Automatic Colorization for Jet Clustering

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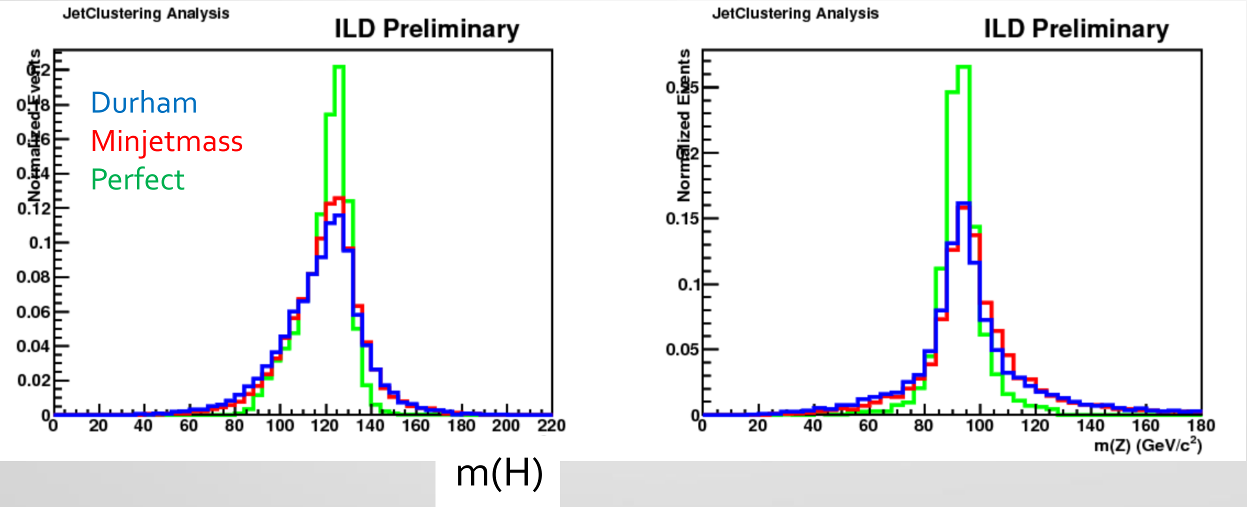
Introduction

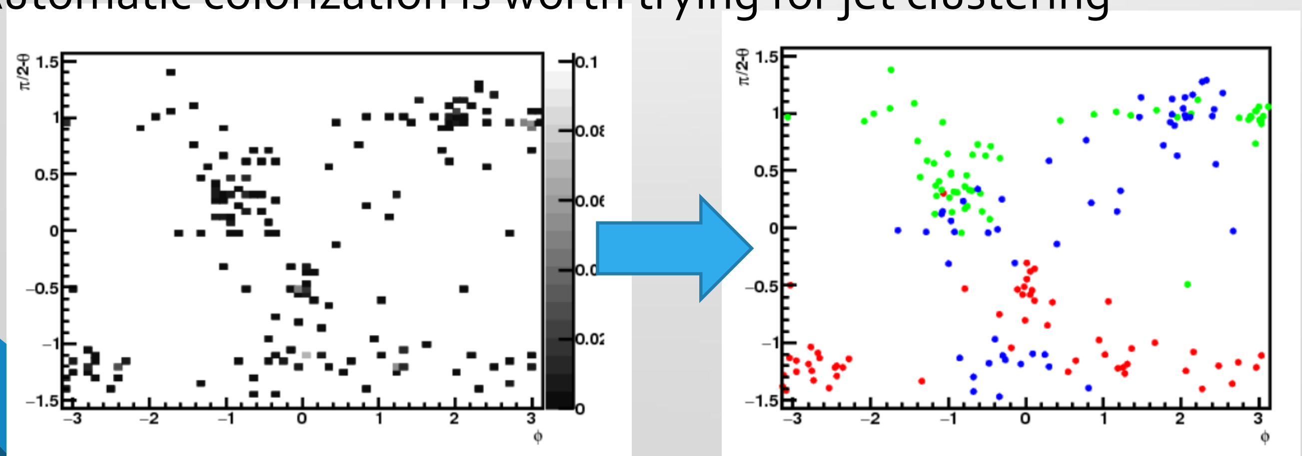
- Jet clustering is one of the main key to obtain better physics results
  - Physics results are strongly limited by mis-clustering
  - To obtain correct jets leads to improve the mass resolution of the resonances
- Present jet clustering is far from good tool for reconstructing jets
  - e.g. Higgs self-coupling@500GeV(ZHH): ～40% improvement if perfect!



