Machine Learning Algorithms and Particle Physics Searches

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Based on JHEP 01 (2021) **076**, JHEP 01 (2022) **154** and EPJC **82**, 826 (2022)

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3rd Workshop on Compact Objects, Gravitational Waves and Deep Learning - University of Minho

The Standard Model (**SM**) is the basis by which all subatomic interactions are described. **However**, some unanswered questions remain ...

- Inability to explain the observed particle spectra (family replication, masses and couplings hierarchies, neutrino masses);
- Lack of a Dark matter (**DM**) candidate;
- Hiearchy problem;
- $(g-2)_\mu$ anomaly, R_{K,K^*} anomalies, matter/anti-matter asymmetry;
- Naive quantization of gravity leads to a non-renormalizable theory, etc;

A simple observation $\Longrightarrow$ **SM is not the ultimate theory**

The story of SM is incomplete, **but we have not found anything new!** That means

- New physics is **heavy**, i.e., of the TeV-PeV order (or beyond);
- New physics is **weakly coupled to the SM**, i.e., low couplings;

As constraints on new physics become increasingly tighter, computational resources become more and more important.

We need

- **Powerful, reliable and proven** methods to deal with weak signals in the ocean of the SM background;
- The methods **must be comfortable** in dealing with **large** datasets.

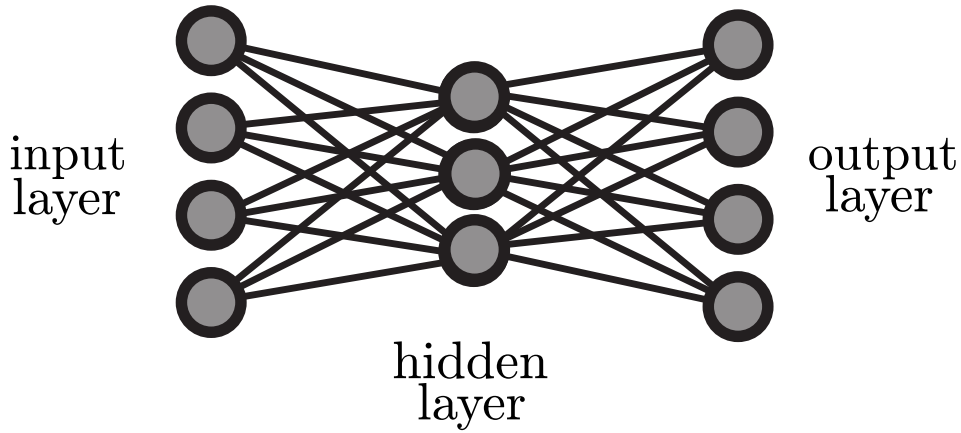
Machine learning to the rescue !

Deep Learning (DL) → Extracting high-level features from input data

Universal approximation theorem [Kurt Hornik, Neural Networks. **4** (2): 251–257]

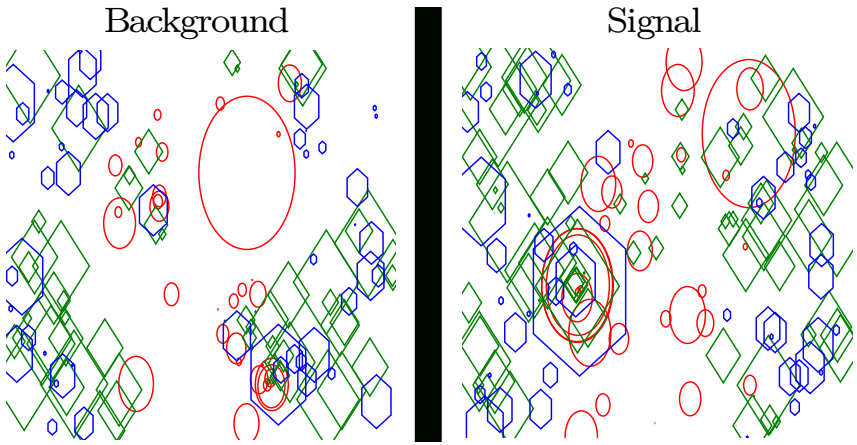
⇓

Approximate any function, for an arbitrary number of layers!



Detects small deviations in classes ⇒ Perfect for **classfication tasks**!

