

Simultaneous Detection and Characterization of Time Delay Attack in Cyber-Physical Systems

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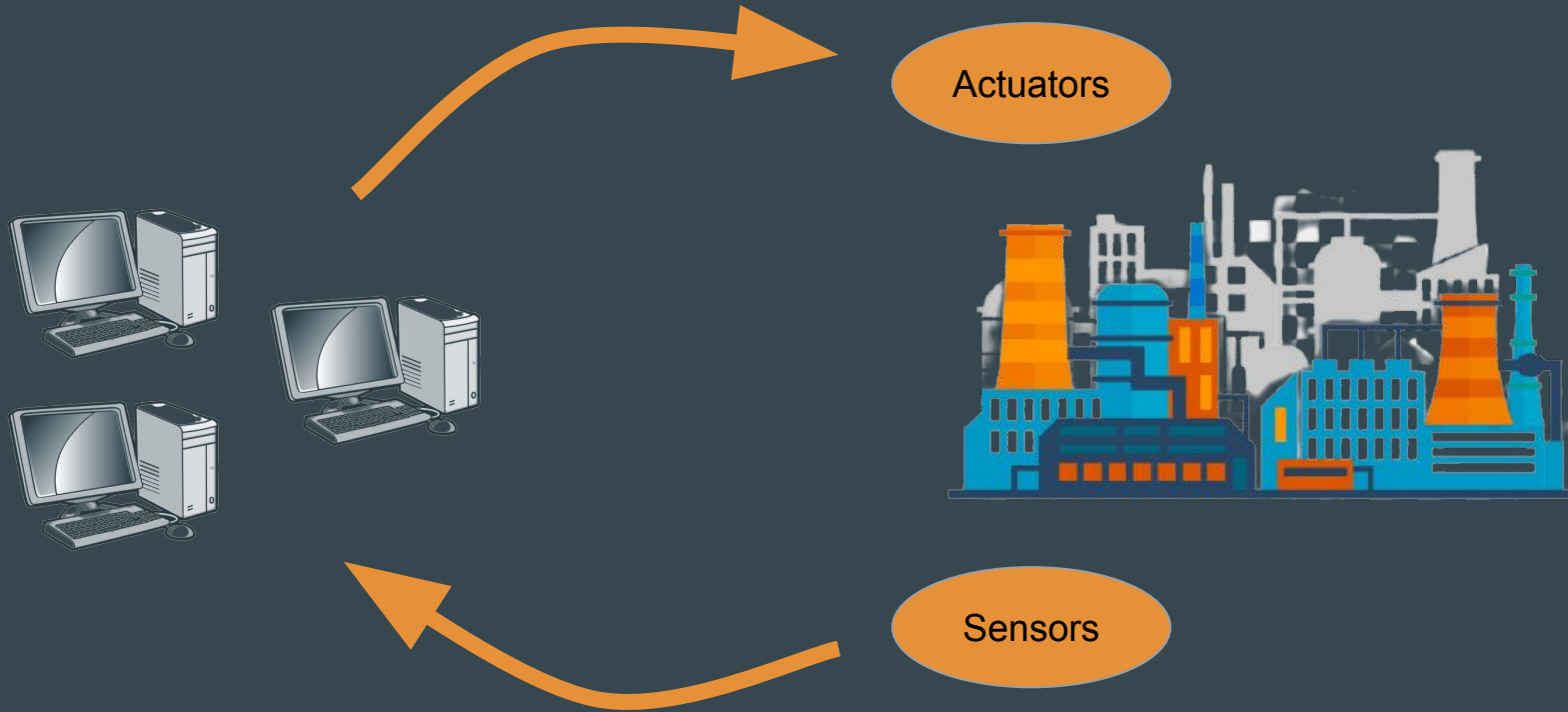
⁴University of Illinois at Urbana-Champaign, USA



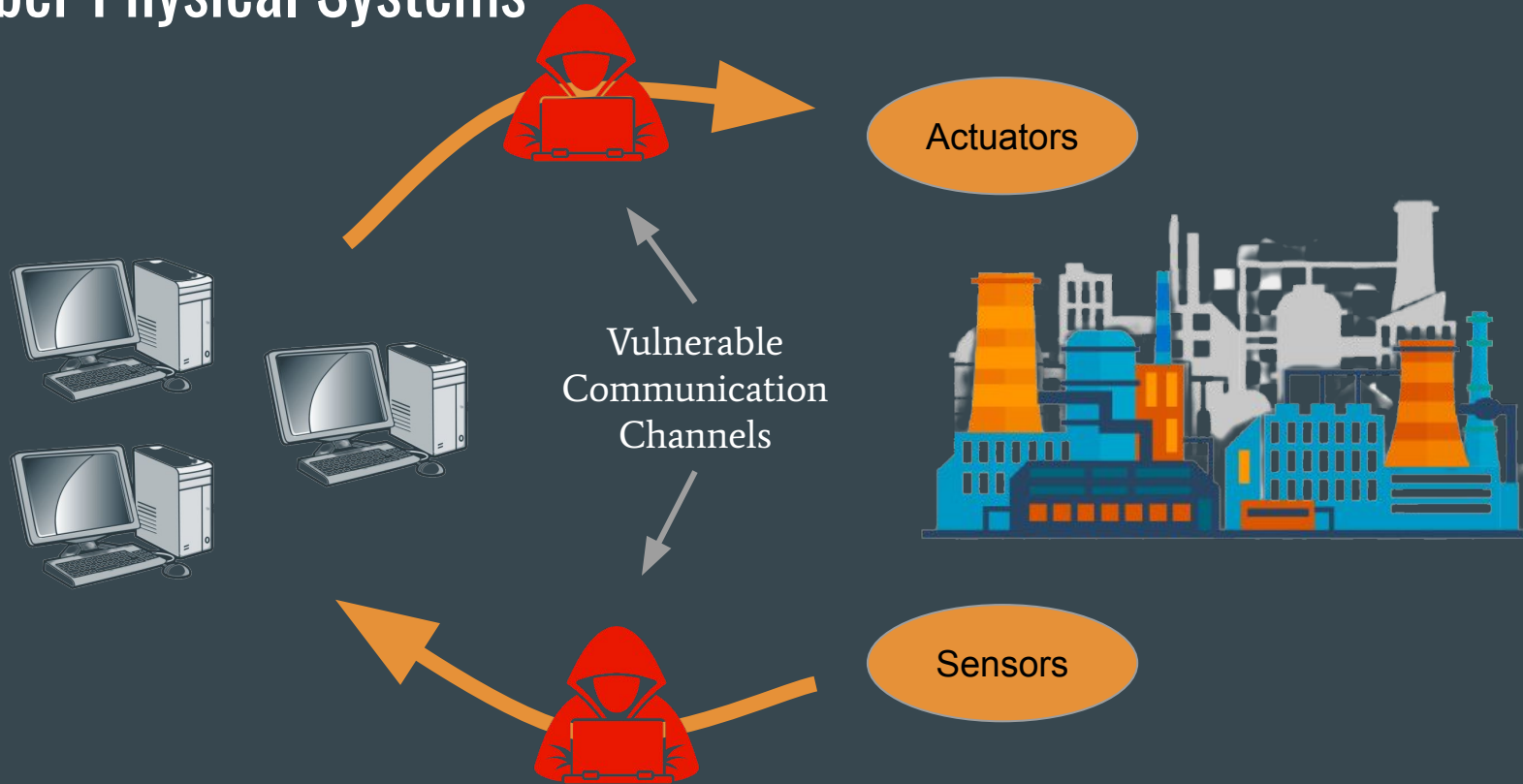
Background

- **Cyber-Physical Systems**
- **Time Delay Attack**
- **System and Threat Models**

