



UNIVERSITÀ
DI SIENA 1240



Statistical methods in the search for cosmological axions

Statistical Data Analysis

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(Extra-brief) Introduction to axion searches

What is an axion

- Introduced to fix the strong CP problem of QCD
- Added term to SM Lagrangian:

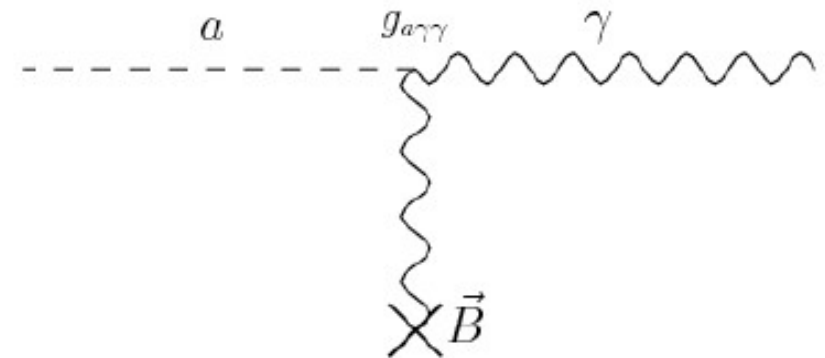
$$\mathcal{L}_{a\gamma\gamma} = \frac{1}{4} g_{a\gamma\gamma} a F^{\mu\nu} \tilde{F}_{\mu\nu}$$

Why search for axions

- **Axion: Cold Dark Matter candidate!!**

How to search for CDM axion

- We exploit the interaction with virtual photons: inverse Primakoff effect



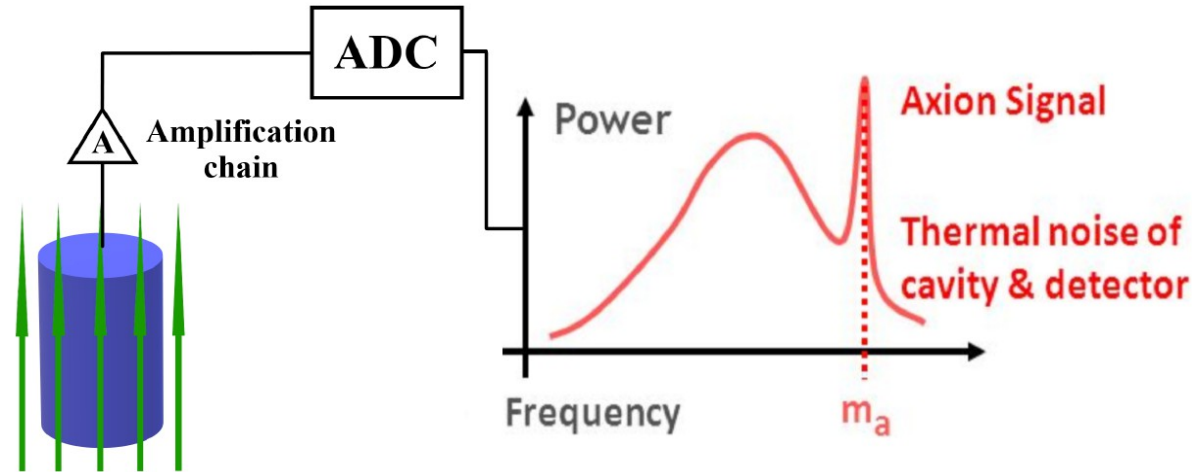
$$g_{a\gamma\gamma} = \alpha g_\gamma / \pi f_a$$

- $g_\gamma \approx 0.36$ for DFSZ model
- $f_a \approx 10^{-8} - 10^{-11}$ Hz
- CDM $\rightarrow \beta \approx 10^{-3} \rightarrow Q_a \approx 10^6$

(Extra-brief) Introduction to axion searches

The Sikivie Haloscope scheme

- We provide virtual photons to scatter on with a high magnetic field
- Signal is boosted integrating inside high-Q factor microwave cavity
- From there, collected with standard MW electronics



$$P_{\text{sig}} = \left(g_{\gamma}^2 \frac{\alpha^2 \hbar^3 c^3 \rho_a}{\pi^2 \chi} \right) \left(\frac{\beta}{1 + \beta} \omega_c \frac{1}{\mu_0} B_0^2 V C_{mnl} Q_L \frac{1}{1 + (2\delta\nu_a / \Delta\nu_c)^2} \right)$$