- ~~Staging~~: even at 250GeV, clustering is very important
  - Separation of ZH/ZZ/WW in hadronic events

Use CNN for automatic colorization

- For jet clustering, we need the global and local information for each event
  - Global: Where is the large energy located?
  - Local: Correlation between neighbors or large energy area?
- Using Convolutional Neural Network(CNN), we will extract both of the features
  - Encorder-Decorder type CNN is used (calls as u-network)
  - Already ～30 layers in CNN! → DEEP LEARNING
- Clustering is equivalent to “colorize” each particle in the same cluster
  - Grey scale ⇒ color
  - So, Automatic colorization is worth trying for jet clustering



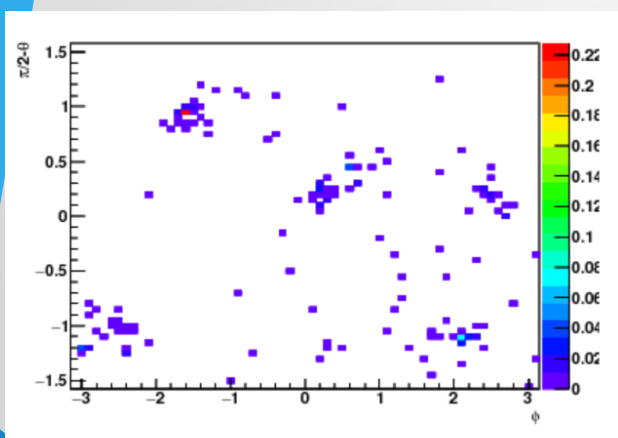
Example

Grey scale | Expectation | Truth

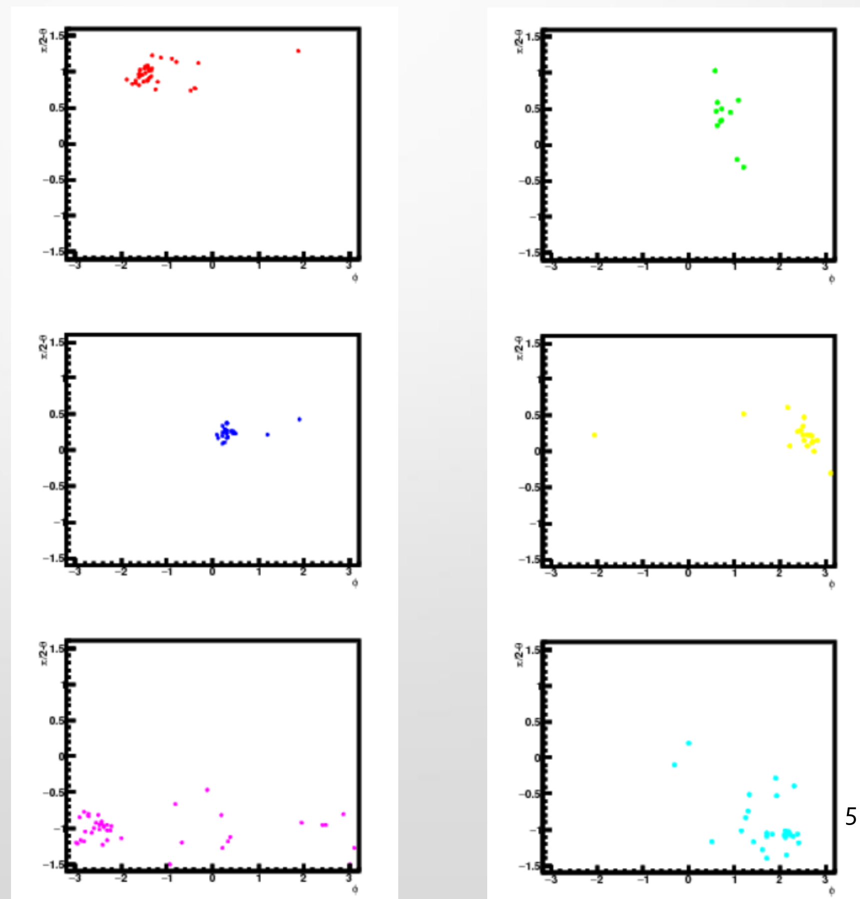
Trial

- Using a certain map(s) of each event, estimate color of each track
  - Do not consider color-singlet state

