# Non-parametric Background Models for Axion Haloscopes.

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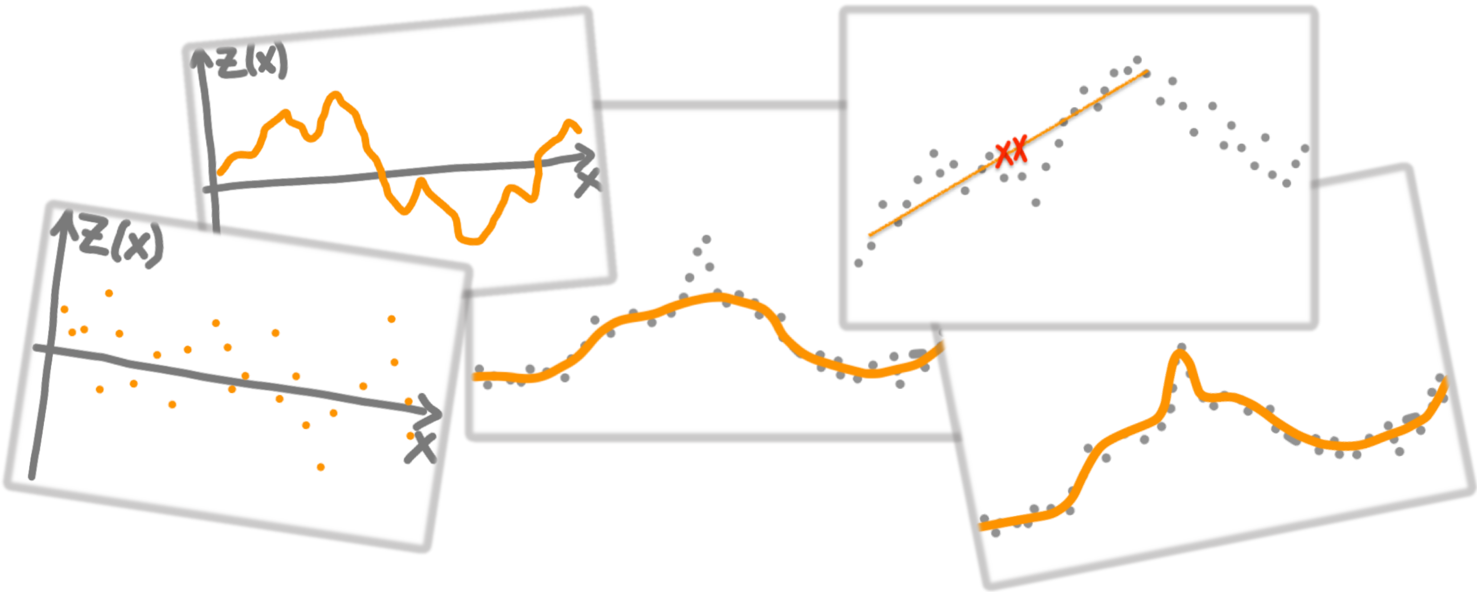


