

# Deep Learning Applications

## RWTH Aachen

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Thorben Quast, Yannik Rath, Marcus Wirtz

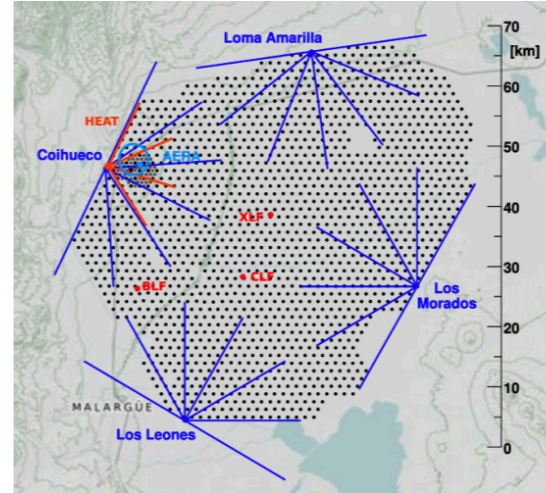
ErUM-Data @KIT

01.10.19





- Top-quark coupling measurements to Higgs boson
- Di-Higgs production measurement
- Event categorization into physics processes using Deep Learning
- Simulation of electromagnetic showers using generative models



- Total energy calibration using radio emission of air showers
- Air-shower reconstruction using Deep Learning
- Search for arrival directions of cosmic rays including galactic magnetic fields

Both groups work on the VISPA Project:

<https://vispa.physik.rwth-aachen.de/>



```
51 # Define model
52 # -----
53 #
54 #
55 #
56 def add_block(x, nfilters, dropout=False, **kwargs):
57     """
58     Add basic convolution block:
59     - 3x3 Convolution with padding
60     - Activation: ReLU
61     - either MaxPooling to reduce resolution, or Dropout
62     - BatchNormalization
63     """
64     x = layers.Convolution2D(nfilters, kernel_size=(3, 3), padding='same', ker
65     x = layers.BatchNormalization()(x)
66     x = layers.Activation('relu')(x)
67     if dropout:
68         x = layers.Dropout(dropout)(x)
69     else:
70         x = layers.MaxPooling2D((2, 2), padding='same')(x)
71     return x
72
73 inp = layers.Input(shape=(32,32,3))
74
75 # convolution part
76 x = add_block(inp, 32, dropout=0.3) # --> (32, 32, 32)
77 x = add_block(x, 32) # --> (16, 16, 32)
78 x = add_block(x, 64, dropout=0.4) # --> (16, 16, 64)
79 x = add_block(x, 64) # --> (8, 8, 64)
80 x = add_block(x, 128, dropout=0.4) # --> (8, 8, 128)
81 x = add_block(x, 128, dropout=0.4) # --> (8, 8, 128)
82 x = add_block(x, 128) # --> (4, 4, 128)
83 x = add_block(x, 256, dropout=0.4) # --> (4, 4, 256)
84 x = add_block(x, 256, dropout=0.4) # --> (4, 4, 256)
85 x = add_block(x, 256) # --> (2, 2, 256)
86
87 # classification part
88 x = layers.Flatten()(x) # --> (1024)
89 x = layers.Dropout(0.5)(x)
90 x = layers.Dense(256)(x) # --> (256)
91 x = layers.BatchNormalization()(x)
92 x = layers.Activation('relu')(x)
93 x = layers.Dropout(0.5)(x)
94 x = layers.Dense(10)(x) # --> (10)
95 x = layers.Activation('softmax')(x)
96
97 model = keras.models.Model(inputs = inp, outputs = x)
98 print(model.summary())
99
```



