X17 Workshop
03/26/2026

Viability of X17 as protophobic vector and Gaussian Process Regression as a Search Technique

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Outline

I. Introductions
II. Consequence of theory refinements to (g-2)
III. Mean favored coupling for gyromagnetic ratio of electron
IV. Phase space of interest to ATOMKI
V. X17 @ JLAB – proof of concept estimates
VI. Gaussian Process Regression Motivations and Next Steps

Quick Introduction

- Stanford High Energy Physics Experiment PhD Candidate
  - Graduating within the next 6 months [looking for postdoc!]
- Advisors: Tim Nelson (SLAC), Philip Schuster (SLAC, Stanford)
- Member of Heavy Photon Search and Light Dark Matter eXperiment Collaborations
- Phenomenological Interests Include True Muonium and X17
  - ArXiv Article: Compatibility of the Updated $(g-2)_\mu$, $(g-2)_e$ and PADME-Favored Couplings with the Preferred Region of ATOMKI X17 [v2: 02/01/2026]

$(g-2)_\mu$ Experiment

Anomalous magnetic moment of the muon

$$a_\mu \equiv \frac{g_\mu - 2}{2}$$

Discrepancy (now less significant!)

$$\Delta a_\mu = a_\mu^{\text{exp}} - a_\mu^{\text{SM}}$$

$$\Delta a_\mu^{\text{WP25}} = 39(64) \times 10^{-11}$$

Final Combined World Average (FNAL and BNL)

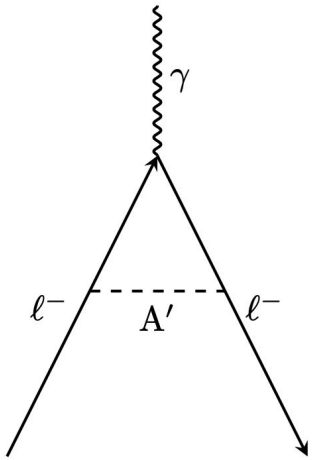
$$a_\mu^{\text{exp}} = 116\,592\,0715\,(145) \times 10^{-11}$$

2025 Model Prediction (w/lattice QCD)

$$a_\mu^{\text{SM,GWP}} = 116\,592\,033\,(630) \times 10^{-11}$$

Muon $g-2$ Collaboration. Measurement of the positive muon anomalous magnetic moment to 127ppb. 2025. https://doi.org/10.1103/7clf-sm2v

Allowable coupling space from magnetic moments



Pospelov (2008)

One loop contribution to gyromagnetic moment

$$\Delta a_\ell^{A'} = \frac{\alpha\varepsilon^2}{2\pi} F_V\left(\frac{m_{A'}}{m_\ell}\right) \quad F_V(r) = \int_0^1 dx \, \frac{2x(1-x)^2}{(1-x)^2 + r^2 x}$$

Mean Leptonic Coupling

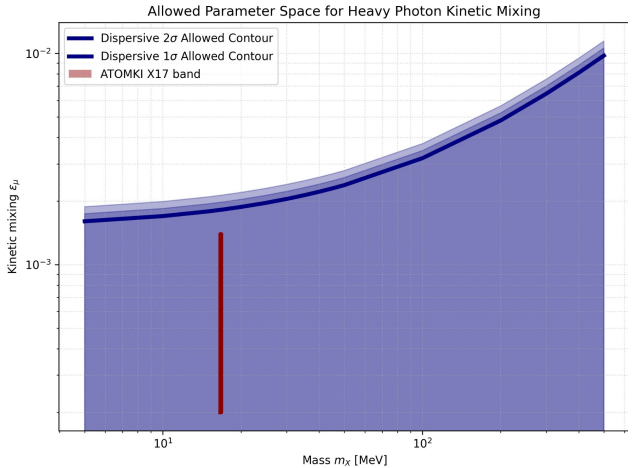
$$\varepsilon_\ell(m_{A'}) = \sqrt{\frac{\Delta a_\ell \, (2\pi/\alpha)}{F_V \, (m_{A'}/m_\ell)}}$$

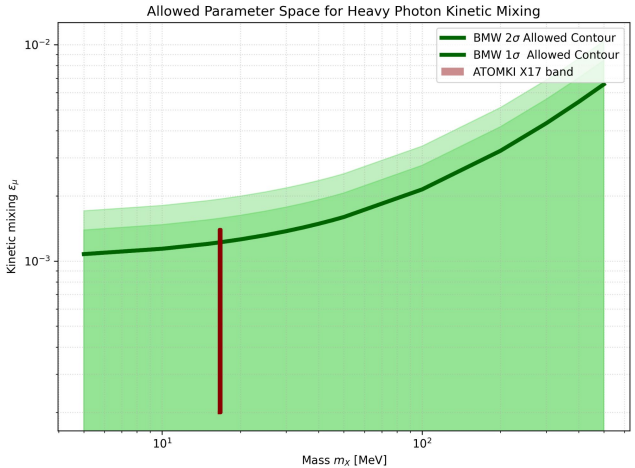
$$a_\mu^{\mathrm{SM,GWP}} = 116\,592\,033\,(630) \times 10^{-11} \longrightarrow \varepsilon_\mu^{\mathrm{WP25}} = 7.03 \times 10^{-4}$$

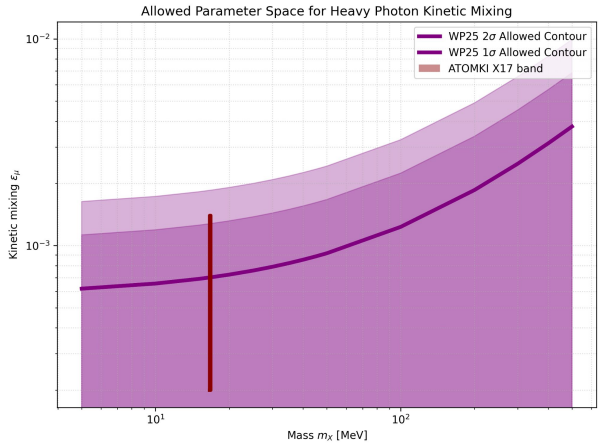
mean value

Theoretical Improvements Further Constrain Allowed Coupling

By using the same experimental 2025 value from (g-2) we can compare to theoretical contributions and see the impact hadronic corrections has had on viable phase space.







