VBF H(cc) analysis

ANN and decorrelation strategy

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ATLAS EXPERIMENT
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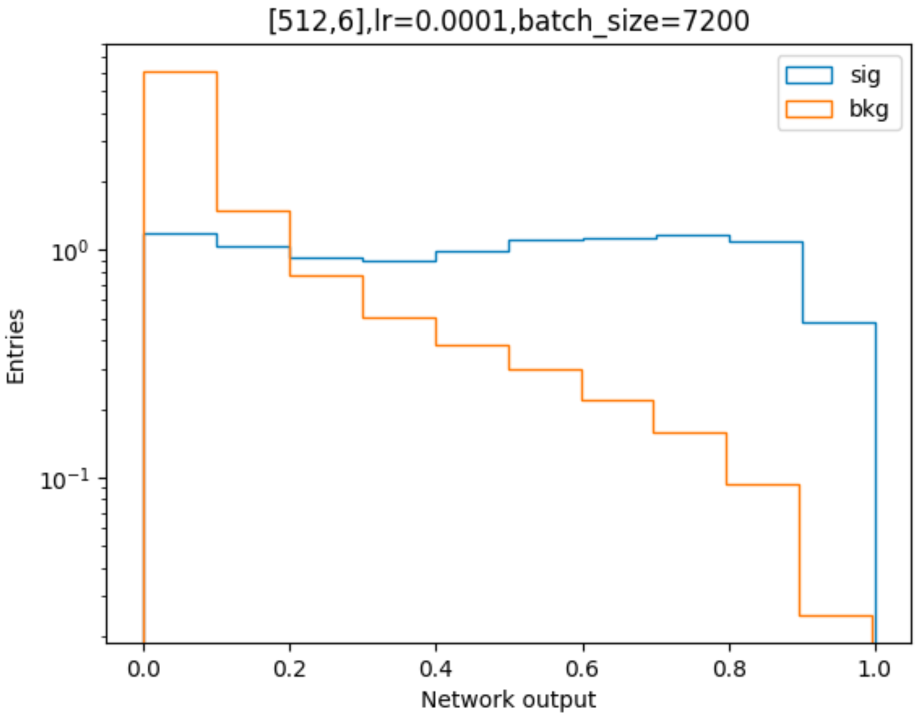
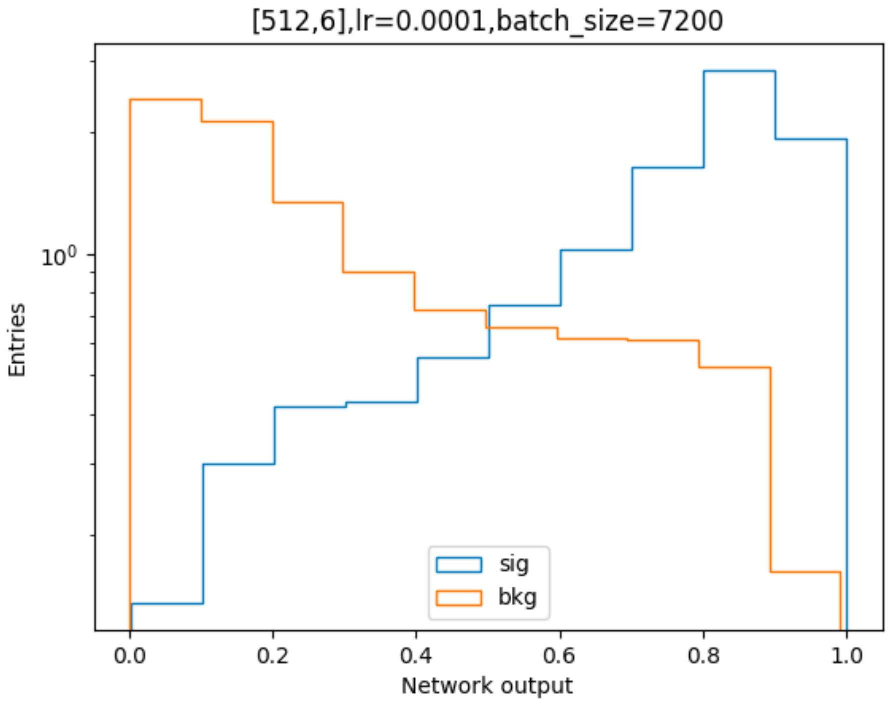
Huge unbalance between signal and background

Total number of train data:	102’618
Total number of validation data	102’938
Fraction of bkg data in training dataset:	0.791
Fraction of bkg data in validation dataset:	0.789
Fraction of sig data in training dataset:	0.209
Fraction of sig data in validation dataset:	0.211



Unbalanced data

Total number of train data:	42’878
Total number of validation data	102’938
Fraction of bkg data in training dataset:	0.500
Fraction of bkg data in validation dataset:	0.789
Fraction of sig data in training dataset:	0.500
Fraction of sig data in validation dataset:	0.211



