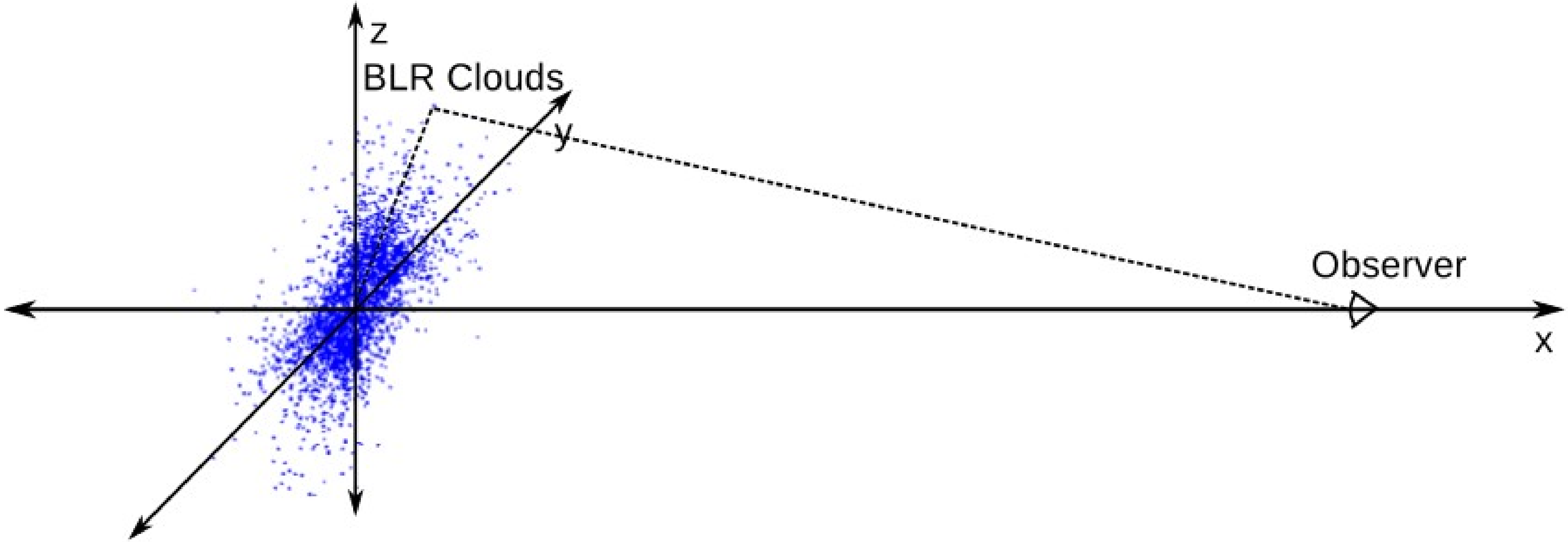
Bayesian Analysis of Reverberation Mapping Data



