Natural Language AI:
Forecasting Ionosphere
by Historical Analogy

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International Workshop on Machine Learning for Space Weather:

ICTP

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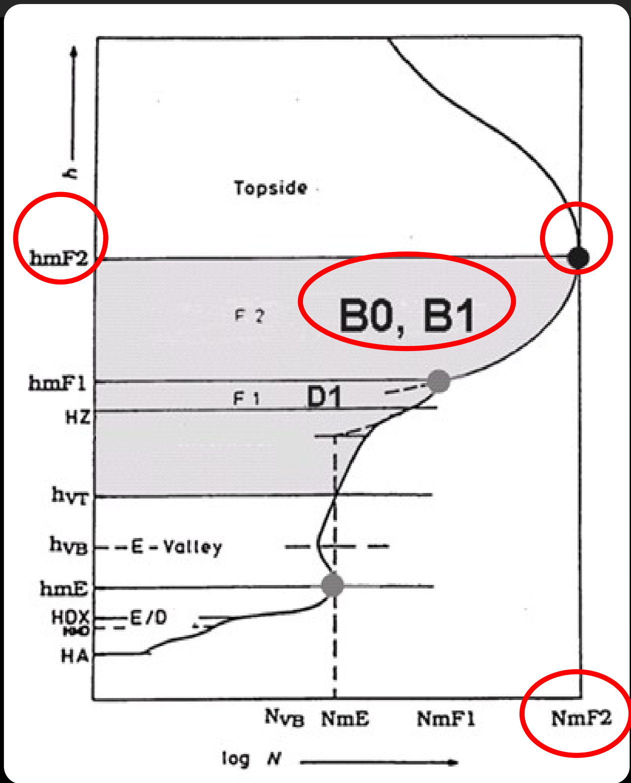
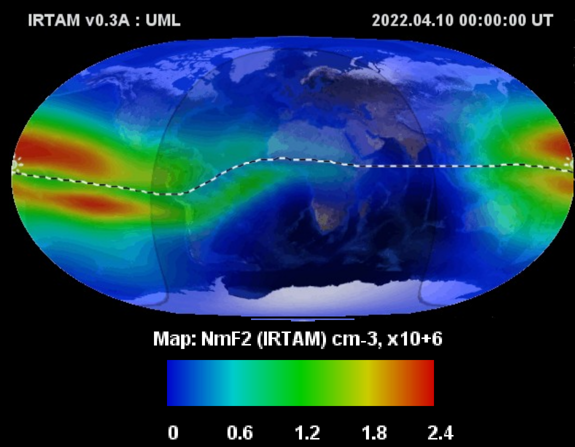
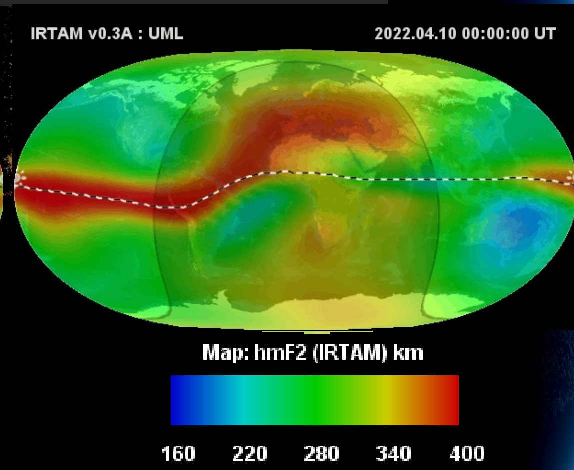
Ionosphere: Galloping introduction

3D volume of plasma and 2D maps of its properties



1D vertical profile of plasma density





N_mF2 h_mF2

One day of ionospheric dynamics

"Ionosphere is a major operational nuisance" © USAF

Layout

- Natural Language AI: Forecasting Ionosphere by Historical Analogy

Deep Learning:
Panacea?
or a Snake Oil…

GNSS PPP / RTK

- **Affected systems: autonomous vehicles and machinery**
- **TID as a *Silent Accuracy Kill***

- **Worse than the loss of lock and**

HF Geo

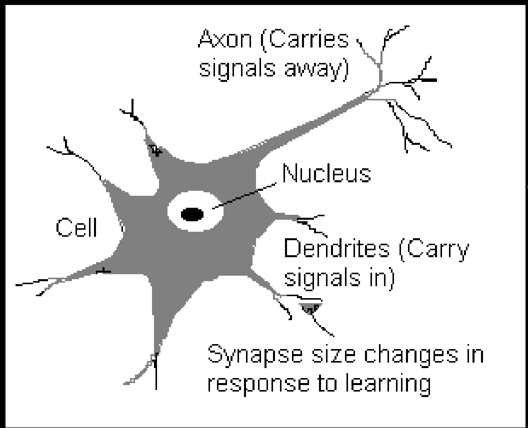
- **Geolocation of uncooperative HF transmitter**
- **Tens of km positioning errors**
- **Short-range catastrophe during TID passage**

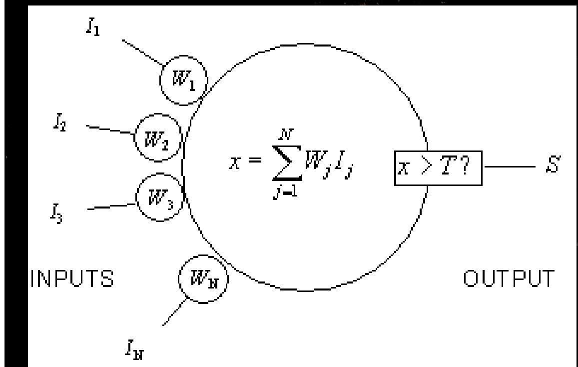
[NRL, 2013]

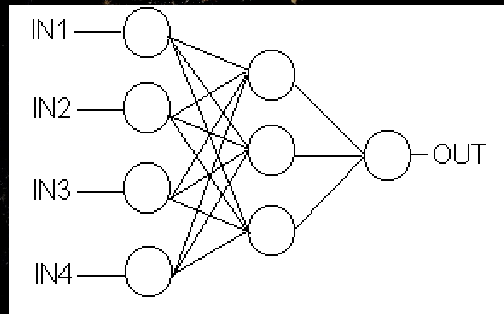
Also, HF comms for civil aviation, spacewalk planning on ISS, etc.