(a) For cats and dogs



(b) For detector images

```
neurons = 512
activ = 'sigmoid'
initl = 'RandomNormal'
loss  = 'binary_crossentropy'
metric = 'accuracy'
a1    = 1.e-7
a2    = 1.e-7
alp   = 0.1
nb_classes = 5

def NN_model():
    model = Sequential()
    #Input layer
    nn = model.add(Dense(neurons, input_dim=X_train.shape[1], kernel_initializer=initl,
                   kernel_regularizer=regularizers.l1_l2(l1=a1, l2=a2)))
    model.add(Activation(activ))

    #2nd layer
    model.add(Dense(neurons, kernel_initializer=initl,
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    #3rd layer
    model.add(Dense(neurons, kernel_initializer=initl,
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    #4th layer
    model.add(Dense(neurons, kernel_initializer=initl,
              kernel_regularizer=regularizers.l1_l2(l1=a1, l2=a2)))
    model.add(Activation(activ))

    # Output layer
    model.add(Dense(nb_classes, init=initl , activation=activ ))

    model.compile(loss=loss, optimizer=Adam(), metrics=[metric])
    return model
```

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- Number of neurons: **Arbitrary**;
- Activation functions: **10** + in `Keras` (with tunable parameters);
- Initializers: **10** + in `Keras` (with tunable parameters);
- ...

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A lot of free parameters to tune in architectural building

⇓

Calls for some optimization procedure → **Genetic algorithms!**

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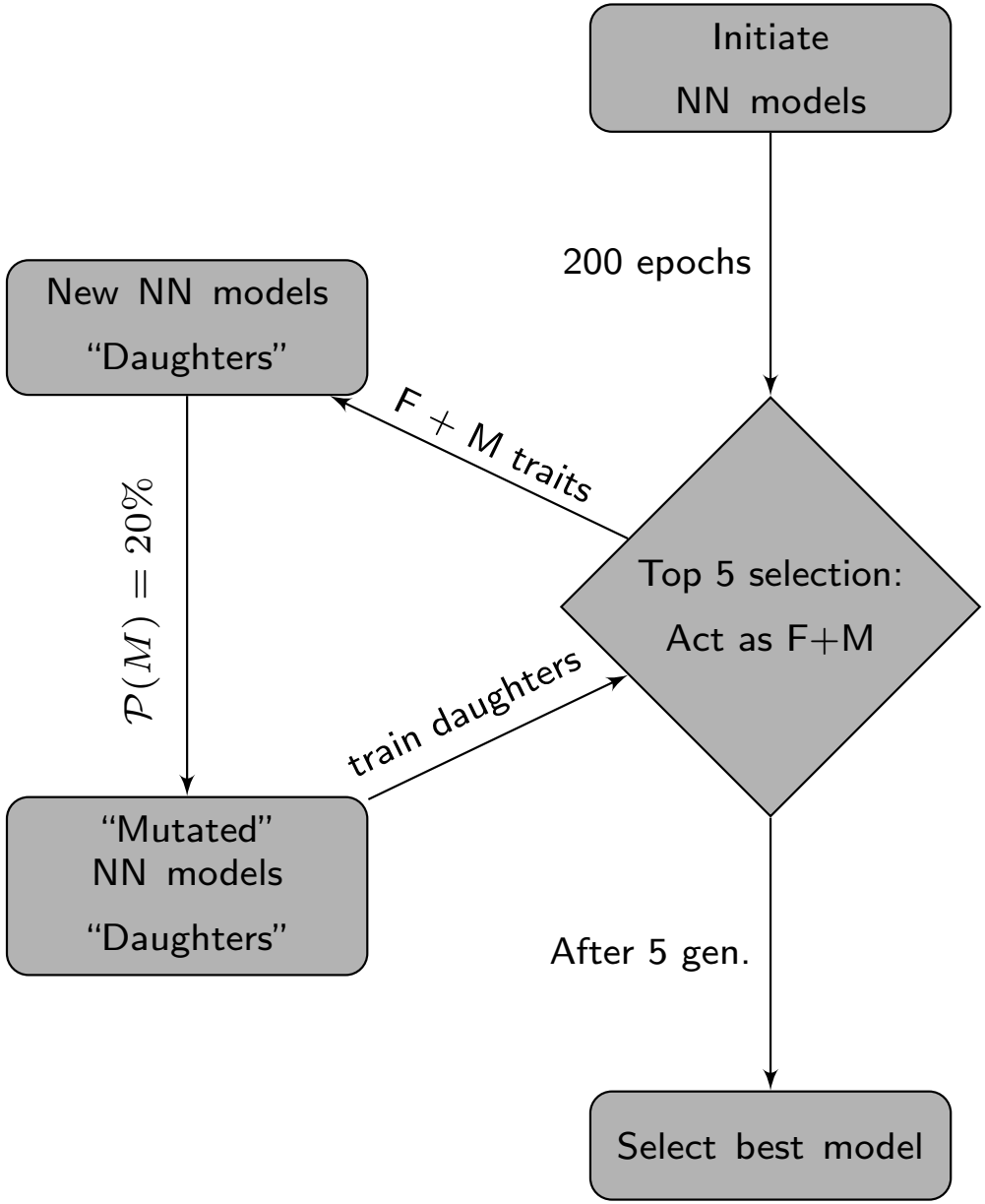
Algorithm Felipe F. Freitas et. al JHEP 01 (2021) 076:

- Randomly generate N models, by pooling a list of hyper-parameters;
- Train: Top 5 models are used to breed daughter networks;
- Add mutation probability. Train daughters and iterate the cycle.

Nice **advantages**:

- Simplifies network construction. Simple way to find the best hyperparameters;
- Straightforward way to maximize distinct metrics.



The best neural model is chosen based on two distinct metrics

- Asimov significance defined as

$$\mathcal{Z}_A = \left[2 \left((s+b) \ln \left(\frac{(s+b)(b+\sigma_b^2)}{b^2 + (s+b)\sigma_b^2} \right) - \frac{b^2}{\sigma_b^2} \ln \left(1 + \frac{\sigma_b^2 s}{b(b+\sigma_b^2)} \right) \right) \right]^{1/2}$$

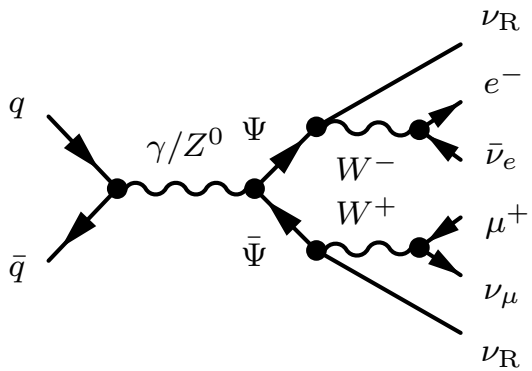
  Loss function is defined as $L = 1/(\mathcal{Z}_A + \epsilon)$. ϵ regularizes the loss function.
  Adam Elwood and Dirk Krücker arXiv:1806.00322

- Accuracy with binary cross-entropy loss function

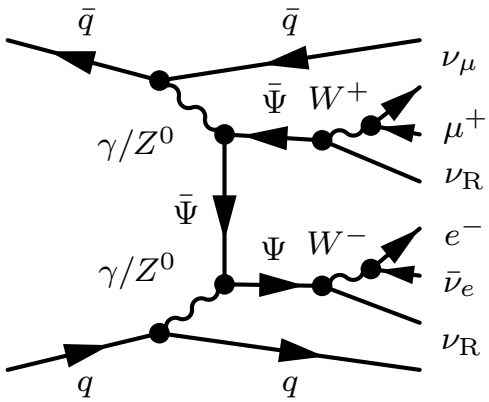
$$L = -\frac{1}{N} \sum_{i=1}^{N} y_i \log(p_{\hat{y}_i}) + (1 - y_i) \log(1 - p_{\hat{y}_i}),$$

  with N being the number of points, y the ground truth label (0 if background and 1 if signal) and p_{y_i} the probability of being signal.

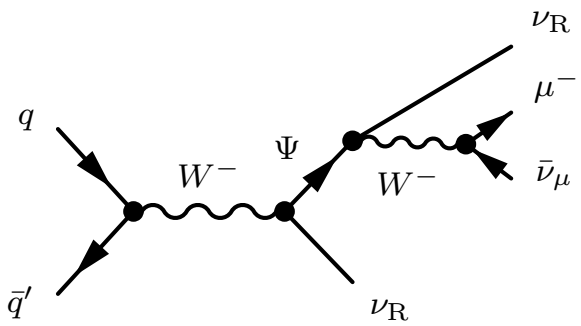
Single and pair-production topologies at the LHC. ν_{R} in the keV range and acts as missing energy.



