of prediction | MAP gain |
|---|---|---|---|
| 39 | 24 | 62% | 3.0% |
| 20 | 15 | 75% | 9.5% |
| 16 | 14 | 88% | 14% |
| 9 | 9 | 100% | 7.2% |

# Example

## Military


## Fighter_Combat


## Individual


## House

. . .



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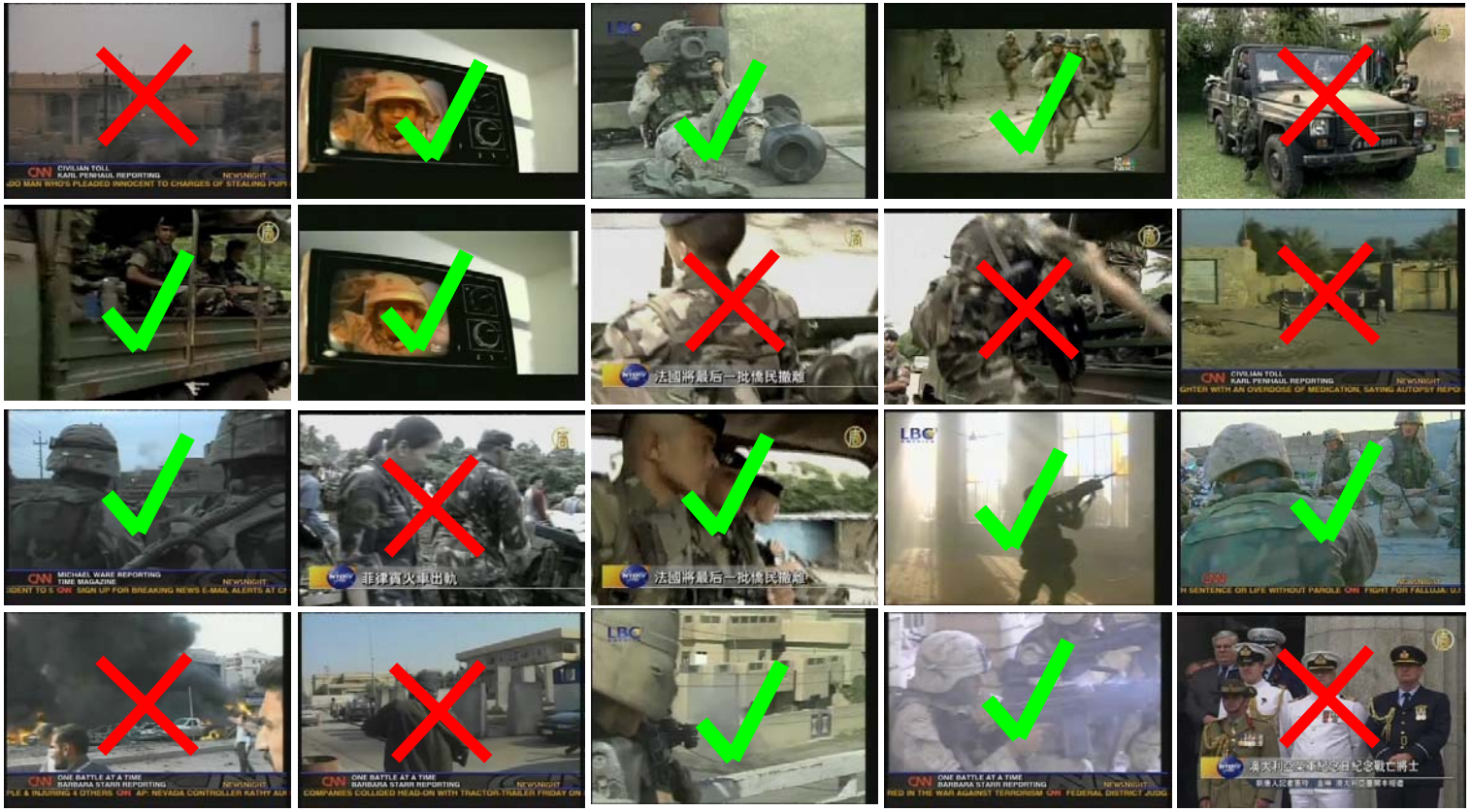
# Example

