



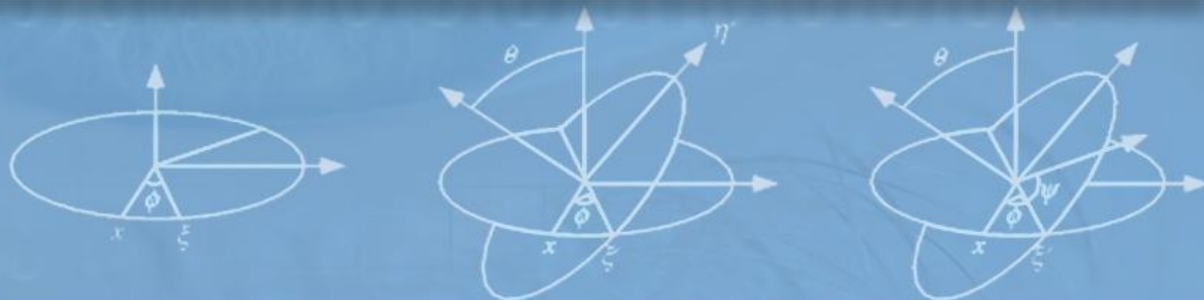
JHU vision lab

# End-to-End Fine-Grained Action Segmentation and Recognition Using Conditional Random Field Models and Discriminative Sparse Coding

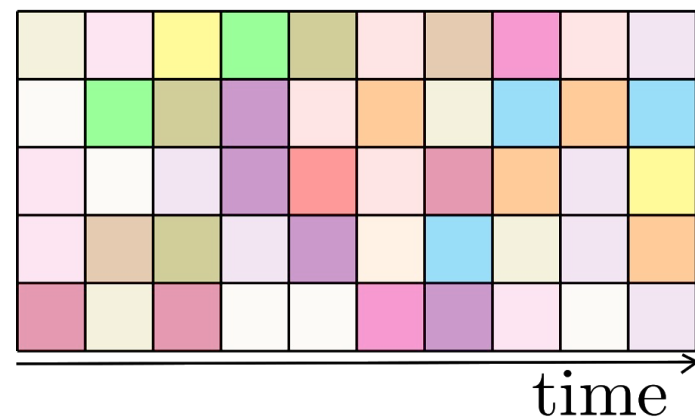
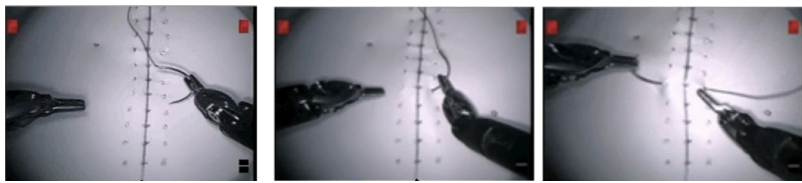
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<sup>1</sup>Johns Hopkins University, <sup>2</sup>University of Virginia

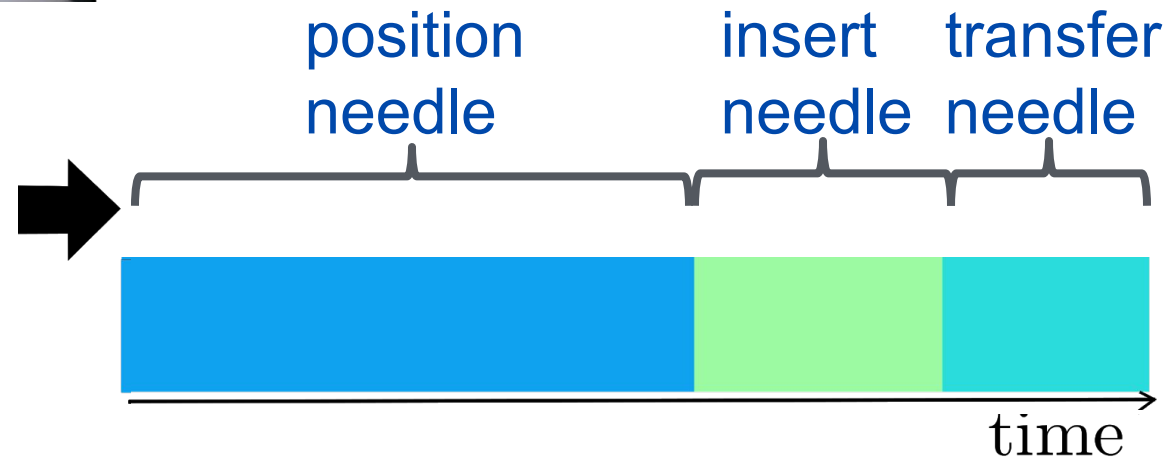
<sup>3</sup>Comcast AI Research



# Fine-grained Action Segmentation and Recognition



Input: Kinematic data  
time-series



Output: Action labels per  
frame

- 1) **Which** actions?
- 2) **When** does each action start/end?