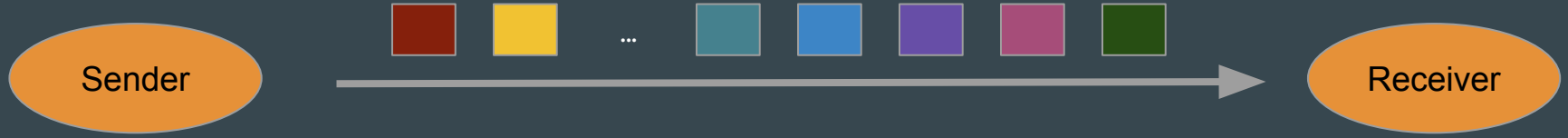
Cyber Physical Systems



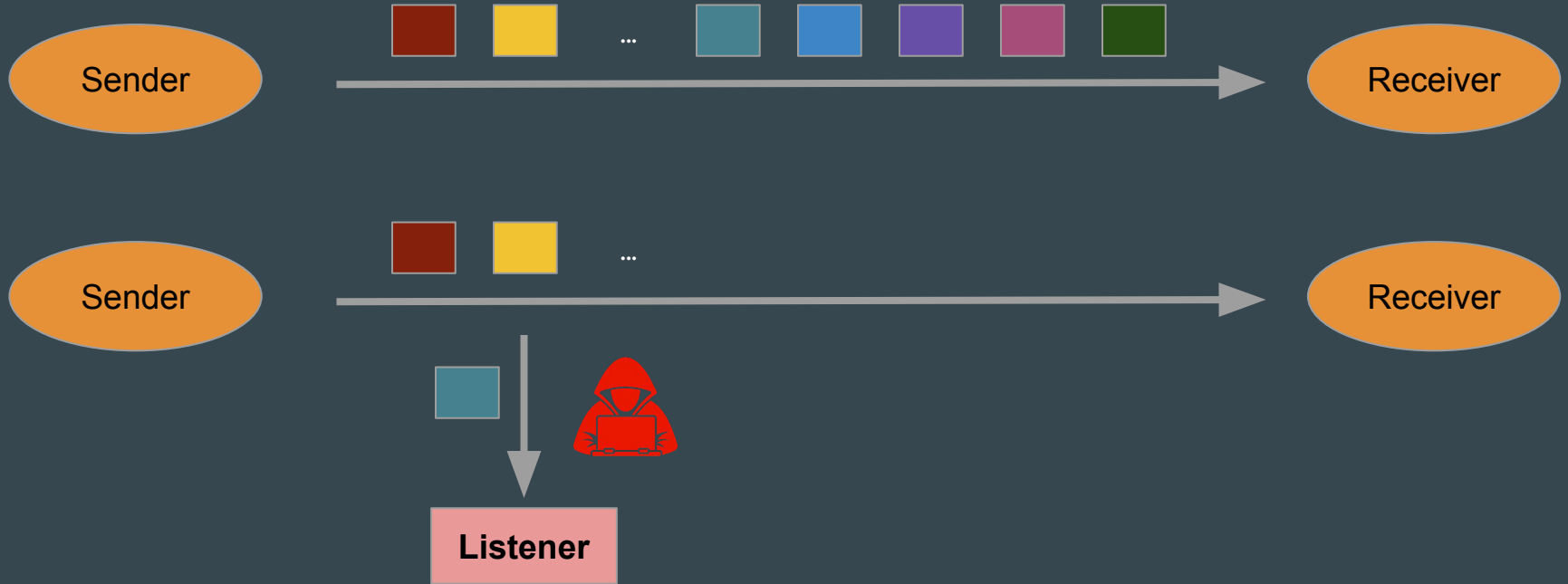
Cyber Physical Systems



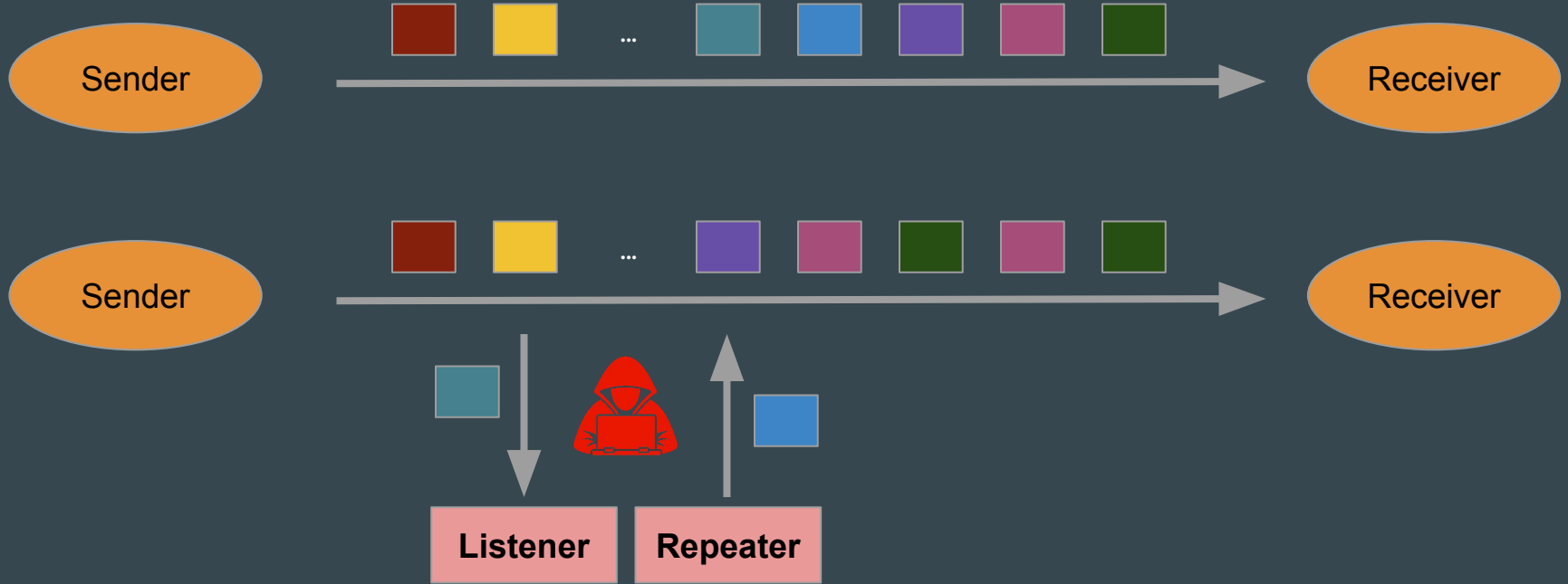
Time Delay Attack



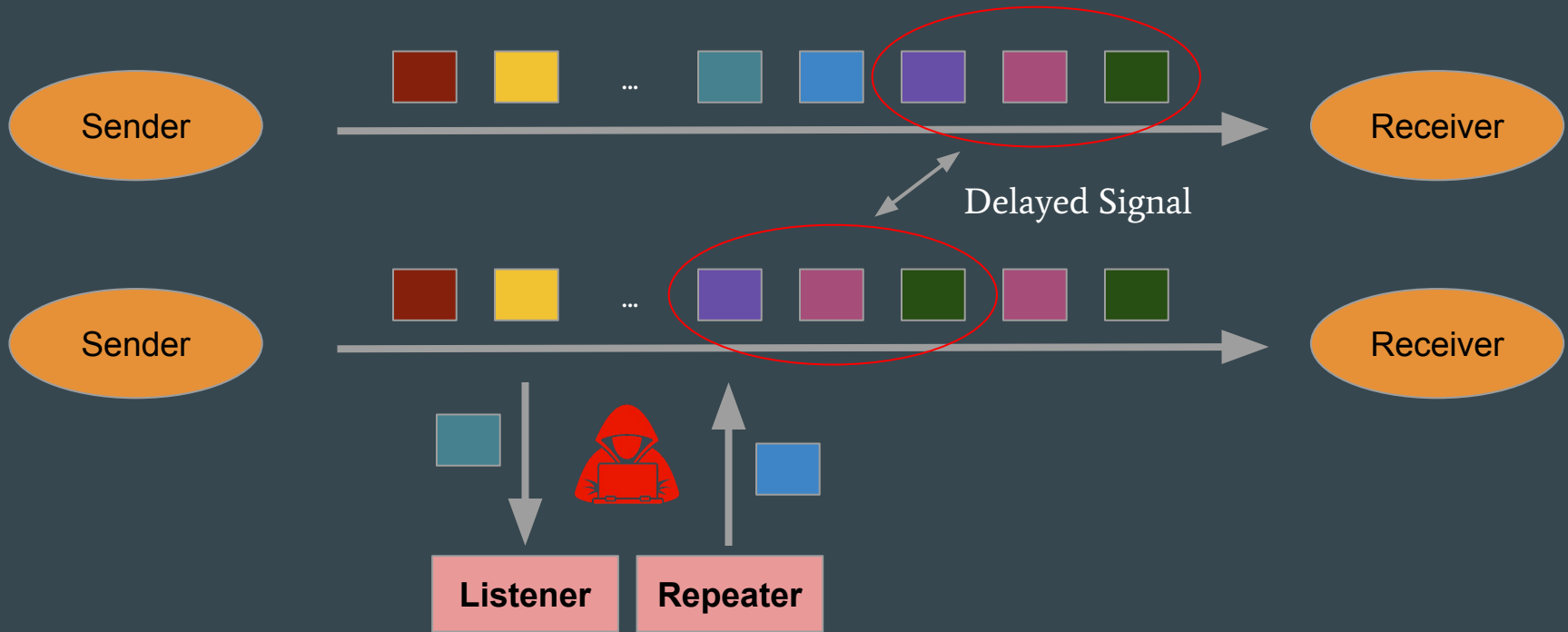
Time Delay Attack



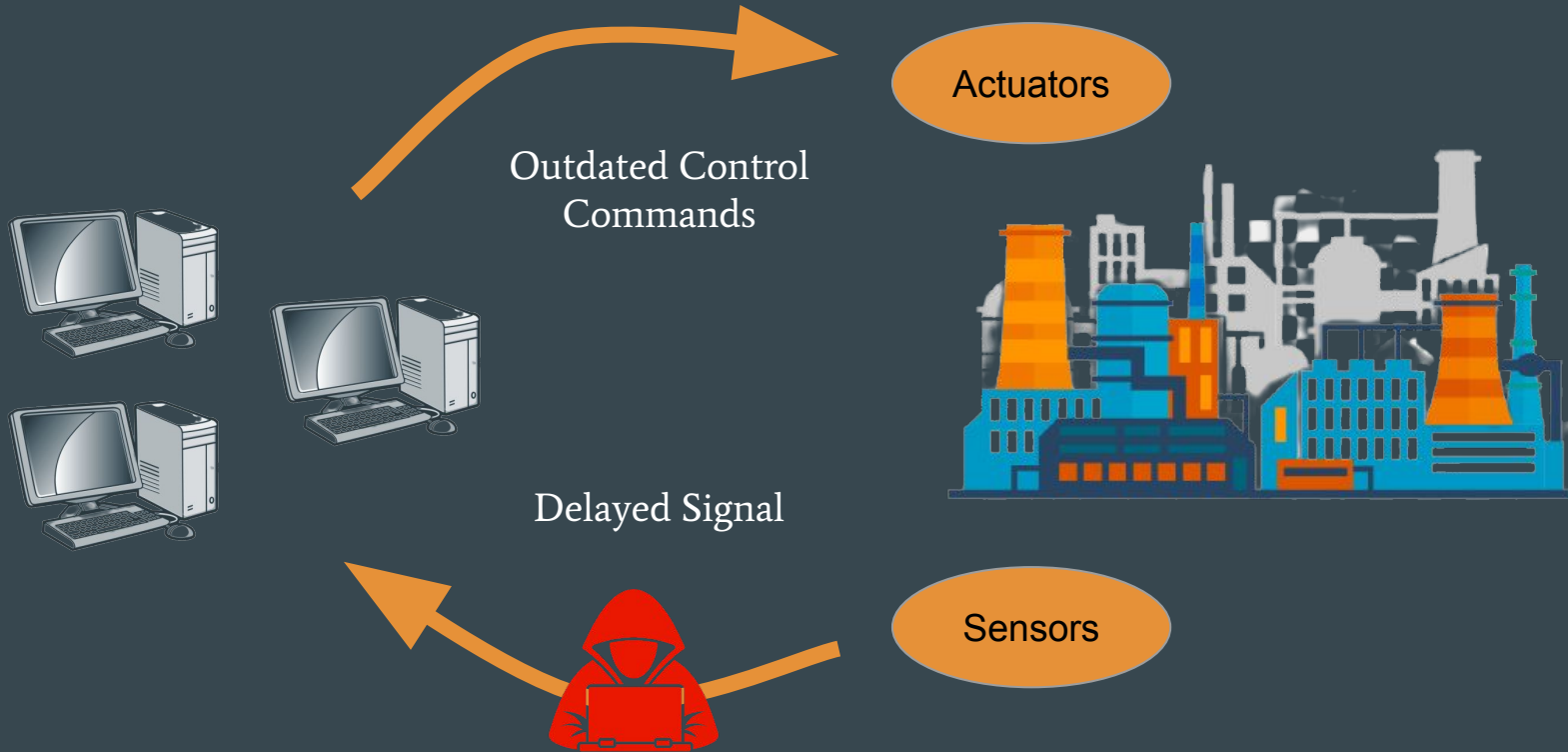
Time Delay Attack



Time Delay Attack



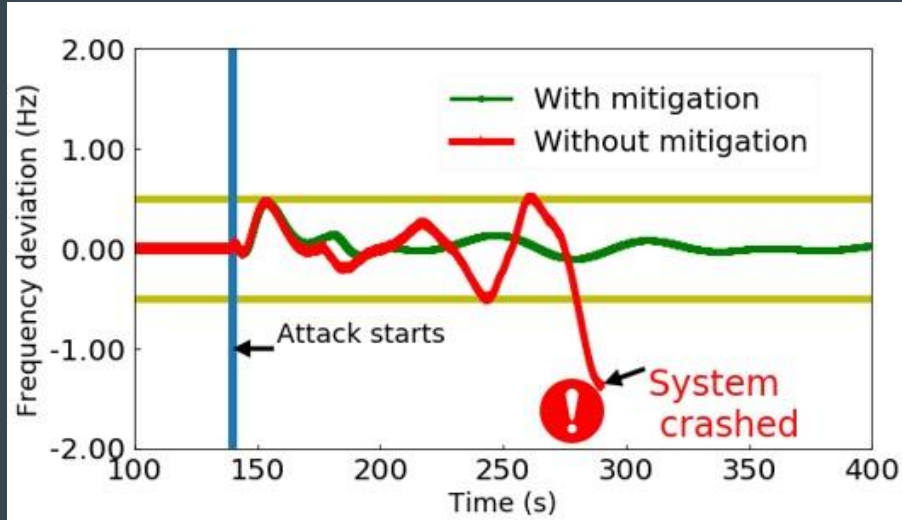
Cyber Physical Systems



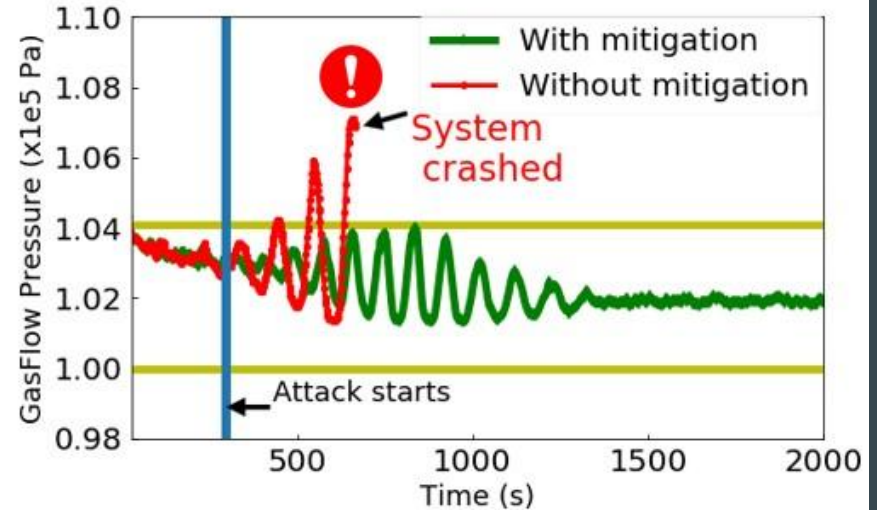
Why TDA?

- No abrupt change in signal traffic
- Does not require breaking the signal encryptions
- Can cause serious damage in closed loop systems

Impact Assessment and Mitigation



(a) AGC output.



(b) Power plant output.

System Model

- Closed loop discrete-time CPS control systems (PPCS and AGC)
- Time is divided into slots
- Running simulations to create both training and testing dataset
- System is subjected to disturbances, e.g., measurement noises, actuation biases, setpoint changes, etc

Threat Model

- Packet is maliciously delayed by τ but not tampered (τ is an integer)
- Attack launched with a random delay value (τ) and a random delay location
- Assumption : Lack of a trustworthy clock synchronization between the controller and the actuator

Challenges & Motivation

- **Model-driven vs Data-driven methods**
