

Protein Unfolding Data Analysis

Spectroscopy

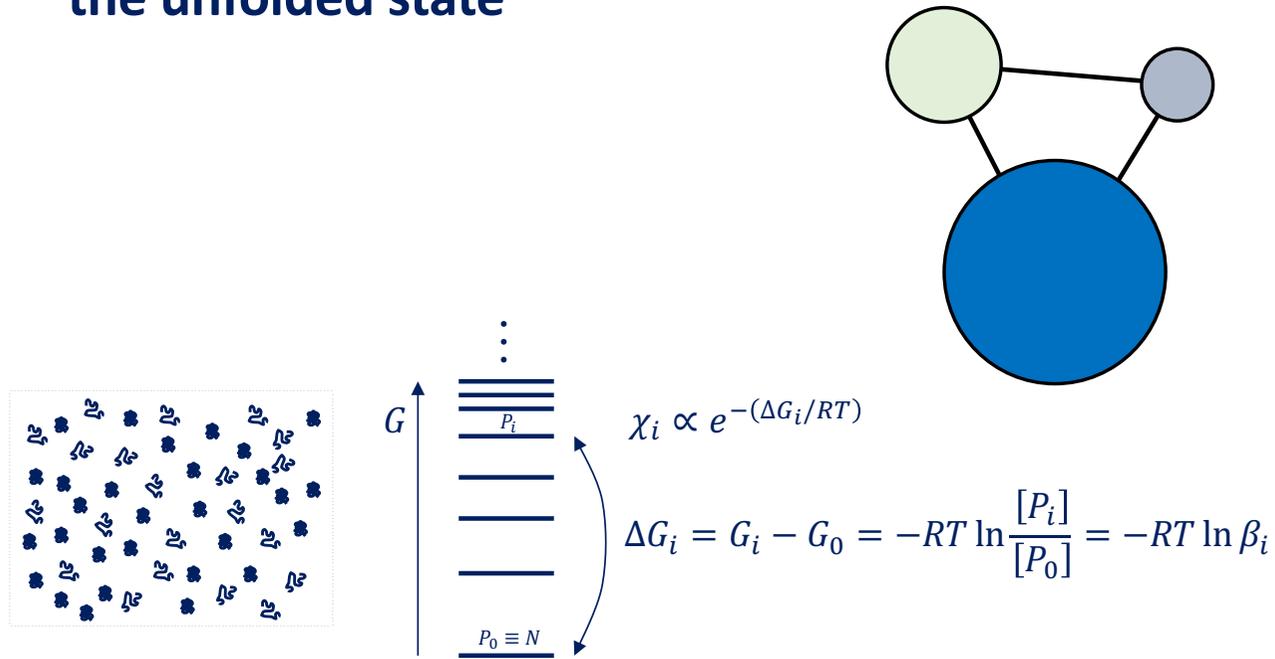
Adrian Velazquez-Campoy



This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 101004806

Stability

ΔG Gibbs energy of stabilization or unfolding
Difference in Gibbs energy between the native state and the unfolded state



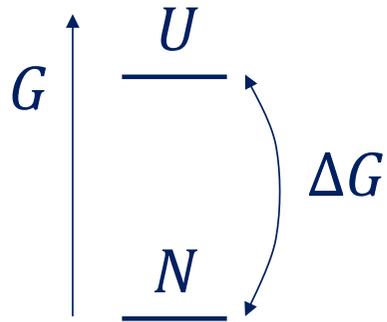
$$\Delta G = \Delta G(T, P, pH, \mu, [D], [L])$$

$$\Delta G([D]) = \Delta G_0 - m[D]$$

$$\Delta G(T) = \Delta H(T_m) \left(1 - \frac{T}{T_m}\right) + \Delta C_P \left(T - T_m - T \ln\left(\frac{T}{T_m}\right)\right)$$

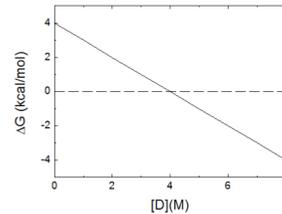
- **Goal:** Increase environmental stress and displace the equilibrium in order to make populations of comparable size, exploring different population ratios between N and U
Calculate/estimate K



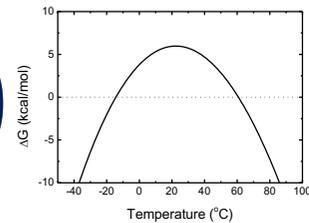


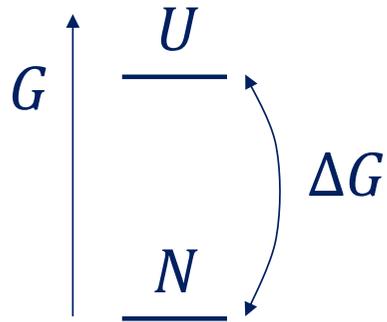
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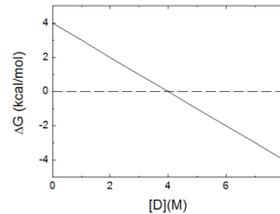
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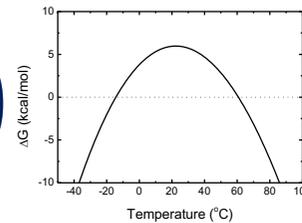