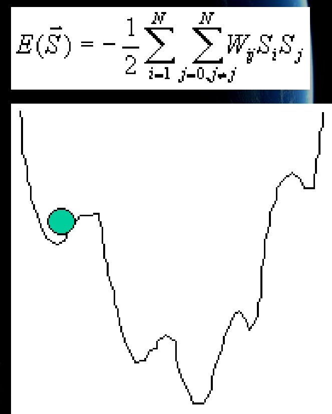
- Pessimist: "when you saw an ionospheric storm, you have seen one storm"
  - a.k.a. "No storms are alike"
- Realist:
  - Yes, the prior ionospheric state does not inform the future state
    - (No inertia… quick reply to drivers)
    - Need the Sun-Earth activity context
  - But individual weather processes admit their

Neural Doctrine: Galloping Introduction





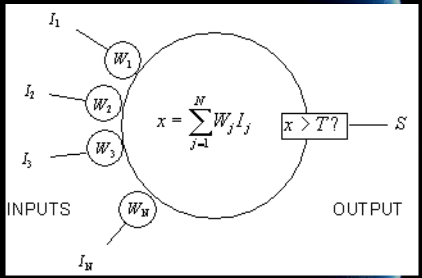


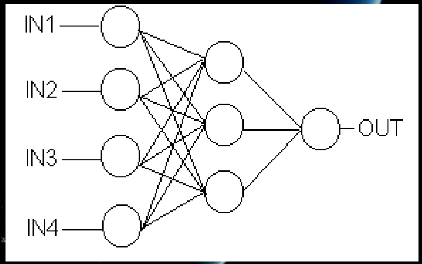


The roaring 1990s: an outburst of algorithmic NNs to replicate human intelligence

Historical Average © Feed-forward NN

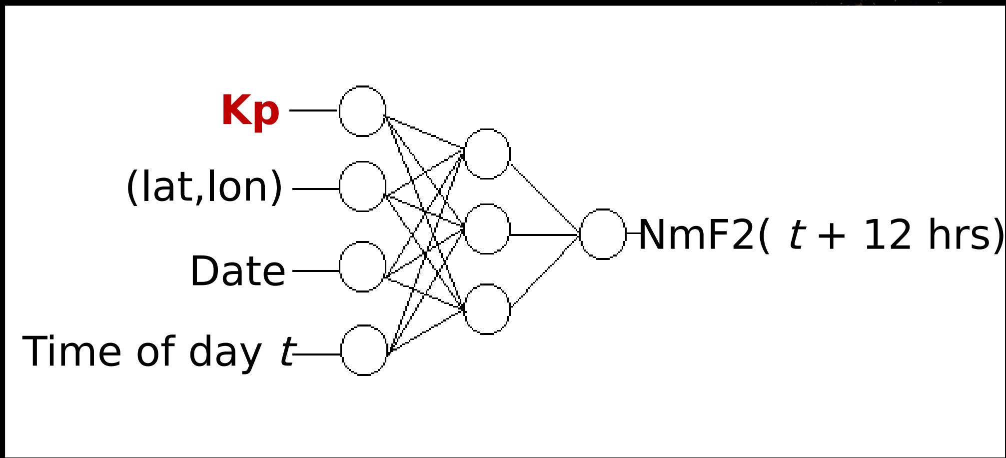
- Training phase
  - present NN with known examples (input and output) for training
    - determining the W_{ij} weights – back-propagation method
- Execution phase
  - WHAT-IF: present trained NN with previously unknown inputs to obtain a predicted output
  - Superior inductive bias of NNs: the capability of gleaning the nature of the system in order to do good WHAT-IFs.
  - Superior but little understood
    - Black-Box: No clue how and why it works well
    - Caused a severe AI Winter in the 2000s
      - NSF would not fund NN projects
      - Physics journals would not publish NN model results
- All feed-forward NN architectures are in "historical analogies" category
  - Subject to *AI Winter*



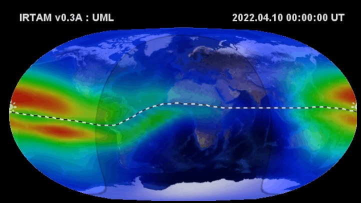


Feed-forward NN for forecasting ionosphere

FORECASTING NN MODEL FOR 12 HOURS AHEAD



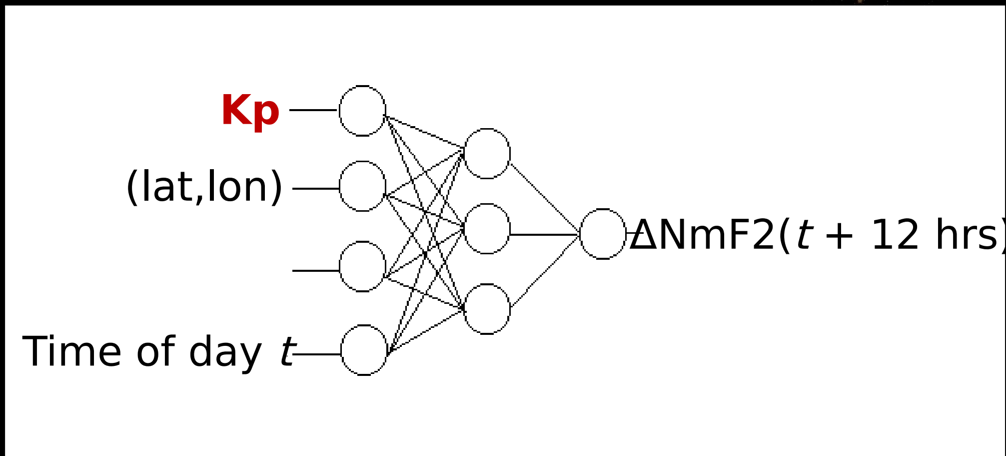
Space Physics community: no-no, this is a SNAKE OIL



- Train a NN to predict peak density in the ionosphere N_mF2 12 hours ahead, as a function of:
  - Time of day
  - Date (year, day of year)
  - Location (lat, lon)
  - Geomag index Kp
- WHAT-IF: run for different Kp values, dates, times, and locations

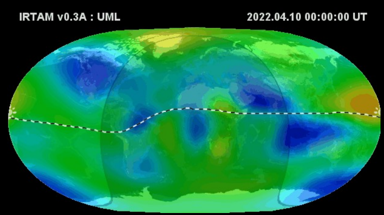
Feed-forward NN for forecasting ionosphere

