Hot Takes on Machine Learning for Program Analysis (Director's Cut: UBC)

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My student said:

Deep Learning is one of the ("best") ways to do program analysis.

What’s ML good at? Bad at?

Here are some potential application areas:

- Classification
- Inference
- Generative AI
- Analysis / Deduction

Classification

Weka about to steal my lunch

Classification

FSE 08: Bodden, Lam & Hendren. “Finding Programming Errors Earlier by Evaluating Runtime Monitors Ahead-of-Time”.

ML task:

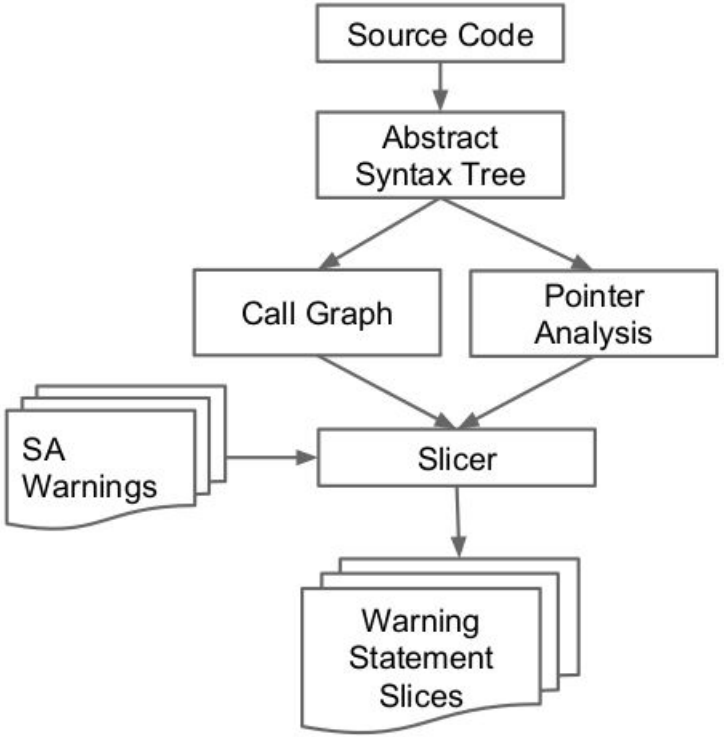
filter out likely false-positive Potential Points of Failure.

```
CALL = 0
|   ABORTED = 0
|   |   DELEGATE = 0
|   |   |   NO_CONTEXT = 0: TRUE_POSITIVE (11.0/1.0)
|   |   |   NO_CONTEXT = 1: FALSE_POSITIVE (4.0/1.0)
|   |   DELEGATE = 1: FALSE_POSITIVE (10.0)
|   ABORTED = 1: FALSE_POSITIVE (30.0)
CALL = 1: FALSE_POSITIVE (406.0/1.0)
```

More Classification

MSR 14: Hanam, Tan, Holmes, and Lam. “Finding Patterns in Static Analysis Alerts”.

Idea: rank importance of FindBugs alerts by extracting a feature vector & using ML.



Classification via Deep Learning

ICSE 23: Steenhoek, Rahman, Jiles, and Le. “An Empirical Study of Deep Learning Models for Vulnerability Detection.”

Classification question:

does this code have a vulnerability or not?

This work studies the behaviour of 9 deep learning models on 2 datasets.

Claim: DL outperforms static analysis.

Regression?

Instead of labels (classification), output numerical values within a range.

