Deriving Constraints on Quasar Lifetime and Obscuration Using Likelihood-Free Inference

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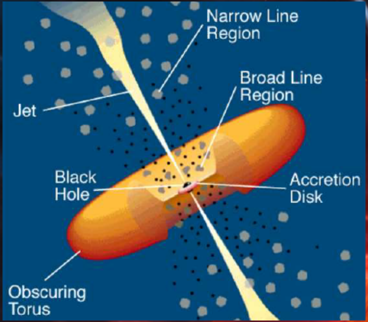
What is a Quasar?

AGN unification model



Explains Type I – Type II dichotomy.

Evolution vs. orientation?

Is each individual quasar 50 % obscured ?

What is a Quasar?

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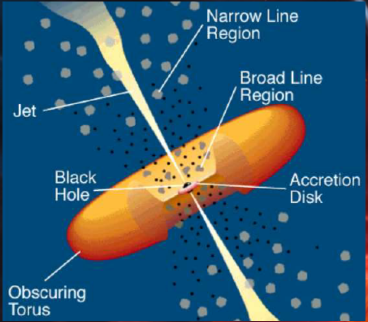

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Is each individual quasar 50 % obscured ?

Quasar lifetime:

poorly constrained: $10^4 - 10^8$ year

no coherent picture emerging

e.g. Schmidt et al. 2018

Related to key aspects of AGNs:

- triggering mechanism
- growth of SMBH
- AGN feedback, galaxy evolution

Project Overview

Goal: Map Quasar Light Echoes in 3D

Infer quasar emission geometry:

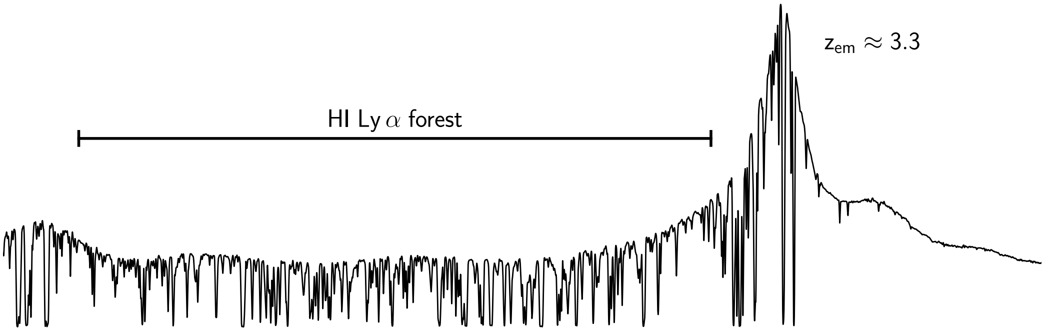
- obscuration
- orientation

Infer quasar emission history:

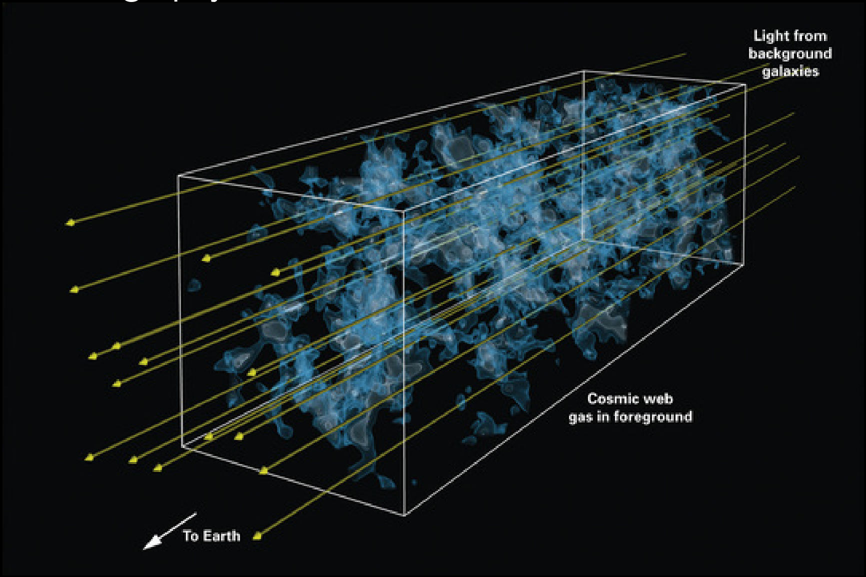
- quasar age
- quasar lifetime
- lightcurve / variability

The Intergalactic Medium

- IGM: low-density gas in space between galaxies
- observable as redshifted Lyα absorption towards distant quasars
- Lyα forest sensitive to
  - density $\quad n_H \sim 10^{-5}\,\mathrm{cm}^{-3}$
  - temperature $\quad T \sim 10^4\,\mathrm{K}$
  - ionization state $\quad \frac{n_{HI}}{n_H} \sim 10^{-5}$

