

A study of systematic uncertainties within the MSHT PDF Framework

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Objectives

- Introduce a Model that can incorporate Error on Errors
- Examining how this model behaves for both uncorrelated and correlated systematic errors
- Investigate what this model tells us about 2 Data Sets - ATLAS W,Z Data and ATLAS 7 TeV Inclusive Jet Distributions
- A brief investigation into de-correlation

Introduction

- Experimental data is becoming increasingly precise
- Experimental Errors are now dominated by systematic uncertainties
- Significant Errors on these systematic uncertainties
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- Significant Errors on these systematic uncertainties
- So we need to include these "errors on errors" to correctly determine the errors in PDF fits
- We need to depart from the simple Gaussian treatment of errors if we want to include these "Error on Errors"

Including Error on Errors 1¹

Gaussian

- Consider a set of data, \mathbf{y} . The probability of \mathbf{y} can be written $P(\mathbf{y}|\mu, \theta)$, where μ are parameters of interest and θ are nuisance parameters that are required for the correctness of the model.

¹Cowan arXiv:1809.05778v3

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- Let $\theta = (\theta_1, \dots, \theta_N)$ be independent Gaussian distributed values $u = (u_1, \dots, u_N)$, with standard deviations $\sigma_u = (\sigma_{u_1}, \dots, \sigma_{u_N})$:

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$$\begin{aligned} L(\mu, \theta) &= P(\mathbf{y}, \mathbf{u}|\mu, \theta) = P(\mathbf{y}|\mu, \theta)P(\mathbf{u}|\theta) \\ &= P(\mathbf{y}|\mu, \theta) \prod_{i=1}^N \frac{1}{\sqrt{2\pi}\sigma_{u_i}} e^{-(u_i - \theta_i)^2 / 2\sigma_{u_i}^2} \end{aligned} \quad (1)$$

¹Cowan arXiv:1809.05778v3

Including Error on Errors 2²

Gaussian plus Gamma

- Model the estimated variances, v_i , of $\sigma_{u_i}^2$, as Gamma distributed gives:

$$L(\mu, \theta, \sigma_{u_i}^2) = P(y|\mu, \theta) \prod_{i=1}^N \frac{1}{\sqrt{2\pi}\sigma_{u_i}} e^{-(u_i - \theta_i)^2 / 2\sigma_{u_i}^2} \frac{\beta_i^{\alpha_i}}{\Gamma(\alpha_i)} v_i^{\alpha_i - 1} e^{-\beta_i v_i}$$

$$\alpha_i = \frac{1}{4r_i^2} \quad \beta_i = \frac{1}{4r_i^2 \sigma_{u_i}^2}$$

- r_i is defined as the relative uncertainty in the estimate of the systematic error. The parameters r_i can therefore be referred to as the "error on errors".

²Cowan arXiv:1809.05778v3

Including Error on Errors 3

Gaussian plus Gamma = t-distribution

- This model can be identically reinterpreted as a Student's t-distribution

$$L(\mu, \theta, \sigma_{u_i}^2) = P(y|\mu, \theta) \prod_{i=1}^N \frac{\Gamma(\frac{\nu_i+1}{2})}{\sqrt{\nu_i\pi}\Gamma(\nu_i/2)} \left(1 + \frac{t_i^2}{\nu_i}\right)^{-\frac{\nu_i+1}{2}} \quad (2)$$

where $t_i = \frac{u_i - \theta_i}{\sqrt{\nu_i}}$ and $\nu_i = \frac{1}{2r_i^2}$.

- So we can treat our nuisance parameters as t-distributed!

- Consider the case:

$$y_i = d_i + \text{errors} = d_i + \sigma_i z_i + \sigma_{u_i} t_{u_i} + \sum_{j=1}^M \beta_{ij} t'_j \quad (3)$$

where for each observable y_i we have

- One statistical error σ_i , with a z_i that is a Normally distributed fluctuating variable.
- One uncorrelated systematic error σ_{u_i} with a t_{u_i} that is a t-distributed fluctuating variable with dof of $\nu = 1/2r_{\chi^2}^2$
- M correlated systematic errors, β_{ij} , each with a fluctuation t'_j that are t-distributed with dof of $\nu = 1/2r_{\chi^2}^2$. These fluctuations are the same for all i.