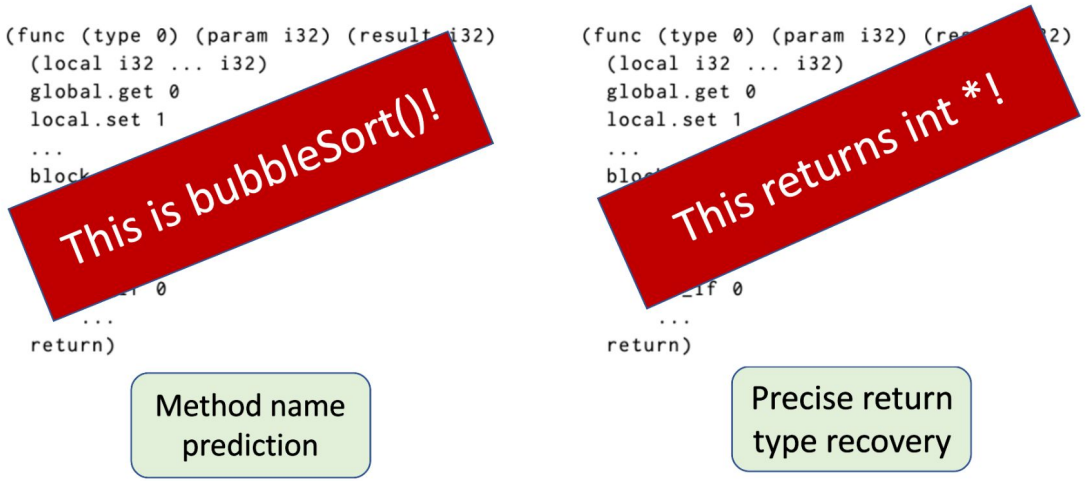
Not as amenable to PL/SE applications?

Inference

Code Representations for Improved Program Analysis

submitted to ICSE 24, by Shirzad and Lam:

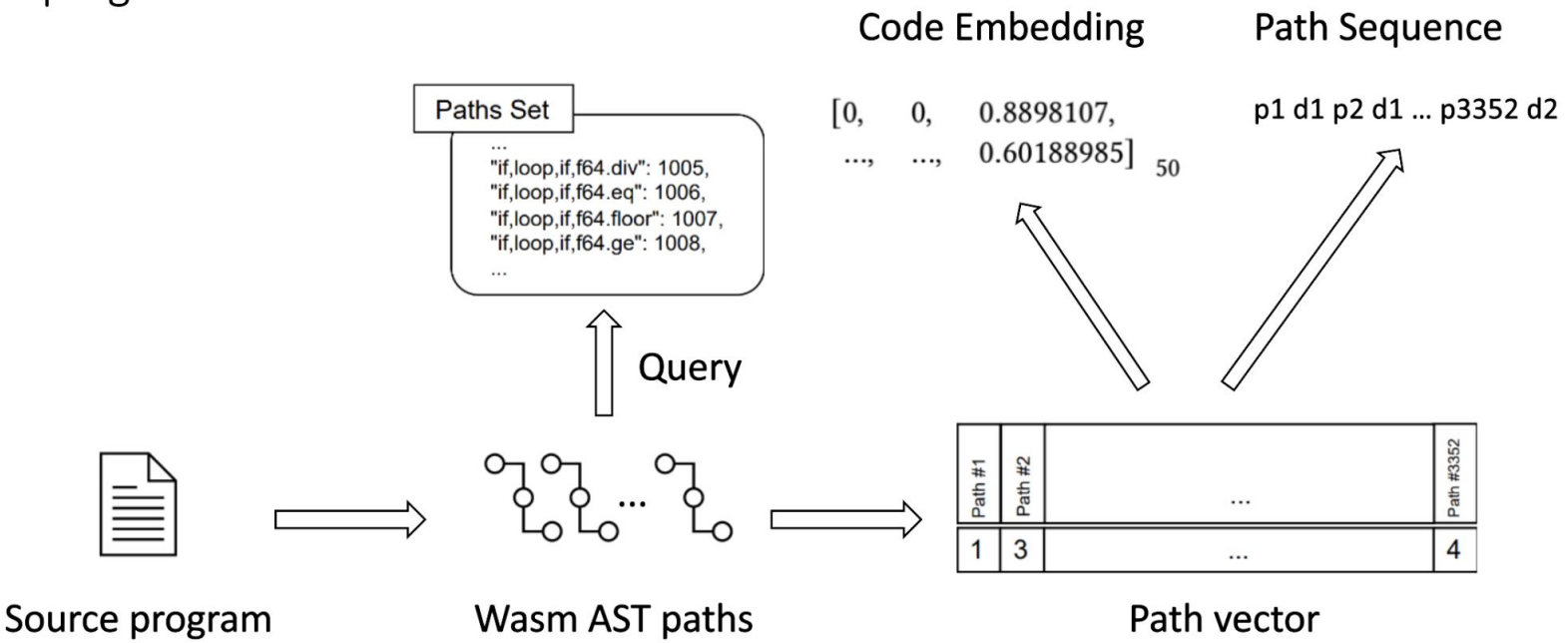
The power of our code representations



How We Compute Our Code Representations

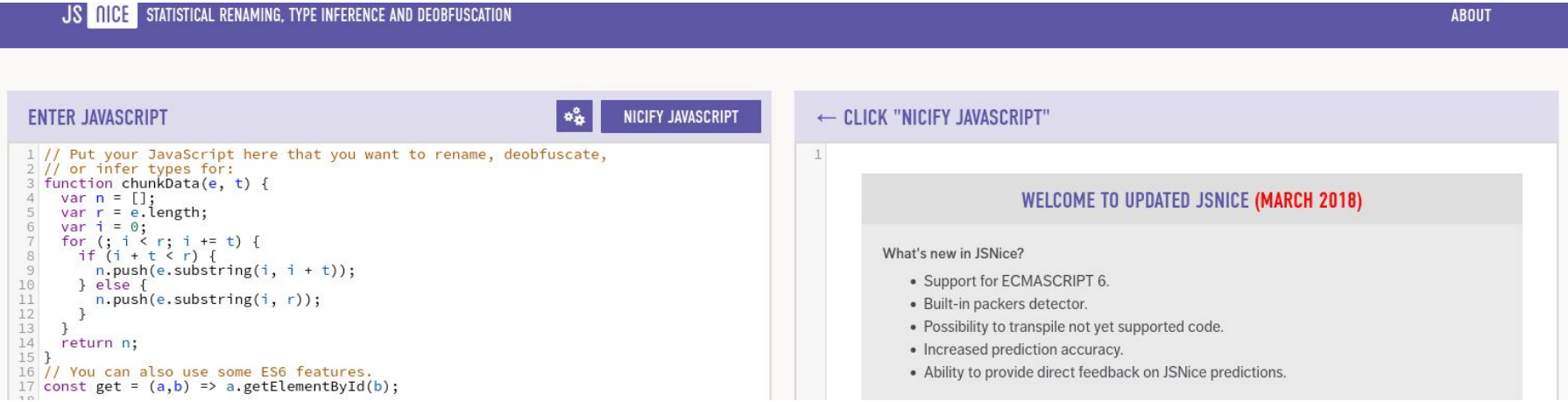
C program ---> Path vector

method name prediction, Motivating Example
precise return type recovery



Another Application: JSNice–deobfuscating JavaScript

POPL 15. Raychev, Vechev & Krause. “Predicting Program Properties from “Big Code”.”



Infers likely identifier names and types via machine learning.

Other applications of (broadly) inference

- Test generation
- Program repair
- Program synthesis

(Typically not machine learning techniques).

Test Generation

Dan, Lam, Hoefler, and Vechev. OOPSLA 16. Modeling and Analysis of Remote Memory Access Programming.


```
X = 1                    Y = 0
P0:                      P1:
a = X                    put(X^0, Y)
                         Y = get(X^0)
                         flush(0)
                         b = Y
```

Expected outputs: $\langle a, b \rangle \in \{\langle 0, 0 \rangle, \langle 1, 2 \rangle\}$.

Program Repair & Synthesis

Per Armando Solar-Lezema:

- Program Synthesis corresponds to a class of techniques that are able to generate a program from a collection of artifacts that establish semantic and syntactic requirements for the generated code.

