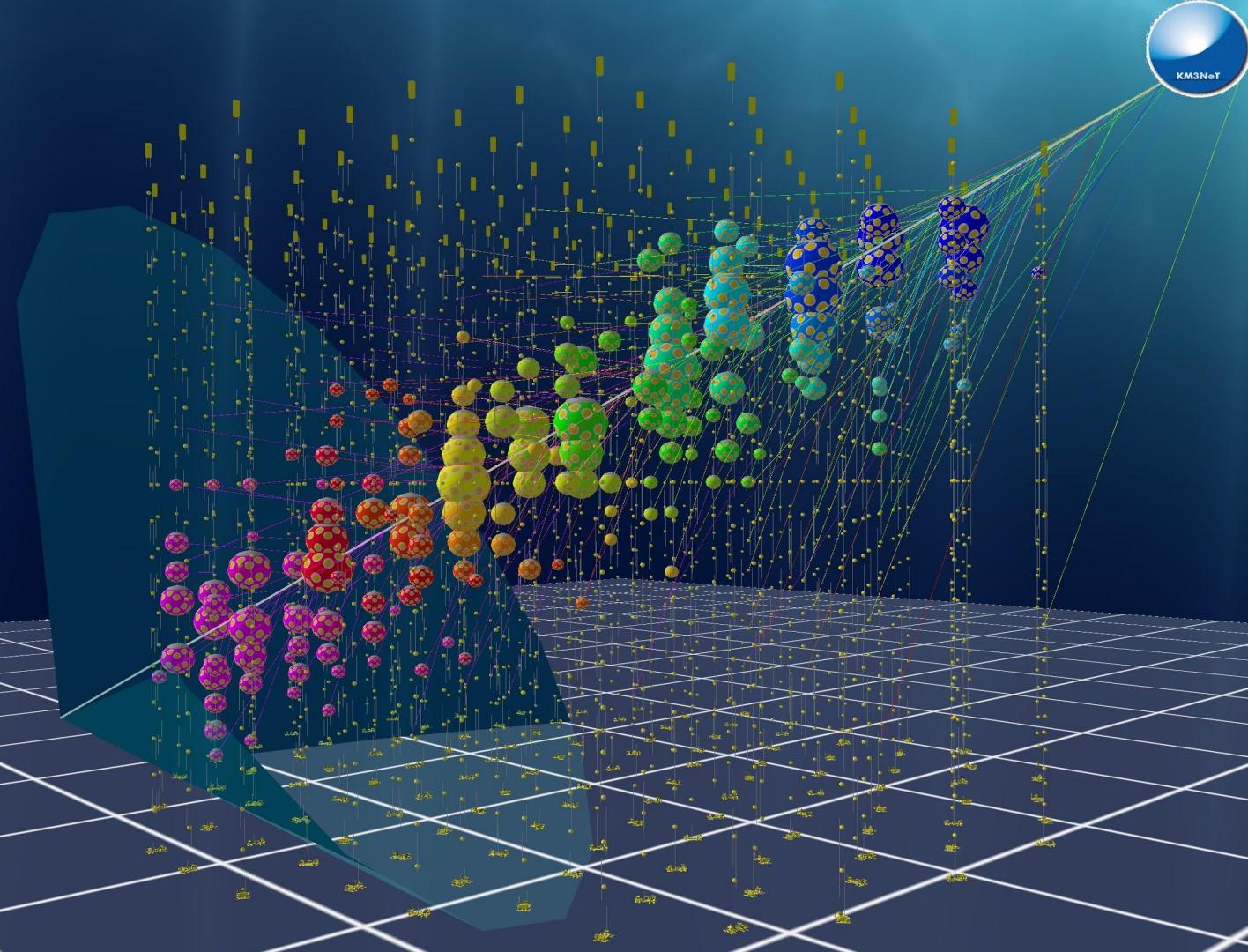


KM3NeT Neutrino Detection with PointNet

Background

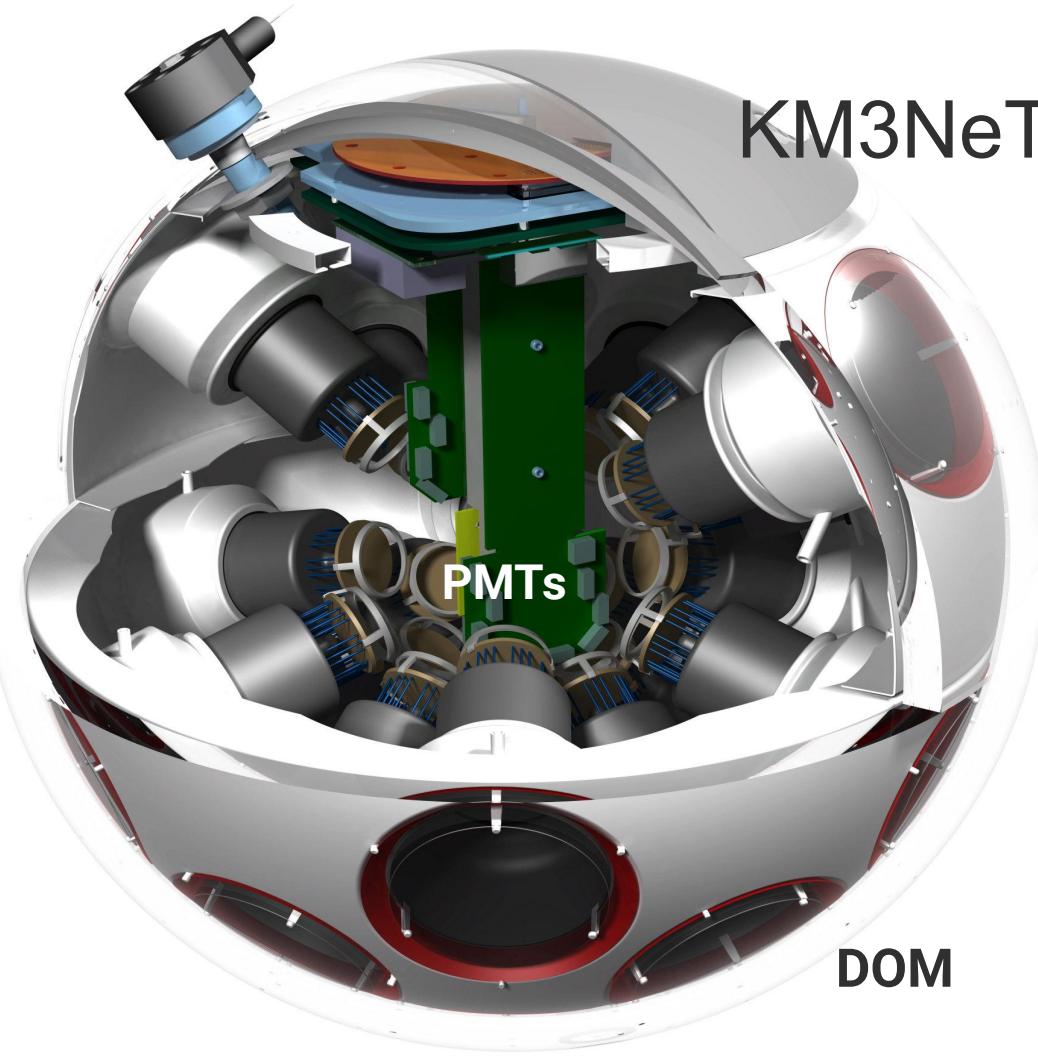


Neutrinos



Cherenkov
Light

KM3NeT



- Event Triggers - L0, L1, L2 [1]
- GPU Pipeline [2]
- CNN Experiment [1,3]

Motivation & Research Contributions

Motivation

- Assess state-of-the-art architectures
- Improve data acquisition for KM3NeT
- Shortcomings of CNNs [4, 5, 6]

Contributions

- Novel 3D mesh representation
- First known use of PointNet
- Improvement over L1 Trigger

Research Questions

RQ 1.0

Can PointNet classify noise timeslices and event timeslices?

RQ 1.1

Can PointNet obtain a Recall score of 0.9 for the positive class?

RQ 2.0

Can the KM3NeT dataset be effectively represented using 3D meshes?

RQ 2.1

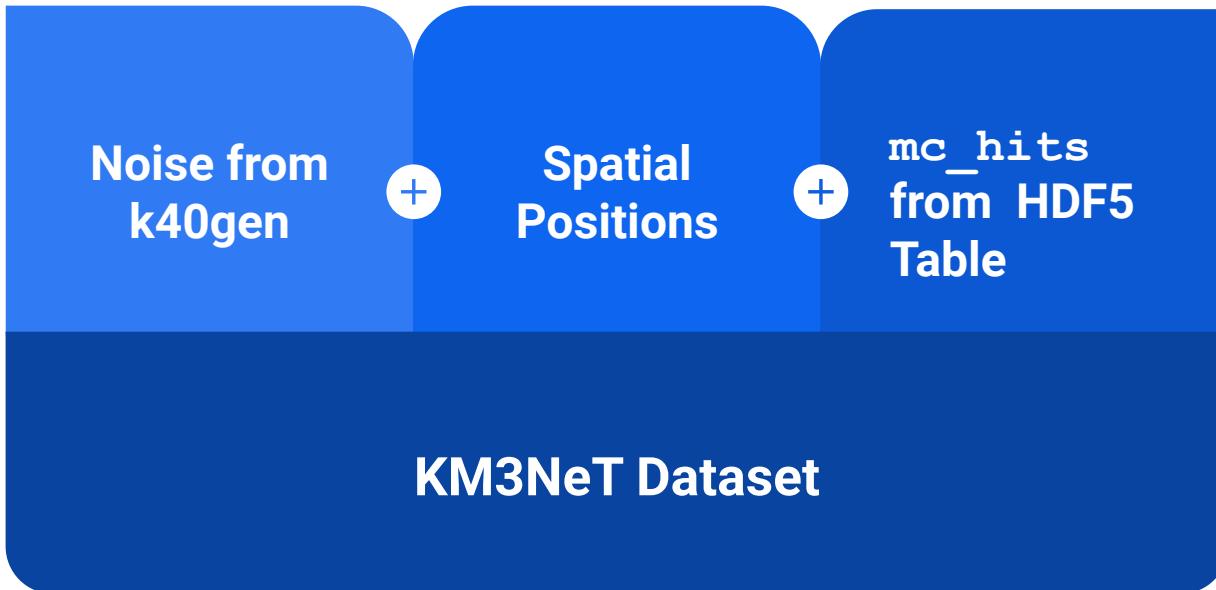
Which meshing algorithm would be suitable for representing data?

RQ 3.0

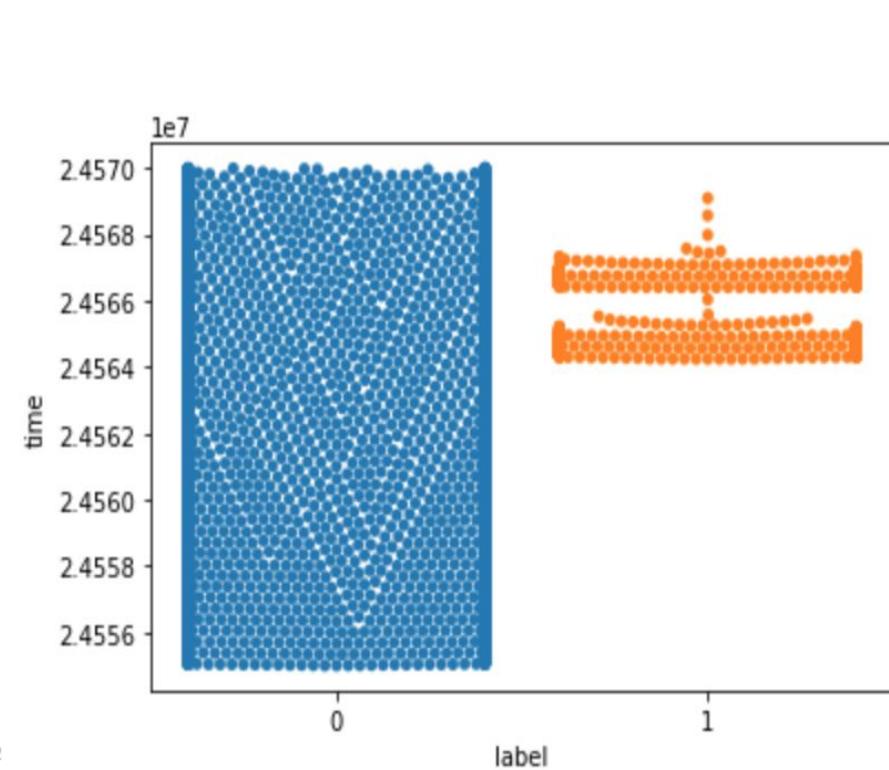
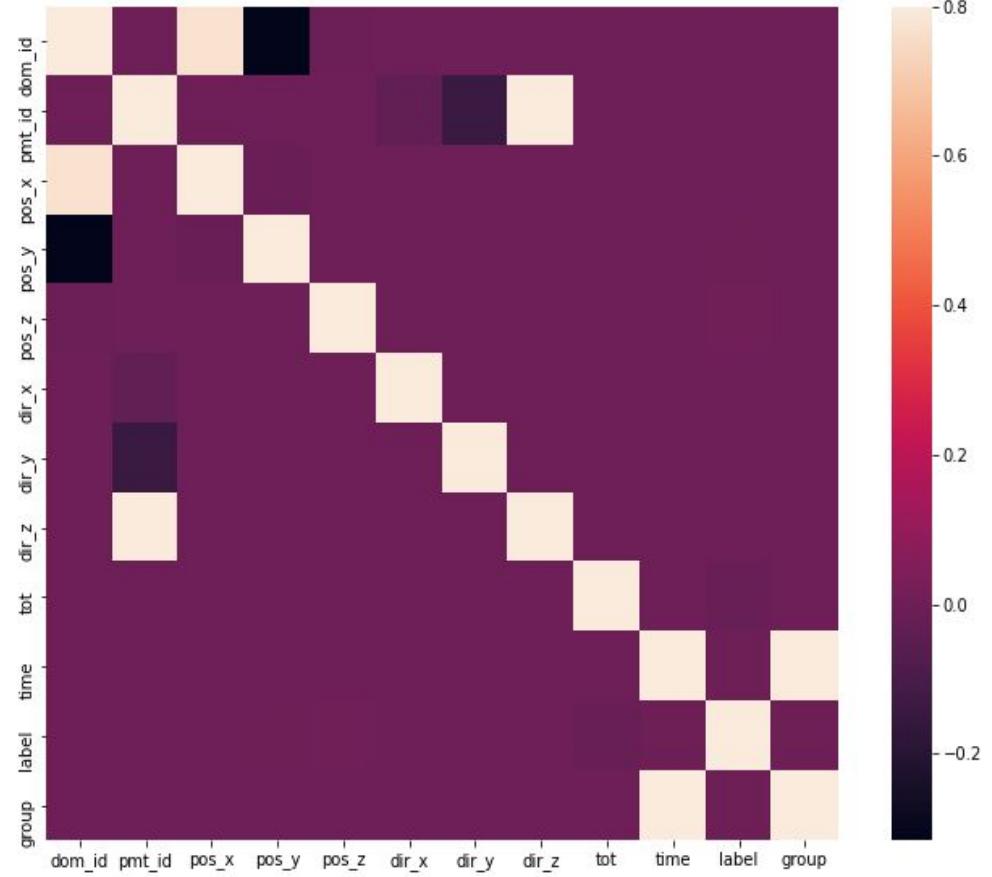
Can PointNet be extended for energy inference from events?