Treating our z_i , t_{u_i} and t' as independent

- The likelihood function can be written up to some constants as:

$$L \propto \prod_{i=1}^N \exp \left[-\frac{1}{2} \frac{(y_i - d_i - t_{u_i} \sigma_{u_i} - \sum_{j=1}^M \beta_{ij} t'_j)^2}{\sigma_i^2} \right] \left(1 + \frac{t_{u_i}^2}{\nu} \right)^{-\frac{\nu+1}{2}} \\ \times \prod_{j=1}^M \left(1 + \frac{t_j'^2}{\nu} \right)^{-\frac{\nu+1}{2}} \quad (4)$$

- Naturally leading to the Loglikelihood equation:

$$\chi^2 \equiv -2 \text{Ln} L = \sum_{i=1}^N \left(\frac{m_i - d_i - \sigma_{u_i} t_{u_i} - \sum_j \beta_{ij} t'_j}{\sigma_i} \right)^2 \\ + (\nu + 1) \sum_{i=1}^N \text{Ln} \left(1 + \frac{t_{u_i}^2}{\nu} \right) + (\nu + 1) \sum_{j=1}^M \text{Ln} \left(1 + \frac{t_j'^2}{\nu} \right) \quad (5)$$

Treating our z_i , t_{u_i} and t' as independent (Cont.)

- If we minimize with respect to t_{u_i} we obtain:

$$t_{u_i}^3 \frac{\sigma_{u_i}^2}{\sigma_i^2} \frac{1}{\nu} - \frac{t_{u_i}^2}{\nu} (y_i - d_i - \sum_j \beta_j t'_j) \frac{\sigma_{u_i}}{\sigma_i^2} + t_{u_i} \left(\frac{\sigma_{u_i}^2}{\sigma_i^2} + \frac{\nu + 1}{\nu} \right) - \frac{(y_i - d_i - \sum_j \beta_j t'_j) \sigma_{u_i}}{\sigma_i^2} = 0$$

- Minimizing with respect to t'_j yields

$$\sum_{i=1}^N \frac{\beta_{ij}^2}{\nu \sigma_i^2} (t'_j)^3 + \frac{D}{\nu} (t'_j)^2 + \left(\left(\sum_{i=1}^N \frac{\beta_{ij}^2}{\sigma_i^2} \right) + \frac{\nu + 1}{\nu} \right) t'_j + D = 0$$

$$D = - \sum_{i=1}^N \frac{(y_i - d_i - \sigma_{u_i} t_{u_i} - \sum_{j \neq j'} \beta_{ij} t'_j) \beta_{ij'}}{\sigma_i^2}$$

- Solved Simultaneously. t_{u_i} solved analytically, t'_j has to be fitted.

Behaviour as $r \rightarrow 0$

- As $r \rightarrow 0$, $v \rightarrow \infty$:

$$-2LnL = \sum_{i=1}^N \left(\frac{y_i - d_i - \sigma_{u_i} t_{u_i} - \sum_j \beta_{ij} t'_j}{\sigma_i} \right)^2 + \sum_{i=1}^N t_{u_i}^2 + \sum_j^M t'^2_{j=1} \quad (6)$$

- Taking derivatives with respect to t_{u_i} and setting to zero gives:

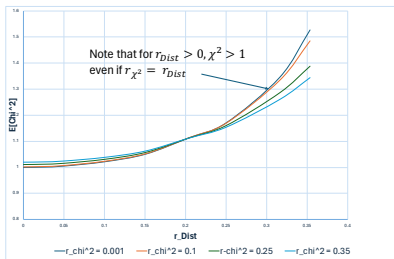
$$\frac{\partial(-2LnL)}{\partial t_{u_i}} = 0 \implies t_{u_i} = \frac{\sigma_{u_i} (y_i - d_i - \sum_j \beta_{ij} t'_j)}{\sigma_i^2 + \sigma_{u_i}^2} \quad (7)$$

