TeV4LHC Workshop

CERN April 29, 2005

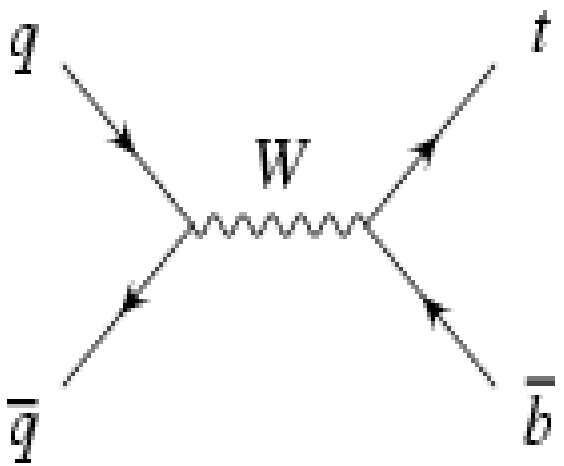
Single Top Searches at the Tevatron

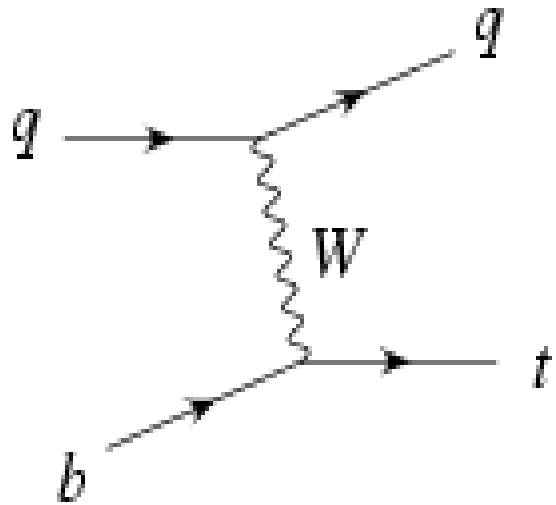
- Electroweak top quark production
- Signal and background modeling, b-tagging
- CDF analysis
  - s-channel, t-channel, combined results
- DØ analysis
  - Cut-based, Decision Trees, Neural Networks
- Cross section limits
- Outlook

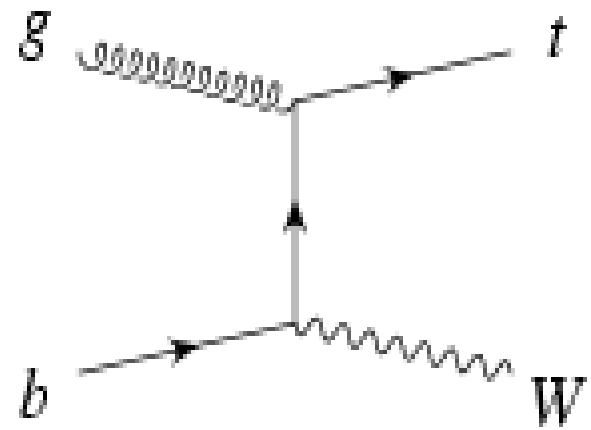
Arán García-Bellido
on behalf of CDF and DØ
UNIVERSITY OF WASHINGTON

Top quark electroweak production

	s-channel	t-channel	associated tW
TeV:	0.88±0.11 pb	1.98±0.25 pb	<0.1 pb
LHC:	10.6±1.1 pb	246.6±0.25 pb	$62.0^{+16.6}_{-3.6}$ pb





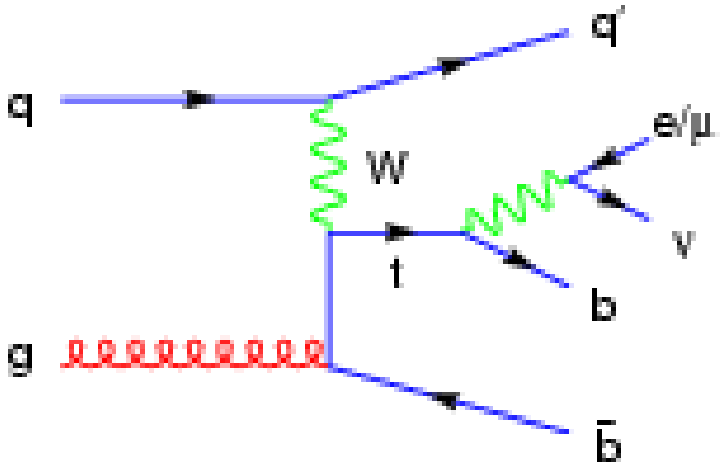


Harris, Laenen, Phaf, Sullivan, Weinzierl: hep-ph/0207055
Cao and Yuan: hep-ph/0408180

Tait: hep-ph/9909352
Belyaev, Boos: hep-ph/0003260

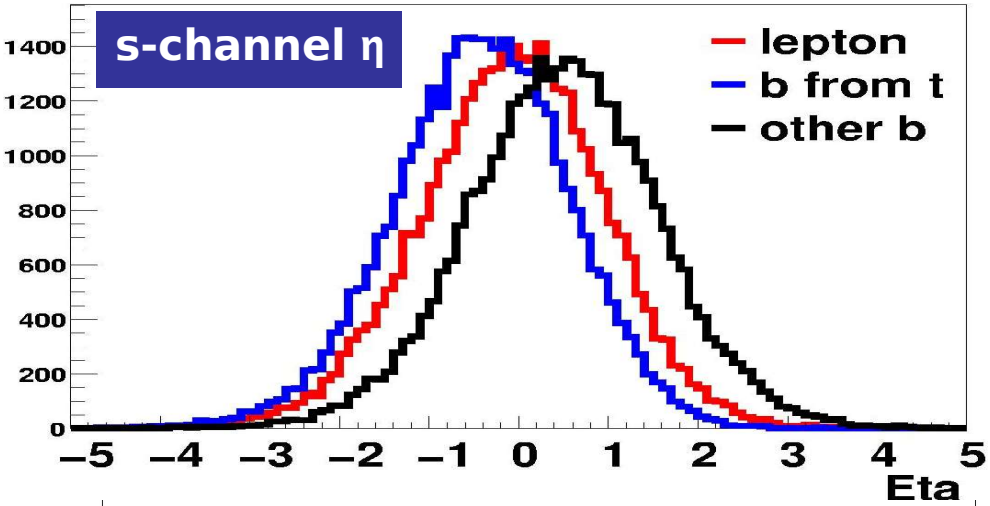
- Observe single top quark production in Run II ← Final Goal!
- Direct access to V_{tb} CKM matrix element
- Look for new physics: FCNC, 4th generation, W', SUSY,...
- Probe W+jets understanding and help SM higgs searches

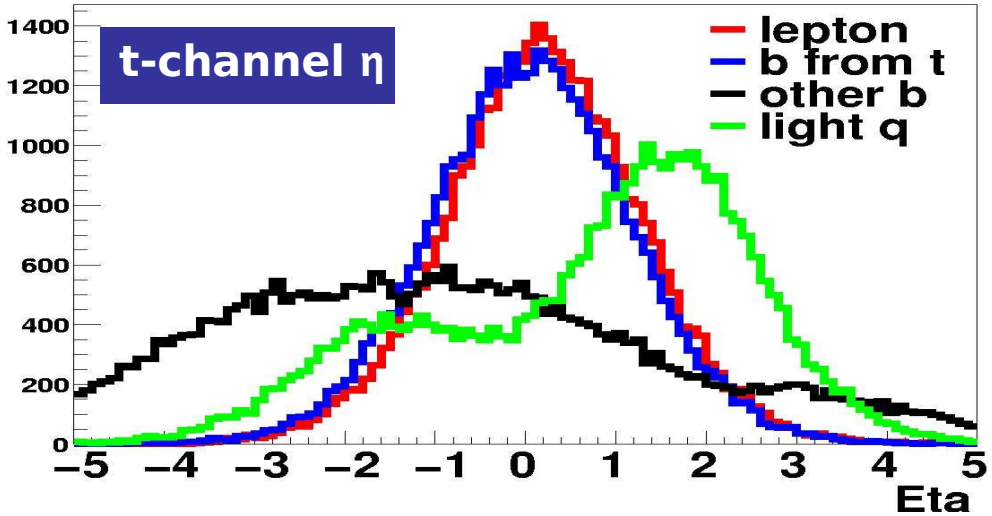
Signal topology

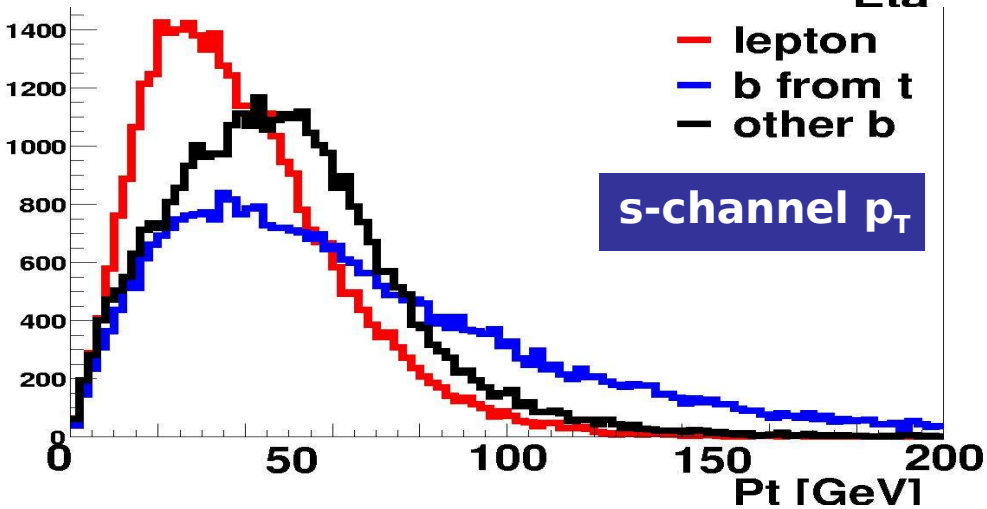


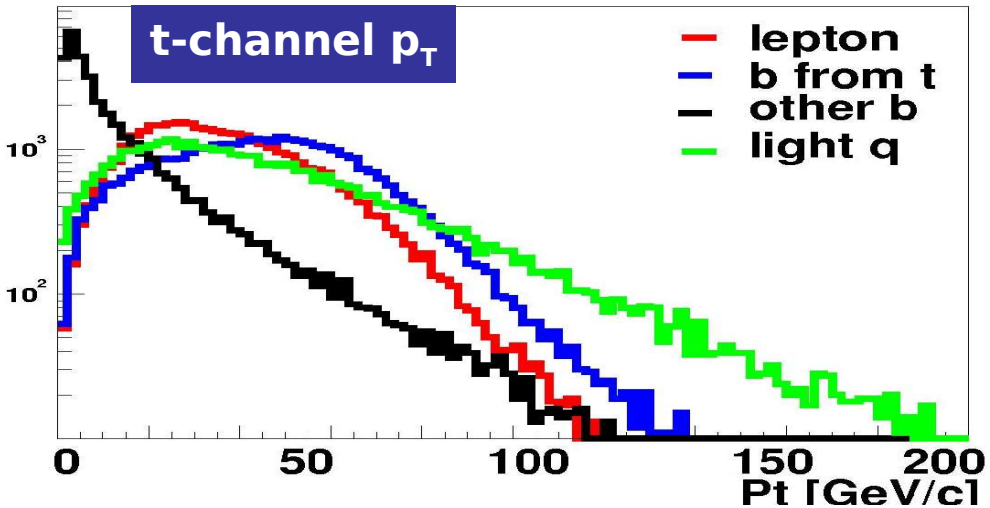
We are looking for:

- 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









Signal modeling

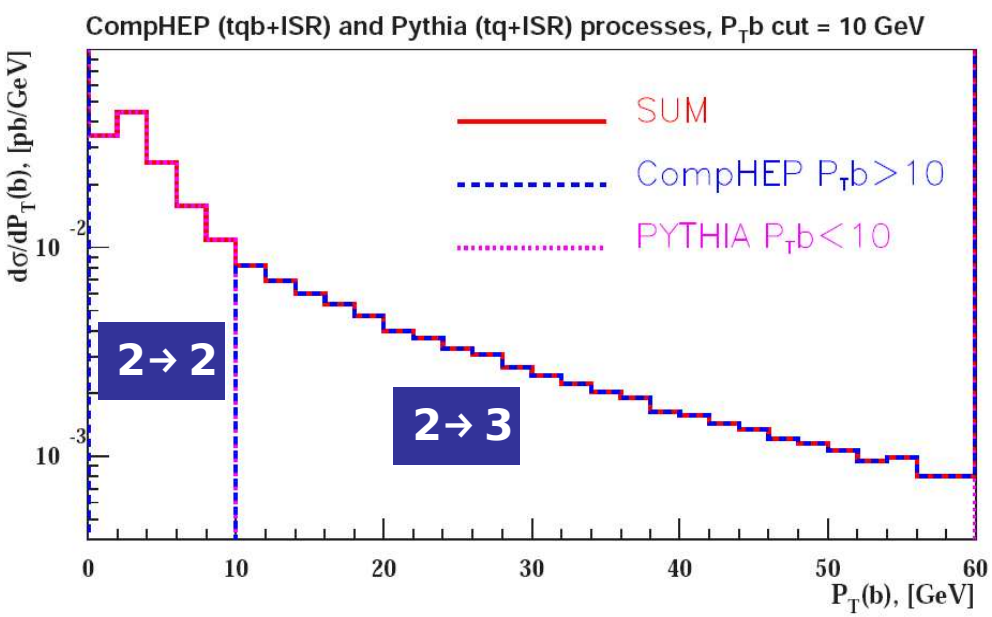
Have to get the t-channel right:
Avoid double counting when different diagrams produce same final states in different kinematic regions
Use ZTOP as NLO benchmark http://home.fnal.gov/~zack/ZTOP

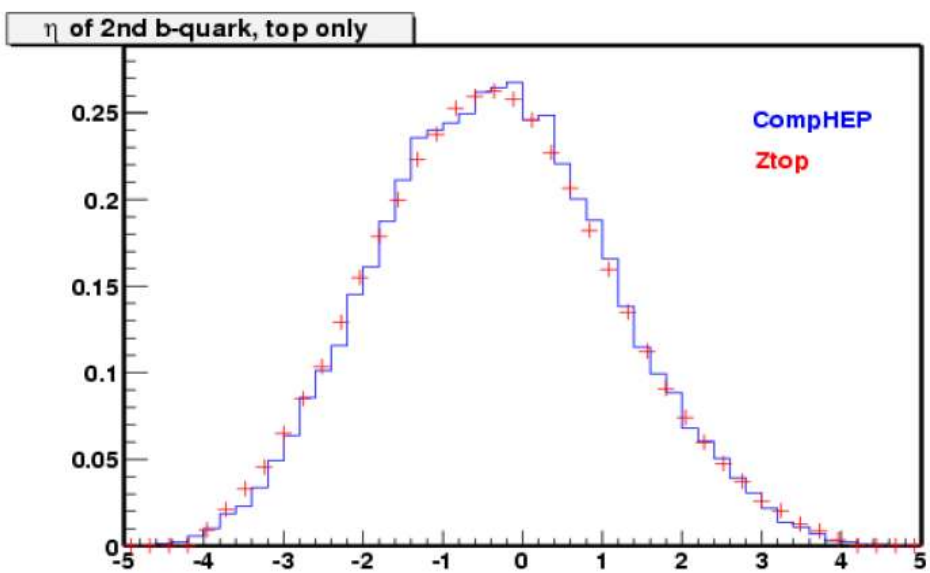
- CDF: Reweight MADEVENT to fit ZTOP

Generate: b+q→t+q' and g+q→t+b+q' separately and merge them to reproduce the b p_T spectrum from NLO

- DØ: "Effective" NLO CompHEP (also used in CMS)

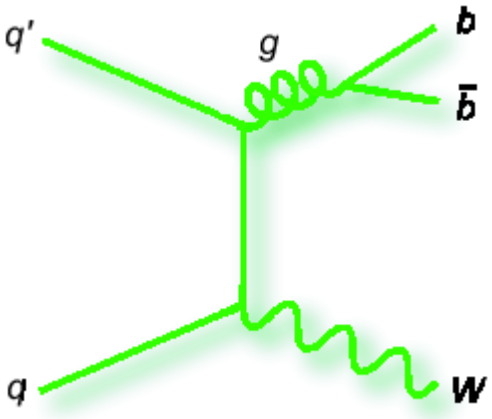
Match 2→2 and 2→3 processes using b p_T for cross over, normalize to NLO σ
Resulting distributions reproduce ZTOP & MCFM



