



**Jet Propulsion Laboratory**  
California Institute of Technology

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

Kyongsik Yun<sup>1</sup>, Thomas Lu<sup>1</sup>, Shaun Heath<sup>2</sup>

<sup>1</sup>Bio-Inspired Technologies and Systems Group, NASA Jet Propulsion Laboratory,  
California Institute of Technology

<sup>2</sup>Launch Site Work Control Systems, Kennedy Space Center

[kyongsik.yun@jpl.nasa.gov](mailto:kyongsik.yun@jpl.nasa.gov)

Ground Systems and Architecture Workshop (GSAW)

February 2019

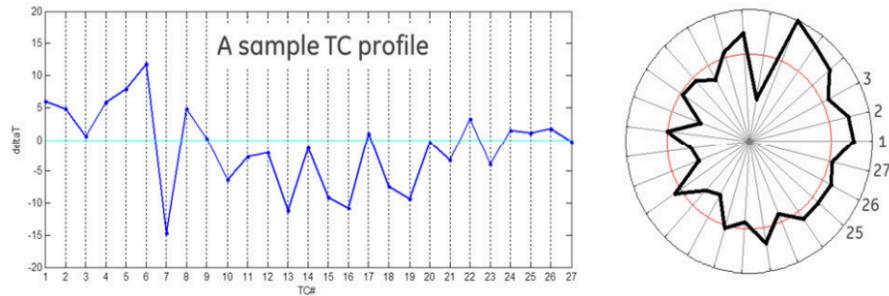
# Problems

- 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

# State-of-the-art anomaly detection on unimodal data



Gas turbine sensors  
(Ya, Yu 2015, GE)

