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Geolocating Particulate Filters from the IMS Based on Machine Learning as a Means of Identifying Anomalies

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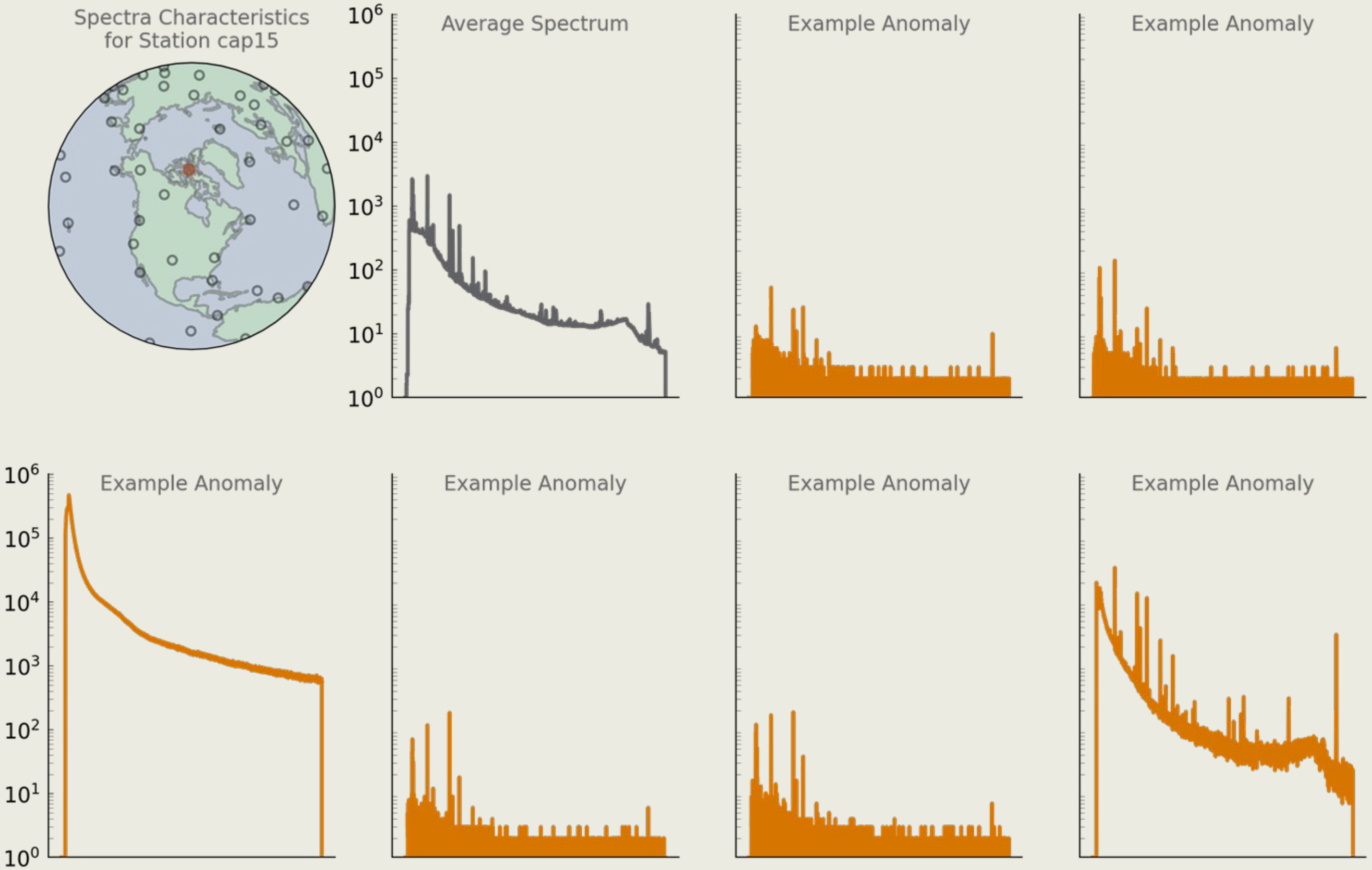
Motivation