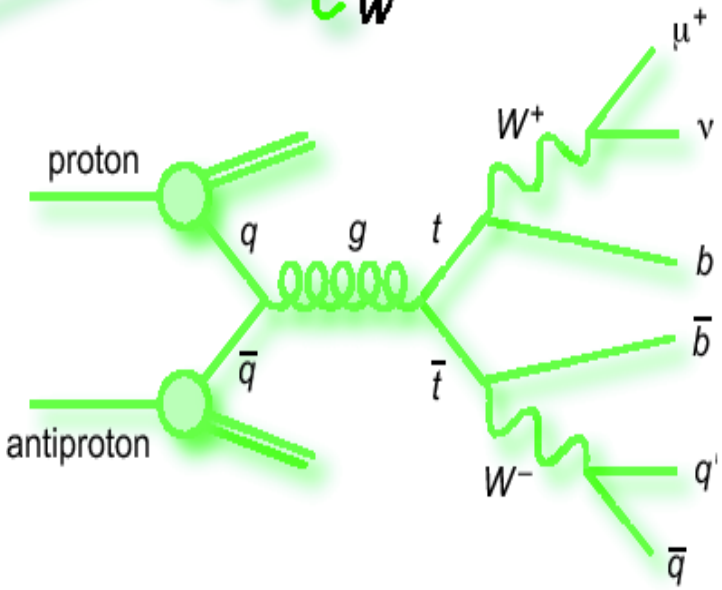


Background modeling

- W+jets
  - Distributions from Alpgen
  - Normalization from data
  - Flavor fractions from Alpgen

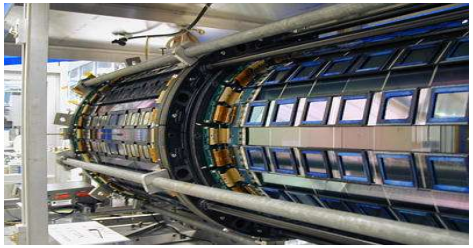


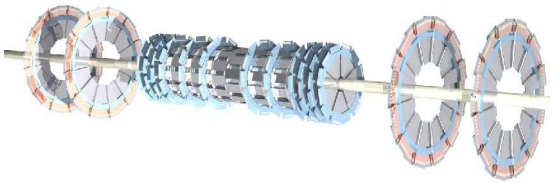
- Top pairs
  - Use Pythia (CDF) and Alpgen (DØ)

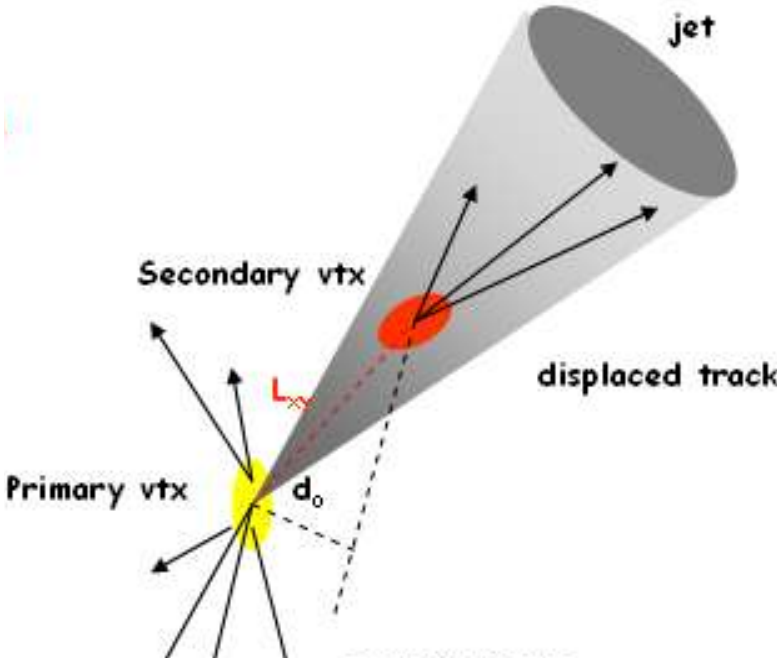


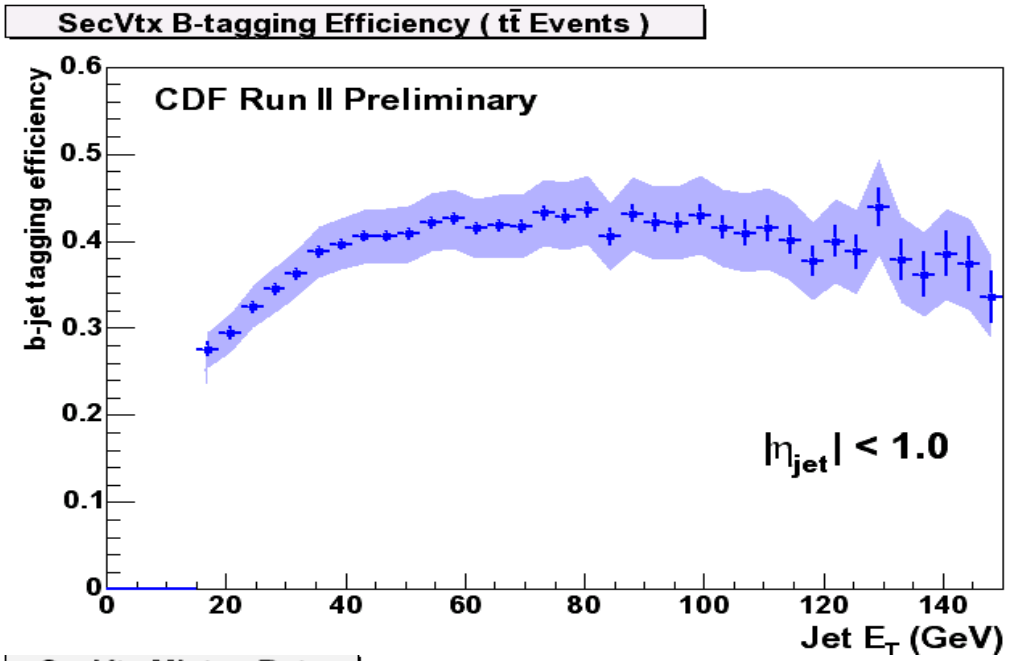
- Multijet events (misidentified lepton)
  - From data
- Diboson (WZ, WW)
  - Estimated from Pythia (CDF) and Alpgen (DØ)

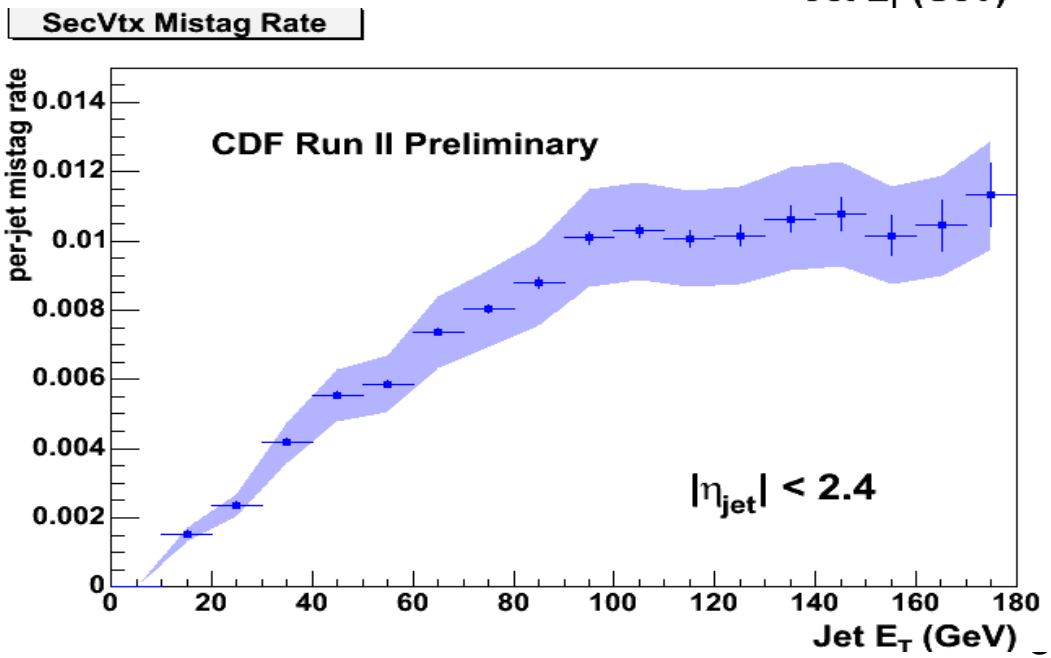
Tagging b-jets











Both CDF and DØ use a secondary vertex reconstruction algorithm

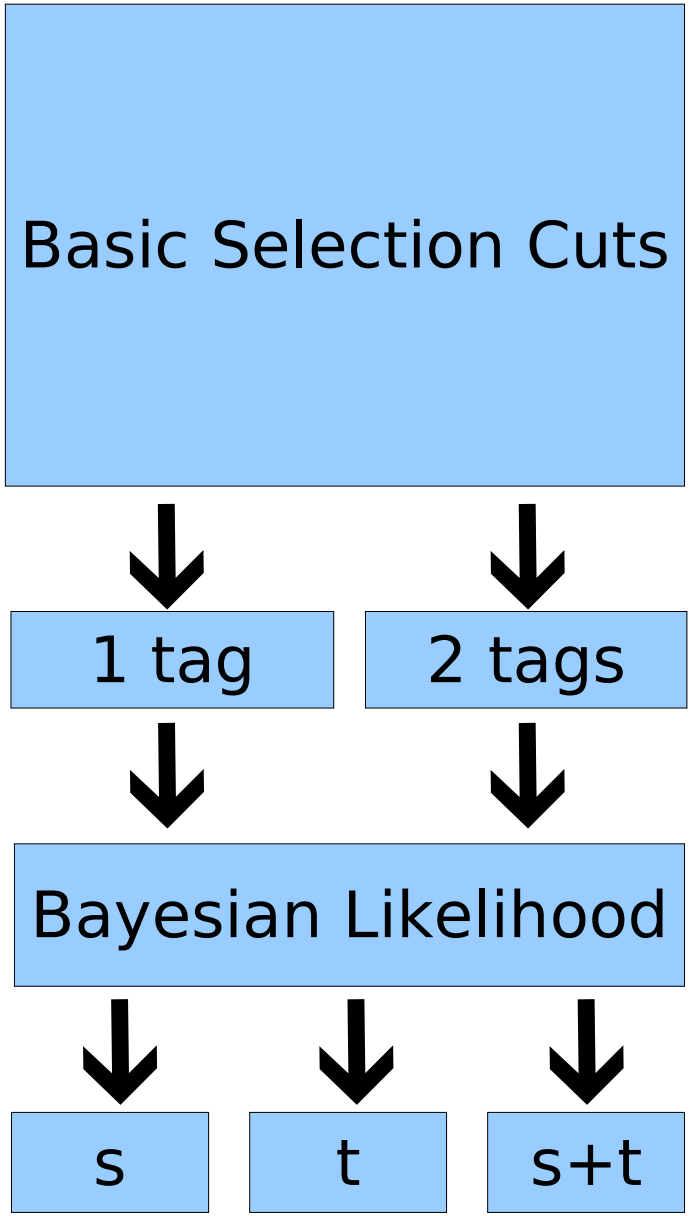
~40% b-jet efficiency

~ 1% mistag efficiency (light jets)

Charm tagging rate ~30% of b

- DØ performance is very similar
- CDF has recently released an improved version (15% better)

CDF search strategy



Phys.Rev.D71, 012005 (2005)

Lepton(e,μ): p_T>20 GeV, |η|<1.0

Jets: N_{jets}=2, E_T>15GeV,|η|<2.8

MET: MET>20GeV

Other clean-up cuts

b-tagging: At least one SVT jet

m_t window: 140<M($\ell\nu$b)<210GeV

s, t and combined searches

Joint likelihood for separate searches

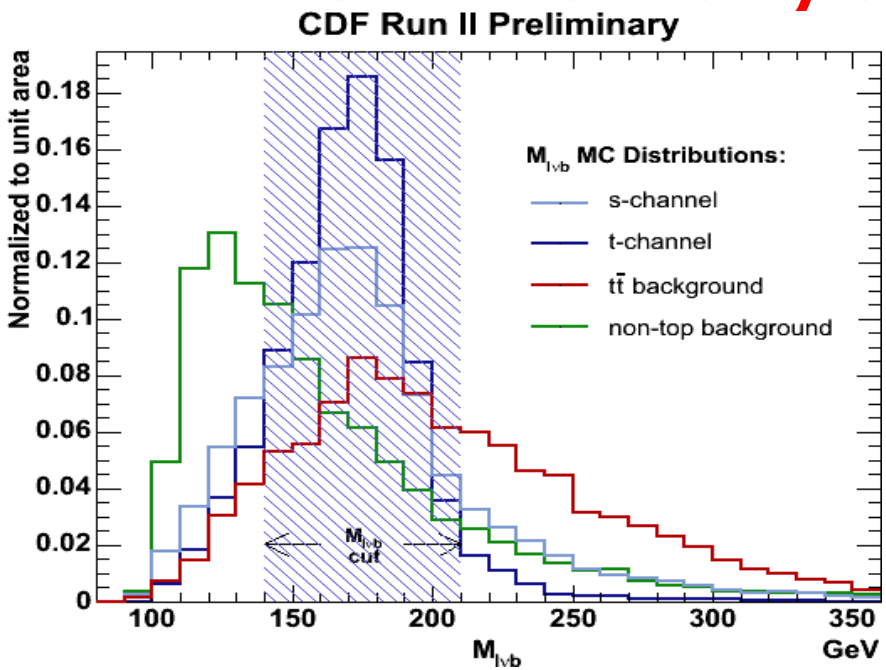
Likelihood with H_T distribution for s+t

s-channel: use two tagged events

t-channel: use 1 tag Q×η distribution

Combined (s+t): use H_T distribution

CDF analysis after selection

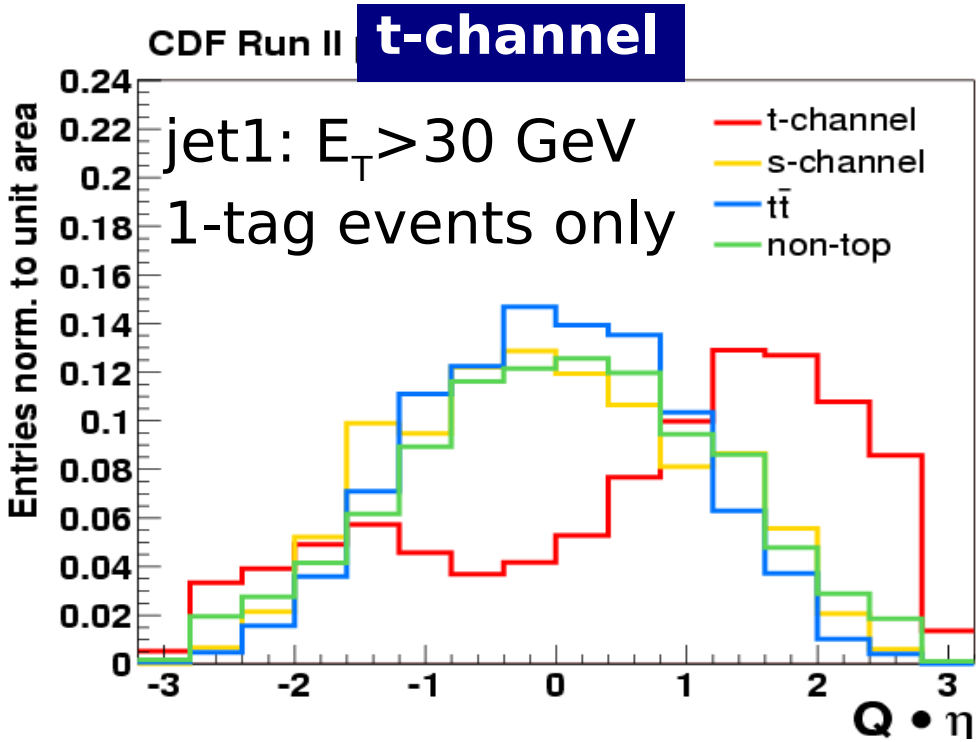


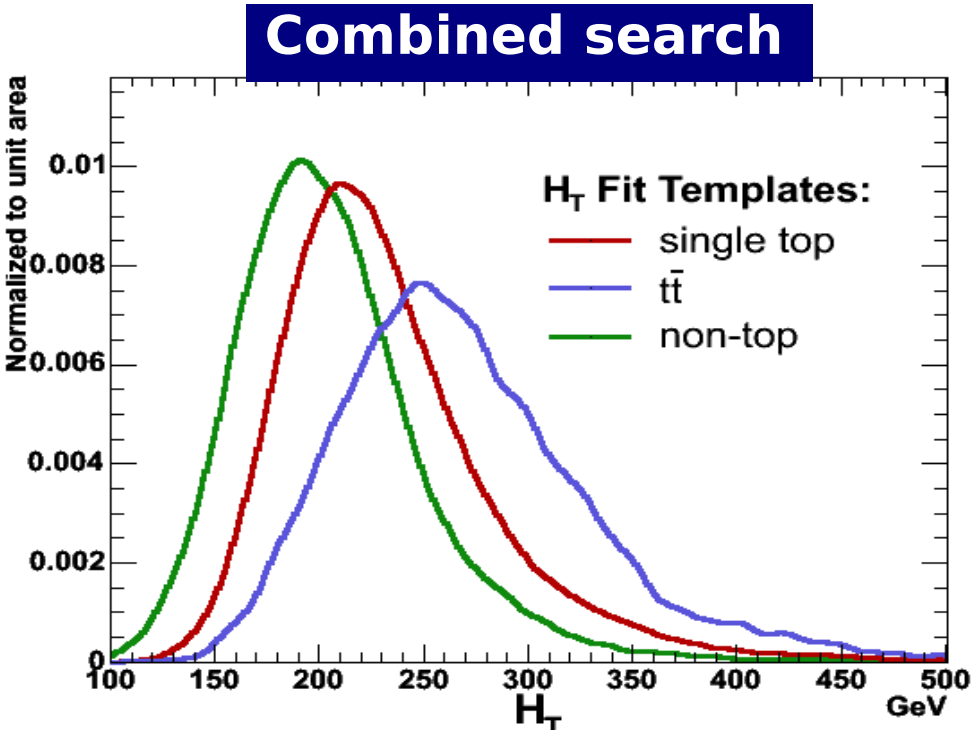
Process	Combined	1-tag	2-tag
t-channel	2.8 ± 0.5	2.7 ± 0.4	0.02 ± 0.01
s-channel	1.5 ± 0.2	1.1 ± 0.2	0.32 ± 0.05
$t\bar{t}$	3.8 ± 0.9	3.2 ± 0.7	0.60 ± 0.14
Nontop	30.0 ± 5.8	23.3 ± 4.6	2.59 ± 0.71
Total background	33.8 ± 5.9	26.5 ± 4.7	3.19 ± 0.72
Total expected	38.1 ± 5.9	30.3 ± 4.7	3.53 ± 0.72
Observed	42	33	6

