

# Whistler Detection Using Machine Learning

*Course: Radiation Belt Dynamics and Remote Sensing of the Earth's Plasmasphere*

*09/27/2022*

**\*Prof. Vijay Harid<sup>1</sup>**

Prof. Chao Liu<sup>1</sup>

Prof. Mark Golkowski<sup>1</sup>

Prof. Morris Cohen<sup>2</sup>

Dr. Poorya Hosseini<sup>3</sup>

Yan Pang<sup>1</sup>

Akimun Alvina Jannat<sup>1</sup>

<sup>1</sup>Department of Electrical Engineering, University of Colorado Denver

<sup>2</sup>School of Electrical and Computer Engineering, Georgia Institute of Technology

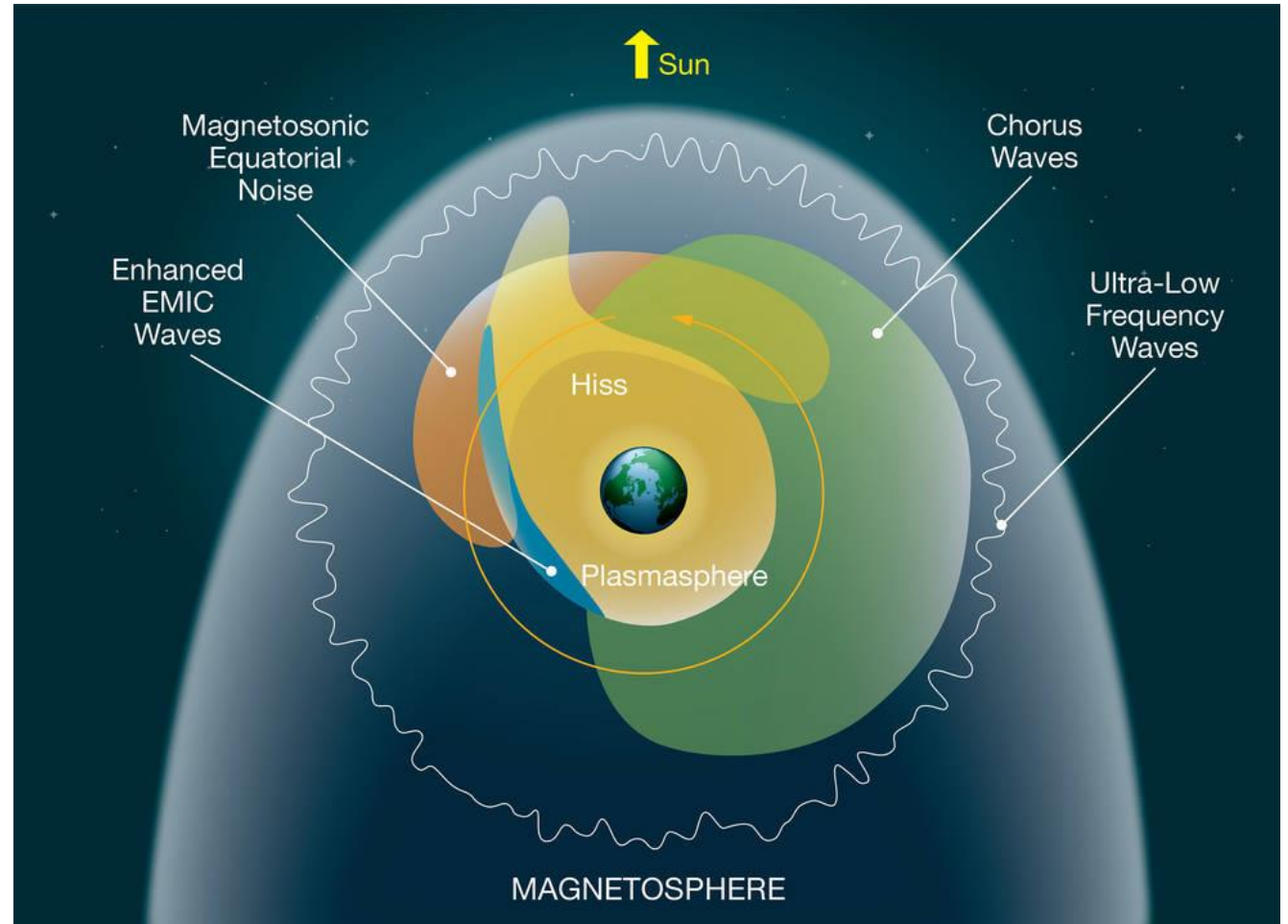
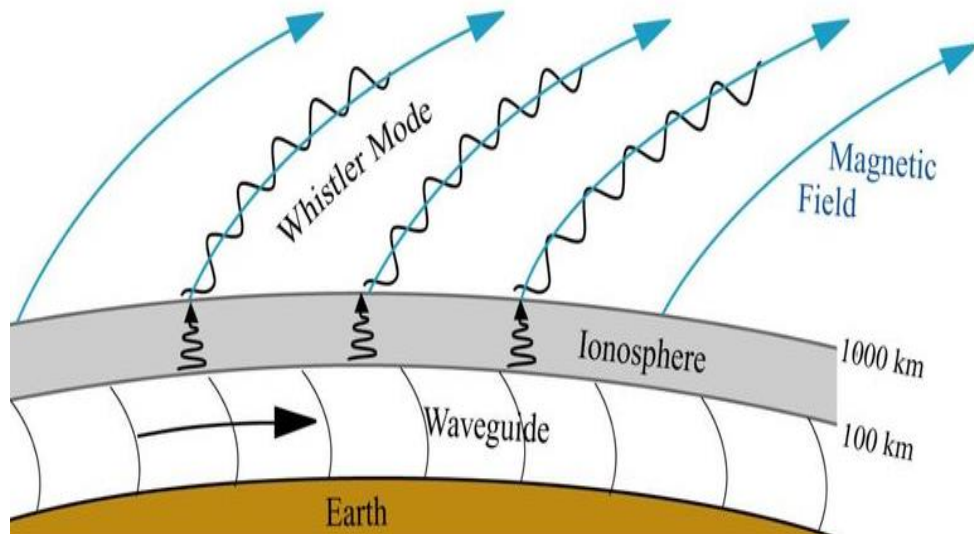
<sup>3</sup>Johns Hopkins University Applied Physics Laboratory

1. Overview of Whistler Mode Waves
2. Traditional Methods of Signal Detection
3. Basic Overview of Neural Networks
4. Whistler Extraction using MSRCNN
5. Summary and Future Work

1. Overview of Whistler Mode Waves
2. Traditional Methods of Signal Detection
3. Basic Overview of Neural Networks
4. Whistler Extraction using MSRCNN
5. Summary and Future Work

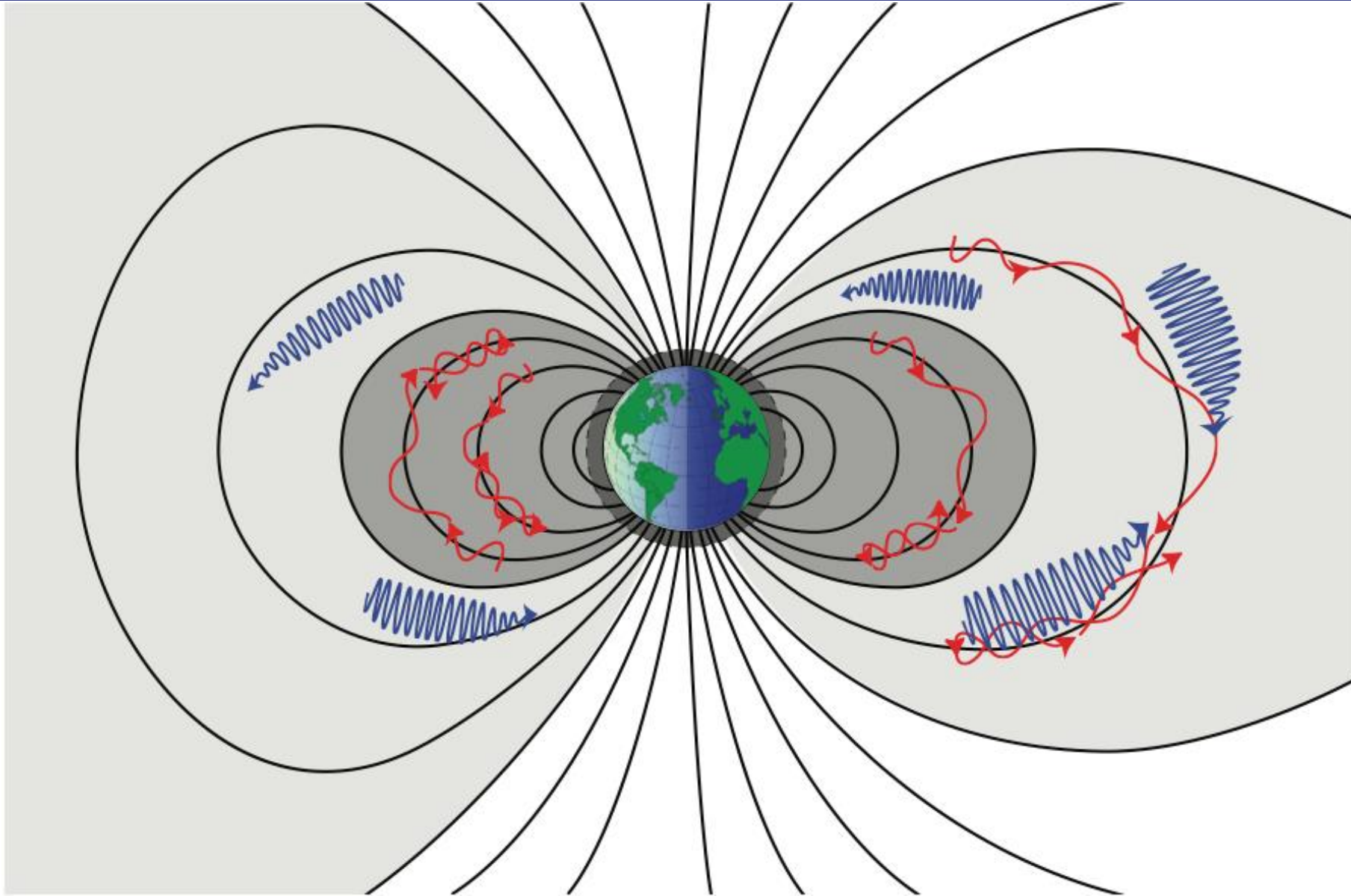
# Waves in Near-Earth Space

- Radio waves in the near-Earth space environment are generated via several different processes
- One major classes of waves are **whistler-mode** waves in the **ELF/VLF band** (<30 kHz).

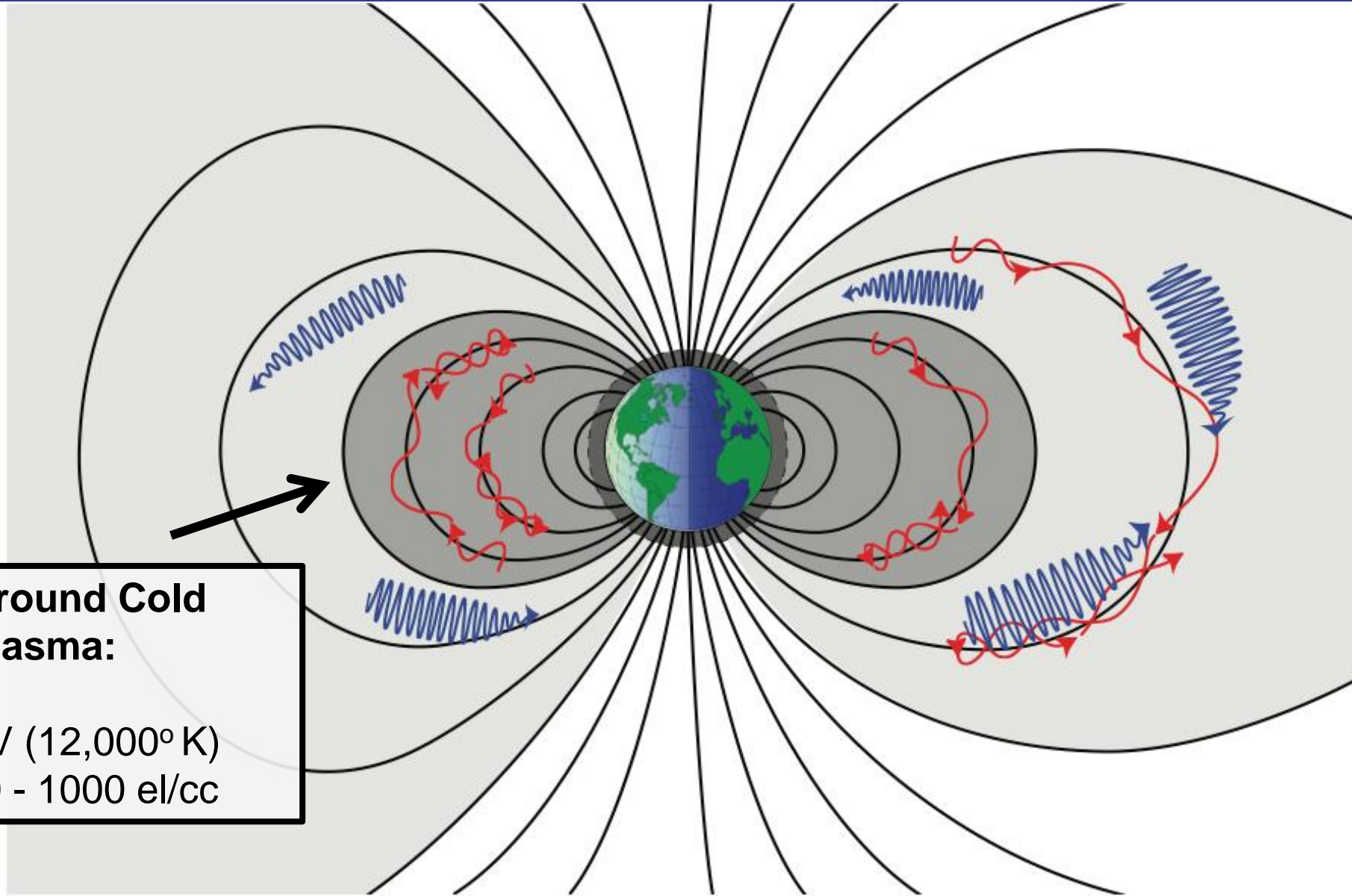


*Credits: NASA's Goddard Space Flight Center/Mary Pat Hrybyk-Keith*

# Inner Magnetosphere



# Inner Magnetosphere

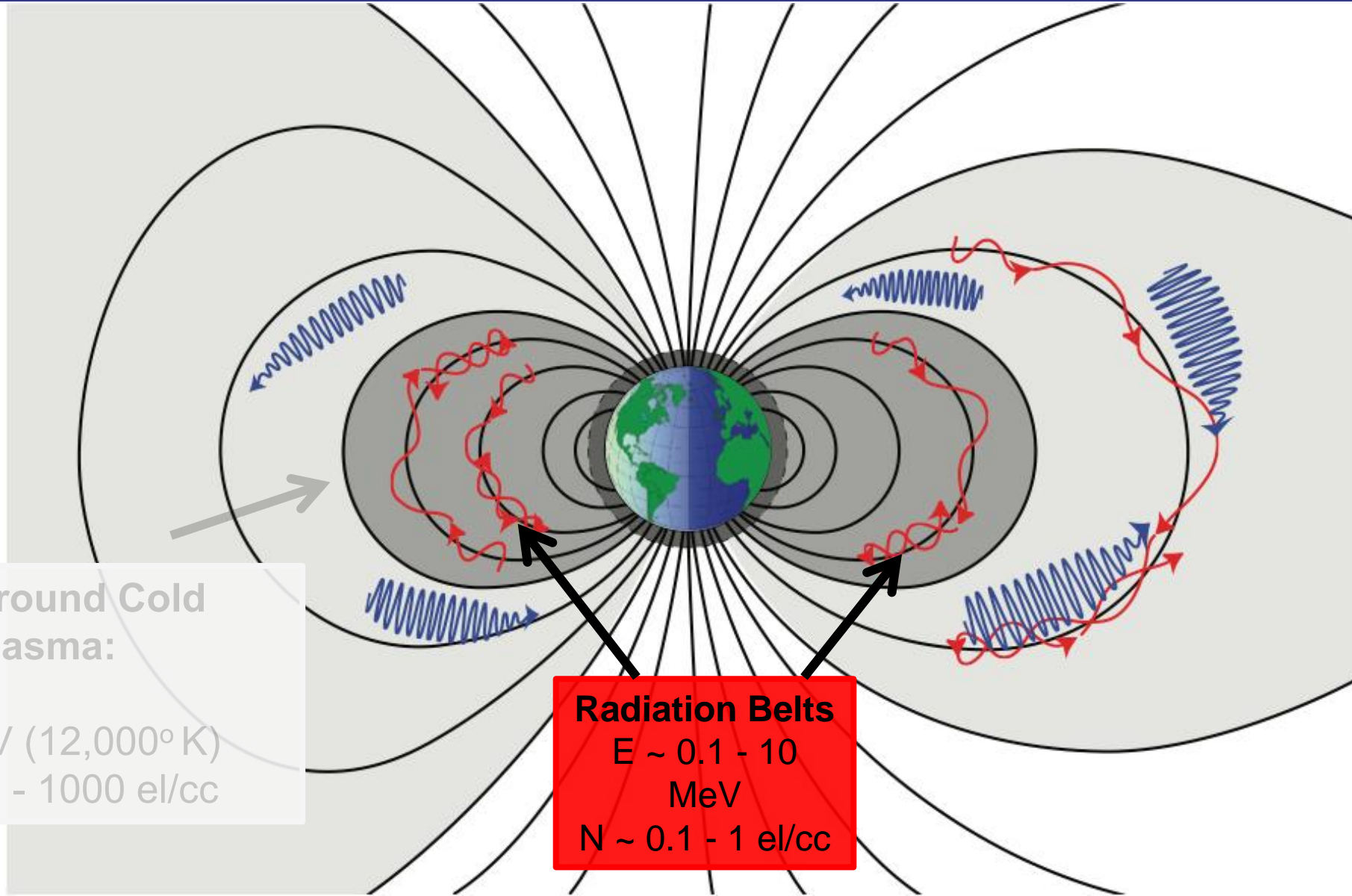


**Background Cold  
Plasma:**

$E \sim 1 \text{ eV}$  ( $12,000^\circ \text{ K}$ )

$N \sim 100 - 1000 \text{ el/cc}$

# Inner Magnetosphere



**Background Cold  
Plasma:**

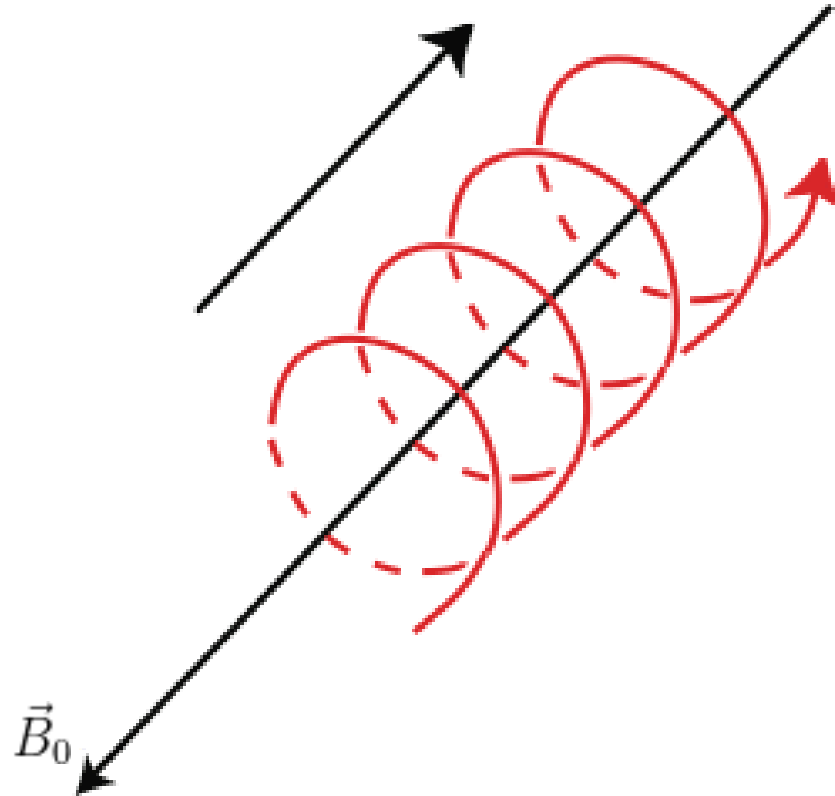
$E \sim 1 \text{ eV}$  ( $12,000^\circ \text{K}$ )  
 $N \sim 100 - 1000 \text{ el/cc}$

**Radiation Belts**

$E \sim 0.1 - 10$   
 $\text{MeV}$   
 $N \sim 0.1 - 1 \text{ el/cc}$

# Inner Magnetosphere

- Electron gyromotion due to geomagnetic field.

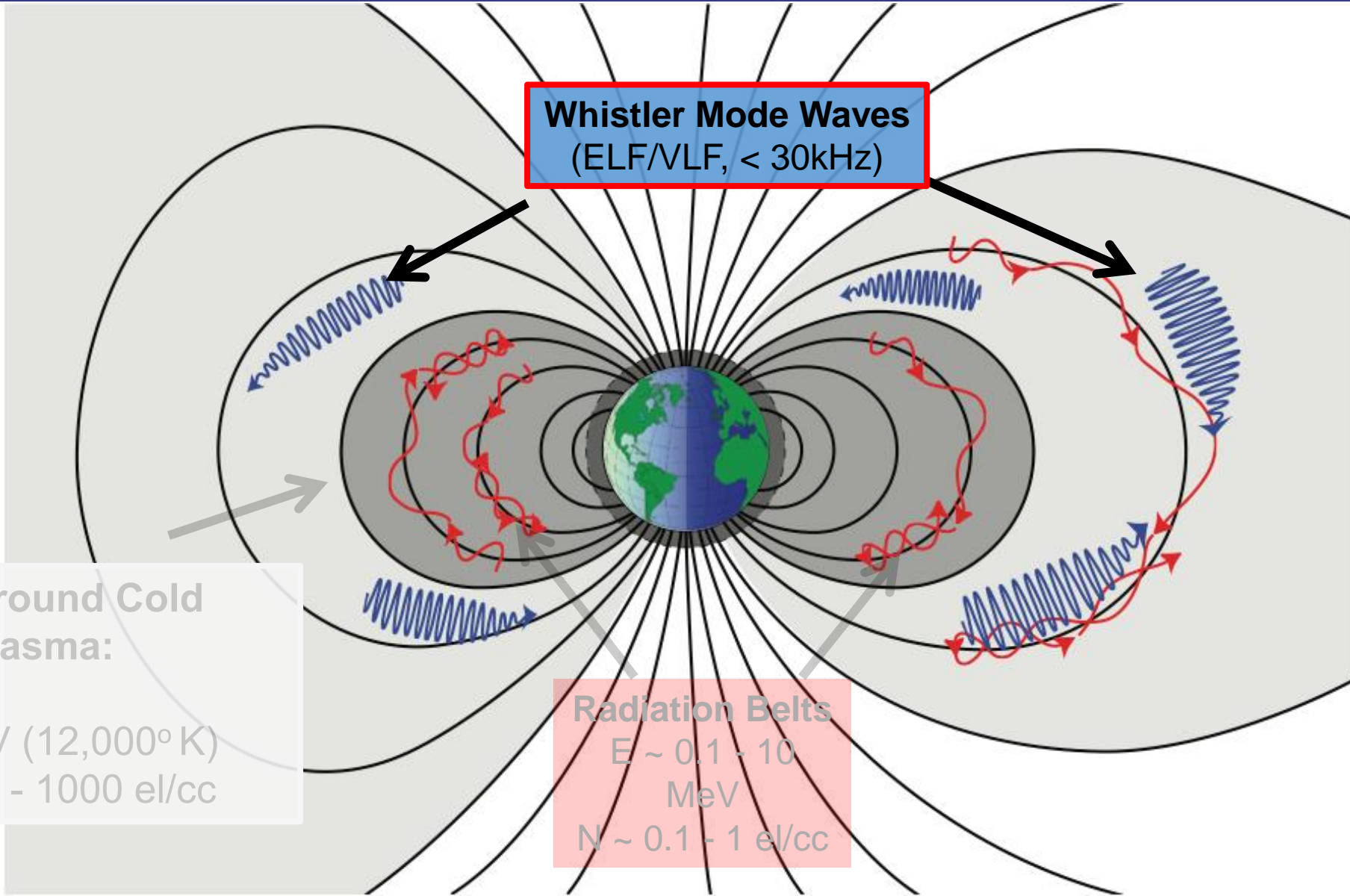


$$\omega_c = \frac{qB_0}{m}$$

**Gyro-frequency**  
( $f_c = \frac{\omega_c}{2\pi}$ , 1-100 kHz range)



# Inner Magnetosphere



**Background Cold Plasma:**

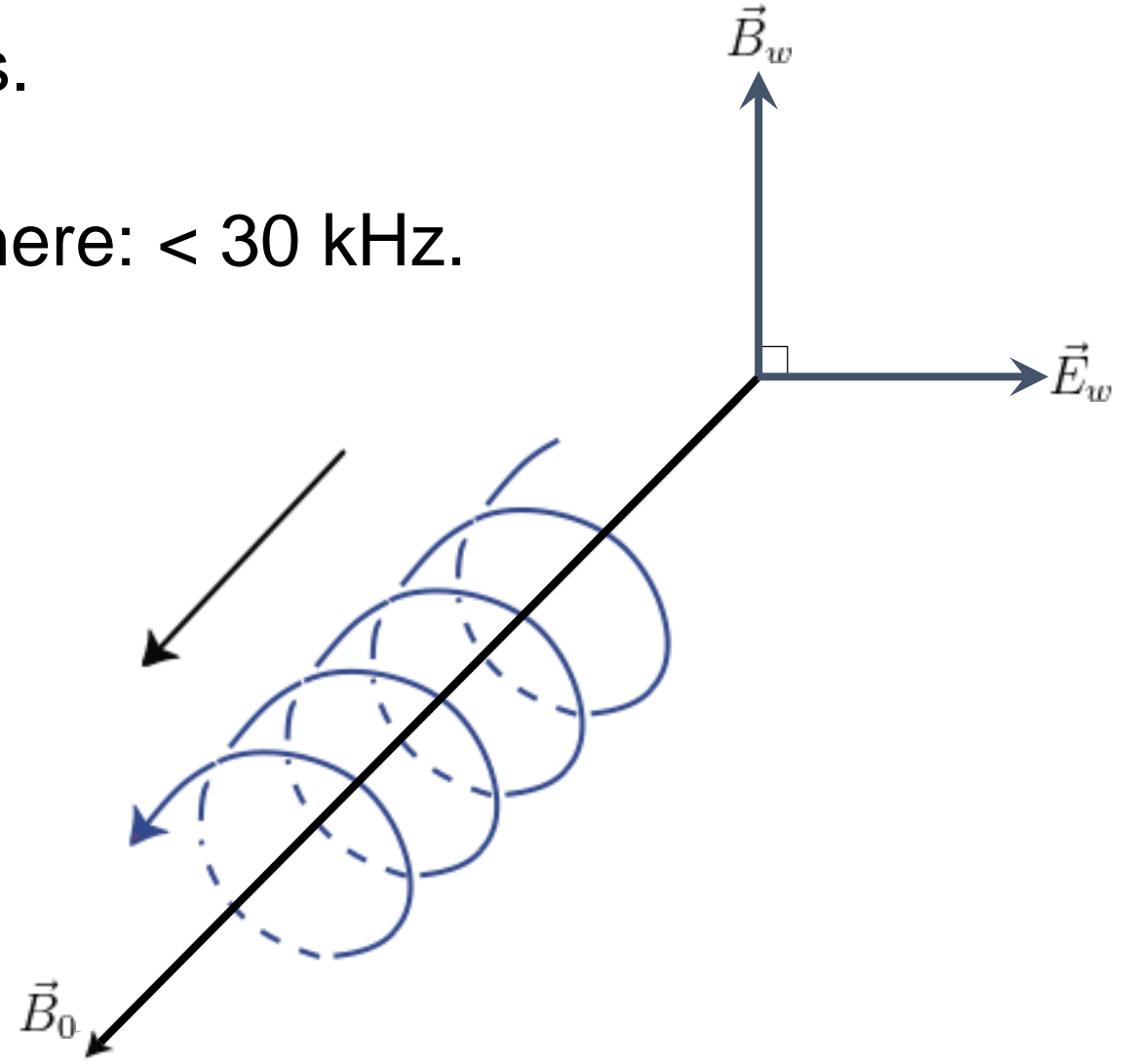
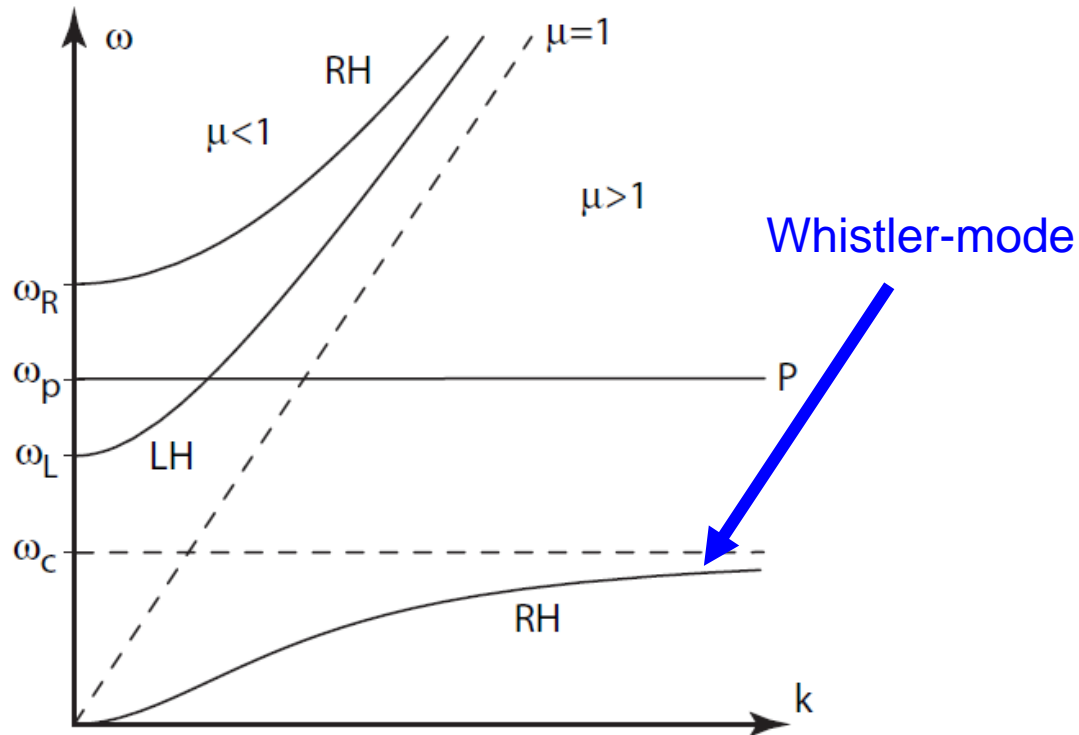
$E \sim 1 \text{ eV}$  ( $12,000^\circ \text{K}$ )  
 $N \sim 100 - 1000 \text{ el/cc}$

**Radiation Belts**

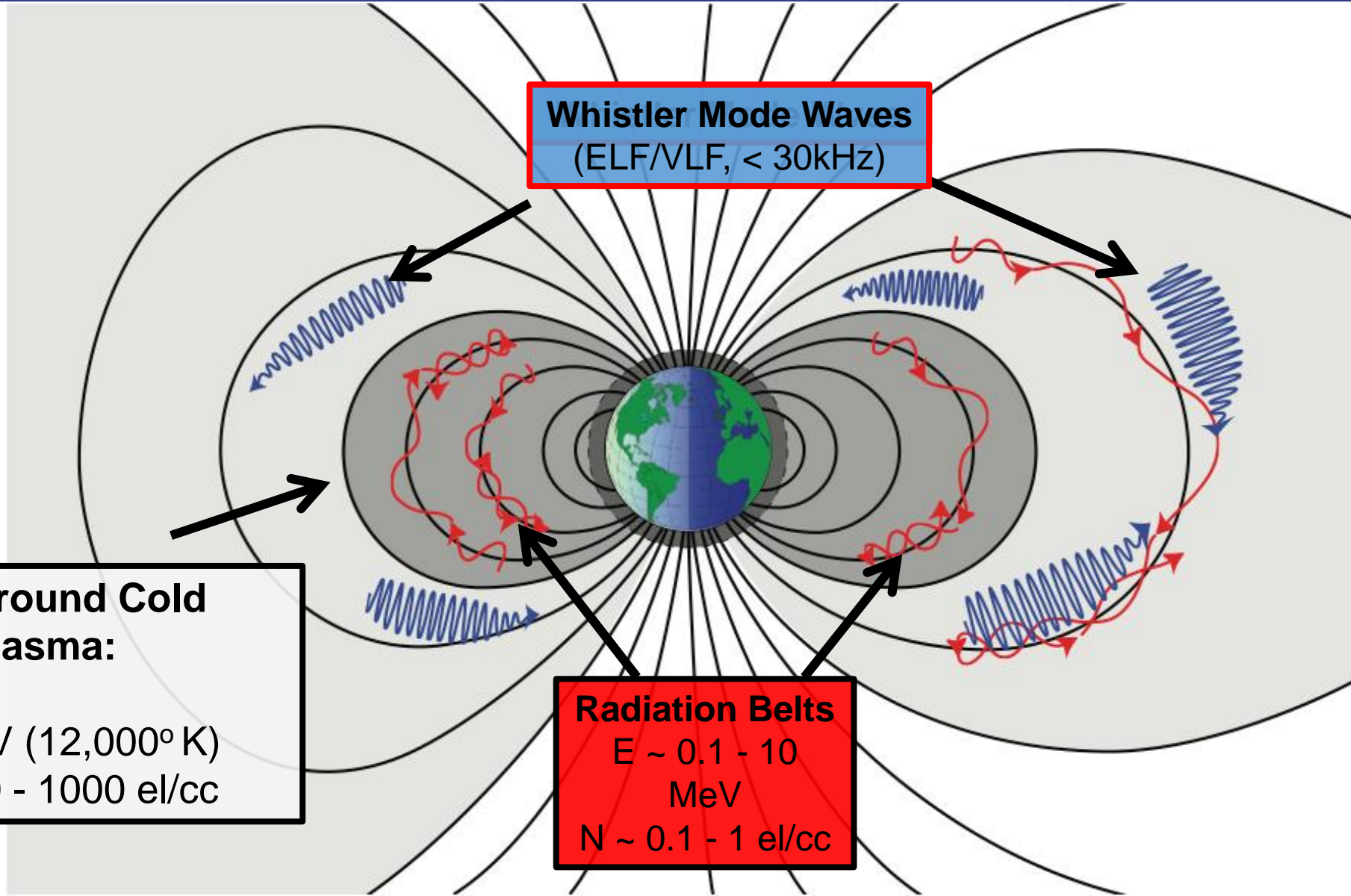
$E \sim 0.1 - 10 \text{ MeV}$   
 $N \sim 0.1 - 1 \text{ el/cc}$

# Whistler Mode Waves

- Exists only in magnetized plasmas.
- ELF/VLF range in the magnetosphere:  $< 30$  kHz.



# Inner Magnetosphere



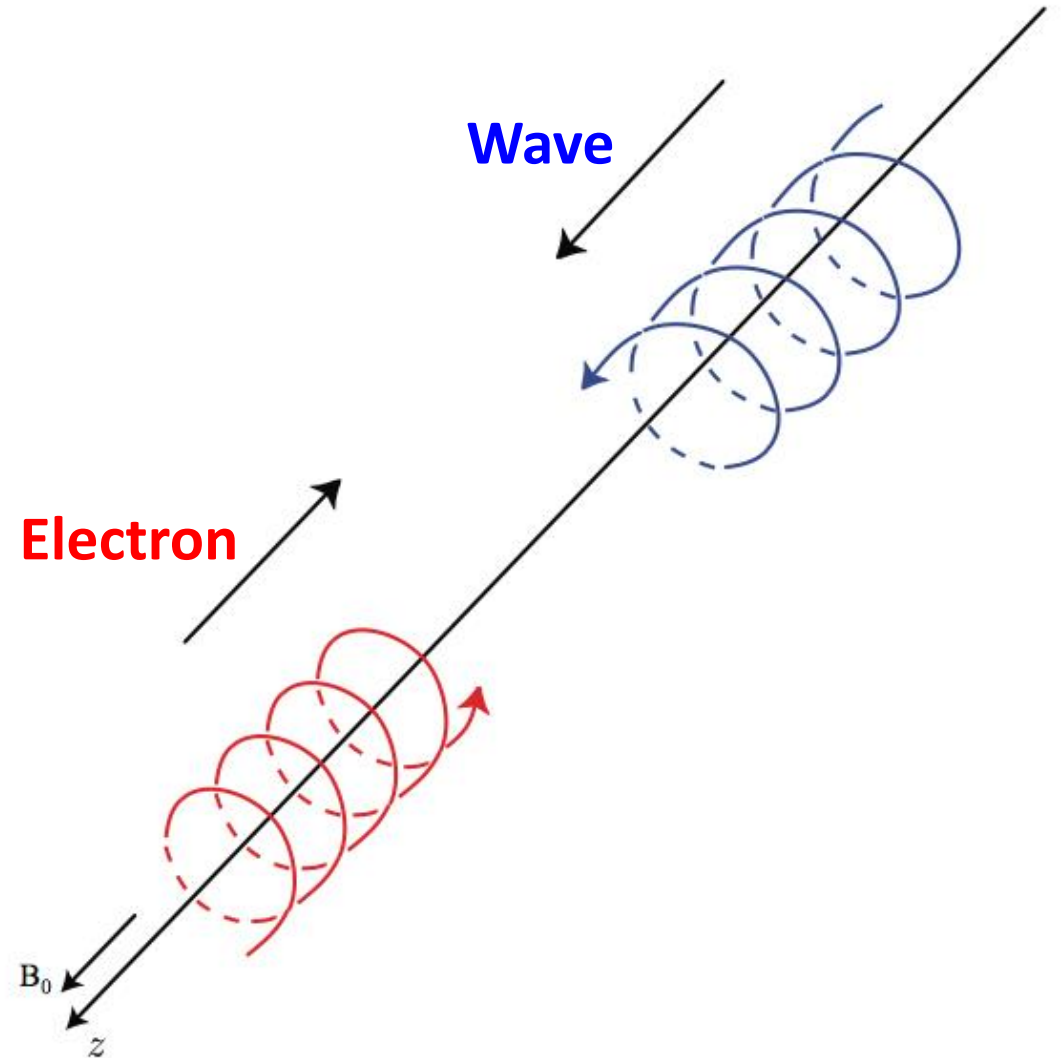
**Whistler Mode Waves**  
(ELF/VLF, < 30kHz)

**Background Cold Plasma:**  
 $E \sim 1 \text{ eV}$  ( $12,000^\circ \text{K}$ )  
 $N \sim 100 - 1000 \text{ el/cc}$

**Radiation Belts**  
 $E \sim 0.1 - 10 \text{ MeV}$   
 $N \sim 0.1 - 1 \text{ el/cc}$

# Wave-Particle Interactions

- Whistler-mode Waves can interact with electrons via Doppler-shifted-cyclotron resonance (gyro-resonance).
- Resonant electrons can transfer large amounts of energy to/from waves.
- Understanding characteristics of whistler-mode waves is crucial to space weather modeling!