(a) ZA topology



(b) VBF topology



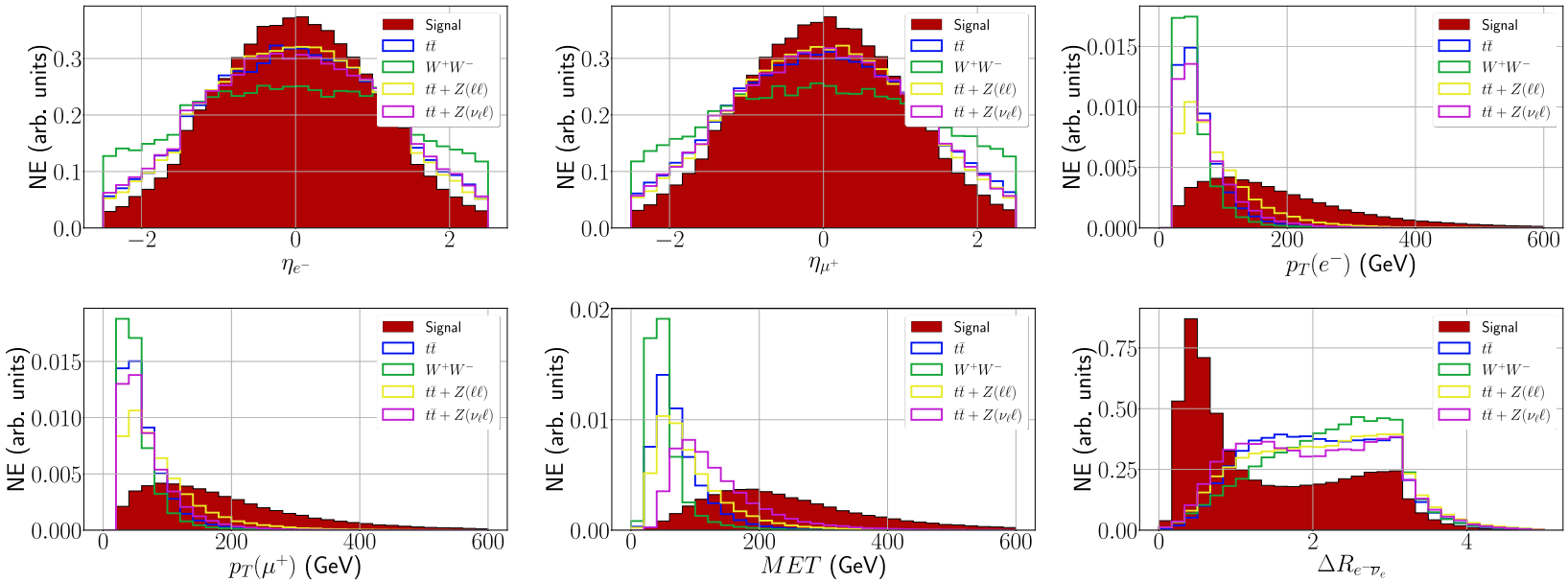
(c) VLBSM topology

For simplicity, we consider flavour opposite final states. Event selection via simple cuts:

1. Charged leptons with $p_T > 25$ GeV and $|\eta| \leq 5$;
2. Missing transverse energy $\not{E}_T > 15$ GeV;
3. Jets: $\Delta R = 1.0$, $p_T > 35$ GeV and $|\eta| \leq 5$.

Event generation flow: `SARAH` $\rightarrow$ `MadGraph` $\rightarrow$ `Pythia8` $\rightarrow$ `Delphes` $\rightarrow$ `ROOT`.

From paper: Phenomenology of vector-like leptons with Deep Learning at the Large Hadron Collider. **J. Gonçalves**, Felipe F. Freitas, António P. Morais, Roman Pasechnik. doi: 10.1007/JHEP01(2021)076



Feed the neural net high-level kinematics (mass distributions, pseudorapidity, transverse momentum, etc) for signal/background topologies.