$$\Delta G = \Delta G(T, P, pH, \mu, [D], [L])$$

$$\Delta G([D]) = \Delta G_0 - m[D]$$



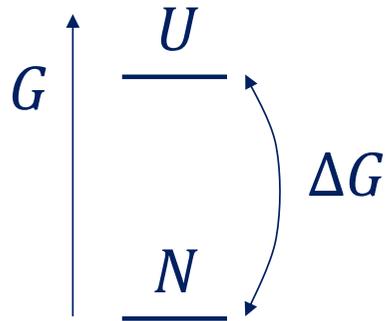
$$\Delta G(T) = \Delta H(T_m) \left(1 - \frac{T}{T_m}\right) + \Delta C_P \left(T - T_m - T \ln \left(\frac{T}{T_m}\right)\right)$$



ΔG_0 Stability energy
 m Susceptibility against denaturant concentration

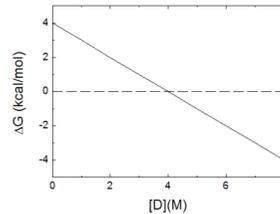
$\Delta H(T_m)$ Unfolding enthalpy
 T_m Unfolding temperature
 ΔC_P Unfolding heat capacity



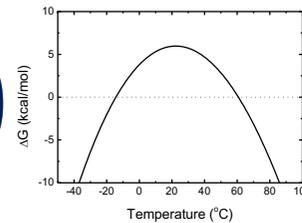


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$$\Delta G([D]) = \Delta G_0 - m[D]$$



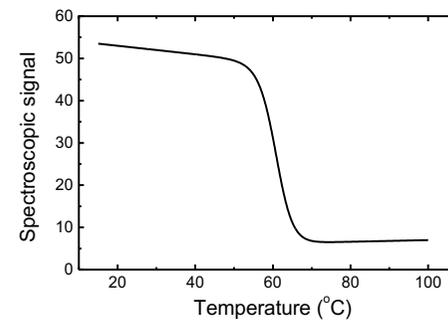
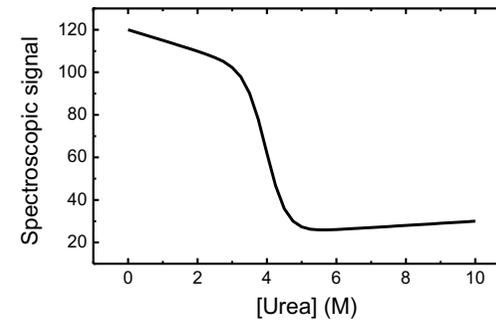
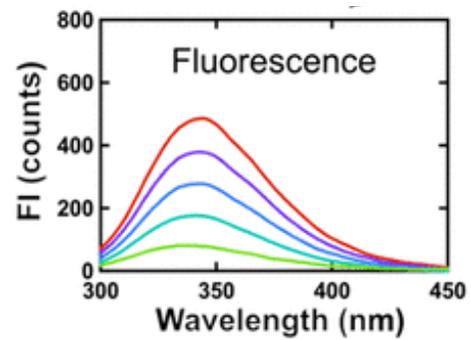
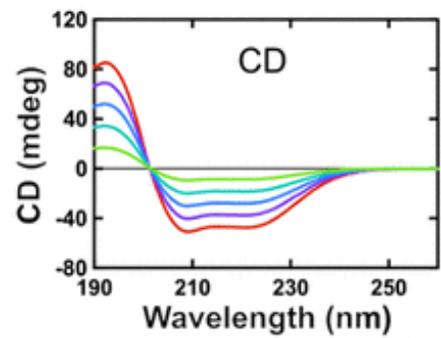
$$\Delta G(T) = \Delta H(T_m) \left(1 - \frac{T}{T_m}\right) + \Delta C_P \left(T - T_m - T \ln \left(\frac{T}{T_m}\right)\right)$$

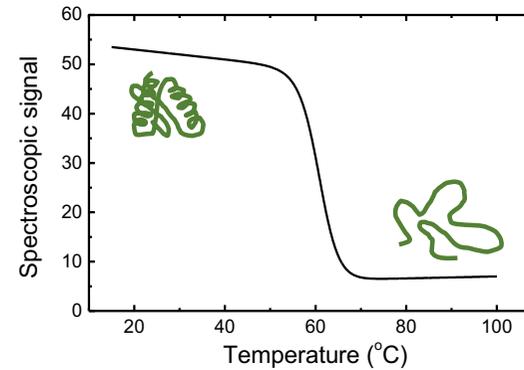
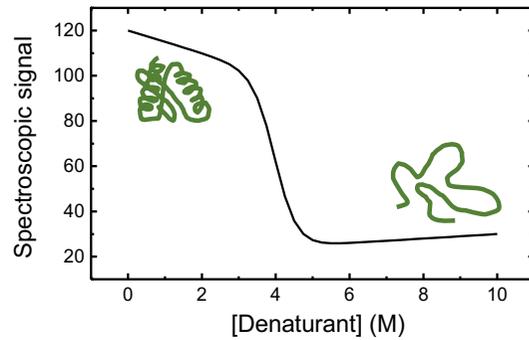


