

Information Geometry of Magnetic Systems.

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The Big Picture :-

- ① Geometry is the Perception of Structure.
- ② The Abstraction from SpatioTemporal Geometry to Parametric Geometry.
- ③ Giving Geometric Meaning to Statistics.
- ④ What essence do these Geometric Objects carry?

Why Bother at all, about Geometry?

- ① For Long, Many-Body Evolution has been dealt within Statistics, which contains only algebraic-differential structures.
- ② Information is Pattern - and so is within an interactive system.
- ◆ The Geometry is already underneath.

Riemannian Geometry:

① Theorema Egregium (1827 - Gauss):

→ There are intrinsic properties of a geometric object, like curvature, torsion, geodesics, irrespective of how you coordinate it.

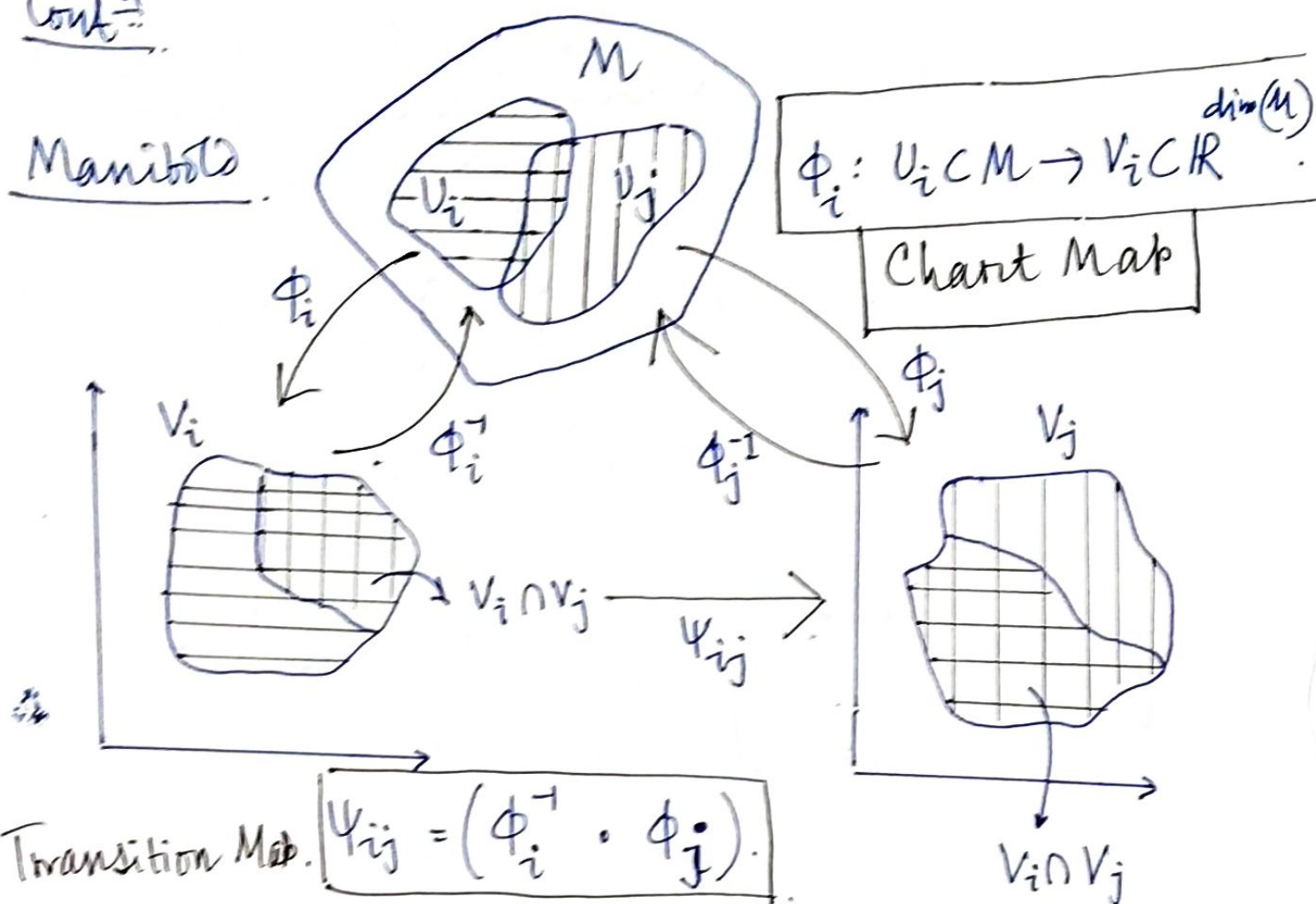
② Riemann (1853):

