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Transforming Unstructured Data into Insight for Anomaly Detection in Exploration Ground Systems

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Problems

- All communication within the firing room occurs over the intercom, relying on verbal confirmation
- System engineers have to monitor multiple screens and voice channels simultaneously, resulting in human errors
  - Example: Teams experience problems on multiple systems simultaneously. The problems appear completely irrelevant, but a later inspection concludes that the sensors on both systems are routed through a common, damaged connector.
- Analyzing multiple physical documents delay decision making in the launch process

Opportunity

- Recent advances in deep neural network architectures enable us to automatically ingest unstructured data and transform them into insight
- Our unique capability of **transfer learning, incremental retraining, and data augmentation** schemes now enable us to deal with highly specialized, limited amount of KSC EGS data sets
- We suggest a **human-in-the-feedback-loop system** that can continuously improve and adapt, based on input from engineers

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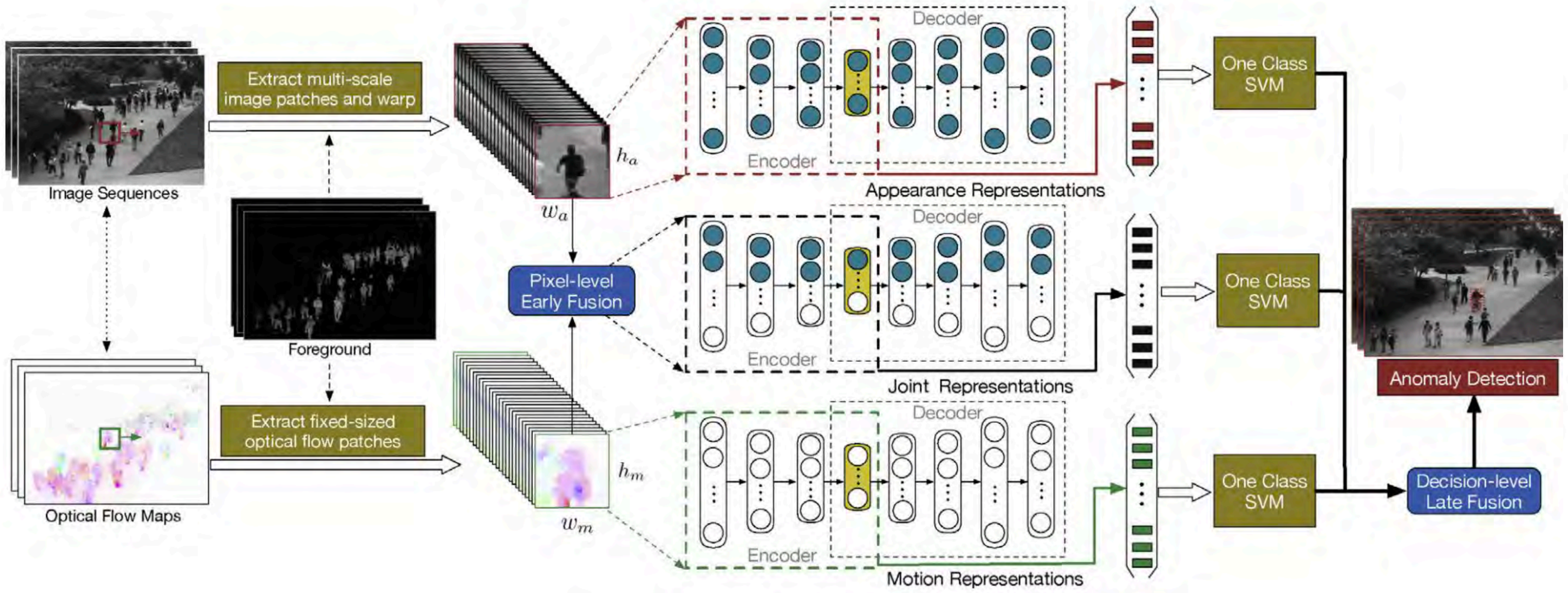
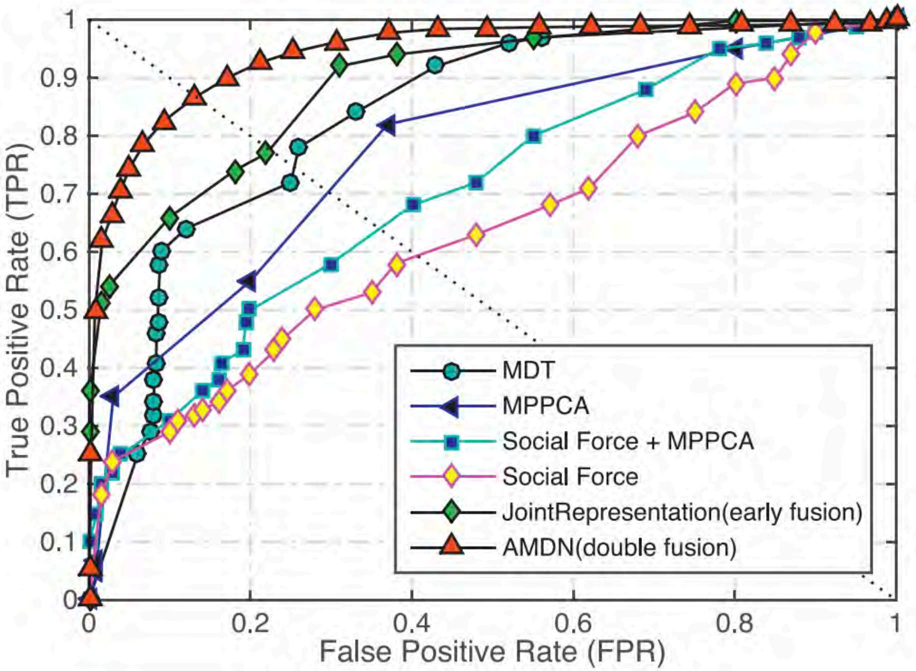
Anomaly detection using appearance and motion features (divide and conquer)





