TokyoTech at TRECVID 2016

Localization using Faster R-CNN and Multi-Frame Fusion

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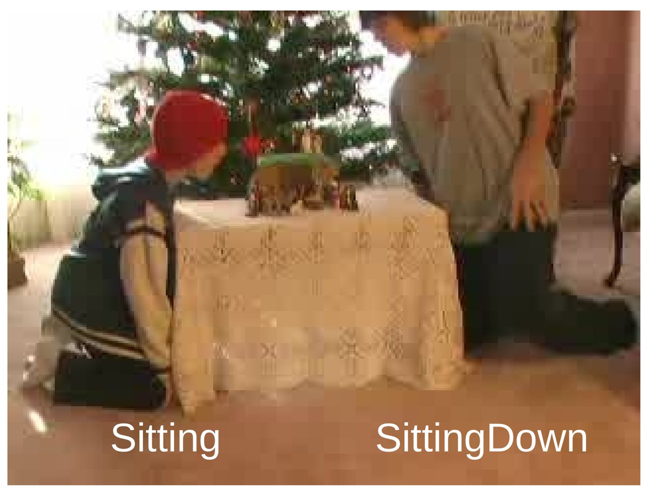
Motivation

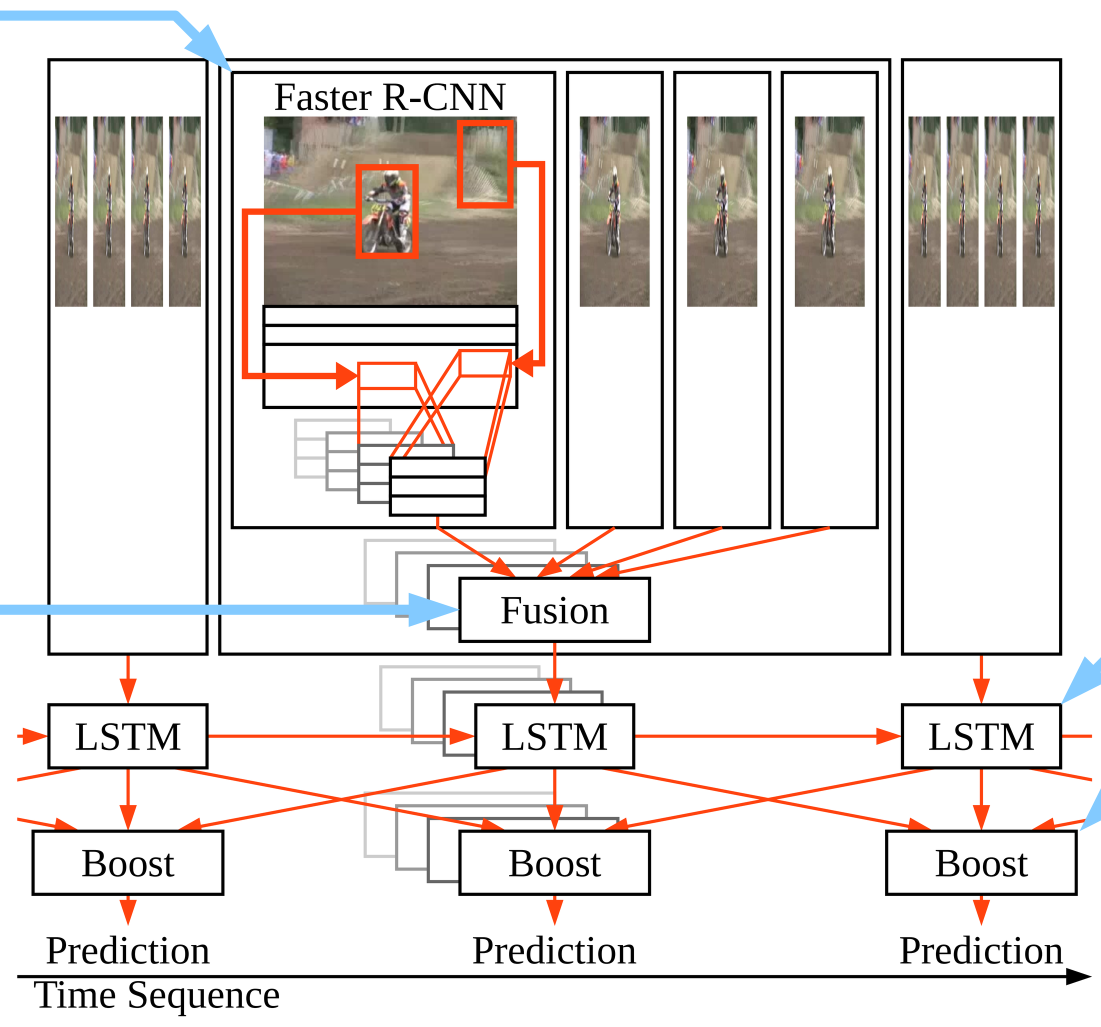
- Localization task now includes not only static object, but also some action concepts
- We focus on "SittingDown", one of action concepts
  - Hard to distinguish from still Sitting only with static image input
  - Utilizing dynamic information is important to detect it precisely



