Using Dynamic Polarization as Leverage to Extract the Global Signal

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Why do we pursue the global 21-cm signal?

- Interaction of excitation temperature, TS, of HI’s 21-cm transition with radiation fields produces signal which opens up the first billion years after recombination to new inquiry

A: Collisions between H atoms no longer relevant to TS because CMB temperature exceeds kinetic temperature of H gas

B: First stars ignite, coupling TS to the strength of their Lyman-α radiation

C: First black holes begin accretion, heating gas to warmer than the CMB

D: Reionization drives signal to zero since only neutral hydrogen emits 21-cm radiation

Signals generated with Jordan Mirocha’s Accelerated Reionization Era Simulations (ares) code available at https://bitbucket.org/mirochaj/ares
Difficulty of measuring 21-cm signal

- Strong galactic foregrounds combine with antenna beam chromaticity to produce complicated spectral structure.
- Foregrounds have steep spectra with spectral index of -2.5, i.e.

\[ T_{FG}(\nu, \theta, \phi) \approx A(\theta, \phi) \times \nu^{-2.5} \]

\[ T_{BWFG}(\nu) = \int_0^\pi \int_0^{2\pi} B(\nu, \theta, \phi) T_{FG}(\nu, \theta, \phi) \sin \theta \, d\phi \, d\theta \]

Galaxy map from Haslam et al. (1982) scaled to 80 MHz

Traditional approach to measurement

- Experiments such as EDGES attempt to calibrate out beam chromaticity from single spectra and then fitting a polynomial or polynomial-like model simultaneously with a chosen signal model.
- The beam corrections rely on the temperature of the sky model and the simulation of the beam model being correct.

\[
BCF(\nu) = \frac{\int_0^\pi \int_0^{2\pi} B(\nu, \theta, \phi) T_{FG}(\nu, \theta, \phi) \sin \theta \, d\phi \, d\theta}{\int_0^\pi \int_0^{2\pi} B(\nu_n, \theta, \phi) T_{FG}(\nu, \theta, \phi) \sin \theta \, d\phi \, d\theta}
\]

Beam chromaticity factor

Model of beam weighted foreground

\[
M_{BWFG}(\nu) = \sum_{k=0}^{N-1} a_k \nu^{-2.5+k}
\]

Our new method, SVD/MCMC

- We have developed a technique to analyze many spectra at once.
  - The information relating different spectra (such as different foregrounds caused by looking in a different direction) can help extract the signal, which doesn’t change from spectrum to spectrum, more rigorously.
- By simulating training sets for these sets of spectra, we can create models specifically suited for that dataset, instead of relying on an a priori model.
- We also use training sets of the signal derived from physical simulations.
Using SVD to generate optimal basis vectors

- Singular Value Decomposition (SVD) is a factorization of the training set that provides the optimal basis vectors with which to fit that training set.
Simultaneously fitting foreground and signal

- Once we have SVD models for both foreground and signal, we fit them simultaneously to the data.
- The uncertainties in this separation of the two components depend on how similar their models are.
  - If the foreground and signal training sets are different enough and the experiment is designed well enough, then the signal can be constrained rigorously.
Drift-scan measurements

- One example of experimental design that can lower the overlap/similarity between foreground and signal is drift-scan.

- Time introduces valuable structure into sky-averaged data because the antenna beam points at different points in the sky at different times.

- This leads to multiple spectra with the same signal but different foregrounds.
Effect of multiple pointings

- Looking at multiple independent directions is a discrete form of drift-scan.

- The forecasted errors are smaller and the signals are less biased when simulating data with multiple antenna pointings instead of one.
Other benefits of SVD/MCMC generalization

- Since our pipeline does not require a foreground model to be given beforehand (only training sets), data aspects with no obvious extension in the polynomial-like approach can be utilized.
- One of these effects is polarization, which is measured in terms of the Stokes parameters $I$, $Q$, $U$, and $V$.

\[
\begin{align*}
I &= \langle |E_X|^2 + |E_Y|^2 \rangle \\
Q &= \langle |E_X|^2 - |E_Y|^2 \rangle \\
U &= 2 \text{Re}(E_X^*E_Y) \\
V &= 2 \text{Im}(E_X^*E_Y)
\end{align*}
\]

Single antenna experiments (e.g. EDGES, SARAS)

Dual antenna experiments (e.g. DAPPER, CTP)
Induced polarization

- Projection onto the instrument’s antennas induces a polarization signal measured by dual antenna instruments, which can help constrain foreground.
SVD takes advantage of structure

- SVD naturally provides a model which accounts for connections between Stokes parameters

A: Training set of Stokes parameters accounting for induced polarization.

B: Training set with average subtracted

C: Optimal basis vectors to fit training set, provided SVD
Effects of induced polarization data on constraints

Stokes I Only

Note the large scale difference between the plots.
Results with signal model from EDGES paper

- When using a training set of flattened Gaussian models defined as in EDGES Nature paper (Bowman et al. 2018), we obtain the confidence intervals on the right.
- These simulations include both induced polarization and multiple antenna pointings.
Summary and ongoing work

- We have been developing a pipeline for extracting the 21-cm global signal from sky-averaged spectral data.
- Our training set based pipeline allows any effect that can be simulated to be included in the analysis.
- In our simulations, we include multiple antenna pointing directions (precursor to drift-scan measurements) and Stokes parameters because they lower the overlap between foreground and signal, decreasing uncertainties.
- In the past year, we have for the first time completed the pipeline to extract physical parameters from our 21-cm signal constraints in frequency space (see David R.’s talk)