MDT: Mixture Dynamic Texture (Mahadevan et al., 2010)
MPPCA: Probabilistic Principal Component Analyzers (Kim and Grauman, 2009)
Social Force: representing crowd activity patterns using optical flow (Mehran et al., 2009)
AMDN: Appearance and Motion DeepNet

Xu et al., 2017

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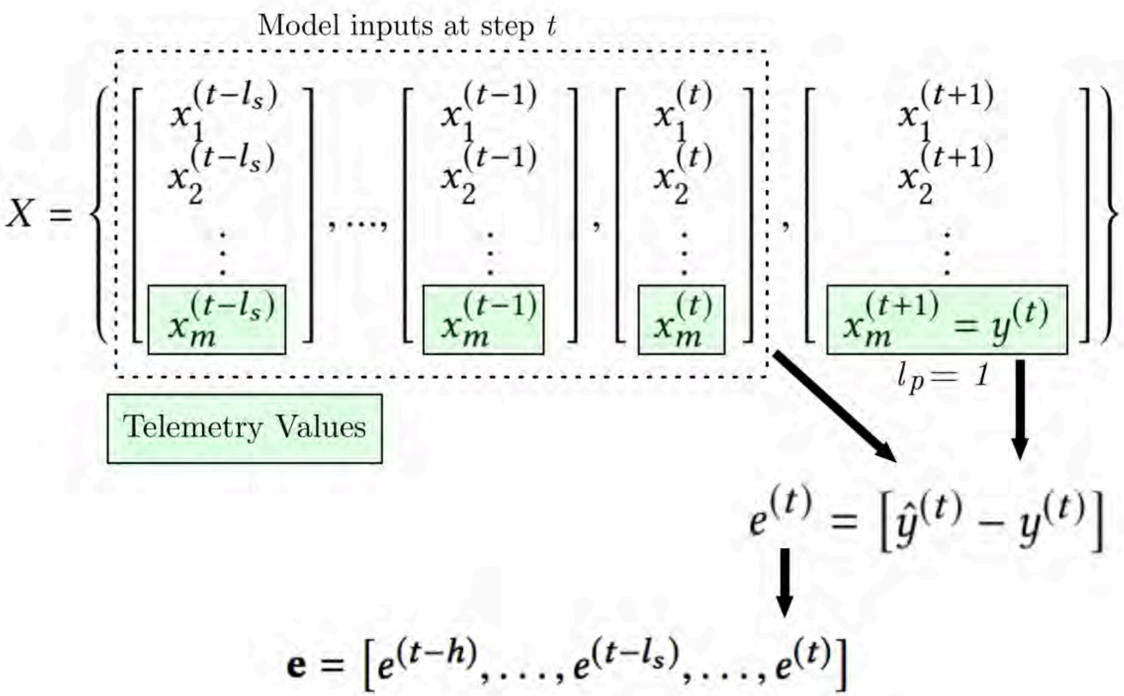
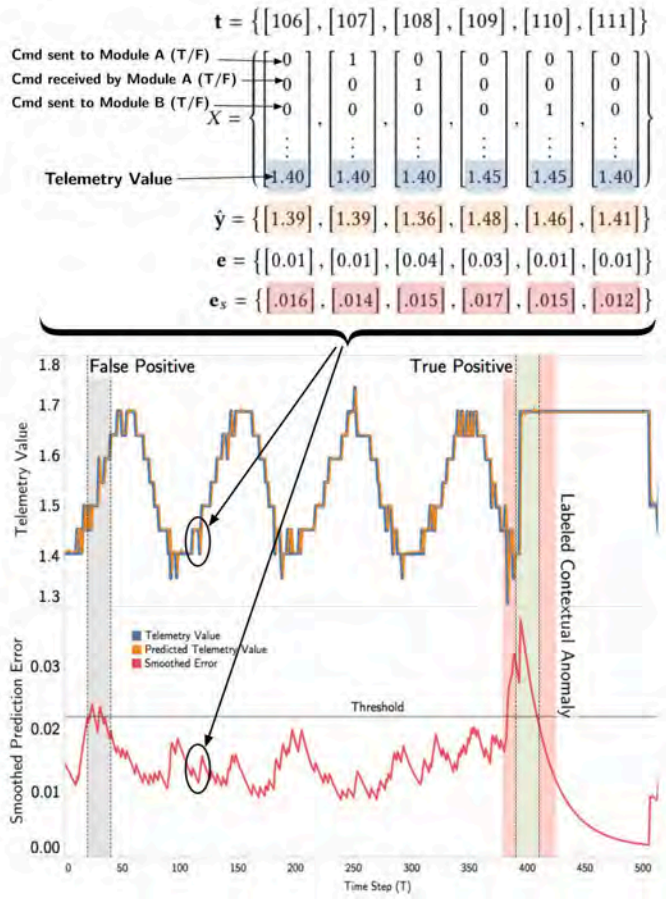
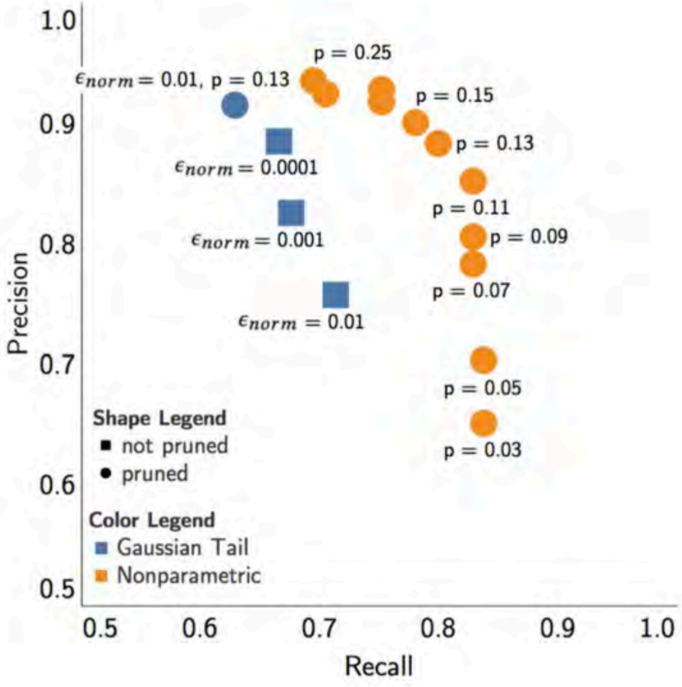
Detecting spacecraft anomalies using LSTMs and Nonparametric Dynamic Thresholding

