

Signatures to help interpretability of anomalies

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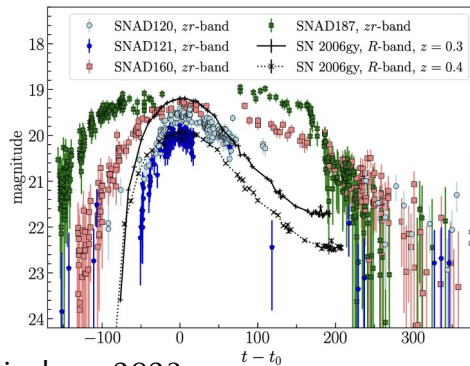


What is an anomaly ?

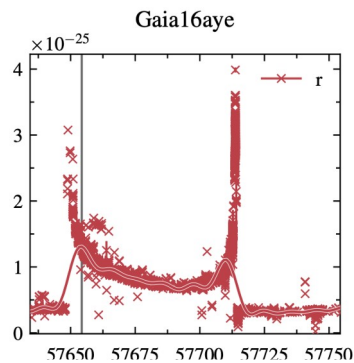
An anomaly is a pattern that does not conform to expected normal behavior, and is suspected to be generated by a different mechanism.

Some challenges :

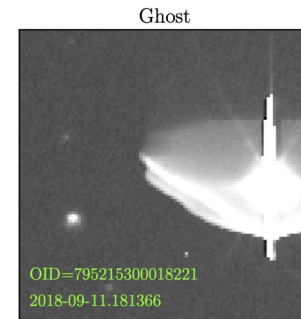
- Normal behavior may be not known
 - Usually in large data sets → Unsupervised learning, fast algorithms.
- Interpreting the underlying behavior/properties of anomalous data
 - Field expert knowledge needed



SLSN
Pruzhinskaya 2023



Binary microlens event
Pruzhinskaya 2019



Bogus finder
Malanchev 2021

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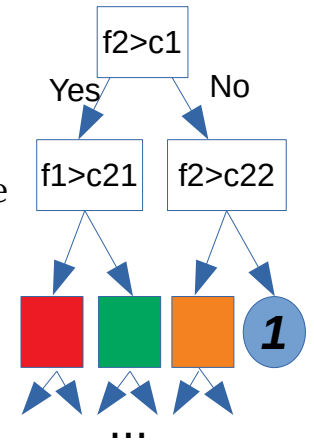
How to help the astronomer ?

- Find anomalies
- **Understand** Machine decision
- Find **more interesting** anomalies
- Discard uninteresting anomalies

Isolation Forest Density Estimation

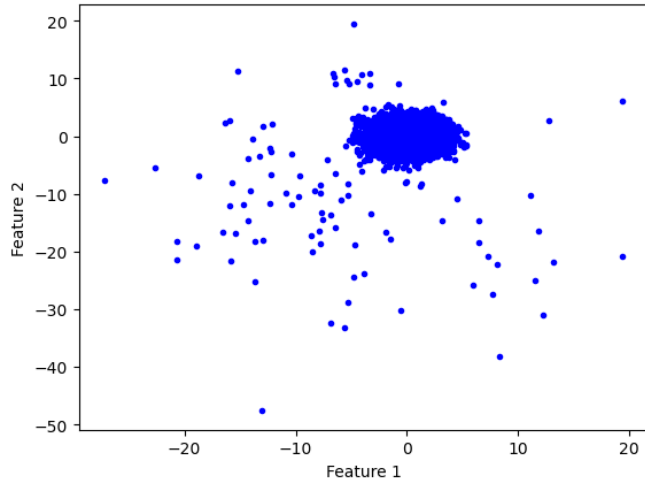
- **Random Tree:**

- Select a feature randomly
- Select a random threshold within the range spanned by the feature for the (sub) sample
- Repeat for each subsample
- Stop when only 1 point in the sub-partition

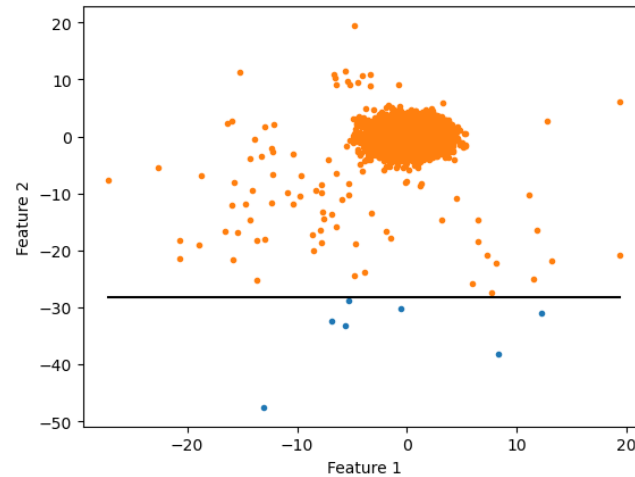


- **Random Forest:**

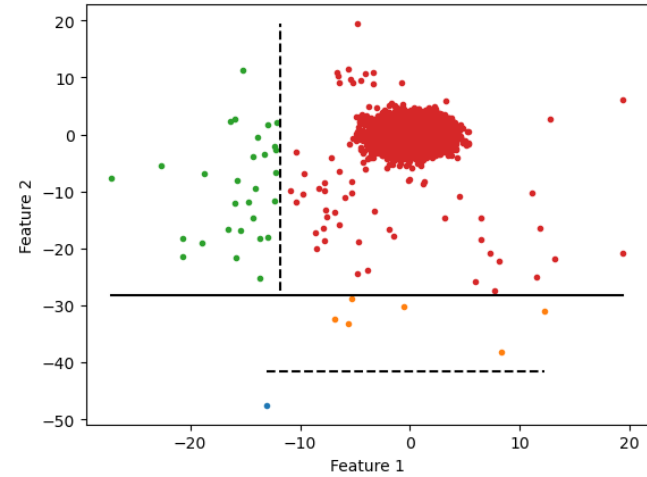
- Average depth on T trees (proxy for local density)



Depth 0

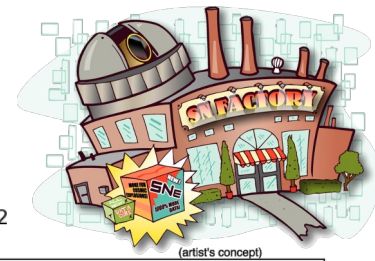


Depth 1



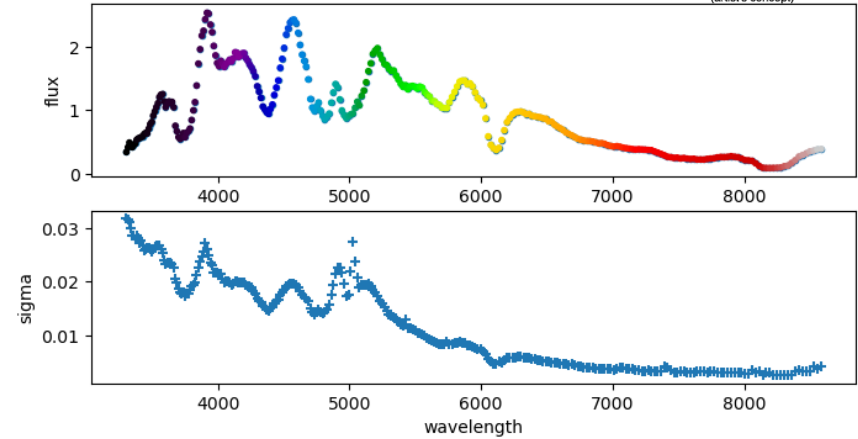
Depth 2

SNFactory dataset



Spectrum 1612

(artist's concept)

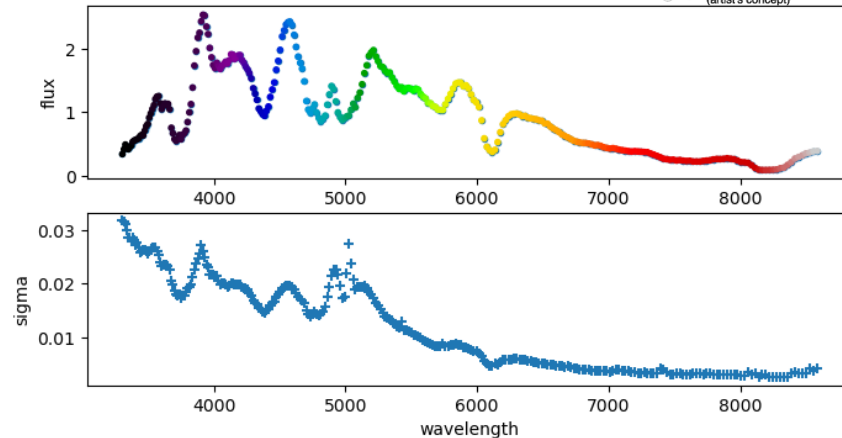


- **Public astronomical dataset**
[arXiv:2005.03462](https://arxiv.org/abs/2005.03462)
 - **2323 spectra** of Type Ia supernovae
 - 288 spectral bins
 - With noise estimate
- **576 features**

SNFactory dataset

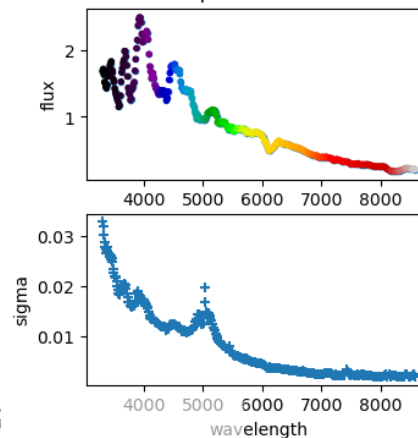


Spectrum 1612

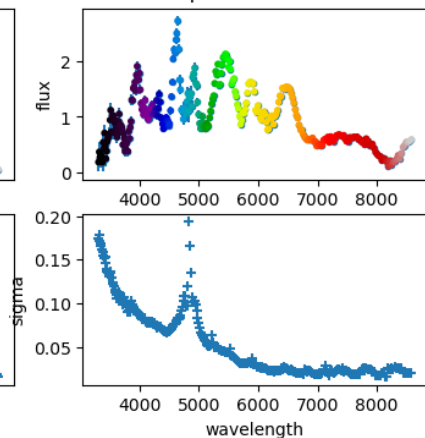


- Public astronomical dataset
- Interest of this dataset for anomalies
 - High **internal variability**
 - **Expert knowledge** for anomalies
 - Many **different class** of anomalies
 - **Noisy data** making the task difficult
 - Local **data artifacts**

