



GPT-3 and Me

**How Supercomputer-scale Neural Network Models Apply to
Defensive Cybersecurity Problems**

*Younghoo Lee, Principal Research Scientist, Sophos
Joshua Saxe, Chief Scientist, Sophos*

Your presenters



- **Joshua Saxe / @joshua_saxe**
- Chief Scientist at Sophos
- Author of “Malware Data Science” from No Starch Press, with Hillary Sanders
- 15 years of experience doing academic and applied research at the intersection of cybersecurity and machine learning



- **Younghoo Lee**
- Principal Research Engineer at Sophos
- Author of multiple peer-reviewed papers and patents on applying machine learning to cybersecurity
- Principal researcher behind multiple ML systems deployed to millions of networks

Theses in this talk

- Model scale has fundamentally changed machine learning's capabilities
- Self-supervised learning has fundamentally changed machine learning's capabilities
- It's time that the security data science research community comes together to understand what this means for our work
- This talk just reflects early work in this space, we hope much more community work will ensure

Results in this talk:

A GPT-3 based approach can describe complex commandlines, reducing SOC analyst cognitive load

```
1 C:\\WINDOWS\\system32\\cmd.exe /Q /c echo dir \"C:\\Users\\admin\\OneDrive ADMINISTRATORS INC\" ^> \\127.0.0.1\\C$\\__output 2^>^&1 > C:\\WINDOWS\\TEMP\\execute.bat & C:\\WINDOWS\\system32\\cmd.exe /Q /c C:\\WINDOWS\\TEMP\\execute.bat & del C:\\WINDOWS\\TEMP\\execute.bat
```

GPT-3 based approach

The command will create a file called "execute.bat" in the C:\\WINDOWS\\TEMP folder. It will then run the command "dir C:\\Users\\admin\\OneDrive ADMINISTRATORS INC" and output the results to the __output file on the local machine. The batch file will then execute itself and delete itself afterwards.

Results in this talk:

A GPT-3 based approach can learn to detect malicious documents using tiny training volumes

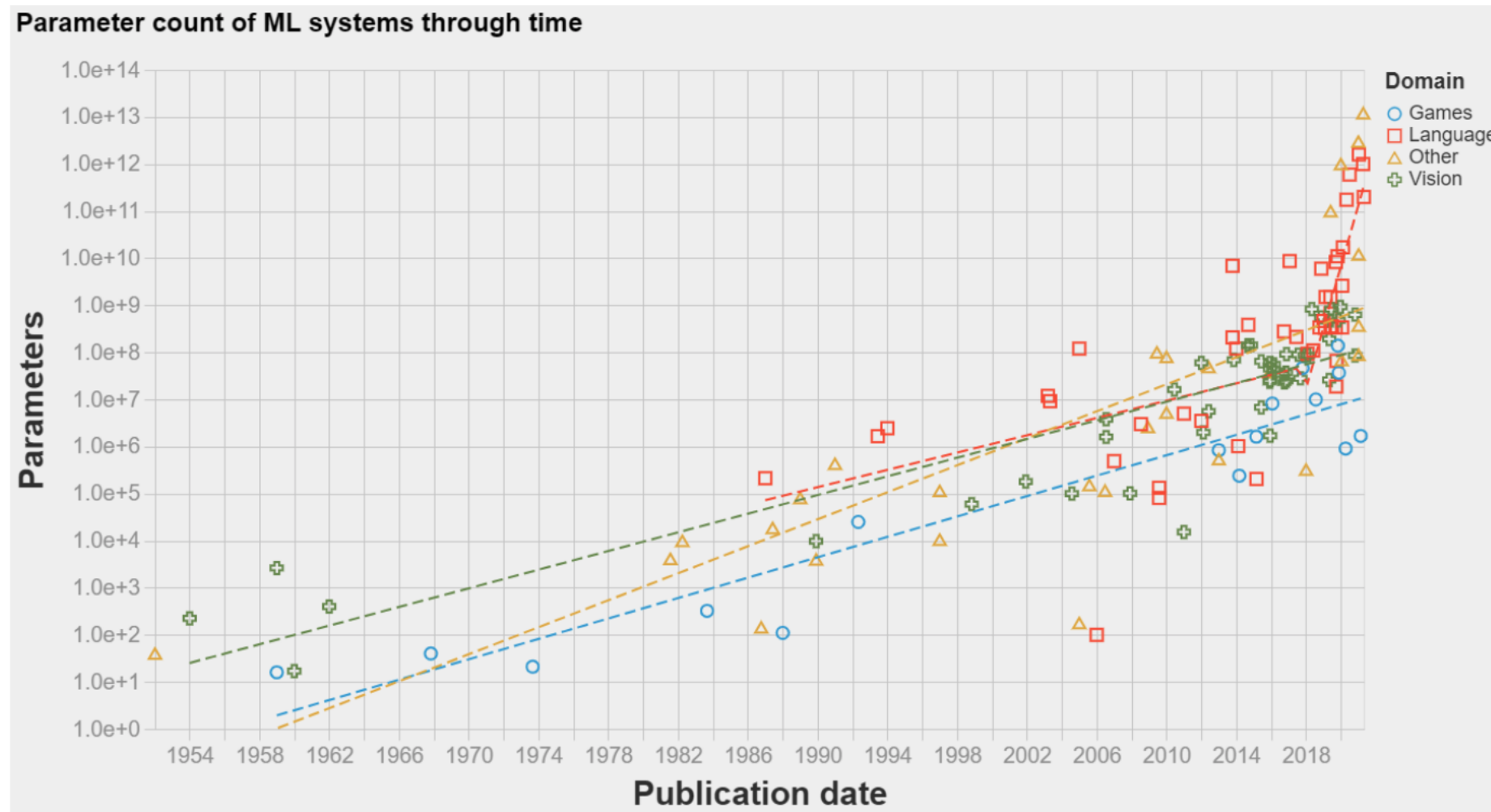
		GPT-3 F1-score	Random Forest F1-score
Training samples	1 ham, 1 spam	0.90	0.55
	4 ham, 4 spam	0.95	0.79

We would need far more data to learn to detect a spam campaign using traditional methods!