KM3NeT Dataset

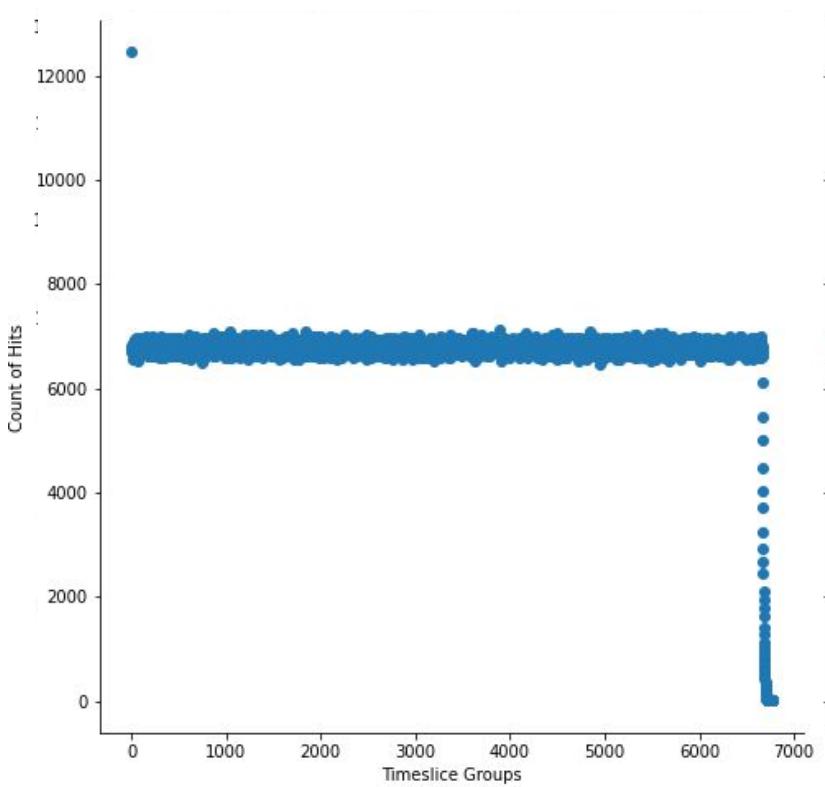
Data Preparation



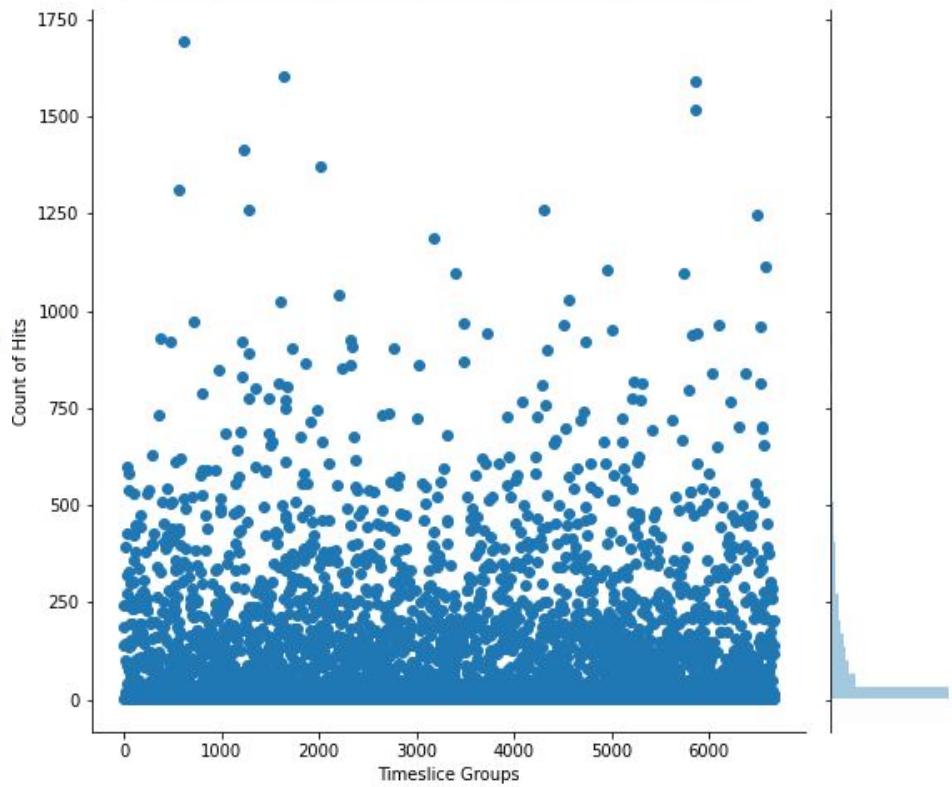
Attribute	Description
dom_id	[Unique ID for sensor module.]
pmt_id	[Unique ID for photomultiplier (PMT) tubes within DOMs.]
pos_x, pos_y, pos_z	[Spatial coordinates (in meters) of hit within the detector.]
dir_x, dir_y, dir_z	[Direction of PMT tubes within DOMs to look for Cherenkov Light.]
tot	[Time-over-threshold (ToT) indicates the amount of light transformed to charge which is interpreted as the length of the square wave pulse over a given threshold (26).]
time	[Time at which the hit was recorded.]
label	[0 or 1 class label indicating whether hit is from noise or event respectively.]
group	[Timeslice numbers starting from 0 for the purpose of identification.]



