Unravelling Machine Learning, Anomaly Detection, and Collaborative Intelligence

Zhuowei Wang

Australia’s National Science Agency

Presentation Outline

Machine Learning and Deep Learning

Anomaly Detection

Collaborative Intelligence (CINTEL)


Image of a single ASKAP antenna, CSIRO

Presentation Outline

- Machine Learning and Deep Learning
- Anomaly Detection
- Collaborative Intelligence (CINTEL)

Image Classification in Space

Main challenge

- Lack of large-scale dataset
- Large amounts of unlabeled data

Unsupervised learning

- Discover unknown radio morphologies,
- Astronomical Society of Australia

Semi-supervised

- Reduce the amount of manual labelling for effective radio galaxy morphology classification.

Anomaly Detection in Space

- **In space setting:**
  - Reducing false positives in satellite systems, CIKM 2020
  - Time series anomaly detection, IGARSS 2021
- **Main questions**
  - Human-AI collaboration workflow
  - Usefulness and usability of such a system

Object Detection in Space

01 Locating and classifying an object based on predefined categories

02 Datasets

- DOTA, Aerial Images
- xView, Overhead Imagery
- SpaceNet, Remote Sensing

03 Main challenges

- Ultra-high image resolutions
- Extreme class imbalances
- Sparse annotations

Object Detection in Space

05 Two-stage detectors

- Faster RCNN, Cascade RCNN
- More accurate, more robust
- Better at small- resolution objects in the space setting

06 One-stage detectors

- YOLO, SSD
- Faster at the cost of lower accuracy

Semantic Segmentation in Space

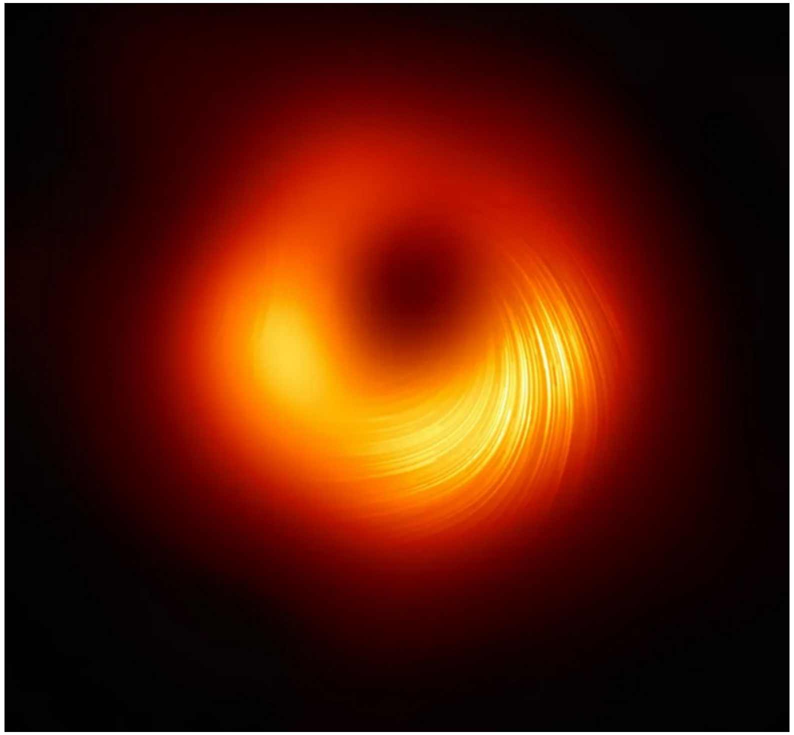
Learning a class label for each pixel in an image