$$\varepsilon_\mu^{\mathrm{WP20}} = 1.82 \times 10^{-3}, \qquad \varepsilon_\mu^{\mathrm{BMW21}} = 1.22 \times 10^{-3}, \qquad \varepsilon_\mu^{\mathrm{WP25}} = 7.03 \times 10^{-4}$$

Gyromagnetic Moment of Electron

Experimental measurement comes from one-electron quantum cyclotron.

$$a_e^{\text{exp}} = 0.001\,159\,652\,180\,59(13)$$

Using the two atomic determinations of fine structure constant gives us the ability to determine favored vector contributions.

$$a_e^{\text{SM}}(\alpha) = a_e^{\text{QED}}(\alpha) + a_e^{\text{had}} + a_e^{\text{EW}}$$

$$\Delta a_e^{(i)} \equiv a_e^{\text{exp}} - a_e^{\text{SM}}(\alpha_i)$$

$$\alpha_{\text{Cs18}}^{-1} = 137.035\,999\,046(27)$$

$$\alpha_{\text{Rb20}}^{-1} = 137.035\,999\,206(11)$$

$$\Delta a_e^{(\text{Cs 2018})} = a_e^{\text{exp}} - a_e^{\text{SM}}(\alpha_{\text{Cs18}}) = -102(26) \times 10^{-10}$$

$$\Delta a_e^{(\text{Rb 2020})} = a_e^{\text{exp}} - a_e^{\text{SM}}(\alpha_{\text{Rb20}}) = 34(16) \times 10^{-10}.$$

$$\varepsilon_e^{\text{CS18}} = 1.19(15) \times 10^{-3}$$

$$\varepsilon_e^{\text{RB20}} = 0.69(15) \times 10^{-3}$$

X. Fan, T. G. Myers, B. A. D. Sukra, and G. Gabrielse. Measurement of the electron magnetic moment. *Phys. Rev. Lett.*, 130:071801, Feb 2023.

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Luc Morel, Zhibin Yao, Pierre Cladé, and Saïda Guellati-Khélifa. Determination of the fine-structure constant with an accuracy of 81 parts per trillion. *Nature*, 588:61–65, 2020.

$$\sigma^2(\Delta a_e^{(i)}) = \sigma^2(a_e^{\text{exp}}) + \left(\frac{\partial a_e^{\text{SM}}}{\partial \alpha}\right)^2_{\alpha_i} \sigma^2(\alpha_i) + \sigma^2_{\text{th,res}}$$

Gyromagnetic Moment of Electron

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Using the two atomic determinations of fine structure constant gives us the ability to determine favored vector contributions.

$\alpha^{-1}_{\text{Cs18}} = 137.035\,999\,046(27)$	$\Delta a_e^{(\text{Cs 2018})} = a_e^{\text{exp}} - a_e^{\text{SM}}(\alpha_{\text{Cs18}}) = -102(26) \times 10^{-10}$	$\varepsilon_e^{\text{CS18}} = 1.19(15) \times 10^{-3}$
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$\Longrightarrow$ Physically Motivated Vector Favored Contour

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Conclusions to draw from gyromagnetic moments

Muonic moment no longer favored contour

- at X17, experimental mean muonic coupling of a heavy photon for full agreement with standard model is ~ 7*10^-4

$$\varepsilon_\mu^{\mathrm{WP20}} = 1.82 \times 10^{-3}, \qquad \varepsilon_\mu^{\mathrm{BMW21}} = 1.22 \times 10^{-3}, \qquad \varepsilon_\mu^{\mathrm{WP25}} = 7.03 \times 10^{-4}$$

Electronic moments have conflicting interpretations

- with Cs measurement, gyromagnetic contribution is negative ⟹ unphysical thus only report mean
- Rb measurement indeed has a favored contour which excludes some of atomki phase space and imposes upper bound at a 2sigma level for ~9.8*10^-4

$$\varepsilon_e^{\mathrm{CS18}} = 1.19 \times 10^{-3} \qquad \varepsilon_e^{\mathrm{RB20}} = 6.91 \times 10^{-4}$$

Universal leptonic coupling remains possible for a protophobic vector at ~7*10^-4.

Model Assumptions for Viable Particle Explanations

NA48/2 exclusion necessitates protophobic coupling

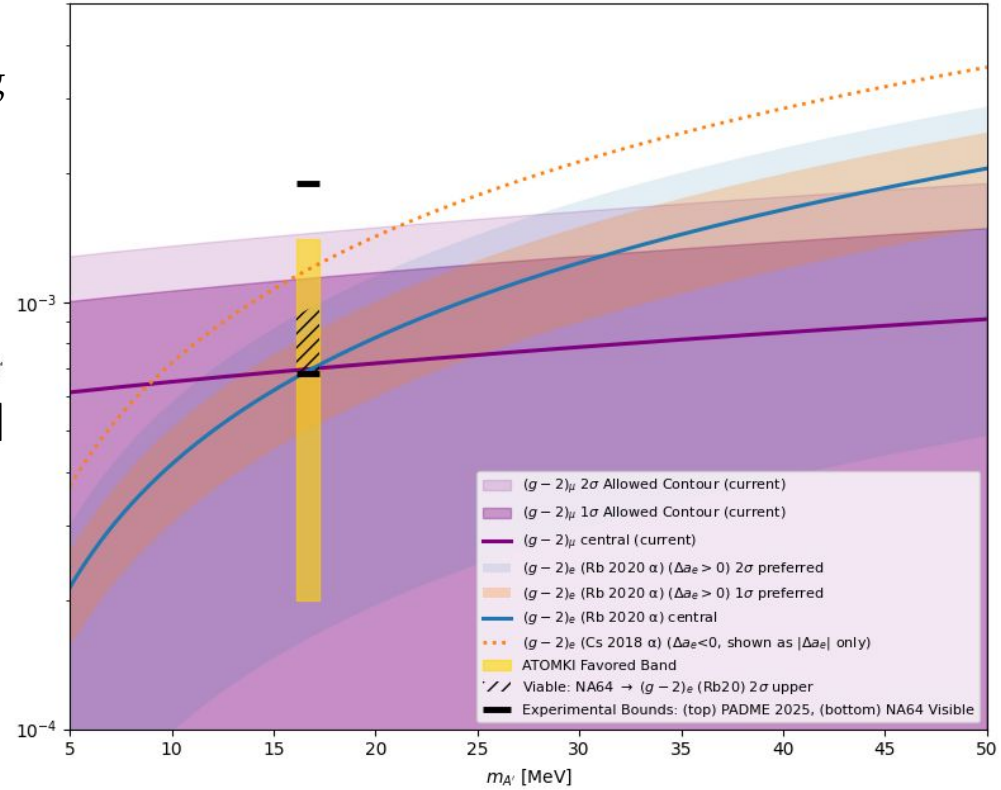
$$\pi^0 \to \gamma A' \to \gamma e^+ e^-$$

