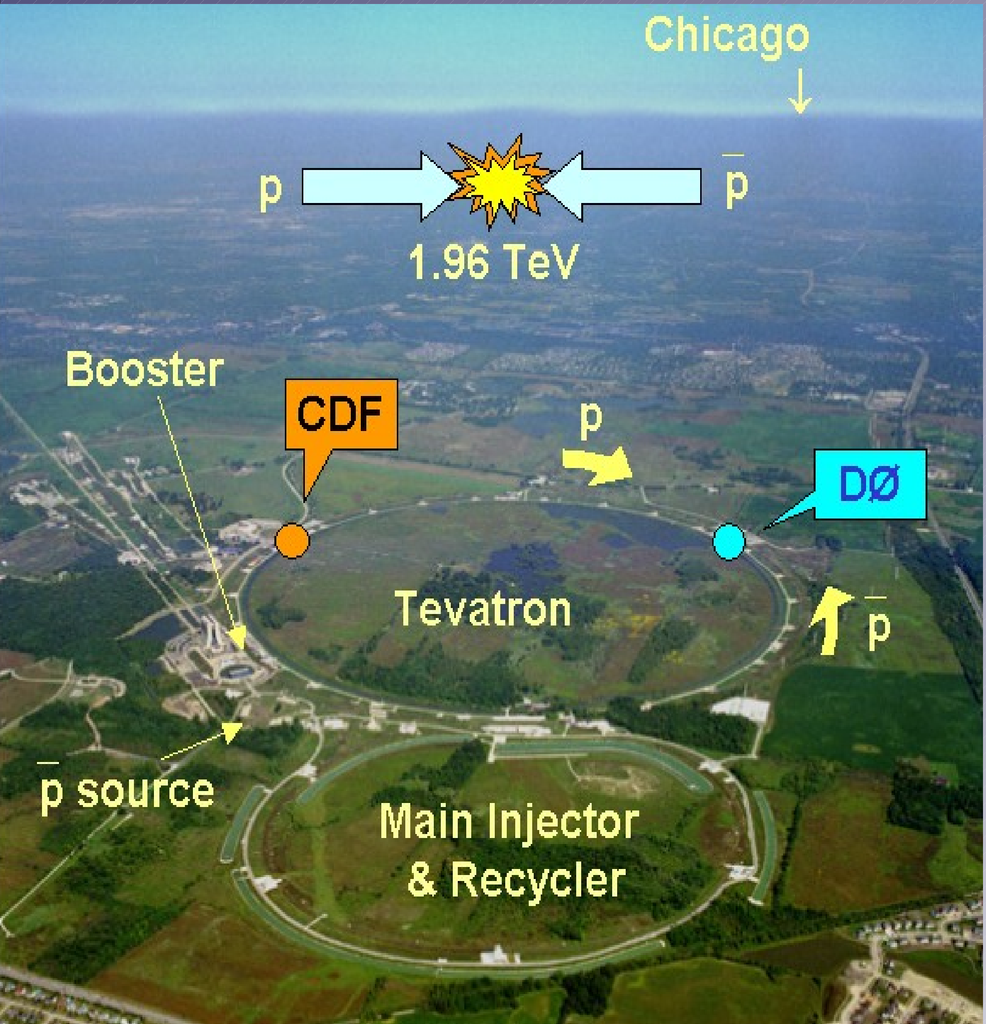
Determination of the $t\bar{t}$ production cross section in the full hadronic channel at CDF

Phys. Rev. D **76**, 072009 (2007)



Outline:

- Introduction
- Dataset and trigger
- Analysis tools
- Method
- Results

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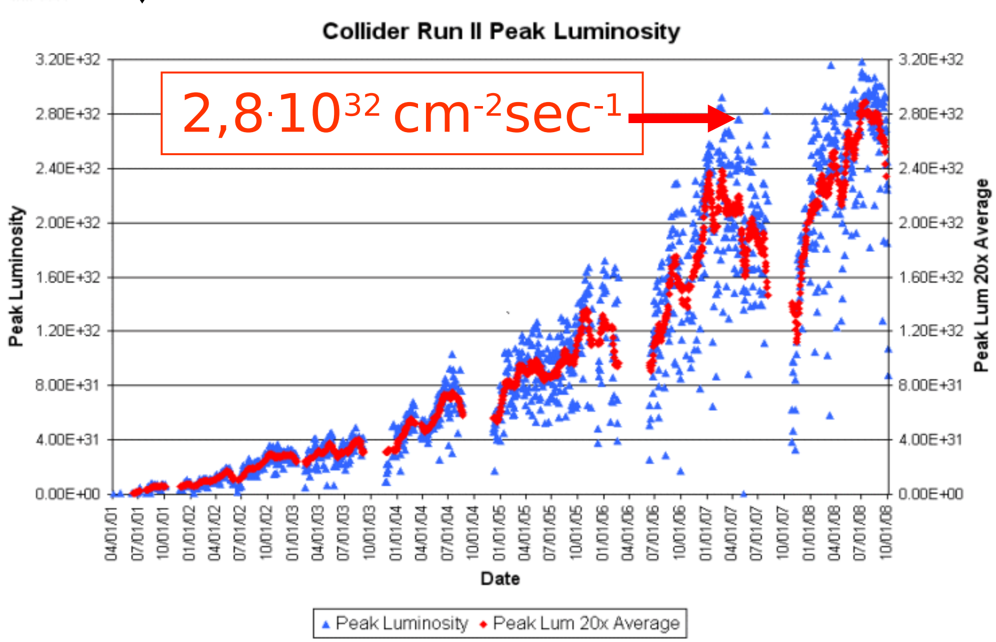
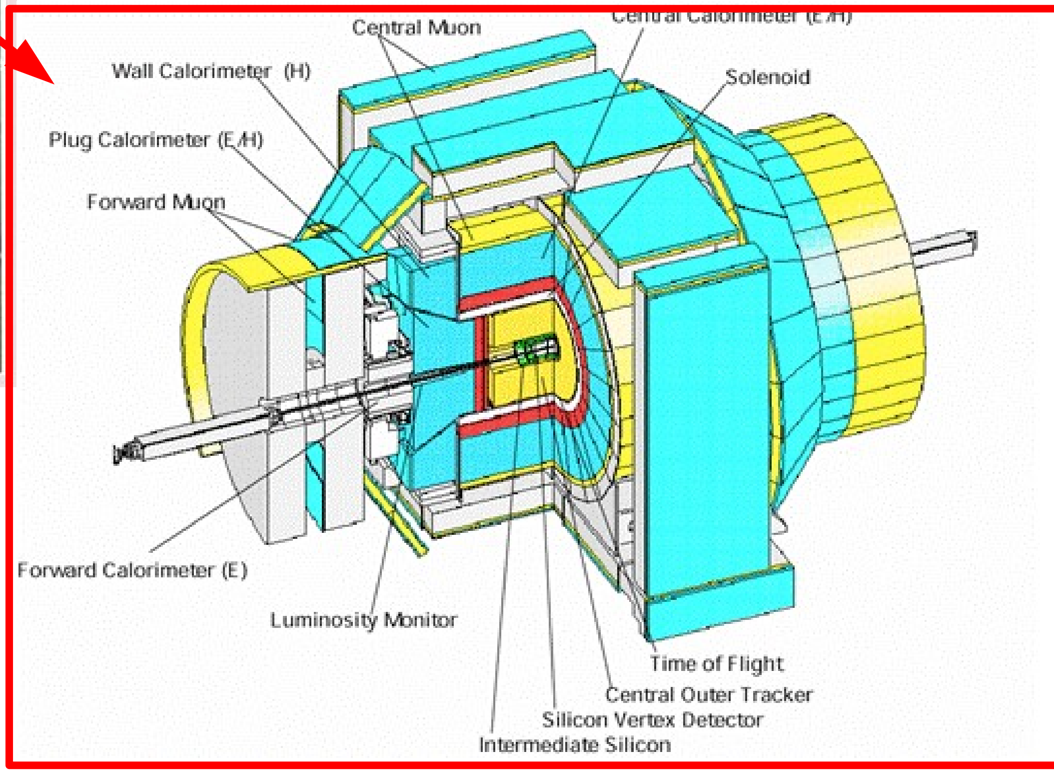
3rd Top Workshop at Grenoble:
from the TeVatron to ATLAS
23 – 25 October 2008