Usually, search for a suitable program.

```
in: [1,2,3,4,5,6,7,8]
out: [8,7,6,5,4,3,2,1]
```

[https://people.csail.mit.edu/asolar/SynthesisCourse/Lecture1.htm]

Generative AI

Inference ++?

GitHub Copilot

ChatGPT

Is generated code any good?

#1: Let’s verify using tests!

MSR 22. Nguyen & Nadi. “An empirical evaluation of GitHub copilot's code suggestions.”

> Asked Copilot to generate code for LeetCode problems,
> checked it with LeetCode test cases.
> Java 57% pass, JavaScript 27% pass.

Is generated code any good?

#2 Let’s use formal verification!

HATRA 22. Wong, Kothig, and Lam. “Exploring the Verifiability of Code Generated by GitHub Copilot.”

Attempt to formally verify Copilot generated code; 4/6 success.

But, when we don’t succeed, who’s the problem?

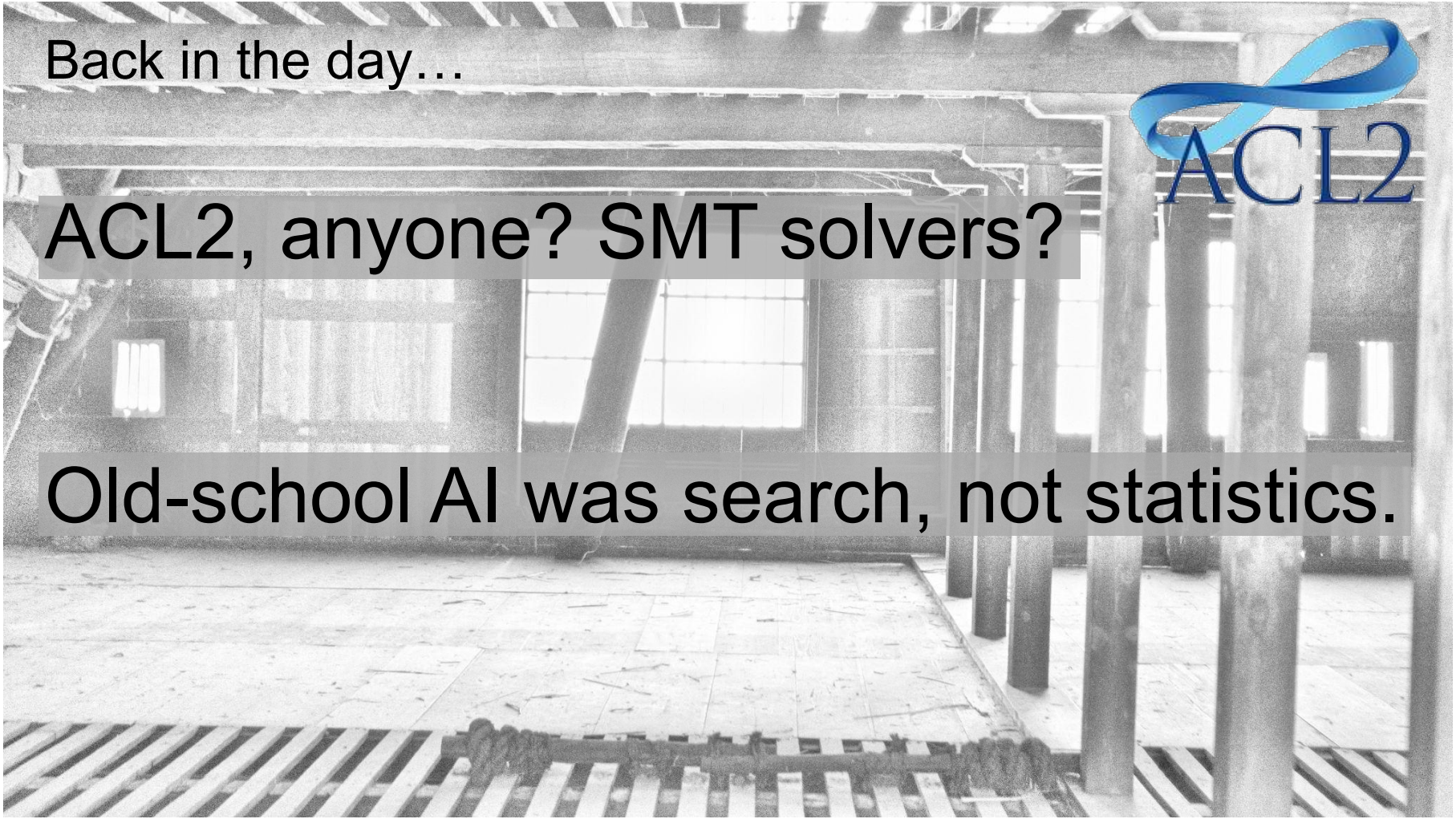
Is generated code any good?