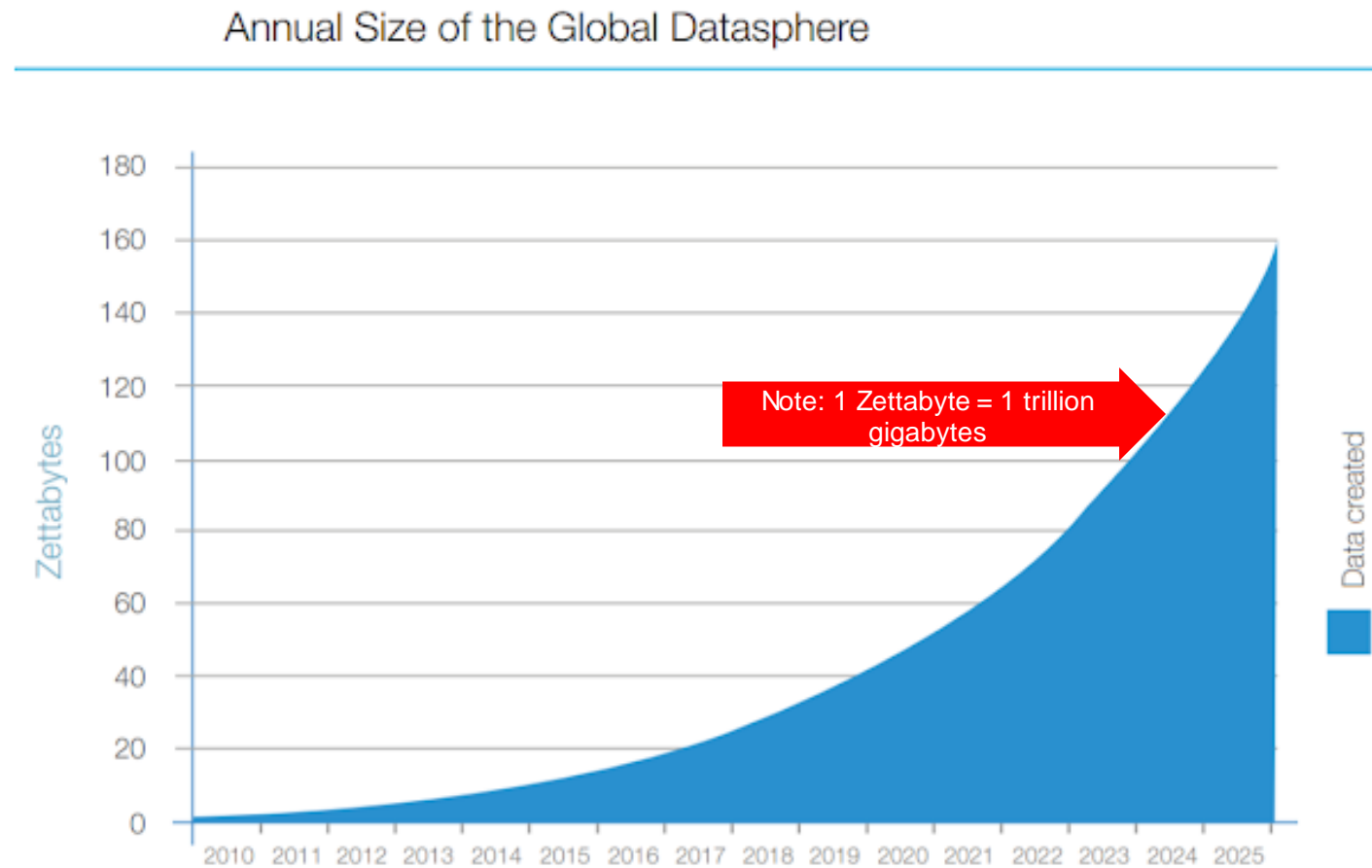
Background: how large language models and self-supervised learning are transforming machine learning

Deep learning models are getting bigger



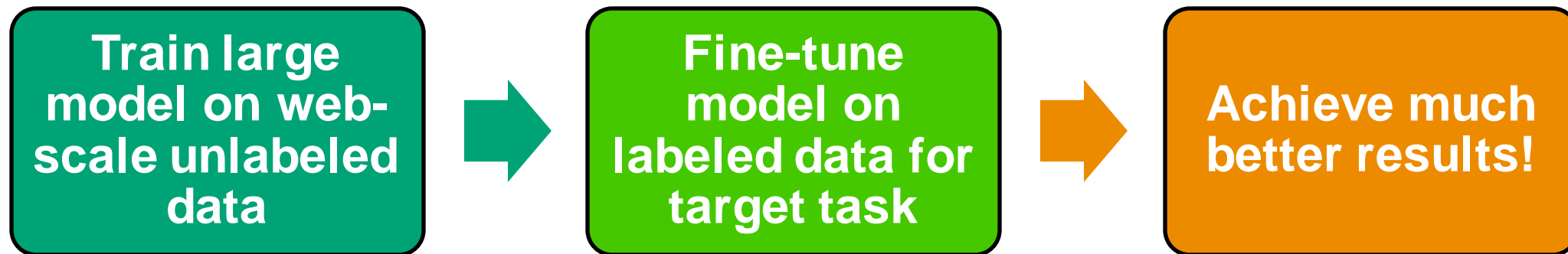
<https://towardsdatascience.com/parameter-counts-in-machine-learning-a312dc4753d0>

