

# Time fractional gradient flows: Theory and numerics

Abner J. Salgado

Department of Mathematics, University of Tennessee

BIRS Workshop 22w5043  
Inverse Problems for Anomalous Diffusion Processes  
February 21 — 25, 2022

Joint work with Wenbo Li (UTK)

Partially supported by NSF grants DMS-1720213 and DMS-2111228



# Outline

Introduction

Classical gradient flows: theory

Fractional gradient flows: theory

Classical gradient flows: numerics

Fractional gradient flows: numerics

Numerical illustrations

Conclusions and future work

# Outline

## Introduction

Classical gradient flows: theory

Fractional gradient flows: theory

Classical gradient flows: numerics

Fractional gradient flows: numerics

Numerical illustrations

Conclusions and future work

# Motivation

- Fractional derivatives and integrals are powerful tools to describe memory and hereditary properties of materials.
- Fractional partial differential equations (FPDEs) are emerging as a new powerful tool for modeling many difficult complex systems, i.e., systems with overlapping microscopic and macroscopic scales or systems with long-range time memory and long-range spatial interactions.
- In “classical” diffusion

$$\partial_t u - \Delta u = 0$$

the mean squared displacement in time scales as  $t \sim \langle x^2(t) \rangle$ .

- In the **superdiffusive** case  $t^\alpha \sim \langle x^2(t) \rangle$  with  $\alpha > 1$ .
- In the **subdiffusive** case  $\alpha \in (0, 1)$ , thus giving rise to

$$D_t^\alpha u - \Delta u = 0,$$

where  $D_t^\alpha$  is the so-called Caputo derivative.

- This is usually used to model **memory effects**.

## (Fractional) heat equation

- The (time fractional) heat equation

$$D_t^\alpha u - \Delta u = f.$$

- Define the energy

$$\Phi_2(w) = \frac{1}{2} \int_{\Omega} |\nabla w|^2 dx,$$

its derivative (in the  $L^2$ -sense) is

$$\langle D\Phi_2(w), \varphi \rangle = \int_{\Omega} \nabla w \nabla \varphi dx = \langle -\Delta w, \varphi \rangle.$$

- The (time fractional) heat equation can be understood as

$$D_t^\alpha u + D\Phi_2(u) = f.$$

# (Fractional) parabolic $p$ -Laplace problem

- More generally, for  $p > 1$ , consider

$$D_t^\alpha u - \nabla \cdot (|\nabla u|^{p-2} \nabla u) = f.$$

- Define

$$\Phi_p(w) = \frac{1}{p} \int_{\Omega} |\nabla w|^p dx,$$

then

$$\langle D\Phi_p(w), \varphi \rangle = \int_{\Omega} |\nabla w|^{p-2} \nabla w \nabla \varphi dx.$$

- Our problem reads

$$D_t^\alpha u + D\Phi_p(u) = f.$$

# (Fractional) ODE with obstacles I



- Consider the motion of a particle inside a well. If the particle does not touch the walls then it moves by “its usual” law of motion:

$$u(t) \in (-1, 1) \implies D_t^\alpha u(t) = f(t).$$

- If it touches one of the walls it gets reflected. Say it touches the **right one**. If

$$D_t^\alpha u \leq 0$$

the wall does not do anything, as the particle will move to the left anyways. If that is not the case, since right before it touches we had

$$D_t^\alpha u = f = f^+ - f^-$$

the reflection means

$$D_t^\alpha u = -f^-.$$

# (Fractional) ODE with obstacles II



- In short

$$\begin{cases} D_t^\alpha u(t) = -f^-(t), & u(t) = 1, \\ D_t^\alpha u(t) = f(t), & u(t) \in (-1, 1), \\ D_t^\alpha u(t) = f^+(t), & u(t) = -1. \end{cases}$$

► Subdifferential



# (Fractional) parabolic obstacle problems

- Define

$$\mathcal{K} = \{w \in \tilde{H}^s(\Omega) : w \geq g \text{ a.e. } \Omega\},$$

for some sufficiently nice  $g$ .

- Consider the problem given by the complementarity conditions

$$D_t^\alpha u + (-\Delta)^s u \geq f, \quad u \geq g, \quad (D_t^\alpha u + (-\Delta)^s u - f)(u - g) = 0.$$

- This is equivalent to the **evolution variational inequality**

$$\int_{\Omega} D_t^\alpha u(u - w) \, dx + \langle (-\Delta)^s u, u - w \rangle \leq \int_{\Omega} f(u - w) \, dx, \quad \forall w \in \mathcal{K}.$$

► Subdifferential

## Problem statement

- Ambient space: Let  $\mathcal{H}$  be a (separable) Hilbert space.
- Energy:  $\Phi : \mathcal{H} \rightarrow \mathbb{R} \cup \{+\infty\}$  convex and l.s.c.
- Initial condition:  $u_0 \in \mathcal{H}$ .
- Right hand side:  $f : [0, T] \rightarrow \mathcal{H}$ .

We need to find  $u : [0, T] \rightarrow \mathcal{H}$  such that

$$\begin{cases} D_t^\alpha u(t) + \partial\Phi(u(t)) \ni f(t), & t \in (0, T], \\ u(0) = u_0. \end{cases}$$

- Here  $D_t^\alpha$  denotes the Caputo derivative, and  $\partial\Phi(w)$  is the subdifferential of  $\Phi$  at point  $w$ .
- $D_t^\alpha = \partial_t$  for  $\alpha = 1$  and we get a **classical** gradient flow.
- If  $f = 0$  this can be understood as **steepest descent** to find the minimum of  $\Phi$ .