- Data quality is fundamental to International Monitoring System (IMS) operation, but data corruption, mistakes, or detector degradation impact system operational effectiveness

- Automated data quality monitoring is needed

- The following case study was performed on particulate spectra data



Several example anomalies in reported spectra from station cap15

Supervised Learning

We utilized supervised learning, i.e., machine learning where the network is trained on labelled data

-To do this we used a randomly-selected 80% of the data from 5 years for 29 stations (> 200k spectra)

-Verification done with the remaining 20% of the data

-Needed to make all spectra have 8192 channels

-The goal of the training is to minimize the difference between actual and predicted values

We trained neural networks to:

- Predict the location from a spectrum: network produces a location on the globe and minimizes the haversine distance from the prediction to the real location
- Predict the station from a spectrum: station classification was done by cross entropy, i.e., measuring the difference between two probability distributions

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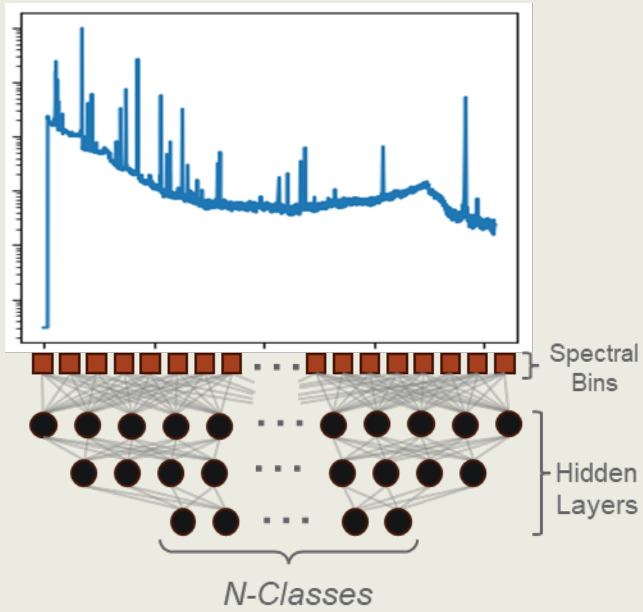
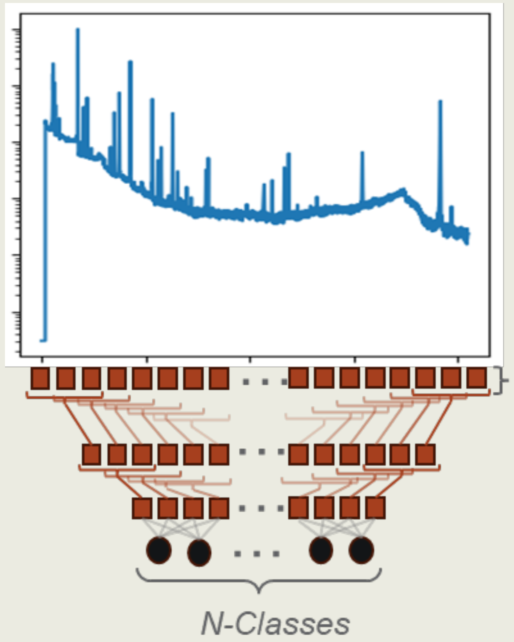
3 Neural Network Types Tried

Multilayer Perceptron



Convolutional Neural Network



Multilayer Perceptron – fully connected neurons, i.e., information from every channel connected to others immediately

Convolutional Neural Network – less computational; good at learning features through filter optimization

