

# **2D Image Processing & Augmented Reality**

## **Winter Semester 2019/2020**

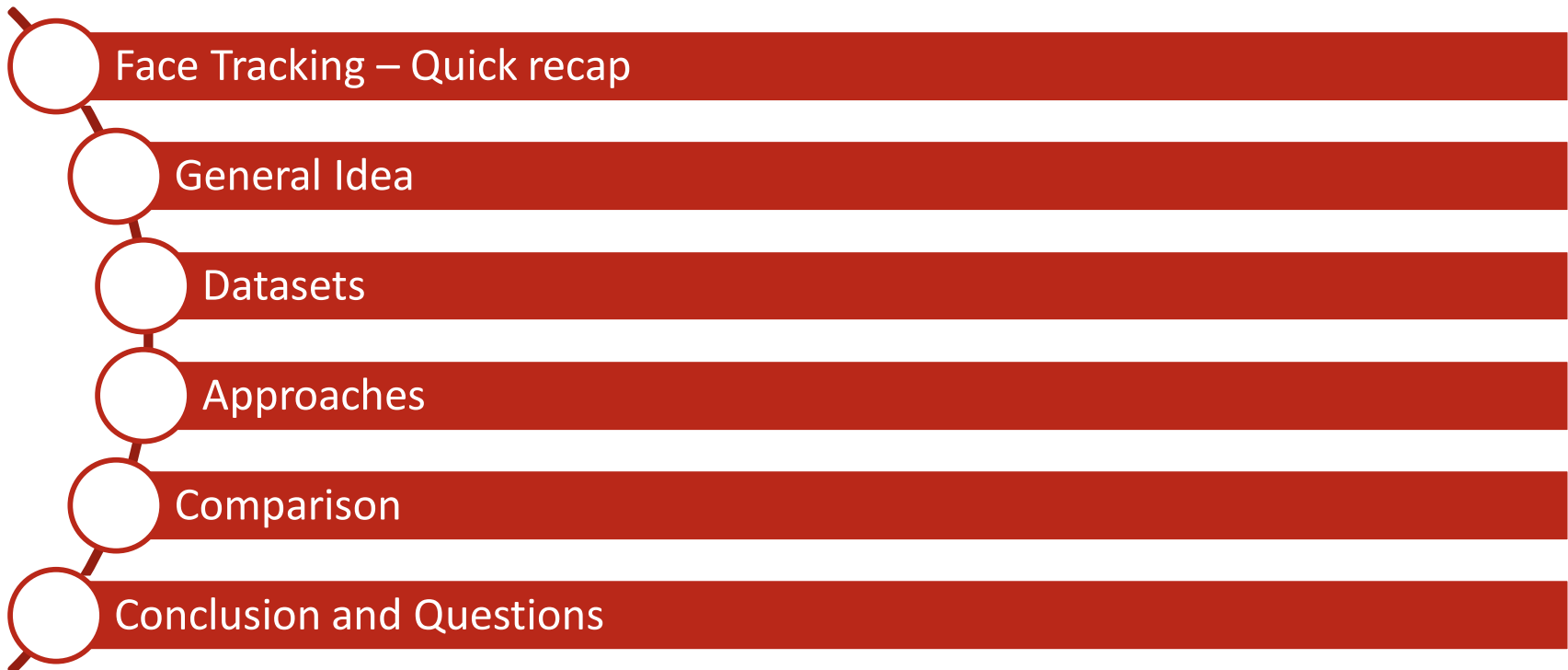
### **Survey on Face Tracking with Deep Learning**

**Vinay Balasubramanian**

**v\_balasubr18@cs.uni-kl.de**

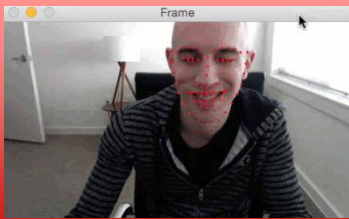
**Supervisor: Jilliam Diaz Barros**

# Outline



# Quick recap

# Face Tracking



Tracking a face across all frames of a video.

Can be bounding-box based tracking or landmark based (track specific number of keypoints around facial components)



Applications - Face analysis, Person identification, Activity recognition, Expression analysis, Face modeling etc.