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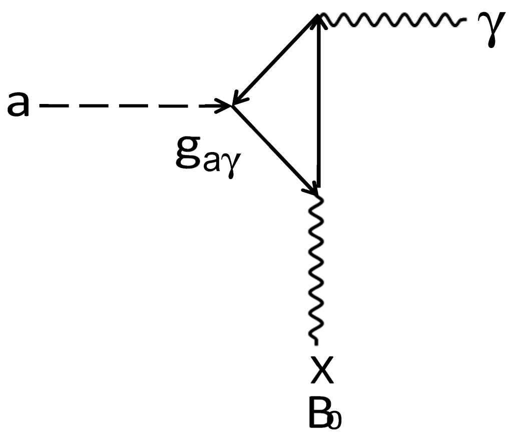
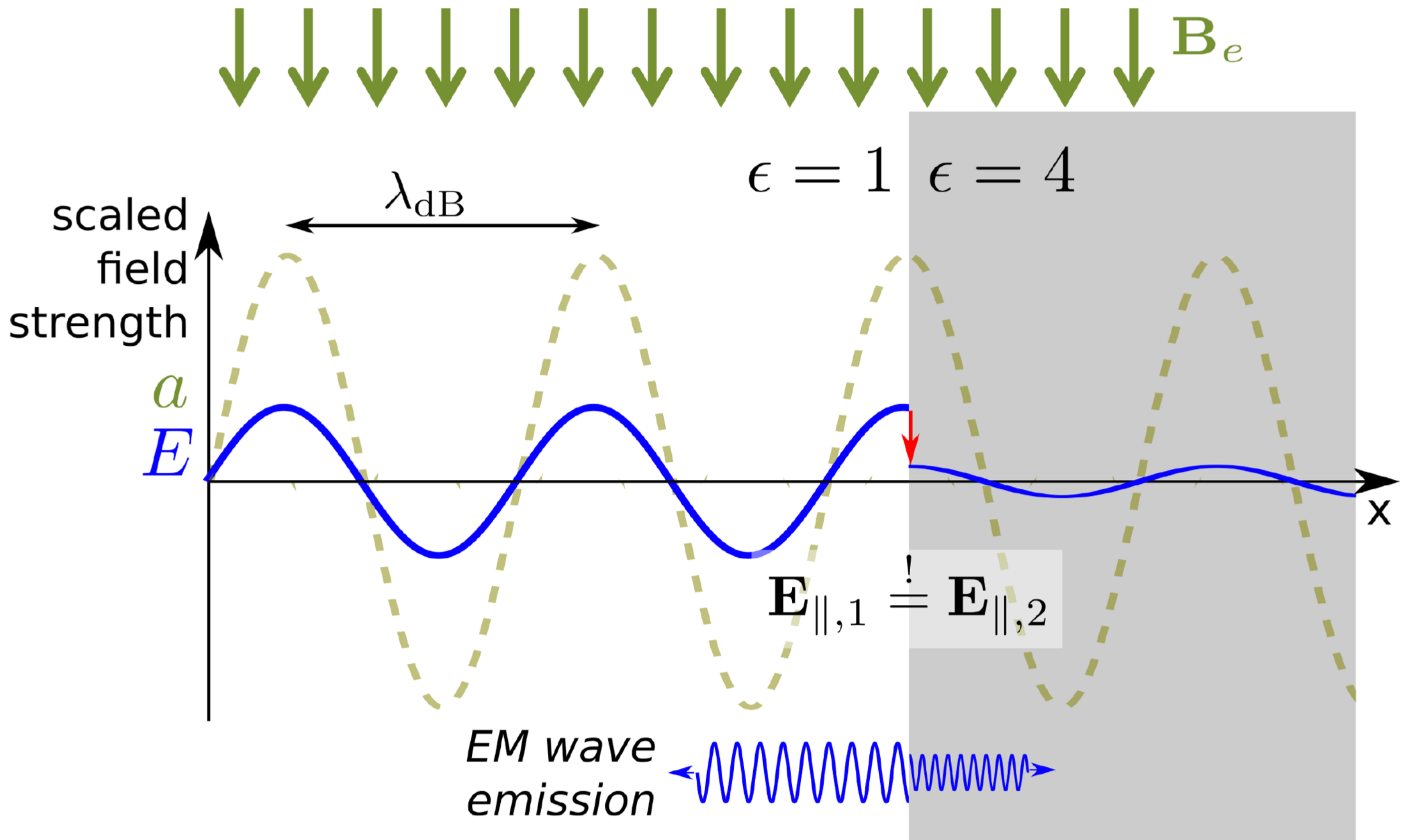
# Axion…

- Predicted by advanced QCD
- Non-thermal production → Dark Matter candidate
- Extremely light ($m_a \sim 10^{-5}$ eV) → $\lambda_{dB}$ macroscopic
- (weakly) interacting with photons