- Deep Convolutional Networks (DCNs)
- Probabilistic Graphical Models

Same challenges as object detection

- Low quality of data
- High density of objects in an image

Federated Learning v.s. Space: an analogy



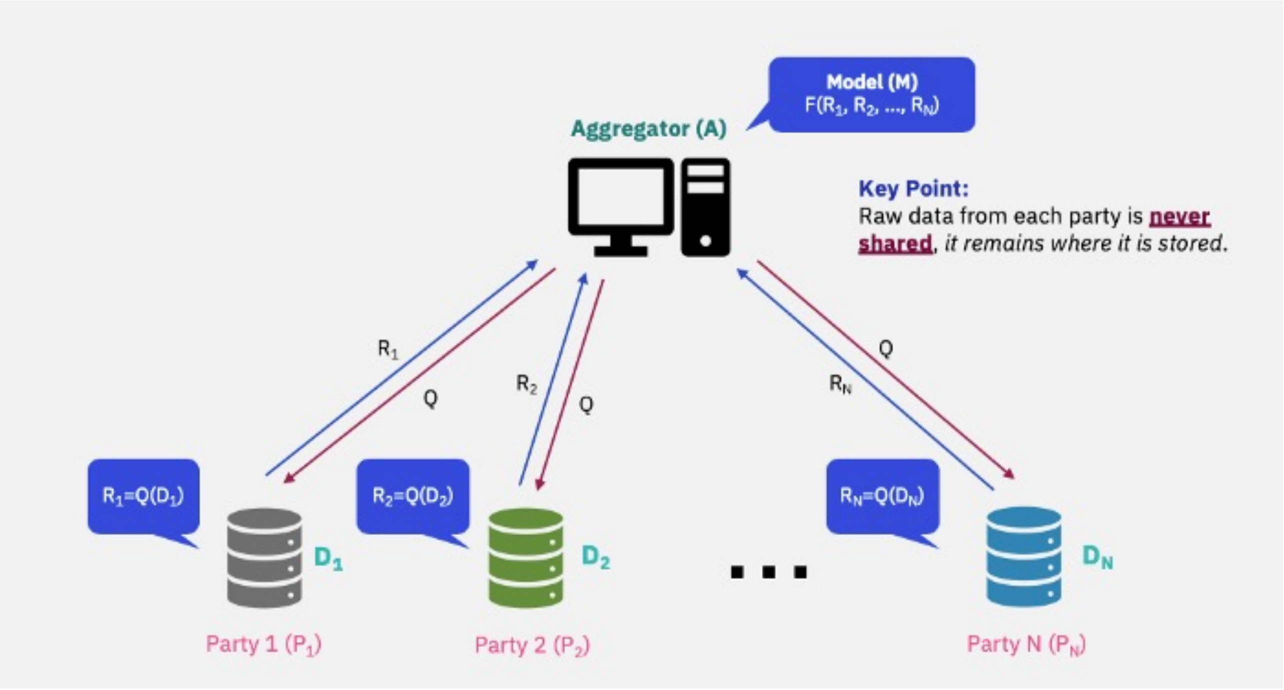
The first ever image of a black hole produced by The Event Horizon Telescope (EHT)

- Observe blackhole
- Scientists require a single disk telescope that needs to be as big as the size of the earth!
- Instead, a network of telescopes was brought together from across the world
  - The Event Horizon Telescope
  - An aperture of the same diameter as that of the earth

Federated Learning

- Explore **decentralised data** and **decentralised computing power**
- Provide a more personalized experience
- Without compromising on **user privacy**

Image retrieved from IBM Data Science: the framework of FL



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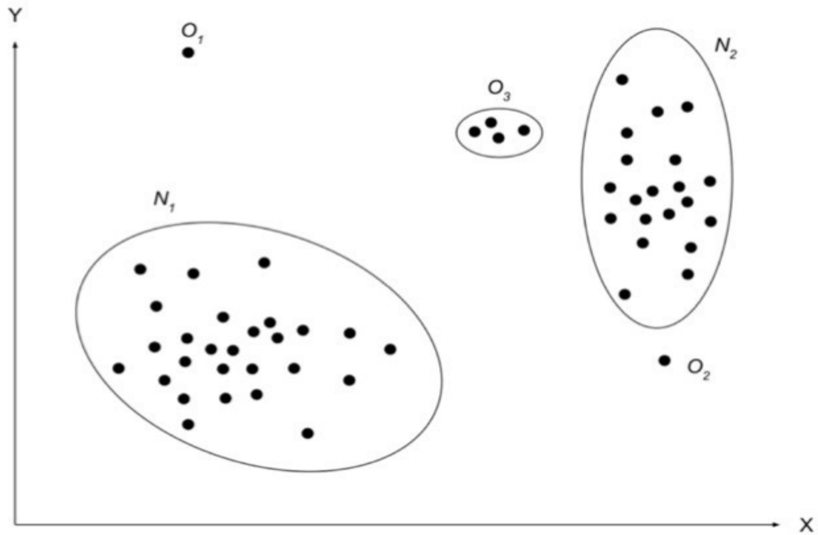
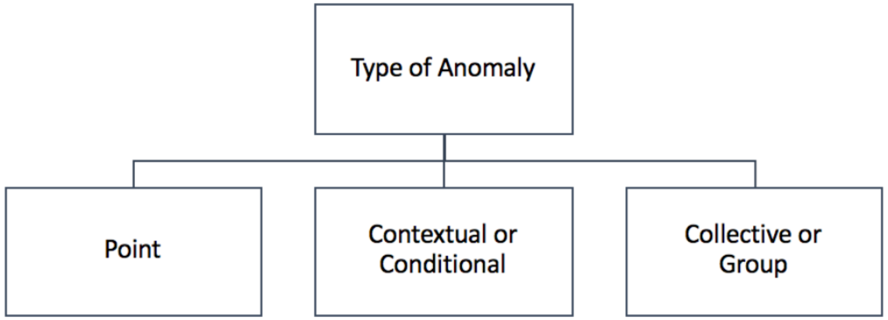
What are anomalies

