Bayesian Diagnostic Analysis at JET:

Interferometry and Polarimetry

Oliver Ford

Thanks to:

Dr J. Svensson
PhD Supervisor (JET)
Dr A. Boboc
Inteferometry/Polarimetry

JET Contributors

Talk Outline

- Project Outline
- Bayesian / forward modelling principles.
- A simple example: Interferometry inversion.
- Polarimetry:
  - Basics
  - Complications
  - A side result: High Temperature Effects

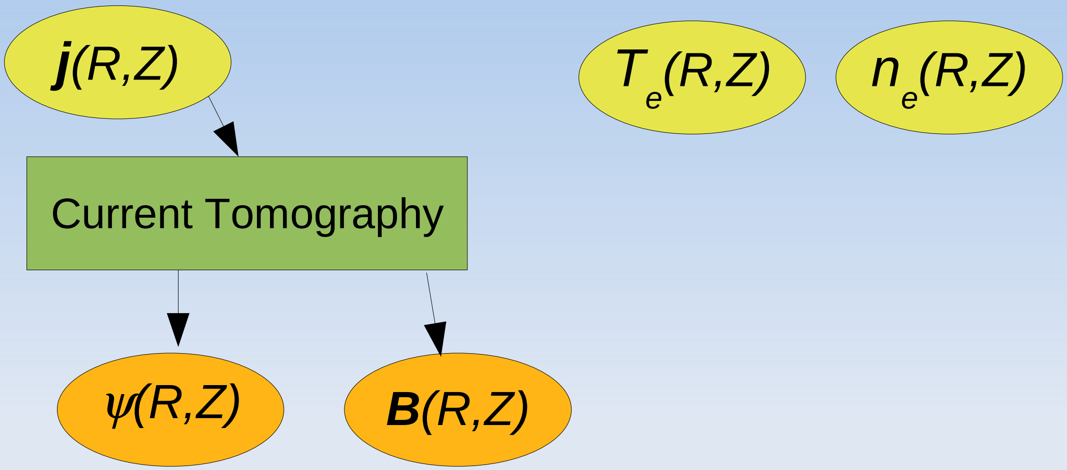
Integrated Analysis

$\boldsymbol{j}(R,Z)$

$T_e(R,Z)$ $n_e(R,Z)$

Model for the basic physical quantities.

Integrated Analysis



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- Models for the prediction of other required quantities.

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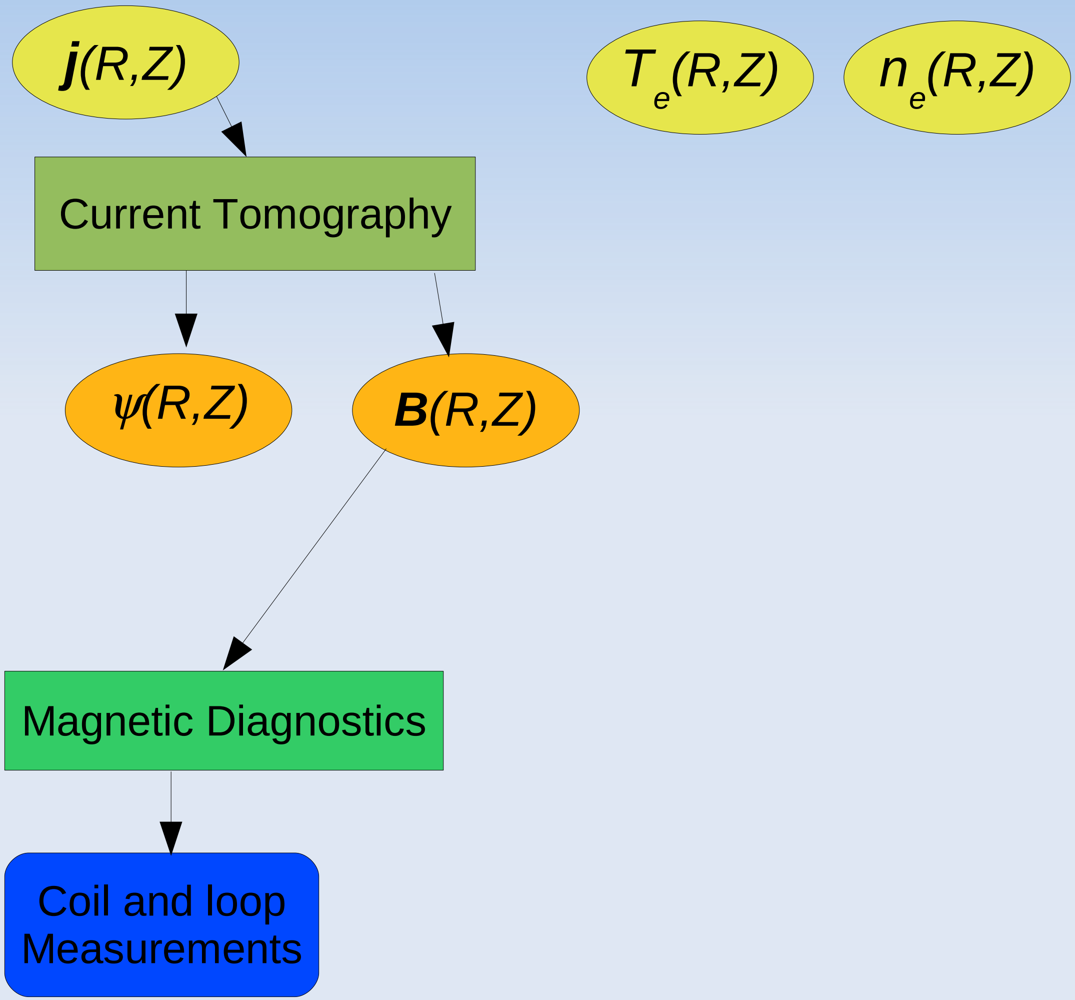

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- Complete model for each diagnostic system, predicting the data it reports. The "*Forward Function*".

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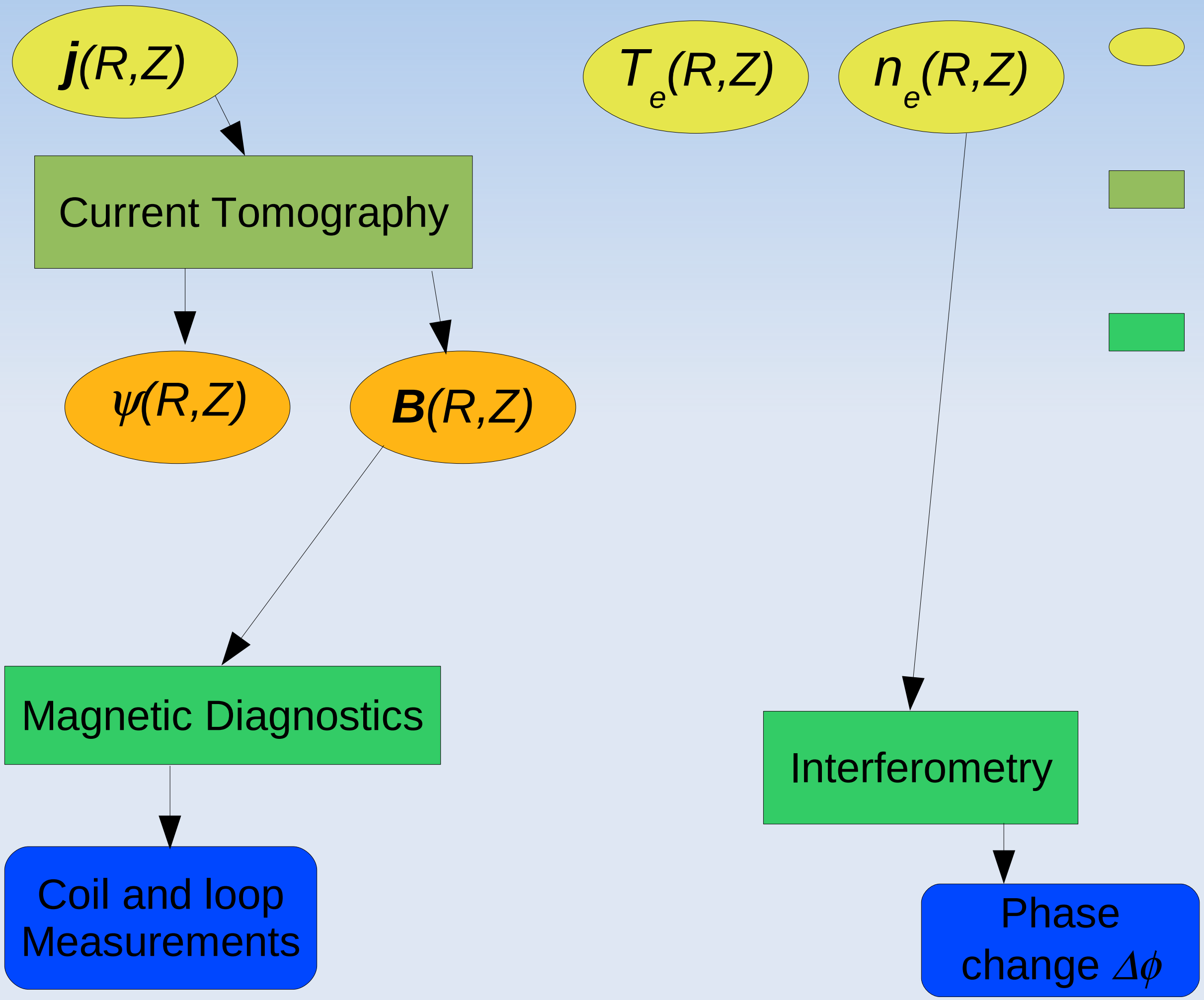

