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Machine Learning Techniques for Automated ULF Wave Recognition in Swarm Time Series

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Outline

- Introductory part
  - ESA Swarm Mission
  - ULF Waves
  - Time-Frequency Analysis (TFA) Tool for Automated ULF Wave Recognition
  - Swarm ULF Wave Events & Power Maps

- Machine Learning Approach (MLA) for Automated ULF Wave Recognition

ESA Swarm mission

Each satellite is measuring:

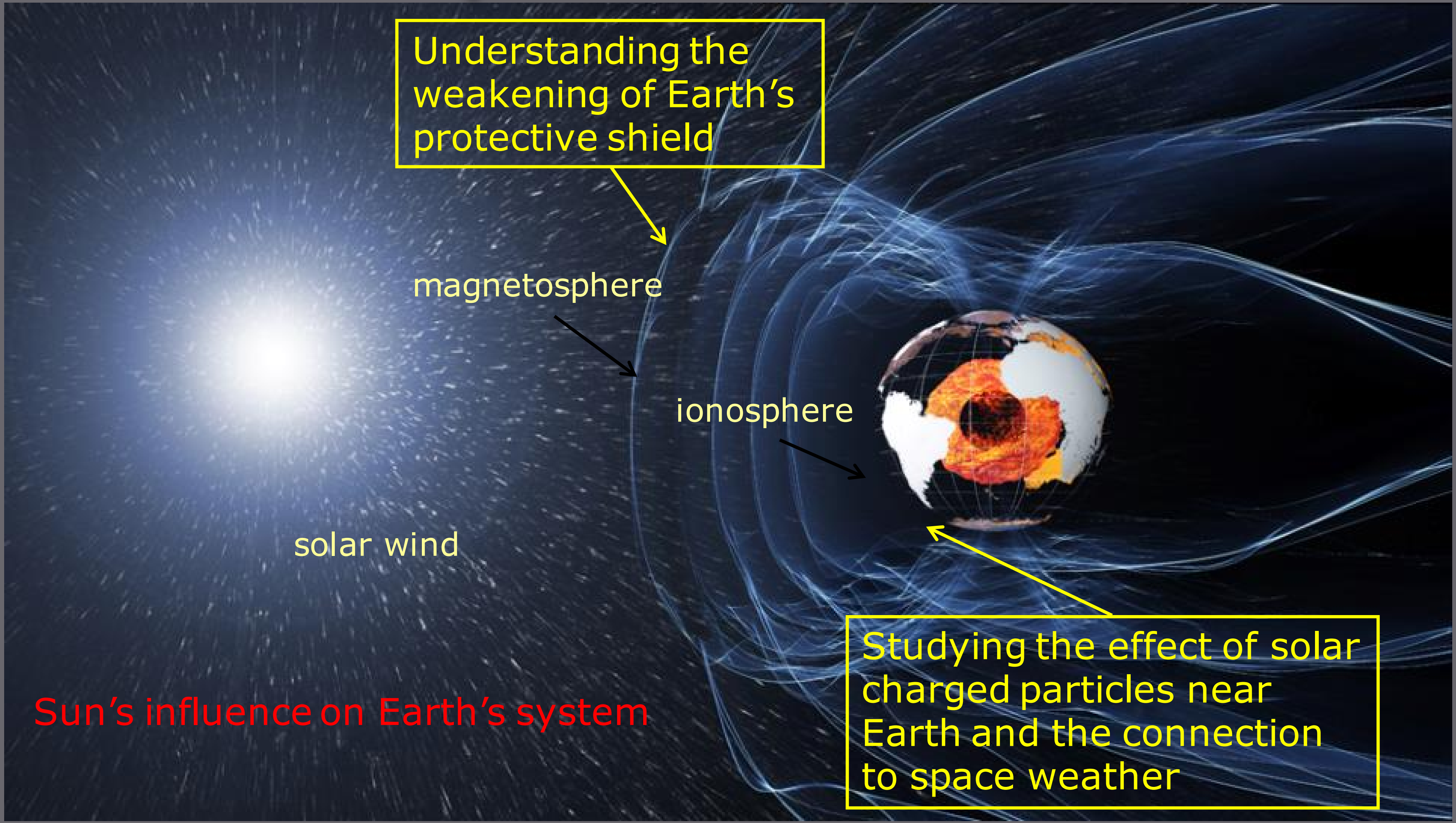
- ✓ Strength and direction of the magnetic field
- ✓ Plasma conditions and characteristics
- ✓ Location

The Constellation:

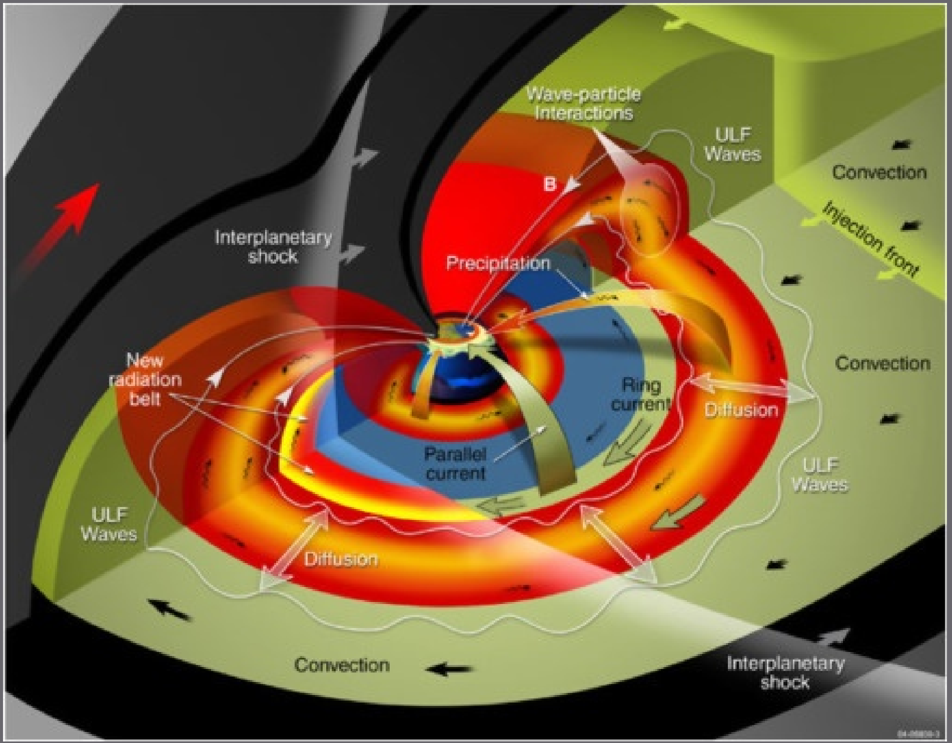
- ✓ 3 identical satellites:
  - 2 side-by-side in low orbit (<460km)
  - 1 in higher orbit
  - (< 530km)
- ✓ three orbital planes for optimal coverage in space and time
- ✓ **Launch 22 November 2013: initially 4 years of operations, currently extended through 2021**

The primary aim of the mission is to provide the best survey ever of the geomagnetic field and the first global representation of its variations on time scales from less than a second to several years.

Looking into the force that protects Earth



ULF Waves



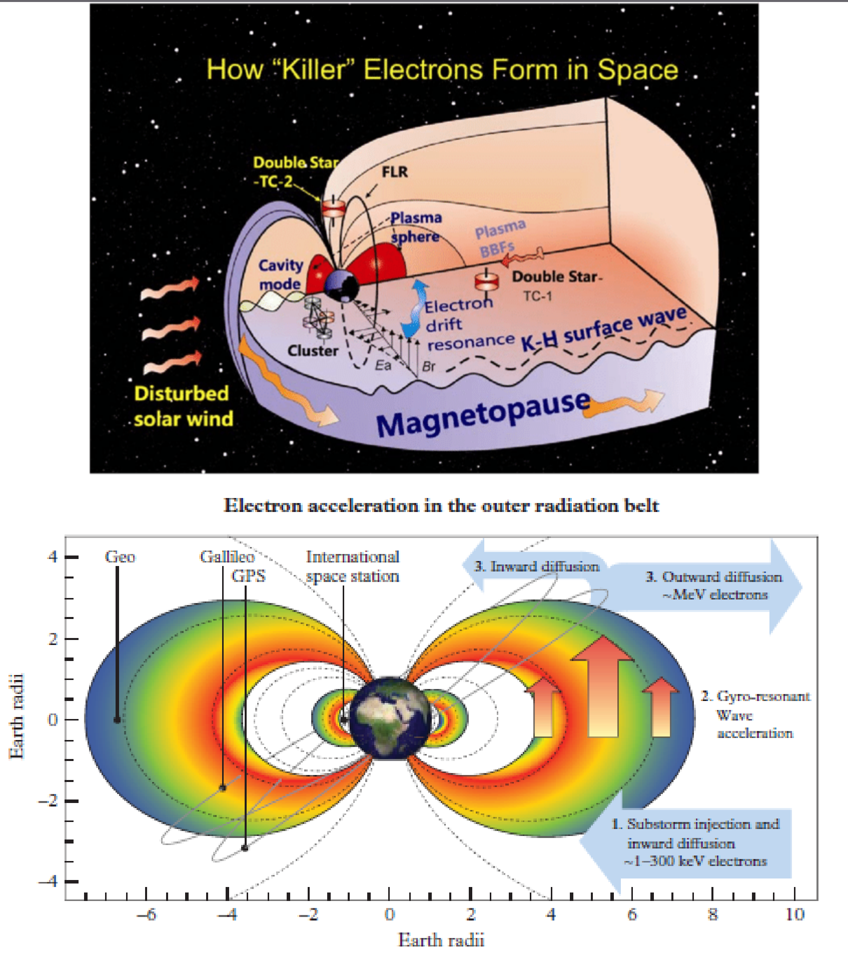
	Pulsation classes						
	Continuous pulsations					Irregular pulsations	
	Pc 1	Pc 2	Pc 3	Pc 4	Pc 5	Pi 1	Pi 2
T [s]	0.2-5	5-10	10-45	45-150	150-600	1-40	40-150
f	0.2-5 Hz	0.1-0.2 Hz	22-100 mHz	7-22 mHz	2-7 mHz	0.025 -1 Hz	2-25 mHz