→ For smooth geometric objects, there is a "metric tensor" that tells you everything about it.

$$g_{ab}(p) := (\tilde{e}_a|_p \cdot \tilde{e}_b|_p)$$

Cont^y

Manifold



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Cont^y.

[*] Smoothness of M , must be carried on the smoothness of ψ_j .

[•] A metric d is $d(a, b)$

i. Positive definite

ii. Symmetric

iii. Bilinear.

⑥ One needs a metric over manifolds.

[•] Riemann (1853): $g_{ab}(p) : T_p M \times T_p M \rightarrow \mathbb{R}$

$$ds^2 = g_{ab} dx^a dx^b.$$

[•] A manifold, Equipped with a smooth (g_{ab}) is a Riemannian manifold.

What about distance?

For a curve $\gamma: [a, b] \rightarrow M$

$$\begin{aligned} L(\gamma) &= \int_a^b \|\dot{\gamma}(\tau)\| d\tau \\ &= \int_a^b \sqrt{g_{ij} \dot{\gamma}^i \dot{\gamma}^j} d\tau \end{aligned}$$

Geodesic! $\gamma_{GD}: [a, b] \rightarrow M$ such that

$$L(\gamma_{GD}) = \inf_{\text{all } \gamma} \int_a^b \sqrt{g_{ij} \dot{\gamma}^i \dot{\gamma}^j} d\tau$$

Distance: $d(a, b) = L(\gamma_{GD})$

□ the Whole Idea of Differential Geometry is that — once you have g_{ab} , you have every information of the manifold.

Formula for Curvature Tensor/Scalar:

$$\Gamma^i_{jk} = [\partial_j g^i_k + \partial_k g^i_j - \partial^i g_{jk}]$$

$$R^l_{ijk} = [\partial_j \Gamma^l_{ik} - \partial_i \Gamma^l_{jk}] + [\Gamma^p_{ik} \Gamma^l_{jp} - \Gamma^p_{jk} \Gamma^l_{ip}]$$

$$R_{ik} = R^l_{ilk}$$

$$\boxed{R = g^{ik} R_{ik}}$$

the Ricci Scalar:

Statistical Manifold :- (M).

Gibbs Measure :- $p(x, \theta) = q(x) \exp \left(- \sum_i \theta^i H_i - W(\theta) \right)$.

Consider a REAL Hilbert Space :-

[Equipped with some metric g_{ab}]. $\Psi_\theta(x) = \sqrt{p(x, \theta)}$
 $\in \mathcal{H}$.

□ Normalization : $\|\Psi_\theta(x)\|^2 = 1 = \left(g_{ab} \Psi_\theta^a \Psi_\theta^b \right)$

\Rightarrow The system resides within the unit sphere S in \mathcal{H} .

□ With $\mathcal{P} := \{\text{parameters}\}$ the Parameter Space and
 $f: \mathcal{P} \rightarrow \mathcal{H}$. $\mathcal{M} = \text{Image}(f) \cap S$ Statistical Manifold.

- Now the Statistical System is a point in M .
- The probabilistic evolution of the system, is trajectories in M .
- But We Still Need a Metric Structure to Give it a Riemannian Signature.
- There are Fisher-Rao Information metric, Entropy Derivative metric, Kulbeck-Leibler Divergence (Symmetrised), Jensen metric \rightarrow As Dissimilarity measures of probability distribution functions.