These large models are taking advantage of unlabeled web-scale data

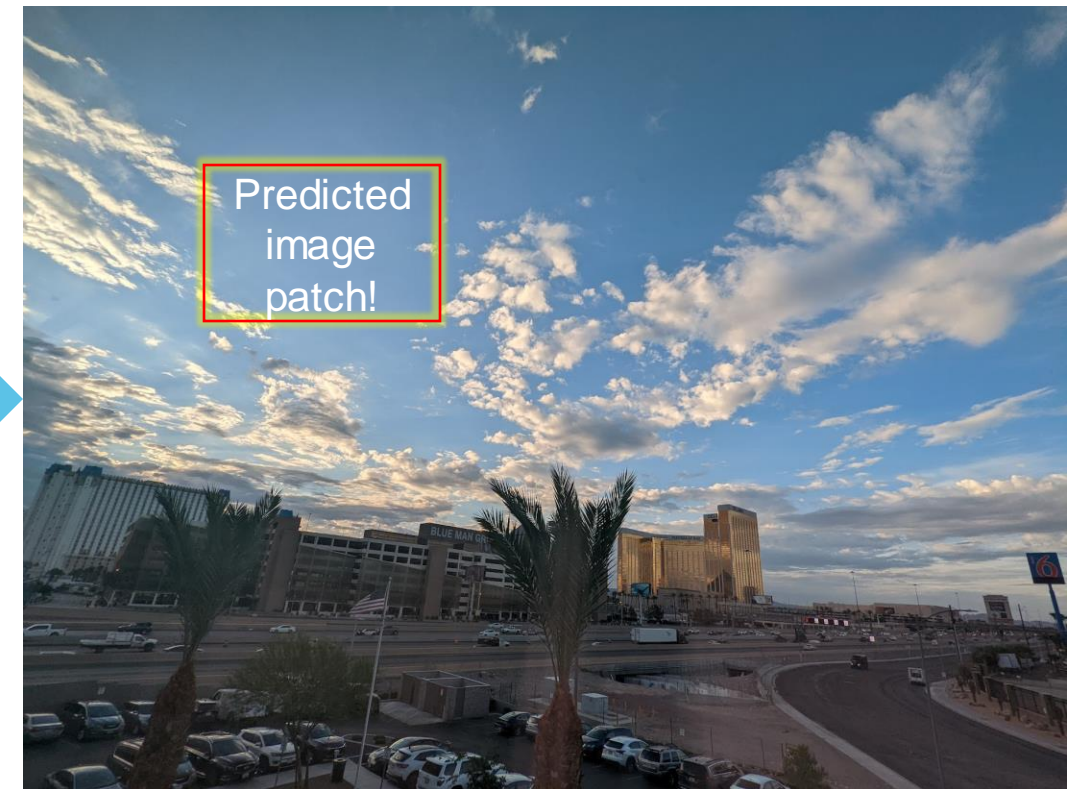
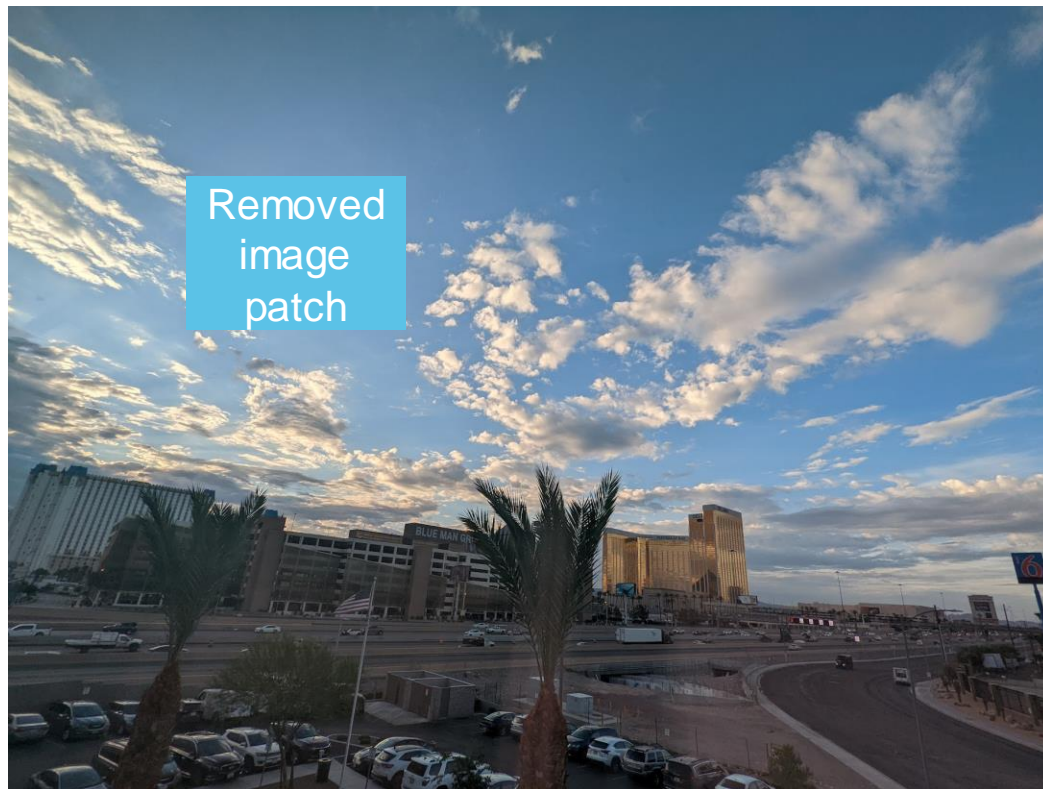


