AI-powered calorimeter clustering with coatjava integration

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Presentation Outline

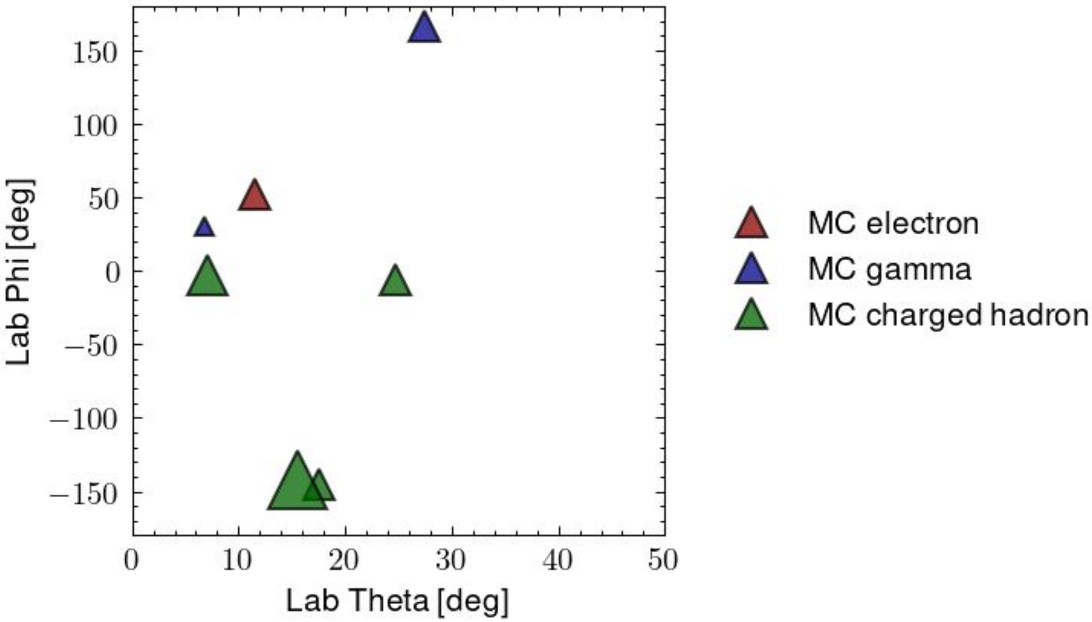
1. Why do we need to improve neutral clustering at CLAS12 (γ's vs. n's)?
2. How does COATJAVA reconstruct clusters and what are its flaws?
3. Introduce ★**Object Condensation**★ – a *grid-free* machine learning approach to object clustering
4. GravNet nearest-neighbor model architecture – training parameters/features
5. Training metrics on Monte Carlo – How well does the model perform?
6. Custom COATJAVA pipeline for this project

Model Evaluation (COATJAVA vs. Object Condensation)

A. Neutron Gun events
B. Incoherent J/Psi production off deuterium (with the help of Richard Tyson)
C. Monte Carlo DIS events

Neutral Clustering at CLAS12

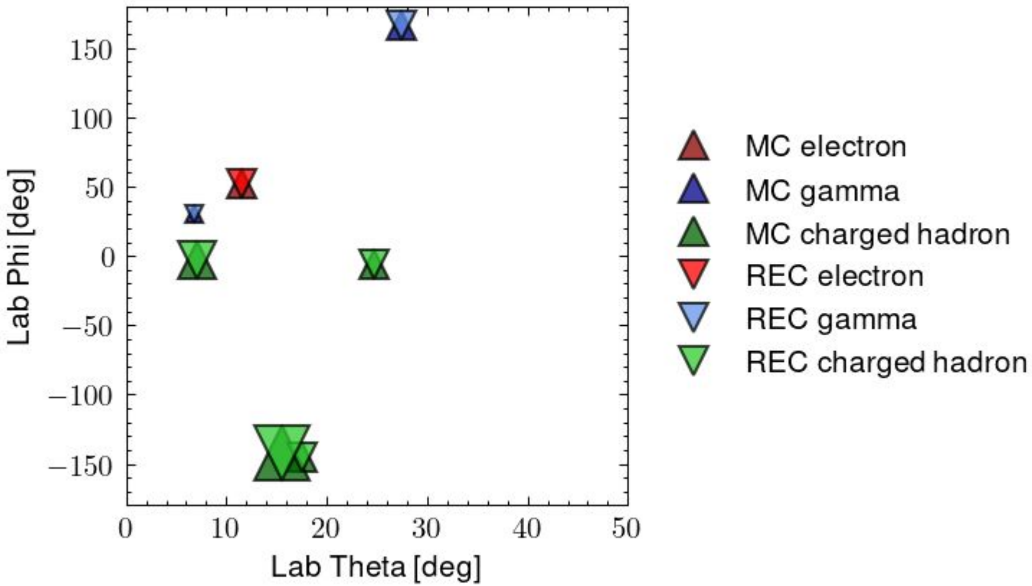
- Shown is the (θ,ϕ) distribution of **Monte Carlo** particles from a sample SIDIS event (upwards facing triangles)



Neutral Clustering at CLAS12

- Shown is the (θ,ϕ) distribution of **Monte Carlo** particles from a sample SIDIS event (upwards facing triangles)

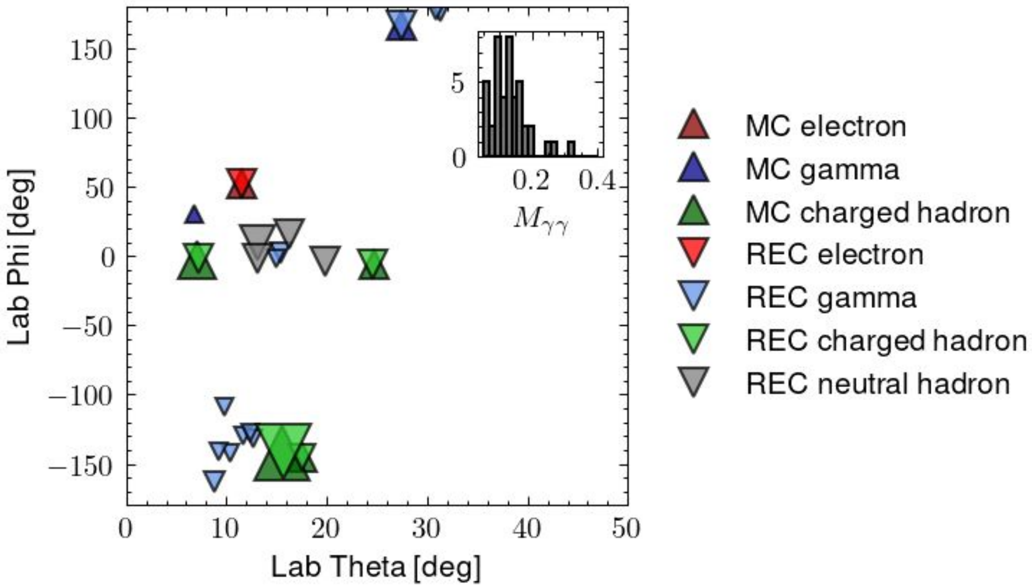
- In an ideal world, the **Reconstructed** particles (downwards facing triangles) would be exactly on top of the thrown MC particles



Neutral Clustering at CLAS12

- Shown is the (θ,ϕ) distribution of **Monte Carlo** particles from a sample SIDIS event (upwards facing triangles)

- However, issues in neutral particle clustering lead to many false neutrals being reconstructed



Non-combinatorial backgrounds emerge for π^0 studies for instance, where one of the photons in the pair is ***fake***

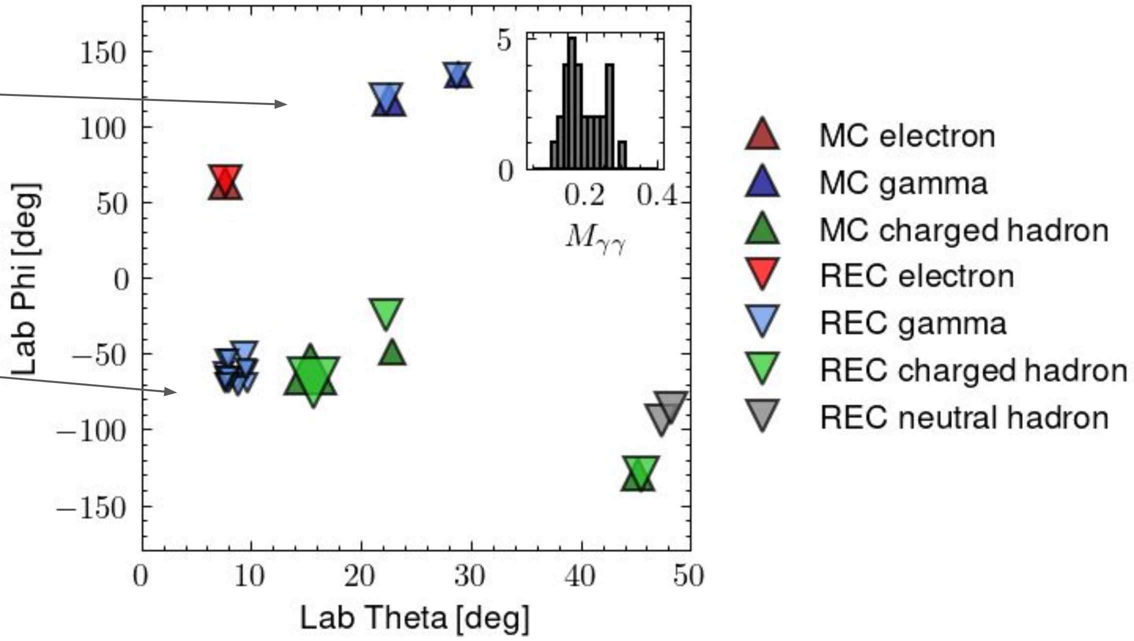
Resolving the Photon Clustering Issue

- In turns out the information in **REC::Calorimeter** and **REC::Particle** is plenty to address the false photon backgrounds

- Unlikely for false photons to collect around true photons

- More likely for false photons to collect around many other false photons

A simple **Gradient Boosted Tree** model with nearest neighbor features cleans up the photons at CLAS12



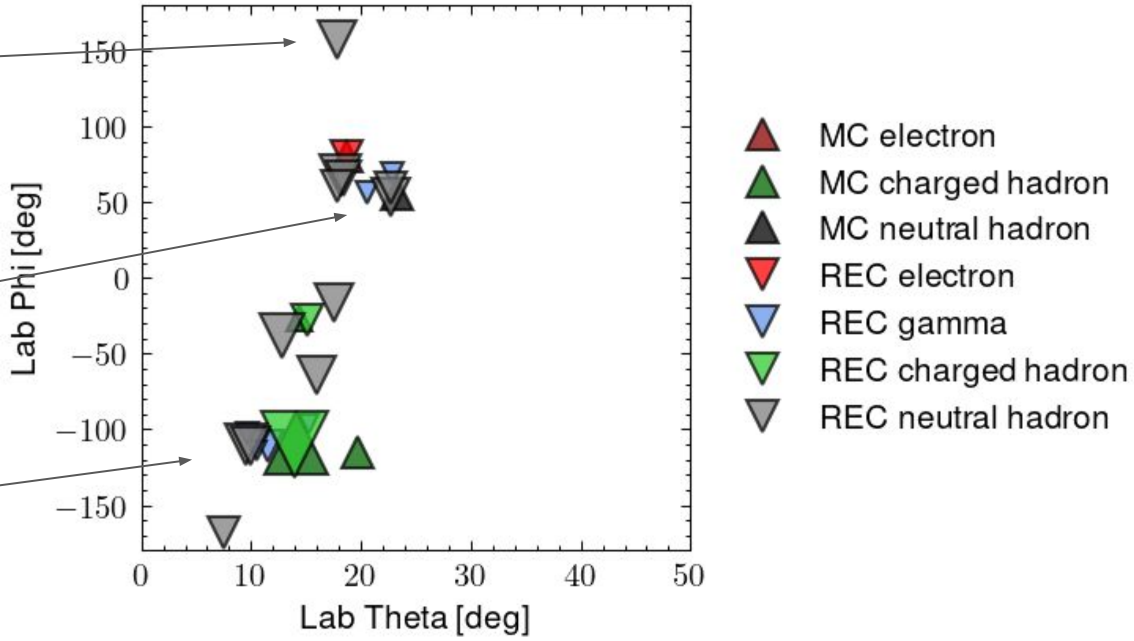
Why Neutrons pose a challenge

- In turns out the information in **REC::Calorimeter** and **REC::Particle** is NOT ENOUGH to address the false neutron backgrounds

- Neutrons can be fairly separated in (θ,ϕ) yet definitely false

- Bundles of false neutrons can be found near a true neutron

- They can also be found with no true neutron nearby

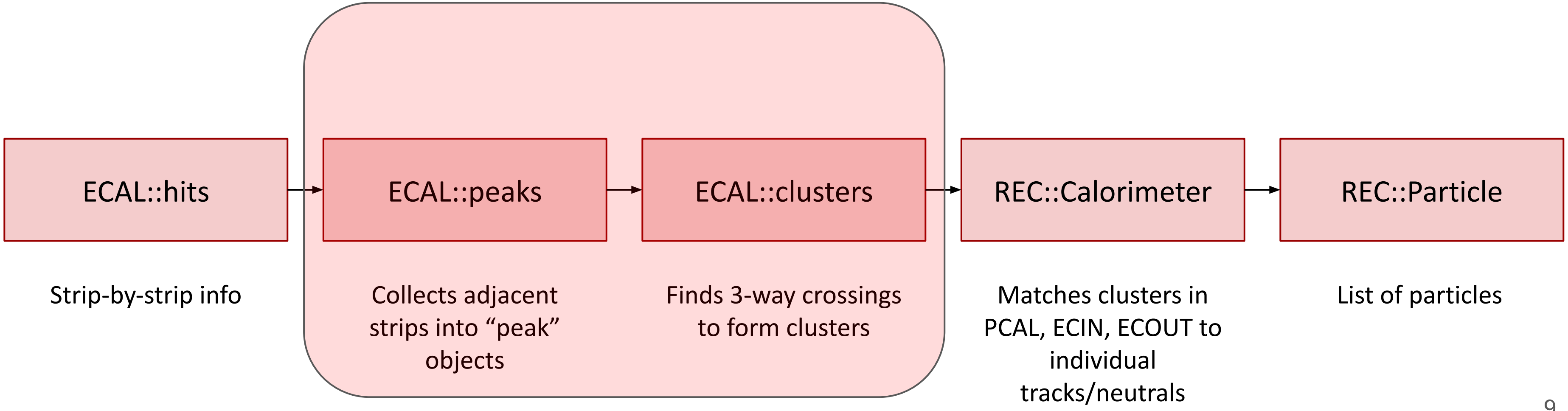


Relevant COATJAVA EventBuilder Pipeline

ECAL::hits	ECAL::peaks	ECAL::clusters	REC::Calorimeter	REC::Particle
Strip-by-strip info	Collects adjacent strips into “peak” objects	Finds 3-way crossings to form clusters	Matches clusters in PCAL, ECIN, ECOUT to individual tracks/neutrals	List of particles

Relevant COATJAVA EventBuilder Pipeline

★ **Issues** in this step lead to faulty clustering of excess neutral particles



Relevant COATJAVA EventBuilder Pipeline

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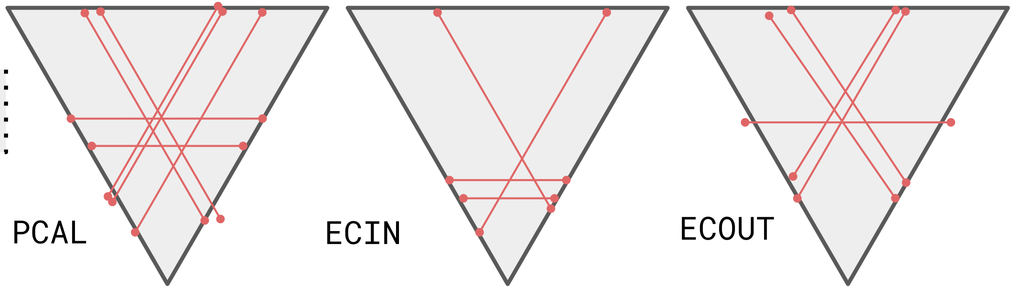
Thrown pion →



ECAL::hits → ECAL::peaks → ECAL::clusters → REC::Calorimeter → REC::Particle

- **ECAL::hits**: Strip-by-strip info
- **ECAL::peaks**: Collects adjacent strips into "peak" objects
- **ECAL::clusters**: Finds 3-way crossings to form clusters
- **REC::Calorimeter**: Matches clusters in PCAL, ECIN, ECOUT to individual tracks/neutrals
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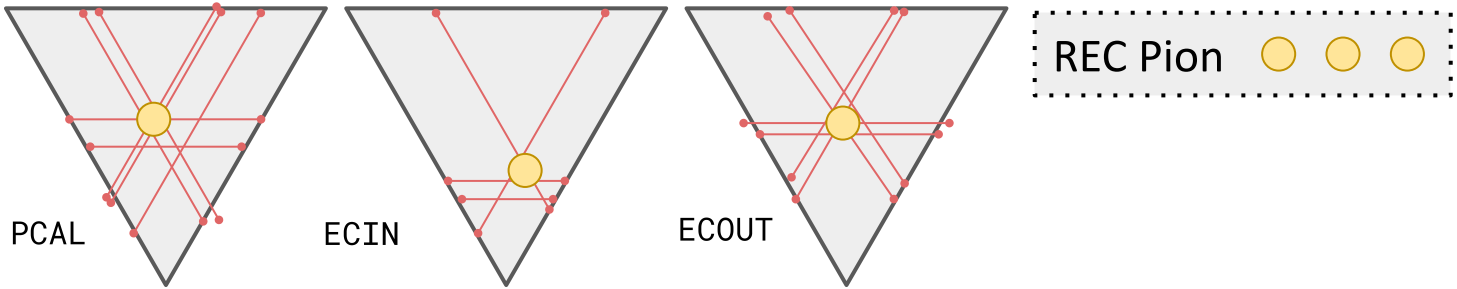
… ***Coatjava*** may find 3 **clusters** in and correctly associate them with one another…



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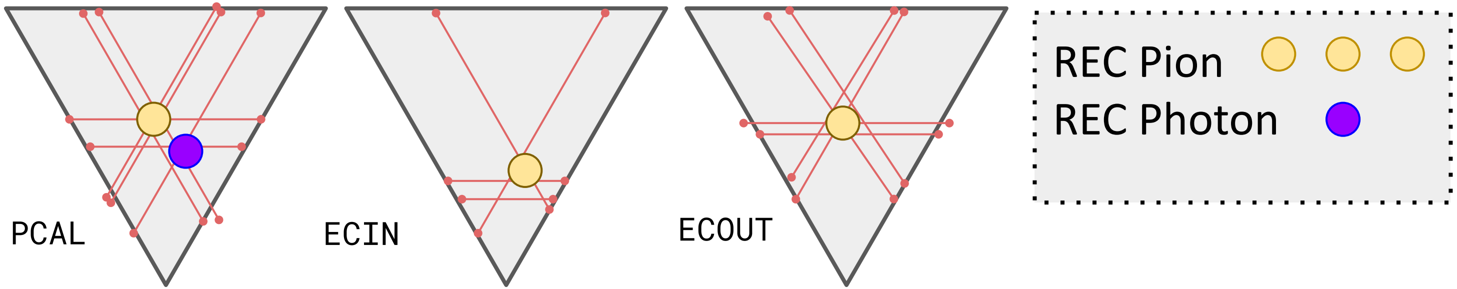
… ***Coatjava*** may find 3 **clusters** in and correctly associate them with one another… but it may accidentally **find more**!



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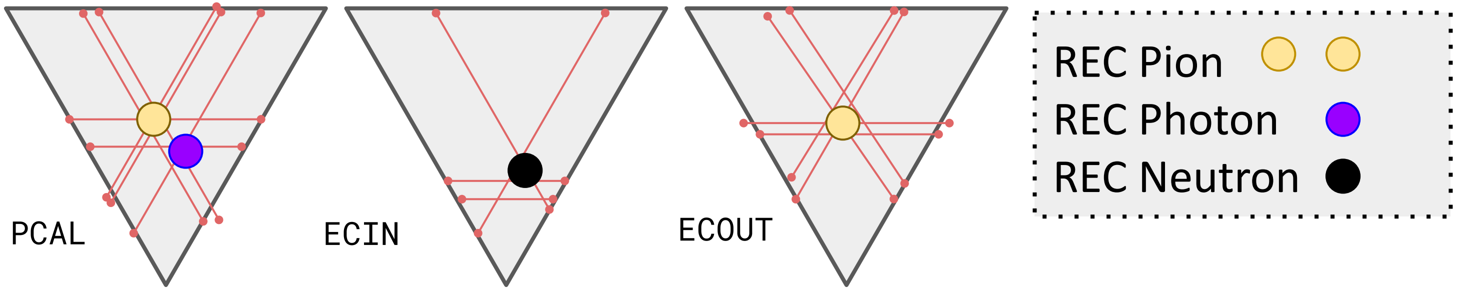
Relevant COATJAVA EventBuilder Pipeline

★ **Issues** in this step lead to faulty clustering of excess neutral particles

… ***Coatjava*** may find 3 **clusters** in and correctly associate them with one another… but it may accidentally **find more**!

… The clusters may also **fail to be associated**!



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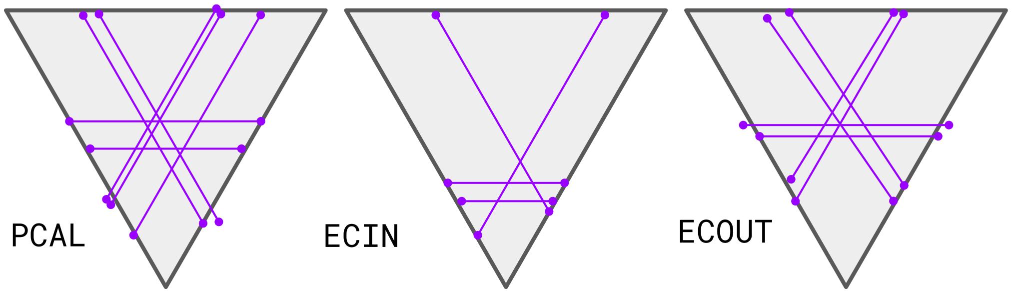
AI-assisted Neutral Clustering

★ Our AI organizes groups of strips separate **single objects** (particles)



ECAL::hits → AI assisted ECAL::clusters bank → REC::Calorimeter → REC::Particle

Strip-by-strip info

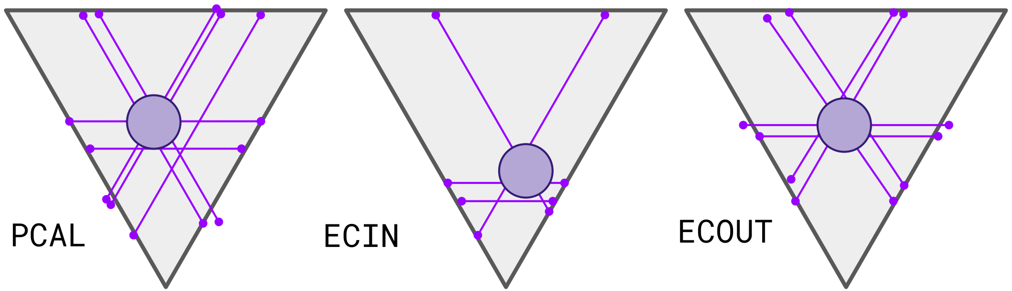
An AI finds groups of strips likely to come from the same particle

Matches clusters in PCAL, ECIN, ECOUT to individual tracks/neutrals

List of particles

AI-assisted Neutral Clustering

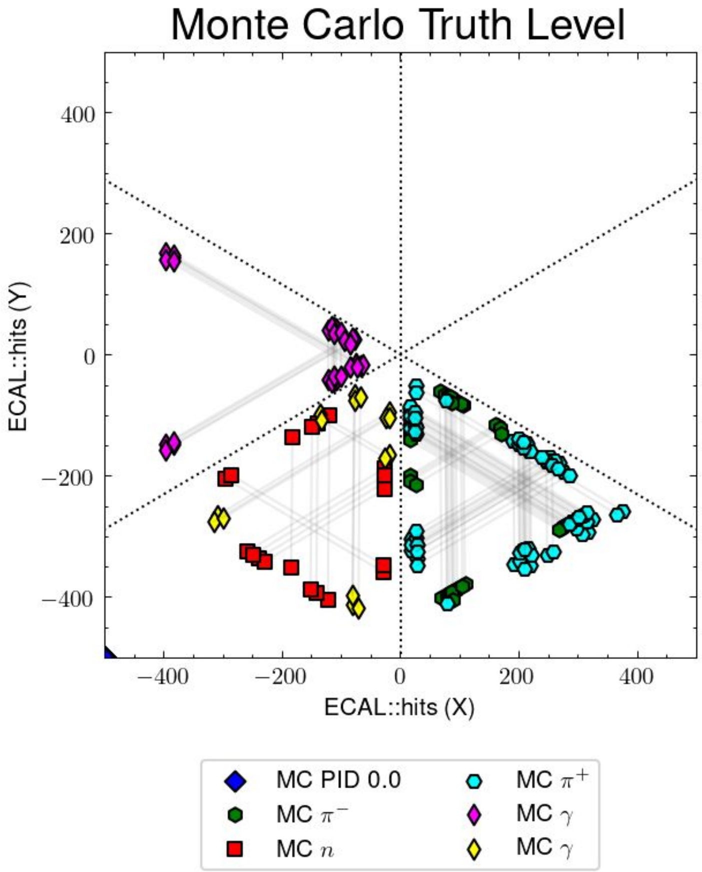
★ Our AI organizes groups of strips separate **single objects** (particles)
★ Then we manually calculate one cluster (x,y,z,E,t) for each ECAL type



ECAL::hits → AI assisted ECAL::clusters bank → REC::Calorimeter → REC::Particle

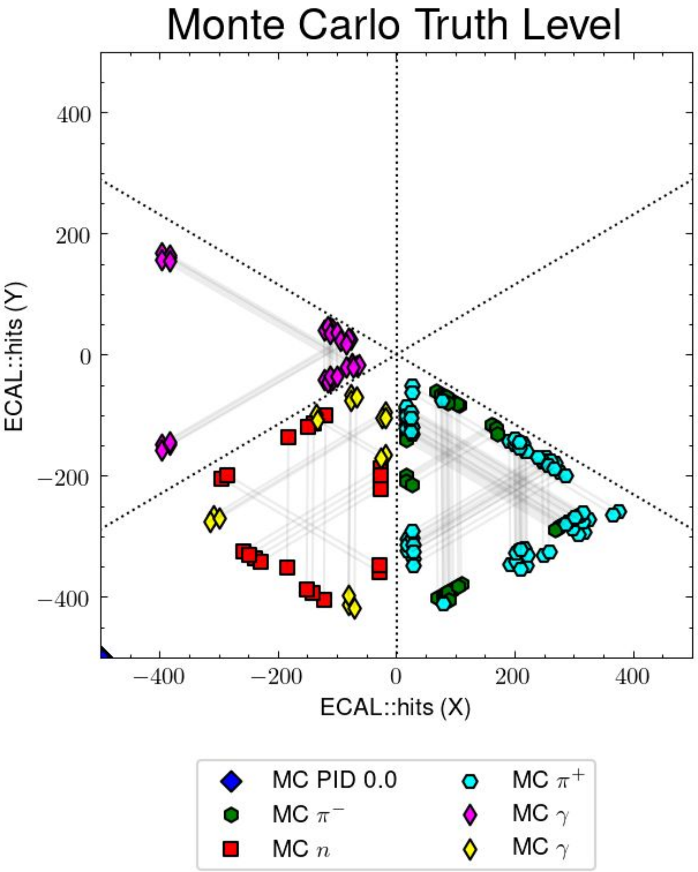
ECAL::hits	AI assisted ECAL::clusters bank	REC::Calorimeter	REC::Particle
Strip-by-strip info	An AI finds groups of strips likely to come from the same particle Then we calculate a new ECAL::clusters bank	Matches clusters in PCAL, ECIN, ECOUT to individual tracks/neutrals	List of particles