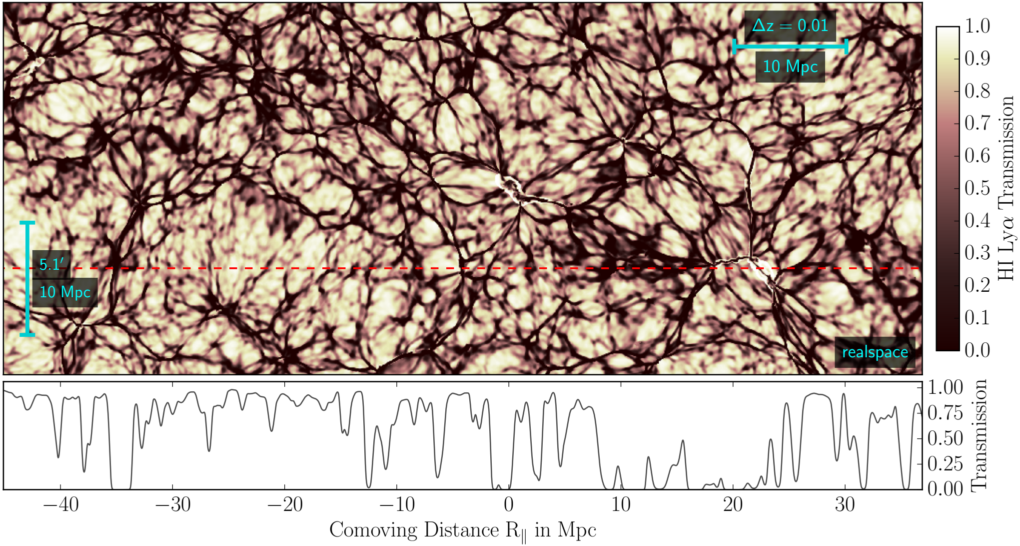


Lyα Forest Tomography



see CLAMATO survey by Lee et al. 2014, 2016, 2018

Simulation of the H I Proximity Effect



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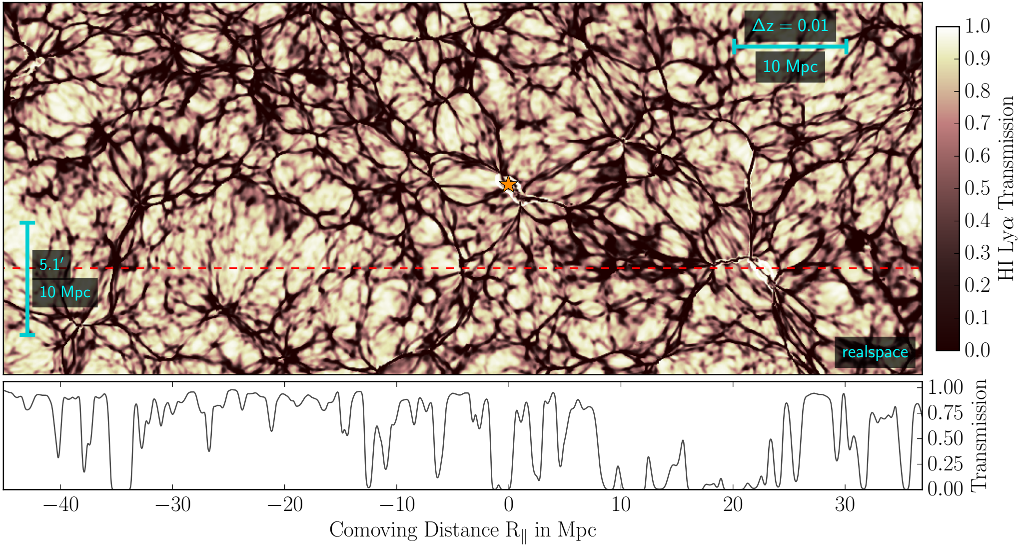

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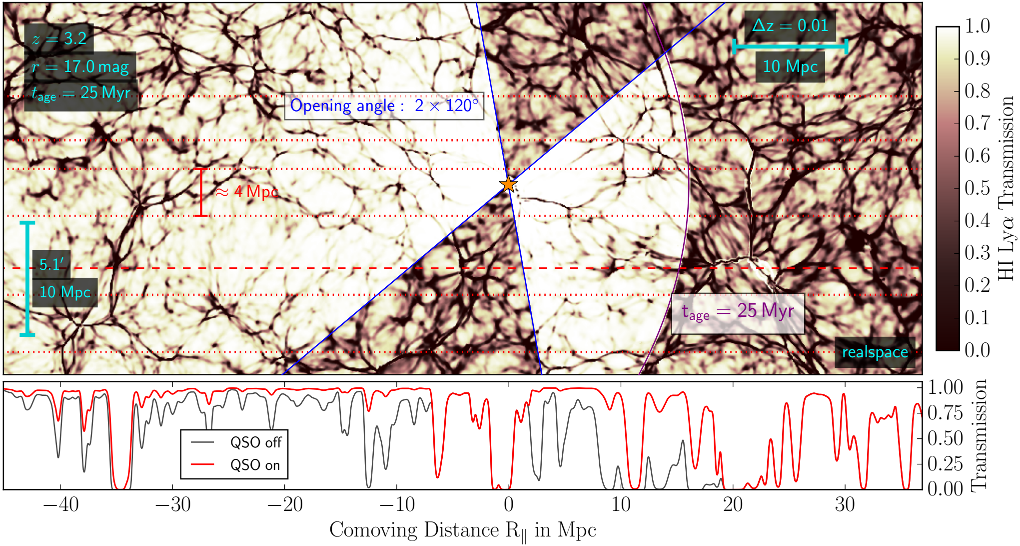


Lyα Forest Absorption as a Precision Probe of the IGM

Parameter inference requires a quantitative comparison of Data and Model!
Analysis has to be Bayesian!

