

1 Abstract Lipschitz Continuity

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10 — Abstract —

11 We introduce *Abstract Lipschitz Continuity* (ALC), a generalization of standard Lipschitz Continuity,
12 that ensures proportionally bounded differences in the *semantic approximations* of outputs when the
13 *semantic approximations* of inputs differ slightly. ALC distinguishes between two complementary
14 notions of approximation: *quantitative* differences, expressed via pre-metrics, and *qualitative* (or
15 *semantic*) differences, captured through upper closure operators. ALC allows for reasoning about
16 bounded changes in output properties in settings where standard Lipschitz continuity is too restrictive
17 or inapplicable, such as in program analysis and verification, where understanding semantic properties
18 of inputs and outputs is of key importance.

19 In the specific context of programs, we formally relate ALC to other well-established program
20 properties, including (Partial) Completeness and (Abstract) program Robustness. Notably, we show
21 that ALC is a stronger requirement than Partial Completeness, a consolidated notion modeling
22 precision loss in program analysis.

23 Finally, we propose a language- and domain-agnostic deductive system, parametric on the
24 quantitative and semantic approximations of interest, for proving the ALC of programs. The
25 goal in designing this deductive system is to track the assumptions required for ALC to ensure a
26 compositional proof.

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1 Introduction

In mathematical analysis, *Lipschitz continuity* is a strong form of uniform continuity for functions computing over metric spaces, which guarantees that changes in the output are bounded proportionally to changes in the input. It finds numerous applications in various areas of mathematics, including analysis, where it ensures uniform continuity and differentiable properties [14], and optimization, where it plays a key role in convergence guarantees for iterative algorithms [32]. In machine learning, it is used to study robustness, stability and convergence of machine learning models, particularly in adversarial settings [15, 23, 24, 39]. Lipschitz continuity is also relevant and interesting for software, notably to reason about robustness of programs that execute on uncertain inputs [8, 9, 10].

The standard definition of Lipschitz continuity requires that both the input and output spaces of a function (e.g., a program) be equipped with metrics, thereby assuming that controlled variation can be meaningfully captured within the structure imposed by these raw spaces. However, this requirement is often too rigid and fails to account for forms of Lipschitz continuity that remain practically relevant in many important applications. In particular, small changes in the raw representation may correspond to negligible or even irrelevant *semantic* differences. Thus, the lack of a controlled function variation with respect to the raw inputs does not preclude the possibility of a meaningful controlled variation: variations may still be well-behaved when viewed through the lens of *semantic properties* of the inputs and outputs (cf. Ex. 11). This is particularly relevant in many applications, including machine learning [1, 19, 25] and program analysis and verification [13, 18, 36, 37], where the focus often lies on the *semantic properties* of program inputs and outputs.

Our Contribution. To address these limitations, we introduce *Abstract Lipschitz Continuity* (ALC), which ensures that small differences in *semantic approximations* of inputs lead to proportionally bounded differences in the *semantic approximations* of outputs.

We formalize semantic (or *qualitative*) approximations as *upper closure operators*, which are also used in the abstract interpretation framework to model domain abstractions [11, 12]. Values (e.g., character strings) are approximated by considering all other values sharing the same semantic property (e.g., length), admitting an error semantically related to the data. In other words, qualitative or semantic approximations add noise in the *meaning* of what is approximated (cf. Sec. 3).

Abstract Lipschitz Continuity combines these semantic approximations with *quantitative* approximations through their distance in general *pre-metric spaces* [7], i.e., not restricted to metric spaces as the standard definition of Lipschitz continuity (cf. Sec. 3).

We relate ALC for programs to other important and well-studied properties such as (Partial) Completeness in abstract interpretation [4, 7, 20] which limits the imprecision of program analysis (cf. Sec. 4), as well as (Abstract) Robustness [19] in machine learning (cf. Sec. 6). Notably, we show that any abstract Lipschitz continuous function is 0-partial complete, meaning that it does not introduce imprecision — relative to the chosen distance function — when computations are performed over semantic approximations of inputs.

Finally, we propose a novel deductive system for verifying ALC for programs, which is parametric with respect to the chosen input and output semantic approximations and distance functions (cf. Sec. 5). As a particular instance of our general deductive system, when no input and output semantic approximation is performed (i.e., the input and output semantic approximation functions are the identify functions), we find the deductive system proposed by Chaudhuri et al. [9, 10] for proving program robustness.

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	pre-	quasisemi-	pseudosemi-	semi-	quasi-	pseudo-	metric
(non-negativity)	✓	✓	✓	✓	✓	✓	✓
(if-identity)	✓	✓	✓	✓	✓	✓	✓
(iff-identity)	✗	✓	✗	✓	✓	✗	✓
(symmetry)	✗	✗	✓	✓	✗	✓	✓
(triangle-inequality)	✗	✗	✗	✗	✓	✓	✓
Example		$\delta_{\underline{\quad}}$	δ_{pat}^{Int}	δ_{pat}		$\delta_{siz}, \delta_{\Sigma}$	δ_2
Reference		Ex. 20	Ex. 7	Ex. 7		Ex. 3, 11	Ex. 2

■ **Figure 1** Metrics and their weakening.

2 Preliminaries

We review key preliminaries on metrics, Lipschitz continuity, and abstract interpretation.

Distances. Let \mathbb{R}^∞ be the set of real numbers extended with the infinite symbol ∞ , such that for all $r \in \mathbb{R}$, $r < \infty$. Let $\mathbb{R}_{\geq n}$ be the restriction of \mathbb{R} to values greater or equal than $n \in \mathbb{N}$. For instance, $\mathbb{R}_{\geq 0} \stackrel{\text{def}}{=} \{r \in \mathbb{R} \mid r \geq 0\} \cup \{\infty\}$.

► **Definition 1 (Metric).** Given a non-empty set L , a metric is a binary function $\delta : L \times L \rightarrow \mathbb{R}^\infty$ with the following properties $\forall x, y, z \in L$:

- (1) $\delta(x, y) \geq 0$; (non-negativity)
- (2) $x = y \Leftrightarrow \delta(x, y) = 0$; (iff-identity)
- (3) $\delta(x, y) = \delta(y, x)$; (symmetry)
- (4) $\delta(x, y) \leq \delta(x, z) + \delta(z, y)$. (triangle-inequality)

The pair $\langle L, \delta \rangle$ is called a metric space.

► **Example 2 (Euclidean Distance).** Consider the set of real numbers \mathbb{R} . We define the distance δ_2 between two real values $x, y \in \mathbb{R}$ as the absolute value of their difference, i.e., $\delta_2(x, y) \stackrel{\text{def}}{=} |x - y|$. This is the one-dimensional Euclidean distance, well-known to be a metric.

Due to their axioms, metrics are among the strongest types of distances. As we will see in the next sections, depending on what kind of data we want to measure and its abstraction, a distance may not satisfy one or more metric axioms.

A metric that does not satisfy symmetry is called a *quasi-metric*, while a metric that does not satisfy the \Leftarrow implication of (*iff-identity*) is called a *pseudo-metric*. Semi-metrics satisfy all the axioms except for the triangle inequality. The function δ is called a *pre-metric* if it only satisfies (*non-negativity*) and the \Rightarrow implication of the (*iff-identity*), i.e., the (*if-identity*) axiom. All the other metric axioms are not required, making the definition of pre-metric one of the weakest possible distance function. By composing the words pseudo-, quasi- and semi- we obtain different distance flavors by simply keeping the axioms that are satisfied by all the combined words. For instance, a quasisemi-metric is a pre-metric that additionally satisfies the (*iff-identity*), while a pseudosemi-metric only satisfies (*symmetry*) other than (*if-identity*). Fig. 1 summarizes the above distance notions and their properties. The last two rows display the distance symbol and the example in which the distance is defined and used for the first time. We will occasionally use the subscript $\delta_{\underline{\quad}}$ in cases where the set L may not be immediately clear from the context. The same convention will be adopted to orderings \preceq . From this point forward, whenever we say that a function δ is a distance, we assume that it satisfies, at least, the axioms of a pre-metric.

110 ► **Example 3** (Size Distance). Consider the powerset $\wp(L)$ of a set L . We write $size(S)$ for
 111 the number of elements in the set $S \in \wp(L)$. We define the distance $\delta_{siz}: \wp(L) \times \wp(L) \rightarrow \mathbb{R}^\infty$
 112 between two sets $S_1, S_2 \in \wp(L)$ as the absolute value of the difference in their size, i.e.,
 113 $\delta_{siz}(S_1, S_2) \stackrel{\text{def}}{=} |size(S_2) - size(S_1)|$. Note that δ_{siz} is a pseudo-metric since it does not satisfy
 114 the (*iff-identity*) axiom: two sets may have the same size yet being different.

115 **Lipschitz Continuity.** In mathematical analysis, Lipschitz continuity is a strong form of
 116 uniform continuity of functions that establishes a quantitative relationship between changes to
 117 the inputs of a function and its outputs. Specifically, it imposes that perturbations to the in-
 118 puts of a function lead to at most proportional changes to its outputs. The standard definition
 119 of Lipschitz continuity assumes that both the input and output domains are metric spaces.

120 ► **Definition 4** (Lipschitz Continuity). Let $\langle C, \delta_C \rangle$ and $\langle D, \delta_D \rangle$ be metric spaces. Let $k \in \mathbb{R}_{\geq 0}$.
 121 A function $f: C \rightarrow D$ satisfies k -Lipschitz continuity w.r.t. $\langle \delta_C, \delta_D \rangle$ if and only if:

$$122 \quad \forall x, y \in C: \delta_D(f(x), f(y)) \leq k \delta_C(x, y).$$

123 A function f satisfies Lipschitz continuity w.r.t. $\langle \delta_C, \delta_D \rangle$ if and only if there exists $k \in \mathbb{R}_{\geq 0}$
 124 such that f satisfies k -Lipschitz continuity w.r.t. $\langle \delta_C, \delta_D \rangle$.

125 The Lipschitz constant k provides an upper bound on the rate of change for the output of the
 126 function f , i.e., $\delta_D(f(x), f(y)) / \delta_C(x, y) \leq k$. Note that, k -Lipschitz continuity can be equivalently
 127 formulated as follows:

$$128 \quad \forall x, y \in C: \forall \varepsilon' \geq 0: \delta_C(x, y) \leq \varepsilon' \Rightarrow \delta_D(f(x), f(y)) \leq k \varepsilon'$$

129 **Abstract Interpretation.** Abstract interpretation [11] provides a general framework for
 130 approximating functions by interpreting them over an abstract domain A rather than their
 131 exact concrete domain C . It is particularly useful in settings where exact computations are
 132 infeasible: decidability is obtained in exchange of an unavoidable information loss. We thus
 133 say that A is an *abstraction* of C . Abstractions, originally defined using Galois insertions [11],
 134 can equivalently be expressed in terms of upper closure operators [12] (ucos or closures, for
 135 short), a formulation we adopt in this work.

