

EdgeFinder

A proof-of-concept for unbiased kinematic edge measurements
in heavily polluted samples

David Curtin

[arXiv:1112.1095](https://arxiv.org/abs/1112.1095), PRD



MC4BSM Workshop
Cornell University, Ithaca, NY

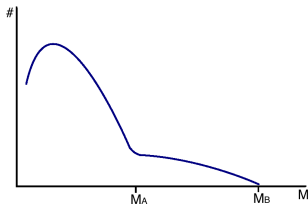
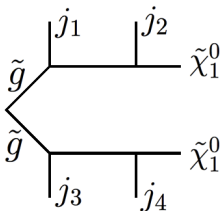
March 23, 2012





Problem:

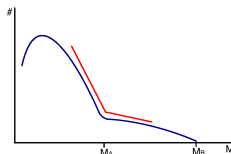
- You have some kinematic distribution (M_{jj}, M_{T2}, \dots)



- Don't know the global shape, but you want to **measure the position of the edge/endpoint** because it gives you some information about the masses in the decay chain.
- How do you measure this edge?**

Old Solution

Construct a fit function (commonly a linear kink, maybe with detector-motivated smearing, or something else depending on the shape of your edge) and fit to find the edge:



This has a lot of problems:

- The fit function is only an approximation to the shape of some subset of the distribution near the edge feature. **Which subset? Where to fit? How good an approximation?**
- This **systematic error** will not be included in the statistical uncertainty of the fit
- Do you introduce **bias** by picking a fit-domain?
- **Dreaming up more clever fit functions won't solve this problem.** Edges are difficult and ill-defined features.

Why Care?

- 1 Edge Measurements are difficult but important.
 - New kinematic variables like M_{T2} are extremely **powerful** and we would like to use them to perform mass measurements at the LHC.
 - Unfortunately they are very **fragile** to contamination and wash-out, making their endpoints/edges difficult to measure.
 - **Need a reliable way to extract low-quality edges that accurately includes the uncertainty in their position.**
- 2 Edge Measurements are not just difficult but deceiving!
 - **Fake measurements** can arise from combinatorics, cut artifacts, background, low statistics **Worst-Case Scenartio!**
 - You can deal with the false-positive problem by **using two 'orthogonal' ways of cleaning up your distribution, measuring all the edges and only keeping those where both methods agree.** (Examples later.)
 - **This requires a way of extracting all the edges from a distribution without bias, stressing accurate uncertainties** (otherwise we have no concept of two edge measurements 'agreeing' with each other).

New Solution

Objective

Find **all** the edges in a distribution, find their **uncertainties**, include **systematic errors**, do it **automatically (no bias)**, and use as much or as little information about the **shape** of the edge as we want.

EdgeFinder

Non-Deterministic Edge Measurement

Idea: a 'Monte-Carlo' based approach.

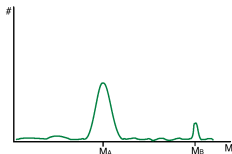
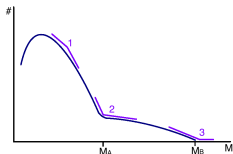
- Come up with a **fit function** that includes as much or as little info as you'd like (linear kink, linear kink + smearing, ...)
 - Generate **a lot** of random fit domains over your data (no bias)
 - Fit your function over each fit domain. Each fit returns a possible edge position. (Could weigh it with a goodness-of-fit test.)
- **Build up a distribution of found edges.**
- **True edges show up as peaks.** You've just turned *edge measurement* into *bump hunting*.
 - Finds **all the edges** without bias.
 - Width of peaks give uncertainties that includes just about all possible sources. **Self-measuring measurement resolution!**

This **Edge-to-Bump Method** obviously needs more exploration & verification, but let's see how it works in a simple proof-of-concept.

