

Types from data: Making structured data first-class citizens in F#

Abstract

Most modern applications interact with external services and access data in structured formats such as XML, JSON and CSV. Static type systems do not understand such formats, often making data access more cumbersome. Should we give up and leave the messy world of external data to dynamic typing and runtime checks? Of course, not!

In this paper, we integrate external structured data into the F# type system. As most real-world data does not come with an explicit schema, we develop a shape inference algorithm that infers a shape from representative sample documents and integrate it into the F# type system using type providers.

Our library significantly reduces the amount of data access code and it provides additional safety guarantees when contrasted with the widely used weakly typed techniques.

Categories and Subject Descriptors D.3.3 [*Programming Languages*]: Language Constructs and Features

Keywords F#, Type Providers, Inference, JSON, XML

1. Introduction

Social network clients, applications for finding tomorrow's weather or searching train schedules all communicate with external services. Increasing number of such services provide REST-based end-points that return data as CSV, XML or JSON. Despite many schematization efforts, most services do not come with an explicit schema. At best, the documentation provides sample responses for typical requests.

For example, <http://openweathermap.org/current> provides an end-point to get the current weather. The documentation shows one sample to illustrate the typical response. Using standard JSON and web libraries, we might write:

```
let doc = Http.Request("http://api.owm.org/?q=NYC")
match JsonValue.Parse(doc) with
| Record(root) →
    match Map.find "main" root with
    | Record(main) →
        match Map.find "temp" main with
        | Number(num) → printfn "Lovely %f!" num
        | _ → failwith "Incorrect format"
    | _ → failwith "Incorrect format"
    | _ → failwith "Incorrect format"
```

The code assumes that the response has a particular shape described in the documentation. The root node must be a record with a "main" field, which has to be another record containing a numerical "temp" field. When the shape is different, the code simply fails with an exception. While not immediately unsound, the code is manifestly prone to errors if strings are misspelled or incorrect shape assumed.

Using the JSON type provider from F# Data, we can write code with exactly the same functionality in two lines:

```
type W = JsonProvider<"http://api.owm.org/?q=NYC">
printfn "Lovely %f!" (W.GetSample().Main.Temp)
```

`JsonProvider<"...">` invokes a type provider at compile-time with the URL as a sample. The type provider infers the structure of the response and provides a type with a `GetSample` method that returns a parsed JSON with nested properties `Main.Temp`, returning the temperature as a number.

In short, *the types come from the sample data*. In our experience, this technique is immensely practical and surprisingly effective in achieving sound information interchange in heterogeneous systems. This paper presents our approach:

- We present F# Data type providers for XML, CSV and JSON (§2) and practical aspects of their implementation that contributed to their industrial adoption (§6).
- We describe a predictable shape inference algorithm for structured data formats, based on a *preferred shape* relation, that underlies the type providers (§3).
- We give a formal model (§4) and use it to prove *relativized type safety* for the type providers (§5). This adapts the ML-style type safety for the context of the web.

The supplementary screencast illustrates the practical developer experience using F# Data with JSON, XML and CSV.

2. Type providers for structured data

We start with an informal overview that shows how F# Data type providers simplify working with JSON and XML. We introduce the necessary aspects of F# type providers along the way. The examples in this section illustrate the key design principles of the shape inference algorithm:

- The mechanism is predictable. The user directly works with the provided types and should understand why a specific type was produced from a given sample.¹
- The type providers prefer F# objects with properties. This is to allow extensible (open-world) data formats (§2.2). It also interacts well with developer tooling as most F# editors provide auto-completion on “.” and so objects are easier to use than types that require pattern matching.
- Finally, the mechanism handles practical concerns important in the real world. This includes support for different numerical types, `null` values and missing data.

2.1 Working with JSON documents

The JSON format is a popular data exchange format based on JavaScript data structures. The following is the definition of `JsonValue` used earlier (§1) to represent JSON data:

```
type JsonValue =  
    | Number of float | Boolean of bool  
    | String of string | Null  
    | Record of Map<string, JsonValue>  
    | Array of JsonValue[]
```

The earlier example used only a nested record containing a number. To demonstrate other aspects of the JSON type provider, we look at an example that also involves an array:

```
[ { "name": "Jan", "age": 25 }, { "name": "Tomas" },  
  { "name": "Alexander", "age": 3.5 } ]
```

The standard approach to print the names and ages would be to pattern match on the parsed `JsonValue`, check that the top-level node is a `Array` and iterate over the elements checking that each element is a `Record` with certain properties. We would throw an exception for values of an incorrect shape. As before, the code would specify field names as strings, which is error prone and can not be statically checked.

Assuming `people.json` is the above example and data is a string containing JSON of the same shape, we can write:

```
type People = JsonProvider<"people.json">  
for item in People.Parse(data) do  
    printf "%s " item.Name  
    Option.iter (printf "(%f)") item.Age
```

In contrast to the earlier example, we now use a local file `people.json` as a sample for the type inference, but then processes data from another source. The code achieves a similar simplicity as when using dynamically typed languages, but it is statically type-checked.

Type providers. The notation `JsonProvider<"people.json">` passes a *static parameter* to the type provider. Static parameters are resolved at compile-time and have to be constant. The provider analyzes the sample and generates a type `People`. Most F# editors also execute the type provider in the background at development-time and use the provided types in auto-completion and background type-checking.

The `JsonProvider` uses a shape inference algorithm and provides the following F# types for the sample:

```
type Entity =  
    member Name : string  
    member Age : option<float>  
  
type People =  
    member GetSample : unit → Entity[]  
    member Parse : string → Entity[]
```

The type `Entity` represents the person. The field `Name` is available for all sample values and is inferred as `string`. The field `Age` is marked as optional, because the value is missing in one sample. The two age values are an integer 25 and a float 3.5 and so the common inferred type is `float`.

The type `People` has two methods for reading data. `GetSample` parses the sample used for the inference and `Parse` parses a JSON string. This lets us read data at runtime, provided that it has the same shape as the static sample.

Error handling. In addition to the structure of the types, the type provider also specifies what code should be executed at run-time in place of `item.Name` and other operations. The runtime behaviour is the same as in the earlier hand-written sample (§1) – a member access throws an exception if data does not have the expected shape.

Informally, the safety property (§5) states that if the inputs are compatible with one of the static samples (i.e. the samples are representative), then no exceptions will occur. In other words, we cannot avoid all failures, but we can prevent some. Moreover, if <http://openweathermap.org> changes the shape of the response, the code in §1 will not re-compile and the developer knows that the code needs to be changed.

The role of objects with properties. The sample code is easy to write thanks to the fact that most F# editors provide auto-completion when “.” is typed (see the supplementary screencast). The developer does not need to look at the sample JSON file to see what fields are available. To support this scenario, our type providers map the inferred shapes to F# objects with (possibly optional) properties.

This is demonstrated by the fact that `Age` becomes an optional member. An alternative is to provide two different record types (one with `Name` and other with `Name` and `Age`), but this would complicate the processing code. It is worth noting that languages with stronger tooling around pattern matching such as Idris [11] might have different preferences.

¹ In particular, we do not use probabilistic methods where adding an additional sample could completely change the shape of the type.

2.2 Processing XML documents

XML documents are formed by nested elements with attributes. We can view elements as records with a field for each attribute and an additional special field for the nested contents (which is a collection of elements).

