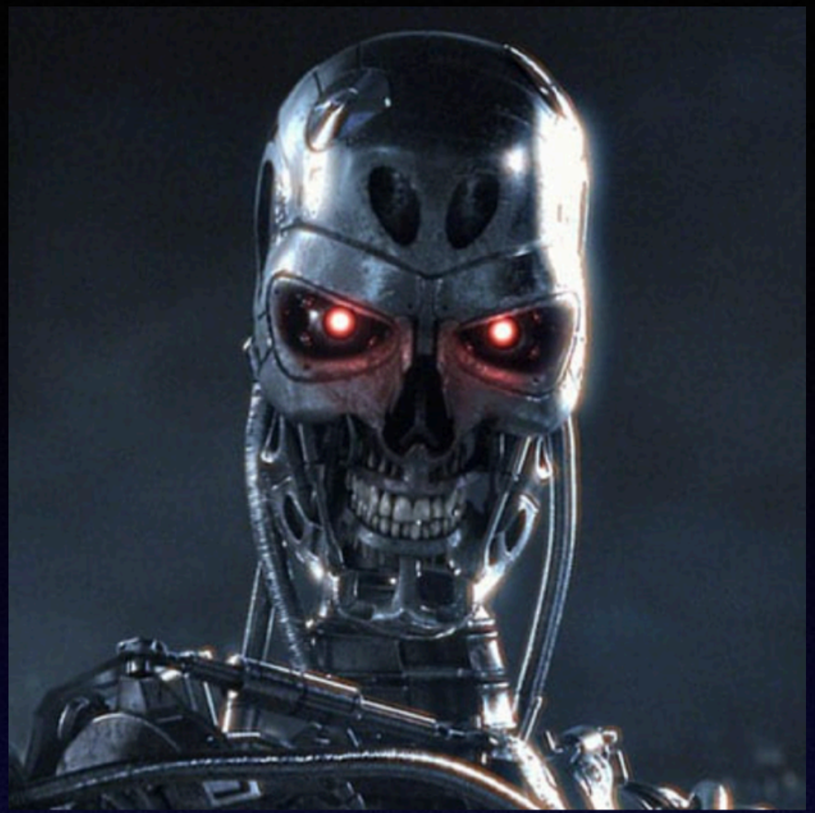
Bimodality & Naturalness:
LLMS! LLMS!! LLMS!!

When Stochastic Parrots Write Code…..



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Reality Check

FACT: Codex, GPT-x, etc are now widely used to generate code.

- How much are people ***using*** this generated code? Does it help?
- How ***good*** is this code?

Does Codex help coders In "Vivo"?

Understanding the Usability of AI Programming Assistants

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ABSTRACT

The software engineering community recently has witnessed widespread deployment of AI programming assistants, such as GitHub Copilot. However, in practice, developers do not accept AI programming assistants' initial suggestions at a high frequency. This leaves

1. Usage Characteristics
- A Usage patterns
- B Motivation for using
- C Motivation for not using
- D Successful use cases

2. Usability of AI Programming Assistants

n=410, survey, Github Devs;
30% code generated;
Helps productivity
74% "<u>quick check</u>"
..but…Non-func reqmnts?
Hard to control?

Expectation vs. Experience: Evaluating the Usability of Code Generation Tools Powered by Large Language Models

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ABSTRACT

Recent advances in Large Language Models (LLM) have made automatic code generation possible for real-world programming tasks in general-purpose programming languages such as Python. However, there are few human studies on the usability of these tools and how

on two different kinds of approaches: (1) program synthesis algorithms that search over a large program space defined by a domain-specific language (DSL) [2, 7, 10, 12, 14, 19, 24, 25, 30, 31, 34, 43], and (2) deep learning models that are trained on a large amount of existing code and can generate new code given some forms of

n=24; controlled study
+interview; @ Univ.
CoPilot not much help,
Many defects,
hard to Grok code,
..but subjects like it anyway!

Do LLMs help coders In “Vivo”?

BLOG ›

ML-Enhanced Code Completion Improves Developer Productivity

TUESDAY, JULY 26, 2022

Posted by Maxim Tabachnyk, Staff Software Engineer and Stoyan Nikolov, Senior Engineering Manager, Google Research

Update — 2022/09/06: *This post has been updated to remove a statement about an observed reduction in context switches that could not be confirmed with statistical significance.*

n=10k; Telemetry

3% code generated,

6% “Iteration” time reduction

>30% suggestion acceptance

Productivity Assessment of Neural Code Completion

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n=2.6K; Survey + Telemetry

23%-28% suggestion acceptance

Acceptance rate correlates with self-reported productivity.