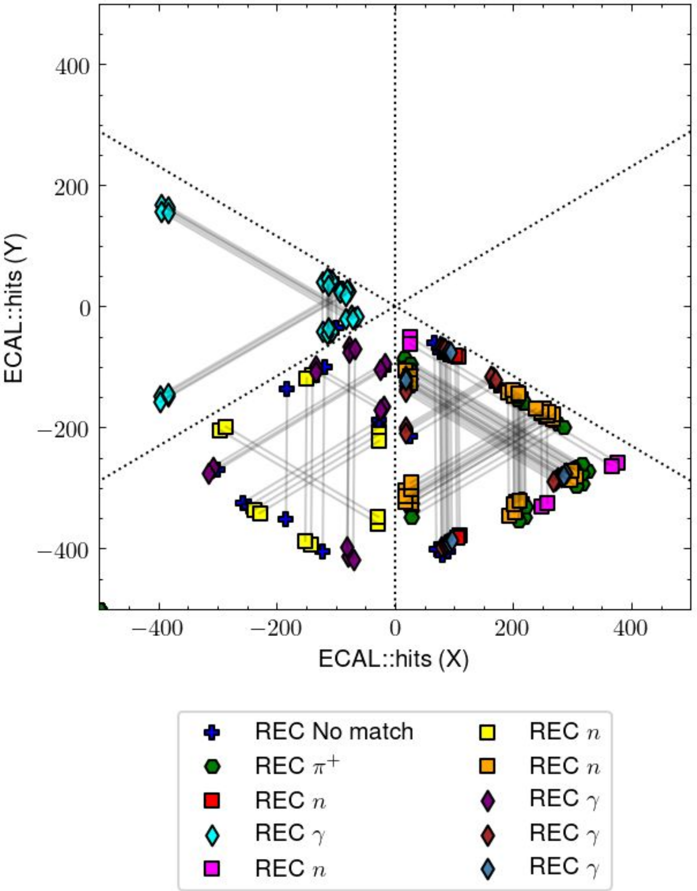
Sample Monte Carlo Event



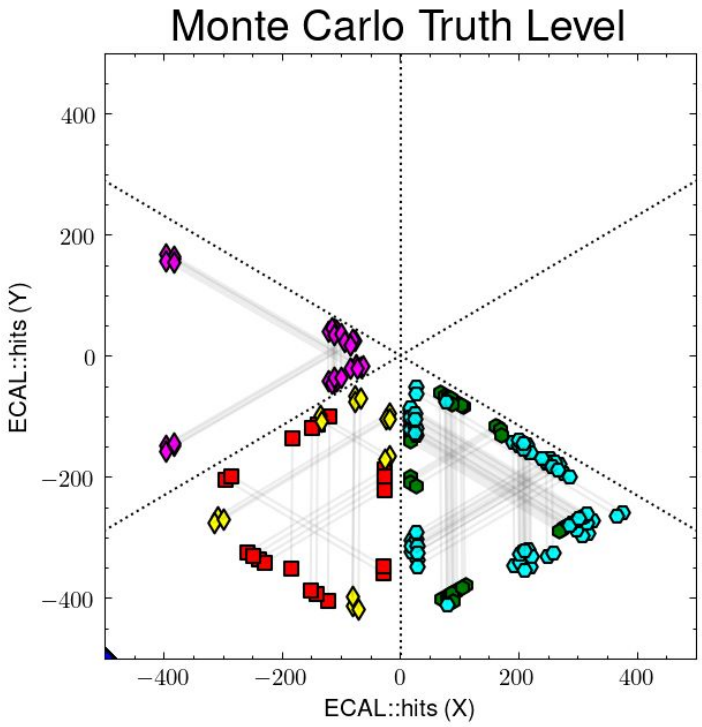
- Left Plot shows the final state Monte Carlo particles generated in SIDIS that are *responsible* for the ECAL strip hits
  - **Colors** → Different particles
  - **Shapes** → Different MC PIDs
- PCAL, ECIN, and ECOUT are overlaid
- For each strip hit, there is an "origin" and "endpoint" (x,y,z) as well as edep and timing
- In general, Coatjava looks for 3-way intersections in the PCAL, ECIN, and ECOUT (separately) to create *clusters*
- Track <-> Cluster matching determines if we need to make a neutral particle

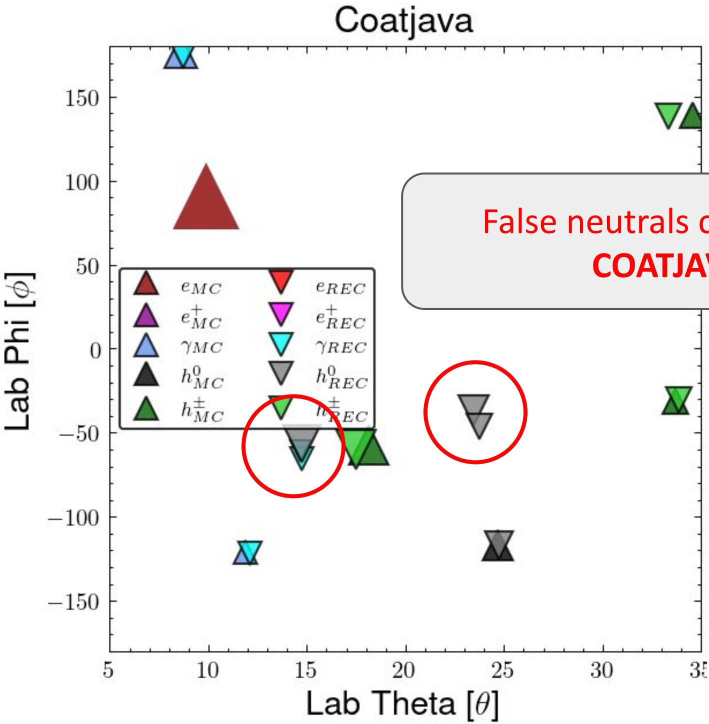
Sample Monte Carlo Event





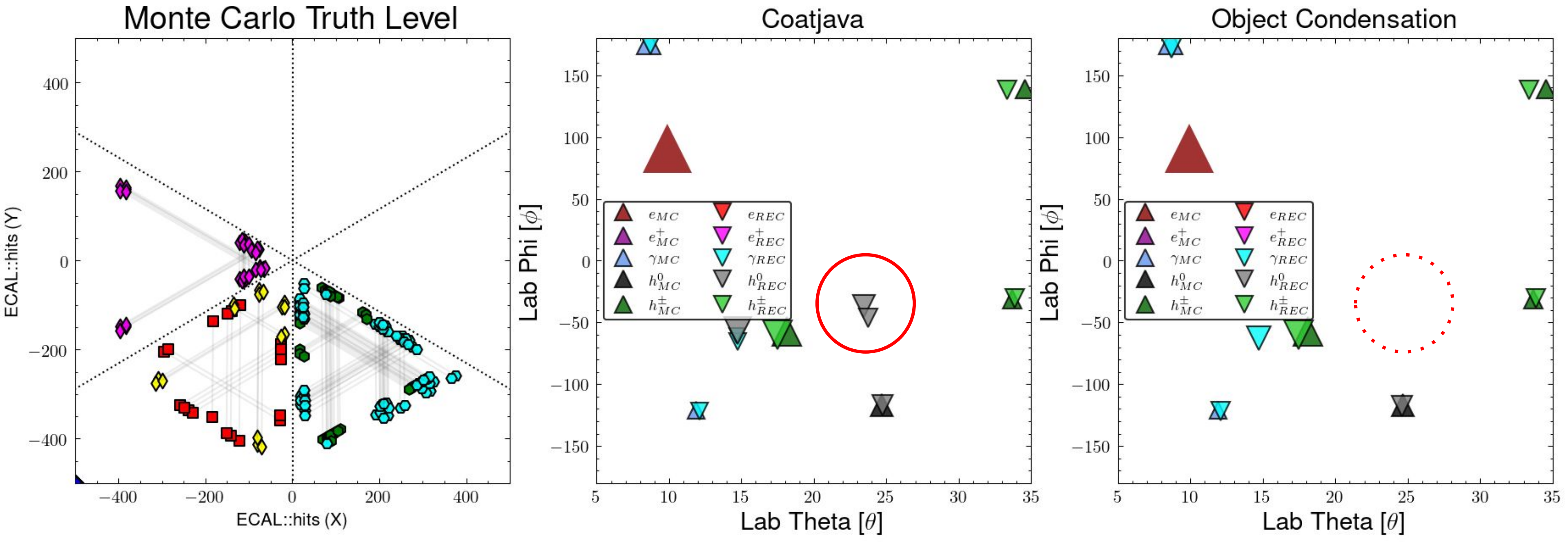
Sample Monte Carlo Event





False neutrals created by **COATJAVA**

Sample Monte Carlo Event

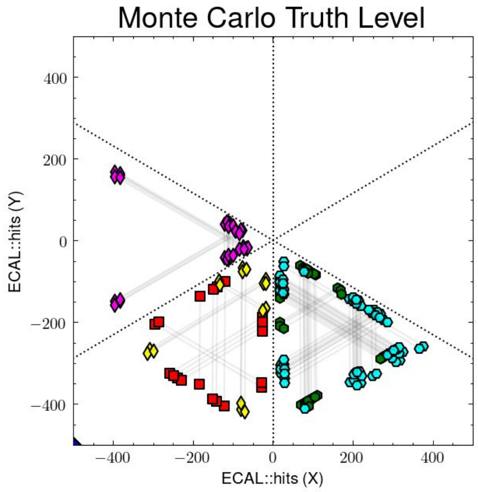


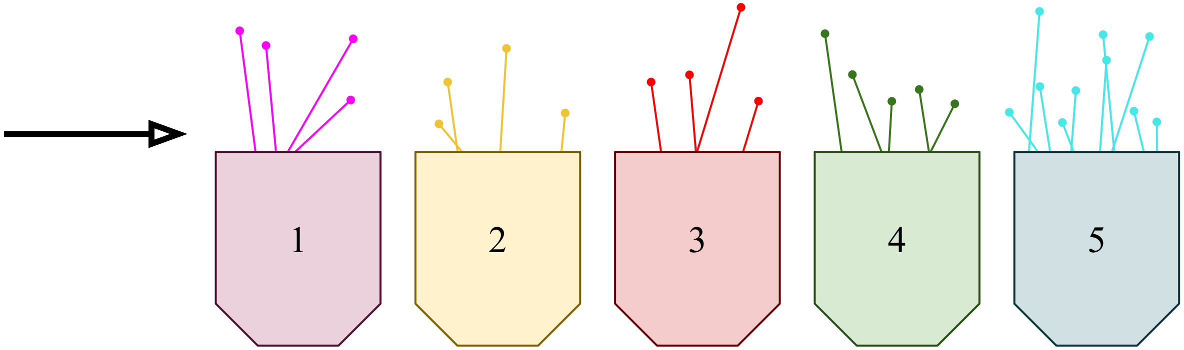
New **Machine Learning** approach effectively reduces the number of false neutrals without losing true neutrals

Defining the Problem

- **Input:** ***Point Cloud*** of ECAL strips with several features (layer, sector, E, t, x, y, z, etc)
  - For training we are aware of the Monte Carlo particle responsible for the strip hit
- **Output:** Distinct groups/clusters of strips that *belong to the same particle*

*This is a much more abstract version of **Image-within-Image** classification*



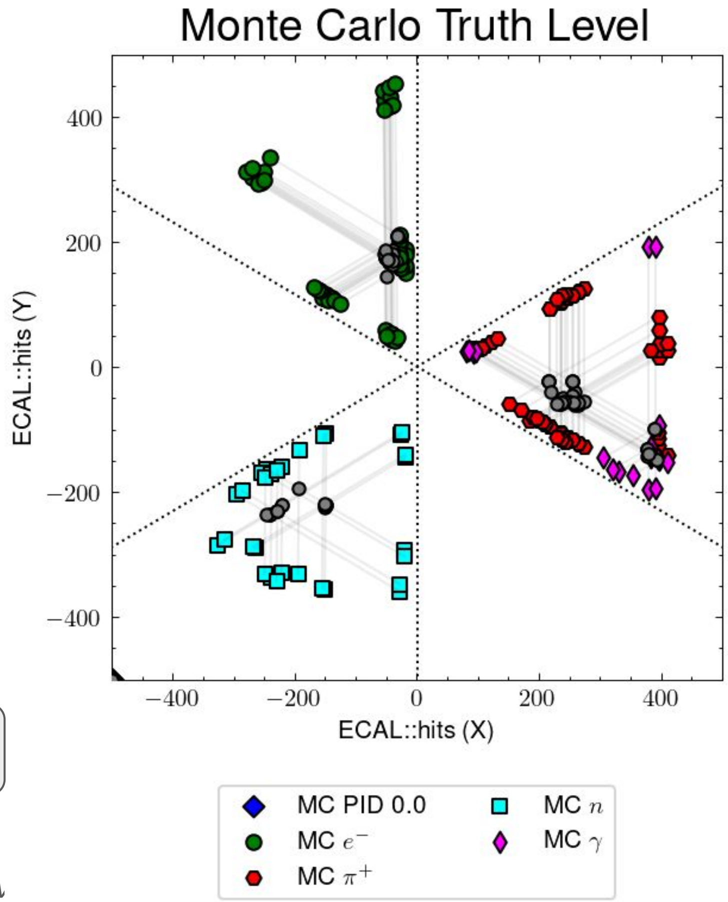


ML Input Considerations

Model Input Features (22)

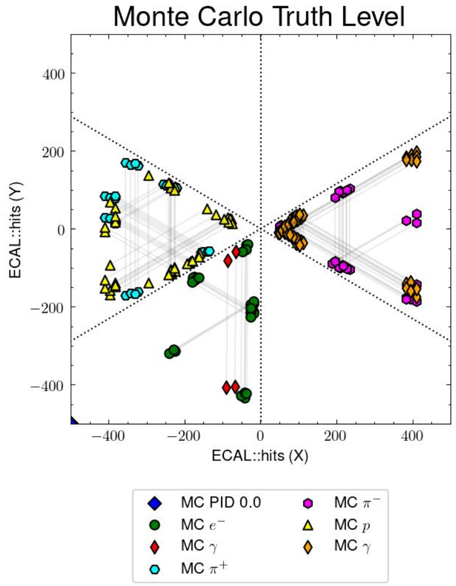
- **[+3]** Strip Origin Point (x_1 , y_1 , z_1)
- **[+3]** Strip End Point (x_2 , y_2 , z_2)
  - **Red** features scaled [-500,500] -> [0,1]
  - **Blue** features are scaled [550-950] -> [0,1]
- **[+1]** Energy Deposition (already [0,1])
- **[+3]** Strip's most energetic centroid (x,y,z)
  - **[+2]** One-hot encode for either 3 way or 2 way
- **[+1]** Timing Information [0,1000] $\longrightarrow$ [0,1]
- **[+9]** Layer
  - One-hot-encoded, 9 feature bits [0,1] total

Grey circles (right plot) show location of the energetic centroids



What is ★Object Condensation★?

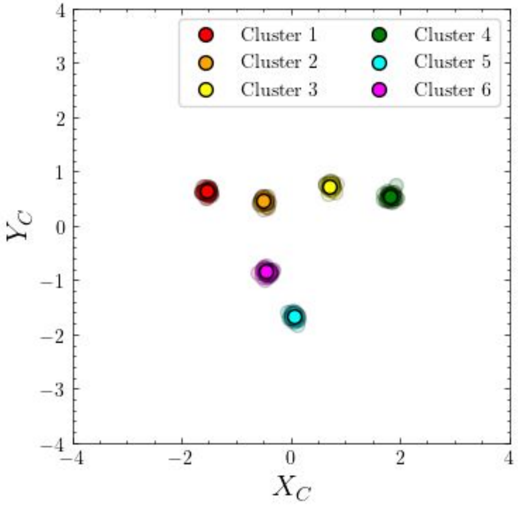
- ➢ Object Condensation defines a loss function that a neural network will try to minimize
- ➢ If this loss function is minimized, the ***Point Cloud*** is mapped to a clustered latent space
- ➢ Each ECAL strip learns its own point in the latent space **(x_c , y_c)** as well as a brightness **(0<□<1)**
- ➢ For each object (particle) only one latent space pixel is “bright” (□ near 1)



→

Feature Extractor
(Front-end Neural Network)

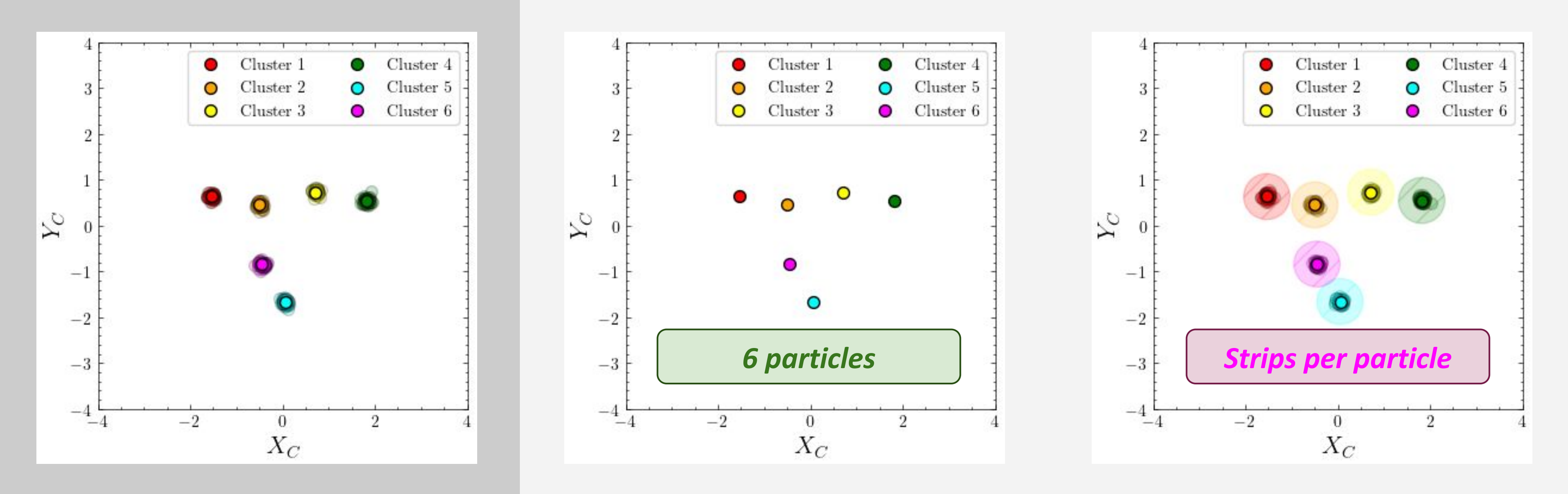
→



What is ★Object Condensation★?

By viewing this clustered latent space ($\mathbf{x}_c$, $\mathbf{y}_c$) we can get…

- ➢ The number of particles – threshold away the dim □'s and count them!
- ➢ The strips for each particle – for a bright □, collect all dim □'s within some radius



★Object Condensation★ Recap

- Input → $v_{in}(N, F)$
  - **N:** Number of nodes (in our case number of strips)
  - **F:** Number of features per node (in our case 22)
- Output → $v_{out}(N, 3)$ → *i.e. each strip learns 3 variables*
  - $\mathbf{v_{out}[:,0]}$ is the x-coordinate in a latent space (called $\mathbf{x_c}$)
  - $\mathbf{v_{out}[:,1]}$ is the y-coordinate in a latent space (called $\mathbf{y_c}$)
  - $\mathbf{v_{out}[:,2]}$ is the *brightness* of the node (strip) in the latent space [0,1] (called □)

Object Condensation (OC) defines a loss function $L(x_c, y_c, □)$ that is ***minimum*** if…

1. The (x_C, y_C) of nodes that belong to the same cluster are close (**attractive loss**)
2. The (x_C, y_C) of nodes that belong to different clusters are far (**repulsive loss**)
3. Only one node per cluster has a large brightness □~1 (**coward loss**)

Object Condensation Loss

$$L_V = \frac{1}{N}\sum_{j=1}^{N} q_j \sum_{k=1}^{K} \left(M_{jk}\breve{V}_k(x_j) + (1 - M_{jk})\hat{V}_k(x_j) \right).$$

$$q_i = \operatorname{arctanh}^2 \beta_i + q_{\min}$$

Attractive Loss

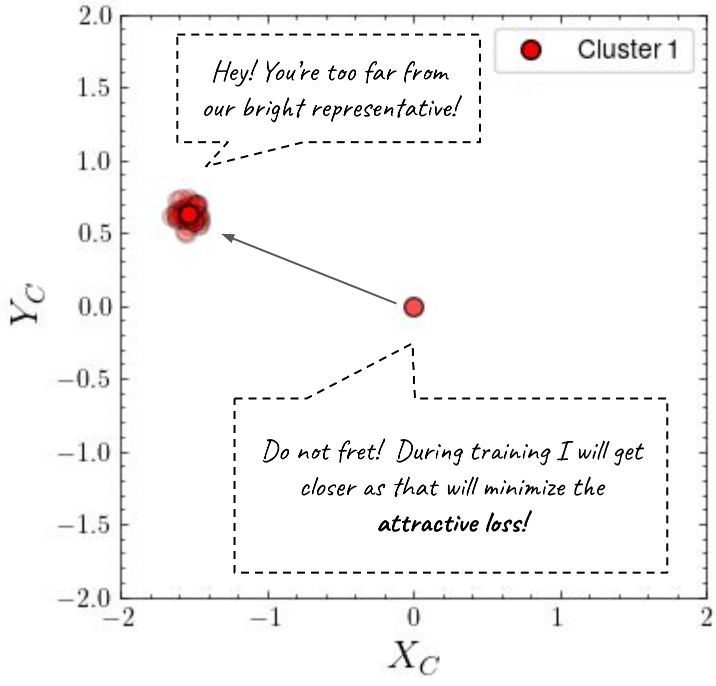
Each individual strip calculates one piece of the **attractive loss**

Very similar to E&M **U = qV**

For each strip (j), punish the loss function the further it is from the *brightest beta* for its particle (k)

The *brightest* strip for particle (*k*) is αk

$$\breve{V}_k(x) = ||x - x_\alpha||^2 q_{\alpha k}$$



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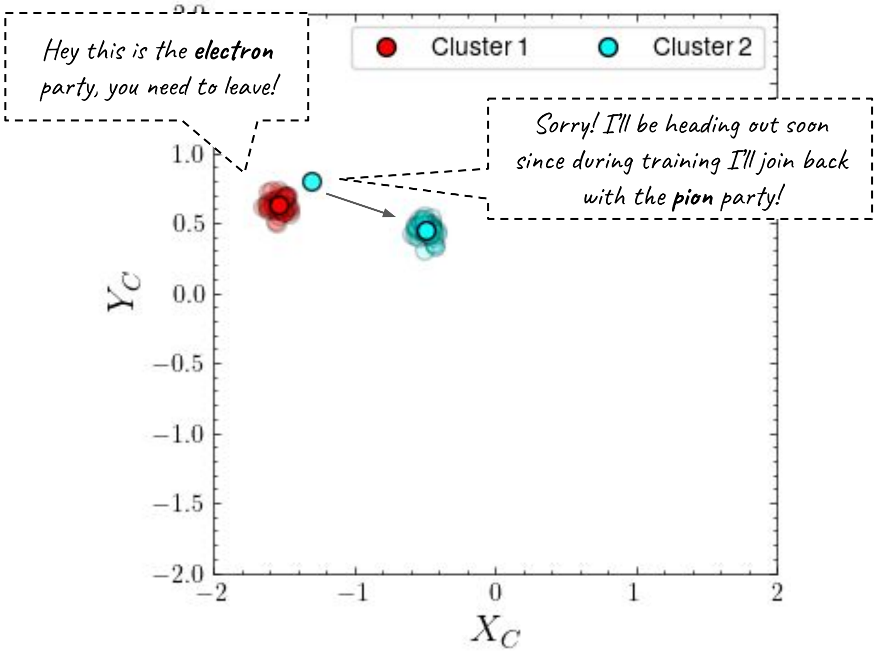


Repulsive Loss

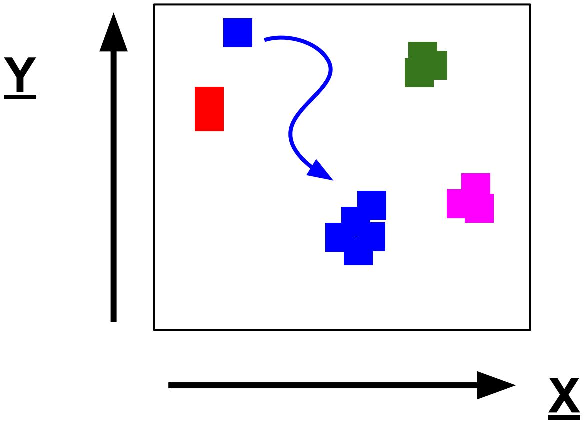
Each individual strip calculates **K-1** pieces of the **repulsive loss**

$$\hat{V}_k(x) = \max(0, 1 - ||x - x_\alpha||)q_{\alpha k}.$$

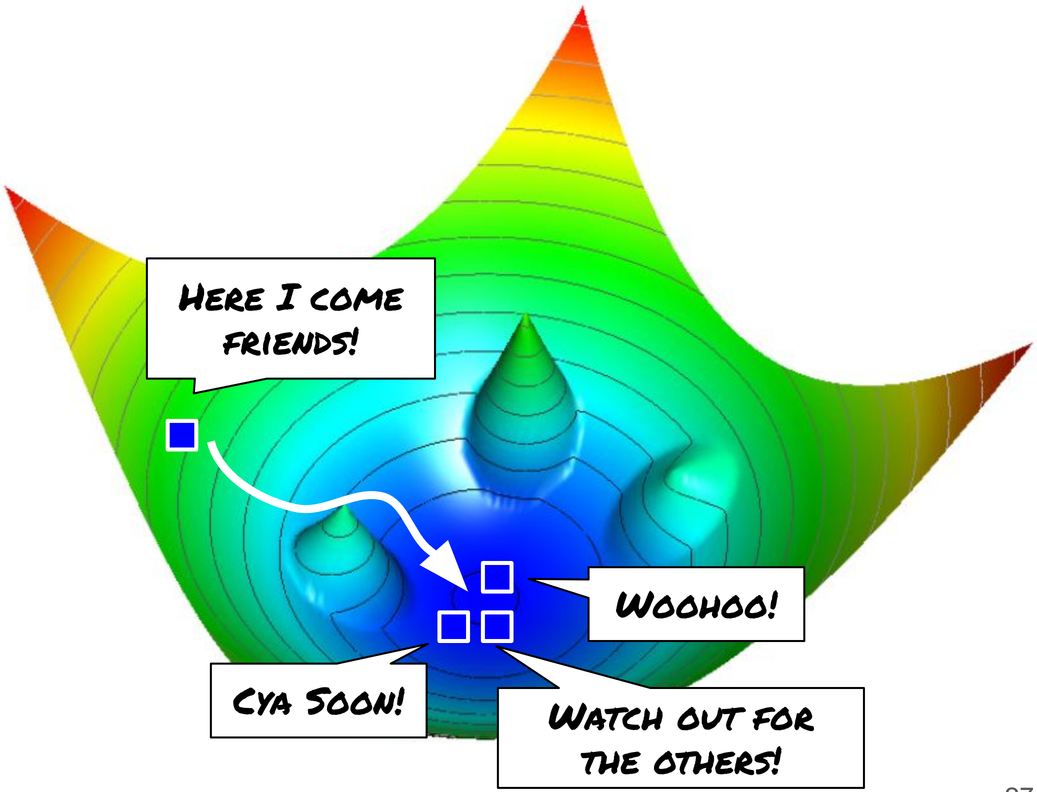
For each strip (j), punish the loss function the closer it is to the *brightest beta* of <u>any other particle</u> (k)