136 ► **Definition 5** (Upper Closure Operator). An upper closure operator (*uco*) on a partially
 137 ordered set (*poset*, for short) $\langle C, \preceq \rangle$ is a function $\rho: C \rightarrow C$ with the following properties
 138 $\forall c, c' \in C$:

$$139 \quad (i) \quad c \preceq c' \Rightarrow \rho(c) \preceq \rho(c'); \quad (\text{monotonicity})$$

$$140 \quad (ii) \quad c \preceq \rho(c); \quad (\text{extensivity})$$

$$141 \quad (iii) \quad \rho(\rho(c)) = \rho(c). \quad (\text{idempotence})$$

142 A key property of closures is that they are uniquely determined by the set of their fixpoints
 143 $\rho(C) = \{c \in C \mid \rho(c) = c\}$. The set of all upper closure operators on C is denoted by
 144 $uco(C)$. As an example, the closure $\text{Sign} \in uco(\wp(\mathbb{Z}))$ abstracts a set of integers by discarding
 145 all information except the sign of its values, except when the set contains only the value 0.
 146 The closure is defined by the set of fixpoints:

$$147 \quad \text{Sign}(\wp(\mathbb{Z})) \stackrel{\text{def}}{=} \{\emptyset, \{0\}, \{z \in \mathbb{Z} \mid z \leq 0\}, \{z \in \mathbb{Z} \mid z \geq 0\}, \mathbb{Z}\}$$

148 **3 Abstract Lipschitz Continuity**

149 **Semantic and Quantitative Approximations.** In many domains, approximations are a
 150 fundamental tool for simplifying reasoning while preserving essential properties. Broadly,
 151 we can distinguish between *qualitative* (or *semantic*) approximations, and *quantitative*
 152 approximations.

153 Qualitative approximations preserve *properties* of the approximated data. For instance,
 154 let $\text{Int}: \wp(\mathbb{Z}) \rightarrow \wp(\mathbb{Z})$ be the function that transforms a set of integers $S \in \wp(\mathbb{Z})$ into the
 155 smallest interval $[l, u] \stackrel{\text{def}}{=} \{i \in \mathbb{Z} \mid l \leq i \leq u\}$ that contains it, namely such that $S \subseteq [l, u]$,
 156 where $l \in \mathbb{Z} \cup \{-\infty\}$, $u \in \mathbb{Z} \cup \{+\infty\}$ and $l \leq u$. So, for instance, the set of integers $\{0, 1, 4\}$
 157 can be semantically approximated by the interval $[0, 4]$ through Int . More formally, qualitative
 158 approximations can be modeled using upper closure operators (e.g., $\text{Int} \in \text{uco}(\wp(\mathbb{Z}))$). Given
 159 a poset $\langle C, \preceq \rangle$ and $\rho \in \text{uco}(C)$, an element $x \in C$ is semantically approximated by $\rho(x)$,
 160 and the set $\{y \in C \mid \rho(y) = \rho(x)\}$ represents all elements in C sharing the same semantic
 161 approximation as x . Continuing the example, the set $\{\{0,4\}, \{0,1,4\}, \{0,2,4\}, \{0,3,4\},$
 162 $\{0,1,2,4\}, \{0,1,3,4\}, \{0,1,2,3,4\}\}$ contains all the sets of integers S such that $\text{Int}(S) = [0, 4]$.

163 Quantitative approximations preserve *closeness* of the approximated data, typically
 164 measured using a distance function in a suitable topological space. More formally, given a
 165 pre-metric space $\langle C, \delta \rangle$ and a fixed constant $\varepsilon \in \mathbb{R}_{\geq 0}^{\infty}$, an element $x \in C$ is quantitatively
 166 approximated by any element in the set $\{y \in C \mid \delta(x, y) \leq \varepsilon\}$. For instance, using the size
 167 distance δ_{siz} (cf. Ex. 3), we may approximate the set $\{0, 1, 4\}$ by any set of integers whose
 168 maximum distance from it is at most $\varepsilon = 1$, e.g. by the set $\{0, 1\}$ or $\{5, 6, 8, 10\}$.

169 By *combining* the two forms of approximation, we obtain a general approximation that
 170 incorporates a quantitative error within a qualitative abstraction, while still keeping the two
 171 types of approximations distinct. Let $\langle C, \preceq \rangle$ be a poset and $\langle C, \delta \rangle$ be a pre-metric space,
 172 and let $\rho \in \text{uco}(C)$ be an abstraction. We define $\delta^{\rho}: C \times C \rightarrow \mathbb{R}_{\geq 0}^{\infty}$ as:

$$173 \quad \delta^{\rho}(x, y) \stackrel{\text{def}}{=} \delta(\rho(x), \rho(y))$$

174 that is, δ^{ρ} calculates the distance between the semantic approximations of x and y with
 175 ρ . Clearly, when considering the identity function $\text{id} \in \text{uco}(C)$ as abstraction (i.e., $\forall x \in$
 176 $C. \text{id}(x) \stackrel{\text{def}}{=} x$), it holds that $\delta^{\text{id}}(x, y) = \delta(x, y)$ for any $x, y \in C$. Note that even if the distance
 177 δ satisfies the (*iff-identity*) axiom (thus qualifying as a quasisemi-metric), the derived distance
 178 δ^{ρ} may no longer satisfy this axiom due to the input approximation introduced by ρ . This
 179 observation also highlights why requiring metric spaces in Def. 4 would be overly restrictive
 180 when aiming to define a distance that accounts for both forms of approximation. Nevertheless,
 181 δ^{ρ} remains a pre-metric.

182 ► **Proposition 6.** *Let $\langle C, \preceq \rangle$ be a poset and let $\rho \in \text{uco}(C)$. If $\langle C, \delta \rangle$ is a pre-metric space,
 183 then $\langle C, \delta^{\rho} \rangle$ is also a pre-metric space.*

184 ► **Example 7 (Path-Length Distance).** Let us consider the poset $\langle \wp(\mathbb{Z}), \subseteq \rangle$ and the closure
 185 $\text{Int} \in \text{uco}(\wp(\mathbb{Z}))$. We define the path-length distance $\delta_{\text{pat}}: \wp(\mathbb{Z}) \times \wp(\mathbb{Z}) \rightarrow \mathbb{N}^{\infty}$ as follows:
 186 $\delta_{\text{pat}}(S_1, S_2) \stackrel{\text{def}}{=} k$ with $k \in \mathbb{N}$ if $S_1 \subseteq S_2 \vee S_2 \subseteq S_1$ and S_2 has k more elements than S_1 or
 187 viceversa. For all other cases, the distance is ∞ . So, for instance, $\delta_{\text{pat}}(\{0, 1, 4\}, \{0, 1, 4, 10\}) =$
 188 $\delta_{\text{pat}}(\{0, 1, 4, 10\}, \{0, 1, 4\}) = 1$ because $\{0, 1, 4, 10\}$ has one more integer than $\{0, 1, 4\}$ namely
 189 the number 10, while $\delta_{\text{pat}}(\{0, 1, 4\}, \{1, 4, 10\}) = \infty$ because both $\{0, 1, 4\} \not\subseteq \{1, 4, 10\}$ and
 190 $\{0, 1, 4\} \not\supseteq \{1, 4, 10\}$ hold. Note that δ_{pat} may differ from δ_{siz} even between comparable
 191 sets: $\delta_{\text{pat}}(\mathbb{Z}_{>0}, \mathbb{Z}_{\geq 0}) = 1 \neq \infty = \delta_{\text{siz}}(\mathbb{Z}_{>0}, \mathbb{Z}_{\geq 0})$. In fact, $\langle \wp(\mathbb{Z}), \subseteq \rangle$ can be seen as a
 192 weighted graph where each edge has weight 1 and it connects two sets S_1, S_2 such that



(a) Controlled input/output semantic approximations. (b) Suppression of input semantic approximation.

■ **Figure 2** Abstract Lipschitz Continuity.

193 $S_1 \subset S_2 \vee S_2 \subset S_1$ and there is no other set S' such that $S_1 \subset S' \subset S_2 \vee S_2 \subset S' \subset S_1$.
 194 Then the distance $\delta_{pat}(S_1, S_2)$ corresponds to the minimum weighted path between S_1 and
 195 S_2 . The pair $\langle \wp(\mathbb{Z}), \delta_{pat} \rangle$ forms a semi-metric space. It is not a metric space because δ_{pat}
 196 does not satisfy the triangle-inequality axiom: $\delta_{pat}(\{0, 1, 4\}, \{1, 4, 10\}) = \infty \not\leq 2 = 1 + 1 =$
 197 $\delta_{pat}(\{0, 1, 4\}, \{0, 1, 4, 10\}) + \delta_{pat}(\{0, 1, 4, 10\}, \{1, 4, 10\})$.

198 By considering the interval abstraction $\text{Int} \in \text{uco}(\wp(\mathbb{Z}))$, we can combine the two forms of
 199 approximation, namely δ_{pat} and Int , into $\delta_{pat}^{\text{Int}}$: this new distance calculates the number of
 200 more elements between two interval abstractions rather than considering the original input
 201 sets. Note that $\delta_{pat}^{\text{Int}}$ loses the (*iff-identity*) axiom as one interval might represent more than
 202 one set in $\wp(\mathbb{Z})$, thus $\langle \wp(\mathbb{Z}), \delta_{pat}^{\text{Int}} \rangle$ forms a pseudosemi-metric space.

203 We can now formally define general approximations.

204 ► **Definition 8** (General Approximation). Let $\langle C, \preceq \rangle$ be a poset and $\langle C, \delta \rangle$ be a pre-metric space,
 205 and let $\rho \in \text{uco}(C)$. An element $x \in C$ is semantically approximated with ρ and quantitatively
 206 approximated by δ , up to $\varepsilon \in \mathbb{R}_{\geq 0}^\infty$, by any element in the set $\{y \in C \mid \delta^\rho(x, y) \leq \varepsilon\}$.

207 Continuing Ex. 7, the set $\{0, 1, 4\}$ can be semantically and quantitatively approximated
 208 by $\delta_{pat}^{\text{Int}}$ and $\varepsilon = 1$ in any set in

$$209 \quad \{S \in \wp(\mathbb{Z}) \mid \delta_{pat}^{\text{Int}}(\{0, 1, 4\}, S) \leq 1\} = \{S \in \wp(\mathbb{Z}) \mid \text{Int}(S) = [-1, 4] \vee \text{Int}(S) = [0, 5]\}$$

210 **Abstract Lipschitz Continuity.** When approximations are introduced to the inputs of a
 211 function (e.g., a program), they propagate through its computations, affecting the output.
 212 Understanding how approximations evolve during computations provides insight into the
 213 behavior of the function (e.g., the program).

214 Abstract Lipschitz Continuity (ALC) imposes a *controlled* (linear) error propagation from
 215 a *general approximation of the inputs* to the *general approximation of the result of a function*
 216 *computation* (cf. Fig. 2a).

217 ► **Definition 9** (Abstract Lipschitz Continuity). Let $\langle C, \preceq_C \rangle$ and $\langle D, \preceq_D \rangle$ be the input and
 218 output domains (posets), respectively. Let $\langle C, \delta_C \rangle$ and $\langle D, \delta_D \rangle$ be pre-metric spaces. Let
 219 $\eta \in \text{uco}(C)$ and $\rho \in \text{uco}(D)$ be the abstractions of the input and output domains, respectively,
 220 and $k \in \mathbb{R}_{\geq 0}$. A function $f: C \rightarrow D$ satisfies Abstract k -Lipschitz Continuity (k -ALC, for
 221 short) w.r.t. $\langle \delta_C^\eta, \delta_D^\rho \rangle$ when:

$$222 \quad \forall x, y \in C. \delta_D^\rho(f(x), f(y)) \leq k \delta_C^\eta(x, y)$$

223 A function f satisfies Abstract Lipschitz Continuity (ALC) if and only if there exists $k \in \mathbb{R}_{\geq 0}$
 224 such that f satisfies Abstract k -Lipschitz Continuity.

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225 When k -ALC holds, the constant k will be called the *abstract Lipschitz constant*.

