OPTYPER: Probabilistic Type Inference by Optimising Logical and Natural Constraints

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We present a new approach to the type inference problem for dynamic languages. Our goal is to combine logical constraints, that is, deterministic information from a type system, with natural constraints, uncertain information about types from sources like identifier names. To this end, we introduce a framework for probabilistic type inference that combines logic and learning: logical constraints on the types are extracted from the program, and deep learning is applied to predict types from surface-level code properties that are statistically associated, such as variable names. The main insight of our method is to constrain the predictions from the learning procedure to respect the logical constraints, which we achieve by relaxing the logical inference problem of type prediction into a continuous optimisation problem.

To evaluate the idea, we built a tool called OPTYPER to predict a TypeScript declaration file for a JavaScript library. OPTYPER combines a continuous interpretation of logical constraints derived by a simple program transformation and static analysis of the JavaScript code, with natural constraints obtained from a deep learning model, which learns naming conventions for types from a large code base. We evaluate OPTYPER on a data set of 5,800 open-source JavaScript projects that have type annotations in the well-known DefinitelyTyped repository. We find that combining logical and natural constraints yields a large improvement in performance over either kind of information individually, and produces 50% fewer incorrect type predictions than previous approaches.

Additional Key Words and Phrases: Type Inference, Dynamic Languages, Continuous Relaxation, Numerical optimisation, Deep Learning, TypeScript

1 INTRODUCTION

Statically-typed programming languages aim to enforce correctness and safety properties on programs by guaranteeing constraints on program behaviour. A large scale user-study suggests that programmers benefit from type safety [Hanenberg et al. 2014]; use of type has also been show to prevent field bugs [Gao et al. 2017]. However, type safety comes at a cost: these languages often require explicit type annotations, which imposes the burden of declaring and maintaining these annotations on the programmer. Strongly statically-typed, usually functional languages, like Haskell or ML, offer type inference procedures that reduce the cost of explicitly writing types but come with a steep learning curve [Tirronen et al. 2015].

Dynamically typed languages, which either lack or do not require type annotations, are relatively more popular [Meyerovich and Rabkin 2012]. Initially designed for quick and dirty scripting or rapid prototyping, these languages have begun reaching the limits of what can be achieved without the help of type annotations, as witnessed by the heavy industrial investment in and proliferation of static type systems for these languages (TypeScript [Microsoft 2019] and Flow [Facebook 2019] are just two examples). Retrofit for dynamic languages, these type systems include gradual [Siek and Taha 2006] and optional type systems [Bracha 2004]. Like classical type systems, these type systems require annotations to provide benefits. Hence, reducing the annotation type tax for dynamic languages remains an open research topic.
1.1 Problem of Creating TypeScript Signatures for JavaScript Libraries

TypeScript is a superset of JavaScript that adds static typing to the language. In fact, as JavaScript libraries and frameworks are very popular, many TypeScript applications need to use untyped JavaScript libraries. To support static type checking of such applications the typed APIs of the libraries are expressed as separate TypeScript declaration files (`.d.ts`). [DefinitelyTyped 2019] is a public repository that contains declaration files for more than 5000 libraries and has more than 10000 contributors. Although this manual approach has been proven effective, it raises the challenge of how to automatically maintain valid declaration files as library implementations evolve. We investigate the above problem by building OptTyper (from “optimising for optional types”), a tool based on a new probabilistic type inference approach, that allows us to generate TypeScript signatures with respect to logical constraints extracted from JavaScript code at test time.

1.2 Probabilistic Type Inference

Probabilistic type inference has recently been proposed as an attempt to reduce the burden of writing and maintaining type annotations [Hellendoorn et al. 2018; Raychev et al. 2015; Wei et al. 2020]. Just as the availability of large data sets has transformed artificial intelligence, the increased volume of publicly available source code, through code repositories like GitHub\(^1\) or GitLab\(^2\), enables a new class of applications that leverage statistical patterns in large codebases [Allamanis et al. 2018]. For type inference, machine learning allows us to develop less strict type inference systems that learn to predict types from uncertain information, such as comments, names, and lexical context, even when traditional type inference procedures fail to infer a useful type.

The classic literature on conventional type systems takes great care to demonstrate that type inference only suggests sound types [Milner 1978; Pierce 2002]. Probabilistic type inference takes a different perspective: a tool for probabilistic type inference usefully reduces the human annotation burden as long as it frequently makes correct predictions, even if predictions are sometimes wrong. Hence, we evaluate probabilistic type inference with statistical metrics.

Probabilistic type inference is not in conflict with classical type inference but complements it. There are settings, like TypeScript, where correct type inference is too imprecise. In these settings, probabilistic type inference helps the human in the loop to move a partially typed codebase—one lacking so many type annotations that classical type inference can make little progress—to a sufficiently annotated state that classical type inference can take over and finish the job.

Two examples of probabilistic type inference systems are JSNice [Raychev et al. 2015], which uses probabilistic graphical models to statistically infer types of identifiers in programs written in JavaScript, and DeepTyper [Hellendoorn et al. 2018], which targets TypeScript via deep learning techniques. Previous approaches all use machine learning to capture the structural similarities between typed and untyped source code and to extract a statistical model for the text [Allamanis et al. 2018]. However, none explicitly models the underlying type inference rules, and thus their predictions ignore useful logical information.

1.3 Our Contribution

Current type inference systems rely on one of two sources of information

(I) **Logical Constraints** on type annotations that follow from the type system. These are the constraints used by standard deterministic approaches for static type inference.

(II) **Natural Constraints** are statistical constraints on type annotations which can be inferred from relationships between types and surface-level properties such as names and lexical context.

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\(^1\)https://github.com

\(^2\)https://gitlab.com
These constraints can be learned by applying machine learning to large code bases. They are the constraints that are currently employed by probabilistic typing systems.

Our goal is to improve the accuracy of probabilistic type inference by combining both kinds of constraints into a single analysis, unifying logic and learning. To do this, we define a new probabilistic type inference procedure that combines programming language and machine learning techniques into a single framework. We start with a formula that defines the logical constraints on the types of a set of identifiers in the program, and a machine learning model, such as a deep neural network, that makes a probabilistic prediction of the type of each identifier.

Our method is based on two key ideas. First, we relax the logical formula into a continuous function by relaxing type environments to probability matrices and defining a continuous semantic interpretation of logical expressions; the relaxed logical constraints are now compatible with the predicted probability distribution. This allows us to define a continuous function over the continuous version of the type environment that sums the logical and natural constraints. Second, once we have a continuous function, we can optimise it: we set up an optimisation problem that returns the most natural type assignment for a program while at the same time respecting the logical constraints.

Our contributions can be summarised as

- We introduce a principled framework to combine logical and natural constraints for type inference, based on transforming a type inference procedure into a numerical optimisation problem.
- As an instantiation of this framework, we implement OptTyper, a tool to generate probabilistic type signatures on TypeScript from JavaScript libraries. OptTyper seeks to predict types for functions that are declared in a TypeScript declaration file.
- We evaluate OptTyper on a corpus of 5800 JavaScript libraries for which the DefinitelyTyped [DefinitelyTyped 2019] repository provides type declaration files. We find that combining natural and logical constraints has better performance than either alone. Further, OptTyper outperforms state-of-the-art systems, JSNice and DeepTyper. OptTyper achieves a 50% reduction in error (measured relatively) over these previous systems.
- OptTyper achieves its high performance by combining logical and natural constraints at test time; to the best of our knowledge, it is the first tool for probabilistic type inference to do so.

2 GENERAL FRAMEWORK FOR PROBABILISTIC TYPE INFERENCE

This section introduces our general framework, shown in Fig. 1 which we instantiate in the next section by building a tool for predicting types in TypeScript. Fig. 2 illustrates our general framework through a running example of predicting types.

2.1 An Outline of Probabilistic Type Inference

We consider a dynamic language of untyped programs that is equipped with an existing deterministic type system, that requires type annotations on identifiers. Given a program $U$ plus a typing environment $\Gamma$ let $\Gamma \vdash U$ mean that the program $U$ is well-typed according to the (deterministic) type system, given types for identifiers provided by $\Gamma$. A typing environment $\Gamma$ is a finite function with domain $\{x_v \mid v \in 1 \ldots V\}$, where $x_v$ is an identifier, and range $\{l_\tau \mid \tau \in 1 \ldots T\}$, where each $l_\tau$ is a literal type. Given an untyped program $U$, let probabilistic type inference consist of these steps:

1. We choose a finite universe consisting of $T$ distinct literal types $\{l_\tau \mid \tau \in 1 \ldots T\}$.
2. We compute a set $\{x_v \mid v \in 1 \ldots V\}$ of a number $V$ of distinct identifiers in $U$ that need to be assigned types.
(3) We extract a set of constraints from $U$.
(4) By optimising these constraints, we construct a matrix $P$ with $V$ rows and $T$ columns, such that each row is a probability vector (over the $T$ literal types).
(5) For each identifier $x_v$, we set type $t_v$ to the literal type $l_{\tau}$ which we compute from the $v$th probability vector (the one for identifier $x_v$). In this work, we pick the column $\tau$ that has the maximum probability in $x_v$’s probability vector.
(6) The outcome is the environment $\Gamma = \{x_v : t_v \mid v \in 1 \ldots V\}$.