Quark Level Coupling Assumptions

$$g_V^p \equiv 2g_V^u + g_V^d, \qquad g_V^n \equiv g_V^u + 2g_V^d, \qquad |g_V^p| \ll |g_V^n|$$

Neutrino Suppressed Coupling Benchmark required from CEνNS

$$|\varepsilon_{\nu_\alpha}| \ll |\varepsilon_e|$$



Phase Space of Interest

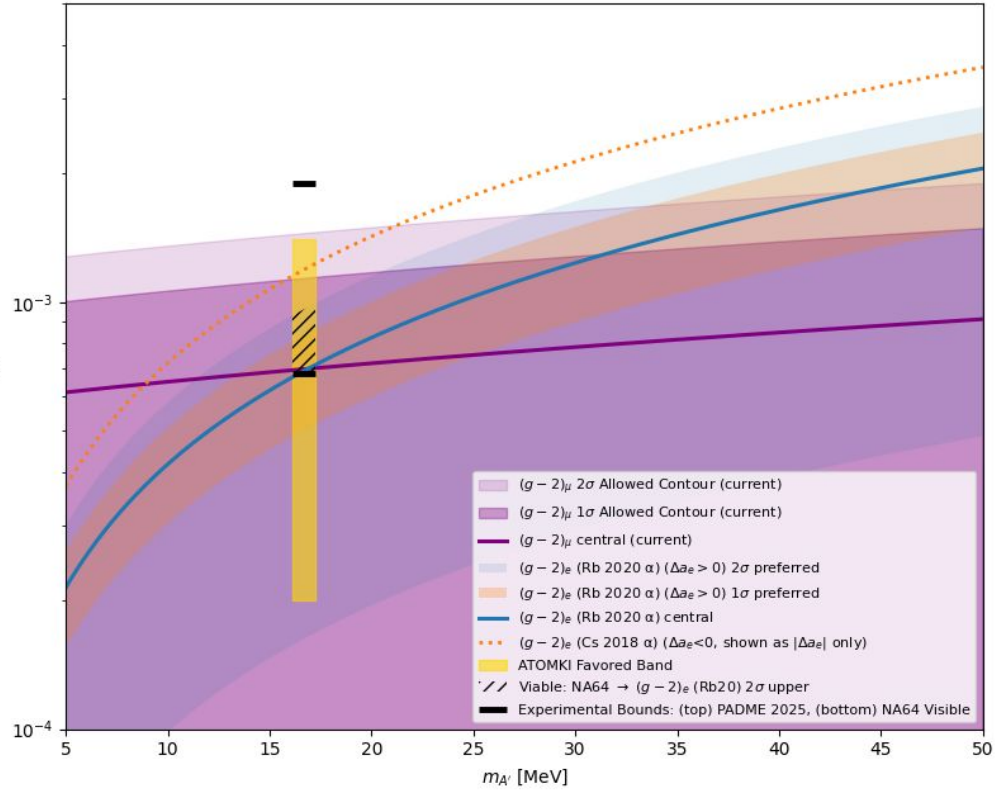
PADME Observed Limit

$$\mathcal{L} \supset g_{ve} X_\mu \bar{e}\gamma^\mu e \qquad \varepsilon_e = \frac{g_{ve}}{e}$$

$$\varepsilon_e^{(\mathrm{PADME})}(16.90\ \mathrm{MeV}) \lesssim \frac{5.6 \times 10^{-4}}{e} \simeq 1.9 \times 10^{-3}$$

NA64 Visible Limit

$$1.2 \times 10^{-4} < \varepsilon_e^{(\mathrm{NA64})} < 6.8 \times 10^{-4}$$



X17 Collaboration at JLAB: Introduction

Hall B - X17 search is a forward-angle, fully exclusive electroproduction from a tungsten target resonance search at Jefferson Lab.

Apparatus is based on the Proton radius experiment setup: thin Ta target, HyCal calorimeter, and two GEM planes for charged/neutral discrimination and exclusivity cuts.

The design emphasizes full final-state reconstruction and target consistency rather than displaced-vertex sensitivity.

Expected to take place Summer 2026!

Internal Note: Bumphunting with the X17 Collaboration

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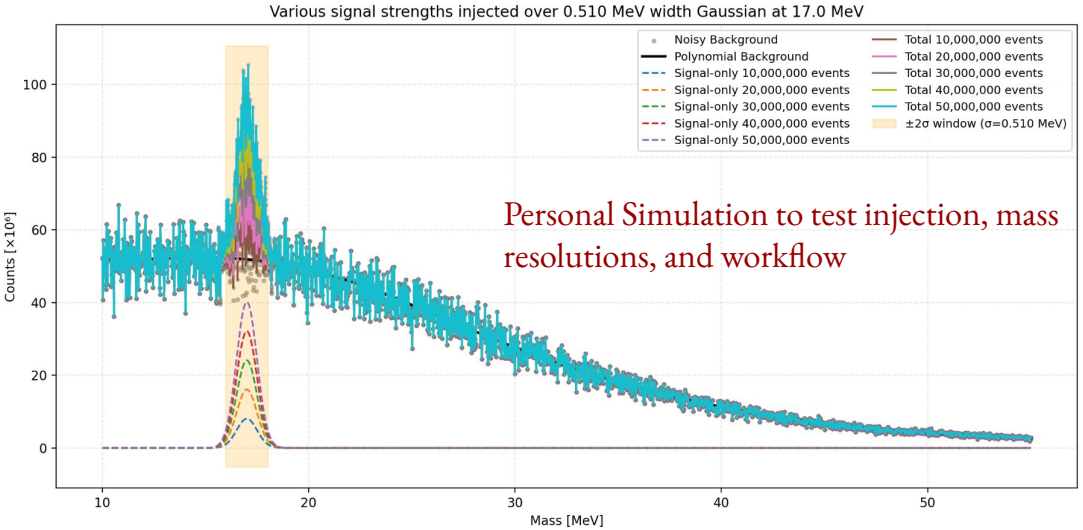
[1]Department of Physics, Stanford University, Stanford, CA 94305, USA
[2]SLAC National Accelerator Laboratory, Menlo Park, CA 94025, USA



Proof of Principal Upper Limit Calculations – *not official*

SLAC

Idealistic Scenario

- Calculated from pure polynomial form
- first order approximation, not official!

