Video Action Transformer Network

Based on: Girdhar el al.[2019]
Advisor: Maria Bravo

Christian Leininger

Block-Seminar on Deep Learning
for Bio-Medical Data Analysis

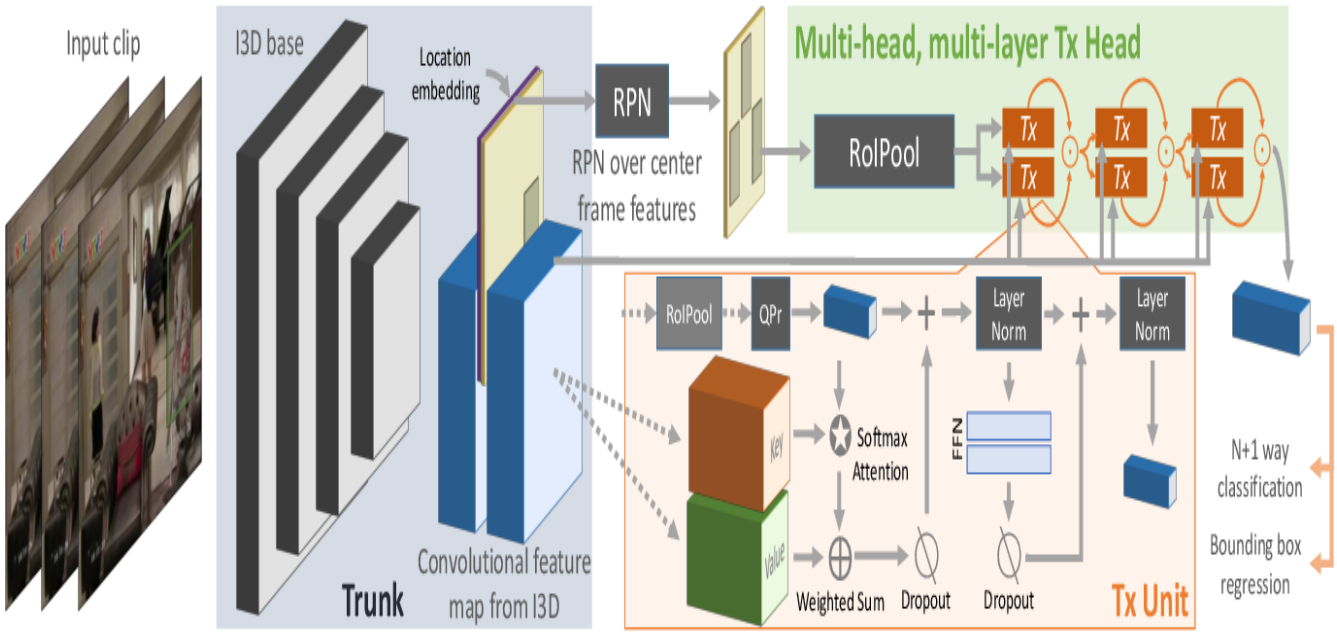
April 4, 2020

Objective of this work

- Localize all Humans and recognize their actions in a Video Clip
- Overcome the limitations of RNNs with self-attention
- Extract contextual Information without supervision

Video Action Transformer Network

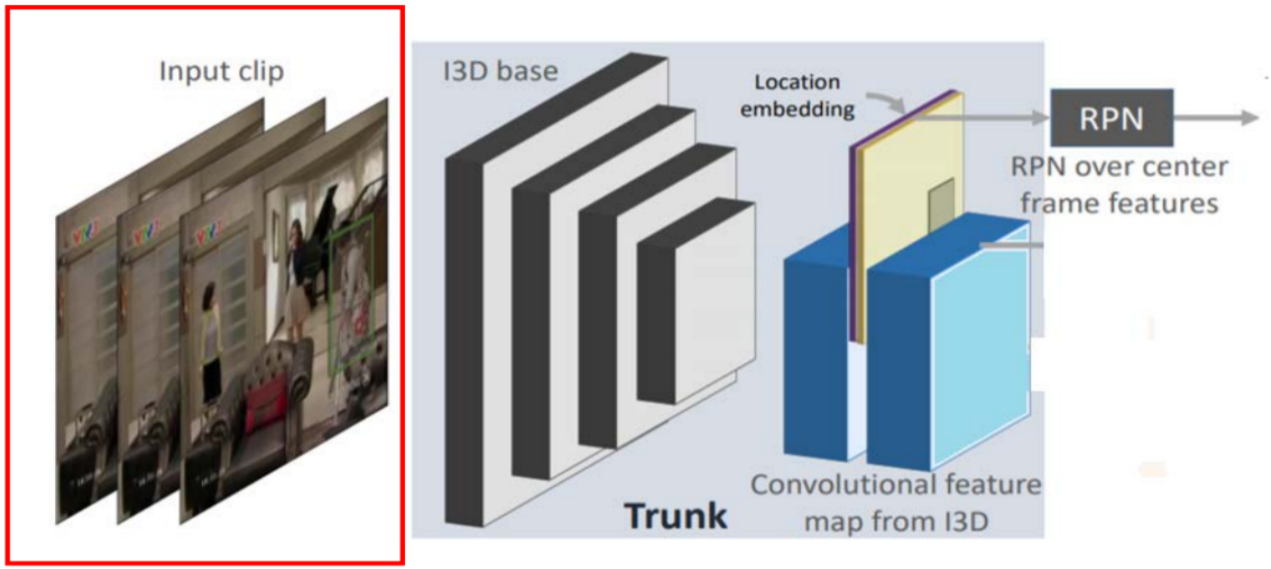
Video Action Transformer



Source: https://www.crcv.ucf.edu/wp-content/uploads/2019/03/adcv/ppt.pdf
Figure: Overview of the proposed model

Video Action Transformer Network

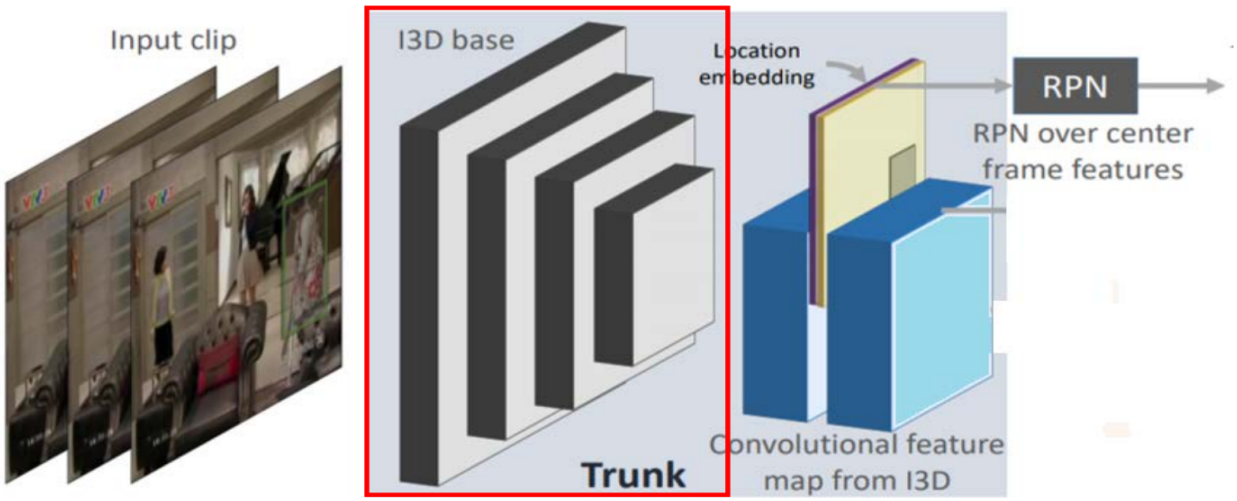
Trunk Region



Source: https://www.crcv.ucf.edu/wp-content/uploads/2019/03/adcv/ppt.pdf
Figure: T-frame Input of the model

