

January 8, 2007

Evidence for production of single top quarks at DØ and a first direct measurement of $|V_{tb}|$

- ▶ Electroweak production of top quarks at DØ
- ▶ Event selection and background estimation
- ▶ Multivariate methods
 - Decision Trees, Matrix Elements, Bayesian NN
- ▶ Cross checks. Expected sensitivity
- ▶ Cross sections and significance
- ▶ First direct measurement of $|V_{tb}|$
- ▶ Summary

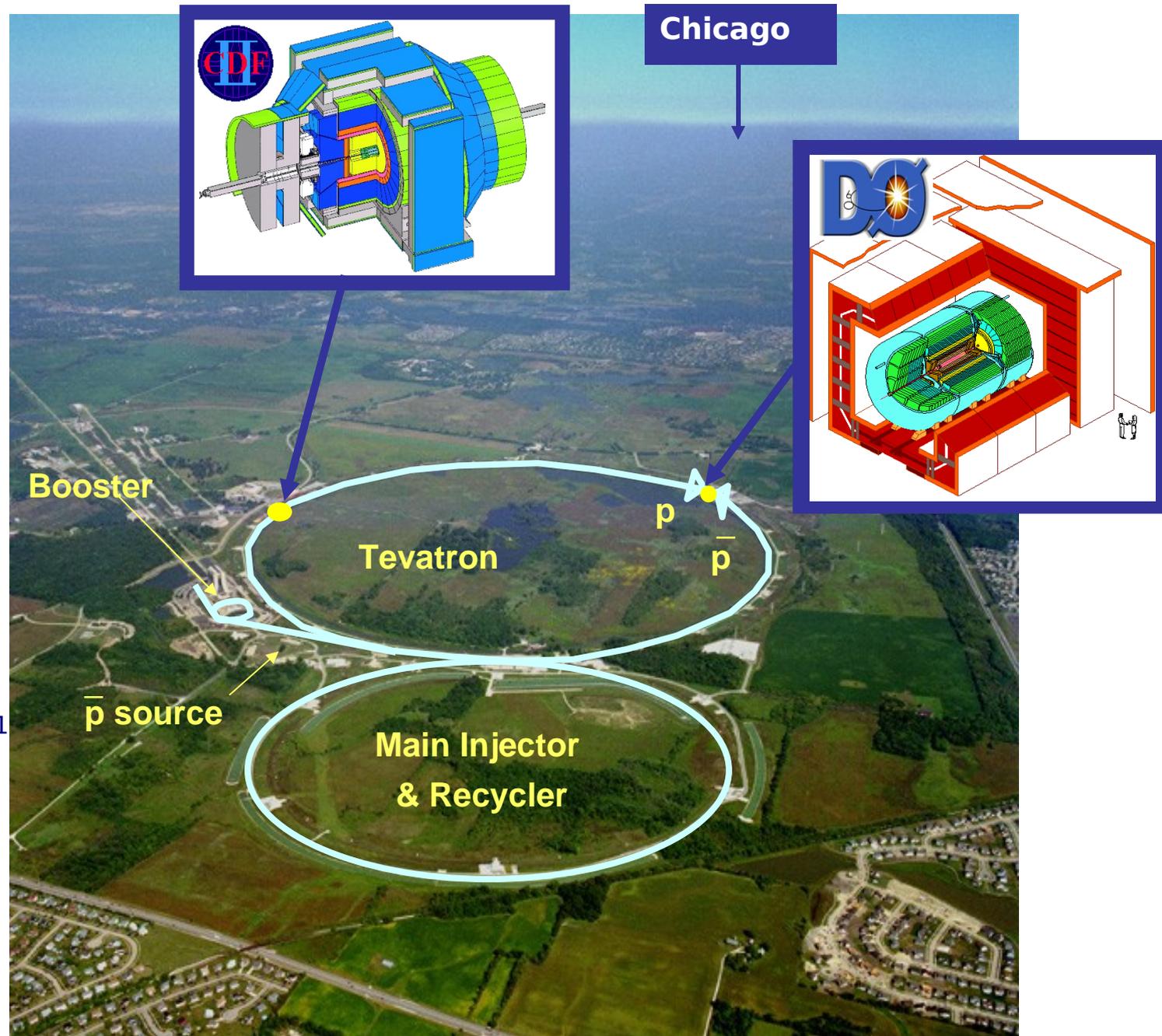
The Tevatron

The highest energy particle accelerator in the world!

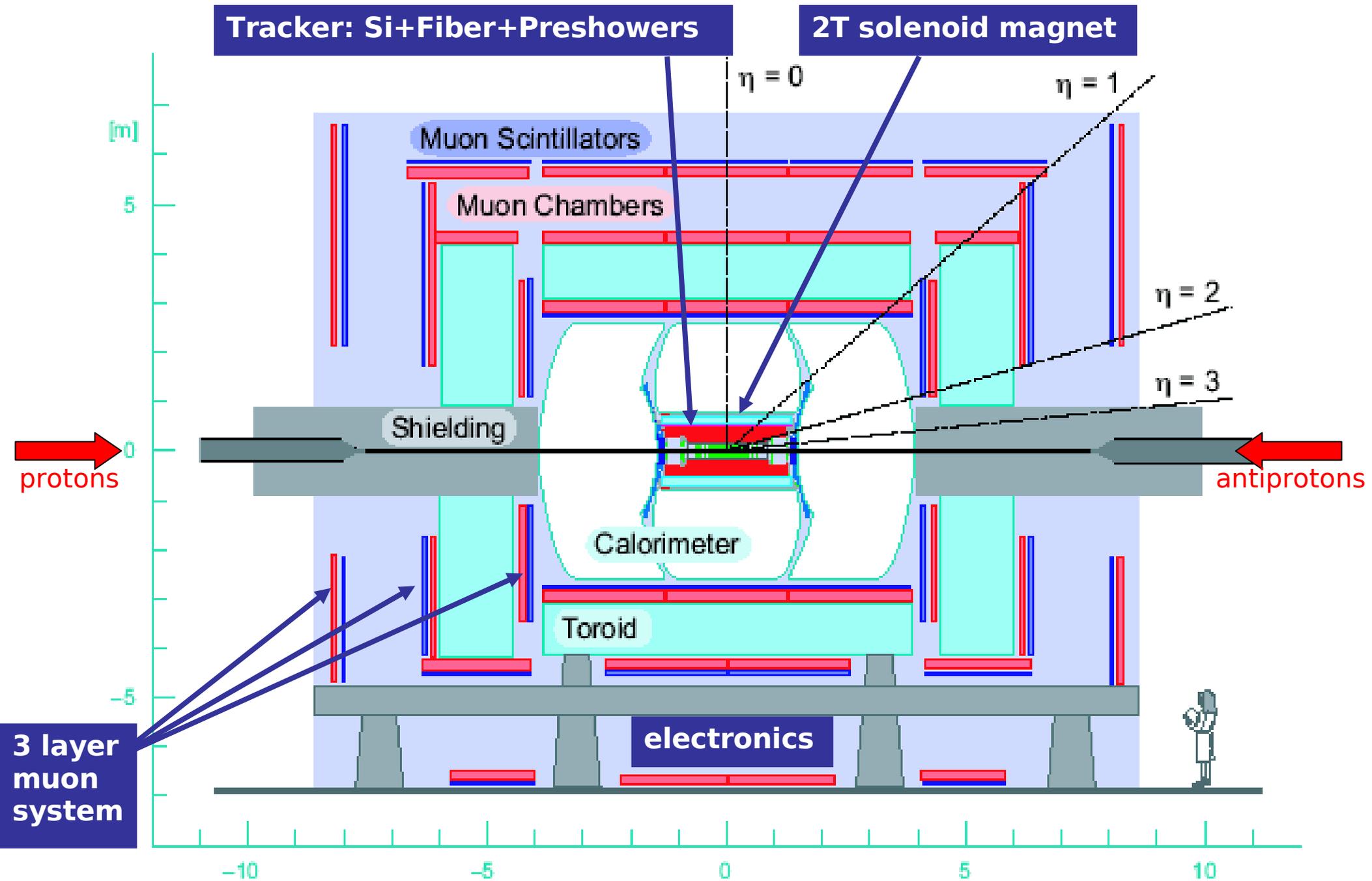
Proton-antiproton collider

Run I 1992-1995
Top quark discovered!

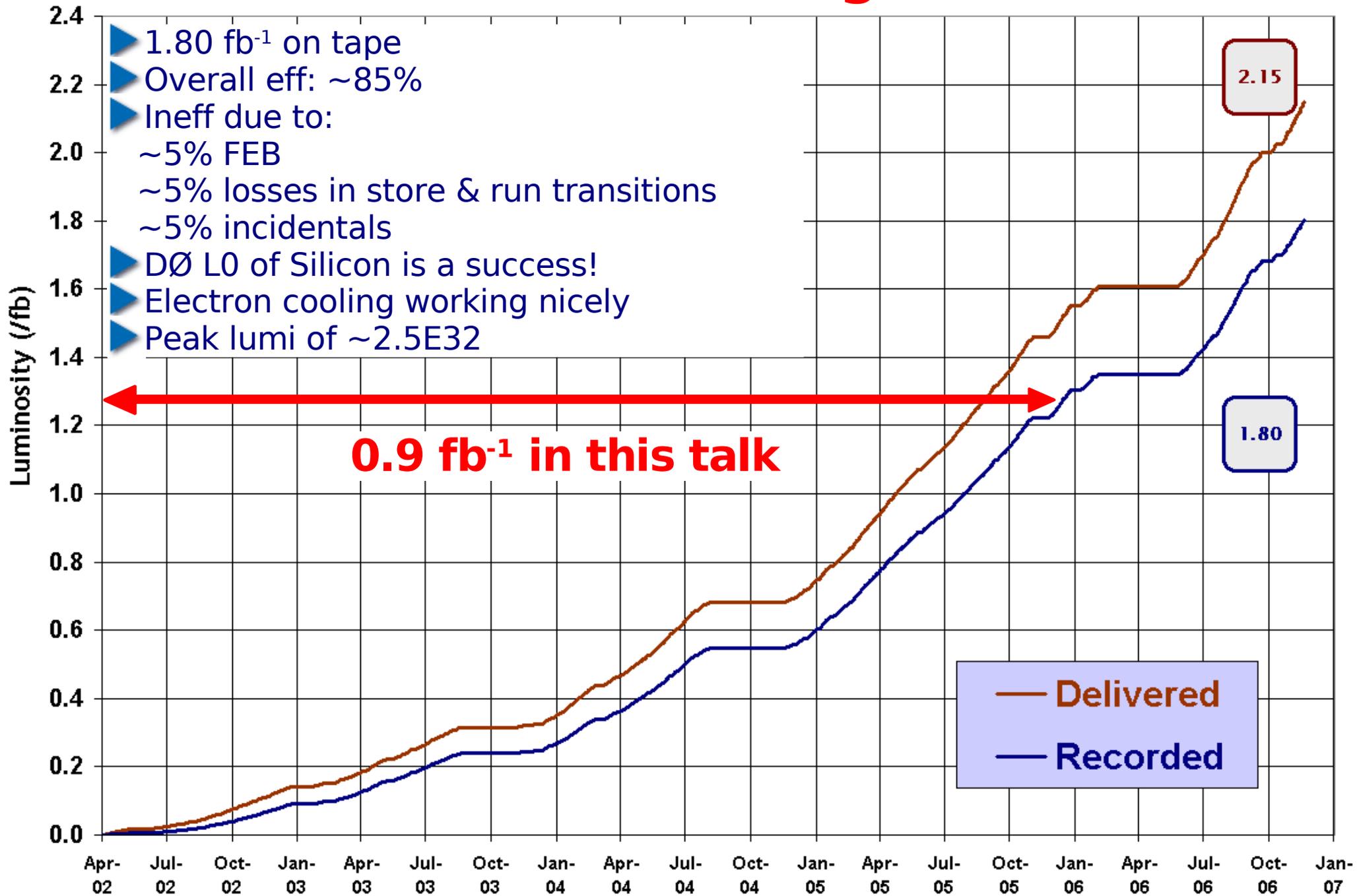
Run II 2001-09(?)
 $\sqrt{s} = 1.96 \text{ TeV}$
 $\Delta t = 396 \text{ ns}$
>2fb⁻¹ delivered
Peak Lum: $2 \cdot 10^{32} \text{ cm}^{-2} \text{ s}^{-1}$



DØ for Run II



Data taking



Top quark physics

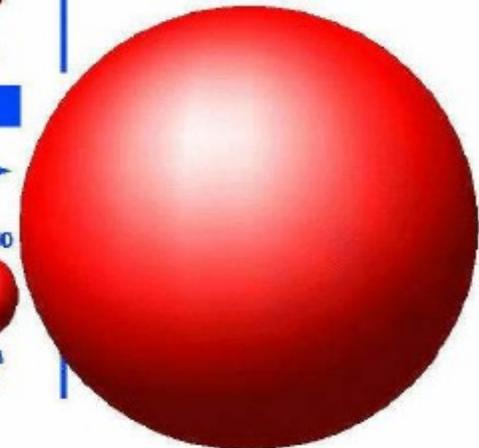
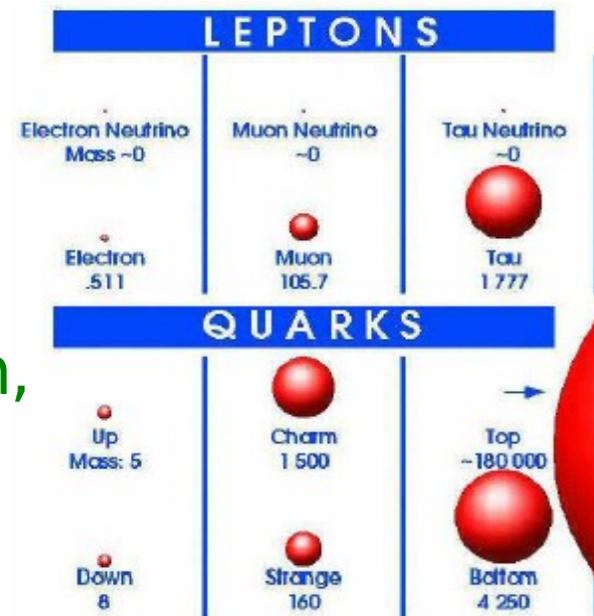
The top quark is a very special fermion:

- ▶ Heaviest known particle: $171.4 \pm 2.1 \text{ GeV}$
 - ▶ $m_t \sim v/\sqrt{2}$, $\lambda_t \sim 1 \rightarrow$ Related to EWSB!
 - ▶ Sensitive probe for new physics, FCNCs, ...
- ▶ Decays as a free quark: $\tau_t = 5 \times 10^{-25} \text{ s} \ll \Lambda_{\text{QCD}}^{-1}$
 - ▶ Spin information is passed to its decay products
 - ▶ Test V-A structure of the SM

We still don't know: spin, width, lifetime

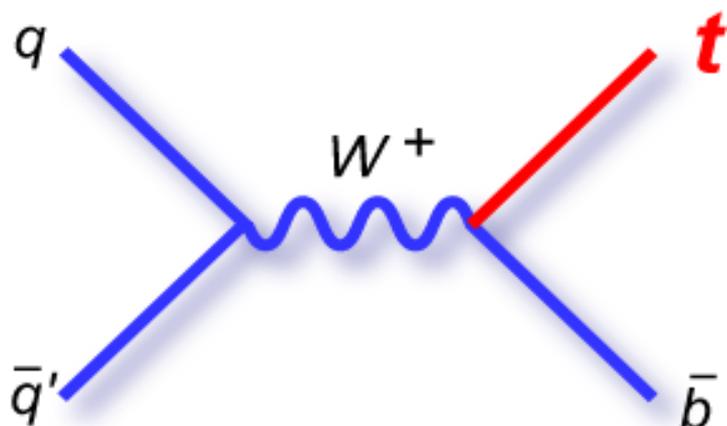
We know the mass, cross section, charge and its $\text{BR}(t \rightarrow Wb) \sim 1$

Plenty of room for new physics



Top quark electroweak production

PRD 66 (02) 054024
hep-ph/0408049



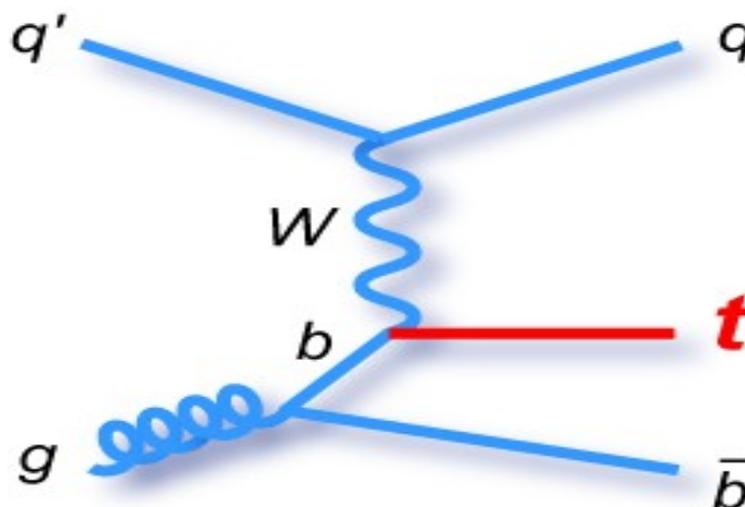
s-channel (tb)

$$\sigma_{\text{NLO}} = 0.88 \pm 0.11 \text{ pb}$$

Current limits @ 95% C.L.:

$$D\emptyset (370 \text{ pb}^{-1}) \quad \sigma_{\text{tb}} < 5.0 \text{ pb}$$

$$\text{CDF} (700 \text{ pb}^{-1}) \quad \sigma_{\text{tb}} < 3.1 \text{ pb}$$



t-channel (tqb)

$$\sigma_{\text{NLO}} = 1.98 \pm 0.25 \text{ pb}$$

Current limits @ 95% C.L.:

$$D\emptyset (370 \text{ pb}^{-1}) \quad \sigma_{\text{tqb}} < 4.4 \text{ pb}$$

$$\text{CDF} (700 \text{ pb}^{-1}) \quad \sigma_{\text{tqb}} < 3.2 \text{ pb}$$

Why search for single top?

► Access W-t-b coupling

- measure V_{tb} directly → more on this later

- test unitarity of CKM

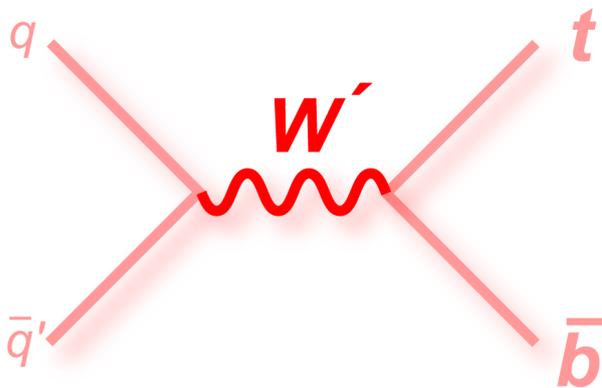
► New physics:

- s-channel sensitive to resonances: W' , top pions, SUSY, etc...

- t-channel sensitive to FCNCs, anomalous couplings

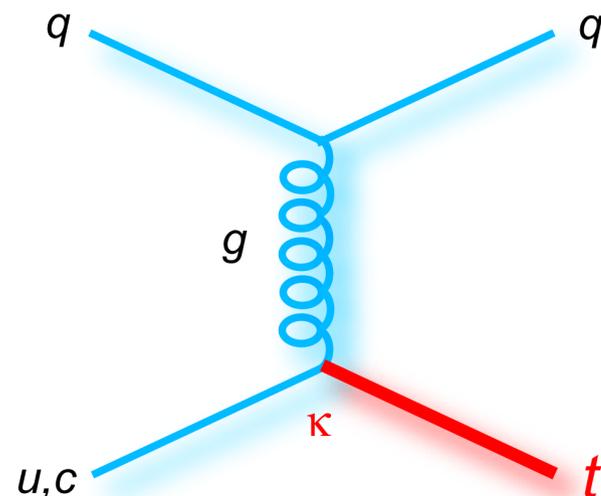
► Source of polarized top quarks

► Extract small signal out of a large background



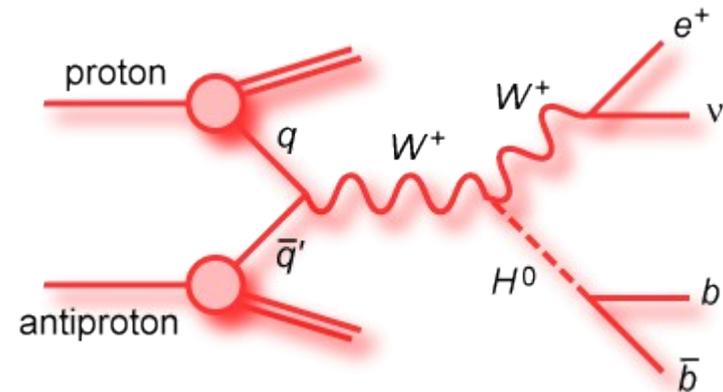
DØ search: hep-ex/0607102

Arán García-Bellido



DØ search: t.b.s. PRL

First evidence for single top



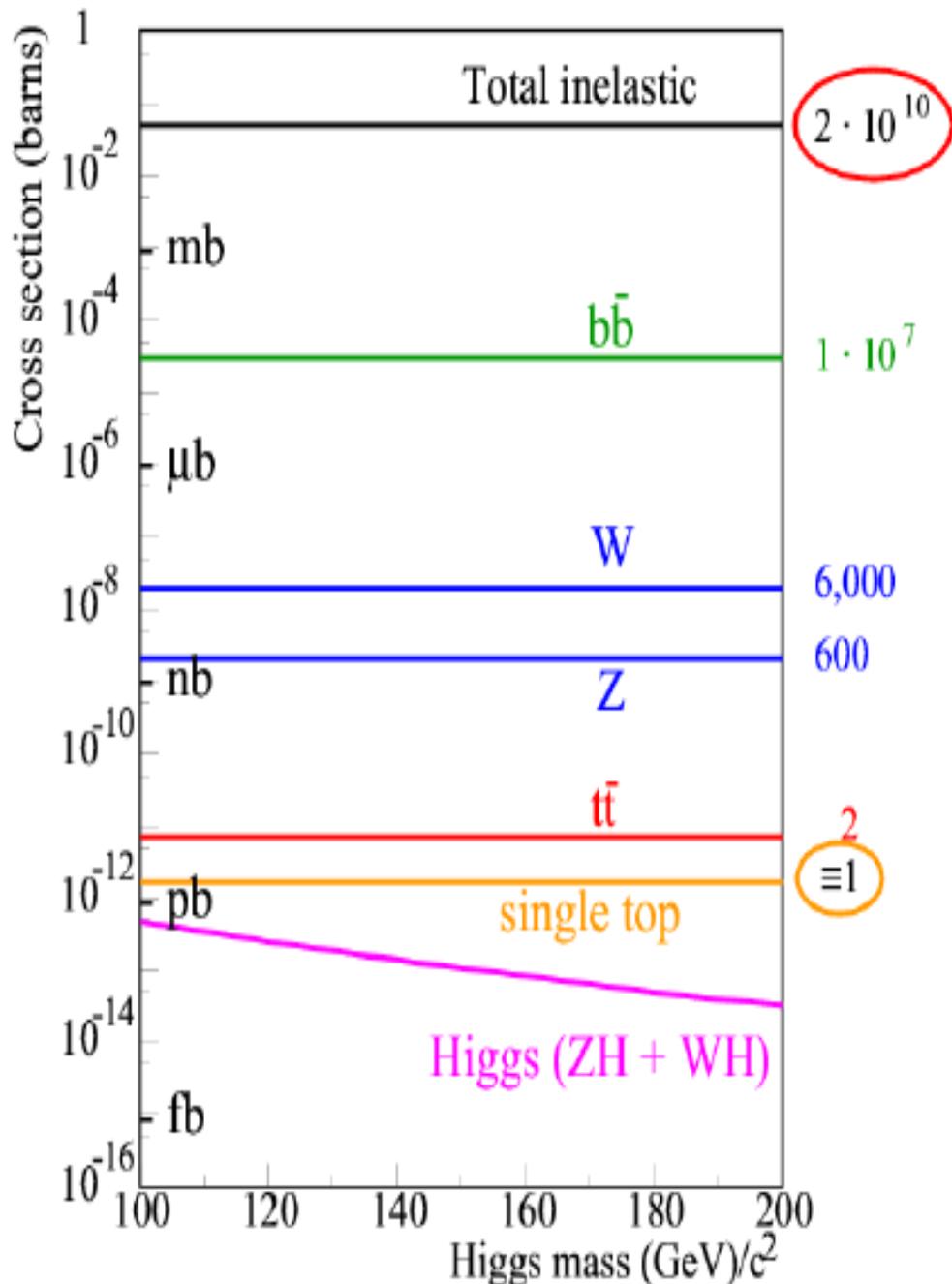
A big challenge!

~20 single top events produced per day

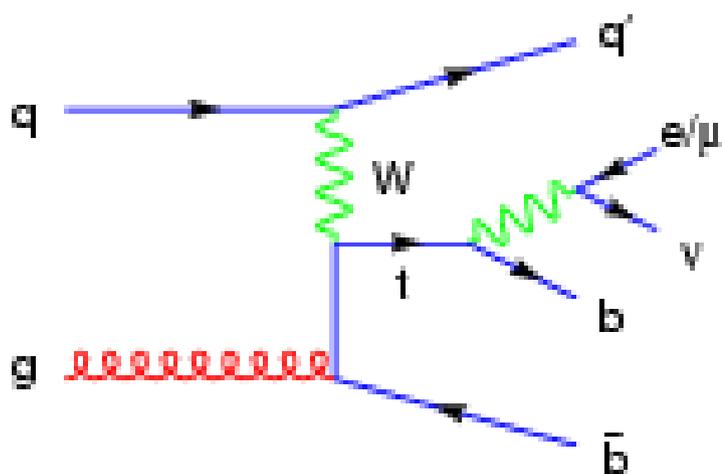
But huge backgrounds!

