Artificial Intelligence for Space Communications and Navigation

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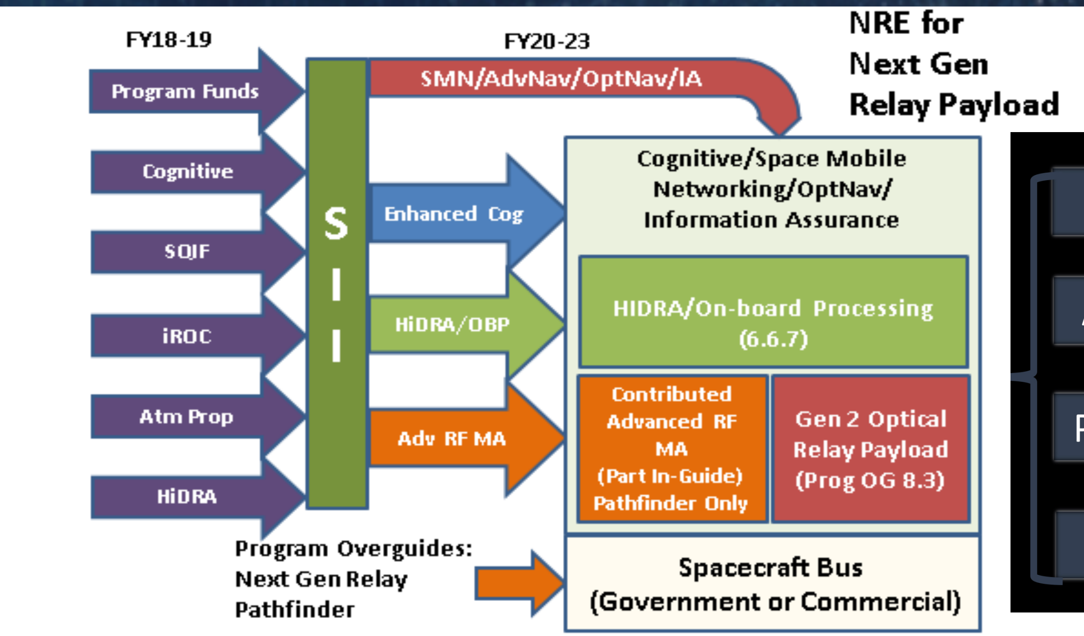
Current Methods

System-wide Intelligence

General Cognitive Engines to Target Specific Applications

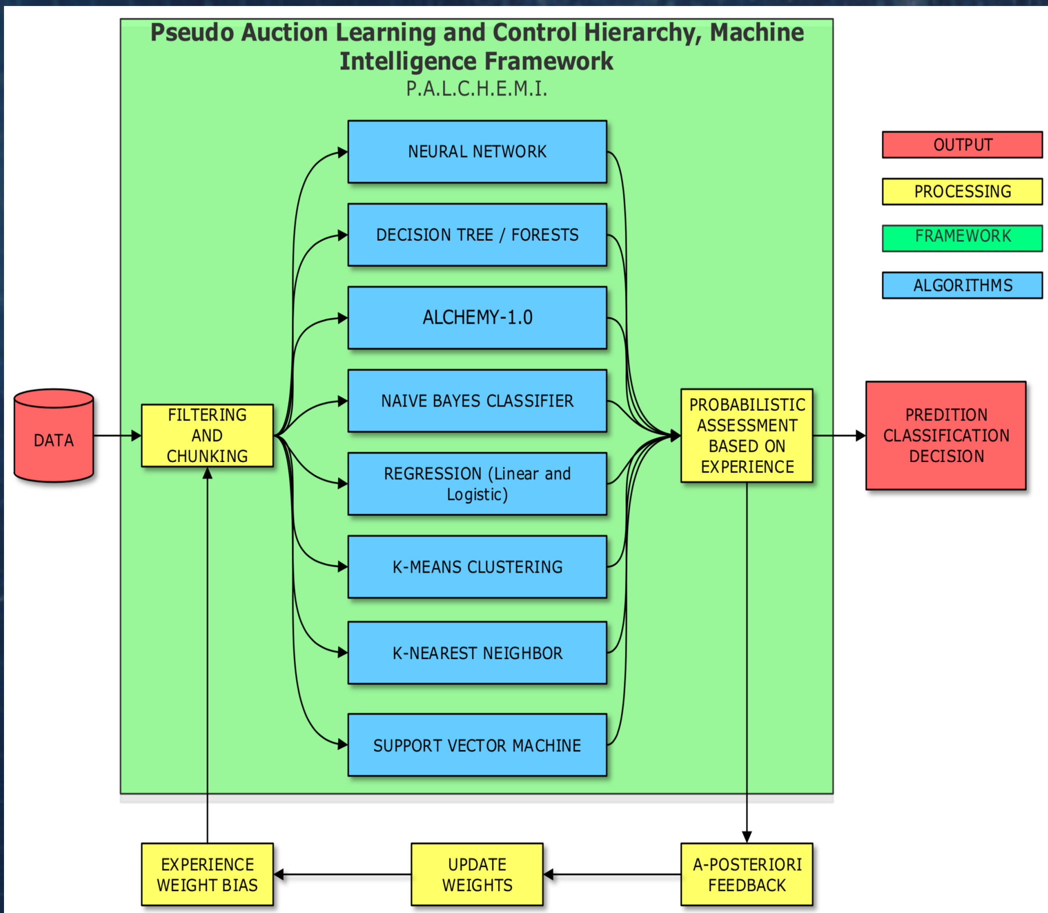


iROC	Control Switching and Optimization for Link
Atm Prop	Characterize Expected Behavior on a Link to Optimize Throughput
Pathfinder	Control Network Node Links and Predict Events for Scheduling
HiDRA	Control Link Parameters to Optimize Throughput

