

Systematic Uncertainties: Principle and Practice

Outline

- 1. Introduction to Systematic Uncertainties**
- 2. Taxonomy and Case Studies**
- 3. Issues Around Systematics**
- 4. The Statistics of Systematics**
- 5. Summary**

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Introduction

- **Systematic uncertainties play key role in physics measurements**
 - Few formal definitions exist, much “oral tradition”
 - “Know” they are different from statistical uncertainties

Random Uncertainties

- Arise from stochastic fluctuations
- Uncorrelated with previous measurements
- Well-developed theory
- Examples
 - measurement resolution
 - finite statistics
 - random variations in system

Systematic Uncertainties

- Due to uncertainties in the apparatus or model
- Usually correlated with previous measurements
- Limited theoretical framework
- Examples
 - calibrations uncertainties
 - detector acceptance
 - poorly-known theoretical parameters

Literature Summary

■ Increasing literature on the topic of “systematics”

A representative list:

- R.D.Cousins & V.L. Highland, NIM **A320**, 331 (1992).
- C. Guinti, Phys. Rev. D **59** (1999), 113009.
- G. Feldman, “Multiple measurements and parameters in the unified approach,” presented at the FNAL workshop on Confidence Limits (Mar 2000).
- R. J. Barlow, “Systematic Errors, Fact and Fiction,” hep-ex/0207026 (Jun 2002), and several other presentations in the Durham conference.
- G. Zech, “Frequentist and Bayesian Confidence Limits,” Eur. Phys. J, **C4:12** (2002).
- R. J. Barlow, “Asymmetric Systematic Errors,” hep-ph/0306138 (June 2003).
- A. G. Kim et al., “Effects of Systematic Uncertainties on the Determination of Cosmological Parameters,” astro-ph/0304509 (April 2003).
- J. Conrad et al., “Including Systematic Uncertainties in Confidence Interval Construction for Poisson Statistics,” Phys. Rev. D **67** (2003), 012002
- G.C.Hill, “Comment on “Including Systematic Uncertainties in Confidence Interval Construction for Poisson Statistics”,” Phys. Rev. D **67** (2003), 118101.
- G. Punzi, “Including Systematic Uncertainties in Confidence Limits”, CDF Note in preparation.

I. Case Study #1: W Boson Cross Section

■ Rate of W boson production

– Count candidates $N_s + N_b$

– Estimate background N_b & signal efficiency ε

$$\sigma = (N_c - N_b) / (\varepsilon L)$$

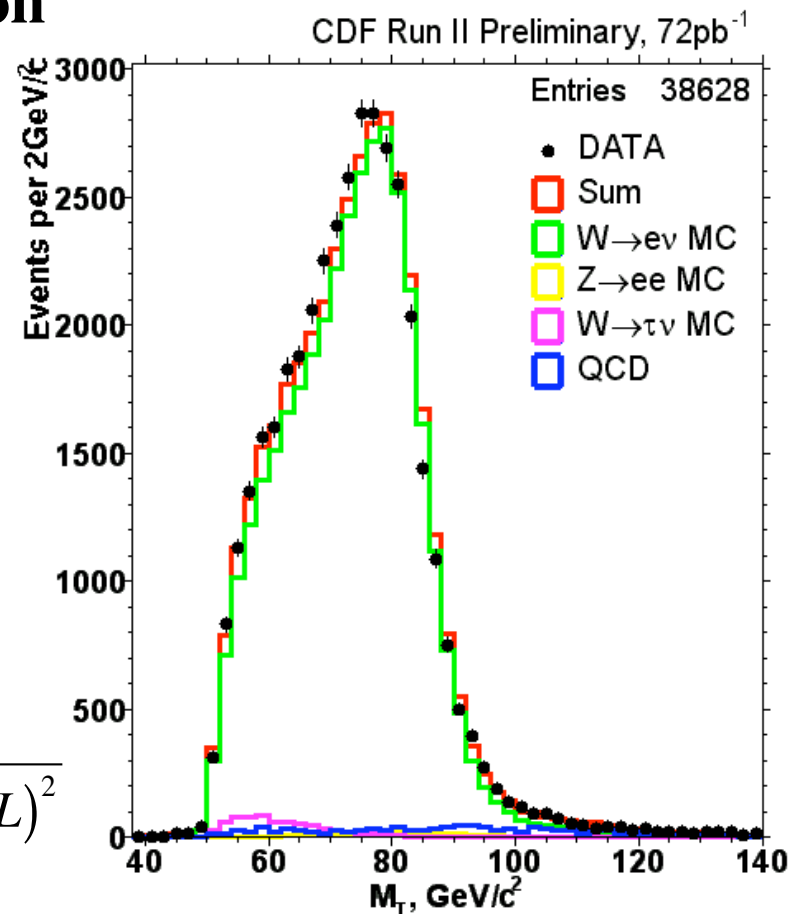
– Measurement reported as

$$\sigma = 2.64 \pm 0.01 \text{ (stat)} \\ \pm 0.18 \text{ (syst) nb}$$

– Uncertainties are

$$\sigma_{stat} \cong \sigma_0^{stat} \sqrt{1/N_c}$$

$$\sigma_{syst} \cong \sigma_0^{syst} \sqrt{(\delta N_b / N_b)^2 + (\delta \varepsilon / \varepsilon)^2 + (\delta L / L)^2}$$