Source: IDC's Data Age 2025 study, sponsored by Seagate, April 2017

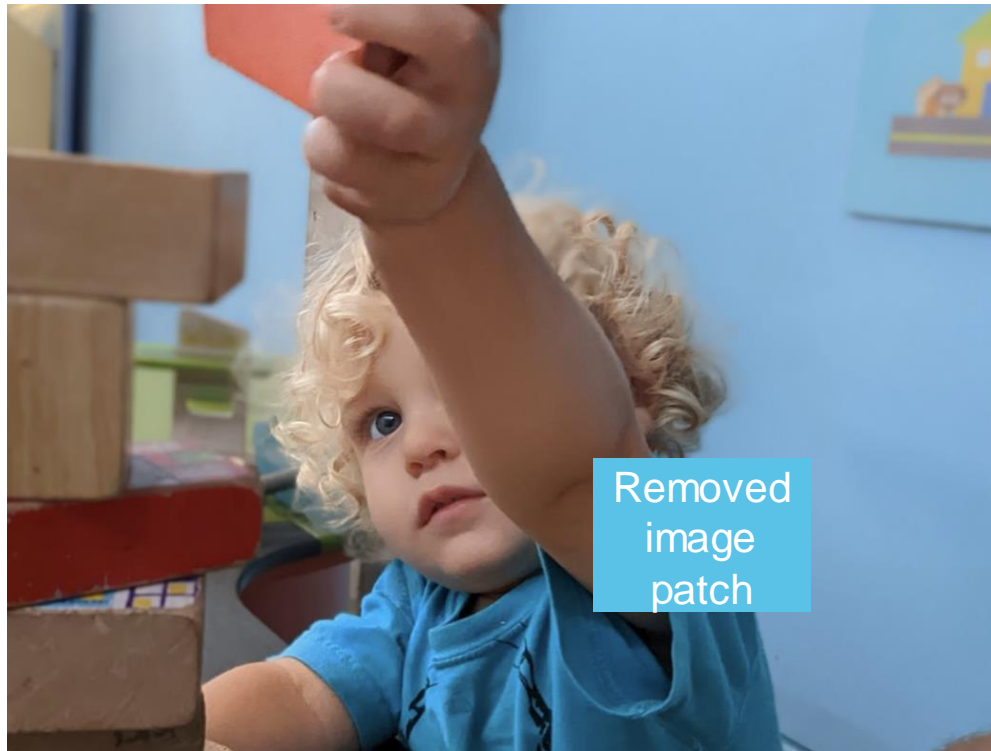
How self-supervised learning works



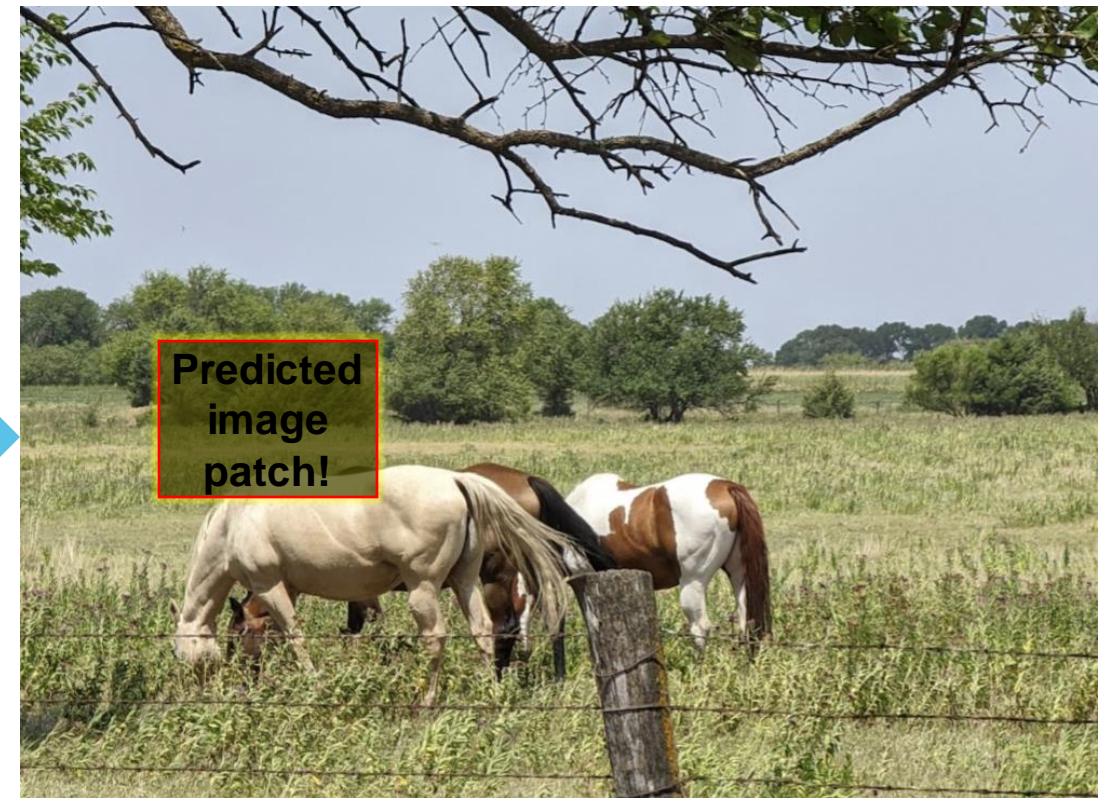
How self-supervised learning works



How self-supervised learning works



How self-supervised learning works



How self-supervised learning works

How self supervised learning **works**

Neural network
input

Prediction
target

How self-supervised learning works

Model input: “Horses graze in a bucolic Kansas field, a tree is in the foreground above them, a fence separates the viewer from the horses, and grass and trees stretch into the distance”

Neural network
input

Prediction target:
the actual pixels
in this image!



Capabilities emerge with self-supervised learning + scale

A portrait photo of a kangaroo wearing an orange hoodie and blue sunglasses standing on the grass in front of the Sydney Opera House holding a sign on the chest that says Welcome Friends!



Capabilities emerge with self-supervised learning + scale

A portrait photo of a kangaroo wearing an orange hoodie and blue sunglasses standing on the grass in front of the Sydney Opera House holding a sign on the chest that says Welcome Friends!



350 million model parameters

Capabilities emerge with self-supervised learning + scale

A portrait photo of a kangaroo wearing an orange hoodie and blue sunglasses standing on the grass in front of the Sydney Opera House holding a sign on the chest that says Welcome Friends!



3 billion model parameters

Capabilities emerge with self-supervised learning + scale

A portrait photo of a kangaroo wearing an orange hoodie and blue sunglasses standing on the grass in front of the Sydney Opera House holding a sign on the chest that says Welcome Friends!



20 billion model parameters

Another example of model scaling

A map of the United States made out of sushi. It is on a table next to a glass of red wine.

350M



750M



3B



20B



Google's "Parti" model in all its 20 billion parameter glory



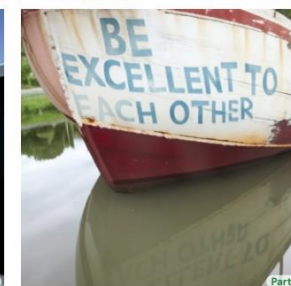
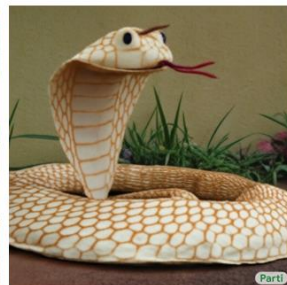
A. A photo of a frog reading the newspaper named "Tooday" written on it. There is a frog printed on the newspaper too.



B. A portrait of a statue of the Egyptian god Anubis wearing aviator goggles, white t-shirt and leather jacket. The city of Los Angeles is in the background. Hi-res DSLR photograph.



C. A high-contrast photo of a panda riding a horse. The panda is wearing a wizard hat and is reading a book. The horse is standing on a street against a gray concrete wall. Colorful flowers and the word "PEACE" are painted on the wall. Green grass grows from cracks in the street. DSLR photograph. daytime lighting.