## Independent Detector

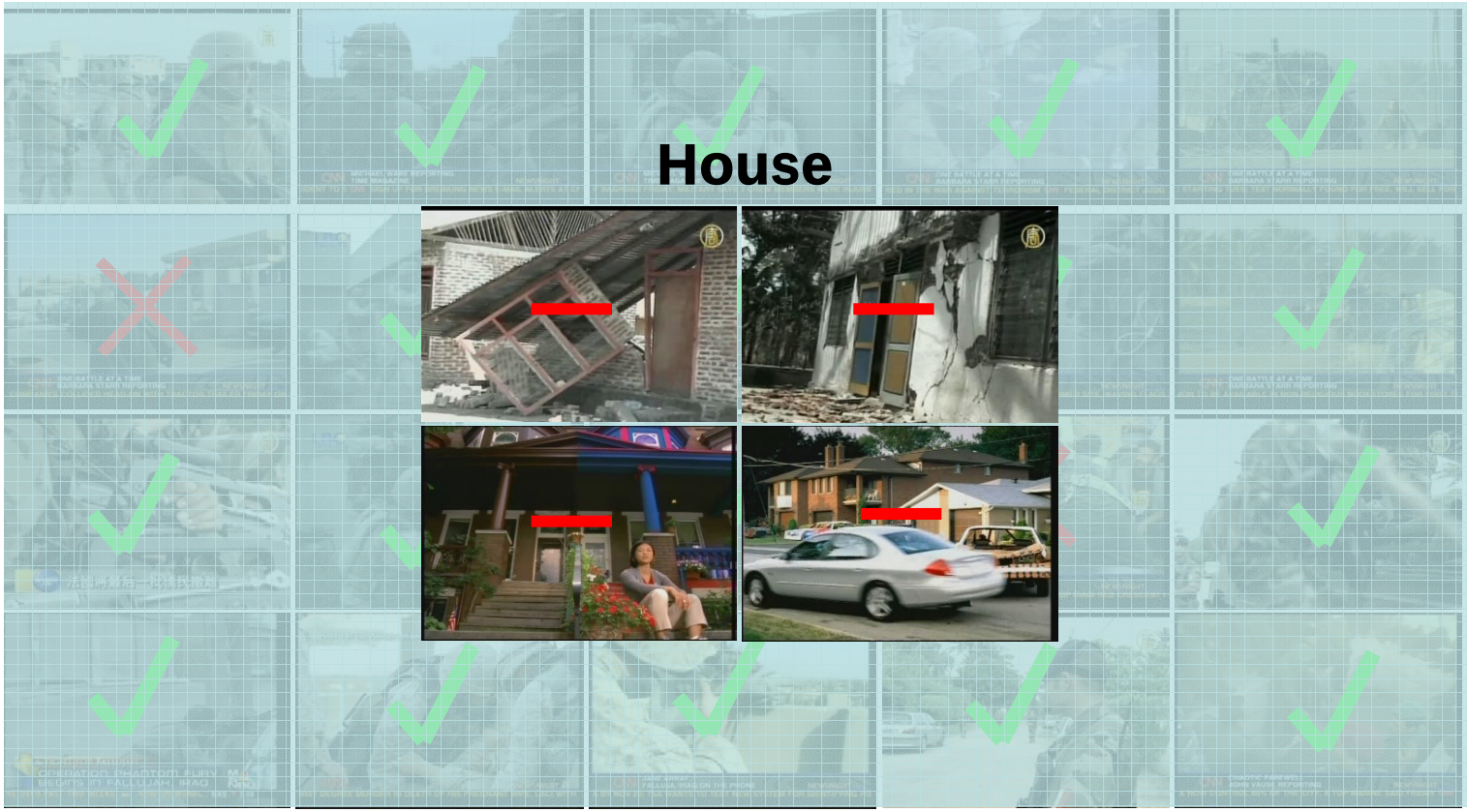


# Example

## Context-based concept fusion

# Example

## Context-based concept fusion



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# Example

## Context-based concept fusion

**Positive frames are moved forward with the help of Fighter_Combat**



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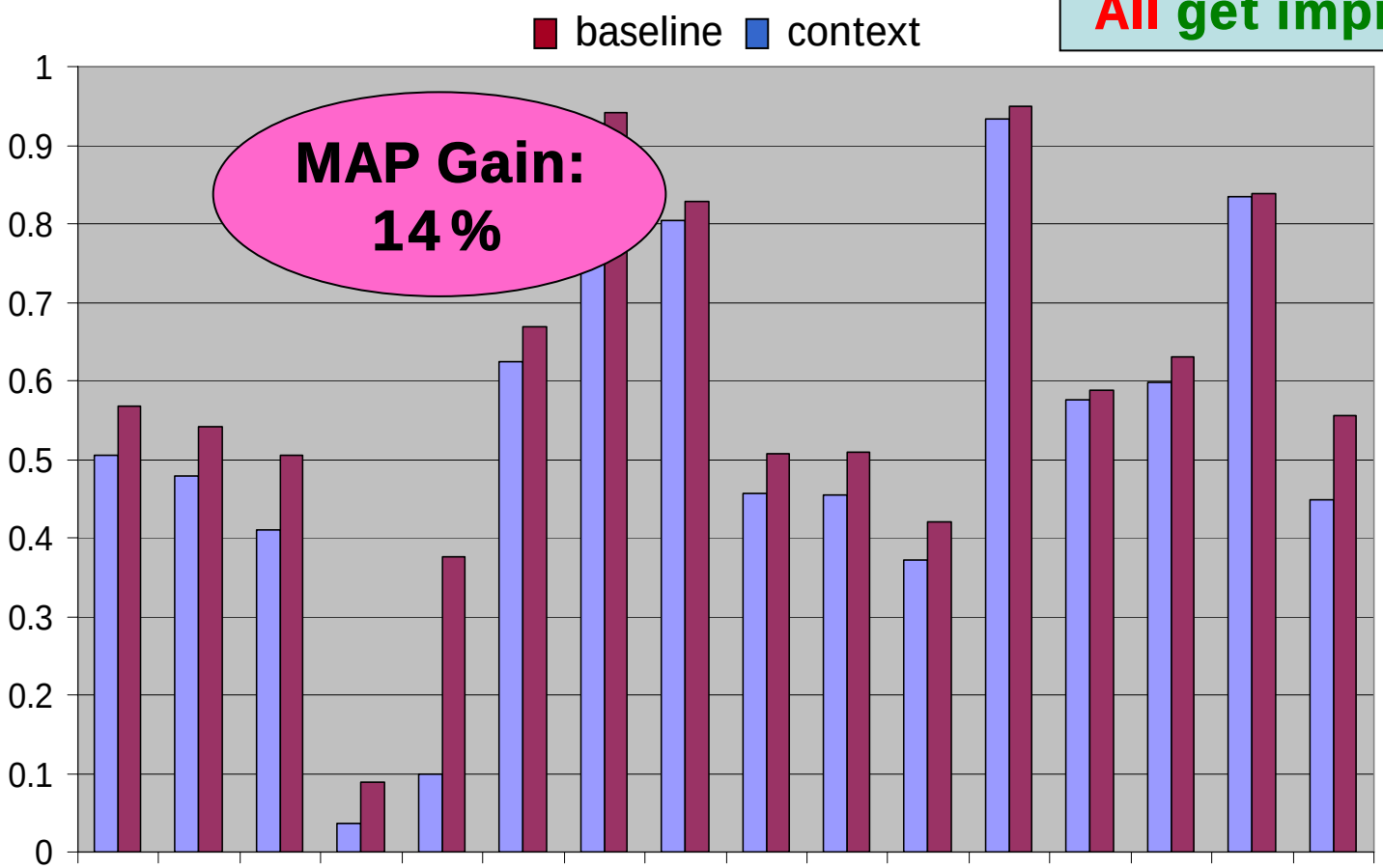
# Context-Based Fusion + Baseline