General Cognitive Engine → Specific Training and Tuning → Cognitive Engine Validation and Verification

- General Cognitive Engine: PALCHEMI
- Specific Training and Tuning: SPoC, TLNO, MBEC, etc …
- Cognitive Engine Validation and Verification: Experiments and Demonstrations

PALCHEMI
Call or Create a Cognitive Engine



Using the framework to call a Cognitive Engine and predict a value

```
In [1]: import palchemi as p

In [2]: SPoC = p.joblib.load('StatePredictorOfClassifica
   ...: ty.cognitive')

In [3]: SPoC.predict('Enter data here') #...etc..etc
```

Using the framework to create a Cognitive Engine

```
from palchemi import *
```

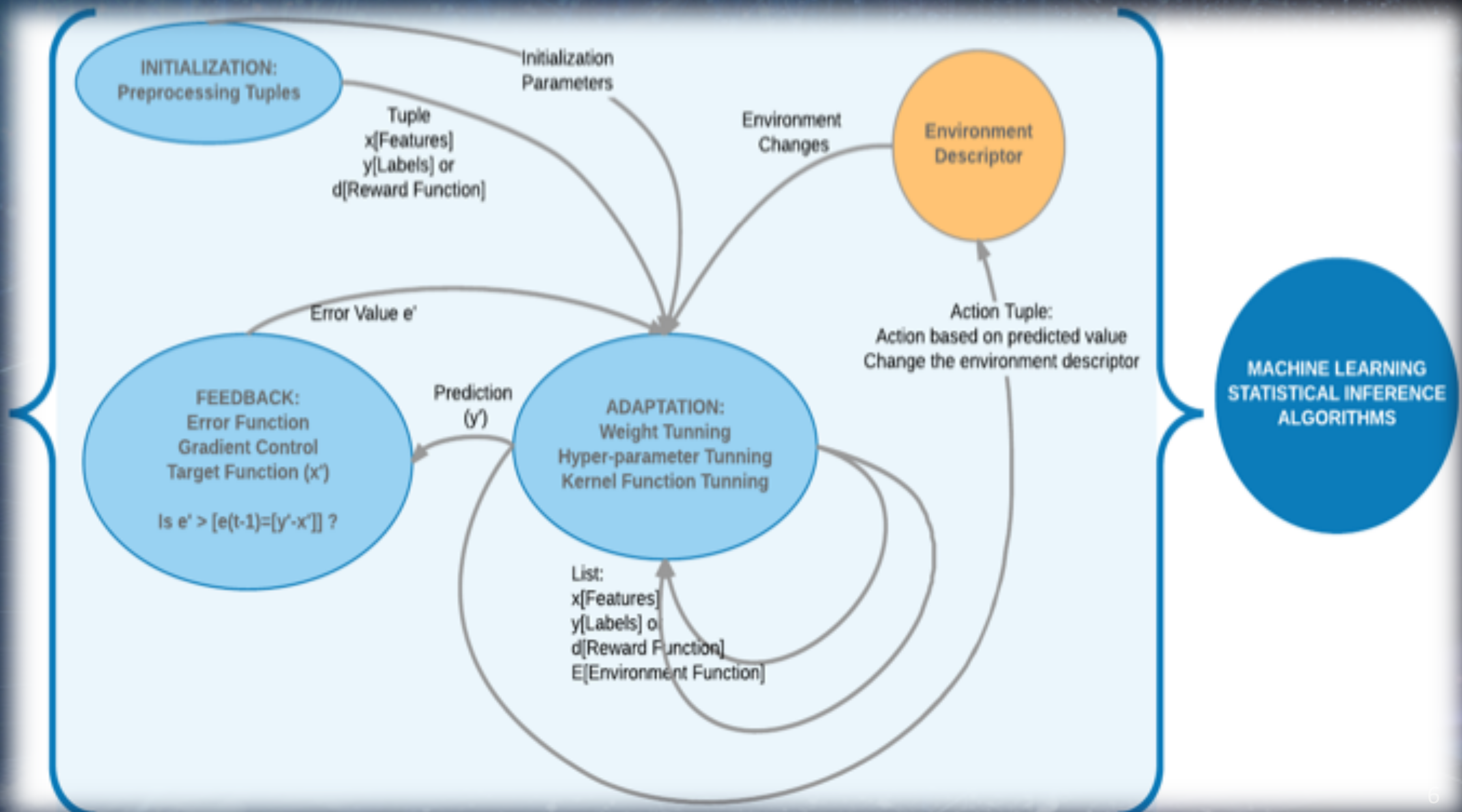
- Call preset models
- Call individual models
- Set mode for supervised, unsupervised or reinforcement and let the framework choose for you
- Create you own model from scratch if desired

