Detect to Track and Track to Detect

Christoph Feichtenhofer, Axel Pinz, Andrew Zisserman, "Detect to Track and Track to Detect", ICCV 2017

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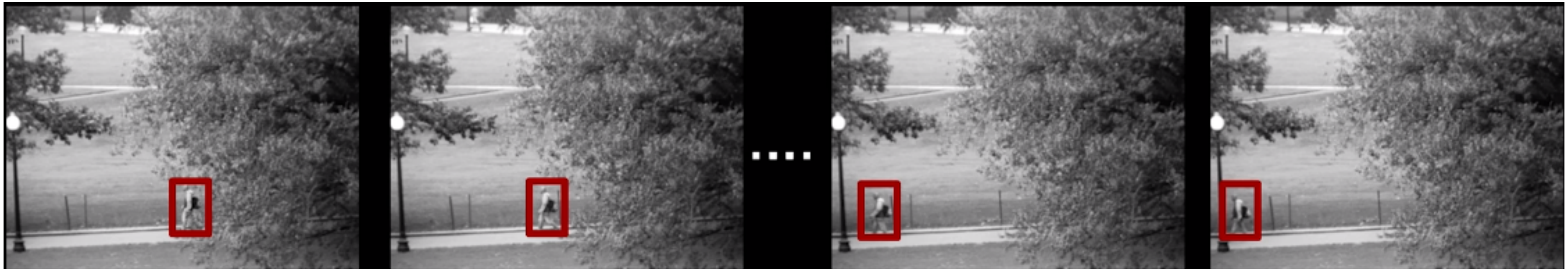
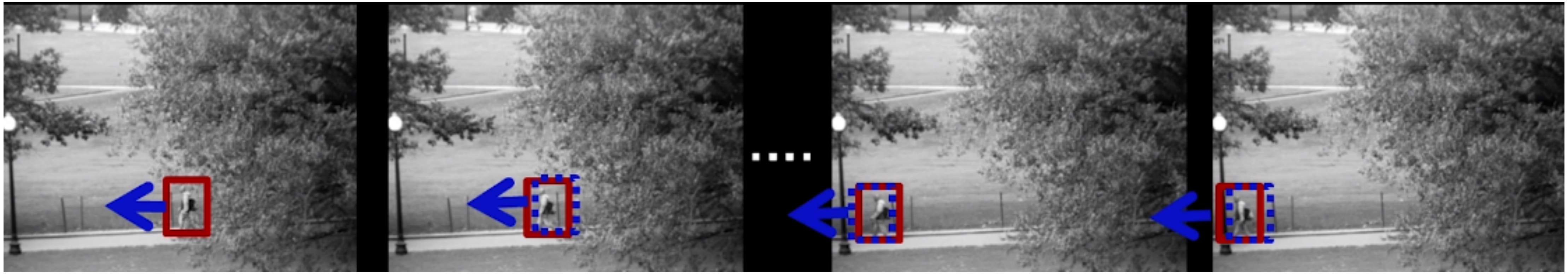
Detection vs. tracking



Detection: We detect the object **independently** in each frame

Detection vs. tracking

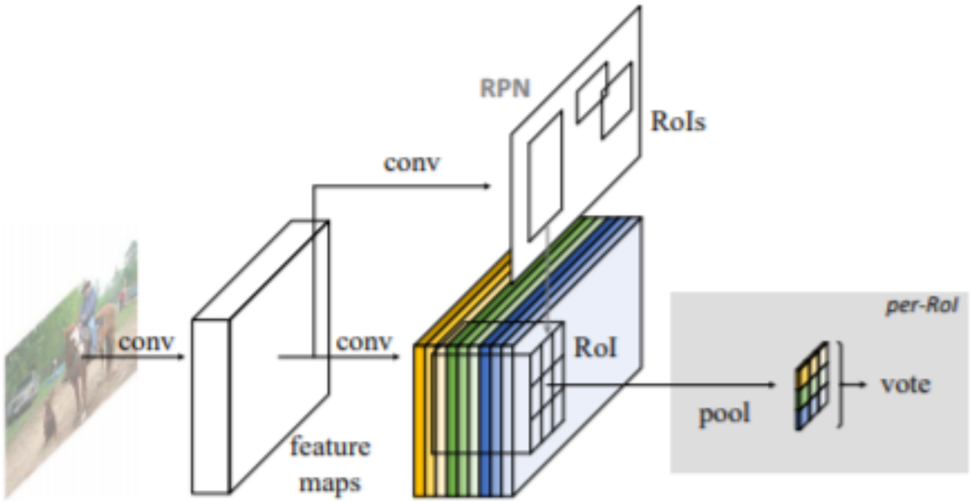


Tracking: We **predict** the new location of the object in the next frame using **estimated dynamics**. Then we **update** based upon measurements.

