

Local Type Inference for Polarised System F with Existentials

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CHANGE!! This paper addresses the challenging problem of type inference for Impredicative System F with existential types, a critical aspect of many programming languages. While System F serves as the basis for type systems in numerous languages, existing type inference techniques for Impredicative System F are undecidable due to the presence of existential (\exists) and polymorphic (\forall) types. Consequently, current algorithms are often ad-hoc and sub-optimal. This paper presents novel contributions in the form of a local type inference algorithm for Impredicative System F with existential types. The algorithm introduces innovative techniques, such as a unique combination of unification and anti-unification, a full correctness proof, and the use of control structures inspired by Call-By-Push-Value. Additionally, the paper discusses a type inference framework that allows the algorithm to be applied to different type systems, offering insights into the under-researched area of impredicative existential type inference.

CCS Concepts: • **Do Not Use This Code** → **Generate the Correct Terms for Your Paper**; *Generate the Correct Terms for Your Paper*; Generate the Correct Terms for Your Paper; Generate the Correct Terms for Your Paper.

Additional Key Words and Phrases: Type Inference, System F, Call-by-Push-Value, Polarized Typing, Focalisation, Subtyping

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1 INTRODUCTION

- There has been very little work on type inference for existentials.
- The state of the art in languages like Ocaml and Haskell is the Odersky-Läufer algorithm, which makes existentials a second-class construct tied to datatypes.
- More recently, there's the existential crisis paper, which showed how to extend ML-style inference with some support for existentials. However, it is (a) predicative-only, (b) restricted for $\forall\exists$ types, and (c) does not have a declarative specification. (In fact, the authors comment on the need for such.)
- In this paper, we lift all of these restrictions. We give a local type inference algorithm which supports first-class existentials, for impredicative types, with no restrictions on nested quantifiers, and we have declarative specification we prove our algorithm sound and complete with respect to.
- Developing the algorithm required us to break some of the fundamental invariants of HM-style typin, and as a result, our algorithm needs to mix unification and anti-unification, and works over a call-by-push-value metalanguage to control how quantifiers are instantiated and things like function arities.

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- Unfortunately, local type inference does not infer types anywhere nearly as comprehensively as full Damas-Milner type inference. We do guarantee that all type applications (for \forall -elimination) and all packs (for \exists -introduction) are inferred, but functions and some let-bindings still need annotations on their arguments.
- The original local type inference paper combined local type inference with bidirectional typechecking to minimize the number of needed annotations, but we show how existential types complicate the integration of bidirectionality with local type inference, and we explore the design space to show how the same scheme could be applied to work with different type systems.

Neel: We need to explain what local type inference is, and how it is and isn't related to bidirectional typechecking.

2 OVERVIEW

2.1 What types do we infer?

2.2 The Language of Types

The types of $F^\pm\exists$ are given in fig. 1. They are stratified into two syntactic categories (polarities): positive and negative, similarly to the Call-By-Push-Value system [Levy 2006]. The negative types represent computations, and the positive types represent values:

- α^- is a negative type variable, which can be taken from a context or introduced by \exists .
- a function $P \rightarrow N$ takes a value as input and returns a computation;
- a polymorphic abstraction $\forall \vec{\alpha}^+. N$ quantifies a computation over a list of positive type variables $\vec{\alpha}^+$. The polarities are chosen to follow the definition of functions.
- a shift $\uparrow P$ allows a value to be used as a computation, which at the term level corresponds to a pure computation **return** v .
- + α^+ is a positive type variable, taken from a context or introduced by \forall .
- + $\exists \vec{\alpha}^+. P$, symmetrically to \forall , binds negative variables in a positive type P .
- + a shift $\downarrow N$, symmetrically to the up-shift, thunk a computation, which at the term level corresponds to $\{c\}$.

Negative declarative types

N, M, K

::=

α^-
 $\uparrow P$
 $P \rightarrow N$
 $\forall \vec{\alpha}^+. N$

Positive declarative types

P, Q, R

::=

α^+
 $\downarrow N$
 $\exists \vec{\alpha}^+. P$

Fig. 1. Declarative Types of $F^\pm\exists$

Definitional Equalities. For simplicity, we assume that alpha-equivalent terms are equal. This way, we assume that substitutions do not capture bound variables. Besides, we equate $\forall \vec{\alpha}^+. \forall \vec{\beta}^+. N$ with $\forall \vec{\alpha}^+, \vec{\beta}^+. N$, as well as $\exists \vec{\alpha}^+. \exists \vec{\beta}^+. P$ with $\exists \vec{\alpha}^+, \vec{\beta}^+. P$, and lift these equations transitively and congruently to the whole system.

2.3 The Language of Terms

In fig. 2, we define the language of terms of $F^{\pm}\exists$. The language combines System F with the Call-By-Push-Value approach.

- + x denotes a (positive) term variable; *Ilya: why no negatives? Following CBPV*
- + $\{c\}$ is a value corresponding to a thunked or suspended computation;
- $\pm (c : N)$ and $(v : P)$ allow one to annotate positive and negative terms;
- **return** v is a pure computation, returning a value;
- $\lambda x : P. c$ and $\Lambda\alpha^+. c$ are standard lambda abstractions. Notice that we require the type annotation for the argument of λ ;
- **let** $x = v ; c$ is a standard let, binding a value v to a variable x in a computation c ;
- Applicative let forms **let** $x : P = v(\vec{v}) ; c$ and **let** $x = v(\vec{v}) ; c$ operate similarly to the bind of a monad: they take a suspended computation v , apply it to a list of arguments, bind the result (which is expected to be pure) to a variable x , and continue with a computation c . If the resulting type of the application is unique, one can omit the type annotation, as in the second form: it will be inferred by the algorithm;
- **let** $^{\exists}(\vec{\alpha}, x) = v ; c$ is the standard unpack of an existential type: expecting v to be an existential type, it binds the packed negative types to a list of variables $\vec{\alpha}$, binds the body of the existential to x , and continues with a computation c .

Missing constructors. Notice that the language does not have first-class applications: their role is played by the applicative let forms, binding the result of a *fully applied* function to a variable. Also notice that the language does not have a type application (i.e. the eliminator of \forall) and dually, it does not have pack (i.e. the constructor of \exists). This is because the instantiation of polymorphic and existential types is inferred by the algorithm. *Ilya: refer to the extension chapter*

Computation Terms	Value Terms
$c, d ::=$	$v, w ::=$
$(c : N)$	x
$\lambda x : P. c$	$\{c\}$
$\Lambda\alpha^+. c$	$(v : P)$
return v	
let $x = v ; c$	
let $x : P = v(\vec{v}) ; c$	
let $x = v(\vec{v}) ; c$	
let $^{\exists}(\vec{\alpha}, x) = v ; c$	

Fig. 2. Declarative Terms of $F^{\pm}\exists$

2.4 The key ideas of the algorithm

3 DECLARATIVE SYSTEM

The declarative system serves as a specification of the type inference algorithm. It consists of two main parts: the subtyping and the type inference.

3.1 Subtyping

It is represented by a set of inference rules shown in fig. 3.

$\boxed{\Gamma \vdash N \leq M}$ Negative subtyping

$$\overline{\Gamma \vdash \alpha^- \leq \alpha^-} \quad (\text{VAR}_{\leq})$$

$$\frac{\Gamma \vdash P \simeq^< Q}{\Gamma \vdash \uparrow P \leq \uparrow Q} \quad (\uparrow^<)$$

$$\frac{\Gamma \vdash P \geq Q \quad \Gamma \vdash N \leq M}{\Gamma \vdash P \rightarrow N \leq Q \rightarrow M} \quad (\rightarrow^<)$$

$$\frac{\Gamma, \vec{\beta}^+ \vdash \sigma : \vec{\alpha}^+ \quad \Gamma, \vec{\beta}^+ \vdash [\sigma]N \leq M}{\Gamma \vdash \forall \vec{\alpha}^+. N \leq \forall \vec{\beta}^+. M} \quad (\forall^<)$$

$\boxed{\Gamma \vdash N \simeq^< M}$ Negative equivalence

$$\frac{\Gamma \vdash N \leq M \quad \Gamma \vdash M \leq N}{\Gamma \vdash N \simeq^< M} \quad (\simeq_{\leq})$$

$\boxed{\Gamma \vdash P \geq Q}$ Positive supertyping

$$\overline{\Gamma \vdash \alpha^+ \geq \alpha^+} \quad (\text{VAR}_{\geq})$$

$$\frac{\Gamma \vdash N \simeq^< M}{\Gamma \vdash \downarrow N \geq \downarrow M} \quad (\downarrow^>)$$

$$\frac{\Gamma, \vec{\beta}^- \vdash \sigma : \vec{\alpha}^- \quad \Gamma, \vec{\beta}^- \vdash [\sigma]P \geq Q}{\Gamma \vdash \exists \vec{\alpha}^-. P \geq \exists \vec{\beta}^-. Q} \quad (\exists^>)$$

$\boxed{\Gamma \vdash P \simeq^< Q}$ Positive equivalence

$$\frac{\Gamma \vdash P \geq Q \quad \Gamma \vdash Q \geq P}{\Gamma \vdash P \simeq^< Q} \quad (\simeq_{\geq})$$

Fig. 3. Declarative Subtyping

Quantifiers. Symmetric rules $(\forall^<)$ and $(\exists^>)$ specify the subtyping between top-level quantified types. Usually, the polymorphic subtyping is represented by two rules introducing quantifiers to the left and to the right-hand side of the subtyping. For conciseness of representation, we compose these rules into one. First, our rule extends context Γ with the quantified variables from the right-hand side ($\vec{\beta}^+$ or $\vec{\beta}^-$), as these variables must remain abstract. Second, it verifies that the left-hand side quantifiers ($\vec{\alpha}^+$ or $\vec{\alpha}^-$) can be instantiated to continue subtyping recursively.