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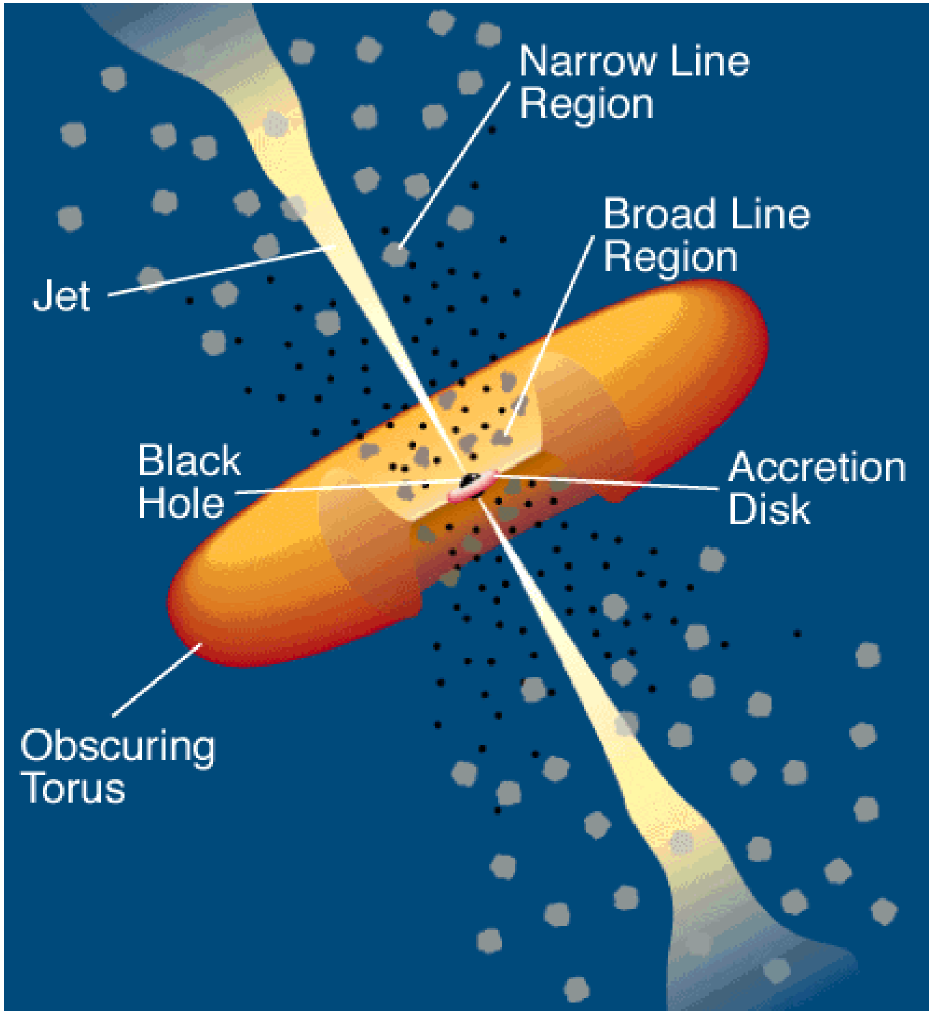
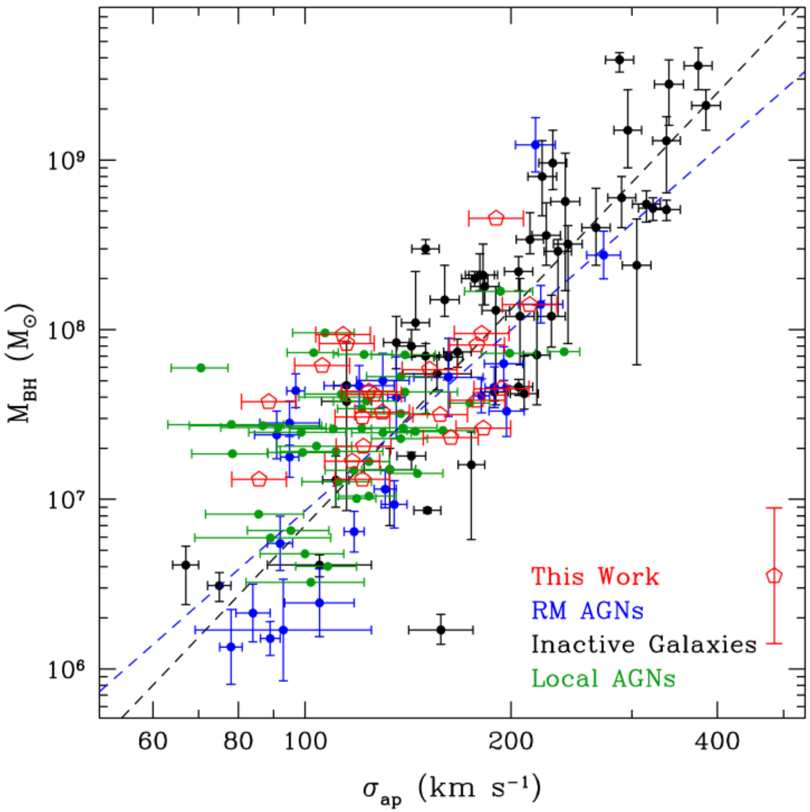
Standard AGN Model



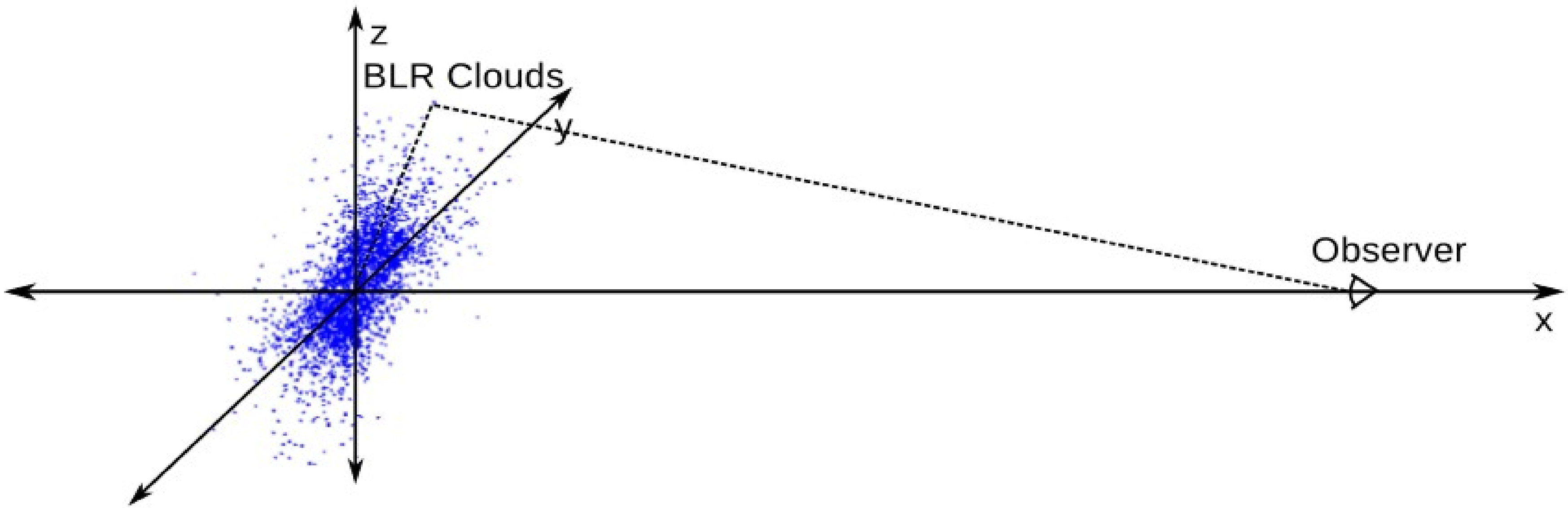
- Explains different categories of AGN as the same kind of object but viewed from different angles
- In this talk I will be focusing on the black hole mass and the Broad Line Region (BLR)