Related work

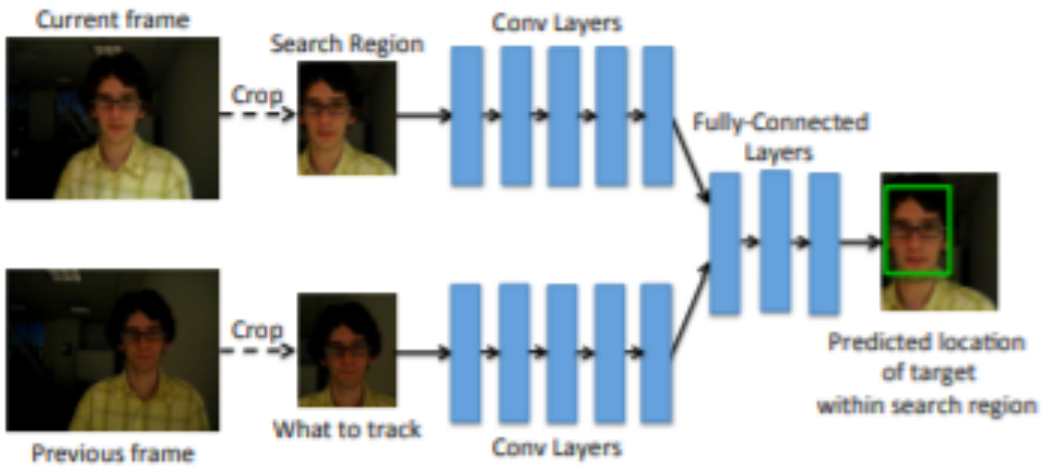
• Object detection:

R-FCN



• Tracking:

Learning to Track at 100 FPS with Deep Regression Networks



Detect & Track Architecture

FCN

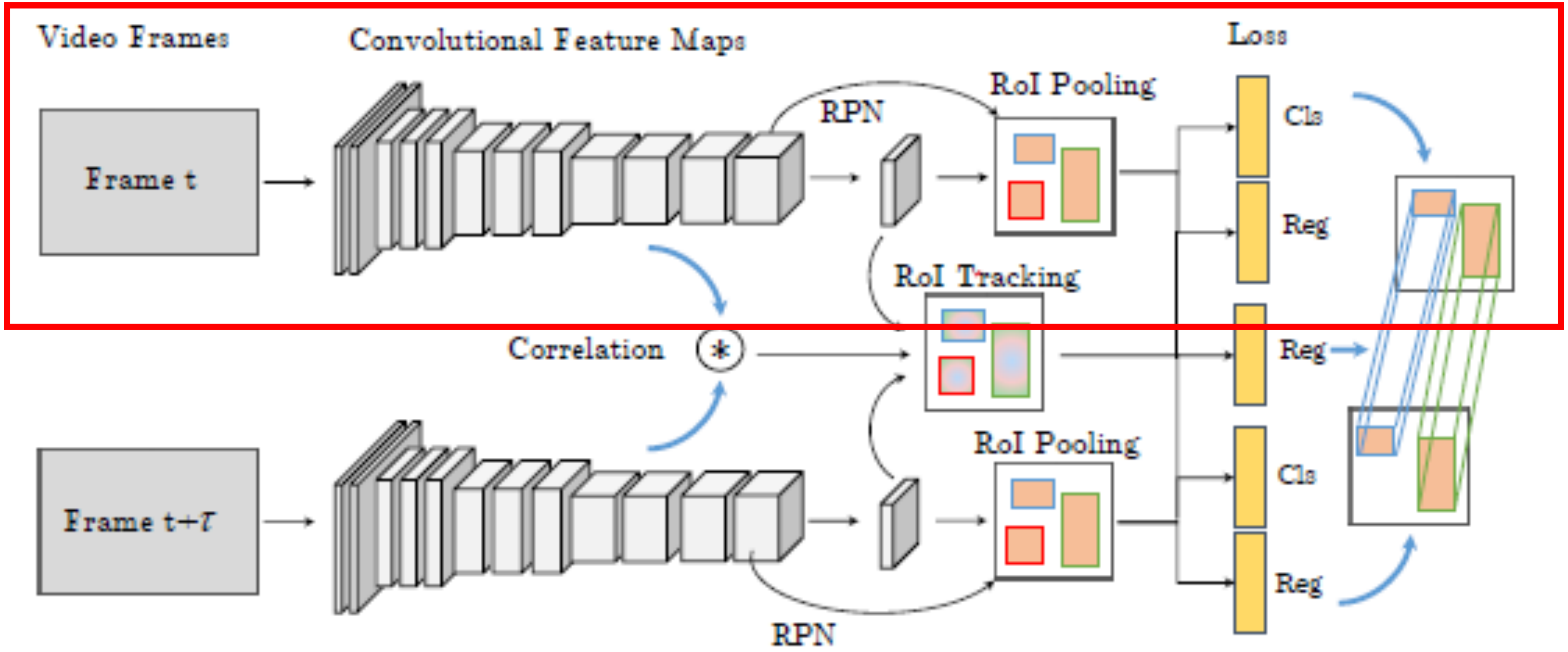


Figure 2. Architecture of our Detect and Track (D&T) approach (see Section 3 for details).