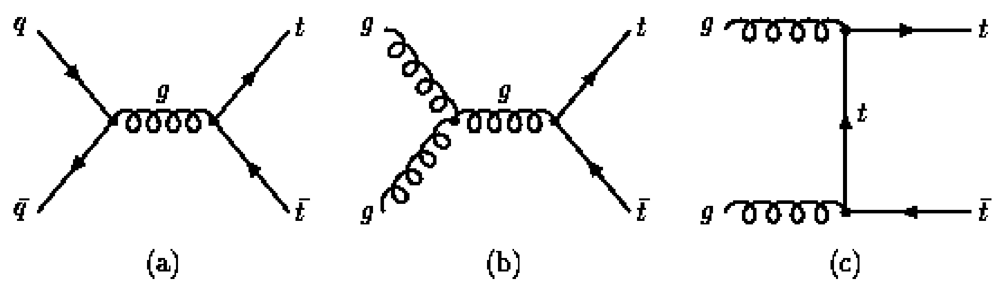
Accelerator and Detector Overview



CDF

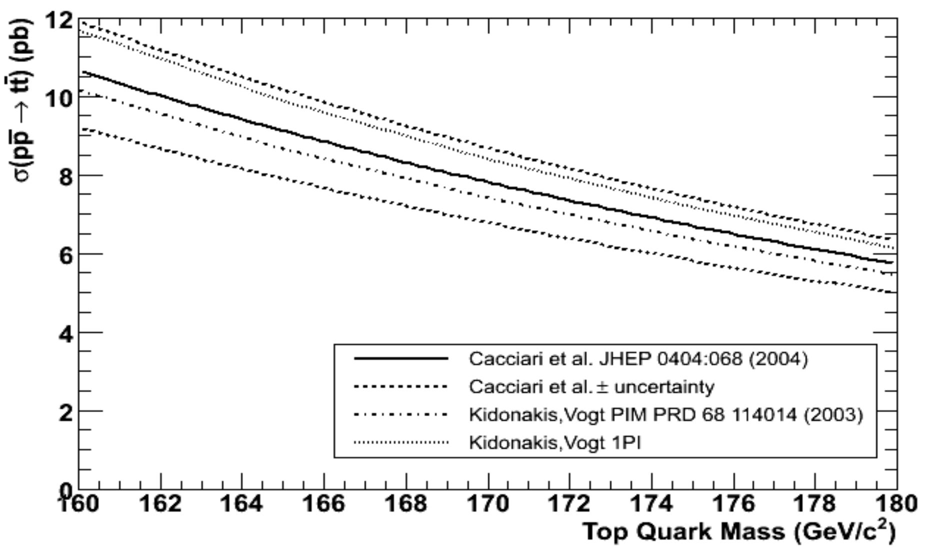


Top quark production at $\sqrt{s}$ = 1.96 TeV



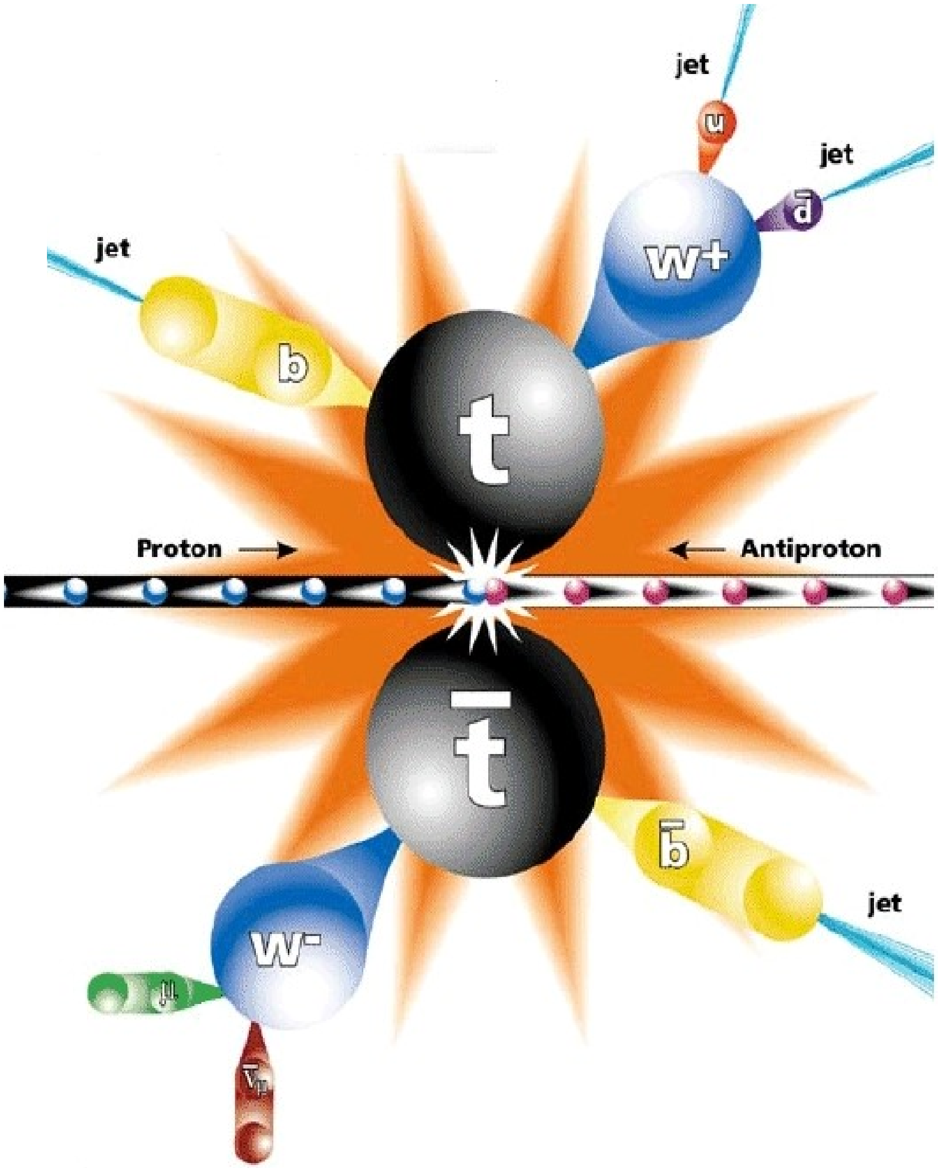
q qbar annihilation (85%)

gluon fusion (15%)



Cross section (M_{top} = 175 GeV/c^2):

pair production → **$6.7^{+0.7}_{-0.9}$ pb**



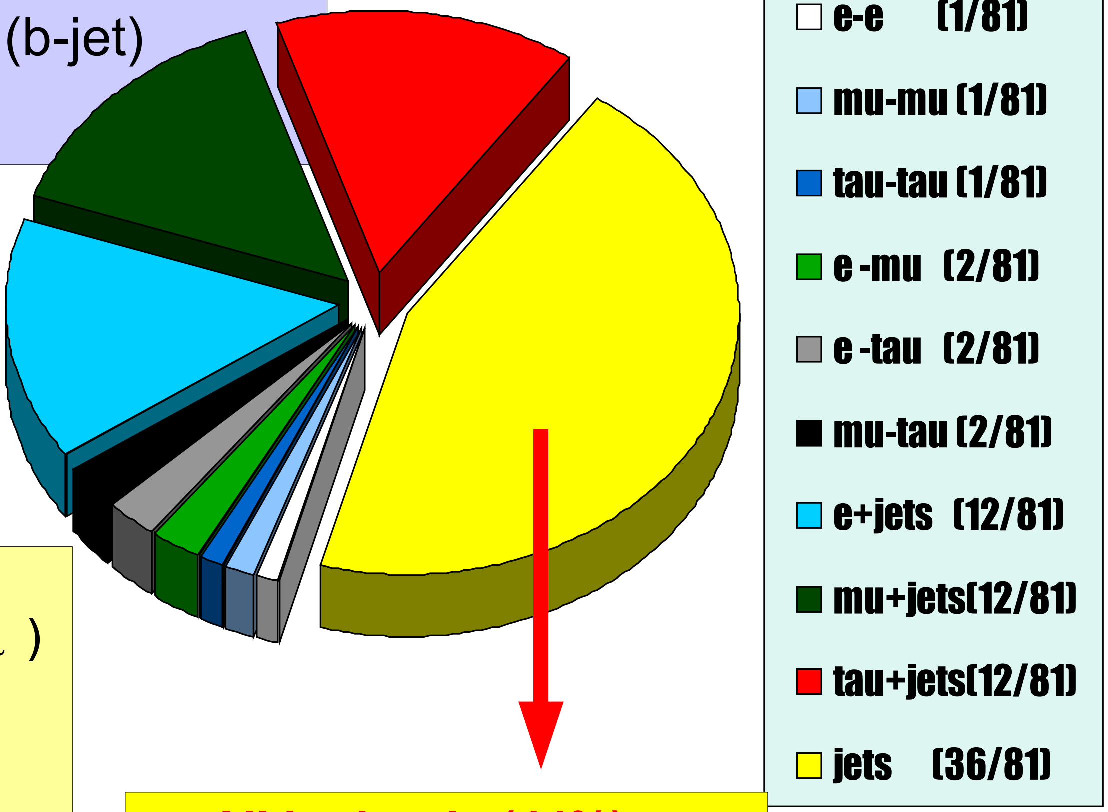
...but only one over 10^{10} inelastic collisions produces top quark pairs!