20 NVIDIA GTX 1080

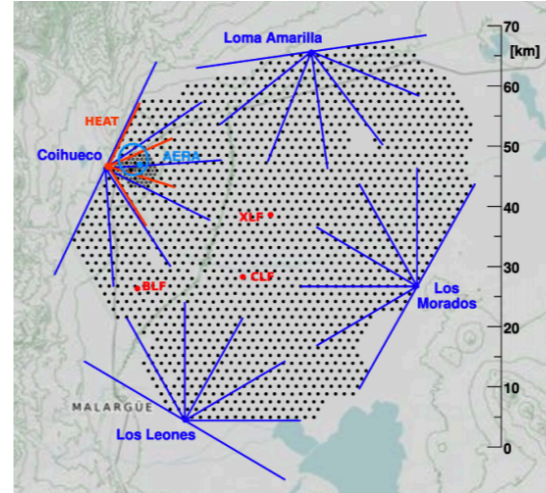
Storage, NFS, Network

~200 CPU cores

Upcoming upgrade: +9 GPU RTX5000/6000



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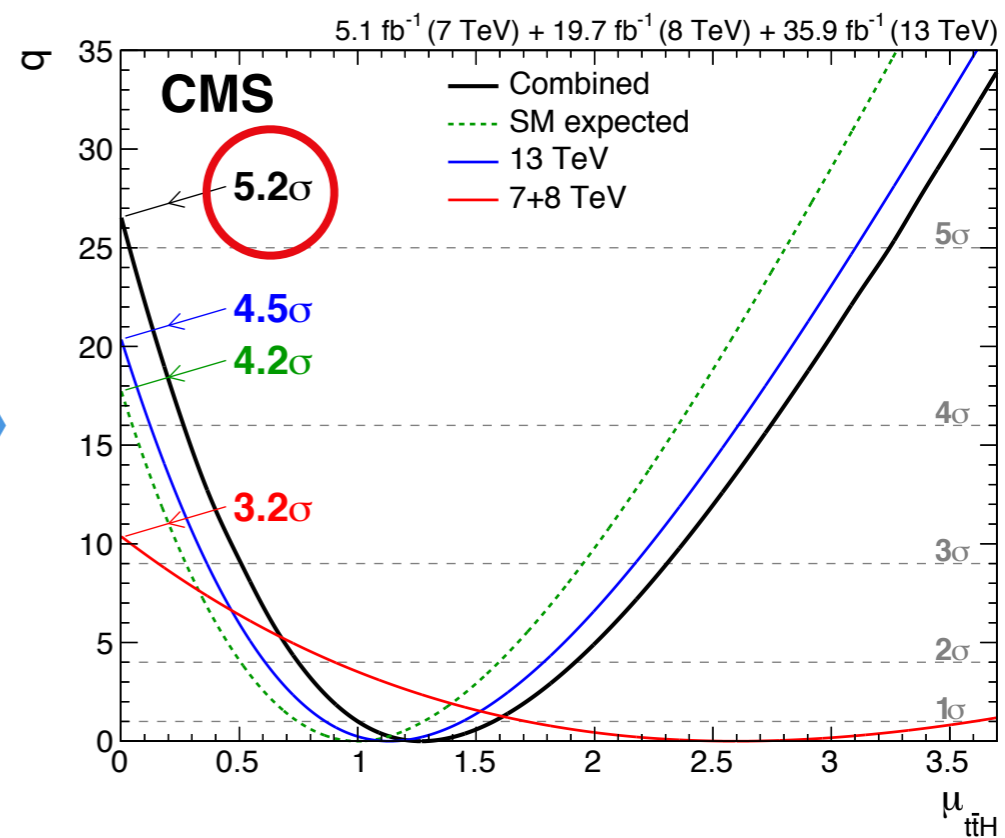
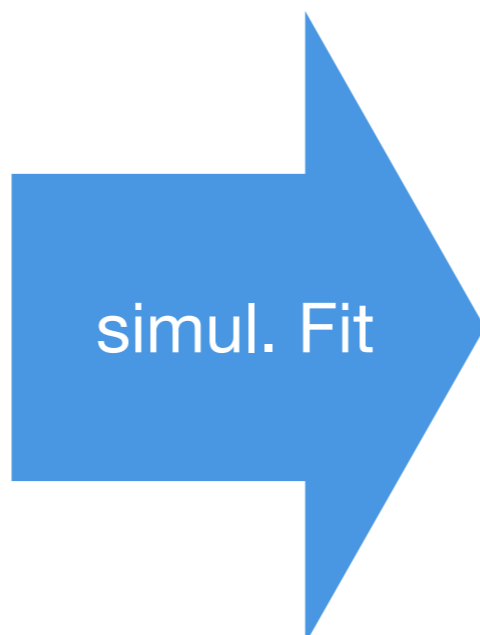
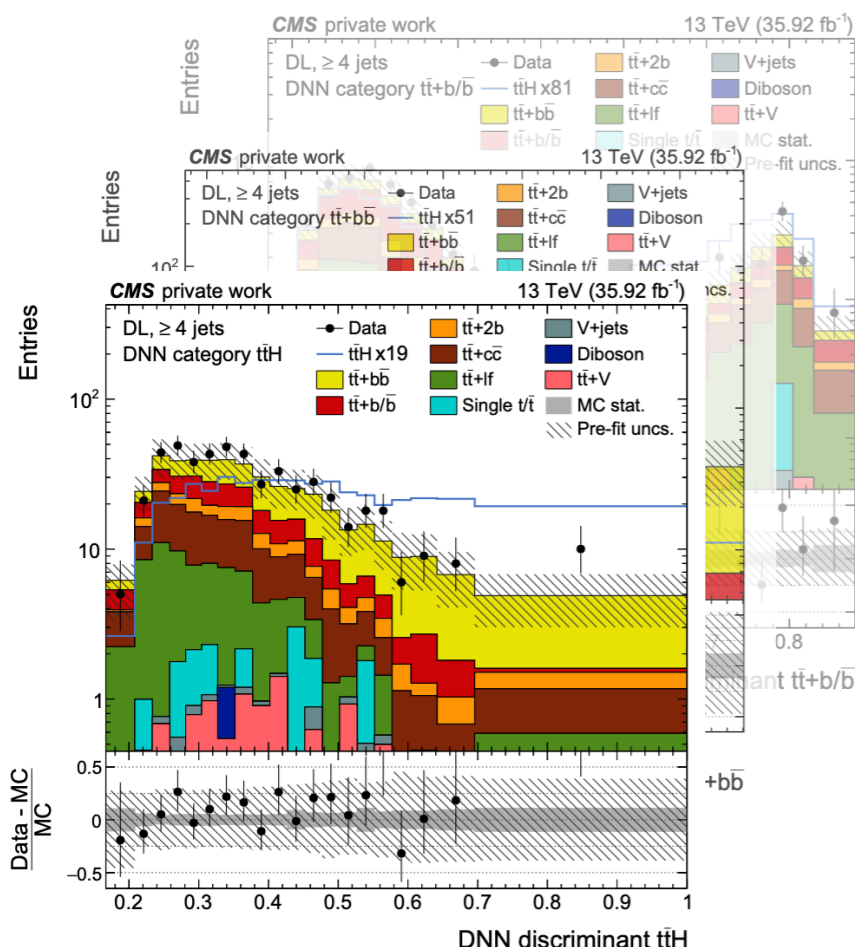
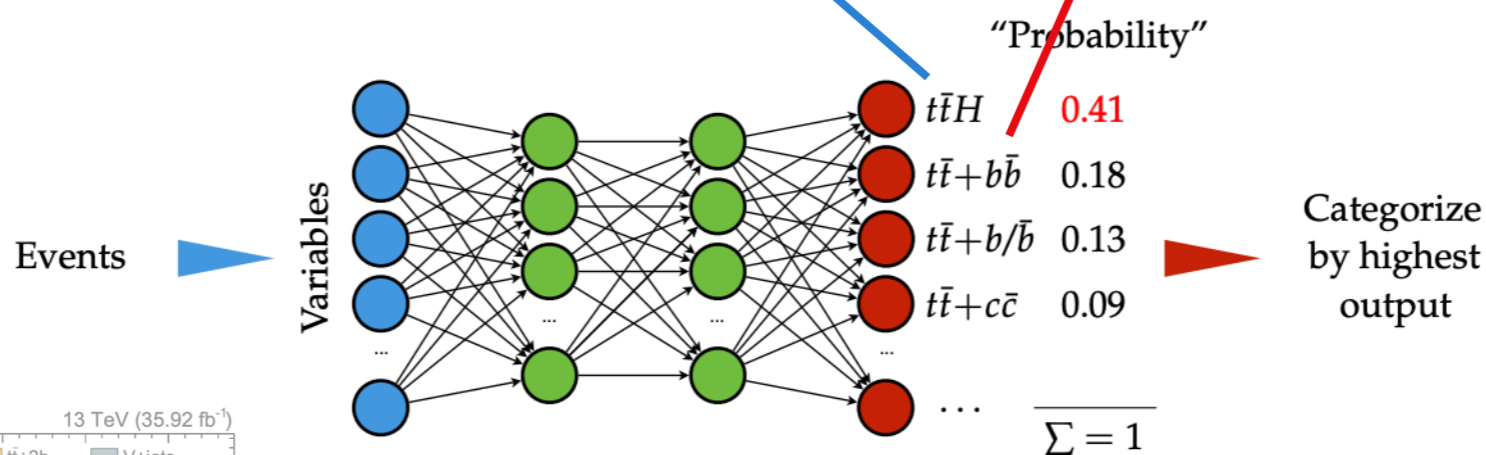
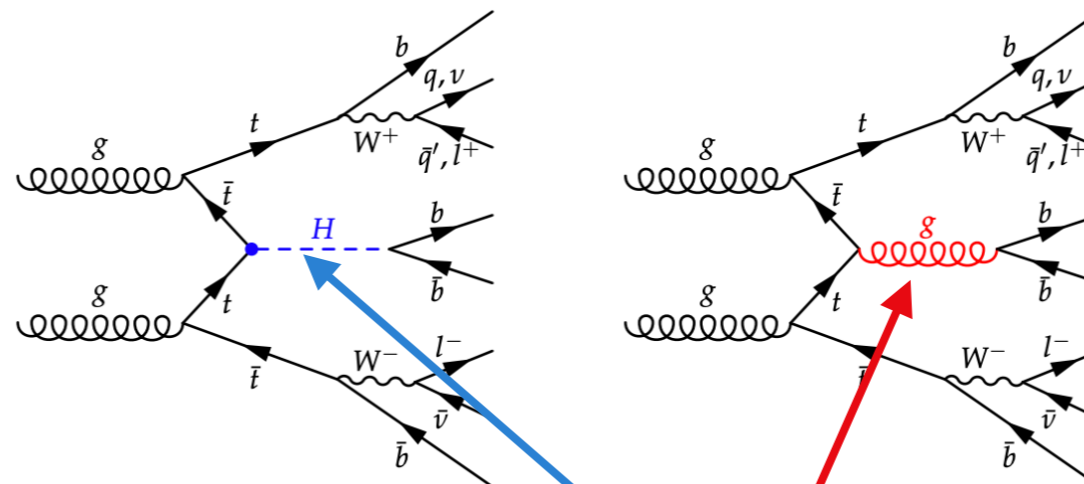