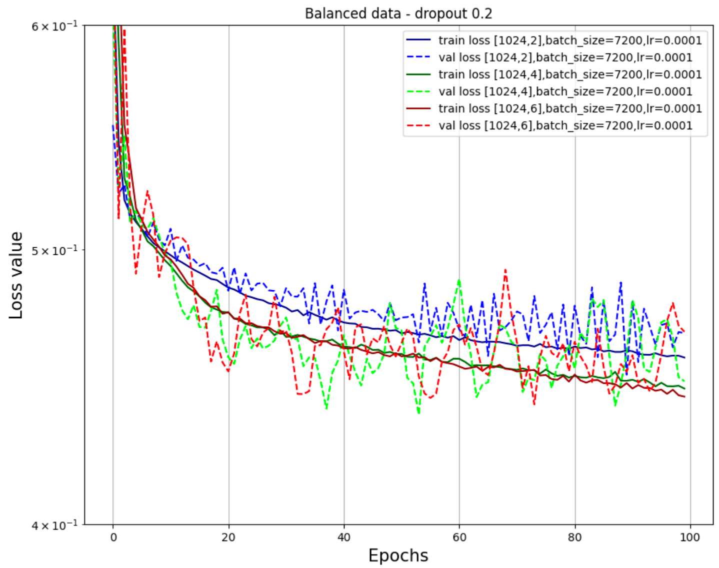
Balanced data on train dataset

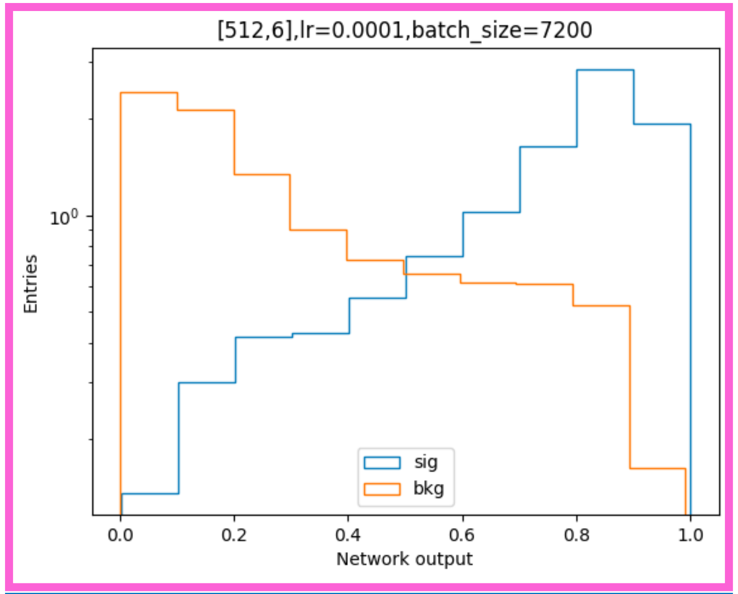
Pytorch network
- Sample: cc
- Epochs = 100
- Mod = 0
- Dropout = 0.2

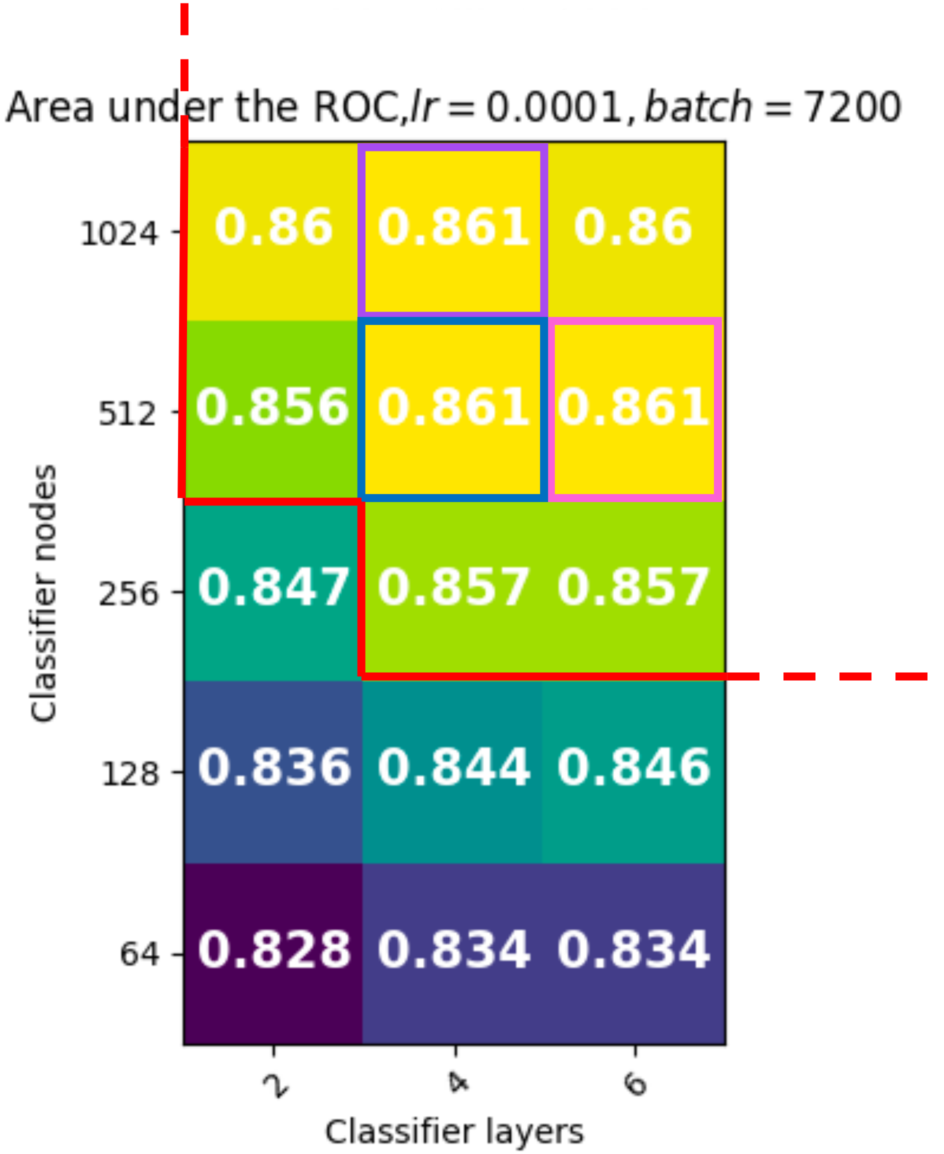
Downsampling of the training dataset.