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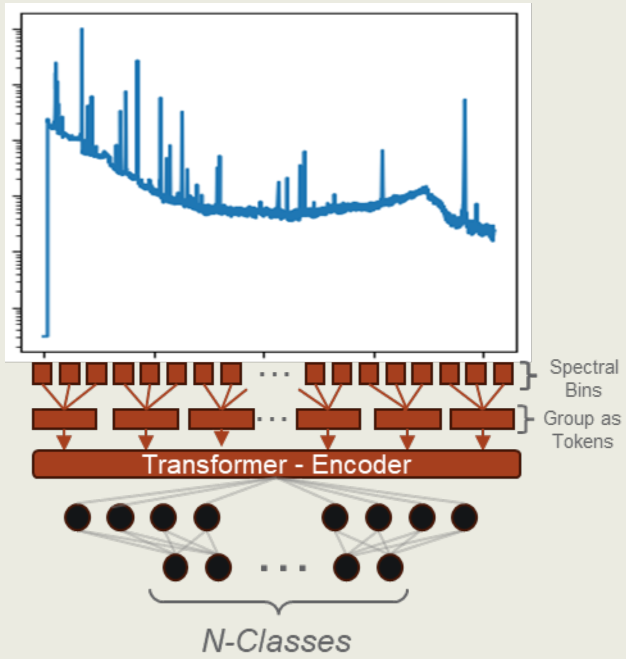
3 Neural Network Types Tried

Transformer



Transformer – newer machine learning approach; can be trained on data with different numbers of channels since the data is grouped

Results were about the same, no matter which neural network type used

>95% of location predictions within 150 km of true location (station)