We say that probabilistic type inference is successful if $\Gamma \vdash U$, that is, the untyped program $U$ is well-typed according to the deterministic type system. Since several steps may involve approximation, the prediction $\Gamma$ may only be partially correct. Still, given a known $\hat{\Gamma}$ such that $\hat{\Gamma} \vdash U$ we can measure how well $\Gamma$ has predicted the identifiers and types of $\hat{\Gamma}$. A key idea is that there are two sorts of constraints in step (3): logical constraints and natural constraints.

A logical constraint is a formula $E$ that describes necessary conditions for $U$ to be well-typed. In principle, $E$ can be any formula such that if $\Gamma \vdash U$, then $\Gamma$ satisfies $E$. Thus, the logical constraints do not need to uniquely determine $\Gamma$. For this reason, a natural constraint encodes less-certain information about $\Gamma$, for example, based on comments or names. Just as we can conceptualise the logical constraints as a function to $\{0, 1\}$, we can conceptualise the natural constraints as functions that map $\Gamma$ to $[0, 1]$, which can be interpreted as a prediction of the probability that $\Gamma$ would be successful. To combine these two constraints, we relax the boolean operations to continuous operators on $[0, 1]$. Since we can conceptualise $E$ as a function that maps $\Gamma$ to a boolean value $\{0, 1\}$, we relax this function to map to $[0, 1]$, using a continuous interpretation of the semantics of $E$. Similarly, we relax $\Gamma$ to a $V \times T$ matrix of probabilities. Having done this, we formalise type inference as a problem in numerical optimisation, with the goal to find a relaxed type assignment that satisfies as much as possible both sorts of constraints. The result of this optimisation procedure is the $P$ matrix of probabilities described in step (4).
When we numerically optimise the resulting expression, we obtain the matrix in Box (e); it predicts that both variables are strings with high probability. Although the objective function is symmetric between \( E \) and \( \mathbb{I} \), the solution in (e) is asymmetric because it depends on the initialization of the optimiser. Finally, Box (f) also shows the solution matrix and Box (g) shows the induced type annotations, now all predicted to be string.

**Fig. 2.** Our input is a minimal JavaScript function with no type annotations on its parameters or result. By default, TypeScript’s compiler assigns its wildcard type any to parameters. Our goal is to exploit both logical and natural constraints to suggest more specific types. To begin, in Box (a), we propose fresh type annotations \texttt{START} and \texttt{END} (upperscasing the identifier) for each parameter and \texttt{ADDNUM} for the return type. We insert these annotations into the definition of the function. Our logical constraints on these types represent knowledge obtained by a symbolic analysis of the code in the body of the function. In our example, the use of a binary operation implies that the two parameter types are equal. Box (c) shows a minimal set of logical constraints that state that \texttt{addNum}’s two operands have the same type. In general, the logical constraints can be much more complex than our simple example. If we only have logical constraints, we cannot tell whether \texttt{string} or \texttt{number} is a better solution, and so may fall back to the type \texttt{any}. The crux of our approach is to take into account natural constraints; that is, statistical properties learnt from a source code corpus that seek to capture human intention. In particular, we use a machine learning model to capture naming conventions over types. We represent the solution space for our logical or natural constraints or their combination as a \( V \times T \) matrix \( P \) of the form in Box (b); each row vector is a discrete probability distribution over our universe of \( T = 3 \) concrete types (number, string, and any) for one of our \( V = 3 \) identifiers. Box (d) shows the natural constraints \( M \) induced by the identifier names for the parameters and the function name itself. Intuitively, Box (d) shows that a programmer is more likely to name a variable \texttt{start} or \texttt{end} if she intends to use it as a \texttt{number} than as a \texttt{string}. We can relax the boolean constraint to a numerical function on probabilities as shown in Box (c). When we numerically optimise the resulting expression, we obtain the matrix in Box (e); it predicts that both variables are strings with high probability. Although the objective function is symmetric between \texttt{string} and \texttt{number}, the solution in (e) is asymmetric because it depends on the initialization of the optimiser. Finally, Box (f) shows an optimisation objective that combines both sources of information: \( E \) consists of the logical constraints and each probability vector \( \mu_v \) (the row of \( M \) for \( v \)) is the natural constraint for variable \( v \).
2.2 Logical Constraints in Continuous Space

Logical constraints are extracted from our untyped input program \( U \) using standard program analysis techniques. Here, we rely on a Constraints Generator for this purpose. Section 3.3 describes its realisation. The generator takes into account a set of rules that the type system enforces and produces a boolean type constraints for them.

In this work, we consider the following logical constraints.

**Definition 2.1 (Grammar of Logical Constraints).** A logical constraint is an expression \( E \) of the following form

\[
E ::= x_v \text{ is } l_r \quad | \quad \text{not } E \quad | \quad E \text{ and } E \quad | \quad E \text{ or } E.
\]

Let \( \mathcal{E} \) be the set of all logical constraints.

**Continuous Relaxation.** We explain how to specify a continuous relaxation of the discrete logical semantics. A formula \( E \) can be viewed as a boolean function \( f_E : \{0, 1\}^{V \times T} \rightarrow \{0, 1\} \) that maps binary matrices to \( \{0, 1\} \). To see this, we can convert an environment \( \Gamma \) into a \( V \times T \) binary matrix \( B \) by setting \( B_{v, r} = 1 \) if \((x_v, l_r) \in \Gamma\), and 0 otherwise. Let \( B(\Gamma) \) be the binary matrix corresponding to \( \Gamma \). Also, define \( \Pi^{V \times T} \) to be the set of all probability matrices of size \( V \times T \), that is, matrices of the form

\[
P = \begin{bmatrix} p_1 & \cdots & p_V \end{bmatrix}^T,
\]

where each \( p_v = [p_{v,1} \cdots p_{v,T}]^T \) is a vector that defines a probability distribution over concrete types. Finally, a relaxed semantics is a continuous function that always agrees with the logical semantics, that is, a relaxed semantics is a function \( \tilde{f}_E : \Pi^{V \times T} \rightarrow [0, 1] \) such that for all formulas \( E \) and environments \( \Gamma \), \( \tilde{f}_E(B(\Gamma)) = f_E(B(\Gamma)) := \|E\|_{B(\Gamma)} \).

To define a relaxed semantics, we introduce a continuous semantics of \( E \) based on generalizations of two-valued logical conjunctions to many-valued [Hájek et al. 1996]. Specifically, we use the product \( \ominus \) based on generalizations of two-valued logical conjunctions to many-valued [Hájek et al. 1996]. Specifically, we use the product \( \ominus \) based on generalizations of two-valued logical conjunctions to many-valued [Hájek et al. 1996]. Specifically, we use the product \( \ominus \) based on generalizations of two-valued logical conjunctions to many-valued [Hájek et al. 1996]. Specifically, we use the product \( \ominus \) based on generalizations of two-valued logical conjunctions to many-valued [Hájek et al. 1996]. Specifically, we use the product \( \ominus \) based on generalizations of two-valued logical conjunctions to many-valued [Hájek et al. 1996]. Specifically, we use the product \( \ominus \) based on generalizations of two-valued logical conjunctions to many-valued [Hájek et al. 1996]. Specifically, we use the product \( \ominus \) based on generalizations of two-valued logical conjunctions to many-valued [Hájek et al. 1996].

The continuous semantics \( \|E\|_p \) is a function \( \Pi^{V \times T} \times \mathcal{E} \rightarrow [0, 1] \), defined as

\[
\|x_v \text{ is } l_r\|_p = p_{v, r},
\|\text{not } E\|_p = 1 - \|E\|_p,
\|E_1 \text{ and } E_2\|_p = \|E_1\|_p \cdot \|E_2\|_p,
\|E_1 \text{ or } E_2\|_p = \|E_1\|_p + \|E_2\|_p - \|E_1\|_p \cdot \|E_2\|_p.
\]

In the actual implementation, we use logits instead of probabilities for numerical stability, see Appendix A. We note also, that our relaxation for the or operator, depends on the random initialization of the optimiser, and thus the final answer will be either \( \|E_1\|_p \) or \( \|E_2\|_p \) with high probability but not always the same.

