Jet Templates

Searches for High Multiplicity New Physics

Jay Wacker

Quora

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+ 1302.1870
+1402.0516

w/ E. Izaguirre
A. Hook
M. Lisanti
S. El Hedri
M. Jankowiak
T. Cohen
H. Lou

New Physics Searches

Rely heavily on one object
that QCD doesn't directly produce

Gives parametric control of QCD background

Why are we waiting for discovery?

Signals could be just out of reach

Is there something that we’re missing?

One dark corner:
Hadronic Final States

Missing usual
handles to control
QCD

Baryonic R-Parity Violation

Eviscerates MET

$$\int d^2\theta \;\; \lambda''_{ijk}\, U^c_i D^c_j D^c_k$$

Makes LSP decay

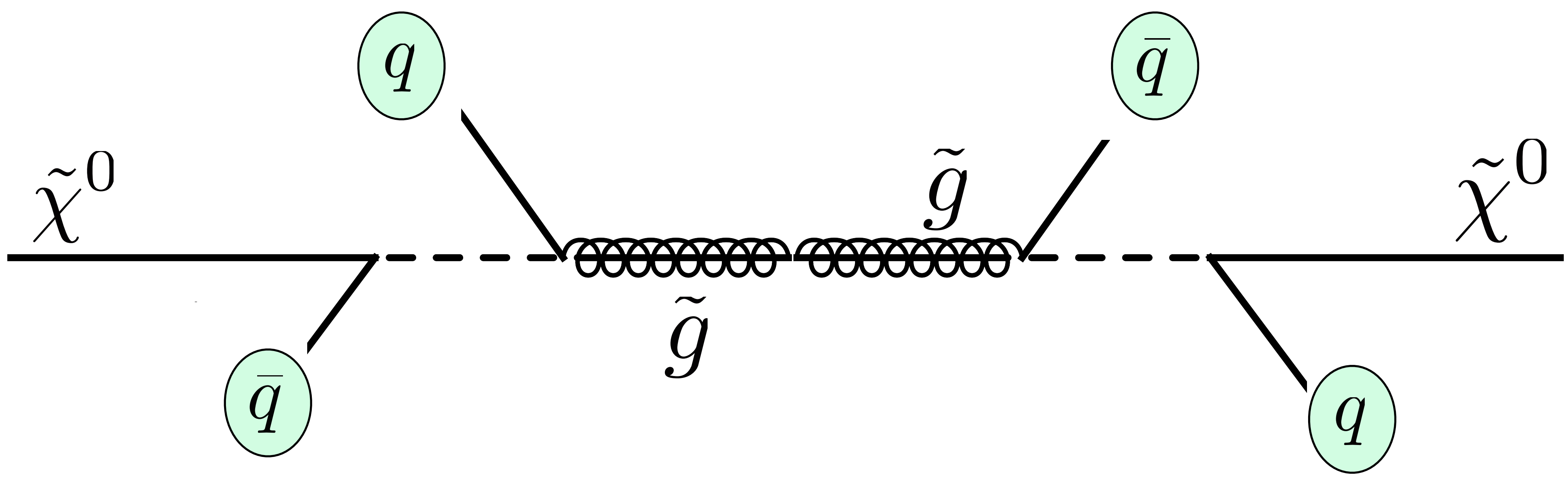
to 3 quarks (most LSPs)

to 2 quarks (squark LSPs)

(one quark could be top → +2j)

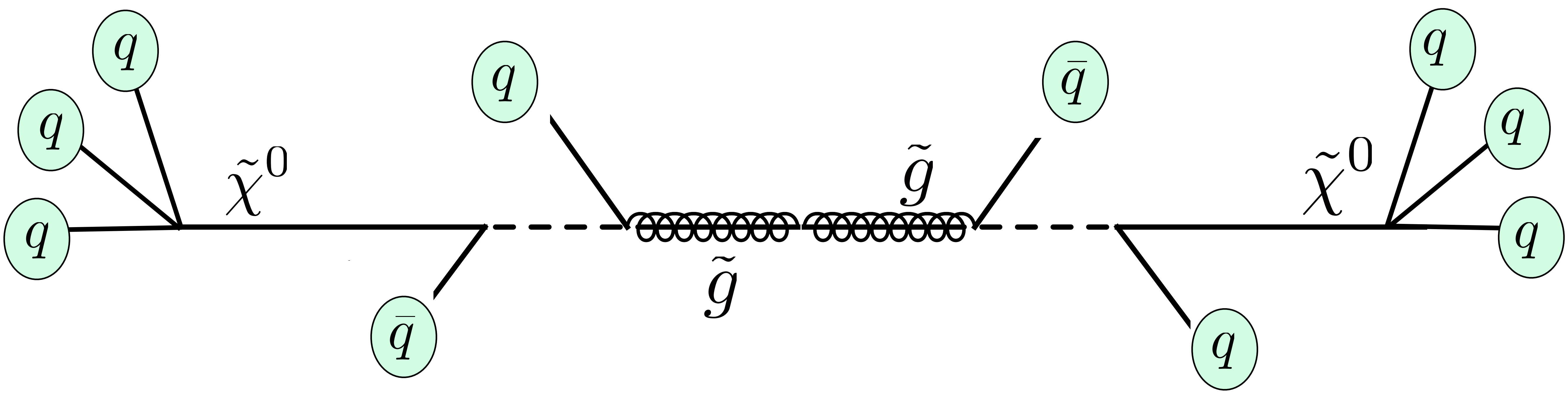
Increases multiplicity significantly

The Classic Susy Signature



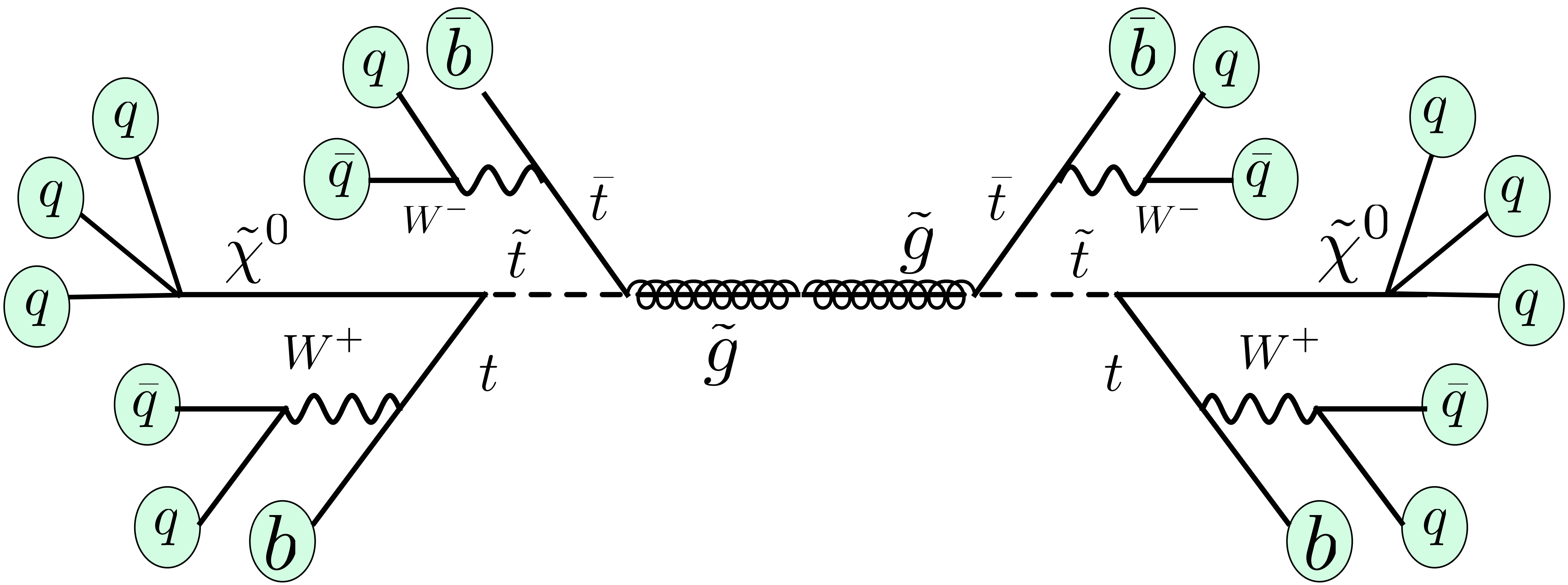
The Less-Classic Susy Signature

10^+ Partons no MET



The Less-Classic Natural Susy Signature

18^+ Partons



Still some MET from W decays, but much less

Don’t want to pay SSDL branching ratio (lepton isolation is hard)

Main Point:

Many signals of new physics produce lots of final state quarks or gluons

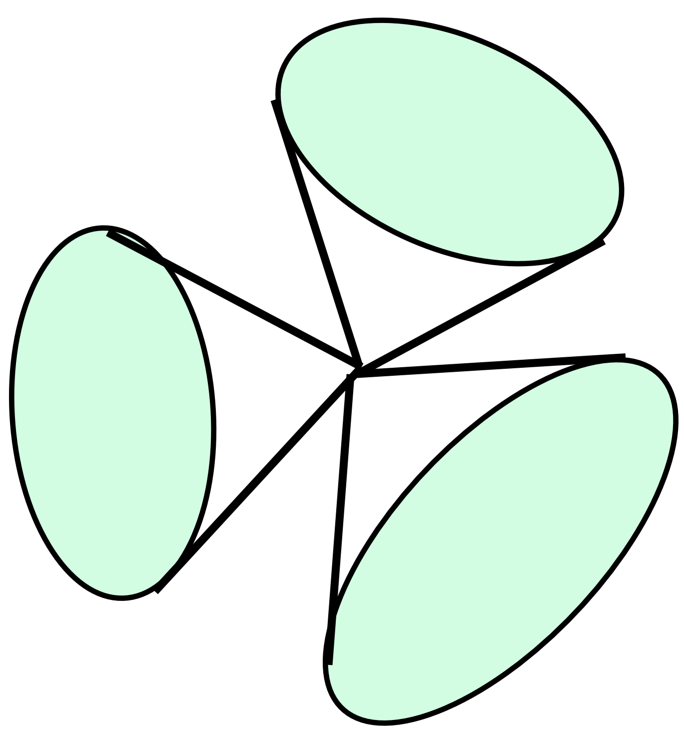
Easy to come up with other signals
with high multiplicity signals