Spectrum 135

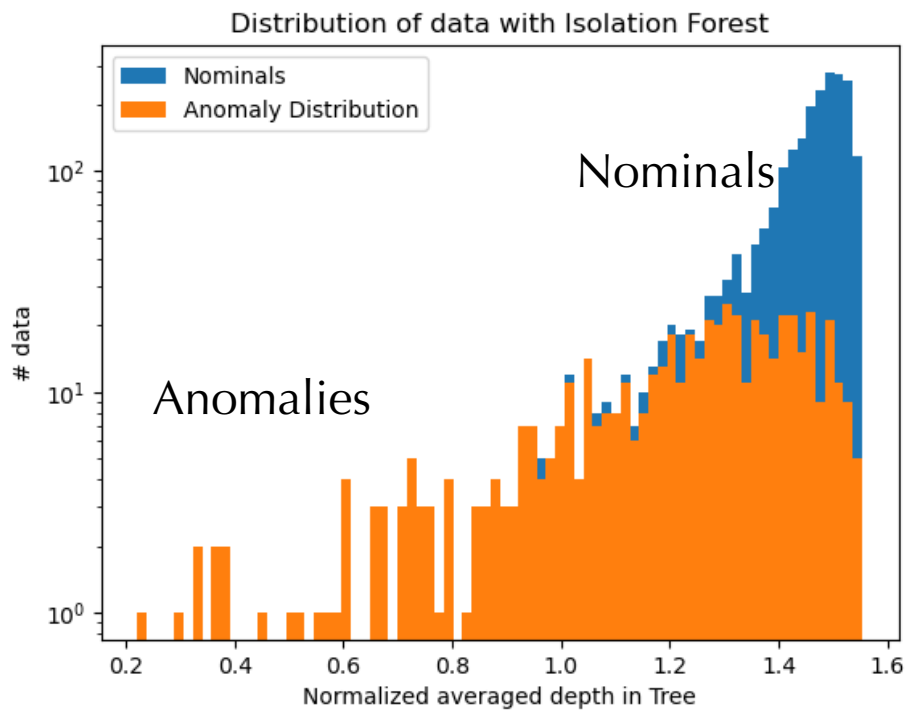


Spectrum 2306

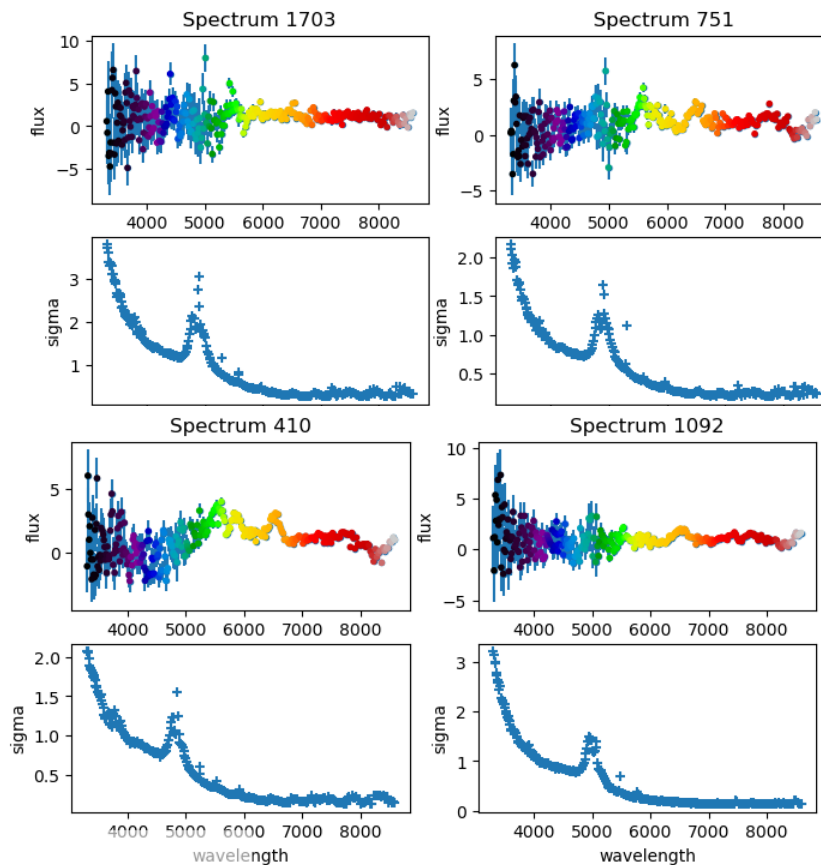


Isolation Forest for SNFactory dataset

Top 4 outliers

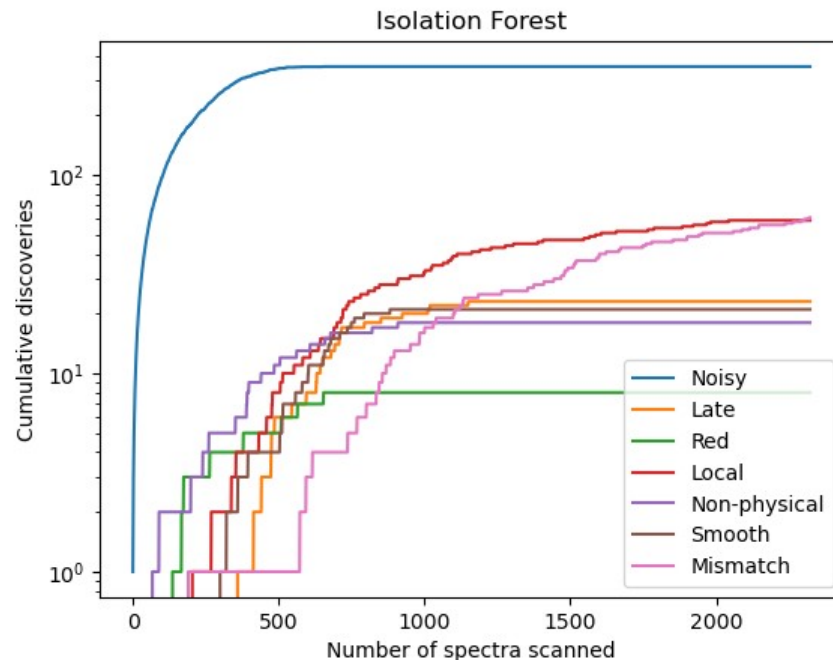


Outliers are anomalies of the “noisy” type



Discovery efficiency

- IF very efficient for **dominant anomaly**
 - Noisy data dominate ($AUC=0.985$)
- Less efficient for **other classes**
 - **Rank** of last anomaly type discovered: 360 (expected 326)
 - For non-noise anomalies : $AUC=0.61$

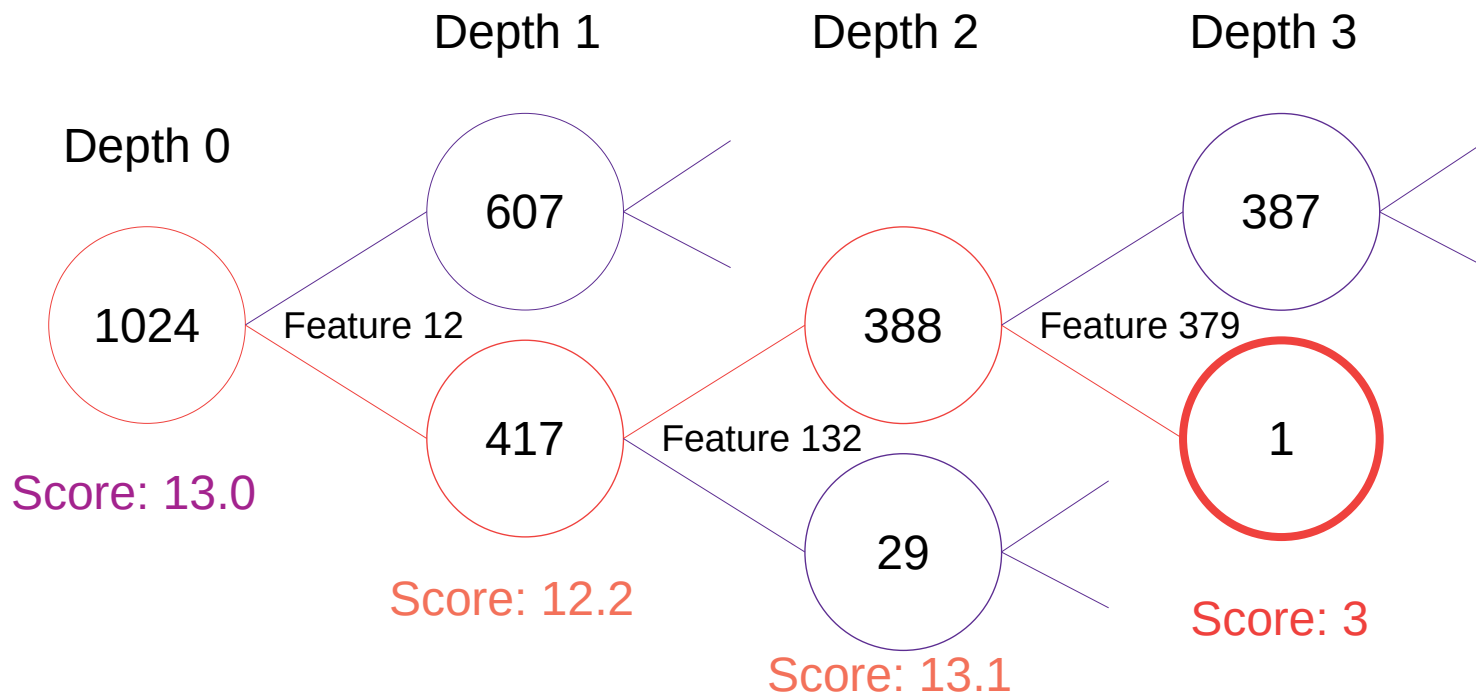


Some common Questions:

- **Why** are some data tagged as anomalies ?
- Are there **different classes** of anomalies ?
- Can I improve discovery of **new anomalies** ?
- Can I find **more anomalies** of a given kind ?

