

maxsmooth: rapid maximally smooth function fitting with applications in Global 21-cm cosmology

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<https://arxiv.org/abs/2007.14970>

What are Maximally Smooth Functions?



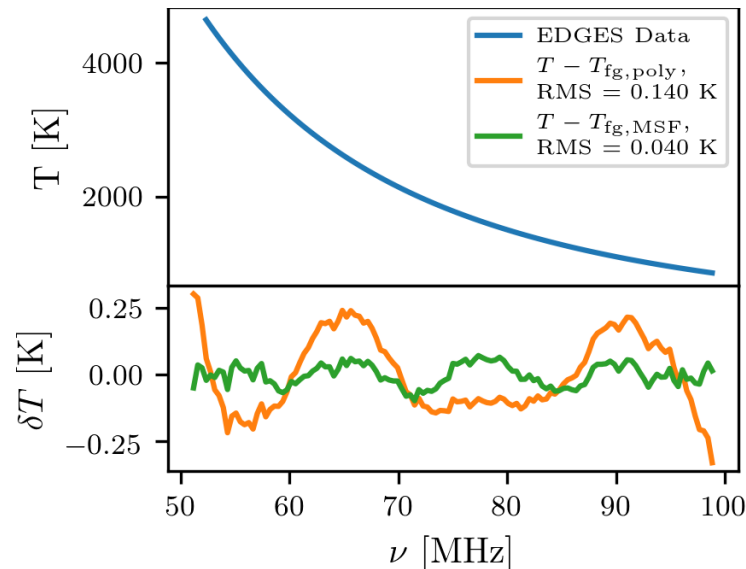
- Originally proposed in Sathyanarayana Rao et al. (2015, 2017)

- Functions constrained by:

$$\frac{d^m y}{dx^m} \geq 0 \quad \text{or} \quad \frac{d^m y}{dx^m} \leq 0$$

with $m \geq 2$.

- Example function $y = y_0 \sum_{k=0}^N a_k \left(\frac{x}{x_0}\right)^k$
- Smooth properties ideal for modelling foregrounds
- Generalise to Derivative Constrained Functions (DCFs) with different constraints on derivatives
- Example using the EDGES data

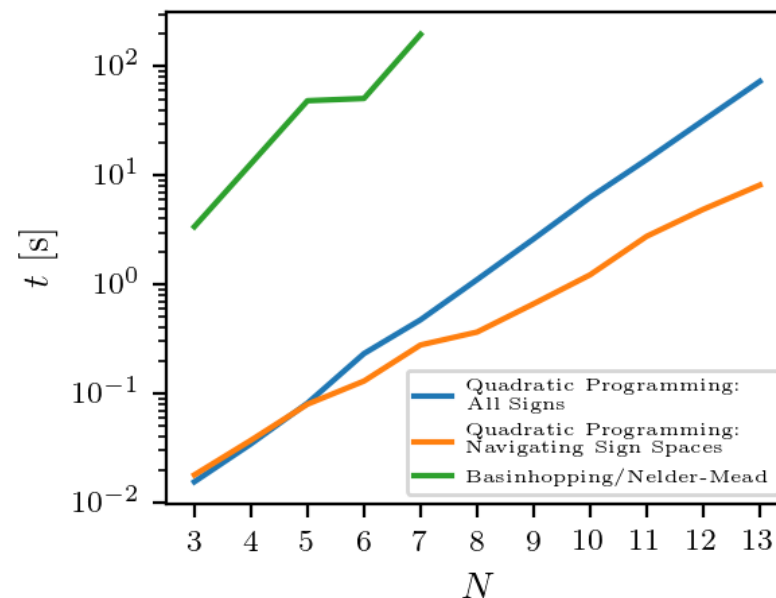


What is maxsmooth?