Bounding-Box Annotations

- For static objects, annotated on a key-frame for each positive shot
  - 31K boxes on 26K shots
- For SittingDown, frame-wisely annotated to train LSTM
  - 515 boxes on 92 shots

Our System



Faster R-CNN (Ren 2015)

- Efficient End-to-End object localizer
  - Generate region proposals from sparse sliding windows by a network itself
  - Predict each region using CNN features generated while generating proposals
- We use ZF Net (Zeiler 2014)

Multi-Frame Score Fusion (Inoue 2015)

- Average pooling over 4 frames

Long-Short Term Memory (Donahue 2015)

- Widely used for action detection
- Applied only to SittingDown

Multi-Shot Score Boosting (Inoue 2015)

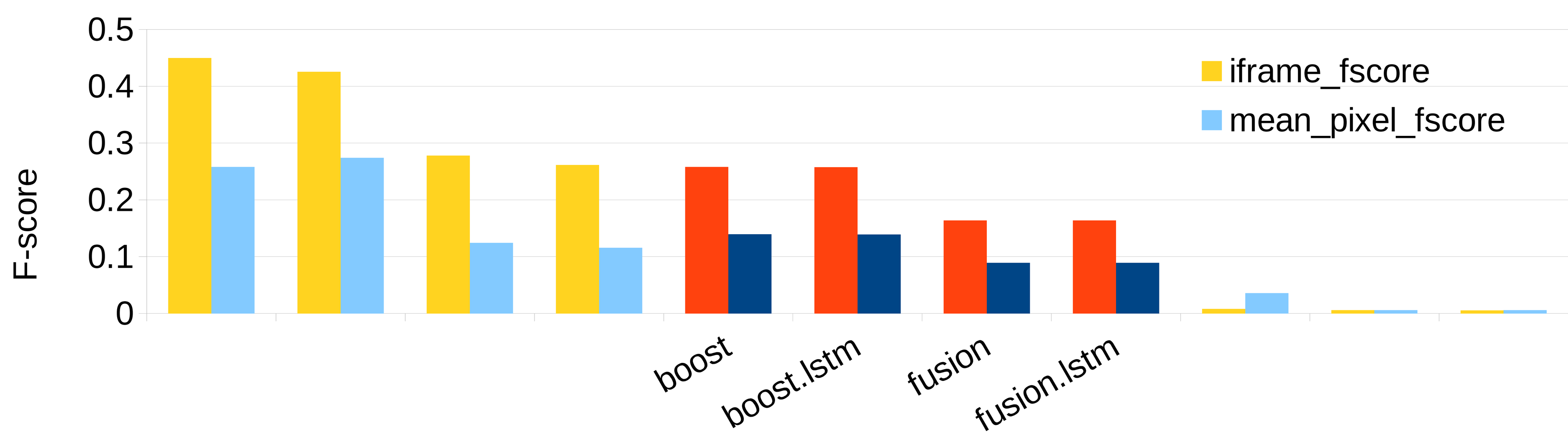
- Add adjacent shot scores

$$\mathrm{score}^{\mathrm{boost}}(r_i^t) = \mathrm{score}(r_i^t) + \beta \max_j \frac{r_i^t \cap r_j^{t\pm1}}{r_i^t \cup r_j^{t\pm1}}$$

r_i^t: ith region in time t; β: multiplier

Results

- We archived 2nd among all 3 teams



System output
Ground truth

Annimal (Fusion + Boost)

