# The University of Texas at Austin

### Bayesian inference of excited state population densities and equilibrium temperatures in argon plasmas using emission spectroscopy

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### Motivation

- Plasmas are relevant in material processing, medicine, energy production, hypersonics, and space propulsion.
- Complex chemistry and non-equilibrium states: challenging for predictive modeling efforts.
- Argon plasma: well known but limited diagnostic approaches.
- Emission spectroscopy both simple and applicable but many uncertain parameters.

Bayesian inference for UQ and higher fidelity results:
 →Has been done for singular transition in fusion device [1,2].
 →Extract information over a larger spectral range.

- $\rightarrow$ Include knowledge about transition parameters.
- $\rightarrow$ Extract temperature and excited species number densities.

[1] Kwak et al., "Bayesian modelling of the emission spectrum of the Joint European Torus Lithium Beam Emission Spectroscopy system", *Rev. Sci. Inst.* (2016)

[2] Kwak et al., "Bayesian electron density inference from JET lithium beam emission spectra using Gaussian processes", *Nucl. Fusion* (2017)







### **Experimental Setup**

#### Argon spectroscopy



#### **Measured signal counts**

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$$S(\lambda) = \int_{A} \eta_{\lambda} \tau_{\lambda} \frac{\Omega}{4\pi} \int_{\Delta L} \sum n_{j} A_{ji} \frac{hc}{\lambda_{ji}} \varphi(\lambda_{ji}, w) \, dl \, dy \frac{d\lambda}{dx} dx$$

#### ICP plasma torch Capacitive glow discharge



### **Bayesian Formulation**



- Take x to be quantities of interest: T,  $n_i$
- x can include additional uncertain parameters:  $\Delta L, w, A_{ji}$
- *b* is a vector of **observations**, i.e. the data that has been collected,
  - could be raw camera counts,
  - could be intensity corrected spectra,
  - could be emission coefficients.

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#### Applied to capacitive glow discharge

- Measurement  $\bar{\epsilon}_{ji} = \int_{\Delta\lambda} C(\lambda) S_{ji}(\lambda)$  and model  $\widehat{\bar{\epsilon}_{ji}} = n_j A_{ji} \frac{hc}{\lambda_{ji}} \Delta L$  with  $\bar{\epsilon}_{ji} = \widehat{\bar{\epsilon}_{ji}} + \varepsilon$  or more generic  $b = \hat{b} + \varepsilon$
- The error  $\varepsilon$  is additive and a combination of random and shot noise, *approximated by* Gaussian PDFs  $\rightarrow$  Likelihood: multi-variate normal (MVN) distribution

$$p(\boldsymbol{b} \mid \boldsymbol{n}_{\boldsymbol{j}}, \boldsymbol{A}_{\boldsymbol{j}\boldsymbol{i}}, \Delta L = \boldsymbol{x}) = \frac{1}{\sqrt{(2\pi)^{m} \det(\Gamma_{e})}} exp\left\{-\frac{1}{2} \left[\boldsymbol{b} - \widehat{\boldsymbol{b}}(\boldsymbol{x})\right]^{T} \Gamma_{e}^{-1} \left[\boldsymbol{b} - \widehat{\boldsymbol{b}}(\boldsymbol{x})\right]\right\}$$
$$\Gamma_{e} \approx \frac{1}{N-1} \sum_{i=1}^{N} \left(\boldsymbol{b}_{ref}^{(i)} - \overline{\boldsymbol{b}}_{ref}\right) \left(\boldsymbol{b}_{ref}^{(i)} - \overline{\boldsymbol{b}}_{ref}\right)^{T} + \boldsymbol{C} \operatorname{diag}(\boldsymbol{\mu}_{S}) \boldsymbol{C}^{T}$$

#### **Assumptions:**

- Intensity correction  $C(\lambda)$  and baseline have no uncertainty
- Each measurement is completely independent
- No model uncertainty from choice of lineshape

• Priors:

- $n_j$ : Gaussian, locally flat with very large standard deviation, mean is first guess from LSQ solution
- *A<sub>ji</sub>*: Gaussian, data from NIST,
  marginalized out of likelihood to reflect knowledge
- $-\Delta L$ : Gaussian, from auxiliary measurements
- Observed 26 transitions from 10 states



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Least-squares solution: maximize unweighted likelihood





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#### **Bayesian Result**



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## Results – Population Density

- $\overline{\Delta L} = 1.8 \pm 0.4$  cm (compare to 10 cm diameter of glow discharge).
- Itorr results on same order of magnitude as detailed collisionalradiative model [1].

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[1] lordanova & Koleva, "Optical emission spectroscopy diagnostics of inductively-driven plasmas in argon gas at low pressures", Spect. Acta B (2007)

### Bayesian Formulation – Temperature

#### Applied to ICP plasma torch

• Measurement model in thermal equilibrium:

$$\hat{L}_{e,\lambda}(\lambda) = \sum g_j e^{-E_j/kT} \frac{A_{ji}}{\lambda_{ji}} \varphi(\lambda_{ji}, w) = \hat{b}$$
$$b = \hat{C}(\lambda)S(\lambda)$$

- Likelihood: assume additive error as before, x = (T, w)
- Priors:
  - -T: Gaussian, locally flat with very large standard deviation, mean is first guess from LSQ solution
  - -w: Gaussian, from preliminary processing tests
- Assumptions: same as in population density approach  $\rightarrow$  marginalization in  $A_{ji}$  is work in progress.
- Posterior: sampled using emcee package (Markov-Chain Monte-Carlo): 5,000 samples, mean acceptance ratio ~0.64



#### Results – Temperature

- Temperatures:
  - <sup>–</sup> Median: 5953 K
  - 5%: 5858 K
  - 95%: 6051 K
- Voigt lineshape  $(w_G, w_L)$ 
  - <sup>-</sup> Median: (0.30,0.20)
  - 5%: (0.29,0.20)
  - 95%: (0.30,0.21)
- Temperature from Boltzmann plot method: 5918 ±1000 K

 $\rightarrow$  Uncertainties in Bayesian result very low due to missing marginalization in  $A_{ji}$ .





### Conclusions

- Bayesian framework to extract information from emission spectroscopic data.
- Includes a priori knowledge about spectroscopic and instrument parameters.
- Provides direct estimate of uncertainties.

#### **Future work**

- Add inference of intensity calibration and baseline.
- Unify treatment of population densities and temperature.
- Extract additional information with more complex measurement model
  - <sup>-</sup> Electron number density
  - Multi-temperature EEDFs
  - Molecular Species

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#### THANK YOU! Questions?