Don't want to have a dedicated
search for every possibility

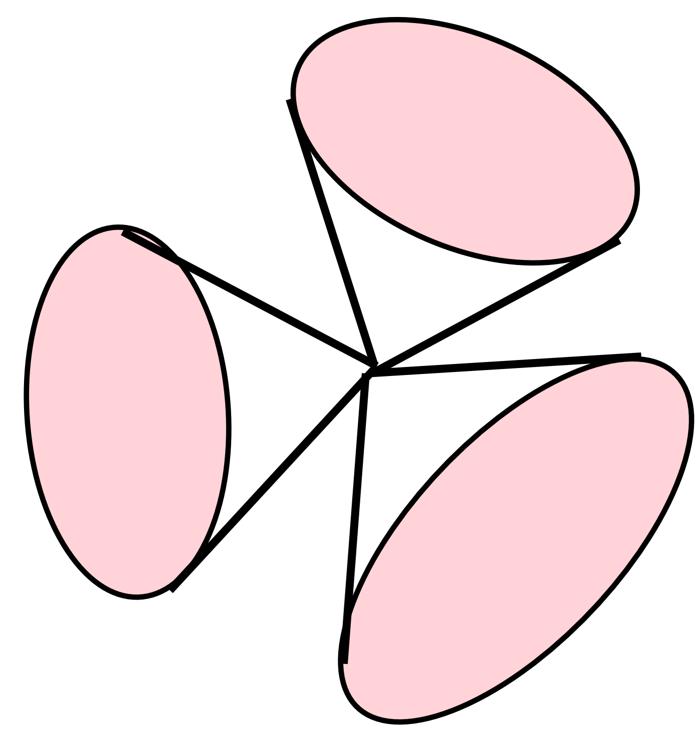
Want to use the multiplicity to distinguish SM from BSM

Need a handle to distinguish

Normal QCD Multijet



BSM Multijet



Fat Jets

Fat Jets Coarse Grain the Phase Space

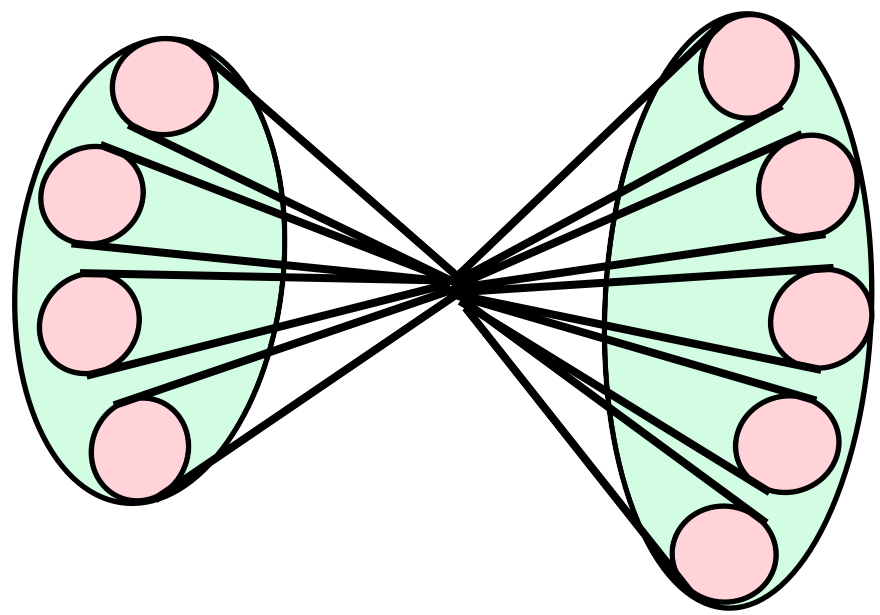
Easy to construct inclusive kinematic signals using fat jets

Thin Jets are great at determining multiplicity,
but constructing meaningful variables
out of a heterogeneous high dimensionful space is hard

Identify high multiplicity based
upon Fat Jet observables

Truth Of QCD Multijets

Many QCD Multijets are glorified Dijets

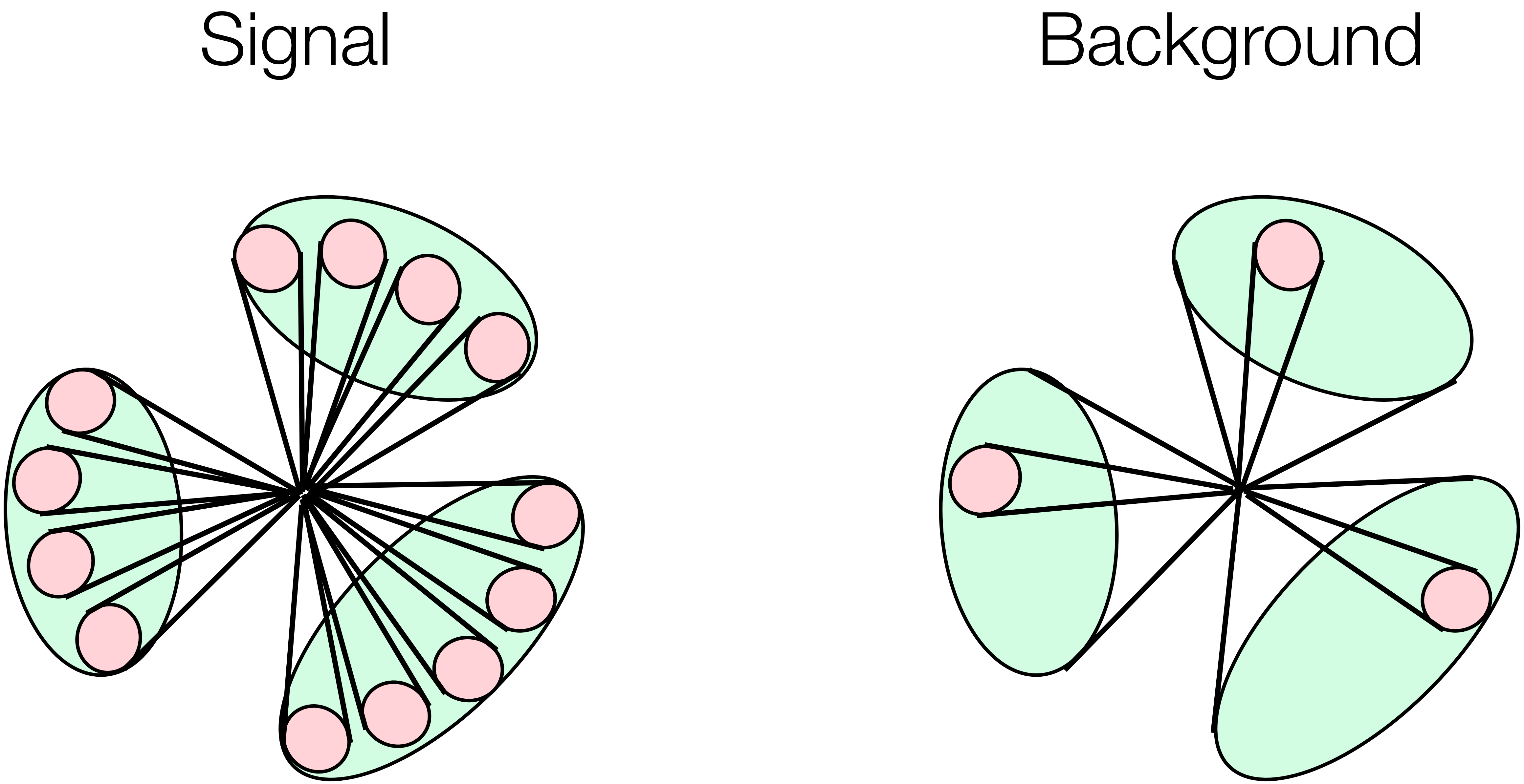


Requiring 3 or 4 Fat Jets is a serious reduction in QCD rate

4 Fat jets is really a 2 → 4 process

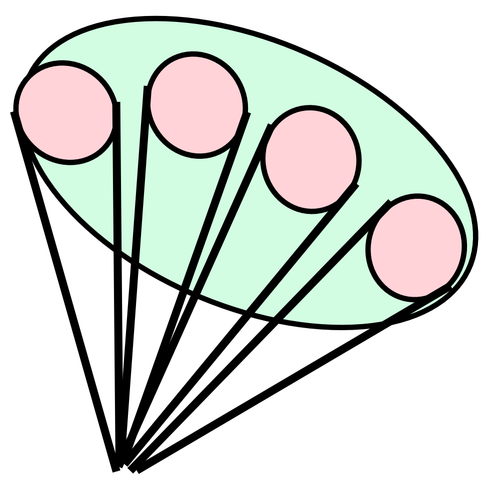
6 Thin jets is dominated by 2 → 2 + parton showering

Still need to distinguish



The difference between them is clear

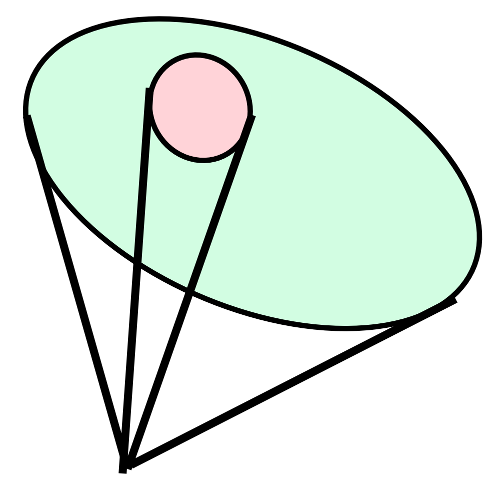
Large Invariant Mass



$$\frac{m_j}{p_T} \sim 1$$

More jet substructure

Small Invariant Mass



$$\frac{m_j}{p_T} \sim 0.3$$

Less jet substructure

Introduce Jet Observables

Sum of Jet Masses

$$M_J = \sum_{n=1}^{N_J} m_{j_n}$$

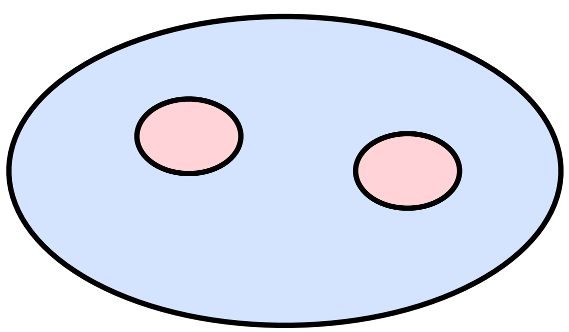
QCD jets have most of their mass generated by the parton shower