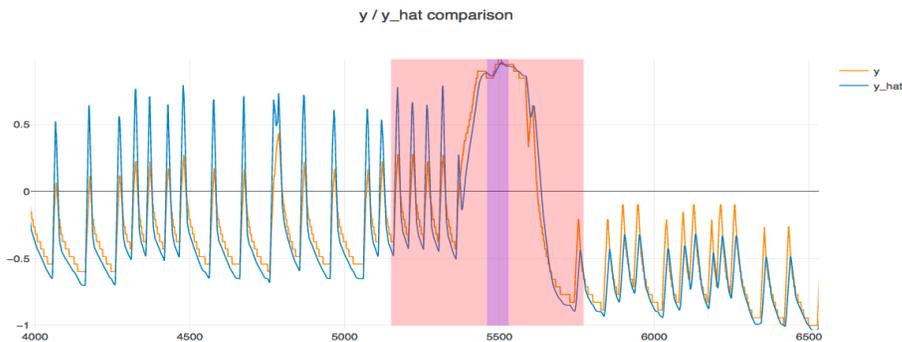
Test Samples



Anomaly Mask

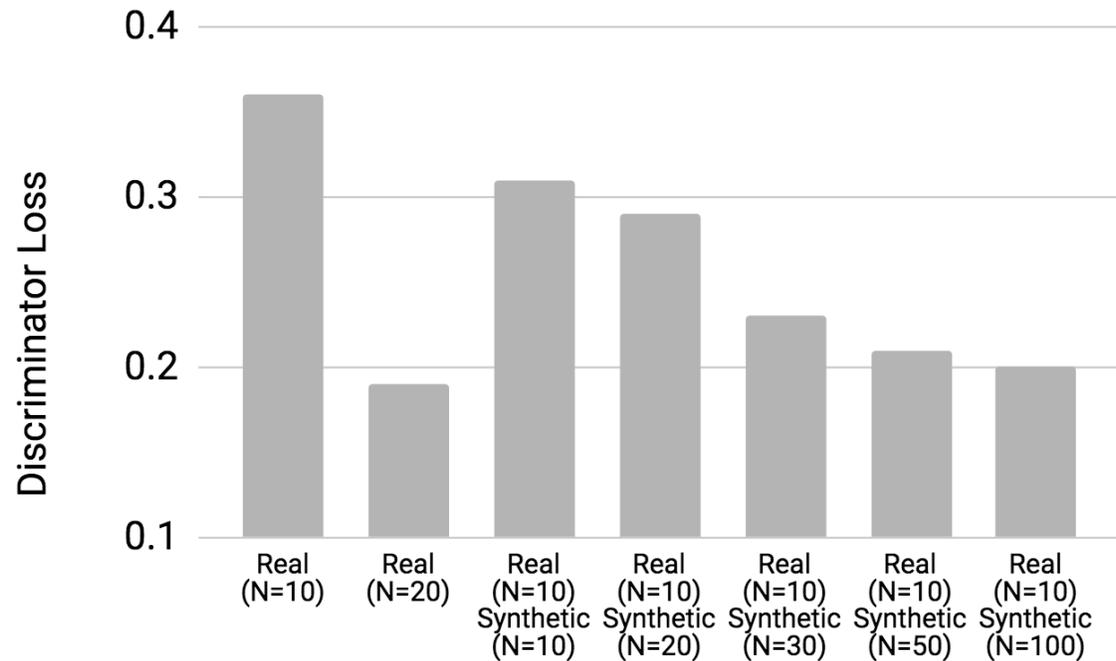


Video sequence  
(Xu et al. 2017, U Trento)



Multivariate time series of SMAP data  
(Hundman et al. 2018 JPL)

# Data augmentation using synthetic data



Real Visible



Real IR



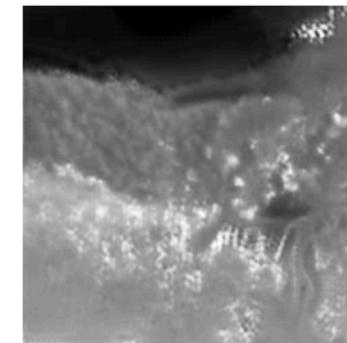
Synthetic Visible



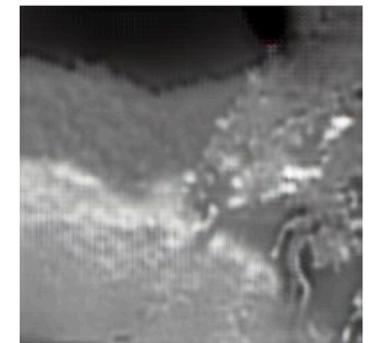
Synthetic IR



Real visible



Transformed IR  
(real N=10)



Transformed IR  
(real N=10, synthetic =100)

Neural network performance of various real and synthetic data combinations



DOD Automated Test Object-ID and Measurement (ATOM)

