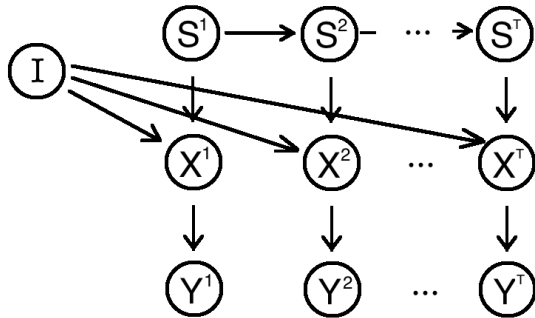


# STORM imaging

- ▶ microscopy, the diffraction limit
- ▶ “super-resolution”: techniques to break this barrier.
- ▶ masks: with telescopes, you can control them
- ▶ masks: in our microscopy setting, we cannot control them, or even observe them... we assume that they change gradually.

# The Graphical Model



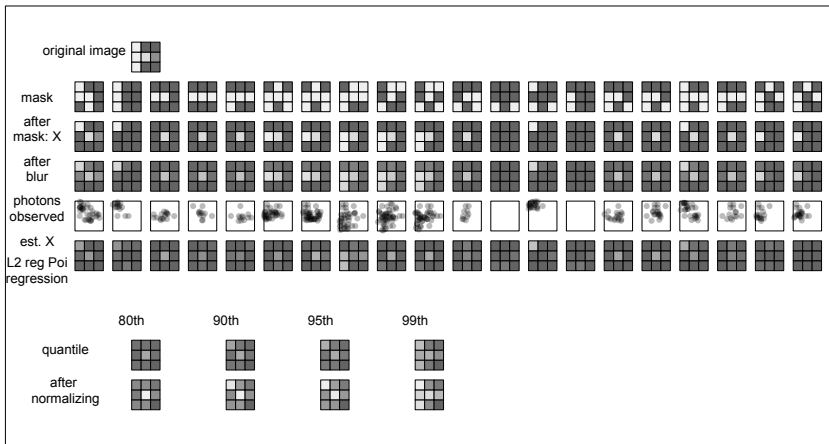
- ▶ We are interested in the original image  $I$ .
- ▶ for each pixel  $(m, n)$ ,  $Y_{mn}^t \sim \text{Poi}(\gamma[AX^t]_{mn})$
- ▶  $A$  is the Gaussian blur matrix.  $\gamma$  is the exposure time of each picture.  $Y_{mn}^t$  is the number of photons observed at that pixel and time.
- ▶ the masks  $S^t$  follow a Markov chain:  $S^{t+1} \sim Q(S^t)$

# Inference ideas

- ▶ **direct inference**, i.e. maximizing  $P(Y|I)$  would require integrating out all  $S^t$ , i.e.  $TU^2$  parameters.
- ▶ for each  $t$ , let  $\hat{X}^t = \underset{X^t}{\operatorname{argmax}} \log P(Y^t|X^t) - \lambda \|X^t\|_2^2$
- ▶  $\hat{X}^t$  is a noisy realization of  $X^t$ :  
 $E[\hat{X}^t] = X^t$ ,  $\operatorname{Var}(\hat{X}^t) = A^{-1}X^t$ .  
... and since  $X^{t+1}$  depends on  $X^t$ , maybe we can treat this as an HMM with Poisson emissions.
- ▶ but perhaps the simplest thing to do is realize that most pixels are unmasked at some point, so one hack is:  $\hat{I}_{mn} = \max_t \hat{X}_{mn}^t$ .  
... or better: take a high empirical quantile (e.g. 95th quantile).

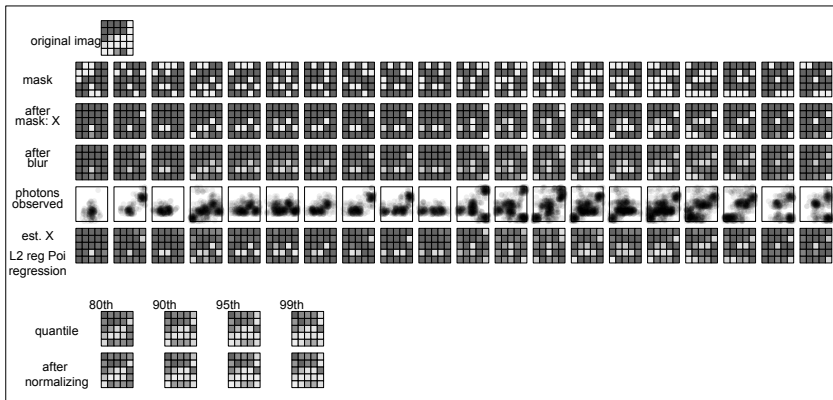
# Simulation: 3x3

T=20 exposure time = 20



# Simulation: 5x5

T=20 exposure time = 100



# Future work

- ▶ assume sparsity of  $I$ , or the spatial derivatives of  $I$ .
- ▶ take advantage of the knowledge that adjacent masks are similar

Thanks to Liam Paninski and Eftychios Pnevmatikakis for discussions.