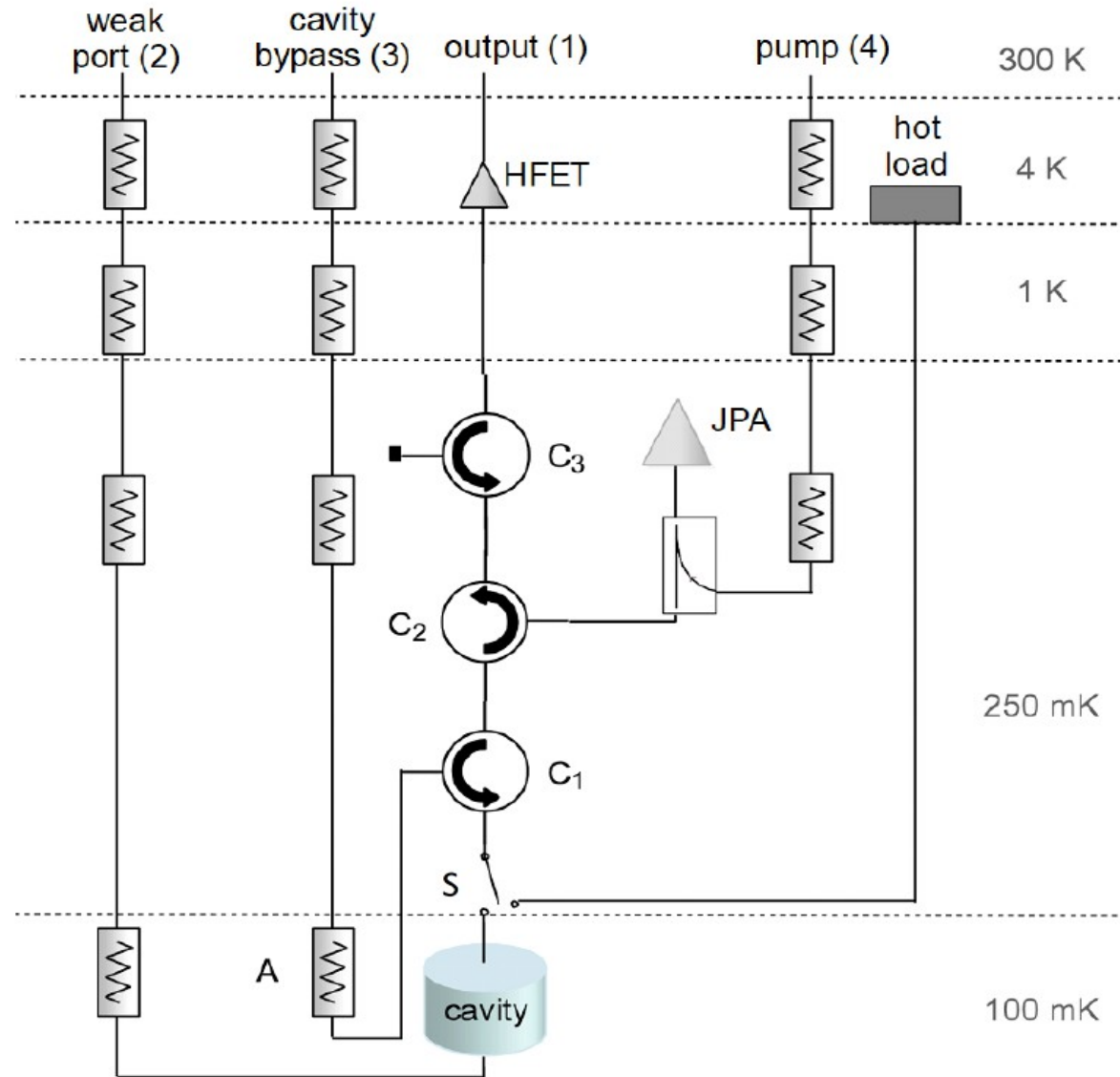
$$P_{\text{axion}} = 2.2 \times 10^{-23} \text{W} \left(\frac{\beta}{1 + \beta} \right) \left(\frac{V}{136 \ell} \right) \left(\frac{B}{7.6 \text{ T}} \right)^2 \left(\frac{C_{010}}{0.4} \right) \left(\frac{g_{\gamma}}{0.36} \right)^2$$

$$\left(\frac{\rho}{0.45 \text{ GeVcm}^{-3}} \right) \left(\frac{Q_{\text{axion}}}{10^6} \right) \left(\frac{f}{740 \text{ MHz}} \right) \left(\frac{Q_L}{30,000} \right) \left(\frac{1}{1 + (2\delta f_a / \Delta f)^2} \right)$$

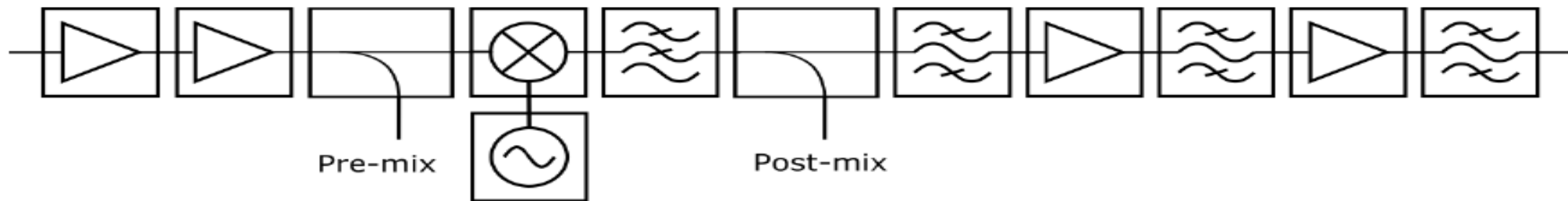
ADMX Run 1B: Experimental Setup

Receiver Chain

- Switch \rightarrow two modes of operation:
 - cavity readout
 - Noise characterization
- Amplifiers:
 - JPA (Josephson Parametric Amplifier)
 - HFET (Heterostructure Field-Effect Transistor)
- Mixer and bandpass filters at room temperature



ADMX Run 1B: Hardware signal treatment



Signal digitization

- Signal bandwidth after last filter 150 kHz
 - ADC sampling rate 25 MS/s
 - Single sample total sampling time 10 ms
- by [Nyquist-Shannon Theorem](#) we can reconstruct the signal

FFT (Fast Fourier Transform)

- 48.8 kHz-wide window
- 512 x 95 Hz-wide bins
- Total integration time: 100 s → 10^4 samples/bin