# Outline

Introduction

Classical gradient flows: theory

Fractional gradient flows: theory

Classical gradient flows: numerics

Fractional gradient flows: numerics

Numerical illustrations

Conclusions and future work

# Energy solutions

$$\xi \in \partial\Phi(u) \iff \Phi(u) - \Phi(w) \leq \langle \xi, u - w \rangle$$

- Let us consider the classical case. We set  $\alpha = 1$  to get

$$\begin{cases} u'(t) + \partial\Phi(u(t)) \ni f(t), & t \in (0, T], \\ u(0) = u_0. \end{cases}$$

## Definition (energy solution)

A function  $u \in H^1(0, T; \mathcal{H})$  is an **energy solution** if  $u(0) = u_0$  and

$$\langle u'(t), u(t) - w \rangle + \Phi(u(t)) - \Phi(w) \leq \langle f(t), u(t) - w \rangle, \quad \forall w \in \mathcal{H}.$$

# Energy solutions: uniqueness

## Theorem (uniqueness )

*Energy solutions are unique.*

### Proof.

If  $u_1$  and  $u_2$  are energy solutions,

$$\langle u_1'(t), u_1(t) - w \rangle + \Phi(u_1(t)) - \Phi(w) \leq \langle f(t), u_1(t) - w \rangle, \quad w \leftarrow u_2,$$

$$\langle u_2'(t), u_2(t) - w \rangle + \Phi(u_2(t)) - \Phi(w) \leq \langle f(t), u_2(t) - w \rangle, \quad w \leftarrow u_1,$$

adding, we get

$$\frac{1}{2} \frac{d}{dt} \|u_1(t) - u_2(t)\|^2 \leq 0.$$

Since  $u_1(0) = u_2(0) = u_0$  we conclude. □

# Energy solutions: existence I

- To show existence of solutions we employ a **minimizing movements scheme**.
- Introduce a partition

$$\mathcal{P} = \{0 = t_0 < t_1 < \dots < t_N = T\}, \quad \tau_n = t_n - t_{n-1}, \quad \tau = \max_{n=1}^N \tau_n.$$

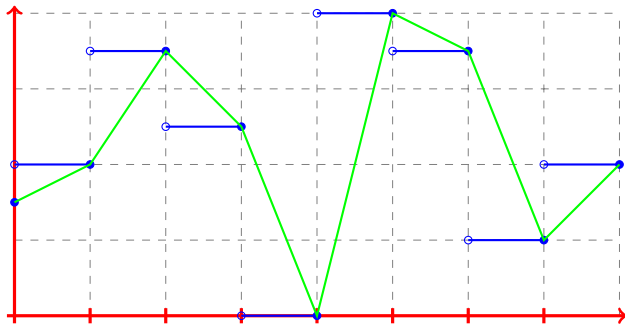
- We introduce approximations  $U_n \approx u(t_n)$  via: set  $F_n = \int_{t_{n-1}}^{t_n} f \, dt$ ,  $U_0 = u_0$  and define

$$U_n = \operatorname{argmin}_{w \in \mathcal{H}} \left[ \frac{1}{2\tau_n} \|w - U_{n-1}\|^2 + \Phi(w) - \langle F_n, w \rangle \right].$$

- Since we are in a Hilbert space this problem has a unique solution.
- The minimization problem is equivalent to (implicit Euler)

$$\frac{1}{\tau_n} (U_n - U_{n-1}) + \partial\Phi(U_n) \ni F_n$$

## Energy solutions: existence II



- The function  $\bar{U}$  is piecewise constant

$$\bar{U}(t) = U_n, \quad t \in (t_{n-1}, t_n].$$

- The function  $\hat{U}$  is piecewise linear

$$\hat{U}(t) = \frac{t_n - t}{\tau_n} U_{n-1} + \frac{t - t_{n-1}}{\tau_n} U_n, \quad t \in (t_{n-1}, t_n].$$

and its time derivative satisfies

$$\hat{U}'(t) = \tau_n^{-1} (U_n - U_{n-1}).$$

## Energy solutions: existence III

- The minimizing movements scheme can then be written as

$$\langle \widehat{U}'(t), \bar{U}(t) - w \rangle + \Phi(\bar{U}(t)) - \Phi(w) \leq \langle \bar{F}(t), \bar{U}(t) - w \rangle, \quad \forall w \in \mathcal{H}.$$

- Setting  $w = U_{n-1}$  we get

$$\tau_n \|\widehat{U}'\|^2 + \Phi(U_n) - \Phi(U_{n-1}) \leq \tau_n \|F_n\| \|\widehat{U}'\|,$$

which, provided  $f \in L^2(0, T; \mathcal{H})$  and  $\Phi(U_0) < +\infty$ , gives

$$\widehat{U}' \in L^2(0, T; \mathcal{H})$$

uniformly in  $\mathcal{P}$ .

- The previous estimate “is enough” to pass to the limit  $\tau \rightarrow 0$  by compactness.

### Theorem (existence )

*If  $f \in L^2(0, T; \mathcal{H})$  and  $\Phi(u_0) < \infty$  the classical gradient flow has an energy solution.*



# Classical gradient flows: the heart of the matter

To develop this theory we required:

- **Uniqueness:** The inequality

$$\frac{1}{2} \frac{d}{dt} \|u_1 - u_2\|^2 \leq \langle (u_1 - u_2)', u_1 - u_2 \rangle.$$

- **Existence:** A minimizing movements scheme to obtain  $\{U_n\}_{n=0}^N$ .
- **Existence:** A suitable interpolation  $\widehat{U}$  such that its derivative  $\widehat{U}'$  is piecewise constant.

# Outline

Introduction

Classical gradient flows: theory

**Fractional gradient flows: theory**

Classical gradient flows: numerics

Fractional gradient flows: numerics

Numerical illustrations

Conclusions and future work

# The Caputo derivative

- For sufficiently smooth functions

$$D_t^\alpha w(t) = I^{1-\alpha}[w'](t) = \frac{1}{\Gamma(1-\alpha)} \int_0^t (t-s)^{-\alpha} w'(s) ds.$$

- **Question:** Can we define the Caputo derivative for rougher functions?
- **Yes!** There are several approaches<sup>[5]</sup>. We define it as follows<sup>[5]</sup>:

$$\begin{aligned} D_t^\alpha w(t) &= \frac{d}{dt} I^{1-\alpha}[w(t) - w(0)\theta(t)] \\ &= \frac{1}{\Gamma(1-\alpha)} \frac{d}{dt} \int_0^t (t-s)^{-\alpha} [w(t) - w(0)\theta(t)] ds \end{aligned}$$

where  $\theta$  is the Heaviside function.

- If  $w \in L^1_{loc}([0, \infty))$ ,  $\int_0^t \|w(s) - w(0)\| ds \rightarrow 0$ , and  $D_t^\alpha w \in L^1_{loc}([0, \infty))$  then

$$w(t) = w(0) + I^\alpha[D_t^\alpha w](t) = w(0) + \frac{1}{\Gamma(\alpha)} \int_0^t (t-s)^{\alpha-1} D_t^\alpha w(s) ds.$$

---

<sup>[5]</sup> Marchaud 1927; Feng, Sutton 2020; ...