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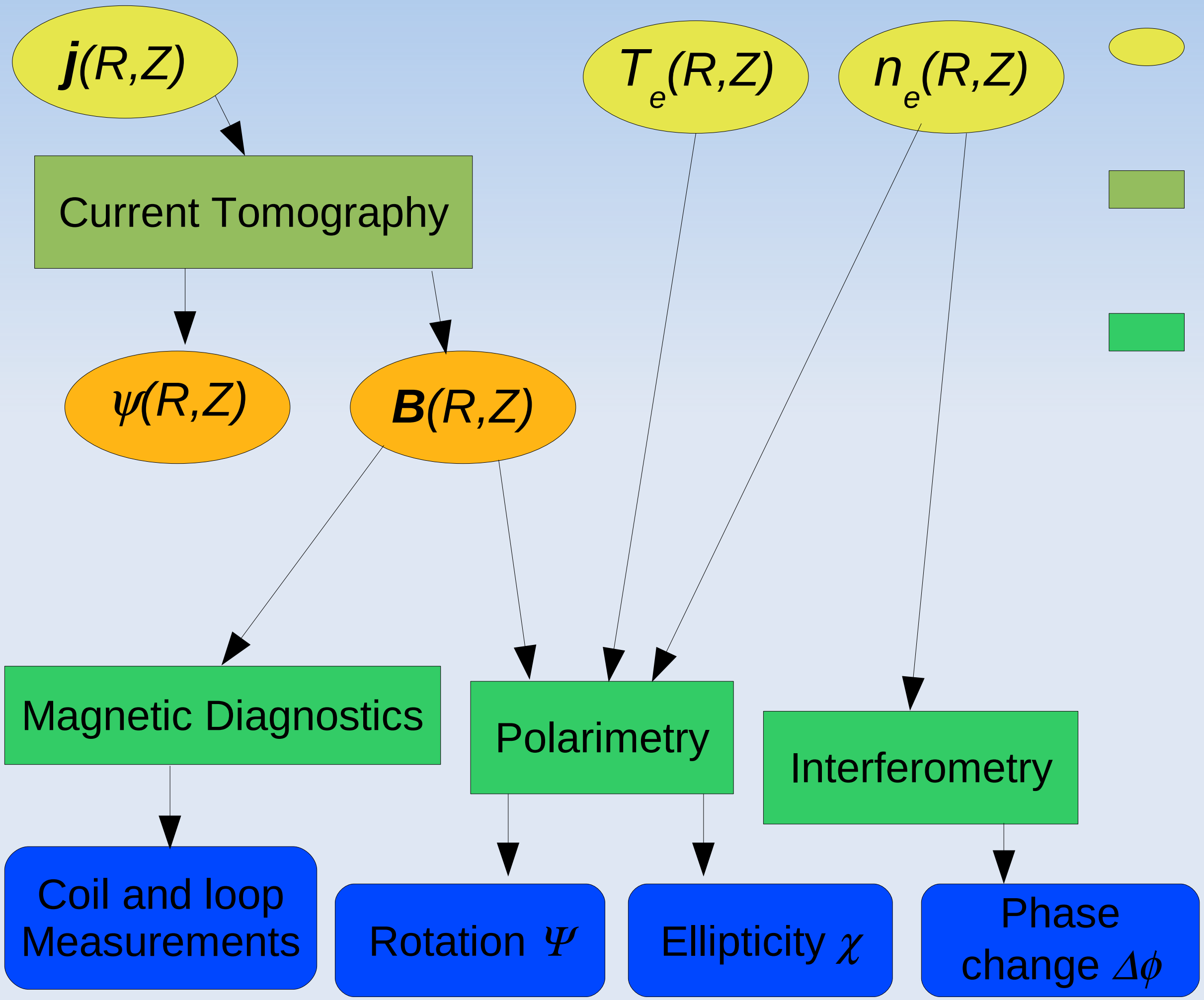

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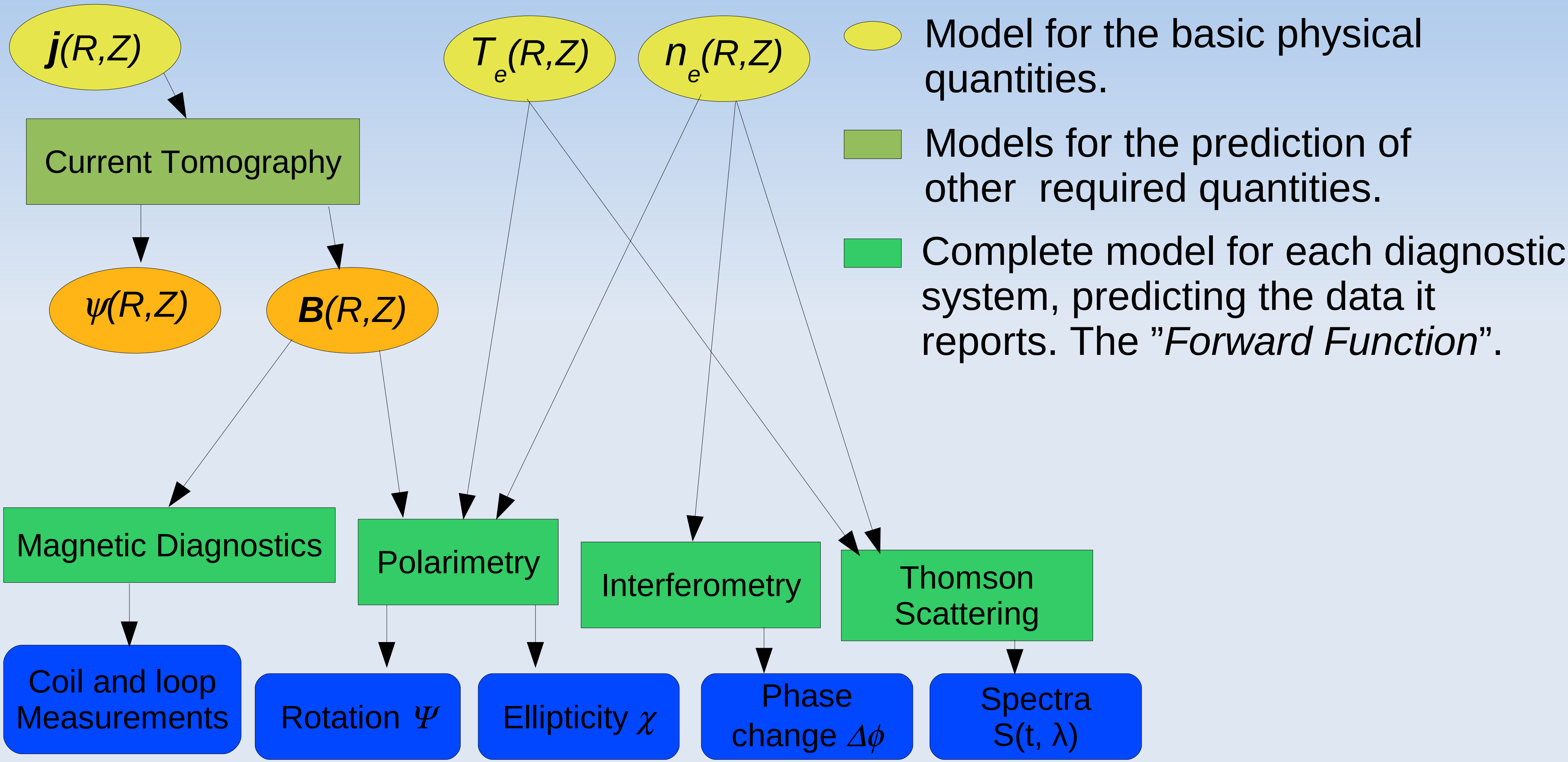

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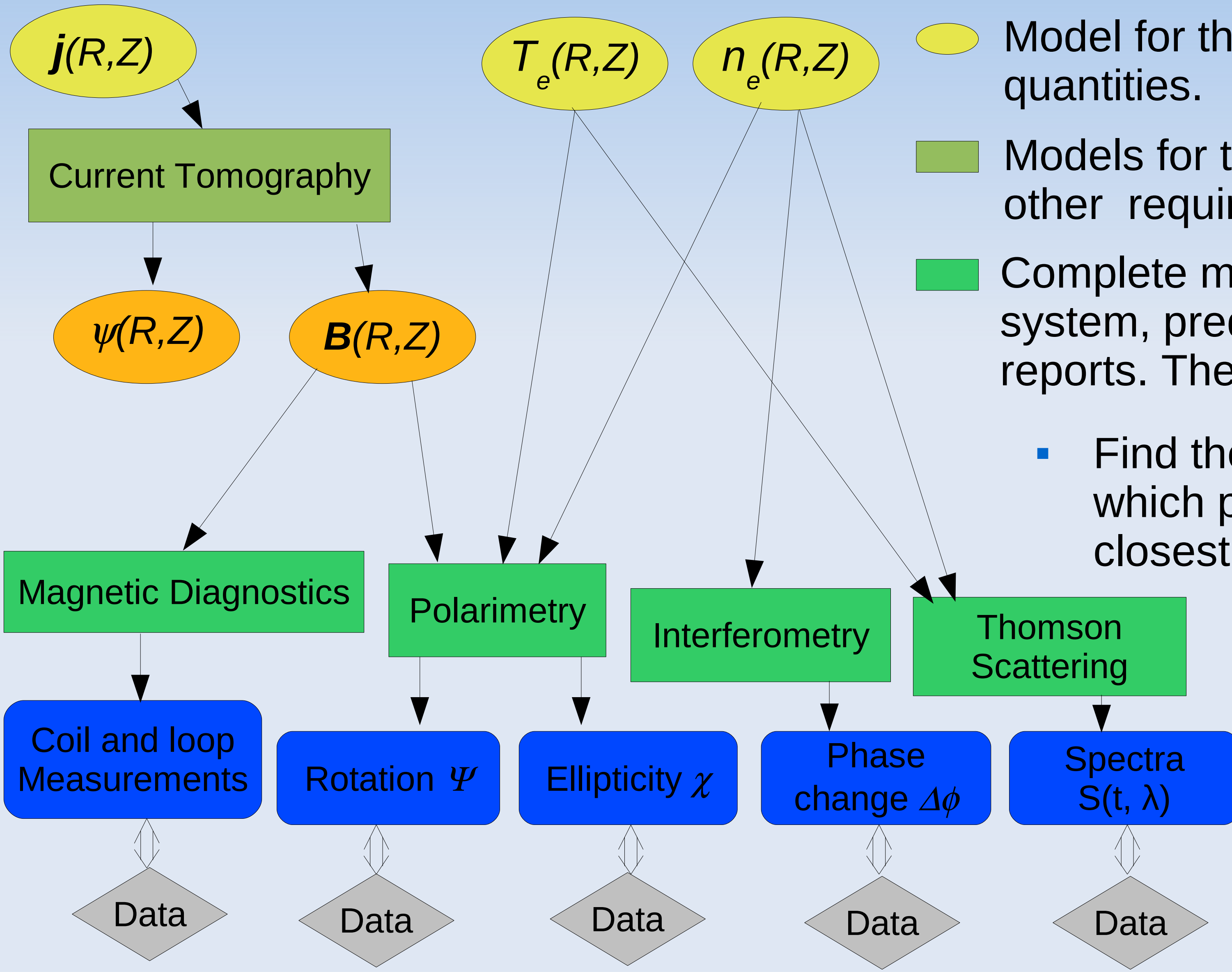