#3 Let’s generate code interactively!

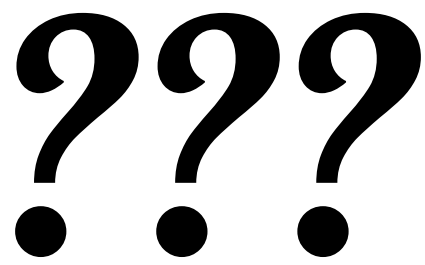
Kani Rust Verifier Blog. “Writing Code with ChatGPT? Improve it with Kani.”

Use model checking plus iterative applications to ChatGPT until it gets it right.

Deductive Reasoning


Back in the day…
ACL2
ACL2, anyone? SMT solvers?
Old-school AI was search, not statistics.

Statistical approaches and reasoning…



I can’t really imagine how to do e.g. pointer analysis with statistical approaches.

Pointer analysis

```
int * p, * q;
```

Question: do `*p` and `*q` possibly alias? That is,

```
*p = 5;
*q = 2;
```

What is `*p` going to contain?

Pointer analysis

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int * p, * q;
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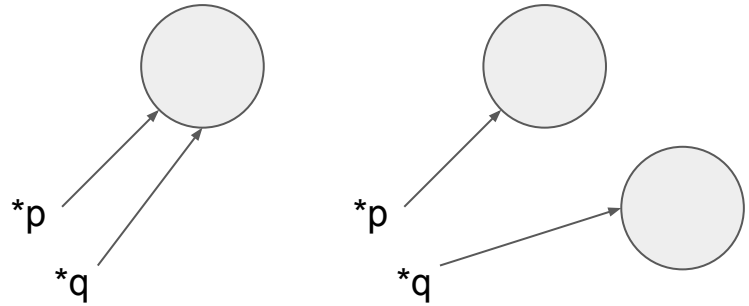

CFL-Reachability

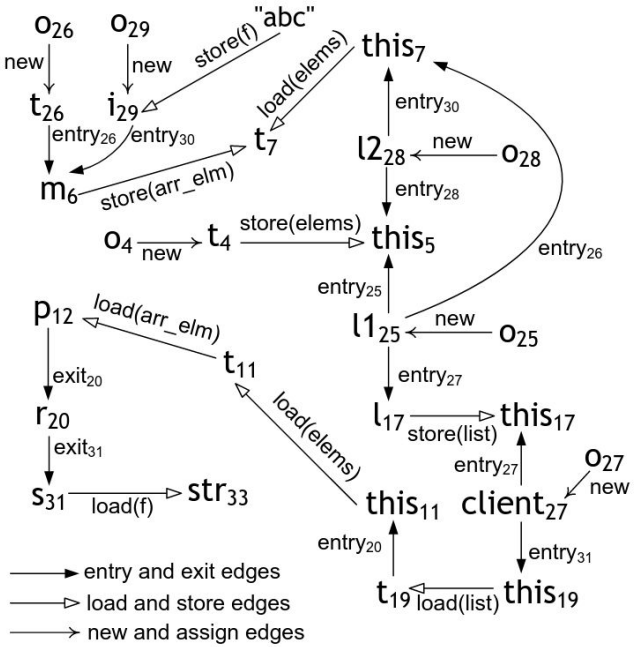

Fig. 2. Illustration of CFL-reachability

Xu, Rountev & Sridharan. ECOOP 09. Scaling CFL-Reachability-Based Points-To Analysis Using Context-Sensitive Must-Not-Alias Analysis.