# Applications

VISION LAB

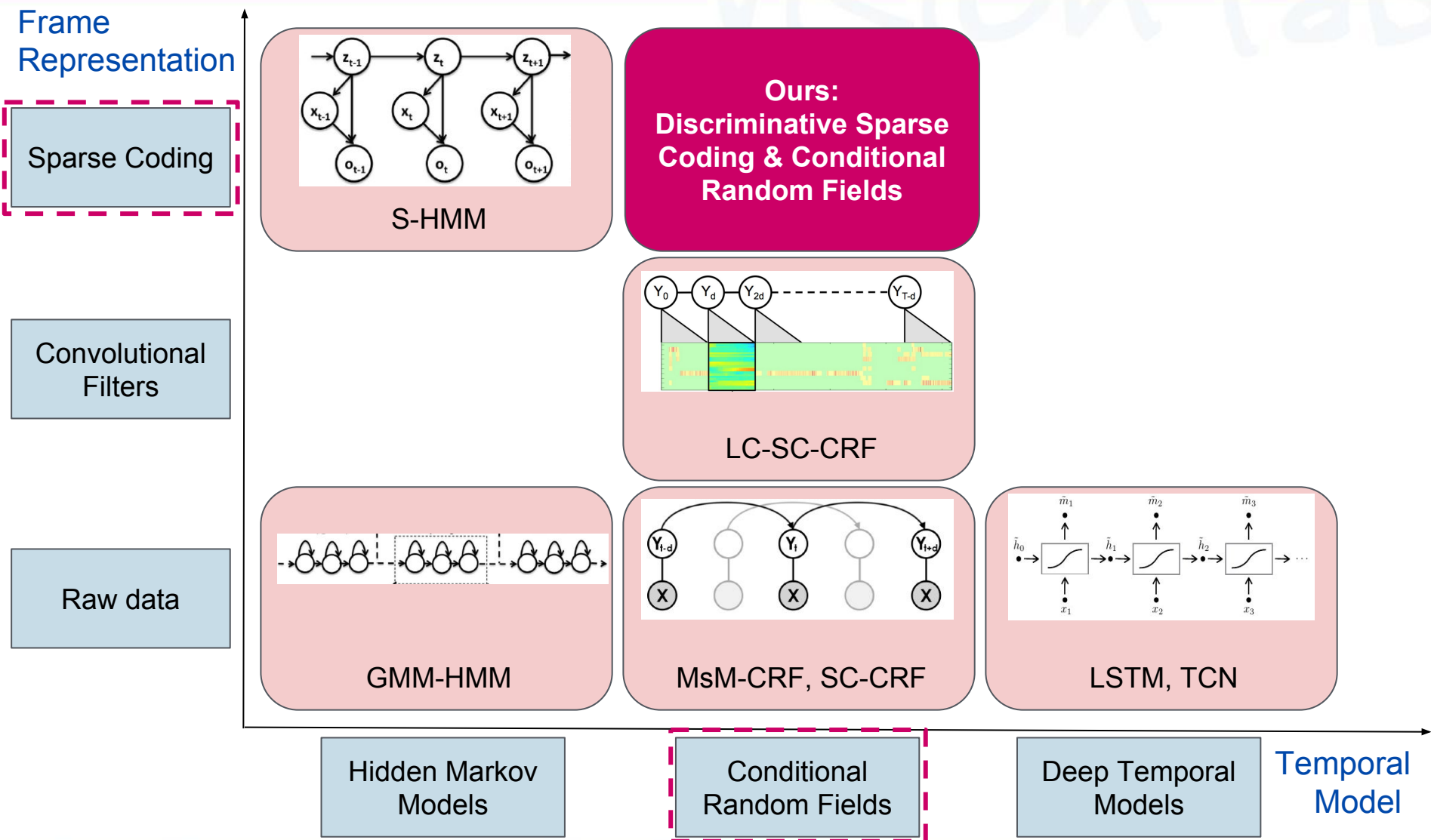


Automatic Surgical Skill Assessment



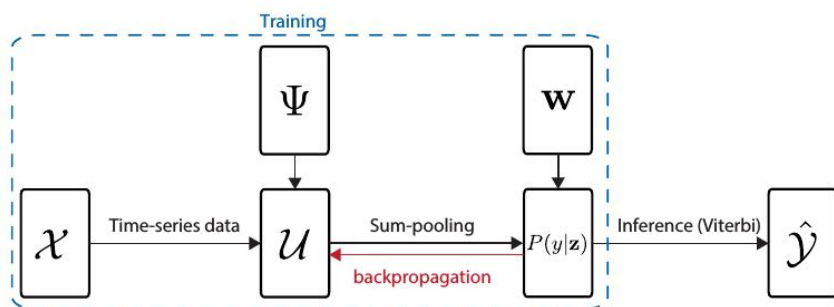
Assisted Living And Smart Home Environments

