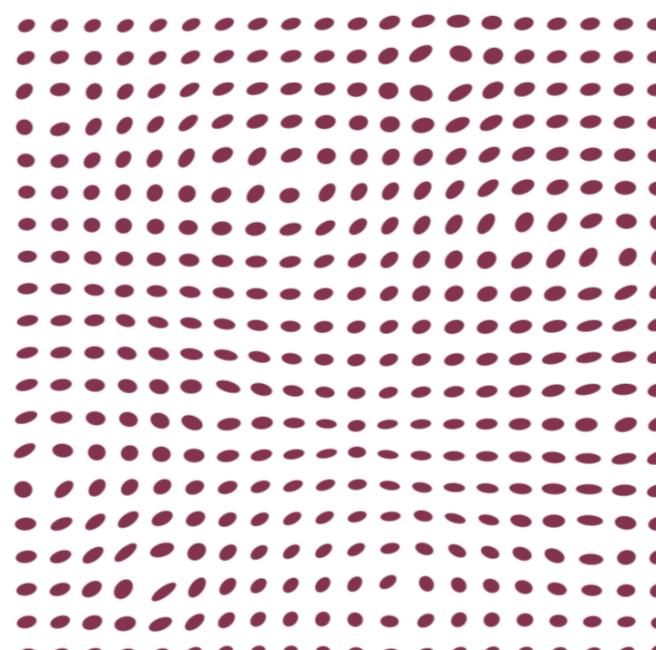
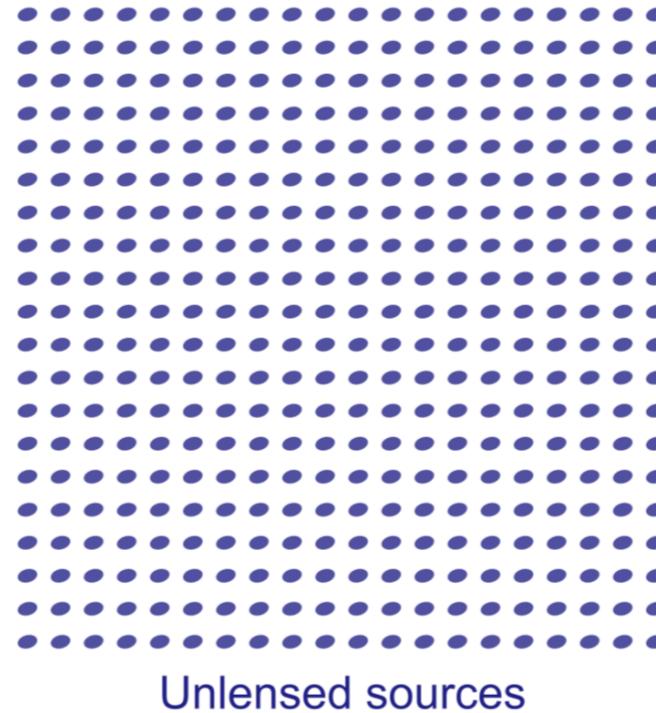
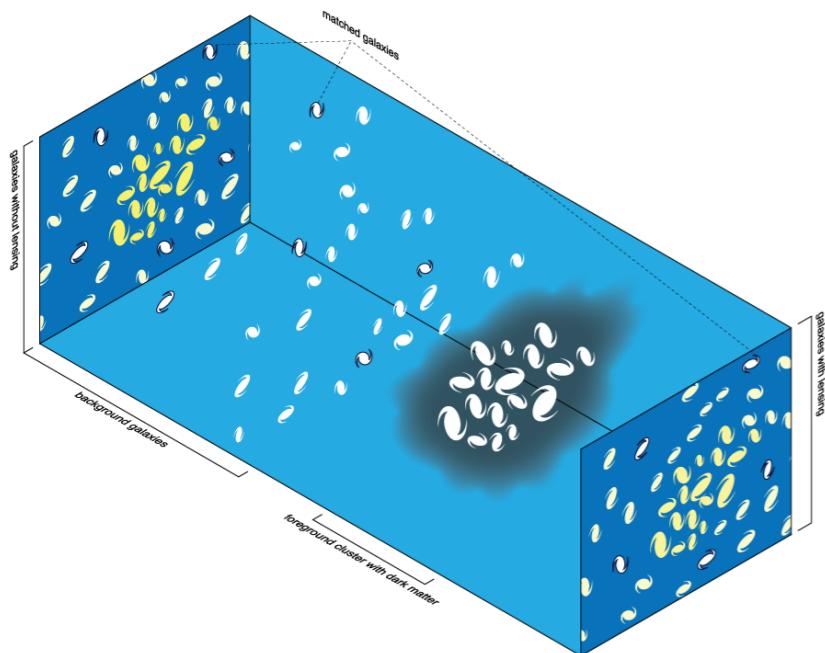