- Robust and fast algorithm for fitting DCFs
- 2 orders of magnitude faster than historically used Basin-hopping/Nelder-Mead routines
- Based in quadratic programming and a division of the parameter space determined on the constraints (more details in the paper)

$$\frac{d^m y}{dx^m} \geq 0 \quad \text{or} \quad \frac{d^m y}{dx^m} \leq 0$$

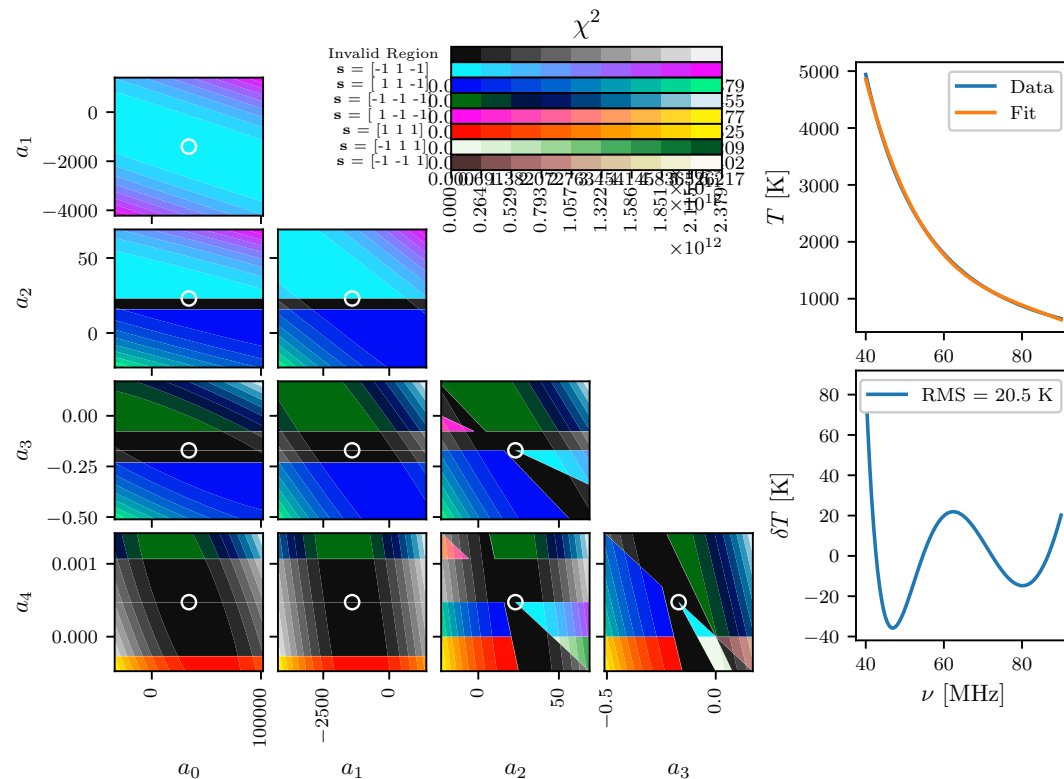


What is maxsmooth?



- Division of the parameter space
- For Basin-hopping each region acts as a basin but these aren't always explored
- maxsmooth allows you to explore the entire parameter space
- Available on Github:
<https://github.com/htjb/maxsmooth>
- `pip install maxsmooth`