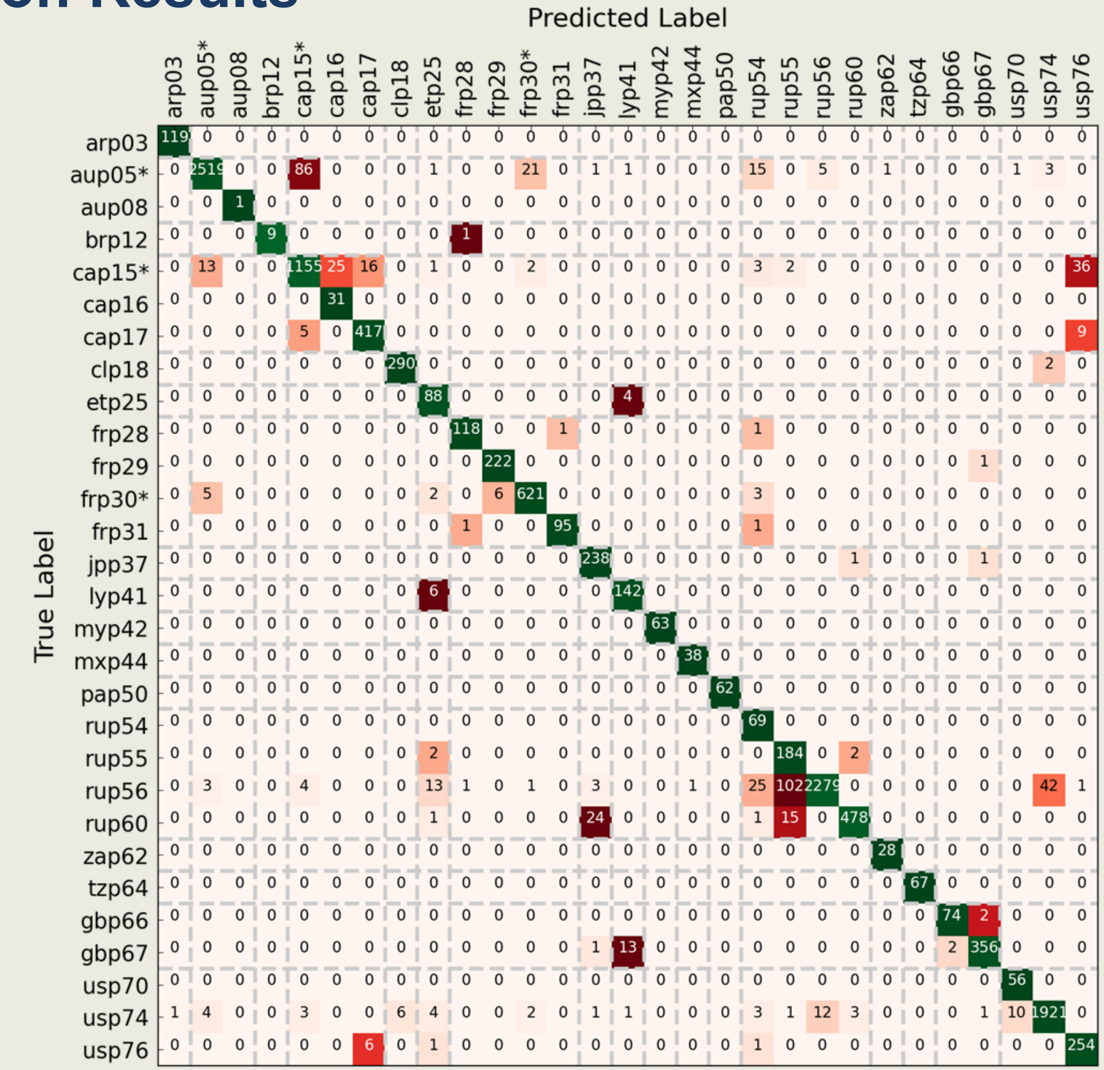
97% station classification performance

Localization Results

- Confusion matrix showing predicted station on x-axis and true station on y-axis

- White to red to purple on the off-diagonals shows the misclassifications (largest are 5-10%)

