D³TW: Discriminative Differentiable Dynamic Time Warping for Weakly Supervised Action Alignment and Segmentation

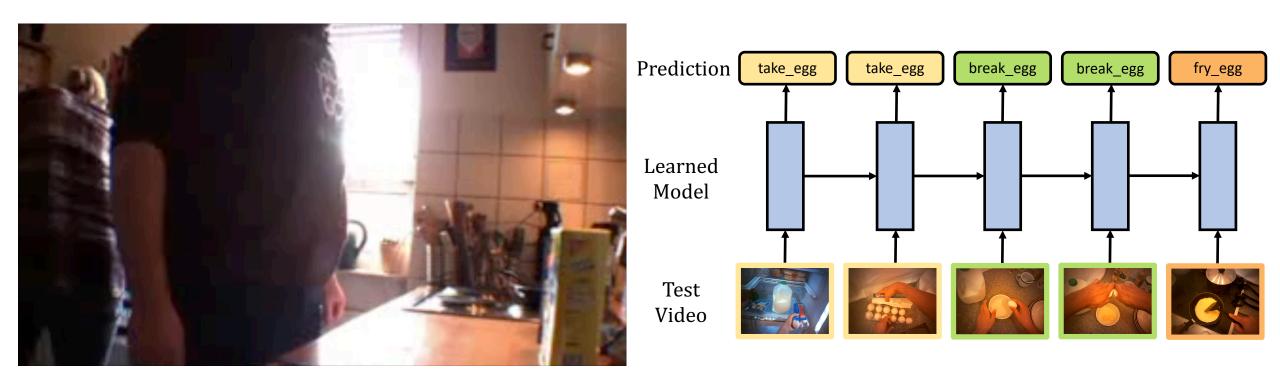
Chien-Yi Chang, De-An Huang, Yanan Sui, Li Fei-Fei, Juan Carlos Niebles



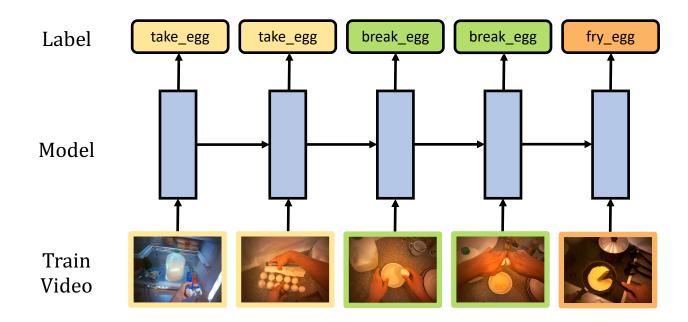




Temporal Action Segmentation

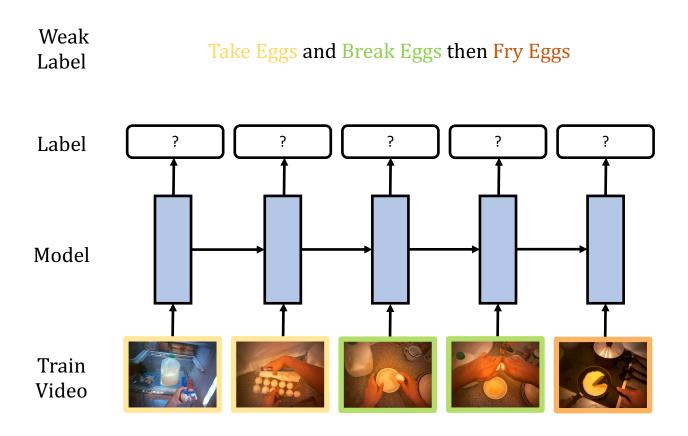


Fully Supervised Learning



- Requires many training videos with per frame action labels
- Expensive to annotate!