We define a logical satisfaction relation \( \Gamma \models E \), as follows

\[
\Gamma \models x_v \text{ is } l_r \iff \Gamma(x_v) = l_r
\]
\[
\Gamma \models \text{not } E \iff \text{not } \Gamma \models E
\]
\[
\Gamma \models E_1 \text{ and } E_2 \iff \Gamma \models E_1 \text{ and } \Gamma \models E_2
\]
\[
\Gamma \models E_1 \text{ or } E_2 \iff \Gamma \models E_1 \text{ or } \Gamma \models E_2.
\]
Now we can show the following theorem, that give us a correspondence between numerical semantics and typing environments.

**Theorem 2.2.** For all $E$ and $\Gamma$, $\llbracket E \rrbracket_{B(\Gamma)} = 1 \iff \Gamma \models E$.

To motivate further this continuous semantics, recall that in our setting, we know $E$ but do not know $P$. We argue that the continuous semantics, when considered as a function of $P$, can serve as a sensible objective for an optimisation problem to infer $P$. The reason is that it relaxes the deterministic logical semantics of $E$, and it is maximised by probability matrices $P$ which correspond to satisfying type environments. The following theorem formalises the idea:

**Theorem 2.3.** For all $\Gamma$ and all $E$, $\Gamma \models E$ if and only if $B(\Gamma) \in \arg \max_{P \in \prod V \times T} \llbracket E \rrbracket P$.

For proofs see Appendix B.

### 2.3 Natural Constraints via Machine Learning

A complementary source of information about types arises from statistical dependencies in the source code of the program. For example, names of variables provide information about their types [Xu et al. 2016], natural language in method-level comments provide information about function types [Malik et al. 2019], and lexically nearby tokens provide information about a variable’s type [Hellendoorn et al. 2018]. This information is indirect, and extremely difficult to formalise, but we can still hope to exploit it by applying machine learning to large corpora of source code.

Recently, the software engineering community has adopted the term *naturalness of source code* to refer to the concept that programs have statistical regularities because they are written by humans [Hindle et al. 2012]. Following the idea that the naturalness in source code may be in part responsible for the effectiveness of this information, we refer generically to indirect, statistical constraints about types as *natural constraints*. Because natural constraints are uncertain, they are naturally formalised as probabilities. A natural constraint is a mapping from a type variable to a vector of probabilities over possible types.

**Definition 2.4 (Natural Constraints).** For each identifier $x_v$ in a program $U$, a natural constraint is a probability vector $\mu_v = [\mu_v^1, \ldots, \mu_v^T]^T$. We aggregate the probability vectors of the learning model in a matrix defined as $M = [\mu_1 \ldots \mu_V]^T$.

In principle, natural constraints can be defined based on any property of $U$, including names and comments. In this paper, we consider a simple but practically effective example of natural constraint, namely, a deep network that predicts the type of a variable from the characters in its name. We consider each variable identifier $x_v$ to be a character sequence $(c_{v1} \ldots c_{vN})$, where each $c_{vi}$ is a character. (This instantiation of the natural constraint is defined only on types for identifiers that occur in the source code, such as a function identifier or a parameter identifier.) This is a classification problem, where the input is $x_v$, and the output classes are the set of $T$ concrete types. Ideally, the classifier would learn that identifier names that are lexically similar tend to have similar types, and specifically which subsequences of the character names, like `lst`, are highly predictive of the type, and which subsequences are less predictive. One simple way to do so is to use a recurrent neural network (RNN).

For our purposes, an RNN is simply a function $(h_{i-1}, z_i) \mapsto h_i$ that maps a state vector $h_{i-1} \in \mathbb{R}^H$ and an arbitrary input $z_i$ to an updated state vector $h_i \in \mathbb{R}^H$. (The dimension $H$ is one of the hyperparameters of the model, which can be tuned to obtain the best performance.) The RNN has continuous parameters that are learned to fit a given data set, but we elide these parameters to lighten the notation, because they are trained in a standard way. We use a particular variant of an RNN called a long-short term memory network (LSTM) [Hochreiter and Schmidhuber 1997],
which has proven to be particularly effective both for natural language and for source code [Khanh Dam et al. 2016; Melis et al. 2017; Sundermeyer et al. 2012; White et al. 2015]. We write the LSTM as $\text{LSTM}(h_{i-1}, z_i)$.

With this background, we can describe the specific natural constraint that we use. Given the name $x_v = (c_{v1} \ldots c_{vN})$, we input each character $c_{vi}$ to the LSTM, obtaining a final state vector $h_N$, which is then passed as input to a small neural network that outputs the natural constraint $\mu_v$. That is, we define

$$h_i = \text{LSTM}(h_{i-1}, c_{vi}) \quad i \in 1, \ldots, N$$

(4a)

$$\mu_v = F(h_N),$$

(4b)

where $F : \mathbb{R}^H \rightarrow \mathbb{R}^T$ is a simple neural network. In our instantiation of this natural constraint, we choose $F$ to be a feedforward neural network with no additional hidden layers, as defined in (9). We provide more details regarding the particular structure of our neural network in Section 3.4.

This network structure is, by now, a fairly standard architectural motif in deep learning. More sophisticated networks could certainly be employed, but are left to future work.

2.4 Combining Logical and Natural Constraints to Form an Optimisation Problem

Logical constraints pose challenges to the probabilistic world of machine learning. Neural networks cannot handle hard constraints explicitly and thus it is not straightforward how to incorporate the logical rules that they must follow. Our way around that problem is to relax the logical constraints to numerical space and combine them with the natural constraints through a continuous optimisation problem.

Intuitively, we design the optimisation problem to be over probability matrices $P \in \Pi^{V \times T}$; we wish to find $P$ that is as close as possible to the natural constraints $M$ subject to the logical constraints being satisfied. A simple way to quantify the distance is via the Euclidean norm $\| \cdot \|_2$ of a vector, which is a convex function and thus well suited with our optimisation approach.

Hence, we obtain the constrained optimisation problem

$$\begin{align*}
\min_{P \in \mathbb{R}^{V \times T}} & \sum_v \| p_v - \mu_v \|^2_2 \\
\text{subject to} & \quad p_{v\tau} \in [0, 1] \quad \forall v, \tau \\
& \quad \sum_{\tau=1}^T p_{v\tau} = 1 \quad \forall v \\
& \quad \|E\|_P = 1.
\end{align*}$$

(5)

We use Mean Squared Error (MSE) here to quantify the performance of our fitting. We could have used the Cross Entropy (CE), another common loss function. The MSE is a proper scoring rule [Gneiting and Raftery 2007], meaning that smaller values correspond to better matching of our optimisation variables with the logical constraints. We do not claim any particular advantage of MSE versus CE.

To solve a constrained optimisation problem like Equation 5, an effective technique is to transform it to an unconstrained one using penalization; this is done, for example, in interior point methods. Here, we use an approach tailored to the specifics of our problem. First, we reparameterise the problem to remove the probability constraints. The softmax function

$$\sigma(x) = \begin{bmatrix}
\exp\{x_1\}, \exp\{x_2\}, \ldots \\
\sum_i \exp\{x_i\}, \sum_i \exp\{x_i\}, \ldots
\end{bmatrix}^T$$

(6)
maps real-valued vectors to probability vectors. Our transformed problem takes the form

$$\min_{Y \in \mathbb{R}^{V \times T}} \sum_{v} ||\sigma(y_v) - \mu_v||^2_2$$

subject to $\left\lbrack [E]_{\sigma(y_1), \ldots, \sigma(y_V)} \right\rbrack^T = 1$.  

(7)

It is easy to see that if $Y$ minimises (7), then $P = [\sigma(y_1), \ldots, \sigma(y_V)]^T$ minimises (5). We remove the last constraint by introducing a Lagrange multiplier $\lambda > 0$, yielding the final form of our optimisation problem

$$\min_{Y \in \mathbb{R}^{V \times T}} \sum_{v} ||\sigma(y_v)^T - \mu_v||^2_2 - \lambda \left\lbrack [E]_{\sigma(y_1), \ldots, \sigma(y_V)} \right\rbrack^T.  

(8)$$

This can now be solved numerically using first-order unconstrained optimisation methods, such as gradient descent. The parameter $\lambda$ trades off the importance of the two different kinds of constraints. In the limiting case where $\lambda \to \infty$, the second term in the objective function (8) is dominant and we obtain the solution that best satisfies the relaxed logical constraints. If these constraints are consistent, then the obtained probability vectors correspond to one-hot vectors. Similarly, for $\lambda \to 0$ the first term dominates and we obtain the solution that best matches the natural constraints, which is naturally $M$ itself. By choosing $\lambda$ well, we can trace the Pareto frontier between the two types of constraints, and identify a value that minimises the original problem (5).