Anomaly signature

- Anomaly score for 1 tree



For this outlier :

Feature 12 = - 0.8

Feature 132 = + 0.9

Feature 379 = - 10.1

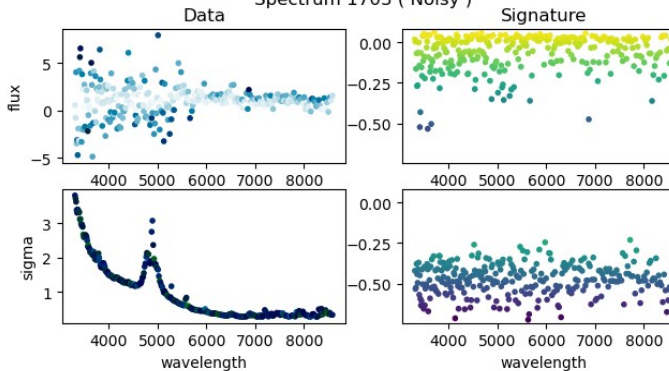
Signature & interpretability

Top 1
Anomaly

Data

Signature

Spectrum 1703 (Noisy)

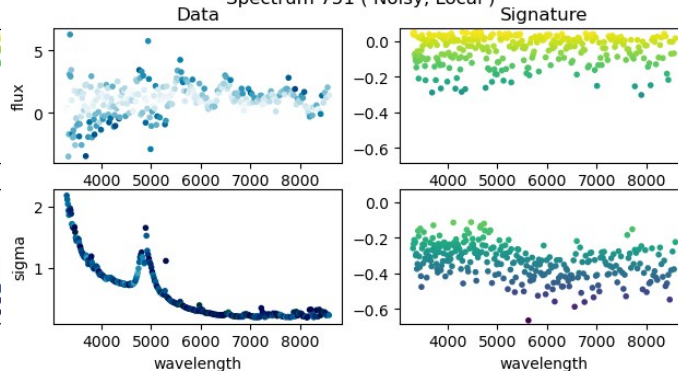


Top 2
Anomaly

Data

Signature

Spectrum 751 (Noisy, Local)

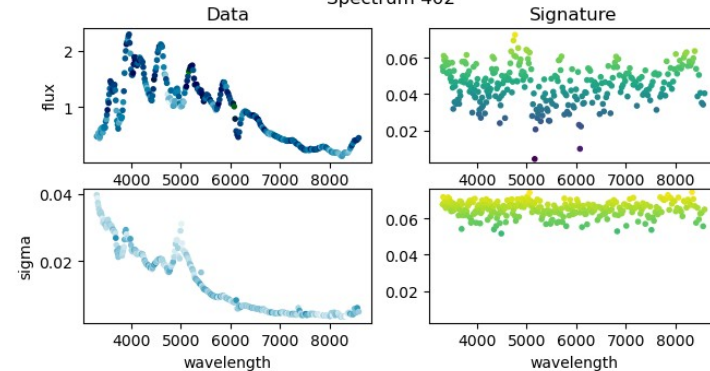


Top 1 Nominal

Data

Signature

Spectrum 402

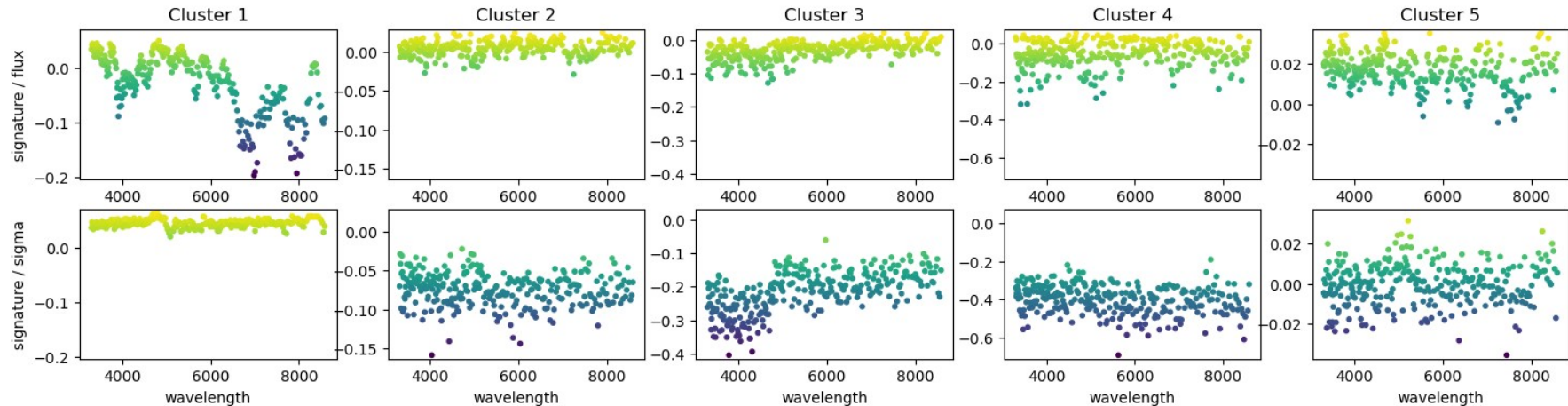


- Signature highlights where the data is anomalous
 - Negative score = anomalous
 - Interpretation : decision based on sigma

- Positive score = nominal

Signatures & Clustering

- K-means on signatures for **top 10 % anomalous data** (232 spectra)
 - Very unbalanced : 90 % of those are tagged “Noisy”
 - Contains 7 % of nominals



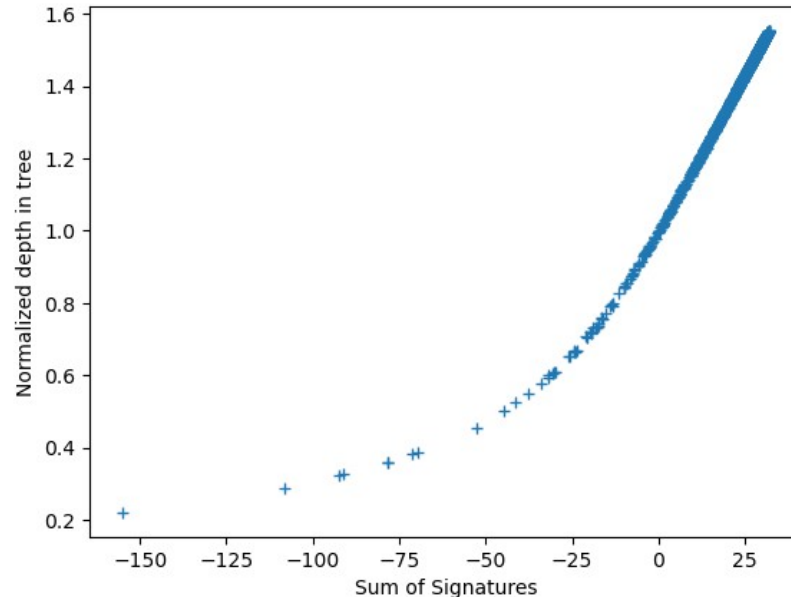
- All anomalies belong to Cluster 1 !
- Only 39 elements : easier to analyse
- Still 2 classes of anomalies not found... + Choice of K is empirical

Recursive approach to novelty discovery with signatures

- Signature allow to derive a weighted anomaly score

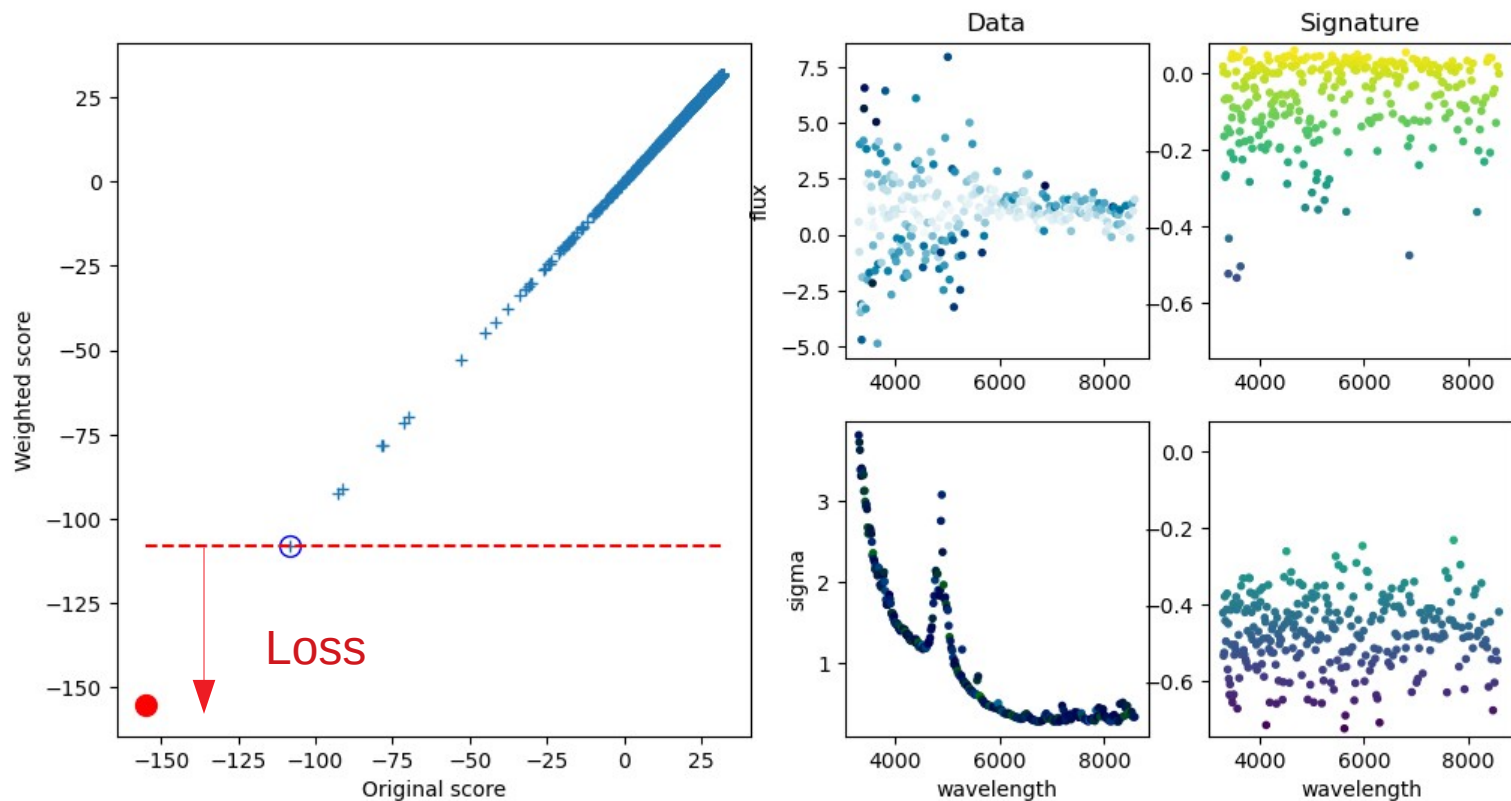
$$S^j = \sum_i \alpha_i S_{f_i}^j$$

- Initialization of weights to 1
- For each data examined by the expert :
 - Tag as either wanted or unwanted
 - Update the weights / Hinge loss function
 - Propose to the expert the next mostly anomalous