<sup>[5]</sup> Li and Liu, 2018, 2019

# The Caputo derivative

- **Key inequality:** For  $\Psi : \mathcal{H} \rightarrow \mathbb{R}$  convex, we have

$$D_t^\alpha \Psi(w) \leq \langle \partial \Psi(w), D_t^\alpha w \rangle.$$

- This is the needed **analogue** of

$$\frac{1}{2} \frac{d}{dt} \|w\|^2 \leq \langle w, w' \rangle,$$

when  $\Psi(w) = \frac{1}{2} \|w\|^2$ .

# Energy solutions

$$\xi \in \partial\Phi(u) \iff \Phi(u) - \Phi(w) \leq \langle \xi, u - w \rangle$$

$$\begin{cases} D_t^\alpha u(t) + \partial\Phi(u(t)) \ni f(t), & t \in (0, T], \\ u(0) = u_0. \end{cases}$$

## Definition (energy solution)

A function  $u \in L^2(0, T; \mathcal{H})$  such that  $D_t^\alpha u \in L^2(0, T; \mathcal{H})$  is an **energy solution** if

$$\int_0^t \|u(s) - u_0\|^2 ds \rightarrow 0$$

and

$$\langle D_t^\alpha u(t), u(t) - w \rangle + \Phi(u(t)) - \Phi(w) \leq \langle f(t), u(t) - w \rangle, \quad \forall w \in \mathcal{H}.$$

# Energy solutions: uniqueness

## Theorem (uniqueness)

*Energy solutions are unique.*

## Proof.

Recall the **key inequality**

$$D_t^\alpha \Psi(w) \leq \langle \partial \Psi(w), D_t^\alpha w \rangle$$

and repeat the idea for the classical case:

If  $u_1$  and  $u_2$  are energy solutions,

$$\begin{aligned} \langle D_t^\alpha u_1(t), u_1(t) - w \rangle + \Phi(u_1(t)) - \Phi(w) &\leq \langle f(t), u_1(t) - w \rangle, & w \leftarrow u_2, \\ \langle D_t^\alpha u_2(t), u_2(t) - w \rangle + \Phi(u_2(t)) - \Phi(w) &\leq \langle f(t), u_2(t) - w \rangle, & w \leftarrow u_1, \end{aligned}$$

adding, we get

$$\langle D_t^\alpha (u_1(t) - u_2(t)), u_1(t) - u_2(t) \rangle \leq 0.$$

We set  $\Psi(w) = \frac{1}{2} \|w\|^2$  in the key inequality. Since  $u_1(0) = u_2(0) = u_0$

$$\Psi(u_1 - u_2)(t) = \cancel{\Psi(u_1 - u_2)(0)} \overset{0}{+} \frac{1}{\Gamma(\alpha)} \int_0^t (t-s)^{\alpha-1} D_t^\alpha \Psi(u_1 - u_2)(s) \, ds \leq 0.$$



## Energy solutions: existence I

- To define a **fractional minimizing movements** we need to find a discretization of the Caputo derivative.
- Starting from

$$w(t) = w(0) + \frac{1}{\Gamma(\alpha)} \int_0^t (t-s)^{\alpha-1} D_t^\alpha w(s) ds.$$

If  $\mathcal{P}$  is a partition of  $[0, T]$  and  $D_t^\alpha w(s)$  is **piecewise constant** over this partition we obtain

$$\mathbf{W} = W_0 \mathbf{1} + \mathbf{K}_{\mathcal{P}} \mathbf{V}_\alpha,$$

where  $\mathbf{V}_\alpha = \{D_t^\alpha w(t_n)\}_{n=1}^N \in \mathcal{H}^N$ ,  $W_0 = w(0)$  and  $\mathbf{W} = \{w(t_n)\}_{n=1}^N$ .

## Energy solutions: existence II

- The matrix  $\mathbf{K}_{\mathcal{P}}$  is lower triangular and nonsingular.
- We define the **discrete Caputo derivative** by inverting this matrix

$$D_{\mathcal{P}}^{\alpha} \mathbf{W} = \mathbf{V}_{\alpha} = \mathbf{K}_{\mathcal{P}}^{-1} (\mathbf{W} - W_0 \mathbf{1}) \in \mathcal{H}^N$$

- If  $\mathcal{P}$  is **uniform**, the matrix  $\mathbf{K}_{\mathcal{P}}$  is Toeplitz. Matrix multiplication can be understood as convolution

$$\mathbf{W} = W_0 \mathbf{1} + \mathbf{K}_{\mathcal{P}} \star \mathbf{V}_{\alpha},$$

and this discretization is usually called a **deconvolution scheme**

$$\mathbf{V}_{\alpha} = \mathbf{K}_{\mathcal{P}}^{-1} \star (\mathbf{W} - W_0 \mathbf{1})$$

We will **NOT** assume that  $\mathcal{P}$  is uniform!



## Energy solutions: existence III

### Theorem (properties of $\mathbf{K}_{\mathcal{P}}$ )

For *any* partition, all  $n \in \{1, \dots, N\}$ , and all  $i \in \{0, \dots, n-1\}$ ,

$$\mathbf{K}_{\mathcal{P},nn}^{-1} > 0, \quad \mathbf{K}_{\mathcal{P},ni}^{-1} < 0, \quad \mathbf{K}_{\mathcal{P},ni}^{-1} < \mathbf{K}_{\mathcal{P},(n+1)i}^{-1}$$

where  $\mathbf{K}_{\mathcal{P},n0}^{-1} = -\sum_{j=1}^n \mathbf{K}_{\mathcal{P},nj}^{-1}$ .