Noise Timeslices

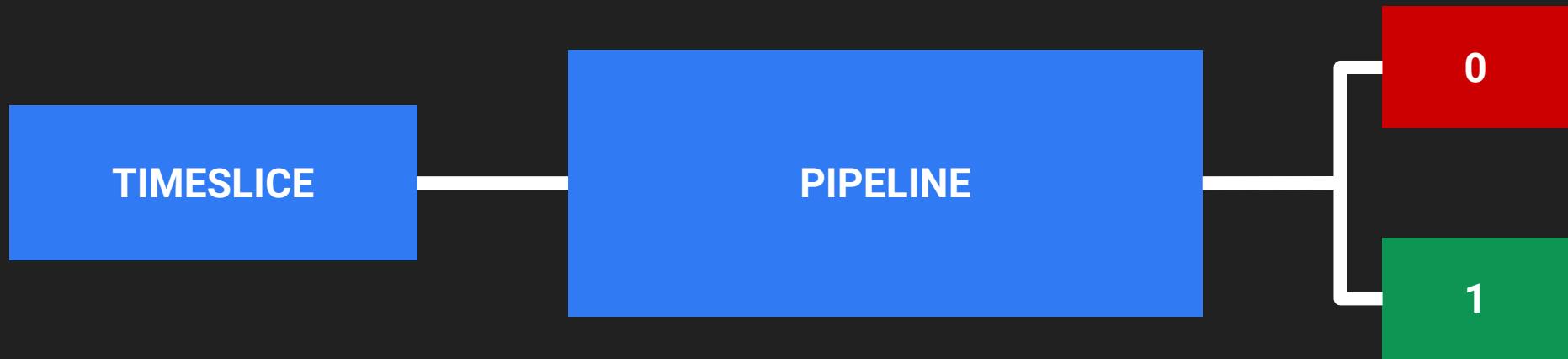


Event Timeslices



The Pipeline

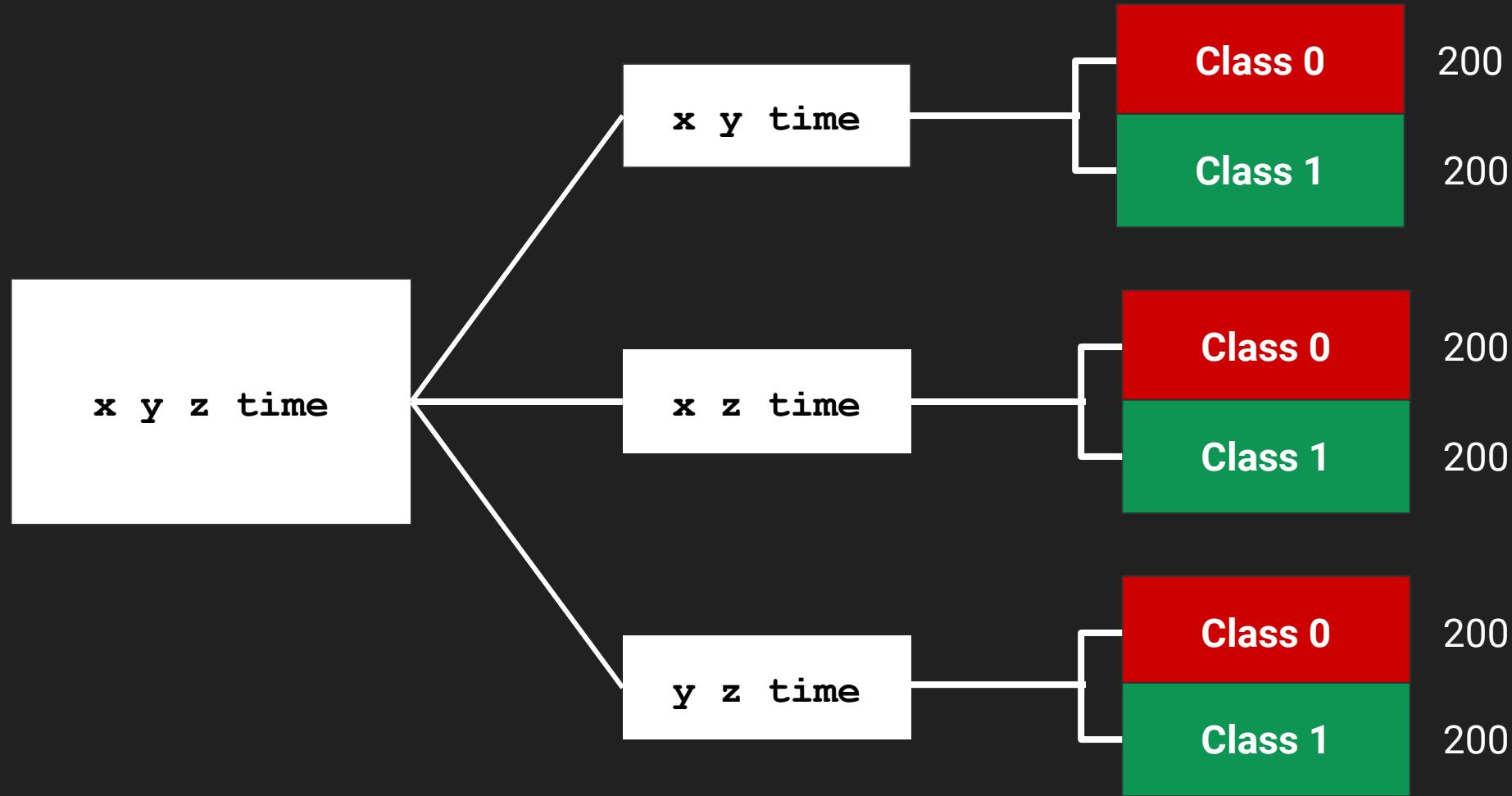
Design Goal



Noise
Timeslices : `class_0`

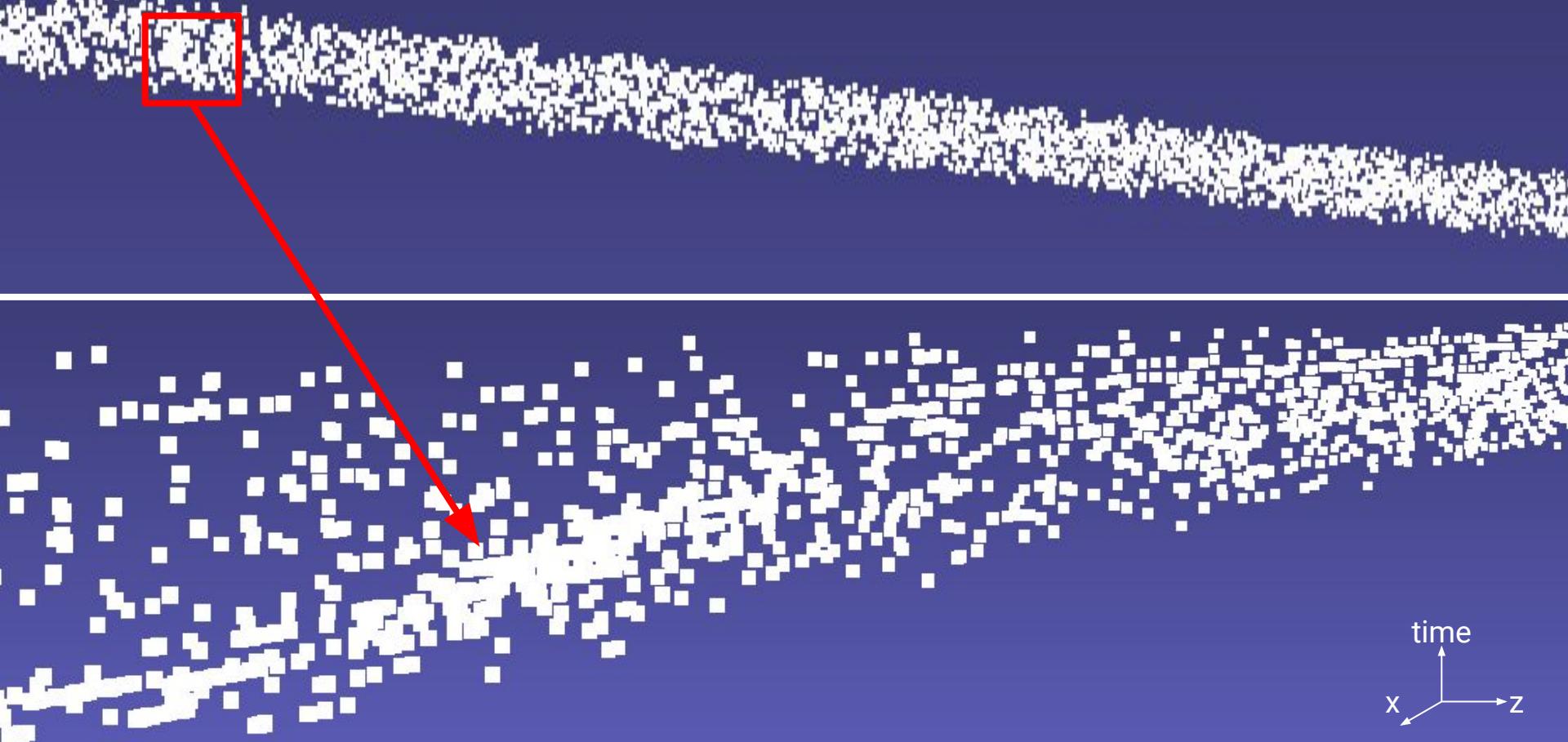
Event
Timeslices : `class_1`

Step 1: 3D Coordinates



Step 2: Feature Engineering

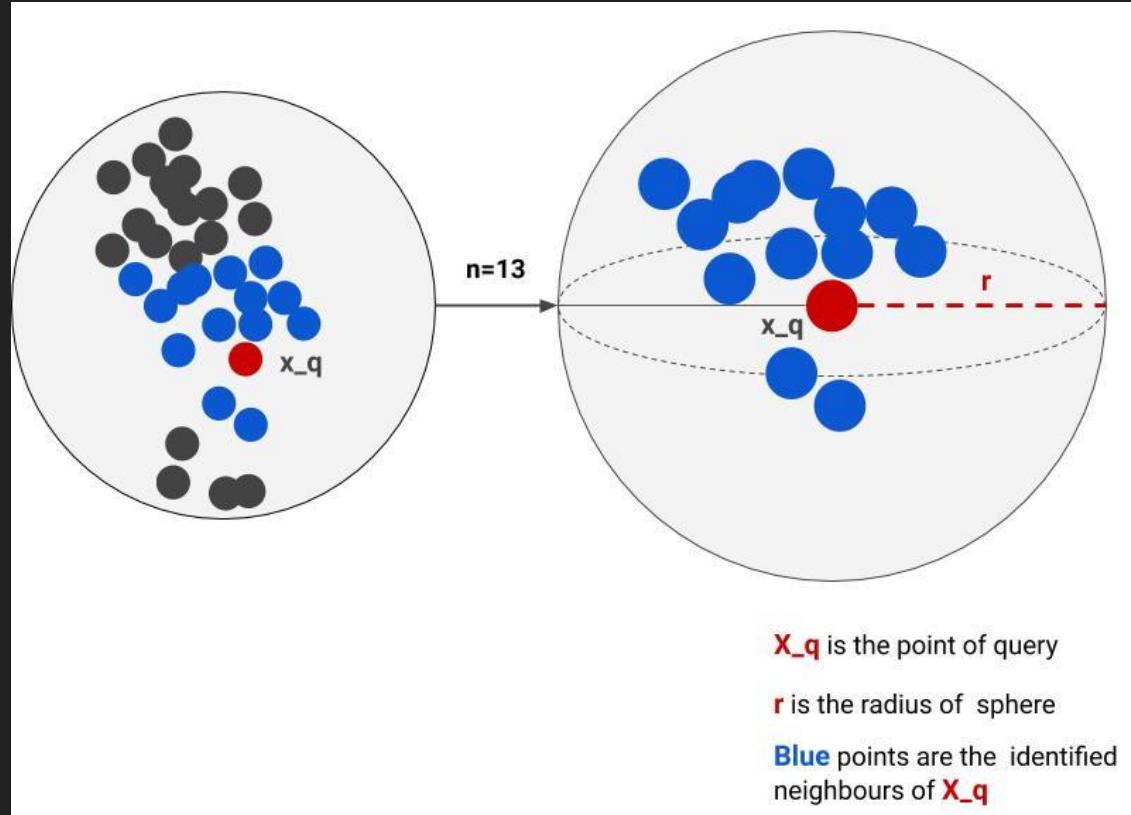
Identified Problem



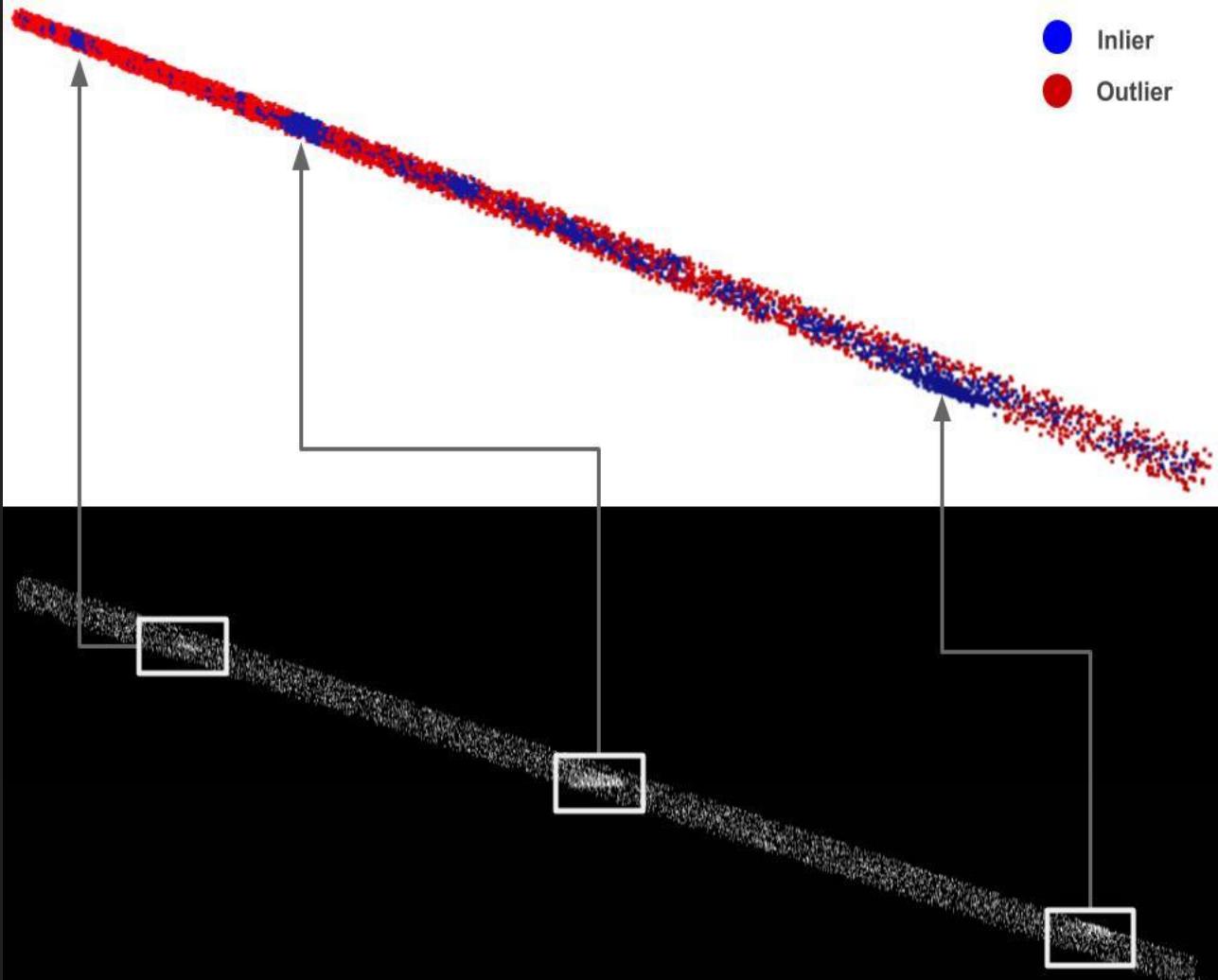
time
x → z

Proposed Solution: Radius-based Outlier Filter (RBOF)

A point is an outlier if it contains fewer than specified neighbours

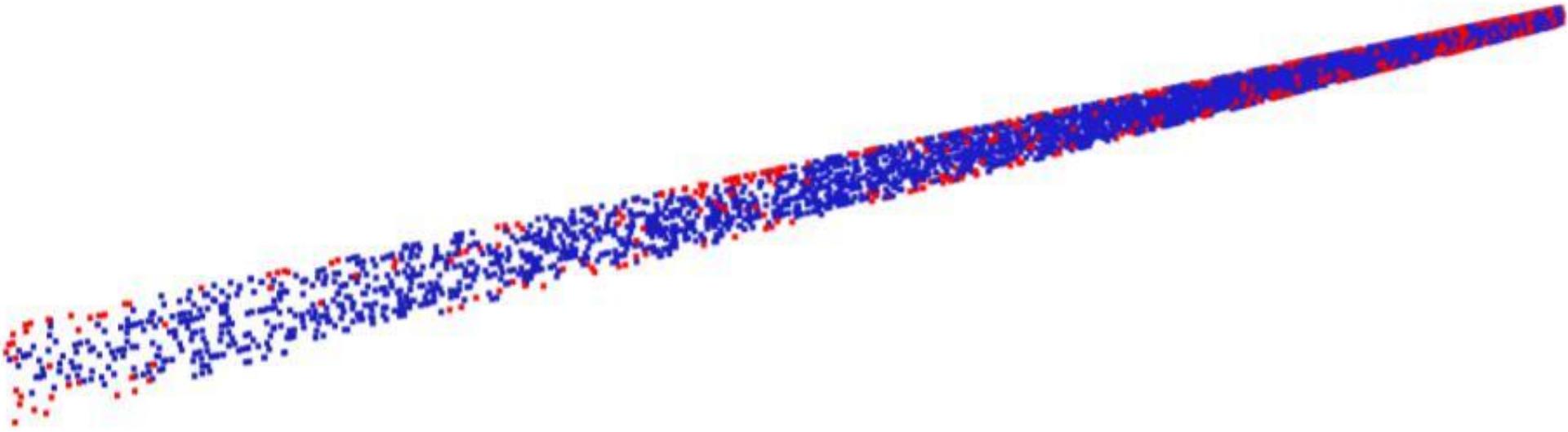


Outlier Detection Applied on An Event Timeslice

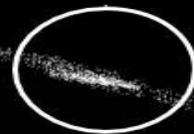


Outlier Detection Applied on Noise Timeslice

- Inlier
- Outlier



Timeslices After RBOF

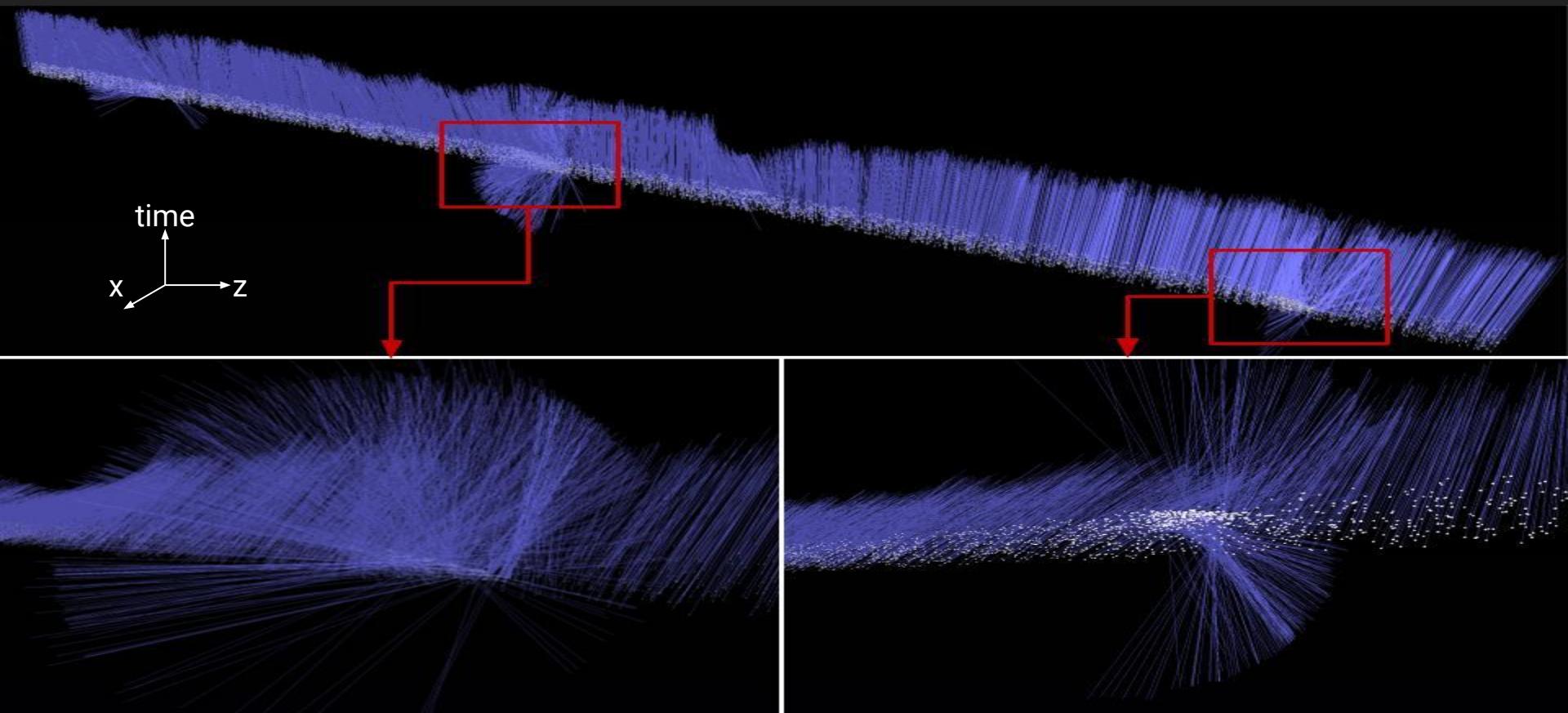


Event Timeslice

Noise Timeslice

Step 3: 3D Mesh Generation

Computing Normals

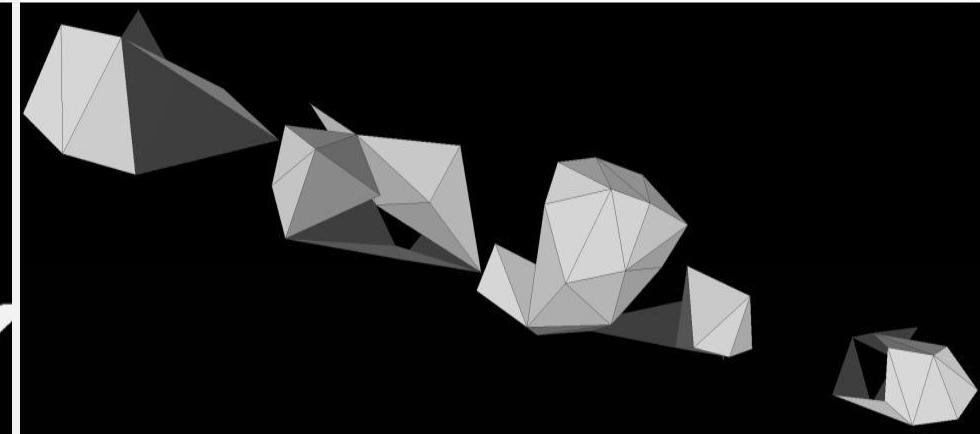
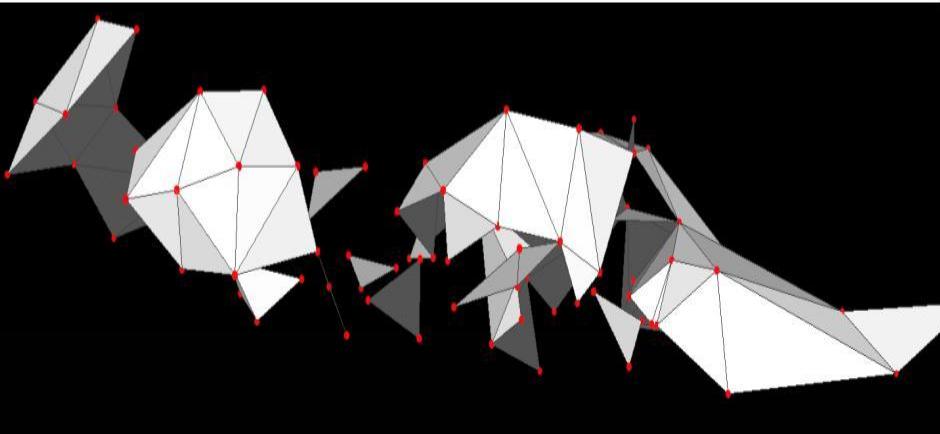
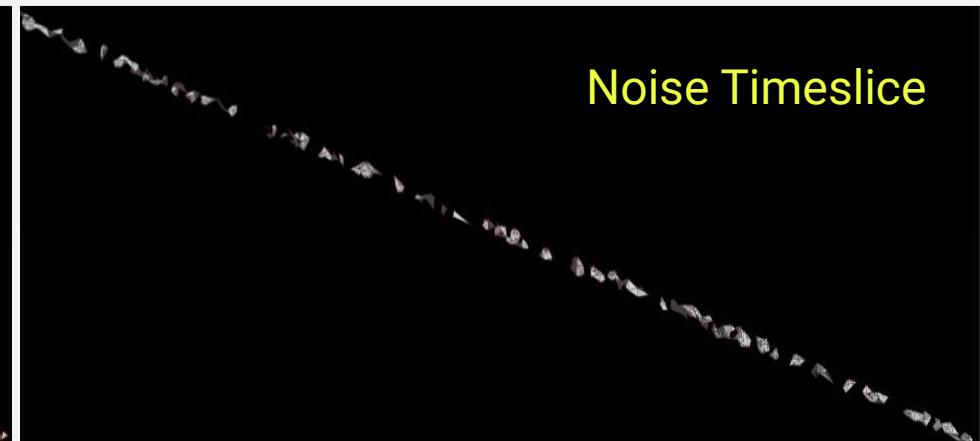