The instantiation of quantifiers is modeled by substitution σ . The notation $\Gamma_2 \vdash \sigma : \Gamma_1$ specifies its domain and range. For instance, $\Gamma, \vec{\beta}^+ \vdash \sigma : \vec{\alpha}^+$ means that σ maps the variables from $\vec{\alpha}^+$ to (positive) types well-formed in $\Gamma, \vec{\beta}^+$. This way, application $[\sigma]N$ instantiates (replaces) every α_i^- in N with $\sigma(\alpha_i^-)$.

Invariant Shifts. An important restriction that we put on the subtyping system is that the subtyping on shifted types requires their equivalence, as shown in $(\downarrow^>)$ and $(\uparrow^<)$. Relaxing both of these invariants make the system equivalent to System F, and thus, undecidable. However, after certain changes $(\uparrow^<)$ can be relaxed to the covariant form, as we will discuss in ??.

Functions. Standardly, the subtyping of function types is covariant in the return type and contravariant in the argument type.

Variables. The subtyping of variables is defined reflexively, which is enough to ensure the reflexivity of subtyping in general. The algorithm will use the fact that the subtypes of a variable coincide with its supertypes, which however is not true for an arbitrary type.

3.1.1 Properties of the Declarative Subtyping. A property that we extensively use is that the subtyping is reflexive and transitive, and agrees with substitution.

PROPERTY 1 (SUBTYPING FORMS A PREORDER). *Let us say that two types N_1 and N_2 are in the subtyping relation if there exists a context Γ such that $\Gamma \vdash N_1 \leq N_2$; symmetrically, two types P_1 and*

P_2 are in the subtyping relation if there exists Γ such that $\Gamma \vdash P_2 \geq P_1$. Then the subtyping relation defined this way is reflexive and transitive.

PROPERTY 2 (SUBTYPING AGREES WITH SUBSTITUTION). Suppose that σ is a substitution such that $\Gamma_2 \vdash \sigma : \Gamma_1$. Then

- $\Gamma_1 \vdash N \leq M$ implies $\Gamma_2 \vdash [\sigma]N \leq [\sigma]M$, and
- + $\Gamma_1 \vdash P \geq Q$ implies $\Gamma_2 \vdash [\sigma]P \geq [\sigma]Q$.

Moreover, any two positive types have the least upper bound, which makes the positive subtyping semilattice. The positive least upper bound can be found algorithmically, which we will discuss in the next section.

PROPERTY 3 (POSITIVE LEAST UPPER BOUND EXISTS). Suppose that P_1 and P_2 are positive types well-formed in Γ . Then there exists the least common supertype—a type P such that

- $\Gamma \vdash P \geq P_1$ and $\Gamma \vdash P \geq P_2$, and
- for any Q such that $\Gamma \vdash Q \geq P_1$ and $\Gamma \vdash Q \geq P_2$, $\Gamma \vdash Q \geq P$.

Negative Greatest Lower Bound does not exist. However, the symmetric construction—the greatest lower bound of two negative types does not always exist. Let us consider the following counterexample. Let us consider the following types:

- N and Q are arbitrary closed types,
- P, P_1 , and P_2 are non-equivalent closed types such that $\cdot \vdash P_1 \geq P$ and $\cdot \vdash P_2 \geq P$, and none of the types is equivalent to Q .

What is the greatest common subtype of $Q \rightarrow \downarrow \uparrow Q \rightarrow \downarrow \uparrow Q \rightarrow N$ and $P \rightarrow \downarrow \uparrow P_1 \rightarrow \downarrow \uparrow P_2 \rightarrow N$? One of the common subtypes is $\forall \alpha^+, \beta^+, \gamma^+. \alpha^+ \rightarrow \downarrow \uparrow \beta^+ \rightarrow \downarrow \uparrow \gamma^+ \rightarrow N$, which, however is not the greatest one.

One can find two greater candidates: $M_1 = \forall \alpha^+, \beta^+. \alpha^+ \rightarrow \downarrow \uparrow \alpha^+ \rightarrow \downarrow \uparrow \beta^+ \rightarrow N$ and $M_2 = \forall \alpha^+, \beta^+. \beta^+ \rightarrow \downarrow \uparrow \alpha^+ \rightarrow \downarrow \uparrow \beta^+ \rightarrow N$. Instantiating α^+ and β^+ with Q ensures that both of these types are subtypes of $Q \rightarrow \downarrow \uparrow Q \rightarrow \downarrow \uparrow Q \rightarrow N$; instantiating α^+ with P_1 and β^+ with P_2 demonstrates the subtyping with $P \rightarrow \downarrow \uparrow P_1 \rightarrow \downarrow \uparrow P_2 \rightarrow N$, as P is a subtype of both P_1 and P_2 .

By analyzing the inference rules, we can prove that both M_1 and M_2 are maximal common subtypes. Since M_1 and M_2 are not equivalent, it means that none of them is the greatest.

3.2 Equivalence and Normalization

The subtyping relation forms a preorder on types, and thus, it induces an equivalence relation a.k.a. bicoercibility [Tiuryn 1995]. The declarative specification of subtyping must be defined up to this equivalence. Moreover, the algorithms we use must withstand changes in input types within the equivalence class. To deal with non-trivial equivalence, we use normalization—a function that uniformly selects a representative of the equivalence class.

Using normalization gives us two benefits: (i) we do not need to modify significantly standard operations such as unification to withstand non-trivial equivalence, and (ii) if the subtyping (and thus, the equivalence) changes, we only need to modify the normalization function, while the rest of the algorithm remains the same.

In our system, equivalence is reacher than equality. Specifically,

- (ii) one can introduce redundant quantifiers. For example, $\forall \alpha^+, \beta^+. \uparrow \alpha^+$ is equivalent but not equal to $\forall \alpha^+. \uparrow \alpha^+$;
- (i) one can reorder quantifiers. For example, $\forall \alpha^+, \beta^+. \alpha^+ \rightarrow \beta^+ \rightarrow \gamma^-$ is equivalent but not equal to $\forall \alpha^+, \beta^+. \beta^+ \rightarrow \alpha^+ \rightarrow \gamma^-$;
- (iii) the transformations (i) and (ii) can happen at any position in the type.

It turns out that the transformations (i-iii) are complete, in the sense that they generate the whole equivalence class. This way, to normalize the type, one must

- (i) remove the redundant quantifiers,
- (ii) reorder the quantifiers to the canonical order,
- (iii) do the procedures (i) and (ii) recursively on the subterms.

The normalization algorithm is shown in fig. 4. The steps (i-ii) are implemented by the ordering function, which takes a set of variables *vars* and a type and returns a list of variables from *vars* that occur in the type in the order of their first occurrence. Its formal definition can be found in ??.

$\boxed{\text{nf}(N) = M}$ $\frac{}{\text{nf}(\alpha^-) = \alpha^-} \quad (\text{VAR}_-^{\text{NF}})$ $\frac{\text{nf}(P) = Q}{\text{nf}(\uparrow P) = \uparrow Q} \quad (\uparrow^{\text{NF}})$ $\frac{\text{nf}(P) = Q \quad \text{nf}(N) = M}{\text{nf}(P \rightarrow N) = Q \rightarrow M} \quad (\rightarrow^{\text{NF}})$ $\frac{\text{nf}(N) = N' \quad \text{ord } \vec{\alpha}^+ \text{ in } N' = \vec{\alpha}^{+'}}{\text{nf}(\forall \vec{\alpha}^+. N) = \forall \vec{\alpha}^{+'}. N'} \quad (\forall^{\text{NF}})$	$\boxed{\text{nf}(P) = Q}$ $\frac{}{\text{nf}(\alpha^+) = \alpha^+} \quad (\text{VAR}_+^{\text{NF}})$ $\frac{\text{nf}(N) = M}{\text{nf}(\downarrow N) = \downarrow M} \quad (\downarrow^{\text{NF}})$ $\frac{\text{nf}(P) = P' \quad \text{ord } \vec{\alpha}^- \text{ in } P' = \vec{\alpha}^{-'}}{\text{nf}(\exists \vec{\alpha}^-. P) = \exists \vec{\alpha}^{-'}. P'} \quad (\exists^{\text{NF}})$
<p>ord vars in N returns a list of variables $\text{vars} \cap \text{fv}(N)$ in the order of their first occurrence in N</p>	<p>ord vars in P returns a list of variables $\text{vars} \cap \text{fv}(P)$ in the order of their first occurrence in P</p>

Fig. 4. Type Normalization Procedure

For the normalization procedure, we prove soundness and completeness w.r.t. the equivalence relation.

PROPERTY 4 (CORRECTNESS OF NORMALIZATION).