- Total energy calibration using radio emission of air showers
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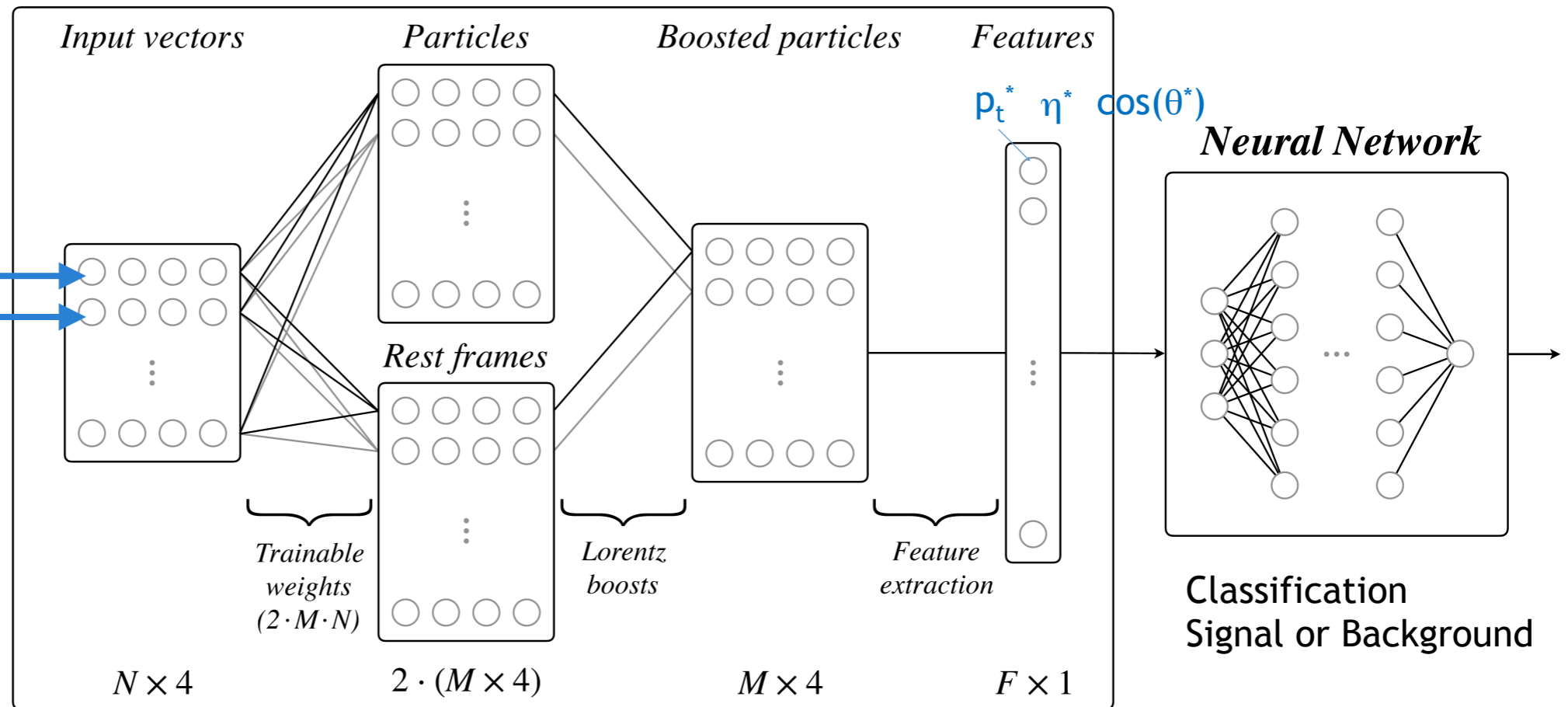
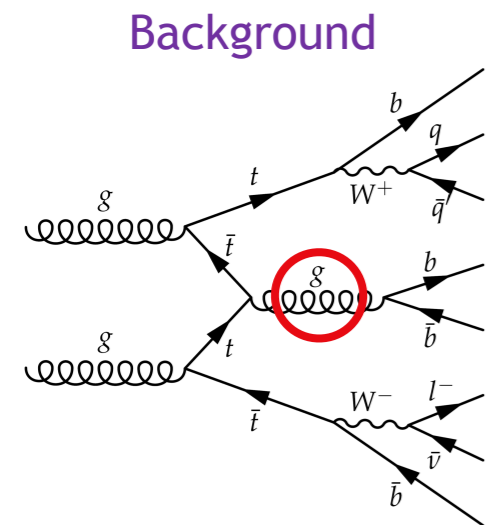
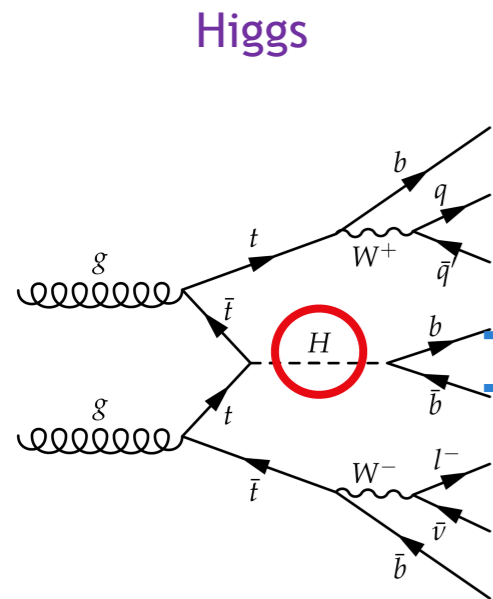
Both groups work on the VISPA Project:

<https://vispa.physik.rwth-aachen.de/>

## Rath master thesis



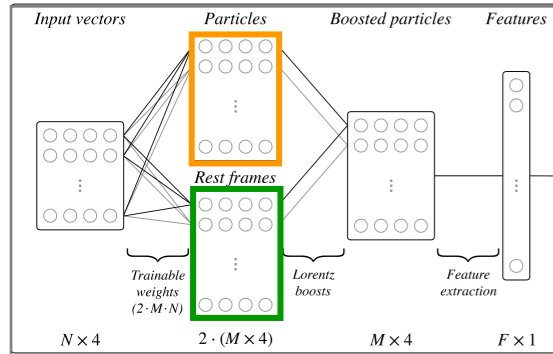
JINST 14 (2019) P06006



normalized weights

Input final	$b_1$	39	0	8	51	7	90	0	0	40	0	10	51	47	Higgs	
	$b_2$	61	0	1	21	8	0	32	0	3	0	84	18	16		
	$b_{had}$	0	68	14	0	22	7	12	1	17	11	1	2	0		
	$q_1$	0	17	13	0	27	0	9	1	22	12	1	12	1	Top	
	$q_2$	0	15	16	2	27	2	11	0	10	21	1	1	9		
	$b_{lep}$	0	0	13	3	2	0	11	68	0	18	1	13	4	Top	
	$lep$	0	0	16	8	0	0	14	25	8	38	1	3	13		
	$\nu$	0	0	19	15	5	0	10	6	0	0	1	1	9		
			0	1	2	3	4	5	6	7	8	9	10	11	12	
			Combined particle													

- generates meaningful particle combinations

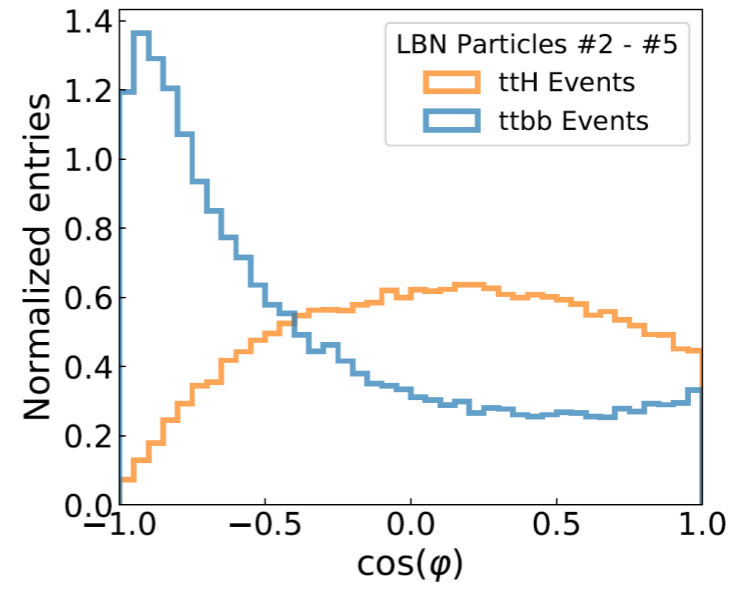


combined particles in  $b$ -quark rest frame

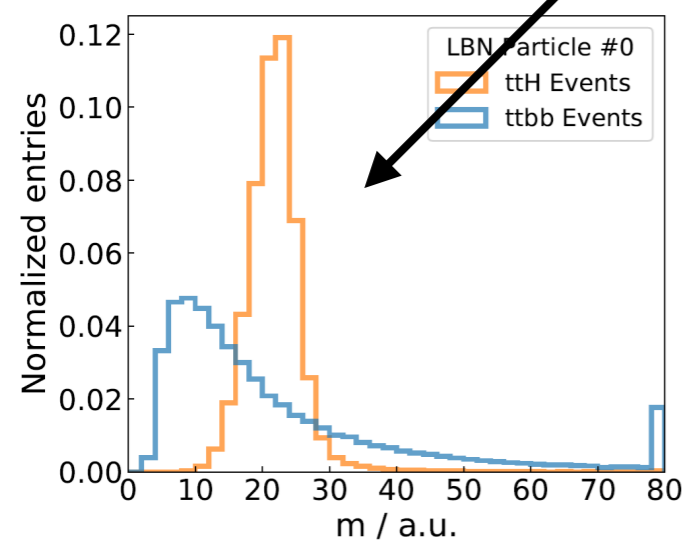
$b$ -quark in combined particles rest frame

Input particle	0	1	2	3	4	5	6	7	8	9	10	11	12
$b_1$	39	0	8	51	7	90	0	0	40	0	10	51	47
$b_2$	61	0	1	21	8	0	32	0	3	0	84	18	16
$b_{had}$	0	68	14	0	22	7	12	1	17	11	1	2	0
$q_1$	0	17	13	0	27	0	9	1	22	12	1	12	1
$q_2$	0	15	16	2	27	2	11	0	10	21	1	1	9
$b_{lep}$	0	0	13	3	2	0	11	68	0	18	1	13	4
$lep$	0	0	16	8	0	0	14	25	8	38	1	3	13
$\nu$	0	0	19	15	5	0	10	6	0	0	1	1	9
0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0