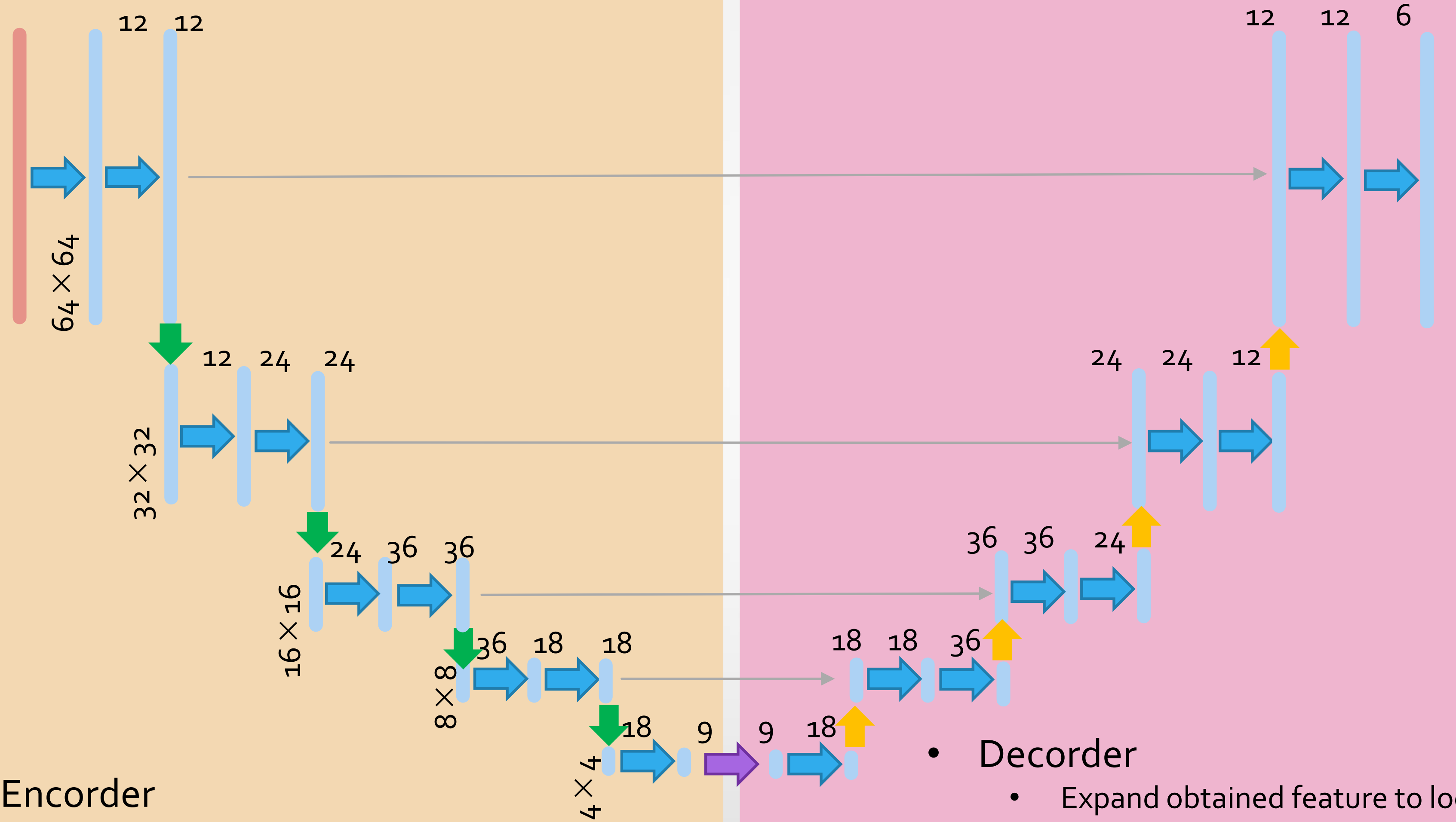
Input(64×64pixel figure)
e.g.) energy map



Output(64×64pixel figure)