Several Models Available under PALCHEMI

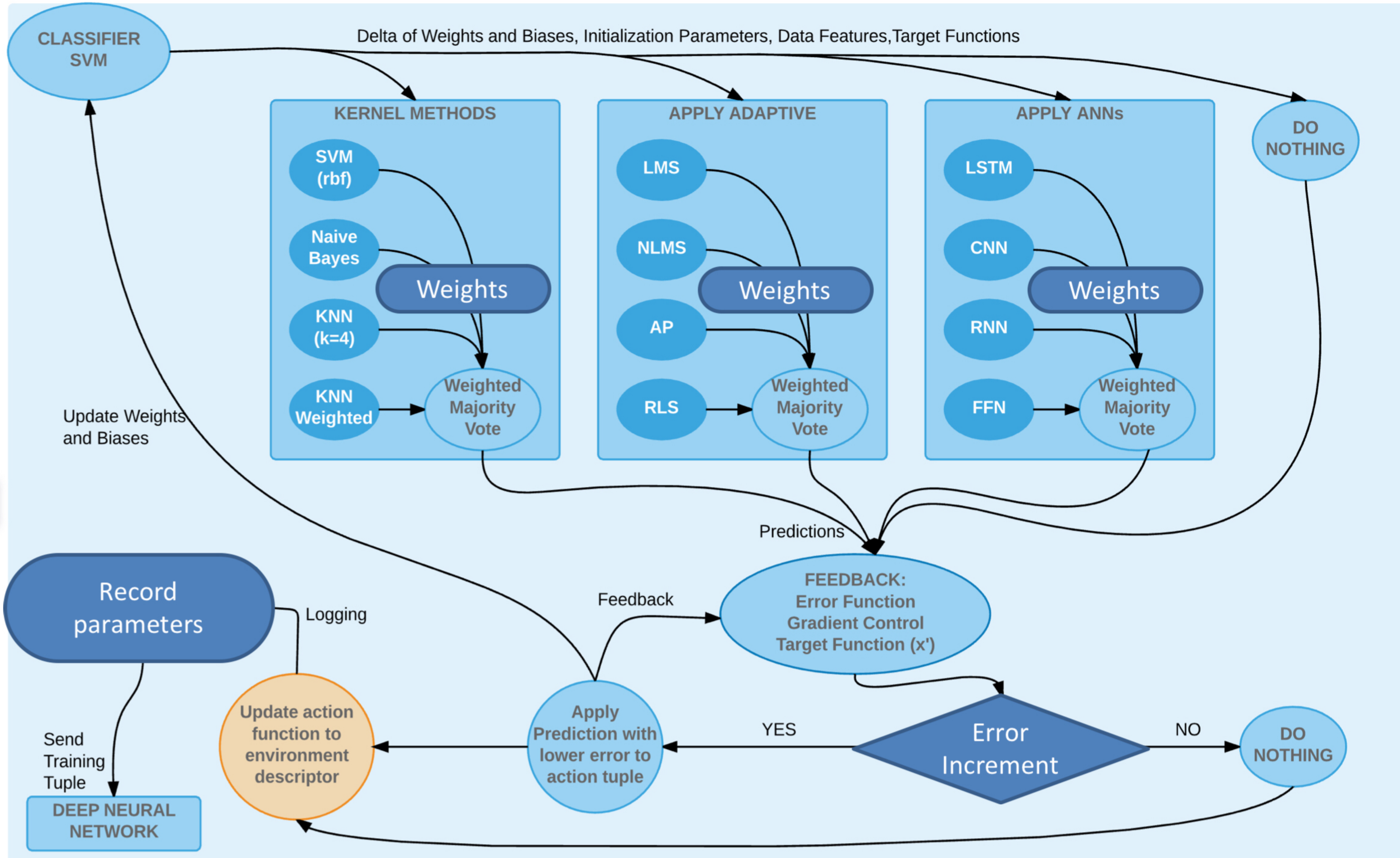
State Predictor of Classification (SPoC) — used for link analysis using kernel methods
Meta Brain for a embedded Cognition (MBEC) – used for unsupervised feature extraction
Transfer Learning for Node Optimization (TLNO) – used for reinforcement learning and DNNs

Decision Process

Task: Create a standard state machine for reaching decisions using ML models for all the presented cognitive engines.



Anatomy of a Cognitive Engine



State Predictor of Classification (SPoC)

The objective of this study is to utilize machine learning with link data from several experiments with SCaN testbed to determine heavy multi path fading and use that detection to change ModCod to avoid data loss.

- Relevance: This is a practical application of supervised machine learning to the characterization of space communication links, specifically the detection of unwanted states and taking the appropriate actions to mitigate the problem.

