Non-Gaussian Processes

- Why do you need models for Non-Gaussian Processes?
  - Point predictions are quite robust to model misspecification
  - Correct estimation of non-Gaussian processes leads to big improvement in estimates of variability
  - Identify outlying regions, spatial outliers (Palacios and Steel, 2006)
- What features do you need your model to capture?
  - Non-Gaussian and/or non-stationary
  - Sharp vs smooth changes in the field over space
  - Low frequency vs high frequency signal
  - Interpolation versus parameter (effect) inference
  - Non-Gaussian models can look like Gaussian model. Often the problem is that you only have one replication.
- Approaches: SPDE/process convolution versus transforming Gaussian
  - Drawback with transformed Gaussian fields is that you can't change the conditionals.
    - Need models that account for sharp transitions
    - Gaussian models are too smooth to allow for this
- Non normal likelihood with a non-normal latent field
  - Need to distinguish between non-Gaussian data (easy) and non-Gaussian latent fields (hard)
  - If you have binary data for example, getting these covariance models to work will be challenging
  - Do you even need a heavy tailed process when the data are binary?
- Computation
  - 1st question for any new model: Can you estimate the model parameters? Easy to create a new fancy model, but in practice they are very hard to estimate
  - How difficult are the computations for these models?
    As the number of locations increases, it can get computationally intensive
  - How to extend to big data?
  - Extra computational complexity if you move from 1-D to 2-D MRF
  - How do you know that you are getting the answer correctly from a computational method if there is only one way to compute it?
- Diagnostics
  - How to figure out whether we are modeling the complex dependencies correctly
  - Problem is high dimensional: Maybe we can think about conditional distributions to simplify the diagnostic problem
  - Need something that looks like replicates