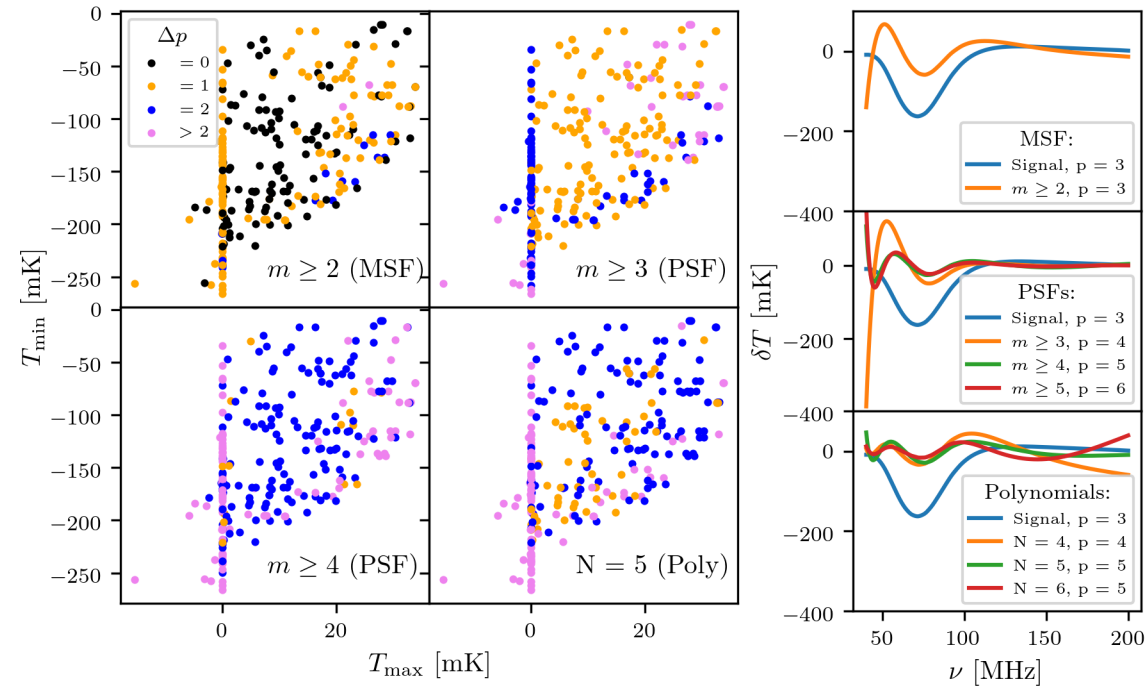
```
1 import numpy as np
2 from maxsmooth.DCF import smooth
3
4 n_samples = 242
5 x = np.linspace(60, 200, n_samples)
6 y = 5e7*x**(-2.5) + np.random.normal(0, 0.2, n_samples)
7
8 N = 10
9
10 res = smooth(x, y, N)
```



DCFs and 21-cm Cosmology



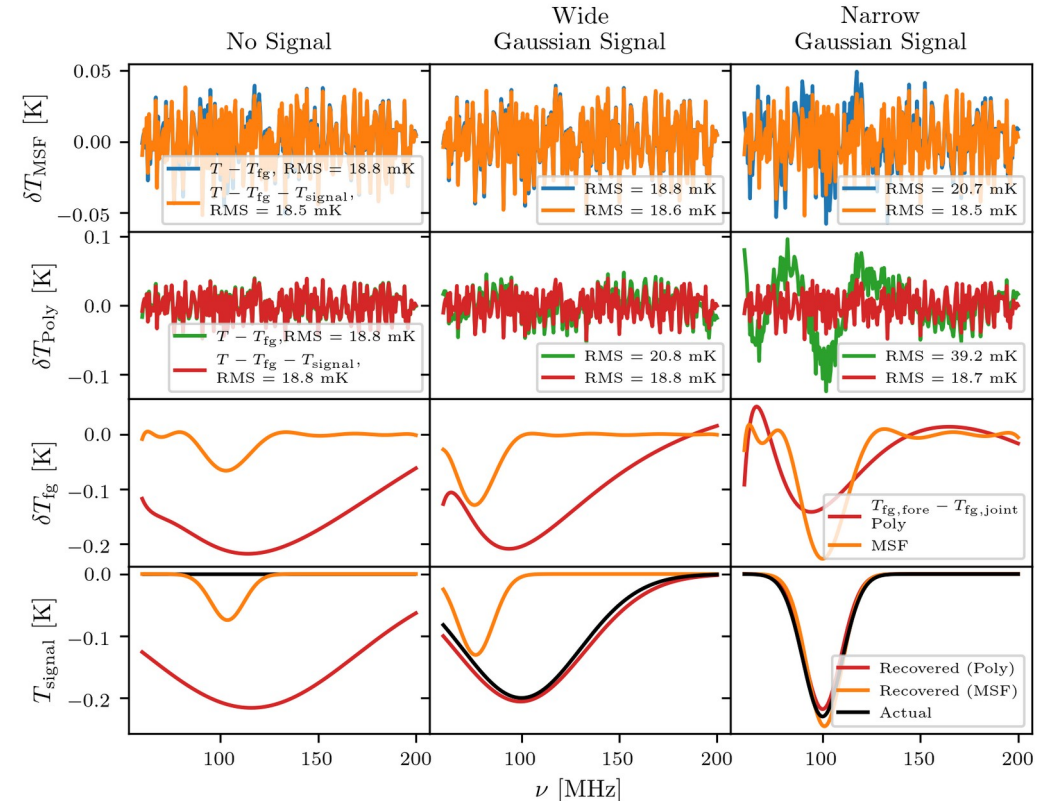
- 264 mock signals and a $\nu^{-2.5}$ power law foreground.
- Models from Cohen et al. (2017) and used by Singh et al. (2018)
- Fit and remove different foreground models
- Count turning points, p , in residuals and compare with those in the signal
- $\Delta p=0$ indicates a strong remnant of the signal in the residuals