Parameters define the stability profile or diagram: $\Delta G([D])$ y $\Delta G(T)$
Parameters can be determined experimentally



► Unfolding experiment





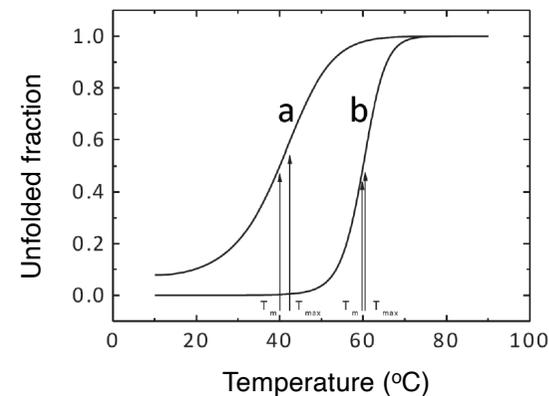
Cooperative unfolding → Reduction in the number of accessible states

Partially folded states are not significantly populated



► Data analysis?

- Unless you are doing a screening evaluation, never use sigmoidal fittings (e.g., Boltzmann function)
- Never apply “naïve” normalization
- The inflection point in chemical denaturation provides $[D]_m$
- The inflection point in thermal denaturation **DOES NOT** provide T_m ($T_m \lesssim T_{max}$)



► Standard approach based on the partition function Q



$$[P_i] = \beta_i [P_0]$$
$$[P_i] = \left(\prod_{r=1}^i K_r \right) [P_0]$$
$$Q = \sum_{i=0}^n \frac{[P_i]}{[P_0]} = \sum_{i=0}^n \beta_i = \sum_{i=0}^n e^{-(\Delta G_i/RT)}$$

Wyman & Gill. "Binding and Linkage", University Science Books, 1990



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► Standard approach based on partition function Q

$$Q = \sum_{i=0}^n \frac{[P_i]}{[P_0]} = \sum_{i=0}^n \beta_i$$

$$\chi_i = \frac{[P_i]}{[P]_T} = \frac{\beta_i}{Q}$$

$$\beta_i = \exp(-\Delta G_i/RT)$$

$$\Delta G_i = \Delta G_i(T, pH, \mu, [D], [L], a_w, \dots)$$

$$\Delta G_i([D]) = \Delta G_{0,i} - m_i[D]$$

$$\Delta G_i(T) = \Delta H_i(T_{m,i}) \left(1 - \frac{T}{T_{m,i}}\right) + \Delta C_{P,i} \left(T - T_{m,i} - T \ln \frac{T}{T_{m,i}}\right)$$



► Standard approach based on the partition function Q

$$Q = \sum_{i=0}^n \frac{[P_i]}{[P_0]} = \sum_{i=0}^n \beta_i$$

$$\chi_i = \frac{[P_i]}{[P]_T} = \frac{\beta_i}{Q}$$

$$\beta_i = \exp(-\Delta G_i/RT)$$

$$\langle S \rangle = \sum_{i=0}^n \chi_i S_i = \frac{\sum_{i=0}^n \beta_i S_i}{\sum_{i=0}^n \beta_i}$$