U-network

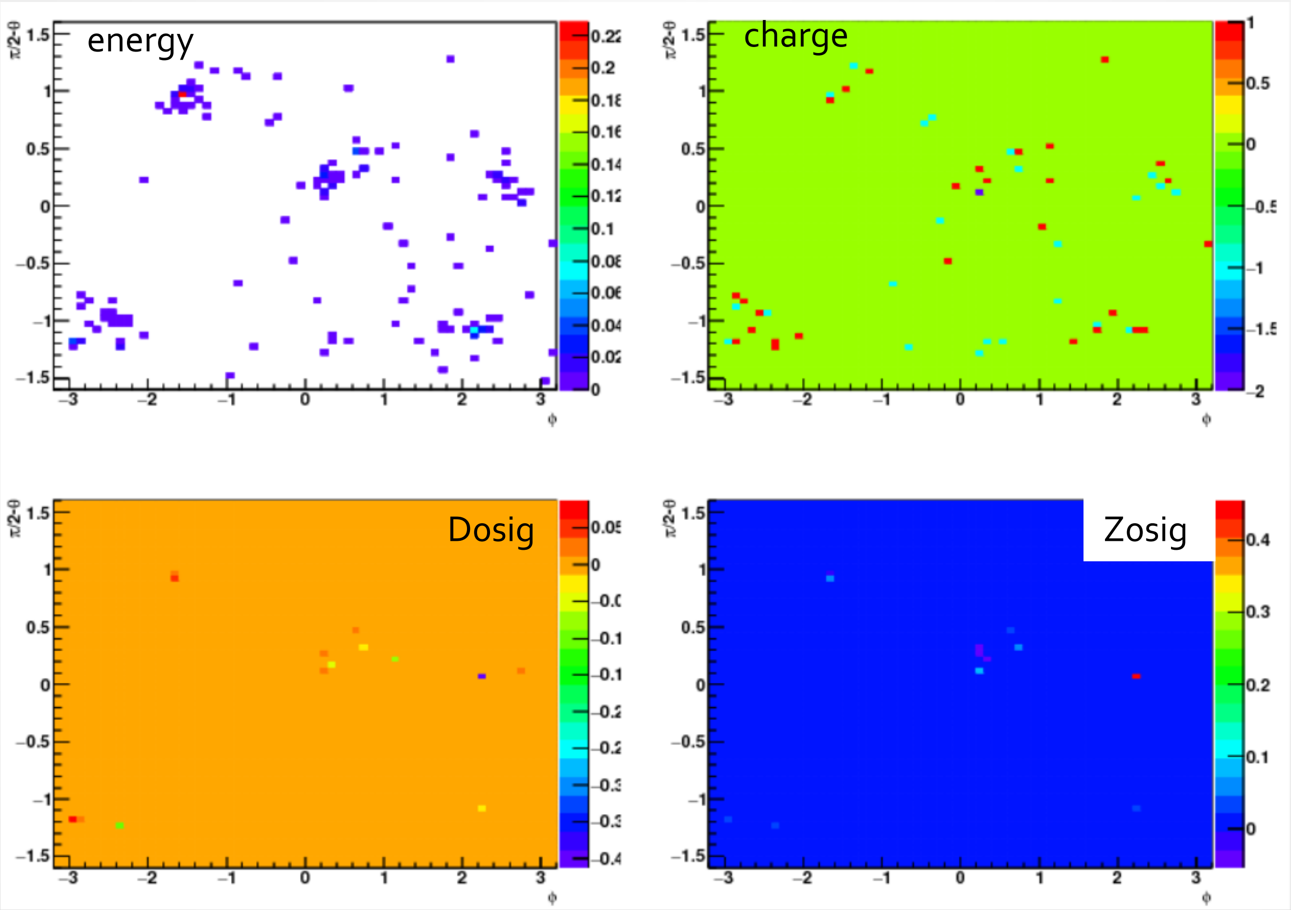


- Encorder
  - Extract global & higher order feature
  - Downsample to make network robust for distortion & shift effect
  - Lost position information
- Decorder
  - Expand obtained feature to local
  - Upsample to recover position information
  - Merge encoder nodes to get precise position information

- Consider periodic condition in ϕ direction

Multiple input

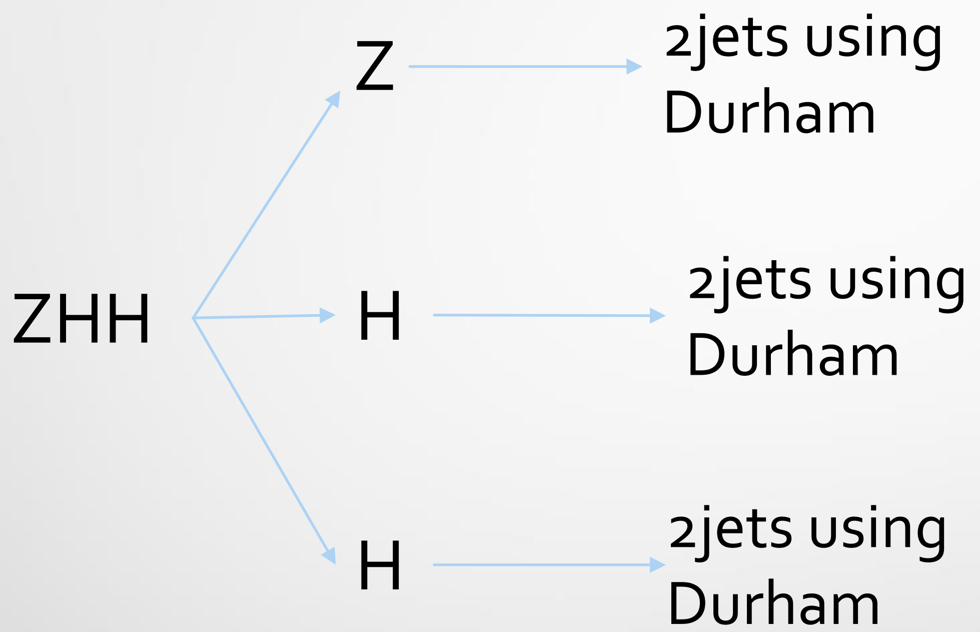
- Several variables are used for input image
  - Energy map
  - Charge map
  - Dosig map
  - Zosig map



- Training goes to quicker convergence than that of energy only
  - Not guaranteed good input variable set: need much time to check…
- Trying to include Ecal and Hcal maps: investigate now
- dE/dx??