The M_{BH}-σ Relation

- Figure from Bennert et al 2011
- Connection between galaxy formation and growth of the black hole



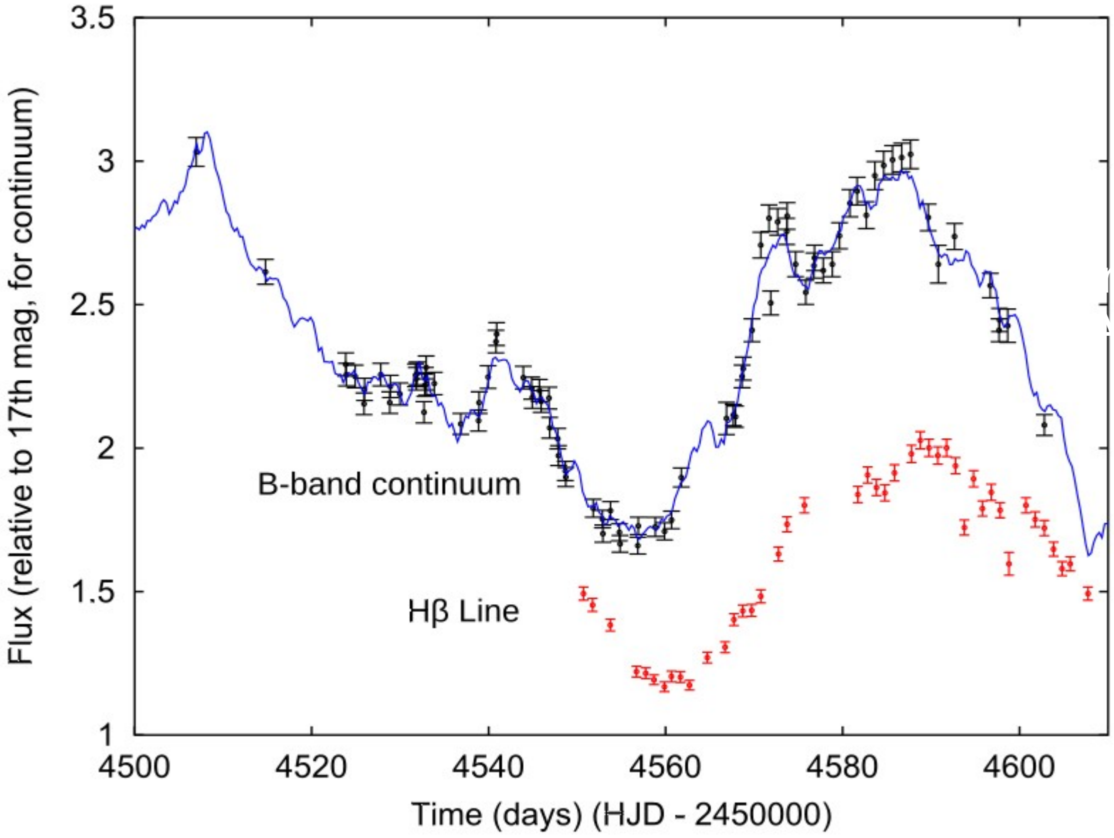
Reverberation Mapping Intro



- The central continuum source fluctuates with time, this causes the emission lines to fluctuate with time, but with time delay
- The mix of time delays depends on the BLR size and shape.

Reverberation Mapping Data

- Continuum data consist of flux as a function of time, line data consists of spectrum as a function of time



Standard Analysis

- Measure the average lag τ from the time series, e.g. by cross-correlation methods, or inferring the transfer function (histogram of lags)
- Measure the line width σ_l from spectra → velocities

$$M_{BH} = f\sigma_l^2 c\tau / G$$

- But what is *f*, and are we making full use of the data?

Our Direct Modelling Approach

- What are the things we want to know?

  Black hole mass, geometry of BLR, dynamics of BLR

- What are the things we do know?