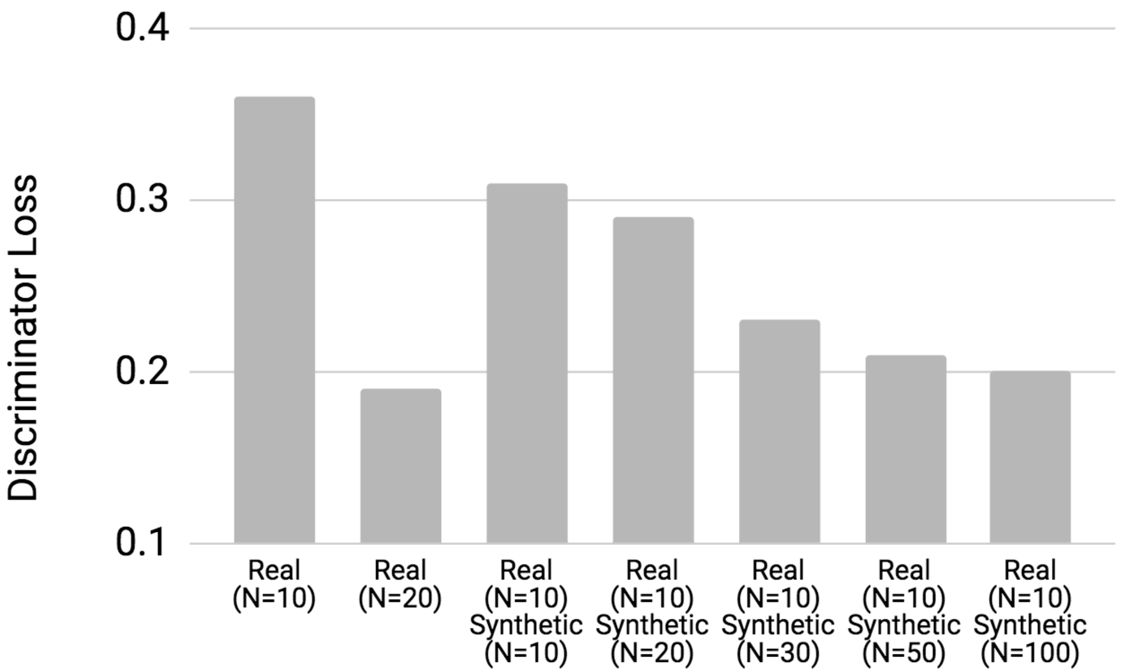






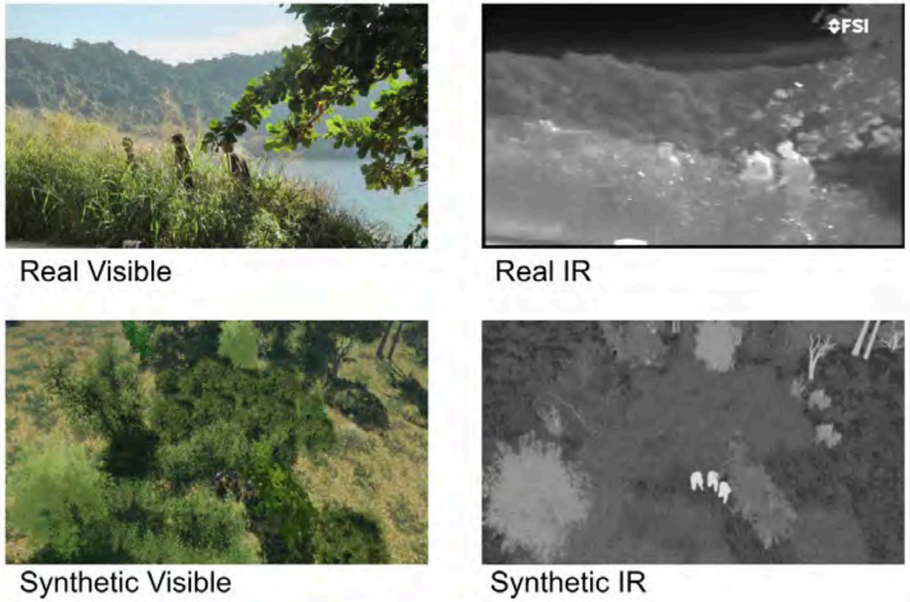
Hundman et al. 2018

Data augmentation using synthetic data in training neural networks for anomaly detection



Neural network performance of various real and synthetic data combinations

DOD Automated Test Object-ID and Measurement (ATOM)



AUDREY (Assistant for Understanding Data through Reasoning, Extraction, & sYnthesis)

- Uses bio-inspired hybrid neural network and symbolic reasoning
  - training large neural networks with objects, relationships, and dynamics
  - building symbolic models based on deep and organized representations
- Capabilities:
  - Simultaneously perform inference and learning in real time
  - Deal with missing or contradictory data
  - Automatically synthesize workflows to answer questions