Create answer

- Supervised learning - Create “answer” jets: perfect Durham jet clustering

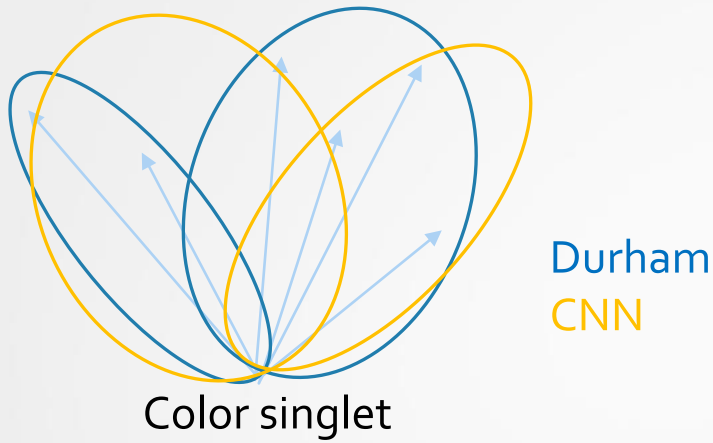


So far, do not consider color singlet state: number of jets is 6

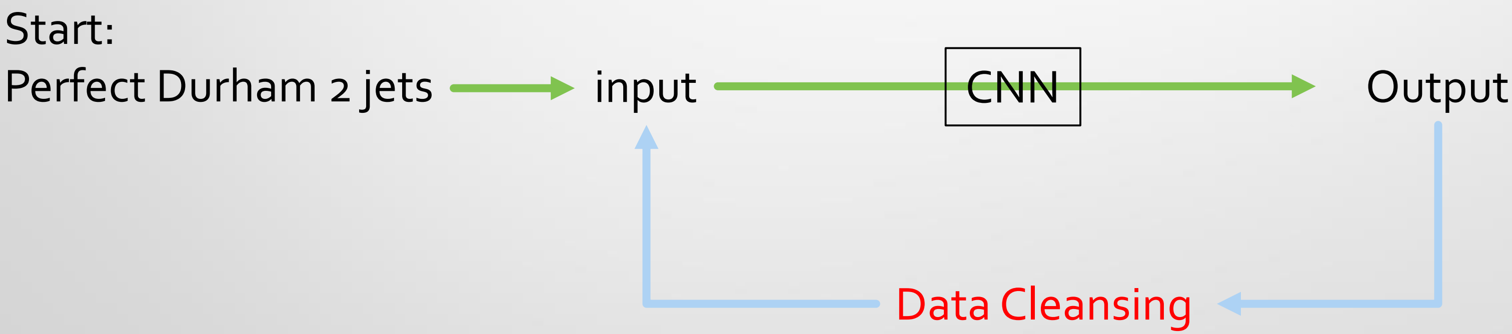
ZHH→(qq)(bb)(bb)→6jets

Data Cleansing

- Perfect Durham clustering is not always the best clustering into 2 jets for CNN



- By using the preliminary training weights, clustering into 2 jets is performed



Clustering particles to make loss function minimum

Iterate some times

status

- Use ZHH→(qq)(bb)(bb): 6jets clustering
- Use 50000 events for training
- Don't consider color singlet state for network training
  - But use the freedom of color singlet state: Data cleansing for better performance
- Input: 4 images output: 6 images
- Structure: u-network + CRF(don't mention today)

Over fit check

- This is still test stage, so cannot check overfitting well
- Just estimate using loss function(small is better):

$$L = -\frac{1}{N}\sum_{jet}\sum_{track} f\left(\frac{E_{track}}{E_{jet}}\right) \cdot \mathrm{Log}(y_{track})$$

- Cross entropy is weighted by the function of track energy to introduce the importance
  - Energetic tracks should be colored correctly
- If no overfitting, L is almost same between test and train

With CRF Num. of training events ALCW2018	Loss Train	Loss Test
900	0.308	1.25
11500	0.485	0.642

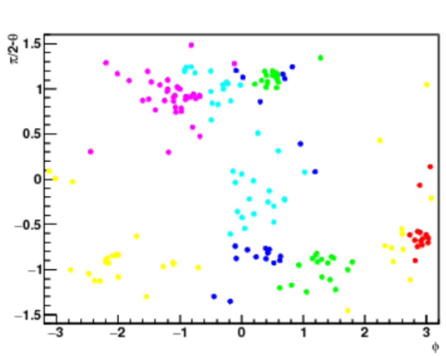
With CRF Num. of training events	Loss Train	Loss Test
50000	**0.375**	**0.406**

- Over fitting will vanish if num. of training events is O(10000-100000)
  - Reaches 50000 evts., still slightly overfitting, but ALMOST THERE
  - Going to be better performance, but need more!!

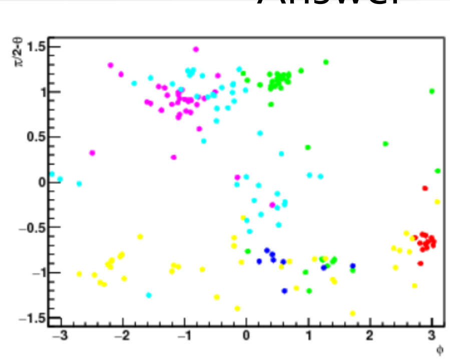
Examples(good)