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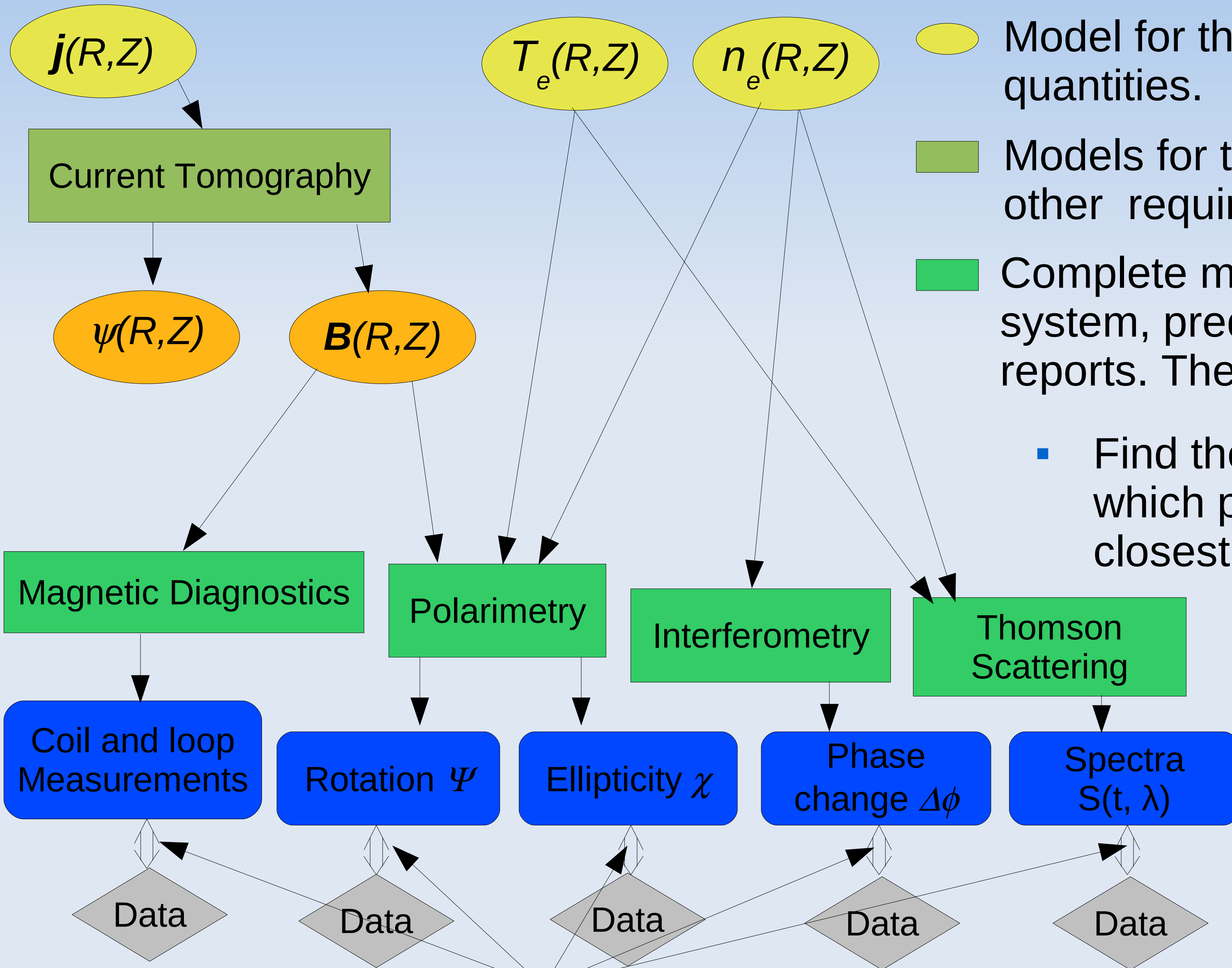

P(Data | 'Real' Measurement) - Likelihood

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From probability theory...
Bayes Theorem:

$$P(A \mid B) = \frac{P(B \mid A)\ P(A)}{P(B)}$$

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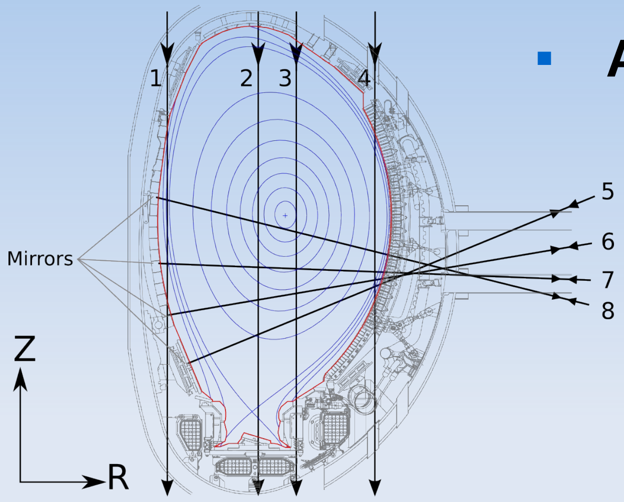
- Combining diagnostics: $P(n_e, T_e, \mathbf{j} \mid \text{All Data}) =$
  - $P(D_{Polarimetry} \mid n_e, T_e, \mathbf{j}) \times P(D_{Interferrometry} \mid n_e) \times P(D_{Magnetics} \mid \mathbf{j}) \times P(n_e, T_e, \mathbf{j})$

Interferometry Inversion I



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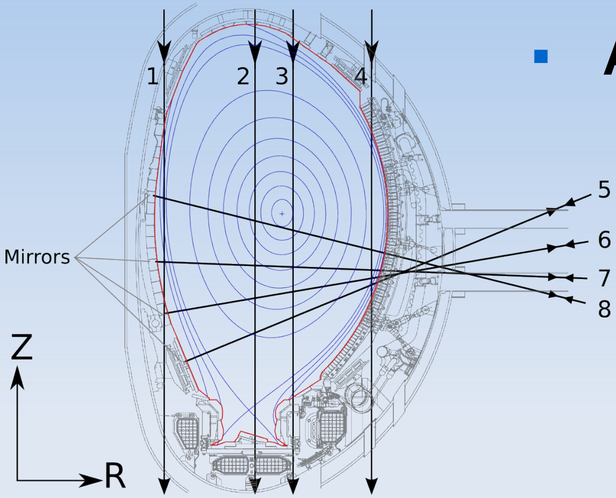

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Weights determined by surfaces and lines of sight.

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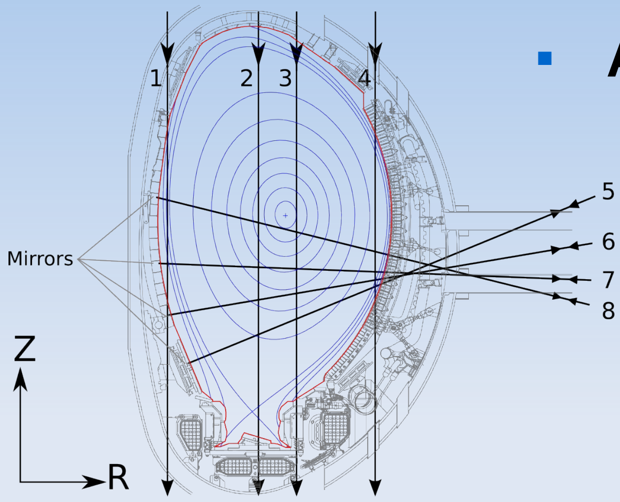

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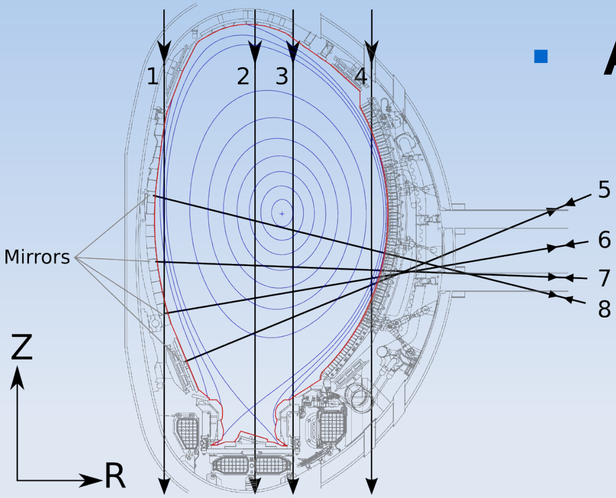

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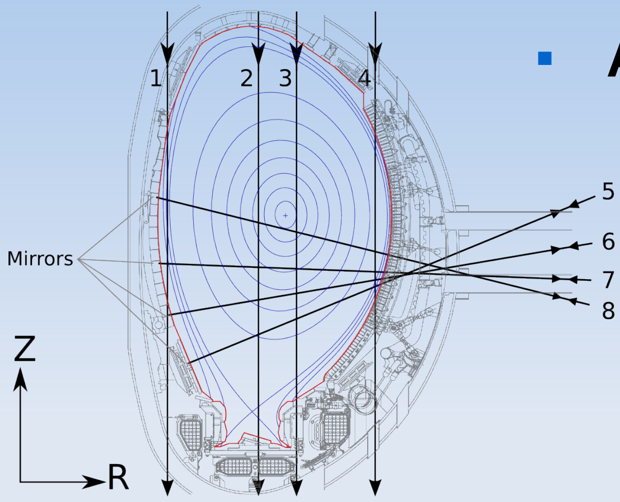

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- Posterior: Rewrite likelihood and prior as multivariate Gaussians:

$$P\left(\underline{\mathrm{n_e}} \middle| \underline{\mathrm{D}}\right) \propto \begin{cases} \mathcal{G}\left(\underline{\mathrm{D}};\ \underline{\underline{\mathrm{W}}}\,\underline{\mathrm{n_e}},\ \underline{\underline{\sigma_\mathrm{D}}}\right) \mathcal{G}\left(\underline{\mathrm{n_e}};\ \underline{0},\ \underline{\underline{\sigma_\mathrm{P}}}\right) & \text{for all } n_{e_j} \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

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\text{with} \quad \underline{\mathrm{n}_{e0}} &= \underline{\underline{\sigma_{\mathrm{n}_e}}}\, \underline{\underline{\mathrm{W}}}^T \underline{\underline{\sigma_{\mathrm{D}}}}^{-1} \underline{\mathrm{D}} \\
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Truncated multivariate Gaussian.

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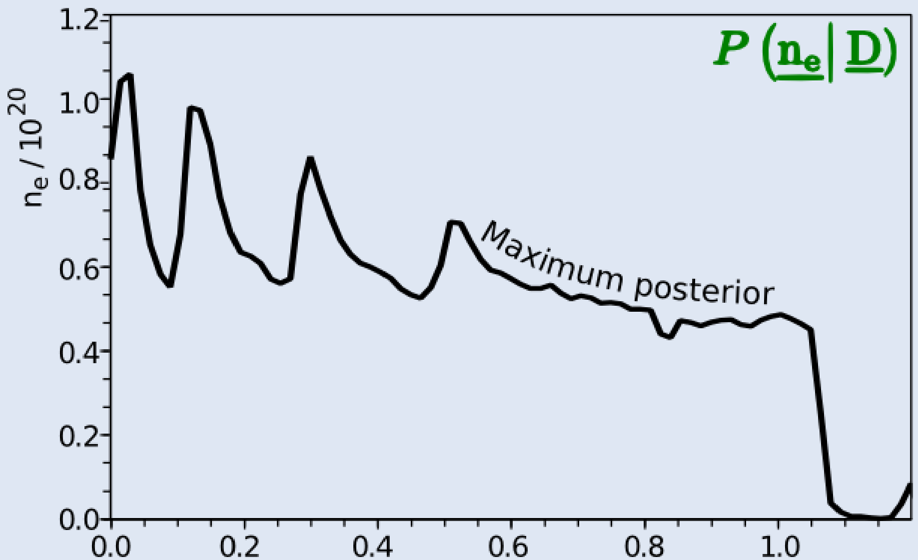

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- To examine the posterior, show maximum posterior and draw samples to represent uncertainty.