### Corollary (discrete key inequality)

For any convex  $\Psi$  and  $\mathbf{W} \in \mathcal{H}^N$  set  $\Psi(\mathbf{W}) = \{\Psi(W_n)\}_{n=1}^N$ . Then,

$$(D_{\mathcal{P}}^{\alpha} \Psi(\mathbf{W}))_n \leq \langle \partial \Psi(\mathbf{W})_n, (D_{\mathcal{P}}^{\alpha} \mathbf{W})_n \rangle.$$

Proof.

$$\begin{aligned} (D_{\mathcal{P}}^{\alpha} \Psi(\mathbf{W}))_n &= \sum_{i=0}^{n-1} \mathbf{K}_{\mathcal{P},ni}^{-1} (\Psi(W_i) - \Psi(W_n)) \leq \left\langle \partial \Psi(W_n), \sum_{i=0}^{n-1} \mathbf{K}_{\mathcal{P},ni}^{-1} (W_i - W_n) \right\rangle \\ &= \langle \partial \Psi(\mathbf{W})_n, (D_{\mathcal{P}}^{\alpha} \mathbf{W})_n \rangle. \end{aligned}$$

## Energy solutions: existence IV

- We can now define a fractional minimizing movements scheme via:

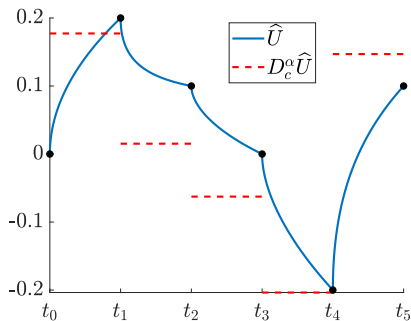
$$U_n = \operatorname{argmin}_{w \in \mathcal{H}} \left[ \frac{1}{2} \sum_{i=0}^{n-1} (-\mathbf{K}_{\mathcal{P},ni}^{-1}) \|w - U_i\|^2 + \Phi(w) - \langle F_n, w \rangle \right].$$

- This is equivalent to

$$(D_{\mathcal{P}}^{\alpha} \mathbf{U})_n + \partial\Phi(U_n) \ni F_n.$$

- **Question:** What is the analogue of (the piecewise linear)  $\hat{U}$ ?

## Energy solutions: existence V



- Define  $\{\varphi_i\}_{i=1}^N$  as functions with  $(D_{\mathcal{P}}^\alpha \varphi_i)_j = \delta_{i,j}$ . Then

$$\widehat{U}(t) = \sum_{i=0}^n U_i \varphi_i(t).$$

- The minimizing movements becomes

$$\langle D_t^\alpha \widehat{U}(t), \bar{U}(t) - w \rangle + \Phi(\bar{U}(t)) - \Phi(w) \leq \langle \bar{F}, \bar{U}(t) - w \rangle, \quad \forall w \in \mathcal{H}.$$

# Energy solutions: existence VI

- Judicious choices of  $w$  and some algebra yield

$$\|D_t^\alpha \widehat{U}\|_{L^2(0,T;\mathcal{H})}^2 \lesssim \Phi(U_0) + \sup_{t \in [0,T]} \int_0^t (t-s)^{\alpha-1} \|\bar{F}(s)\|^2 ds < \infty.$$

- As expected, we must require  $\Phi(u_0) < \infty$ . What about the other quantity?

## Proposition (continuity)

For any partition  $\mathcal{P}$

$$\sup_{t \in [0,T]} \int_0^t (t-s)^{\alpha-1} \|\bar{F}(s)\|^2 ds \lesssim \sup_{t \in [0,T]} \int_0^t (t-s)^{\alpha-1} \|f(s)\|^2 ds.$$

## Proof.

For  $\alpha \in (0, 1)$ , the weight  $\omega(s) = |s|^{\alpha-1} \in A_2$ .



# Energy solutions: existence VII

- We have enough estimates to pass to the limit.

## Theorem (existence )

Assume that  $\Phi(u_0) < \infty$  and

$$\sup_{t \in [0, T]} \int_0^t (t-s)^{\alpha-1} \|f(s)\|^2 ds < \infty,$$

then the fractional gradient flow problem has an energy solution which, moreover, satisfies  $u \in C^{0, \alpha/2}([0, T]; \mathcal{H})$ .

- Recall that in the **classical** gradient flow ( $\alpha = 1$ ) an energy solution satisfies  $u \in H^1(0, T; \mathcal{H}) \hookrightarrow C^{0, 1/2}([0, T]; \mathcal{H})$ .

# Outline

Introduction

Classical gradient flows: theory

Fractional gradient flows: theory

**Classical gradient flows: numerics**

Fractional gradient flows: numerics

Numerical illustrations

Conclusions and future work

## A posteriori error estimate I

- Recall that the discrete solution is obtained via

$$\frac{1}{\tau_n} (U_n - U_{n-1}) + \partial\Phi(U_n) \ni F_n,$$

which is equivalent to

$$\left\langle \frac{1}{\tau_n} (U_n - U_{n-1}), U_n - w \right\rangle + \Phi(U_n) - \Phi(w) \leq \langle F_n, U_n - w \rangle, \quad \forall w \in \mathcal{H}.$$

- Set  $w = U_{n-1}$  and define the quantity

$$\begin{aligned} \mathcal{E}_n &= \left\langle F_n - \frac{1}{\tau_n} (U_n - U_{n-1}), \frac{1}{\tau_n} (U_n - U_{n-1}) \right\rangle - \frac{\Phi(U_n) - \Phi(U_{n-1})}{\tau_n} \\ &\geq 0 \end{aligned}$$

## A posteriori error estimate II

- Recall that

$$\langle \widehat{U}'(t), \bar{U}(t) - w \rangle + \Phi(\bar{U}(t)) - \Phi(w) \leq \langle \bar{F}(t), \bar{U}(t) - w \rangle, \quad \forall w \in \mathcal{H}.$$

- Using that  $\Phi$  is convex and that  $\widehat{U}(t)$  is a convex combination of  $U_n$  and  $U_{n-1}$  we get

$$\langle \widehat{U}'(t), \widehat{U}(t) - w \rangle + \Phi(\widehat{U}(t)) - \Phi(w) \leq \langle \bar{F}(t), \widehat{U}(t) - w \rangle + (t_n - t)\bar{\mathcal{E}}.$$

- Combining with the continuous problem we get the a posteriori error estimate

$$\|u - \widehat{U}\|_{L^\infty(0,T;\mathcal{H})} \lesssim \|f - \bar{F}\|_{L^2(0,T;\mathcal{H})} + \left( \sum_{n=1}^N \tau_n^2 \mathcal{E}_n \right)^{1/2}.$$



# A priori error estimate

- A simple calculation reveals that

$$\sum_{n=1}^N \tau_n \mathcal{E}_n \lesssim \Phi(U_0) + \|\bar{F}\|_{L^2(0,T;\mathcal{H})}^2$$

- So that **provided**  $\Phi(u_0) < \infty$  we get the a priori estimate

$$\|u - \hat{U}\|_{L^\infty(0,T;\mathcal{H})} \lesssim \tau^{1/2}.$$

- This is **optimal** with respect to the regularity  $u \in C^{0,1/2}([0,T];\mathcal{H})$ .

