

Free energy in non-convex mean-field spin glass models

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Rencontres de Probabilités 2024 in Rouen
27.09.2024

Outline

- The Sherrington—Kirkpatrick model
- Convex vs non-convex
- A PDE approach

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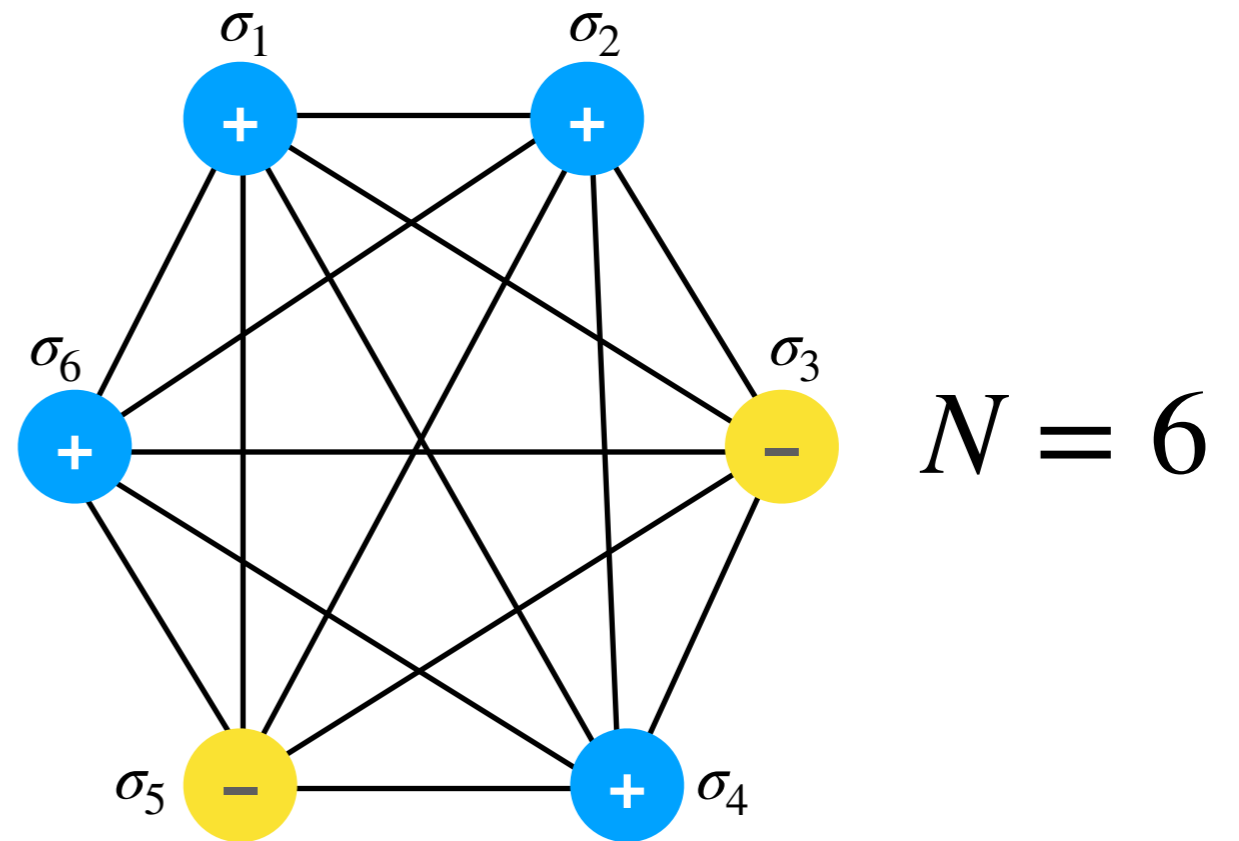
Spin configuration:

$\sigma = (\sigma_1, \sigma_2, \dots, \sigma_N) \in \{-1, +1\}^N$

Sherrington – Kirkpatrick model ('75)

$$N = 6$$

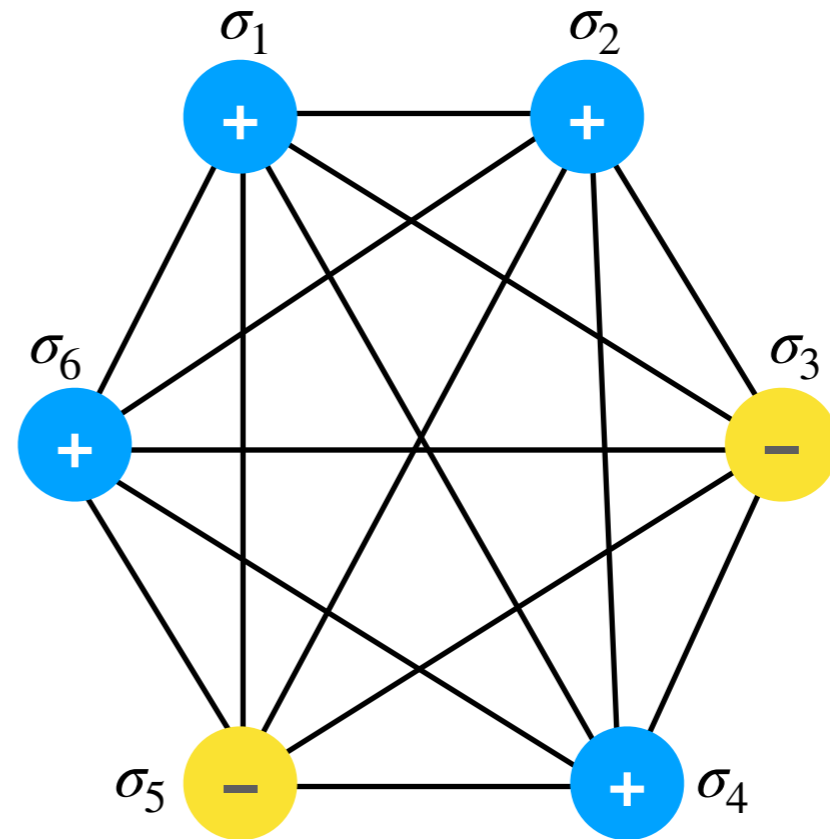
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Energy/Hamiltonian

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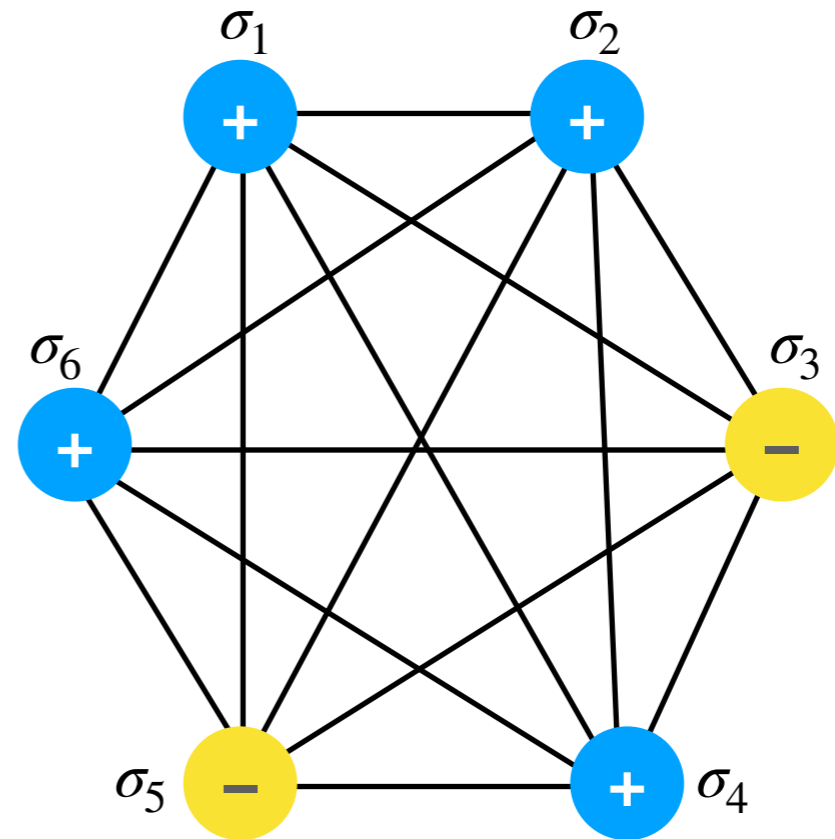


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Average (g_{ij})

