Inclusive and Exclusive Accuracy in Resummed Cross Sections

Jonathan Walsh, UC Berkeley

work with Daniele Bertolini, Mikhail Solon, and Frank Tackmann

Resummed Cross Sections

resummation predicts two quantities:

 $\displaystyle{\frac{d\sigma}{d\tau}(\mu_i)}$: spectrum

 $\Sigma(\mu_i, \tau)$: cumulant

•
$$
\Sigma(\mu_i, \tau) = \int_0^{\tau} d\tau' \frac{d\sigma}{d\tau'}
$$

RGE, fixed order matching implemented by profile scales: $\mu_i = \mu_i(\tau)$

profile scale variations used to assess scale uncertainties

I will take τ to be thrust for this talk, but generically it can be any jet resolution variable

Resummed Cross Sections

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RGE, fixed order matching implemented by profile scales: $\mu_i = \mu_i(\tau)$

simple problem: typically, these two predictions are inconsistent

Two Paths to the Spectrum

d $d\tau$ $\Sigma(\mu_i(\tau), \tau)$ vs. $\frac{d\sigma}{d\tau}$ $d\tau$ vs. $\frac{d\sigma}{d\tau}(\mu_i(\tau))$: difference probes the commutator $\left[\mu_i=\mu_i(\tau),\,d/d\tau\right]$ *cumulant (free scales)* → **spectrum** *(free scales)* → **spectrum (profiles)** *cumulant (free scales)* \rightarrow *cumulant (profiles)* \rightarrow spectrum (profiles) $[\mu_i = \mu_i(\tau)] \times$ *d* $d\tau$ \times $[\mu_i = \mu_i(\tau)]$ *d* $d\tau$

in terms of full/partial derivatives:

$$
\frac{d}{d\tau} = \frac{\partial}{\partial \tau} + \frac{d\mu_i}{d\tau} \Rightarrow \left[\frac{d}{d\tau} \Sigma(\mu_i(\tau), \tau) - \frac{d\sigma}{d\tau}(\mu_i(\tau)) \right] \propto \frac{d\mu_i}{d\tau} \times \text{(higher order)}_{\text{Almeida, Ellis, Lee, Shemeida, Ellis, Lee, Sternan, Sung, JW}\atop 1401.4460}
$$

Lee.

Two Paths to the Spectrum

 $\frac{d}{d\tau}\Sigma(\mu_i(\tau),\tau)$ vs. $\frac{d\sigma}{d\tau}(\mu_i(\tau))$: difference probes the commutator $[\mu_i = \mu_i(\tau), d/d\tau]$ cumulant (free scales) \rightarrow **spectrum** (free scales) \rightarrow **spectrum (profiles)** $\frac{d}{d\tau} \times [\mu_i = \mu_i(\tau)]$
cumulant (free scales) \rightarrow cumulant **(profiles)** \rightarrow **spectrum (profiles)** $[\mu_i = \mu_i(\tau)] \times \frac{d}{d\tau}$

in terms of full/partial derivatives:

 $\overline{0.2}$

 0.1

 $\overline{0.3}$

 τ

0.4

$$
\frac{d}{d\tau} = \frac{\partial}{\partial \tau} + \frac{d\mu_i}{d\tau} \implies \left[\frac{d}{d\tau} \Sigma(\mu_i(\tau), \tau) - \frac{d\sigma}{d\tau}(\mu_i(\tau))\right] \propto \frac{d\mu_i}{d\tau} \times \text{(higher order)} \\
\text{cumulant vs. integrated spectrum}\n\tag{3.1401.4460}\n\left.\n\begin{array}{c}\n\text{Sumular} \\
\text{Sterman, Sung, JW}\n\end{array}\n\right\}
$$
\n
$$
\begin{array}{c}\n\text{MIL'+NLO}\n\end{array}
$$

 0.5

Accuracy of Each Resummed Cross Section

$$
\Sigma(\mu_i(\tau),\tau) \qquad \qquad \text{vs}
$$

- \triangle inclusive cross section
- **← correlations in uncertainties**
- poor large τ behavior in spectrum
- poor point-by-point uncertainties in the spectrum

accurate in the *inclusive/integrated* sense

 $d\sigma$ $d\tau$ **vs.** $\frac{uo}{d\tau}(\mu_i(\tau))$

- ***** accurate shape in the transition/tail
- ***** robust point-by-point uncertainties
- **Example 21 inclusive cross section**
- correlations in uncertainties

accurate in the *exclusive/differential* sense

Accuracy of Each Resummed Cross Section

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\Sigma(\mu_i(\tau),\tau) \qquad \qquad \text{vs}
$$