An observation that deviates so significantly from other observations as to arouse suspicion that it was generated by a different mechanism. Also called outliers, novelties.



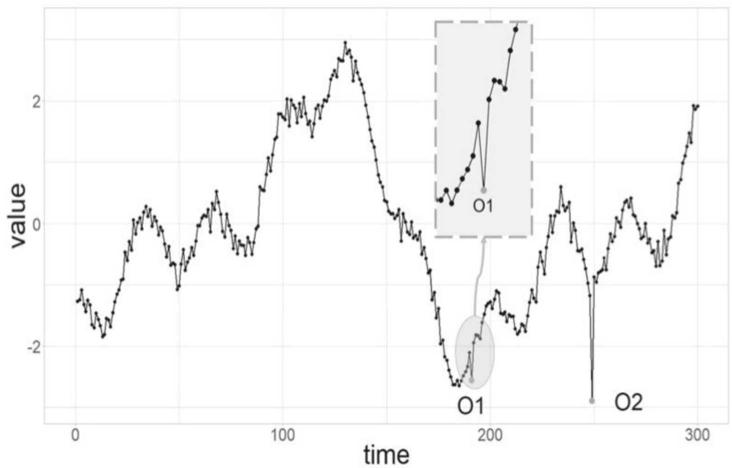
Types of anomalies



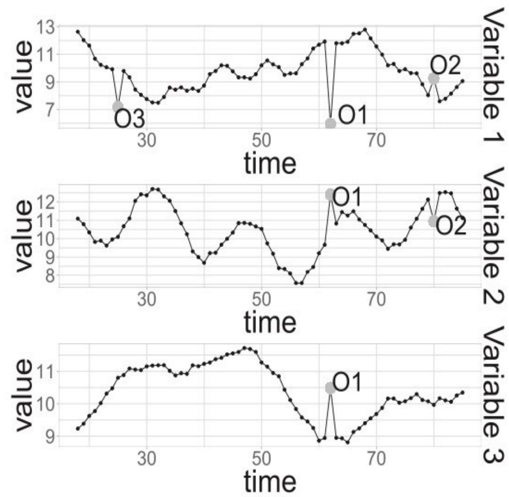
May-22	1:14 pm	FOOD	Monaco Café	$1,127.80	Point Anomaly
May-22	2:14 pm	WINE	Wine Bistro	$28.00	
...					
Jun-14	2:14 pm	MISC	Mobil Mart	$75.00	
Jun-14	2:05 pm	MISC	Mobil Mart	$75.00	
Jun-15	2:06 pm	MISC	Mobil Mart	$75.00	
Jun-15	11:49 pm	MISC	Mobil Mart	$75.00	
May-28	6:14 pm	WINE	Acton shop	$31.00	Collective Anomaly
May-29	8:39 pm	FOOD	Crossroads	$128.00	
Jun-16	11:14 am	MISC	Mobil Mart	$75.00	
Jun-16	11:49 am	MISC	Mobil Mart	$75.00	

Time Series Anomaly Detection

Time series



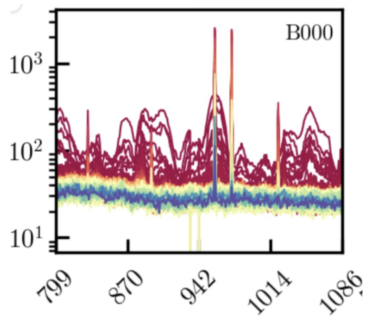
(a) Univariate time series.



(b) Multivariate time series.