## TRECVID 2005 development set

**All get improved !**



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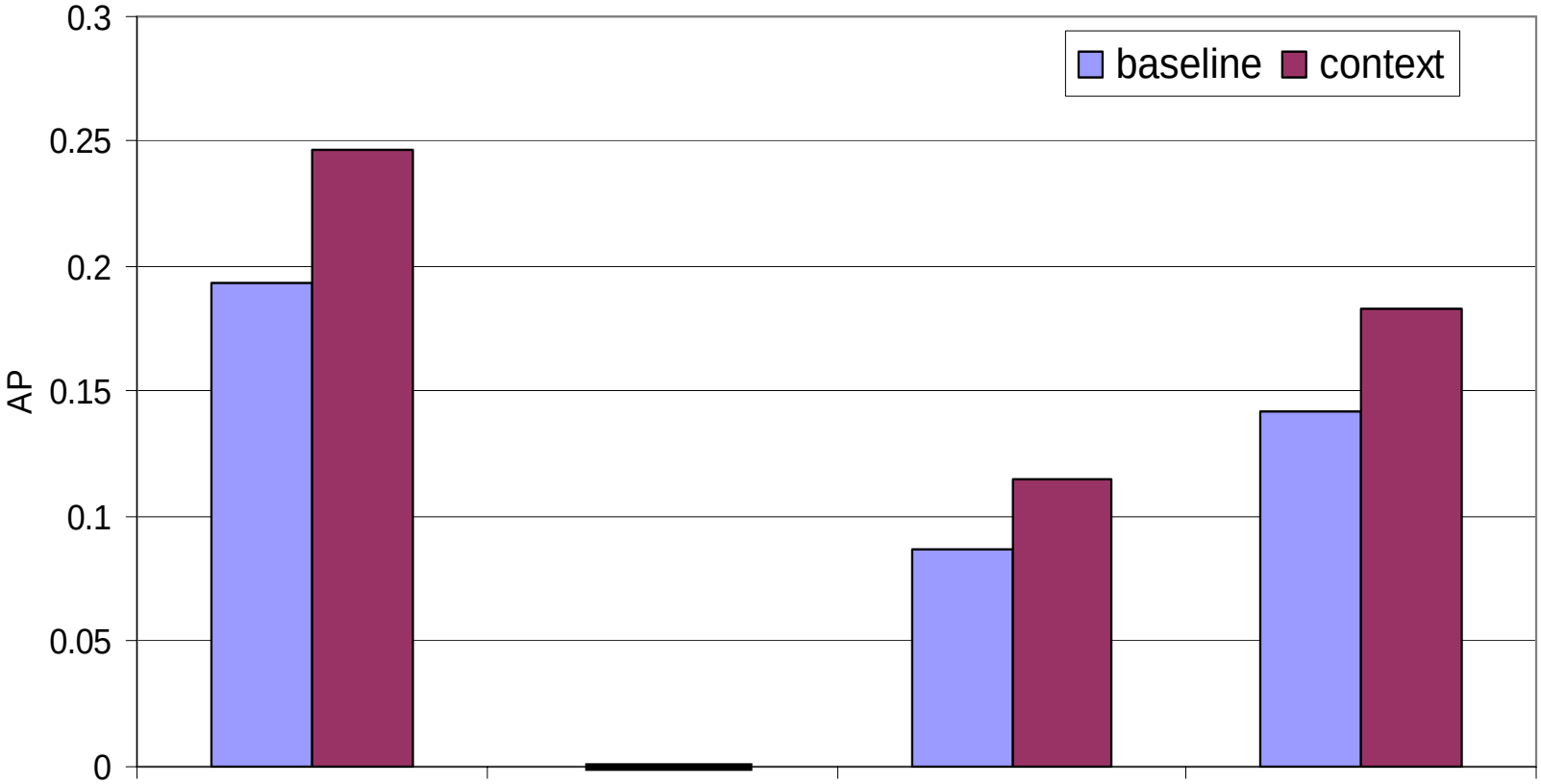
# Context-Based Fusion + Baseline

## TRECVID 2006 evaluation

**4 concepts** **Similar to results over TRECVID 2005 set !**



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# Discussion

**Quality of context:**

**The smaller the better**

$$\frac{\sum_{C_j, j \neq i} I(C_j; C_i) E(C_j)}{\sum_{C_j, j \neq i} I(C_j; C_i)}$$

**Concepts with performance improved: 3.23**

**Concepts with performance degraded: 4.17**

**Adding context – strong relationship and robust**


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# Individual Methods: (3) LSPM

Local features (SIFT)

Spatial layout


Spatial Pyramid Matching (SPM) [*Lazebnik et al. CVPR, 2006*]
multi-resolution histogram matching in spatial domain, bags-of-features

Appropriate size for visual lexicon ?
Lexicon-Spatial Pyramid Matching (LSPM)
SPM matching guided by multi-resolution lexicons