Top events have their mass capped near 400 GeV

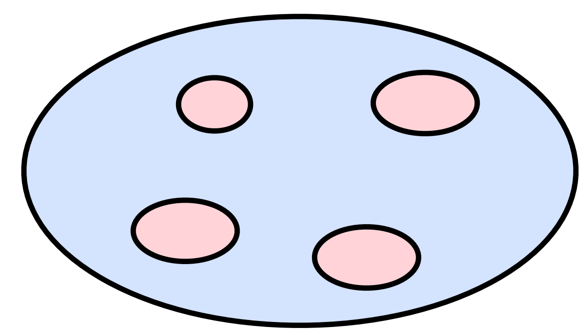
Subjettiness

Jet mass is the coarsest measure of jet substructure

Equal pT and mass jets



versus



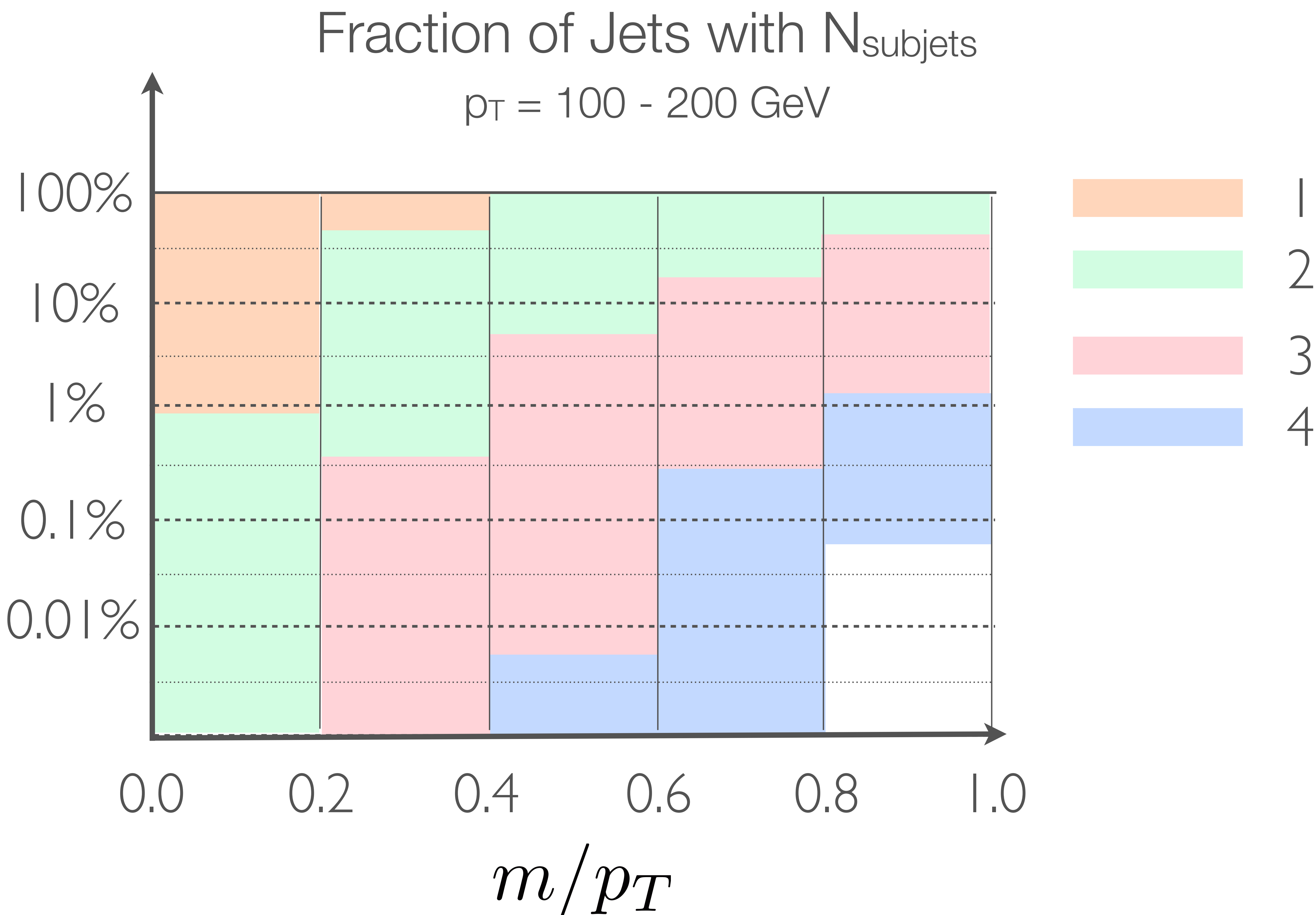
Massive QCD jets mostly have 2 subjets

High multiplicity signals are more subjets

Used kT method of counting subjets

(1302.1870)