ASKAP Datasets: Diagnostic

channel	bl0	bl1	bl2	bl3	bl4	bl5	bl6	bl7	bl8	bl9	bl10
0	196.4119908	126.6023951	170.6465873	243.1849962	105.5455237	57.48388899	81.71041553	65.12605614	50.86755767	57.5821205	48.40226953
1	212.8483102	135.8646901	172.3574354	260.6357737	133.8869789	56.94442317	104.003129	58.2638159	60.69694246	67.31118228	48.82873188
2	212.2061589	120.4141095	161.1380493	292.4515861	129.7958714	66.07854387	96.61642325	67.90514878	61.51475604	62.91717057	53.36631269
3	224.3845515	117.0524579	166.1957103	294.5611172	106.3538167	58.49560482	90.97509031	61.69322906	60.19500511	61.0394912	54.80038878
4	238.7028649	114.5779081	163.2726648	304.0740749	129.977944	60.81779123	96.17481029	57.28166842	61.97201699	68.57664744	50.32958139
5	239.564796	100.8786311	179.5808434	286.9137286	122.8564313	66.97142726	102.0749106	52.88799447	57.11981371	65.80476784	53.31496391
6	205.7455041	103.4643594	164.6133584	275.9637609	119.3547133	68.71163321	106.5444827	61.44930487	58.69612159	60.25101677	48.85449558
7	205.3992359	106.0016437	161.8111751	255.0241424	105.6818561	61.16905961	94.60579244	61.33883308	61.24439892	61.98716986	50.21951795
8	193.0553278	89.98085173	138.7663559	216.9792489	99.1216327	66.04721377	96.27093225	58.62264751	62.61826592	56.05982252	53.96919254
9	175.14149	82.41004954	141.1904653	218.8029445	87.01797441	64.65804208	99.18998007	52.48929001	55.94676851	65.71633835	58.95115
10	169.5086401	83.29180597	142.9230216	235.9708824	93.88733481	73.4719987	92.36048312	57.96426025	59.25688259	73.27877214	57.9497338
11	160.2447665	85.30867657	134.3358192	216.5223014	87.45853524	71.58803002	87.3051453	67.04381037	55.58420488	61.78497371	56.69992587
12	134.8281245	93.62616567	136.5219329	206.1011239	94.82459745	72.45016662	73.81198224	68.58270084	55.48859577	54.26060603	56.95451462
13	152.1123755	89.538508	132.1629496	189.6532803	81.84071494	70.72726676	74.80790152	61.69326739	64.07389005	69.40316574	62.42024059
14	146.4693485	85.28560268	108.7600083	156.4575287	91.74748918	63.57979727	82.32633827	63.33657527	53.25228479	62.14991686	60.71655433
15	136.0828512	83.71178136	97.32699742	146.0425763	86.69660397	69.49907246	73.8589447	65.86112269	60.92866365	55.80179366	62.74867472
16	127.9363801	77.70660513	91.32504707	139.4626776	72.63196028	62.47974536	68.30148581	55.58369885	56.78781547	61.96419431	52.88695618
17	123.929884	80.45868301	93.17876967	130.5943788	78.35828505	67.14793599	63.71341789	63.87926471	52.39182702	54.7604017	62.50202209
18	108.6676972	76.20877337	91.86810147	125.400577	63.58605195	58.67624391	52.48236467	67.12910281	64.35923614	60.41096003	47.88842278
19	114.5967059	74.15543626	88.03889647	94.64930209	70.10022282	69.7789439	64.51047822	55.71212923	55.47903498	51.41516855	52.28729468
20	105.4126129	60.62189717	82.02002734	89.79972691	71.47413421	59.5786705	53.90902383	56.92351945	47.88946998	57.10410428	50.65265222
21	91.11000542	61.71036239	76.0300914	88.34285826	70.07759077	52.61422468	51.45000573	55.92687814	41.39256119	49.88803709	52.4012867
22	99.42506214	67.77823364	67.44809771	90.31444121	56.40622645	50.821244	50.85252545	54.13618032	50.16470201	47.22725408	49.00979225
23	84.91182514	66.30463856	73.12697316	86.01209811	64.04837403	58.73543966	58.72169738	46.71985101	50.48021356	57.91450692	46.95540037
24	83.36601231	62.98753137	67.48767658	77.33535782	61.13900577	52.64001239	57.5331416	50.24212779	54.21016411	43.81618796	49.77043471
25	84.1505253	55.83063058	68.81059612	87.97892055	55.4973938	51.95808419	51.76158288	45.92123182	47.8357991	51.74089796	50.46972319
26	72.79194012	53.90426988	85.9517325	91.04945698	53.62908577	57.27861431	54.41117205	52.37327982	45.96637067	50.26662647	50.33255939