- Substituting equation (7) into (6) gives our expected Gaussian formulation:

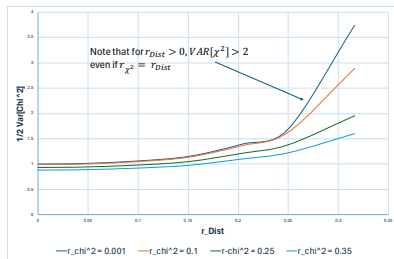
$$-2LnL = \sum_{i=1}^N \frac{(y_i - d_i - \sum_j \beta_{ij} t'_j)^2}{\sigma_i^2 + \sigma_{u_i}^2} + \sum_{j=1}^M t'^2 \quad (8)$$

Expectation and Variance of χ^2 as a Function of r

- Let's consider the case: $y_i = d_i + \sigma_i z_i + \sigma_{u_i} t_{u_i}$,
with $z_i \sim N(0, 1)$, $t_{u_i} \sim t(0, \nu = 1/2r_{Dist}^2)$.
i.e. focus on the uncorrelated systematic behaviour ($\beta_{ij} = 0$).



Graph of $E[\chi^2]$ as a Function of r_{Dist}
for 4 different r_{χ^2} ($\sigma_i = \sigma_{u_i} = 1$)



Graph of $Var[\chi^2]$ as a Function of r_{Dist}
for 4 different r_{χ^2} ($\sigma_i = \sigma_{u_i} = 1$)

Standard Deviation of the Simple Mean as a Function of r

- Consider the case: $y_i = d_i + \sigma_i z_i + \sigma_{u_i} t_{u_i}$,
with $z_i \sim N(0, 1)$, $t_{u_i} \sim t(0, \nu = 1/2r_{Dist}^2)$. Also let $E[d_i] = d$
- The standard deviation of the simple mean, $y_{mean} = \sum_{i=1}^N y_i / N$, is:

$$\sigma_{Mean} \approx \frac{\sqrt{\sum_{i=1}^N \sigma_i^2 + \sigma_{u_i}^2 \nu / (\nu - 2)}}{N} = \frac{\sqrt{\sum_{i=1}^N E[\chi_i^2(r_{\chi^2} \rightarrow 0)](\sigma_i^2 + \sigma_{u_i}^2)}}{N}$$

- Table showing σ_{mean} as a function of r and N (with $\sigma_i = \sigma_{u_i} = 1$)

r_{Dist}	N=2	N=3	N=5	N=10	N=100	N=500	$\frac{\sigma_{r_{Dist}}}{\sigma(r_{Dist}=0.001)}$ N = 500
0.001	0.995	0.819	0.630	0.449	0.142	0.064	1.000
0.100	0.991	0.814	0.641	0.452	0.143	0.064	1.005
0.250	1.092	0.884	0.679	0.481	0.152	0.069	1.077
0.300	1.122	0.926	0.705	0.504	0.161	0.071	1.108
0.408	1.417	1.148	0.901	0.637	0.197	0.089	1.393

- This table gives the standard deviation for the fitted mean if $r_{\chi^2} = 0.0001$

Standard Deviation of the Fitted Mean as a Function of r

- What happens if we minimize the χ^2 , calculated with $r_{\chi^2} = r_{Dist}$, with respect to our mean?
- Table showing σ_{FIT} as a function of r and N (with $\sigma_i = \sigma_{u_i} = 1$)

r	N=2	N=3	N=5	N=10	N=100	N=500	$\frac{\sigma_{FIT}}{\sigma_{r_{Dist} = r_{\chi^2} = 0.001}}$ N=500
0.001	0.995	0.819	0.630	0.449	0.142	0.064	1.000
0.100	0.991	0.814	0.641	0.452	0.143	0.064	1.004
0.250	1.092	0.883	0.675	0.479	0.150	0.068	1.069
0.300	1.122	0.916	0.697	0.493	0.157	0.069	1.087
0.408	1.417	1.162	0.809	0.547	0.169	0.076	1.186