  The data :-)

- Use Bayesian Inference

Bayesian Inference: How it Works

- Rate the plausibility of each hypothesis you want to test. Assign *prior probabilities* accordingly. Prob(H) for each H
- For each hypothesis, describe your predictions for observed data. Prob(D|H) for all D and H
- Observe particular data D*. New plausibilities are the *posterior probabilities*:

Bayes' Rule

- $P(H|D^*) \propto P(H)P(D^*|H)$

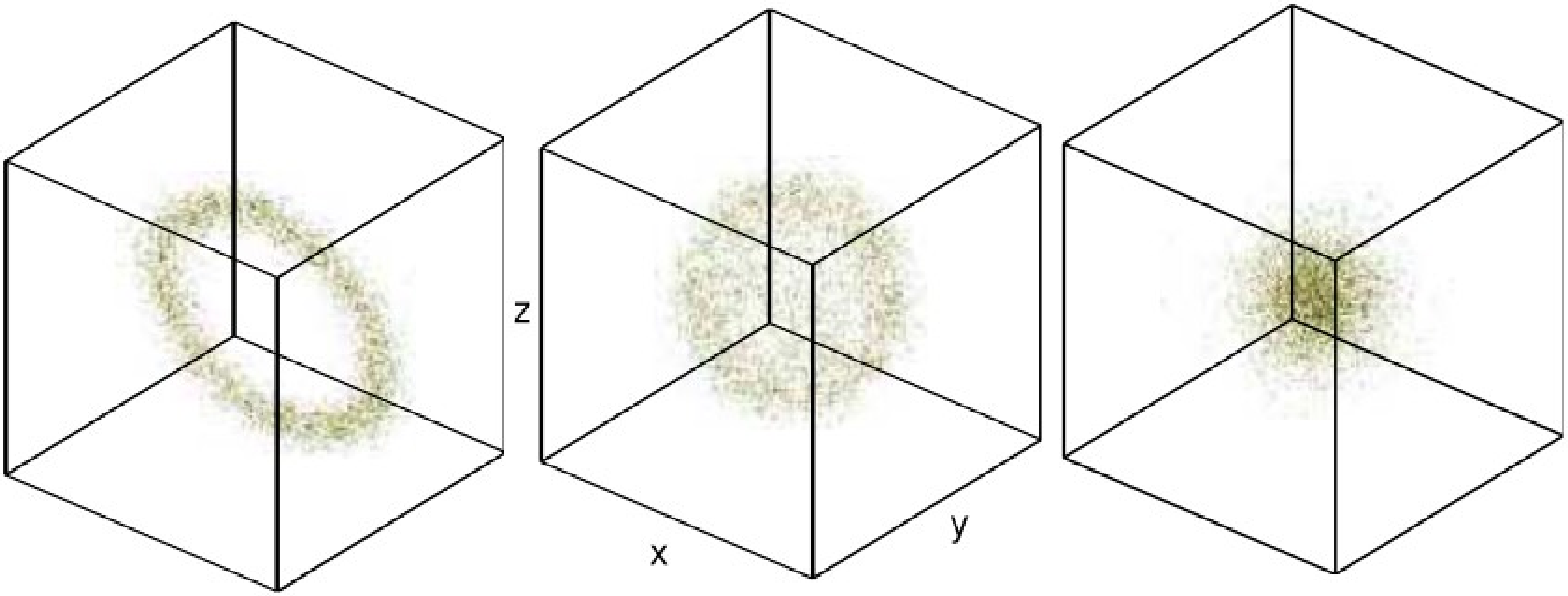
What were the odds of *that*?

Bayes' Rule

- Observe particular data D*
- New plausibilities are the *posterior probabilities*: $P(H|D^*) \propto P(H)P(D^*|H)$
- Probability for each hypothesis gets scaled according to how well each one predicted the data that we actually got.
- $P(D^*|H)$ as a function of H is called the *likelihood function*.

