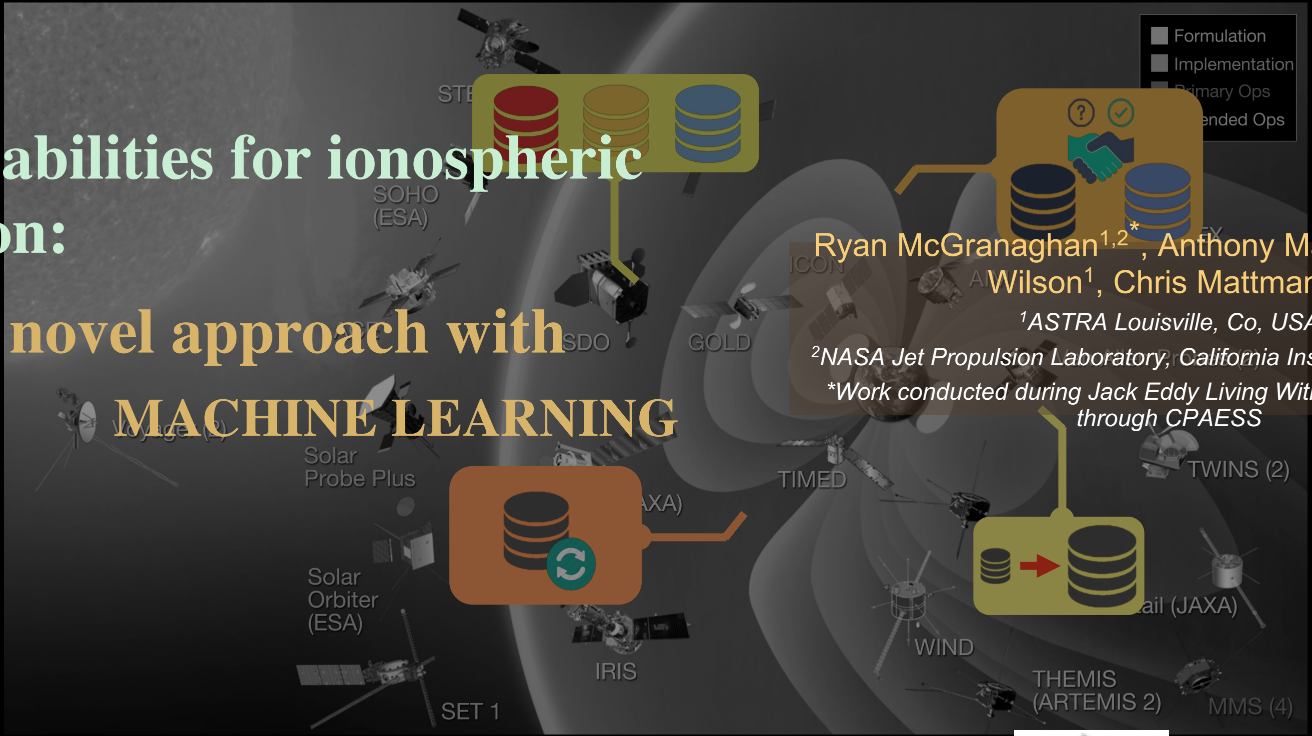
New capabilities for ionospheric prediction:

A novel approach with MACHINE LEARNING



Ryan McGranaghan[1,2*], Anthony Mannucci[1], Brian Wilson[1], Chris Mattmann[1]

[1]ASTRA Louisville, Co, USA

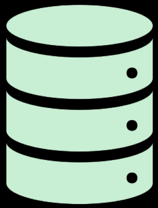
[2]NASA Jet Propulsion Laboratory, California Institute of Technology

**Work conducted during Jack Eddy Living With a Star Fellowship through CPAESS*

ASTRA

CPAESS

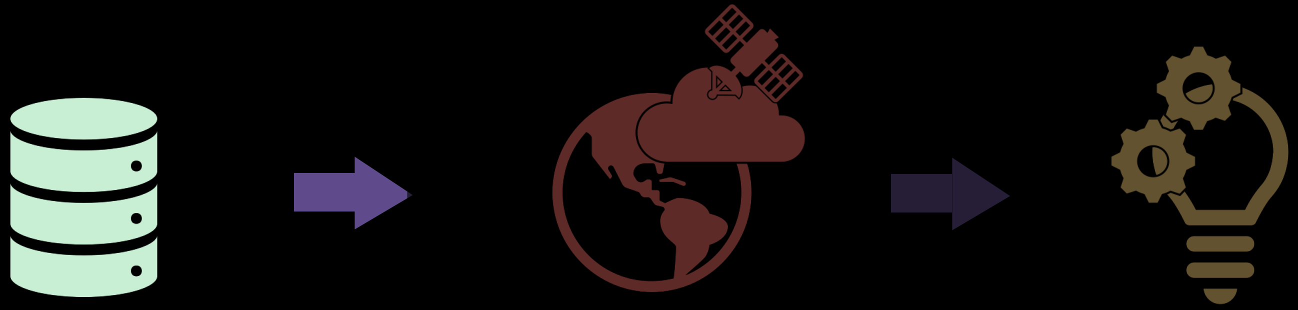
Agenda



How is CEDAR evolving and why do we need data science?

Why is ionospheric scintillation a fantastic use case and what progress have we made?

What *trends* does this reveal?



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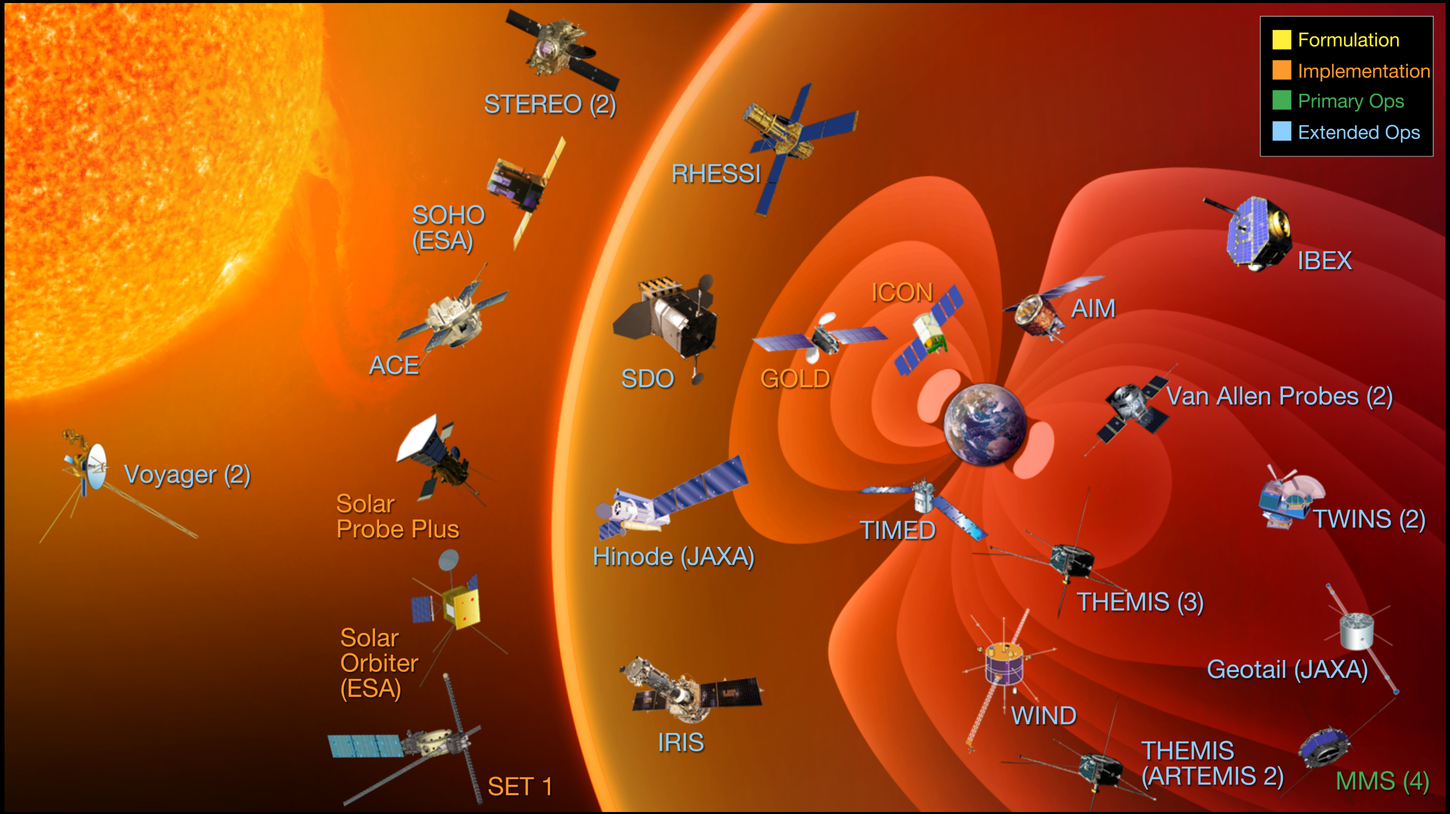

