Global Fitting of the 2015 Invariant Mass Distribution

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Overview

- Motivation for DM
- HPS
- The Resonance Search at HPS
- Invariant Mass 2015 Data set
- Challenges of Fitting
- Fit & Residuals
    - Code explanation
- Interesting Commonality Among Residual Plots

SLAC Confluence

Motivation for Dark Matter

- Galaxy Rotation Curves (Spiral Galaxies) →

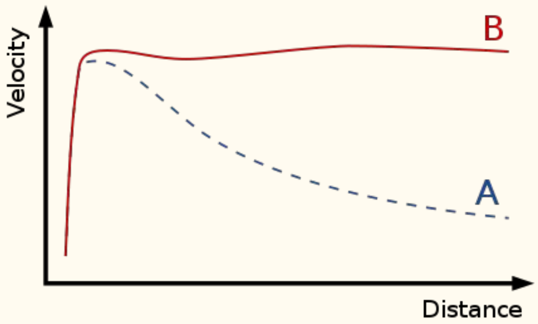
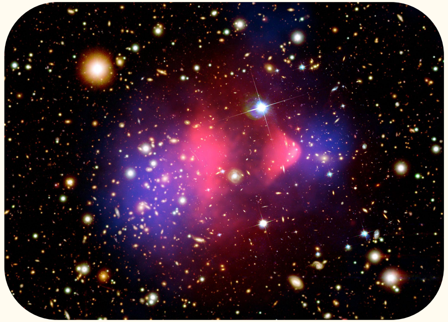


Figure credit: Hibbs, Phil. *Expected (A) and observed (B) star velocities as a function of distance from the galactic center.*

- Galaxy Clusters
  - Mass of galaxy clusters is significantly greater than that of the visible matter
    - Motion of galaxies within clusters, gravitational lensing, hot gas temperature analysis
- Main Role of DM
  - Baryonic Matter vs. Dark Matter
  - Dark matter clumps more effectively (because it does not interact electromagnetically*) → amplifies the wells in spacetime for baryonic matter to interact with
  - Density fluctuations (from CMB) seeded galaxy/cluster formation



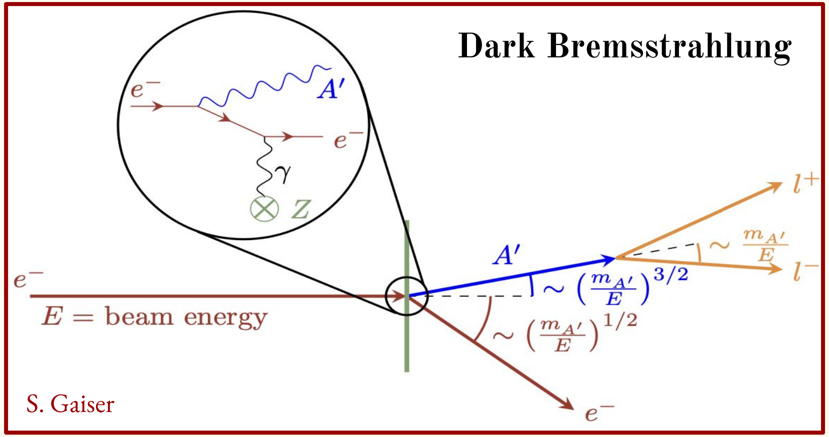
Bullet Cluster (esa)