Definitions are Relative

■ Efficiency uncertainty estimated using Z boson decays

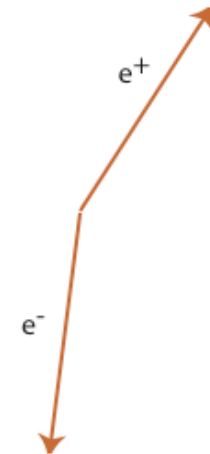
- Count up number of Z candidates N_Z^{cand}
 - > Can identify using charged tracks
 - > Count up number reconstructed N_Z^{recon}

$$\varepsilon = \frac{N_Z^{recon}}{N_Z^{cand}} \Rightarrow \delta\varepsilon \cong \sqrt{\frac{N_Z^{recon} (N_Z^{cand} - N_Z^{recon})}{N_Z^{cand}}}$$

– Redefine uncertainties

$$\sigma_{stat} \cong \sigma_0 \sqrt{1/N_c + (\delta\varepsilon/\varepsilon)^2}$$

$$\sigma_{syst} \cong \sigma_0 \sqrt{(\delta N_b / N_b)^2 + (\delta L / L)^2}$$



Lessons:

- Some systematic uncertainties are really “random”
- Good to know this
 - Uncorrelated
 - Know how they scale
- May wish to redefine
- Call these
“CLASS 1” Systematics

Top Mass Good Example

■ Top mass uncertainty in template analysis

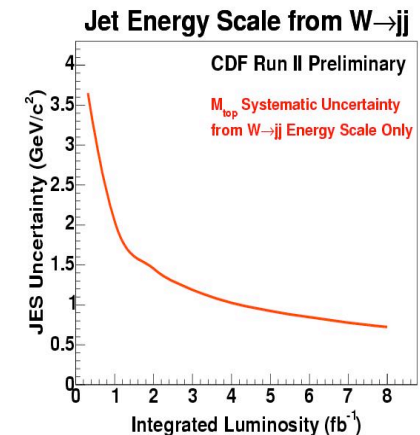
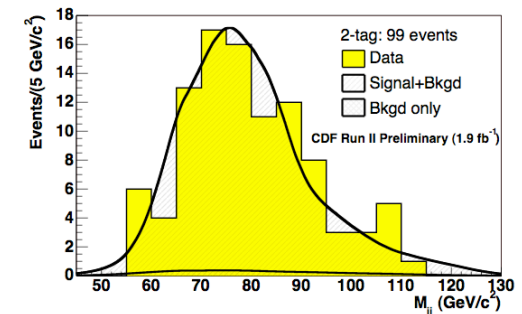
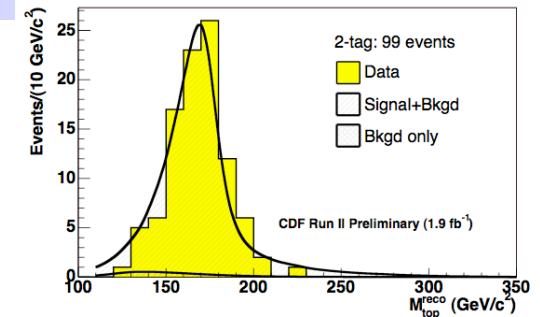
- Statistical uncertainty from shape of reconstructed mass distribution and statistics of sample
- Systematic uncertainty coming from jet energy scale (JES)
 - > Determined by calibration studies, dominated by modelling uncertainties
 - > 5% systematic uncertainty

■ Latest techniques determine JES uncertainty from dijet mass peak ($W \rightarrow jj$)

