Fission event classification using machine learning methods

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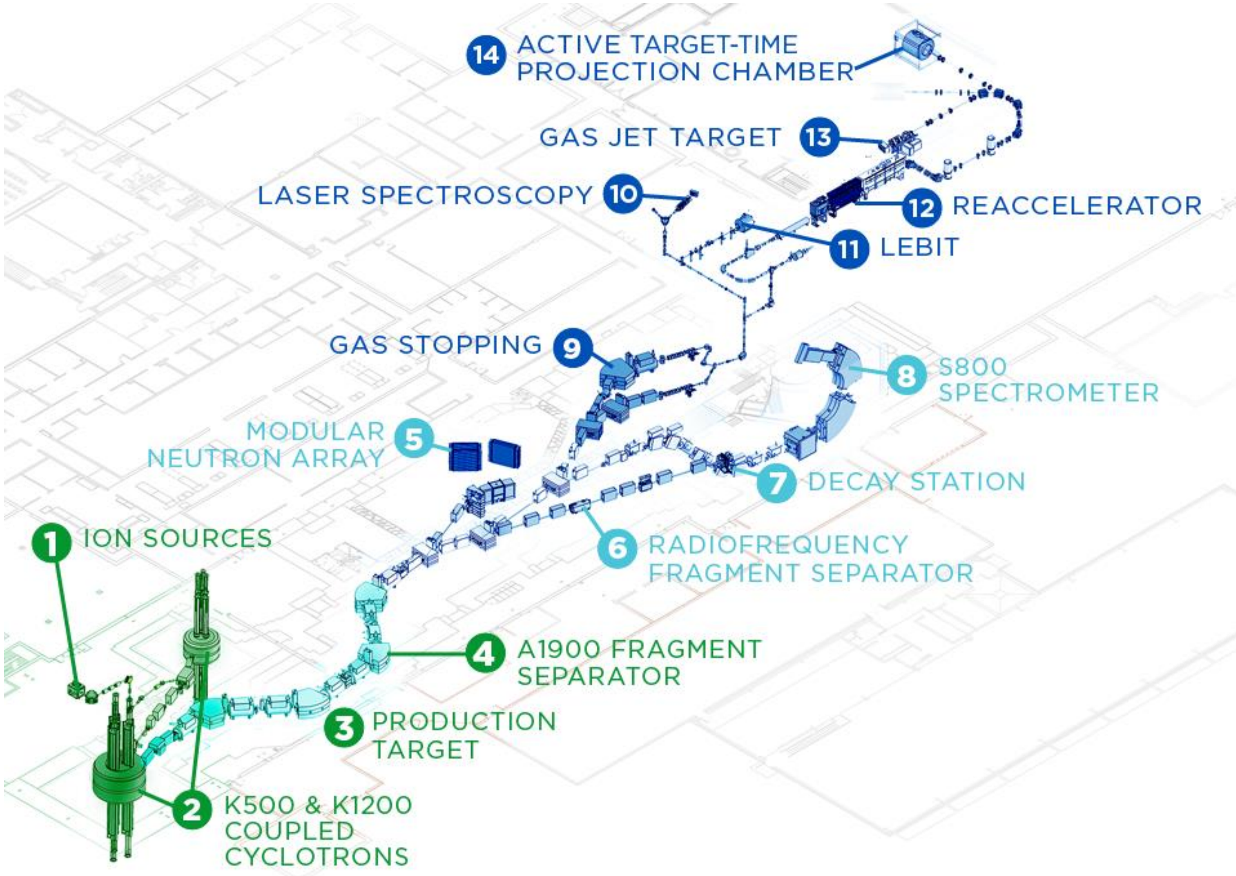
FRIB

- Facilities for Rare Isotope Beams
- Nuclear physics user facility operated by Michigan State University
- Formerly National Superconducting Cyclotron Laboratory (NSCL)

