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LIP | Laboratório de

Instrumentação e Física

Experimental de Partículas

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COMPASS

LHC

SPS

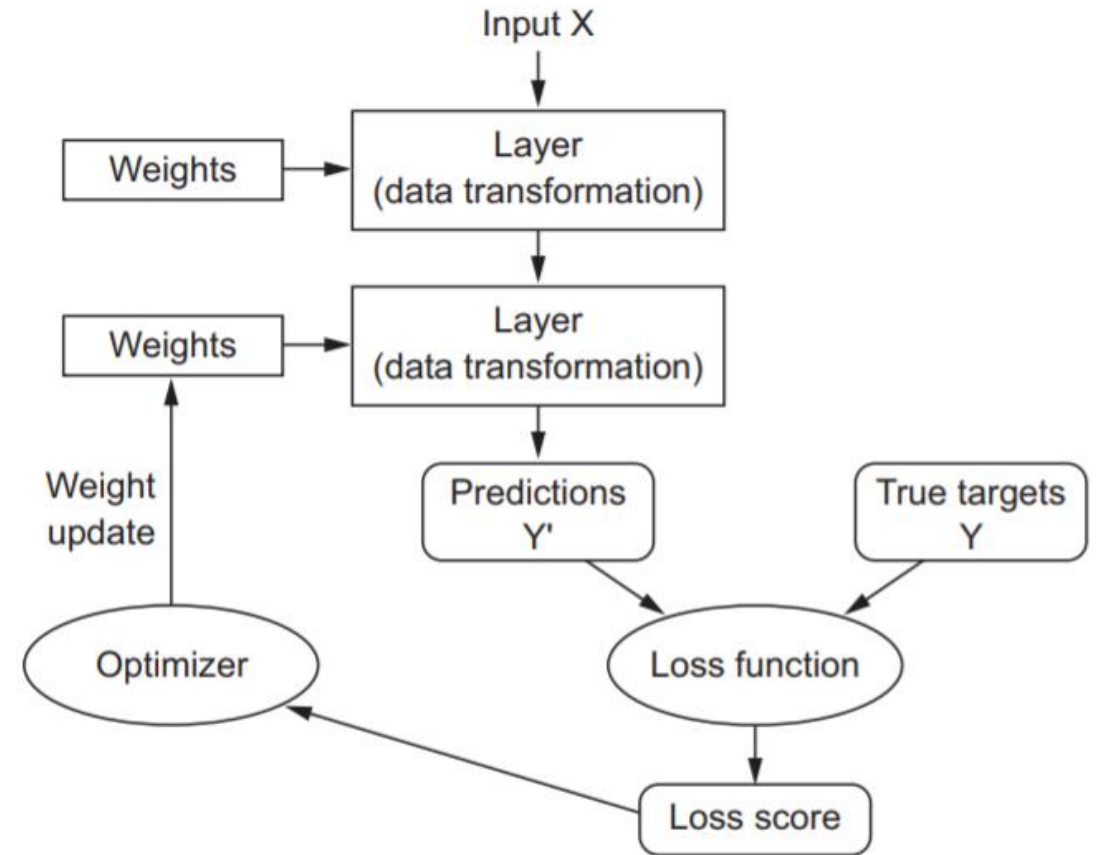
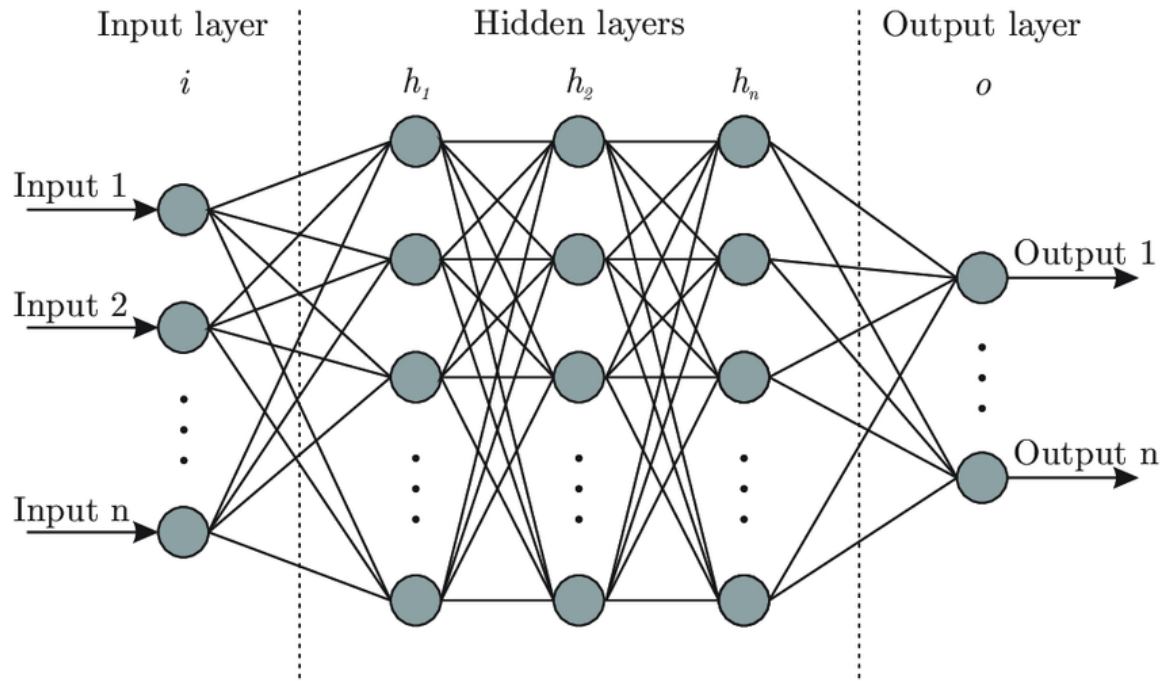
COMPASS acceptance obtained using Machine Learning Techniques

