ATLAS EXPERIMENT

THE UNIVERSITY of EDINBURGH
School of Physics and Astronomy

Deep Learning & the Higgs Boson

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Deep Learning & the Higgs Boson

Classification with Fully Connected and Adversarial Networks.

- **Lecture1: The Higgs boson and event classification:**
  - Event classification with a fully connected neural network (NN) with Keras API.

- **Lecture2: Solving the background sculpting challenge:**
  - Event classification with adversarial neural network (ANN).
  - Hands-on knowledge of manipulating neural networks in Tensorflow.

- **Lecture3: Putting it all together:**
  - Compare ANN classification performance to the fully connected network.

Lecture2: classification with adversarial neural network

- **What were we doing in Lecture1?**
  Classification with fully connected neural network.

- **What is the issue with classification from Lecture1?**
  The discriminant has an undesired bias.

- **How do we solve this issue?**
  Classification with adversarial neural network (ANN).

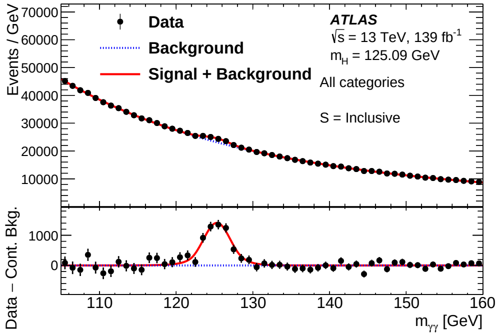
Reminder: Our Challenge

Classification: separate

- Signal with Higgs boson.
- Background with no Higgs boson.

Approach:

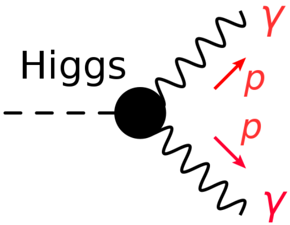
- use synthetic data.
- Introduce no bumps in the $m_{\gamma\gamma}$ distribution; these would hamper the background estimate.
  $\Rightarrow$ this lecture.



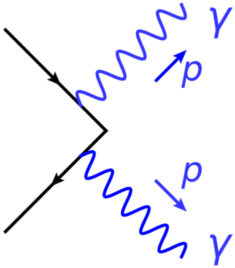
Reminder: What is in the data?

Two photons (γ) per event, with momenta p.

Signal, label=1

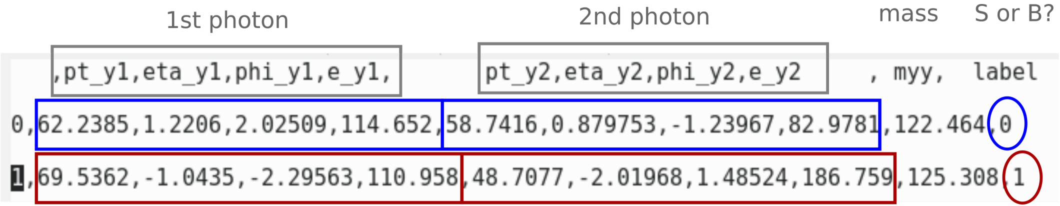


Background, label=0



Reminder: What is in the data?

- Momenta p are 4-dimensional (Lorentz) vectors.
- They are passed in cylindrical coordinates.