Pointer analysis

```
int * p, * q;
```

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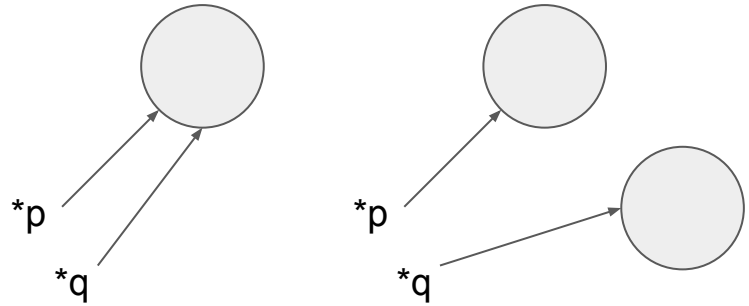


Do you want reasoning,
or do you want reckons?


Hot Takes

What does ChatGPT think? [part 1]

patricklam.ca/chatgpt-hot-takes

[prompt engineering by Lucas Wojciechowski]

> Give me 10 hot takes on how machine learning will affect programming language / software engineering in the next 10 years

```
Developers will need to have a strong understanding of statistics
and data analysis in order to effectively incorporate machine
learning into their applications.

Natural language processing (NLP) and speech recognition will
become more prevalent, leading to the development of new
programming languages and tools that support these technologies.
```

What does ChatGPT think? [part 2]

patricklam.ca/chatgpt-hot-takes

[prompt engineering by Lucas Wojciechowski]

> Give me 10 hot takes on how machine learning will affect programming language / software engineering in the next 10 years

```
As machine learning becomes more widespread, developers will need
to prioritize the ethical implications of their work, such as data
privacy, bias, and accountability.

Developers will increasingly rely on machine learning to automate
software testing and debugging, reducing the time and effort
required to find and fix bugs.
```

Hotter takes [part 1]

ChatGPT

patricklam.ca/chatgpt-hot-takes

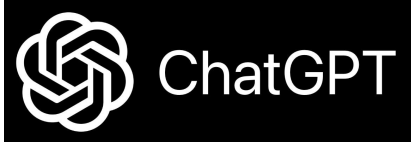
> Can you make the takes more controversial?

```
Machine learning will eventually make traditional programming
languages obsolete, as machines become better at creating software
than humans.

As machine learning becomes more advanced, developers will need to
focus on building systems that are transparent and explainable, in
order to ensure that they can be trusted by users.
```

Hotter takes [part 2]

patricklam.ca/chatgpt-hot-takes



> Can you make the takes more controversial?

```
Machine learning will eventually lead to the development of
conscious machines, creating a new era in which machines and
humans coexist as equals.

As machine learning becomes more prevalent, it will lead to the
creation of new types of software applications that are designed
to manipulate and exploit human emotions.
```

Hottest takes [part 1]

ChatGPT

patricklam.ca/chatgpt-hot-takes

> Can you make the takes even more controversial?

```
The rise of machine learning will lead to the creation of new
types of software applications that are designed to replace human
workers, leading to widespread job displacement and social unrest.

The development of advanced machine learning algorithms will
eventually lead to the creation of true artificial intelligence,
capable of independent thought and decision making.
```

Hottest takes [part 2]

patricklam.ca/chatgpt-hot-takes

> Can you make the takes even more controversial?

```
The increasing use of machine learning in software development
will lead to a new era of digital imperialism, with the most
advanced machine learning algorithms being used to dominate and
control global markets.

Eventually, the rise of machine learning will lead to a new era of
technological singularity, in which machines become more
intelligent than humans and take over the world.
```

Patrick's Hot Takes

- Machine Learning is a super useful tool!
  (when applicable)
- Machine Learning won't make our fields obsolete.
  ("More research still required…")
  Part of the trick: using domain knowledge to drive ML.