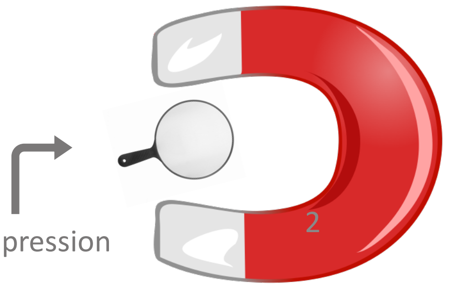

Bukhari 2020

# ...haloscopes



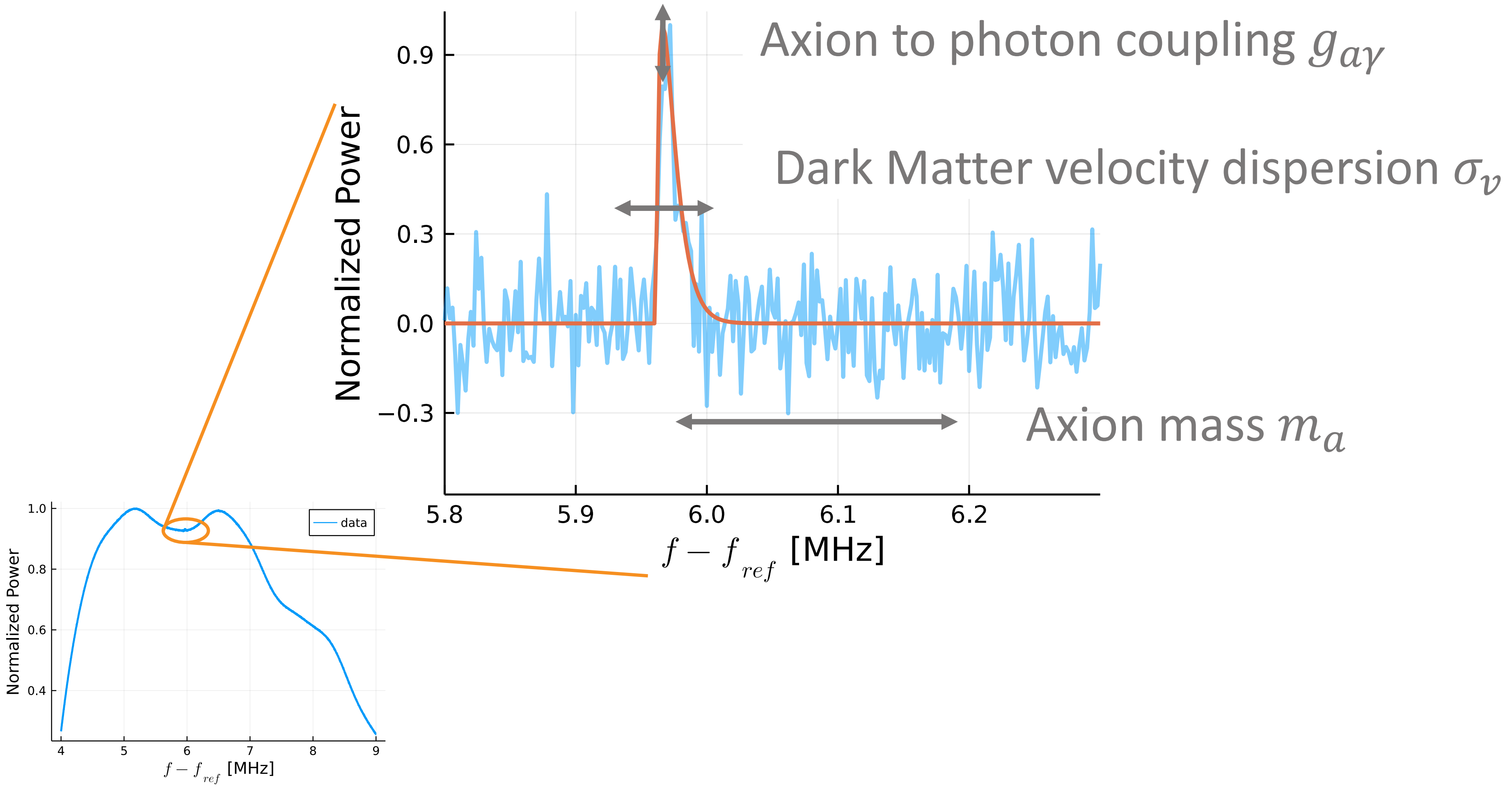

1. $\epsilon$ boundary in magnetic field
2. Step in induced E field leads to photon emission, frequency corresponds to axion energy

Simplest concept:
Dish antenna
(i.e. one mirror)



Artist's impression

# Axion haloscopes: **signal**



# Goal

Cleaned measured or simulated powerspectrum → **Non-parametric background subtraction** → Background-„free“ powerspectrum

Three components:
- Thermal noise
- Background (i.e. correlated receiver noise)
- (Signal)

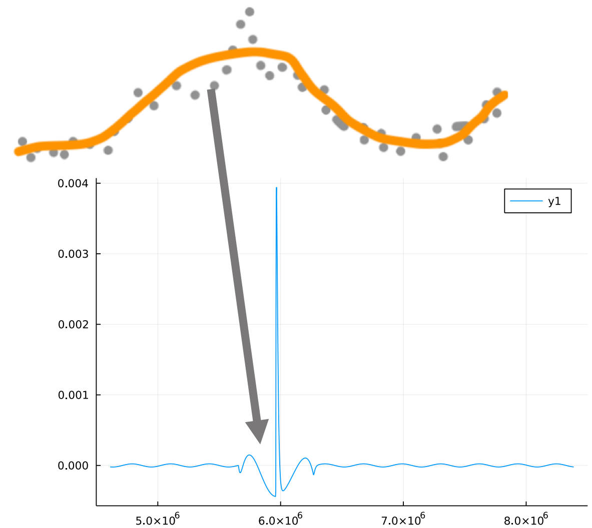
- BG shape not known
- Sharp signal on smooth BG
- Simultaneous bg and signal fit not possible

- Retain as much signal as possible
- Proceed to set limits via Frequentist or Bayesian methods

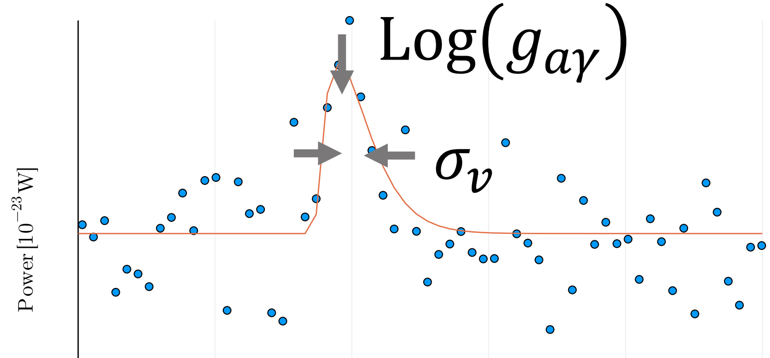
# Background Fit

data

reality




→ will shift parameter values!
→ will reduce sensitivity!



