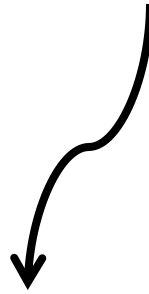


Wall Model PLR Integration

Shaun Alsum

Typical Case

$$\mathcal{L}_{M+P} \left((\mu, \vec{k}) \middle| \vec{X} \right) = \text{Pois} (n_{\text{obs}}; n_{\text{exp}}) \cdot \prod_{\vec{x}_i \in \vec{X}} \left[\underbrace{\mu k_{\mathcal{S}} \mathcal{P}_{\mathcal{S}}(\vec{x}_i)}_{\text{Extended term}} + \underbrace{\sum_j k_j \mathcal{P}_{\mathcal{B}_j}(\vec{x}_i)}_{\text{Shape term}} \right] \cdot \underbrace{\prod_{k_i \in \vec{k}} \mathcal{P}(k_j)}_{\text{Profile term}}$$



$$\prod_{\vec{x}_i \in \vec{X}} \left[\mu k_{\mathcal{S}} \mathcal{P}_{\mathcal{S}}(s1_i, s2_i, r_i, d_i, \phi_i, t_i) + \sum_j k_j \mathcal{P}_{\mathcal{B}_j}(s1_i, s2_i, r_i, d_i, \phi_i, t_i) \right]$$



$$\prod_{\vec{x}_i \in \vec{X}} \left[\mu k_{\mathcal{S}}(c_i) \mathcal{P}_{\mathcal{S}}(s1_i, s2_i \mid c_i) \mathcal{P}_{\mathcal{S}l}(r_i, d_i, \phi_i \mid c_i) + \sum_j k_j(c_i) \mathcal{P}_{\mathcal{B}_j}(s1_i, s2_i \mid c_i) \mathcal{P}_{\mathcal{B}_j}(r_i, d_i, \phi_i \mid c_i) \right]$$

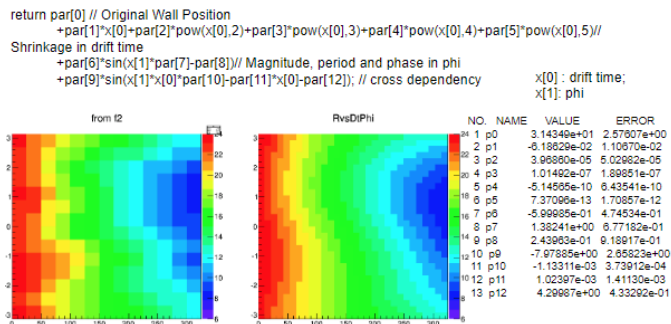
Implemented via RooHistPdf(r, drift, phi) X RooHistPdf(s1, s2)

Wall Model

- Histogram in s1, s2, drift, phi tells you how many events are at each location in this 4d space.
- Gaussian in r tells you how they are distributed radially.

$$P(r, \phi, \text{Drift}, S2) = \frac{1}{\pi\sqrt{2}\sigma} \exp \left[-\frac{(r - r_{\text{wall}})^2}{2\sigma^2} \right]$$

- r_{wall} depends strongly on drift and phi
- σ depends strongly on s2 (and s2 on s1)
- Therefore the Gaussian is a fully 5d function.



r_{wall} dependence on
drift and phi

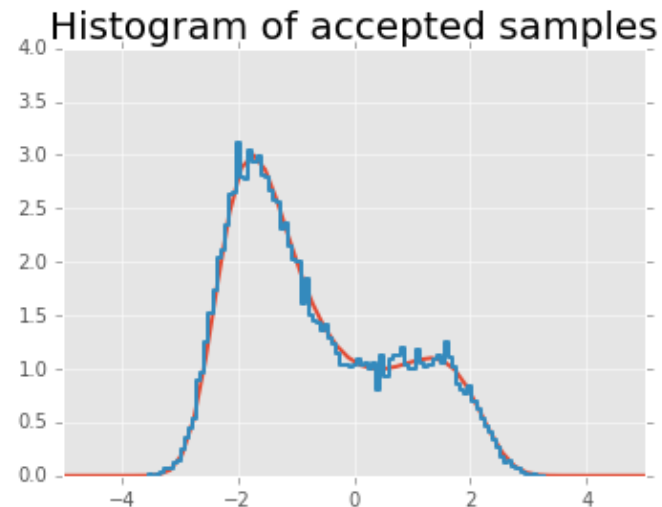
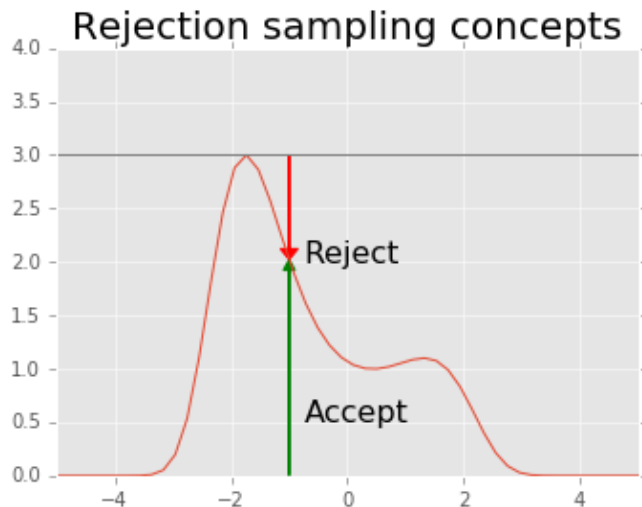
Wall Model Correlations

