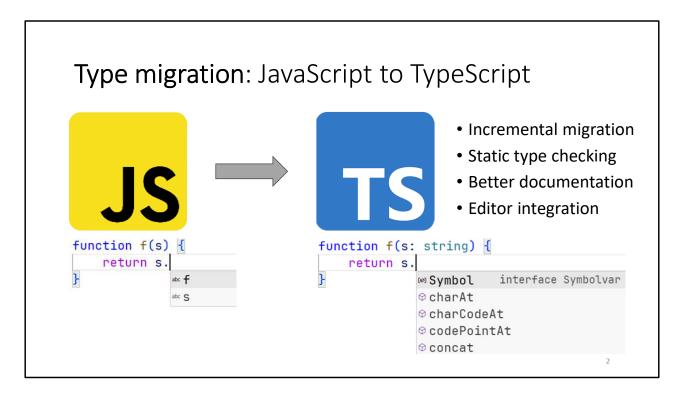


- 0:15 for this slide
- Hello everyone, and thanks for coming to my presentation.
- Today, I want to talk about TypeScript, machine learning models that predict TypeScript types, and how we can evaluate these systems.



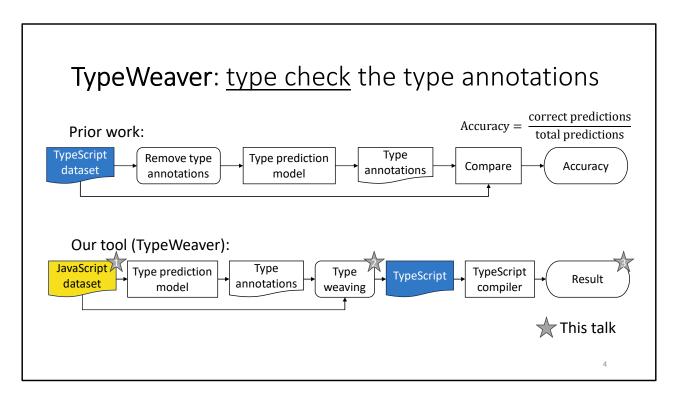
- 1:00 to finish this slide

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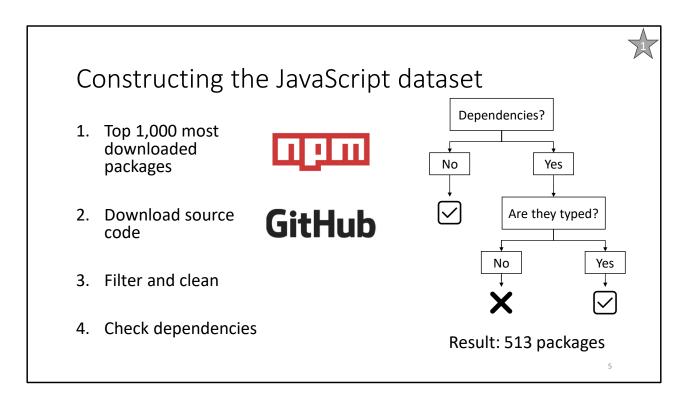
- So, let's say you have a code base in JavaScript, and you want to migrate it to TypeScript.
 - You can do this by incrementally adding type annotations to your code.
 - As your code becomes more typed, you benefit from static type checking, better documentation, and editor integration.
- For example, here's a small code fragment.
 - The code is untyped, so my text editor can't provide me with useful information.
- But if we look at a typed version of that fragment, we see that s is annotated as a string.
 - As a result, my text editor can show me the methods available on a string.
- So there are clear benefits for using TypeScript, and a migration path to get from JavaScript to TypeScript.
 - Unfortunately, *manual* type migration is a laborious process.

Machin	e learnii	ng for ty	pe prec	liction
Predict tl	he most likely	v type annota	ition for the	e given code fragment
DeepTyper	[ESEC/FSE 2018]	LambdaNe	et [<u>ICLR 2020]</u>	InCoder [ICLR 2023]
	function retur }	f(<mark>x</mark>) { rn x + 1;		<pre>function f(x: _hole_) return x + 1; }</pre>
Type of x	Probability	Type of x	Probability	
number	0.4221	string	0.9512	<pre>function f(x: number)</pre>
any	0.2611	number	0.0474	return $x + 1;$
string	0.2558	Function	0.0006	}
other		other		

- 3:00 to finish this slide
- To automate type migration, there has been research in using machine learning approaches.
 - The idea is to frame the problem as type prediction: "Predict the most likely type annotation for the given code fragment."
- For our paper, we studied three systems, but any system can be adapted for our framework.
 - DeepTyper (ESEC/FSE 2018) was an early work and uses a recurrent neural network.
 - LambdaNet (ICLR 2020) uses a graph neural network.
 - InCoder (ICLR 2023) is a general-purpose, multi-language transformer
- DeepTyper and LambdaNet are similar:
 - Given a code fragment, for each identifier, they produce a list of the most likely type annotations and their probabilities.
 - You can think of the output as a table of results.
 - I've only shown the type predictions for x, which is the only identifier that can be annotated.
- InCoder is a bit different, because it supports a "fill-in-the-middle" task.
 - We can insert a hole into where the type annotation should go, and InCoder will condition on the text before and after the hole as context and predict what goes into the middle.
 - InCoder returns an updated code fragment, with the hole filled in as "number."
- How do we know these models are doing the right thing? What do we do for evaluation?