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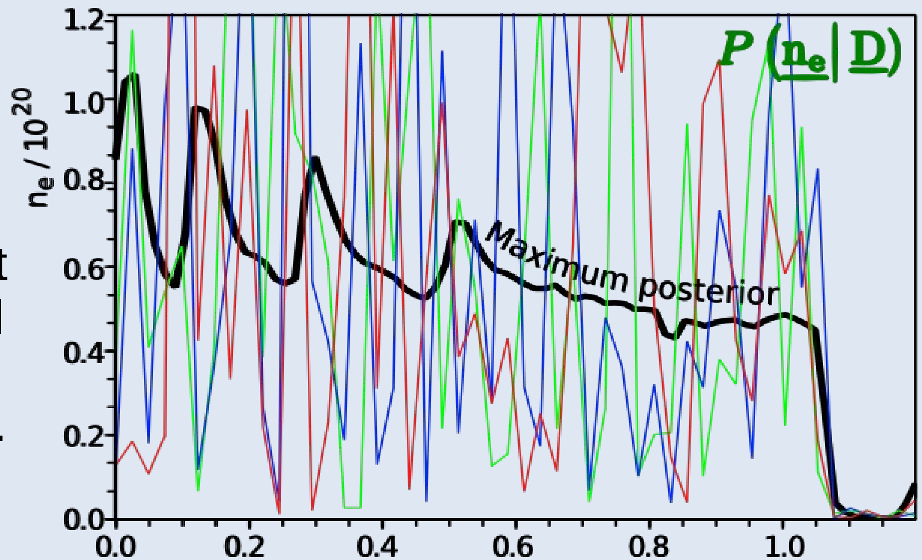

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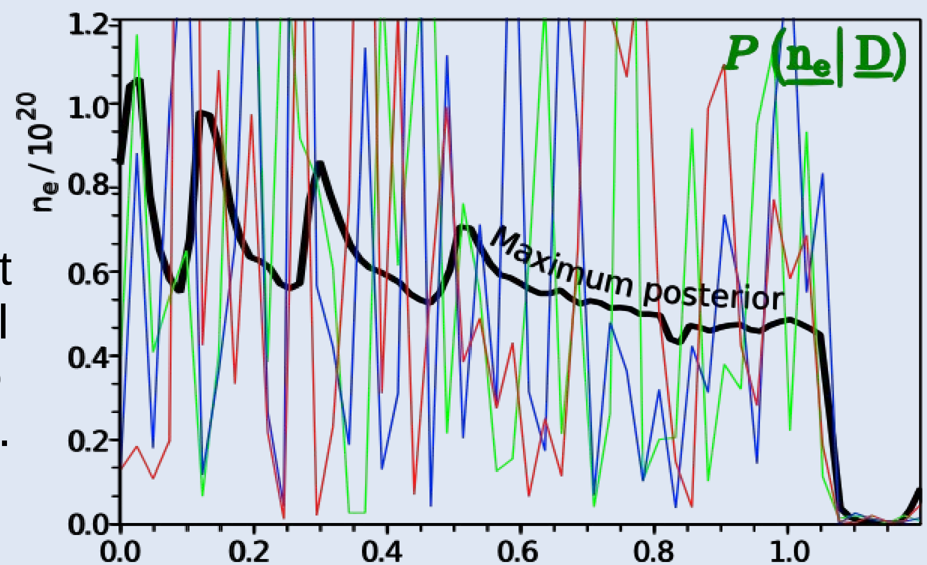

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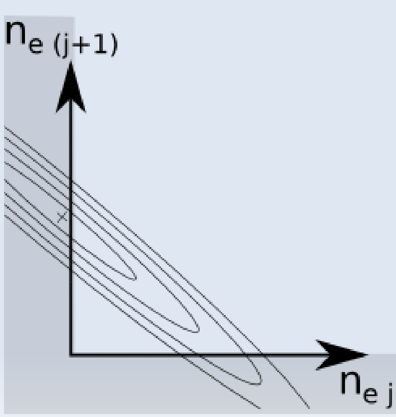

Interferometry Inversion III

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$$P(\underline{\mathrm{N_e}}) \propto \prod_{j=1}^{N-1} \mathcal{G}\left(\frac{\left(N_{e_{(j+1)}} - N_{e_j}\right)}{\Delta\psi};\ 0,\ \sigma_{\frac{dN_e}{d\psi}} \right) \text{ with } \sigma_{\frac{dN_e}{d\psi}} = 2.5 \times 10^{20}$$

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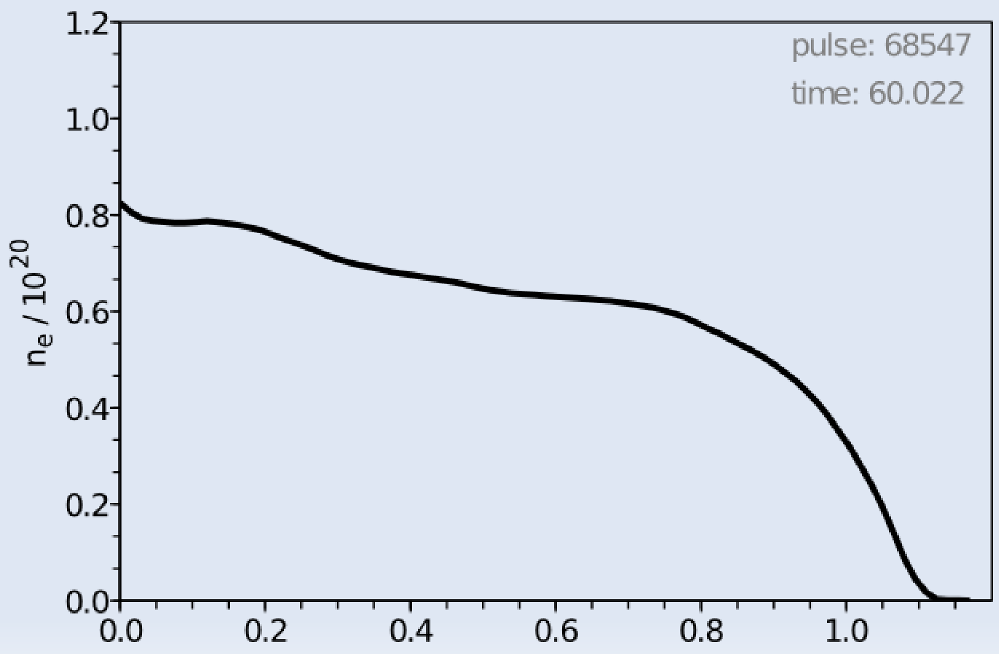

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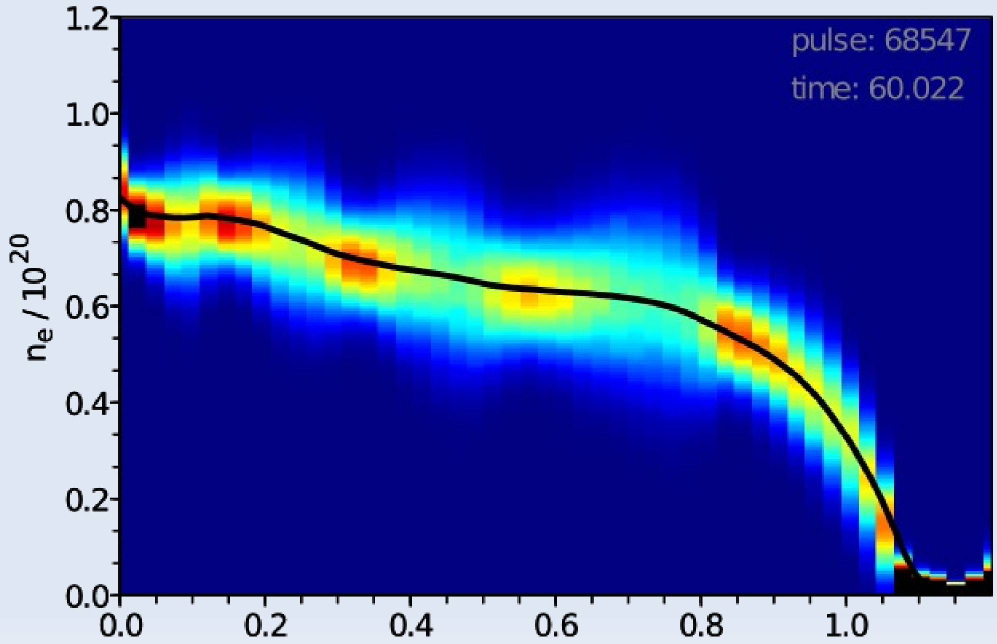

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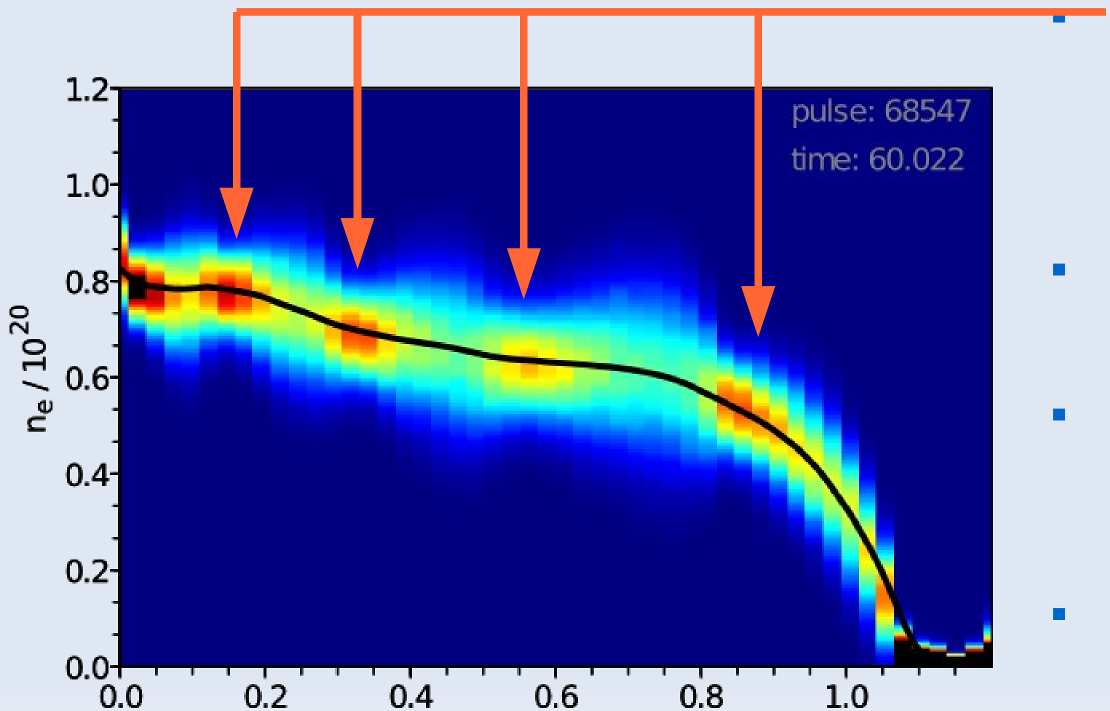

- Can now see density is better known where integration is more heavily weighted, i.e where the lines of sight are almost tangential to surfaces.
- This 'looks nicer', but the former posterior better represents what is actually **known**.
- Many non-physical profiles are given a high probabilty in the former but the 'real' profile will also be given a high probability.
- With the extra prior, sharp changes in the real profile will mean its given a low probability.