Ultra-low frequency (ULF) magnetospheric waves originate when magnetic fields and plasma interact in the Earth's magnetosphere (Alfven MHD waves in plasmas).

A fast compressional mode wave was assumed to originate at the magnetopause and propagate earthward through regions of increasing Alfven speed.

At the point where the wave frequency matches the local field line eigenfrequency, the compressional mode disappears and its energy is transferred into the transverse, shear Alfven mode.

ULF wave importance

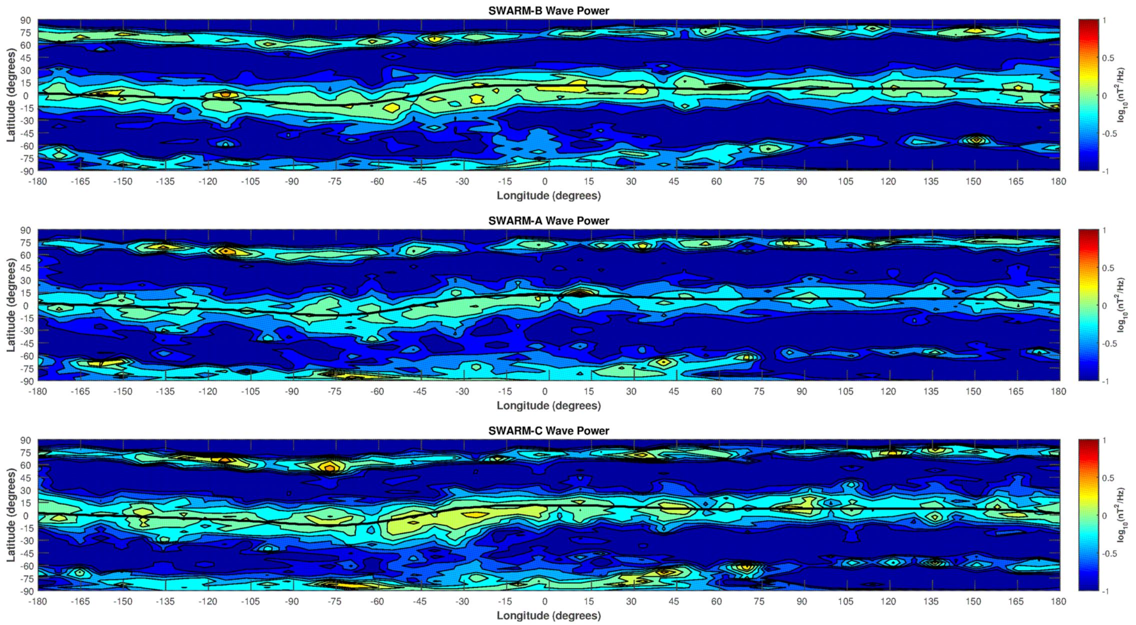


(after Zong, 2011; Horne, 2007)

- ULF waves play a central role in the dynamics of the inner magnetosphere.
- They are thought to be an important mechanism for energy transfer from the solar wind to magnetosphere and for accelerating and scattering higher energy particles in the radiation belts through radial diffusion and pitch-angle scattering.
- They can also result in adverse space weather effects, such as errors in GPS signals, enhanced Joule heating, and geomagnetically induced currents that affect power networks.

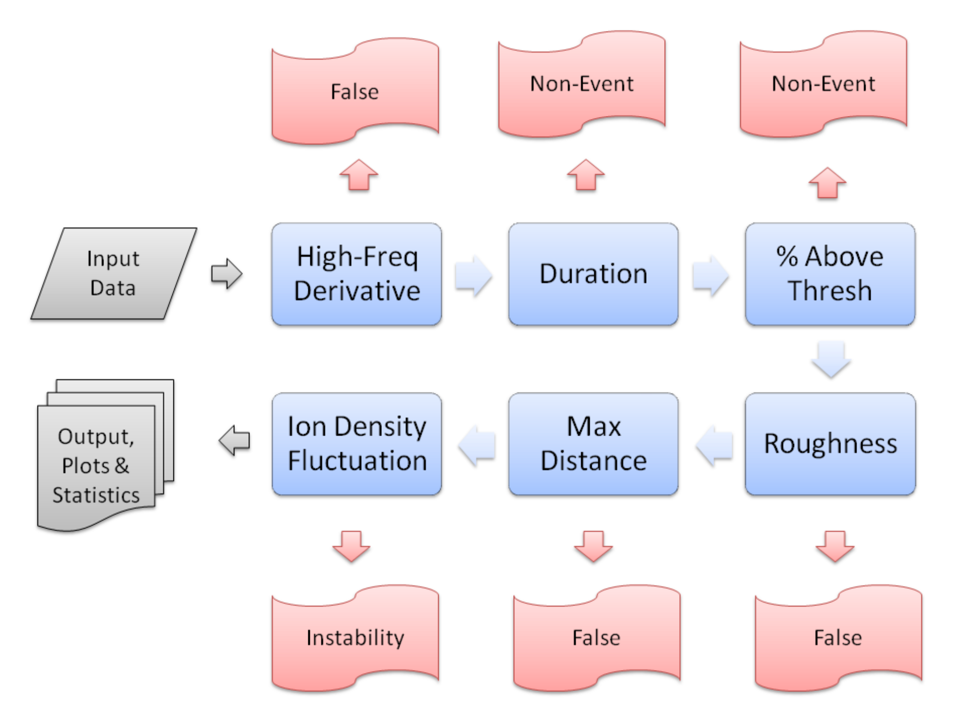
Swarm Pc3 power wavemaps (2 years, 20000 tracks/satellite)

South Atlantic Anomaly



Balasis et al. (*GRL*, 2015)

ULF Wave Detection & Classification



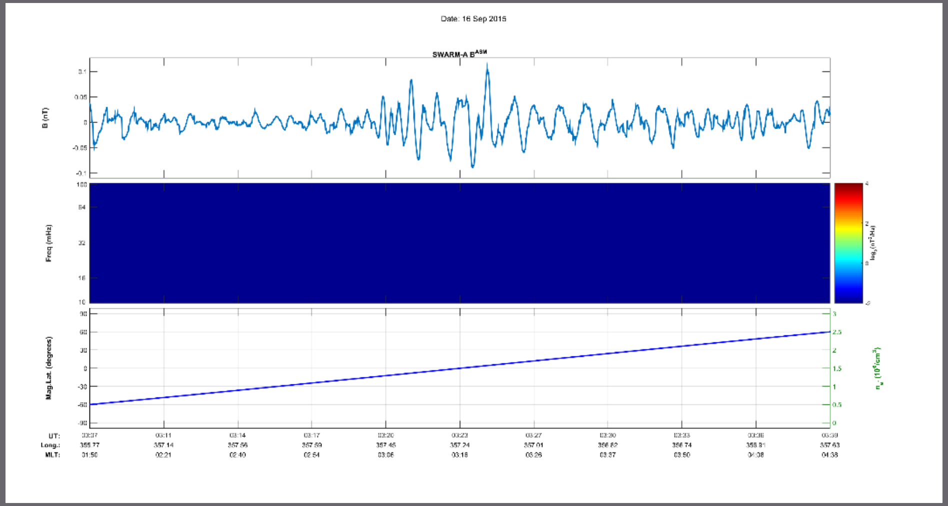
- Magnetic Field Data
- High-Pass Filtered at 20 mHz
- Wavelet Spectrum
- Separated into Tracks
- For each track:
  - Identify times of consecutive points which show Pc3 activity
  - Pass each such candidate through a series of tests to identify its nature

- Final Classification Categories
  - Background
  - Pc3 Events
  - False Positives
  - Plasma Instabilities (IBI & FAC related)