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,pt_y1,eta_y1,phi_y1,e_y1,pt_y2,eta_y2,phi_y2,e_y2,myy,label
0,62.2385,1.2206,2.02509,114.652,58.7416,0.879753,-1.23967,82.9781,122.464,0
1,69.5362,-1.0435,-2.29563,110.958,48.7077,-2.01968,1.48524,186.759,125.308,1
```

Lecture1: Classification

Fully connected deep neural network.

Inputs:

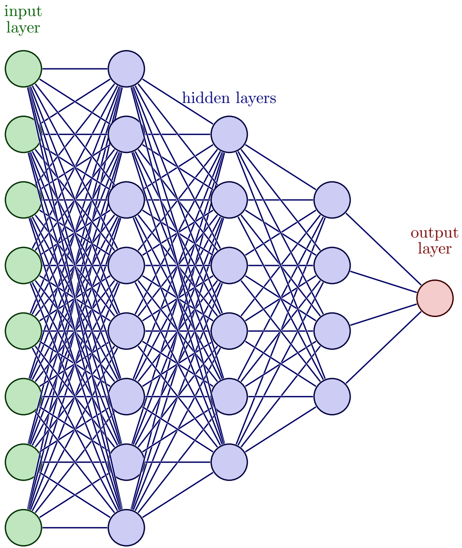
- Features x: photon 4-vectors.
- Labels y: signal (1) or background (0).

Training:

- Combine 8 inputs into 1 classifier.
- Objective: minimise classifier loss L_{clf}.
- Training determines node weights θ_{clf}.

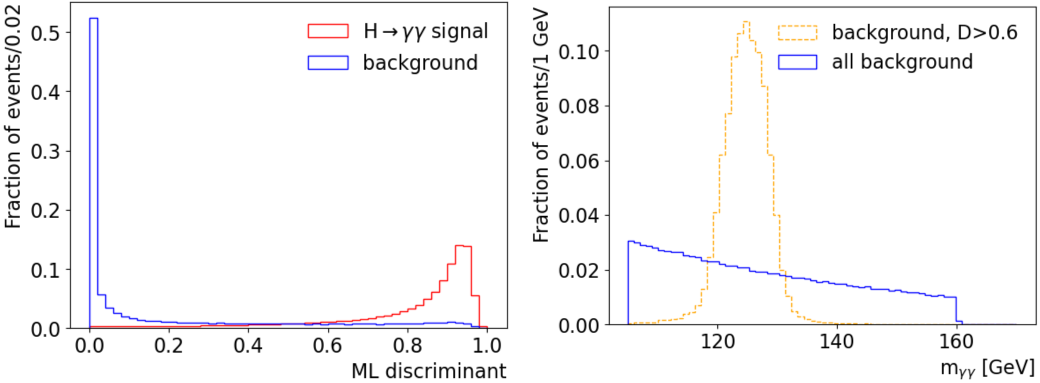
Output:

- discriminant: $z = p_{clf}(y|x, \theta_{clf})$.



Lecture1: Classification Results

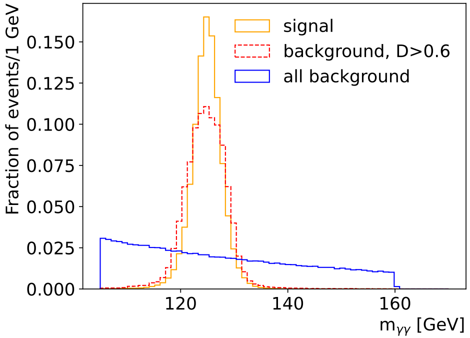
We can separate Signal from Background.

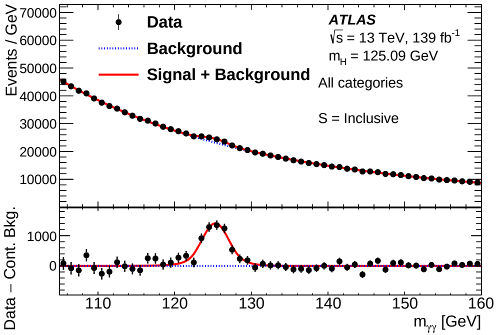


However: Background grows a bump at high discriminant values.

Lecture1: Classification Issue

We can separate Signal from Background.
However: Background grows a bump at high discriminant values.



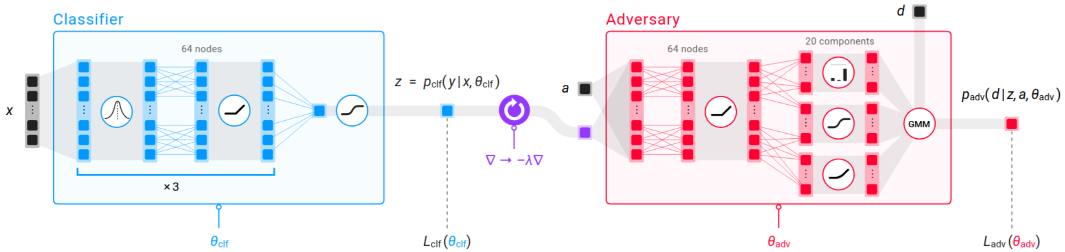


This would prevent us from reliably estimating the background.
Can we design classification which does not sculpt $\mathrm{m}_{\gamma\gamma}$?

Adversarial Neural Network

Can we design classification which does not sculpt $\mathrm{m}_{\gamma\gamma}$?

- Pit classifier network against adversary.
- Classifier tries to guess event label y (0 or 1) from inputs x.
- Adversary tries to guess $\mathrm{m}_{\gamma\gamma}$ from classifier output.
- If possible, the classifier is penalised.

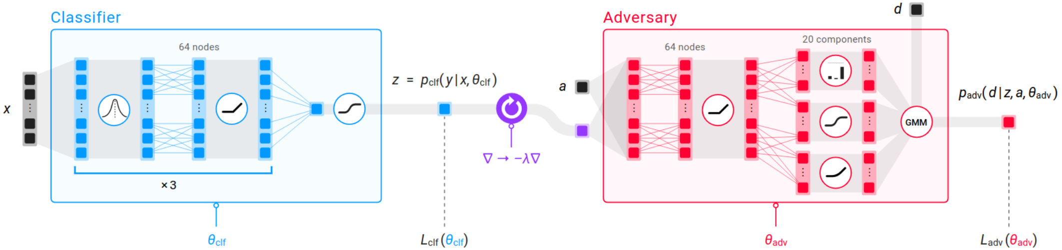


Adapted from: A. Sogaard's, lecture on adversarial NN.

Di-photon mass decorrelation

Can we design classification which does not sculpt $\mathrm{m}_{\gamma\gamma}$?