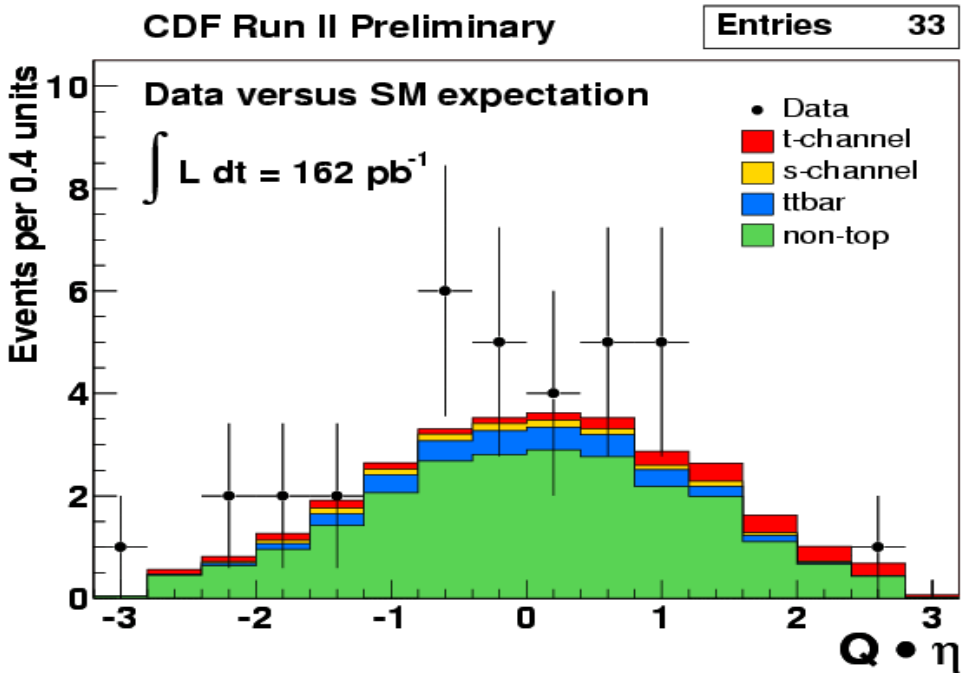
	Systematics	t-channel	s-channel	Combined
1	JES	$^{+2.4}_{-6.7}$	$^{+0.4}_{-3.1}$	$^{+0.1}_{-4.3}$
2	ISR	± 1.0	± 0.6	± 1.0
3	FSR	± 2.2	± 5.3	± 2.6
4	PDF	± 4.4	± 2.5	± 3.8
5	Generator	± 5	± 2	± 3
6	Top quark mass	$^{+0.7}_{-6.9}$	-2.3	-4.4
7	ϵ_{trig}, ϵ_{ID}, luminosity	± 9.8	± 9.8	± 9.8

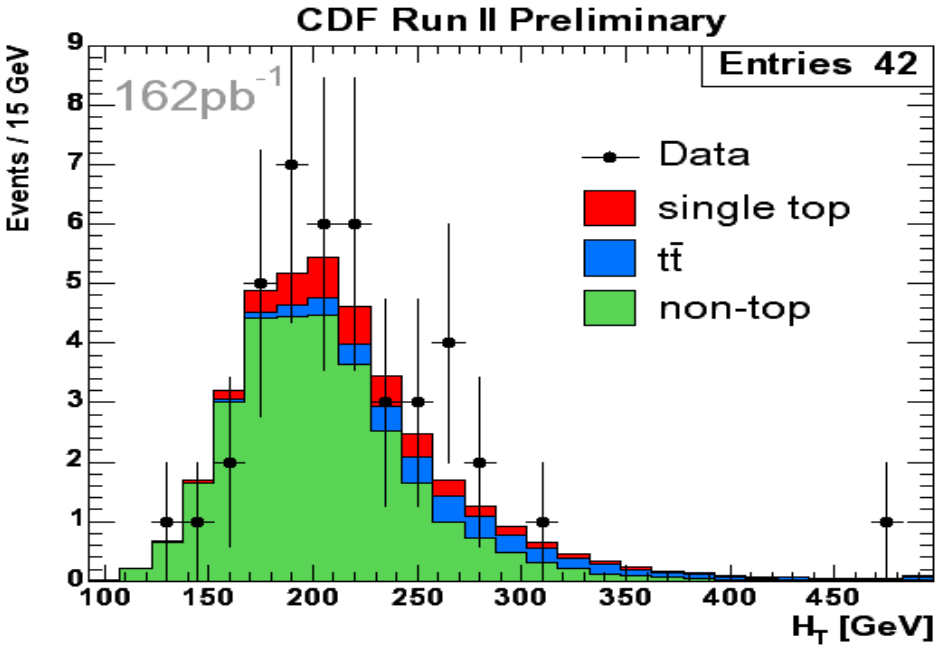
- Acceptance:
  1.06±0.08% (s-channel)
  0.89±0.07% (t-channel)
- Main systematics:
  B-ID 7%
  Luminosity 6%
  m_t 4%
  JES 4%

CDF distributions



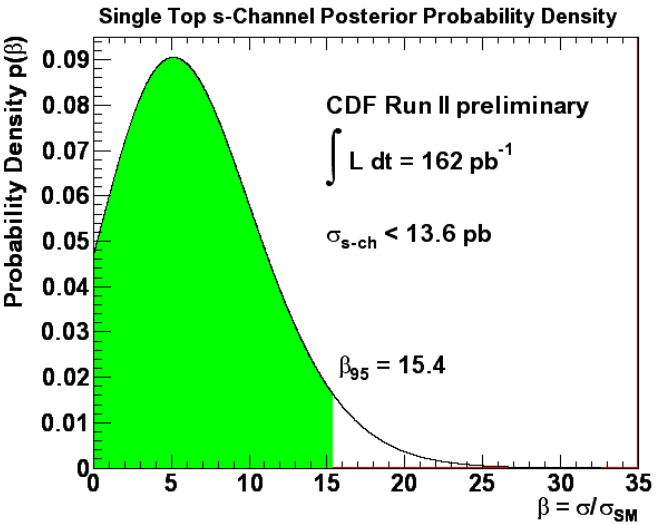


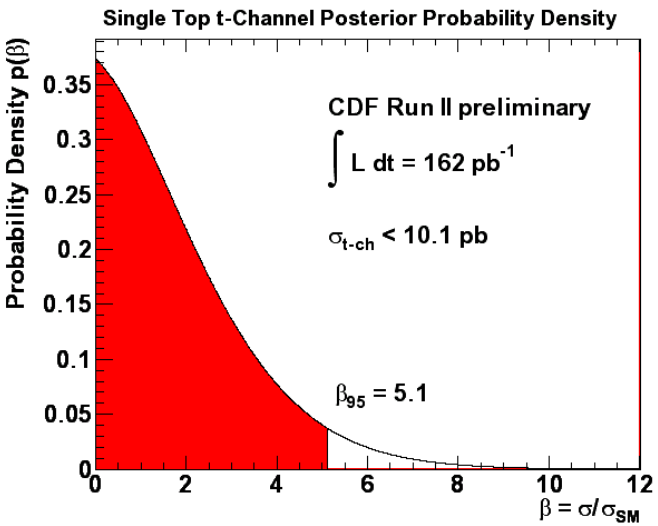


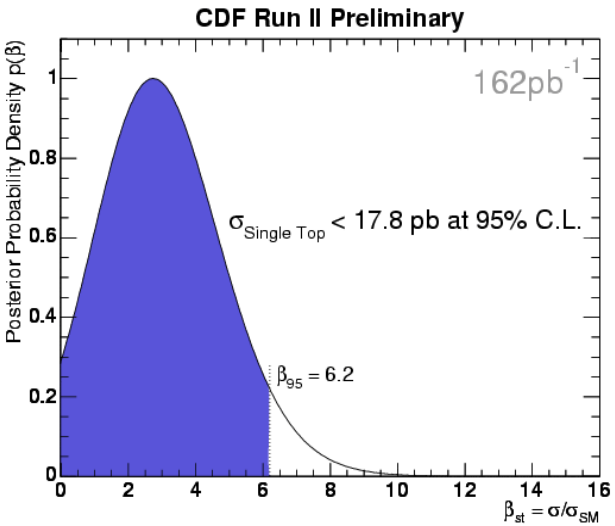


CDF limits

- Build a likelihood as a function of $\beta_i=\sigma_i/\sigma_i^{SM}$
- Background is allowed to float but is constrained to expectation
- Find maximum of the likelihood:
  - L(separate)=L(2tag events)⊗L(1tag Q×η distribution)
  - L(comb)=L(H_T distribution)
- Shape of systematic uncertainties included in the likelihood



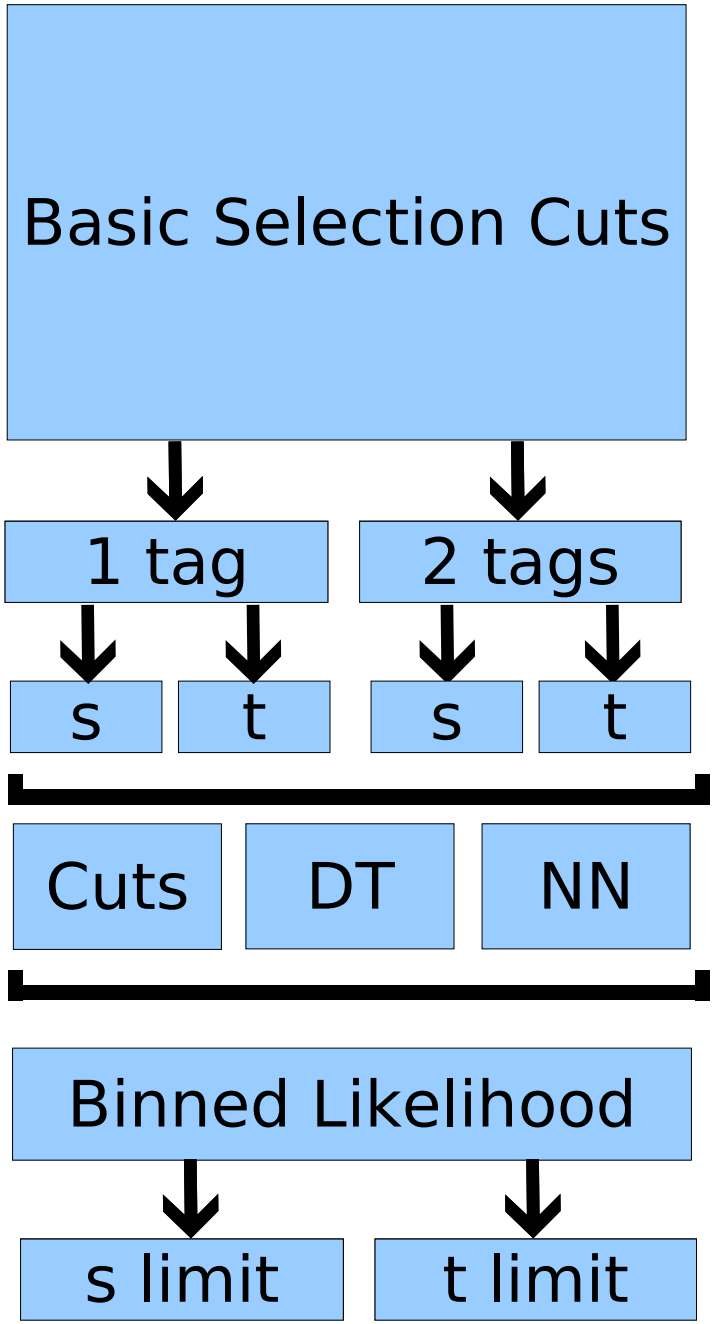




Cross section upper limits (pb) at 95% CL: $\mathscr{L}$=162pb^{-1}

s-channel		t-channel		Combined	
Observed	Expected	Observed	Expected	Observed	Expected
13.6	12.1	**10.1**	11.2	**17.8**	13.6

DØ search strategy



Lepton(e,μ): p_T>15 GeV, $|\eta_{e(\mu)}|$<1.1 (2.0)

Jets: $2 \leq N_{jets} \leq 4$, E_T>15 GeV,$|\eta|$<3.4

Jet1: E_T>25 GeV

MET: MET>15 GeV

Other clean-up cuts

Require =1 and ≥2 SVT tags

t-channel: at least one non-b-tagged jet

Multivariate analysis: Simple cuts, Decision Trees, Neural Networks

Cut analysis: count events

DT, NN: use 2D output in a likelihood

DØ analysis after selection

- DØ optimizes selection to maximize acceptance
- Allows a lot of background at this stage!
- Then use multiple distributions to separate signal-background

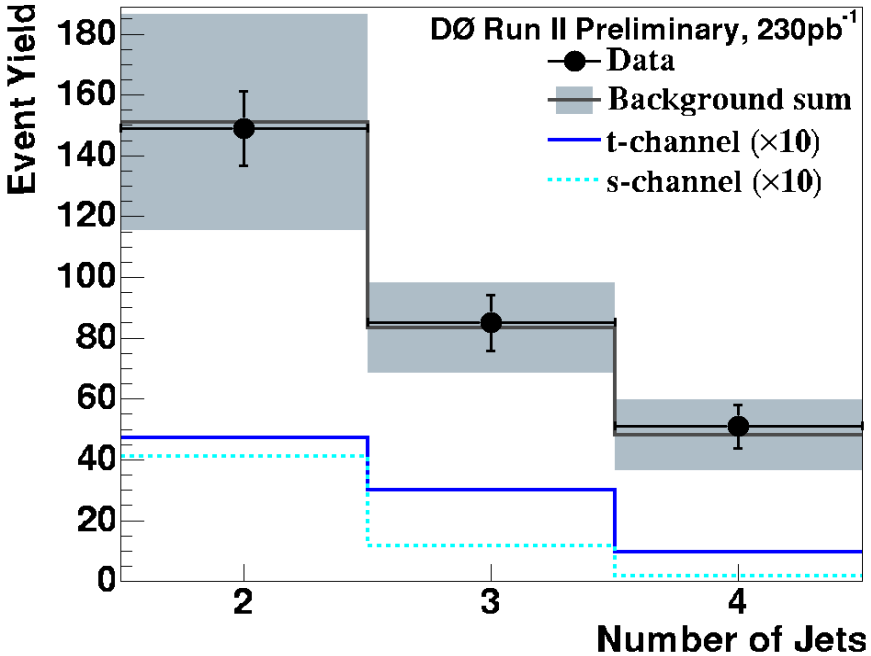
Source	s-channel search	t-channel search
tb	5.5 ± 1.3	4.7 ± 1.0
tqb	8.6 ± 1.9	8.5 ± 1.9
$t\bar{t}$	78.3 ± 18.3	75.9 ± 17.6
W+jets	169.1 ± 20.1	163.9 ± 18.7
Multijet	31.4 ± 3.3	31.3 ± 3.2
Total background	287.4 ± 43.6	275.8 ± 40.6
Observed events	283	271

- Acceptance: 2.7±0.2% (s-channel) and 1.9±0.2% (t-channel)

CDF has a more restrictive selection: optimize S/B to maximize separation and use one distribution

Systematic Uncertainites

Monte Carlo Systematic Uncertainties	
Theory cross sections	15 %
SVT modeling, single (double) tag	10 %(20 %)
Jet Energy Scale	10 %
Trigger Modeling	6 %
Jet Fragmentation	6 %
Jet ID	5 %
ℓ ID	5 %