Model:

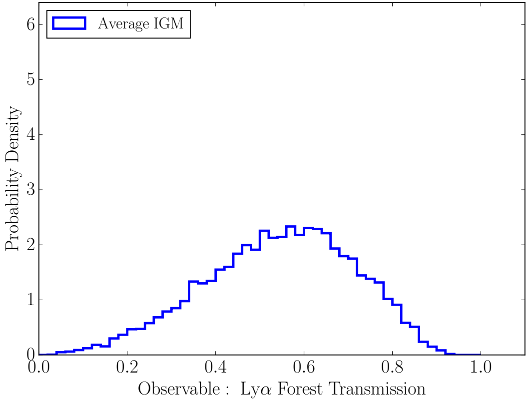
- Lyα forest can be accurately modeled
- NYX cosmological hydrodynamical simulations L100 N4096
- post-processing with custom photoionization model

Lyα Forest Transmission:

- traces the filamentary structure of the cosmic web
- Lya forest transmission stochastic
- natural source of variance / uncertainty

Parameter Inference Without Analytic Likelihood Function

- Lyα forest transmission stochastic
- natural $\simeq 20\%$ scatter on 1 Mpc scales



Sample PDFs by randomly drawing IGM realizations:

$p\,(\,F\,|\,\Theta_{\rm off}\,)$ average IGM

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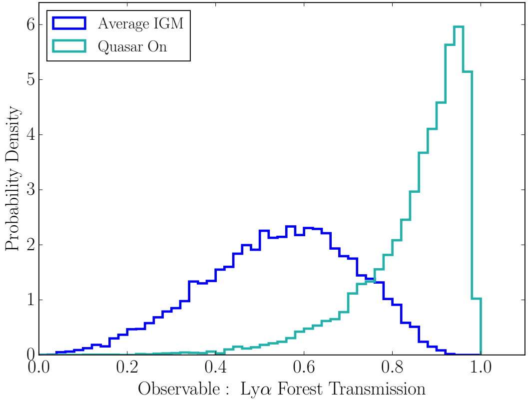

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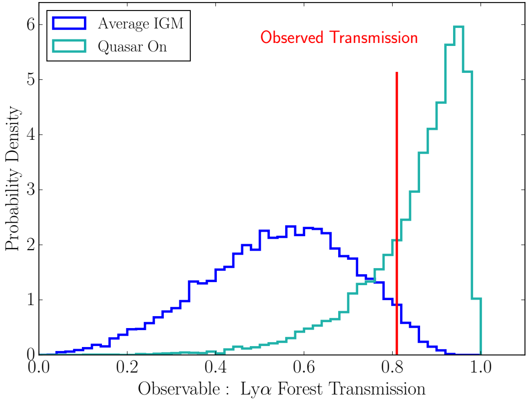

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$p\,(\,F\,|\,\Theta_{\rm off}\,)$ average IGM
$p\,(\,F\,|\,\Theta_{\rm on}\,)$ illuminated by Quasar

$$\mathcal{L}\,(\,F_{\rm obs}\,|\,\Theta_{\rm off}\,) = p\,(\,F = F_{\rm obs}\,|\,\Theta = \Theta_{\rm off}\,)$$
$$\mathcal{L}\,(\,F_{\rm obs}\,|\,\Theta_{\rm on}\,) = p\,(\,F = F_{\rm obs}\,|\,\Theta = \Theta_{\rm on}\,)$$

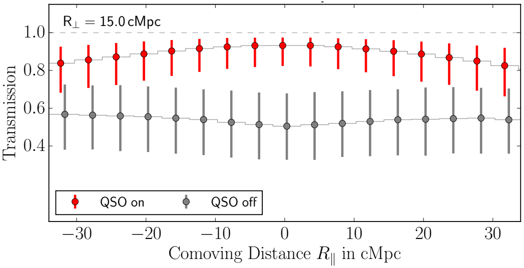
Can be inverted to get posterior probablility: $p(\,\Theta\,|\,F_{\rm obs}\,)$

The Curse of Dimensionality

Not one observable but many!

- transmission measurement in 20 to 100 bins per spectrum
- in total 10 to 100 spectra

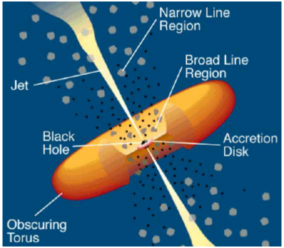
$$\boldsymbol{F} = \vec{F} = \langle F_{n,m} \rangle$$



Far more complex model!

- quasar age: t_{age}
- orientation: $\langle\, \theta,\ \phi\, \rangle$
- obscuration or opening angle: α

$$\boldsymbol{\Theta} = \vec{\Theta} = \langle\, t_{\mathrm{age}},\ \theta,\ \phi,\ \alpha\, \rangle$$



Brute-force sampling completely illusory!