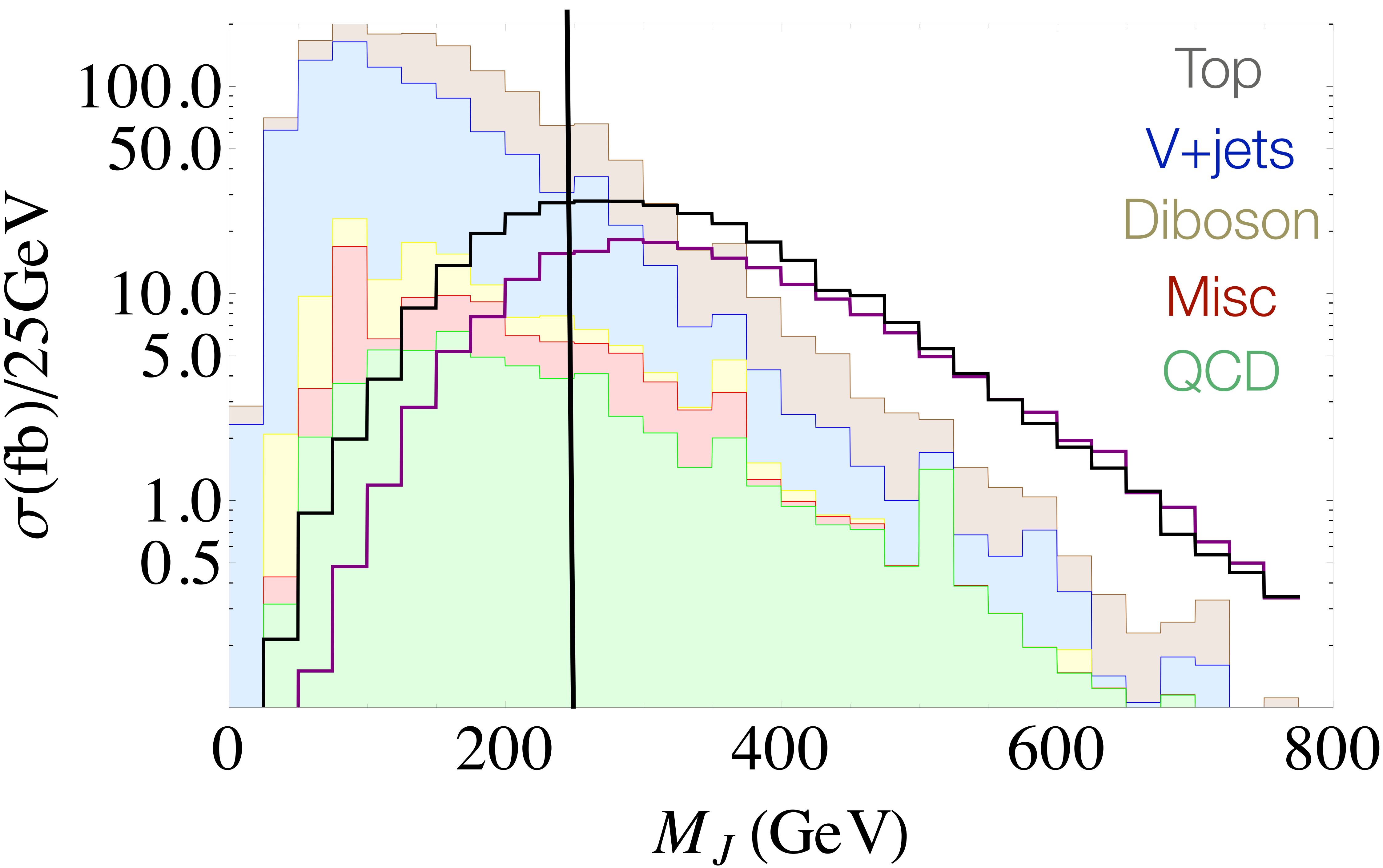
More than a Mass Cut



4 Fat Jets, $p_T > 100$ GeV

After $\not{E}_T > 150$ GeV

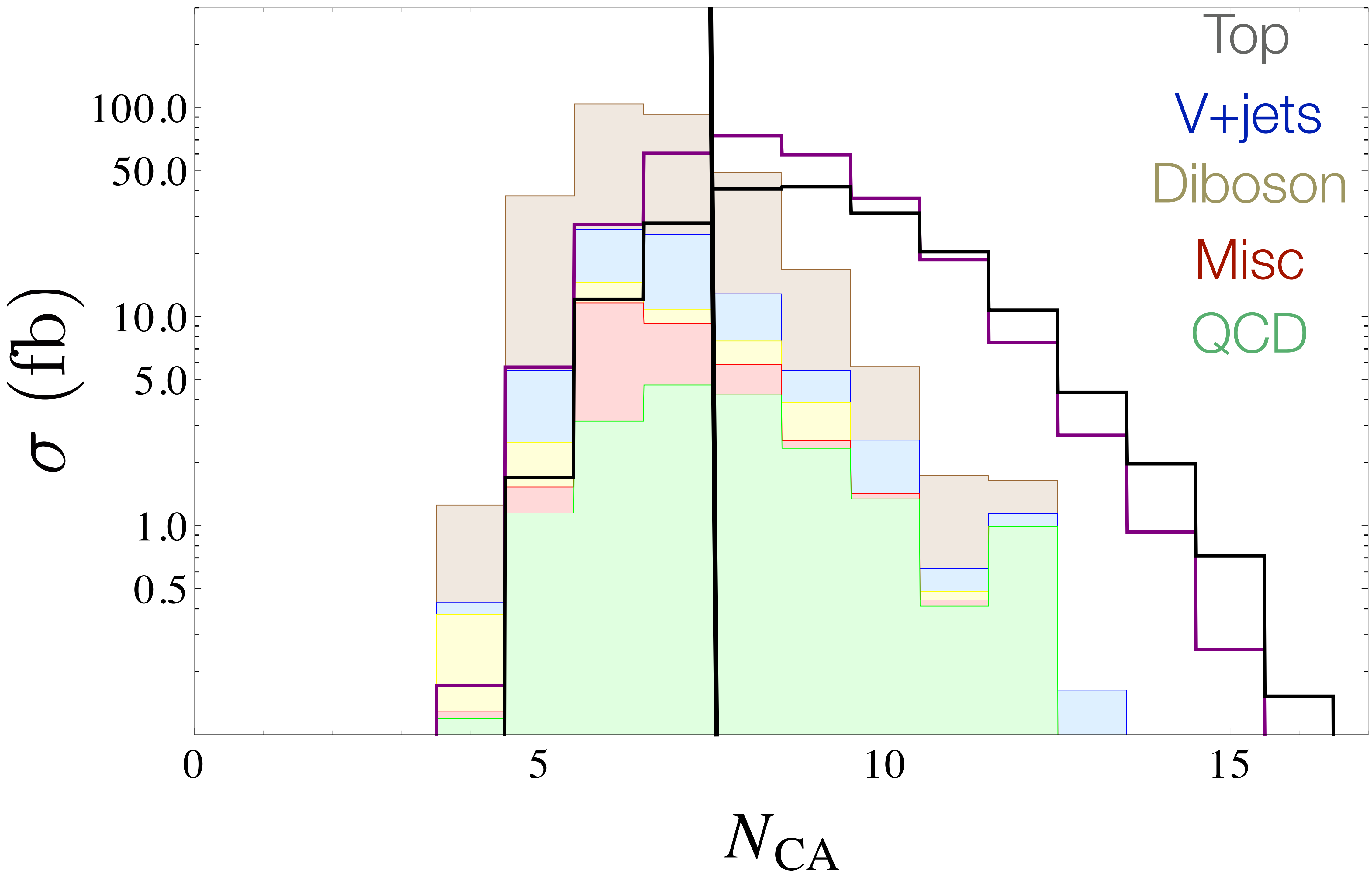
M_J Distribution



4 Fat Jets, p_T > 100 GeV

After $\not{E}_T > 150$ GeV & M_J > 280 GeV

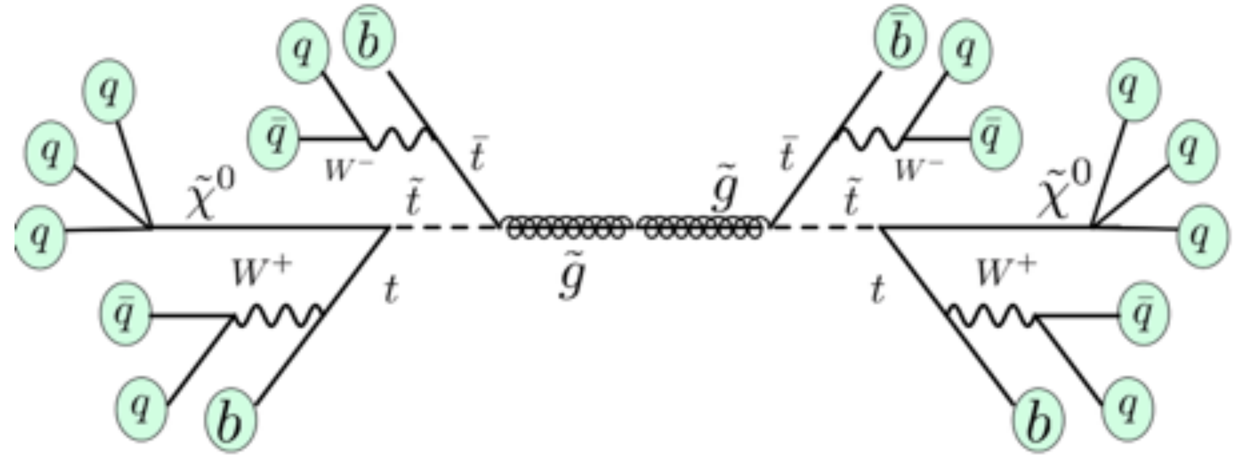
N_J Distribution

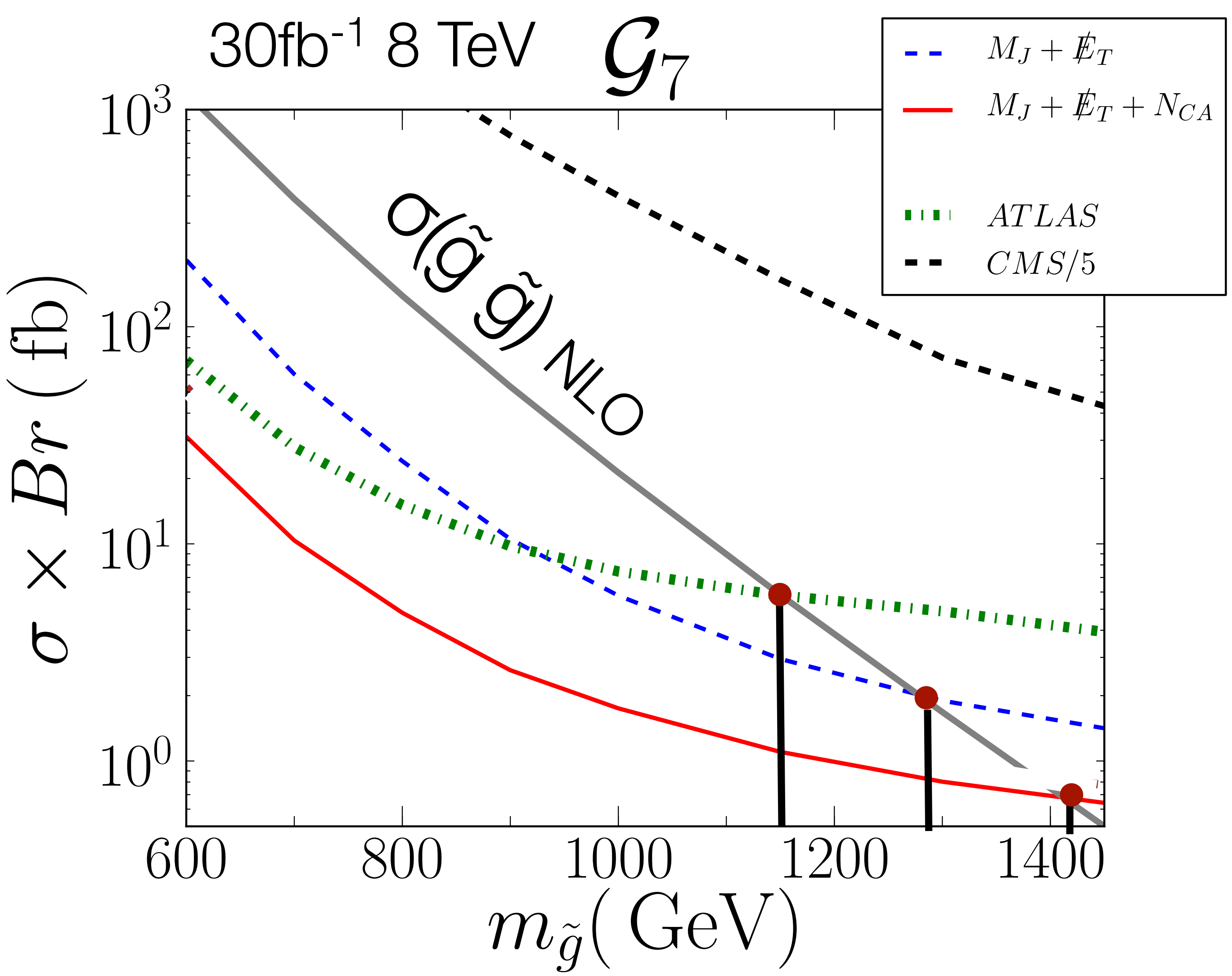


Improvements of N_J vs M_J only Search

$\not{E}_T > 125$ GeV $M_J \geq 425$ GeV $N_J > 14$

A little bit of MET from W-decays





$\sigma_{SM} \simeq 0.07$fb

Factor of 8 improvement in cross section, factor of 64 less luminosity

Variables are Great

… but Monte Carlos can't reproduce
all of jet substructure

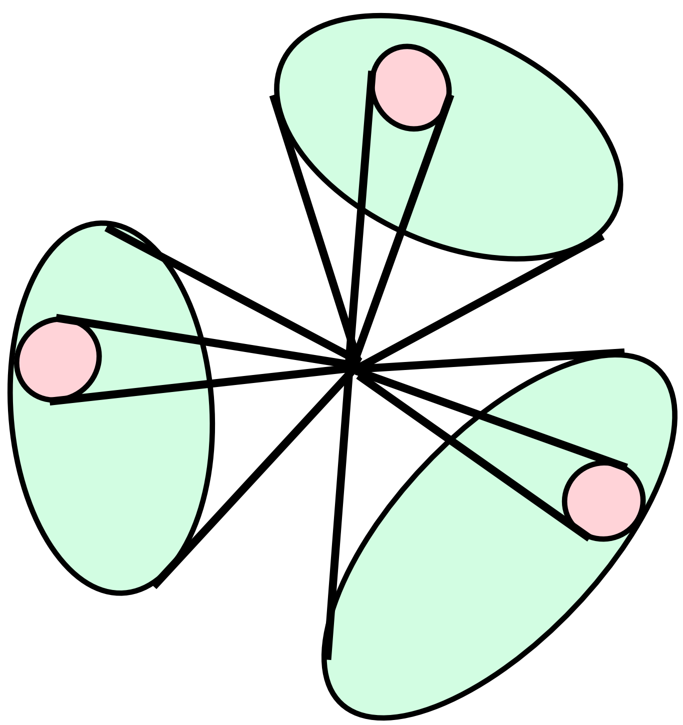
How to get backgrounds?