**Average of any system property
(measurement)**

$$NLSF \rightarrow \{T_{mi}, \Delta H_i, \Delta C_{pi}; i = 1, \dots, n\}$$





i	G	ΔG	$\exp(-\Delta G/RT)$
988	G_N	0	1
27	G_U	ΔG	K

$$Q = 1 + \beta = 1 + K$$

$$\chi_N = \frac{1}{1 + K}$$

$$\chi_U = \frac{K}{1 + K}$$



Chemical Denaturation

$$\Delta G([D]) = \Delta G_0 - m[D]$$

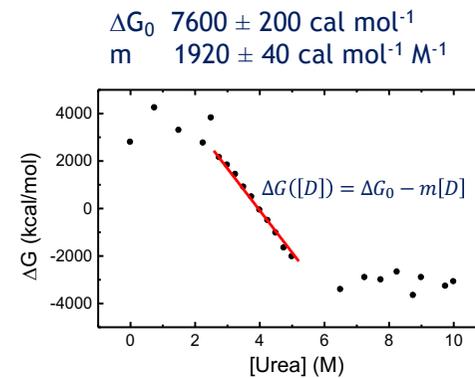
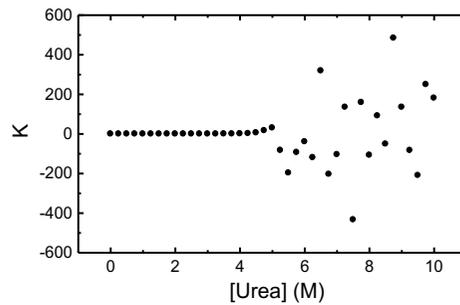
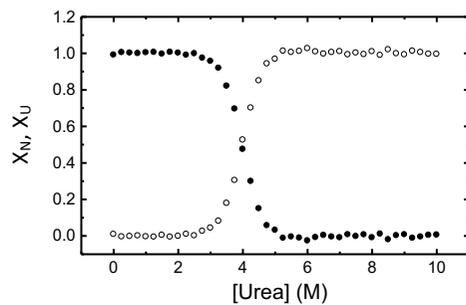
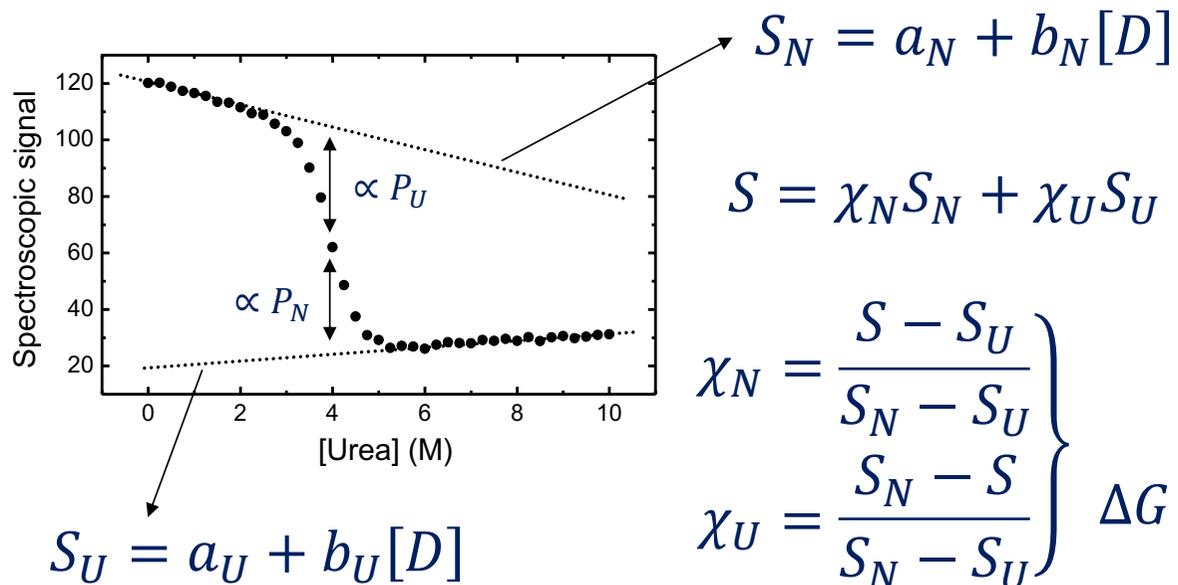
$$\Delta G_0 = \Delta G([D]) \Big|_{[D]=0} \quad m = - \left(\frac{\partial \Delta G([D])}{\partial [D]} \right)_{T,P}$$