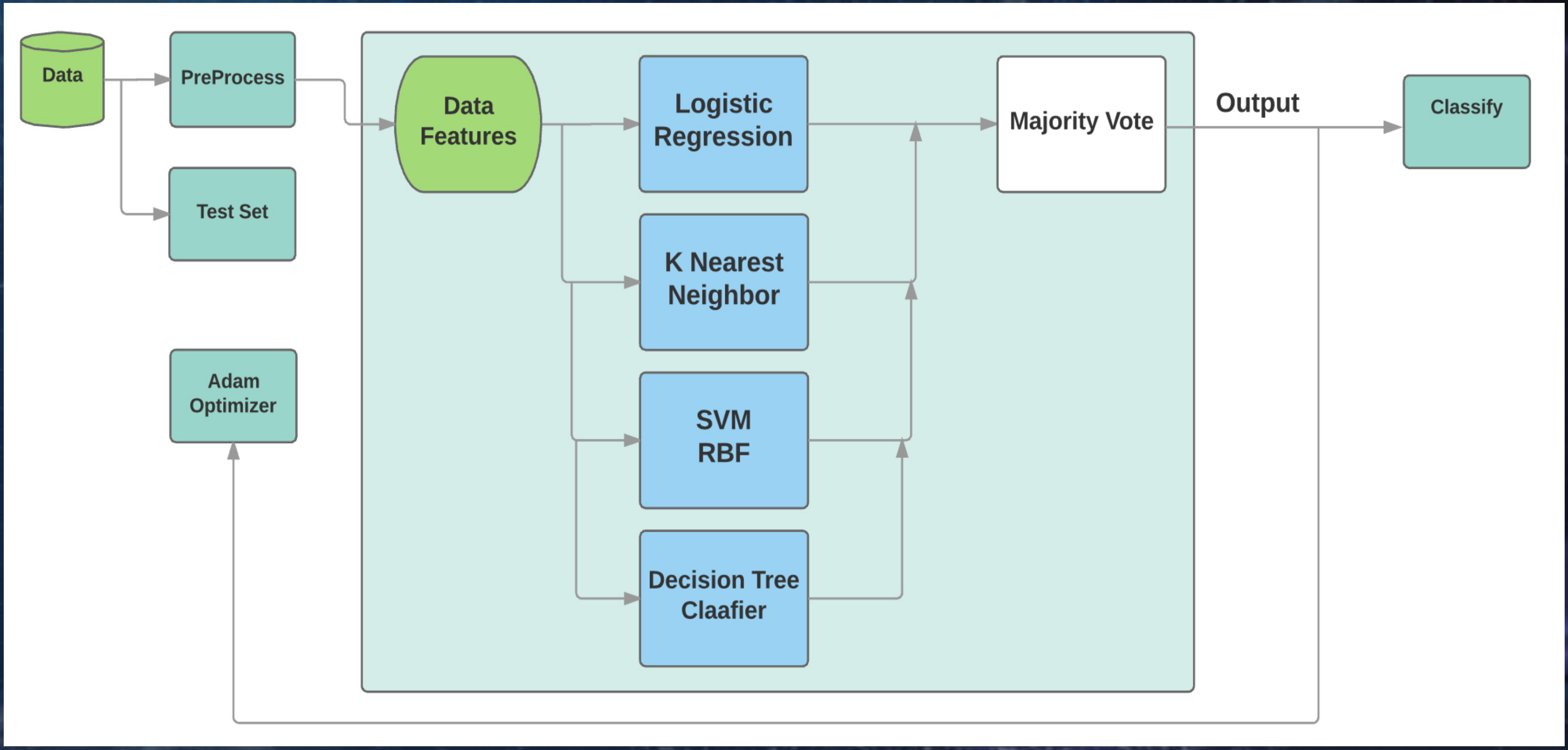
- Process:
  - The data was retrieved from ground station recordings of events conducted with testbed.
  - Using PALCHEMI, a model was created with restricted ensembles to minimize computational complexity, training time and prediction time.
  - A database of EsNo (dB) over time was created to train the model
  - The data was hand labeled with states and batched to sets of 100 samples :
    - The features selected are: mean, median, standard deviation and kurtosis.
  - The data was divided into a training and a testing set and the model was trained and optimized using cross validation

SPoC (Continued)

Task: Classify whether a channel is experiencing fading and change modulation encoding schematic to prevent data loss

- Use PALCHEMI's kernel methods ensemble with a fitting optimizer to Create the CE.

SPoC Architecture:



SPoC (Continued)

- A dataset was created of fading/no-fading events

- The model (SPoC) was trained on a subsection of that dataset

	precision	recall	f1-score	support
0	0.99	0.98	0.99	11493
1	0.98	0.99	0.99	13587
avg / total	0.99	0.99	0.99	25080