Particularly challenging when
variables are correlated

Jet Factorization

QCD jets only have small correlations

Data driven background predictions possible



$$x = m_j / p_T$$

$$P_3(x_1, x_2, x_3) \simeq P_1(x_1) P_1(x_2) P_1(x_3)$$

P_1: Probability of a jet with $m/p_T = x$

P_3: Probability of getting 3 jets with x_1, x_2, x_3

Measure in one sample and extrapolate

Also can use other control regions (MET/leptons/bjets)

Natural "Data-Driven" approach to backgrounds

Measure $P_1(x; p_T)$ in dijets, use in multijets

Predict event-by-event acceptances

(probability an event passes cut)

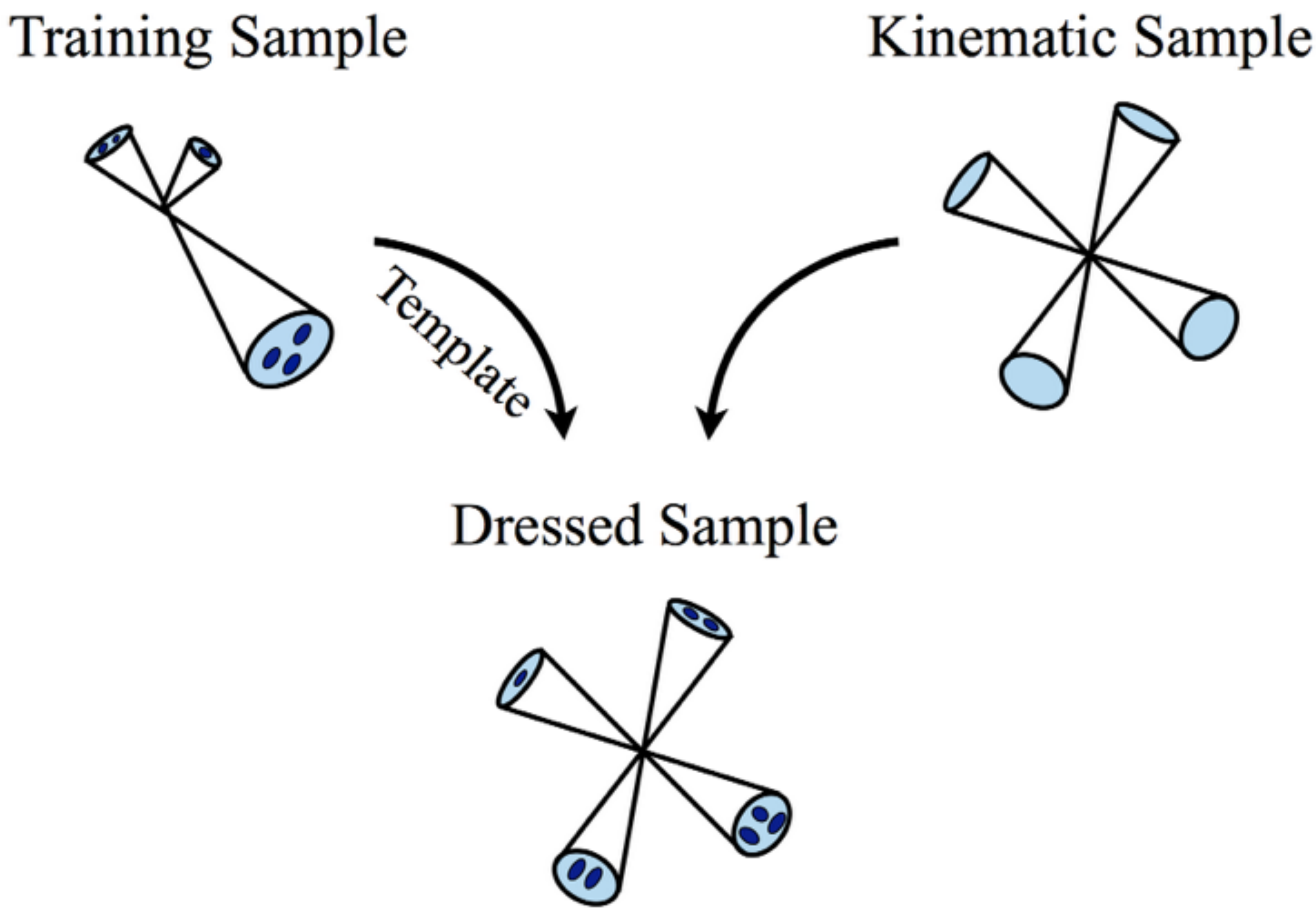
$$A(p_{T\,1}, p_{T\,2}, p_{T\,3}) = \int_{M_J > m_{\rm cut}} d^3x \quad P_1(x_1; p_{T\,1}) P_1(x_2; p_{T\,2}) P_1(x_3; p_{T\,3})$$

Differential acceptance rate as a function of the kinematic variables

Can make an M_J prediction based upon the events *measured*

Don't need to be able to calculate M_J distribution from first principles

The Basic Idea of Jet Templates



More Formally

k are kinematic variables

x are substructure variables

$$\frac{\mathrm{d}^{2N_j}\sigma(\vec{x}_i, \vec{\mathrm{k}}_i,)}{\mathrm{d}\vec{x}_1 \ldots \mathrm{d}\vec{x}_{N_j} \mathrm{d}\vec{\mathrm{k}}_1 \ldots \mathrm{d}\vec{\mathrm{k}}_{N_j}}$$

More Formally

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$$\frac{\mathrm{d}^{2N_j}\sigma(\vec{x}_i, \vec{\mathrm{k}}_i,)}{\mathrm{d}\vec{x}_1 ... \mathrm{d}\vec{x}_{N_j} \mathrm{d}\vec{\mathrm{k}}_1 ... \mathrm{d}\vec{\mathrm{k}}_{N_j}} = \frac{\mathrm{d}^{N_j}\sigma(\vec{\mathrm{k}}_i)}{\mathrm{d}\vec{\mathrm{k}}_1 ... \mathrm{d}\vec{\mathrm{k}}_{N_j}}\, \rho(\vec{x}_1, ..., \vec{x}_{N_j} | \vec{\mathrm{k}}_1, ..., \vec{\mathrm{k}}_{N_j})$$

More Formally

k are kinematic variables

x are substructure variables

$$\frac{\mathrm{d}^{2N_j}\sigma(\vec{x}_i, \vec{\mathrm{k}}_i,)}{\mathrm{d}\vec{x}_1 \ldots \mathrm{d}\vec{x}_{N_j} \mathrm{d}\vec{\mathrm{k}}_1 \ldots \mathrm{d}\vec{\mathrm{k}}_{N_j}} = \frac{\mathrm{d}^{N_j}\sigma(\vec{\mathrm{k}}_i)}{\mathrm{d}\vec{\mathrm{k}}_1 \ldots \mathrm{d}\vec{\mathrm{k}}_{N_j}} \, \rho(\vec{x}_1, \ldots, \vec{x}_{N_j} | \vec{\mathrm{k}}_1, \ldots, \vec{\mathrm{k}}_{N_j})$$

Approximate the multivariate joint distribution function
as independent distribution functions

$$\frac{\mathrm{d}^{N_j}\sigma(\vec{\mathrm{k}}_i)}{\mathrm{d}\vec{\mathrm{k}}_1 \ldots \mathrm{d}\vec{\mathrm{k}}_{N_j}} \, \rho(\vec{x}_1, \ldots, \vec{x}_{N_j} | \vec{\mathrm{k}}_1, \ldots, \vec{\mathrm{k}}_{N_j}) = \frac{\mathrm{d}^{N_j}\sigma(\vec{\mathrm{k}}_i)}{\mathrm{d}\vec{\mathrm{k}}_1 \ldots \mathrm{d}\vec{\mathrm{k}}_{N_j}} \prod_{i=1}^{N_j} \rho_i(\vec{x}_i | \vec{\mathrm{k}}_i) \, .$$

MEASURING THE TEMPLATES

Getting the central value is easy
Getting error bars is hard

Used Kernel Smoothing

Take every event and replace its properties with a Gaussian

$$\rho(m) = \sum_i \delta(m - m_i) \rightarrow \sum_i \exp\left(-\frac{(m - m_i)^2}{\sigma^2}\right)$$

What is σ ?