Breaking the Problem Into Pieces

Model: unavoidable to create a model grid $\{\vec{\Theta}_i\}$

but for now deal only with quasar age: $\boldsymbol{\Theta} = \vec{\Theta} = \langle\, t_{\rm age}\, \rangle$

Dimensionality has to be reduced:

Proper Likelihood:

$$\mathcal{L} = p(\, \boldsymbol{F} \,|\, \boldsymbol{\Theta}\,) = p\,(\, \vec{F} \,|\, \vec{\Theta}\,)$$

Pseudo-Likelihood:

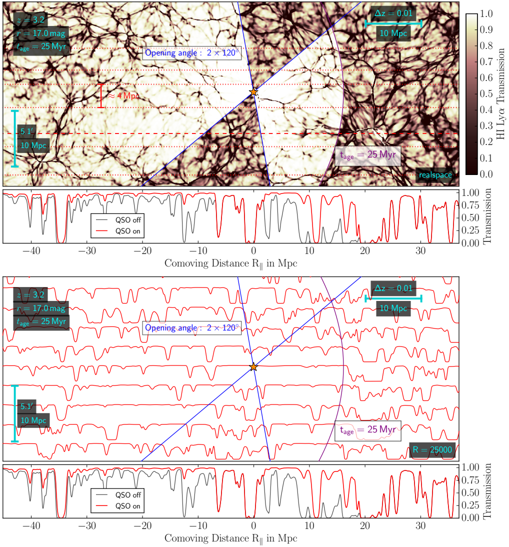
$$\mathcal{L}' = \prod_{n,m} p_{n,m}\,(\, F_{n,m} |\, \vec{\Theta}\,)$$

Replaces one 10 000-dimensional problem by 10 000 one-dimensional problems!

Breaking the Problem Into Pieces

Strategy

- create set of mock skewers for given Θ_i
- measure Lyα forest transmission in bins



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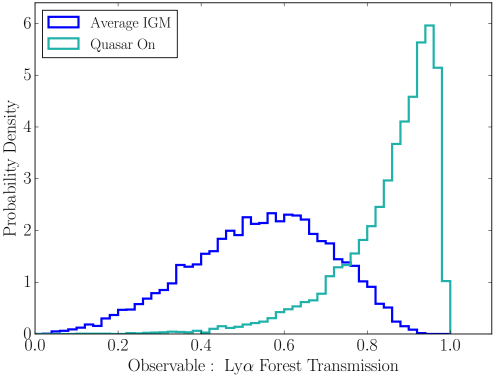

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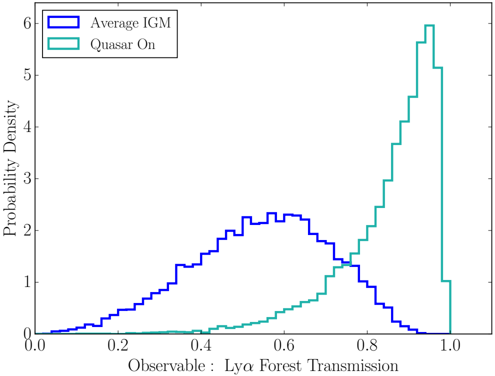

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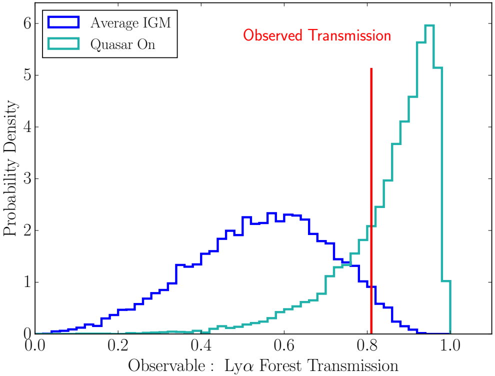
- evaluate $p_{n,m}$ at observed $F_{n,m}$



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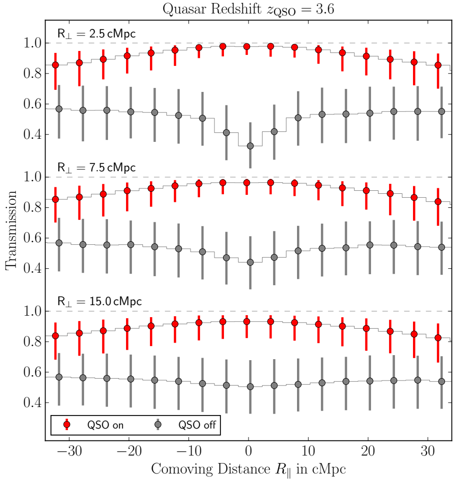
$$\mathcal{L}' = \prod_{n,m} p_{n,m}\left(F_{n,m} \middle| \vec{\Theta}\right)$$



Pseudo likelihood

Pseudo-Likelihood $\mathcal{L}'$

- is the correct likelihood in absence of correlations
- properly treats non-Gaussianities of observable
- gives certainly not the right uncertainties
- probably gives good representation for ML estimate

Maximum Pseudo-Likelihood Estimate: $\hat{\boldsymbol{\Theta}}$

find $\boldsymbol{\Theta}$ that maximizes $\mathcal{L}'\,(\,\boldsymbol{F}\,|\,\boldsymbol{\Theta}\,)\;p\,(\,\boldsymbol{\Theta}\,)$

$\hat{\boldsymbol{\Theta}}$ contains the essence of observation $\boldsymbol{F}_{\mathrm{obs}}$

reduces dimensionality of the data to the dimensionality of the model

Concept inspired by Davies et al. 2018 and Alsing et al. 2018

Mapping Maximum Pseudo-Likelihood to Posterior Probabilities

Generative model:

- create mock data with given model parameter $\mathbf{\Theta}$
- fit mock data with models and determine $\hat{\mathbf{\Theta}}$
- sample joint distribution:

$$p\,(\,\hat{\mathbf{\Theta}}\,|\,\mathbf{\Theta}\,)\;p\,(\,\mathbf{\Theta}\,)$$

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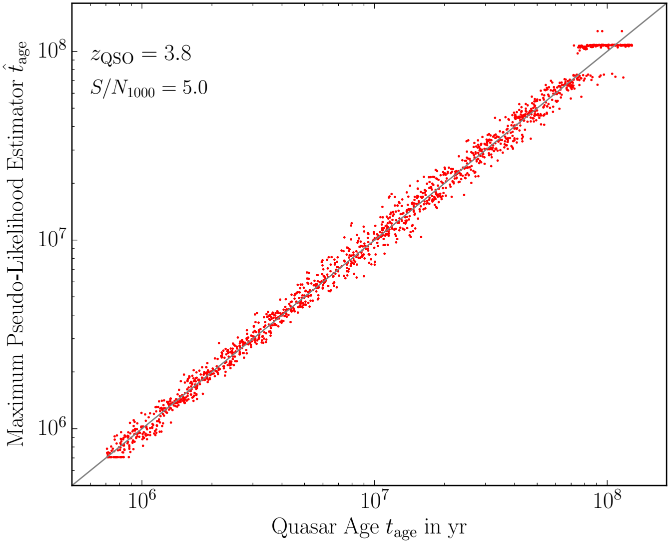

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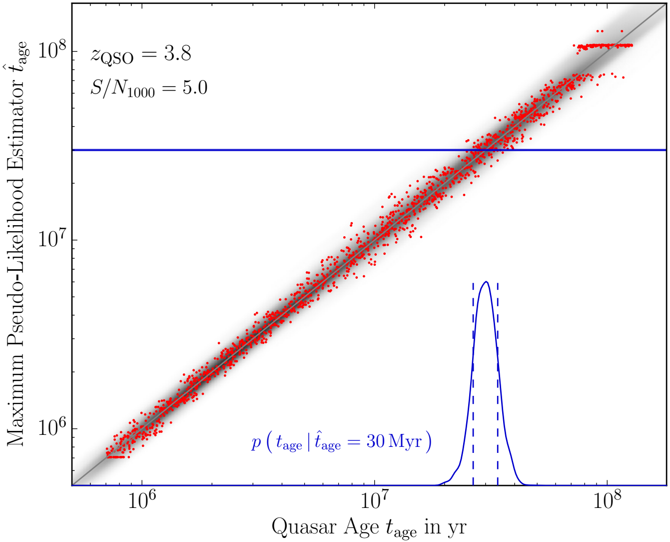
Measurement:

- measure $\boldsymbol{F}_{\rm obs} = \langle\, F^{\rm obs}_{m,n}\,\rangle$
- find $\hat{\boldsymbol{\Theta}}$ that maximizes $\mathcal{L}'\,(\,\boldsymbol{F}_{\rm obs}\,|\,\boldsymbol{\Theta}\,)\,p\,(\,\boldsymbol{\Theta}\,)$
- determine $p\,(\,\boldsymbol{\Theta}\,|\,\hat{\boldsymbol{\Theta}}[\boldsymbol{F}_{\rm obs}]\,)$ by slicing $p\,(\,\hat{\boldsymbol{\Theta}},\boldsymbol{\Theta}\,)$

$\Rightarrow$ **posterior probability** $p\,(\,\boldsymbol{\Theta}\,|\,\boldsymbol{F}_{\rm obs}\,)$

Mapping Maximum Pseudo-Likelihood to Posterior Probabilities



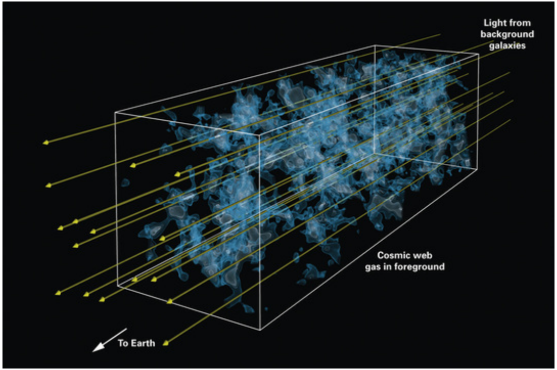
Application to Lyα Forest Tomography

Map the IGM around high-z quasars with many background sightlines:

- high sightline density: $\simeq 500\,\mathrm{deg}^{-2}$
- small sightline separation: $\simeq 4\,\mathrm{cMpc}$

$\Rightarrow$ quasar not abundant enough as background sources

- one has to use faint **galaxies** as background sources
- analyze Lyα forest in spectra of $\simeq$25 mag LBG



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Limiting magnitude:

$S/N \approx 5$ @ $r_{\mathrm{lim}} = 24.7\,\mathrm{mag}$
$t_{\mathrm{exp}} = 10\,000\,\mathrm{s}$

Spectral resolution:

$R = 1000$

Field of view:

16′ diameter
2×2 mosaic with LRIS, FORS
3×1 mosaic with DEIMOS

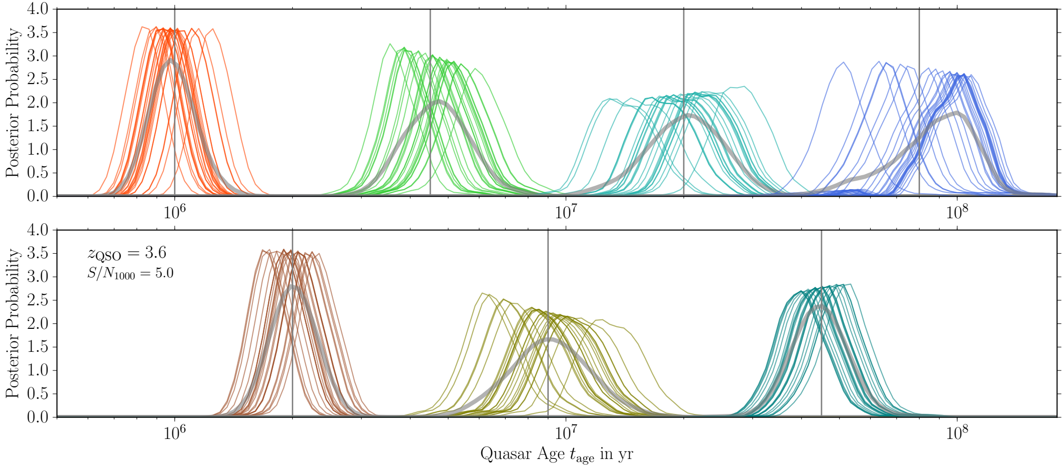
Quasar luminosity:

always the brightest!
$M_{1450} \approx -28.5\,\mathrm{mag}$

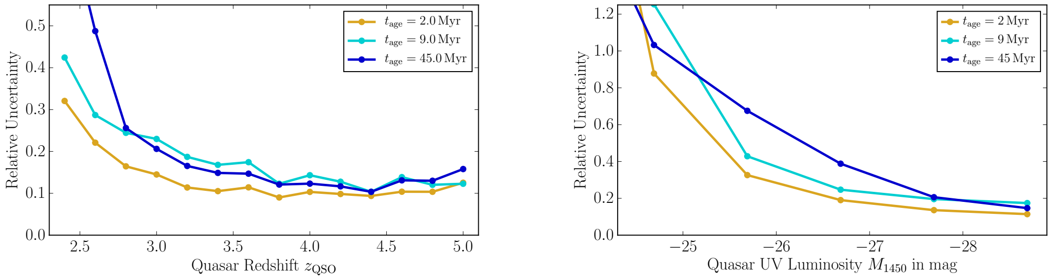
Constraining the Quasar Age

End-to-end demonstration of the method.

Posterior probabilities $p\left(t_{age}\,|\,\langle F^{\rm obs}_{n,m}\rangle\right)$ for mock datasets:



Parameter Study in t_{age}, z_{QSO}, S/N, M_{1450}



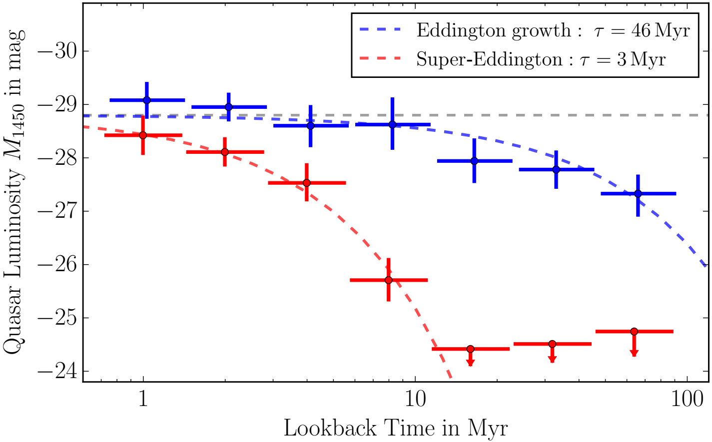
Determine individual quasar ages
with 10 % to 20 % precision for:

$$t_{age} = 10^6 - 10^8\,\mathrm{yr}$$

$$3 < z_{QSO} < 5.$$

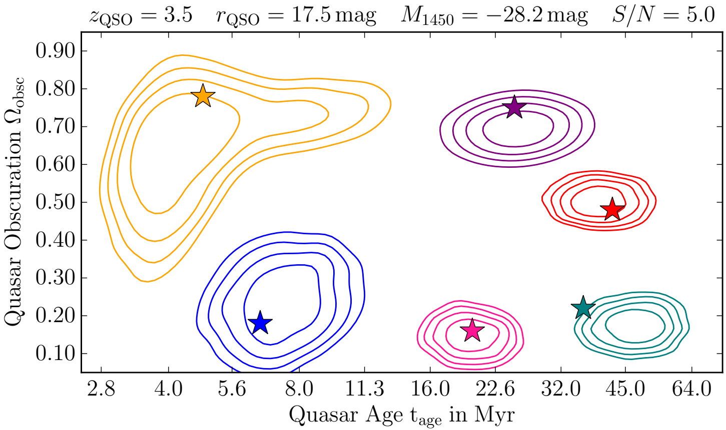
quasars brighter $M_{1450} < -27.5$ mag.

Outlook: Constraining the Full Quasar Lightcurve



Sensitivity to detailed emission history of last 100 Myr.
Opportunity to constrain long-term quasar variability.