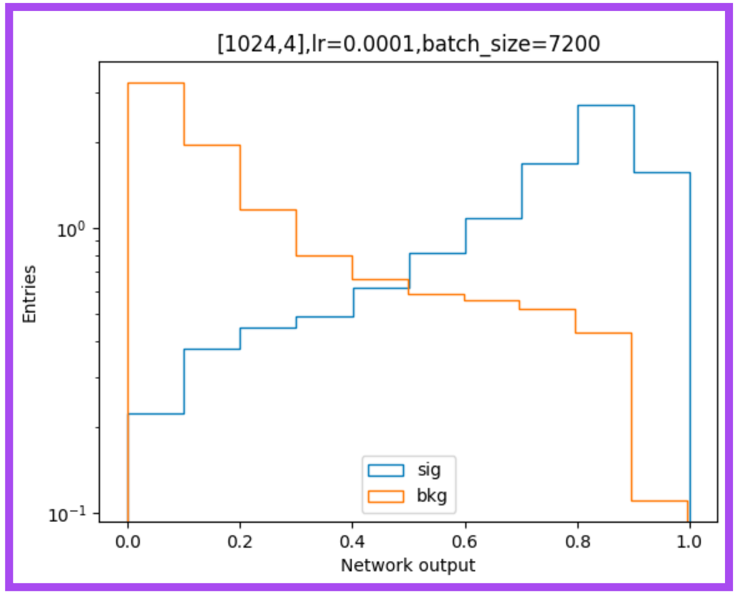
60% reduction of the training dataset.