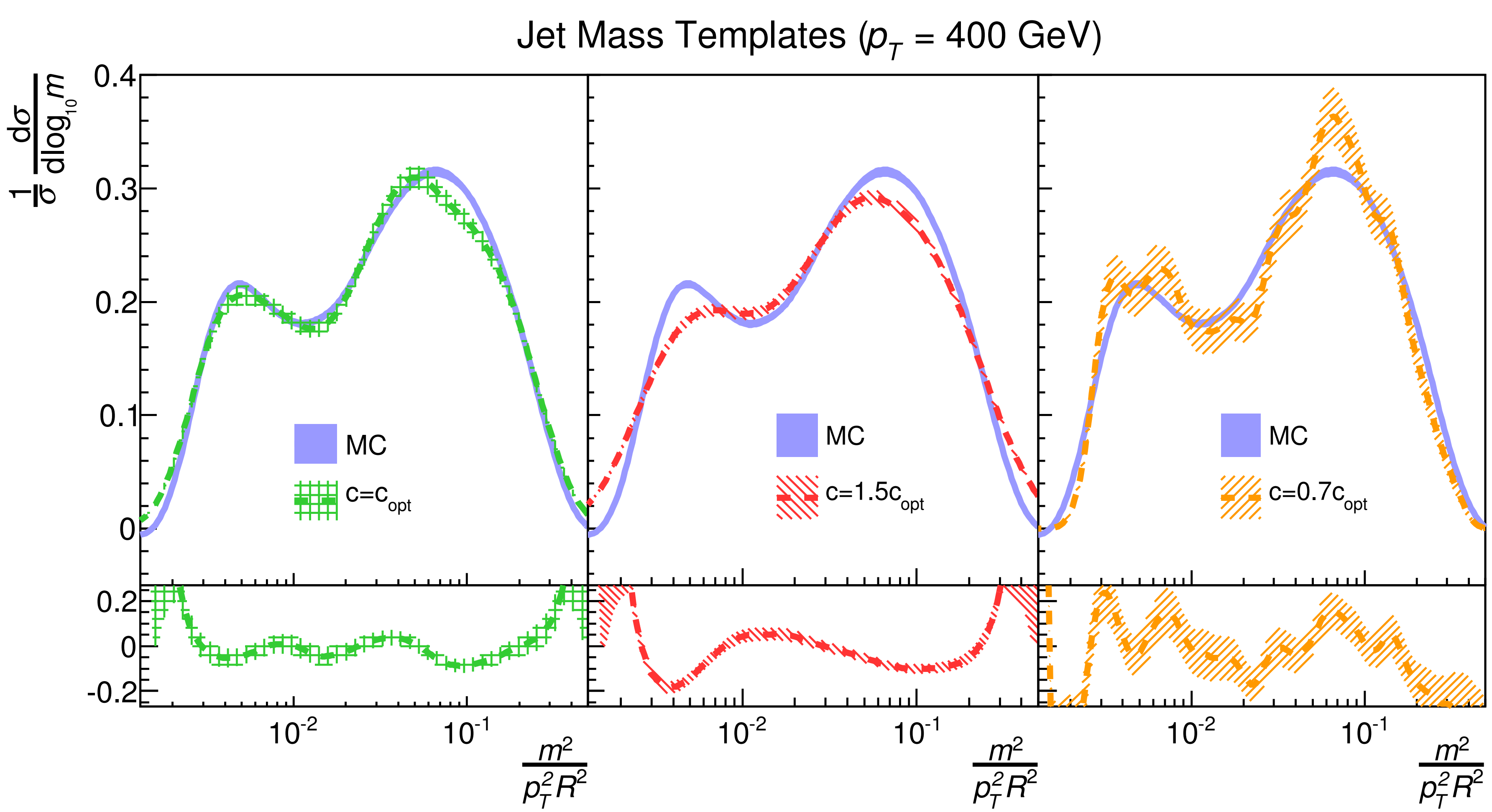
CHOOSING THE BANDWIDTH

Two separate errors arise in any procedure like this

Variance & Bias

If you choose σ too small, then there
is a lot of statistical noise

If you choose σ too big, then there
the distribution systematically moves away from the true one



OPTIMAL BANDWIDTH

Typically chosen by "AMISE"
(asymptotic mean integrated square error)

$$\mathrm{AMISE}(\sigma) = \int dm \, \Big(\rho_0(m) - \rho(m;\sigma)\Big)^2$$

Can prove lots of things about this

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But minimizing this is not the right thing to do

Variance is a Gaussian distribution

Bias is not, has non-Gaussian tails

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Variance is a Gaussian distribution

Bias is not, has non-Gaussian tails

Want Variance to dominate over Bias

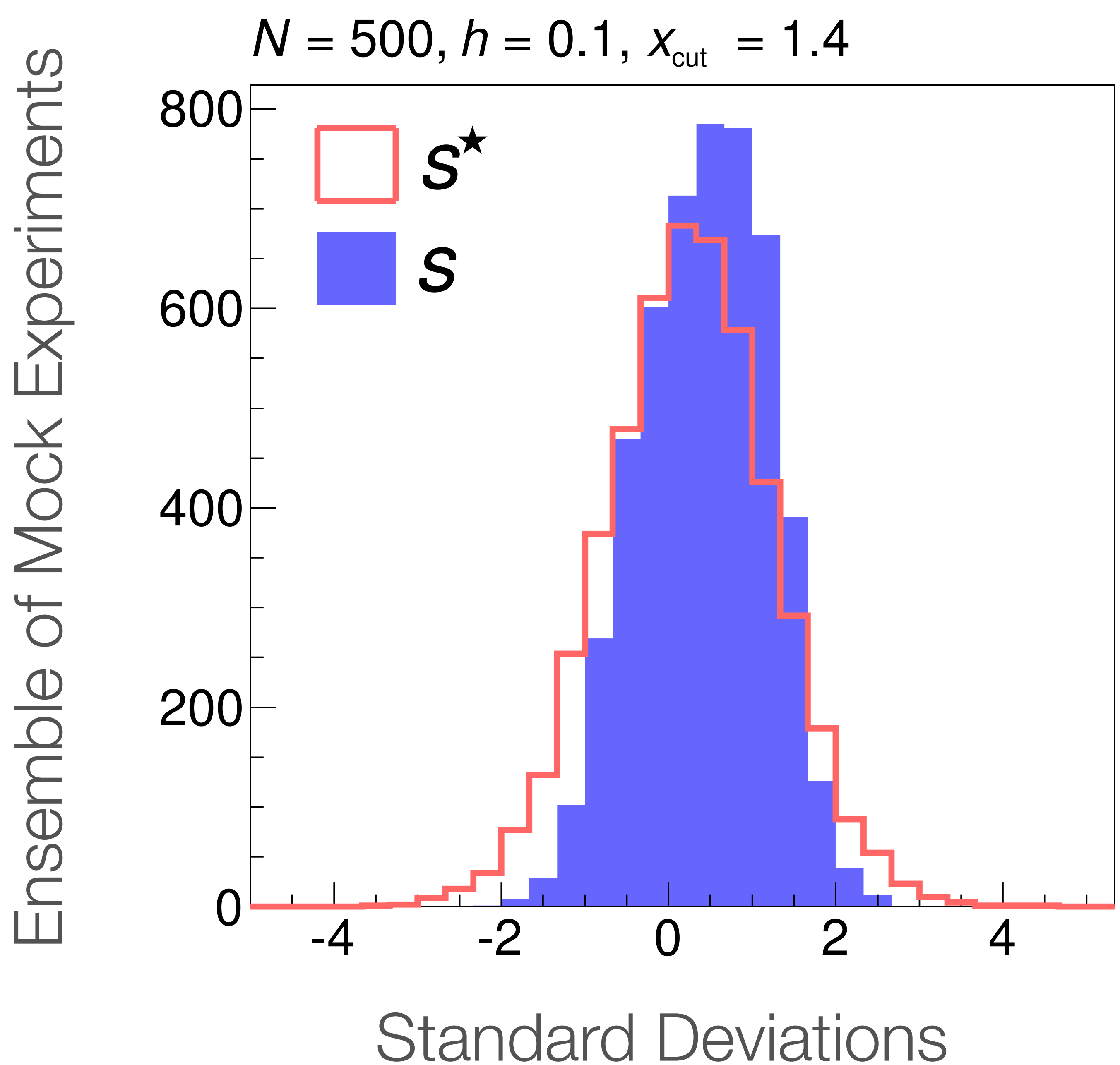
AMISE is a relatively function of bandwidth

Want to “undersmooth” the distribution

BIAS-CORRECTED TEMPLATES

Can measure the bias and correct for it at leading order

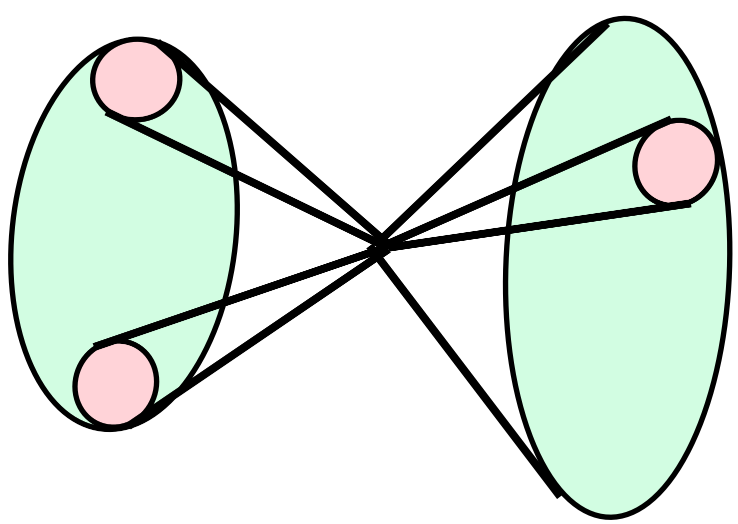
Distributions are Gaussian, with width 1 and centered at 0