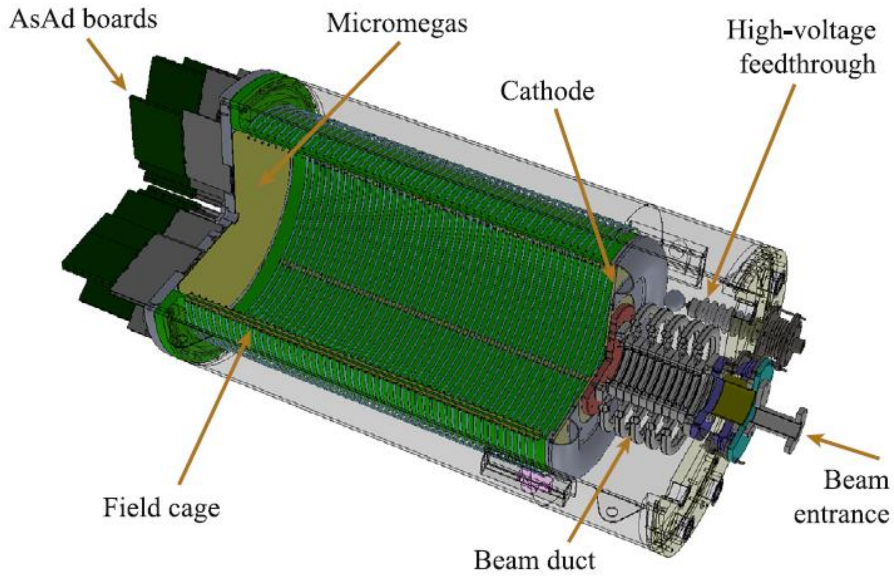
A short tour to NSCL

- It accelerates and produces rare isotope

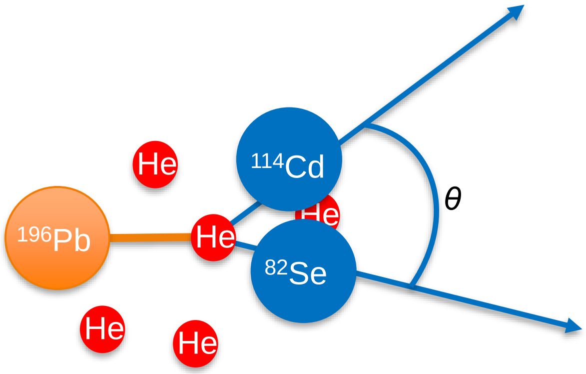


The experiment

- Experiment Performed in Active-Target Time Projection Chamber (AT-TPC) at the National Superconducting Cyclotron Laboratory (NSCL)



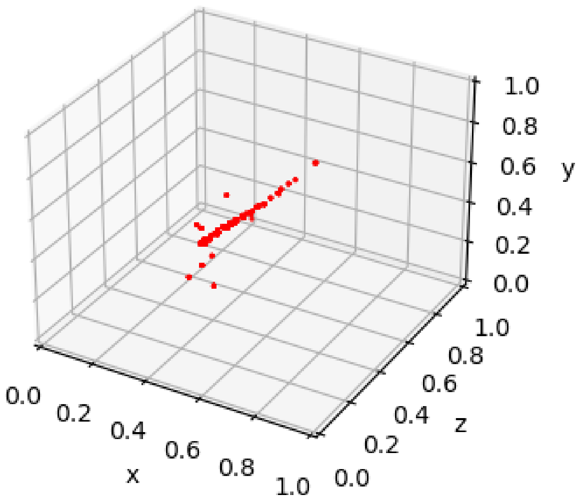
- Fusion-fission reaction



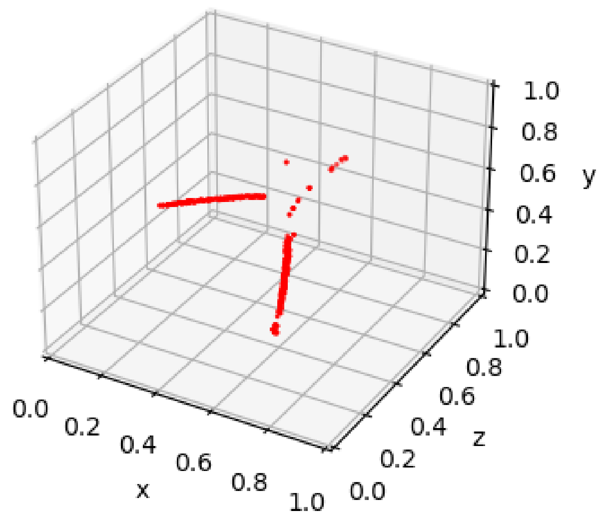
- Study fission properties of exotic nuclei near lead region

Project Objective

- Since fission events occur with low probability (~3%), we need to filter out fission events from background events
- Filter out fission events using unsupervised machine learning method



background



fission

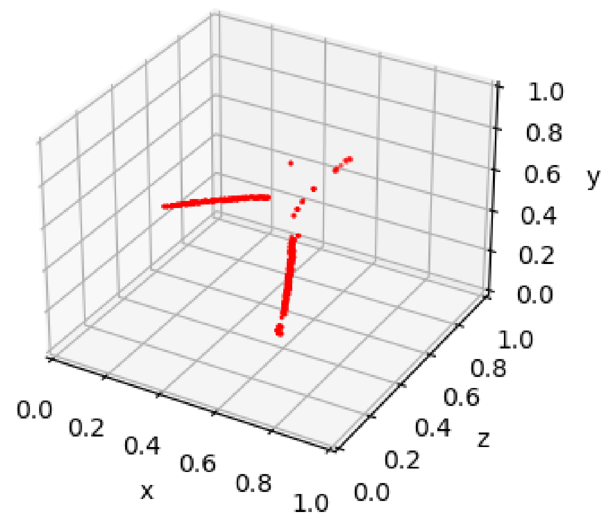
Complications

- Point clouds are ordered
  - Intrinsic order to input
  - But we should have permutation invariance
  - E.g.