Weakly-Supervised Learning



- Only use action ordering
- Easy to obtain from closed captions

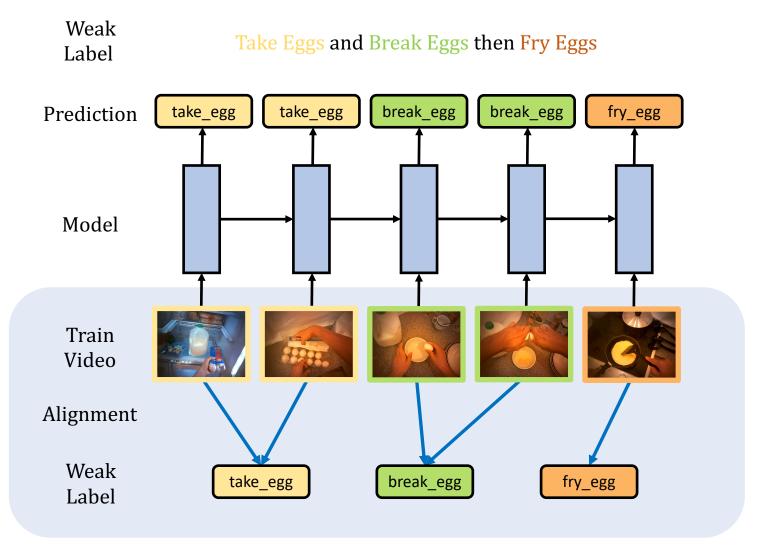
Key Contributions

#1 Pose temporal action segmentation as **dynamic** alignment between two sequences

#2 Apply continuous relaxation to make our model end-to-end differentiable

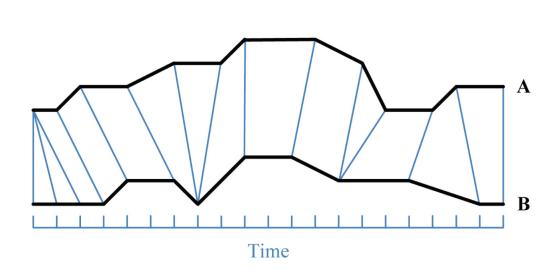
Key Contribution #1

Train temporal action segmentation model as alignment

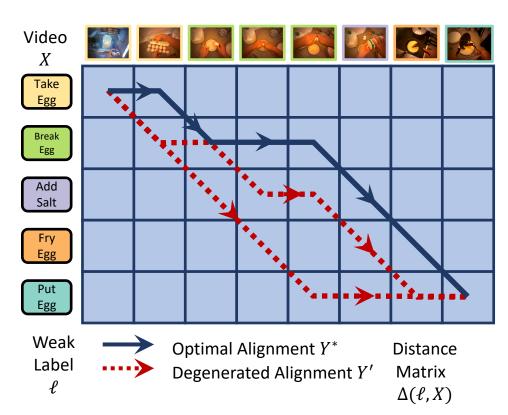


Key Contribution #1

Solve the alignment problem with modified **Dynamic Time** Warping (DTW)



Classical DTW



Our DTW

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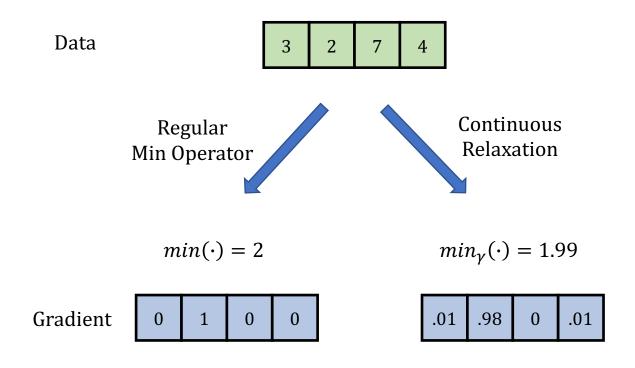
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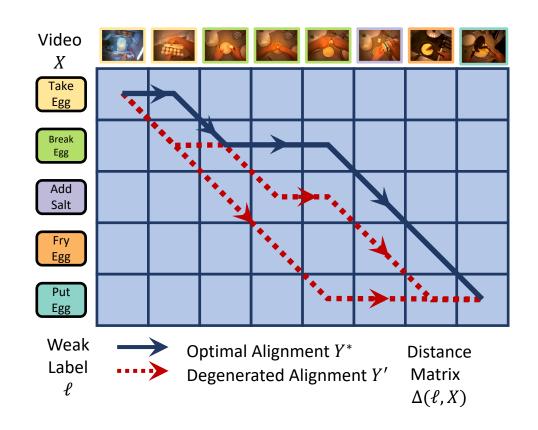
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Key Contribution #2