Interested in $\lim_{N \rightarrow \infty} F_N(\beta)$

Solving the SK model

$$H_N(\sigma) = \frac{1}{\sqrt{N}} \sum_{i,j=1}^N g_{ij} \sigma_i \sigma_j$$

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Nobel 2021

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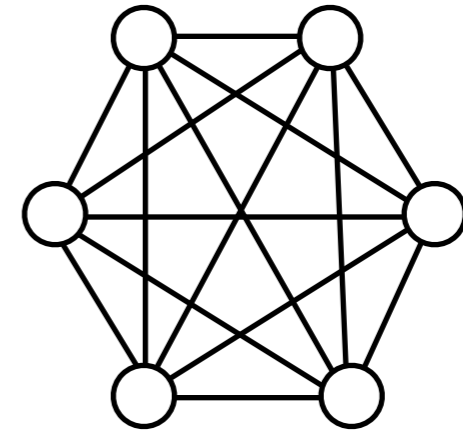
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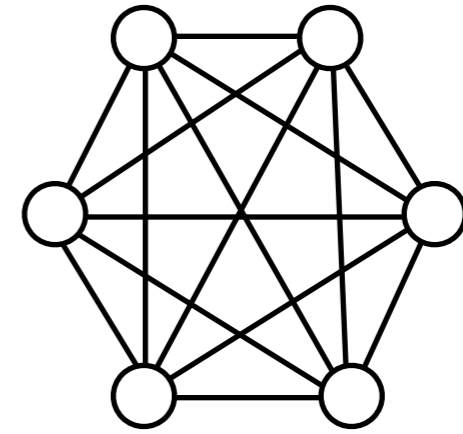
Panchenko ('13+) gave a more insightful proof

SK is convex

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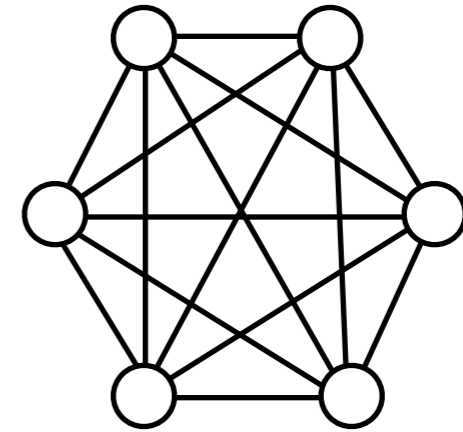
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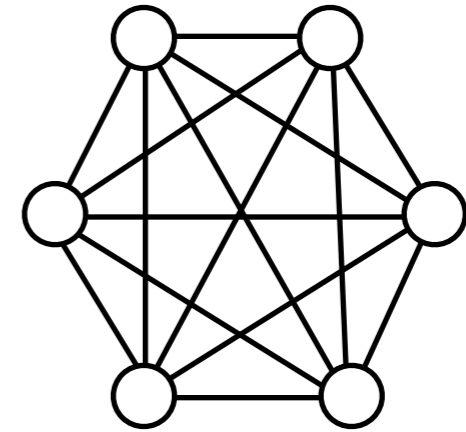


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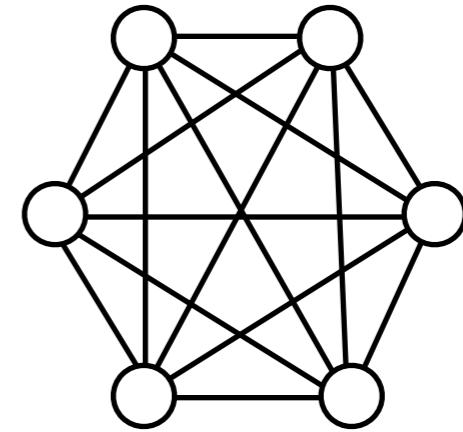
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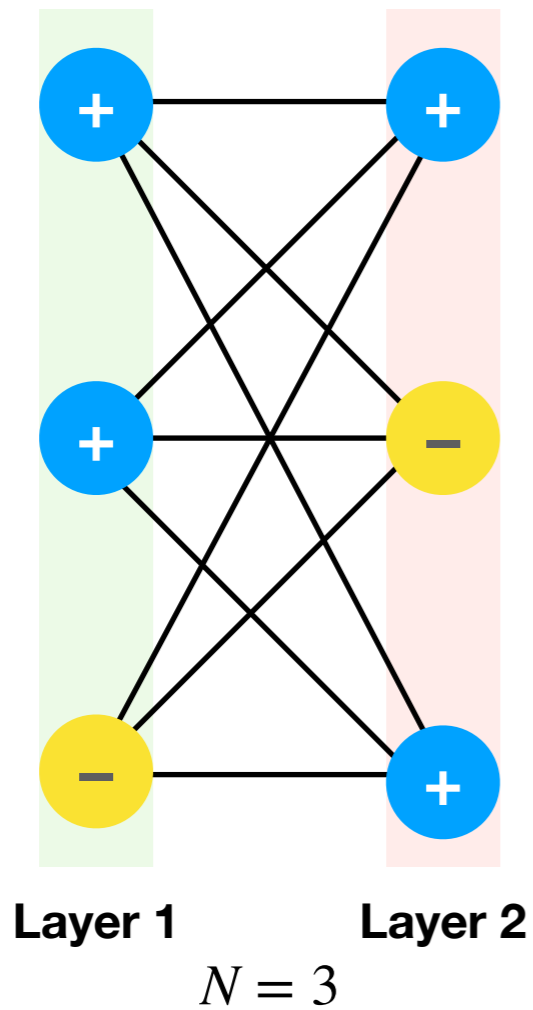
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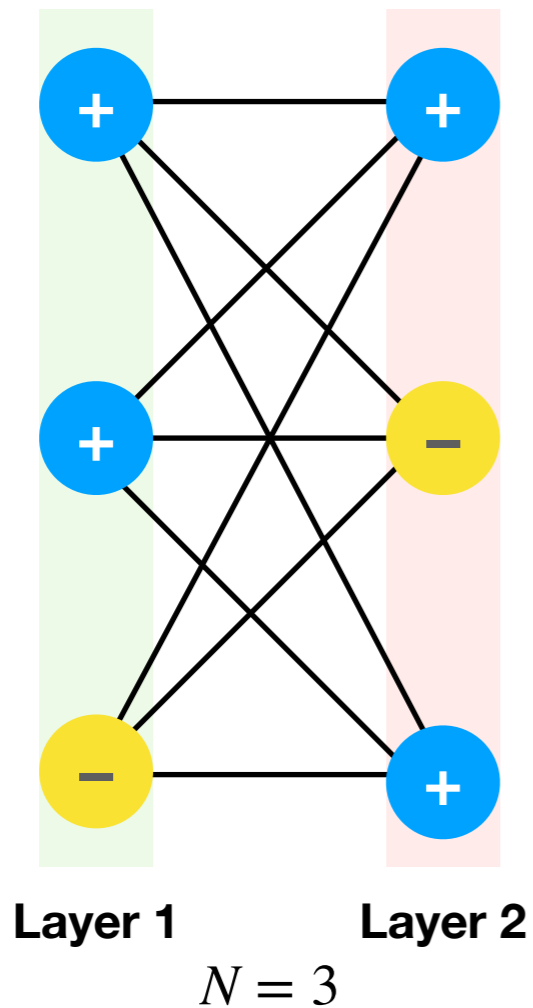