Geometry of the BLR

- How do we parameterize the geometry of the BLR? Ring/disk/shell model



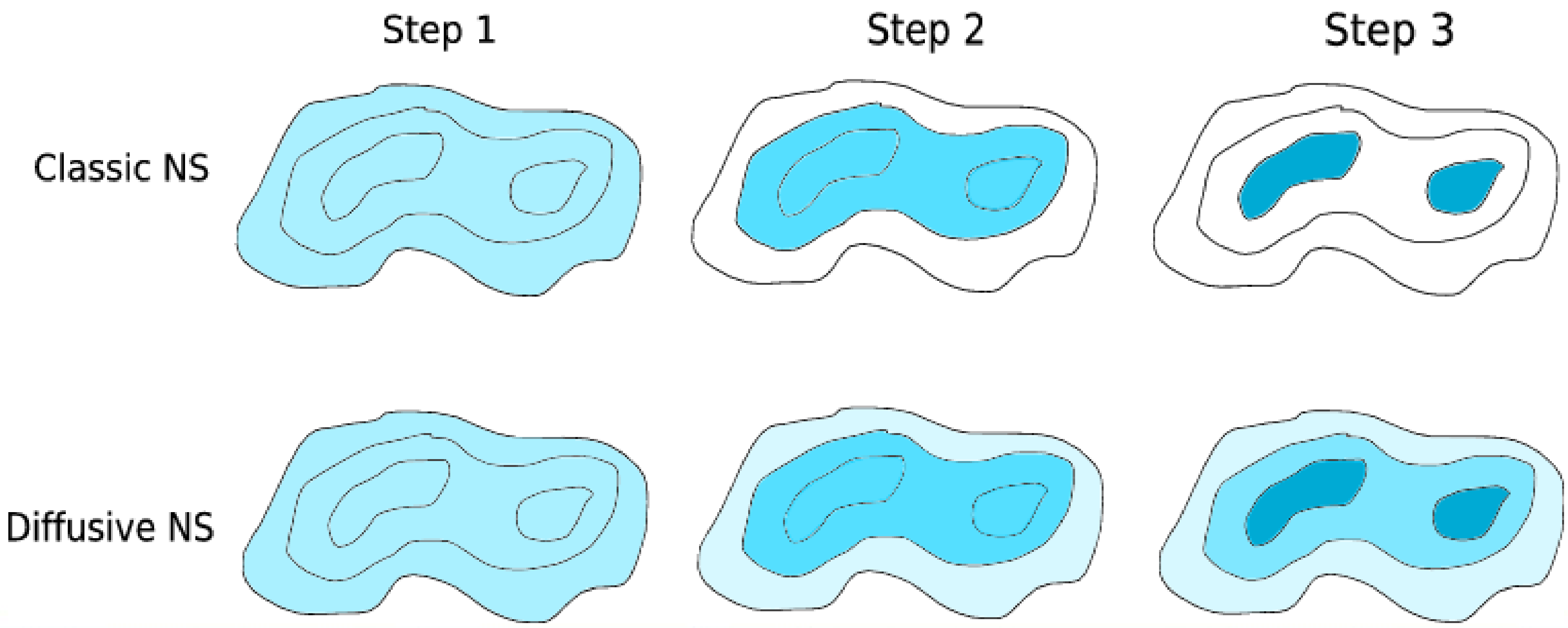
Predicting the Data

- Loop over all clouds
- Get the continuum flux at the relevant time in the past
- Add flux at the relevant velocity bin.
- Blur by instrumental/seeing resolution

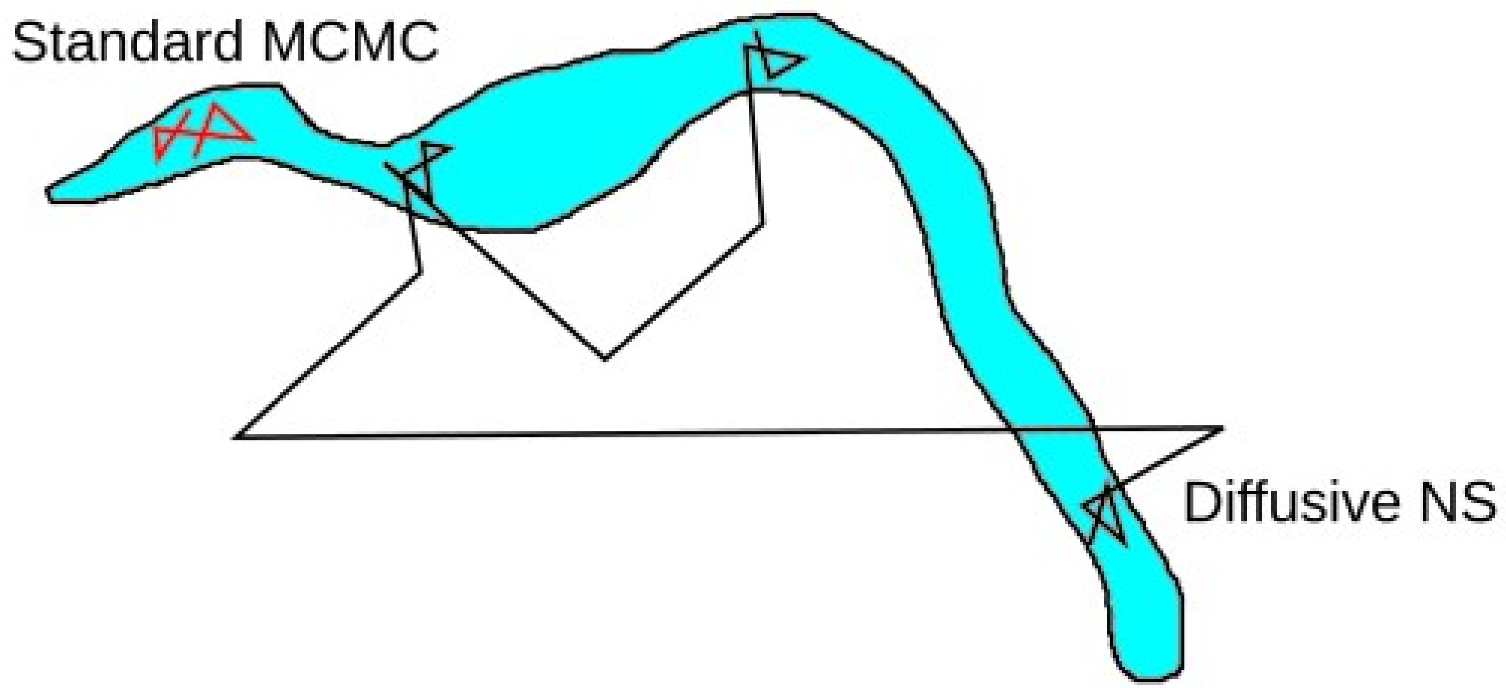
$$f_{\rm line}(v_x, t) = A\sum_{i=1}^{N} f_{\rm cont}(t - \tau_i)\delta\left(v_x - v_{x,i}\right)$$

Sampling the Posterior Distribution

- We use the Diffusive Nested Sampling method (Brewer et al 2010).
- Can handle strong correlations and multiple modes.



