The Light at the End of the Tunnel: Uncertainties in Atomic Physics, Bayesian Inference, and the Analysis of Solar and Stellar Observations

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International Space Science Institute [ISSI] Team "Improving the Analysis of Solar and Spectral Data"

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ISSI Team: Improving the Analysis of Solar and Stellar Observations

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The Problem: We need physical quantities (density, temperature, velocity, magnetic field) but we only observe intensity

We must infer the physical properties of the solar atmosphere using atomic physics

How accurately can we do this?

DAHLBURG ET AL

alysis of the dimensionless form

MHD equations

compressible er collocation retization that rallel thermal et al. 2010, beratures and the "heating us dissipation fling. Recent at temperature resolution in ucir footpoints temperature shaped strucguide field

lved loops to such as the asure (DEM) ons. There has distribution Del Zanna & i et al. 2008, tively narrow unclear how ry. xial magnetic

xial magnetic peratures and ne intensities

$$\frac{\partial n}{\partial t} = -\nabla \cdot (nv), \qquad (1)$$

$$\frac{\partial nv}{\partial t} = -\nabla \cdot (nv) - \beta \nabla p + \mathbf{J} \times \mathbf{B} + \frac{1}{S_v} \nabla \cdot \zeta$$

$$+ \frac{1}{Fr^2} n \Gamma(z) \hat{e}_z \qquad (2)$$

$$\frac{\partial T}{\partial t} = -\mathbf{v} \cdot \nabla T - (\gamma - 1) (\nabla \cdot \mathbf{v}) T$$

$$+ \frac{1}{n} \left\{ \frac{1}{Pr S_v} \left[\mathbf{B} \cdot \nabla \left(\kappa_{\parallel} T^{5/2} \frac{\mathbf{B} \cdot \nabla T}{B^2} \right) \right] + \kappa_{\perp}(n, \rho, T) \nabla \cdot \left(\frac{\mathbf{B} \times (\nabla T \times \mathbf{B})}{B^2} \right) \right]$$

$$+ \frac{(\gamma - 1)}{\beta} \left[\frac{1}{S_v} \zeta_{ij} \frac{\partial v_i}{\partial x_j} + \frac{1}{S} (\nabla \times \mathbf{B})^2 - \frac{1}{P_{rad} S_v} n^2 \Lambda(T) + \frac{\beta}{(\gamma - 1)} n C_N \right] \right\}, \qquad (3)$$

$$\frac{\partial \mathbf{B}}{\partial t} = \nabla \times \mathbf{v} \times \mathbf{B} - \frac{1}{S} \nabla \times \nabla \times \mathbf{B}, \qquad (4)$$

with the solenoidality condition $\nabla \cdot \boldsymbol{B} = 0$. The system is closed by the equation of state

p = nT. (5) The nondimensional variables are defined in the following way: p(r, t) is the number density, $p(r, t) = (r, y, y_t)$ is the flow



Example: We want to use the DEM to constrain models of coronal heating, but how well can it be computed? Errors in the atomic data are currently unaccounted for and likely dominate the calculation



Test Problem: Propagate the errors in the atomic data to the measurement of the densities with EIS Fe XIII ratios

AIA 171 Å + HMI Magnetic Field

"Moss" loop footpoints





Example EIS Spectrum Near 200 Å: 5 Fe XIII Lines



Least-Squares Fit to the Intensities



Phase 1: Perturb CHIANTI collision strengths and decay rates uniformly, generate 1000 realizations of the atomic data



Re-Analyze the Data

Original CHIANTI

Example with 10% perturbation

model log_n = 9.48 +- 0.016				$model log_n = 9.80 + -0.026$								
model $\log_d s = 9.14 + 0.031$ chi2 = 153.2					$model log_ds = 8.53 +- 0.050$ chi2 = 68.5							
Line	Imodel	Iobs	SigmaI	dI/Sigma	dI/I	Line	Imodel	Iobs	SigmaI	dI/Sigma	dI/I	
200.021	2064.02	1809.67	32.90	7.73	14.1	200.021	1775.97	1809.67	32.90	1.02	1.9	
201.121	2506.85	2946.72	51.14	8.60	14.9	201.121	2608.44	2946.72	51.14	6.62	11.5	
202.044	4299.64	4153.84	64.85	2.25	3.5	202.044	4283.36	4153.84	64.85	2.00	3.1	
203.152	932.87	1071.74	48.20	2.88	13.0	203.152	997.34	1071.74	48.20	1.54	6.9	
203.826	10223.57	10620.57	160.95	2.47	3.7	203.826	11290.98	10620.57	160.95	4.17	6.3	



But a uniform 10% is not right! . . . the rates for some transitions are better known that this, some are much more uncertain

Giulio Del Zanna compared rates from recent calculations and estimated the uncertainty as a function of collision strength



Phase 2: Perturb CHIANTI collision strengths and decay rates with GDZ method, generate 1000 realizations of the atomic data

How do we "learn" from the data? . . . pragmatic and full Bayes [Nathan Stein, David Stenning, David van Dyke, Jessi Cisweski]

> assume that the observations and the atomic data are independent

- Pragmatic Bayes: Assume that $P(A | Y) \stackrel{\bullet}{=} P(A)$ such that $P(\Theta, A | Y) = P(\Theta | A, Y) P(A)$
 - For I = 1, ..., L:

Step 1: Sample A_l from its prior distribution: $A_l \sim P(A)$.

Step 2: For k = 1, ..., K: sample $\Theta^{(k)}$ from its joint posterior distribution given A_l :

$$\Theta^{(k)} \sim P(\Theta \mid Y, A_l).$$

assume that the observations are conditional on the atomic data

- Full Bayes: $P(\Theta, A | Y) = P(\Theta | A, Y) \stackrel{\bullet}{P} (A | Y)$.
- The fully Bayesian posterior distribution on Θ can be thought of as a weighted version of that under Pragmatic Bayes:

$$P(\Theta \mid Y) = \int P(\Theta \mid A, Y) \frac{P(A \mid Y)}{P(A)} P(A) dA.$$

 Alternative computational techniques are used to obtain samples from P(Θ | Y).

Pragmatic vs Full Bayes

Pragmatic Bayesian Solution



This is only applied to a single set of intensities

Analysis of full data set: consider all combinations of 1000 sets of EIS intensities and 1000 realizations of CHIANTI

Result: another set of atomic rates fits the data much better

A clue that EIS analysis or atomic data can be improved

• Use Laplace's method to approximate

$$p(y_k|A_m) = \int p(y_k|\theta_k, A_m) p(\theta_k) d\theta_k$$

for the kth pixel and the mth atomic data curve

- From these, we can directly compute:
 - Separate analyses: $p(A_m|y_k) = p(y_k|A_m) / \sum_i p(y_k|A_i)$
 - Joint analysis: $p(A_m|y_1, \ldots, y_K) = \prod_k p(y_k|A_m) / \sum_i \prod_k p(y_k|A_i)$
- Use Gaussian approximations for posterior distributions $p(\theta_k|y_k, A_m)$
- Computing time for 1000 pixels: 6.5 hours









Summary and Conclusions

For the first time we have considered the analysis of spectroscopic data including both statistical errors and uncertainties in the atomic data

Uncertainties in the atomic data dominate, but are not catastrophic . . . phew!

More work is in progress

- Analysis of stellar O VII/O VIII spectra
- Analysis of collision rate covariance structure from first principle calculation
- Test problems using MHD simulation results