226 Note the difference between Def. 4 of Lipschitz Continuity, and Def. 9 of Abstract Lipschitz
 227 Continuity. The former states that the quantitative (metric) distance between two function
 228 outputs is at most k times the quantitative (metric) distance between the inputs. The
 229 latter captures that the quantitative distance between the semantic approximations (i.e.,
 230 the properties) of two function outputs ($\delta_D^\rho(f(x), f(y))$) is at most k times the quantitative
 231 distance between the semantic approximations of the inputs ($\delta_C^\eta(x, y)$). The two definitions
 232 naturally coincide when both $\langle C, \delta_C \rangle$ and $\langle D, \delta_D \rangle$ are metric-spaces, and the input and output
 233 domain abstractions introduce no semantic approximation, namely when $\eta = \rho = id$. In this
 234 specific scenario, requiring Lipschitz Continuity w.r.t. $\langle \delta_C, \delta_D \rangle$ is equivalent to requiring ALC
 235 w.r.t. $\langle \delta_C^{id}, \delta_D^{id} \rangle$. This also explains why Def. 9 is a generalization of Def. 4 when the input
 236 and output domains are considered as posets.

237 Abstract 0-Lipschitz Continuity represents another special case in which the function
 238 computation completely suppresses the input property approximation (cf. Fig. 2b).

239 Similarly to the concrete definition of k -Lipschitz Continuity (cf. Def. 4), k -ALC can be
 240 equivalently reformulated as follows:

241 ► **Proposition 10.** *Consider the premises of Def. 9. A function $f: C \rightarrow D$ satisfies k -ALC
 242 w.r.t. $\langle \delta_C^\eta, \delta_D^\rho \rangle$ if and only if: $\forall x, y \in C. \forall \varepsilon' \geq 0. \delta_C^\eta(x, y) \leq \varepsilon' \Rightarrow \delta_D^\rho(f(x), f(y)) \leq k\varepsilon'$.*

243 ► **Example 11.** Let Σ be a chosen alphabet (finite set of characters) and let Σ^* be the
 244 Kleene closure of Σ , i.e., the set of all strings of finite length over Σ . We write $length(w)$ to
 245 denote the length of the string $w \in \Sigma^*$. We consider the poset $\langle \wp(\Sigma^*), \subseteq \rangle$ and the semantic
 246 property $\text{Prefix} \in uco(\wp(\Sigma^*))$ which approximates a set $W \in \wp(\Sigma^*)$ of finite strings with the
 247 set of all prefixes of at least one string in W : $\text{Prefix}(W) \stackrel{\text{def}}{=} \{w \in \Sigma^* \mid \exists w' \in \Sigma^*: ww' \in W\}$.
 248 We define $\delta_\Sigma: \wp(\Sigma^*) \times \wp(\Sigma^*) \rightarrow \mathbb{N}^\infty$ to compute the absolute difference between the number
 249 of string lengths in W_1 and W_2 , namely:

$$250 \quad \delta_\Sigma(W_1, W_2) \stackrel{\text{def}}{=} \delta_{siz}(\{length(w_1) \mid w_1 \in W_1\}, \{length(w_2) \mid w_2 \in W_2\})$$

251 where δ_{siz} is the size distance of Ex. 3, forming the pseudo-metric space $\langle \wp(\Sigma^*), \delta_\Sigma \rangle$. Given
 252 $|W_1| = n_1$ (e.g., $W_1 = \{a\}$, with $n_1 = 1$) and $|W_2| = n_2$ (e.g., $W_2 = \{bb, ccc\}$, with $n_2 = 2$)
 253 with, w.l.g., $n_2 \geq n_1$, then in the worst case all strings in both sets have different lengths,
 254 therefore in general $\delta_\Sigma(W_1, W_2) \leq n_2 - n_1$ (in the example $\delta_\Sigma(W_1, W_2) = 2 - 1 = 1$). The
 255 function $f: \wp(\Sigma^*) \rightarrow \wp(\Sigma^*)$ defined as $f(W) \stackrel{\text{def}}{=} \{w_1 w_2 \mid w_1, w_2 \in W\}$ concatenates all pairs
 256 of strings in W . In the example, $f(W_1) = \{aa\}$, while $f(W_2) = \{bbbb, bbccc, cccbb, cccccc\}$.
 257 We can observe that, in the worst case, in $f(W_i)$ we have $\frac{1}{2}n_i(n_i + 1)$ different lengths (the 2
 258 factor division comes from the fact $|w_1 w_2| = |w_2 w_1|$). In the example, we do have the worst
 259 case, having $\frac{1}{2}n_2(n_2 + 1) = 3$ different lengths. Then we can show that $\delta_\Sigma(f(W_1), f(W_2)) \leq$
 260 $\frac{1}{2}(n_2 + n_1 + 1)(n_2 - n_1)$, which implies that f cannot satisfy ALC w.r.t. $\langle \delta_\Sigma^{id}, \delta_\Sigma^{id} \rangle$ since, in
 261 the worst case, the distance $\delta_\Sigma(f(W_1), f(W_2))$ increases the distance $\delta_\Sigma(W_1, W_2)$ by a factor
 262 $(\frac{1}{2}(n_2 + n_1 + 1))$ which is not constant, as Lipschitz continuity would require.

263 Consider now $\delta_\Sigma^{\text{Prefix}}$, which adds all strings of smaller lengths up to the maximum length
 264 present in the set. Then, if $l_1 = \max\{length(w) \mid w \in W_1\}$ and $l_2 = \max\{length(w) \mid w \in$
 265 $W_2\}$, we have $\delta_\Sigma^{\text{Prefix}}(W_1, W_2) \leq l_2 - l_1$ (supposing w.l.g., $l_2 \geq l_1$). By definition, the longest
 266 string in $f(W_i)$ has length $2l_i$, therefore, in general, we have

$$267 \quad \delta_\Sigma^{\text{Prefix}}(f(W_1), f(W_2)) \leq 2l_2 - 2l_1 \leq 2\delta_\Sigma^{\text{Prefix}}(W_1, W_2)$$

268 which shows that f satisfies 2-ALC w.r.t. $\langle \delta_\Sigma^{\text{Prefix}}, \delta_\Sigma^{\text{Prefix}} \rangle$.

$$\begin{array}{ll}
a \in \text{AExp}, x \in \mathbb{X}, b \in \text{BExp} & \llbracket P_1 ; P_2 \rrbracket c \stackrel{\text{def}}{=} \llbracket P_2 \rrbracket \circ \llbracket P_1 \rrbracket c \\
\text{Stm} \ni c ::= \text{skip} \mid x := a \mid b? & \llbracket P_1 \oplus P_2 \rrbracket c \stackrel{\text{def}}{=} \llbracket P_1 \rrbracket c \vee \llbracket P_2 \rrbracket c \\
\text{Prog} \ni P ::= c \mid P ; P \mid P \oplus P \mid P^* & \llbracket P^* \rrbracket c \stackrel{\text{def}}{=} \bigvee \{ \llbracket P \rrbracket^n c \mid n \in \mathbb{N} \}
\end{array}$$

(a) Language syntax.

(b) Semantics of programs.

■ **Figure 3** Syntax and semantics of Prog.

4 Abstract Lipschitz Continuity for Programs

269

270 Up to this point, the ALC notion has been defined for generic functions. In this section,
 271 we focus on two specific aspects: (1) the application of ALC to programs, in particular, to
 272 functions representing (monotone) semantics of programs; and (2) a comparison between
 273 ALC and the notion of (Partial) Completeness in Abstract Interpretation, a well-established
 274 property used to characterize precision loss in program analysis.

275 **Programs.** In the following, we will consider programs written in the language Prog of regular
 276 commands [3, 33], which is general enough to cover deterministic imperative languages [3] as
 277 well as other programming paradigms that include, e.g., non-deterministic and probabilistic
 278 computations. The syntax of the language is given in Fig. 3a, where \oplus denotes non-
 279 deterministic choice and $*$ is the Kleene closure. We completed the grammar in [3] with an
 280 explicit grammar for basic commands in Stm (skip, variable assignments, Boolean tests), and
 281 we assume a standard grammar for arithmetic expressions in AExp and Boolean expressions in
 282 BExp. Variables x range from a denumerable set \mathbb{X} while values v range from a denumerable
 283 set \mathbb{V} (e.g., integer or natural numbers).

284 We assume to have a concrete monotone semantics $\llbracket c \rrbracket: C \rightarrow C$ for basic commands
 285 $c \in \text{Stm}$ on the complete lattice $\langle C, \preceq, \vee, \wedge, \top, \perp \rangle$, where \preceq is the partial order, \vee is the least
 286 upper bound (lub), \wedge the greatest lower bound (glb), \top is the supremum of C and \perp is the
 287 infimum of C . Then, the *concrete semantics* $\llbracket \cdot \rrbracket: \text{Prog} \rightarrow C \rightarrow C$ for programs is inductively
 288 defined on program syntax as in Fig 3b. It is easy to note that, for any program $P \in \text{Prog}$,
 289 $\llbracket P \rrbracket$ is monotone by construction. Given a program $P \in \text{Prog}$, the semantics $\llbracket P \rrbracket$ is said to be
 290 additive when it preserves arbitrary joins, i.e., $\forall S \subseteq C. \bigvee \{ \llbracket P \rrbracket c \mid c \in S \} = \llbracket P \rrbracket (\bigvee S)$.

291 ► **Example 12** (Collecting semantics). As an example, consider the complete lattice $\langle \wp(\mathbb{M}), \subseteq$
 292 $, \cup, \cap, \mathbb{M}, \emptyset \rangle$ of program memories, where a program memory $\mathfrak{m} \in \mathbb{M}$ is a function map-
 293 ping variables to values, namely $\mathfrak{m}: \mathbb{X} \rightarrow \mathbb{V}$. We can define a collecting big-step semantics
 294 $\llbracket P \rrbracket: \wp(\mathbb{M}) \rightarrow \wp(\mathbb{M})$ for a program $P \in \text{Prog}$ as the standard predicate transformer semantics
 295 on sets of program memories $\wp(\mathbb{M})$. Assume a big-step evaluation semantics \Downarrow_a for arithmetic
 296 expressions and \Downarrow_b for Boolean expressions. Given a set of program memories $S \in \wp(\mathbb{M})$, the
 297 semantics of basic commands is defined as:

$$\begin{array}{l}
298 \quad \llbracket \text{skip} \rrbracket S \stackrel{\text{def}}{=} S \\
299 \quad \llbracket x := a \rrbracket S \stackrel{\text{def}}{=} \{ \mathfrak{m}[x \leftarrow v] \mid \mathfrak{m} \in S \wedge \mathfrak{m} \Downarrow_a v \} \\
300 \quad \llbracket b? \rrbracket S \stackrel{\text{def}}{=} \{ \mathfrak{m} \in S \mid \mathfrak{m} \Downarrow_b \text{tt} \}
\end{array}$$

301 The collecting semantics for basic commands is monotone by construction on the powerset
 302 lattice of memories, and so $\llbracket P \rrbracket$ is also monotone for any program $P \in \text{Prog}$. Moreover, it is
 303 easy to note that $\llbracket P \rrbracket: \wp(\mathbb{M}) \rightarrow \wp(\mathbb{M})$ satisfies additivity as well.