- \bullet inclusive cross section
- **← correlations in uncertainties**
- **Proof large τ behavior in spectrum**
- poor point-by-point uncertainties in the spectrum

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accurate in the *exclusive/differential* sense

I will describe a resummation method that gives a spectrum accurate both *exclusively* and *inclusively*

Accuracy of Resummed Cross Sections

I will describe a resummation framework that gives a spectrum accurate both exclusively and inclusively

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Connection to Known Problems

Want to associate scale variation to specific components of uncertainty

general covariance matrix decomposition:

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general covariance matrix decomposition:

soft, jet scale variations should not change the inclusive cross section:

 μ_J , μ_S variations map directly onto migration uncertainties *iff they leave the inclusive cross section unchanged*

this is not the case for standard profile variations

The Main Idea

Define a resummation method with two novel features:

- 1. Add higher order terms to the spectrum that bring the inclusive cross section close to the fixed order value
	- must maintain a sensible distribution in the tail region
	- must be consistent across fixed order scales (convergence)
- 2. Use an algorithm to identify families of soft and jet profiles that preserve the total cross section
	- use these families to determine the soft, jet scale uncertainties
	- our algorithm can identify arbitrarily many profiles preserving the total cross section, and we can test its robustness

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Use the fact that the cumulant derivative / spectrum difference is higher order:

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Use the fact that the cumulant derivative / spectrum difference is higher order:

2. Use an algorithm to identify families of soft and jet profiles that preserve the total cross section

we will attempt to *fill* the standard scale variation band with profiles that all preserve the inclusive cross section

preserve reliable point-by-point uncertainties *and* capture long-distance correlations

2. Use an algorithm to identify families of soft and jet profiles that preserve the total cross section

This can be cast as a math problem: find *μ*(τ) such that

$$
\sigma_{\rm incl} = \int_0^{\tau_{\rm max}} d\tau \, \frac{d\sigma}{d\tau} (\mu(\tau), \tau)
$$

subject to some simple constraints on *μ* (monotonicity, smoothness, fixed shape near endpoints)

Quiz: what is Bolzano's Theorem? This is a fairly generic problem, and we have devised a generic algorithm to solve it

The Intermediate Value Theorem (Bolzano's Theorem)

for continuous functions: *a b f*

 $f(a) < 0 < f(b) \implies \exists c \in [a, b] \text{ with } f(c) = 0$

Bernard Bolzano (1781-1848)

fun application:

At any time, on any great circle, there are two points on opposite sides of the Earth with the same temperature

 $T(p) - T(\bar{p})$

Extensions of Bolzano's Theorem

Extensions of Bolzano's Theorem

suppose we want to find *g(x)* satisfying

"parametric line" case (our case)

$$
\int dx R[g(x),x] = A
$$
 where *A* is a non-extremal constant

take two *g* satisfying

$$
\int dx R[g_{\text{down}}(x), x] = A_{\text{down}} < A
$$

$$
\int dx R[g_{\text{up}}(x), x] = A_{\text{up}} > A
$$

z
Z then there is some g such that $\ \int\,dx\,R[g_*(x),x]=A$

$$
\text{for instance} \quad g_* = a_* g_{\text{up}} + (1 - a_*) g_{\text{down}} \,, \quad a_* \in [0, 1]
$$

in fact, there are infinitely many *g*✻ such that

 $\forall x, g_{\text{down}}(x) \leq g_*(x) \leq g_{\text{up}}(x) \text{ or } g_{\text{down}}(x) \geq g_*(x) \geq g_{\text{up}}(x)$