Analysis strategy

Signal low → search for power fluctuations above average noise background

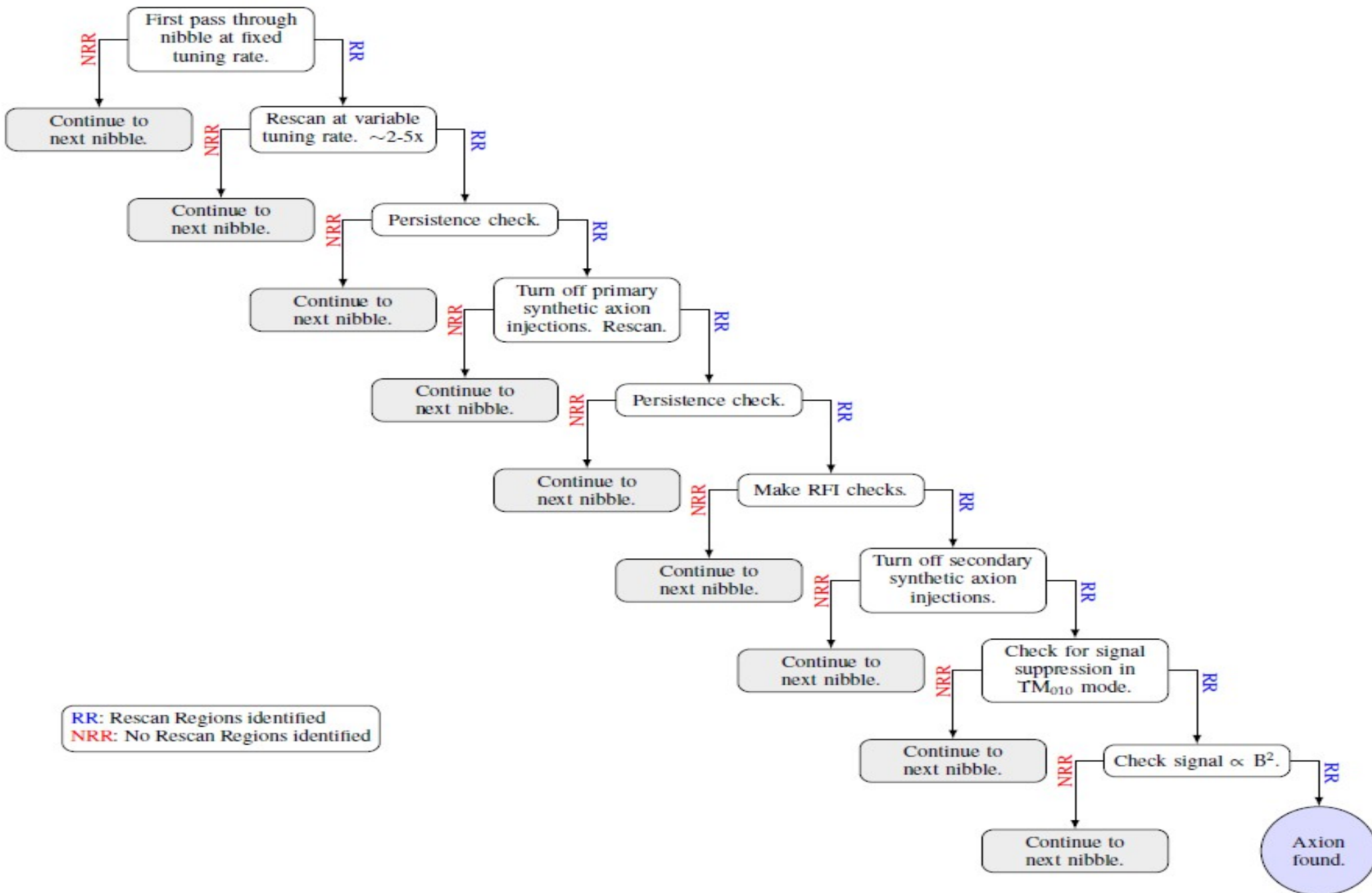
We need:

- **Threshold** for axion detection
→ Needs to be high to limit number of candidates!
- A way to identify **false signals**
- A procedure to estimate the **noise background**

Run cadence

Process	Frequency	Fraction of Time per Iteration
Transmission Measurement	Every Iteration	< 1%
Reflection Measurement	Every Iteration	< 1%
JPA Rebias	Every 5-7 Iterations	25%
Check for SAG Injection	Every Iteration	< 1%
Digitize	Every Iteration	98% ^a
Move Rods	Every Iteration	< 1%

Data-taking decision tree



System noise characterization

We define the overall noise temperature of the system T_{sys} :

$$T_{\text{sys}} = T_{\text{cav}} + T_{\text{amp}} \rightarrow P_n = k_B T_{\text{sys}} b$$

with P_n the noise power in the measured bandwidth b

$0.03 \text{ K} \approx hf/k_B \ll T_{\text{sys}} \rightarrow$ Quantum fluctuations negligible!

Then, the Signal to Noise Ratio at integration time t is:

$$\text{SNR} = \frac{P_{\text{axion}}}{k_B T_{\text{sys}}} \sqrt{\frac{t}{b}}$$

But how to measure T_{sys} ?

System noise characterization

We use **Y-factor measurements**:

1) Hot Load method (Feb., Sept.):

- JPA off (saturation, unstable gain with thermal load) \rightarrow acts as mirror, can be used for wide bandwidth (5MHz) power measurement

$$P = G_{\text{HFET}} k_B [T_{\text{JPA}} (1 - \epsilon) + T_{\text{load}} \epsilon + T_{\text{HFET}}]$$

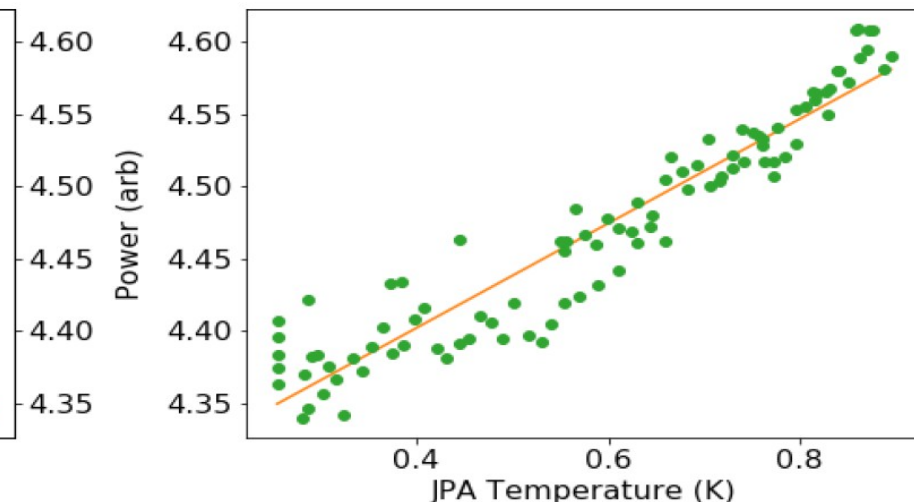
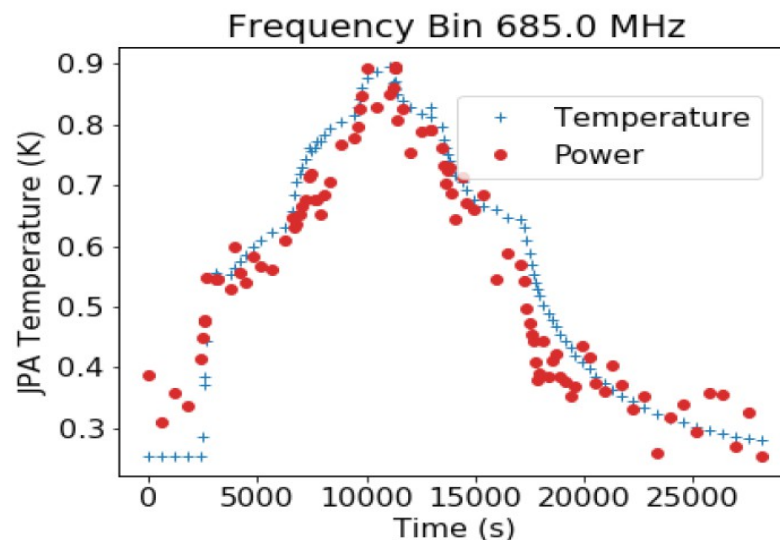
2) Heating Switch (Jul., Sept.):