304 We are now ready to instantiate Def. 9, originally stated for generic functions, to the
 305 specific case of monotone semantic functions by employing the program semantics of interest
 306 together with a chosen distance. Let $\langle C, \preceq \rangle$ be a poset and $\langle C, \delta \rangle$ a pre-metric space over
 307 the same domain. Let $\eta, \rho \in uco(C)$ be the input and output abstractions, respectively, and
 308 $k \in \mathbb{R}_{\geq 0}$. Consider a monotone program semantics $\llbracket \cdot \rrbracket: \text{Prog} \rightarrow C \rightarrow C$. We say that *the*
 309 *semantics* $\llbracket P \rrbracket$ of a program $P \in \text{Prog}$ satisfies Abstract k -Lipschitz Continuity w.r.t. $\langle \delta^\eta, \delta^\rho \rangle$:

$$310 \quad \forall c_1, c_2 \in C. \delta^\rho(\llbracket P \rrbracket c_1, \llbracket P \rrbracket c_2) \leq k \delta^\eta(c_1, c_2)$$

311 **(Partial) Completeness.** Given a monotone function $f: C \rightarrow D$ over posets $\langle C, \preceq_C \rangle$ and
 312 $\langle D, \preceq_D \rangle$ (such as the collecting big-step semantics $\llbracket P \rrbracket: \wp(\mathbb{M}) \rightarrow \wp(\mathbb{M})$ defined above over
 313 $\langle \wp(\mathbb{M}), \subseteq, \cup, \cap, \mathbb{M}, \emptyset \rangle$), the abstractions $\eta \in uco(C)$ and $\rho \in uco(D)$ can be used to approx-
 314 imate computations, thus defining an abstract version $f^\sharp: \eta(C) \rightarrow \rho(D)$ of f . An abstract
 315 function $f^\sharp: \eta(C) \rightarrow \rho(D)$ is *sound* when $\rho \circ f \preceq_D f^\sharp \circ \eta$ [11]. A sound by construction approx-
 316 imation is $\bar{f} \stackrel{\text{def}}{=} \rho \circ f \circ \eta$, called the *best correct approximation* (bca) [12] of f . Any f^\sharp soundly
 317 approximating f is, in fact, equal or less precise than the bca, formally: $\rho \circ f \preceq_D \bar{f} \preceq_D f^\sharp \circ \eta$ [11].
 318 In the following, we will often shorten the composition of functions such as $\rho \circ f \circ \eta$, by $\rho f \eta$.

319 A sound abstract computation $f^\sharp: \eta(C) \rightarrow \rho(D)$ performs a precise approximation of a
 320 (concrete) monotone function $f: C \rightarrow D$ whenever $\rho f = f^\sharp \eta$. It has been proved that for a
 321 precise abstract approximation to exist, the bca $\bar{f} \stackrel{\text{def}}{=} \rho \circ f \circ \eta$ must also be precise [12, 20]. In
 322 particular, if f^\sharp is a precise abstract approximation of f then $f^\sharp = \bar{f}$. *Completeness* [12, 20]
 323 in abstract interpretation is a desirable property that ensures the existence of a precise
 324 abstract approximation of a (concrete) monotone function f . Proving the completeness of f
 325 means proving the bca \bar{f} is precise. Formally,

326 **► Definition 13** (Completeness [12, 20]). *Let $\langle C, \preceq_C \rangle$ and $\langle D, \preceq_D \rangle$ be posets, and let $\eta \in uco(C)$
 327 and $\rho \in uco(D)$ be the input and output abstractions, respectively. A monotone function
 328 $f: C \rightarrow D$ satisfies Completeness w.r.t. $\langle \eta, \rho \rangle$ if and only if $\forall x \in C: \rho f(x) = \rho f \eta(x)$.*

329 In practice, Completeness is rarely satisfied. For this reason, Campion et al. [4, 6, 7]
 330 introduced a weaker notion of completeness, called *Partial Completeness*, by the use of
 331 pre-metrics compatible with the ordering of the underlying poset.

332 **► Definition 14** (Order-Compatible Distance [7]). *Let $\langle L, \preceq \rangle$ be a poset. A distance $\delta: L \times L \rightarrow$
 333 \mathbb{R}^∞ is said to be compatible with the ordering \preceq or, in short, \preceq -compatible, if and only if it
 334 also satisfies the following property $\forall x, y, z \in L$:*

$$335 \quad x \preceq y \preceq z \Rightarrow \delta(x, y) \leq \delta(x, z) \wedge \delta(y, z) \leq \delta(x, z). \quad (\text{chains-order})$$

336 *A poset $\langle L, \preceq \rangle$ equipped with a \preceq -compatible distance δ is called a distance compatible space
 337 and is denoted by the triple $\langle L, \preceq, \delta \rangle$.*

338 The purpose of the (*chains-order*) axiom is to give a meaning to distances between
 339 comparable elements. Notably, let f_1^\sharp and f_2^\sharp be sound abstract approximations of a concrete
 340 monotone function $f: C \rightarrow D$, i.e., $\rho \circ f \preceq_D f_1^\sharp \circ \eta$ and $\rho \circ f \preceq_D f_2^\sharp \circ \eta$. If f_1^\sharp is more precise than
 341 f_2^\sharp , i.e., $f_1^\sharp \preceq_D f_2^\sharp$, we expect a decrease in the imprecision (distance) with respect to the concrete
 342 computation when using f_1^\sharp rather than f_2^\sharp , i.e., $\forall x \in D: \delta(\rho f(x), f_1^\sharp \eta(x)) \leq \delta(\rho f(x), f_2^\sharp \eta(x))$.

343 **► Example 15.** The poset $\langle \mathbb{R}, \leq \rangle$ equipped with the Euclidean distance δ_2 from Ex. 2 is a met-
 344 ric compatible space. The poset $\langle \wp(L), \subseteq \rangle$ and the size distance δ_{siz} from Ex. 3 form a pseudo-
 345 metric compatible space. In Ex. 7, $\langle \wp(\mathbb{Z}), \subseteq, \delta_{\text{pat}}^{\text{Int}} \rangle$ is a pseudosemi-metric compatible space.

346 Def. 14 is general enough to be instantiated with other definitions of distances used in
347 the literature of abstract interpretation (see, e.g., [4, 26, 27, 35, 38]).

348 We can now recall the definition of ε -Partial Completeness.

349 ► **Definition 16** (ε -Partial Completeness [4, 7]). *Let $\langle C, \preceq_C \rangle$ be a poset and $\langle D, \preceq_D, \delta_D \rangle$ be
350 a pre-metric compatible space, let $\eta \in \text{uco}(C)$ and $\rho \in \text{uco}(D)$ be the input and output
351 abstractions, respectively. Let $\varepsilon \in \mathbb{R}_{\geq 0}^\infty$. A monotone function $f : C \rightarrow D$ satisfies ε -Partial
352 Completeness w.r.t. $\langle \eta, \delta_D^\rho \rangle$ if and only if $\forall x \in C : \delta_D^\rho(f(x), f\eta(x)) \leq \varepsilon$.*

353 The equality requirement of Def. 13 is relaxed by admitting a bounded imprecision, i.e. a
354 bounded distance, between $\rho f(x)$ and the bca $\rho f\eta(x)$ for all $x \in C$, which must not exceed
355 ε . The imprecision to be measured and bounded is encoded in the pre-metric \preceq_D -compatible
356 δ_D defined over the output domain D .

357 ► **Example 17.** Let $\langle \wp(\mathbb{Z}), \subseteq, \delta_{\text{siz}} \rangle$ be an instance of the pseudo-metric compatible space from
358 Ex. 3. Consider the program $M : x := x \bmod 2$ and its collecting semantics $\llbracket M \rrbracket : \wp(\mathbb{Z}) \rightarrow$
359 $\wp(\mathbb{Z})$. Let $\rho = \eta = \text{Int}$ where $\text{Int} \in \text{uco}(\wp(\mathbb{Z}))$ is the interval abstraction defined in Sec. 3.
360 Then $\llbracket M \rrbracket$ does not satisfy Completeness w.r.t. $\langle \text{Int}, \text{Int} \rangle$ because for the input $\{2, 4\}$ we get:

$$361 \quad \text{Int}(\llbracket M \rrbracket\{2, 4\}) = [0, 0] \subset [0, 1] = \text{Int}(\llbracket M \rrbracket\{2, 3, 4\}) = \text{Int}(\llbracket M \rrbracket \text{Int}(\{2, 4\}))$$

362 However, if we allow an imprecision quantified by $\varepsilon = 1$, we get:

$$363 \quad \delta_{\text{siz}}^{\text{Int}}(\llbracket M \rrbracket\{2, 4\}, \llbracket M \rrbracket(\text{Int}(\{2, 4\}))) = \delta_{\text{siz}}([0, 0], [0, 1]) \leq 1$$

364 In particular, it is easy to note that $\delta_{\text{siz}}^{\text{Int}}(\llbracket M \rrbracket S, \llbracket M \rrbracket(\text{Int}(S))) \leq 1$, for all sets $S \in \wp(\mathbb{Z})$, which
365 implies that $\llbracket M \rrbracket$ is 1-Partial Complete with respect to $\langle \text{Int}, \delta_{\text{siz}}^{\text{Int}} \rangle$.

366 It is worth noting that, if a function f is proved to satisfy Completeness for abstractions
367 $\langle \eta, \rho \rangle$, then f is also 0-Partial Complete for $\langle \eta, \delta^\rho \rangle$ with respect to any pre-metric order-
368 compatible δ (thanks to the (*if-identity*) axiom). However, the converse does not hold if the
369 (*iff-identity*) axiom is not satisfied by δ , e.g., when δ is a pseudo-metric.

370 **Abstract Lipschitz Continuity and Partial Completeness.** It turns out that ALC (cf.
371 Def 9) is a much stronger requirement than Partial Completeness (cf. Def. 16) for a program
372 (semantics, or a monotone function). Indeed, satisfying ALC is sufficient to also satisfy
373 0-Partial Completeness:

374 ► **Theorem 18.** *Let $\langle C, \preceq_C, \delta_C \rangle$ and $\langle D, \preceq_D, \delta_D \rangle$ be pre-metric compatible spaces, let $\eta \in$
375 $\text{uco}(C)$, $\rho \in \text{uco}(D)$ be abstractions, and let $k \in \mathbb{R}_{\geq 0}$. Consider a monotone function
376 $f : C \rightarrow D$. Then, if f satisfies k -ALC w.r.t. $\langle \delta_C^\eta, \delta_D^\rho \rangle$, it also satisfies 0-Partial Completeness
377 w.r.t. $\langle \eta, \delta_D^\rho \rangle$, namely:*

$$378 \quad [\forall x, y \in C. \delta_D^\rho(f(x), f(y)) \leq k\delta_C^\eta(x, y)] \Rightarrow [\forall x \in C. \delta_D^\rho(f(x), f\eta(x)) \leq 0]$$

379 Proofs of the above result, as well as of the corollary below, are provided in Appendix A.
380 Knowing that a monotone function f is k -ALC for $\langle \delta_C^\eta, \delta_D^\rho \rangle$ leads to conclude that the bca $\rho f\eta$
381 is 0-partial complete for the same abstractions. Specifically, $\rho f\eta$ will produce *no imprecision*
382 according to δ_D , when used to approximate f .

383 When δ_D is a quasisemi-metric, then the above result implies that $\rho f\eta$ is a complete
384 approximation of f thanks to the (*iff-identity*) axiom.

