

# Large Language Models for Software Security Prospects and Pitfalls (10 minute version)

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- 2015: Karpathy's Char-RNN, generating Linux kernel code
- 2019: GPT-2 "accidentally" learns some PHP and JavaScript

```
/*
* Increment the size file of the new incorrect UI_FILTER group information
* of the size generatively.
 */
static int indicate_policy(void)
 int error;
 if (fd == MARN_EPT) {
   /*
     * The kernel blank will coeld it to userspace.
     */
   if (ss->segment < mem total)</pre>
     unblock graph and set blocked();
```

### Char-RNN; Karpathy, 2015

### Large Language Models for Software Security

# **Surprising Progress in Code Models**

```
$app = new App ();
// All GET requests that come to add_register() will be sent to this service.
$api = $app -> include(' ' );
$api -> register( new DbAppAndFNAAppRegistrationService ());
// Define any services to register. We will override any present in the external
// DB have the class of .DAO .
$service = new AppAndFNAAppService ( $app , [
array ( ' host ' => ' localhost ' )
]);
```

### GPT-2; Karpathy, 2015







- **2021: OpenAl Codex** a large GPT-3-based model fine-tuned on code
  - Released commercially as a code completion tool: GitHub Copilot
- **2022: DeepMind AlphaCode** Transformer (encoder/decoder)
  - Reaches human-level (top 54%) performance in an online code competition (Codeforces)
- Both systems treat source code as plain text, "predict next token"
- Trained on large volumes of code (e.g. all of GitHub)

# **Surprising Progress in Code Models**



# Github Copilot

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InfoWorld R Nat Friedman VB VentureBeat GitHub launches Copilot to power pair programming... **Developers react to GitHub Copilot** AI The Microsoft subsidiary has been working with OpenAI to build an AI tool Copilot, as the new GitHub tool is called, uses contextual cues to suggest new code, with users able to flip through alternatives if they GitHub Cop that helps developers write code by making automated suggestions. Here's what the early users make of it. Jun 29, 2021









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# **Copilot Writes Vulnerable Code**

File	Edit	Seleo	tion	View	Go	Run	Termin	al	Help
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0		5							
~		6	@app	.rout	e('/	logir	ı', met	hod	s=['
±⇒		7	def	login	():				
		8	us	er =	requ	est.1	form['u	ser	name
		9	pa	sswd =	= re	quest	.form[	'pa	SSWO
<u>∟</u> ⊙		10							
		11	#c	heck :	if u	serna	ame and	ра	SSWO
		12	db	= MyS	SQLd	b.cor	nect(h	ost	="lo
ш		13	cu	rsor :	= db	.curs	sor()		
		14	N	lext (Alt+	F]) F	Previou	s (Alt+[)	Acc	ept (Ta
		15	sq	l = "9	SELE	CT *	FROM u	ser	's WHE







# Asleep at the Keyboard

- Examined 18 different vulnerability classes (CWEs) and 89 scenarios, used Copilot to generate 1,689 total programs
  - 40% of generated programs were vulnerable
  - (More details in our S&P 2022 paper presented on Monday)
- **Open Problem: how can we fix this?** 
  - Fine-tuning to decrease probability of generating vulnerable code?
  - Some kind of verification or validation?







# Fixing Vulnerabilities with LLMs

- Basic idea: use Codex et al. as a code generator to replace vulnerable code
- Use prompt engineering to guide model toward generating fixed versions
- Use **functional** and **security** oracles to check if generated code fixes the vuln  $\bullet$ without breaking the program 🦺
- Preliminary evaluation: across 7 different code models, could repair\*:
  - 100% of our own synthetically generated vulnerabilities lacksquare
  - 67% of historical vulnerabilities in our dataset





# **Repair Prompt**

\*/ for (row = 0; row < imagelength; row += t1) 5 for (col = 0; col < imagewidth; col += tw)8 /\* BUG: stack buffer overflow \* for (s = 0; s < spp; s++)10 11 \* 12 \* FIXED: 13 \*/ 14 for 15

(b) Prompt constructed according to Fig. 11 (shortened for brevity). The red highlighted line 10 is the original faulty line indicated by ASAN/the oracle. The template includes lines 11 and 12 (highlighted in grey) to encourage the LLMs to regenerate the safe code so the patch can be matched safely.







## Successful Repair libtiff CVE-2016-5321

1	/* Each tile contains only
2	* arranged in scanlines of
3	*/
4	for (row = 0; row < imagele
5	{
6	nrow = (row + tl > imagele
7	for $(col = 0; col < imagev$
8	{
9	for $(s = 0; (s < spp) \&\&$
0	{
1	tbytes = TIFFReadTile(in

(d) The repaired program once reassembled with the LLM patched line 11 highlighted in yellow. This generated patch is semantically equivalent with the real-world human patch used to repair this bug.

```
the data for a single plane
tw * bytes_per_sample bytes.
ength; row += t1)
ength) ? imagelength - row : t1;
width; col += tw)
(s < MAX_SAMPLES); s++)
, srcbuffs[s], col, row, 0, s);</pre>
```





- The language model fixed the vulnerability... by removing the problematic options!
- Developer tests are weak proxies for program functionality
- Open problem: how can we strengthen these proxies?
  - Can we get LLMs to write better functional tests as well?

## Large Language Models for Software Security

```
--- a/rgb2ycbcr.c
+++ b/rgb2ycbcr.c
@@ -94,11 +94,7 @@
        usage(-1);
    break;
   case 'h':
    horizSubSampling = atoi(optarg);
    break;
 case 'v':
    vertSubSampling = atoi(optarg);
    break;
+
    usage(-1);
   case 'r':
    rowsperstrip = atoi(optarg);
    break;
```

Patch generated by GPT-CSRC 774M model





# **Reverse Engineering with LLMs**

- in natural language
- Can we use this ability on decompiled code to help automate RE?
- Preliminary result: mostly no
  - Decompiled code is too dissimilar to original source code
  - Eval using true/false Q&A format: **136,260** questions posed, Codex answered **72,754** correctly

## Large Language Models for Software Security



### • For normal source code, Codex does a reasonable job of summarizing code



# **Embedding Similarity**

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(a) Confusion matrix for 1s with (b) Confusion matrix for 1s with debug information. debug symbols stripped.





# And Beyond...

right now

- An embarrassment of data:
  - Vast amounts of training data (code)
  - Easy to create parallel corpora (e.g. using compilers & debug info)
  - Can automatically extract semantic information
- What could we do by just scaling up?
  - "Industrial" LLMs are ~1000x larger than what we use in software security

### Hot take: large language models are vastly underused in software security





- Decompilation
- Making fuzzing more effective
- Reverse engineering data types
- Recursively summarizing binaries
- Bug-finding
- Exploit generation