# Prior Work



# Related Work

- Discriminative Sparse Dictionary Learning (SDSDL) [1]

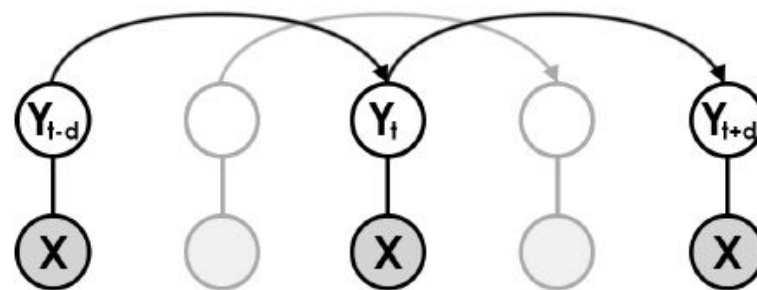


✓ Spatial model:  
Discriminative  
Sparse Coding

✗ Temporal model:  
Precomputed  
transition  
probabilities

Dictionary shared  
between actions  
and jointly trained  
with per-frame  
SVM classifier.

- Skip Chain Conditional Random Field (SC-CRF) [2]



✗ Spatial model:  
Raw Kinematic  
Data

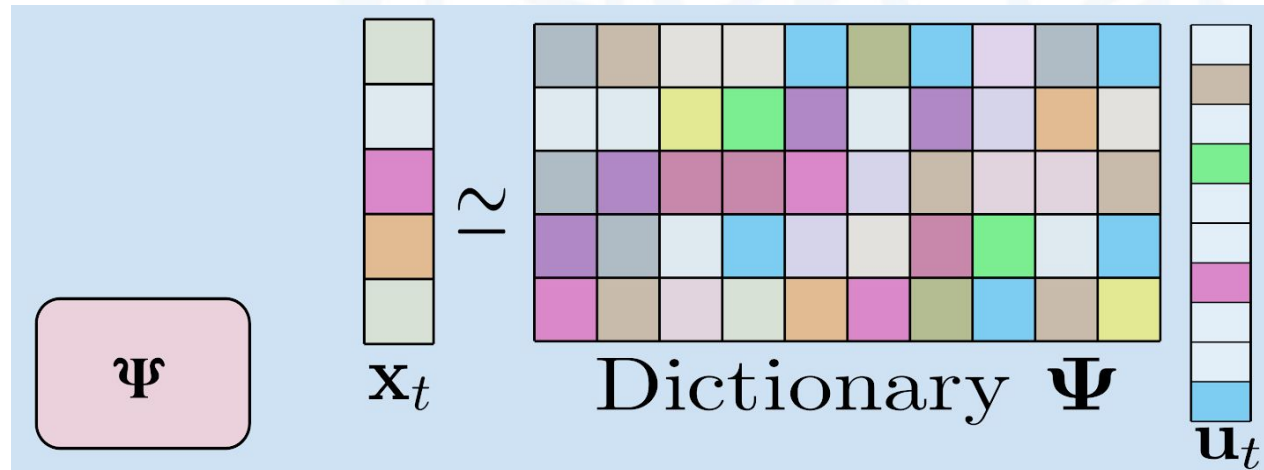
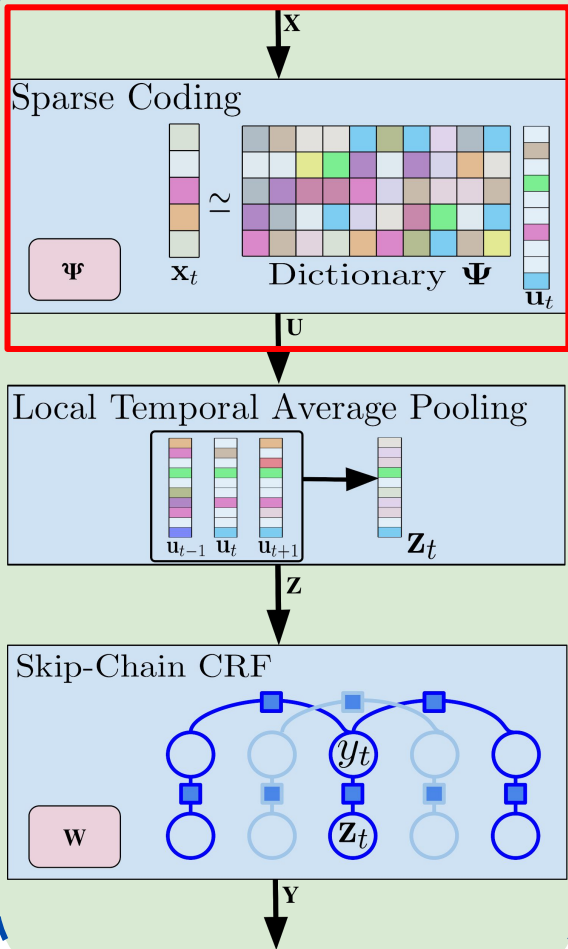
✓ Temporal  
model: Skip-Chain  
CRF

SC-CRF can  
model action to  
action transitions  
over large  
periods of time.