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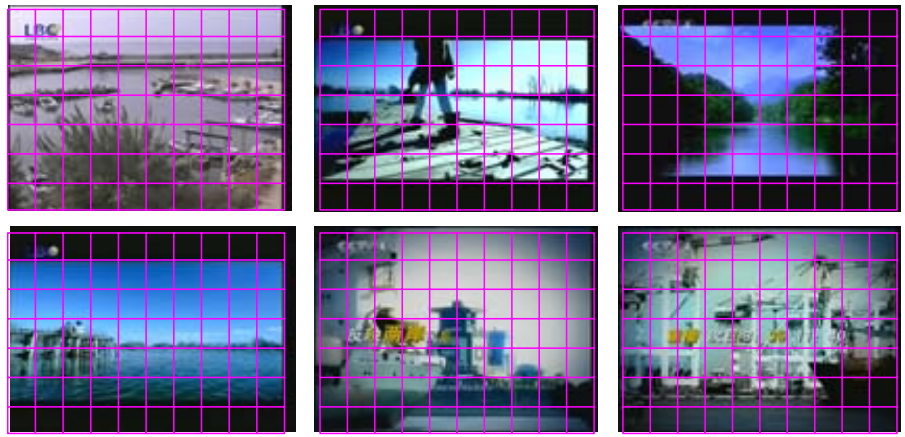
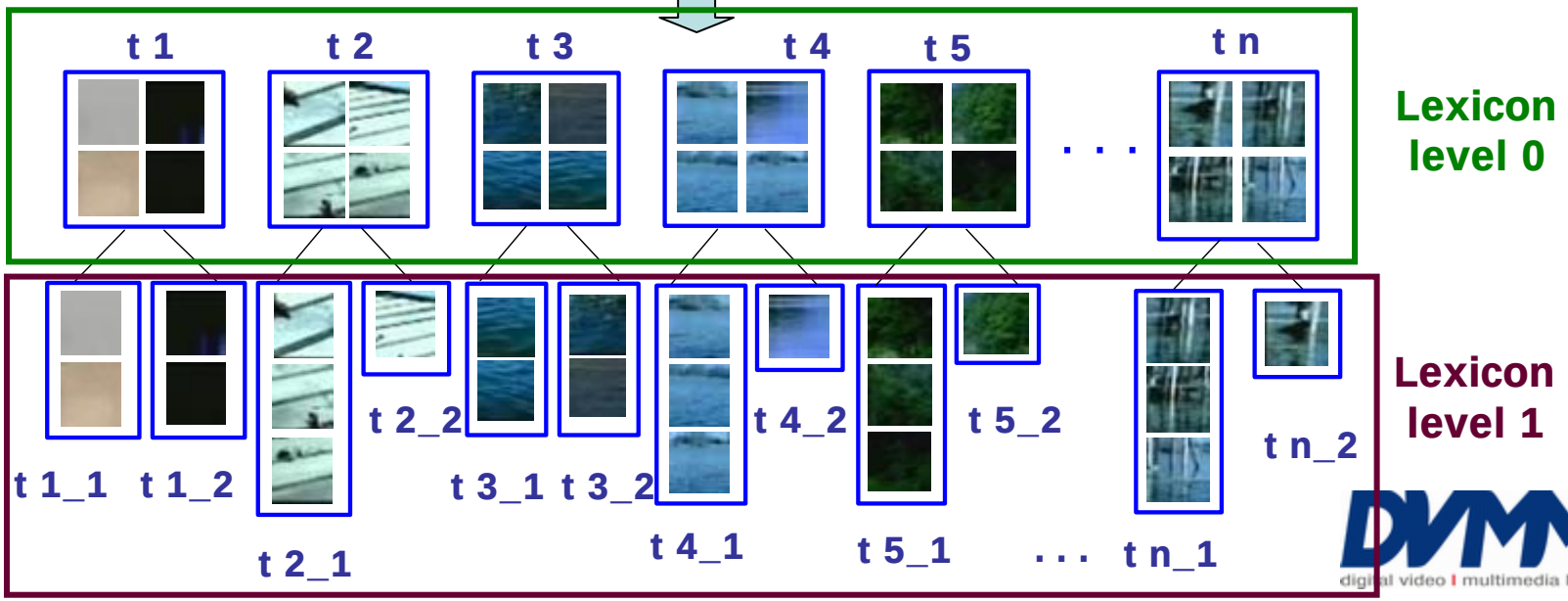
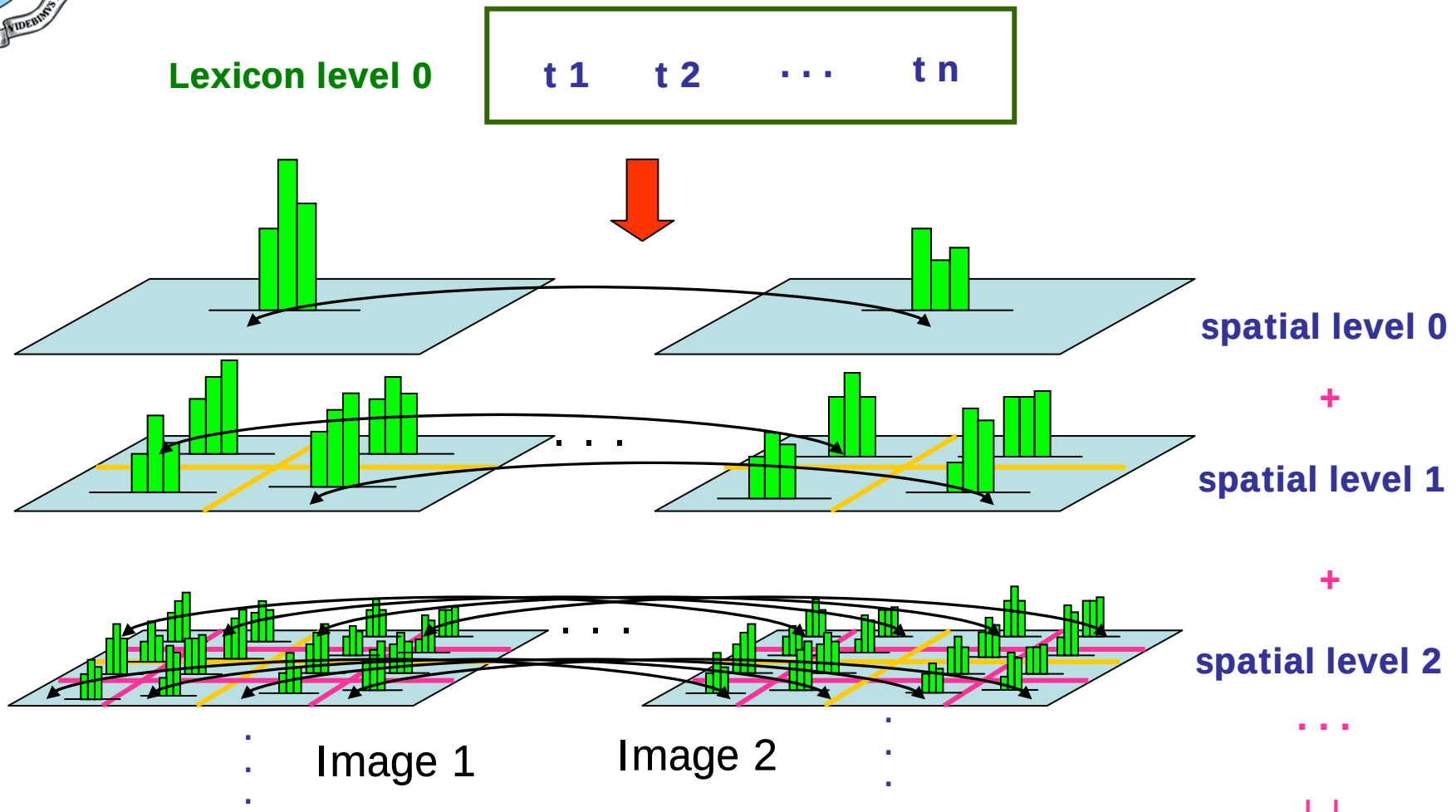
# Individual Methods: (3) LSPM