- For N and M well-formed in Γ , $\Gamma \vdash N \simeq^< M$ is equivalent to $\text{nf}(N) = \text{nf}(M)$;
- + analogously, for P and Q well-formed in Γ , $\Gamma \vdash P \simeq^< Q$ is equivalent to $\text{nf}(P) = \text{nf}(Q)$.

3.3 Type Inference

The declarative specification of the type inference is shown in fig. 5. The positive typing judgment $\Gamma; \Phi \vdash v : P$ is read as “under the type context Γ and variable context Φ , the term v is allowed to have the type P ”, where Φ —the variable context—is defined standardly as a set of pairs of the form $x : P$. The negative typing judgment is read similarly.

The *Application typing* judgment infers the type of the application of a function to a list of arguments. It has form of $\Gamma; \Phi \vdash N \bullet \vec{v} \Rightarrow M$, which reads “under the type context Γ and variable context Φ , the application of a function of type N to the list of arguments \vec{v} is allowed to have the type M ”.

Let us discuss the rules of the declarative system in more detail.

Variables. Rule $(\text{VAR}^{\text{INF}})$ allows to infer the type of a variable from the context. In literature can be found another version of this rule, that enables inferring a type *equivalent* to the type from the context. In our case, the inference of equivalent types is admissible in general case by (\simeq_+^{INF}) .

$\Gamma; \Phi \vdash c : N$ Negative typing	$\Gamma; \Phi \vdash v : P$ Positive typing
$\frac{\Gamma \vdash P \quad \Gamma; \Phi, x : P \vdash c : N}{\Gamma; \Phi \vdash \lambda x : P. c : P \rightarrow N} \quad (\lambda^{\text{INF}})$	$\frac{x : P \in \Phi}{\Gamma; \Phi \vdash x : P} \quad (\text{VAR}^{\text{INF}})$
$\frac{\Gamma, \alpha^+; \Phi \vdash c : N}{\Gamma; \Phi \vdash \Lambda \alpha^+. c : \forall \alpha^+. N} \quad (\Lambda^{\text{INF}})$	$\frac{\Gamma; \Phi \vdash c : N}{\Gamma; \Phi \vdash \{c\} : \downarrow N} \quad (\{\}^{\text{INF}})$
$\frac{\Gamma; \Phi \vdash v : P}{\Gamma; \Phi \vdash \text{return } v : \uparrow P} \quad (\text{RET}^{\text{INF}})$	$\frac{\Gamma \vdash Q \quad \Gamma; \Phi \vdash v : P \quad \Gamma \vdash Q \geq P}{\Gamma; \Phi \vdash (v : Q) : Q} \quad (\text{ANN}_+^{\text{INF}})$
$\frac{\Gamma; \Phi \vdash v : P \quad \Gamma; \Phi, x : P \vdash c : N}{\Gamma; \Phi \vdash \text{let } x = v; c : N} \quad (\text{LET}^{\text{INF}})$	$\frac{\Gamma; \Phi \vdash v : P \quad \Gamma \vdash P \simeq^{\leq} P'}{\Gamma; \Phi \vdash v : P'} \quad (\simeq_+^{\text{INF}})$
$\frac{\begin{array}{l} \Gamma; \Phi \vdash v : \downarrow M \\ \Gamma; \Phi \vdash M \bullet \vec{v} \Rightarrow \uparrow Q \text{ unique} \\ \Gamma; \Phi, x : Q \vdash c : N \end{array}}{\Gamma; \Phi \vdash \text{let } x = v(\vec{v}); c : N} \quad (\text{LET}_{@}^{\text{INF}})$	$\Gamma; \Phi \vdash N \bullet \vec{v} \Rightarrow M \quad \text{Application typing}$
$\frac{\begin{array}{l} \Gamma \vdash P \quad \Gamma; \Phi \vdash v : \downarrow M \\ \Gamma; \Phi \vdash M \bullet \vec{v} \Rightarrow \uparrow Q \\ \Gamma \vdash \uparrow Q \leq \uparrow P \quad \Gamma; \Phi, x : P \vdash c : N \end{array}}{\Gamma; \Phi \vdash \text{let } x : P = v(\vec{v}); c : N} \quad (\text{LET}_{@}^{\text{INF}})$	$\frac{\Gamma \vdash N \simeq^{\leq} N'}{\Gamma; \Phi \vdash N \bullet \cdot \Rightarrow N'} \quad (\emptyset_{\bullet \Rightarrow}^{\text{INF}})$
$\frac{\begin{array}{l} \Gamma; \Phi \vdash v : \exists \vec{\alpha}^+. P \\ \text{nf}(\exists \vec{\alpha}^+. P) = \exists \vec{\alpha}^+. P \\ \Gamma, \vec{\alpha}^+; \Phi, x : P \vdash c : N \quad \Gamma \vdash N \end{array}}{\Gamma; \Phi \vdash \text{let}^{\exists}(\vec{\alpha}^+, x) = v; c : N} \quad (\text{LET}_{\exists}^{\text{INF}})$	$\frac{\begin{array}{l} \Gamma; \Phi \vdash v : P \quad \Gamma \vdash Q \geq P \\ \Gamma; \Phi \vdash N \bullet \vec{v} \Rightarrow M \end{array}}{\Gamma; \Phi \vdash Q \rightarrow N \bullet v, \vec{v} \Rightarrow M} \quad (\rightarrow_{\bullet \Rightarrow}^{\text{INF}})$
$\frac{\Gamma \vdash M \quad \Gamma; \Phi \vdash c : N \quad \Gamma \vdash N \leq M}{\Gamma; \Phi \vdash (c : M) : M} \quad (\text{ANN}_{-}^{\text{INF}})$	$\frac{\vec{v} \neq \cdot \quad \vec{\alpha}^+ \neq \cdot \quad \Gamma \vdash \sigma : \vec{\alpha}^+}{\Gamma; \Phi \vdash [\sigma] N \bullet \vec{v} \Rightarrow M} \quad (\forall_{\bullet \Rightarrow}^{\text{INF}})$
$\frac{\Gamma; \Phi \vdash c : N \quad \Gamma \vdash N \simeq^{\leq} N'}{\Gamma; \Phi \vdash c : N'} \quad (\simeq_{-}^{\text{INF}})$	

Fig. 5. Declarative Inference

Annotations. Subtyping is also used by the annotation rules $(\text{ANN}_{-}^{\text{INF}})$ and $(\text{ANN}_{+}^{\text{INF}})$. The annotation is only valid if the inferred type is a subtype of the annotation type.

Abstractions. The typing of lambda abstraction is standard. Rule (λ^{INF}) first checks that the given type annotating the argument is well-formed, and then infers the type of the body in the extended context. As a result, it returns an arrow type of function from the annotated type of the argument to the type of the body. Rule (Λ^{INF}) infers polymorphic \forall -type. It extends the type context with the quantifying variable α^+ and infers the type of the body. As a result, it returns a polymorphic type quantifying the abstracted variable α^+ over the type of the body.

Return and Thunk. Rules $(\text{RET}^{\text{INF}})$ and $(\{\}^{\text{INF}})$ add the corresponding shifts to the type of the body

Unpack. Rule ($\text{LET}_{\exists}^{\text{INF}}$) types elimination of \exists . First, it infers the normalized type of the existential package. The normalization is required to fix the order of the quantifying variables to bind them. After the bind, the rule infers the type of the body and checks that it does not use the bound variables so that they do not escape the scope.

Applicative Let Binders. Rules ($\text{LET}_{@}^{\text{INF}}$) and ($\text{LET}_{@}^{\text{INF}}$) infer the type of the applicative let binders. Both of them infer the type of the head v and invoke the application typing to infer the type of the application before recursing on the body of the let binder. The difference is that the former rule is for the *unannotated* let binder, and thus it requires the resulting type of application to be unique (up to equivalence), so that the type of the bound variable x is known before it is put into the context. The latter rule is for the *annotated* binder, and thus, the type of the bound x is given, however, the rule must check that this type is a supertype of the inferred type of the application. This check is done by invoking the subtyping judgment $\Gamma \vdash \uparrow Q \leq \uparrow P$. This judgment is more restrictive than checking bare $\Gamma \vdash P \geq Q$, however, it is necessary to make the algorithm complete as it allows us to preserve certain invariants (see ??). In ?? we discuss how this restriction can be relaxed together with invariant shift subtyping.

Typing up to Equivalence. As discussed in section 3.2, the subtyping, as a preorder, induces a non-trivial equivalence relation on types. The system must not distinguish between equivalent types, and thus, type inference must be defined up to equivalence. For this purpose, we use rules (\simeq_{+}^{INF}) and (\simeq_{-}^{INF}). They allow one to replace the inferred type with an equivalent one.

Application to an Empty List of Arguments. The base case of the application type inference is represented by rule ($\emptyset_{\bullet \Rightarrow}^{\text{INF}}$). If the head of the type N is applied to no arguments, the type of the result is allowed to be N or any equivalent type. We need to relax this rule up to equivalence to ensure the corresponding property globally: the inferred application type can be replaced with an equivalent one. Alternatively, we could have added a separate rule similar to (\simeq_{+}^{INF}), however, the local relaxation is sufficient to prove the global property.

Application of a Polymorphic Type \forall . The complexity of the system is hidden in the rules, whose output type is not immediately defined by their input and the output of their premises (a.k.a. not mode-correct [Dunfield et al. 2020]). In our typing system, such rule is ($\forall_{\bullet \Rightarrow}^{\text{INF}}$): the instantiation of the quantifying variables is not known a priori. The algorithm we present in ?? delays this instantiation until more information about it (in particular, typing constraints) is collected.