DHS S&T Science & Technology

NGFR NEXT GENERATION FIRST RESPONDER PROTECTED, CONNECTED & FULLY AWARE

U.S. COAST GUARD AIR STATION HOUSTON

HASTINGS QUINTE PARAMEDIC

MACC 911

Distributed AUDREY agents for search and rescue mission

Collaboration among multiple AUDREY agents for high-resolution video analysis

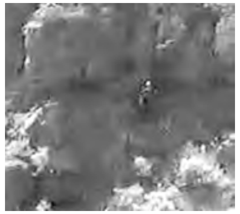
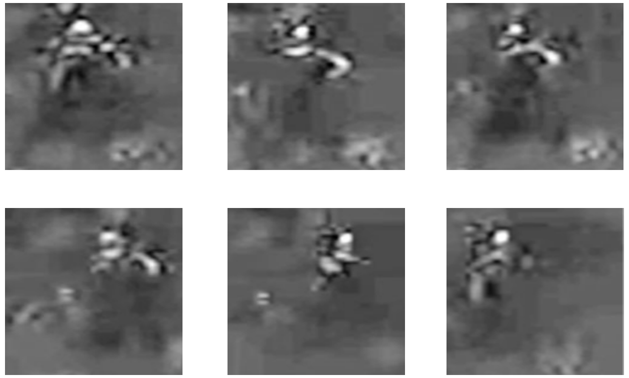


Image contrast enhancement



Training small features

Recognizing small humans

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AUDREY detecting a man on water for the US Coast Guard