- Misidentifications are generally within a country or close region

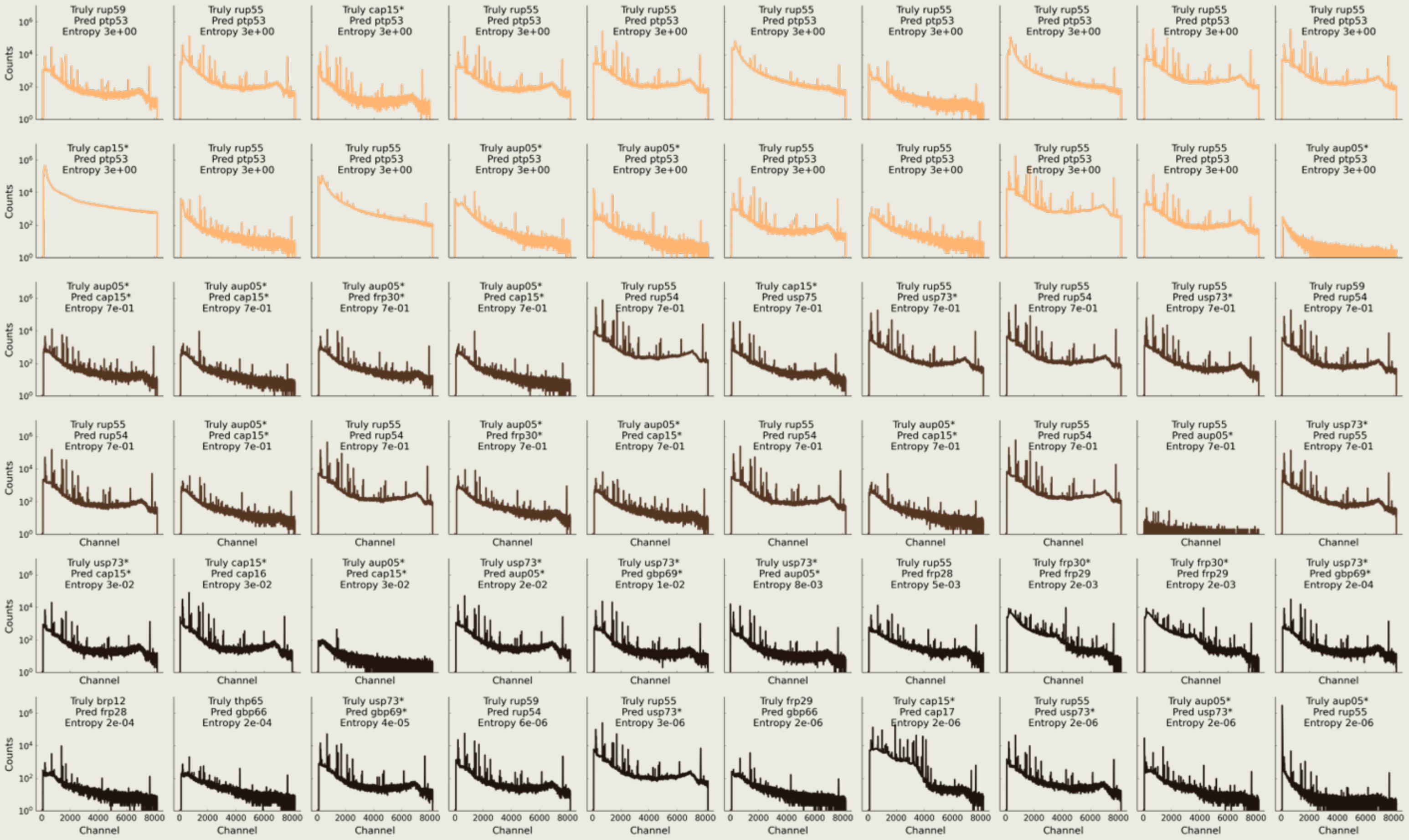


	arp03	aup05*	aup08	brp12	cap15*	cap16	cap17	clp18	etp25	frp28	frp29	frp30*	frp31	jpp37	lyp41	myp42	mxp44	pap50	rup54	rup55	rup56	rup60	zap62	tzp64	gbp66	gbp67	usp70	usp74	usp76
arp03	119	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
aup05*	0	2519	0	0	86	0	0	0	1	0	0	21	0	1	1	0	0	0	15	0	5	0	1	0	0	0	1	3	0
aup08	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
brp12	0	0	0	9	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
cap15*	0	13	0	0	1155	25	16	0	1	0	0	2	0	0	0	0	0	0	3	2	0	0	0	0	0	0	0	0	36
cap16	0	0	0	0	0	31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
cap17	0	0	0	0	5	0	417	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9
clp18	0	0	0	0	0	0	0	290	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0
etp25	0	0	0	0	0	0	0	0	88	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0
frp28	0	0	0	0	0	0	0	0	0	118	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
frp29	0	0	0	0	0	0	0	0	0	0	222	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
frp30*	0	5	0	0	0	0	0	0	2	0	6	621	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0
frp31	0	0	0	0	0	0	0	0	0	1	0	0	95	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
jpp37	0	0	0	0	0	0	0	0	0	0	0	0	0	238	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0
lyp41	0	0	0	0	0	0	0	0	6	0	0	0	0	0	142	0	0	0	0	0	0	0	0	0	0	0	0	0	0
myp42	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	63	0	0	0	0	0	0	0	0	0	0	0	0	0
mxp44	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	38	0	0	0	0	0	0	0	0	0	0	0	0
pap50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	62	0	0	0	0	0	0	0	0	0	0	0
rup54	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	69	0	0	0	0	0	0	0	0	0	0
rup55	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	184	0	2	0	0	0	0	0	0	0
rup56	0	3	0	0	4	0	0	0	13	1	0	1	0	3	0	0	1	0	25	102	2279	0	0	0	0	0	0	42	1
rup60	0	0	0	0	0	0	0	0	1	0	0	0	0	24	0	0	0	0	1	15	0	478	0	0	0	0	0	0	0
zap62	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	28	0	0	0	0	0	0
tzp64	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	67	0	0	0	0	0
gbp66	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	74	2	0	0	0
gbp67	0	0	0	0	0	0	0	0	0	0	0	0	0	1	13	0	0	0	0	0	0	0	0	0	2	356	0	0	0
usp70	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	56	0	0
usp74	1	4	0	0	3	0	0	6	4	0	0	2	0	1	1	0	0	0	3	1	12	3	0	0	0	1	10	1921	0
usp76	0	0	0	0	0	0	6	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	254