# Background fit: Savitzky-Golay Filter

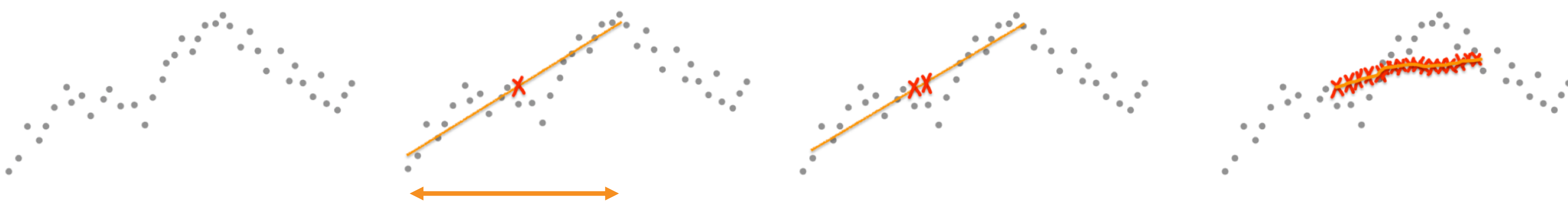
## Example: SG fit, polynomial order 1, width 25

Data, equally spaced

Fit polynom, take middle value

Shift window to the right, repeat

Repeat for all datapoints



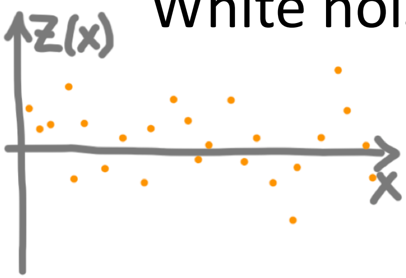
Width: 25 datapoints

→ Bandpass filter with properties depending on order and width

→ used by many axion haloscopes

# Background fit: Gaussian Processes

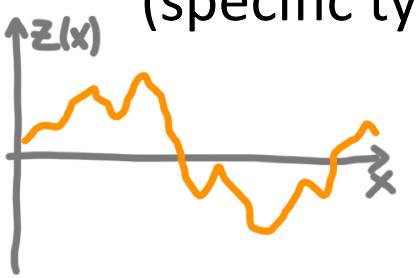
White noise




Auto-covariance function $(x_1 \neq x_2)$

$$cov\big(Z(x_1), Z(x_2)\big) = 0$$

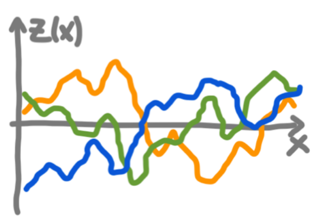
random process (specific type)




$$cov\big(Z(x_1), Z(x_2)\big) = k(|x_1 - x_2|)$$

Turn it around!