# Error analysis: the heart of the matter

- A positive quantity  $\mathcal{E}_n$  that depends **only** on the computed approximations.
- The function  $\hat{U}$  solves a **perturbed gradient flow**, where  $\mathcal{E}_n$  is the perturbation.
- The fact that our interpolant  $\hat{U}$  is a **convex combination** of the computed approximations.

# Outline

Introduction

Classical gradient flows: theory

Fractional gradient flows: theory

Classical gradient flows: numerics

**Fractional gradient flows: numerics**

Numerical illustrations

Conclusions and future work

# A posteriori error analysis I

- Recall that our minimizing movements scheme reads

$$(D_{\mathcal{P}}^{\alpha} \mathbf{U})_n + \partial\Phi(U_n) \ni F_n,$$

and that this can be rewritten as

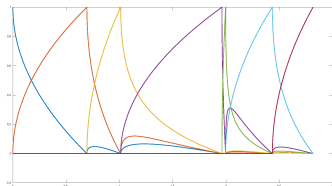
$$\left\langle D_t^{\alpha} \hat{U}(t), \bar{U}(t) - w \right\rangle + \Phi(\bar{U}(t)) - \Phi(w) \leq \left\langle \bar{F}(t), \bar{U}(t) - w \right\rangle, \quad \forall w \in \mathcal{H}.$$

- We define

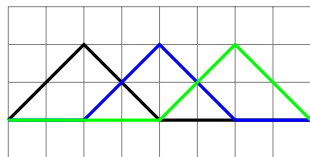
$$\mathcal{E}_{\alpha}(t) = \left\langle D_t^{\alpha} \hat{U}(t) - \bar{F}(t), \hat{U}(t) - \bar{U}(t) \right\rangle + \Phi(\hat{U}(t)) - \Phi(\bar{U}(t)) \geq 0,$$

which depends only on the discrete solutions, and is thus **computable**.

# A posteriori error analysis II

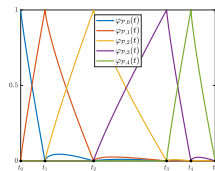
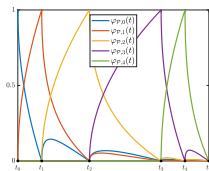
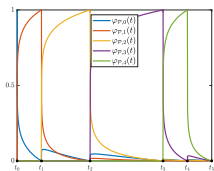


$\alpha = 0.1$



$\alpha = 0.5$

$\alpha = 0.9$



## A posteriori error analysis III

- The functions  $\{\varphi_i\}$  used to define  $\hat{U}$  are all nonnegative, and  $\sum_i \varphi_i = 1$ .
- The value of the interpolant  $\hat{U}(t)$  is a **convex combination** of  $\{U_i\}_{i=0}^n$  with  $t \in (t_{n-1}, t_n]$ .
- The interpolant  $\hat{U}$  satisfies, for every  $w \in \mathcal{H}$ ,

$$\left\langle D_t^\alpha \hat{U}(t), \hat{U}(t) - w \right\rangle + \Phi(\hat{U}(t)) - \Phi(w) \leq \left\langle \bar{F}(t), \hat{U}(t) - w \right\rangle + \mathcal{E}_\alpha(t),$$

where, again, the quantity  $\mathcal{E}_\alpha$  is a **perturbation**.

# A posteriori error analysis IV

## Theorem (a posteriori error estimate<sup>Li</sup>)

Assume that  $\Phi(u_0) < \infty$ . For every  $\mathcal{P}$  we have

$$\begin{aligned} \|u - \hat{U}\|_{L^\infty(0,T;\mathcal{H})} &\lesssim \sup_{t \in [0,T]} \int_0^t (t-s)^{\alpha-1} \|f - \bar{F}\|(s) \, ds \\ &\quad + \left( \sup_{t \in [0,T]} \int_0^t (t-s)^{\alpha-1} \mathcal{E}_\alpha(s) \, ds \right)^{1/2}. \end{aligned}$$

## Proof.

Combine the inequalities that  $u$  and  $\hat{U}$  satisfy to get

$$\langle D_t^\alpha(u - \hat{U}), u - \hat{U} \rangle \leq \langle f - \bar{F}, u - \hat{U} \rangle + \mathcal{E}_\alpha(t).$$

Use the discrete key inequality. □

# A priori error analysis I

- Recall

$$\mathcal{E}_\alpha(t) = \left\langle D_t^\alpha \widehat{U}(t) - \bar{F}(t), \widehat{U}(t) - \bar{U} \right\rangle + \Phi(\widehat{U}(t)) - \Phi(\bar{U}(t)).$$

- Since there is a bound for  $D_t^\alpha \widehat{U}$ , and  $\widehat{U}(t_n) = \bar{U}(t_n) = U_n$

$$\sup_{t \in [0, T]} \int_0^t (t-s)^{\alpha-1} \|\widehat{U} - \bar{U}\|^2(s) ds \lesssim \tau^{2\alpha}.$$

- Since  $\widehat{U}(t)$  is a convex combination of  $\{U_i\}_{i=0}^n$  with  $t \in (t_{n-1}, t_n]$

$$\Phi(\widehat{U}(t)) - \Phi(\bar{U}(t)) \leq \sum_{i=1}^n \Phi(U_i) \varphi_i(t) - \Phi(\bar{U}(t)),$$

which implies

$$\sup_{t \in [0, T]} \int_0^t (t-s)^{\alpha-1} \left( \Phi(\widehat{U}(s)) - \Phi(\bar{U}(s)) \right) ds \lesssim \tau^\alpha.$$



## A priori error analysis II

Theorem (a priori error estimate<sup>[5]</sup>)

Assume that  $\Phi(u_0) < \infty$  and that

$$\sup_{t \in [0, T]} \int_0^t (t-s)^{\alpha-1} \|f(s)\|^2 ds < \infty.$$

Then, for every  $\mathcal{P}$ , we have

$$\|u - \hat{U}\|_{L^\infty(0, T; \mathcal{H})} \lesssim \tau^{\alpha/2}.$$

- Recall that energy solutions satisfy  $u \in C^{0, \alpha/2}([0, T]; \mathcal{H})$  so this is optimal.

