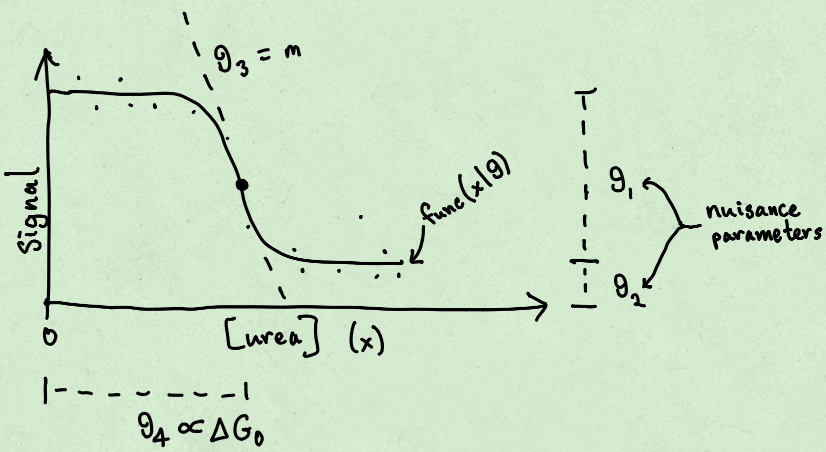
$$\underset{\text{(high signal)}}{\text{folded}} \xrightleftharpoons{\Delta G_{unf}} \underset{\text{(low signal)}}{\text{unfolded}}$$

we'll call x

assume $\Delta G_{unf} = \Delta G_0 + m[\text{urea}]$

what we want — proportionality constant

At equilibrium, $F_{folded} = \dfrac{1}{1+e^{-\beta \Delta G_{unf}}}$ partition function




## Nonlinear least squares

Minimize the sum of squared errors over our data:

$$\left(y_1 - \underset{\uparrow\, = y_{pred}}{\text{func}(x_1|\theta)}\right)^2 + \left(y_2 - \text{func}(x_2|\theta)\right)^2 + \ldots$$

by adjusting the parameters $\theta$

we can see that minimizing this is effectively equivalent to maximizing

## Bayesian inference

Assume Gaussian measurement noise:

$$p(y|\theta) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y-\text{func}(x|\theta))^2}{2\sigma^2}}$$

$\mu = y_{pred}$

$\sigma^2$ is a new nuisance parameter, the variance in y due to measurement noise

$$\ln p(y|\theta) = -\frac{(y-\text{func}(x|\theta))^2}{2\sigma^2} - \frac{\ln(2\pi\sigma^2)}{2}$$

$$\ln p(\text{data}|\theta) = \ln p(y_1|\theta) + \ln p(y_2|\theta) + \ldots$$

Bayes' theorem:

$$p(\theta|\text{data}) = \frac{p(\text{data}|\theta)\cdot p(\theta)}{\text{normalization}}$$

"posterior distribution" what we want to sample

"prior distribution" we'll use uniform