SIFT features

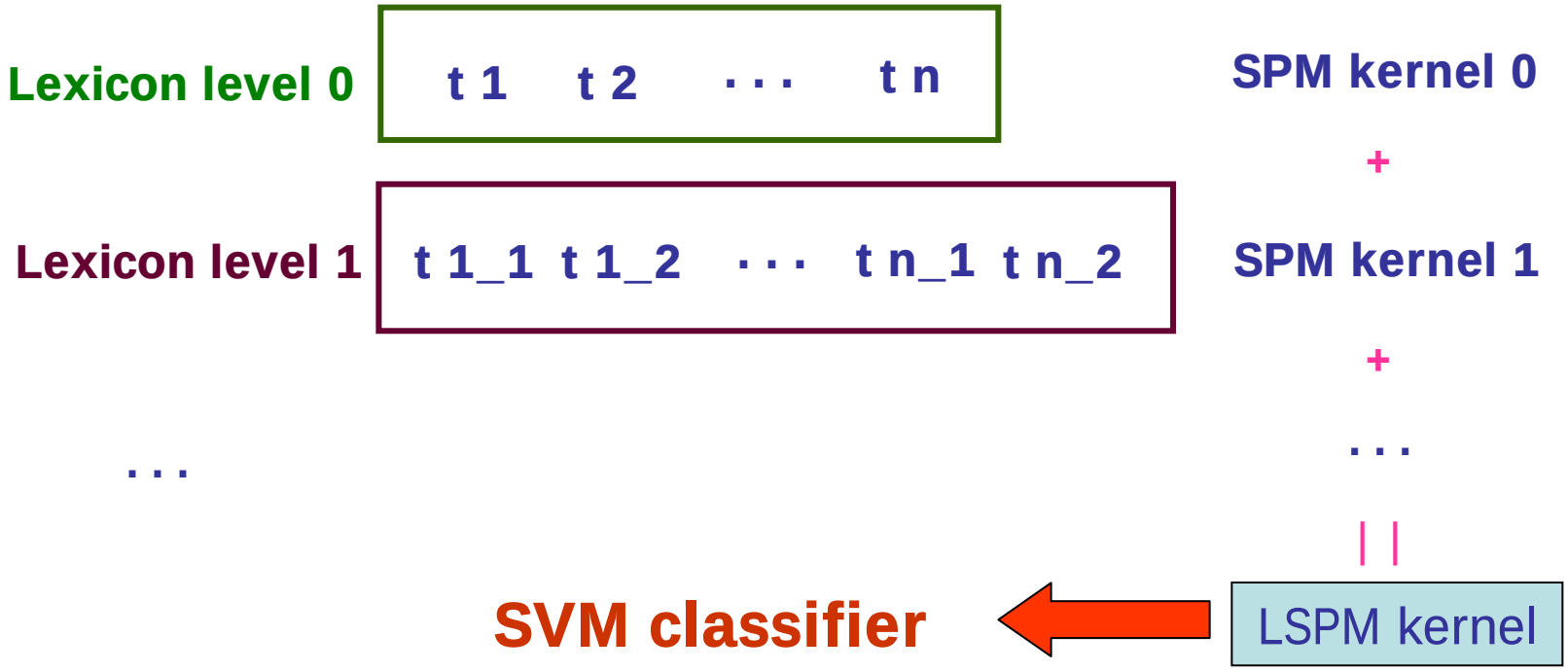


# Individual Methods: (3) LSPM




**Local features & Spatial layout of local features**

# Individual Methods: (3) LSPM

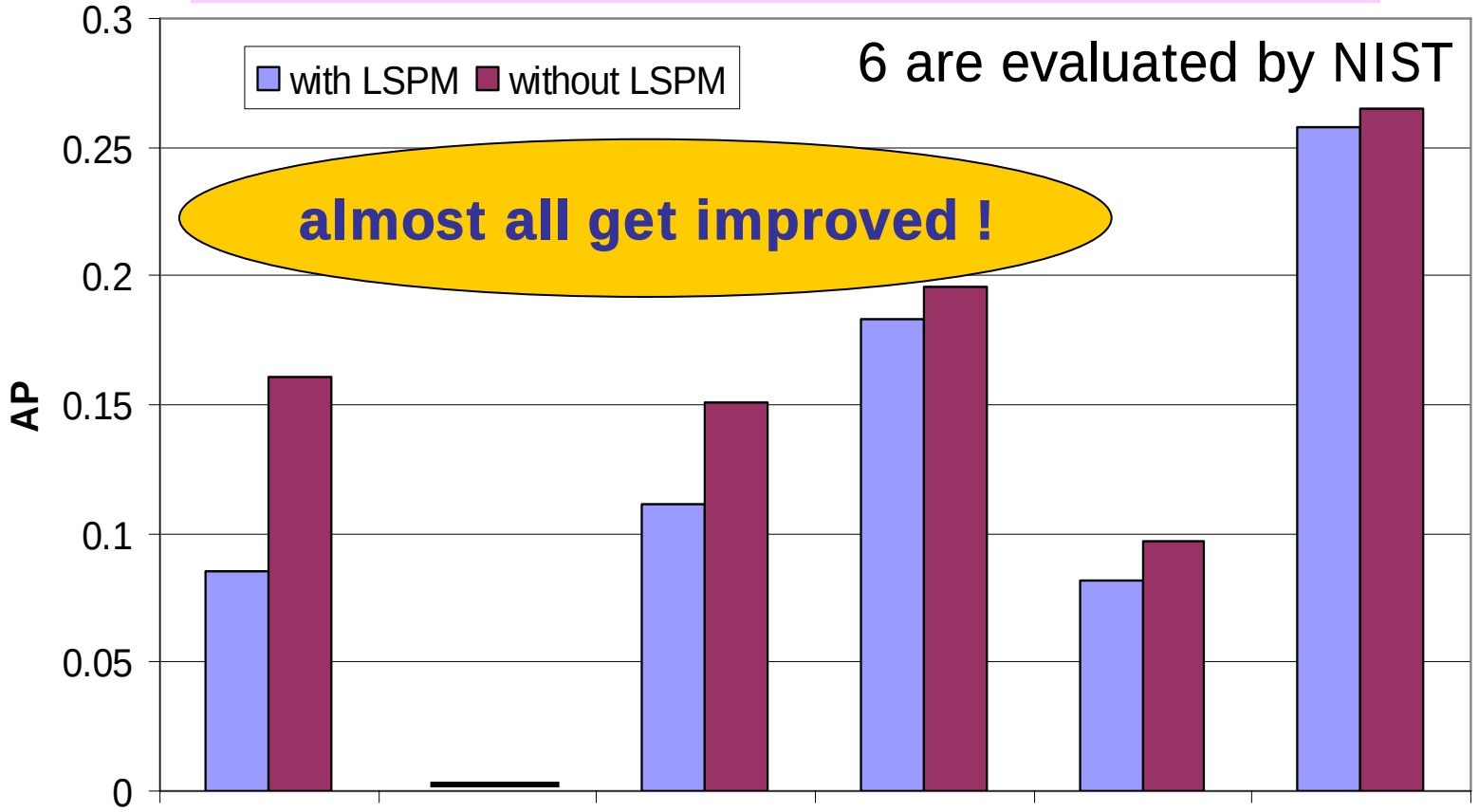


# Individual Methods: (3) LSPM

We apply LSPM to 13 concepts:

flag-us, building, maps, waterscape-waterfront, car, charts, urban, road, boat-ship, vegetation, court, government-leader