Some cuts may be imposed to reduce backgrounds $\rightarrow$ **Unbalanced datasets!**

- Generate more Monte-Carlo: **Computational inefficient**;
- Oversample minority classes (e.g. `SMOTE` algorithm N. V. Chawla et. al JAIR: Vol 16, Issue 1, Jan. 2002);

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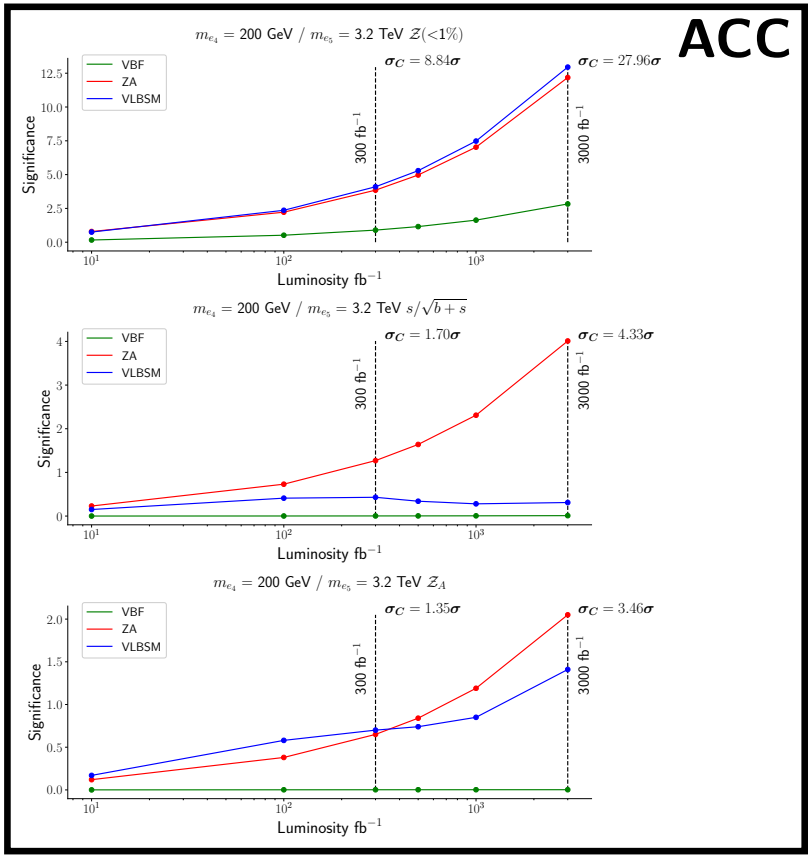