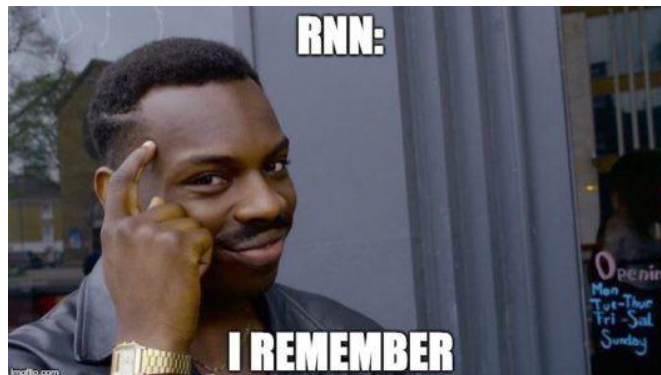


Challenges - Videos can be captured in unconstrained conditions.

May have illumination variations, large head poses, occlusions, etc.

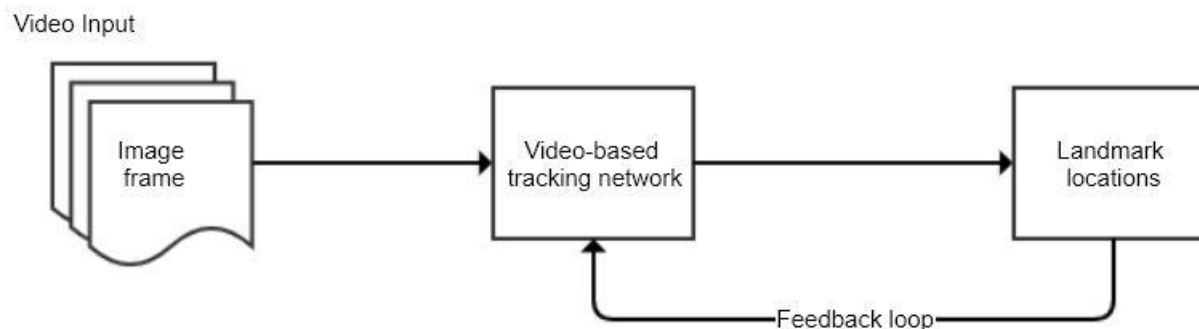
# General Idea

- Video – Sequence of frames with temporal connection
- Sequence data? (Use RNN)



# General Idea

- **Video – Sequence of frames with temporal connection**
- **Sequence data? (Use RNN)**
- **Give frames in temporal order, detect landmarks, feedback along with next frame.**



# Why Deep Learning?

- **State-of-the-art in image processing tasks**
- **Operate directly on data**
- **Learn more generic features directly from data**
- **Computational efficiency**
- **Domain knowledge is never obsolete**

# Datasets

- AFLW
- COFW
- Helen
- IBUG
- LFPW
- LFW
- 3D Menpo
- 300-W
- BIWI
- FM
- RWMB
- SynHead
- TF
- 300-VW



# Approaches

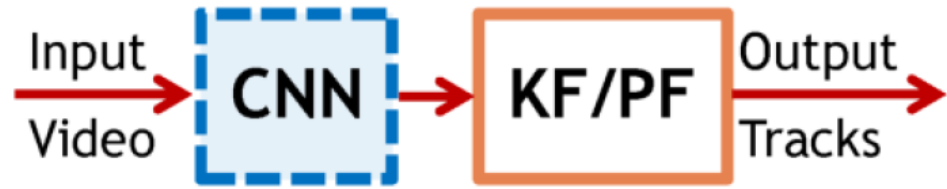
- **RNN**
- **Two-stream network**
- **LSTM**
- **Encoder-Decoder network**
- **Deep reinforcement learning**

# Using RNNs

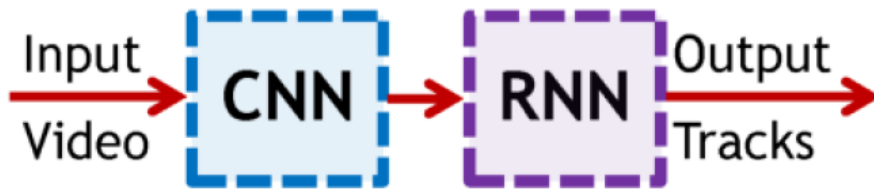
- RNNs and Bayesian filters are operationally similar