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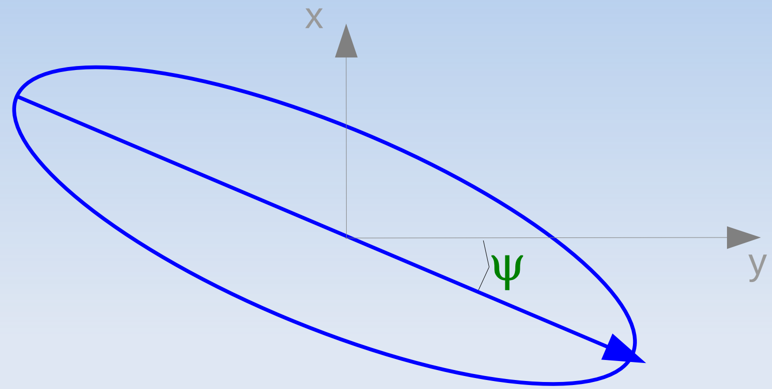
- Polarisation state described by rotation ψ and ellipticity *tan* χ.



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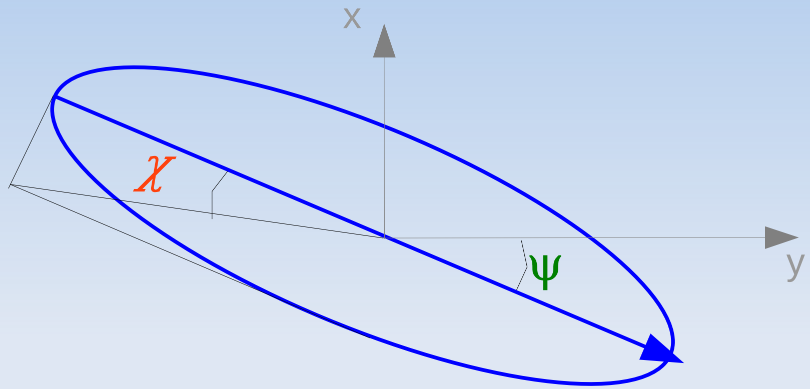

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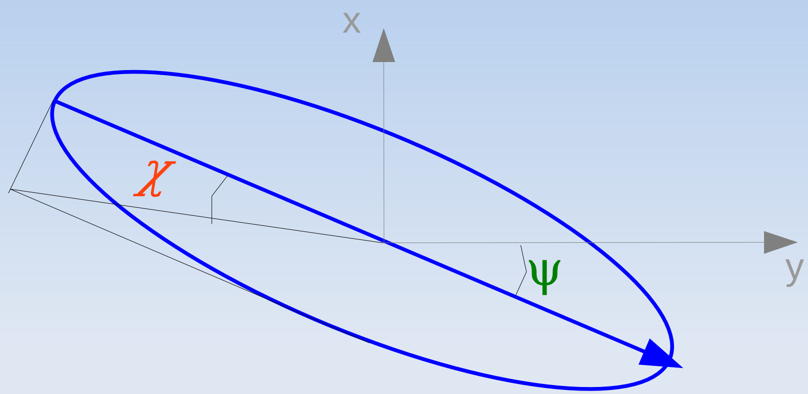

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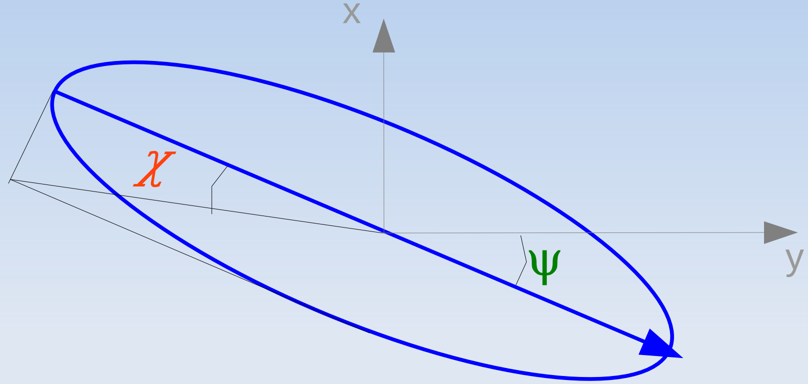

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- **B**⊥**z**: Cotton-Mouton effect:

$$\psi = 45^{\circ} \text{ to B}$$

$$\chi \propto \int B_{\perp}^{2}\, n_e\, dz$$

- For ***B*** at an arbitary angle *θ* to ***z*** and with large effects, these are not valid!

Polarimetry: Full Model

[1]: S. E. Segre, Plasma Phys. Controlled Fusion 41, R57-R100 (1999)

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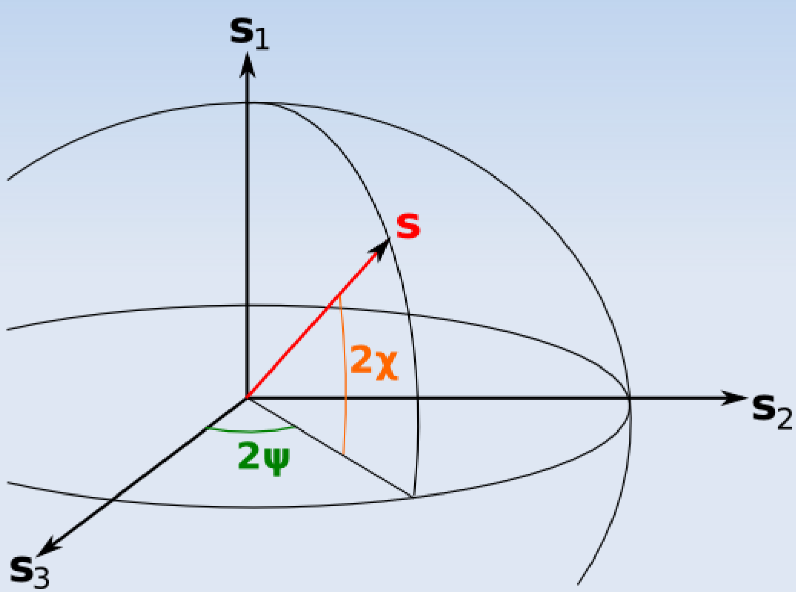

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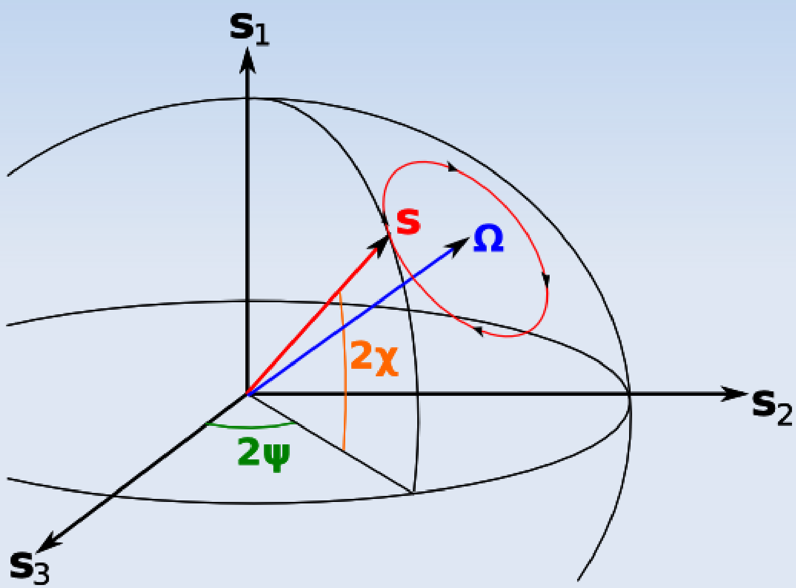

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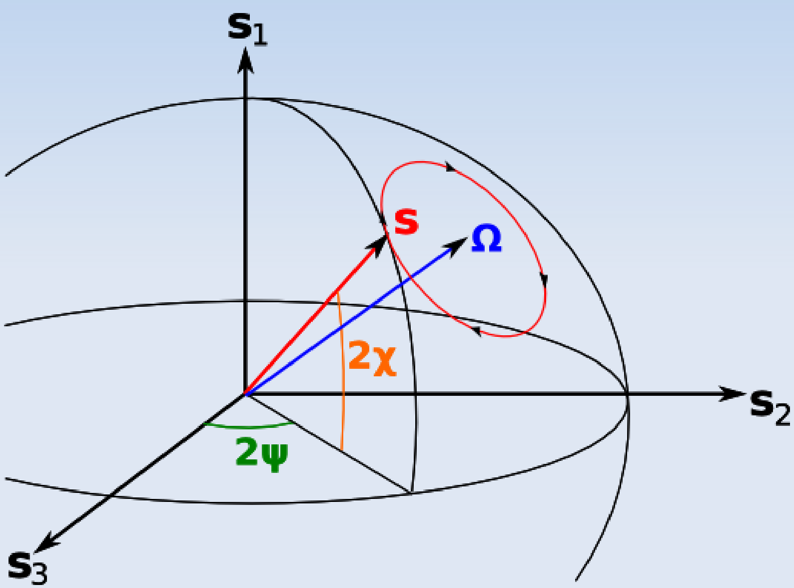

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Cold plasma model (Te < 5 keV):

$$\underline{\Omega} = \frac{\omega_p^2}{2c\omega^3\left(1-\omega_c^2/\omega^2\right)} \begin{bmatrix} (e/m)^2 & \left(B_x^2 - B_y^2\right) \\ (e/m)^2 & 2B_x B_y \\ 2\omega\,(e/m) & B_z \end{bmatrix}$$

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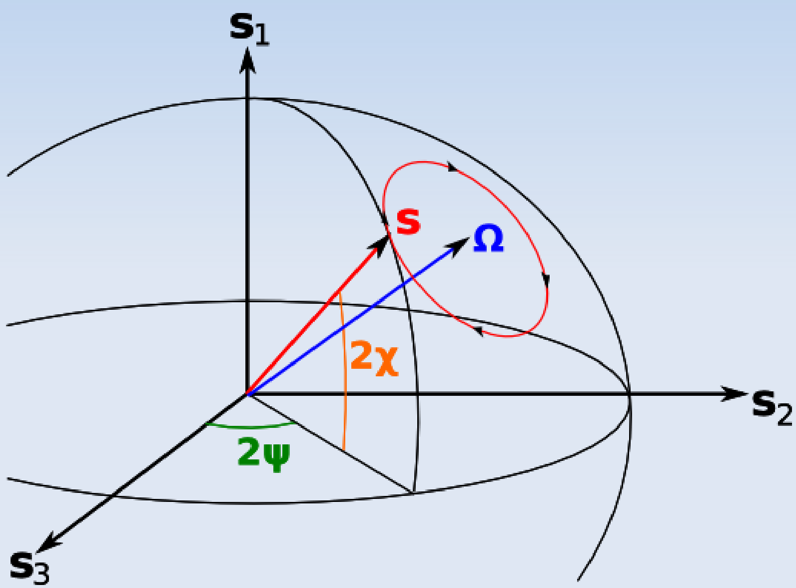


$$\frac{d\underline{s}}{dz} = \underline{\Omega} \times \underline{s}$$

Integrate along line of sight.