 - **Real-Time vs Post-mortem analysis**
 - **Long Input Streams**
-

Model-driven vs Data-driven methods

- Mathematical modeling creates highly complex models which are not robust to real-world noise
- Data-driven methods can learn to extract useful latent features that cannot be modelled manually
- Data-driven methods are easier to generalize and does not require domain expertise

Real-time vs Post-mortem analysis

Real-time Analysis

- Can help prevent damage
- Input information is a continuous data stream
- Can be inaccurate initially, but has the ability to improve over time

Post-mortem Analysis

- Does not have any direct practical use
- Complete input trace is available.
- Can be fairly accurate as it has seen the complete input signal

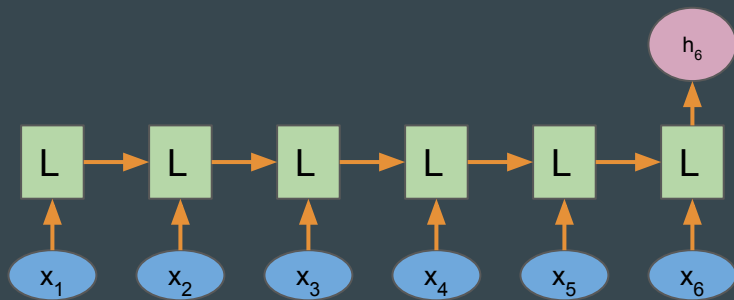
Long continuously running input stream

- Updating the output based on only the new input
- Processing the complete input signal at every time step can be very expensive
- Long input streams can lose information from the past. Traditional LSTMs are not suitable for the task

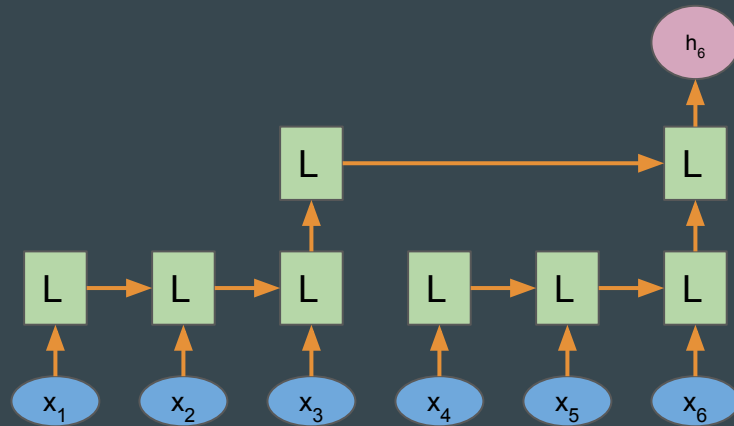
Our Solution

- **Hierarchical LSTM**
 - **Multi-head Output**
 - **Asynchronous Training**
 - **Interpretation Strategies**
 - **Evaluation Results**
-