Signal yield per limit calculation from
[1307.2487] Statistics for Searches at the LHC

- Currently scans for a **Counting Excess**
  - Integral of events above background in ± 1.5 σ window
  - Does not yet take into account signal shape

Preliminary upper limits on signal yield and coupling determined for 25 and 40 days.

Upper Limit on Signal Yield

$$s_{\mathrm{up}} = \frac{1}{2} F_{\chi^2}^{-1}[p, 2(n+1)] - b,$$

$$p = 1 - \alpha \left(1 - F_{\chi^2}[2b, 2(n+1)]\right),$$

$$\mathrm{CL}_s(\mu) = \frac{p_\mu}{1 - p_b} \qquad \mathrm{CL}_s(N_{sig}^{up}) = 0.05$$

Upper Limit on Signal Yield

$$\epsilon^2 = \frac{2\alpha N_{\mathrm{sig}}^{\mathrm{up}}}{3\pi m_{A'} f_{\mathrm{rad}} \frac{\mathrm{d}N_{\mathrm{bkg}}}{\mathrm{d}m}}$$

Radiative Frac: Fixed 4%
From: https://arxiv.org/pdf/0906.0580

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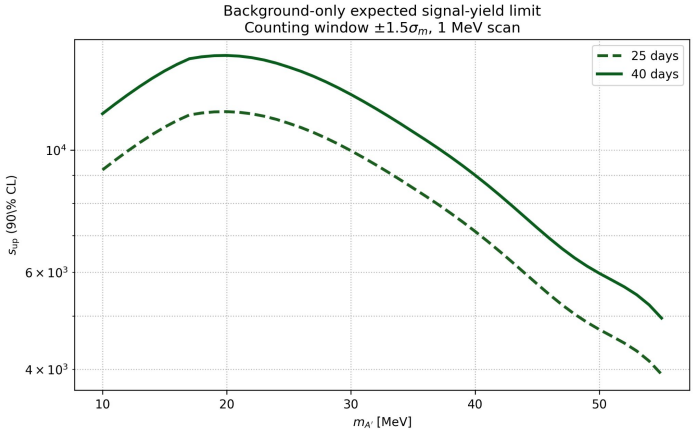
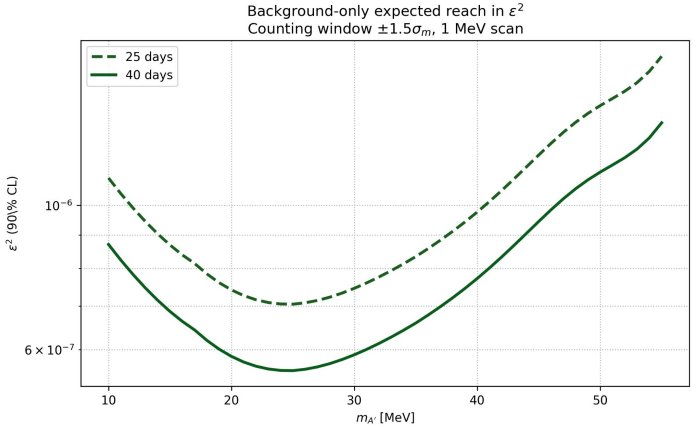
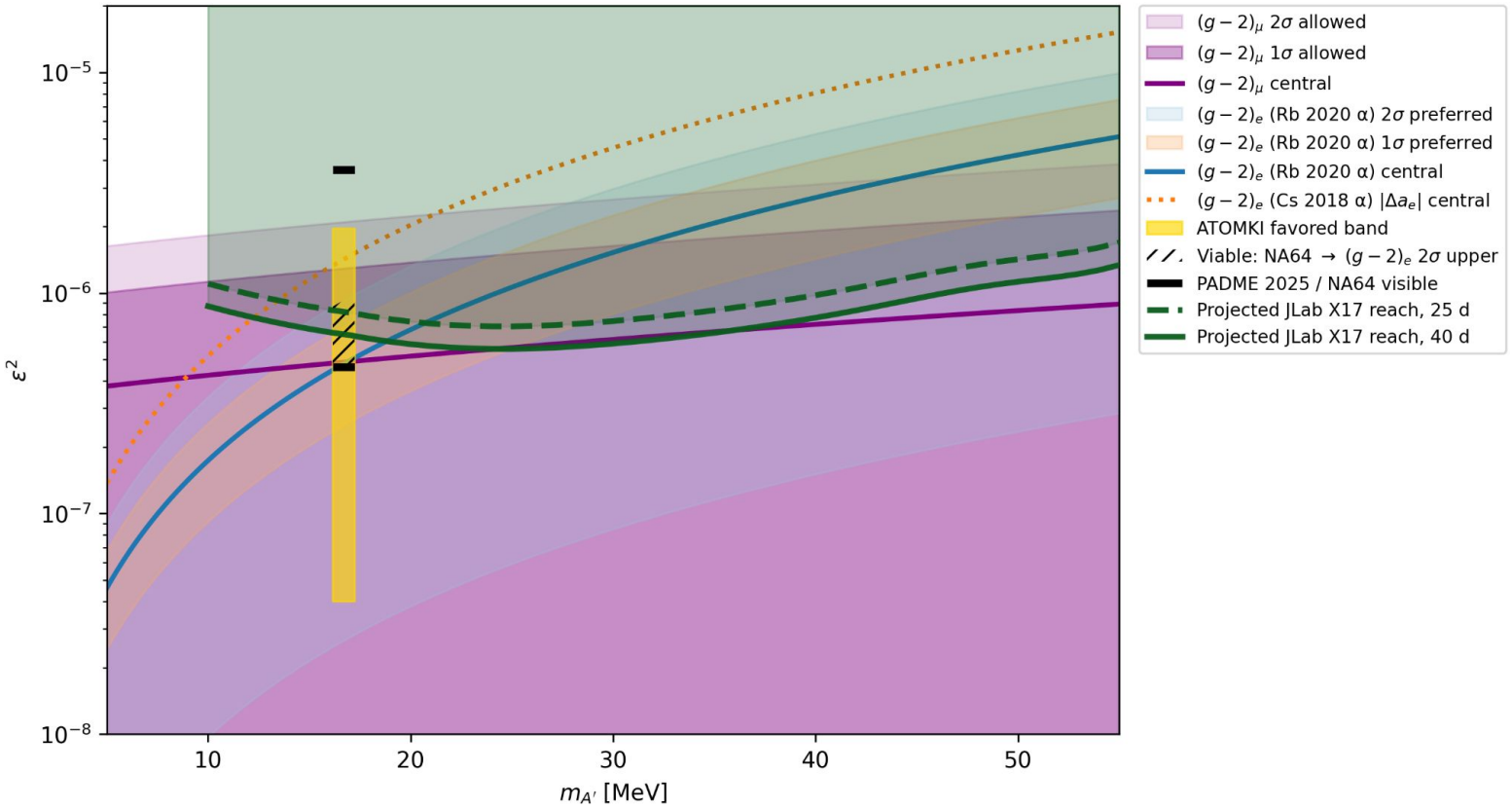