Cold plasma model (Te < 5 keV):

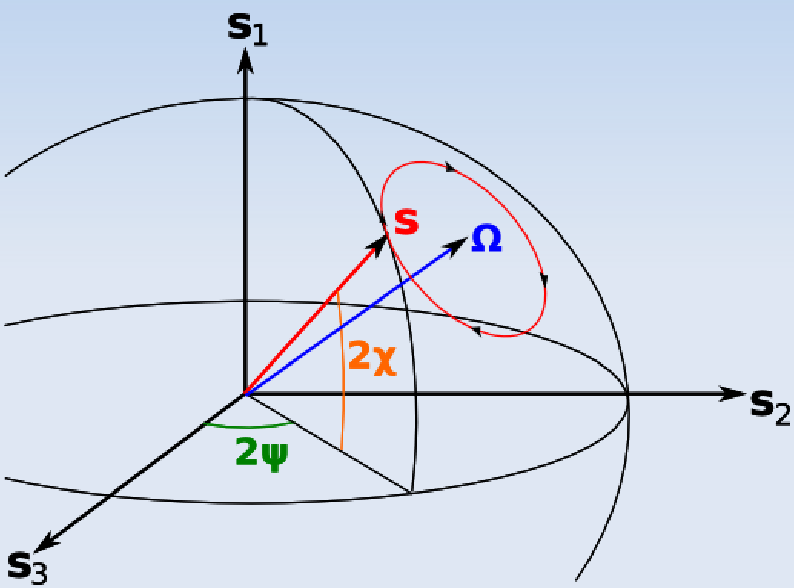
$$\underline{\Omega} = \frac{\omega_p^2}{2c\omega^3\left(1-\omega_c^2/\omega^2\right)}\begin{bmatrix} (e/m)^2 & (B_x^2 - B_y^2) \\ (e/m)^2 & 2B_xB_y \\ 2\omega\,(e/m) & B_z \end{bmatrix}$$

- Typically one effect is minimised to avoid this, e.g. lateral channels.
- Forward modelling and Bayesian approaches allow maximum use of both effects.

Polarimetry: Full Model

[1]: S. E. Segre, Plasma Phys. Controlled Fusion 41, R57-R100 (1999)

- Better model[1] describes polarisation as stokes vector s:



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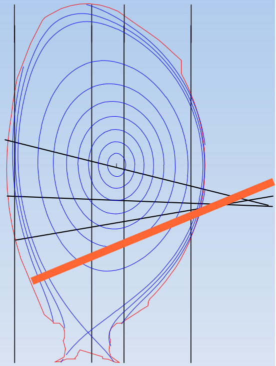
- Typically one effect is minimised to avoid this, e.g. lateral channels.
- Forward modelling and Bayesian approaches allow maximum use of both effects.
- To test model: Perform interferometry inversion and draw 300 sample n_e profiles. Predict ψ and χ for each sample using **B** from EFIT.
- This gives *P(ψ | D,* ***B*** *)* and *P(χ | D, B)* - what can be inferred about what *ψ* and χ 'should be', given only the interferometry data (and EFIT **B**).

Polarimetry: Comparison I (Channel 5)

Compare these with measured values (at 500ms intervals for 1313 pulses)...
Channel 5:



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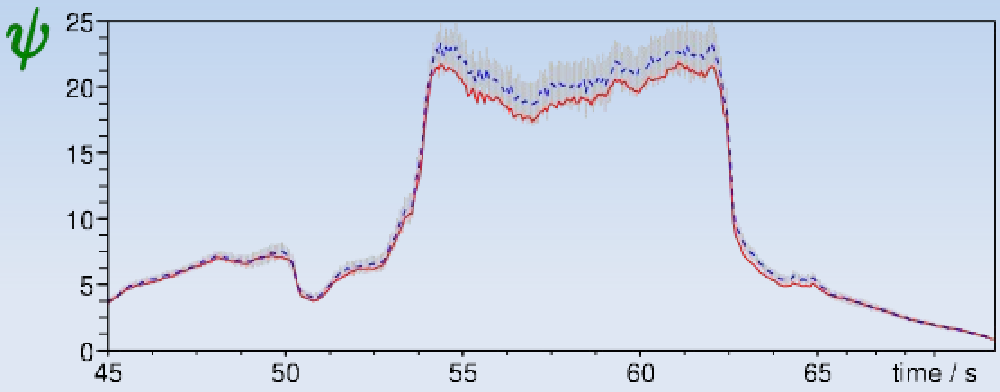

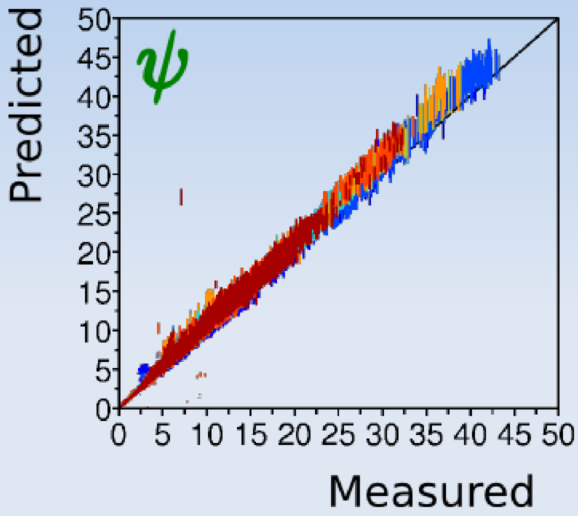

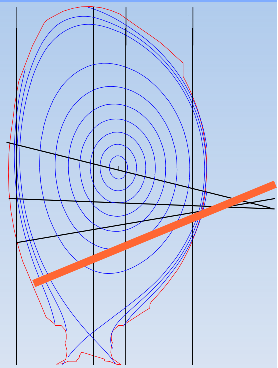

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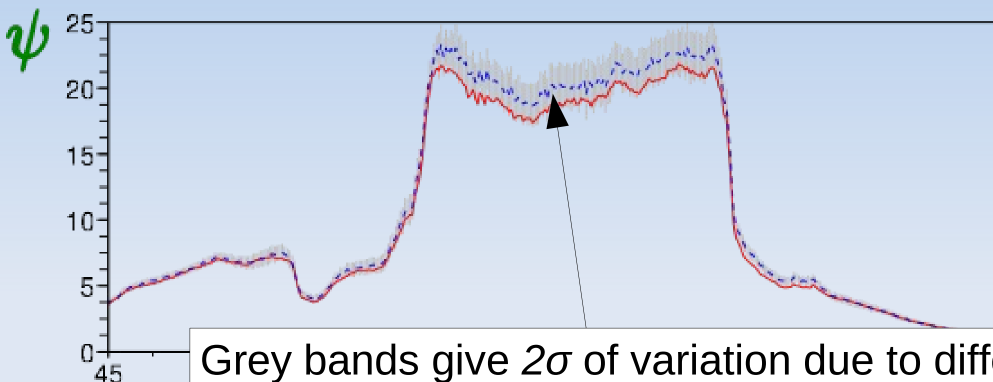
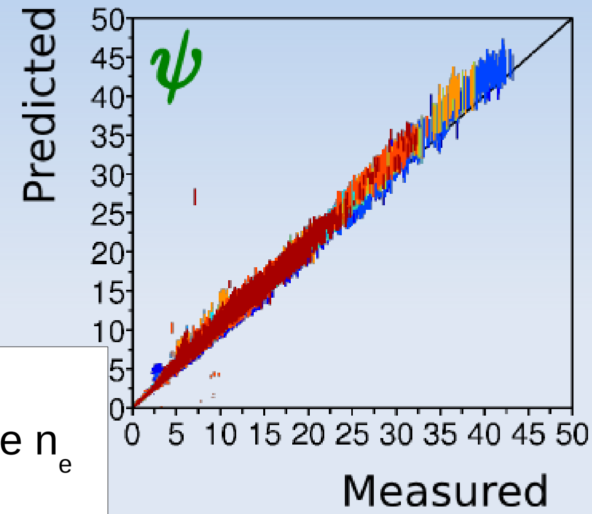
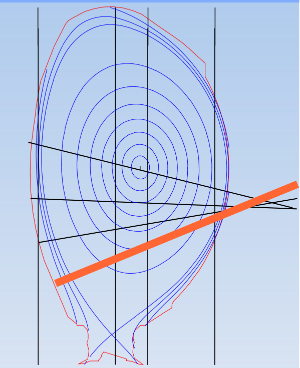


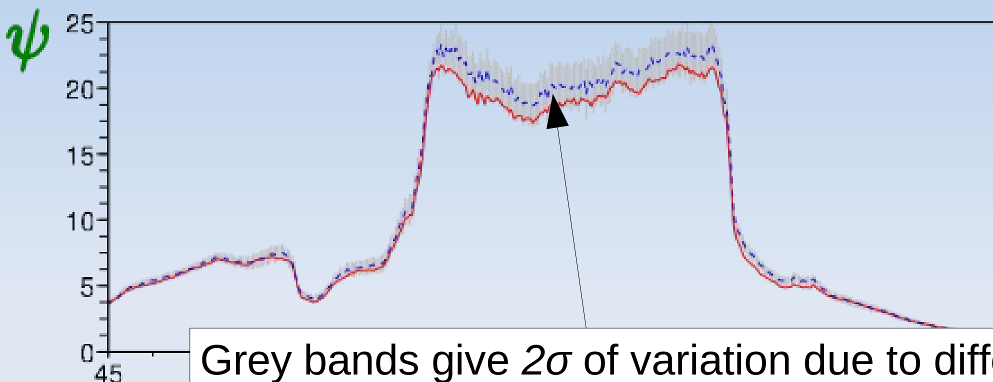
Grey bands give *2σ* of variation due to different n_e profiles consistent with interferometry. Despite huge n_e shape variation – these are quite well determined!