To obtain a final hard assignment $\Gamma$, we first solve (8) to obtain the optimal $Y$, compute the associated probability vector $P = [\sigma(y_1), \ldots, \sigma(y_V)]^T$. Then, for each identifier $x_v$, we select the element of the corresponding probability vector that is closest to one.

An important theoretical question is whether the logical constraints are satisfied at the optimum of the combined logical and natural constraints. We conjecture there is a value $\lambda_0$ such that if we pick $\lambda > \lambda_0$, then the logical constraints are satisfied at the optimum of (8). We leave this question for future work; instead, this paper presents an empirical evaluation of a system based on optimising objective (8).

3 OPTTYPER: PREDICT TYPESCRIPT TYPE SIGNATURES FOR JAVASCRIPT LIBRARIES

To evaluate our approach in a real-world scenario, we implement an end-to-end application, called OptTyper, which aims to infer TypeScript declaration files for an underlying JavaScript library.

3.1 Background: TypeScript’s Type System

TypeScript [Microsoft 2019] is a typed superset of JavaScript designed for developing large-scale, stable applications. TypeScript’s compiler typechecks TypeScript programs then emits plain JavaScript to leverage the fact that JavaScript is the only cross-platform language that runs in any browser, any host, and any OS. Structural type systems consider record types (classes), whose fields or members have the same names and types, to be equal. TypeScript supports a structural type system because it permits TypeScript to handle many JavaScript idioms that depend on dynamic typing. One of the main goals of TypeScript’s designers is to support idiomatic JavaScript to provide a smooth transition from JavaScript to TypeScript. Therefore, TypeScript’s type system is deliberately unsound [Bierman et al. 2014]. It is an optional type system, whose annotations can be omitted and have no effect on runtime. TypeScript erases them when transpiling to JavaScript [Bierman et al. 2014]. TypeScript’s type system defaults to assigning its any type to unannotated identifiers, like parameters. Function returns are an exception; here, TypeScript does seek to infer a more specific type.
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exports.byteLength = byteLength
...

function getLens (b64) {
  ... return validLen, placeHoldersLen
}

function byteLength (b64) {
  var lens = getLens(b64)
  var validLen = lens[0]
  var placeHoldersLen = lens[1]
  return ((validLen +
    placeHoldersLen) * 3 / 4)
    - placeHoldersLen
}
...

export function
byteLength(b64: any): any;

export function
byteLength(b64: string):
number;

Fig. 3. Center: Example of untyped JavaScript code. This an excerpt from the library base64-js. Left: Declaration file after the Structure stage, Right: Declaration file after the Type stage.

TypeScript applications and libraries commonly take advantage of JavaScript’s flourishing ecosystem and use untyped JavaScript libraries. To support static type checking of such applications, the types of such JavaScript libraries’ APIs are expressed as separate TypeScript declaration files (.d.ts). The TypeScript community actively supports this process by manually writing and maintaining declaration files, available in the DefinitelyTyped [DefinitelyTyped 2019] repository. Although this manual approach has proven useful, it raises the challenge of keeping declaration files in sync with the library implementations.

Ideally, we would like to automatically infer the typed APIs of such libraries. For generating definition files for existing JavaScript libraries, the DefinitelyTyped community officially recommends dts-gen [Microsoft 2017]. This tool uses runtime information to produce a .d.ts file that helps to define the shape of the input API but does not provide type information for function arguments and returns. Because dts-gen only collects dynamic information it eventually emits many any types that the developer must refine manually. It is only meant to be used as a starting point for writing a high-quality declaration file.
Table 1. The five different type errors from which generate the logical constraints.

| Constraint-Id | Description |
|---------------|-------------|
| Property      | Property X does not exist in type Y. |
| Binop         | Operator ⊕ cannot be applied to types X and Y. |
| Index         | Type X cannot index type Y. |
| ArithLHS      | The left-hand side of an arithmetic operation must be an enum type or have type any or number. |
| ArithRHS      | The right-hand side of an arithmetic operation must be an enum type or have type any or number. |

3.2 Problem Statement

We consider the problem of predicting a TypeScript declaration file for an underlying JavaScript library. We approach this problem by defining two consecutive subproblems:

- The Structure subproblem has as a goal to generate a declaration file containing the exported functions with every type annotated as any.
- The Type subproblem aims to generates types to fill the holes left in the declaration files following the Structure subproblem.

Input: Our implementation takes as input three files:

1. A JavaScript library file.
2. The output of the Structure subproblem. We obtain this file from dts-gen [Microsoft 2017].
3. TypeScript’s default library declaration file, that is, the built-in types defined by the standard library.3

An example input, showing all three files, is shown in Fig. 3.

Output: A TypeScript declaration file for the JavaScript library, that we call it predicted.d.ts and includes type predictions for

- the return type of the function, denoted as fnRet, and
- type annotations for the function’s arguments, denoted as param.

The output of our tool is essentially the declaration file from the Structure subproblem but with some, or, ideally all, of the any types substituted with built-in types, but not including user-defined ones. In Section 4, we present metrics on the performance of tools, including OptTyper, on the Type subproblem, given skeleton definition files produced by the Structure subproblem.

3.3 Logical Constraints for TypeScript

To generate the logical constraints of Section 2.2, we exploit the information from tsc, the TypeScript compiler [Microsoft 2019]. Instead of modifying tsc to emit logical constraints, a substantial engineering effort especially given the speed of tsc’s evolution, we devised the following technique to obtain constraints from the unmodified compiler. We harvest type constraints from type errors tsc generates. We trigger these errors by explicitly assigning a fresh generic type variable to each formal of each function, then invoking tsc. We parse the error messages to construct our logical constraints. We also include return types inferred by the compiler as logical constraints.

We identify 5 common type errors (Table 1) that the tsc compiler emits, and turn them into type constraints. The main problem with this approach in isolation is that it produces an average total

3https://github.com/Microsoft/TypeScript/blob/master/lib/lib.d.ts
function toByteArray<B64, TOBYTEARRAY>(b64: B64): TOBYTEARRAY {
  ...
  var len = b64.length; // B64 <: .length
  ...
  tmp = (revLookup[b64.charCodeAt(i)] << 18) // B64 <: .charCodeAt()
}

Fig. 4. TypeScript code snippet of base64-js library augmented with type parameters for each of the formal variables and the return type, along with two constraint on lines 3 and 5.

of only around 10 constraints per library. The first row of Table 1 refers to identifying properties or methods that a type should implement and using them to generate a type constraint. The file lib.d.ts includes interfaces for the built-in types of the language. These interfaces contain the typed signatures of each property and method that a built-in type implements. We use these interfaces to construct a set of possible built-in types that we could assign to our injected type and therefore a proper type constraint. For a concrete example of this procedure, see Fig. 4 and Table 2.

Our purpose is to establish the principle that a combination of natural and logical constraints can outperform either on its own, and outperforms the state-of-the-art. To measure our method versus other tools on our gold files, we had to find a way to generate logical constraints from tsc. We judged it better to generate a limited set of constraints by processing the TypeScript error messages than to attempt to modify tsc, a highly optimised, complex, and quickly evolving piece of software. Our logical constraints include propositional logic, and therefore seem able to express a wide range of interesting type constraints. This technique seems a useful device that could be employed in other situations, and serves our purpose. Having established the general principle, we will aim to show how to modify a type-checker to omit constraints directly in future work.

3.4 Natural Constraints for TypeScript
We now focus our attention on extracting natural constraints. The TypeScript community has already made a huge effort to support this process by writing and maintaining the declaration files for over five thousand of the most popular JavaScript libraries. These files are available on the DefinitelyTyped [2019] repository. The declaration files on this repository provide an excellent opportunity for statistical learning algorithms. We use a Char-Level LSTM trained on (id, type) pairs to learn naming conventions for identifiers, treated as sequences of characters. The main intuition behind this choice is that developers commonly use multiple abbreviations for the same word and this family of abbreviations shares a type. A Char-Level LSTM is well-suited to predict the type for any identifier in abbreviation families. Our universe of types consists of the 78 types that appear at least 10,000 times in our training set. These are built-in TypeScript types and some commonly used unions of them. We note that our system cannot distinguish between a primitive and a complex type. We note that we consider only built-in types to ensure that we do not introduce types that are not available to the compiler. Handling a larger set of types is straightforward, but we decide to work with a small set of types for the shake of rapid prototyping. We leave measuring the effect of varying the number of types known to OPT Typer to future work.
Regarding the implementation details of the LSTM network, for the $F$ in (4b), we use a feedforward neural network

$$F(h) = \log \left( \sigma \left( hA^T + b \right) \right),$$

(9)

where the log function is applied componentwise, and $A$ and $b$ are learnable weights and bias. The softmax function (6) corresponds to the last layer of our neural network and essentially maps the values of the previous layer to $[0, 1]$, while the sum of all values is 1 as expected for a probability vector as already explained. We work in log space to help numerical stability since computing (6) directly can be problematic. As a result, $F$ outputs values in $[-\infty, 0]$.