We have benefited greatly from the following improvements for this analysis:

- ▶ Background model improvements (PS↔ME matching: MLM)
- ▶ Fully reprocessed dataset: new calibrations, jet thresholds, JES,...
- ▶ New more efficient NN b-tagger
- ▶ Split channels by jet multiplicity
- ▶ Combined s+t search added (SM s:t ratio is assumed)

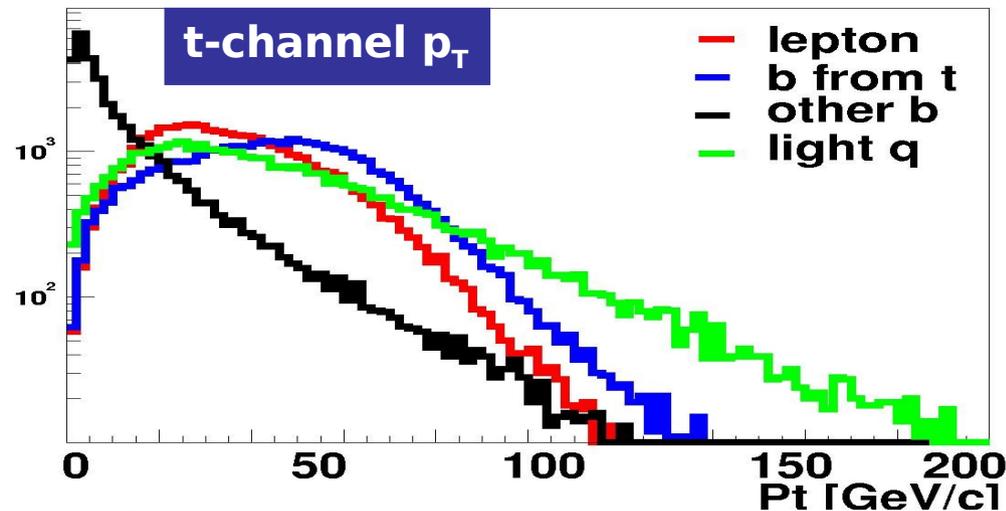
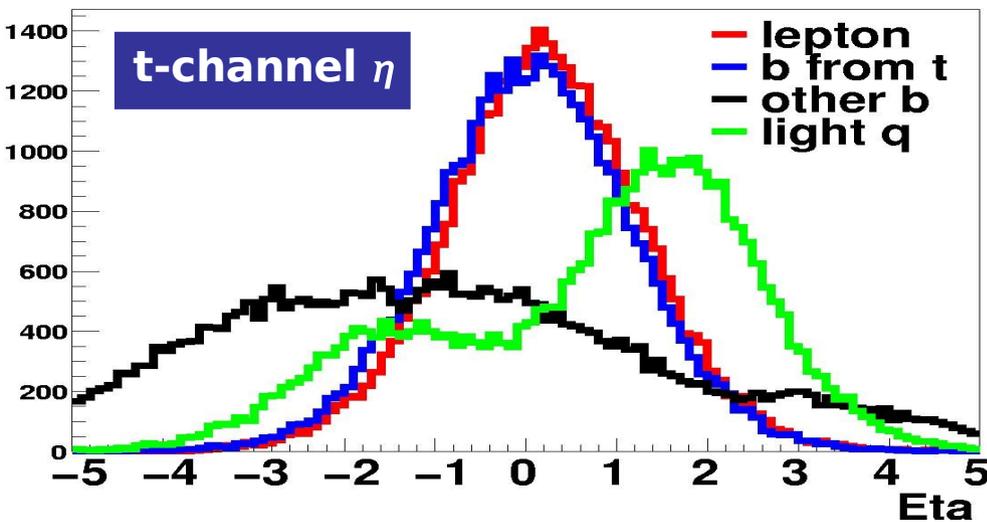


Signal selection



Signature:

- One high p_T isolated lepton (from W)
- MET (ν from W)
- One b-quark jet (from top)
- A light flavor jet and/or another b-jet



Event selection:

▶ Only one tight (no loose) lepton:

● e: $p_T > 15$ GeV and $|\eta^{\text{det}}| < 1.1$

● μ : $p_T > 18$ GeV and $|\eta^{\text{det}}| < 2.0$

▶ MET > 15 GeV

▶ 2-4 jets: $p_T > 15$ GeV and $|\eta^{\text{det}}| < 3.4$

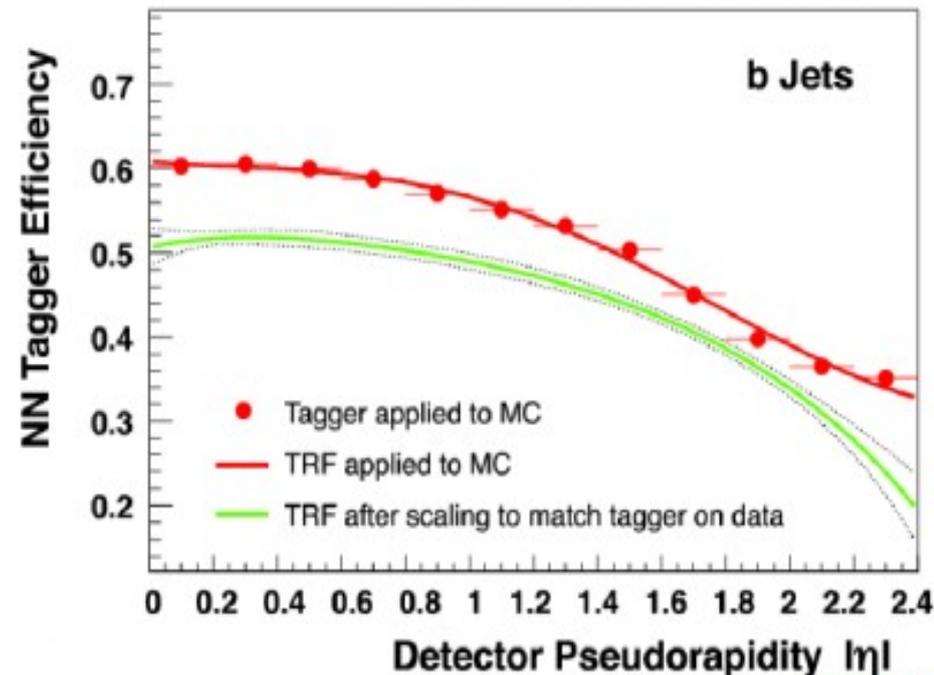
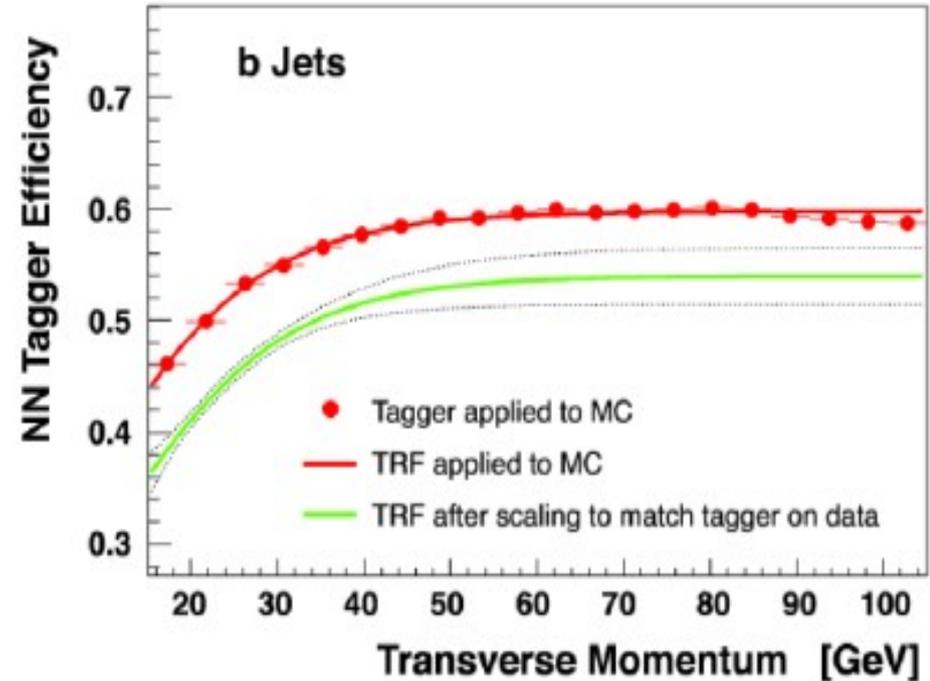
● Leading jet: $p_T > 25$ GeV ; $|\eta^{\text{det}}| < 2.5$

● Second leading jet: $p_T > 20$ GeV

▶ One or two b-tagged jets

NN b-jet tagger

- ▶ NN trained on 7 input variables from SVT, JLIP and CSIP taggers
- ▶ **Much improved performance!**
 - Fake rate reduced by 1/3 for same b-efficiency relative to previous tagger
 - Smaller systematic uncertainty
- ▶ Tag Rate Functions (TRFs) in η , p_T and z-PV derived in data are applied to MC
- ▶ Our operating point:
 - b-jet efficiency: $\sim 50\%$
 - c-jet efficiency: $\sim 10\%$
 - Light-jet efficiency: $\sim 0.5\%$



Background modeling

► W+jets: $\sim \mathcal{O}(1000)$ pb

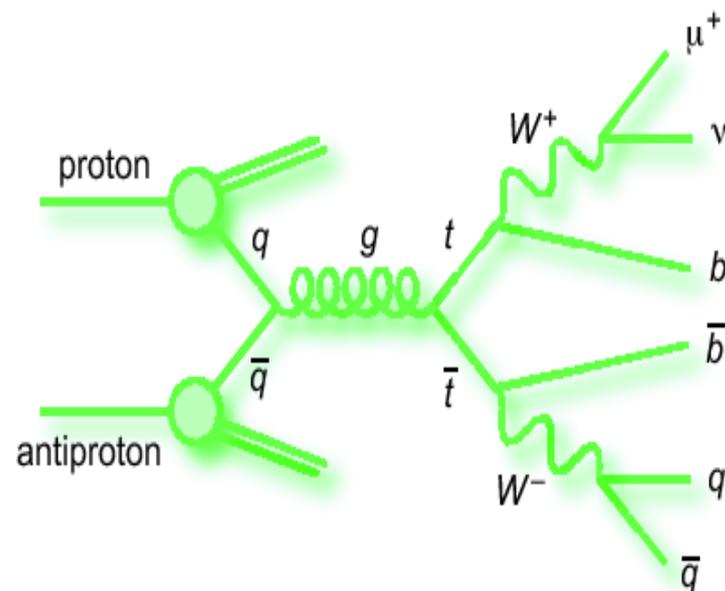
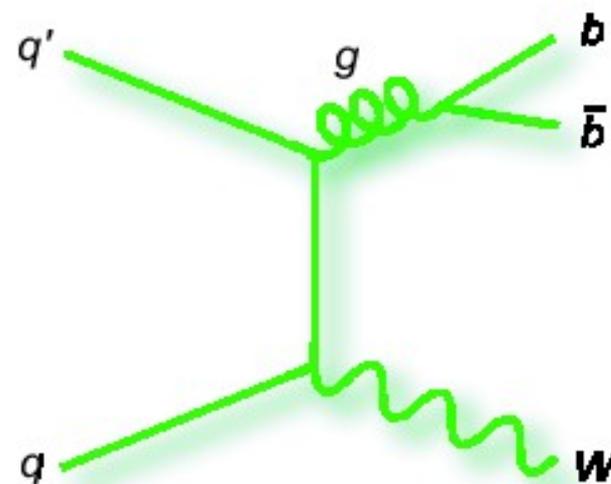
- Distributions from Alpgen 2.0
- Normalization from data
- Heavy flavor fractions from data

► Top pairs: ~ 7 pb

- Topologies: dilepton and ℓ +jets
- Use Alpgen 2.0 with MLM matching
- Normalize to NNLO σ

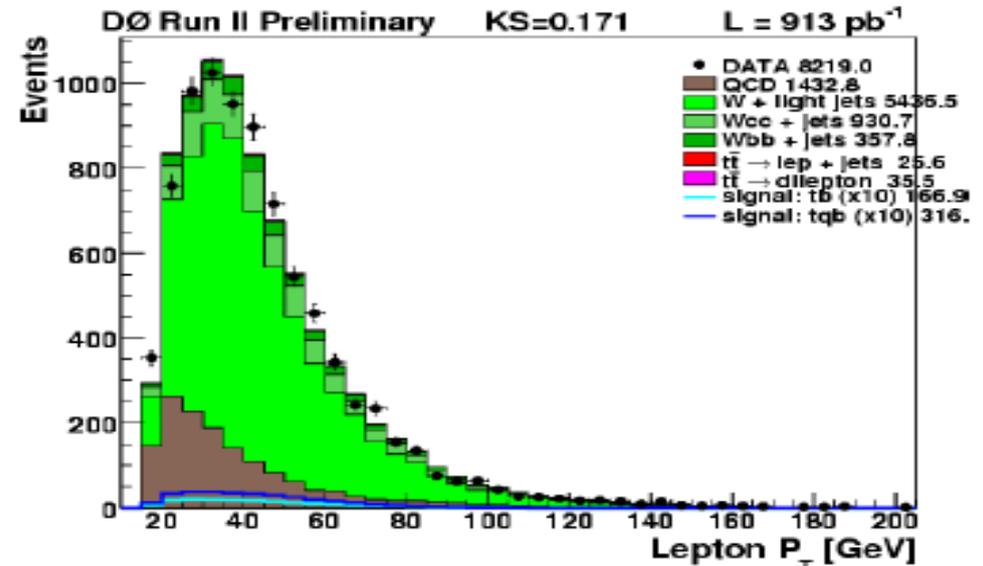
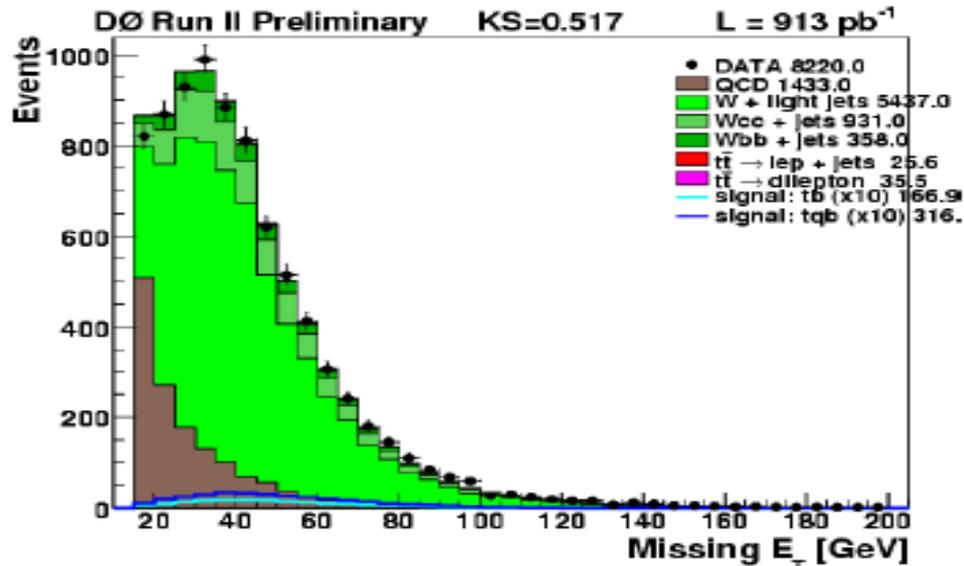
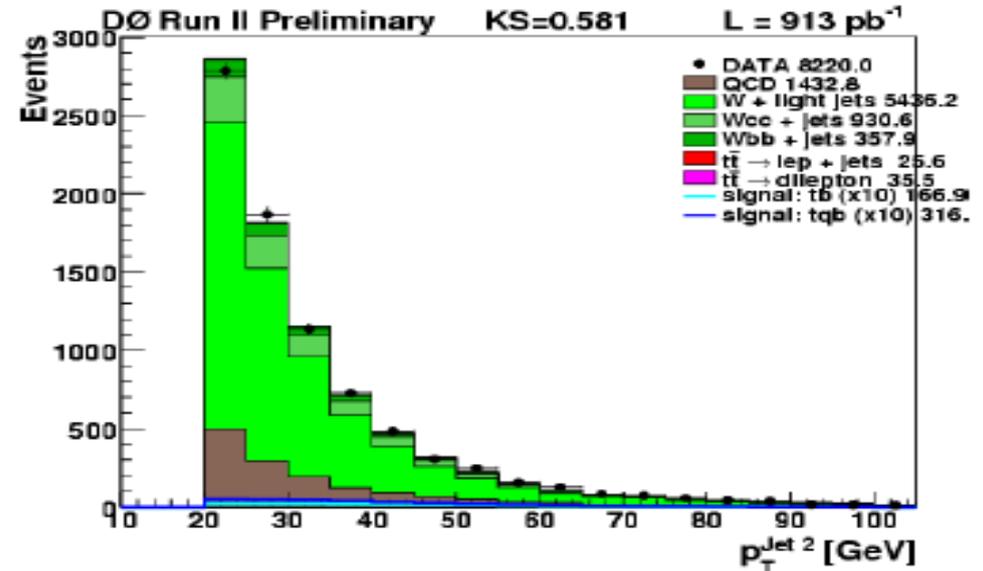
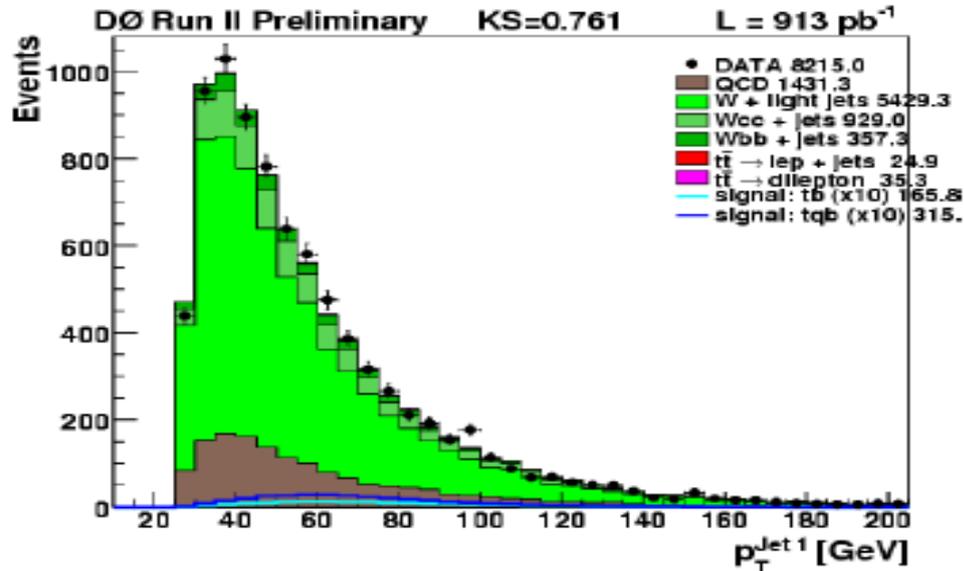
► Multijet events (misidentified lepton)

- From data



Agreement before tagging

- ▶ Normalize W+jets and QCD yields to data before tagging
- ▶ Check 90 variables (in e,mu x 2,3,4 jets)
- ▶ Good description of data



Yields after event selection

Source	Event Yields in 0.9 fb ⁻¹ Data		
	Electron+muon, 1tag+2tags combined		
	2 jets	3 jets	4 jets
<i>tb</i>	16 ± 3	8 ± 2	2 ± 1
<i>tqb</i>	20 ± 4	12 ± 3	4 ± 1
<i>t\bar{t} → ll</i>	39 ± 9	32 ± 7	11 ± 3
<i>t\bar{t} → l+jets</i>	20 ± 5	103 ± 25	143 ± 33
<i>W+bb\bar{b}</i>	261 ± 55	120 ± 24	35 ± 7
<i>W+c\bar{c}</i>	151 ± 31	85 ± 17	23 ± 5
<i>W+jj</i>	119 ± 25	43 ± 9	12 ± 2
Multijets	95 ± 19	77 ± 15	29 ± 6
Total background	686 ± 131	460 ± 75	253 ± 42
Data	697	455	246

- ▶ Optimized the selection to maximize acceptance
- ▶ Allow a lot of background at this stage!
- ▶ Then use multiple distributions to separate signal-background

Event selection and S:B

Percentage of single top *tb+tb* selected events and S:B ratio (white squares = no plans to analyze)

Electron + Muon	1 jet	2 jets	3 jets	4 jets	≥ 5 jets
0 tags	10% 1 : 3,200	25% 1 : 390	12% 1 : 300	3% 1 : 270	1% 1 : 230
1 tag	6% 1 : 100	21% 1 : 20	11% 1 : 25	3% 1 : 40	1% 1 : 53
2 tags		3% 1 : 11	2% 1 : 15	1% 1 : 38	0% 1 : 43

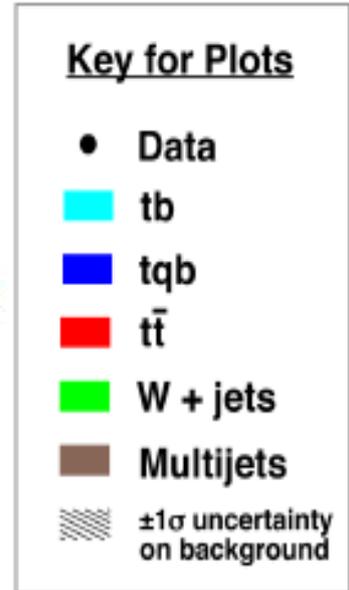
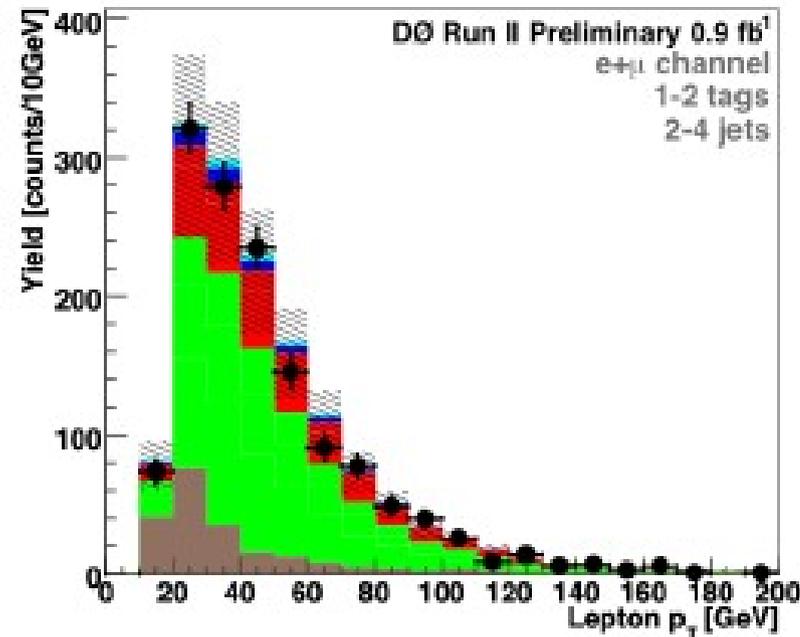
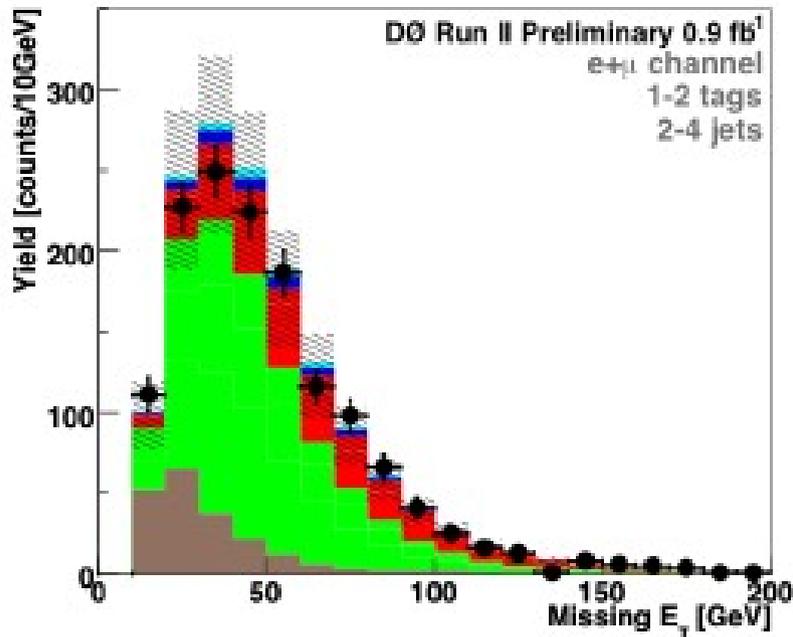
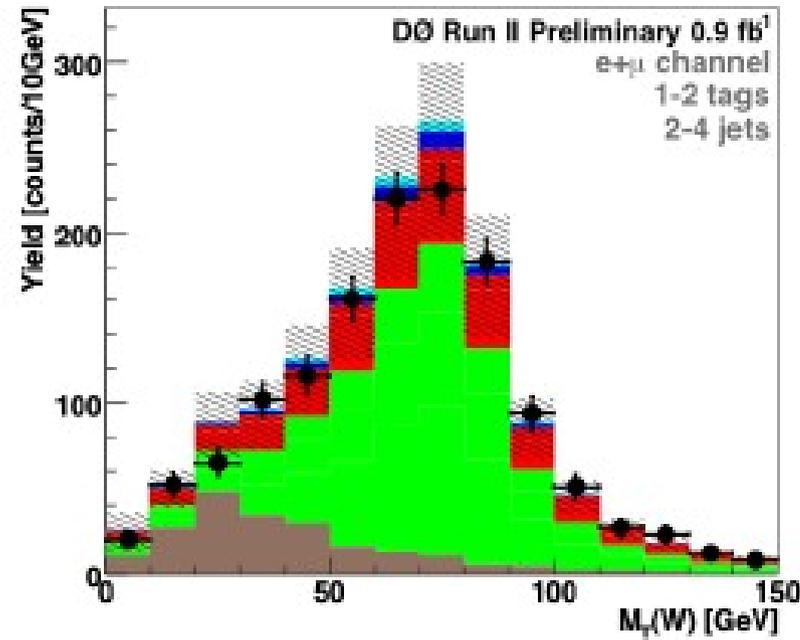
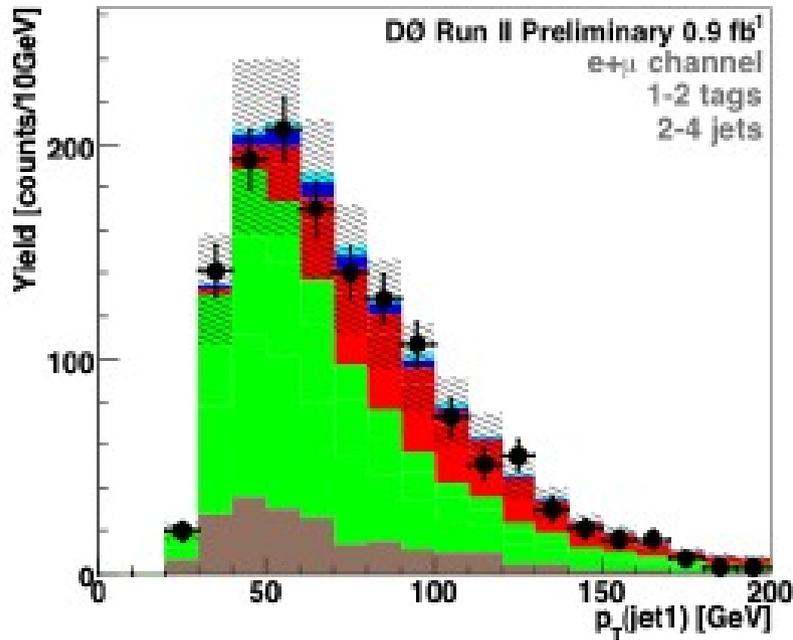
Systematic uncertainties

- ▶ Uncertainties are assigned per background, jet multiplicity, lepton channel, and number of tags
- ▶ Uncertainties that affect both the **normalization** and the **shapes**: JES and tag rate functions
- ▶ Correlations between channels and sources are taken into account

Examples of Relative Systematic Uncertainties

$t\bar{t}$ cross section	18%
Luminosity	6%
Electron trigger	3%
Muon trigger	6%
Jet energy scale	wide range
Jet fragmentation	5–7%
Heavy flavor ratio	30%
Tag-rate functions	2–16%

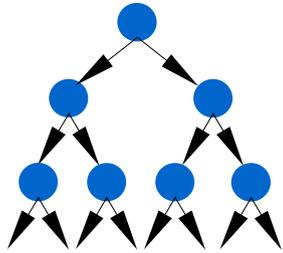
And check 1000s of plots again...