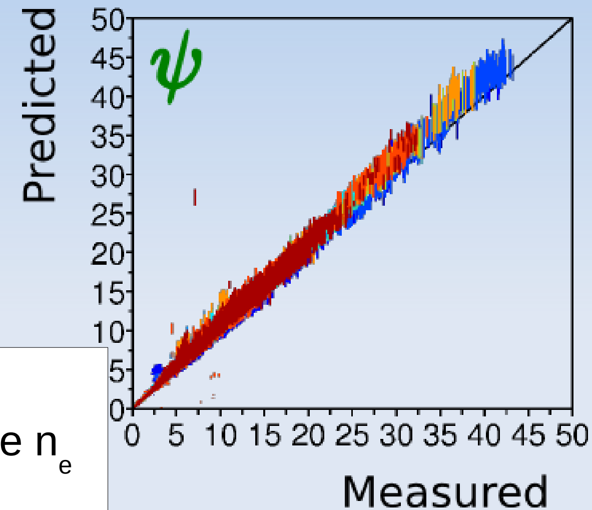


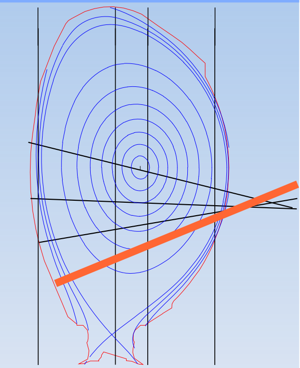


Polarimetry: Comparison I (Channel 5)

Compare these with measured values (at 500ms intervals for 1313 pulses)...
Channel 5: Good agreement for both ψ and χ.

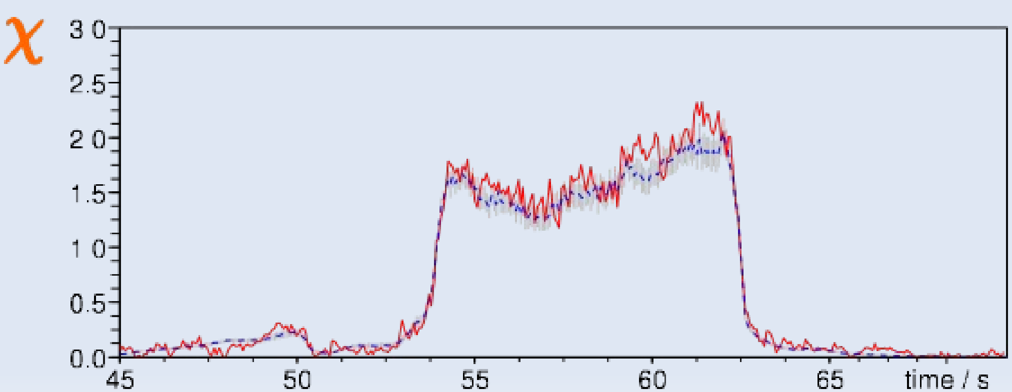


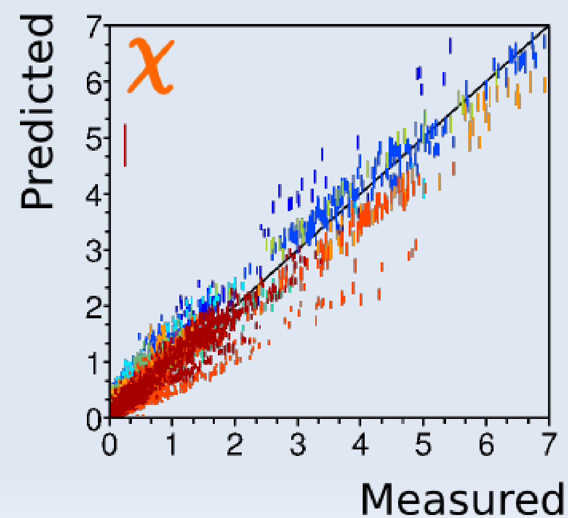




Grey bands give *2σ* of variation due to different n_e profiles consistent with interferometry. Despite huge n_e shape variation – these are quite well determined!

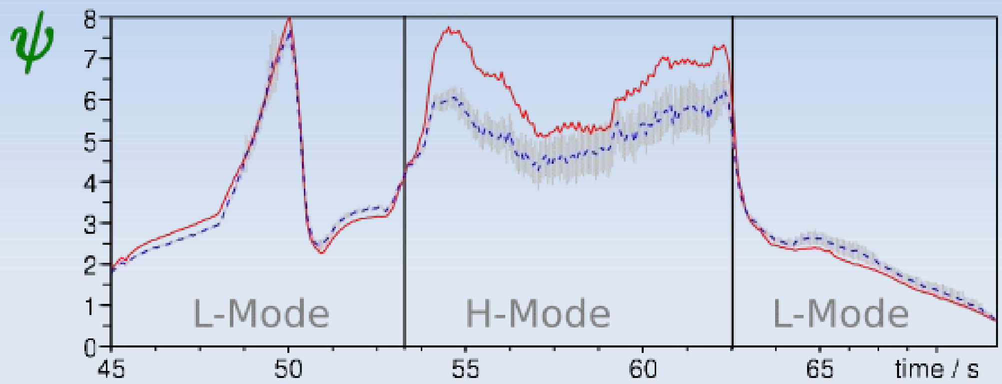
Can only make predictions for this channel with the full model. χ is heavily dependant on ψ – provides extra information on Bpol.

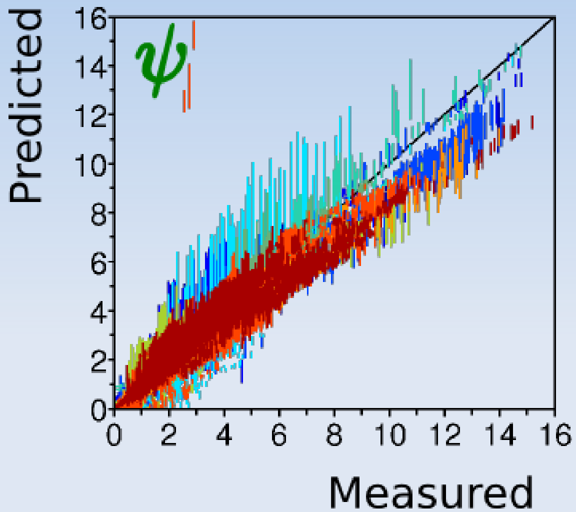


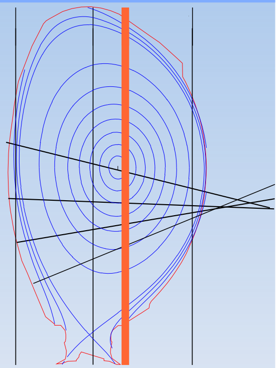


Polarimetry: Comparison II (Channel 3)

Channel 3 (core) shows a systematic disgreement on ψ during H-mode phase.
Suspected due to inaccurate magnetic axis position from EFIT.







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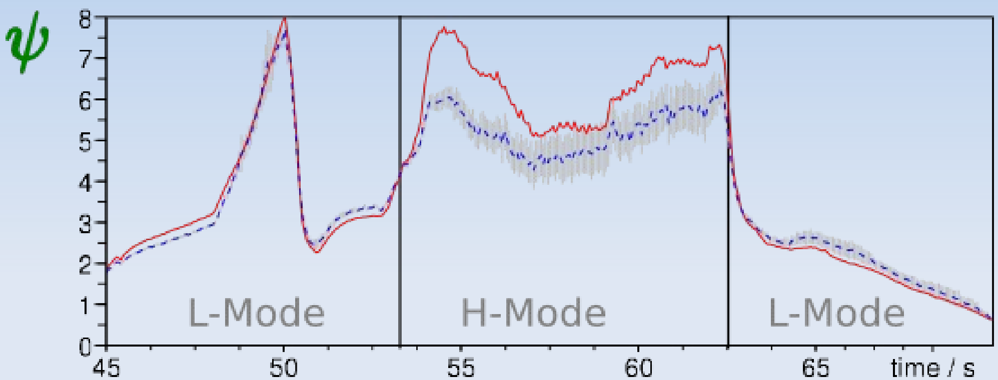
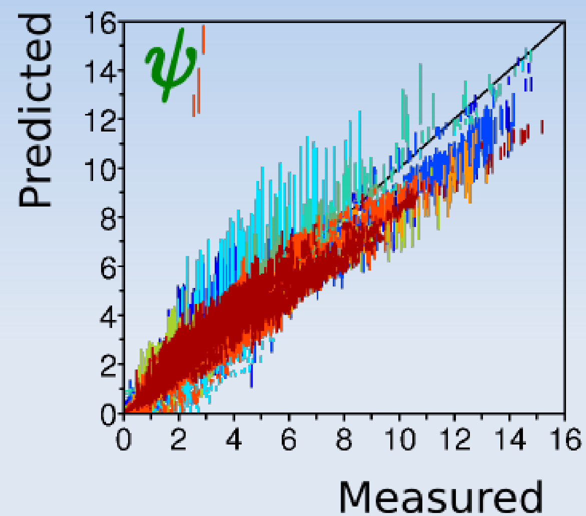
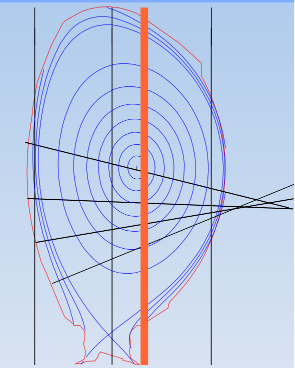
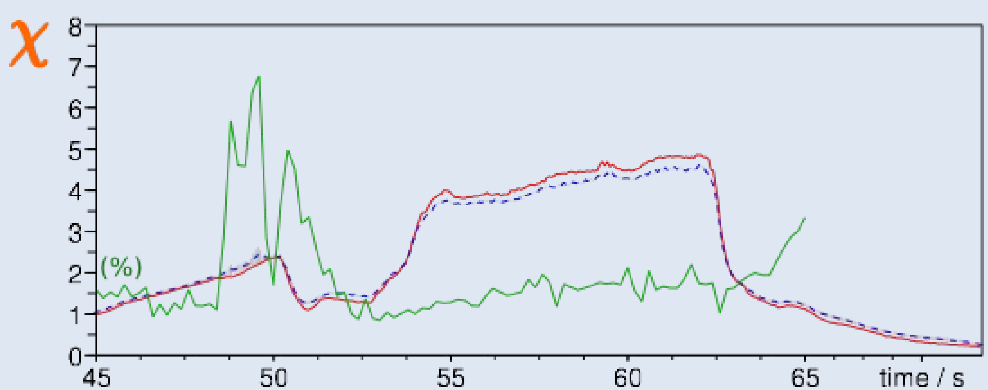
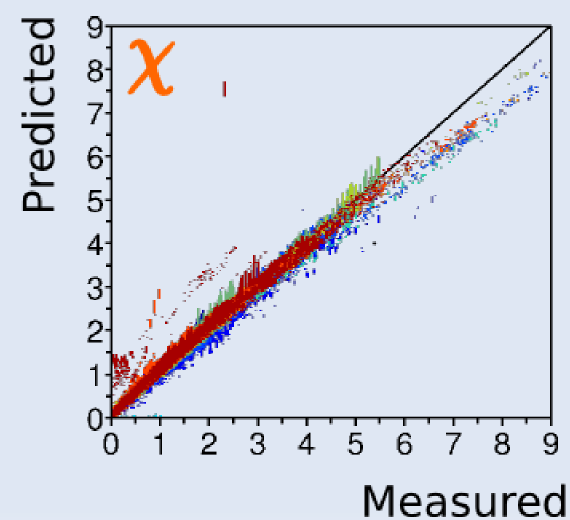






Systematic disgreement at very high n_e. - Calibration Suspected!!