We train the model by supplying sets of variable identifiers together with their known types, and minimizing a loss function. Our loss function is the negative log likelihood function—conveniently combined with our log output—defined as

$$L(y) = - \sum_i \log(y_i).$$

(10)

Essentially, we select, during training, the element that corresponds to the correct label from the output $F$ and sum all the values of the correct labels for the entire training set.

### 3.5 Realisation of OptTyper

Here, we describe the implementation of OptTyper. Both the code for the deep learning and the combined optimisation part is written in PyTorch [Paszke et al. 2017]. We base most of our design choices on empirically observing what maximises OptTyper’s performance.

**Natural Constraints.** We use ADAM [Kingma and Ba 2014], an extension of stochastic gradient descent [Robbins and Monro 1951], as our optimisation algorithm for the natural constraints. The main difference between ADAM and classical stochastic gradient descent is the use of adaptive
instead of fixed learning rates. Although there exist other algorithms with adaptive learning rates like ADAGRAD [Duchi et al. 2011] and RMSPROP [Tieleman and Hinton 2014], ADAM tends to have better convergence [Ruder 2016]. We used all the 5,800 projects available from the DefinitelyTyped repository on 17th July 2019, all of these projects were popular enough as to a declaration file was written for them. We trained our model for 1,000 epochs, for 78 different types, and obtained a validation accuracy of 0.79. Fig. 5 shows a summary, while for specific implementation details of the LSTM refer to Appendix C.

Our dataset was randomly split by project into 80% training data, 10% validation data and 10% test data. Splitting the available data in these three different sets is a common practice in machine learning to ensure that the learning model does not simply memorise the training data but is able to generalise to unseen inputs.

Logical Constraints. Solving the relaxed logical constraints corresponds to an optimization problem as described in (2). To find the minimum of the generated functions for the logical constraints, we use another alternative to stochastic gradient descent optimisation algorithm [Robbins and Monro 1951], known as RMSPROP [Tieleman and Hinton 2014]. We set the maximum number of iterations to 2,000, which suffices in practice for the loss to stabilise.

Combined Optimisation. We use $\lambda = 10$ in (8) for combining the natural and logical constraints to a single optimisation problem and solve it using RMSPROP [Tieleman and Hinton 2014] over 2,000 iterations.

4 EVALUATION OF OPTTYPER

To measure the performance of our tool OPTTYPER we make the following assumption: the existing declaration files on the DefinitelyTyped repository define the gold standard for our predictions. It is an assumption in the sense that some files may contain errors [Williams et al. 2017]. Based on it, we measure the performance of our tool as well as other related tools by comparing the output declaration file for a given input JavaScript library with the corresponding gold declaration file included in the DefinitelyTyped repository. Next, we define the metrics used to perform this comparison. Traditionally, there have been two measures when comparing a result set (here the output declaration file) with human judgement (the gold declaration file): Precision and Recall [Russell and Norvig 2016]. We use these two metrics to evaluate the output structure and types for each of the exported functions in a library. Here, we focus solely on functions and discard the other exported entities, such as variables, methods, and properties. The metrics presented next can easily
be extended to evaluate to those exported entities we currently exclude. The following definitions formalise these metrics.

**Experimental Setup.** All experiments are conducted on an NVIDIA Titan Xp with 12GB VRam, in combination with a 2-core Intel Core i5 CPU with 8GB of RAM. Our resulting model requires about 400MB of RAM to be loaded into memory and can be run on both a GPU and CPU. It computes type annotations on average for 58 files in about 60 seconds for solving logical constraints and natural constraints, and in about 65 seconds for the combined optimisation.

### 4.1 Precision and Recall for Declaration Files

**Definition 4.1 (Paths).** Let a path be either a structural path, or a type path. A structural path is a fully-qualified name \( n \). A type path is a pair \((n,ty)\) of a fully-qualified name \( n \) and a type \( ty \). Let the variable \( X \) range over sets of paths.

Let \( S \) be the set of all structural paths, which is partitioned into the following subsets
- function identifiers \( S_{\text{fnRet}} \)
- function parameters \( S_{\text{param}} \)
- either function or parameter identifiers \( S_{\text{total}} = S_{\text{fnRet}} \cup S_{\text{param}} \).

Let \( T \) be the set of all type paths, which is partitioned into the following subsets
- type returned by each function \( T_{\text{fnRet}} \)
- type of each function parameter \( T_{\text{param}} \)
- type for either function result or parameter \( T_{\text{total}} = T_{\text{fnRet}} \cup T_{\text{param}} \).

We call the predicted declaration file \( \text{predicted.d.ts} \) while for the gold standard file we use the term \( \text{gold.d.ts} \).

**Definition 4.2 (Functions Paths and Filter \( X \)).** To capture the contents of a file, we define the function \( \text{Paths}(\ast.d.ts) \), which takes as an input a TypeScript declaration file and returns a set of paths to represent the structure and types of the file. In the next step we apply a \( \text{Filter}_X \) function to filter the output of the \( \text{Paths} \) function to keep only the paths in the set \( X \), that is, \( \text{Filter}_X(Y) = X \cap Y \).

As we are interested in evaluating both Structure and Type—the core elements of our pipeline as analysed in Section 3—and not only the final output, we measure the precision and recall for both stages independently.

Precision for Structure measures the proportion of entities found in \( \text{predicted.d.ts} \) that are also included in \( \text{gold.d.ts} \). For example, if we get an 80% Structure precision that means that, on average, out of the 10 entities that we found, 8 exist in \( \text{gold.d.ts} \), while 2 do not. Recall for Structure measures the proportion of entities that exist in \( \text{gold.d.ts} \) that we found in \( \text{predicted.d.ts} \). For example, if we compute a 70% Structure recall that means that, on average, out of 10 entities in \( \text{gold.d.ts} \), we successfully identified 7 of them, while 3 were not recognised.

For measuring Type, we exclude all entities that we found in \( \text{predicted.d.ts} \) but not found in \( \text{gold.d.ts} \) since we do not have a means to evaluate their validity. Precision for Type measures the proportion of correct types found in the corresponding \( \text{predicted.d.ts} \) file with respect to the types defined in \( \text{gold.d.ts} \). For example, we interpret a 90% Type precision as finding on average 9 correct types out of the 10 predicted. Recall for Type measures the percentage of correct types found in \( \text{gold.d.ts} \) with respect to the total number of types defined in \( \text{gold.d.ts} \). For example, we interpret a 60% Type recall as correctly predicting on average 6 types out of the 10 found in \( \text{gold.d.ts} \). We compute the precision and recall for both subproblems using the formulas defined next. We define \( X \in \{S, T\} \) (Structure and Type) to denote the subproblem for which we perform measurements.
$X$’s range could be extended to include, for instance, $S_{\text{fnRet}}$ (function identifiers) to perform a finer analysis.

**Definition 4.3 (Precision and Recall for $X$).** Given a declaration file $\text{predicted.d.ts}$, an ideal declaration file $\text{gold.d.ts}$, and a class of paths $X$, we define precision and recall for $X$ as

$$P(X) = \frac{|\text{Filter}_X(\text{Paths(\text{predicted.d.ts})}) \cap \text{Filter}_X(\text{Paths(\text{gold.d.ts})})|}{|\text{Filter}_X(\text{Paths(\text{predicted.d.ts})})|}$$  

(11)

$$R(X) = \frac{|\text{Filter}_X(\text{Paths(\text{predicted.d.ts})}) \cap \text{Filter}_X(\text{Paths(\text{gold.d.ts})})|}{|\text{Filter}_X(\text{Paths(\text{gold.d.ts})})|}.$$  

(12)

The maximum precision and recall that we can obtain is equal to 1. For Structure, the larger the precision the more relevant entities are returned than irrelevant ones, while the larger the recall the more existing entities are discovered. Similarly, for Type, the larger the precision the more precise are the identified types, while the larger the recall the more existing types are discovered.

Our contributions presented in Sections 2 and 3 concern the second subproblem of the workflow, that is, the type prediction phase. Here, we describe an integrated, end-to-end approach so we focus on presenting a holistic evaluation of the problem. Thus, we also present results from the first subproblem, although our method does not contribute to its improvement.

**4.2 Comparison for Structure Subproblem**

For tackling the first subproblem, that is predict the structure of a declaration file for JavaScript library, we compare two tools that can output a structure file: declFlag and dts-gen. We summarise each tool as follows

- **declFlag**: The TypeScript compiler, when called with the flag `--declaration`, statically generates some exported definitions.
- **dts-gen**: A tool that dynamically examines JavaScript objects at runtime to generate exported definitions.