	x	y	z
point 1	1	1	1
point 2	2	2	2
point 3	3	3	3

is same as

	x	y	z
point 1	2	2	2
point 2	1	1	1
point 3	3	3	3



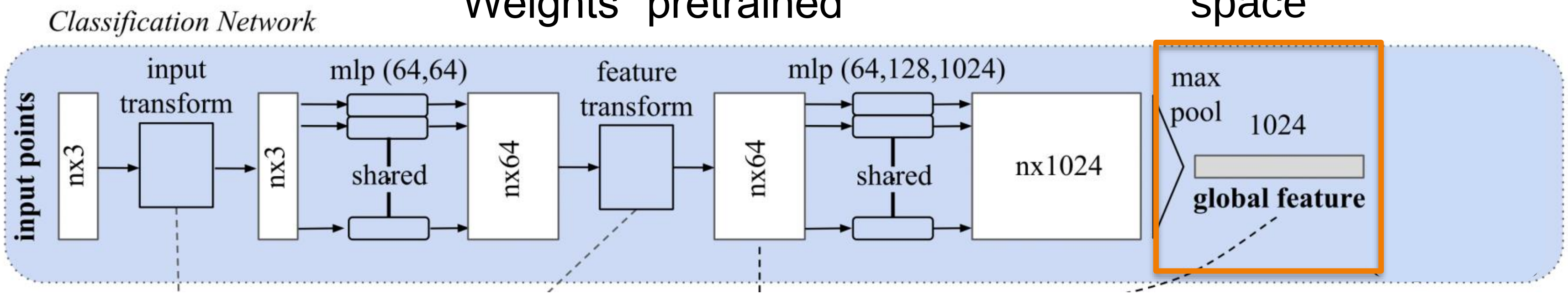
  - Not all machine learning model can handle the invariance

Solution: PointNet

- Need to map the point cloud into a **feature space**
- The **feature space** is **permutation invariant**
- Get the feature space from a ***pretrained*** network using PointNet architecture
- Pretrain????
  - We have to set the weights of the model
  - Can be done by train the model to do another task first

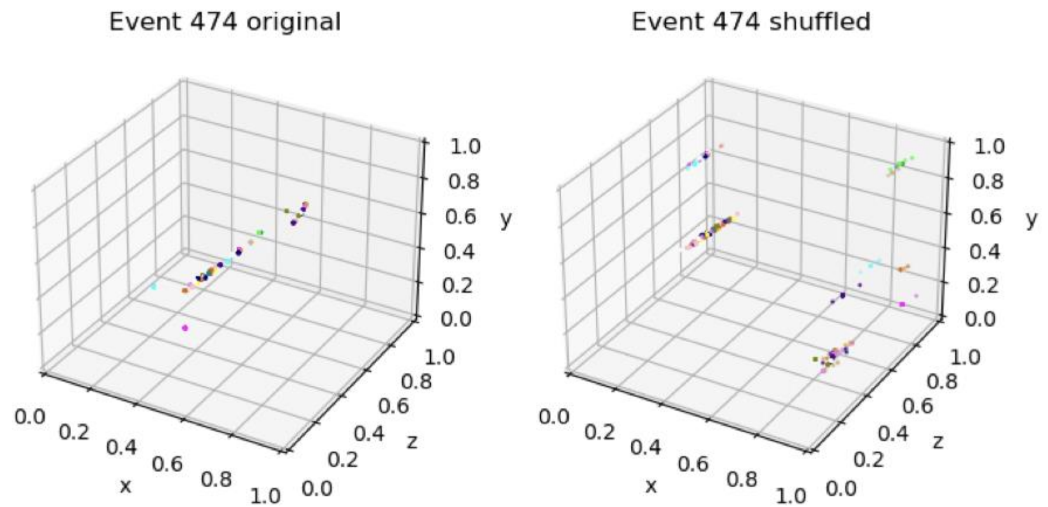
Feature space

Weights “pretrained”



Pretraining

- Pretraining task
  - Train a model to perform jigsaw reconstruction task
- Jigsaw reconstruction task
  - Divide chamber space into 63 (3*3*7) voxels
  - Each point has a voxel number (0-62)
  - Shuffle the voxels
  - Train the model to predict the true voxel number
- Why?
  - Self-supervised
  - The model learn how to handle event point cloud data through the training



Classifying model

PointNet

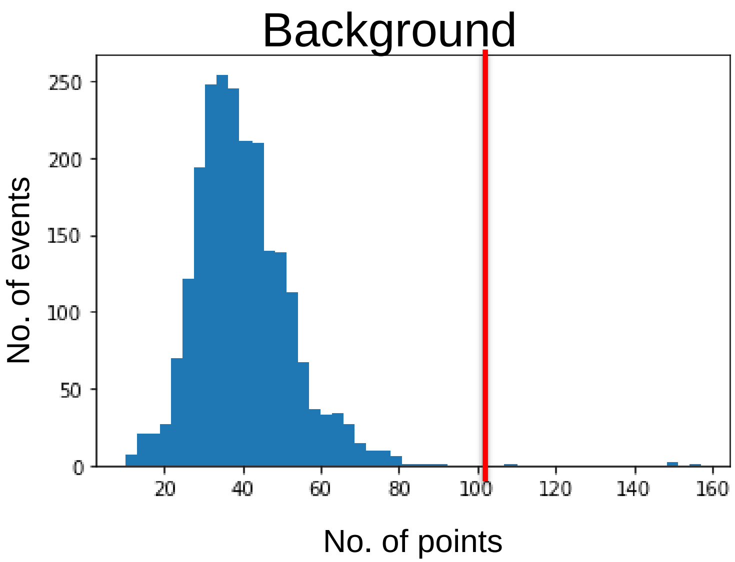
Different classifying models

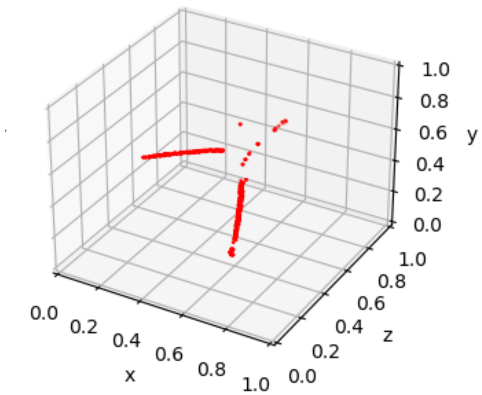
Point cloud -> feature space -> label (fission/non-fission)