Formulation
Implementation
Primary Ops
Extended Ops
STEREO (2)
RHESSI
SOHO (ESA)
ACE
SDO
GOLD
ICON
AIM
IBEX
Van Allen Probes (2)
Voyager (2)
Solar Probe Plus
Hinode (JAXA)
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THEMIS (3)
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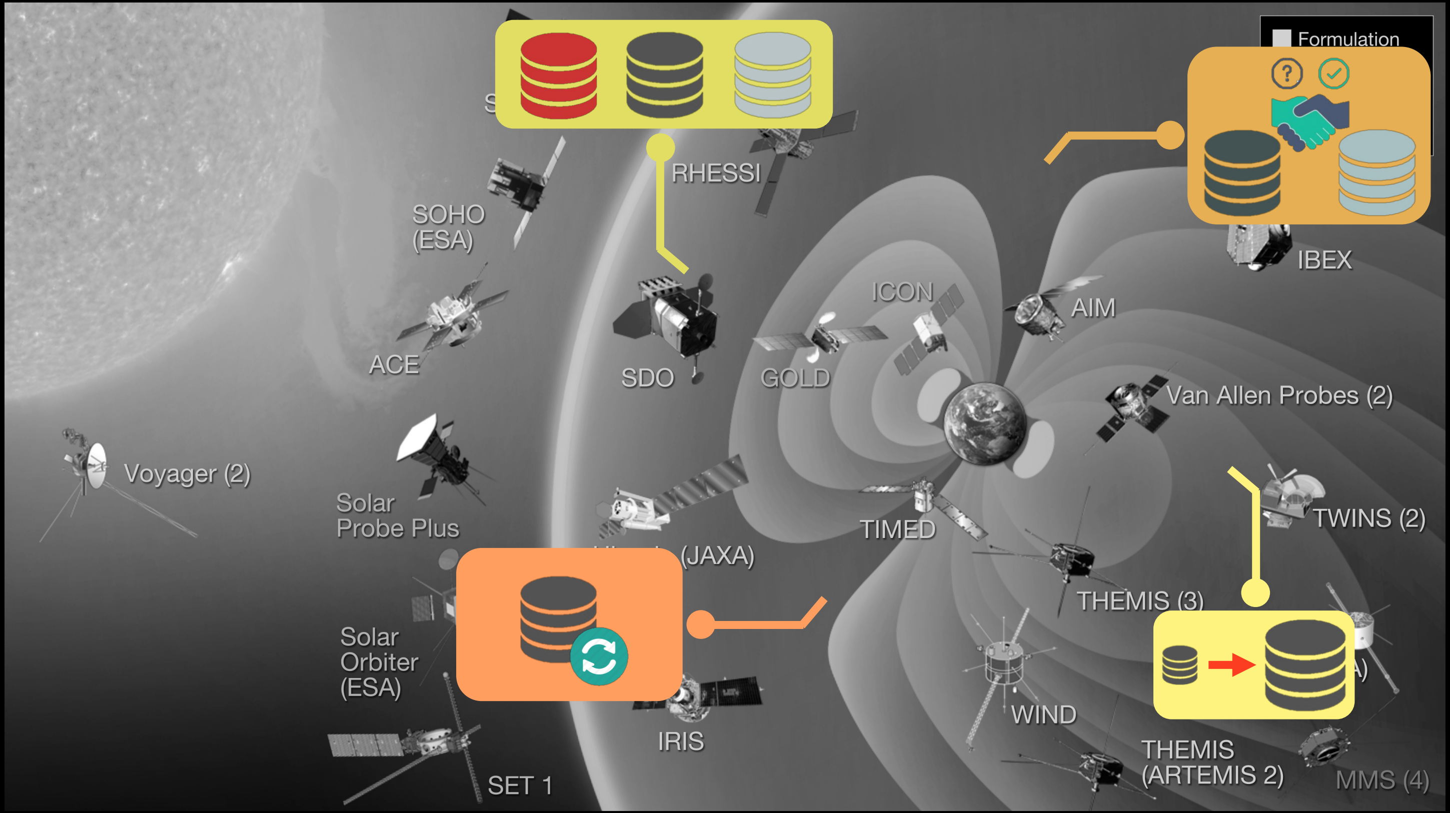
WIND
IRIS
SET 1
THEMIS (ARTEMIS 2)
MMS (4)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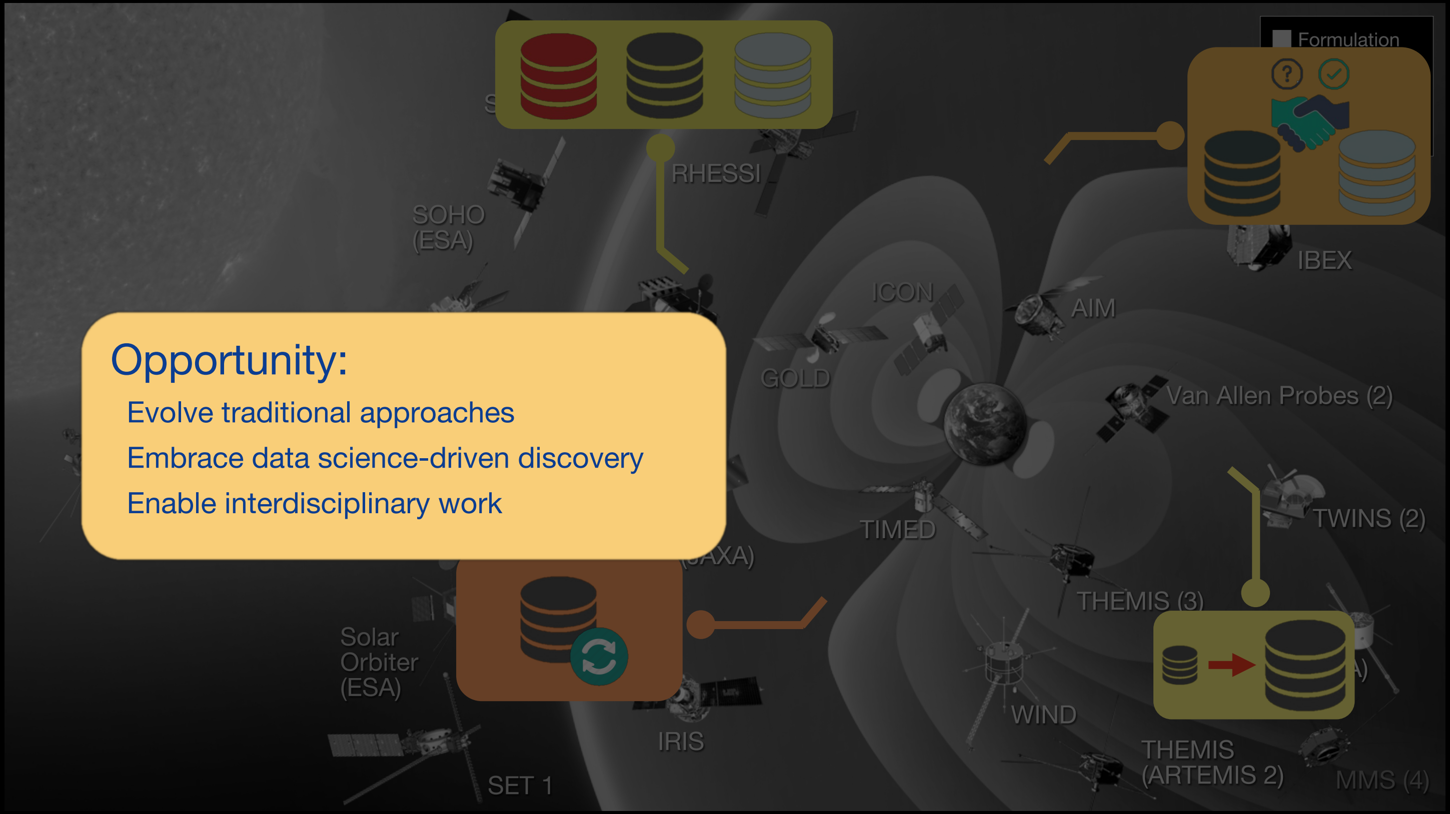


Opportunity:

Evolve traditional approaches

Embrace data science-driven discovery

Enable interdisciplinary work

Opportunity:

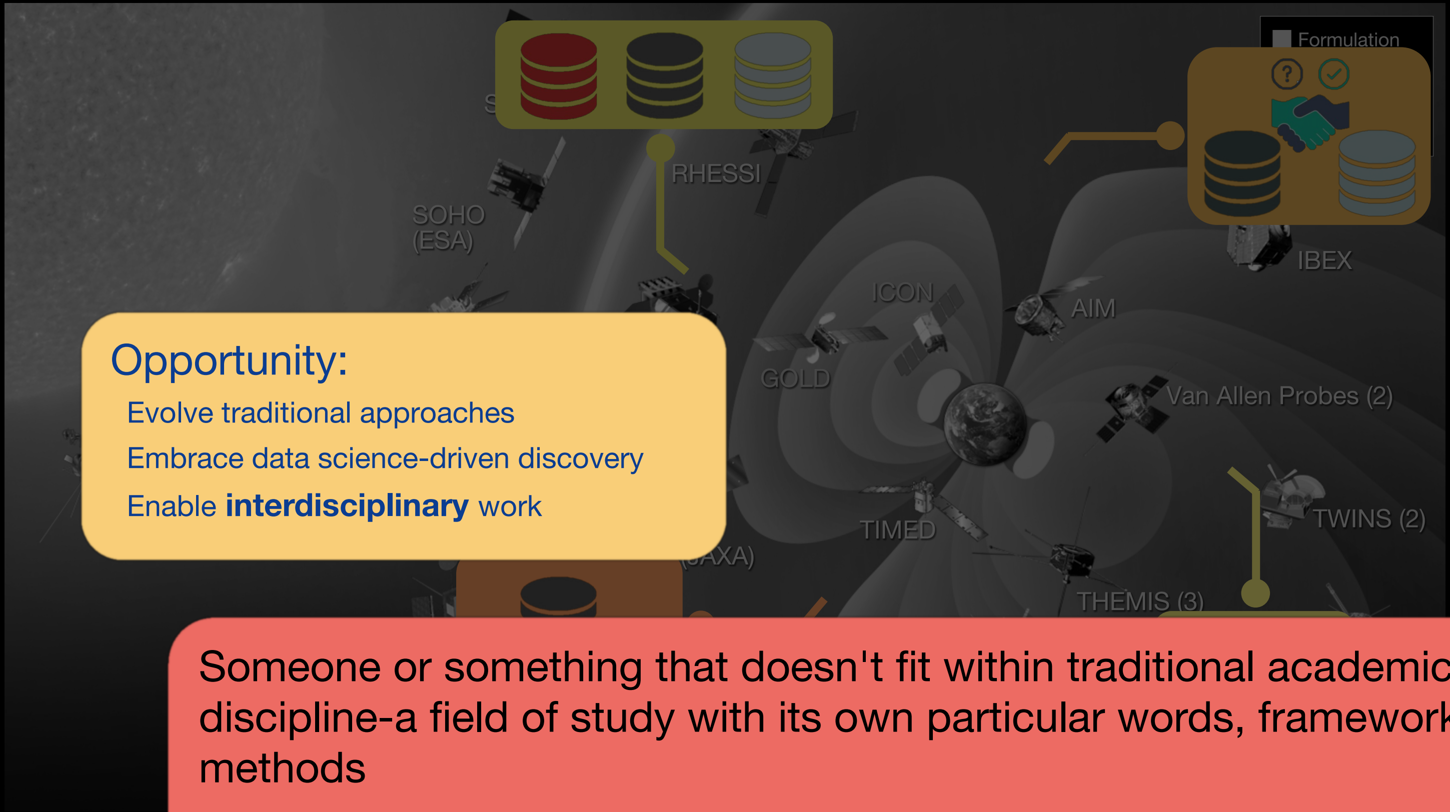
Evolve traditional approaches

Embrace **data science-driven** discovery

Enable interdisciplinary work

Scalable architectural approaches, techniques, software and algorithms which alter the paradigm by which data are collected, managed and analyzed.

Dan Crichton, JPL



Opportunity:

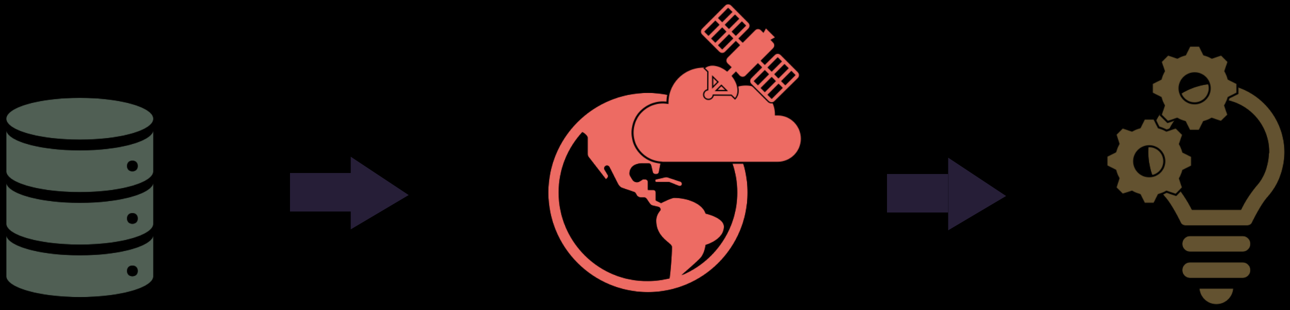
Evolve traditional approaches

Embrace data science-driven discovery

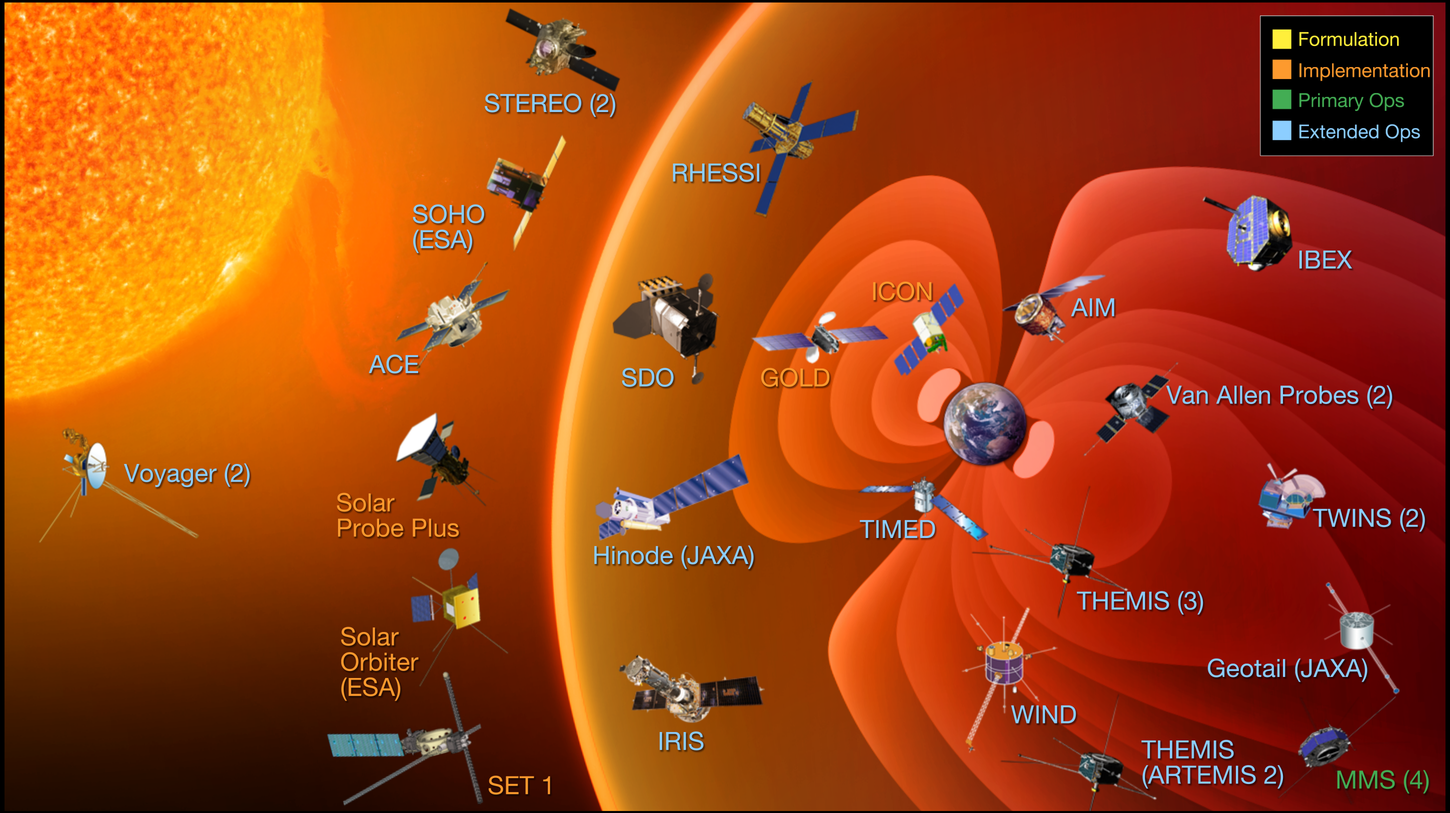
Enable **interdisciplinary** work

Someone or something that doesn't fit within traditional academic discipline-a field of study with its own particular words, frameworks, and methods

Joi Ito, MIT Media Lab, “Antidisciplinary”



Why is ionospheric scintillation a fantastic use case and what progress have we made?



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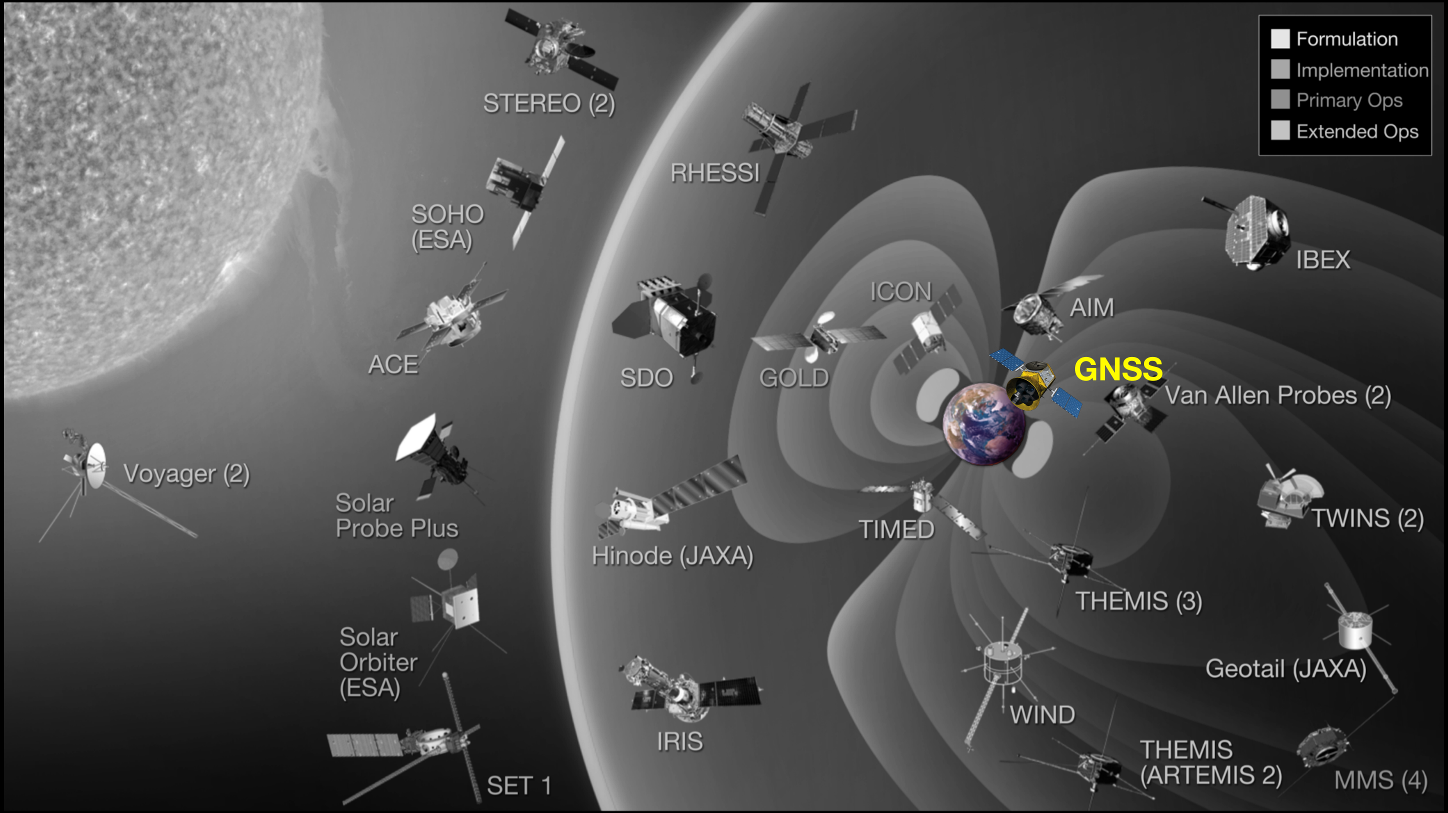

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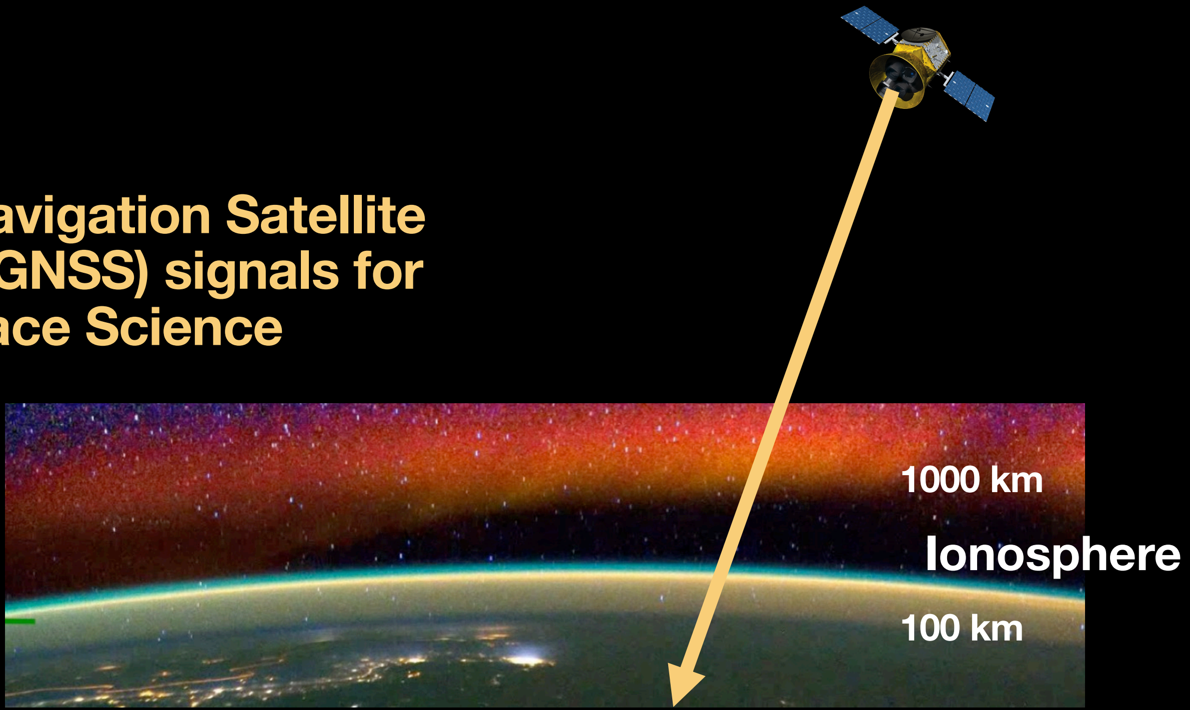
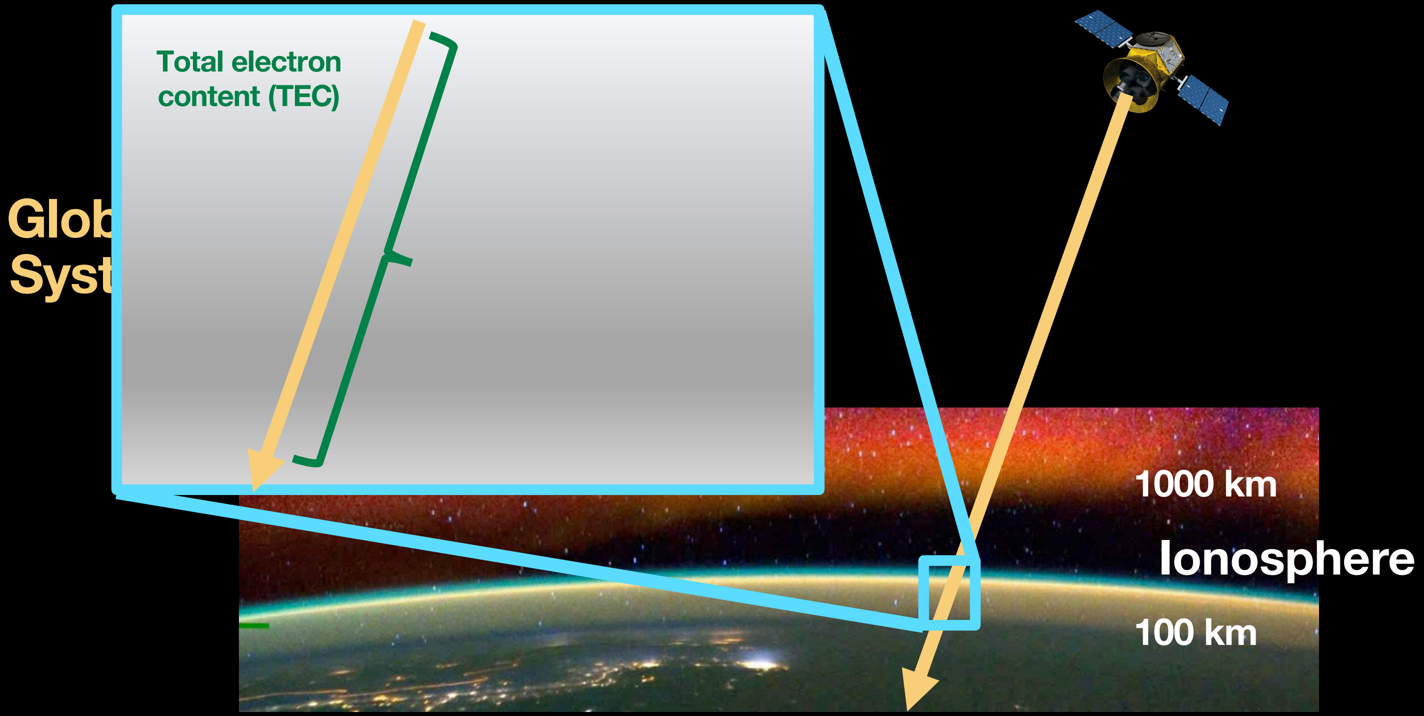
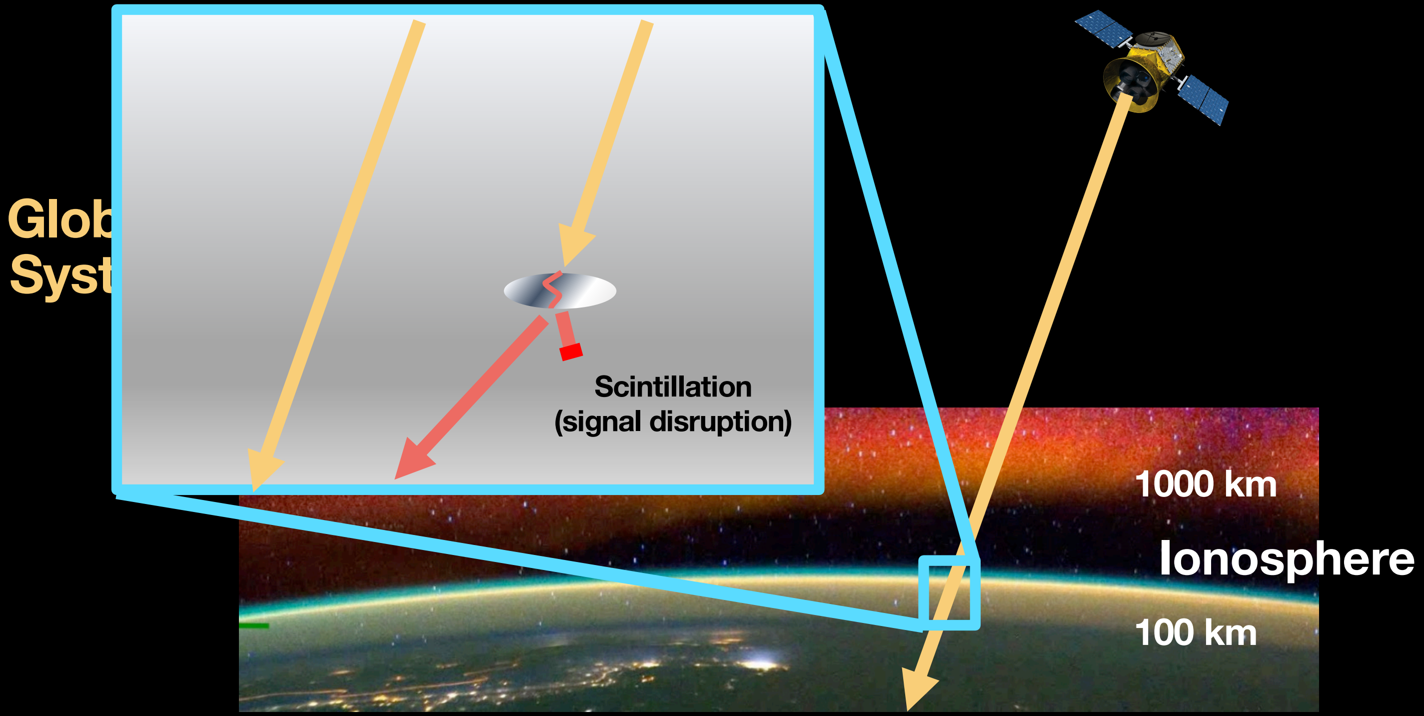
Global Navigation Satellite System (GNSS) signals for Space Science