# Hierarchical Probabilistic Inference of Multivariate Galaxy Properties

Karan Shah  
Michael D. Schneider  
(Lawrence Livermore National Lab)

Bay Area LSST & Machine Learning Workshop  
12/20/2018

# Gravitational Lensing



Cosmic shear signal is comparable  
to ellipticity of the Earth, ~0.3%

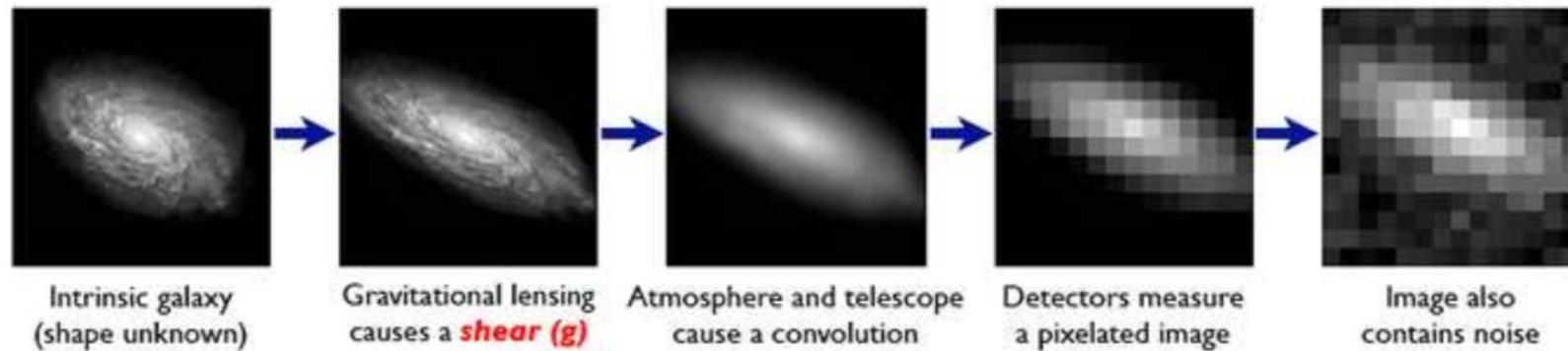
- D. Wittman

## Weak Shear Regime

$$\epsilon_{sh} \approx \epsilon_{int} + g$$

# Hierarchical Bayesian Model

**Galaxies:** Intrinsic galaxy shapes to measured image:



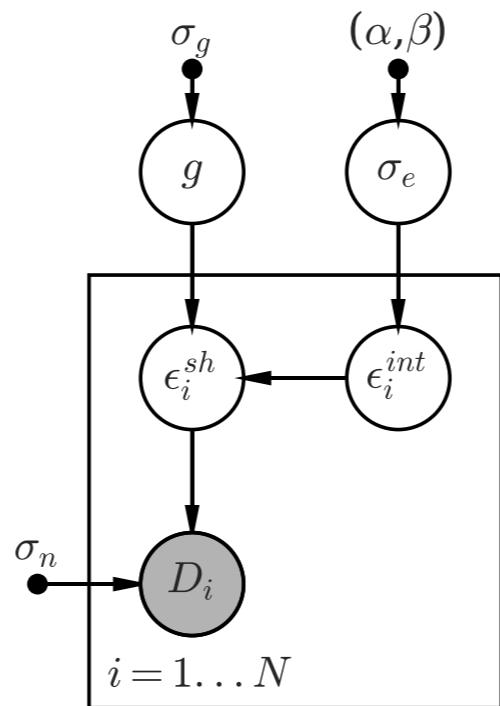
$$P(\gamma | \{D_i\}_1^N) \propto P(\{D_i\}_1^N | \gamma)P(\gamma)$$