Consider a simple extensible document format where a root element `<doc>` can contain a number of document elements, one of which is `<heading>` representing headings:

```
<doc>
  <heading>Working with JSON</heading>
  <p>Type providers make this easy.</p>
  <heading>Working with XML</heading>
  <p>Processing XML is as easy as JSON.</p>
  <image source="xml.png" />
</doc>
```

The F# Data library has been designed primarily to simplify reading of data. For example, say we want to print all headings in the document. The sample shows a part of the document structure (in particular the `<heading>` element), but it does not show all possible elements (say, `<table>`). Assuming the above document is `sample.xml`, we can write:

```
type Document = XmlProvider<"sample.xml">
let root = Document.Load("c:/pldi/another.xml")
for elem in root.Doc do
  Option.iter (printf " - %s") elem.Heading
```

The example iterates over a collection of elements returned by `root.Doc`. The type of `elem` provides a typed access to elements known from the sample and so we can write `elem.Heading`, which returns an optional string value.

Open world. By its nature, XML is extensible and the sample cannot include all possible nodes.² This is the important *open world assumption* about external data. Actual input might be an element about which nothing is known.

For this reason, we do not infer a closed choice between heading, paragraph and image. In the subsequent formalization, we introduce a *top shape* (§3.1) and extend it with labels capturing the statically known possibilities (§3.4). The *labelled top shape* is mapped to the following type:

```
type Element =
  member Heading : option<string>
  member Paragraph : option<string>
  member Image : option<Image>
```

This provides access to the elements known statically from the sample. However the type is deliberately ‘weak’, because the user needs to explicitly handle the case when a value is not a statically known element. The above code uses `Option.iter` to skip all unknown elements.

The provided type is also consistent with our design principles, which prefers optional properties. The gain is that the provided types support both open-world data and developer tooling. It is also worth noting that our shape inference uses labelled top shapes only as the last resort (Theorem 2, §6.3).

2.3 Summary

Throughout the introduction, we used data sets that demonstrate the typical problems that are frequent in the real-world (*missing data*, *inconsistent encoding* of primitive values and *heterogeneous shapes*). In our experience, these are the most common issues. The following JSON response with government debt information returned by the World Bank³ demonstrates all three problems:

```
[ { "page": 1, "pages": 5 },
  [ { "indicator": "GC.DOD.TOTL.GD.ZS",
      "date": "2012", "value": null },
    { "indicator": "GC.DOD.TOTL.GD.ZS",
      "date": "2010", "value": "35.14229" } ] ]
```

First of all, the top-level element is a collection containing two values of different kind. The first is a record with meta-data about the current page and the second is an array with data. The actual F# Data implementation supports a concept of heterogeneous collections (briefly outlined in §6.3) and provides a type with properties `Record` for the former and `Array` for the latter. Second, the value field is `null` for some records. Third, numbers can be represented in JSON as numeric literals (without quotes), but here, they are returned as string literals instead.⁴

In addition to type providers for JSON and XM, F# Data also implements a type provider for CSV (§6.2). We treat CSV files as lists of records (with field for each column) and so CSV is handled directly by our inference algorithm.

3. Shape inference for structured data

The shape inference algorithm for structured data is based on a shape preference relation. When inferring the shape, it infers the most specific shapes of individual values (CSV rows, JSON or XML nodes) and recursively finds a common shape of all child nodes or all sample documents.

We first define the shape of structured data σ . We use the term *shape* to distinguish shapes from programming language types τ (type providers generate the latter from the former). Next, we define the preference relation on shapes σ and describe the algorithm for finding a common shape.

3.1 Inferred shapes

We distinguish between *non-nullable shapes* that always have a valid value (written as $\hat{\sigma}$) and *nullable shapes* that encompass missing and `null` values (written as σ). We write ν for record names and record field names. In the rest of the paper, we assume that record fields can be freely reordered:

$$\begin{aligned}\hat{\sigma} &= \nu \{ \nu_1 : \sigma_1, \dots, \nu_n : \sigma_n \} \\ &\quad | \text{float} \mid \text{int} \mid \text{bool} \mid \text{string} \\ \sigma &= \hat{\sigma} \mid \text{nullable}(\hat{\sigma}) \mid [\sigma] \mid \text{any} \mid \text{null} \mid \perp\end{aligned}$$

² Even when the document structure is defined using XML Schema, documents may contain elements prefixed with other namespaces.

³ Available at <http://data.worldbank.org>

⁴ This is often used to avoid non-standard numerical types of JavaScript.

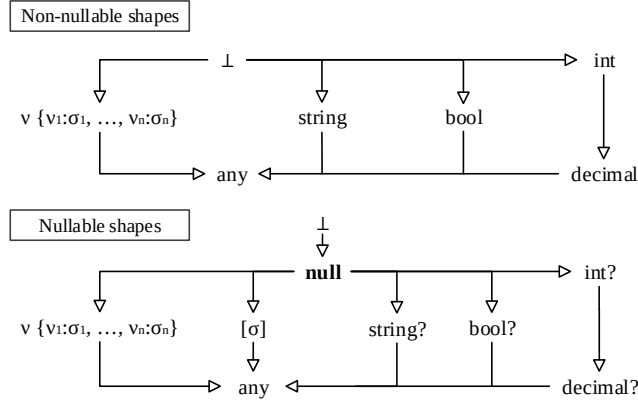


Figure 1. Subtype relation between structural types

Non-nullable shapes include records (consisting of a name and fields with their shapes) and primitives. Names of records arising from XML are the names of the XML elements while JSON records always use a single name \bullet .

We include two numerical primitives, `int` for integers and `float` for floating-point numbers. The two are related by the preference relation and we prefer `int`.

Any non-nullable shape $\hat{\sigma}$ can be wrapped as `nullable` $\langle\hat{\sigma}\rangle$ to explicitly permit the `null` value. Type providers map `nullable` shapes to the F# option type. A collection `[σ]` is also nullable and `null` values are treated as empty collections. The shape `null` is inhabited by the `null` value (using an overloaded notation) and \perp is the bottom shape. The `any` shape is the top shape, but we revisit it later by adding labels for statically known alternative shapes (§3.4) as discussed earlier (§2.2).

3.2 Preferred shape relation

Figure 1 provides an intuition about the preference between shapes. The upper part shows non-nullable shapes (with records and primitives) and the lower part shows nullable shapes with `null`, collections and nullable shapes. In the diagram, we abbreviate `nullable` $\langle\sigma\rangle$ as $\sigma?$ and we omit links between the two parts; a shape $\hat{\sigma}$ is preferred over `nullable` $\langle\hat{\sigma}\rangle$.

Definition 1. We write $\sigma_1 \sqsupseteq \sigma_2$ to denote that σ_2 is preferred over σ_1 . The shape preference relation is defined as a transitive reflexive closure of the following rules:

$$\begin{aligned}
 & \text{float} \sqsupseteq \text{int} & (\text{P1}) \\
 & \sigma \sqsupseteq \text{null} & (\text{iff } \sigma \neq \hat{\sigma}) \quad (\text{P2}) \\
 & \text{nullable}\langle\hat{\sigma}\rangle \sqsupseteq \hat{\sigma} & (\text{for all } \hat{\sigma}) \quad (\text{P3}) \\
 & \text{nullable}\langle\hat{\sigma}_1\rangle \sqsupseteq \text{nullable}\langle\hat{\sigma}_2\rangle & (\text{if } \hat{\sigma}_1 \sqsupseteq \hat{\sigma}_2) \quad (\text{P4}) \\
 & [\sigma_1] \sqsupseteq [\sigma_2] & (\text{if } \sigma_1 \sqsupseteq \sigma_2) \quad (\text{P5}) \\
 & \sigma \sqsupseteq \perp & (\text{for all } \sigma) \quad (\text{P6}) \\
 & \text{any}\langle\sigma_1, \dots, \sigma_n\rangle \sqsupseteq \sigma & (\text{P7}) \\
 & \nu \{ \nu_1 : \sigma_1, \dots, \nu_n : \sigma_n \} \sqsupseteq & \nu \{ \nu_1 : \sigma'_1, \dots, \nu_n : \sigma'_n \} \quad (\text{if } \sigma_i \sqsupseteq \sigma'_i) \quad (\text{R1})
 \end{aligned}$$

$$\nu \{ \nu_1 : \sigma_1, \dots, \nu_n : \sigma_n \} \sqsupseteq \nu \{ \nu_1 : \sigma_1, \dots, \nu_m : \sigma_m \} \quad (\text{when } m \geq n) \quad (\text{R2})$$

$$\nu \{ \nu_1 : \sigma_1, \dots, \nu_n : \sigma_n, \nu_{n+1} : \text{null} \} \sqsupseteq \nu \{ \nu_1 : \sigma_1, \dots, \nu_n : \sigma_n \} \quad (\text{R3})$$