The Bolzano Algorithm

- 1. Identify a set of candidate profiles *μ*
- 2. Separate candidate profiles by whether or not they give an inclusive cross section less than or greater than the true inclusive cross section $\{\mu\} \rightarrow \{\mu_{\text{up}}\}, \{\mu_{\text{down}}\}$
- 3. On every pair of "down" and "up" profiles, find *a*✻ such that

$$
\mu_* = a_* \mu_{\rm up} + (1 - a_*) \mu_{\rm down}
$$

has the correct inclusive cross section

- 4. Select all *μ*✻ satisfying desired properties:
	- Monotonicity
	- Smoothness

$$
-\forall \tau \, , \, \mu_{\text{down}}^{\text{vary}}(\tau) \leq \mu_*(\tau) \leq \mu_{\text{up}}^{\text{vary}}(\tau)
$$

can replace step 3 with a spectrum-space solution: *^N* candidate profiles

$$
\mu_* = \sigma^{-1} \big[\sigma_* = b_* \sigma(\mu_{\rm up}) + (1 - b_*) \sigma(\mu_{\rm down}) \big]
$$

give ~*N*2/4 solutions

Profiles: Algorithm and Solutions

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Comparison between Resummation Methods

Comparison between Resummation Methods

Convergence

slight non-convergence in the peak region exists also in the standard resummed spectrum (artifact of pinching in resummation scale dependence)

Correlations

can study correlations across T:

$$
S = \frac{d\sigma}{d\tau}(\mu_i) - \frac{d\sigma}{d\tau}(\mu_{\text{central}})
$$

"gap" regions hard to fill, require precise correlations at small and large T

Correlations

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$$
S = \frac{d\sigma}{d\tau}(\mu_i) - \frac{d\sigma}{d\tau}(\mu_{\text{central}})
$$

Two-Point Correlations

can study correlations across T:

$$
\frac{d\sigma}{d\tau}(\mu_i) - \frac{d\sigma}{d\tau}(\mu_{\text{central}})
$$

 $\tau_1 = 0.03$, $\tau_2 = 0.12$

Two-Point Correlations

can study correlations across T:

$$
\frac{d\sigma}{d\tau}(\mu_i) - \frac{d\sigma}{d\tau}(\mu_{\text{central}})
$$

 $\tau_1 = 0.03$, $\tau_2 = 0.06$

Two-Point Correlations

can study correlations across T:

$$
\frac{d\sigma}{d\tau}(\mu_i) - \frac{d\sigma}{d\tau}(\mu_{\text{central}})
$$

 $\tau_1 = 0.03$, $\tau_2 = 0.3$

Future Directions N2LL 3 2 2 3 2 22 22 22 23 23 24 25 26 27 28 29 20 21 22 23 24 25 26 27 28 29 29 20 21 \sim 3 \sim 333 \sim 33

µ^H = *µ^J* = *µ^S* = *R*. large canonical regime

persistent disagreement with data across theoretical predictions (resummation, Monte Carlo generators)

possible discrepancies in matching

Conclusions

- Resummation improves the accuracy of many exclusive cross sections, but loses accuracy in the corresponding inclusive cross section
- We have defined a method for resummation to preserve the accuracy at both the inclusive and exclusive level
	- An algorithm is used to find profile scales preserving the total cross section
	- Rigorously connects physical components of uncertainty with parameters of the factorization theorem
- Studies on thrust in e⁺e⁻ are very promising
	- Follow-up studies for event shapes, especially hadronic collisions

Extra Slides

fixed order uncertainties estimated via variation of renormalization, factorization scales

consider two jet bins: $Z + 0$ jets, $Z + \ge 1$ jets separated by a jet p_T veto

covariance matrix has the form:

$$
\sigma(\mu_R, \mu_F) = \int \hat{\sigma}(\mu_R, \mu_F) \mathcal{L}(\mu_F)
$$

$$
\sigma_0(p_T^{\text{cut}}), \sigma_{\geq 1}(p_T^{\text{cut}})
$$

$$
\sigma_{\text{incl}} = \sigma_0(p_T^{\text{cut}}) + \sigma_{\geq 1}(p_T^{\text{cut}})
$$

$$
C = \begin{pmatrix} \Delta_{0y}^2 & \Delta_{0y} \Delta_{\geq 1y} \\ \Delta_{0y} \Delta_{\geq 1y} & \Delta_{\geq 1y}^2 \end{pmatrix} + \begin{pmatrix} \Delta_{\text{cut}}^2 & -\Delta_{\text{cut}}^2 \\ -\Delta_{\text{cut}}^2 & \Delta_{\text{cut}}^2 \end{pmatrix}
$$