Mispredicted Spectra: Electronic vs. Nuclides

- Electronic issues led to higher entropy predictions – low prediction confidence

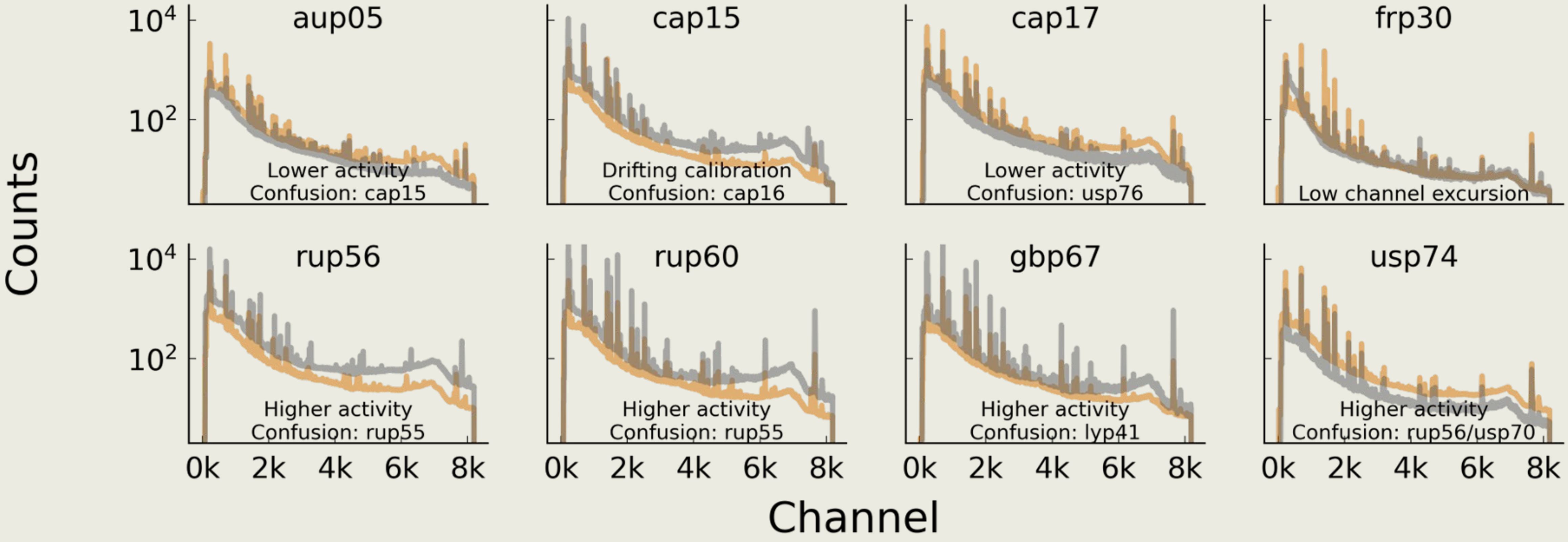
- Nuclide differences lead to low entropy predictions – confident predictions of wrong station