Hierarchical LSTM

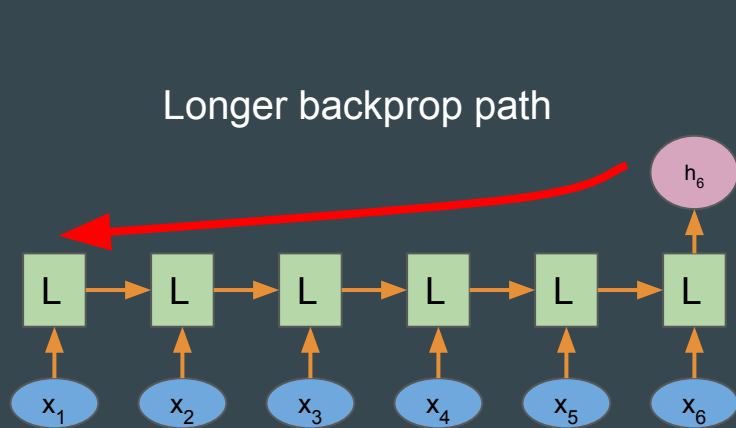


Traditional LSTM

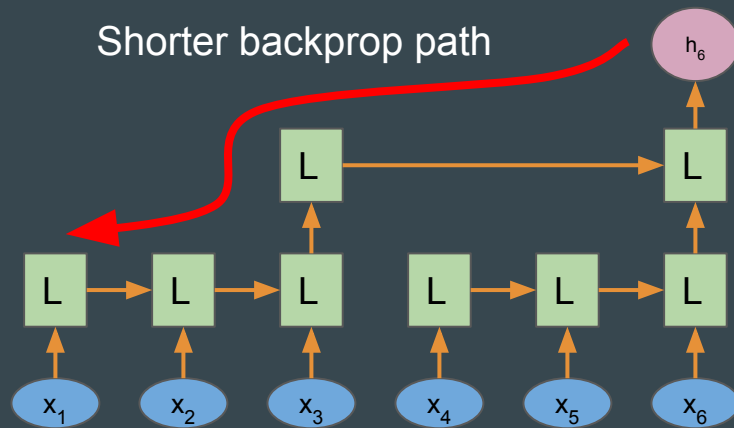


Hierarchical LSTM

Hierarchical LSTM

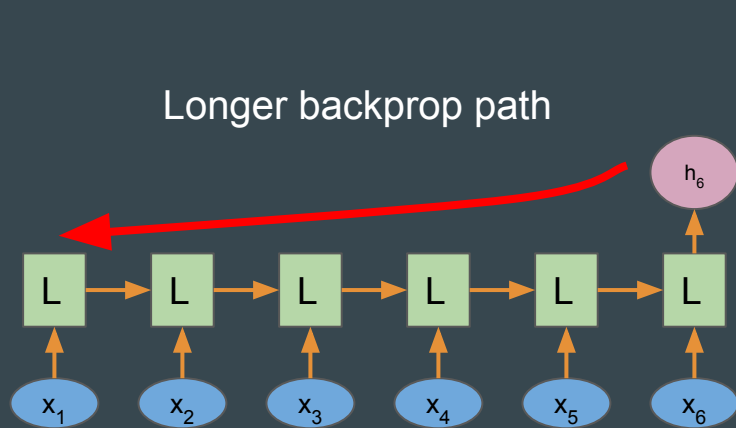


Traditional LSTM

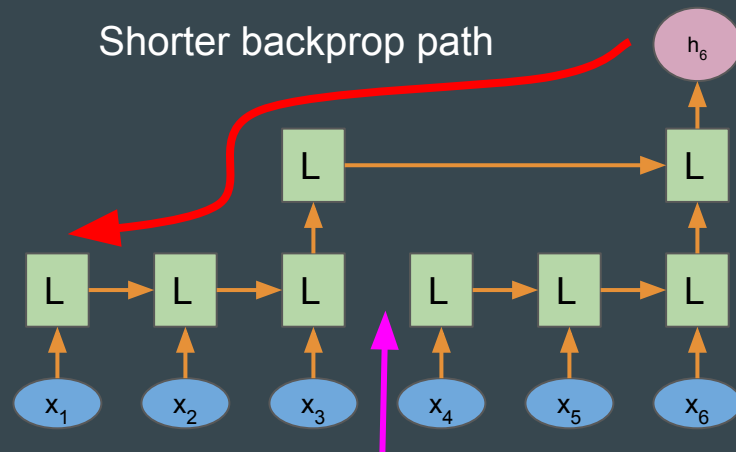


Hierarchical LSTM

Hierarchical LSTM



Traditional LSTM



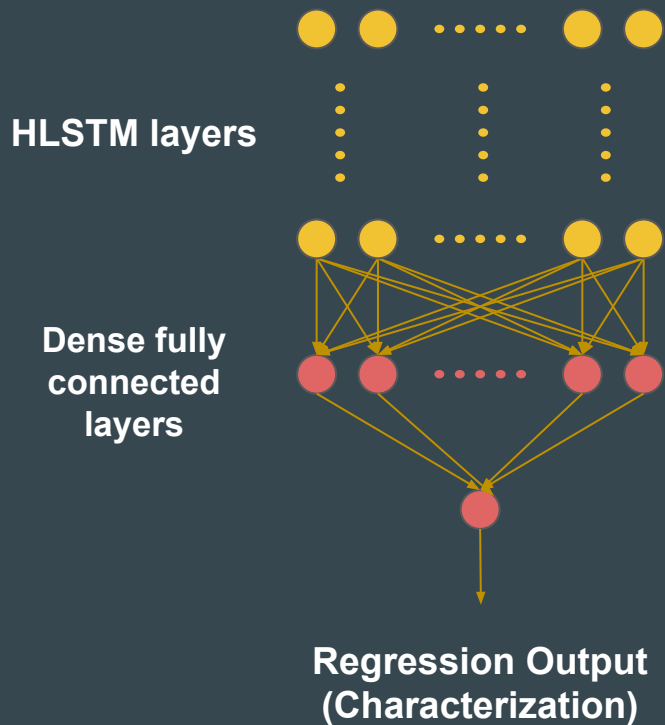
Periodic removed links in lower LSTM

Hierarchical LSTM

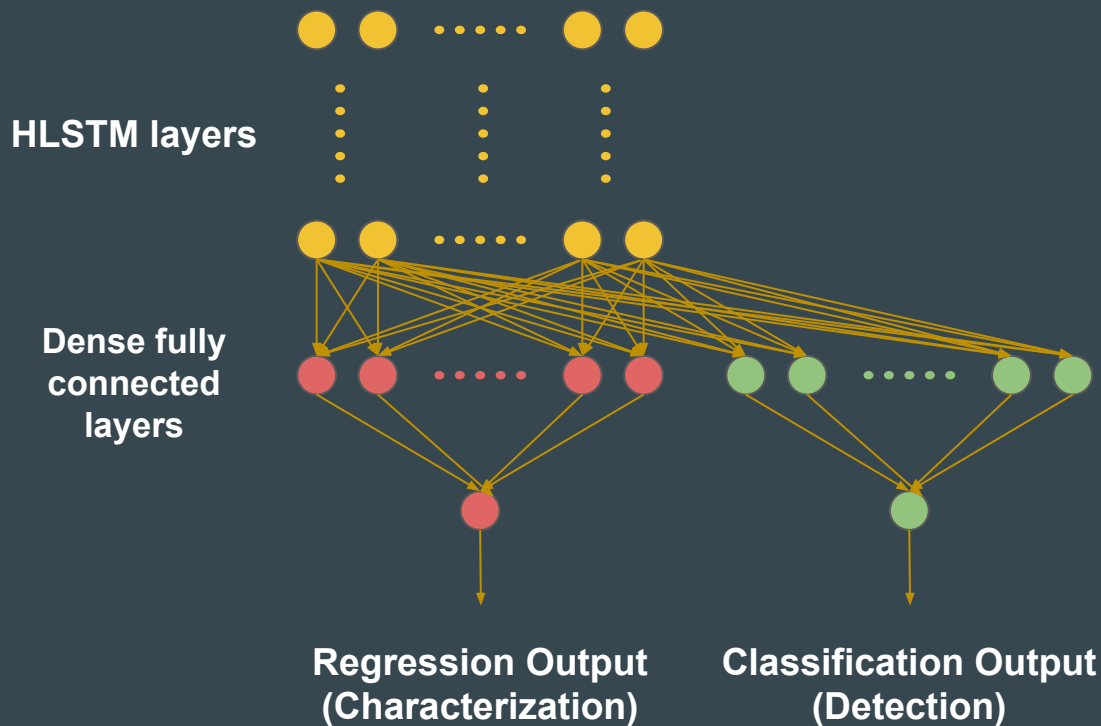
Specialized Detection and Characterization



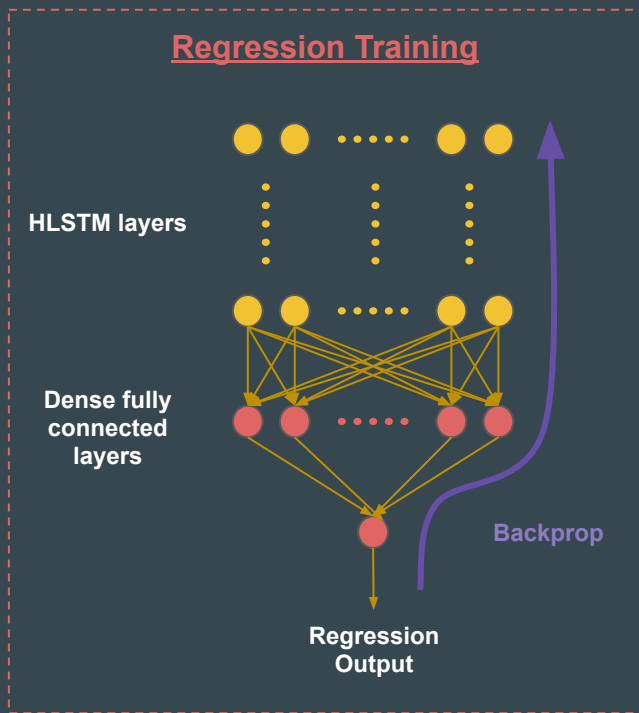
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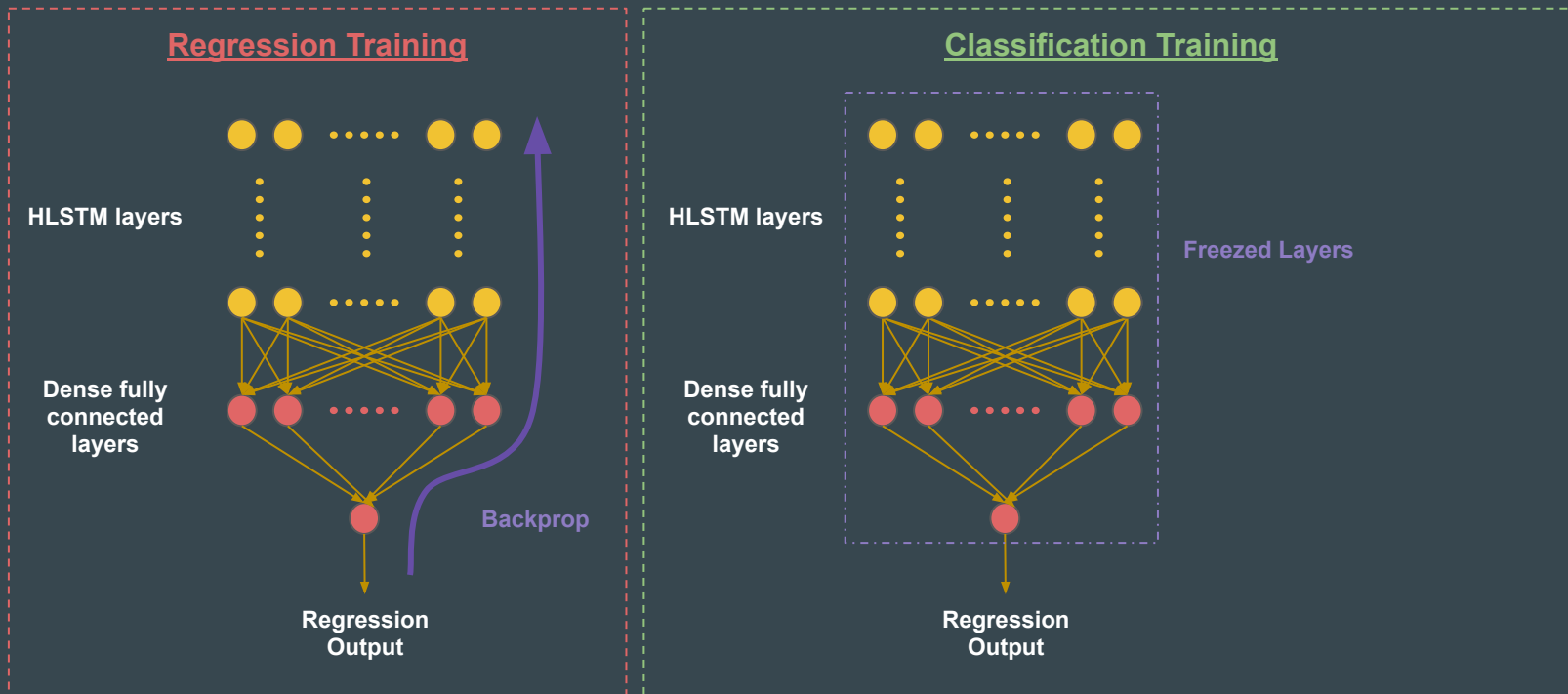
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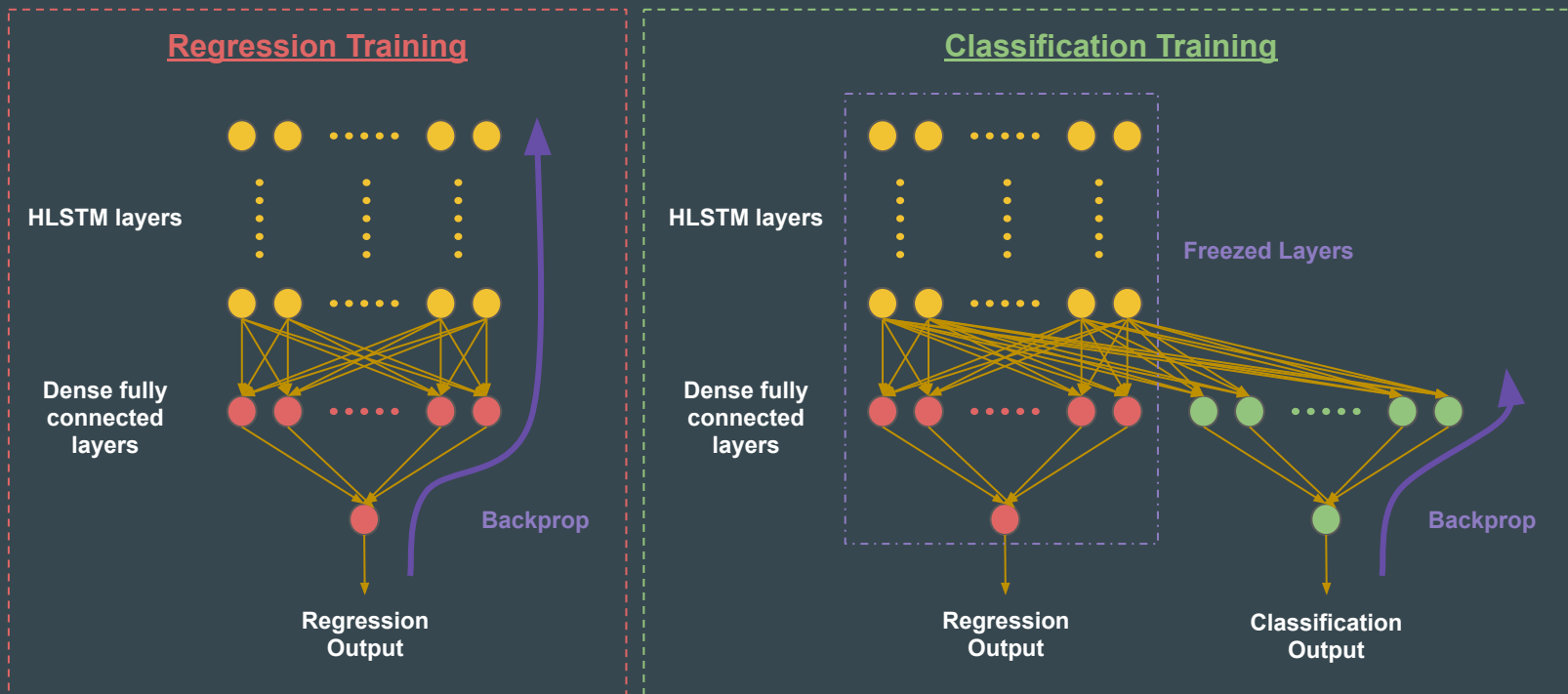
Asynchronous Training