$$k(|x_1 - x_2|)$$

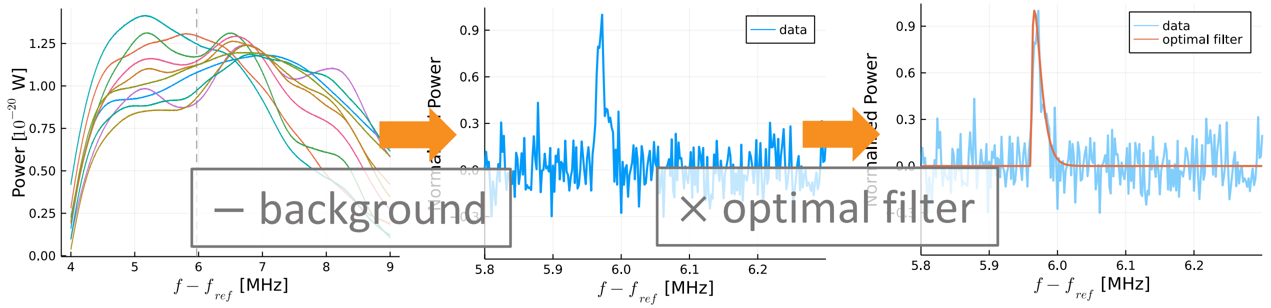


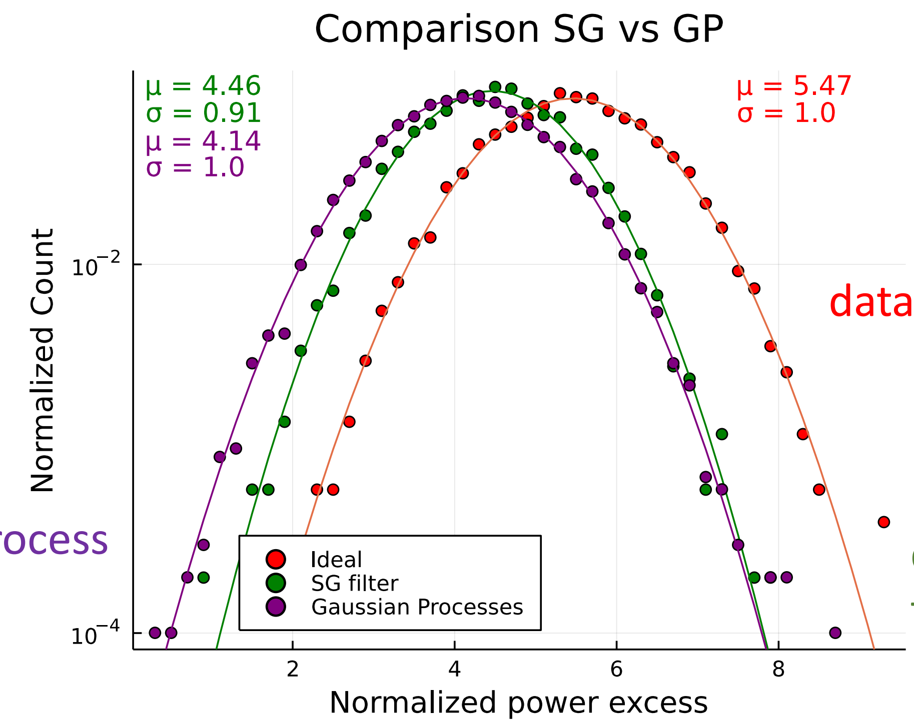

Generate realization of random process

#dofs = #points, but same correlation structure

# Quantify over-/underfitting

- Reproduce HAYSTAC analysis

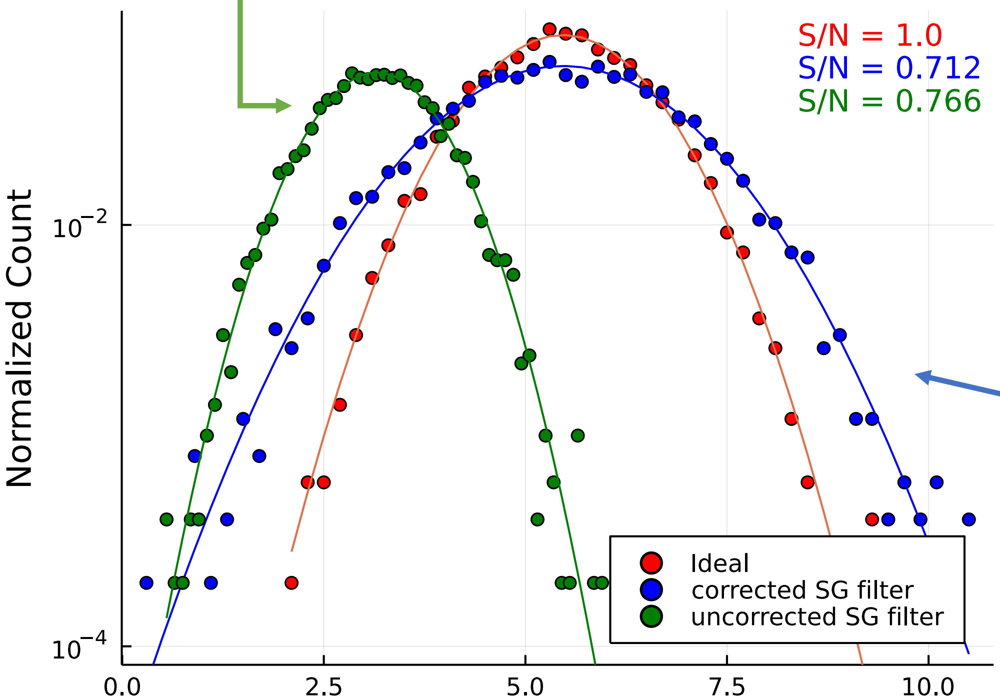


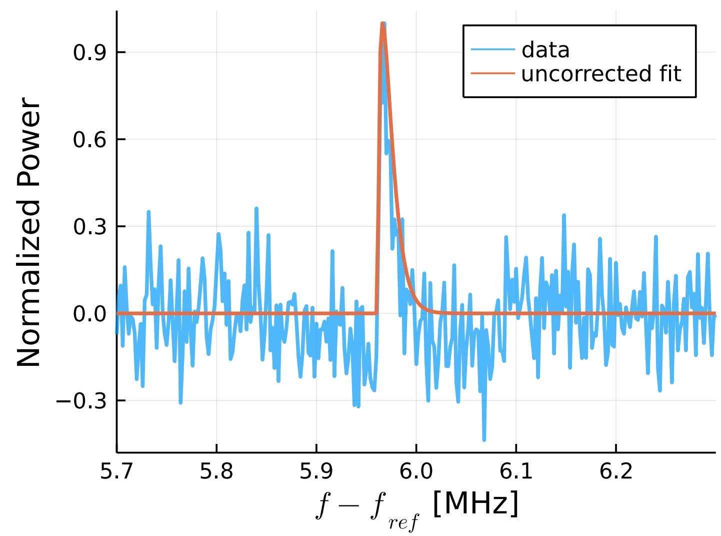



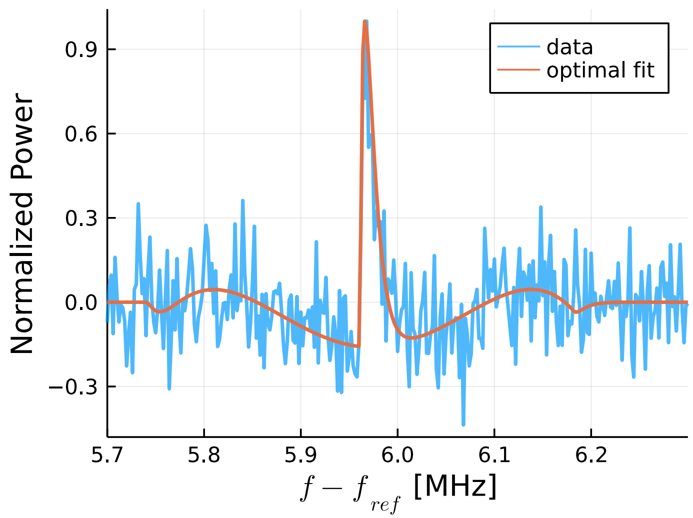
# Getting rid of bias

signal expectation →
signal expectation after bg fit

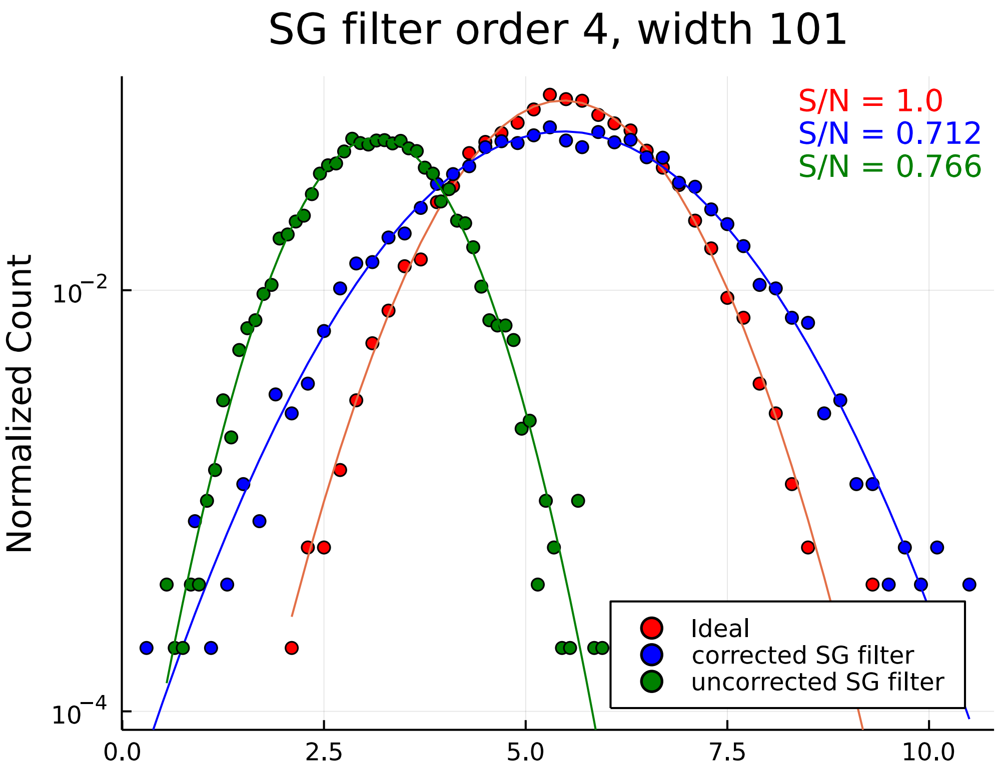
SG filter order 4, width 101



# Effect on sensitivity

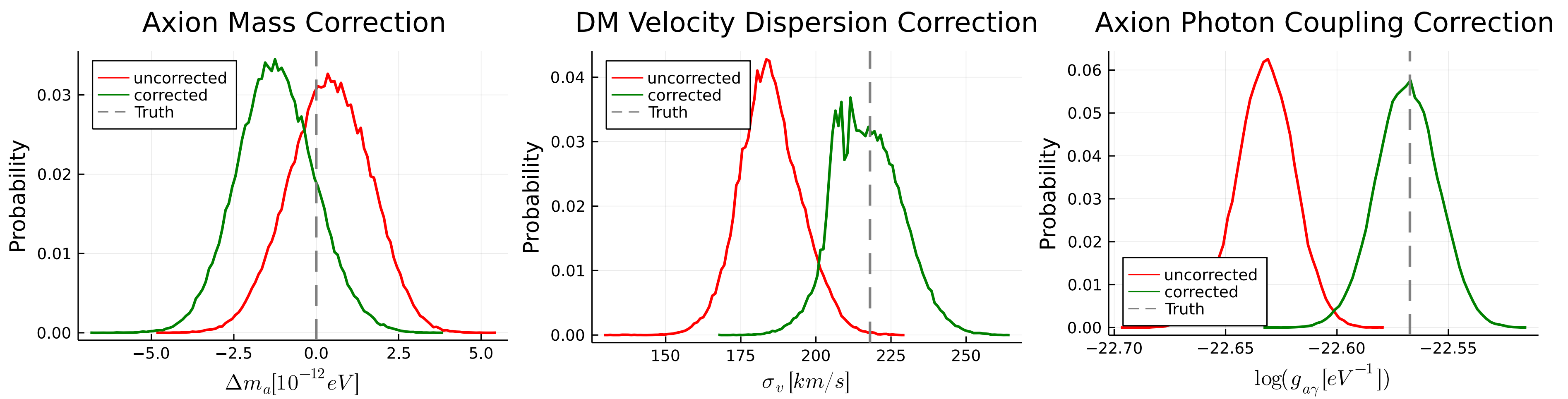



- $\mu$ stays same, $\sigma$ bigger
- Before: $\mu$ smaller, $\sigma$ smaller