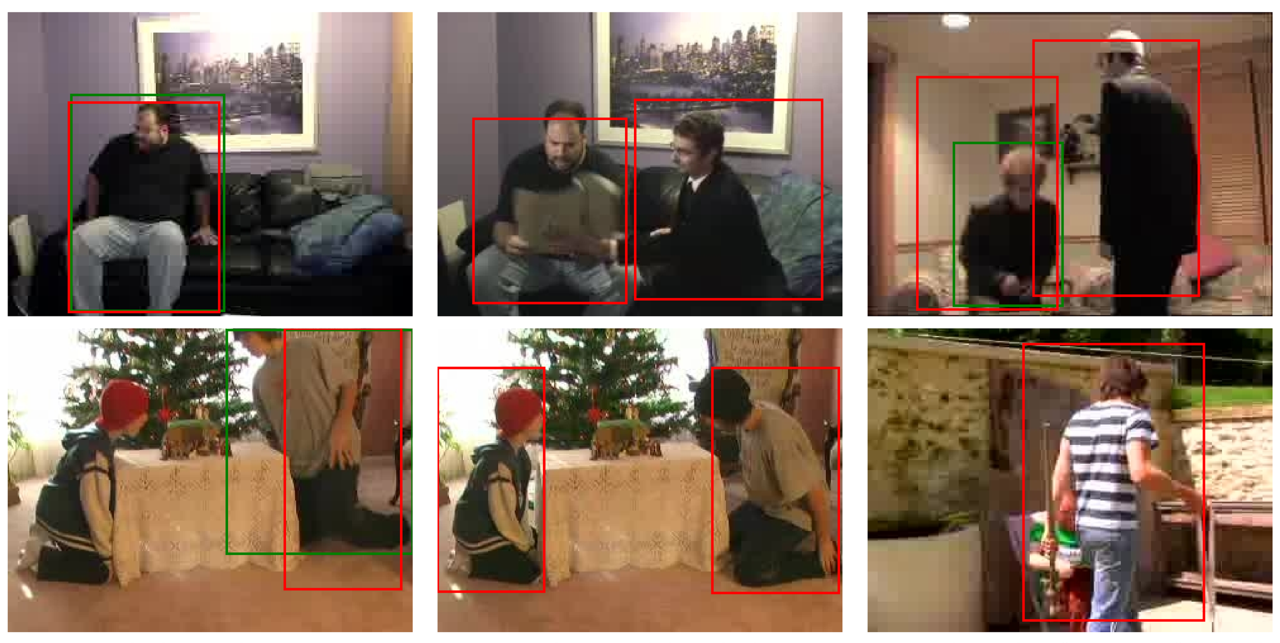
Faster R-CNN | Score Fusion | Score Boosting

A dog is about to move, Faster R-CNN failed to detect

Many small objects, Fusion and Boost are failed to detect

SittingDown (Re-trained LSTM 64 units)

Good cases | Bad cases



Sitting down | Moving with sitting | Passing in front of chair

- We got the best for SittingDown
  - Frame-wise annotation helped
  - LSTM with 4096 units did not work, seems over-fitted
- After submission, we confirmed LSTM with 64 units works well

Scores of SittingDown

Method	I-frame F-score	Pixel F-score
Without LSTM*	0.63	0.22
LSTM with 4096 units*	0.00	0.00
LSTM with 64 units	**11.96**	**4.51**

Methods with * are submitted

Conclusion

- We achieved 2nd among all 3 teams
- Best for SittingDown, LSTM did not work totally
- After submission, we confirmed LSTM works well