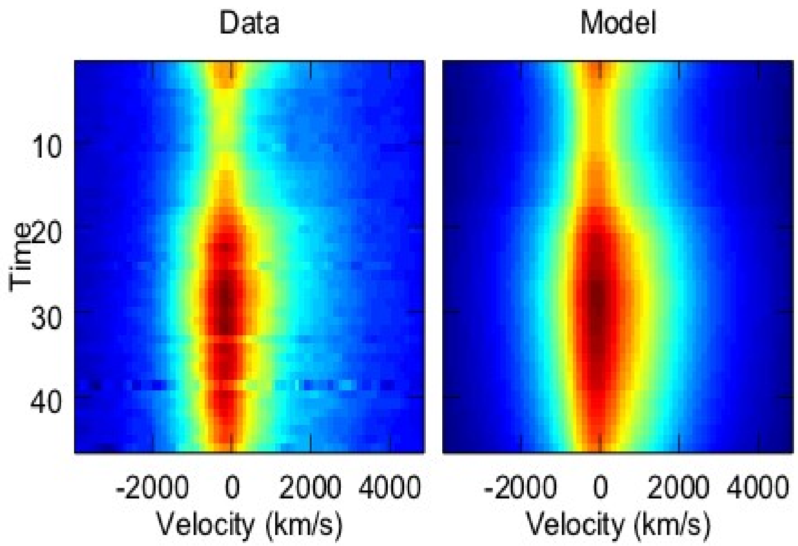
Sampling the Posterior Distribution

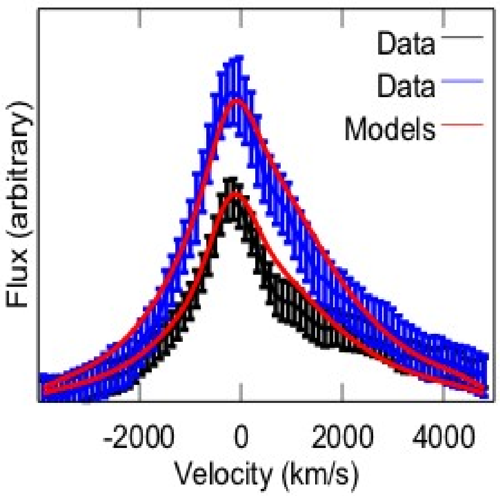


Application to Arp 151

Models fit the data

- Measurement errors are very small
- We do not fit to within them
- Need to increase size of the error bars