Video Action Transformer Network

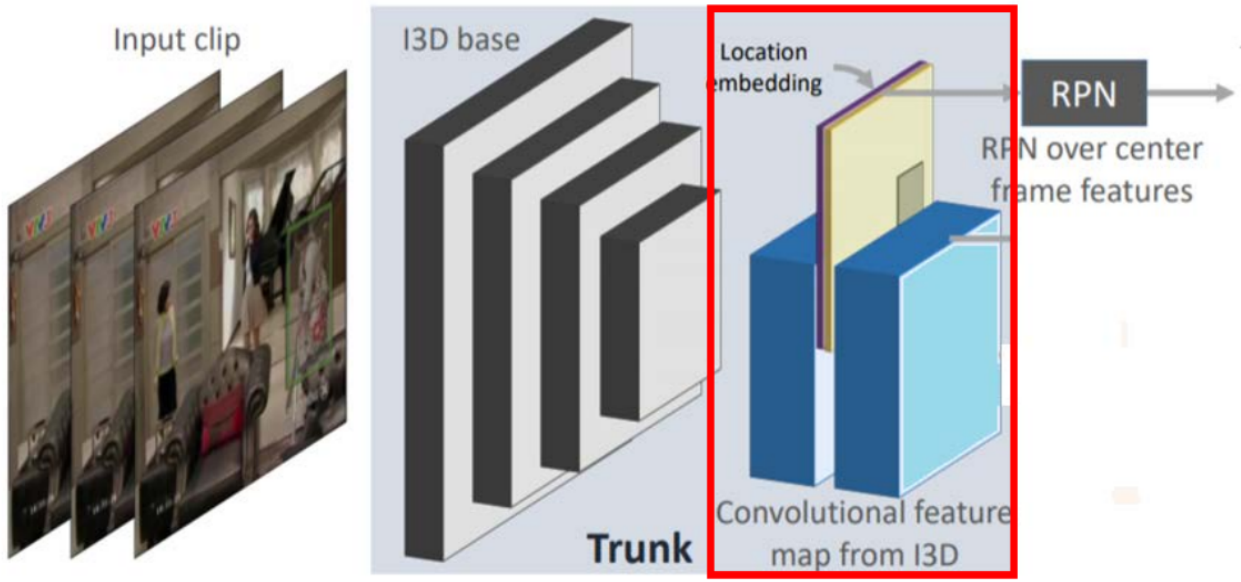
Trunk Region



Source: https://www.crcv.ucf.edu/wp-content/uploads/2019/03/adcv/ppt.pdf
Figure: I3D Base of the Trunk Region

Video Action Transformer Network

Trunk Region



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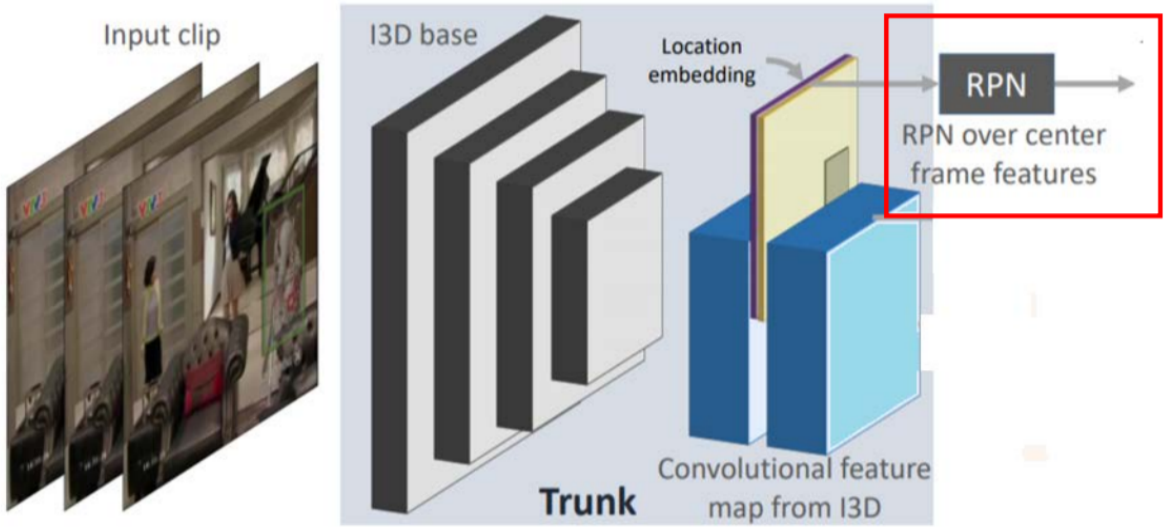
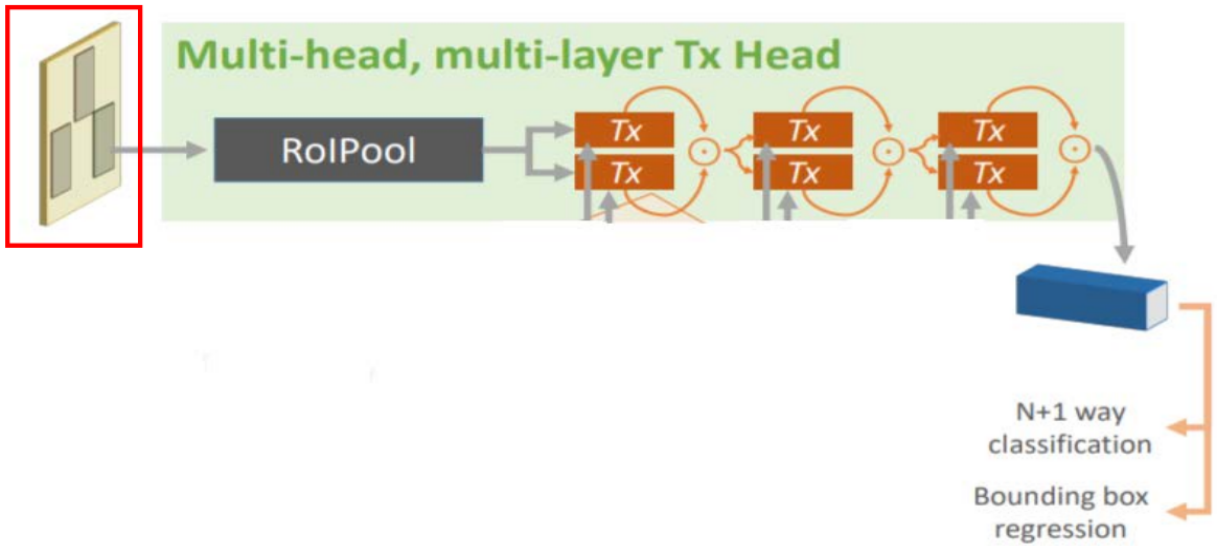
Trunk Region



