

AdamsFormer for Spatial Action Localization in the Future

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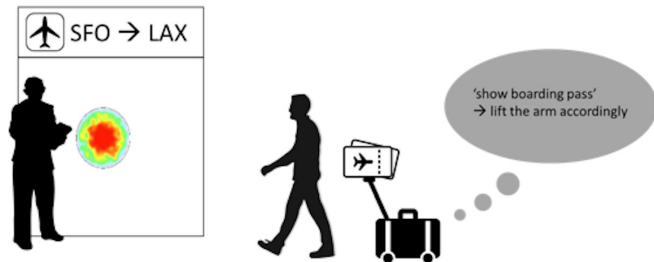


Introduction

- Look for a location where current actions appear in the future.
- I.e., By understanding the exact location of future activities, the robot agent can provide more comfortable cooperation form the end application.

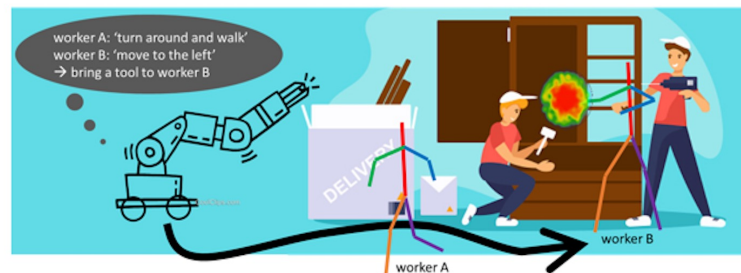
Activity forecasting with Future action localization

Micromobility

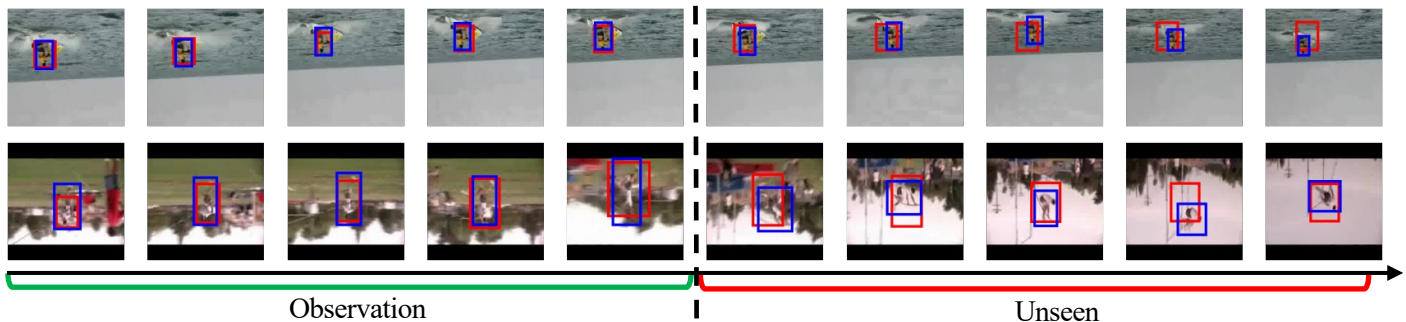


Activity forecasting with Pose Prediction

Affordance awareness



Spatial Action Localization in the Future



- We introduce a new task that aims to localize action in both observation and unseen frames.

Initial Value Problem and Neural ODE

$$z'(t) = \frac{dz}{dt} = f(t, z), z(t_0) = z_0,$$

- IVP: Ordinary differential equation with an initial condition.
- Neural ODE (NeurIPS18) : it models $f(t, z)$ with a neural network.