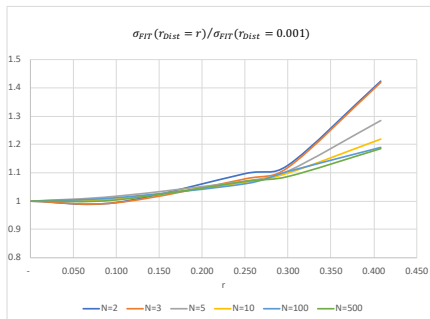
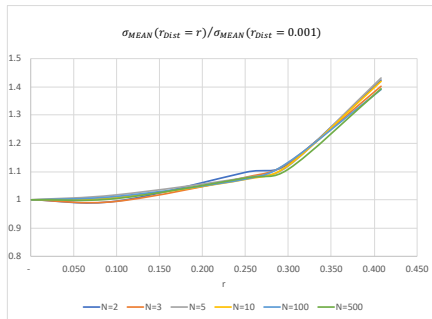
Data obtained using MC

- For Gaussian statistical errors and t-distributed uncorrelated systematic errors:

$$\sigma_{FIT} = \sqrt{\sum_{i=1}^N E[\chi_i^2(r_{\chi^2} = r_{Dist})] (\sigma_i^2 + \sigma_{u_i}^2)} / N$$

Standard Deviation of the Mean Fitted Mean

- Graph on left shows ratio of $\frac{\sigma_{Mean}}{\sigma_{Mean}(r_{Dist}=0.001)}$ as a function of r and N .
- Graph on right shows ratio of $\frac{\sigma_{Fit}(r_{Dist}=r_{\chi^2=r})}{\sigma_{Fit}(r_{Dist}=r_{\chi^2=0.001})}$ as a function of r and N .



Expectation and Variance of χ^2 as a Function of r

- Consider the case of N observables each with a Gaussian statistical and M t-distributed correlated systematic errors :

$$y_i = d_i + \sigma_i z_i + \sum_{j=1}^M \beta_{ij} t_j' \quad z_i \sim N(0, 1), t_j' \sim t(0, \nu = 1/2r_{Dist}^2)$$

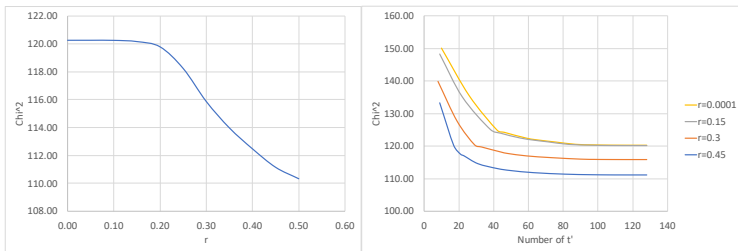
- In the case where $r_{Dist} = r_{\chi^2}$, and $\sigma_i = \beta_{ij} = 1$:

N	M	r	ν	$E[\chi^2(d_i)]$	σ_{χ^2}	$\sigma_{FIT}^{r_{\chi^2}=0.001}$	$\sigma_{\varphi FIT}$	$\sigma_{\varphi FIT} / \sigma_{\varphi MEAN}$	$\frac{\sigma_{\varphi FIT}}{\sigma_{\varphi FIT}(r_{Dist}=r_{\chi^2}=0.001)}$
2	2	0.001	500000	1.99949	2.05734	1.58114	1.58114	1.000	1.000
2	2	0.25	8	2.28779	2.31064	1.78103	1.78970	1.005	1.132
2	2	0.40824829	3	2.87634	2.98990	2.51644	2.32738	0.925	1.472
5	5	0.001	500000	4.99873	3.20452	2.28036	2.28036	1.000	1.000
5	5	0.25	8	5.42717	3.44951	2.62217	2.62208	1.000	1.150
5	5	0.40824829	3	6.53625	4.49232	3.81179	3.51314	0.922	1.541
10	5	0.001	500000	9.99746	4.58094	2.25832	2.25833	1.000	1.000
10	5	0.25	8	10.47021	4.68864	2.64291	2.63296	0.996	1.166
10	5	0.40824829	3	11.61824	5.53776	4.08220	3.48161	0.853	1.542
10	10	0.001	500000	9.99746	4.53088	3.17806	3.17806	1.000	1.000
10	10	0.25	8	10.37782	4.69332	3.67337	3.64109	0.991	1.146
10	10	0.40824829	3	11.91221	5.81006	5.40928	4.72917	0.874	1.488