Entropy Derivative Metric :-

$$g_{ij} = - \partial_i \partial_j F$$

$$\partial_i \equiv \frac{\partial}{\partial \theta^i}$$

F = Free Energy.

Application to Mean Field Magnetic System

$$\mathcal{H} = - \frac{J}{(N-1)} \sum_{\langle ij \rangle} \sigma_i \sigma_j - h \sum_i \sigma_i$$

In the Thermodynamic limit :- $\left[\text{with } \begin{cases} \alpha = \frac{h}{kT} \\ \beta = \frac{J}{kT} \end{cases} \right]$

$$\ln Z(\alpha, \beta) \sim \frac{1}{2} \ln \left[\frac{4}{1-m^2} \right] - 4\beta m^2 \quad \left[m = \text{magnetisation} \right]$$

$$\text{with: } m = \tanh(q\beta m + \alpha)$$

$$\sim (q\beta m + \alpha) \quad \left[\tanh(x) \approx x - \frac{x^3}{3} \quad \forall x \rightarrow 0 \right]$$

$$\begin{aligned} \Rightarrow \ln Z(\alpha, \beta) &\sim \frac{1}{2} \ln 4 + \frac{1}{2} (1-q\beta) \frac{\alpha^2}{(1-q\beta)^2} + \frac{1}{4} \frac{\alpha^4}{(1-q\beta)^4} \\ &= \left[\ln 2 + \frac{\alpha^2}{2(1-q\beta)^2} + \frac{\alpha^4}{4(1-q\beta)^4} \right] \end{aligned}$$

It's a 2D model: (parametrically & spatially).

The Information metric:

$$[g_{ij}] = \begin{pmatrix} \frac{1}{1-q\beta} + \frac{3\alpha^2}{(-1+q\beta)^4} & \frac{q\alpha(-4\kappa^2+(-1+q\beta)^3))}{(-1+q\beta)^5} \\ \frac{q\alpha(-4\kappa^2+(-1+q\beta)^3))}{(-1+q\beta)^5} & -\frac{q^2\alpha^2(-5\kappa^2+(-1+q\beta)^3))}{(-1+q\beta)^6} \end{pmatrix}$$

$$\boxed{\det[g] = -\frac{q^2\kappa^6}{(-1+q\beta)^{10}}}$$

A Formula for the Scalar Curvature:

$$R = -\frac{1}{2 \det[q]} \begin{vmatrix} \ln Z_{,11} & \ln Z_{,12} & \ln Z_{,22} \\ \ln Z_{,11} & \ln Z_{,12} & \ln Z_{,12} \\ \ln Z_{,12} & \ln Z_{,12} & \ln Z_{,22} \end{vmatrix}$$

where: $\ln Z_{,123} = [\partial_1 \partial_2 \partial_3 \ln Z]$.

With this, the Scalar Curvature takes the form:-

$$R = \frac{q^2}{(q^\beta - 1)^3}$$

$$\beta_c = \frac{1}{q}$$

$$\Rightarrow \frac{J}{k T_c} = \frac{1}{4} \Rightarrow T_c = \frac{4J}{k}$$

⊙ Scalar Curvature Diverges @ Critical Point.

⊙ $R \sim \left(\frac{\beta - \beta_c}{\beta_c} \right)^{-3}$ ⊙ Changes sign from $\beta < \beta_c$ to $\beta > \beta_c$.