Overlap \sim # spins with the same sign

Nonconvex: bipartite model



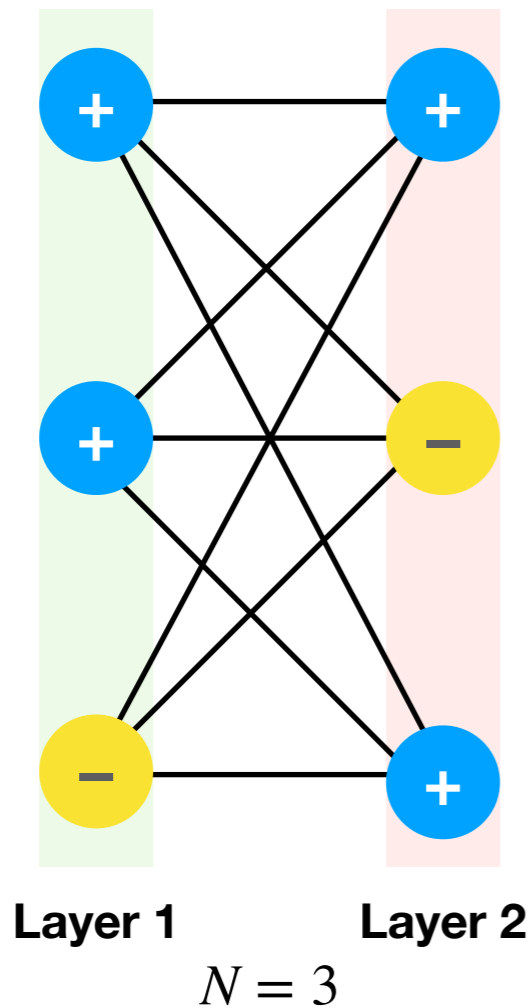
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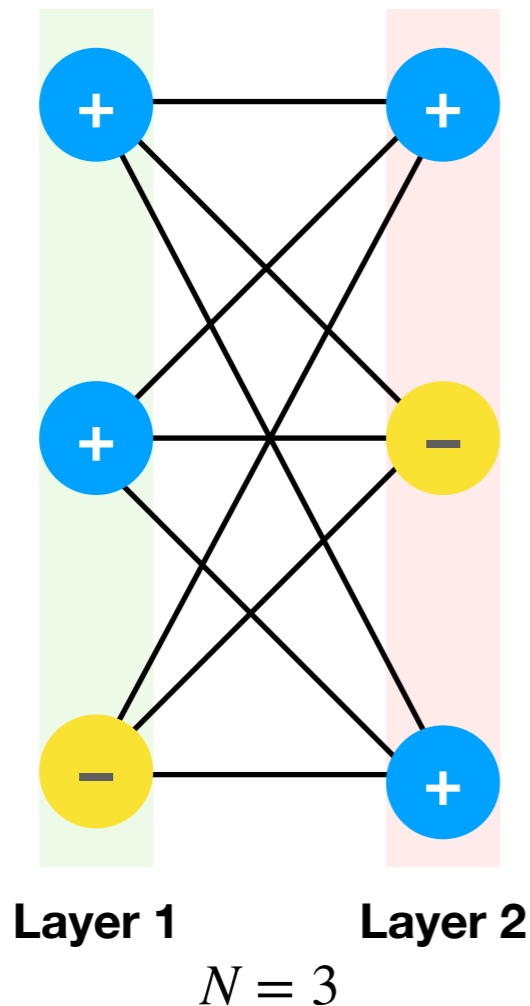
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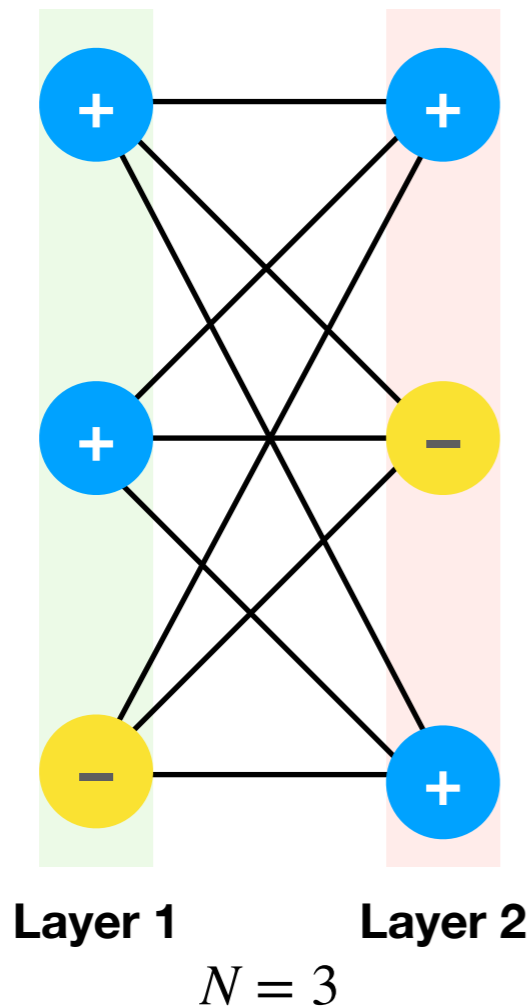
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Problem: theory based on Parisi formula is not available!

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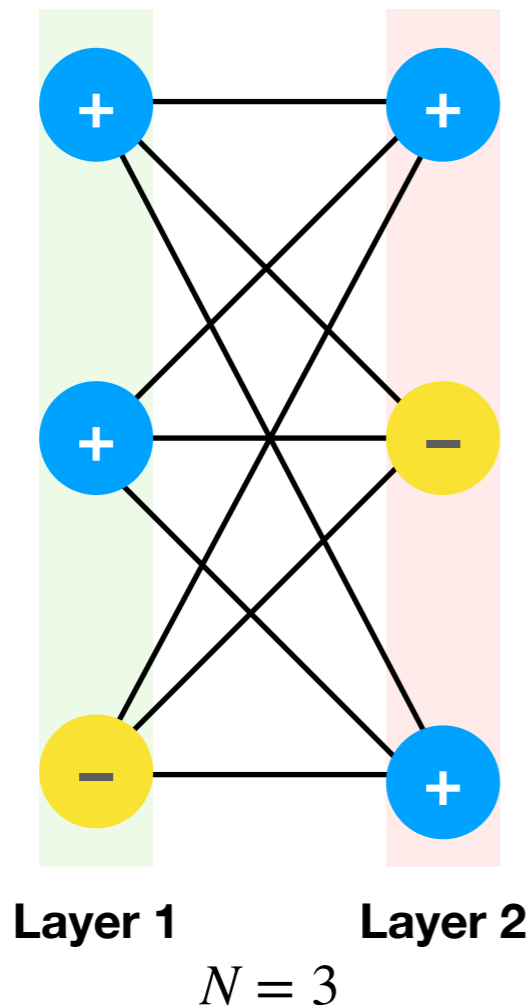
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Guerra $\lim F_N(\beta) \leq \inf \mathcal{P}_\beta(\mu)$ **Breaks down**

Talagrand/Panchenko $\lim F_N(\beta) \geq \inf \mathcal{P}_\beta(\mu)$ **Maybe not sharp**

General vector spin glass

$$\sigma = (\sigma_1, \sigma_2, \dots, \sigma_N) \in (\mathbb{R}^D)^N$$

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If ξ is convex, Parisi formula is correct 

If ξ is not convex, Parisi formula is not correct 
No prediction for the limit

A PDE perspective

Physics: Agliari, Barra, Burioni, Di Biasio, Guerra, Tantari... (2010s)

Math: Mourrat (2019+)

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$z = (z_1, \dots, z_N)$ independent Gaussians

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$$\langle g(\sigma) \rangle = \frac{1}{Z} \sum_{\sigma} g(\sigma) e^{\sqrt{2t}H_N(\sigma) + \sqrt{h}z \cdot \sigma}$$

Where $Z = \sum_{\sigma} e^{\sqrt{2t}H_N(\sigma) + \sqrt{h}z \cdot \sigma}$

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For SK, $\xi(o) = o^2$; r.h.s. is $-\text{Var}_{\mathbb{E}\langle \cdot \rangle}(\mathbf{O})$

A PDE perspective

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$$\partial_t f + \xi(-\partial_h f) = 0$$

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(Hamilton–Jacobi equation)

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Conjecture *In general case, even when ξ is non-convex,*

$$\lim_{N \rightarrow \infty} F_N = f$$

Digression to PDE


 External field $\sqrt{2\hbar z} \cdot \sigma$, for $h \geq 0$

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on an infinite dimensional cone (empty interior)

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on an infinite dimensional cone (empty interior)

Theorem [C. – Xia 20, 22a, 22b]

The Cauchy problem of (HJ) is well-posed: existence, uniqueness, and comparison principle.

Moreover, 1) natural finite-dimensional approximations exist; 2) variational formulas for solution exist when ξ is convex or $f(0, \cdot)$ is concave.

A PDE perspective

$$\partial_t f + \xi(-\partial_h f) = 0; \quad f(0, \cdot) = \lim F_N(0, \cdot)$$

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Theorem (convex) [Mourrat 22]

If ξ is convex, then $\lim_{N \rightarrow \infty} F_N = f$.

A PDE perspective

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Needs **Panchenko's** ultrametricity result.