# Toy Models

$$P(D \mid \epsilon_{sh}, \sigma_n) = N_D(\epsilon_{sh}, \sigma_n^2)$$

$$P(\epsilon_{int}) = N_{\epsilon_{int}}(0, \sigma_e^2)$$

$$\epsilon_{sh} \approx \epsilon_{int} + g$$



# Toy Models

For a single galaxy,

$$P(D | \epsilon_{int}, g) = P(D | \epsilon_{sh}(\epsilon_{int}, g))$$

We can marginalize out  $\epsilon_{int}$

$$P(D_n | g) \propto \int d\epsilon_{(int,n)} P(D_n | \epsilon_{(int,n)}, g) P(\epsilon_{(int,n)} | \sigma_e^2)$$

**We specify an interim prior for  $\epsilon_{sh}$  as  $P(\epsilon_{sh}) \sim I$**

$$P(D_i | \sigma_e^2) \propto \int d\epsilon_{sh} P(D_i | \epsilon_{sh}) P(\epsilon_{sh} | I) \frac{P(\epsilon_{int}(\epsilon_{sh}, g) | \sigma_e^2)}{P(\epsilon_{sh} | I)}$$

# Toy Model

$$P(D_i | \sigma_e^2) \propto \int d\epsilon_{sh} P(D_i | \epsilon_{sh}) P(\epsilon_{sh} | I) \frac{P(\epsilon_{int}(\epsilon_{sh}, g) | \sigma_e^2)}{P(\epsilon_{sh} | I)}$$

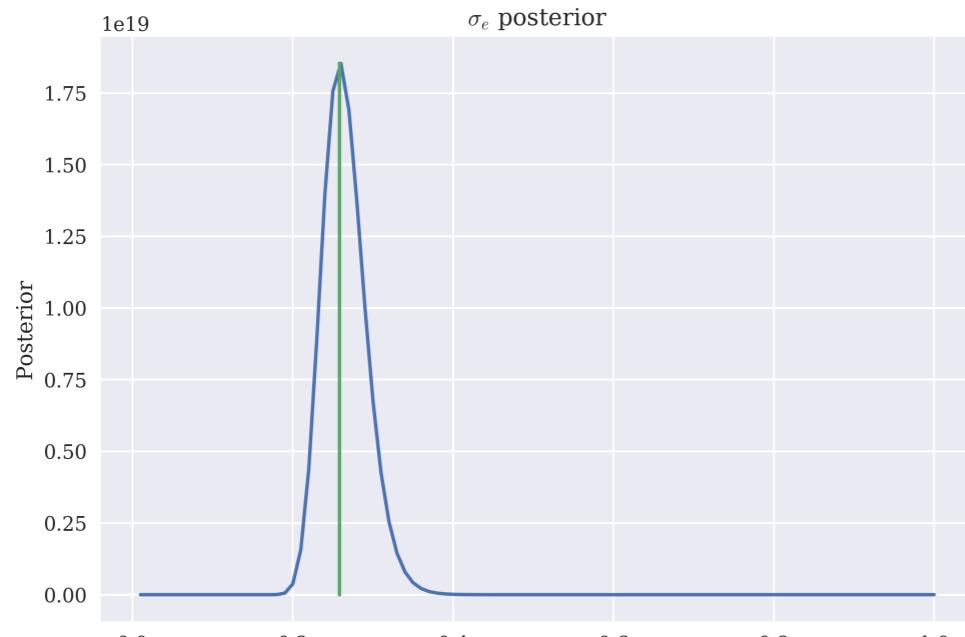
**Importance Sampling:**

$$P(D_i | \sigma_e^2) \propto \frac{Z_i}{K} \sum_{j=1}^K \frac{P(\epsilon_{int}(\epsilon_{sh,j}, g) | \sigma_e^2)}{P(\epsilon_{sh,j} | I)}$$