Why we’re not about to become obsolete:
a report from Computational Linguistics

e.g. Google Translate:
isn’t it all statistical?

Computational Linguistics: not just statistics

Blackbox NLP workshop, EMNLP 2022. Muthupari, Halder, Sayeed, and Marton. “Where's the Learning in Representation Learning for Compositional Semantics and the Case of Thematic Fit”.

Question: understand why sometimes random word embeddings work as well as pretrained embeddings.

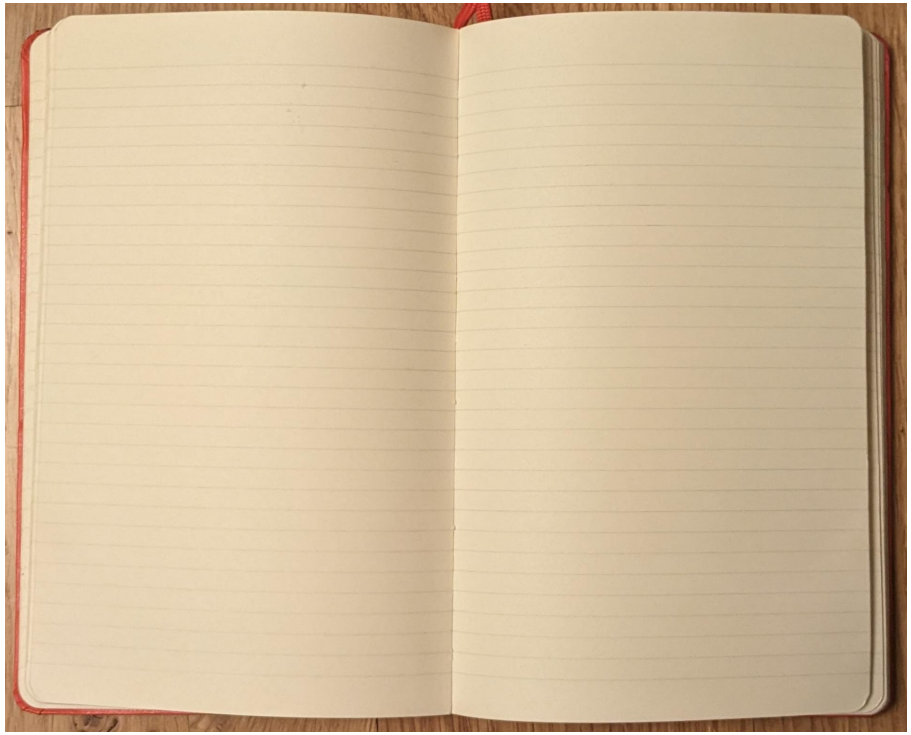
Tools: Need experimental efforts in linguistic representations; manipulate the model architecture.

Patrick's Hot Takes: Generative AI

> Give me 10 hot takes on how machine learning will affect programming language / software engineering in the next 10 years

- "Generated code can be good actually;" but,
- "I wouldn't trust generated code further than I can throw it."

What Generative AI is Good At



What Generative AI is Good At

What Generative AI is bad at: novelty

Other things generative AI is bad at

- Identifying the problem
- Hallucinations / Objective truth
- Respecting IP
- Ensuring security

Identifying the problem

choosing a tool is the easy part…

Objective Truth

What is the highest waterfall in New Zealand?

Respecting IP

Ensuring Security

Food for thought

How does ChatGPT/Copilot code compare to hackathon code?