Here is a summary of the key aspects of the definition:

- Numeric shape with smaller range is preferred (P1) and we choose 32-bit `int` over `float` when possible.
- The `null` shape is preferred over all nullable shapes (P2), i.e. all shapes excluding non-nullable shapes $\hat{\sigma}$. Any non-nullable shape is preferred over its nullable version (P3); nullable shapes and collections are covariant (P4, P5).
- There is a bottom shape (P6) and `any` behaves as the top shape, because any shape σ is preferred over `any` (P7).
- The record shapes are covariant (R1) and preferred record can have additional fields (R2). The rule (R3) implies that records can omit fields, provided that `null` is a valid value for the field (i.e. the field is optional).

The rule that allows preferred shapes to have fewer fields (R3) is particularly important. This is important, because it allows us to prefer records over the `any` shape. Given `{name : string}` and `{name : string, age : int}`, we find a common shape `{name : string, age : int option}`. This is a least upper bound and more usable than the top shape `var`.

Some of the aspects of our system (numeric types and handling of missing data) offer a range of choices. For example, OCaml also has different numerical types, but would likely always handle `null` explicitly.

3.3 Common preferred shape relation

Given two shapes, the *common preferred shape* relation finds a least upper bound (Theorem 2). It prefers records, which is important for usability as discussed earlier.

Definition 2. A common preferred shape of shapes σ_1 and σ_2 is a shape σ , written $\sigma_1 \nabla \sigma_2 \vdash \sigma$, obtained according to the inference rules in Figure 2.

We define shape *tags* to identify shapes that have a common preferred shape which is not the top shape. When finding a common shape of two records (*record*), we return a record that has the union of their fields. The shape of shared fields becomes the common preferred shape of their respective shapes; fields that are present in only one record are marked as nullable using the function $\lceil - \rceil$.

We can find a common shape of two different numbers (*prim*); for two collections, we combine their elements (*list*). When one shape is nullable (*nullable*), we find the common non-nullable shape and wrap it in `nullable`; if one of the shapes is `null`, we make the other one nullable (*null*). Finally, if the two shapes do not have matching tags (and they are not nullable), we have to infer the `any` shape as there is no better alternative. The remaining rules for reflexivity, symmetry and the bottom shape are standard.

$$\begin{array}{lcl}
\text{tag} = \begin{array}{|l|l|} \hline \text{collection} & \text{number} \\ \hline \text{nullable} & \text{string} \\ \hline \nu & \text{any} \\ \hline \end{array} & \begin{array}{l} \text{tagof(string)} = \text{string} \\ \text{tagof(bool)} = \text{bool} \\ \text{tagof(int)} = \text{number} \\ \text{tagof(float)} = \text{number} \end{array} & \begin{array}{l} \text{tagof}(\text{any}\langle\sigma_1, \dots, \sigma_n\rangle) = \text{any} \\ \text{tagof}(\nu \{ \nu_1 : \sigma_1, \dots, \nu_n : \sigma_n \}) = \nu \\ \text{tagof}(\text{nullable}\langle\hat{\sigma}\rangle) = \text{nullable} \\ \text{tagof}([\sigma]) = \text{collection} \end{array} \\
\\
[\hat{\sigma}] = \text{nullable}\langle\hat{\sigma}\rangle & (\text{non-nullable shapes}) & [\text{nullable}\langle\hat{\sigma}\rangle] = \hat{\sigma} \quad (\text{nullable shape}) \\
[\sigma] = \sigma & (\text{otherwise}) & [\sigma] = \sigma \quad (\text{otherwise}) \\
\\
(\text{nullable}) \frac{\hat{\sigma}_1 \nabla \sigma_2 \vdash \sigma}{\text{nullable}\langle\hat{\sigma}_1\rangle \nabla \sigma_2 \vdash \text{nullable}\langle[\sigma]\rangle} & (\text{any}) \frac{\text{tagof}(\sigma_1) \neq \text{tagof}(\sigma_2) \quad \text{tagof}(\sigma_1) \neq \text{nullable} \neq \text{tagof}\sigma_2}{\sigma_1 \nabla \sigma_2 \vdash \text{any}} & \\
\\
(\text{record}) \frac{(\nu_i = \nu'_j) \Leftrightarrow (i = j) \wedge (i \leq k) \quad \forall i \in \{1..k\}. (\sigma_i \nabla \sigma'_i \vdash \sigma''_i)}{\nu \{ \nu_1 : \sigma_1, \dots, \nu_k : \sigma_k, \dots, \nu_n : \tau_n \} \nabla \nu \{ \nu'_1 : \sigma'_1, \dots, \nu'_k : \sigma'_k, \dots, \nu'_m : \tau'_m \} \vdash \nu \{ \nu_1 : \sigma''_1, \dots, \nu_k : \sigma''_k, \nu_{k+1} : [\sigma_{k+1}], \dots, \nu_n : [\sigma_n], \nu'_{k+1} : [\sigma'_{k+1}], \dots, \nu'_m : [\sigma'_m] \}} & & \\
\\
(\text{list}) \frac{\sigma_1 \nabla \sigma_2 \vdash \sigma}{[\sigma_1] \nabla [\sigma_2] \vdash [\sigma]} & (\text{sym}) \frac{\sigma_1 \nabla \sigma_2 \vdash \sigma}{\sigma_2 \nabla \sigma_1 \vdash \sigma} & (\text{refl}) \sigma \nabla \sigma \vdash \sigma \quad (\text{null}) \sigma \nabla \text{null} \vdash [\sigma] \quad (\sigma \neq \perp) \\
& (\text{bot}) \perp \nabla \sigma \vdash \sigma & (\text{prim}) \text{int} \nabla \text{float} \vdash \text{float}
\end{array}$$

Figure 2. Inference judgements that define the common preferred shape relation

Properties. The set of shapes does not have a *unique* least upper bound, but it has a least upper bound with respect to an equivalence between mutually preferred shapes. The common preferred shape relation defines a function (Theorem 1) that finds a least upper bound (Theorem 2).

The equivalence on shapes groups records by their non-nullable fields. Given $\sigma_1 = A \{a : \text{int}, b : \text{nullable}\langle\text{int}\rangle\}$, $\sigma_2 = A \{a : \text{int}\}$ and $\sigma_3 = A \{a : \text{int}, b : \text{int}\}$, it is the case that $\sigma_1 \sqsubseteq \sigma_2$ and $\sigma_1 \sqsupseteq \sigma_2$ but $\sigma_3 \sqsubseteq \sigma_1$ and not vice versa.

Similarly to labels on the labelled top type (§3.4), the nullable fields of records serve as annotations that provide access to additional values that may or may not be available in the input. In the provided code, these always have to be protected by a runtime check.