Explicit Validation

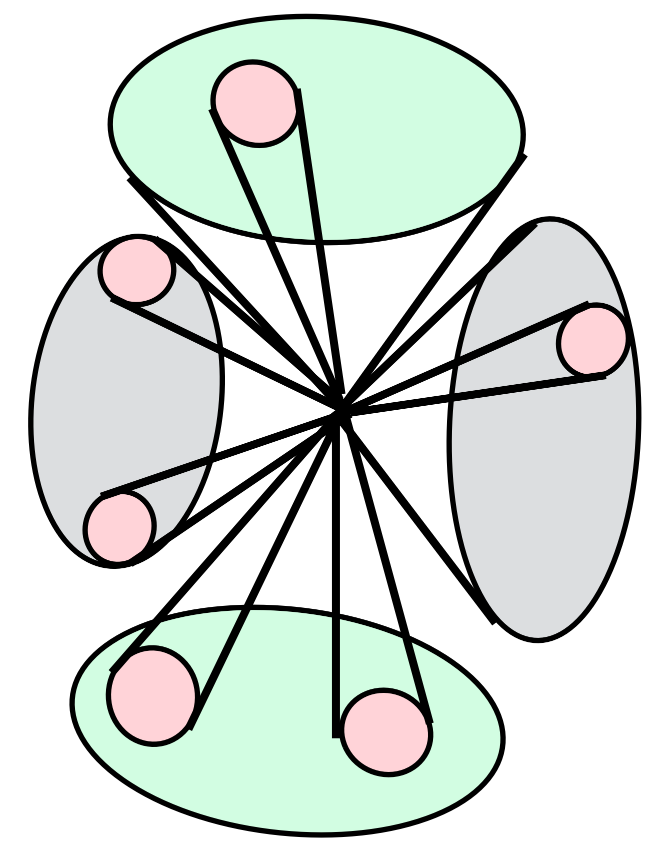
Control Region

Exclusive 2-Jets Events



Signal Region

Leading 2 Jets of 4-Jet Events



Test 2 Variables

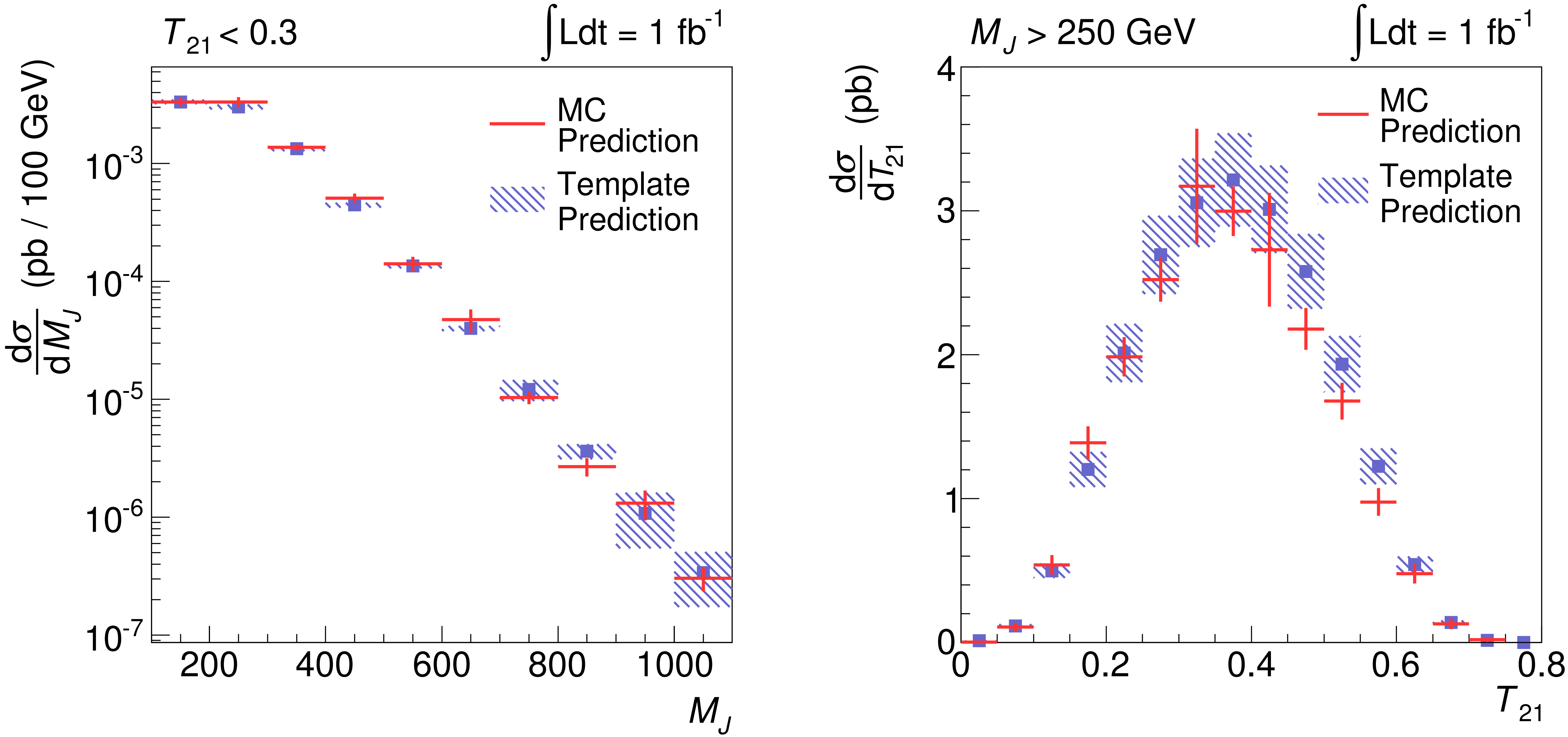
$$M_J = m(j_1) + m(j_2)$$

$$T_{21}{}^2 = \tau_{21}(j_1)\ \ \tau_{21}(j_2)$$

Works well in Monte Carlo

Take Exclusive Dijets and apply it to leading 2 jets in 4-Jet events

< 10% systematic differences



Minimally, jets in MC have less information,
can get more mileage with smaller MC calculations

Works similarly well in Search Regions

$$\hat{\rho}^{\star} = \hat{\rho}^{\star}\left(-\log_{10}\left(\frac{m}{p_T}\right),\, \tau_{21},\, \ln\left(\frac{p_T}{200\ \mathrm{GeV}}\right)\right)$$

c	M_J cut [GeV]	T_{21} cut	MC	Template $\pm\,\hat{\sigma}_V \pm \hat{\sigma}_B$
0.37	500	0.3	20.3 ± 2.2	$19.2 \pm 2.3 \pm 0.6$
0.52	750	0.3	0.86 ± 0.10	$0.96 \pm 0.19 \pm 0.05$
0.37	500	0.6	45.8 ± 3.5	$45.2 \pm 3.7 \pm 1.3$
0.52	750	0.6	1.67 ± 0.14	$1.90 \pm 0.19 \pm 0.13$

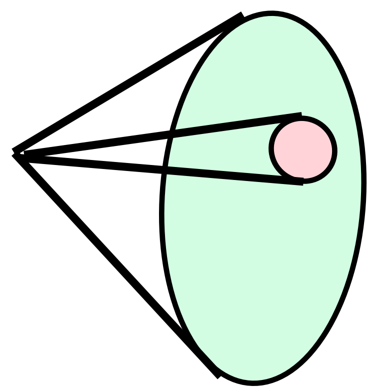
Always under-smoothed to make the calculated bias smaller than the expected variance dominate

Did this have to work?

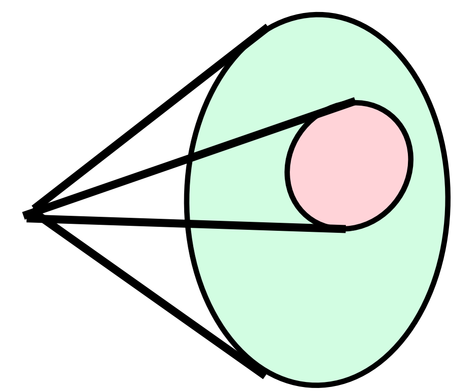
No! A non-trivial check

For instance, Quark vs Gluon Jets

Quarks:
Smaller Color, Less radiation



Gluons:
Bigger Color, More radiation



Full Dijet Sample is

$$\rho_{12}(\vec{x}_1,\vec{x}_2) = c_{qq}\rho_{qq}(\vec{x}_1,\vec{x}_2) + c_{qg}\rho_{qg}(\vec{x}_1,\vec{x}_2) + c_{gq}\rho_{gq}(\vec{x}_1,\vec{x}_2) + c_{gg}\rho_{gg}(\vec{x}_1,\vec{x}_2),$$

Approximating by

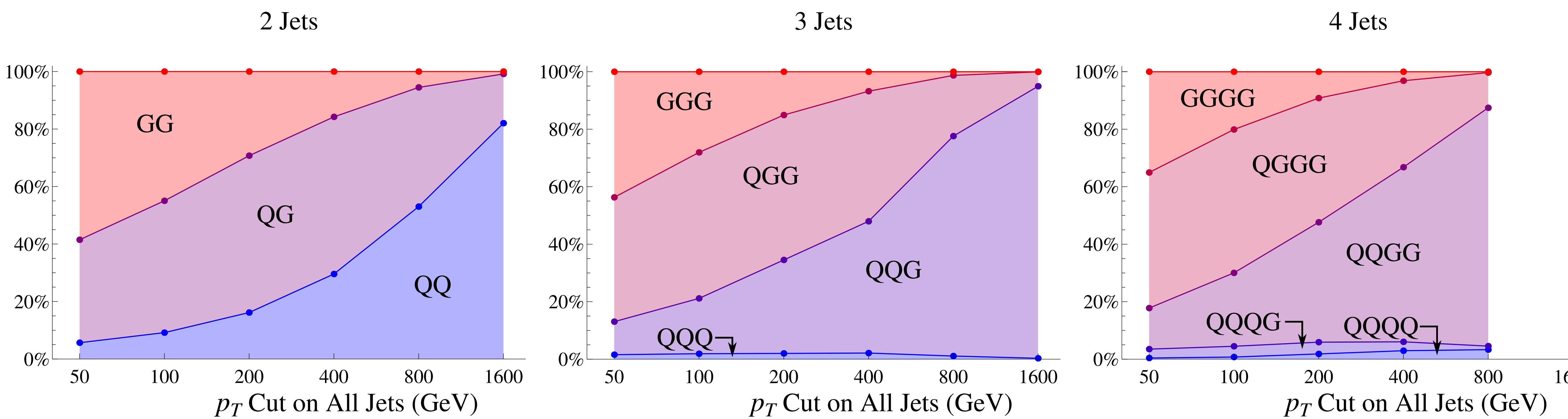
$$\tilde{\rho}(\vec{x}_1,\vec{x}_2) = \tilde{\rho}(\vec{x}_1)\tilde{\rho}(\vec{x}_2)$$

$$\tilde{\rho}(\vec{x}) = \left(c_{qq} + \frac{c_{qg}+c_{gq}}{2}\right)\rho_q(\vec{x}) + \left(c_{gg} + \frac{c_{qg}+c_{gq}}{2}\right)\rho_g(\vec{x}).$$