To ensure the priority of application between this rule and ($\emptyset_{\bullet \Rightarrow}^{\text{INF}}$), we also check that the list of arguments is not empty.

Application of an Arrow Type. Another important application rule is ($\rightarrow_{\bullet \Rightarrow}^{\text{INF}}$). This is where the subtyping is used to check that the type of the argument is convertible to (a subtype of) the type of the function parameter. In the algorithm (??), this subtyping check will provide the constraints we need to resolve the delayed instantiations of the quantifying variables.

3.3.1 Declarative Typing Properties. An important property that the declarative system has is that the declarative specification is correctly defined for equivalence classes.

PROPERTY 5 (DECLARATIVE TYPING IS DEFINED UP TO EQUIVALENCE). *Let us assume that $\Gamma \vdash \Phi_1 \simeq^{\leq} \Phi_2$, i.e., the corresponding types assigned by Φ_1 and Φ_2 are equivalent in Γ . Also, let us assume that $\Gamma \vdash N_1 \simeq^{\leq} N_2$, $\Gamma \vdash P_1 \simeq^{\leq} P_2$, and $\Gamma \vdash M_1 \simeq^{\leq} M_2$. Then*

- $\Gamma; \Phi_1 \vdash c: N_1$ holds if and only if $\Gamma; \Phi_2 \vdash c: N_2$,
- + $\Gamma; \Phi_1 \vdash v: P_1$ holds if and only if $\Gamma; \Phi_2 \vdash v: P_2$, and
- $\Gamma; \Phi_1 \vdash N_1 \bullet \vec{v} \Rightarrow M_1$ holds if and only if $\Gamma; \Phi_2 \vdash N_2 \bullet \vec{v} \Rightarrow M_2$.

Ilya: Other properties?

4 THE ALGORITHM

In this section, we present the algorithmization of the system described before. Shadowing the declarative system, the algorithm has two main parts: the subtyping and the type inference, which we discuss in this section one after another.

4.1 Algorithmic Syntax

First, let us discuss the syntax of the algorithmic system.

Positive Algorithmic Variables $\widehat{\alpha}^+, \widehat{\beta}^+, \widehat{\gamma}^+, \dots$

Negative Algorithmic Variables $\widehat{\alpha}^-, \widehat{\beta}^-, \widehat{\gamma}^-, \dots$

Positive Algorithmic Types $P = \dots \mid \widehat{\alpha}^+$

Negative Algorithmic Types $N = \dots \mid \widehat{\alpha}^-$

Algorithmic Type Context $\Xi = \{\widehat{\alpha}_1^\pm, \dots, \widehat{\alpha}_n^\pm\}$ where $\widehat{\alpha}_1^\pm, \dots, \widehat{\alpha}_n^\pm$ are pairwise distinct

Algorithmic Variables. Both subtyping and the inference algorithms are represented by sets of inference rules, to simplify the soundness and completeness proofs w.r.t. the declarative specification. The terms these rules manipulate we call *algorithmic*. They extend the previously defined declarative terms and types by adding *algorithmic type variables* (a.k.a. unification variables). The algorithmic variables represent unknown types, which cannot be inferred immediately but are promised to be instantiated as the algorithm proceeds.

We denote algorithmic variables as $\widehat{\alpha}^+, \widehat{\beta}^-, \dots$ to distinguish them from normal variables α, β, \dots and also to smooth out the transition from the declarative to the algorithmic system, when we replace the quantified variables $\vec{\alpha}^+$ with their algorithmic counterpart $\vec{\widehat{\alpha}}^+$. The procedure of replacing declarative variables with algorithmic ones we call *algorithmization* and denote as $\vec{\alpha}^+ / \vec{\widehat{\alpha}}^+$ and $\vec{\alpha}^- / \vec{\widehat{\alpha}}^-$.

Algorithmic Types. The syntax of algorithmic types is the syntax of declarative types extended with algorithmic type variables: we add positive algorithmic variables $\widehat{\alpha}^+$ to the positive types, and negative algorithmic variables $\widehat{\alpha}^-$ to the negative types. Notice that these variables cannot be abstracted by the quantifiers \forall and \exists . We denote the algorithmic types

Algorithmic Contexts and Well-formedness. To specify when algorithmic types are well-formed, we define algorithmic contexts Ξ as sets of algorithmic variables. Then $\Gamma; \Xi \vdash P$ and $\Gamma; \Xi \vdash N$ represent the well-formedness judgment of algorithmic terms defined as expected: in addition to the declarative definition ??, we also check that each algorithmic variable is in the context Ξ .

$$\begin{array}{ccc} \vdots & & \vdots \\ \frac{\widehat{\alpha}^+ \in \Xi}{\Gamma; \Xi \vdash \widehat{\alpha}^+} & (\text{UVar}_+^{\text{WF}}) & \frac{\widehat{\alpha}^- \in \Xi}{\Gamma; \Xi \vdash \widehat{\alpha}^-} & (\text{UVar}_-^{\text{WF}}) \end{array}$$

Fig. 6. Well-formedness of Algorithmic Types

Algorithmic Normalization. Similarly to well-formedness, the normalization of algorithmic types is defined by extending the declarative definition trivially with the algorithmic variables.

$$\frac{}{\text{nf}(\widehat{\alpha}^+) = \widehat{\alpha}^+} \quad (\text{UVar}_+^{\text{NF}}) \qquad \frac{}{\text{nf}(\widehat{\alpha}^-) = \widehat{\alpha}^-} \quad (\text{UVar}_-^{\text{NF}})$$

Fig. 7. Normalization of Algorithmic Types

4.2 Type Constraints

As the algorithm proceeds, it accumulates the information about the algorithmic type variables in the form of *constraints*. In our system, the constraints can be of two kinds: *subtyping constraints* and *unification constraints*. The subtyping constraint can only have a positive shape $\widehat{\alpha}^+ : \geq P$, i.e., it restricts a positive algorithmic variable to be a supertype of a certain declarative type—this is one of the invariants that we preserve in the algorithm. The unification constraint can have either a positive form $\widehat{\alpha}^+ : \simeq P$ or a negative form $\widehat{\alpha}^- : \simeq N$, however, the right-hand side of the constraint cannot contain algorithmic type variables. The set of constraints is denoted as C . We assume that the constraints in C restrict distinct variables.

We separately define UC as a set consisting of unification constraints only. This is done to simplify the representation of the algorithm. The unification, which we use as a subroutine of the subtyping algorithm, can only produce unification constraints. A set of unification constraints can be resolved in a simpler way than a general constraint set. This way, the separation of the unification constraint resolution into a separate procedure allows us to better decompose the structure of the algorithm, and thus, simplify the inductive proofs.

Constraint Entry	Unification Constraint Entry
$e ::=$	$ue ::=$
$\widehat{\alpha}^+ : \simeq P$	$\widehat{\alpha}^+ : \simeq P$
$\widehat{\alpha}^- : \simeq N$	$\widehat{\alpha}^- : \simeq N$
$\widehat{\alpha}^+ : \geq P$	
Constraint Set	Unification Constraint Set
$C ::= \{e_1, \dots, e_n\}$	$UC ::= \{ue_1, \dots, ue_n\}$

Fig. 8. Constraint Entries and Sets

Constraint Contexts. When one instantiates an algorithmic variable, they may only use type variables available in its scope. As such, each algorithmic variable must remember the context at the moment when it was introduced. In our algorithm, this information is represented by a *constraint context* Θ —a set of pairs associating algorithmic variables and declarative contexts.

$$\Theta ::= \{\widehat{\alpha}_1^\pm \{\Gamma_1\}, \dots, \widehat{\alpha}_n^\pm \{\Gamma_n\}\}$$

Fig. 9. Constraint Contexts

Auxiliary Functions. We define $\text{dom}(C)$ —a domain of a constraint set C as a set of algorithmic variables that it restricts. Similarly, we define $\text{dom}(\Theta)$ —a domain of constraint context as a set of algorithmic variables that Θ associates with their contexts. We write $\Theta(\widehat{\alpha}^\pm)$ to denote the context associated with $\widehat{\alpha}^\pm$ in Θ .

4.3 Subtyping Algorithm

For convenience and scalability, we decompose the subtyping algorithm into several procedures. Figure 10 shows these procedures and the dependencies between them: arrows denote the invocation of one procedure from another. The label «nf» annotating arrows means that the calling procedure normalizes the input before passing it to the callee.