Single-step VS Multi-Step

- Single-Step

- i.e. Euler method $z_{n+1} = z_n + hf(t_n, z_n).$

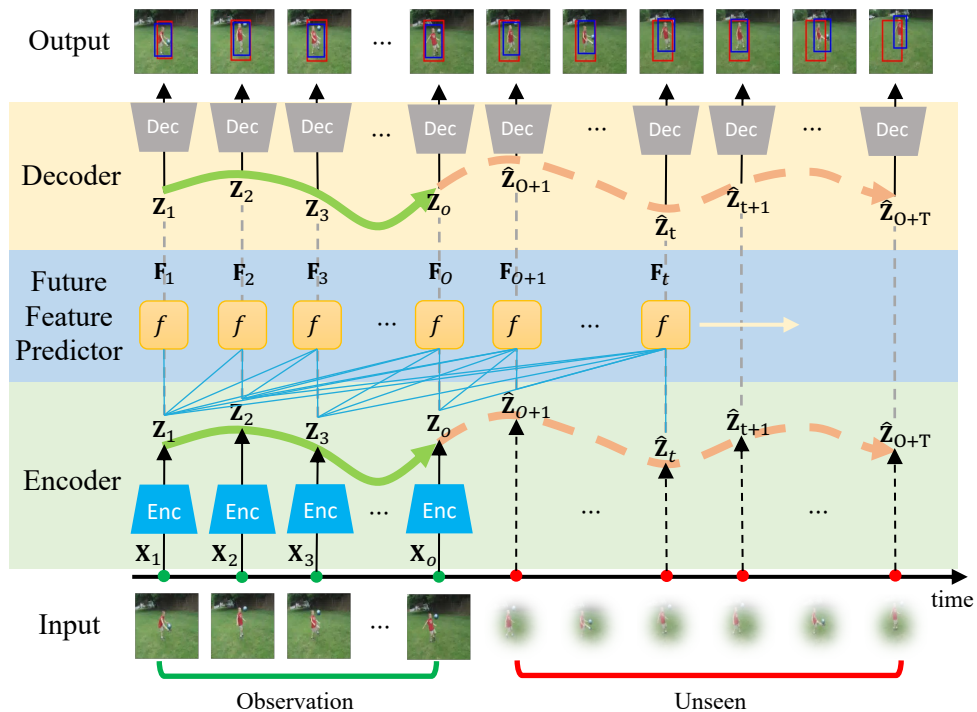
- Multi-Step

- i.e. Adams method

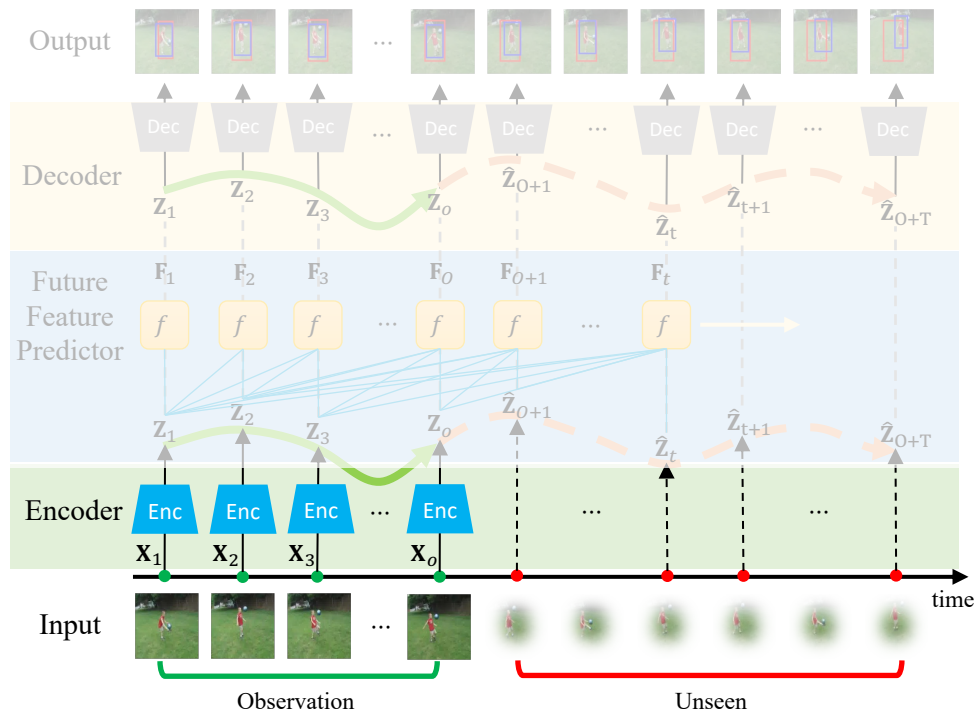
N=2 $z_{n+1} = z_n + \frac{h}{2}[3f(t_n, z_n) - f(t_{n-1}, z_{n-1})].$

N=3 $z_{n+1} = z_n + h[\frac{12}{23}f(t_n, z_n) - \frac{16}{23}f(t_{n-1}, z_{n-1}) + \frac{5}{12}f(t_{n-2}, z_{n-2})].$