Darker spectrum -> lower entropy, but all are mispredictions

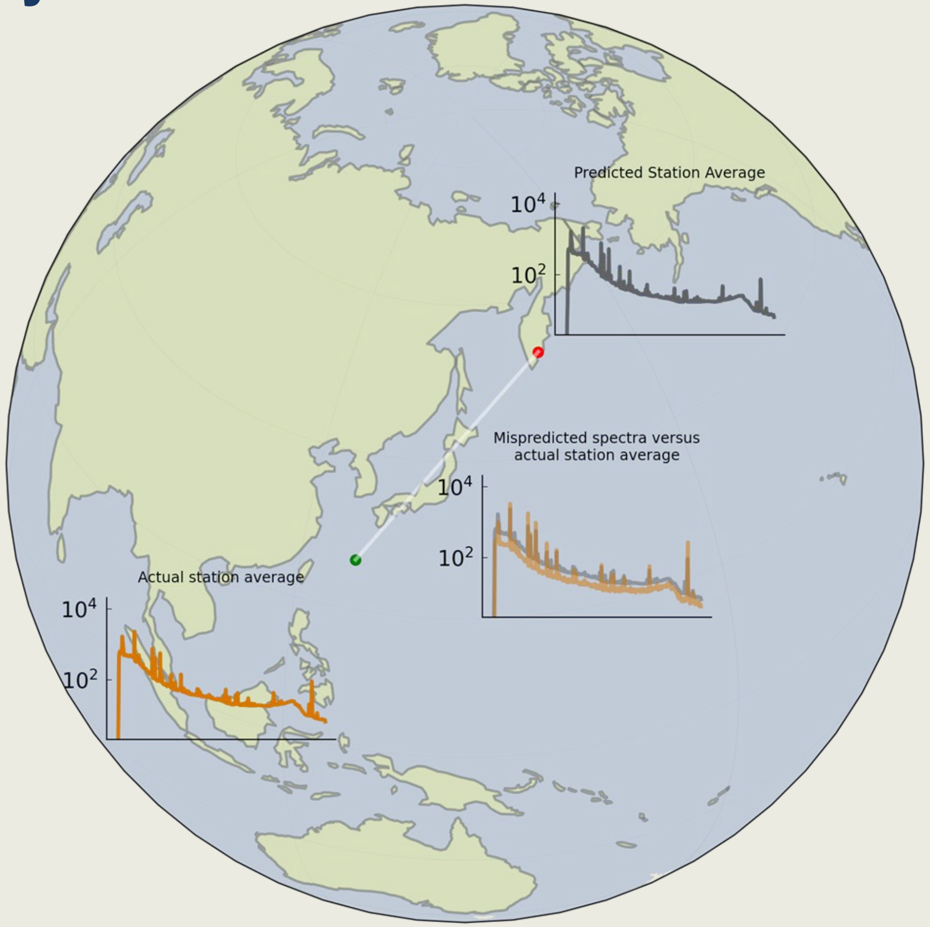
Closer Look at Mispredictions

Comparison of average mispredicted spectrum (grey) vs. predicted spectrum (orange) for stations with more than 10 mispredictions as another station



Operational Anomaly Detection

- Automated Triage
  - Data quality
  - Data corruption
  - Detector issues and changes
- Station expectations
  - Nuclides
  - Overall activity
- Connections to ATM and climatic regions could provide further context
- Classification success implies the ability to compare sets of stations or readings for trend analysis or event analysis


Predicted Station Average
10^4
10^2
Mispredicted spectra versus actual station average
10^4
10^2
Actual station average
10^4
10^2

Automated identification of spectra more indicative of another station is followed by human triage

Machine Learning Operations

- Supervised learning (SL) is ideal for
  - Automation of “easy tasks”
  - Metrics
  - Effect detection
- Operationalization of SL requires
  - Alignment with mission metrics
  - Dimension reduction
  - Input monitoring and alerting
  - Automated retraining
- Risks
  - Input drift, e.g. change in expected nuclides change, detectors change
  - *Often, you must start from scratch*

Alternatives

- Unsupervised Learning (UL)
  - Dimensions reduced and combined into a representation with appropriate invariances
  - Two sample tests or other statistical techniques performed on dimension reduced space
- Machine learning guided signature discovery
  - Techniques like the previously presented identify features which can be used without ML in the future

Conclusions

- Particulate spectra reported to the IDC may have anomalous or corrupted data from
    - Electronic and maintenance state of the detector
    - Reporting issues
    - Other
- Assuring the authenticity and quality of data is critical to the IMS performance
- Particulate spectra contain information about location and time of measurement
- Supervised neural networks can predict originating station by evaluating raw spectra
- Prediction performance is 97% by station classification, 95% by location regression
- Mispredictions often indicative of anomalous spectra
- High performance implies a high information content in spectra and possibilities for later, more advanced analyses