2.2)

Measuring performance: the ROC curve

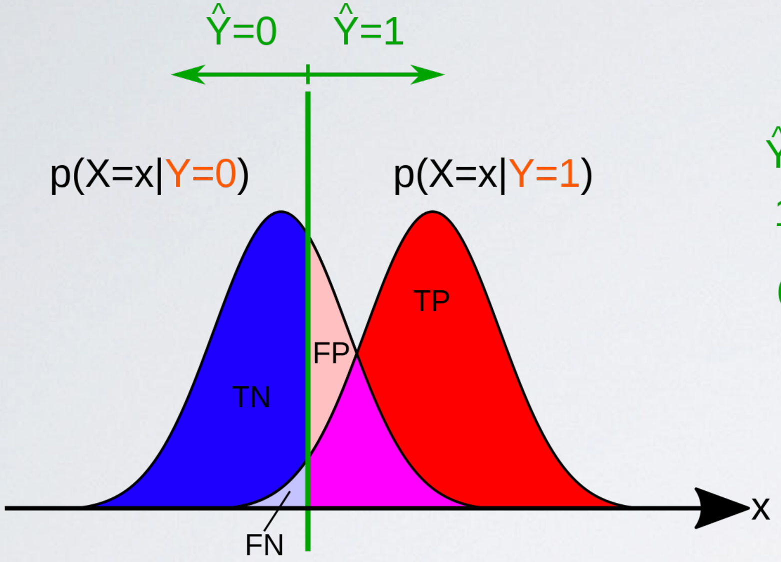
ROC = Receiver Operating Characteristic

Once we've trained a classifier how do we intepret the inferred values?

- take a test: pass sample values to the trained model
- outcome is a probability between 0, 1of the likelihood the test is positive. Let's say >1/2 means True and <1/2 is False

		actual result	
		True	False
test result	positive	True Positive	False Positive
	negative	False Negative	True Negative

2.2) Measuring performance: the ROC curve



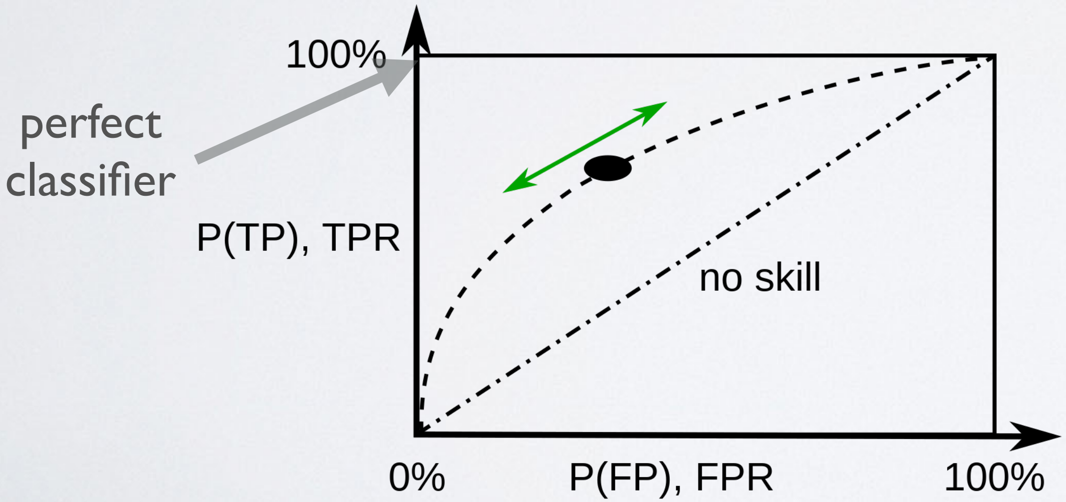
Ŷ \ Y	1	0
1	TP	FP
0	FN	TN

Y is the actual result

$P(X=x|Y=1)$ is the result from the model

$P(X=x|Y=0) = 1 - P(X=x|Y=0)$

$\hat{Y} = 1$ if $P(X=x|Y=1) >$ threshold,
$= 0$ if $P(X=x|Y=1) <$ threshold



(…figure from Wikipedia…)