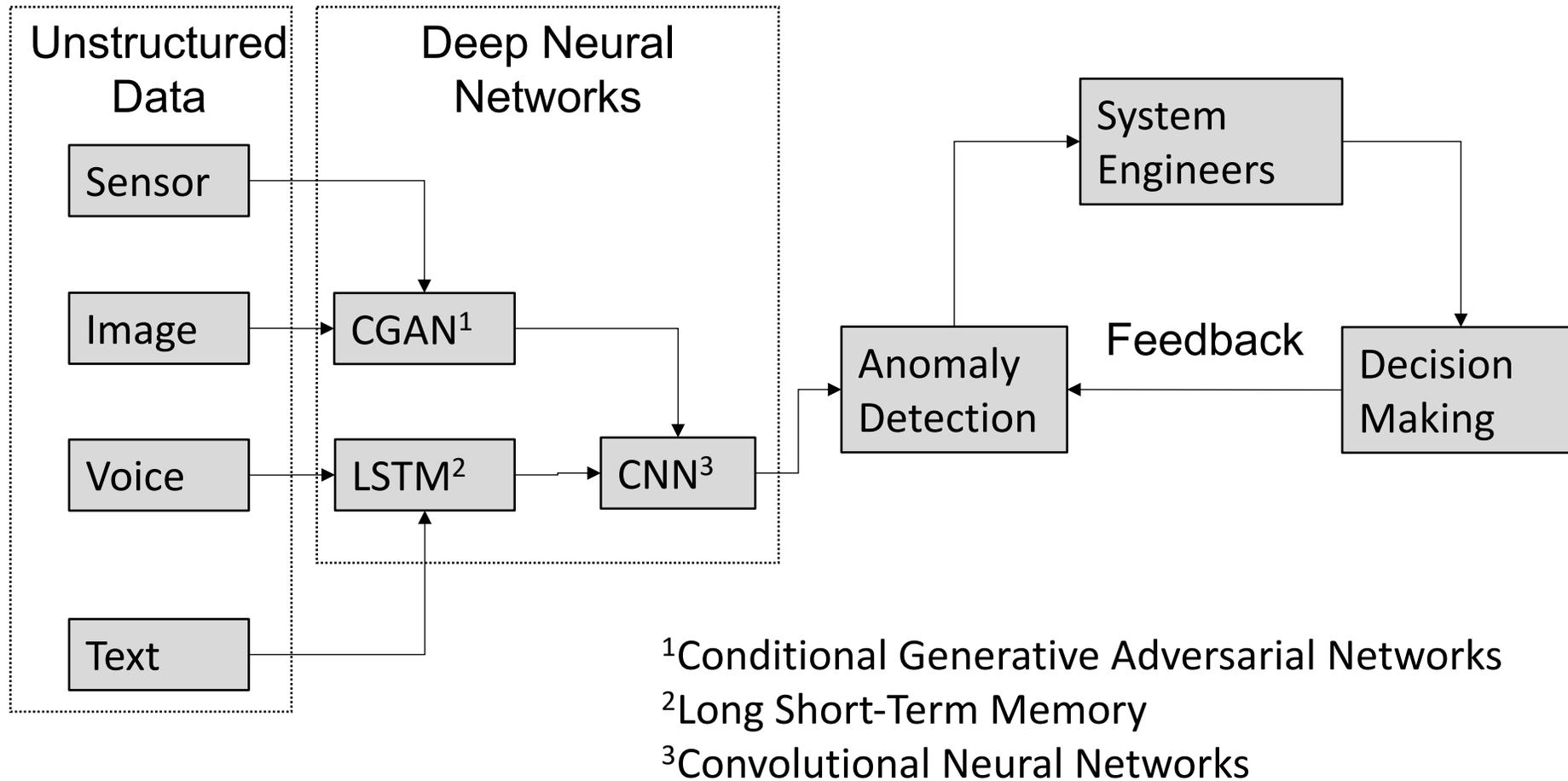
# Objectives

- **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

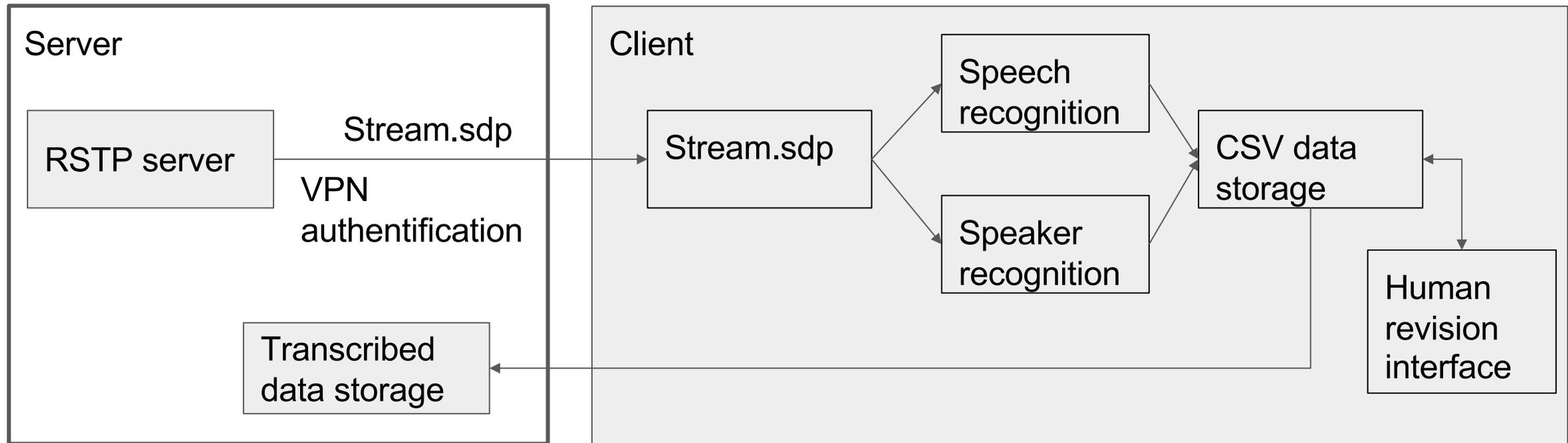
# Technical Approach

- Transform images to labels, voice to text, text to process, and sensor data to actionable information to detect anomaly using **state-of-the-art deep neural networks** (CGAN, LSTM)
- Provide alert to engineers about the anomaly
- Generate a feedback loop from engineers to the system to **continuously fine-tune the algorithm**