Source: https://www.crcv.ucf.edu/wp-content/uploads/2019/03/adcv/ppt.pdf
Figure: Region Proposal Network of the Trunk Region

Video Action Transformer Network

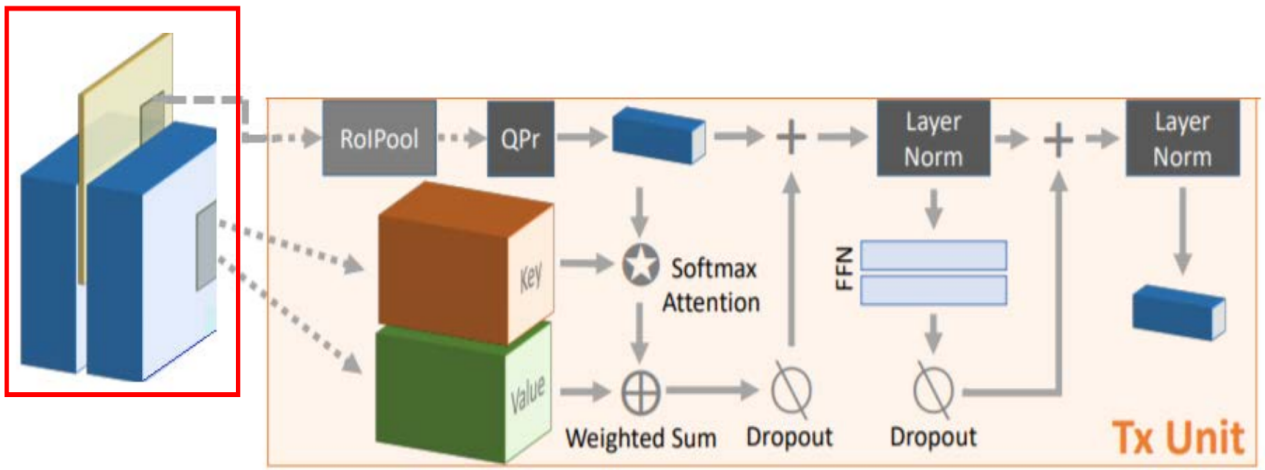
Head Region



Source: https://www.crcv.ucf.edu/wp-content/uploads/2019/03/adcv/ppt.pdf
Figure: Action Transformer of the Head Region

Video Action Transformer Network

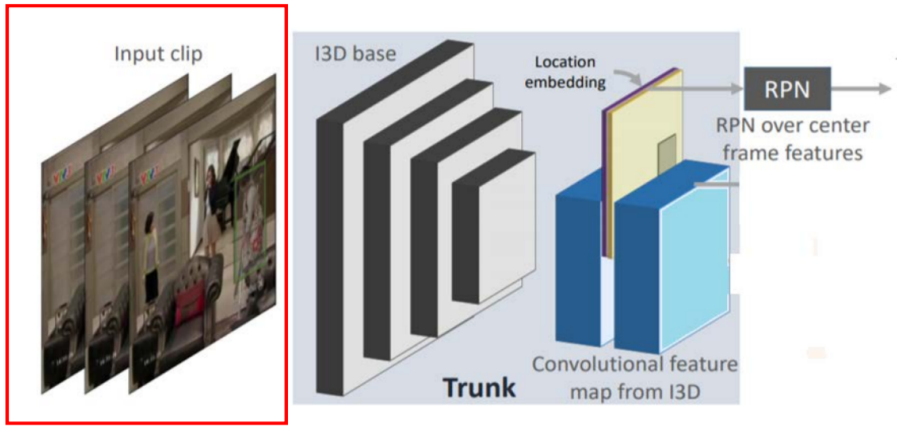
Action Transformer Tx-Unit



Source: https://www.crcv.ucf.edu/wp-content/uploads/2019/03/adcv/ppt.pdf
Figure: Tx-Unit

Video Action Transformer Network

Trunk Region

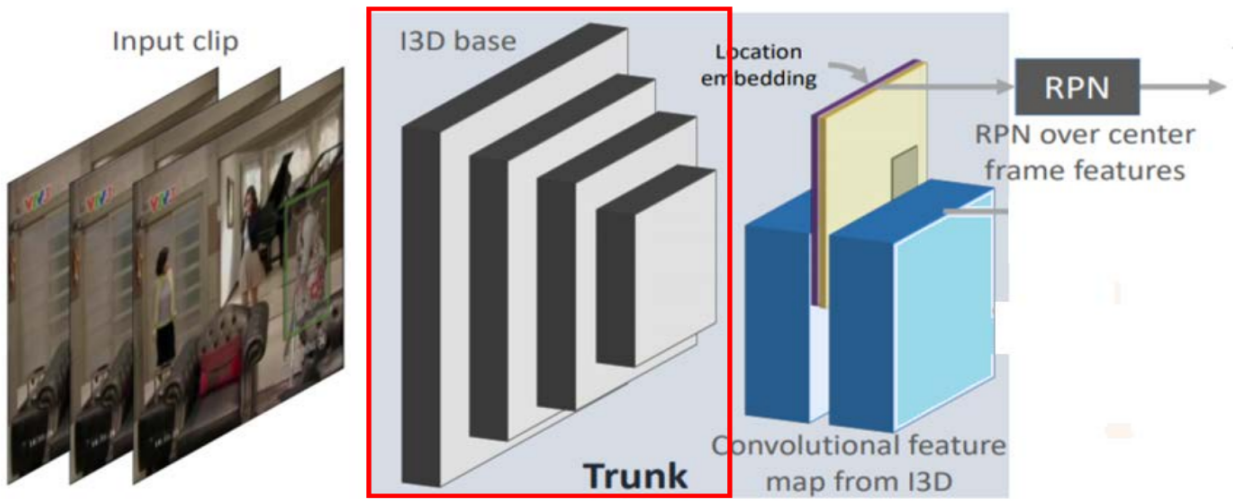


Source: https://www.crcv.ucf.edu/wp-content/uploads/2019/03/adcv/ppt.pdf
Figure: T-frame Input of the model

