

# Temporal Perception and Prediction in Ego-Centric Video

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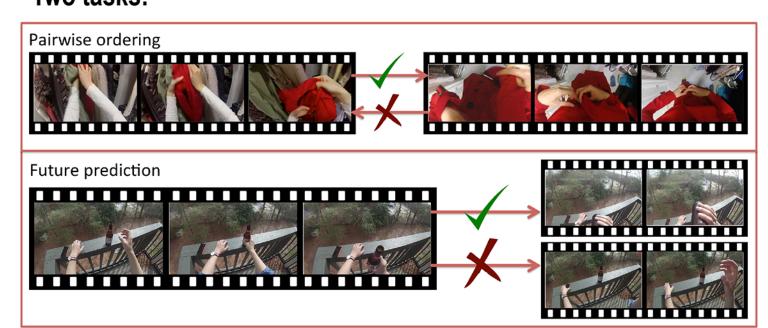
#### **Overview**

#### Abstract:

Given a video of an activity, can we predict what will happen next? In this paper we explore two simple tasks related to temporal prediction in egocentric videos of everyday activities. We provide both human experiments to understand how well people can perform on these tasks and computational models for prediction.

Developing methods for temporal prediction could have far reaching benefits for robots or intelligent agents to anticipate what a person will do, before they do it.

#### Two tasks:



- In the pairwise ordering task (above) the goal is to provide the correct temporal ordering for two short snippets of video from an activity.
- In the future prediction task (below), given a longer context video of an activity and two video snippets, the goal is to determine which snippet will occur (closest in time) after the context video.

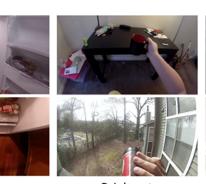
#### **Contributions:**

- Definition of two new tasks for temporal prediction in video: pairwise ordering and future prediction.
- A new dataset of ego-centric videos of everyday activities, including both individuals and families living in the same location.
- Experiments to evaluate human performance on each of the proposed temporal prediction tasks.
- Evaluation of deep features for object, scene, and motion estimation incorporated into several classification methods for pairwise ordering and future prediction.

## First Person Personalized Activities (FPPA) Dataset

#### **Example frames:**









## Statistics:

| Activities     | Avg No.of    | Avg No.of | Totall No.of |  |
|----------------|--------------|-----------|--------------|--|
|                | videos/sub   | locs/sub  | videos/locs  |  |
| Wash hands     | 24.2 (19-34) | 3.2 (2-7) | 121/16       |  |
| Put on shoes   | 22.8 (21-29) | 3.0 (2-6) | 114/15       |  |
| Use fridge     | 26.4 (21-31) | 1.6 (1-3) | 132/8        |  |
| Drink water    | 23.2 (16-31) | 3.6 (2-7) | 116/18       |  |
| Put on clothes | 21.6 (16-26) | 3.4 (2-5) | 108/17       |  |

#### **Characteristics:**

FPPA dataset enables learning both general and personalized models for temporal prediction.

## **Human experiments**

Before we can design our tasks we would like to know several things: the feasibility of this task for people, and what specific implementation features should be used for the task.

#### Two experiments:

Snippet size: To evaluate the effect of snippet length on human perceptions of pairwise ordering.

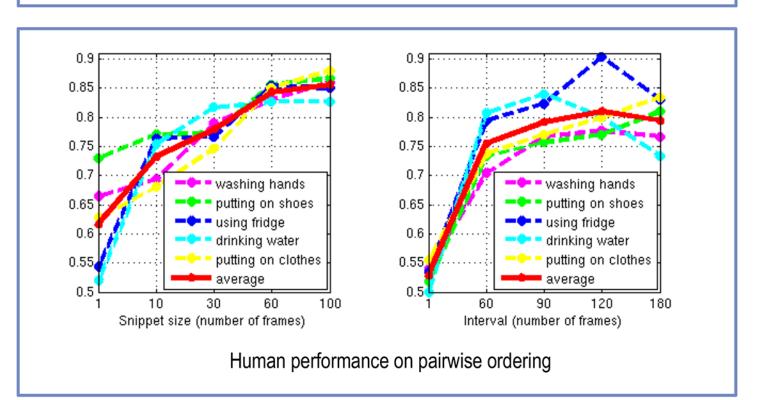
Snippet interval: To explore how the temporal distance between two snippets affects human pairwise ordering performance.