Recall **Guerra's** upper bound fails when non-convex

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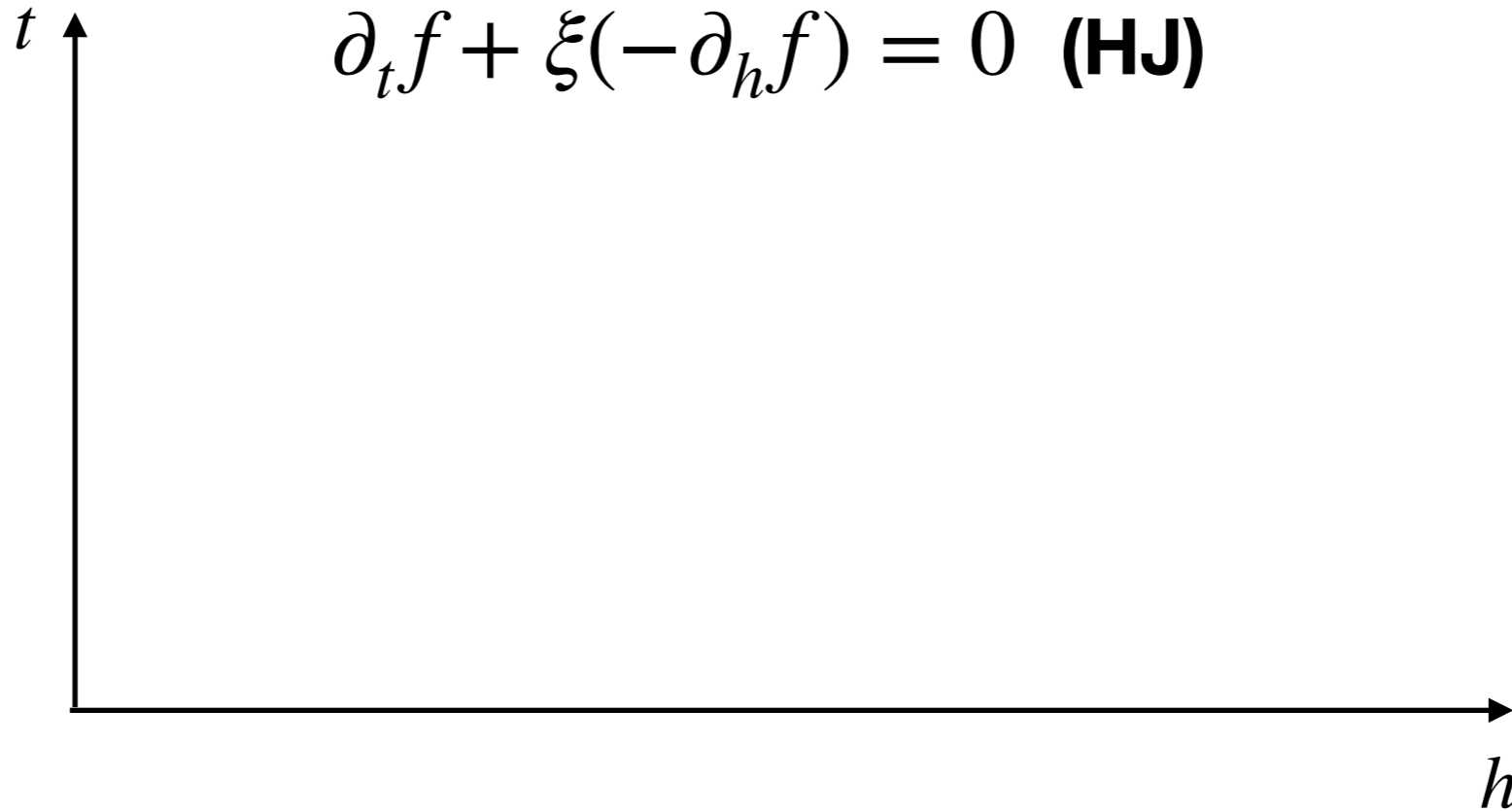
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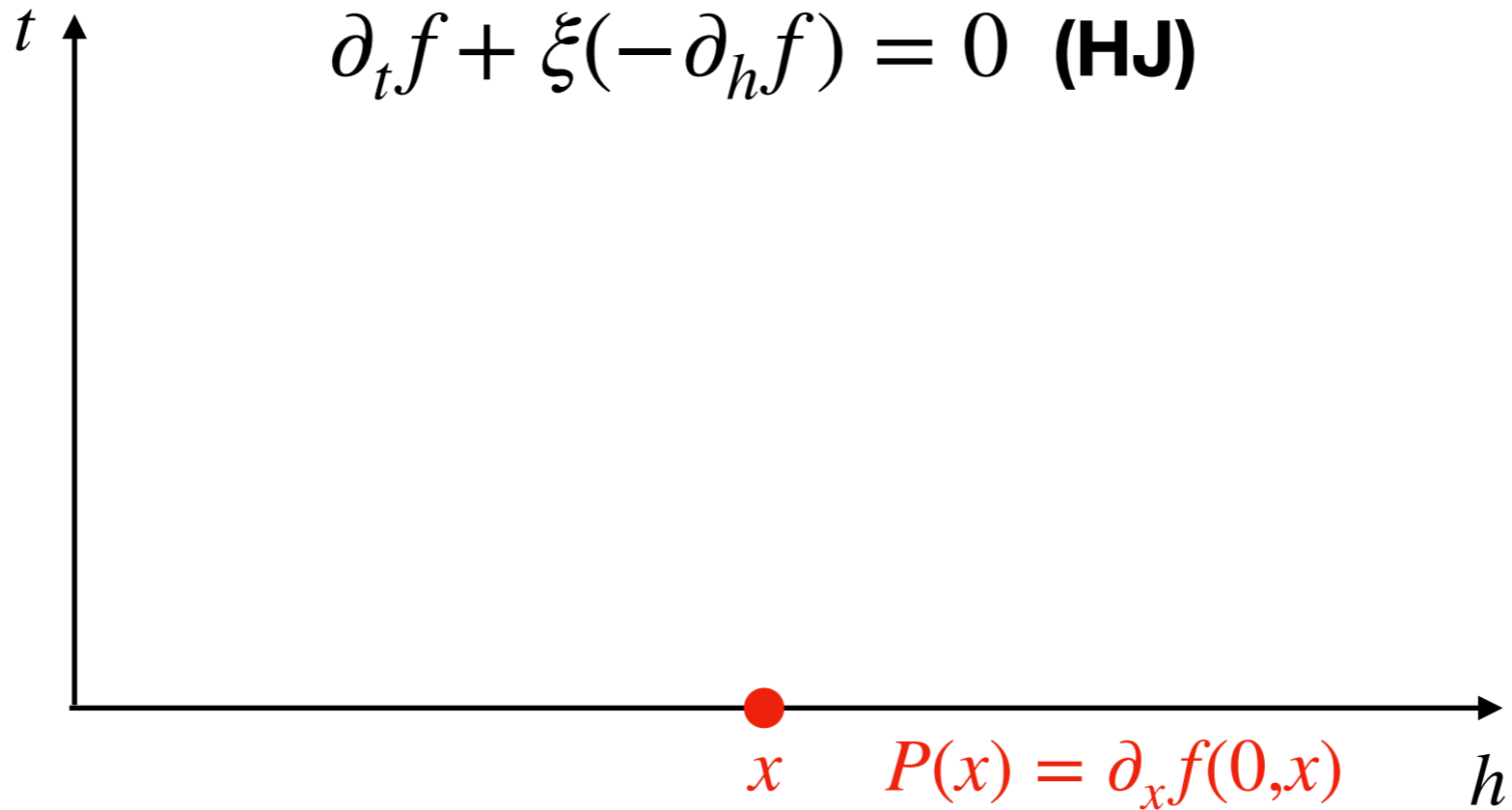
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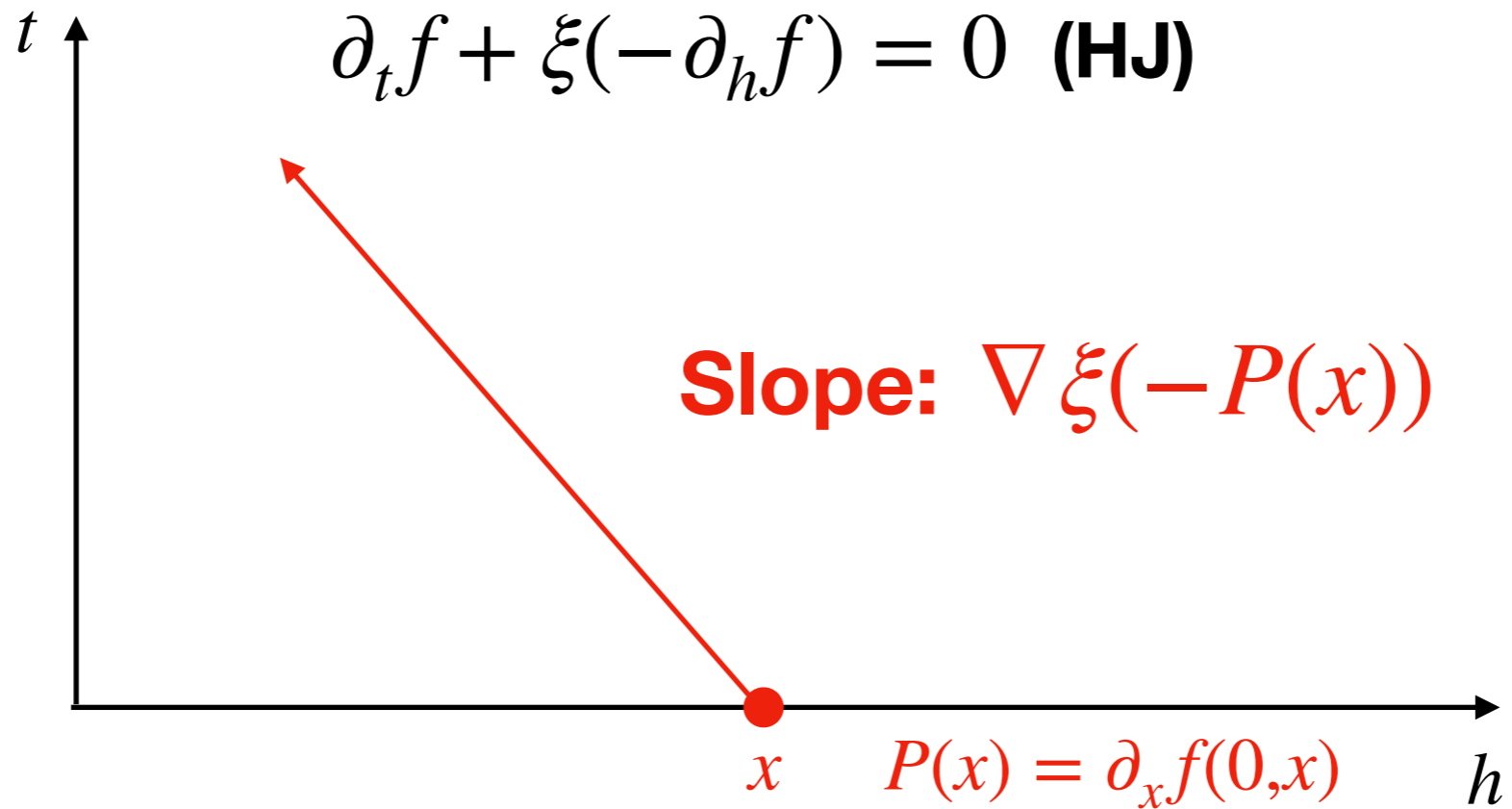
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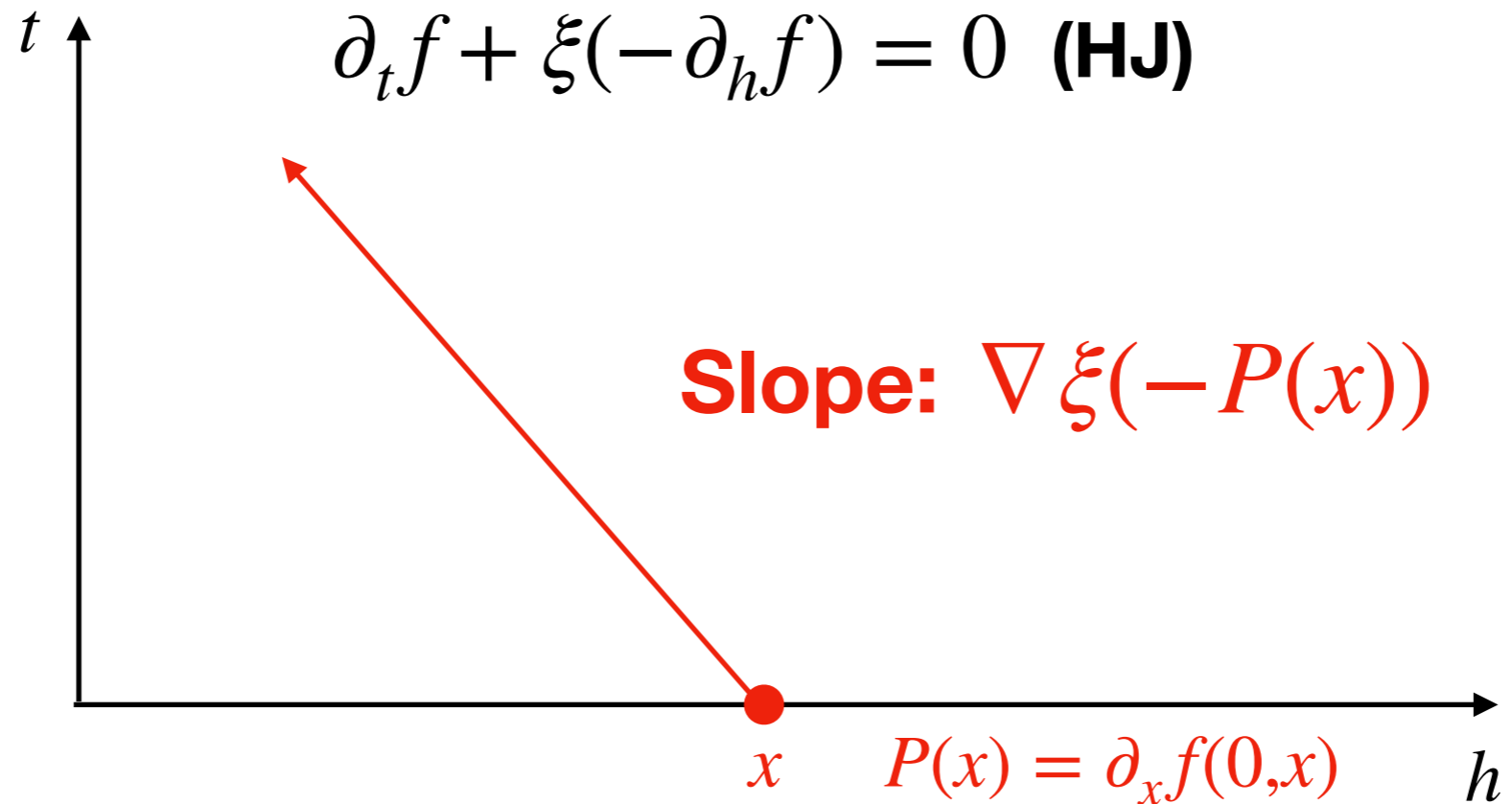