AdamsFormer - Overview



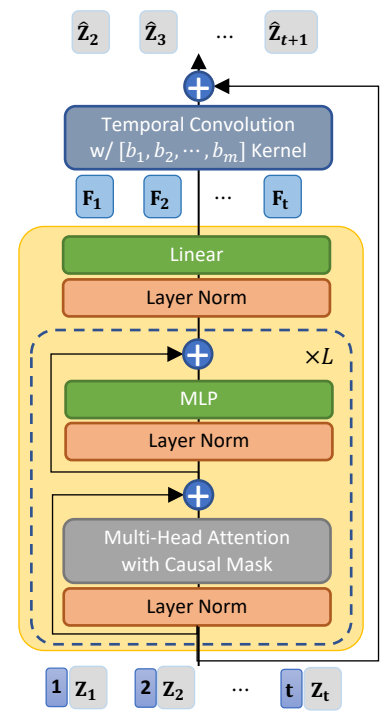
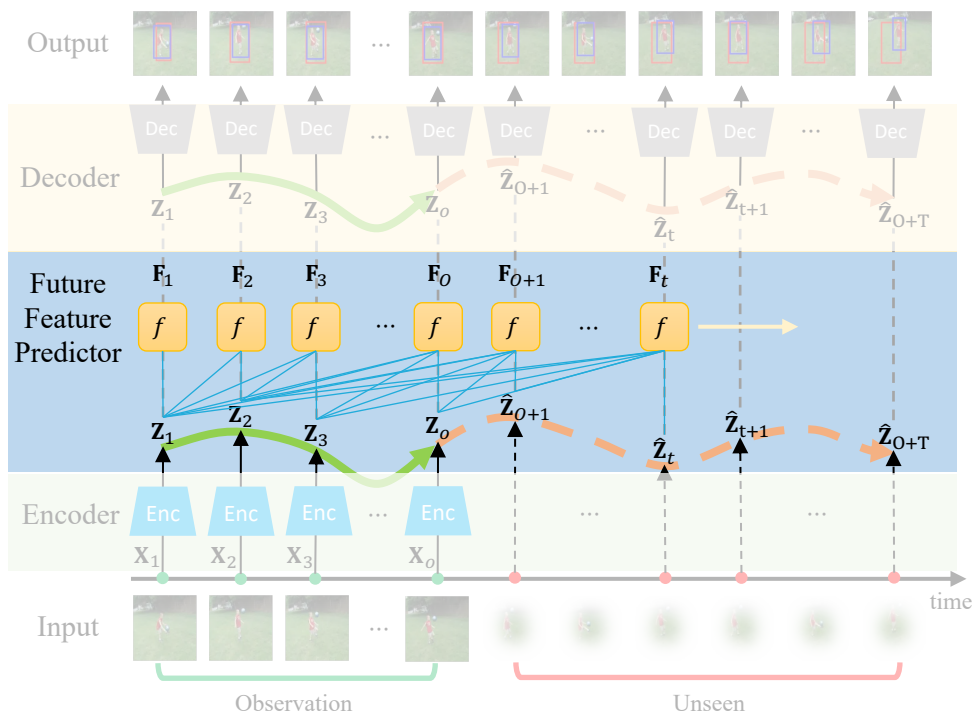
Encoder



- Combination of 2D-CNN and 3D-CNN to fully utilize temporal information.