Analysis methods

- ▶ Once we understand our data, need to measure the signal
- ▶ We cannot use simple cuts to extract the signal:
use **multivariate techniques**
- ▶ DØ has implemented three analysis methods to extract the signal from the same dataset:

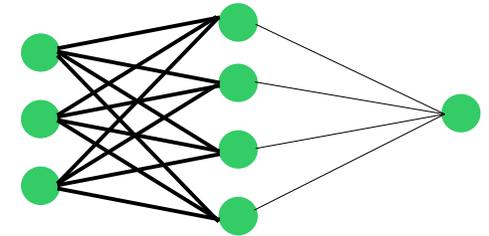
Decision Trees



Matrix Elements

$$\int M$$

Bayesian NNs



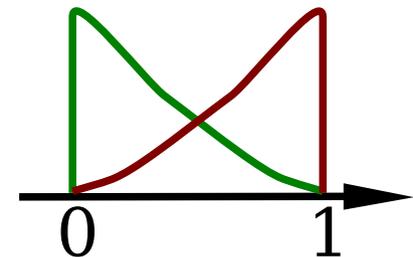
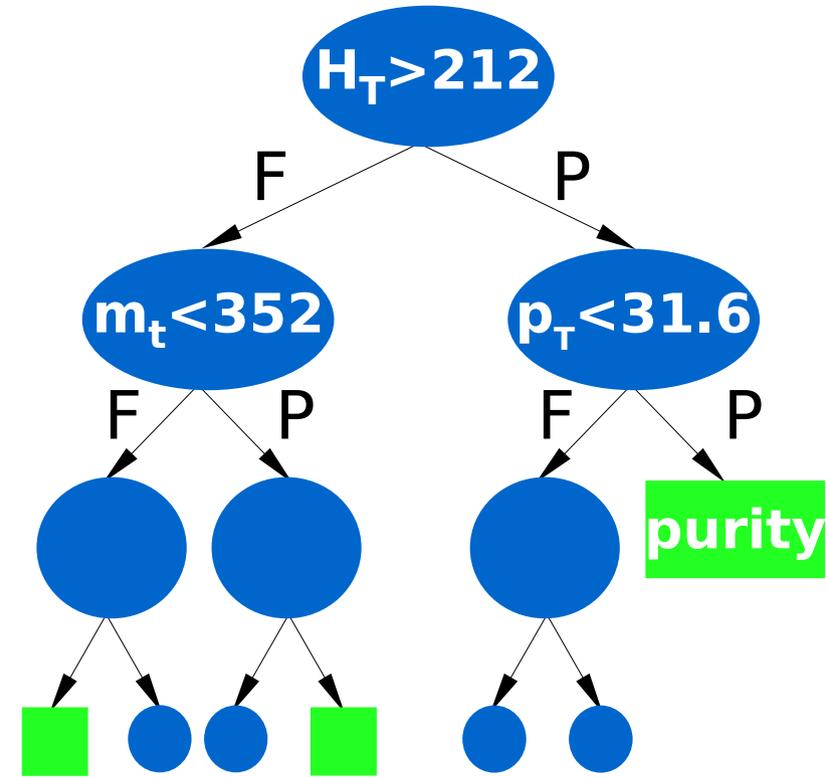
- DT and BNN use same pool of discriminating variables
- ME method uses 4-vectors of reconstructed objects
- Optimized separately for s-channel, t-channel and s+t
- Test response and robustness with ensemble testing

Decision Trees

Machine learning technique widely used in social sciences

Idea: recover events that fail criteria in cut-based analysis

- ▶ Start with all events (first node ●)
- ▶ For each variable, find the splitting value with best separation between children
- ▶ Select best variable and cut: produce **P**ass and **F**ailed branches
- ▶ Repeat recursively on each node
- ▶ Stop when improvement stops or when too few events left
- ▶ Terminal node: leaf ■ with $\text{purity} = N_S / (N_S + N_B)$
- ▶ Output: purity for each event



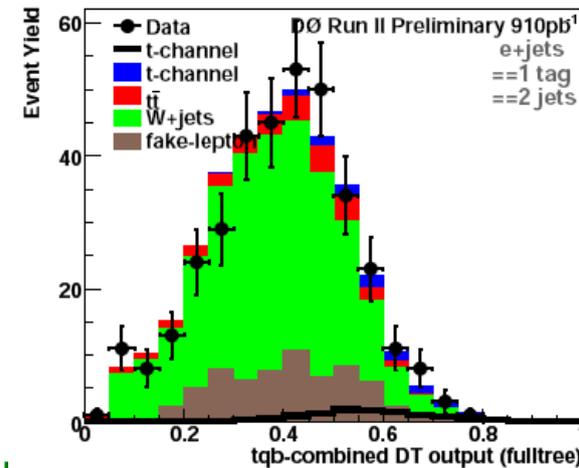
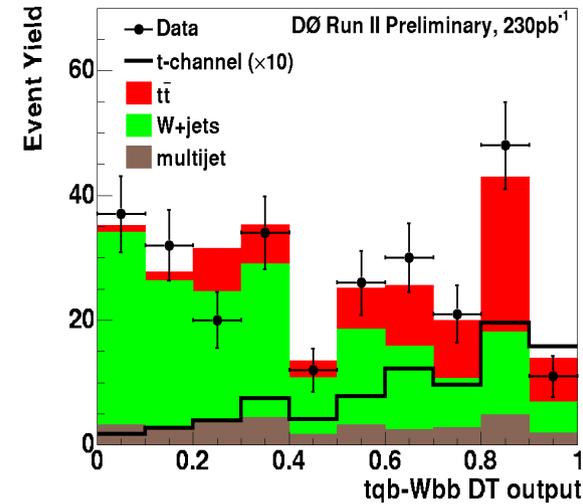
Decision Trees + Boosting

Boosting is a recent technique to improve the performance of any weak classifier: recently used in DTs by GLAST and MiniBooNE

AdaBoost algorithm: adaptive boosting

- 1) Train a tree T_k
- 2) Check which events are **misclassified** by T_k
- 3) Derive tree weight α_k
- 4) Increase weight of misclassified events
- 5) Train again to build T_{k+1}

- We have trained 36 separate trees: (s, t, s+t)x(e,mu)x(2,3,4 jets)x(1,2 tags)
- Use 1/3 of MC events for training
- For each signal, train against sum of backgrounds
- Signal leaf if purity > 0.5; Minimum leaf size = 100 events; Goodness of split: Gini factor; Adaboost $\beta = 0.2$; boosting cycles = 20



Decision Trees: 49 variables

Object Kinematics

$p_T(\text{jet1})$
 $p_T(\text{jet2})$
 $p_T(\text{jet3})$
 $p_T(\text{jet4})$
 $p_T(\text{best1})$
 $p_T(\text{notbest1})$
 $p_T(\text{notbest2})$
 $p_T(\text{tag1})$
 $p_T(\text{untag1})$
 $p_T(\text{untag2})$

Angular Correlations

$\Delta R(\text{jet1}, \text{jet2})$
 $\cos(\text{best1}, \text{lepton})_{\text{besttop}}$
 $\cos(\text{best1}, \text{notbest1})_{\text{besttop}}$
 $\cos(\text{tag1}, \text{alljets})_{\text{alljets}}$
 $\cos(\text{tag1}, \text{lepton})_{\text{btaggedtop}}$
 $\cos(\text{jet1}, \text{alljets})_{\text{alljets}}$
 $\cos(\text{jet1}, \text{lepton})_{\text{btaggedtop}}$
 $\cos(\text{jet2}, \text{alljets})_{\text{alljets}}$
 $\cos(\text{jet2}, \text{lepton})_{\text{btaggedtop}}$
 $\cos(\text{lepton}, Q(\text{lepton}) \times Z)_{\text{besttop}}$
 $\cos(\text{lepton}, \text{besttopframe})_{\text{besttopCMframe}}$
 $\cos(\text{lepton}, \text{btaggedtopframe})_{\text{btaggedtopCMframe}}$
 $\cos(\text{notbest}, \text{alljets})_{\text{alljets}}$
 $\cos(\text{notbest}, \text{lepton})_{\text{besttop}}$
 $\cos(\text{untag1}, \text{alljets})_{\text{alljets}}$
 $\cos(\text{untag1}, \text{lepton})_{\text{btaggedtop}}$

Event Kinematics

Aplanarity(alljets, W)
 $M(W, \text{best1})$ ("best" top mass)
 $M(W, \text{tag1})$ ("b-tagged" top mass)
 $H_T(\text{alljets})$
 $H_T(\text{alljets} - \text{best1})$
 $H_T(\text{alljets} - \text{tag1})$
 $H_T(\text{alljets}, W)$
 $H_T(\text{jet1}, \text{jet2})$
 $H_T(\text{jet1}, \text{jet2}, W)$
 $M(\text{alljets})$
 $M(\text{alljets} - \text{best1})$
 $M(\text{alljets} - \text{tag1})$
 $M(\text{jet1}, \text{jet2})$
 $M(\text{jet1}, \text{jet2}, W)$
 $M_T(\text{jet1}, \text{jet2})$
 $M_T(W)$
Missing E_T
 $p_T(\text{alljets} - \text{best1})$
 $p_T(\text{alljets} - \text{tag1})$
 $p_T(\text{jet1}, \text{jet2})$
 $Q(\text{lepton}) \times \eta(\text{untag1})$
 $\sqrt{\hat{s}}$
Sphericity(alljets, W)

- Adding variables does not degrade performance
- Tested shorter lists, lose some sensitivity
- Same list used for all channels

Matrix Elements method

- ▶ The idea is to use all available kinematic information from a **fully differential cross-section calculation**
- ▶ Calculate an event probability for signal and background hypothesis

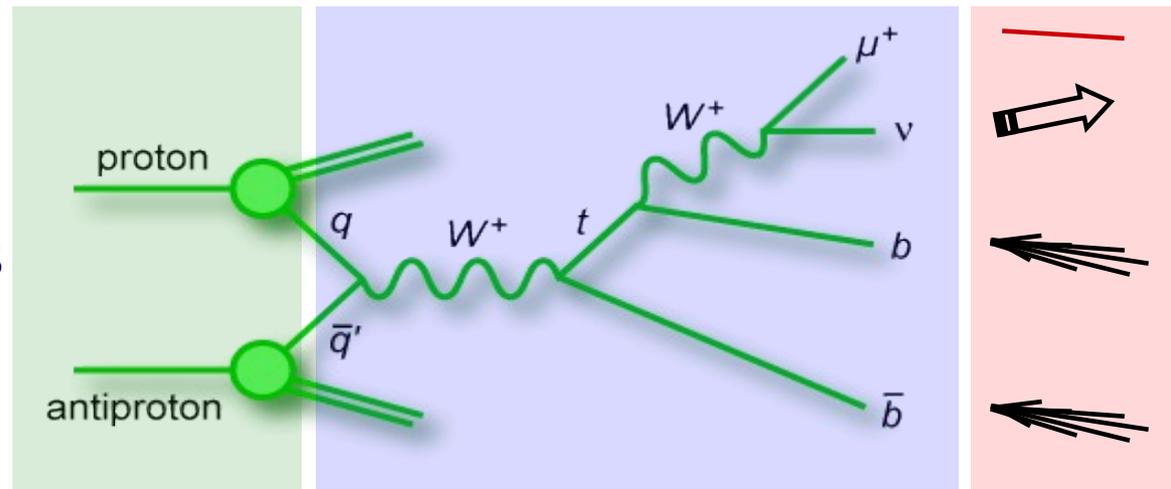
$$P(\vec{x}) = \frac{1}{\sigma} \int f(q_1; Q) dq_1 f(q_2; Q) dq_2 \times |M(\vec{y})|^2 \phi(\vec{y}) dy \times W(\vec{x}, \vec{y})$$

Parton distribution functions CTEQ6

Differential cross section (LO ME from Madgraph)

Transfer Function: maps parton level (y) to reconstructed variables (x)

- ▶ Uses the 4-vectors of all reconstructed ℓ s and jets
- ▶ This analysis: 2&3 jet events only, match partons to jets
- ▶ Apply b-tagging information



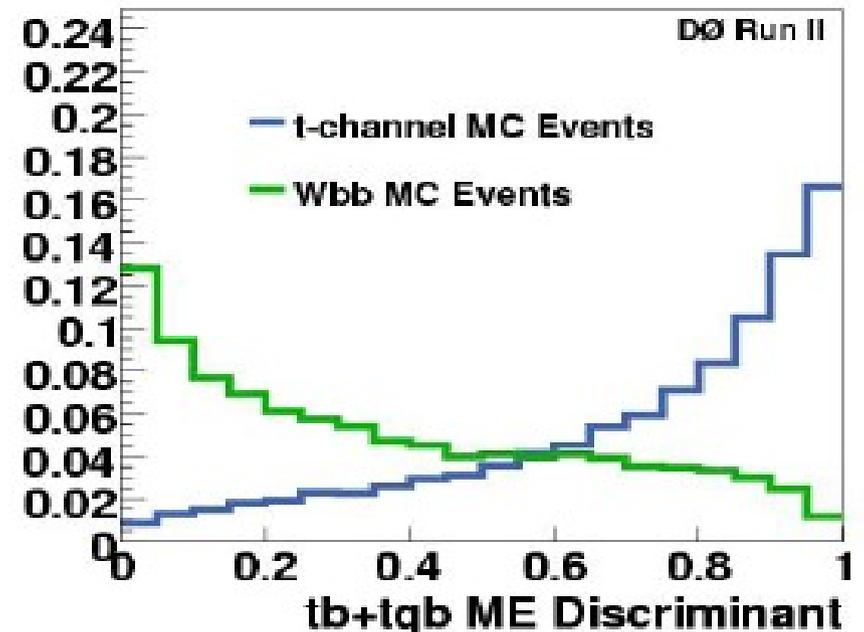
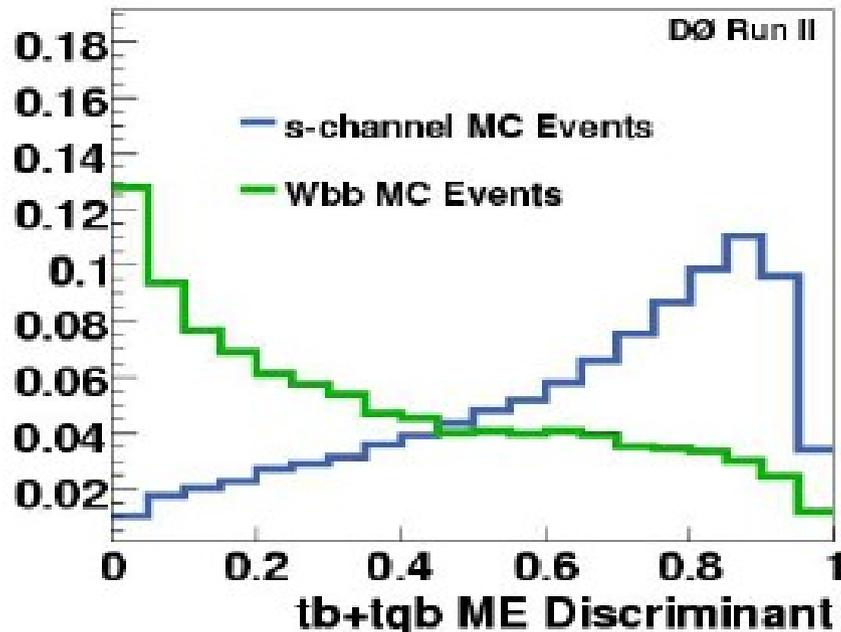
- ▶ Need to integrate over 4 independent variables: assume angles well measured, known masses, momentum and energy conservation

ME discriminant

- ▶ Define discriminant based on event probabilities for signal and background

$$D_s(\vec{x}) = P(S|\vec{x}) = \frac{P_{Signal}(\vec{x})}{P_{Signal}(\vec{x}) + P_{Background}(\vec{x})}$$

- ▶ In 2 jet events: use ME for Wbg, Wcg and Wgg backgrounds
- ▶ In 3 jet events: use ME for Wbbg background
- ▶ No ttbar ME used thus far: no separation in the 3rd jet bin!



Bayesian Neural Networks

A different sort of NN (<http://www.cs.toronto.edu/radford/fbm.software.html>):

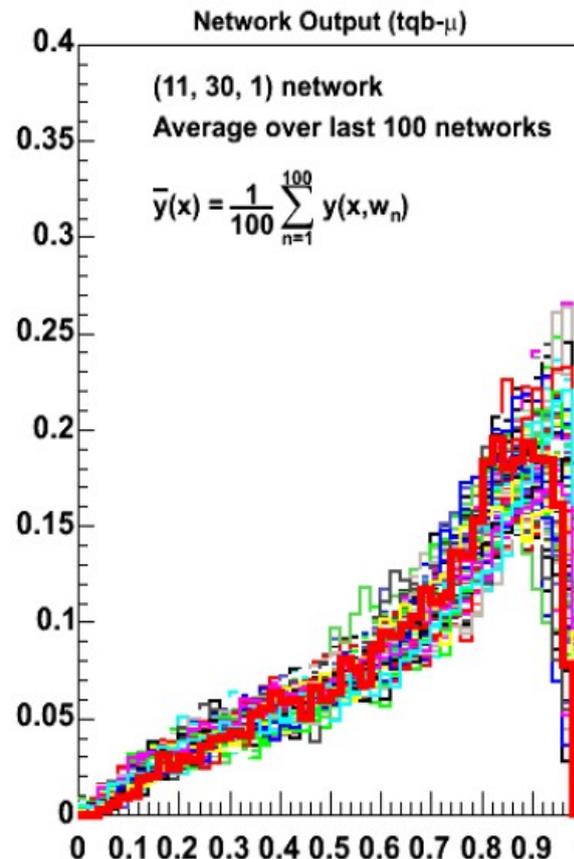
- ▶ Instead of choosing one set of weights, find posterior probability density over all possible weights
- ▶ Averages over many networks weighted by the probability of each network given the training data
- ▶ Use 24 variables (subset of the DT variables) and train against sum of backgrounds

Advantages:

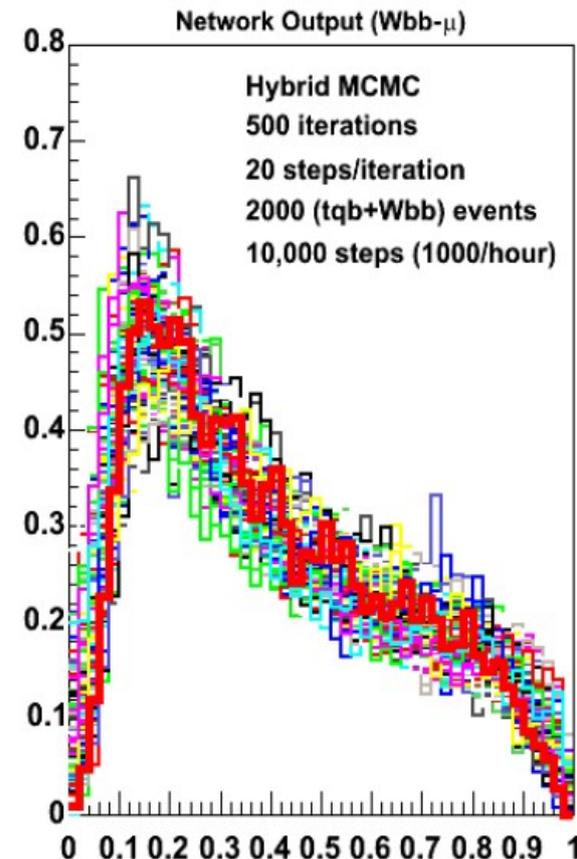
- ▶ Less prone to overfitting, because of Bayesian averaging
- ▶ Network structure less important: can use large networks!
- ▶ Optimized performance

Disadvantages:

- ▶ Computationally demanding!



First evidence for single top



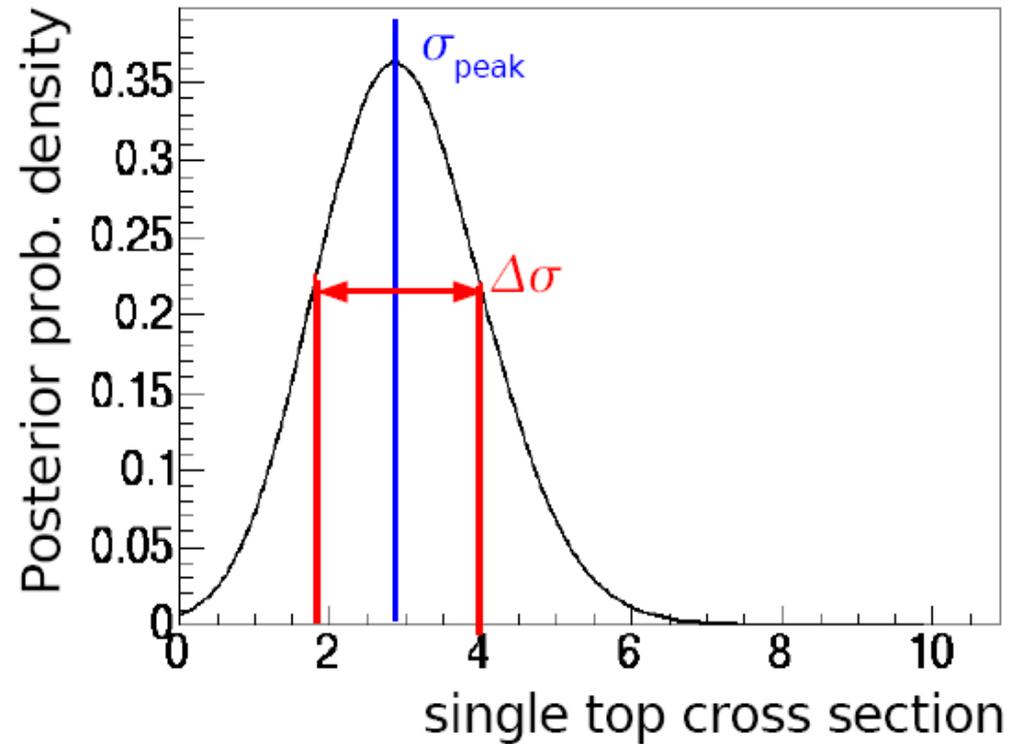
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Measuring the cross section

- ▶ We form a binned likelihood from the discriminant outputs
- ▶ Probability to observe data distribution D , expecting y :

$$y = \alpha l \sigma + \sum_{s=1}^N b_s \equiv a \sigma + \sum_{s=1}^N b_s$$

$$P(D|y) \equiv P(D|\sigma, a, b) = \prod_{i=1}^{nbins} P(D_i|y_i)$$



- ▶ And obtain a Bayesian posterior probability density as a function of the cross section:

$$Post(\sigma|D) \equiv P(\sigma|D) \propto \int_a \int_b P(D|\sigma, a, b) \text{Prior}(\sigma) \text{Prior}(a, b)$$

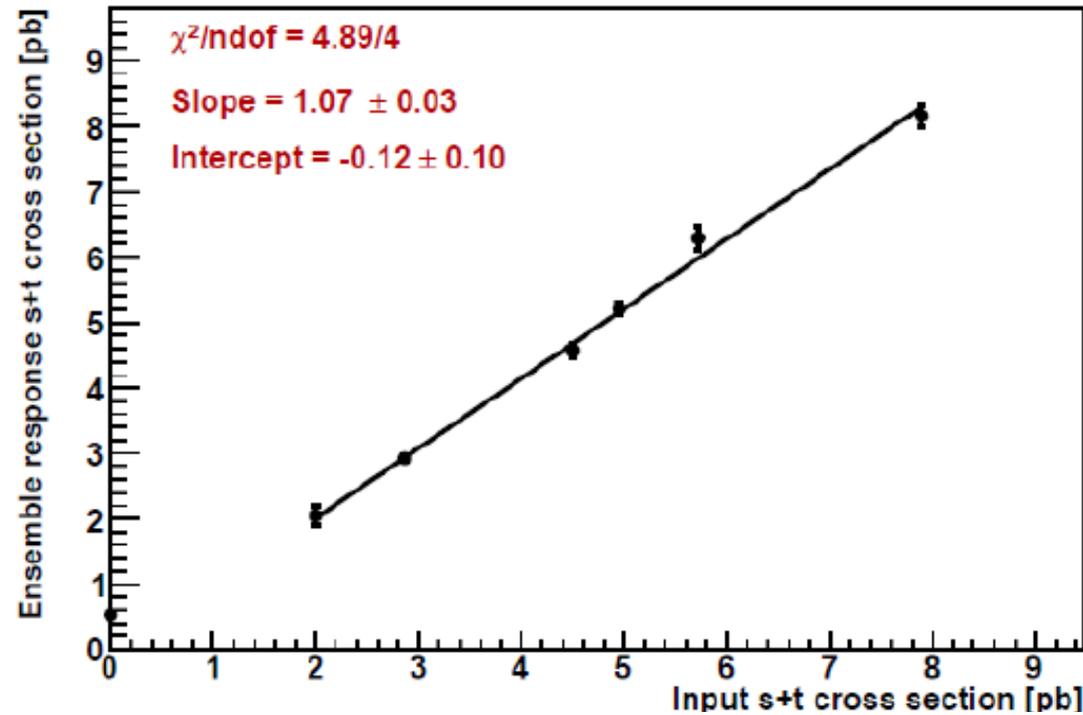
- Shape and normalization systematics treated as nuisance parameters
- Correlations between uncertainties properly accounted for
- Flat prior in signal cross section

Ensemble testing

- ▶ To verify that all this machinery is working properly, we test with many sets of **pseudo-data**
- ▶ Wonderful tool to test analysis methods! Run $D\emptyset$ experiment 100s of times
- ▶ Use pool of MC events to draw events with bkgd. yields fluctuated according to **uncertainties**, reproducing the **correlations** between components introduced in the normalization to data
- ▶ Randomly sample a Poisson distribution to simulate **statistical** fluctuations
- ▶ Generated ensembles include:
 - 1) 0-signal ensemble ($\sigma_{s+t} = 0$ pb)
 - 2) SM ensemble ($\sigma_{s+t} = 2.9$ pb)
 - 3) “Mystery” ensembles to test analyzers ($\sigma_{s+t} = ??$ pb)
 - 4) Ensemble at measured cross-section ($\sigma_{s+t} = \sigma_{\text{measured}}$)
 - 5) A high luminosity ensemble
- ▶ Each analysis tests linearity of “response” to single top

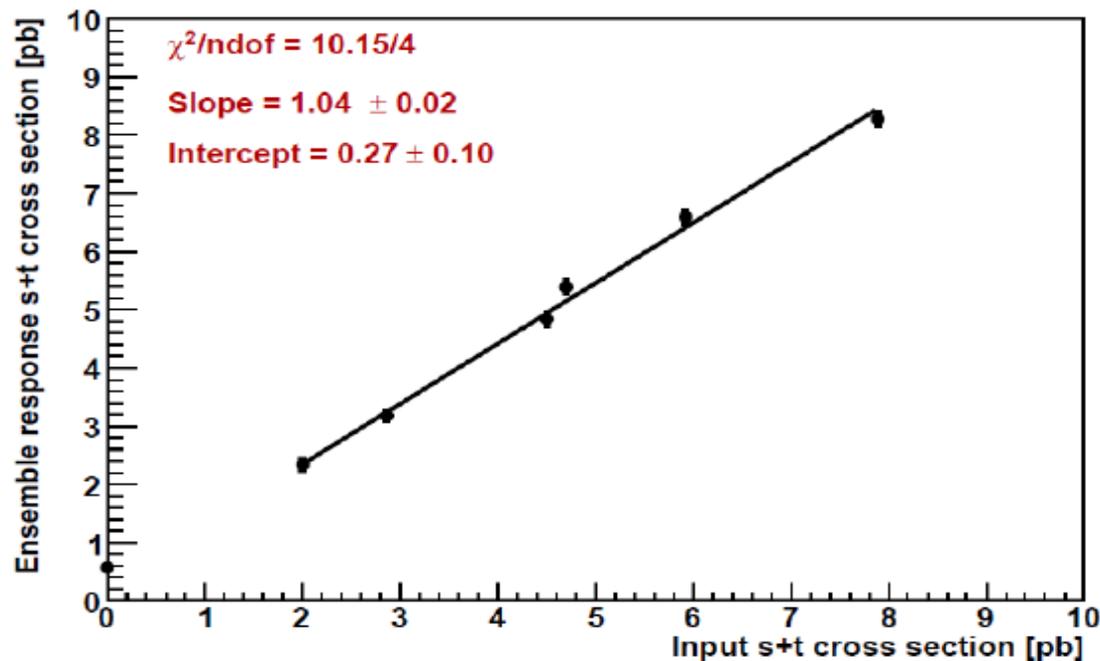
Responses

DT analysis

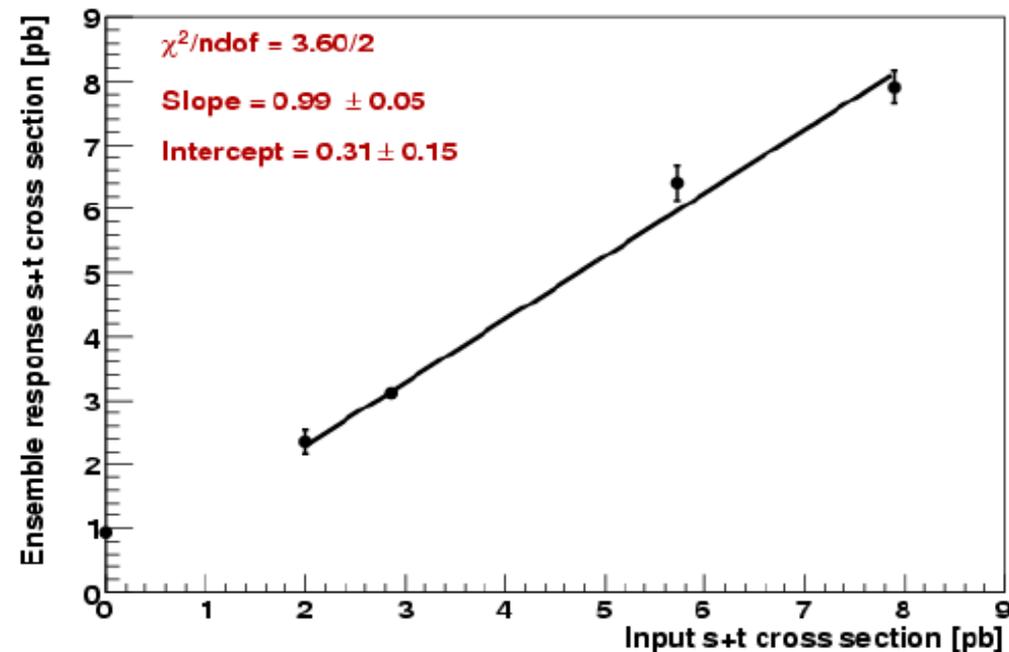


- Using the ensemble tests:
- SM ensemble is returned at the right value
 - “Mystery” ensembles are unraveled
 - Linear response is achieved

ME analysis



BNN analysis



Sensitivity and Significance

We have used our 0-signal ensembles to determine a significance for each measurement

Expected p-value: the fraction of 0-signal pseudo-datasets in which we measure at least 2.9 pb

Observed p-value: the fraction of 0-signal pseudo-datasets in which we measure at least the measured cross section