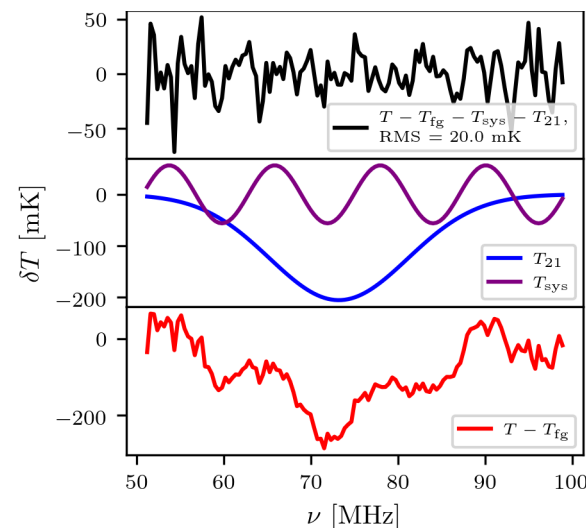
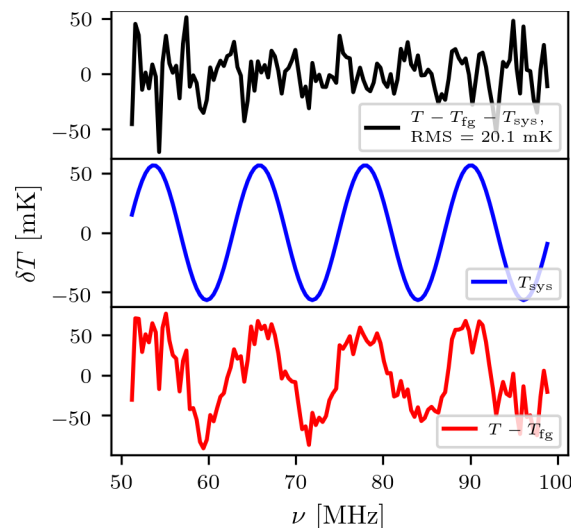
Limitations of DCFs



- Three data sets with same foreground and noise but different signals
- Pure foreground and Joint fits of signal with MSFs and an unconstrained polynomial
- Find evidence that MSFs struggle with recovery of 'smooth' signals and identification of signals in the absence of any real signal
- Similar problems with polynomials
- Evidence is a strong indicator of presence of smooth signals