2.2) Discriminating signal from background

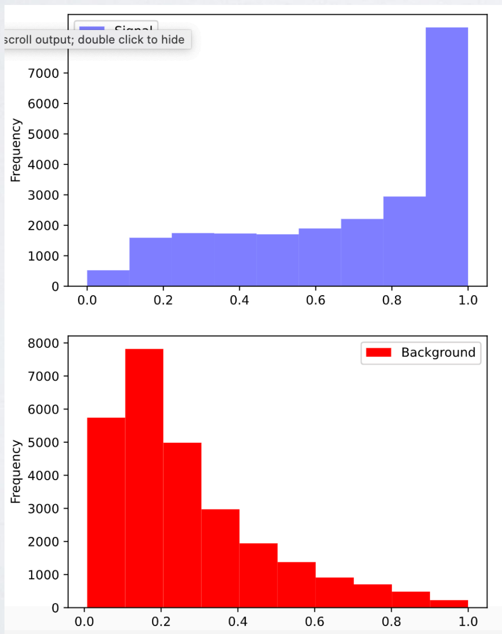
tutorial from: https://github.com/drckf/mlreview_notebooks/tree/master/jupyter_notebooks/notebooks

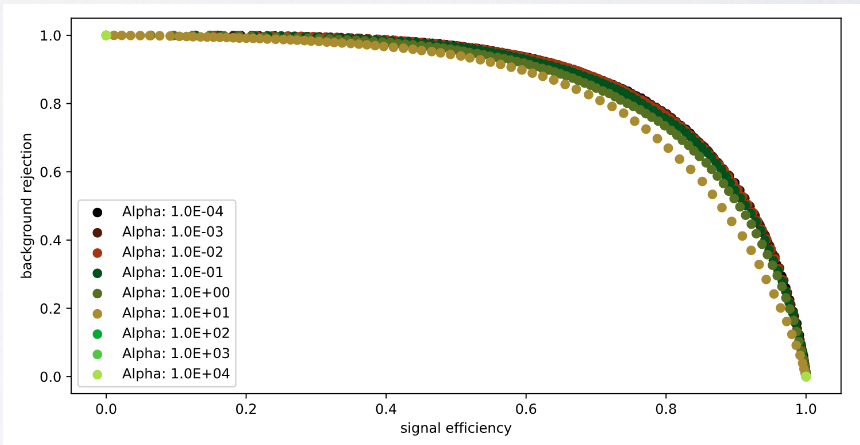
Super-symmetry has been a popular model for physics Beyond the Standard Model. LHC data has almost completely ruled out an realistic SUSY scenario

also in our repository with dataset:
`LogisticRegression_SUSY.ipynb`

- use generic pre-generated 'SUSY' dataset

MC generated samples based on theory models of Standard Model (SM = background) and supersymmetry (SUSY = signal)



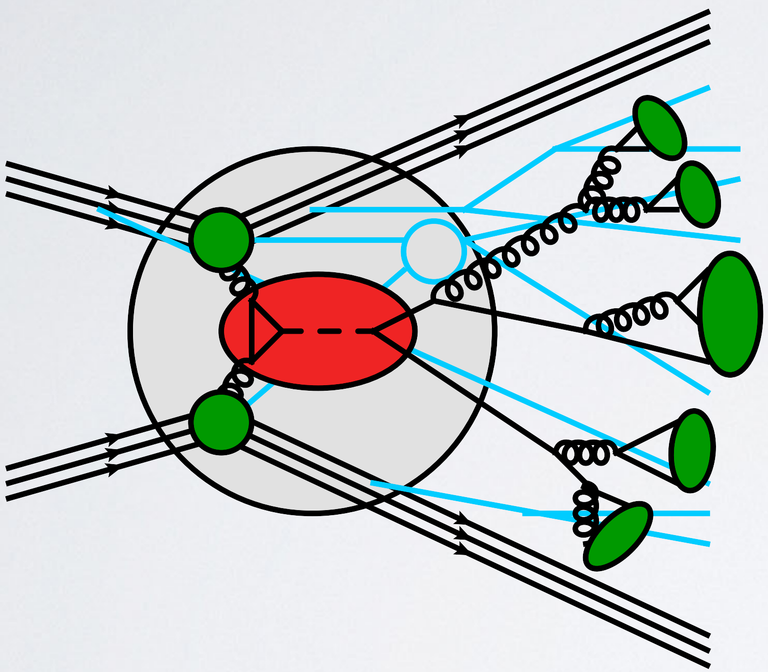


NB: Signal efficiency / Acceptance vs Background Rejection = TNR vs TPR
TNR = TN/SN = 1-FP/SN = 1- FPR