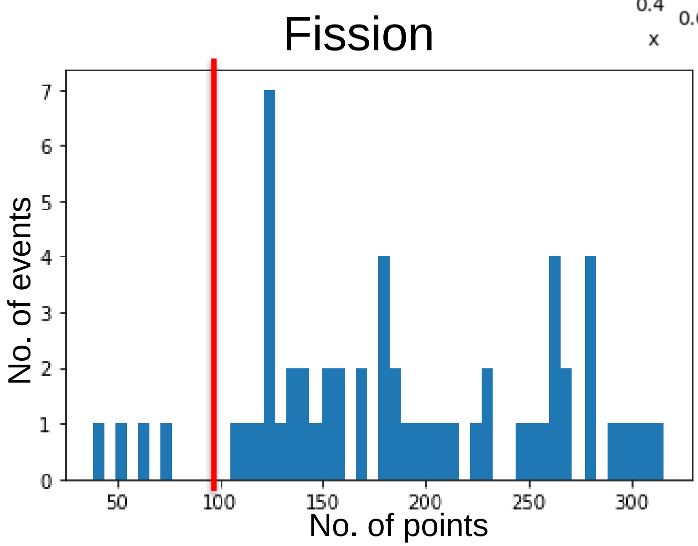
- Models used:
- Cut method (non-machine learning, for reference)
- One-class Support Vector Machine
- K-means clustering
- One-class Support Vector Machine + k-means clustering

Cut method (1)

- Non-machine learning
- Classify fission events using “number of points” of event