FORECASTING NN MODEL FOR 12 HOURS AHEAD



- Train a NN to predict *deviation* of N_mF2 from the expected quiet-time behavior 12 hours ahead, as a function of:
  - Time of day
  - Location (lat, lon)
  - Geomag index Kp
- Run it for different Kp values and locations (what-if)
  - Obtain 2D map of ΔNmF2
  - Apply Δ to quiet-time predicted 2D map of NmF2

Space Physics community: still not good



"Storm" option of NmF2 in IRI

FORECASTING MODEL FOR UP TO 24 HOURS AHEAD

$$\{\mathbf{Ap}\} \longrightarrow \Delta\mathrm{NmF2}(\mathrm{lat},\mathrm{lon},t_{fore})$$

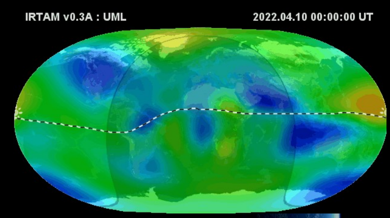
$$t_{fore} = (t,\ t + 24\ \mathrm{hrs})$$

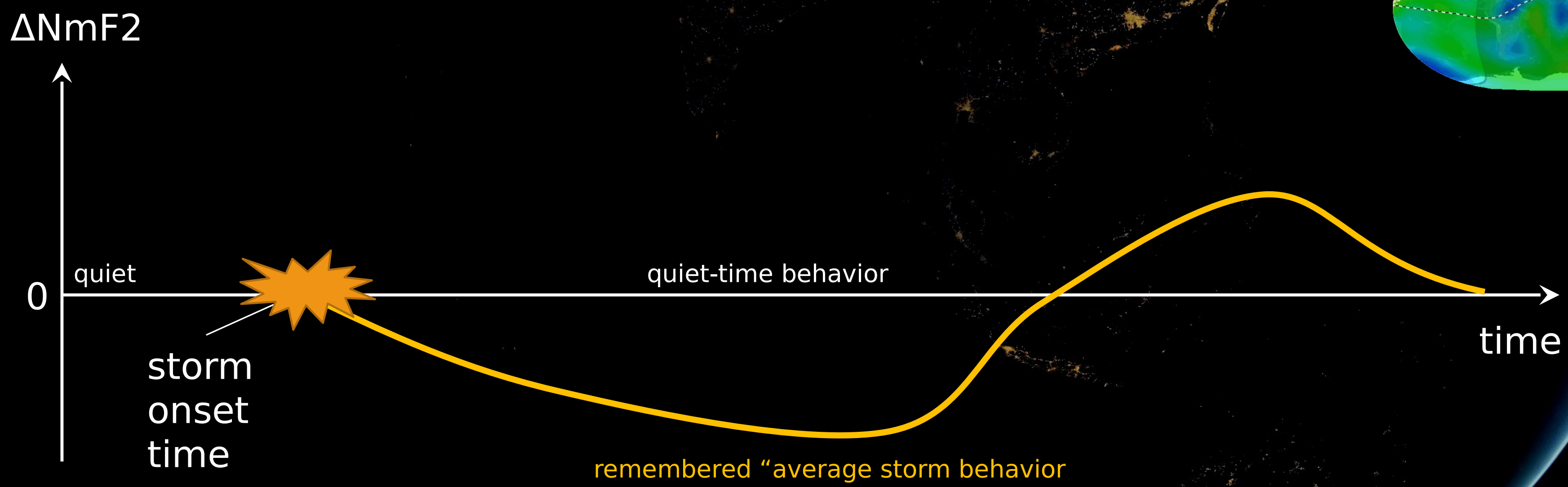
Research funding agencies:
but this is an empirical model… oh well

- "Storm" option for NmF2 forecast in IRI, [Fuller-Rawell et al, 1999]
  - Ap is tested for a threshold value to determine if the day is **quiet** or **disturbed**
  - This is an "average" **storm behavior** of ionosphere on disturbed days
  - The storm behavior is stored as ΔNmF2 for any location and forecast time up to 24 hours ahead
- Other "storm" options are pursued based on this principle
  - Blanch and Altadill [2012]

International Workshop on Machine Learning for Space Weather:

Concept of the “Triggered” storm option



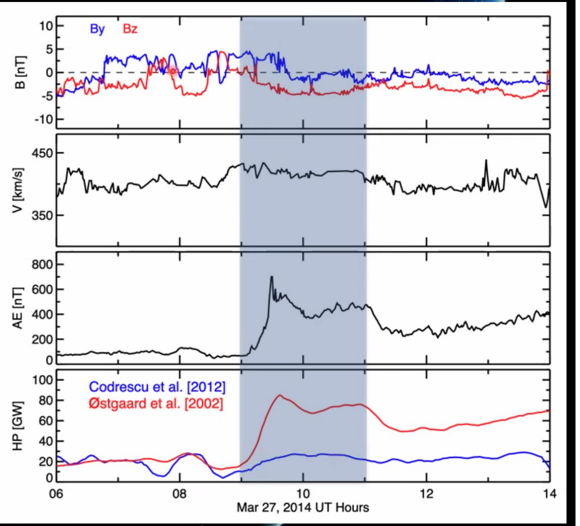


Forecast by analogy to an average “anomaly” timeline

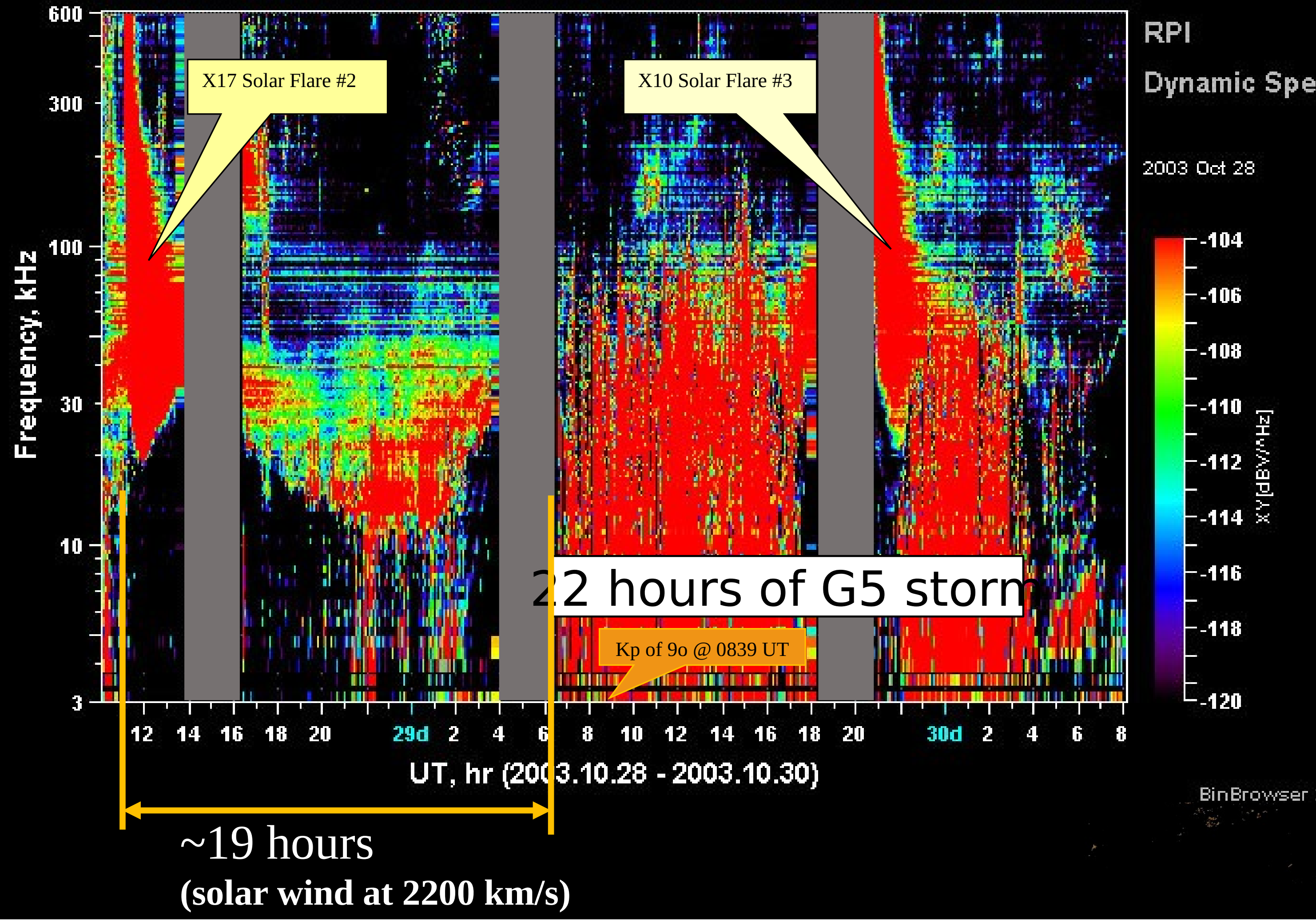
Next step: Library of the storm storylines

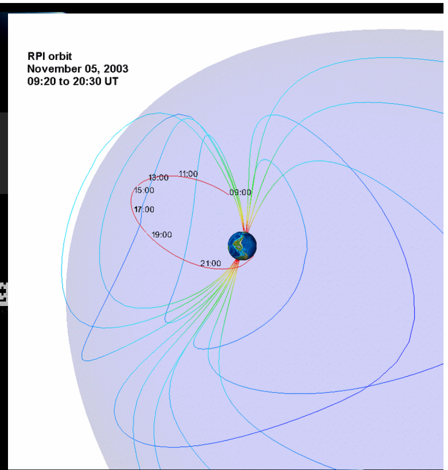
instead of the “average storm timeline”

- Instead of an “average” storm, keep a library of previous storm storylines of ΔNmF2
  - To forecast, just find the most relevant storm in the library
- Each storyline must be remembered in the context of the activity in the Sun-Earth environment
  - i.e., not just replay a storm line using one “trigger”
  - Need to build a grand storyline of driving events in the heliospace and geospace
  - Assumption: if we know all driver stories well, the ionosphere can be explained
    - This is a strong assumption
- Need good ideas for
  - The storm library
  - Search-and-retrieval algorithms
  - *Tweaking the library copy to current conditions*