• Continuous relaxation: $\min_{\gamma}\{a_1, \dots, a_n\} = -\gamma \log \sum_{i=1}^n e^{-\frac{a_i}{\gamma}}, \gamma > 0$





Key Contributions

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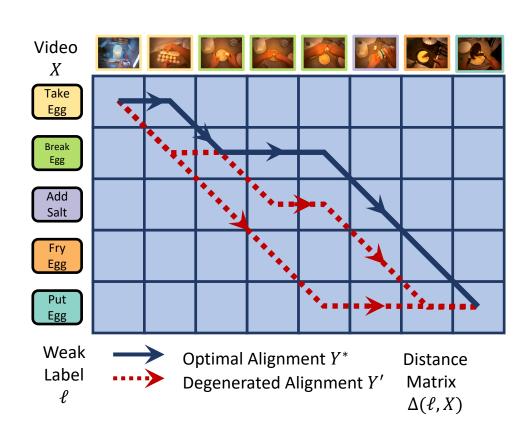
Key Contributions

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Key Contribution #3

Design a loss function with only weak supervision



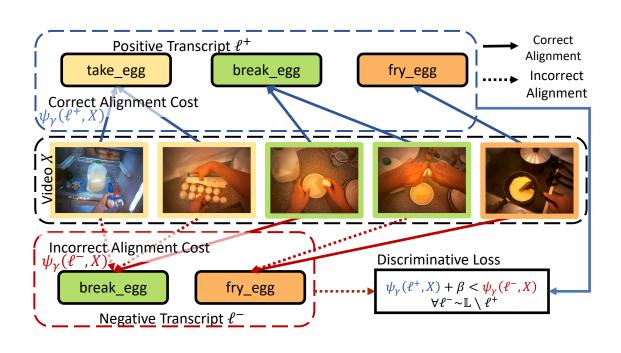
- Full Supervision:
 - Known ground truth alignment \widehat{Y}
 - Straightforward loss function $CE(Y^*, \hat{Y})$
- Weak Supervision:
 - \hat{Y} is unknown
 - Previous work resorts to generating pseudo \hat{Y}

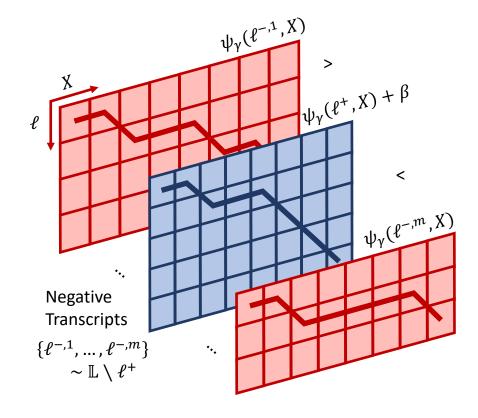
Key Contribution #3

Discriminative loss:

$$\psi_{\gamma}(\ell^+, X) + \beta < \psi_{\gamma}(\ell^-, X), \qquad \forall \ell^- \sim \mathbb{L} \setminus \ell^+$$

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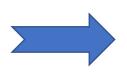
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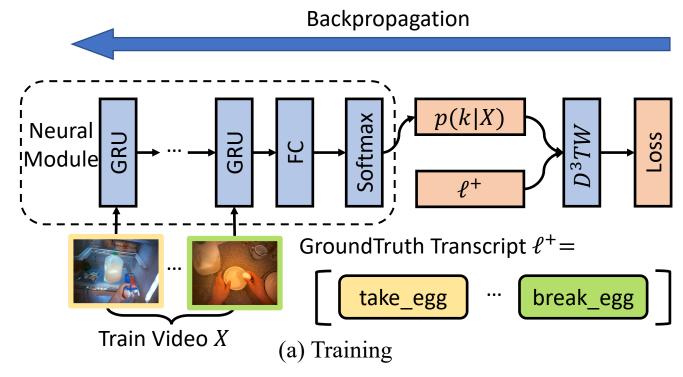
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#3 Propose the first **discriminative** model for weak ordering supervision



D³TW: **Discriminative Differentiable Dynamic** Time Warping for Weakly Supervised Action Alignment and Segmentation