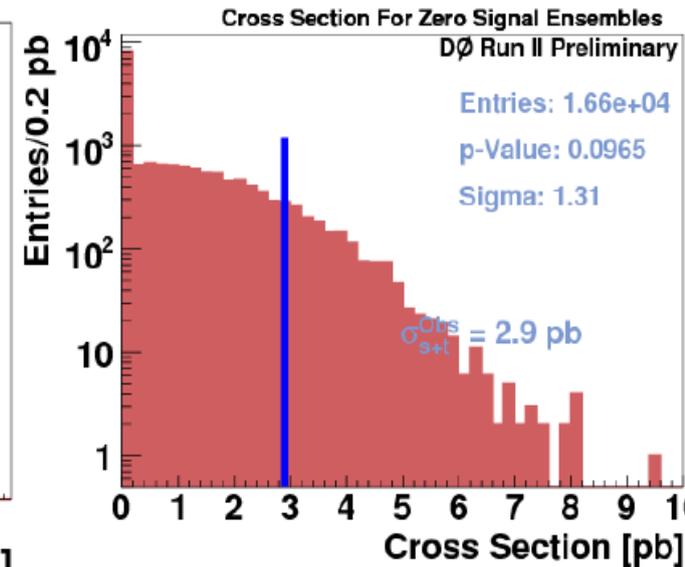
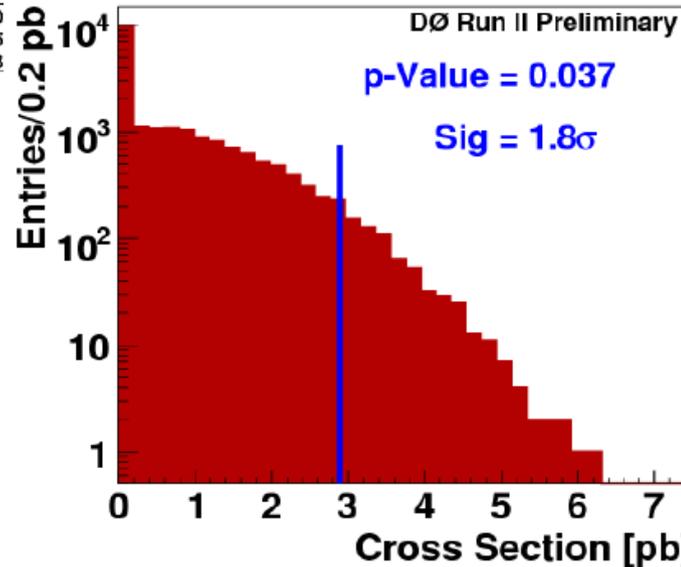
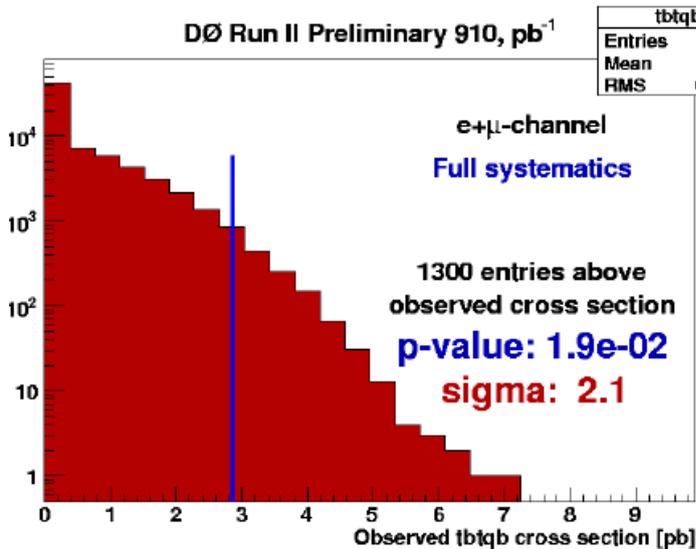
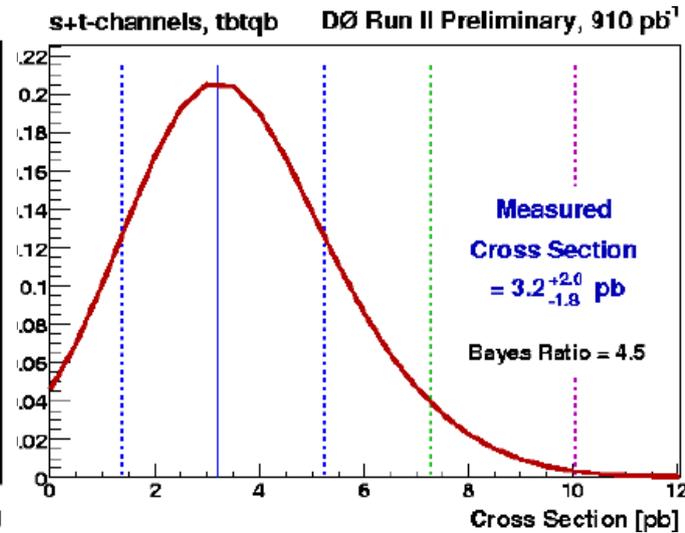
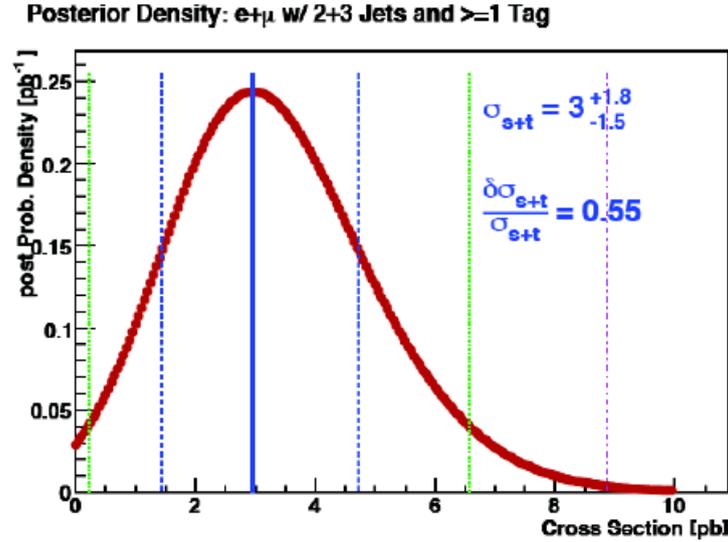
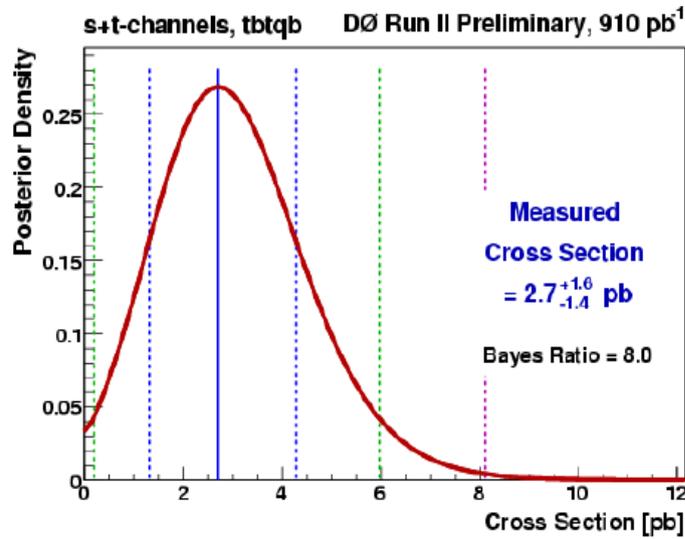
► We also use the SM ensembles to see how compatible our measured value is with the SM

Expected p-values

Decision Trees
p-value 1.9%

Matrix Elements
p-value 3.7%

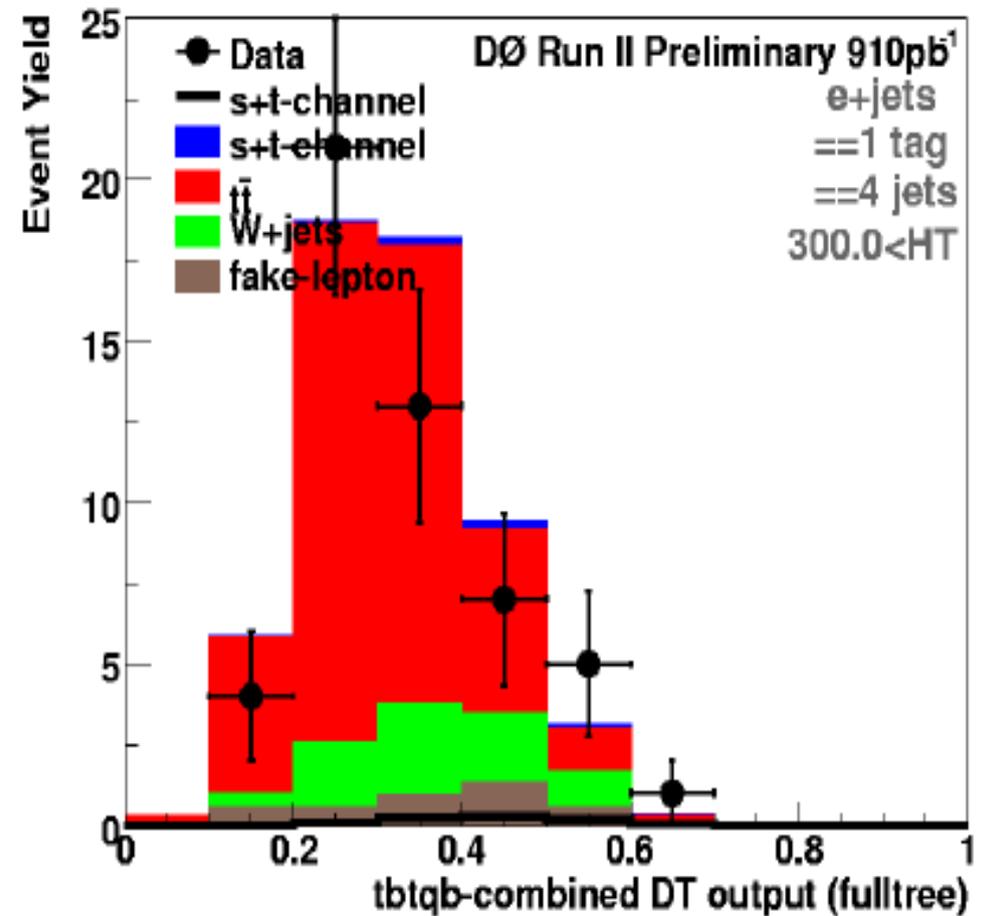
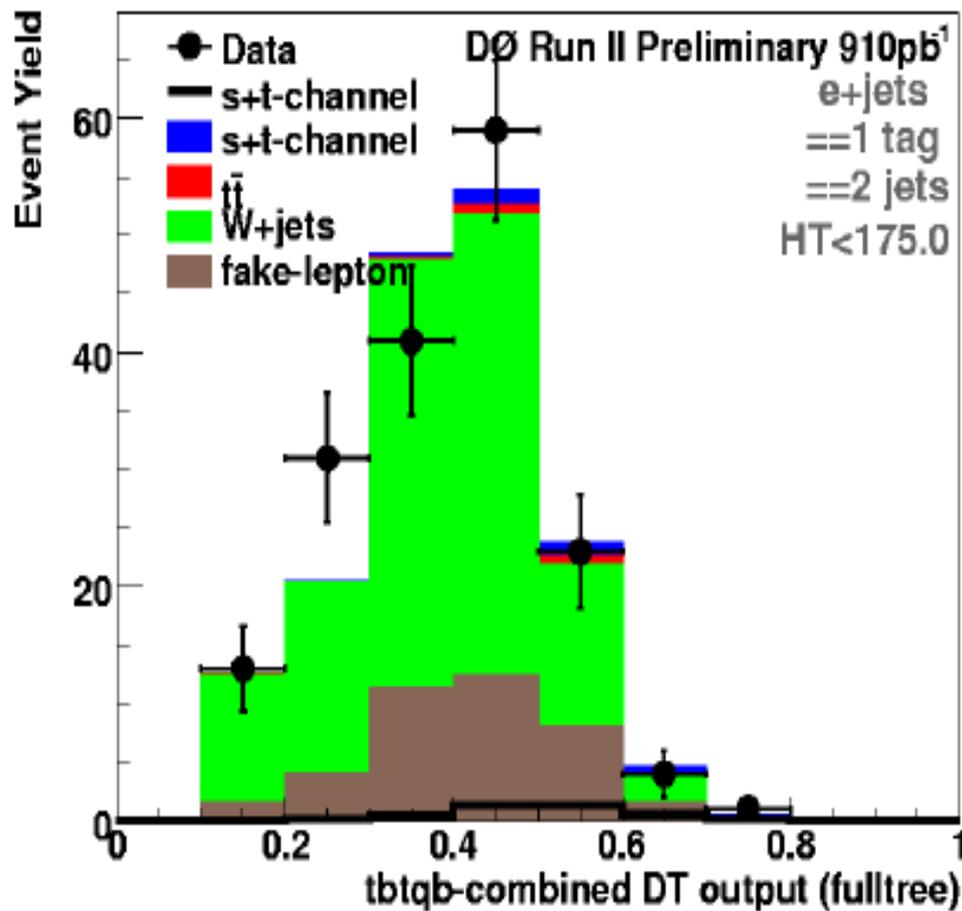
Bayesian NN
p-value 9.7%



DT cross check samples

Check the description of the data in the DT output

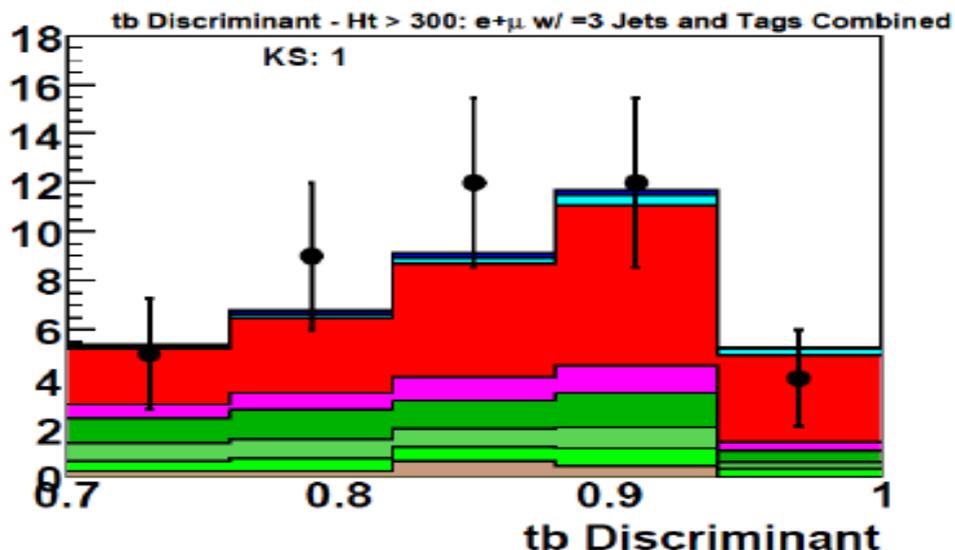
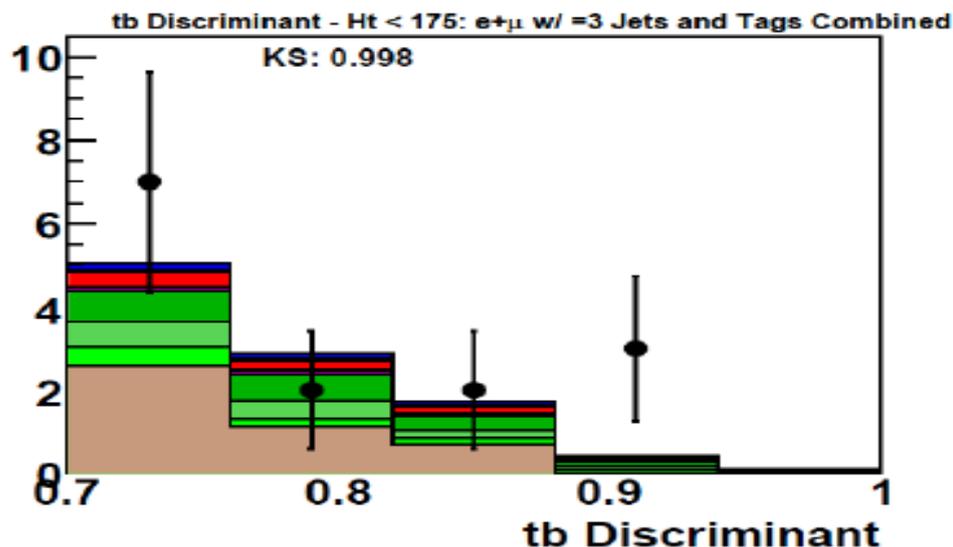
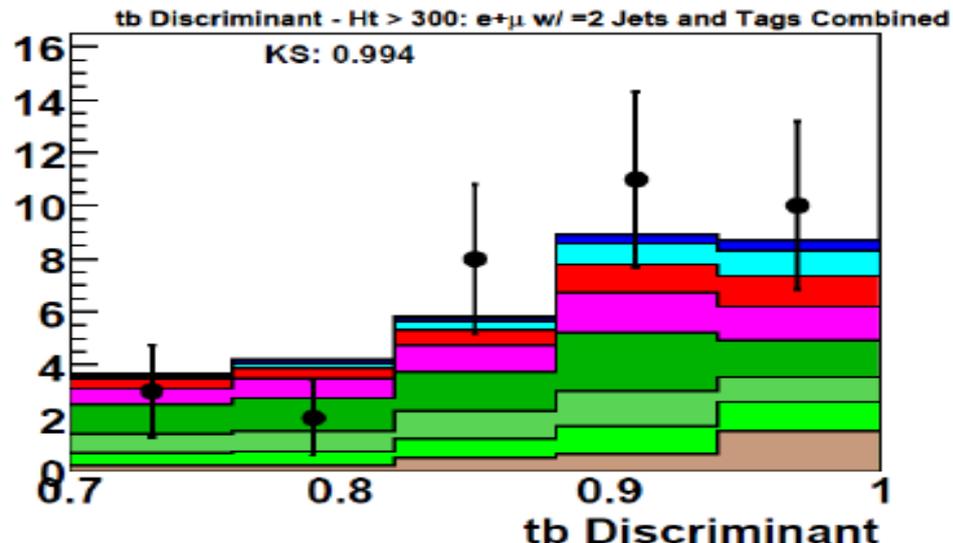
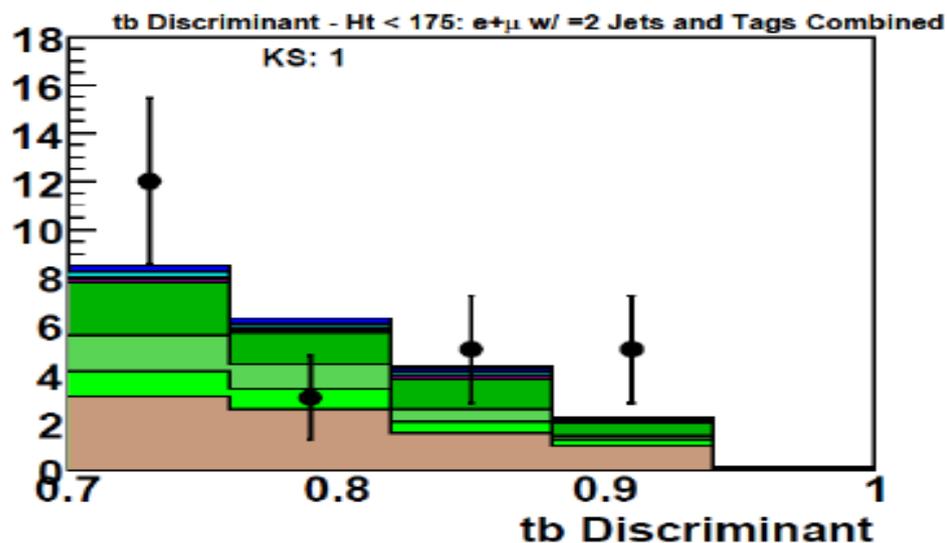
- W+jets: 2 jets and $H_T(\text{lepton}, \text{MET}, \text{alljets}) < 175 \text{ GeV}$
- tt: 4 jets and $H_T(\text{lepton}, \text{MET}, \text{alljets}) > 300 \text{ GeV}$



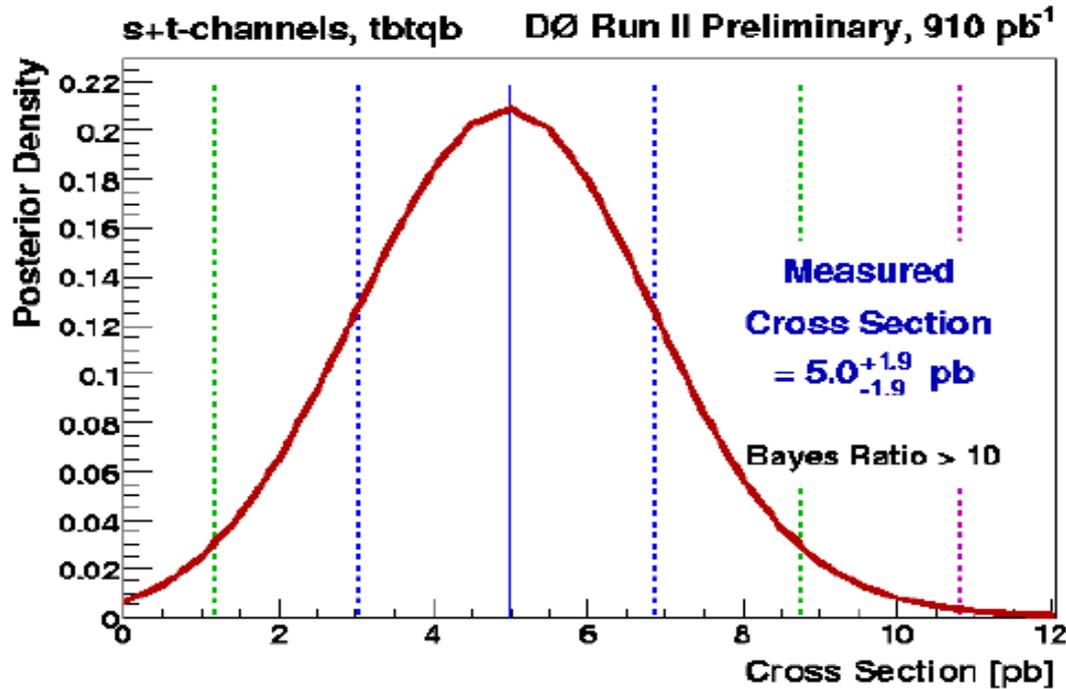
ME cross check samples

Check the description of the data in the ME output

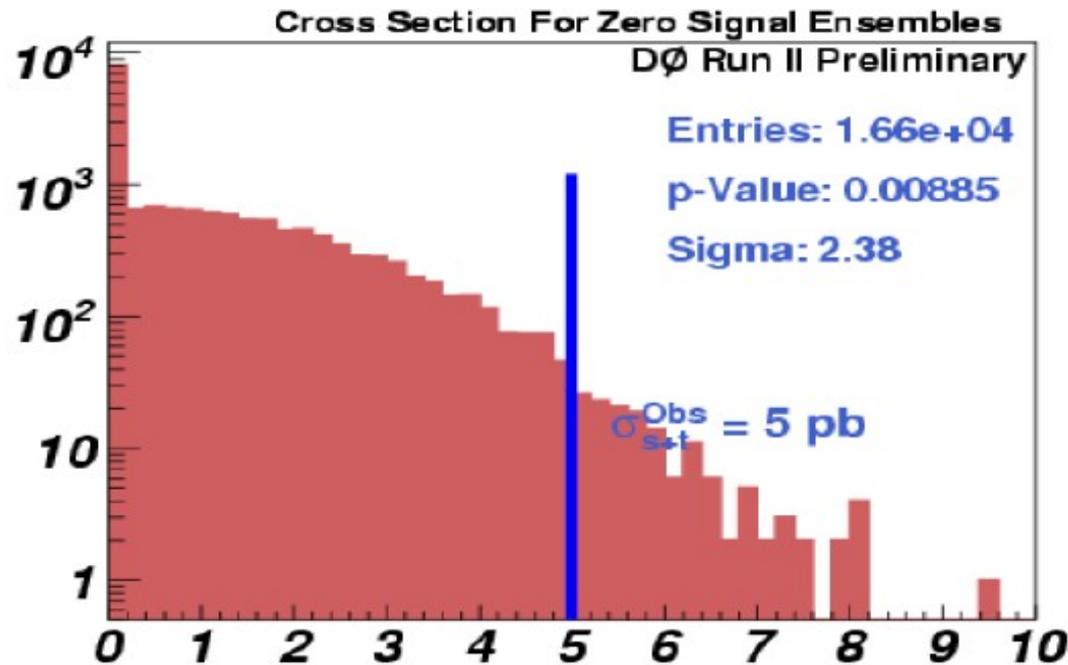
- Soft W+jets: $H_T(\text{lepton}, \text{MET}, \text{alljets}) < 175 \text{ GeV}$
- Hard W+jets: $H_T(\text{lepton}, \text{MET}, \text{alljets}) > 300 \text{ GeV}$



Bayesian NN observed results

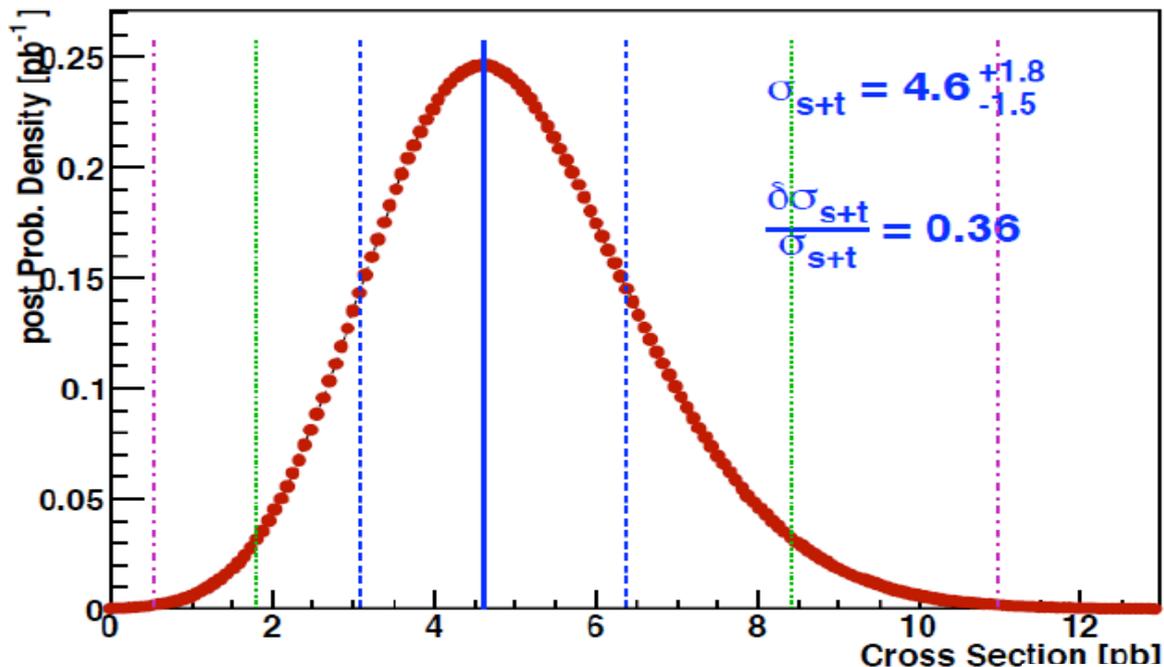


Least sensitive (a-priori) analysis sees a 2.4σ effect!