Polarimetry: High Te Effects

- For Te > ~5keV, the cold plasma model ($\boldsymbol{\Omega_0}$) is not sufficient...
- High velocity electrons see Doppler shifted incident wave.
  - Calculate polarisation evolution **Ω** in terms of dielectric tensor **ε**.
  - Take **ε** from integration of Vlasov equation over Maxwellian.
  - Expand in T_e and take linear terms [2].
  - Leads to correction from the cold plasma of:

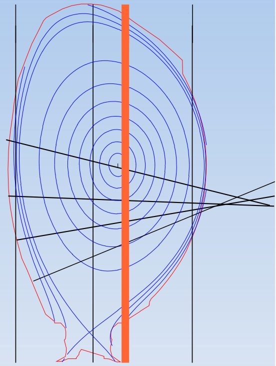
$$\underline{\Omega_1} \approx \underline{\Omega_0} + \frac{T_e}{mc^2}\begin{bmatrix} 12 & \Omega_{0_1} \\ 12 & \Omega_{0_2} \\ 3 & \Omega_{0_2} \end{bmatrix}$$

- But high velocity electrons also have relativistic mass increase.
  - Take **ε** from integration of relativistic Vlasov equation over relativistic Maxwellian [3].
  - Now have more terms linear in T_e but in the opposite direction:

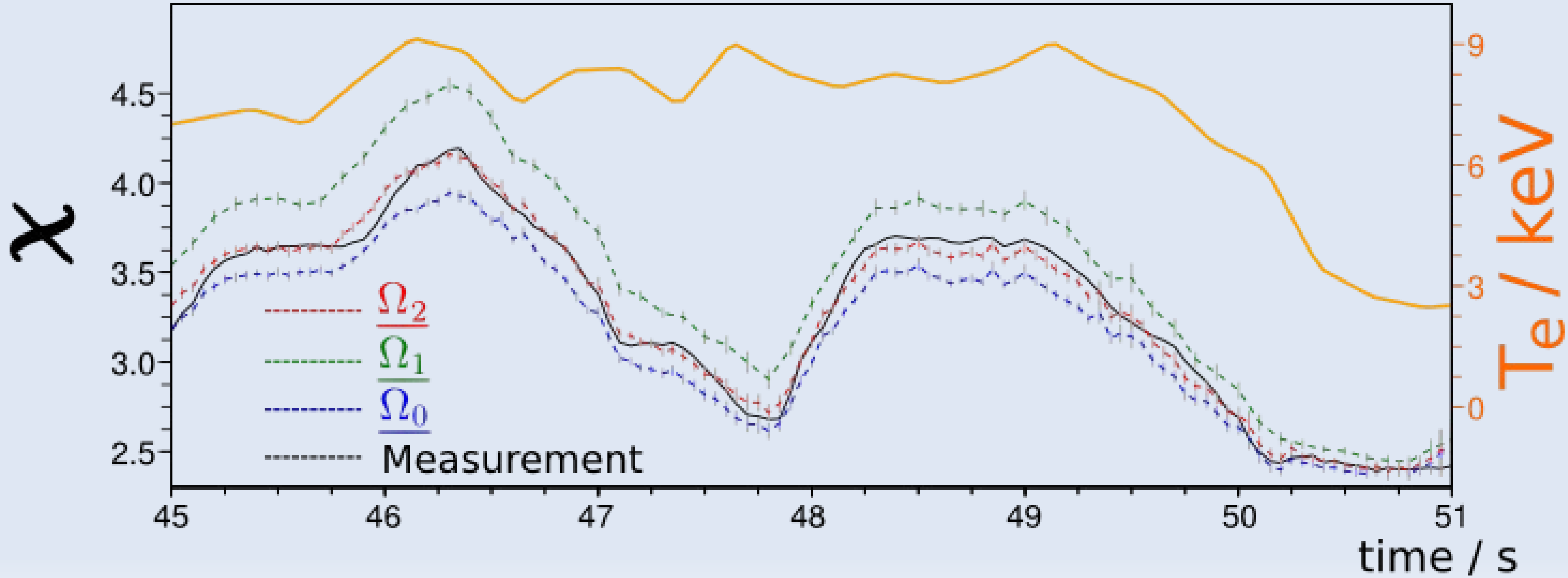
$$\underline{\Omega_2} \approx \underline{\Omega_0} + \frac{T_e}{mc^2}\begin{bmatrix} 4\frac{1}{2} & \Omega_{0_1} \\ 4\frac{1}{2} & \Omega_{0_2} \\ -2 & \Omega_{0_2} \end{bmatrix}$$

[2]: S. E. Segre et al, Phys. Plasmas 9 2919 (2002)
[3]: V. V. Mirnov, Phys. Plasmas 14 102105 (2007)

Polarimetry: High Te Effects



- Channel 3 passes through very core of plasma where Te can be up to 10KeV.
- For all but very high n_e, χ of channel 3 works.
- Evaluate full model based on interferometry invesion for cold model and both corrections.
- Pulses with Te > 8keV and where calibration has worked well show clearly better agreement with Ω_2:



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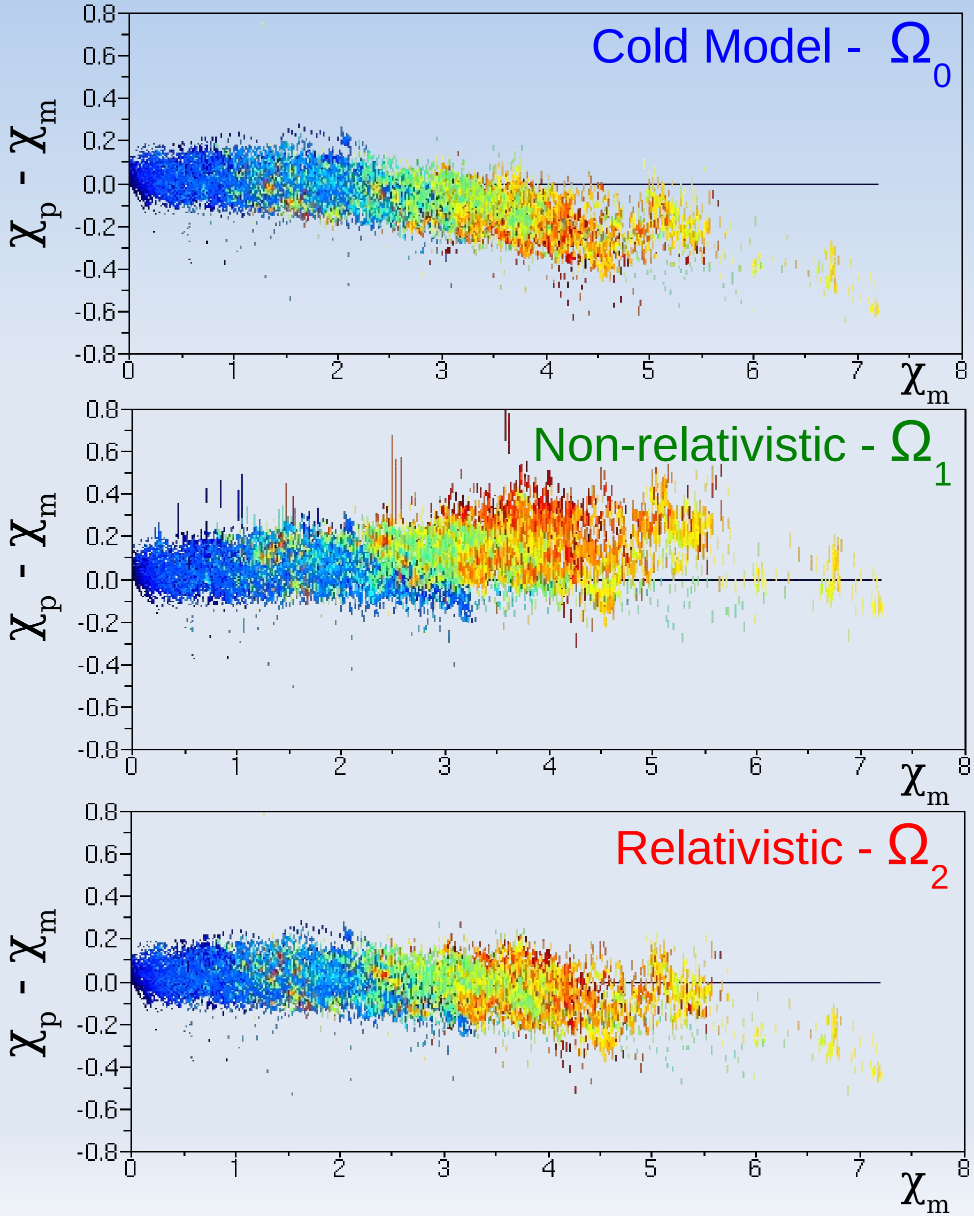
Polarimetry: High Te Effects

Coloured by Te: 0KeV to 10KeV



- In general, calibration and noise uncertainty are bigger than difference between the models. To prove it we must look at lots of data...
- 300 pulses with Te > 5keV.
- Very slight systematic underestimate by Ω_0 and overestimate by Ω_1. Ω_2 looks straighter in comparison.

Work In Progress

- Understand/fix polarimetry calibration!
- Develop probabalistic model for the polarimetry detectors.
- Combine magnetics, interferometry and polarimetry to simultaneously find *$P(n_e, \boldsymbol{j} \mid \text{All Data})$*
- Include LIDAR, Edge LIDAR (already built) and HRTS models to include Te.

Oliver Ford

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