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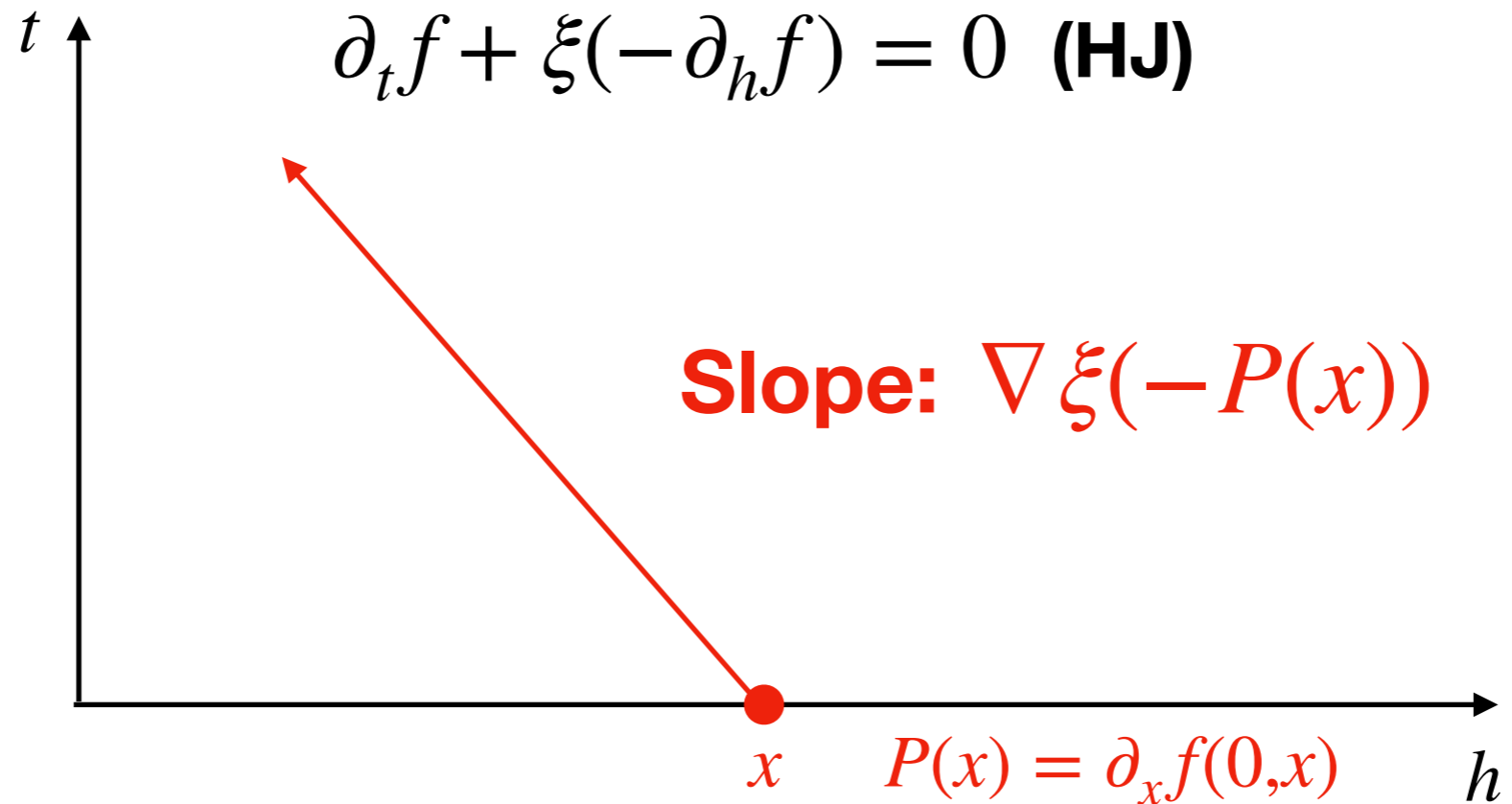


A PDE perspective



Characteristic line (starting at x): $X(s, x) = x + s \nabla \xi(-P(x)), \quad s \geq 0$