For a type universe consists of 78 types, and 48 JavaScript libraries as input with 2012 identifiers in total, the aggregate Structure precision and recall across all modules are $P(\text{S}_{\text{total}}) = 0.08, R(\text{S}_{\text{total}}) = 0.11$ for declFlag, $P(\text{S}_{\text{total}}) = 0.8, R(\text{S}_{\text{total}}) = 0.79$ for dts-gen respectively. Clearly dts-gen outperforms declFlag across all tasks. As a result, we used the output of dts-gen as input in our type prediction subproblem.

The Structure subproblem itself it is not enterly being solved. As a JavaScript module can export functions by arbitrary execution of code, a simple syntactic process it is not adequate. To obtain full accuracy we would need to execute the code rather than simply parse it, as dts-gen does to an extend.

**4.3 Evaluation of Type Subproblem**

For evaluating type predictions, we compare both the logical and the natural approach on their own, and then their combination. Two kinds of input may be required by these packages: the JavaScript library file or a declaration file containing the exported functions. We summarise below the characteristics of each package and the provided input.

- **Logical**: Using the JavaScript library and the declaration file as an input, we utilise the compiler in a pragmatic way allowing us to generate logical constraints as logical formulas and then solve them by using their continuous relaxation (Section 3.3).
Table 3. Aggregate Type precision and recall for 58 JavaScript libraries with 1272 identifiers in total (610 \textit{funRet}, 662 \textit{param}). We use the notation \(P(T_{\text{funRet}})\) for \(P(T_{\text{funRet}} \cap T)\), where \(T\) is the number of types in our universe of types.

| Tool       | \(P(T_{\text{funRet}})\) | \(R(T_{\text{funRet}})\) | \(P(T_{\text{param}})\) | \(R(T_{\text{param}})\) | \(P(T_{\text{total}})\) | \(R(T_{\text{total}})\) |
|------------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|--------------------------|
| \textit{Logical} \((T = 78)\) | 0.42                     | 0.41                     | 0.15                     | 0.15                     | 0.29                     | 0.28                     |
| \textit{Natural} \((T = 78)\) | 0.48                     | 0.48                     | 0.61                     | 0.56                     | 0.55                     | 0.52                     |
| \textit{OptTyper} \((T = 78)\) | \textbf{0.61}            | \textbf{0.59}            | \textbf{0.63}            | \textbf{0.58}            | \textbf{0.62}            | \textbf{0.58}            |

- \textit{Natural}: We query our pre-trained Char-Level LSTM to give us predictions for every identifier found in the declaration file (Section 3.4). It requires as input the declaration file only.
- \textit{OptTyper}: The output of the optimisation problem for the corresponding combination of the logical and natural approach (Section 3.5). Since this tool depends on the other too, we provide both the JavaScript library and the declaration file as input.

Furthermore, we report separately in Table 3 the precision and recall for predicting the function return types (first and second column) and the types of the functions’ parameters (third and fourth column).

Since we consider 78 types in total and the \textit{gold.d.ts} contains a larger number, we first compute the maximum achievable precision and recall if only 78 types can be predicted, even if all the type predictions were correct. The precision for the function return types is 0.61 and the recall 0.59, while the precision for the parameters’ types is 0.63 and the recall 0.58. The combined precision and recall are 0.62 and 0.58, respectively. The results presented in Table 3 are normalised based on these upper precision and recall limits.

Regarding the \textit{Logical} approach, the results are significantly better for function return types than parameters’ types. This happens because the TypeScript compiler generates much richer constraints for all—exported or not—return types of functions. For the parameters’ types, the compiler disregards any information and infers all types as \textit{any}; a situation that produces no useful logical constraints. To mitigate this issue, we define some simple heuristics that allow the \textit{Logical} tool to generate non-trivial constraints. A more systematic approach could improve the results regarding the parameters’ type inference, but we leave this to future work.

Furthermore, we observe for all tools that the precision and recall for both tasks are close. By comparing these two metrics in Definition 4.3, their similarity can be traced to the similarity of their denominators. As we discuss in Section 4.2, the \textit{Structure} subproblem can identify the majority (over 80\%) of the function signatures; hence, the denominators are close and subsequently so are the precision and recall.

Finally, for \textit{OptTyper} we find that the combination of the output of the \textit{Logical} and the \textit{Natural} tool improves our precision and recall for both tasks. Overall, the combination of the logical and natural constraints in \textit{OptTyper} greatly improves our type inference capabilities.

### 4.4 \textit{OptTyper} at the Type Subproblem

To evaluate \textit{OptTyper} we compare against two state-of-the-art tools that utilise machine learning techniques, both aiming to give type suggestions to the programmer. Neither tool was designed explicitly for predicting TypeScript declaration files, so we made the necessary adjustments to meet the requirements of our setting. For all of our evaluations we have used the same Structure file, that is, the one produced by \textit{dts-gen}. The two tools that we compare against are...
Table 4. Aggregate Type precision and recall across all evaluated modules for DeepTyper and JSNice; as input we use 41 JavaScript libraries with 860 identifiers in total (270 funRet, 590 param). The superscript $T$ has the same meaning as in Table 3, where $T = 6$ consists of the six types predicted by JSNice. Boldface indicates the best results of the full set of $T = 78$ types.

| Tool              | $P(T_{\text{funRet}})$ | $R(T_{\text{funRet}})$ | $P(T_{\text{param}})$ | $R(T_{\text{param}})$ | $P(T_{\text{total}})$ | $R(T_{\text{total}})$ |
|-------------------|-------------------------|-------------------------|------------------------|------------------------|------------------------|------------------------|
| TSINFER ($T = 78$) | 0.14                    | 0.19                    | 0.01                   | 0.00                   | 0.08                   | 0.01                   |
| DeepTyper ($T = 78$) | 0.20                    | 0.20                    | 0.50                   | 0.52                   | 0.35                   | 0.36                   |
| JSNice ($T = 6$)   | 0.15                    | 0.15                    | 0.78                   | 0.80                   | 0.47                   | 0.48                   |
| JSNice ($T = 78$)  | 0.12                    | 0.12                    | 0.62                   | 0.64                   | 0.37                   | 0.38                   |
| **OptTyper ($T = 78$)** | **0.68**                | **0.68**                | **0.67**               | **0.67**               | **0.68**               | **0.68**               |

- TSINFER [Kristensen and Møller 2017]: A tool based on a combination of a static and dynamic analysis that uses a recorded snapshot of a concretely initialised library to generate TypeScript declaration files from JavaScript libraries.
- DeepTyper [Hellendoorn et al. 2018]: A tool based on deep learning which learns types for every identifier. The network is trained using previously annotated TypeScript code.
- JSNice [Raychev et al. 2015]: A tool based on probabilistic graphical models which analyzes relationships between program elements to infer types for JavaScript files.

Since DeepTyper has a vocabulary of 11000 types, we measure the results on our set of 78 types and give every other type we encounter OutOfVoc, so that it does not contribute to the final result. JSNice’s vocabulary is smaller than ours that’s why we have two rows for JSNice on Table 4, for $T = 6$, which is a set of types appearing both in the JSNice implementation and ours. The results for the types of the parameters are almost identical to the ones of the original JSNice paper. Table 4 summarises the results of our comparisons.

The relative error reduction is a standard way to express performance improvement in machine learning. In our case, it is how many fewer errors ProdTS makes as a proportion of the errors that JSNice makes. The JSNice $T = 78$ precision of 0.37 implies an error rate 0.63, whereas the OptTyper $T = 78$ precision of 0.68 implies an error rate 0.32. So the relative reduction in error is $(0.63 - 0.32)/0.63 = 49.2\%$.

Comparison with TSINFER. TSINFER addresses the same problem as we do but without using any form of learning. TSINFER uses a dynamic analysis to construct the interface that a type implements and often gives fresh type annotations, like `interface_1342`, that lack meaning. As our evaluation is based on a nominal view for typings, TSINFER performs poorly under our evaluation.

Comparison with DeepTyper. DeepTyper is a deep learning framework that outputs a type vector for every identifier based on information from the source-code context. It utilises information in the vicinity of the identifier to predict the type. In contrast, our LSTM is trained on identifiers and types; we focus on obtaining information based on the identifier alone and not its context.

For the results shown in Table 4, DeepTyper often returns any as the most relevant suggestion for the type of an identifier. In this case, to keep the comparison meaningful, we select the second best candidate.

Even though our LSTM is trained only on identifiers and types—while DeepTyper utilises more context—predictions for both tools are comparable for parameters’ types. For function return types, our Char-Level LSTM clearly outperforms DeepTyper. This shows that taking into account
information in the vicinity can be problematic; function definitions may be placed relatively far away from their calls and hence the context is not very informative.