- Turn JES uncertainty into a largely statistical one
- Introduce other smaller systematics

$$M_{top} = 171.8 \pm 1.9(\text{stat} + \text{JES}) \pm 1.0 (\text{syst}) \text{ GeV}/c^2$$

$$= 171.9 \pm 2.1 \text{ GeV}/c^2$$



Case Study #2: Background Uncertainty

■ Look at same W cross section analysis

- Estimate of N_b dominated by QCD backgrounds

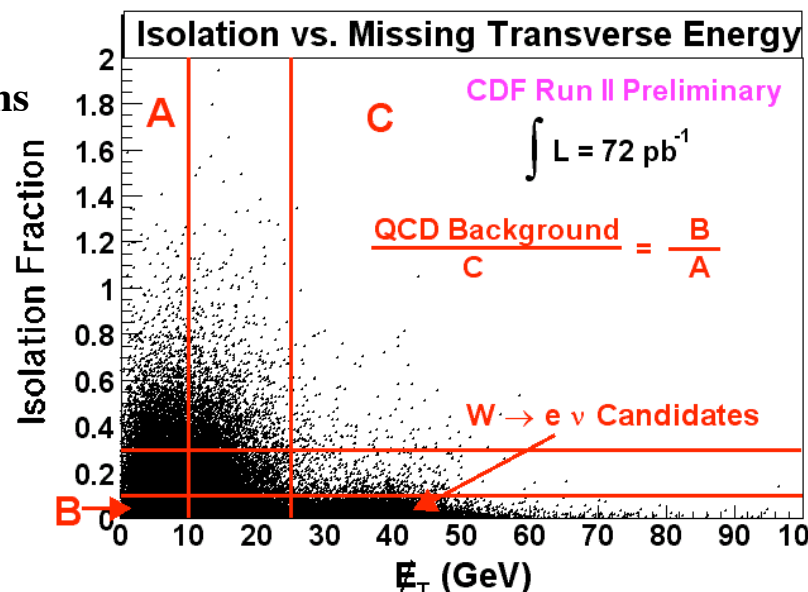
- > Candidate event

- Have non-isolated leptons
 - Less missing energy

- > Assume that isolation and MET uncorrelated

- > Have to estimate the uncertainty on N_b^{QCD}

- No direct measurement has been made to verify the model
- Estimates using Monte Carlo modelling have large uncertainties



Estimation of Uncertainty

- **Fundamentally different class of uncertainty**
 - Assumed a model for data interpretation
 - Uncertainty in N_b^{QCD} depends on accuracy of model
 - Use “informed judgment” to place bounds on one’s ignorance
 - > Vary the model assumption to estimate robustness
 - > Compare with other methods of estimation
- **Difficult to quantify in consistent manner**
 - Largest possible variation?
 - > Asymmetric?
 - Estimate a “1 σ ” interval?
 - Take $\sigma \approx \frac{\Delta}{\sqrt{12}}$?

Lessons:

- Some systematic uncertainties reflect ignorance of one’s data
- Cannot be constrained by observations
- Call these
“CLASS 2” Systematics

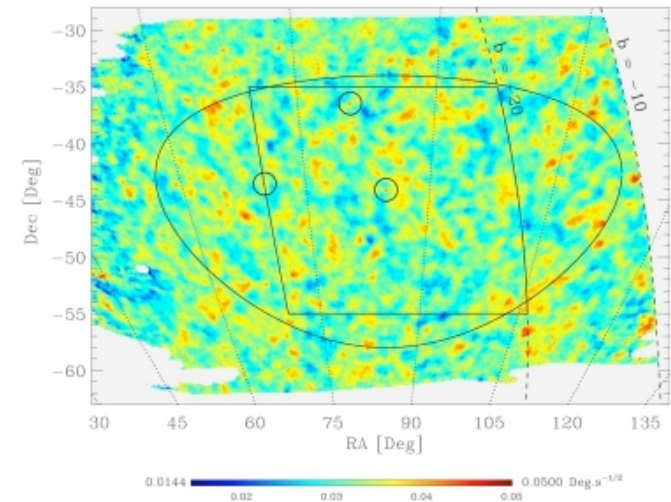
Case Study #3: Boomerang CMB Analysis

- **Boomerang is one of several CMB probes**

- Mapped CMB anisotropy
- Data constrain models of the early universe

- **Analysis chain:**

- **Produce a power spectrum for the CMB spatial anisotropy**
 - > Remove instrumental effects through a complex signal processing algorithm
- **Interpret data in context of many models with unknown parameters**