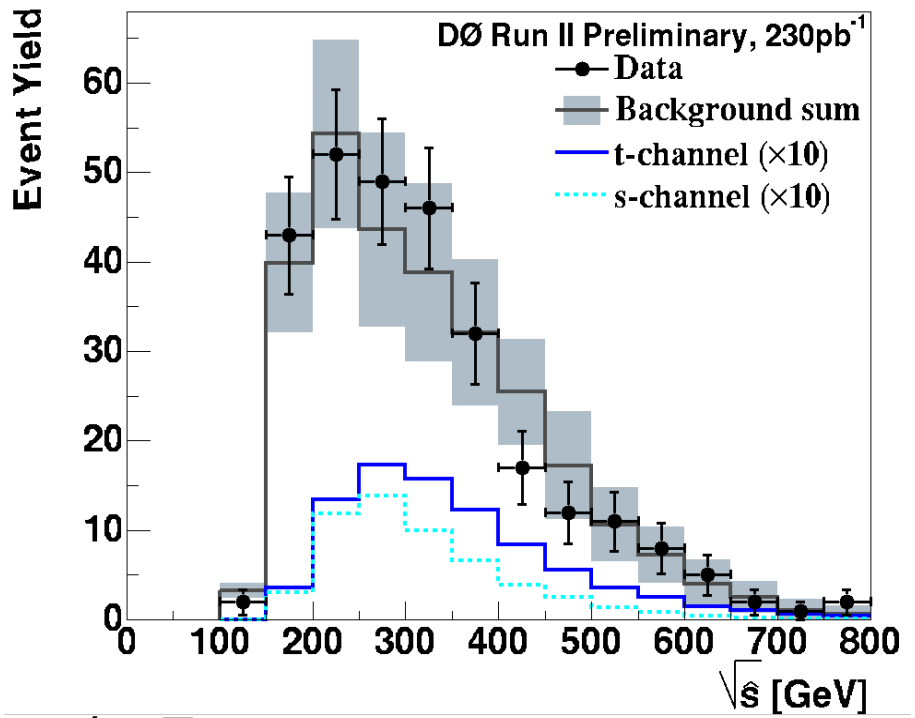
- Some systematic uncertainties also affect shape:

  JES, b-tag and trigger modeling

- Total uncertainty:

	1 tag	2 tags
Signal acceptance	15%	25%
Background sum	10%	26%

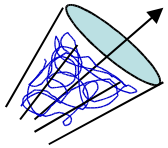
- Result is statistics limited



Discriminating variables

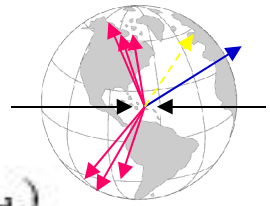
Individual object kinematics

- $p_T(\text{jet1}_{\text{tagged}})$
- $p_T(\text{jet1}_{\text{untagged}})$
- $p_T(\text{jet2}_{\text{untagged}})$
- $p_T(\text{jet1}_{\text{nonbest}})$
- $p_T(\text{jet2}_{\text{nonbest}})$



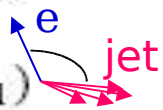
Global event kinematics

- $M_T(\text{jet1}, \text{jet2})$
- $p_T(\text{jet1}, \text{jet2})$
- $M(\text{alljets})$
- $H_T(\text{alljets})$
- $M(\text{alljets} - \text{jet1}_{\text{tagged}})$
- $H(\text{alljets} - \text{jet1}_{\text{tagged}})$
- $H_T(\text{alljets} - \text{jet1}_{\text{tagged}})$
- $p_T(\text{alljets} - \text{jet1}_{\text{tagged}})$
- $M(\text{alljets} - \text{jet}_{\text{best}})$
- $H(\text{alljets} - \text{jet}_{\text{best}})$
- $H_T(\text{alljets} - \text{jet}_{\text{best}})$
- $M(\text{top}_{\text{tagged}}) = M(W, \text{jet1}_{\text{tagged}})$
- $M(\text{top}_{\text{best}}) = M(W, \text{jet}_{\text{best}})$
- $\sqrt{\hat{s}}$



Angular variables

- $\Delta R(\text{jet1}, \text{jet2})$
- $Q(\text{lepton}) \times \eta(\text{jet1}_{\text{untagged}})$
- $\cos(\text{lepton}, Q(\text{lepton}) \times z)_{\text{top}_{\text{best}}}$
- $\cos(\text{lepton}, \text{jet1}_{\text{untagged}})_{\text{top}_{\text{tagged}}}$
- $\cos(\text{alljets}, \text{jet1}_{\text{tagged}})_{\text{alljets}}$
- $\cos(\text{alljets}, \text{jet}_{\text{nonbest}})_{\text{all jets}}$



This is where our phenomenology friends come so handy!

Three broad categories:

- Object kinematics
- Global event kinematics
- Angular correlations

Reconstruct W: from ℓ and ν

To reconstruct the top quark:

- s-channel: “best” jet algorithm

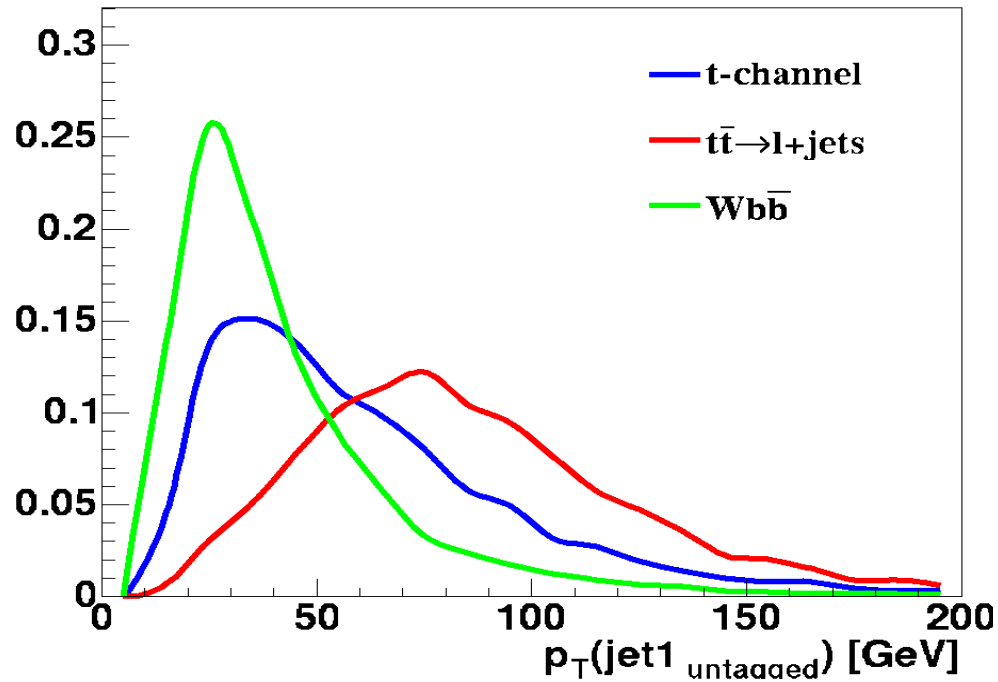
Chose the jet that gives m_t closest to 175GeV

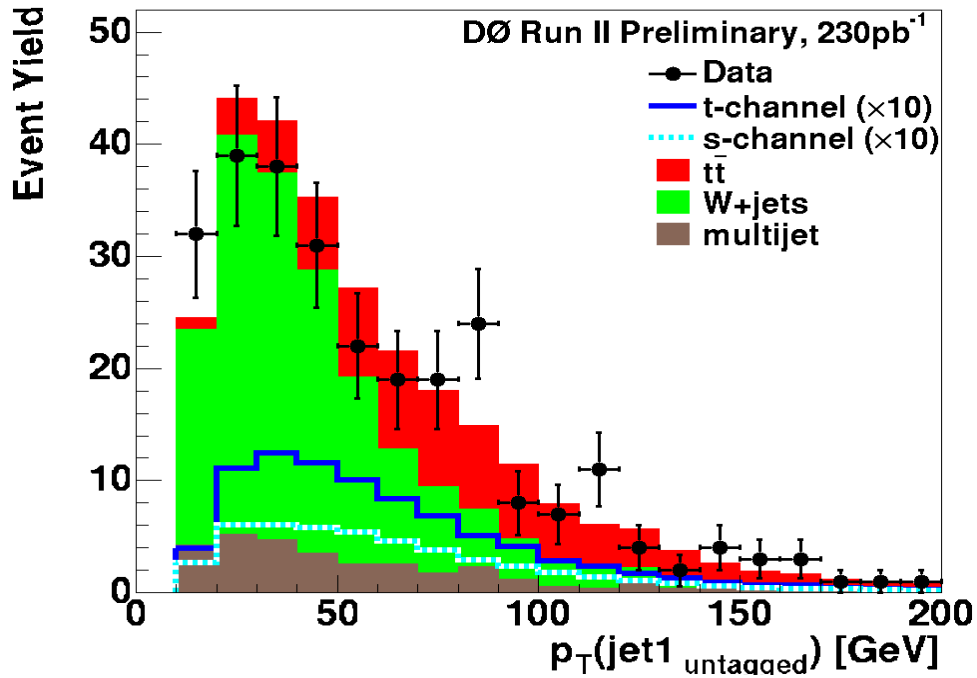
- t-channel: lead b-tagged jet + W

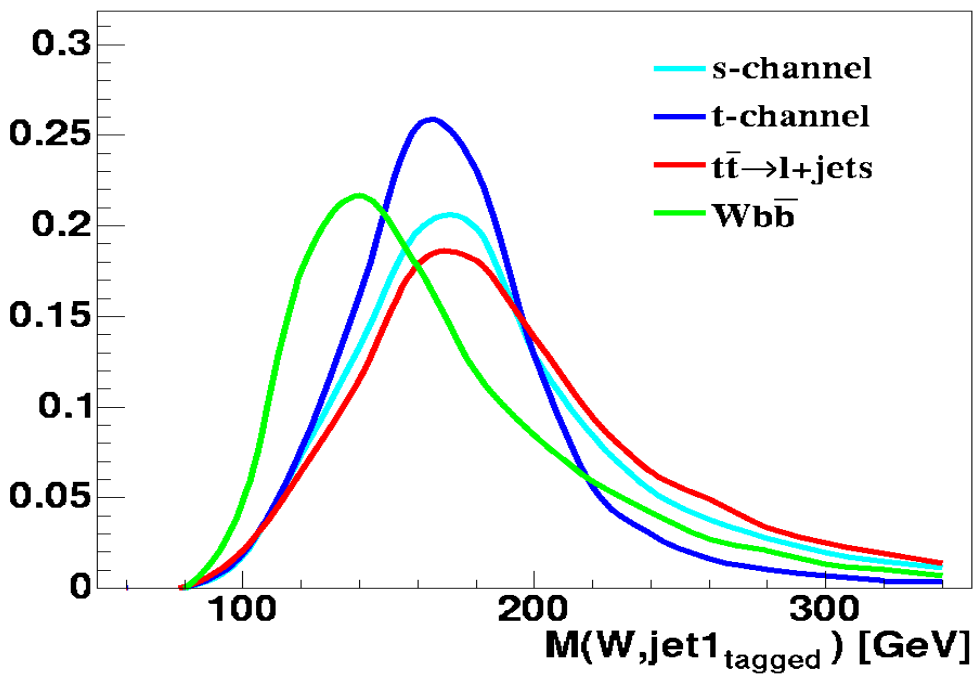
Reconstruct q': lead untagged jet

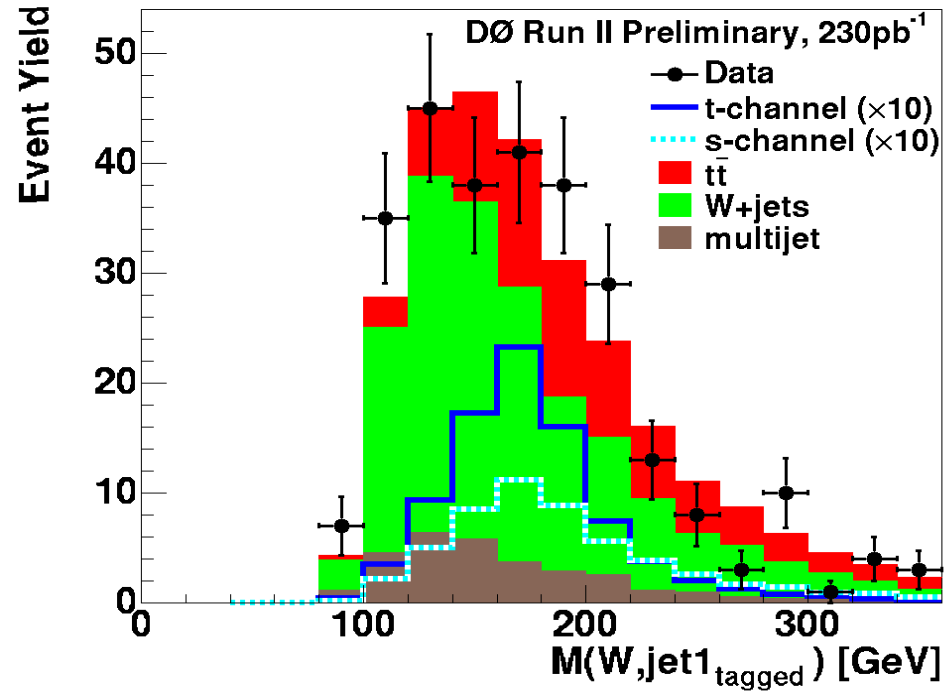
- **s-channel search only**
- **t-channel search only**
- **used in both**