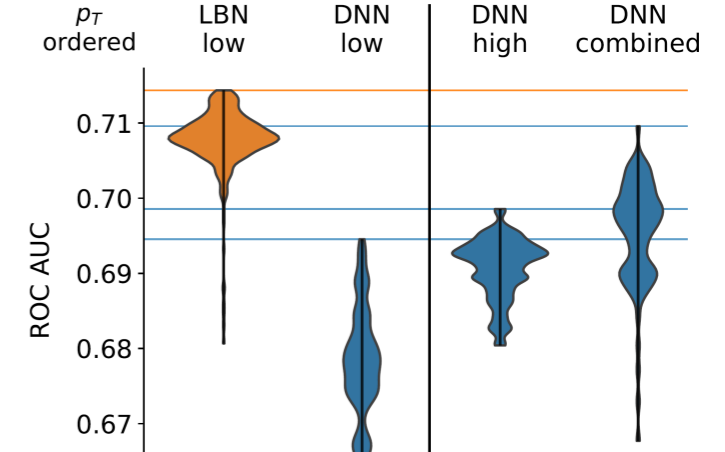
Angular distributions



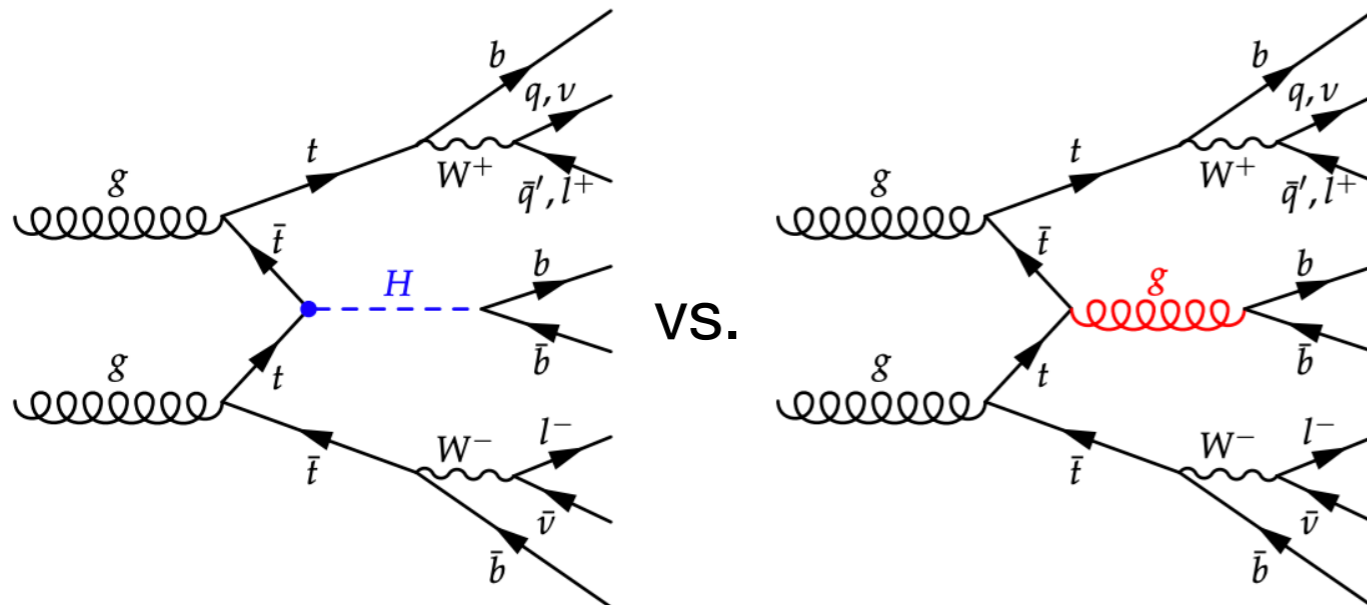
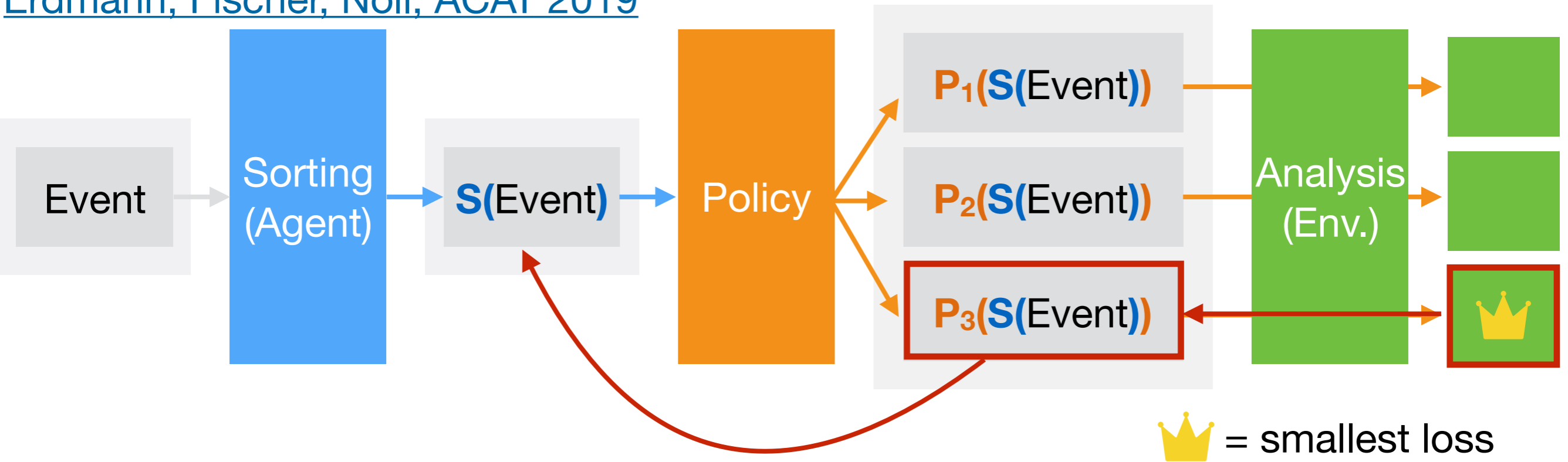
Mass distributions



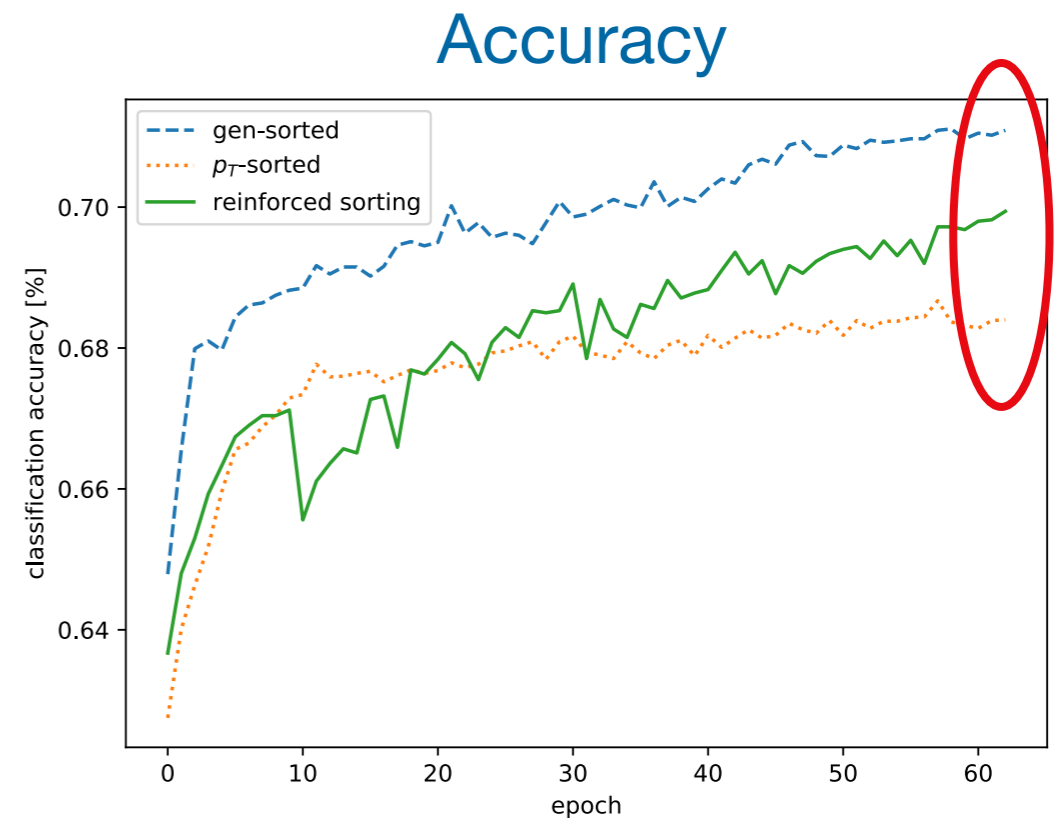
Even for  $p_T$ -ordered jets: best result by autonomous variables