## **Naturally Sourced:**

- Chorus
- Hiss
- Lightning-Whistlers

## **Artificially Sourced:**

- VLF transmitters + Triggered Emissions

## Naturally Sourced:

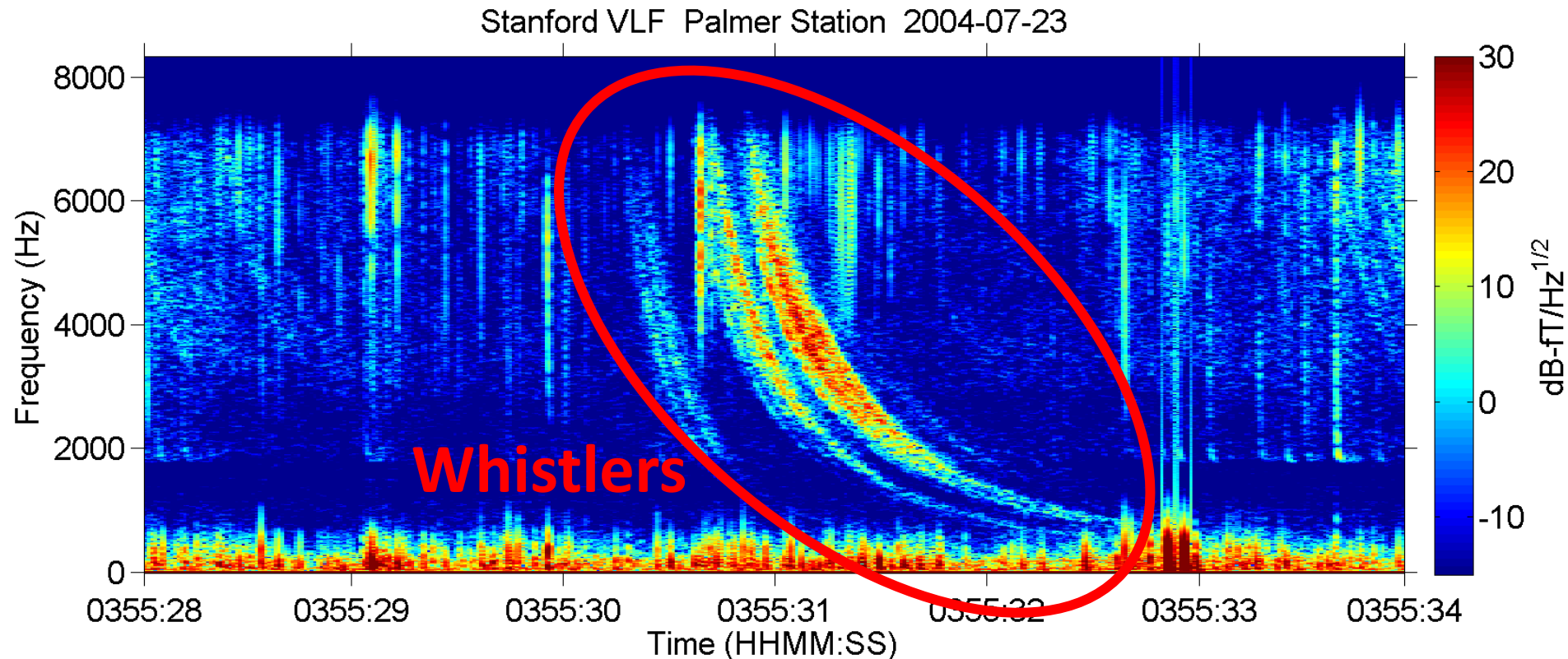
- Chorus
- Hiss
- **Lightning-Whistlers**

## Artificially Sourced:

- VLF transmitters + Triggered Emissions

# Lightning Whistlers

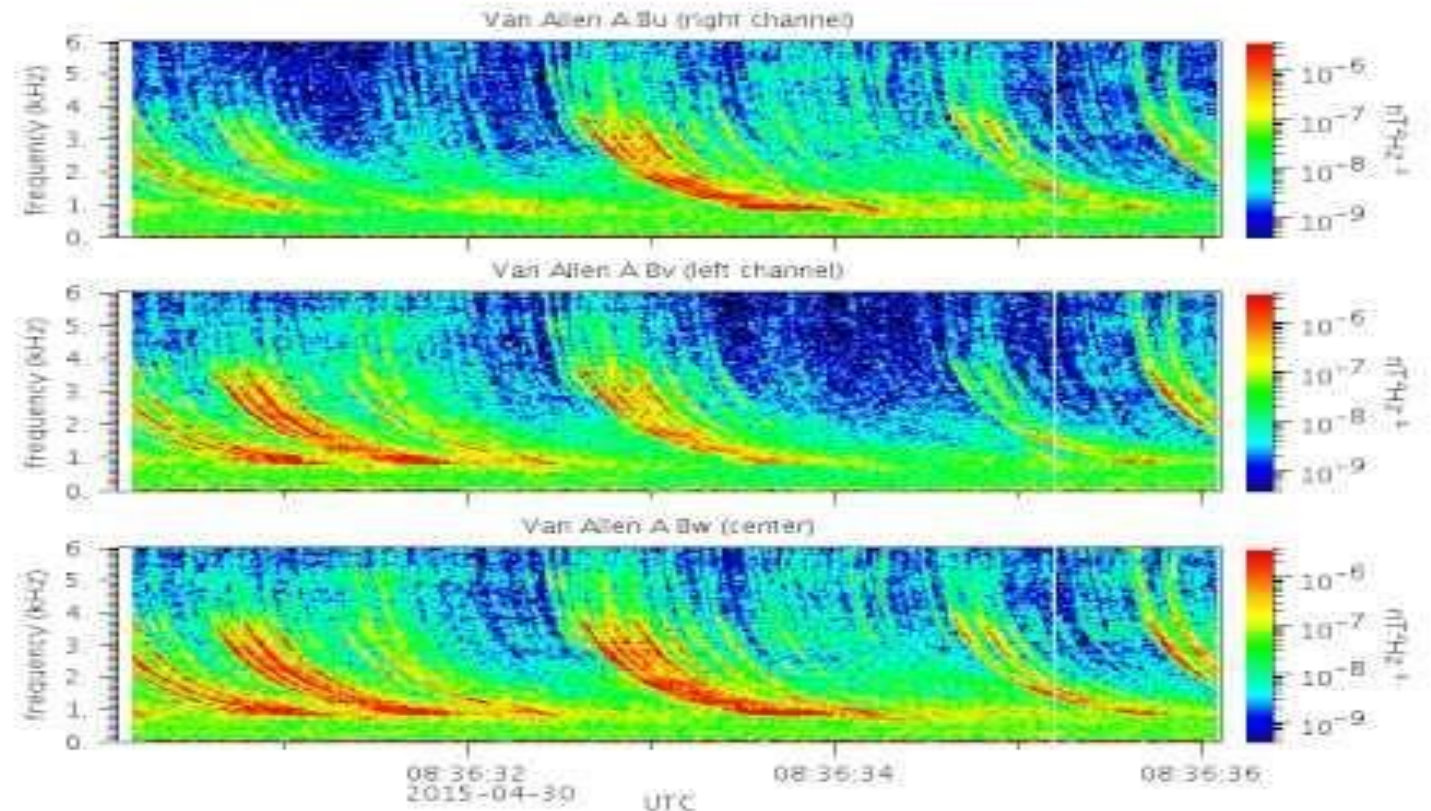
- ELF/VLF waves are typically analyzed using spectrograms (STFT).
- Whistlers are observed on a spectrogram as descending tones.



# Lightning Whistlers

- Whistlers are in the VLF band (<30 kHz).
- Acoustic waves in the VLF band are audible.
- The name “whistler” reflects the descending whistle-like sound when listened to.

From RBSP in 2015 (<https://youtu.be/ZVIZ5ikvet8>)





# Very Brief History of Whistlers

- First comprehensive investigation of whistlers was by *Storey, 1953*.

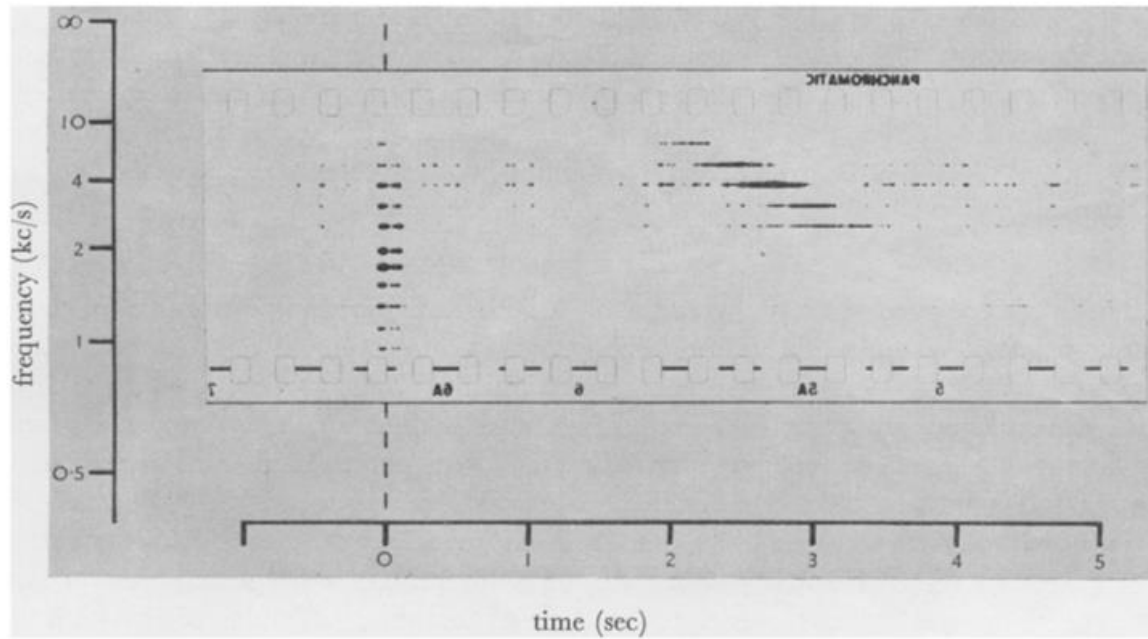


FIGURE 1. Sound spectrograph record of a whistler following an atmospheric click.

# Very Brief History of Whistlers

- First comprehensive investigation of whistlers was by *Storey, 1953*.

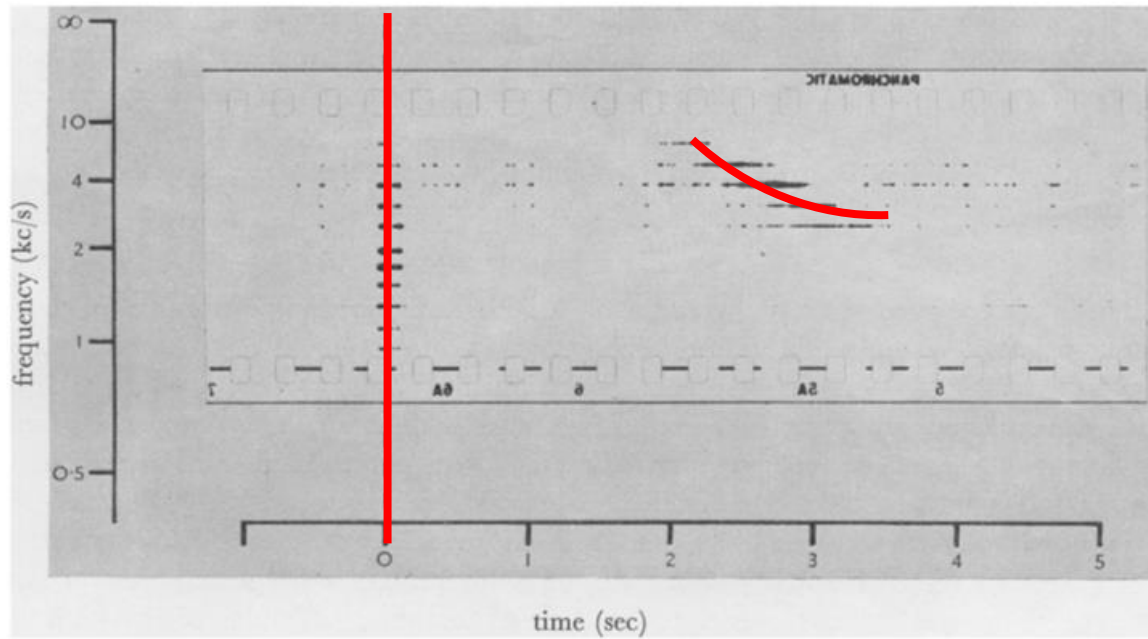


FIGURE 1. Sound spectrograph record of a whistler following an atmospheric click.

# Very Brief History of Whistlers

- First comprehensive investigation of whistlers was by *Storey, 1953*.

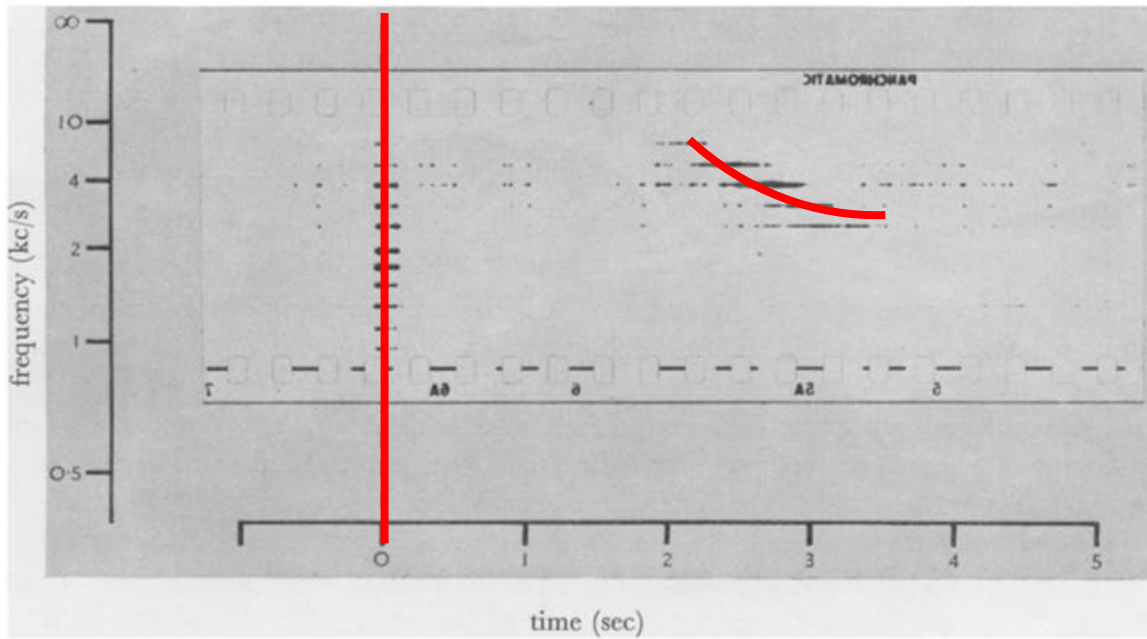
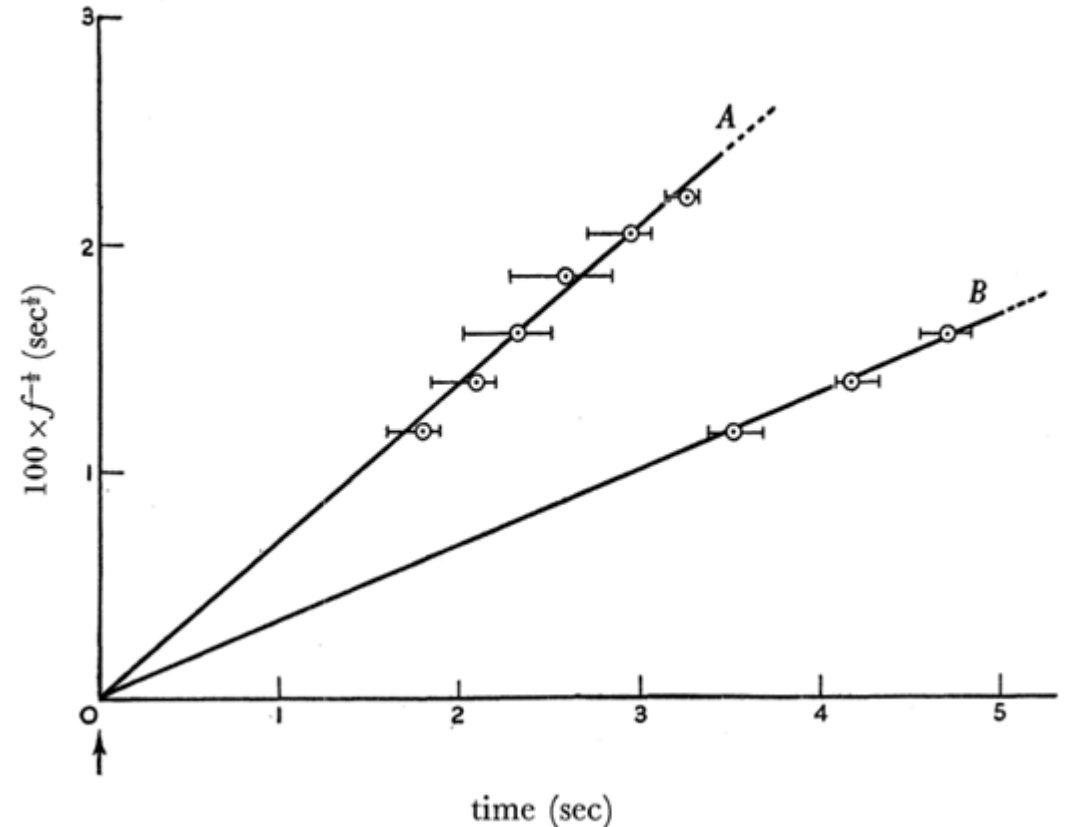


FIGURE 1. Sound spectrograph record of a whistler following an atmospheric click.



# Very Brief History of Whistlers

- First comprehensive investigation of whistlers was by *Storey, 1953*.

As already mentioned, the theory of Barkhausen & Eckersley predicted that the frequency ( $f$ ) in the whistler should be related to the time ( $t$ ) after the original lightning flash by the expression

$$t = D \times f^{-1}.$$

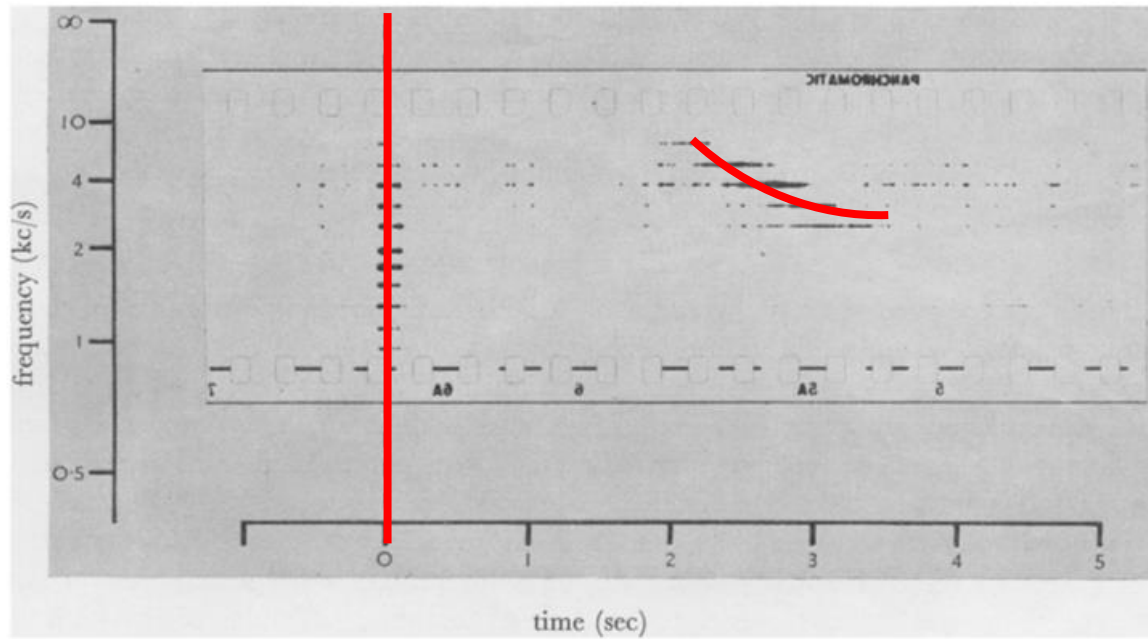
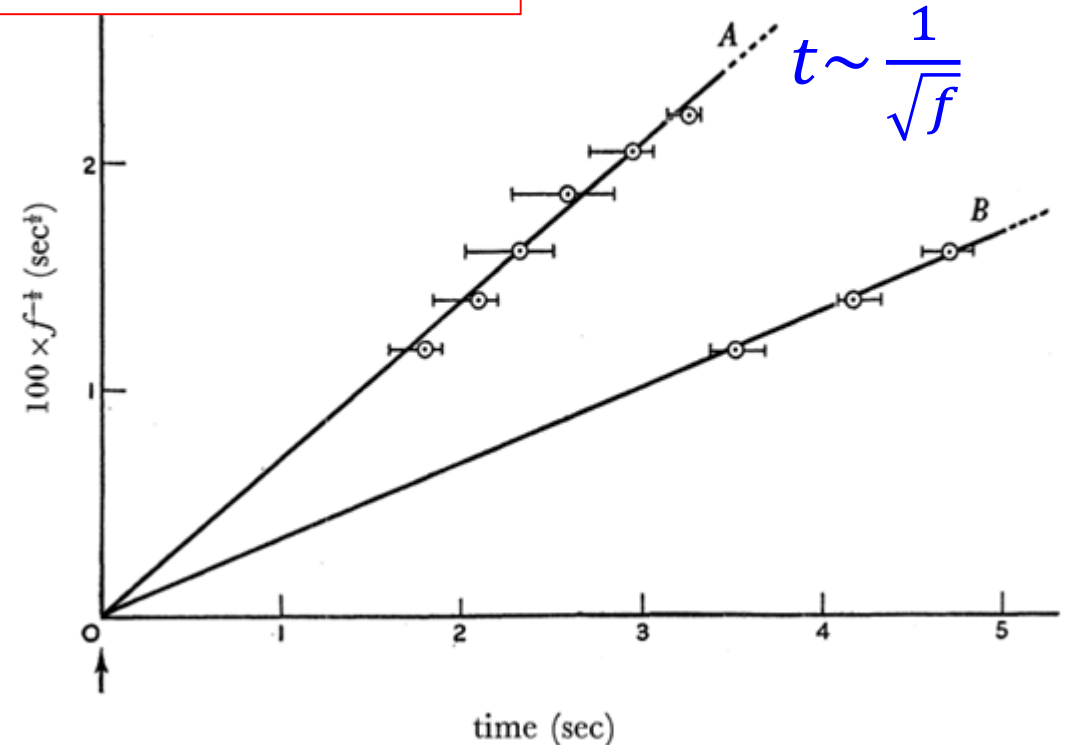
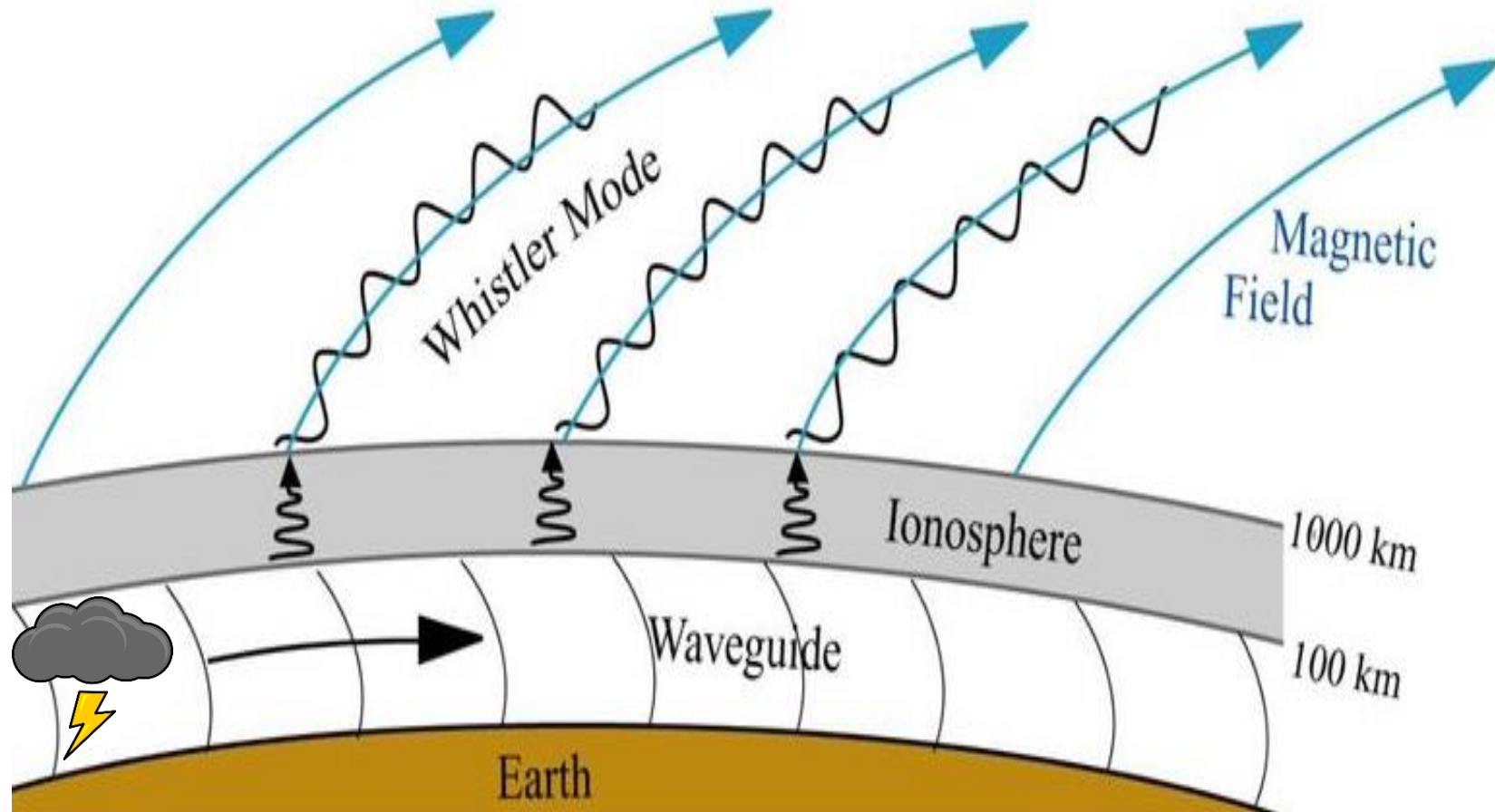


FIGURE 1. Sound spectrograph record of a whistler following an atmospheric click.

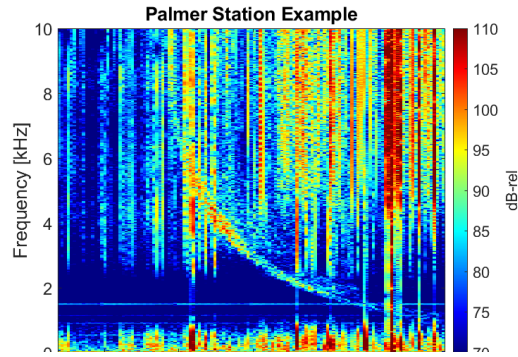


# Where do Whistlers Come From?

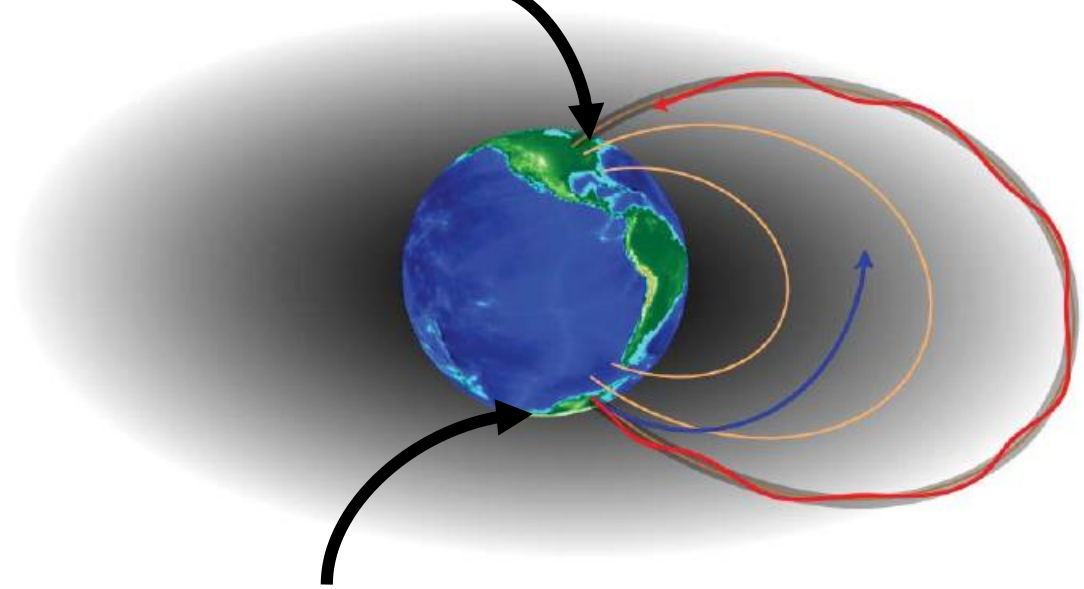
- Lightning EMPs (spheric) can leak into the magnetosphere and propagated in the whistler-mode:



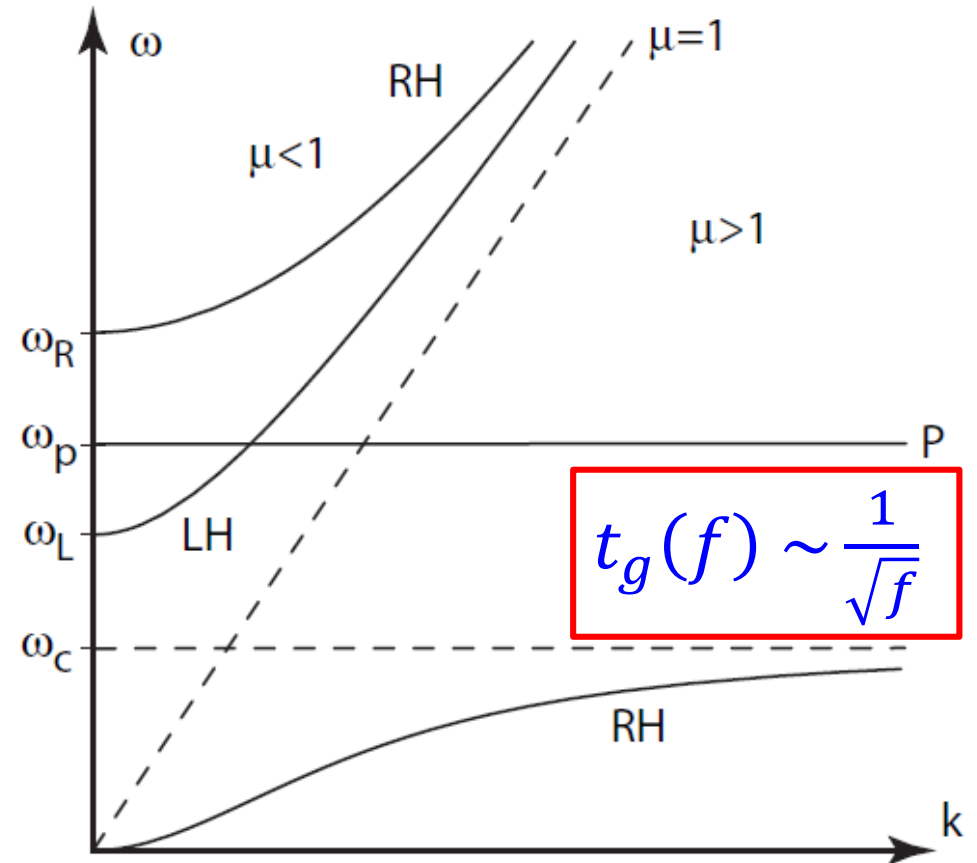
# Where do Whistlers Come From?



Whistler



Source Lightning "Sferic"

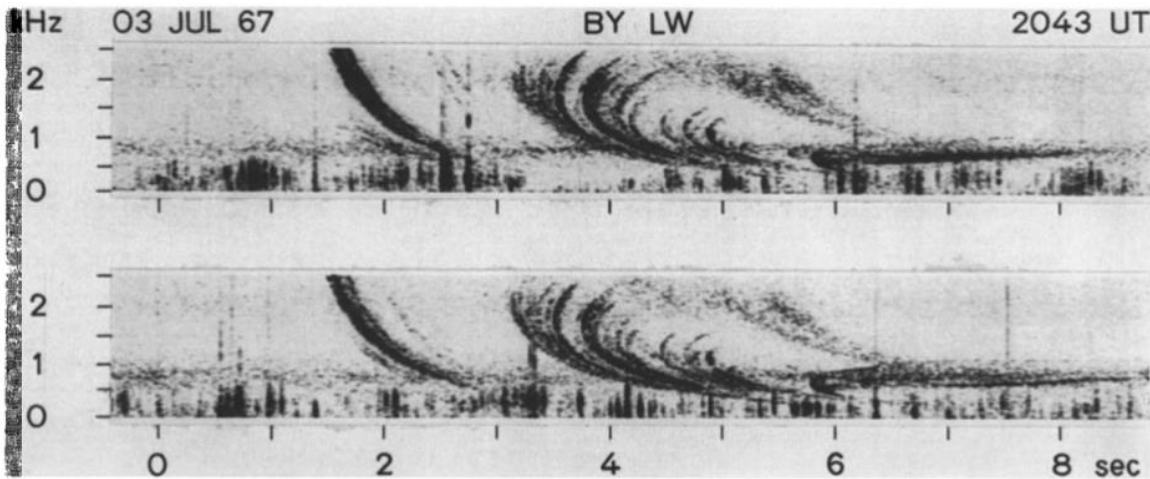




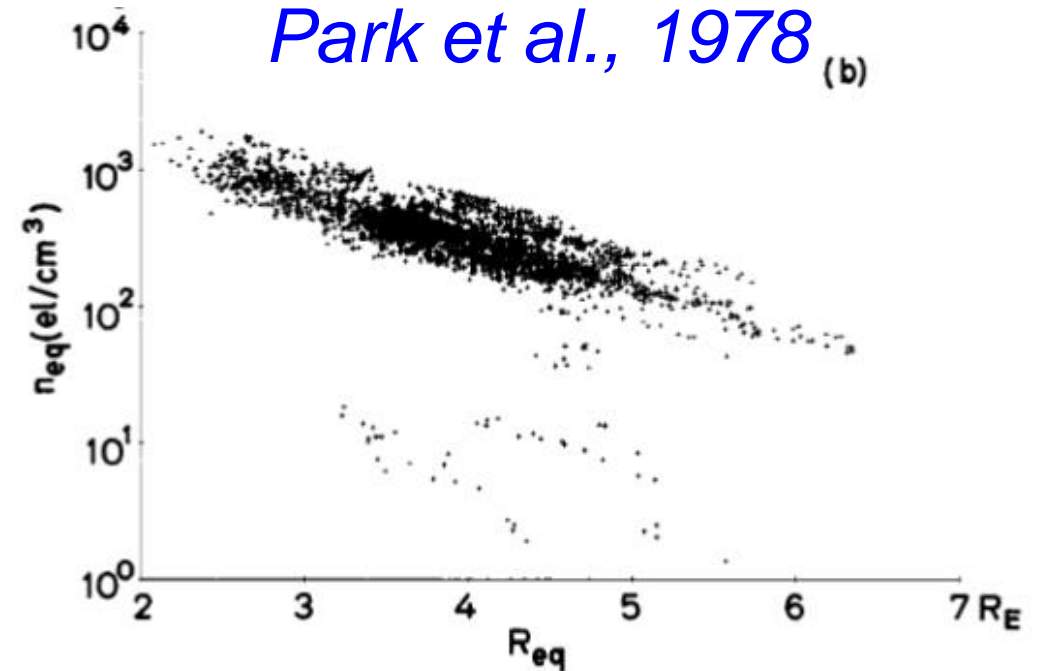
# Whistlers: Plasmasphere Remote Sensing

- The whistler shape (and/or “nose frequency”) can be used to remotely determine the plasmasphere’s electron density...  $t_g \sim \sqrt{N_e}$

*Carpenter, 1988*



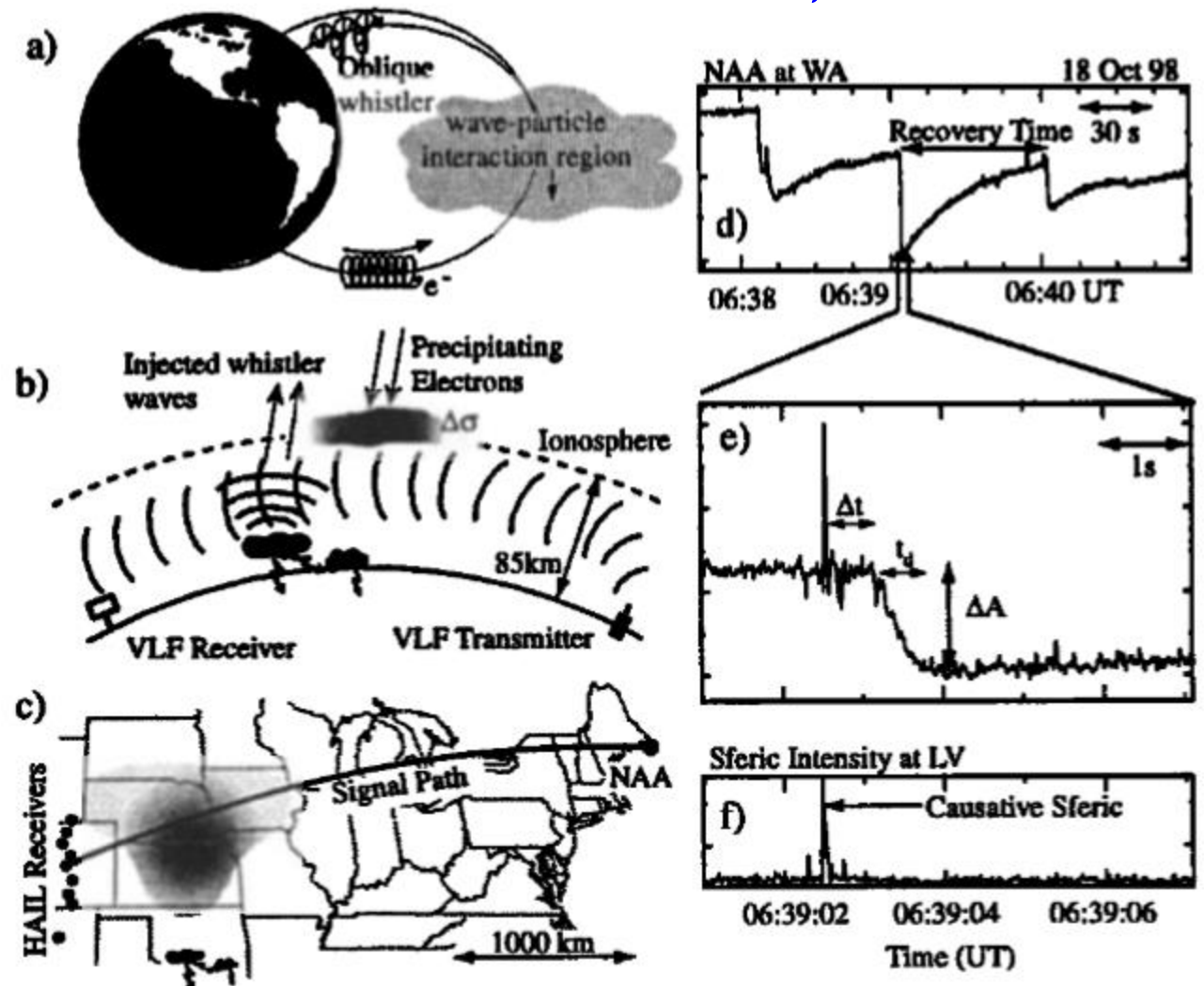
*Park et al., 1978 (b)*



# Whistlers: LEP Events

*Johnson et al., 1999*

- Whistlers can interact with radiation belt electrons via gyro-resonance.
- Some of these electrons can precipitate onto the atmosphere/ionosphere.
- Precipitation can distort sub-ionospheric VLF signals.