Input Shape 64x400x400

Video Action Transformer Network

Trunk Region



Source: https://www.crcv.ucf.edu/wp-content/uploads/2019/03/adcv/ppt.pdf
Figure: Layer wights of I3D base are pre-trained on Kinematics-400

downsampled feature map of Shape 16x25x25

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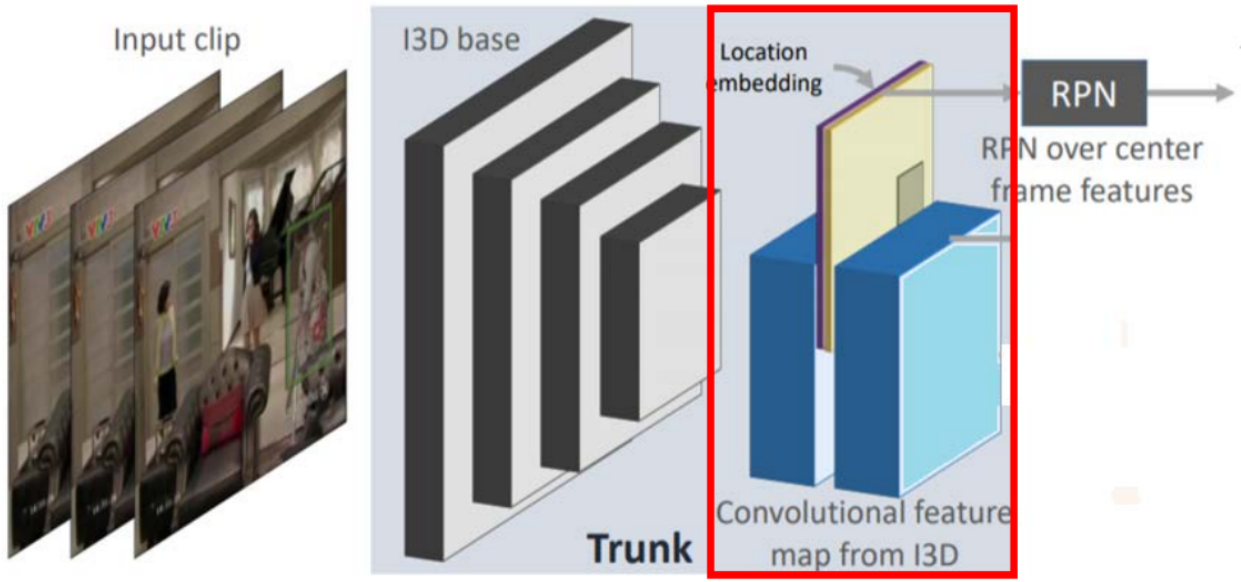
Trunk Region



Source: https://www.crcv.ucf.edu/wp-content/uploads/2019/03/adcv/ppt.pdf

Figure: feature map of the Mixed_4 *fLayer* $\frac{T}{4} x \frac{W}{16} x \frac{H}{16}$

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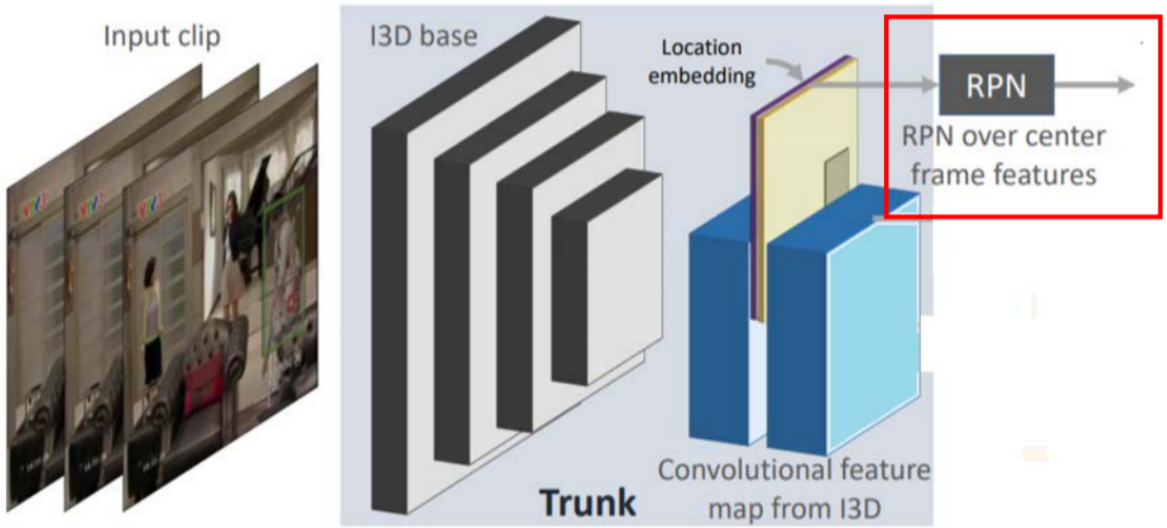
Trunk Region



Source: https://www.crcv.ucf.edu/wp-content/uploads/2019/03/adcv/ppt.pdf
Figure: Region Proposal Network of the Trunk Region

Query Tensor $\in 25x25$

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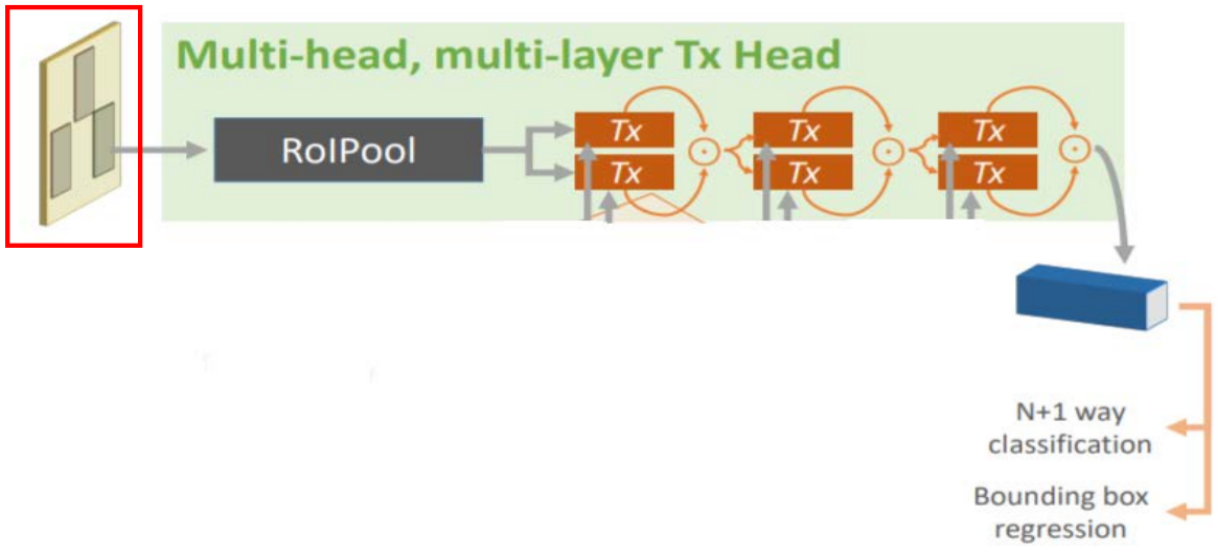
Head Region



Source: https://www.crcv.ucf.edu/wp-content/uploads/2019/03/adcv/ppt.pdf
Figure: Region Proposals as Query Input of the Head Region