(a) Per-Frame



(b) Bayesian Filters

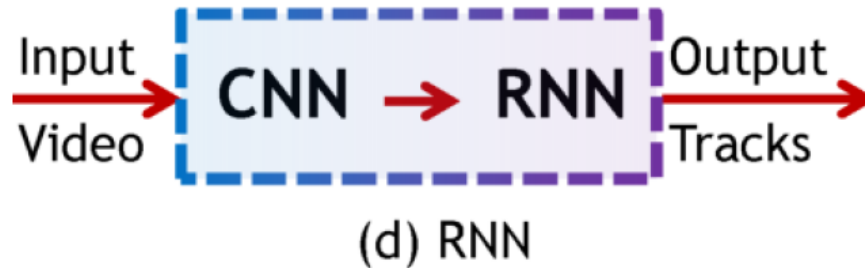


(c) Post-RNN



(d) RNN

# Using RNNs

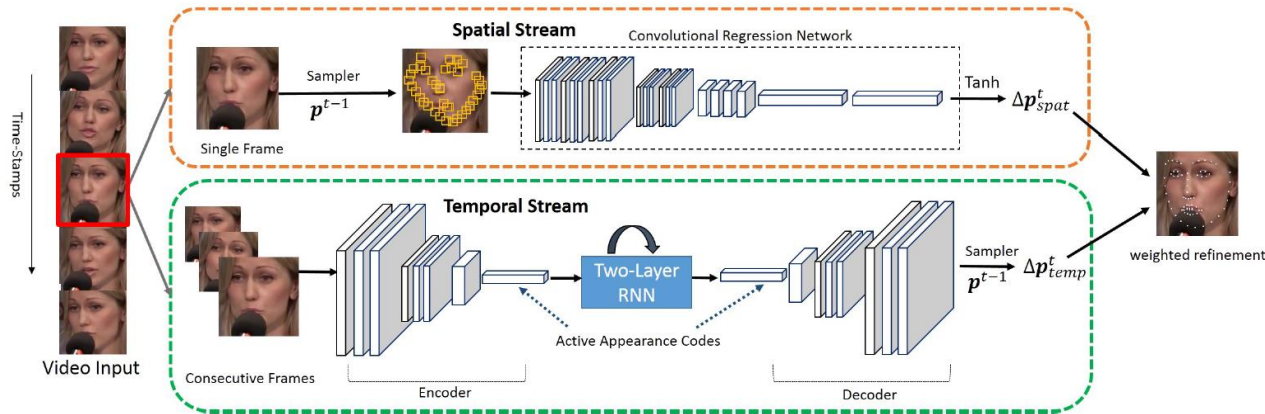


- FC-RNN is used to retain generalization of pre-trained CNN
- Trained end-to-end
- **SynHead** dataset for head pose estimation
- **300-VW** dataset for facial landmark localization
- L2 loss function
- Evaluation - Area Under the Curve (AUC), Failure Rate (FR %)

# Two-stream network

- **Exploit both appearance information from still frames(spatial) and temporal information across frames(temporal)**
- **Spatial stream – Image pixels (still) -> landmark locations**
- **Temporal stream – Compress video as active appearance codes(whole face changes across frames)**