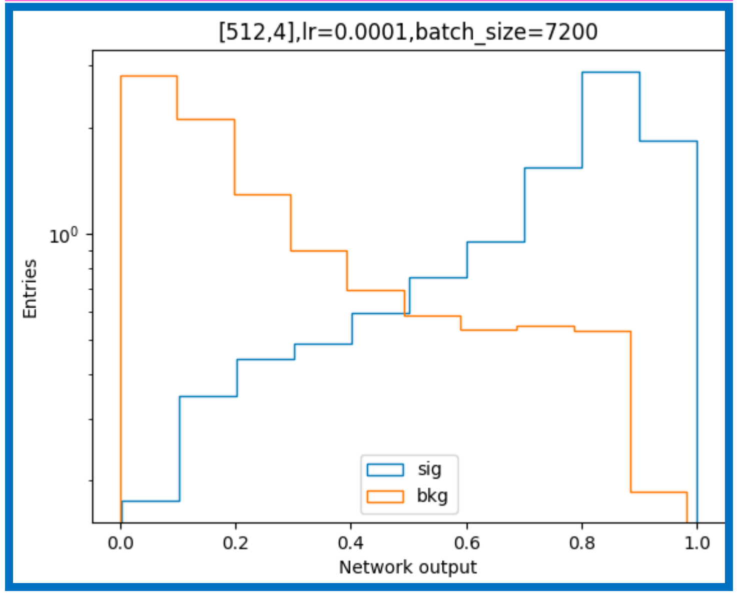
Balanced data results



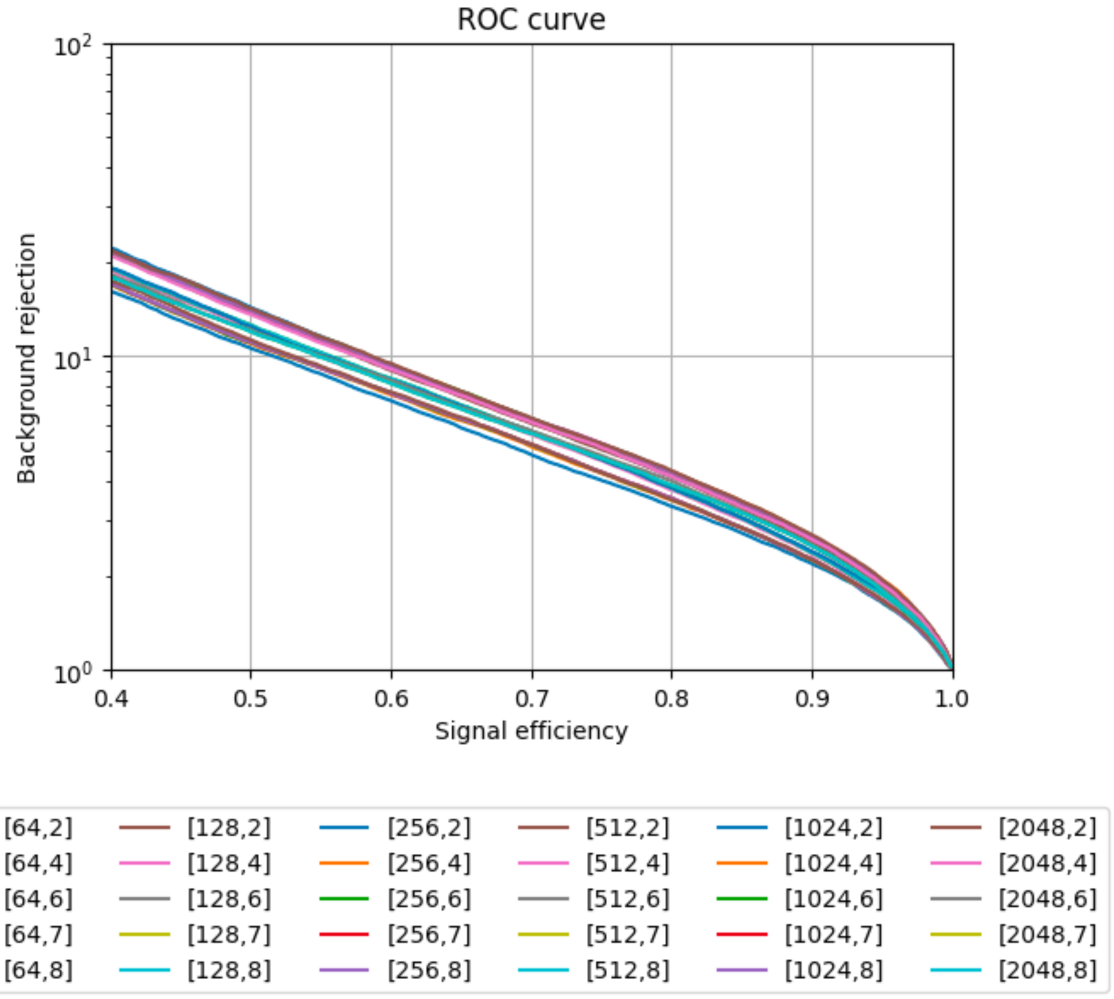


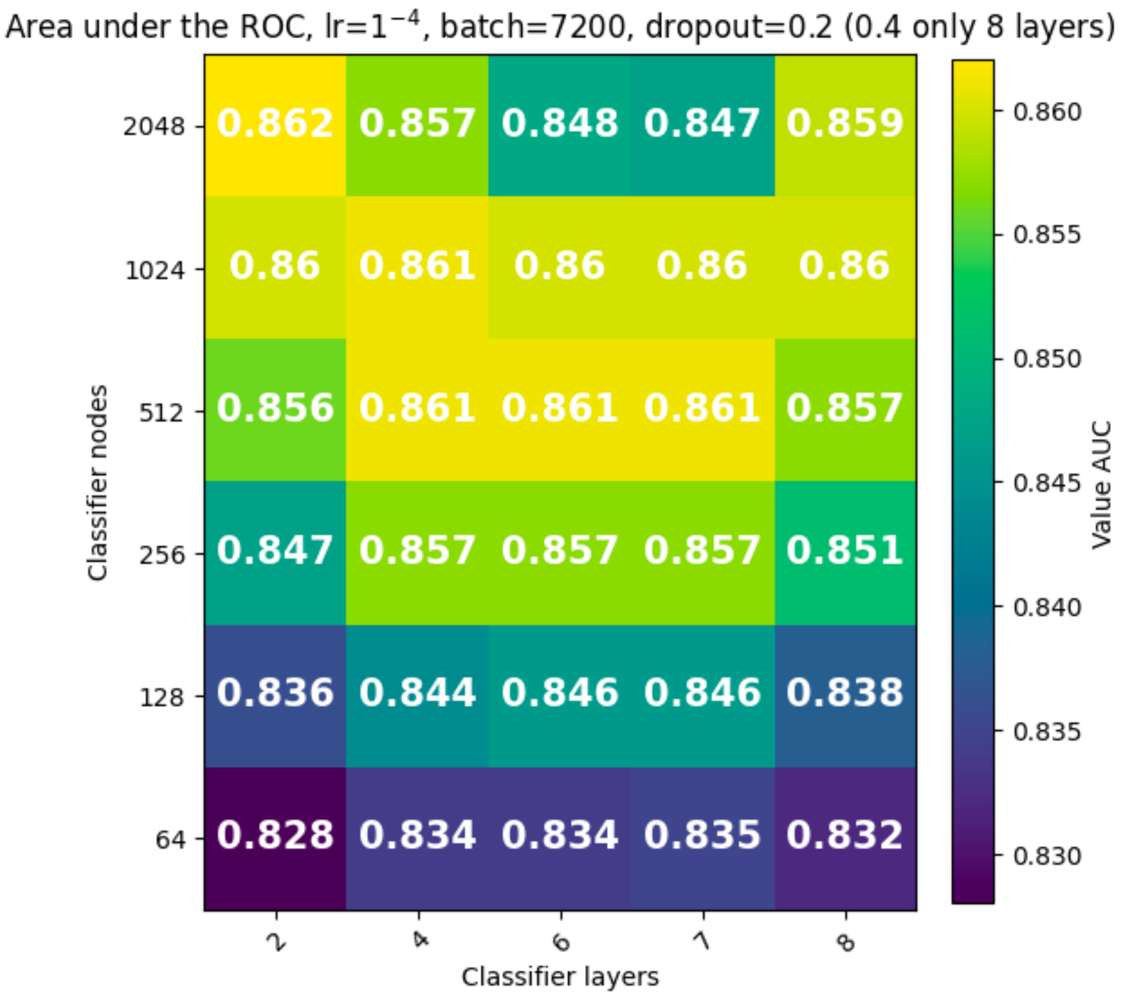






Extended results





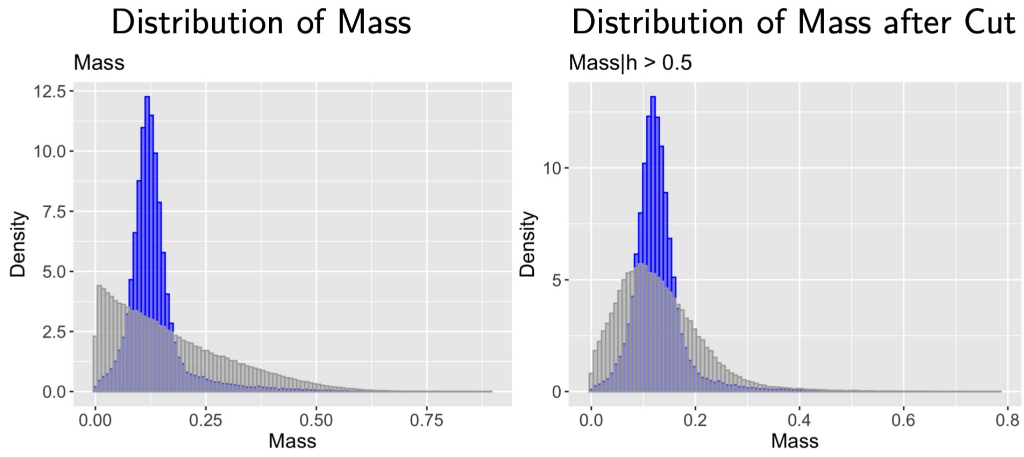
Conclusion

- Increase the number of events for training
- Overfitting under control with the dropout and large batch size
- Study on the batch size as Luke suggested