Edge-to-Bump Method

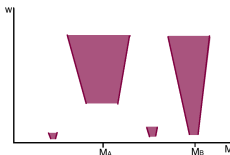
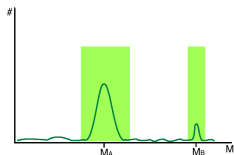
Step-by-Step:

1. Fit a simple kink function (**no smearing**) 1000's of times to random subdomains of data (without domain length or position bias).



Obtain Kink Distribution

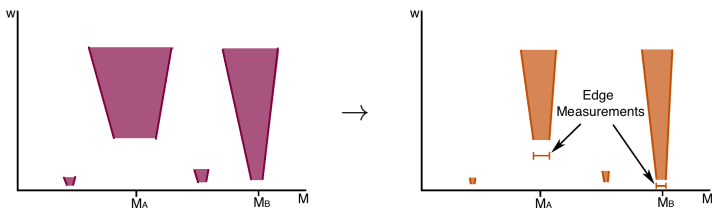
2. Detect Peaks in Kink Distribution → **Edge Detection.**



Scan over peak width w looking for 3σ excesses in central vs side bins

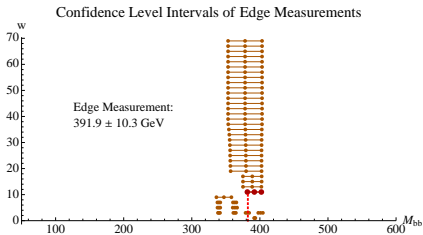
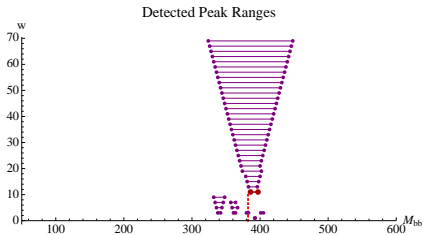
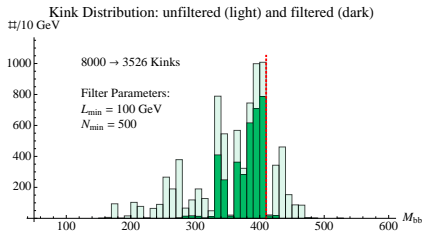
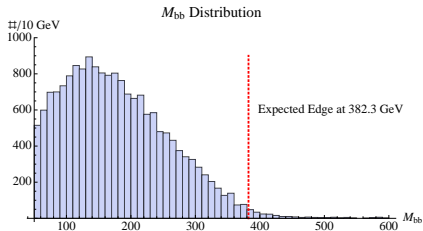
Edge-to-Bump Method

3. Turn these found peaks into **edge measurements** by taking the mean & standard deviation of the edge distribution around the peak:



*(The absence of an edge is signaled by the absence of clear peaks in the kink-distribution. **Works very reliably.**)*

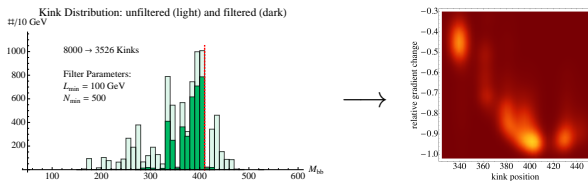
Example



Possible Extensions

Main Idea: analyze a *distribution* of fits rather than a single fit.

- One could imagine **much more sophisticated ways of analyzing the distribution of fits**, can almost treat them like “events”



→ Could also include a **statistical weight** for each found edge.

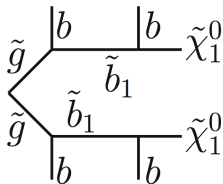
- The method is completely **general**: to detect different kinds of features just use different fit functions.

EdgeFinder

- Publicly available `Mathematica` implementation of the Edge-to-Bump method:

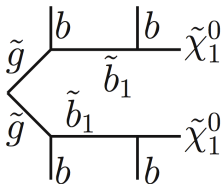
<http://insti.physics.sunysb.edu/~curtin/edgefinder/>

- Simple proof-of-concept: many refinements & optimizations possible.
- We demonstrate its utility in a few collider studies (including **blind verification**) by measuring **all the masses in a fully hadronic 2-step symmetric decay chain with maximal combinatorial ambiguity**:



Practical Demonstration

Use M_{T2} endpoints to measure all the masses in



Combinatorial worst-case!