Finally, it is worth pointing out that DeepTyper has a type vocabulary of size $T = 11000$, much larger than our vocabulary of size $T = 78$, because it includes user-defined types. If DeepTyper were trained on a smaller vocabulary the results—at least for the predicted types of parameters—might improve. Further, perhaps taking into account user-defined types needs extra consideration; simply learning user-defined identifier and type pairs, as DeepTyper does, might be inadequate and may even worsen its performance.

We conjecture that OptTyper outperforms DeepTyper for two reasons. First, OptTyper’s Character LSTM captures the type of a variable, despite variations in its spelling (Section 3.4). Second, OptTyper’s logical constraints define a wider, lexically independent, prediction context that notably captures function returns.

Comparison with JSNice. JSNice is a tool that learns statistical correlations between program elements by exploiting their relationship for a certain depth. Its purpose is for type inference (and other tasks) on JavaScript using statistics from dependency graphs learned on a large corpus. The evaluation on our data had to be performed manually because JSNice is only available via a website interface.

JSNice targets a type lattice that contains $T = 6$ primitive types plus some additional types under Object, but as the exact details are not available we compare ourselves against these 6 known types. JSNice exploits the relation paths between types up to depth 3, thus it may not capture some typing relevant element dependencies. Because JSNice prediction space is smaller than ours we cannot directly compare it to OptTyper, so, instead, we report JSNice’s results on two tasks. In the first task, we calculate its results over the 6 primitive types it targets; while, for the second, we report its results on OptTyper’s set of $T = 78$. The first task advantages JSNice; the second advantages OptTyper. On predicting parameter type in the first task, JSNice outperforms OptTyper, as Table 4 shows.

Otherwise, OptTyper outperforms JSNice. We conjecture that this is due to the same two reasons we believe OptTyper outperforms DeepTyper: OptTyper’s grouping together of names that share a type despite minor variations in their names and its use of a more expansive context due to its logical constraints, as opposed to JSNice depth 3 traversal of program element relations.

NL2Type, a tool by [Malik et al. 2019], also uses a deep learning approach to the problem, and relies on JSDoc comments as an additional type hint. We could not compare directly to NL2Type because there are few examples with both JSDoc and available declaration files in the DefinitelyTyped repository. Finally, it would be fairly simple to extend our method to include natural constraints generated by DeepTyper, NL2Type or indeed any other deep learning approach that offers similar information. For example, we could simply add more terms to the combined objective function, including an extra term for every additional source of natural constraints.

5 RELATED WORK

OptTyper is a new form of probabilistic type inference that optimises over both logical and natural constraints. Related spans classical, deterministic type inference and earlier machine learning approaches.

5.1 Classical Type Inference

Rich type inference mitigates the cost of explicitly annotating types. This feature is an inherent trait of strongly, statically-typed, functional languages (like Haskell or ML).
Dynamic languages have also started to pay more attention to typings. Several JavaScript extensions, like Closure Compiler [Google 2019], Flow [Facebook 2019] and TypeScript (see Section 3.1) are all focusing on enabling sorts of static type checking for JavaScript. However, these extensions often fail to scale to realistic programs that make use of dynamic evaluation and complex libraries, for example jQuery, which cannot be analysed precisely [Jensen et al. 2009]. There are similar extensions for other popular scripting languages, like [The-Mypy-Project 2014], an optional static type checker for Python, or RuboCop [Bastov 2018b], which serves as a static analyzer for Ruby by enforcing many of the guidelines outlined in the community Ruby Style Guide [Bastov 2018a].

The quest for more modular and extensible static analysis techniques has resulted in the development of richer type systems. Refinement types, that is, subsets of types that satisfy a logical predicate (like Boolean expression), constrain the set of values described by the type, and hence allow the use of modern logic solvers (such as SAT and SMT engines) to extend the scope of invariants that can be statically verified. An implementation of this concept comes with Logically Qualified Data Types, abbreviated to Liquid Types. DSOLVE is an early application of liquid type inference in OCAML [Rondon et al. 2008]. A type-checking algorithm, which relies on an SMT solver to compute subtyping efficiently for a core, first order functional language enhanced with refinement types [Bierman et al. 2012], provides a different approach. LiquidHaskell [Vazou et al. 2014] is a static verifier of Haskell based on Liquid Types via SMT and predicate abstraction. DependentJS [Chugh et al. 2012] incorporates dependent types into JavaScript.

5.2 Machine Learning Over Source Code

Although the interdisciplinary field between machine learning and programming languages is still young, complete reviews of this area are already available. Allamanis et al. [2018] extensively survey work that probabilistically model source code via a learning component and complex representations of the underlying code. Vechev and Yahav [2016] give a detailed description of the area, whilst Gottschlich et al. [2018]’s position paper examines this research area by categorizing the challenges involved in three main, overlapping pillars.

A sub-field of this emerging area applies probabilistic models from machine learning to infer semantic properties of programs, such as types. Chibotaru et al. [2019] use control and data flow analyses to extract the desired statistical graphical model. Xu et al. [2016] also use probabilistic graphical models to statistically infer types of identifiers in programs written in Python. Their tool trains the classification model for each type in the domain and uses a different approach to build the graphical model as it allows to leverage type hints derived from data flow, attribute accesses, and naming conventions for types. Two earlier approaches for probabilistic typing are JSNice [Raychev et al. 2015] and DeepTyper [Hellendoorn et al. 2018]. Indeed, they serve as baselines in our evaluation, where we discuss them in detail (Section 4.4).

Wei et al. [2020] propose a different approach to probabilistic type inference for TypeScript. LambdaNet is based on graph neural networks [Allamanis et al. 2017], which learn type dependency graphs extracted by static code analysis on the training data. Their type dependency graph has edges that are either logical or contextual, corresponding to what we call logical or natural constraints. While, they are also able to predict user-defined types using open vocabulary techniques. However, the problem they are targeting is different than ours, as they do not consider the problem of generating TypeScript signature files from a JavaScript file, but instead predict types for native unnotated TypeScript.

5.3 Soft Logic

Recently, there is a resurgence of interest for soft logic in the context of machine learning. By soft logic we mean a many-valued logic, where the truth values lie on the unit interval [0, 1]. The reason
for this resurgence is twofold: First, soft logic allows the modeling of multiple notions of similarity. Second, and more relevant for our interests, the resulting compound formulas are amenable to continuous optimisation approaches. Thus, they provide a framework to exploit the relational structure of different problems [Kimmig et al. 2012].

In the context of fuzzy logic, the three most important extensions are: Gödel logic, Łukasiewicz logic, and product logic [Hájek 1998], with the latter two attracting more interest. For example, the Łukasiewicz logic is used in Bach et al. [2017] due to its convenient relationship to their relaxed MAX SAT problem formulation. In our case, the relationships expressed by the logical constraints are non-convex and we focus on smooth optimisation formulations; the product logic is more suitable since the other two are non-smooth and would require relaxations. For deep learning, this logic is also important as it allows to perform back-propagation [Evans and Grefenstette 2018].

6 CONCLUSION AND FUTURE WORK

This paper proposes a new type inference approach for dynamically typed languages, leveraging different sources of information. To conceptualise this we define a general probabilistic framework that combines information from traditional analyses with statistical reasoning for source code text, and thus enables us to to predict naturally occurring types. We evaluate our framework by implementing OptTyper, a tool that generates typed TypeScript declaration files for untyped JavaScript libraries. Our experiments show that OptTyper predicts function types signatures with a precision and recall score of almost 70% for the top-most prediction, that is 50% relatively better than previous works. We believe that the probabilistic type inference approach presented here is a basis for constructively combining different type analyses using numerical methods. We have limited to advancing the state of the art in the probabilistic inference of primitive types; we leave open the challenge inferring user-defined types.

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A APPENDIX: CONTINUOUS RELAXATION IN THE LOGIT SPACE

In Section 2.2, we present the continuous interpretation based on probabilities. As already mentioned, in the actual implementation we use logit instead for numerical stability. The logit of a probability is the logarithm of the odds ratio. It is defined as the inverse of the softmax function; that is, an element of a probability vector $p \in [0, 1)$ corresponds to

$$\pi = \log \frac{p}{1 - p}.$$ 

It allows us to map probability values from $[0, 1)$ to $[-\infty, \infty]$.
Given the matrix $\mathcal{L}$, which corresponds to the logit of the matrix $P$ in Section 2.2, we interpret an expression $E$ as a number $[E]_P \in \mathbb{R}$ as follows:

\[
\begin{align*}
\llbracket x_v \text{ is } l_r \rrbracket &= \pi_{v, r} \\
\llbracket \text{not } E \rrbracket &= \log(1 - \text{sigmoid}(\llbracket E \rrbracket_\mathcal{L})) \\
\llbracket E_1 \text{ and } E_2 \rrbracket &= \llbracket E_1 \rrbracket_\mathcal{L} + \llbracket E_2 \rrbracket_\mathcal{L} \\
\llbracket E_1 \text{ or } E_2 \rrbracket &= \text{LogSumExp}(\llbracket E_1 \rrbracket_\mathcal{L} + \llbracket E_2 \rrbracket_\mathcal{L} - \llbracket E_1 \rrbracket_\mathcal{L} \cdot \llbracket E_2 \rrbracket_\mathcal{L}).
\end{align*}
\]

The sigmoid function is defined as

\[
\text{sigmoid}(a) = \frac{\exp(a)}{1 + \exp(a)},
\]

while the LogSumExp function is defined as

\[
\text{LogSumExp}(x) = \log \left( \sum_i \exp(x_i) \right).
\]

\section*{B \hspace{1em} APPENDIX: FORMAL PROOFS}

\subsection*{B.1 Proofs for Logical Constraints}

**Lemma B.1.** For all $E$ and $\Gamma$, $[E]_{B(\Gamma)} \in \{0, 1\}$.

Proof. By structural induction on the continuous semantics.