Object kinematics

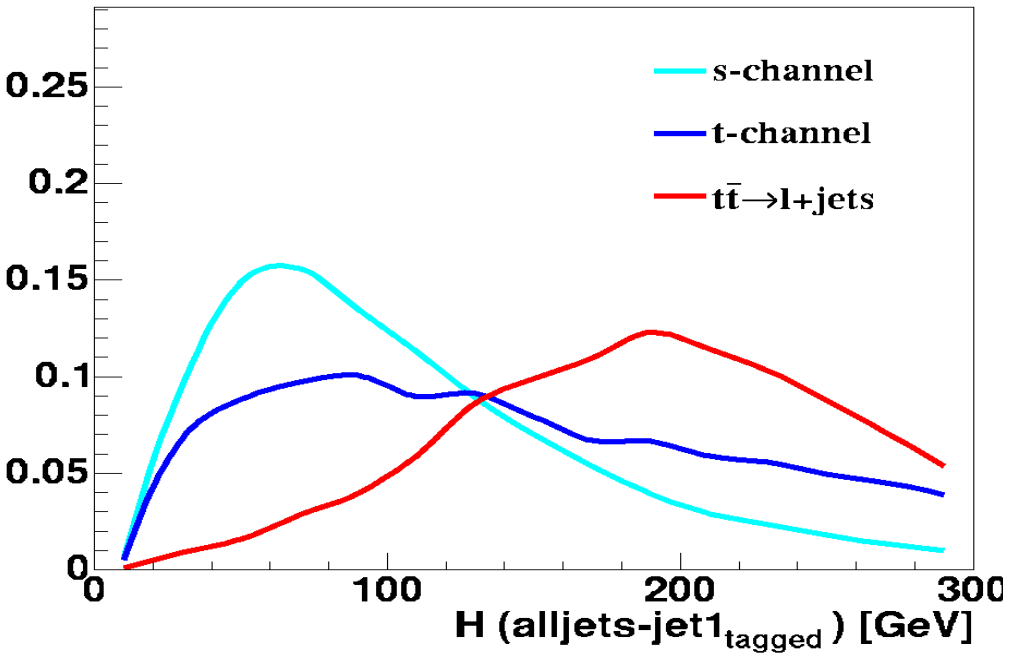


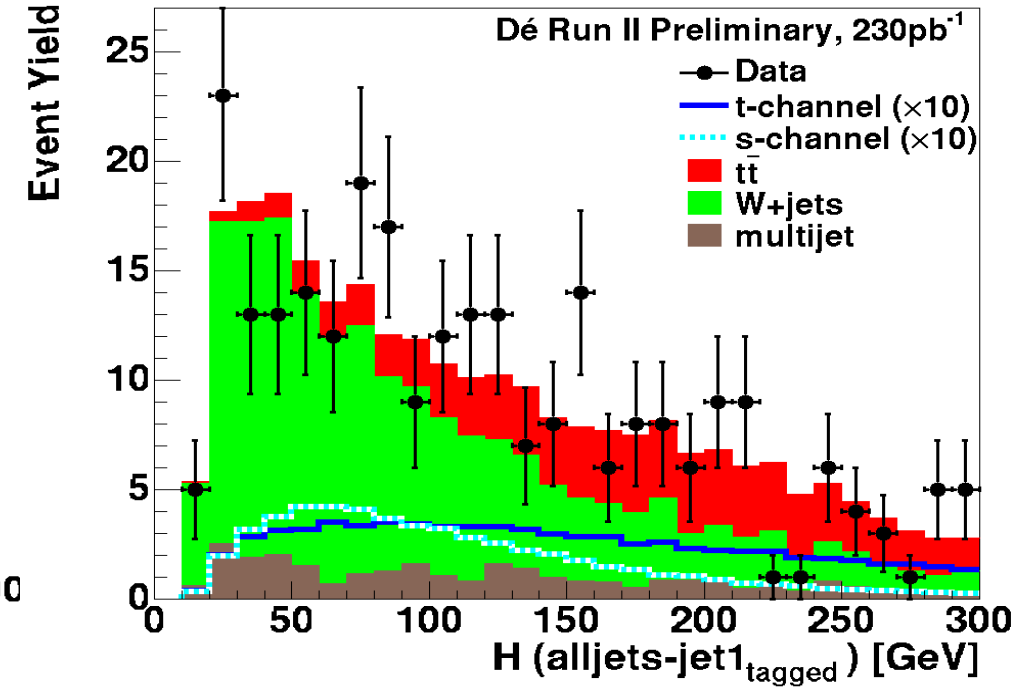


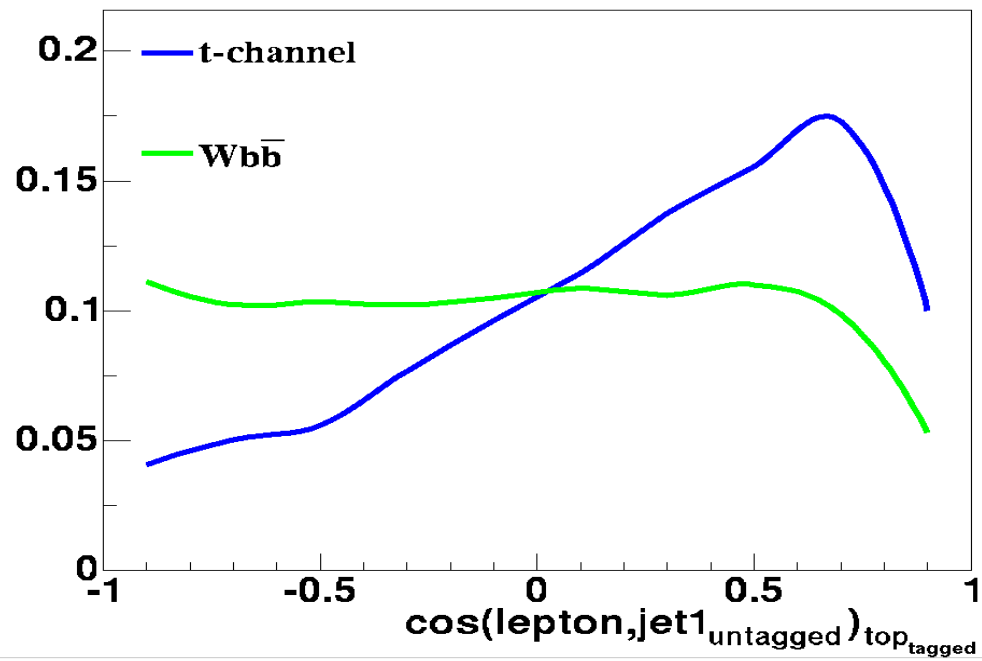


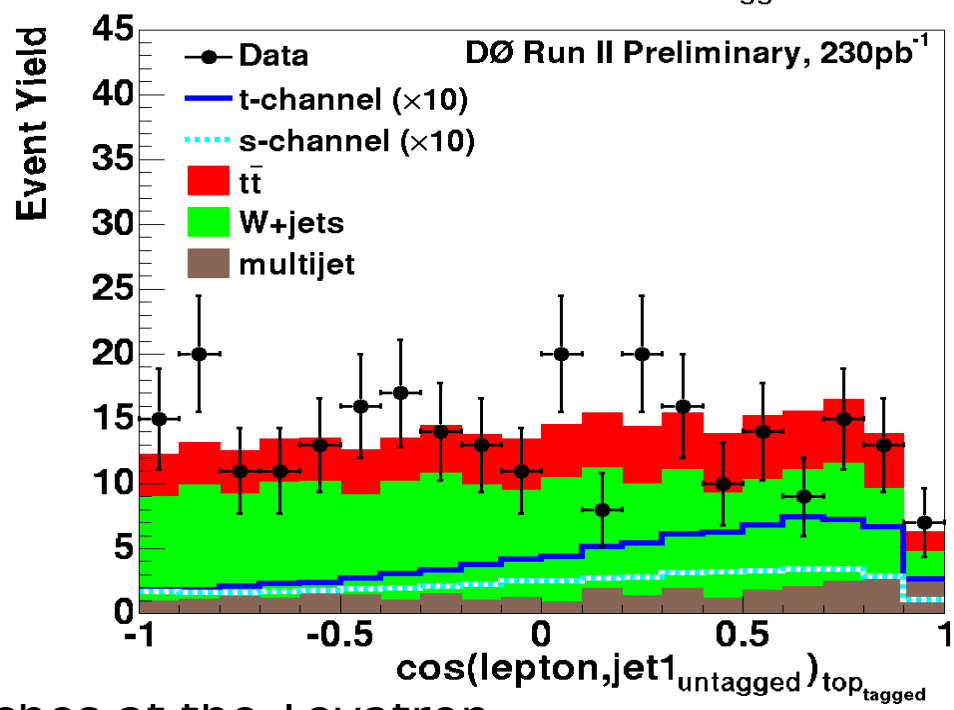


Event kinematics & angular variable





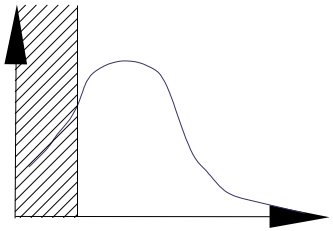




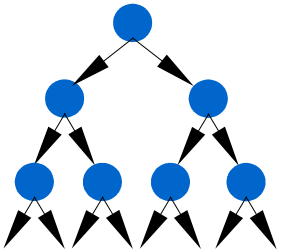
Separating signal from backgrounds

DØ has implemented three analysis methods:

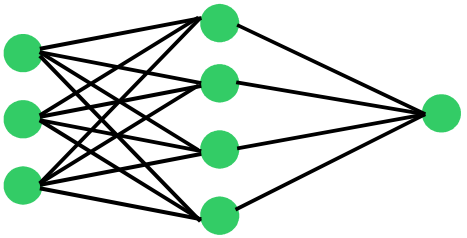
Cut-based



Decision Trees



Neural Networks



- Use same pool of discriminating variables for all 3 analyses
- Optimize separately for s-channel and t-channel

  Input variables are independent of ℓ flavor, but optimize separately for e and μ datasets, given the different coverage and resolutions

- Focus on two dominant backgrounds: Wbb and tt→ ℓ+jets
- A total of 8 sets of cuts/trees/networks:

  tb-Wbb, tb-tt→ ℓ+jets, tqb-Wbb & tqb-tt→ℓ+jets (for e and μ)

Cut-based analysis

1) Rate each discriminant variable according to its optimal cut

Optimal cut values are obtained minimizing the expected limit with respect to cut values derived from the signal sample

2) Try several sets of ANDed variables and re-optimize

3) Select the set that yields the lowest expected limit

	s-channel	t-channel
tb	4.5 ± 1.0	3.2 ± 0.8
tqb	5.5 ± 1.2	7.0 ± 1.6
$t\bar{t}$	27.6 ± 7.6	55.9 ± 12.3
W+jets	102.9 ± 13.7	72.6 ± 9.7
Mis-ID'd lepton	17.2 ± 2.0	17.0 ± 2.0
Background sum	153.1 ± 24.5	148.7 ± 24.8
Observed events	152	148

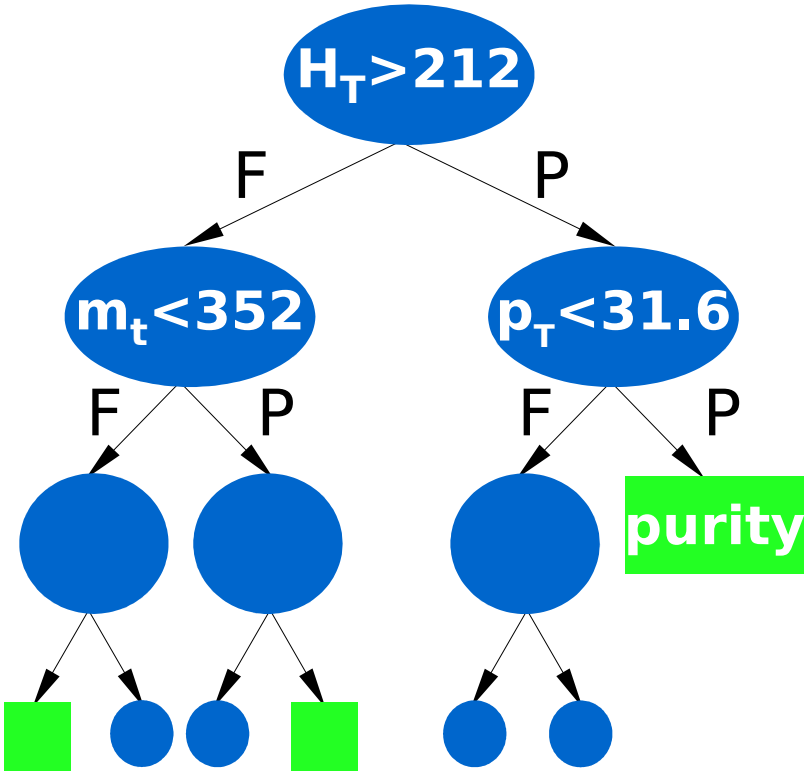
before cuts	S/B =	1/52	1/32
after cuts	S/B =	1/34	1/21

Cut-based analysis: cuts

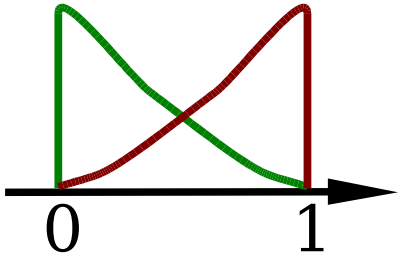
Channel	s-channel Variables	Cuts	t-channel Variables	Cuts
Electron				
=1 Tag	$p_T(\text{jet1}_{\text{tagged}})$	> 27 GeV	$H_T(\text{alljets})$	> 71 GeV
	$M(\text{alljets} - \text{jet1}_{\text{tagged}})$	< 70 GeV	$M(\text{alljets})$	> 57 GeV
	$\sqrt{\hat{s}}$	> 196 GeV	$\sqrt{\hat{s}}$	> 203 GeV
			$\lvert 175 - M(\text{top}_{\text{tagged}})\rvert$	< 57 GeV
			$p_T(\text{jet1}_{\text{tagged}})$	> 21 GeV
$\geq$2 Tags	$p_T(\text{jet1}_{\text{tagged}})$	> 42 GeV	$p_T(\text{jet1}_{\text{tagged}})$	> 34 GeV
	$M(\text{alljets} - \text{jet1}_{\text{tagged}})$	< 98 GeV	$M(\text{alljets} - \text{jet1}_{\text{tagged}})$	< 75 GeV
	$H(\text{alljets} - \text{jet1}_{\text{tagged}})$	< 304 GeV	$H(\text{alljets} - \text{jet1}_{\text{tagged}})$	< 504 GeV
	$H(\text{alljets} - \text{jet}_{\text{best}})$	< 304 GeV	$H(\text{alljets} - \text{jet}_{\text{best}})$	< 504 GeV
Muon				
=1 Tag	$p_T(\text{jet1}_{\text{tagged}})$	> 33 GeV	$\lvert 175 - M(\text{top}_{\text{tagged}})\rvert$	< 60 GeV
	$M(\text{alljets} - \text{jet1}_{\text{tagged}})$	< 74 GeV	$\sqrt{\hat{s}}$	> 210 GeV
	$H(\text{alljets} - \text{jet1}_{\text{tagged}})$	< 504 GeV	$M(\text{alljets})$	> 70 GeV
	$H(\text{alljets} - \text{jet}_{\text{best}})$	< 504 GeV	$H_T(\text{alljets})$	> 58 GeV
$\geq$2 Tags	$p_T(\text{jet1}_{\text{tagged}})$	> 33 GeV	$\lvert 175 - M(\text{top}_{\text{tagged}})\rvert$	< 213 GeV
	$M(\text{alljets} - \text{jet1}_{\text{tagged}})$	< 74 GeV		
	$H(\text{alljets} - \text{jet1}_{\text{tagged}})$	< 504 GeV		
	$H(\text{alljets} - \text{jet}_{\text{best}})$	< 504 GeV		

Decision Trees

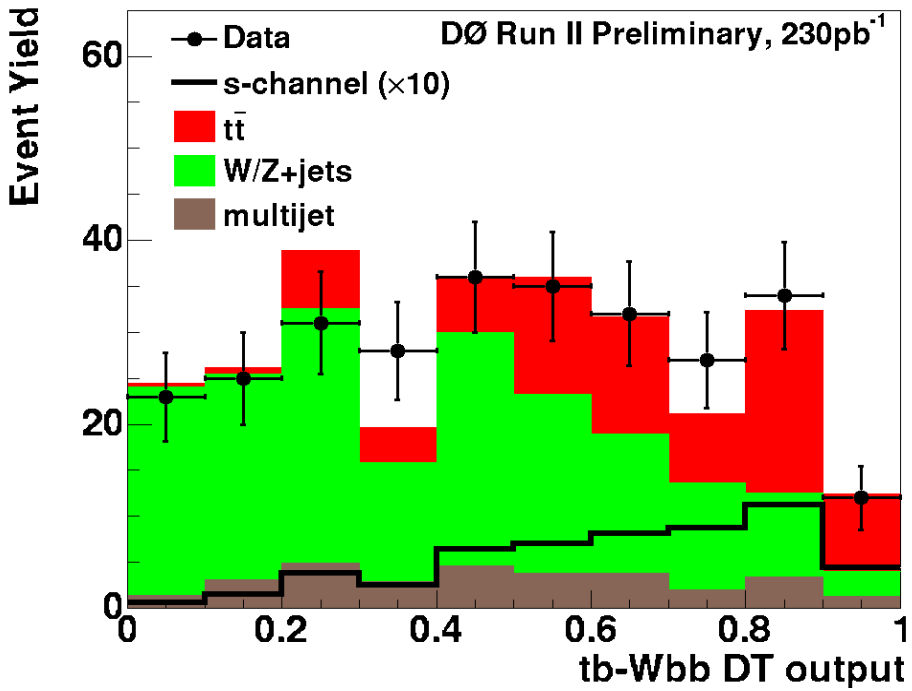
Multivariate technique widely used in social sciences
Recently applied to HEP: MiniBooNE (object ID)
Gives probability for an event to be signal

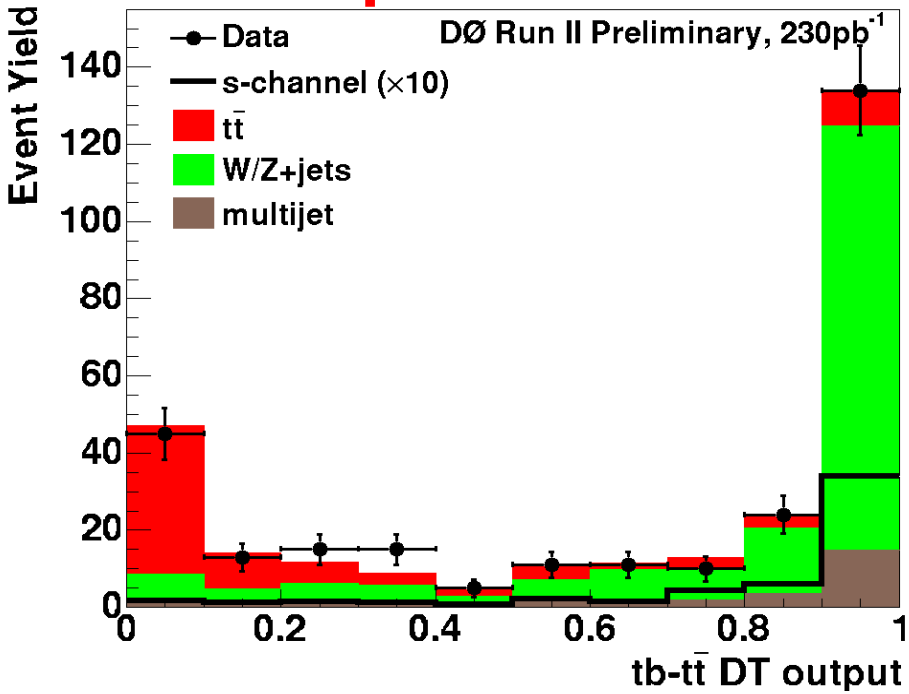


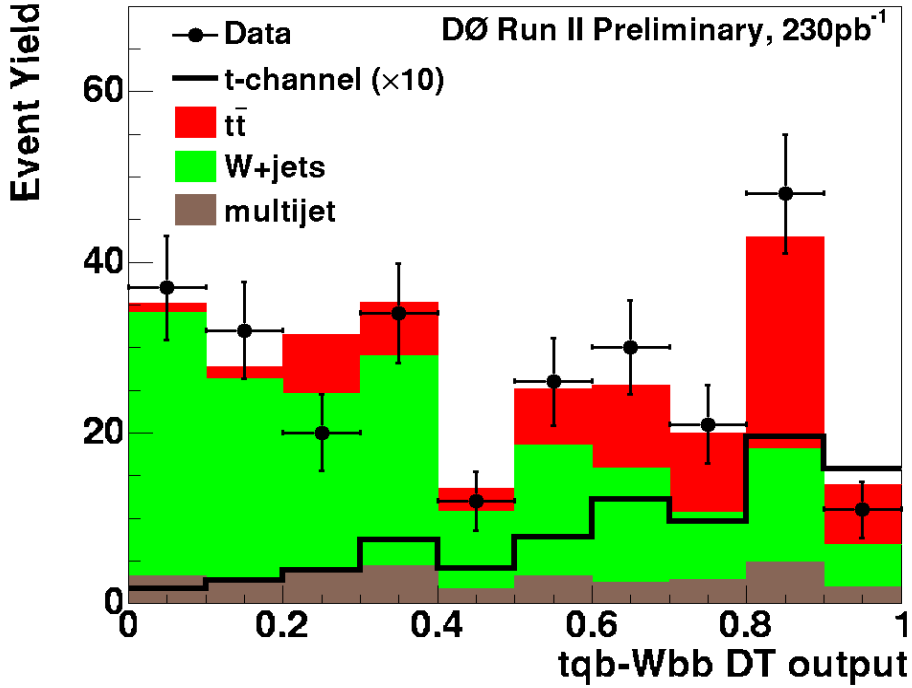
- Send each event down the tree
- Each node corresponds to a cut
  - Pass cut (P): right branch
  - Fail cut (F): left branch
- A leaf corresponds to a node without branches
- Define purity= $N_S/(N_S+N_B)$
- Training: optimize Gini improvement
  - Gini=2 $N_S N_B /(N_S + N_B)$
- Output: purity for each event