The *brightest* strip for particle (*k*) is αk

Object Condensation Attractive & Repulsive



(*Right)* The total potential V experienced by the blue square as it navigates past 3 unaffiliated objects (peaked condensation points) towards its clustering home (the bottom of the well, another condensation point)



Object Condensation Loss

$$L_\beta = \frac{1}{K}\sum_k (1-\beta_{\alpha k}) + s_B \frac{1}{N_B}\sum_i^N n_i \beta_i,$$

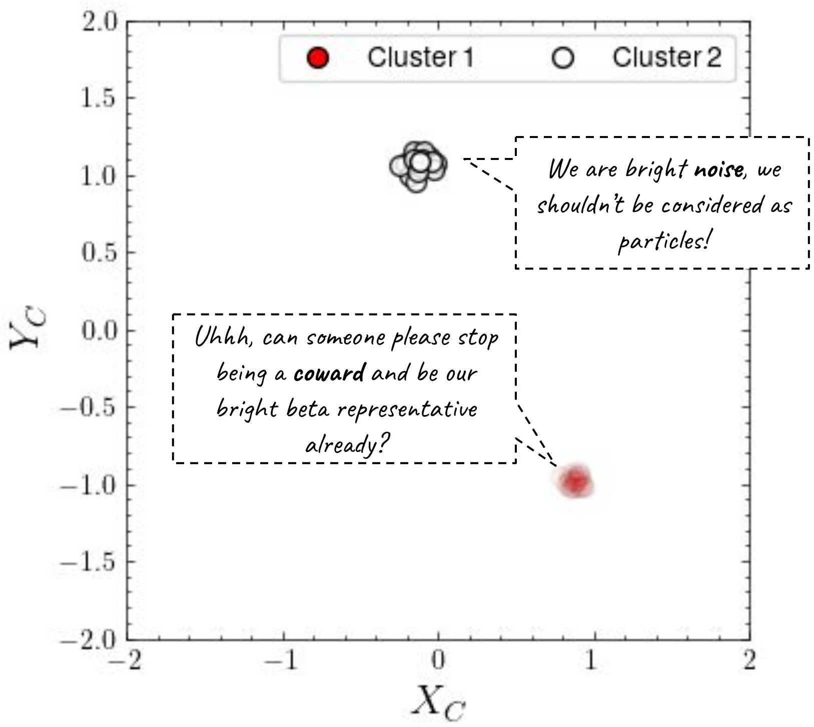
Coward Loss

For each particle (k) , punish the **coward loss** if the object's *brightest beta* is dim (near 0)

Noise Loss

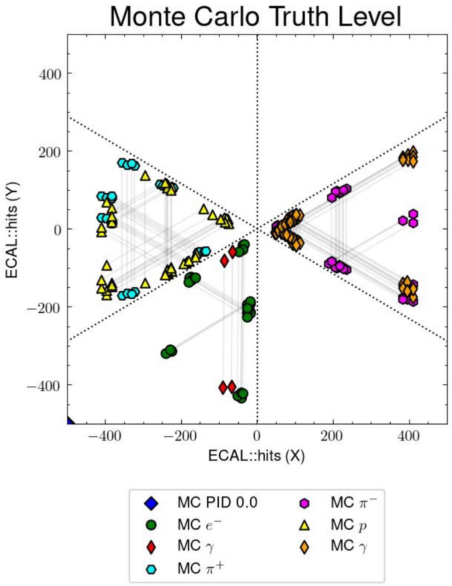
For each strip (i) punish the **noise loss** if the strip is noise (ex: 0-padded) and has a high *brightness beta*

Here n_i is a bit that is 1 if strip (i) is noise

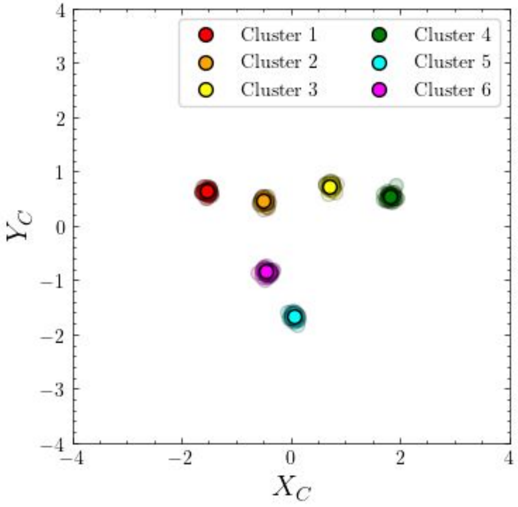


Object Condensation Summary

- A feature extractor maps the (N,F) strip input space into a (x_C , y_C) space
- The weights/biases of the feature extractor are backpropagated to minimize four Object Condensation losses (**attractive, repulsive, coward, noise**)

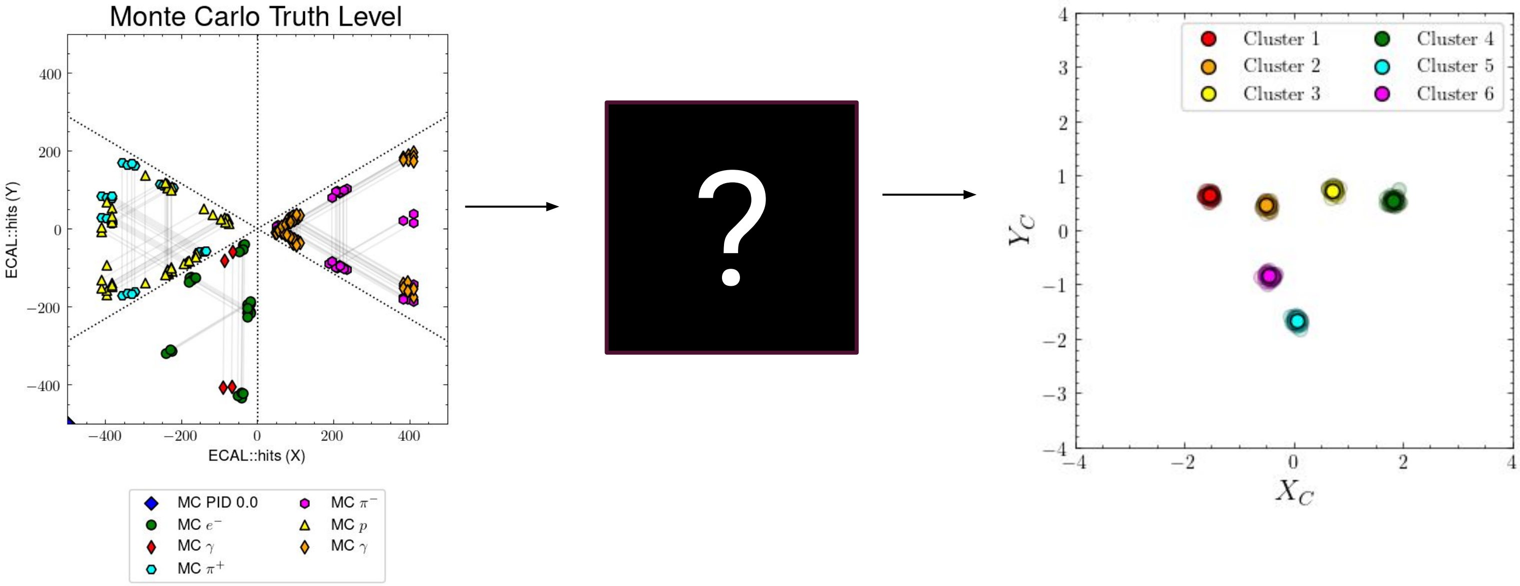


Feature Extractor (Front-end Neural Network)

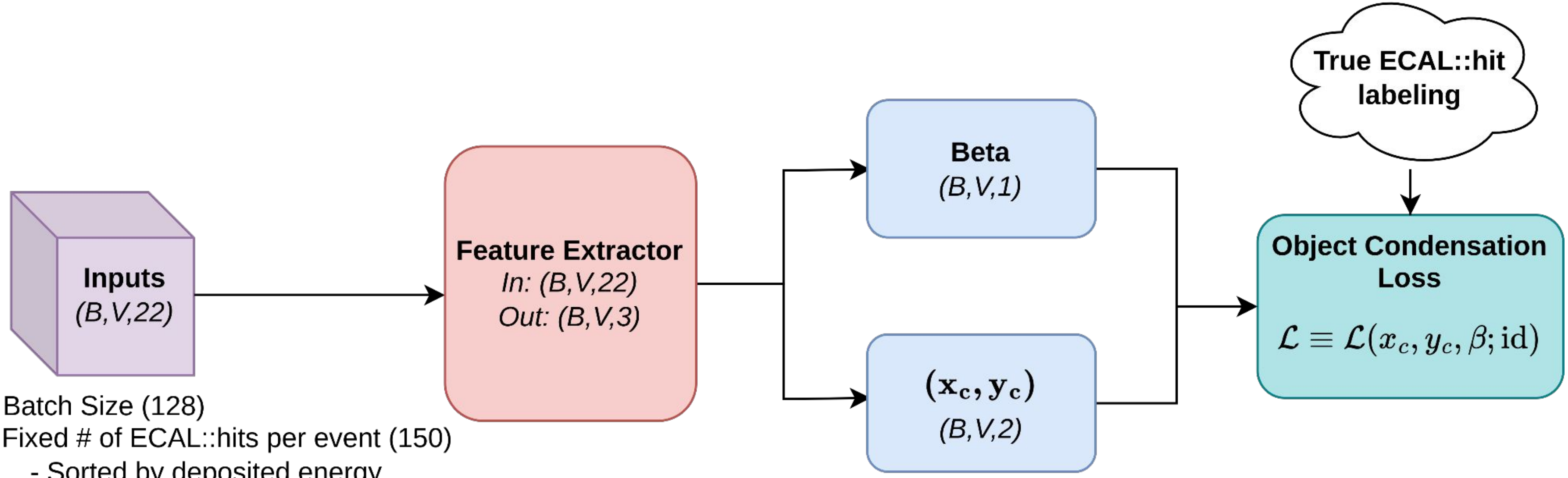


Object Condensation Summary

What is the Feature Extractor we use?



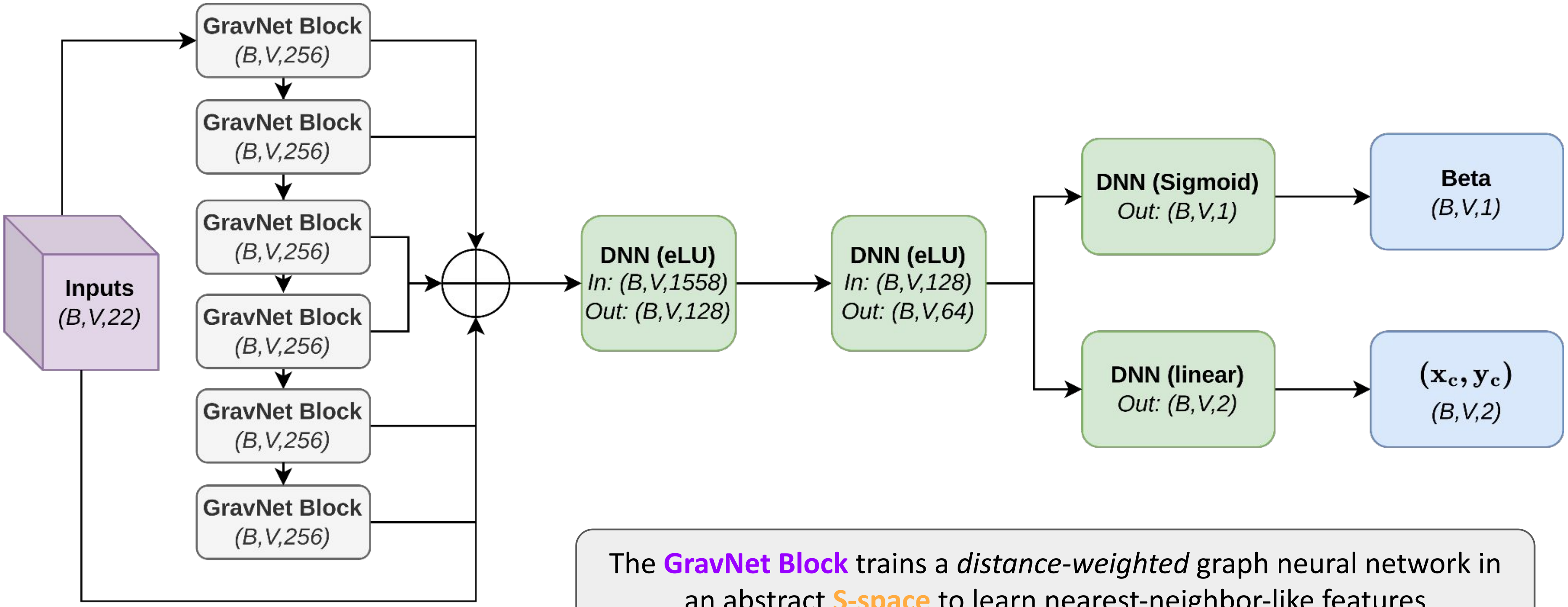
Model Architecture



B: Batch Size (128)
V: Fixed # of ECAL::hits per event (150)
- Sorted by deposited energy
- Otherwise, 0-padded

Backpropagation w/ cyclical LR (1e^{-6} <-> 1e^{-5} every 20 batches)

Feature Extractor

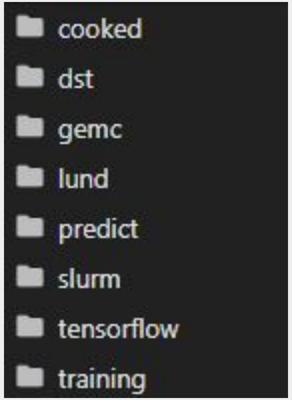


The **GravNet Block** trains a *distance-weighted* graph neural network in an abstract **S-space** to learn nearest-neighbor-like features

Subsequent **GravNet Blocks** are concatenated with the original input and fed into **DNNs** to extract **Beta** and **(x_c , y_c)** for each strip

Data Generation (see repository)

1. 1M **e+p** DIS events simulated using **clasdis** split into 1000 batches
2. Detector readout simulated using **gemc** with `MC::True` saved (see here)
3. Create `ECAL::hits` and other familiar banks with **recon-util**
   a. Custom coatjava fork uses `MC::True` to give **true/rec** pid to each strip
4. Use **hipopy** to read `ECAL::hits` into csv files (see here)
   a. Also parse `REC::Particle` (for comparisons) and `MC::Particle` (for training)
5. Preprocess the csv files into h5 files for training (ex: scaling features, get centroids)



3 → cooked

Filtered banks from **Step 3** → dst

2 → gemc

1 → lund

AI-assisted reconstructed hipo banks → predict

Slurm scripts → slurm

Model training info (checkpoints, configuration, plots, etc.) → tensorflow

4,5 → training

Training Information

- 128 events per batch
- 100 epochs (~45 per 24hrs training on 1 TitanRTX GPU)
- 80% - 20% Training/Validation splitting
- GravNet Feature Extractor Information
  - 10 GravNet blocks – 10 nearest neighbors – 4 S-space dimensions – 32 hidden features – 256 output
  - Total trainable parameters = 637,934
- Hyperparameters
  - $q_{min} = 0.1$
  - $s_B = 1$ (only noise considered is 0-padded anyway, not hard for model to figure that out)
  - $t_B = 0.5$ (minimum *brightness* threshold)
  - $t_D = 0.28$ (radius of cluster in latent space, decided by eye, but need to develop rigorous metric)
- Cyclical Learning rate between 10^{-6} <-> 10^{-5} every 20 batches (help navigate out of local minima)
- Stopping Procedure
  - Stop if validation loss does not improve for 10 epochs (not yet seen)

Loss Function

$$L_V = \frac{1}{N}\sum_{j=1}^{N} q_j \sum_{k=1}^{K}\left(M_{jk}\breve{V}_k(x_j) + (1 - M_{jk})\hat{V}_k(x_j)\right).$$

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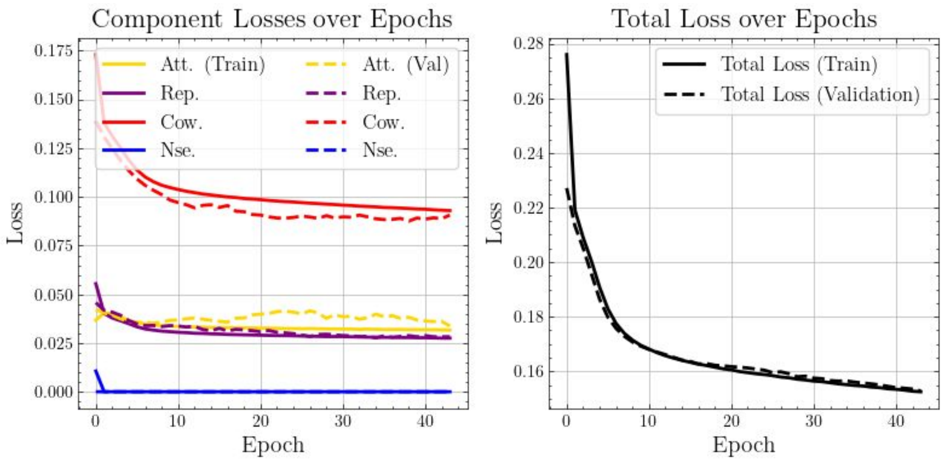
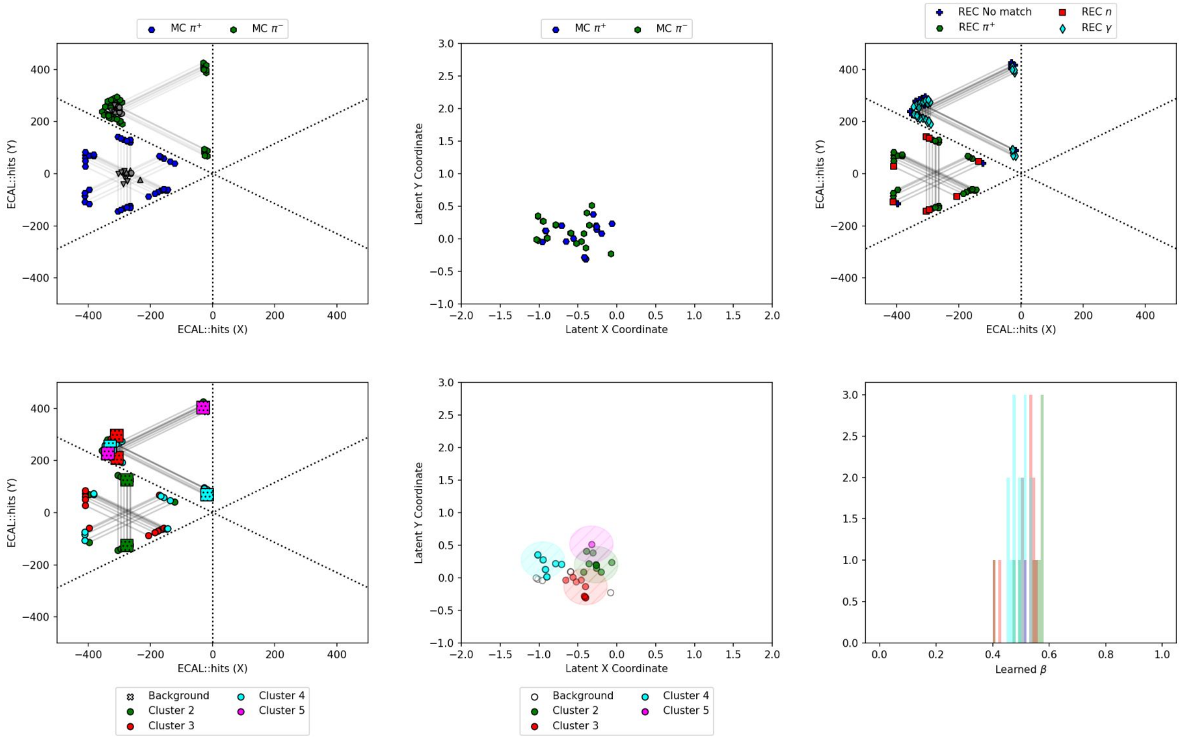


- ★ Per epoch evaluation of **Obj. Condensation Loss**
- ★ Solid lines = Training /// Dotted lines = Validation
- ★ Since validation loss is evaluated at the end of each epoch, the fast-learning early epochs have validation loss < train loss
- ★ Overfitting not yet seen, but training stopped at 24 hours. Working on extending training

Training Visualization **(Event A)**

Smaller model used to make plots quickly

Epoch 1, Batch 0000, Loss = 1.0922



Top Left

Monte Carlo true hits

Top Middle

True hits in latent space [x_C , y_C] (colors match TL plot)

Top Right

REC::Particle reco hits

Bottom Left

Hits clustered in latent space

** Box = Brightess Beta **

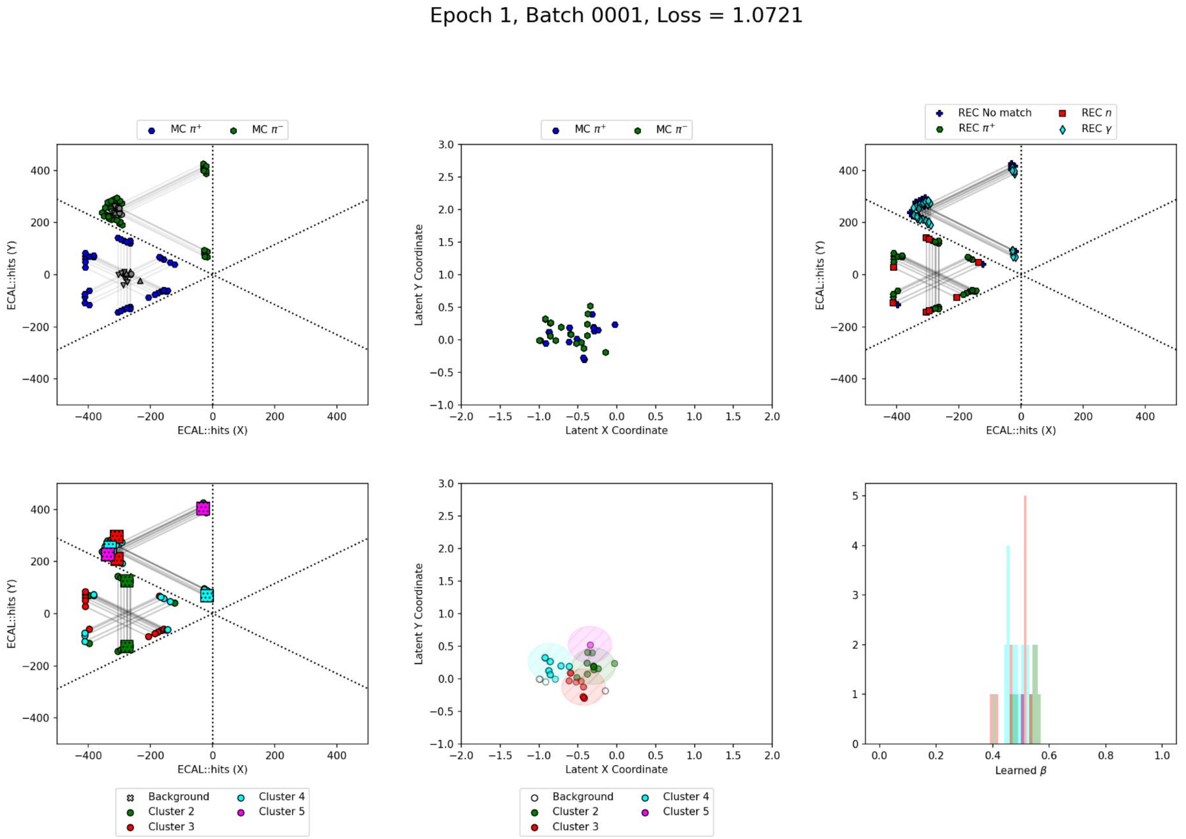
Bottom Middle

Latent space with t_B=0.5and t_D=0.28 used to determine clusters (colors match BL plot)

Bottom Right

Histogram of the strip brightness (□) values

Training Visualization **(Event A)**



Top Left

Monte Carlo true hits

Top Middle

True hits in latent space [x_C , y_C] (<u>colors match TL plot</u>)

Top Right

REC::Particle reco hits

Bottom Left

Hits clustered in latent space

** Box = Brightess Beta **

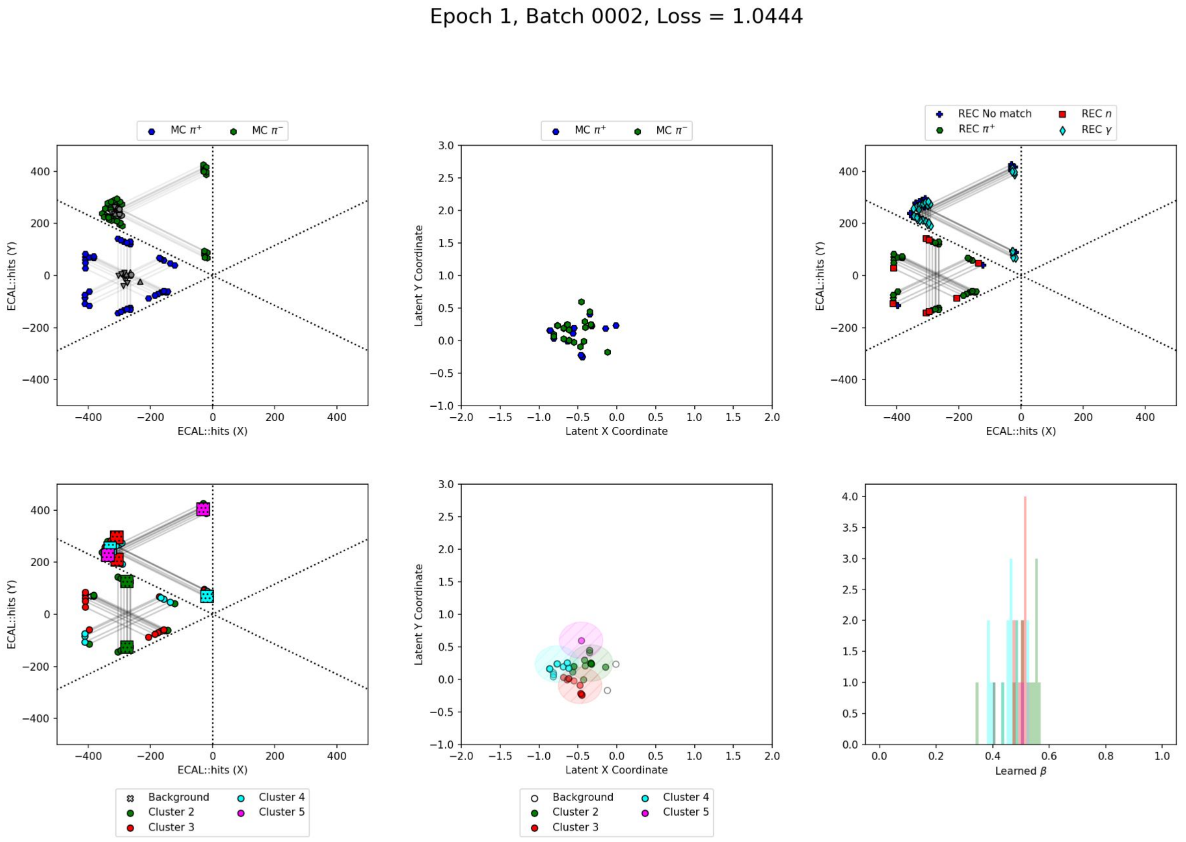
Bottom Middle

Latent space with t_B=0.5and t_D=0.28 used to determine clusters (<u>colors match BL plot</u>)