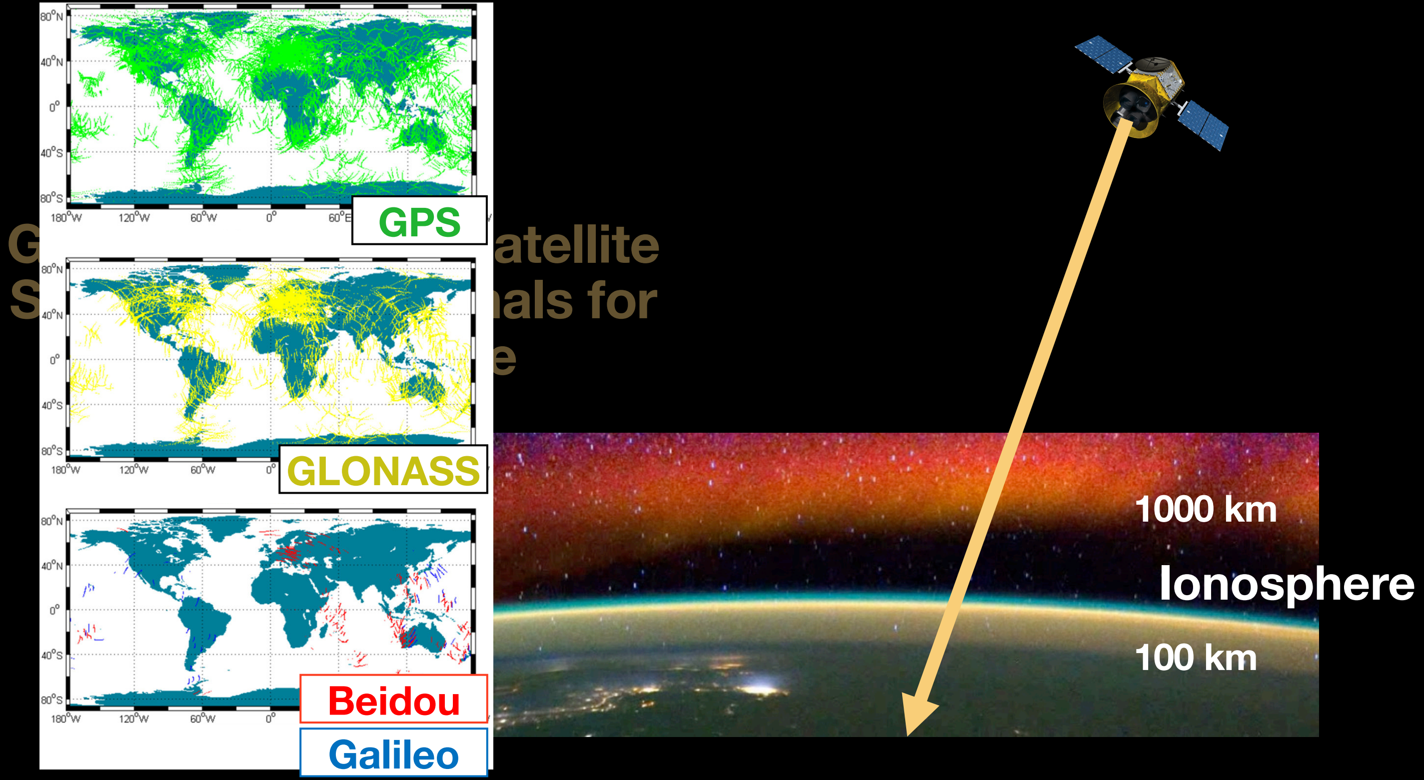




Total electron content (TEC)
Glob
Syst
1000 km
Ionosphere
100 km



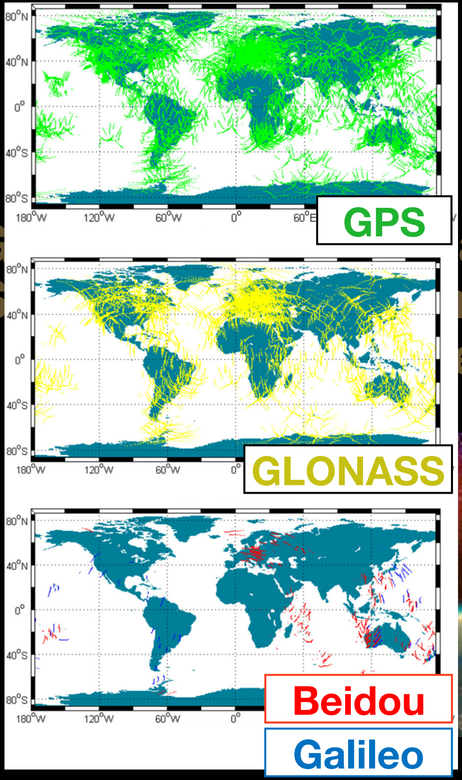
Glob
Syst
Scintillation
(signal disruption)
1000 km
Ionosphere
100 km


GPS
GLONASS
Beidou
Galileo
1000 km
Ionosphere
100 km

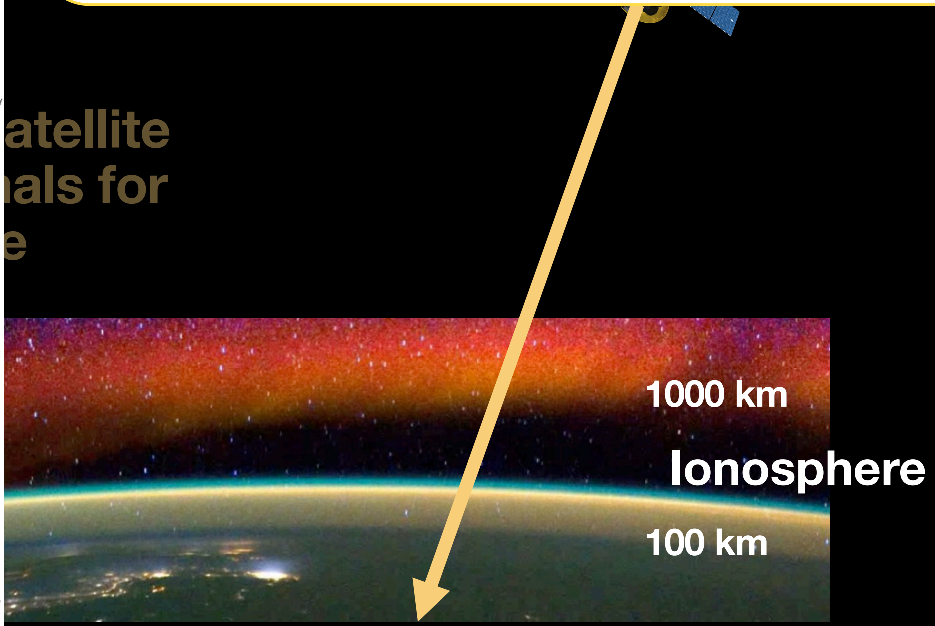
Support Vector Machine (SVM) — **Decision Trees** — **Random Forests** — **Neural Networks**

Easily explainable → *Difficult to explain*

Create a narrative of new scientific understanding across spectrum of machine learning approaches