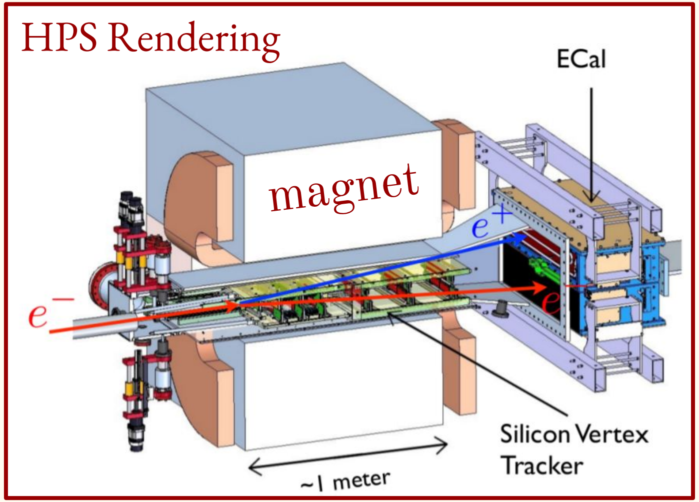
*dm mediator may interact electromagnetically

HPS - Heavy Photon Search

- Searching for hidden-sector photon, **A′**
  - Also known as dark/heavy photon
  - Weakly couples w/ electrons, then decays into e^-e^+ pairs

- Implementation:
  - HPS uses the Continuous Electron Beam Accelerator Facility (CEBAF) (Jefferson Lab)
  - High energy beam of electrons focused at a target → can produce heavy photons (via **dark bremsstrahlung**), search for e^-e^+ resonance
  - Tungsten— high atomic # increases chances of bremsstrahlung, optimal interaction cross-section and density, high relative radiation effective for detection, durable

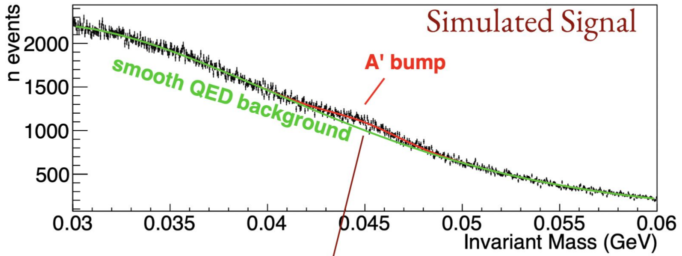




The Resonance Search at HPS

- Distinct (prompt) A’ Bump on Invariant Mass Distribution
  - Indication of Dark Photon
- I. Fitting with Background Only Model (Currently working on)
- II. Fitting with Background + Signal Model (Summer Goal)
  - use HPS internal software to determine amount of heavy photon signal in data
- III. Residual Plots (Currently working on with Background Only Model)

If A′ exists within the acceptance of HPS, it will present itself as a gaussian excess above background in the IMD.



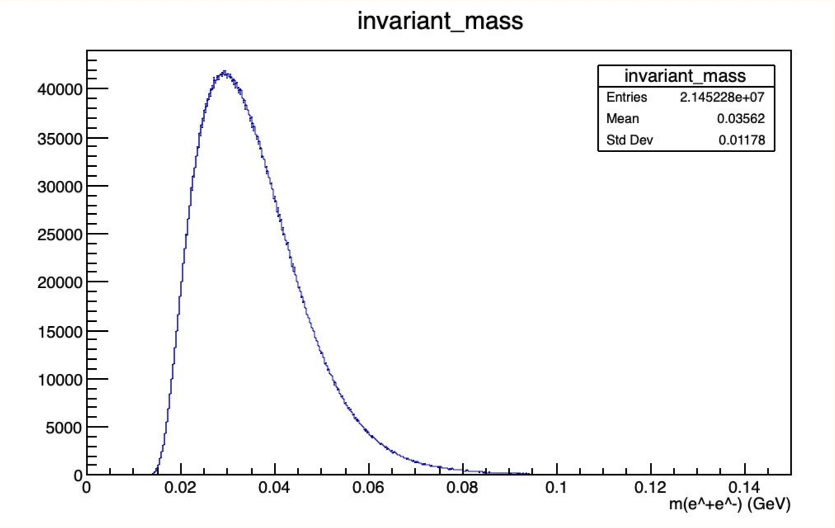
natural width of A′ << detector resolution
observed signal width = experimental mass resolution