# Anomaly Detection Process



# KSC speech/speaker recognition with the transcript-revision interface



# 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

# Distributed AUDREY agents for search and rescue mission



Collaboration among multiple AUDREY agents for high-resolution video analysis

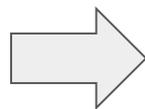
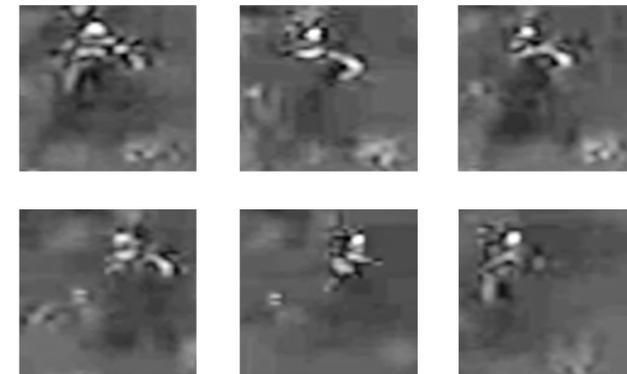
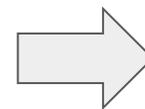
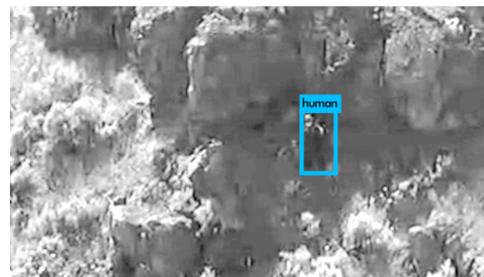