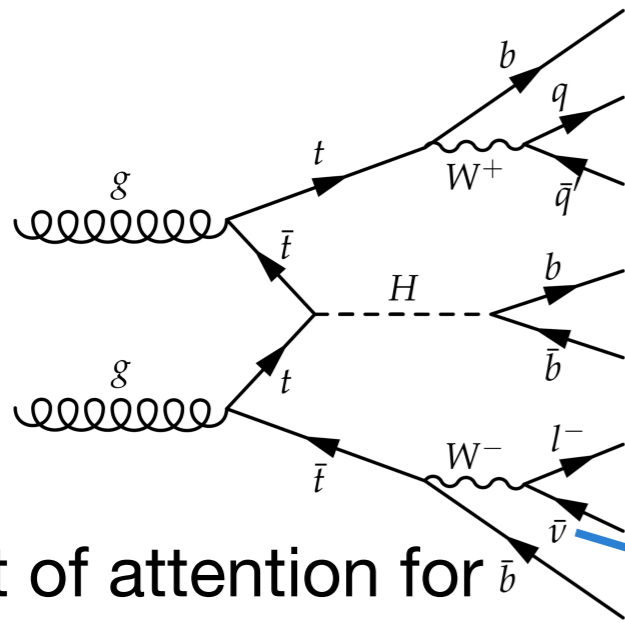
Erdmann, Fischer, Noll, ACAT 2019



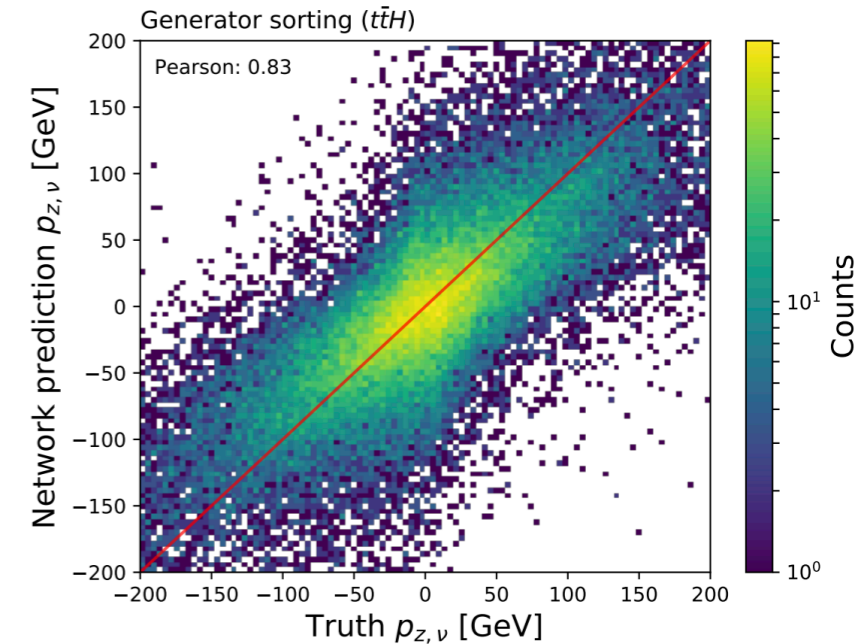
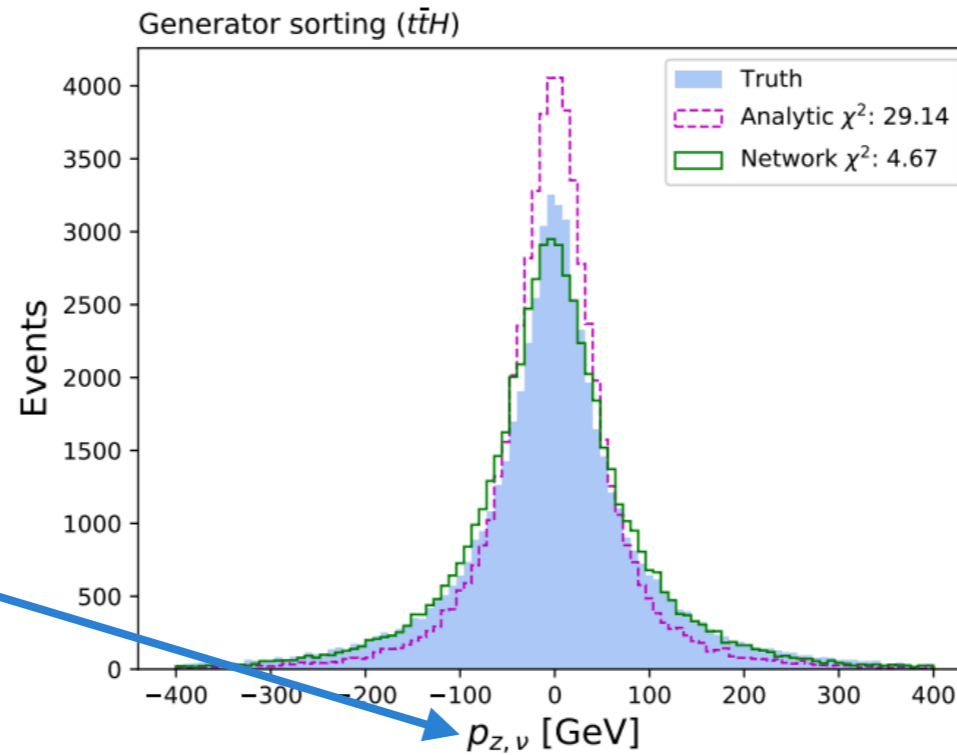
Classification performance improves with proper particle sorting!







A lot of attention for lepton & neutrino!



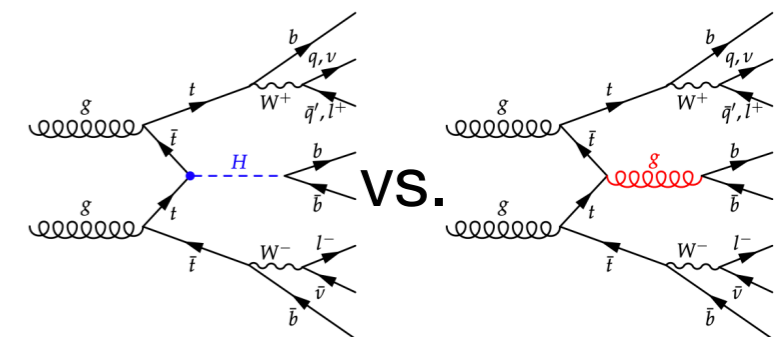
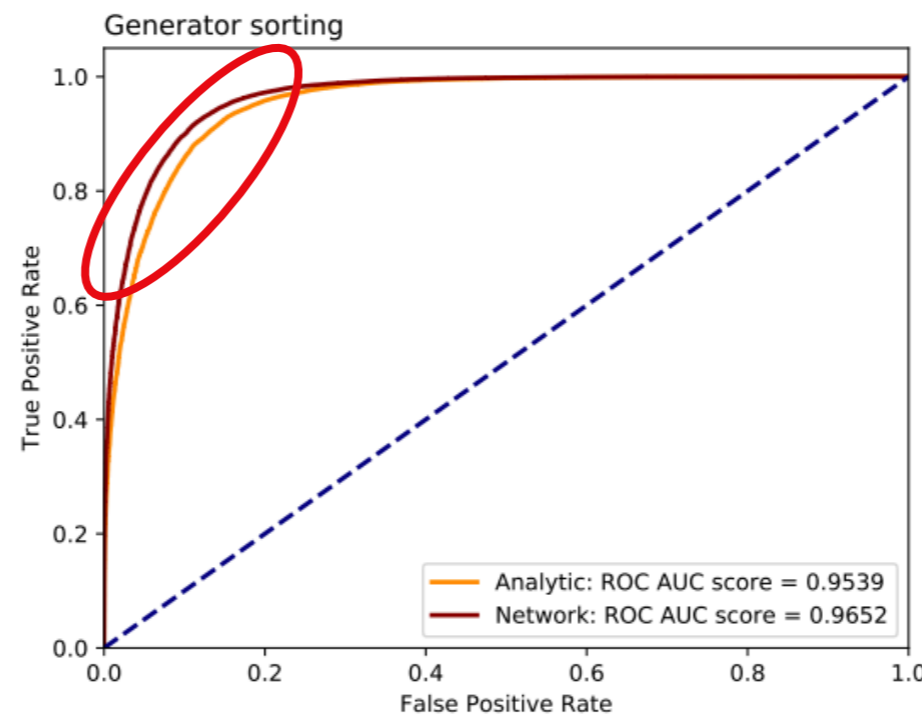
Generator sorting ( $t\bar{t}H$ )