- Adversary: parametrises $d = \mathrm{m}_{\gamma\gamma}$ conditional on classifier output; $p_{adv}(\mathrm{m}_{\gamma\gamma}|z)$.
- Trained with: adversary loss $L_{adv}(\theta_{adv})$.
- Gradient minimising L_{adv} is back-propagated to classifier: gradient reversal layer.



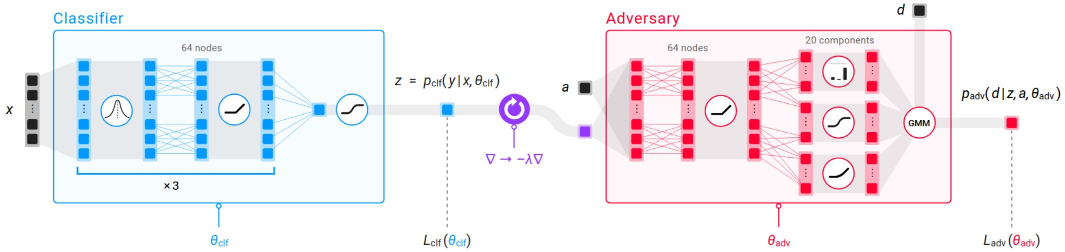
Adapted from: A. Sogaard's, lecture on adversarial NN.

Di-photon mass decorrelation

- Both networks trained simultaneously with a loss:

$$L = L_{clf}(\theta_{clf}) - \lambda L_{adv}(\theta_{clf}, \theta_{adv})$$

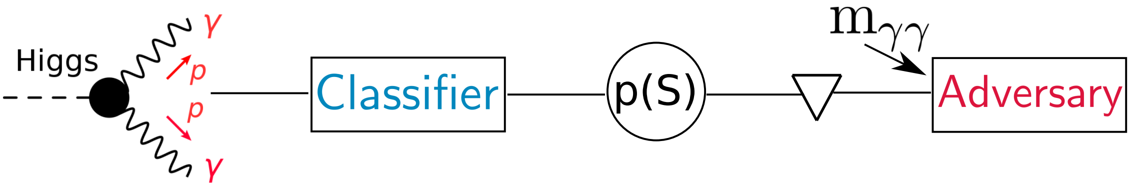
- Classifier: tries to guess event label (y = signal or background).
- Adversary: tries to guess $d = \mathrm{m}_{\gamma\gamma}$.
- Trade-off controlled by parameter λ.



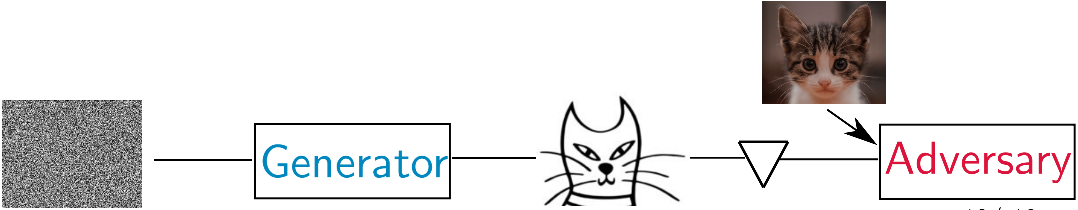
Adapted from: A. Sogaard's, lecture on adversarial NN.

Aside: Generative adversarial network

Our Lecture: Adversarial Neural Network (ANN). Higgs classification.



Computer vision: Generative Adversarial Network (GAN). Synthetic image generation.



Hands-on work

Classification with fully connected network (NN) & adversarial network (ANN):
Using data_200k.csv:

- Run git repository: code/final/ann_classification.ipynb
- Look through the notebook; do you understand how the ANN works?
- Share your understanding in survey (link).

Optional: after lecture:

- run ann_classification.ipynb over data_2M.csv ($\sim$ 3h running time on laptop).

Reminder:

- Download the data: https://cern.ch/dl23data
- Set up the environment: https://cern.ch/dl23code

Extra

Correlation

$\mathrm{m}_{\gamma\gamma}$ is not used as input feature to fully connected network (NN) classifier.

Q: Why does the background get sculpted?

A: Some of the input features are correlated to $\mathrm{m}_{\gamma\gamma}$.