2.2)

Discriminating signal from background

overview of data and event generation



Monte Carlo integration for a given final state (including phase-space cuts) results in a set of **momenta** and **particle types** together with a weight (e.g. squared amplitude x PDFs)

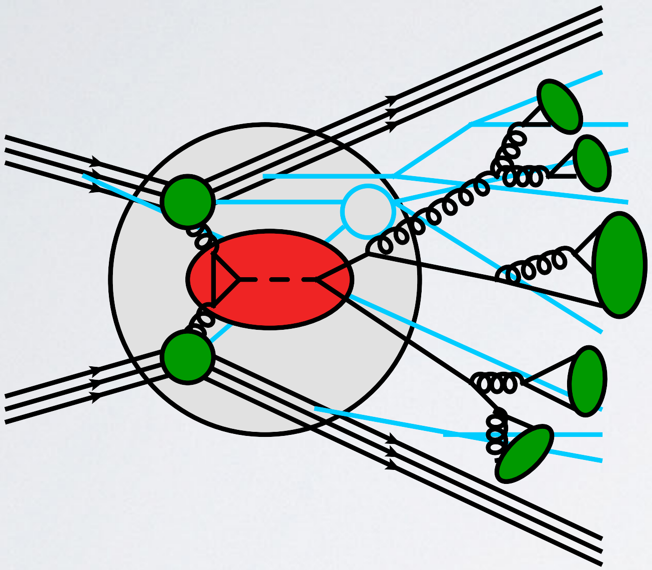
from this data we can compute:

- observable kinematic quantities (transverse momentum, rapidity, azimuthal angle,…)
- differential distributions - histogram weights according to value of a given observable

2.2)

Discriminating signal from background

overview of data and event generation



y - rapidity

p_T - transverse momentum

m_T - transverse mass

Φ - azimuthal angle

$$(E, p_x, p_y, p_z) = (m_T \cosh(y), p_T \cos(\phi), p_T \sin(\phi), m_T \sinh(y))$$
$$\stackrel{m=0}{=} p_T(\cosh(y), \cos(\phi), \sin(\phi), \sinh(y))$$

$$E\frac{d^3\sigma}{d\vec{p}} = \frac{d^3\sigma}{d\phi\, dy\, dp_T}$$

2.2)

Discriminating signal from background

overview of data and event generation

$$y = \frac{1}{2}\ln\left(\frac{E+p_z}{E-p_z}\right)$$

rapidity

angle from z-axis

$$y = \frac{1}{2}\ln\frac{\cos^2(\theta/2)+m^2/4p^2+\ldots}{\sin^2(\theta/2)+m^2/4p^2+\ldots}$$

$$\overset{m^2 \ll p^2}{\approx} -\ln\tan(\theta/2) \equiv \eta$$

pseudo rapidity

	signal	lepton 1 pT	lepton 1 eta	lepton 1 phi	lepton 2 pT	lepton 2 eta	lepton 2 phi	missing energy magnitude	missing energy phi	MET_rel	axial MET	M_R
0	0.0	0.972861	0.653855	1.176225	1.157156	-1.739873	-0.874309	0.567765	-0.175000	0.810061	-0.252552	1.921887
1	1.0	1.667973	0.064191	-1.225171	0.506102	-0.338939	1.672543	3.475464	-1.219136	0.012955	3.775174	1.045977
2	1.0	0.444840	-0.134298	-0.709972	0.451719	-1.613871	-0.768661	1.219918	0.504026	1.831248	-0.431385	0.526283
3	1.0	0.381256	-0.976145	0.693152	0.448959	0.891753	-0.677328	2.033060	1.533041	3.046260	-1.005285	0.569386
4	1.0	1.309996	-0.690089	-0.676259	1.589283	-0.693326	0.622907	1.087562	-0.381742	0.589204	1.365479	1.179295

SM or 'other model' as defined by simulation

MET - missing transverse energy