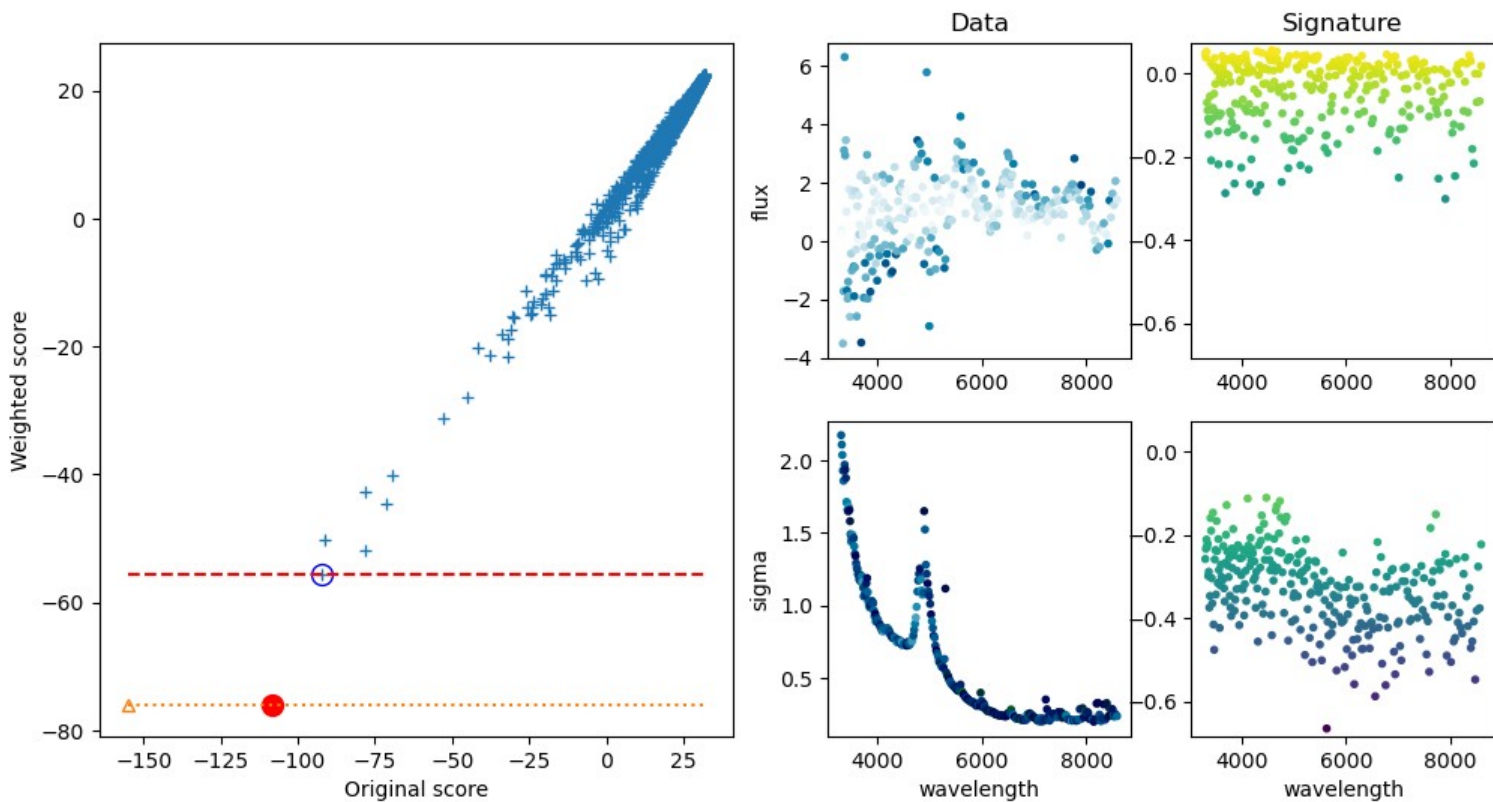
Recursive approach to novelty discovery with signatures

Scan 1: Spectrum 1703 (Noisy)



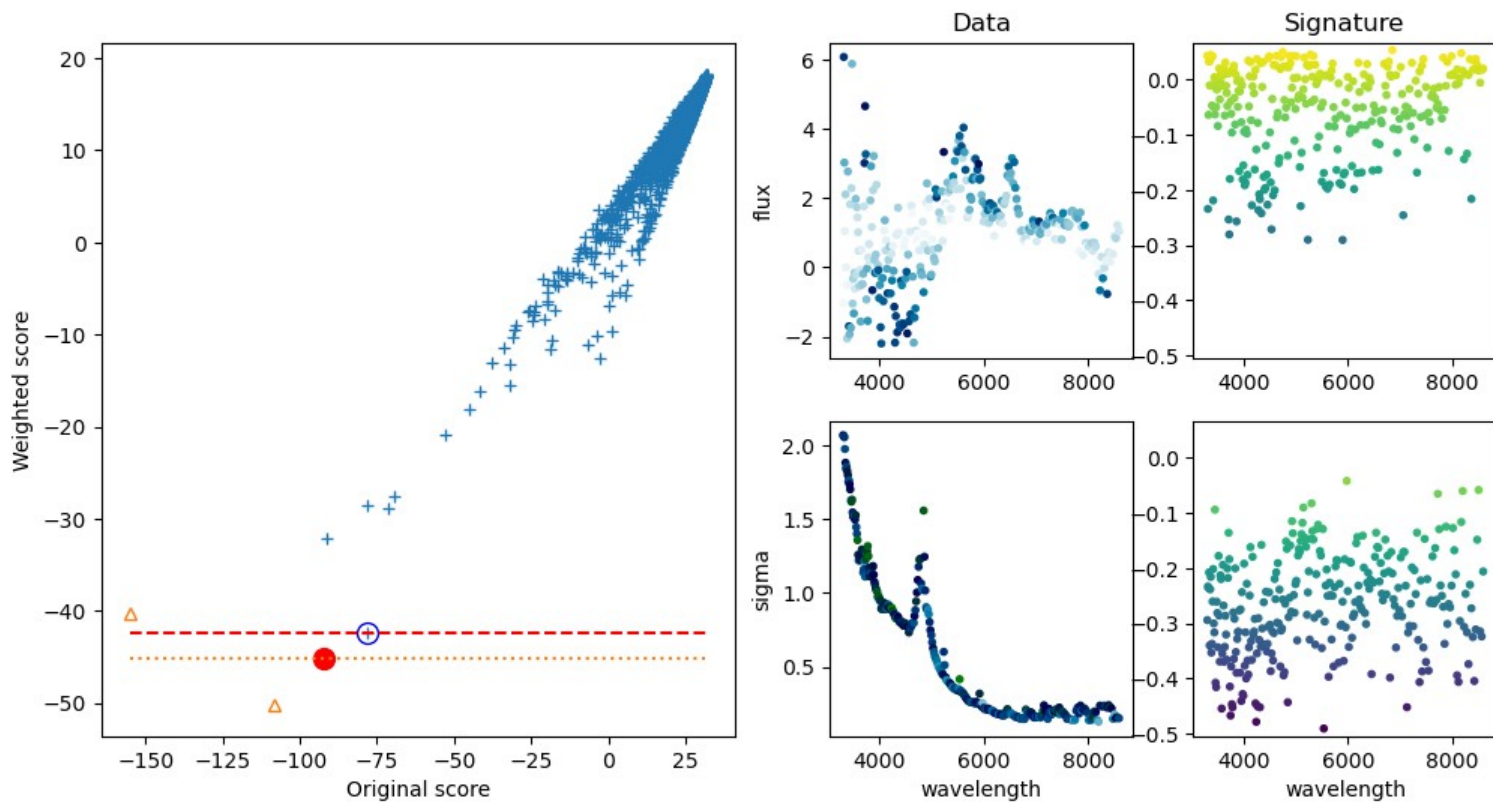
Recursive approach to novelty discovery with signatures

Scan 2: Spectrum 751 (Noisy, Local)



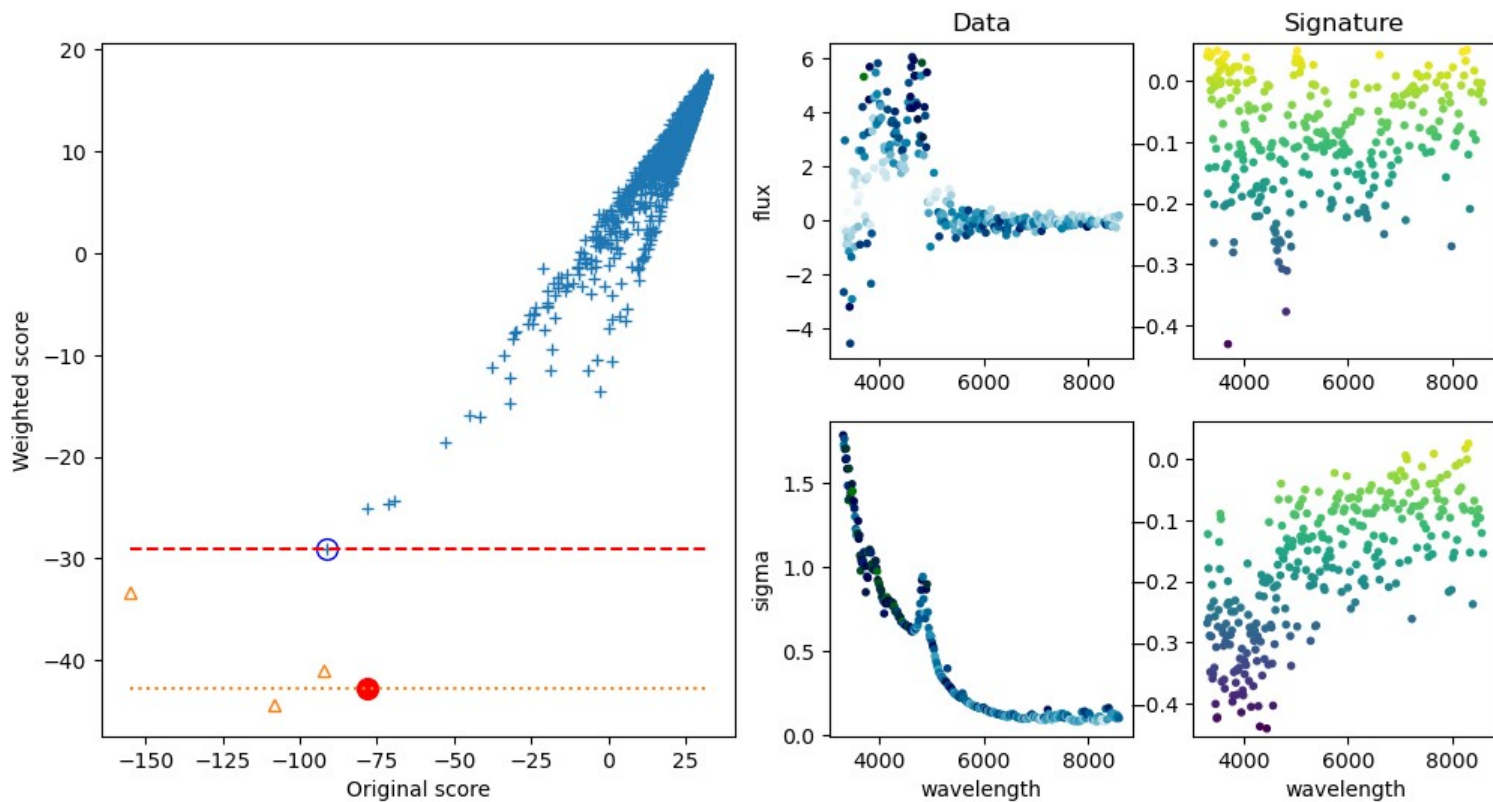
Recursive approach to novelty discovery with signatures