Theorem 1 (Preferred shape function). *For all σ_1 and σ_2 there exists exactly one σ such that $\sigma_1 \nabla \sigma_2 \vdash \sigma$.*

Proof. The pre-conditions of rules in Figure 2 are disjoint, with the exception of (sym) and (refl), but applying those does not affect the result. Reflexivity is preserved recursively and all rules, symmetry does not enable different derivations, even for non-symmetric (nullable) and (prim). \square

Theorem 2 (Least upper bound). *If $\sigma_1 \nabla \sigma_2 \vdash \sigma$ then σ is a least upper bound, i.e. $\sigma \sqsupseteq \sigma_1$ and $\sigma \sqsupseteq \sigma_2$ and for all σ' such that $\sigma' \sqsupseteq \sigma_1$ and $\sigma' \sqsupseteq \sigma_2$, it holds that $\sigma' \sqsupseteq \sigma$.*

Proof. By induction over \vdash . The algorithm only infers the top shape **any** when for non-nullable shapes of distinct tags and so no better preferred shape exists. \square

Next, we extend the core model (sufficient for the relativized safety) with *labelled top types* discussed earlier.

3.4 Adding labelled top type

When analyzing the structure of shapes, it suffices to consider a single top shape **any**. However, the type providers need more information to provide typed access to the possible alternative shapes of data, such as XML nodes. To support track the possible shapes, we label the **any** shape:

$$\sigma = \dots \mid \text{any}\langle\sigma_1, \dots, \sigma_n\rangle$$

The shapes $\sigma_1, \dots, \sigma_n$ represent statically known shapes that appear in the sample and that we expose in the provided type. As discussed earlier (§2.2) this is important when reading external *open world* data. The labels do not affect the preferred shape relation and $\text{any}\langle\sigma_1, \dots, \sigma_n\rangle$ should still be seen as the top type, regardless of the labels.

The common preferred shape relation is extended to find a labelled top shape that best represents the sample. We limit the number of labels and avoid nesting by grouping shapes by the shape tag introduced earlier (Figure 2). For example, rather than inferring $\text{any}\langle\text{int}, \text{any}\langle\text{bool}, \text{float}\rangle\rangle$, our algorithm finds the common preferred shape of **int** and **float** and produces $\text{any}\langle\text{float}, \text{bool}\rangle$.

The three rules in Figure 3 replace the earlier (top). When combining a top with another shape (top-1), the labelled top shape may or may not already contain a case with the tag of the other shape. If it does, the two shapes are combined, otherwise a new case is added. When combining two top types (top-2), we group the labels that have shared tags. Finally, (top-3) covers the case when we are combining two distinct non-top shapes. As top shapes implicitly permit **null** values, we use an auxiliary function $[-]$ to make nullable shapes non-nullable (when possible) to simplify the label.

$$\begin{array}{c}
\text{(top-1)} \quad \frac{\exists i. \text{tagof}(\sigma_i) = \text{tagof}(\lfloor \sigma \rfloor) \quad \sigma \nabla \sigma_i \vdash \sigma'_i \quad \text{tagof}(\sigma) \neq \text{any}}{\sigma \nabla \text{any}\langle \sigma_1, \dots, \sigma_n \rangle \vdash \text{any}\langle \sigma_1, \dots, \lfloor \sigma'_i \rfloor, \dots, \sigma_n \rangle} \quad \frac{\nexists i. \text{tagof}(\sigma_i) = \text{tagof}(\lfloor \sigma \rfloor) \quad \text{tagof}(\sigma) \neq \text{any}}{\sigma \nabla \text{any}\langle \sigma_1, \dots, \sigma_n \rangle \vdash \text{any}\langle \sigma_1, \dots, \sigma_n, \lfloor \sigma \rfloor \rangle} \\
\\
\text{(top-2)} \quad \frac{(\text{tagof}(\sigma_i) = \text{tagof}(\sigma'_j)) \Leftrightarrow (i = j) \wedge (i \leq k) \quad \forall i \in \{1..k\}. (\sigma_i \nabla \sigma'_i \vdash \sigma''_i)}{\text{any}\langle \sigma_1, \dots, \sigma_k, \dots, \sigma_n \rangle \nabla \text{any}\langle \sigma'_1, \dots, \sigma'_k, \dots, \sigma'_m \rangle \vdash \text{any}\langle \sigma''_1, \dots, \sigma''_k, \sigma_{k+1}, \dots, \sigma_n, \sigma'_{k+1}, \dots, \sigma'_m \rangle} \quad \text{(top-3)} \quad \frac{(\forall i \in \{1, 2\}) \quad \text{tagof}(\sigma_1) \neq \text{tagof}(\sigma_2) \quad \text{tagof}(\sigma_i) \neq \text{any} \quad \nexists \sigma'_i. (\sigma_i = \text{option}\langle \sigma'_i \rangle)}{\sigma_1 \nabla \sigma_2 \vdash \text{any}\langle \lfloor \sigma_1 \rfloor, \lfloor \sigma_2 \rfloor \rangle}
\end{array}$$

Figure 3. Extending the common preferred shape relation for labelled top shapes

Properties. The revised algorithm still finds a shape which is the least upper bound. This means that labelled top shape is only inferred when there is no other alternative.

Stating properties of the labels requires a finer relation than *preferred shape*. In particular, it can only be done with respect to the *sample*. We leave the details to future work, but we note that the algorithm infers the best labels in the sense that there are labels that enable typed access to every possible value in the sample, but not more. The same is the case for nullable fields of records.

3.5 Inferring shapes from values

The common preferred shape relation is at the core of the shape inference. What remains to be specified is how we obtain the shape from data. We represent JSON, XML and CSV documents using the same first-order *data* value (§6.2):

$$d = i \mid f \mid s \mid \text{true} \mid \text{false} \mid \text{null} \mid [d_1; \dots; d_n] \mid \nu \{ \nu_1 \mapsto d_1, \dots, \nu_n \mapsto d_n \}$$

The first few cases represent primitive values (i for integers, f for floating point numbers and s for strings) and the **null** value. A collection is written as a list of values in square brackets. A record starts with a name ν , followed by a sequence of field assignments $\nu_i \mapsto d_i$.

The following defines a mapping $\langle\langle d_1, \dots, d_n \rangle\rangle$ which turns a collection of sample data d_1, \dots, d_n into a shape σ :

$$\begin{aligned}
\langle\langle i \rangle\rangle &= \text{int} & \langle\langle \text{null} \rangle\rangle &= \text{null} & \langle\langle \text{true} \rangle\rangle &= \text{bool} \\
\langle\langle f \rangle\rangle &= \text{float} & \langle\langle s \rangle\rangle &= \text{string} & \langle\langle \text{false} \rangle\rangle &= \text{bool} \\
\langle\langle d_1, \dots, d_n \rangle\rangle &= \sigma_n \quad \text{where} \\
\sigma_0 &= \perp, \forall i \in \{1..n\}. \sigma_{i-1} \nabla \langle\langle d_i \rangle\rangle \vdash \sigma_i \\
\langle\langle [d_1; \dots; d_n] \rangle\rangle &= [\langle\langle d_1, \dots, d_n \rangle\rangle] \\
\langle\langle \nu \{ \nu_1 \mapsto d_1, \dots, \nu_n \mapsto d_n \} \rangle\rangle &= \\
&\nu \{ \nu_1 : \langle\langle d_1 \rangle\rangle, \dots, \nu_n : \langle\langle d_n \rangle\rangle \}
\end{aligned}$$

We overload the notation and write $\langle\langle s \rangle\rangle$ when inferring shape from a single value. Primitive values are mapped to their corresponding shapes. For records, we return infer field shapes from the individual values.

When inferring a shape from multiple samples, we use the common preferred shape relation to find a common shape for all values (starting with \perp). This operation is used at the top-level (when calling a type provider with multiple samples) and also when inferring the shape of collection elements.