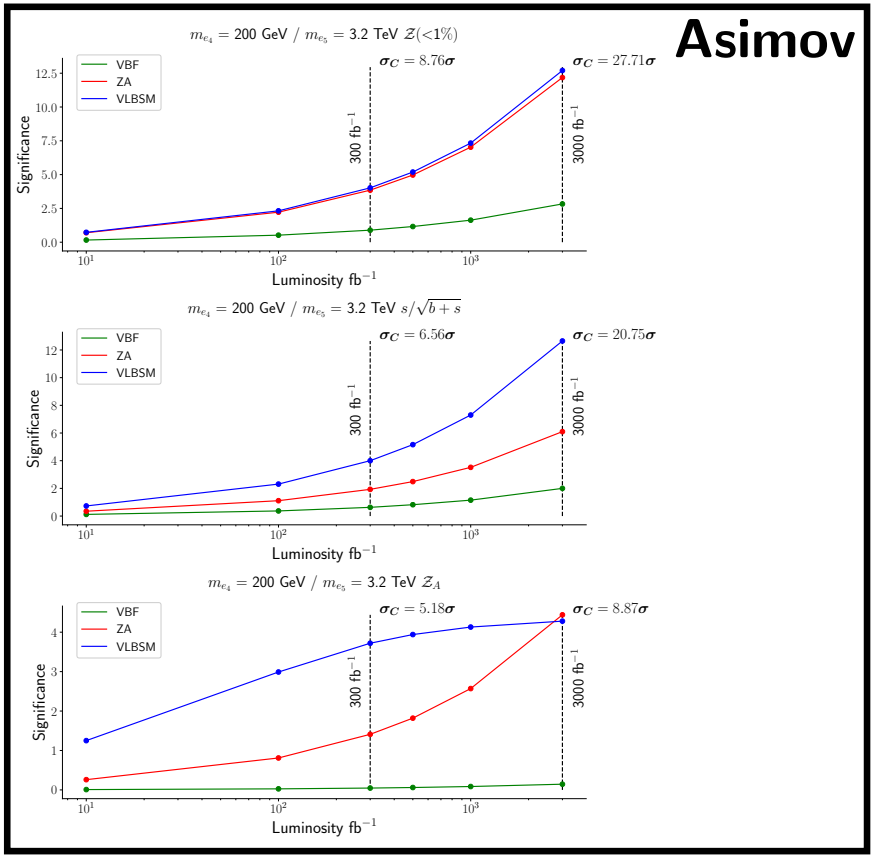

- Significance as a function of luminosity. $300\ \mathrm{fb}^{-1} \rightarrow$ Run-III;
- Utilizing the Asimov metric in the genetic algorithm, we can already obtain results above 5σ **for all** three metrics. We can **already probe them** at run-III of the LHC.

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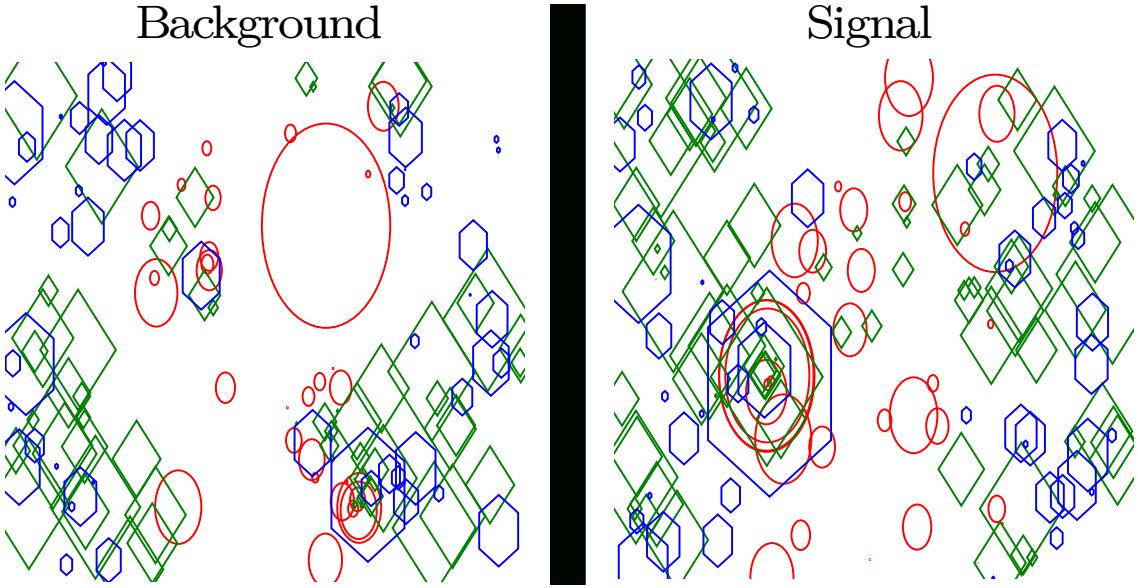
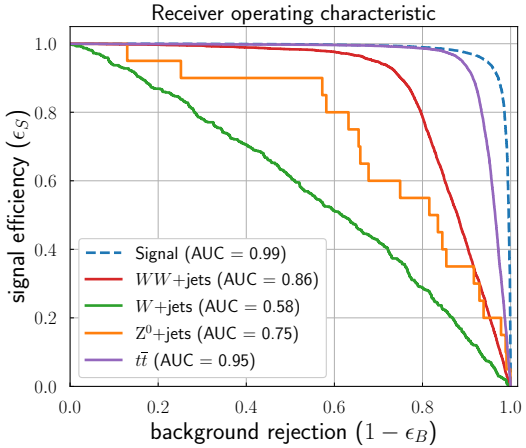


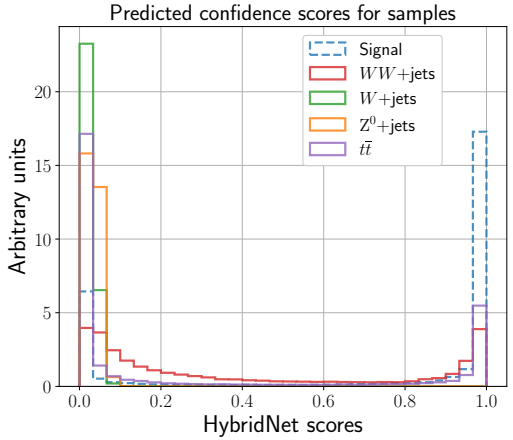
New physics at TeV order $\rightarrow$ Highly boosted decay products that needs to separated from multijet background at hadron colliders;

Jet Images: Associate energy deposited in the calorimeter with a pixel in the (η, ϕ) plane [Luke de Oliveira et. al JHEP 07 (2016) 069].