Objective of this internship

- Using Neural Networks to produce the acceptance of COMPASS experiment;
- Learning more about the COMPASS experiment;
- Learning more about the use of Neural Network.



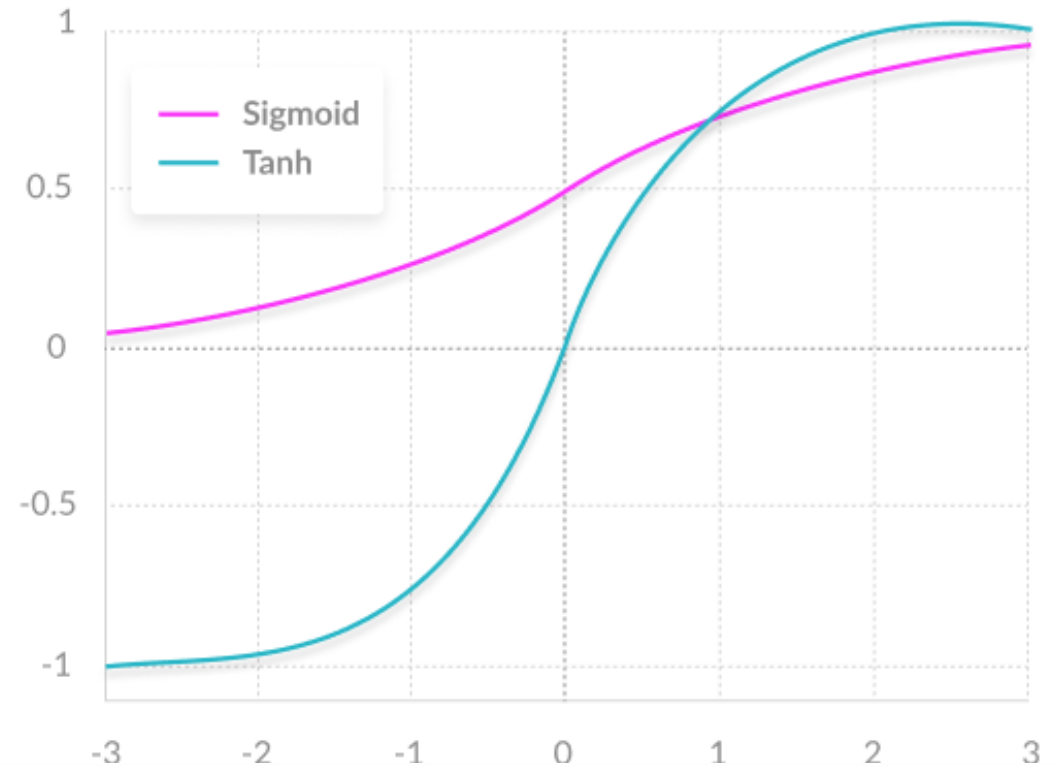
Neural Network



Neural Network

Activation function

- Transforms the input to some other form;
- Attached to each neuron;
- Determines whether it should be activated or not;
- Helps normalization of the output.