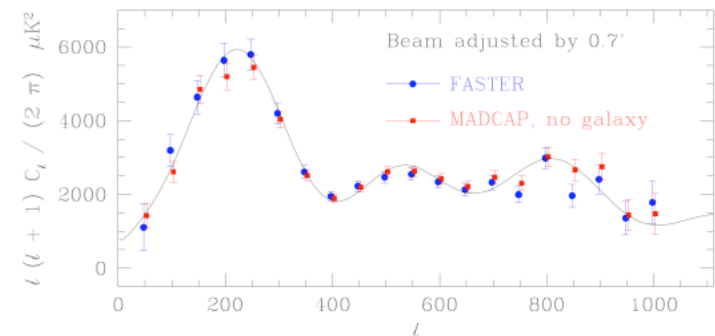
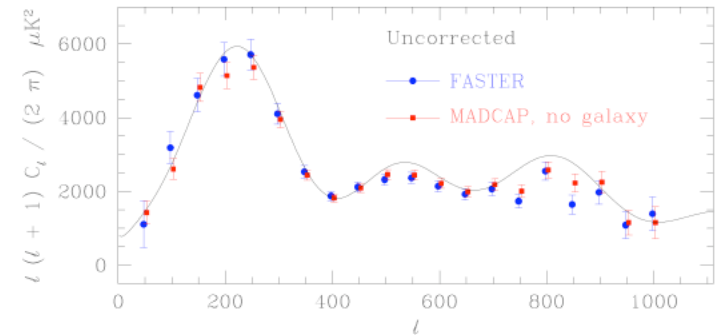
Incorporation of Model Uncertainties

■ Power spectrum extraction includes all instrumental effects

- Effective size of beam
- Variations in data-taking procedures

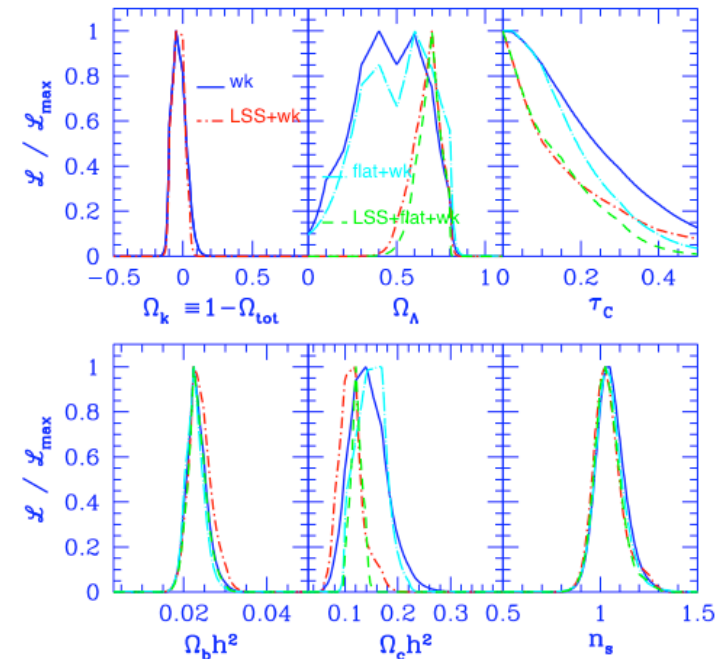
■ Use these data to extract 7 cosmological parameters

- Take Bayesian approach
 - > Family of theoretical models defined by 7 parameters
 - > Define a 6-D grid (6.4M points), and calculate likelihood function for each



Marginalize Posterior Probabilities

- Perform a Bayesian “averaging” over a grid of parameter values
 - Marginalize w.r.t. the other parameters
 - > NB: instrumental uncertainties included in approximate manner
 - Chose various priors in the parameters
- Comments:
 - Purely Bayesian analysis with no frequentist analogue
 - Provides path for inclusion of additional data (eg. WMAP)



Lessons:

- Some systematic uncertainties reflect paradigm uncertainties
- No relevant concept of a frequentist ensemble
- Call these “CLASS 3” Systematics

Proposed Taxonomy for Systematic Uncertainties

- **Three “classes” of systematic uncertainties**
 - Uncertainties that can be constrained by ancillary measurements
 - Uncertainties arising from model assumptions or problems with the data that are poorly understood
 - Uncertainties in the underlying models
- **Estimation of Class 1 uncertainties straightforward**
 - Class 2 and 3 uncertainties present unique challenges
 - In many cases, have nothing to do with statistical uncertainties
 - > Driven by our desire to make inferences from the data using specific models

II. Estimation Techniques

- **No formal guidance on how to define a systematic uncertainty**
 - Can identify a possible source of uncertainty
 - Many different approaches to estimate their magnitude
 - > Determine maximum effect Δ
- **General rule:**
 - Maintain consistency with definition of statistical intervals
 - Field is pretty glued to 68% confidence intervals
 - Recommend attempting to reflect that in magnitudes of systematic uncertainties
 - Avoid tendency to be “conservative”