- Using test samples

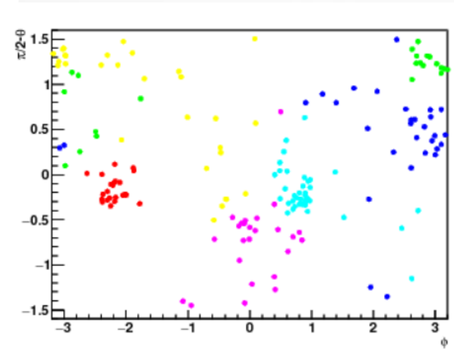
Example 1 Estimation



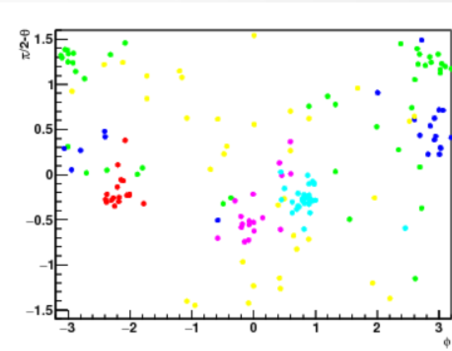
Answer



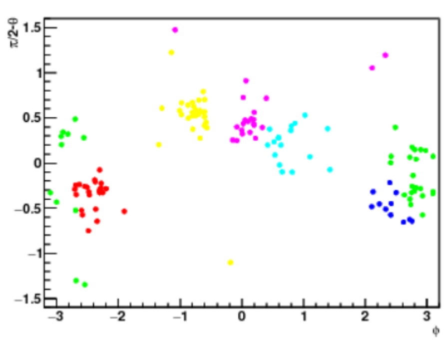
Example 2 Estimation



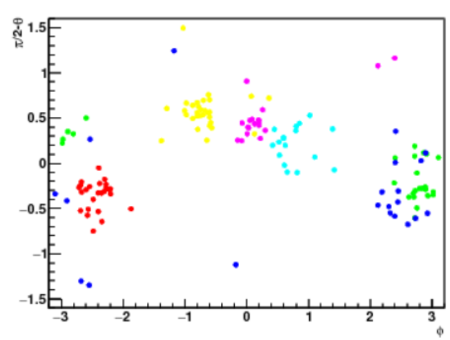
Answer



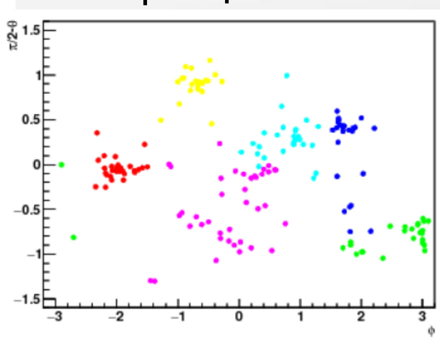
Example 3 Estimation



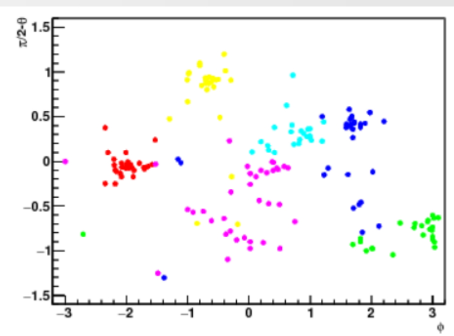
Answer



Example 4 Estimation



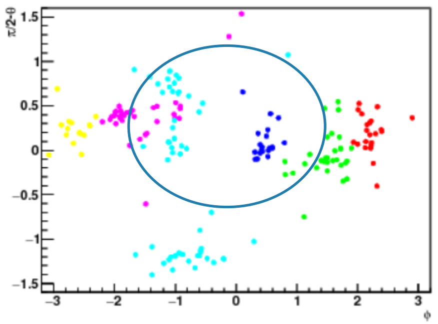
Answer



Examples(bad)

- Using test samples

Example 1 Estimation



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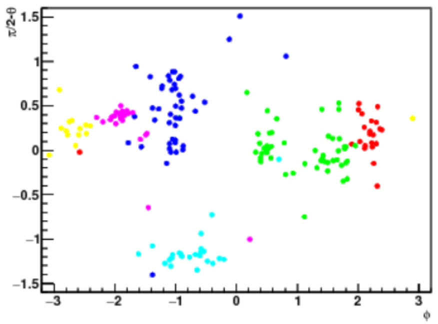
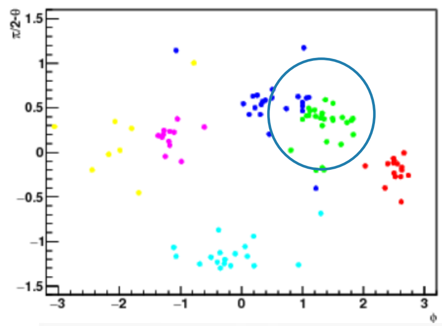