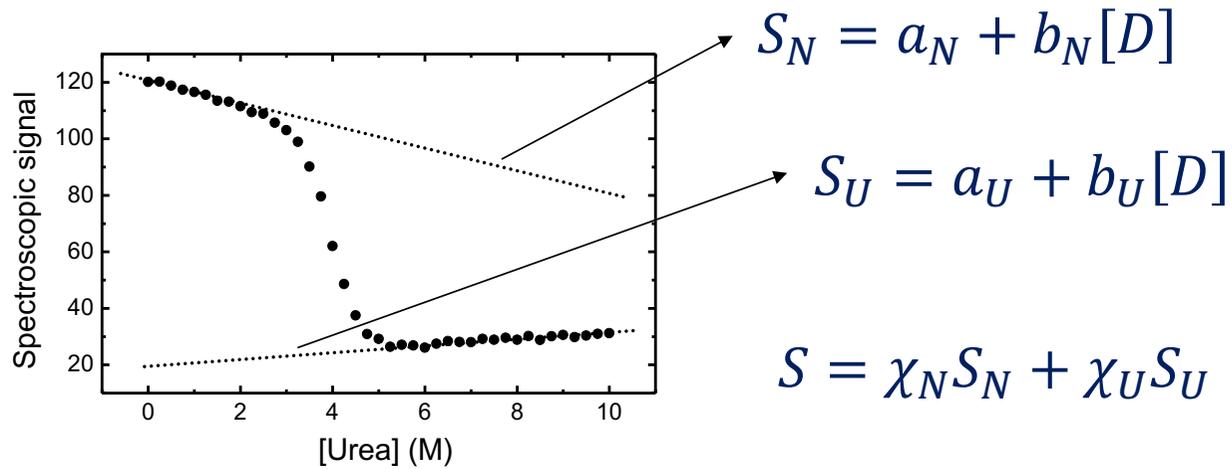
$$\Delta G([D]) = -RT \ln K([D])$$

$$\Delta G([D]_m) = 0 \rightarrow [D]_m = \frac{\Delta G_0}{m}$$

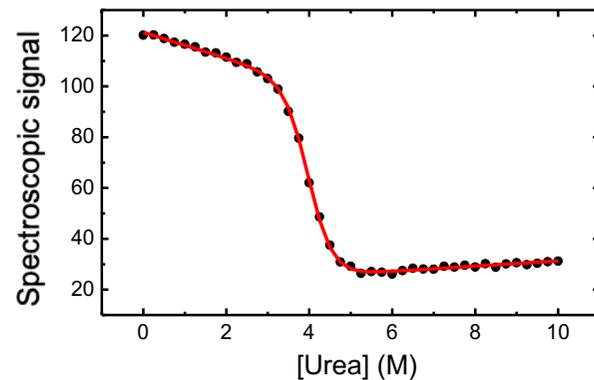
$$\Delta G([D]_m) = 0 \rightarrow \begin{cases} K = 1 \\ \chi_N = \chi_U = 0.5 \end{cases}$$







$$S = \frac{(a_N + b_N[D]) + e^{-(\Delta G_0 - m[D])/RT} (a_U + b_U[D])}{1 + e^{-(\Delta G_0 - m[D])/RT}}$$



ΔG_0 8200 ± 50 cal mol⁻¹
 m 2050 ± 10 cal mol⁻¹ M⁻¹



Thermal Denaturation

$$\Delta G(T) = \Delta H(T_m) \left(1 - \frac{T}{T_m}\right) + \Delta C_P \left(T - T_m - T \ln \left(\frac{T}{T_m}\right)\right)$$

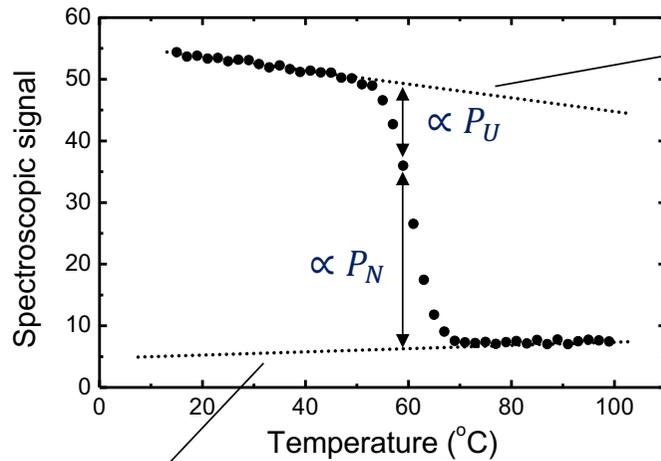
$$\Delta H(T_m) = \Delta H(T) \Big|_{T=T_m}$$

$$\Delta C_P = \left(\frac{\partial \Delta H(T)}{\partial T}\right)_P = T \left(\frac{\partial \Delta S(T)}{\partial T}\right)_P$$

$$\Delta G(T) = -RT \ln K(T)$$

$$\Delta G(T_m) = 0 \rightarrow \begin{cases} K = 1 \\ \chi_N = \chi_U = 0.5 \\ \Delta S(T_m) = \frac{\Delta H(T_m)}{T_m} \end{cases}$$





$$S_U = a_U + b_U T$$

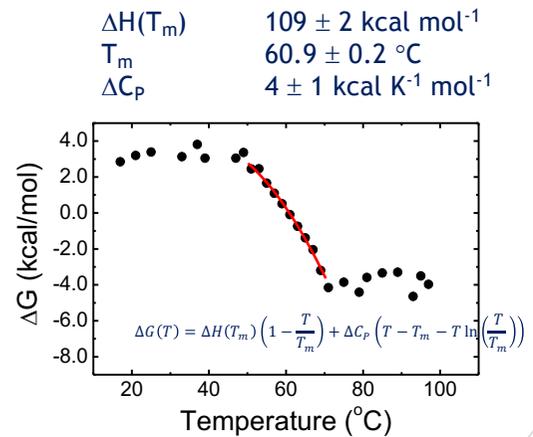
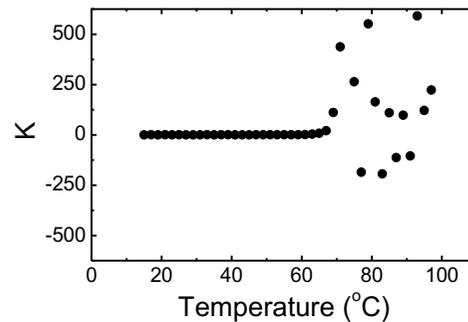
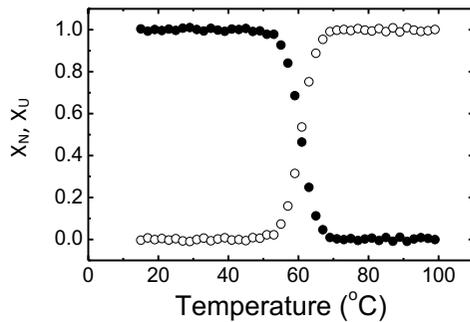
$$S_N = a_N + b_N T$$