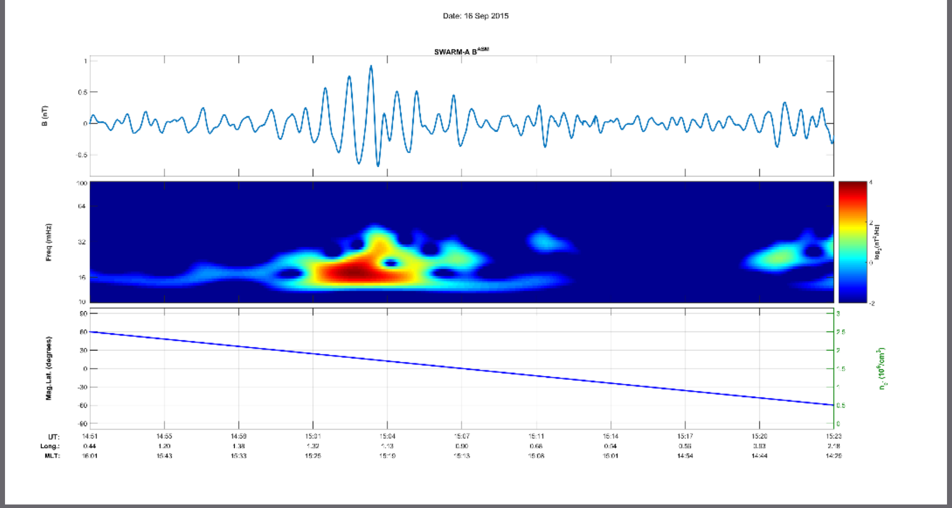
Balasis et al. (2013), "Magnetospheric ULF wave studies in the frame of Swarm mission: a time-frequency analysis tool for automated detection of pulsations in magnetic and electric field observations". *Earth Planets Space*, 65 (11), 1385–1398.

ULF Wave Detection & Classification

Background Signal

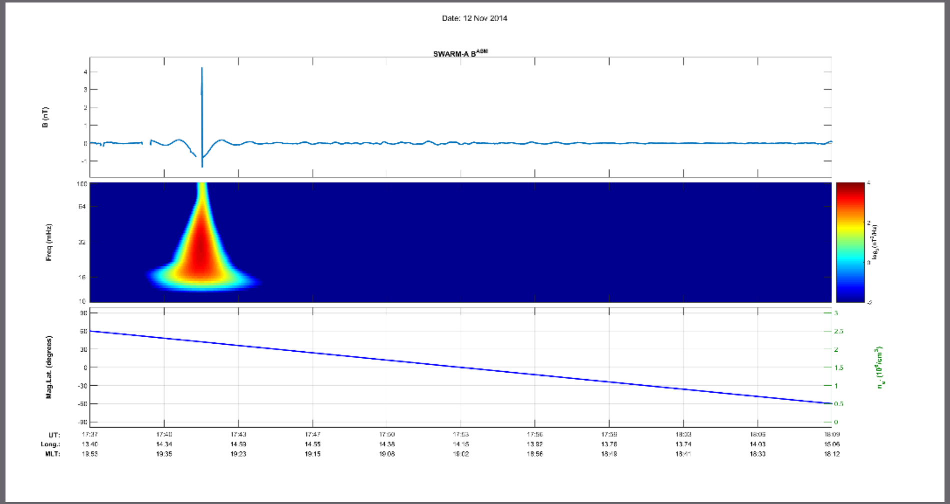


Pc3 Event

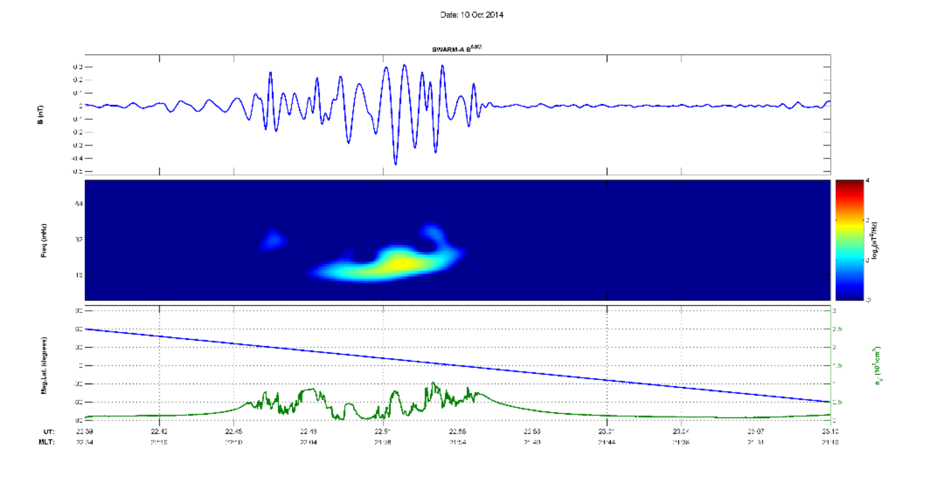


ULF Wave Detection & Classification

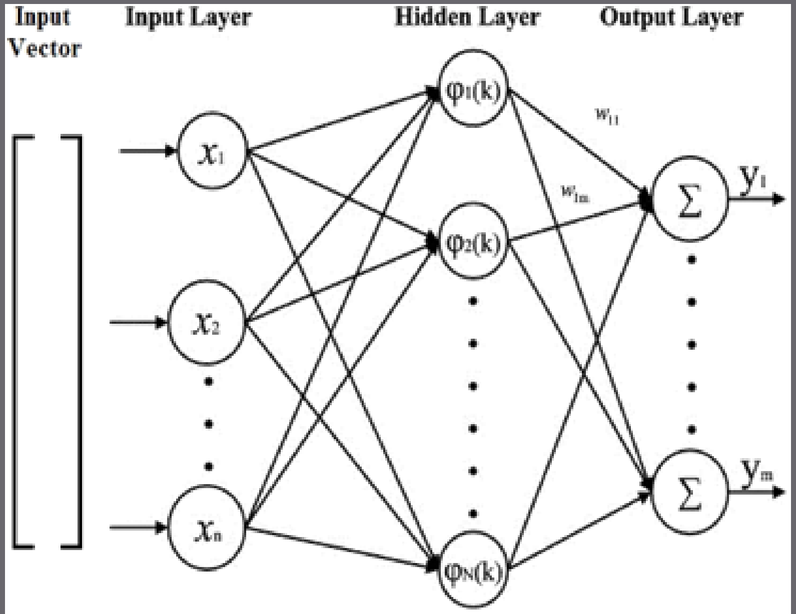
False Positive

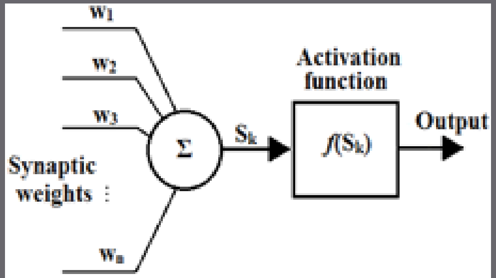


Plasma Instability



Artificial Neural Networks





- Input parameters define the input layer
- Weighted sums of them are being passed to the "neurons" of the hidden layer where a certain "activation function" resides

$$f(x_i, c) = \exp[-\beta \| x_i - c \|^2]$$

- The output of this function becomes a new input for the next hidden layer

… the process continues for all the hidden layers…

- At the final step, the outputs are weighted and summed to produce the final value(s)
- Classification tasks usually operate by assigning a series of thresholds to this value and performing the categorization accordingly

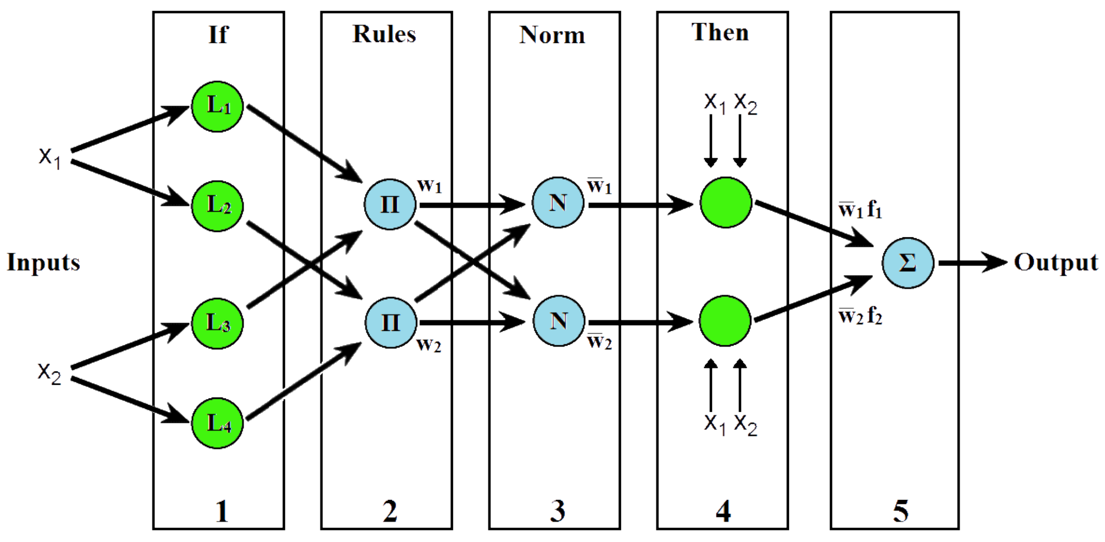
[-Inf, a_1] -> $Class_1$

(a_1, a_2] -> $Class_2$

…

(a_N, +Inf] -> $Class_{N+1}$

Adaptive Neuro-Fuzzy Inference System (ANFIS)