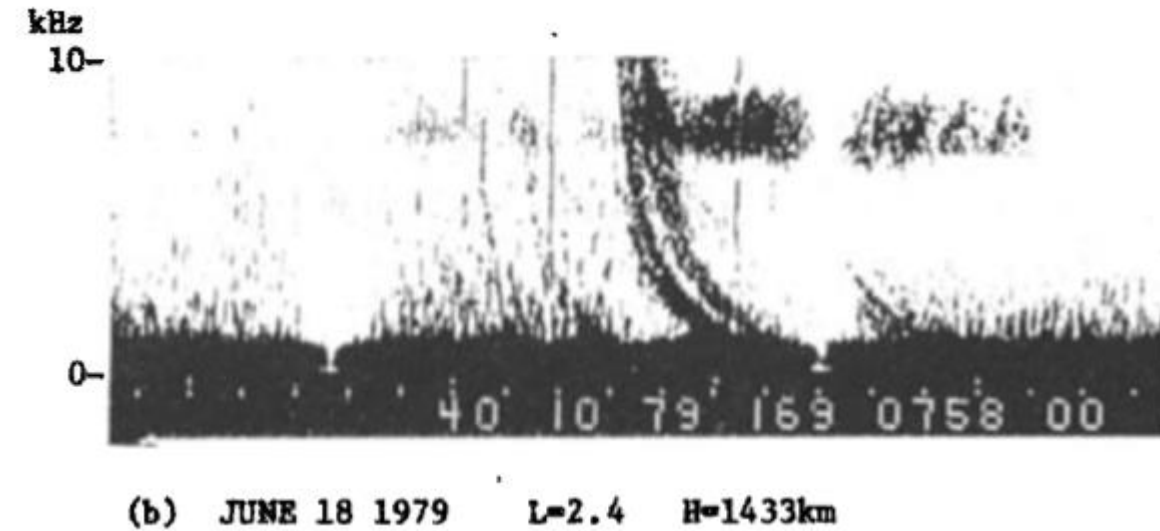




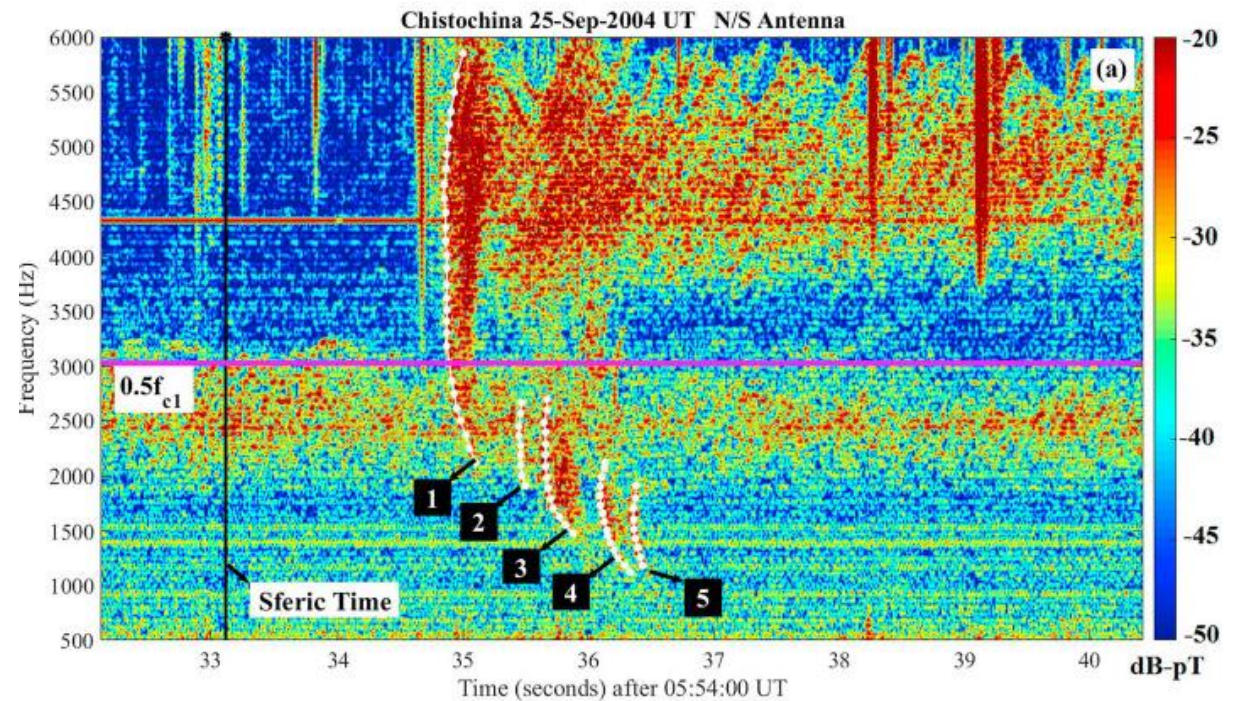
# Whistlers: Triggering

- Whistlers can trigger free-running emissions and emissions that resemble upper-band chorus.

*Nakamura and Ondoh, 1989*

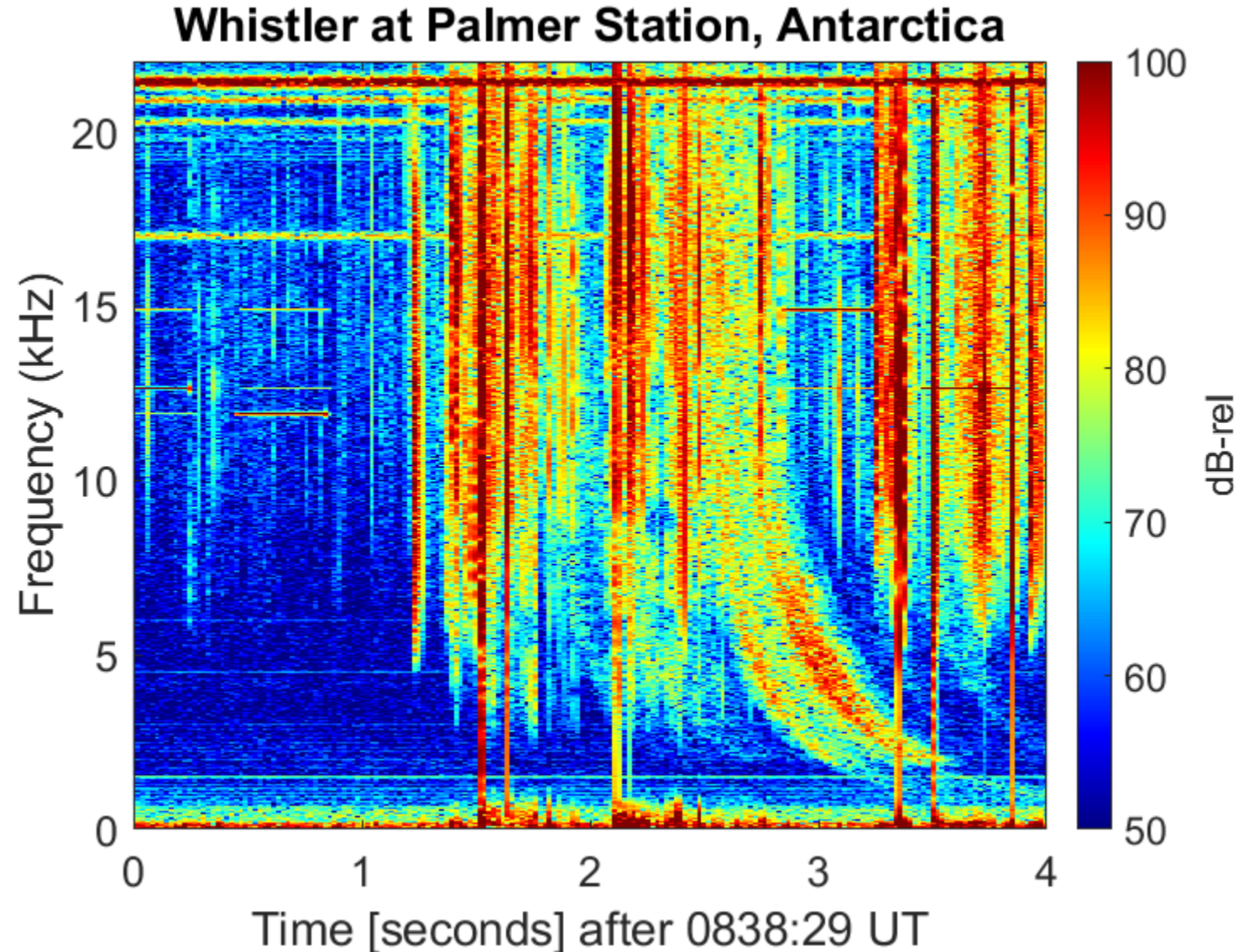


*Hosseini et al., 2019*



# Detecting Whistlers

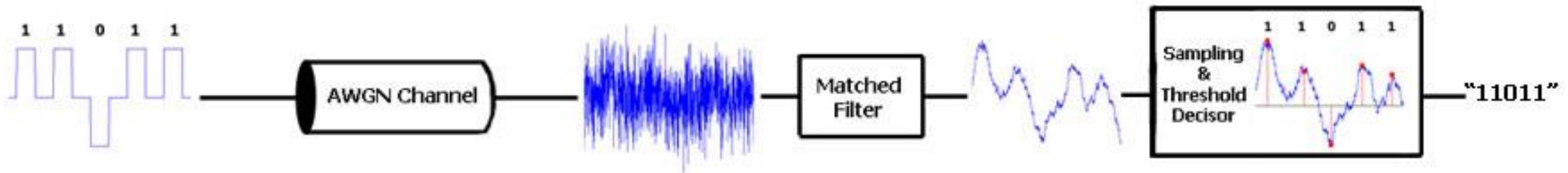
- Understanding whistler impacts is an important component space weather.
- Automated detection is required to gain a thorough statistical picture.
- Realistic data (especially ground-based data), is very noisy which makes automation difficult.



1. Overview of Whistler Mode Waves
2. Traditional Methods of Signal Detection
3. Basic Overview of Neural Networks
4. Whistler Extraction using MSRCNN
5. Summary and Future Work

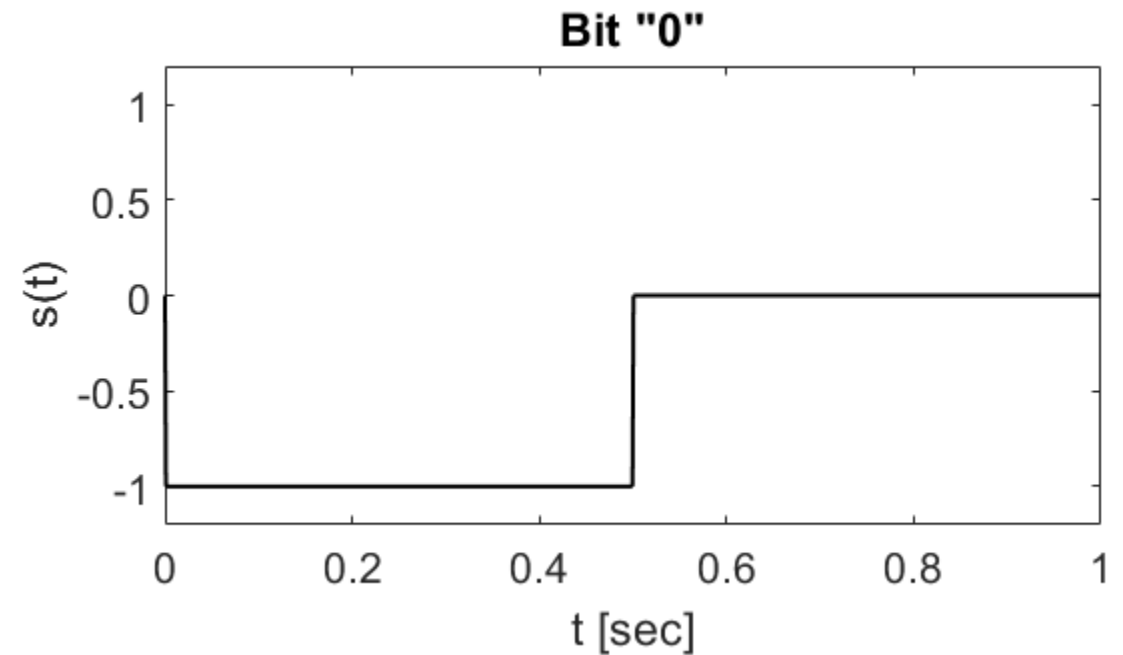
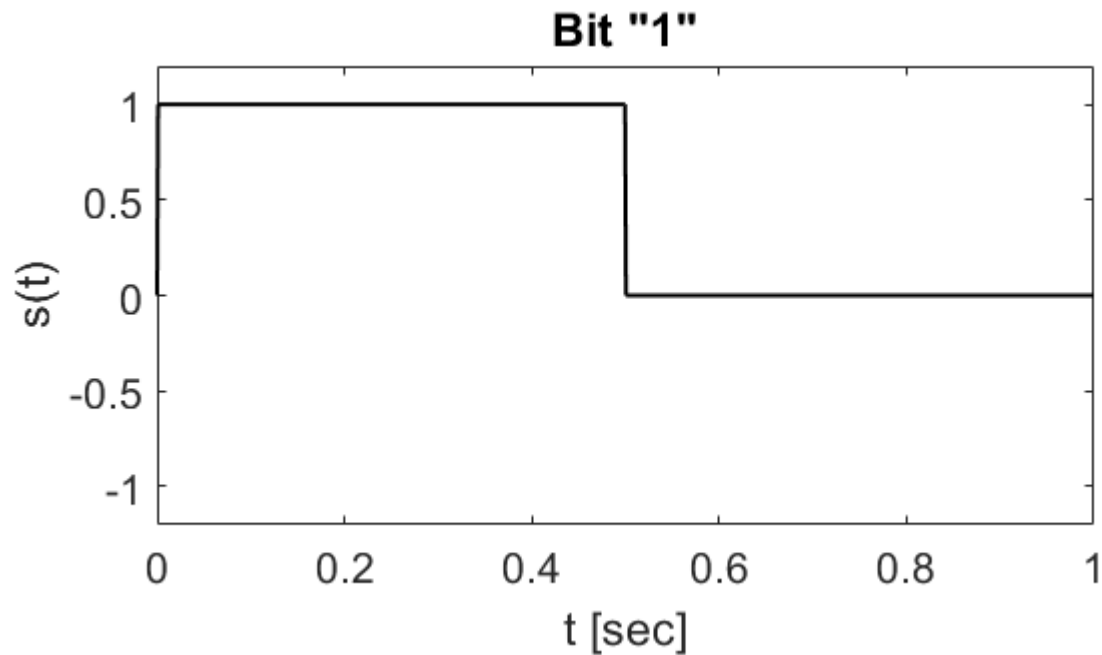
# Traditional Signal Detection

- Traditional signal detection techniques utilize information about the signal's structure (shape, duration, etc.).
- The most common method utilizes a cross-correlating with the expected signal. This is known as a **matched filter**.



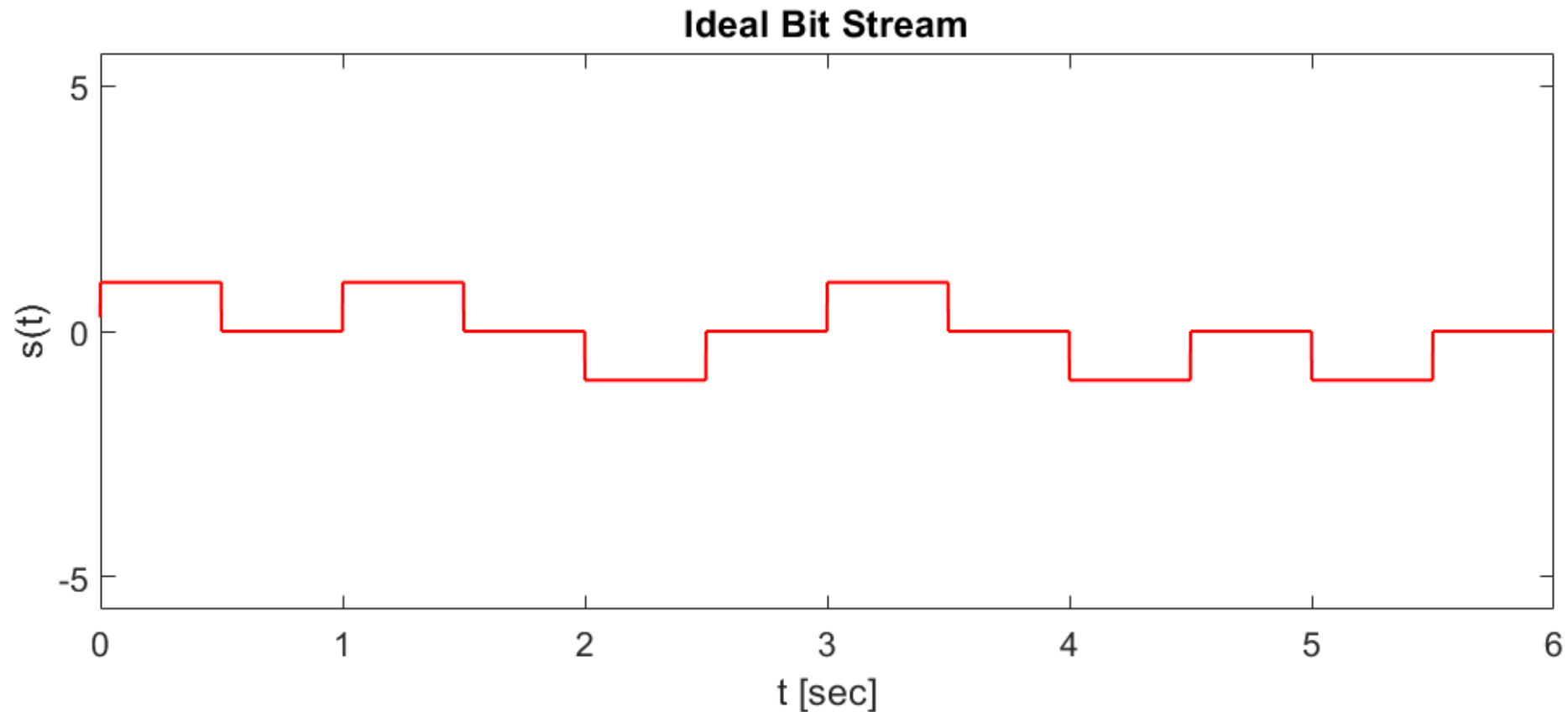
# Example: Bit Stream Detection

- Consider the case of detecting bits represented by rectangular pulses
- Examples of “1” and “0” are below:



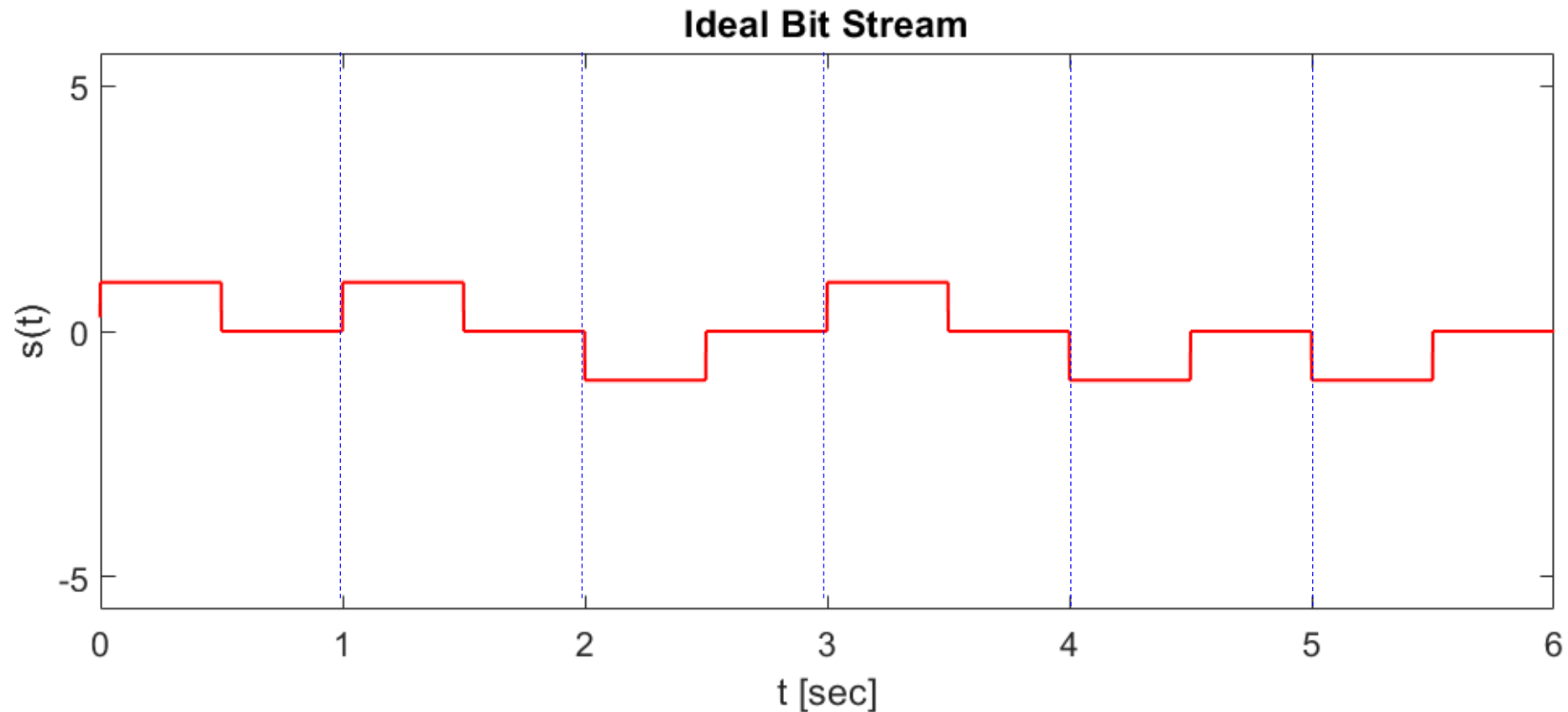
# Example: Bit Stream Detection

- More generally a bit stream can be represented by a sequence of 1s and 0s:



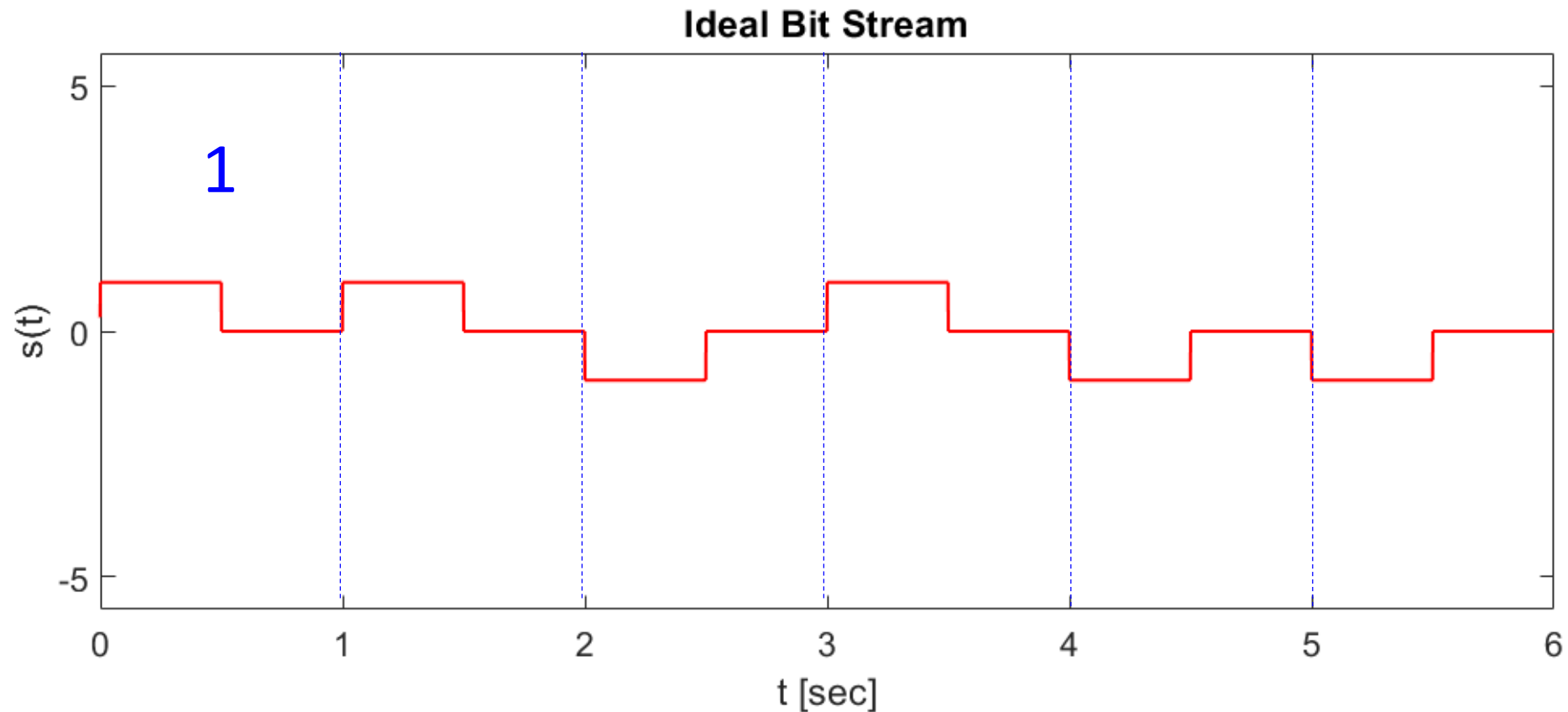
# Example: Bit Stream Detection

- More generally a bit stream can be represented by a sequence of 1s and 0s:



# Example: Bit Stream Detection

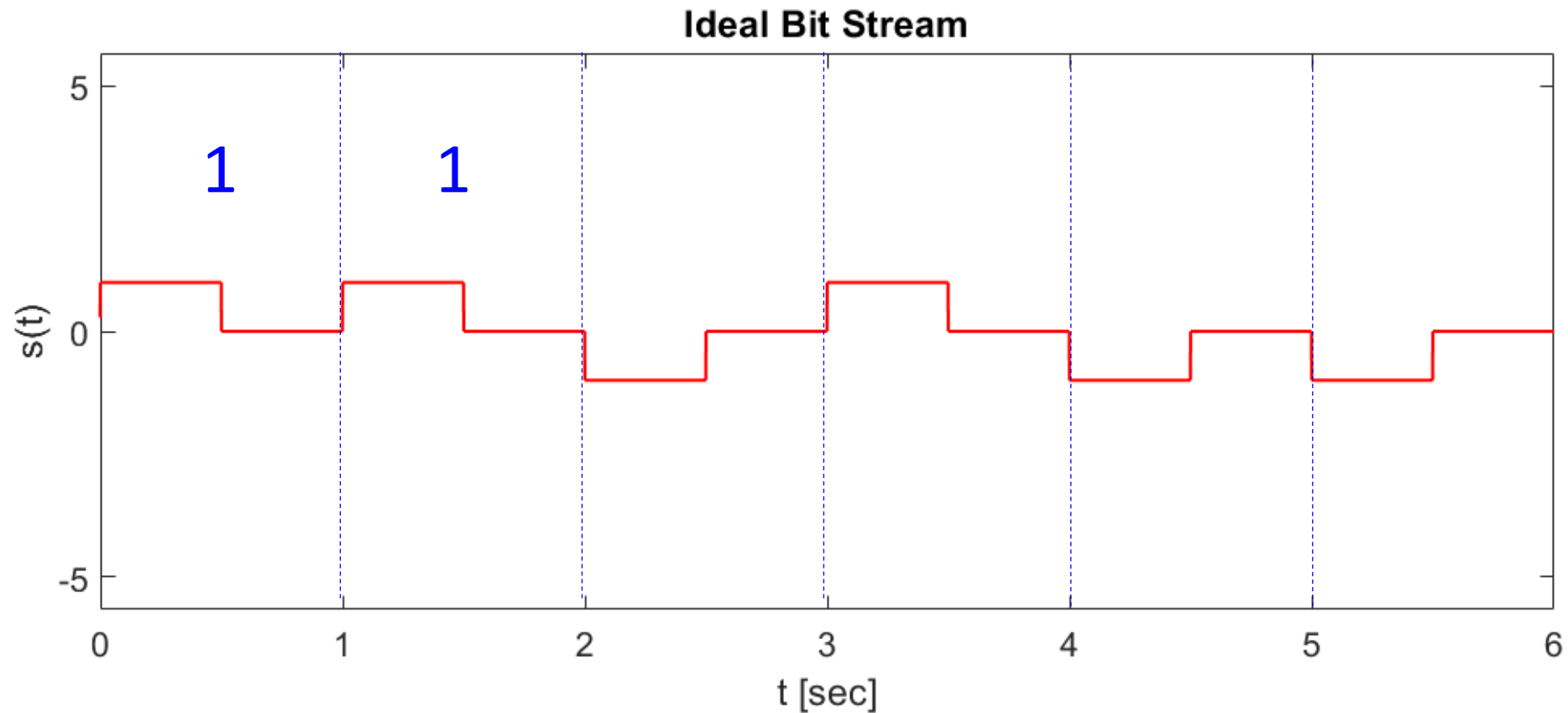
- More generally a bit stream can be represented by a sequence of 1s and 0s:





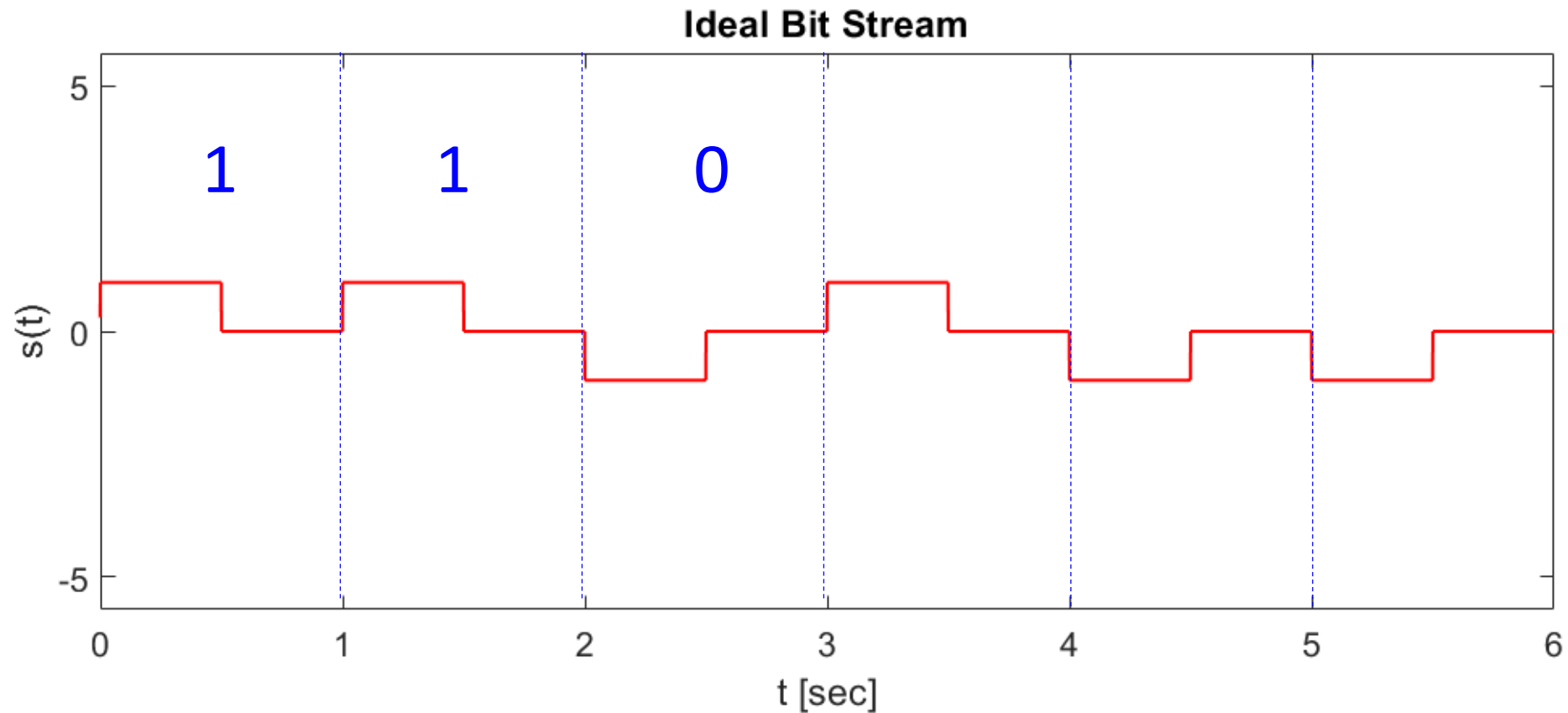
# Example: Bit Stream Detection

- More generally a bit stream can be represented by a sequence of 1s and 0s:



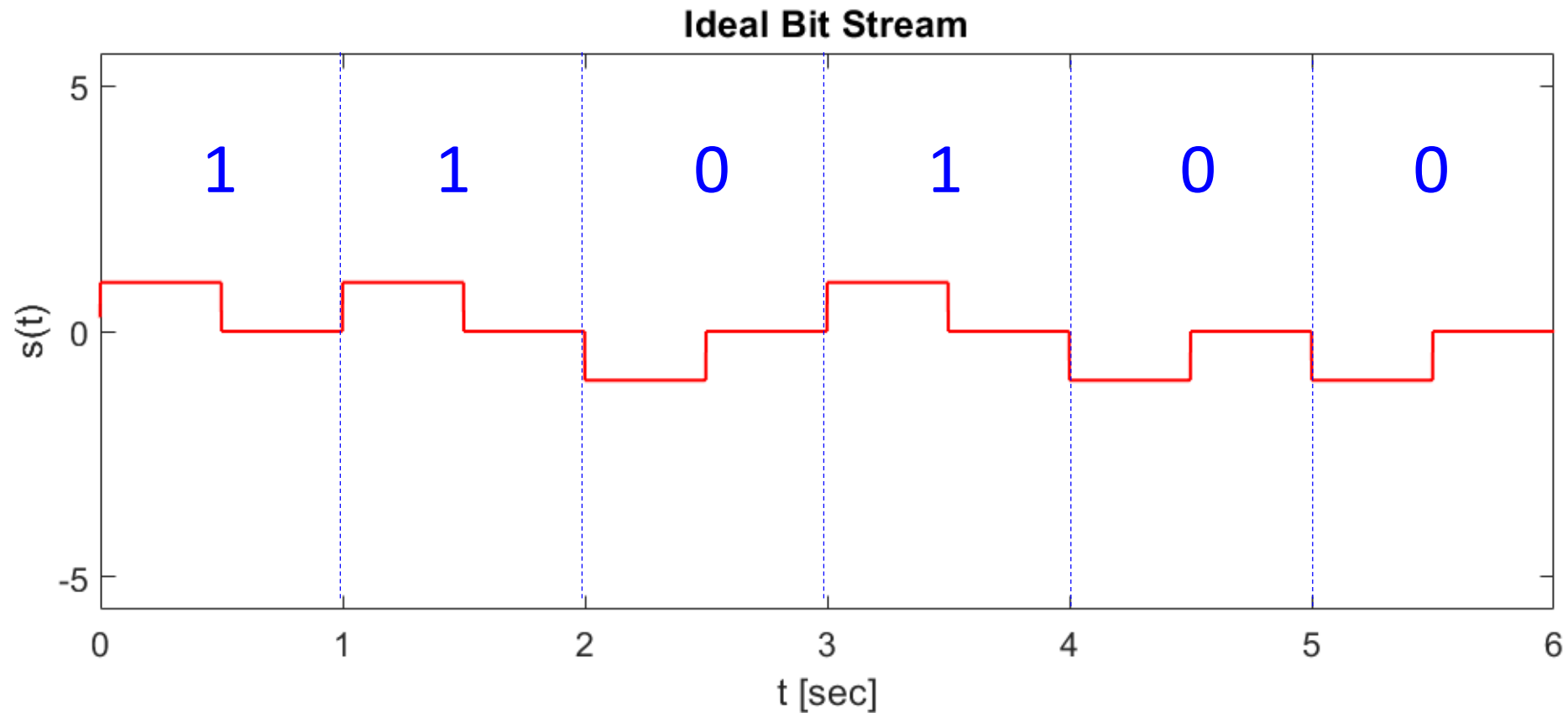
# Example: Bit Stream Detection

- More generally a bit stream can be represented by a sequence of 1s and 0s:



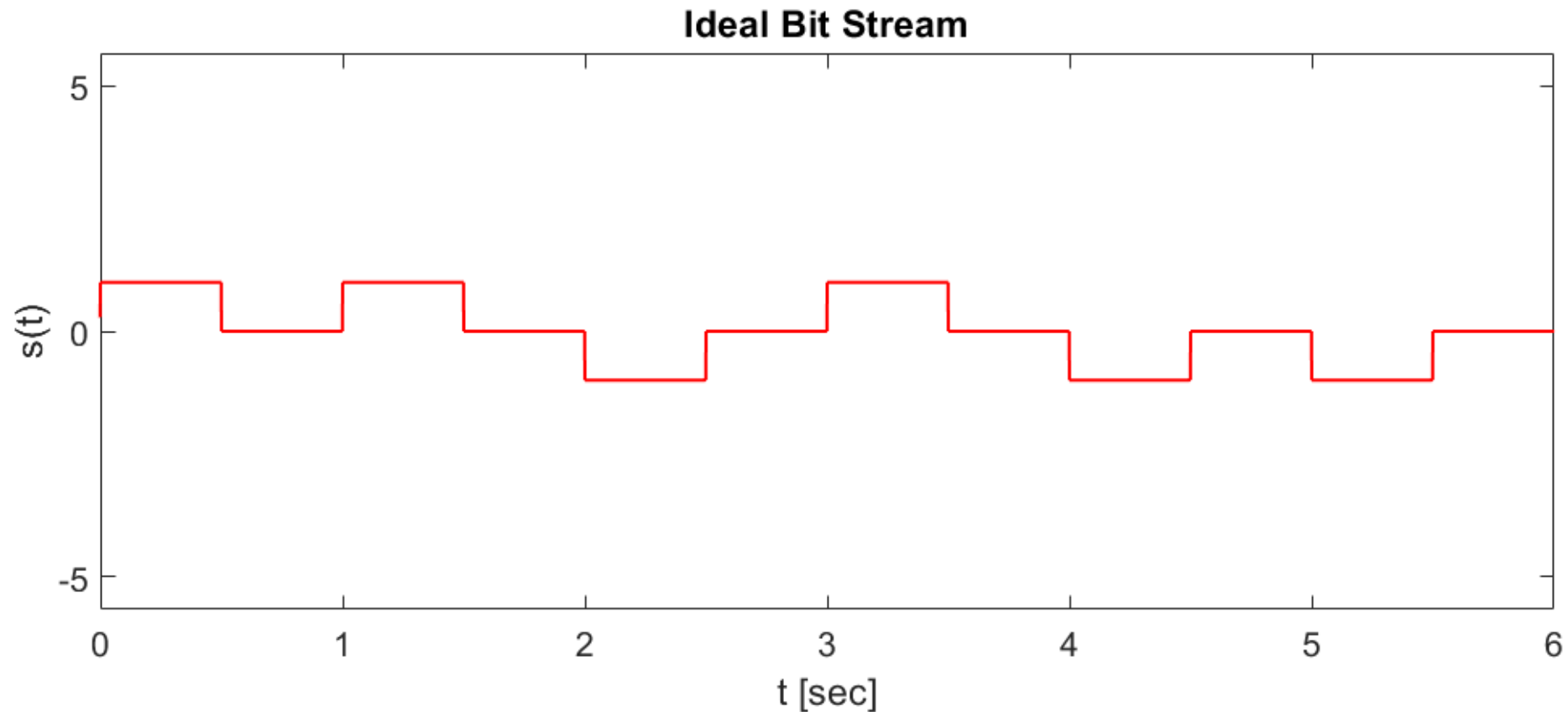
# Example: Bit Stream Detection

- More generally a bit stream can be represented by a sequence of 1s and 0s:



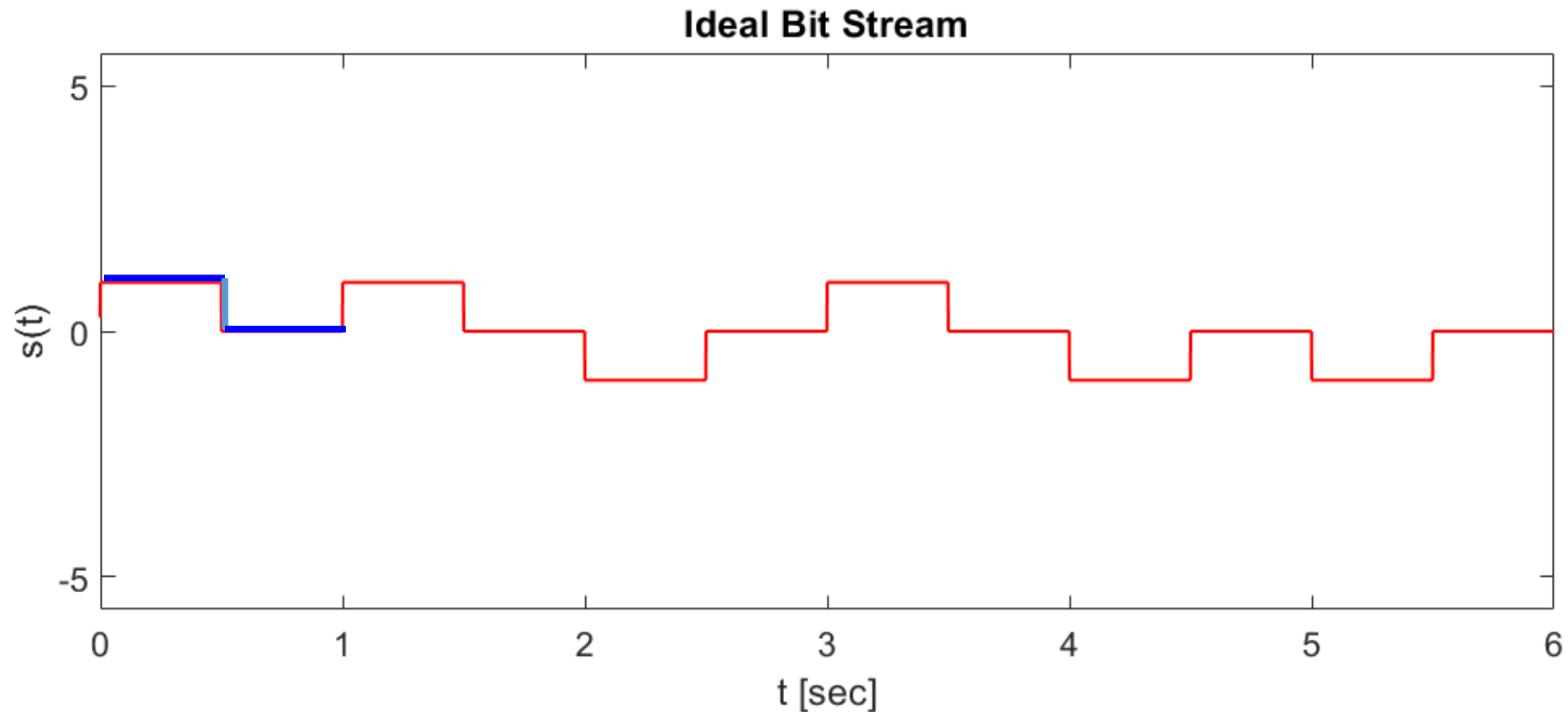
# Example: Bit Stream Detection

- The individual bits can be detected using a **matched filter** (cross-correlation):



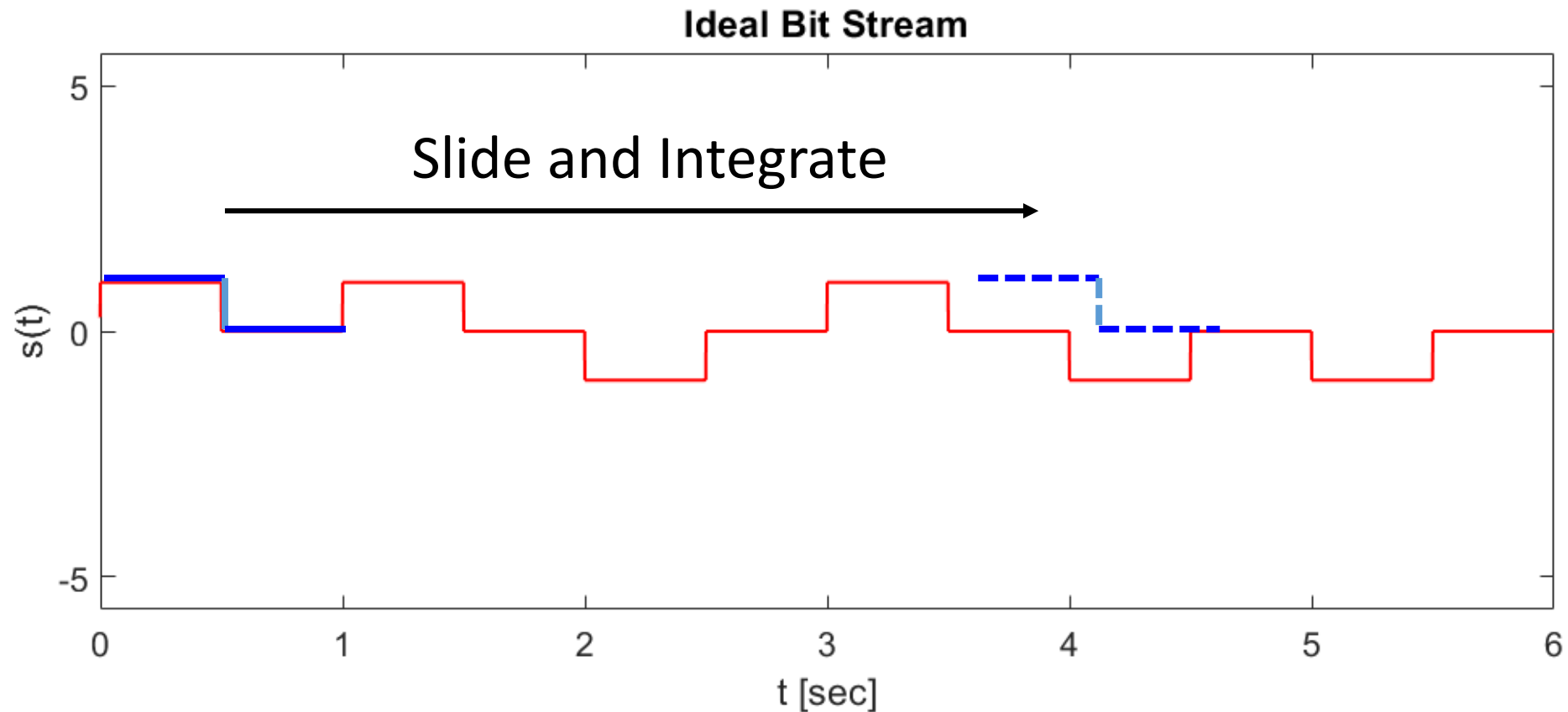
# Example: Bit Stream Detection

- The individual bits can be detected using a **matched filter** (cross-correlation):



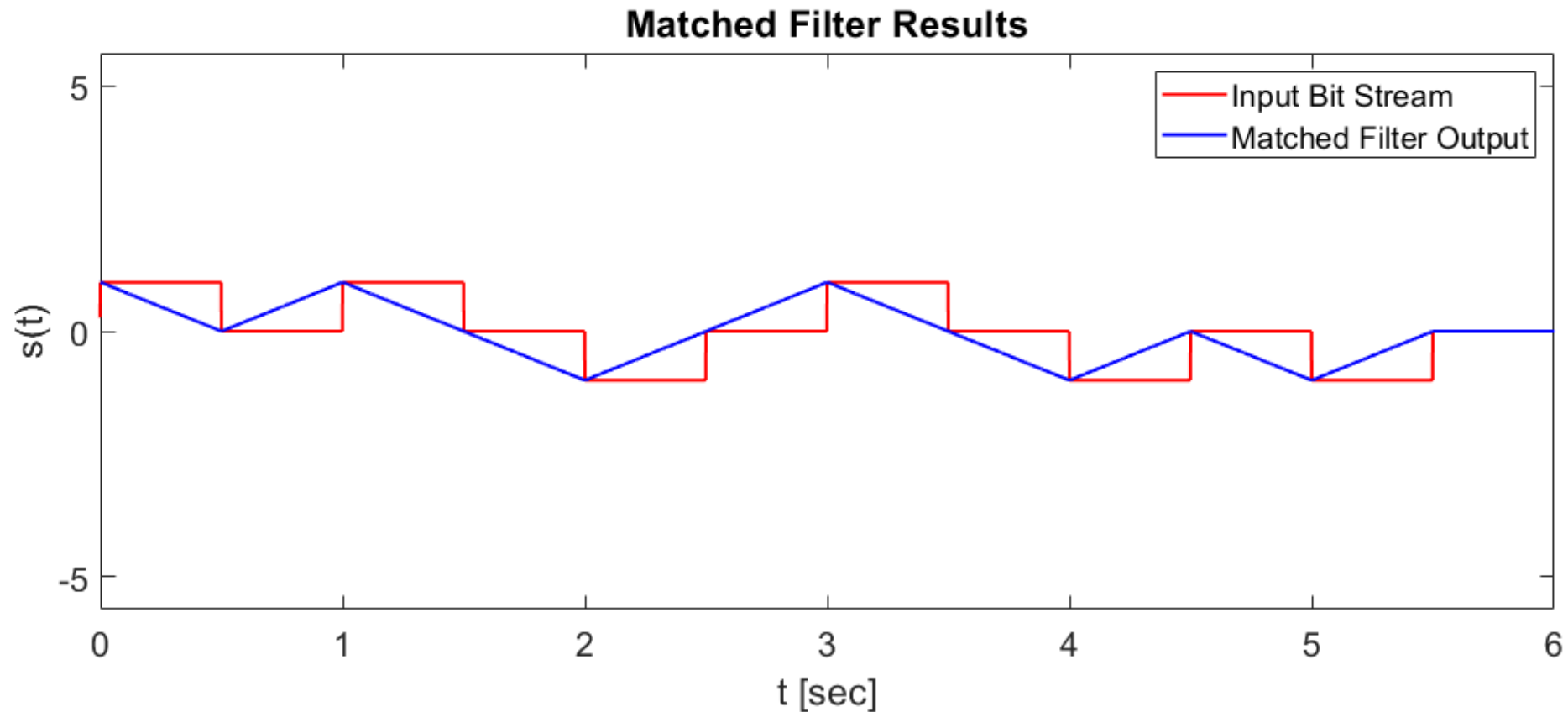
# Example: Bit Stream Detection

- The individual bits can be detected using a **matched filter** (cross-correlation):



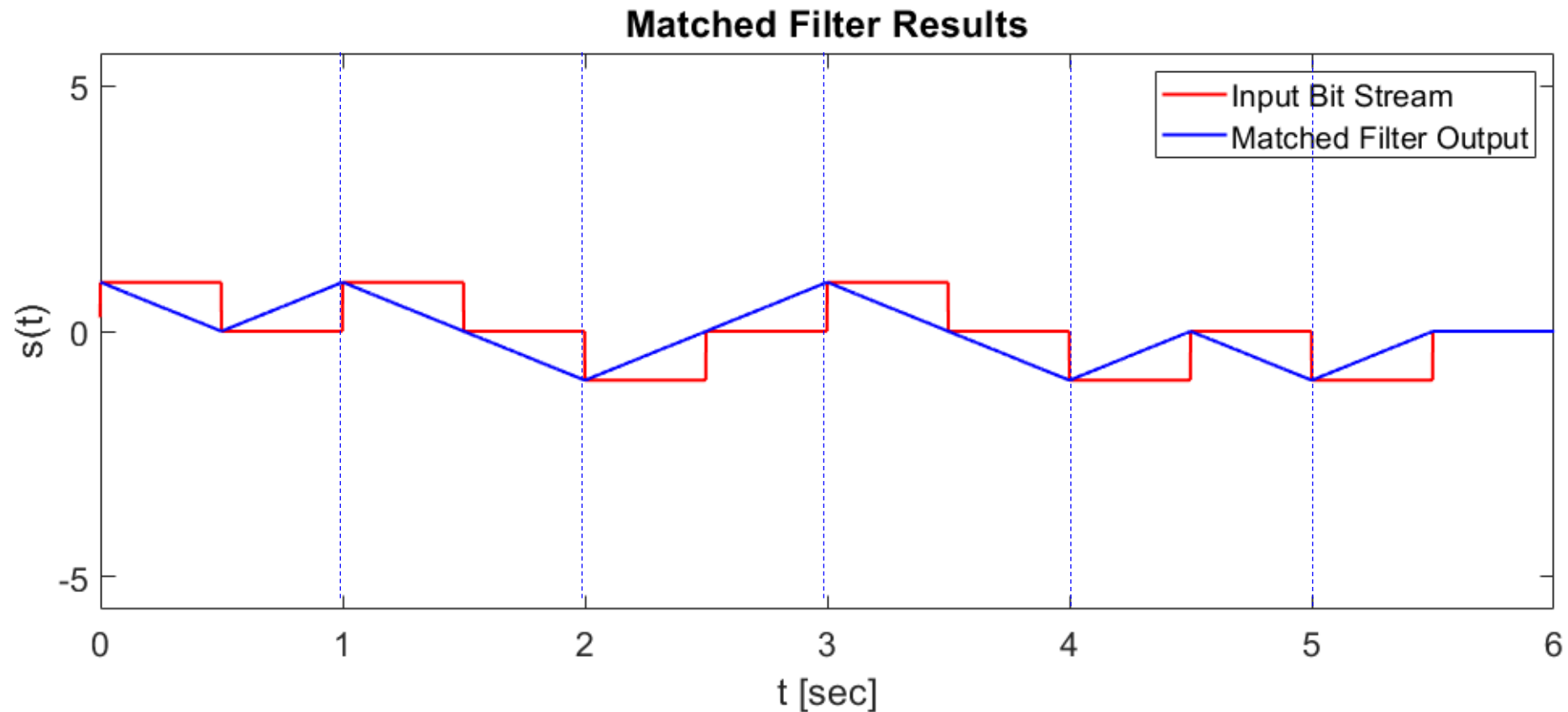
# Example: Bit Stream Detection

- The output of the matched filter has positive peaks for “1” and negative peaks for “0”.



# Example: Bit Stream Detection

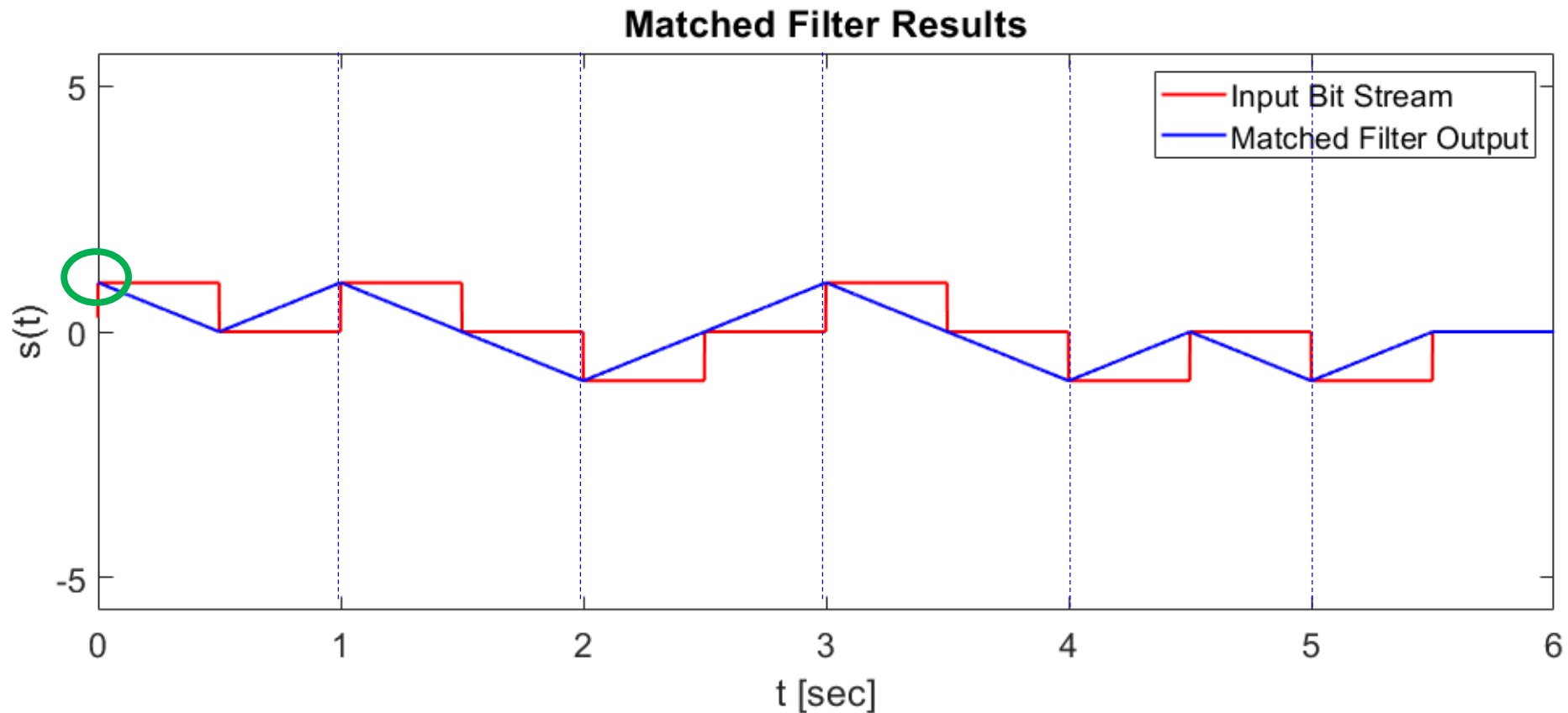
- The output of the matched filter has positive peaks for “1” and negative peaks for “0”.





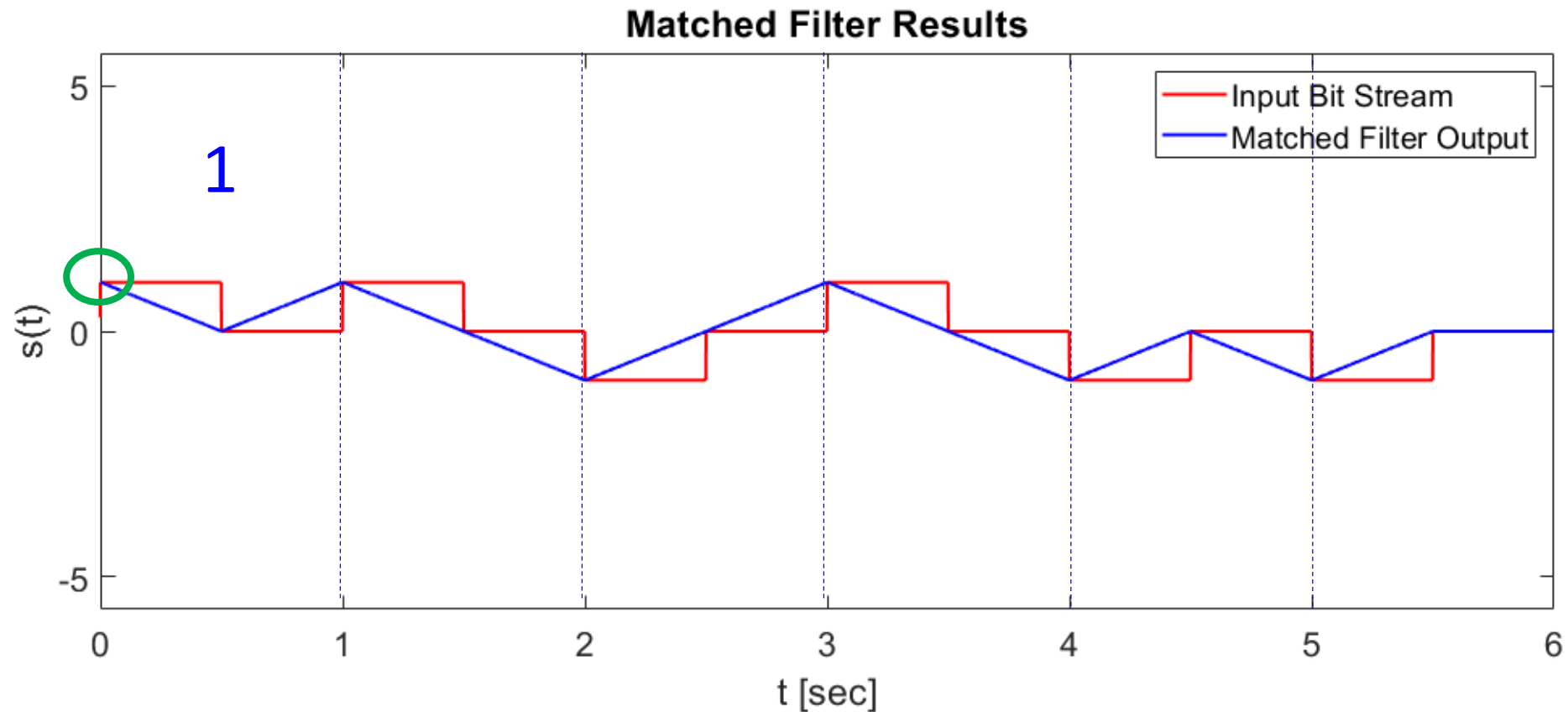
# Example: Bit Stream Detection

- The output of the matched filter has positive peaks for “1” and negative peaks for “0”.



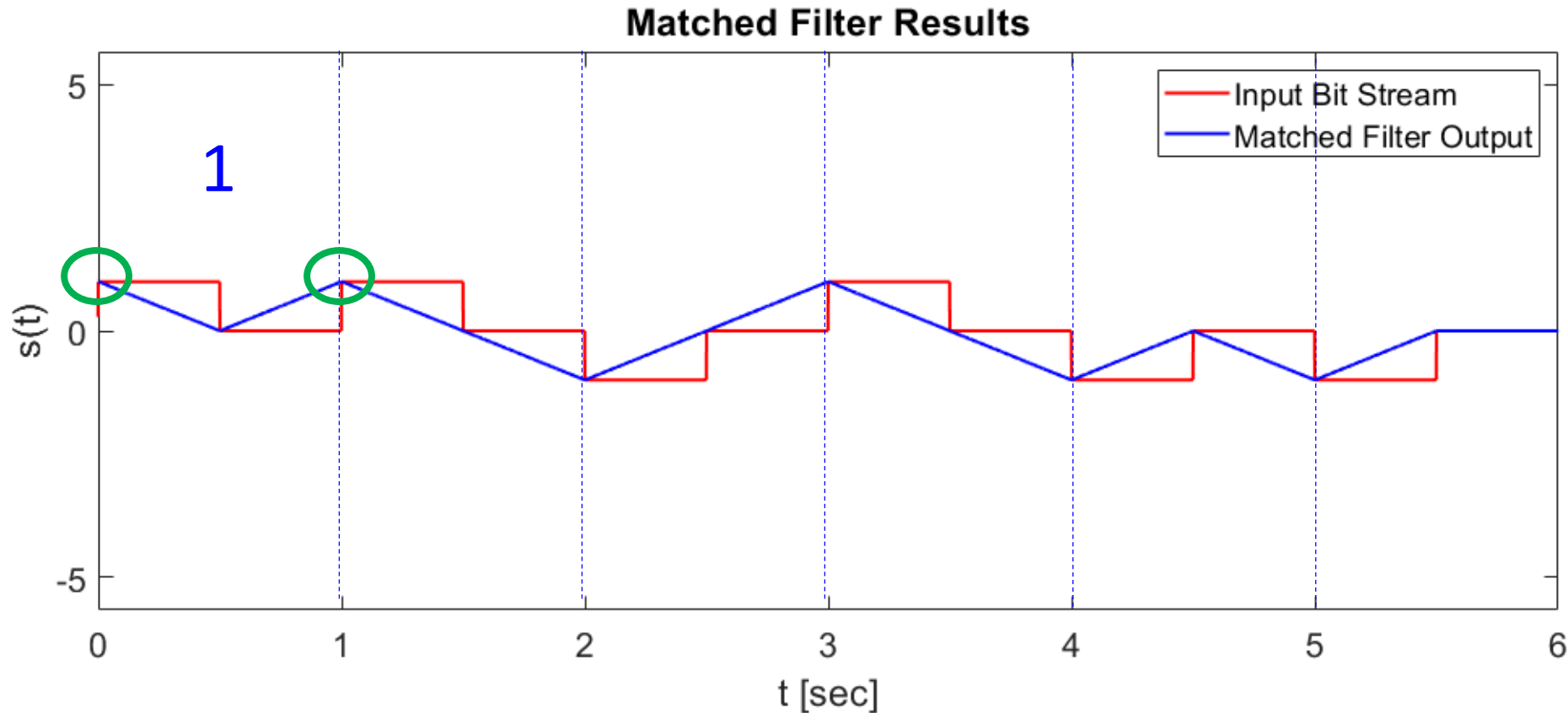
# Example: Bit Stream Detection

- The output of the matched filter has positive peaks for “1” and negative peaks for “0”.



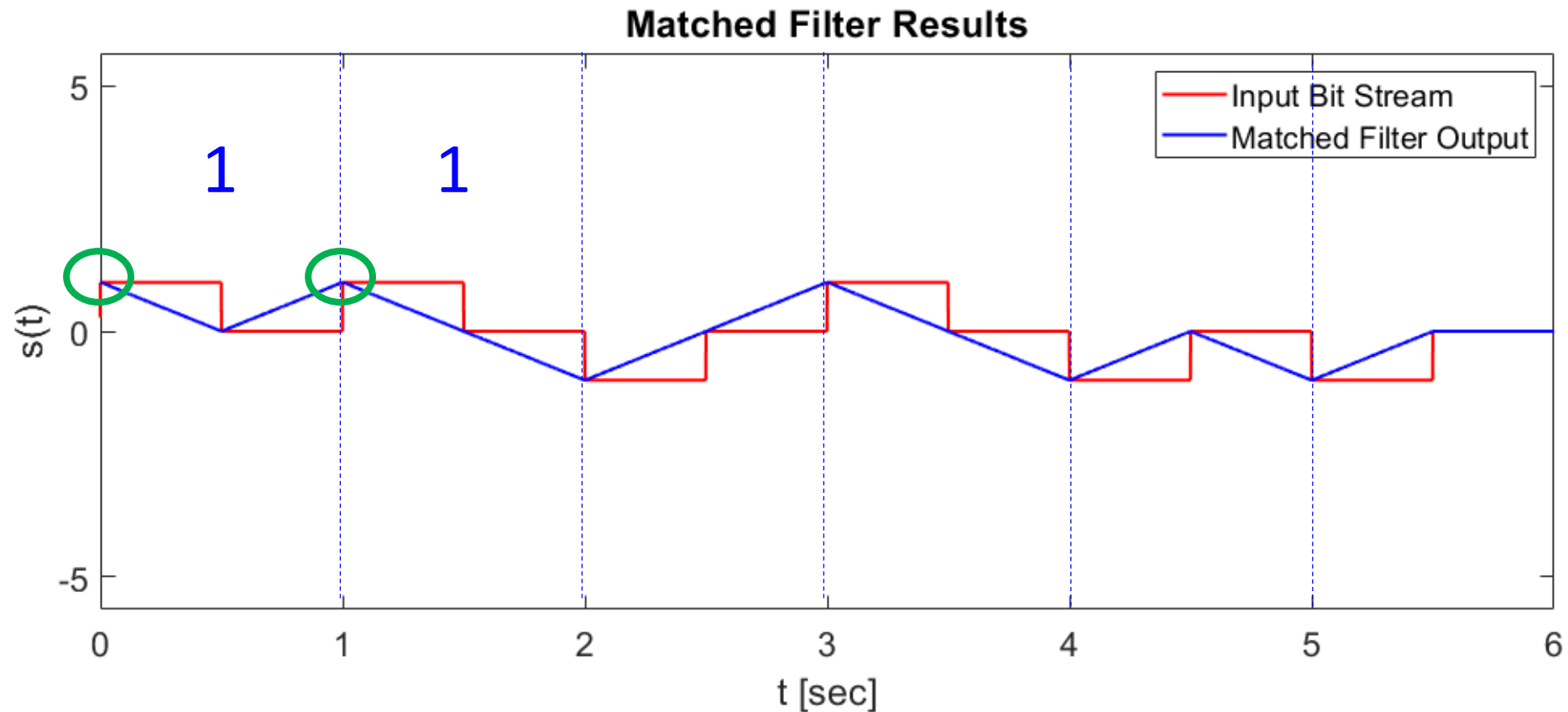
# Example: Bit Stream Detection

- The output of the matched filter has positive peaks for “1” and negative peaks for “0”.



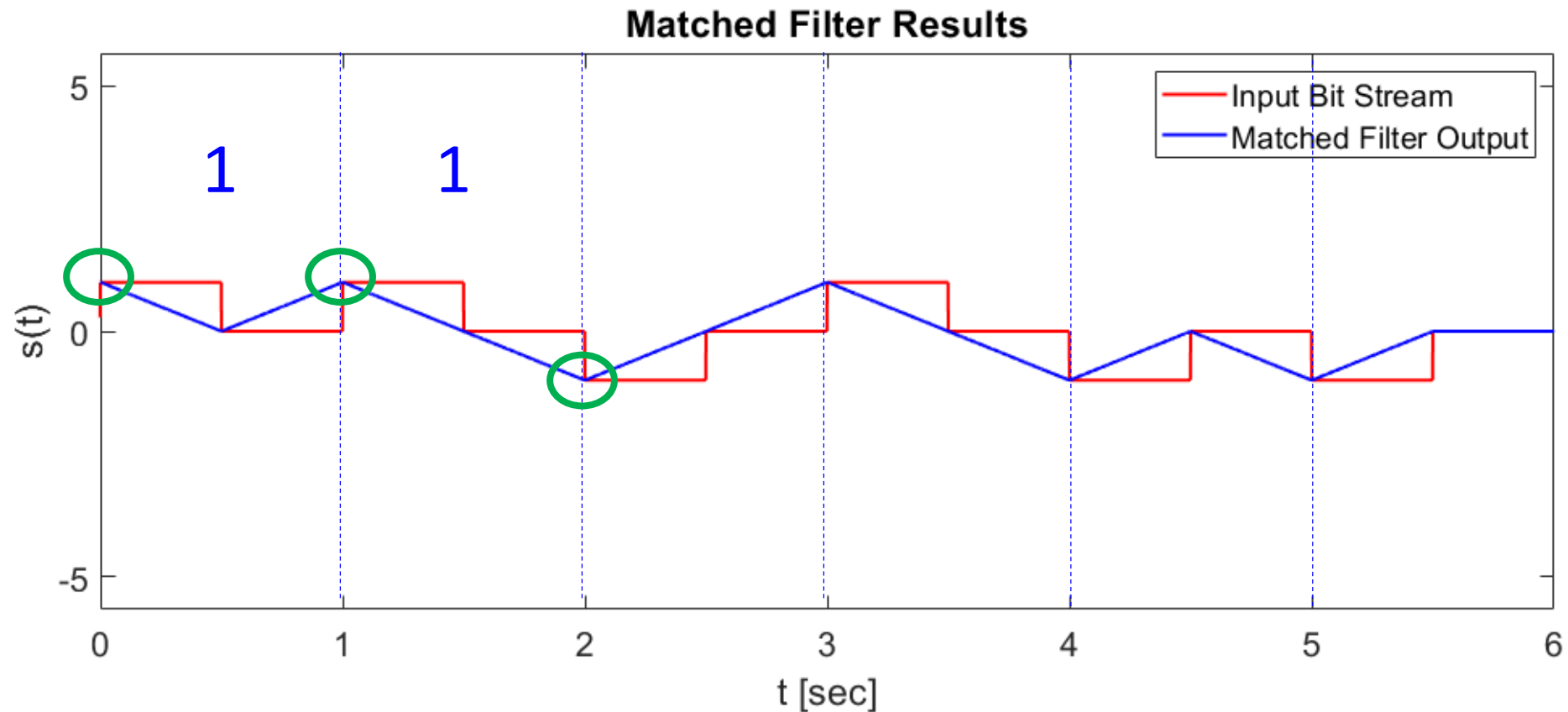
# Example: Bit Stream Detection

- The output of the matched filter has positive peaks for “1” and negative peaks for “0”.



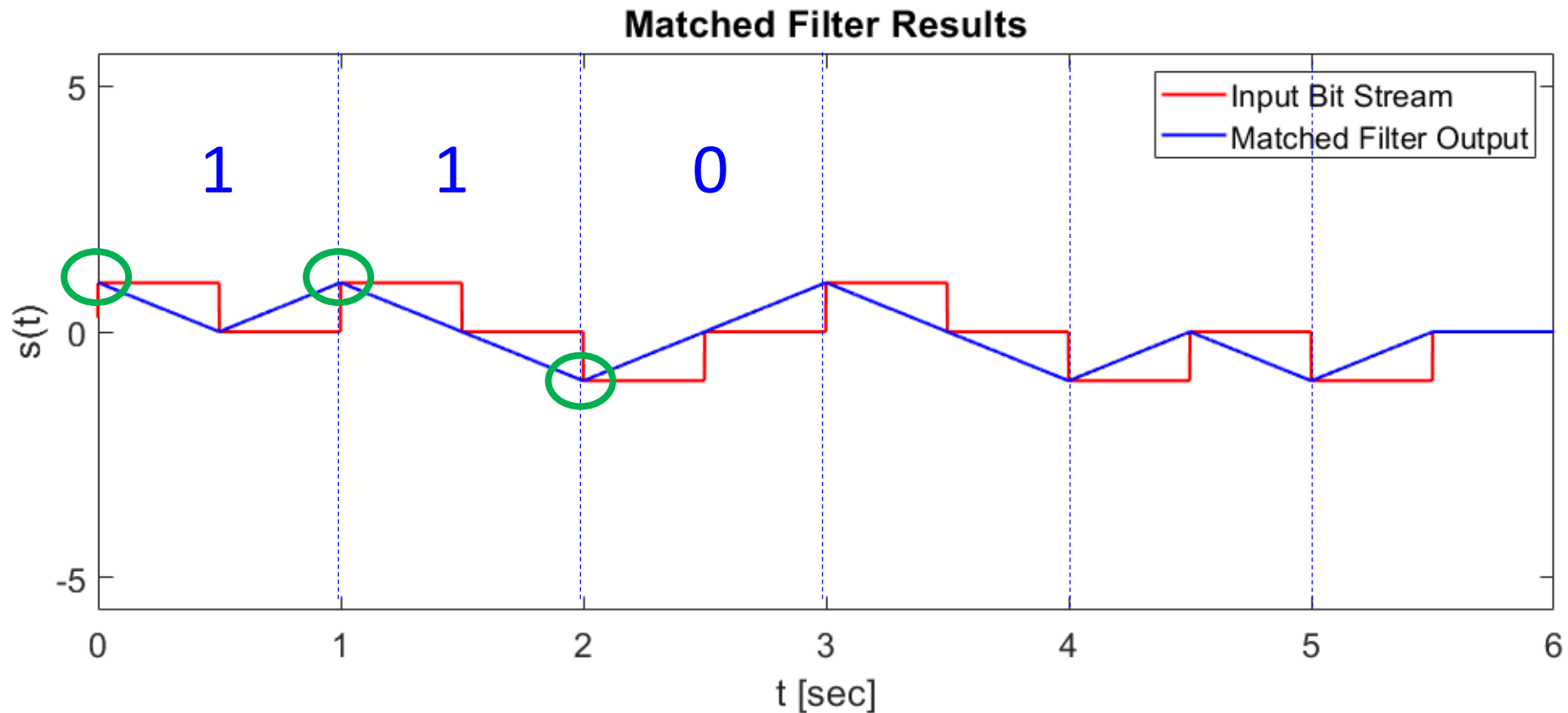
# Example: Bit Stream Detection

- The output of the matched filter has positive peaks for “1” and negative peaks for “0”.