	S1	S2	DT	ϕ
S1				
S2				
DT				
ϕ				

- s1, s2, drift strongly correlated.
- phi weakly correlated to drift

First Pass Implementation

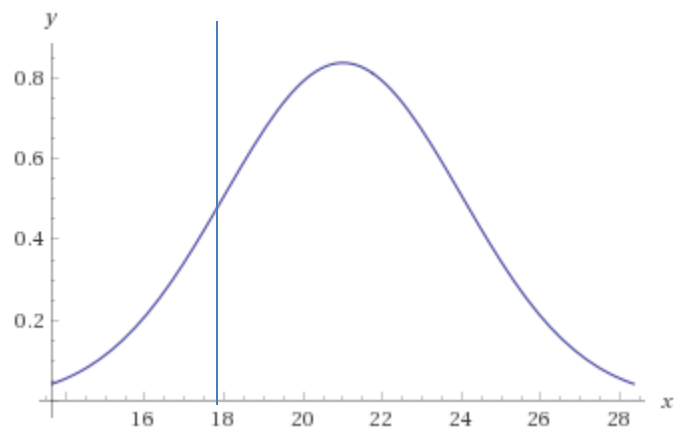
- Try $[\text{Hist}(s1, s2, \text{drift}) \times \text{Hist}(\text{phi})] \times f(r \mid s1, s2, \text{drift}, \text{phi})$
- Implemented via $\text{RooHistPdf} \times \text{RooHistPdf} \times \text{Conditional}(\text{customRooPdf})$
- Unfortunately, integration rather slow, event generation veeeeeeery slow.
 - Uses numeric integration
 - Uses “Accept Reject” event generation



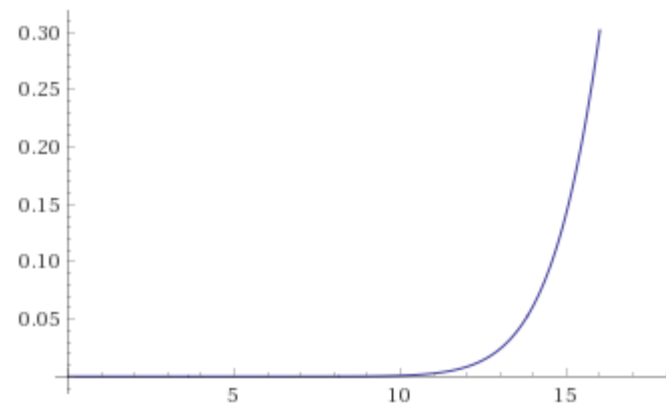
New Implementation

- Create 1 pdf object
 - Store a 3d vector array of number of events (s1, s2, drift)
 - Store a 1d vector that is a linearized version of this with each bin added to the previous to form a cumulative distribution function (cdf)
 - Store a 1d vector array of number of events (phi)
 - Store the corresponding cdf
 - Define a function for the wall position $r_{\text{wall}} = f(s1, s2, \text{drift}, \text{phi})$
 - Define a function for the std of the distribution $r_{\text{std}} = f2(s1, s2, \text{drift}, \text{phi})$
 - Define the radial pdf as a function of the other observables
 - $f(r \mid r_{\text{wall}}, r_{\text{std}}) = \{\text{Gaus}(r \mid r_{\text{wall}}, r_{\text{std}}) \text{ if } r < r_{\text{wall}} - 3, 0 \text{ otherwise}\} / \text{Normalization factor}$
 - Define the inverse cdf of the radial function

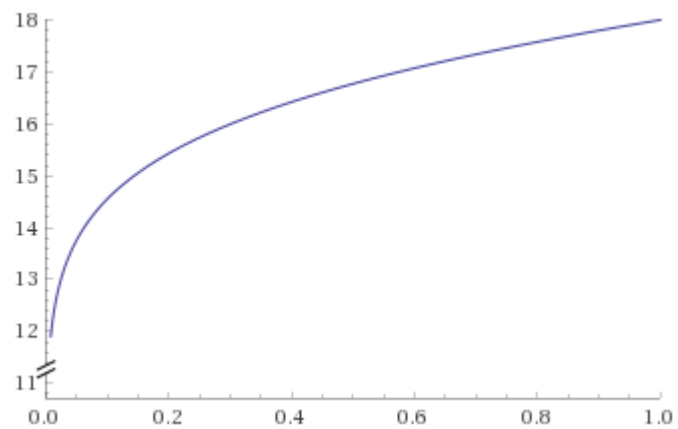
Gaussian



CDF



Inverse CDF



Integration

- Radial analytically integrates to 1 for any values of r_{wall} and r_{std}
so integral is simply $\text{Sum}(\text{vector}(s1, s2, \text{drift})) * \text{Sum}(\text{vector}(\text{phi}))$
- Event

Event Generation

- Generate 3 random numbers form 0 to 1:
 - s1S2Drift number
 - Phi number
 - r number
- Step through s1S2Drift cdf vector until we exceed the s1S2Drift random number, and randomly draw an event from the corresponding bin in (s1, s2, drift)
- Step through phi cdf vector until we exceed the phi random number, then draw an event from the corresponding bin
- Calculate the wall and std for these values of s1, s2, drift, and phi.
- Evaluate the inverse cdf function at these values with the r random number to obtain a value for r.
- This is at least 10^5 times faster than the default accept reject method, probably more. And is in fact faster than the 3d HistPdf generation.