Complements baseline by considering local features

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# Individual Methods: (4) Text

Problems:

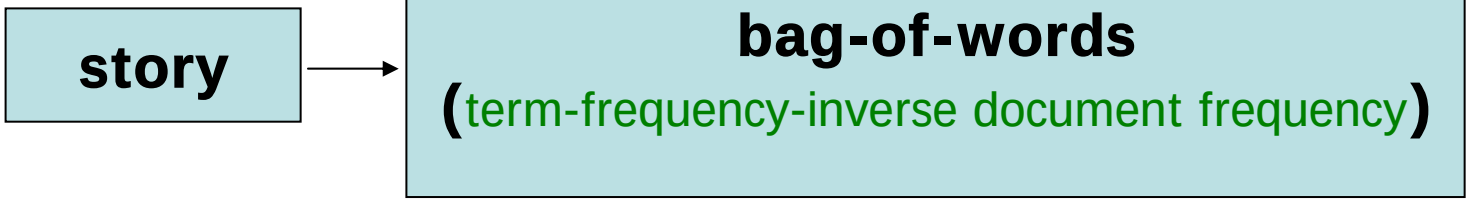
asynchrony between the words being spoken and the visual concepts appearing in the shot

Solution:

incorporate associated text from the entire sto
automatically detected story boundaries