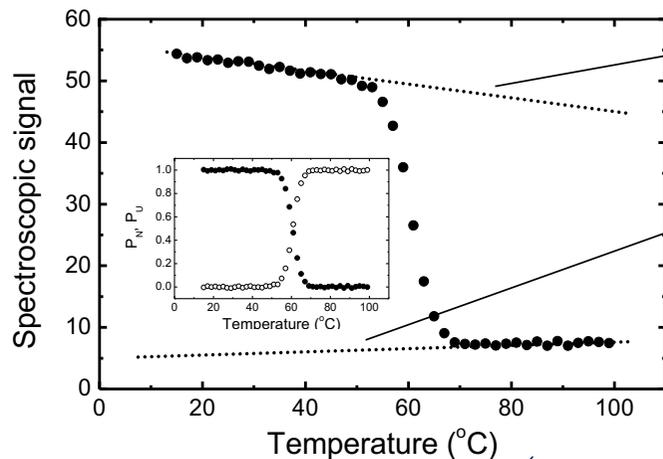
$$S = \chi_N S_N + \chi_U S_U$$

$$\left. \begin{aligned} \chi_N &= \frac{S - S_U}{S_N - S_U} \\ \chi_U &= \frac{S_N - S}{S_N - S_U} \end{aligned} \right\}$$

$$K = \frac{\chi_U}{\chi_N}$$

$$\Delta G = -RT \ln K$$





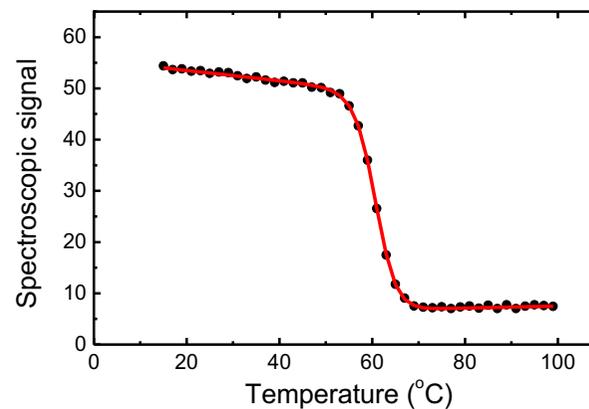
$$S_N = a_N + b_N T$$

$$S_U = a_U + b_U T$$

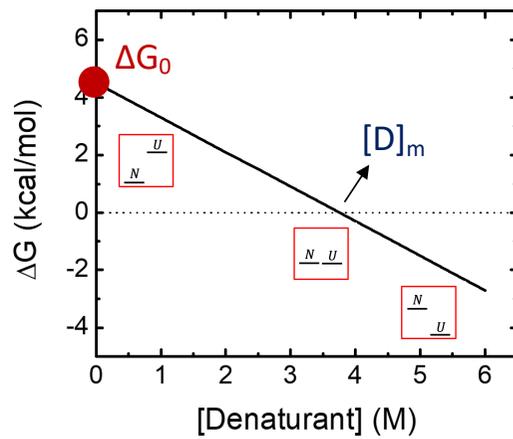
$$S = \chi_N S_N + \chi_U S_U$$

$$S = \frac{(a_N + b_N T) + e^{-\left(\Delta H(T_m)\left(1 - \frac{T}{T_m}\right) + \Delta C_P\left(T - T_m - T \ln\left(\frac{T}{T_m}\right)\right)\right)/RT} (a_U + b_U T)}{1 + e^{-\left(\Delta H(T_m)\left(1 - \frac{T}{T_m}\right) + \Delta C_P\left(T - T_m - T \ln\left(\frac{T}{T_m}\right)\right)\right)/RT}}$$

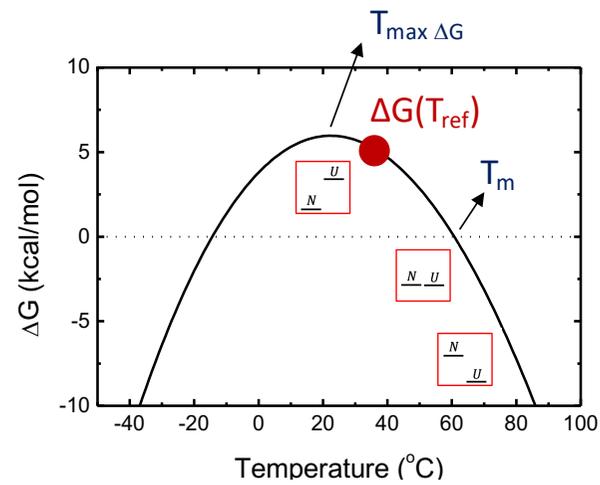
$\Delta H(T_m)$	$101 \pm 2 \text{ kcal mol}^{-1}$
T_m	$60.69 \pm 0.04 \text{ }^\circ\text{C}$
ΔC_P	$2.2 \pm 0.7 \text{ kcal K}^{-1} \text{ mol}^{-1}$