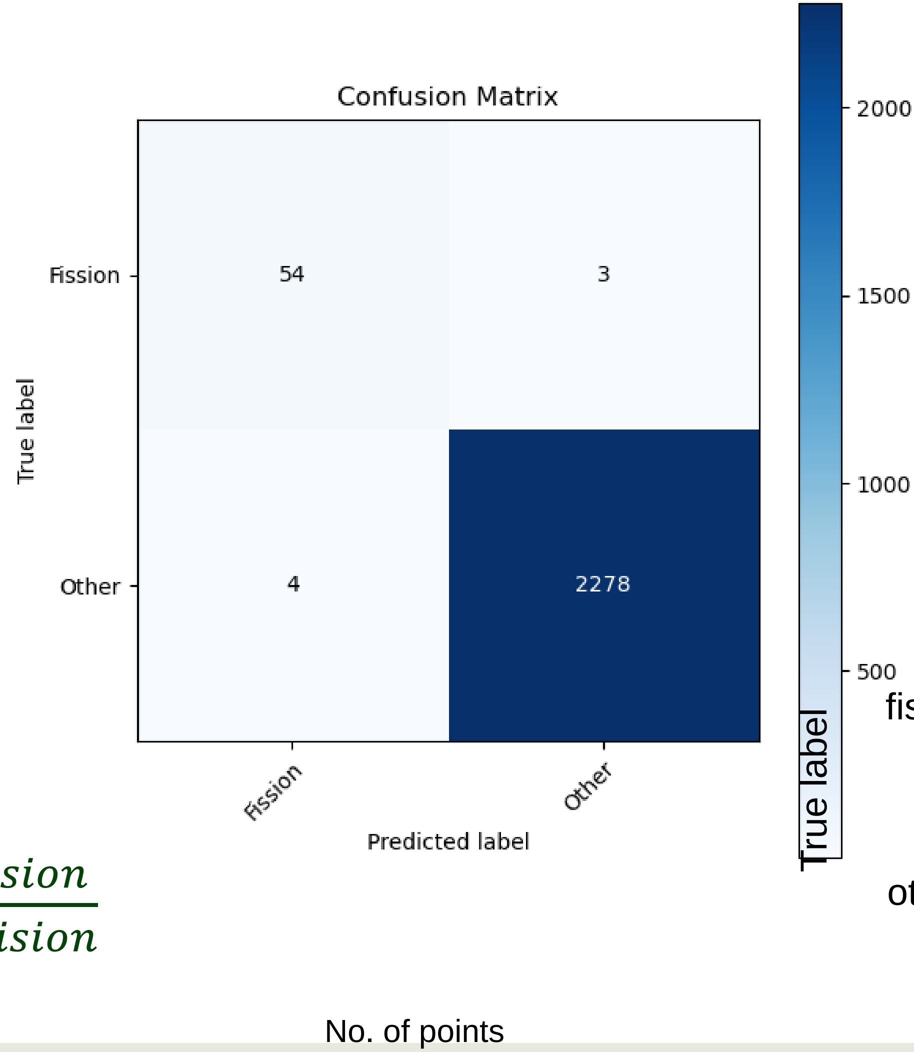


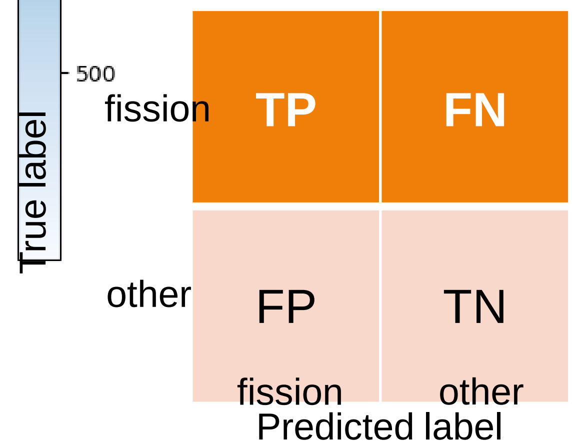


- Apply a 100-points cut

Cut method (2)

- Cut: 100 points
  - Recall: 95%
  - Precision: 93%
  - F1: 94%

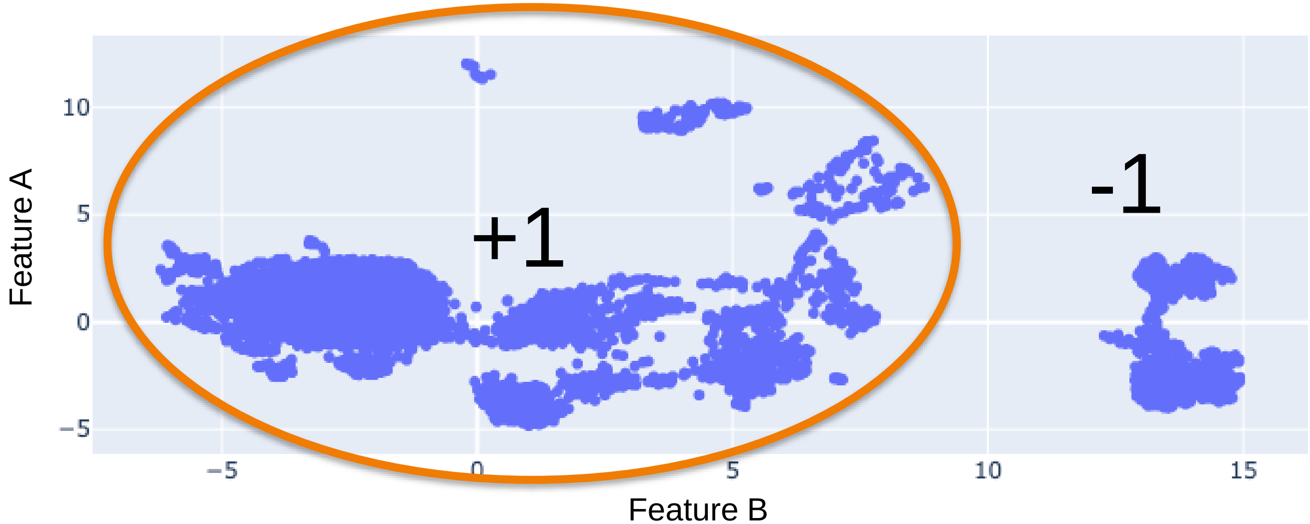




- Recall: $\frac{TP}{TP+FN}$
- Precision: $\frac{TP}{TP+FP}$
- F1: $2 \times \frac{Recall \cdot Precision}{Recall + Precision}$

One-class SVM (1)