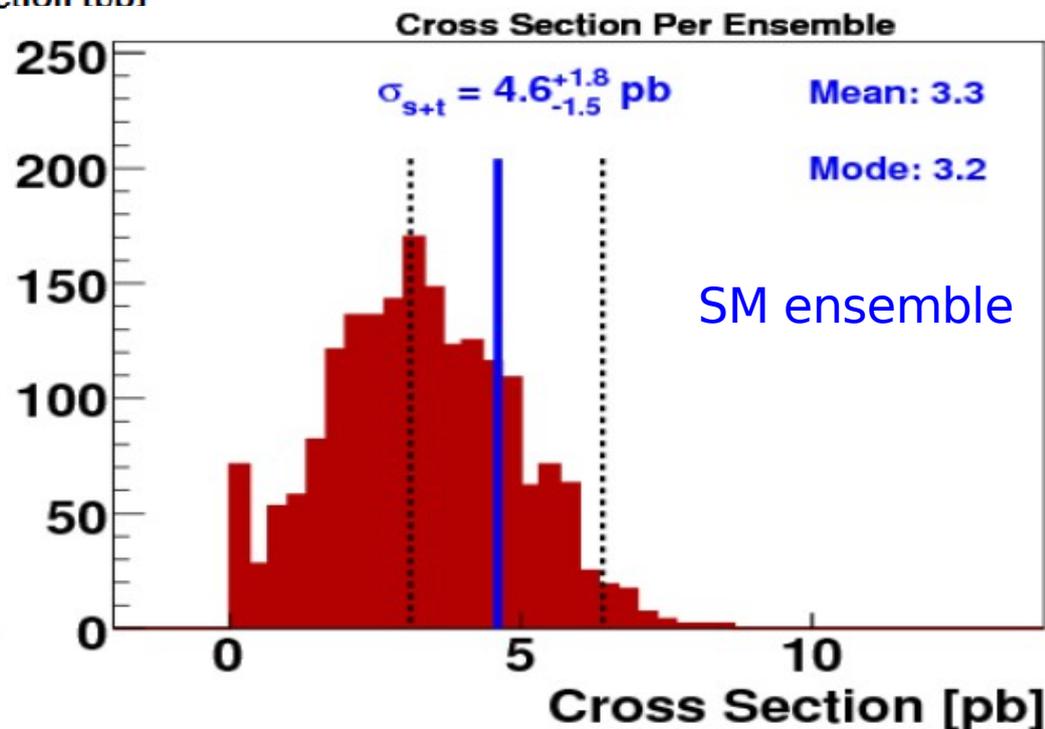
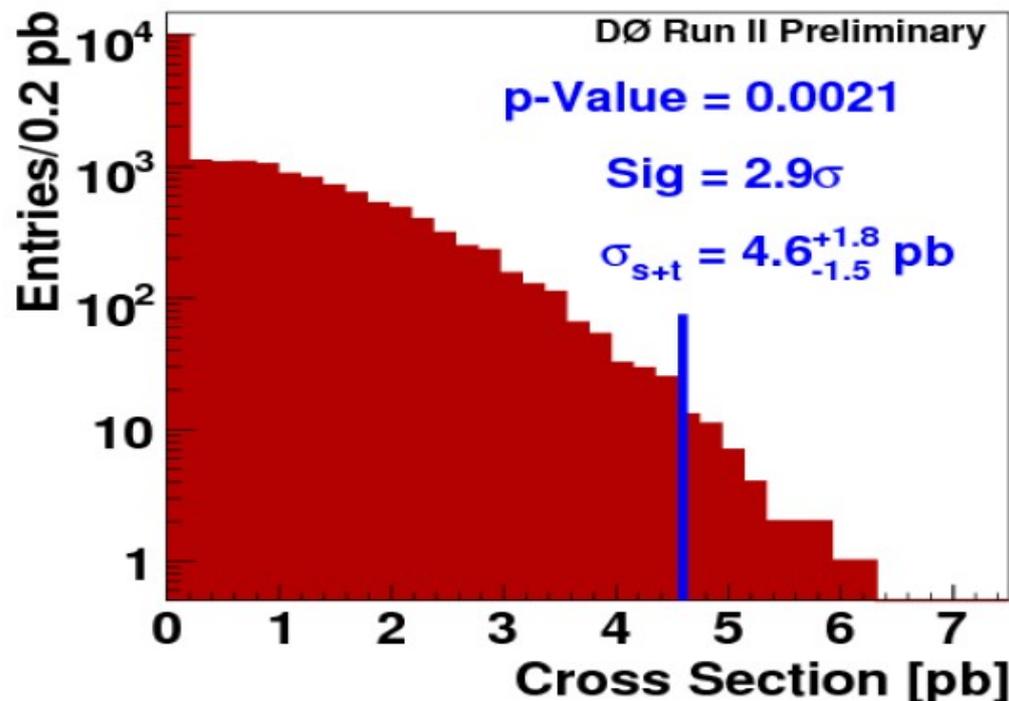


Matrix Elements observed results

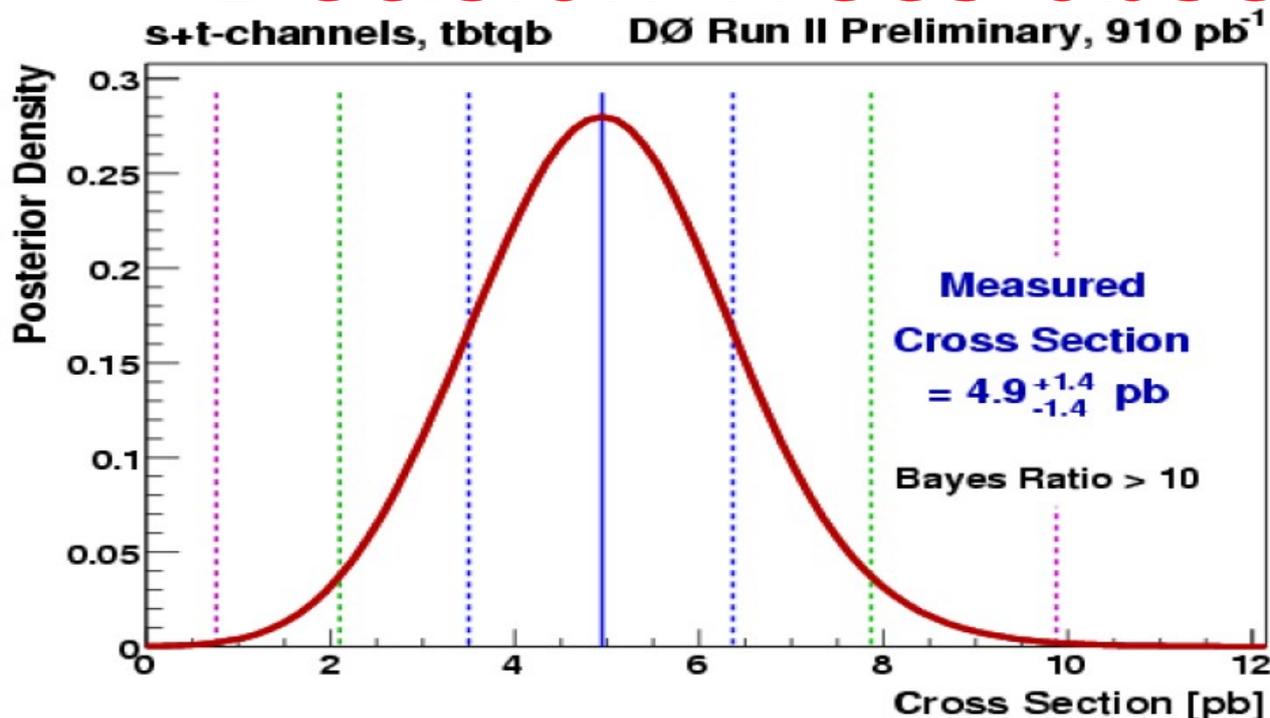
Posterior Density: $e+\mu$ w/ 2+3 Jets and ≥ 1 Tag



2.9 σ excess!
SM compatibility = 21%



Decision Trees observed results



$$\sigma = 4.9 \pm 1.4 \text{ pb}$$

3.4 σ excess!

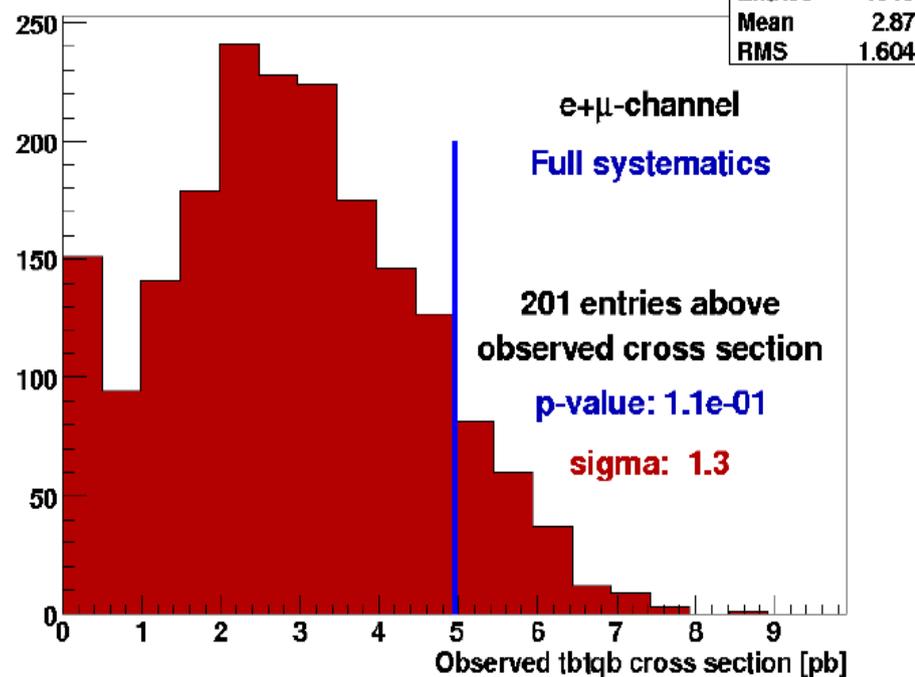
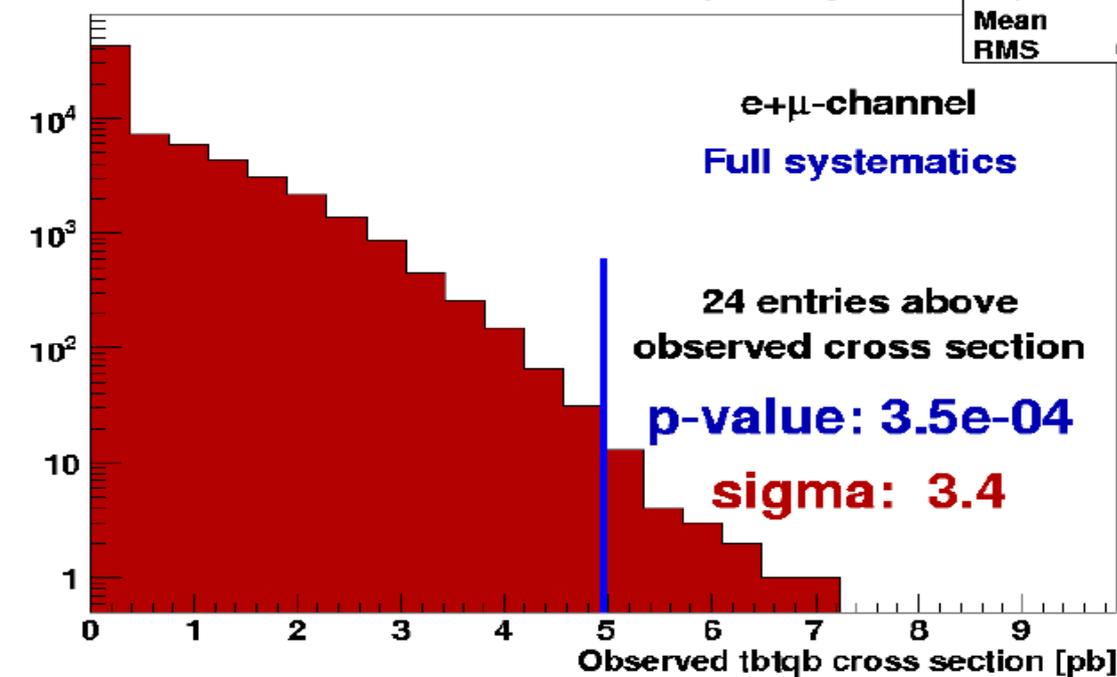
SM compatibility = 11%

DØ Run II Preliminary 910, pb⁻¹

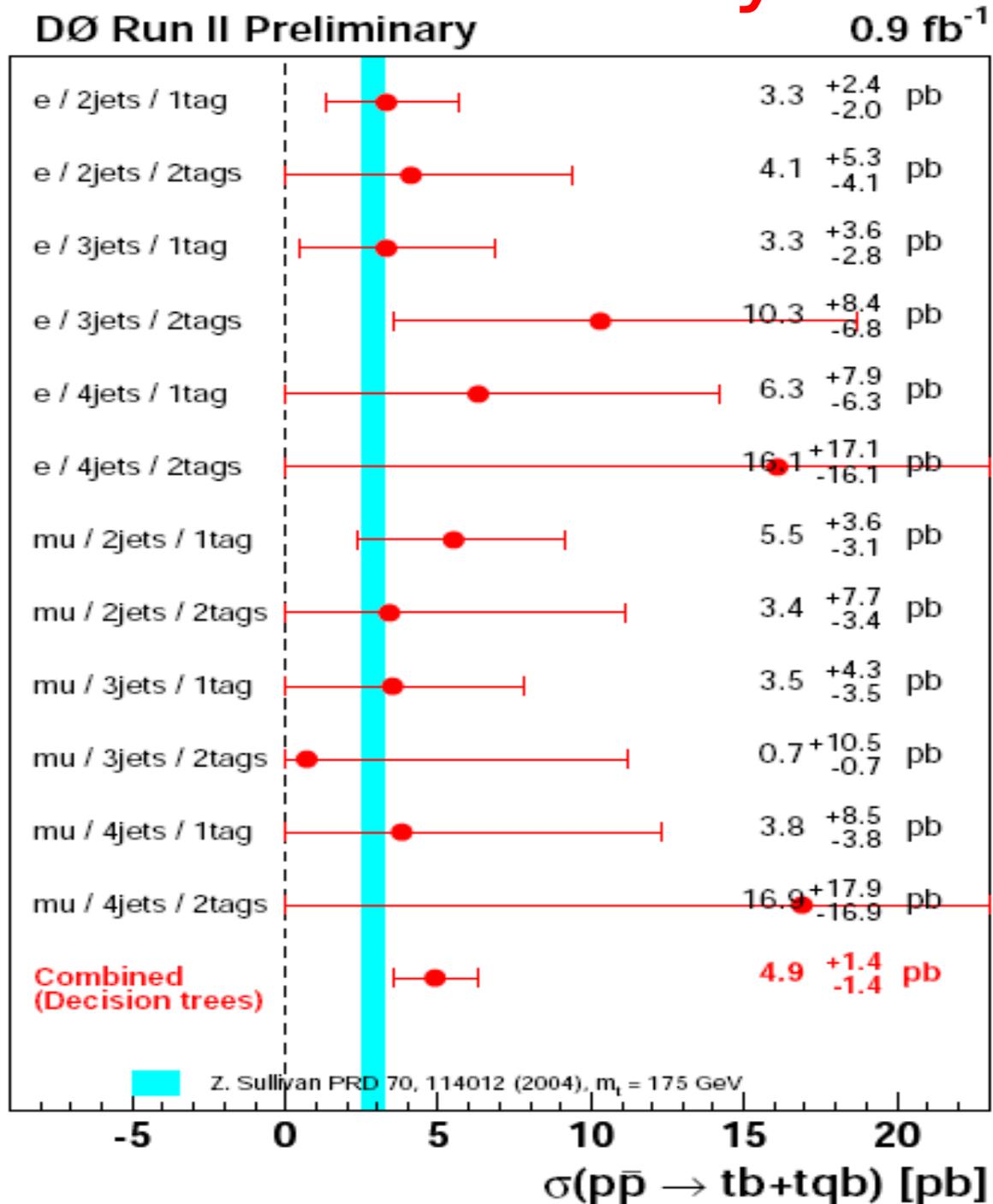
tbtqb	
Entries	681
Mean	0.5
RMS	0.79

SM Ensemble

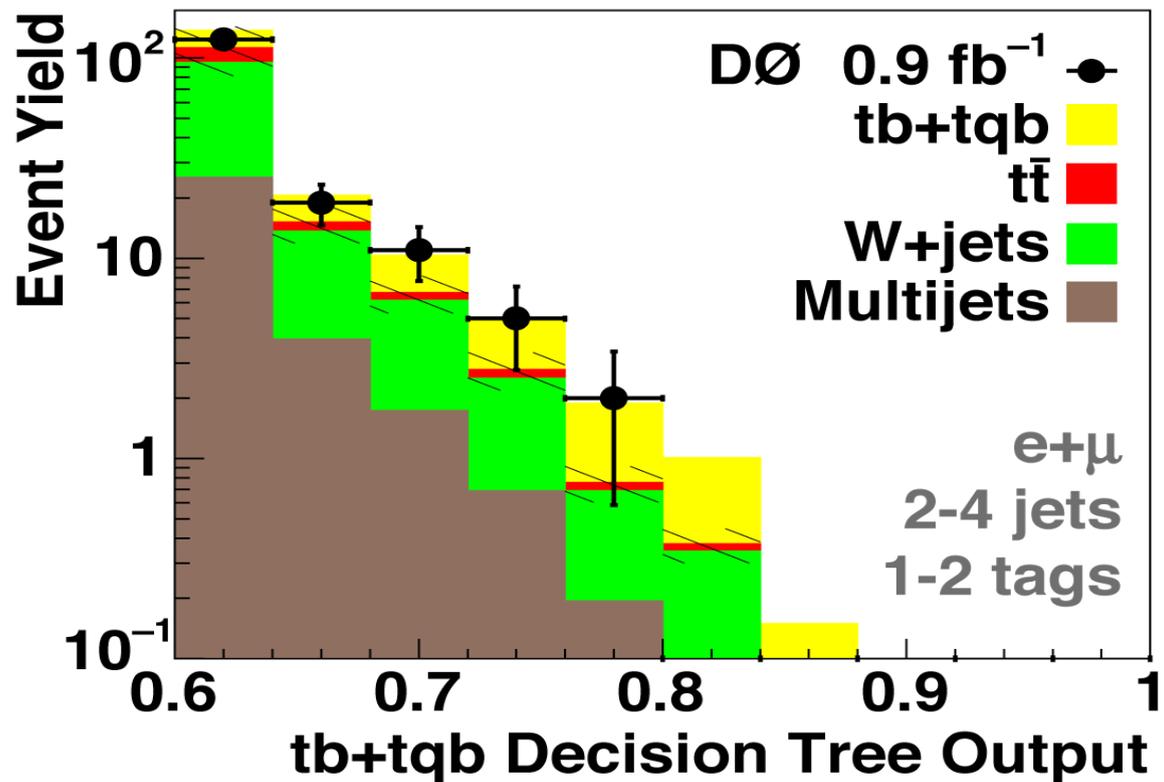
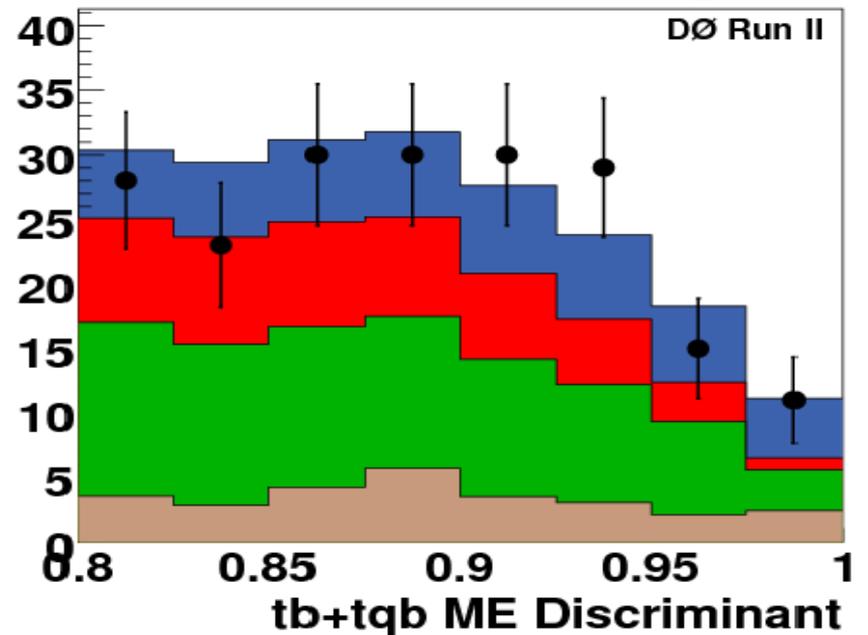
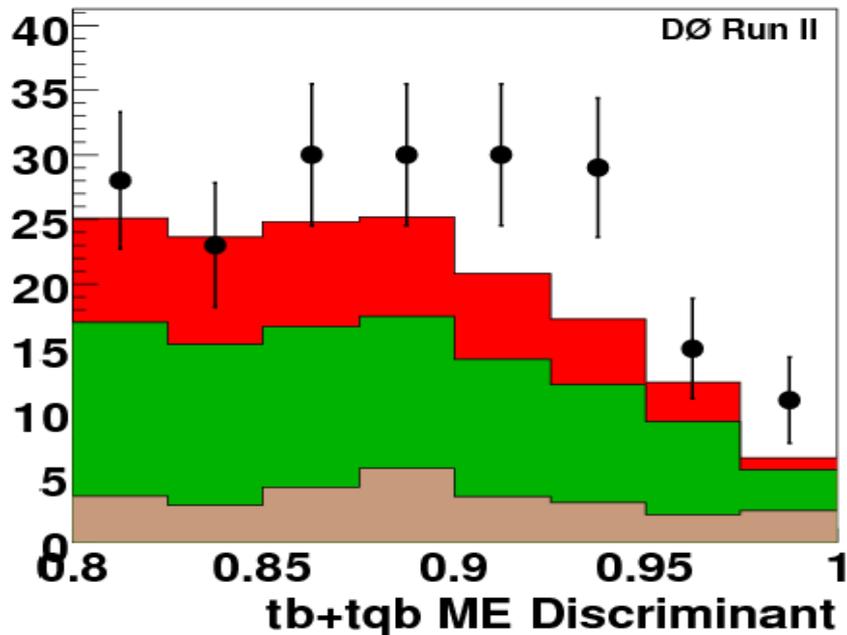
tbtqb	
Entries	1910
Mean	2.87
RMS	1.604



DT summary

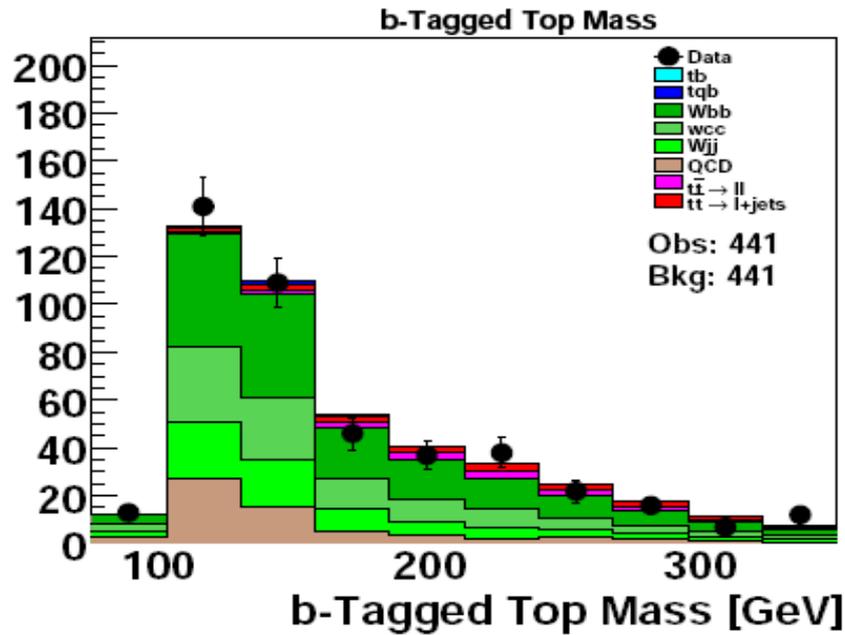


Excess in the high discriminant regions

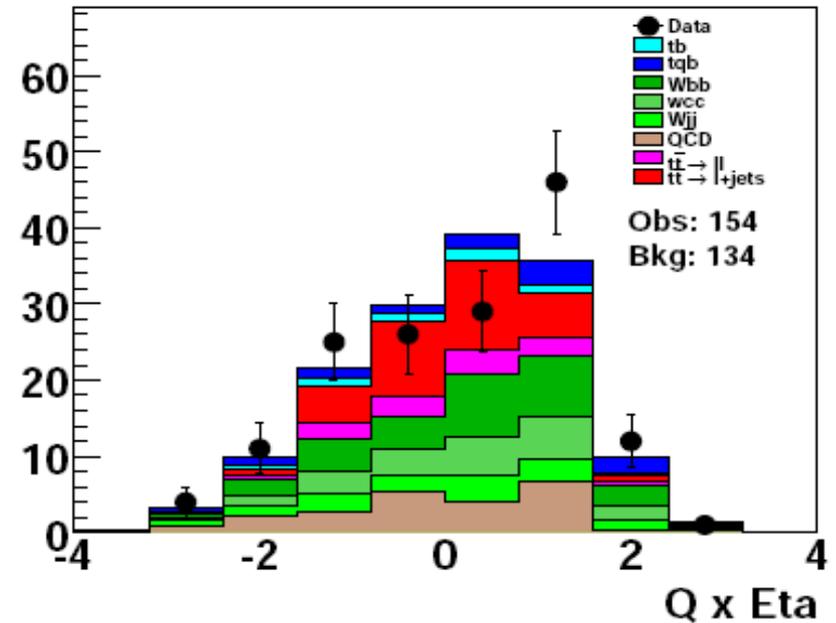
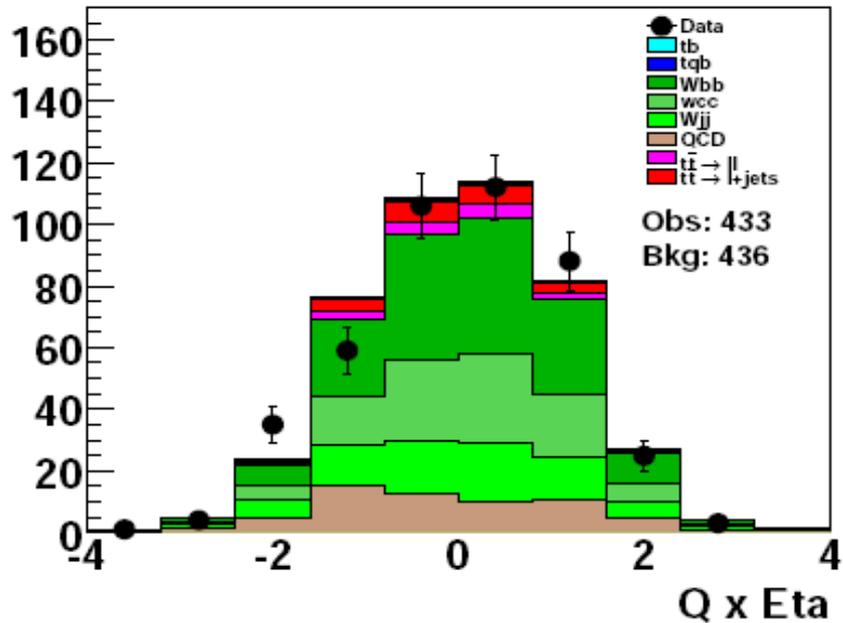
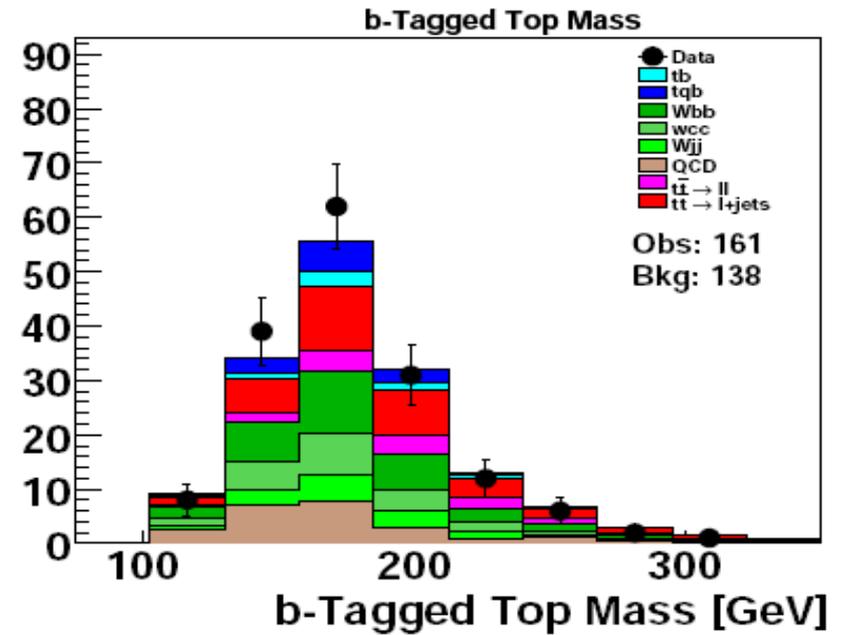