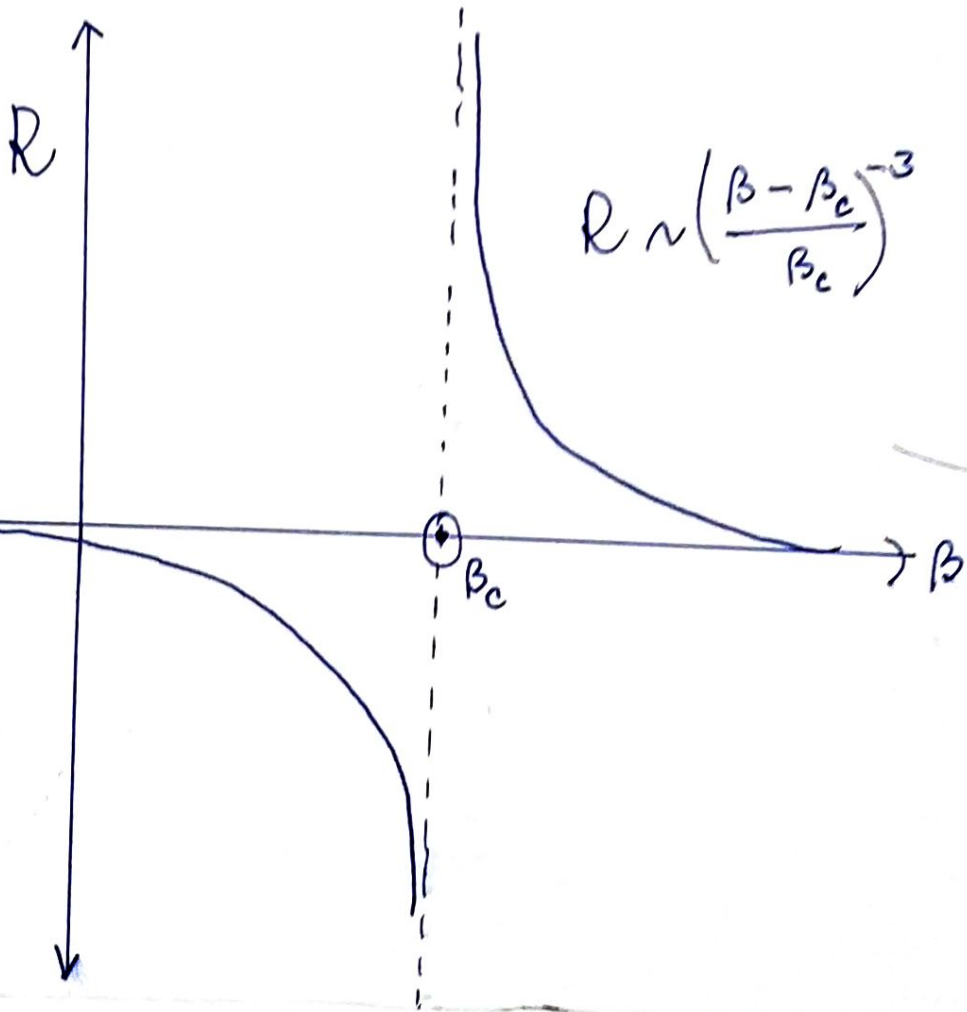
■ The Scalar Curvature Contains rich Information of Phase Transition.

Emergence of

Power Law

(a)

Criticality.



Trouble with Mean-Field Schemes:-

- ① Our Standard Approach of $\sigma_i \rightarrow \langle \sigma_i \rangle + \delta \sigma_i$ and ignoring $(\delta \sigma_i \delta \sigma_j) \rightarrow 0$ terms, gives us:

$$\ln Z = - \frac{q N \beta J m^2}{2} + N \ln 2 + N \ln [\cosh(\beta q m + \kappa)],$$

Considering Intrinsic properties: $\frac{\ln Z}{N} \rightarrow \ln Z$.

$$[g_{ab}] = \begin{pmatrix} m^2 \operatorname{sech}^2(\beta q m + \kappa) & m \operatorname{sech}^2(\beta q m + \kappa) \\ m \operatorname{sech}^2(\beta q m + \kappa) & \operatorname{sech}^2(\beta q m + \kappa) \end{pmatrix}.$$

$$\Rightarrow \det[g] = 0 \Rightarrow \boxed{R = -\infty}.$$

- ② Subtle Discrepancies Between Mean Field Schemes.

Thank You For Your
KIND ATTENTION

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