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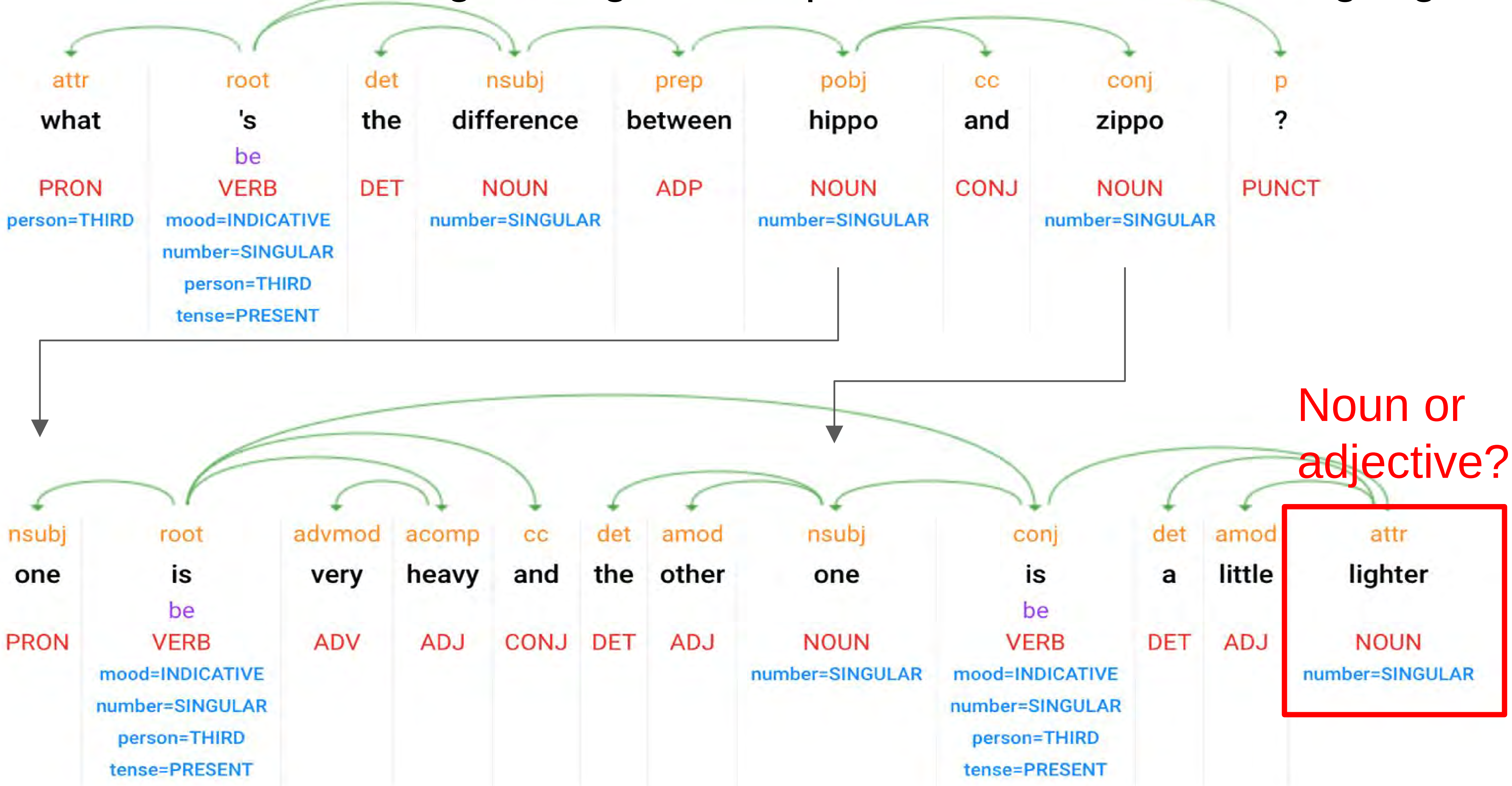
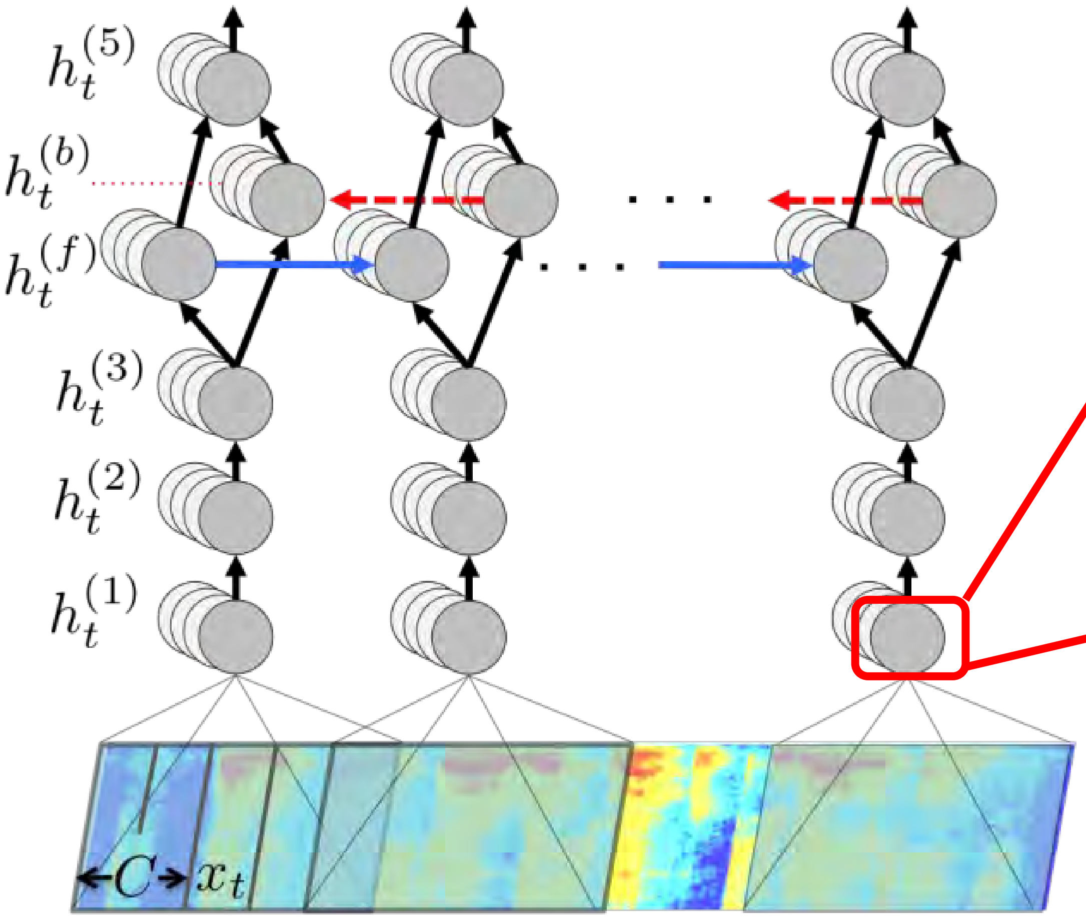
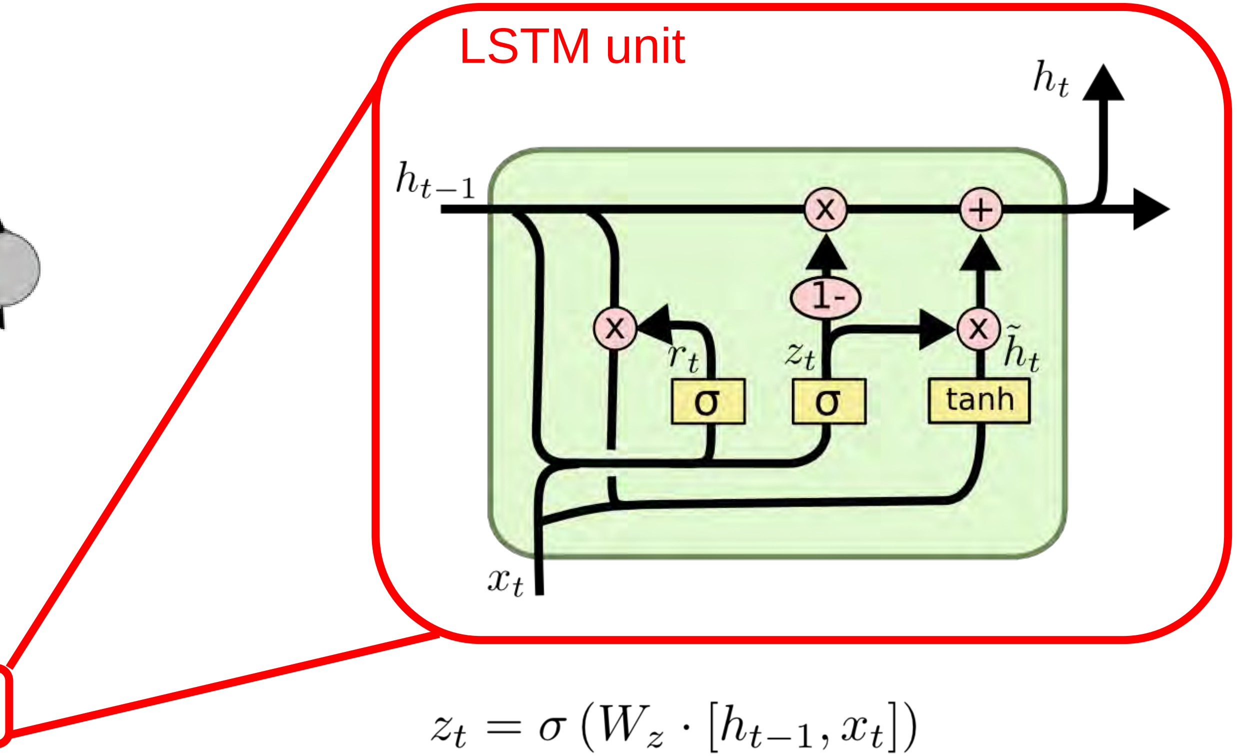
Contextual understanding of long-term dependencies in human language