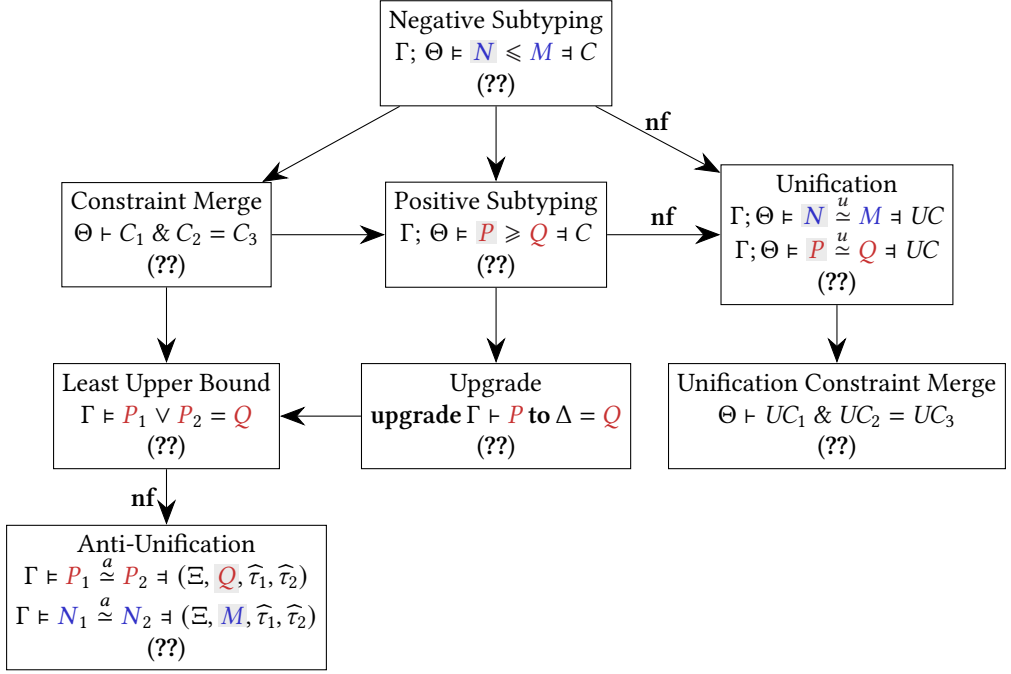


Fig. 10. Dependency graph of the subtyping algorithm

In the remainder of this section, we will delve into each of these procedures in detail, following the top-down order of the dependency graph. First, we present the subtyping algorithm itself.

As an input, the subtyping algorithm takes a type context Γ , a constraint context Θ , and two types of the corresponding polarity: N and M for the negative subtyping, and P and Q for the positive subtyping. We assume the second type (M and Q) to be declarative (with no algorithmic variables) and well-formed in Γ , but the first type (N and P) may contain algorithmic variables, whose instantiation contexts are specified by Θ .

Notice that the shape of the input types uniquely determines the applied subtyping rule. If the subtyping is successful, it returns a set of constraints C restricting the algorithmic variables of the first type. If the subtyping does not hold, there will be no inference tree with such inputs.

The rules of the subtyping algorithm bijectively correspond to the rules of the declarative system. Let us discuss them in detail.

Variables. Rules (VAR^{\leq}) and (VAR^{\geq}) say that if both of the input types are equal declarative variables, they are subtypes of each other, with no constraints (as there are no algorithmic variables).

Shifts. Rules (\Downarrow^{\geq}) and (\Uparrow^{\leq}) cover the downshift and the upshift cases, respectively. If the input types are constructed by shifts, then the subtyping can only hold if they are equivalent. This way, the algorithm must find the instantiations of the algorithmic variables on the left-hand side, which

$\Gamma; \Theta \models \underline{N} \leq \underline{M} \models C$ Negative subtyping	$\Gamma; \Theta \models \underline{P} \geq \underline{Q} \models C$ Positive supertyping
$\frac{}{\Gamma; \Theta \models \alpha^- \leq \alpha^- \models \cdot} \text{ (VAR}^{\leq})$	$\frac{}{\Gamma; \Theta \models \alpha^+ \geq \alpha^+ \models \cdot} \text{ (VAR}^{\geq})$
$\frac{\Gamma; \Theta \models \text{nf}(\underline{P}) \stackrel{u}{\approx} \text{nf}(\underline{Q}) \models UC}{\Gamma; \Theta \models \uparrow \underline{P} \leq \uparrow \underline{Q} \models UC} \text{ (}\uparrow^{\leq}\text{)}$	$\frac{\vec{\alpha}^- \text{ are fresh}}{\Gamma, \vec{\beta}^-; \Theta, \vec{\alpha}^- \{ \Gamma, \vec{\beta}^- \} \models [\vec{\alpha}^- / \alpha^-] \underline{P} \geq \underline{Q} \models C} \text{ (}\exists^{\geq}\text{)}$
$\frac{\vec{\alpha}^+ \text{ are fresh}}{\Gamma, \vec{\beta}^+; \Theta, \vec{\alpha}^+ \{ \Gamma, \vec{\beta}^+ \} \models [\vec{\alpha}^+ / \alpha^+] \underline{N} \leq \underline{M} \models C} \text{ (}\forall^{\leq}\text{)}$	$\frac{\Gamma; \Theta \models \text{nf}(\underline{N}) \stackrel{u}{\approx} \text{nf}(\underline{M}) \models UC}{\Gamma; \Theta \models \downarrow \underline{N} \geq \downarrow \underline{M} \models UC} \text{ (}\downarrow^{\geq}\text{)}$
$\frac{\Gamma; \Theta \models \forall \vec{\alpha}^+. \underline{N} \leq \forall \vec{\beta}^+. \underline{M} \models C \setminus \vec{\alpha}^+}{\Gamma; \Theta \models \underline{P} \geq \underline{Q} \models C_1 \quad \Gamma; \Theta \models \underline{N} \leq \underline{M} \models C_2 \quad \Theta \vdash C_1 \ \& \ C_2 = C} \text{ (}\rightarrow^{\leq}\text{)}$	$\frac{\text{upgrade } \Gamma \vdash \underline{P} \text{ to } \Theta(\vec{\alpha}^+) = \underline{Q}}{\Gamma; \Theta \models \vec{\alpha}^+ \geq \underline{P} \models (\vec{\alpha}^+ \geq \underline{Q})} \text{ (UVar}^{\geq}\text{)}$

Fig. 11. Subtyping Algorithm

make it equivalent to the right-hand side. For this purpose, the algorithm invokes the unification procedure ?? preceded by normalization of the input types. It returns the resulting constraints given by the unification algorithm.

Quantifiers. Rules (\forall^{\leq}) and (\exists^{\geq}) are symmetric. According to the declarative specification, the quantified variables on the left-hand side must be instantiated with types, which, however, are not known in advance. We deal with it by algorithmization (??) of the quantified variables: we introduce fresh algorithmic variables $\vec{\alpha}^+$ or $\vec{\alpha}^-$, put them into the constraint context Θ (specifying that they must be instantiated in the extended context $\Gamma, \vec{\beta}^+$ or $\Gamma, \vec{\beta}^-$) and substitute the quantified variables for them in the input type.

After that, the algorithm proceeds with the recursive call, returning constraints C . As the output, the algorithm removes the freshly introduced algorithmic variables from the constraint context. This operation is sound: it is guaranteed that C always has a solution, but the specific instantiation of the freshly introduced algorithmic variables is not important, as they do not occur in the input types.

Functions. To infer the subtyping of the function types, the algorithm makes two calls: (i) a recursive call ensuring the subtyping of the result types, and (ii) a call to positive subtyping (or rather super-typing) on the argument types. The resulting constraints are merged (using a special procedure defined later in ??) and returned as the output.

Algorithmic Variable. If one of the sides of the subtyping is a unification variable, the algorithm must create a new restriction. Because the right-hand side of the subtyping is always declarative, it is only the left-hand side that can be a unification variable. Moreover, another invariant we preserve prevents the negative algorithmic variables from occurring in types during the negative subtyping algorithm. It means that the only possible form of the subtyping here is $\vec{\alpha}^+ \geq \underline{P}$, which is covered by (UVar^{\geq}) .

The potential problem here is that the type \underline{P} might be not well-formed in the context required for $\vec{\alpha}^+$ by Θ , because this context might be smaller than the current context Γ . As we wish the resulting constraint set to be sound w.r.t. Θ , we cannot simply put $\vec{\alpha}^+ \geq \underline{P}$ into the output. Prior

to that, we update the type P to its lowest supertype Q well-formed in $\Theta(\widehat{\alpha}^+)$. It is done by the *upgrade* procedure, which we discuss in detail in ??.

To summarize, the subtyping algorithm uses the following additional subroutines: (i) rules (\downarrow^{\geq}) and (\uparrow^{\leq}) invoke the *unification* algorithm to equate the input types; (ii) rule (\rightarrow^{\leq}) *merges* the constraints produced by the recursive calls on the result and the argument types; and (iii) rule (UVar^{\geq}) *upgrades* the input type to its least supertype well-formed in the context required by the algorithmic variable. The following sections discuss these additional procedures in detail.

4.4 Unification

As an input the unification context takes a type context Γ , a constraint context Θ , and two types of the required polarity: N and M for the negative unification, and P and Q for the positive unification. It is assumed that only the left-hand side type may contain algorithmic variables, this way, the left-hand side is well-formed as an algorithmic type in Γ and Θ , whereas the right-hand side is well-formed declaratively in Γ .

Since only the left-hand side may contain algorithmic variables, that the unification instantiates, we could have called this procedure *matching*. However, in ?? we will discuss several modifications of the type system, where this invariant is not preserved, and thus, this procedure becomes a genuine first-order pattern unification [Miller 1991].

As the output, the unification algorithm returns the weakest set of unification constraints UC such that any instantiation satisfying these constraints unifies the input types.