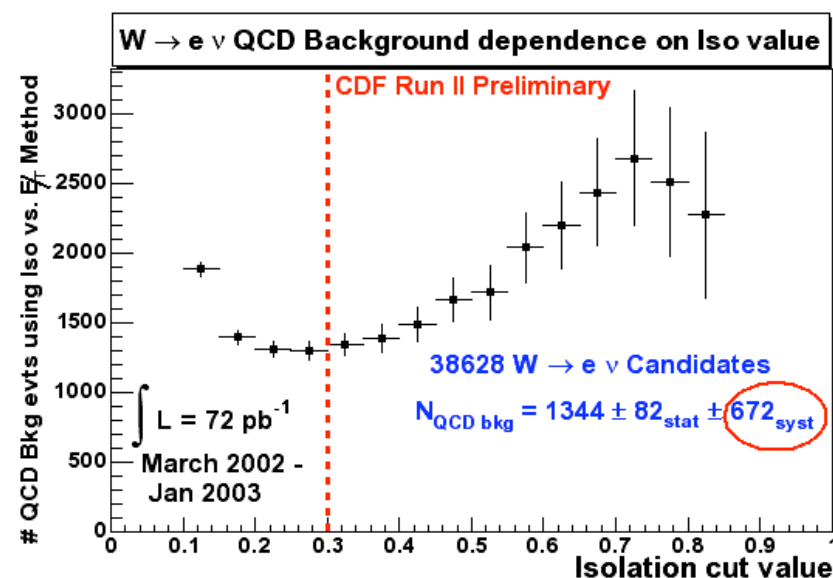
$$\sigma = \frac{\Delta}{2}?$$

$$\sigma = \frac{\Delta}{\sqrt{12}}?$$

Estimate of Background Uncertainty in Case Study #2

■ Look at correlation of Isolation and MET

- Background estimate increases as isolation “cut” is raised
- Difficult to measure or accurately model
 - > Background comes primarily from very rare jet events with unusual properties
 - > Very model-dependent



■ Assume a systematic uncertainty representing the observed variation

- Authors argue this is a “conservative” choice

Cross-Checks Vs Systematics

- **R. Barlow makes the point in Durham(PhysStat02)**
 - A cross-check for robustness is not an invitation to introduce a systematic uncertainty
 - > Most cross-checks confirm that interval or limit is robust,
 - They are usually not designed to measure a systematic uncertainty
- **More generally, a systematic uncertainty should**
 - Be based on a hypothesis or model with clearly stated assumptions
 - Be estimated using a well-defined methodology
 - Be introduced *a posteriori* only when all else has failed

III. Statistics of Systematic Uncertainties

- **Goal has been to incorporate systematic uncertainties into measurements in coherent manner**
 - **Increasing awareness of need for consistent practice**
 - > Frequentists: interval estimation increasingly sophisticated
 - Neyman construction, ordering strategies, coverage properties
 - > Bayesians: understanding of priors and use of posteriors
 - Objective vs subjective approaches, marginalization/conditioning
 - **Systematic uncertainties threaten to dominate as precision and sensitivity of experiments increase**
- **There are a number of approaches widely used**
 - Summarize and give a few examples
 - Place it in context of traditional statistical concepts

Formal Statement of the Problem

- **Have a set of observations $x_i, i=1, n$**
 - **Associated probability distribution function (pdf) and likelihood function**

$$p(x_i | \theta) \Rightarrow \mathcal{L}(\theta) = \prod_i p(x_i | \theta)$$

- > Depends on unknown random parameter θ
- > Have some additional uncertainty in pdf
 - **Introduce a second unknown parameter λ**

$$\mathcal{L}(\theta, \lambda) = \prod_i p(x_i | \theta, \lambda)$$

- **In some cases, one can identify statistic y_j that provides information about λ**

$$\mathcal{L}(\theta, \lambda) = \prod_{i,j} p(x_i, y_j | \theta, \lambda)$$

- **Can treat λ as a “nuisance parameter”**

Bayesian Approach

- **Identify a prior $\pi(\lambda)$ for the “nuisance parameter” λ**
 - Typically, parametrize as either a Gaussian pdf or a flat distribution within a range (“tophat”)
 - Can then define Bayesian posterior
$$\mathcal{L}(\theta, \lambda) \pi(\lambda) d\theta d\lambda$$
 - Can marginalize over possible values of λ
 - > Use marginalized posterior to set Bayesian credibility intervals, estimate parameters, etc.
- **Theoretically straightforward**
 - Issues come down to choice of priors for both θ, λ
 - > No widely-adopted single choice
 - > Results have to be reported and compared carefully to ensure consistent treatment