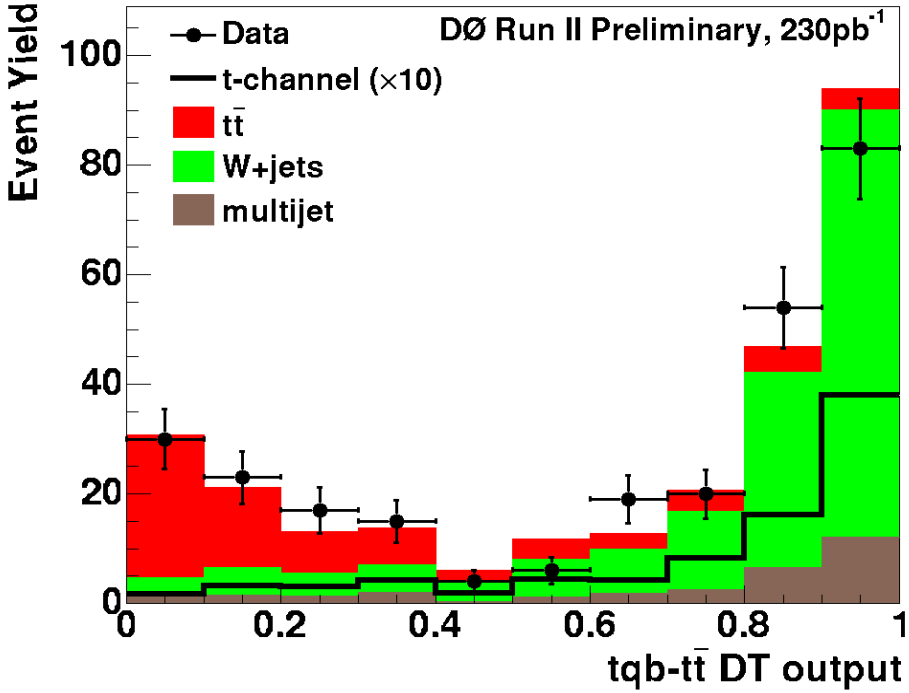


Decision Tree outputs



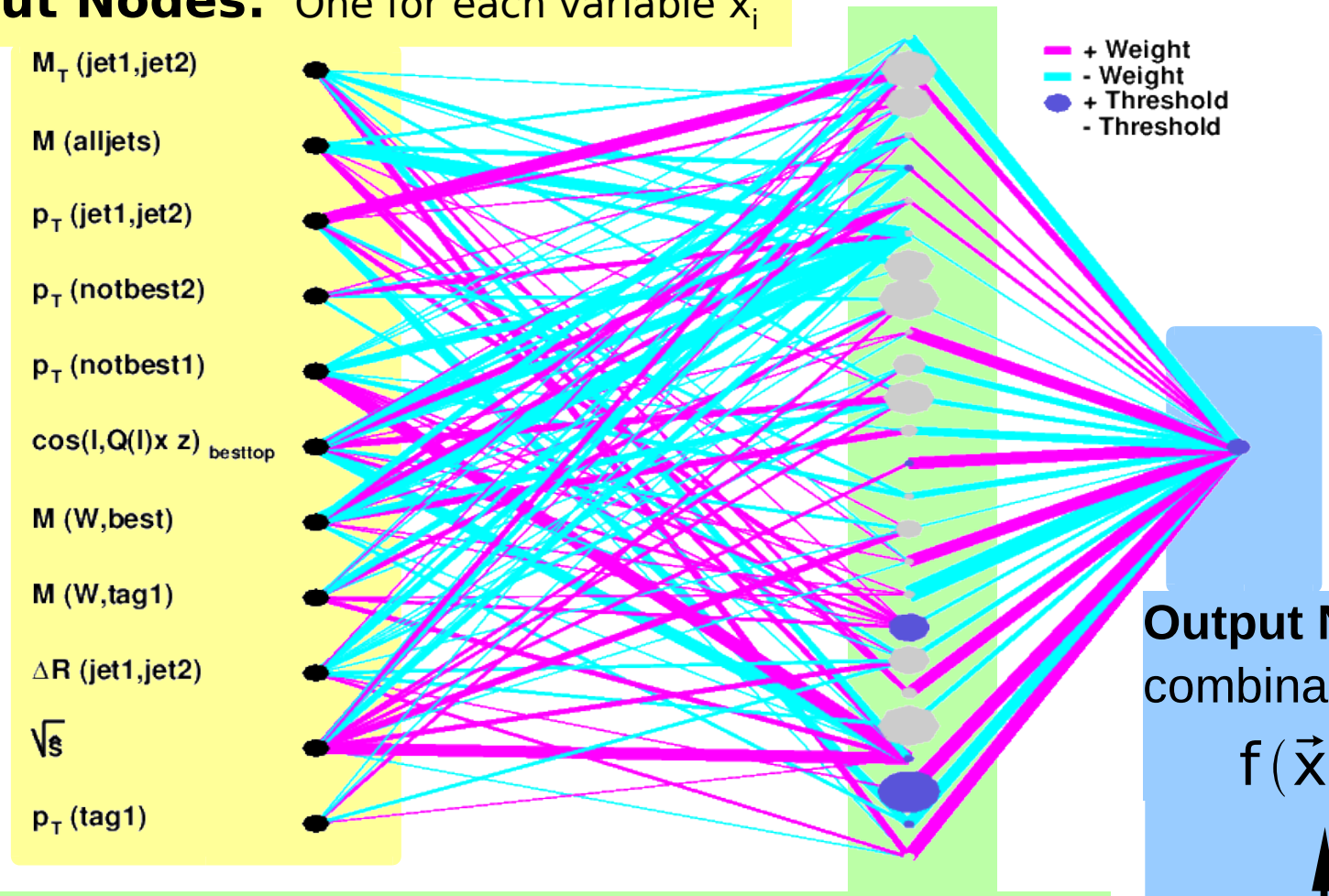






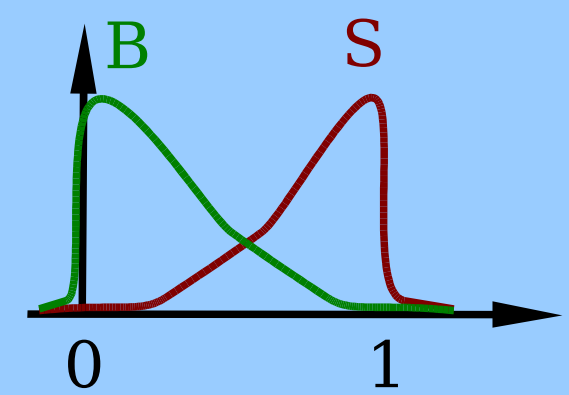
Neural Networks

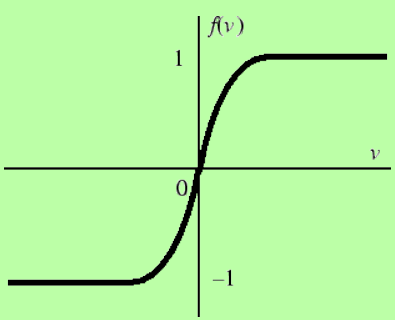
Input Nodes: One for each variable x_i



Output Node: linear combination of hidden nodes

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





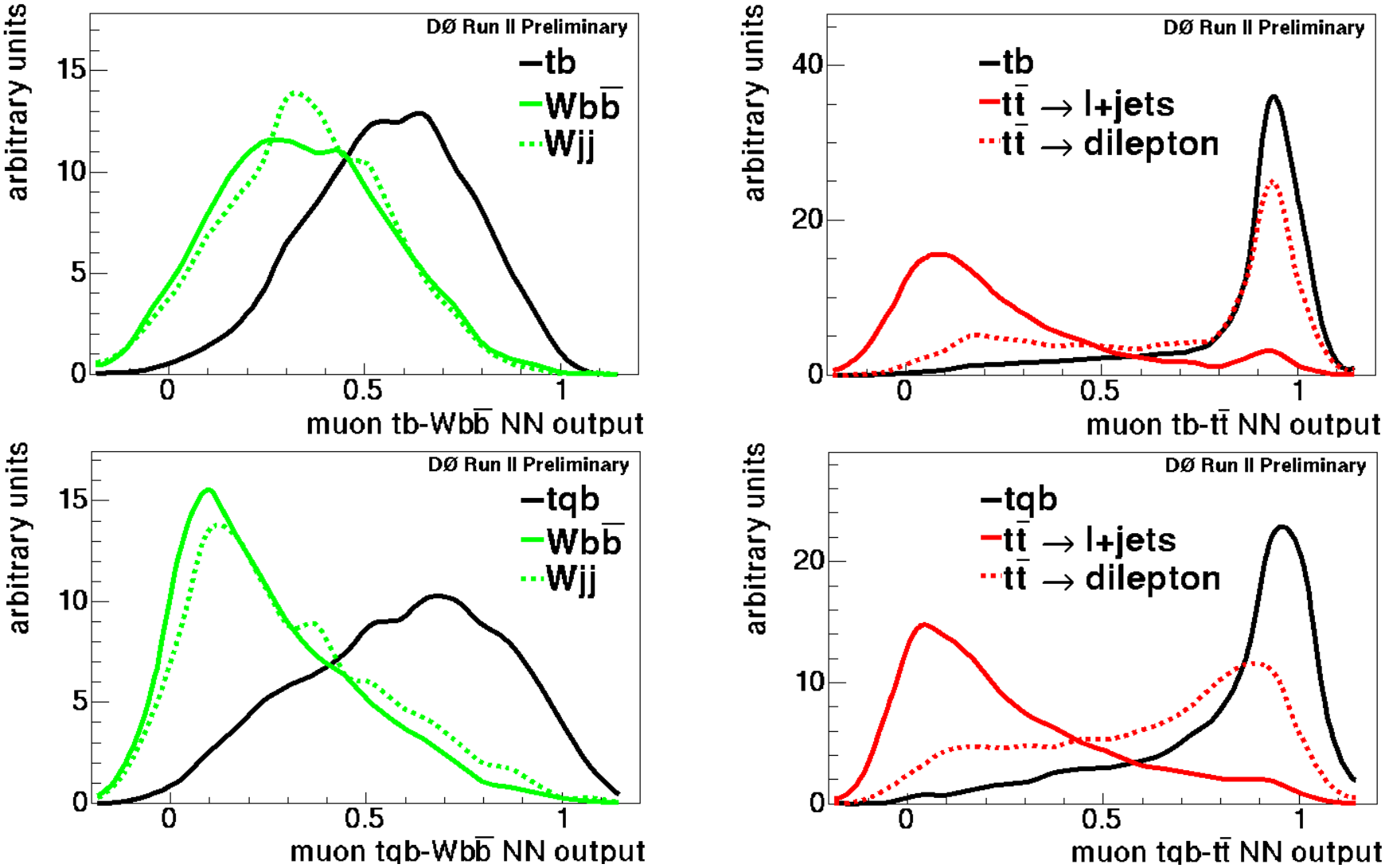
Hidden Nodes: Each is a sigmoid dependent on the input variables

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

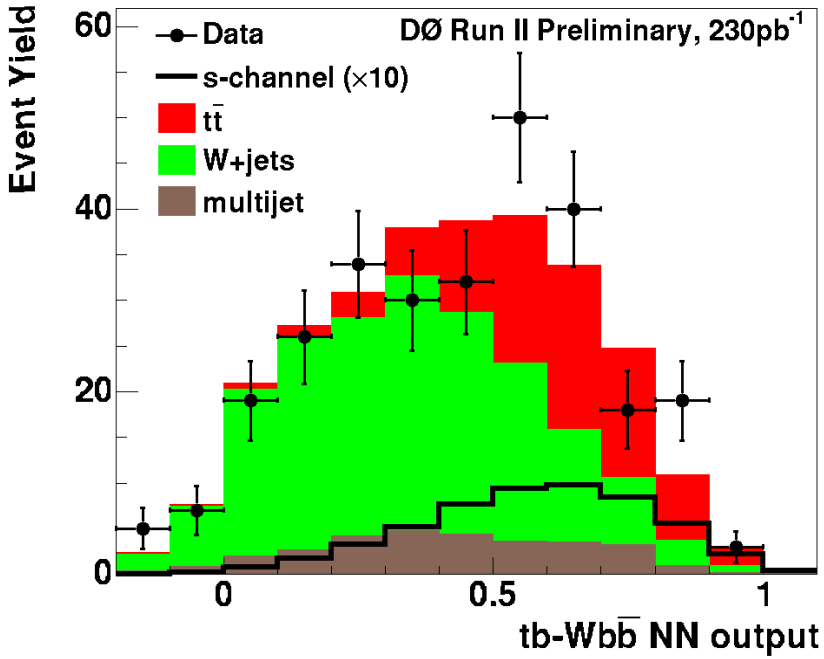
Neural Networks separation

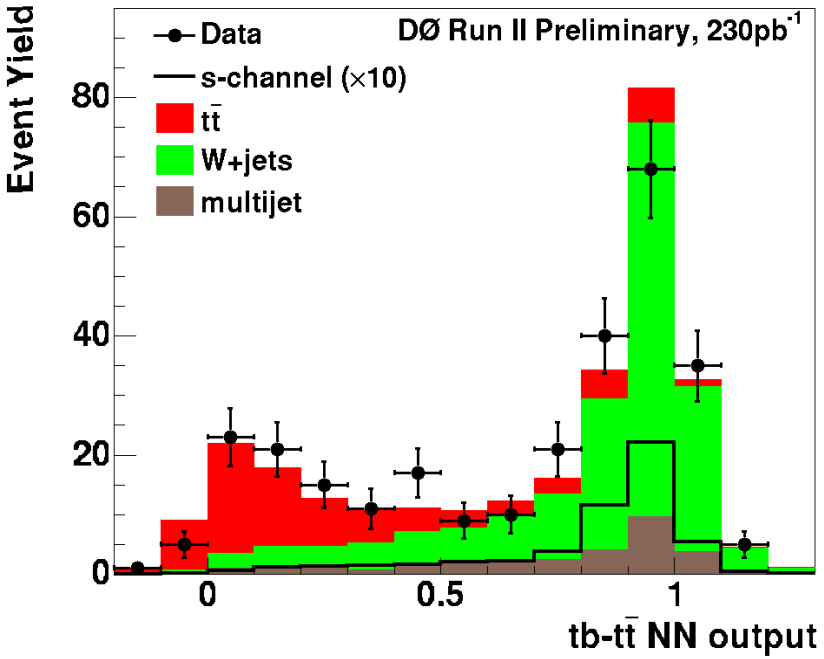
Focus on two main backgrounds:

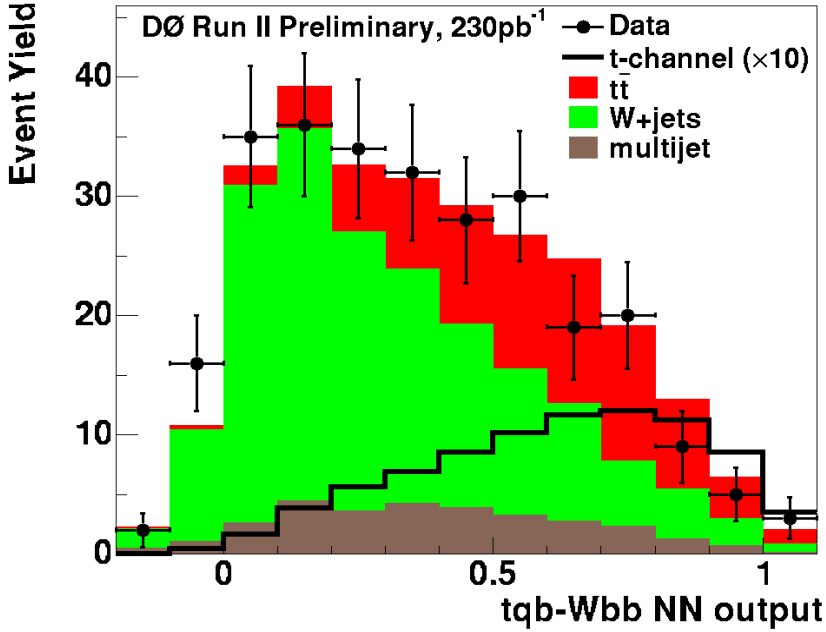
- Wbb takes care well of Wjj (j=g,u,d,s,c)
- tt→ dilepton is small compared to tt→ ℓ+jets