<div style="border: 1px solid black; padding: 5px; margin-bottom: 10px;"> $\Gamma; \Theta \models \underline{N} \stackrel{u}{\simeq} \underline{M} \dashv UC$ </div> <p style="text-align: center;">Negative unification</p> $ \begin{array}{c} \frac{}{\Gamma; \Theta \models \underline{\alpha}^- \stackrel{u}{\simeq} \underline{\alpha}^- \dashv \cdot} \quad (\text{VAR}_{-}^u) \\ \\ \frac{\Gamma; \Theta \models \underline{P} \stackrel{u}{\simeq} \underline{Q} \dashv UC}{\Gamma; \Theta \models \uparrow \underline{P} \stackrel{u}{\simeq} \uparrow \underline{Q} \dashv UC} \quad (\uparrow^u) \\ \\ \frac{\Gamma; \Theta \models \underline{P} \stackrel{u}{\simeq} \underline{Q} \dashv UC_1 \quad \Gamma; \Theta \models \underline{N} \stackrel{u}{\simeq} \underline{M} \dashv UC_2}{\Gamma; \Theta \models \underline{P} \rightarrow \underline{N} \stackrel{u}{\simeq} \underline{Q} \rightarrow \underline{M} \dashv UC_1 \ \& \ UC_2} \quad (\rightarrow^u) \\ \\ \frac{\Gamma, \vec{\alpha}^+; \Theta \models \underline{N} \stackrel{u}{\simeq} \underline{M} \dashv UC}{\Gamma; \Theta \models \forall \vec{\alpha}^+. \underline{N} \stackrel{u}{\simeq} \forall \vec{\alpha}^+. \underline{M} \dashv UC} \quad (\forall^u) \\ \\ \frac{\Theta(\widehat{\alpha}^-) \vdash \underline{N}}{\Gamma; \Theta \models \widehat{\alpha}^- \stackrel{u}{\simeq} \underline{N} \dashv (\widehat{\alpha}^- \simeq \underline{N})} \quad (\text{UVar}_{-}^u) \end{array} $	<div style="border: 1px solid black; padding: 5px; margin-bottom: 10px;"> $\Gamma; \Theta \models \underline{P} \stackrel{u}{\simeq} \underline{Q} \dashv UC$ </div> <p style="text-align: center;">Positive unification</p> $ \begin{array}{c} \frac{}{\Gamma; \Theta \models \underline{\alpha}^+ \stackrel{u}{\simeq} \underline{\alpha}^+ \dashv \cdot} \quad (\text{VAR}_{+}^u) \\ \\ \frac{\Gamma; \Theta \models \underline{N} \stackrel{u}{\simeq} \underline{M} \dashv UC}{\Gamma; \Theta \models \downarrow \underline{N} \stackrel{u}{\simeq} \downarrow \underline{M} \dashv UC} \quad (\downarrow^u) \\ \\ \frac{\Gamma, \vec{\alpha}^+; \Theta \models \underline{P} \stackrel{u}{\simeq} \underline{Q} \dashv UC}{\Gamma; \Theta \models \exists \vec{\alpha}^+. \underline{P} \stackrel{u}{\simeq} \exists \vec{\alpha}^+. \underline{Q} \dashv UC} \quad (\exists^u) \\ \\ \frac{\Theta(\widehat{\alpha}^+) \vdash \underline{P}}{\Gamma; \Theta \models \widehat{\alpha}^+ \stackrel{u}{\simeq} \underline{P} \dashv (\widehat{\alpha}^+ \simeq \underline{P})} \quad (\text{UVar}_{+}^u) \end{array} $
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Fig. 12. Unification Algorithm

The algorithm works as one might expect: if both sides are formed by constructors, it is required that the constructors are the same, and the types unify recursively. If one of the sides is a unification variable (in our case it can only be the left-hand side), we create a new unification constraint restricting it to be equal to the other side. Let us discuss the rules that implement this strategy.

Variables. The variable rules (VAR_-^u) and (VAR_+^u) are trivial: as the input types do not have algorithmic variables, and are already equal, the unification returns no constraints.

Shifts. The shift rules (\downarrow^u) and (\uparrow^u) require the input types to be formed by the same shift constructor. They remove this constructor, unify the types recursively, and return the resulting set of constraints.

Quantifiers. Similarly, the quantifier rules (\forall^u) and (\exists^u) require the quantifier variables on the left-hand side and the right-hand side to be the same. This requirement is complete because we assume the input types of the unification to be normalized, and thus, the equivalence implies alpha-equivalence. In the implementation of this rule, an alpha-renaming might be needed to ensure that the quantified variables are the same, however, we omit it for brevity.

Functions. Rule (\rightarrow^u) unifies two functional types. First, it unifies the argument types and their result types recursively. Then it merges the resulting constraints using the constraint merge procedure (??).

Notice that the resulting constraints can only have *unification* entries. It means that they can be merged in a simpler way than general constraints. In particular, the merging procedure does not call any of the subroutines discussed here, but rather simply checks the matching constraint entries for equality.

Algorithmic Variable. Finally, if the left-hand side of the unification is an algorithmic variable, (VAR_-^u) or (VAR_+^u) is applied. It simply checks that the right-hand side type is well-formed in the required constraint context, and returns a newly created constraint restricting the variable to be equal to the right-hand side type.

As one can see, the unification procedure is standard, except that it makes sure that the resulting instantiations agree with the input constraint context Θ . As a subroutine, the unification algorithm only uses the (unification) constraint merge procedure and the well-formedness checking.

4.5 Constraint Merge

The merge procedure that we discuss in this section, allows one to combine two constraint sets into one. It might seem that just taking the union of the two sets would be enough, however, we require the constraint sets to have a certain structure, in particular not to have two entries restricting the same algorithmic variable—we call such entries *matching*. The matching entries must be combined into one constraint entry, that would represent their conjunction. This way, to merge two constraint sets, we unite the entries of two sets, and then merge the matching pairs.

Merging Matching Constraint Entries. Two *matching* entries formed in the same context Γ can be merged as shown in fig. 13. Suppose that e_1 and e_2 are input entries. The result of the merge $e_1 \& e_2$ must be the weakest entry which implies both e_1 and e_2 .

Suppose that one of the input entries, say e_1 , is a unification constraint entry. Then the resulting entry $e_1 \& e_2$ must coincide with it (up-to-equivalence), and thus, it is only required to check that e_2 is implied by e_1 .

- If e_2 is also a restricting entry, then the types on the right-hand side of e_1 and e_2 must be equivalent, as given by rules ($\simeq \&^+ \simeq$) and ($\simeq \&^- \simeq$).
- If e_2 is a supertype restriction $\hat{\alpha}^+ \geq P$, the algorithm must check that the type assigned by e_1 is a supertype of P . The corresponding symmetric rules are ($\geq \&^+ \simeq$) and ($\simeq \&^+ \geq$).

$$\boxed{\Gamma \vdash e_1 \ \& \ e_2 = e_3} \quad \text{Subtyping Constraint Entry Merge}$$

$$\frac{\Gamma \models P_1 \vee P_2 = Q}{\Gamma \vdash (\widehat{\alpha}^+ : \geq P_1) \ \& \ (\widehat{\alpha}^+ : \geq P_2) = (\widehat{\alpha}^+ : \geq Q)} \quad (\geq \ \&^+ \ \geq)$$

$$\frac{\Gamma; \cdot \models P \geq Q \dashv \cdot}{\Gamma \vdash (\widehat{\alpha}^+ : \simeq P) \ \& \ (\widehat{\alpha}^+ : \simeq Q) = (\widehat{\alpha}^+ : \simeq P)} \quad (\simeq \ \&^+ \ \geq)$$

$$\frac{\Gamma; \cdot \models Q \geq P \dashv \cdot}{\Gamma \vdash (\widehat{\alpha}^+ : \geq P) \ \& \ (\widehat{\alpha}^+ : \simeq Q) = (\widehat{\alpha}^+ : \simeq Q)} \quad (\geq \ \&^+ \ \simeq)$$

$$\frac{\text{nf}(P) = \text{nf}(P')}{\Gamma \vdash (\widehat{\alpha}^+ : \simeq P) \ \& \ (\widehat{\alpha}^+ : \simeq P') = (\widehat{\alpha}^+ : \simeq P)} \quad (\simeq \ \&^+ \ \simeq)$$

$$\frac{\text{nf}(N) = \text{nf}(N')}{\Gamma \vdash (\widehat{\alpha}^- : \simeq N) \ \& \ (\widehat{\alpha}^- : \simeq N') = (\widehat{\alpha}^- : \simeq N)} \quad (\simeq \ \&^- \ \simeq)$$

Fig. 13. Merge of Matching Constraint Entries

If both input entries are supertype restrictions: $\widehat{\alpha}^+ : \geq P$ and $\widehat{\alpha}^+ : \geq Q$, then their conjunction is $\widehat{\alpha}^+ : \geq P \vee Q$, as given by $(\geq \ \&^+ \ \geq)$. The least upper bound— $P \vee Q$ is the least supertype of both P and Q , and this way, $\widehat{\alpha}^+ : \geq P \vee Q$ is the weakest constraint entry that implies $\widehat{\alpha}^+ : \geq P$ and $\widehat{\alpha}^+ : \geq Q$. The algorithm for finding the least upper bound is discussed in ??.

Merging Constraint Sets. The algorithm for merging constraint sets is shown in fig. 14. As discussed, the result of merge C_1 and C_2 consists of three parts: (i) the entries of C_1 that do not match any entry of C_2 ; (ii) the entries of C_2 that do not match any entry of C_1 ; and (iii) the merge (fig. 13) of matching entries.