- Optimal filter has $\sigma \approx 1$
- S/N stays roughly equal

# Effect on parameters

- Do MCMC w/ uncorrected and corrected signal model

| Parameter | Uncorrected | Corrected | True |
| --- | --- | --- | --- |
| $m_a[\mu\text{eV}]$ | $45.513 \pm 1\times10^{-6}$ | $45.513 \pm 1\times10^{-6}$ | 45.513 |
| $\sigma_v$ [km/s] | $184 \pm 10$ | $217 \pm 11$ | 218 |
| $\text{Log}(g_{a\gamma}[eV^{-1}])$ | $-22.632 \pm 0.013$ | $-22.569 \pm 0.014$ | $-22.567$ |



# Summary

- Challenge: Non-parametric background subtraction
  - Background shape not known
  - Sharp signal on smooth background
  - Simultaneous background and signal fit impossible
- Insights:
  - Tested Savitzky-Golay filter and Gaussian Processes
    → hard to improve on Savitzky-Golay filter
  - Can quantify S/N loss due to background fitting
  - Background fit introduces parameter bias
    → get rid by modifying signal model

# Backup Slides

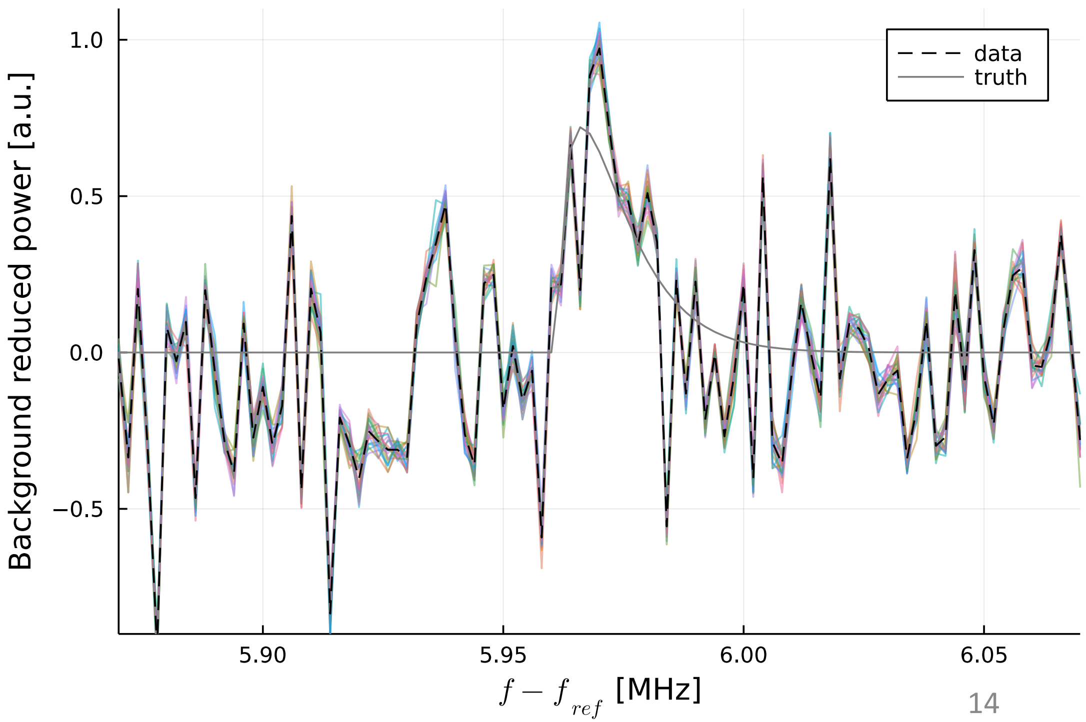
# Background samples

- Background fit is uncertain, but signal fit treats it as fixed → draw background samples to reflect uncertainty, correct exclusion limit

- SG fit:
  - 221 datapoints
  - 5 free params

→ sys. uncertainty small

→ small influence on exclusion



# Method comparison

Savitzky Golay (SG) Filter

- Moving polynomial fit
- Two free parameters (pol. order, nr. datapoints i.e. width)
- Bandpassfilter
- Used by HAYSTAC, ADMX