# Two-stream network



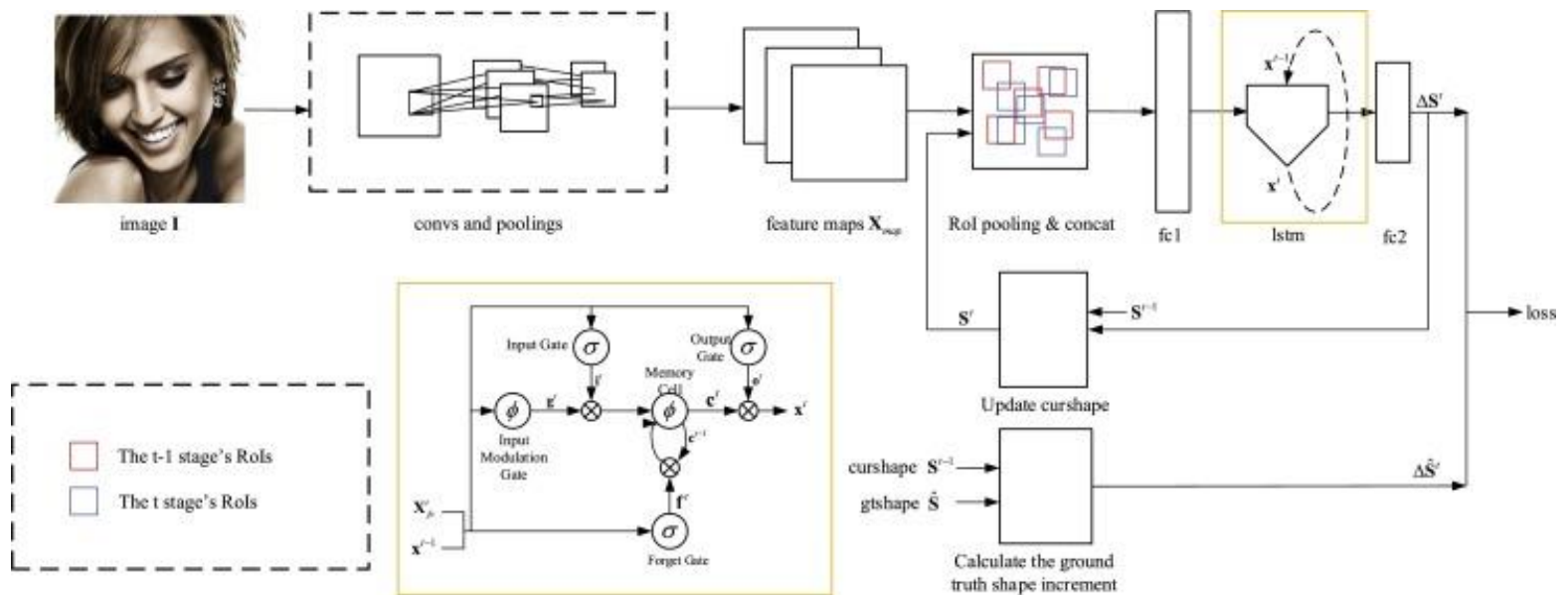
- Spatial stream transforms local facial patches to shape residuals used to refine current face shape from previous.
- Temporal stream – Encoder-decoder network with 2-layer RNN. Capture facial dynamics in temporal dimension
- Final prediction is a weighted fusion of spatial and temporal streams shape updates

# Two-stream network

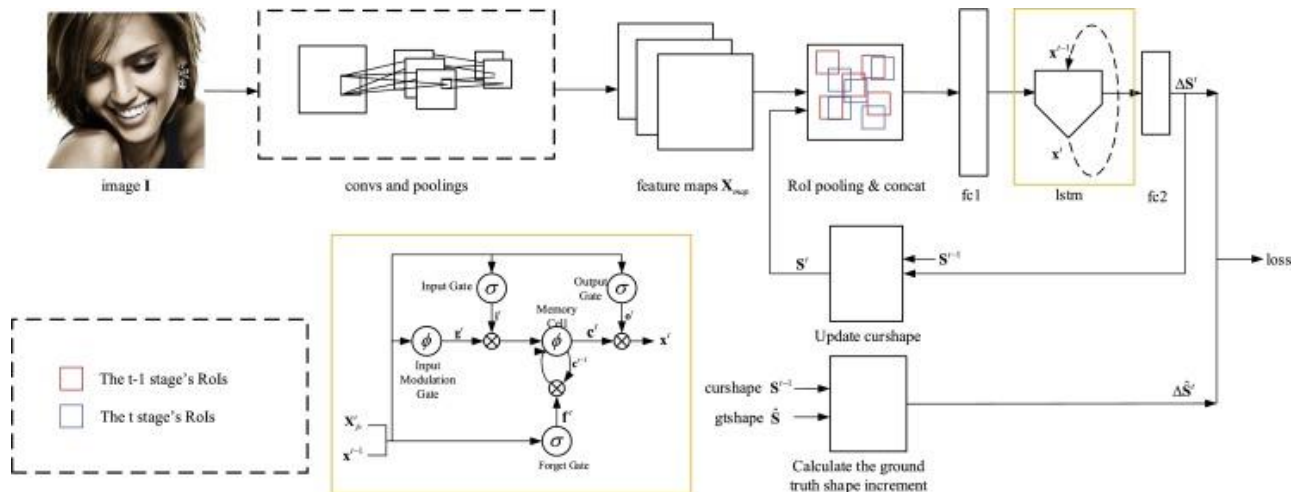
- Tested on **300-VW** and **TF** datasets
- Evaluation – Normalized RMSE and Cumulative Error Distribution plots
- Weighted fusion –  $\beta_1$  and  $\beta_2 = 0.5$  yields the best performance