But let's introduce M_{T2} first. . .

Some useful M_{T2} references:

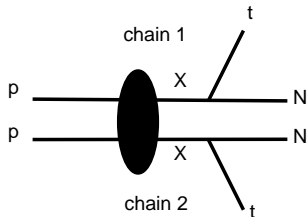
- Barr, Lester, Stephens '03 [hep-ph/0304226] (old-skool M_{T2} review)
- Cho, Choi, Kim, Park '07 [0711.4526] (analytical expressions for M_{T2} event-by-event without ISR, M_{T2} -edges)
- Burns, Kong, Matchev, Park '08 [0810.5576] (definition of M_{T2} -subsystem variables, analytical expressions for endpoints & kinks w. & w.o. ISR)
- Konar, Kong, Matchev, Park '09 [0910.3679] (Definition of $M_{T2\perp}$ to project out ISR-dependence)

(More in the paper.)

Classical M_{T2} Variable

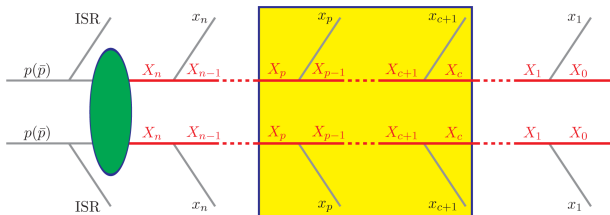
$$M_{T2}(\vec{p}_{t1}^T, \vec{p}_{t2}^T, \tilde{m}_N) = \min_{\vec{q}_1^T + \vec{q}_2^T = \vec{p}^T} \left\{ \max \left[m_T(\vec{p}_{t1}^T, \vec{q}_1^T, \tilde{m}_N), m_T(\vec{p}_{t1}^T, \vec{q}_2^T, \tilde{m}_N) \right] \right\}$$

- If p_{N1}^T, p_{N2}^T were known, this would give us a lower bound on m_X
- However, we only know total \vec{p}^T
 \Rightarrow minimize wrt all possible splittings, get 'worst' but not 'incorrect' lower bound on m_X .
- We don't even know the invisible mass m_N ! Insert a testmass \tilde{m}_N .

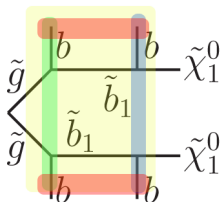


For the correct testmass, $M_{T2}^{\max} = m_X \Rightarrow$ **Effectively get $m_X(m_N)$.**

Multi-Step: M_{T_2} -Subsystem Variables



Complete Mass Determination Possible for 2+ Step Decay Chain.



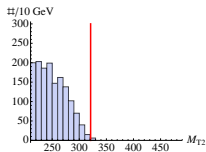
Measure 3 masses. Available variables:

$$M_{bb},$$

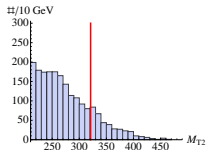
$$M_{T_2}^{221}, M_{T_2}^{210}, M_{T_2}^{220}$$

M_{T2} combinatorics are awful...

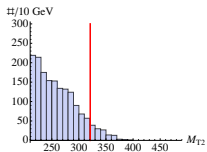
Correct Assignment



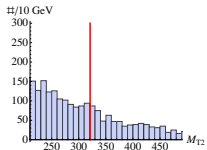
Upstream \rightarrow Downstream



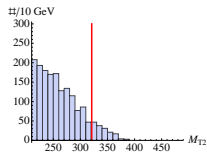
One Up + Other Down \rightarrow Downstream



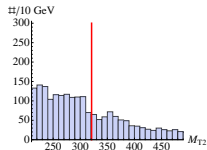
Same Chain \rightarrow Downstream



One Up + Other Down \rightarrow Downstream



Same Chain \rightarrow Downstream



M_{T2} Combinatorics Problem

M_{T2} is 'powerful but fragile', much more problematic than M_{jj} :

- There are more wrong-sign combinations.
- Edges are shallow → less well defined, more easily washed out (ISR, detector effects, background).
- The combinatorics background has nontrivial structure → **Fake Edges!**
- No one method of reducing combinatorics background works reliably all of the time.