385 ► **Corollary 19.** *If $\langle D, \preceq_D, \delta_D \rangle$ is a quasisemi-metric compatible space then k -ALC w.r.t.
386 $\langle \delta_C^\eta, \delta_D^\rho \rangle$ implies Completeness w.r.t. $\langle \eta, \rho \rangle$.*

387 ► **Example 20.** Let R be the following program:

388 $(x > 0?; x := x - 1) \oplus (x \leq 0?; x := x + 1)$

389 which increments all non-negative values by 1 and decrements all non-positive values by
390 1. Let us consider the program R^* , which is the Kleene closure of R , and its collecting
391 semantics $\llbracket R^* \rrbracket : \wp(\mathbb{Z}) \rightarrow \wp(\mathbb{Z})$. Let $\langle \wp(\mathbb{Z}), \subseteq, \delta_{\subseteq} \rangle$ be a quasisemi-metric compatible space
392 where, for any two sets $S_1, S_2 \in \wp(\mathbb{Z})$, $\delta_{\subseteq}(S_1, S_2) \stackrel{\text{def}}{=} \delta_{\text{siz}}(S_1, S_2)$ (cf. Ex. 3) if $S_1 \subseteq S_2$, ∞
393 otherwise. Compared to δ_{siz} , the distance δ_{\subseteq} looses the (*symmetry*) and the (*triangle-*
394 *inequality*) axioms but gains the (*iff-identity*) axiom. Let us also consider again the interval
395 closure $\text{Int} \in \text{uco}(\wp(\mathbb{Z}))$. The collecting semantics $\llbracket R^* \rrbracket$ satisfies 1-ALC w.r.t. $\langle \delta_{\subseteq}^{\text{Int}}, \delta_{\subseteq}^{\text{Int}} \rangle$.
396 Indeed, $\llbracket R^* \rrbracket$ is monotone by definition, thus preserving the inclusion relation, and either
397 reduces the distance of input intervals or leaves them unchanged. For instance:

$$\begin{aligned} 398 \quad \delta_{\subseteq}^{\text{Int}}(\llbracket R^* \rrbracket([2, 6]), \llbracket R^* \rrbracket([0, 7])) &= \delta_{\subseteq}^{\text{Int}}([0, 6], [0, 7]) = 1 \leq 3 = \delta_{\subseteq}^{\text{Int}}([2, 6], [0, 7]) \\ 399 \quad \delta_{\subseteq}^{\text{Int}}(\llbracket R^* \rrbracket([-5, -2]), \llbracket R^* \rrbracket([-7, 0])) &= \delta_{\subseteq}^{\text{Int}}([-5, 1], [-7, 1]) = 2 \leq 5 = \delta_{\subseteq}^{\text{Int}}([-5, -2], [-7, 0]) \\ 400 \quad \delta_{\subseteq}^{\text{Int}}(\llbracket R^* \rrbracket([-2, 3]), \llbracket R^* \rrbracket([-5, 3])) &= \delta_{\subseteq}^{\text{Int}}([-2, 3], [-5, 3]) = 3 \leq 3 = \delta_{\subseteq}^{\text{Int}}([-2, 3], [-5, 3]) \end{aligned}$$

401 By Thm. 18, the semantics $\llbracket R^* \rrbracket$ also satisfies 0-Partial Completeness w.r.t. $\langle \text{Int}, \delta_{\subseteq}^{\text{Int}} \rangle$, i.e.,
402 $\delta_{\subseteq}^{\text{Int}}(\llbracket R^* \rrbracket S, \llbracket R^* \rrbracket \text{Int}(S)) \leq 0$, for any $S \in \wp(\mathbb{Z})$. Moreover, since δ_{\subseteq} is a quasisemi-metric we
403 can also conclude that $\llbracket R^* \rrbracket$ is complete w.r.t. $\langle \text{Int}, \text{Int} \rangle$, namely, its bca $\text{Int} \circ \llbracket R^* \rrbracket \circ \text{Int}$ does
404 not add any imprecision when approximating $\llbracket R^* \rrbracket$. It is easy to note that 1-ALC w.r.t.
405 $\langle \delta_{\subseteq}^{\text{Int}}, \delta_{\text{pat}}^{\text{Int}} \rangle$ also holds for $\llbracket R^* \rrbracket$.

406 Another way to interpret Cor. 19 (and analogously Thm. 18) is as follows: if a monotone
407 function f does not admit a precise bca f over $\langle \eta, \rho \rangle$, then f cannot be ALC for $\langle \delta_{\subseteq}^{\eta}, \delta_{\subseteq}^{\rho} \rangle$,
408 where δ_{\subseteq} and δ_{ρ} are any quasisemi-metric order-compatible distances. This is because Partial
409 Completeness only compares the output results (of ρf and $\rho f \eta$) on the same chain of the
410 poset $\langle D, \preceq_D \rangle$, a consequence of the soundness condition $\rho f \preceq_D \rho f \eta$.

411 ► **Example 21.** Consider the pseudo-metric order-compatible space $\langle \wp(\mathbb{Z}), \subseteq, \delta_{\text{siz}} \rangle$ and
412 the interval closure $\text{Int} \in \text{uco}(\wp(\mathbb{Z}))$. The semantics $\llbracket R \rrbracket$ from Ex. 20 does not satisfy 0-
413 Partial Completeness w.r.t. $\langle \text{Int}, \delta_{\text{siz}}^{\text{Int}} \rangle$: given $X = \{-1, 1\}$, we have $\delta_{\text{siz}}^{\text{Int}}(\llbracket R \rrbracket X, \llbracket R \rrbracket \text{Int}(X)) =$
414 $\delta_{\text{siz}}^{\text{Int}}([0, 0], [0, 1]) = 1 \neq 0$. Thus, $\llbracket R \rrbracket$ cannot satisfy ALC for $\langle \delta_{\text{siz}}^{\text{Int}}, \delta_{\text{siz}}^{\text{Int}} \rangle$. In fact, it is easy to
415 note that $\llbracket R \rrbracket$ satisfies 1-Partial Completeness for all inputs.

416 In Section 6 we also relate ALC to other important program properties in the literature.

417 5 Proving Abstract Lipschitz Continuity for Programs

418 Deductive systems for the verification of Completeness [16], Partial Completeness [4] and
419 (concrete) Lipschitz continuity [9, 10] properties of programs have already been formalized
420 in the literature. In this section we introduce a novel deductive system, inductively defined
421 on the program's syntax, that is able to soundly prove the new ALC notion of an additive
422 program semantics w.r.t. the input and output abstractions $\langle \eta, \rho \rangle$ and a given pre-metric δ .
423 Our objective in designing this deductive system has been to track the assumptions of ALC
424 needed for having a compositional proof. Soundness here means that when the semantics of
425 a program P is typed as k -ALC w.r.t. $\langle \delta^{\eta}, \delta^{\rho} \rangle$ by the deductive system, then $\llbracket P \rrbracket : C \rightarrow C$
426 is certainly k -ALC for $\langle \delta^{\eta}, \delta^{\rho} \rangle$. Conversely, the deductive system is not complete, namely,
427 not all abstract Lipschitz continuous program semantics proofs can be derived through the

$$\begin{array}{c}
\frac{\llbracket c \rrbracket \in k\text{-Lip}\langle \delta^\eta, \delta^\rho \rangle}{k \vdash [\delta^\eta] c (\delta^\rho)} \text{ (base)} \\
\\
\frac{k' \vdash [\delta^{\eta'}] P (\delta^{\rho'}) \quad k' \leq k \quad \eta' \in t\text{-Lip}\langle \delta^\eta, \delta^{\eta'} \rangle \quad \rho \in s\text{-Lip}\langle \delta^{\rho'}, \delta^\rho \rangle}{stk \vdash [\delta^\eta] P (\delta^\rho)} \text{ (weaken)} \\
\\
\frac{k_1 \vdash [\delta^\eta] P_1 (\delta^\rho) \quad k_2 \vdash [\delta^\eta] P_2 (\delta^\rho) \quad \eta \in t\text{-Lip}\langle \delta^\rho, \delta^\eta \rangle}{k_1 k_2 \vdash [\delta^\eta] P_1; P_2 (\delta^\rho)} \text{ (seq)} \\
\\
\frac{k_1 \vdash [\delta^\eta] P_1 (\delta^\rho) \quad k_2 \vdash [\delta^\eta] P_2 (\delta^\rho) \quad \rho \in t\text{-Lip}\langle \delta^{id}, \delta^\rho \rangle \quad \oplus\text{-Bound}(\langle \delta^\eta, \delta^\rho \rangle, \mathfrak{b})}{t\mathfrak{b}(k_1, k_2) \vdash [\delta^\eta] P_1 \oplus P_2 (\delta^\rho)} \text{ (join)} \\
\\
\frac{k \vdash [\delta^\eta] P (\delta^\rho) \quad \eta \in t\text{-Lip}\langle \delta^\rho, \delta^\eta \rangle \quad *\text{-Bound}(P^*, m)}{(tk)^m \vdash [\delta^\eta] P^* (\delta^\rho)} \text{ (star)}
\end{array}$$

■ **Figure 4** A deductive system for proving ALC for Prog.

deductive system. This means that we are performing an under-approximation of the set of all abstract Lipschitz continuous program semantics.

We first introduce the following set

$$k\text{-Lip}\langle \delta^\eta, \delta^\rho \rangle \stackrel{\text{def}}{=} \{f \in C \rightarrow C \mid f \text{ is Abstract } k\text{-Lipschitz Continuous w.r.t. } \langle \delta^\eta, \delta^\rho \rangle\}$$

of all abstract k -Lipschitz continuous functions on the complete lattice $\langle C, \preceq \rangle$ for $\langle \delta^\eta, \delta^\rho \rangle$. The following lemma outlines some basic properties of this class.

► **Lemma 22.** *The following hold for all functions $f \in C \rightarrow C$, closures $\eta, \rho \in \text{uco}(C)$, pre-metric δ and $k \in \mathbb{R}_{\geq 0}$:*

- (i) $k \geq 1 \Rightarrow \rho \in k\text{-Lip}\langle \delta^\rho, \delta^\rho \rangle$
- (ii) f is k -Lipschitz continuous w.r.t. $\langle \delta, \delta \rangle \Leftrightarrow f \in k\text{-Lip}\langle \delta^{id}, \delta^{id} \rangle \wedge \delta$ metric
- (iii) $\rho \in k\text{-Lip}\langle \delta^{id}, \delta^{id} \rangle \Leftrightarrow \rho \in k\text{-Lip}\langle \delta^{id}, \delta^\rho \rangle$

(i) states that, when considering the same input-output abstractions (i.e. $\eta = \rho$), then the abstraction function is k -ALC for any $k \geq 1$. Moreover, for the statement (ii), when both input-output abstractions are the identity function id and the distance δ is a metric, then the class $k\text{-Lip}\langle \delta^{id}, \delta^{id} \rangle$ corresponds precisely to the set of all (concrete) k -Lipschitz continuous functions (cf. Def. 4). Finally, (iii) shows that, when a closure ρ satisfies ALC w.r.t. $\langle \delta^{id}, \delta^{id} \rangle$, then ρ also satisfies k -ALC for $\langle \delta^{id}, \delta^\rho \rangle$. This is due to the idempotence property of closure operators.

From now on, we fix an additive program semantics of interest $\llbracket \cdot \rrbracket: \text{Prog} \rightarrow C \rightarrow C$ as well as the complete lattice $\langle C, \preceq, \vee, \wedge, \top, \perp \rangle$, and we will also use the statement “ P is k -ALC w.r.t. $\langle \delta^\eta, \delta^\rho \rangle$ ” to indicate that the semantics $\llbracket P \rrbracket$ is abstract k -Lipschitz continuous w.r.t. $\langle \delta^\eta, \delta^\rho \rangle$, i.e. $\llbracket P \rrbracket \in k\text{-Lip}\langle \delta^\eta, \delta^\rho \rangle$.

The deductive rules are provided in Fig. 4. The judgments take the form:

$$k \vdash [\delta^\eta] P (\delta^\rho)$$

We will later show that deriving a judgment $k \vdash [\delta^\eta] P (\delta^\rho)$ through the deductive rules in Fig. 4, implies that $\llbracket P \rrbracket \in k\text{-Lip}\langle \delta^\eta, \delta^\rho \rangle$. Let us examine each rule and provide an intuitive, informal explanation for better understanding.