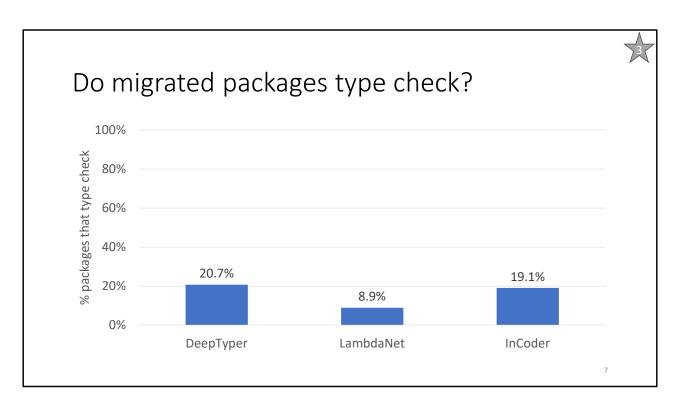
- 5:00 to finish this slide
- In our paper, we propose type checking the type annotations; we created TypeWeaver to do this.
- To recap, let's walk through the existing evaluation workflow:
 - We start with a TypeScript dataset.
 - The type annotations are removed, and the untyped code is given to a type prediction model, which produces type annotations.
 - The predicted type annotations are then compared to the original type annotations, and accuracy is computed.
 - Accuracy is the number of correct predictions divided by the total number of predictions.
 - Correct means an exact textual match, and requires a ground truth of existing, handwritten type annotations.
- In our paper, we propose and use a different workflow.
 - We start with a JavaScript dataset, and feed that to the type prediction model.
 - We want our evaluation to reflect how type migration would be done in practice, which is to migrate JavaScript to TypeScript.
 - Next, we perform a step called type weaving, which combines the type annotations with the original JavaScript code to produce TypeScript.
 - This allows us to run the type checker on the code, and we get a result.
- For the rest of this talk, I'll be discussing three contributions: our dataset, type weaving, and our results.



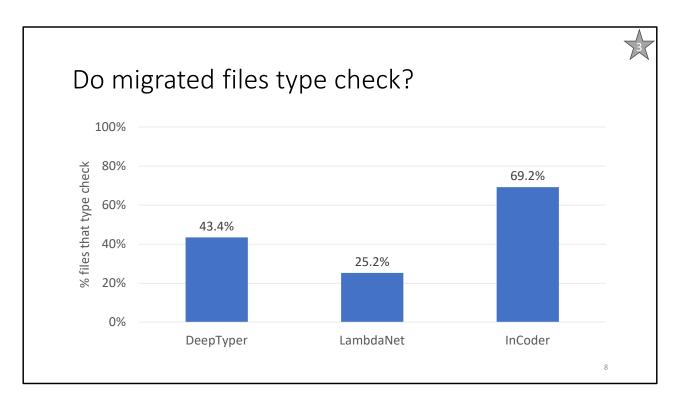
- 7:00 to finish this slide
- Our first contribution is our dataset.
- We start with the top 1,000 most downloaded packages from the npm Registry.
- Next, we download the source code from GitHub.
- Then we apply several filtering and cleaning steps.
 - For example, some packages do not contain any code, or were implemented in some other language, so we filter those out.
- Finally, we check the package dependencies.
 - If there are no dependencies, then we're all set, and we can use the package as-is.
 - If the package has dependencies, we must ensure that we handle those dependencies.
 - Fortunately, we only need the *type declarations* for the dependencies, not the entire source code.
 - There is a community-maintained repository called DefinitelyTyped, where developers contribute type declarations for popular packages.
 - If we can't find type declarations for a dependency, then we discard the package.
 - In other words, we ensure that if a package has dependencies, then all those dependencies are typed.
- This leaves us with a final dataset of 513 packages.

Type weaving : JS + type annotations = TS						
	Token	Туре	Probability			
<pre>function f(x: string, y: number): string {</pre>	function					
return x + y;	f	string	0.6381			
}	(
	Х	string	0.4543			
FunctionDeclaration	I					
Identifier	у	number	0.4706			
Parameter Identifier)					
Parameter	{					
Identifier	return					
Block	х	number	0.3861			
ReturnStatement	+					
	У	number	0.5039			
	;					
	}					