4. Formalising type providers

In this section, we build the theoretical framework for proving relativised type safety of structural type providers. We discuss the runtime representation of documents and primitive operations (§4.1), we embed these into a formal model of an F# subset (§4.2) and we describe how structural type providers turn inferred structural types into F# types (§4.3).

4.1 Structural values and conversions

As indicated by the subtyping, our system permits certain runtime conversions (e.g. an integer **1** can be treated as a floating-point **1.0**). The following primitive operations implement the conversions and other helpers:

$$\begin{aligned}
op &= \text{asDec}(s) \mid \text{asFloat}(s) \mid \text{getChildren}(s) \\
&\mid \text{getField}(\nu?, \nu, s) \mid \text{isNull}(s) \mid \text{hasType}(\sigma, s)
\end{aligned}$$

The operations are used in code generated by type providers. Their behavior is defined by the rules in Figure 4. The conversion functions (**asDec** and **asFloat**) only perform conversions required by the subtyping (our actual implementation is more lax and performs additional conversions).

The **getField** operation is used to access a field of a record. The operation ensures that the actual record name matches the expected name (we write \bullet for the name of an unnamed record). The **getChildren** operation returns elements of a list and turns **null** into an empty collection.

Finally, we also define two helper functions. The **isNull** operation is used to check whether value is **null** and **hasType** is a runtime type test. The most complex case is handling of records where we check that for each field ν_1, \dots, ν_n in the type, the actual record value has a field of the same name with a matching type. The last line defines a “catch all” pattern, which returns **false** for all remaining cases. Although not elegant, the rules can be expressed using just Featherweight F#, discussed in the next section.

4.2 Featherweight F#

We now extend the semantics discussed so far and add a minimal subset of F# needed to model F# Data. Type providers use classes and so we focus on the F# object model and combine aspects of SML [14] and Featherweight Java [9].

We only need classes with parameter-less members and without inheritance. A class has a single implicit construc-

$\text{asFloat}(i) \rightsquigarrow f \quad (f = i)$	$\text{hasType}(\nu\{\nu_1:\sigma_1, \dots, \nu_n:\sigma_n\}, \nu'_1\{s_1, \dots, \nu'_m\{s_m\}\}) \rightsquigarrow (\nu = \nu'_1) \wedge$
$\text{asFloat}(d) \rightsquigarrow f \quad (f = d)$	$((\nu_1 = \nu'_1) \wedge \text{hasType}(\sigma_1, s_1)) \vee \dots \vee ((\nu_1 = \nu'_m) \wedge \text{hasType}(\sigma_1, s_m)) \vee \dots \vee$
$\text{asFloat}(f) \rightsquigarrow f$	$((\nu_n = \nu'_1) \wedge \text{hasType}(\sigma_n, s_1)) \vee \dots \vee ((\nu_n = \nu'_m) \wedge \text{hasType}(\sigma_n, s_m))$
$\text{asDec}(i) \rightsquigarrow d \quad (d = i)$	$\text{hasType}([\sigma], [s_1; \dots; s_n]) \rightsquigarrow \text{hasType}(\sigma, s_1) \wedge \dots \wedge \text{hasType}(\sigma, s_n)$
$\text{asDec}(d) \rightsquigarrow d$	$\text{hasType}([\sigma], \text{null}) \rightsquigarrow \text{true}$
$\text{isNull}(\text{null}) \rightsquigarrow \text{true}$	$\text{hasType}(\text{string}, t) \rightsquigarrow \text{true}$
$\text{isNull}(_) \rightsquigarrow \text{false}$	$\text{hasType}(\text{bool}, s) \rightsquigarrow \text{true} \quad (\text{when } s \in \{\text{true}, \text{false}\})$
$\text{getField}(\nu, \nu_i, \nu \{ \dots, \nu_i = s_i, \dots \}) \rightsquigarrow s_i$	$\text{hasType}(\text{float}, s) \rightsquigarrow \text{true} \quad (\text{when } s = i, s = d \text{ or } s = f)$
$\text{getField}(\bullet, \nu_i, \{ \dots, \nu_i = s_i, \dots \}) \rightsquigarrow s_i$	$\text{hasType}(\text{decimal}, s) \rightsquigarrow \text{true} \quad (\text{when } s = i \text{ or } s = f)$
$\text{getField}(\nu, \nu', \nu \{ \dots, \nu_i = s_i, \dots \}) \rightsquigarrow \text{null} \quad (\nexists i. \nu_i = \nu')$	$\text{hasType}(\text{int}, i) \rightsquigarrow \text{true}$
$\text{getField}(\bullet, \nu', \{ \dots, \nu_i = s_i, \dots \}) \rightsquigarrow \text{null} \quad (\nexists i. \nu_i = \nu')$	$\text{hasType}(\text{option} \langle \sigma \rangle, s) \rightsquigarrow \text{hasType}(\sigma, s)$
$\text{getChildren}([s_1; \dots; s_n]) \rightsquigarrow [s_1; \dots; s_n]$	$\text{hasType}(\text{option} \langle \sigma \rangle, s) \rightsquigarrow \text{true}$
$\text{getChildren}(\text{null}) \rightsquigarrow []$	$\text{hasType}(\text{any} \langle \dots \rangle, s) \rightsquigarrow \text{true}$
	$\text{hasType}(_, _) \rightsquigarrow \text{false}$

Figure 4. Reduction rules for conversion functions

(member)	$\frac{\text{type } C(\overline{x}:\overline{\tau}) = \dots \text{member } N_i : \tau_i = e_i \dots}{(\text{new } C(\overline{v})).N_i \rightsquigarrow e_i[\overline{x} \leftarrow \overline{v}]}$
(eq1)	$v = v \rightsquigarrow \text{true}$
(eq2)	$v = v' \rightsquigarrow \text{false}$
(cond1)	$\text{if true then } e_1 \text{ else } e_2 \rightsquigarrow e_1$
(cond2)	$\text{if false then } e_1 \text{ else } e_2 \rightsquigarrow e_2$
(match1)	$\frac{\text{match None with } \text{Some}(x) \rightarrow e_1 \mid \text{None} \rightarrow e_2}{\rightsquigarrow e_2}$
(match2)	$\frac{\text{match Some}(v) \text{ with } \text{Some}(x) \rightarrow e_1 \mid \text{None} \rightarrow e_2}{\rightsquigarrow e_1[x \leftarrow v]}$
(match3)	$\frac{\text{match } [v_1; \dots; v_n] \text{ with } [x_1; \dots; x_m] \rightarrow e_1 \mid _ \rightarrow e_2}{\rightsquigarrow e_2 \quad (m \neq n)}$
(match4)	$\frac{\text{match } [v_1; \dots; v_n] \text{ with } [x_1; \dots; x_n] \rightarrow e_1 \mid _ \rightarrow e_2}{\rightsquigarrow e_1[\overline{x} \leftarrow \overline{v}]}$
(map)	$\text{map } (\lambda x. e) [v_1; \dots] \rightsquigarrow [e[x \leftarrow v_1]; \dots]$
(ctx)	$E[e] \rightsquigarrow E[e'] \quad (\text{when } e \rightsquigarrow e')$

Figure 5. Featherweight F# – Remaining reduction rules

tor and the declaration closes over constructor parameters. To avoid including all of ML, we only pick constructs for

working with options and lists that we need later.