Scan 3: Spectrum 410 (Noisy)



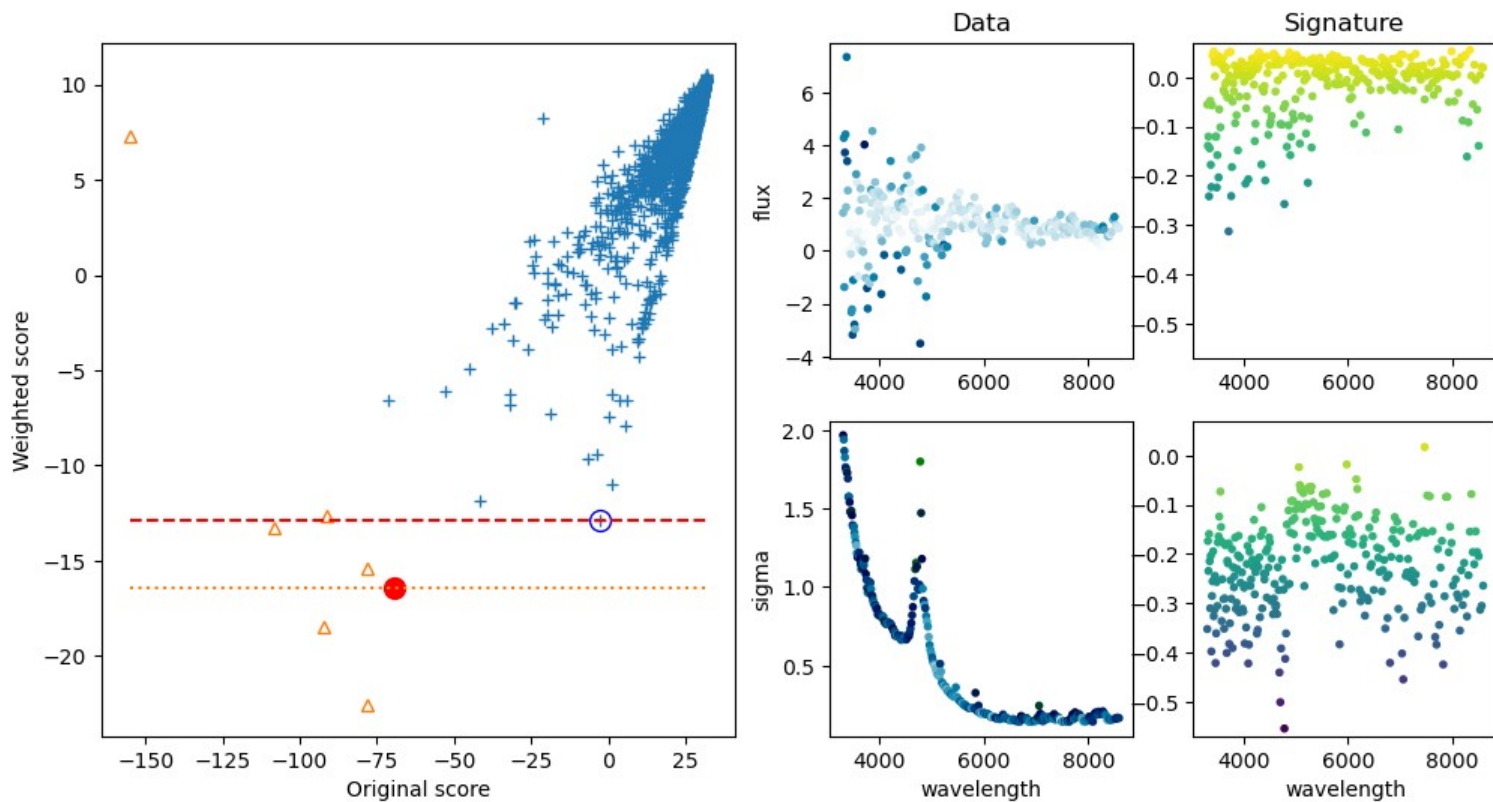
Recursive approach to novelty discovery with signatures

Scan 4: Spectrum 1422 (Noisy)



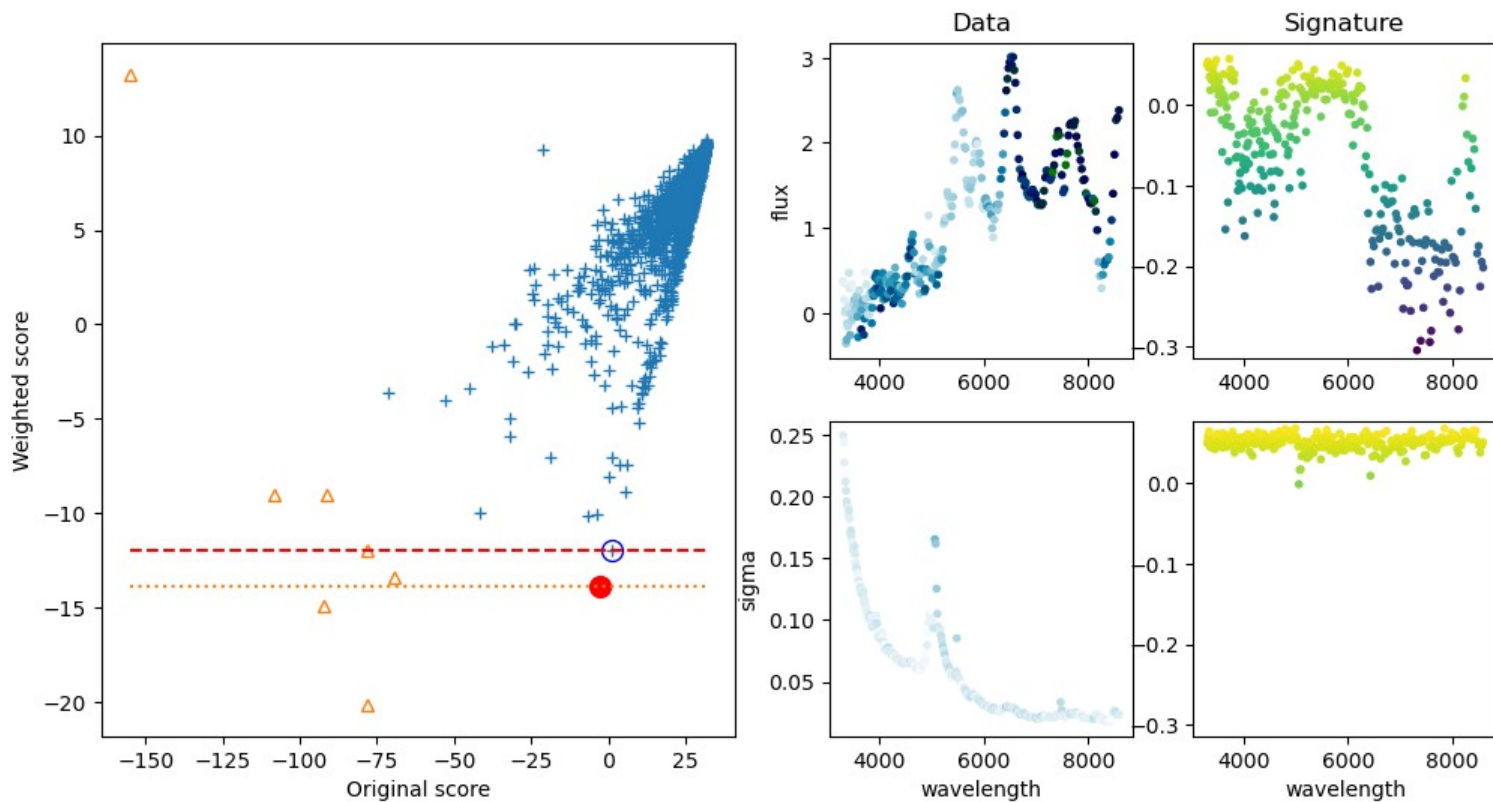
Recursive approach to novelty discovery with signatures

Scan 7: Spectrum 57 (Noisy)