- The model was tested on untrained data with binary classification

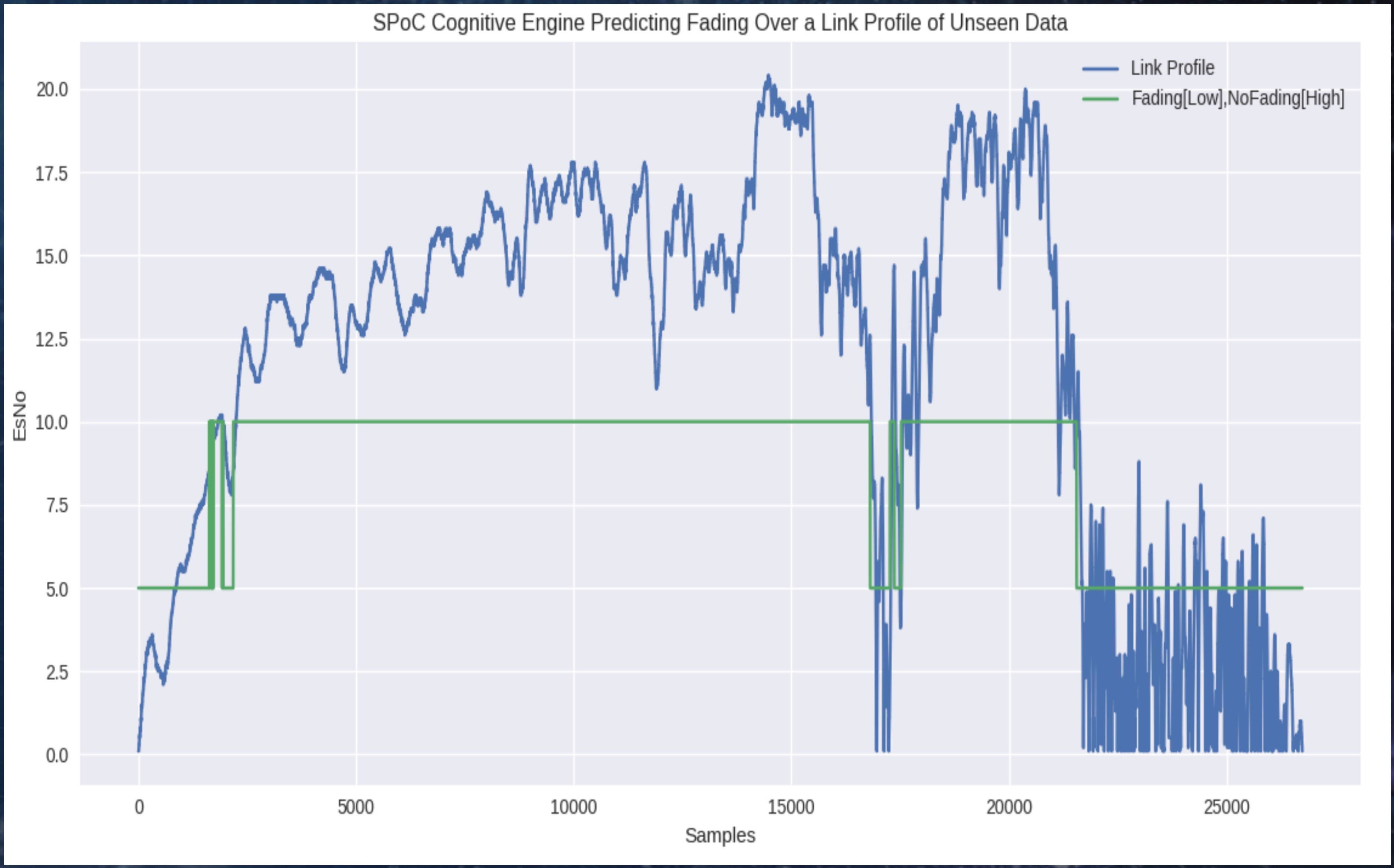
Confusion matrix:

True positives [[11279 214] **False positives**
False Negatives [73 13514]] **True Negatives**

- The model was placed with hardware in the loop to make decisions on an unknown channel running in real time

The experiment resulted in ZERO frames dropped over simulated events

SPoC Demo


SPoC Cognitive Engine Predicting Fading Over a Link Profile of Unseen Data
Link Profile
Fading[Low],NoFading[High]
EsNo
Samples
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
0
5000
10000
15000
20000
25000

Clustering Experiment Executive Summary

The objective of this study is to utilize propagation data from several ground stations around the world to create a clustering model able to predict expected values for link characteristics

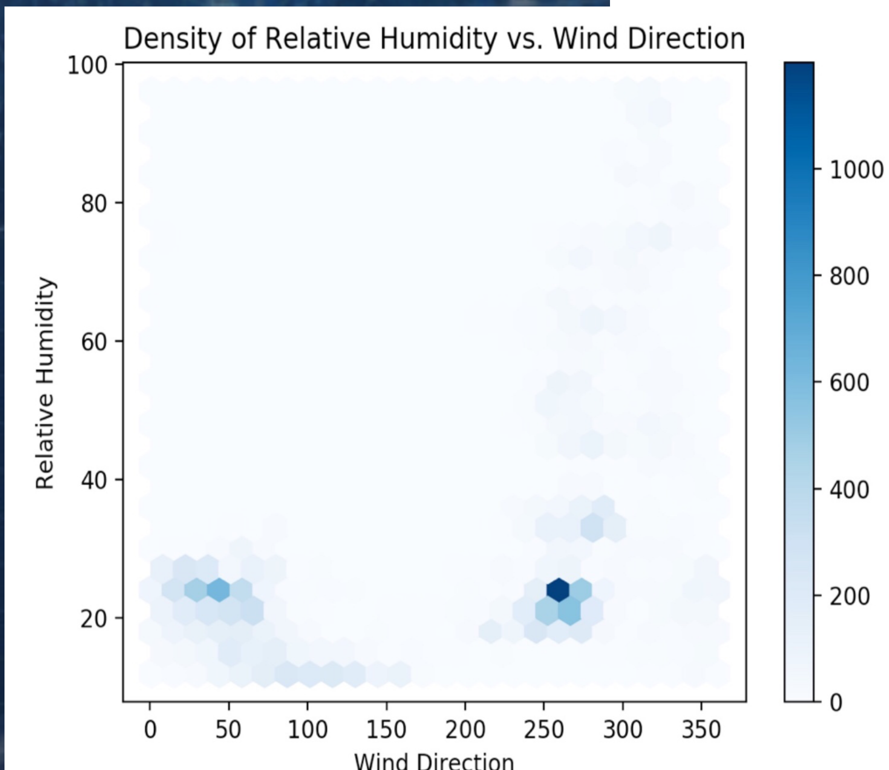
- **Relevance**: This is a practical application of unsupervised and semi-supervised machine learning to the characterization of communication systems, specifically the prediction of link characteristics directly from data.