Shing, Jyh & Jang, Roger - ANFIS: Adaptive-Network-Based Fuzzy Inference System, IEEE Transactions On Systems, Man and Cybernetics, Vol. 23, No. 3, May/June 1993

Similar structure to general ANNs, but trying to implement "If-Then" types of rules

In the simple 1st order case:

Rule 1: If x_1 is L_1 and x_2 is L_3 Then f_1

Rule 2: If x_1 is L_2 and x_2 is L_4 Then f_2

with f1 and f2 simple linear functions

$$f_1 = p_1 x_1 + q_1 x_2 + r_1$$

$$f_2 = p_2 x_1 + q_2 x_2 + r_2$$

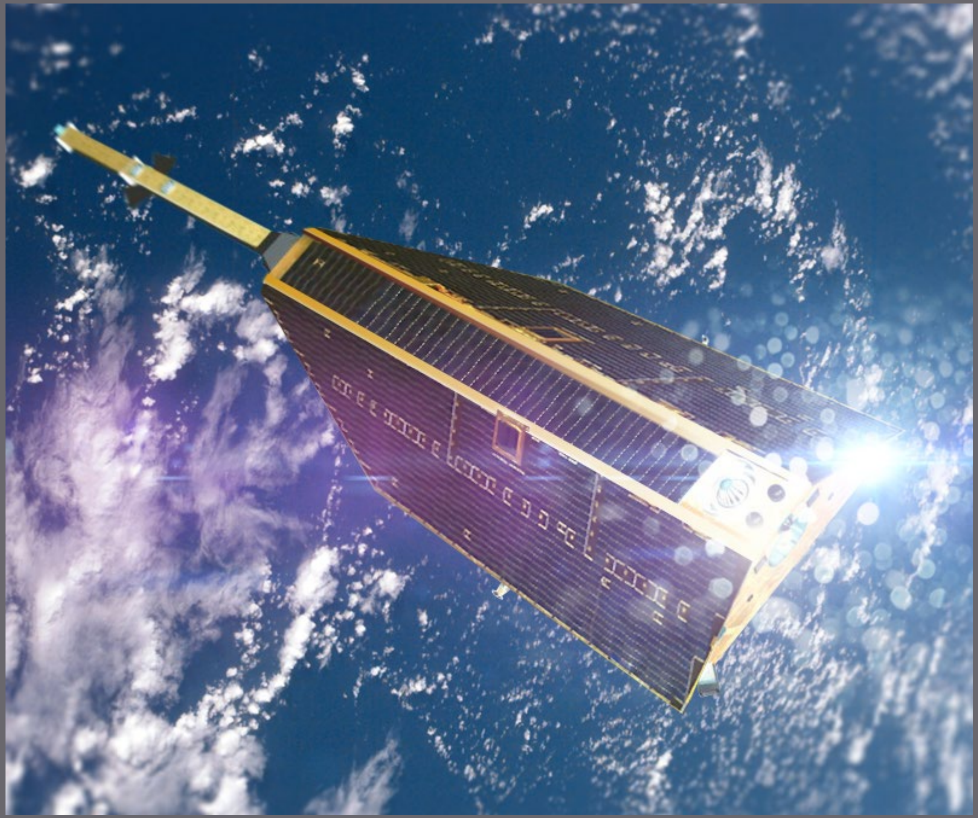
Dataset 1

- CHAMP FGM Total Magnetic Field
- High passed at 20 mHz
- Separated into tracks
- Separated into Dayside & Nightside sets
- **Manually** selected cases (most representative of each class)
- Half for training – Half for validation (random)

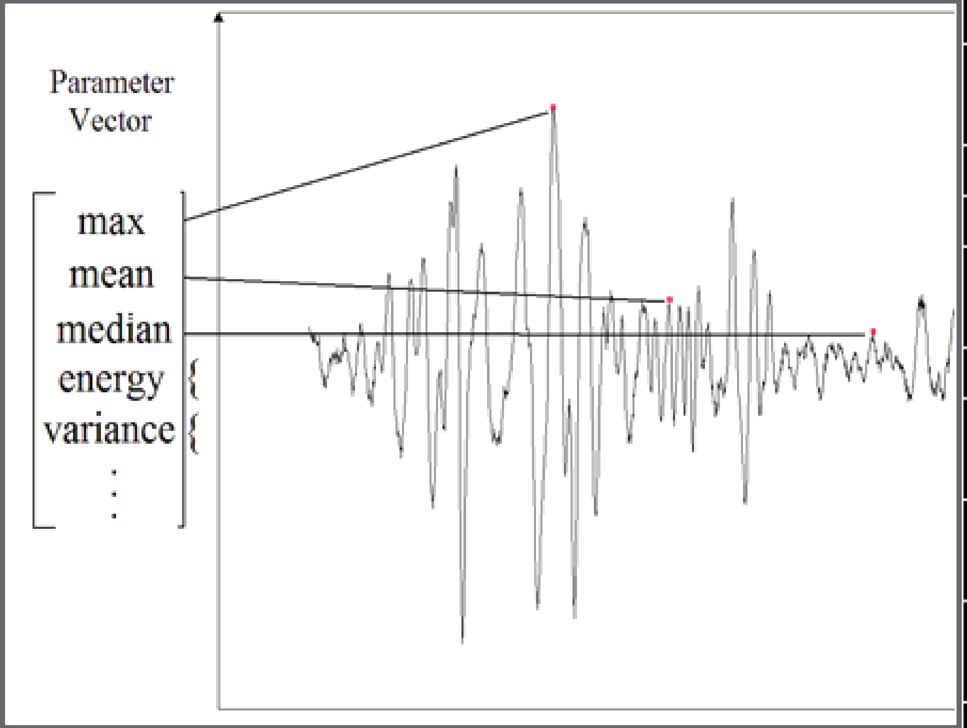
Class	No Tracks
Background	240
Pc3 Events	193
False Positives	150

- No Spectral Information!
- No Plasma Instability Class

(no ion density information was provided to the system)

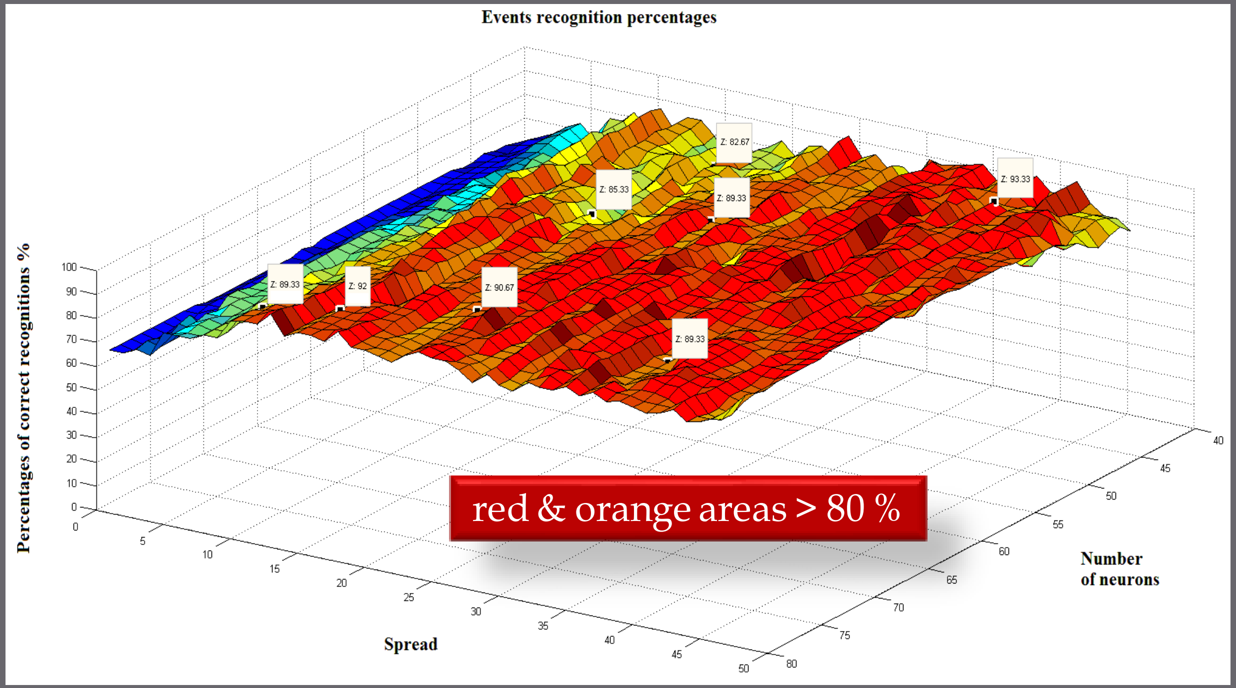


Input Parameters



#	Name	Description
1	Energy	Sum of squared values of signal
2	Roughness	Roughness of the signal measured in absolute differences of consecutive point couples slopes'
3	Variance	variance of the track
4	Max-minus-median	maximum value minus median value
5	Fraction over half-max	The fraction of the signal's values that are greater from 40% of its maximum value
6	RMS	Root mean square value of the track
7	Fractal dimension	The fractal dimension of the signal with value 1-2
8	Stdev of variances	The standard deviation of the variance values of the signal using a sliding window of 100 measurement
9	Maximum	maximum value of track
10	Zero-cross area variance	the variance of the integral from one zero-crossing of the signal to another
11	Zero-cross norm area variance	the variance of the integral from one zero-crossing of the signal to another normalized by it duration
12	Zero-cross area difference mean	the mean difference of consecutive integrals from one zero-crossing of the signal to another
13	Zero-cross area difference variance	the variance of the differences of consecutive integrals from one zero-crossing of the signal to another