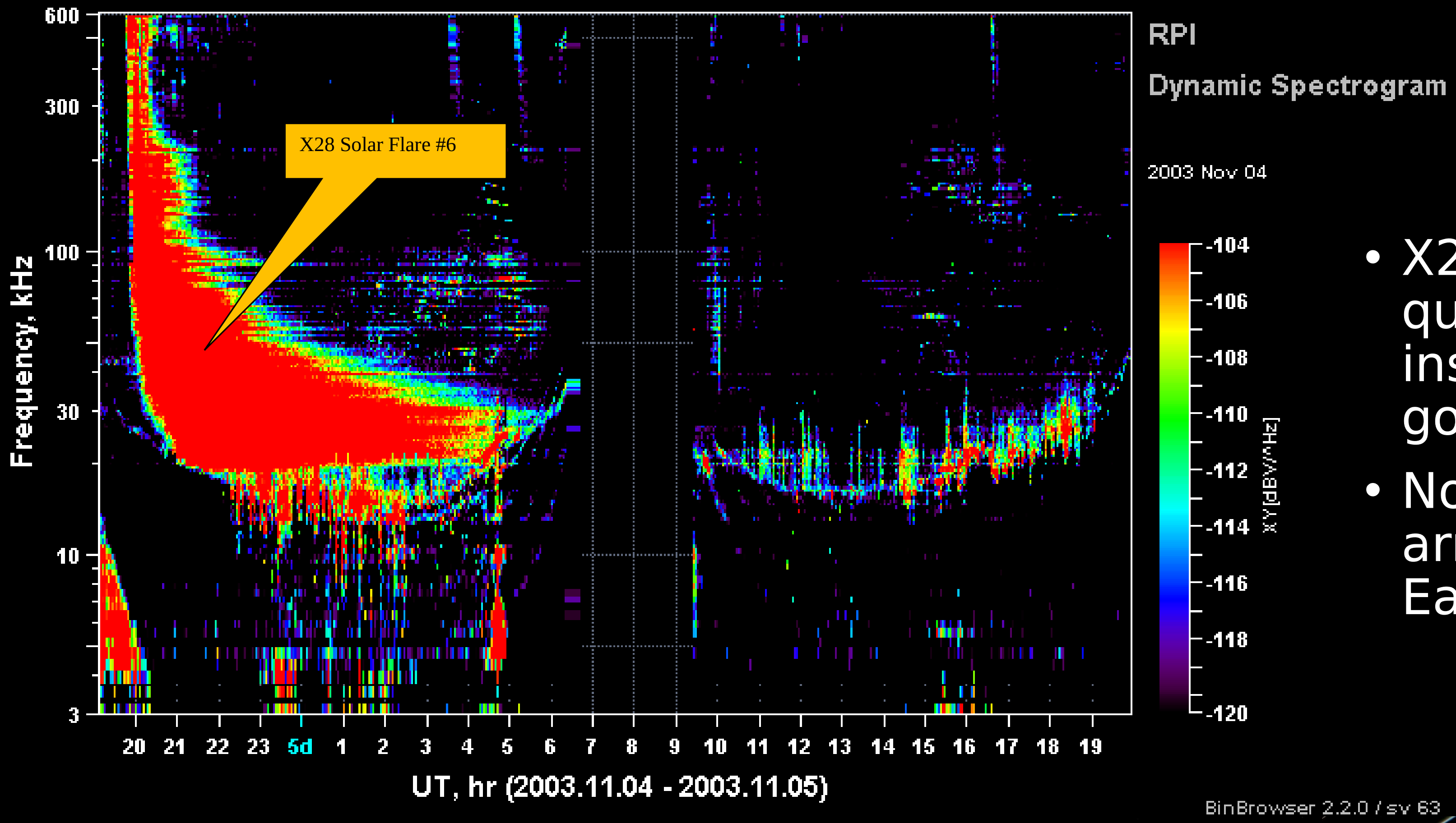
Example: Halloween storm as seen by RPI





- Solar wind velocity can vary
- Timelines will vary as well
- But… natural language AI will come to the rescue!
    - varying speed of words

Unrelated example: mega-flare 6 days later

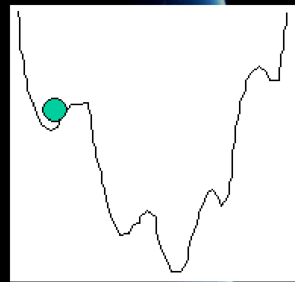


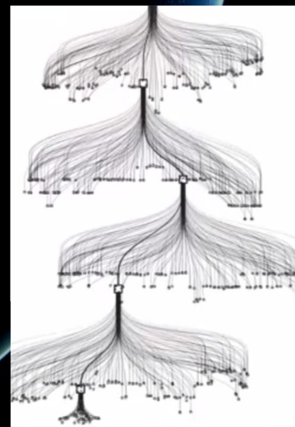
- X28 ranking is questioned: instruments got blinded!!
- Nothing arrived to the Earth, though

International Workshop on Machine Learning for Space Weather:

Alexa, play Yesterday by The Beatles

- "Yesterday" is interpreted in the context of "play"
  - Not a reference to one day earlier
  - A title to be fetched from the database of song titles
- DEEP LEARNING: multi-layered recurrent (feed-back) network topologies
  - Support interpretation of subelements in the context of other cues
    - Starting position of NN (the green ball) is determined from the context
    - Network evolves into the closest stable condition (remembered state)
    - That state propagates to the next layer of the network
  - Appears matching to the idea of interpreting ionospheric dynamics in the context of the external forces acting on it
    - Context: reports of ongoing Sun-Earth activity
    - Output: ionospheric dynamics fetched from the historical record database
    - What is different? Deep Learning the interplay of helio- and geo-activity markers





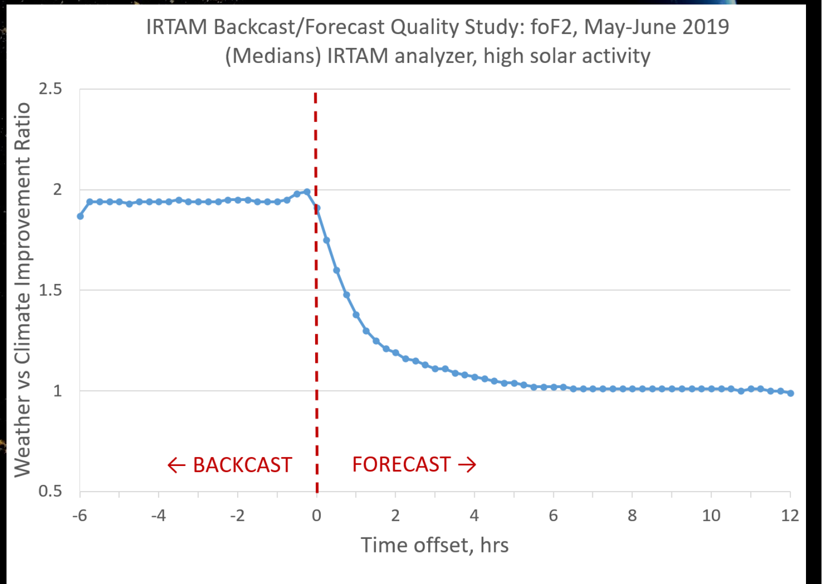
Natural Language AI for space weather?

- Detect “Alexa!”
  - Recognition of the storm onset
    - Solar flare?.. signature of CME?.. Solar wind pressure?.. lots of ideas!
    - Maybe all of the markers must be used to determine reference time
- Then, somehow, interpret the available “Play Yesterday by The Beatles”
  - Extract **context cues** to retrieve the best-matching storyline in the Storm Library
  - Context of the sentence == Context of the relevant system driver storylines
  - Combination of context cues and their relative strength = Deep Learning
- Retrieve and *process* the closest storm storyline from the library
  - Process? Encoding is needed to avoid varying timing of the processes
    - [to support varying speed of word pronunciation]
- Apply the processed storyline to forecast the upcoming departure of the stormy weather from the quiet-time model
- REPEAT

International Workshop on Machine Learning for Space Weather:

Capturing Context of Ionospheric Dynamics

- Ionosphere: immediate response to external forcing
  - Thus its current conditions do not inform future states
- Need to use storylines of all external drivers as context
  - Cannot be just one instant “triggering” driver (e.g., Kp=6)
  - Driver dynamics is matched (paired) to the ionospheric storm dynamics
    - Across the complete forecast storyline from onset to end
  - Important: which driver is relevant out of the set? (Deep Learning helps; *inductive bias*)