E. Peets, et. al

Invariant Mass - 2015 Data Set

Reconstructed e^-e^+ pair invariant mass distribution

- Beam Energy: 1.06 GeV
- Total Luminosity: 1.2 pb^{-1} (Accumulated Charge)
- x-axis: inv. mass of detected e^-e^+ pairs (giga-electron Volts)
- y-axis: #events (entries s.t. e^-e^+ pairs w/ respective inv. mass)

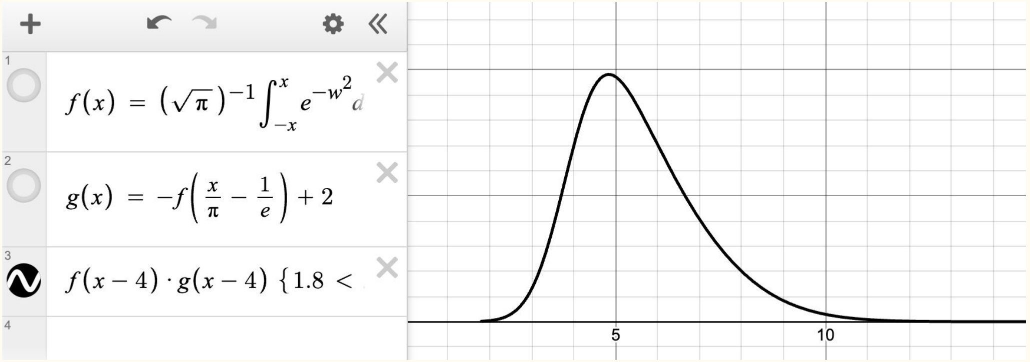


Challenges of Fitting IMD - 2015 Data Set

Previous Attempts:

- Gaussian Product, Polynomial Regression, Poisson Distribution don’t work
    - IMD contains high statistics

$$P(X = k) = \frac{\lambda^k e^{-\lambda}}{k!}$$



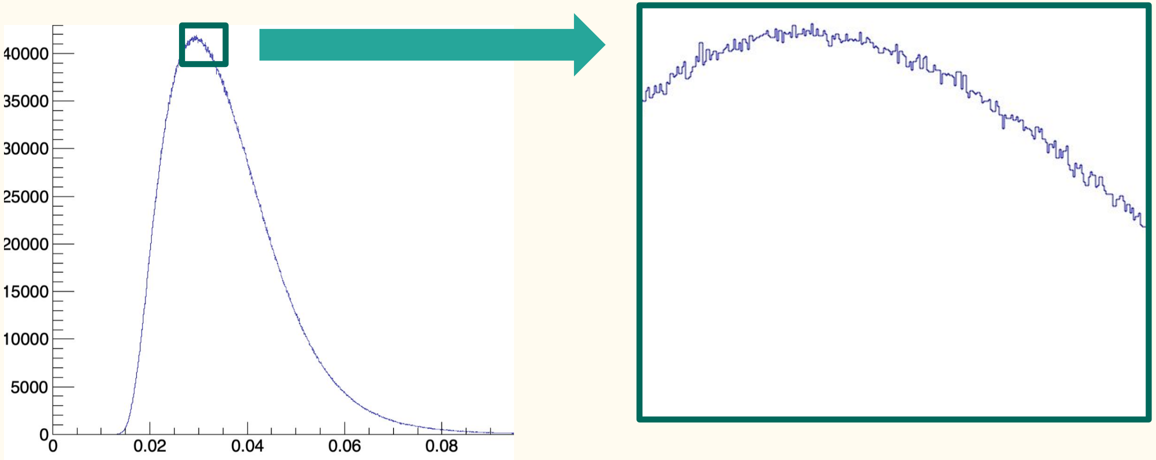

```
// Define the TF1 with a Taylor polynomial of degree 10
TF1 *fitFunction = new TF1("fitFunction", "[0] + [1]*x + [2]*x^2 + [3]*x^3 + [4]*x^4 + [5]*x^5 + [6]*x^6 + [7]*x^7 + [8]*x^8 + [9]*x^9 + [10]*x^10", 0.02, 0.1);

// Set initial parameter values (if needed)
for (int i = 0; i <= 10; ++i) {
    fitFunction->SetParameter(i, 1);
}

// Perform the fit in the specified range
int fitStatus = hist->Fit(fitFunction, "SMRQ", "", 0.02, 0.1);
std::cout << "Fit status: " << fitStatus << std::endl;
```