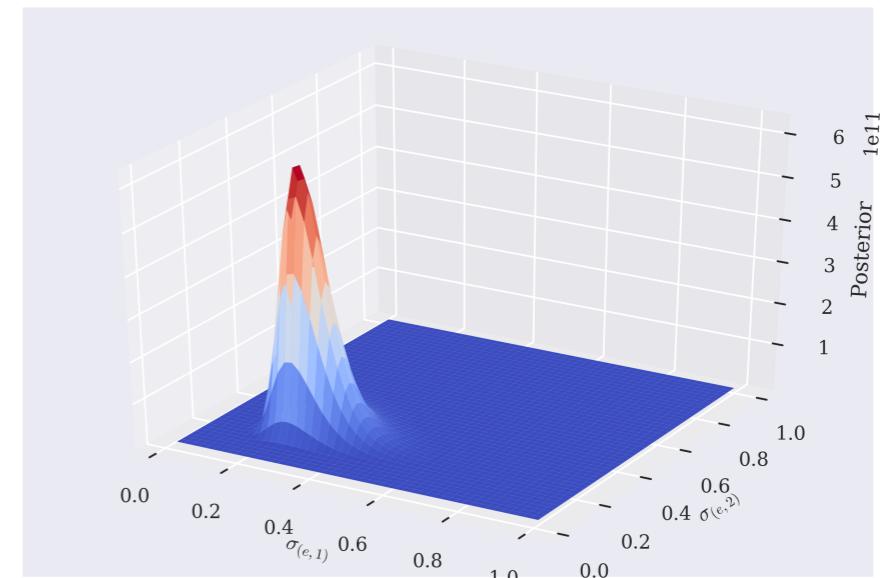
**For N galaxies:**

$$P(\{D_i\}_{i=1}^N | \sigma_e^2) \propto \prod_{i=1}^N \frac{Z_i}{K} \sum_{j=1}^K \frac{P(\epsilon_{int}(\epsilon_{sh,j}, g) | \sigma_e^2)}{P(\epsilon_{sh,j} | I)}$$