Image contrast enhancement



Training small features



Recognizing small humans

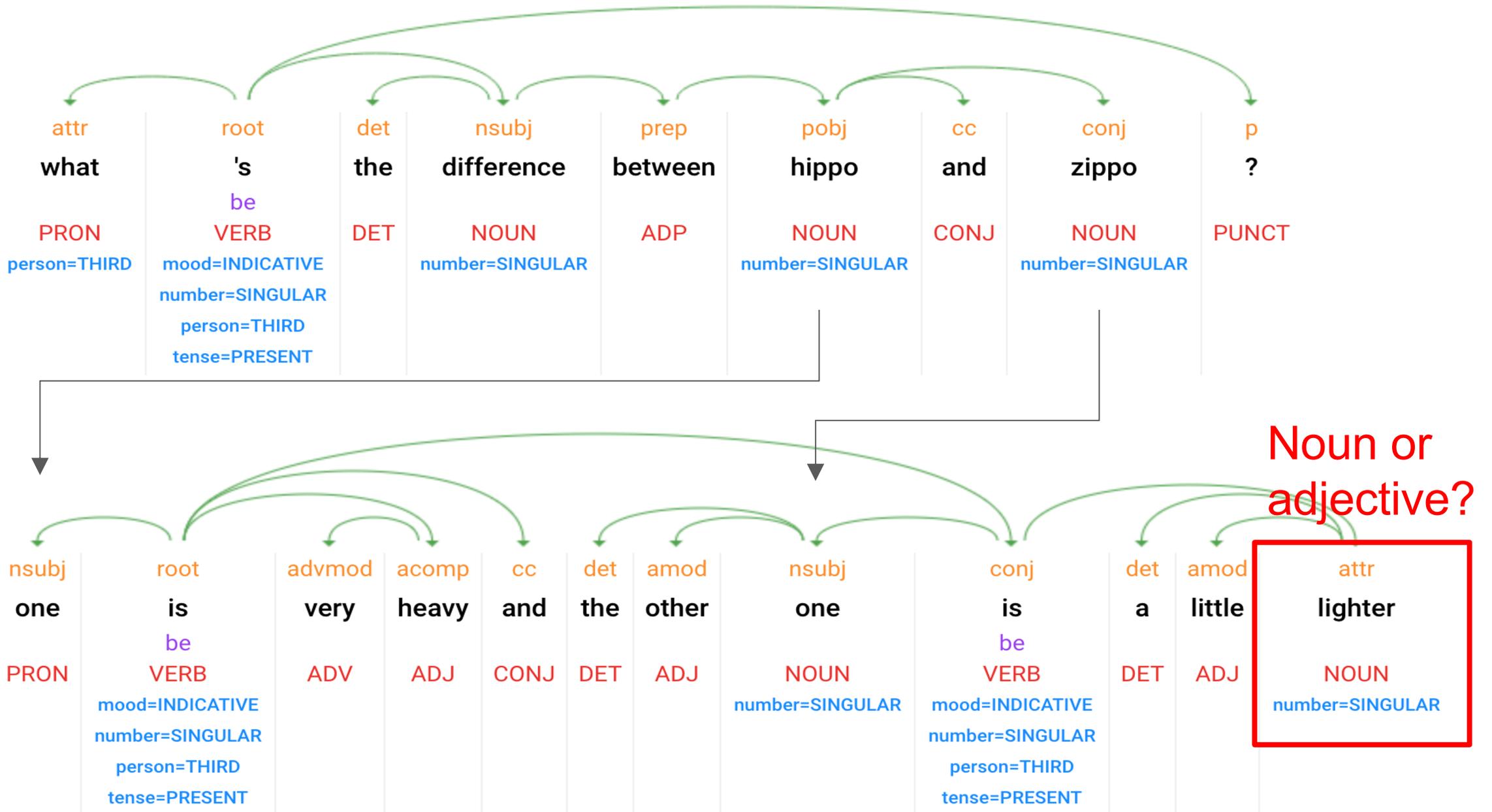
Small human detection in UAV



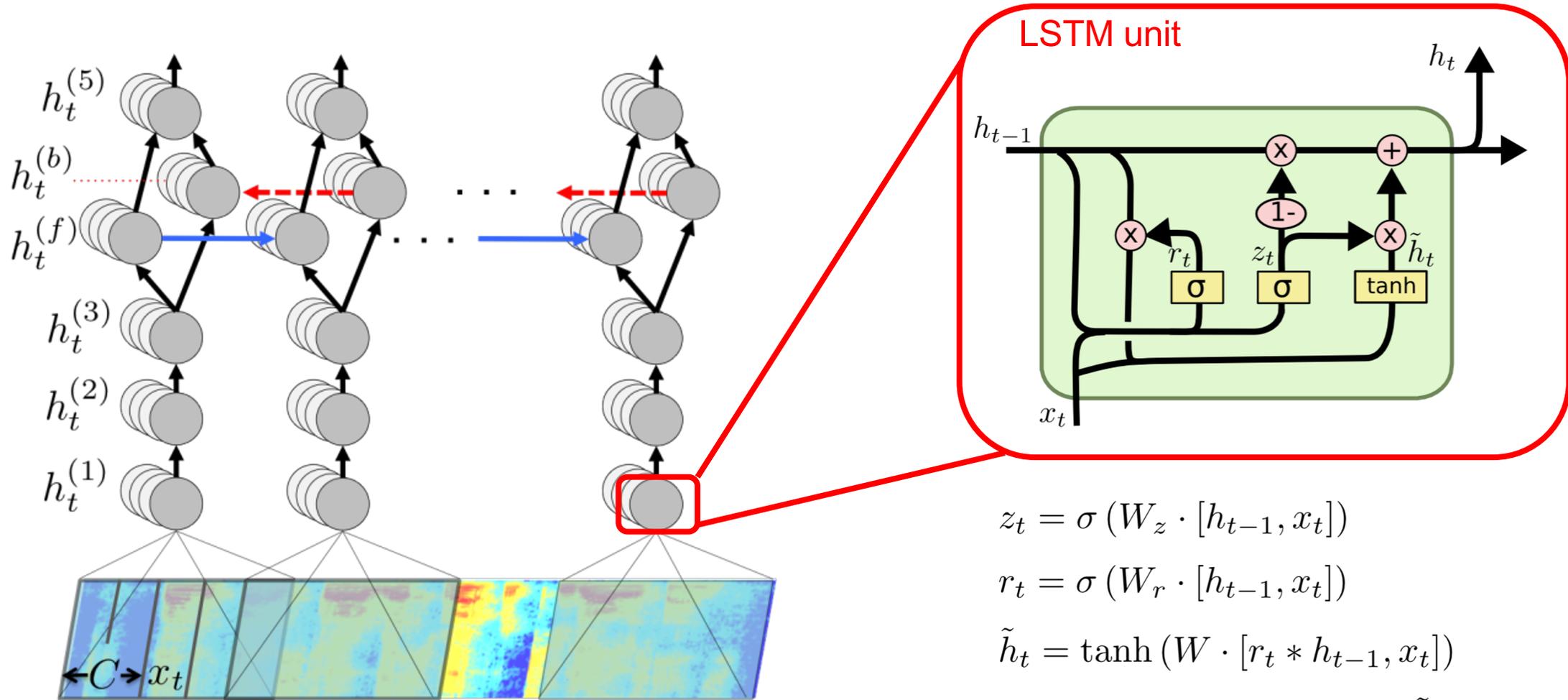
# AUDREY detecting a man on water



# Contextual