- One-class Support Vector Machine (SVM)
  - Detect abnormal events

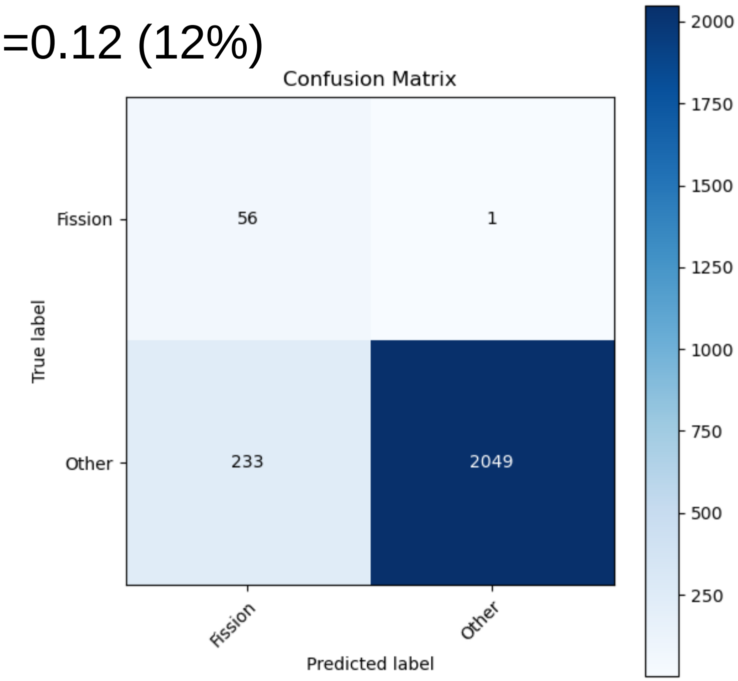


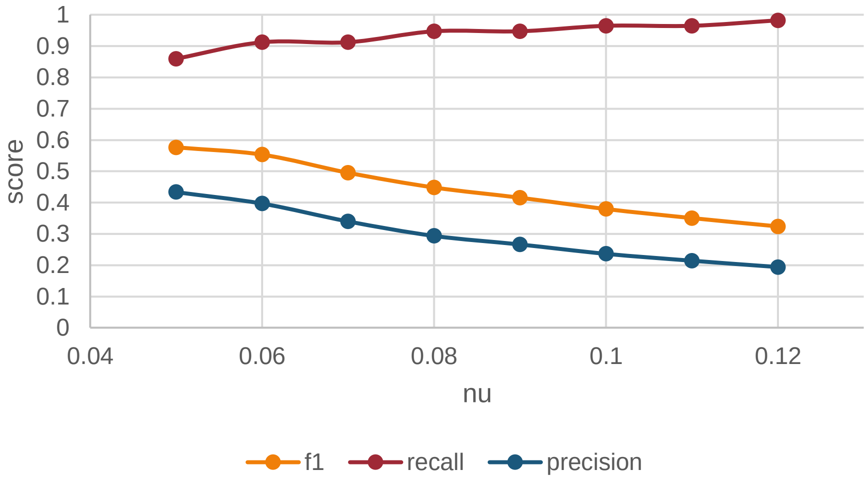
  - Fission events are rare. In principle, fission should be predicted -1
  - One important hyperparameter: nu
    - » nu = percentage of events “outside the circle”

One-class SVM (2)

- Result:
  - High **recall** (>98% for nu = 0.12)
  - Low precision (~20% for nu = 0.12)
    - » vs ~3% before extraction

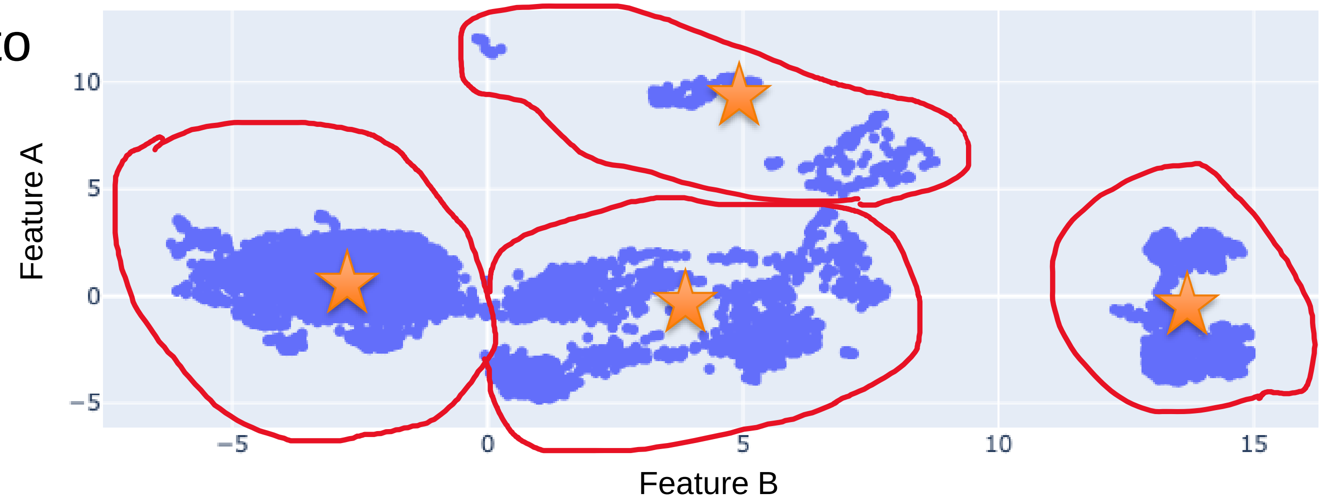
nu=0.12 (12%)





Clustering (1)

- k-means clustering
  - Classify events into different groups
  - Set centroids
  - Classify according to *closest centroid*