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455 The rule (**base**) allows to derive the triple $k \vdash [\delta^\eta] \mathbf{c} (\delta^\rho)$ for all basic transfer functions
 456 $\mathbf{c} \in \mathbf{Stm}$ (i.e., for **skip**, assignments and Boolean guards) by assuming that we have a proof
 457 of k -ALC of them, encoded by the predicate $\llbracket \mathbf{c} \rrbracket \in k\text{-Lip}(\delta^\eta, \delta^\rho)$.

458 The rule (**weaken**) allows to weaken both the abstract Lipschitz constant and the
 459 abstractions considered. In particular, when we are able to derive the k' -ALC for program
 460 P w.r.t. $\langle \delta^{\eta'}, \delta^{\rho'} \rangle$, then we can always deduce a higher abstract Lipschitz constant $k \geq k'$
 461 without changing the validity of the triple. For the input abstraction η' , we can consider a
 462 new input abstraction η whenever η' is proved to be t -ALC w.r.t. $\langle \delta^\eta, \delta^{\eta'} \rangle$ with η as input
 463 abstraction. This weakening comes at the cost of multiplying the already deduced constant
 464 k' with the new constant t . This could happen, for instance, when η is in fact widening the
 465 distance $\delta^{\eta'}(c_1, c_2)$ between any two elements $c_1, c_2 \in C$, by a constant factor of t , namely
 466 by $t\delta^{\eta'}(c_1, c_2)$. Conversely, we can weaken the output abstraction ρ' by a new abstraction
 467 ρ whenever ρ is proved to be ALC for $\langle \delta^{\rho'}, \delta^\rho \rangle$ namely with ρ' as input abstraction. Here
 468 ρ could represent a narrow output abstraction in terms of distance δ between elements in
 469 C with respect to ρ' , namely having distance $\delta^\rho(c_1, c_2) \leq s\delta^{\rho'}(c_1, c_2)$ and thus introducing
 470 a new abstract Lipschitz constant s . Note that the rule (**weaken**) allows also for selecting
 471 which weakening we want to apply. For instance, if we want to weaken the abstract Lipschitz
 472 constant k' only, then we can set $\eta' \in 1\text{-Lip}(\delta^{\eta'}, \delta^{\eta'})$ and $\rho' \in 1\text{-Lip}(\delta^{\rho'}, \delta^{\rho'})$ in the premises
 473 as they always hold (cf. statement (i) of Lem. 22) without modifying any abstraction.

474 Composition of programs is treated by the rule (**seq**). Although it is well known that
 475 composing two (concrete) Lipschitz continuous functions f_1 and f_2 with Lipschitz constants
 476 k_1 and k_2 , respectively, gives as result a new k_1k_2 -Lipschitz continuous function $f_2 \circ f_1$, this in
 477 general does not always hold for ALC as abstractions come into play. However, when we
 478 have a derivation for P_1 and P_2 with abstract Lipschitz constants k_1 and k_2 , respectively,
 479 and we are able to prove that the input abstraction η is t -ALC w.r.t. $\langle \delta^\rho, \delta^\eta \rangle$, then this
 480 is a sufficient condition for deriving the k_2tk_1 -ALC of the composition $P_1;P_2$. Requiring
 481 $\eta \in t\text{-Lip}(\delta^\rho, \delta^\eta)$ corresponds to require $\delta^\eta(c_1, c_2) \leq t\delta^\rho(c_1, c_2)$, namely that we have a linear
 482 relation between their distances: when $t \geq 1$ then ρ is widening the distance, while when
 483 $0 < t < 1$ then ρ is narrowing their distances, both cases with a constant factor of t . Note
 484 that, when the input and output abstractions coincide, i.e. $\eta = \rho$, then $\rho \in 1\text{-Lip}(\delta^\rho, \delta^\rho)$
 485 holds trivially (cf. statement (i) of Lem. 22). As a consequence, the ALC property is closed
 486 under composition, analogously to the standard Lipschitz continuity property.

487 The rule (**join**) involves the join operator. Similarly for the composition, the join of two
 488 ALC functions is not necessarily ALC. The problem here stems in the fact that the resulting
 489 abstract Lipschitz constant bound could not be determined by knowing only the abstract
 490 Lipschitz constants of both P_1 and P_2 . This is because the distance between the execution of
 491 $P_1 \oplus P_2$ and the join of the two post-conditions, relies on the underlying structure of the input
 492 and output abstractions considered. Our solution, inspired by [4, 8], consists of introducing a
 493 new predicate $\oplus\text{-Bound}(\langle \delta^\eta, \delta^\rho \rangle, \mathfrak{b})$ parameterized by a binary function $\mathfrak{b} : \mathbb{R}_{\geq 0} \times \mathbb{R}_{\geq 0} \rightarrow \mathbb{R}_{\geq 0}$
 494 producing a new abstract Lipschitz constant.

495 ► **Definition 23** ($\oplus\text{-Bound}$). Consider a binary function $\mathfrak{b} : \mathbb{R}_{\geq 0} \times \mathbb{R}_{\geq 0} \rightarrow \mathbb{R}_{\geq 0}$. The
 496 predicate $\oplus\text{-Bound}(\langle \delta^\eta, \delta^\rho \rangle, \mathfrak{b})$ holds when the function \mathfrak{b} satisfies the following condition for
 497 any $P_1, P_2 \in \mathbf{Prog}$:

$$498 \quad \llbracket P_1 \rrbracket \in k_1\text{-Lip}(\delta^\eta, \delta^\rho) \text{ and } \llbracket P_2 \rrbracket \in k_2\text{-Lip}(\delta^\eta, \delta^\rho) \Rightarrow \rho \llbracket P_1 \rrbracket \oplus \rho \llbracket P_2 \rrbracket \in \mathfrak{b}(k_1, k_2)\text{-Lip}(\delta^\eta, \delta^\rho)$$

499 ► **Example 24.** Consider the pseudo-metric space $\langle \wp(\mathbb{Z}), \subseteq, \delta_{\text{siz}} \rangle$ and the collecting semantics
 500 $\llbracket \cdot \rrbracket$. Let the input and output abstractions be $\rho = \eta = \mathbf{Int}$. If we define $+(k_1, k_2) \stackrel{\text{def}}{=} k_1 + k_2$ for
 501 any $k_1, k_2 \in \mathbb{R}_{\geq 0}$, then the predicate $\oplus\text{-Bound}(\langle \delta_{\text{siz}}^{\mathbf{Int}}, \delta_{\text{siz}}^{\mathbf{Int}} \rangle, +)$ holds. In other words, having

502 an ALC proof for both P_1 and P_2 , with abstract Lipschitz constants k_1, k_2 , respectively, gives
 503 as result:

$$\begin{aligned}
 504 \quad \delta_{siz}((\text{Int}[\![P_1]\!] \oplus \text{Int}[\![P_2]\!])c_1, (\text{Int}[\![P_1]\!] \oplus \text{Int}[\![P_2]\!])c_2) &\leq k_1\delta_{siz}(\text{Int}(c_1), \text{Int}(c_2)) \\
 505 &\quad + k_2\delta_{siz}(\text{Int}(c_1), \text{Int}(c_2)) \\
 506 &= (k_1 + k_2)\delta_{siz}(\text{Int}(c_1), \text{Int}(c_2))
 \end{aligned}$$

507 This is because, when considering δ_{siz} as distance and Int as input and output abstractions,
 508 the size of the join of two intervals can be over-approximated by the sum of the number of
 509 the elements inside the two intervals. A similar reasoning holds for the quasisemi-metric
 510 space $\langle \wp(\mathbb{Z}), \subseteq, \delta_{\subseteq} \rangle$ defined in Ex. 20.

511 The premise of the rule (**join**) asks for the validity of the following predicates: assume
 512 that we have an ALC derivation $k_1 \vdash [\delta^\eta] P_1 (\delta^\rho)$ for P_1 , and $k_2 \vdash [\delta^\eta] P_2 (\delta^\rho)$ for P_2 ; if ρ
 513 is t -ALC w.r.t. $\langle \delta^{id}, \delta^\rho \rangle$, and the predicate \oplus -Bound($\langle \delta^\eta, \delta^\rho \rangle, \mathfrak{b}$) holds, then we can soundly
 514 conclude that the join $P_1 \oplus P_2$ is ALC with abstract Lipschitz constant $t\mathfrak{b}(k_1, k_2)$.

515 Finally, the rule (**star**) deals with loop iterations. It requires that the program P is
 516 k -ALC for $\langle \delta^\eta, \delta^\rho \rangle$ and that the input abstraction η is t -ALC for $\langle \delta^\rho, \delta^\eta \rangle$, similar to the
 517 (**seq**) rule. In addition, (**star**) requires the assertion $*$ -Bound(P^*, m) stating that the loop
 518 P^* reaches a least fixpoint in m or less iterations, where m is a constant. This condition can
 519 be established either via an auxiliary checker, e.g. an SMT solver, or by manual annotation.
 520 Under these premises, we can soundly apply (**star**) in the same way we apply (**seq**), and
 521 obtain an abstract Lipschitz constant k^m for the iterations multiplied by the constant t^m
 522 generated by applying m -times the abstraction, thus concluding with the $(tk)^m$ -ALC of P^* .

523 The following theorem shows that our proposed deductive system is sound, namely, if
 524 $k \vdash [\delta^\eta] P (\delta^\rho)$ can be derived by applying the rules of Fig. 4, then $\llbracket P \rrbracket$ satisfies k -ALC w.r.t.
 525 $\langle \delta^\eta, \delta^\rho \rangle$. The proof can be found in Appendix B.

526 ► **Theorem 25** (Soundness). *Let $P \in \text{Prog}$, δ be a pre-metric and $\eta, \rho \in \text{uco}(C)$ be the input
 527 and output abstractions, respectively. Then:*

$$528 \quad k \vdash [\delta^\eta] P (\delta^\rho) \Rightarrow \llbracket P \rrbracket \in k\text{-Lip}\langle \delta^\eta, \delta^\rho \rangle$$

529 ► **Example 26.** Consider the following program ReLU:

$$530 \quad (x < 0? ; x := 0) \oplus (x \geq 0? ; \text{skip})$$

531 implementing the ReLU rectifier function in artificial neural networks [31], that filters the
 532 input below 0. Consider the quasisemi-metric space $\langle \wp(\mathbb{Z}), \subseteq, \delta_{\subseteq} \rangle$ and the input and output
 533 abstraction $\eta = \rho = \text{Int}$. We want to prove that the collecting semantics $\llbracket \text{ReLU} \rrbracket : \wp(\mathbb{Z}) \rightarrow \wp(\mathbb{Z})$
 534 satisfies 1-ALC for $\langle \delta_{\subseteq}^{\text{Int}}, \delta_{\subseteq}^{\text{Int}} \rangle$. Let us start by analyzing the base commands on the left of
 535 \oplus . Because the Boolean guard $x < 0?$ is either preserving or removing values from the
 536 input, by the rule (**base**), we can derive $1 \vdash [\delta_{\subseteq}^{\text{Int}}] x < 0? (\delta_{\subseteq}^{\text{Int}})$. The command $x := 0$
 537 is neutralizing any distance between input sets since $\delta_{\subseteq}^{\text{Int}}(\llbracket x := 0 \rrbracket S_1, \llbracket x := 0 \rrbracket S_2) = 0$ for
 538 any $S_1, S_2 \in \wp(\mathbb{Z})$. So we can derive $0 \vdash [\delta_{\subseteq}^{\text{Int}}] x := 0 (\delta_{\subseteq}^{\text{Int}})$ by the rule (**base**). Since
 539 $\text{Int} \in 1\text{-Lip}\langle \delta_{\subseteq}^{\text{Int}}, \delta_{\subseteq}^{\text{Int}} \rangle$ follows from Lem. 22, we can infer $0 \vdash [\delta_{\subseteq}^{\text{Int}}] x < 0? ; x := 0 (\delta_{\subseteq}^{\text{Int}})$ by
 540 the rule (**seq**). For the base commands on the right of \oplus , we get $1 \vdash [\delta_{\subseteq}^{\text{Int}}] x \geq 0? (\delta_{\subseteq}^{\text{Int}})$
 541 with rule (**base**). The **skip** command does not modify the distance of the input sets, so
 542 $1 \vdash [\delta_{\subseteq}^{\text{Int}}] \text{skip} (\delta_{\subseteq}^{\text{Int}})$ can be derived by (**base**). Since $\text{Int} \in 1\text{-Lip}\langle \delta_{\subseteq}^{\text{Int}}, \delta_{\subseteq}^{\text{Int}} \rangle$ holds, the rule
 543 (**seq**) derives $1 \vdash [\delta_{\subseteq}^{\text{Int}}] x \geq 0? ; \text{skip} (\delta_{\subseteq}^{\text{Int}})$. Now for the \oplus operation, we consider \mathfrak{b} as the sum
 544 operation $+$ as shown in Ex. 24, thus guaranteeing a sound upper bound for the abstract