Future Work

- Find better way to detect SittingDown

TokyoTech at TRECVID 2016

Multimedia Event Detection Using Deep Features and LSTM

Na Rong, Nakamasa Inoue and Koichi Shinoda, Tokyo Institute of Technology

Proposed Method: Deep Features + LSTM

We propose a system using deep features and LSTM

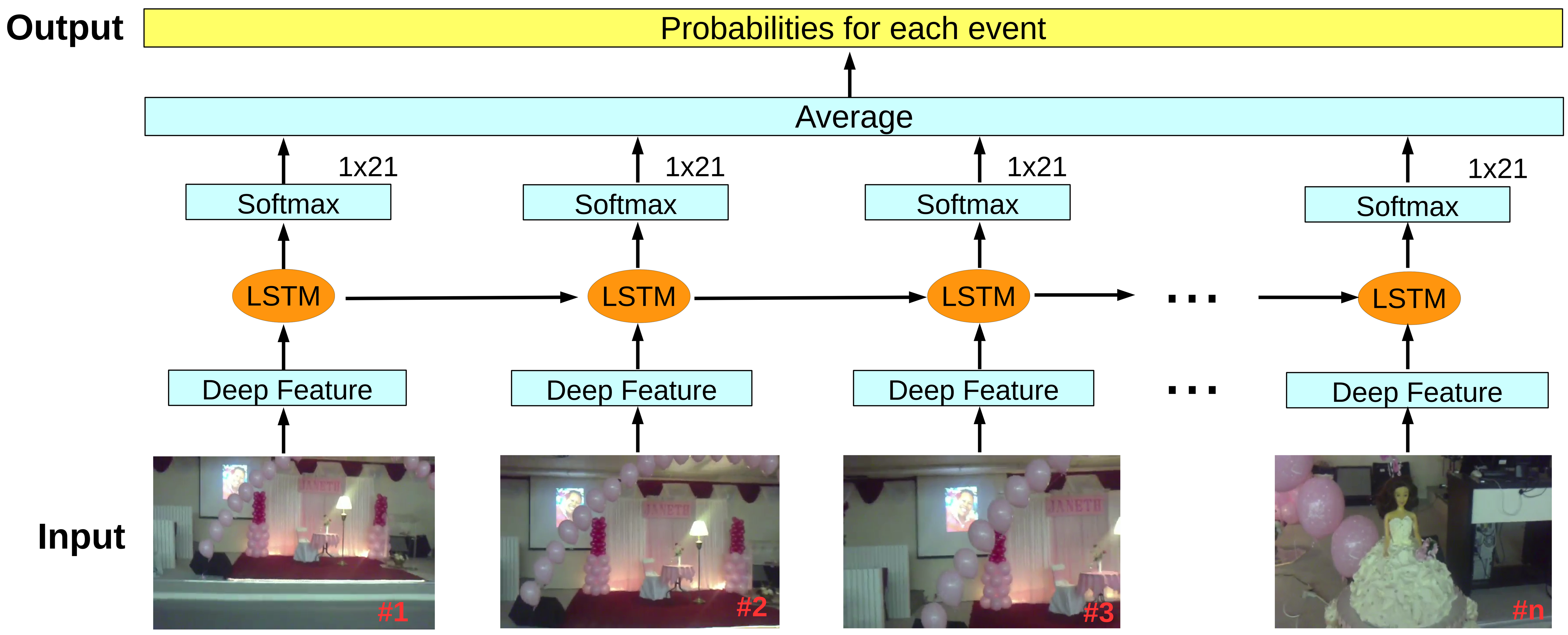
Motivation: Unless CNN, LSTM can make use of sequential information,which makes it applicable to MED.

Event detection framework:

Step 1. Extract deep features for each frame of input video

Step 2. Input deep features into an LSTM

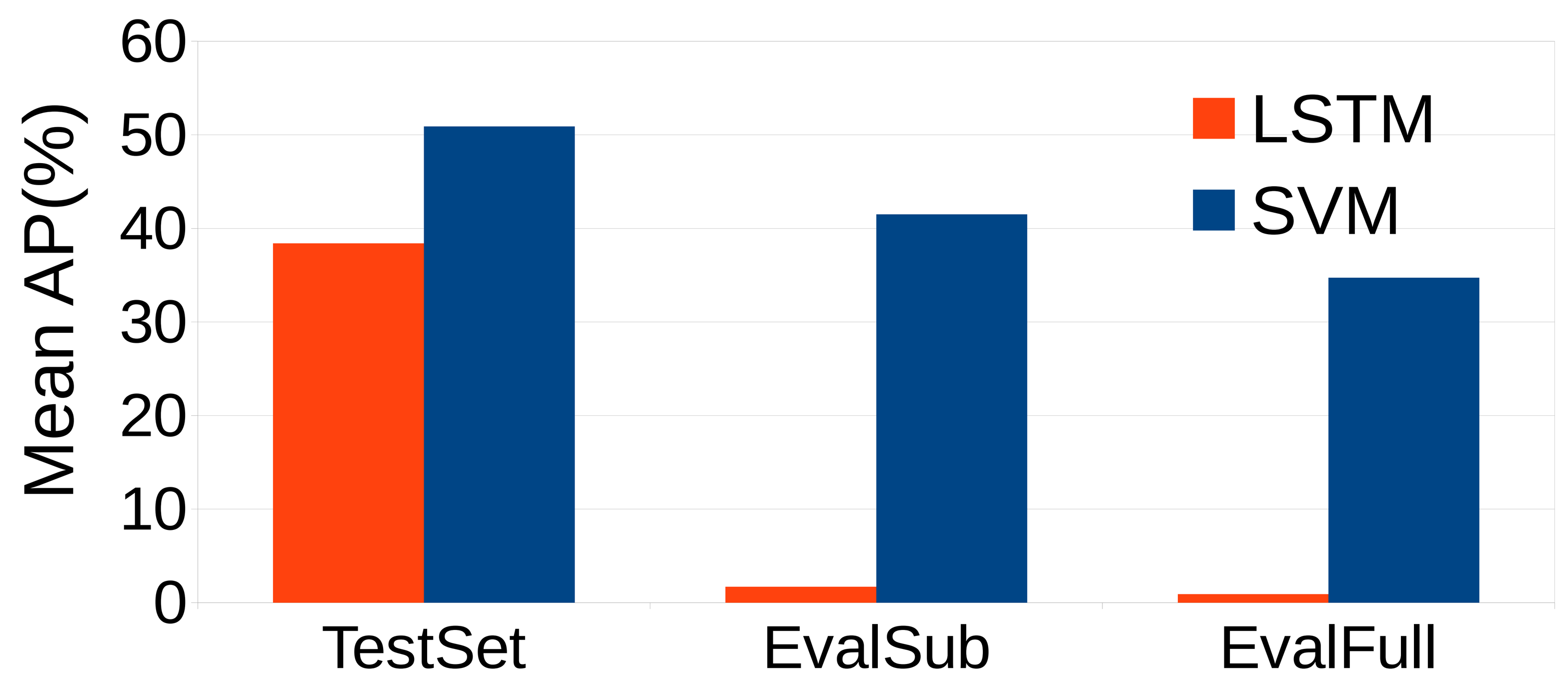
There are 21 classes of the LSTM: 20 events and background.