Recurrent neural network for long-term dependencies in human language





$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

Graves et al. 2013, Hannun et al. 2014

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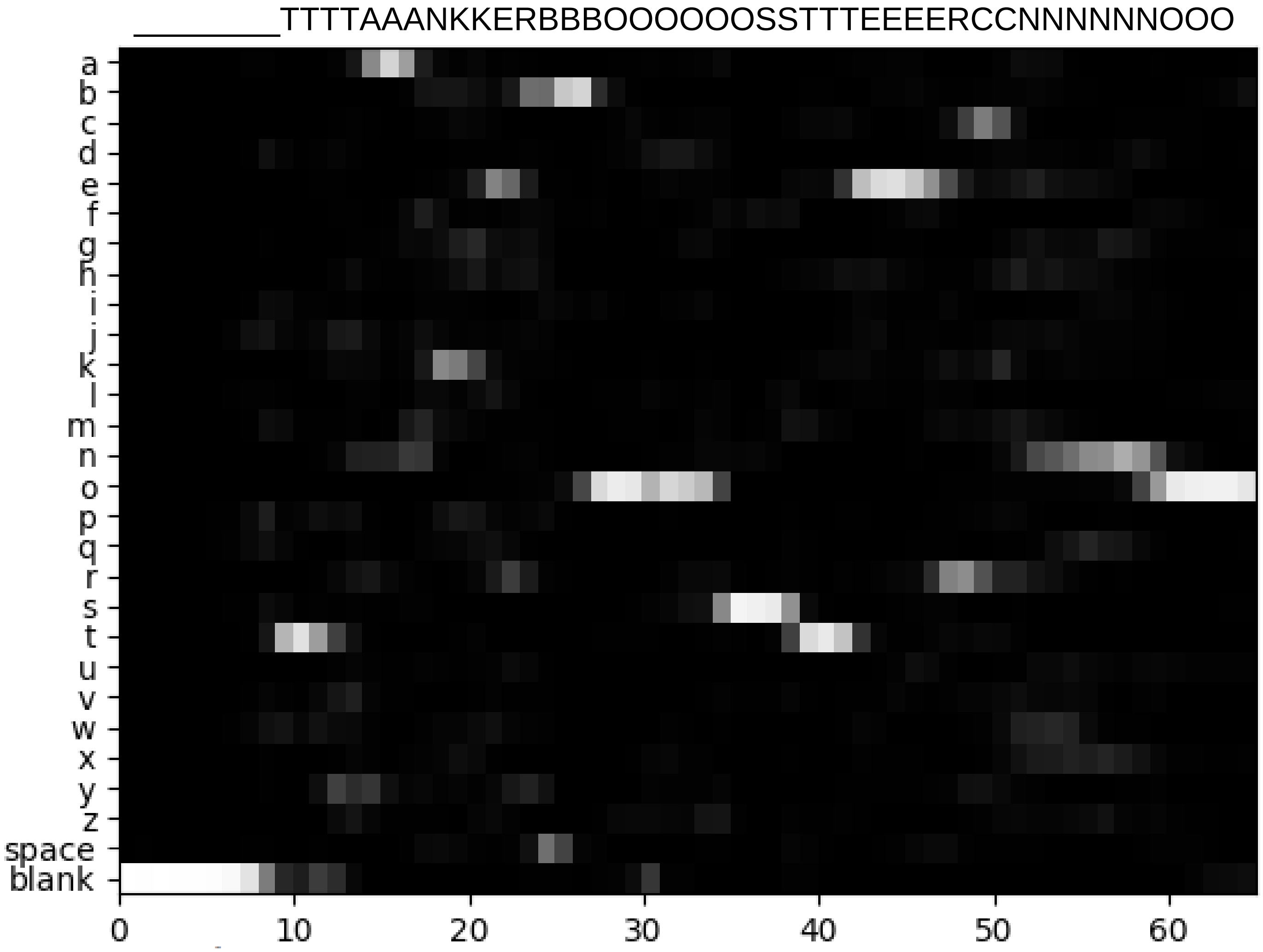
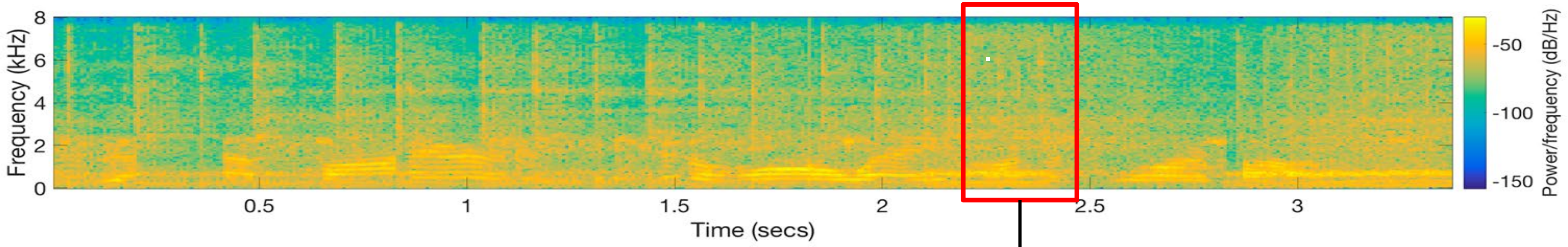
Example of recurrent neural network output

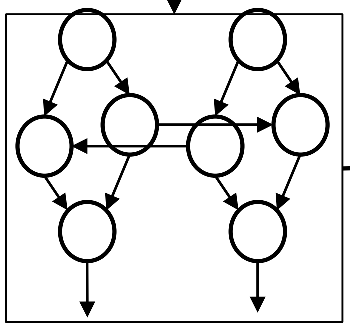


Truth: tanker booster go, Prediction: tanker booster go
Test loss: 0.0259571466595