- D³TW, a differentiable layer that
 - captures regularities in the input sequences
 - imposes prior structure on the output as alignment



	Breakfast		Hollywood	
	Facc.	Uacc.	Facc.	Uacc.
ECTC[1]	27.7	35.6	-	-
GRU reest.[2]	33.3	-	-	-
TCFPN[3]	38.4	-	28.7	-
NN-Viterbi[4]	43.0	-	26.2	25.5

Breakfast Actions

- 3,600,000 frames
- 48 action classes
- ~ 6.9 action instances per video

•Hollywood Extended

- 800,000 frames
- 16 classes
- ~ 2.5 action instances per video

^[1] Huang et al. ECCV 2016

^[2] Richard et al. CVPR 2017

^[3] Ding et al. CVPR 2018

^[4] Richard et al. CVPR 2018

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Ours Discriminative Differentiable Dynamic	45.7	47.4	33.6	30.5

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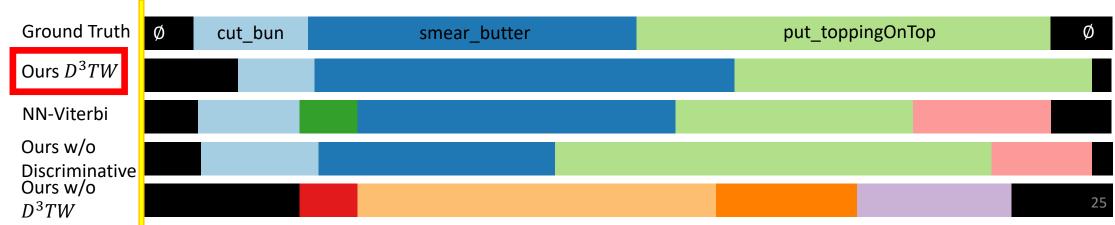
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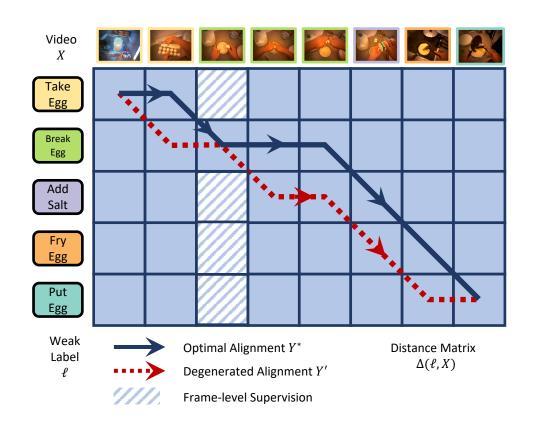
Qualitative Results of Temporal Action Segmentation



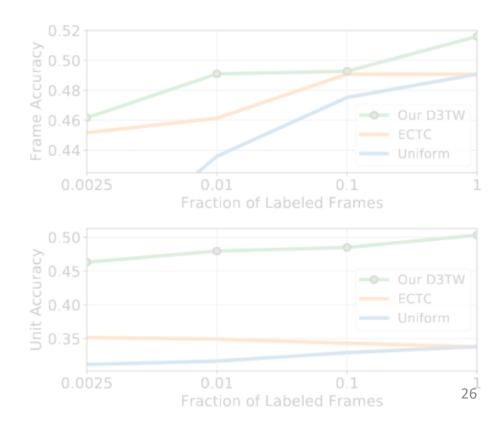


Semi-Supervised Learning with Our Framework

 Using semi-supervision by imposing path constraints



 Model performance compared with previous work

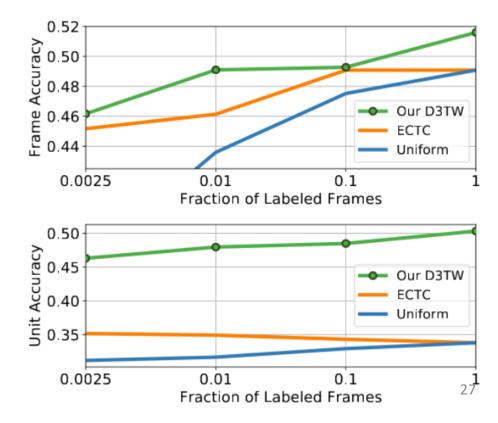


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Thank You!