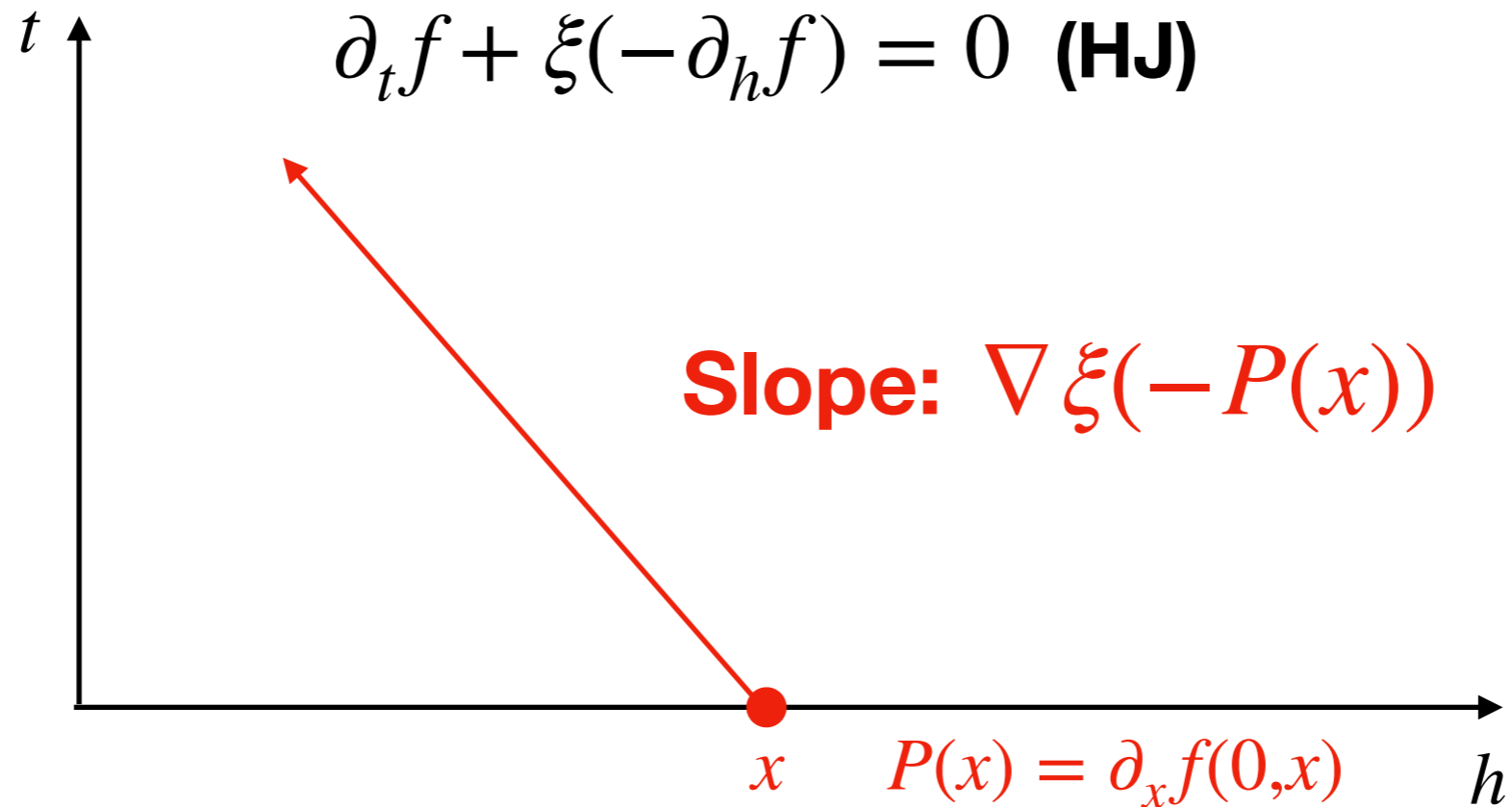
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If f is a “reasonable” solution of (HJ),

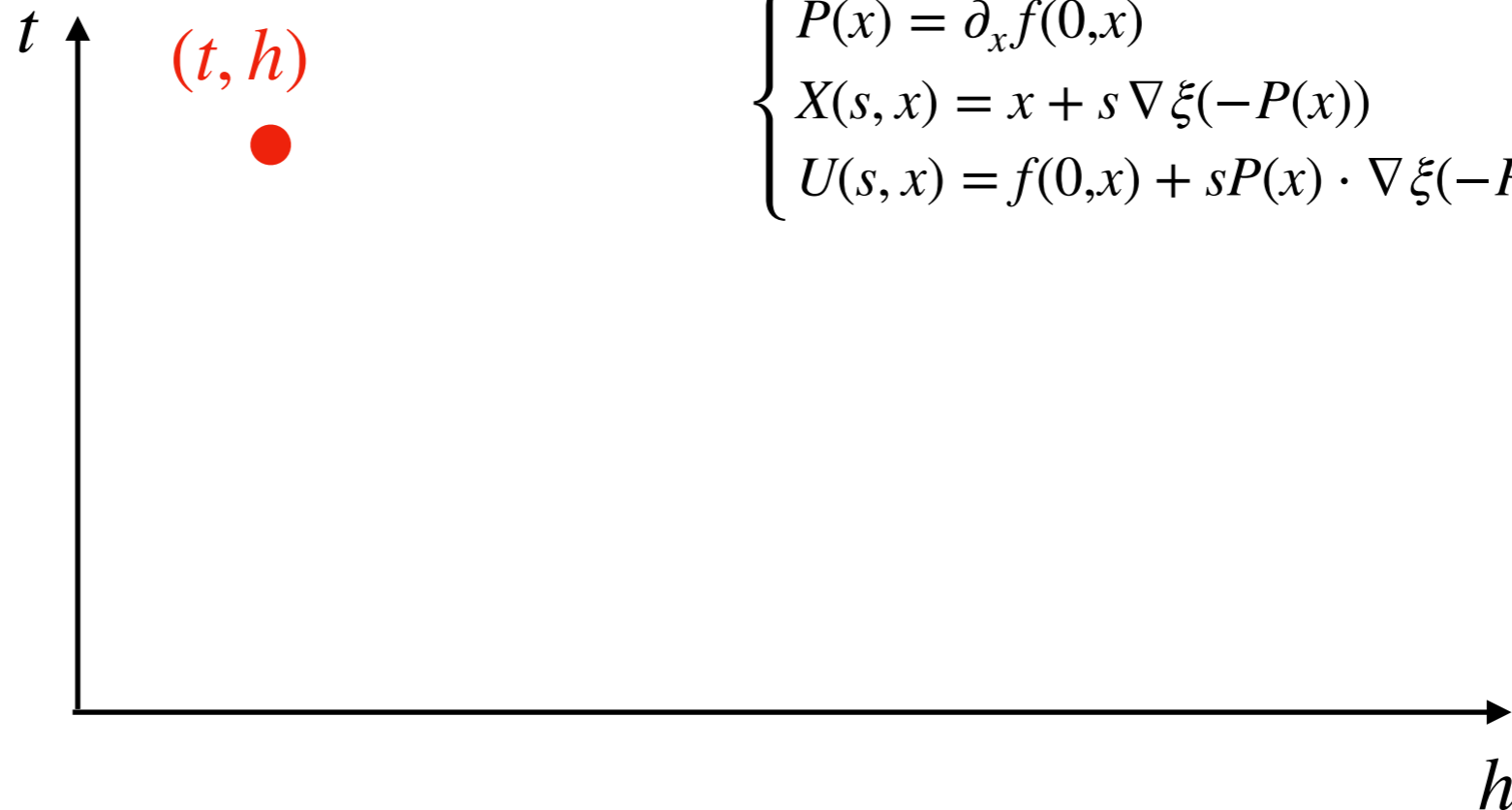
then $f \equiv U(\cdot, x)$ on $X(\cdot, x)$

before colliding with other char. lines.

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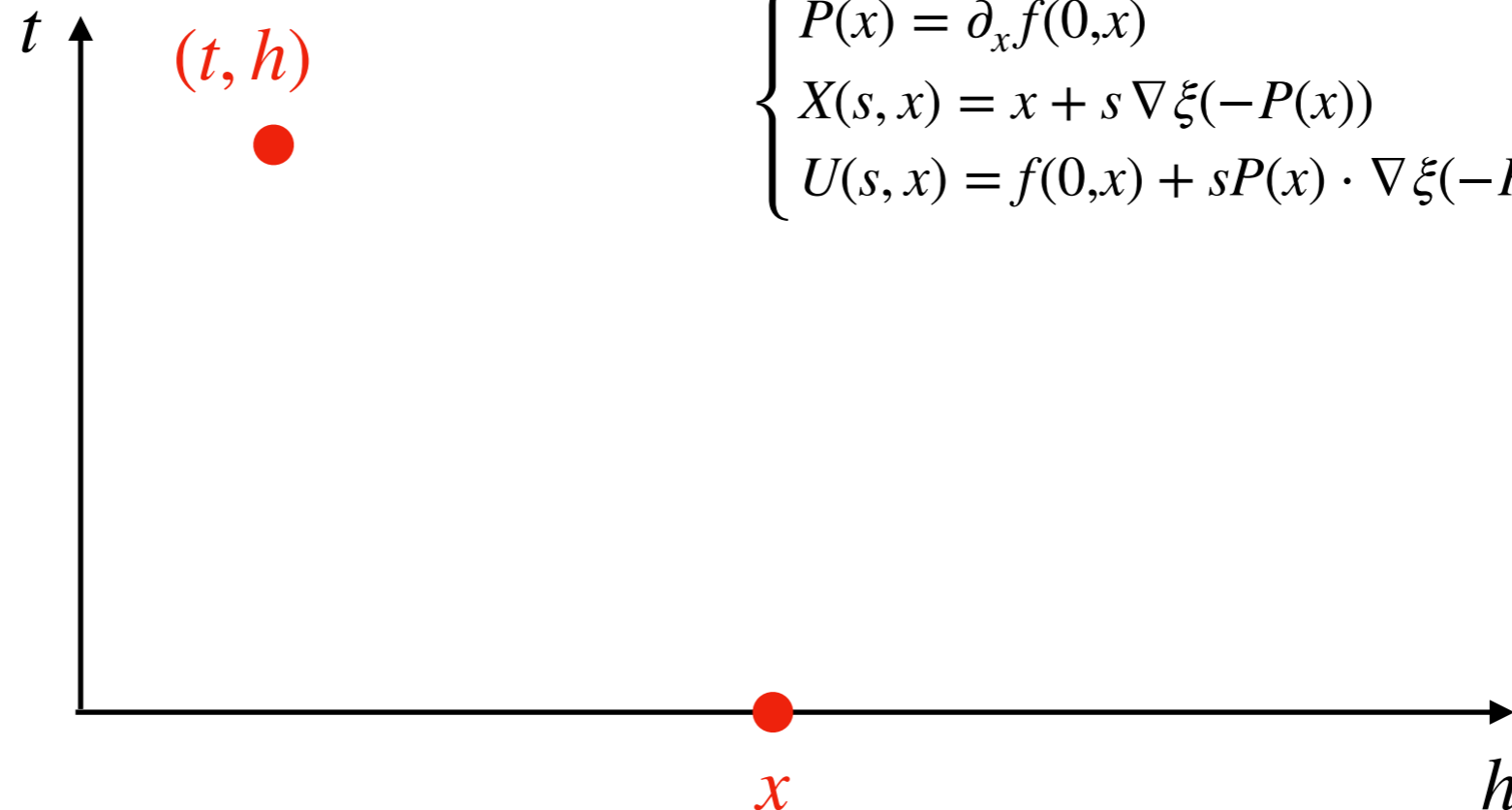