# Toy Model

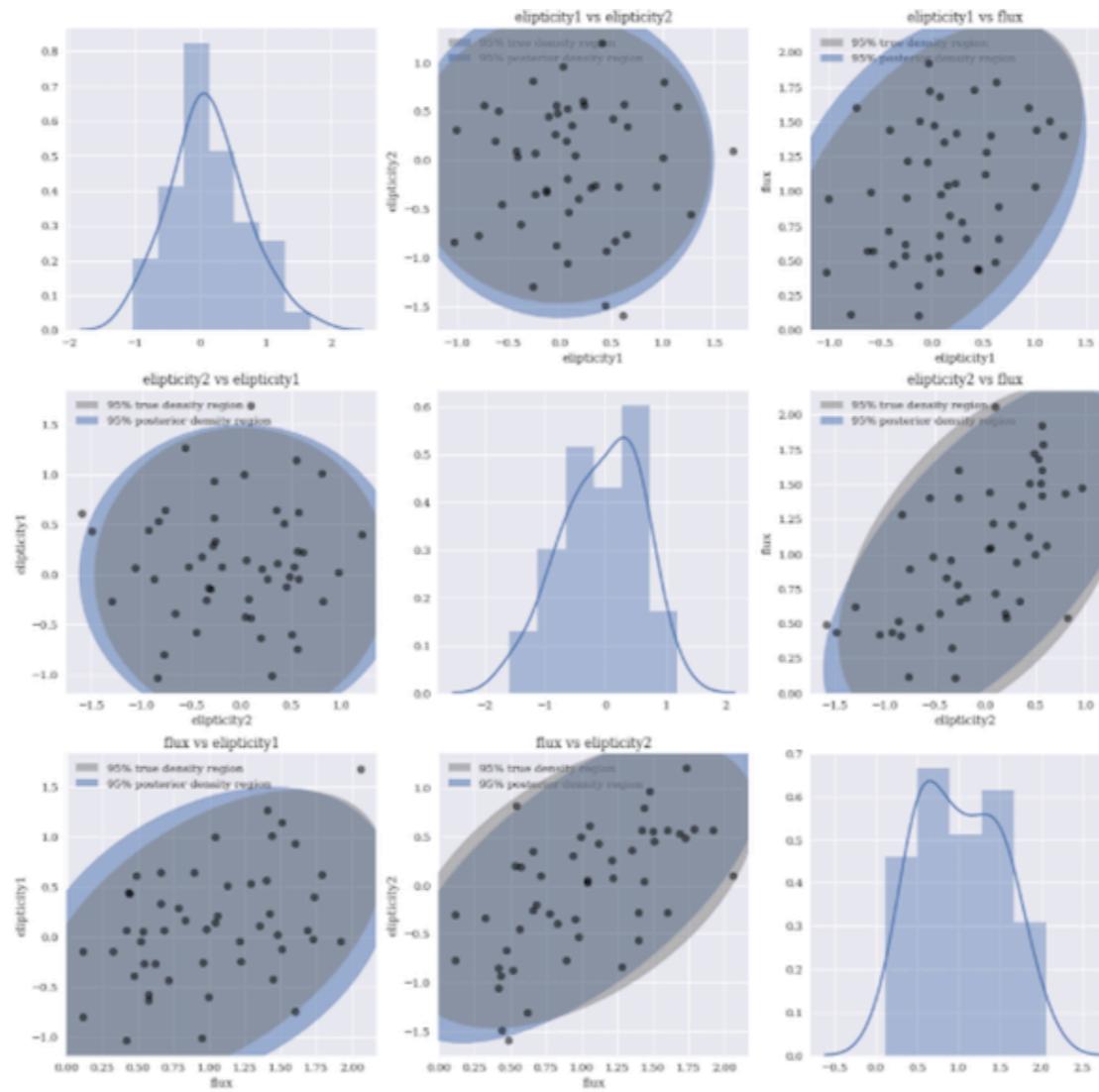


**Estimation of  $\sigma_{e,1}$  (Univariate)**



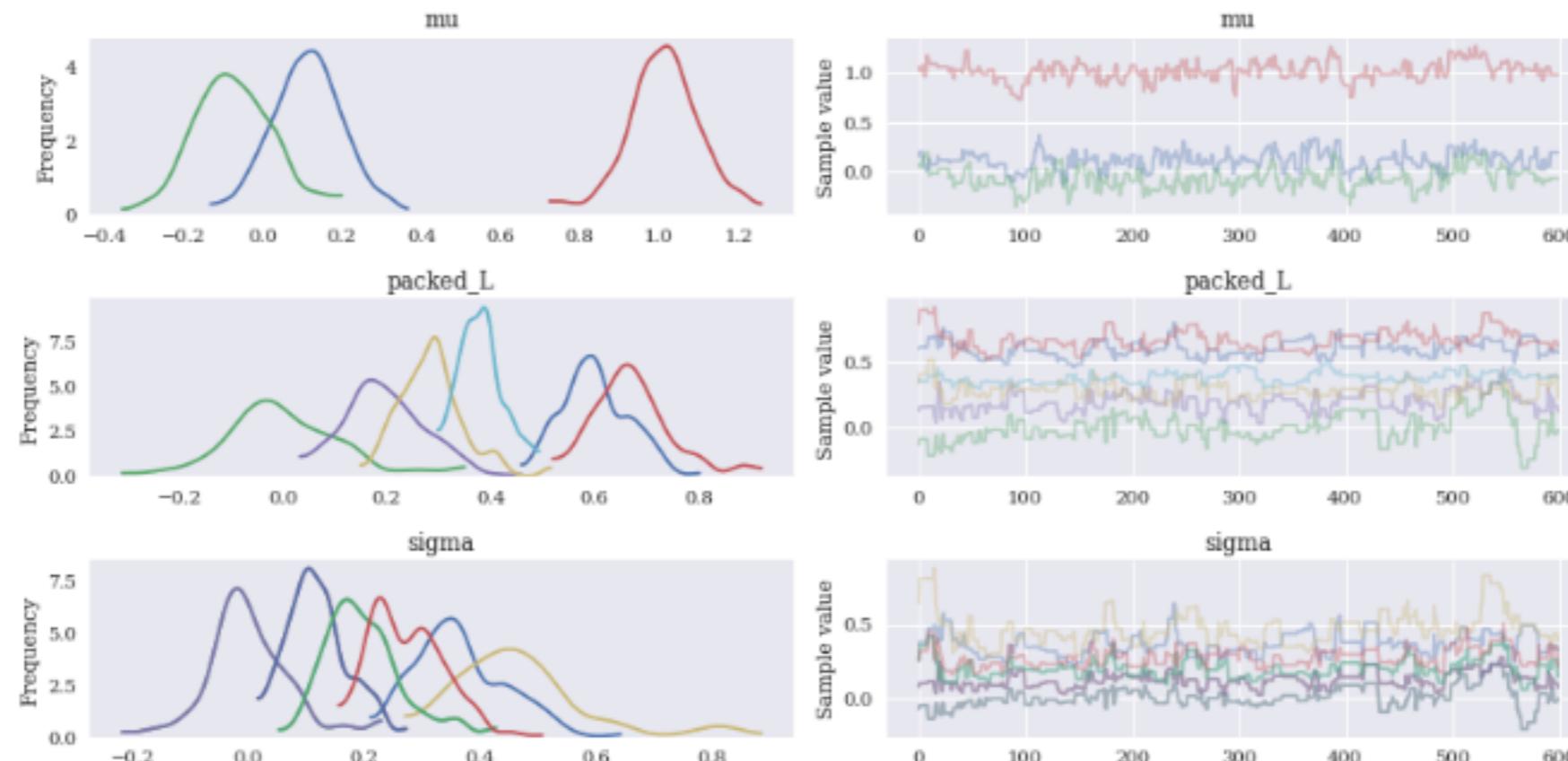
**Estimation of  $\sigma_{e,1}$  and  $\sigma_{e,2}$  (Bivariate)**