Decorrelation strategy

Correlation metrics

GOAL: measure how the cut on the network output affects the background distribution of c/b- tagged jets invariant mass



[1]

The Jensen-Shannon

$$JSD(P||Q) = \frac{1}{2}(KL(P||M) + KL(Q||M))$$ [2]

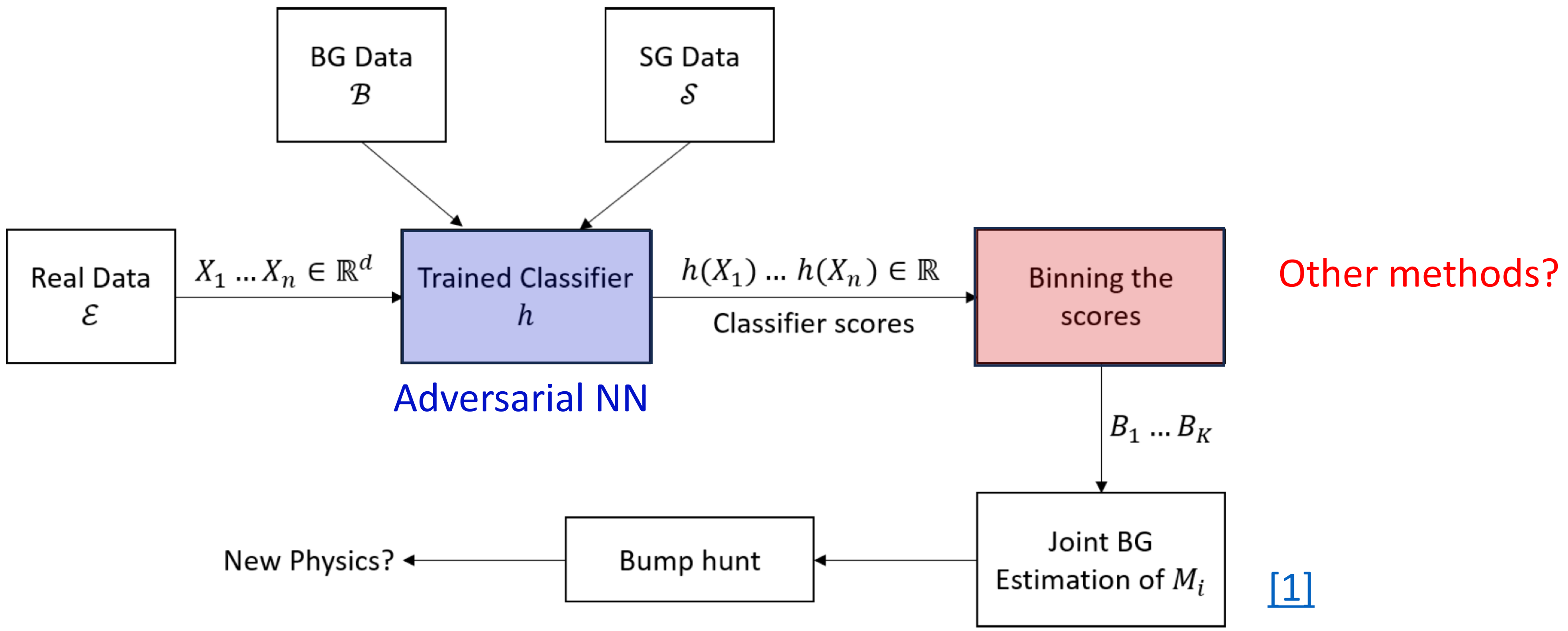
with $M = \frac{P+Q}{2}$ and KL the Kullback-Leibler divergence

