

# A computational study of a class of recursive inequalities

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- ▶ One can sometimes also produce negative results demonstrating that computable realisers cannot be produced
- ▶ There are also metatheorems that sometimes tell us what type of computational content we can hope to extract

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- ▶ A natural question to ask is, from a proof of convergence can one find a computable function  $f : \mathbb{Q} \rightarrow \mathbb{N}$  such that  $\forall \varepsilon \in \mathbb{Q}_+ \forall n \in \mathbb{N} (n \geq N \implies |a_i - a_j| \leq \varepsilon)$

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- ▶ Specker showed this was not always possible, through his famous construction of a monotone sequence of rational numbers converging to a non-computable number
- ▶  $\forall \varepsilon \in \mathbb{Q}_+ \forall g : \mathbb{N} \rightarrow \mathbb{N} \exists n \forall i, j \in [n, n + g(n)] (|a_i - a_j| \leq \varepsilon)$

## Our analyse of recursive inequalities

- ▶ For a contraction mapping  $T$  with constant  $c \in [0, 1)$  and  $x^*$  a fixed point of  $T$ , the distance  $\mu_n := d(T^n x_0, x^*)$  satisfies  $\mu_{n+1} \leq c\mu_n$  and thus converges to 0

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  - (bII)  $\gamma_n / \alpha_n \rightarrow 0$  as  $n \rightarrow \infty$ 
    - ▶ Both conditions are a strengthening of  $\gamma_n \rightarrow 0$  as  $n \rightarrow \infty$

# Applications of our abstract study of recursive inequalities

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- ▶ We were also able to explain why the authors could not find a rate of convergence for their result
- ▶ We surveyed the proof mining literature and were able to demonstrate how many known results can be seen as special cases of our analysis

## Subgradient decent

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- ▶ where  $\{\alpha_n\}$  satisfies  $\sum_{i=0}^{\infty} \alpha_i = \infty$  and  $\sum_{i=0}^{\infty} \alpha_i^2 < \infty$ ,  $\{\varepsilon_n\}$  is a sequence of nonnegative error terms with  $\varepsilon_n \leq \mu \alpha_n$  for some  $\mu > 0$  and  $\nu_n := \max\{1, \|u_n\|\}$ . The algorithm halts if  $0 \in \partial_{\varepsilon_n} f(x_n)$  at any point

## Metastable subgradient decent

Let  $x^* \in C$  be a minimizer of  $f$  on  $C$ , and suppose that  $\{x_n\}$  is an infinite sequence generated by the algorithm, whose components satisfy all of the properties outlined above. Suppose that  $\rho > 1$  is such that  $\|u_n\| \leq \rho$  for all  $n \in \mathbb{N}$ . Then  $f(x_n) \rightarrow f(x^*)$ . Moreover, if  $r$  is a rate of divergence for  $\sum_{i=0}^{\infty} \alpha_i = \infty$  and  $L, K > 0$  are such that  $\sum_{i=0}^{\infty} \alpha_i^2 \leq L$  and  $\|x_0 - x^*\|^2 \leq K$ , then for all  $\varepsilon > 0$  and  $g : \mathbb{N} \rightarrow \mathbb{N}$  we have

$$\exists n \leq \Phi(\varepsilon, g) \forall k \in [n, n + g(n)] (f(x_k) \leq f(x^*) + \varepsilon)$$

where

$$\Phi(\varepsilon, g) := \tilde{h}^{(\lceil 4\theta e / \varepsilon^2 \rceil)}(0)$$

$$\tilde{h}(n) := r\left(n + g(n), \frac{\varepsilon}{2\theta}\right) + 1$$

$$e := \frac{\rho(L + K)}{2} + (\mu + 2\rho)L$$

$$\theta := \rho + \mu$$

## Future work and concluding remarks

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- ▶ We have started formalising aspects of applied proof theory of the Lean theorem prover <sup>1</sup>

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<sup>1</sup><https://github.com/mneri123/Proof-mining> 