Detect & Track Architecture

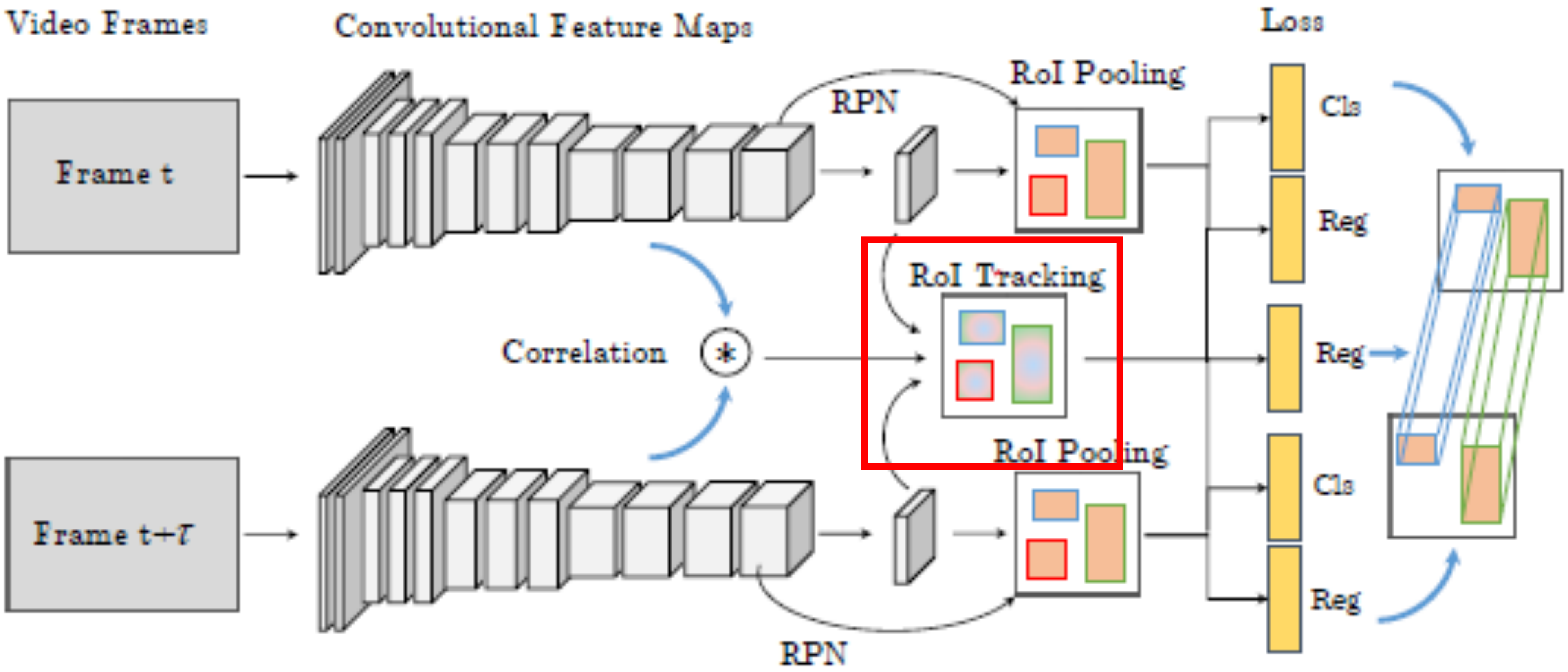


Figure 2. Architecture of our Detect and Track (D&T) approach (see Section 3 for details).