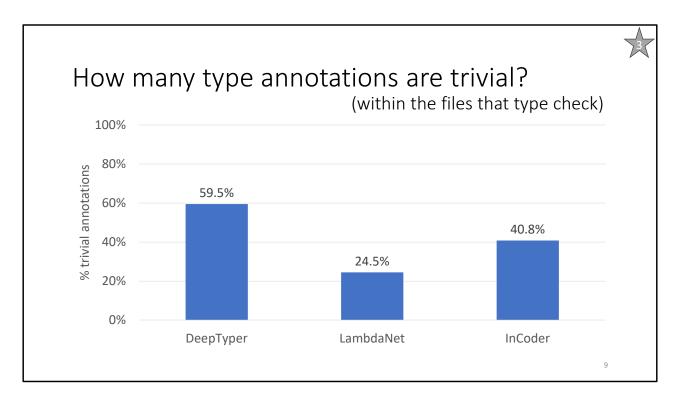
- 9:00 to finish this slide
- Our second contribution is type weaving: this is the process where JavaScript is combined with type annotations to produce TypeScript.
- There are some tricky implementation details, but the overall idea is simple.
 - Let's walk through an example. We start with JavaScript code.
 - Next, we take the type predictions from the model.
 - For this example, I only list the most likely prediction for each token, and I've also cleaned up the table a little.
 - I made up this example and gave it to a system.
 - We use the TypeScript compiler to parse the JavaScript to get an abstract syntax tree.
 - Now we traverse the syntax tree, and every time we encounter a declaration node, we look up the type prediction from the table, and update the program.
 - In this example, we find the function f has return type string, x is string, and y is number.
 - There are other types in this table, assigned to other identifiers, but we ignore them for simplicity.
- The result is an annotated TypeScript file.
 - And this program actually type checks, even though it's not what was intended.
 - The number is coerced to a string and + is string concatenation, so the function returns a string.
- Now we are ready to type check.



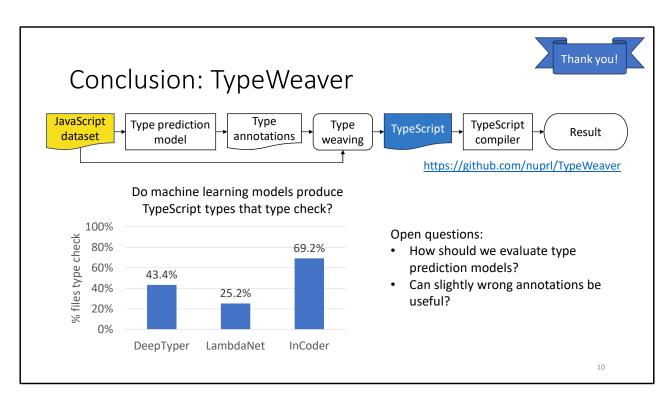
- So the first question to ask is: do migrated packages type check?
 - Unfortunately, the results are disappointing.
- DeepTyper and InCoder perform about the same, with a 20% success rate, while LambdaNet is closer to 9%.
- Type checking is a very high standard, because all type annotations need to be correct.
 - Even a single incorrect type annotation will cause a package to fail to type check.
- If you were someone trying to migrate their JavaScript project, this metric isn't very helpful.
 - It simply gives you a pass/fail result for an entire package.
- So let's ask a different, more fine-grained question.



- Do migrated files type check?
- Instead of grading an entire package, we grade each file individually.
 - Our intuition is that each file is a separate module and can be type checked individually.
 - This seems to be a reasonable way to triage errors, when trying to migrate an entire package.
 - However, we still need to be aware that even if a module type checks successfully, we may need to adjust its type annotations if it isn't consistent with other modules.
- This result is much more promising: InCoder has a success rate of 69%.



- 12:00 to finish this slide
- Finally, there's one more chart I'd like to show.
- We need to be careful with our metric, because we can "cheat" by predicting "any" for all type annotations.
 - This result will type check, but the type annotations are useless, and no different from having an untyped program.
- So we counted the proportion of type annotations that are trivial.
 - These are the type annotations for the files that type checked.
 - This is "any" and related type annotations, like array of any, or the generic Function type with unspecified argument types.
- These results are interesting:
 - On the previous slides, DeepTyper performed better than LambdaNet.
 - But now we see that may be because DeepTyper predicted more trivial types.
 - InCoder was somewhere in between but still performed the best.



- 13:00 to finish this slide
- So, to summarize our work:
 - We built TypeWeaver, a framework for evaluating type prediction systems.
 - It uses our JavaScript dataset, but it's possible to build your own dataset.
 - We run the dataset through type prediction models, and you can plug in your own model.
 - The model produces type annotations, and we perform type weaving to get TypeScript.
 - And this allows us to type check the resulting code.
- Now, we can finally answer the question: do machine learning models produce TypeScript types that type check?
 - If we're asking about packages, the results are a bit disappointing.
 - But if we look at individual files, the results are more promising.
- Of course, there are more avenues for future work and open questions to answer:
 - How should we evaluate type prediction models? Can we do better than type checking?
 - What if a system produces types that are "slightly wrong"? They would fail to type check, but how can we use those types?
- I'd be happy to chat if you have any thoughts about this.
- Thanks for listening to my talk, and I can take questions now.