First Results with RBF ANNs



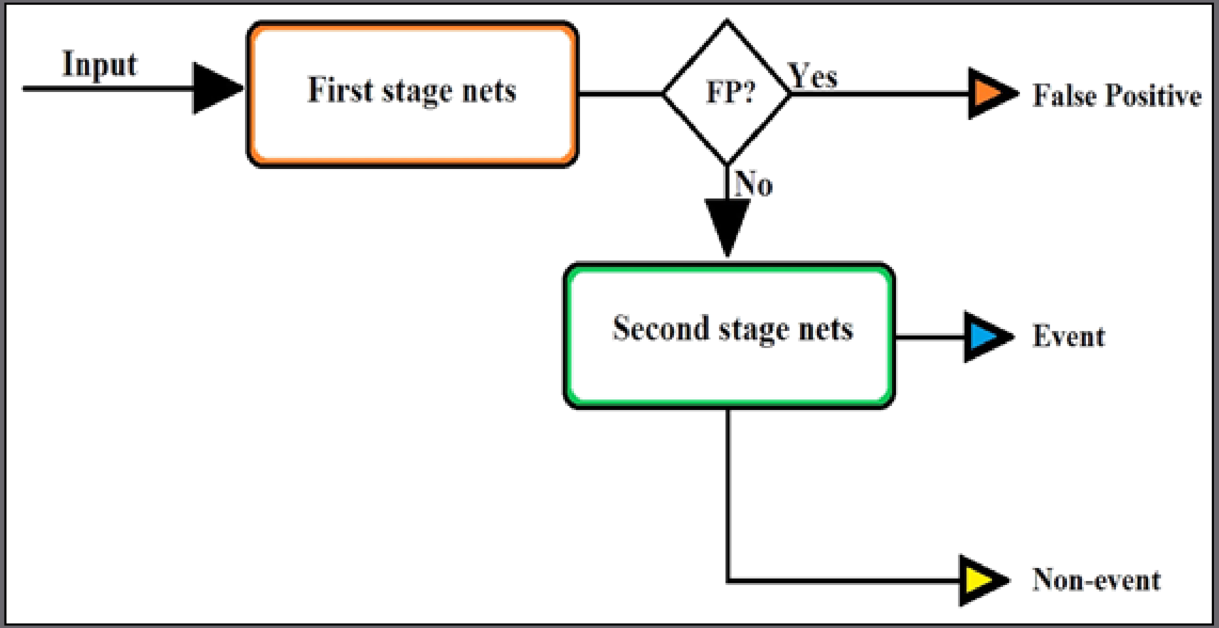
Dayside Results

- Background ~ 90%
- Pc3 Events ~ 90%
- False Positives ~ 100%

Nightside Results

- Background ~ 85%
- Pc3 Events ~ 85%
- False Positives ~ 100%

Two-Stage Network Approach



2-Stage Approach

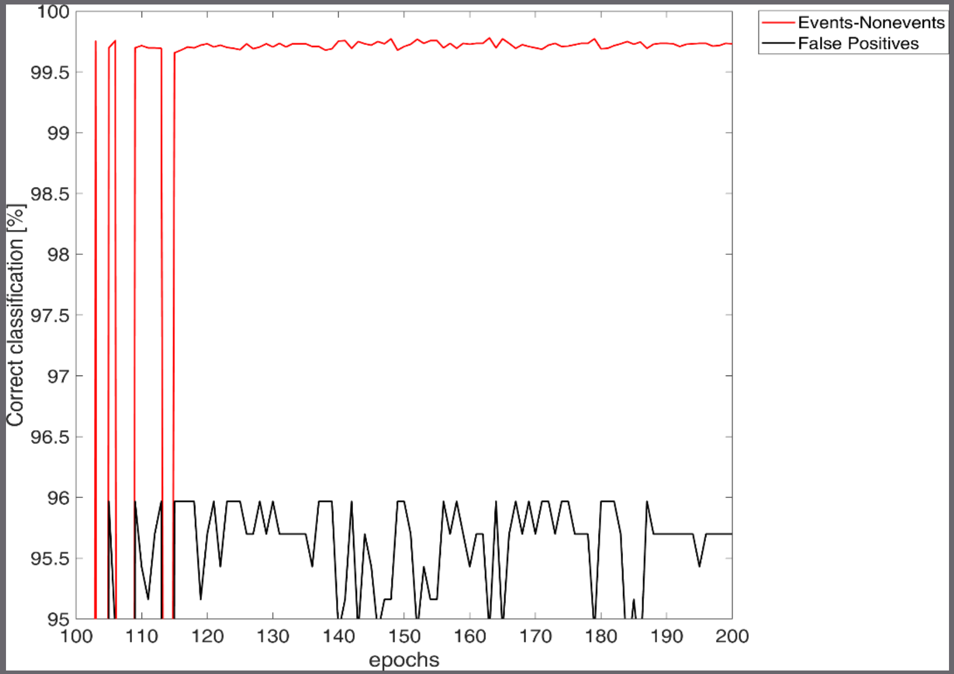
- ANFIS Networks
- Binary Classification Scheme
- Specialized ANN for each task
- Different sets of input parameters at each stage

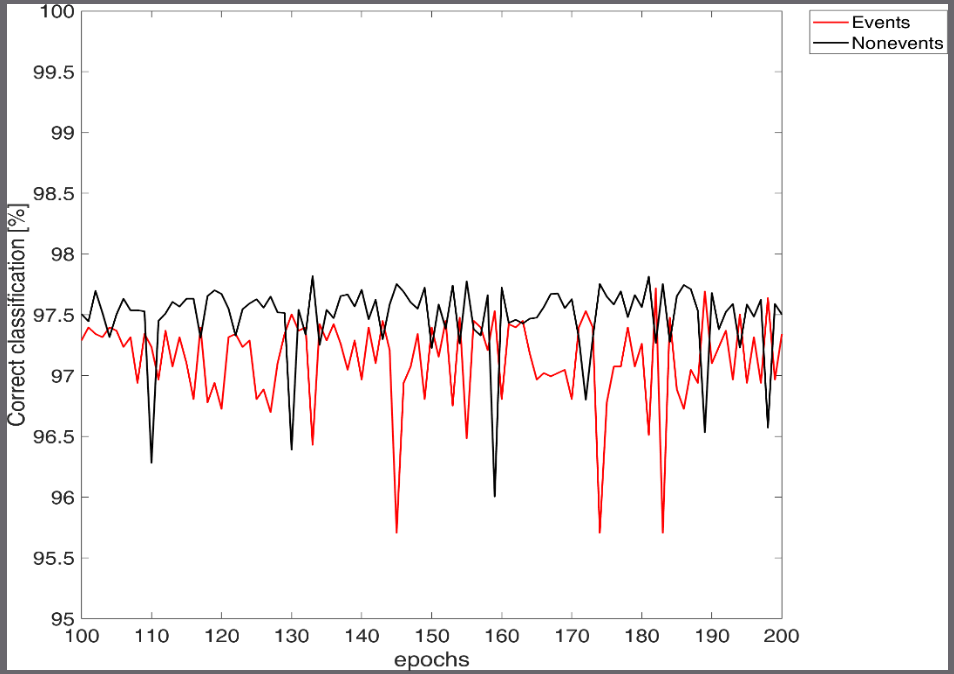
Dataset 2

Automatically Classified
CHAMP Tracks (2003-2007)