Detect & Track Architecture

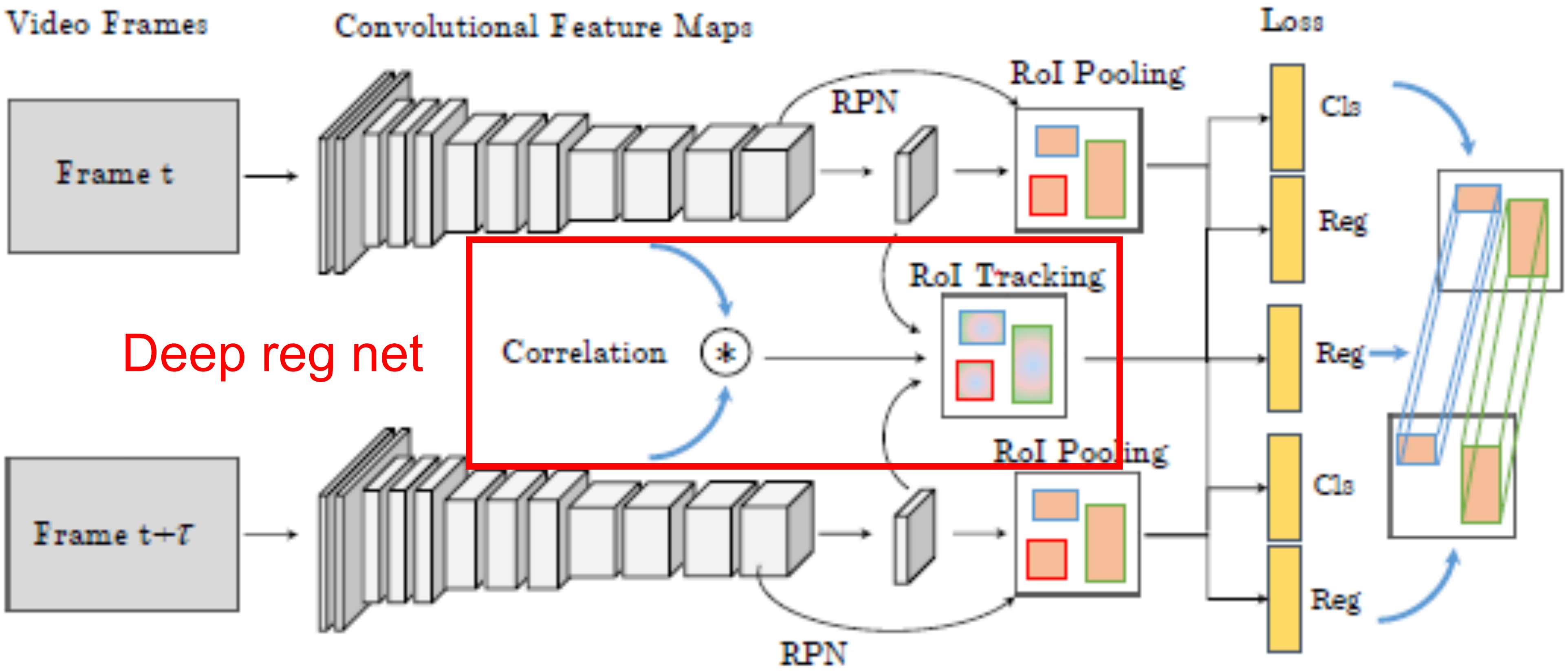