understanding of long-term dependencies in human language



# Recurrent neural network for long-term dependencies in human language



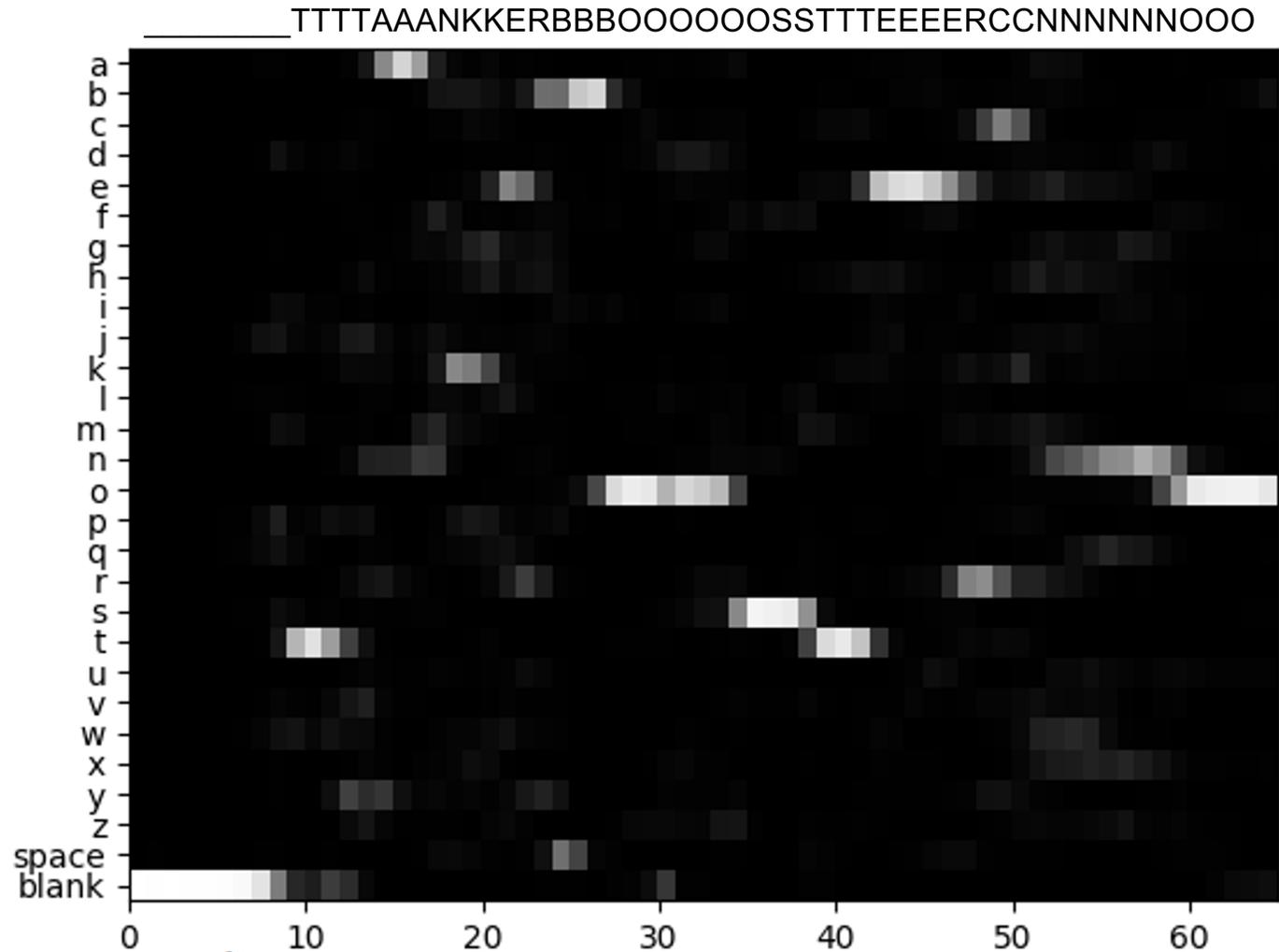
$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t])$$