$\tau = \text{int} \mid \text{decimal} \mid \text{float} \mid \text{bool} \mid \text{string}$
 $\mid C \mid \text{StructVal} \mid \text{list} \langle \tau \rangle \mid \text{option} \langle \tau \rangle$

$L = \text{type } C(\overline{x}:\overline{\tau}) = \overline{M}$
 $M = \text{member } N : \tau = e$

$v = s \mid \text{None} \mid \text{Some}(v) \mid \text{new } C(\overline{v}) \mid [v_1; \dots; v_n]$
 $e = s \mid op \mid e.N \mid \text{new } C(\overline{e}) \mid \text{if } e_1 \text{ then } e_2 \text{ else } e_3$
 $\mid \text{None} \mid \text{match } e \text{ with } \text{Some}(x) \rightarrow e_1 \mid \text{None} \rightarrow e_2$
 $\mid \text{Some}(e) \mid [e_1; \dots; e_n] \mid \text{map } (\lambda x \rightarrow e_1) e_2$
 $\mid e = e \mid \text{match } e \text{ with } [x_1; \dots; x_n] \rightarrow e_1 \mid _ \rightarrow e_2$

The type `StructVal` is a type of all structural values s . A class definition L consists of a constructor and zero or more members. Values v include previously defined structural values s and values for the option and list type; finally expressions e include previously defined operations op , class construction, member access, conditionals and expressions for working with option values and lists. We include `map` as a special construct to avoid making the language too complex.

Reduction. The reduction relation is of the form $e \rightsquigarrow e'$. We also write $e \rightsquigarrow^* e'$ to denote the reflexive and transitive closure of \rightsquigarrow . The reduction rules for operations op were discussed earlier. Figure 5 shows the remaining rules.

The *(ctx)* rule performs a reduction inside a sub-expression specified by an evaluation context. This models the eager evaluation of F#. An evaluation context E is defined as:

$E = [\overline{v}; E; \overline{e}] \mid E.N \mid \text{new } C(\overline{v}, E, \overline{e})$
 $\mid \text{map } (\lambda x \rightarrow e) E \mid \text{if } E \text{ then } e_1 \text{ else } e_2$
 $\mid \text{Some}(E) \mid op(E) \mid E = e \mid v = E$
 $\mid \text{match } E \text{ with } \text{Some}(x) \rightarrow e_1 \mid \text{None} \rightarrow e_2$
 $\mid \text{match } E \text{ with } [x_1; \dots; x_n] \rightarrow e_1 \mid _ \rightarrow e_2$

The evaluation first reduces arguments of functions and the evaluation proceeds from left to right as denoted by $\overline{v}, E, \overline{e}$ in constructor arguments or $\overline{v}; E; \overline{e}$ in list initialization.

$$\begin{array}{c}
\frac{L; \Gamma \vdash e_1 : \text{StructVal}}{L; \Gamma \vdash [e_1; \dots; e_n] : \text{StructVal}} \quad \frac{}{L; \Gamma \vdash n : \text{int}} \\
\frac{L; \Gamma \vdash e_1 : \tau}{L; \Gamma \vdash [e_1; \dots; e_n] : \text{list}(\tau)} \quad \frac{}{L; \Gamma \vdash s : \text{StructVal}} \\
\frac{\text{type } C(\overline{x} : \tau) = \dots \text{ member } N_i : \tau_i = e_i \dots \in L}{L; \Gamma \vdash e.N_i : \tau_i} \\
\frac{L; \Gamma \vdash e_i : \tau_i \quad \text{type } C(x_1 : \tau_1, \dots, x_n : \tau_n) = \dots \in L}{L; \Gamma \vdash \text{new } C(e_1, \dots, e_n) : C}
\end{array}$$

Figure 6. Featherweight F# – Fragment of type checking

We write $e[\bar{x} \leftarrow \bar{v}]$ for the result of replacing variables \bar{x} by values \bar{v} in an expression. The (*member*) rule reduces a member access using a class definition in the assumption to obtain the body of a member. The remaining six rules give standard reductions for conditionals and pattern matching.

We omit expressions $e \vee e$ and $e \wedge e$ that are used in Figure 4, as those can be easily defined as syntactic sugar using *if*. All expressions reduce to a value in a finite number of steps or get stuck due to an error condition. An error condition can be a wrong argument passed to conditional, pattern matching or one of the primitives from Figure 4.

Type checking. Typing rules in Figure 6 are written using a judgement $L; \Gamma \vdash e : \tau$ where the context also contains a set of class declarations L . The fragment demonstrates the key differences from Standard ML and Featherweight Java:

- All structural values s have the type `StructVal`, but some have other types (Booleans, strings, integers, etc.) as illustrated by the rule for n . For other values, `StructVal` is the only type – this includes records and `null`.
- A list containing other structural values $[s_1; \dots; s_n]$ has a type `StructVal`, but can also have the `list(τ)` type. Conversely, lists that contain non-structural values like objects or options are not of type `StructVal`.
- Operations *op* (omitted) are treated as functions, accepting `StructVal` and producing an appropriate result type.
- Rules for checking class construction and member access are similar to corresponding rules of Featherweight Java.

An important part of Featherweight Java that is omitted here is the checking of type declarations (ensuring the members are well-typed). We consider only classes generated by our type providers and those are well-typed by construction.

4.3 Type providers

So far, we defined the type inference algorithm which produces a structural type σ from one or more sample documents (§3) and we defined a simplified model of evaluation

of F# (§4.2) and F# Data runtime (§4.3). In this section, we define how the type providers work, linking the two parts.

All F# Data type providers take (one or more) sample documents, infer a common supertype σ and then use it to generate F# types that are exposed to the programmer.⁵

Type provider mapping. A type provider produces an F# type τ together with an expression that wraps an input value (of type `StructVal`) as a value of type τ and a collection of class definitions. We express it using the following mapping:

$$\llbracket - \rrbracket_- : (\sigma \times e) \rightarrow (\tau \times e' \times L)$$

The mapping $\llbracket \sigma \rrbracket_e$ takes an inferred structural type σ and an expression e , which represents code to obtain a structural value that is being wrapped. It returns an F# type τ , an expression e' which constructs a value of type τ using e and also a set of generated class definitions L .

Figure 7 shows the rules that define $\llbracket - \rrbracket_-$. Primitive types are all handled by two rules – for decimal and float, we insert a call to an appropriate conversion function from Figure 4.

For records, we generate a class C that takes a structural value as constructor parameter. For each record field, we generate a member with the same name as the field.⁶ The body of the member calls `getField` and then wraps this expression using $\llbracket \sigma_i \rrbracket$ which maps the field (structural value of type σ_i) into an F# value of type τ_i . The returned expression creates a new instance of C and the mapping returns the class C together with all recursively generated classes. Note that the class name C is not directly accessed by the user and so we can use arbitrary name, although the actual implementation in F# Data attempts to infer a reasonable name.⁷

A collection type becomes an F# `list(τ)`. The returned expression calls `getChildren` (which turns `null` into an empty list) and then uses `map` to convert nested values to values of an F# type τ . The handling of option type is similar; if the value is not `null`, we wrap the recursively generated conversion expression e' in the `Some` constructor.

As discussed earlier, variant types are also generated as F# classes with properties. Given a variant `any($\sigma_1, \dots, \sigma_n$)`, we get corresponding F# types τ_i and generate n members of type `option(τ_i)`. When the member is accessed, we need to perform a runtime type test using `hasType` to ensure that the value has the right type (similarly to runtime type conversions from the top type in languages like Java). If the type matches, a `Some` value is returned. The type inference algorithm also guarantees that there is only one case for each type tag (§3.3) and so we can use the tag when naming the generated member (using the `nameof` function).

⁵ The actual implementation provides *erased types* as described in [21]. Here, we treat the code as actually generated. This is an acceptable simplification, because F# Data type providers do not rely on laziness that is available through erased types.

⁶ The actual F# Data implementation also capitalizes the names.