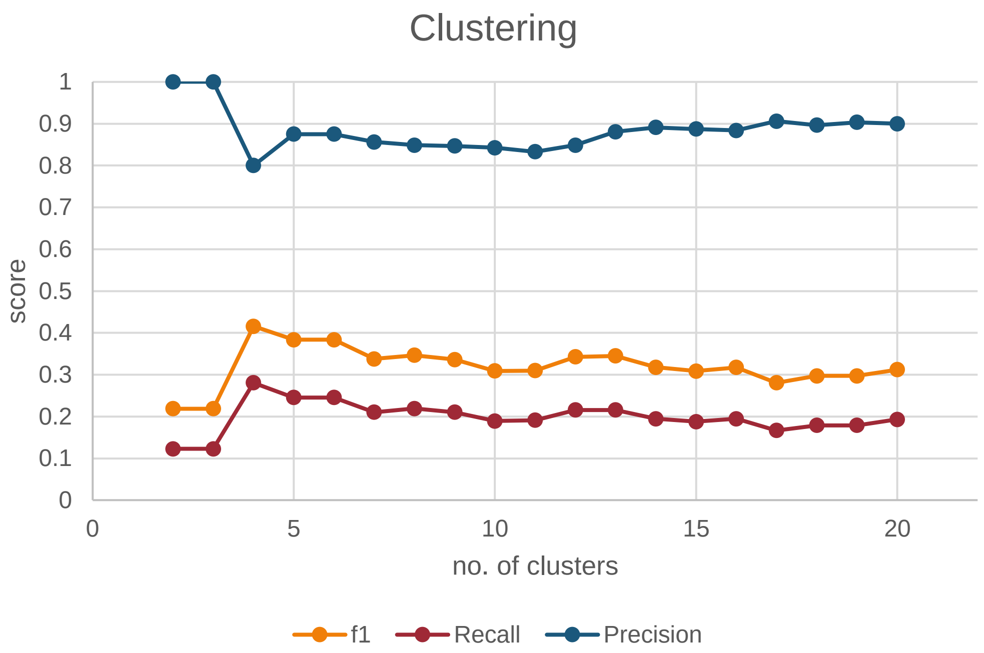


  - Hyperparameter: number of clusters
  - Select groups that are mostly fission events

Clustering (2)

- Result
  - High Precision
  - Low **Recall**

  - Not something we want
  - Not a suitable model
  - Why? Data imbalance:
    fission events are much rare than background



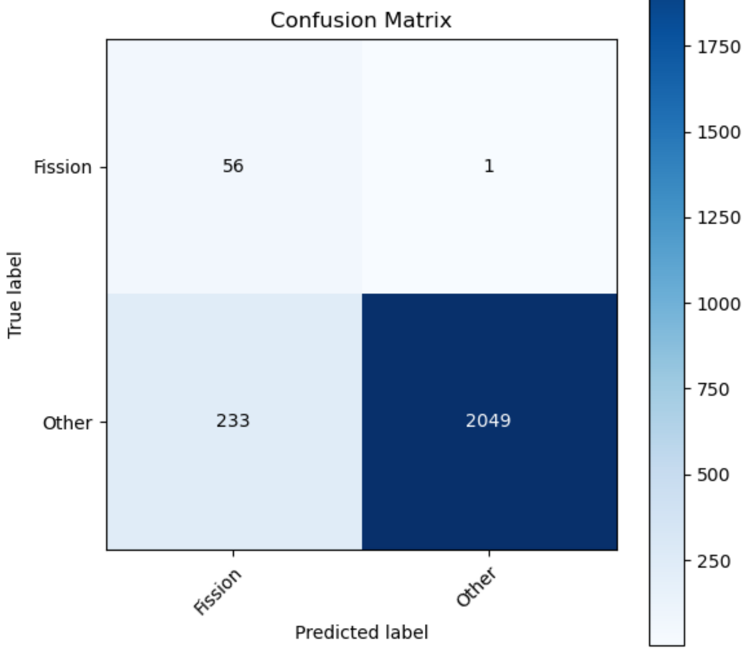
One-class SVM + Clustering (1)

- One-class SVM model:
  - High **recall**
  - Low precision
- K-means clustering model:
  - Low recall
  - High precision
- Proposal: One-class SVM follow by k-means clustering
  - Extracted events labeled “-1” in one-class SVM
    - » Fission events not as rare as before (~3% vs ~20%)
  - Train with k-means clustering model on this subset of data
  - Goal: high recall and high precision at the same time

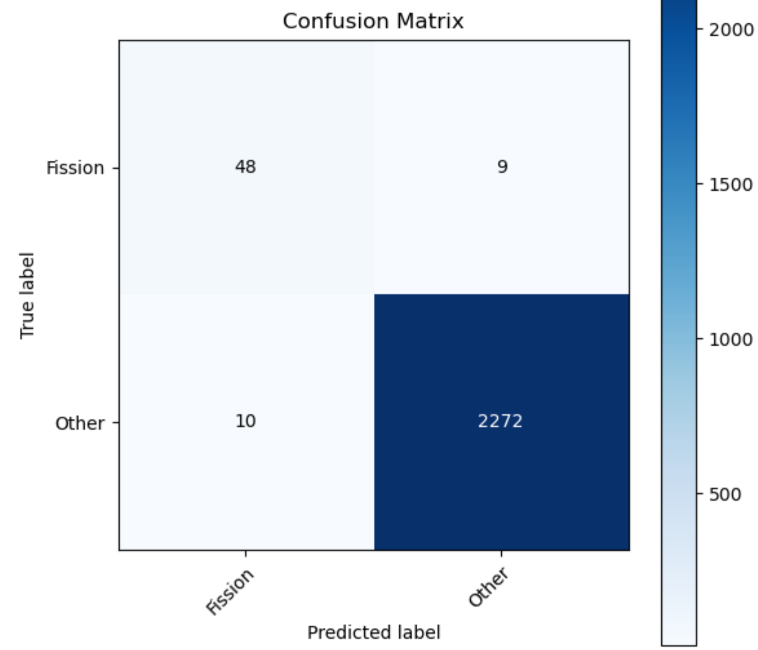
One-class SVM + Clustering (2)