Challenges of Fitting IMD - 2015 Data Set

Previous Attempts:

- Gaussian Product, Polynomial Regression, Poisson Distribution don't work
    - **IMD contains high statistics**

- 10-parameter multiplex function is employed
    - Dynamic algorithm optimizes parameters, window range selected through testing
    - Error function for the rising part, other components for falling part



Candidate Background Model Functional Form

$$\mathcal{C} \cdot \left[\mathrm{Er}_1 \cdot (1-x)^{p[1]} \cdot e^{p[2]\cdot \log(x)} + \mathrm{Er}_2 \cdot q[1] \cdot (1-x)^{q[2]} \cdot (1+x)^{q[3]\cdot x} \right]$$

Global Normalization Constant

E. Peets

Background Model Parameter Searching Method

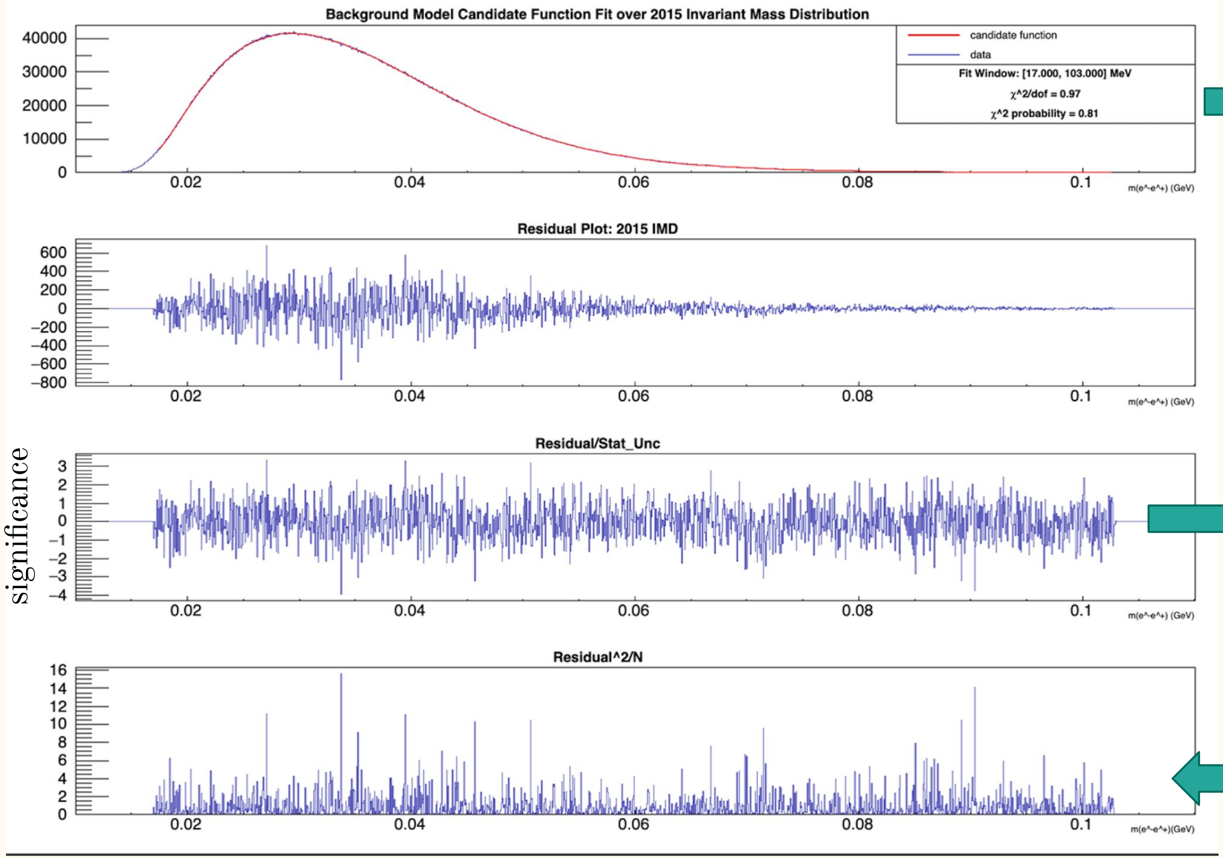
Dynamic Algorithm checks chi2 prob and optimises gaussian size for X loops— “shotgun approach”

```
#loop 1
for j in range(len(initial_params)):
    gen_param = ran_gen.Gaus(vary_params[j], .1 * vary_params[j] + 0.1 * vary_params[j] * vary_params[len(initial_params)])
    f1.SetParameter(j, gen_param)
```