Top decay modes

Top lifetime ≈ 10^{-25} s → top decays before hadronizing

BR(t→Wb) ≈ 100% in Standard Model

b hadronizes producing a jet of particles (b-jet)
W can decay into hadrons or leptons



Lepton + Jet (30%)
One Ws → lν (l = e or μ)
1 lepton
Missing Et
4 jets (2 b-jets, 2 W-jets)

Dilepton (5%)
Both Ws → lν (l = e or μ)
2 leptons
Missing Et
2 b-jets

All hadronic (44%)
Both W into jets
6 jets (2 b-jets, 4 W-jets)

Main ttbar Decay Mode

Huge QCD background

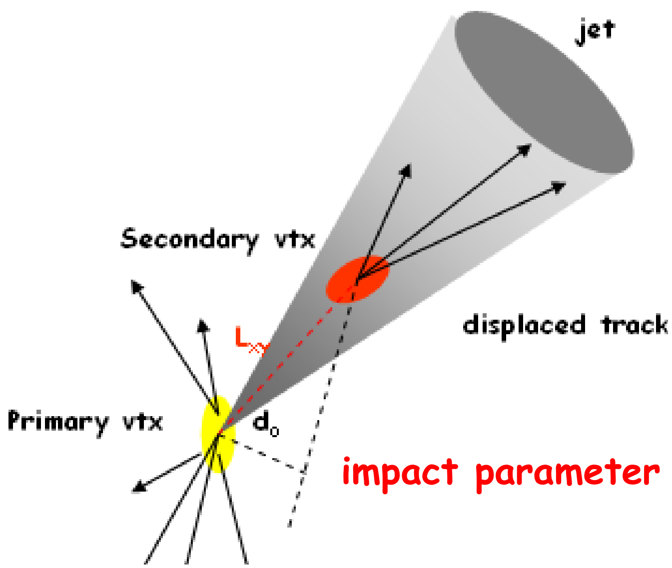
→

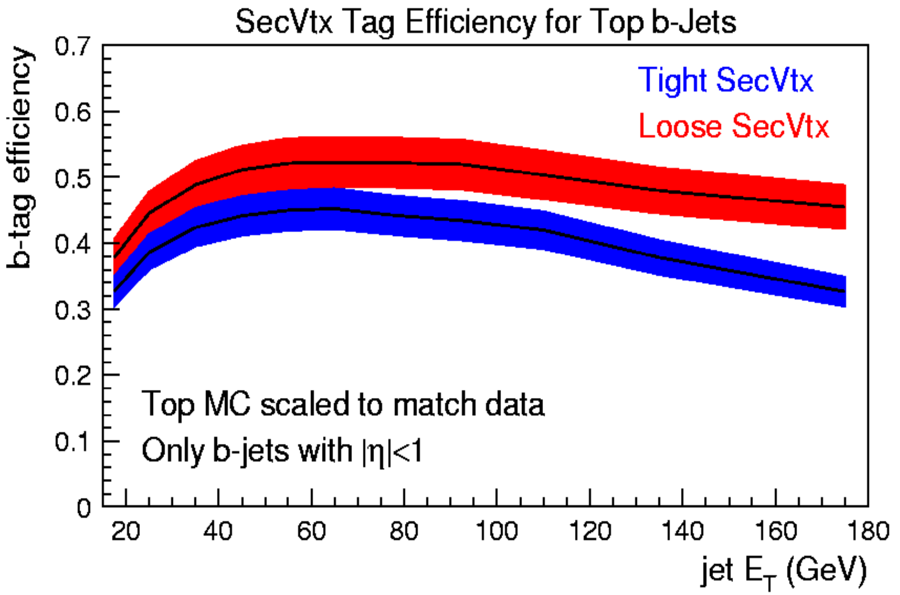
Needs an optimized kinematical selection

Needs b-jet identification to increase S/N

b-jets identification

a B Hadron travels some mm before decaying:
→ secondary vertex displaced from primary one
→ tracks have high impact parameter





SECondary **V**er**T**e**X** tagging:
search a displaced secondary vertex among high impact parameter tracks using an iterative fit.

Efficiency is tuned on data:
→ is around 50% for ttbar central b-jets
→ mistag rate kept under 2% for tight SecVtX

Datasets and Method

Optimized multi jet trigger:

TOP_MULTI_JET dataset, integrated luminosity: **1.02 fb^{-1}**

- **L1**: at least 1 cal. tower with $E_T \geq 10$ GeV
- **L2**: at least 4 cal. clusters with $E_T \geq 15$ GeV, $\sum E_T \geq 175$ GeV
- **L3**: at least 4 jets (Cone Radius = 0.4) , $E_T \geq 10$ GeV

MC : **Pythia v6.2 ttbar** $M_{top} = 175$ GeV/c^2

See Talk by G.Cortiana

High Missing E_T cut

MET + jets anaysis

Low Missing E_T cut

All hadronic analysis

Background: mainly QCD multiparton production

MC modeling: suffers from poorly known cross sections, need huge QCD samples.

Allows separation of heavy flavour from light flavour

Data driven background: tag rate parametrization evaluated in a control sample

No such complications, but also no distinction between real heavy flavour and fakes

- **Method 1**: positive tagging rate matrix approach to predict the absolute amount of background
- Optimized **Kinematical Selection**
- Require **≥ 1 SECVTX** positive tag
- Get the cross section:

$$\sigma_{ttbar} = \frac{N_{obs}^{tag} - N_{exp}^{tag}}{\varepsilon_{kin} \cdot \varepsilon_{tag}^{ave} \cdot L}$$

Kinematical Selection

Preselections:

- Good Run List (Detector fully operational)
- Trigger simulation (for MC and "old" data)
- Tight leptons (e /μ) **veto** (no overlap L+J analyses)
- Vertex requirements:
  - well centered
  - primary vertex close to jet clustering vertex
- Low Missing Energy (**$\not{E}_T^{sig}$ < 3 GeV ½**) → no neutrinos
- ΔR_{jets}(η–Φ space) > 0.5 (to avoid jet overlaps)

S/B still very low ~1/1000

$$\not{E}_T^{sig} = \frac{\not{E}_T}{\sqrt{\sum E_T}}$$

Event Topology Cut:

6 ≤ Njets(E_T>15 GeV, |η| < 2.0) ≤ 8

S/B still very low ~1/370

The old tecnique

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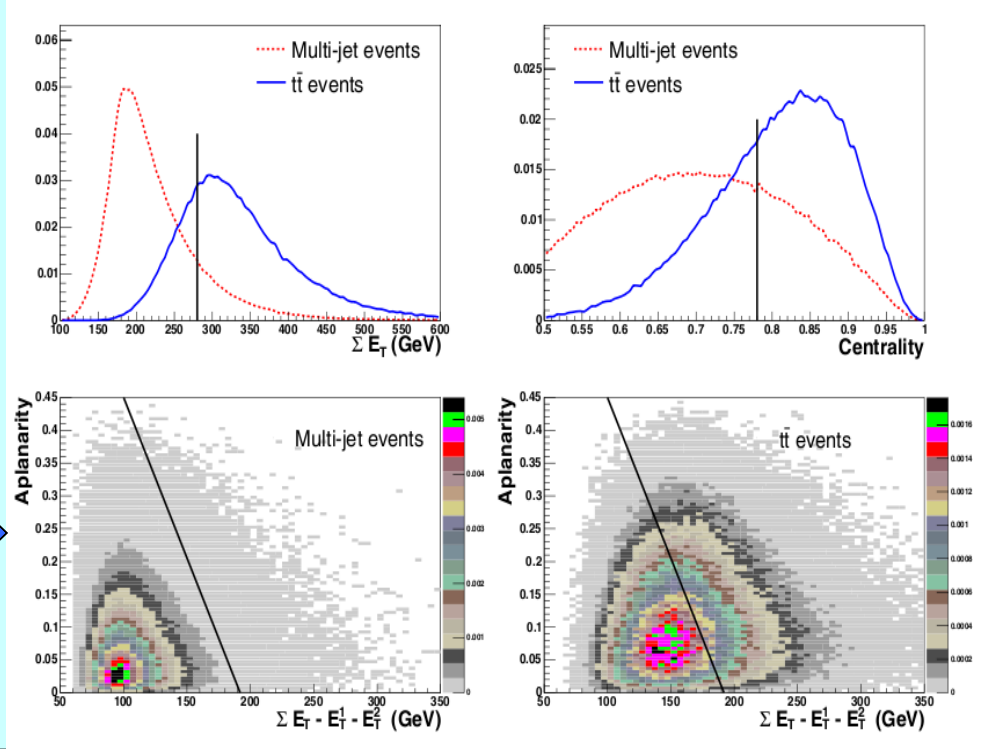
A cross section measurement in the all hadronic channel was already performed in Run II on 311pb^{-1}: old kinematical selection was chosen in order to maximize the S/√(S+B) ratio, also exploiting correlation among dinamical variables

- Centrality ≥ 0.78
- $\sum E_T$ ≥ 280 GeV
- (Aplanarity + 0.005 $\sum E_T^3$) ≥ 0.96

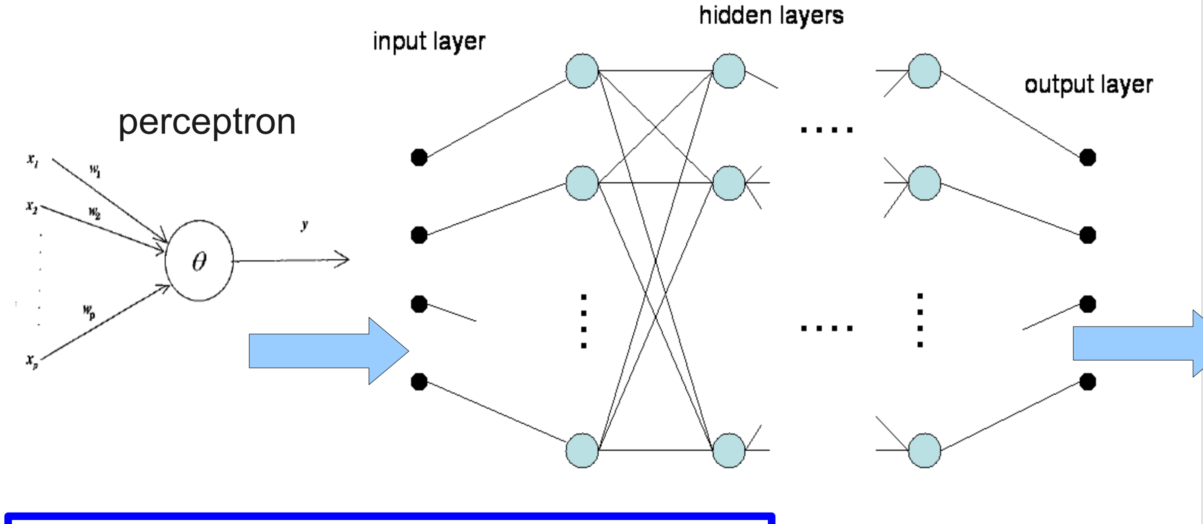
Reached **S/B~1/24**, and efficiency ~**6.7%**

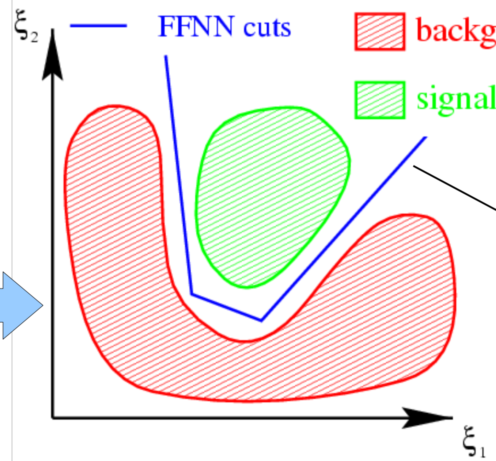


Neural Networks

Want to improve the old selection, Neural Networks come up as natural candidates!