► Stability profile



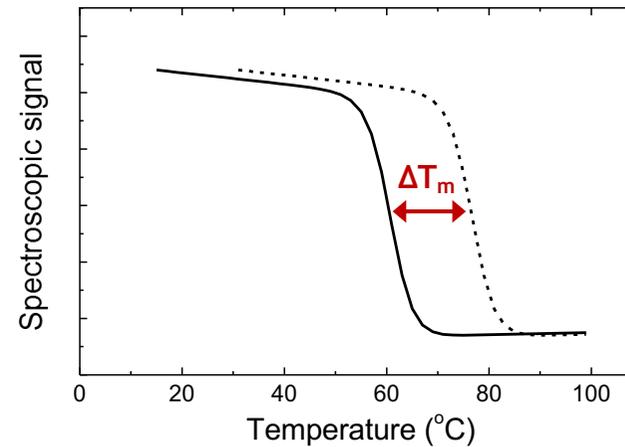
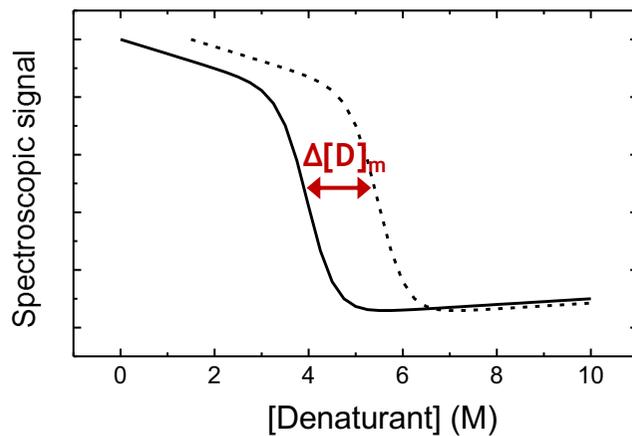
$$\Delta G([D]) = \Delta G_0 - m[D]$$



$$\Delta G(T) = \Delta H(T_m) \left(1 - \frac{T}{T_m}\right) + \Delta C_P \left(T - T_m - T \ln \frac{T}{T_m}\right)$$



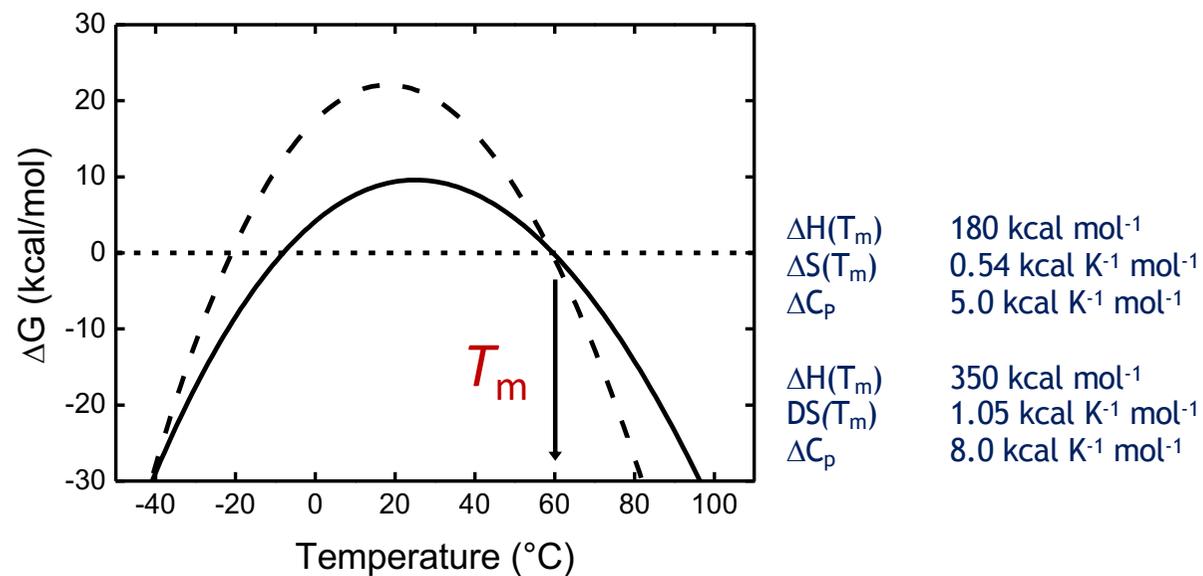
► Stability differences?