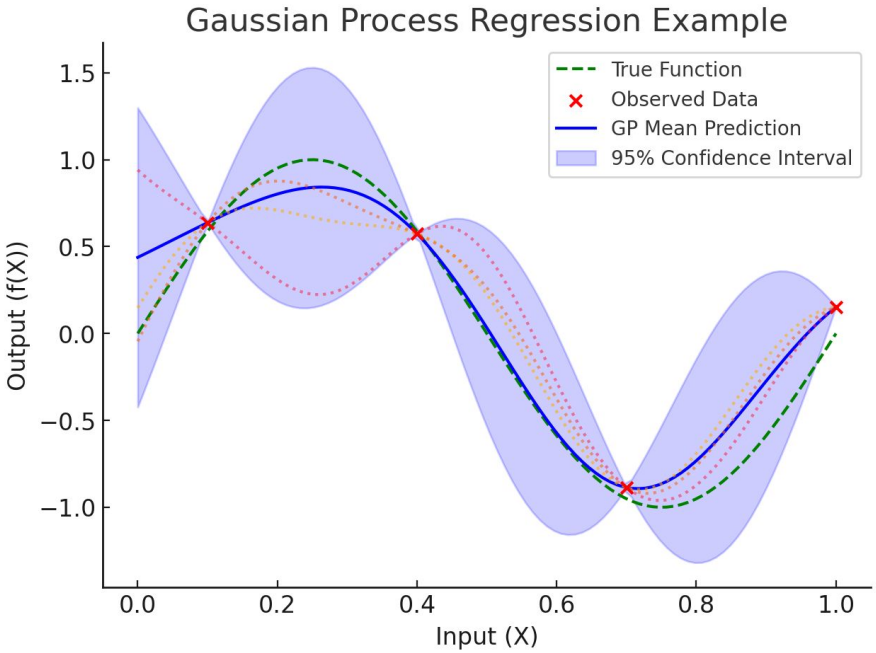
Proof of Principal Sensitivity Estimates – *not official*



Gaussian Process Regression at HPS

What is Gaussian Process Regression (GPR)?

- A **flexible, non-parametric Bayesian approach** that models distributions over functions.
- Unlike traditional regression, **GPR does not assume a fixed set of parameters**—it learns a distribution of possible functions.
- **Built-in uncertainty quantification** makes it ideal for noisy and complex datasets.



The kernel function (covariance function) governs how data points interact and influence one another.

Kernel of Choice: Constant X Radial Basis Function (RBF)

$$K_{ij} = k(y_i, y_j; C, \ell) = C \exp\left(-\frac{(y_i - y_j)^2}{2\,\ell^2}\right)$$

The choice of kernel shapes the model's **smoothness, flexibility, and generalization ability**, making it crucial for capturing underlying data patterns.

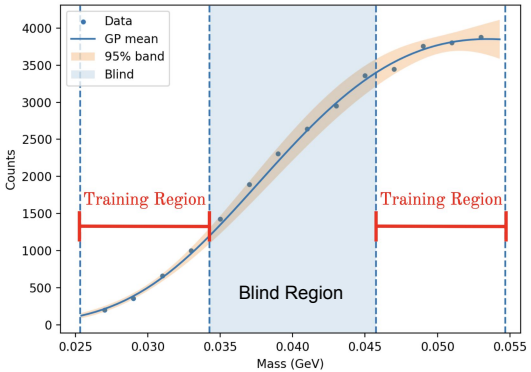
Gaussian Process Regression at HPS

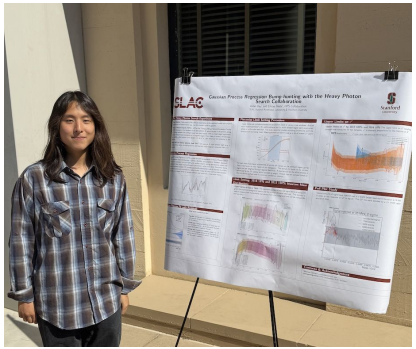
Collaboration of Emrys Peets (Stanford/SLAC), Aidan Hsu (Stanford), Tom Eichlersmith (Minnesota), Joseph Bailey (Stanford), Takumi Britt (UCLA).