- Small ΔV applied to switch
- all quantum amplifier package heats

$$P = G_{\text{HFET}} k_B [T_{\text{JPA}} (1 - \epsilon) + T_{\text{cav}} \epsilon + T_{\text{HFET}}]$$

- If $T_{\text{JPA}} \approx T_{\text{cav}}$:

$$P = G_{\text{HFET}} k_B [T_{\text{JPA}} + T_{\text{HFET}}]$$



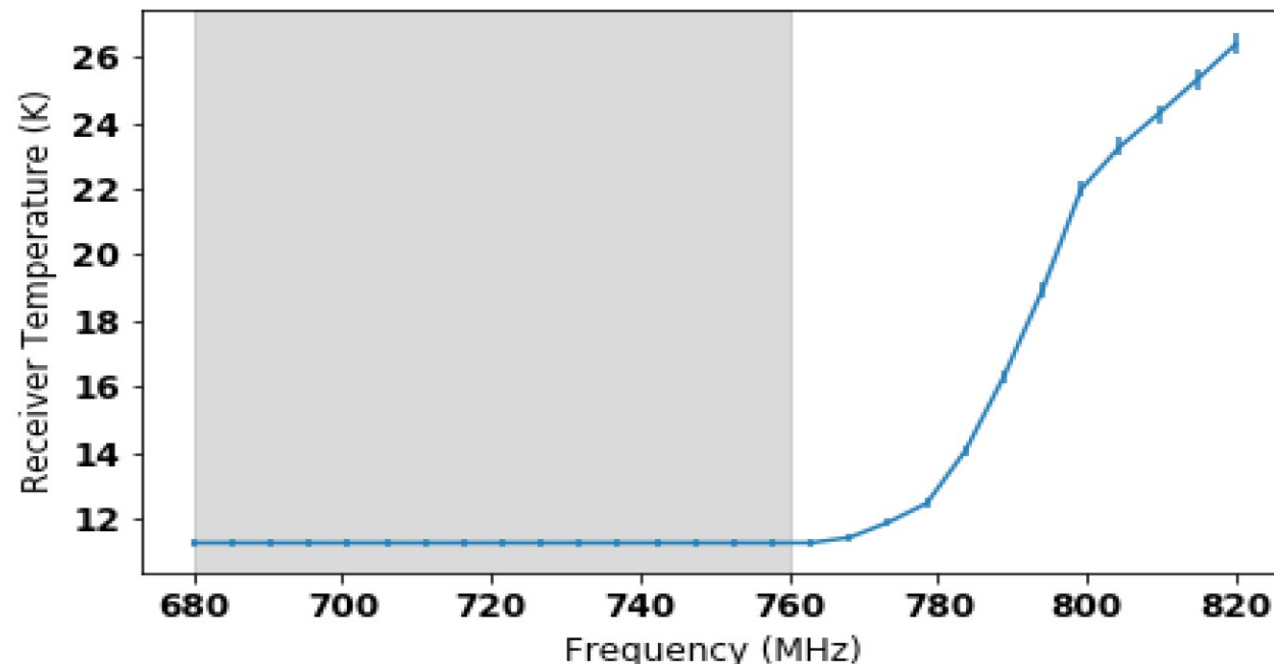
System noise characterization: results

No changes observed → assumption: T_{HFET} , G_{HFET} stable

- All 4 measurements put together, **Least squares fit** on combined results:

Receiver noise temperature $T_{\text{HFET}} = (11.3 \pm 0.1) \text{ K}$

(mostly from square root of covariance)

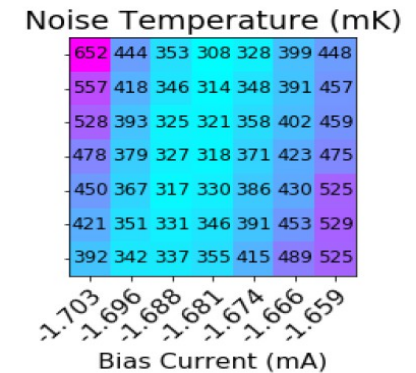
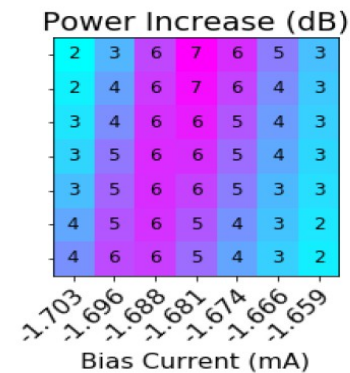
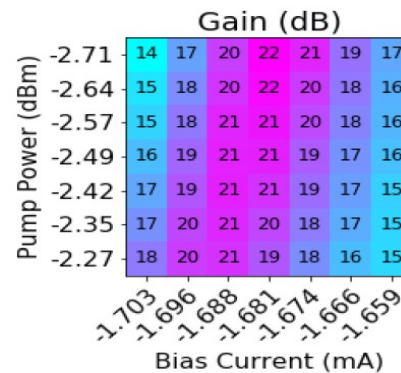