*[Hsu et al., ADVENT Technical Report , Columbia Univ., 2005 ]*

**by frequency -- top k most frequent words**



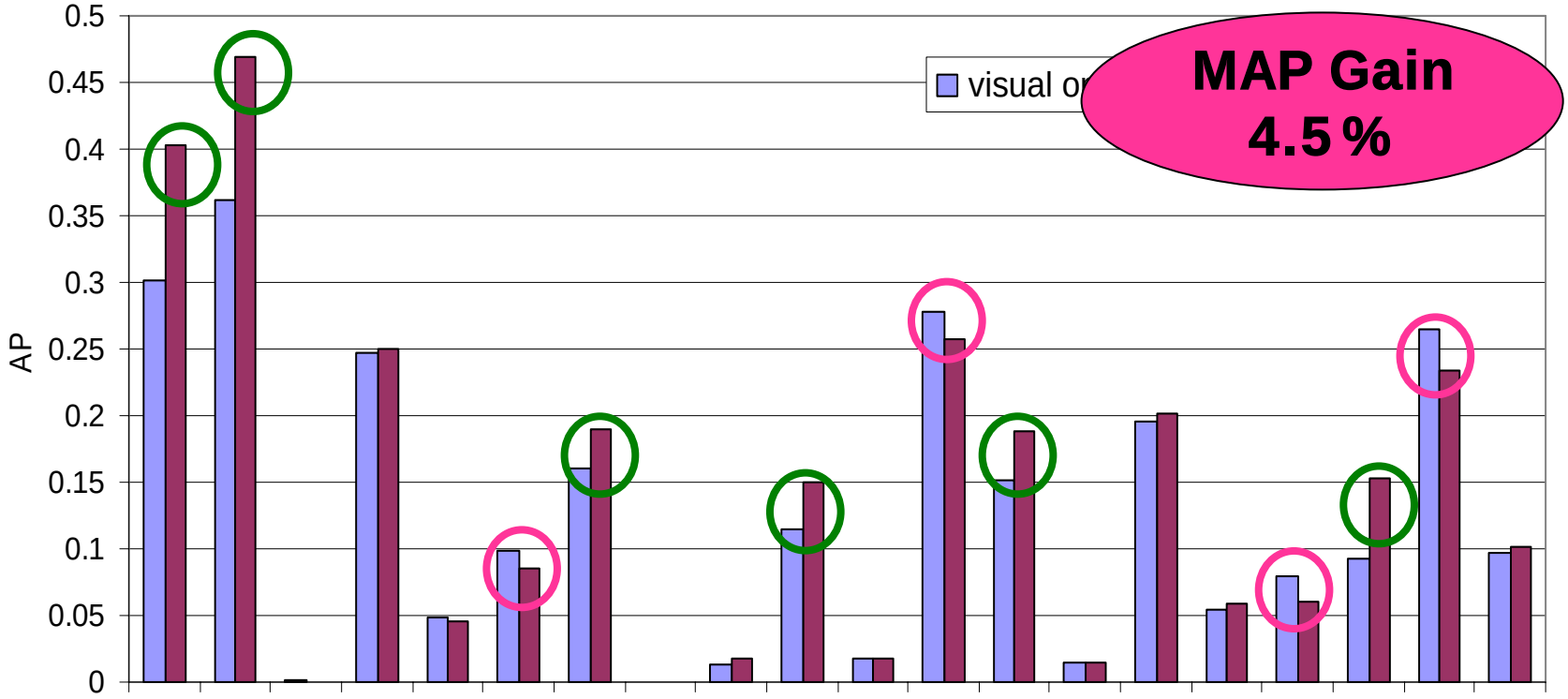

training data: bag-of-words features of stories

ground-truth label: positive – one shot is positive

} SVM

# Individual Methods: (4) Text

0.2 text + 0.8 visual

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# Individual Methods: (5) Event

Event detection: Key frame v.s. Multiple frames


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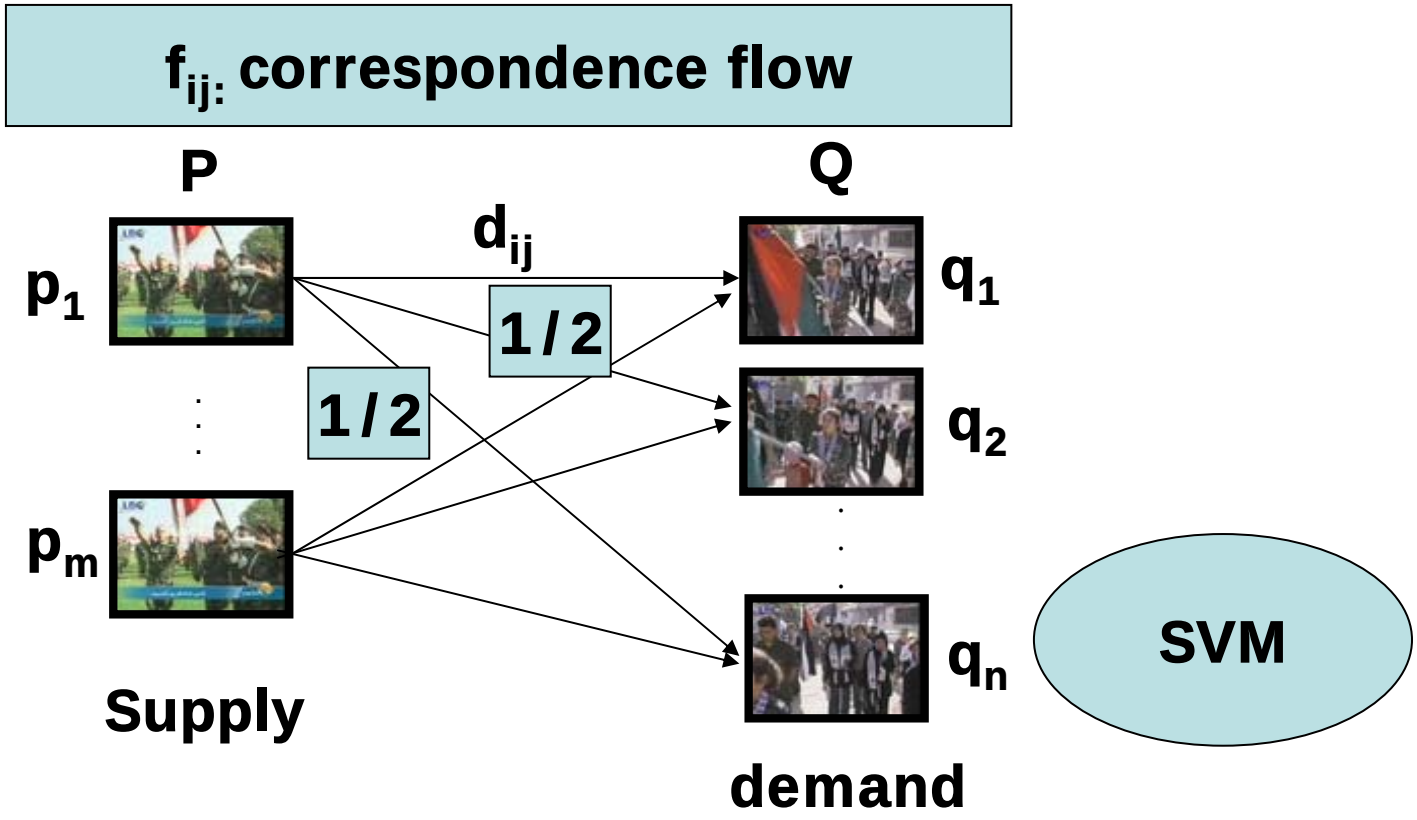
Event detection: Key frame v.s. Multiple frames