In our case, the divergence is used to measure the difference between the normalised mass distributions of the background jets passing and failing, respectively, a given jet tagger cut:

$$JSD(P||Q) = JSD\left(\frac{N_{bkg}^{pass}(m)}{\sum_i N_{bkg}^{pass}} || \frac{N_{bkg}^{fail}(m)}{\sum_i N_{bkg}^{fail}}\right)$$

Decorrelation methods

GOAL: use a decorrelation method that doesn't affect the network classification performance



Make cuts on transformed classifier output $T(h(X))$, where $T(h(X))$ is independent of the protected variable $m_{bb/cc}$ for background data.

Optimal Transport (OT) [3]

GOAL: learn a monotonic transformation $\mathrm{T}(\cdot\,|c)$ between the input feature space $Q(\cdot\,|c)$ and a target feature space $\mathrm{P}(\cdot)$

A solution to this problem is the optimal transport map that gives us:

$$\nabla_x g(Q;\theta) = P \quad \& \quad \nabla_x f(P;\theta) = Q$$

Where θ represents the trainable parameters of the network and f, g are two convex functions.

The problem is solved by finding f, g → Input Convex Neural Networks [4]

The ICNN gives the transport function $\nabla_x f(x, c; \theta)$ with $f(x, c; \theta)$ a convex function in x but not in c.

Benefits:

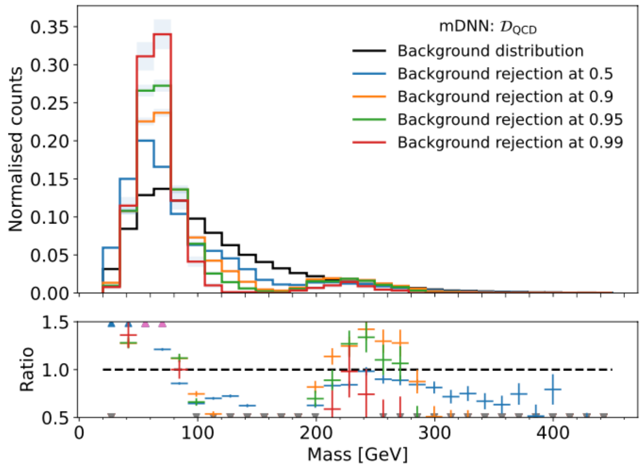
1. We make the output of the classifier INDEPENDENT from the invariant mass.
2. We do not affect the classifier's performance.

Results [3]

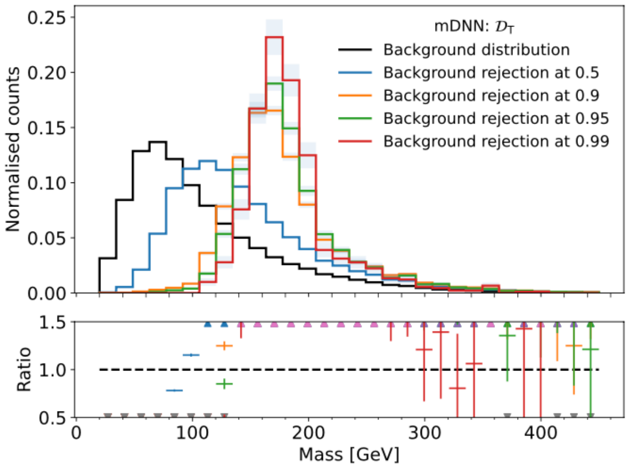
$$D_{QCD} = \frac{p_{QCD}}{p_T + p_{VB}}$$

$$D_T = \frac{p_T}{p_{QCD} + p_{VB}}$$

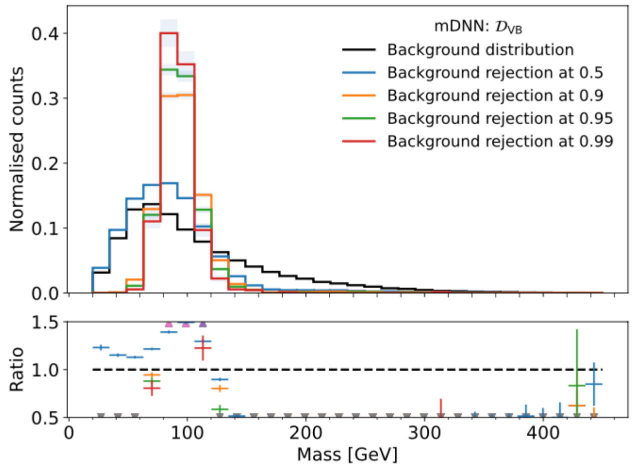
$$D_{VB} = \frac{p_{VB}}{p_{QCD} + p_T}$$