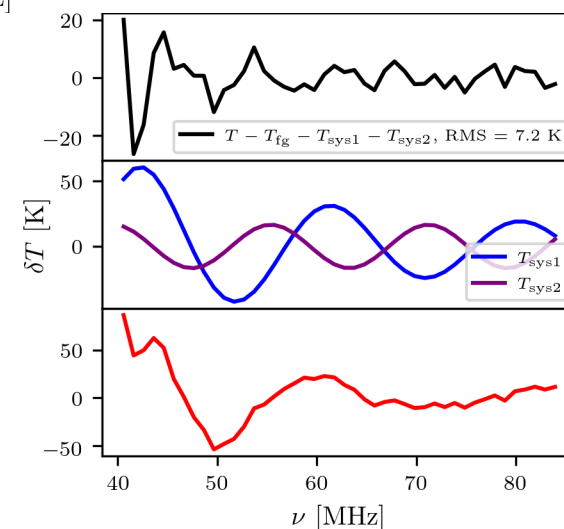
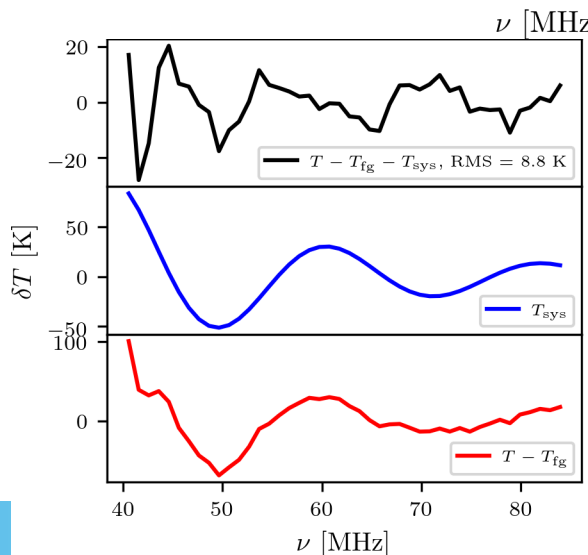
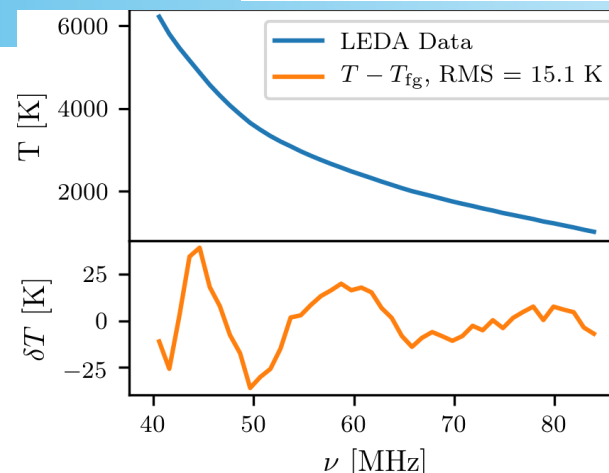


- Testing `maxsmooth` on the EDGES data
- Previously analysed with MSFs by Singh and Subrahmanyan (2019)
- Pure foreground fit has $\log(Z)=216.80\pm0.09$
- Found evidence for sinusoidal systematic, $\log(Z)=302.99\pm0.08$
- We can recover a theoretically plausible Gaussian signal
- However the evidence is lower than for the systematic fit, $\log(Z)=292.67\pm0.17$



$$N = 11 \quad y = \sum_{k=0}^N a_k (x - x_0)^k$$

- Fit LEDA data, taken in 2016, for the first time with MSFs
- Large RMS and $\log(Z) = -185.45 \pm 0.09$
- Perform Joint fit with a damped sinusoidal systematic and return $\log(Z) = -175.50 \pm 0.19$
- Additional sinusoidal structure which we can fit and find $\log(Z) = -168.34 \pm 0.19$
- Systematic described by the leading order terms in a damped Fourier series
- Similarities between the systematics here and in EDGES might highlight larger causes in Global 21-cm experimentation



Best Case Scenario:

- `maxsmooth` can be used as an independent foreground modelling technique alongside the existing Bayesian pipeline to confirm a detection.

Worst Case Scenario:

- `maxsmooth` can be used to confidently identify systematics in the data set leading to quicker identification and improvements to the REACH experiment.

- `maxsmooth` is a fast and robust tool for fitting MSFs and related functions.
- 2 times faster than historically used methods for fitting MSFs
- MSFs are shown to be better suited for modelling foregrounds than commonly used unconstrained polynomials.
- There are limitations to the usefulness of MSFs
- We can use MSFs to identify the presence of non-smooth systematics in 21-cm experiments like LEDA and EDGES

Paper: <https://arxiv.org/abs/2007.14970>

Github: <https://github.com/htjb/maxsmooth>