Loss function

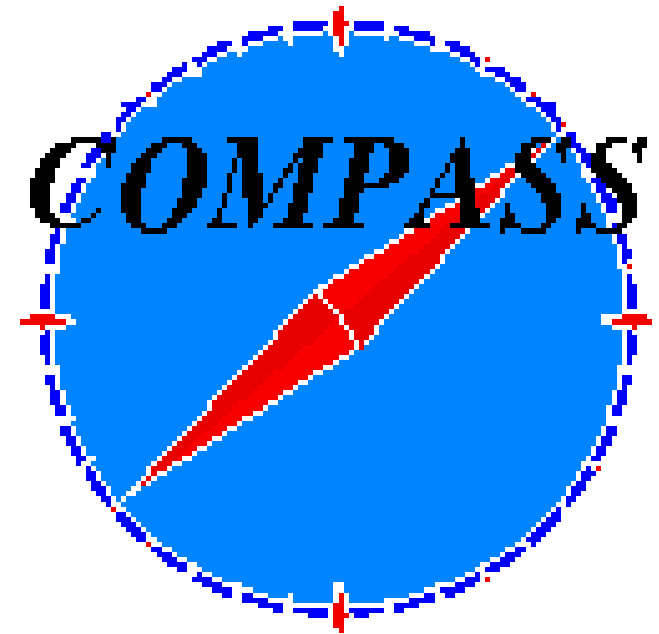
$$L = -\frac{1}{N} \sum_i y_i \log p_i + (1 - y_i) \log(1 - p_i)$$