Personal take on Code LLMs

- Developers like them, Use them.
- Not clear they always fully understand the code they're using, and what the "PSP" is for this.
- *Prediction:* In an astonishingly short time, every computer: laptops, mobile phones, toasters, microwaves, air-traffic control, nuclear power plants, cruise missiles…

Will be running code generated by an LLM!!!

AI-generated code will
Be running
Everywhere!!

Do LLMs generate
buggy code?

Large Language Models and Simple, Stupid Bugs

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Methodology

- Simple, Stupid, Bugs 4 Java… One line bug fixes from 1000 projects. *(SStubs4J, Karampatsis & Sutton 2020)*
- Go back in history, and find when they were injected (by human dev)
- Try the with the prefix, and see…

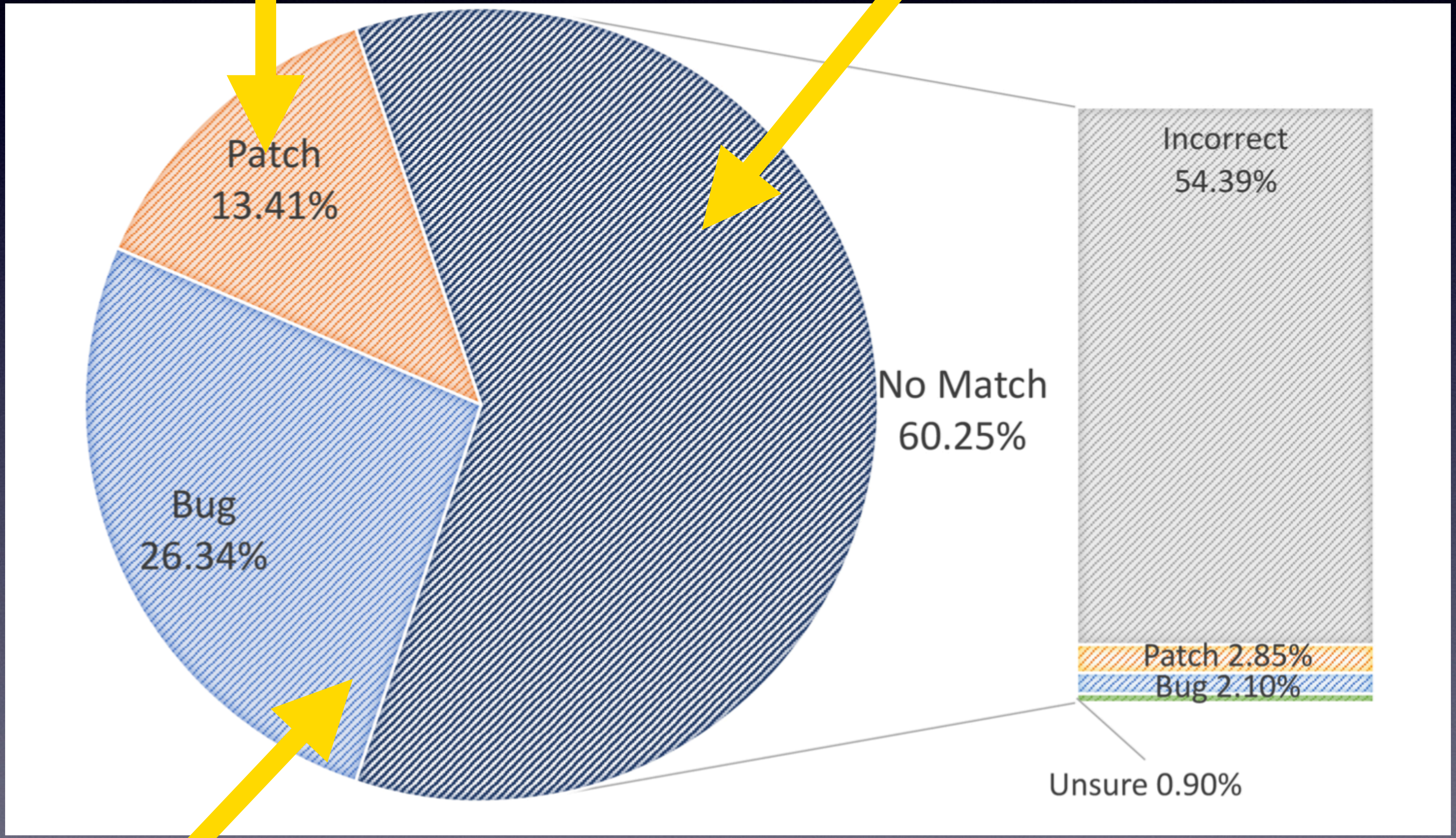
…….Does produce the 🪰 Or the 🩹

All samples in dataset used
were fixed before
LLM training data was gathered.