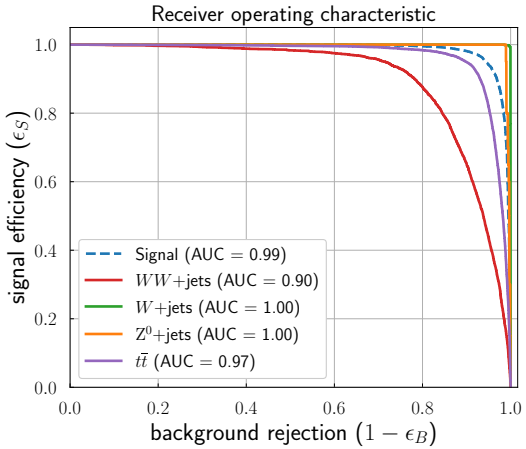
- Enhance classification with **jet kinematics** (multiplicity, mass, ΔR, ...);
- **Abstract Images**: Richer substructure;
- We have obtained efficiencies **greater** than only using kinematic data [Felipe F. Freitas et. al EPJC **82**, 826 (2022)].

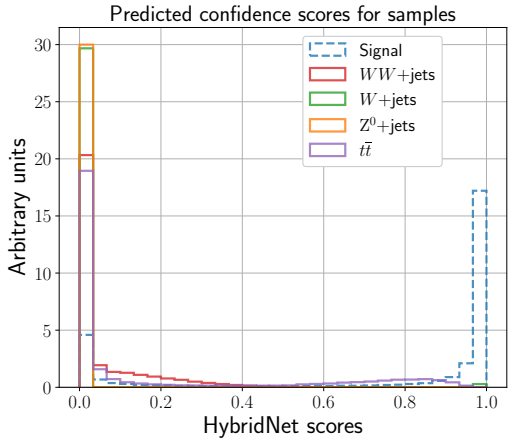
From paper: Phenomenology at the large hadron collider with deep learning: the case of vector-like quarks decaying to light jets. **J. Gonçalves**, Felipe F. Freitas, António P. Morais, Roman Pasechnik. doi: 10.1140/epjc/s10052-022-10799-8



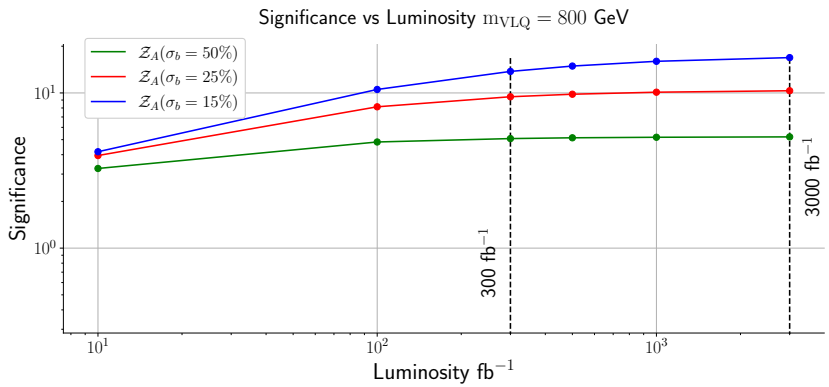


(d) Kinematic





(e) Kinematic + Abstract Images



1. Focusing on VLQ signatures for **decays into light jets**.
2. Use of **Abstract Images** heavily improves the **accuracy** of the neural network
3. Can exclude VLQs at the high-luminosity/run-III phase of the LHC, even for systematics of **50% !**

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To summarize . . .

- I have discussed how **Deep learning** algorithms can be used in collider phenomenology of generic BSM models;
- I shown these tools in action for various BSM models, including models with **vector-like fermions** of both quark and lepton types;
- For optimization of neural networks, I have presented a **genetic algorithm** that best maximize the statistical significance;
- In principle, the process itself is **model-independent**, in the sense that the neural models are agnostic to the BSM details. They only need the data.

Machine Learning Algorithms and Particle Physics Searches

Thank you for your attention

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