Theory Uncertainties from Nuisance Parameters.

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SCET 2019 Workshop San Diego, March 27, 2019

[arxiv:1904.sooon]

Theory Uncertainties and Correlations.

Reliable theory uncertainties are essential for any precision studies and interpretation of experimental measurements

- Especially when theory uncertainties \gtrsim experimental uncertainties
- Correlations can have significant impact
 - In fact, whenever one combines more than a single measurement, one should ask how the theory uncertainties in the predictions for each measurement are correlated with each other
 - Correlations among different points in a resummed spectrum
 - ► Correlations between predictions for different *Q*, processes, observables, ...
- So far we have (mostly) been skirting the issue
 - However, experimentalists have to treat theory uncertainties like any other systematic uncertainty, and in absence of anything better they have to make something up based on naive scale variations
 - In likelihood fits, some (possibly enveloped) scale variation impact will get treated as a free nuisance parameter and floated in the fit

Example: Measurement of the W Mass.

Small $p_T^W < 40 \, { m GeV}$ is the relevant region for m_W

- Needs very precise predictions for p^W_T spectrum
- $\simeq 2\%$ uncertainties in p_T^W translate into $\simeq 10 \, {
 m MeV}$ uncertainty in m_W
- Direct theory predictions for p_T^W are insufficient



- \Rightarrow Strategy: Exploit precisely measured $Z p_T$ spectrum to get best possible description for W
 - ► Regardless how precisely dσ(W)/dp_T can be calculated directly, one always wants to exploit Z data to maximize precision

Extrapolating from Z to W.



Ratio is just a proxy

- More generally: Combined fit to both processes
- Tuning Pythia on Z and using it to predict W is one example of this

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- Ratio is just a proxy
 - More generally: Combined fit to both processes
 - Tuning Pythia on Z and using it to predict W is one example of this
- Crucial Caveat: Cancellation fundamentally relies on theory correlations
 - Take 10% theory uncertainty on $d\sigma(W)$ and $d\sigma(Z)$
 - \rightarrow 99.5% correlation yields 1% uncertainty on their ratio
 - \rightarrow 98.0% correlation yields 2% uncertainty on their ratio 2× larger!
- One of many examples, this happens whenever experiments extrapolate from some control region or process to the signal region

Theory Correlations.

Correlations only come from common sources of uncertainties

• Straightforward for unc. due to input parameters $(\alpha_s(m_Z), PDFs, ...)$

What to do about perturbative theory uncertainties?

- X Scale variations are not quantitatively reliable to begin with
- X Moreover, they are inherently ill-suited for correlations
 - Scales are not physical parameters with an uncertainty that can be propagated, they simply specify a particular perturbative scheme
 - They are not the underlying source of uncertainty, i.e., they do not become better known at higher order
 - X Taking an envelope is not a linear operation and so does not propagate
 - Trying to decide how to correlate scale variations (e.g. between processes) is really just a bandaid, but not addressing the real problem

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 - X Trying to decide how to correlate scale variations (e.g. between processes) is really just a bandaid, but not addressing the real problem
- X Even the most sophisticated profile scale variations are insufficient
 - The profile shapes are designed to turn off resummation and match to fixed-order, not to capture correlations in the spectrum
 - X See e.g. inconsistent uncertainties from spectrum vs. cumulant scales

Power Expansion.

Define scaling variable $au\equiv p_T^2/m_V^2, \mathcal{T}_0/m_V,...$ and expand in powers of au

$$\begin{aligned} \frac{\mathrm{d}\sigma}{\mathrm{d}\tau} &= \delta(\tau) + \alpha_s \Big[\frac{\ln\tau}{\tau} + \frac{1}{\tau} + \frac{1}{\tau} + \delta(\tau) + f_1^{\mathrm{nons}}(\tau) \Big] \\ &+ \alpha_s^2 \Big[\frac{\ln^3\tau}{\tau} + \frac{\ln^2\tau}{\tau} + \frac{\ln\tau}{\tau} + \frac{1}{\tau} + \delta(\tau) + f_2^{\mathrm{nons}}(\tau) \Big] \\ &+ \vdots & \vdots & \vdots & \ddots + \dots \Big] \\ &= & \mathrm{d}\sigma^{(0)}/\mathrm{d}\tau + \mathcal{O}(\tau)/\tau \end{aligned}$$

• For small $au \ll 1$

- Logarithmic terms completely dominate perturbative series
- Their all-order structure is actually simpler and more universal, which allows their resummation
- Also holds the key for a rigorous treatment of theory correlations



Factorization and Resummation.

Leading-power spectrum factorizes into hard, collinear, and soft contributions, e.g. for p_T $\frac{d\sigma^{(0)}}{d\vec{p}_T} = \sigma_0 H(Q,\mu) \int d^2 \vec{k}_a \, d^2 \vec{k}_b \, d^2 \vec{k}_s$ $\times B_a(\vec{k}_a, Qe^Y, \mu, \nu) B_b(\vec{k}_b, Qe^{-Y}, \mu, \nu)$ $\times \frac{S(\vec{k}_s, \mu, \nu)}{\delta(\vec{p}_T - \vec{k}_a - \vec{k}_b - \vec{k}_s)}$

- Each function is a renormalized object with an associated RGE
 - Structure depends on type of variable but is universal for all hard processes
- \Rightarrow Dependence on p_T and Q is fully determined to all orders by a coupled system of differential equations
 - Their solution leads to resummed predictions
 - Each resummation order (only) requires as ingredients anomalous dimensions and boundary conditions entering the RG solution

Simplest Example: Multiplicative RGE.