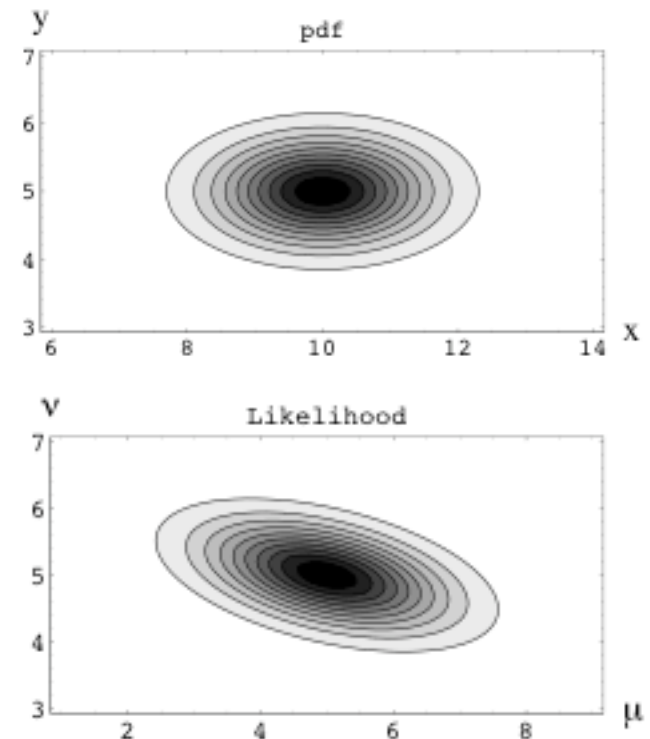
Frequentist Approach

- **Start with a pdf for data** $p(x_i, y_j | \theta, \lambda)$
 - In principle, this would describe frequency distributions of data in multi-dimensional space
 - Challenge is take account of nuisance parameter
 - Consider a toy model

$$p(x, y | \mu, \nu) = G(x - (\mu + \nu), 1)G(y - \nu, s)$$

> Parameter s is Gaussian width for ν

- **Likelihood function ($x=10, y=5$)**
 - Shows the correlation
 - Effect of unknown ν



Formal Methods to Eliminate Nuisance Parameters

- **Number of formal methods exist to eliminate nuisance parameters**
 - **Of limited applicability given the restrictions**
 - **Our “toy example” is one such case**

> Replace x with $t=x-y$ and parameter v with

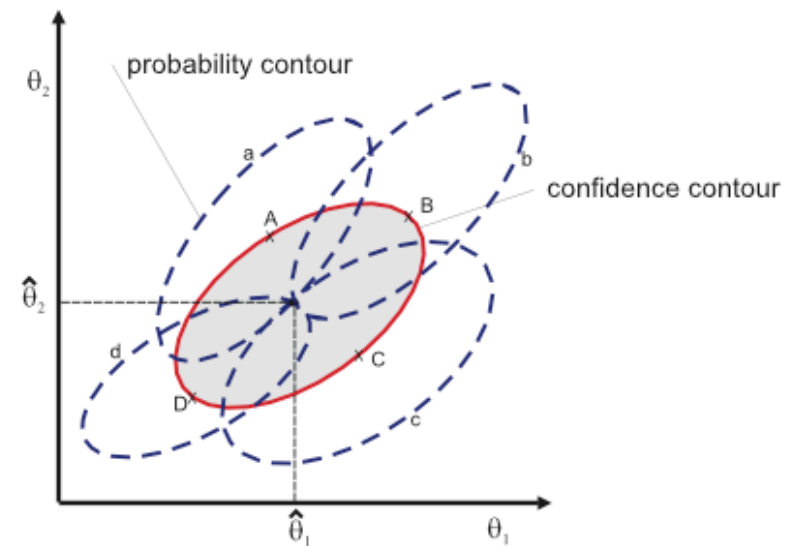
$$v' \equiv v + \frac{\mu s^2}{1 + s^2}$$

$$\Rightarrow p(t, y | \mu, v') = G\left(t - \mu, \sqrt{1 + s^2}\right) G\left(y - v' + \frac{ts^2}{1 + s^2}, \frac{s}{\sqrt{1 + s^2}}\right)$$

- > Factorized pdf and can now integrate over v'
- > Note that pdf for μ has larger width, as expected
- **In practice, one often loses information using this technique**

Alternative Techniques for Treating Nuisance Parameters

- **Project Neyman volumes onto parameter of interest**
 - “Conservative interval”
 - Typically over-covers, possibly badly
- **Choose best estimate of nuisance parameter**
 - Known as “profile method”
 - Coverage properties require definition of ensemble
 - Can possible under-cover when parameters strongly correlated
 - > Feldman-Cousins intervals tend to over-cover slightly (private communication)



From G. Zech

Example: Solar Neutrino Global Analysis

- **Many experiments have measured solar neutrino flux**
 - Gallex, SuperKamiokande, SNO, Homestake, SAGE, etc.
 - Standard Solar Model (SSM) describes ν spectrum
 - Numerous “global analyses” that synthesize these
- **Fogli et al. have detailed one such analysis**
 - 81 observables from these experiments
 - Characterize systematic uncertainties through 31 parameters
 - > 12 describing SSM spectrum
 - > 11 (SK) and 7 (SNO) systematic uncertainties
- **Perform a χ^2 analysis**
 - Look at χ^2 to set limits on parameters