Bottom Right

Histogram of the strip brightness (□) values

Training Visualization **(Event A)**



Top Left

Monte Carlo true hits

Top Middle

True hits in latent space [x_C , y_C] (<u>colors match TL plot</u>)

Top Right

REC::Particle reco hits

Bottom Left

Hits clustered in latent space

** Box = Brightess Beta **

Bottom Middle

Latent space with t_B=0.5and t_D=0.28 used to determine clusters (<u>colors match BL plot</u>)

Bottom Right

Histogram of the strip brightness (□) values

Training Visualization **(Event A)**

Top Left
Monte Carlo true hits
Top Middle
True hits in latent space [x_C , y_C]
(<u>colors match TL plot</u>)
Top Right
REC::Particle reco hits

Bottom Left
Hits clustered in latent space
** Box = Brightess Beta **
Bottom Middle
Latent space with t_B=0.5and t_D=0.28 used to determine clusters (<u>colors match BL plot</u>)
Bottom Right
Histogram of the strip brightness (□) values

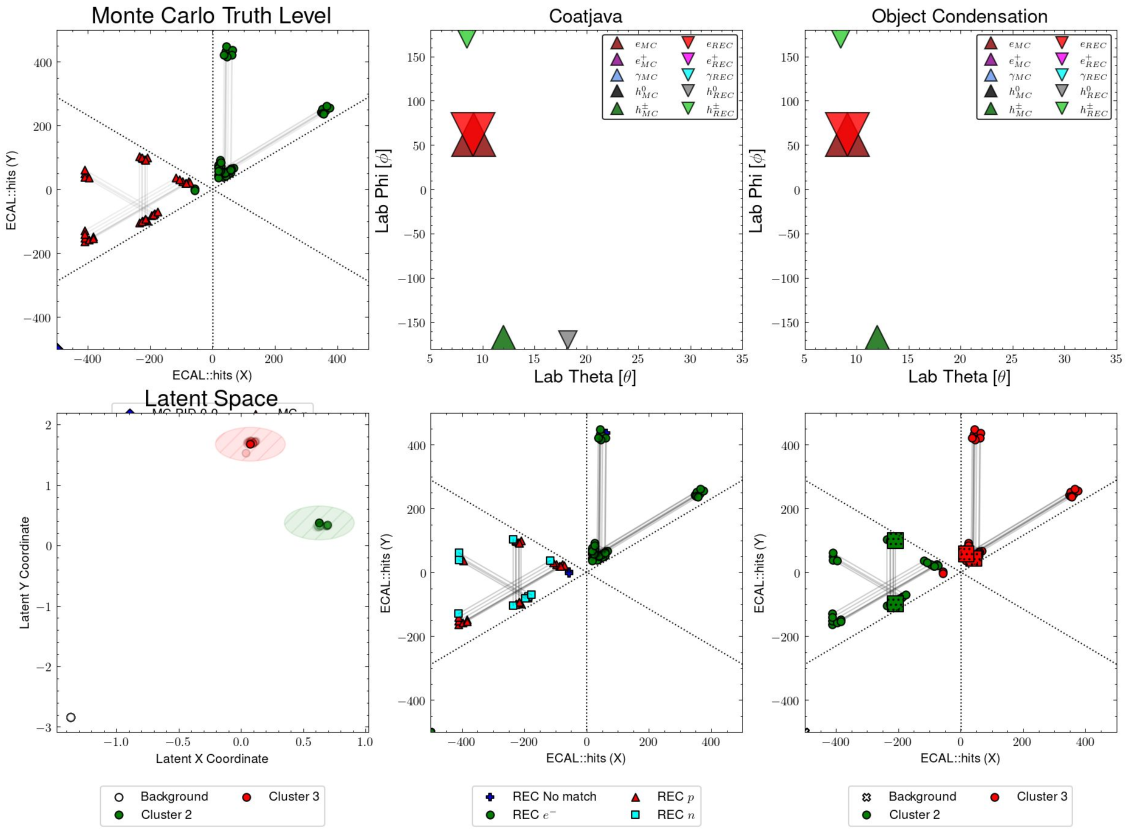
Training Visualization **(Event B)**

Actual model used to make this plot

Top Left
Monte Carlo true hits
Top Middle
True hits in latent space [x_C , y_C]
(<u>colors match TL plot</u>)
Top Right
REC::Particle reco hits

Bottom Left
Hits clustered in latent space
** Box = Brightess Beta **
Bottom Middle
Latent space with t_B=0.5and t_D=0.28 used to determine clusters (<u>colors match BL plot</u>)
Bottom Right
Histogram of the strip brightness (□) values

Training Results **(Event C)**

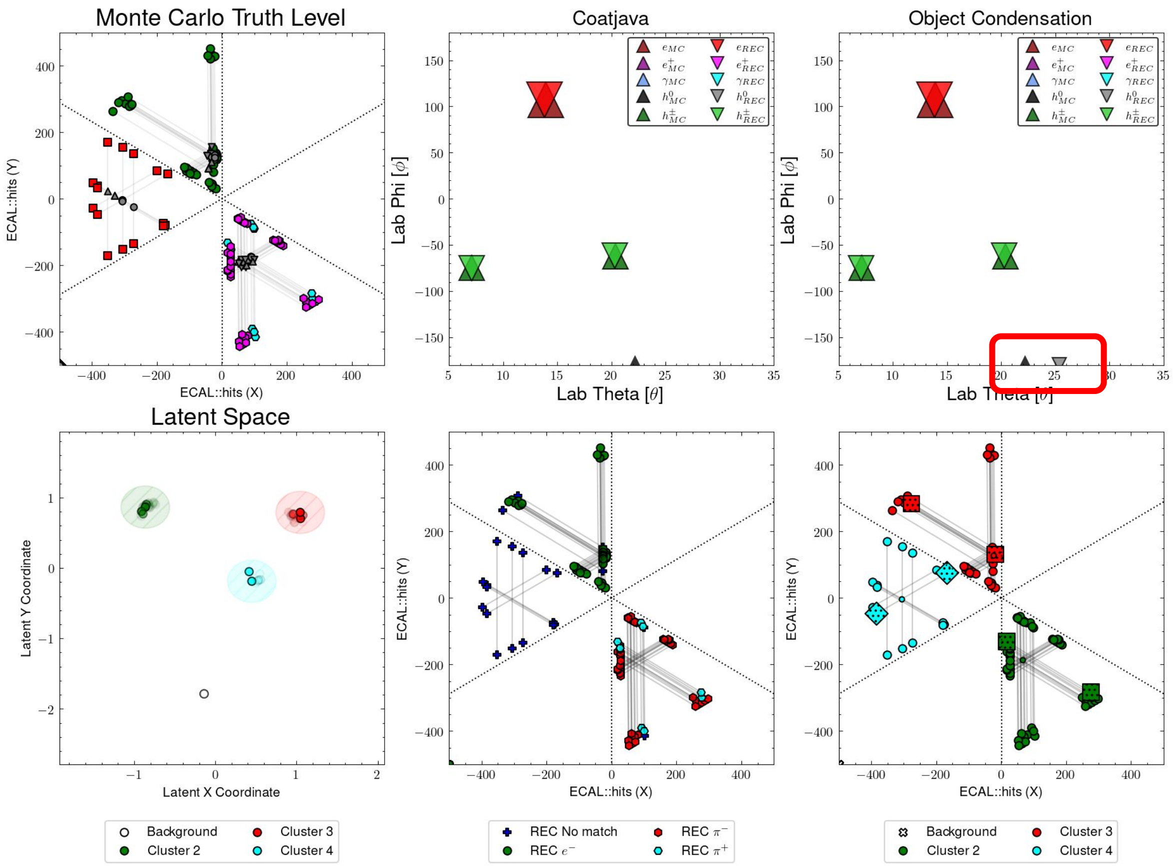


Coatjava (middle column) reconstructs an extra false neutral particle in Sector 4

Object Condensation (right column) does not make this mistake, finding one cluster here

Obj. Cond.=More comprehensive understanding of what should be considered a cluster

Training Results **(Event D)**

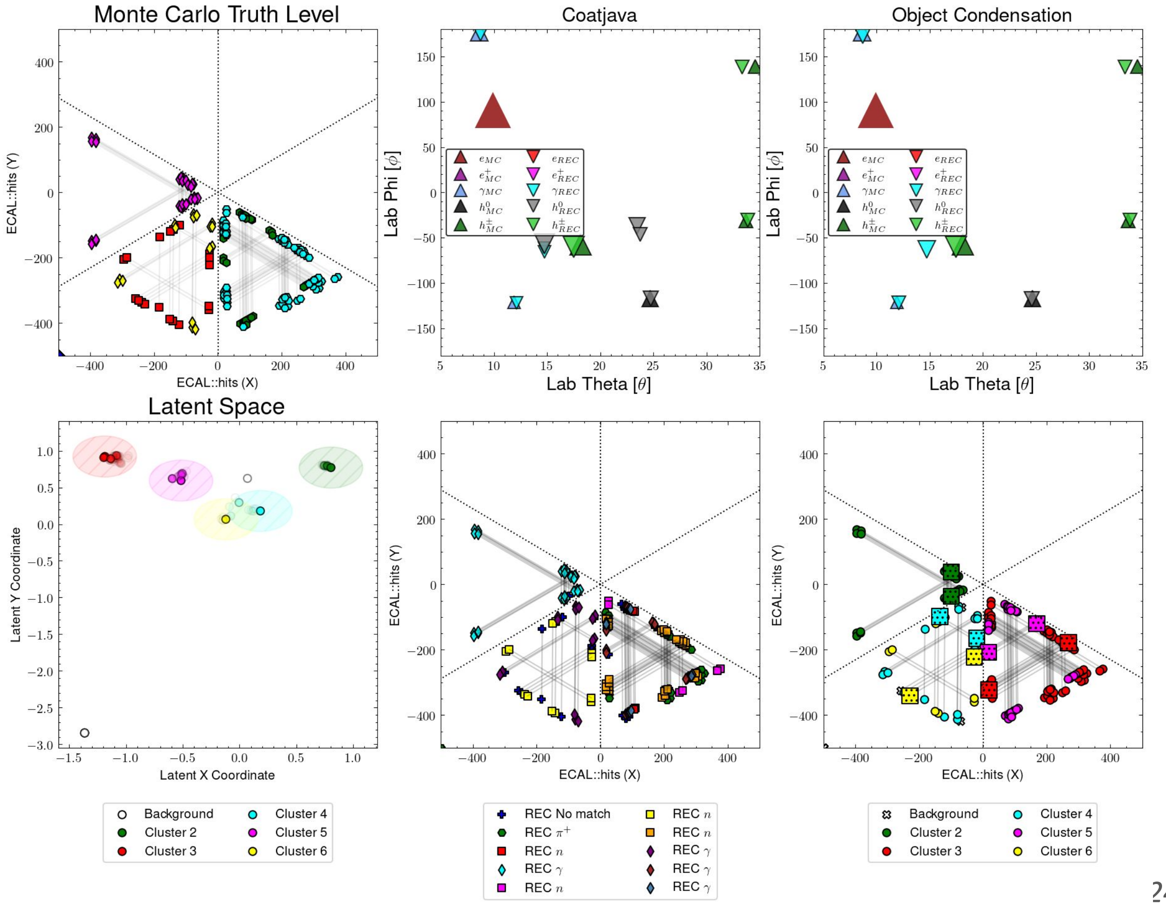


Coatjava (middle column) does not find the neutron in Sector 4

Object Condensation (right column) <u>does find this neutron</u> but the ambiguity of the 3-way intersection leads to a misreconstruction of **theta**

Obj. Cond.=Could use more development in calculating the centroid location after clustering

Training Results **(Event E)**



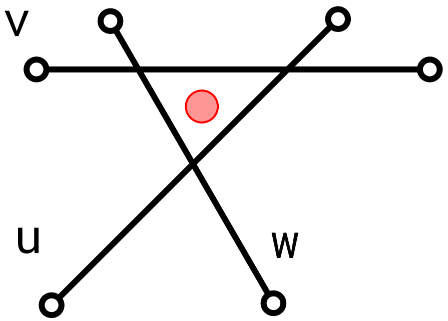
Coatjava (middle column) finds a swamp of neutrals in Sector 6

Object Condensation (right column) correctly identifies only two unique clusters in Sector 6.

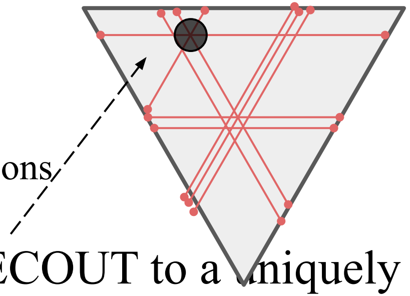
Obj. Cond.=Can handle multiple particles in a sector and still predict their centroid effectively

Creating new `ECAL::clusters` bank (python)

1. Loop over PCAL, ECIN, and ECOUT strips
2. For each strip (j) belonging to cluster (k)
   a. Find its most energetic ($\sum_j E_j$) 3-way intersection. A 3-way intersection is determined by the average (x,y,z) of closest approach for **uv, vw, uw** strips. E_j is energy corrected to account for attenuation!



3. For each cluster (k) containing (**N**) 3-way intersections
   a. Only consider 3-way intersections in the sector with a 50%+ majority
   b. Calculate the z-score $\mathbf{z_i}$ for each 3-way intersection (x,y,z)
   c. Report the centroid's (x,y,z) as the weighted sum of the 3-way intersections where $\mathbf{w_i = (1+z^2)^{-1}}$ to lessen the impact of ***distantly separately 3-way's***



4. Purposefully assign `ECAL::cluster` status of PCAL, ECIN, ECOUT to a uniquely identifiable status value to force REC::Calorimeter to recognize them as a group
5. Generate new `ECAL::clusters`, `ECAL::calib` (empty) and `ECAL::moments` (empty)

Creating new `ECAL::clusters` bank (python)

index :	2	3	1	0
pindex :	1	1	2	3
detector :	7	7	7	7
sector :	3	3	2	5
layer :	1	4	1	7
energy :	0.1823	0.0090	0.3472	0.2481
time :	149.9131	151.2900	149.1106	155.7128
path :	764.8085	801.8519	744.9232	770.0773
chi2 :	0.0000	0.0000	0.0000	0.0000
x :	-37.5027	-29.0460	93.4869	-120.4040
y :	70.6440	58.9809	78.6126	-239.4463
z :	752.1381	794.9993	735.1639	722.0366
hx :	-39.3423	-38.3846	93.4869	-120.4040
hy :	68.0255	66.5349	78.6126	-239.4463
hz :	753.1024	790.1033	735.1639	722.0366
lu :	0.0000	0.0000	0.0000	0.0000
lv :	0.0000	0.0000	0.0000	0.0000
lw :	0.0000	0.0000	0.0000	0.0000
du :	0.0000	0.0000	0.0000	0.0000
dv :	0.0000	0.0000	0.0000	0.0000
dw :	0.0000	0.0000	0.0000	0.0000
m2u :	0.0000	0.0000	0.0000	0.0000
m2v :	0.0000	0.0000	0.0000	0.0000
m2w :	0.0000	0.0000	0.0000	0.0000
m3u :	0.0000	0.0000	0.0000	0.0000
m3v :	0.0000	0.0000	0.0000	0.0000
m3w :	0.0000	0.0000	0.0000	0.0000
status :	2	2	1	0

Purposefully assign `ECAL::cluster` status of PCAL, ECIN, ECOUT to a uniquely identifiable status value to force REC::Calorimeter to recognize them as a group

Implementation added in personal coatjava fork in order to force all clusters with identical status to be assigned to the same REC::Particle

See *processNeutralTracks_OC* in EventBuilder.java

```
// Group DetectorResponses by their status
for (DetectorResponse response : allResponses) {
    int status = response.getStatus();
    groupedResponses.computeIfAbsent(status, k -> new ArrayList<>()).add(response);
}
```

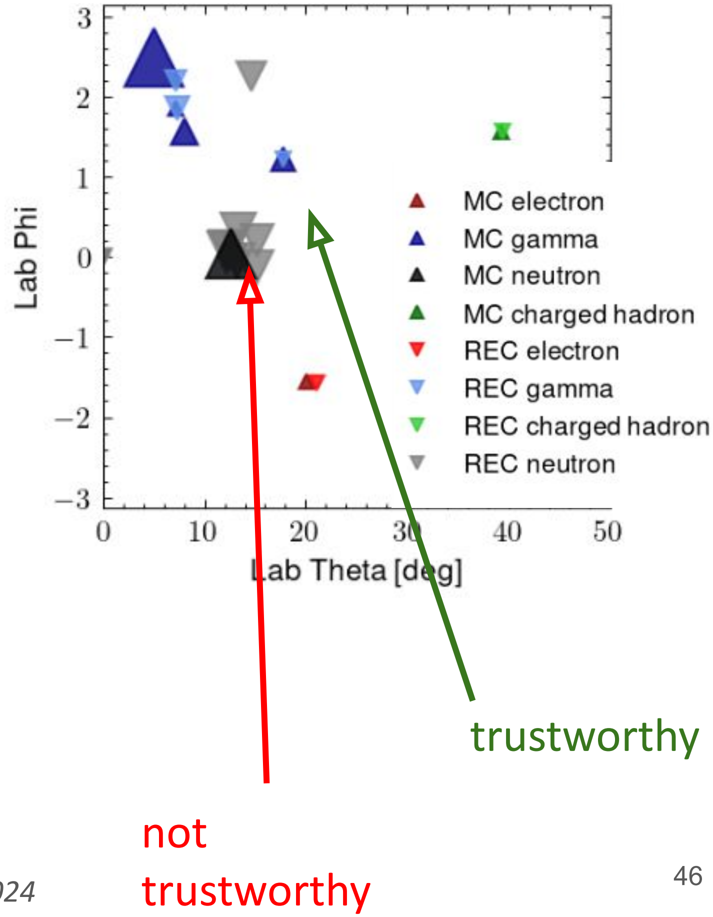
Benchmarks – Coatjava vs. Obj Condensation

Next we will discuss three of the ways I directly compared the two clustering methods

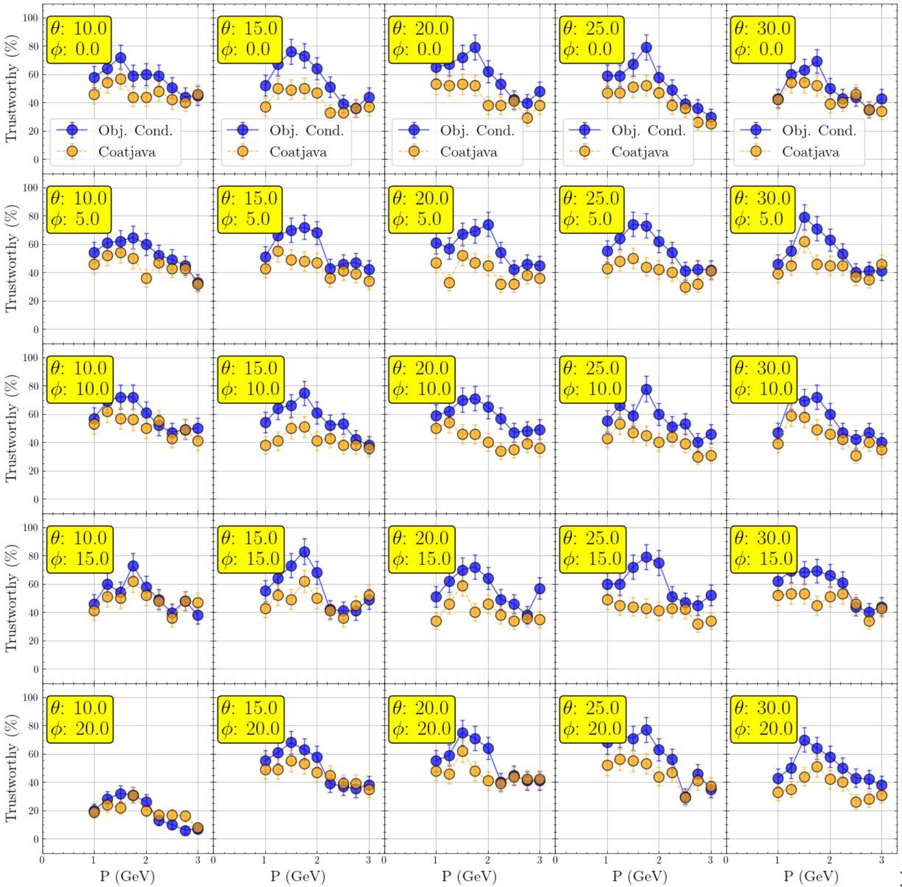
1. (P, θ, ϕ) binned neutron gun events
2. Incoherent J/Psi production off deuterium (e+n → e'+J/Psi+n')
3. clasdis Monte Carlo SIDIS events

We classify REC::Particle's as ***trustworthy*** if …

A. There is an MC::Particle within … $\delta\theta < 4$ [deg] and $\delta\varphi < 8$ [deg]
B. The matched MC::Particle has the same pid as the REC::Particle
C. There are no other REC::Particles that also satisfy this requirement for that MC::Particle



Particle Gun Benchmark



- 1000 **e+n** events in each bin
- Columns: θ=10,15,20,25,30 [deg]
- Rows: ϕ=0,5,10,15,20 [deg]
- Data points: 1 < P < 3 [GeV]

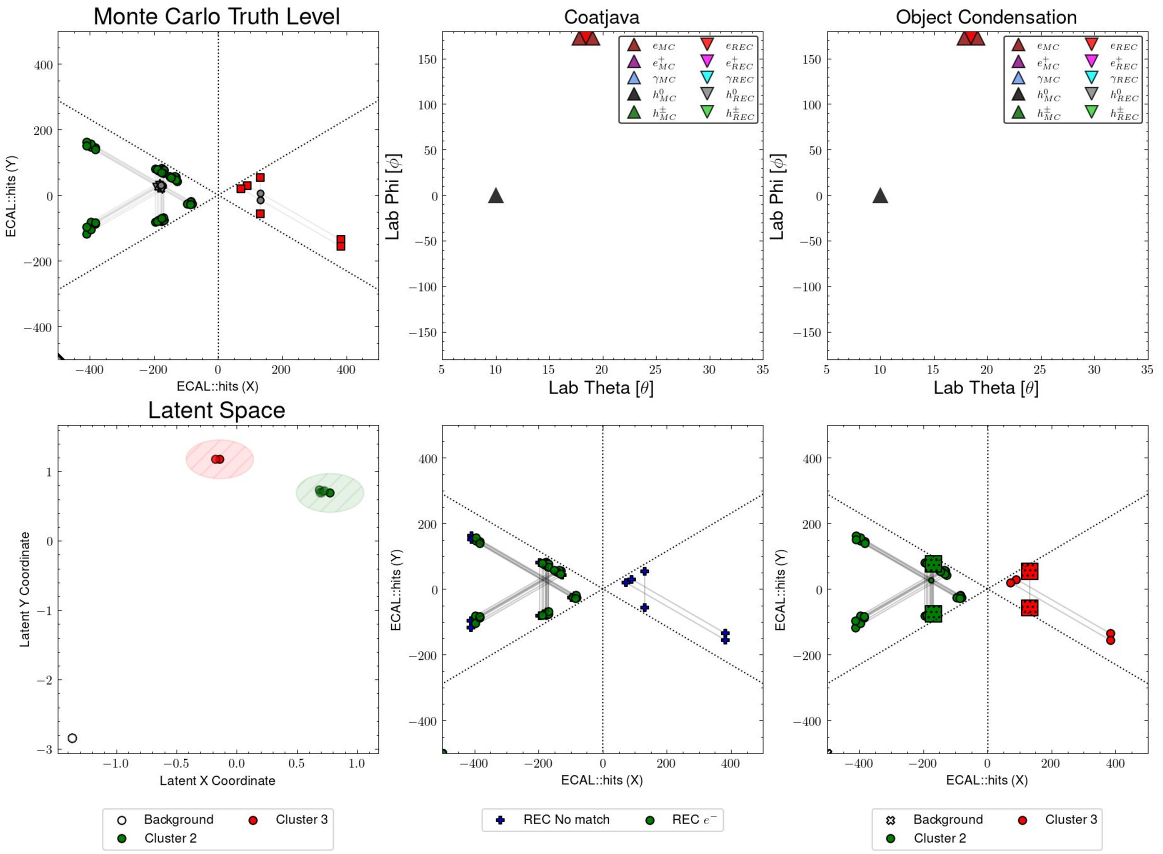
Observations:

Average improvement of **Object Condensation** vs. **Coatjava** of 20-40%

Can be further improved because of the 3-way intersection issue…(see next slide)

Should extend study to smaller momentum

Particle Gun Benchmark



Here, the electron and neutron are thrown and leave hits in sectors 4 and 1, respectively…

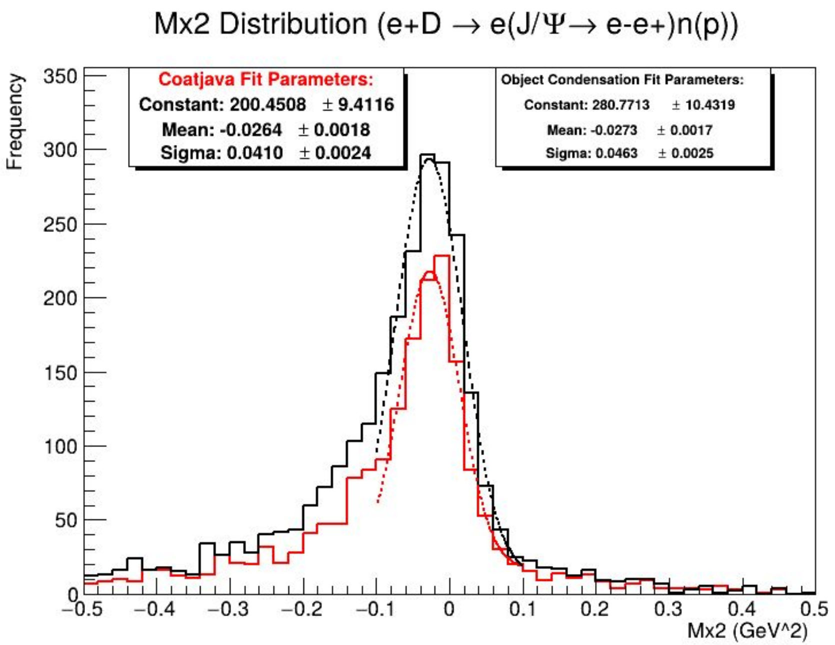
Despite **Object Condensation** clustering the neutron hits as an object (bottom right red cluster), since there is no 3-way intersection, we do not assign it as a REC::Particle later

Future: Train Obj. Cond. to predict neutral particle Px, Py, Pz and bypass needing ECAL cluster

Incoherent J/Psi Production Benchmark

- 1M spherically generated $e+n \rightarrow e' + (J/\psi \rightarrow e^+e^-) + n$ events (w/ Fermi motion)
- For comparison, we make simple cuts
  - $N_{electrons} = 2$
  - $N_{positrons} = 1$
  - $N_{neutrons} = 1$
- We see that Object Condensation provides a roughly 40% increase

Richard Tyson is completing a more thorough comparison using his analysis pipeline to come to a more accurate conclusion