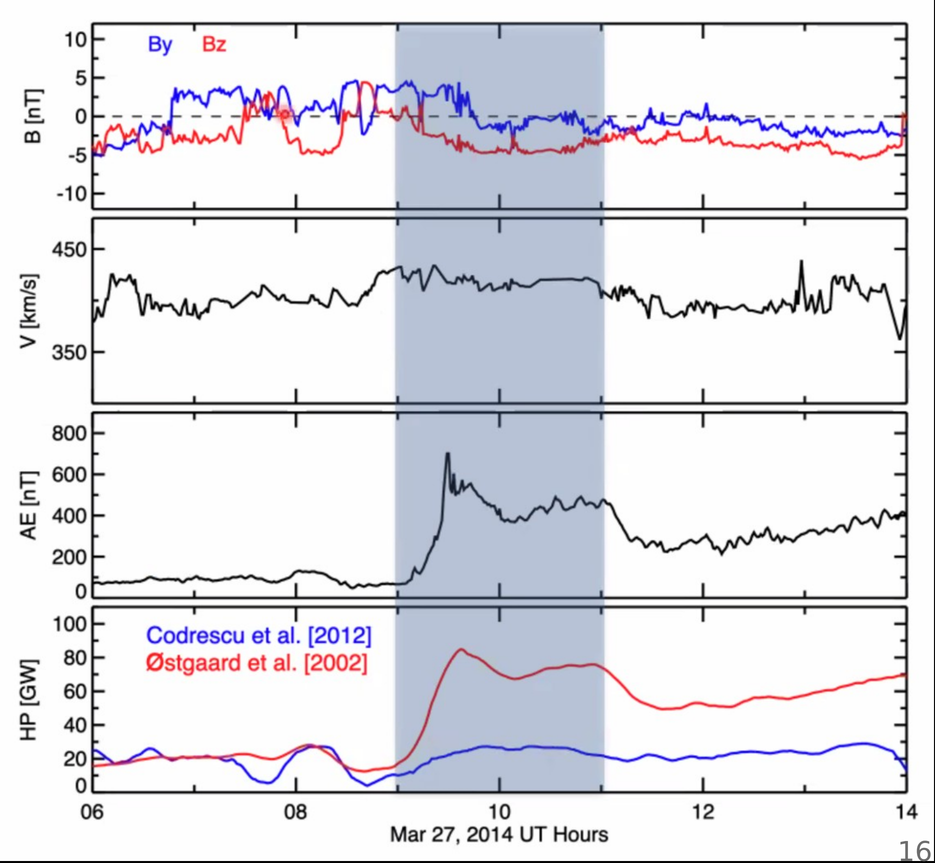


Sensor data @ 2 hour latency are useless

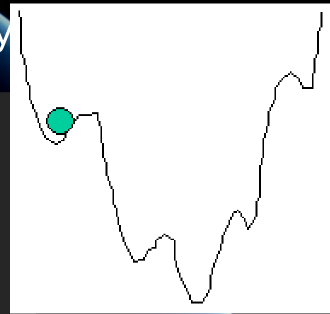
high solar activity, mostly quiet time

Why “REPEAT” step is needed?

- Ionospheric response to the storm-time impacts is not just a “triggered option for a disturbed plasma day”
  - Context of the disturbed ionosphere dynamics is a continuous function of *t*
    - Driver storylines need to be complete to retrieve the best matching storm in the library
    - But in the forecast scenario, only an initial fragment of the storylines may be available
- Forecast shall be repeated as time progresses and larger fragments of the storylines become available

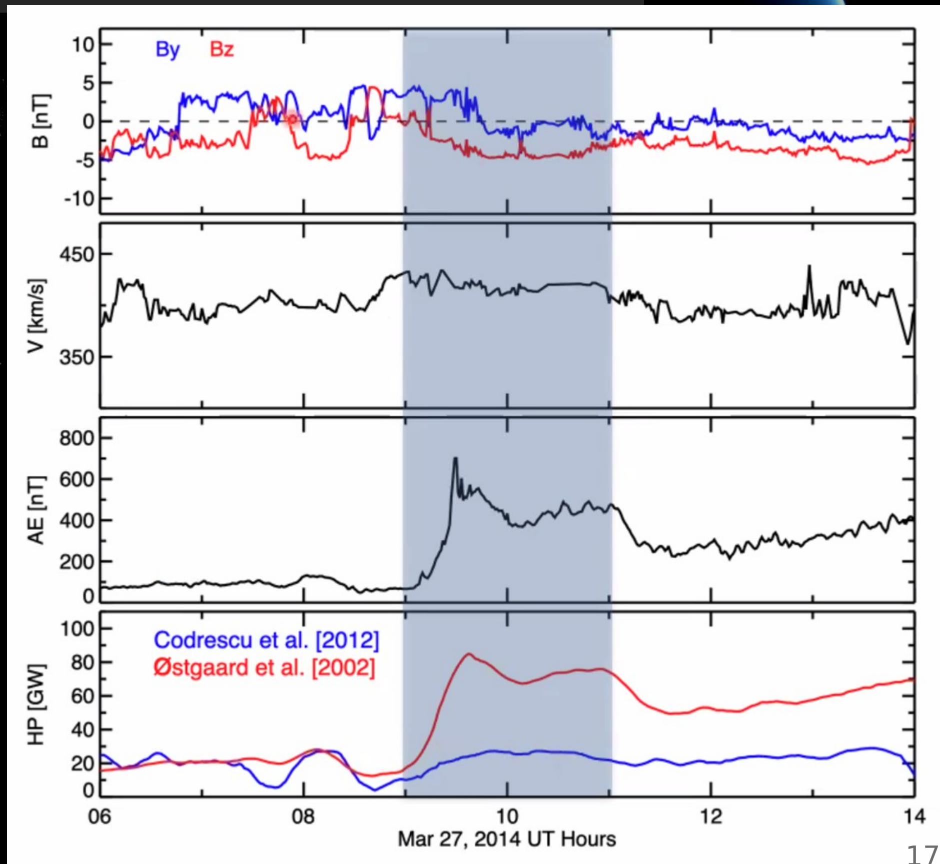


Associative memory



How to get storyline from a fragment

- Note: not the storyline of the storm, but of the storm *drivers*
  - Simpler task… *divide and conquer*
  - It is the interplay of drivers that matters
- Associative Memory is one possibility
  - Used in recognition of handwriting
  - Also for recalling stored data from their noisy and incomplete realizations
- Recursive, feed-back NN architecture
  - Hopfield networks
  - No input layer, no output layer
  - Neurons are clipped to available data and evolve into the nearest local minimum of E