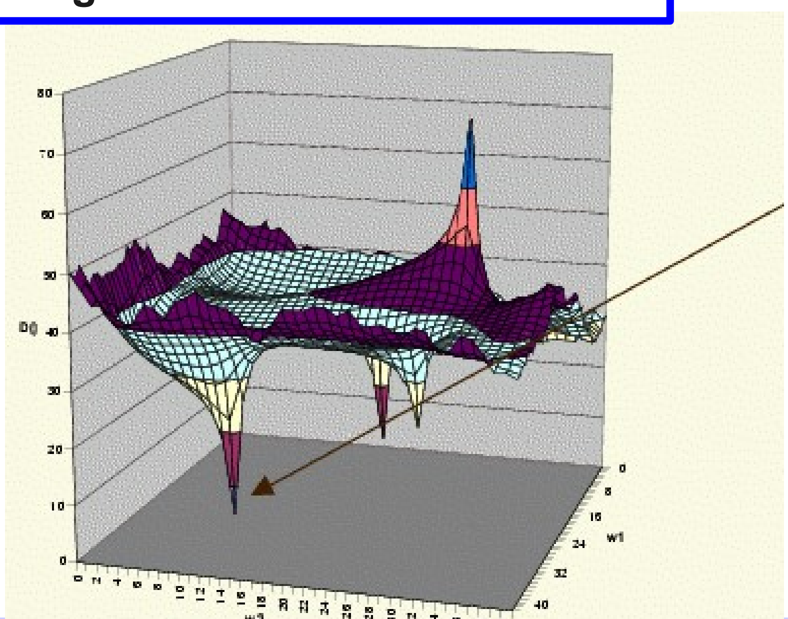
Neural network → computing system aimed at approximating a given mapping from a subset D of $\mathbf{R}^n$ (input variables) into **[0,1]** on the basis of known examples → training set, made of known events (already classified)





Substitute discrete selection with a continuous one over multiple vars

Training Process → Trial and Error



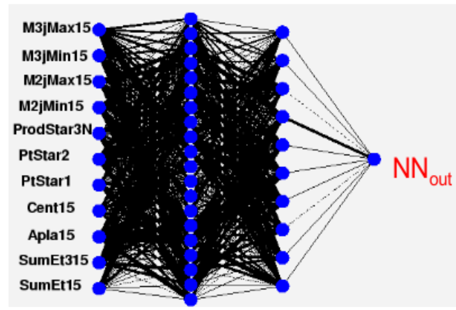
Compare expected values of the mapping against those actually given by a specific configuration of the network and calculate an **error function** that depends on the weights and is evaluated over all the given examples.

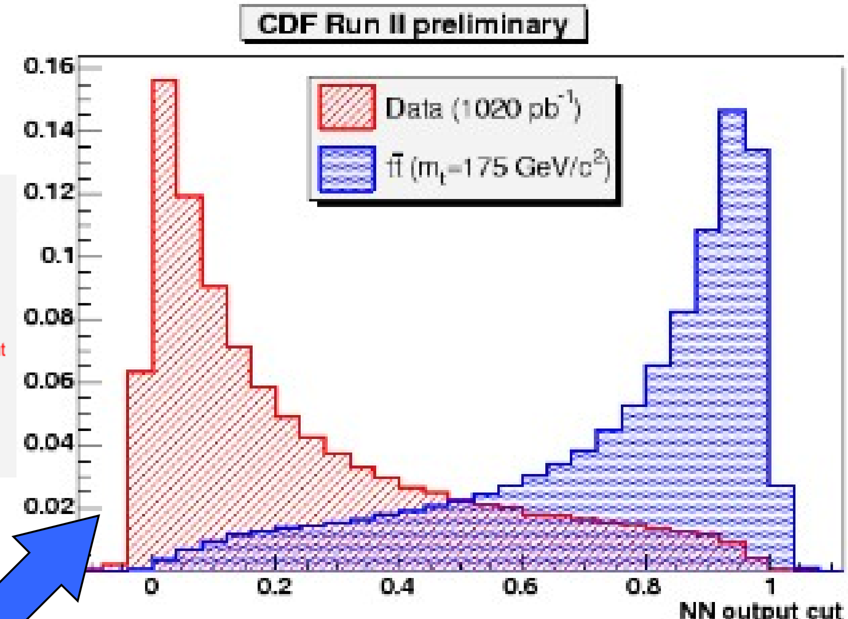
This defines an hypersurface (**error surface**), the net learns searching for an optimal **minimum on the error surface.**
We will use the **BFGS** algorithm.

Neural Network Selection

Build a Neural Network with 11 input variables, 2 hidden layers, and single output

Variable	Description
$\sum E_T$	Scalar sum of the transverse energies of all jets
$\sum_3 E_T$	As above, except the two highest-E_T jets
C	Centrality
A	Aplanarity
M_{2j}^{min}	Minimum dijet invariant mass
M_{2j}^{max}	Maximum dijet invariant mass
M_{3j}^{min}	Minimum trijet invariant mass
M_{3j}^{max}	Maximum trijet invariant mass
$E_T^{\star,1}$	$E_T \sin^2\theta^\star$ for the highest-E_T jet
$E_T^{\star,2}$	$E_T \sin^2\theta^\star$ for the next-to-highest-E_T jet
$\langle E_T^\star \rangle$	Geometric mean over the remaining jets



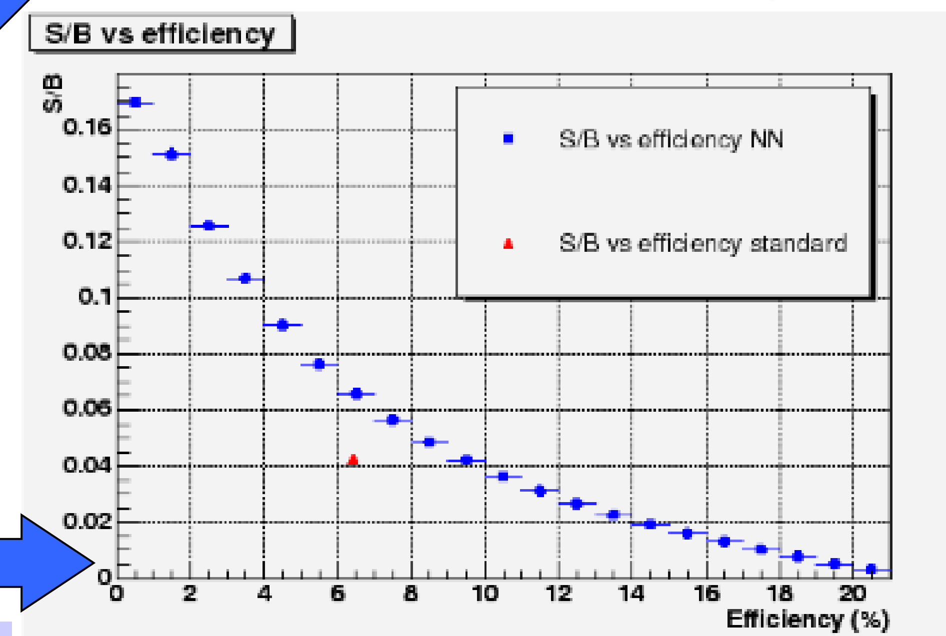


Events with ≥ 6 jets have still a poor **S/B** (~0.3%):

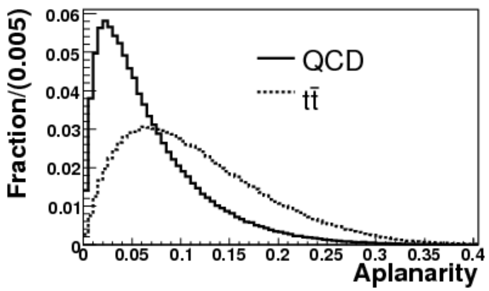
- the dataset is background dominated, so data themselves can be used as a representation of the background.

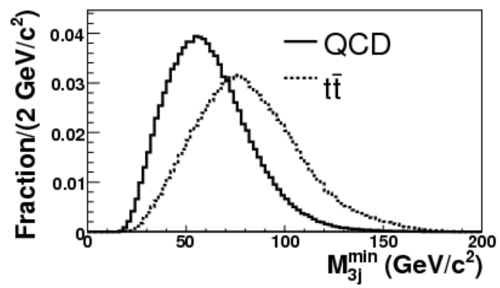
Training is performed on same size (~500,000) samples of signal (ttbar PYTHIA) and data.

Performace:
Can improve S/B with respect to old analysis retaining the same efficiency!