- First loop generates, then floats all parameters from initial parameter guesses:
    - Optimizes all params except for p2
- Second loop fixes **all parameters** <u>except</u> for normalization constant

```
#loop 2
for i in range(param_num):
    if i == 2:
        f1.SetParameter(i, f1_params[i])
        best_fit_info.append(f1_params[i])
    else:
        f1.FixParameter(i, f1_params[i])
        best_fit_info.append(f1_params[i])
```

Updated Display Tools



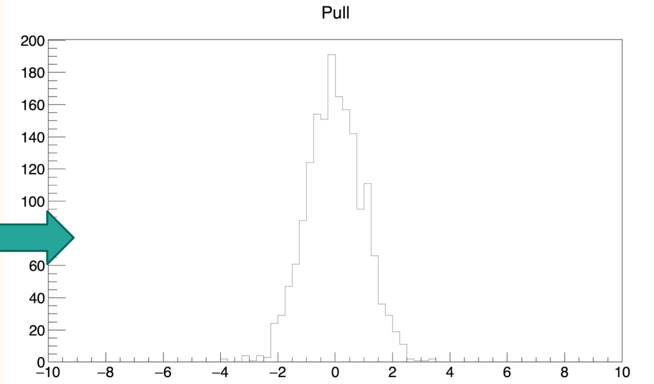
significance

Fit Information:

Fit Window: [17.000, 103.000] MeV

χ^2/dof = 0.97

χ^2 probability = 0.81

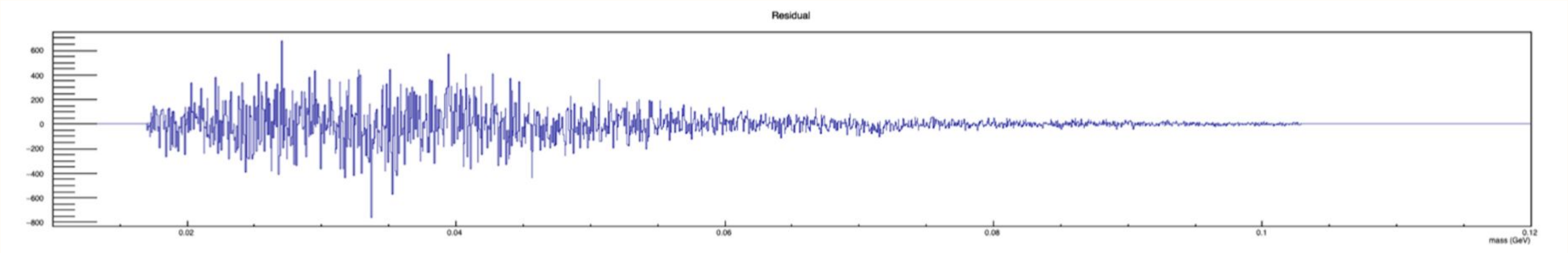


Chi2 Contribution

Residual Plot

Residual Plot: (Background - Fit)