PITHIA-NRF and T-FORS: European SW

- Real-time data for forecasting by historic analogy are not easy to come about
  - Need a consortium of real-time data providers
- PITHIA-NRF is an emerging space physics data infrastructure in Europe
    - Look it up! www.pithia-nrf.eu
    - HORIZON 2020 project
    - Based on EGI Foundation mega-facility of computing resources
      - Public funding = better prospects of longevity
    - And a Network of Research Facilities (BRF)
      - some facilities have decades of uninterrupted operation
  - T-FORS is the pilot project to leverage PITHIA-NRF collections
    - TID Forecasting System
    - HORIZON 2020 project
    - Listen to Elvira Astafyeva talk later this morning (TID)

The EU Framework Programme for Research and Innovation
HORIZON 2020

PITHIA-NRF Research Infrastructure

egi
www.egi.eu

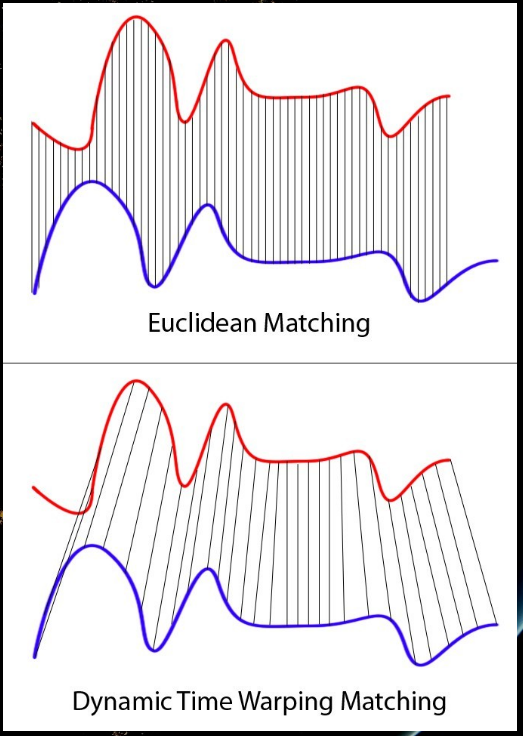
UMASS LOWELL

Forecast Architecture

REPEAT: forecast quality improves with each iteration as longer storylines are coming in

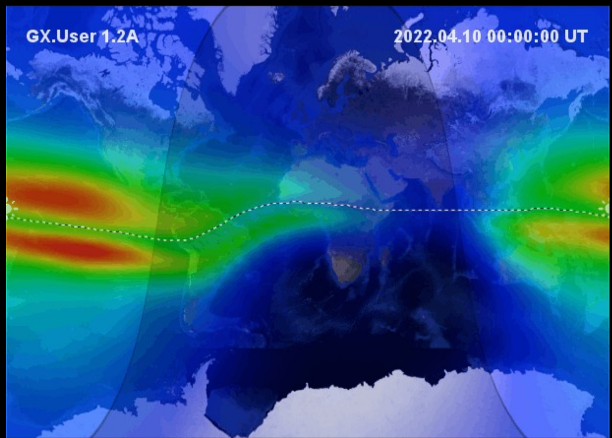
Dynamic Time Warping (DTW)

- Warp library-provided storm storyline
  - DTW finds similarity between 2 storylines
  - Driver storylines may be indicative of *how different* the actual storm timing is from the Library copy
  - Corresponding time warping shall be applied to the correction ΔNmF2