What capability emergence does for images it does for text and code

My “prompt”

```
1 def compute_mean_and_stddev(data):  
2     """  
3     Compute mean and standard deviation of the input data in pure Python and render  
4     the result in flashy html on a page titled  
5     "DON'T TRUST SUMMARY STATISTICS"  
6     """
```

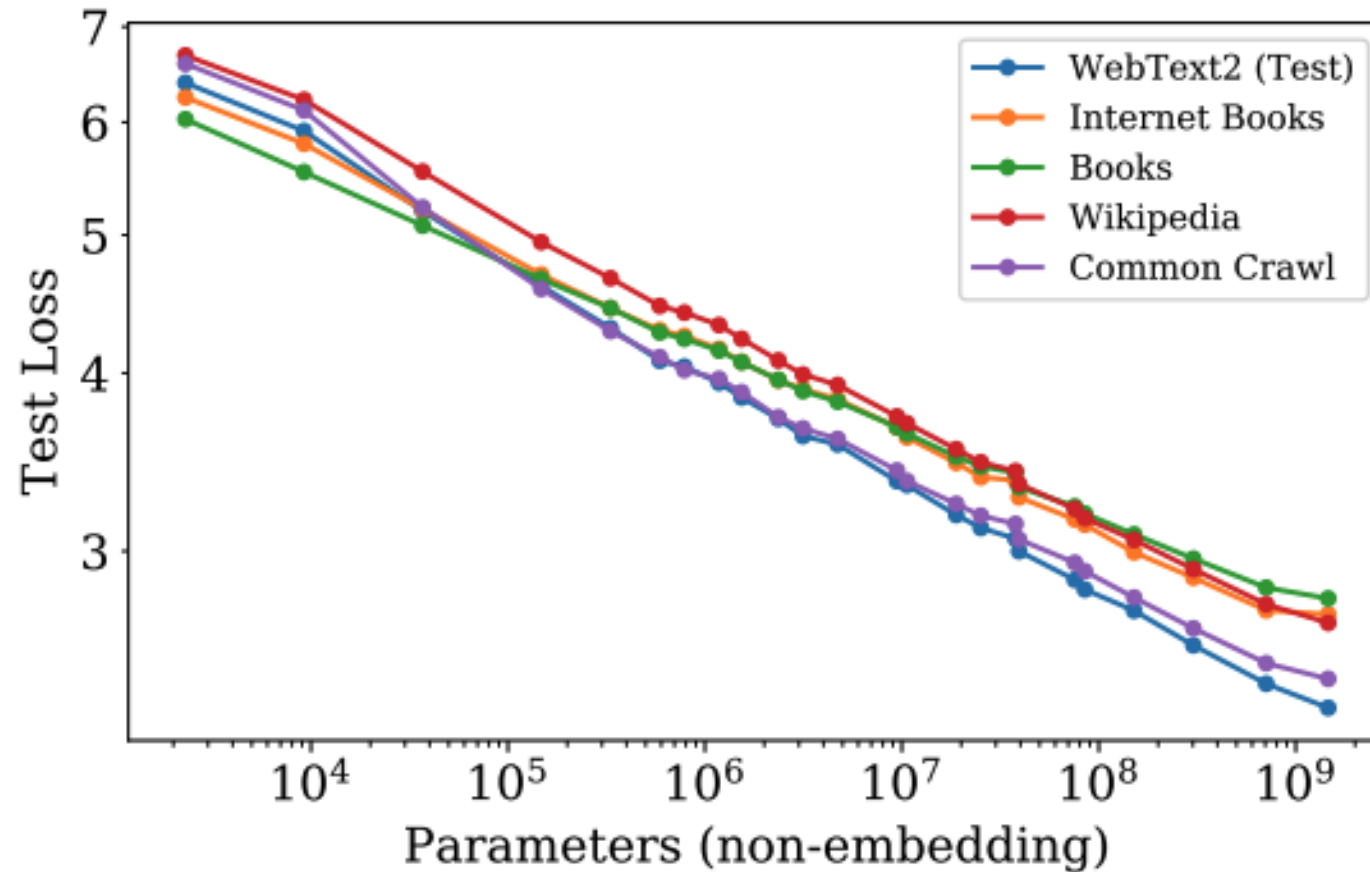
What capability emergence does for images it does for text and code

My "prompt"

```
1 def compute_mean_and_stddev(data):
2     """
3     Compute mean and standard deviation of the input data in pure Python and render
4     the result in flashy html on a page titled
5     "DON'T TRUST SUMMARY STATISTICS"
6     """
7     # Compute mean and standard deviation in pure Python
8     mean = sum(data) / len(data)
9     stddev = math.sqrt(sum([(x - mean)**2 for x in data]) / len(data))
10    # Render the result in flashy html on a page titled "DON'T TRUST SUMMARY
11    STATISTICS"
12    html = "<html><head><title>DON'T TRUST SUMMARY STATISTICS</title></head><body>
13    <h1>Mean: %f</h1><h1>Standard deviation: %f</h1></body></html>" % (mean, stddev)
14    return html
```