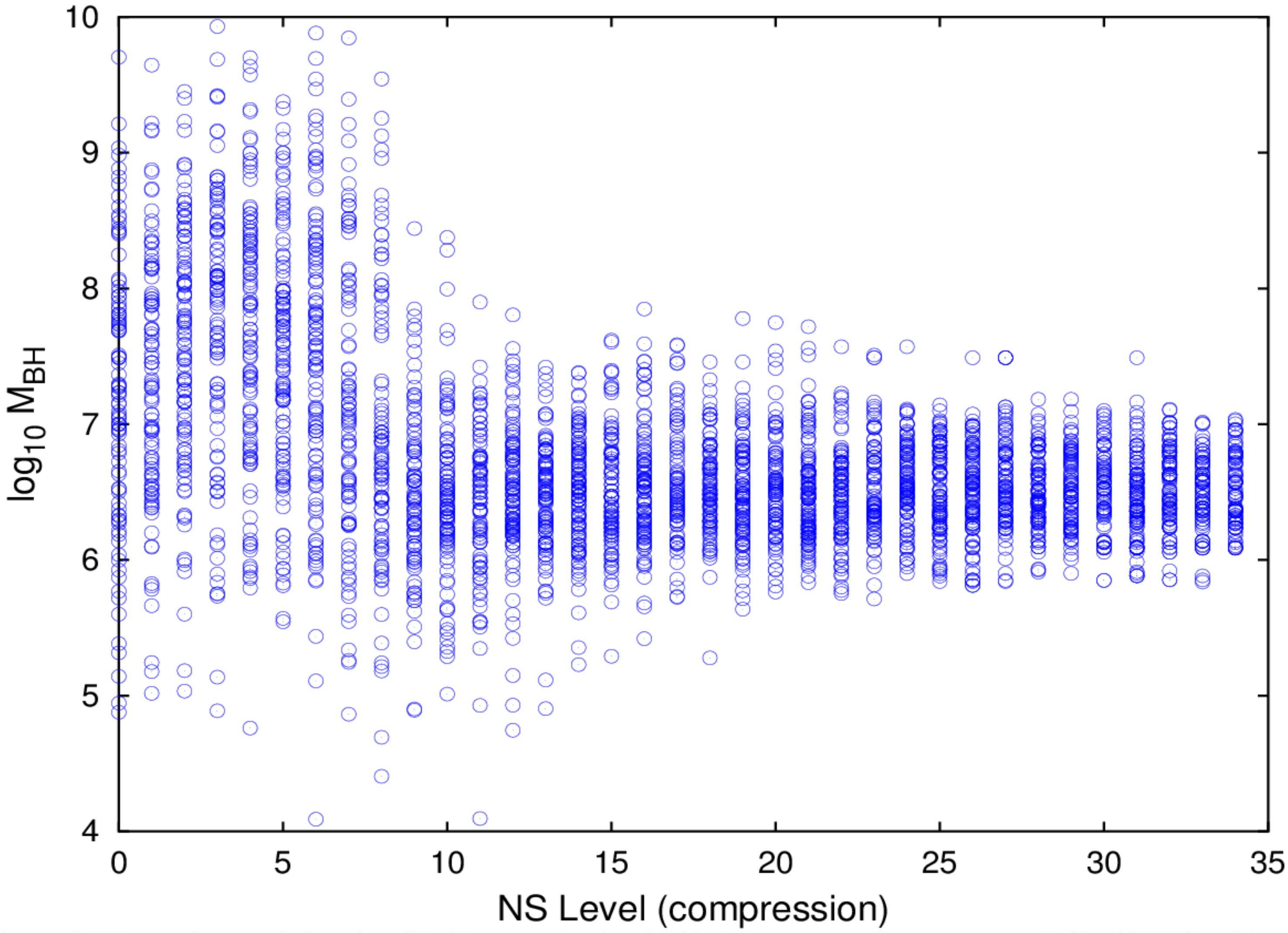
Aside on Simply-Parameterized Models

- Using simply-parameterized models when you don't believe them can cause overconfident results
- Can regard simple models as summary statistics about the complex true situation
- e.g. take a galaxy image, fit it with a Sersic profile
- The Sersic parameters tell you something about the profile of the galaxy, even though the galaxy itself isn't Sersic.

Aside on Simply-Parameterized Models

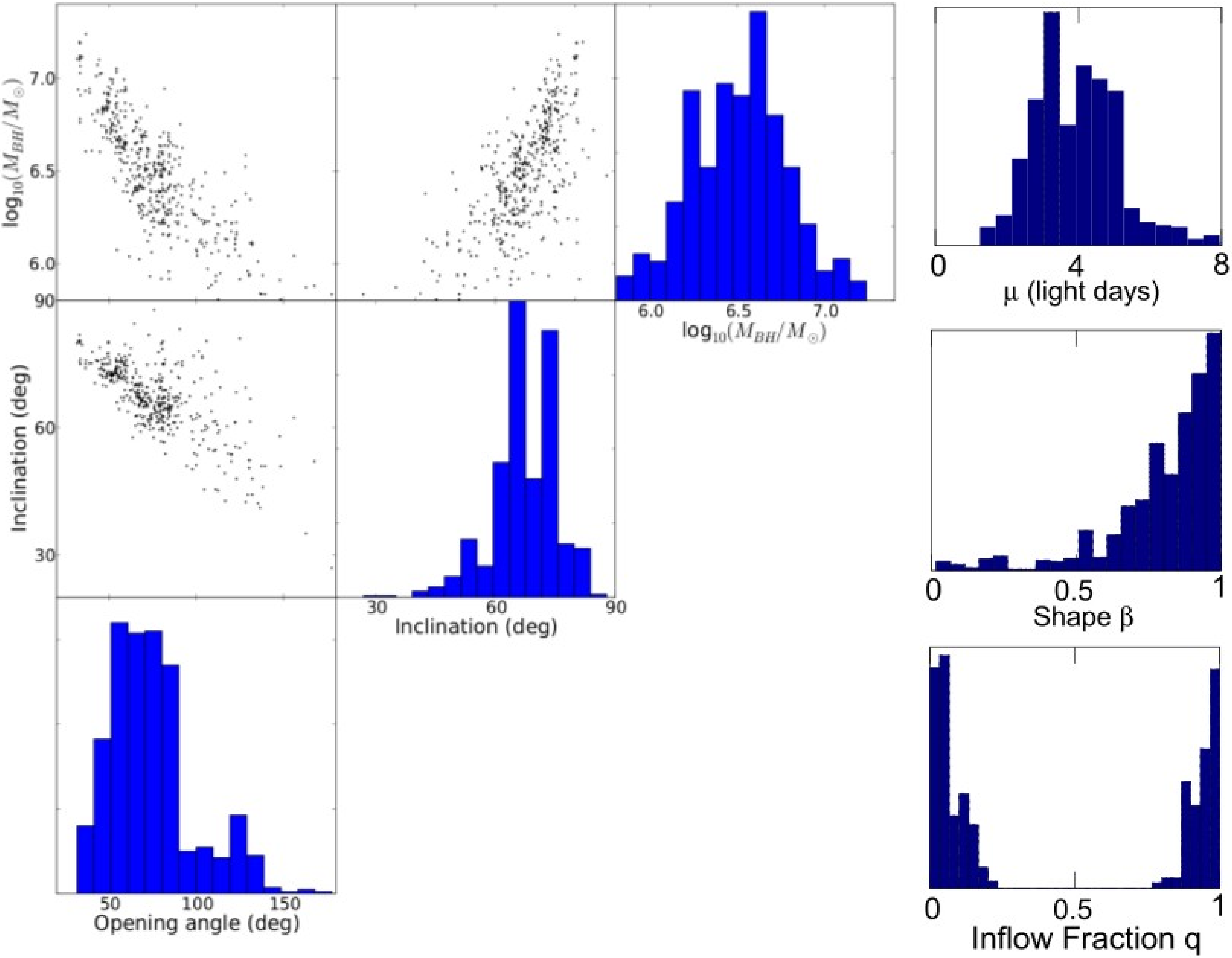
- Therefore, when using simply parameterized models, we are really trying to infer the summaries of the true situation
- Likelihood function needs to be modified to p(D|summaries), not p(D|complex reality)
- i.e. it needs to be softened
- Nested Sampling gives alternative likelihoods for free...just use more of the worse-fitting models than you otherwise would