System noise characterization: results

Signal to Noise Ratio Improvement (SNRI):

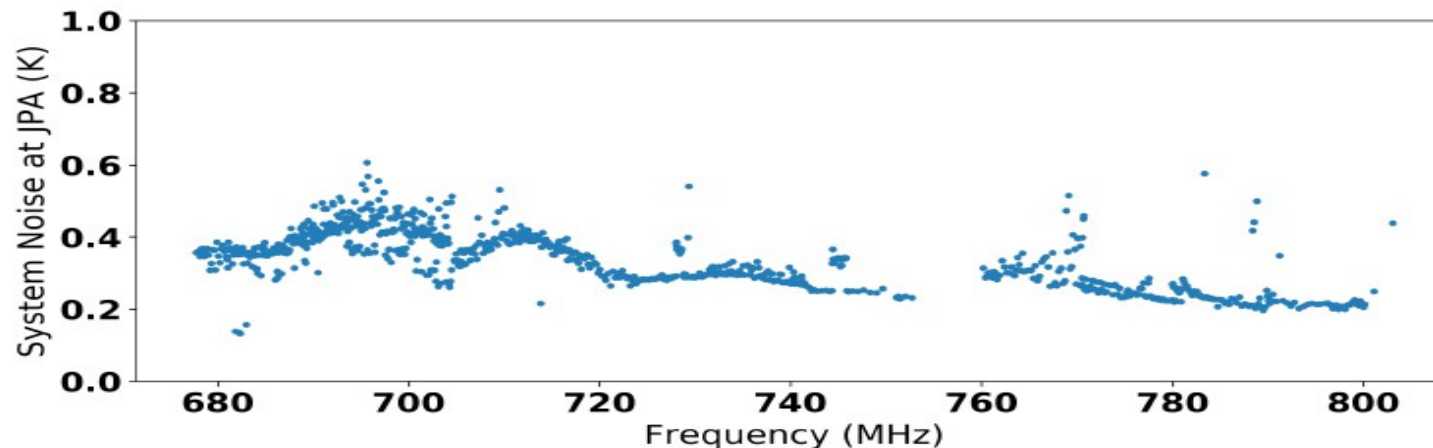
Monitored throughout the run every ≈ 10 minutes

$$\text{SNRI} = \frac{G_{\text{on}}}{G_{\text{off}}} \frac{P_{\text{off}}}{P_{\text{on}}}$$



Changes over course of run since JPA gain is unstable for $\Delta T \approx 300/400$ mK

By definition, allows to monitor T_{sys} : $T_{\text{sys}} = T_{\text{HFET}} / \text{SNRI}$



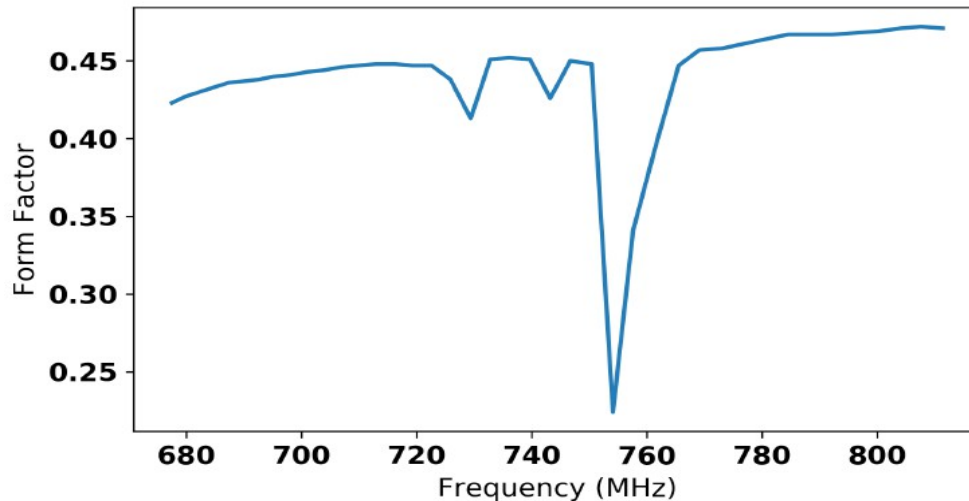
Model parameters and systematics

Other parameters to be fed to proper data analysis:

- ω_0 and Q_L of cavity \rightarrow from Lorentzian fit to transmission measurement
- β coefficient \rightarrow from fit to reflection meas.

$$\Gamma = \frac{\beta - 1 - (2iQ_0\delta\omega/\omega_0)}{\beta + 1 + (2iQ_0\delta\omega/\omega_0)}$$

- Form factor C_{010} (from finite element simulations)



Statistical and systematical errors:

Source	Fractional Uncertainty
B^2VC_{010}	0.05
Q	0.011
Coupling	0.0055
RF model fit	0.029
Temperature Sensors	0.05
SNRI measurement	0.042
Total on power	0.088

