

# Coherence and Regularity of Modelled Distributions

Higher structures emerging from renormalisation -  
ESI

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joint work with

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**Motivation:** Want a systematic understanding of how to glue together deterministic ODE/PDE arguments at larger time (and space) scales with local solution theory from Gubinelli's Branched Rough Paths/Hairer's Theory of Regularity Structures to get a priori bounds on solutions with the aim of getting global in time (and space) well-posedness.

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**Recent work:** Studying equations with strong damping terms and proving strong "coming down from infinity" type bounds:

The  $\Phi^4$  equation:

$$(\partial_t - \Delta)\varphi = -\varphi^3 + \xi ,$$

where formally  $\varphi : \mathbb{R}_+ \times \mathbb{R}^d \rightarrow \mathbb{R}$  and  $\xi$  is a rough random space-time process (like space-time white noise).

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Previous work on a priori bounds/global well-posedness:

For  $\Phi_3^4$ : [Mourrat, Weber], [Gubinelli, Hofmanová], [Albeverio, Kusuoka], [Moinat, Weber]

[C., Moinat, Weber] extends analysis to the entire subcritical/super-renormalizable regime.

Rough Differential Equations with strong damping:

$$\partial_t Y(t) = -|Y(t)|^{m-1} Y(t) dt + \sum_{\mu=1}^d \sigma_\mu(Y(t)) dX^\mu(t)$$

where  $m > 1$ ,  $Y : \mathbb{R}_+ \rightarrow \mathbb{R}^k$  and  $X = (X^\mu)_{\mu=1}^d : \mathbb{R}_+ \rightarrow \mathbb{R}^d$  is a rough ( $\alpha$ -Hölder, for  $\alpha > 0$  but arbitrarily small) driving noise, and  $\sigma_\mu : \mathbb{R}^k \rightarrow \mathbb{R}^k$  are relatively nice vector fields.

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Joint work in progress using approach from SPDE with Bonnefoi, Moinat, and Weber. Example of coming down from infinite bound: if  $\sigma_\mu$  has a certain class of derivatives bounded and if  $Y$  solves the above equation on  $[0, 1]$  then

$$\sup_{t \in (0,1]} |Y(t)| \lesssim \max \left\{ t^{-\frac{1}{m-1}}, \max_{h \in \dot{\mathcal{I}}} [\mathbf{X} : h]^{\frac{1}{m\alpha|h|}} \right\}$$

uniformly over the initial data  $Y(0)$ .

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- ▶ **Solution:** Can construct new spaces of function/distributions that admit good local approximations (non-classical Taylor Expansions) in terms of these iterated integrals - and the equation can be reformulated on this space in a way that makes it locally well-posed there.

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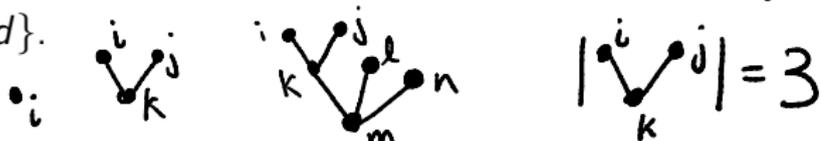
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- ▶ **Solution - Algebra/Combinatorics:** Can show that a solution to a Rough Differential Equation has additional relations between these generalised derivatives (*coherence* - [Bruned, Chevyrev, Prei, Friz], [Bruned, Chevyrev, C., Hairer] )

## Quick overview of branched Rough Paths

- Let  $N = \lfloor \frac{1}{\alpha} \rfloor$ , we define  $\mathcal{T}$  to consist of all rooted trees with no more than  $N$  nodes, each of which is decorated by the set  $\{1, \dots, d\}$ .



- Driving noise along with Iterated integrals encoded by map  $\mathbf{X}_{s,t} : \mathcal{T} \rightarrow \mathbb{R}$ ,  $\mathcal{T} \ni h \mapsto \langle \mathbf{X}_{s,t}, h \rangle$ .

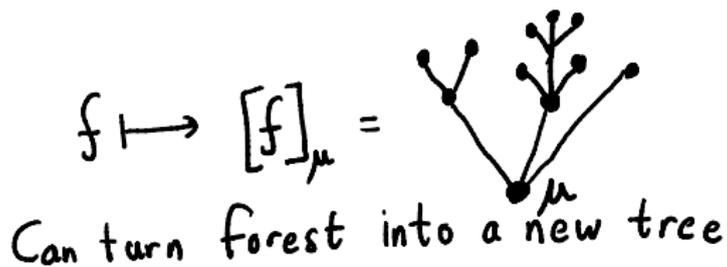
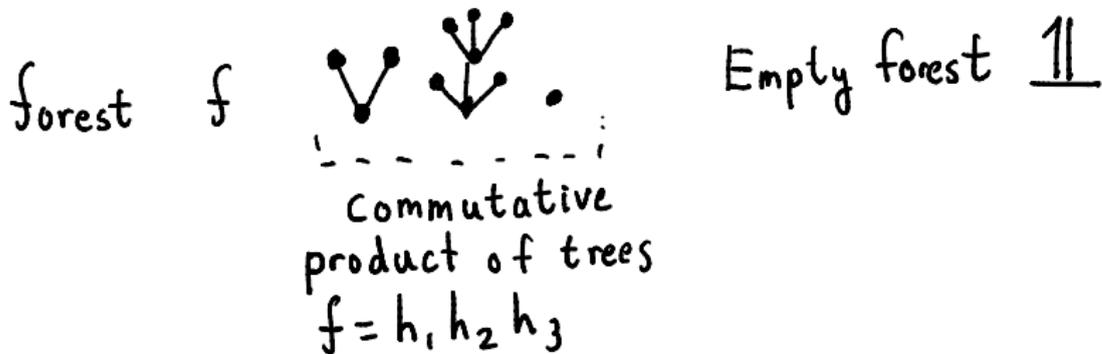
$$\langle \mathbf{X}_{s,t}, \bullet_i \rangle = \int_s^t dX^i(r) = X^i(t) - X^i(s)$$