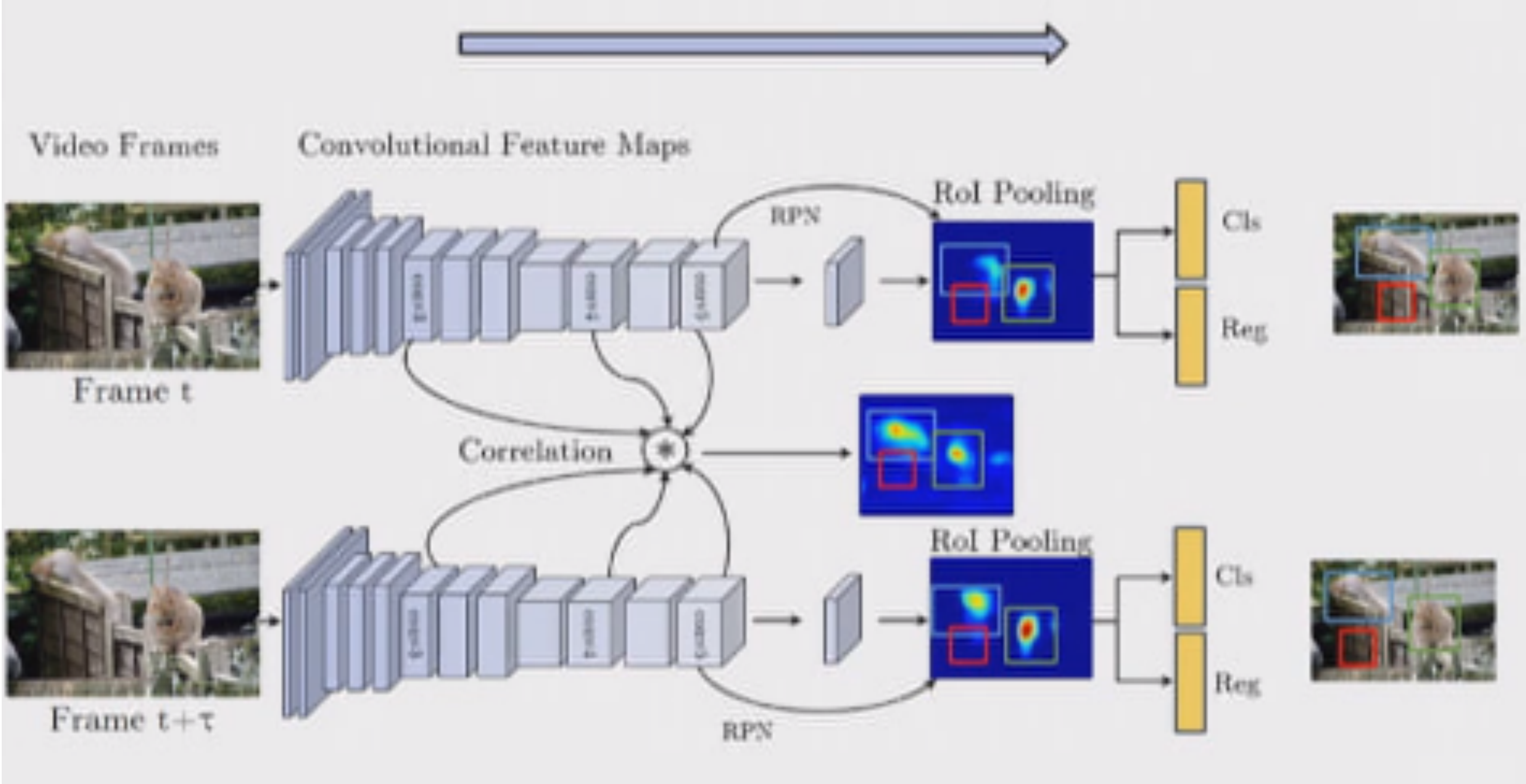
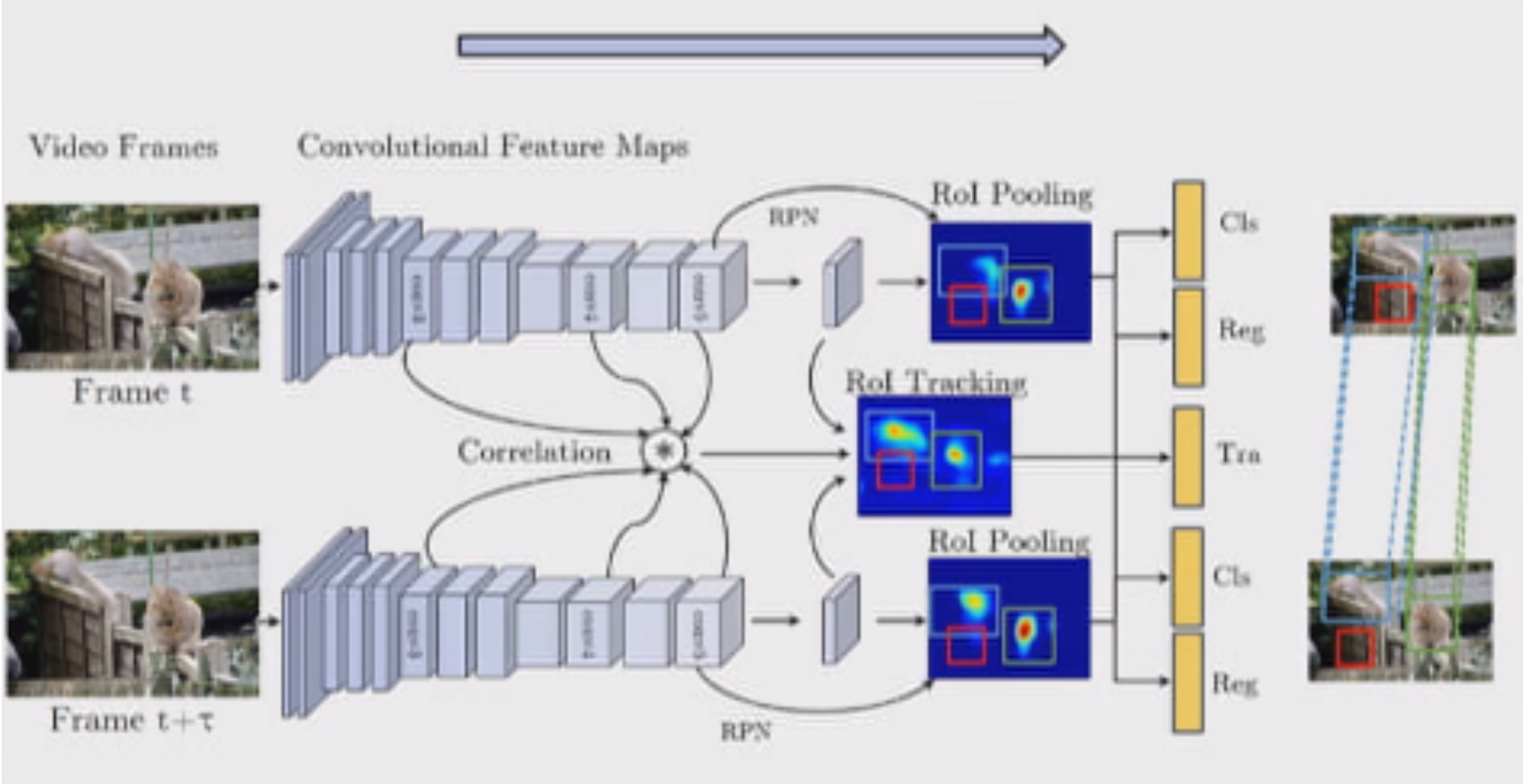


