An application of proof mining to the proximal point algorithm in CAT(0) spaces
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Dedicated to the memory of Professor Solomon Marcus (1925-2016)

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(joint work with Andrei Sipoş)

Input: Ineffective proof P of C

Goal: Additional information on C:

- effective bounds, algorithms
- weak dependency or independence from certain parameters,
- generalizations of proofs: weakening of premises

Kohlenbach, Applied Proof Theory: Proof Interpretations and their Use in Mathematics, Springer Monographs in Mathematics (2008).

- inspired by Kreisel's program of unwinding of proofs (50's)
- name of proof mining suggested by Dana Scott

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Terence Tao's proposal of hard analysis (finitary, quantitative arguments), instead of soft analysis (infinitary, qualitative arguments)

Tao, Soft analysis, hard analysis, and the finite convergence principle, 2007: "There are rigorous results from proof theory which can allow one to automatically convert certain types of qualitative arguments into quantitative ones."

- interpret formulas A occurring in the proof: $A \mapsto A^{I}$
- ► the interpretation C¹ of the conclusion contains the additional information
- construct by recursion on P a new proof P^{I} of C^{I}
- our approach is based on novel extensions of Gödel's functional interpretation

Monotone functional interpretation - Kohlenbach (90's)

 systematically transforms any statement in the proof into a new version with explicit uniform bounds General metatheorems: "If a sentence has a certain logical form and can be proved in a theory \mathcal{T} , then the following strengthened version holds: ...".

- ► guarantee the extractability of uniform bounds for ∀∃-sentences
- can be used as a black box: infer new uniform existence results without any proof analysis
- extract an explicit uniform bound
- new mathematical proof that uses NO logical tools

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$$(x_n) \text{ Cauchy} \Leftrightarrow \forall k \in \mathbb{N} \exists N \in \mathbb{N} \forall p \in \mathbb{N} \left(d(x_{N+p}, x_N) < \frac{1}{k+1} \right)$$

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IDEA: Herbrand normal form

Metatheorems guarantee that we can extract $\Phi(k, g, \ldots)$ s.t.

$$(\star) \quad \forall k \in \mathbb{N} \, \forall g : \mathbb{N} \to \mathbb{N} \, \exists N \leq \Phi \, \forall i, j \in [N, N + g(N)] \, \left(d(x_i, x_j) < \frac{1}{k+1} \right)$$

- (*) = monotone functional interpretation of the negative translation of Cauchyness
 - Kreisel's no-counterexample interpretation of the Cauchy property

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Popularized in the last years by Tao as the metastability of (x_n) :

- Tao, Soft analysis, hard analysis, and the finite convergence principle (2007)
- Tao, Norm convergence of multiple ergodic averages for commuting transformations, Ergod. Th. Dynam. Syst. (2008)
- Walsh, Norm convergence of nilpotent ergodic averages, Ann. Math. (2012)

Proximal point algorithm in CAT(0) spaces

 The proximal point algorithm is a fundamental tool of convex optimization, going back to Martinet (1970), Rockafellar (1976) and Brézis and Lions (1978).

Let X be a CAT(0) space, $f : X \to (-\infty, +\infty]$ be a convex, lower semicontinuous (lsc) proper function.

- A minimizer of f is a point x ∈ X s. t. f(x) = inf_{y∈X} f(y). We denote the set of minimizers of f by Argmin(f).
- For $\gamma > 0$, the resolvent of f of order γ is the mapping

$$J_f^{\gamma}: X \to X, \quad J_f^{\gamma}(x) := \operatorname{argmin}_{y \in X} \left[\gamma f(y) + \frac{1}{2} d^2(x, y) \right].$$

defined by Jost (1995)

For any
$$\gamma > 0$$
, $Fix(J_f^{\gamma}) = Argmin(f)$.

Let $(\gamma_n)_{n \in \mathbb{N}}$ be a sequence in $(0, \infty)$. The proximal point algorithm $(x_n)_{n \in \mathbb{N}}$ starting with $x \in X$ is defined as follows:

$$x_0 := x, \qquad x_{n+1} := \int_f^{\gamma_n} x_n \text{ for all } n \in \mathbb{N}.$$

Theorem Bačák (2013)

Assume that X is a totally bounded CAT(0) space, $Argmin(f) \neq \emptyset$ and that $\sum_{n=0}^{\infty} \gamma_n = \infty$. Then (x_n) is Cauchy. If, furthermore, X is complete, then (x_n) converges strongly to a a minimizer of f.

 The following quantitative version of Bačák's result is obtained by using proof mining methods. Theorem

Let b > 0, $\alpha, \theta : \mathbb{N} \to \mathbb{N}$, $M : \mathbb{N} \to (0, \infty)$.

Then there exists $\Psi_{b,\theta,M,\alpha}: \mathbb{N} \times \mathbb{N}^{\mathbb{N}} \to \mathbb{N}$ such that for

- all totally bounded CAT(0) spaces with modulus of total boundedness α;
- all convex lsc proper mappings f : X → (-∞,∞] with Argmin(f) ≠ Ø;
- ▶ all $x \in X$ such that $d(x, p) \leq b$ for some minimizer p of f;
- ▶ all sequences (γ_n) in $(0, \infty)$ such that $\sum_{n=0}^{\infty} \gamma_n = \infty$ with rate of divergence θ and $M(k) \ge \max_{0 \le i \le k} \gamma_i$ for all $k \in \mathbb{N}$,

 $\Psi_{b,\theta,M,\alpha}$ is a rate of metastability for the proximal point algorithm (x_n) starting with x, i.e. for all $k \in \mathbb{N}$ and all $g : \mathbb{N} \to \mathbb{N}$,

$$\exists N \leq \Psi_{b,\theta,M,\alpha}(k,g) \forall i,j \in [N,N+g(N)] \left(d(x_i,x_j) \leq \frac{1}{k+1} \right).$$

$$\begin{split} \Psi_{b,\theta,M,\alpha}(k,g) &:= (\Psi_0)_{b,\theta,M}(\alpha(4k+3),k,g) \\ (\Psi_0)_{b,\theta,M}(0,k,g) &:= 0 \\ (\Psi_0)_{b,\theta,M}(n+1,k,g) &:= \Phi_{b,\theta,M}(\chi_g^M((\Psi_0)_{b,\theta,M}(n,k,g),4k+3)) \end{split}$$

where

$$\begin{split} \chi_{g}^{M}(n,r) &:= \max_{i \leq n} \max\{i + g(i) - 1, g(i)(r+1)\} \\ \Phi_{b,\theta,M}(k) &:= \lceil b^{2}(k+1)^{2} \rceil + \beta_{b,\theta}(\lceil 2(k+1)^{2}M(k) \rceil - 1) \\ \beta_{b,\theta}(k) &:= \theta^{M}(\lceil b^{2}(k+1)/2 \rceil) + 1 \\ \theta^{M}(n) &:= \max_{i \leq k} \theta(i). \end{split}$$