Code generated by
large neural
network

Neural scaling laws: power-law relationship between scale and accuracy



Scaling Laws for Neural Language Models

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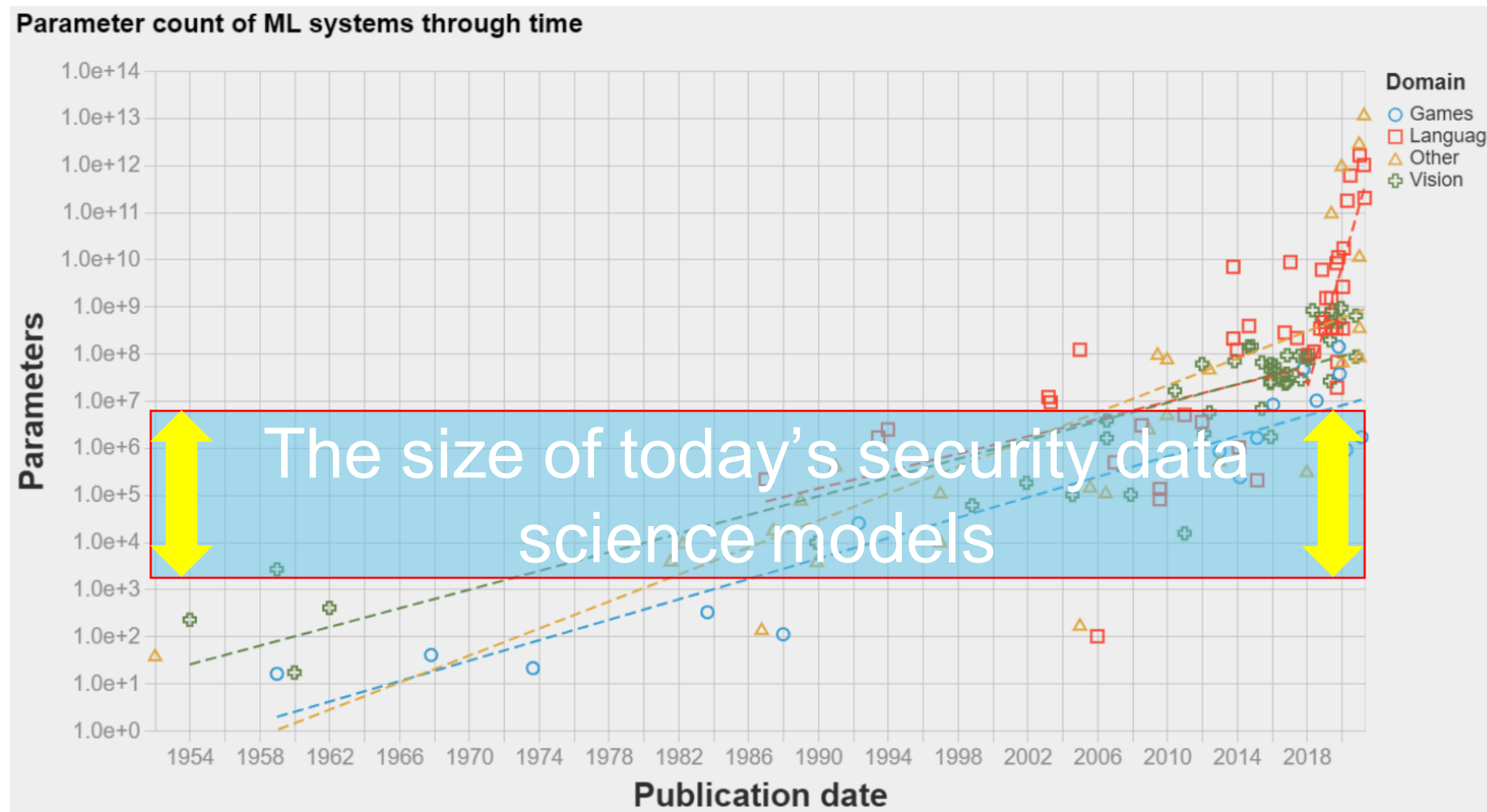
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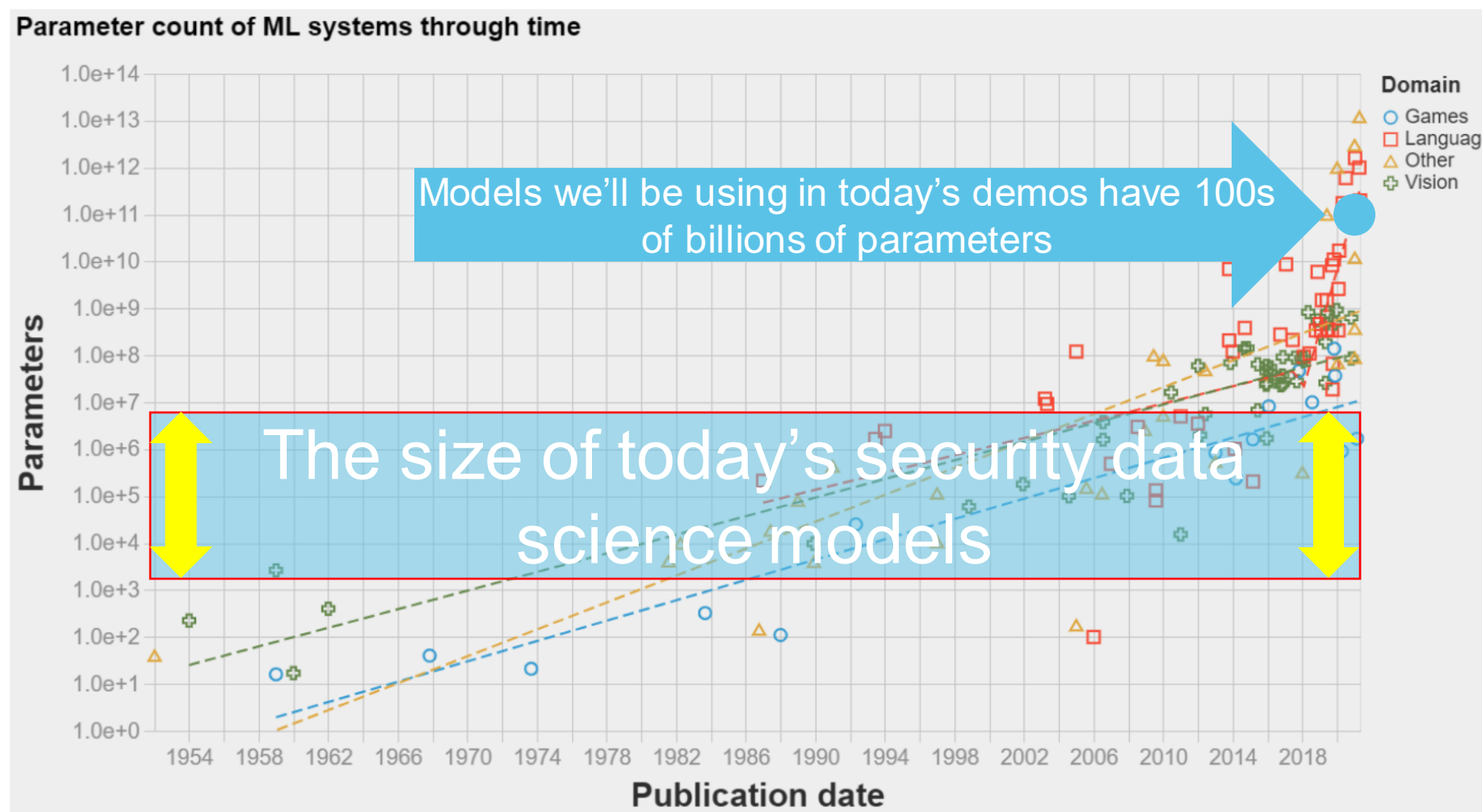
Dario Amodei
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Worth noting: Security machine learning models are still “small” and are not self-supervised