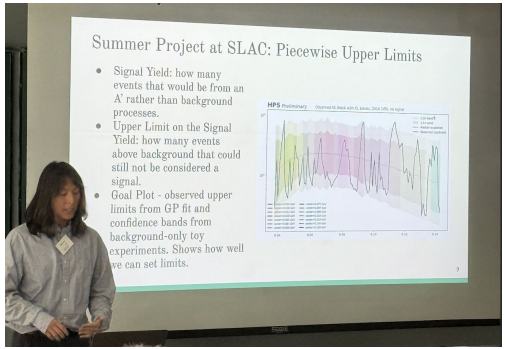
Kernel selection previously defined by soft-max selection from ensemble of kernels, now motivated by recent paper (with change to alpha definition):

Gaussian Process Regression as a Sustainable Data-driven Background Estimate Method at the (HL)-LHC

Monte Carlo Illustrative Display







Mentee Aidan Hsu presenting GPR research at (left) Stanford Undergraduate Summer Research Symposium, (right) APS Far West Regional Conference at UCSC.

HPS-GP Internal Physics Note

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Finalizing Generalizable Methodology Now

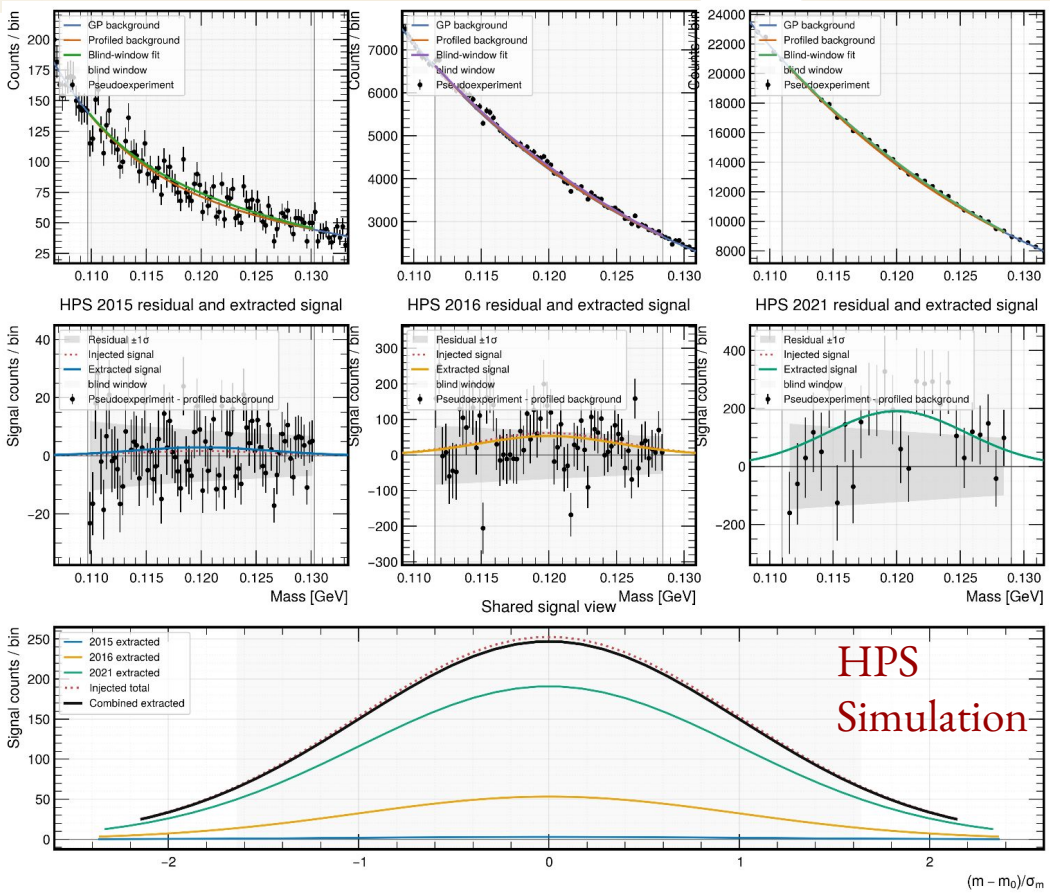
Primary dissertation analysis is on search for a heavy photon in the e+e- invariant mass distributions of the HPS 2015, 2016, and 2021 runs. (~170pb^{-1} integrated luminosity)

Have developed a GPR background modeling technique and am conducting a simultaneous search with a likelihood test using a shared coupling parameter.

$$s_d(\varepsilon^2; m) = \varepsilon^2 K_d(m) w_d(m)$$

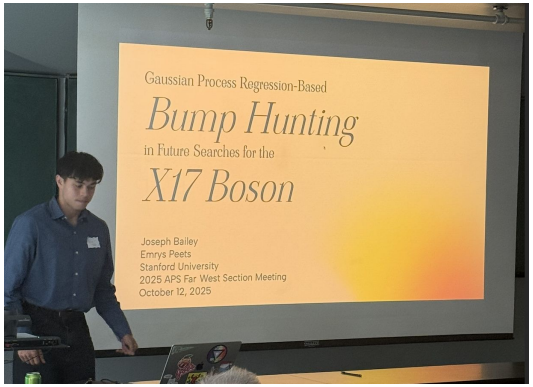
$$s(\varepsilon^2) = (s_1(\varepsilon^2), s_2(\varepsilon^2), \ldots)$$

$$q(\varepsilon^2) = -2 \ln \lambda(\varepsilon^2) = -2 \ln \frac{\mathcal{L}(\varepsilon^2, \hat{\hat{\theta}}, \hat{\hat{\eta}})}{\mathcal{L}(\hat{\varepsilon^2}, \hat{\theta}, \hat{\eta})}$$

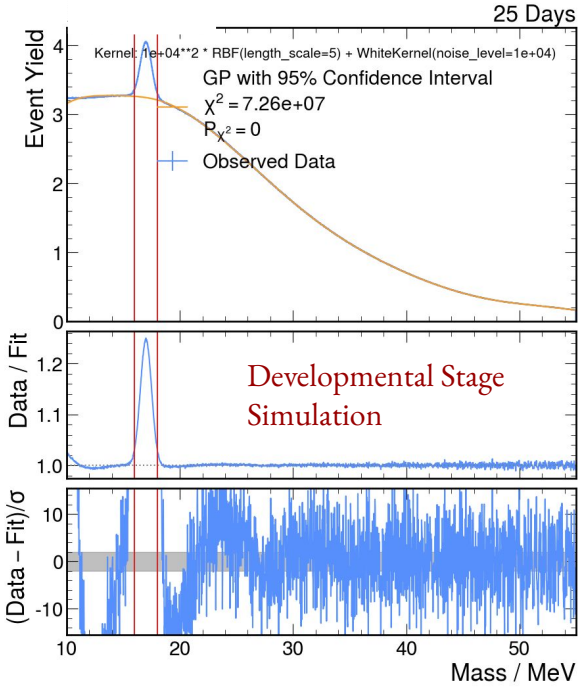


Developing GPR for the X17 Collaboration

Presented Progress at X17 Collaboration Meeting, working with cospokesperson Rafayel Paremuzyan and mentoring student on writing software.