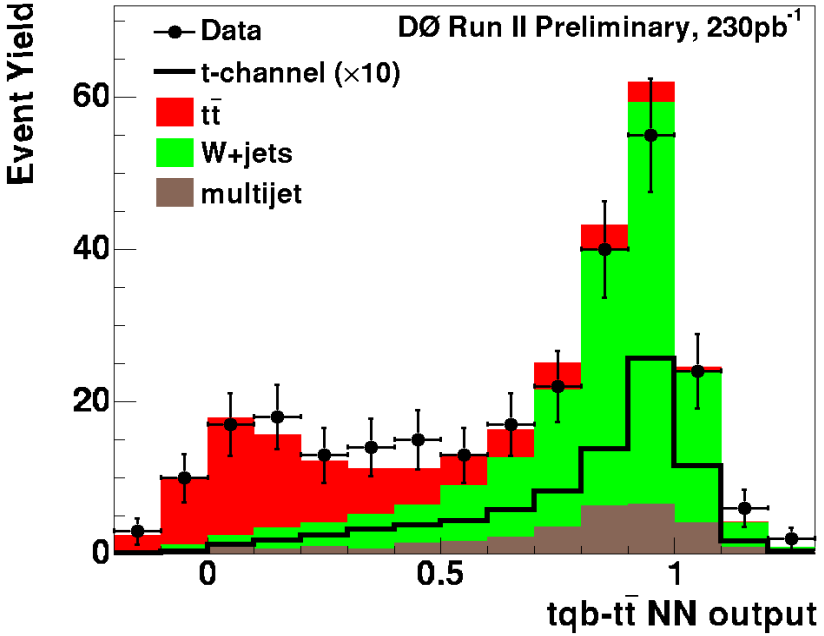


Neural Networks output





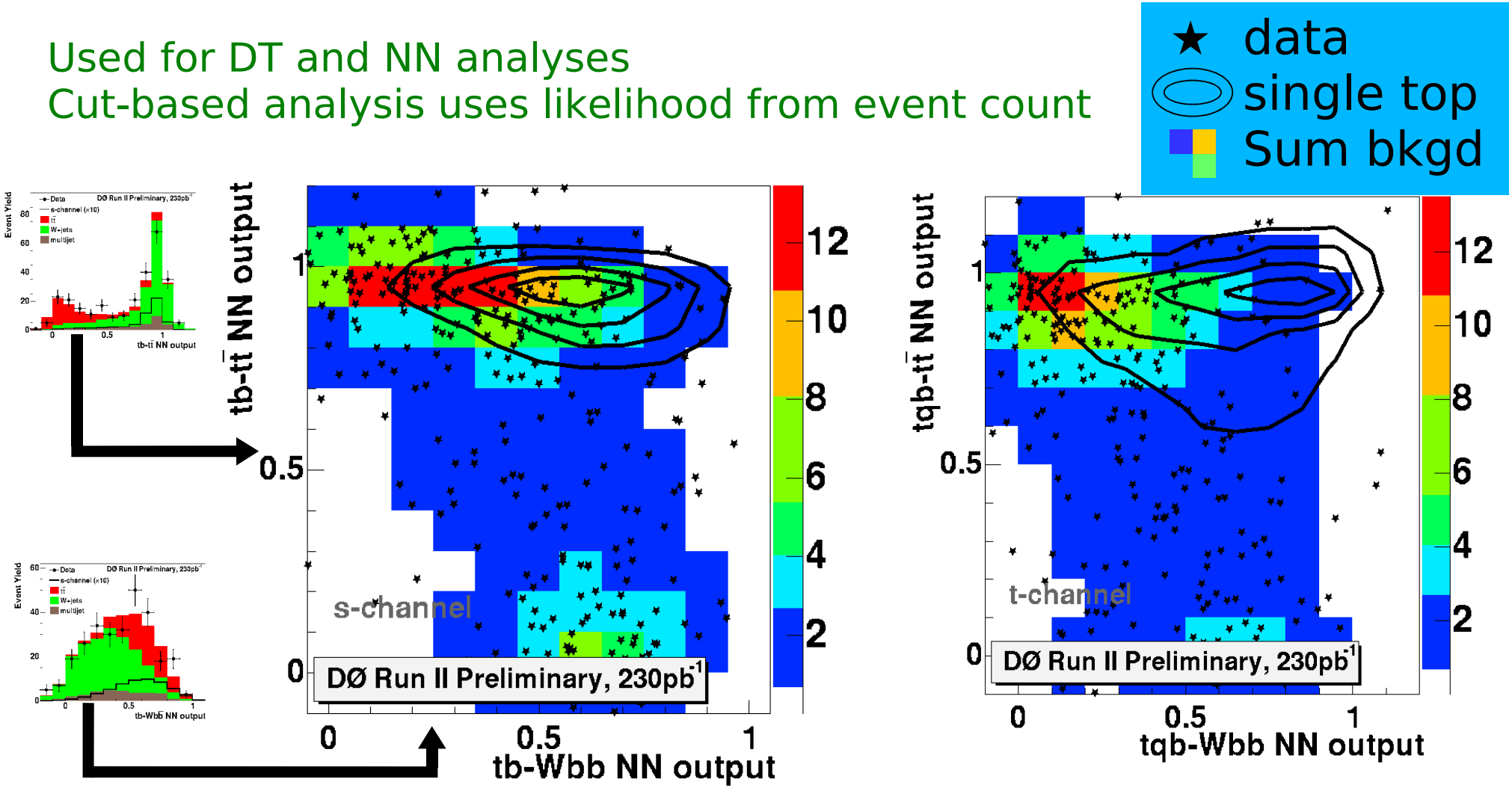




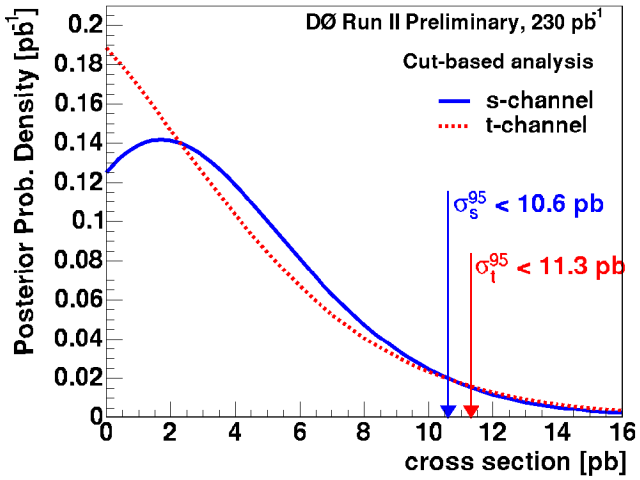
Limits from binned likelihood

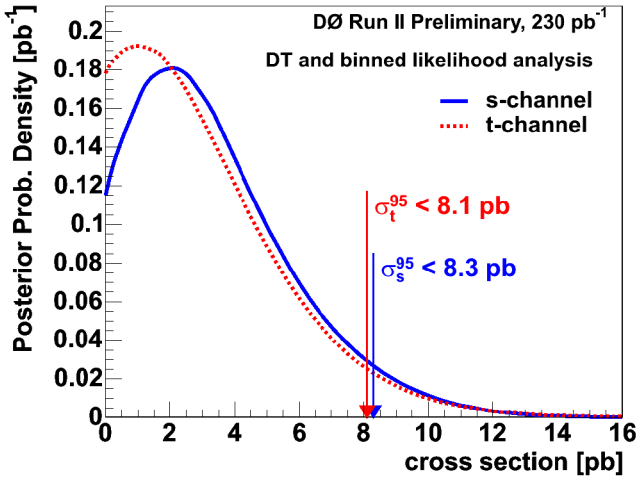
- No evidence for single top signal
- Set 95% CL upper cross section limit with Bayesian approach
- Use 2D histograms as input to build binned likelihood
- Including bin-by-bin systematics and correlations

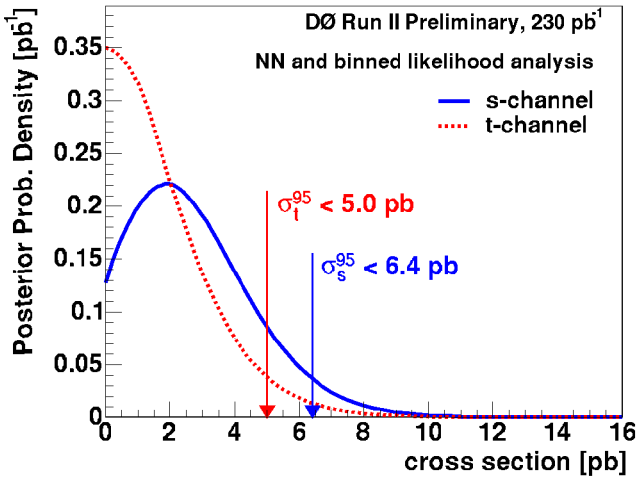
Used for DT and NN analyses
Cut-based analysis uses likelihood from event count



DØ results







$\mathscr{L}$=230pb^{-1}

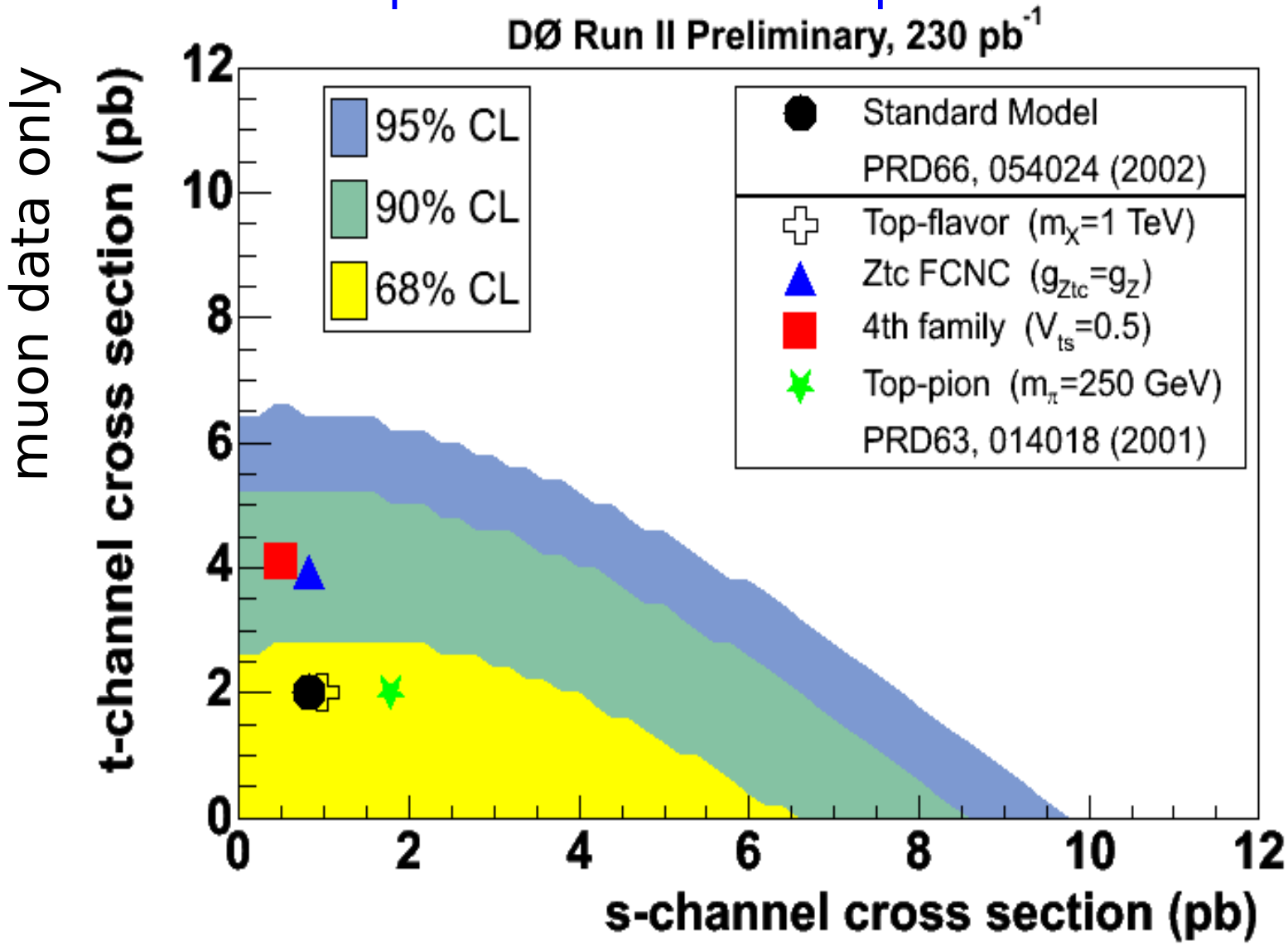
	Cut-based		Decision Trees		Neural Networks	
	Observed	Expected	Observed	Expected	Observed	Expected
s-channel	**10.6**	9.8	**8.3**	4.5	**6.4**	4.5
t-channel	**11.3**	12.4	**8.1**	6.4	**5.0**	5.8

- Use Bayesian approach to combine channels (e, μ and 1 tag, 2 tags)
- Take systematics and correlations into account
- Decision Trees and Neural Networks have similar sensitivity
- Multivariate analysis + shape information from output:

  → **factor 2 better than simple cuts**

Beyond the SM

DØ exclusion contours on the (σ_s ,σ_t) plane, built from a joint likelihood with independent data samples



muon data only

electron data only

Summary and next steps

95% CL Measured Upper Limits in pb	s-channel	t-channel
DØ Run I, 90 pb^{-1}	17	22
CDF Run II, 162 pb^{-1}	13.6	10.1
DØ Run II , 230 pb^{-1} cuts	10.6	11.3
DTs & binned likelihood	8.3	8.1
NNs & binned likelihood	**6.4**	**5.0**
NLO theory	=0.88	=1.98

Current analyses need a few fb^{-1} for observation

Upgrade to improved b-tagging
Explore multivariate methods:
Kinematic fitter, Neural Network, Matrix Element, optimized likelihoods

Optimizing current analyses
Increasing acceptance
Improving object ID
New methods under study

Increased dataset!

Conclusions

- Single top search at the Tevatron is more challenging than anticipated (see Matt Bowen's talk next)
- Signal generators are well established
- W+jets & heavy flavor fractions estimation are the big issues
- Need advanced analysis techniques to extract signal, but these require to understand well the systematics

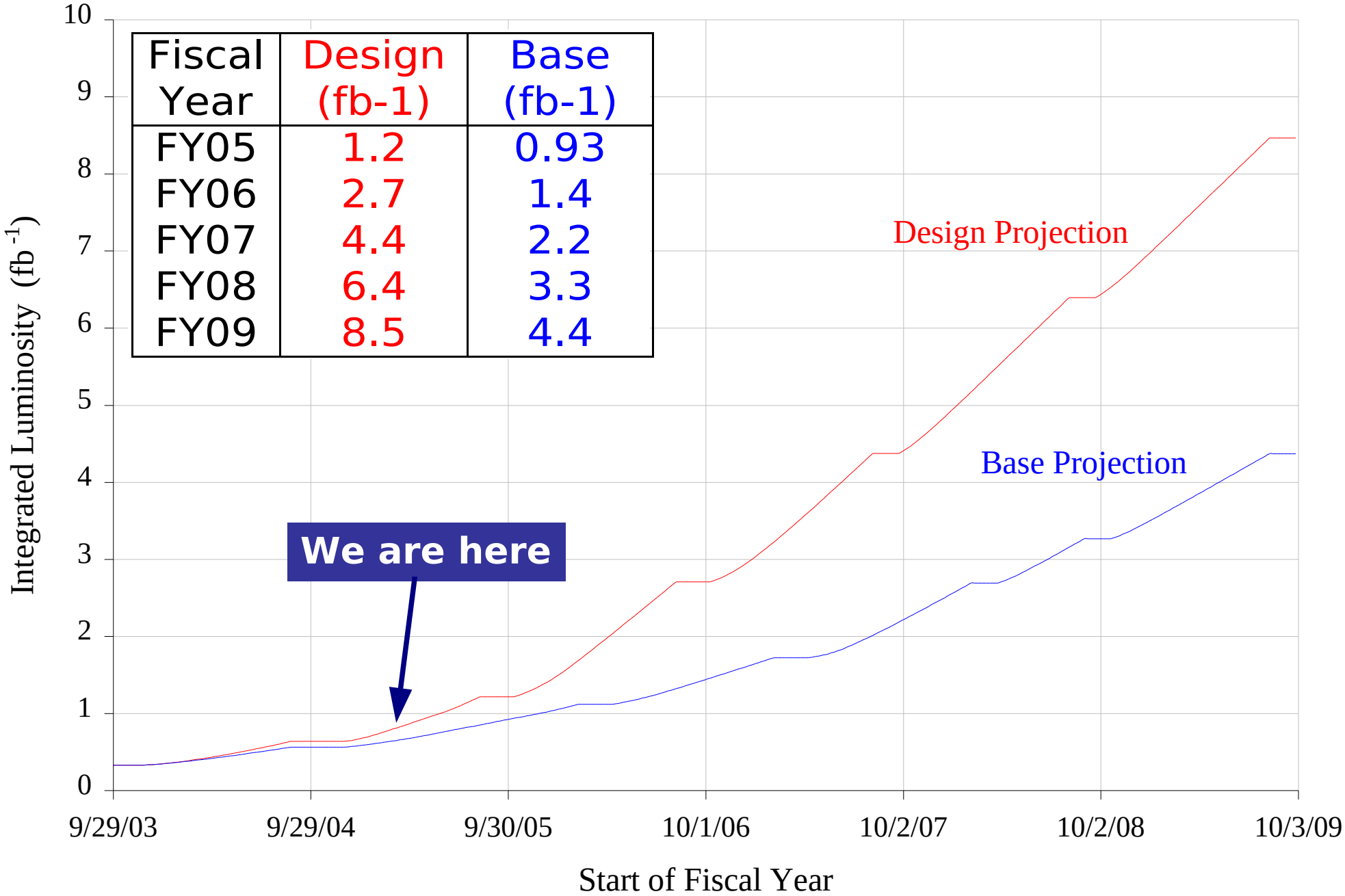
- CDF has published the first Run II limits
- DØ is about to submit the results presented here
- Reaching sensitivity to new Physics