ASKAP Datasets: Monitoring

result	table	_time	_value	_field	_measurement	chiller	units
	0	2021-02-16T07:21:07.026Z	25	chiller_ChilledWaterDiffPressLowAlmVal	bms.chiller.kPa	chill01	kPa
	0	2021-02-19T01:30:41.802Z	25	chiller_ChilledWaterDiffPressLowAlmVal	bms.chiller.kPa	chill01	kPa
	0	2021-02-22T04:38:55.497Z	25	chiller_ChilledWaterDiffPressLowAlmVal	bms.chiller.kPa	chill01	kPa
	0	2021-02-22T07:22:17.951Z	25	chiller_ChilledWaterDiffPressLowAlmVal	bms.chiller.kPa	chill01	kPa
	0	2021-02-23T06:15:40.695Z	25	chiller_ChilledWaterDiffPressLowAlmVal	bms.chiller.kPa	chill01	kPa
	0	2021-03-02T03:33:11.56Z	25	chiller_ChilledWaterDiffPressLowAlmVal	bms.chiller.kPa	chill01	kPa
	0	2021-03-02T06:57:12.84Z	25	chiller_ChilledWaterDiffPressLowAlmVal	bms.chiller.kPa	chill01	kPa
	0	2021-03-09T01:07:21.851Z	0	chiller_ChilledWaterDiffPressLowAlmVal	bms.chiller.kPa	chill01	kPa
	0	2021-03-09T01:07:32.618Z	25	chiller_ChilledWaterDiffPressLowAlmVal	bms.chiller.kPa	chill01	kPa
	0	2021-03-16T03:33:05.873Z	0	chiller_ChilledWaterDiffPressLowAlmVal	bms.chiller.kPa	chill01	kPa
	0	2021-03-16T03:33:15.989Z	25	chiller_ChilledWaterDiffPressLowAlmVal	bms.chiller.kPa	chill01	kPa
	0	2021-03-22T22:02:23.608Z	25	chiller_ChilledWaterDiffPressLowAlmVal	bms.chiller.kPa	chill01	kPa
	0	2021-03-25T04:54:26.77Z	25	chiller_ChilledWaterDiffPressLowAlmVal	bms.chiller.kPa	chill01	kPa
	0	2021-03-29T06:29:12.17Z	25	chiller_ChilledWaterDiffPressLowAlmVal	bms.chiller.kPa	chill01	kPa
	0	2021-03-29T08:33:30.934Z	25	chiller_ChilledWaterDiffPressLowAlmVal	bms.chiller.kPa	chill01	kPa
	0	2021-03-30T02:03:04.634Z	25	chiller_ChilledWaterDiffPressLowAlmVal	bms.chiller.kPa	chill01	kPa
	0	2021-04-06T02:21:52.951Z	25	chiller_ChilledWaterDiffPressLowAlmVal	bms.chiller.kPa	chill01	kPa
	0	2021-04-30T05:47:43.838Z	25	chiller_ChilledWaterDiffPressLowAlmVal	bms.chiller.kPa	chill01	kPa
	0	2021-04-30T06:26:52.192Z	25	chiller_ChilledWaterDiffPressLowAlmVal	bms.chiller.kPa	chill01	kPa