$$\begin{cases} P(x) = \partial_x f(0, x) \\ X(s, x) = x + s \nabla \xi(-P(x)) \\ U(s, x) = f(0, x) + s P(x) \cdot \nabla \xi(-P(x)) + s \xi(-P(x)) \end{cases}$$

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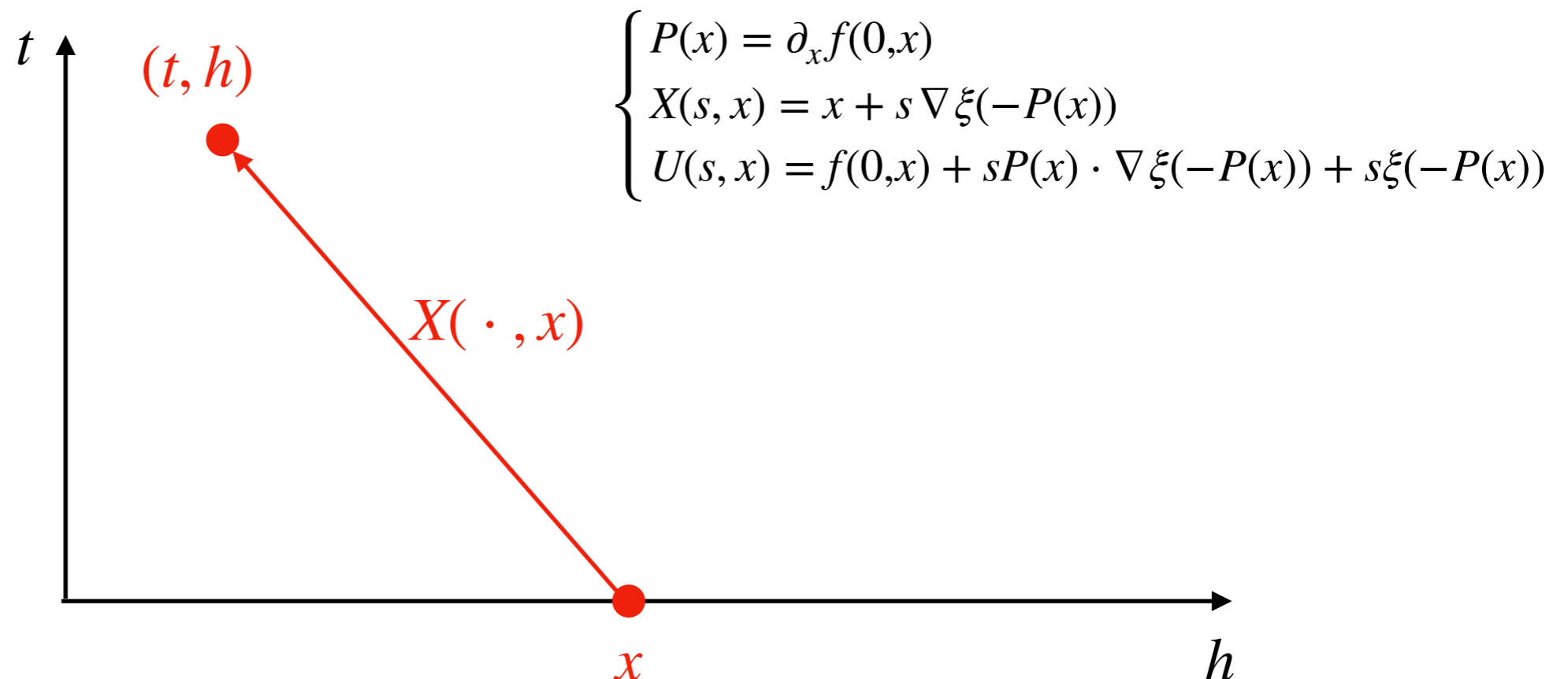
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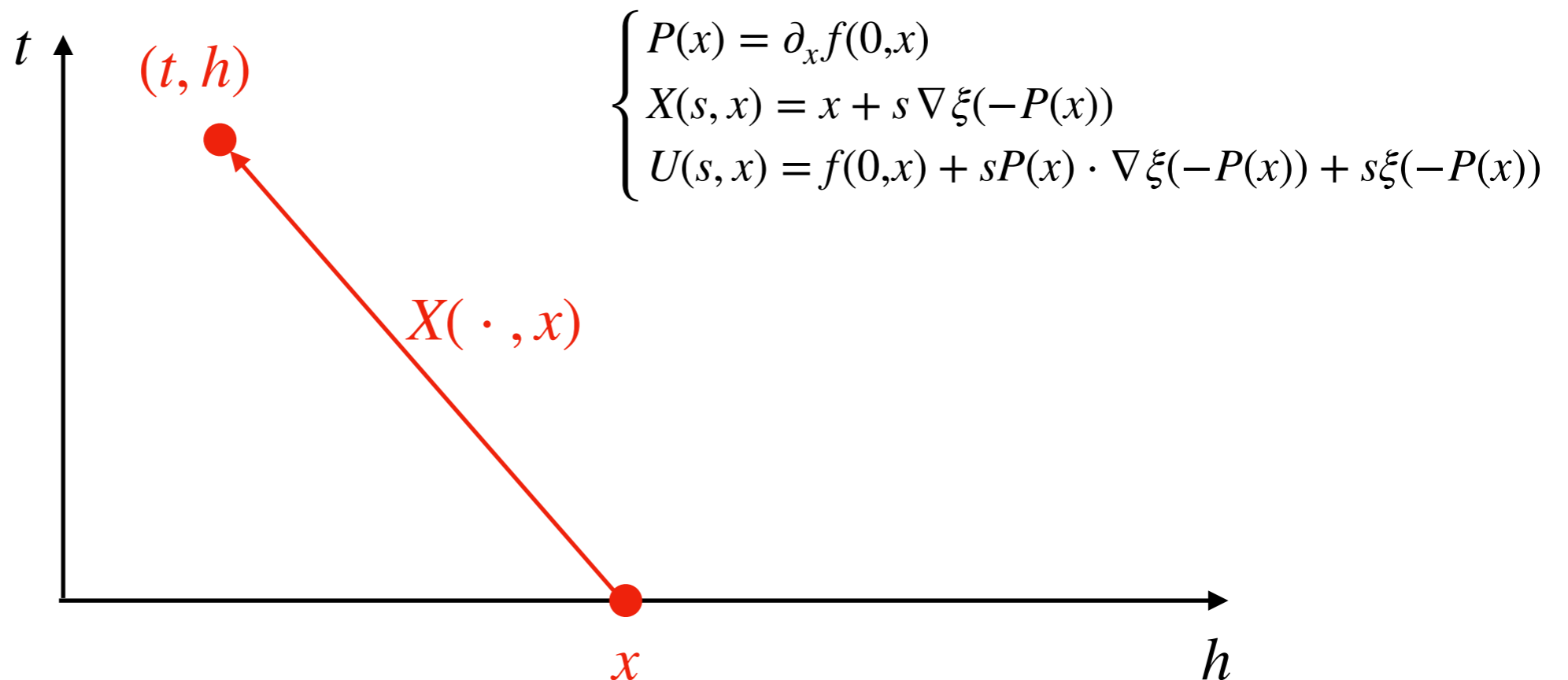