Ball Pivoting Algorithm

Event Timeslice

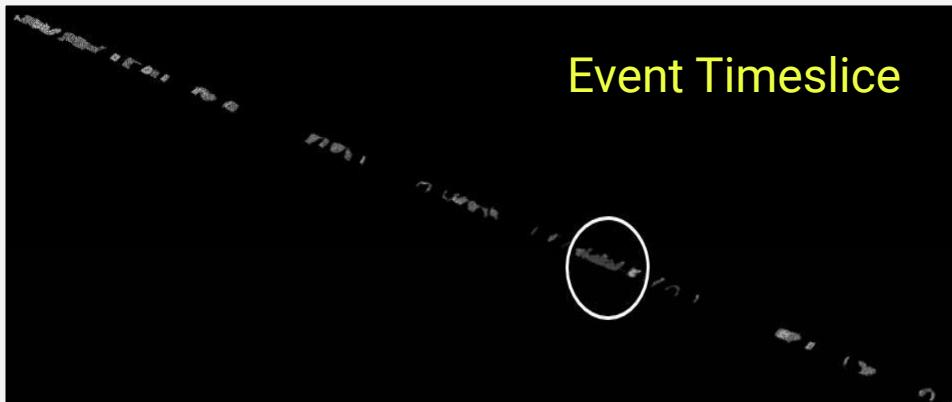


Noise Timeslice

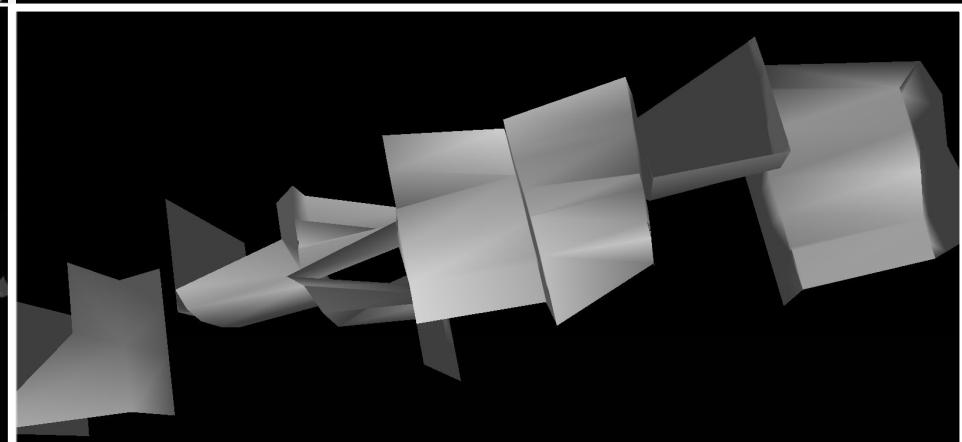
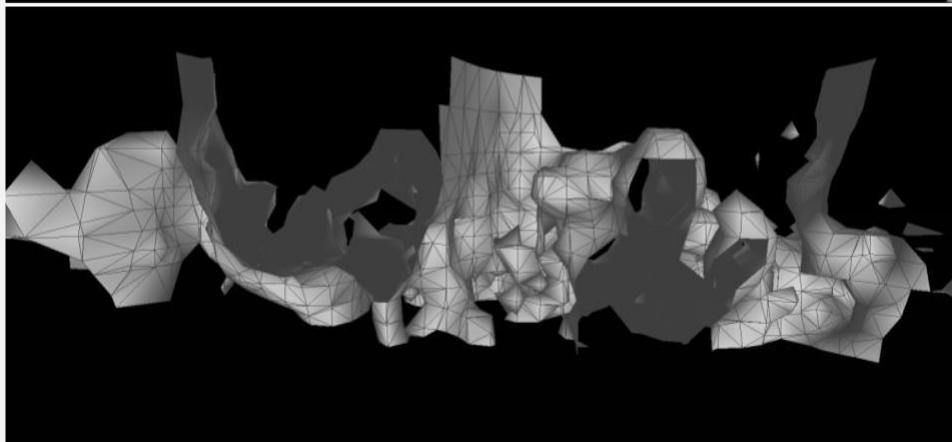
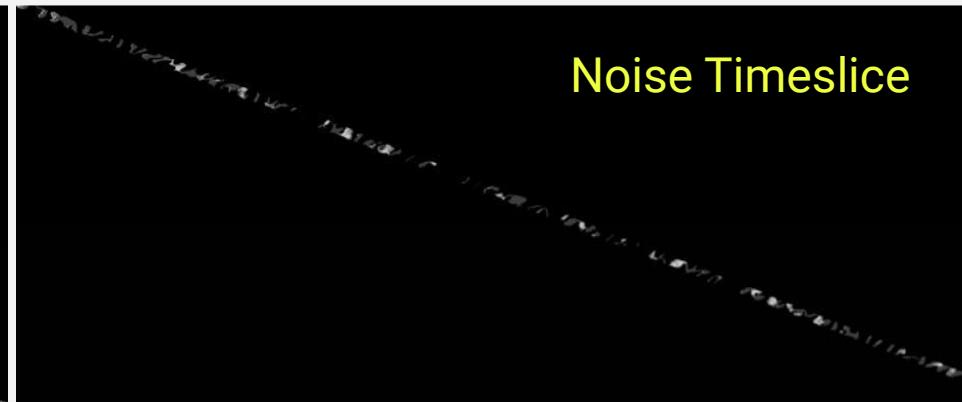


Surface Poisson Reconstruction

Event Timeslice

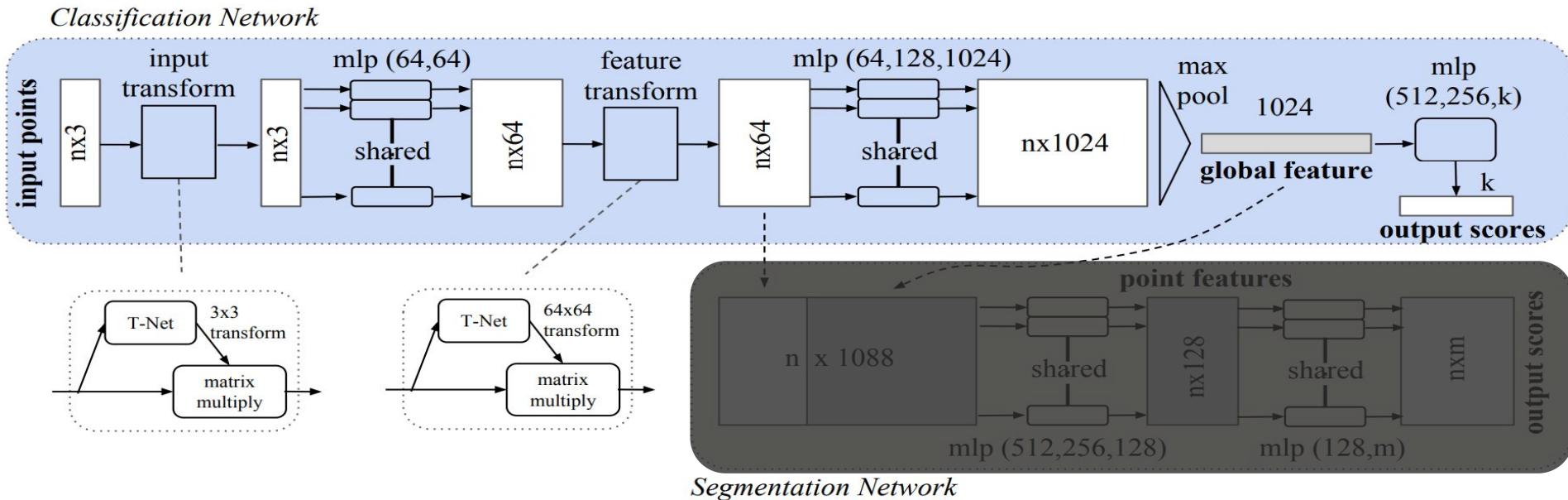


Noise Timeslice



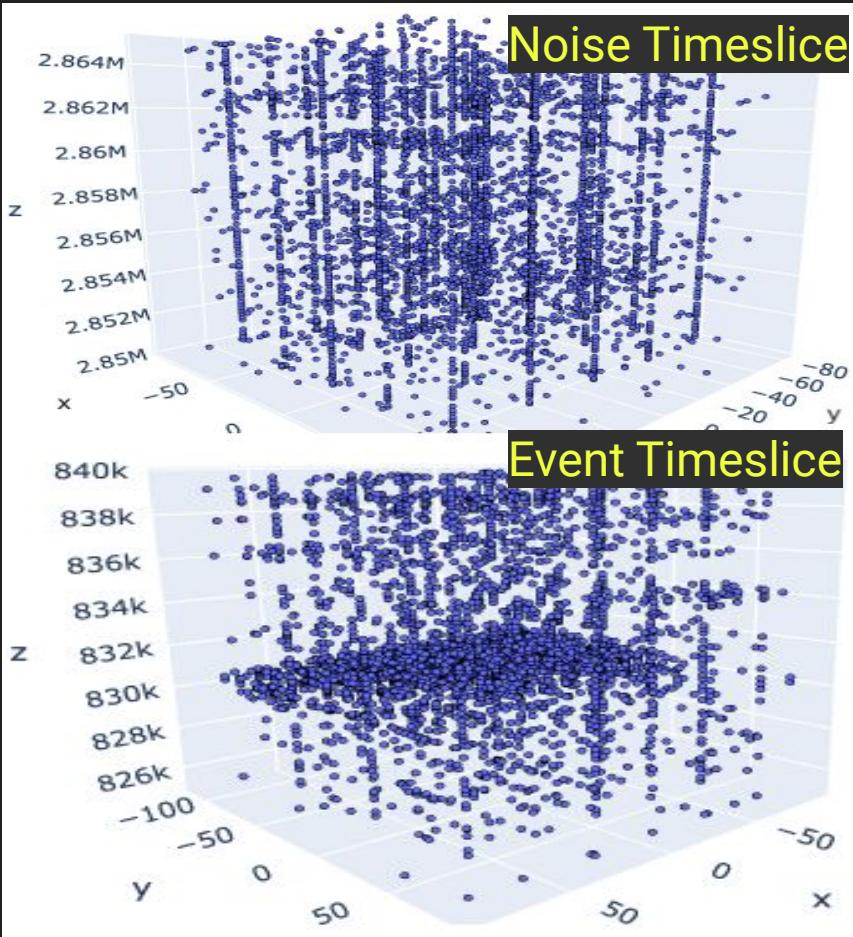
Step 4: Training & Evaluation

PointNet Background

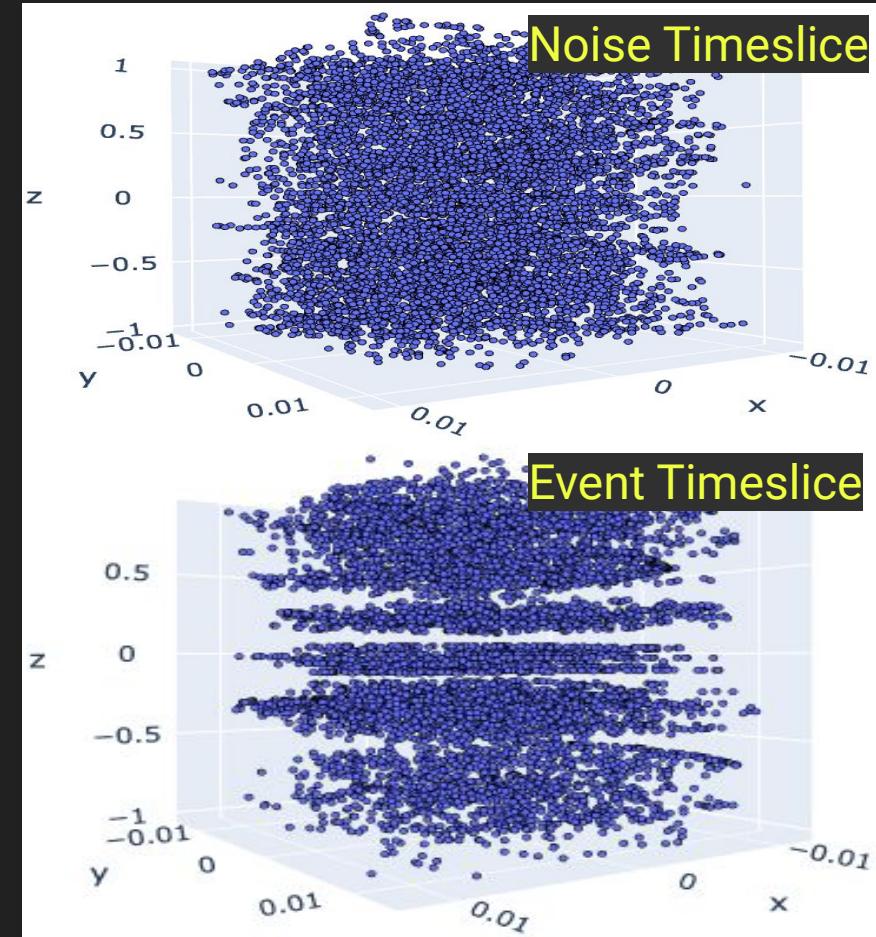


1. Fixed Sample of Points Per Cloud [7].
2. Unordered and invariant to permutations [7].
3. Invariant to transformations [7].

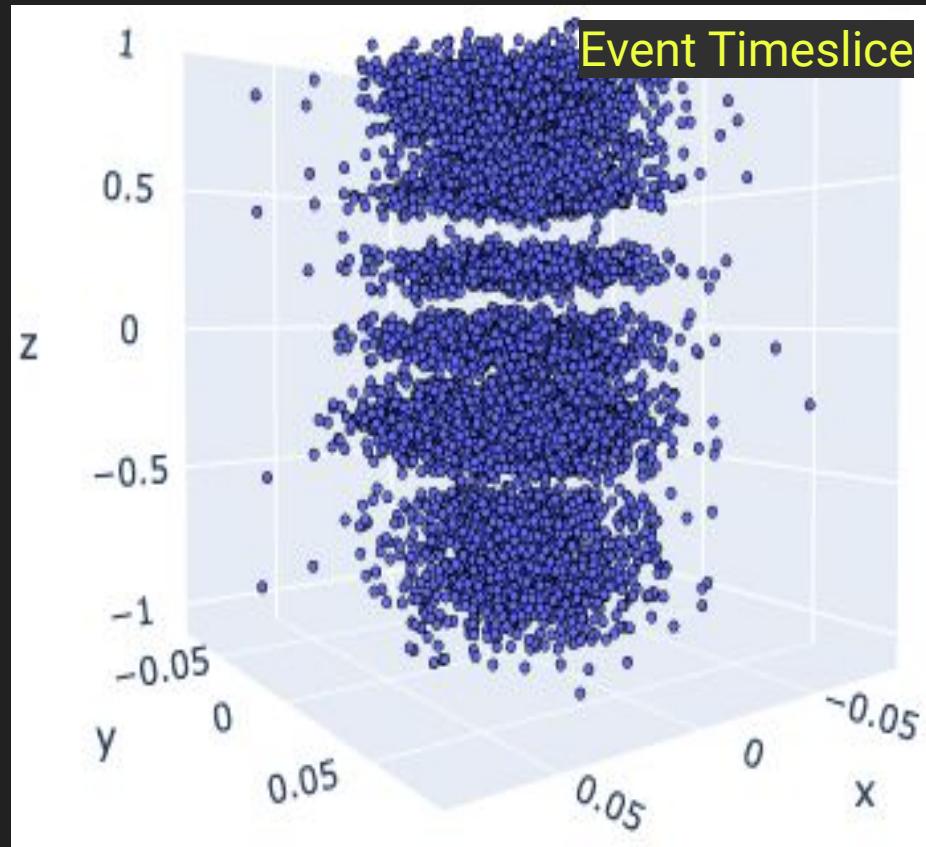
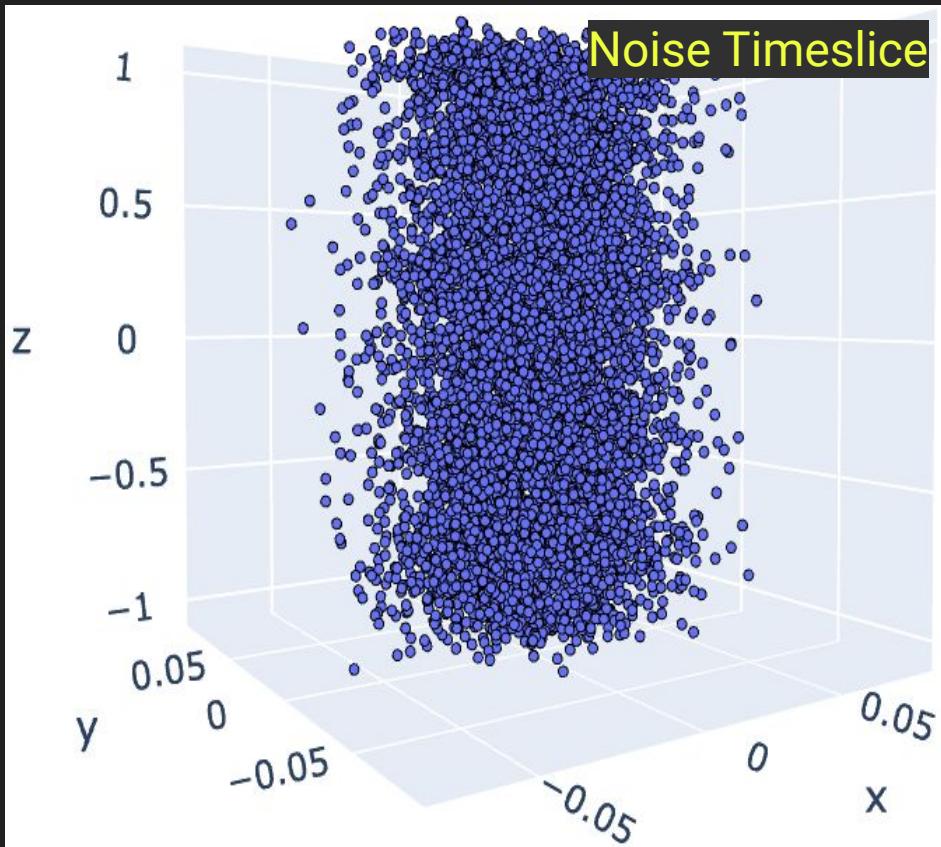
Sampling



Normalisation



Jitter & Random Rotation



Evaluation Methodology

80/20 training-testing split

120 Epochs

Majority Voting Ensemble [11]