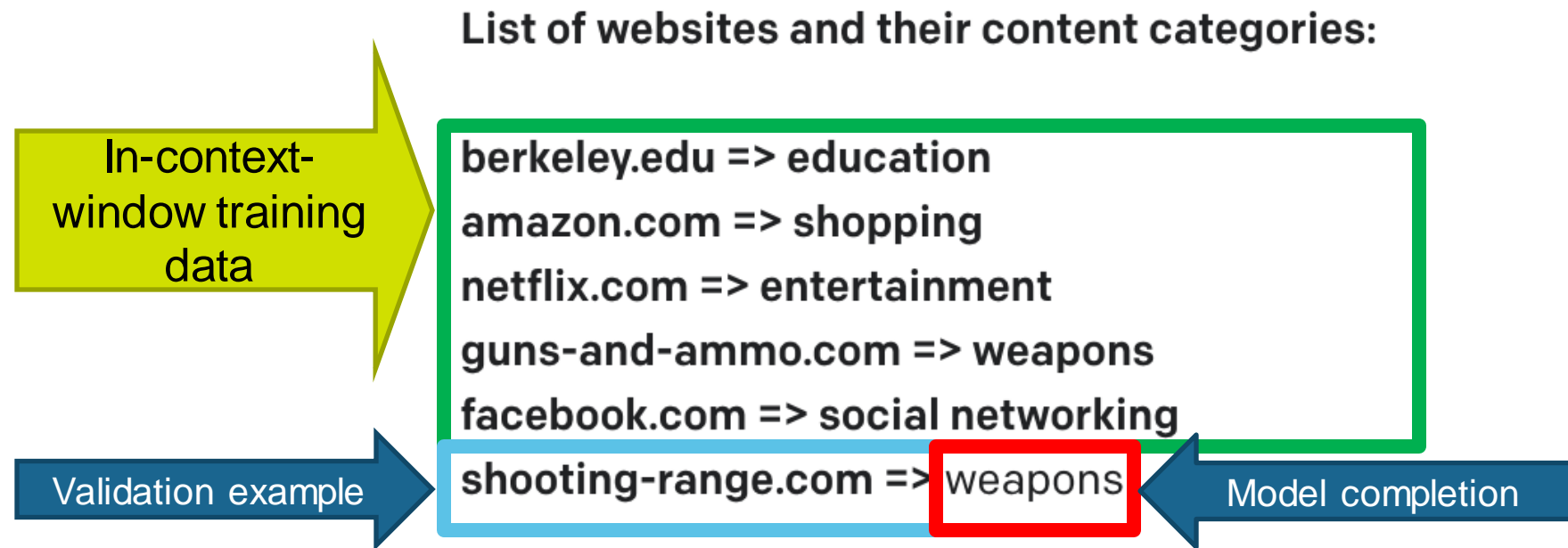
<https://towardsdatascience.com/parameter-counts-in-machine-learning-a312dc4753d0>

Worth noting: Security machine learning models are still “small” and are not self-supervised



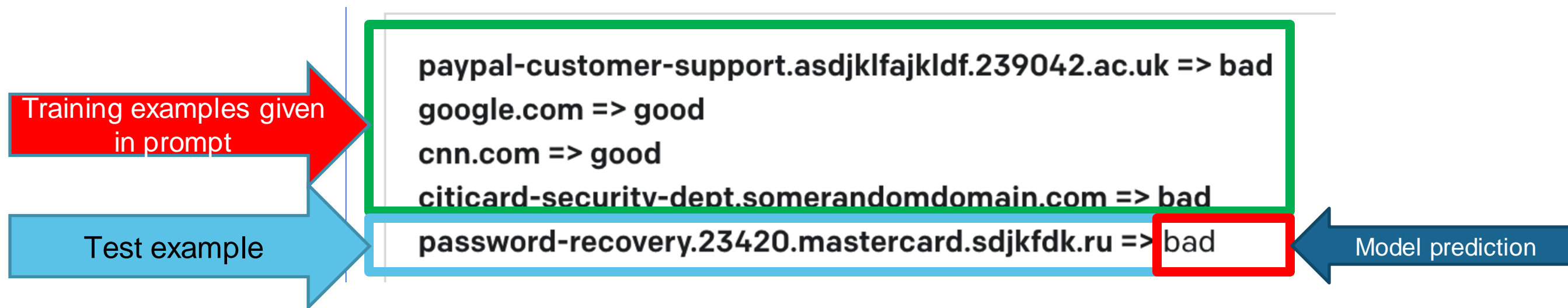
<https://towardsdatascience.com/parameter-counts-in-machine-learning-a312dc4753d0>

Why large-scale self-supervised learning matters for detection problems



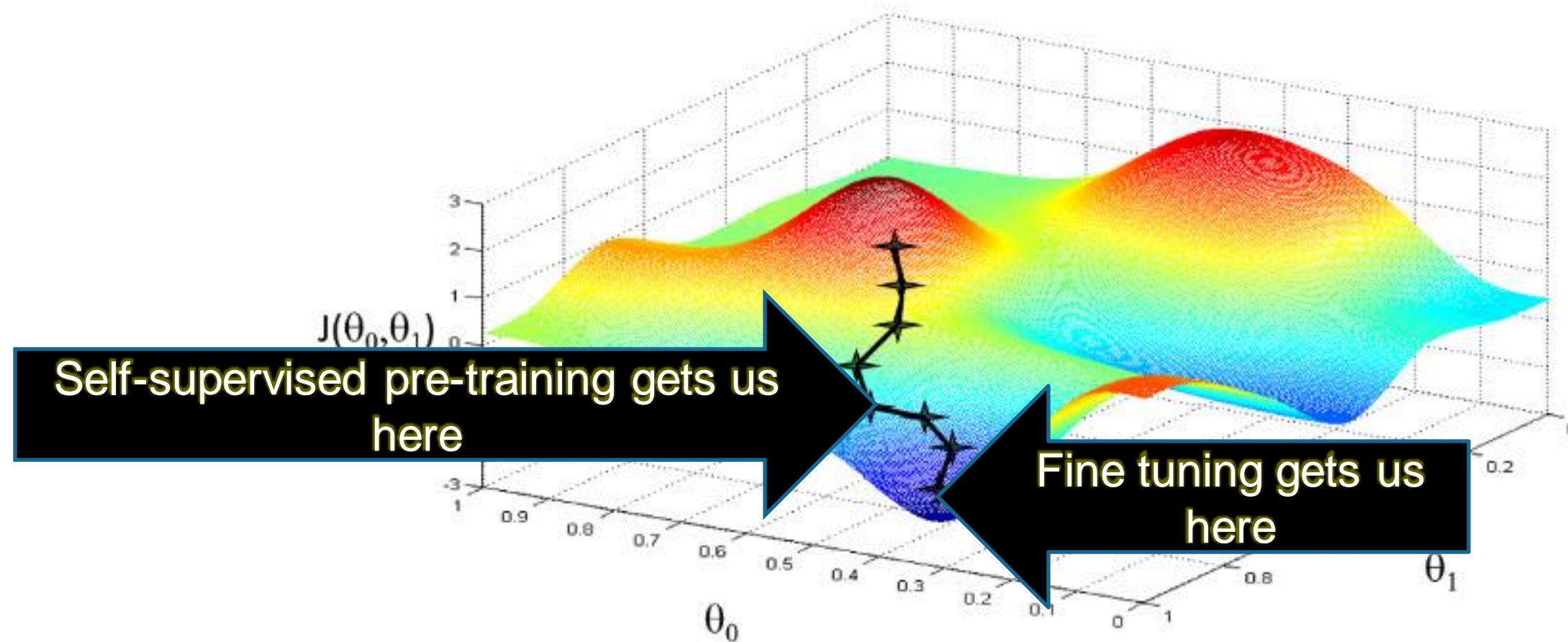
Source: OpenAI model playground, Davinci model