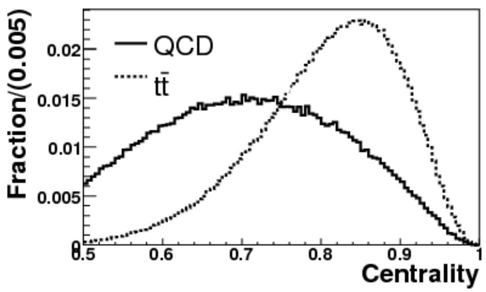
Neural Network Input Variables

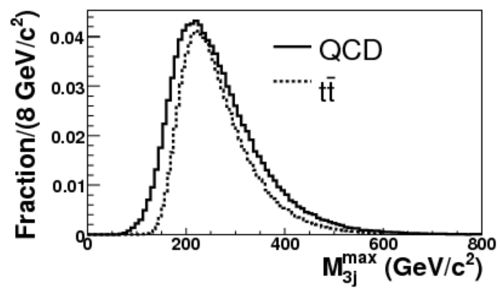


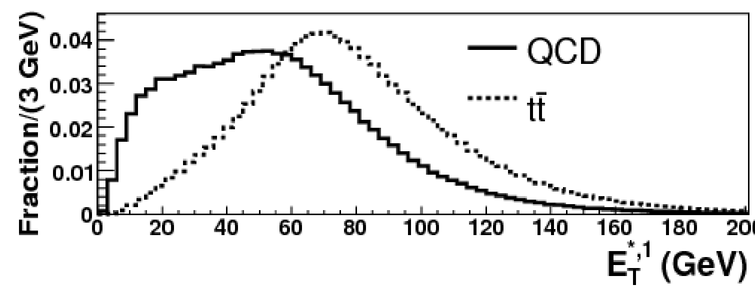


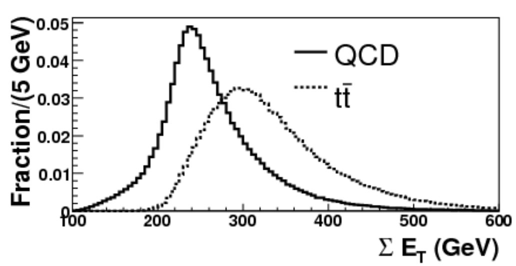
Define a kinematical selection based on dynamical and topological properties of the events.

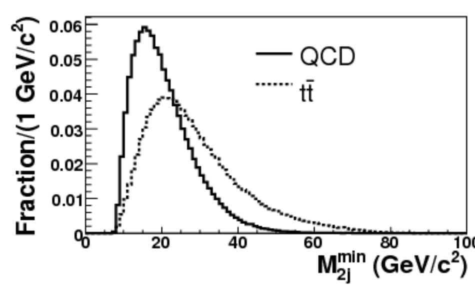
We build a neural network based on 11 input variables