inclusive cross section constraint: $\sigma_{\rm incl} = \sigma_0 + \sigma_{\rm 1} \Rightarrow \Delta_{\rm incl} = \Delta_{\rm 0y} + \Delta_{\rm 1y}$

$$
C = \begin{pmatrix} \Delta_{\text{incl}}^2 + \Delta_{\geq 1}^2 - 2\Delta_{\text{incl}}\Delta_{\geq 1y} & -\Delta_{\geq 1}^2 + \Delta_{\text{incl}}\Delta_{\geq 1y} \\ -\Delta_{\geq 1}^2 + \Delta_{\text{incl}}\Delta_{\geq 1y} & \Delta_{\geq 1}^2 \end{pmatrix}
$$

2 degrees of freedom: $\Delta_{\geq 1 \mathrm{y}},\, \Delta_{\geq 1} = \left(\Delta_{\geq 1 \mathrm{y}}^2 + \Delta_{\mathrm{cut}}^2 \right)^{1/2}$

unclear how to estimate parameters from scale variation: assumptions needed

$$
C = \begin{pmatrix} \Delta_{\text{incl}}^2 + \Delta_{\geq 1}^2 - 2\Delta_{\text{incl}}\Delta_{\geq 1y} & -\Delta_{\geq 1}^2 + \Delta_{\text{incl}}\Delta_{\geq 1y} \\ -\Delta_{\geq 1}^2 + \Delta_{\text{incl}}\Delta_{\geq 1y} & \Delta_{\geq 1}^2 \end{pmatrix}
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 $C =$ $\left(\begin{array}{cc} \Delta_{\rm incl}^2 + \Delta_{\geq 1}^2 & -\Delta_{\geq 1}^2 \end{array} \right)$ $-\Delta_{\geq 1}^2$ $\Delta_{\geq 1}^2$ ◆ Stewart-Tackmann method: assume $\Delta_{\geq 1y} = 0 \; \Rightarrow$

i.e. inclusive cross sections of different multiplicity have uncorrelated uncertainties Stewart, Tackmann

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i.e. inclusive cross sections of different multiplicity have uncorrelated uncertainties Stewart, Tackmann 1107.2117

cause of uncertainty pinch:

$$
C = \begin{pmatrix} \Delta_{\text{incl}}^2 + \Delta_{\geq 1}^2 - 2\Delta_{\text{incl}}\Delta_{\geq 1y} & -\Delta_{\geq 1}^2 + \Delta_{\text{incl}}\Delta_{\geq 1y} \\ -\Delta_{\geq 1}^2 + \Delta_{\text{incl}}\Delta_{\geq 1y} & \Delta_{\geq 1}^2 \end{pmatrix}
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i.e. inclusive cross sections of different multiplicity have uncorrelated uncertainties Stewart, Tackmann 1107.2117

efficiency method: assume 0-jet efficiency, total cross section uncertainties uncorrelated

$$
\Rightarrow \Delta_{0y} = \Delta_{\rm incl} \epsilon_0, \ \Delta_{\geq 1y} = \Delta_{\rm incl} (1 - \epsilon_0), \ \Delta_{\rm cut} = \sigma_{\rm incl} \Delta_{\epsilon 0}
$$

Banderighi
1203.5773

both approaches physically well-motivated, although not always ideal

Uncertainties: Resummed

Uncertainties assessed by variation of factorization scales

 $\delta\{\mu, \mu_H, \mu_J, \mu_S\} \rightarrow \Delta(\tau)$

standard approach: 3 types of scale variation

 $\Delta^S_\text{res}(\tau)$: soft scale variation (probes logarithms, fixes fixed order scale) $\Delta^J_{\rm res}(\tau)$: jet scale variation (probes logarithms, fixes fixed order scale) $\Delta_{\mu}(\tau)$: collective variation of all scales (fixes logarithms, probes fixed order scale)

associate scale variation with components of uncertainty:

 $|\Delta_\mu| \rightarrow |\Delta_\mathrm{v}|$ $\Delta^J_{\rm res},\,\Delta^S_{\rm res}\,\rightarrow\,\Delta_{\rm cut}$

these assignments are physically well-motivated, although not necessarily valid

Two Paths to Resummation