Example 2 Estimation



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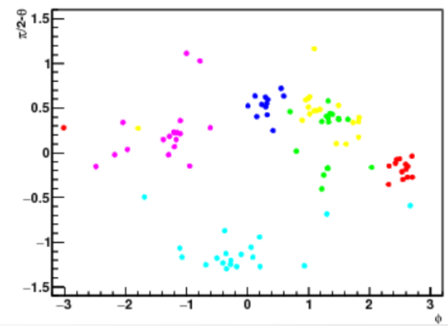
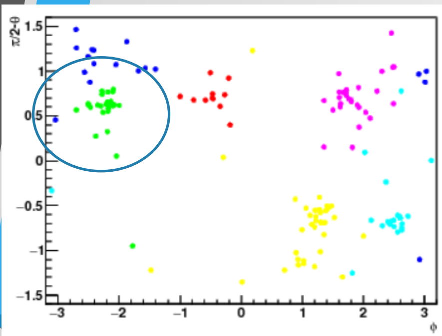
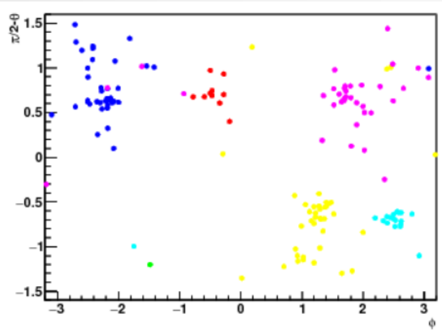


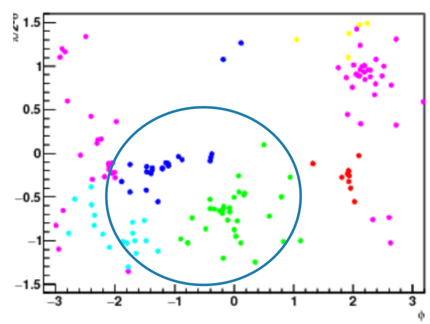
Example 3 Estimation



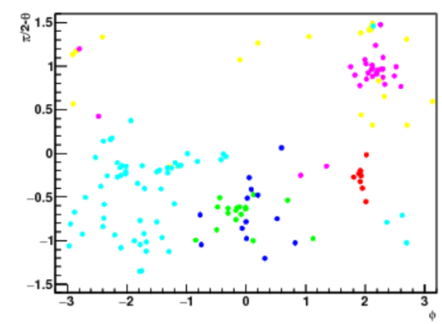
Answer



Example 4 Estimation



Answer



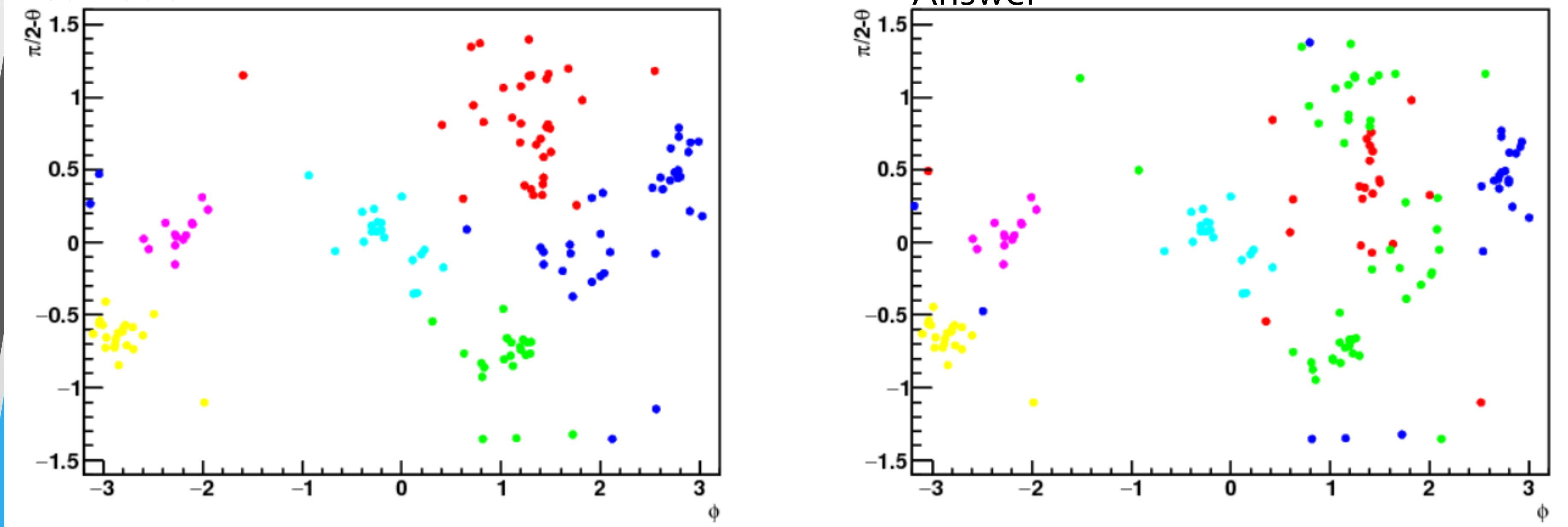
- Need to investigate mis-colorize
- Seems going to higher stage than ALCW2018(insensitive in ϕ direction vanished)
- Of course some events are very difficult to colorize correctly…