Outlook: Constraining Obscuration AND Lifetime



Simultaneous fit for quasar age and obscuration / opening angle

Summary

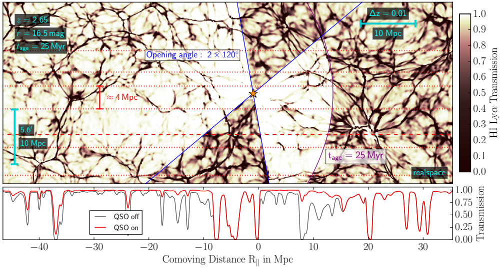
- Lyα Forest Tomography requires a fully Bayesian treatment of non-Gaussian observables
- A maximum pseudo-Likelihood approach offers an efficient compression from the dimensionality of the data to the dimensionality of the model
- The maximum pseudo-Likelihood can be mapped to proper posterior probabilities, requiring a reasonable amount of samples

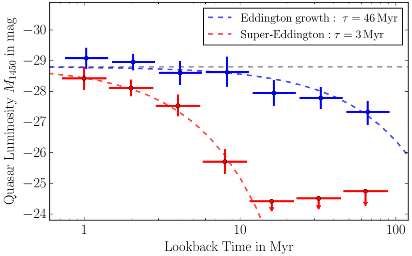
Allows to derive posterior probabilities for a case where classical likelihood computation is impossible

Summary

Lyα Forest Tomography can:

- map quasar light echos in 3D with unprecedented fidelity
- constrains the emission history and emission geometry of quasars
- is possible with current instruments LRIS, DEIMOS, FORS II
- first data has been obtained this semester
- will do much better with Subaru/PFS !





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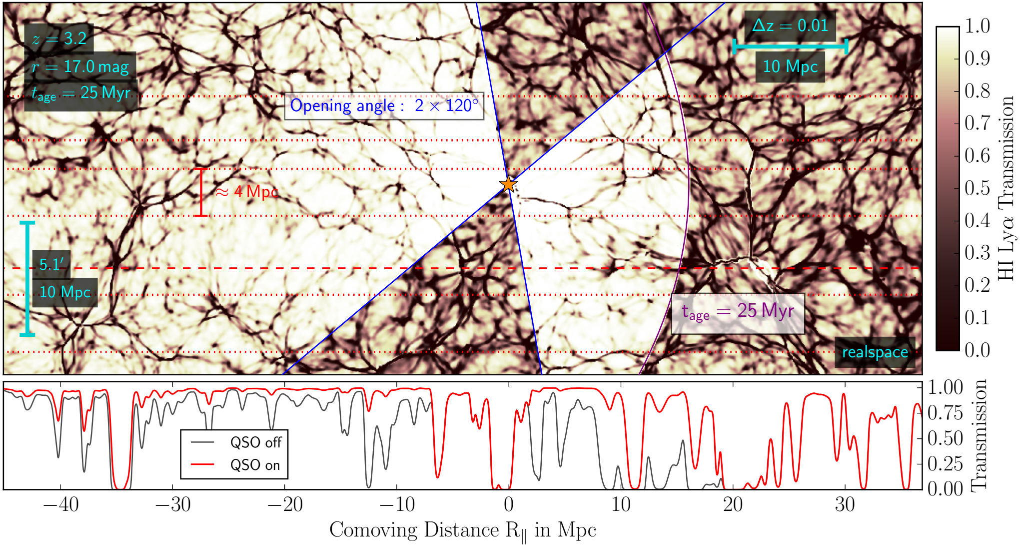

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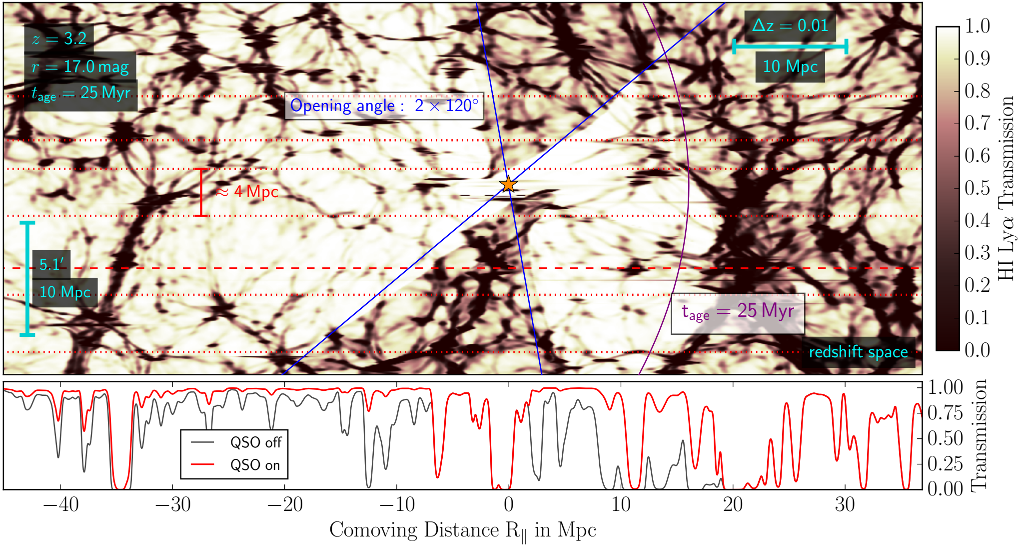