Desperately Seeking Correlations

Have seen no evidence yet of correlations

Look at samples with different compositions



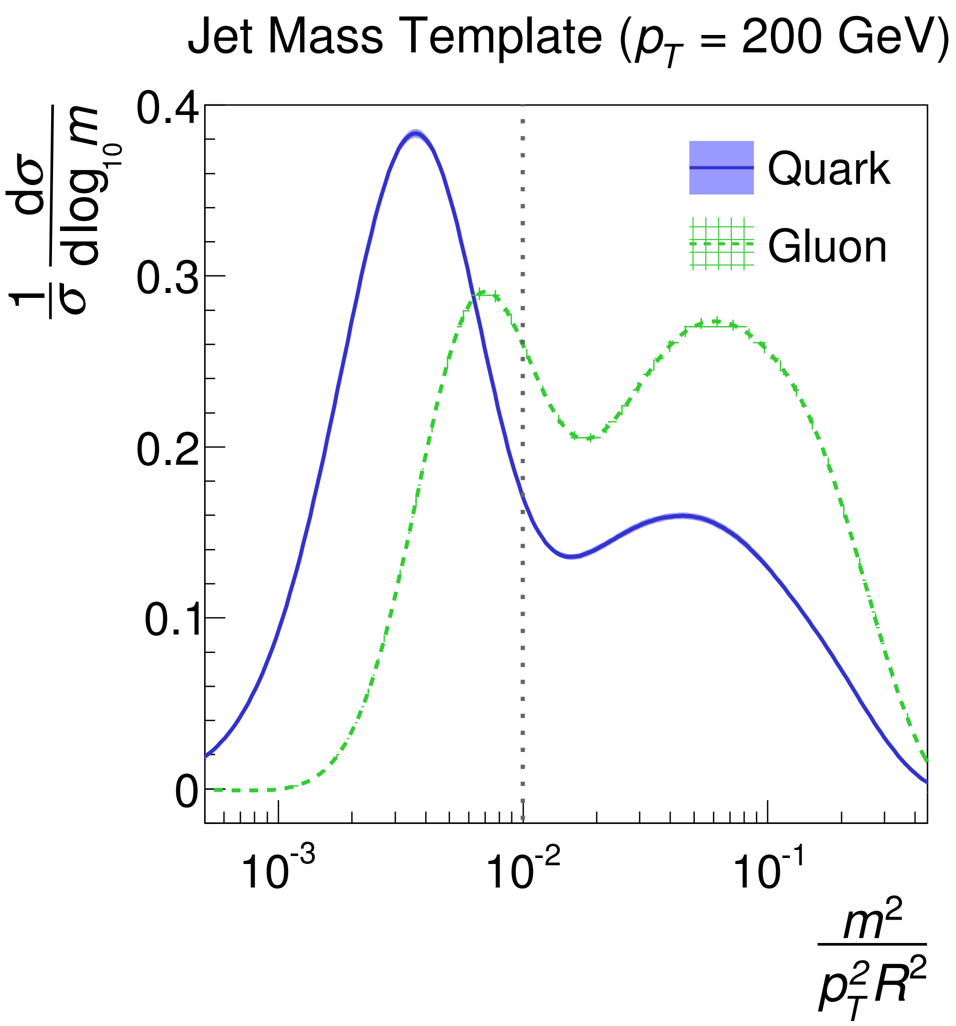
Leading 2 jets similar enough in composition between 2Jets & 4Jets

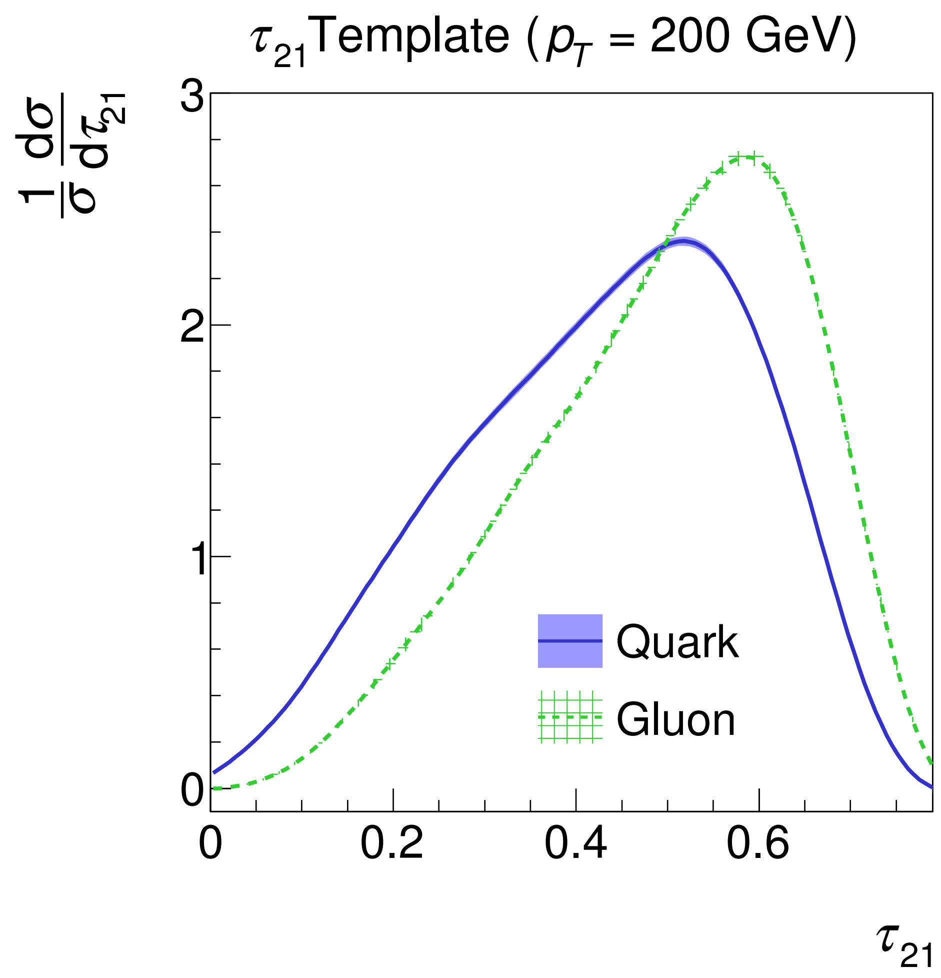
Using single template on all 4 jets doesn't work

Schwartz & Gallichio 2012

Q vs G Distributions Are Different

Have similar shapes and compositions cancel





Follow up work will use multiple templates

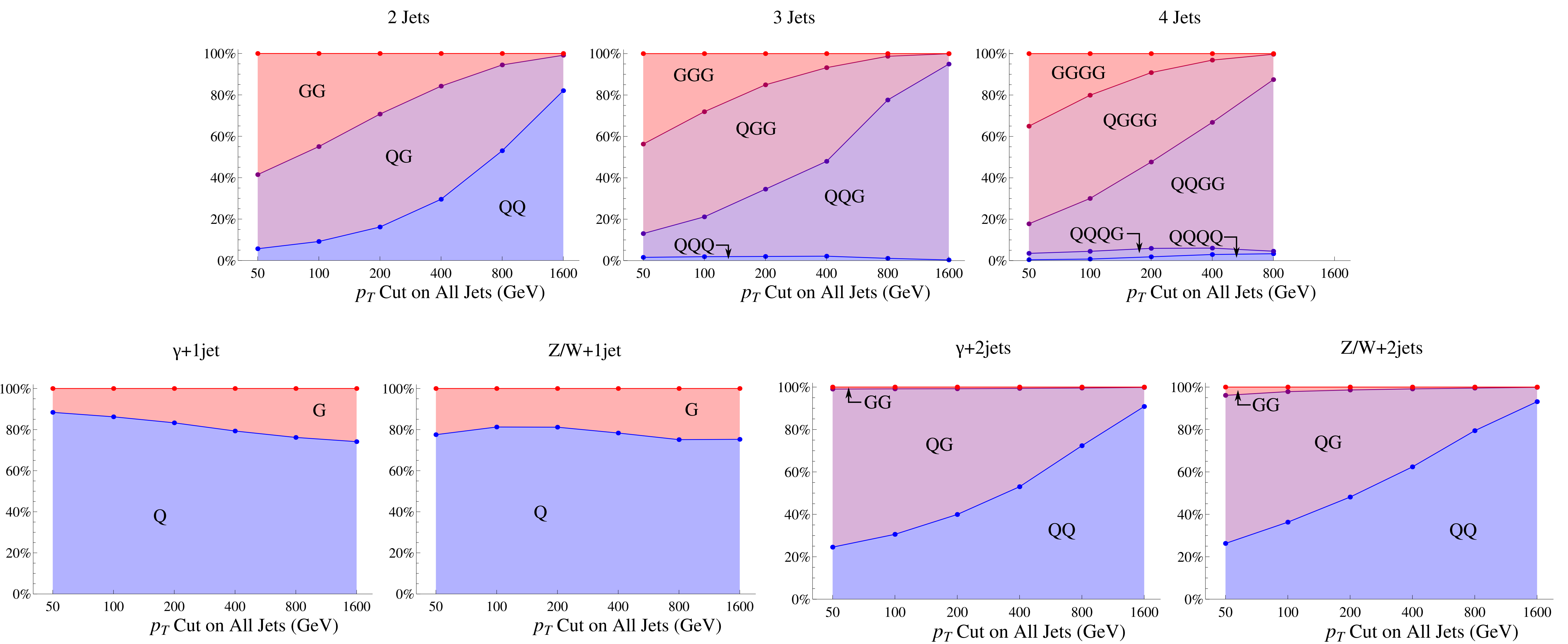
Apply to 3rd and 4th Jets

Higher Jets Saw Larger Deviations

Transition from Quark Dominated Jets to Gluon Dominated Jets

Could hope to regress out the different compositions

Look at samples with different compositions



Schwartz & Gallichio 2012

Outlook

High Multiplicity Signals are Challenging
But Powerful Signal

M_J & N_J are powerful new tools to separate
new physics from QCD

Novel approaches to backgrounds exist
using Jet Factorization approximation

Learning how to have low background
searches without MET

Thank You!

Boosted Community has been great to me

Grown from the small group in 2009

to this 115 person conference in its 6th iteration