Examples(Extremely bad)

Example

Estimation

Answer



- Training event
- The events with:
  - Gluon splitting very large – some events seem colored correctly, but difficult
  - Overlapping with imbalanced energy jets
    - Difficult to extract small energy jets
  - Jets spread very wide area(like the event above…)

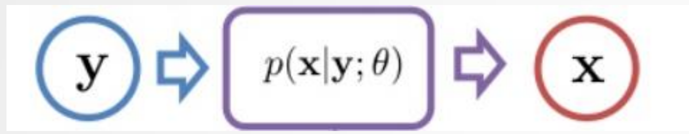
Summary and Outlook

- Mis-colorize is going to higher stage (than ALCW2018)
- Following cases seem difficult:
  - Gluon emission: cluster divides into 2(or more)
  - Overlapping energy-imbalanced jets
  - Jets spread wide area(and overlapping with other jets)
- Still needs some idea for better performance
  - Start to check & classify the cause of mis-colorize
  - Training strategy to recognize gluon emission
  - Construct the strategy for better performance
- Time to check mass resolution of Higgs and Z boson
- 250GeV 4 jets case should be tried

backups

Conditional Random Fields

- Inference of a latent variable from measured variables
  - x: measured variables → energy, momentum, charge, etc.
  - y: latent variable → the jet which a particle is coming from



  - We have to estimate good conditional probability distribution
- Use Conditional Random Fields:
  - Estimate parameters to maximize the Boltzmann probability:

$$p(x|y;\theta) = \frac{1}{Z}\exp(-E(x))$$

$$E(\mathbf{x}) = \sum_{(i,j)\in\mathcal{E}} f_{ij}(x_i, x_j) + \sum_{i=1}^{N} f_i(x_i)$$

- Same structure as Ising model (because inspired by Ising model):

$$H(\sigma) = -J \sum_{i=1,...,L} \sigma_i \sigma_{i+1} - h \sum_i \sigma_i$$

- Optimization procedure is very similar to Ising model
  - Mean field approximation, Gibbs sampling, etc.

Preliminary architecture

- CRF is used for post-processing of CNN

$$E(\mathbf{x}) = \underbrace{\sum_{(i,j)\in\mathcal{E}} f_{ij}(x_i, x_j)}_{\text{Constraint for pairwise tracks}} + \underbrace{\sum_{i=1}^{N} f_i(x_i)}_{\text{Output of u-network for each track}}$$

- In first term, we will be able to impose physics constraints
  - Now, simplest case: impose Durham distance measure:

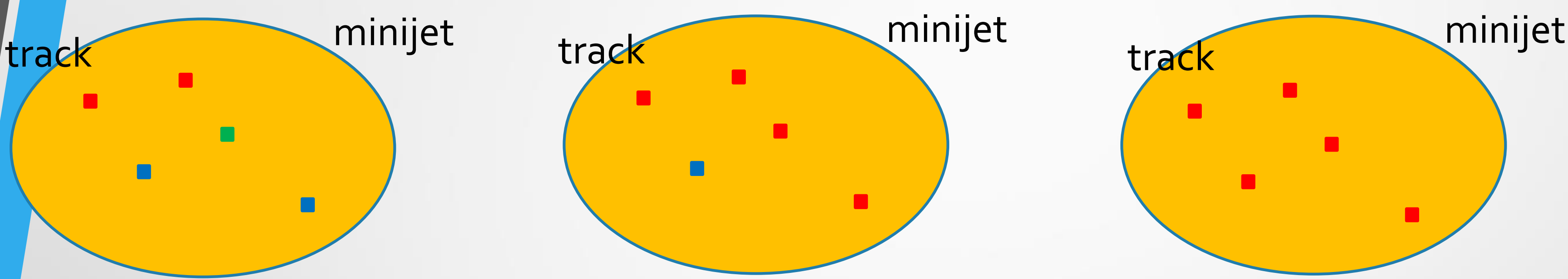
$$f_{ij} = \omega \cdot \exp(-\alpha \frac{2Min\left(E_i^2, E_j^2\right)}{Evis^2}(1 - cos\theta))$$

  - Based on the fact that jet products will fly colinearly
- We can impose any physics constraint
  - I don't know what is good…
  - Vertex constraint?
  - Other distance measure(anti-kt?)

  Something else?

Including physics effect naturally

- Include minijet effect
- Like spin correlation of Ferromagnetism, members inside minijets should be same status to make energy minimum



High energy state | Middle energy state | Low energy state

- Energy of Boltzmann probability:

$$E(x) = \sum_{i} f_i(x_i) + \sum_{(i,j)} f_{ij}(x_i, x_j) + \sum_{minijet} f_{minijet}(\boldsymbol{x_{trks}})$$

External field (output of CNN) | Pairwise effect | Status inside each minijet

- Can include vertex constraint with same way
- Now: no reason, but 30 minijets created