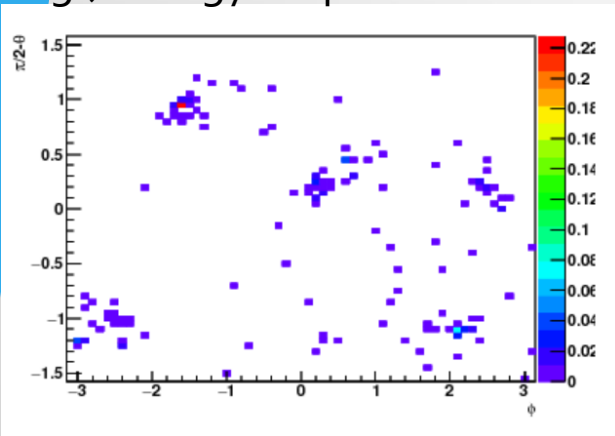


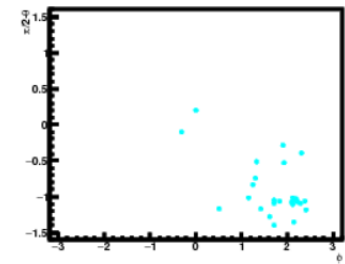
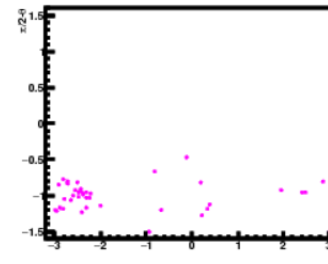
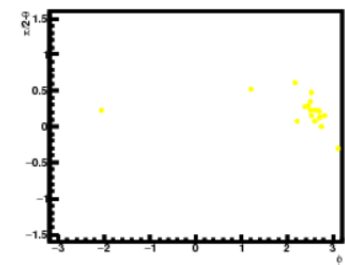
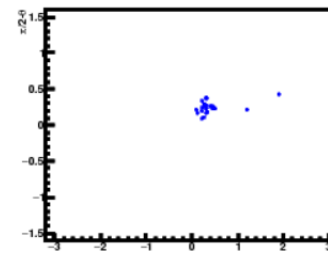
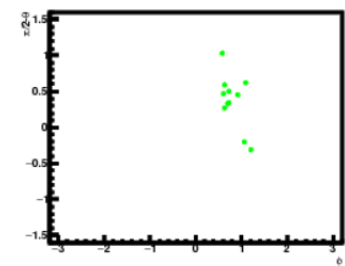
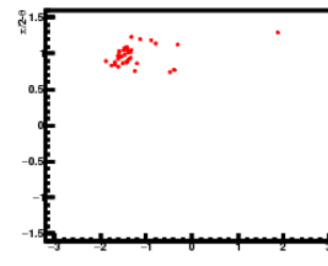
Trial

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

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



Output(64×64 pixel figure)



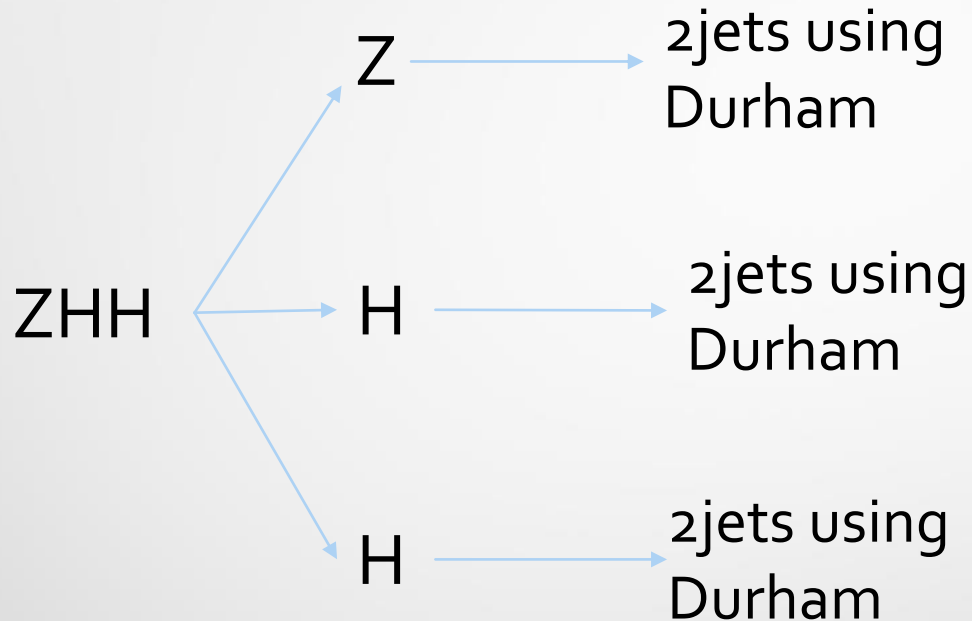
9 input images
Energy map
Charge map
Dosig map
Zosig map
Ecal map
Hcal map