Which one comes first in temporal order?





Amazon Mturk Interface



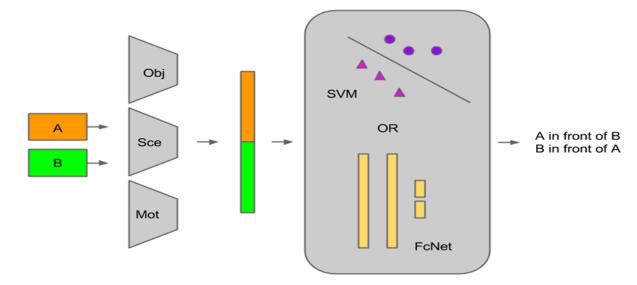
## Pairwise ordering task

#### Video snippet representation:

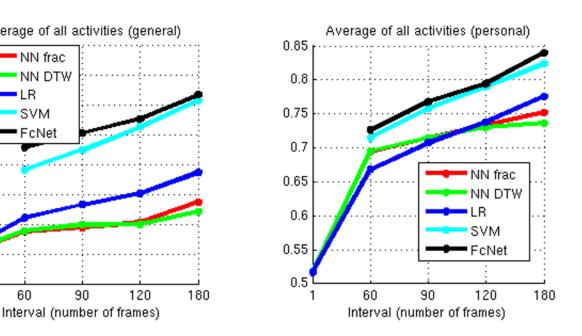
Object representation + Scene representation + Motion representation

## Prediction methods: NN Frac, NN DTW, LR, SVM, FcNet

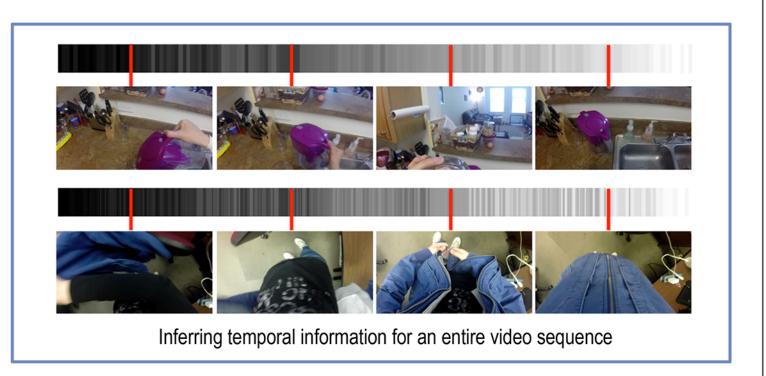
The first two are nearest neighbor based methods. LR applies linear regression to estimate the temporal position of a video snippet. And the last two directly predict the order of two snippets using linear SVM or a three layer fully-connected network.



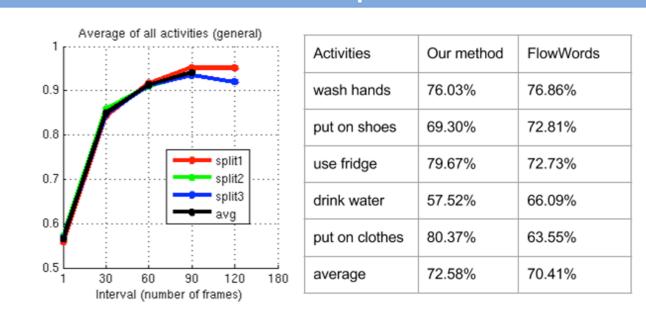
Overview of SVM or FcNet method



General(left) and personal(right) model performance on pairwise ordering



# **Additional experiments**



Left is the pairwise ordering accuracy of subset of UCF101 dataset. Right is the forward/backward classification accuracy of our method and Flow-Words method in [1] testing on our dataset.