$$\langle \mathbf{X}_{s,t}, \begin{array}{c} \bullet_i \\ | \\ \bullet_j \end{array} \rangle = \int_s^t \int_s^{r_1} dX^i(r_2) dX^j(r_1)$$

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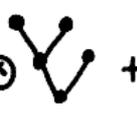
$$\langle \mathbf{X}_{s,t}, \begin{array}{c} \bullet_i \quad \bullet_i \\ / \quad \backslash \\ \bullet_j \end{array} \rangle = \int_s^t \left( \int_s^{r_1} dX^i(r_2) \right)^2 dX^j(r_1)$$

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- ▶  $\Delta : \text{Span}(\mathcal{F}) \rightarrow \text{Span}(\mathcal{F}) \otimes \text{Span}(\mathcal{F})$  is the Grassman-Larson co-product

$\Delta$   =  $\mathbb{1} \otimes$   +   $\otimes \mathbb{1}$  +   $\otimes$  

+ ...  $\otimes$  

+ ...

*Sum over admissible cuts*


$$\Delta(h_1, h_2, \dots, h_n) = (\Delta h_1) (\Delta h_2) \cdots (\Delta h_n)$$

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- ▶  $\Delta : \text{Span}(\mathcal{F}) \rightarrow \text{Span}(\mathcal{F}) \otimes \text{Span}(\mathcal{F})$  is the Grassman-Larson co-product
- ▶ We call  $\mathbf{X}$  a branched rough path if for all  $h \in \mathring{\mathcal{T}}$ ,

$$[\mathbf{X}, h] \stackrel{\text{def}}{=} \sup_{0 < |s-t| < 1} \left| \frac{\langle \mathbf{X}_{s,t}, h \rangle}{|s-t|^{\alpha|h|}} \right| < \infty$$

and  $\langle \mathbf{X}_{s,u} \otimes \mathbf{X}_{u,t}, \Delta h \rangle = \langle \mathbf{X}_{s,t}, h \rangle$

Our solution is a Controlled Rough Path:  $\mathbf{Y} : [0, 1] \rightarrow \text{Span}(\mathcal{T})$ ,  
that is a family of local expansions

$$\mathbf{Y}_s = \sum_{h \in \mathcal{T}} \langle h, \mathbf{Y}_s \rangle h = Y_s \mathbb{1} + \sum_{h \in \dot{\mathcal{T}}} \langle h, \mathbf{Y}_s \rangle h.$$

↙ "generalised  
h-derivative  
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└──────────────────┘  
Encodes Taylor expansion of Y

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with the following regularity property,

*Taylor expansion of  $\langle h, \mathbf{Y}_s \rangle$  evaluated at  $t$*

$$R_{s,t}^h = \langle h, \mathbf{Y}_t \rangle - \langle \mathbf{X}_{s,t} \otimes h, \Delta \mathbf{Y}_s \rangle, \text{ want } |R_{s,t}^h| \lesssim |s - t|^{(N-|h|)\alpha}$$

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Space of controlled rough paths is a vector space where we can solve the equation as a fixed point problem, but in this space there are no clear relations between  $R_{s,t}^h$  for different  $h$ .

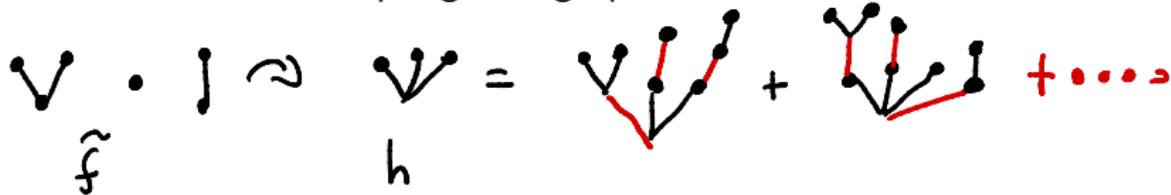
Can show that solutions to equation solve the non-linear coherence constraint  $\langle h, \mathbf{Y}_t \rangle = \Upsilon[h](Y_s)$  for some functions  $\Upsilon[h](\cdot)$  built inductively in  $h$  - if  $h = [h_1 \cdots h_n]_\mu$  then

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**Thanks for listening!**