Hep-ph/0206162, 18 Jun 2002

Formulation of χ^2

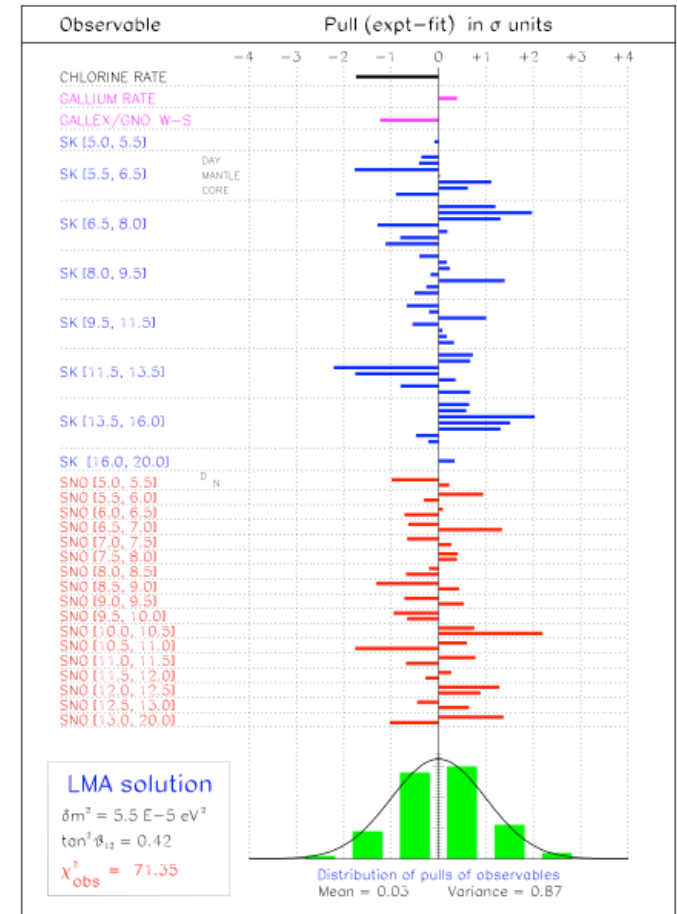
- In formulating χ^2 , linearize effects of the systematic uncertainties on data and theory comparison

$$\chi_{pull}^2 \equiv \min_{\{\xi\}} \left[\sum_{n=1}^N \left(\frac{R_n^{\text{expt}} - R_n^{\text{theor}} - \sum (c_n^k \xi_k)}{u_n} \right)^2 + \sum_{k=1}^K \xi_k^2 \right]$$

- > Uncertainties u_n for each observable
- Introduce “random” pull ξ_k for each systematic
 - > Coefficients c_k^n to parameterize effect on n th observable
 - > Minimize χ^2 with respect to ξ_k
 - > Look at contours of equal $\Delta \chi^2$

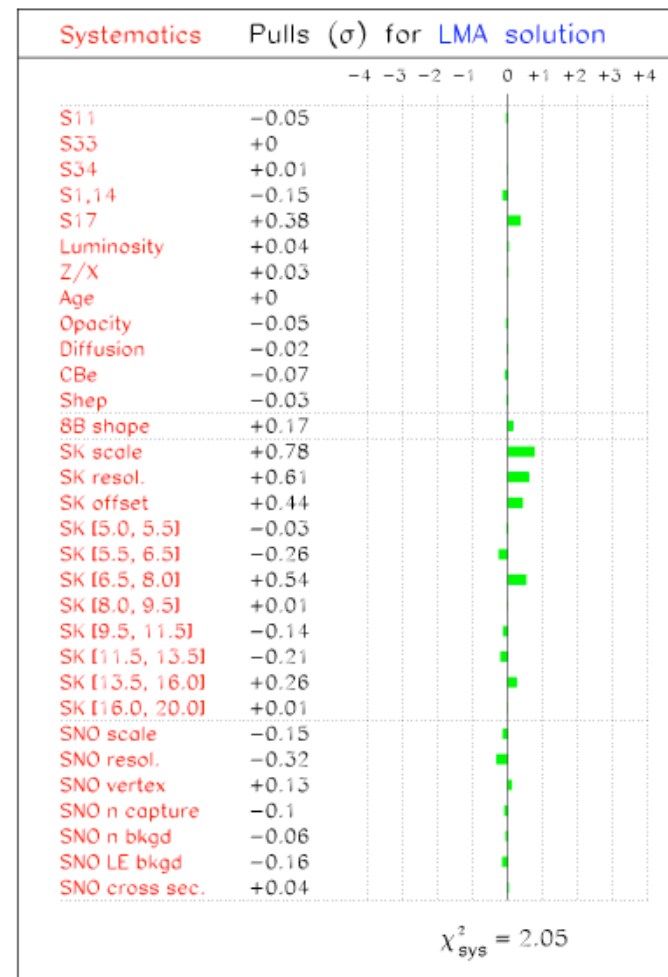
Solar Neutrino Results

- Can look at “pulls” at χ^2 minimum
 - Have reasonable distribution
 - Demonstrates consistency of model with the various measurements
 - Can also separate
 - > Agreement with experiments
 - > Agreement with systematic uncertainties