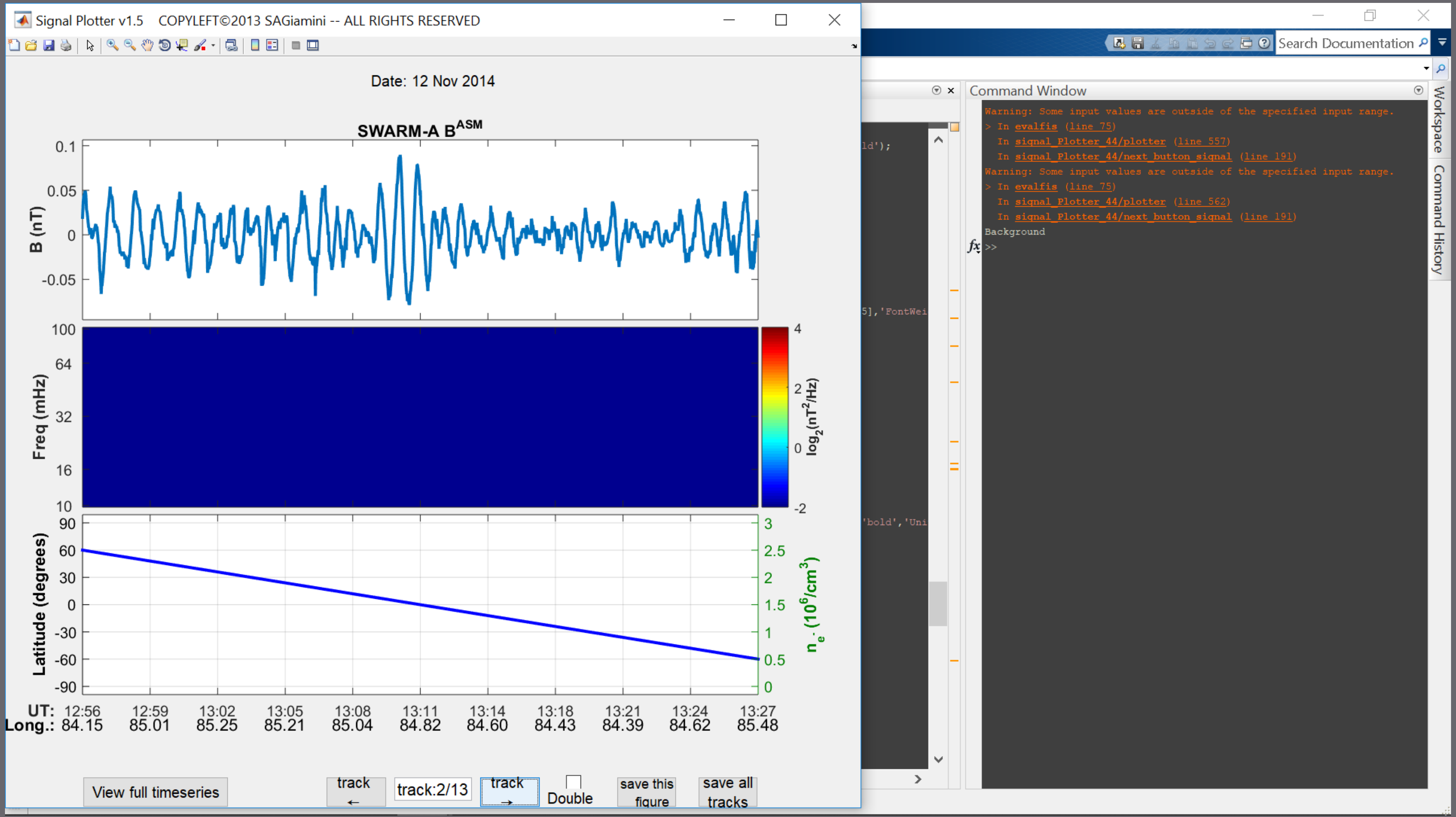
- 23,000 Background Tracks
- 3,700 Events
- 372 False Positives

1st Stage Training Set	1st Stage Test Set	2nd Stage Training Set	2nd Stage Test Set
300 False Positives 300 Events & 300 Bkgr	372 False Positive signals 3700 Events & 23000 Bkgr	300 Events 300 Background	3700 Events 23000 Background