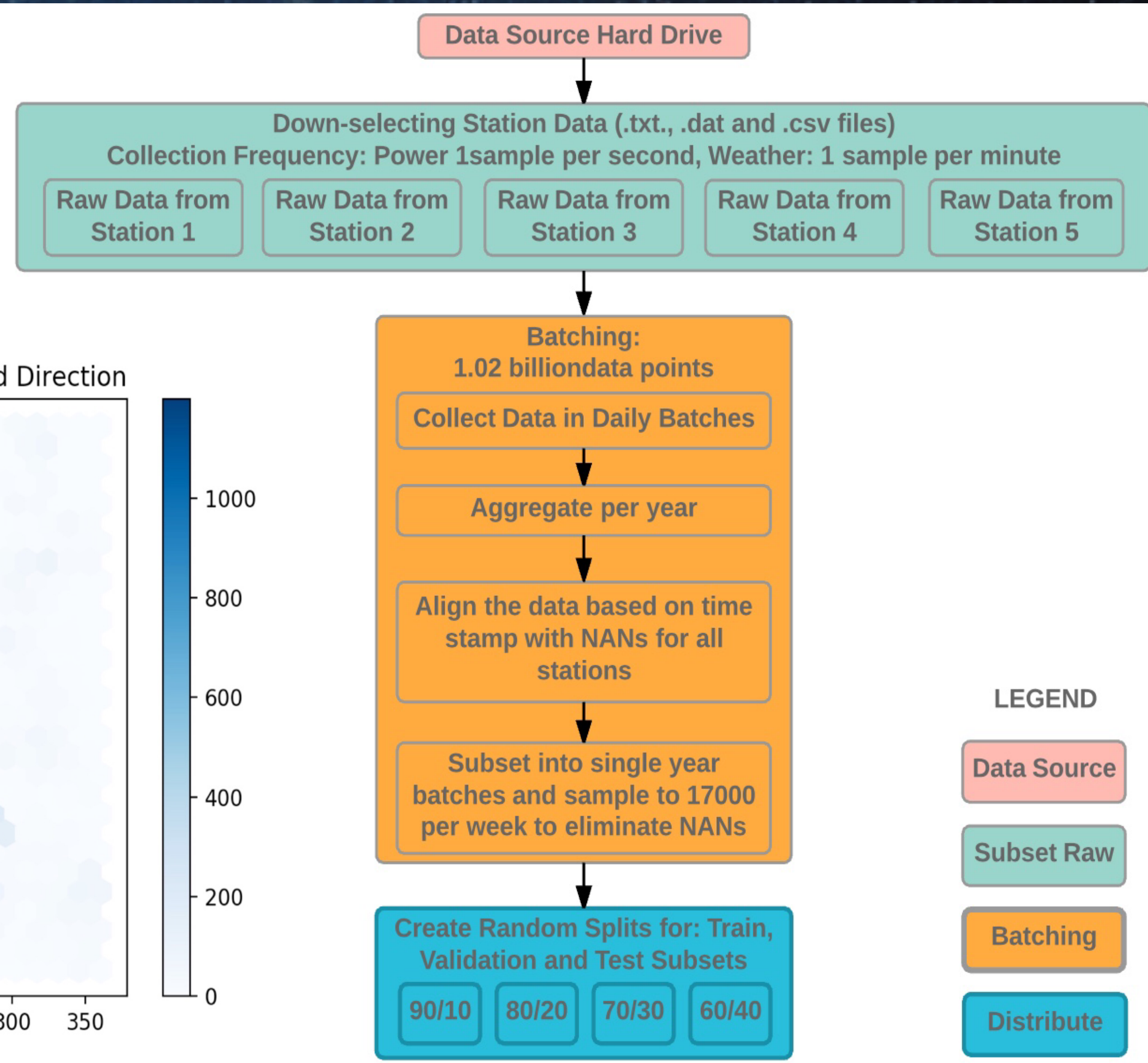
- **Process**:
  - The data was retrieved from ground station at Goldstone, Guam, Italy, Scotland, and White Sands.
  - Power and weather data from each station was selected for analysis.
  - Down selection, time alignment and null removals was performed
  - 17 million samples with 7 features were used:
    - The features are: power signal, air temperature, relative humidity, pressure, wind speed, wind direction, and rainfall.
  - The data was subset into weekly batches, and randomly sampled to 17000 samples.