$b_{had}$	3	14	13	0	20	26	0	1	0	2	5	50	1
$lj_1$	1	12	14	0	12	18	0	2	1	2	5	25	1
$lj_2$	1	14	21	0	16	22	0	2	1	1	5	24	1
$bj_1$	2	12	1	49	4	1	0	2	0	45	5	0	1
$bj_2$	2	12	2	50	0	3	0	2	0	43	6	0	1
$lep$	0	11	0	0	18	14	89	0	97	1	0	0	0
$met$	90	24	48	0	10	0	9	77	0	0	60	0	0
$b_{lep}$	1	0	1	0	21	17	1	14	0	5	14	0	94
	1	2	3	4	5	6	7	8	9	10	11	12	13

Improved classification with LBN-reconstructed neutrino momentum

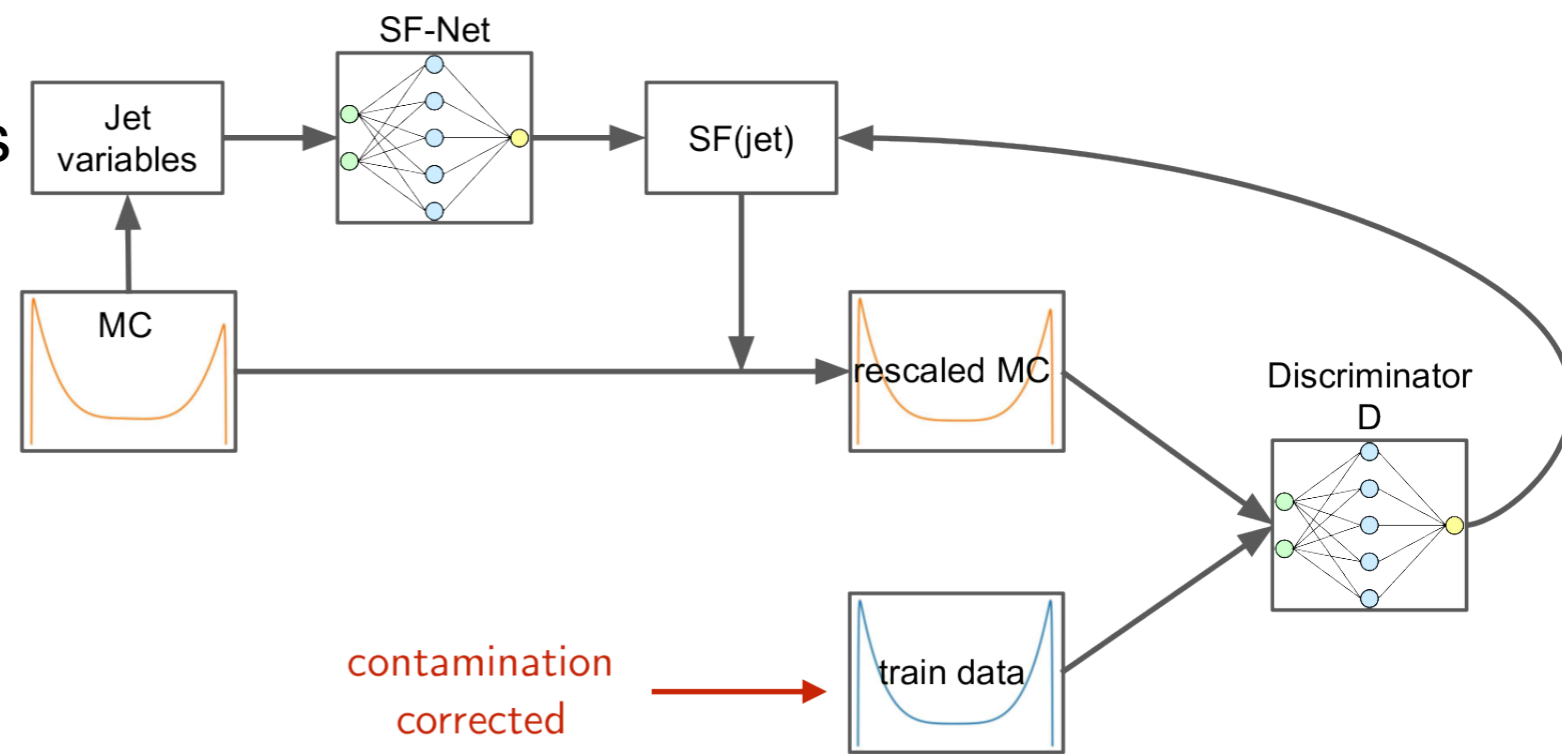
Generator sorting ( $t\bar{t}H$ )

$b_{had}$	0	0	13	0	2	0	1	1	8	0	0	47	2
$lj_1$	0	0	7	0	1	0	1	2	7	0	0	25	2
$lj_2$	0	0	9	0	0	0	1	2	9	0	0	24	2
$bj_1$	0	0	6	47	47	0	1	2	9	1	0	1	3
$bj_2$	1	0	7	53	46	0	1	2	8	1	0	1	3
$lep$	31	0	32	0	1	0	8	52	49	1	99	1	65
$met$	1	0	8	0	1	98	0	29	0	97	0	1	2
$b_{lep}$	66	99	20	0	2	0	88	10	10	0	0	1	22
	1	2	3	4	5	6	7	8	9	10	11	12	13