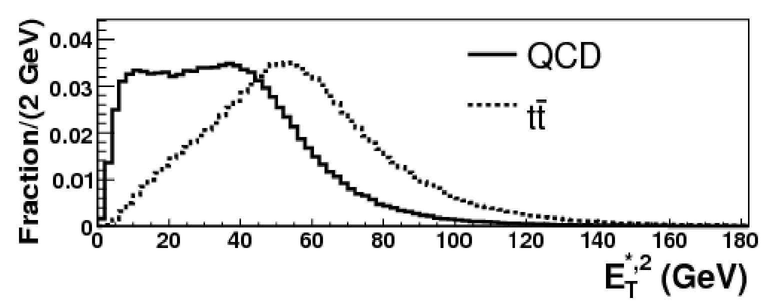


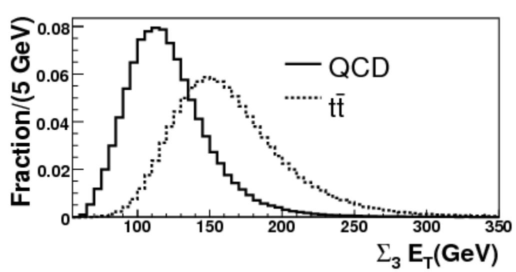


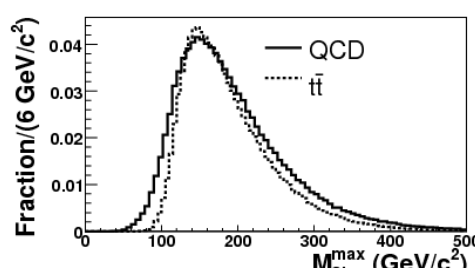


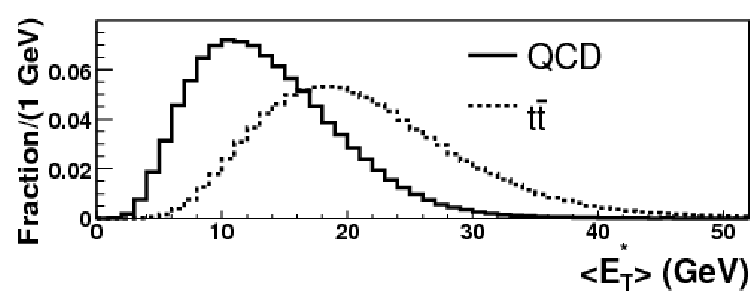


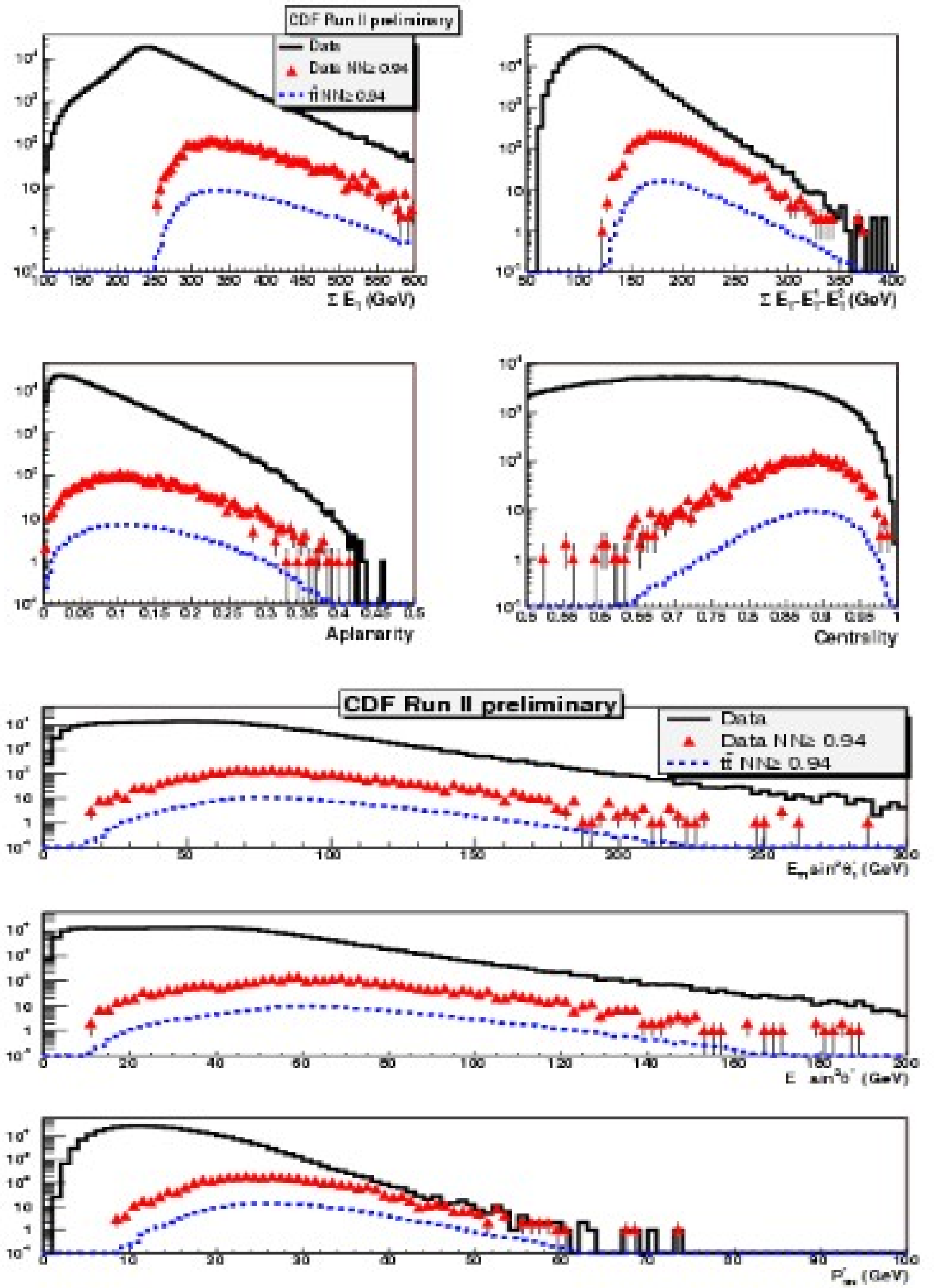


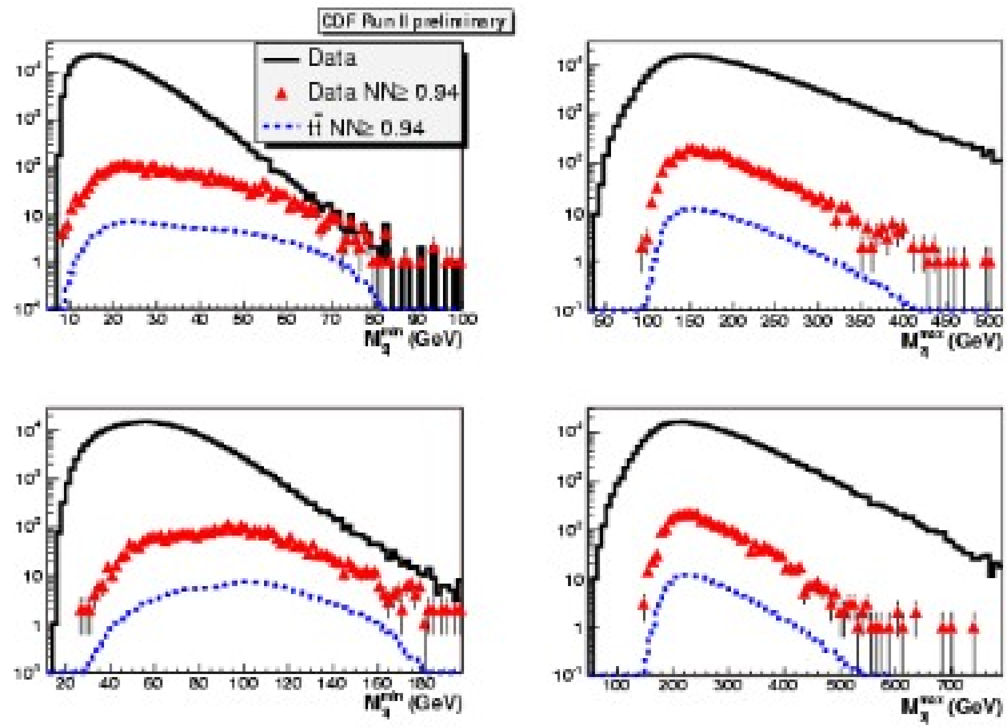












NN Selection
(here shown events with NNout ≥ 0.94)
indeed selects events that behave like ttbar...

Background Estimate Method

We will require SecVtx tags in the selected sample, need to estimate the background after selection

Basic Idea:

b-jet identification rates are different on ttbar and background processes, this allows to distinguish between the two components.

Method:

- Derive b-tag rates directly from TOP_MULTI_JET data
- Use **4** (E_T > 15 GeV, $|\eta|$ < 2.0) **jet** events
- Take the vars by which the tag-rate mainly depends to build a tag matrix

Signal contamination needs to be as low as possible in the sample used to parametrize the tagging rates in order to avoid biases in the background estimate!

Bkg Estimation:

Use the Tagging rate dependencies observed in 4-jet data events to predict the number of tagged jets at higher jet multiplicities and on kinematically selected data samples.

Warning:

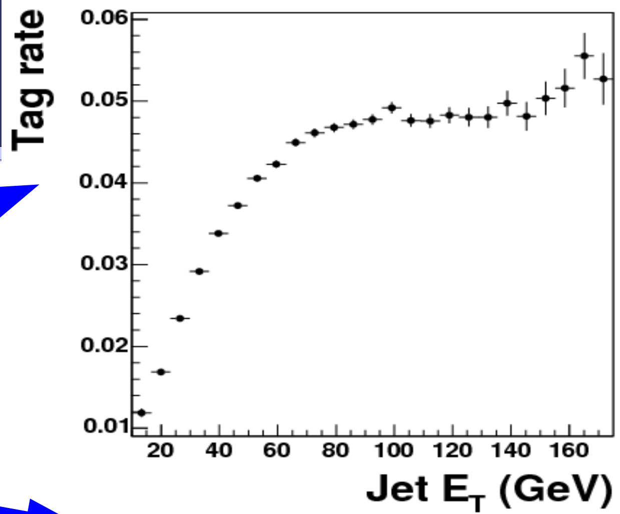
Variables used for the tagging rate parametrization need to be able to track possible sample composition changes introduced by a given selection cut.

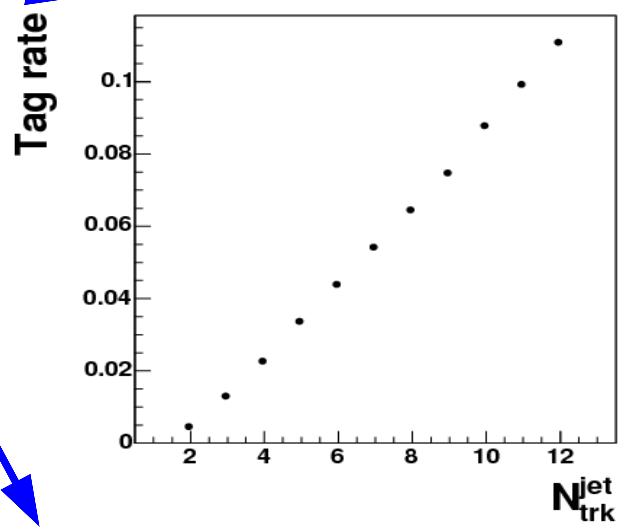
Method assumes that the tag rate does not depend on jet multiplicity, need to verify it!

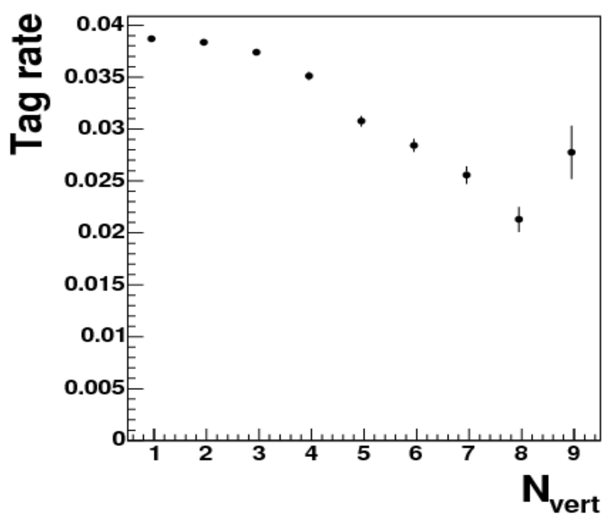
Tagging Rate Parametrization

B-tag rates are found to depend strongly on:

- **Jet E_T**
- **Jet Ntrk** , the number of tracks reconstructed in the vertex detector and associated with the jet
- **N_{VERT}** , the number of primary vertices in the event





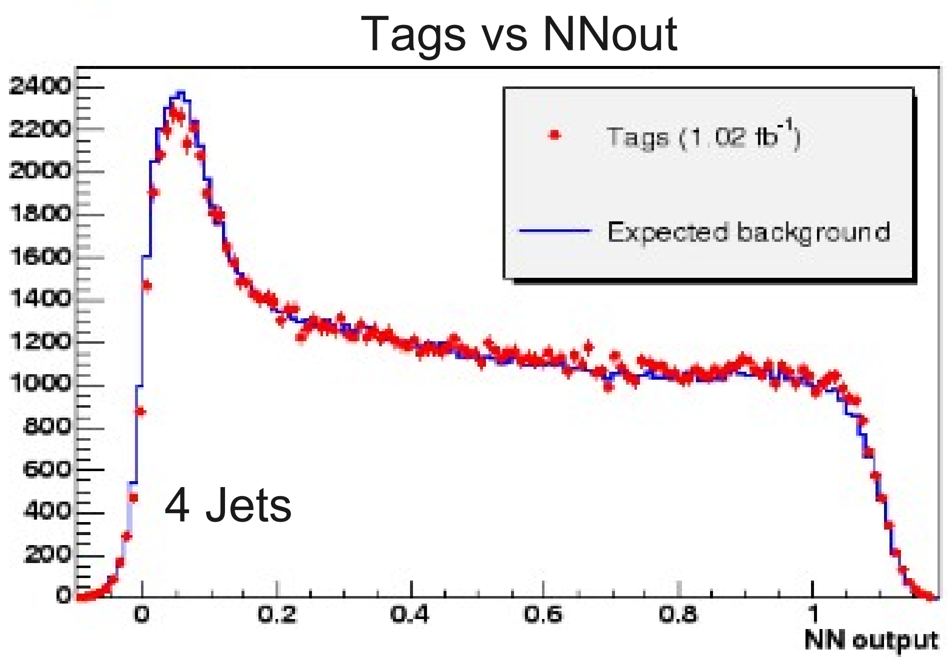


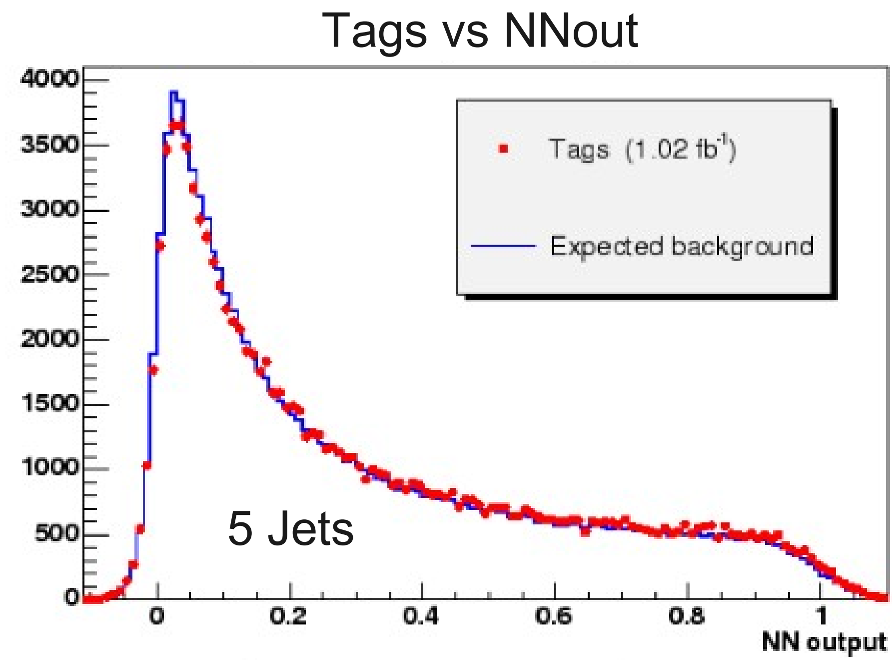
Build a
3-D (E_T, Ntrk, N_{VERT}) b-tag rate matrix on 4 jet events