water cooling system

WaterFlowRate

Temperature

Three categories of AD algorithms

Rule based method

- PersistAD
- VolatilityShiftAD
- QuantileAD

Supervised learning method

- AutoregressionAD
- SeasonalTrendDecompositionAD

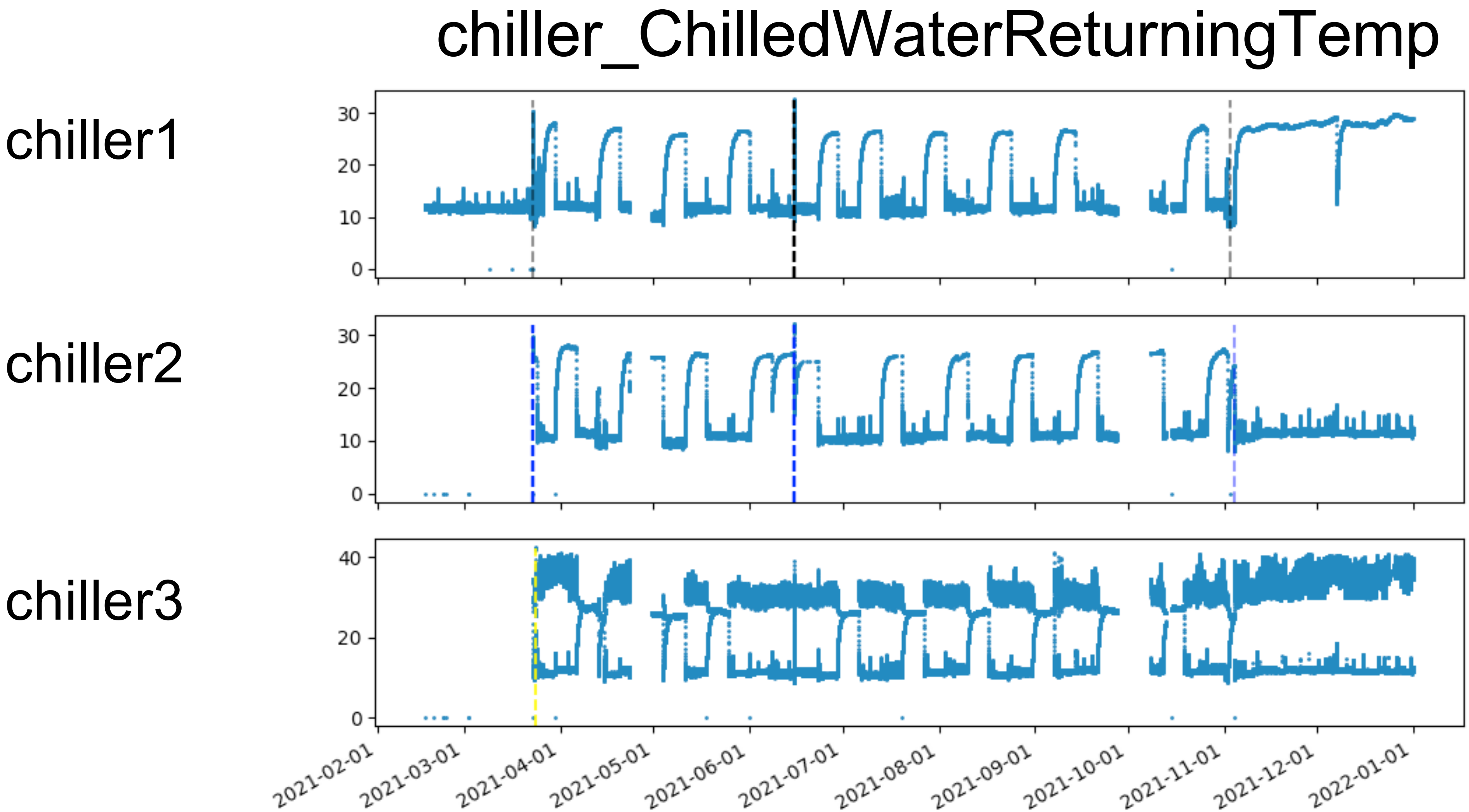
Unsupervised learning method

- KNN
- SingularSpectrumAnalysisAD
- MatrixProfileAD

Results on diagnostic datasets

bl0	[array([160, 177])]	[2145.771119 1267.439293]
bl1	[array([160, 177])]	[2193.987471 332.1608001]
bl2	[array([160, 177])]	[766.6189853 424.5358196]
bl3	[array([160, 177])]	[1337.753346 540.0146046]
bl4	[array([177, 224])]	[1660.676756 249.3180131]
bl5	[array([160, 224])]	[2140.040057 304.8624357]
bl6	[array([160, 177])]	[1251.527186 2074.310464]
bl7	[array([160, 177])]	[1298.909474 586.9551666]
bl8	[array([160, 177, 224])]	[1573.740237 1031.626559 131.0893167]
bl9	[array([160, 177])]	[2514.821055 1226.429744]
bl10	[array([177, 224])]	[1829.787146 195.0024956]
bl11	[array([160, 177])]	[1261.034997 2283.697991]
bl12	[array([160, 177, 224])]	[2196.930645 363.7142437 207.0551584]
bl13	[array([160, 177, 224])]	[1240.246771 587.6416155 293.4216757]
bl14	[array([160, 177, 224])]	[761.7295329 448.4381218 116.9992457]
bl15	[array([32, 160, 177])]	[287.7546749 2225.590476 1817.033444]
bl16	[array([160, 177])]	[755.6058269 122.2636323]
bl17	[array([160, 177])]	[1841.751513 1701.813195]
bl18	[array([177])]	[1117.824569]
bl19	[array([160, 177, 224])]	[939.9830685 1478.132727 118.4113615]
bl20	[array([177])]	[935.492844]
bl21	[array([160, 177])]	[1209.214332 1711.035782]
bl22	[array([160, 177, 224])]	[1171.793589 598.5918929 227.9825174]