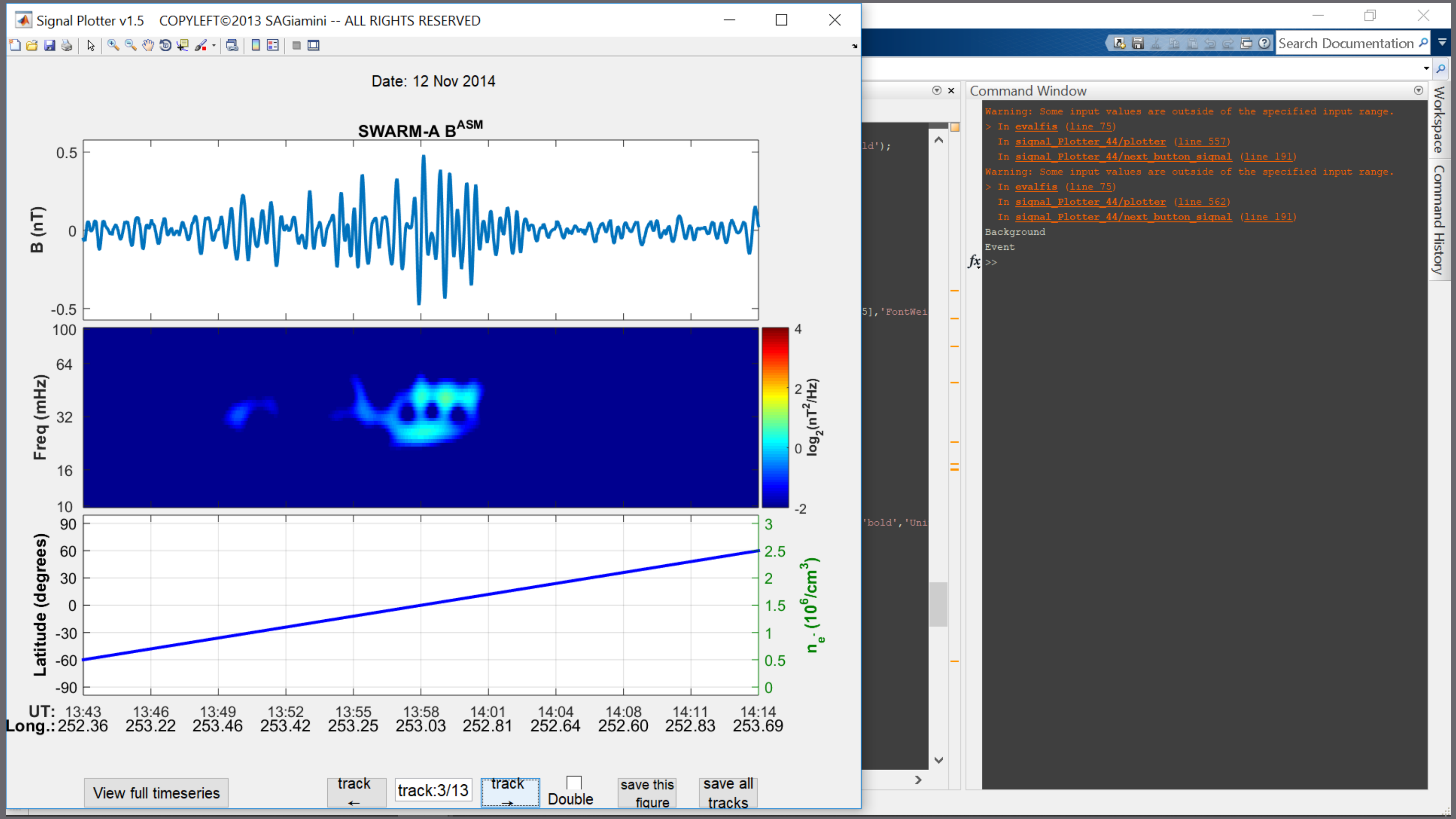




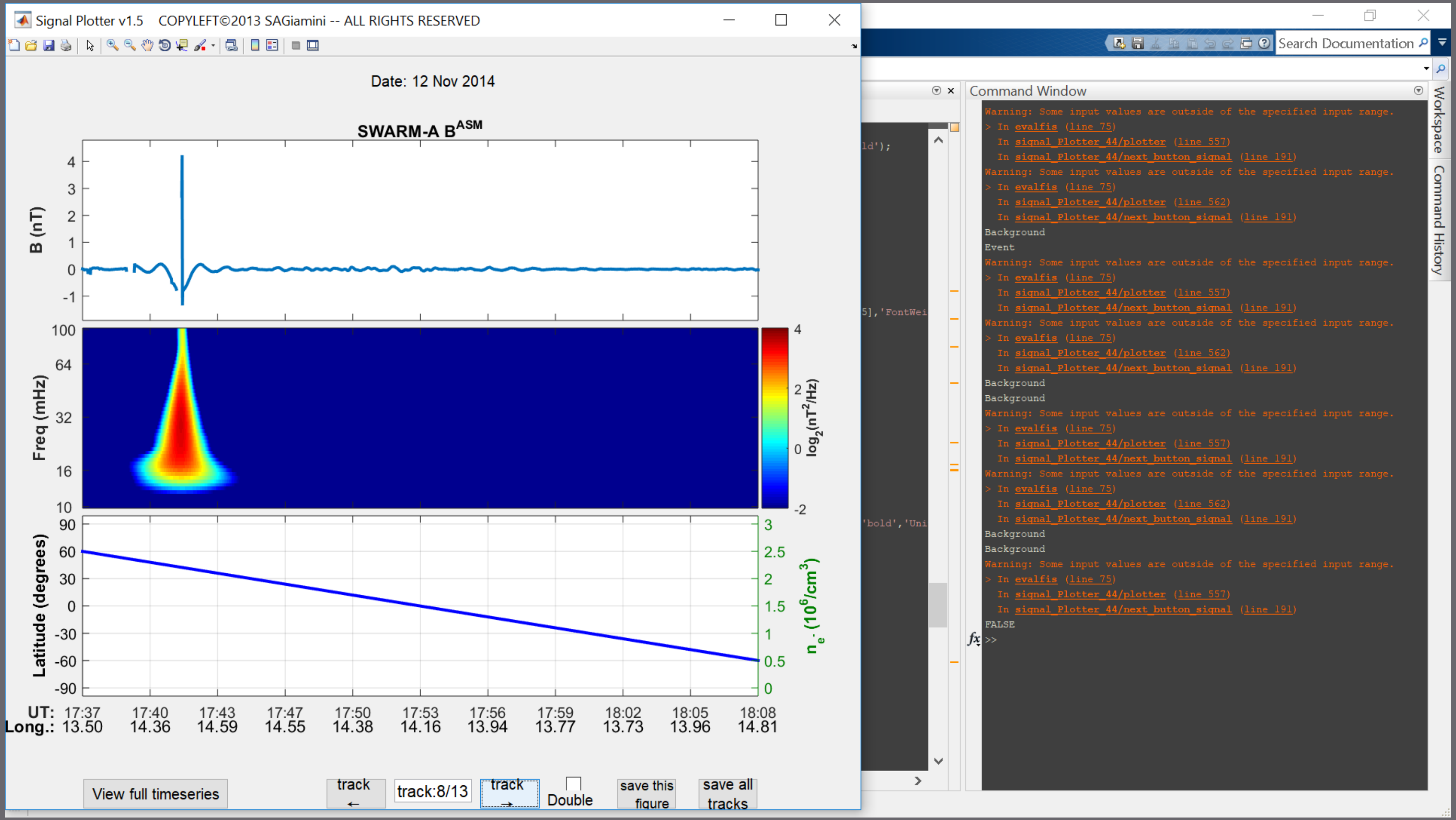
Swarm Test Case Demo



Swarm Test Case Demo



Swarm Test Case Demo



Key Reference

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System Science: Application to Space Weather Analysis, Modelling, and Forecasting

RESEARCH ARTICLE **OPEN ACCESS**

A machine learning approach for automated ULF wave recognition

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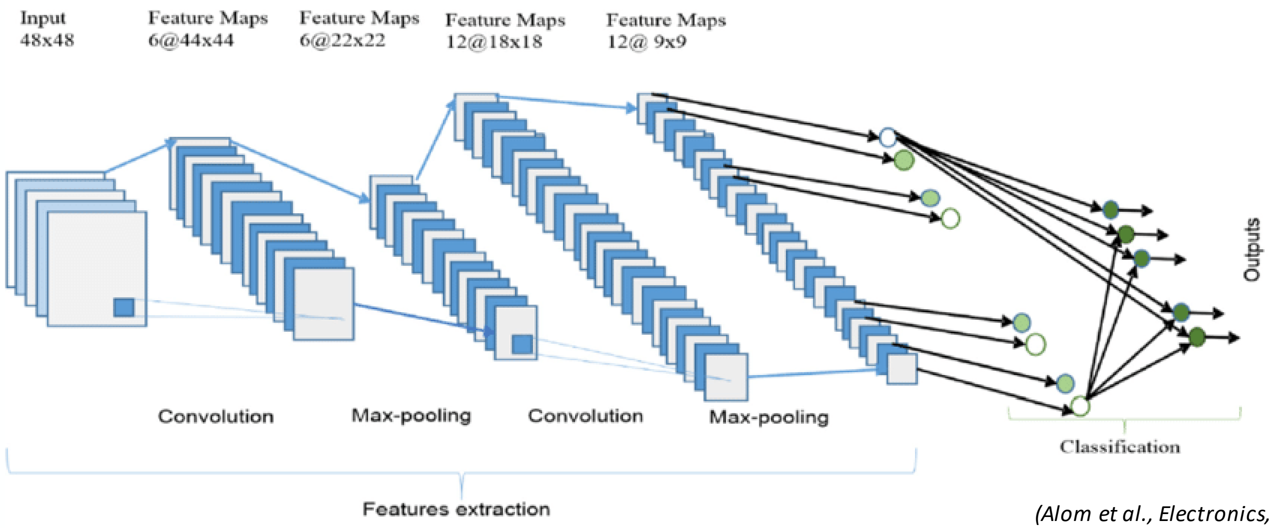
Abstract – Machine learning techniques have been successfully introduced in the fields of Space Physics and Space Weather, yielding highly promising results in modeling and predicting many disparate aspects of the geospace environment. Magnetospheric ultra-low frequency (ULF) waves can have a strong impact on the dynamics of charged particles in the radiation belts, which can affect satellite operation. Here, we employ a method based on Fuzzy Artificial Neural Networks in order to detect ULF waves in the time series of the magnetic field measurements on board the low-Earth orbit CHAMP satellite. The outputs of the method are validated against a previously established, wavelet-based, spectral analysis tool, that was designed to perform the same task, and show encouragingly high scores in the detection and correct classification of these signals.

Keywords: machine learning / ULF waves / LEO satellites

ConvNets



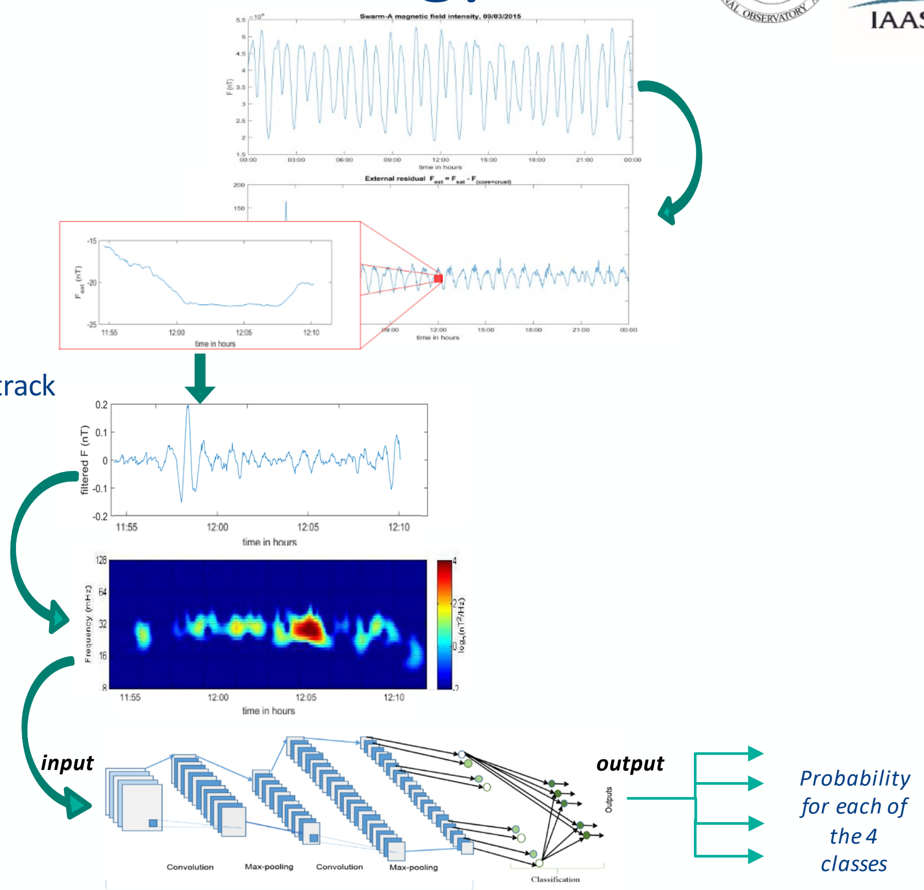
(Alom et al., Electronics, 2019)

The overall architecture of the Convolutional Neural Network (ConvNet) includes an input layer, multiple alternating convolution and max-pooling layers, one fully-connected layer and one classification layer.