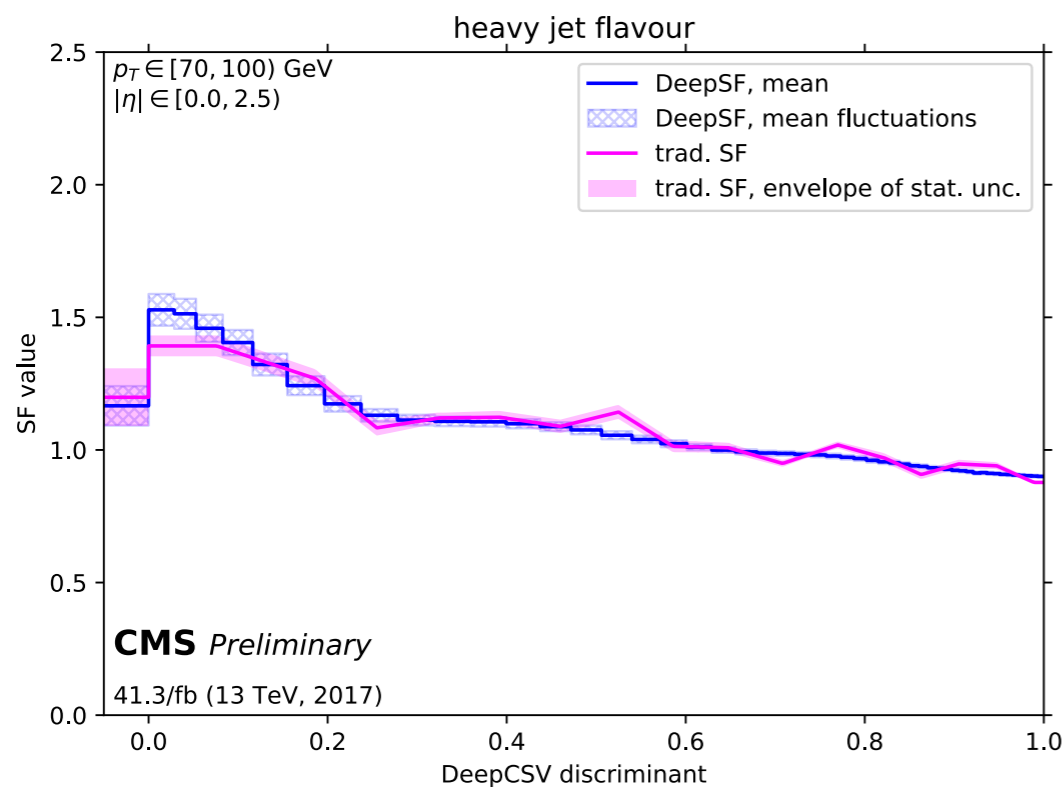


## Erdmann, Fischer, ACAT 2019

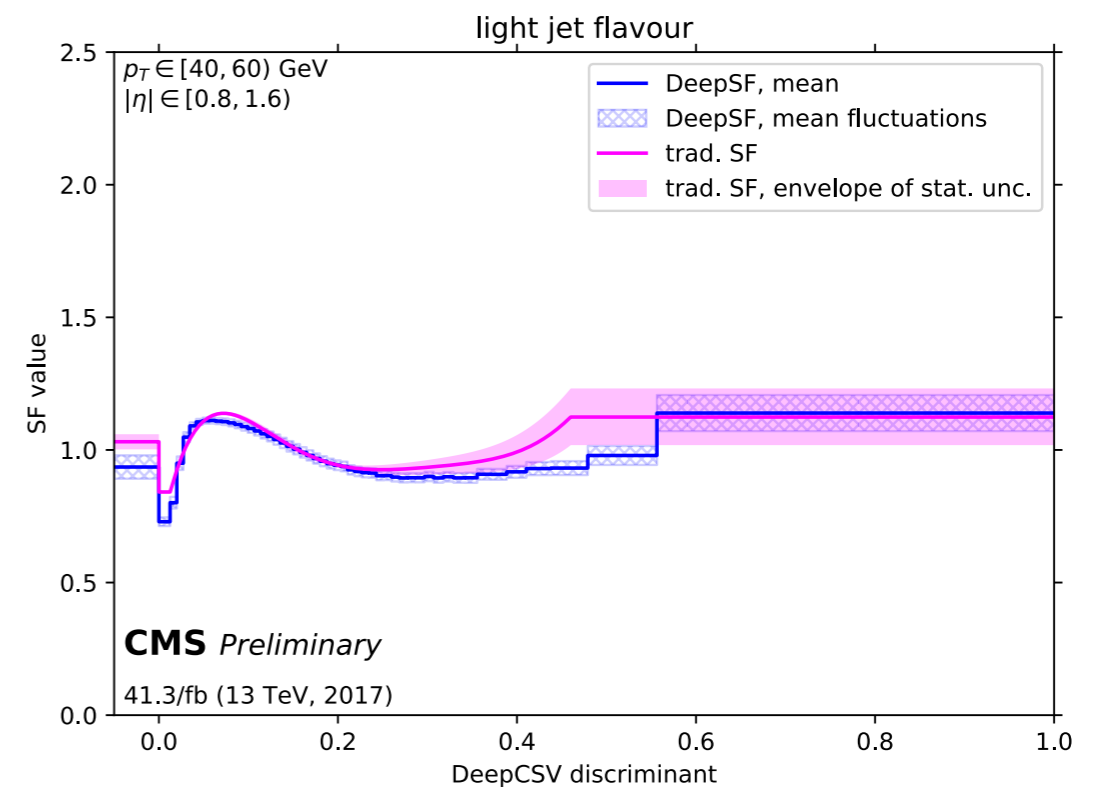
1. SF is calculated with jet variables from MC
2. MC is rescaled with SF
3. Discriminator (adversarial) discr. between data & rescaled MC
4. SF are recalculated with adversarial feedback



### b jets

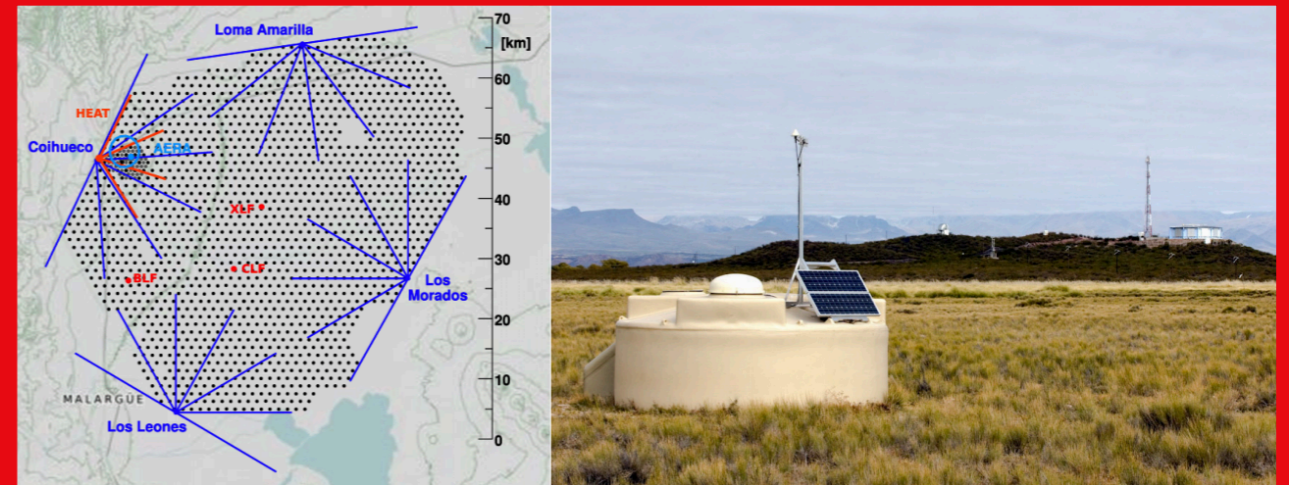


### light jets





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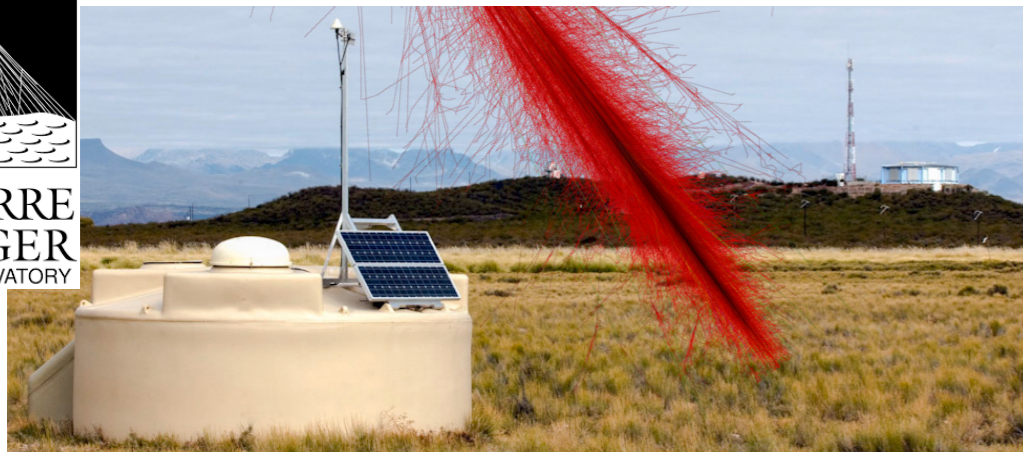
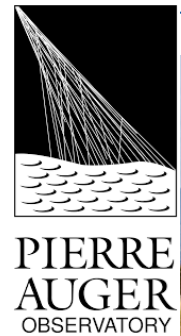


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Both groups work on the VISPA Project:

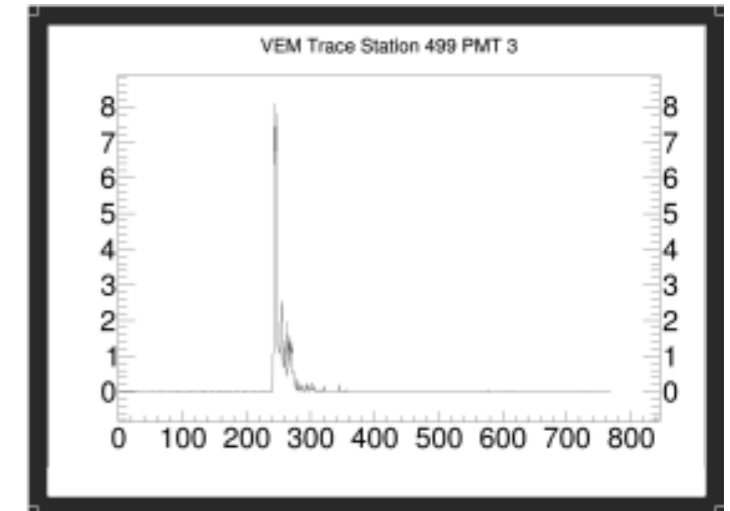
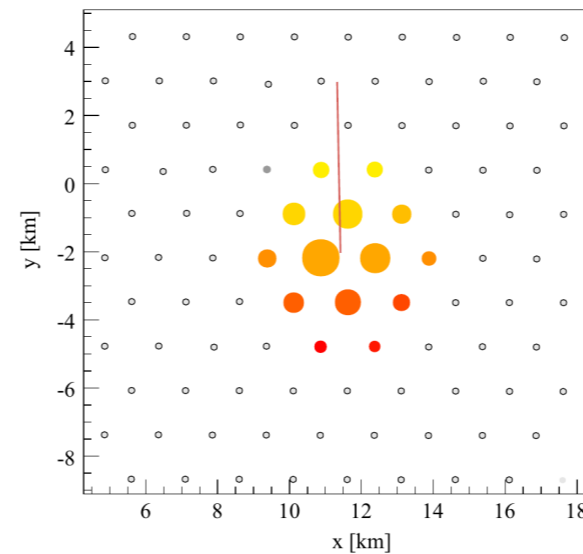
<https://vispa.physik.rwth-aachen.de/>