# Outline

Introduction

Classical gradient flows: theory

Fractional gradient flows: theory

Classical gradient flows: numerics

Fractional gradient flows: numerics

**Numerical illustrations**

Conclusions and future work

## A linear example I

- Consider, on  $\Omega = (0, 1)$ ,

$$D_t^\alpha u - \Delta u = 0, \quad u(x, 0) = u_0(x),$$

supplemented with homogeneous Dirichlet boundary conditions. The exact solution is

$$u(t) = \sum_{k=0}^{\infty} u_{0,k} E_\alpha(-\lambda_k t^\alpha) \varphi_k(x), \quad u_{0,k} = \int_{\Omega} u_0(x) \varphi_k(x) dx,$$

where  $E_\alpha$  is the Mittag–Leffler function, and  $\{(\lambda_k, \varphi_k)\}_{k=1}^{\infty}$  are the eigenpairs of the Dirichlet Laplacian.

- Set  $T = 1$ . Spectral discretization in space with  $m = 100$  modes, and uniform  $\mathcal{P}$ .
- We measure

$$e_{end} = \|u(T) - U_N\|_{L^2(\Omega)}, \quad e_{inf} = \max_n \|u(t_n) - U_n\|_{L^2(\Omega)}.$$

## A linear example II

- Set

$$u_{0,k} = k^{-1.5+\delta}, \quad \delta \ll 1,$$

so that  $u_0 \in D(\Phi) = H_0^1(\Omega)$ , but  $u_0 \notin D(\partial\Phi) = H^2(\Omega) \cap H_0^1(\Omega)$ .

$\alpha = 0.3$				
$\tau$	$e_{\text{inf}}$	rate	$e_{\text{end}}$	rate
5.00e-02	1.09e-02	—	1.71e-03	—
2.50e-02	9.74e-03	0.166	9.03e-04	0.921
1.25e-02	8.72e-03	0.159	4.70e-04	0.940
6.25e-03	7.84e-03	0.153	2.43e-04	0.954
3.13e-03	7.07e-03	0.150	1.25e-04	0.964
1.56e-03	6.37e-03	0.149	6.35e-05	0.971
7.81e-04	5.75e-03	0.149	3.23e-05	0.977
3.91e-04	5.18e-03	0.150	1.63e-05	0.982
1.95e-04	4.67e-03	0.150	8.25e-06	0.985
9.77e-05	4.21e-03	0.150	4.16e-06	0.988

$\alpha = 0.7$				
$\tau$	$e_{\text{inf}}$	rate	$e_{\text{end}}$	rate
5.00e-02	2.72e-02	—	5.97e-03	—
2.50e-02	2.13e-02	0.350	3.03e-03	0.979
1.25e-02	1.67e-02	0.350	1.53e-03	0.988
6.25e-03	1.31e-02	0.350	7.68e-04	0.993
3.13e-03	1.03e-02	0.350	3.85e-04	0.996
1.56e-03	8.08e-03	0.350	1.93e-04	0.997
7.81e-04	6.34e-03	0.350	9.65e-05	0.998
3.91e-04	4.98e-03	0.350	4.83e-05	0.999
1.95e-04	3.90e-03	0.350	2.41e-05	0.999
9.77e-05	3.06e-03	0.351	1.21e-05	1.000

- Convergence rate of  $\mathcal{O}(\tau^{\alpha/2})$ , as predicted by our theory.

## A linear example III

- Set

$$u_{0,k} = k^{-2.5+\delta}, \quad \delta \ll 1,$$

so that  $u_0 \in D(\partial\Phi) = H^2(\Omega) \cap H_0^1(\Omega)$ .

$\alpha = 0.3$

$\tau$	$e_{\text{inf}}$	rate	$e_{\text{end}}$	rate
5.00e-02	8.44e-03	—	1.64e-03	—
2.50e-02	6.88e-03	0.296	8.66e-04	0.919
1.25e-02	5.57e-03	0.305	4.52e-04	0.939
6.25e-03	4.50e-03	0.308	2.33e-04	0.953
3.13e-03	3.63e-03	0.307	1.20e-04	0.963
1.56e-03	2.94e-03	0.305	6.11e-05	0.971
7.81e-04	2.38e-03	0.303	3.10e-05	0.977
3.91e-04	1.93e-03	0.302	1.57e-05	0.981
1.95e-04	1.57e-03	0.301	7.94e-06	0.985
9.77e-05	1.27e-03	0.301	4.00e-06	0.988

$\alpha = 0.7$

$\tau$	$e_{\text{inf}}$	rate	$e_{\text{end}}$	rate
5.00e-02	1.05e-02	—	5.81e-03	—
2.50e-02	6.48e-03	0.702	2.95e-03	0.977
1.25e-02	3.99e-03	0.701	1.49e-03	0.987
6.25e-03	2.45e-03	0.700	7.49e-04	0.992
3.13e-03	1.51e-03	0.700	3.76e-04	0.995
1.56e-03	9.30e-04	0.700	1.88e-04	0.997
7.81e-04	5.73e-04	0.700	9.42e-05	0.998
3.91e-04	3.52e-04	0.700	4.71e-05	0.999
1.95e-04	2.17e-04	0.700	2.36e-05	0.999
9.77e-05	1.34e-04	0.700	1.18e-05	1.000

- Convergence rate of  $\mathcal{O}(\tau^\alpha)$ . We have a theory that includes this case!

## A (fractional) parabolic obstacle problem I

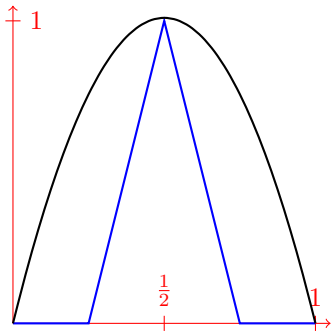
- Consider, in  $\Omega = (0, 1)$ ,

$$D_t^\alpha u + (-\Delta)^s u \geq f, \quad u \geq g, \quad (D_t^\alpha u + (-\Delta)^s u - f)(u - g) = 0.$$

supplemented with periodic boundary conditions.