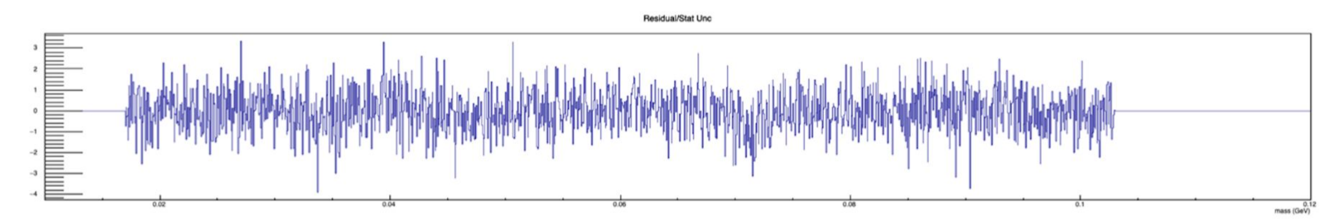
- Visual representation of goodness of fit
- Ideal: Random distribution with **no distinct pattern**



More Residuals

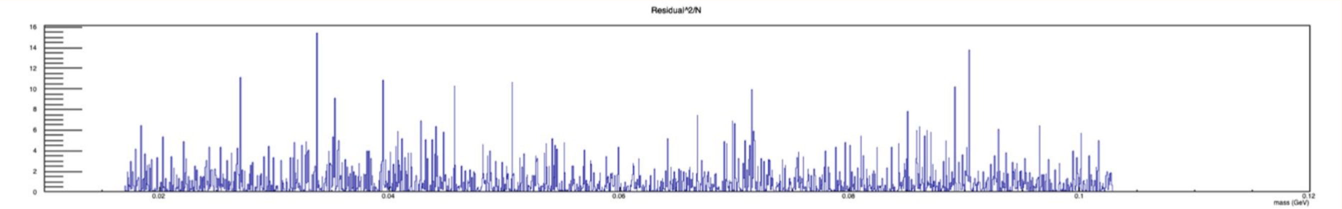
Residual/Statistical Uncertainty

- Sqrt(N)
- "Standardized Residual"
- Identifying outliers
- Goodness of Fit

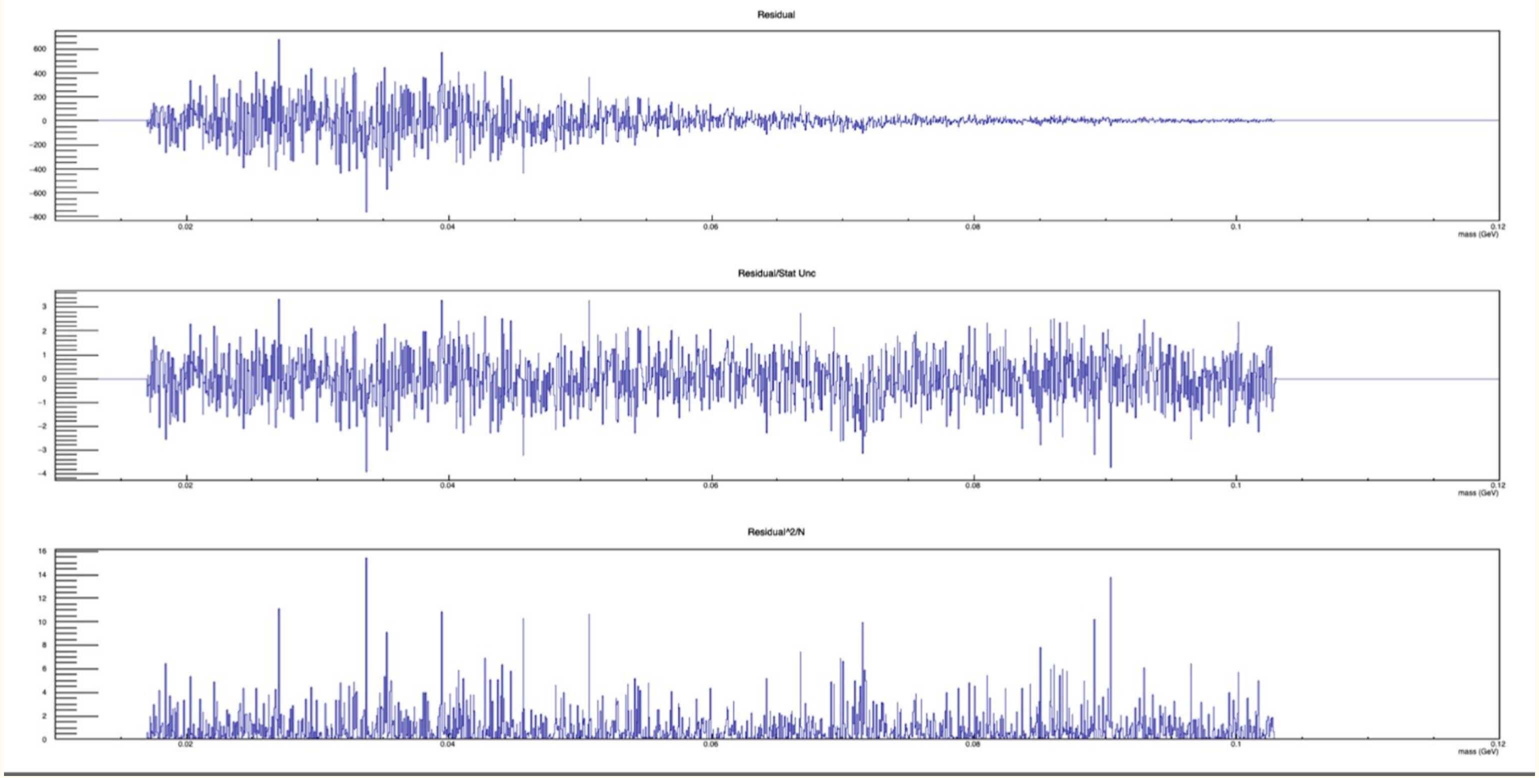


Residual^2/Statistical Uncertainty^2

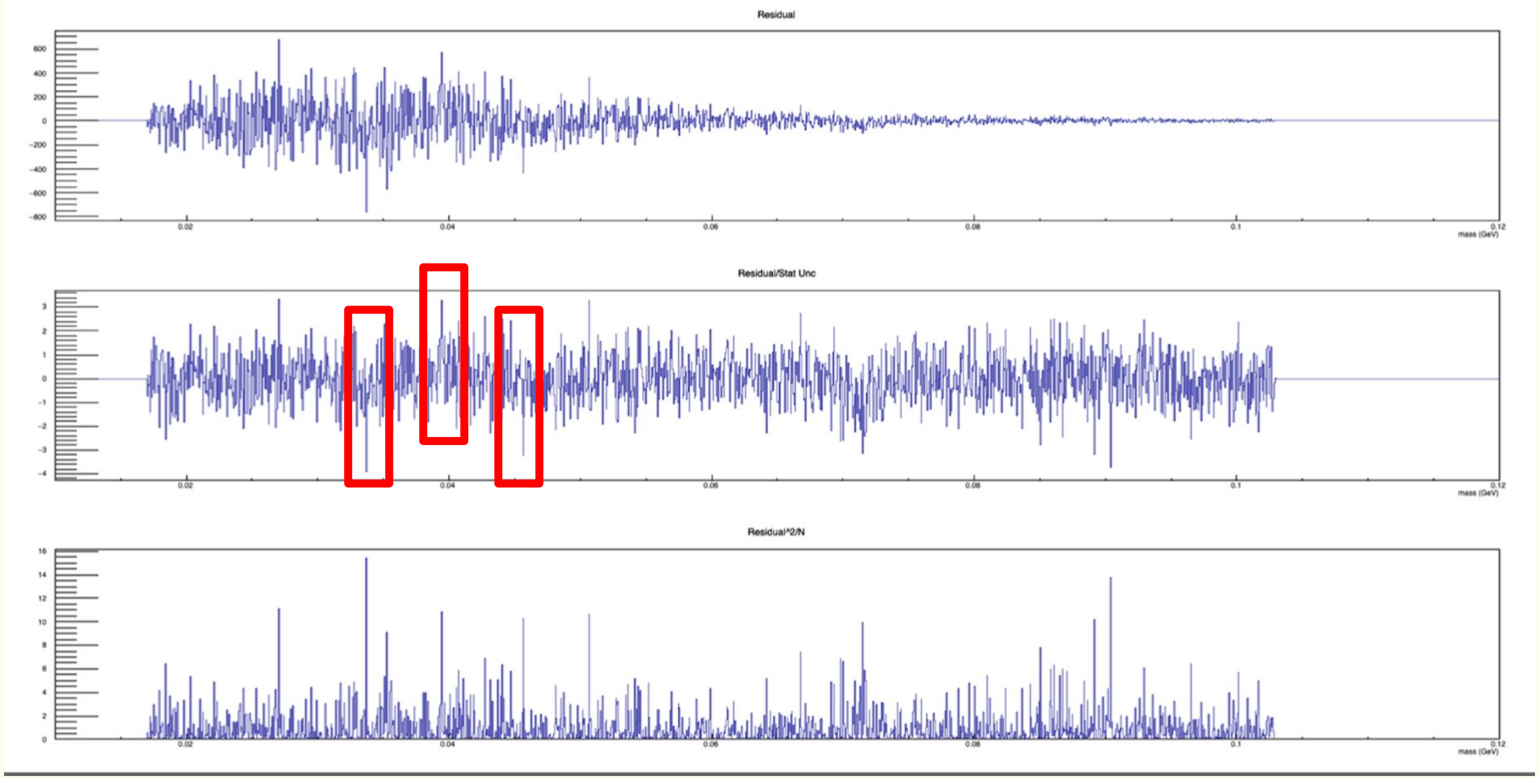
- Chi^2 Contribution Plot
- Allows for a quantitative interpretation of fit quality
- Provides insight/context into chi^2/ndf (reduced chi-squared statistic)
    - Sum of bins/#bins
    - Differentiating between over/underfitting or good fit