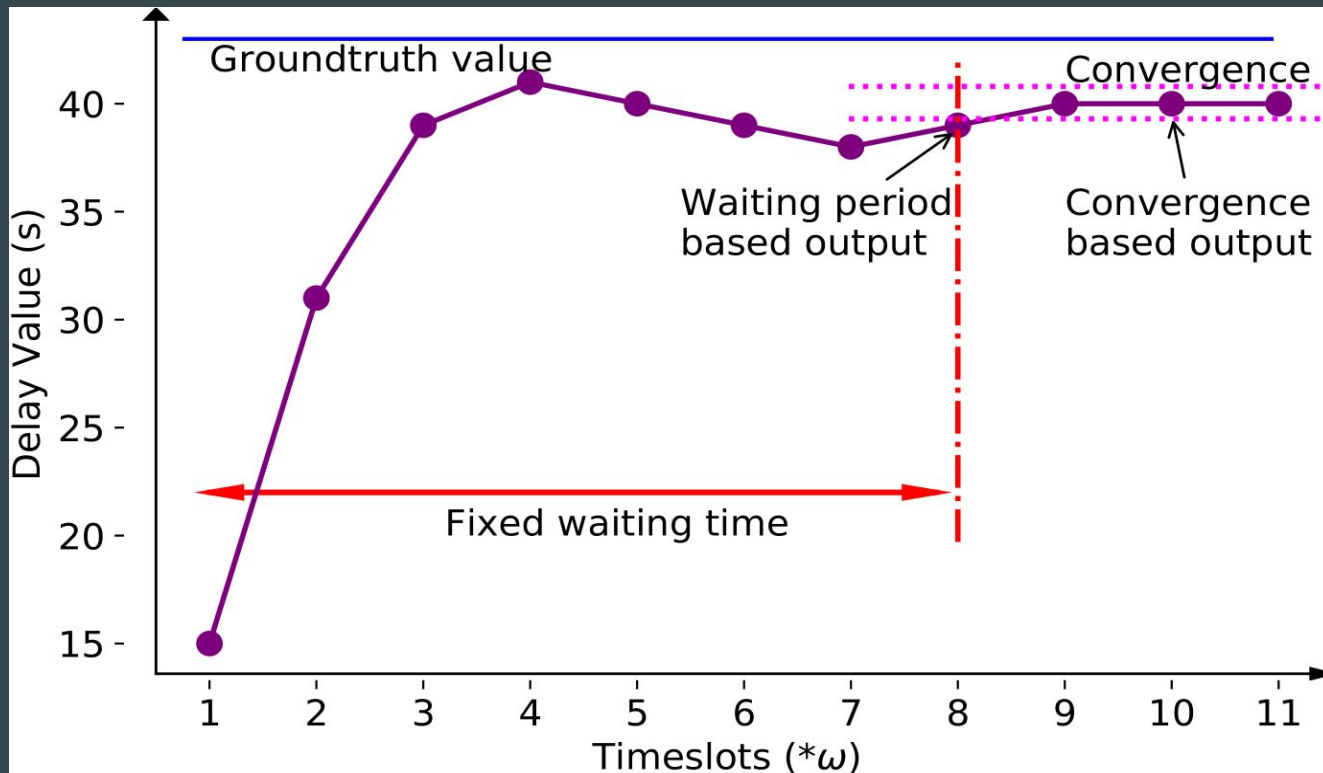
Asynchronous Training



Asynchronous Training

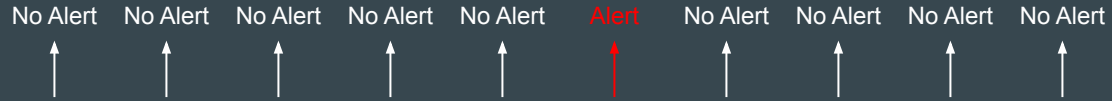


Flexible Interpretability (Regression)



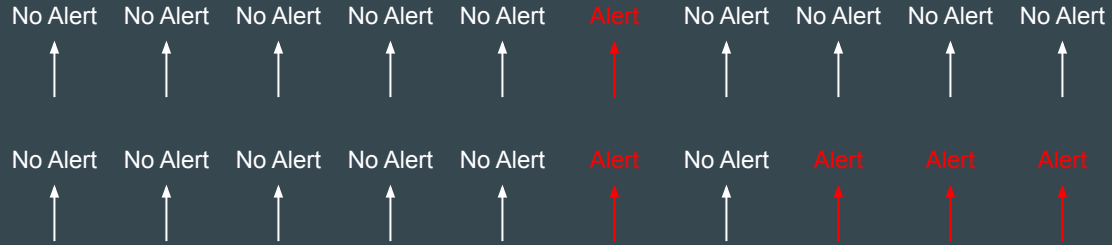
Flexible Interpretability (Classification)

No Alert No Alert No Alert No Alert No Alert **Alert** No Alert No Alert No Alert No Alert



↑ ↑ ↑ ↑ ↑ ↑ ↑ ↑ ↑ ↑

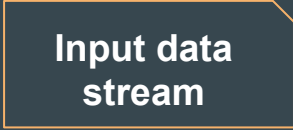
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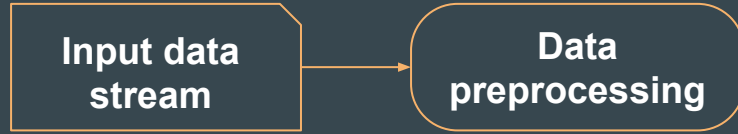