Future Feature Predictor

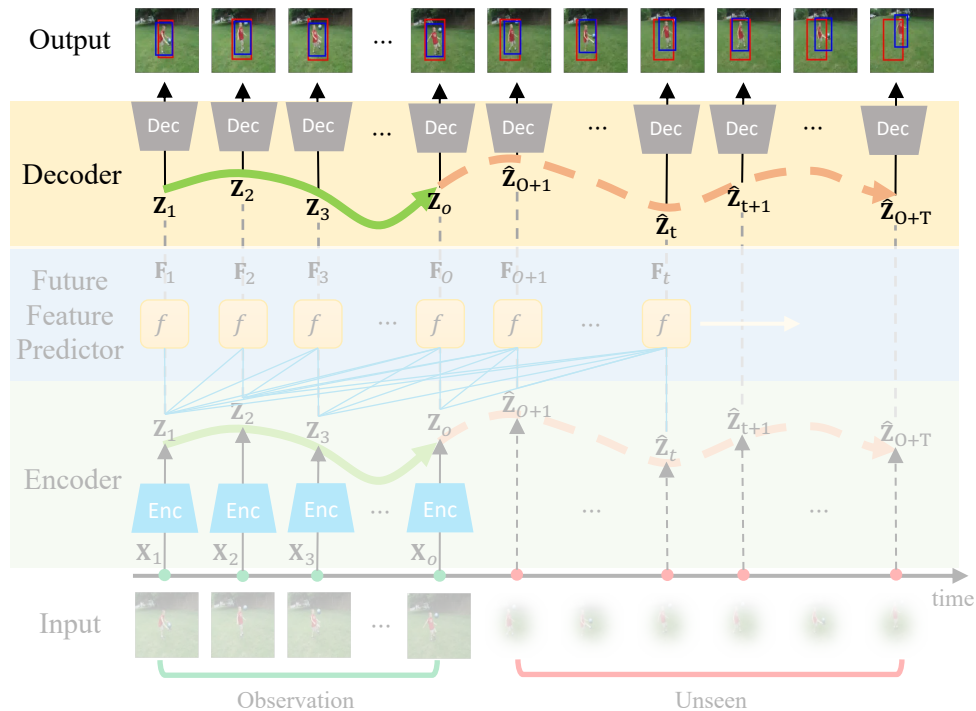
$$\mathbf{Z}_{t+1} = \mathbf{Z}_t + h \sum_{j=1}^m b_j \mathbf{F}_{t-j},$$



$$\mathbf{F} = f(\mathbf{t}_i, \mathbf{Z}_i)$$

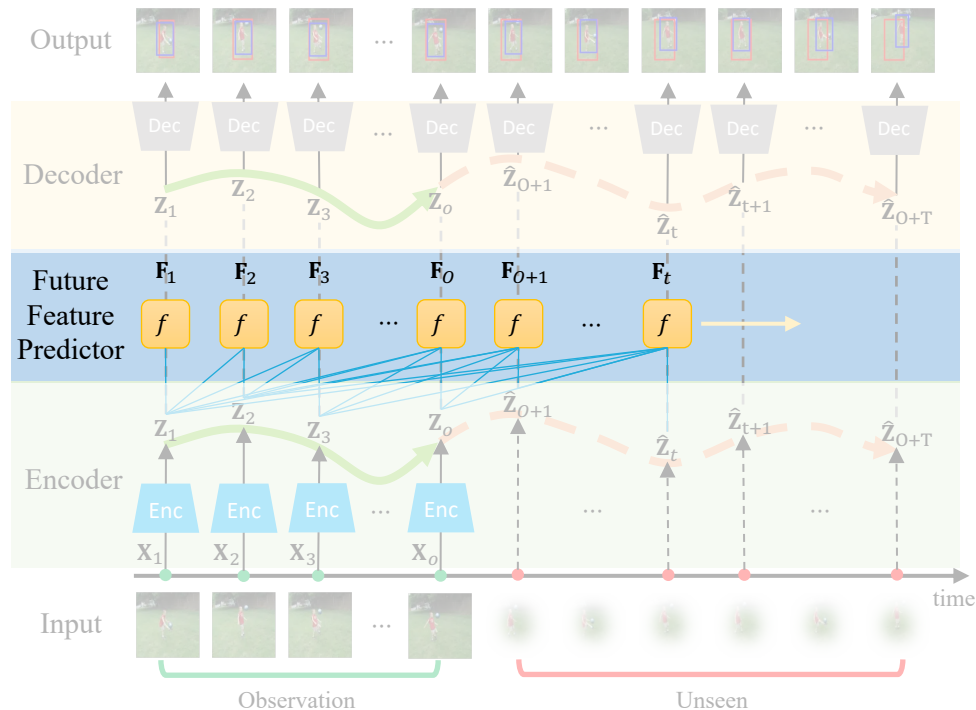
$$\mathbf{F} = f(\mathbf{t}_{1:i}, \mathbf{Z}_{1:i})$$

Decoder



- Decoder regresses the tensor to action location and category.