Figure 2. Architecture of our Detect and Track (D&T) approach (see Section 3 for details).

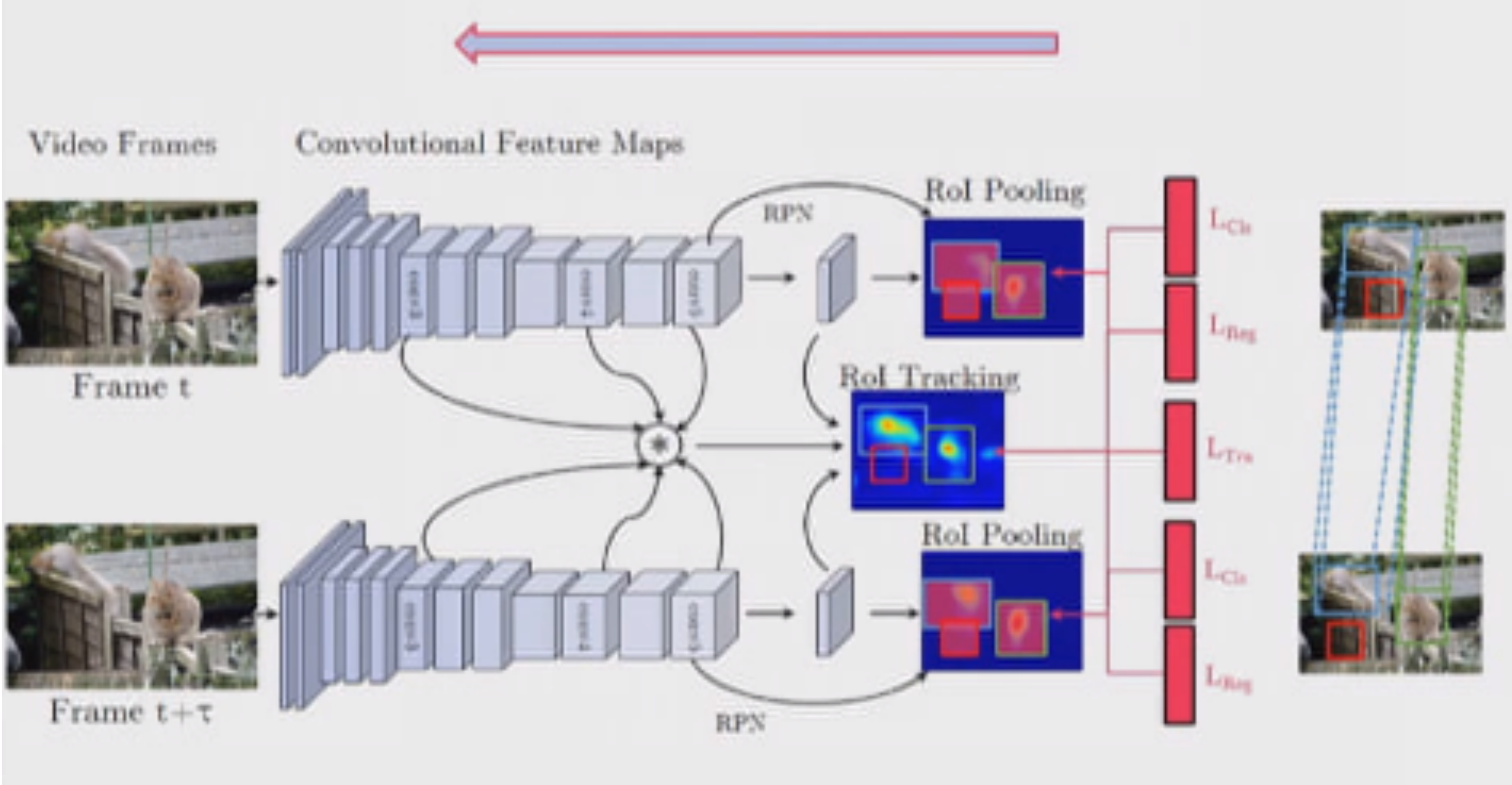
Detect & Track Training: Forward pass



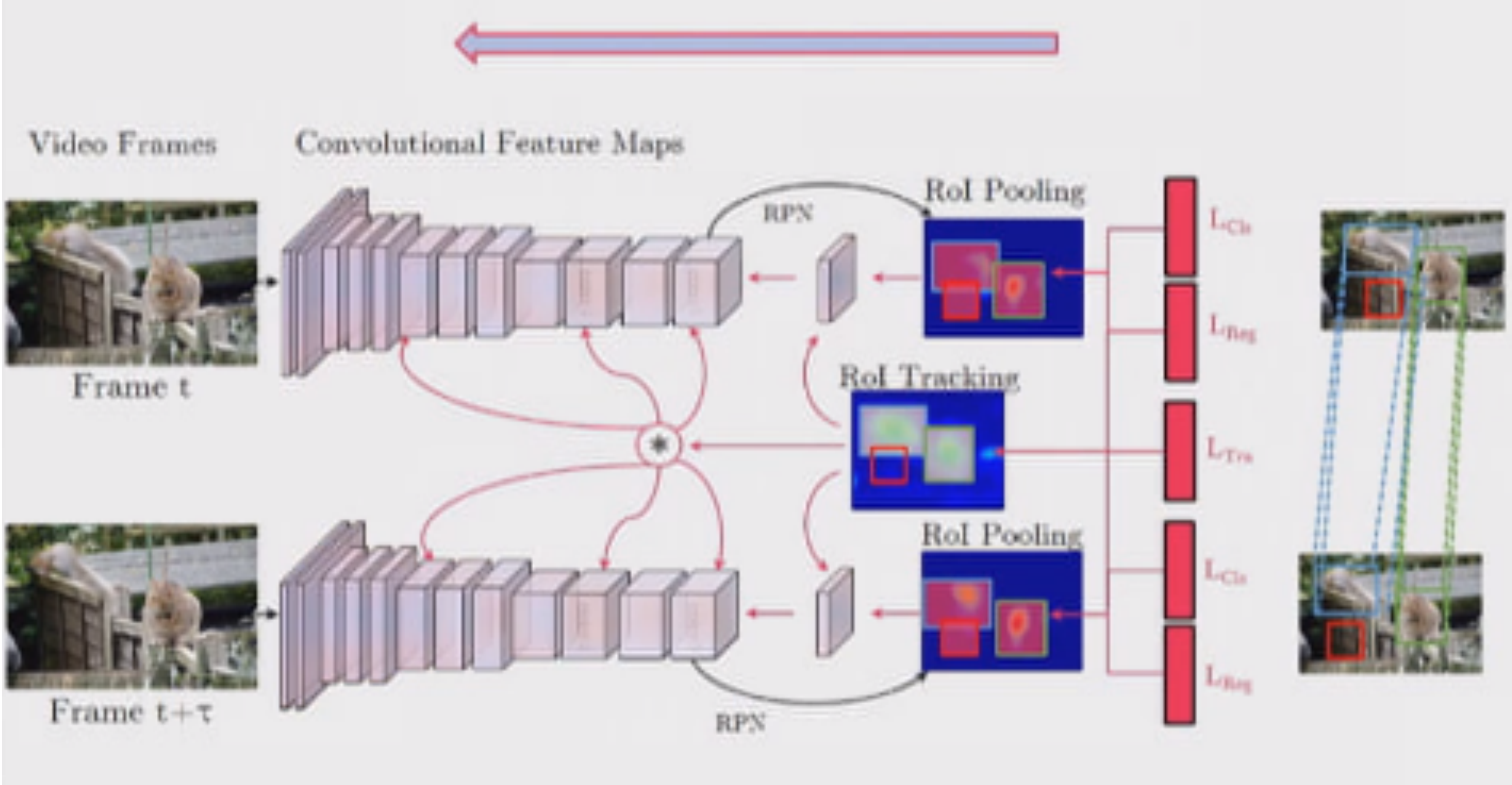
Detect & Track Training: Forward pass



Detect & Track Training: Backward pass



Detect & Track Training: Backward pass



objective

$$L(\{p_i\},\{t_i\}) = \frac{1}{N_{cls}}\sum_i L_{cls}(p_i, p_i^*) + \lambda\frac{1}{N_{reg}}\sum_i p_i^* L_{reg}(t_i, t_i^*)$$

$$L(\{p_i\},\{b_i\},\boxed{\{\Delta_i\}}) = \frac{1}{N}\sum_{i=1}^{N} L_{cls}(p_{i,c^*})$$

$$+\lambda\frac{1}{N_{fg}}\sum_{i=1}^{N}[c_i^* > 0] L_{reg}(b_i, b_i^*)$$

$$\boxed{+\lambda\frac{1}{N_{tra}}\sum_{i=1}^{N_{tra}} L_{tra}(\Delta_i^{t+\tau}, \Delta_i^{*,t+\tau}).}$$

bounding box regression features $\{\mathbf{x}_{reg}^{t}, \mathbf{x}_{reg}^{t+\tau}\}$