(a) $\mathcal{D}_{\mathrm{QCD}}$ projection



(b) $\mathcal{D}_{\mathrm{Top}}$ projection



(c) $\mathcal{D}_{\mathrm{VB}}$ projection

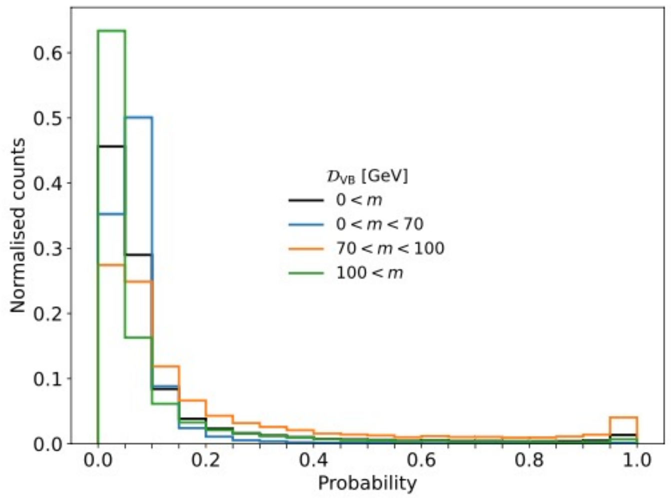
Jet generated from quark/gluon of QCD background