G atellite
S als for
e



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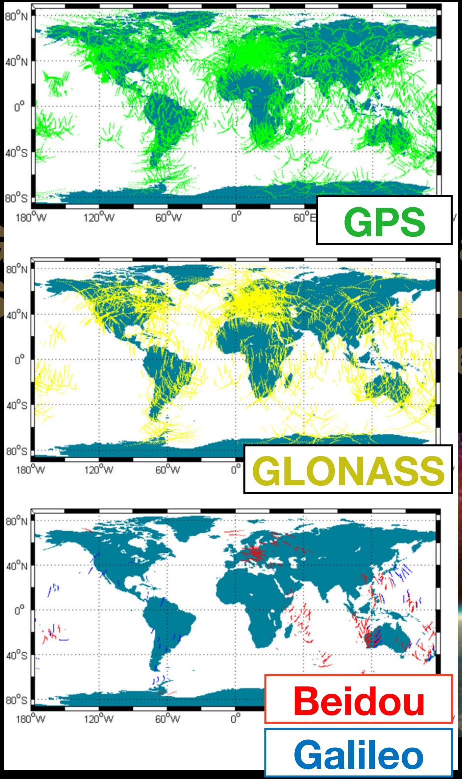
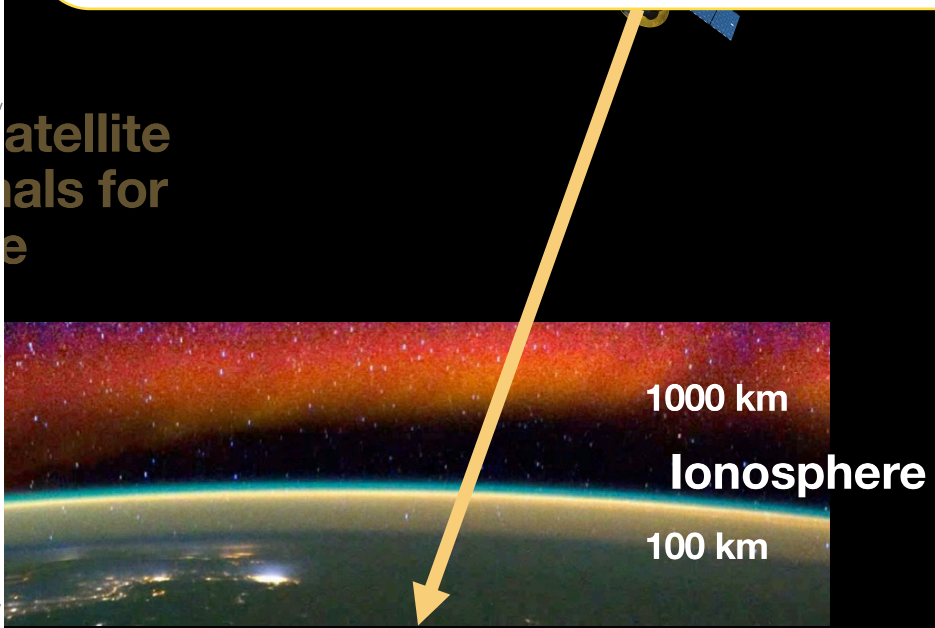
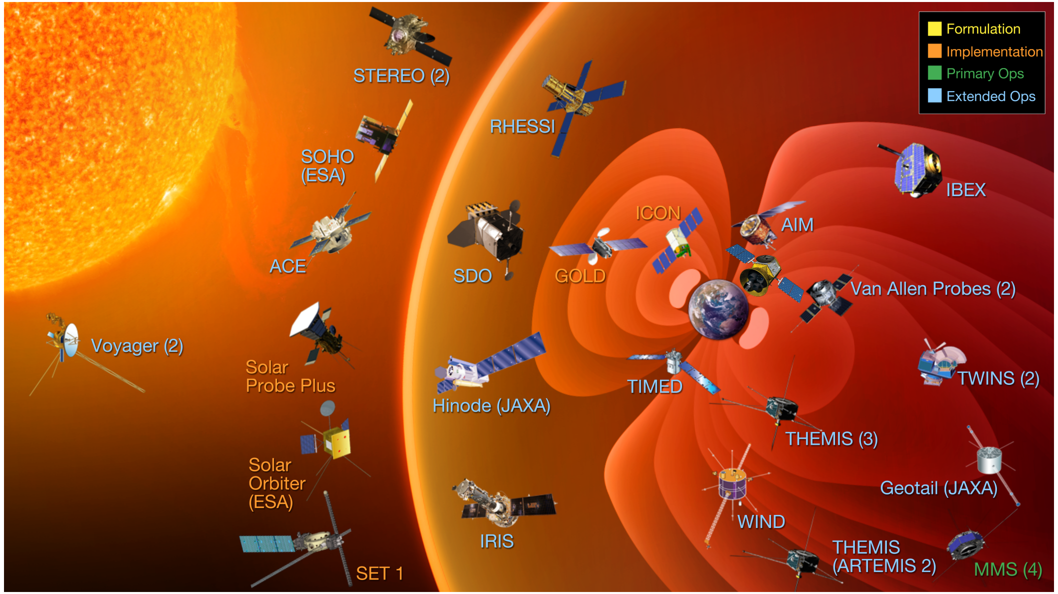




Step 1:
Obtain solar, geomagnetic, and ionospheric data



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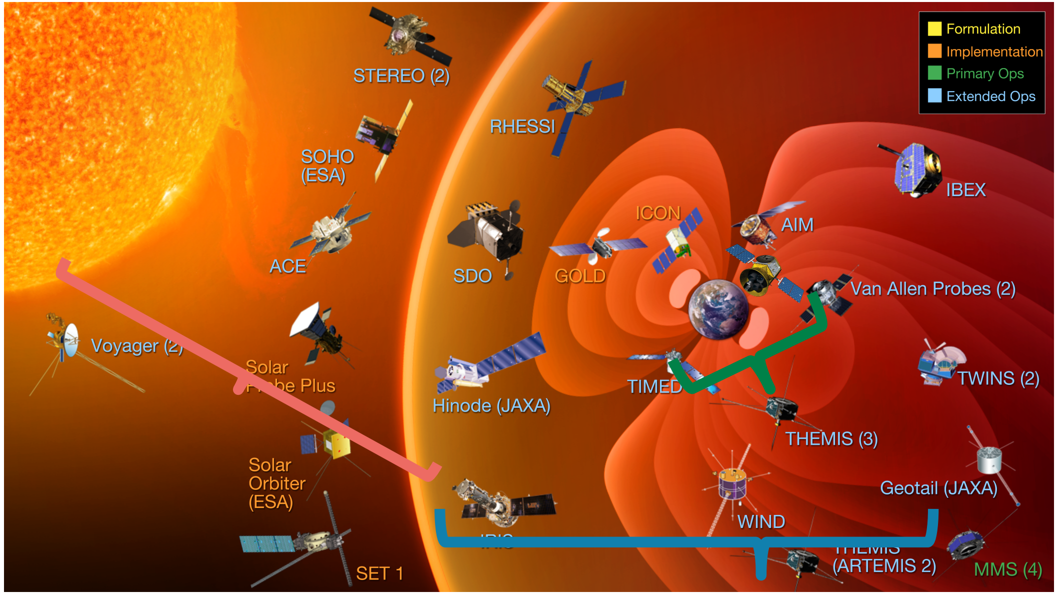

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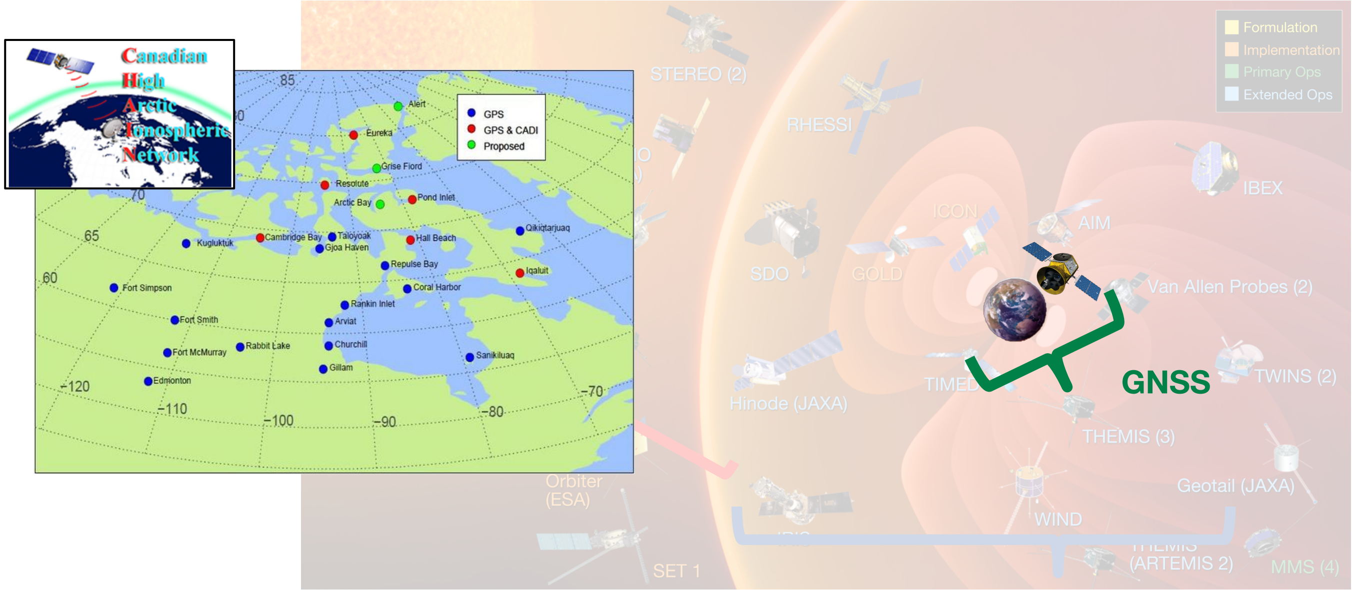
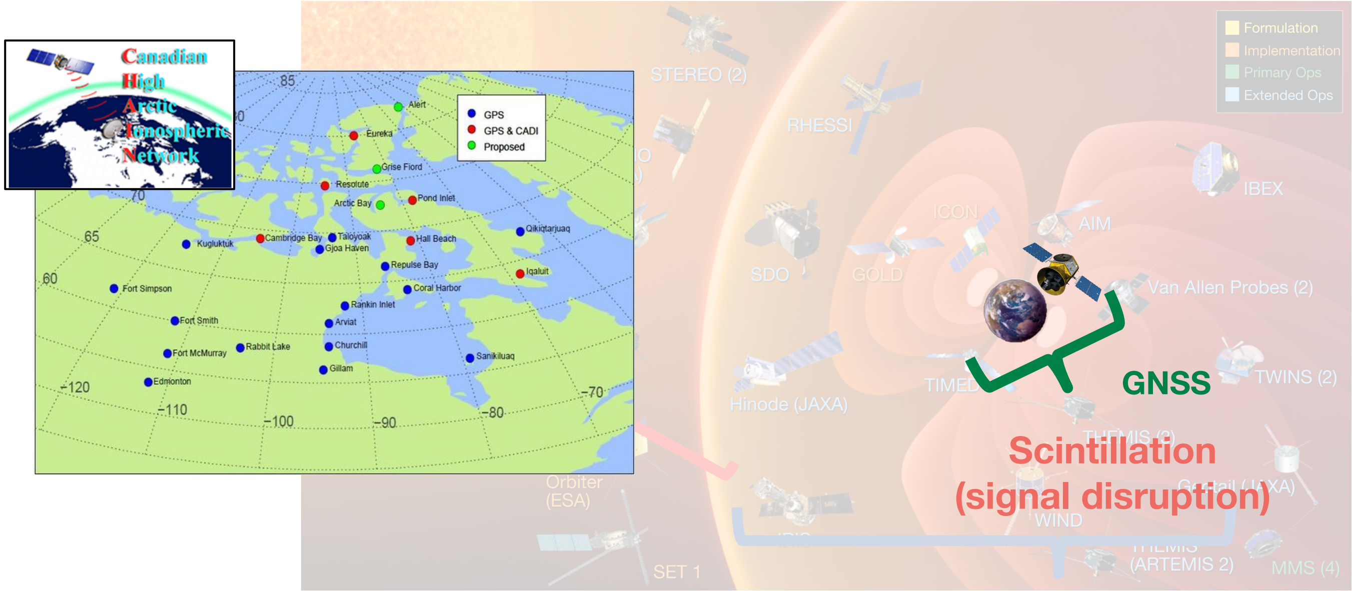


Step 2:

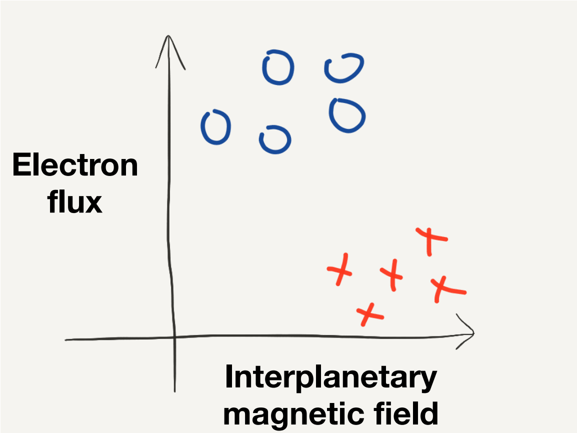
Define the predictive task



Step 3:

Machine learning algorithm for prediction

Support Vector Machine



Cortes and Vapnik (1995)

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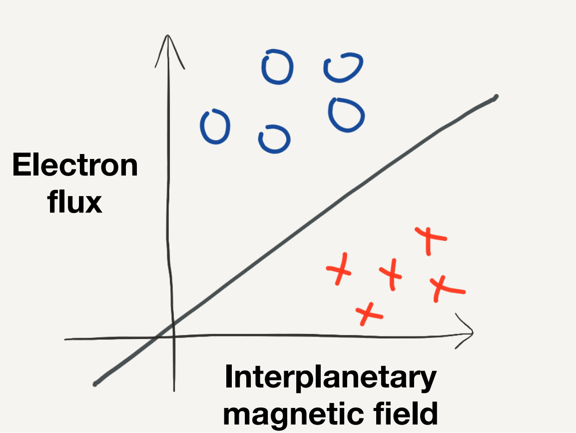

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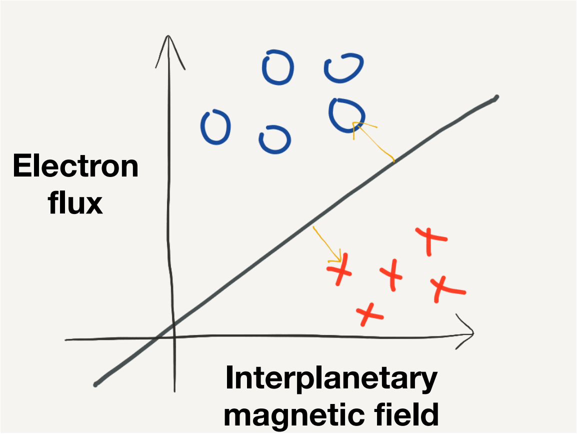

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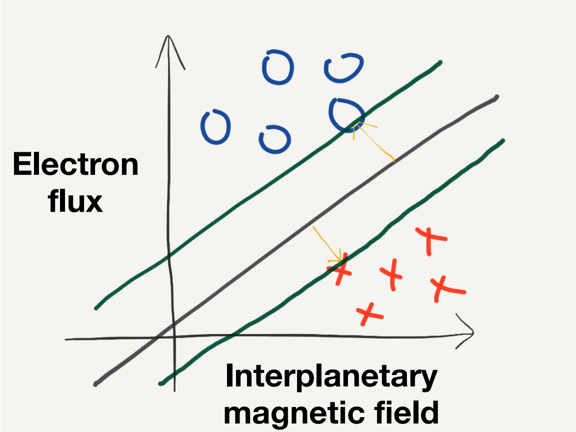

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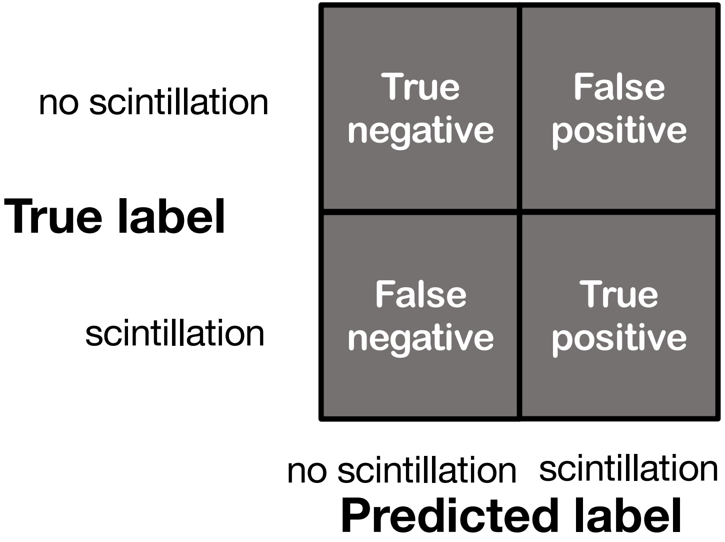

McGranaghan et al., (2018)

Step 3:
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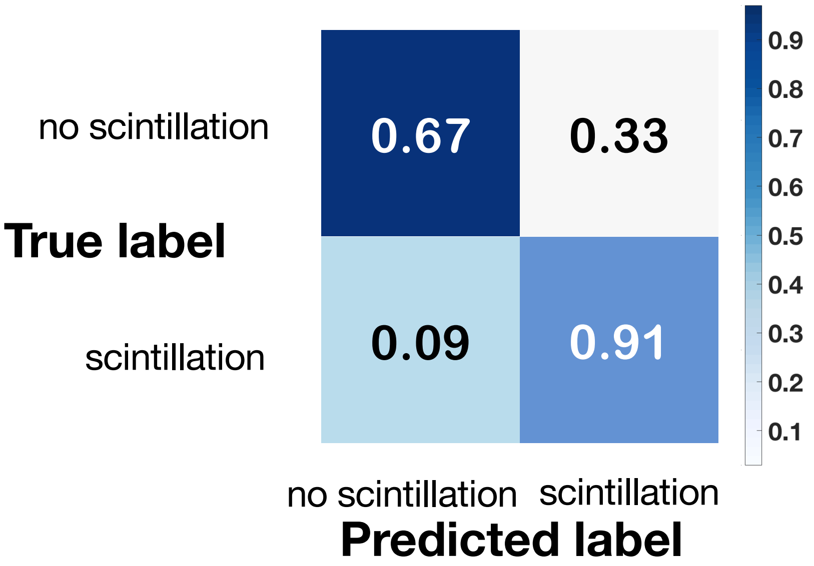


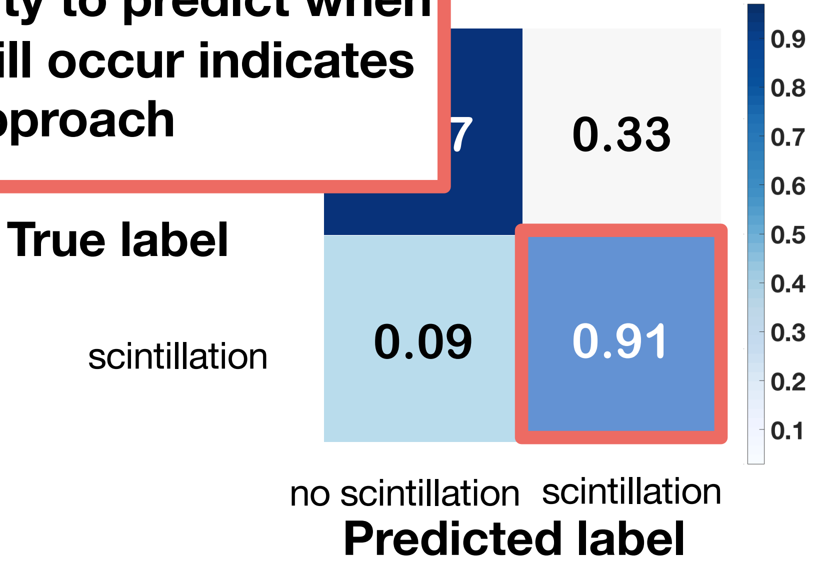
McGranaghan et al., (2018)

Step 3:

Machine learning algorithm for prediction

91%

Improved ability to predict when scintillation will occur indicates potential of approach



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Step 3:

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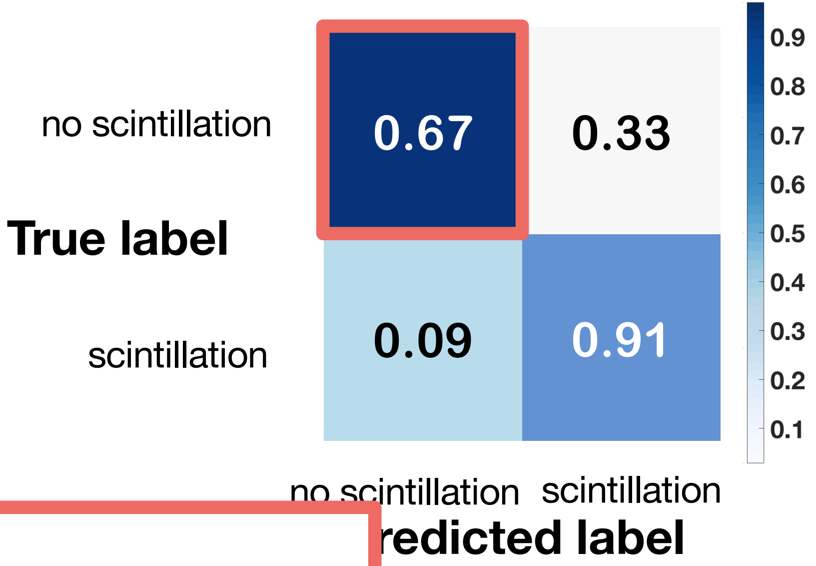

67%

High accuracy predicting when scintillation would not occur

Step 4:

Interrogate the model

Step 4:
Interrogate the model

Evaluation

Step 4:
Interrogate the model

Evaluation

True Skill Statistic (TSS)

$$\mathrm{TSS} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} - \frac{\mathrm{FP}}{\mathrm{FP} + \mathrm{TN}}$$

True label \ **Predicted label**	no scintillation	scintillation
no scintillation	True negative	False positive
scintillation	False negative	True positive

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Evaluation

True Skill Statistic (TSS)

$$\mathrm{TSS} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} - \frac{\mathrm{FP}}{\mathrm{FP} + \mathrm{TN}}$$

TSS

-1
Worst

+1
Perfect

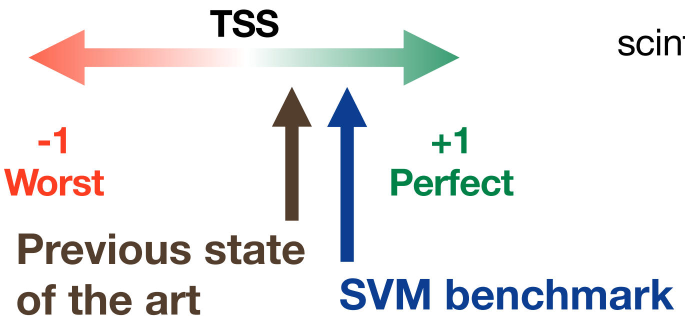
True label \ **Predicted label**	no scintillation	scintillation
no scintillation	**True negative**	**False positive**
scintillation	**False negative**	**True positive**

Step 4:
Interrogate the model

Evaluation

True Skill Statistic (TSS)

$$\mathrm{TSS} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} - \frac{\mathrm{FP}}{\mathrm{FP} + \mathrm{TN}}$$



True label \ Predicted label	no scintillation	scintillation
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Step 4:

Interrogate the model

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Step 4:
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Step 4:
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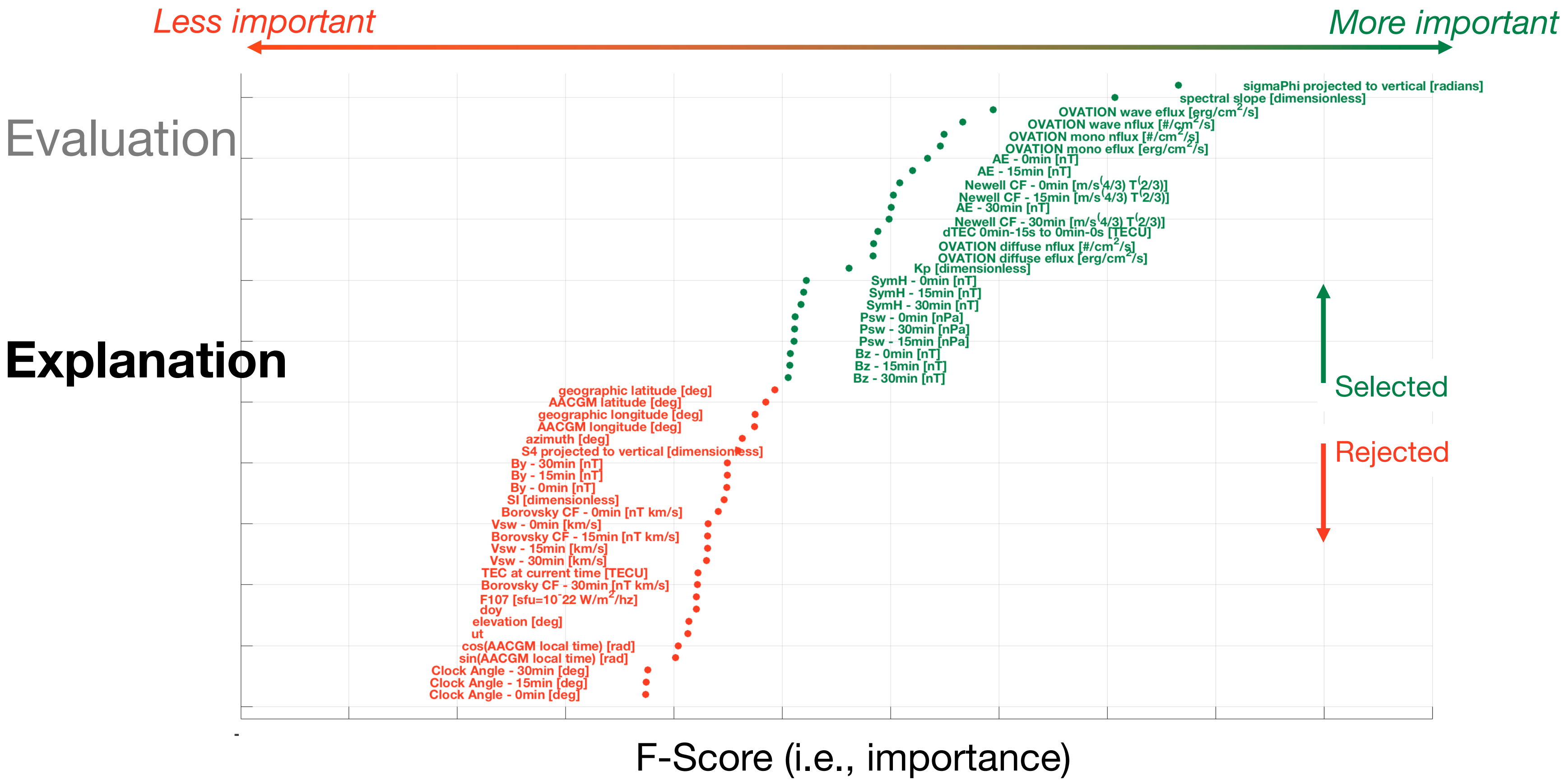

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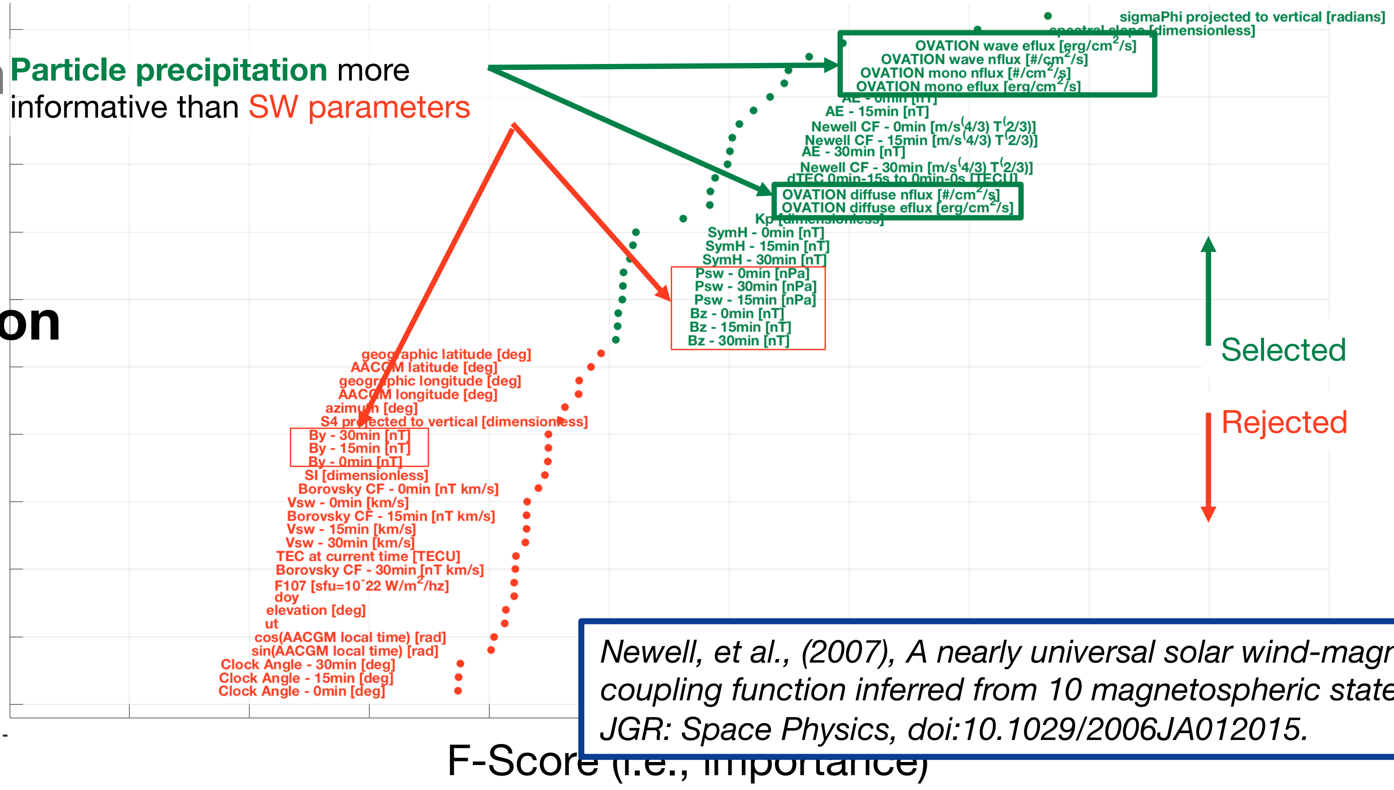

Newell, et al., (2007), A nearly universal solar wind-magnetosphere coupling function inferred from 10 magnetospheric state variables, JGR: Space Physics, doi:10.1029/2006JA012015.

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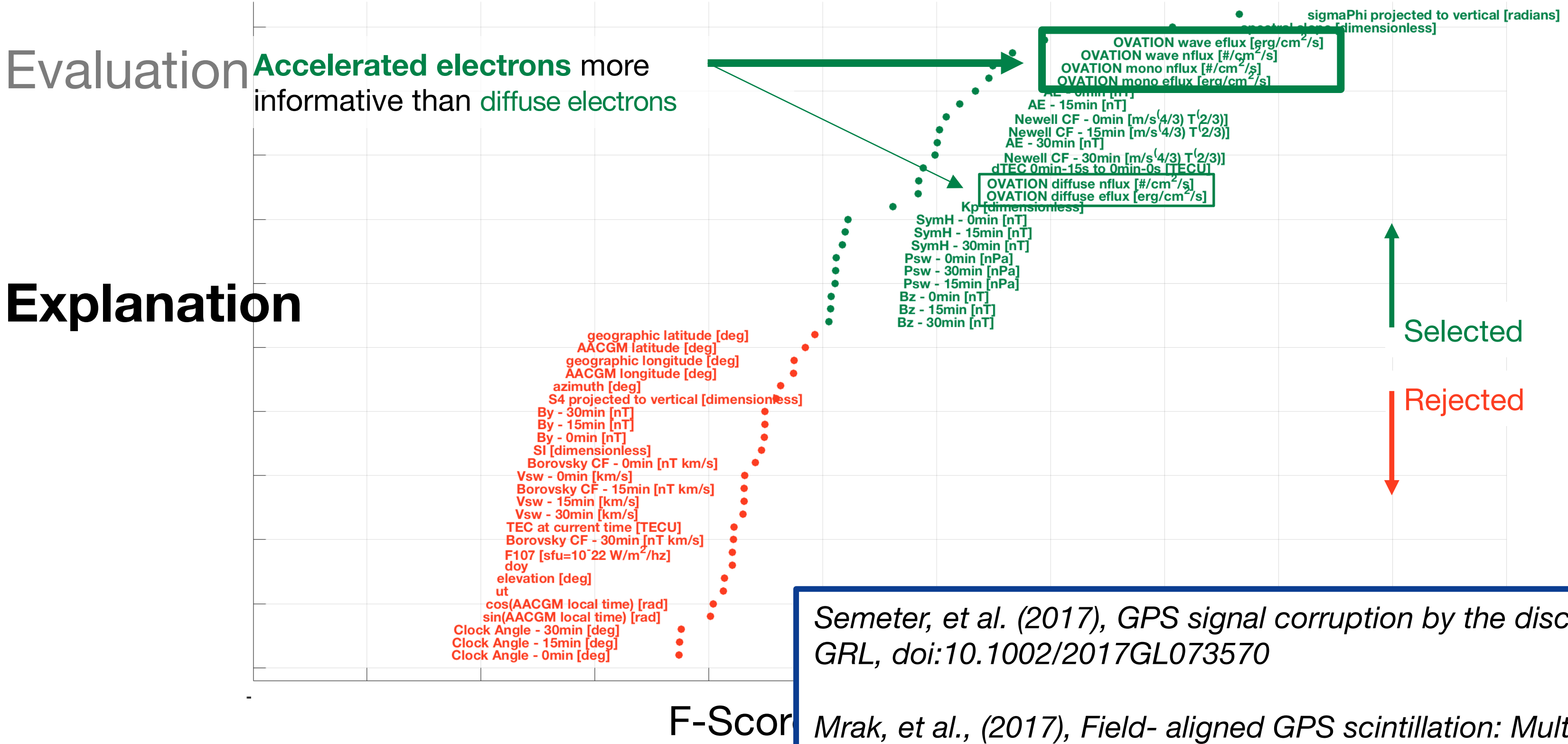
Interrogate the mode



Semeter, et al. (2017), GPS signal corruption by the discrete aurora. GRL, doi:10.1002/2017GL073570

Mrak, et al., (2017), Field- aligned GPS scintillation: Multisensor data fusion, JGR: Space Physics, doi:10.1002/2017JA024557.