J. Bailey on GPR X17 Resonance Searches at UCSC APS Fall Regional Meeting.



Exaggerated signal injected over the background for 25 days of beamtime

- **No background model given**
- Clear significance of signal

Expecting to take operational shifts this coming summer and then work with analysis group on the resonance search.

Discussion Questions

I. Supposing X17 is found/resolved in the next 2-3 years, what is next?
   - Are there other light targets to pursue ⟹
   - Do we make more X17?
     - Small scale experiments might be able to increase statistics and refine coupling

II. Exotic Physics is interesting to me!
   - Spectroscopy of hard to produce bound states (true muonium, tauonium) could lead to better understanding of standard model

Additional Slides

I. GPR Training Procedure (Piecewise)
II. GPR Kernels + GPR Alpha
III. CMS Group Study Assumptions and overview

GPR Training Procedure

I. Split data inputs and kernels into training/blind blocks

$$X_S = \{x_i\}_{i \in S}, \quad X_B = \{x_i\}_{i \in B}$$

$$K_{SS} = \left[k(x_i, x_j)\right]_{i,j \in S}$$

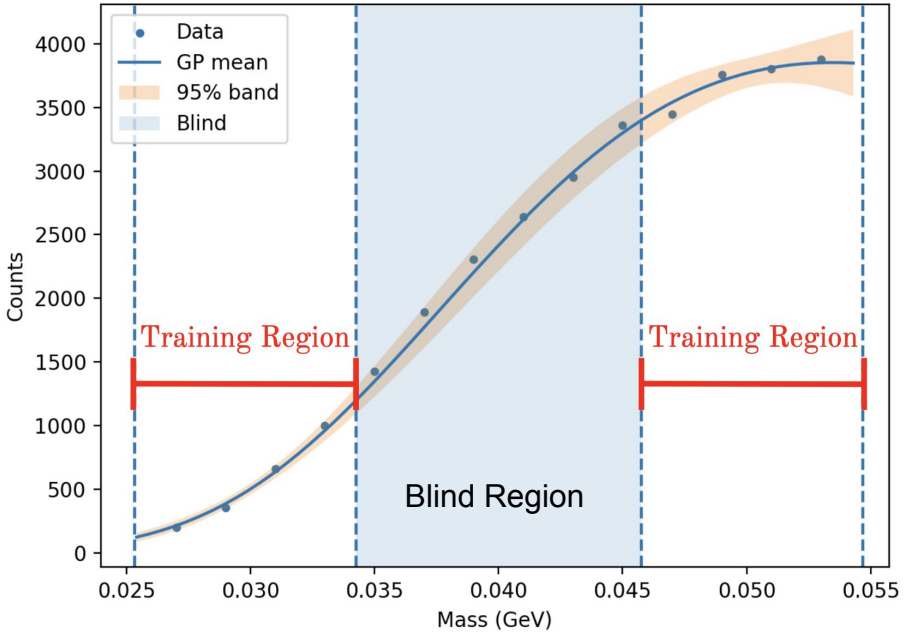
$$K_{BB} = \left[k(x_i, x_j)\right]_{i,j \in B}$$

$$K_{BS} = \left[k(x_b, x_s)\right]_{b \in B,\, s \in S}$$

II. Convert bins to log-space and alpha to variance form for stability

$$z_i = \begin{cases} \log y_i, & y_i > 0, \\ 0, & y_i = 0, \end{cases} \qquad \alpha_i = \begin{cases} 1/y_i, & y_i > 0 \\ 1, & y_i = 0 \end{cases}$$

Monte Carlo Illustrative Display



GPR Training Procedure

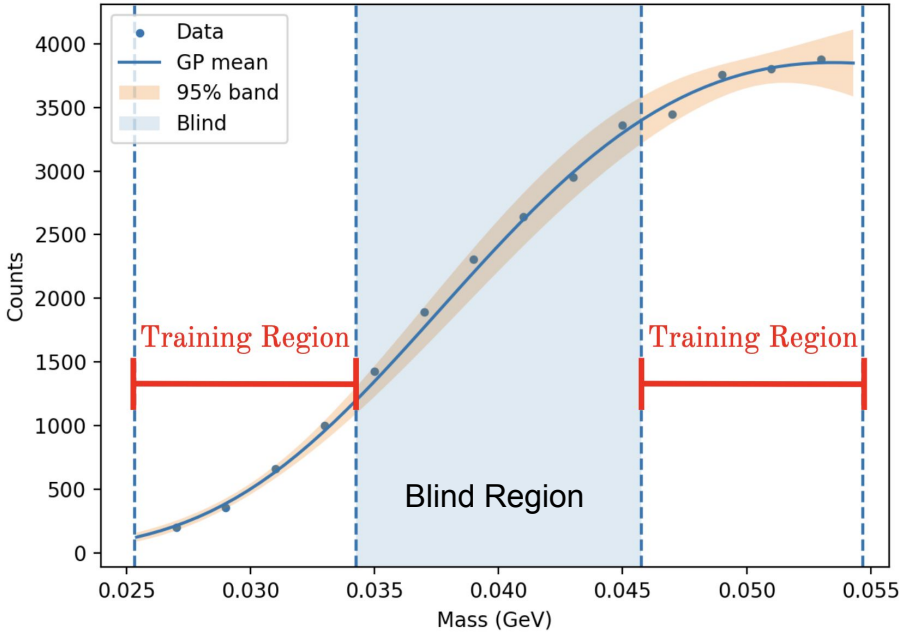
III. Determining log-space posterior trained on sidebands only

$$\mu_B^{(\log)} = K_{BS}\, A^{-1}\, z_S, \qquad A \equiv K_{SS} + \mathrm{diag}(\alpha_S)$$
$$\Sigma_{BB}^{(\log)} = K_{BB} \;-\; K_{BS}\, A^{-1}\, K_{SB}.$$