where $E[\chi^2(d_j)]$ means that $E[\chi^2]$ calculated with a mean equal to d_j

ATLAS W,Z Data analysis³

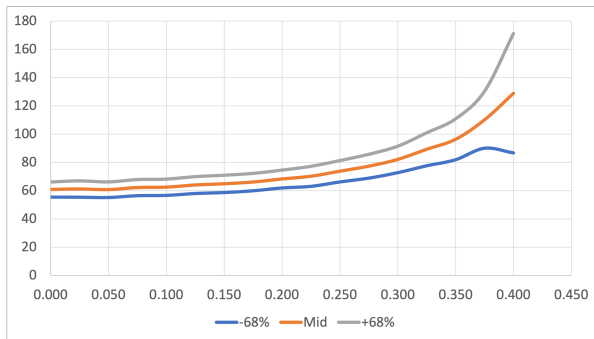
This very precise data gives strong constraint on the strange quark.
 However fit is poor $\chi^2/N_{pt} \sim 1.9$ for MSHT20 (NNLO). $N_{pt} = 61$



- Graph on the left shows the χ^2 as a function of relative error, r .
- Graph on the right shows how χ^2 is impacted by only considering the N largest t' for different relative errors: $r = 0.0001$, $r = 0.15$, $r = 0.3$, $r = 0.45$

³<https://www.hepdata.net/record/ins1502620> Tables 9 - 15

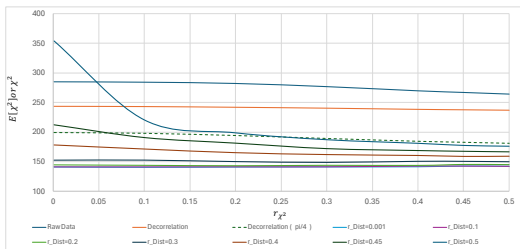
ATLAS W,Z Data analysis



- Graph shows the χ^2 calculated using $r = 0.001$ as a function of relative error, r_{Dist} of the simulated underlying systematic errors.
- Included is both the Expectation and the standard deviation
- For a χ^2 of 120 $r \approx 0.4$

ATLAS 7 TeV Inclusive Jet Distributions Analysis

- This ATLAS data⁴, combined with availability of NNLO corrections provides constraints on the Gluon PDF at high x.
- Graph shows the χ^2 or $E[\chi^2]$ as a function of relative error, r_{χ^2} .
 - Raw data refers to just the raw data provided by ATLAS. 140 Data points.
 - Difficult to fit all rapidity bins simultaneously. De-correlation refers to χ^2 calculated with small number (3) of the "two point" systematic uncertainties de-correlated⁵
 - Other lines show the $E[\chi^2]$ using pseudo data produced using $r_{Dist} = 0.0001, 0.1, 0.2, 0.3, 0.4, 0.45, 0.5$.