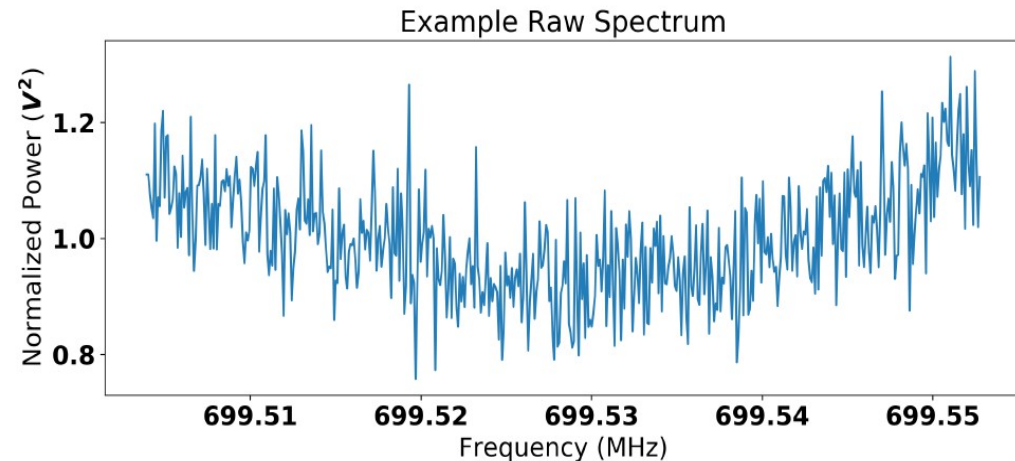
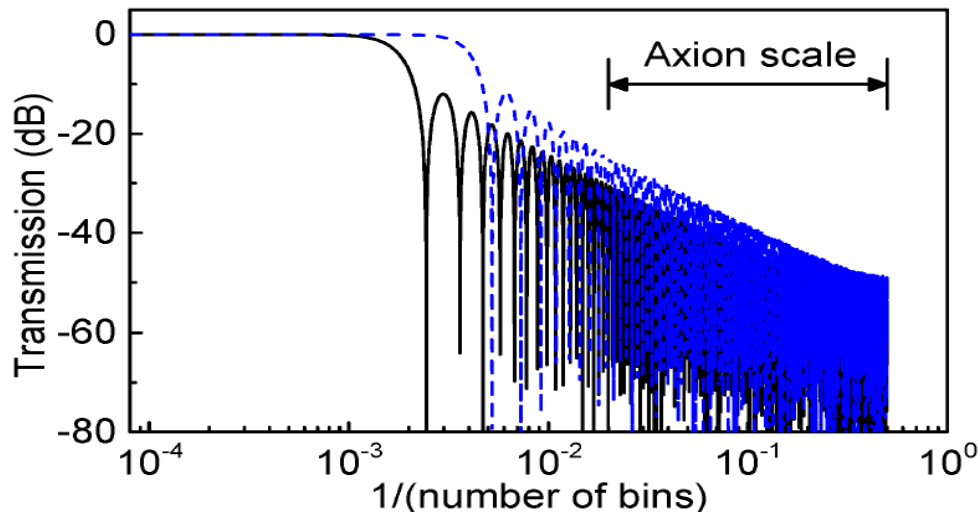
Axion search data processing: baseline removal

Raw data contains gain variations superimposed on the signal

- mostly from room temperature components

→ we use Savitzky-Golay filter to remove them, but:

- Passband ripple → residual unfiltered features
- Imperfect stopband attenuation → signal attenuation, introduces small negative correlations btw processed run bins



Assumption: noise statistically equivalent to thermodynamic noise at $T = T_{\text{sys}}$

→ p.d.f. of bin exp. value is Gaussian, fluctuations in subspectrum are $\chi^2(2)$

then, by the Central Limit Theorem:

after averaging over 10^4 samples, the distribution of the noise power fluctuations will be Gaussian!

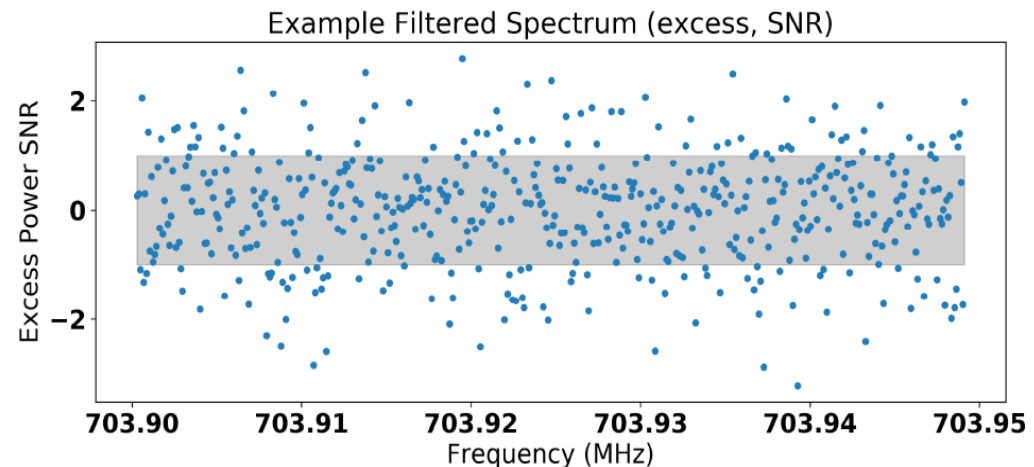
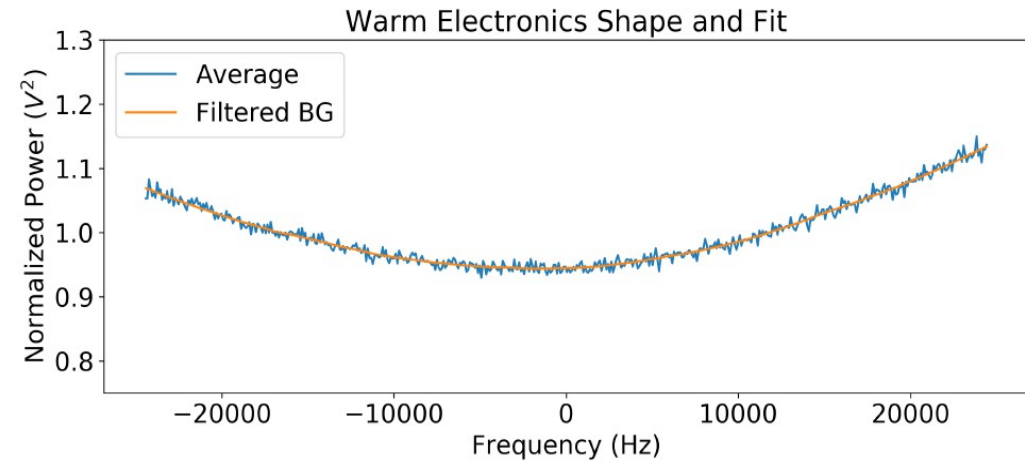
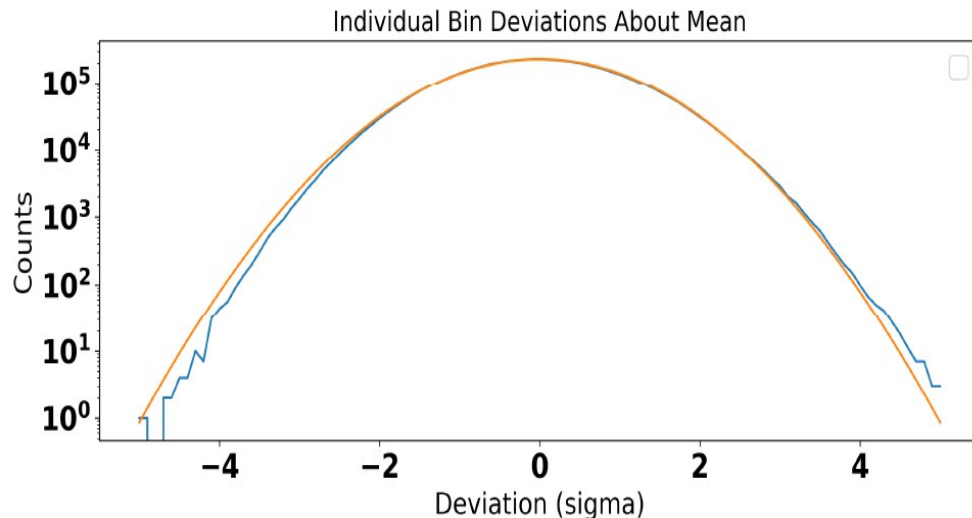
Cryogenic baseline removal and spectrum processing