Infer the expected number of tags (not events) from non-signal processes in the selected sample from the data themselves through the tagging rate matrix:

$$N_{exp} = \sum_{i}^{N_{evts}} \sum_{j}^{N_{taggable\ jets}} P(E_T^j, N_{trk}^j, N_{vert}^j)$$

Matrix Checks



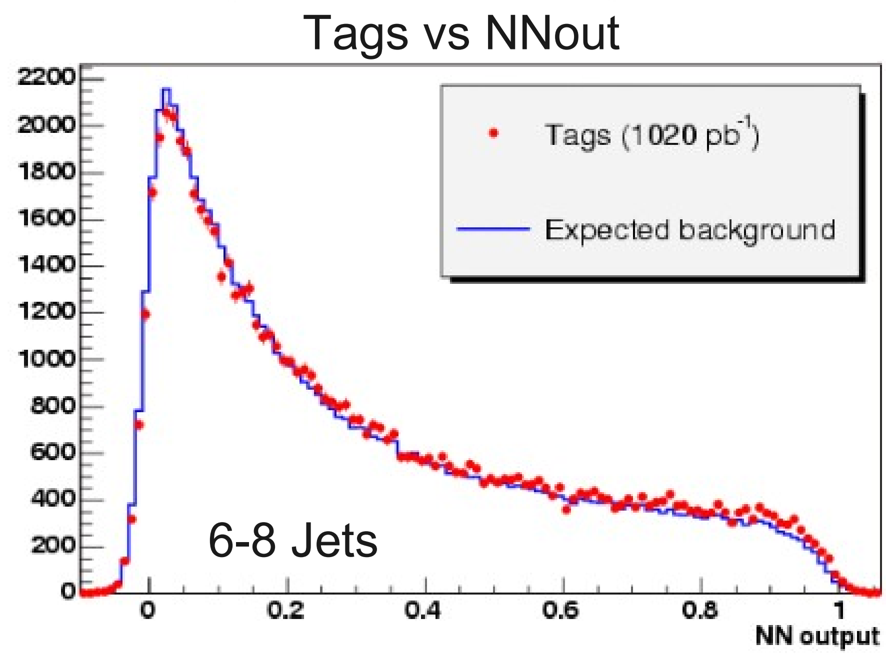


- Check matrix predictions by weighting events before b-tag with the tag rate.

- Very good agreement overall neural network spectrum and for different jet multiplicities.

- The discrepancy between data and the expected background is evaluated and treated as a systematic uncertainty of 2.5% on the background normalization.

Note that events with multiple tags have multiple entries in the plots



Kinematical Selection Optimization

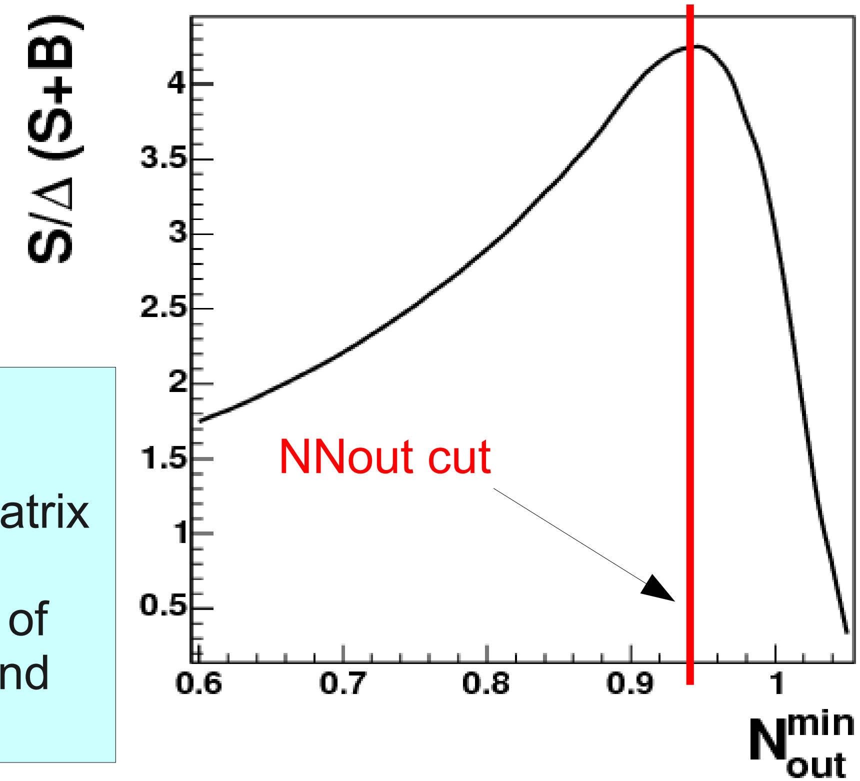
The cut on NNout is optimized in order to maximize the signal significance after the request of btagging

Scan each cut on NN output:
- get expected amount of tags from signal using MC
- get expected amount of tags from bkg using Tag Matrix
- Calculate signal significance as the ratio between expected signal and the total uncertainty on the sum of signal and background, considering both statistical and systematic uncertainties

Best Cut: NNout ≥ 0.94, Efficiency ~ 4.8%,

S/B~1/12 before tagging,

S/B~1/2 after SecVtX tags

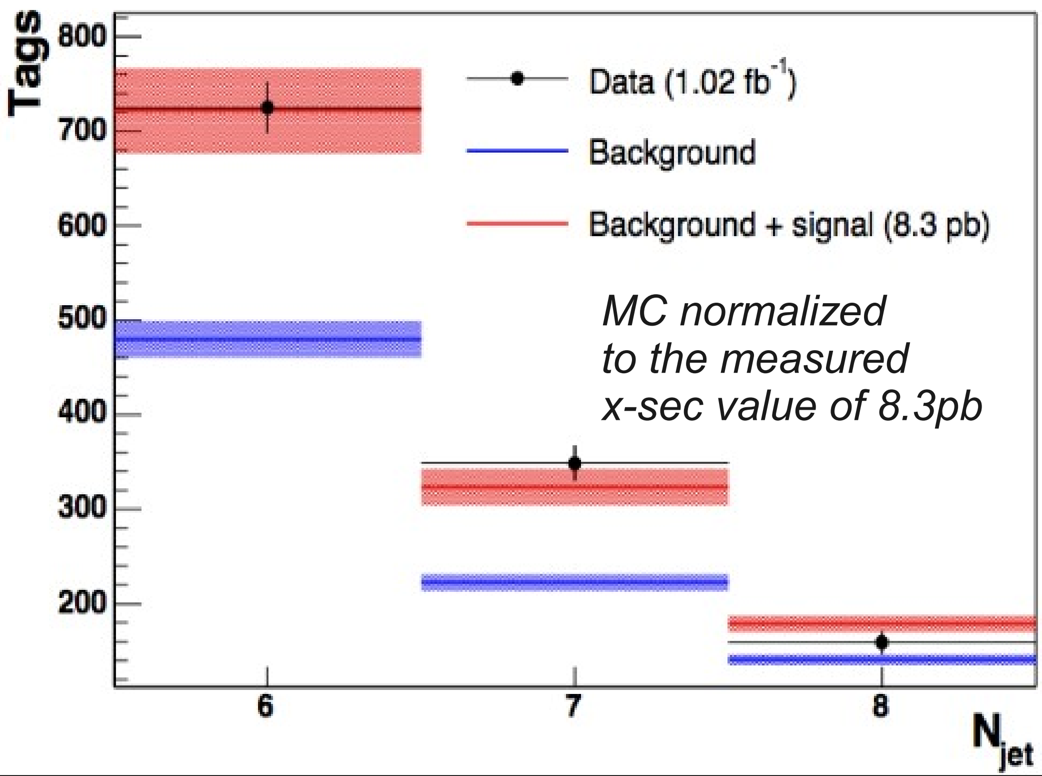


~50% improvement with respect to the old selection!