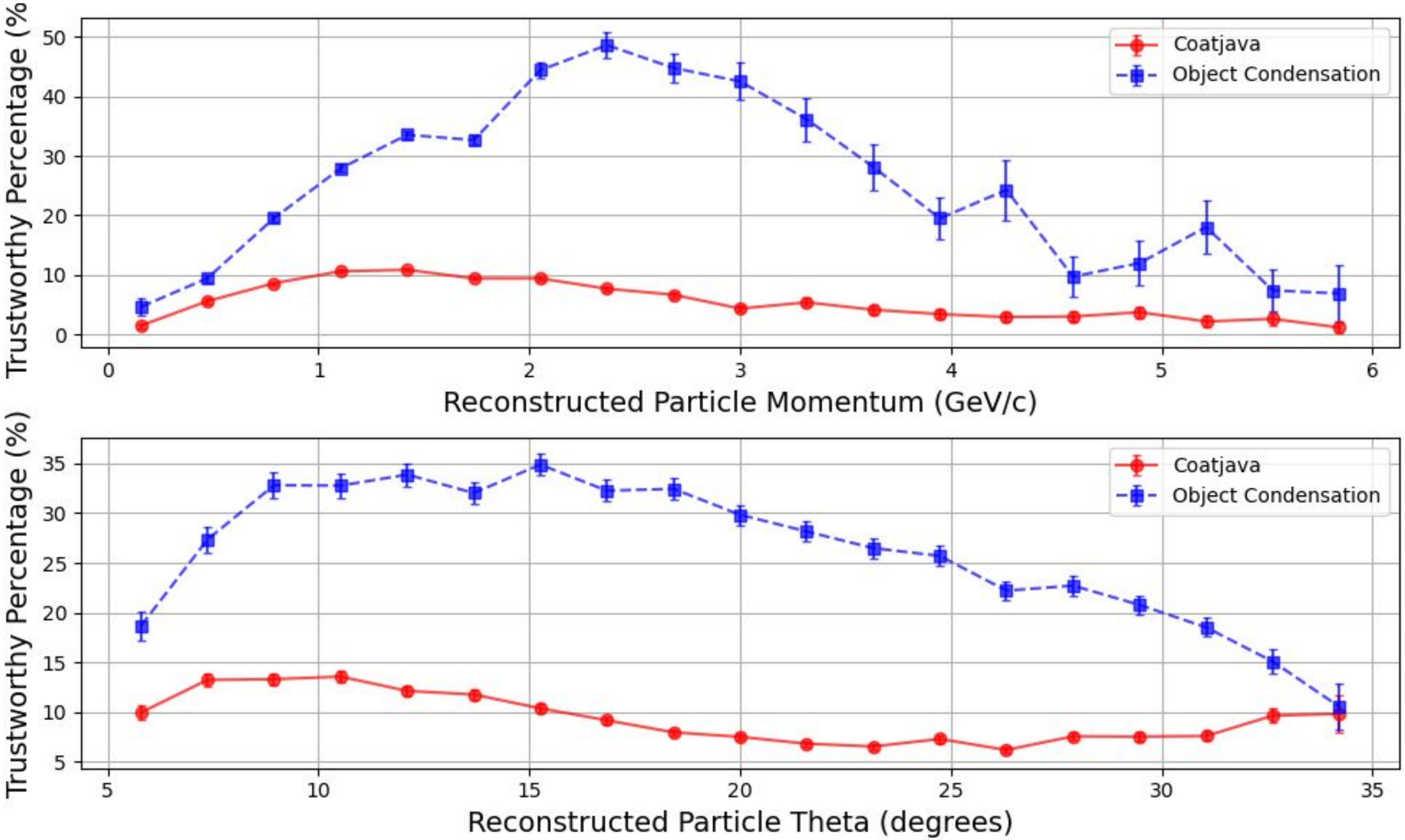
SIDIS Monte Carlo Benchmark

- Provides the most complex comparison…ex: multiple particles/types per sector
- One major advantage *currently* for **Coatjava** is that <u>one strip can belong to two particles/clusters in the same layer</u>…still working how to adjust for this in Obj. Cond.
- Typically, photons leave less hits in the calorimeter per cluster than neutrons which means Obj. Cond. has a disadvantage in finding photons

In the next slides, we compare the **Momentum** and **Theta** dependence of trustworthy neutrons/photons between Coatjava and Object Condensation…

1M e+p DIS events simulated using **clasdis** separate from what was used during training

Trustworthy **REC::Neutron** Percentage



Coatjava

87383 REC neutrons

- 14164 w/ match
- 7708 trustworthy

Object Condensation

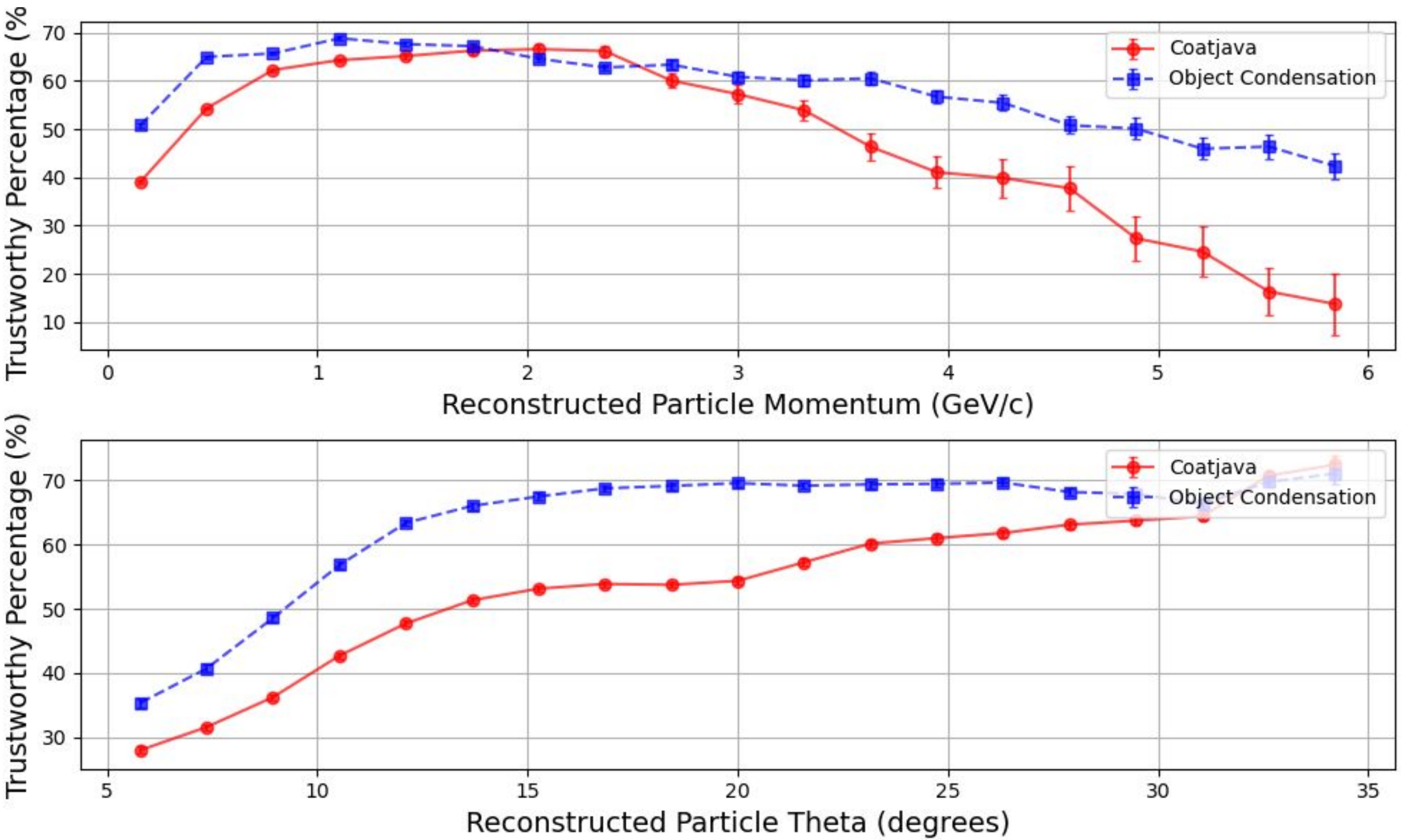
29858 REC neutrons

- 8187 w/ match
- 8187 trustworthy

3.1x increase in the trustworthiness of a REC::Neutron

(8.82% → 27.4%)

Trustworthy **REC::Photon** Percentage



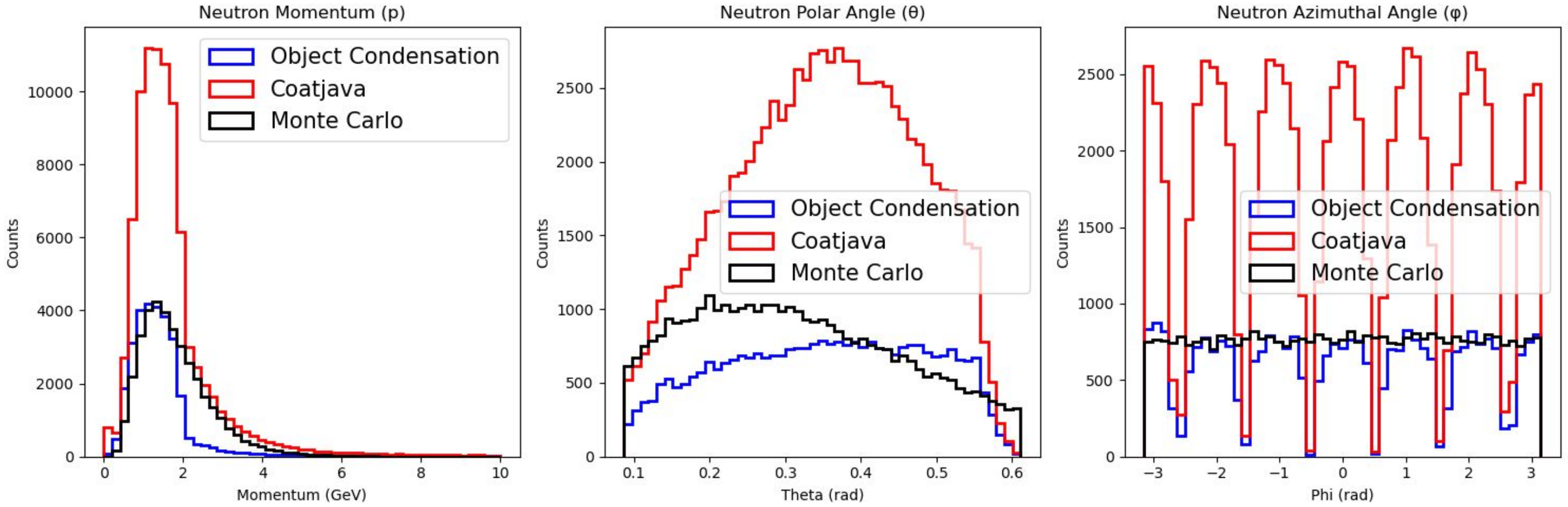
Coatjava
179039 REC photons
- 100245 w/ match
- 92233 trustworthy

Object Condensation
131555 REC photons
- 82817 w/ match
- 82798 trustworthy

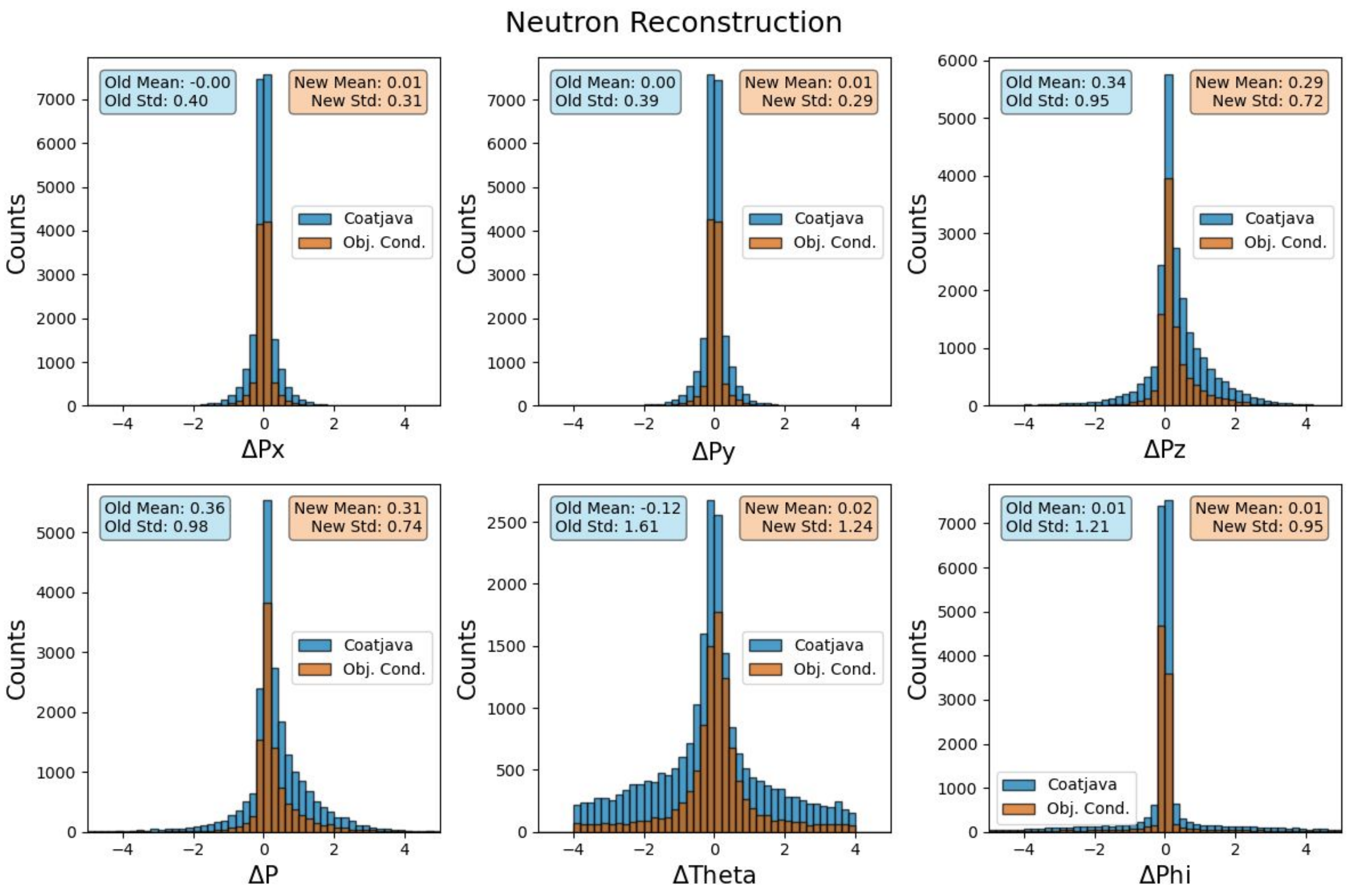
11% less trustworthy photons, but higher trustworthy %-age overall

Neutron Kinematics

- ➢ Yields for **Object Condensation** and **Monte Carlo** seem to more closely match for *p<2 GeV* which corresponds to β<0.9
- ➢ In **Coatjava** there is an if-statement that assigns β>0.9 particles to neutrons if it has no PCAL cluster (hence why there are *p>2 GeV* neutrons)
- ➢ Since **Object Condensation** finds clusters more effectively, this if-statement fails



Neutron Kinematic Resolutions

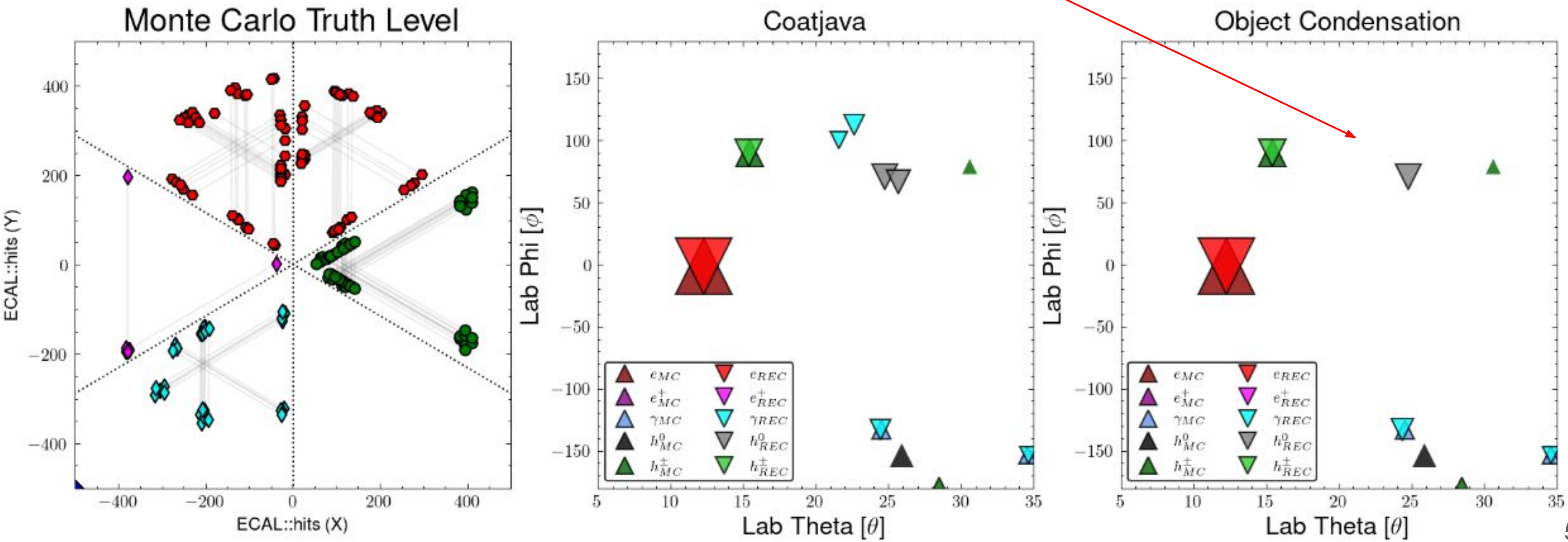


Plots shown for all REC neutrons with a Monte Carlo match

We see the resolution is improved and the mean is essentially the same between **Coatjava** and **Object Condensation**

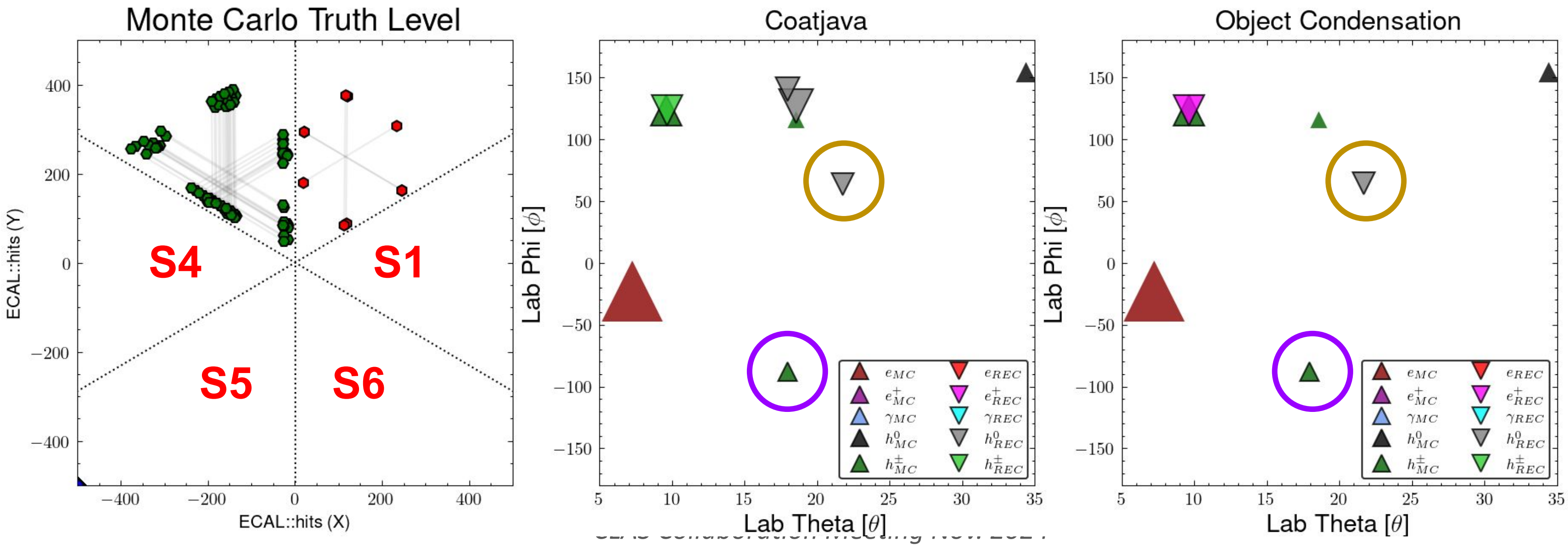
Intersector Tracks

- Coatjava and Object Condensation will be prone to scenarios where accidental neutral clustering is *unavoidable*
  - Ex: Below, a **Pi+** left hits in S2 and S3 (φ ~ 60 - 100 [deg])
  - Both Coatjava and Object Condensation find a stray neutral

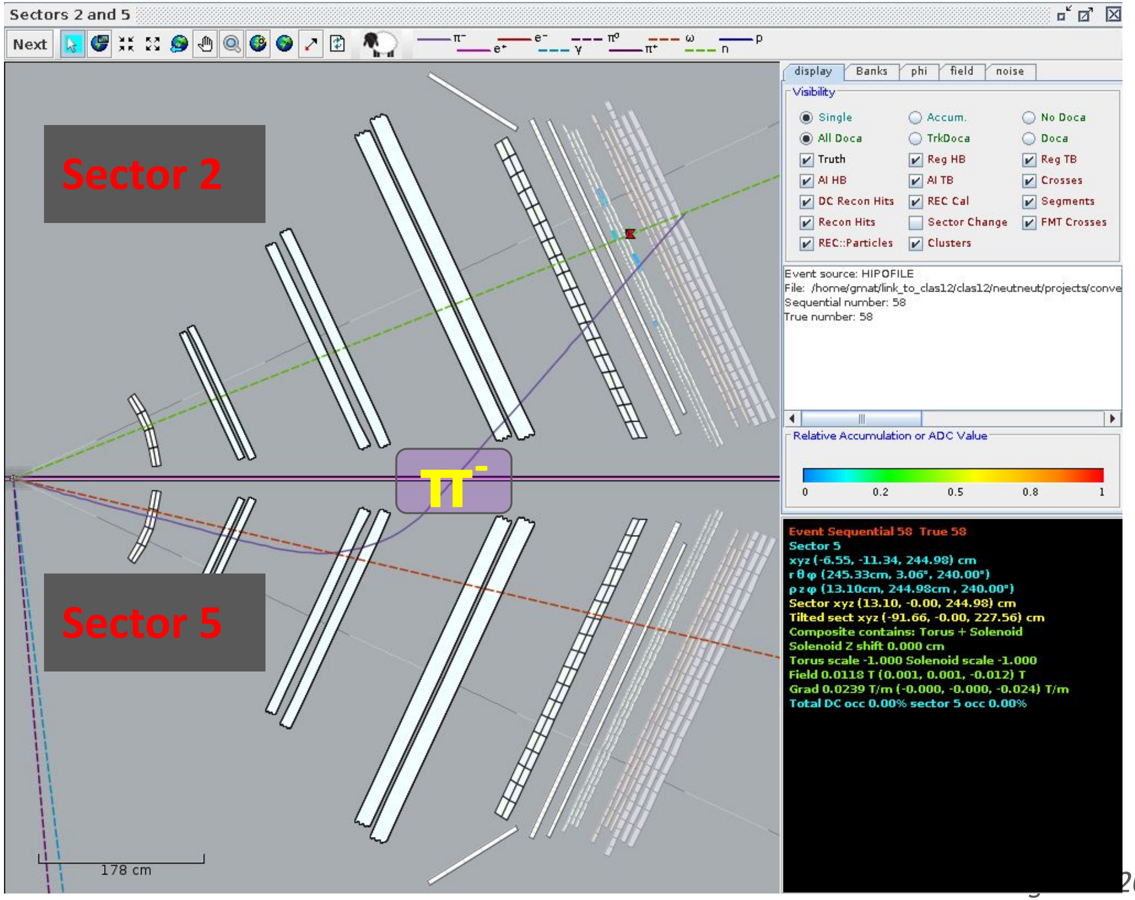


Intersector Tracks

- In this other example, a **Pi- Generated in Sector 5** crosses into sector 2. This pion leaves hits in **Sector 2 which is registered as a Neutron**
  - It *makes sense* that Object Condensation would see the **Sector 2** 3-way intersection as a viable cluster

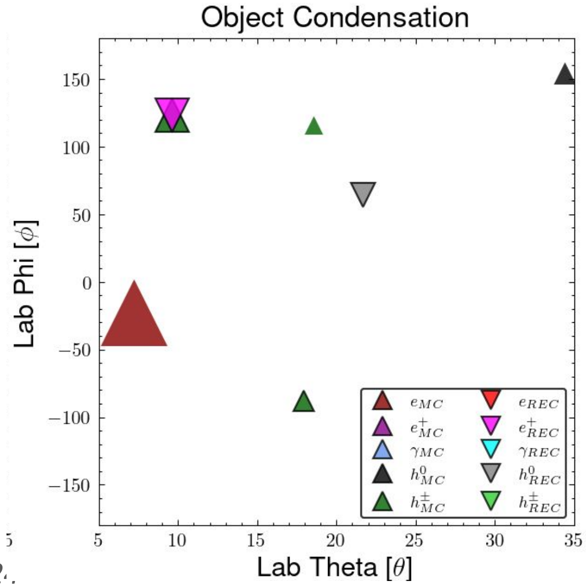


Intersector Tracks



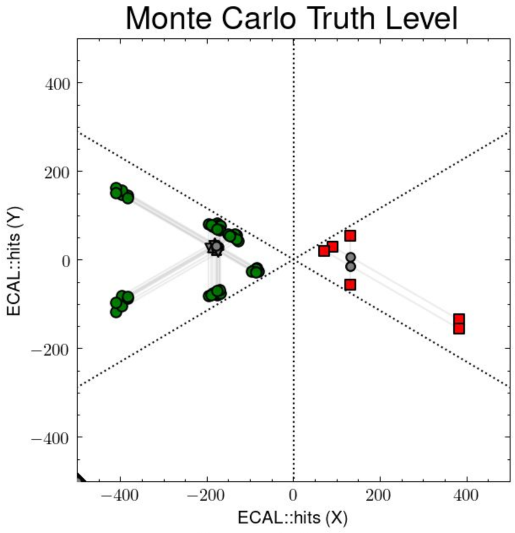
Track might actually leave hits in all 3 DC's (albeit different sectors)

Does the track algorithm account for this in anyway?



Areas to Improve

- The latent space clusters in Object Condensation have the ability to learn features
  - This can be used during training to predict **PID, Cluster X,Y,Z** perhaps more efficiently than just using 3-way intersections
  - This would also allow for non-traditional clusters to be reconstructed, such as 2-way intersections



- On the left is a strip plot from our neutron gun events
- Since there is no 3-way intersection here, neither Obj. Condensation nor Coatjava will reconstruct a particle

Can predicting cluster X,Y,Z help resolve this problem?

Also, what can we do to add/improve our definition of noise?