Results

Accuracy

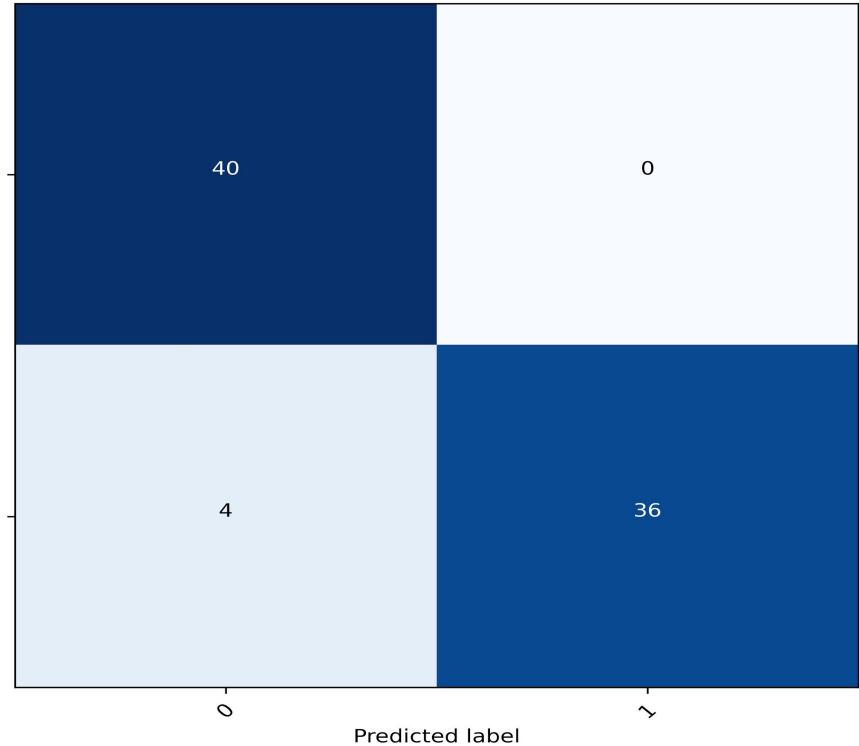
x, y, time	95% (loss = 0.003)
x, z, time	90% (loss = 0.006)
y, z, time	99% (loss = 0.005)
Ensemble 1: Hard Voting	97%
Ensemble 2: Soft Voting	90%

Table 7.1: Accuracy Scores

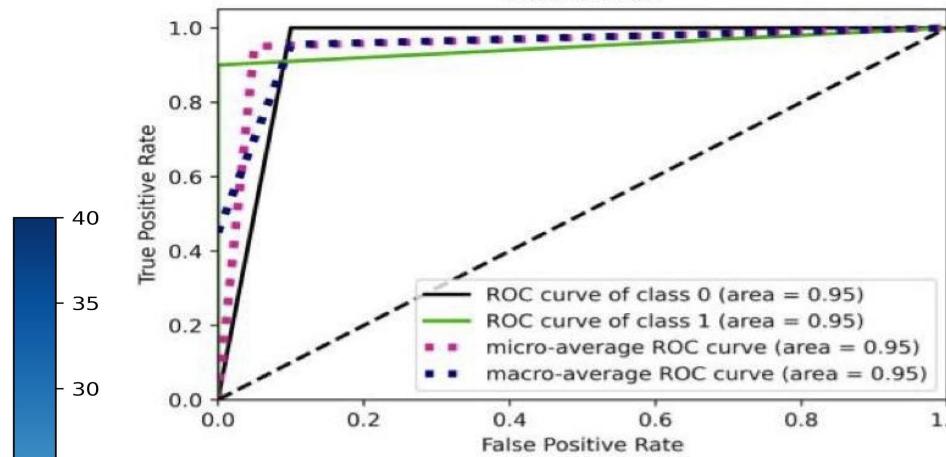
Dataset 1: x y time

	precision	recall	F1-score	support
class_0	0.91	1.00	0.95	40
class_1	1.00	0.90	0.95	40

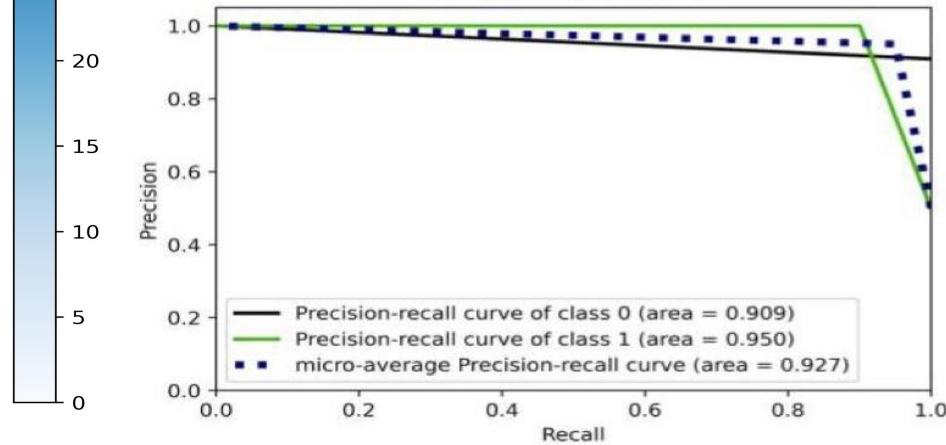
Confusion matrix



ROC Curves

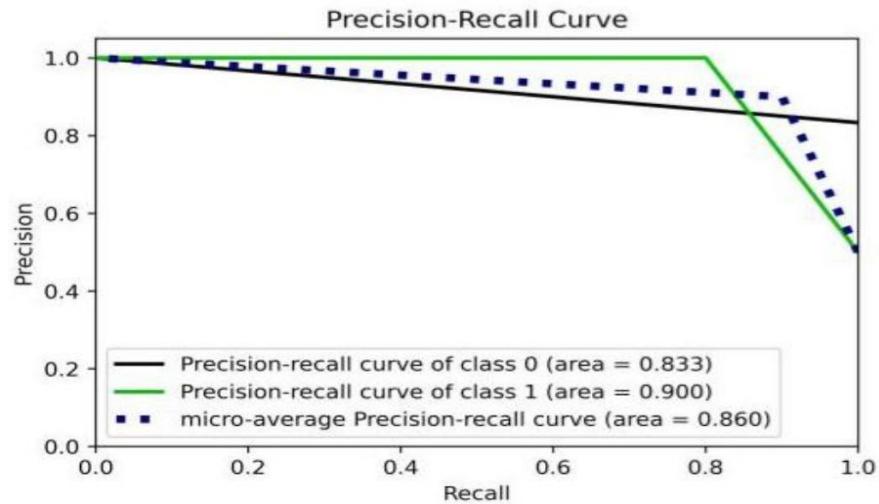
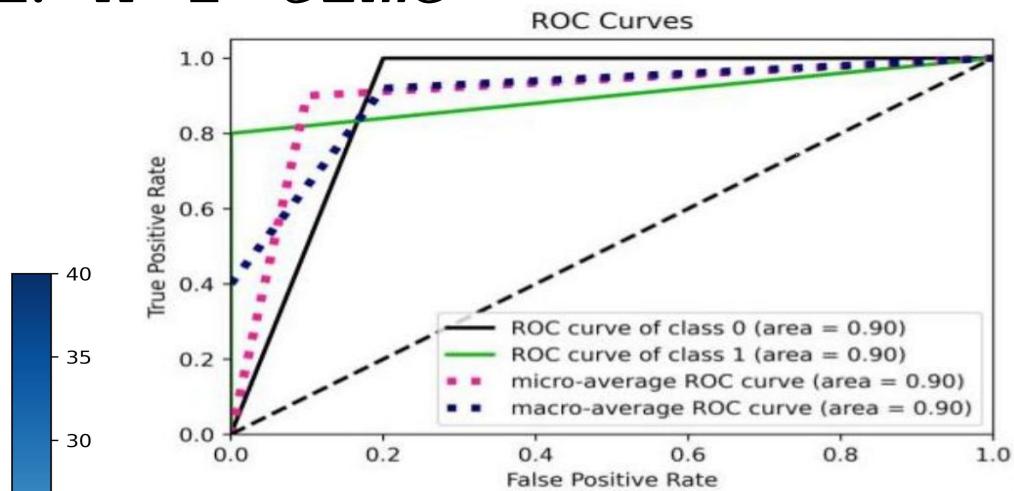
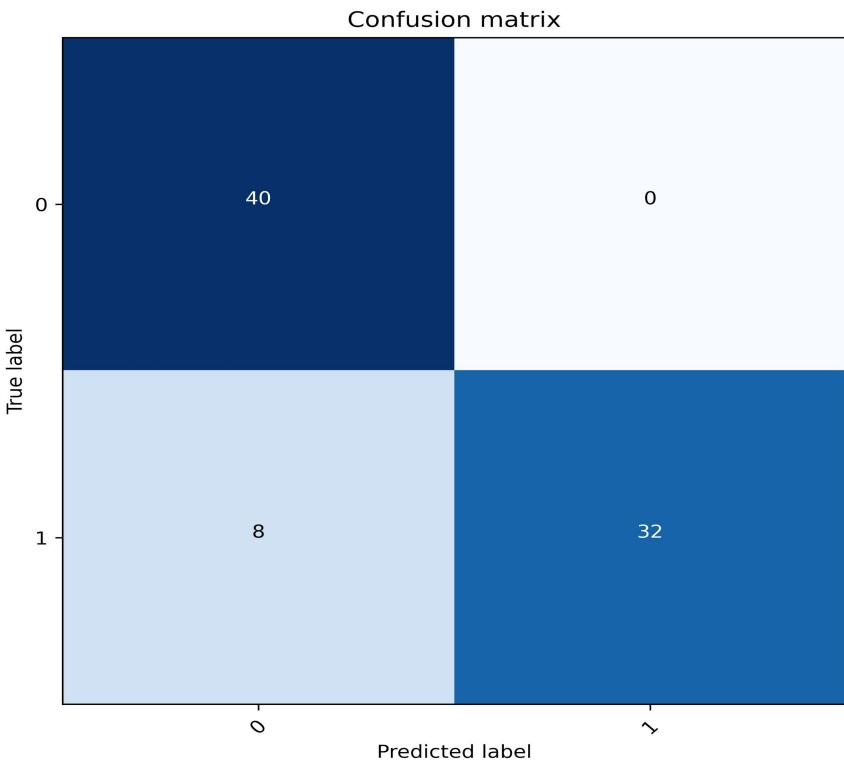


Precision-Recall Curve



Dataset 2: x z time

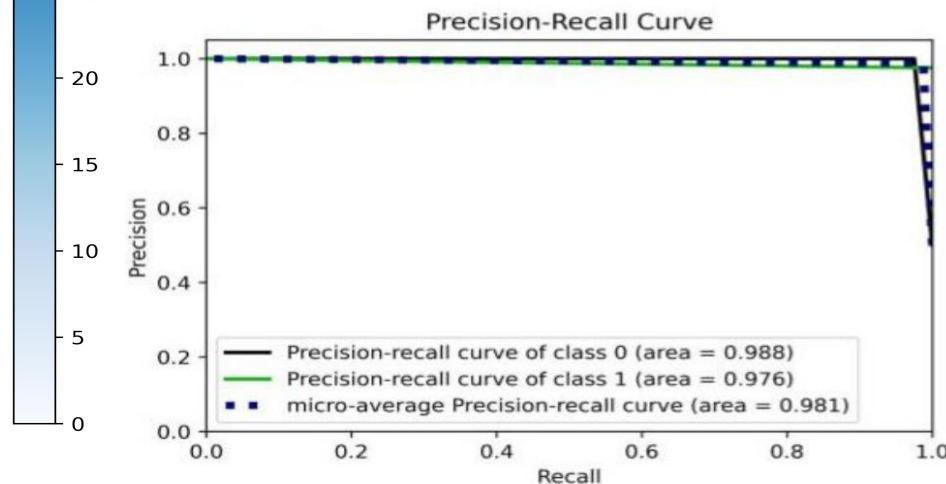
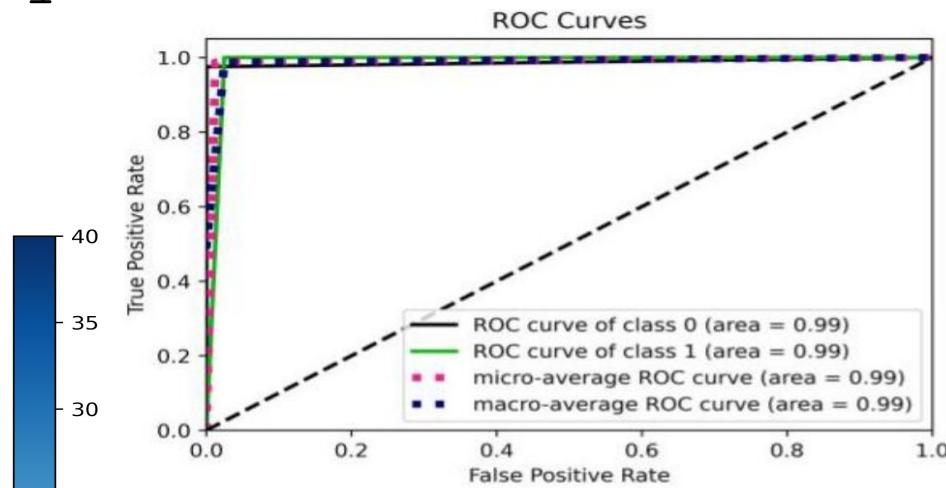
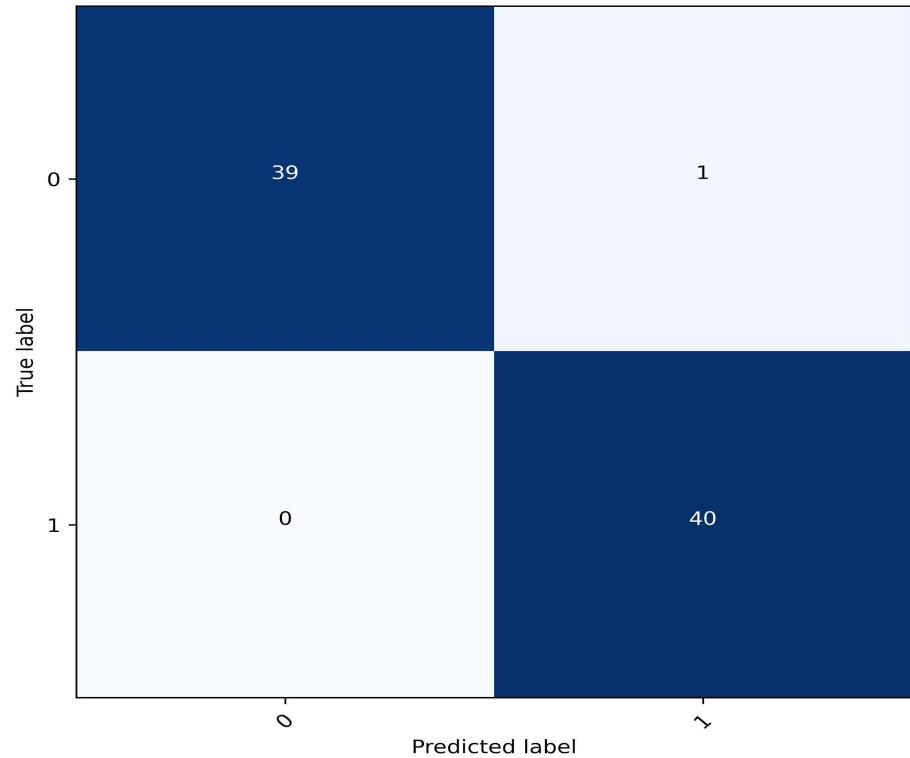
	precision	recall	F1-score	support
class_0	0.83	1.00	0.91	40
class_1	1.00	0.80	0.89	40



Dataset 3: y z time

	precision	recall	F1-score	support
class_0	1.00	0.97	0.99	40
class_1	0.98	1.00	0.99	40

