

## Following Baez

Recall that  $\rho = \sum p_i |\psi_i\rangle\langle\psi_i|$ , or

often  $\rho = \frac{1}{Z} e^{-\beta H}$ . If  $\rho^2 = \rho$ ,

then  $\rho \sim$  pure state. Otherwise,  $\rho \sim$  mixed state, a statistical mixture of pure states.

In general,  $\text{tr}(\rho) = \sum p_i = 1$ .

Thinking more generally, suppose we have fixed various quantities (operators)  $X_1, \dots, X_n$ .

Then, we want  $\rho_*$  which maximizes

$S(\rho) = -\text{Tr}(\rho \ln \rho)$  & satisfies  $\langle X_i \rangle = x_i$ .

Lagrange multipliers:

$$\bar{S}(\rho, \lambda_i) = S(\rho) + \sum_i \lambda_i (\langle X_i \rangle_\rho - x_i)$$

$$\frac{\partial \bar{S}}{\partial \rho} = \frac{\partial \bar{S}}{\partial \lambda_i} = 0 \quad ; \quad \frac{\partial}{\partial \rho} = \sum_{ij} \frac{\partial}{\partial p_{ij}}$$

$$\text{Diagonalize } \rho \Rightarrow S = - \sum_k (p_{kk} \ln p_{kk})$$

$\underbrace{\hspace{1.5cm}}_{\langle x_i \rangle_k = \langle \phi_k | x_i | \phi_k \rangle}$

$$\Rightarrow -(\ln(p_{kk}) + 1) + \sum_i \lambda_i \langle x_i \rangle_k = 0$$

$$p_{kk} = e^{\sum_i \lambda_i \langle x_i \rangle_k - 1}$$

$$\text{Take } x_i = I \Rightarrow \text{Tr}(\rho) = 1$$

$$\begin{aligned} \Rightarrow p_{kk} &= e^{\lambda_1 - 1 + \sum_i \lambda_i \langle x_i \rangle_k} \\ &= Z^{-1} e^{\sum_i \lambda_i \langle x_i \rangle_k} \end{aligned}$$

$$\rho = Z^{-1} e^{\sum_i \lambda_i \hat{x}_i}$$

$$\text{since } p_{kk} = \langle \phi_k | \rho | \phi_k \rangle = Z^{-1} e^{\sum_i \lambda_i \overbrace{\langle \phi_k | \hat{x}_i | \phi_k \rangle}^{\langle x_i \rangle_k}}$$

$$\text{Note: } \text{tr}(\rho) = 1 \Rightarrow Z = \text{tr}(e^{\sum_i \lambda_i \hat{x}_i})$$

## Enter Statistics

cumulant generating function

$$\text{mean} \quad \langle x_i \rangle = - \frac{\partial}{\partial \lambda_i} \ln Z$$

$$\text{variance} \quad \langle x_i^2 \rangle - \langle x_i \rangle^2 = \frac{\partial^2}{\partial \lambda_i^2} \ln Z$$

||

$$\langle (x_i - \langle x_i \rangle)^2 \rangle$$

covariance :

$$\langle (x_i - \langle x_i \rangle)(x_j - \langle x_j \rangle) \rangle = \frac{\partial^2}{\partial \lambda_i \partial \lambda_j} \ln Z$$

Since  $[\hat{x}_i, \hat{x}_j] \neq 0$  in general.

$$\text{Define } g_{ij} = \text{Re} \left( \frac{\partial^2}{\partial \lambda_i \partial \lambda_j} \ln Z \right)$$

so that  $g_{ij} = g_{ji}$  (how to prove)

## Geometry

For each  $x = (x_1, \dots, x_n) \in \mathbb{R}^n$ , we

have a Gibbs state  $\rho$  st.  $\langle X_i \rangle = x_i$ .

Hoping  $g_{ij}$  is positive definite  $\Rightarrow g_{ij} \sim$  <sup>Riemannian</sup> metric

At  $T_x \mathbb{R}^n$ , ... what?

First, ~~at~~ each point on  $\mathbb{R}^n$  we interpret as the mean of a random vector  $\vec{X} \in T_x \mathbb{R}^n$  st.  $E[\vec{X}] = x^i e_i$ ,

whose distribution is given by  $\rho$ . Associate  $\langle \psi_{\vec{x}} \rangle \sim \vec{X}$

& assume non-degeneracy. Then we get  $\vec{X}$  with

$$\text{prob}(\vec{X}) = \frac{1}{Z} e^{\sum_i \lambda^i \langle X_i \rangle \psi_{\vec{x}}}$$