⇒ Combinatorics Background doesn't just reduce quality of edge measurement, it can invalidate measurement completely.
Have to reject fakes!

Golden Rule for M_{T2} Measurements

Always use more than one method to reduce combinatorics background.

Only accept endpoint measurement if they agree

For each M_{T2} variable we perform the following steps:

- 1 Apply two CB reduction methods \rightarrow two M_{T2} distributions.
- 2 Apply Edge-to-Bump to each \rightarrow two kink distributions.
- 3 **Good quality edges in both distributions that agree?**

YES: merge & accept measurement

(can increase error bars)

NO: discard variable.

(e.g. disagreeing edges, no edge in one distribution, ...)

Combinatorics Background: DL Method

If we're going to analyze multi-step decay chains we need to get a handle on combinatorics background.

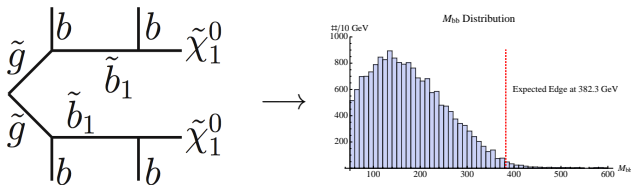
Simplest thing you could do: drop largest few M_{T2} 's per event.

- For each event, the true M_{T2} is a **lower bound** for M_{T2}^{max} .
 - If there are several M_{T2} -possibilities per event, the largest one(s) are more likely to be wrong.
- Discard Them!
- **Works surprisingly well, some of the time.**

Combinatorics Background: KE Method

What else could we do?

Edge in M_{bb} -distribution (invariant mass of decay chain) is relatively easy to measure using Edge-to-Bump, combinatorics are benign.



Could we make use of this M_{bb}^{max} information?

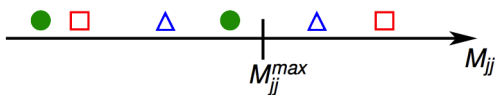
Combinatorics Background: KE Method

Known M_{bb}^{max}

M_{12}, M_{34} : ● ● ✓

M_{13}, M_{24} : □ □

M_{14}, M_{23} : △ △



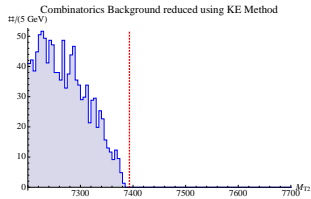
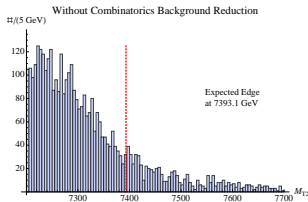
⇒ deduce correct decay chain assignment for 15 – 30% of events.

100% purity! (Before mismeasurement & detector effects)

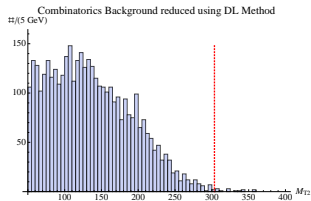
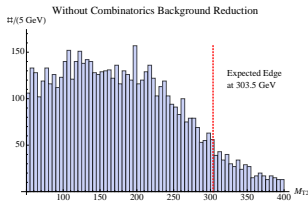
Extremely simple & high-yield method for determining decay chain assignment.

CB Reduction Example

$$M_{T2}^{220}(E_b):$$



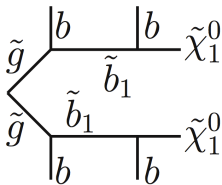
$$M_{T2}^{221}(0):$$



No one method works reliably all of the time. Sometimes they fail, sometimes they produce **fake edges**.