Results on monitoring datasets



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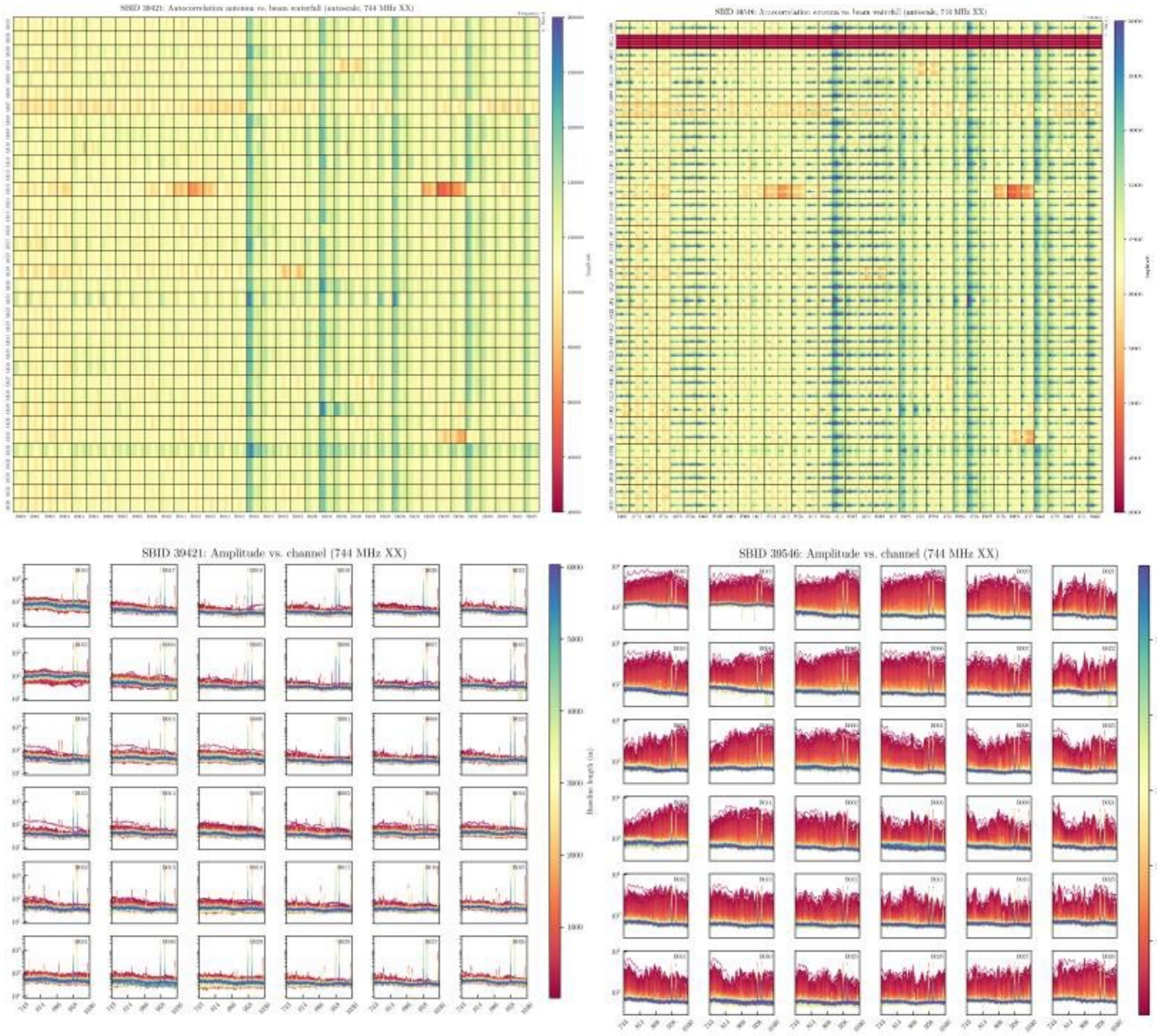
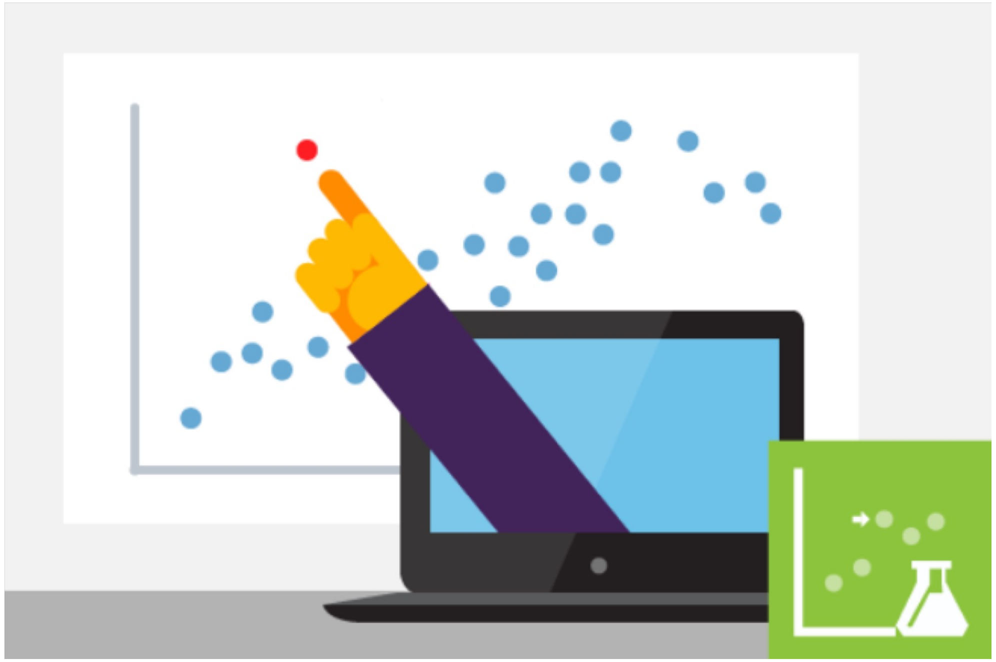
Data Explosion