# Our model: Frame Representation

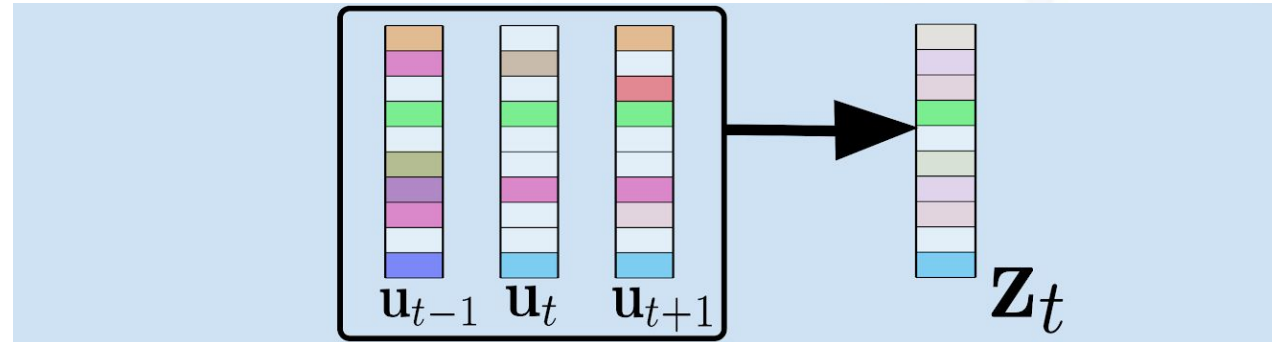
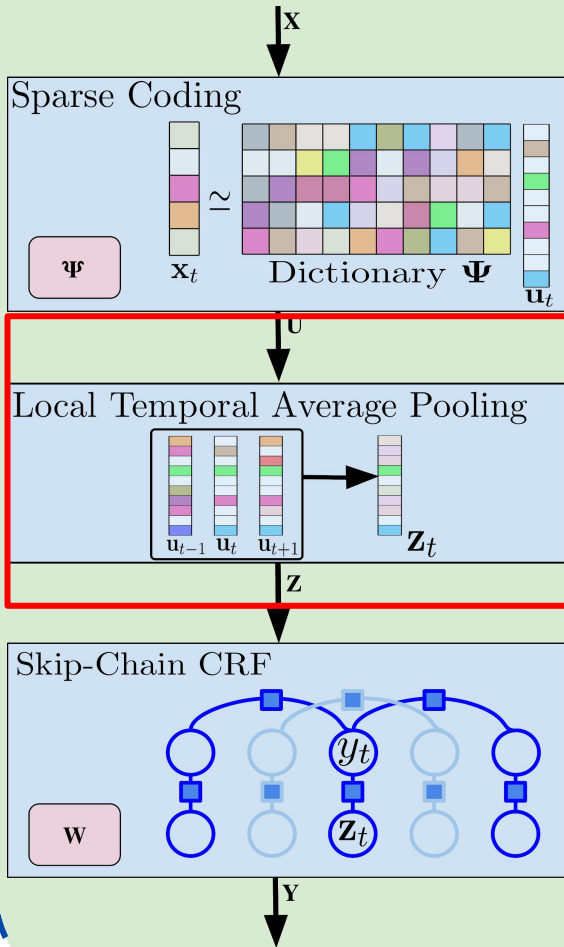
## Model Overview



**Sparse coding:** represent input kinematic data at time  $t$  as a combination of a small number of atoms from dictionary  $\Psi$ .