After division with S-G filter:

- Spectrum is convolved with **additional 6th order Padé filter** to remove residual frequency-dependent variations due to cryogenic receiver transfer function

Power normalised by dividing every bin for overall mean, then we subtract 1

→ **every bin becomes random sample from Gaussian distribution with mean $\mu=0$**



Data quality control and rescan procedure

12,492/197,680 out of raw spectra eliminated due to analysis cuts

- Timestamp cuts due to various aberrant run conditions and engineering studies
- Max. Std. Dev. Increase condition refers to normalized χ^2 of Padé filter fit

Rescan thresholds:

- Power excess in bin $> 3\sigma$
- Expected SNR for DFSZ axion < 2.4
- Limits set at that frequency do not meet required DFSZ sensitivity (measured power + candidate threshold power $>$ DFSZ axion power)
- Candidate power $>$ DFSZ axion power + 0.5σ

Cut Parameter	Scans Removed	Constraint
Timestamp cuts	7,189	N/A
Quality Factor	316	$10,000 < Q < 120,000$
System Noise	4,514	$0.1 < T_{\text{sys}} < 2.0$
Max Std. Dev. Increase	224	2.0
Error in filter shape	249	N/A

Frequency (MHz)	Notes	Power (DFSZ)
780.255	Maximized off-resonance	1.49
730.195	Synthetic blind	1.51
686.310	Maximized off-resonance	2.36

Combining spectra into a Grand Spectrum

How to merge together data for the same frequency bin but acquired in different conditions?

- Every bin of every spectrum is divided by the relative signal power that would be generated due to the sample parameters and Lorentzian lineshape
- Discrepancies due to differing noise levels are mitigated by scaling the each bin by $k_B T_{\text{sys}}$
- Finally, the power in each bin is convolved with a filter given by the axion lineshape

Bins are combined via weighed mean, where the weights are such that they maximize the SNR . The weights are found by imposing that the **Maximum Likelihood estimation of the **true mean value μ** of the power excesses is **the same for all contributing bins****

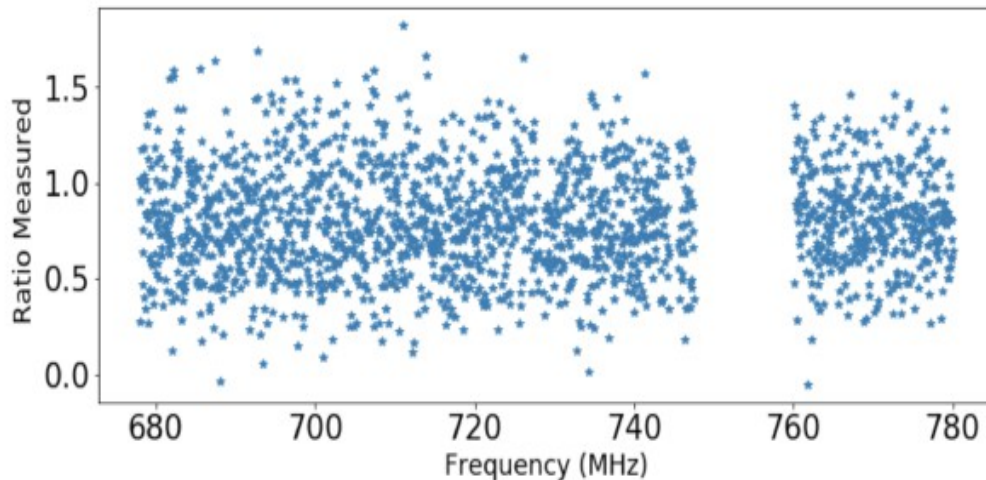
Since it is a weighted mean of independent Gaussian random variables with same mean, one finds:

$$P_w = \frac{\sum_{j=0}^N \frac{P^j_{scaled}}{\sigma_j^2}}{\sum_{j=0}^N \frac{1}{\sigma_j^2}} \quad \sigma_w = \sqrt{\frac{1}{\sum_{j=0}^N \frac{1}{\sigma_j^2}}}$$