ME event characteristics

ME Discriminant < 0.4

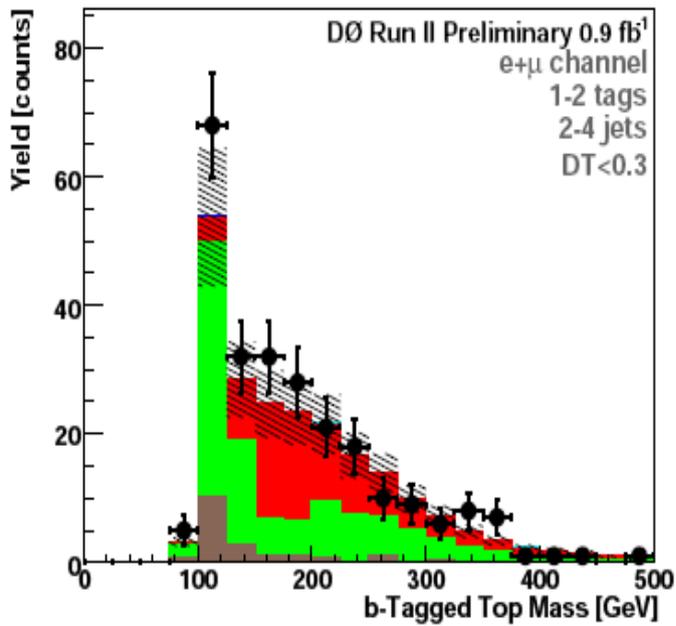


ME Discriminant > 0.7

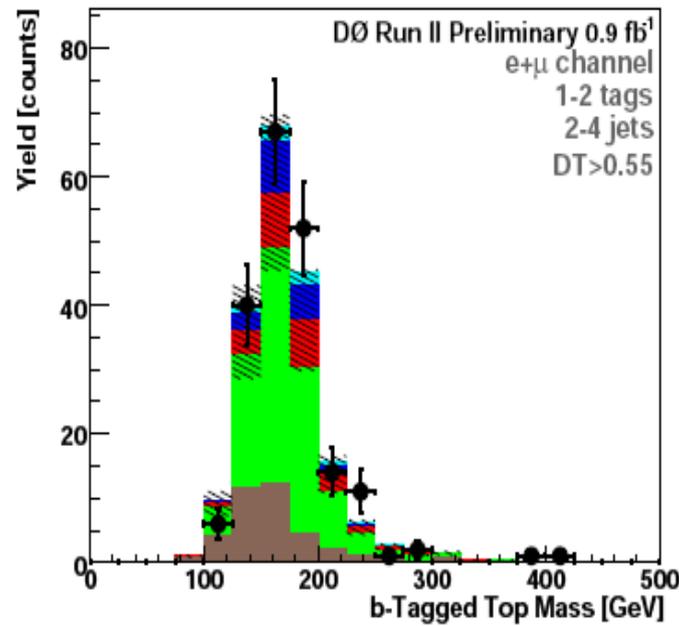


DT event characteristics

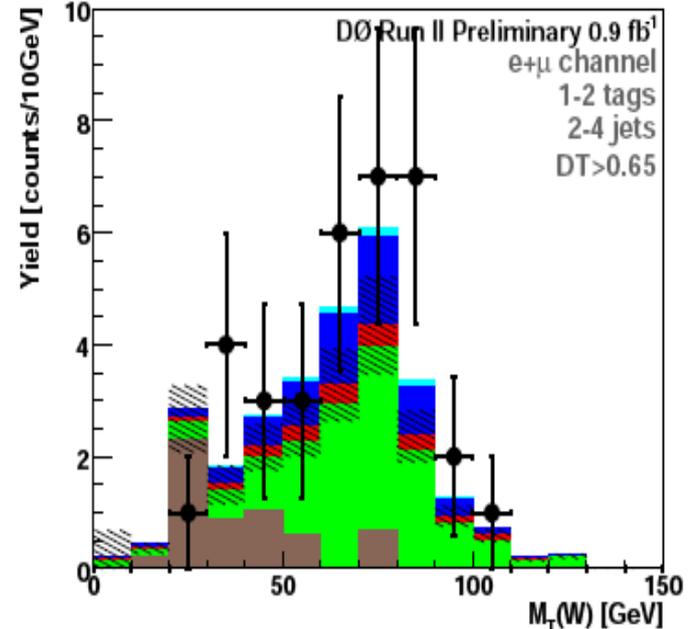
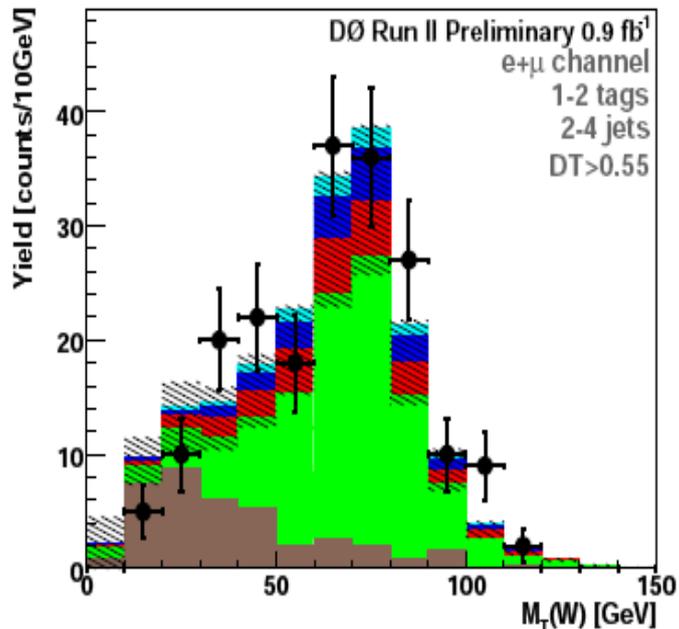
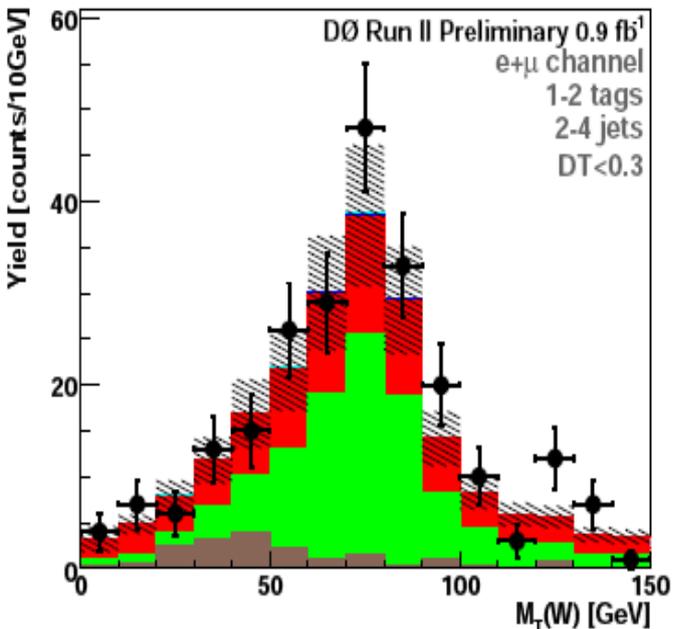
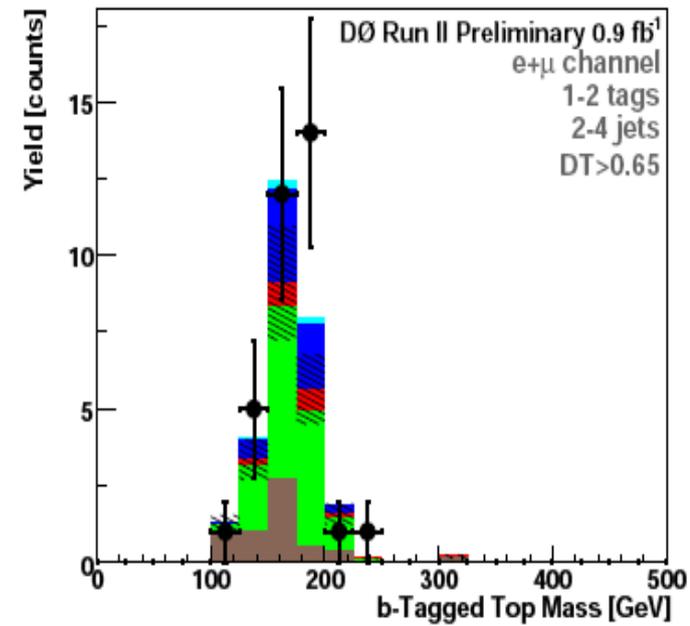
DT Discriminant < 0.3



DT Discriminant > 0.55



DT Discriminant > 0.65



A candidate event

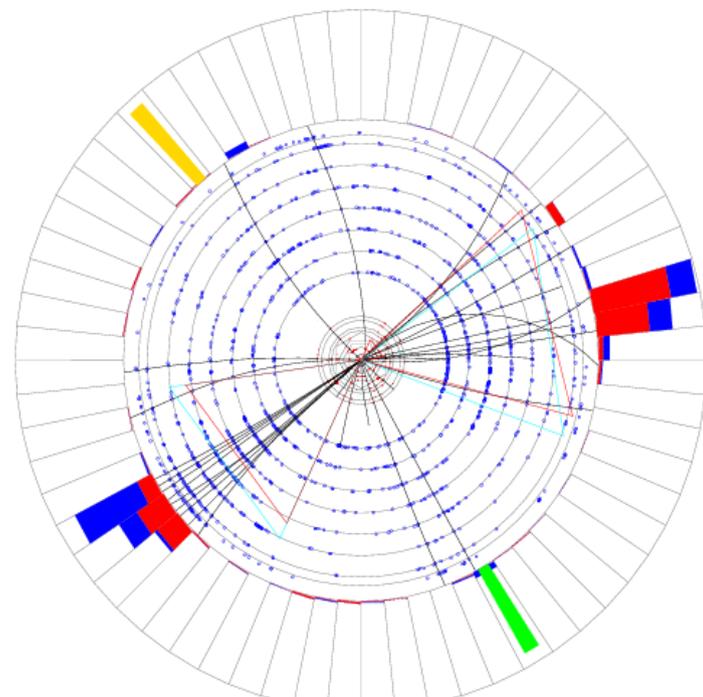
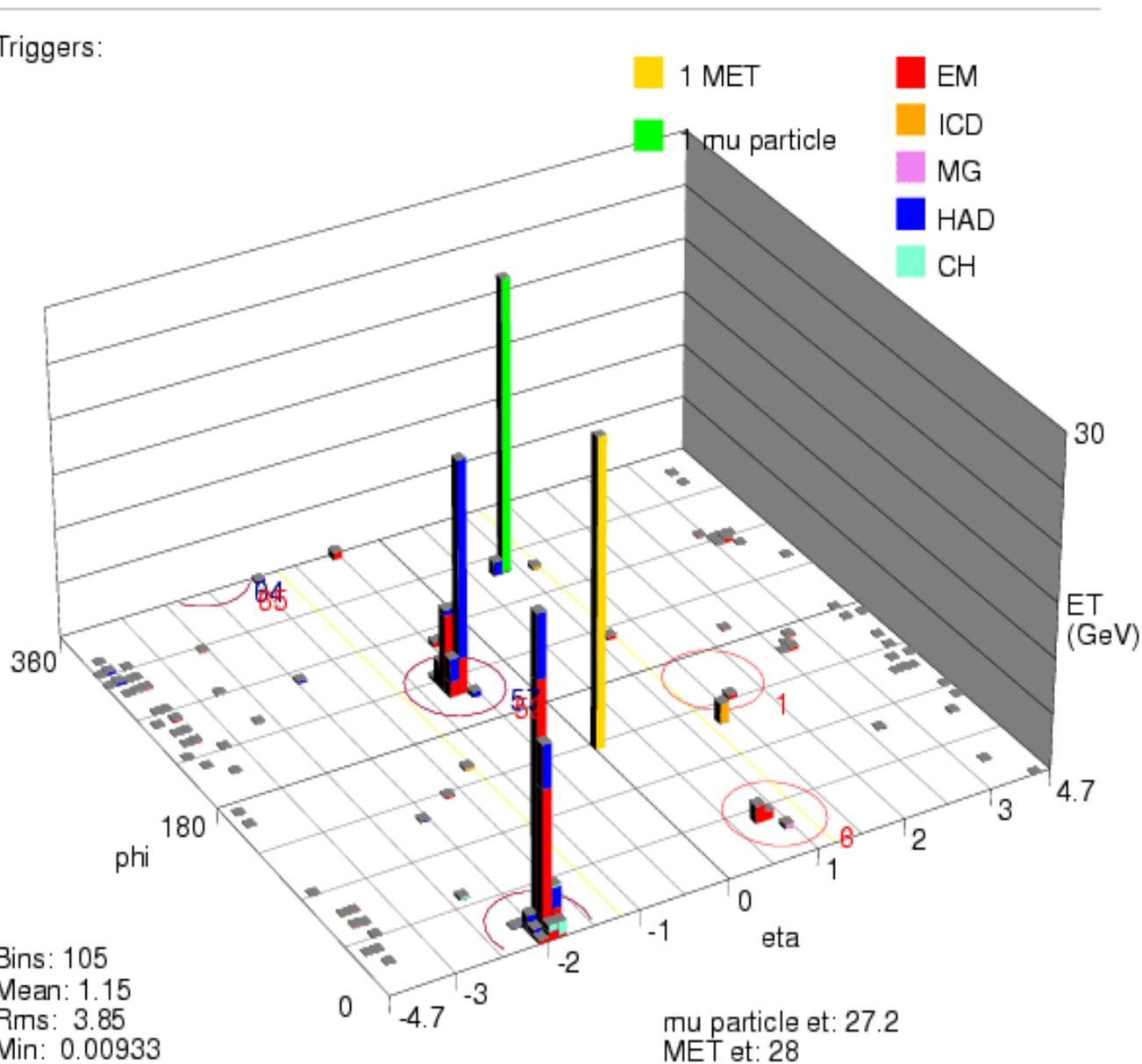
Run 177034 Evt 10482925

Run 177034 Evt 10482925

ale: 31 GeV

Triggers:

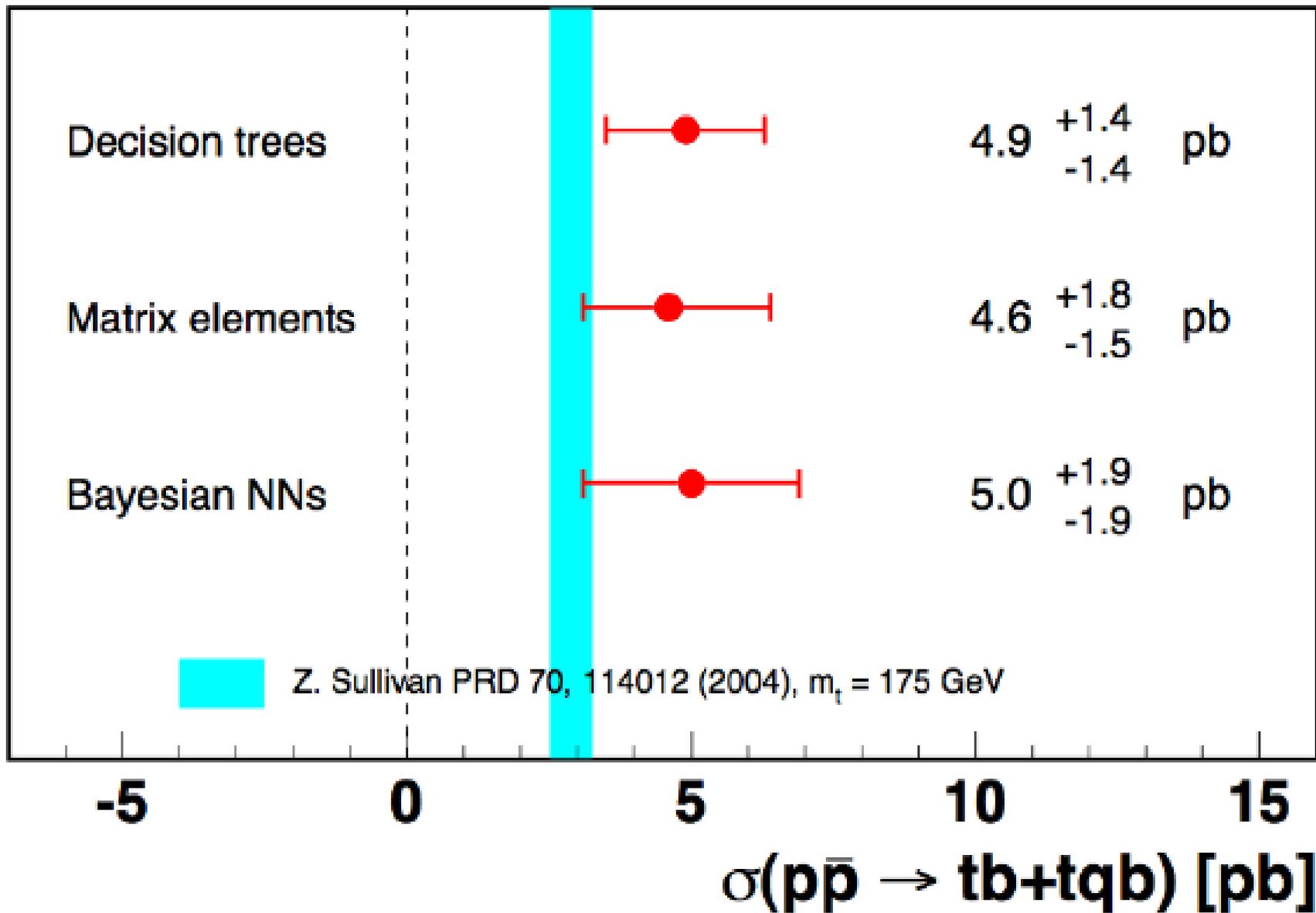
- 1 MET
- mu particle
- EM
- ICD
- MG
- HAD
- CH



s+t summary: all methods

DØ Run II

0.9 fb⁻¹



Correlations

- ▶ Take the 50 highest ranked data events in each method and look for overlap:

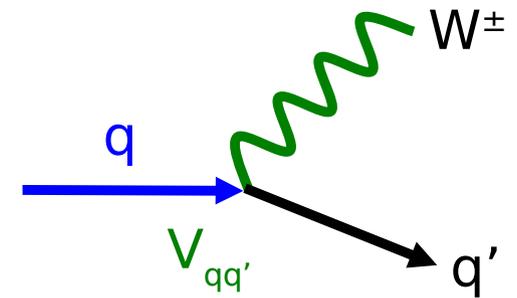
Technique	Electron	Muon
DT vs ME	52%	58%
DT vs BNN	56%	48%
ME vs BNN	46%	52%

- ▶ Calculate the linear correlation between the measured cross sections in the same 400 members of the SM ensemble

	DT	ME	BNN
DT	100%	39%	57%
ME		100%	29%
BNN			100%

CKM matrix element V_{tb}

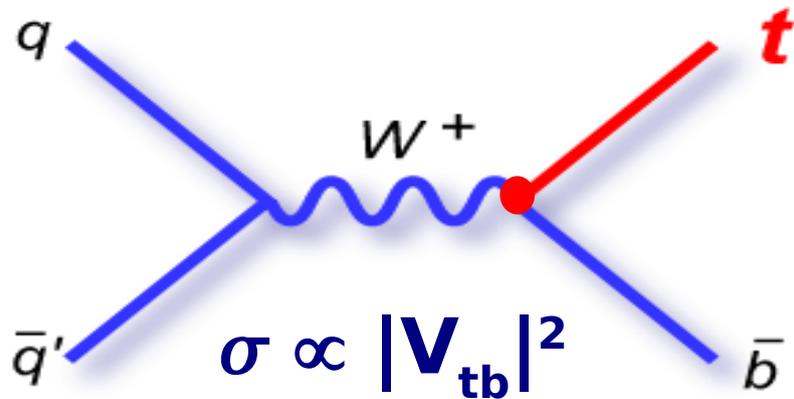
$$\begin{pmatrix} d' \\ s' \\ b' \end{pmatrix} = \begin{pmatrix} V_{ud} & V_{us} & V_{ub} \\ V_{cd} & V_{cs} & V_{cb} \\ V_{td} & V_{ts} & \boxed{V_{tb}} \end{pmatrix} \begin{pmatrix} d \\ s \\ b \end{pmatrix}$$



- ▶ Weak interaction eigenstates and mass eigenstates are not the same: there is **mixing** between quarks → **CKM matrix**
- ▶ In SM: top must decay to W and d, s or b quark
 - $V_{td}^2 + V_{ts}^2 + V_{tb}^2 = 1$
 - Strong constraints on V_{td} and V_{ts} : $V_{tb} > 0.998$
 - Assuming unitarity and 3 generations: $B(t \rightarrow Wb) \sim 100\%$
- ▶ If there is new physics:
 - $V_{td}^2 + V_{ts}^2 + V_{tb}^2 < 1$
 - No constraint on V_{tb}
 - Interactions between the top quark and weak gauge bosons are extremely interesting!

Measuring $|V_{tb}|$

- ▶ Once we have a cross section measurement, we can make the first direct measurement of $|V_{tb}|$
- ▶ Use the same infrastructure as for the cross section measurement, but make a posterior in $|V_{tb}|^2$



Additional theoretical errors are needed

	s	t
top mass	13%	8.5%
scale	5.4%	4.0%
PDF	4.3%	10.0%
α_s	1.4%	0.01%

hep-ph/0408049

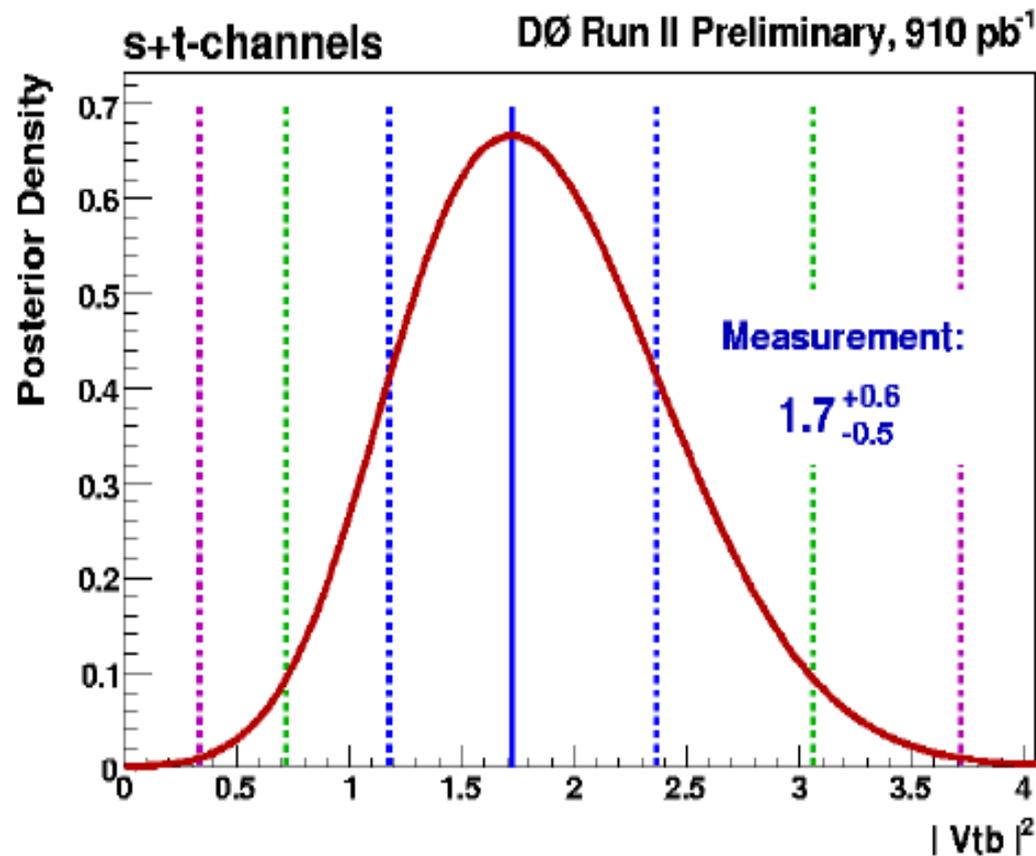
- ▶ Caveat: **assume SM decays**
- ▶ Most general Wtb vertex:

$$\Gamma_{tbW}^\mu = -\frac{g}{\sqrt{2}} V_{tb} \left\{ \gamma^\mu \left[f_1^L P_L + f_1^R P_R \right] - \frac{i \sigma^{\mu\nu}}{M_W} (p_t - p_b)_\nu \left[f_2^L P_L + f_2^R P_R \right] \right\}$$

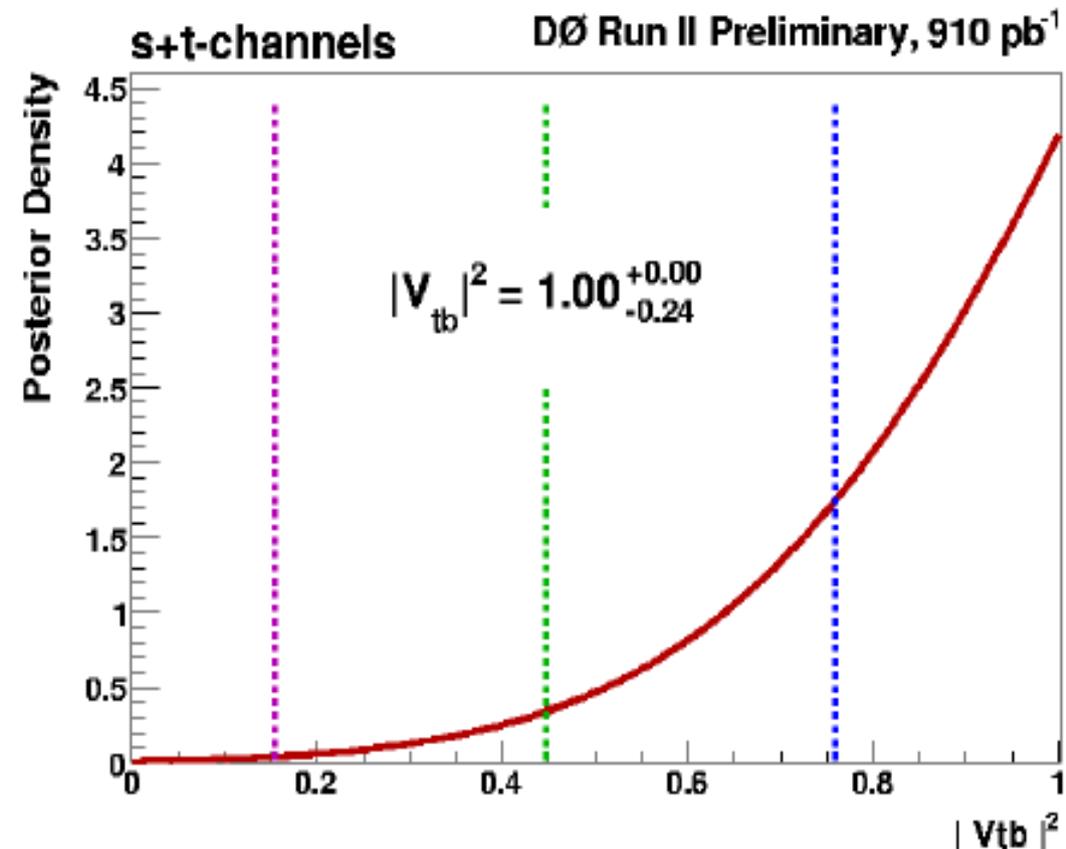
SM: $f_1^L = 1$ and $f_1^R = f_2^L = f_2^R = 0 \rightarrow$ CP is conserved

We are effectively measuring the **strength of the V-A coupling:**
 $|V_{tb} f_1^L|$, which can be >1

First direct measurement of $|V_{tb}|$



$$|V_{tb} f_1^L| = 1.3 \pm 0.2$$



$$|V_{tb}| > 0.68 \text{ @ 95 C.L.}$$

(assuming: $f_1^L = 1$)

This measurement does not assume 3 generations or unitarity

Conclusions

First direct evidence for single top quark production
and measurement of $|V_{tb}|$

(hep-ex/0612052 submitted to PRL)

$$\sigma(s+t) = 4.9 \pm 1.4 \text{ pb}$$

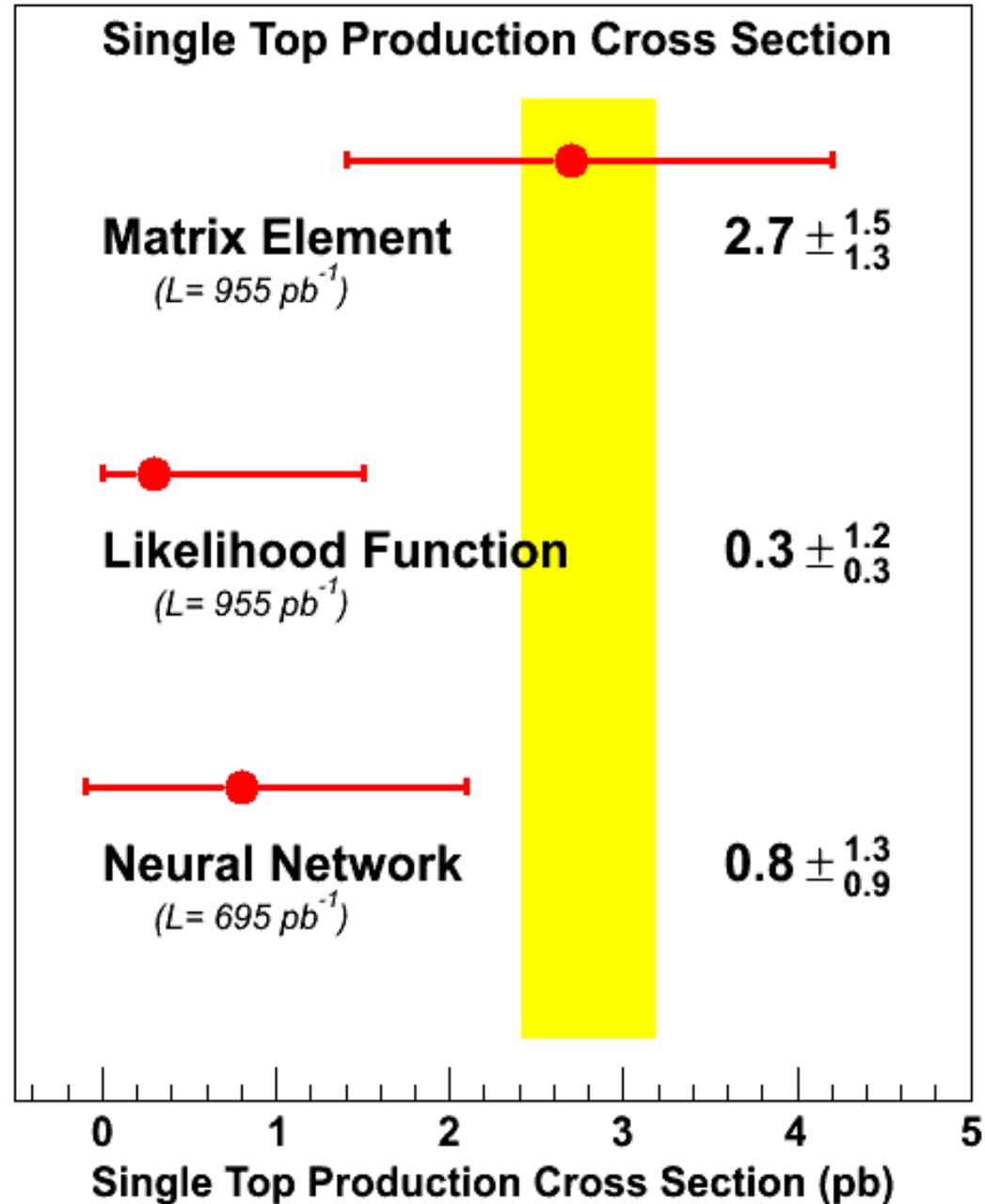
3.4σ significance!

$$|V_{tb}| > 0.68 \text{ @ } 95\% \text{C.L.}$$

- Working on the combination and more!
- Expand to searches of new phenomena
- We now have double the data to analyze!

