Likelihood approximations for large-scale CMB data

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Motivation

Problem
- noise- & systematics-dominated signal
- No exact analytic likelihood (masked sky)

Physical motivation
- $\tau$ relevant for $M_\nu$, $A_s$, $n_s$, $\sigma_8$
- Constraints on reionization models

Solution
- Improved noise and systematics modelling
- Three Bayesian frameworks:
  - From likelihood-approximation$^{1,2}$ to simulation-based$^{3,4}$ schemes

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1 Pagano et al. (2020)
2 Gratton (2017)
3 Planck Collaboration XLVI (2016)
4 Alsing et al. (2018)
Brief history of the Universe
Optical depth to reionization $\tau$ (CMB)

- Measure $\tau$ on 100x143GHz $Planck$ low-\(l\) HFI maps
  - $Planck$ 2018$^1$ & SRoll2$^2$ data

Joint likelihood for $\tau$ using TT, TE & EE data
Parameter inference in Bayesian framework

1. Compress observed data to a summary statistic \( d_0 \) (e.g., power spectrum)

2. Determine unknown parameters \( \theta \) of a given model \( \mathcal{M} \)

3. Generate mock data in pairs \( \{d_i, \theta_i\} \) to train models

\[
P(\theta | d_0, \mathcal{M}) \propto P(d_0 | \theta, \mathcal{M})P(\theta | \mathcal{M})
\]

- Posterior density
- Likelihood
- Prior
Comparison of likelihoods

<table>
<thead>
<tr>
<th>SimBaL(^1)</th>
<th>DELFI(^2)</th>
<th>GLASS(^3)</th>
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<tbody>
<tr>
<td>Simulation-based likelihoods</td>
<td></td>
<td>Principle of maximum entropy</td>
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<tr>
<td>Assumption: functional form for distribution of spectra</td>
<td>Neural network</td>
<td>Only noise covariance matrix</td>
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<td>Normalizing flow(^4)</td>
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<tr>
<td>(\mathcal{L} = \sum_{\ell=2}^{29} \ln \mathcal{P}(C^\text{data}_\ell; \tau, \theta))</td>
<td>(\mathcal{L} : \text{compute moments of data } \rightarrow \text{analytically (or simulations)})</td>
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<td>C-SimLow</td>
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<td>Sampling: integrate along (C_{\text{fid}} \rightarrow C_{\text{th.}}) to get change in (\ln \mathcal{L})</td>
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<tr>
<td>(\mathcal{P}(C^\text{sim}_\ell</td>
<td>\ell, \tau, \theta))</td>
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1 Planck Collaboration XLVI (2016)  
2 Alsing et al. (2018)  
3 Gratton (2017)  
4 Papamakarios (2018)
Sounds nice in theory, does it work?
Test: 100 end-to-end simulations\(^1\) with realistic noise & systematics

\[^1\] Planck Collaboration XLVI (2016)
Joint TTTEEE likelihood results

Cross-correlations between TT, TE, EE pull posterior upwards

\[ \sigma(T_{EE}) \sim 5-10\% \text{ smaller} \]

\[ \sigma(T_{TTTEE}) \]
Effect of score compression on posterior

Sub-optimal compression leads to ~7% wider posteriors

Compression:
\[ \tau_c = \nabla_{\tau} \ln \mathcal{P}(\hat{C}_\ell^{XY}) \bigg|_{\theta^*} \]
Exploring cosmological parameter space

\[
\tau_{SRoll1} = 0.0552^{+0.0056}_{-0.0065}
\]

\[
\tau_{SRoll2} = 0.0627^{+0.0050}_{-0.0058}
\]

Camspec12.5 + Planck lowl TT + Planck lowl EE
Camspec12.5 + Planck lowl TT + momento (EE)
CamSpec12.5 + momento(TTTEEE)
Next steps
Please get in touch if you want to chat more!

• Consistent results for three Bayesian methods
  – momento uses most physical information

• Tighter constraints than Planck 2018/SRoll2:
  – Improved noise & systematics modelling
  – Quadratic cross-spectrum estimation
  – First joint likelihood TT, TE, EE for $\tau$

• relevant for future large-scale CMB surveys such as LiteBIRD
  – Measure tensor-to-scalar ratio $r$

Applying for postdocs this fall!
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