Clustering
Semi-Supervised Analysis of Propagation

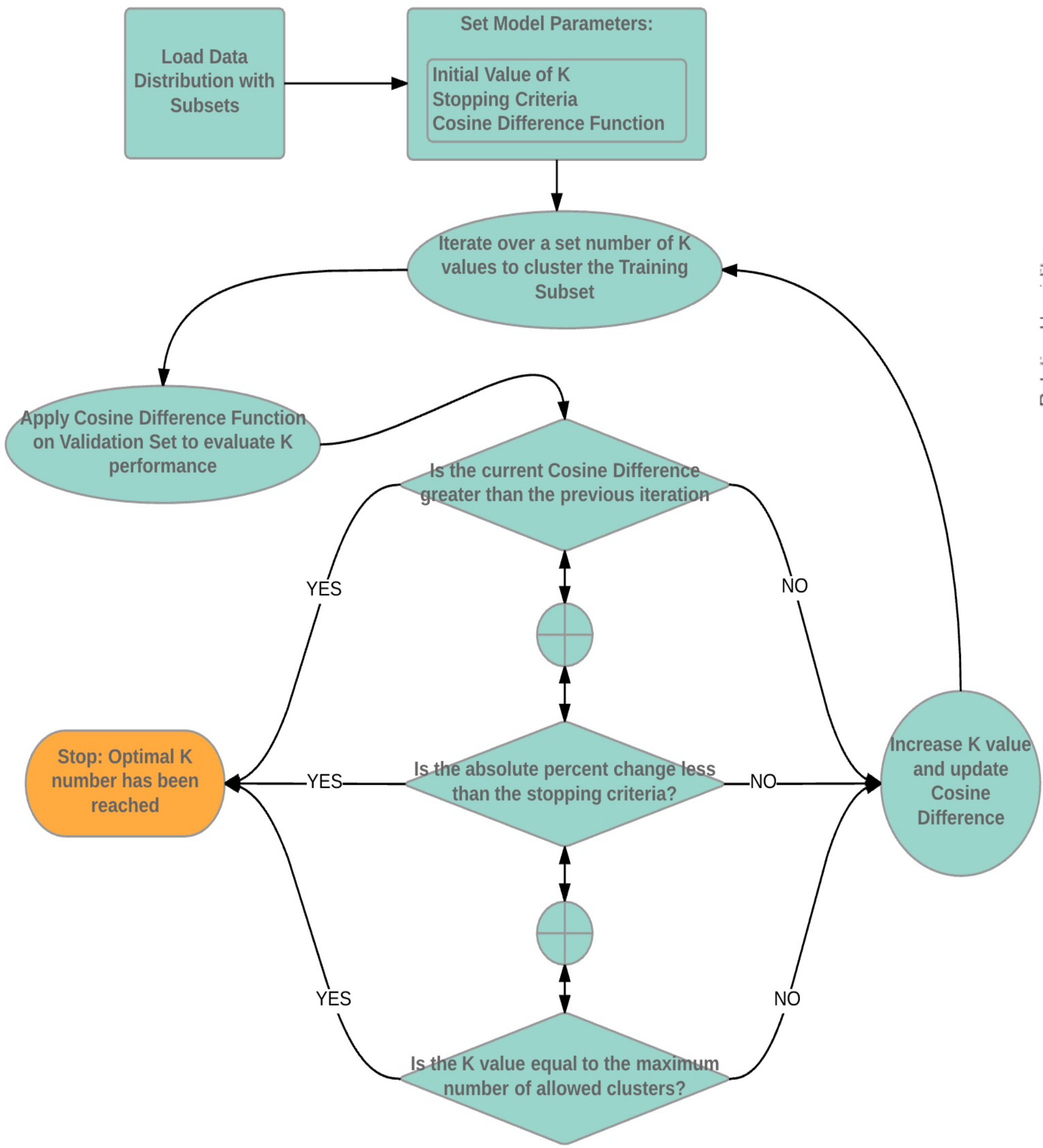
Date Pre-Processing:

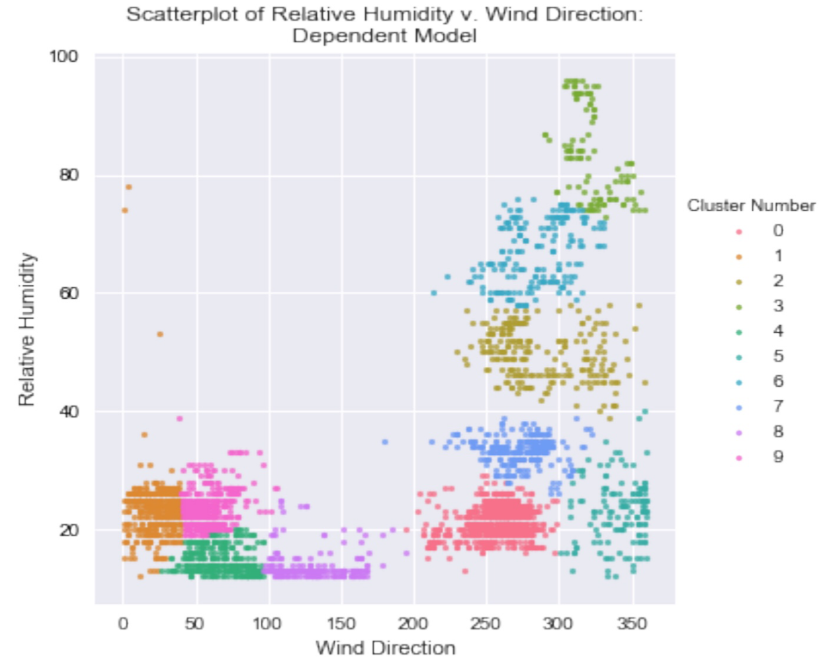
- Down-selection
- Batching
- Random Splits
- Data exploration