Extra slides

CDF's latest results



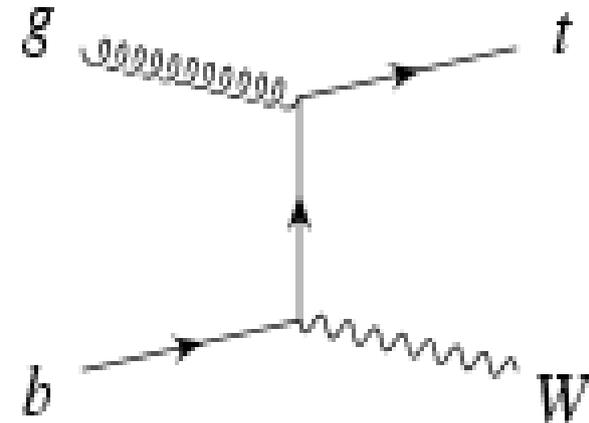
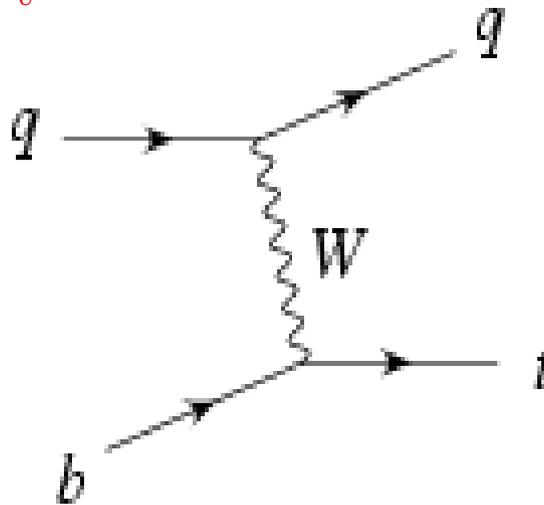
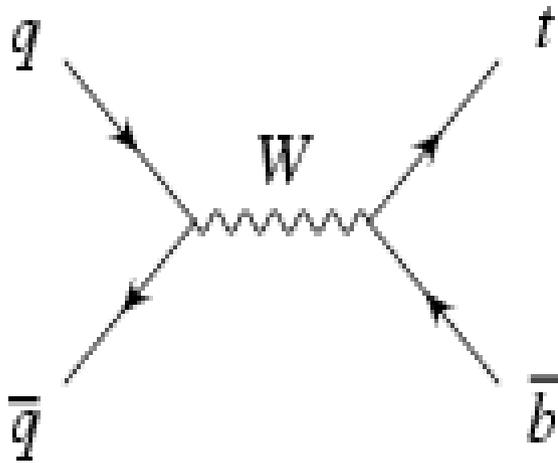
Single top in a couple of years

- ▶ By 2007 we will have observed single top and measured its cross section to $\sim 10\%$ at the Tevatron
- ▶ Then the LHC will start with huge production rates:

$$\sigma_s = 10.6 \pm 1.1 \text{ pb}$$

$$\sigma_t = 246.6 \pm 0.25 \text{ pb}$$

$$\sigma_{tW} = 62.0^{+16.6}_{-3.6} \text{ pb}$$



- ▶ Observe all three channels (s-channel will be tough)
- ▶ tW mode offers new window into top physics
- ▶ Measure V_{tb} to a few %
- ▶ Large samples: study properties

Preparing the way for the LHC

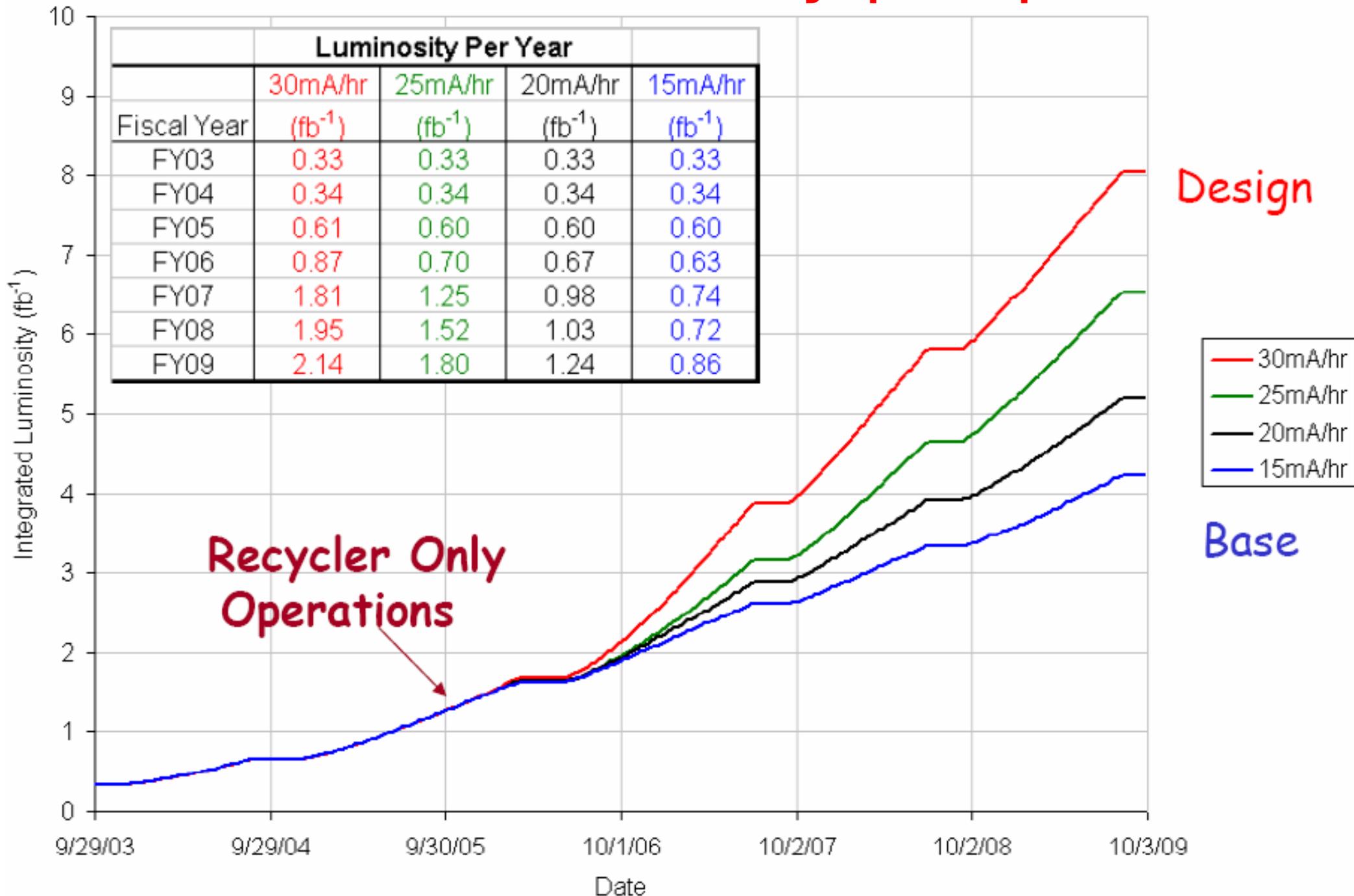
Studies at the Tevatron will help the LHC:

- ▶ Wbb measurement (will also help WH search) (DØ: hep-ex/0410062)
Current limit at 4.6 pb for $p_T(b) > 20\text{GeV}$
- ▶ In general, W+jets background determination techniques
tt will be main background, but large uncertainties come from W+jets
Effect of jet vetoes ($N_{\text{jet}}=2$), check other methods planned in LHC analyses
- ▶ Study charge asymmetries (Bowen, Ellis, Strassler: hep-ph/0412223)
Signal shows asymmetry in $(Q_\ell \times \eta_j, Q_\ell \times \eta_\ell)$ plane at TeV
- ▶ Study kinematics of forward jets in t-channel (WW→H at LHC)
- ▶ Even measure asymmetry in production rate (Yuan: hep-ph/9412214)
(probe CP-violation in the top sector):

$$A_t = \frac{\sigma(p\bar{p} \rightarrow tX) - \sigma(p\bar{p} \rightarrow \bar{t}X)}{\sigma(p\bar{p} \rightarrow tX) + \sigma(p\bar{p} \rightarrow \bar{t}X)}$$

TeV4LHC workshop report to appear soon

Tevatron luminosity prospects



Crash course in Bayesian probability

Bayes' theorem expresses the degree of belief in a hypothesis A, given another B. "Conditional" probability $P(A|B)$:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

In HEP: $B \rightarrow N_{\text{observed}}$, $A \rightarrow n_{\text{predicted}} = n_{\text{signal}} + n_{\text{bkgd}}$, $n_s = \text{Acc} * L * \sigma$

$P(B|A)$: "model" density, or likelihood: $L(N_{\text{observed}} | n_{\text{predicted}}) = n^N e^{-n} / N!$

$P(A)$: "prior" probability density $\Pi(n_{\text{pred}}) = \Pi(\text{Acc} * L, n_b) \Pi(\sigma)$
 $\Pi(n_s, n_b)$ multivariate gaussian ; $\Pi(\sigma)$ assumed flat

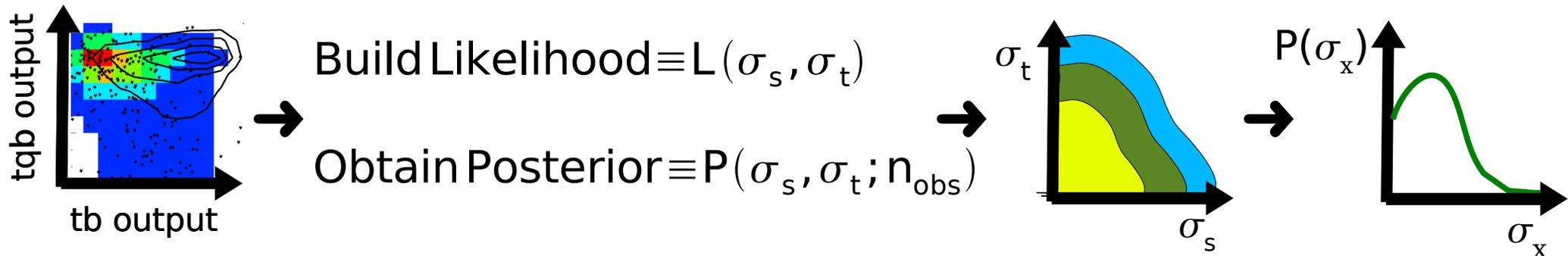
$P(B)$: normalization constant Z: $P(N_{\text{observed}})$

$P(A|B)$: "posterior" probability density $P(n_{\text{predicted}} | N_{\text{observed}})$

$$P(n_{\text{predicted}} | N_{\text{observed}}) = 1/Z L(N_{\text{observed}} | n_{\text{predicted}}) \Pi(n_{\text{pred}})$$

Full 2D limits

The goal is to obtain σ_s , σ_t , and σ_{s+t} , without any SM assumption
 Previously we have used σ_s^{SM} to derive σ_t and vice versa
 As before, use likelihood from 2D discriminant output
 Float σ_s and σ_t and consider flat priors



$$P(\sigma_s; n_{obs}) = \int P(\sigma_s, \sigma_t; n_{obs}) d\sigma_t$$

$$P(\sigma_t; n_{obs}) = \int P(\sigma_s, \sigma_t; n_{obs}) d\sigma_s$$

$$P(\sigma_{z=s+t}; n_{obs}) = \frac{1}{\sigma_z} \int P(\sigma_z, \sigma_t; n_{obs}) d\sigma_t$$

- ▶ For the combined limit:
replace: $s \rightarrow z-t$ where $z=s+t$
at the Likelihood level
- ▶ Additional constraint on priors:
 $t \leq z \rightarrow$ the prior for t depends on z

$$\sigma_x^{95} = \int_0^{\sigma_x^{95}} P(\sigma_x; n_{obs}) d\sigma_x$$

Non-SM couplings

Top is a good place to look for deviations from SM:

σ under control, one dominant decay $t \rightarrow Wb$, no top hadrons, ...

► Generalized Lagrangian for the Wtb interaction ([hep-ph/0503040](https://arxiv.org/abs/hep-ph/0503040)):

$$\mathcal{L}_{tbW} = \frac{g}{\sqrt{2}} W_{\mu}^{-} \bar{b} \gamma^{\mu} (f_1^L P_L + f_1^R P_R) t - \frac{g}{\sqrt{2} M_W} \partial_{\nu} W_{\mu}^{-} \bar{b} \sigma^{\mu\nu} (f_2^L P_L + f_2^R P_R) t + h.c.$$

f_1 : “vector”-like

f_2 : “tensor”-like

$P_{R(L)} = (1 \pm \gamma_5)/2$

In SM: $f_1^L = V_{tb} \sim 1$;

$f_1^R = f_2^L = f_2^R = 0$

► Effective single top production cross section:

There are strong bounds on tensor couplings:

from unitarity $|f_2| < 0.6$, and from $b \rightarrow s\gamma$: $|f_2^L| < 0.004$

But Tevatron can set direct limits. The goal is:

- Set limits simultaneously on all four couplings
- Set individual limits

Non-SM couplings strategy

f_1^L and f_1^R have same p_T distributions

Angular variables and spin are different

► Separate data into s-channel (2 tags) and t-channel (1tag+ \geq 1untag) samples based on NN output

► Top quark spin correlations separate between L and R couplings

tb: Helicity basis θ (lepton, top direction)

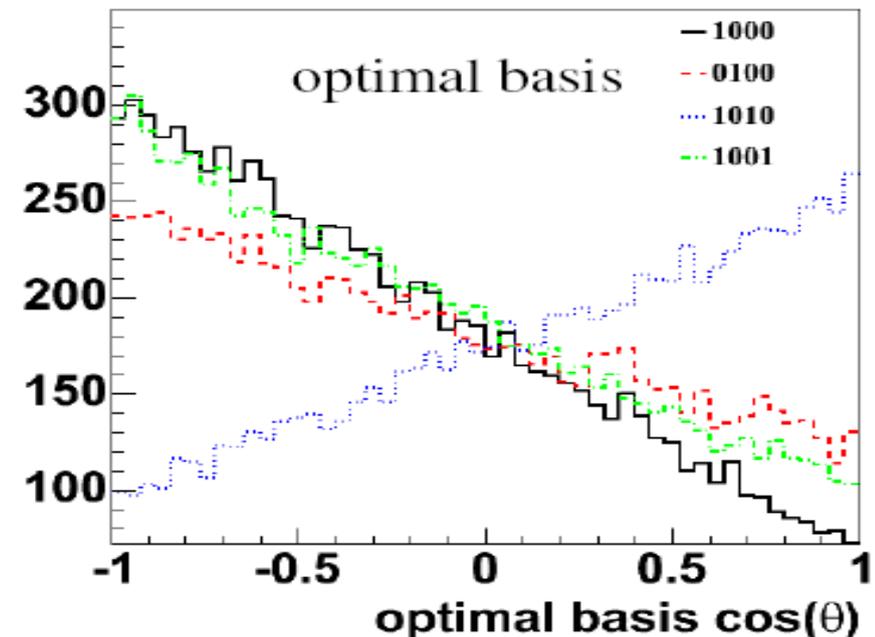
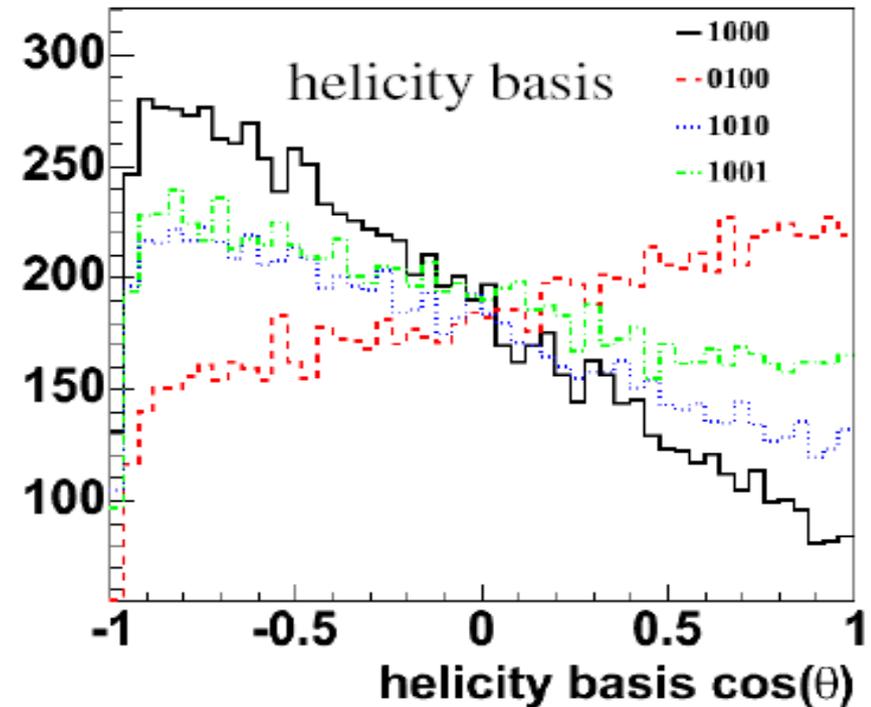
tqb: Optimal basis θ (lepton, pbar)

► Use flat prior for four square terms:

$$|f_1^L|^2, |f_1^R|^2, |c_1 f_1^L + f_2^R|^2, |c_1 f_1^R + f_2^L|^2$$

c_1 is a fixed constant

► Obtain limits on these four terms



Signal modeling

Have to get the t-channel right:

Avoid double counting when different diagrams produce same final states in different kinematic regions

Use ZTOP as NLO benchmark <http://home.fnal.gov/~zack/ZTOP>

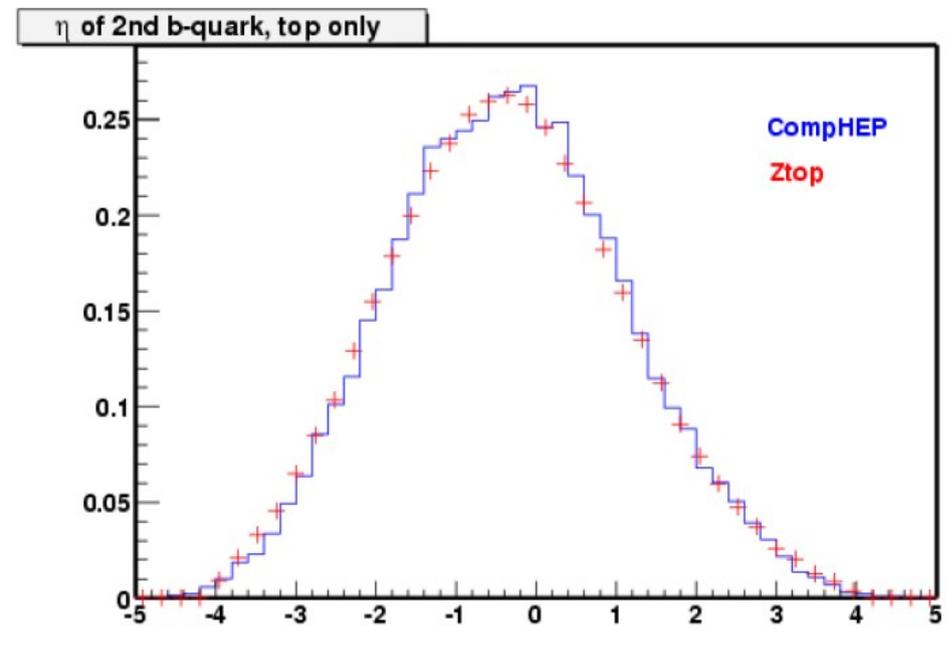
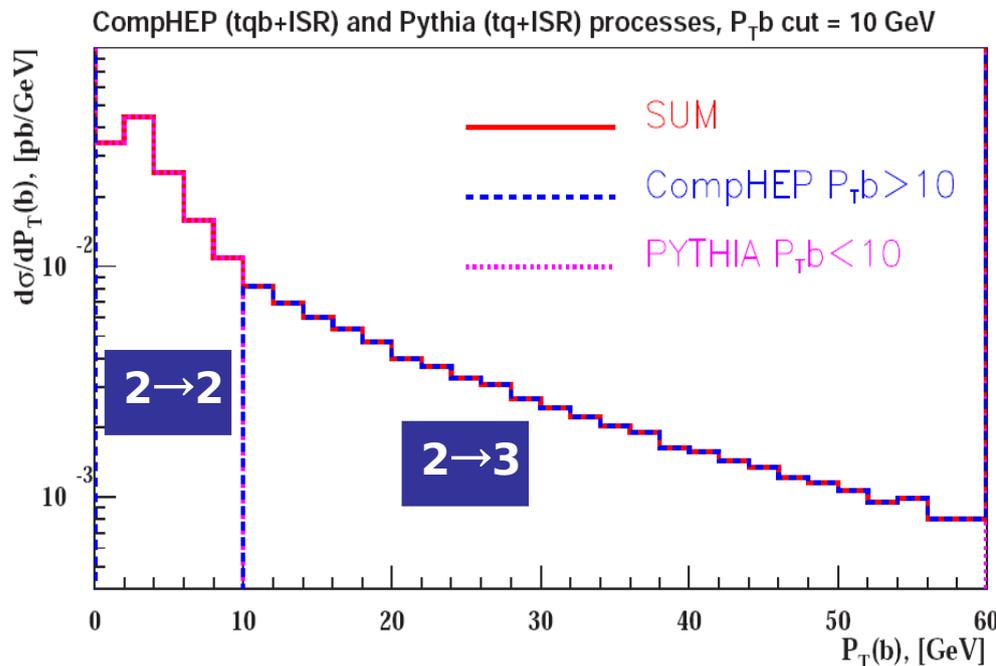
► DØ: “Effective” NLO CompHEP (also used in CMS)

Match $2 \rightarrow 2$ and $2 \rightarrow 3$ processes using $b p_T$ for cross over, normalize to NLO

σ

Resulting distributions agree well with ZTOP & MCFM

► Recently available: MC@NLO, Alpgen 2, C.-P. Yuan et al.