# LSTMs

- LSTM is used to exploit spatial and temporal information



# LSTMs



- **Input – Image and Initial face shape**
- **Output – Predicted shape increment for the initial face shape**
- **Input -> several conv + max pooling -> ROI pooling for initial face shape -> concat -> FC layer -> LSTM -> predicted shape increment**
- **Update initial shape according to predicted shape increment**



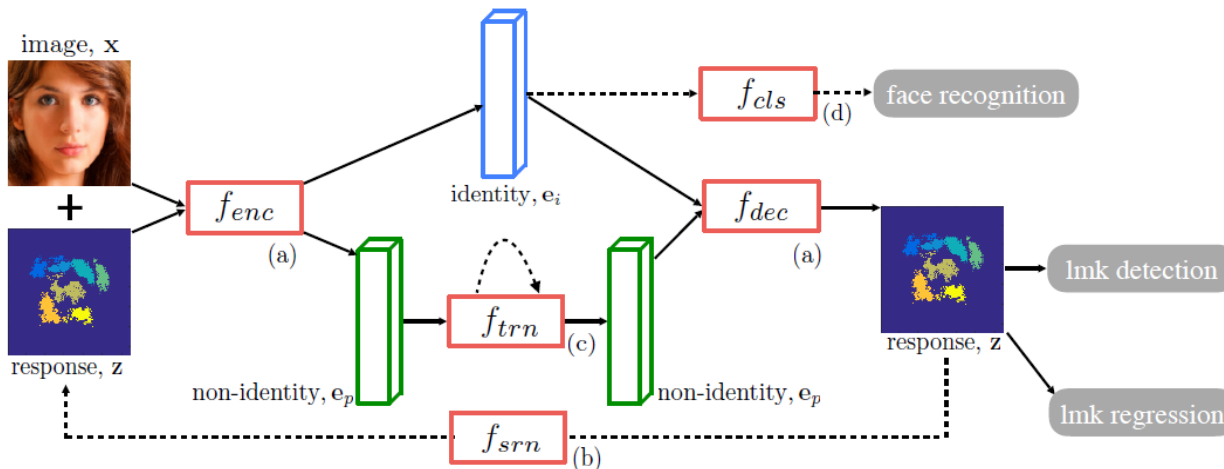
# LSTMs

- Landmark detection method
- Trained on **COFW, LFPW, Helen, AFW**
- Evaluation – Point-to-point RMSE
- Runtime – 18ms

# Encoder-Decoder Network

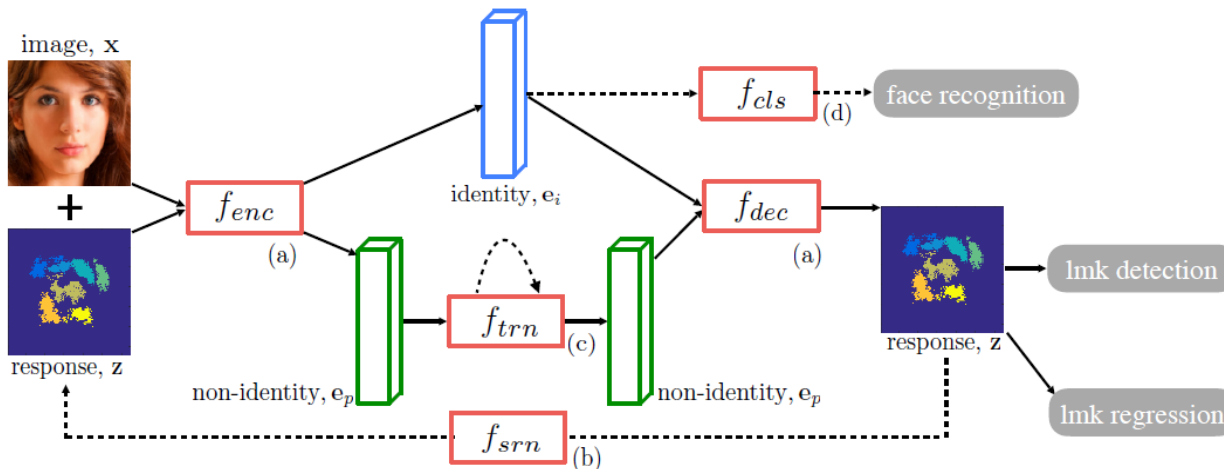
- **Encoder – Image pixels -> Low dimensional feature space**
- **Decoder – Features in low dimensional space -> facial landmark heatmaps**
- **Feedback loop between the output(facial points) and the input**