# Our model: Local Temporal Representation

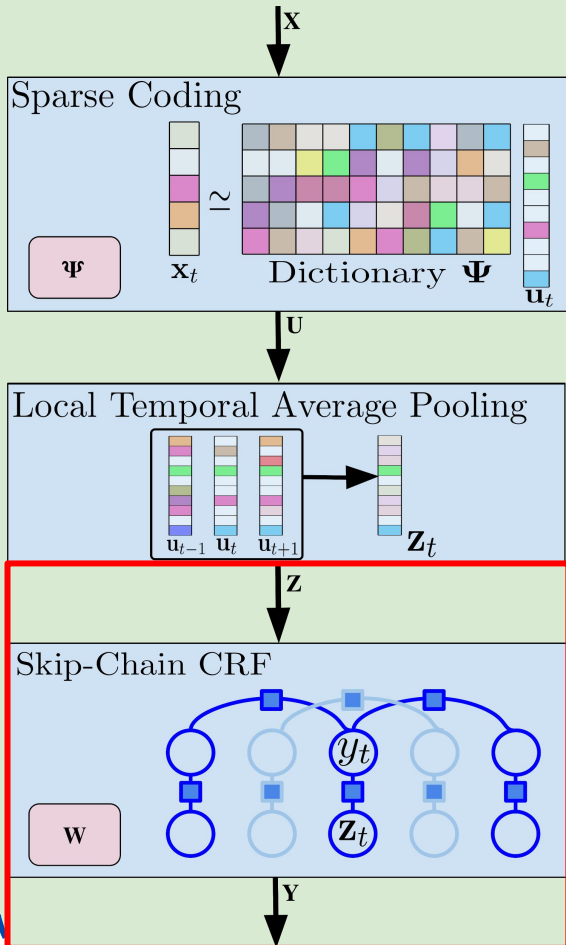
## Model Overview



Obtain frame feature by **average pooling** sparse codes in a short temporal window.

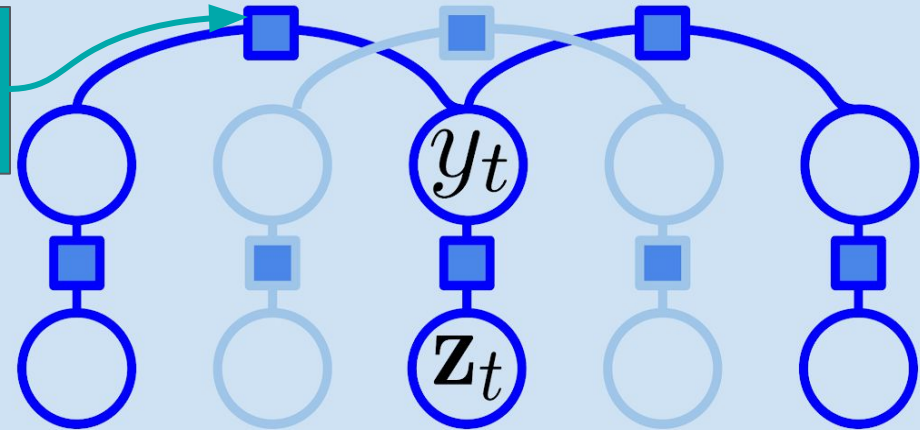
# Our model: Global Temporal Representation

## Model Overview



Skip-chain  
 $d = 2$

$W$



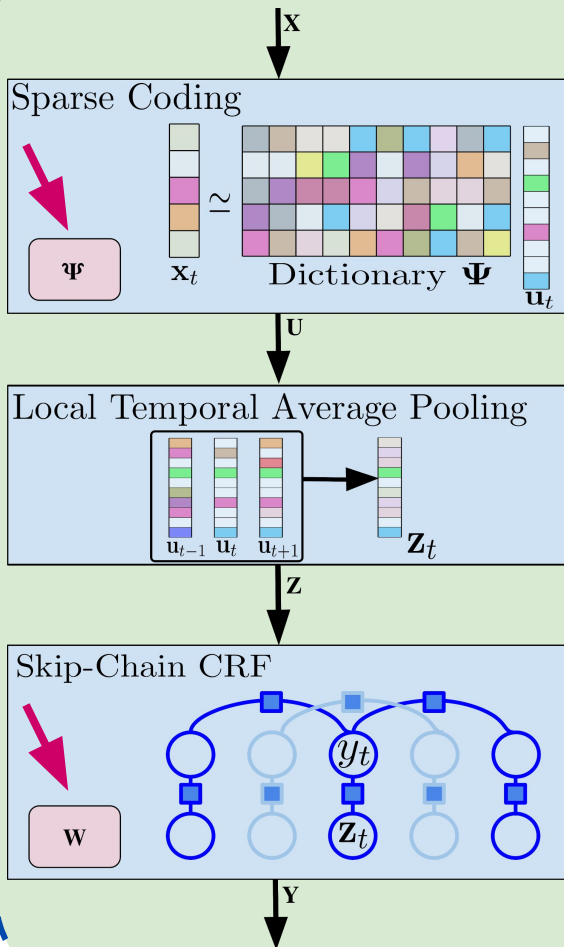
**Unary potentials:** cost of assigning a label  $y_t$  to frame  $t$ .