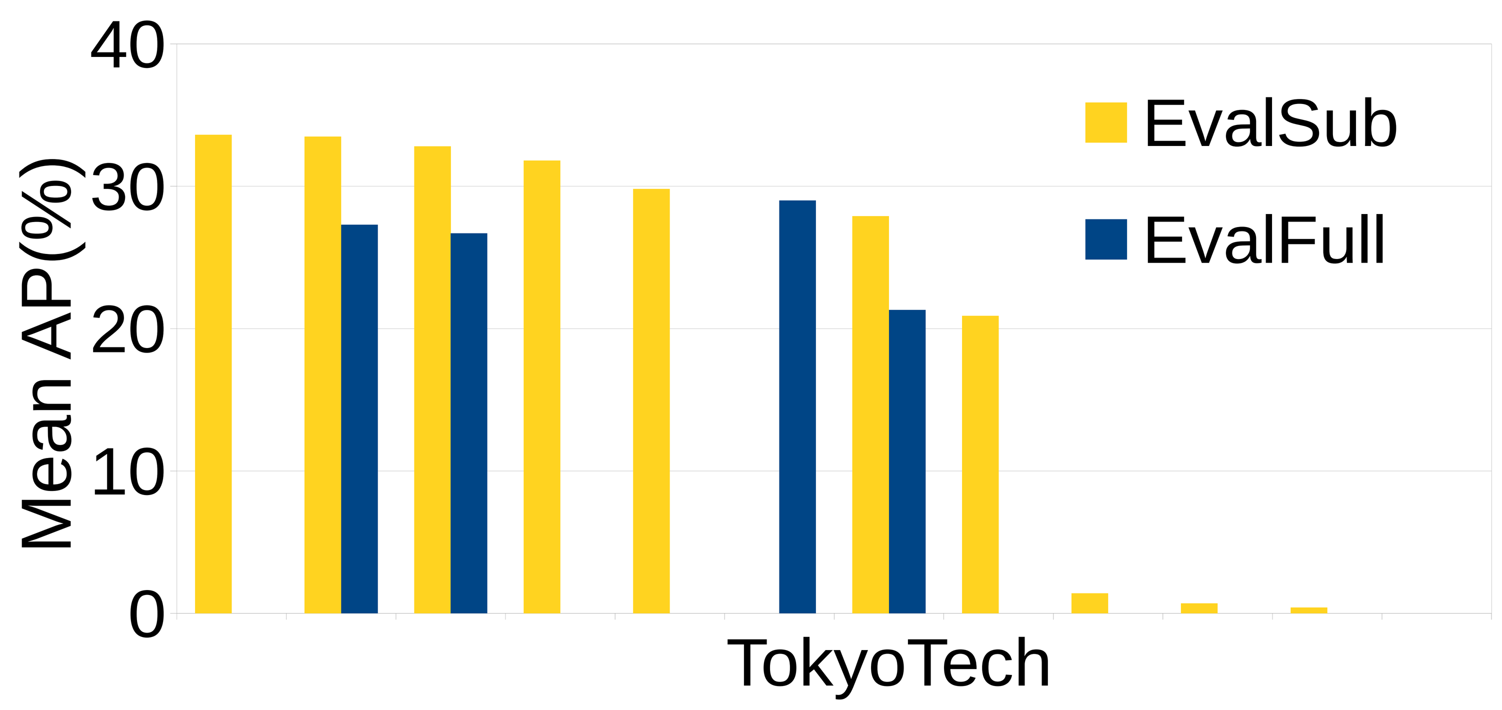
Experiments

Experimental Settings

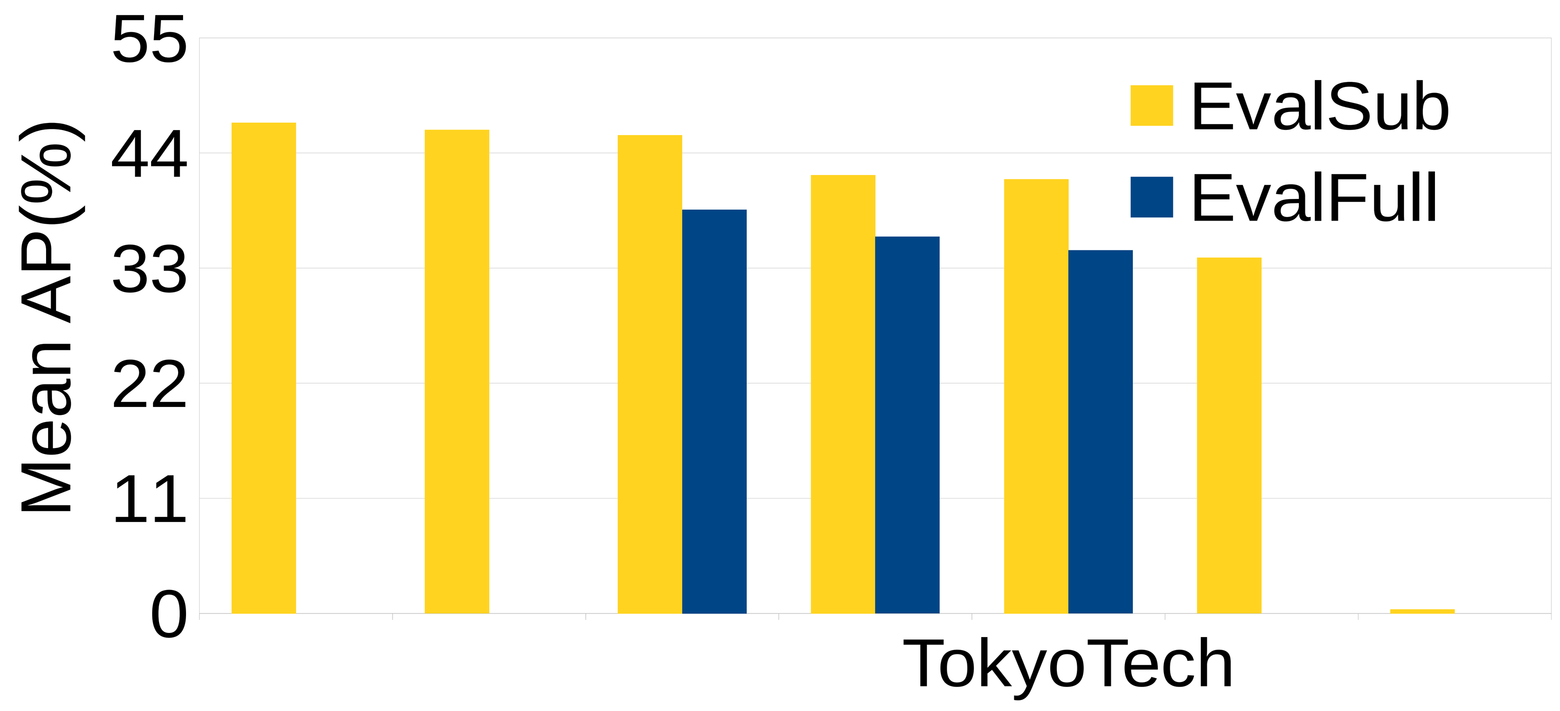
- Extract frame every two seconds.
- Deep features [1,2] are extracted from the pool5 layer of GoogLeNet trained on ImageNET
- Dimension of deep feature: 1,024
- Compare LSTM (256 units) and SVM