**Earth Mover's Distance:** minimum weighted distance by linear programming

handle temporal shift:

a frame at the beginning of P can map to a frame at the end of Q

Handle scale variations: a frame from P can map to multiple frames in Q

# Individual Methods: (5) Event

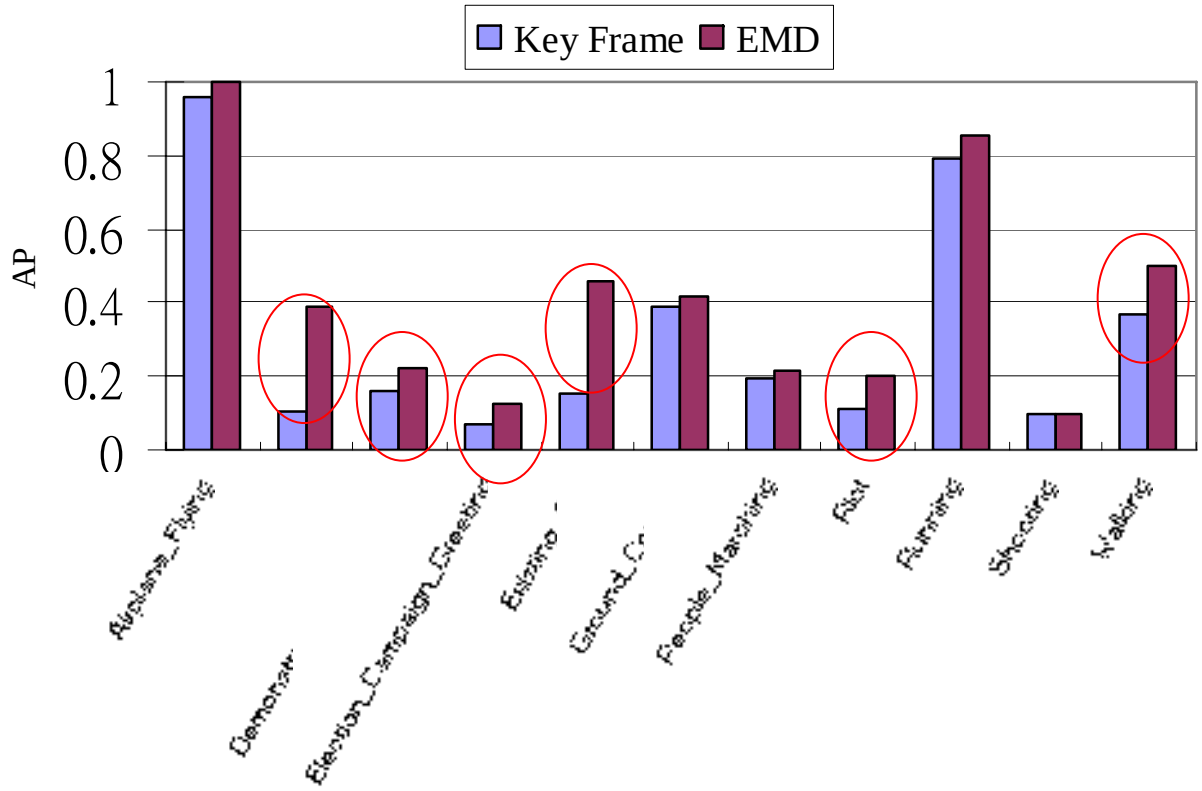
## experimental results

Performance over TRECVID 2005 development set

11 events: airplane_flying, people_marching, car_crash,

exiting_car, demonstration_or_protest, election_campaign_greeting,

parade, riot, running, shooting, walking




# Conclusion

- TRECVID 2006 offers a mature opportunity for evaluating concept interaction
  - We have built 374 concept detectors
  - Models and feature will be released soon
- Context-Based Fusion
  - Propose a systematic framework for predicting the effect of context fusion
  - (TRECVID 2005) 14 out of 16 predicted concepts show performance gain
  - (TRECVID 2006) 3 out of 4 predicted concepts show performance gain
  - Promising methodology for scaling up to large-scale systems (374 models)
- Results from Parts-based model (LSPM) are mixed
  - But show consistent improvement when fused with SVM baseline
  - 3 out of 6 concepts improve by more than 10%
- Temporal event modeling
  - We propose a novel matching and detection method based on EMD+SVM
  - Show consistent gains in 2005 data set
  - Results in 2006 are incomplete and lower than expected

- More information at
  - http://www.ee.columbia.edu
- Features and models for baseline detectors for 374 LSCOM concepts coming soon