**Pairwise potentials:** capture transitions between actions and encourage smoothness of labels.



# Our model: Training

## Model Overview

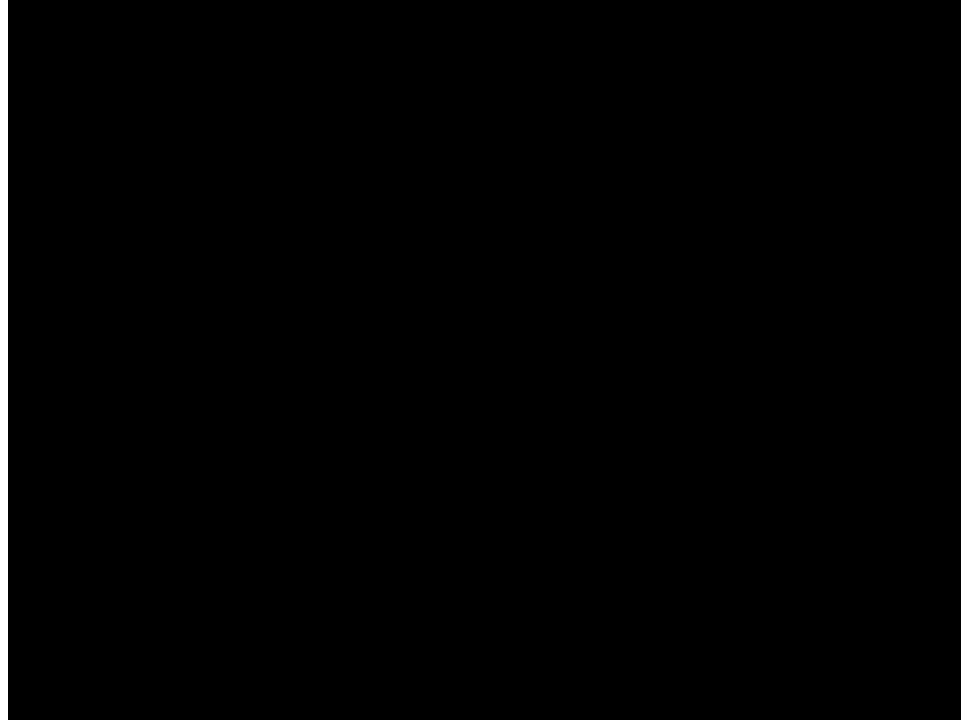


- End-to-end training of task-driven discriminative dictionary  $\Psi$  and CRF parameters  $W$ .
- Use max-margin formulation for structured prediction and optimize using Stochastic Gradient Descent.
- Key challenge: Computing gradient w.r.t dictionary  $\Psi$ .