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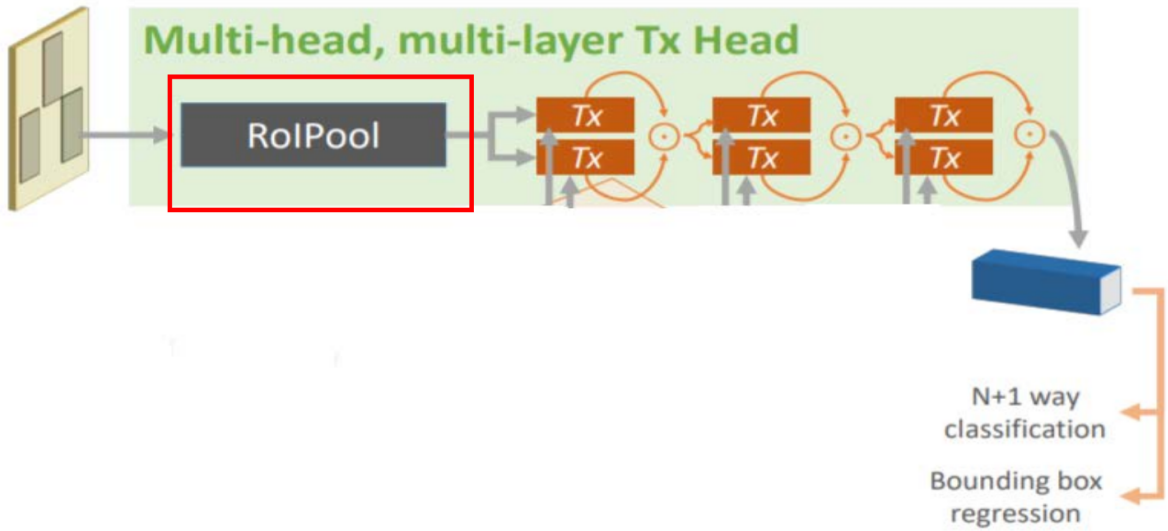
Head Region



Source: https://www.crcv.ucf.edu/wp-content/uploads/2019/03/adcv/ppt.pdf
Figure: Region of Interest Pooling Operation

Query processed by RoIPool in to $\in [7x7]$

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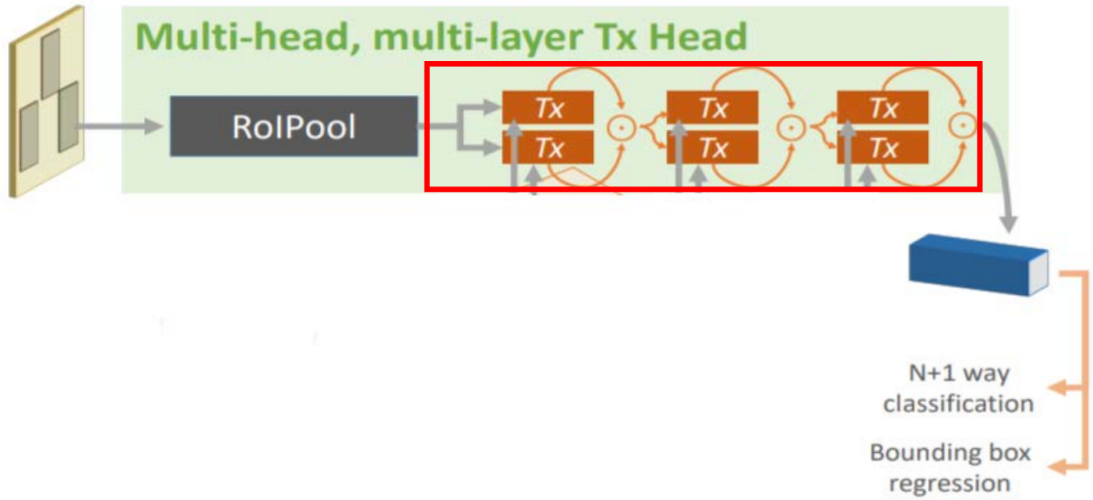
Head Region



Source: https://www.crcv.ucf.edu/wp-content/uploads/2019/03/adcv/ppt.pdf
Figure: Tx-Unit stackt

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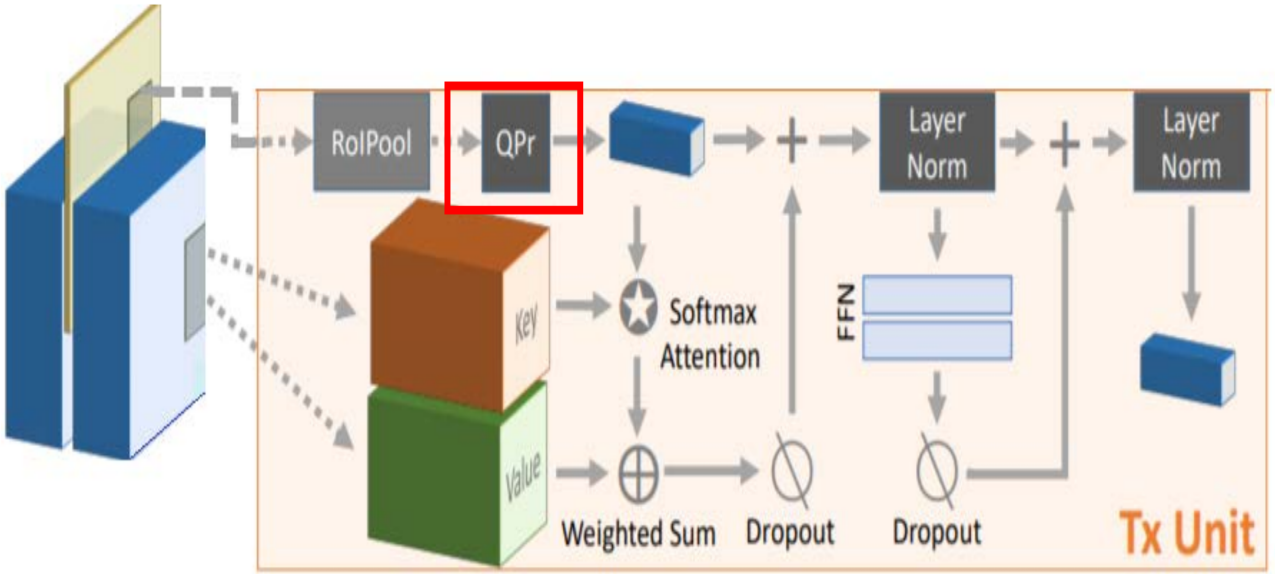
Head Region



Source: https://www.crcv.ucf.edu/wp-content/uploads/2019/03/adcv/ppt.pdf
Figure: Query Preprocessor

The HighRes/LowRes query preProcesser transforms the Query in to $Q^r \in [1x1x128]$