Gradient descent

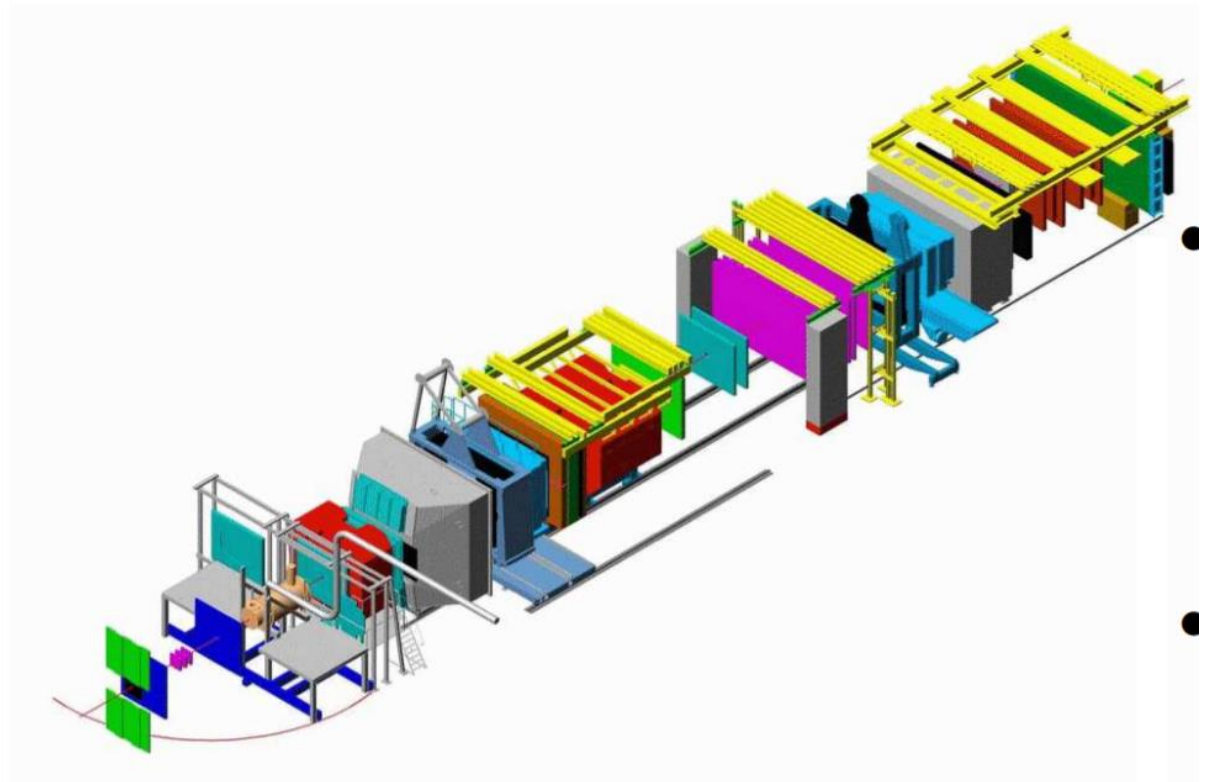
$$w^{t+i} = w^t - \eta \nabla L$$

Compass

- Fixed target experiment;
- General purpose spectrometer;
- Muon and hadron beams;
- Polarised target (longitudinally and transversely polarised NH_3 and ^6LiD).



COMPASS



- **DETECTOR**

- two stage spectrometer
- 60 m length
- 2 (3) magnets
- about 350 detector planes

- **POLARIZED TARGET**

- ^6LiD (NH_3) target
- 2-3 cells (120 cm total length)
- $\pm 50\%$ (90%) polarization
- polarization reversal every 8h-24h

- **POLARIZED BEAM**

- μ^+ at 160 GeV/c (200 GeV/c in 2011)
- polarization -80%

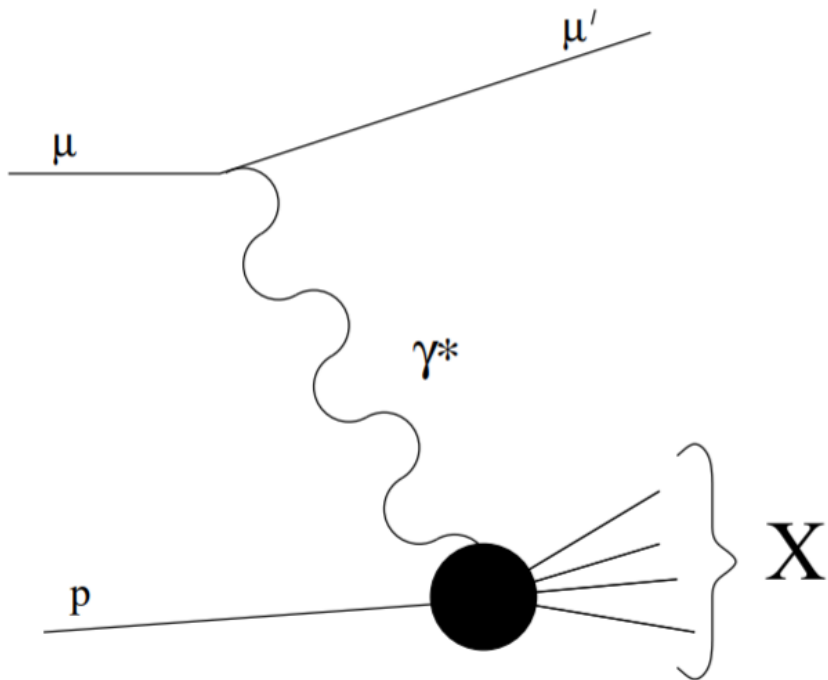
- **FEATURES**

- angular acceptance: ± 70 mrad (± 180 mrad from 2006)
- track reconstruction: $p > 0.5$ GeV/c
- identification h, e, μ : calorimeters and muon filters
- identification: π, K, p (RICH) $p > 2, 9, 18$ GeV/c respectively