+ direction vector(x, y, z)

+ no particle

Create answer

- Supervised learning - Create "answer" jets: perfect Durham jet clustering



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

$ZHH \rightarrow (qq)(bb)(bb) \rightarrow 6\text{jets}$

Pseudo-labelling

- Output: inference of the probability of the color to be assigned
 - $\sum y_i = 1.0$

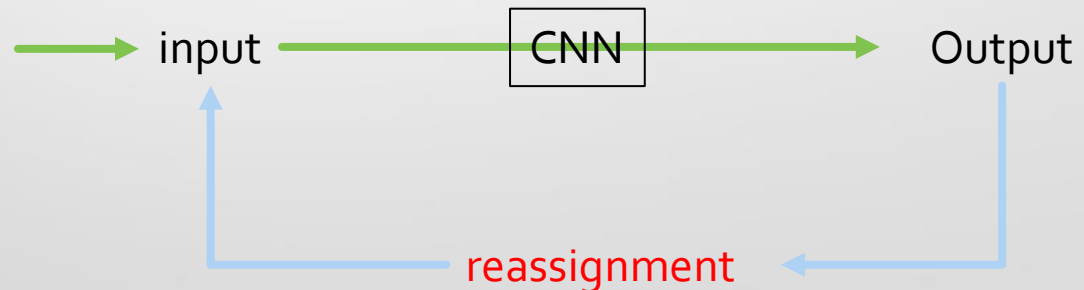
output



- The combination of color assignments is arbitrary, so assign them so that the loss function is minimized.
 - Using preliminary results after a training, re-assign the color combination
 - Minimize cross entropy $L = \frac{1}{n} \sum y_i \log p_j$

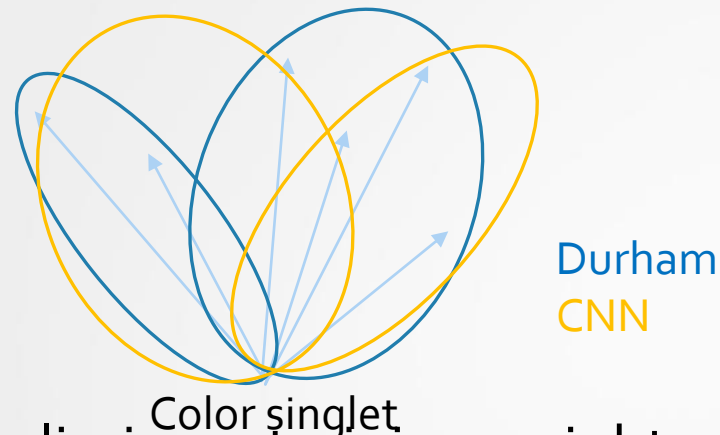
Start:

Energy ordering
Of jets



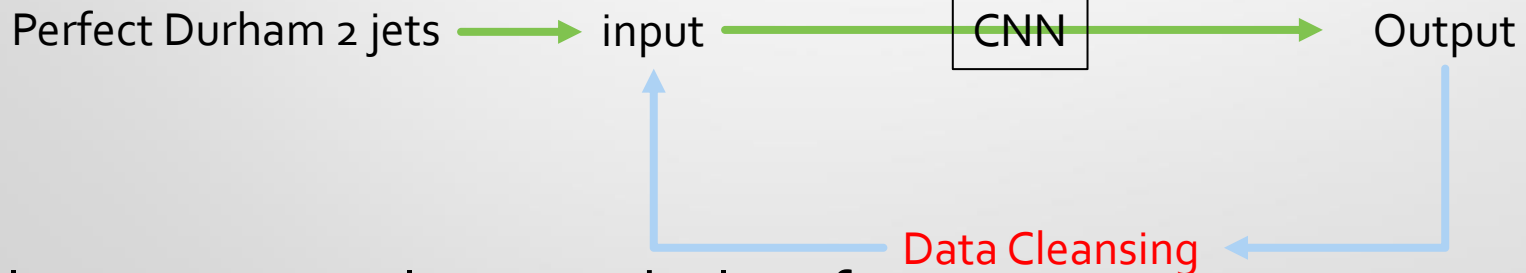
Data Cleansing

- 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

Start:



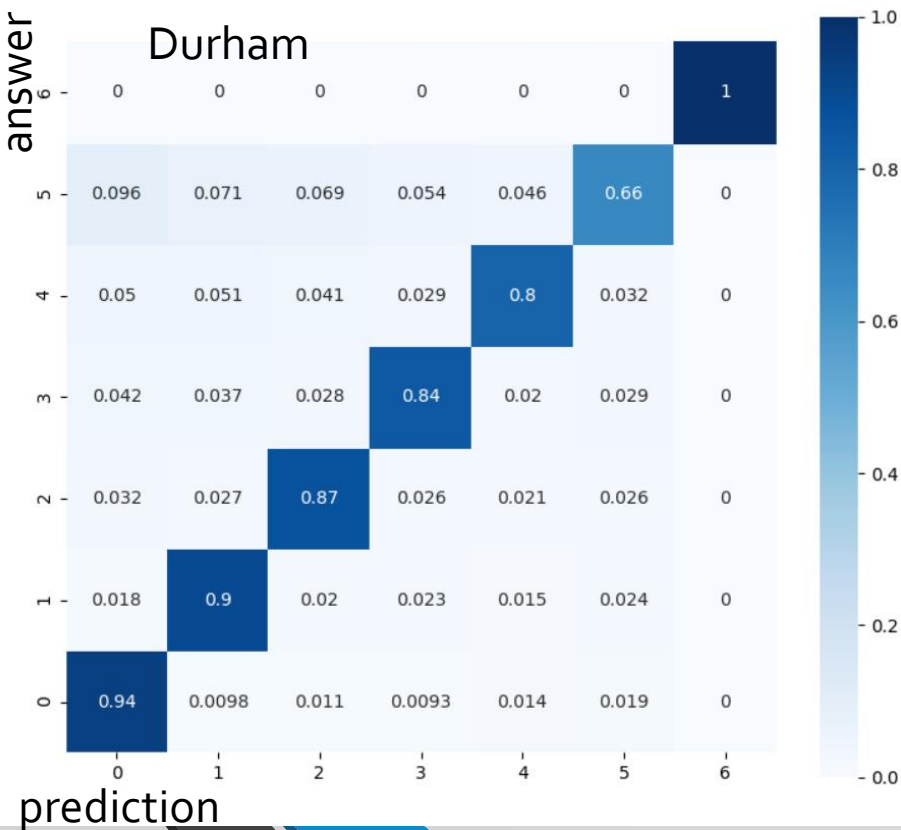
- Clustering particles to make loss function minimum
- First pseudo-labeling. After that, data cleansing
 - Is there better way?

status

- Use $ZHH \rightarrow (qq)(bb)(bb)$: 6jets clustering
 - q: uds
- Use 80000 events for training(72000 train, 8000 validation)
 - Very weak or no over fitting can be seen
- Don't consider color singlet state for network training
- Input: 6 + 3 images output: 6 + 1 images

Comparison with Durham

- Seems to start to exceed Durham performance!
 - Mis-clustering to adjacent jets
 - Need to remove it as much as possible
- Need to improve an efficiency in circle to get better performance





backups

Basics: convolution

- Convolution: Apply the filters to extract the feature

- Sum of the product of each pixel and filter weights:

$$y_{kl} = \sum_{i,j} w_{ij} \cdot x_{(k+i)(l+j)} (+b)$$

- Slide filters over all the pixels

1 _{x1}	1 _{x0}	1 _{x1}	0	0
0 _{x0}	1 _{x1}	1 _{x0}	1	0
0 _{x1}	0 _{x0}	1 _{x1}	1	1
0	0	1	1	0
0	1	1	0	0