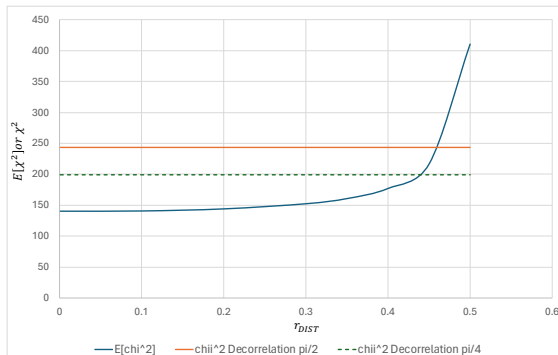


⁴ <https://www.hepdata.net/record/ins1325553> - tables 7-12 for "R=0.6"

⁵ MSHT20 arXiv:2012.04684

ATLAS 7 TeV Inclusive Jet Distributions Analysis

- Graph shows $E[\chi^2]$, calculated with $r_{\chi^2} = 0.00001$, where systematic errors are sampled from t-distribution with d.o.f $1/2r_{Dist}^2$.
- Line at 243.43 is χ^2 calculated using $r_{\chi^2} = 0.0001$ for de-correlated data.



De-correlation

- Sometimes we use decorrelation techniques for systematic errors.
- E.g. would be when a systematic error is the calculated as the difference between two different Monte Carlo runs with different input parameters.
- For the ATLAS 7 TeV Jet Data, as is done in the MSHT20 paper, we could use a paramaterisation which allow data points that are distant in (y_j, p_{\perp}^j) space to have different systematic variations:

$$x_{p_{\perp}} = \frac{\log(p_{\perp}^j) - \log(p_{\perp, \min}^j)}{\log(p_{\perp, \max}^j) - \log(p_{\perp, \min}^j)}$$

$$x_y = \frac{y_j - y_{j, \min}}{y_{j, \min} - y_{j, \max}}$$

$$r = \frac{1}{\sqrt{2}} \sqrt{x_{p_{\perp}}^2 + x_y^2}, \quad \phi = \arctan\left(\frac{x_y}{x_{p_{\perp}}}\right)$$

$$L_{\text{trig}}(z, z_{\min}, z_{\max}) = \cos\left[\pi\left(\frac{z - z_{\min}}{z_{\max} - z_{\min}}\right)\right]$$

$$\beta_i^{(1)} = L_{\text{trig}}(r, 0, 1) \cdot L_{\text{trig}}\left(\phi, 0, \frac{\pi}{2}\right) \beta_i^{\text{tot}}$$

$$\beta_i^{(2)} = \sqrt{1 - L_{\text{trig}}(r, 0, 1)^2} \cdot L_{\text{trig}}\left(\phi, 0, \frac{\pi}{2}\right) \beta_i^{\text{tot}}$$

$$\beta_i^{(3)} = L_{\text{trig}}(r, 0, 1) \cdot \sqrt{1 - L_{\text{trig}}\left(\phi, 0, \frac{\pi}{2}\right)^2} \beta_i^{\text{tot}}$$

$$\beta_i^{(4)} = \sqrt{1 - L_{\text{trig}}(r, 0, 1)^2} \cdot \sqrt{L_{\text{trig}}\left(\phi, 0, \frac{\pi}{2}\right)^2} \beta_i^{\text{tot}}$$

- If we implement this for the , then if $r = 0.0001$, then the $\chi^2 = 243.43$.

Correlation Structure

- So what happens if we change the $\pi/2$ to $\pi/4$?
- Firstly there is a big fall in χ^2 . It goes from 243.43 to 199.18
- The Correlation matrix becomes:

id	id1	id2	id3	id4	id5	id6	id7	id8	id9	id10	id11	id12	id13	id14	id15	id16	id17	id18	id19	id20	id21	id22	id23	id24	id25	id26	id27	id28	id29	id30	id31	id32	id33	id34	id35	id36	id37	id38	id39	id40	id41	id42	id43	id44	id45	id46	id47	id48	id49	id50	id51	id52	id53	id54	id55	id56	id57	id58	id59	id60	id61	id62	id63	id64	id65	id66	id67	id68	id69	id70	id71	id72	id73	id74	id75	id76	id77	id78	id79	id80	id81	id82	id83	id84	id85	id86	id87	id88	id89	id90	id91	id92	id93	id94	id95	id96	id97	id98	id99	id100									
0.0367184	0.0681633	0.0671266	0.0048881	0.0241318	0.0462505	0.0458727	0.0056825	0.0292216	0.0504486	0.0550655	0.0026568	0.0028051	0.0135399	0.0339462	0.0507491	0.0424293	0.0204046	0.0116800	0.0089216	0.0056313	0.0037475	0.0025952	0.0019385	0.0016830	0.0017655	0.0020773	0.0023091	0.0026140	0.0029319	0.0032532	0.0035636	0.0038611	0.0041454	0.0044164	0.0046736	0.0049160	0.0051437	0.0053559	0.0055520	0.0057323	0.0058970	0.0060466	0.0061816	0.0063025	0.0064090	0.0065017	0.0065804	0.0066450	0.0066964	0.0067345	0.0067602	0.0067744	0.0067782	0.0067716	0.0067557	0.0067295	0.0066941	0.0066500	0.0065975	0.0065370	0.0064689	0.0063938	0.0063124	0.0062254	0.0061327	0.0060351	0.0059324	0.0058254	0.0057140	0.0055981	0.0054786	0.0053555	0.0052296	0.0051018	0.0049721	0.0048406	0.0047073	0.0045722	0.0044354	0.0042970	0.0041572	0.0040161	0.0038737	0.0037300	0.0035852	0.0034393	0.0032924	0.0031446	0.0029959	0.0028464	0.0026961	0.0025450	0.0023931	0.0022405	0.0020873	0.0019335	0.0017790	0.0016239	0.0014683	0.0013124	0.0011562	0.0010000	0.0008437	0.0006875	0.0005314	0.0003754	0.0002195	0.0000637	0.0000000

- In some parts of the matrix this looks better, but in others worse than the desired outcome!

Conclusions

- We have shown how we can incorporate Errors on Errors into the calculation of a χ^2
- Expected χ^2 and Variance of χ^2 increase as the relative errors of the systematic errors increase
- We have noted that for both data sets $r \approx 0.4$. If we compare the expected standard deviation of the mean, calculated with $r_{\chi^2} = 0.001$, where the systematic errors have an $r_{Dist} = 0.4$ to that where $r_{Dist} = 0.001$ we obtain a ratio of approx. 1.2 – 1.5. This is suggestive of using a tolerance in the region of 1.2 – 1.5 in these test cases.
- When de-correlating systematic errors we need to be incredibly careful about the correlation matrix that we are producing

Back Up Slides

Closer Look at the Correlation Matrix - $\pi/2$ versus $\pi/4$

In some parts of the correlation matrix using $\pi/2$ looks better, but in other parts it looks worse.

Worse Better

	x (P T)	0.02572464	0.23994183	0.51009257	0.74286895	0.95880057	0.02572464	0.23994183	0.51009257	0.74286895	0.93724088
x (P T)	x_y	0.08333333	0.08333333	0.08333333	0.08333333	0.08333333	0.25	0.25	0.25	0.25	0.25
0.02572464	0.08333333	0.99974556	-0.2784397	-0.3488771	-0.0705975	0.26125823	0.86256755	0.50062405	-0.0291488	-0.0074044	0.16656448
0.23994183	0.08333333	-0.2784397	0.99974555	0.78504325	0.41223169	-0.0025533	-0.6418794	0.57461627	0.74366462	0.38358978	-0.0195558
0.51009257	0.08333333	-0.3488771	0.78504325	0.9997457	0.86694258	0.54252776	-0.7172612	0.25926028	0.82672441	0.78554601	0.52416333
0.74286895	0.08333333	-0.0705975	0.41223169	0.86694258	0.99974561	0.88687464	-0.4106197	0.114004	0.71176327	0.90750779	0.84133983
0.95880057	0.08333333	0.26125823	-0.0025533	0.54252776	0.88687464	0.99974552	0.00822859	0.02654636	0.47350771	0.81963561	0.93970072
0.02572464	0.25	0.86256755	-0.6418794	-0.7172612	-0.4106197	0.00822859	0.99974556	0.23816247	-0.3345382	-0.2483446	0.0192284
0.23994183	0.25	0.50062405	0.57461627	0.25926028	0.114004	0.02654636	0.23816247	0.99974544	0.67364362	0.32225615	0.08530261
0.51009257	0.25	-0.0291488	0.74366462	0.82672441	0.71176327	0.47350771	-0.3345382	0.67364362	0.9997456	0.85680031	0.57989632
0.74286895	0.25	-0.0074044	0.38358978	0.78554601	0.90750779	0.81963561	-0.2483446	0.32225615	0.85680031	0.99974561	0.90795241
0.93724088	0.25	0.16656448	-0.0195558	0.52416333	0.84133983	0.93970072	0.0192284	0.08530261	0.57989632	0.90795241	0.99974551