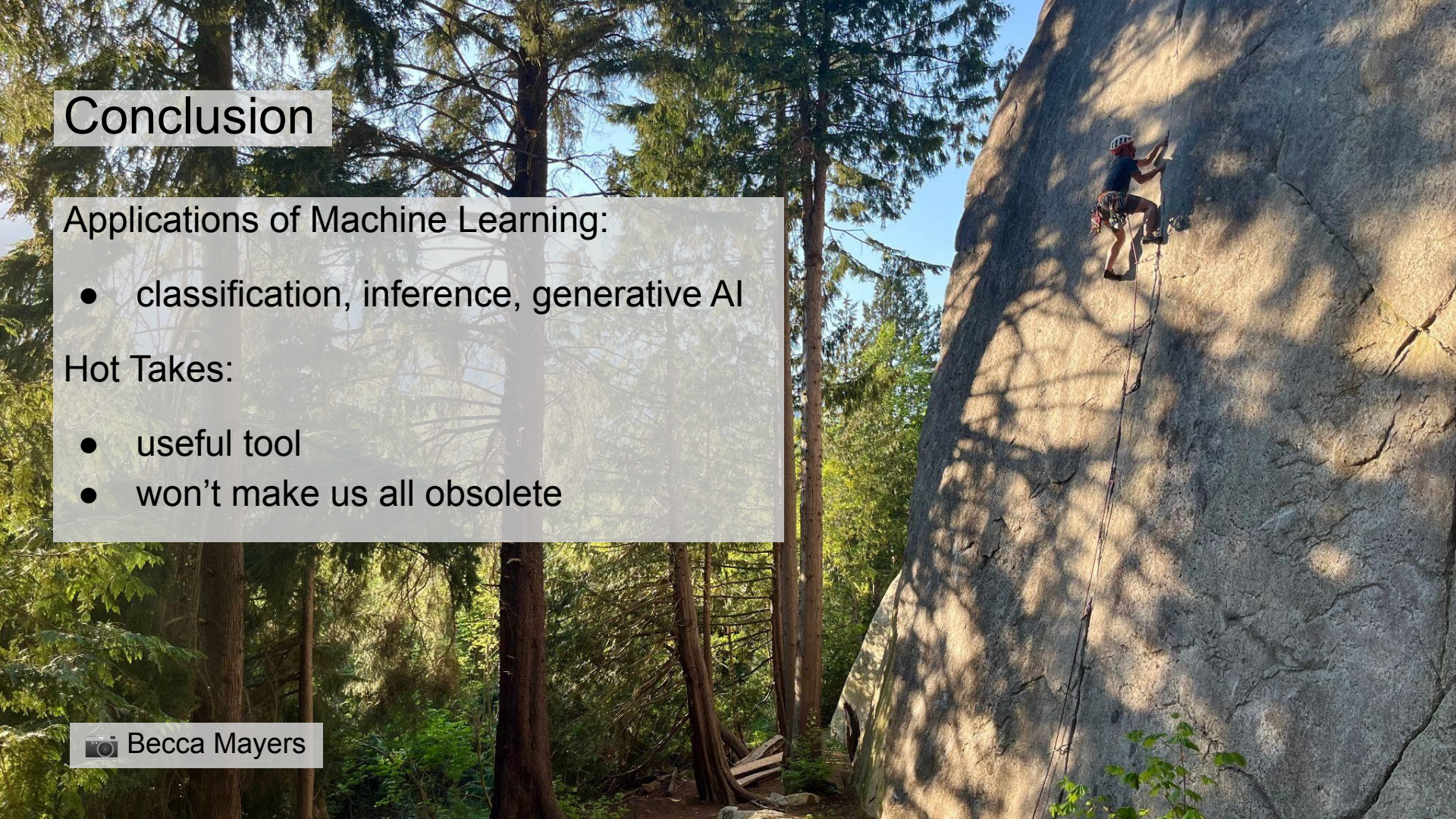
Conclusion

Applications of Machine Learning:

- classification, inference, generative AI

Hot Takes:

- useful tool
- won’t make us all obsolete



📷 Becca Mayers