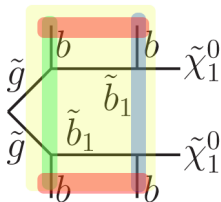
Now we're finally ready for . . .

Monte Carlo Studies



First Monte Carlo Study

Apply our methods to a **fully hadronic combinatorics-worst-case scenario** without other backgrounds.



Measure 3 masses. Available variables:

M_{bb} ,

M_{T2}^{221} , M_{T2}^{210} , M_{T2}^{220}

(use both ISR-binned & \perp versions, for zero and large testmass).

- Choose a particular MSSM **Benchmark Point** w/o **SUSY-BG**.

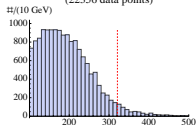
m_{t1}	m_{t2}	s_t	m_{b1}	m_{b2}	s_b	$m_{\tilde{g}}$	$m_{\tilde{\chi}_1^0}$
371	800	-0.095	341	1000	-0.011	525	98

(Already excluded by LHC, but that doesn't matter for us.)

- $\sigma_{g\tilde{g}} \approx 11.6$ pb @ $\sqrt{s} = 14$ TeV. Use $\mathcal{L} = 100$ fb $^{-1}$ (pessimistic).
- Simulate with MadGraph/MadEvent, **Pythia**, **PDG**.
- Require 4 b -tags & MET > 200 GeV \rightarrow **58k Signal Events**, Eliminates **SM BG**.

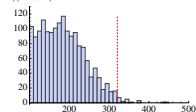
Full M_{T2} Measurement Example

With Full Combinatorics Background
(22356 data points)

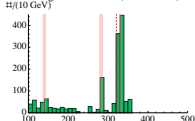


$\leftarrow M_{T2}^{210}(0)$

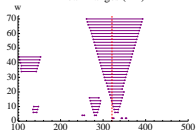
KE Method (2724 data points)



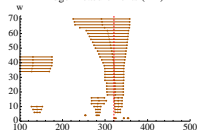
Edge Distribution (KE Method)



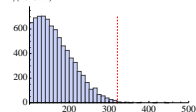
Peak Ranges (KE)



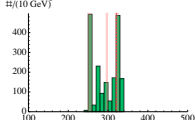
Edge Measurements (KE)



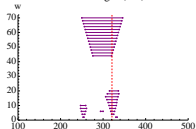
DL Method (14904 data points)



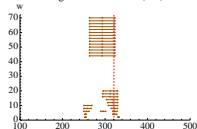
Edge Distribution (DL Method)



Peak Ranges (DL)

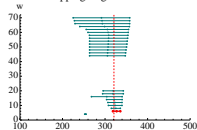


Edge Measurements (DL)



Measurement:
 $327 \pm 8.7 \text{ GeV}$
[320.9]

Overlapping Edge Measurements



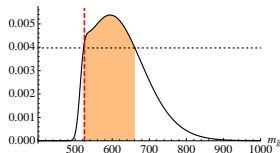
Edge Measurements

Variable	Prediction	Measurement	Deviation/ σ	Quality
M_{bb}	382.3	391.8 ± 10.3	+0.93	—
$M_{T2\perp}^{221}(0)$	303.5	240 ± 140	-0.45	C
$M_{T2}^{221}(0)$		301 ± 47	-0.05	A
$M_{T2\perp}^{221}(E_b)$	7153.4	7154 ± 42	+0.01	A
$M_{T2}^{221}(E_b)$		7171 ± 42	+0.42	A
$M_{T2\perp}^{210}(0)$	320.9	283 ± 44	-0.86	A
$M_{T2}^{210}(0)$		327.2 ± 8.7	+0.72	A
$M_{T2\perp}^{210}(E_b)$	7239.8	7141 ± 54	-1.84	A
$M_{T2}^{210}(E_b)$		7176 ± 37	-1.75	A
$M_{T2\perp}^{220}(0)$	506.7	509 ± 211	+0.01	C
$M_{T2}^{220}(0)$		528 ± 56	+0.38	B
$M_{T2\perp}^{220}(E_b)$	7393.1	7484 ± 106	+0.86	B
$M_{T2}^{220}(E_b)$		7456 ± 70	+0.90	B
$M_{T2\perp,all}^{210}(0)$	312.8	249 ± 52	-1.23	B
$M_{T2\perp,all}^{210}(E_b)$	7158.2	7129 ± 40	-0.73	A

NO FALSE MEASUREMENTS!