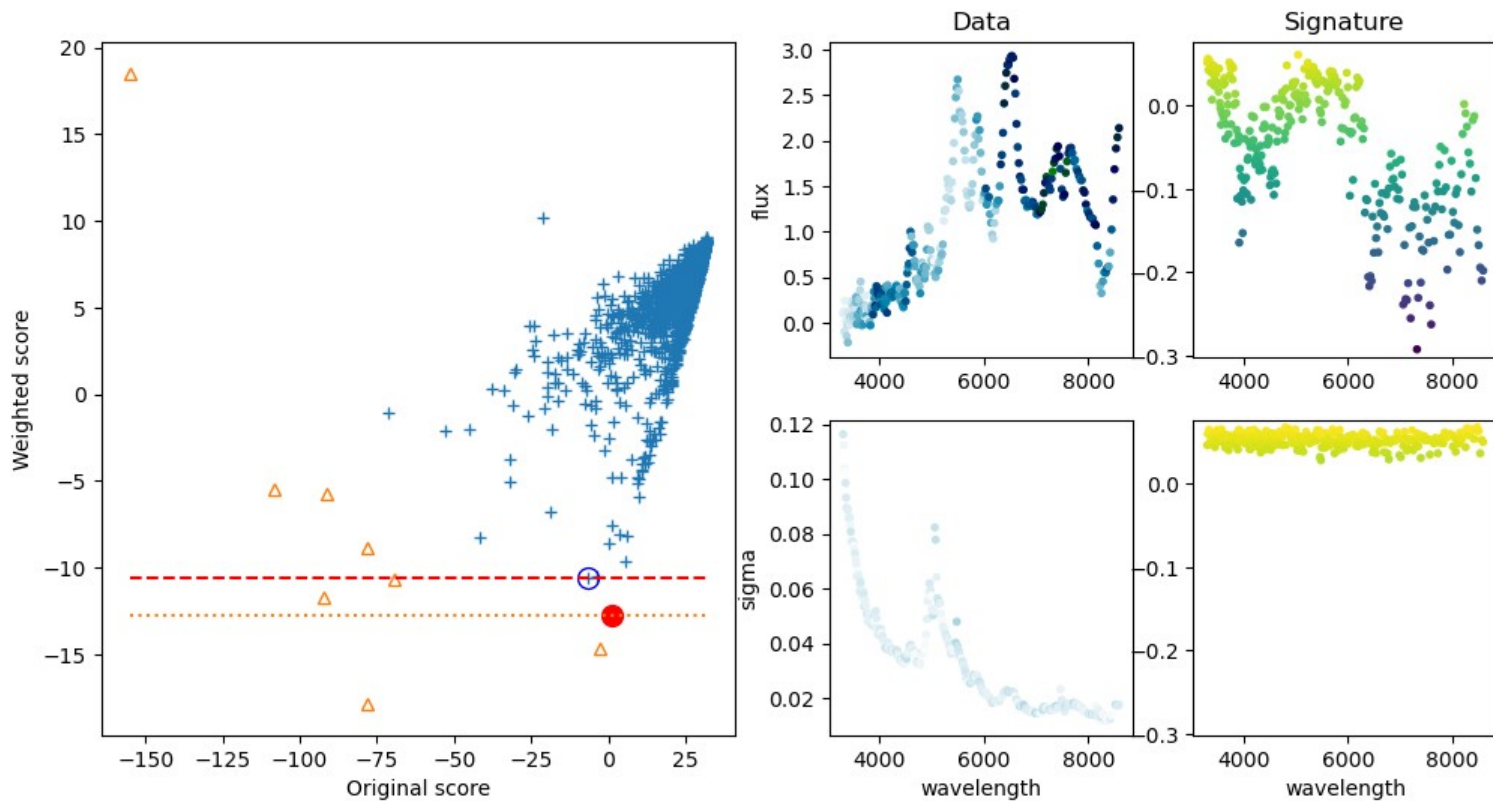
Recursive approach to novelty discovery with signatures

Scan 8: Spectrum 1051 ()



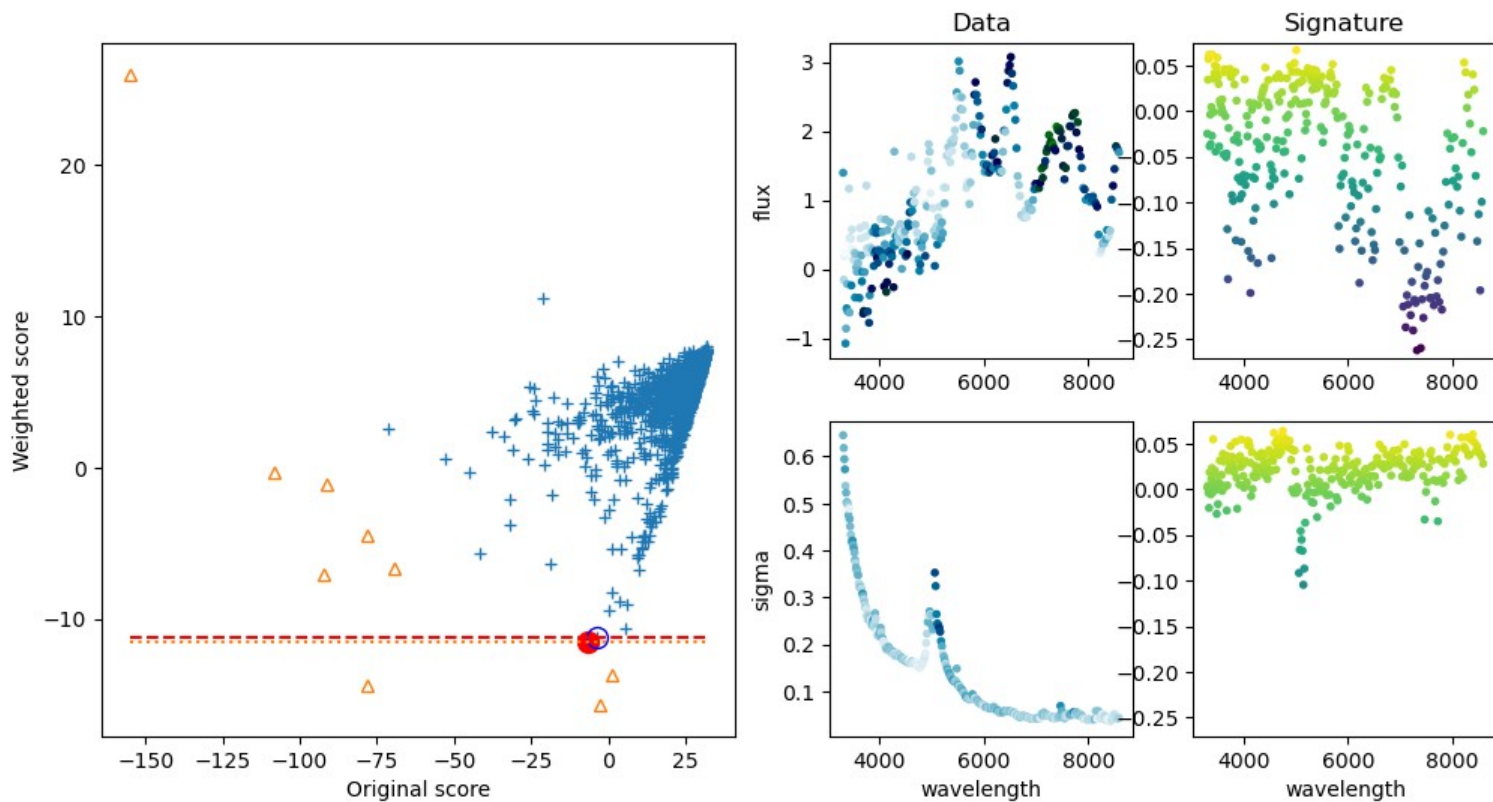
Recursive approach to novelty discovery with signatures

Scan 9: Spectrum 917 ()



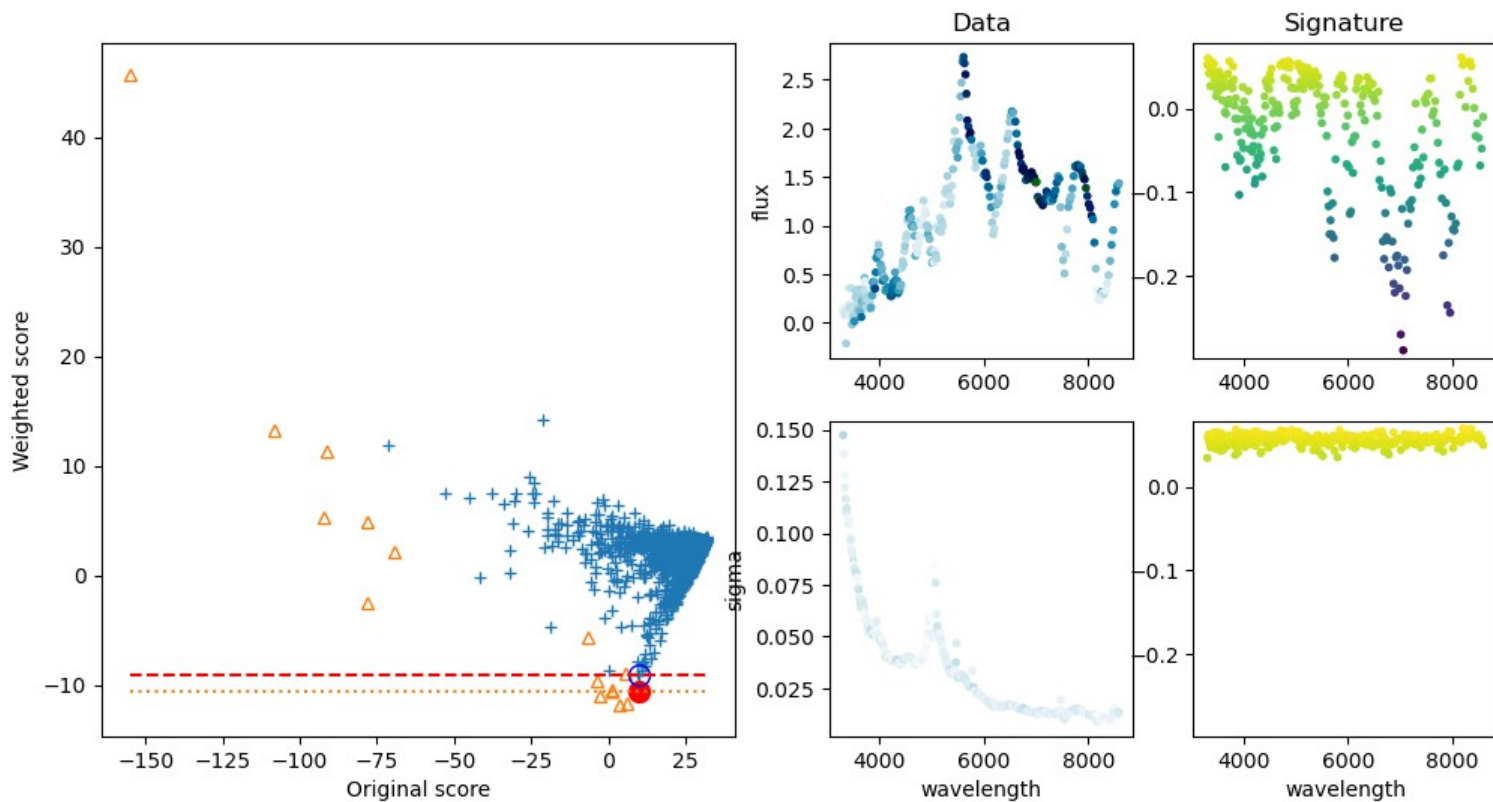
Recursive approach to novelty discovery with signatures

Scan 10: Spectrum 1363 (Noisy)