**Lemma B.2.** For all $E$, $E_1$, $E_2$, and $\Gamma$:

1. $[E]_{B(\Gamma)} = 0 \iff \text{not}(\llbracket E \rrbracket_{B(\Gamma)} = 1)$
2. $[E_1]_{B(\Gamma)} = 1$ and $[E_2]_{B(\Gamma)} = 1 \iff \llbracket E_1 \rrbracket_{B(\Gamma)} \cdot \llbracket E_2 \rrbracket_{B(\Gamma)} = 1$
3. $[E_1]_{B(\Gamma)} = 1$ or $[E_2]_{B(\Gamma)} = 1 \iff \llbracket E_1 \rrbracket_{B(\Gamma)} + \llbracket E_2 \rrbracket_{B(\Gamma)} - \llbracket E_1 \rrbracket_{B(\Gamma)} \cdot \llbracket E_2 \rrbracket_{B(\Gamma)} = 1$

Proof. These follow by cases analyses based on Lemma B.1.

**Lemma B.3.** For all $E$ and $\Gamma$, either $\Gamma \models E$ or $\Gamma \models \text{not } E$.

Proof. By structural induction on the satisfaction relation.

**Restatement of Theorem 2.2.** For all $E$ and $\Gamma$: $[E]_{B(\Gamma)} = 1 \iff \Gamma \models E$.

Proof. The above theorem corresponds to a result in the book of Hájek [19]. We prove the property by structural induction; that is, we prove that $\phi(N)$ holds for all $N$, where $\phi(N)$ is as follows.

\[
\phi(N) \equiv \forall E, \forall \Gamma : \text{size}(E) = N \Rightarrow (\Gamma \models E \iff [E]_{B(\Gamma)} = 1).
\]

We proceed by course-of-values induction on $N$. Consider any $E$, $\Gamma$ and $N = \text{size}(E)$. We proceed by a case analysis at $E$.

**Base Case** For $N = 1$, the base case is $E = (x_v \text{ is } l_r)$. For any $\Gamma$ we are to show

\[
\Gamma \models x_v \text{ is } l_r \iff \llbracket x_v \text{ is } l_r \rrbracket_{B(\Gamma)} = 1.
\]

By definition, $\llbracket x_v \text{ is } l_r \rrbracket_{B(\Gamma)} = p_{v, r}$ where $p_{v, r}$ is the probability that variable $x_v$ has type $l_r$ according to the matrix $B(\Gamma)$. By definition of $B(\Gamma)$ and because $B$ results to a binary matrix, $\llbracket x_v \text{ is } l_r \rrbracket_{B(\Gamma)} = 1$ means that the element $p_{v, r}$ is equal to 1, that is $\Gamma \models x_v \text{ is } l_r$. Also, $\Gamma \models x_v \text{ is } l_r$ implies that $\Gamma(x_v) = l_r$. By definition, that means $\llbracket x_v \text{ is } l_r \rrbracket_{B(\Gamma)} = 1$. 

Case $E \neq not E'$. We are to show $\Gamma \models not E' \iff \|not E'\|_{B(\Gamma)} = 1$. We have that
\[
\|not E'\|_{B(\Gamma)} = 1 \iff \\
1 - \|E'\|_{B(\Gamma)} = 1 \iff \quad \text{(Definition)} \\
\|E'\|_{B(\Gamma)} = 0 \iff \\
not (\|E'\|_{B(\Gamma)} = 1) \iff \quad \text{(Lemma B.1)} \\
not \Gamma \models E' \iff \quad \text{(Induction Hypothesis)} \\
\Gamma \models not E' \iff \quad \text{(Definition)}.
\]

Case $E = (E_1$ and $E_2$). For $\text{size}(E_1) < N$ and $\text{size}(E_2) < N$, we are to show that $\Gamma \models (E_1$ and $E_2) \iff \| (E_1$ and $E_2) \|_{B(\Gamma)} = 1$. Our induction hypothesis is that $\phi(M)$ holds for all $M < N$. We have that
\[
\Gamma \models (E_1$ and $E_2) \iff \\
\Gamma \models E_1$ and $\Gamma \models E_2 \iff \quad \text{(Definition)} \\
\|E_1\|_{B(\Gamma)} = 1$ and $\|E_2\|_{B(\Gamma)} = 1 \iff \quad \text{(Induction Hypothesis)} \\
\|E_1\|_{B(\Gamma)} \cdot \|E_2\|_{B(\Gamma)} = 1 \iff \quad \text{(Lemma B.1)} \\
\|(E_1$ and $E_2)\|_{B(\Gamma)} = 1 \quad \text{(Definition)}
\]
which completes the proof for this case.

Case $E = (E_1$ or $E_2$). For $\text{size}(E_1) < N$ and $\text{size}(E_2) < N$, we are to show that $\Gamma \models (E_1$ and $E_2) \iff \| (E_1$ and $E_2) \|_{B(\Gamma)} = 1$. Our induction hypothesis is that $\phi(M)$ holds for all $M < N$. We have that
\[
\Gamma \models (E_1$ or $E_2) \iff \\
\Gamma \models E_1$ or $\Gamma \models E_2 \iff \quad \text{(Definition)} \\
\|E_1\|_{B(\Gamma)} = 1$ or $\|E_2\|_{B(\Gamma)} = 1 \iff \quad \text{(Induction Hypothesis)} \\
\|E_1\|_{B(\Gamma)} \cdot \|E_2\|_{B(\Gamma)} - \|E_1\|_{B(\Gamma)} - \|E_2\|_{B(\Gamma)} - 1 = 0 \iff \quad \text{(Case Analysis & Lemma B.1)} \\
\|E_1$ or $E_2\|_{B(\Gamma)} = 1.
\]
which completes the proof for this case. \qed

**Lemma B.4.** For all $E$ and for all $P \in [0, 1]^{V \times T}$, then $0 \leq \|E\|_P \leq 1$.

**Proof.** By structural induction on the expression $E$. \qed

**Lemma B.5.** For all $E$,
\[
\max_{P \in \Pi^{V \times T}} \|E\|_P > 0.
\]

**Proof.** For all matrices $Q \in \Pi^{V \times T}$, we have
\[
\max_{P \in \Pi^{V \times T}} \|E\|_P > \|E\|_Q. \quad (13)
\]
Choose $Q \in \Pi^{V \times T}$ such as $q_{u,t} = 1/T$ for all $u \in 1 \ldots V$ and $t \in 1 \ldots T$. We proceed by course-of-value induction on $N$. Consider any $E, P$ and $N = \text{size}(E)$. The proof completes by course-of-values induction on $N$. \qed
Restatement of Theorem 2.3. For all $\Gamma$ and all $E$, $\Gamma \models E$ if and only if $B(\Gamma) \in \arg \max_{P \in \prod V \times T} \|E\|_P$.

Proof. Consider any $\Gamma$ and $E$. Either $\Gamma \models E$ or not.
If $\Gamma \models E$ then the theorem follows as a simple consequence of Theorem 2.2.
Otherwise both sides of the biconditional are always false: $\Gamma \models E$ is false by assumption, and
$B(\Gamma) \in \arg \max_{P \in \prod V \times T} \|E\|_P$ is false by Lemma B.5. (We can show that $\|E\|_{B(\Gamma)} = 0$ by considering
that $\|\neg E\|_{B(\Gamma)} = 1$.) So the biconditional is trivially true. □

C APPENDIX: NEURAL MODEL

In this appendix we present the implementation details of the deep neural used in Section 3.4.

```
LSTMClassifier(
    (embedding): Embedding(90, 128)
    (lstm): LSTM(128, 64)
    (hidden2out): Linear(in_features=64,
        out_features=78, bias=True)
    (softmax): LogSoftmax()
    (optimization fun): ADAM)
```

Listing 1. Our Character Level LSTM model.