W+jets normalization

- ▶ Find fractions of real and fake isolated ℓ in the data before b-tagging. Split samples in loose and tight isolation:

$$N^{loose} = N_{fake}^{loose} + N_{real}^{loose}$$

$$N^{tight} = \varepsilon_{fake} N_{fake}^{loose} + \varepsilon_{real} N_{real}^{loose}$$

Obtain: N_{real}^{loose} and N_{fake}^{loose}

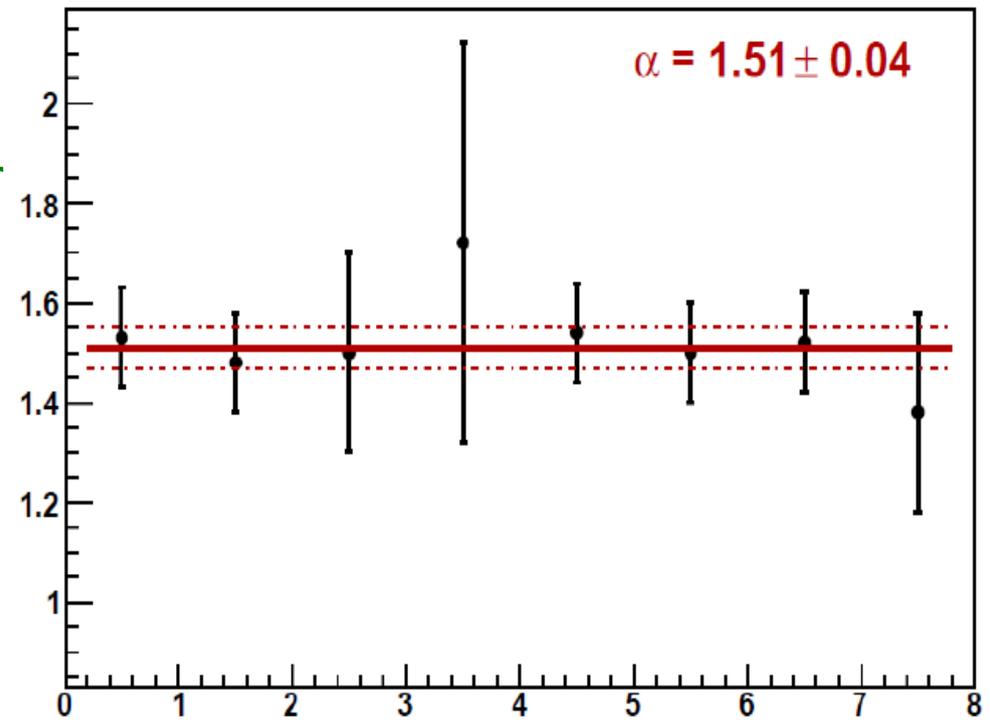
- ▶ Normalize the MC Wjj and Wbb samples to the real ℓ yield found in data, after correcting for the presence of tt events:

$$\varepsilon_{real} N_{real}^{loose} = SF [Y(Wjj) + Y(Wb\bar{b}) + Y(Wc\bar{c})] + Y(t\bar{t}) \quad SF=1.4$$

- ▶ The sum $Y(Wjj) + Y(Wbb) + Y(Wcc)$ is done according to the ratio of $(Wbb+Wcc)/Wjj$ found in 0-tag data $\rightarrow 1.5 \pm 0.5$
- ▶ Then apply b-tagging
 - ▶ Greatly reduce W+jets background ($Wbb \sim 1\%$ of Wjj)
 - ▶ Shift distributions, changes flavor composition

Wbb and Wcc fraction

- We use our own data to derive the Wbb+Wcc fraction: something very close to 1.5 is needed to describe our data
- This is not a measurement of Wbb, but a fraction determination. The full W+jets yield is scaled to data
- Until we have our own measurement, this is the best we can do

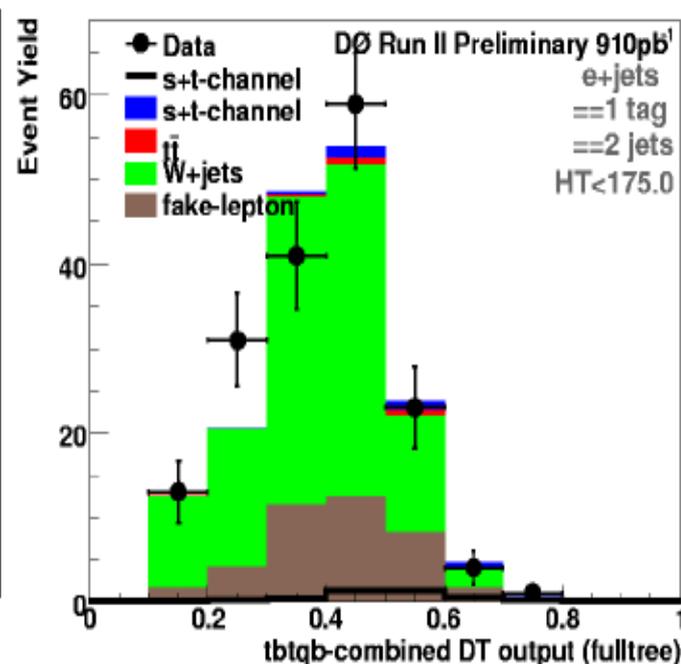
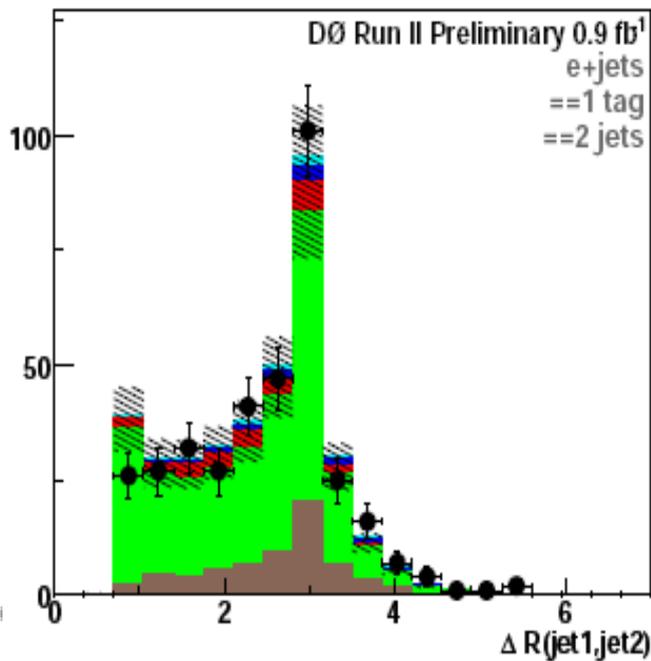
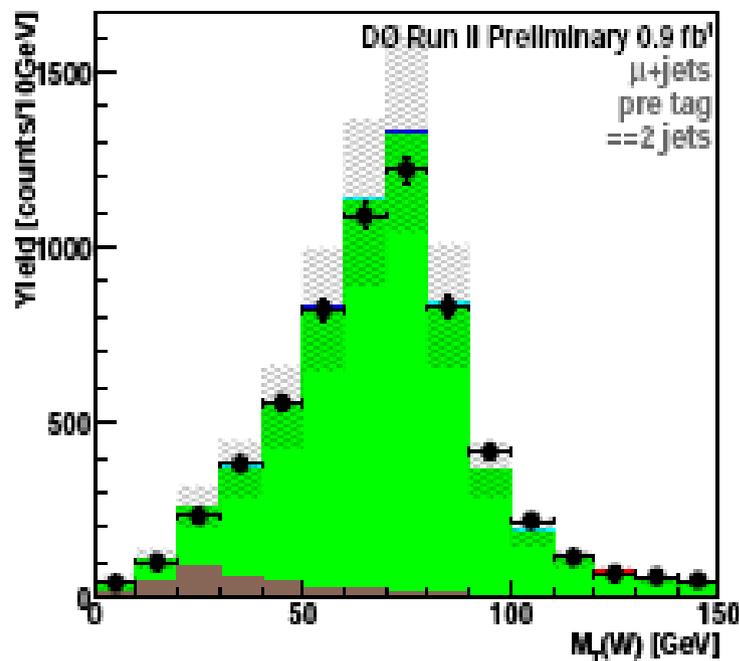


Scale Factor α to Match Heavy Flavor Fraction to Data

	1 jet	2 jets	3 jets	4 jets
Electron Channel				
0 tags	1.53 ± 0.10	1.48 ± 0.10	1.50 ± 0.20	1.72 ± 0.40
1 tag	1.29 ± 0.10	1.58 ± 0.10	1.40 ± 0.20	0.69 ± 0.60
2 tags	—	1.71 ± 0.40	2.92 ± 1.20	-2.91 ± 3.50
Muon Channel				
0 tags	1.54 ± 0.10	1.50 ± 0.10	1.52 ± 0.10	1.38 ± 0.20
1 tag	1.11 ± 0.10	1.52 ± 0.10	1.32 ± 0.20	1.86 ± 0.50
2 tags	—	1.40 ± 0.40	2.46 ± 0.90	3.78 ± 2.80

Wbb shapes

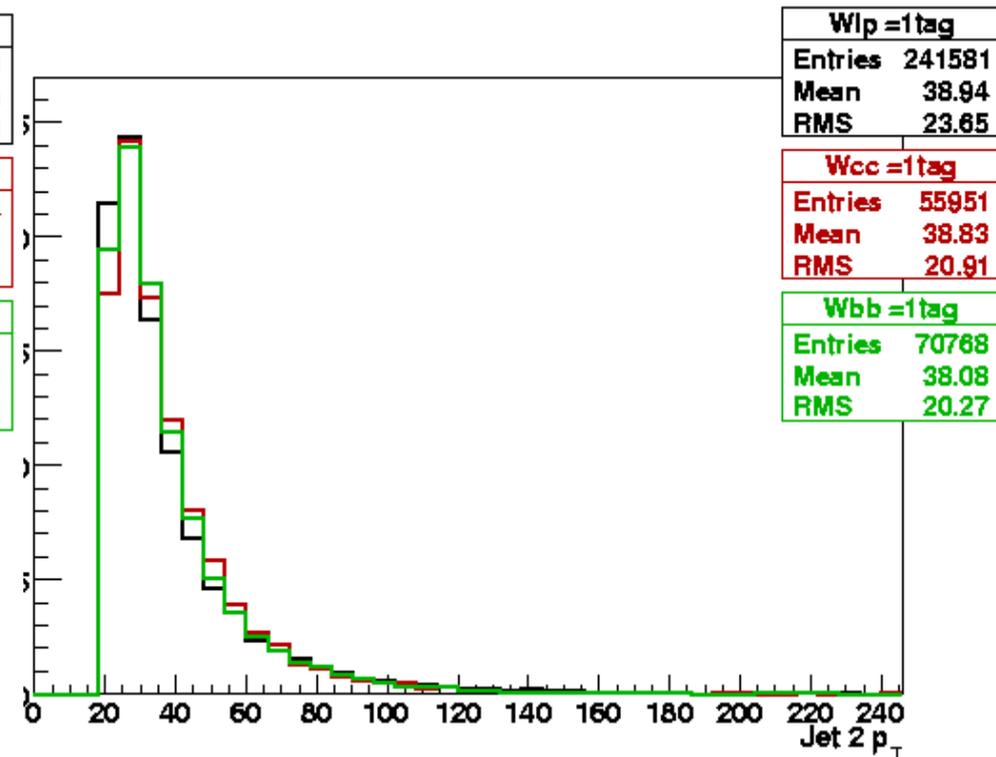
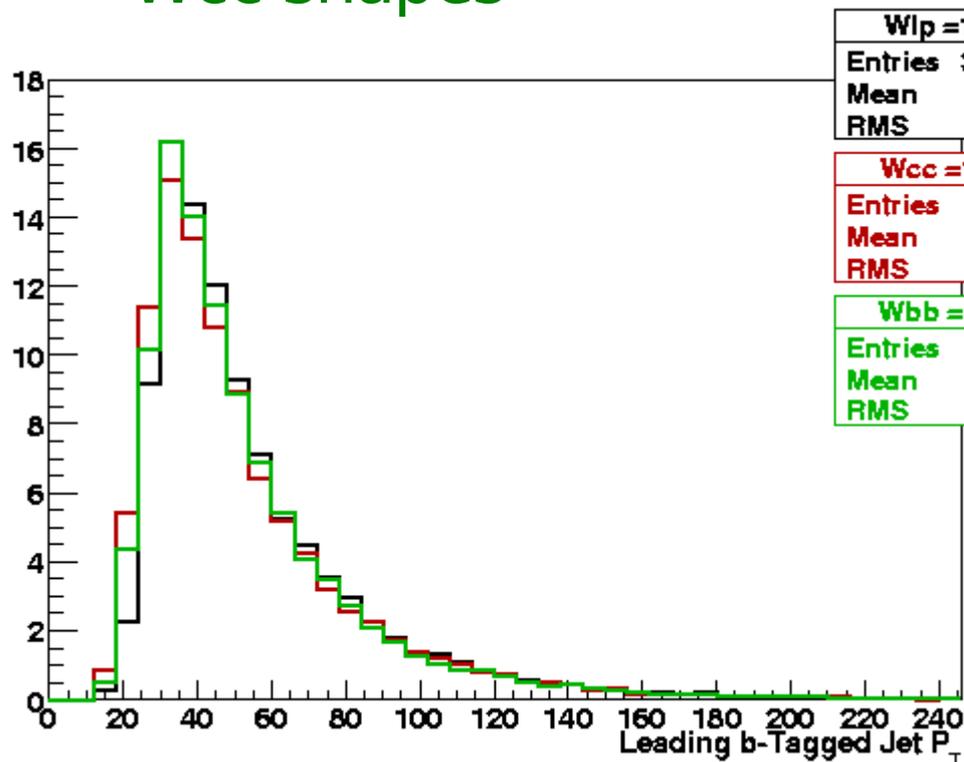
- ▶ The kinematic distributions of the Wbb samples used are in gross disagreement with LO samples using conventional scale choices and with NLO calculations
 - Alpgen v2.05 with MLM matching disagrees with NLO shapes
 - The data should be the judge. We have found overall good agreement in all kinds of distributions inside our acceptance before and after tagging: angular correlations, pTs, background cross check samples, discriminant outputs...



Wbb/Wcc shape difference

► Can you assume that Wbb and Wcc fractions separately can be described by the Wbb+Wcc fraction?

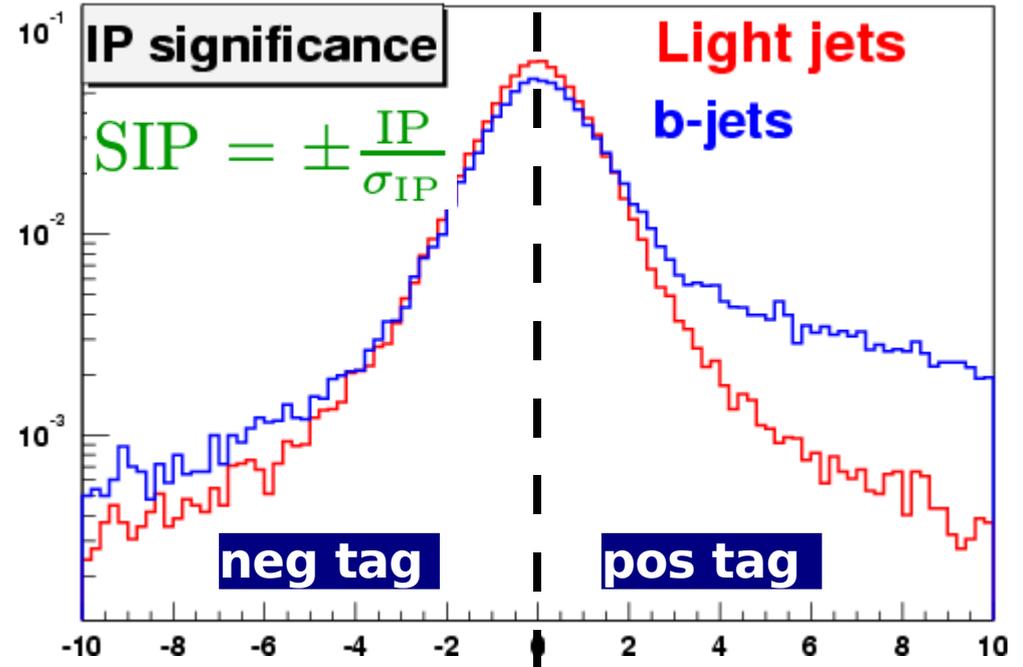
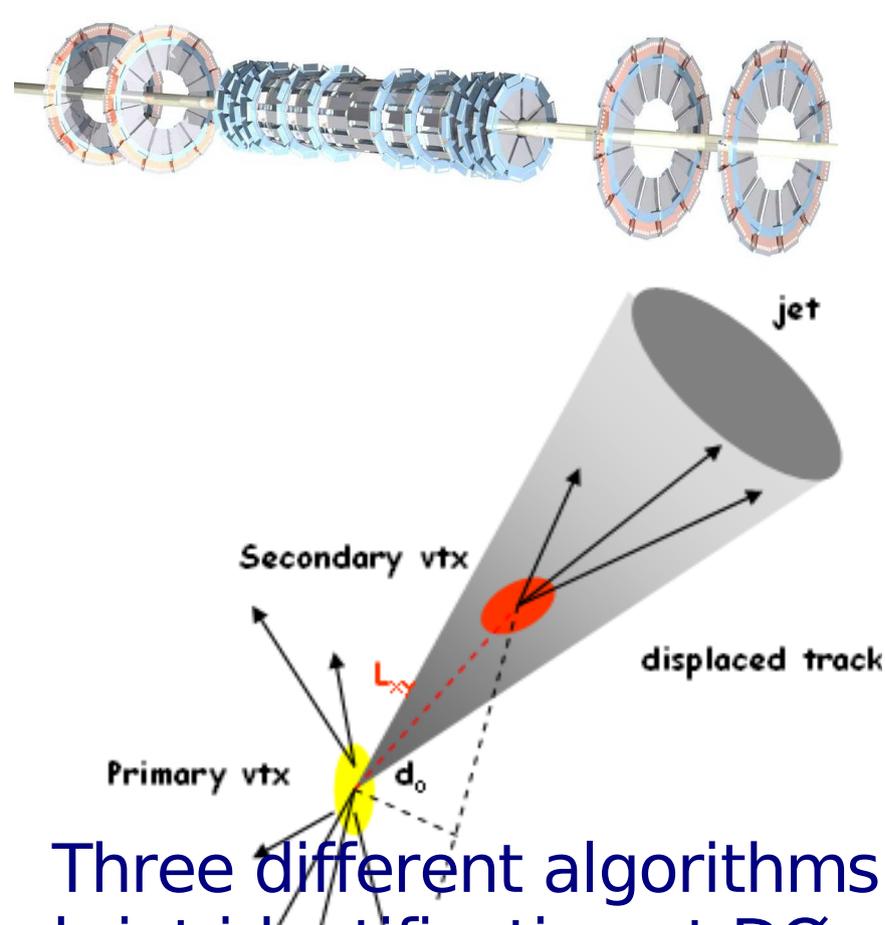
- We changed the Wbb/Wcc ratio by $\pm 10\%$ and re-calculated the single top cross section:
- More Wbb, less Wcc: $\sigma(\text{tb}+\text{tqb})=4.85\pm 1.4\text{pb}$
- Less Wbb, more Wcc: $\sigma(\text{tb}+\text{tqb})=4.98\pm 1.5\text{pb}$
- Weak dependence based on similarity between Wbb and Wcc shapes



Error on the HF fraction

- ▶ How come a 30% error on HF fraction doesn't destroy all sensitivity?
 - This (still) is a statistics limited analysis: 1.2pb out of 1.4pb error comes from stats alone
 - After tagging, the uncertainty on the total W +jets yield is reduced from 30% because:
 - a) Not the entire sample is $W_{bb}+W_{cc}$, the uncertainty on the sum is smaller than 30%
 - b) The anti-correlation between W_{jj} and $W_{bb}+W_{cc}$ due to the normalization before tagging further reduces the uncertainty
 - This uncertainty is still one of the largest in the end

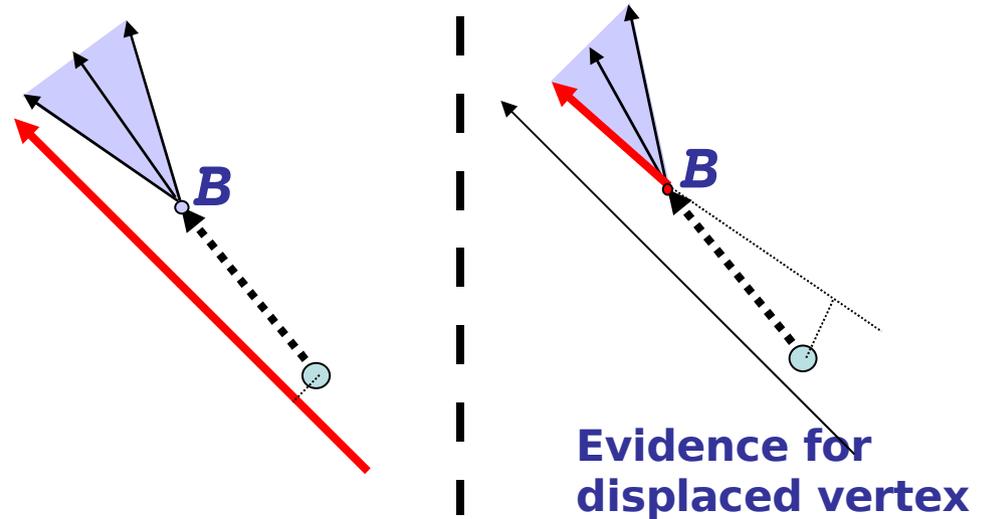
Tagging b-jets



Three different algorithms for b-jet identification at DØ:

- ▶ Two based on tracks with large IP (JLIP, CSIP)
- ▶ One based on secondary vertex reconstruction (SVT)
- ▶ Combine in NN

NEW



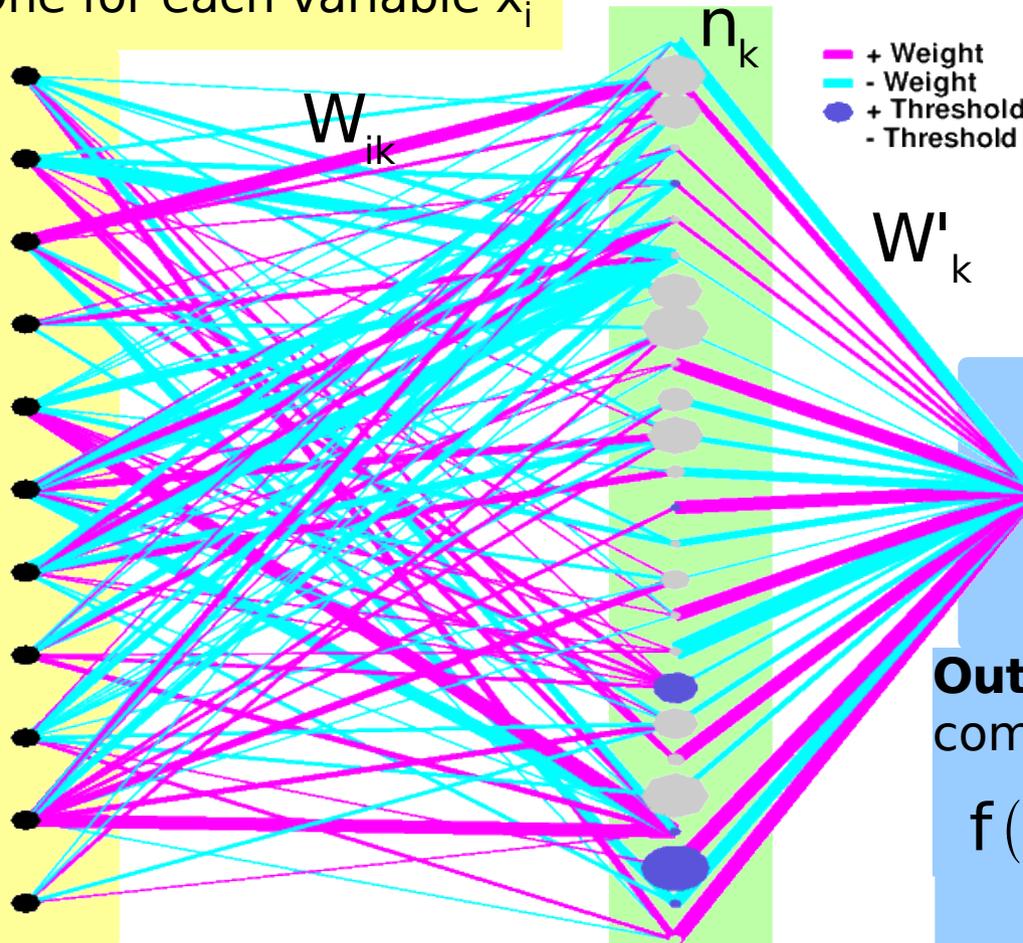
Ensemble testing details

- ▶ Use a pool of weighted signal+background events (about 850k in each of electron and muon)
- ▶ Fluctuate relative and total yields in proportion to **systematic errors**
 - reproducing the **correlations** between backgrounds imposed by our normalization to data
- ▶ Randomly sample from a Poisson distribution about the total yield to simulate **statistical fluctuations**
- ▶ Generate a set of pseudo-data (a member of the ensemble)
- ▶ Pass the pseudo-data through the full analysis chain (including systematic uncertainties)

Neural Networks

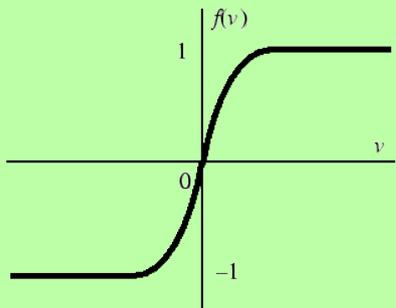
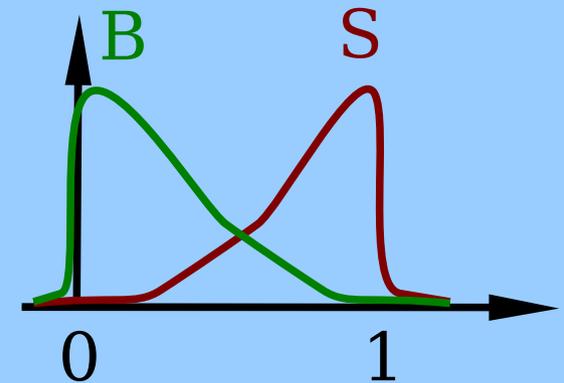
Input Nodes: One for each variable x_i

$M_T(\text{jet1, jet2})$
 $M(\text{alljets})$
 $p_T(\text{jet1, jet2})$
 $p_T(\text{notbest2})$
 $p_T(\text{notbest1})$
 $\cos(\angle, Q(\angle) \times z)_{\text{besttop}}$
 $M(W, \text{best})$
 $M(W, \text{tag1})$
 $\Delta R(\text{jet1, jet2})$
 \sqrt{s}
 $p_T(\text{tag1})$



Output Node: linear combination of hidden nodes

$$f(\vec{x}) = \sum w'_k n_k(\vec{x}, \vec{w}_k)$$

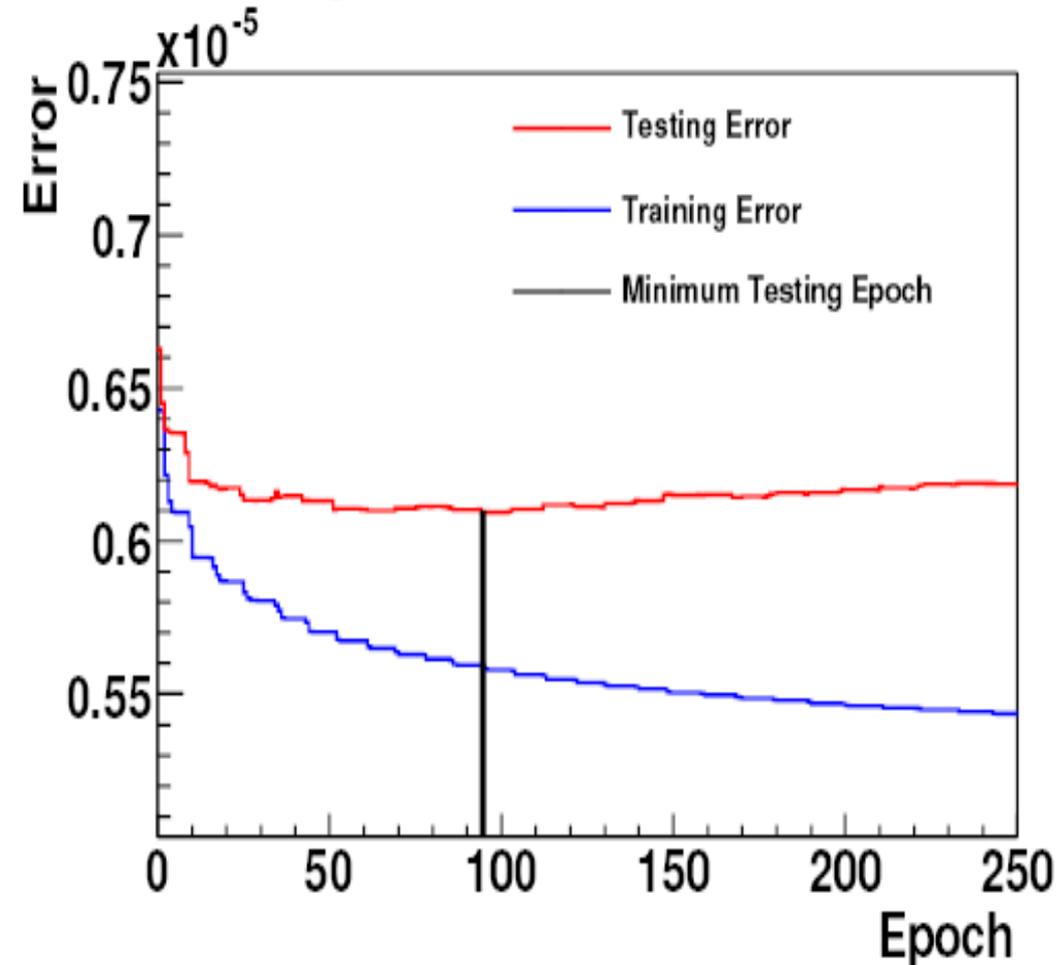


Hidden Nodes: Each is a sigmoid dependent on the input variables

$$n_k(\vec{x}, \vec{w}_k) = \frac{1}{1 + e^{-w_{ik} x_i}}$$

Training method and optimization

- 1) Initialize weights
- 2) Minimize error function on training sample
- 3) Update weights. This is the first epoch.
- 4) Repeat procedure.
After each epoch, apply NN filter on independent testing sample. Stop training when testing error increases



- ▶ Used 60% of events for training, 40% for testing
- ▶ Optimize number of training epochs and number of hidden nodes
- ▶ MLPFit implementation, many others in the market

Systematics

Relative Systematic Uncertainties

$t\bar{t}$ cross section	18%	Primary vertex	3%
Luminosity	6%	Electron reco * ID	2%
Electron trigger	3%	Electron trackmatch & likelihood	5%
Muon trigger	6%	Muon reco * ID	7%
Jet energy scale	wide range	Muon trackmatch & isolation	2%
Jet efficiency	2%	$\epsilon_{\text{real}-e}$	2%
Jet fragmentation	5-7%	$\epsilon_{\text{real}-\mu}$	2%
Heavy flavor fraction	30%	$\epsilon_{\text{fake}-e}$	3-40%
Tag-rate functions	2-16%	$\epsilon_{\text{fake}-\mu}$	2-15%

New physics