# JIGSAWS Dataset

**76-dim robot  
kinematic  
data**

**2-5 min  
trials (30 Hz)**

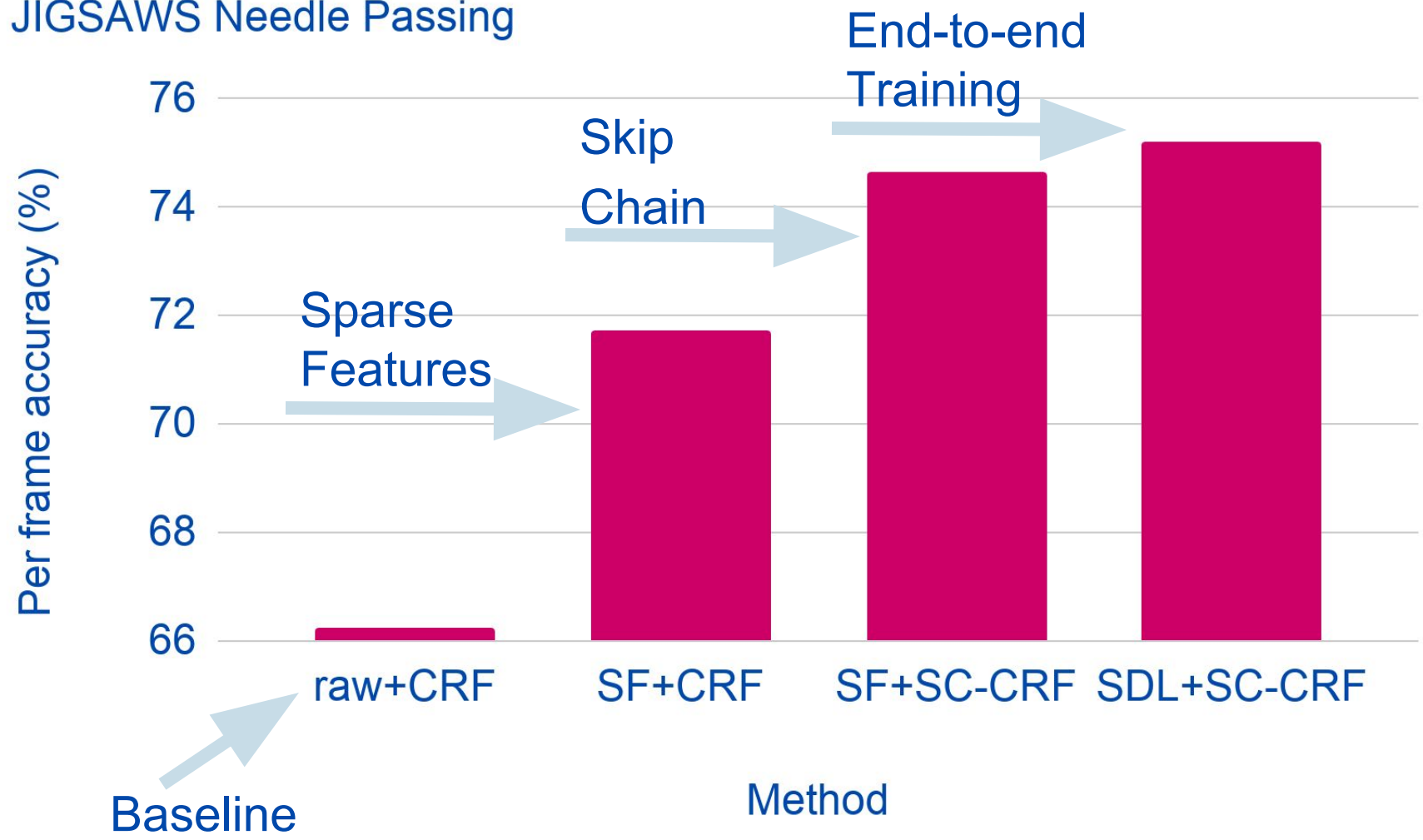


**3 surgical  
tasks  
8 surgeons**

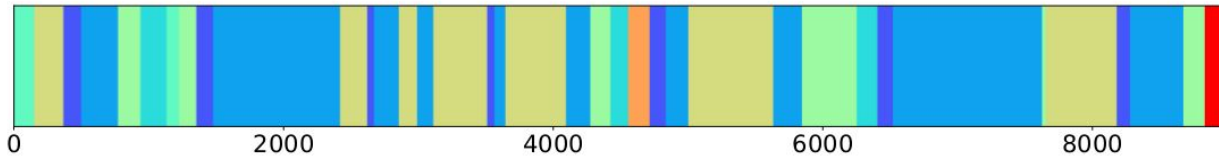
**6-10 action  
classes for  
each task**