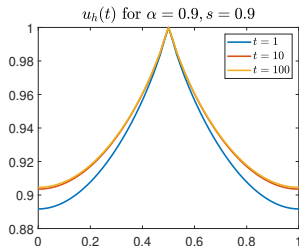
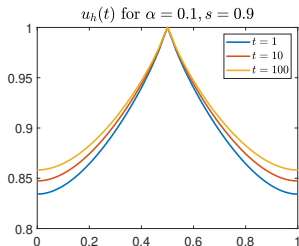
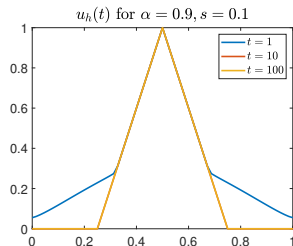
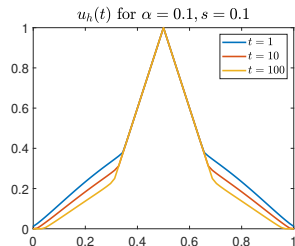
- We set

$$g(x) = (1 - 4|x - \frac{1}{2}|)_+, \quad u_0(x) = \sin(\pi x), \quad f(x, t) = -\frac{1}{2}$$



## A (fractional) parabolic obstacle problem II

- Collocation method with  $M = 64$  nodes,  $\tau = 2e - 6$ .
- Snapshots of discrete solutions of the time fractional parabolic obstacle problem for  $\alpha = 0.1, 0.9$ ,  $s = 0.1, 0.9$ .



# The (fractional) Allen-Cahn equation I

- Consider, in  $\Omega = (0, 1)^2$ ,

$$D_c^\alpha u + (-\Delta)^s u + g(u) = f, \quad u(x, 0) = u_0(x),$$

supplemented by periodic boundary conditions.

- Here

$$g(r) = G'(r), \quad G(r) = \begin{cases} (r-1)^2, & r > 1, \\ \frac{1}{4} (1-r^2)^2, & |r| \leq 1, \\ (r+1)^2, & r < -1. \end{cases}$$

- The energy is **NOT** convex, but a Lipschitz perturbation of a convex one. **We have a theory for this case.**



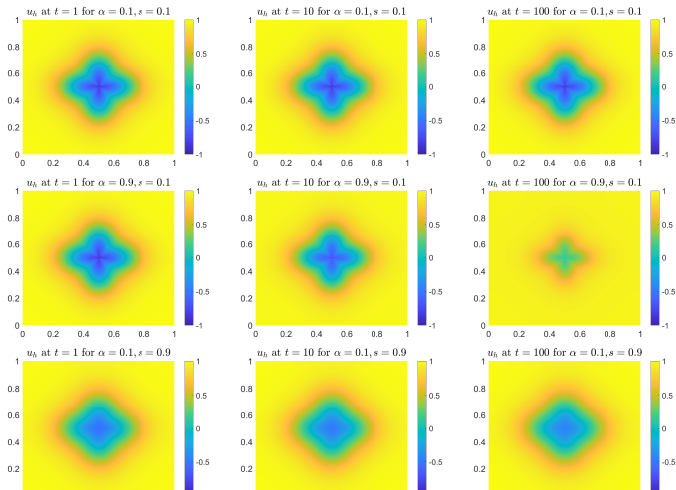
# The (fractional) Allen-Cahn equation II

- Set

$$u_0(x) = \tanh\left(\frac{1}{\sqrt{2}\varepsilon_0}\left(2r - \frac{5}{16} - \frac{\cos(\theta)}{16}\right)\right),$$

where  $(r, \theta)$  are polar coordinates centered at  $(\frac{1}{2}, \frac{1}{2})$ .

- Collocation method with  $M = 64$  nodes and  $\tau = 2e - 6$ .



# The (fractional) Allen-Cahn equation III

$\alpha = 0.3$

$\tau$	$e_{inf}$	rate	$e_{end}$	rate
2.50e-03	9.11e-04	-	3.11e-04	-
1.25e-03	7.29e-04	0.321	1.72e-04	0.859
6.25e-04	5.81e-04	0.328	9.23e-05	0.894
3.13e-04	4.60e-04	0.336	4.88e-05	0.919
1.56e-04	3.65e-04	0.336	2.55e-05	0.938
7.81e-05	2.92e-04	0.320	1.32e-05	0.951
3.91e-05	2.39e-04	0.287	6.77e-06	0.961
1.95e-05	2.02e-04	0.244	3.46e-06	0.969
9.77e-06	1.76e-04	0.203	1.76e-06	0.975

$\alpha = 0.7$

$\tau$	$e_{inf}$	rate	$e_{end}$	rate
2.50e-03	7.24e-04	-	3.84e-04	-
1.25e-03	5.42e-04	0.416	1.97e-04	0.961
6.25e-04	4.04e-04	0.426	1.00e-04	0.977
3.13e-04	3.04e-04	0.411	5.06e-05	0.987
1.56e-04	2.33e-04	0.386	2.54e-05	0.992
7.81e-05	1.82e-04	0.355	1.28e-05	0.995
3.91e-05	1.45e-04	0.326	6.39e-06	0.997
1.95e-05	1.16e-04	0.322	3.20e-06	0.998
9.77e-06	9.01e-05	0.365	1.60e-06	0.999

- The rates for  $e_{inf}$  are close to  $\mathcal{O}(\tau^{\alpha/2})$  predicted in our theory.

# Time adaptivity I

- Consider the linear example with  $\alpha = 0.5$ , and  $u_0 \in H_0^1(\Omega) \setminus H^2(\Omega)$ .
- Given  $\varepsilon > 0$ , choose the time steps  $\tau_n$  to **equidistribute** the error:

$$\max_{t \in (t_{n-1}, t_n]} \mathcal{E}_\alpha(t) \lesssim \varepsilon^2,$$

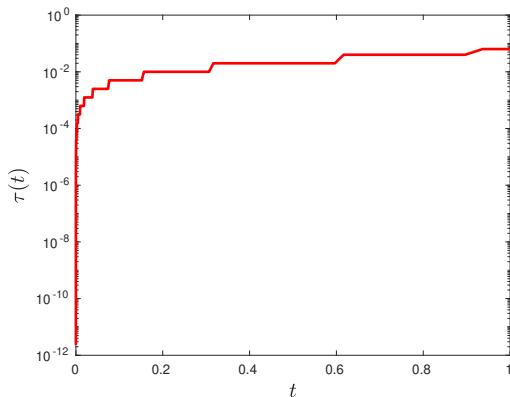
then we can guarantee that

$$\|u - \widehat{U}\|_{L^\infty(0,T;L^2(\Omega))} \lesssim \varepsilon.$$

- Choose  $\varepsilon = 1e - 2$ .
- The adaptive solver requires  $N = \#\mathcal{P} - 1 = 455$  time intervals with minimal timestep  $\tau_{\min} \approx 2.3e - 12$  and maximal timestep  $\tau_{\max} \approx 6.3e - 2$ .
- In comparison, for a similar tolerance we **must set**  $\tau_n = 2.44e - 5$  so that  $N = 40960$ .