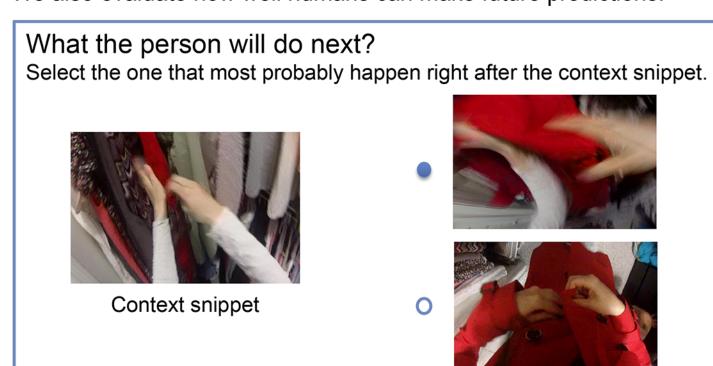
## Future prediction task

#### Computer prediction:

Given an algorithm to predict pairwise orderings between snippets, it is straightforward to extend this algorithm to the future prediction task. We compute all pairwise orderings between snippet A, snippet B, and context snippet C, and then select the snippet that is most likely to happen after C in temporal order.

## **Human prediction:**

We also evaluate how well humans can make future predictions.

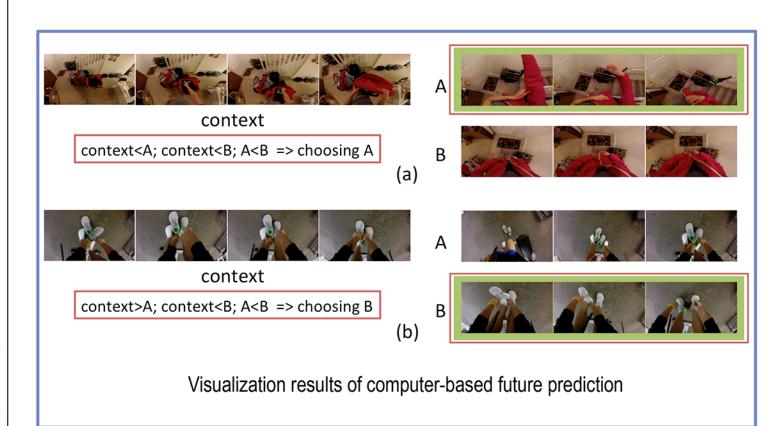


| Activities     | SVMg   | SVMp   | FcNetg | FcNetp | Human  |
|----------------|--------|--------|--------|--------|--------|
| Wash hands     | 0.6350 | 0.7550 | 0.6350 | 0.7900 | 0.7816 |
| Put on shoes   | 0.7000 | 0.7250 | 0.7600 | 0.7700 | 0.8733 |
| Use fridge     | 0.6100 | 0.7100 | 0.6600 | 0.7350 | 0.9284 |
| Drink water    | 0.6500 | 0.7300 | 0.6350 | 0.7500 | 0.8717 |
| Put on clothes | 0.7100 | 0.8350 | 0.6950 | 0.8650 | 0.8866 |
| Average        | 0.6630 | 0.7510 | 0.6770 | 0.7820 | 0.8686 |

Mturk interface of human prediction

Future prediction task accuracy by computational methods and people

We also evaluate future prediction results using snippet A and snippet B from different videos. We consider human predictions as ground truth, the general SVM and FcNet models achieve 66.22% and 66.99% accuracy respectively.



## References

[1] L. C. Pickup, Z. Pan, D. Wei, Y. Shih, C. Zhang, A. Zisserman, B. Scholkopf, and W. T. Freeman. Seeing the arrow of time. In CVPR, 2014.