Semantic language processing

Speech Input





RNN

Autopsy 0.31
OTC 0.29

Acoustic model

$$P(Autopsy|JRPS\ MS1) = \frac{C(JRPS\ MS1\ Autopsy)}{C(JRPS\ MS1)} = 0.0792$$

$$P(OTC|JRPS\ MS1) = \frac{C(JRPS\ MS1\ OTC)}{C(JRPS\ MS1)} = 0.002$$

Semantic language model

JRPS MS1 OTC

Yun et al. SPIE 2018

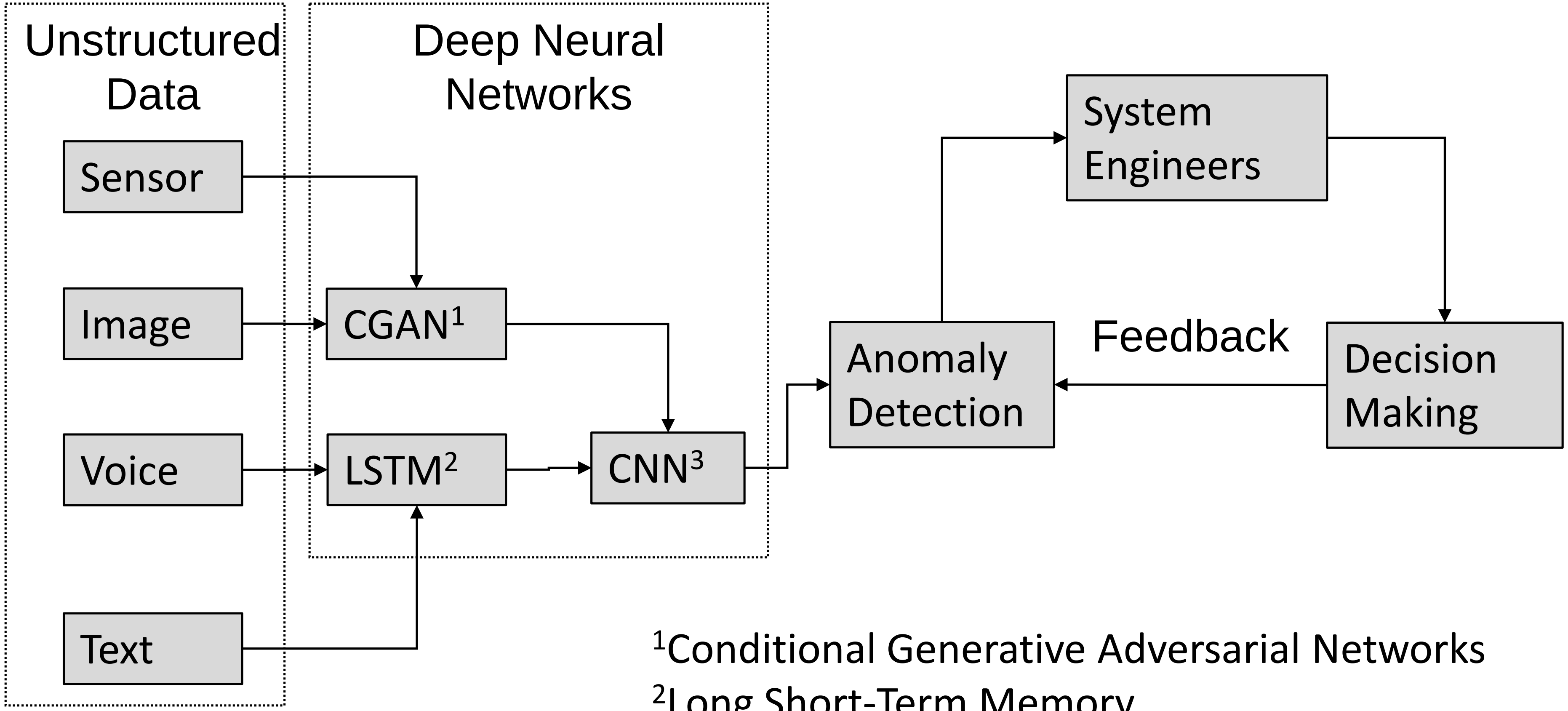
Accurate speech-to-text and automatic report generation

Objectives

- **Accelerate anomaly detection** in the firing room for Exploration Ground Systems (EGS) at Kennedy Space Center (KSC):

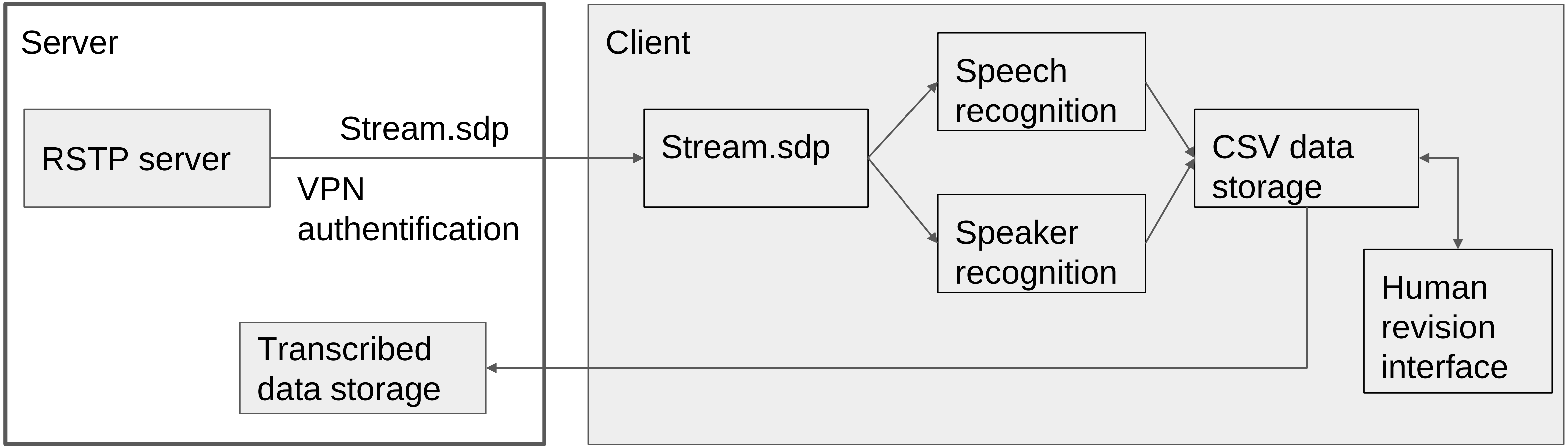
1. Build deep neural networks to transform unstructured data into insight for anomaly detection
2. Validate the feedback loop for the continuous improvement of anomaly detection accuracy
3. Test anomaly detection performance compared to existing human-based system