Experiments



- Setup
 - Replace future feature predictors with long-range temporal modeling methods.
- Baselines
 - RNN
 - ODE-RNN
 - PhyDNet
 - Anticipative Transformer

Comparison with baselines

Datasets	Methods	Observation Ratio									
		10%		20%		30%		40%		50%	
		OBS	UNSEEN	OBS	UNSEEN	OBS	UNSEEN	OBS	UNSEEN	OBS	UNSEEN
UCF101-24	RNN [44]	71.46	32.18	66.75	37.30	67.53	39.29	67.71	42.32	64.41	41.38
	ODE-RNN [6]	-	31.56	-	34.84	-	35.59	-	37.71	-	39.70
	PhyDNet [17]	65.86	29.90	67.16	37.22	67.43	39.69	67.69	41.44	66.42	42.47
	Transformer [14]	59.66	34.21	66.20	37.85	63.62	41.06	63.95	43.73	65.34	44.87
	AdamsFormer	72.01	37.86	77.91	41.00	70.34	42.92	71.00	45.25	73.39	48.74
JHMDB21	RNN [44]	40.64	10.85	40.61	24.76	42.62	32.06	39.95	29.82	38.19	31.19
	ODE-RNN [6]	-	19.99	-	21.63	-	24.57	-	28.86	-	31.69
	PhyDNet [17]	4.09	0.38	34.69	22.22	35.28	29.74	32.31	28.85	33.58	29.41
	Transformer [14]	38.46	35.17	38.61	40.24	41.65	44.09	46.87	50.66	45.34	50.45
	AdamsFormer	51.26	49.39	51.59	49.55	51.21	51.72	51.84	53.28	50.19	52.81

Advantage of the multi-step method

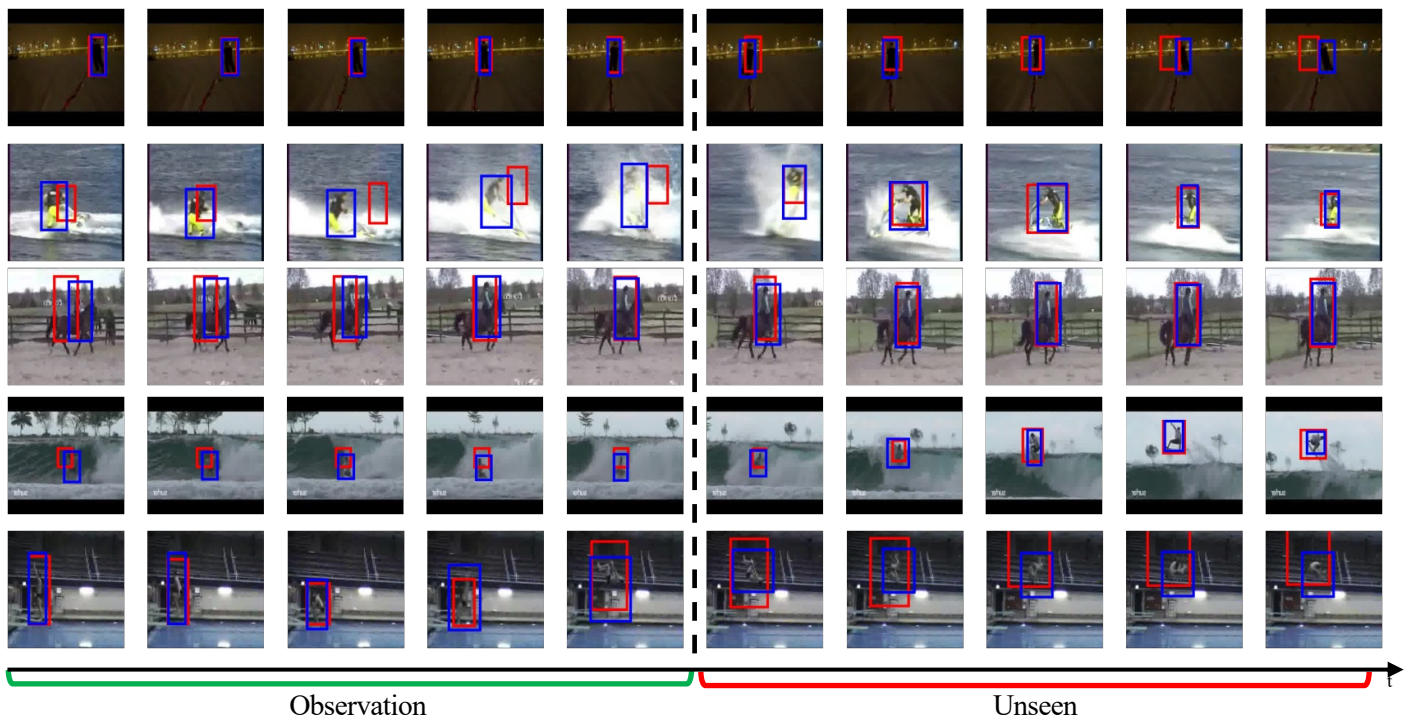
Methods	Observation Ratio									
	10%		20%		30%		40%		50%	
	OBS	UNSEEN	OBS	UNSEEN	OBS	UNSEEN	OBS	UNSEEN	OBS	UNSEEN
Single-step (m=1)	69.27	36.81	70.79	39.54	67.33	42.75	68.49	44.41	70.16	47.39
Multi-step (m=2)	72.01	37.86	74.11	40.04	68.61	42.87	70.91	45.32	72.59	47.19
Multi-step (m=4)	-	-	77.91	41.00	70.34	42.92	71.00	45.25	73.39	48.74
Multi-step (m=6)	-	-	-	-	72.52	42.34	72.83	42.44	75.14	48.00