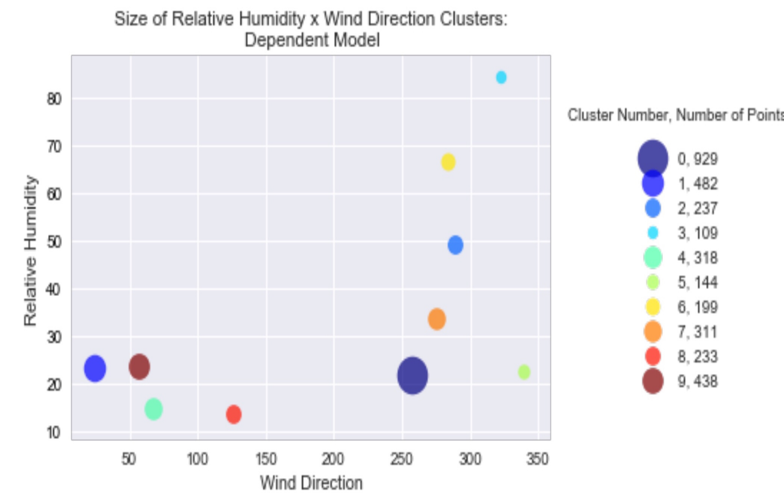




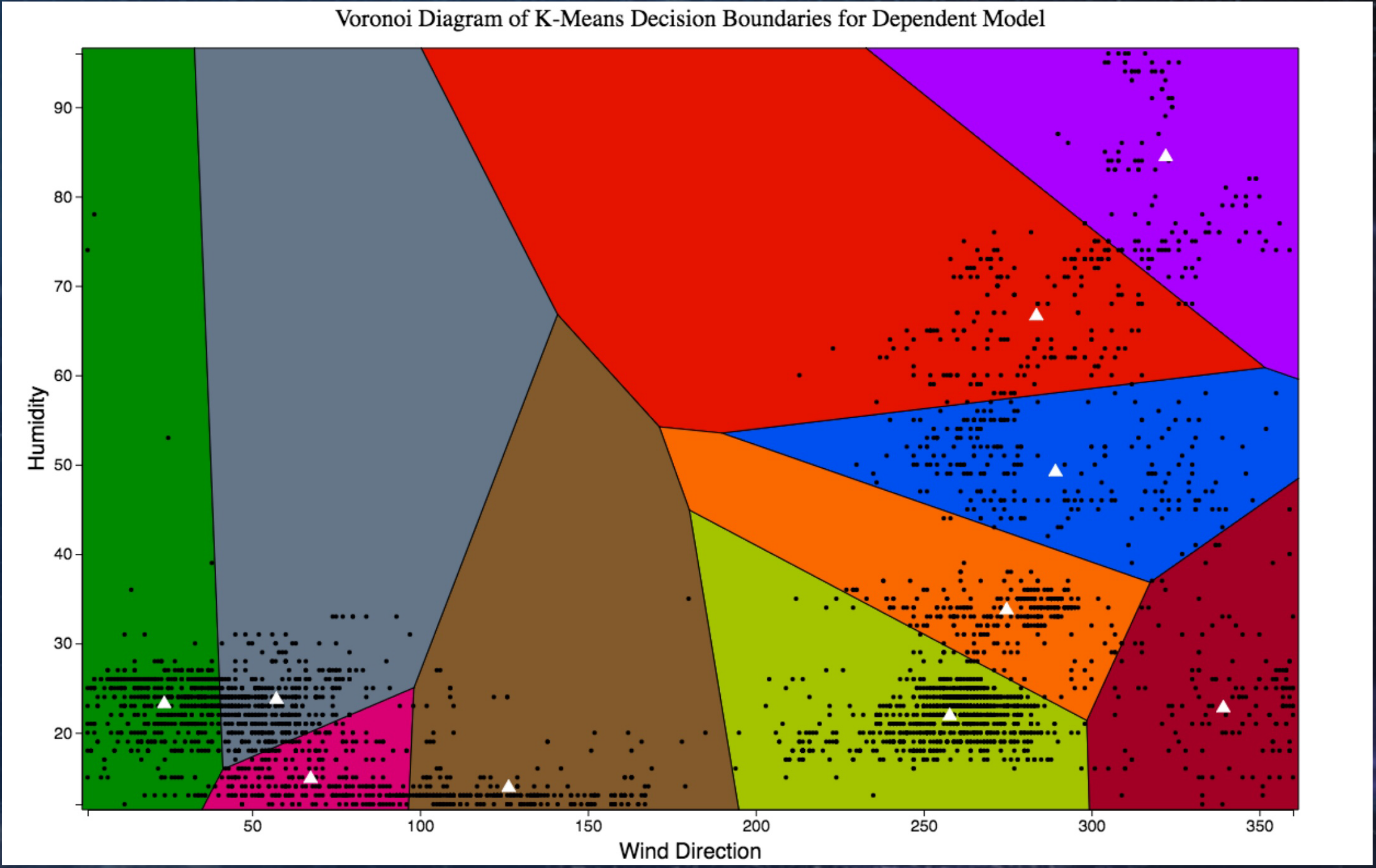
Clustering (Continued)







Clustering (Continued)



Future Experiments (2018)

Q1 2018

Meta Brain for Embedded Cognition (M-BEC) development box for having a unified hardware system, that can be used as a sandbox machine, for implementing statistical learnig methods. With standard ethernet IOs to control external systems, without having to actually be installed in those systems.

Q2 2018

The Transfer Learning for Node Optimization (TLNO) experiment will serve as a demonstration of the adaptation to different SDRs and controllers, performing networking and hopping activities

Q3 2018

Cognitive Communications Demonstrations GUI tool to explain to outside stakeholders what our algorithms are doing in the background, and how they are using data, alongside expert modeling, to come up with decisions.

Q4 2018

Multi Space Radio Control (MSRC) experiment.. to control multiple SDRs in the space environment and correctly optimize how these resources are used to change links in S-band and Ka-band.

Future Experiments (2019)

Q2 2019

Neuromorphic Application for Communication Systems (NACS) experiment to determine the feasibility of using TLNO and MBEC with neuromorphic hardware for machine learning in SWaP constrained environments

Q4 2019

Cube Satellite Smart Communications (CSSC) experiment to demonstrate the application of statistical learning systems in space-to-space communications.

Q4 2019

Reinforcement Learning System Control (RLSC) experiment to control multiple RF and optical space-to-ground links in multiple ground stations around the world.

Thank You!