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545 Lipschitz constants on the program join. By Lem. 22, the condition $\text{Int} \in 1\text{-Lip}\langle \delta_{\subseteq}^{id}, \delta_{\subseteq}^{\text{Int}} \rangle$ is
 546 equivalent to requiring $\delta_{\subseteq}(\text{Int}(S_1), \text{Int}(S_2)) \leq \delta_{\subseteq}(S_1, S_2)$ for all $S_1, S_2 \in \wp(\mathbb{Z})$, which is clearly
 547 satisfied by Int . Therefore, by $\text{Int} \in 1\text{-Lip}\langle \delta_{\subseteq}^{id}, \delta_{\subseteq}^{\text{Int}} \rangle$, $\oplus\text{-Bound}\langle \delta_{\subseteq}^{\text{Int}}, \delta_{\subseteq}^{\text{Int}} \rangle, +$, $+(0, 1) = 1$ and
 548 the two derivations on the left and right parts of \oplus , we can conclude by the rule (**join**):
 549 $1 \vdash [\delta_{\subseteq}^{\text{Int}}] \text{ReLU}(\delta_{\subseteq}^{\text{Int}})$. By Thm. 25, this implies that $\llbracket \text{ReLU} \rrbracket$ satisfies 1-ALC for $\langle \delta_{\subseteq}^{\text{Int}}, \delta_{\subseteq}^{\text{Int}} \rangle$.

550 Although the proof system of Fig. 4 is sound, it is not complete: there might exist
 551 programs that satisfy k -ALC for which the system fails to derive a proof, or for which it only
 552 establishes the property with a larger abstract Lipschitz constant $k' \geq k$.

553 ► **Example 27.** Consider the program R of Ex. 20 together with the quasisemi-metric space
 554 $\langle \wp(\mathbb{Z}), \subseteq, \delta_{\subseteq} \rangle$ and the collecting semantics $\llbracket R \rrbracket : \wp(\mathbb{Z}) \rightarrow \wp(\mathbb{Z})$. By following similar reasoning
 555 done in Ex. 26, we can derive $1 \vdash [\delta_{\subseteq}^{\text{Int}}] x > 0?; x := x - 1 (\delta_{\subseteq}^{\text{Int}})$ and $1 \vdash [\delta_{\subseteq}^{\text{Int}}] x \leq 0?; x :=$
 556 $x + 1 (\delta_{\subseteq}^{\text{Int}})$. The rule (**join**) then concludes with $2 \vdash [\delta_{\subseteq}^{\text{Int}}] R (\delta_{\subseteq}^{\text{Int}})$ because $+(1, 1) = 2$, thus
 557 stating that $\llbracket R \rrbracket$ is 2-ALC w.r.t. $\langle \delta_{\subseteq}^{\text{Int}}, \delta_{\subseteq}^{\text{Int}} \rangle$. Although the conclusion is correct, it is not
 558 precise since $\llbracket R \rrbracket \in 1\text{-Lip}\langle \delta_{\subseteq}^{\text{Int}}, \delta_{\subseteq}^{\text{Int}} \rangle$. The imprecision here arises from the bound function
 559 $\mathfrak{b} = +$, which overestimates the number of elements produced by the join of two intervals.

560 For the program R^* , however, the deductive system cannot prove ALC for any constant k .
 561 This is due to the fact that rule (**star**) cannot be applied when there is no constant bound
 562 m on the number of iterations of R^* , unless the input is restricted to a fixed bound.

563 As a direct consequence of Thm. 25, if we instantiate the abstractions with $\eta = \rho = id$
 564 and δ is a metric, then the deductive rules of Fig. 4 derive judgments for the standard
 565 Lipschitz continuity of programs (cf. Def. 4 with $\llbracket P \rrbracket$ as f). This is because all the predicates
 566 on abstractions, such as $\eta \in t\text{-Lip}\langle \delta^{\rho}, \delta^{\eta} \rangle$ for (**seq**) and (**star**), and $\rho \in t\text{-Lip}\langle \delta^{id}, \delta^{\rho} \rangle$ for
 567 (**join**), are trivially true (cf. Lem. 22).

568 ► **Corollary 28.** *Let $P \in \text{Prog}$ and δ be a metric. Then:*

$$569 \quad k \vdash [\delta^{id}] P (\delta^{id}) \Rightarrow \llbracket P \rrbracket \text{ is } k\text{-Lipschitz continuous w.r.t. } \langle \delta, \delta \rangle$$

570 ► **Example 29.** Consider the metric space $\langle \mathbb{M}, \leq, \delta_2 \rangle$ where \leq is assumed to be component-
 571 wise and δ_2 is the Euclidean distance (cf. Ex 2). Assume that $P \in \text{Prog}$ is an always
 572 terminating program and let $\llbracket P \rrbracket : \mathbb{M} \rightarrow \mathbb{M}$ represents the standard denotational semantics
 573 mapping a program state to the resulting program state after execution of P . If we instantiate
 574 the deductive system of Fig. 4 with the abstraction $\eta = \rho = id$, the semantics $\llbracket P \rrbracket : \mathbb{M} \rightarrow \mathbb{M}$
 575 and the metric δ_2 , then the inductive rules correspond to those proposed by Chaudhuri et al.
 576 in [9]. This shows that the deductive system presented by Chaudhuri et al. in [9] is in fact
 577 an instance of $k \vdash [\delta^{\eta}] P (\delta^{\rho})$.

578 6 Related Work

579 Abstract Lipschitz continuity finds some instances in the literature. For instance, 0-ALC
 580 corresponds to require: $\forall x, y \in C. \delta_D^{\rho}(f(x), f(y)) \leq 0$. When δ_D satisfies the (*iff-identity*)
 581 axiom, the notion collapses to Abstract Robustness [19] with different models of perturbation
 582 (qualitative, quantitative, or combined). In addition, when $\eta = \rho = id$ the notion collapses
 583 to the standard program Robustness notion [19].

584 As we have already discussed in Sec. 4, Partial completeness, whose underlying idea was
 585 to replace indistinguishability (of abstract computations) with similarity (measured by a
 586 pre-metric distance), has a strong relation with ALC. The same idea in the literature led to
 587 another notion that can be seen as an instantiation of our approach, which is Approximate

588 Non-Interference [34]. This notion, originally introduced in a probabilistic process algebra,
 589 requires the *observable* behaviors of two agents under a similarity threshold ε , instead of being
 590 identical (as required by standard Non-Interference [21]). Then, we can see Approximate Non-
 591 Interference as an instance of ALC, where the observation of the output is the abstraction,
 592 and a measured distance between these observables must be under a finite threshold, which
 593 is the finite distance between the input processes.

594 As discussed in Sec. 3, the standard mathematical notion of Lipschitz continuity is an
 595 instance of ALC. In particular, when f is the standard input/output denotational program
 596 semantics $[\cdot]: \text{Prog} \rightarrow \mathbb{M} \rightarrow \mathbb{M}$ and the distance considered is the standard Euclidean metric,
 597 then ALC corresponds to the Lipschitz continuity of programs as formalized by Chaudhuri
 598 et al. in [9, 10] (referred to as *program Robustness*). We have also shown in Ex. 29 that the
 599 proof system in Fig. 4 is a strict generalization of the one in proposed in [9]. This is because
 600 the triple $k \vdash [\delta^n] P (\delta^p)$ enables reasoning about property perturbations, encoded with input
 601 and output abstractions, over weaker distances (pre-metric spaces) of *any* additive program
 602 semantics. It is also worth noting that, in contrast to [9], our proposed deductive system
 603 tracks the necessary assumptions for the base cases $[\mathbf{c}]$ required to apply the inductive rules,
 604 whereas in [9] the authors also provide an analysis for the base cases.

605 7 Conclusion

606 Abstract Lipschitz continuity is a generalization of the classical mathematical notion of
 607 Lipschitz continuity. It is parameterized by input and output pre-metric spaces, as well as by
 608 input and output domain abstractions, which are formalized as upper closure operators. This
 609 generalized framework enables the formalization of properties of the form: “*Perturbations in*
 610 *the input properties induce proportionally bounded (linear) changes in the output properties*”.
 611 We also formally proved its relation with the Partial Completeness property in abstract
 612 interpretation, by isolating the constraint under which the two notions, apparently unrelated,
 613 have a strong relation. Finally, we developed a deductive system for proving the ALC
 614 property of additive semantics of programs.

615 The proposed ALC notion is a *global* property, in the sense that it is universally quantified
 616 over all inputs. As a future work, we plan to formalize its *local* version, namely requiring ALC
 617 over a strict subset of the input domain, and study its relation with other local properties
 618 in the context of abstract interpretation [2, 3, 5]. Dropping the universal quantification
 619 may invalidate the correlation already established between the global counterparts. Also,
 620 reasoning about local properties may be more challenging, as the proposed deductive system
 621 requires nontrivial modifications to be used for proving ALC on a subset of executions.

622 We formalized abstractions as ucos, which have been proven to be equivalent to Galois
 623 insertions [12], namely admitting a surjective best abstraction function. In the future, we
 624 would like to consider weaker abstraction notions able to formalize properties that do not
 625 necessarily admit a best abstraction function, such as the domain of convex polyhedra [22].
 626 In this direction, the notion of weak closures defined in [28] could be considered.

627 Finally, in [28] the authors showed that, under certain assumptions, there is a corres-
 628 pondence between the Completeness property in abstract interpretation and the Abstract
 629 Non-Interference (ANI) property in language based security [17, 18]. While ANI does not
 630 directly model continuity properties of functions, the connection established in [28], together
 631 with Cor. 19, suggests a potential relation between ANI and ALC, which we plan to investig-
 632 ate as future work. The same could also apply to other quantitative program properties, like
 633 Quantitative Input Data Usage [29, 30].