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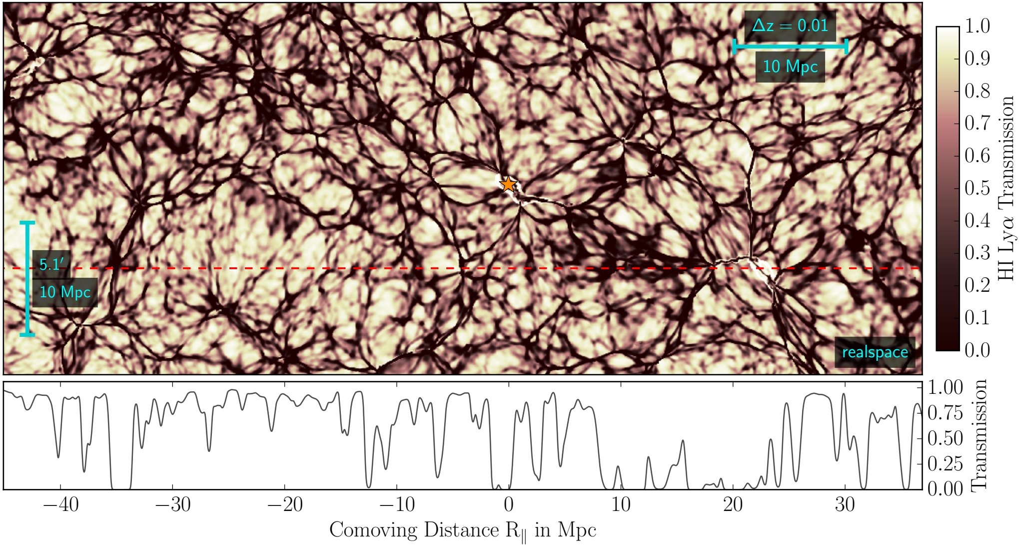
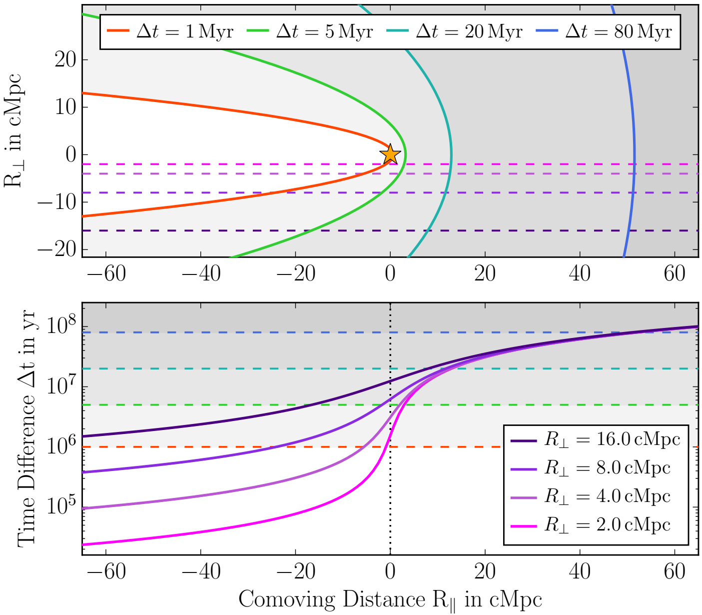
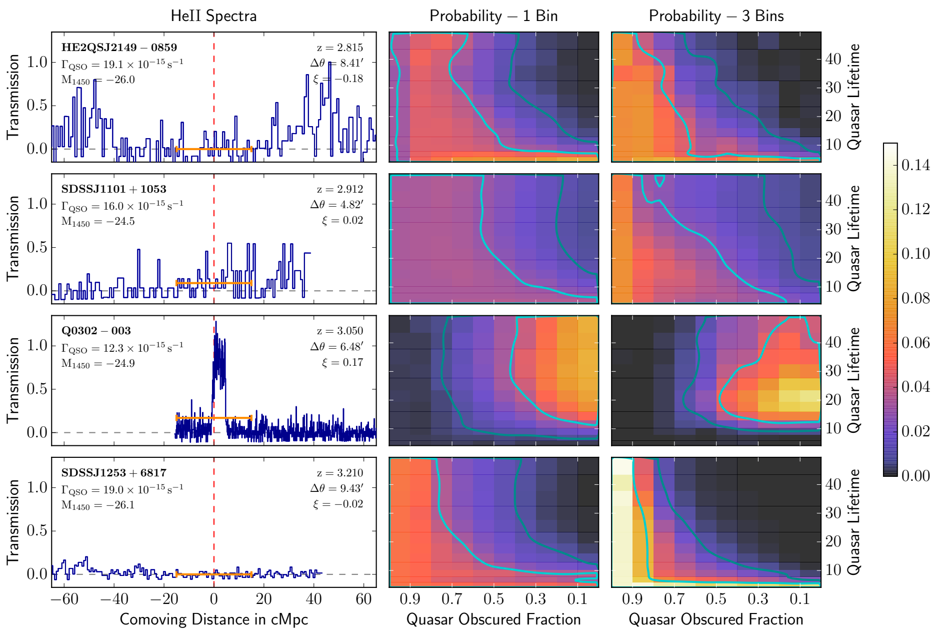




Δt = 1 Myr
Δt = 5 Myr
Δt = 20 Myr
Δt = 80 Myr
R⊥ in cMpc
20
10
0
−10
−20
−60
−40
−20
0
20
40
60
Time Difference Δt in yr
10^8
10^7
10^6
10^5
R⊥ = 16.0 cMpc
R⊥ = 8.0 cMpc
R⊥ = 4.0 cMpc
R⊥ = 2.0 cMpc
Comoving Distance R∥ in cMpc



Schmidt et al. 2018