$\pi/2$

Better Worse

	x (P T)	0.02572464	0.23994183	0.51009257	0.74286895	0.95880057	0.02572464	0.23994183	0.51009257	0.74286895	0.93724088
x (P T)	x_y	0.08333333	0.08333333	0.08333333	0.08333333	0.08333333	0.25	0.25	0.25	0.25	0.25
0.02572464	0.08333333	0.99974556	0.9228621	0.49272974	0.07584232	-0.240455	0.65907332	-0.2405758	0.39051862	0.02322744	-0.3757966
0.23994183	0.08333333	0.9228621	0.99974549	0.64364632	0.28738736	-0.0015913	0.60011925	-0.1478024	0.6775356	0.38337488	-0.0189196
0.51009257	0.08333333	0.49272974	0.64364632	0.99974564	0.85380853	0.52406367	0.80746022	-0.6973689	0.38290406	0.65961034	0.4934031
0.74286895	0.08333333	0.07584232	0.28738736	0.85380853	0.99974562	0.88354433	0.45112934	-0.5477014	0.17837245	0.65642429	0.72844584
0.95880057	0.08333333	-0.240455	-0.0015913	0.52406367	0.88354433	0.99974552	-0.0088366	-0.1829543	0.06056808	0.535064	0.76717266
0.02572464	0.25	0.65907332	0.60011925	0.80746022	0.45112934	-0.0088366	0.99974556	-0.8614181	0.12004887	0.23849793	-0.0207453
0.23994183	0.25	-0.2405758	-0.1478024	-0.6923689	-0.5427014	-0.1829543	-0.8614181	0.99974559	0.28894148	-0.1066135	-0.0796406
0.51009257	0.25	0.39051862	0.6775356	0.38290406	0.17837245	0.06056808	0.12004887	0.28894148	0.99974547	0.76794774	0.44568291
0.74286895	0.25	0.02322744	0.38337488	0.65961034	0.65642429	0.535064	0.23849793	-0.1066135	0.76794774	0.99974561	0.88563822
0.93724088	0.25	-0.3757966	-0.0189196	0.4934031	0.72844584	0.76717266	-0.0207453	-0.0796406	0.44568291	0.88563822	0.99974545

$\pi/4$

Treating our r_i , r_{u_i} and r' as 0 Correlated - Model 2

- In this scenario we obtain the Loglikelihood equation:

$$\begin{aligned}
 -2\text{Ln}L &= \sum_{i=1}^N \left(\frac{y_i - t_i - \sigma_{u_i} r_{u_i} - \sum_j \beta_{ij} r'_j}{\sigma_i} \right)^2 \\
 &+ \sum_{i=1}^N (\nu + 1) \text{Ln} \left(1 + \frac{r_{u_i}^2}{\nu} \right) + (\nu + M) \text{Ln} \left(1 + \frac{\sum_j^M r'_j{}^2}{\nu} \right) \quad (9)
 \end{aligned}$$

- Again we obtain cubic equations for r_{u_i} and r'_j .
- The equation for r_{u_i} can be solved analytically whilst solving for r'_j numerically.
- Model 1 and Model 2 have a different dependence on ν . In order to make Model 1 and Model 2 closer we shall let $\nu \rightarrow M\nu$.