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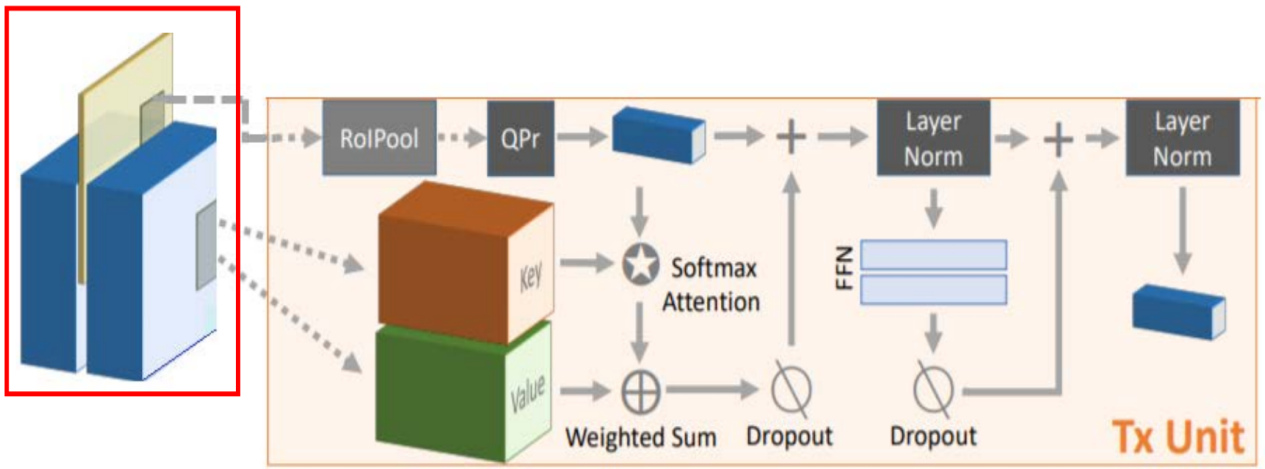
Head Region

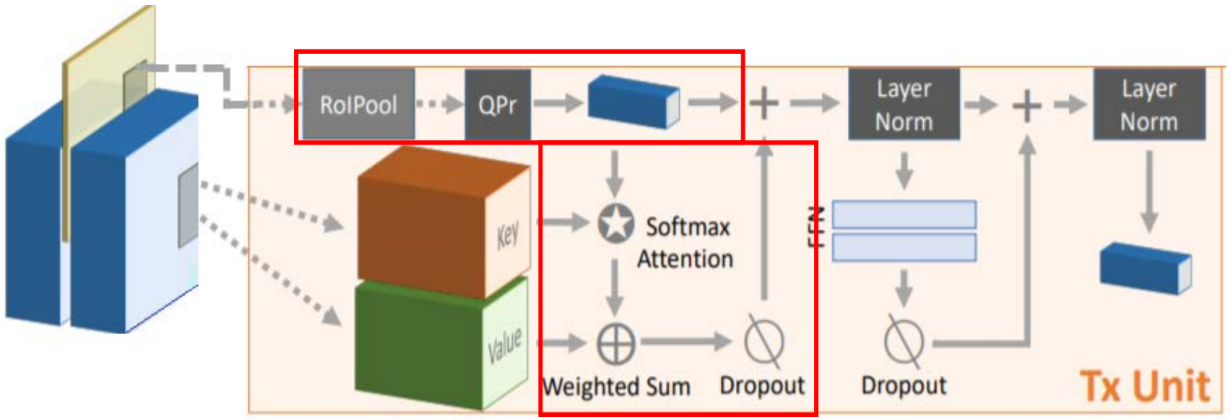


Source: https://www.crcv.ucf.edu/wp-content/uploads/2019/03/adcv/ppt.pdf
Figure: Linear projection of Key and Value

Key Tensor $\in [16x25x25x128]$

Video Action Transformer Network

Head Region



Source: https://www.crcv.ucf.edu/wp-content/uploads/2019/03/adcv/ppt.pdf
Figure: Softmax Attention and Weighted Sum

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Attention Equation

$$a_{xyt}^{(r)} = \frac{Q^{(r)} K_{xyt}^{T}}{\sqrt{D}}; A^{(r)} = \sum_{x,y,t} \left[\text{Softmax}\left(a^{(r)} \right) \right]_{xyt} V_{xyt}$$

Source: https://www.crcv.ucf.edu/wp-content/uploads/2019/03/adcv/ppt.pdf
Figure: Attention Equation

$KQ^r \in [16x25x25x1] A^r \in [1x1x128]$

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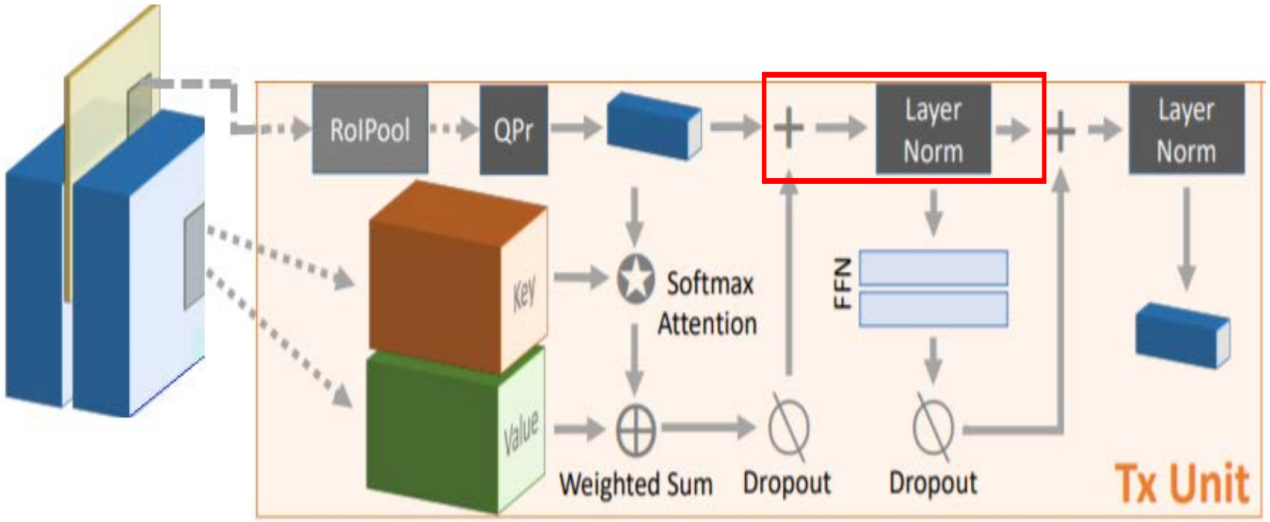
Head Region



Source: https://www.crcv.ucf.edu/wp-content/uploads/2019/03/adcv/ppt.pdf
Figure: Layer Norm

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Head Region

$$Q^{(r)'} = \text{LayerNorm}\left(Q^{(r)} + \text{Dropout}\left(A^{(r)}\right)\right)$$

$$Q^{(r)''} = \text{LayerNorm}\left(Q^{(r)'} + \text{Dropout}\left(\text{FFN}\left(Q^{(r)'}\right)\right)\right)$$

Source: https://www.crcv.ucf.edu/wp-content/uploads/2019/03/adcv/ppt.pdf
Figure: Layer Norm