All-order RGE and its solution

$$\mu rac{\mathrm{d} H(Q,\mu)}{\mathrm{d} \mu} = \gamma_H(Q,\mu) \, H(Q,\mu)$$

$$\Rightarrow \qquad H(Q,\mu) = H(Q) imes \exp \left[\int_Q^\mu rac{\mathrm{d}\mu'}{\mu'} \gamma_H(Q,\mu')
ight]$$

Necessary ingredients

Boundary condition

$$H(Q) = 1 + \alpha_s(Q) h_1 + \alpha_s^2(Q) h_2 + \cdots$$

Anomalous dimension

$$egin{aligned} \gamma_H(Q,\mu) &= lpha_s(\mu)ig[\Gamma_0+lpha_s(\mu)\,\Gamma_1+\cdotsig]\lnrac{Q}{\mu} \ &+ lpha_s(\mu)ig[\gamma_0+lpha_s(\mu)\,\gamma_1+\cdotsig] \end{aligned}$$

⇒ Resummation is determined by coefficients of three fixed-order series
 ▶ True regardless of how RGE is solved in more complicated cases

Perturbative series at leading power is determined to all orders by a coupled system of differential equations (RGEs)

- \rightarrow Each resummation order only depends on a few semi-universal parameters
- → Unknown parameters at higher orders are the actual sources of perturbative theory uncertainty

	boundary conditions			anomaious unitensions			
order	h_n	s_n	$\boldsymbol{b_n}$	γ^h_n	γ_n^s	Γ_n	eta_n
LL	h_0	s_0	b_0	_	_	Γ_0	β_0
NLL'	h_1	s_1	$\boldsymbol{b_1}$	γ_0^h	γ_0^s	Γ_1	$oldsymbol{eta_1}$
NNLL'	h_2	s_2	$\boldsymbol{b_2}$	γ_1^h	γ_1^s	Γ_2	$m{eta_2}$
N ³ LL′	h_3	S 3	b_3	γ^h_2	γ_2^s	Γ_3	β_3
N ⁴ LL′	h_4	s_4	b_4	γ^h_3	γ_3^s	Γ_4	eta_4

houndary conditional anomalous dimensiona

- Basic Idea: Treat them as theory nuisance parameters
 - ✓ Vary them independently to estimate the theory uncertainties
 - Impact of each independent nuisance parameter is fully correlated across all \checkmark kinematic regions and processes
 - Impact of different nuisance parameters is fully uncorrelated
- Price to Pay: Calculation becomes guite a bit more complex

Numerous Advantages.

Immediately get all benefits of parametric uncertainties

- ✓ Encode correct correlations
- ✓ Can be propagated straightforwardly
 - Including Monte Carlo, BDTs, neural networks, ...
- $\checkmark\,$ Can be consistently included in a fit and constrained by data
 - Even okay to use control measurements to reduce theory uncertainties
 - Due to central-limit theorem, total theory uncertainty becomes Gaussian

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Additional theory benefits compared to scale variations

- Uncertainties can be evaluated in one space and propagated to another (Fourier conjugate, cumulant, spectrum)
- Can do partial orders and fully exploit all known higher-order information
 - Can account for new structures appearing at higher order
- Fully factorizes the uncertainties
 - Can study perturbative convergence at level of individual building blocks
 - Much safer against accidental underestimates due to multiple parameters

How to Vary What.

- Level 1: At given order vary parameters around their known values $c_0 + \alpha_s(\mu) [c_1 + \alpha_s(\mu) c_2 + \cdots] \rightarrow c_0 + \alpha_s(\mu) (c_1 + \tilde{\theta}_1)$
 - Simpler but perhaps less robust
- Level 2: Implement the full next order in terms of unknown parameters $c_0 + \alpha_s(\mu)[c_1 + \alpha_s(\mu) c_2 + \cdots] \rightarrow c_0 + \alpha_s(\mu)[c_1 + \alpha_s(\mu) \theta_2]$
 - More involved, but also more robust, allowing for maximal precision
- In general, can have combination of both

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Note: Some parameters are actually functions of additional variables

- E.g. beam function constants, auxiliary dependences (jet radius, ...)
- In principle, one needs to parametrize an unknown function
 - Can e.g. expand/parametrize in terms of appropriate functional basis
 - Compared to scale variations, choices are now explicit and testable

$Z p_T$ Spectrum.

For illustration use

- Level 1: $ilde{ heta}_i = (0 \pm 0.25) imes c_i$
- Level 2: $\theta_i = (0 \pm 2) \times c_i$ (with the true values for c_i)

Relative impact of different nuisance parameters

• *h*₁

• b_1 : q o q, g o q

• s₁

Relative impact [%]

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- Γ₂
- $\gamma_1^{\boldsymbol{\nu}}$
- s₂

Relative impact [%]

W vs. Z.

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Drell-Yan at High Q vs. Z Pole.

Frank Tackmann (DESY)

Summary.

A theory prediction without an uncertainty is about as useful as a measurement without an uncertainty

• Uncertainties need to be reliable (small is not good enough ...)

Theory nuisance parameters overcome many problems of scale variations

- Allow to rigorously quantify pert. theory uncertainties and correlations
- Encode correct correlations
 - Between different p_T values, Q values, partonic channels, hard processes
 - Between different variables $(\vec{p}_T, p_T^{\text{jet}}, \mathcal{T}_0, \tau, C, ...),$
 - Multi-differential cases, cases with auxiliary measurements, ...
- Can be propagated straightforwardly
 - Including Monte Carlo, BDTs, neural networks, ...
 - Crucial for consistent treatment of theory uncertainties by experiments
- \Rightarrow A plethora of applications to explore ...