Complete Model



**Input data
stream**

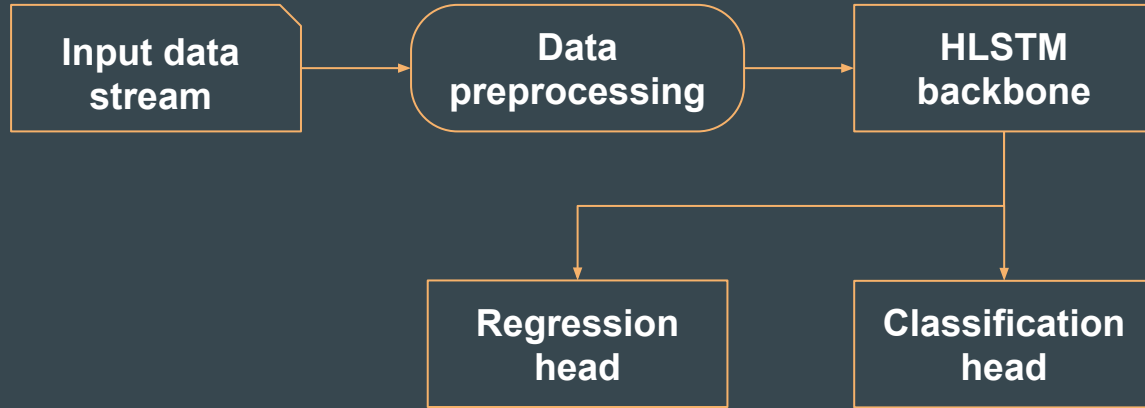
Complete Model



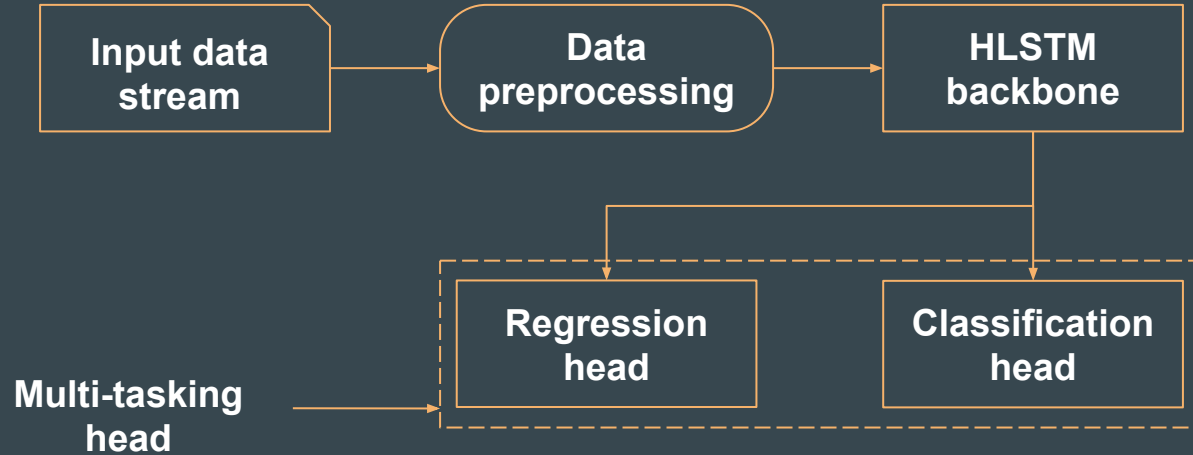
Complete Model



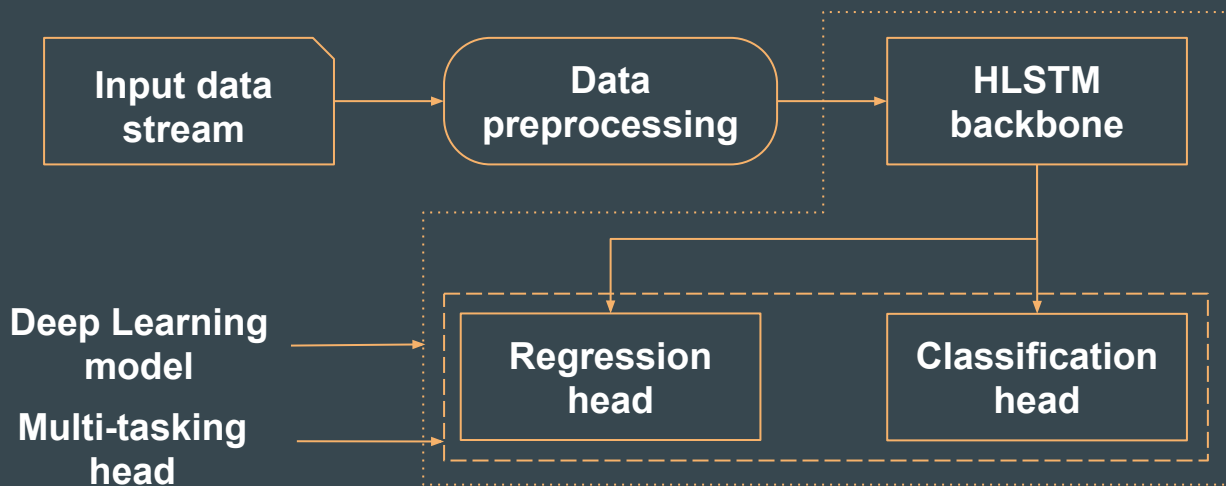
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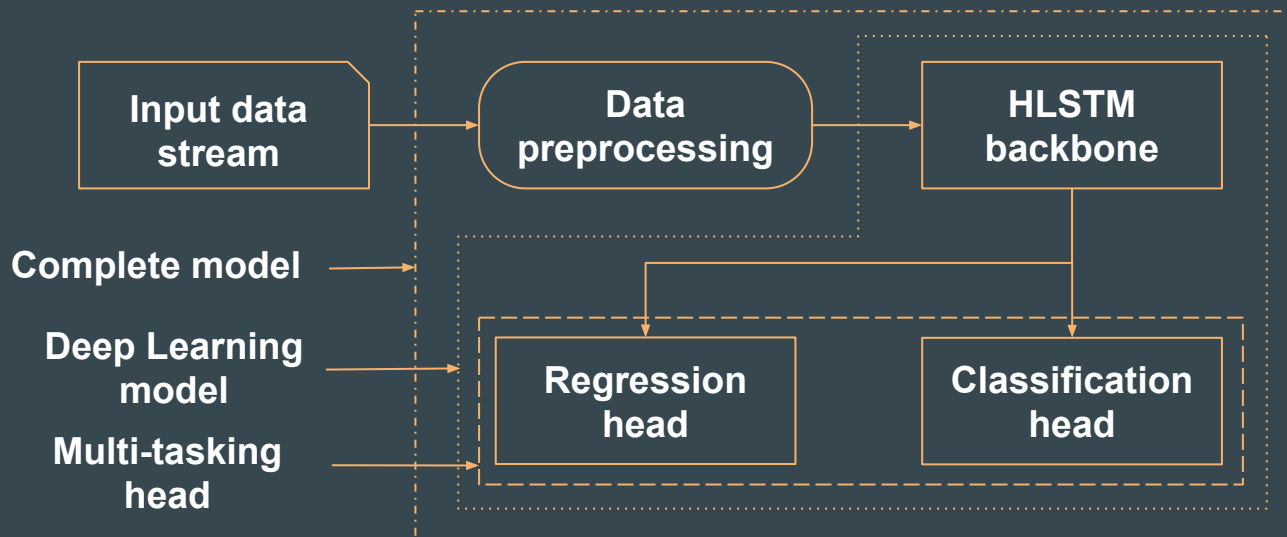
Complete Model



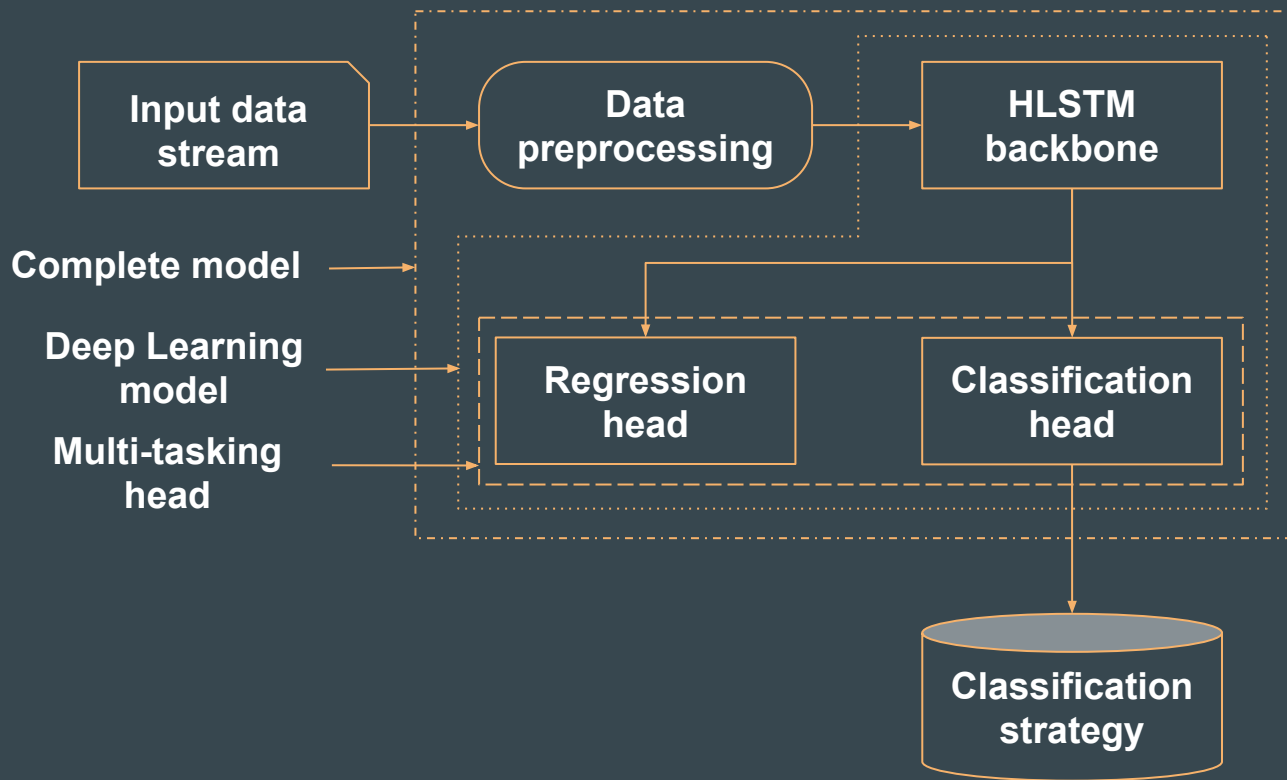
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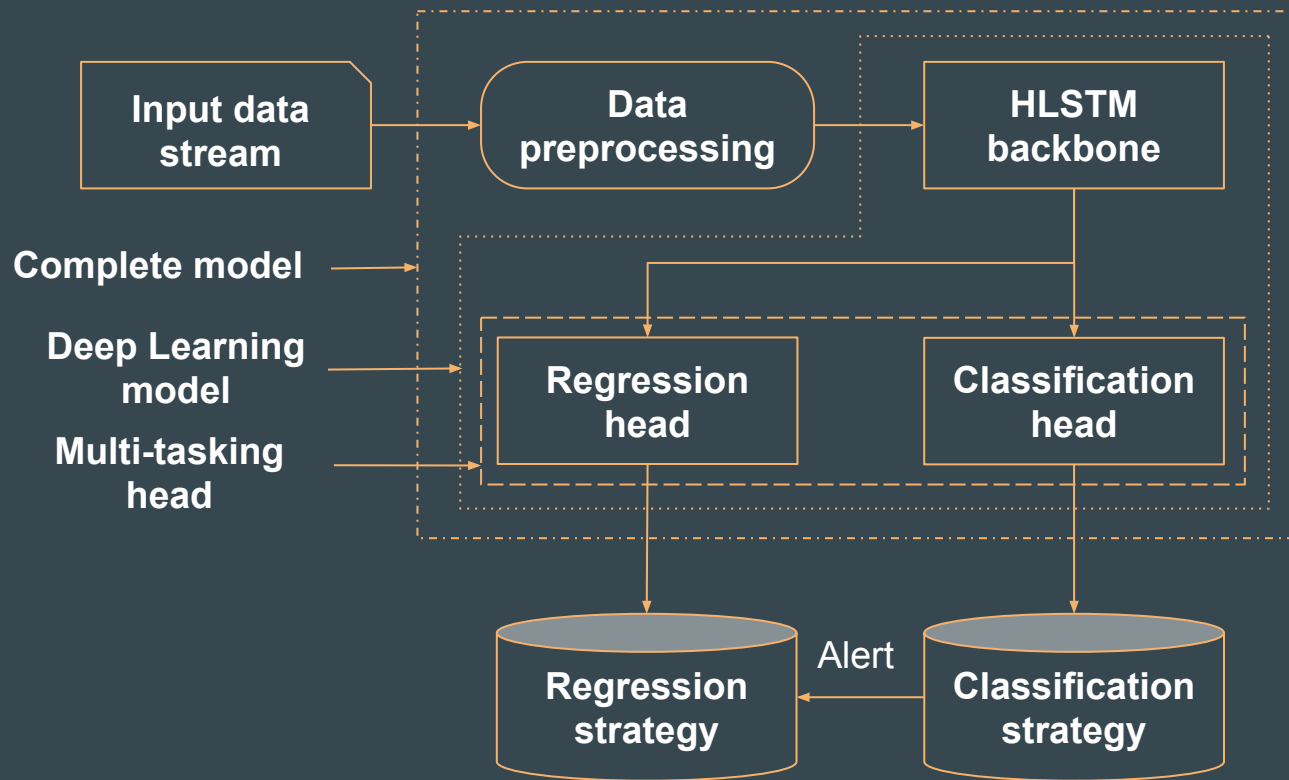
Complete Model