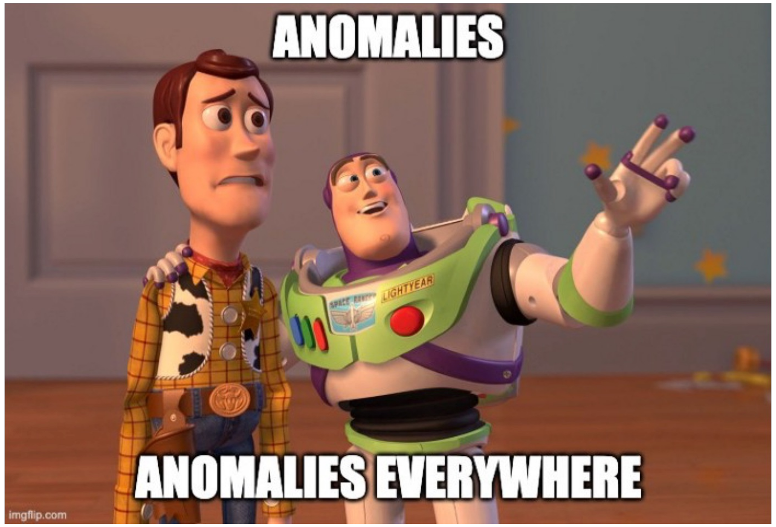
Credit: Vanessa Moss

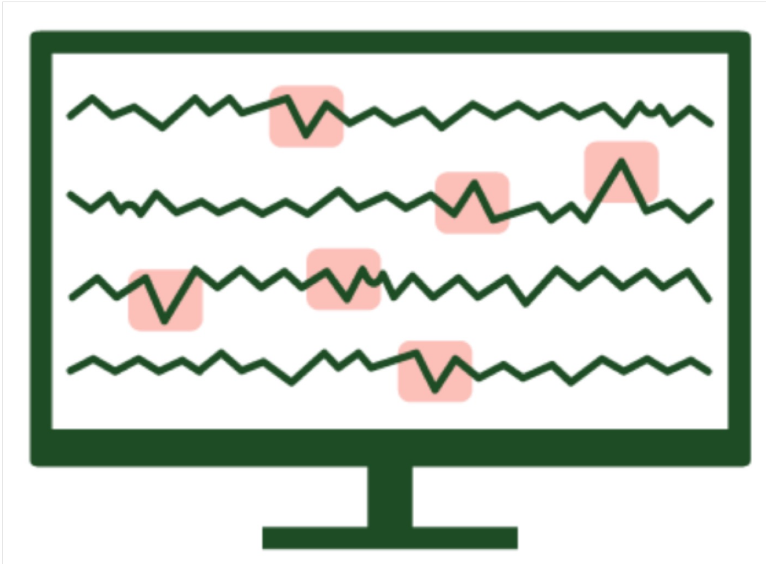
How do we find the unknowns among billions of possibilities?

Anomaly Detection



Anomaly detection is not enough.





Human-AI Collaborative Workflow for Anomaly Detection in ASKAP