# Experimental Results

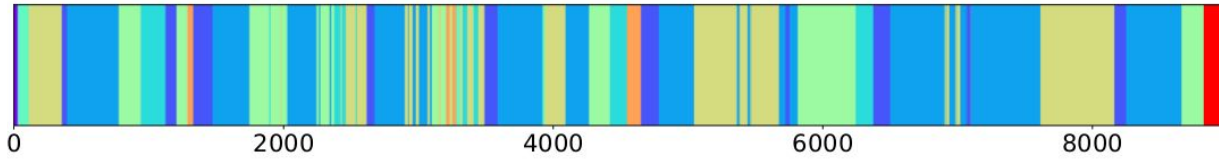
## JIGSAWS Needle Passing



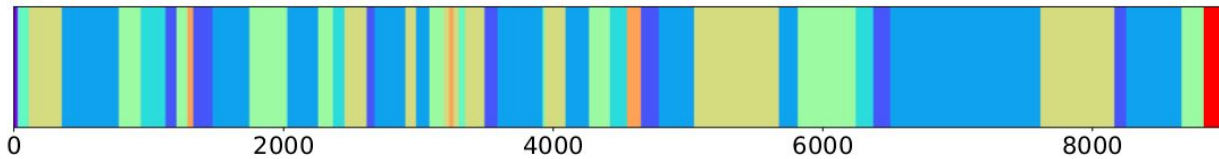
# Qualitative Results



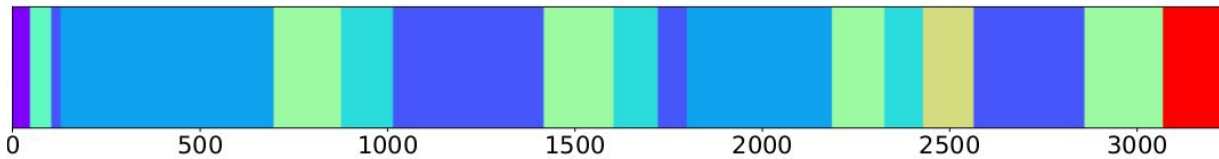
Ground Truth Labels



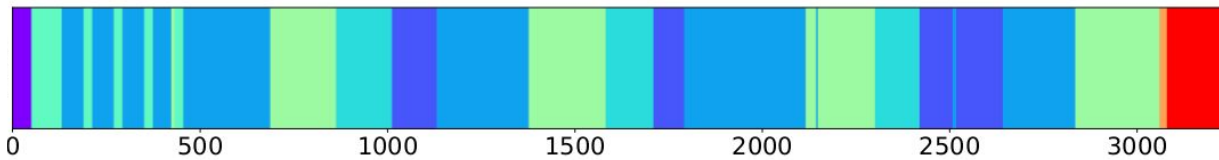
Predicted Labels



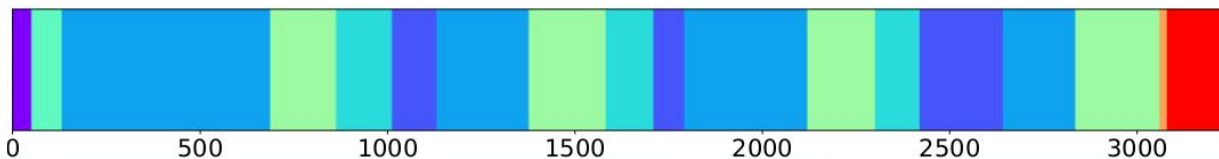
Predicted Labels +  
median filtering



Ground Truth Labels



Predicted Labels



Predicted Labels +  
median filtering

# Quantitative Results

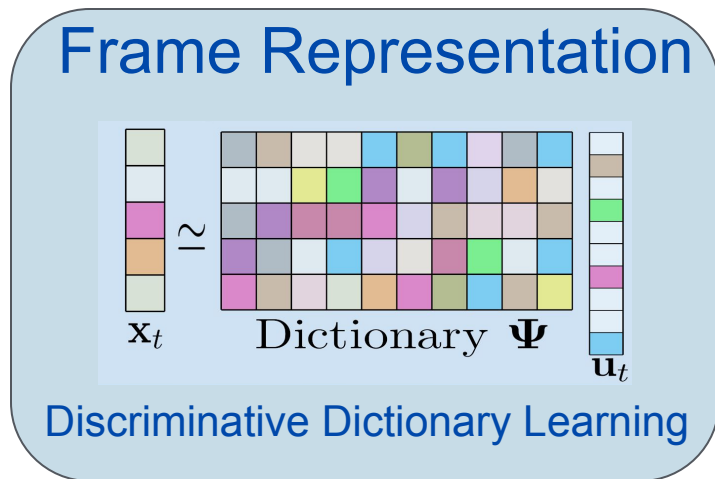
	LOSO			LOUO		
	SU	KT	NP	SU	KT	NP
GMM-HMM	82.22	80.95	70.55	73.95	72.47	64.13
KSVD-SHMM	83.40	83.54	73.09	73.45	74.89	62.78
MsM-CRF	81.99	79.26	72.44	67.84	44.68	63.28
SC-CRF-SL	85.18	<b>84.03</b>	75.09	81.74	<b>78.95</b>	<b>74.77</b>
LC-SC-CRF				<b>83.40</b>		
LSTM				78.38		
BiLSTM				80.15		
TCN				79.6		
SDSDL	<b>86.32</b>	82.54	74.88	78.68	75.11	66.01
<b>Ours</b>	<b>86.21</b>	<b>83.89</b>	<b>75.19</b>	78.16	76.68	66.25

Competitive performance: among 2 best methods for almost all tasks

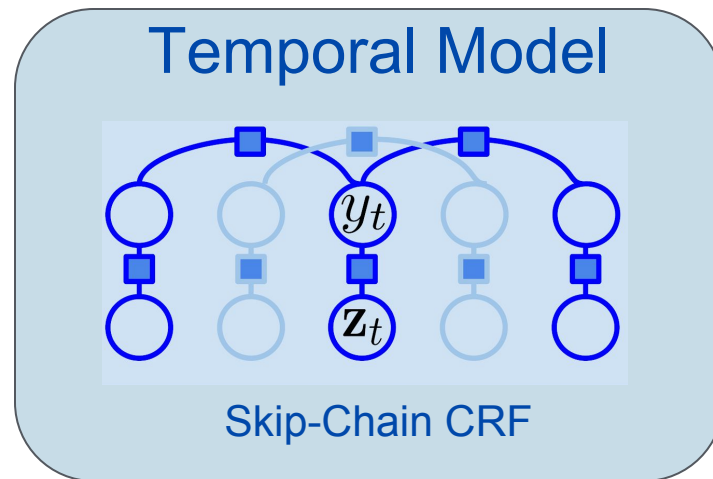


# Conclusions

- A novel spatio-temporal model for fine-grained action segmentation and recognition



+



- A novel end-to-end max-margin learning method

For more details visit poster 3B-2 !

# More information,

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Vision Lab @ Johns Hopkins University

<http://www.vision.jhu.edu>

Center for Imaging Science @ Johns Hopkins University

<http://www.cis.jhu.edu>

Johns Hopkins Mathematical Institute for Data Science

<http://www.minds.jhu.edu>

# Thank You!