Synthetic hardware injections

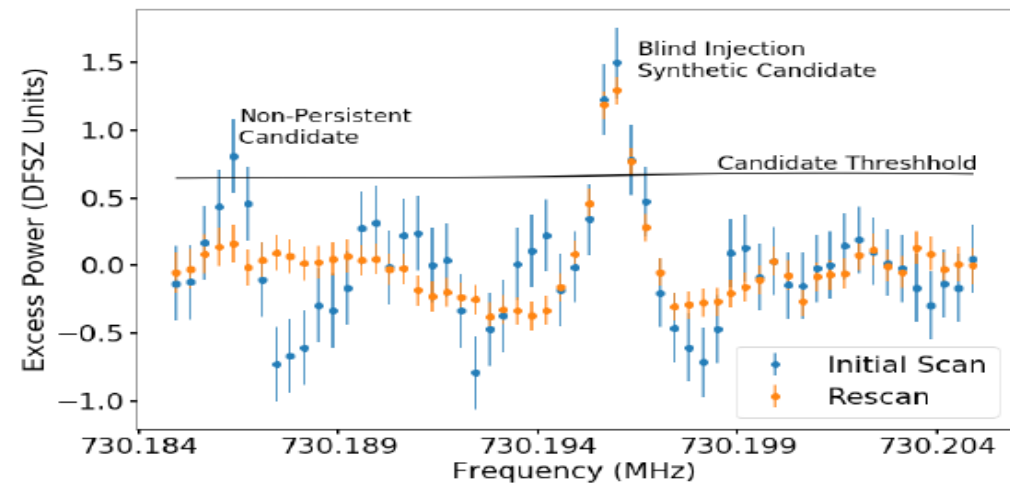
Software: 1773 evenly-spaced axion-like signals injected into real data

- Signals injected with DFSZ power levels
- Of these, **$95 \pm 2\%$ detected**
- Mean power level differs from one \rightarrow from ratio with expected value, we obtain estimate for efficiency of data treatment procedure: **0.818 ± 0.008**



Hardware: axion-like signals physically injected into the system

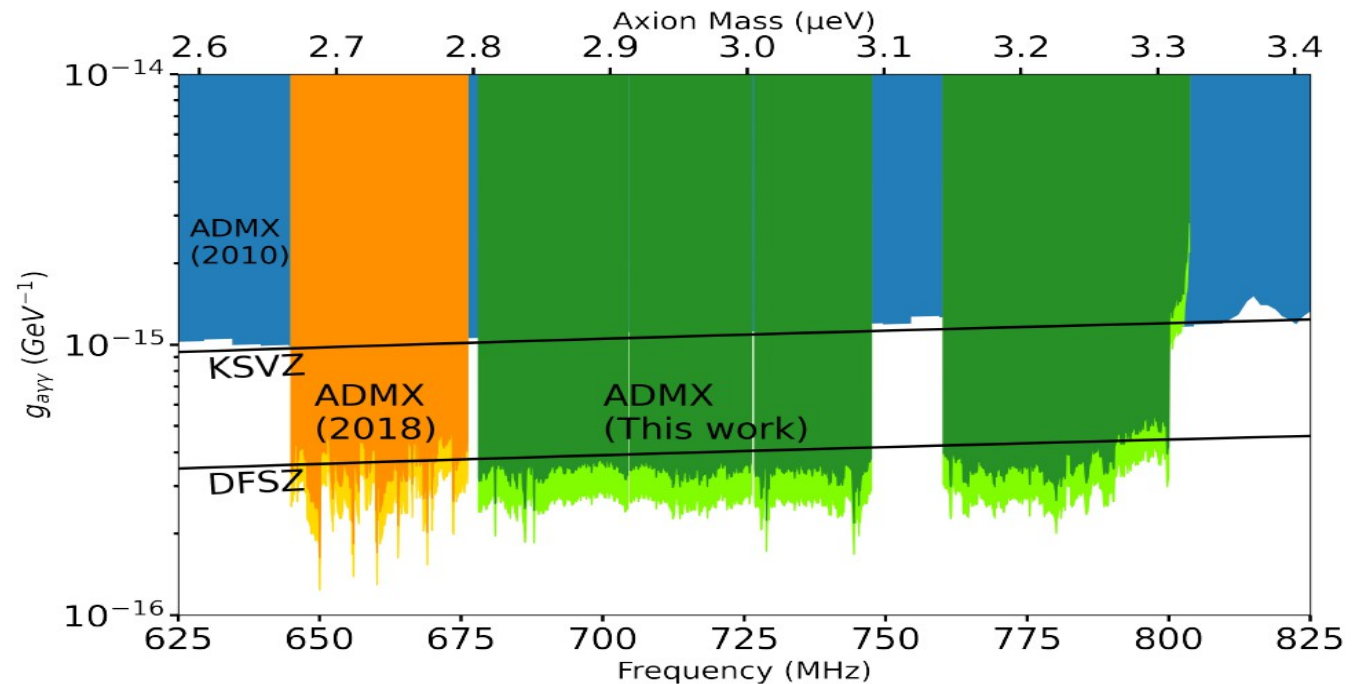
- Signals injected with DFSZ power levels to (previously calibrated) weakly coupled cavity port
- All signals detected



ADMX Run 1B results

Grand Spectrum bins: Gaussian variables of mean μ

- If **no axion** $\rightarrow \mu=0$
- If **axion present** $\rightarrow \mu=g_\nu^2 \cdot \text{SNR}$
- A **90% C.L. single-sided exclusion limit** is set by computing the value of g_ν for which $p(X_i < x_i | g_\nu) < \alpha = 0.1$ (assuming X_i is gaussian random variable of mean μ and standard deviation σ_i)
- **$g_\nu^2 < 0$ is non-physical!** To take this into account, the cumulative distribution function for a truncated Gaussian was used
- Look-elsewhere effect?
No need to correct!



References

- “Axion Dark Matter eXperiment: Run 1B Analysis Details”, C. Bartram et al. (ADMX Collaboration), Phys. Rev. D 103, 032002 (2021)
- “HAYSTAC axion search analysis procedure”, B. M. Brubaker, L. Zhong, S. K. Lamoreaux, K. W. Lehnert, and K. A. van Bibber, Phys. Rev. D 96, 123008 (2017)
- “A Unified Approach to the Classical Statistical Analysis of Small Signals”, G. J. Feldman and R. D. Cousins, Physical Review D 57, 3873–3889 (1998)
- “First results from the HAYSTAC axion search”, Benjamin M. Brubaker, e-Print: 1801.00835 [astro-ph.CO] (Yale U.) (2017)

Thanks for your attention!