Black Hole Mass vs. Goodness of Fit



Caveats

- Involves some subjective judgment
- Choose the “right” posterior from a 1-D family – this involves less subjectivity than the alternative of specifying a complex mismatch model
- Can always average over the choice itself, to be really conservative



$\log_{10}(M_{BH}/M_{\odot})$
7.0
6.5
6.0
90
60
30
Inclination (deg)
30
60
90
Inclination (deg)
6.0
6.5
7.0
$\log_{10}(M_{BH}/M_{\odot})$
50
100
150
Opening angle (deg)
0
4
8
μ (light days)
0
0.5
1
Shape β
0
0.5
1
Inflow Fraction q

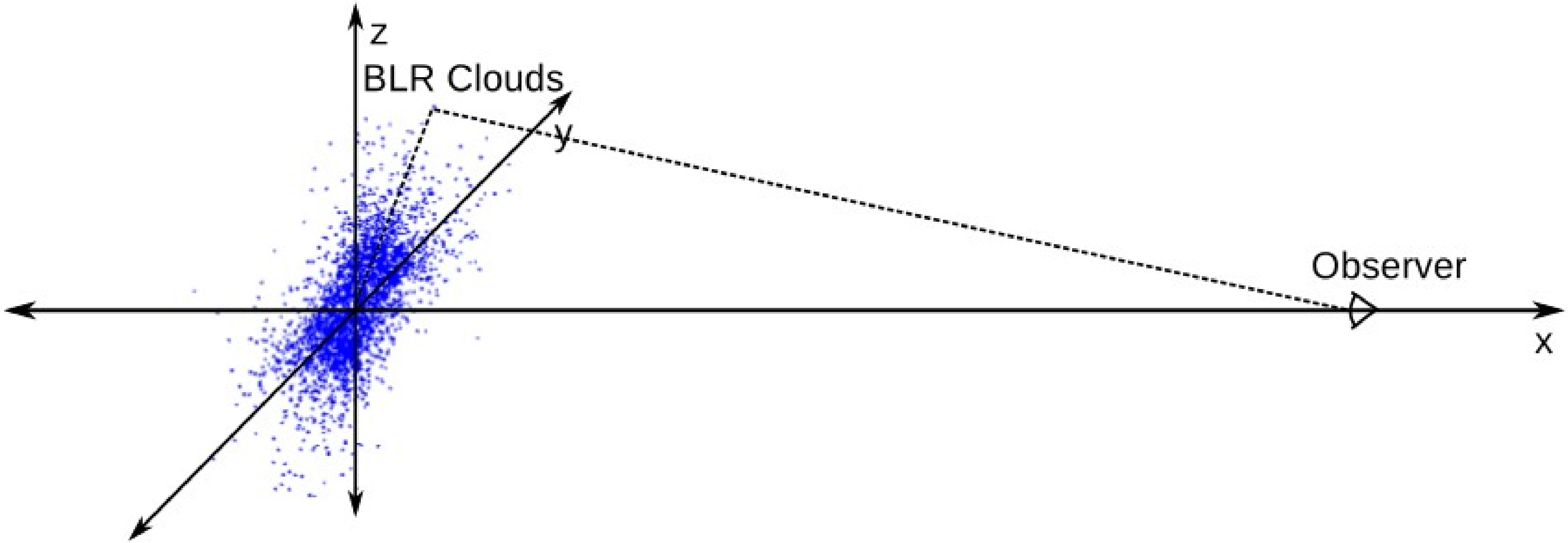
Arp 151 Results

- BLR geometry is an almost face-on disk/torus
- The mean radius is 3.99 +- 1.25 light days
- The black hole mass is $\mathbf{10^{6.51 \pm 0.28}}$ solar masses
- Bentz et al (2008) with fixed *f*: $10^{6.85 \pm 0.07}$

  (Estimated uncertainty on *f* = 0.4 dex)
- Strong correlation between M_{BH} and inclination.

Inferred Geometry

- The picture I have been using all along is the inferred geometry of the BLR in Arp 151.



Conclusions

- We have implemented simple physical models of the BLR that can be used for inference
- Can infer the black hole mass without using the virial coefficient
- Arp 151: We infer the log10 of the black hole mass to within +- 0.3 and that the geometry of the BLR is a nearly face-on disk
- More systems coming soon!