- Plenty of room for improvements:
  - New analysis methods
  - Better object ID, better b-tagging
  - More data helps reduce the systematics

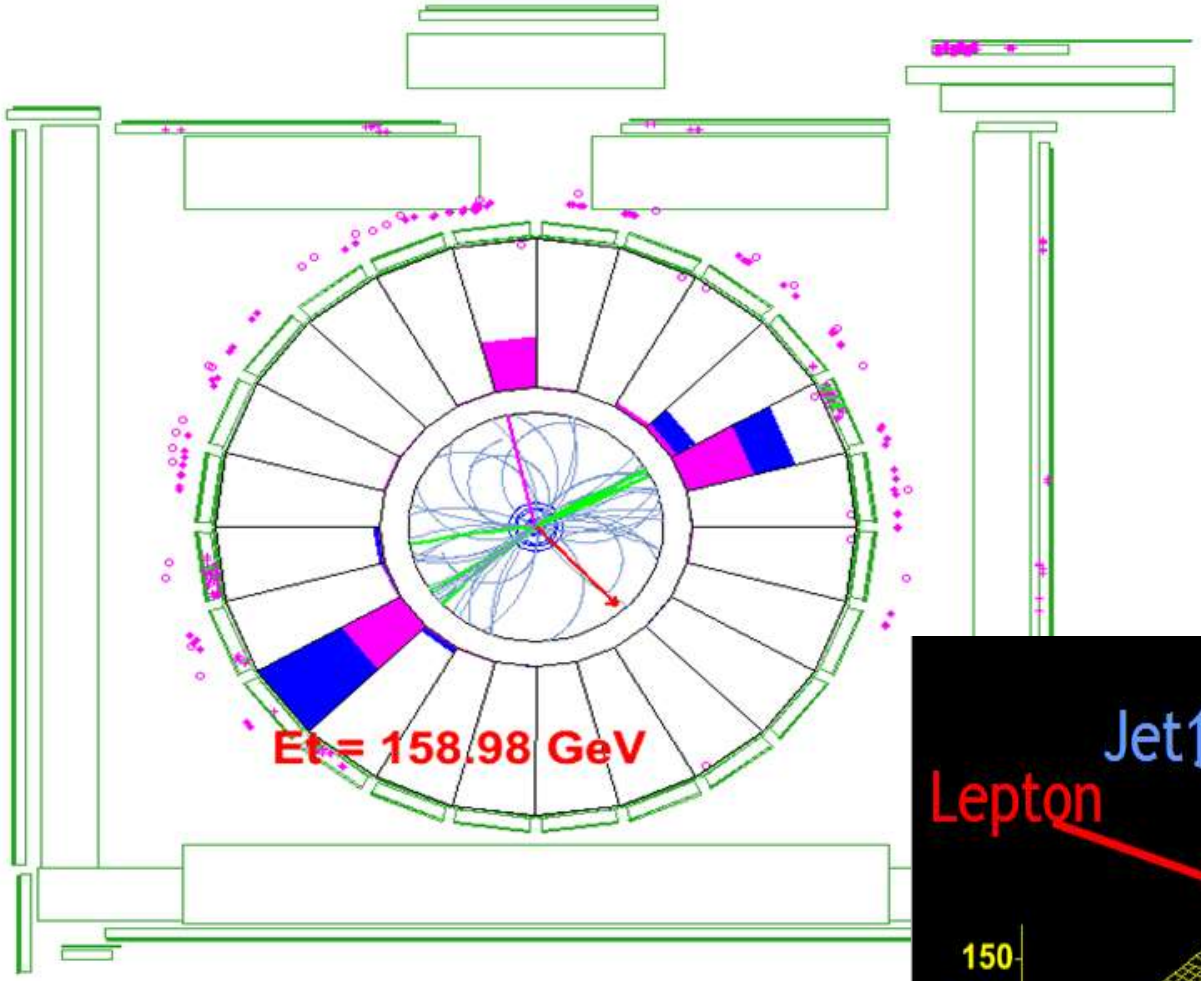
Our detectors are being understood better every day
Data is pouring in (expect ×3 dataset by the end of the year)
This is an exciting time for single top

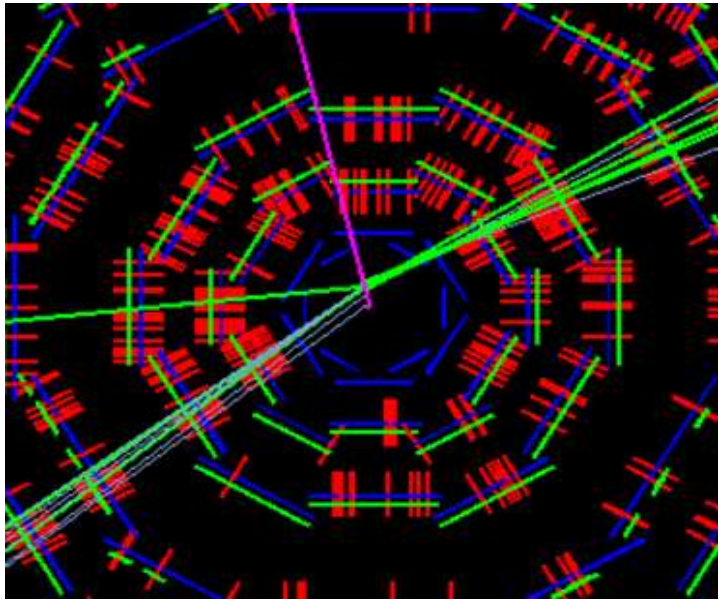
Tevatron luminosity prospects

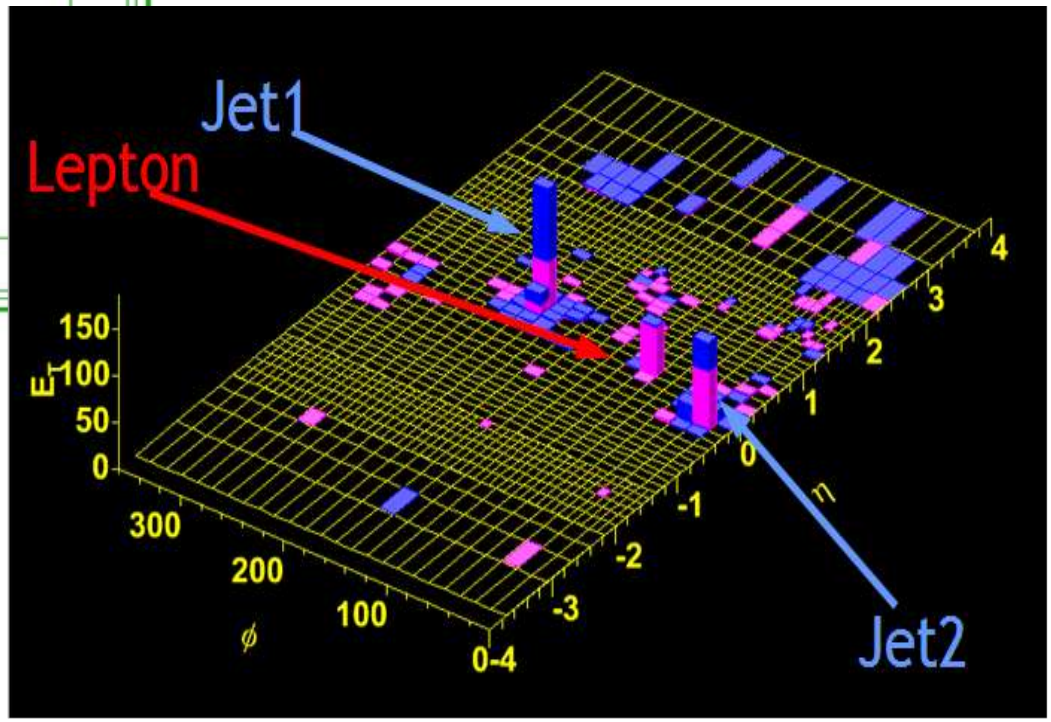
Fiscal Year	Design (fb-1)	Base (fb-1)
FY05	1.2	0.93
FY06	2.7	1.4
FY07	4.4	2.2
FY08	6.4	3.3
FY09	8.5	4.4



Extra1: CDF candidate event

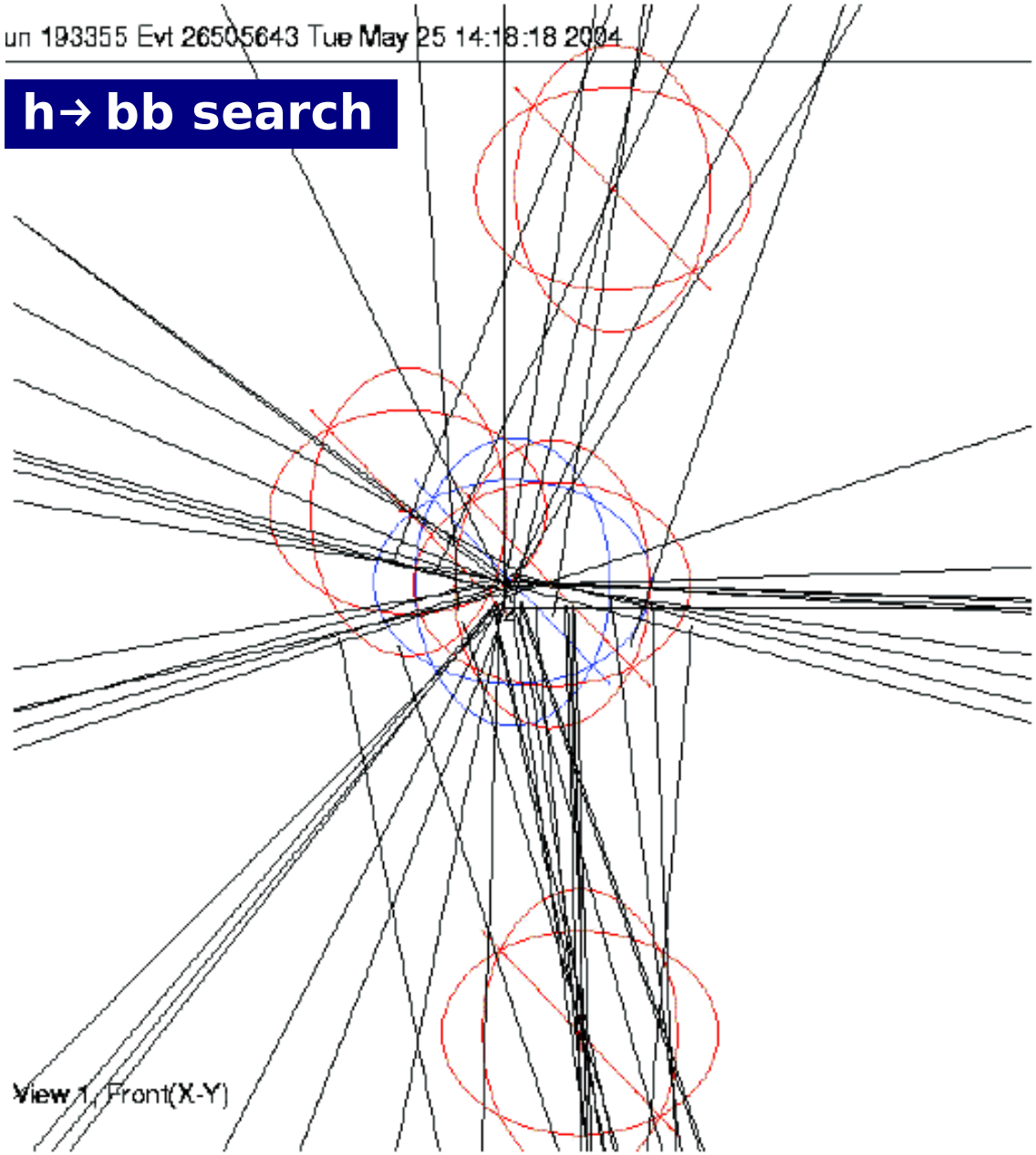


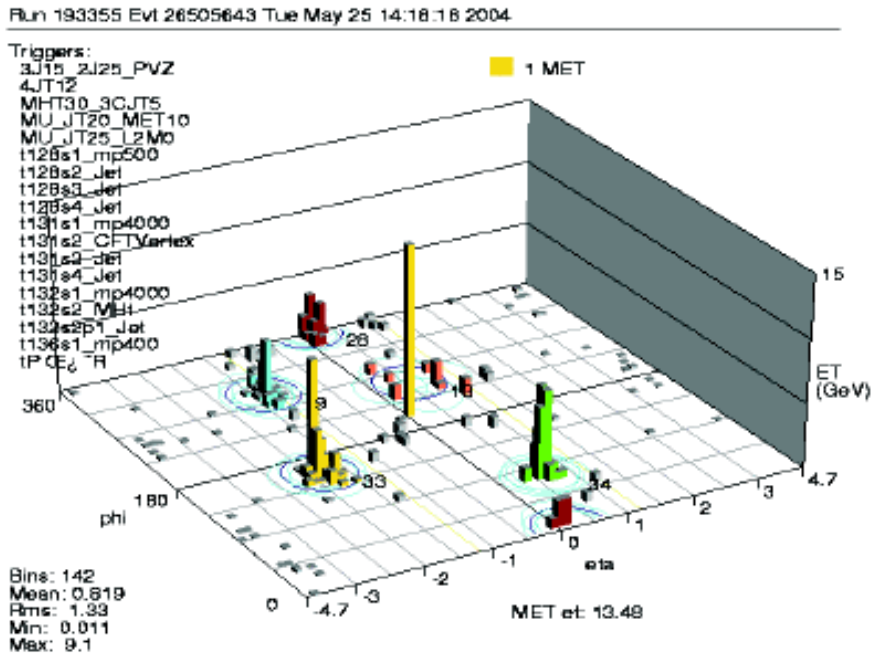


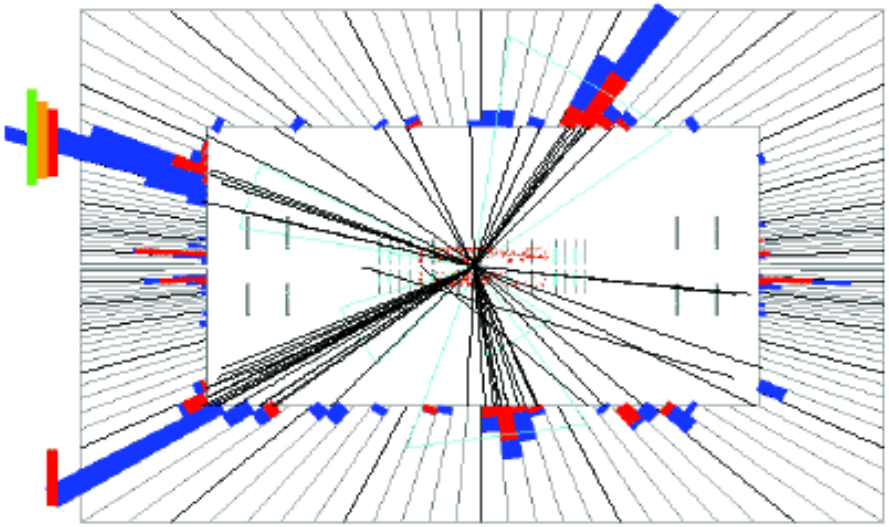


Run 153389 Event 361345
CEM electron E_T=50.9GeV
MET=27.4 GeV
Jet1 E_T=175.2 GeV, η=0.45
Jet2 E_T=147.2 GeV , η=-0.13

Extra2: quadr. b-tagged event in DØ







Extra 3: More info

CDF: http://www-cdf.fnal.gov/physics/new/top/top.html

DØ: http://www-d0.fnal.gov/Run2Physics/WWW/results/top.htm