There is a “*clear*” advantage in choosing the time step adaptively!

## Time adaptivity II



- The step size  $\tau_n$  is very small at the beginning  $\rightarrow$  the singularity of the solution at  $t = 0$ .
- For  $t > 0$  the solution is smooth, so we can take larger time steps.

# Outline

Introduction

Classical gradient flows: theory

Fractional gradient flows: theory

Classical gradient flows: numerics

Fractional gradient flows: numerics

Numerical illustrations

Conclusions and future work

# Conclusions I

- A **discretization** of the Caputo derivative that possesses suitable properties.
- **Existence** and **uniqueness** of energy solutions to fractional gradient flows.
- A posteriori error analysis.
- A priori error estimates **without** additional regularity assumptions. The estimates seem **optimal** given the available regularity.

## Conclusions II

Not discussed but we also have:

- **Extension** to the case of  $\Phi$  being  $\lambda$ -convex, or we have a Lipschitz perturbations of a convex function: Fractional reaction diffusion, Fractional Allen-Cahn, ...
- **Improved** convergence rates for some special cases: linear equations, smooth energies, ...
- **Asymptotic** behavior of the solution. If  $f = 0$  and  $\Phi$  is uniformly convex with parameter  $\mu > 0$ , then

$$\begin{aligned}\Phi(u(t)) - \Phi_{\min} &\leq (\Phi(u_0) - \Phi_{\min}) E_{\alpha}(-2\mu t^{\alpha}) \\ \|u(t) - u_{\min}\|_{\mathcal{H}} &\leq \|u_0 - u_{\min}\|_{\mathcal{H}} E_{\alpha}(-\mu t^{\alpha}).\end{aligned}$$

- **Asymptotic** behavior of the solution. If  $f = 0$  and  $\Phi$  is **merely** convex, then

$$\begin{aligned}\Phi(u(t)) - \Phi_{\min} &\lesssim t^{-\alpha/2} \\ \Phi(U_n) - \Phi_{\min} &\lesssim t_n^{-\alpha/2}.\end{aligned}$$

# Future work

- Some of the experiments show a rate of  $\mathcal{O}(\tau^\alpha)$ ? **Why?** We have **partial answers**.
- **Replace**  $\partial\Phi$  by a maximal monotone operator.
- Evolution in **Banach** spaces.
- **Space** discretization.



THANK YOU!

## (Fractional) ODE with obstacles III

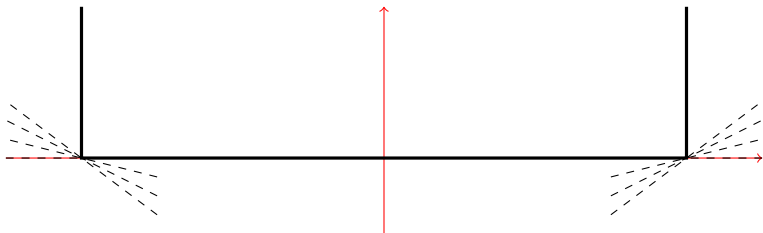
Define

$$\Phi(w) = \begin{cases} 0, & w \in [-1, 1], \\ +\infty, & w \notin [-1, 1]. \end{cases}$$

Then this problem can be succinctly written as

$$D_t^\alpha u + \partial\Phi(u) \ni f,$$

where  $\partial\Phi(w)$  denotes the **subdifferential**.



## (Fractional) parabolic obstacle problems II

- Define

$$\Phi^s(w) = \frac{1}{2}|w|_{H^s(\mathbb{R}^d)}^2 + \begin{cases} 0, & w \in \mathcal{K}, \\ +\infty, & w \notin \mathcal{K}. \end{cases}$$

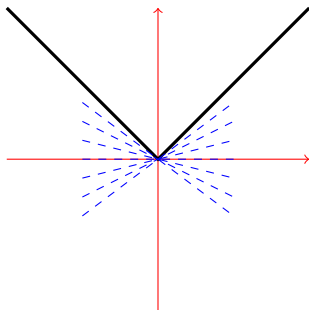
- The evolution variational inequality

$$\int_{\Omega} D_t^\alpha u(u-w) \, dx + \langle (-\Delta)^s u, u-w \rangle \leq \int_{\Omega} f(u-w) \, dx, \quad \forall w \in \mathcal{K}.$$

can be written as

$$D_t^\alpha u + \partial\Phi^s(u) \ni f.$$

# The subdifferential of a convex function



- A convex function  $\Phi$  is not necessarily differentiable.
- However, by convexity, it can be touched from below by planes.
- The **subdifferential**  $\partial\Phi(w)$  is the collection of slopes of the planes that touch from below at  $w$

$$\xi \in \partial\Phi(w) \quad \iff \quad \Phi(w) - \Phi(v) \leq \langle \xi, w - v \rangle .$$

## (Fractional) TV flow

- Why  $p > 1$ ? Consider the equation

$$D_t^\alpha u - \nabla \cdot \left( \frac{\nabla u}{|\nabla u|} \right) = f.$$

- Define

$$\Phi_1(w) = |Dw|(\Omega),$$

where for  $w \in BV(\Omega)$  we denote by  $|Dw|$  its **total variation** (a Radon measure). This functional is **not** differentiable.

- The previous equation must be understood as follows: Find  $u$  and  $\mathbf{z}$  such that

$$\int_{\Omega} D_t^\alpha u w \, dx + \int_{\Omega} \mathbf{z} \cdot Dw = \int_{\Omega} f w \, dx, \quad \forall w \in BV(\Omega) \cap L^2(\Omega),$$

and

$$\int_{\Omega} (\mathbf{q} - \mathbf{z}) \cdot Du \leq 0, \quad \forall \mathbf{q} \in \dots$$