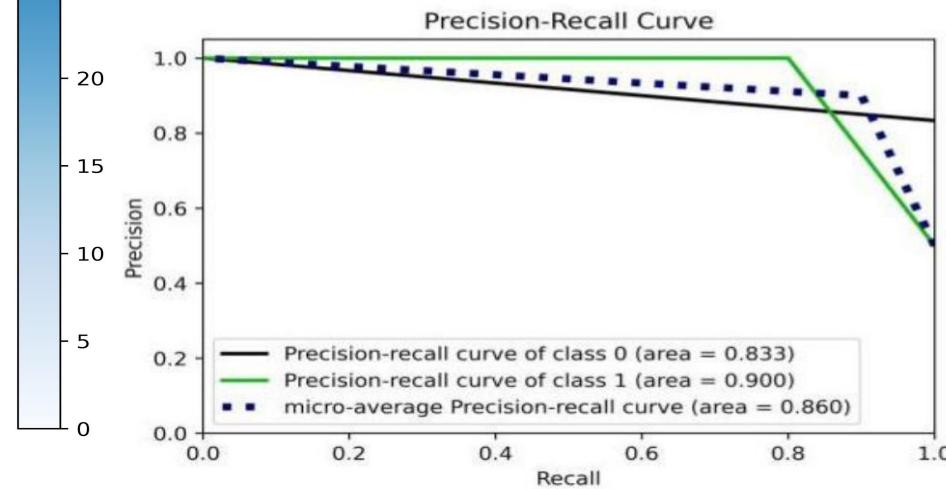
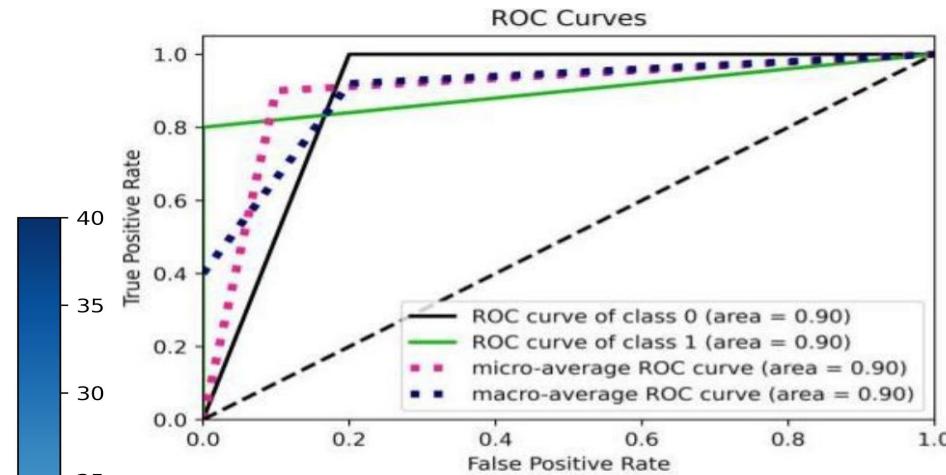
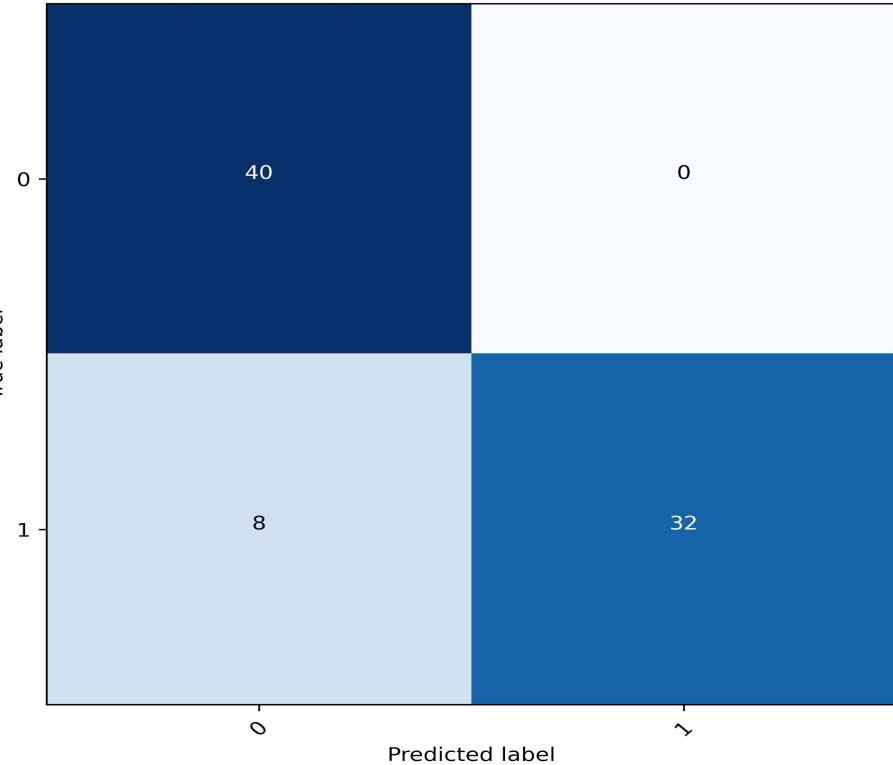
Confusion matrix



Ensemble 1: Soft Voting

	precision	recall	f1-score	support
class_0	0.93	1.00	0.91	40
class_1	1.00	0.80	0.89	40

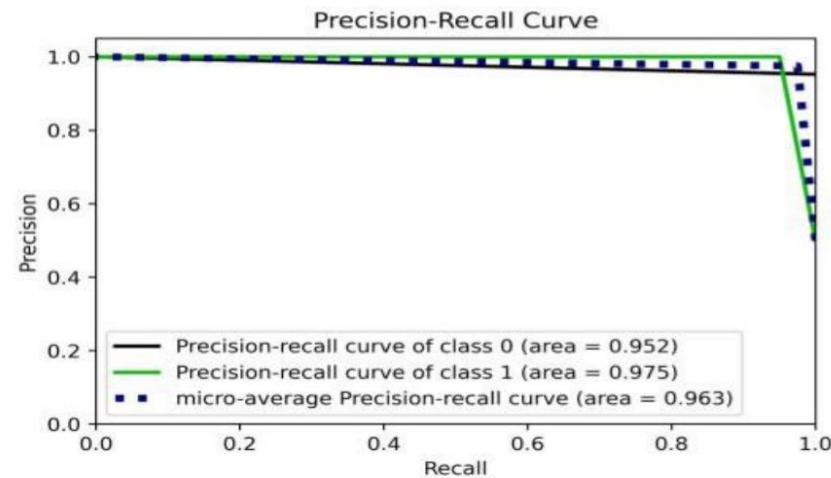
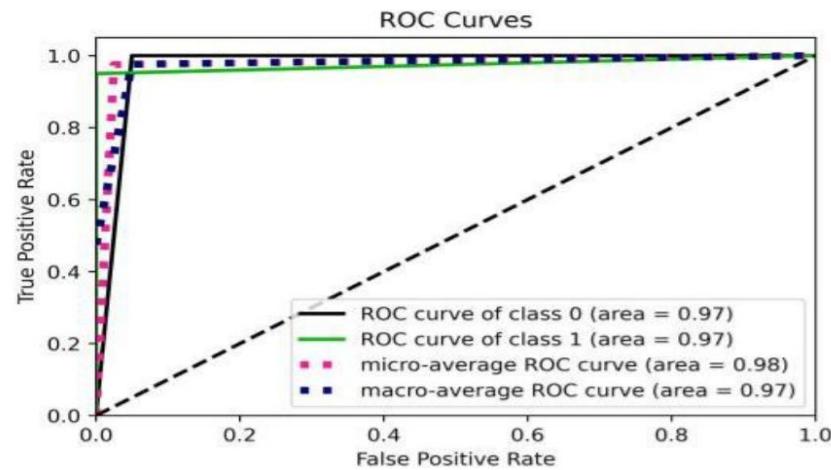
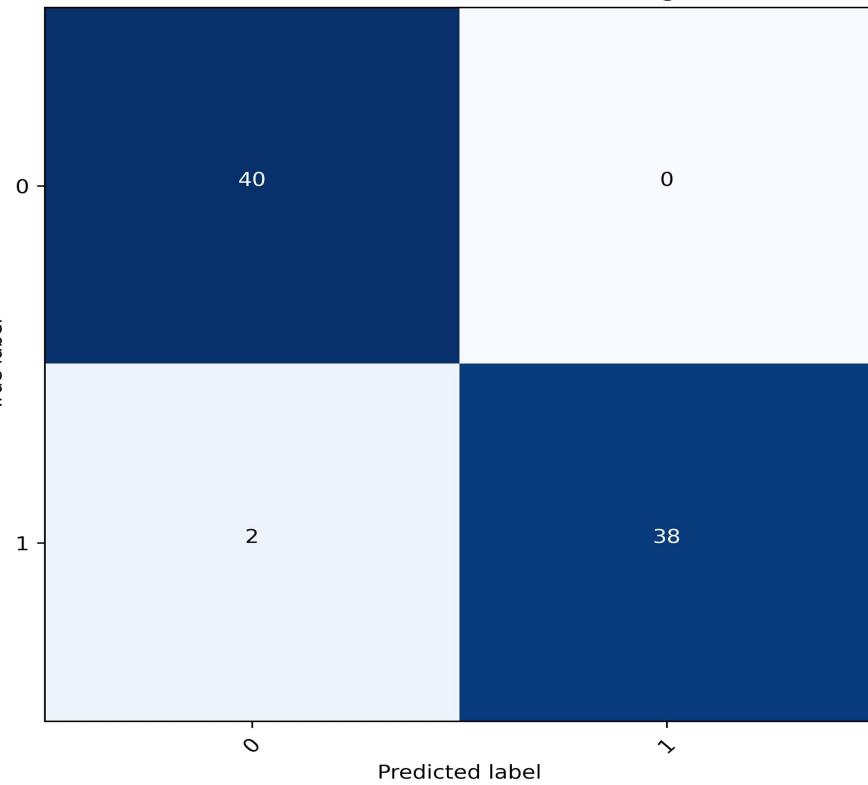
Confusion matrix for Soft Votes



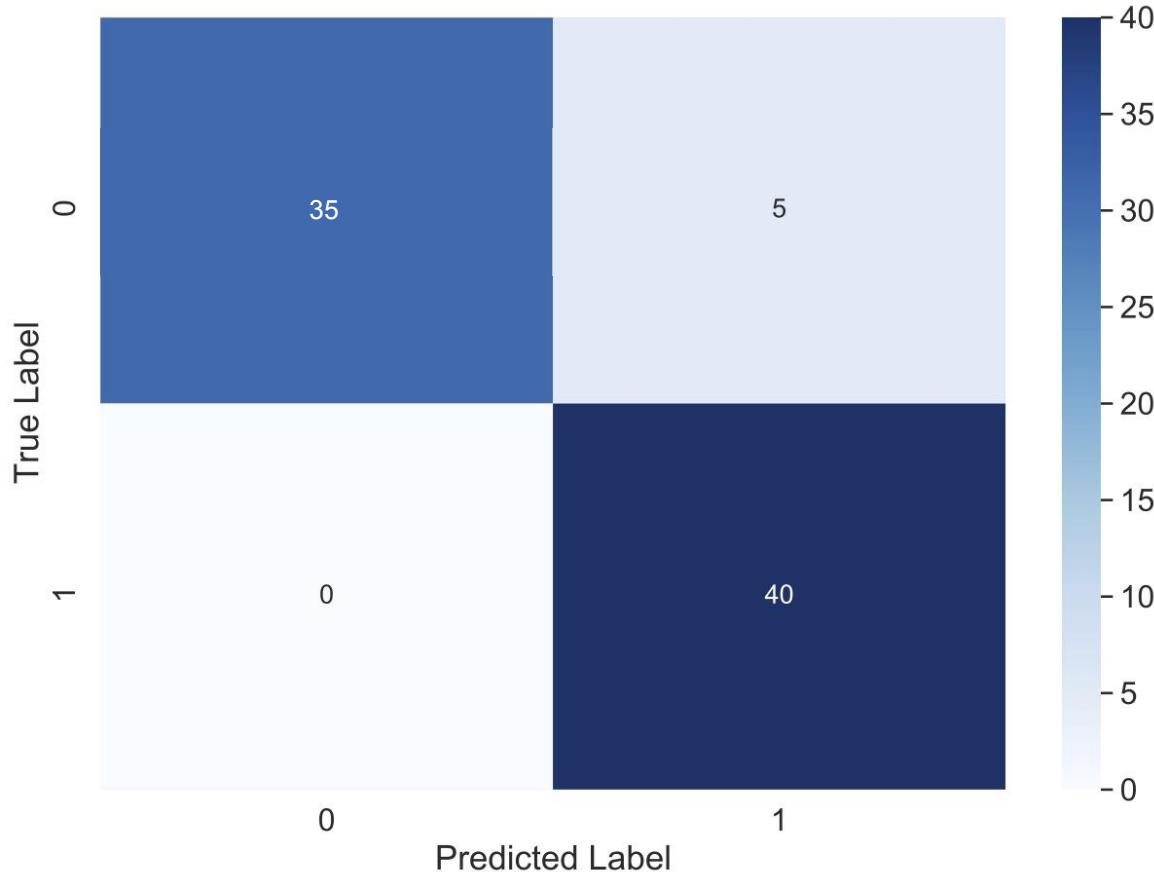
Ensemble 2: Hard Voting

	precision	recall	f1-score	support
class_0	0.95	1.00	0.98	40
class_1	1.00	0.95	0.97	40

Confusion matrix for Hard Voting



L1 Trigger Confusion Matrix



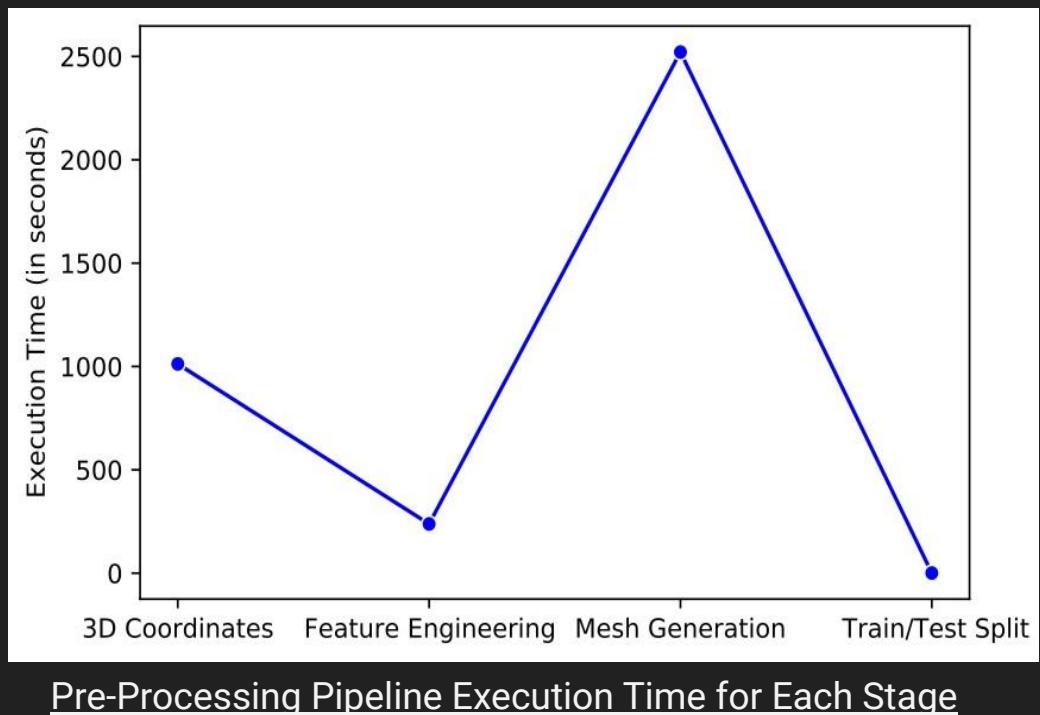
Additional Metrics

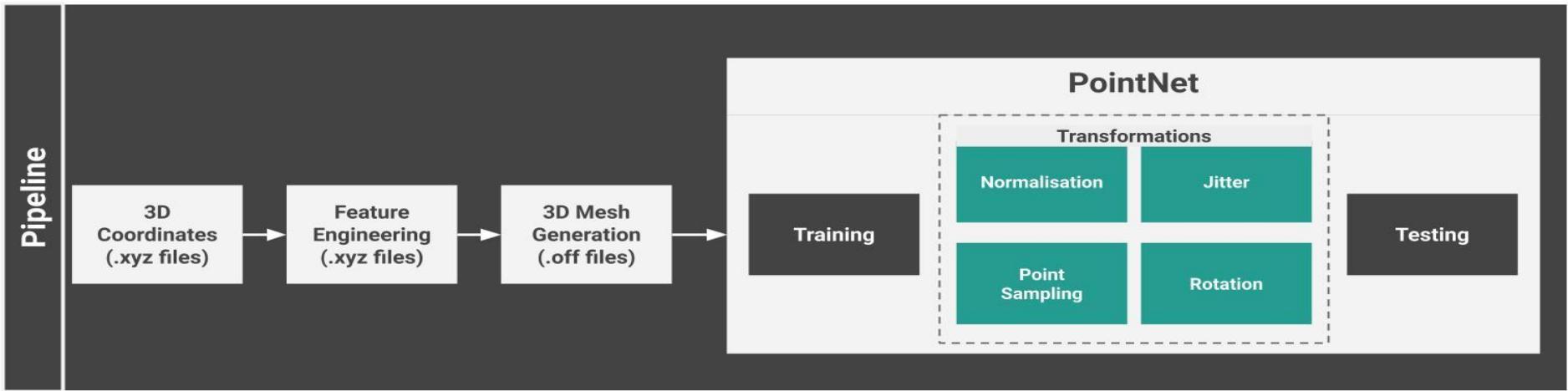
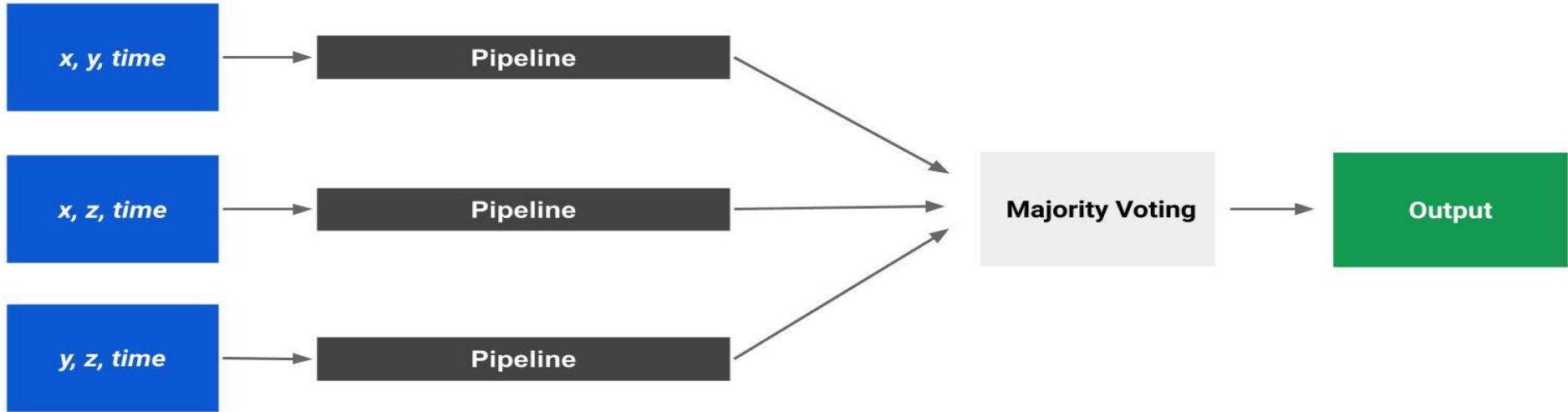
Pre-Processing Execution Time
~ 1.04 hours