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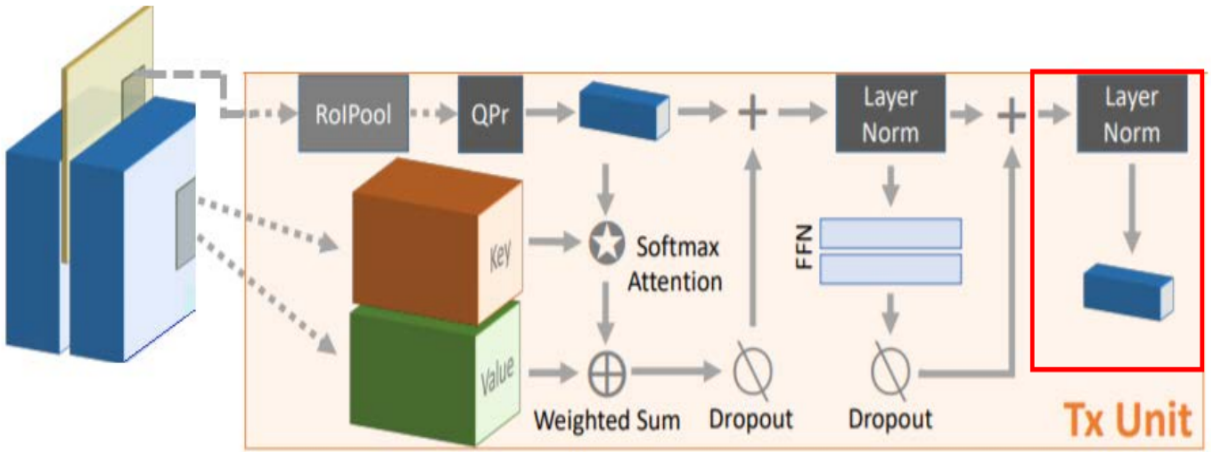
Head Region



Source: https://www.crcv.ucf.edu/wp-content/uploads/2019/03/adcv/ppt.pdf
Figure: Action predicted and bounding box for the human

Experiments

- Atomic Visual Actions (AVA) Dataset
  - Training set 211 K
  - Validation 57 K
  - Test 117 K
- 1 FPS from 430 15 min movie clips
- Key-Frame is labels for action and ground-truth boxes
- Evaluation Metric frame levelmean average precision at IOU threshold of 0.5

Experiments

- Action classification (ground-truth boxes)
- Localization performance (action agnostic)
- Overall performance (compare to State of the art)

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Case 1: Action classification with and without ground-truth boxes

Trunk	Head	QPr	GT Boxes	Params (M)	Val mAP
I3D	I3D	-		16.2	21.3
I3D	I3D	-	✓	16.2	23.4
I3D	Tx	LowRes		13.9	17.8
I3D	Tx	HighRes		19.3	18.9
I3D	Tx	LowRes	✓	13.9	28.5
I3D	Tx	HighRes	✓	19.3	27.6

Source: https://www.crcv.ucf.edu/wp-content/uploads/2019/03/adcv/ppt.pdf
Figure: Evalute the performance of the Action Transformer Head

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Case 2: Localization performance (action agnostic)

RoI source	QPr	Head	Val mAP	
			IOU@0.5	IOU@0.75
RPN	-	I3D	92.9	77.5
RPN	LowRes	Tx	77.5	43.5
RPN	HighRes	Tx	87.7	63.3

Source: https://www.crcv.ucf.edu/wp-content/uploads/2019/03/adcv/ppt.pdf
Figure: Evaluate the localization performance of the Transformer Head

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Overall Performance Compare to other State of the Art models

Method	Modalities	Architecture	Val mAP	Test mAP
Single frame [16]	RGB, Flow	R-50, FRCNN	14.7	-
AVA baseline [16]	RGB, Flow	I3D, FRCNN, R-50	15.6	-
ARCN [42]	RGB, Flow	S3D-G, RN	17.4	-
Fudan University	-	-	-	17.16
YH Technologies [52]	RGB, Flow	P3D, FRCNN	-	19.60
Tsinghua/Megvii [23]	RGB, Flow	I3D, FRCNN, NL, TSN, C2D, P3D, C3D, FPN	-	21.08
Ours (Tx-only head)	RGB	I3D, Tx	24.4	24.30
Ours (Tx+I3D head)	RGB	I3D, Tx	24.9	24.60
Ours (Tx+I3D+96f)	RGB	I3D, Tx	**25.0**	**24.93**

Source: https://www.crcv.ucf.edu/wp-content/uploads/2019/03/adcv/ppt.pdf

Figure: The Action Transformer Network model outperforms other models by a significant margin

Video Action Transformer Network

Performance depending on numbers of heads and layers

#layers↓	#heads→	2	3	6
	2	27.4	28.7	27.6
	3	28.5	28.8	27.7
	6	29.1	28.3	26.5

Source: https://www.crcv.ucf.edu/wp-content/uploads/2019/03/adcv/ppt.pdf
Figure: Different Head combination affect the performance

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Data Augmentation and pre-trained layers

	I3D head	Cls-specific bbox-reg	No Data Aug	From Scratch
Val mAP	21.3	19.2	16.6	19.1

Source: https://www.crcv.ucf.edu/wp-content/uploads/2019/03/adcv/ppt.pdf
Figure: Data Augmentation and pre-trained

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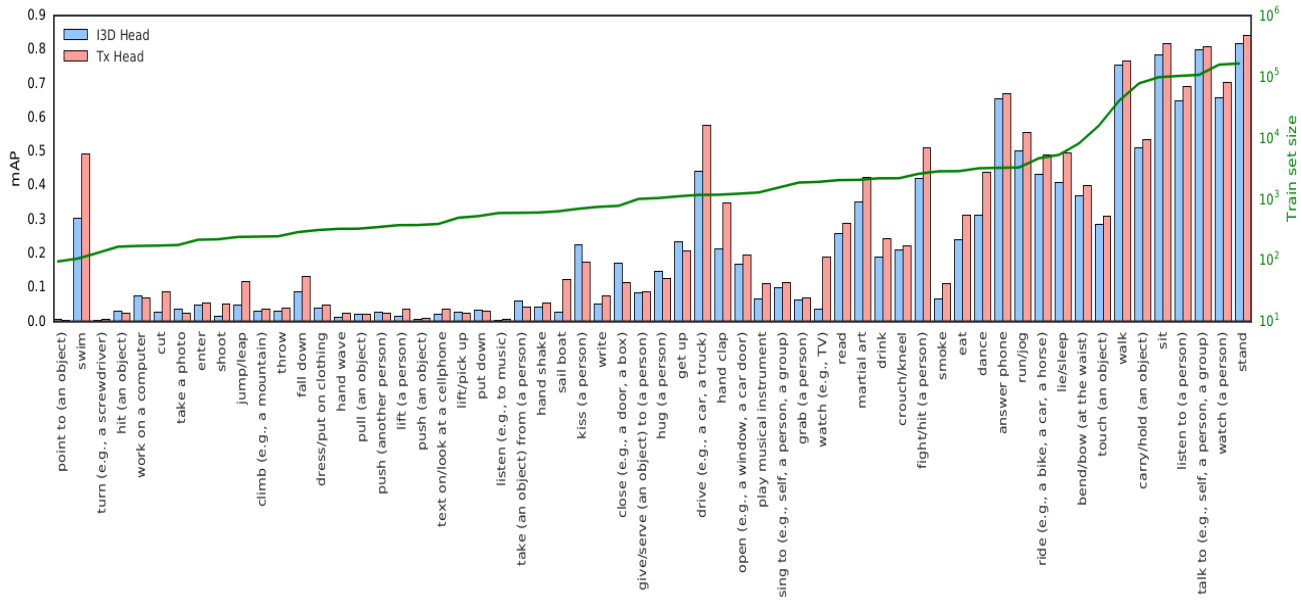
Correlation of performance with train-set size