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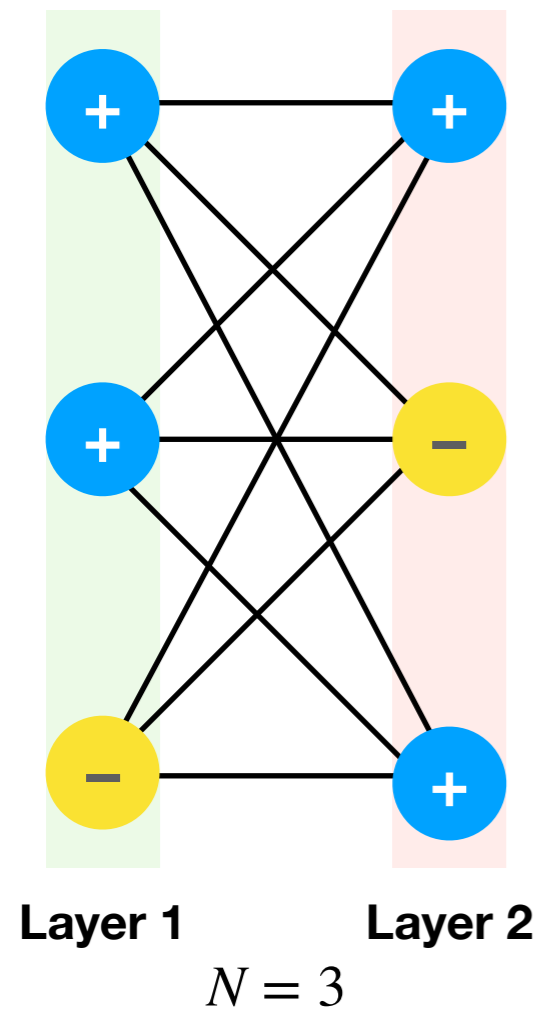
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f is determined by some char. **regardless of colliding**



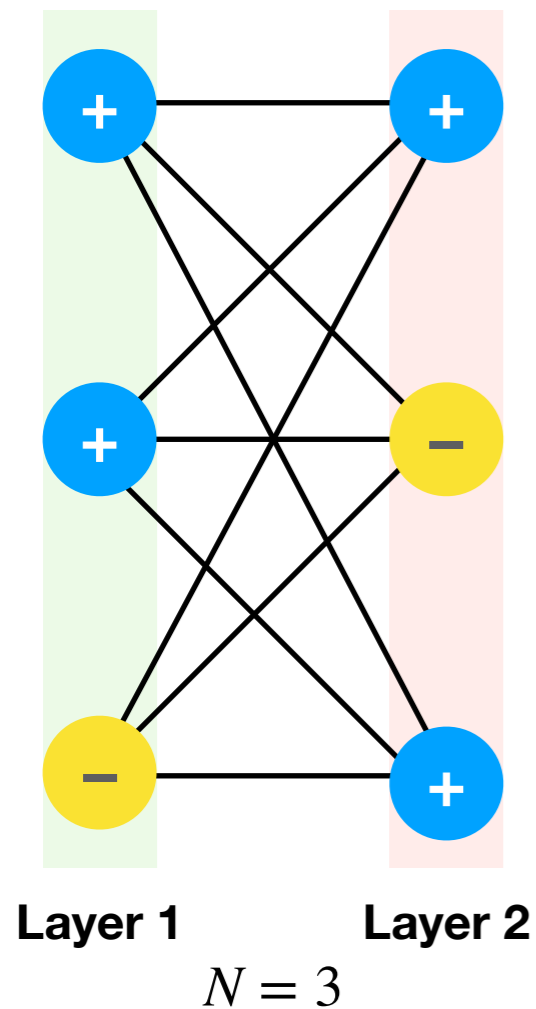
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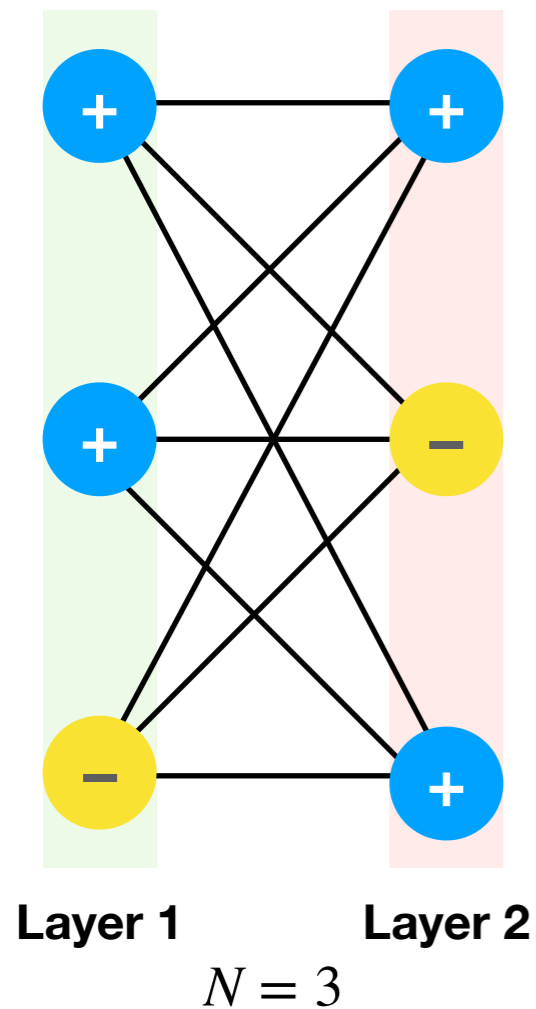


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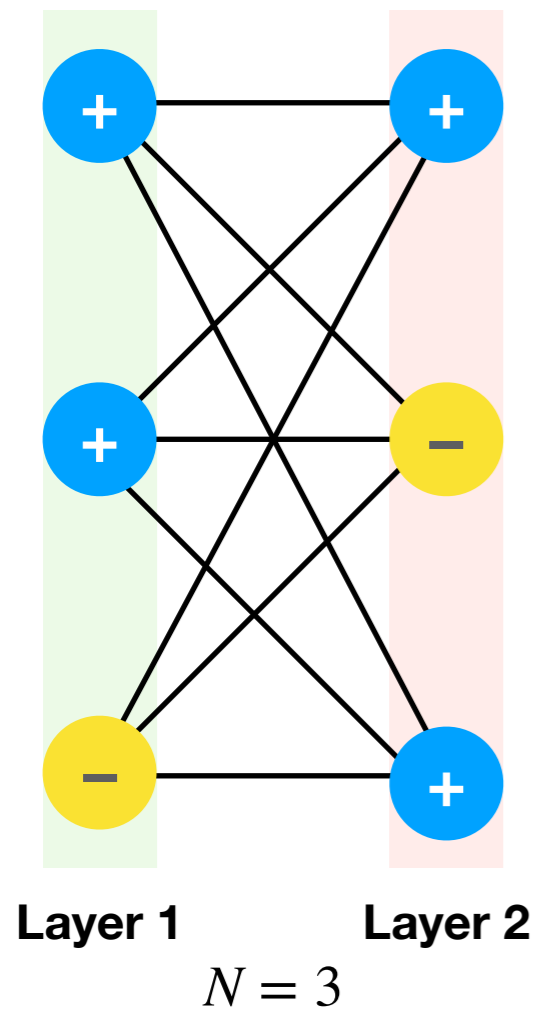
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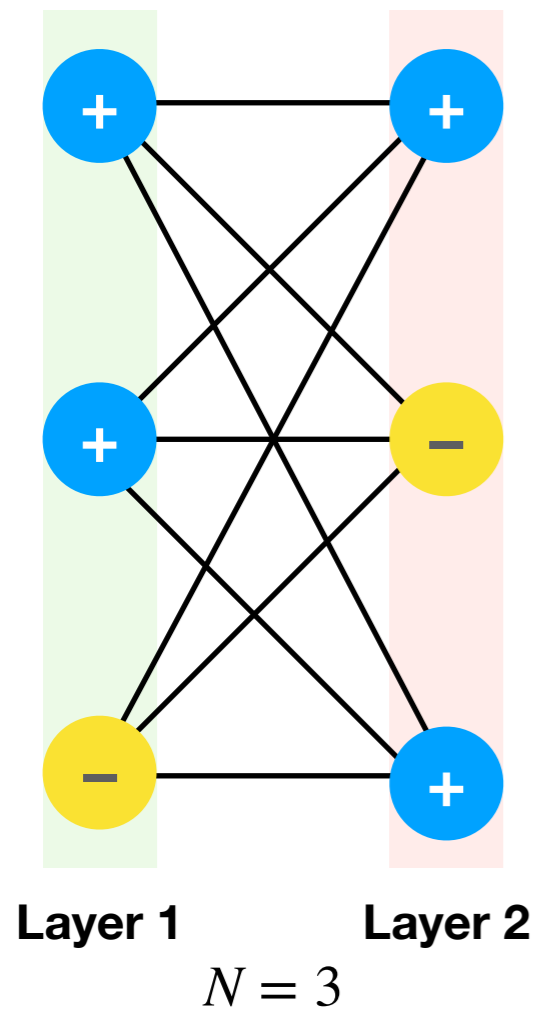
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Conjecture *In general case, even when ξ is non-convex, $\lim_{N \rightarrow \infty} F_N = f$*