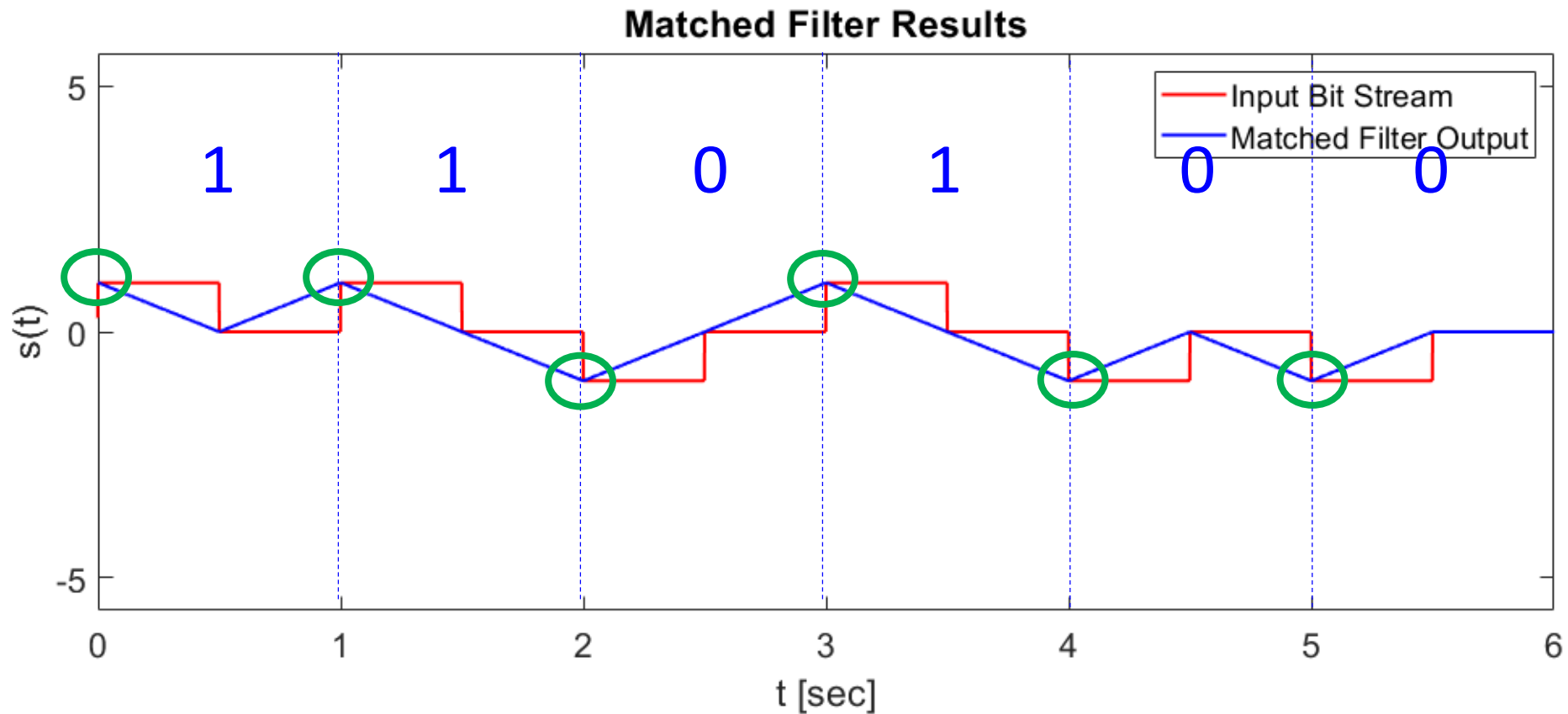
# Example: Bit Stream Detection

- The output of the matched filter has positive peaks for “1” and negative peaks for “0”.



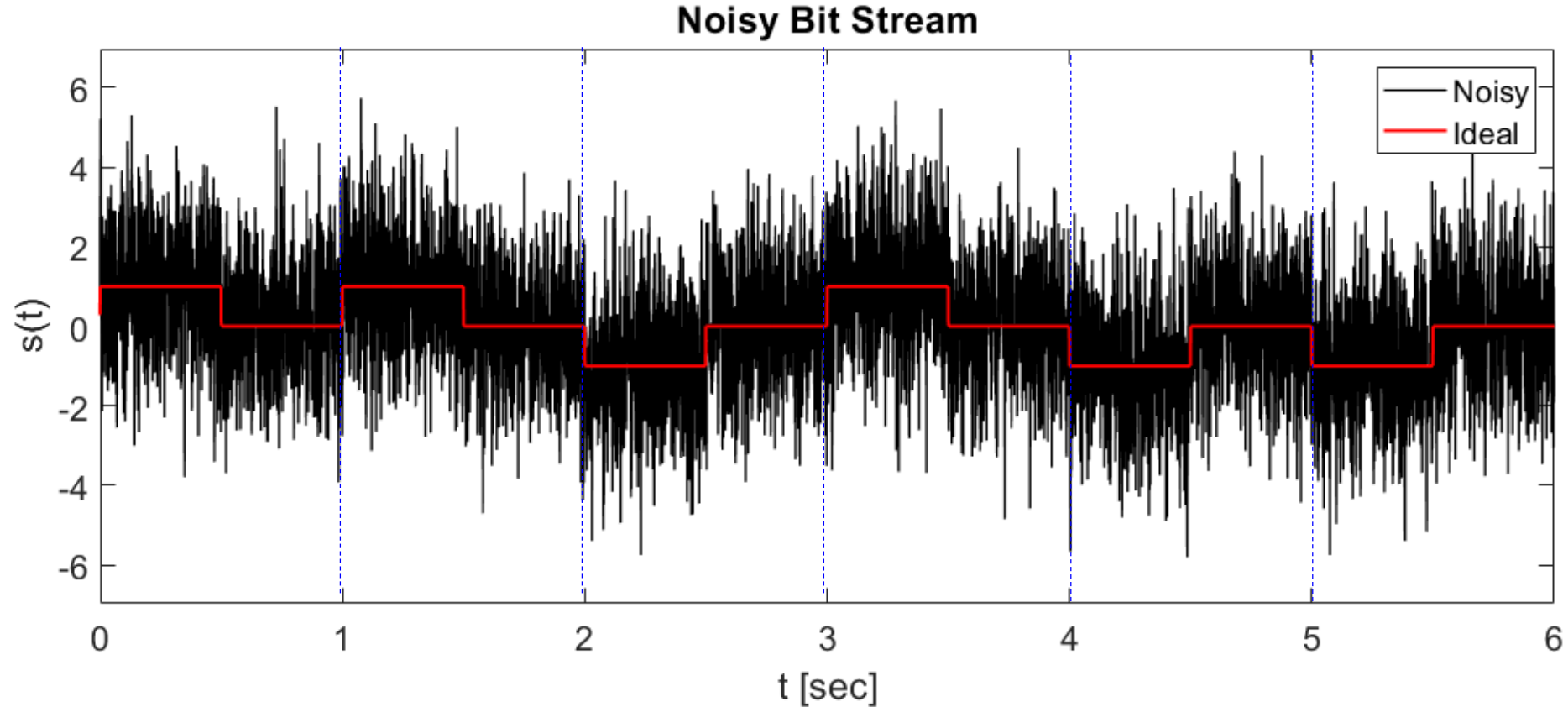
# Example: Bit Stream Detection

- The output of the matched filter has positive peaks for “1” and negative peaks for “0”.



# Example: Noisy Bit Stream Detection

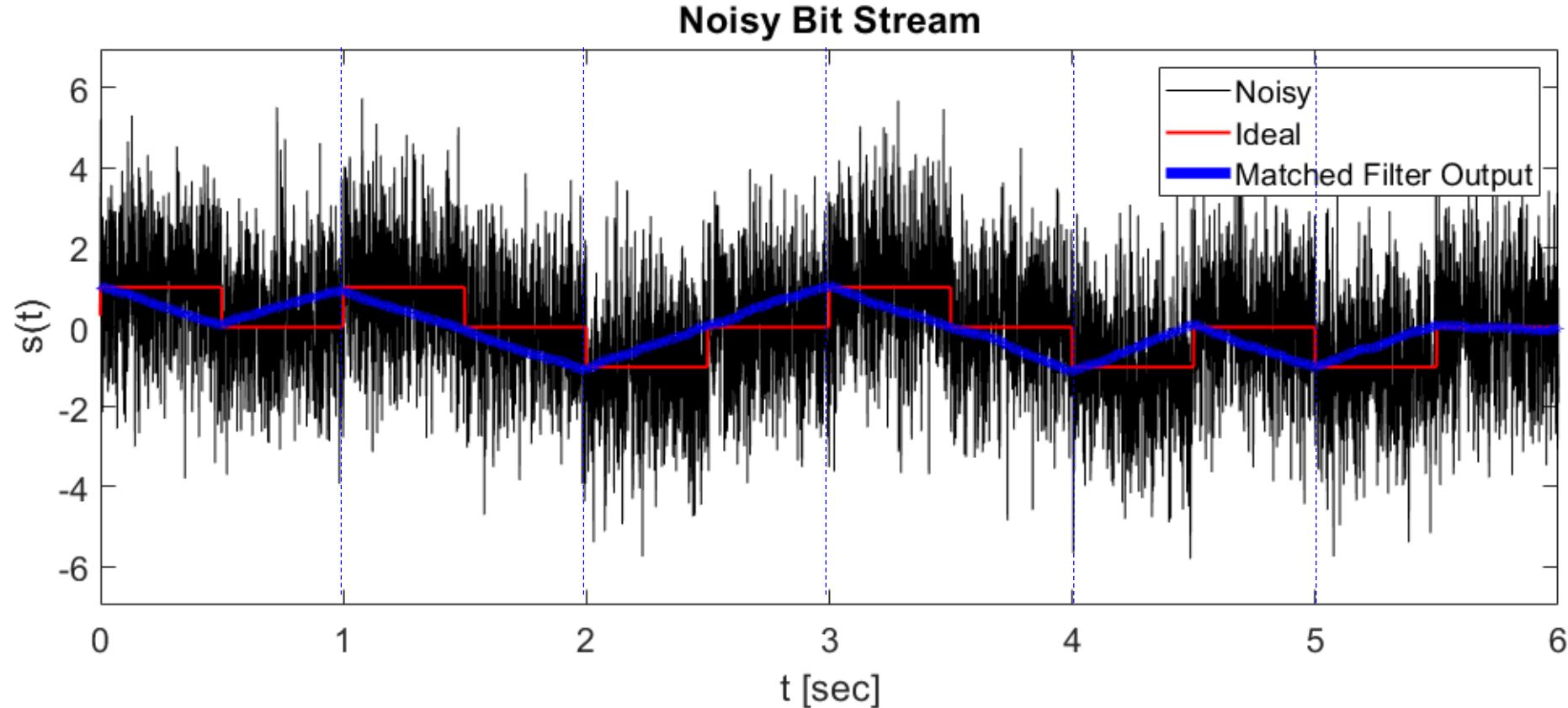
- In practice, realistic signals are received in a noisy environment:





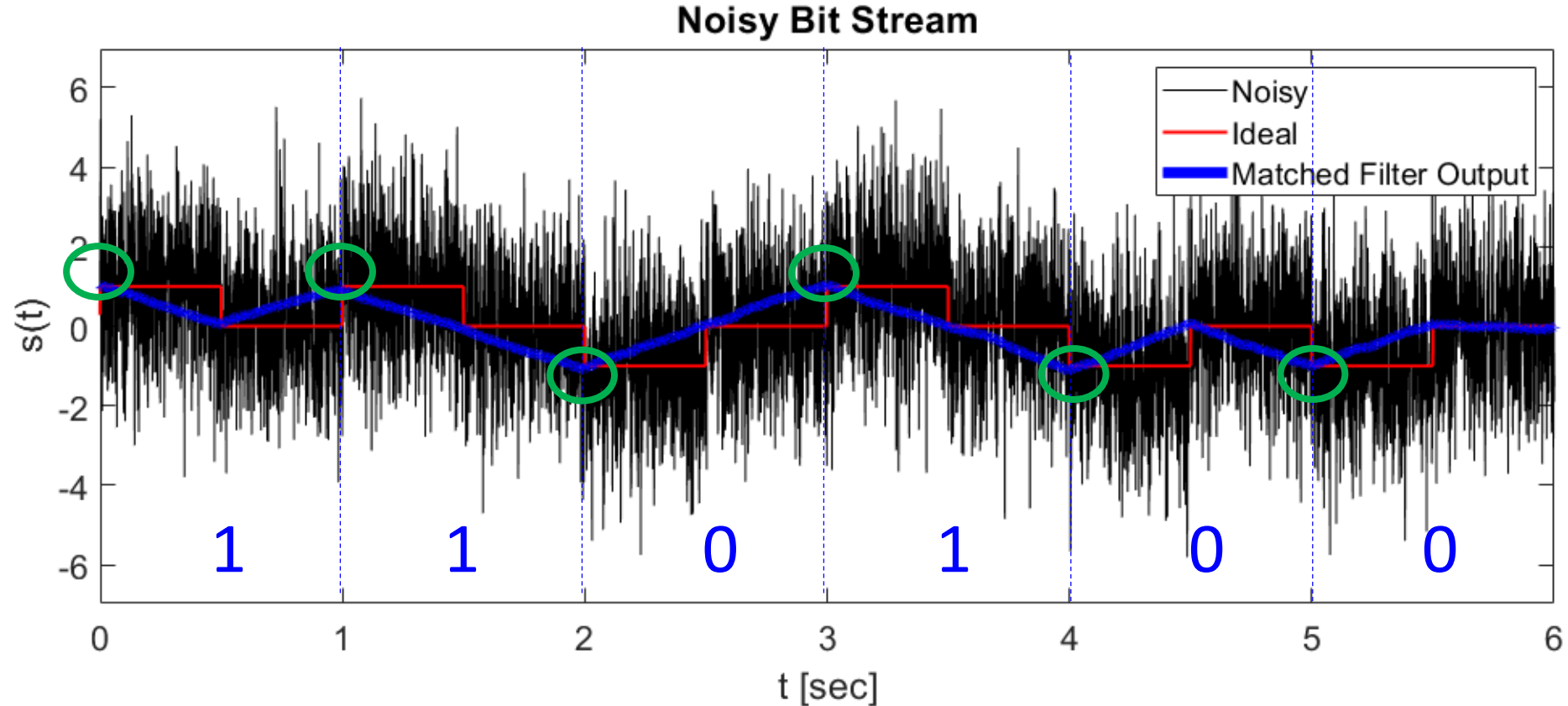
# Example: Noisy Bit Stream Detection

- The matched filter output is almost the same as the for noise-free environment!



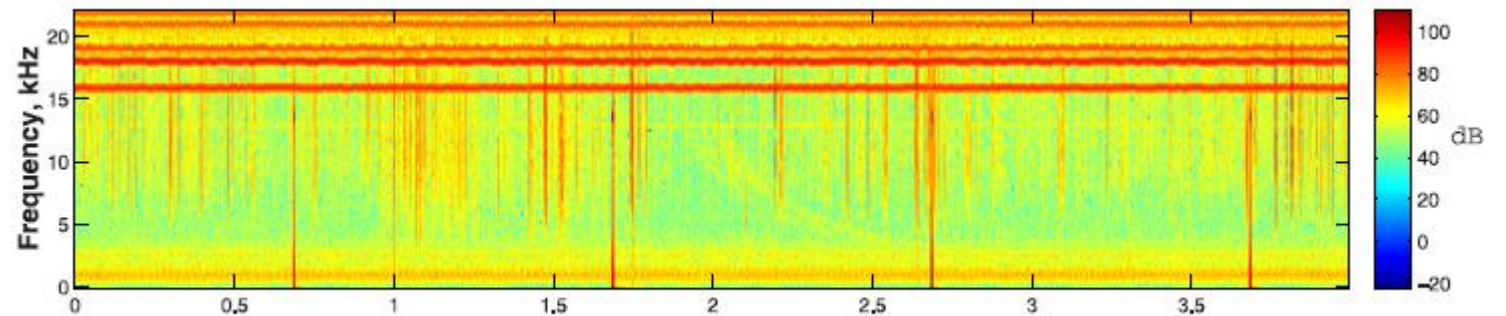
# Example: Noisy Bit Stream Detection

- The matched filter technique works extremely well in a noisy environment!



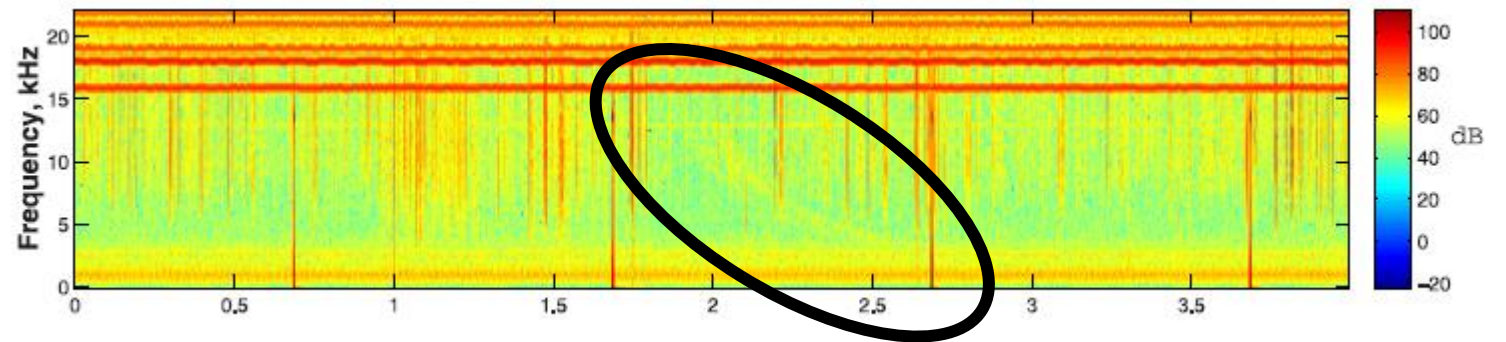
# Extension to Whistler Detection

This type of “template matching” technique has been quite successful when applied to detecting whistlers (see [Lichtenberger et al. 2008](#)):



# Extension to Whistler Detection

This type of “template matching” technique has been quite successful when applied to detecting whistlers (see [Lichtenberger et al. 2008](#)):



# Extension to Whistler Detection

This type of “template matching” technique has been quite successful when applied to detecting whistlers (see [Lichtenberger et al. 2008](#)):

## Whistler Template

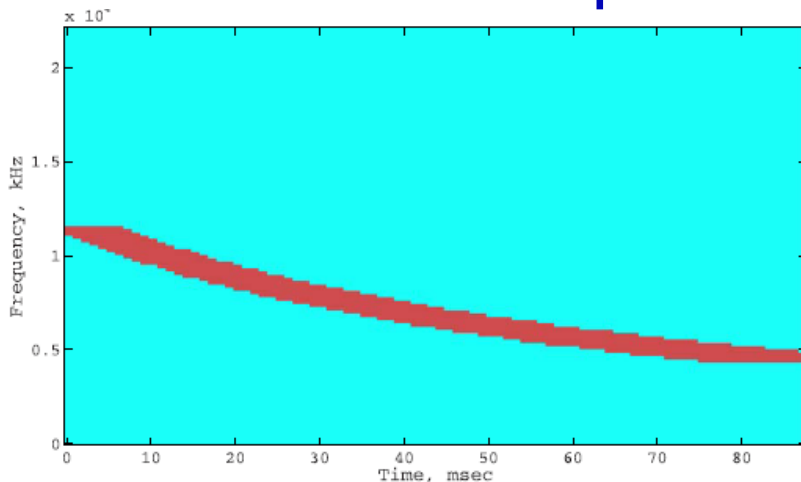
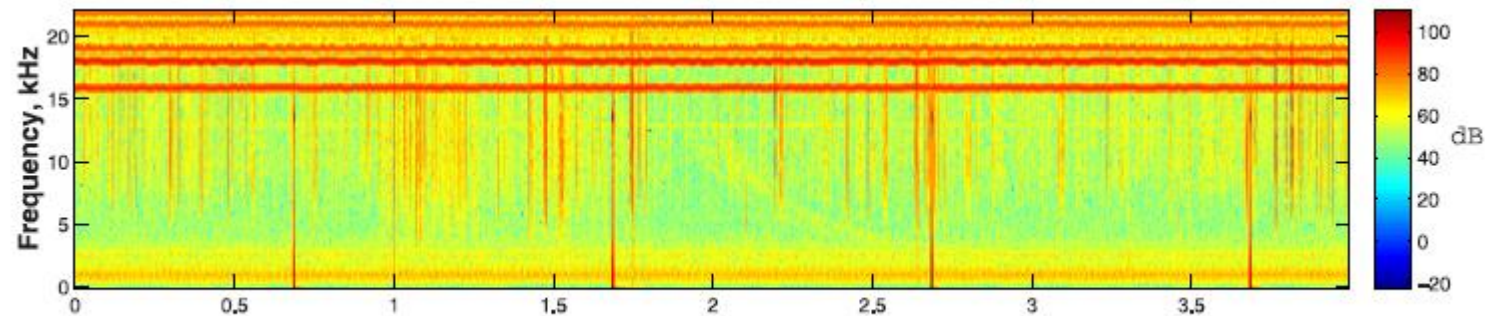


Figure 3. Multidispersion detector pattern.



# Extension to Whistler Detection

This type of “template matching” technique has been quite successful when applied to detecting whistlers (see [Lichtenberger et al. 2008](#)):

## Whistler Template

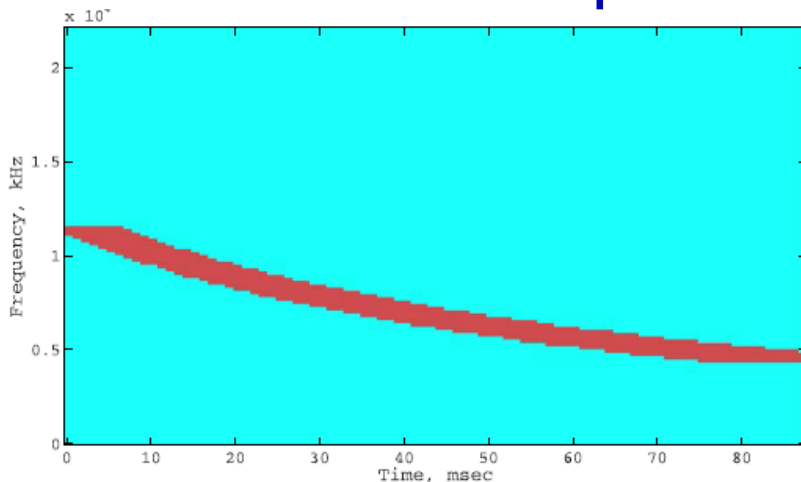
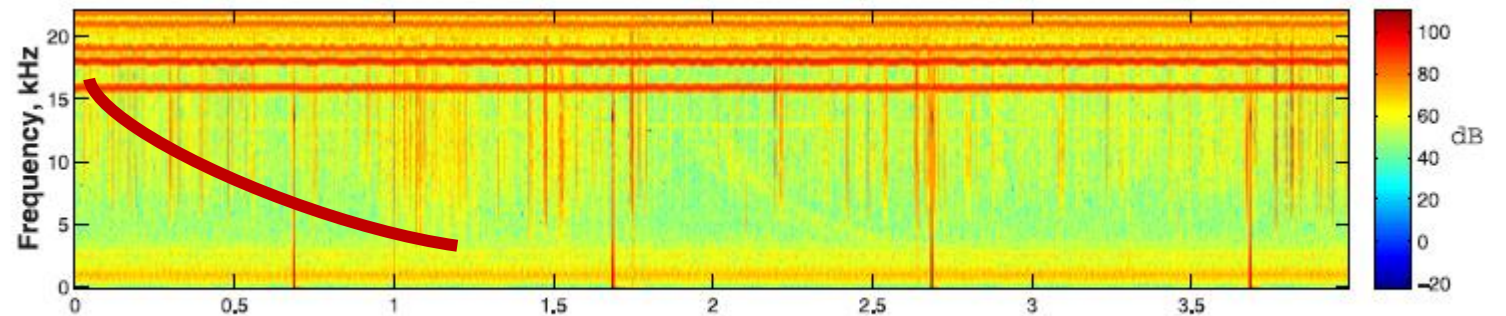


Figure 3. Multidispersion detector pattern.



# Extension to Whistler Detection

This type of “template matching” technique has been quite successful when applied to detecting whistlers (see [Lichtenberger et al. 2008](#)):

## Whistler Template

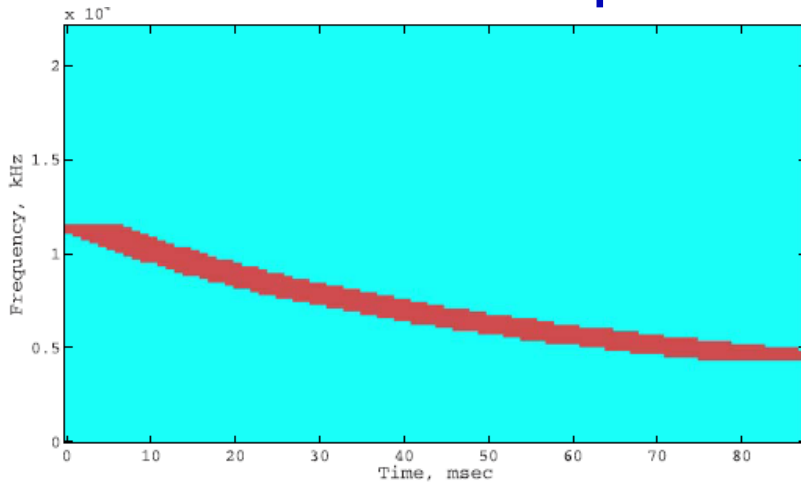
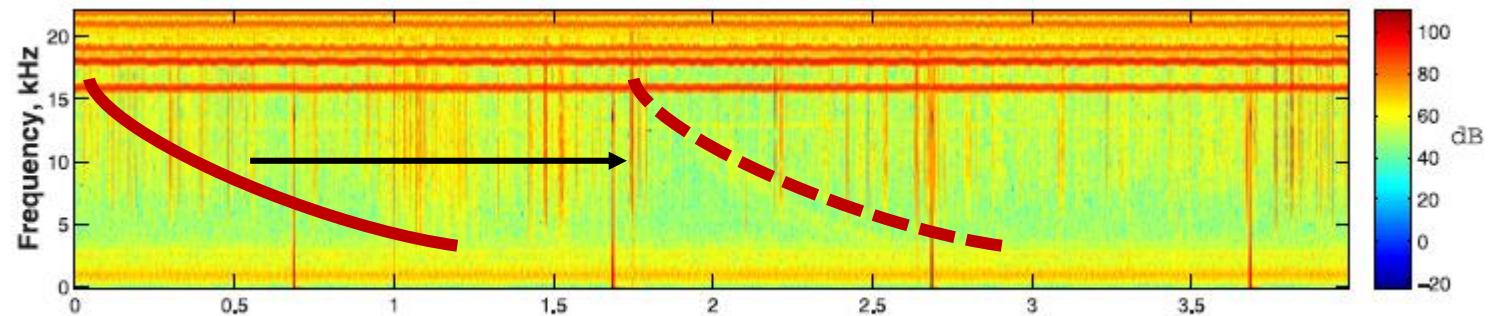


Figure 3. Multidispersion detector pattern.



# Extension to Whistler Detection

This type of “template matching” technique has been quite successful when applied to detecting whistlers (see [Lichtenberger et al. 2008](#)):

## Whistler Template

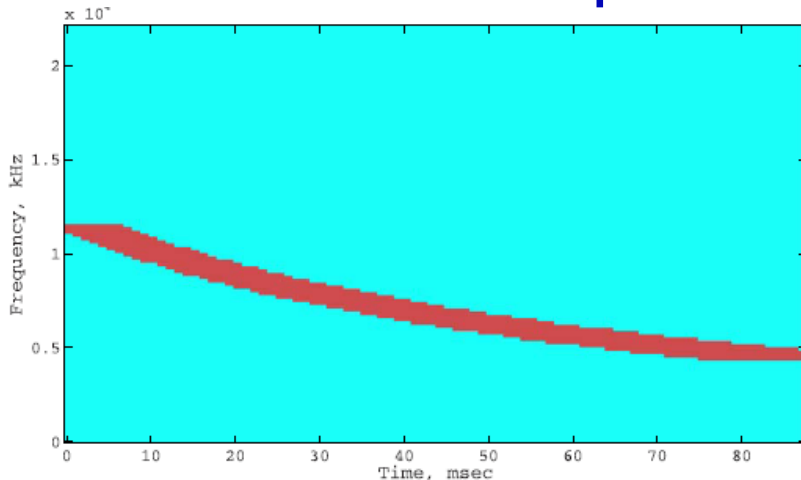
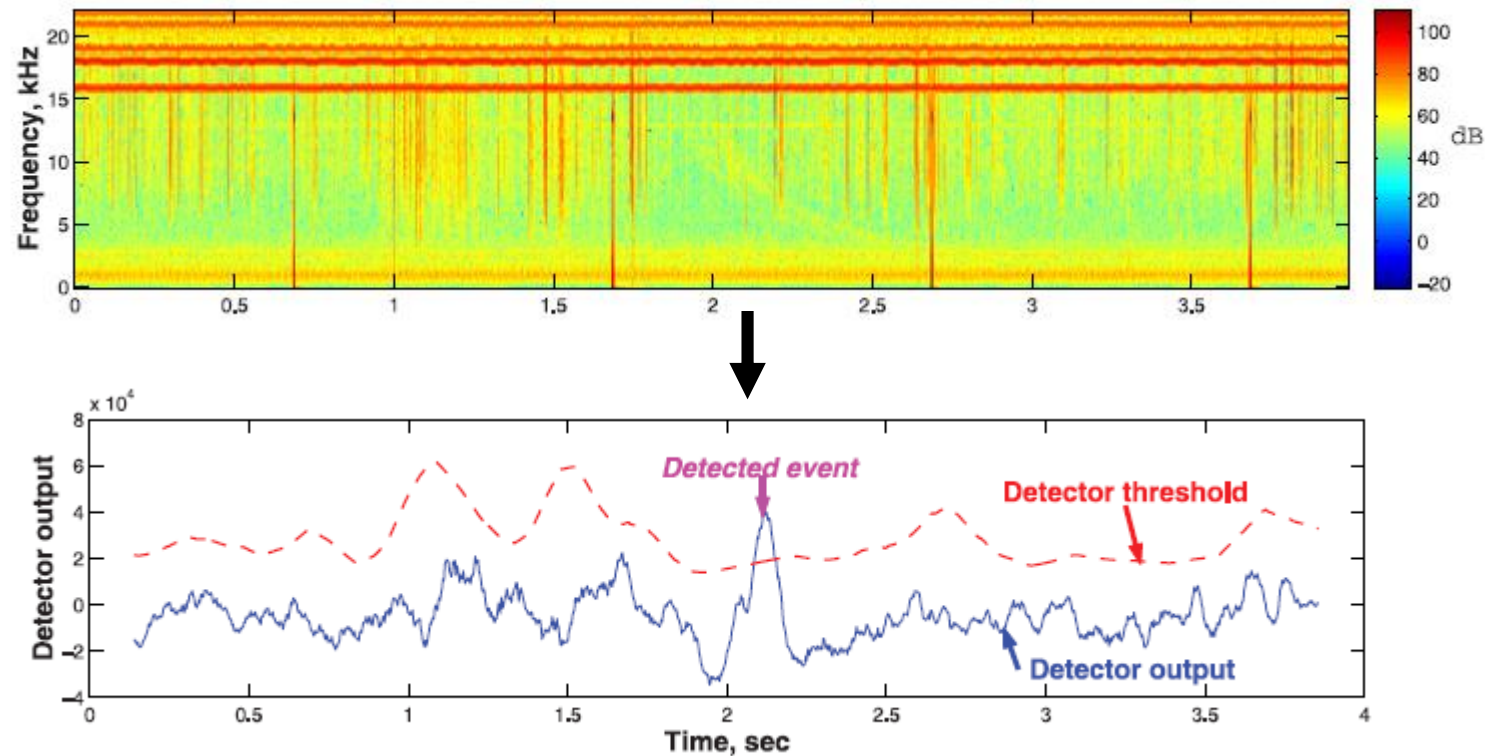


Figure 3. Multidispersion detector pattern.



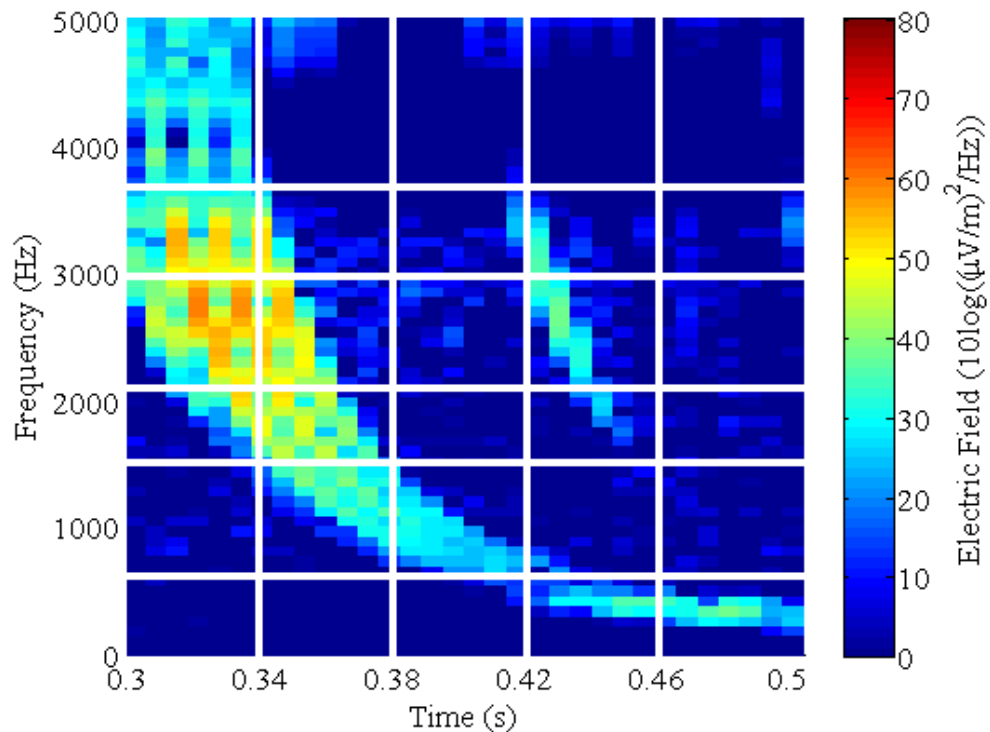




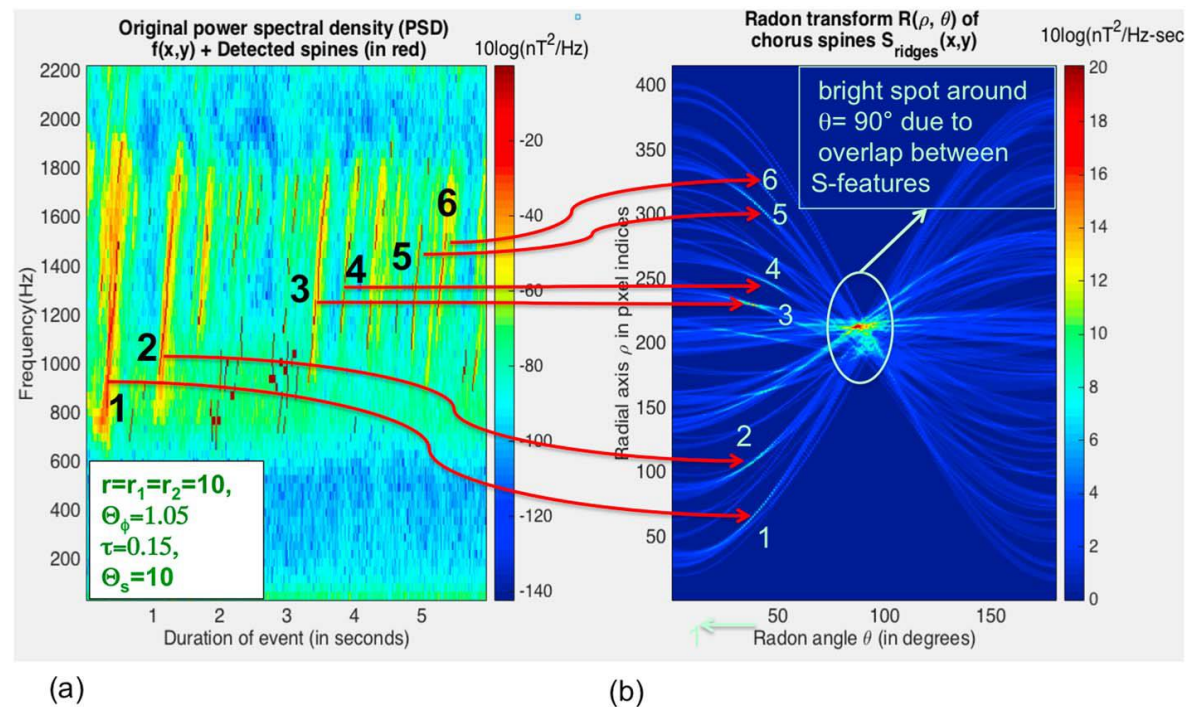
# Traditional Signal Extraction Methods

Modified versions of this technique have been successful when applied to detecting various types of whistler-mode waves...they all **require explicit knowledge of the signal structure!**

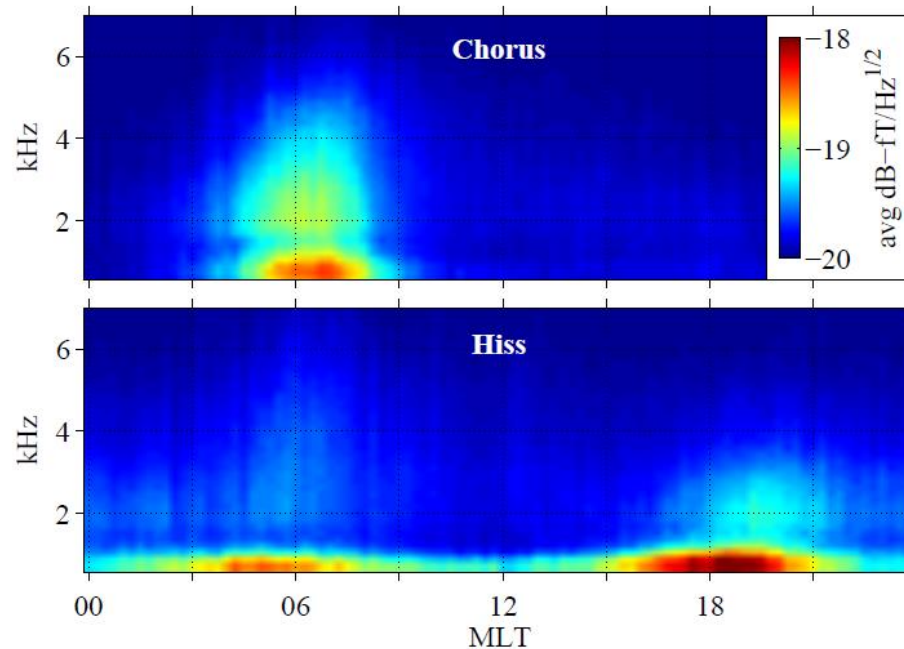
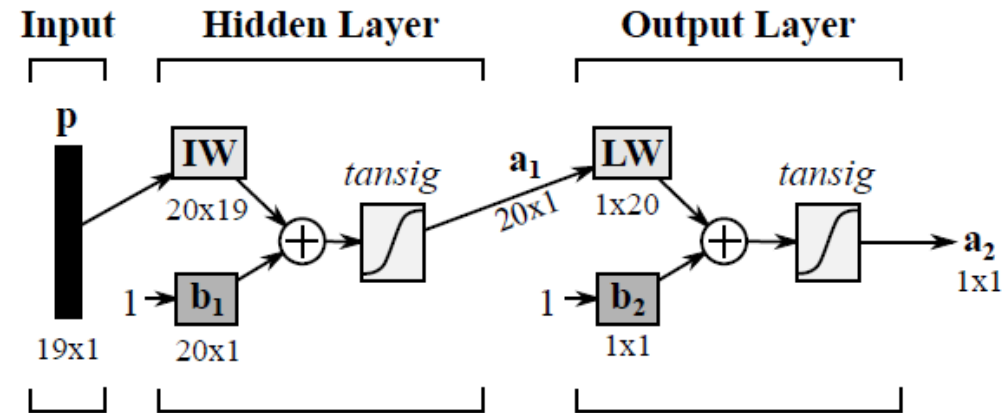
*Compston, 2016*



*Gupta et al., 2021*



- We now have thousands of events of waves relevant to the space environment.
- Large datasets permit the use of data-driven models.
- **Machine learning** approaches are becoming very useful for detecting/extracting signals from the space environment.