[Antonopoulou et al. (in preparation)]

Proposed Methodology

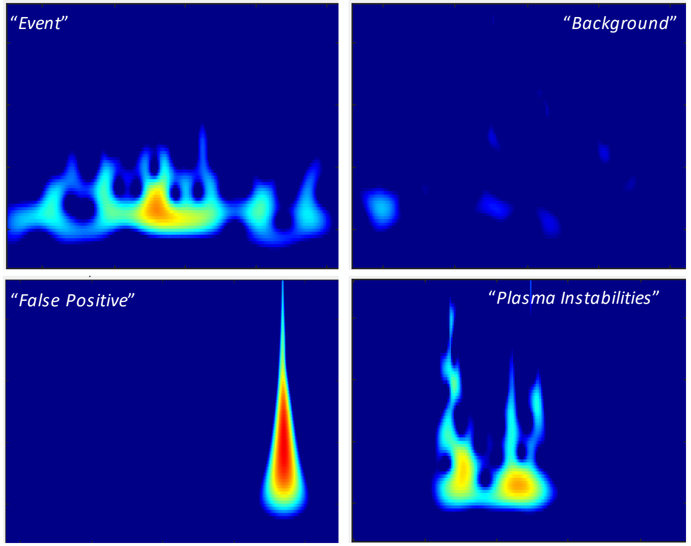
1. Swarm time series
2. Subtract the CHAOS-6 model
   (internal part, i.e., *core+lithosphere*)
3. Smaller windows in time:
   - cut each time series per satellite track
   - keep only mid-latitudes (±45°)
4. High pass (HP) Butterworth filter
   - cut-off = 22 mHz
5. Wavelet transform
6. ConvNet



The 4 classes

- The classification problem: existence or non-existence of ULF wave events in the Pc3 frequency range.

- *We solve a 4-class classification problem, i.e.,*
  - ***1st class ("Events"):*** existence of Pc3 (22 - 100 mHz) ULF wave events
  - ***2nd class ("Background"):*** background noise without significant wave activity (*non-ULF signals*)
  - ***3rd class ("False Positives"):*** artificial signals due to spikes, discontinuities, etc. (*non-ULF signals*)
  - ***4th class ("Plasma Instabilities"):*** attributed primarily to *Equatorial Spread-F events (ESF, "plasma bubbles",* for details see Stolle et al, JGR 2006), which are post-sunset, equatorial-confined ionospheric anomalies (*non-ULF signals*)

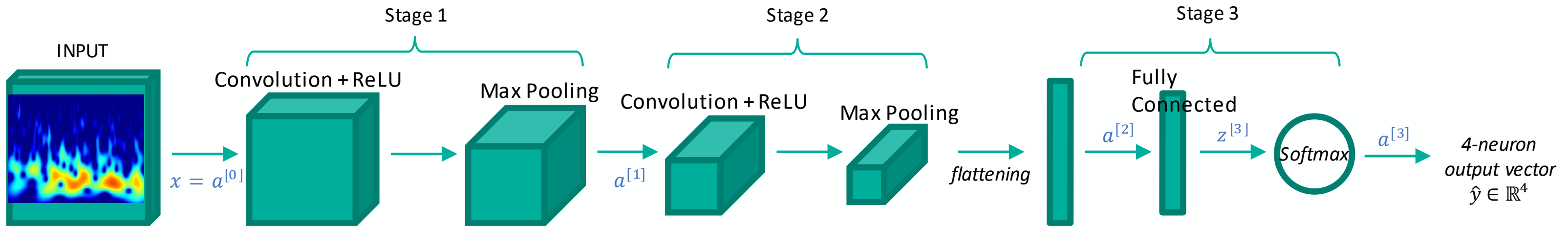


Training of the Network

IAASARS

- *Data used: **total magnitude**, extracted from **Swarm-C** Vector Field Magnetometer **(VFM)** measurements, NEC frame, 1s sampling rate (low resolution **(MAGX_LR_1B Product)**), taken from February, March & April of the year 2015.*
  - **Number of total samples:** 1500 samples, *manually annotated* in 4 classes
  - **Input:** pairs of wavelet power spectrum images & their annotation (class label)
  - **Training / Test set split:** 80% / 20% of total samples
  - **Layers:** 2 alternating convolution & max-pooling layers, 1 fully-connected (FC)
  - **Parameter initializer:** Xavier Initialization
  - **Activation functions:** ReLU, Softmax
  - **Cost function:** Cross-entropy (Log Loss)
  - **Optimizer:** Adam Optimization (*training for 100 epochs*)
  - **Extra:** Batch Normalization, Dropout Regularization

Layers	**Details**
Conv1	8 filters, $f = 4$, $s = 1$
Pool1	$f = 8$, $s = 4$
Conv2	16 filters, $f = 2$, $s = 1$
Pool2	$f = 4$, $s = 4$
FC	*Prediction, 4-neuron output*



Results

- **ConvNet performance: Confusion matrices, Accuracy on each class, Overall accuracy of the model.**

Training set: 80% of total 1501 samples = 1200 samples

	Predicted class					
Actual class	*samples per class*	Background	Events	Plasma Instabilities	False Positives	Accuracy (%)
	Background *331*	312	17	2	0	94.3
	Events *577*	15	555	6	1	96.2
	Plasma Instabilities *263*	0	19	242	2	92.0
	False Positives *29*	1	1	2	25	86.2

Test set: 20% of total 1501 samples = 301 samples

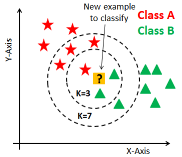
	Predicted class					
Actual class	*samples per class*	Background	Events	Plasma Instabilities	False Positives	Accuracy (%)
	Background *91*	87	3	1	0	95.6
	Events *137*	9	126	2	0	92.0
	Plasma Instabilities *66*	1	10	53	2	80.3
	False Positives *7*	0	0	3	4	57.1

- **Overall accuracy on the training set:** (312+555+242+25)*100 /1200 = **94.7%**
- **Overall accuracy on the test set:** (87+126+53+4)*100 /301 = **89.4%**

Results

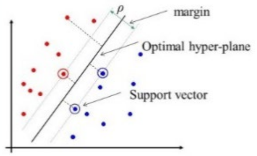
- ***Comparing with other ML classifiers:***
  - ***k-Nearest Neighbors (kNN)***

    → *overall accuracy = **57.5%***
    (for *k* = 5)

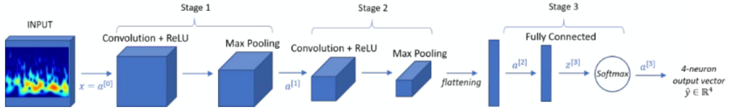


  - ***Support Vector Machines (SVM)***

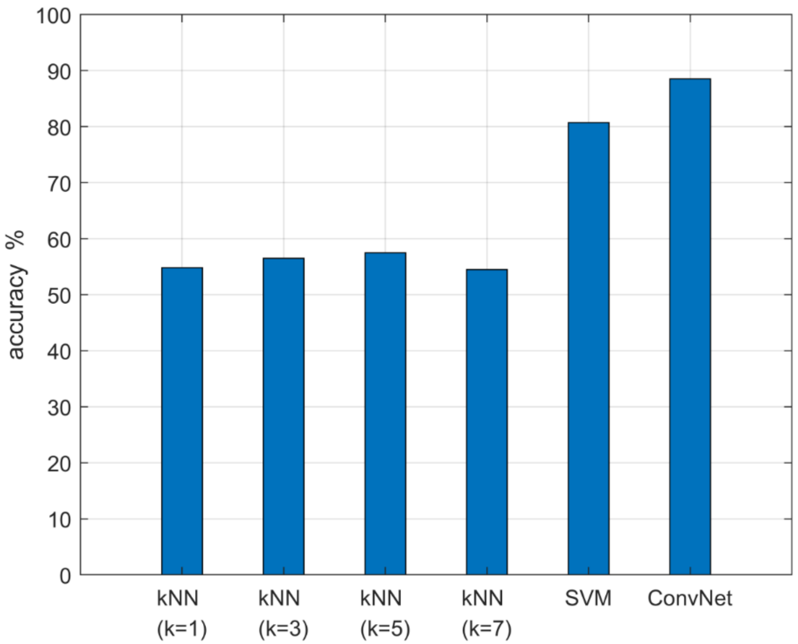
    → *overall accuracy = **80.7%***



  - ***ConvNet***



    → *overall accuracy = **89.4%***



Conclusions & Future Work

Conclusions

- ✓ *Our ConvNet model classifies the wavelet power spectrum images in the 4 classes with **89.4% accuracy** on the test set.*
- ✓ *Comparing with the famous kNN classifier & the very competitive SVM classifier, the ConvNet gives the best results, achieving the highest accuracy.*
- ✓ *The new methodology could be easily applied to investigate:*
  - ➢ *other frequency ranges of ULF waves than Pc3 events (Pc1/EMIC, Pc2, Pc4 and Pc5)*
  - ➢ *observations from other satellite missions*
  - ➢ *ground-based observations*

Future work

1. Re-training with much more data, crucial for our methodology to be better-established.
2. Use cross-validation
   - to decrease the statistical fluctuation in the final error estimations,
   - to better tune the hyper-parameters of the model
3. Introduce useful information during preprocessing (e.g. include Swarm electron density data, separate into nightside/dayside tracks) in order to improve the 4-class manual annotation of the spectral images (especially with respect to the "PI" class).