Kin Sel +≥1 Tag Sample

We can now look at matrix predictions in the data sample after network selection and compare it with SecVtX tagged data

Observed b-tags vs Jets
$6 \leq$ Njets ≤ 8
NNout ≥ 0.94



The data is consistent with
MC+BKG expectations in all jet bins

Note:

matrix-based background prediction is corrected with an iterative procedure to account for the ttbar presence in the pre-tag sample:

$$N'_{exp} = N_{exp} \frac{N_{evts} - N_{tt}}{N_{evts}} = N_{exp} \frac{N_{evts} - (N_{obs} - N_{exp}) / n^{tag}_{ave}}{N_{evts}}$$

The procedure stops when $|N_{exp}' - N_{exp}| < 1\%$

Systematic uncertainties

Source	Relative uncertainty (%)
Energy Scale	16.3
PDFs	1.4
ISR/FSR	2.9
Monte Carlo Modeling	1.1
Multiple interactions	2.5
Average number of tags	7.4
Estimated background	2.5
Integrated luminosity	6.0

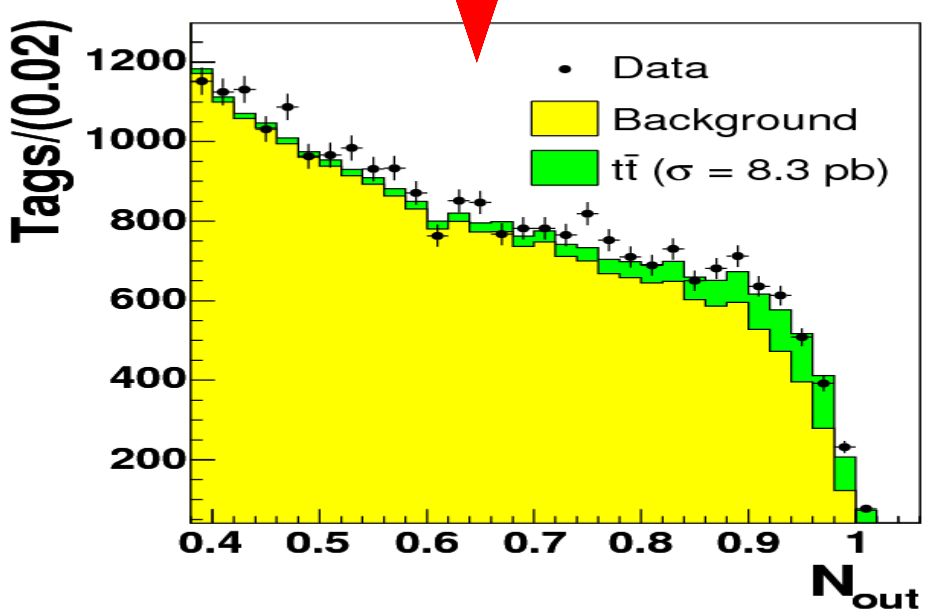
Measurement Systematics dominated mainly by Jet Energy Scale!

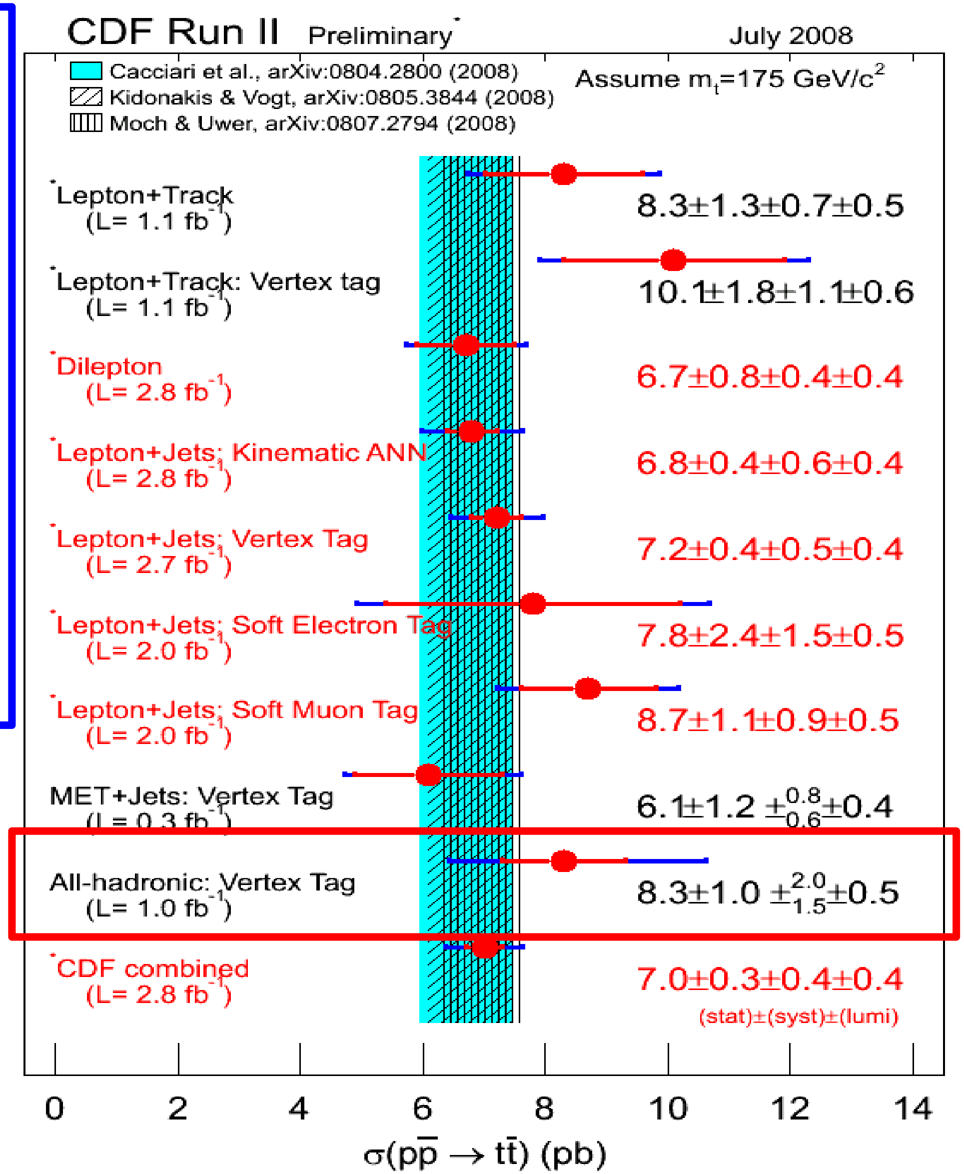
Cross section result

N_{evts} pre tag	-	4205
Obs tags	Nobs	1233
Exp tags	-	937 ± 30
Exp tags corr*	Nbck	846 ± 37
Efficiency	εNN	4.8 ± 0.8 %
Average tags	n_{av}^{etag}	0.95 ± 0.07
Luminosity	L	1.02 ± 0.06 fb-1

$$\sigma_{ttbar} = \frac{N_{obs}^{tag} - N_{exp}^{tag}}{\varepsilon_{kin} \cdot \varepsilon_{tag}^{ave} \cdot L}$$

$$\sigma_{t\bar{t}} = 8.3 \pm 1.0(stat)^{+2.0}_{-1.5}(syst) \pm 0.5(lum)$$





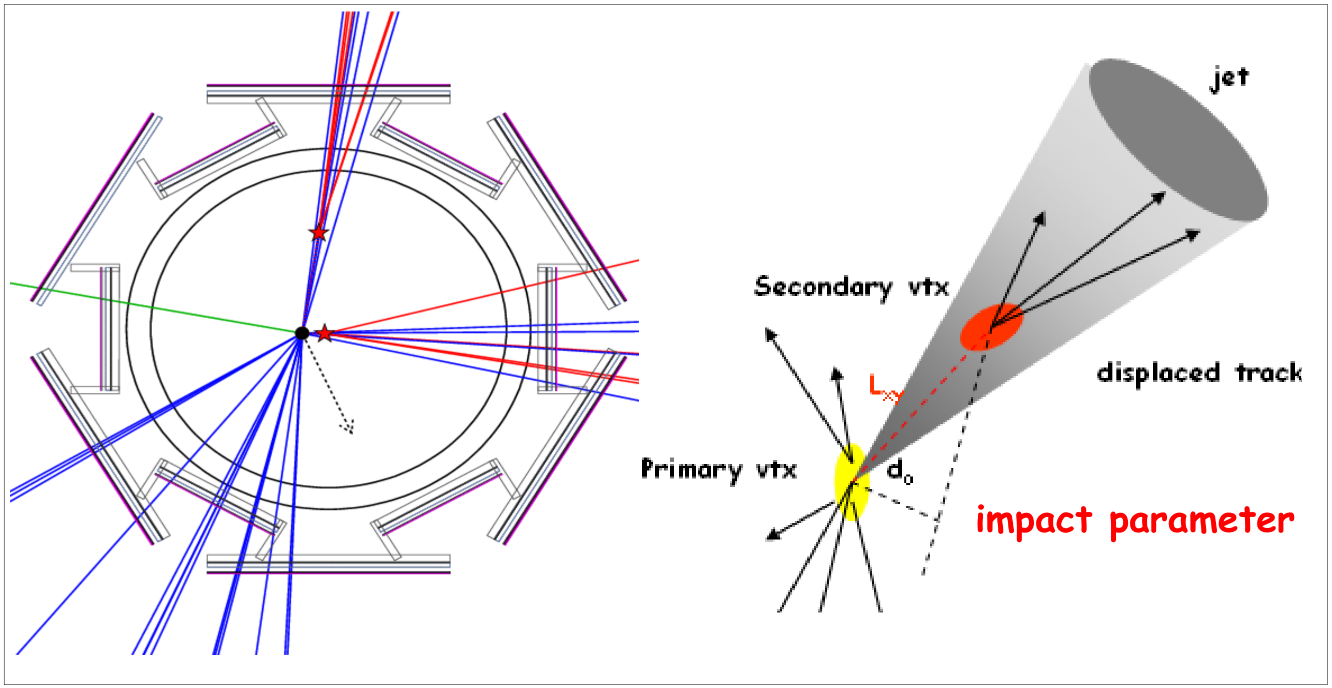
The cross section measurement is in agreement:

- with the Standard Model
- with previous determinations
- with data over a wide NNout range

Backup

b-jets identification

a B Hadron travels some mm before decaying:
- secondary vertex displaced from primary one
- tracks have high impact parameter



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