$$\Delta^{t+\tau} = (\Delta_x^{t+\tau}, \Delta_y^{t+\tau}, \Delta_w^{t+\tau}, \Delta_h^{t+\tau})$$

$$\Delta_x^{*,t+\tau} = \frac{B_x^{t+\tau} - B_x^t}{B_w^t} \qquad \Delta_y^{*,t+\tau} = \frac{B_y^{t+\tau} - B_y^t}{B_h^t}$$

$$\Delta_w^{*,t+\tau} = \log(\frac{B_w^{t+\tau}}{B_w^t}) \qquad \Delta_h^{*,t+\tau} = \log(\frac{B_h^{t+\tau}}{B_h^t})).$$

$$\Delta^{*,t+\tau} = \{\Delta_x^{*,t+\tau}, \Delta_y^{*,t+\tau}, \Delta_w^{*,t+\tau}, \Delta_h^{*,t+\tau}\}$$

Correlation feature for object tracking

$$\mathbf{x}_{corr}^{t,t+\tau}(i,j,p,q) = \left\langle \mathbf{x}_l^t(i,j), \mathbf{x}_l^{t+\tau}(i+p, j+q) \right\rangle$$

where $-d \le p \le d$ and $-d \le q \le d$

defined by the maximum displacement, d

RoI Tracking's input $\{\mathbf{x}_{corr}^{t,t+\tau}, \mathbf{x}_{reg}^{t}, \mathbf{x}_{reg}^{t+\tau}\}$.