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

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

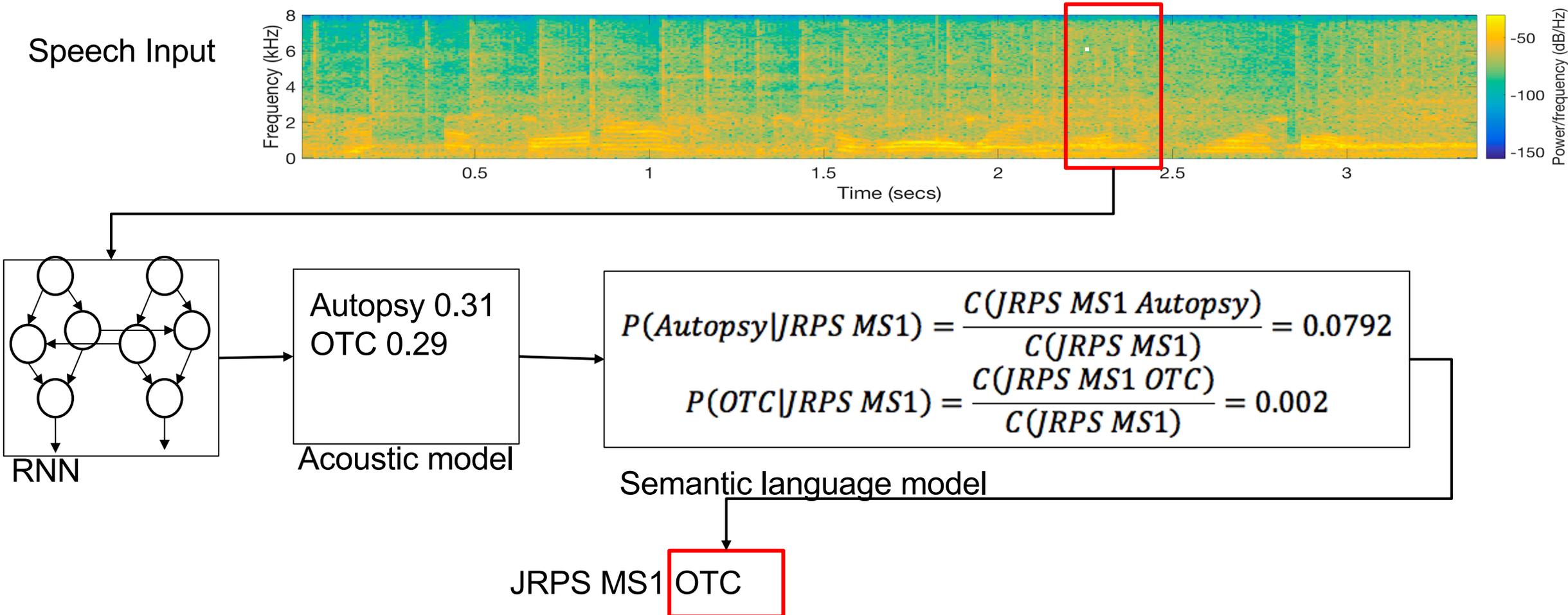
$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