Image

4		

Convolved
Feature

- **Filters are parameters:** CNN can obtain them automatically

- After the convolutional operation, apply non-linear transform

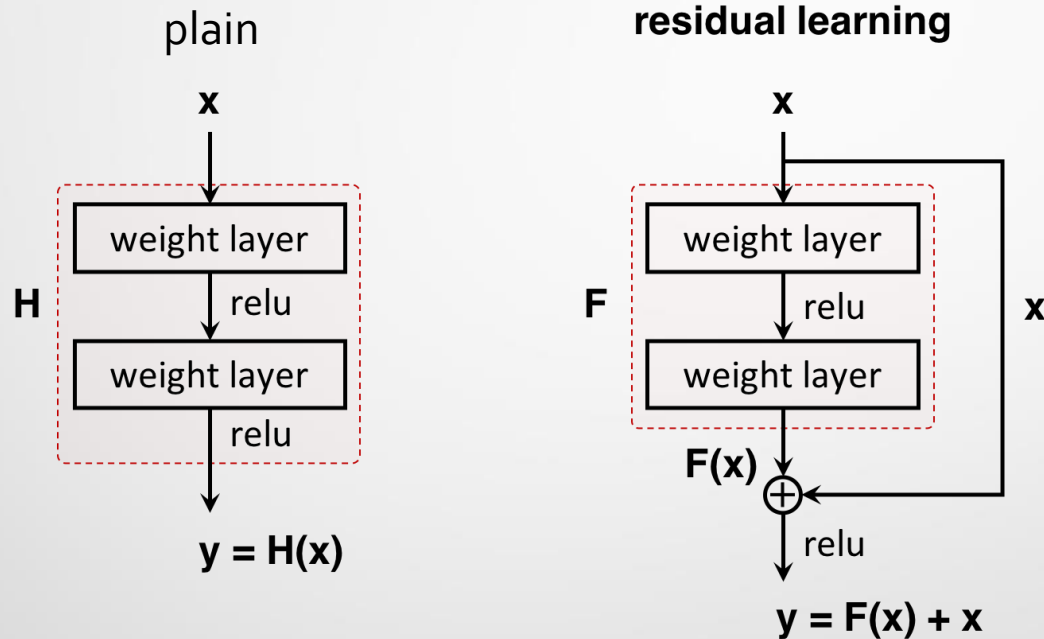
$$z_{kl} = \sigma(y_{kl})$$

- "Non-linear" is important to get good expression

- Stack these operations

Basics: Residual convolution

- Stream is divided into 2 paths:
 - Path with convolution
 - Path without any operation
- Sum up these 2 path in downstream