Conclusion/Future

- ➢ We identified that an AI trained on REC::Calorimeter/REC::Particle would not alleviate the neutral particle clustering effectively → Turn to the source, train an AI-assisted clustering algorithm
- ➢ Coatjava was forked to attach additional truth information to the ECAL::hits bank for training purposes
- ➢ A feature extractor utilizing GravNet blocks was used to accumulate abstract nearest neighbor information
- ➢ Object Condensation was used to optimize the feature extractor, encouraging it to form clusters in a 2-dimensional latent space that represent Monte Carlo particles
- ➢ The ECAL::hits that fall into these clustered regions were processed to calculate a new ECAL::clusters bank
- ➢ The ECAL::clusters bank is fed back into the Coatjava pipeline to form a new REC::Particle bank
- ➢ We see **3 times improvement** in the trustworthiness of REC::Particle neutrons without sacrificing yields

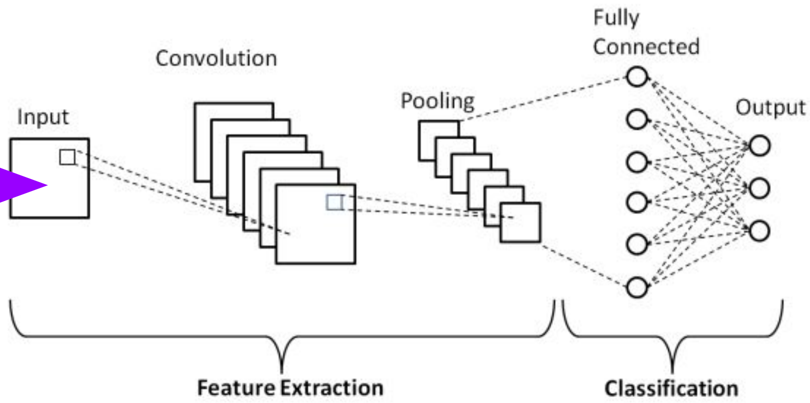
TO DO

- ➢ Streamlining of collaborator usage/testing of my training/coatjava fork
- ➢ Add PID, Px, Py prediction capabilities of neutrals to training
- ➢ Begin hyperparameter search to optimize network
- ➢ With collaborator approval, consider publishing (might be first AI-assisted calorimeter clustering tested on Monte Carlo in a full reconstruction pipeline) Looking into using it for EIC KLM 2nd detector clustering

Extra Slides

Task: Image Classification

NxMx3



dog	(0.025)
car	(0.004)
boat	(0.001)
cat	(0.950)
house	(0.001)
flute	(0.003)
grass	(0.000)
…	…

Given… An isolated ‘grid’ of inputs
Output… A list of prediction scores for each trained category

★Training★ is straightforward. ImageNet has ~14 million labeled images with more than 22,000 categories.

Image *within Image* Classification

NxMx3

???

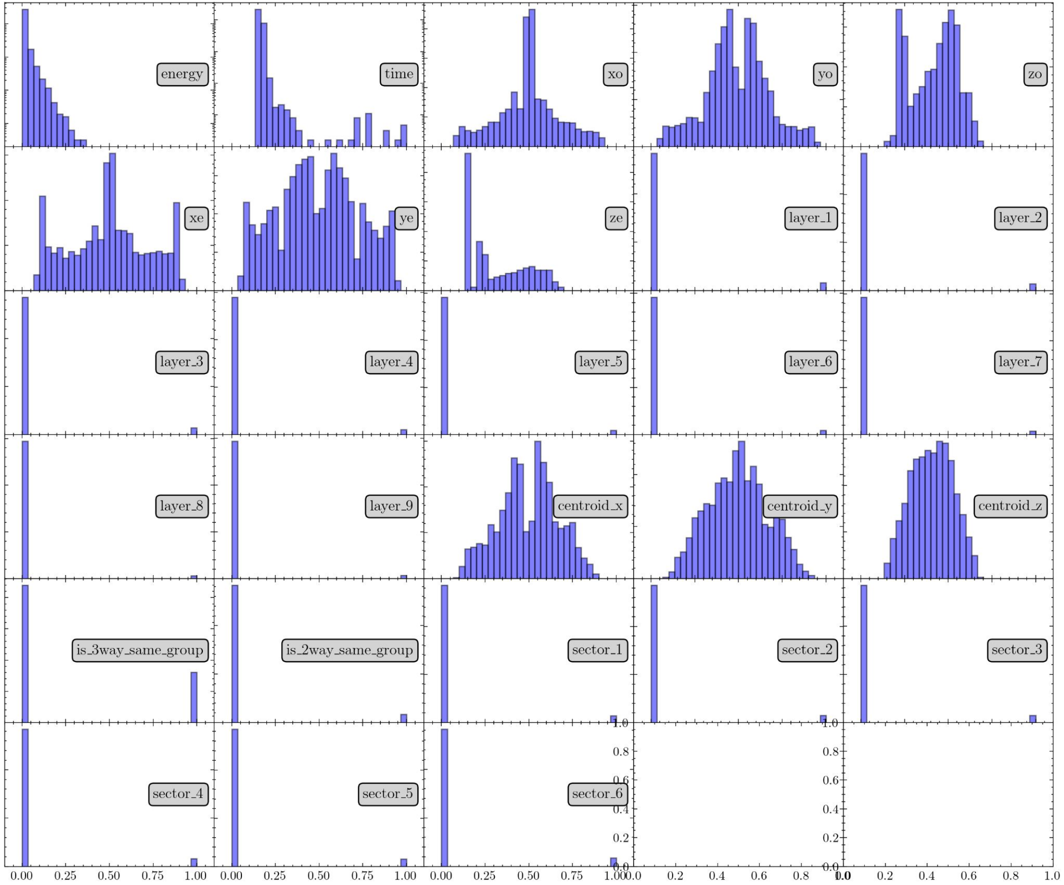
1 person
5 sheep
1 dog

Given… An isolated ‘grid’ of inputs
Output… A potentially arbitrary number of objects, each classified

★**Training** is more difficult!★

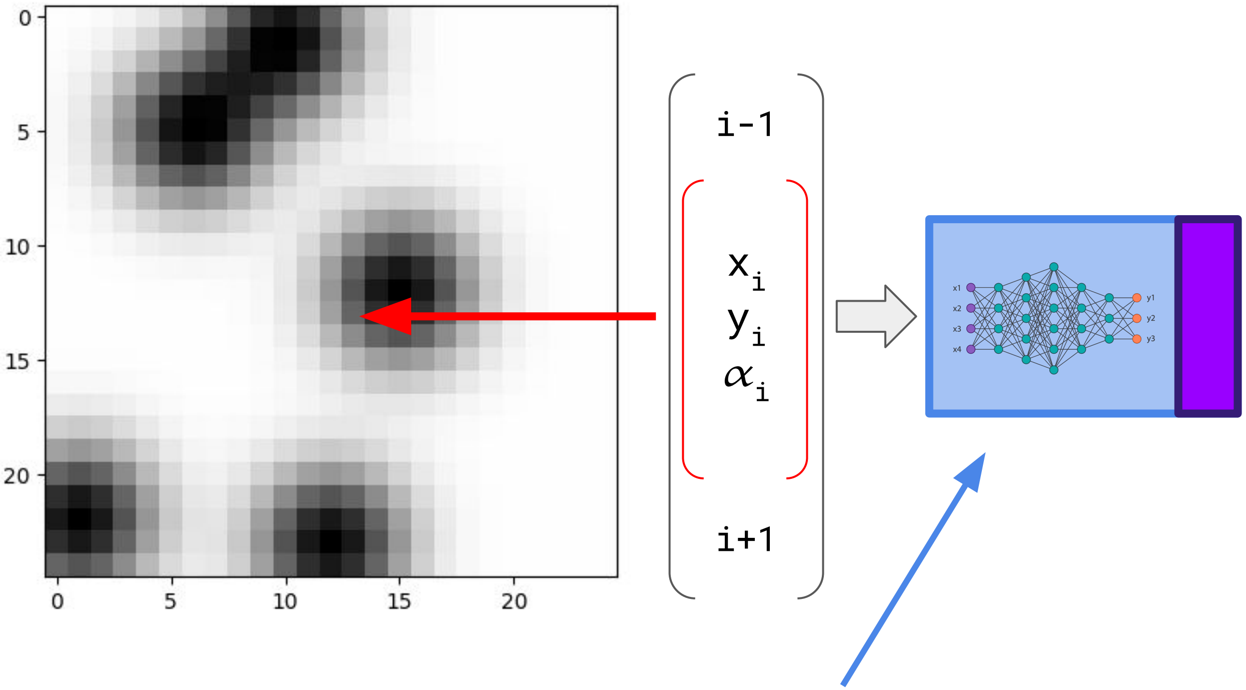
- Cannot easily train for datasets with all possible category combinations
- How would one deal with situations where objects *overlap*?
- The ★**Approach**★ must be changed (can’t do simple CNN)

Machine Learning Input Features



- ➢ Shown are the *per strip* input features (normalized to 1)
- ➢ Energy & Time are log-scaled
- ➢ The one-hot encode for the strip's sector *is not used* because it too strongly correlates with being a unique particle, leading to a quick local minimum during training

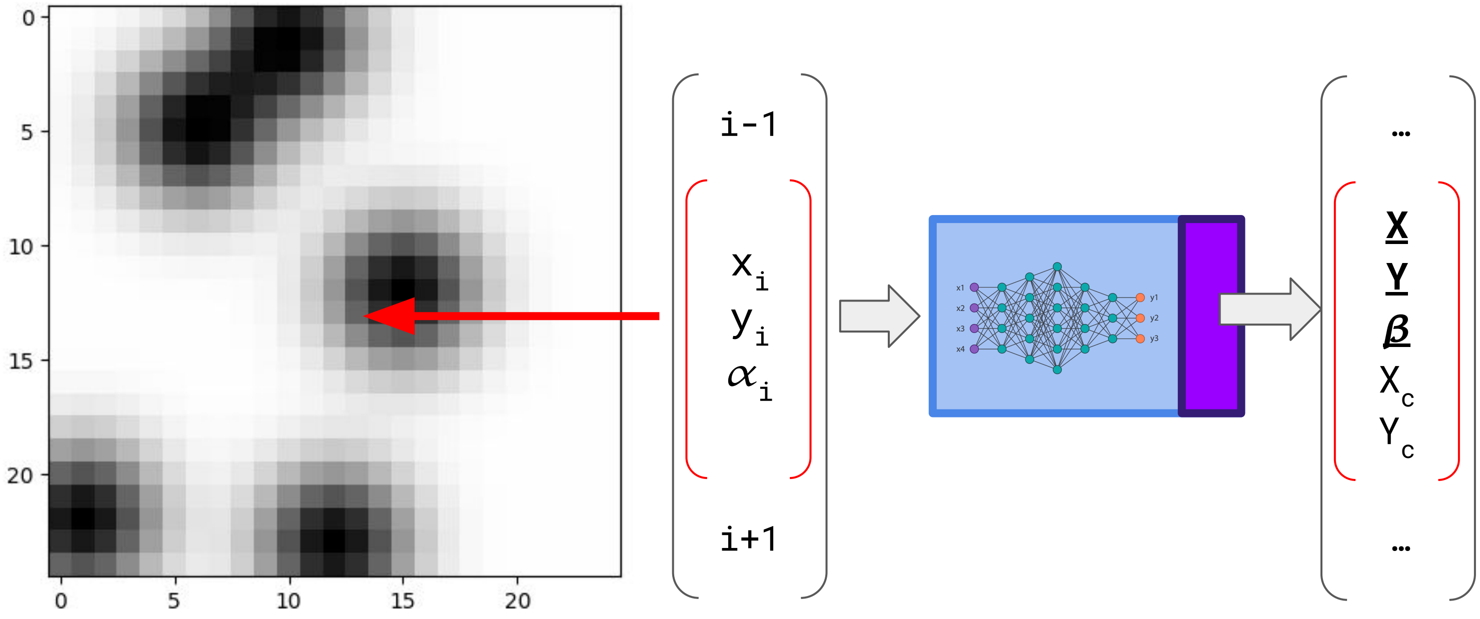
Object Condensation Basics



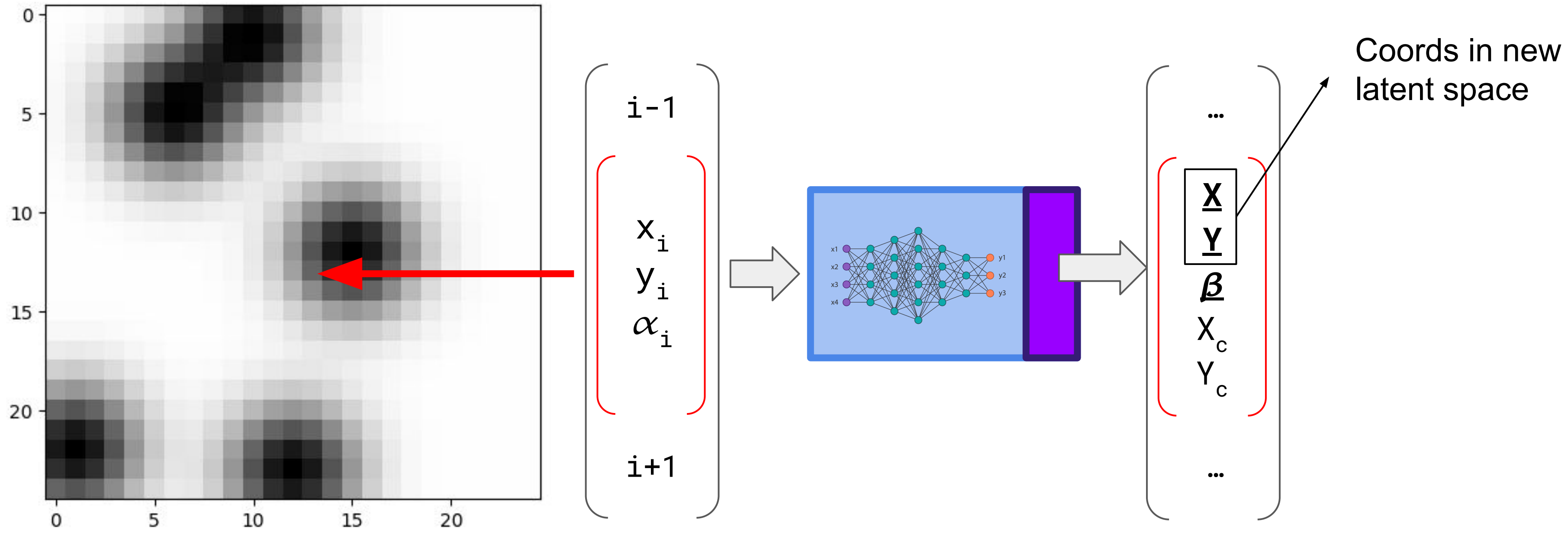
I want my ML model to tell me how many clusters, and their centroids (x_c , y_c)

*Lets see what a **well-trained** model does, then discuss how we even **train** it to perform the task at hand (clustering!)*

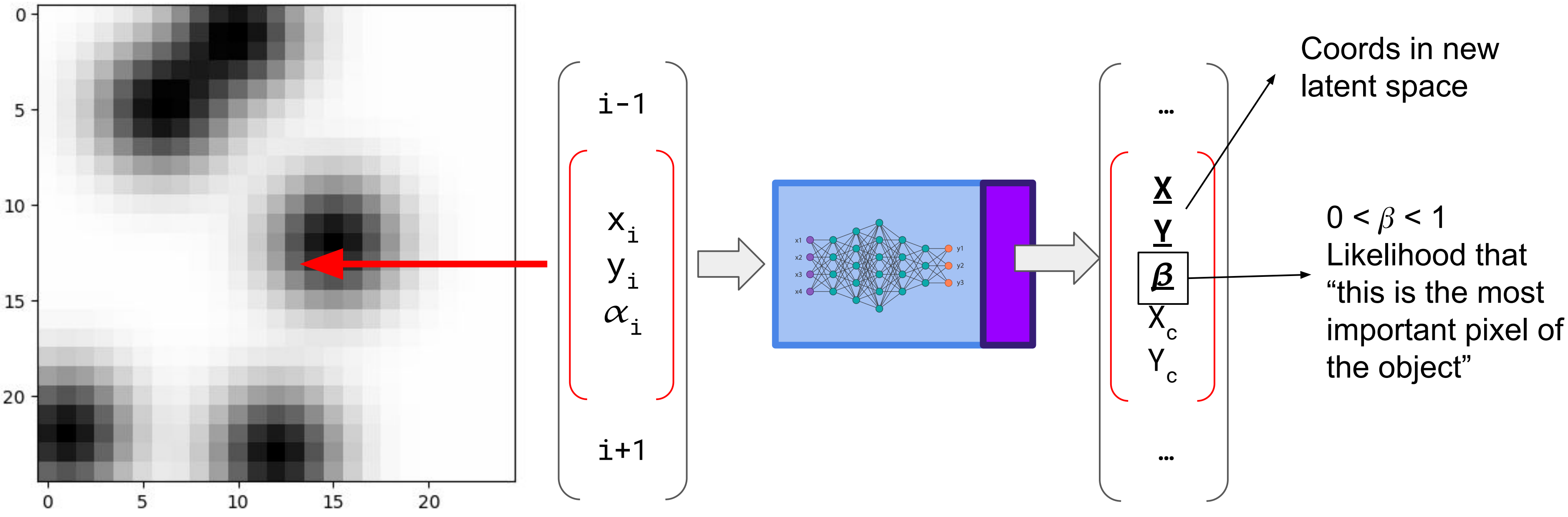
Object Condensation Basics



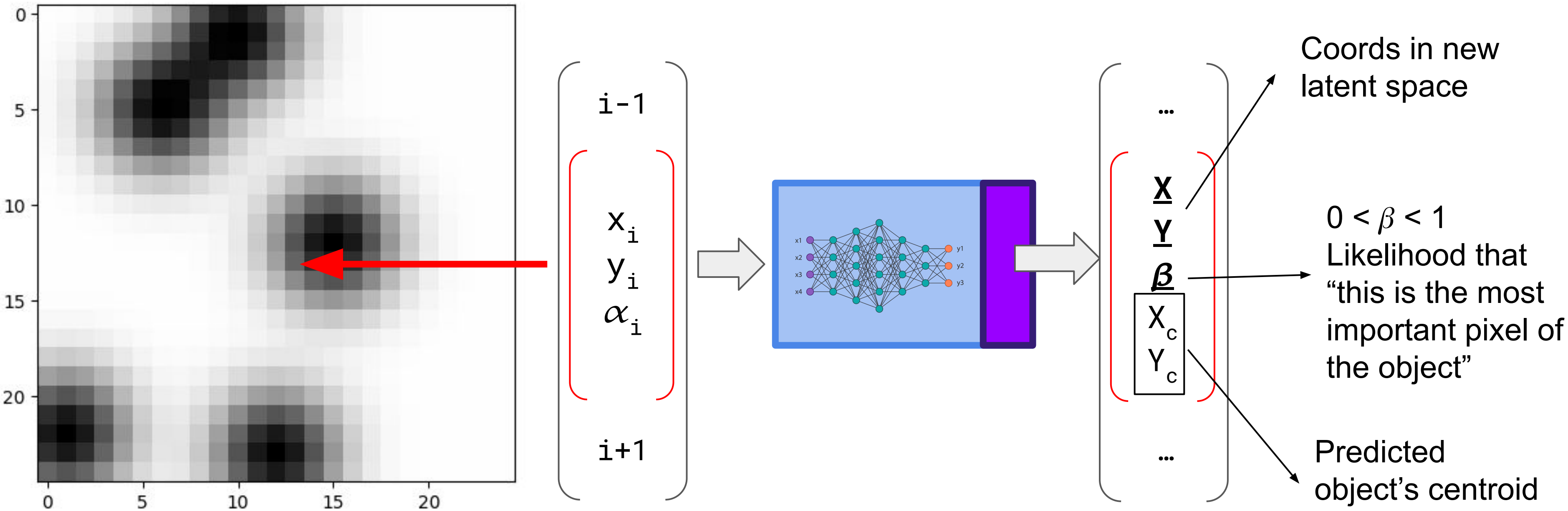
Object Condensation Basics



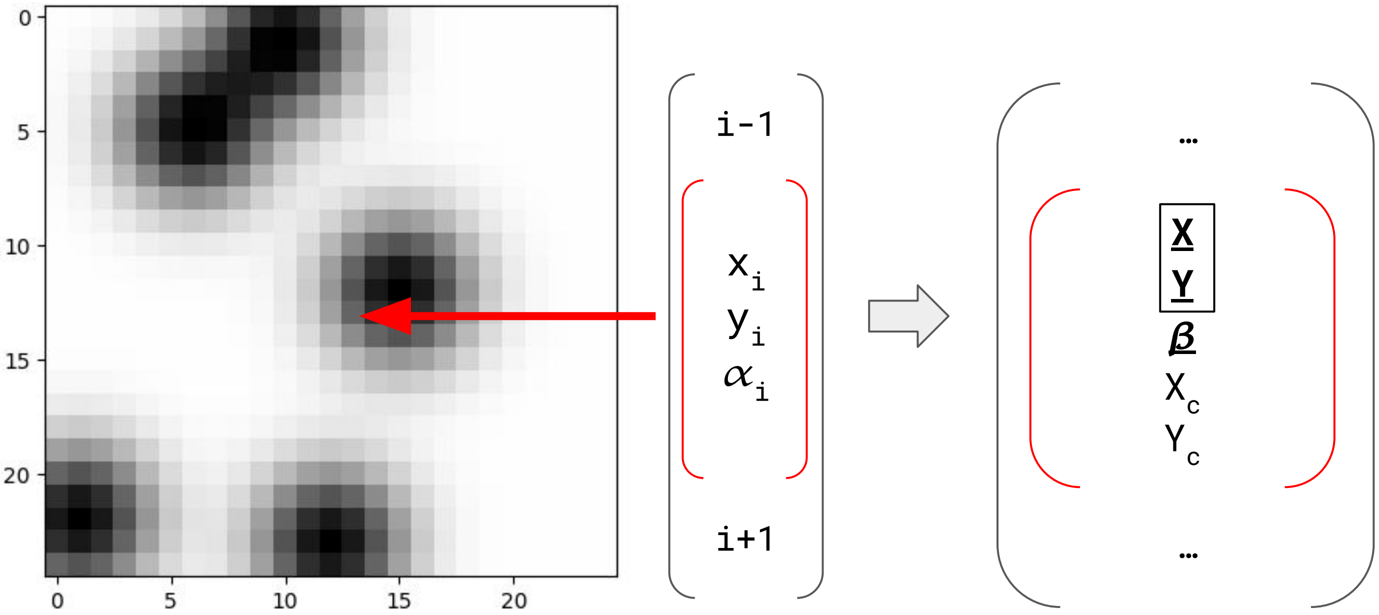
Object Condensation Basics

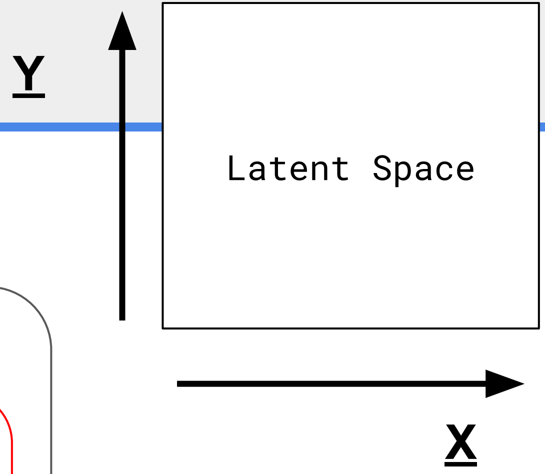


Object Condensation Basics

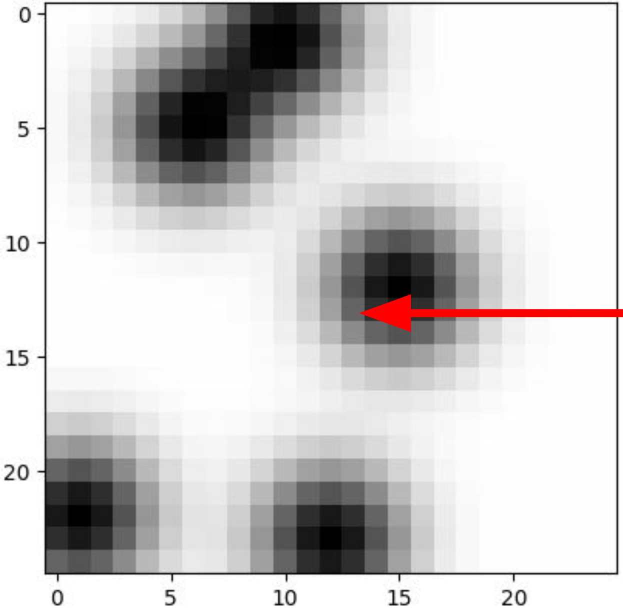


Object Condensation Basics

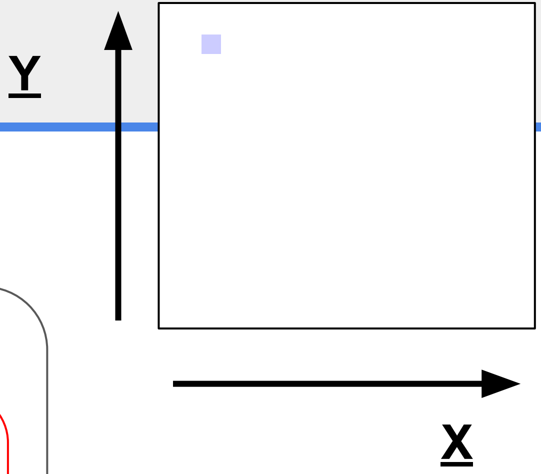




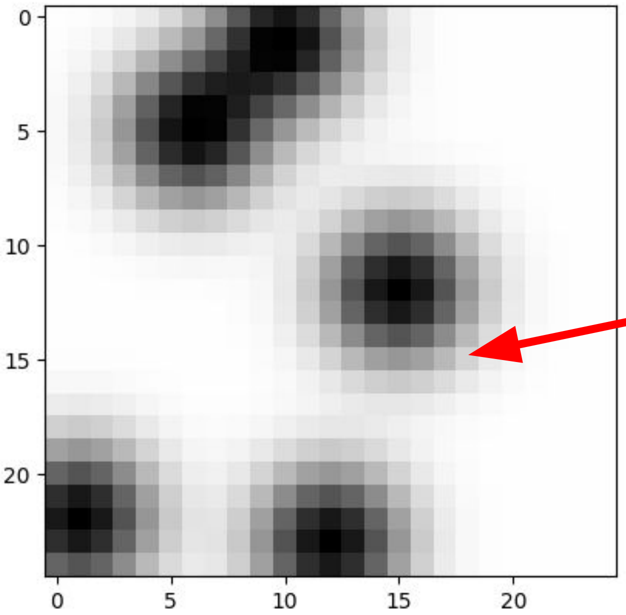
Object Condensation Basics



$$\begin{pmatrix} i-1 \\ \begin{pmatrix} x_i \\ y_i \\ \alpha_i \end{pmatrix} \\ i+1 \end{pmatrix} \Rightarrow \begin{pmatrix} \dots \\ \begin{pmatrix} \underline{X} = 12 \\ \underline{Y} = 55 \\ \underline{\beta} = 0.002 \\ X_c = \dots \\ Y_c = \dots \end{pmatrix} \\ \dots \end{pmatrix}$$



Object Condensation Basics



j-1

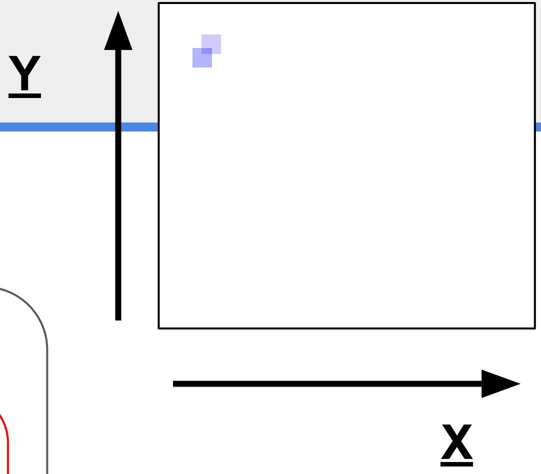
x_j
y_j
α_j

j+1

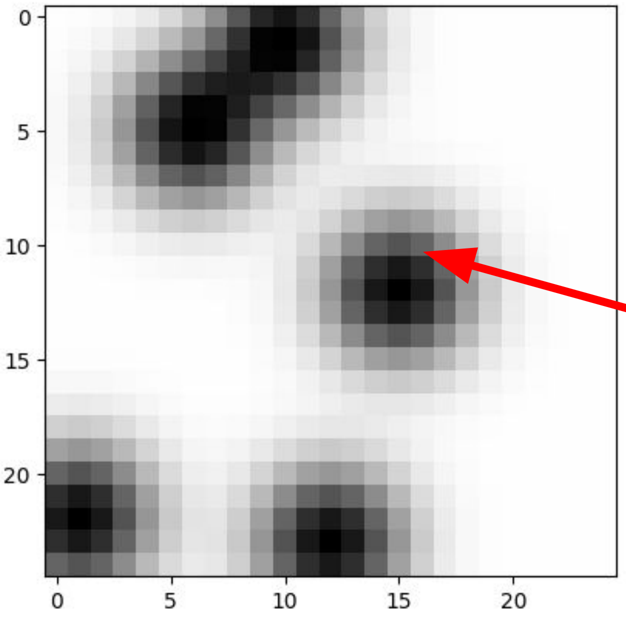
…

$\underline{X}$ = 11
$\underline{Y}$ = 54
$\underline{\beta}$ = 0.01
X_c = ...
Y_c = ...