# Encoder-Decoder Network



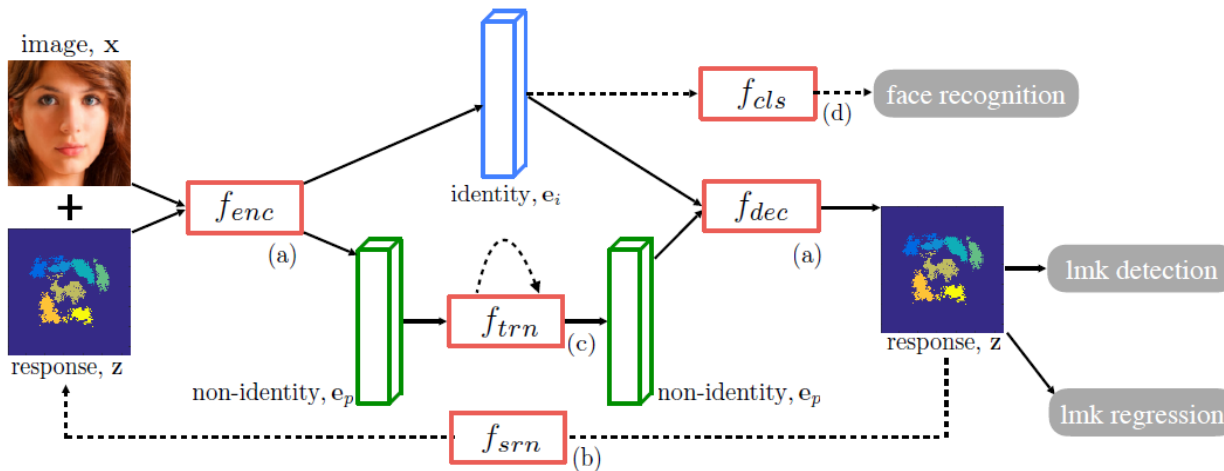
- Encoder -> Feature disentangling on low dimensional representation -> Decoder
- Disentangle temporal-variant and temporal-invariant factors
- Temporal-invariant: Person identity
- Temporal-variant: Pose, expression, illumination

# Encoder-Decoder Network



- **Spatial recurrent learning: Coarse-to-fine landmark search**
- **Feedback loop: Previous prediction + image**
- **Landmark detection: Detect major landmarks**
- **Landmark regression: Refine predicted locations from previous detection step**

# Encoder-Decoder Network



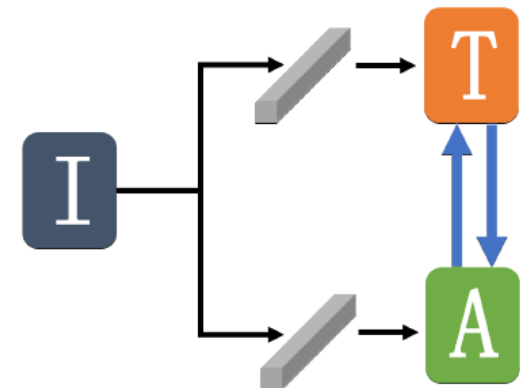
- Temporal recurrent learning: Model non-identity factors (temporal-variant) using LSTM