IV. Map predictions back to count space and interpolate in blind region (log normal moments)

$$\mathbb{E}[\,y_B\,] \;=\; \exp\!\Big(\mu_B^{(\log)} + \tfrac{1}{2}\,\mathrm{diag}\,\Sigma_{BB}^{(\log)}\Big),$$
$$\mathrm{Cov}(y_B) \;=\; \big(\mathbb{E}[y_B]\,\mathbb{E}[y_B]^\top\big) \odot \Big(\exp\!\big(\Sigma_{BB}^{(\log)}\big) - \mathbf{I}\Big)$$

Monte Carlo Illustrative Display



Kernels and Hyper Parameters

In GPR space: for Kernel, K, bin contents (y_i) are described by the gaussian PDF:

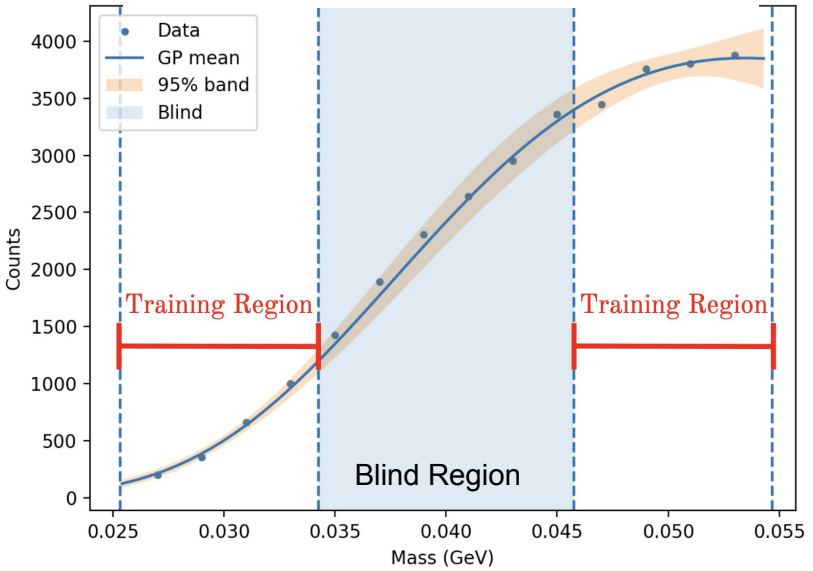
$$p(y_i;\mu_i,\mathbf{K}) = \frac{1}{\sqrt{(2\pi)^n|\mathbf{K}|}}\exp\left(-\frac{1}{2}\sum_{i,j}^{n}(y_i-\mu_i)K_{ij}^{-1}(y_j-\mu_j)\right)$$

Radial Basis Function (RBF)

$$K(x_i,x_j) = \exp\left(-\frac{||x_i-x_j||^2}{2\ell^2}\right)$$

Euclidean metric, radially symmetric

Monte Carlo Illustrative Display



Passing in Alpha

Hyperparameter meant to capture known bin-bin variance

$$y_i = f(x_i) + \varepsilon_i, \qquad \varepsilon_i \sim \mathcal{N}(0, \alpha_i)$$

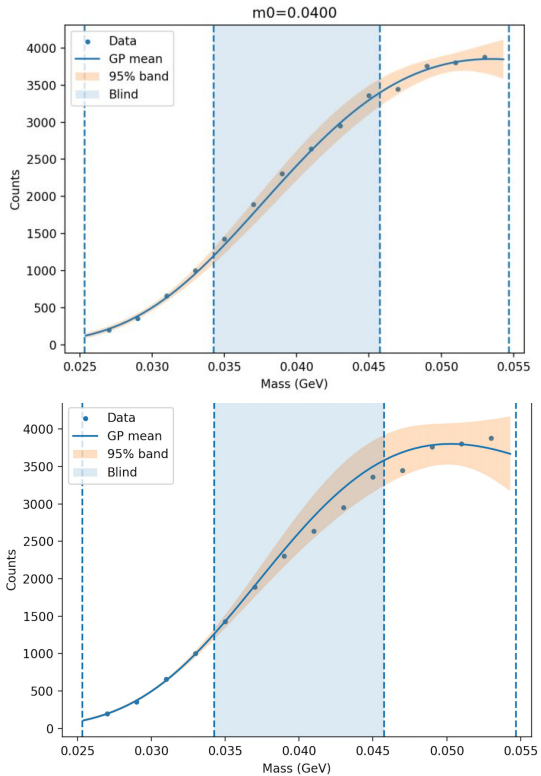
Formally a Kernel with alpha has the covariance form

$$K_\alpha \equiv K(X, X) + \Sigma, \quad \Sigma = \mathrm{diag}(\alpha_1, \ldots, \alpha_n)$$

With impact on log marginal likelihood

$$\log p(y|\theta) = -\tfrac{1}{2} y^\top K_\alpha^{-1} y \; - \; \tfrac{1}{2} \log |K_\alpha| \; - \; \tfrac{n}{2} \log(2\pi)$$

Thus, increase of alpha relaxes the fit and increases the penalty.
(larger predictive uncertainty, preferring longer length scales).
Very small alpha risks fitting bumps.



Key Assumptions from CMS Group

SLAC

Pre-processing

- log(mass) , log(yield) to stabilize wide dynamic range

L2 Regularization
(alpha zones/hyperparameter tuning)

Validation metrics defined for sideband analyses

- KS - pvalue (tests likelihood of normally distributed data)
- Goodness of Fit: χ^2/DoF
- Bumphunter sideband scan
- they tune alpha to pass these metrics

CMS Kernel Hyperparameters

Name	Explanation	Nominal Values
ℓ_0	RBF kernel length scale lower bound	0.5
ℓ_1	RBF kernel length scale higher bound	20
$\mathbf{c}_0$	constant kernel lower bound	10^{-5}
$\mathbf{c}_1$	constant kernel higher bound	10^{18}
α_i	diagonal elements added to the kernel matrix	$\sqrt{y_i}/(y_i \log y_i)$
$\mathbf{f}_i$	multiplication factors applied to α_i	1

CMS Bkg Validation Criterion

Criteria	Nominal
KS p-value > 0.05	86%
χ^2/nDoF < 1.5	65%
BH p-value > 0.1	51%