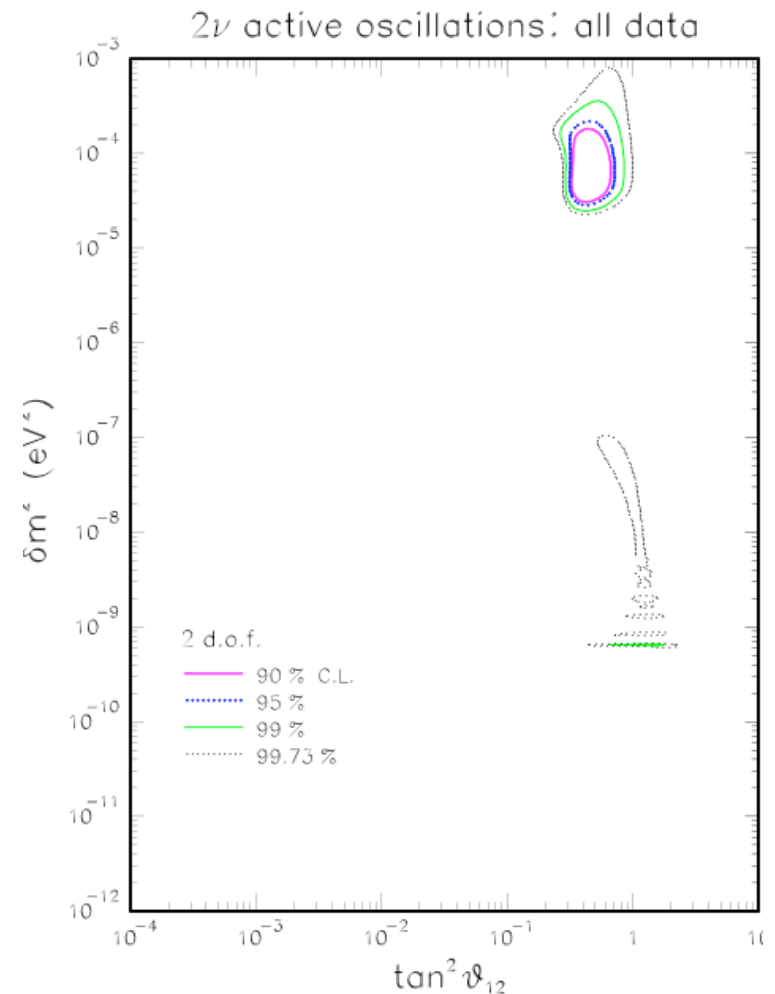
Pull Distributions for Systematics

- Pull distributions for ξ_k also informative
 - Unreasonably small variations
 - Estimates are globally too conservative?
 - Choice of central values affected by data
 - > Note this is NOT a blind analysis
- But it gives us some confidence that intervals are realistic



Typical Solar Neutrino Contours

- **Can look at probability contours**
 - Assume standard χ^2 form
 - Probably very small probability contours have relatively large uncertainties



Hybrid Techniques

- **A popular technique (Cousins-Highland) does an “averaging” of the pdf**

- Assume a pdf for nuisance parameter $g(\lambda)$
- “Average” the pdf for data x

$$p_{\text{CH}}(x|\theta) \equiv \int p(x|\theta, \lambda) g(\lambda) d\lambda$$

- **Argue this approximates an ensemble where**
 - > Each measurement uses an apparatus that differs in parameter λ
 - The pdf $g(\lambda)$ describes the frequency distribution
 - > Resulting distribution for x reflects variations in λ

- **Intuitively appealing**

See, for example, J. Conrad et al.

- But fundamentally a Bayesian approach
- Coverage is not well-defined

Summary

- **HEP & Astrophysics becoming increasingly “systematic” about systematics**
 - **Recommend classification to facilitate understanding**
 - > Creates more consistent framework for definitions
 - > Better indicates where to improve experiments
 - **Avoid some of the common analysis mistakes**
 - > Make consistent estimation of uncertainties
 - > Don’t confuse cross-checks with systematic uncertainties
- **Systematics naturally treated in Bayesian framework**
 - Choice of priors still somewhat challenging
- **Frequentist treatments are less well-understood**
 - Challenge to avoid loss of information
 - Approximate methods exist, but probably leave the “true frequentist” unsatisfied