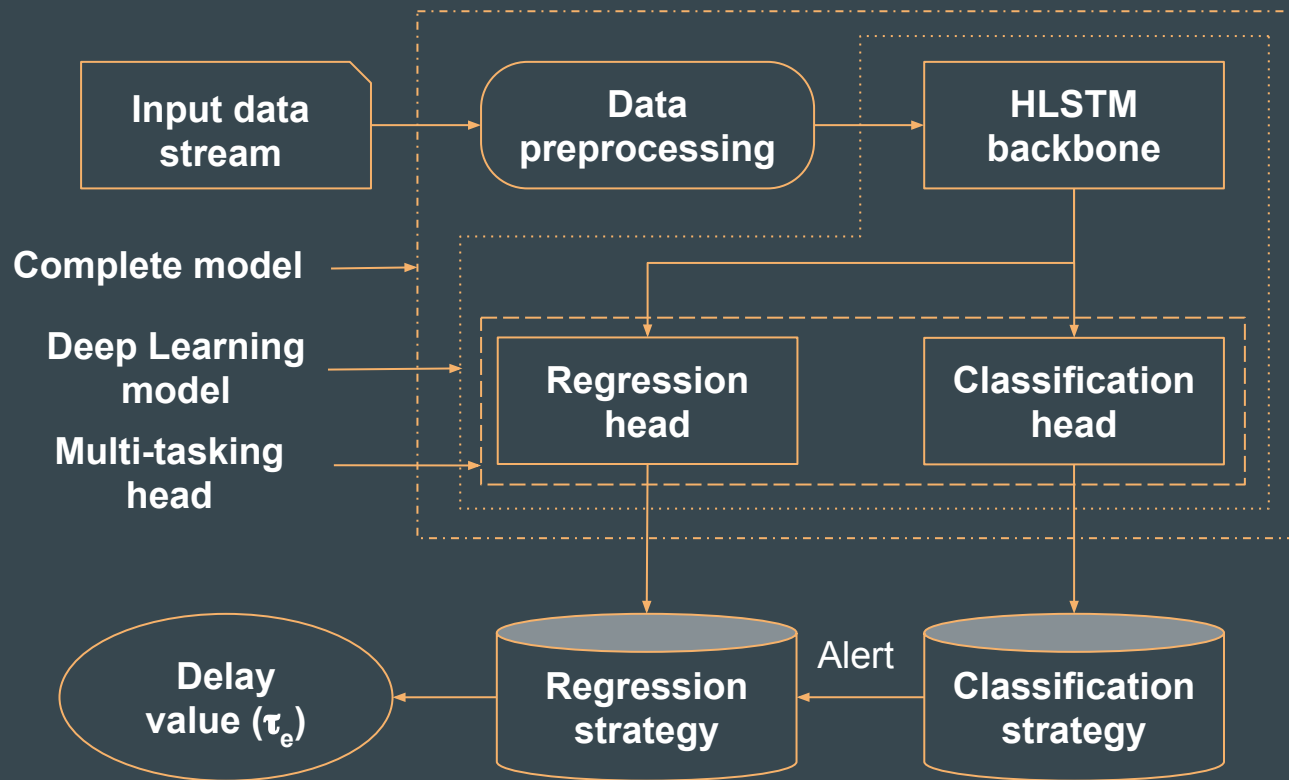
Complete Model



Complete Model



Complete Model



Evaluation Metrics

- MAE and RMSE
 - To evaluate the characterization head
- Accuracy, False Positive and False Negative
 - To evaluate the detection head
- T_{avg}
 - To evaluate average characterization latency

Internal Ablation Study (PPCS)

- HLSTM outperforms Accumulate LSTM or Vanilla LSTM, under the same multi-task head training and testing setup

Approach	Classification (Detection)			Regression (Characterization)		
	Accuracy	FP	FN	MAE	RMSE	T _{avg}
Vanilla LSTM + Multi-task	85.21%	9.7%	5.1%	4.17	8.76	136
Accumulate LSTM + Multi-task	89.76%	7.1%	3.3%	2.76	6.03	168
HLSTM + Multi-task	92.39%	4.7%	2.9%	2.03	5.48	128

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2 HLSTM + Multi-task	93.03%	3.7%	3.2%	2.02	5.53	124

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Comparing Against Baseline Models (PPCS)

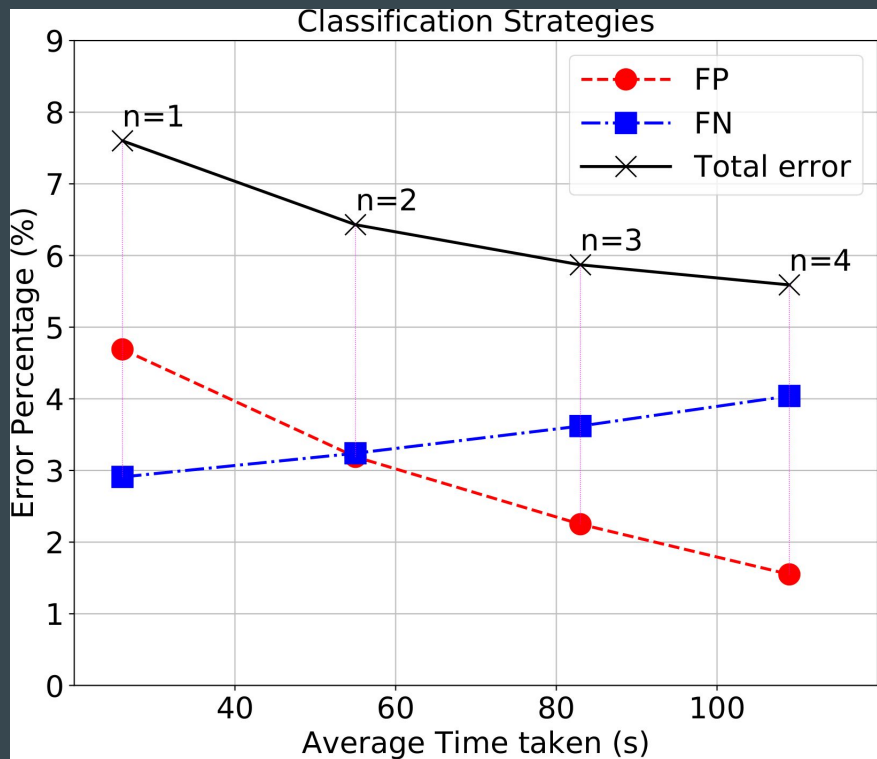
- Deep learning models can reduce the error to almost half, when compared against traditional models like kNN and RF
- All existing methods provide post-mortem analysis, but our method can provide real-time results, reducing the average reaction latency from 300s to 128s while improving the error even further

Approach	Classification (Detection)			Regression (Characterization)		
	Accuracy	FP	FN	MAE	RMSE	T _{avg}
kNN	72.6%	11.8%	15.6%	6.23	9.48	300
Random Forest	80.82%	5.2%	13.9%	6.44	10.32	300
(Lou et al, 2019)	--	--	--	3.73	6.84	300
Our Model	92.39%	4.7%	2.9%	2.03	5.48	128