Anomaly Detection Process



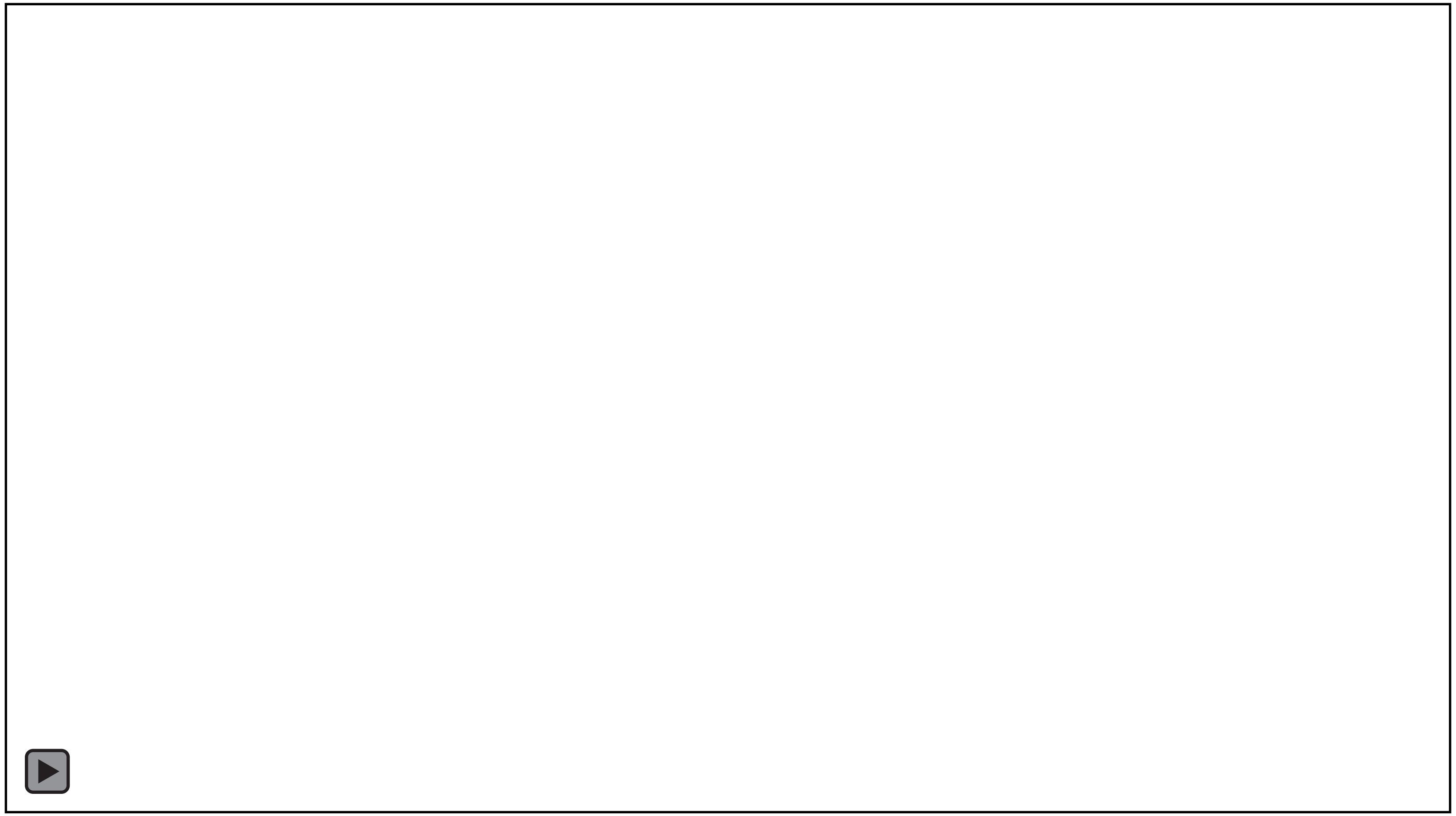
[1]Conditional Generative Adversarial Networks
[2]Long Short-Term Memory
[3]Convolutional Neural Networks

KSC speech/speaker recognition with the transcript-revision interface



Yun et al., SPIE 2018

Speech/Speaker recognition with revision interface



Automatic generation of systems engineer’s report using AUDREY

Chatbot Interface

Incident report (JSON format)

Simulating communication between NASA Test Director (NTD) and a systems engineer reporting anomaly.

AUDREY as an assistant for NTD receives the information and analyze it.

At the same time, AUDREY populates JSON messages to fill out the incident report.

Potential Impact

- Reduce human errors in the firing room by providing alert to system engineers about the anomaly
- Enhance the launch process by automatically transforming unstructured data into insight
- Continuously improve the anomaly detection accuracy by generating a feedback loop from engineers to the system

Path Forward

- Implement **user interface** to empower engineers to maintain awareness of surrounding data to reduce human errors
- Test the system as a support in the firing room during the launch process
- Telemetry anomaly detection for Curiosity using DSN data
- Potential commercial applications, including health care information systems and information technology industry

Primary Technical Hurdles:

- **Data augmentation** to train deep neural networks with lack of relevant data for anomaly detection
- Reliable anomaly detection algorithm development in **complex and unpredictable environment**