- nu = 0.12, 16 clusters
  - F1: 83.5%, Recall: 84.2%, Precision: 82.8%
- nu = 0.12 one-class SVM only
  - F1: 32.4%, Recall: 98.2%, Precision: 19.3%

SVM only



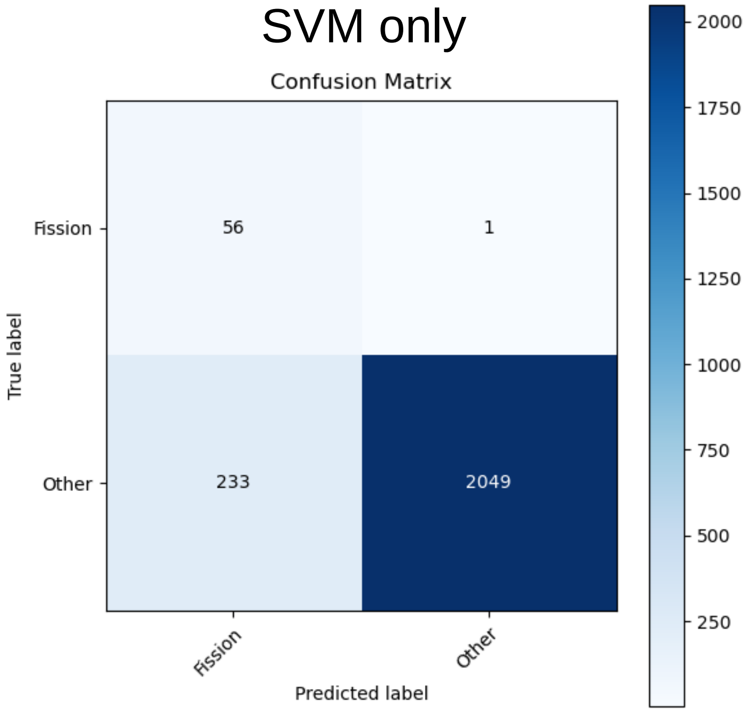
SVM+clustering



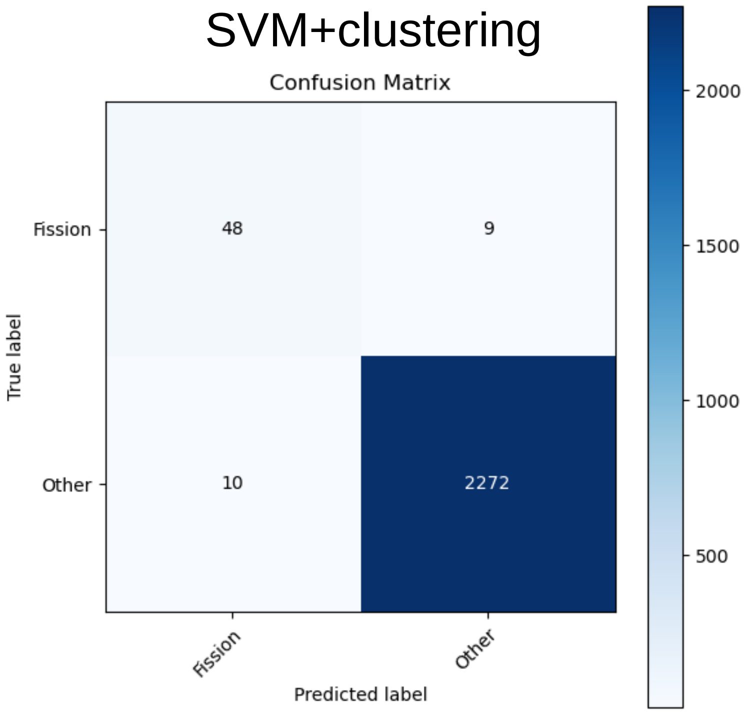
One-class SVM + Clustering (3)

- Compared to one-class SVM model
  - Improved precision
  - But lower recall

SVM only



SVM+clustering



Conclusion (1)

- Various models were used to do the classification task
- Summary:

Model	F1	Recall	Precision
SVM[1]	0.32	**0.98**	0.19
Clustering[2]	0.42	0.28	0.80
SVM+Clustering[3]	0.84	0.84	0.83
Cut	**0.94**	0.95	**0.93**

1: nu = 0.12
2: 4 clusters
3: nu = 0.12, 16 clusters

Conclusion (2)

- Unsupervised/self-supervised learning method can classify fission events
  - SVM model has high recall
    - Although low precision (~20%), still better than before (~3%)
  - No labeling need to be done
  - A completely unrelated task (jigsaw reconstruction) was used to pretrain the model

- Future work
  - Use a different pretraining method
  - Include more information (e.g. charge, number of hit) to the model
    - We only used spatial coordinates

Reference

- Qi, Charles R., et al. "Pointnet: Deep learning on point sets for 3d classification and segmentation." *Proceedings of the IEEE conference on computer vision and pattern recognition* (2017).
- Sauder, Jonathan, and Bjarne Sievers. "Self-supervised deep learning on point clouds by reconstructing space." *Advances in Neural Information Processing Systems* 32 (2019).

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The End

- Questions?