…



Object Condensation Basics



k-1

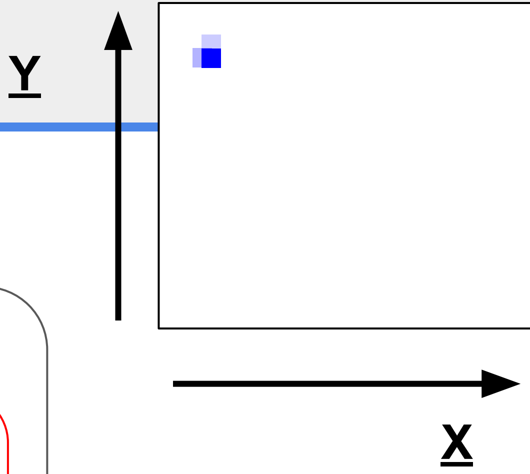
x_k
y_k
α_k

k+1

…

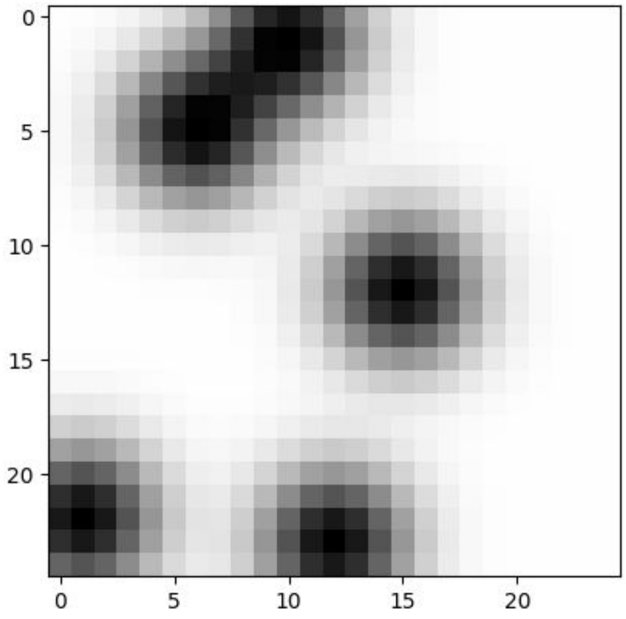
X = 12
Y = 54
β = 0.88
X_c = ...
Y_c = ...

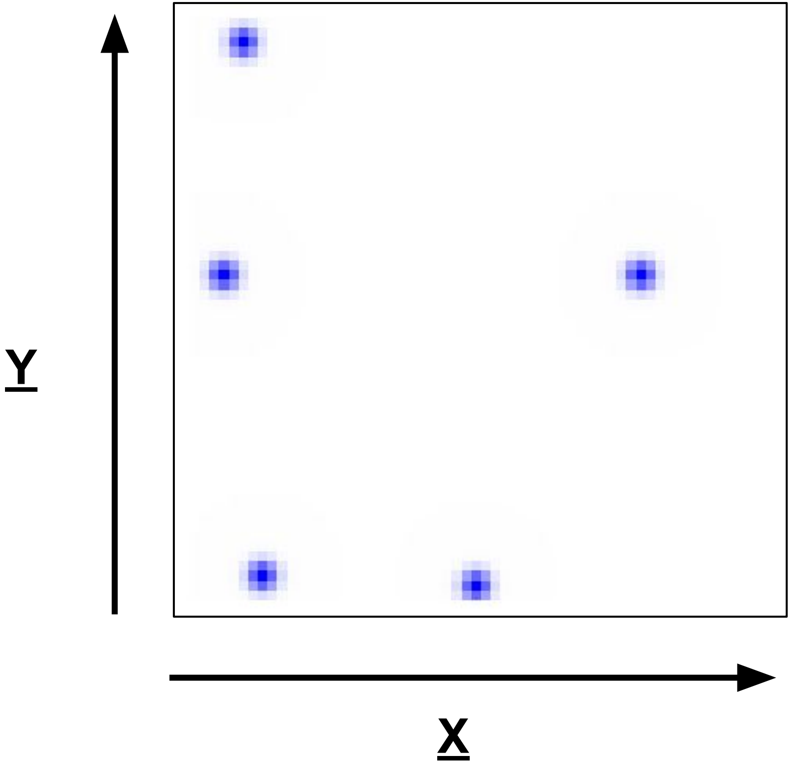
…



High β implies the model thinks this point is very important!

Object Condensation Basics

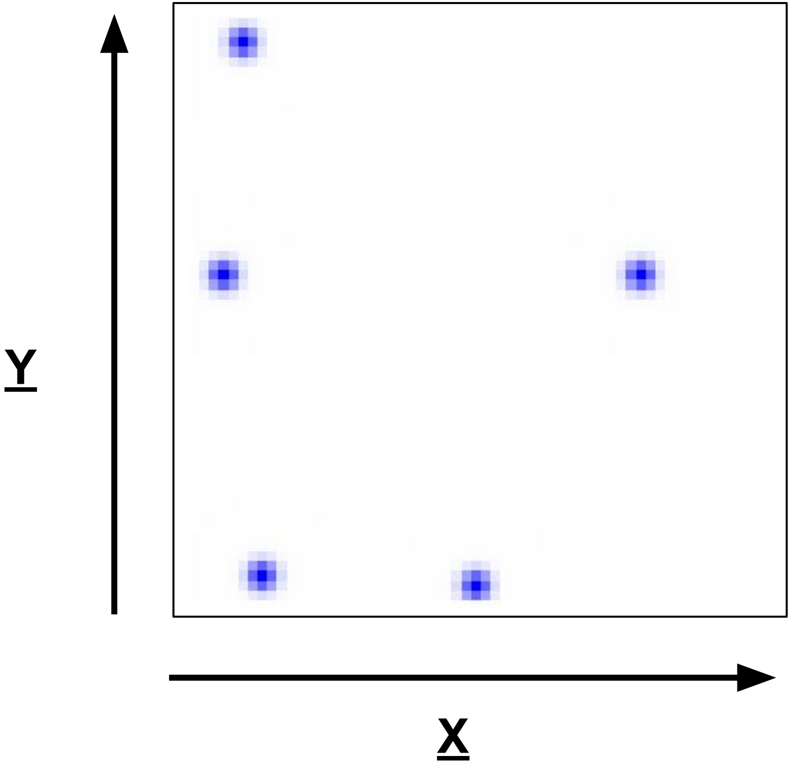




Input: Set of [x,y,α] (625x3)
Output: Set of [**X**,**Y**,β,x_c,y_c] (625x5)

Model is trained to make 1 bright β per object

Object Condensation Basics



Solution becomes much simpler to picture…

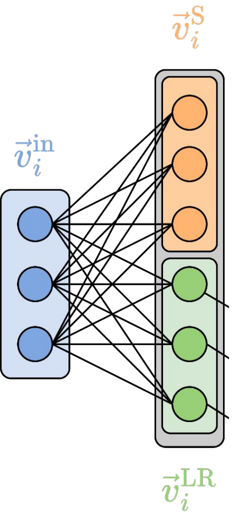
… threshold away dim pixels ($\beta < 0.8$) …

… count the # pixels remaining …

… read off their predicted x_c and y_c …

GravNet Layer

$\mathbf{v}_i^{\mathbf{in}}$ ⟶ Strip i's Input vector to GravNet



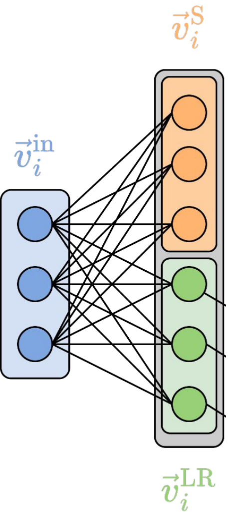
Hyperparameters

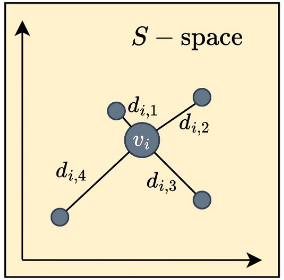
 # S-dims, **# Learned Features**

Procedure (for each strip)

1. A DNN produces a set of coordinates in S-space and hidden features $\mathbf{v}^{\mathbf{LR}}$

GravNet Layer





Hyperparameters

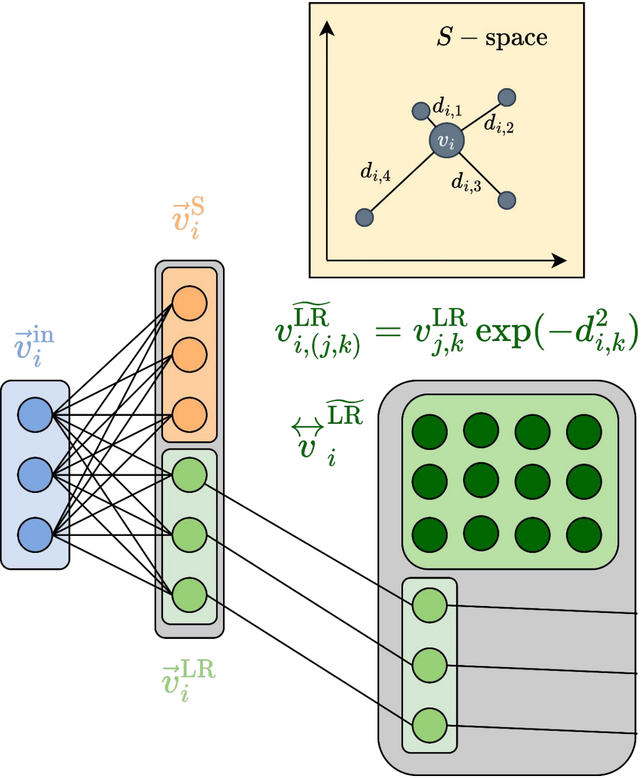
 # S-dims, **# Learned Features**, **# S-Neighbors**

Procedure (for each strip)

1. A DNN produces a set of coordinates in **S-space** and hidden features $\mathbf{v}^{\mathbf{LR}}$

2. Calculate the distance $\mathbf{d_{i,k}}$ for **K** neighbors

GravNet Layer



Hyperparameters

 # S-dims, **# Learned Features**, **# S-Neighbors**

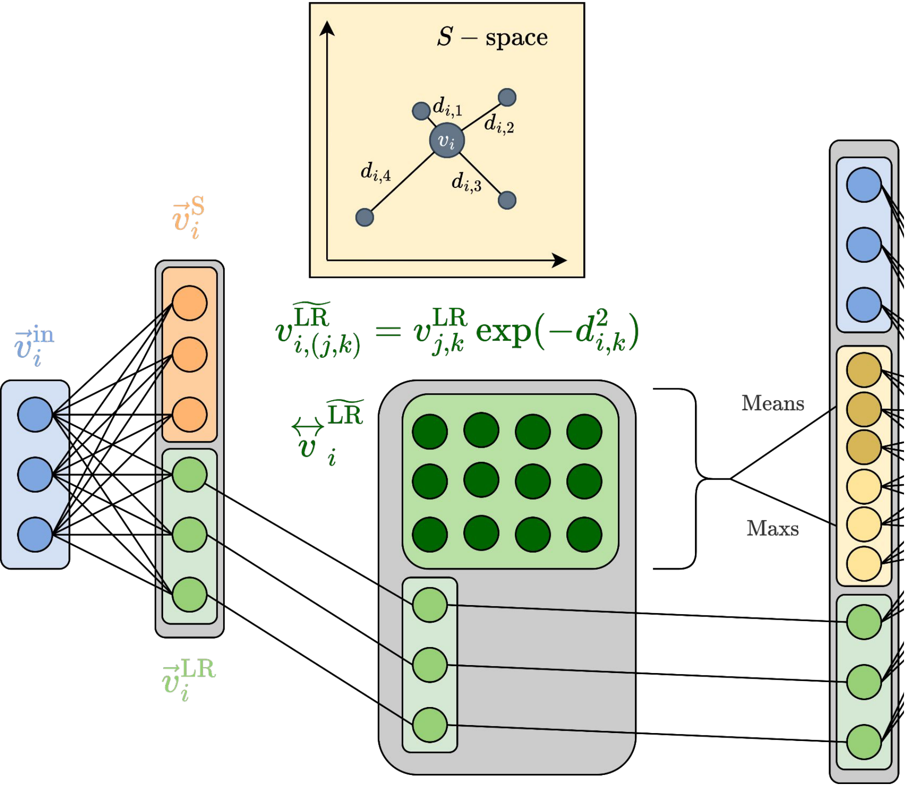
Procedure (for each strip)

1. A DNN produces a set of coordinates in S-space and hidden features $\mathbf{v}^{\mathbf{LR}}$

2. Calculate the distance $\mathbf{d}_{\mathbf{i,k}}$ for **K** neighbors

3. Calculate distance-weighted *j-th* learned **(LR)** feature of the **K** neighbors of strip *i*

GravNet Layer



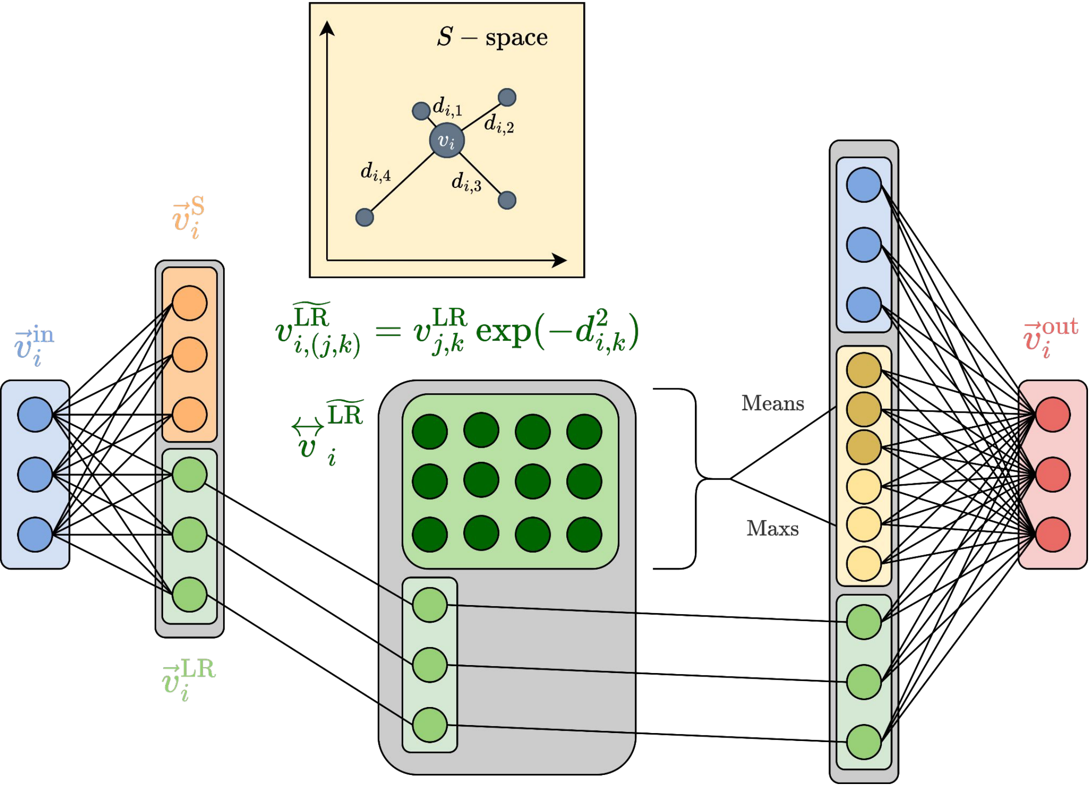
Hyperparameters

 # S-dims, **# Learned Features**, **# S-Neighbors**

Procedure (for each strip)

1. A DNN produces a set of coordinates in **S-space** and hidden features $\mathbf{v^{LR}}$
2. Calculate the distance $\mathbf{d_{i,k}}$ for **K** neighbors
3. Sum the distance-weighted *j-th* learned **(LR)** feature of the **K** neighbors of strip *i*
4. Calculate the **mean** & **max** of each learned features nearest neighbors. Concatenate v^{in} , v^{LR} and the mean(+)max of v\tilde{LR}

GravNet Layer



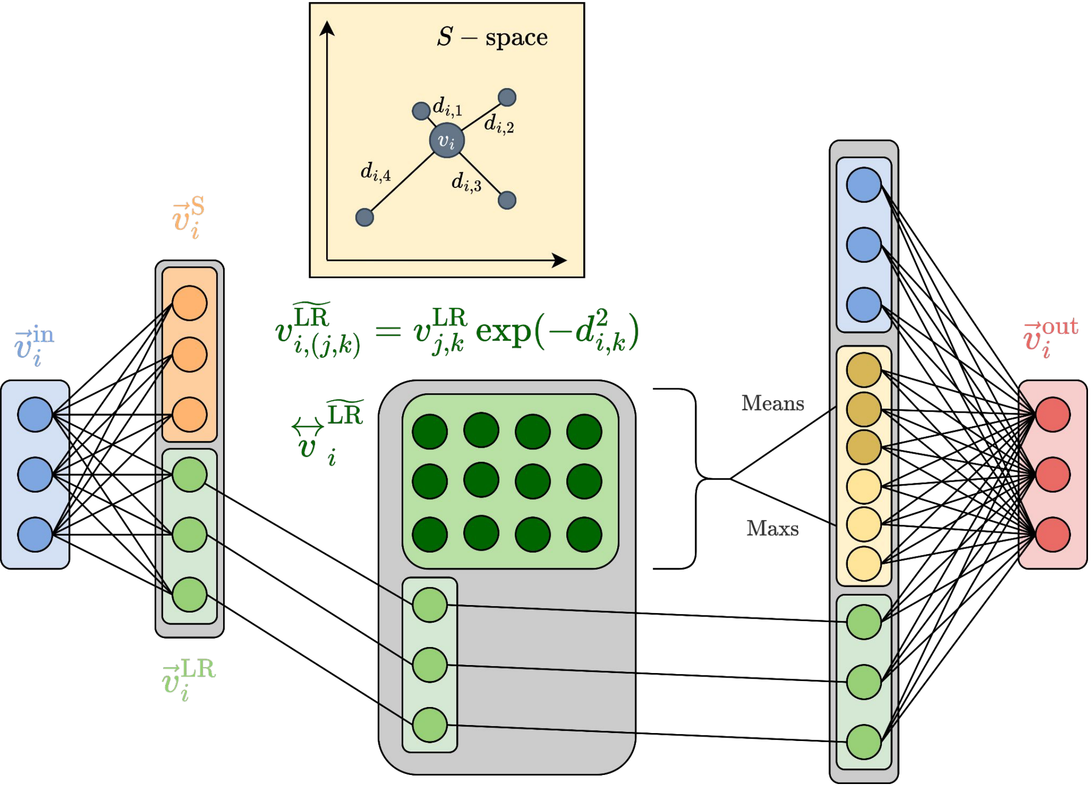
Hyperparameters

 # S-dims, **# Learned Features**, **# S-Neighbors**, **# output features**

Procedure (for each strip)

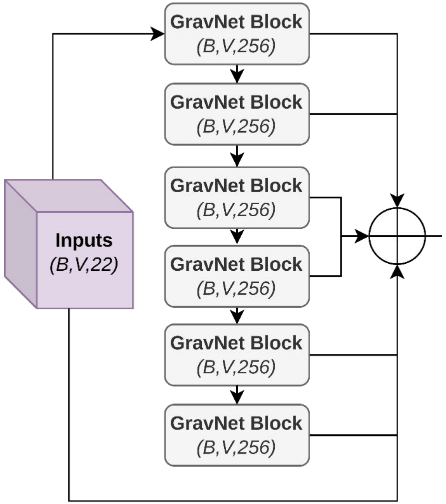
1. A DNN produces a set of coordinates in S-space and hidden features $\mathbf{v}^{LR}$
2. Calculate the distance $\mathbf{d}_{\mathbf{i,k}}$ for **K** neighbors
3. Sum the distance-weighted *j-th* learned **(LR)** feature of the **K** neighbors of strip *i*
4. Calculate the **mean** & **max** of each learned features nearest neighbors. Concatenate v^{in} , v^{LR} and the mean(+)max of $v^{\text{\tilde{LR}}}$
5. DNN the final result to a new output vector $\mathbf{v}^{\mathbf{out}}$

GravNet Layer

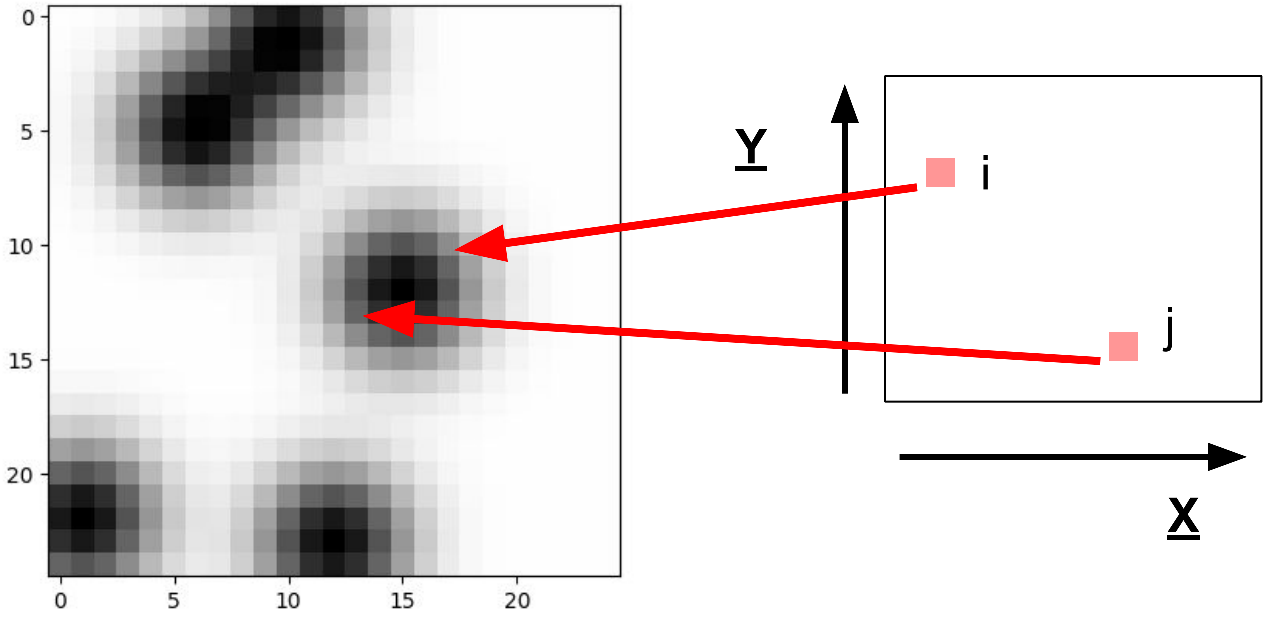


The 1st $\mathbf{v}^{\mathrm{in}}$ to the GravNet blocks have <u>no neighbor info</u>

Each output of the block provides higher level nearest neighbor features



Demand A: Points group together

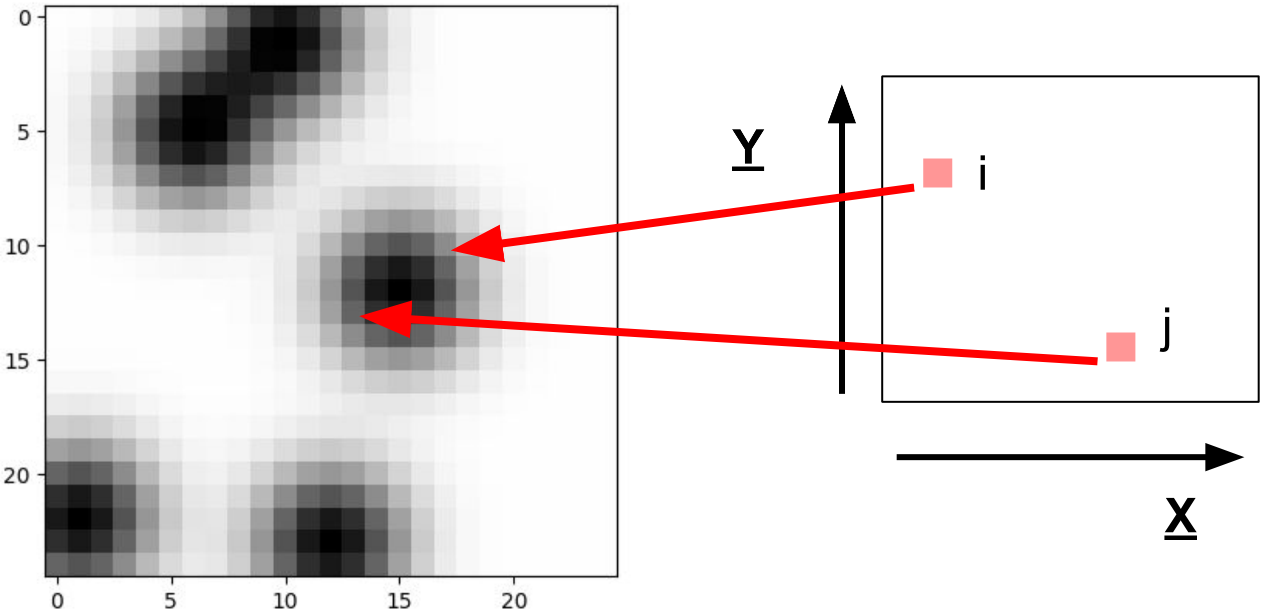


During training, we know these points (i,j) come from the same object…

…we want them to attract to one another in the latent space…

Before training, **X** & **Y** are random

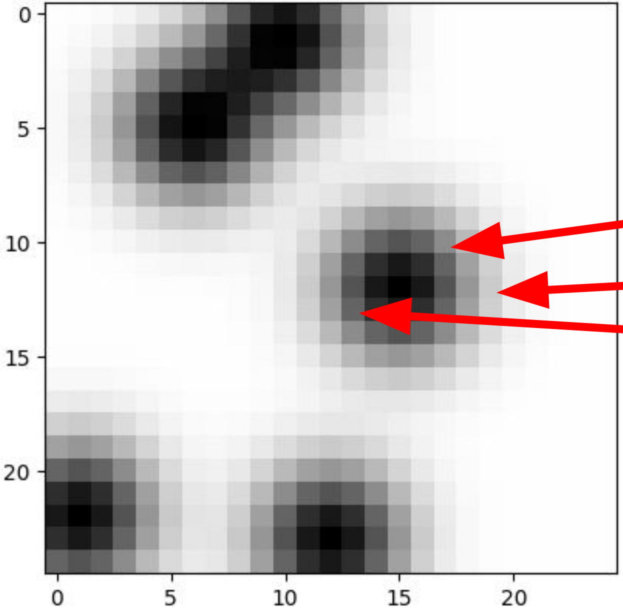
Demand A: Points group together

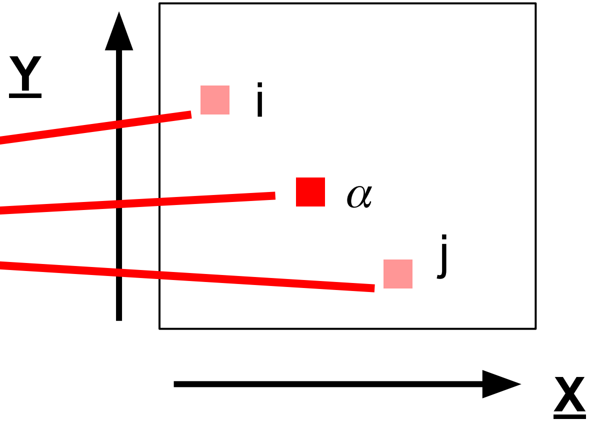


If we want to encourage our frontend model to make these **X,Y** closer, have it minimize some **attractive potential**

How to define?

