PROBLEM 5 Landscapes & Kac-Rice (1/2)

Problem 5: THE KR METHOD & THE COMPLEXITY

The kac-rice formula



such that
$$g(x) = \nabla_{L} E(\vec{e}) = 0$$
. Since this function
is a vector, its derivative has to be replaced by
a matrix, the Hessian: the modulus is replaced
by the absolute value of the determinant.
Therefore, the Kac-Rice formula counting the
total number of stationary points is:
 $\overline{N} = \int d\vec{\sigma} \quad \overline{S}(\nabla_{L} E(\vec{\sigma})) \left[det \nabla_{L}^{2} E(\vec{\sigma}) \right]$
SN
To count only those having a given value of
energy density, one adds the constraint:
 $S(E(\vec{\sigma}) - N\epsilon)$.

2 STATISTICAL ROTATIONAL INVARIANCE

The correlations read: $\overline{E(\vec{\sigma})E(\vec{\sigma}')} = N\left(\frac{\vec{\sigma}\cdot\vec{\sigma}'}{N}\right)^P$ Given two configurations on the sphere, the correlation between the corresponding energies depends only on the overlap between the contigurations $\vec{\sigma} = \int_{-\infty}^{-\infty} \int_{-\infty}^{+\infty} \int_{-\infty$

The Kac-Rice formula reads: $\overline{N(\varepsilon)} = \int d\vec{\sigma} P_{\varepsilon} (\vec{\sigma})$

The fact that the correlations, and thus the statistics of $E(\vec{\sigma})$, is votational invariant implies that $p_{\vec{\sigma}}(\vec{\sigma})$ does not depend on the particular configuration $\vec{\sigma}$, but it is the same for all $\vec{\sigma}$. We fix one value for the vector, $\vec{1} = (1, ..., 1)$, and get:

$$N(\varepsilon) = \int d\vec{\sigma} P_{\varepsilon}(\vec{\sigma}) = P_{\varepsilon}(\vec{1}) \int d\vec{\sigma} \sim P_{\varepsilon}(\vec{\sigma}) (2\pi \varepsilon)^{N/2}$$

SN Volume of sphere

3 GAUSSIANITY & CORRELATIONS

• The quantity $E(I) = \underset{i \leq \cdots \leq i_{p}}{\sum} J_{i \leq \cdots \leq i_{p}}$ is a sum of independent Gaussian Variables, and thus it is a gaussian variable with zero mean and: $\overline{(E(I))^{2}} = N$ Its clistribution is $\frac{dE}{\sqrt{2\pi N}} = e^{-\frac{E_{2N}^{2}}{N}}$; in terms $g \in E_{2N}$, this is $\sqrt{\frac{N}{2\pi}} de = \frac{NE^{2}}{2}$

- The vectors $\nabla_{\perp}E(\underline{n})$ are obtained subtracting to $\nabla E(\underline{n})$ the component parallel to $\underline{1}$: one remains with (N-1) components that are gaussian, with covariances: $\overline{(\nabla_{\perp}E)_{\alpha}}(\overline{\nabla_{\perp}E})_{\beta} = P \delta_{\alpha\beta}$ and with zero average. The probability density is: $P(\nabla_{\perp}E) = \frac{1}{(2\pi p)^{N-2}} \prod_{\alpha=1}^{N-1} e^{-\frac{(\nabla_{\perp}E)_{\alpha}^{2}}{2p}}$ Which computed at $\nabla_{\perp}E=0$ gives $P(\overline{o}) = (\frac{1}{2\pi p})^{\frac{N-1}{2}}$
- Since $\nabla_{LE}(\vec{i})$ is independent of $E(\vec{i}), \nabla_{LE}^{2}(\vec{i}), we have$ $<math>\left| \det \nabla_{LE}^{2}(\vec{i}) \right| \cdot S(\nabla_{LE}(\vec{i})) \cdot S(E(\vec{i}) - N\varepsilon) = \frac{1}{1 + 1 + 2} + \frac{1}{2} \left| \int_{U_{LE}}^{2} dv \left(\int_{U_$
 - $= \left| \det \nabla_{1}^{2} E(\vec{1}) \right| \delta(E(\vec{1}) N\epsilon) \cdot \delta(\nabla_{1} E(\vec{1}))$
 - $= \left| \det \nabla_{\mathbf{i}}^{2} E(\mathbf{\vec{i}}) \right| \, \mathcal{S}(E(\mathbf{\vec{i}}) N\varepsilon) \cdot \mathbb{P}(\nabla_{\mathbf{i}} E(\mathbf{\vec{i}}) = 0)$
 - $= \left| \det \nabla_{1}^{2} E(\vec{1}) \right| \delta(E(\vec{1}) N\epsilon) \cdot \left(\frac{1}{2\pi p}\right)^{\frac{N-1}{2}}$

• Finally, the average of the determinant can be witten
as a conditional average, using the general relation:
$$\overline{X \cdot S(Y-Y)} = \int dx \, dy' \, P(x,y') \cdot x \cdot S(y'-y) = \left(dx \, P(x|y) \cdot x \right) \cdot P(y)$$
$$\int_{P(x|y')}^{P(x|y')} P(Y=y)$$
$$T conditional average$$
Therefore:
$$\overline{Therefore:}$$

 $\left| \det \nabla_{1}^{2} E(\vec{1}) \middle| S(E(\vec{1}) - N\epsilon) = \left| \det \nabla_{1}^{2} E(\vec{1}) \middle| E(\vec{1}) = N\epsilon \cdot P(E = N\epsilon) \right|$ Conditional average

Using the fact that the conditional law of the Hessian matrix $\nabla_{1}^{2} \epsilon(\mathbf{i})$ is the same as matrices $(M - p \epsilon \mathbf{1})$, where M is symmetric with Gaussian entries, we have that this term reduces to:

 $\overline{\left|\det \nabla_{1}^{2} E(\vec{1}) \middle| S(E(\vec{1}) - N\epsilon\right)} = \left(\det \left(M - p\epsilon \mathbf{1}\right) \middle| \cdot \sqrt{\frac{N}{2\pi}} e^{-\frac{N\epsilon^{2}}{2}}\right)$

$$\begin{aligned} & Ombining \ \text{everything}:\\ & \overline{N(\varepsilon)} = \left(2\pi e\right)^{N/2} \left(\frac{1}{2\pi p}\right)^{\frac{N+1}{2}} \sqrt{\frac{N}{2\pi i}} e^{-\frac{N\varepsilon^2}{2}} \left[\det\left(M - p\varepsilon \mathcal{U}\right) \right]^{M} \\ & \left| \frac{N}{2} \log\left(\frac{e}{p}\right) - \frac{N\varepsilon^2}{2} + \log\left[\det\left(M - p\varepsilon \mathcal{U}\right)\right] + O(N) \\ & = e^{-\frac{N}{2}} e^{-\frac{N}{2}} e^{-\frac{N}{2}} \left[\frac{1}{2} e^{-\frac{N}{2}} e^{-\frac{$$

where the Iverage of the determinant is over the ensemble of matrices M that are symmetric, and have independent random entries M_{xp} with $x \le \beta$, with assian statistics.