Processes

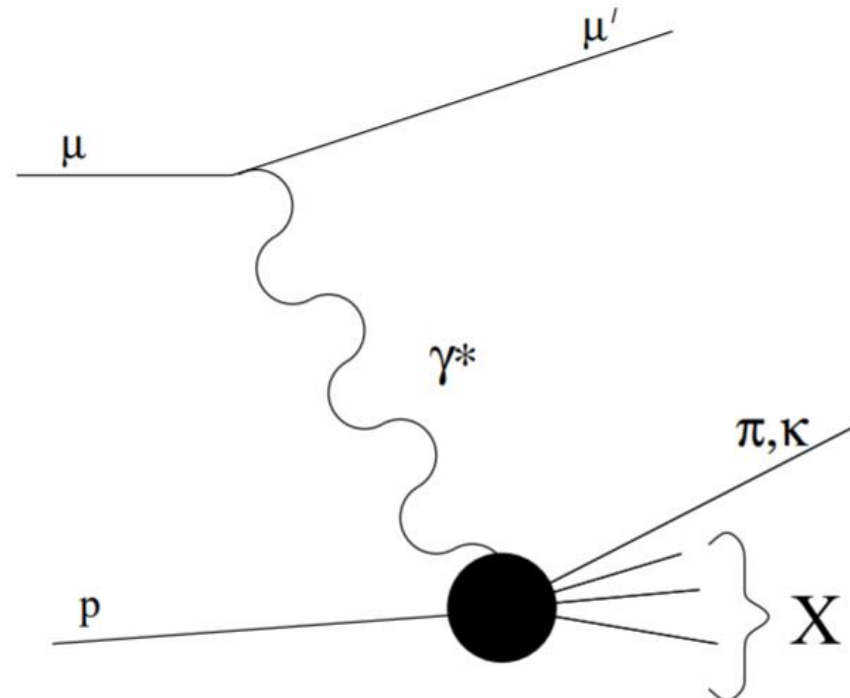
Deep Inelastic Scattering (DIS)

- Variables: x, Q^2 or y



Semi-Inclusive Deep Inelastic Scattering (SIDIS)

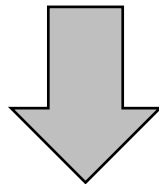
- There is a hadron in the sample
- Variables: x, Q^2, y, z



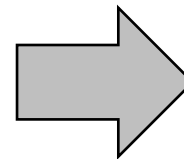
Compass experiment

What may happen to the particles:

- Some may decay;
- Some re-interact and lost;
- Appearance of holes in the detectors;
- ...



We only see between 30-70% of the generated particles



Acceptance

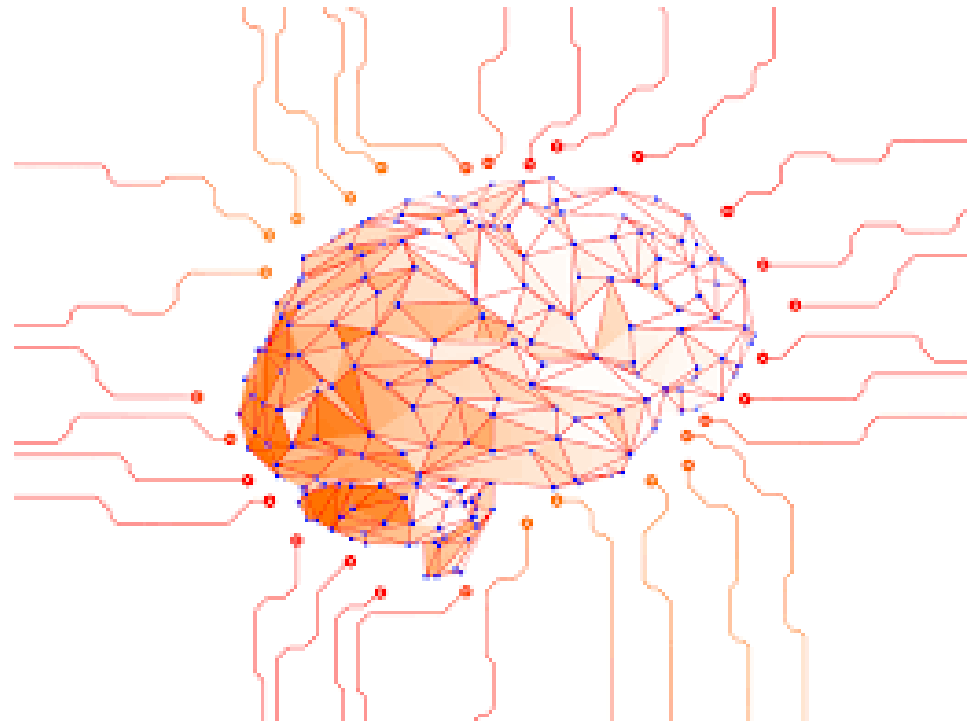
Compass acceptance and Machine Learning

- Check if the output of NN is similar to the one that we have from MC;
- We compare the output of NN and the output of MC;
- We compare the acceptance generated by NN and by MC