Changes in T_m and $[D]_m$ are easily to observe quantify, but they are NOT reliable indexes for stability or stability changes



High and low temperature stability

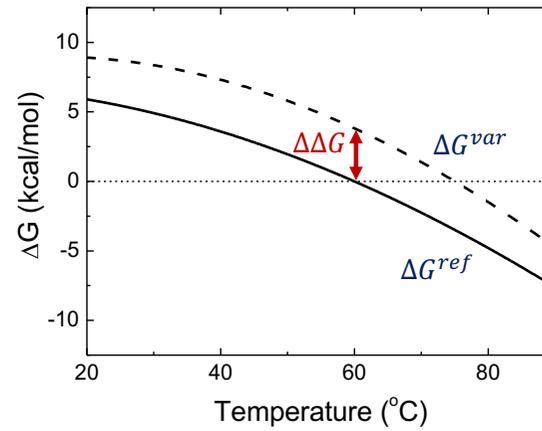
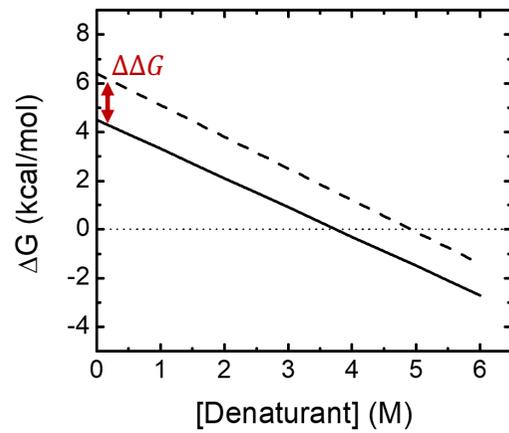


Which protein is more stable?



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► Stability differences?



Two-transition unfolding



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i	ΔG_i	$\exp(-\Delta G_i/RT)$
	0	1
	ΔG_1	K_1
	ΔG_2	K_2
	$\Delta G_1 + \Delta G_2$	$K_1 K_2$

$$Q = 1 + \beta_1 + \beta_2 + \beta_3 = 1 + K_1 + K_2 + K_1 K_2$$

$$\chi_N = \frac{1}{1 + K_1 + K_2 + K_1 K_2} \quad \chi_{I_2} = \frac{K_2}{1 + K_1 + K_2 + K_1 K_2}$$

$$\chi_{I_1} = \frac{K_1}{1 + K_1 + K_2 + K_1 K_2} \quad \chi_U = \frac{K_1 K_2}{1 + K_1 + K_2 + K_1 K_2}$$





i	ΔG_i	$\exp(-\Delta G_i/RT)$
	0	1
	ΔG_1	K_1
	$\Delta G_1 + \Delta G_2$	$K_1 K_2$

$$Q = 1 + \beta_1 + \beta_2 = 1 + K_1 + K_1 K_2$$

$$\chi_N = \frac{1}{1 + K_1 + K_1 K_2}$$

$$\chi_{I_1} = \frac{K_1}{1 + K_1 + K_1 K_2}$$

$$\chi_{I_2} \approx 0$$

$$\chi_U = \frac{K_1 K_2}{1 + K_1 + K_1 K_2}$$



► Selecting an appropriate unfolding model

- Understanding “names” of models, as well as physical idealization and mathematical formalism
- Make sense of estimated parameter values
- Make sense of parameters uncertainties



▶ Best model for analysis?

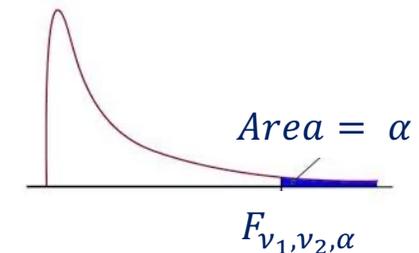
- **Employ structural/functional data, if available**
- **Revise carefully experimental data**
- **Identify unusual features**
- **Start with simplest compatible model (Ockham's razor)**
- **Increase complexity until unnecessary (no statistical improvement or no convergence)**
- **Understand assumptions/constraints of model**
- **Judge critically the estimated parameters**



► When to stop increasing model complexity?

- Select the (statistically) best model

$$\chi^2 \equiv RSS = \sum_{i=1}^n (y(x_i) - f(\theta; x_i))^2$$



Model 1: $n - p_1, \chi_1^2$
 ($p_2 > p_1$) **Model 2:** $n - p_2, \chi_2^2$

$$F = \frac{(\chi_1^2 - \chi_2^2)/(p_2 - p_1)}{\chi_2^2/(n - p_2)} \sim F_{p_2 - p_1, p_2 - p_1}$$

$F \leq F_{p_2 - p_1, p_2 - p_1, \alpha}$ **select Model 1 (H_0)**
 $F > F_{p_2 - p_1, p_2 - p_1, \alpha}$ **select Model 2 (H_1)**

$$AIC = n \ln \left(\frac{\chi^2}{n - p} \right) + 2p$$

$$BIC = n \ln \left(\frac{\chi^2}{n - p} \right) + p \ln n$$

Select model with minimum AIC or BIC



► Global fitting

- Strengthen model selection
- Strengthen parameter estimation
- Reduce uncertainties of estimated parameters
- Overcome experimental limitations



► Global fitting?

- Replicate experiments
- Concentration ranges
- Together with other biophysical techniques

...