Comparison of SVM and LSTM

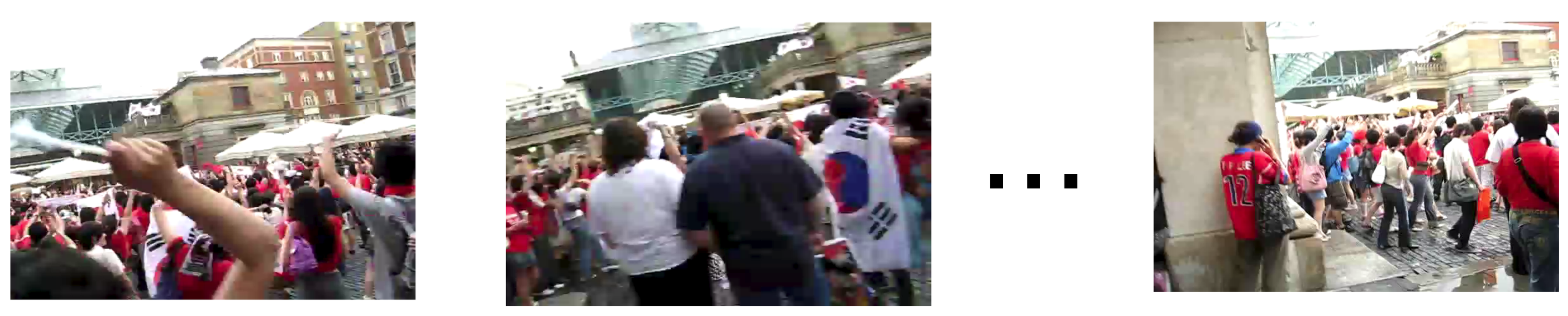


Comparison with other teams (PS 10EX)



Comparison with other teams (PS 100Ex)

Top 1 for “Attempting a bike trick” (SVM)



Top 1 for “Attempting a bike trick” (LSTM)

Conclusion

SVM results are greatly better than the LSTM results in evaluation set while in test dataset the gap between these two methods were not that huge, which may because LSTM is sensitive to the difference between LDC dataset (training and test) and YFCC dataset (evaluation).

[1] P. Mettes, D.C. Koelma, C.G.M. Snoek, “The ImageNet Shuffle: Reorganized Pre-training for Video Event Detection”, Proc. ICMR, 2016.

[2] C. Szegedy, et al., “Going Deeper with Convolutions,” Proc. CVPR, 2015.