Source: https://www.crcv.ucf.edu/wp-content/uploads/2019/03/adcv/ppt.pdf
Figure: trend suggests a positive correlation of performance with train-set size

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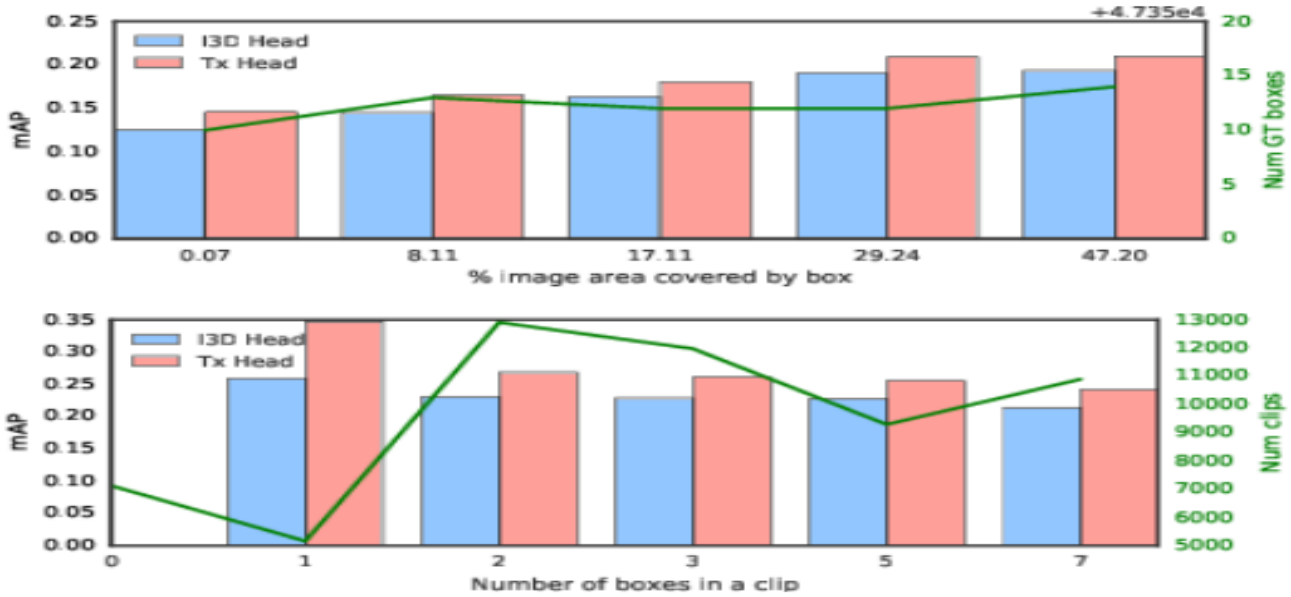
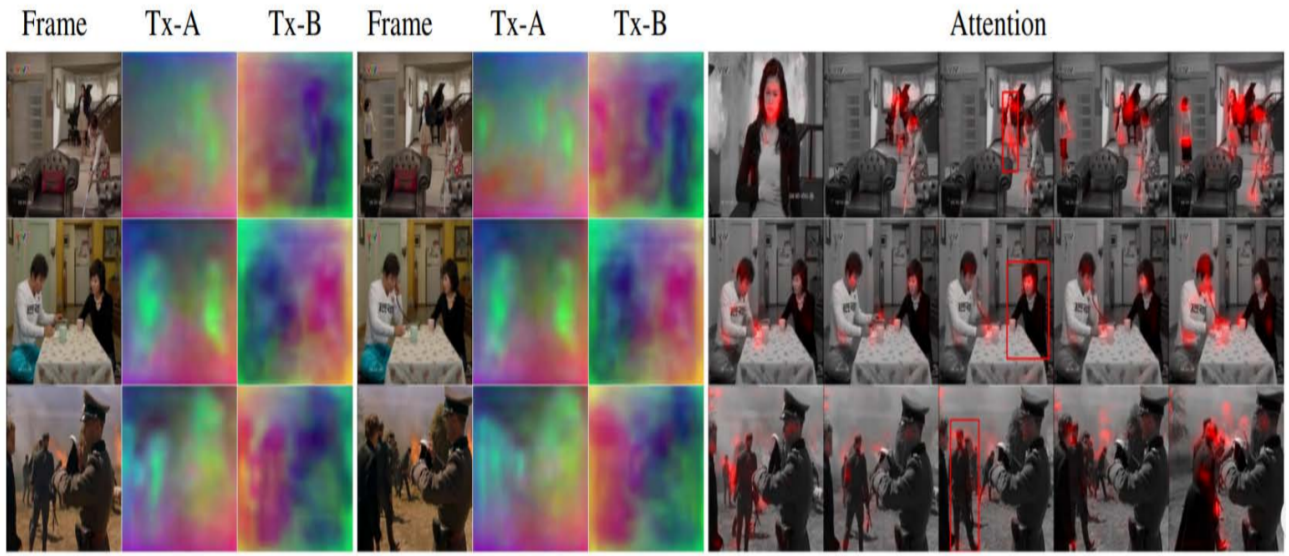
Correlation of performance with Number of Boxes



Source: https://www.crcv.ucf.edu/wp-content/uploads/2019/03/adcv/ppt.pdf
Figure: The trend suggests a positive correlation of performance with train-set size

Video Action Transformer Network

Embedding and Attention



Source: https://www.crcv.ucf.edu/wp-content/uploads/2019/03/adcv/ppt.pdf

Figure: 'Key' embeddings as color-coded 3D PCA projection for two of the six heads in our 2-head 3-layer Tx head

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Examples of Correct Predictions

Source: https://www.crcv.ucf.edu/wp-content/uploads/2019/03/adcv/ppt.pdf
Figure: Actions with contect like 'watching a person', 'holding an object'

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Examples of Incorrect Predictions

Source: https://www.crcv.ucf.edu/wp-content/uploads/2019/03/adcv/ppt.pdf

Figure: The 'smoking' action class obtains low performance even with large amount of training data

Conclusion

- Embeddings and attention maps learned without supervision have a semantic meaning
- Model is able to learn spatio-temporal context from othe r humans and objects
- Outperforms other state of the art models
- Dataset or Objective far from solved

Thank you for your Attention