PointNet Execution Time
~ 3.2 hours

PointNet Throughput
0.34 instances / second

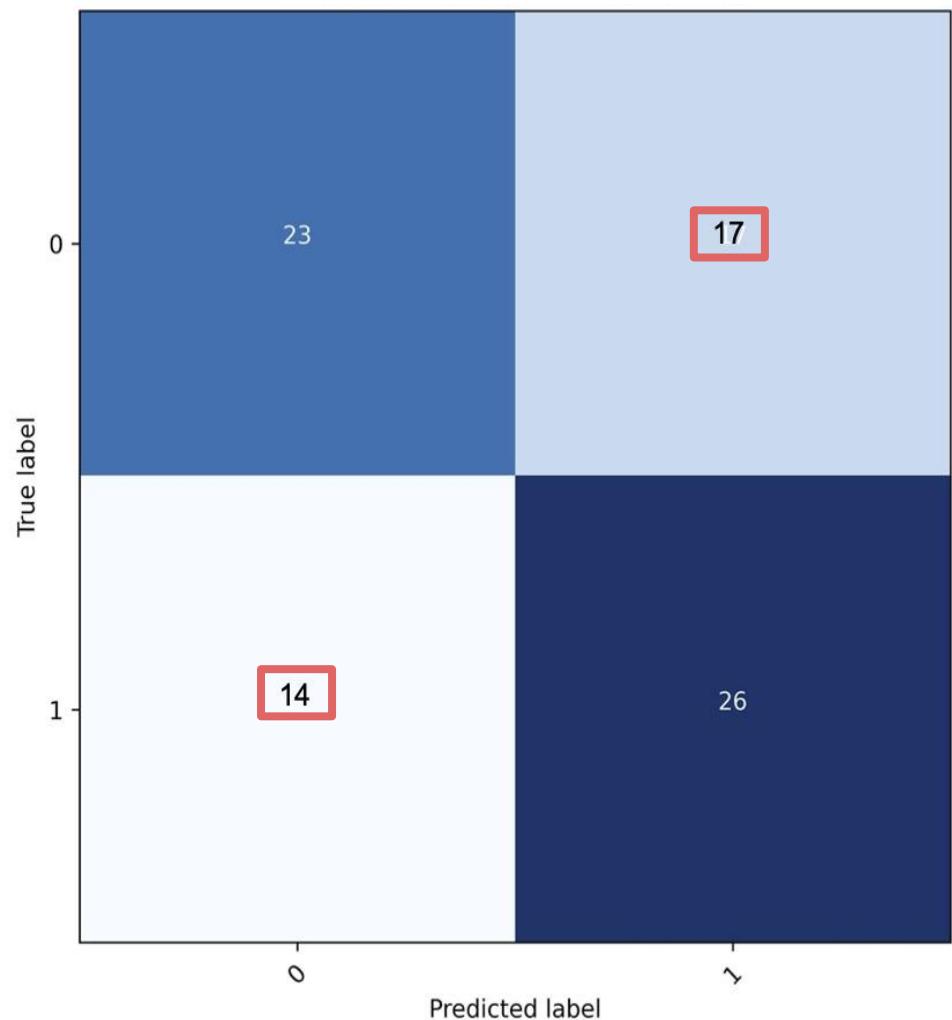
PointNet Energy [12]:
62 g of CO₂ for 120 epochs



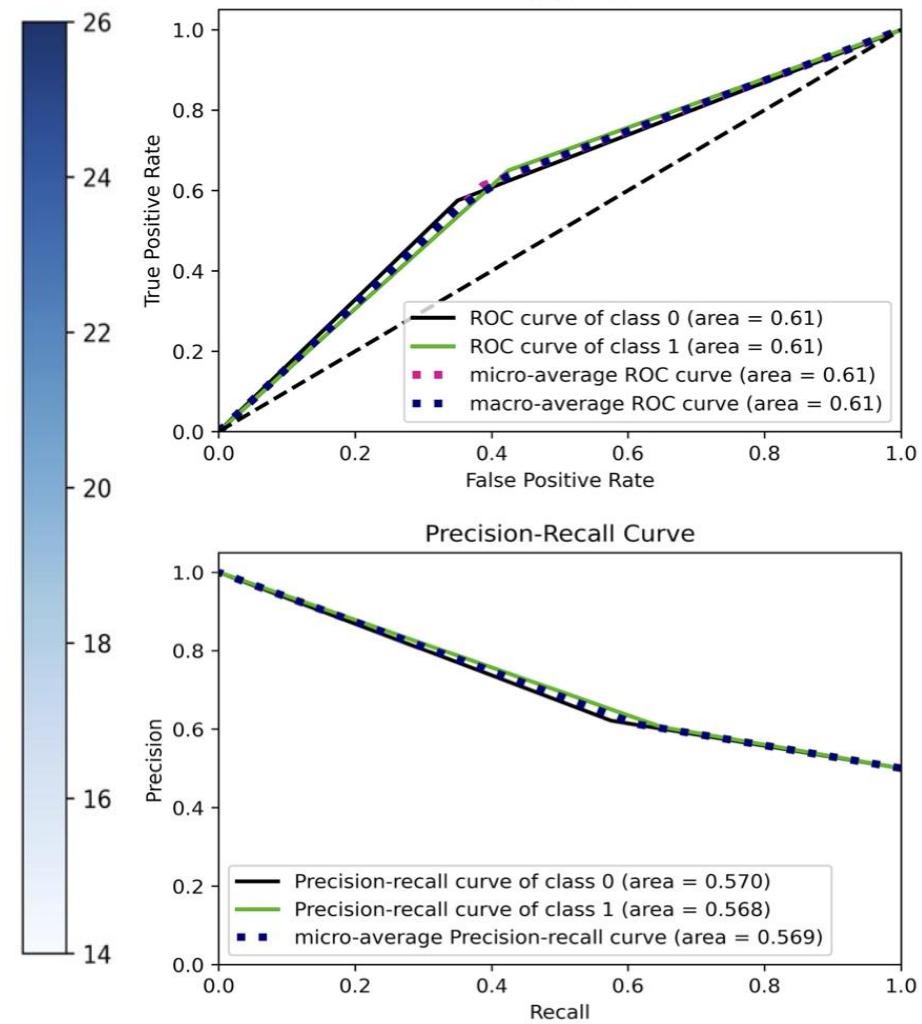


3D PointNet

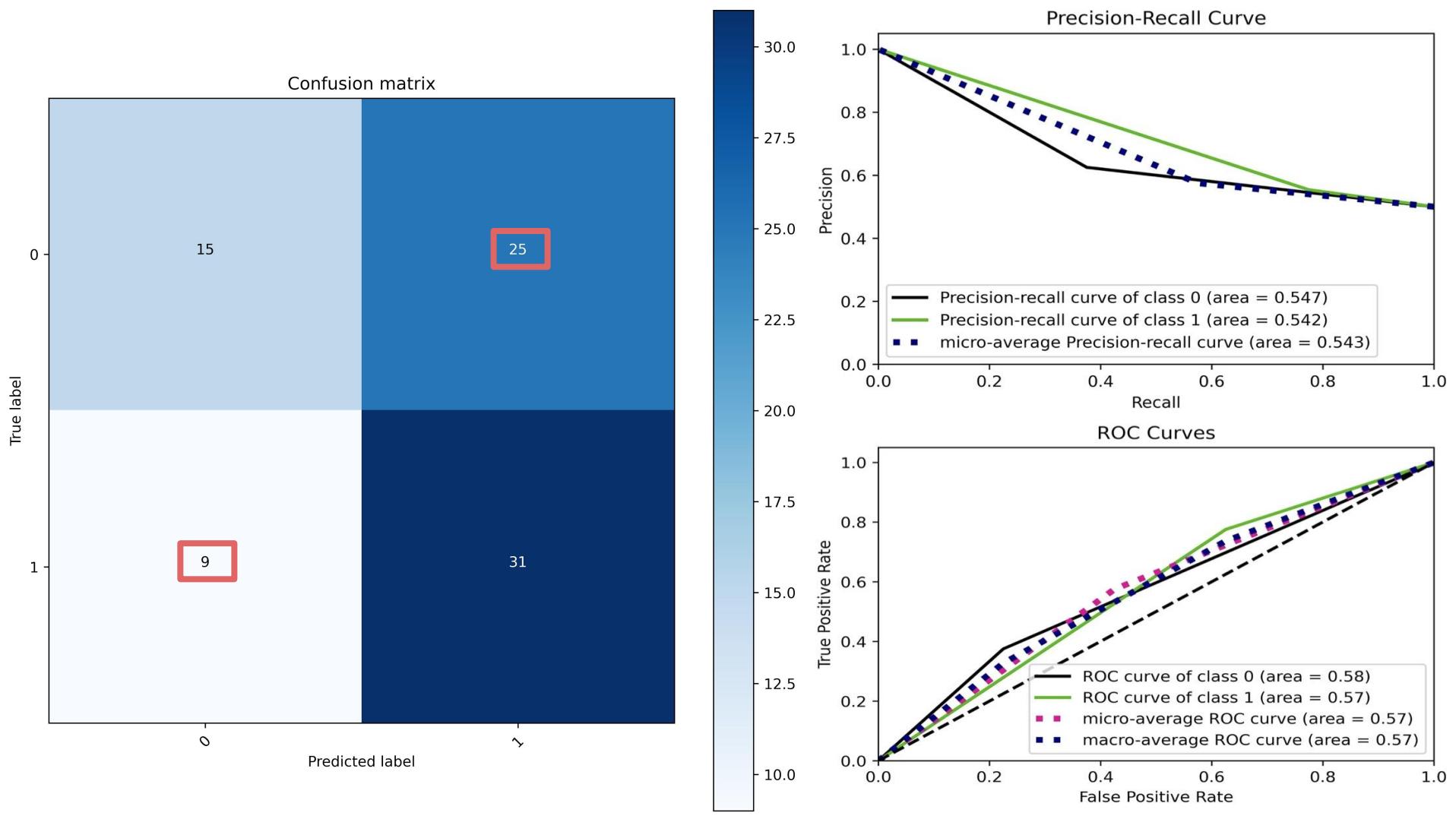
Confusion Matrix



ROC Curves



4D PointNet



Energy Inference

PointNet \neq Regression

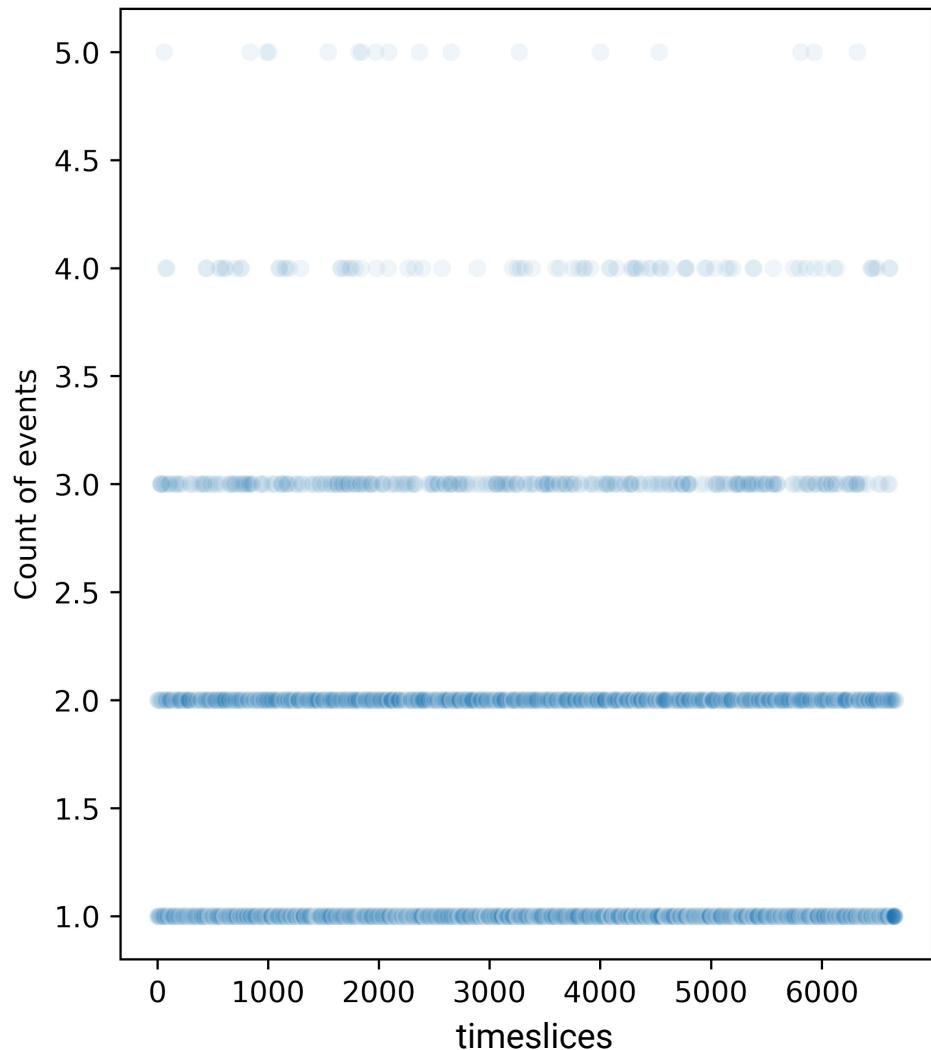
Data

Key Variables:

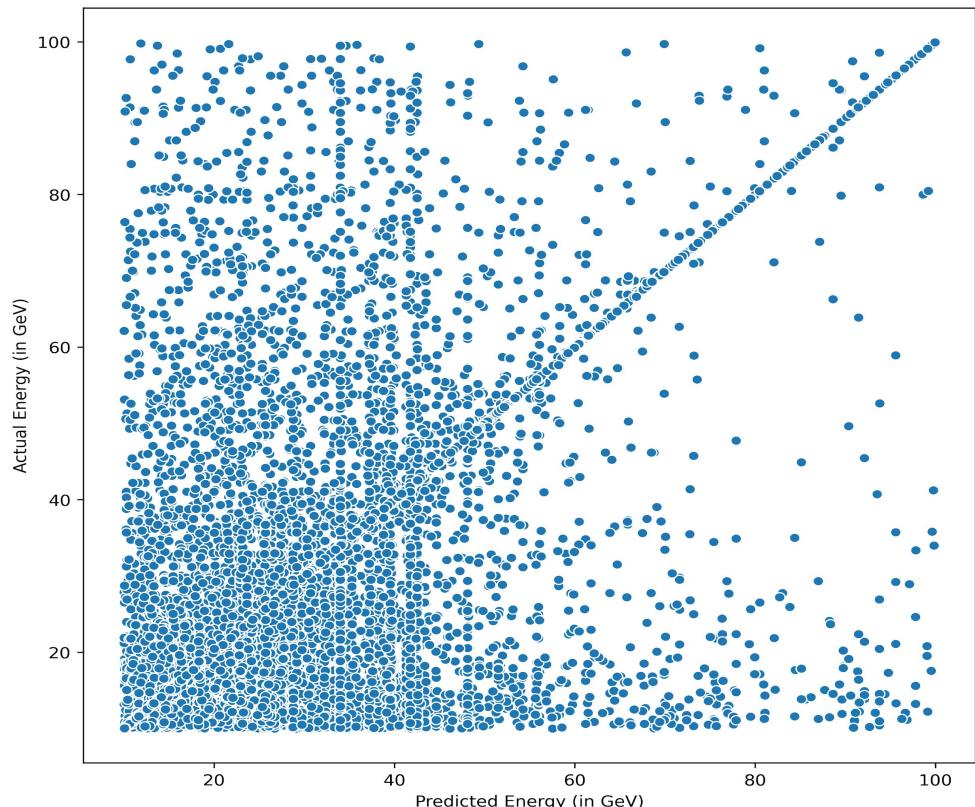
x y z
time
energy
group

No significant correlations

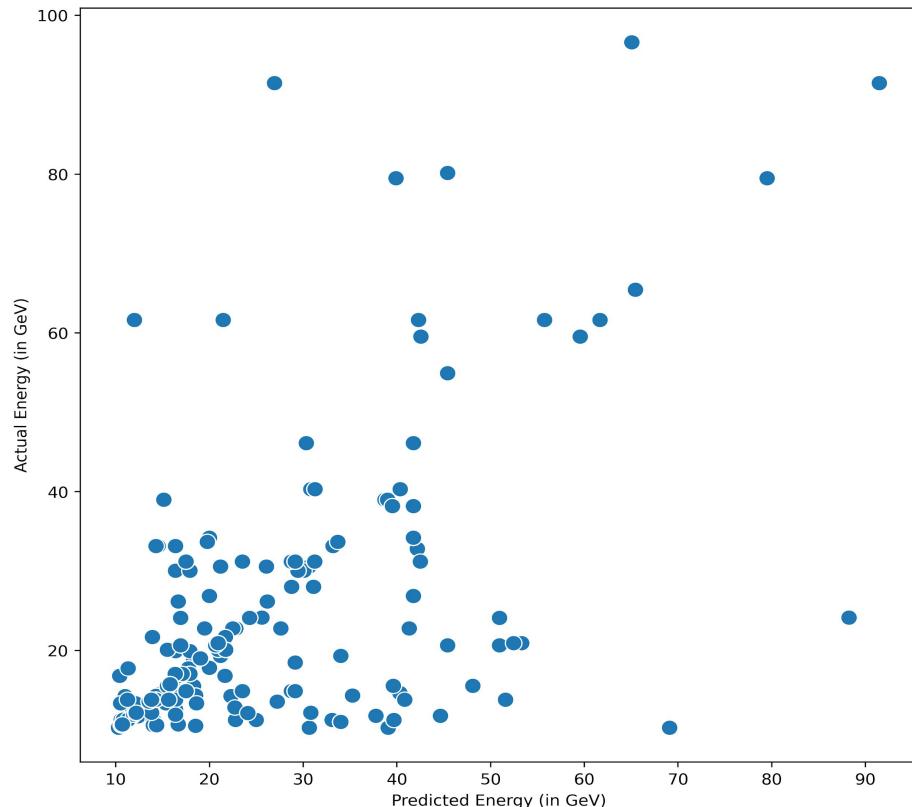
66/34 split & **50** evaluation samples



Decision Trees



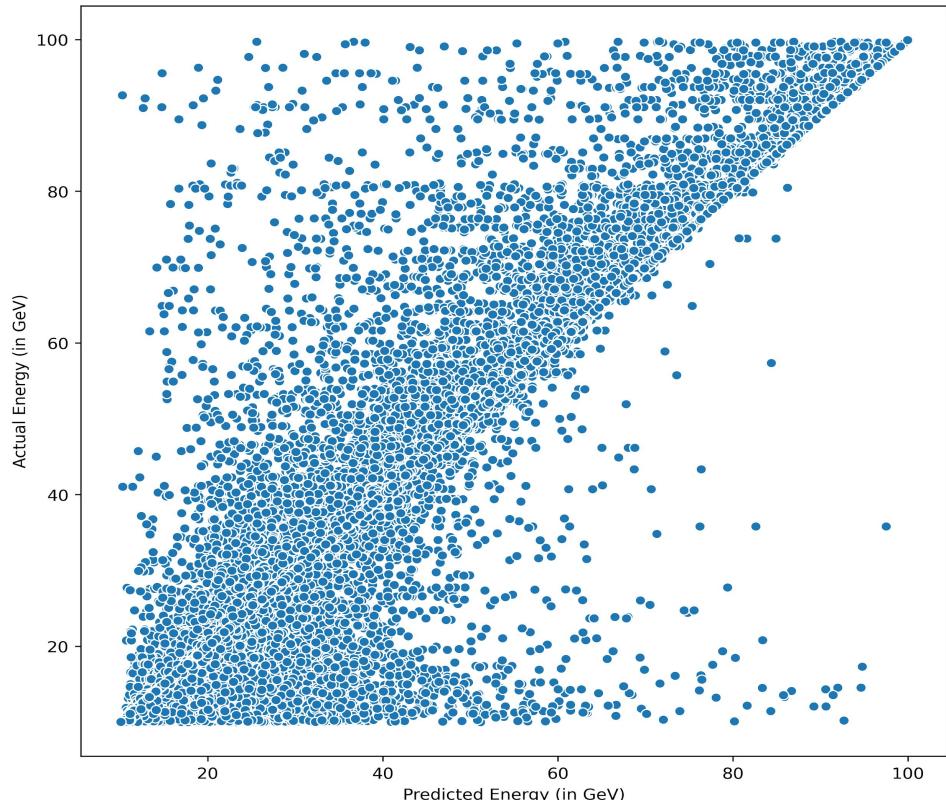
Testing Data



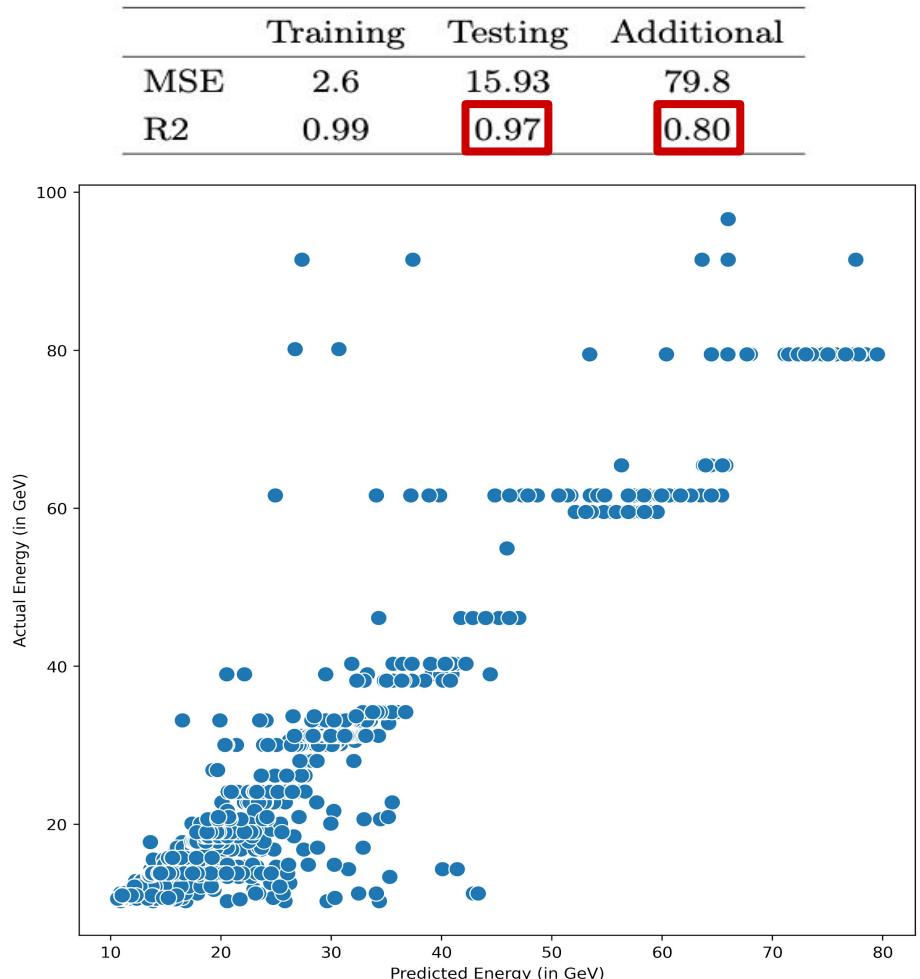
Additional Data

	Training	Testing	Additional
MSE	100.3	116.3	269.0
R2	0.83	0.80	0.31

Random Forest Bootstrapping



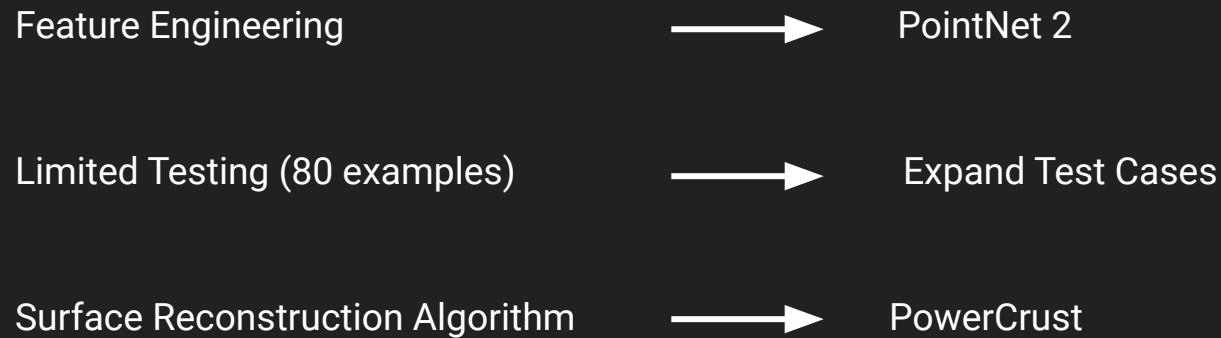
Testing Data



Additional Data

	Training	Testing	Additional
MSE	2.6	15.93	79.8
R2	0.99	0.97	0.80

Limitations & Recommendations



PointNet unsuitable for regression



Faster RCNN

Energy results analysis



Address uncertainties

~3 minutes for classifying new timeslice



GPU and Parallelisation

Revisiting Research Questions

RQ 2.0

Can the KM3NeT dataset be effectively represented using 3D meshes?

RQ 2.1

Which meshing algorithm would be suitable for representing data?

RQ 1.0

Can PointNet classify noise timeslices and event timeslices?

RQ 1.1

Can PointNet obtain a Recall score of 0.9 for the positive class?

RQ 3.0

Can PointNet be extended for energy inference from events?

Thank You!

References

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- [13] Sakia, R. M. (1992). The Box-Cox transformation technique: a review. *Journal of the Royal Statistical Society: Series D (The Statistician)*, 41(2), 169-178.

Appendix

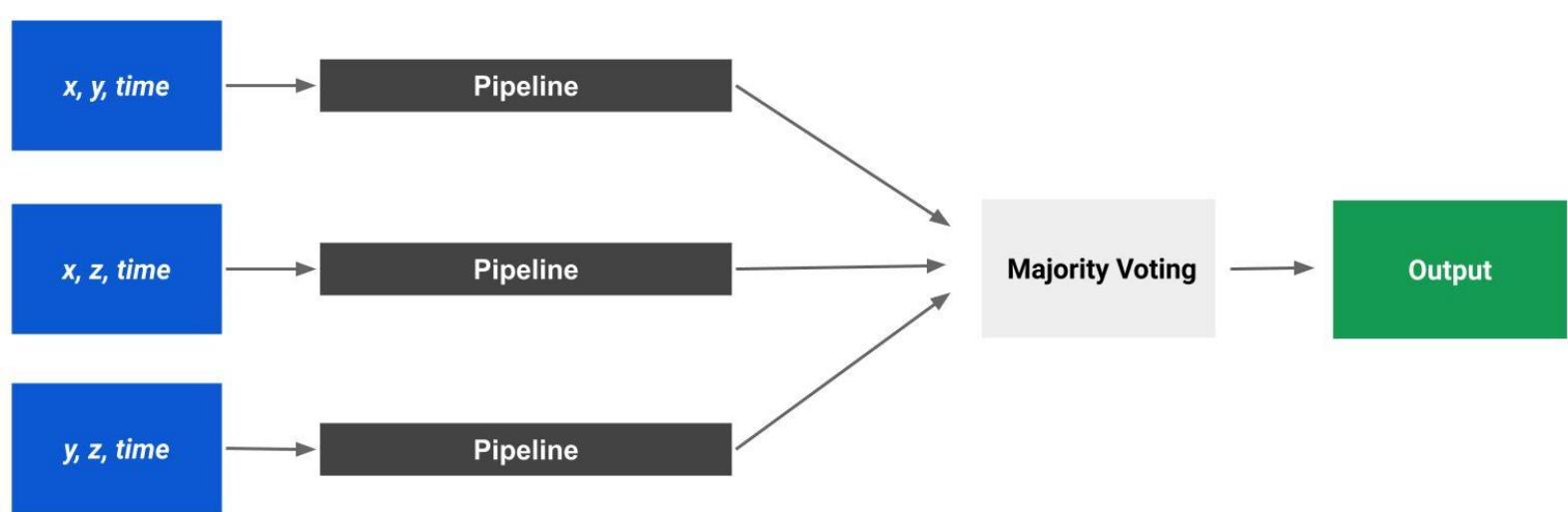
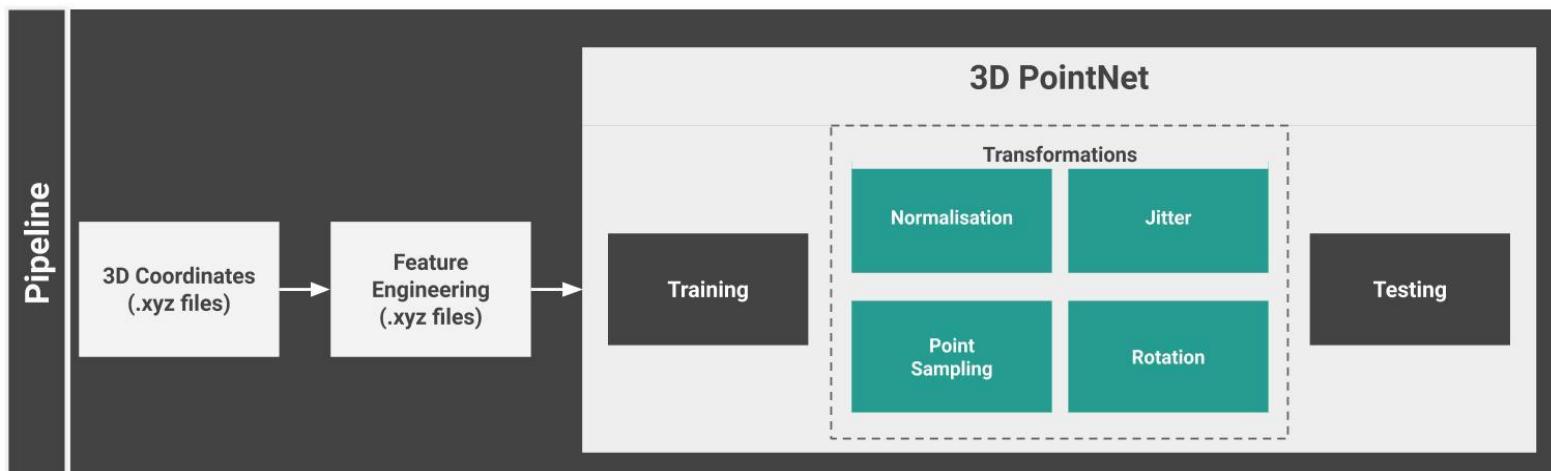
Modifications

1D Convolutions [8]

Average Max Pooling instead of Global Max Pooling [8, 9]

Negative Log Likelihood Loss instead of Cross Entropy Loss
[8, 10]

3D PointNet



4D PointNet