# Example of recurrent neural network output

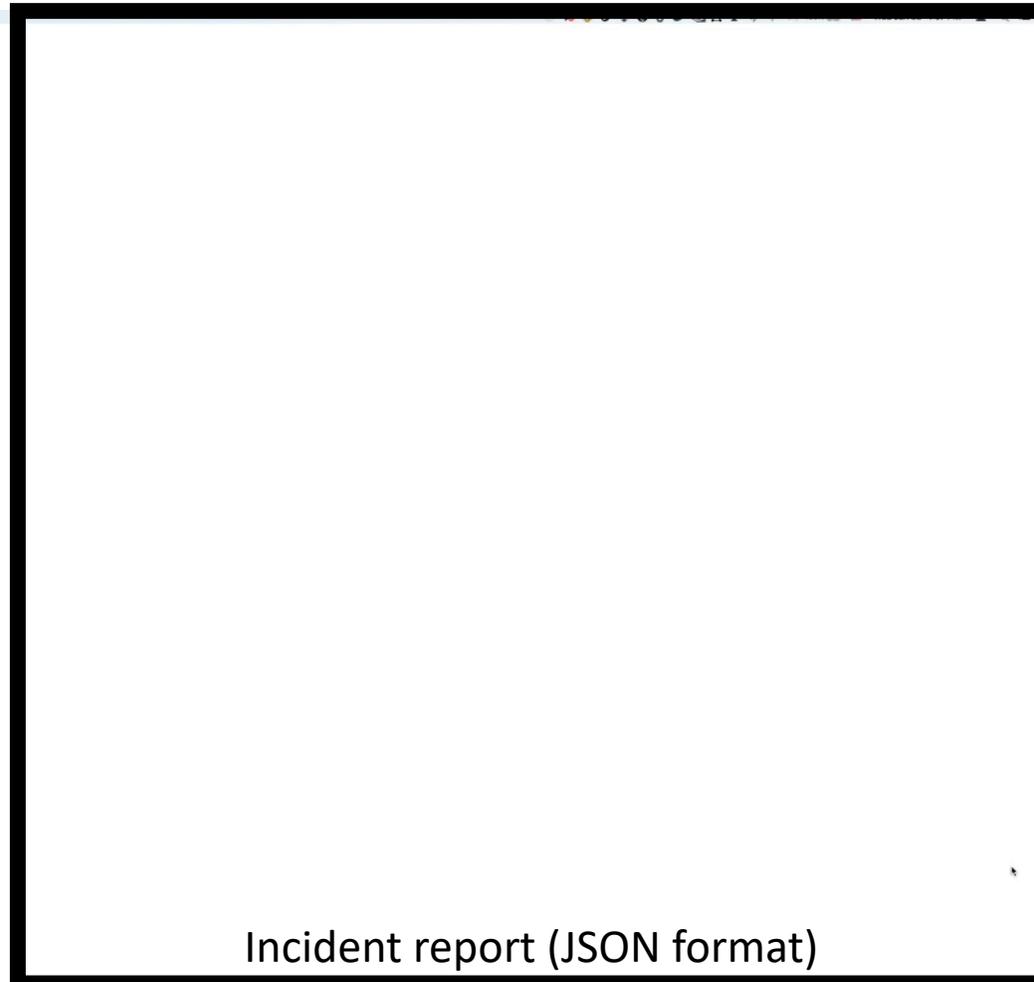
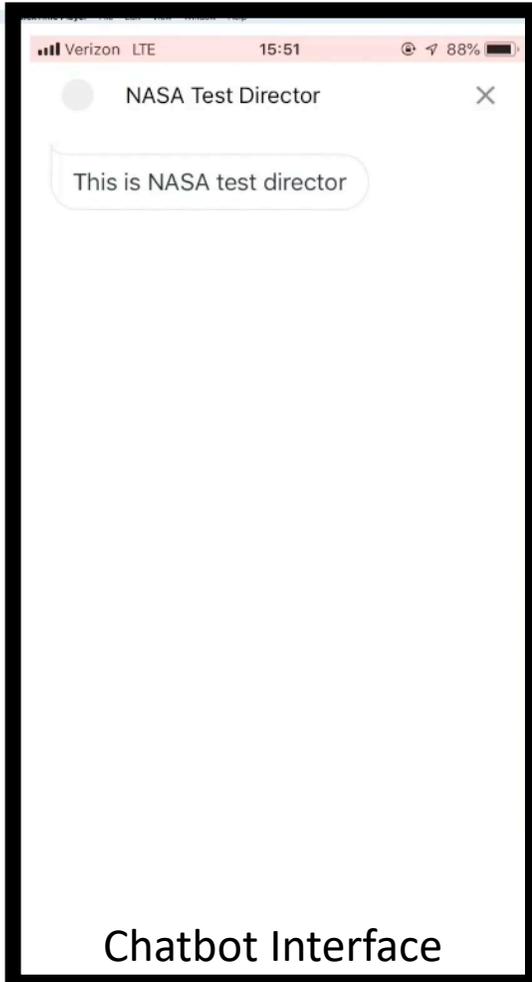


Truth: tanker booster go, Prediction: tanker booster go  
Test loss: 0.0259571466595

# Semantic language processing



# Automatic generation of systems engineer's report using AUDREY



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

AUDREY's job here is assistant for NTD receiving the information and analyzing 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