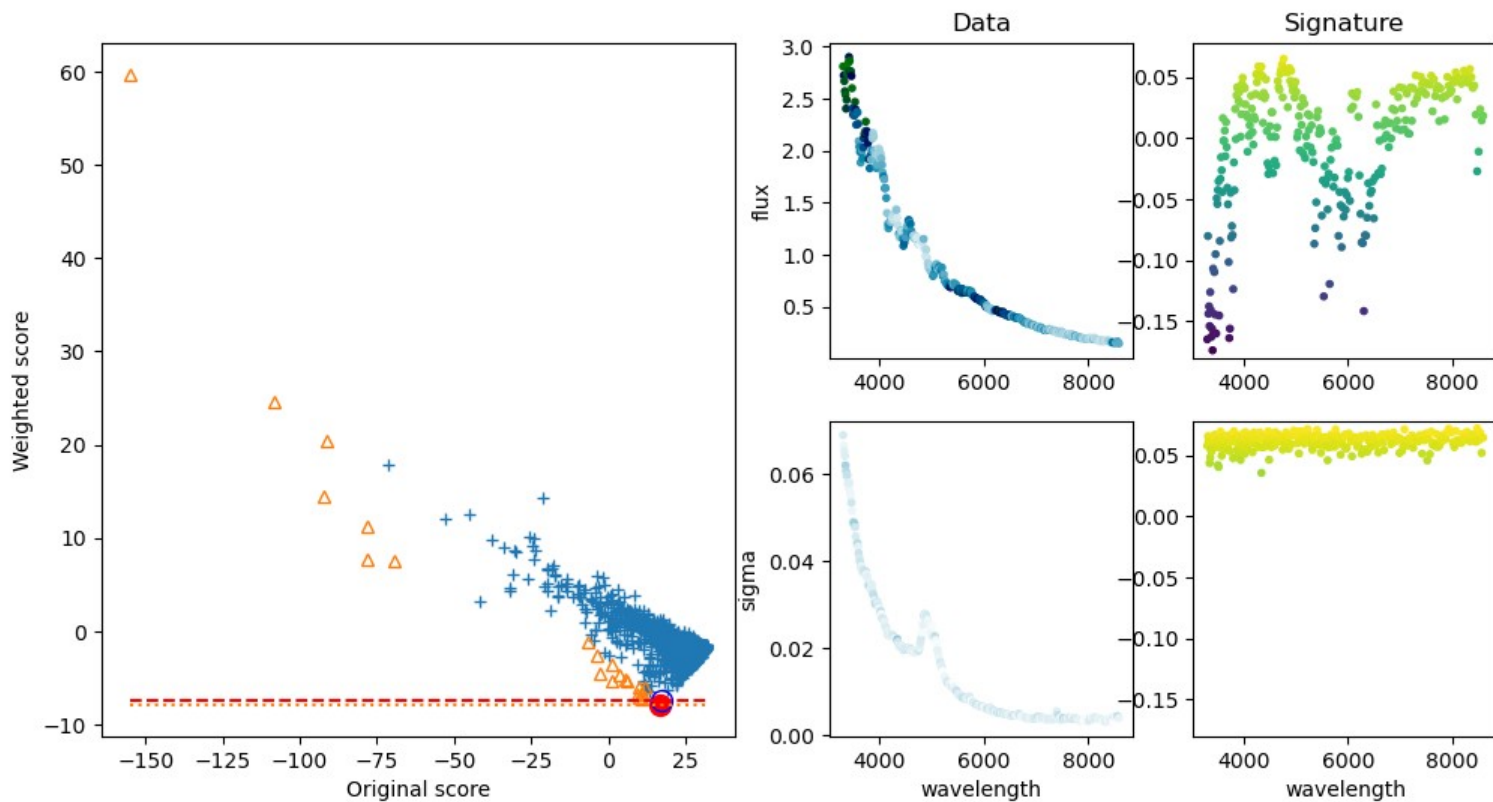
Recursive approach to novelty discovery with signatures

Scan 16: Spectrum 2081 (Red)



Recursive approach to novelty discovery with signatures

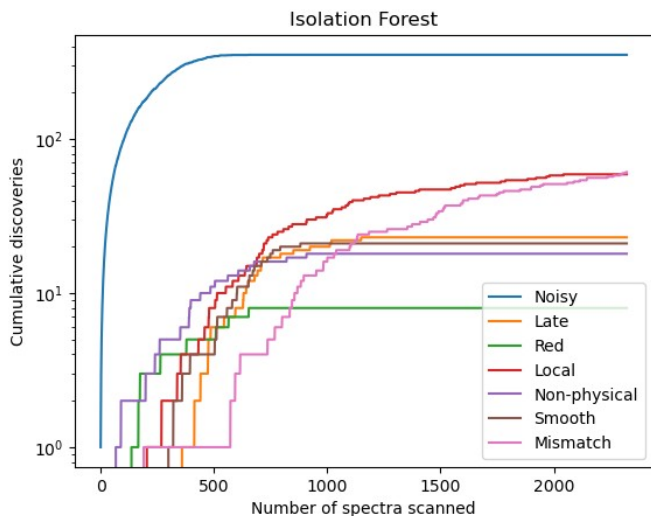
Scan 23: Spectrum 1454 (Smooth)



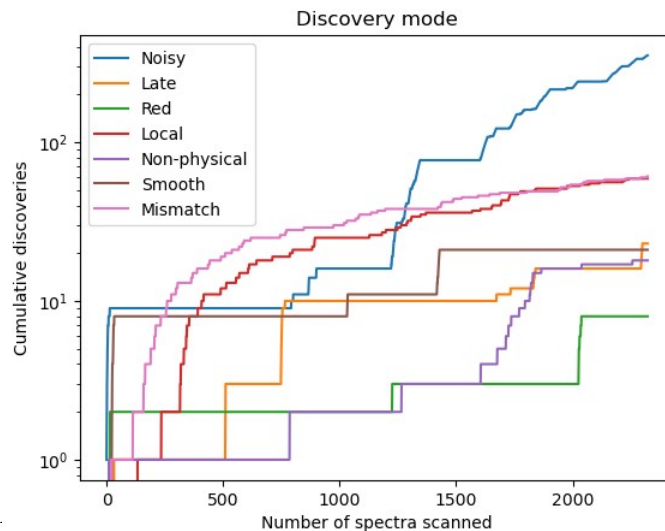
Different tasks :

Factor x3 speed-up
in discoveries

- Isolation Forest
 - Default
 - $AUC(Noisy)=0.98$
 - $AUC(Others)=0.60$
 - Rank of last class=360



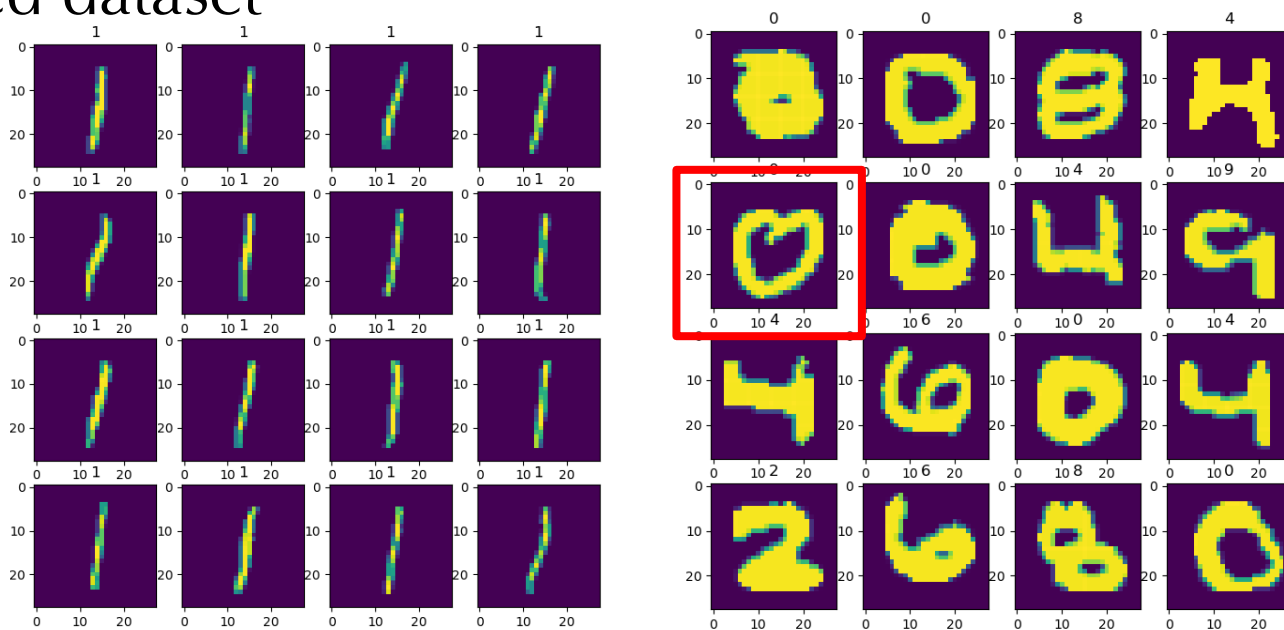
- Discovery mode
 - Optimize on novelty
 - $AUC(Noisy)=0.25$
 - $AUC(Others)=0.51$
 - $Rank$ of last class=133



Using Signatures for Similar Anomalies

Anomaly search within MNIST:

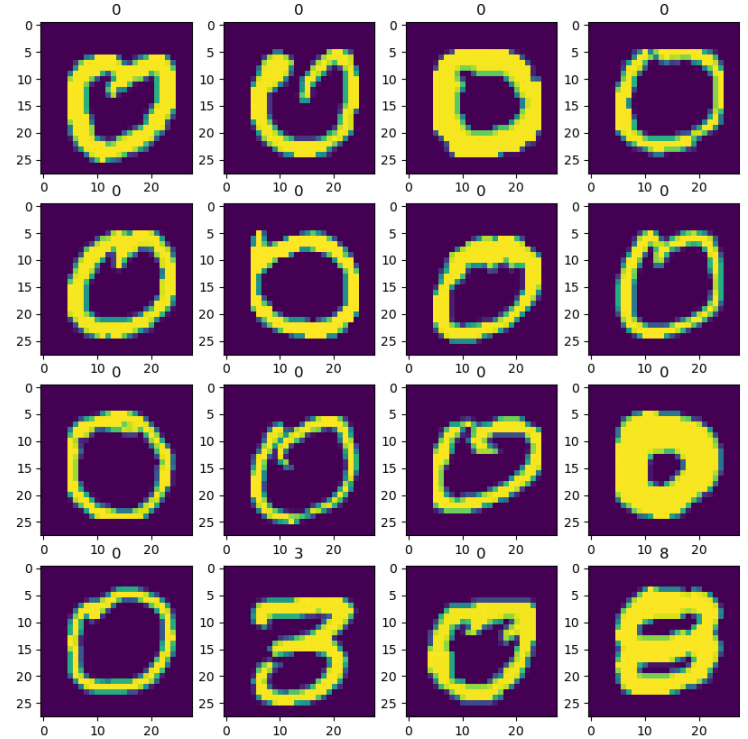
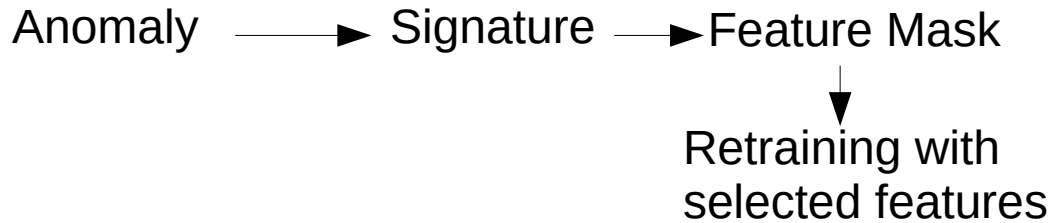
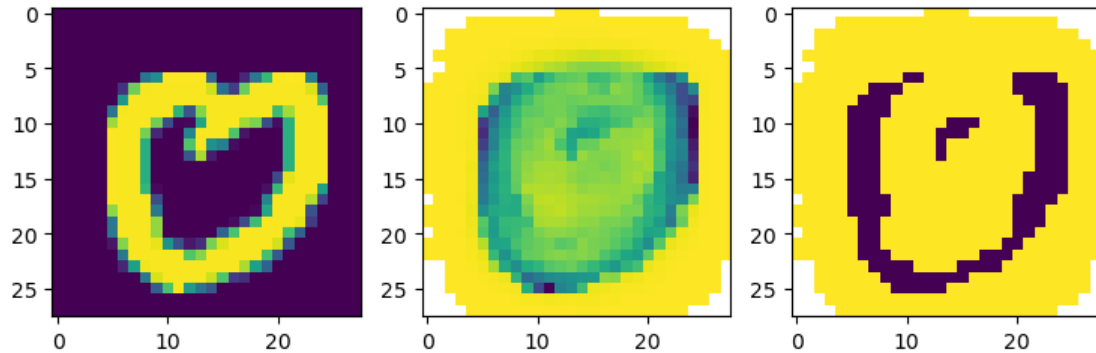
- Handwritten digits
- Curated dataset



16 most Nominals

16 most Outliers

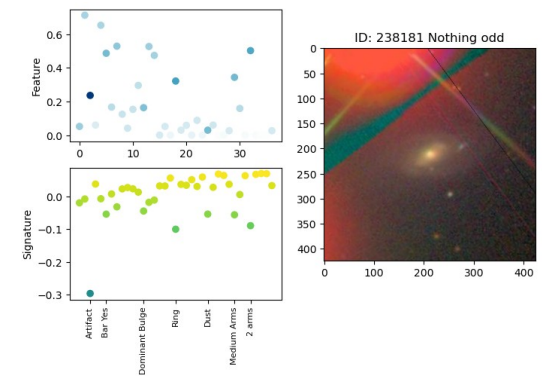
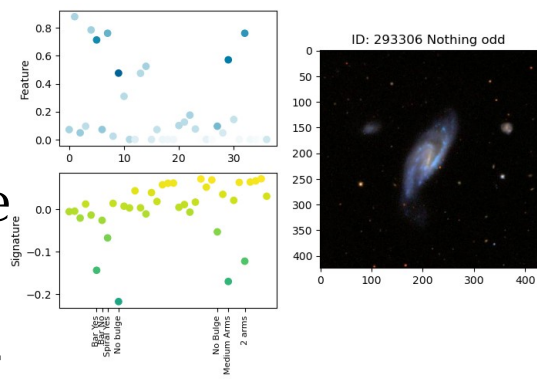
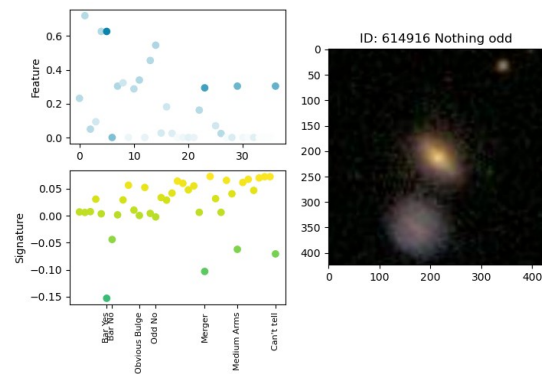
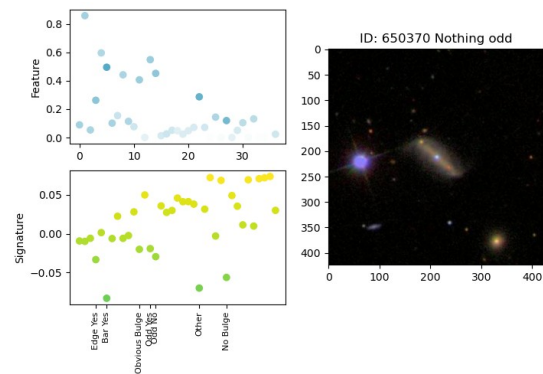
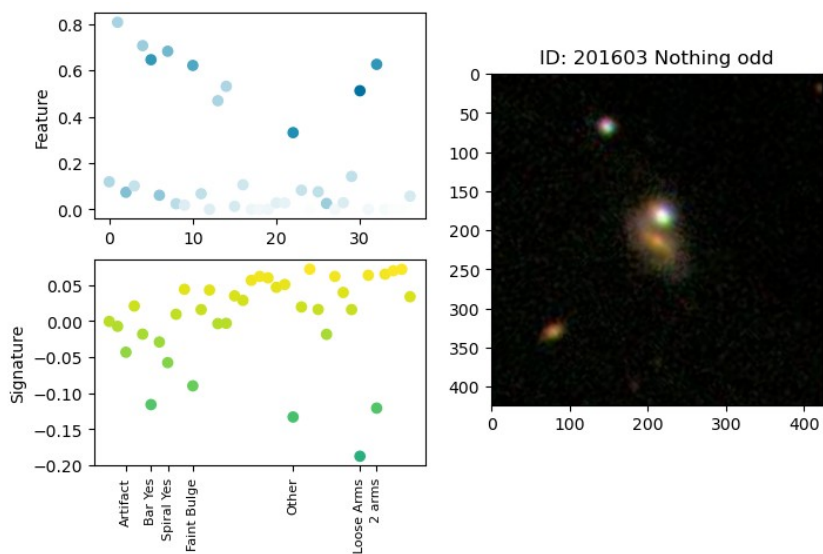
Using signature to select more of the same



Similar Anomalies

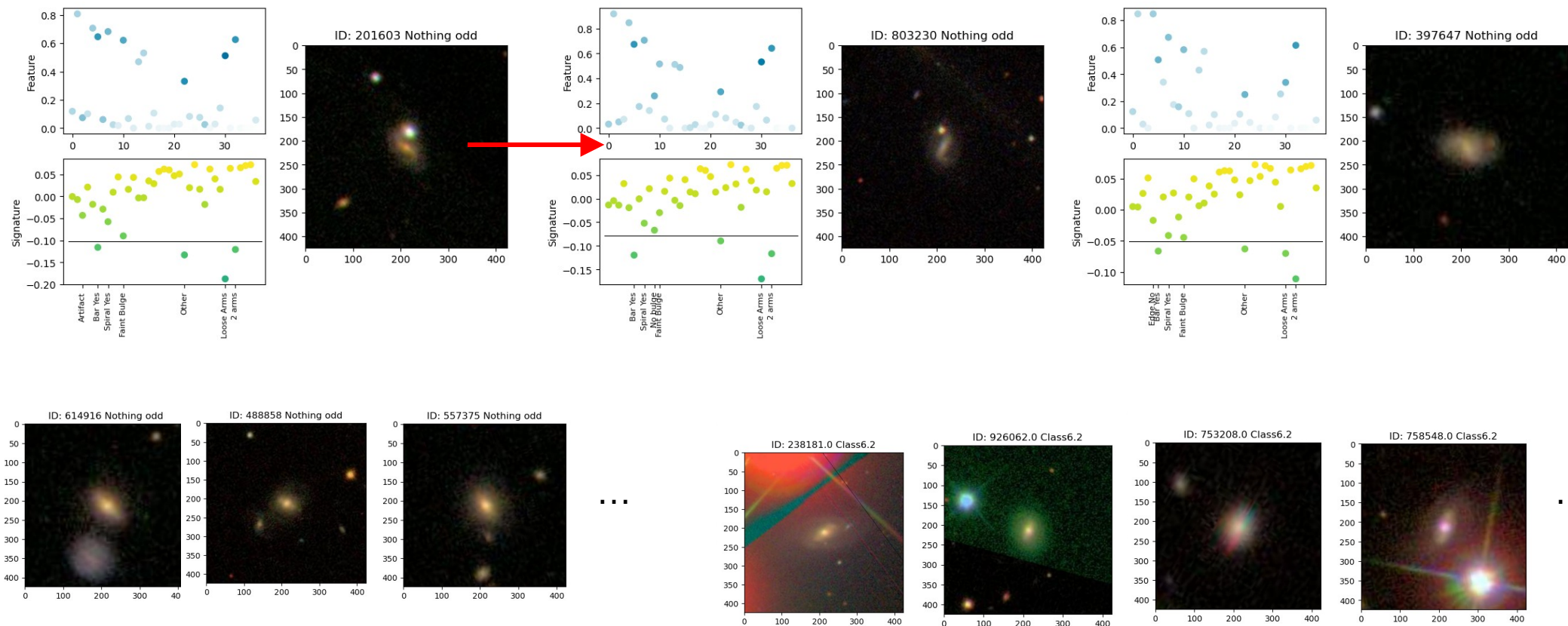
Galaxy Zoo 2 anomalies

- Anomalies = Rare patterns in human decisions



- No obvious pattern in signature
→ diversity

Anomalies by similar signatures



Rare on "Merger + Bar"

Rare on "Artifact"

Conclusions

- **Anomaly Signature** is a metric for feature importance
- **Domain agnostic / method aware** (Isolation Forest)
 - Works with any tabluar data (features, vectorized images...)
- **Many use cases:**
 - Interpretability of the decisions
 - Visualisation of outliers
 - Feature selection
 - Categorization of outliers
 - Active learning of anomalies

This is only the beginning!

Stay tuned on



SNAD

<https://snad.space>

<https://github.com/snad-space/coniferest>