Result

Codex produces fixed code

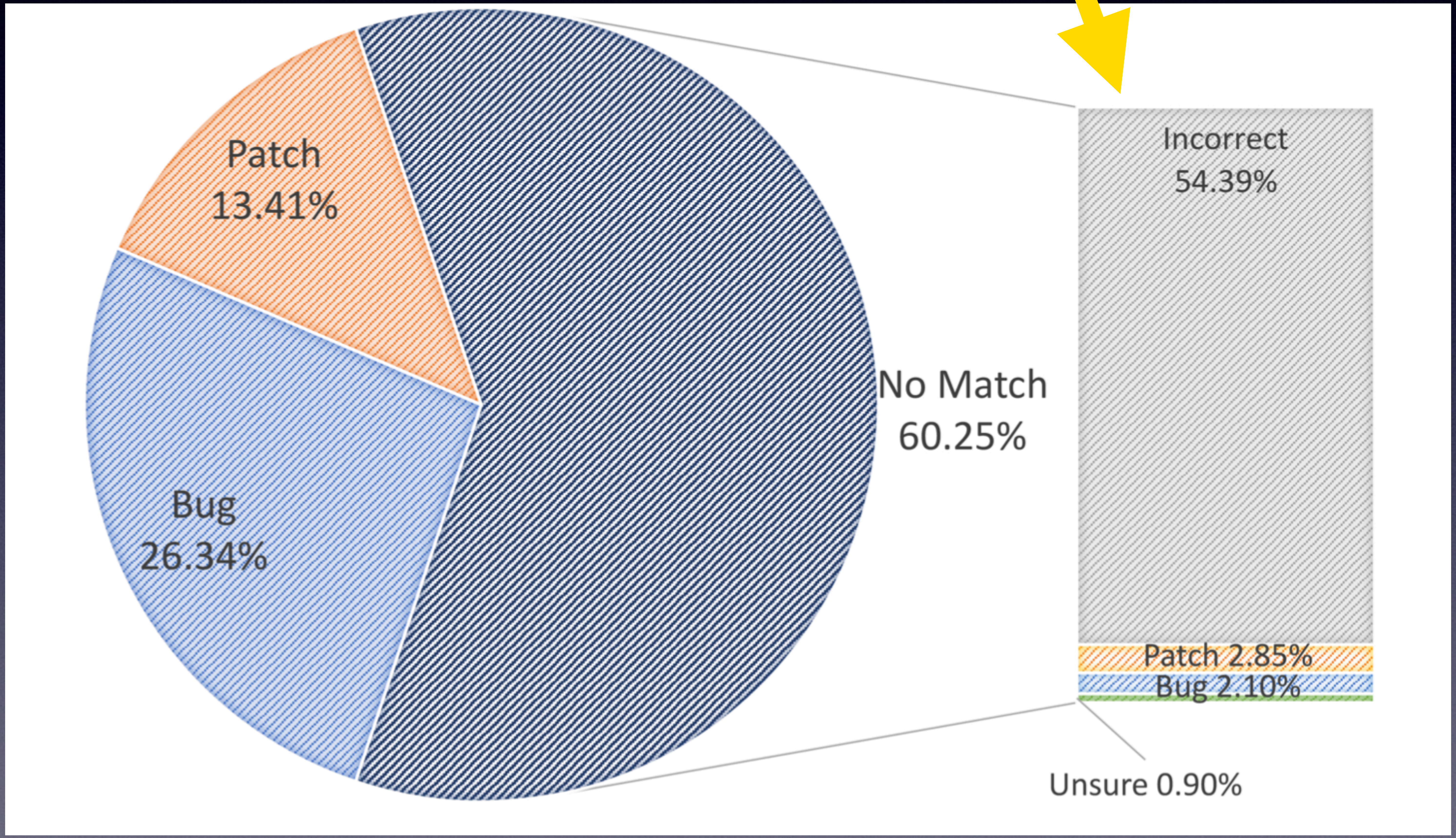
Something else



Codex produces buggy code TWICE as often

Result

Manual Review,
401 samples



Also looked at…

- When CoPilot generates Simple, Stupid Bugs, *were* they “stickier”?

- Good programmers Comment. Do Comments induce CoPilot not repeat human errors?

Take Aways…

- Programmers like LLM-based plugins.
- LLMs often recapitulate human errors.
- …when they do, these errors may be “sticky”.
- …but, we can improve their performance with comments.
- (Worry:) Devs use LLM-generated code without full review.