Linking tracklets to object tubes

$$D_i^{t,c} = \{x_i^t, y_i^t, w_i^t, h_i^t, p_{i,c}^t\}$$

$$T_i^{t,t+\tau} = \{x_i^t, y_i^t, w_i^t, h_i^t; x_i^t + \Delta_x^{t+\tau}, y_i^t + \Delta_y^{t+\tau}, w_i^t + \Delta_w^{t+\tau}, h_i^t + \Delta_h^{t+\tau}\}$$

$$\Downarrow$$

$$s_c(D_{i,c}^t, D_{j,c}^{t+\tau}, T^{t,t+\tau}) = p_{i,c}^t + p_{j,c}^{t+\tau} + \psi(D_i^t, D_j, T^{t,t+\tau})$$

$$\bar{D}_c^\star = \underset{\bar{D}}{\operatorname{argmax}} \frac{1}{\mathcal{T}} \sum_{t=1}^{\mathcal{T}-\tau} s_c(D^t, D^{t+\tau}, T^{t,t+\tau}).$$

Result

Methods	airplane	antelope	bear	bicycle	bird	bus	car	cattle	dog	d. cat	elephant	fox	g. panda	hamster	horse	lion
TCN [18]	72.7	75.5	42.2	39.5	25.0	64.1	36.3	51.1	24.4	48.6	65.6	73.9	61.7	82.4	30.8	34.4
TPN+LSTM [16]	84.6	78.1	72.0	67.2	68.0	80.1	54.7	61.2	61.6	78.9	71.6	83.2	78.1	91.5	66.8	21.6
Winner ILSVRC'15 [17]	83.7	85.7	84.4	74.5	73.8	75.7	57.1	58.7	72.3	69.2	80.2	83.4	80.5	93.1	84.2	67.8
D (R-FCN)	87.4	79.4	84.5	67.0	72.1	84.6	54.6	72.9	70.9	77.3	76.7	89.7	77.6	88.5	74.8	57.9
D (& T loss)	89.4	80.4	83.8	70.0	71.8	82.6	56.8	71.0	71.8	76.6	79.3	89.9	83.3	91.9	76.8	57.3
D&T ($\tau = 1$)	90.2	82.3	87.9	70.1	73.2	87.7	57.0	80.6	77.3	82.6	83.0	97.8	85.8	96.6	82.1	66.7
D&T ($\tau = 10$)	89.1	79.8	87.5	68.8	72.9	86.1	55.7	78.6	76.4	83.4	82.9	97.0	85.0	96.0	82.2	66.0

Methods	lizard	monkey	motorcycle	rabbit	red panda	sheep	snake	squirrel	tiger	train	turtle	watercraft	whale	zebra	mAP (%)
TCN [18]	54.2	1.6	61.0	36.6	19.7	55.0	38.9	2.6	42.8	54.6	66.1	69.2	26.5	68.6	47.5
TPN+LSTM [16]	74.4	36.6	76.3	51.4	70.6	64.2	61.2	42.3	84.8	78.1	77.2	61.5	66.9	88.5	68.4
Winner ILSVRC'15 [17]	80.3	54.8	80.6	63.7	85.7	60.5	72.9	52.7	89.7	81.3	73.7	69.5	33.5	90.2	73.8
Winner ILSVRC'16 [39]	(single model performance)														76.2
D (R-FCN)	76.8	50.1	80.2	61.3	79.5	51.9	69.0	57.4	90.2	83.3	81.4	68.7	68.4	90.9	74.2
D (& T loss)	79.0	54.1	80.3	65.3	85.3	56.9	74.1	59.9	91.3	84.9	81.9	68.3	68.9	90.9	75.8
D&T ($\tau = 1$)	83.4	57.6	86.7	74.2	91.6	59.7	76.4	68.4	92.6	86.1	84.3	69.7	66.3	95.2	**79.8**
D&T ($\tau = 10$)	83.1	57.9	79.8	72.7	90.0	59.4	75.6	65.4	90.5	85.6	83.3	68.3	66.5	93.2	78.6

Table 1. Performance comparison on the ImageNet VID validation set. The average precision (in %) for each class and the mean average precision over all classes is shown. τ corresponds to the temporal sampling stride.