[j.astropartphys.2017.10.006](https://arxiv.org/abs/j.astropartphys.2017.10.006)



## Pierre Auger Observatory

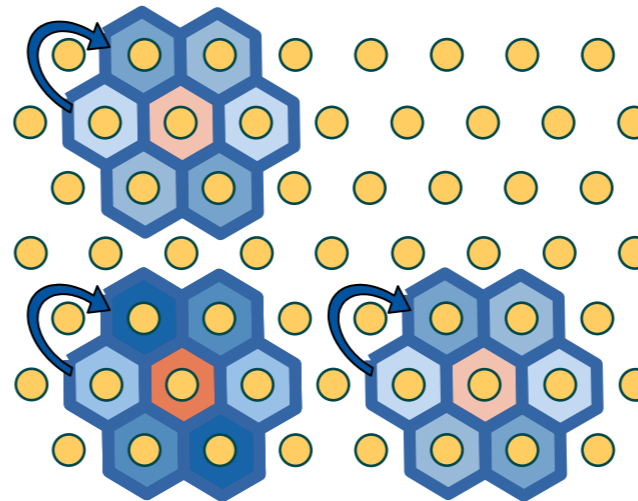
- Detection of cosmic-ray induced air showers
  - 1660 water-Cherenkov stations
  - 27 fluorescence telescopes
- Reconstruction of mass-sensitive information using deep learning
- Model relies on symmetries in data



Hexagonal  
Convolutions



Recurrent  
Networks



"Alexa, turn on  
Welcome Home"

"Alexa, turn on my  
Chill Time"

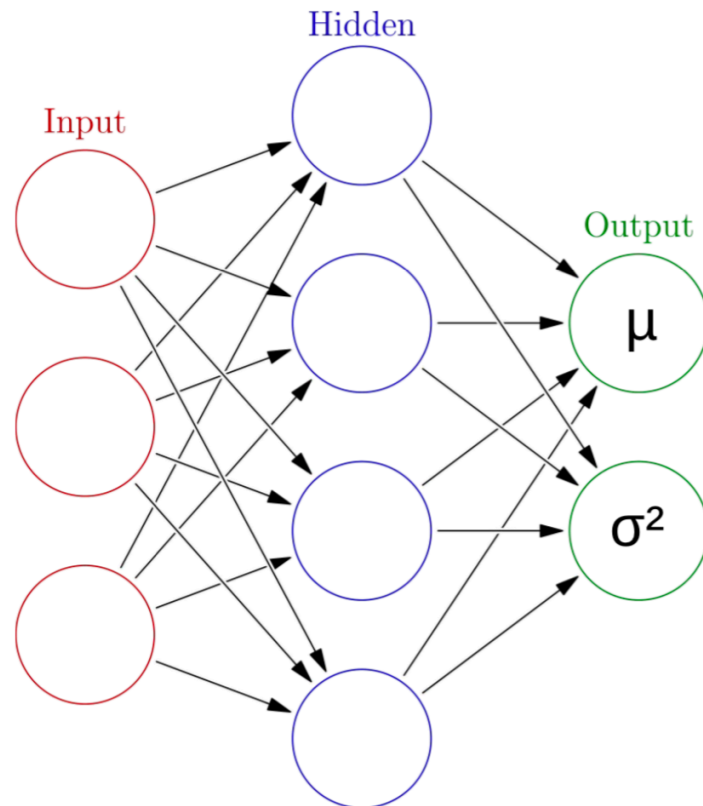
"Alexa, turn off my  
Bedroom Sonos"

"Alexa, turn on  
the TV"



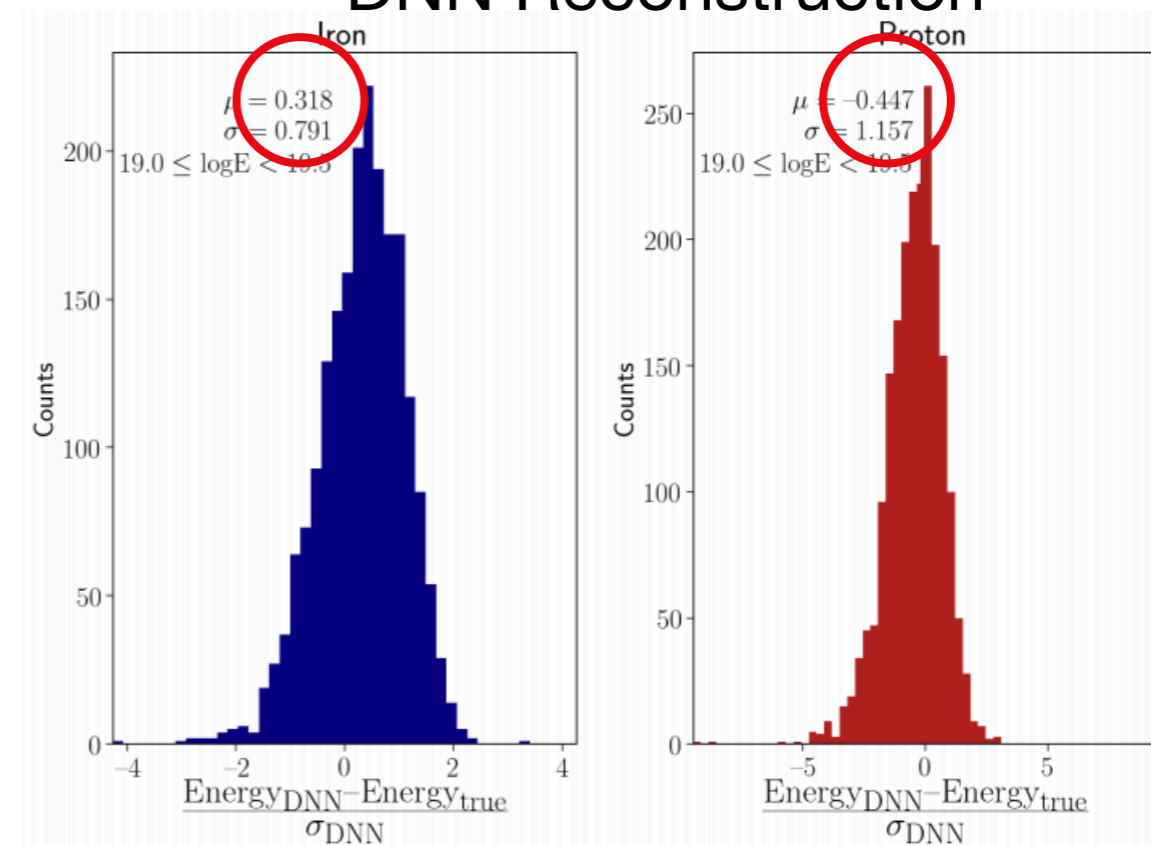
## Straub bachelor thesis, Glombitza

- Allow for estimation of DNN uncertainties
- Assume normal distributed errors  
predict mean and variance
- Extend loss by taking variance into account
- Average over DNN ensemble using Gaussian Mixtures models



$$-\log p_{\theta}(y|x) = \frac{\log \sigma_{\theta}^2(x)}{2} + \frac{(y - \mu_{\theta}(x))^2}{2\sigma_{\theta}^2(x)}$$

## DNN Reconstruction



- Successful application of Deep Learning based algorithms at CMS and Auger
- Interpretable feature engineering with LBN:
  - Classification ttH vs ttbb
  - Neutrino reconstruction for e.g. ttH
- Reinforced particle sorting
- DeepSF: General concept of SF calculation with adversarial training
- Air shower reconstruction:
  - convolution + recurrent
- Uncertainty Estimation for air shower reconstruction with Deep Learning
- VISPA project:
  - First efforts for *Marketplace*
  - Large software environment
  - Access via web browser
  - RWTH setup is backed up by extensive GPU/CPU resources
  - Soon: huge GPU upgrade!