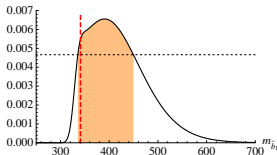
Mass Measurements

Projection of Gaussian Density onto $m_{\tilde{g}}$ axis.



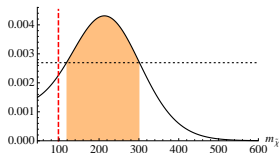
$$m_{\tilde{g}}^{meas} = 592 \pm 69 \quad (525)$$

Projection of Gaussian Density onto $m_{\tilde{b}_1}$ axis.



$$m_{\tilde{b}_1}^{meas} = 393 \pm 57 \quad (341)$$

Projection of Gaussian Density onto $m_{\tilde{\chi}_1^0}$ axis.



$$m_{\tilde{\chi}_1^0}^{meas} = 210 \pm 92 \quad (98)$$

Glino and sbottom masses measured with $\sim 10\%$ precision!

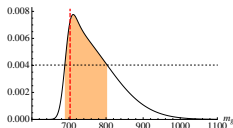
Blind Study

- Want to verify our methods with a different spectrum:

$m_{\tilde{t}_1}$	$m_{\tilde{t}_2}$	$\sin \theta_{\tilde{t}}$	$m_{\tilde{b}_1}$	$m_{\tilde{b}_2}$	$\sin \theta_{\tilde{b}}$	$m_{\tilde{g}}$	$m_{\tilde{\chi}_1^0}$
1016	1029	0.76	404	1012	1	703	84

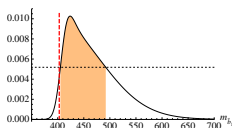
- Somewhat more luminosity to get same number of events. Analysis otherwise identical to first study.
- Did not know the spectrum prior to completing analysis!**
- Worked equally well:**

Projection of Gaussian Density onto $m_{\tilde{g}}$ axis.



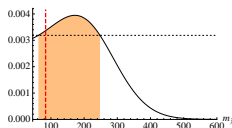
$$m_{\tilde{g}}^{meas} = 746 \pm 57 \quad (703)$$

Projection of Gaussian Density onto $m_{\tilde{b}_1}$ axis.



$$m_{\tilde{b}_1}^{meas} = 449 \pm 44 \quad (403)$$

Projection of Gaussian Density onto $m_{\tilde{\chi}_1^0}$ axis.



$$m_{\tilde{\chi}_1^0}^{meas} = 155 \pm 92 \quad (84)$$

Conclusion

Conclusion

- **Edge-to-Bump Method**: MC-based edge **detection** and **measurement** that addresses most of the edge-measurements problems that were prohibitive to LHC application (**bias**, **systematic error**, self-determined **sensible uncertainties**).
- The **EdgeFinder** `Mathematica` package is a publicly available proof-of-concept of the Edge-to-Bump method. Demonstrated utility, but obviously much room for extension & optimization.
- We showed for the first time that M_{T2} can be used to determine all the masses in a fully hadronic 2-step symmetric decay chain with maximal combinatorial ambiguity.
 - **KE-method of deducing decay chain assignment**: extremely simple & high-yield.
 - **Application to M_{T2}** : Simultaneous use of 2+ methods of reducing combinatorics background allows for **rejection of fake edges & artifacts**.

UPDATE:

These methods might find their way into an upcoming CMS analysis.



So stay tuned :).