# Multivariate Toy Model with Covariance



**Predicted Distribution vs Actual Distribution**

# Multivariate Toy Model with Covariance



**MCMC distribution and chain**

# Including morphological properties

Intrinsic Properties  $\omega$

$$\omega = [\epsilon_1, \epsilon_2, \nu, r, \phi],$$

$$\epsilon_1 \sim N(0, \sigma_{\epsilon_1}).$$

$$\epsilon_2 \sim N(0, \sigma_{\epsilon_2}).$$

$$\nu \sim N(\mu_\nu, \sigma_\nu).$$

$$r \sim lognorm(\mu_r, \sigma_r).$$

$$\phi \sim powerlaw(\alpha).$$

# Including morphological properties

Non-Gaussian distributions transformed into approximately Gaussian distributions via,

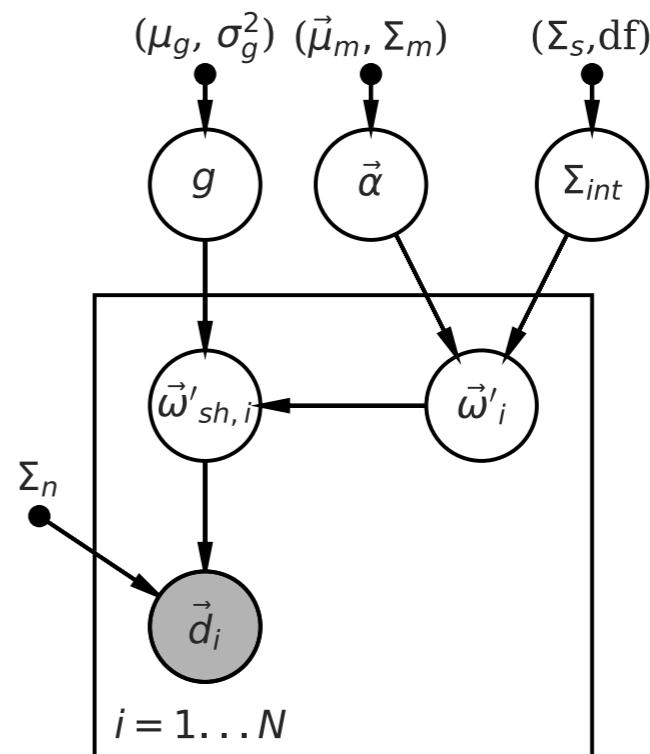
$$g(r) = \log(r)$$
$$h(\phi) = \log\left(\frac{\phi^\alpha}{1 - \phi^\alpha}\right)$$

So the transformed data is,

$$\omega' = [\epsilon_1, \epsilon_2, \nu, g(r), h(\phi)]$$

$$\omega'_{sh} = [\epsilon_1 + g, \epsilon_2 + g, \nu, g(r), h(\phi)]$$

where,  $\omega' \sim N(\alpha, \Sigma_{int})$



We define this transformation as

$$\omega' = f(\omega)$$

# Including morphological properties

$$Pr(\{\mathbf{d}_i\}_{i=1}^N | \Sigma) \propto \prod_{i=1}^N \frac{Z_i}{K} \sum_{j=1}^K J^{-1}(\omega'_{ij}) \frac{Pr(\omega'_{ij} | \omega'_{sh} = f(\omega_{sh}), g) | \alpha, \Sigma_{int}, g)}{Pr(\omega'_{ij,sh} | I)}$$

# Current Challenges

- Transformations from non-Gaussian to Gaussian
- Prior choice: LKJ vs Inv Wishart for Cov Matrix
- Other design factors: MCMC algorithm, interim sampling distributions etc.

# Future Work

- Validate this approach on GalSim generated data
- Unbiased shear estimation through an extended model  
(Schneider et al. 2015)
- Determination of correlations in galaxy properties,  
morphological classification scheme