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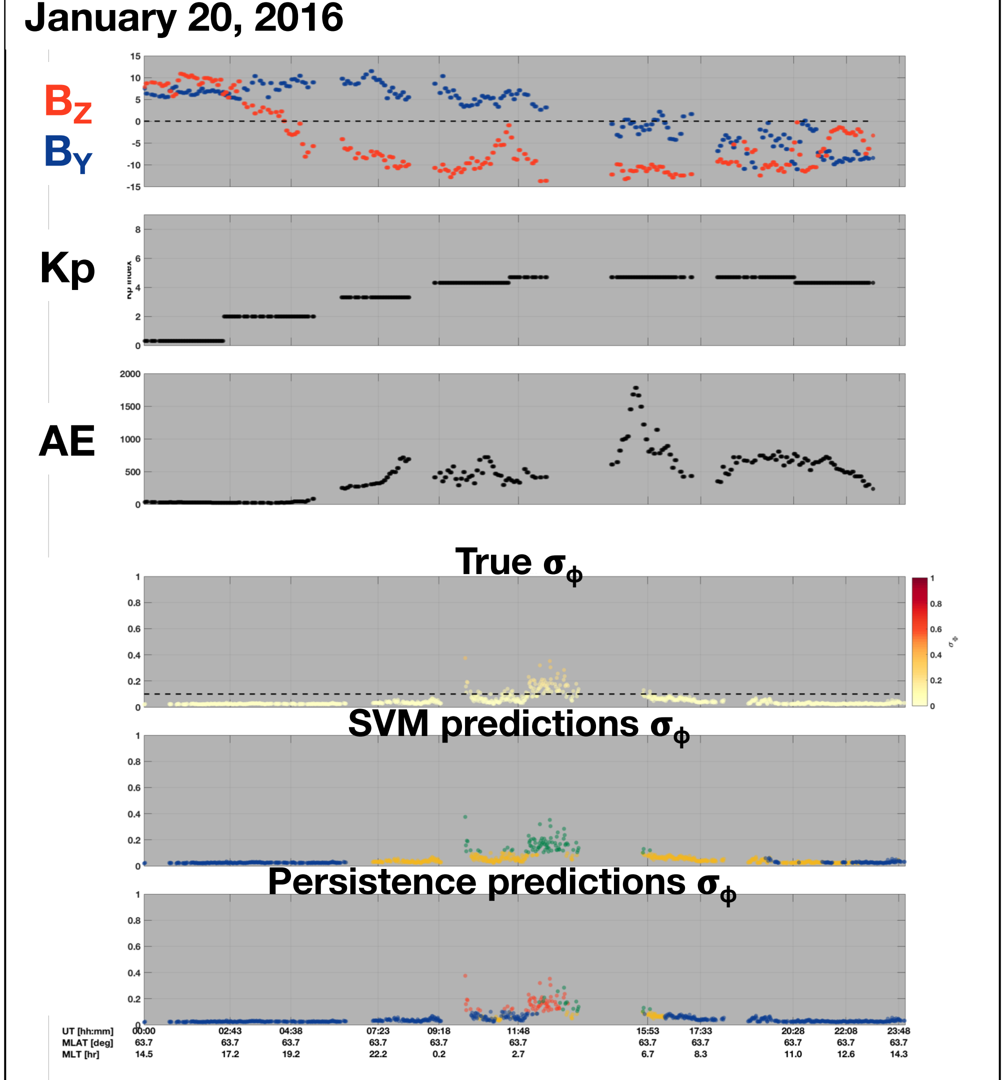

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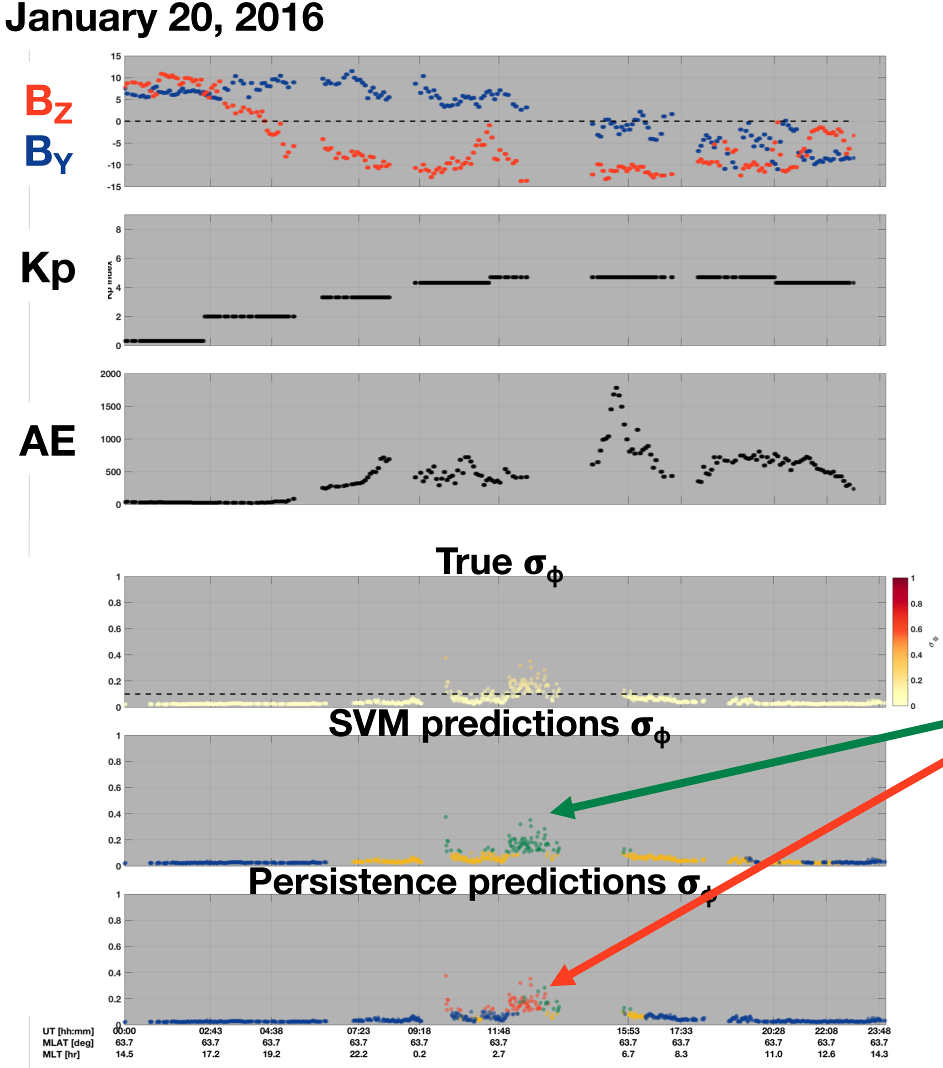
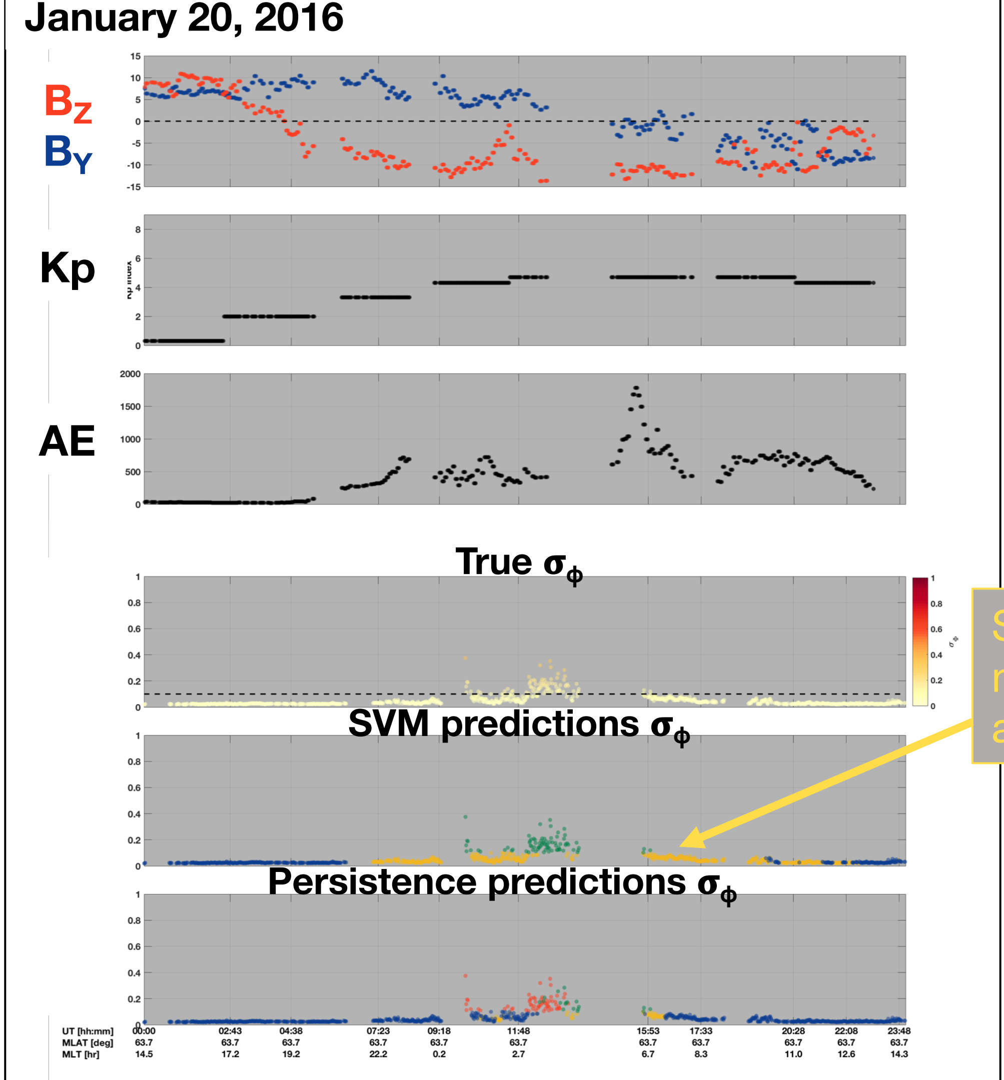


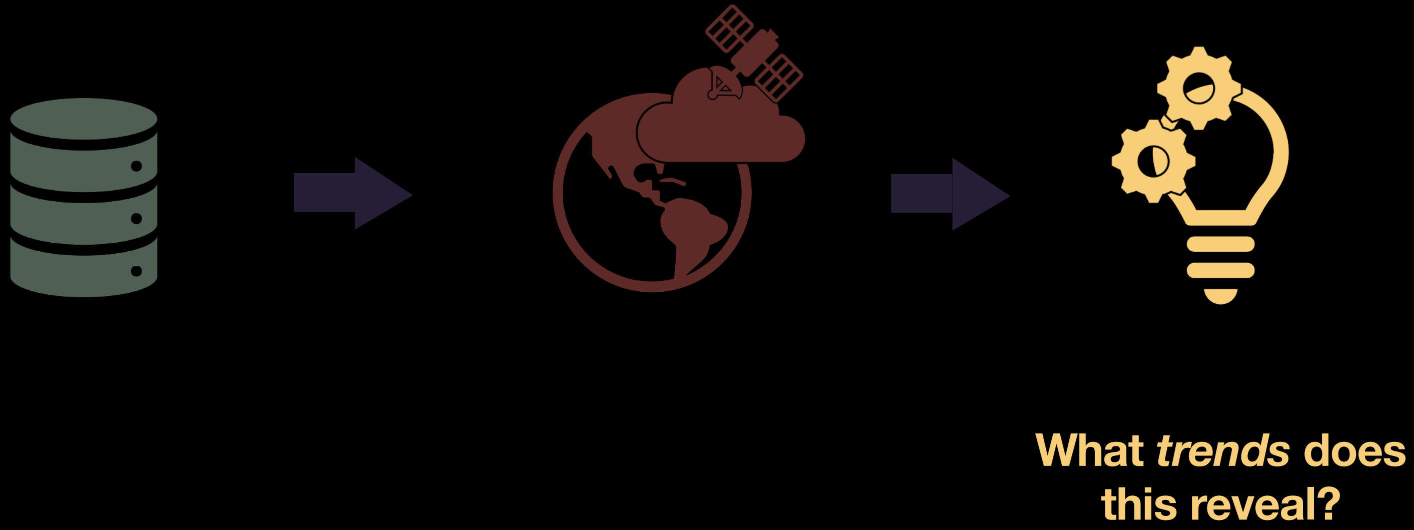
SVM identifies strong scintillation,
persistence does not

Evaluation

Explanation



SVM contains high number of ‘false alarms’


What *trends* does this reveal?

Be antidisciplinary

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Be open by default

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Be open by default

Understand the models

What *trends* does this reveal?

Trends

Be *antidisciplinary*

Be open by default

Understand the models

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ryan.mcgranaghan@gmail.com

RyanMcGranaghan.com

McGranaghan, R. M., Bhatt, A., Matsuo, T., Mannucci, A. J., Semeter, J. L., & Datta-Barua, S. (2017). Ushering in a new frontier in geospace through data science. Journal of Geophysical Research: Space Physics, 122, 12,586–12,590. https://doi.org/10.1002/2017JA024835

McGranaghan, R. M., A.J. Mannucci, B.D Wilson, C.A. Mattmann, and R. Chadwick. (2018), New capabilities for prediction of high-latitude ionospheric scintillation: A novel approach with machine learning, Space Weather, 16. https://doi.org/10.1029/2018SW002018

Curated Sources of Data Science Learning Resources

Ryan McGranaghan running list of resources (Github repository)

- https://github.com/rmcgranaghan/data_science_tools_and_resources

HelioAnalytics website and list of resources

- https://sites.google.com/view/heliodata/resources?authuser=0