*Golden 2011*

1. Overview of Whistler Mode Waves
2. Traditional Methods of Signal Detection
3. Basic Overview of Neural Networks
4. Whistler Extraction using MSRCNN
5. Summary and Future Work

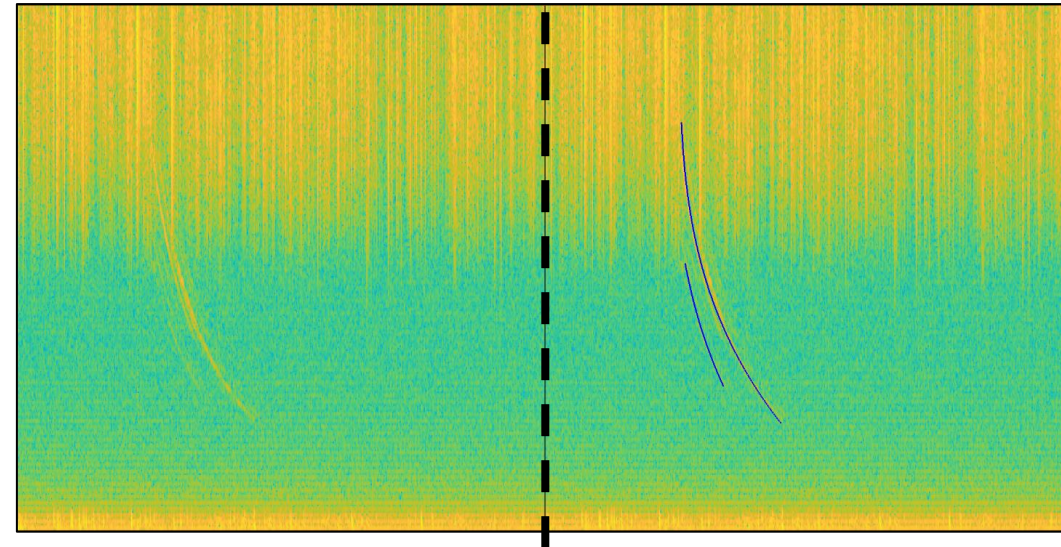
# Machine Learning Applications



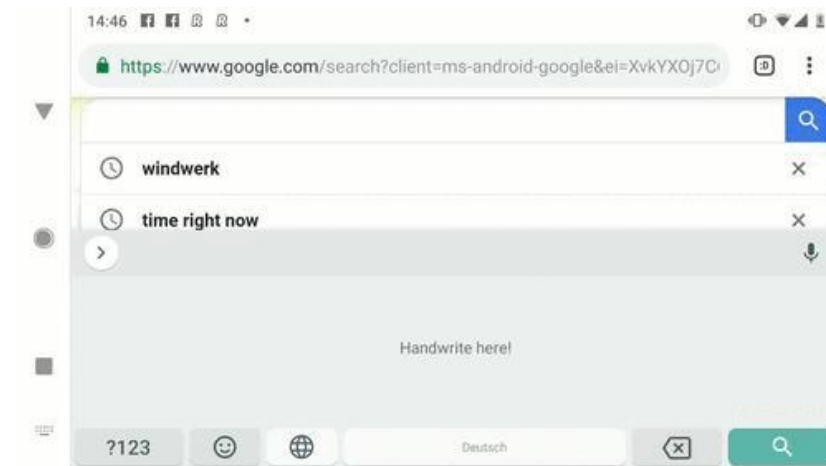
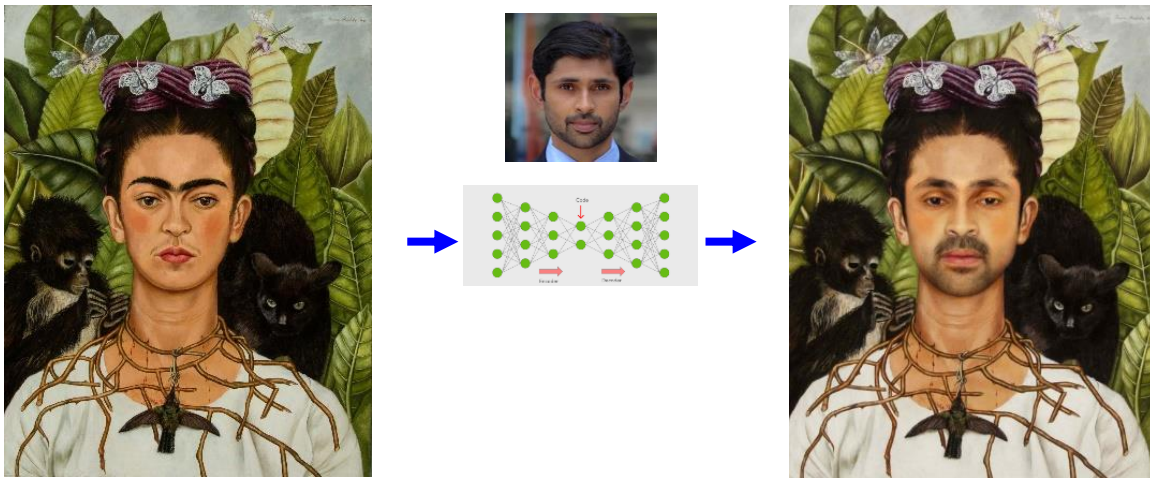
<https://venturebeat.com/2019/05/20/googles-lung-cancer-detection-ai-outperforms-6-human-radiologists/>

Original Spectrogram

Extracted Whistlers

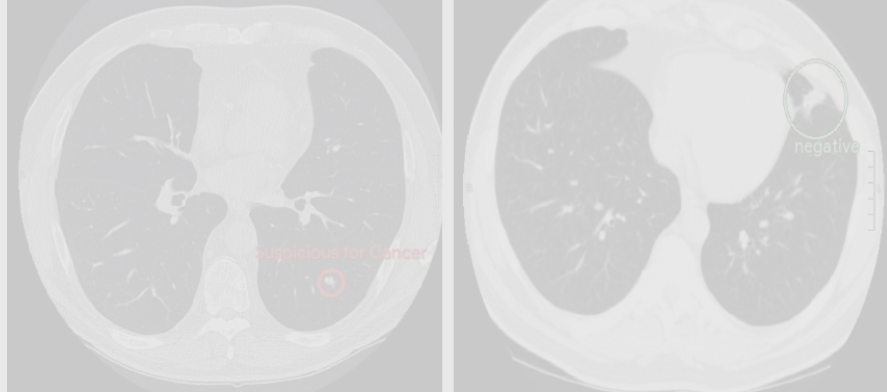


Harid et al., 2021 (GRL)



<https://ai.googleblog.com/2019/03/rnn-based-handwriting-recognition-in.html>

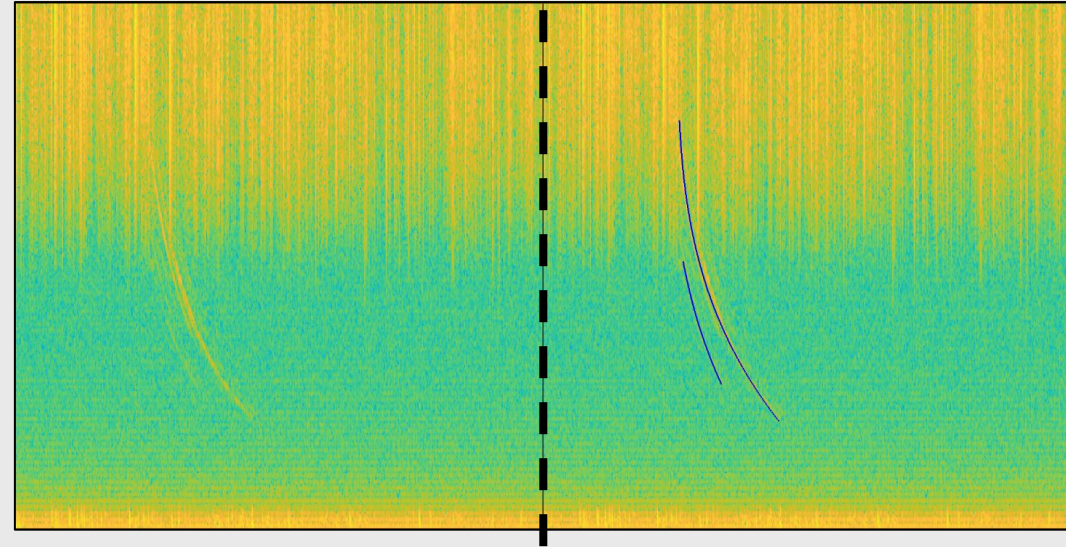
# Machine Learning Applications



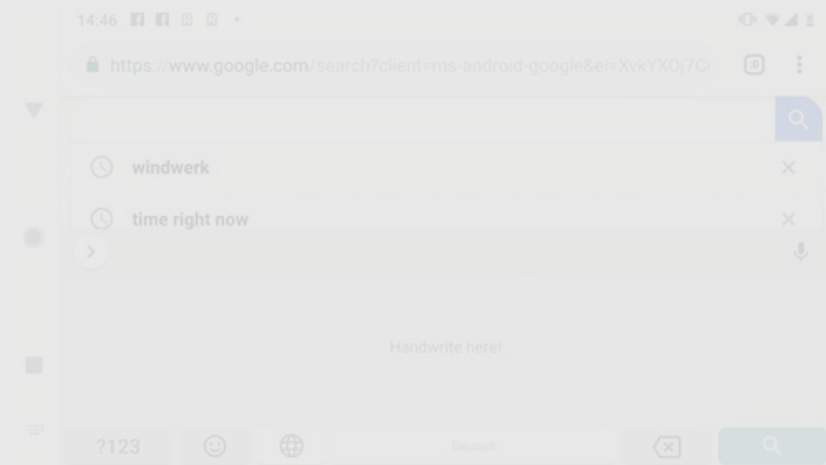
<https://venturebeat.com/2019/05/20/googles-lung-cancer-detection-ai-outperforms-6-human-radiologists/>

Original Spectrogram

Extracted Whistlers



*Harid et al.,  
2021 (GRL)*



<https://ai.googleblog.com/2019/03/rnn-based-handwriting-recognition-in.html>

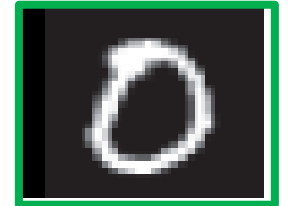
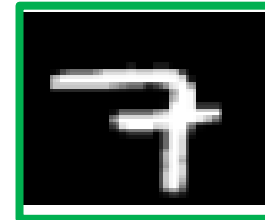
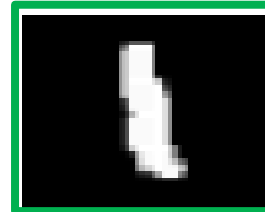
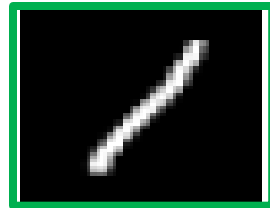
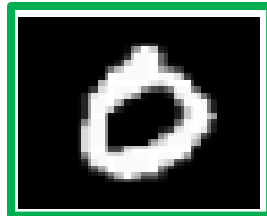
# Supervised Learning

- **Supervised Learning** describes machine learning models that are trained with **labeled** “ground truth” data.

# Supervised Learning

- **Supervised Learning** describes machine learning models that are trained with **labeled** “ground truth” data.

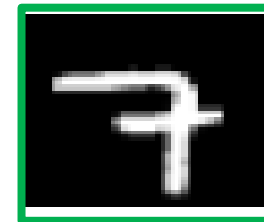
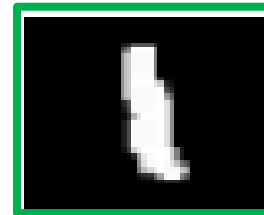
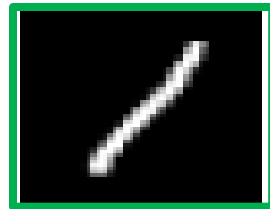
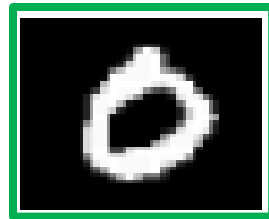
Input Cases



# Supervised Learning

- **Supervised Learning** describes machine learning models that are trained with **labeled** “ground truth” data.

Input Cases



Output Label

0

1

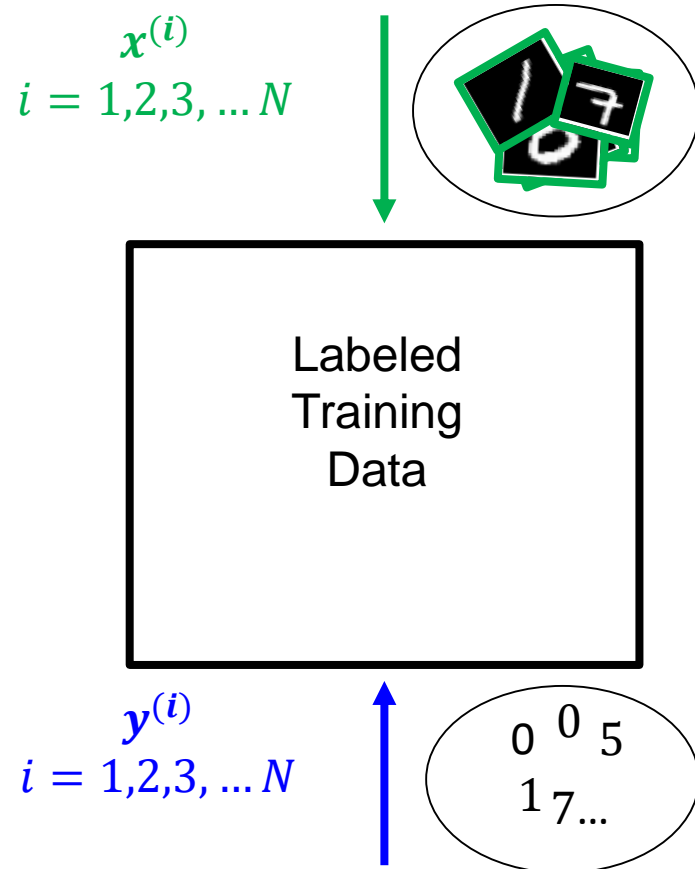
1

7

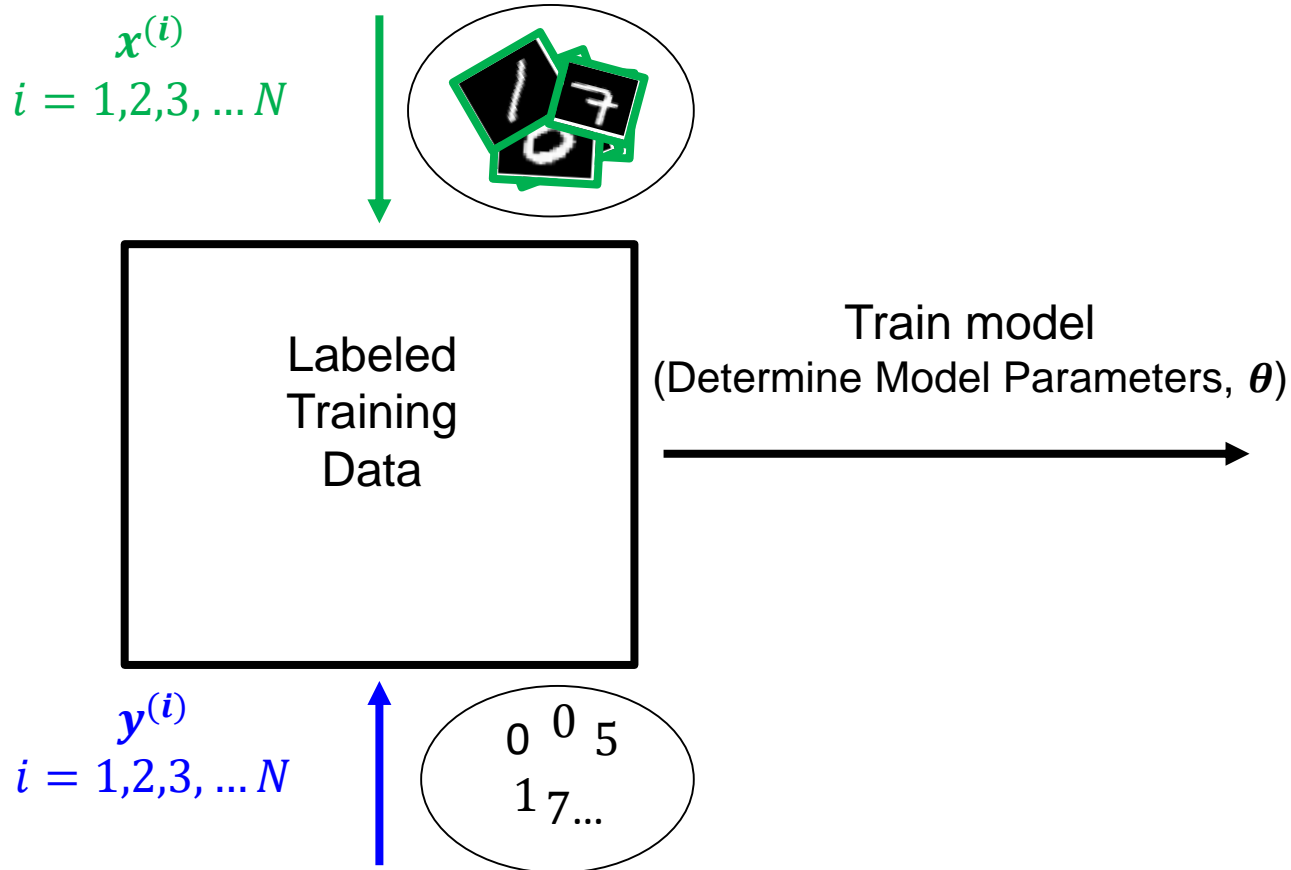
0



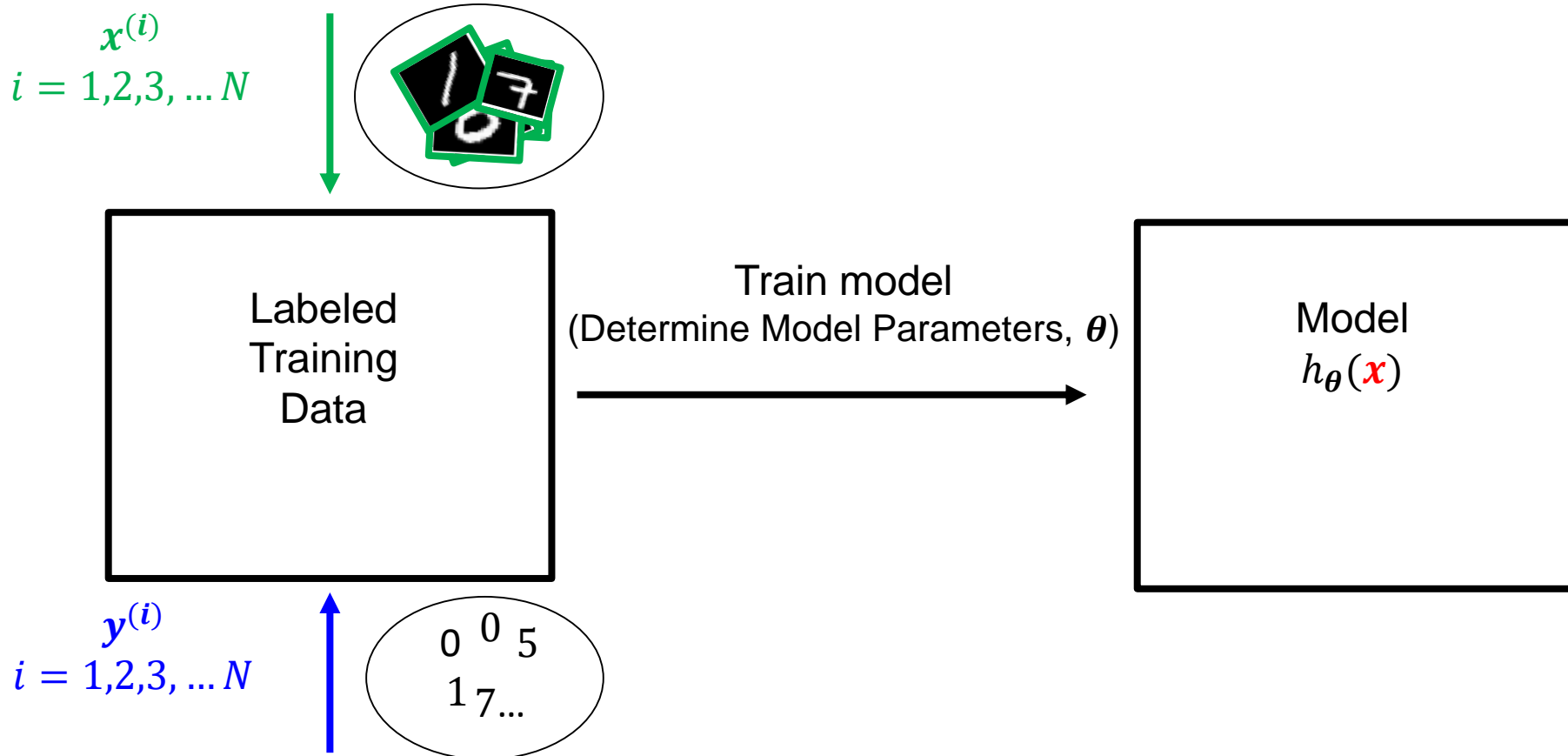
The general flow for supervised learning is:



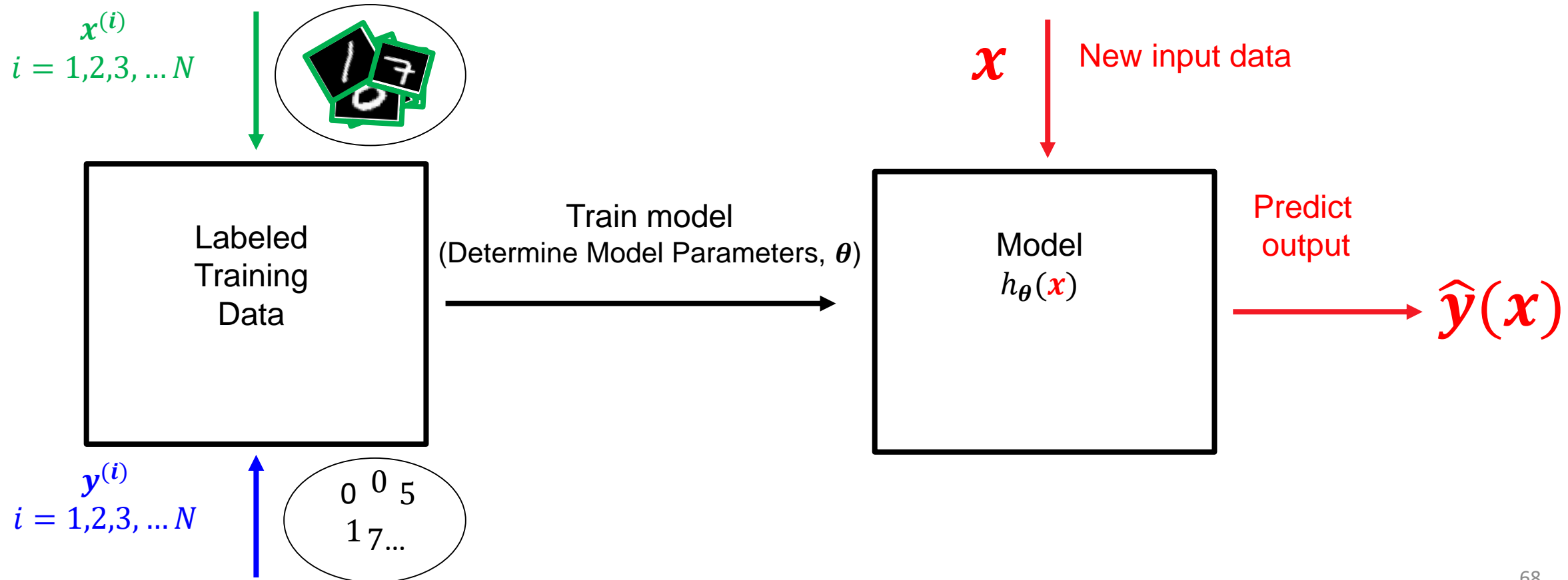
The general flow for supervised learning is:



The general flow for supervised learning is:



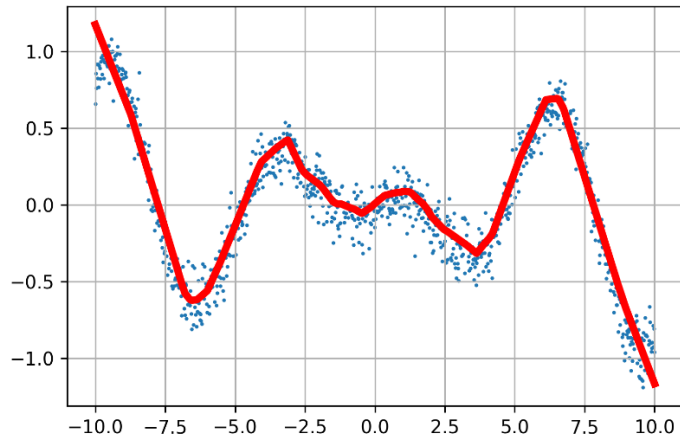
The general flow for supervised learning is:



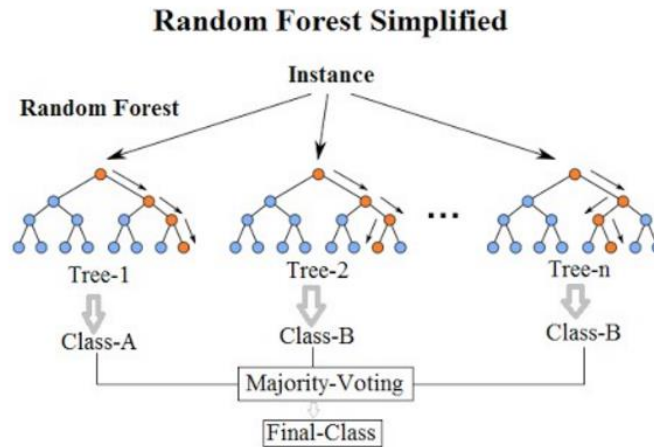
# Choice of ML Model

There are several options for models that vary in expressiveness and complexity:

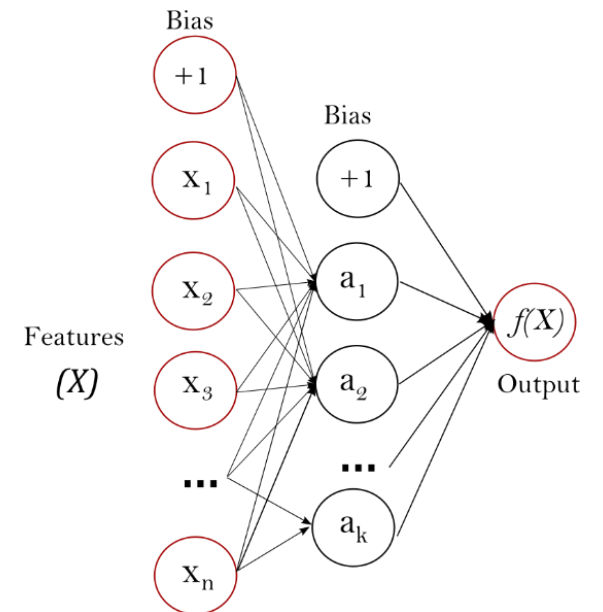
Polynomial Regression



Random Forests



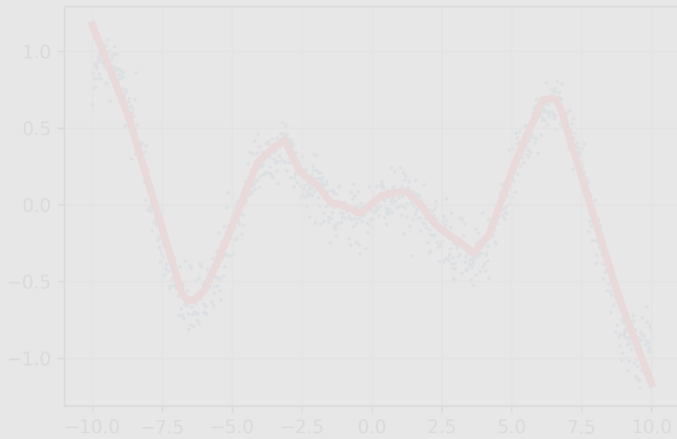
Neural Networks



# Choice of ML Model

There are several options for models that vary in expressiveness and complexity:

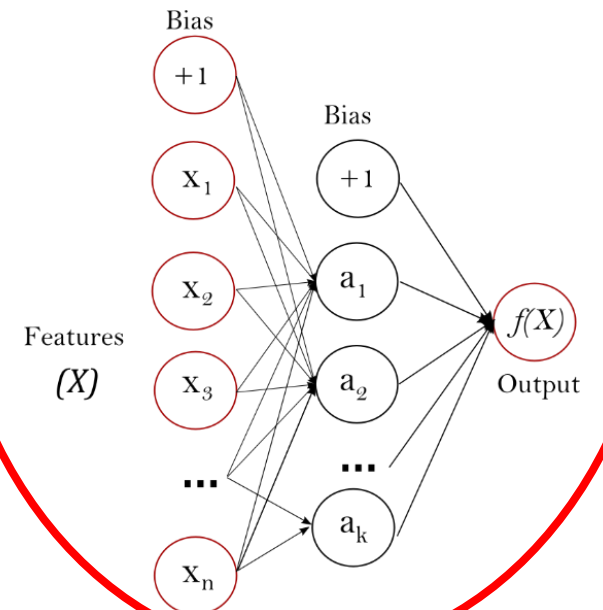
Polynomial Regression



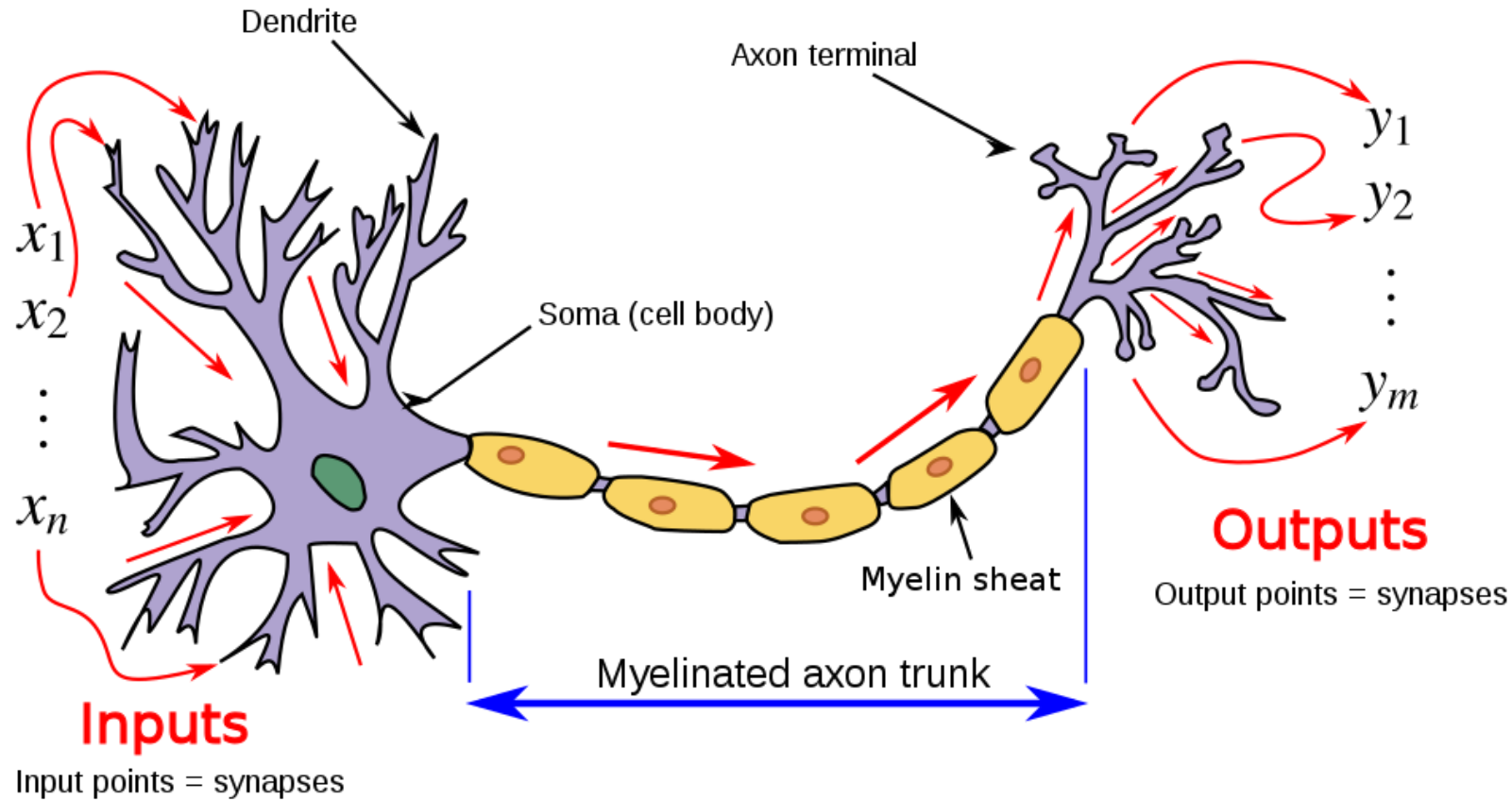
Random Forests



Neural Networks



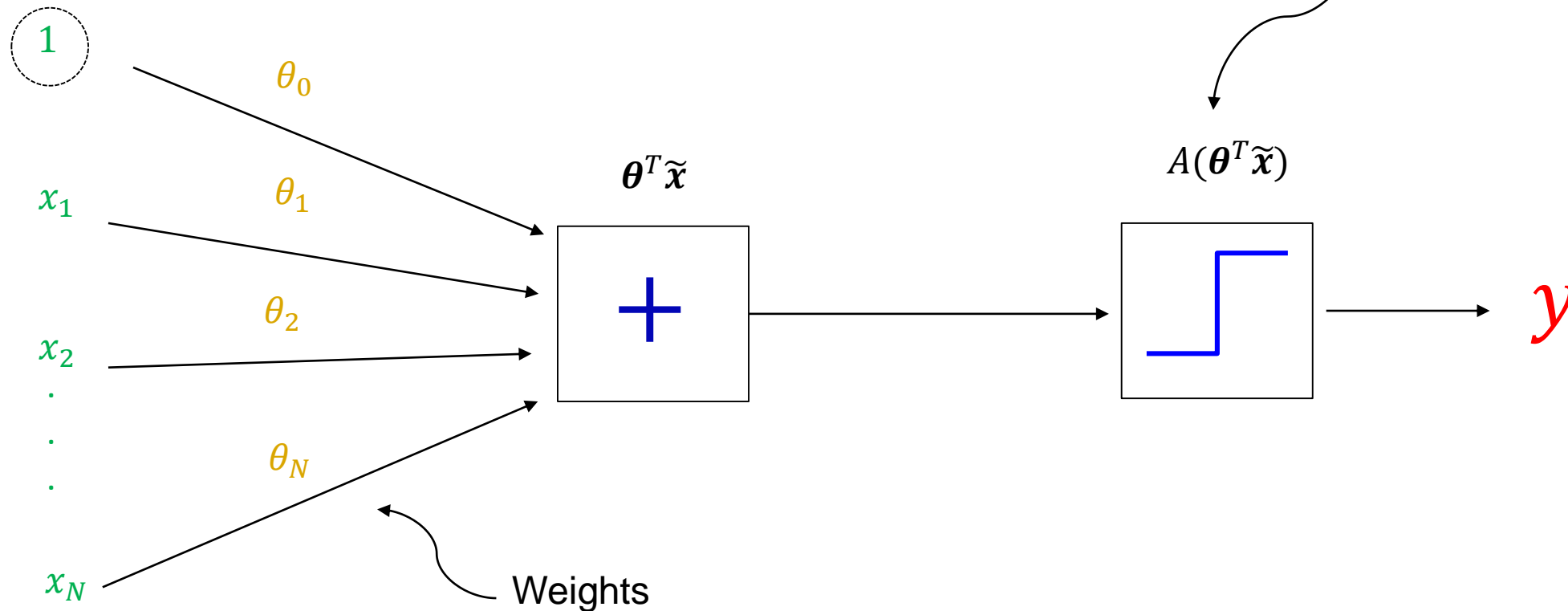
Neural networks take inspiration from biological neurons:



# Artificial Neuron

“Mathematical” neuron architecture:

Nonlinear “Activation” Function

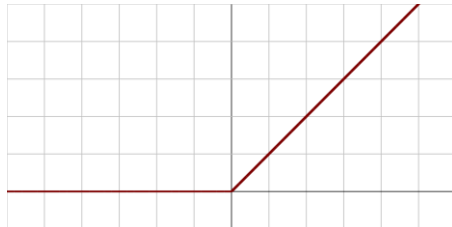




Most common activation functions used in practice:

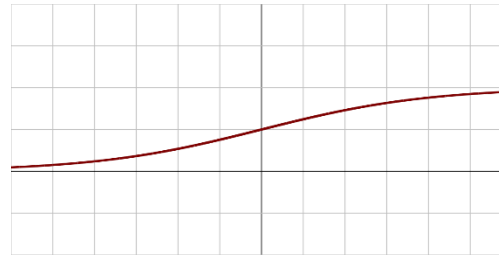
ReLU

$$A(x) = \max\{0, x\}$$



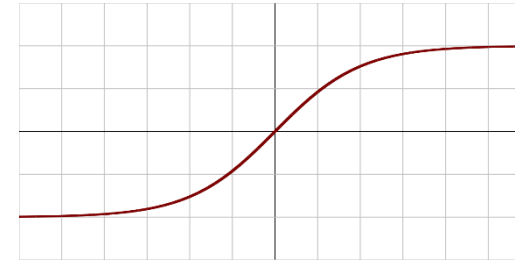
Sigmoid

$$A(x) = \frac{1}{1 + e^{-x}}$$



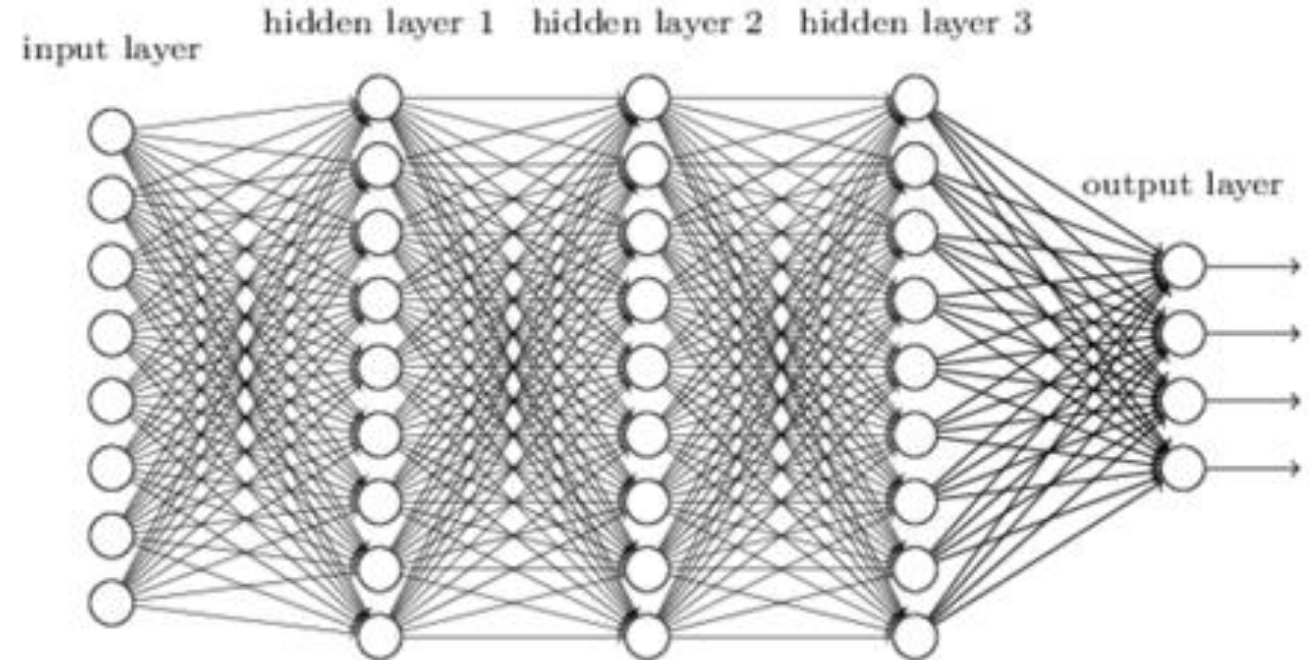
tanh

$$A(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$



# Neural Networks

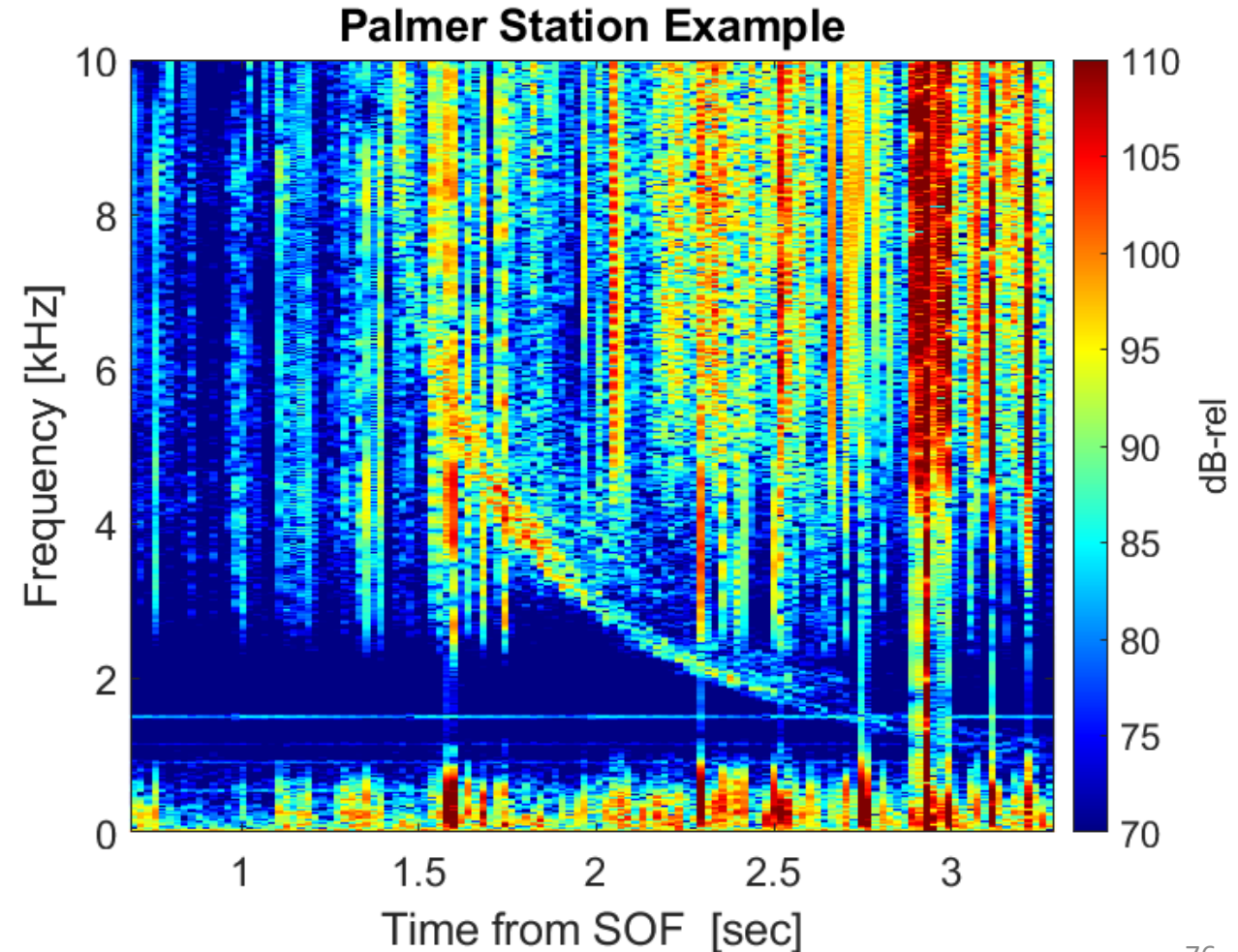
- Uses mathematical neurons as building blocks.
- Neural networks can be tuned to map highly nonlinear input-output relationship.
- Sometimes called a **Universal Approximator**.



1. Overview of Whistler Mode Waves
2. Traditional Methods of Signal Detection
3. Basic Overview of Neural Networks
4. Whistler Extraction using MSRCNN
5. Summary and Future Work

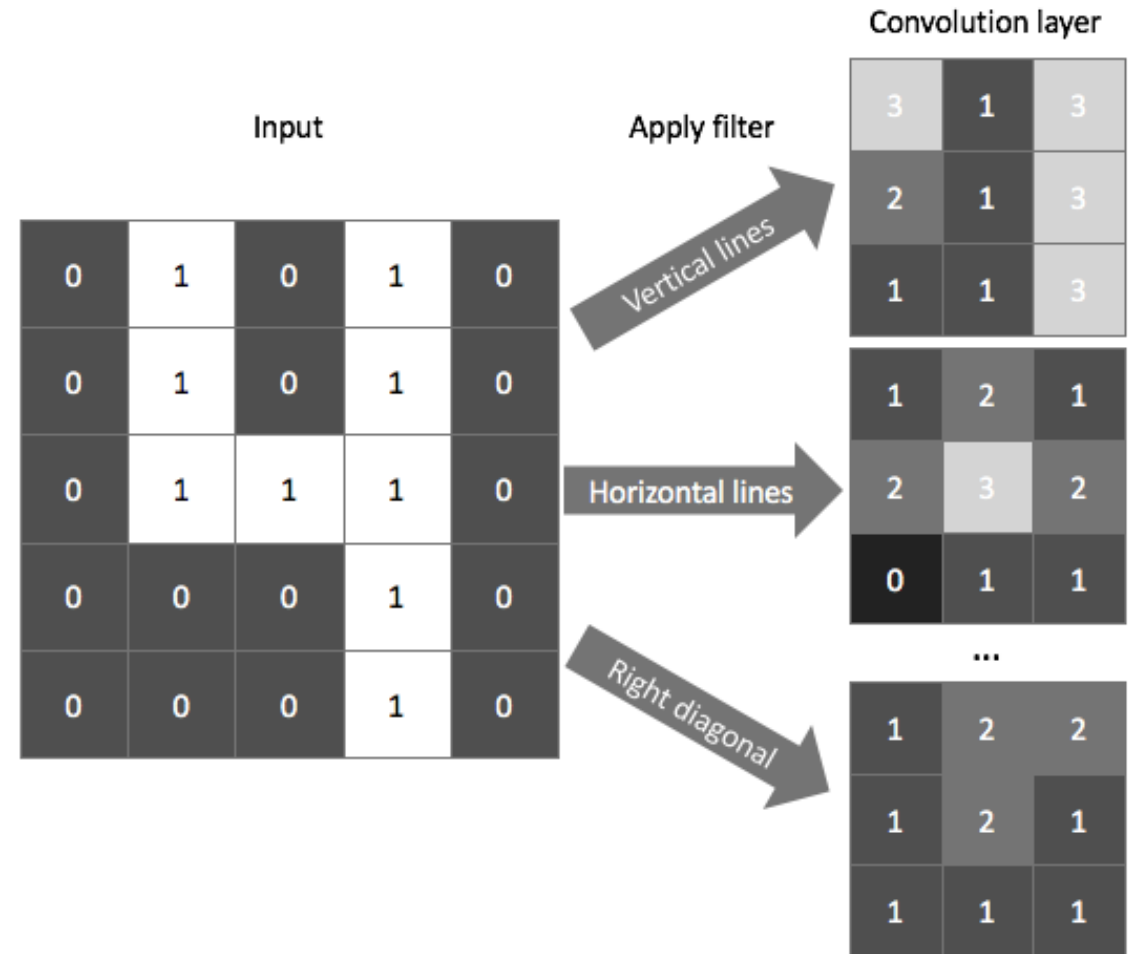
# Extraction of Whistlers

- Spectrograms can be treated as “images”.
- Whistlers are the “objects” in the images.
- When dealing with images, a **Convolutional Neural Network (CNN)** is a more efficient starting point.



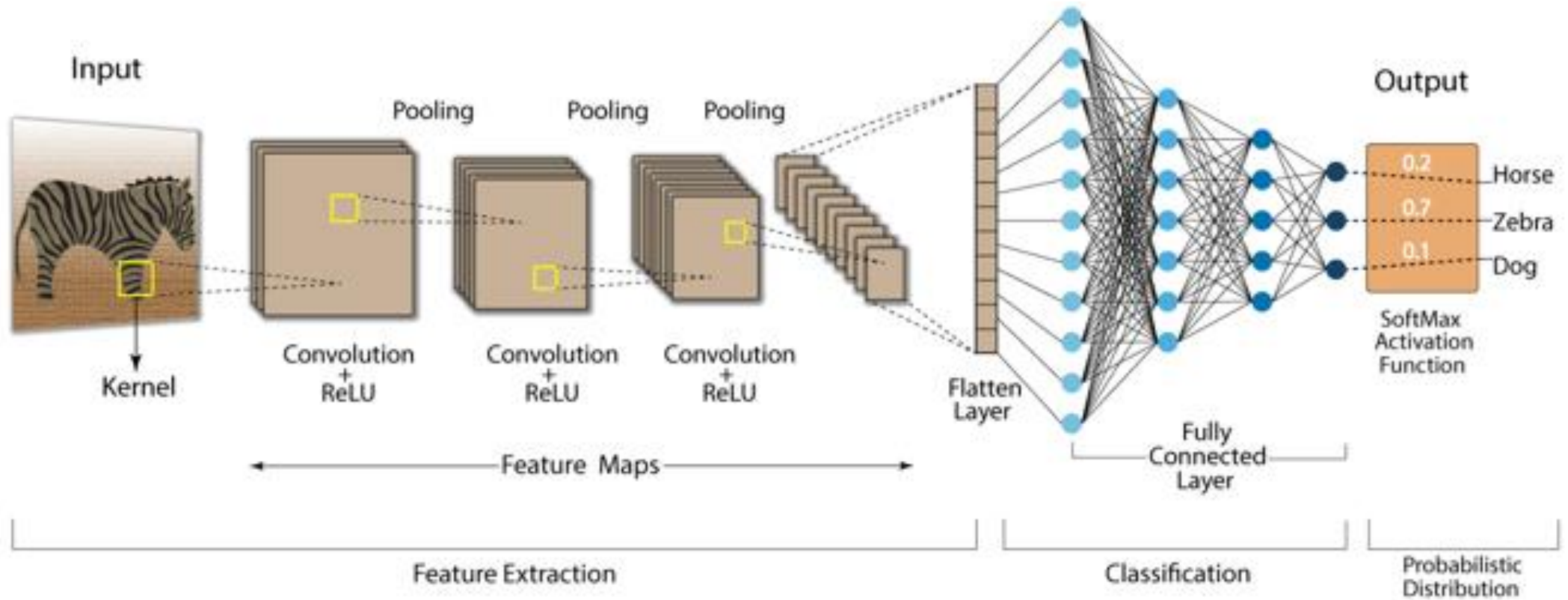
# Convolutional Neural Networks

- 1080p images have ~2M pixels...too many features for a standard neural network.
- A better approach is to first extract higher level features (edges, waviness, etc.).
- Convolutional Neural Networks (CNN) **learn** convolutional filters to reduce dimensionality.



# Convolutional Neural Networks

## End to end architecture of CNN:

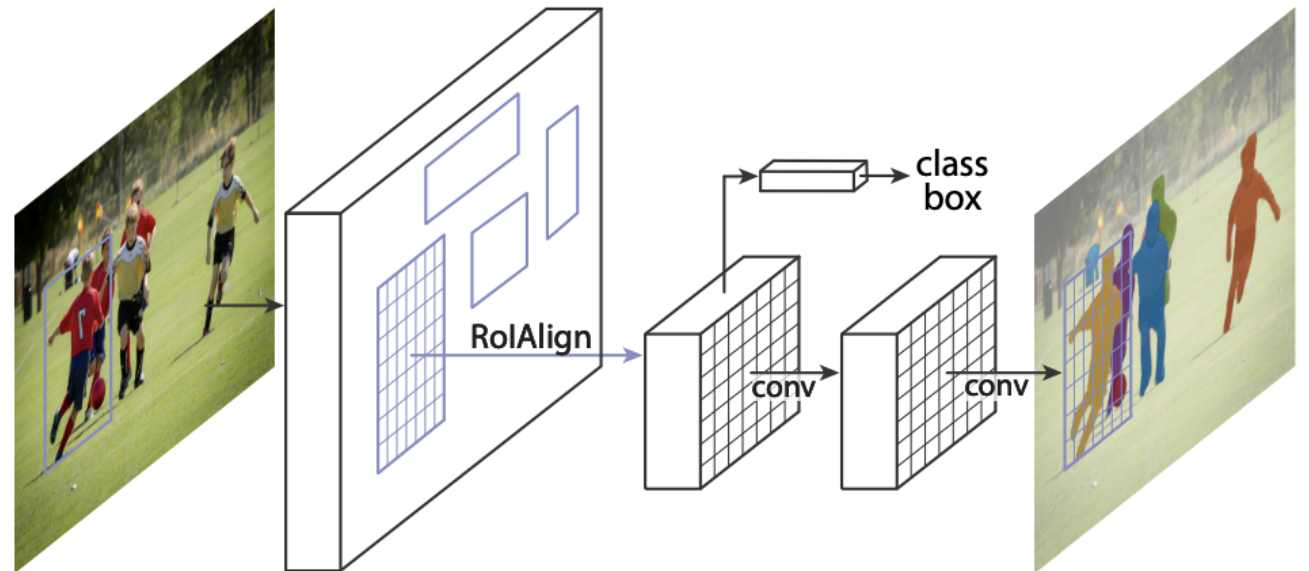


<https://developersbreach.com/convolution-neural-network-deep-learning/>

# Mask Regional CNN

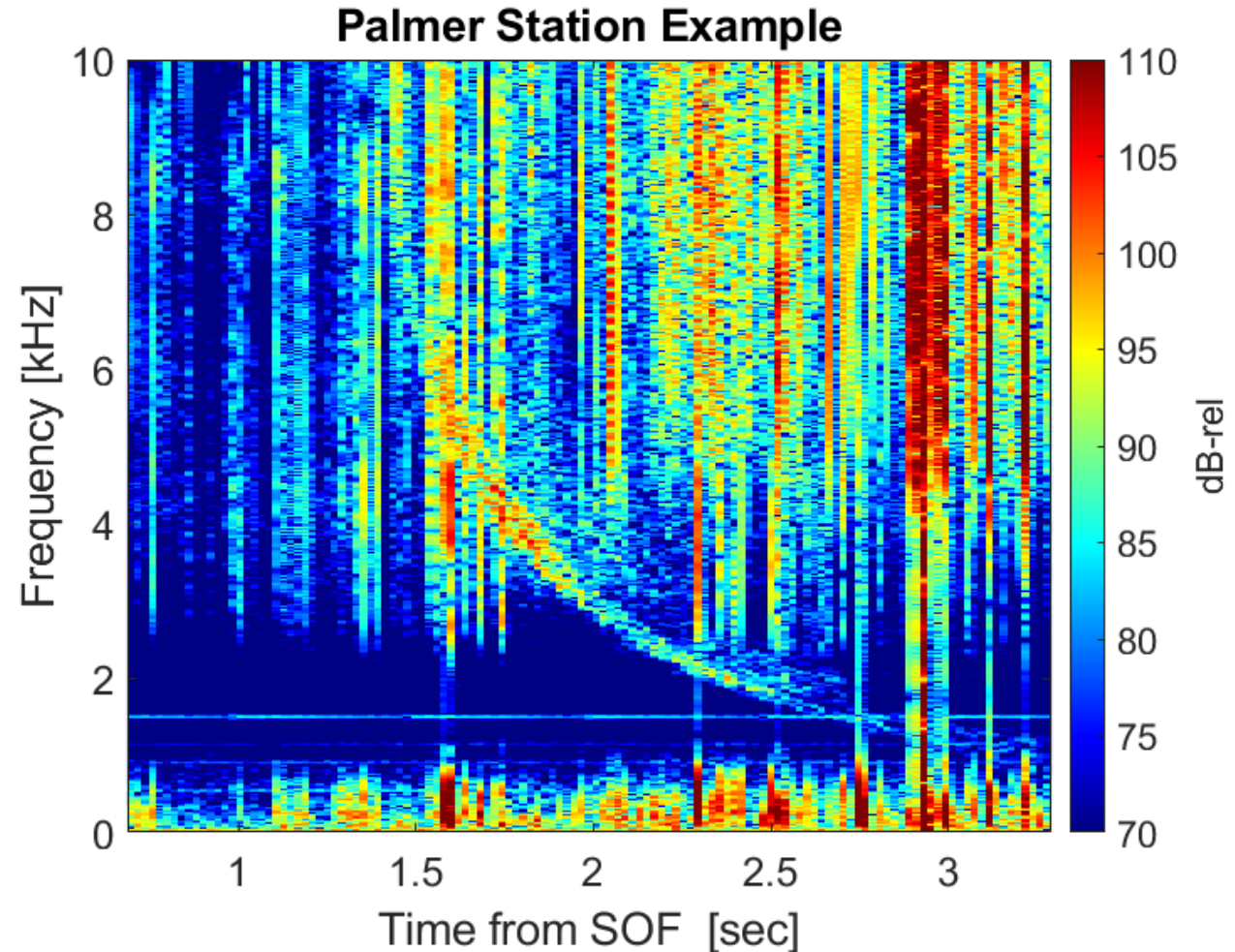
- Mask Regional Convolutional Neural Network (MRCNN) was originally created by Facebook AI Research for object detection/extraction.
- Has two major features:
  - Classifies objects.
  - Determines pixels (mask) corresponding to the object.

**“M-RCNN”**  
*[He et al., 2018]*



# Application to Whistlers

- Spectrograms can be treated as “images”.
- Signals of interest are “objects”.
- The model is being trained on:
  - Whistlers
  - Chorus bands
  - Hiss bands
  - Triggered emissions
  - CW/Transmitter signals

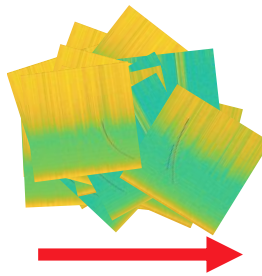
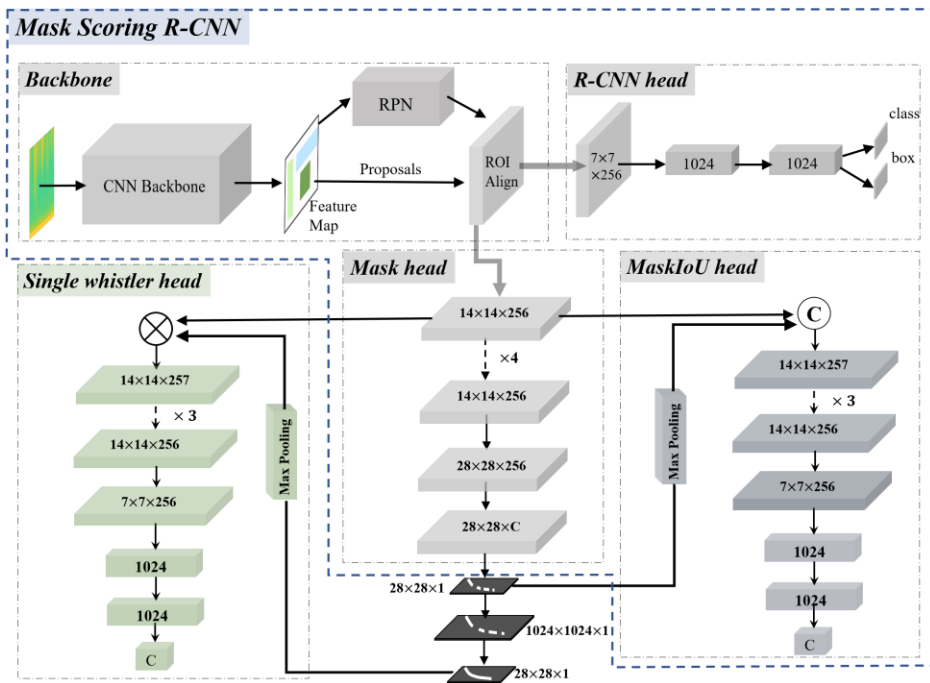




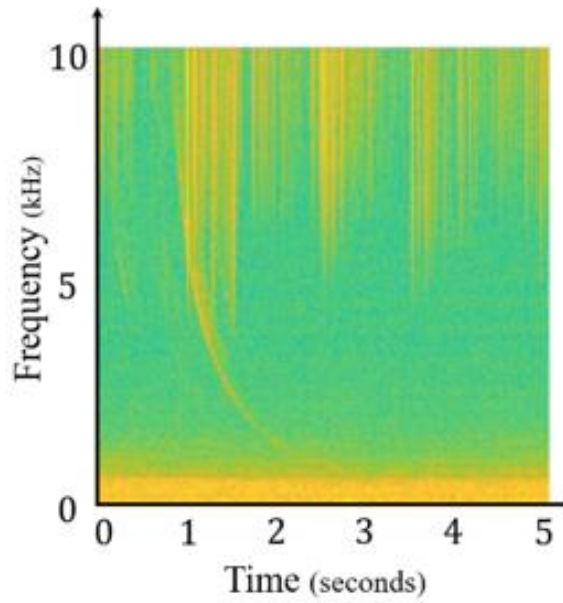
# MSRCNN Results

- *Mask Scoring Regional Convolutional Neural Network (MSRCNN)* is typically used for object detection/extraction in images.
- Spectrograms are treated as images, whistlers are the objects.

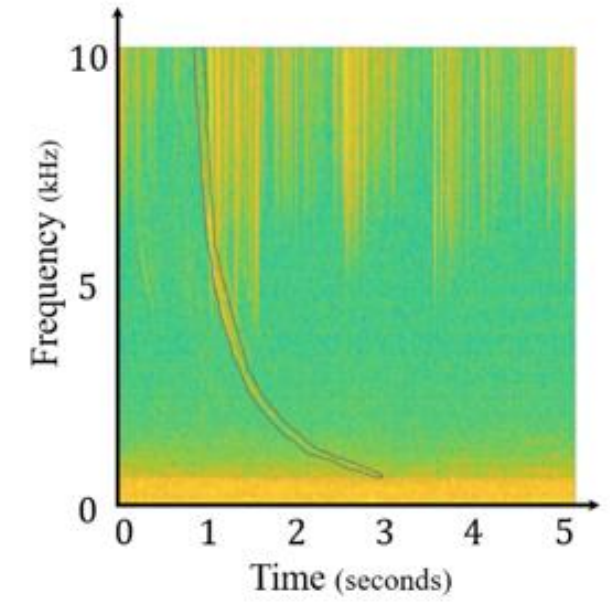
[Harid et al., 2021]



Original Spectrogram



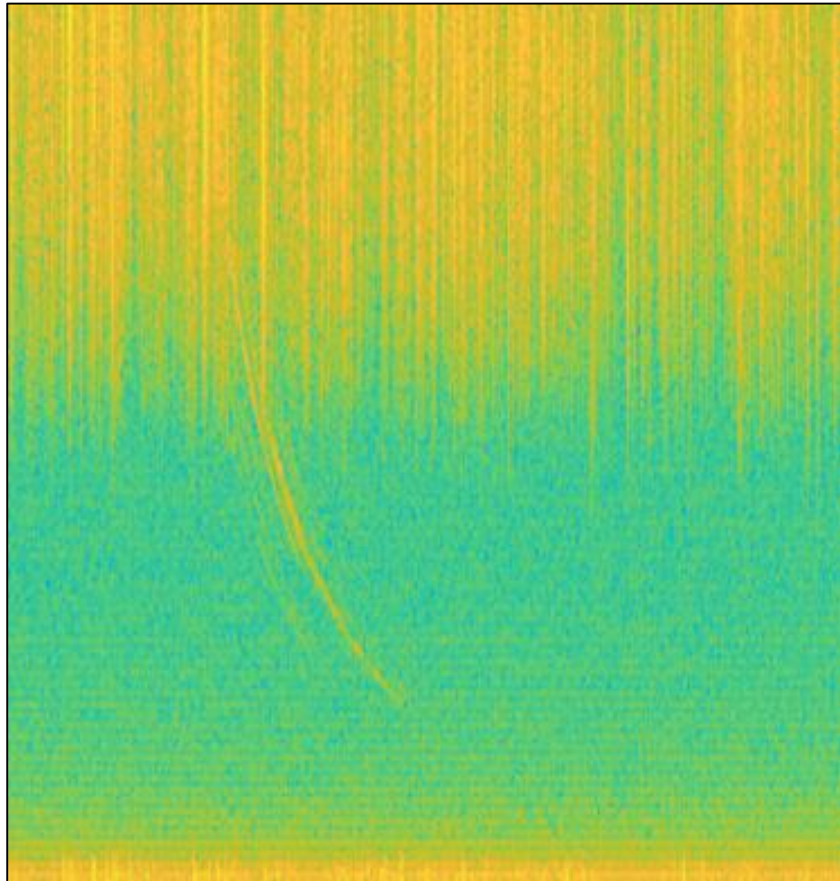
Whistler Track Extraction



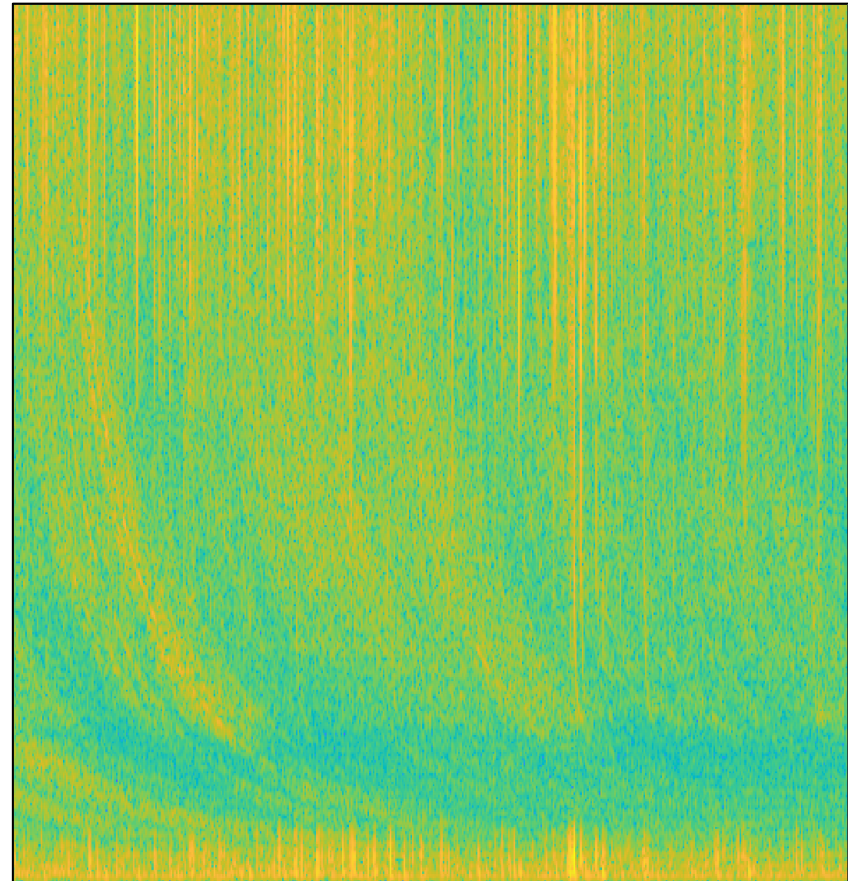
# MSRCNN Results

- This ML approach allows for multiple “classes” of whistlers:

Single Whistler



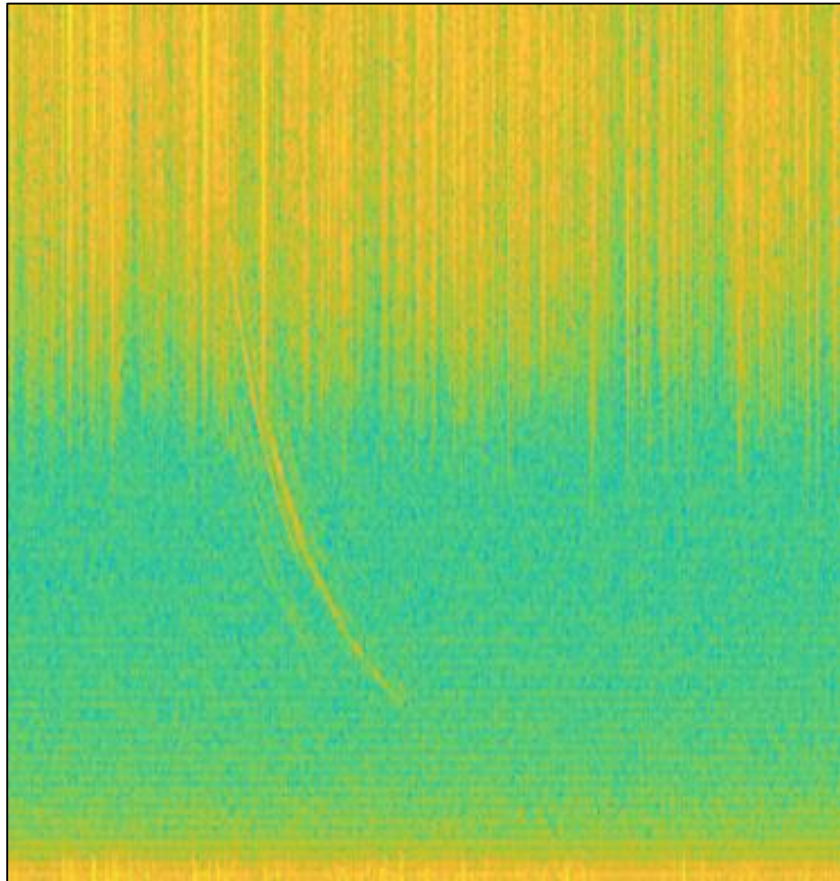
Group Whistlers



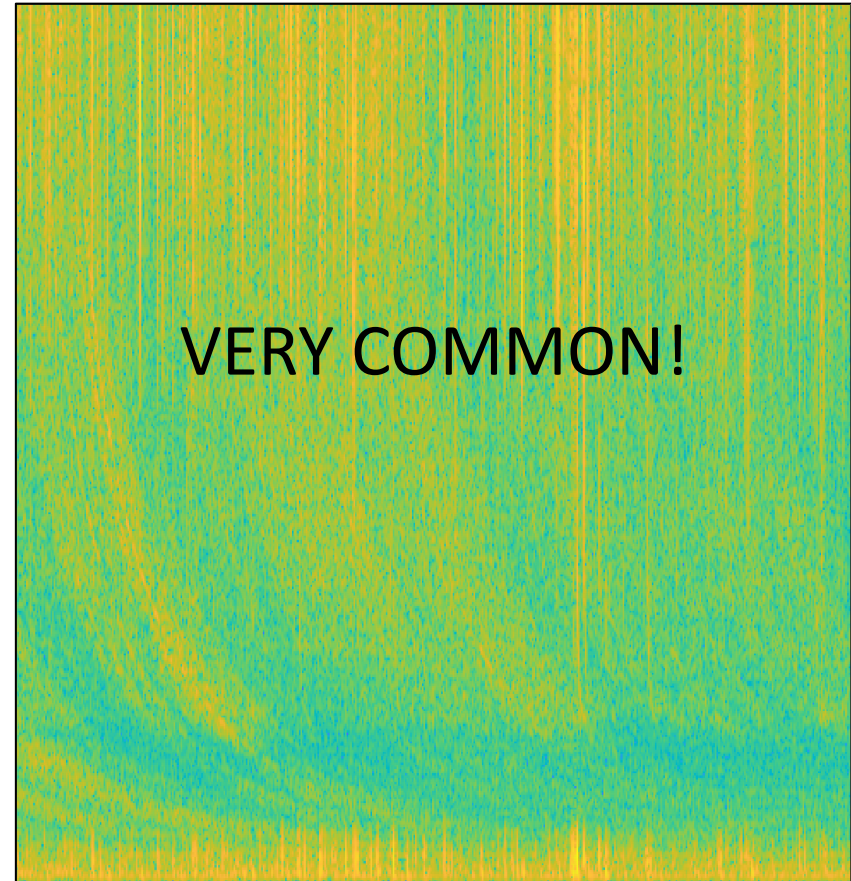
# MSRCNN Results

- This ML approach allows for multiple “classes” of whistlers:

Single Whistler



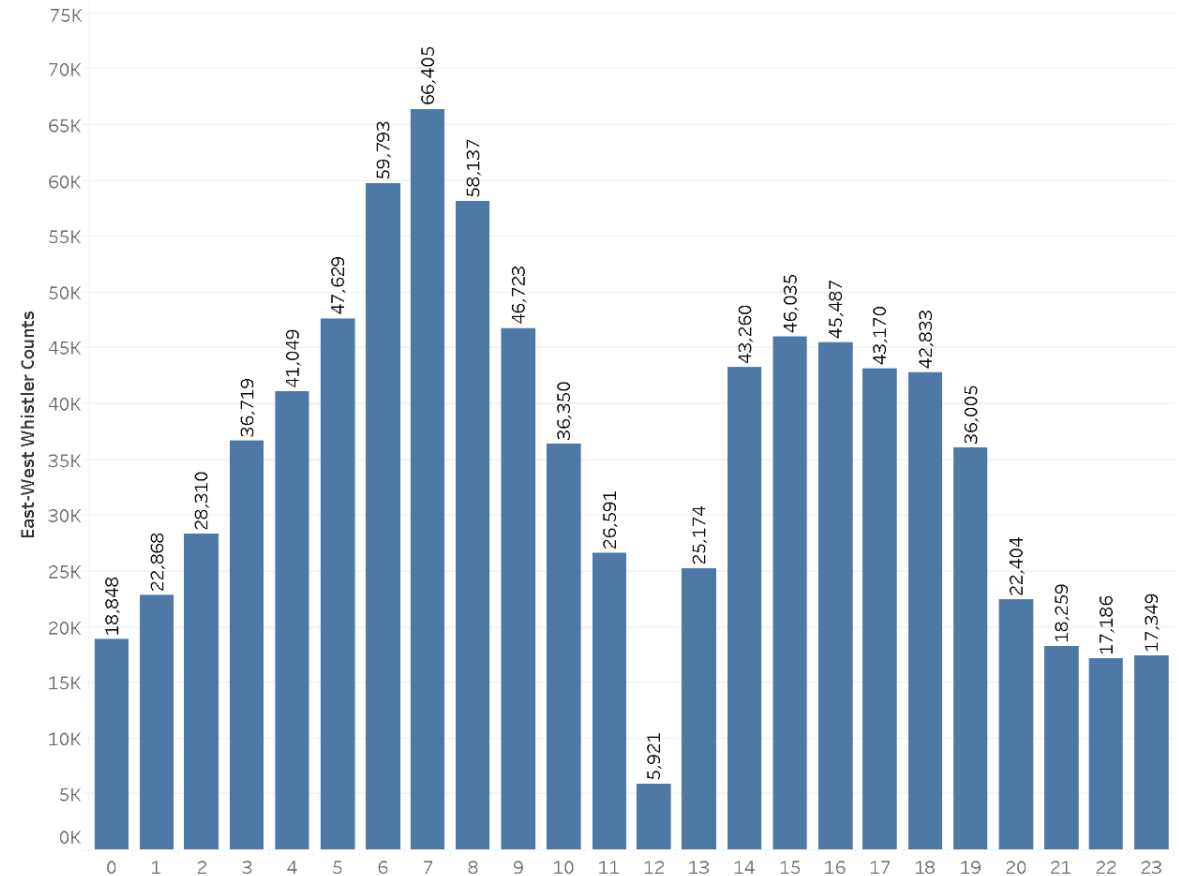
Group Whistlers



# Palmer Station: *Diurnal Variation*

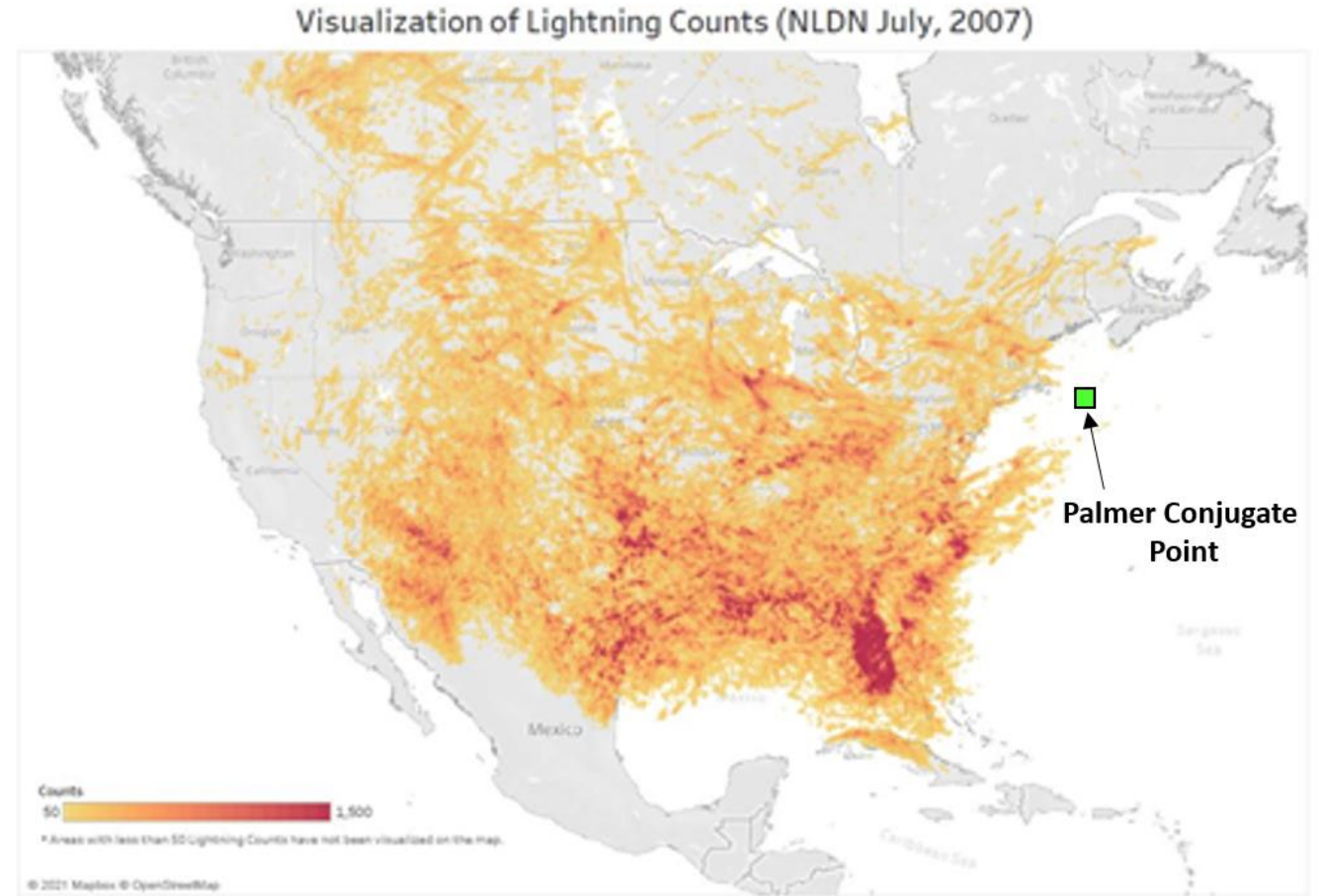
- Diurnal variation (relative to conjugate time) is quantified over the entire course of 2007.
- Results show a deep minimum at noon and local maxima at morning/evening (conjugate time).
- Higher whistler counts are observed during daytime compared to nighttime.
- This strong diurnal dependence can provide insight on the geophysical environment (future work).

2007 East-West Whistler Counts vs Conjugate Local Time (Hr)



# Palmer Station: *Comparison to Lightning*

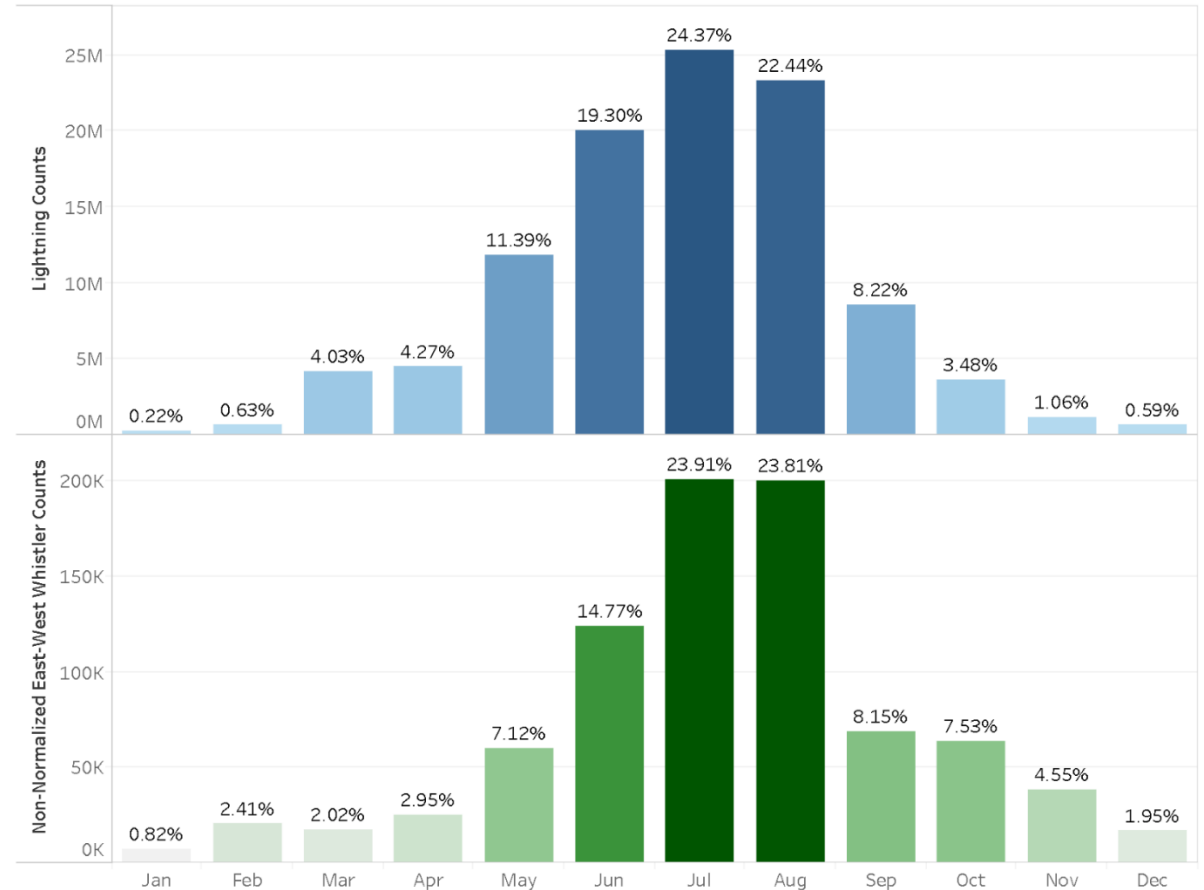
- Palmer conjugate point is located on the east coast of North America.
- Source of whistlers are from lightning across North America.
- Palmer whistlers can be compared to lightning data in North America.



# Palmer Station: Comparison to Lightning

- Results are compared to lightning data in North America using NLDN (National Lightning Detection Network).
- Results shows excellent correlation on monthly timescales for *entirety* of North American lightning.
- Other geophysical parameters are also likely important and impacting correlation (future work).

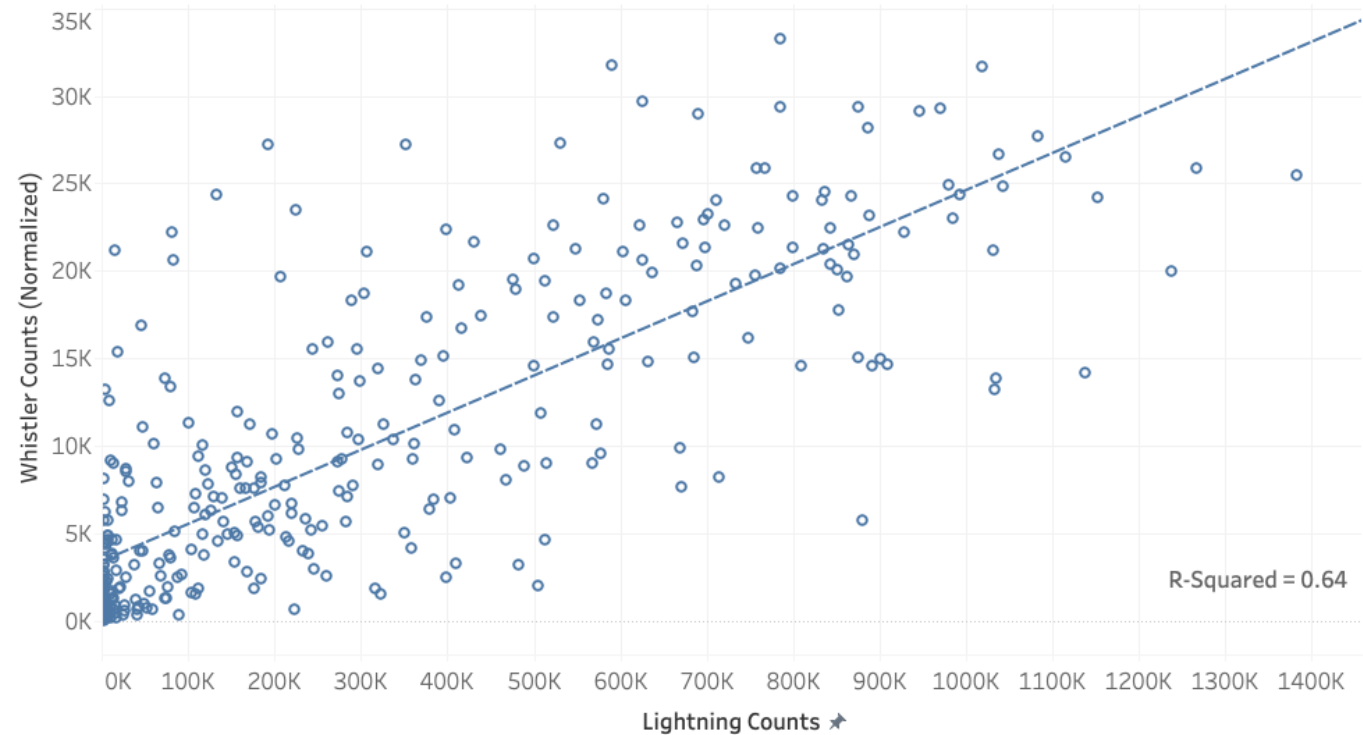
Lightning vs Non-Normalized East-West Whistler Counts (2007)



# Palmer Station: Comparison to Lightning

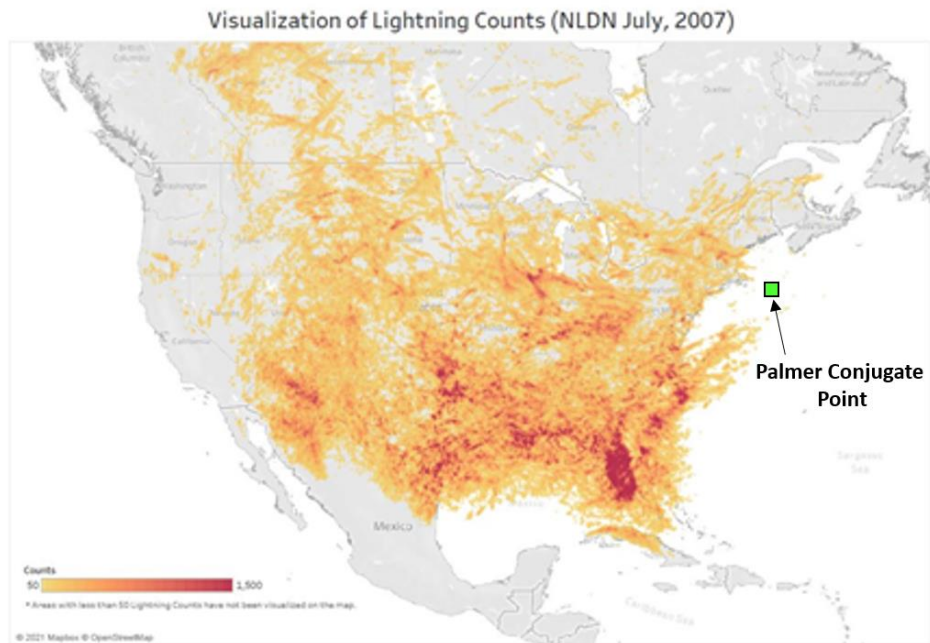
- Results are compared to lightning data in North America using NLDN (National Lightning Detection Network).
- Results shows excellent correlation on monthly timescales for **entirety** of North American lightning.
- Other geophysical parameters are also likely important and impacting correlation (future work).

Scatter Plot - Lightning vs Normalized Whistler Counts 2007



# Non-Localization of Whistlers?

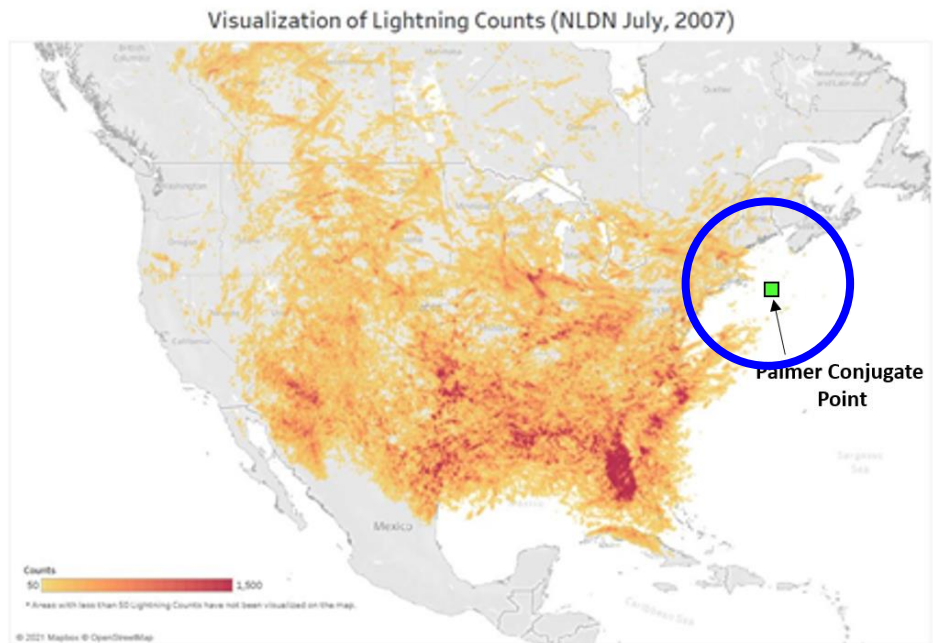
- Correlation can be computed as a function of distance from the conjugate point.





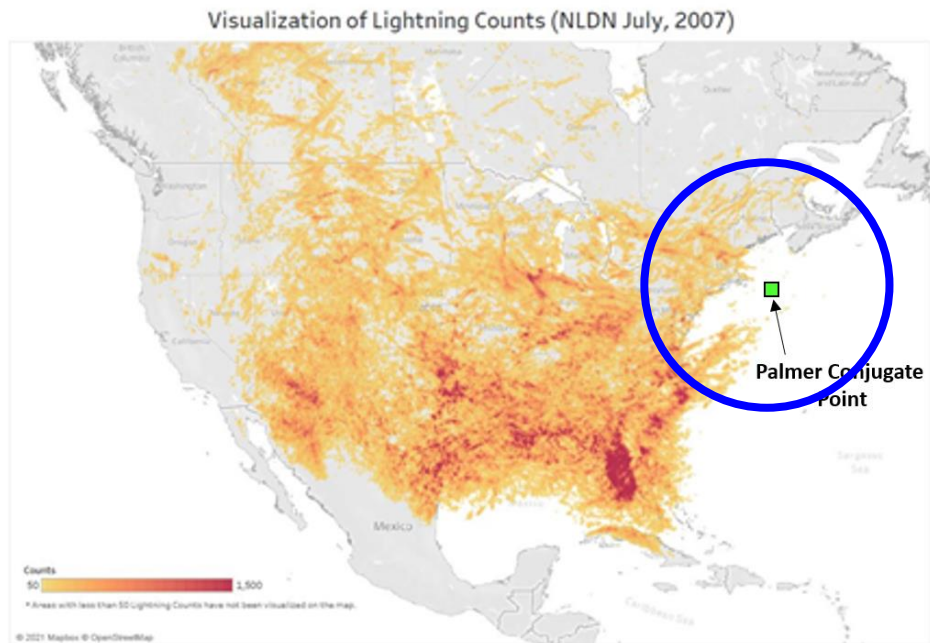
# Non-Localization of Whistlers?

- Correlation can be computed as a function of distance from the conjugate point.



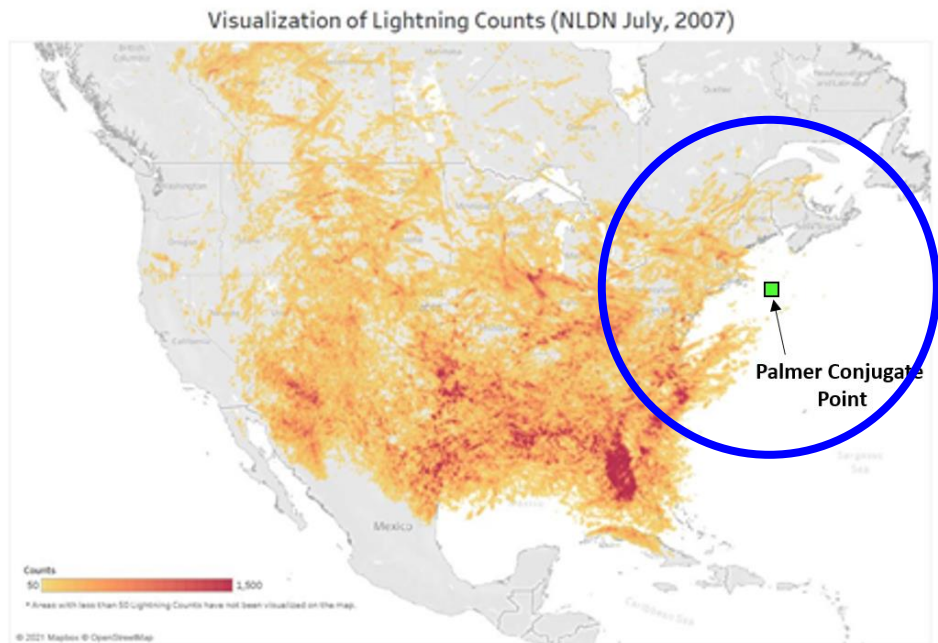
# Non-Localization of Whistlers?

- Correlation can be computed as a function of distance from the conjugate point.



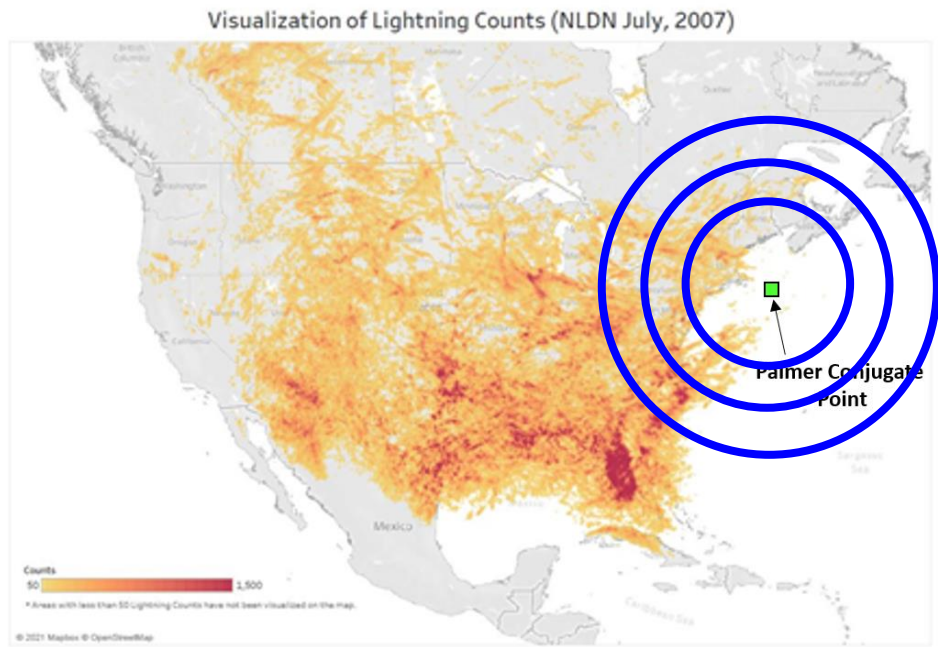
# Non-Localization of Whistlers?

- Correlation can be computed as a function of distance from the conjugate point.

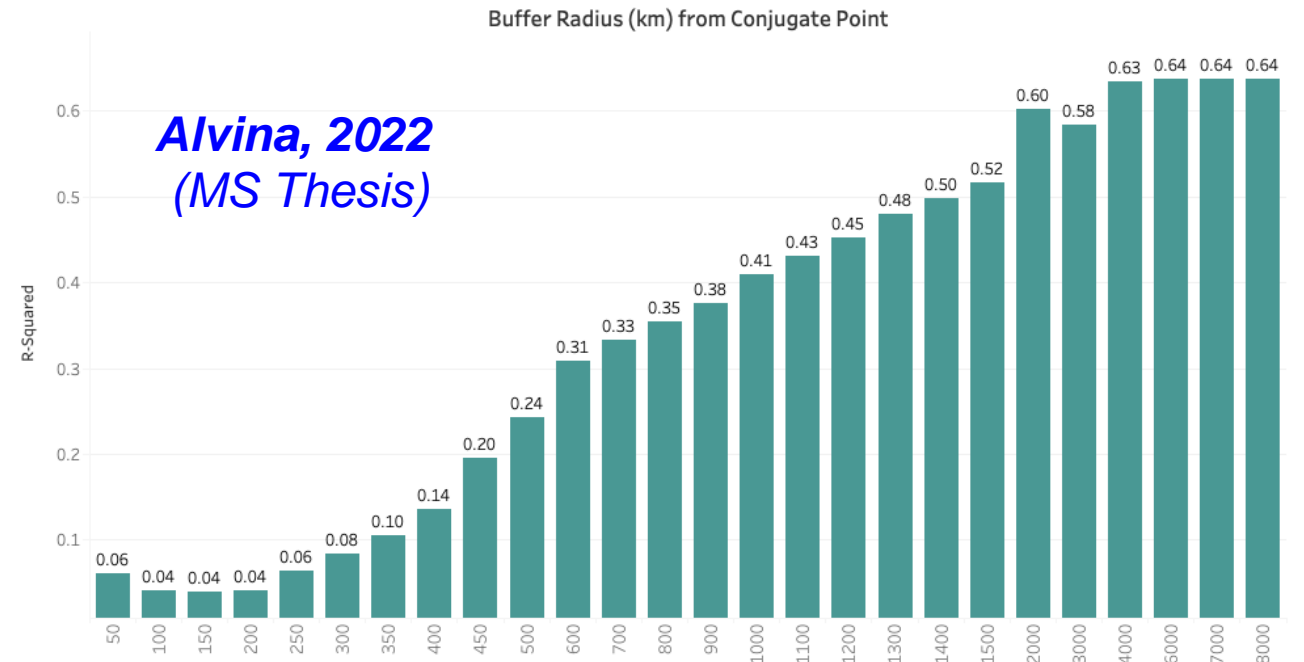


# Non-Localization of Whistlers?

- Correlation can be computed as a function of distance from the conjugate point.
- The causative lightning sources might be more spread out than previously thought.



R-Squared values for Buffer Distances (km) from Conjugate Point for Scatter Plots between NLDN and Normalized Whistler Counts (2007)



Several research groups are now using machine learning methods for automated VLF signal detection:

- ***Pataki et al., 2022*** - Monitoring Space Weather: Using Automated, Accurate Neural Network Based Whistler Segmentation for Whistler Inversion
- ***Maslej-Krešňáková et al., 2021*** - Automatic Detection of Atmospheric and Tweek Atmospheric in Radio Spectrograms Based on a Deep Learning Approach
- ***Jin et al., 2021*** - Advances in the automatic detection algorithms for lightning whistlers recorded by electromagnetic satellite data
- ***Wang et al., 2020*** - Classification of VLF/LF Lightning Signals Using Sensors and Deep Learning Methods
- ***Konan et al., 2020*** - Machine Learning Techniques to Detect and Characterise Whistler Radio Waves
- ***Ahmad et al., 2019*** - Automatic Detection of Lightning Whistlers Observed by the Plasma Wave Experiment Onboard the Arase Satellite Using the OpenCV Library

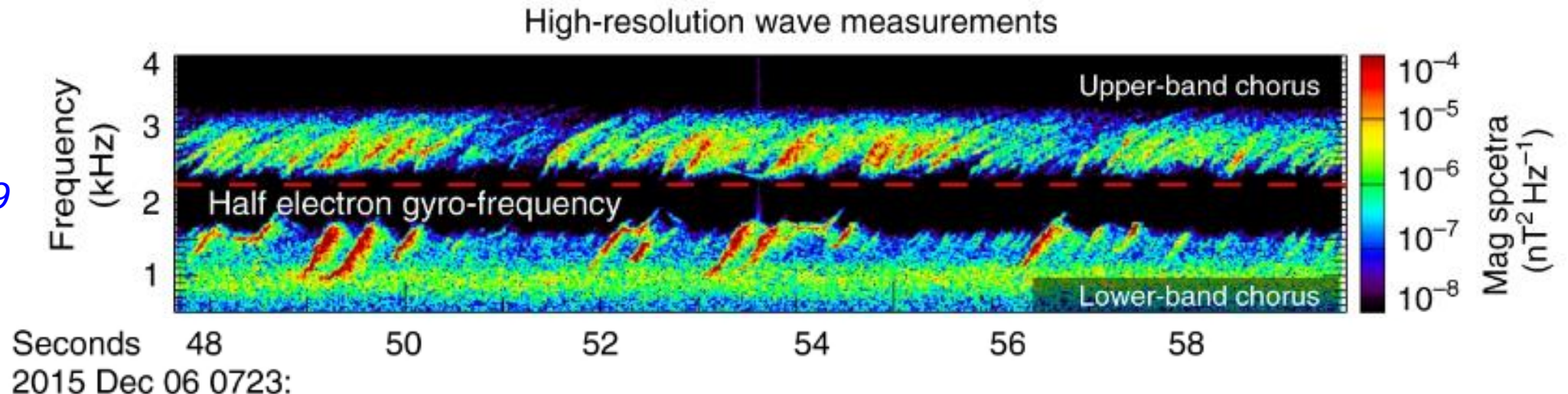
1. Overview of Whistler Mode Waves
2. Traditional Methods of Signal Detection
3. Basic Overview of Neural Networks
4. Whistler Extraction using MSRCNN
5. Summary and Future Work

- ELF/VLF waves are ubiquitous in near-Earth space.
- Waves have frequency-time signatures on spectrograms.
- Large datasets are now available from ground-based and spacecraft measurements.
- We utilized the MSRCNN method for large scale extraction for whistlers from ground-based data.
- Machine learning methods are powerful tools for automatically extracting ELF/VLF signals from spectrogram data.

# Future Work

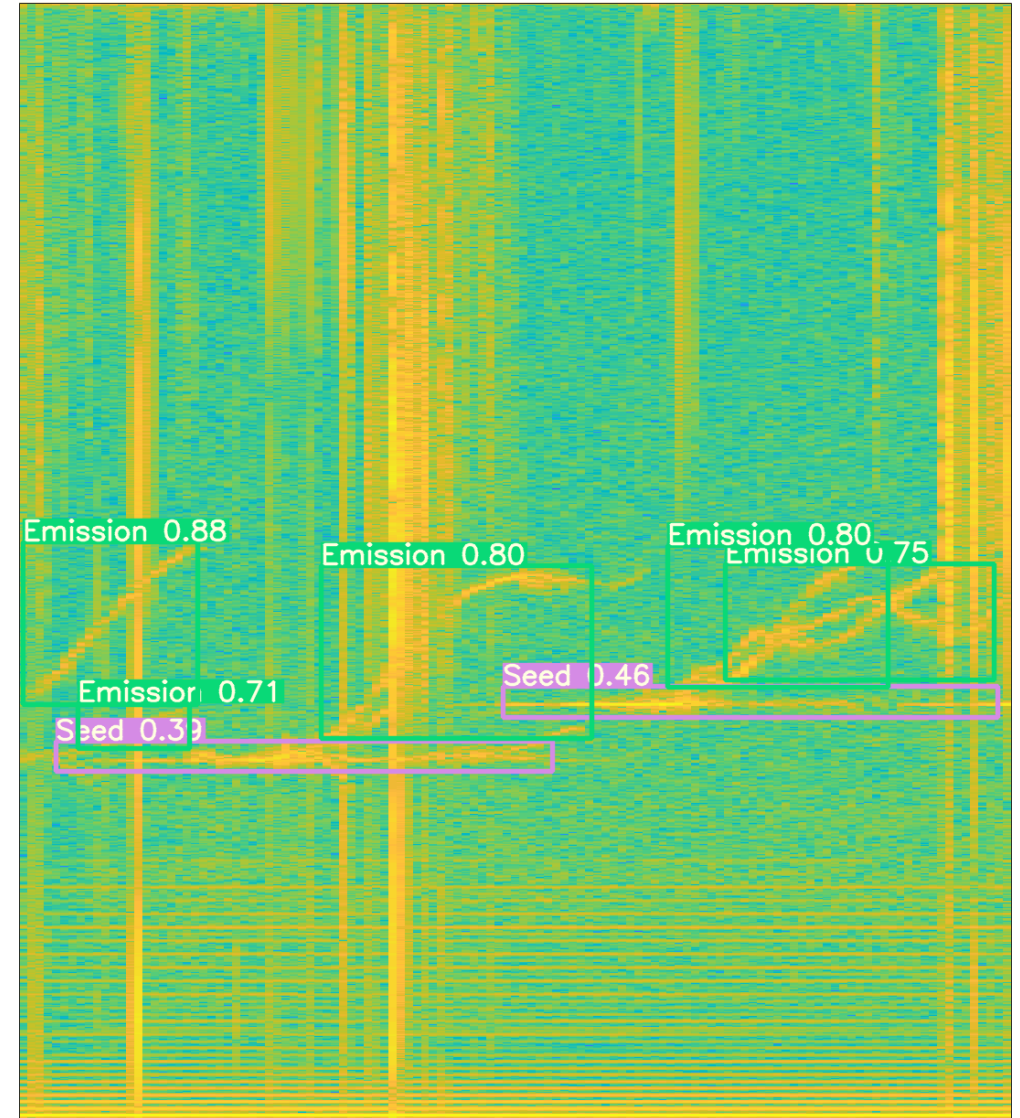
- Other classes of whistler-mode waves also have a characteristic **frequency-time signature** on spectrograms.
- The machine learning formalism is general enough that it can be easily extended to other signals

*Li et al., 2019*



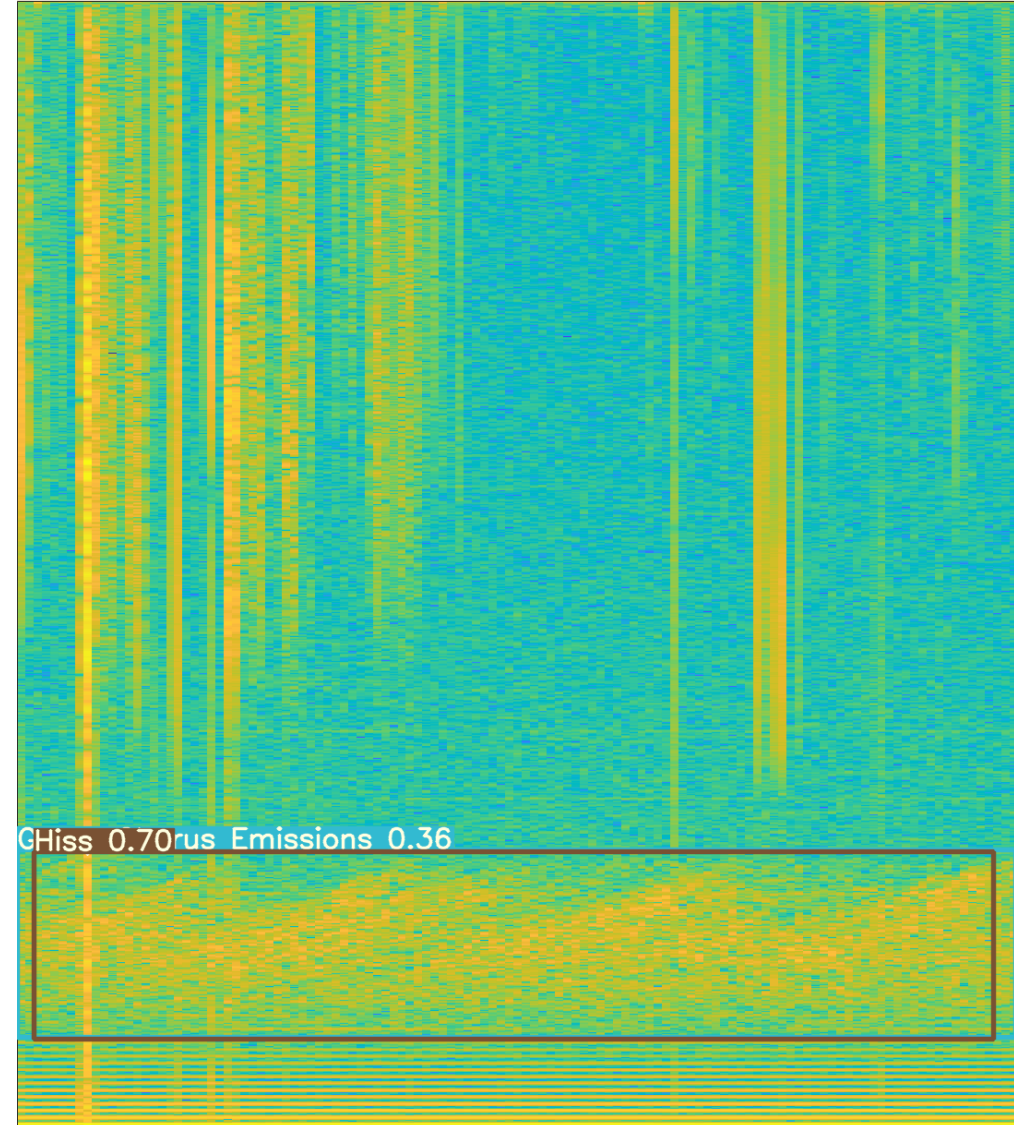


- The model is currently being extended to other signal classes including:
  - Chorus bands
  - Hiss bands
  - Triggered emissions
  - CW/Transmitter signals
- Still very much part of active research...more to come!



# Future Work

- The model is currently being extended to other signal classes including:
  - Chorus bands
  - Hiss bands
  - Triggered emissions
  - CW/Transmitter signals
- Still very much part of active research...more to come!



- Extend machine learning models to other signal classes.
- Run ML models on spacecraft data (such as RBSP/Arase/MMS etc.).
- Begin larger collaborations using machine learning models for signal detection across the space physics community!

**THANK YOU!**

*Questions?*