Suppose that $\Theta \vdash C_1$ and $\Theta \vdash C_2$.

Then $\Theta \vdash C_1 \ \& \ C_2 = C$ defines a set of constraints C such that $e \in C$ iff either:

- $e \in C_1$ and there is no matching $e' \in C_2$; or
- $e \in C_2$ and there is no matching $e' \in C_1$; or
- $\Theta(\widehat{\alpha}^\pm) \vdash e_1 \ \& \ e_2 = e$ for some $e_1 \in C_1$ and $e_2 \in C_2$ such that e_1 and e_2 both restrict variable $\widehat{\alpha}^\pm$.

Fig. 14. Constraint Merge

As shown in fig. 13, the merging procedure relies substantially on the least upper bound algorithm. In the next section, we discuss this algorithm in detail, together with the upgrade procedure, selecting the least supertype ell-formed in a given context.

4.6 Type Upgrade and the Least Upper Bounds

Both type upgrade and the least upper bound algorithms are used to find a minimal supertype under certain conditions. For a given type P well-formed in Γ , the *upgrade* operation finds the least among those supertypes of P that are well-formed in a smaller context $\Delta \subseteq \Gamma$. For given two types P_1 and P_2 well-formed in Γ , the *least upper bound* operation finds the least among common supertypes of P_1 and P_2 well-formed in Γ . These algorithms are shown in fig. 15.

<div style="border: 1px solid black; padding: 5px; margin-bottom: 10px;"> upgrade $\Gamma \vdash P \text{ to } \Delta = Q$ </div> <div style="text-align: center;">Type Upgrade</div> $ \frac{ \begin{array}{l} \Gamma = \Delta, \vec{\alpha}^\pm \\ \vec{\beta}^\pm \text{ are fresh } \quad \vec{\gamma}^\pm \text{ are fresh} \\ \Delta, \vec{\beta}^\pm, \vec{\gamma}^\pm \models [\vec{\beta}^\pm / \vec{\alpha}^\pm] P \vee [\vec{\gamma}^\pm / \vec{\alpha}^\pm] P = Q \end{array} }{ \text{upgrade } \Gamma \vdash P \text{ to } \Delta = Q } \quad (\text{UPG}) $	<div style="border: 1px solid black; padding: 5px; margin-bottom: 10px;"> $\Gamma \models P_1 \vee P_2 = Q$ </div> <div style="text-align: center;">Least Upper Bound</div> $ \frac{ \Gamma, \vec{\alpha}^-, \vec{\beta}^- \models P_1 \vee P_2 = Q }{ \Gamma \models \exists \vec{\alpha}^-. P_1 \vee \exists \vec{\beta}^-. P_2 = Q } \quad (\exists^\vee) $ $ \frac{}{ \Gamma \models \alpha^+ \vee \alpha^+ = \alpha^+ } \quad (\text{VAR}^\vee) $ $ \frac{ \Gamma \models \mathbf{nf}(\downarrow N) \stackrel{a}{\approx} \mathbf{nf}(\downarrow M) \dashv (\Xi, \underline{P}, \widehat{\tau}_1, \widehat{\tau}_2) }{ \Gamma \models \downarrow N \vee \downarrow M = \exists \vec{\alpha}^-. [\vec{\alpha}^- / \Xi] \underline{P} } \quad (\downarrow^\vee) $
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Fig. 15. Type Upgrade and Least Upper Bound Algorithms

The Type Upgrade. The type upgrade algorithm uses the least upper bound algorithm as a subroutine. It exploits the idea that the free variables of a positive type Q cannot disappear in its subtypes. It means that if a type P has free variables not occurring in P' , then any common supertype of P and P' must not contain these variables either. This way, any supertype of P not containing certain variables $\vec{\alpha}^\pm$ must also be a supertype of $P' = [\vec{\beta}^\pm / \vec{\alpha}^\pm]P$, where $\vec{\beta}^\pm$ are fresh; and vice versa: any common supertype of P and P' does not contain $\vec{\alpha}^\pm$ nor $\vec{\beta}^\pm$.

This way, to find the least supertype of P well-formed in $\Delta = \Gamma \setminus \vec{\alpha}^\pm$ (i.e., not containing $\vec{\alpha}^\pm$), we can do the following. First, construct a new type P' by renaming $\vec{\alpha}^\pm$ in P to fresh $\vec{\beta}^\pm$, and second, find the *least upper bound* of P and P' in the appropriate context. However, for reasons of symmetry, in rule (UPG) we employ a different but equivalent approach: we create two types P_1 and P_2 constructed by renaming $\vec{\alpha}^\pm$ in P to fresh disjoint variables $\vec{\beta}^\pm$ and $\vec{\gamma}^\pm$ respectively, and then find the least upper bound of P_1 and P_2 .

The Least Upper Bound. The Least Upper Bound algorithm we use operates on *positive* types. This way, the inference rules of the algorithm analyze the three possible shapes of the input types: a variable type, an existential type, and a shifted computation.

Rule (\exists^\vee) covers the case when at least one of the input types is an existential type. In this case, we can simply move the existential quantifiers from both sides to the context, and make a tail-recursive call. However, it is important to make sure that the quantified variables $\vec{\alpha}^-$ and $\vec{\beta}^-$ are disjoint (i.e., alpha-renaming might be required in the implementation).

Rule (VAR^\vee) applies when both sides are variables. In this case, the common supertype only exists if these variables are the same. And if they are, the common supertypes must be equivalent to this variable.

Rule (\downarrow^\vee) is the most interesting. If both sides are not quantified, and one of the sides is a shift, so must be the other side. However, the set of common upper bounds is not trivial in this case. For example, $\downarrow(\beta^+ \rightarrow \gamma_1^-)$ and $\downarrow(\beta^+ \rightarrow \gamma_2^-)$ have two non-equivalent common supertypes: $\exists \alpha^-. \downarrow \alpha^-$ (by instantiating α^- with $\beta^+ \rightarrow \gamma_1^-$ and $\beta^+ \rightarrow \gamma_2^-$ respectively) and $\exists \alpha^-. \downarrow(\beta^+ \rightarrow \alpha^-)$ (by instantiating α^- with γ_1^- and γ_2^- respectively). As one can see, the second supertype $\exists \alpha^-. \downarrow(\beta^+ \rightarrow \alpha^-)$ is the least among them because it abstracts over a ‘deeper’ negative subexpression.

In general, we must (i) find the most detailed pattern (a type with ‘holes’ at negative positions) that matches both sides, and (ii) abstract over the ‘holes’ by existential quantifiers. The algorithm that finds the most detailed common pattern is called *anti-unification*. As output, it returns $(\Xi, \underline{P}, \widehat{\tau}_1, \widehat{\tau}_2)$, where important for us is \underline{P} —the pattern and Ξ —the set of ‘holes’ represented by

negative algorithmic variables. We discuss the anti-unification algorithm in detail in the following section.

4.7 Anti-Unification

$$\begin{array}{c}
 \boxed{\Gamma \models P_1 \overset{a}{\simeq} P_2 \models (\Xi, \textcolor{red}{Q}, \widehat{\tau}_1, \widehat{\tau}_2)} \\
 \\
 \frac{}{\Gamma \models \alpha^+ \overset{a}{\simeq} \alpha^+ \models (\cdot, \alpha^+, \cdot, \cdot)} \quad (\text{VAR}_+^{\overset{a}{\simeq}}) \\
 \\
 \frac{\Gamma \models N_1 \overset{a}{\simeq} N_2 \models (\Xi, \textcolor{blue}{M}, \widehat{\tau}_1, \widehat{\tau}_2)}{\Gamma \models \downarrow N_1 \overset{a}{\simeq} \downarrow N_2 \models (\Xi, \downarrow \textcolor{blue}{M}, \widehat{\tau}_1, \widehat{\tau}_2)} \quad (\downarrow^{\overset{a}{\simeq}}) \\
 \\
 \frac{\vec{\alpha} \cap \Gamma = \emptyset \quad \Gamma \models P_1 \overset{a}{\simeq} P_2 \models (\Xi, \textcolor{red}{Q}, \widehat{\tau}_1, \widehat{\tau}_2)}{\Gamma \models \exists \vec{\alpha}. P_1 \overset{a}{\simeq} \exists \vec{\alpha}. P_2 \models (\Xi, \exists \vec{\alpha}. \textcolor{red}{Q}, \widehat{\tau}_1, \widehat{\tau}_2)} \quad (\exists^{\overset{a}{\simeq}}) \\
 \\
 \boxed{\Gamma \models N_1 \overset{a}{\simeq} N_2 \models (\Xi, \textcolor{blue}{M}, \widehat{\tau}_1, \widehat{\tau}_2)} \\
 \\
 \frac{}{\Gamma \models \alpha^- \overset{a}{\simeq} \alpha^- \models (\cdot, \alpha^-, \cdot, \cdot)} \quad (\text{VAR}_-^{\overset{a}{\simeq}}) \\
 \\
 \frac{\Gamma \models P_1 \overset{a}{\simeq} P_2 \models (\Xi, \textcolor{red}{Q}, \widehat{\tau}_1, \widehat{\tau}_2)}{\Gamma \models \uparrow P_1 \overset{a}{\simeq} \uparrow P_2 \models (\Xi, \uparrow \textcolor{red}{Q}, \widehat{\tau}_1, \widehat{\tau}_2)} \quad (\uparrow^{\overset{a}{\simeq}}) \\
 \\
 \frac{\vec{\alpha} \cap \Gamma = \emptyset \quad \Gamma \models N_1 \overset{a}{\simeq} N_2 \models (\Xi, \textcolor{blue}{M}, \widehat{\tau}_1, \widehat{\tau}_2)}{\Gamma \models \forall \vec{\alpha}. N_1 \overset{a}{\simeq} \forall \vec{\alpha}. N_2 \models (\Xi, \forall \vec{\alpha}. \textcolor{blue}{M}, \widehat{\tau}_1, \widehat{\tau}_2)} \quad (\forall^{\overset{a}{\simeq}}) \\
 \\
 \frac{\Gamma \models P_1 \overset{a}{\simeq} P_2 \models (\Xi_1, \textcolor{red}{Q}, \widehat{\tau}_1, \widehat{\tau}_2) \quad \Gamma \models N_1 \overset{a}{\simeq} N_2 \models (\Xi_2, \textcolor{blue}{M}, \widehat{\tau}'_1, \widehat{\tau}'_2)}{\Gamma \models P_1 \rightarrow N_1 \overset{a}{\simeq} P_2 \rightarrow N_2 \models (\Xi_1 \cup \Xi_2, \textcolor{red}{Q} \rightarrow \textcolor{blue}{M}, \widehat{\tau}_1 \cup \widehat{\tau}'_1, \widehat{\tau}_2 \cup \widehat{\tau}'_2)} \quad (\rightarrow^{\overset{a}{\simeq}}) \\
 \\
 \frac{\text{if other rules are not applicable} \quad \Gamma \vdash N \quad \Gamma \vdash M}{\Gamma \models N \overset{a}{\simeq} M \models (\widehat{\alpha}_{\{N,M\}}^-, \widehat{\alpha}_{\{N,M\}}^-, (\widehat{\alpha}_{\{N,M\}}^- \mapsto N), (\widehat{\alpha}_{\{N,M\}}^- \mapsto M))} \quad (\text{AU})
 \end{array}$$