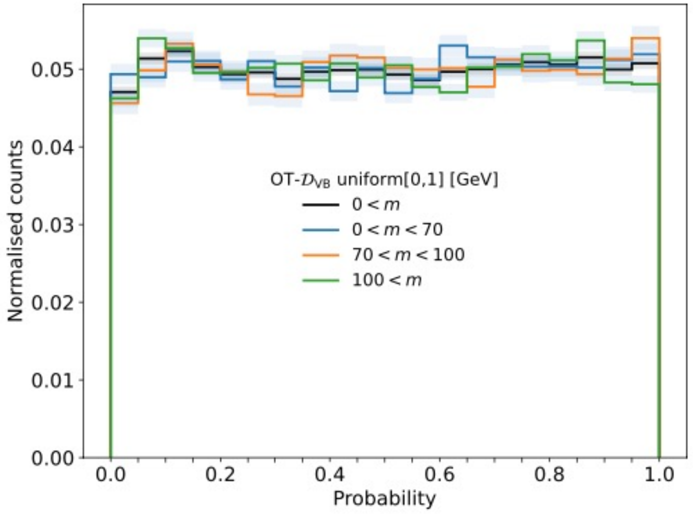
Jet generated from top quarks

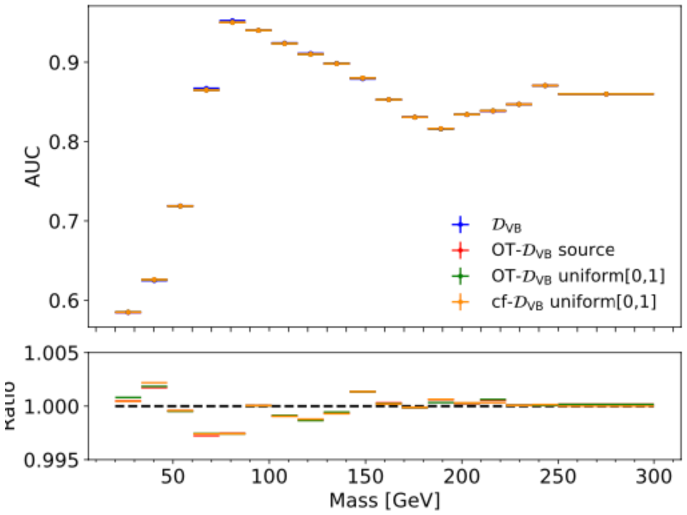
Jet generated from vector bosons

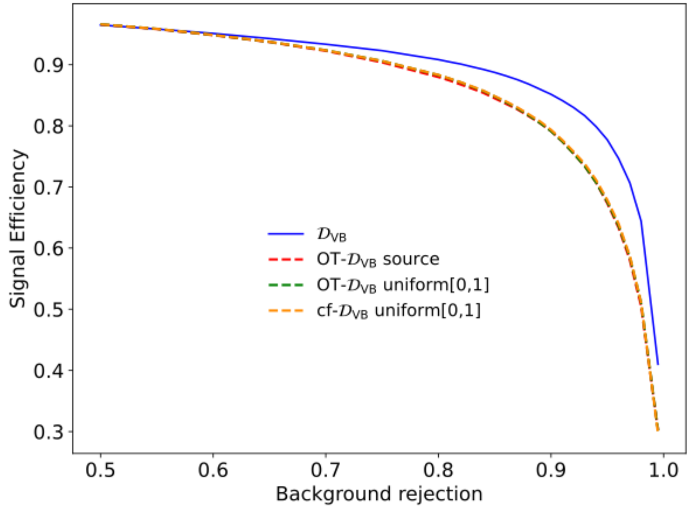
Classifier network

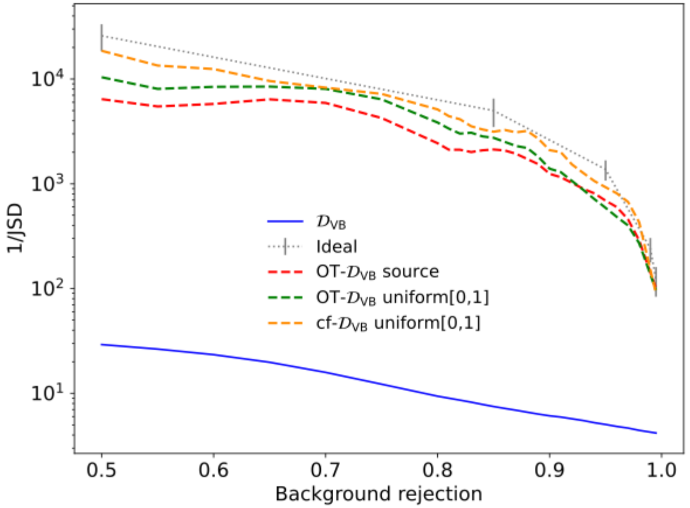
Decorrelation [3]











Conclusion

Backup

Features description

Input features (12)	Description
m_{jj}	Invariant mass of the VBF jet pair
$p_{T,jj}$	Transverse momentum of the VBF jet pair
$p_T^{balance}$	Ratio of the vectorial and scalar sums of the transverse momenta of c_1 , c_2, j_1 and j_2.
$(p_T^{j_1} - p_T^{j_2})\ (p_T^{j_1} + p_T^{j_2})$	Asymmetry in the VBF jet transverse momenta
$\Delta\eta(cc, jj)$	Separation in η between the c-tagged jet pair and the VBF jet pair
$\Delta\phi(cc, jj)$	the separation in ϕ between the c-tagged jet pair and the VBF jet pair
$\tan^{-1}\left(\tan\left(\frac{\Delta\phi(cc)}{2}\right) / \tanh\left(\frac{\Delta\eta(cc)}{2}\right)\right)$	the measure of the relative angle of η and ϕ between the two c-tagged jets.
n_{jets}	the number of jets with p_T > 20 GeV and $\|\eta\|$ < 4.5
$\min \Delta R(j_{1(2)})$	the minimum separation in R between the (sub)leading VBF jet and any jet in the event that is not a part of the b-tagged jet pair or VBF jet pair
$N_{trk}^{j_{1(2)}}$	the number of tracks matched to the (sub)leading VBF jet.

Pytorch Network for Classification task

```python
## Dataset preprocessing
batch_size = int(batch)
scaler = StandardScaler()
X_train=scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)


traindataset_cl = myDataset(X_train,y_train)
testdataset_cl = myDataset(X_test,y_test)


train_loader_cl = torch.utils.data.DataLoader(dataset=traindataset_cl,
                                              batch_size=batch_size,
                                              shuffle=True)
test_loader_cl= torch.utils.data.DataLoader(dataset=testdataset_cl,
                                            batch_size=batch_size,
                                            shuffle=True)
```

Scaling on the whole dataset *(TensorFlow: scaling on the batch with BatchNormalization layer)*

$$X' = \frac{X - mean}{\sigma}$$

$mean$: mean of the training sample → center the data before scaling
σ: unit standard deviation
[sklearn.preprocessing.StandarScaler]()

```python
# Neural Network with customizable number of layers and nodes

class NeuralNet(nn.Module):
    '''
    A DL model with customizable layers and nodes.
    '''
    def __init__(self, input_size, layers):
        super(NeuralNet, self).__init__()
        self.layers = nn.ModuleList()
        last_size = input_size
        for layer_size in layers:
            self.layers.append(nn.Linear(last_size, layer_size))
            last_size = layer_size
        self.layers.append(nn.Linear(last_size, 1))
        self.relu = nn.ReLU()

    def forward(self, x):
        for layer in self.layers[:-1]:
            x = layer(x)
            x = self.relu(x)
        x = self.layers[-1](x)
        return x
```

`Input: Number of features. nodes per layer`
`Output: Single output for binary classification`

```python
model = NeuralNet(len(X_train[0]), [256,256,256])
model
```
✓ 0.0s

```
NeuralNet(
  (layers): ModuleList(
    (0): Linear(in_features=12, out_features=256, bias=True)
    (1-2): 2 x Linear(in_features=256, out_features=256, bias=True)
    (3): Linear(in_features=256, out_features=1, bias=True)
  )
  (relu): ReLU()
)
```

Loss function
Extended results