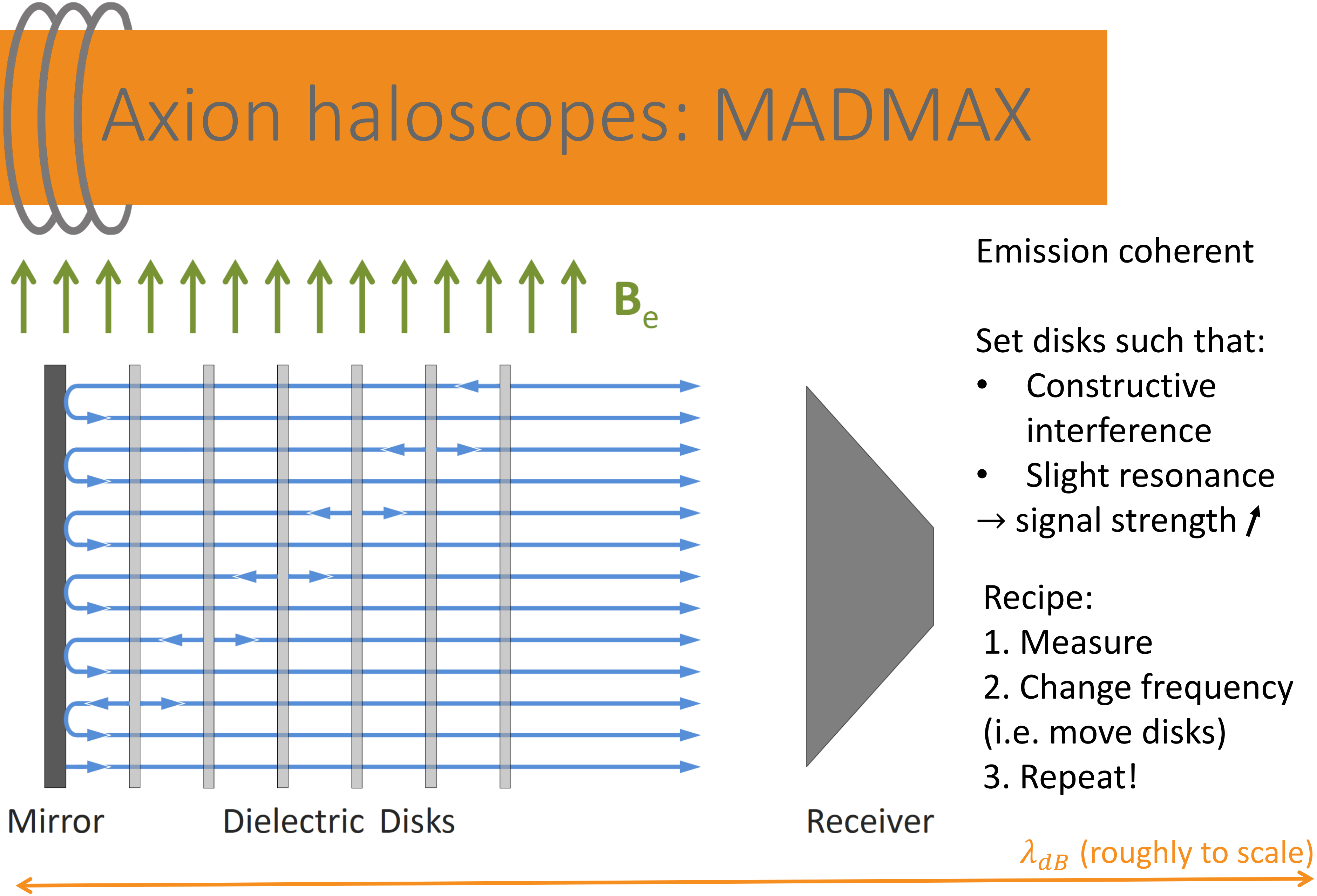
Gaussian Processes

- Machine Learning technique
- # parameters = # datapoints, but correlations fixed

# Ways to do the background fit

- HAYSTAC: iterative Savitzky-Golay filter (moving polynomial fit) arXiv: 1706.08388
- ADMX: similar with Pade filter arXiv: 2010.06183
- Savitzky-Golay (SG) filter may not be optimal for this purpose arXiv: 2003.08510
- Olaf: Piecewise polynomial fit, Fourier-Transform-like filter afterwards
- Idea: Try Gaussian Process as adaptive filter
  arXiv: 1901.11033

# Axion haloscopes: MADMAX




Emission coherent

Set disks such that:

- Constructive interference
- Slight resonance

→ signal strength ↗

Recipe:

1. Measure
2. Change frequency (i.e. move disks)
3. Repeat!

# Mock Dataset

- 5000 „measurements“
- variations down to 100 kHz
- Fake axion @ $f_{rel} = 5.97$ MHz (signal shape unaltered from experiment)

Noise = uncorrelated white noise