⁷ For example, in `{ "person": { "name": "Tomas" } }`, the nested record will be named `Person` based on the name of the parent record field.

nameof(string) = String	nameof(number) = Number	nameof(record) = Record
nameof(bool) = Boolean	nameof(collection) = List	nameof(named ν) = ν

$\llbracket \sigma_p \rrbracket_e = \tau_p, op(e), \emptyset$ where $\tau_p = \sigma_p$
 $\sigma_p, op \in \{ (\text{decimal}, \text{asDec}), (\text{float}, \text{asFloat}) \}$

$\llbracket \nu \{ \nu_1 : \sigma_1, \dots, \nu_n : \sigma_n \} \rrbracket_e =$
 $C, \text{new } C(e), L_1 \cup \dots \cup L_n \cup \{L\}$ where
 C is a fresh class name
 $L = \text{type } C(v : \text{StructVal}) = M_1 \dots M_n$
 $M_i = \text{member } \nu_i : \tau_i = e_i$
 $\tau_i, e_i, L_i = \llbracket \sigma_i \rrbracket_{e'}, e' = \text{getField}(\nu, \nu_i, e)$

$\llbracket [\sigma] \rrbracket_e = \text{list} \langle \tau \rangle, e_b, L$ where
 $e_b = \text{map } (\lambda x \rightarrow e') (\text{getChildren}(e))$
 $\tau, e', L = \llbracket \hat{\sigma} \rrbracket_x$

$\llbracket \perp \rrbracket_e = \llbracket \text{null} \rrbracket_e = \text{StructVal}, e, \emptyset$

$\llbracket \sigma_p \rrbracket_e = \tau_p, e, \emptyset$ where $\tau_p = \sigma_p$
 $\sigma_p \in \{ \text{string}, \text{bool}, \text{int} \}$

$\llbracket \text{any} \langle \sigma_1, \dots, \sigma_n \rangle \rrbracket_e =$
 $C, \text{new } C(e), L_1 \cup \dots \cup L_n \cup \{L\}$ where
 C is a fresh class name
 $L = \text{type } C(v : \text{StructVal}) = M_1 \dots M_n$
 $M_i = \text{member } \nu_i : \text{option} \langle \tau_i \rangle =$
 $\text{if hasType}(\sigma_i, v) \text{ then Some}(e_i) \text{ else None}$
 $\tau_i, e_i, L_i = \llbracket \sigma_i \rrbracket_e, t_i = \text{tagof}(\sigma_i), \nu_i = \text{nameof}(t_i)$

$\llbracket \hat{\sigma} \text{ option} \rrbracket_e =$
 $\text{option} \langle \tau \rangle, \text{if isNull } e \text{ then None else Some}(e'), L$
where $\tau, e', L = \llbracket \hat{\sigma} \rrbracket_e$

Figure 7. Type provider – generation of featherweight F# types from inferred structural types

Example 1. To illustrate how the mechanism works, we consider two examples. First, assume that the inferred type is a record $\{ \text{Age} : \text{option} \langle \text{int} \rangle, \text{Name} : \text{string} \}$. The rules from Figure 7 produce the following class:

```
type Person(v : StructVal) =
  member Age : option<int> =
    if isNull (getField(Person, Age, v)) then None
    else Some(asInt(getField(Person, Age, v)))
  member Name : string =
    asStr(getField(Person, Name, v))
```

The body of the Age member is produced by the case for optional types applied to an expression $\text{getField}(\text{Person}, \text{Age}, v)$. If the returned field is not **null**, then the member calls `asInt` and wraps the result in `Some`. Note that `getField` is defined even when the field does not exist, but it returns **null**. This lets us treat missing fields as optional. An F# type corresponding to the (structural) record is `Person` and a structural value s is wrapped by calling `new Person(s)`.

Example 2. The second example illustrates the remaining types including collections and variants. Reusing `Person` from the previous example, consider $\llbracket \text{any} \langle \text{Person}, \text{string} \rangle \rrbracket_e$, a collection which contains a mix of `Person` and string values:

```
type PersonOrString(v : StructVal) =
  member Person : option<Person> =
    if hasType({Age:option<int>, Name:string}, v)
    then Some(new Person(v)) else None
  member String : option<string> =
    if hasType(string, v)
    then Some(asStr(v)) else None
```

The type provider maps the structural type to an F# type `list<PersonOrString>`. Given a structural document value s , the code to obtain the wrapped F# value is:

```
map (λx → new PersonOrString(x)) (getChildren(s))
```

The `PersonOrString` type contains one member for each of the variant case. In the body, they check that the value has the correct type using `hasType`. This also implicitly handles **null** by returning `false`. As discussed earlier, variants provide easy access to the known cases (string or `Person`), but they are robust with respect to unexpected inputs.

5. Relativized type safety

Informally, the safety property for structural type providers states that, given representative sample documents, any code that can be written using the provided types is guaranteed to work. We call this *relativized safety*, because we cannot avoid *all* errors. In particular, one can always provide an input that has a different structure than any of the samples. In this case, it is expected that the code will throw an exception in the implementation (or get stuck in our model).

More formally, given a set of sample documents, code using the provided type is guaranteed to work if the inferred type of the input is a subtype of any of the samples. Going back to §3.2, this means that:

- Input can contain smaller numerical values (e.g., if a sample contains float, the input can contain an integer)
- Records in the input can have additional fields
- Records in the input can have fewer fields, provided that the type of the field is missing in some of the samples

- When a variant is inferred from the sample, the actual input can also contain any other value

The following lemma states that the provided code (generated in Figure 7) works correctly on an input s' that is a subtype of the sample s . More formally, the provided expression (with input s') can be reduced to a value and, if it is a class, all its members can also be reduced to values.

Lemma 3 (Correctness of provided types). *Given a sample value s and an input value s' such that $\langle s \rangle \sqsubseteq \langle s' \rangle$ and provided type, expression and class declarations $\tau, e, L = \llbracket \langle s \rangle \rrbracket_{s'}$, then $e \rightsquigarrow^* v$ and if τ is a class ($\tau = C$) then for all members N_i of the class C , it holds that $e.N_i \rightsquigarrow^* v$.*

Proof. By induction over the structure of $\llbracket - \rrbracket$. For primitives, the conversion functions accept all subtypes. For other cases, analyze the provided code to see that it can work on all subtypes (e.g. `getChildren` works on `null` values, `getField` returns `null` when a field is missing and, for variants, the value has the correct type as guaranteed by `hasType`). \square

This shows that the provided types are correct with respect to subtyping. Our key theorem states that, for any input (which is a subtype of any of the samples) and any expression e , a well-typed program that uses the provided types does not “go wrong”. Using standard syntactic type safety [24], we prove type preservation (reduction does not change type) and progress (an expression that is not a value can be reduced).

Theorem 4 (Relativized safety). *Assume s_1, \dots, s_n are samples, $\sigma = \langle s_1, \dots, s_n \rangle$ is an inferred type and $\tau, e, L = \llbracket \sigma \rrbracket_x$ are a type, expression and class definitions generated by a type provider.*

For all new inputs s' such that $\exists i. (\langle s_i \rangle \sqsubseteq \langle s' \rangle)$, let $e_s = e[x \leftarrow s']$ be an expression (of type τ) that wraps the input in a provided type. Then, for any expression e_c (user code) such that $\emptyset; y : \tau \vdash e_c : \tau'$ and e_c does not contain primitive operations op as a sub-expression, it is the case that $e_c[y \leftarrow e_s] \rightsquigarrow^ v$ for some value v and also $\emptyset; \vdash v : \tau$.*

Proof. We discuss the two parts of the proof separately as type preservation (Lemma 5) and progress (Lemma 6). \square

Lemma 5 (Preservation). *Given the class definitions L generated by a type provider as specified in the assumptions of Theorem 4, then if $\Gamma \vdash e : \tau$ and $e \rightsquigarrow^* e'$ then $\Gamma \vdash e' : \tau$.*

Proof. By induction over the reduction \rightsquigarrow . The cases for the ML subset of Featherweight F# are standard. For (*member*), we check that code generated by type providers in Figure 7 is well-typed. \square

The progress lemma states that evaluation of a well-typed program does not reach an undefined state. This is not a problem for the (standard) ML subset and object-oriented subset of the calculus. The problematic part are the primitive functions (Figure 4). Given a structural value (of type

`StructVal`), the reduction can get stuck if the value does not have a structure required by a specific primitive.