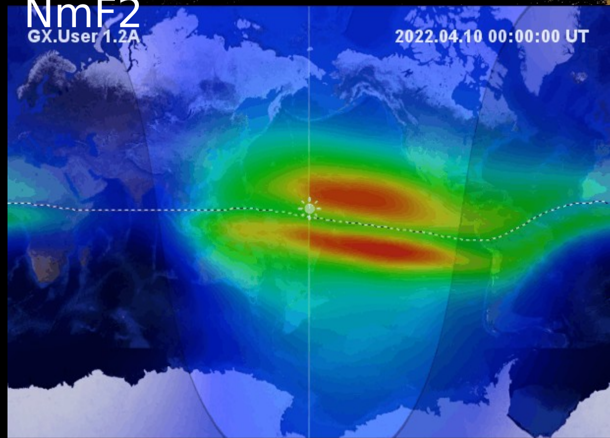


Library of storms in longitude-neutral form

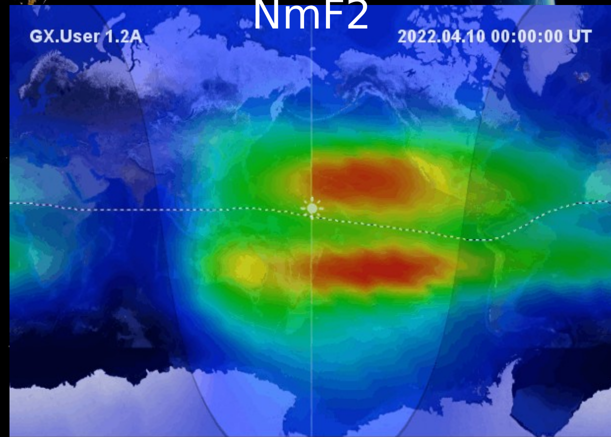
“Classic” view of NmF2

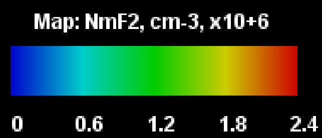


Local Time Noon view of NmF2

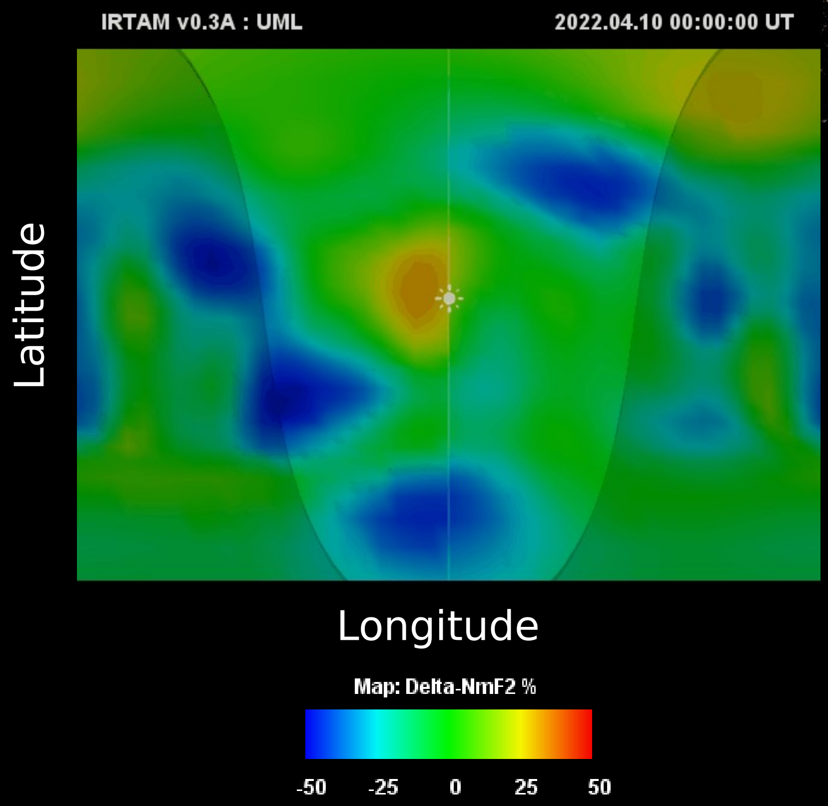


De-magnetized view of NmF2

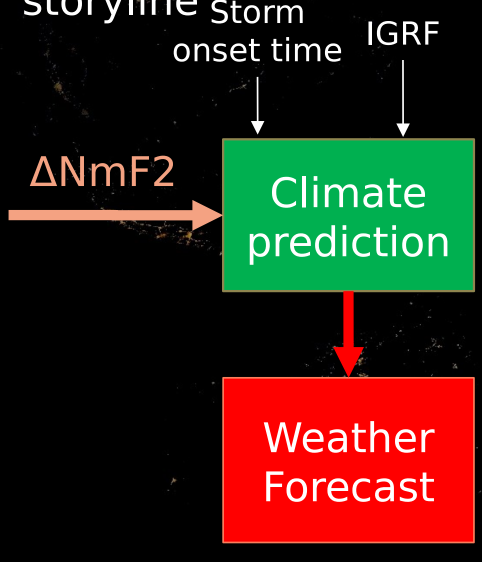




Encoding library storylines of ΔNmF2



- Total 1024 coefficients to store 24 hour global animated 2D maps
- Can be expanded to 2048 coefficients to store 2-day storyline



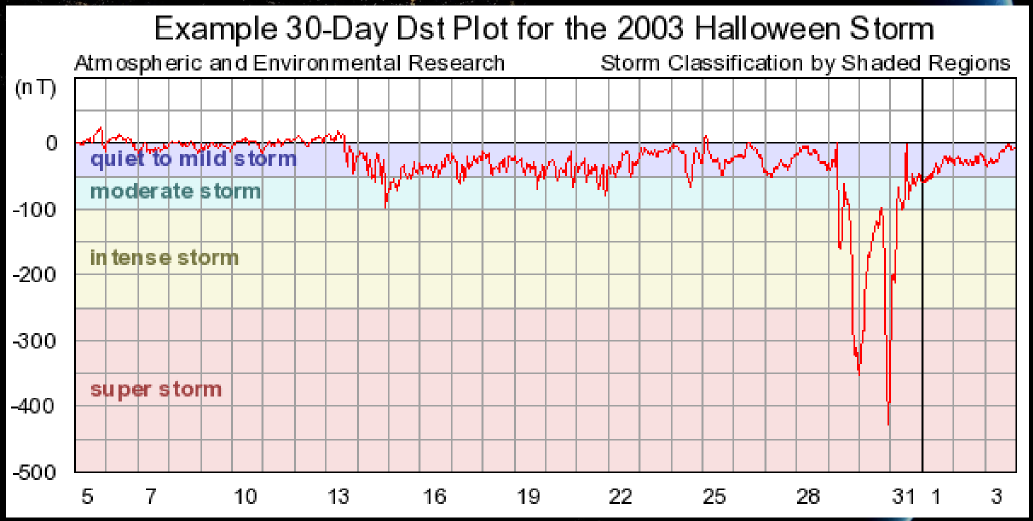
The IGRF model of the Earth magnetic field is needed to re-magnetize the retrieved library

Forecasting by context-driven memory

- NOT to build a least-square regression on 1024 unknowns
- NOT to build a back-prop feed-forward NN with 1024 outputs
- Just memorize them, *cleverly*
  - Associate the timeline of ionospheric dynamics with timelines of ionospheric state drivers
    - Deep Learning: placing the storm vocabulary into the context of a “sentence” of ongoing geospace activity
    - Rely on NN superior inductive bias to build the context
    - Plus other tricks:
      - Dynamic Time Warping (DTW)
      - Associative memory (AM)
        - Restore a driver’s full storm timeline from its initial observed fragment

Natural Language Processing as DTW example

- Analogous to Sound/Syllable recognition
- Custom Language to describe storm progression



Summary

- Deep Learning "Ice-Break" is ongoing in NN-based forecasting
  - DL learns the system from its previous behavior
- A concept study of DL-based forecast of the ionospheric storm storylines:
  - Forecast deviation timeline of the disturbed ionosphere
    - Deviation from the quiet-time LT-centered/demagnetized ionosphere
  - Sync the deviation timeline to the actual/definitive storm onset time (Alexa!)
  - Use Dynamic Time Warping to maintain a smaller vocabulary of the storm behavior
  - Deep Learning to describe ionosphere timeline in the context of key storm driver timelines
  - For each activity driver, use associative memories to retrieve a full-length storyline from the initially observed fragment
- Procedure:
  - Detect storm onset, obtain full-length driver storylines
  - Take 30-day median current ionosphere, LT-center, de-magnetize,
  - Retrieve deviation storyline from the storm library, time-warp to current activity
  - Apply deviation to the median, position at reference LT, re-magnetize.