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A

 Proofs for Section 4 (Abstract Lipschitz Continuity for Programs)

783

784 ▶ **Theorem 18.** Let $\langle C, \preceq_C, \delta_C \rangle$ and $\langle D, \preceq_D, \delta_D \rangle$ be pre-metric compatible spaces, let $\eta \in$
 785 $uco(C)$, $\rho \in uco(D)$ be abstractions, and let $k \in \mathbb{R}_{\geq 0}$. Consider a monotone function
 786 $f : C \rightarrow D$. Then, if f satisfies k -ALC w.r.t. $\langle \delta_C^\eta, \delta_D^\rho \rangle$, it also satisfies 0-Partial Completeness
 787 w.r.t. $\langle \eta, \delta_D^\rho \rangle$, namely:

$$788 \quad [\forall x, y \in C. \delta_D^\rho(f(x), f(y)) \leq k\delta_C^\eta(x, y)] \Rightarrow [\forall x \in C. \delta_D^\rho(f(x), f\eta(x)) \leq 0]$$

789 **Proof.** Let us assume Abstract k -Lipschitz Continuity w.r.t. $\langle \delta_C^\eta, \delta_D^\rho \rangle$, namely $\forall x, y \in$
 790 $C. \delta_D^\rho(f(x), f(y)) \leq k\delta_C^\eta(x, y)$. We have to prove 0-Partial Completeness w.r.t. $\langle \eta, \delta_D^\rho \rangle$,
 791 namely $\forall x \in C. \delta_D^\rho(f(x), f\eta(x)) \leq 0$. Let $y = \eta(x)$. Since Abstract k -Lipschitz Continuity
 792 holds, we have $\forall x \in C. \delta_D^\rho(f(x), f(\eta(x))) \leq k\delta_C^\eta(x, \eta(x))$ and, by idempotence of η , we have
 793 $\delta_C^\eta(x, \eta(x)) = 0$. Hence, 0-Partial Completeness w.r.t. $\langle \eta, \delta_D^\rho \rangle$ holds. ◀ ◀

794 ▶ **Corollary 19.** If $\langle D, \preceq_D, \delta_D \rangle$ is a quasisemi-metric compatible space then k -ALC w.r.t.
 795 $\langle \delta_C^\eta, \delta_D^\rho \rangle$ implies Completeness w.r.t. $\langle \eta, \rho \rangle$.

796 **Proof.** Continuing the proof of Thm. 18, we reached 0-Partial Completeness w.r.t. $\langle \eta, \delta_D^\rho \rangle$
 797 because, by fixing $y = \eta(x)$ and by the idempotence of η , we get $\forall x \in C. \delta_D^\rho(f(x), f\eta(x)) \leq 0$.
 798 Then, since δ_D is a quasisemi-metric, it satisfies the (*iff-identity*) axiom (together with the
 799 (*non-negativity*)), and so $\delta_D^\rho(f(x), f\eta(x)) \leq 0$ corresponds to $\delta_D^\rho(f(x), f\eta(x)) = 0$ which implies
 800 $\forall x \in C. \rho f(x) = \rho f\eta(x)$. ◀

B

 Proofs for Section 5 (Proving Abstract Lipschitz Continuity for Programs)

801

802

803 ▶ **Theorem 25** (Soundness). Let $P \in \text{Prog}$, δ be a pre-metric and $\eta, \rho \in uco(C)$ be the input
 804 and output abstractions, respectively. Then:

$$805 \quad k \vdash [\delta^\eta] P (\delta^\rho) \Rightarrow \llbracket P \rrbracket \in k\text{-Lip}\langle \delta^\eta, \delta^\rho \rangle$$

806 **Proof. (base):** immediate by the definition of $k \vdash [\delta^\eta] c (\delta^\rho)$ and the assumption $\llbracket c \rrbracket \in$
 807 $k\text{-Lip}\langle \delta^\eta, \delta^\rho \rangle$.

808 **(weaken):** The proof for the weakening of k is immediate. Let us show the proof for
 809 weakening the input abstraction η' . Assume $k \vdash [\delta^{\eta'}] P (\delta^\rho)$ and $\eta' \in t\text{-Lip}\langle \delta^\eta, \delta^{\eta'} \rangle$. The
 810 second assumption can be written as $\forall c_1, c_2 \in C: \delta^{\eta'}(\eta'(c_1), \eta'(c_2)) \leq t\delta^\eta(c_1, c_2)$ which, by
 811 the idempotence property of η' , corresponds to $\delta^{\eta'}(c_1, c_2) \leq t\delta^\eta(c_1, c_2)$. We get the following
 812 derivations $\forall c_1, c_2 \in C$:

$$813 \quad \delta^\rho(\llbracket P \rrbracket c_1, \llbracket P \rrbracket c_2) \leq [\text{by } k \vdash [\delta^{\eta'}] P (\delta^\rho)]$$

$$814 \quad k\delta^{\eta'}(c_1, c_2) \leq [\text{by } \eta' \in t\text{-Lip}\langle \delta^\eta, \delta^{\eta'} \rangle]$$

$$815 \quad tk\delta^\eta(c_1, c_2) \Leftrightarrow [\text{by judgment definition}]$$

$$816 \quad tk \vdash [\delta^\eta] P (\delta^\rho)$$

817 The proof for weakening the output abstraction ρ is similar and therefore omitted.

818 **(seq):** Assume we have a derivation $k_1 \vdash [\delta^\eta] P_1 (\delta^\rho)$ for program P_1 , a derivation $k_2 \vdash$
 819 $[\delta^{\eta a}] P_2 (\delta^\rho)$ for program P_2 , and $\eta \in t\text{-Lip}\langle \delta^\rho, \delta^\eta \rangle$. By η idempotent, the last assumption
 820 can be written as: $\forall c_1, c_2 \in C. \delta^\eta(c_1, c_2) \leq t\delta^\rho(c_1, c_2)$. Then we get the following derivations
 821 $\forall c_1, c_2 \in C$:

$$822 \quad \delta^\rho(\llbracket P_1; P_2 \rrbracket c_1, \llbracket P_1; P_2 \rrbracket c_2) = [\text{by definition of } \llbracket P_1; P_2 \rrbracket \text{ and } (if\text{-identity}) \text{ of } \delta^\rho]$$

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$$\begin{aligned}
823 \quad & \delta^\rho(\llbracket P_2 \rrbracket \llbracket P_1 \rrbracket c_1, \llbracket P_2 \rrbracket \llbracket P_1 \rrbracket c_2) \leq [\text{by } k_2 \vdash [\delta^\eta] P_2(\delta^\rho)] \\
824 \quad & \quad k_2 \delta^\eta(\llbracket P_1 \rrbracket c_1, \llbracket P_1 \rrbracket c_2) \leq [\text{by } \eta \in t\text{-Lip}\langle \delta^\rho, \delta^\eta \rangle] \\
825 \quad & \quad tk_2 \delta^\rho(\llbracket P_1 \rrbracket c_1, \llbracket P_1 \rrbracket c_2) \leq [\text{by } k_1 \vdash [\delta^\eta] P_1(\delta^\rho)] \\
826 \quad & \quad k_1 tk_2 \delta^\eta(c_1, c_2) \Leftrightarrow [\text{by judgment definition}] \\
827 \quad & k_1 tk_2 \vdash [\delta^\eta] P_1; P_2(\delta^\rho)
\end{aligned}$$

828 **(join)**: Assume we have a derivation $k_1 \vdash [\delta^\eta] P_1(\delta^\rho)$ for program P_1 , a derivation
829 $k_2 \vdash [\delta^\eta] P_2(\delta^\rho)$ for program P_2 , $\rho \in \delta\text{-Lip}\langle t, id \rangle \rho$, and the predicate $\oplus\text{-Bound}\langle \langle \eta, \rho \rangle, \mathfrak{b} \rangle$ holds
830 for bound function \mathfrak{b} . By Lem. 22, the assumption $\rho \in t\text{-Lip}\langle \delta^{id}, \delta^\rho \rangle$ can be written as:
831 $\forall c_1, c_2 \in C. \delta^\rho(c_1, c_2) \leq t\delta(c_1, c_2)$. Then we get the following derivations $\forall c_1, c_2 \in C$:

$$\begin{aligned}
832 \quad & \delta^\rho(\llbracket P_1 \oplus P_2 \rrbracket c_1, \llbracket P_1 \oplus P_2 \rrbracket c_2) = [\text{by definition of } \llbracket P_1 \oplus P_2 \rrbracket \text{ and } (if\text{-identity}) \text{ of } \delta^\rho] \\
833 \quad & \delta^\rho(\llbracket P_1 \rrbracket c_1 \vee \llbracket P_2 \rrbracket c_1, \llbracket P_1 \rrbracket c_2 \vee \llbracket P_2 \rrbracket c_2) = [\text{by } \rho(\rho(c_1) \vee \rho(c_2)) = \rho(c_1 \vee c_2) \text{ and } (if\text{-identity}) \text{ of } \delta^\rho] \\
834 \quad & \delta^\rho(\rho \llbracket P_1 \rrbracket c_1 \vee \rho \llbracket P_2 \rrbracket c_1, \rho \llbracket P_1 \rrbracket c_2 \vee \rho \llbracket P_2 \rrbracket c_2) \leq [\text{by } \rho \in t\text{-Lip}\langle \delta^{id}, \delta^\rho \rangle] \\
835 \quad & t\delta(\rho \llbracket P_1 \rrbracket c_1 \vee \rho \llbracket P_2 \rrbracket c_1, \rho \llbracket P_1 \rrbracket c_2 \vee \rho \llbracket P_2 \rrbracket c_2) \leq [\text{by } k_1 \vdash [\delta^\eta] P_1(\delta^\rho), k_2 \vdash [\delta^\eta] P_2(\delta^\rho), \oplus\text{-Bound}\langle \langle \eta, \rho \rangle, \mathfrak{b} \rangle] \\
836 \quad & \quad \mathfrak{b}(k_1, k_2) t \delta^\eta(c_1, c_2) \Leftrightarrow [\text{by judgment definition}] \\
837 \quad & \quad \mathfrak{b}(k_1, k_2) t \vdash [\delta^\eta] P_1 \oplus P_2(\delta^\rho)
\end{aligned}$$

838 **(star)**: Assume we have a derivation $k \vdash [\delta^\eta] P(\delta^\rho)$ for program P , $\eta \in t\text{-Lip}\langle \delta^\rho, \delta^\eta \rangle$ and
839 a bound m on the number of iterations by the predicate $*\text{-Bound}(P^*, m)$. We obtain the
840 following inequalities:

$$\begin{aligned}
841 \quad & \delta^\rho(\llbracket P^* \rrbracket c_1, \llbracket P^* \rrbracket c_2) = [\text{by } *\text{-Bound}(P^*, m), \llbracket P \rrbracket \text{ additive and } (if\text{-identity}) \text{ of } \delta^\rho] \\
842 \quad & \delta^\rho(\llbracket P \rrbracket^m c_1, \llbracket P \rrbracket^m c_2) = [\text{by definition of } \llbracket P; P \rrbracket \text{ and } (if\text{-identity}) \text{ of } \delta^\rho] \\
843 \quad & \delta^\rho(\llbracket P \rrbracket \llbracket P \rrbracket^{m-1} c_1, \llbracket P \rrbracket \llbracket P \rrbracket^{m-1} c_2) \leq [\text{by } k \vdash [\delta^\eta] P(\delta^\rho)] \\
844 \quad & \quad k \delta^\eta(\llbracket P \rrbracket^{m-1} c_1, \llbracket P \rrbracket^{m-1} c_2) \leq [\text{by } \eta \in t\text{-Lip}\langle \delta^\rho, \delta^\eta \rangle] \\
845 \quad & tk \delta^\rho(\llbracket P \rrbracket^{m-1} c_1, \llbracket P \rrbracket^{m-1} c_2) \leq [\text{by applying } m-1 \text{ composition steps}] \\
846 \quad & \quad (tk)^m \delta^\eta(c_1, c_2) \Leftrightarrow [\text{by judgment definition}] \\
847 \quad & \quad (tk)^m \vdash [\delta^\eta] P^*(\delta^\rho)
\end{aligned}$$

848