The Lemma 3 guarantees that this does not happen inside the provided type. In Theorem 4, we carefully state that we only consider expressions e_c which “[do] not contain primitive operations op as sub-expressions”. This makes sure that the only code working with structural values is the code generated by the type provider.

Lemma 6 (Progress). *Given the assumptions and definitions from Theorem 4, it is the case that $e_c[y \leftarrow e_s] \rightsquigarrow e'_c$.*

Proof. Proceed by induction over the typing derivation of $L; \emptyset \vdash e_c[y \leftarrow e_s] : \tau'$. The cases for the ML subset are standard. For member access, we rely on Lemma 3. \square

6. Practical experience

The F# Data library has been widely adopted by the industry and is one of the most downloaded F# libraries.⁸ A practical demonstration of development using the library can be seen in an attached screencast and additional documentation can be found at <http://fsharp.github.io/FSharp.Data>.

In this section, we discuss our practical experience with the safety guarantees provided by the F# Data type providers and other notable aspects of the implementation.

6.1 Relativized safety in practice

The *relativized safety* property does not guarantee the same amount of safety as traditional ML type safety, but it reflects the reality of programming with external data sources that is increasingly important [15]. Type providers do not reduce the safety – they simply illuminate the existing issues.

One such issue is the handling of schema change. With type providers, the sample is captured at compile-time. If the schema changes later (so that the input is no longer a subtype of the sample), the program fails at runtime and developers have to handle the exception. This is the same problem that happens when reading data using any other library.

F# Data can help discover such errors earlier. Our first example (§1) points the JSON type provider at a sample using a live URL. This has the advantage that a re-compilation fails when the schema changes, which is an indication that the program needs to be updated to reflect the change.

In general, there is no better solution for plain XML, CSV and JSON data sources. However, some data sources provide versioning support (with meta-data about how the schema changed). For those, a type provider could adapt automatically, but we leave this for future work.

6.2 Parsing structured data

In our formalization, we treat XML, JSON and CSV uniformly as *structural values*. With the addition of named records (for XML nodes), the definition of structural values

⁸ At the time of writing, the library has over 80,000 downloads on NuGet (package repository), 1,821 commits and 44 contributors on GitHub.

is rich enough to capture all three formats⁹. However, parsing real-world data poses a number of practical issues.

Reading CSV data. When reading CSV data, we read each row as an unnamed record and return a collection of rows. One difference between JSON and CSV is that in CSV, the literals have no data types and so we also need to infer the type of primitive values. For example:

```
Ozone, Temp, Date,      Autofilled
41,    67,    2012-05-01, 0
36.3,  72,    2012-05-02, 1
12.1,  74,    3 kveten,   0
17.5,  #N/A,  2012-05-04, 0
```

The value #N/A is commonly used to represent missing values in CSV and is treated as `null`. The Date column uses mixed formats and is inferred as string (we support many date formats and “May 3” would be parsed correctly). More interestingly, we also infer Autofilled as Boolean, because the sample contains only 0 and 1. This is handled by adding a bit type which is a subtype of both int and bool.

Reading XML documents. Mapping XML documents to structural values is perhaps the most interesting. For each node, we create a named record. Attributes become record fields and the body becomes a field with a special name:

```
<root id="1">
  <item>Hello!</item>
</root>
```

This XML becomes a record root with fields `id` and `•` for the body. The nested element contains only the `•` field with the inner text. As with CSV, we infer type of primitive values:

```
root {id ↦ 1, • ↦ [item {• ↦ "Hello!"}]}
```

When generating types for XML documents, we also lift the members nested under the `•` field into the parent type to simplify the structure of the generated type.

The XML type provider also includes an option to use *global inference*. In that case, the inference from values (3.5) unifies the types of all records with the same name. This is useful because, for example, in XHTML all `<table>` elements will be treated as values of the same type.

6.3 Heterogeneous collections

When introducing type providers (§2.3), we mentioned that F# Data implements a special handling of heterogeneous collections. This allows us to avoid inferring a variant types in many common scenarios. In the earlier example, a sample collection contains a record (with `pages` and `page` fields) and a nested collection with values.

Rather than storing a single type for the collection elements as in $[\sigma]$, heterogeneous collections store multiple possible element types together with their *inferred multiplicity* (zero or one, exactly one, zero or more):

$$\begin{aligned} \psi &= 1? \mid 1 \mid * \\ \sigma &= \dots \mid [\sigma_1, \psi_1 \mid \dots \mid \sigma_n, \psi_n] \end{aligned}$$

We omit the details, but finding a common supertype of two heterogeneous collections is analogous to the handling of variants. We merge cases with the same tag (by finding their common super-type) and calculate their new shared multiplicity (for example, by turning 1 and 1? into 1?).

7. Related and future work

We connect two lines of research: integration of external data into statically-typed programming languages and inferring types for real-world data sources. We build on F# type providers [2, 16, 21, 22], but our paper is novel in that it discusses the theory and safety of a concrete type provider.

Extending the type systems. Previous work that integrates external data, such as XML [8, 19] and databases [4, 13], into a programming language, required the user to define the schema or it has an ad-hoc extension that reads the schema.

C ω [12] is the most similar to F# Data. It extends C# with types similar to our structural types (including similar heterogeneous collections), but it does not infer the types from a sample and extends the type system of the host language (rather than using general purpose embedding).

Advanced type systems. A number of other advanced type system features could be used to tackle the problem discussed in this paper. The Ur [1] language has a rich system for working with records; meta-programming [17], [5] and multi-stage programming [23] could be used to generate code for the provided types; and gradual typing [18, 20] can add typing to existing dynamic languages. As far as we are aware, none of these systems have been used to provide the same level of integration with XML, CSV and JSON.

Typing real-world data. Recent work [3] infers a succinct type of large JSON datasets using MapReduce. It fuses similar types based on similarity. This is more sophisticated than our technique, but it makes formal specification of safety (Theorem 4) difficult. Extending our *relativized safety* to *probabilistic safety* is an interesting future work.

The PADS project [6, 10] tackles a more general problem of handling *any* data format. The schema definitions in PADS are similar to our structural type. The structure inference for LearnPADS [7] infers the data format from a flat input stream. A PADS type provider could follow many of the patterns we explore in this paper, but formally specifying the safety property would be challenging.

8. Conclusions

We explored the F# Data type providers for XML, CSV and JSON. As most real-world data do not come with an explicit schema, the library uses *type inference* that deduces a type from a set of samples. Our type inference algorithm is based

⁹ The same mechanism has later been used by the HTML type provider (<http://fsharp.github.io/FSharp.Data/HtmlProvider.html>), which provides similarly easy access to data in HTML tables and lists.

on a common supertype relation. For usability reasons, it prefers records and avoids variant types. The algorithm is predictable, which is important as developers need to understand how changing the samples affects the resulting types.

We explore the programming language theory behind type providers. F# Data is a prime example of type providers, but our work also demonstrates a more general point. The types generated by type providers can depend on external input and so we can only guarantee *relativized safety*, which says that a program is safe only if the actual inputs satisfy additional conditions – in our case, they have to be subtypes of one of the samples.

Type providers have been described before, but this paper is novel in that it explores concrete type providers from the perspective of programming language theory. This is particularly important for F# Data type providers, which have been widely adopted by the industry.

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