    - Overfitting: works well on sample data, not effectively applicable on new data
    - Underfitting: works badly on sample and new data



Interesting Observation



Interesting Observation



Summary of Progress

- Learning about Dark Matter, HPS
- Working with the Invariant Mass 2015 Data Set
    - Fitting
    - Creating Residuals
    - Display Tools
- Observation

Next Steps & Summer Goals

- Perform more fits, continue polishing display tools
  - Experiment w/ setting & fixing diff params
- Create sub-function display tool
- Conduct similar background only model tests with re-binned data sets.
- GOAL:
  - Incorporate display tool options into hpstr Bumphunter
  - Run hpstr Bumphunter to better understand background + signal model
- Learn overleaf & assist with 2015 re-analysis section of a global fitting note.

Thank you to my excellent mentor, Emrys Peets

2015 vs. 2019 Detector (Differentiating Work)

1. Tracking layer addition (Layer 0) – between target, current Layer 1
   - Vertex resolution enhancement allows for greater sensing exactness for position of particle decay
   - More granular allowance for decay vertex analysis (HP → e^-e^+)
2. Adjustment of Layers 2 and 3
   - Improved acceptance for A’ bump identification
3. Hodoscope addition
   - Targets positrons → lowers acceptance losses from Electromagnetic Calorimeter hole