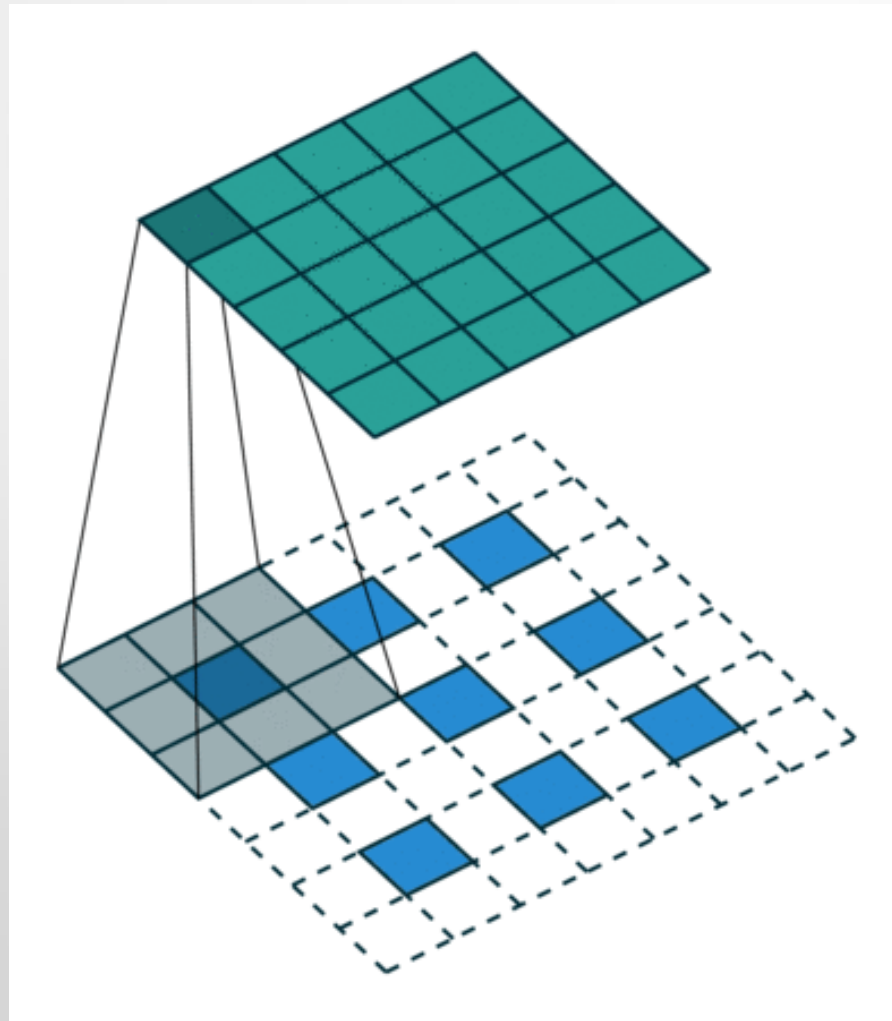


Can learn "Residuals" of previous layer features

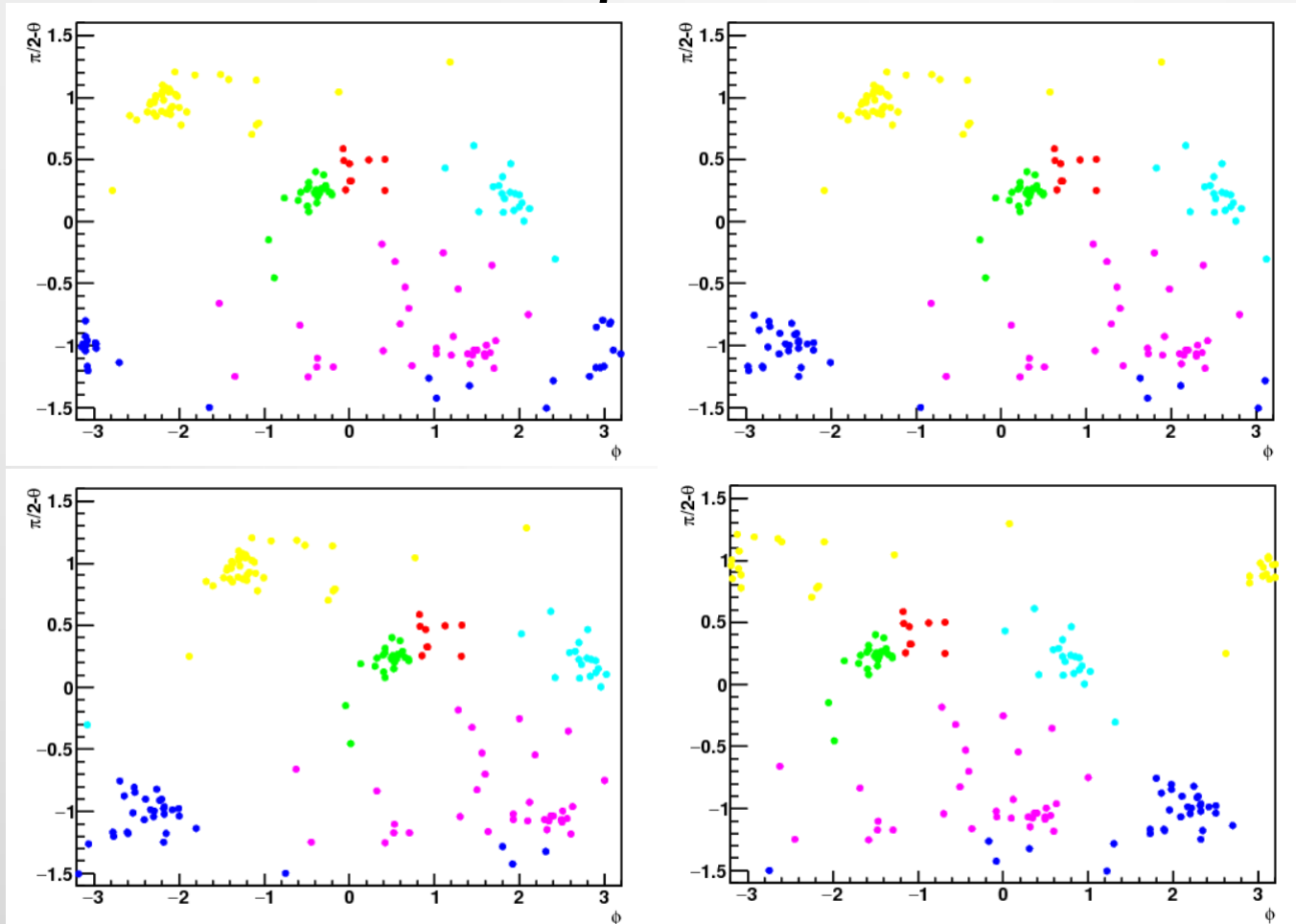
- Can construct very deep network
 - >100 layers can be constructed
 - Deeper will be better performance

Basics: Transposed convolution

- Reverse operation of convolution
 - After adding padding, do convolution
 - Use for upsampling



Data Augmentation



- Random shift for x axis
 - Considering periodic condition of ϕ angle ($f(\Phi+2\pi) = f(\Phi)$)
To suppress over fitting
- Add random y-flip (I think not good from physics point of view, but suppress over-fitting is important)