Demand A: Points group together

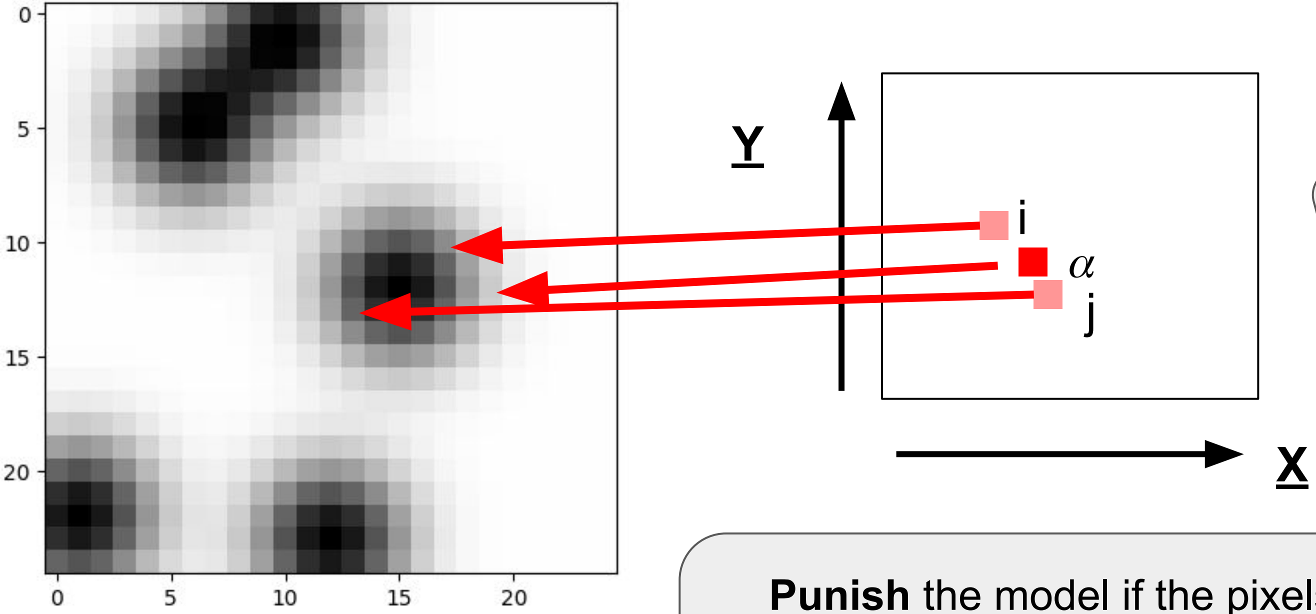




Punish the model if the pixels are "far away" from the *brightest* (highest β) pixel

Label that brightest pixel as $\boldsymbol{\alpha}$

Demand A: Points group together

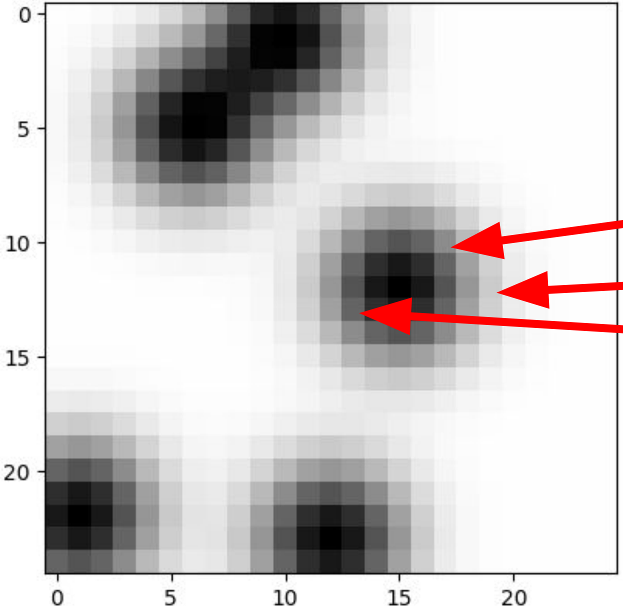


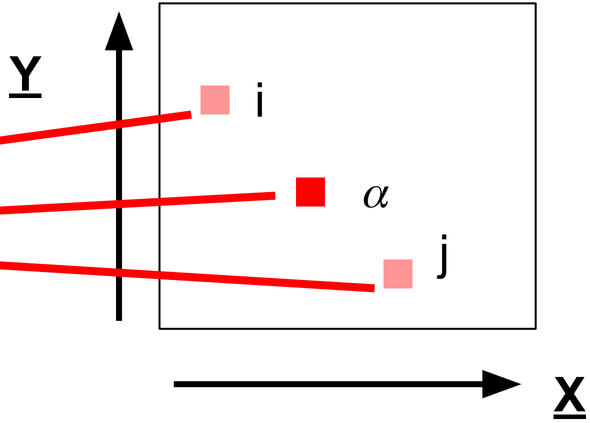
Less punishment !!!

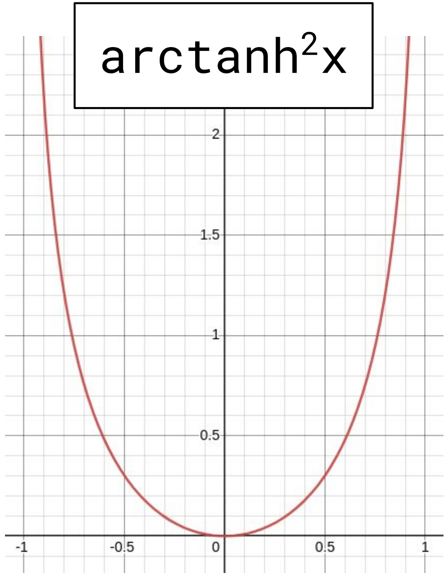
Punish the model if the pixels are "far away" from the *brightest* (highest β) pixel

Label that brightest pixel as $\boldsymbol{\alpha}$

Demand A: Points group together







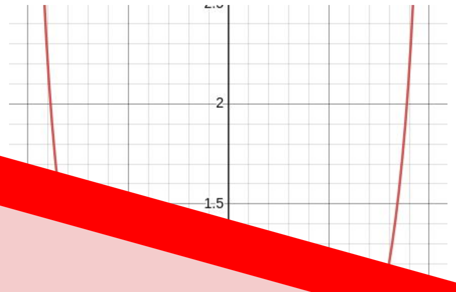
$$q_i = \operatorname{arctanh}^2 \beta_i + q_{\min}.$$

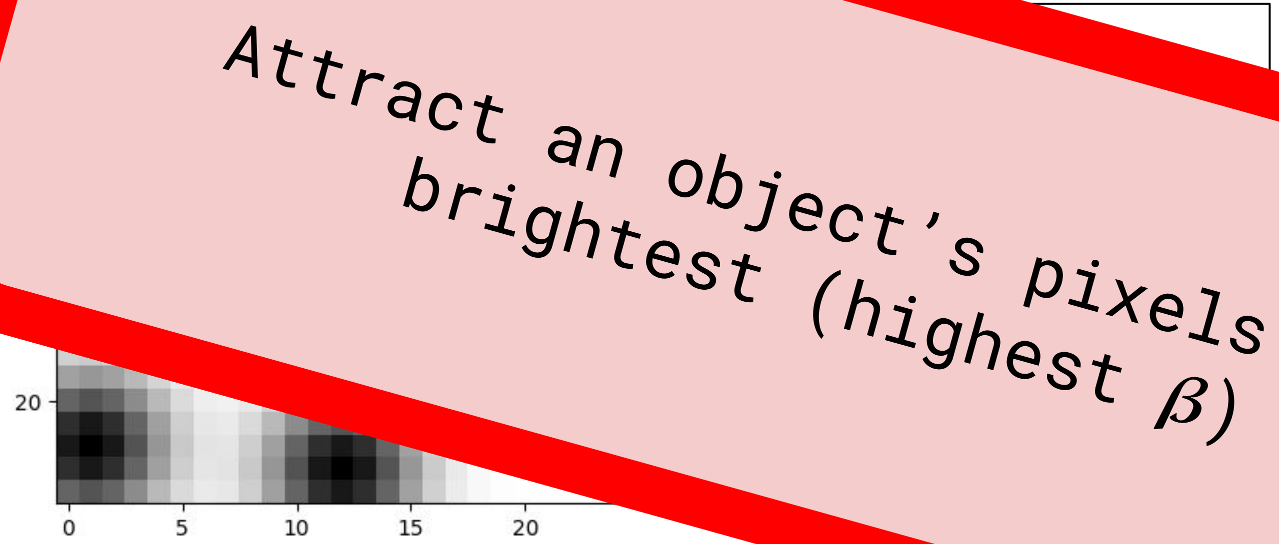
$$\breve{V}_k(x) = ||x - x_\alpha||^2 q_{\alpha k},$$

i → unique id for each pixel [0,1,...,624]
α→per object k, id of pixel with highest charge
k→unique id of the object [0,1,2,3,4]
x → latent space coordinates

Demand A: Points group together

Attract an object's pixels towards its brightest (highest β) member





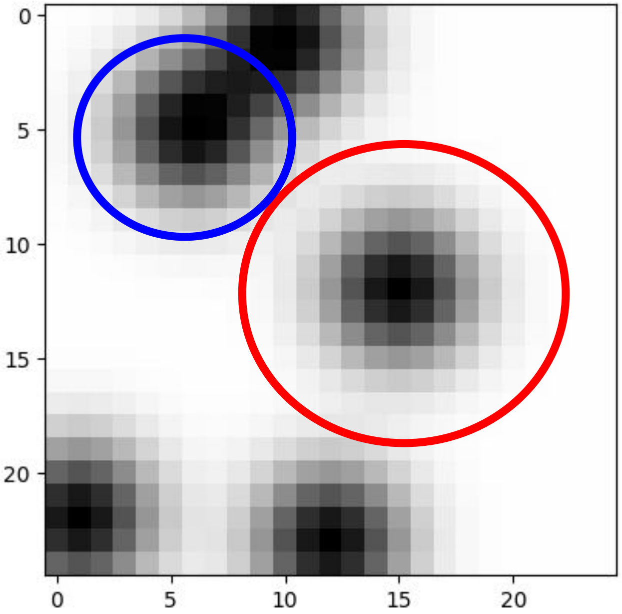
$$\breve{V}_k(x) = ||x - x_\alpha||^2 q_{\alpha k},$$

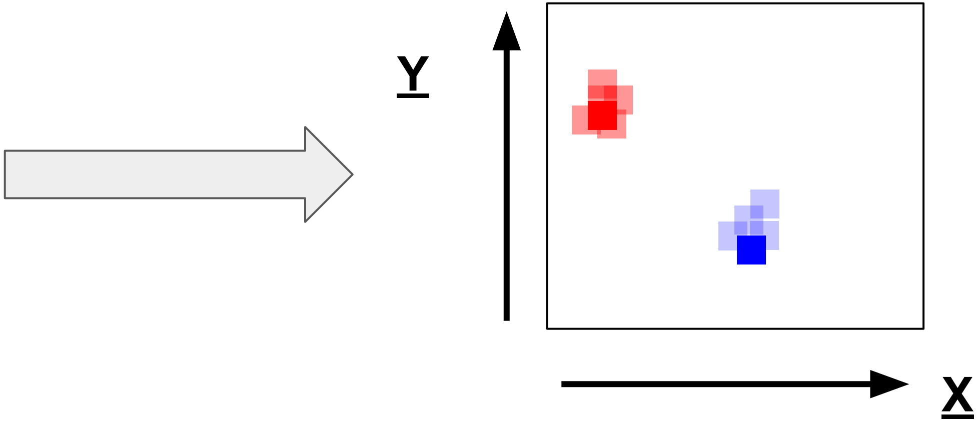
charg

k→unique id of th

x → latent space coordinat

Demand A: Points group together





$$L_V = \frac{1}{N}\sum_{j=1}^{N} q_j \sum_{k=1}^{K} \Big(M_{jk}\check{V}_k(x_j)$$

In words… for each pixel (*j*) we calculate its potential w.r.t each object (*k*) . If that pixel (*j*) is in object (*k*) , punish (increase the **Loss**) if (*j*) is far away … M_{jk} = 1 if (j) is in object (k) , else 0

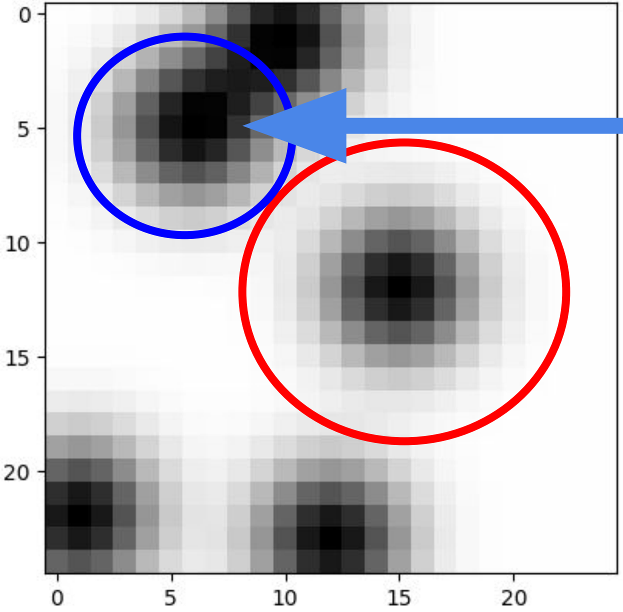
Demand A: Points group together

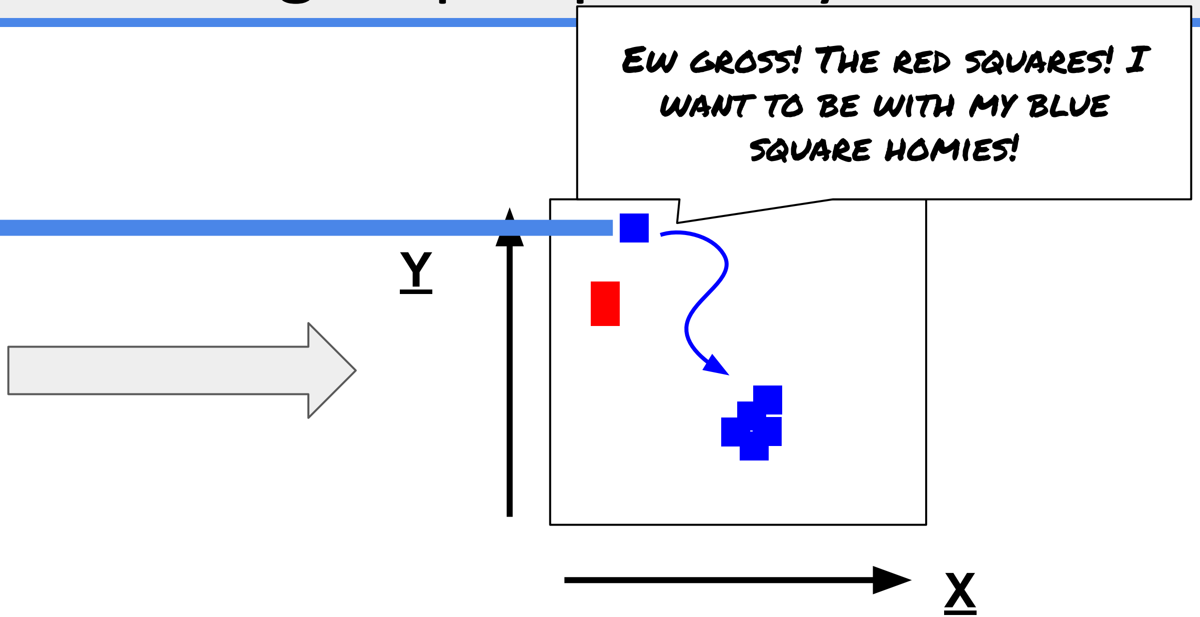
We must also "scare" away pixels from different objects so that they cluster elsewhere...

$$L_V = \frac{1}{N}\sum_{j=1}^{N} q_j \sum_{k=1}^{K} \Big(M_{jk}\breve{V}_k(x_j)$$

In words...
potential w.r.t each ob…
object (*k*) , punish (increase t…
away … M_{jk} = 1 if (j) is in object (k) , el…

Demand B: Points group separately

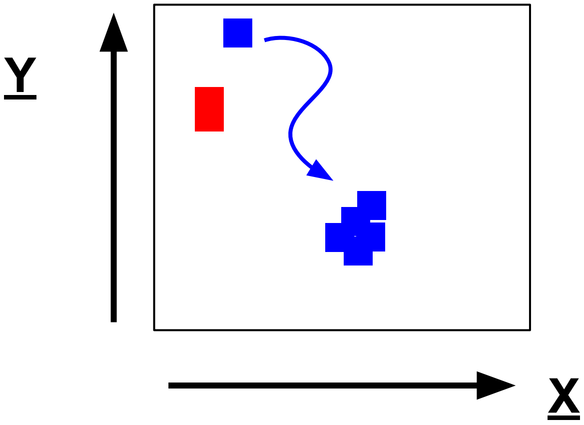


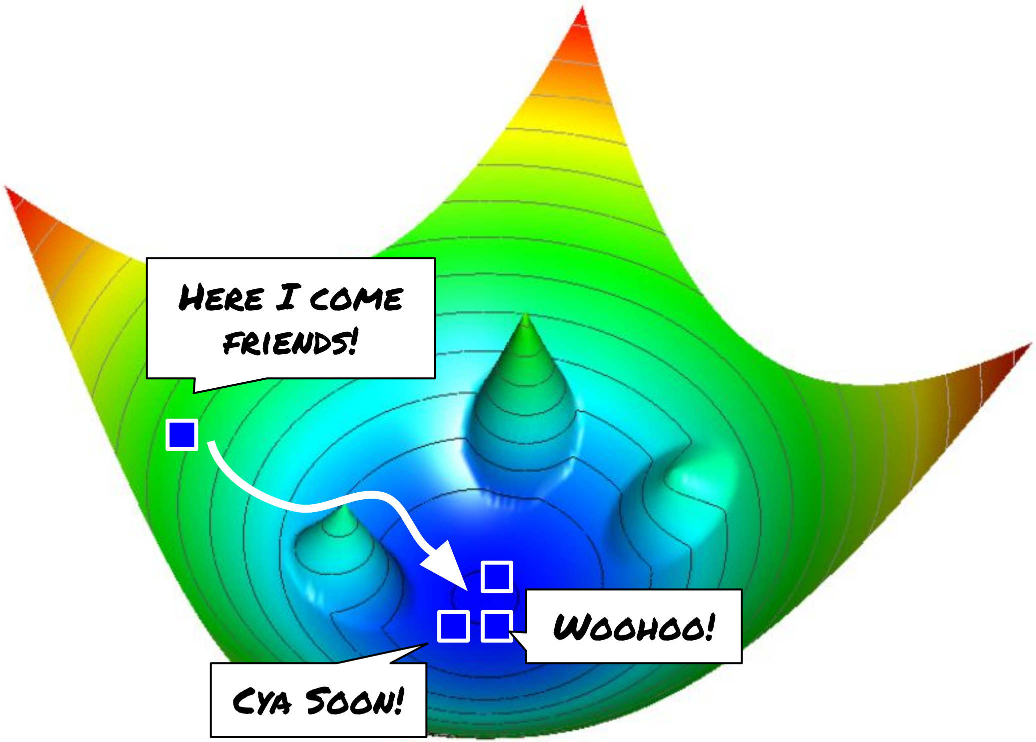


Punish the model if this repulsive term is large. Occurs when pixel (j) is near objects it is not affiliated with…

$$L_V = \frac{1}{N}\sum_{j=1}^{N} q_j \sum_{k=1}^{K} \left(M_{jk}\breve{V}_k(x_j) + \boxed{(1 - M_{jk})\hat{V}_k(x_j)} \right).$$

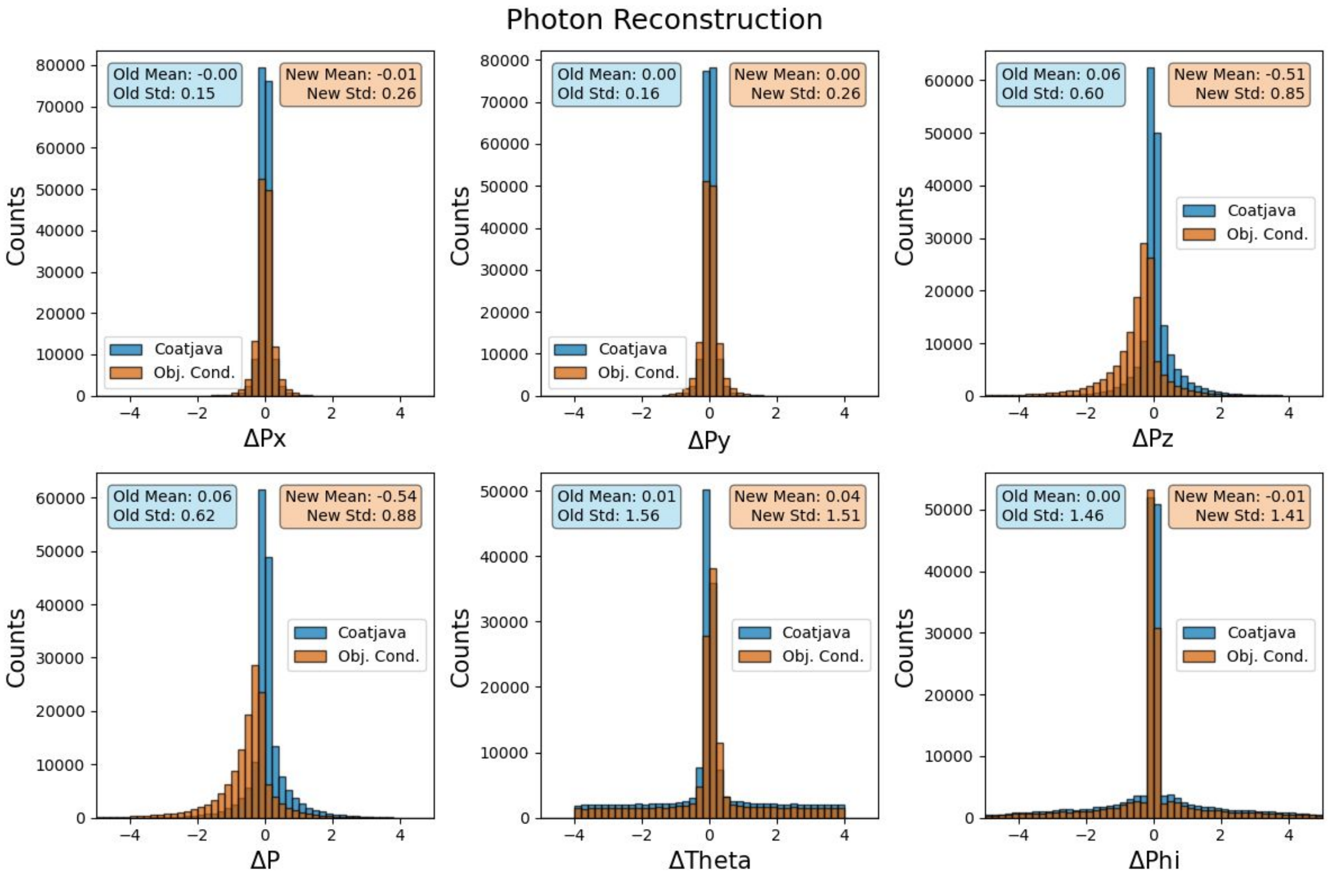
Demand B: Points group separately





(Right) The total potential V experienced by the blue square as it navigates past 3 unaffiliated objects (peaked condensation points) towards its clustering home (the bottom of the well, another condensation point)

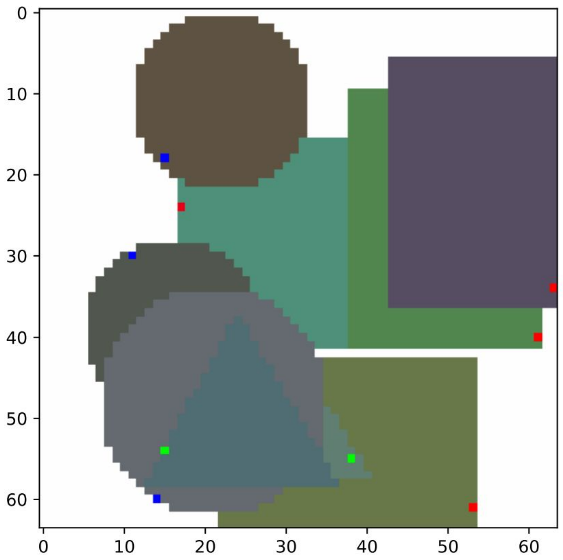
Photon Kinematic Resolutions



Plots shown for all REC photons with a Monte Carlo match

We see the resolution is good apart from the **Pz** and **P** which has a documented parallax fix in the [CLAS12 Electromagnetic Calorimeter](#) paper that I have not implemented (has to do with the cluster's centroid-z coordinate

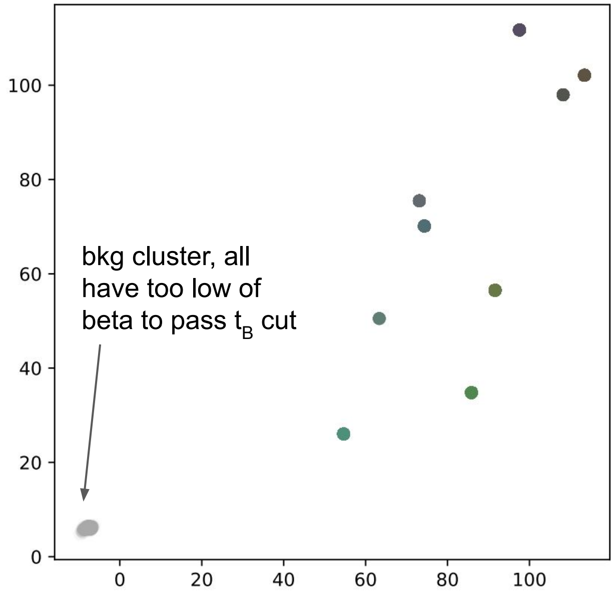
Interesting Example



9 objects

9 clusters

Classifier



Input Space

Latent Space