# Encoder-Decoder Network

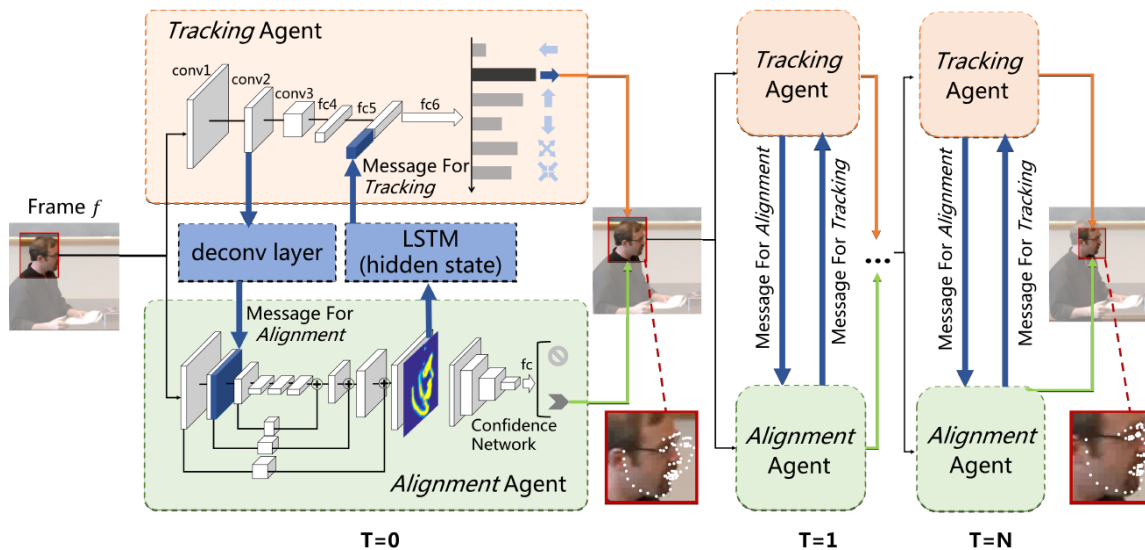
- Evaluated on – **AFLW**, **LFW**, **Helen**, **LFPW**, **TF**, **FM**, **300-VW**
- Evaluation – Inter-ocular distance normalized RMSE

# Reinforcement Learning

- Bounding box generation and facial landmark detection are heavily dependent
- Two agents – bounding box **T**racking and facial landmark **A**lignment



# Reinforcement Learning



- Communication channels between agents (Deep Q-learning)
- Current state initialized to terminal state of previous frame
- Agents decide sequence of actions based on observed state and received messages



# Reinforcement Learning

- Go to next frame when landmarks are finalized
- State – Current image region extracted by bounding box
- Action – Tracking agent(Movement), Alignment agent(stop/continue iterations)



- Reward – Landmark detection accuracy improvements

# Reinforcement Learning

- Evaluated on Category 3 of **300-VW**
- Supervised learning stage –
  - Alignment agent trained on **300-W**
  - Tracking agent trained on **300-VW**
- Reinforcement learning stage –
  - Whole network trained on **300-VW**
- Evaluation – Normalized RMSE and cumulative error distribution plots
- DADRL-3D – Trained with 3D data from **3D Menpo**. More robust to large head pose. 3D landmarks.

# Comparison

Approach	Evaluated on dataset	Evaluation metrics
Dynamic Facial Analysis using RNN	300-VW	AUC, FR
Two stream transformer network	TF, 300-VW	RMSE, CED plot
Face alignment recurrent network	COFW, LFPW, IBUG, 300-VW	RMSE
Recurrent encoder-decoder network	TF, 300-VW	RMSE
Dual agent deep reinforcement learning	300-VW	RMSE and CED plot

# Comparison

Approach	300-VW		TF		Runtime( ms)
	RMSE(68 landmarks )	RMSE(7 landmarks )	RMSE(68 landmarks )	RMSE(7 landmarks )	
Dynamic Facial Analysis using RNN	6.16				
Two stream transformer network	5.59			<b>2.13</b>	33
Face alignment recurrent network	5.9				<b>18</b>
Recurrent encoder-decoder network	5.15	<b>5.29</b>	<b>2.77</b>	2.89	40
Dual agent deep reinforcement learning	<b>3.09</b>				

# References

1. Jinwei Gu, Xiaodong Yang, Shalini De Mello, Jan Kautz: Dynamic Facial Analysis: From Bayesian Filtering to Recurrent Neural Network(2017).
2. Hao Liu, Jiwen Lu, Jianjiang Feng, Jie Zhou: Two-Stream Transformer Networks for Video-based Face Alignment(2017).
3. Qiqi Hou, Jinjun Wang, Ruibin Bai, Sanping Zhou, Yihong Gong: Face Alignment Recurrent Network(2017).
4. Xi Peng, Rogerio S. Feris, Xiaoyu Wang, Dimitris N. Metaxas: RED-Net: A Recurrent Encoder-Decoder Network for Video-based Face Alignment(2017).
5. Minghao Guo, Jiwen Lu, and Jie Zhou: Dual-Agent Deep Reinforcement Learning for Deformable Face Tracking(2018).

# THANK YOU

# QUESTIONS?