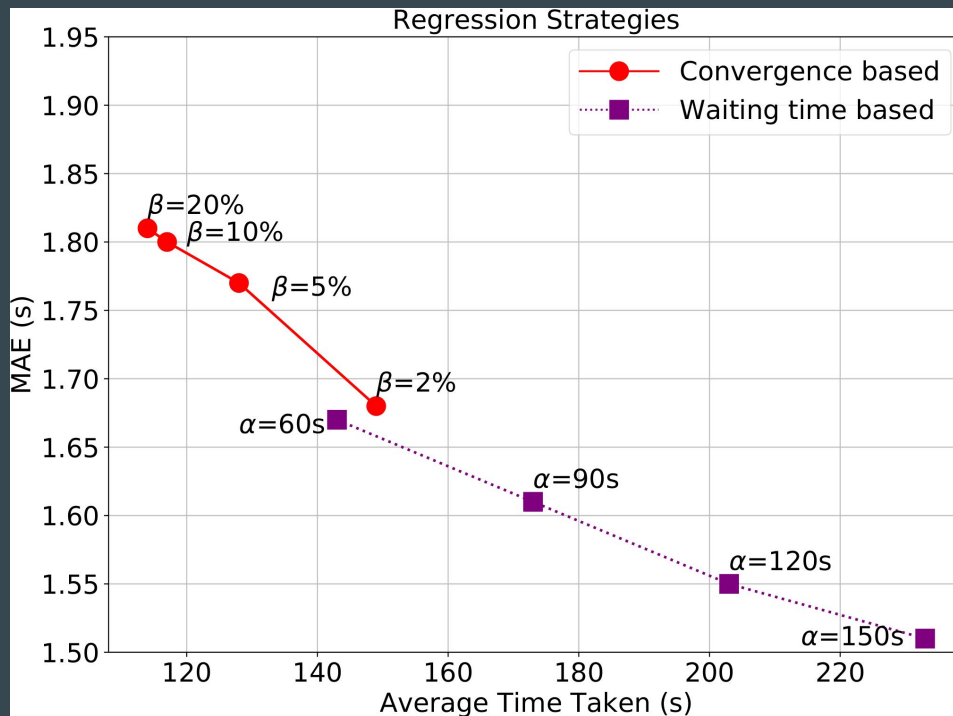
Comparing Against Baseline Models (AGC)

Approach	Classification (Detection)			Regression (Characterization)		
	Accuracy	FP	FN	MAE	RMSE	T _{avg}
kNN	71.29%	--	28.7%	3.27	5.02	200
Random Forest	74.57%	--	25.4%	3.41	4.10	200
(Lou et al, 2019)	--	--	--	1.34	2.17	200
Vanilla LSTM + Multi-task	81.07%	--	18.9%	1.74	3.84	63
Accumulate LSTM + Multi-task	97.71%	--	2.3%	0.77	1.42	65
HLSTM + Regression only	--	--	--	1.07	1.84	81
2 HLSTM + Multi-task	99.09%	--	0.9%	0.47	0.91	57
HLSTM + Multi-task	98.49%	--	1.5%	0.49	0.98	49

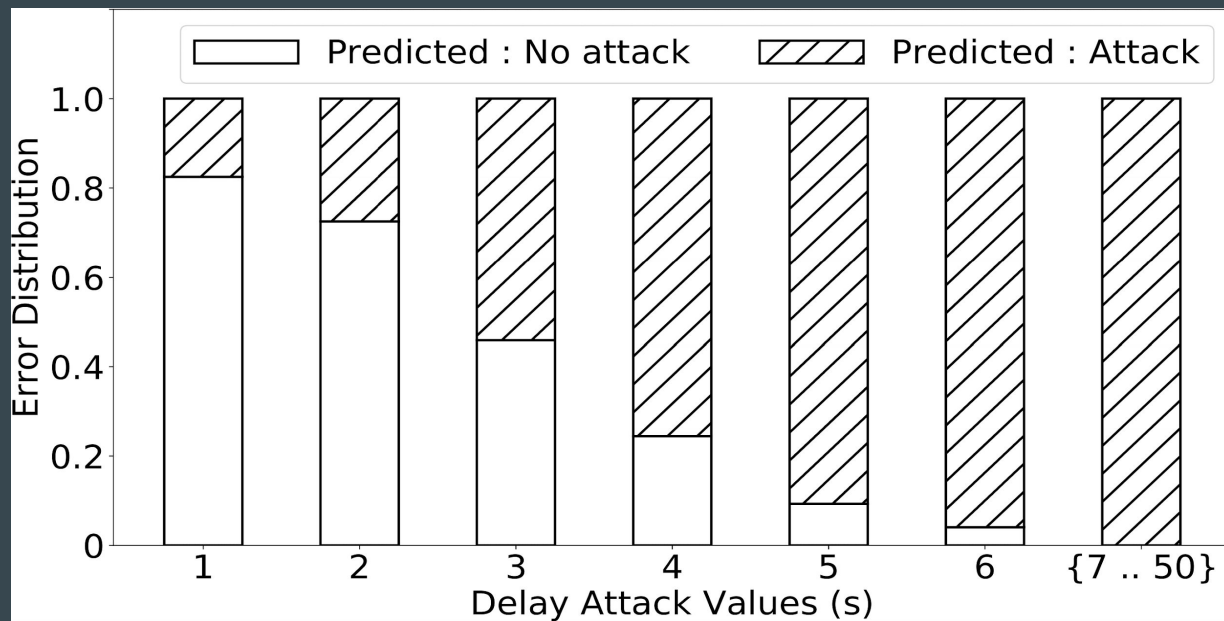
Interpretation Strategies (Classification)



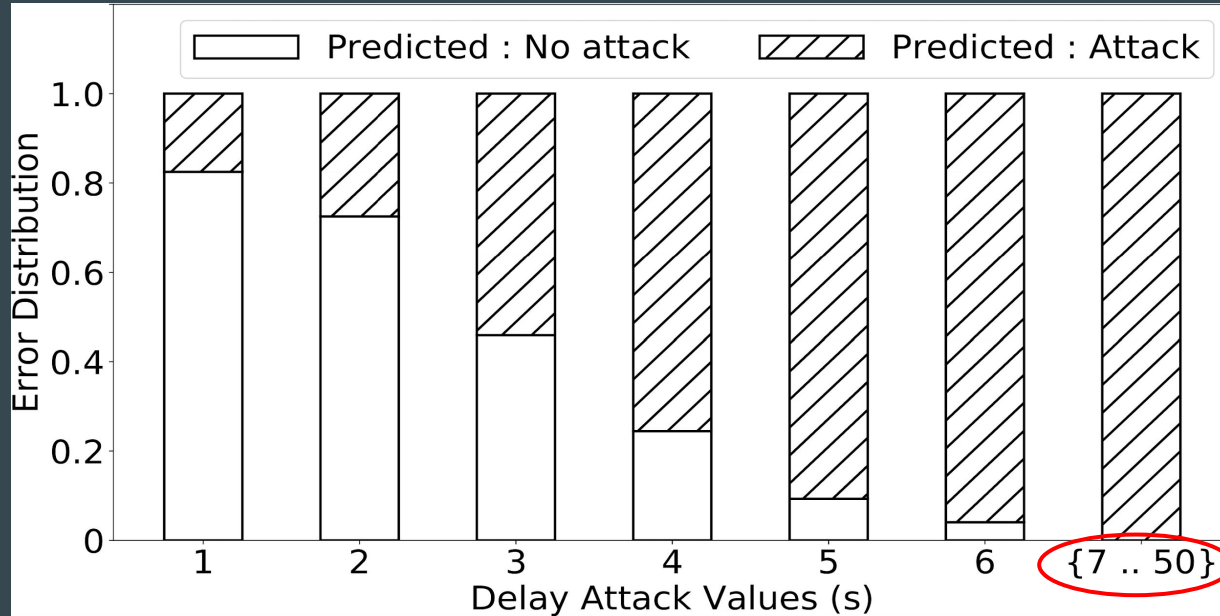
Interpretation Strategies (Regression)



Exploring Model Sensitivity (PPCS)

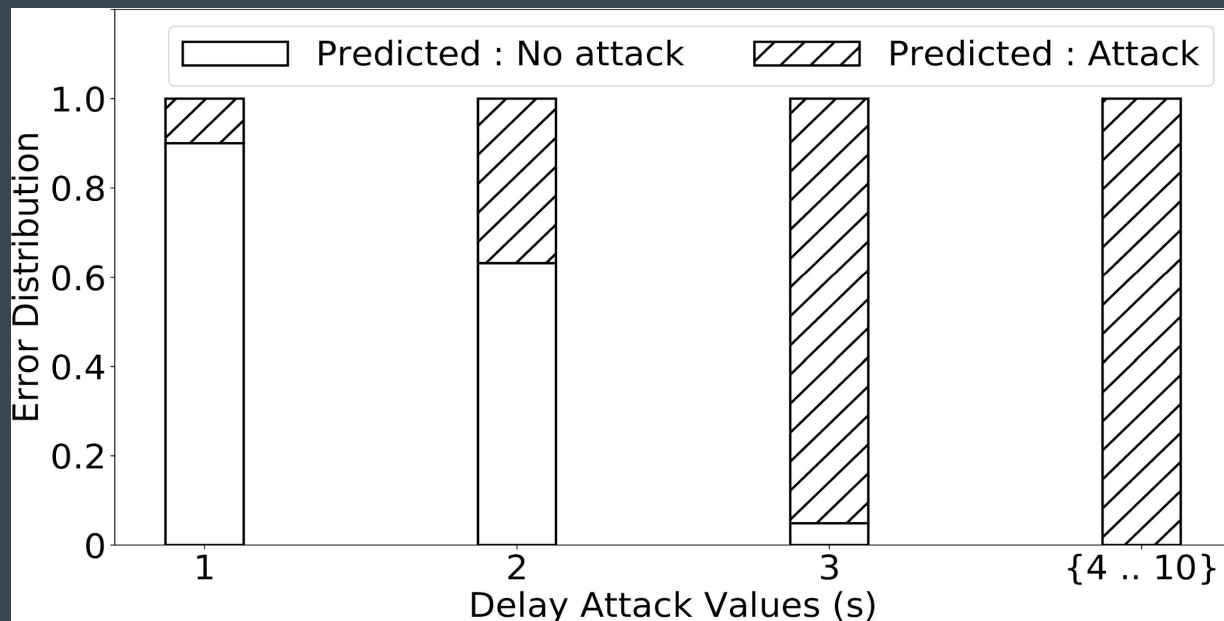


Exploring Model Sensitivity (PPCS)



PPCS can actually tolerate upto $\tau=12$ value delay attack with no harm

Exploring Model Sensitivity (AGC)



In Conclusion

- Time Delay Attacks are unique cyber attacks that are difficult to detect and can cause real harm to the system
- A majority of existing solutions to TDA are dependent on mathematical modelling of the system, and perform post-mortem analysis.
- We propose a learning-based solution to detect and characterize TDA
- We propose hierarchical LSTM backbone to deal with longer sequences, multi-tasking head specialised to do detection and characterization, and various strategies to improve the interpretability of our model.
- We provide significant improvement in accuracy while reducing the reaction latency by 3-4 times.

Thank You