- The multi-step method outperforms the single-step method.

Effect of order of the multi-step method

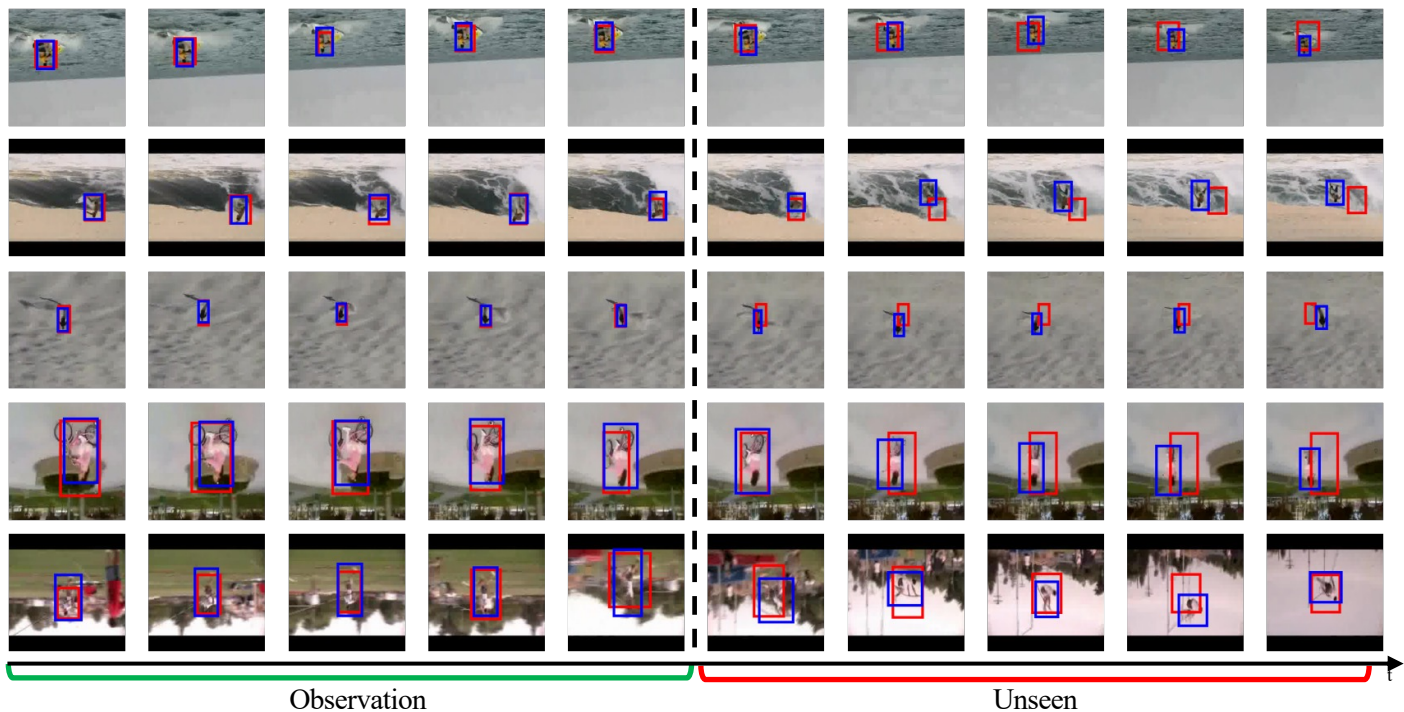
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Qualitative Results



Prediction Ground Truth

Qualitative Results



Prediction Ground Truth

Thank you for listening!