Parameters

- Activation function(relu, sigmoid, tanh,elu, swish ...)
- Number of neurons in each layer;
- Number of epochs
- Number of layers of NN;
- Optimizer;
- Dropout;
- Adding loops.



```
mean=X_train_org.mean(axis=0, keepdims=True)
stdev=np.std(X_train_org,axis=0)

X_train =(X_train_org-mean)/stdev
X_test = (X_test_org -mean)/stdev      #test and training samples are normalized by the mean and stdev from the test sample

model = Sequential()
model.add(Dense(40, activation=swish, input_dim=10))  #input_dim differs from DIS and SIDIS samples
# model.add(Dense(40, activation=swish))
model.add(Dense(40, activation=swish))
model.add(Dense(40, activation=swish))
model.add(Dense(40,activation=swish))
model.add(Dropout(0.4))
model.add(Dense(1, activation='sigmoid')) #for binary crossentropy output should have 'sigmoid'/'linear' activation functionmodel.summary()

NADAM=tf.keras.optimizers.Nadam(learning_rate=0.001,beta_1=0.999, beta_2=0.999 )

model.compile(loss='binary_crossentropy', optimizer=NADAM)
#model.compile(loss='mse', optimizer=NADAM) # mse loss (obs-exp)^2, also returns probability

totalx_min=100 # can be changed to lower values if too many models are saved

for x in range(0,70):
    print('xxxxx',x)
    model.fit(X_train, Y_train,batch_size=10000, epochs=5, verbose=1)
    loss=model.evaluate(X_test, Y_test,batch_size=1000000)
    if(loss<0.6230):
        test=model.predict(X_test[:,], batch_size=1000000)

    a=np.linspace(0,0.50,11)
    totalx=0
    for i in a:
```

Compass acceptance and Machine Learning

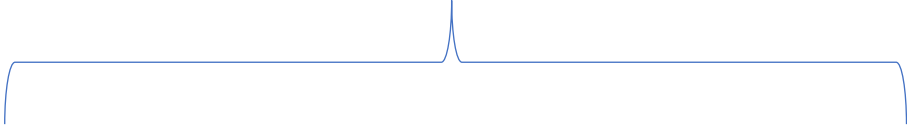
Training

- $\text{Acceptance} = N_{\text{reconstructed}} / N_{\text{generated}}$
- $\text{Output of NN} = N_{\text{reconstructed}} / (N_{\text{reconstructed}} + N_{\text{generated}})$
- Formule do acceptance = $\text{out} / 1 - \text{out}$

Exercises

- The output should be similar to 1.

Best results



```
-rw-r--r-- 1 u20mqueiros comp 111832 Aug 28 20:12 model-0.6215-72.46-405.56.hdf5  
-rw-r--r-- 1 u20mqueiros comp 111832 Aug 28 20:13 model-0.6213-47.50-395.55.hdf5
```

```
-rw-r--r-- 1 u20mqueiros comp 111832 Aug 28 01:39 model-0.6213-38.93-388.90.hdf5  
-rw-r--r-- 1 u20mqueiros comp 111832 Aug 28 01:47 model-0.6222-54.74-411.75.hdf5  
-rw-r--r-- 1 u20mqueiros comp 111832 Aug 28 01:48 model-0.6218-49.98-418.08.hdf5  
-rw-r--r-- 1 u20mqueiros comp 111832 Aug 28 01:48 model-0.6214-30.24-399.86.hdf5
```

```
-rw-r--r-- 1 u20mqueiros comp 111832 Aug 28 16:44 model-0.6212-65.79-386.51.hdf5  
-rw-r--r-- 1 u20mqueiros comp 111832 Aug 28 16:57 model-0.6222-69.82-403.21.hdf5  
-rw-r--r-- 1 u20mqueiros comp 111832 Aug 28 16:58 model-0.6219-44.69-414.80.hdf5
```

```
-rw-r--r-- 1 u20mqueiros comp 111832 Aug 25 15:44 model-0.6222-185.40-433.28.hdf5  
-rw-r--r-- 1 u20mqueiros comp 111832 Aug 25 15:45 model-0.6225-43.33-441.98.hdf5
```

A background image featuring a complex network graph with numerous nodes and edges, rendered in a light gray color. The nodes are represented by small black dots, and the edges are thin gray lines connecting them. The graph is dense and spans the entire width of the image.

Additional work

- Generative Adversarial Networks
- Genetic Algorithm
- Digit recognition

Conclusion

- There are some parametrization that are more stable than other;
- They have still a big chi-squared;
- But there are some results that can be used.





Thank you for your attention!