Fig. 16. Anti-Unification Algorithm

4.8 Type Inference

5 CORRECTNESS

6 EXTENSIONS

7 RELATED WORK

8 CONCLUSION

[Botlan et al. 2003] [dunfieldBidirectionalTyping2020]

$\boxed{\Gamma; \Phi \models c: N}$ Negative typing

$$\frac{\Gamma \vdash M \quad \Gamma; \Phi \models c: N \quad \Gamma; \cdot \models N \leq M \dashv \cdot}{\Gamma; \Phi \models (c: M): \mathbf{nf}(M)} \quad (\text{ANN}_{-}^{\text{INF}})$$

$$\frac{\Gamma \vdash P \quad \Gamma; \Phi, x: P \models c: N}{\Gamma; \Phi \models \lambda x: P. c: \mathbf{nf}(P \rightarrow N)} \quad (\lambda^{\text{INF}})$$

$$\frac{\Gamma, \alpha^+; \Phi \models c: N}{\Gamma; \Phi \models \Lambda \alpha^+. c: \mathbf{nf}(\forall \alpha^+. N)} \quad (\Lambda^{\text{INF}})$$

$$\frac{\Gamma; \Phi \models v: P}{\Gamma; \Phi \models \mathbf{return} v: \uparrow P} \quad (\text{RET}^{\text{INF}})$$

$$\frac{\Gamma; \Phi \models v: P \quad \Gamma; \Phi, x: P \models c: N}{\Gamma; \Phi \models \mathbf{let} x = v; c: N} \quad (\text{LET}^{\text{INF}})$$

$$\frac{\begin{array}{l} \Gamma \vdash P \quad \Gamma; \Phi \models v: \downarrow M \\ \Gamma; \Phi; \cdot \models M \bullet \vec{v} \Rightarrow \uparrow Q \dashv \Theta; C_1 \\ \Gamma; \Theta \models \uparrow Q \leq \uparrow P \dashv C_2 \\ \Theta \vdash C_1 \& C_2 = C \quad \Gamma; \Phi, x: P \models c: N \end{array}}{\Gamma; \Phi \models \mathbf{let} x: P = v(\vec{v}); c: N} \quad (\text{LET}_{@}^{\text{INF}})$$

$$\frac{\begin{array}{l} \Gamma; \Phi \models v: \downarrow M \quad \Gamma; \Phi; \cdot \models M \bullet \vec{v} \Rightarrow \uparrow Q \dashv \Theta; C \\ \mathbf{uv} Q = \mathbf{dom}(C) \quad C \text{ singular with } \widehat{\sigma} \\ \Gamma; \Phi, x: [\widehat{\sigma}] Q \models c: N \end{array}}{\Gamma; \Phi \models \mathbf{let} x = v(\vec{v}); c: N} \quad (\text{LET}_{@}^{\text{INF}})$$

$$\frac{\Gamma; \Phi \models v: \exists \alpha^{\rightarrow}. P \quad \Gamma, \alpha^{\rightarrow}; \Phi, x: P \models c: N \quad \Gamma \vdash N}{\Gamma; \Phi \models \mathbf{let}^{\exists}(\alpha^{\rightarrow}, x) = v; c: N} \quad (\text{LET}_{\exists}^{\text{INF}})$$

Fig. 17. Algorithmic Negative Type Inferences

$\boxed{\Gamma; \Phi \models v: P}$ Positive typing

$$\frac{x: P \in \Phi}{\Gamma; \Phi \models x: \mathbf{nf}(P)} \quad (\text{VAR}^{\text{INF}})$$

$$\frac{\Gamma; \Phi \models c: N}{\Gamma; \Phi \models \{c\}: \downarrow N} \quad (\{\}^{\text{INF}})$$

$$\frac{\begin{array}{l} \Gamma \vdash Q \quad \Gamma; \Phi \models v: P \\ \Gamma; \cdot \models Q \geq P \dashv \cdot \end{array}}{\Gamma; \Phi \models (v: Q): \mathbf{nf}(Q)} \quad (\text{ANN}_{+}^{\text{INF}})$$

Fig. 18. Algorithmic Positive Type Inferences

$\Gamma; \Phi; \Theta_1 \vdash N \bullet \vec{v} \Rightarrow M \dashv \Theta_2; C$ Application typing

$$\frac{}{\Gamma; \Phi; \Theta \vdash N \bullet \cdot \Rightarrow \text{nf}(N) \dashv \Theta; \cdot} (\emptyset_{\bullet \Rightarrow}^{\text{INF}})$$

$$\frac{\begin{array}{l} \Gamma; \Phi \vdash v: P \quad \Gamma; \Theta \vdash Q \geq P \dashv C_1 \\ \Gamma; \Phi; \Theta \vdash N \bullet \vec{v} \Rightarrow M \dashv \Theta'; C_2 \\ \Theta \vdash C_1 \& C_2 = C \end{array}}{\Gamma; \Phi; \Theta \vdash Q \rightarrow N \bullet v, \vec{v} \Rightarrow M \dashv \Theta'; C} (\rightarrow_{\bullet \Rightarrow}^{\text{INF}})$$

$$\frac{\begin{array}{l} \Gamma; \Phi; \Theta, \vec{\alpha}^+ \{\Gamma\} \vdash [\vec{\alpha}^+ / \alpha^+] N \bullet \vec{v} \Rightarrow M \dashv \Theta'; C \\ \vec{\alpha}^+ \text{ are fresh} \quad \vec{v} \neq \cdot \quad \alpha^+ \neq \cdot \end{array}}{\Gamma; \Phi; \Theta \vdash \forall \vec{\alpha}^+. N \bullet \vec{v} \Rightarrow M \dashv \Theta'; C|_{\text{uv}(N) \cup \text{uv}(M)}} (\forall_{\bullet \Rightarrow}^{\text{INF}})$$

Fig. 19. Algorithmic Application Type Inferences

REFERENCES

- Didier Le Botlan and Didier Rémy (Aug. 2003). “MLF Raising ML to the Power of System F.” In: *ICFP '03*. Uppsala, Sweden: ACM Press, pp. 52–63.
- Jana Dunfield and Neel Krishnaswami (Nov. 2020). “Bidirectional Typing.” In: arXiv: 1908.05839.
- Paul Blain Levy (Dec. 2006). “Call-by-Push-Value: Decomposing Call-by-Value and Call-by-Name.” In: *Higher-Order and Symbolic Computation* 19.4, pp. 377–414. doi: 10.1007/s10990-006-0480-6.
- Dale Miller (1991). “A Logic Programming Language with Lambda-Abstraction, Function Variables, and Simple Unification.” In: *J. Log. Comput.* 1.4, pp. 497–536. doi: 10.1093/logcom/1.4.497.
- Jerzy Tiuryn (1995). “Equational Axiomatization of Bicoercibility for Polymorphic Types.” In: *Foundations of Software Technology and Theoretical Computer Science, 15th Conference, Bangalore, India, December 18-20, 1995, Proceedings*. Ed. by P. S. Thiagarajan. Vol. 1026. Lecture Notes in Computer Science. Springer, pp. 166–179. doi: 10.1007/3-540-60692-0_47

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