Why large-scale self-supervised learning matters for detection problems



Source: OpenAI model playground, Davinci model

Beyond in-context learning: fine-tuning



<https://zitaoshen.rbind.io/project/optimization/1-min-of-machine-learning-gradient-decent/>

What might the applications of large models be for cybersecurity?

- **Detection technology that detects previously unseen attack types better**
- **User interfaces that understand natural language user requests from security operators**
- **”Auto-complete on steroids” models for DevSecOps**
- **Models that aid reverse engineering**



Spam detection with GPT-3

What if you have only a few examples of a new spam campaign?

Small scale machine learning with no self-supervision needs more training data to learn new tricks!



<https://www.istockphoto.com/photos/pile-of-dog-treats>

Large scale self-supervised models need far less training data to learn new tricks!



<https://www.youtube.com/watch?v=tyunqxGGD9k>

GPT-3 learns to detect spam using a tiny number of training examples, because of self-supervised pretraining derived “background knowledge”

		GPT-3 F1-score	Random Forest F1-score
Training samples	1 ham, 1 spam	0.90	0.55
	4 ham, 4 spam	0.95	0.79

We would need far more data to learn to detect a spam campaign using traditional methods!

Evaluation data and models

Data source

- Training and test datasets were randomly sampled from the following Spam dataset.
- <https://archive.ics.uci.edu/ml/datasets/sms+spam+collection>

Training datasets

- Sample size for 2, 8, 32, 512, 1024

Test dataset

- Sample size for 256

ML models

- Tree-based Random Forest model with token frequency-based ML features.
- GPT-3's Davinci model with few-shot learning.

Teaching GPT-3 to solve a prediction problems can be as simple as designing a prompt for it to auto-complete

Prompt

Convert movie titles into emoji.

Back to the Future: 🧑🏻🧑🏻🚗🕒

Batman: 🦇🦇

Transformers: 🚗🤖

Star Wars:

“Prompt” showing GPT-3 examples of what you want

Sample response

🌟🌟

GPT-3’s “auto-complete” response for Star Wars

Prompting GPT-3 to detect spam

Prompt: Input data

Classify the Message as Spam or Ham.

Message: FreeMSG You have been awarded . . .

Label: Spam

Message: Going to join tomorrow

Label: Ham

Message: Free Top ringtone -sub to weekly

Label:

Spam

1. The part of the prompt where we tell GPT-3 what we want it to do

2. The part of the prompt where we show GPT-3 some training examples

3. The part of the prompt where we ask GPT-3 to classify our target example

4. GPT-3's correct classification of the new message!

Examples of Spam detection

Classify the Message as Spam or Ham.

Message: FreeMSG You have been awarded ...

Label: Spam

Message: Going to join tomorrow

Label: Ham

Message: URGENT! Your mobile number has been awarded with a \$1000 prize.

Label: Spam

Submit



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Mode



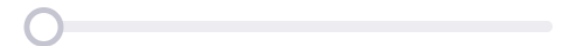
Model

text-davinci-002



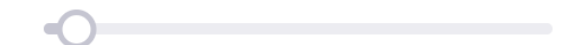
Temperature

0



Maximum length

256



Message: Yes. I'm in office, see you soon.

Label: Ham



Generating human-readable explanations of malicious command lines

Analyzing thousands of suspicious commands over a large enterprise is exhausting for SOC analysts.

Research question: Can large language models make this easier by describing them in simple language?

Real-world suspicious command line. Our goal: automatically describe this in simple language to reduce cognitive load

```
"C:\\WINDOWS\\system32\\cmd.exe /Q /c echo dir "C:\\Users\\admin\\OneDrive - ADMINISTRATORS INC\\" ^> \\\\127.0.0.1\\C$\\__output 2^>^&1 > C:\\WINDOWS\\TEMP\\execute.bat & C:\\WINDOWS\\system32\\cmd.exe /Q /c C:\\WINDOWS\\TEMP\\execute.bat & del C:\\WINDOWS\\TEMP\\execute.bat
```


Takeaway up front: GPT-3 can often do a good job at this task

Command

```
C:\\WINDOWS\\system32\\cmd.exe /Q /c echo dir \"C:\\Users\\admin\\OneDrive ADMINISTRATORS INC\" ^>
\\\\127.0.0.1\\C$\\__output 2^>^&1 > C:\\WINDOWS\\TEMP\\execute.bat &
C:\\WINDOWS\\system32\\cmd.exe /Q /c C:\\WINDOWS\\TEMP\\execute.bat & del
C:\\WINDOWS\\TEMP\\execute.bat
```

Real suspicious command
observed on a real
network!

Description

The command will **create a file** called \"execute.bat\" in the C:\\WINDOWS\\TEMP folder. It will then run the command \"dir C:\\Users\\admin\\OneDrive ADMINISTRATORS INC\" and output the results to the __output file on the local machine. The batch file will then **execute itself and delete** itself afterwards.

Real, accurate
description generated
by GPT-3!

“GPT-3” actually refers to two types of OpenAI large language models



Text-GPT3 for text generation

These models can write interesting stories and poems.

<https://www.digitaltrends.com/computing/openai-gpt-3-text-generation-ai/>



Code-GPT3(Codex) for code generation

These models are proficient in over a dozen of languages including Python, JavaScript, PHP and even Shell.

<https://www.datasciencecentral.com/open-ai-codex-challenge-seen-by-the-participants/>

We use “prompts” to get GPT-3 to auto-complete us a good command line description

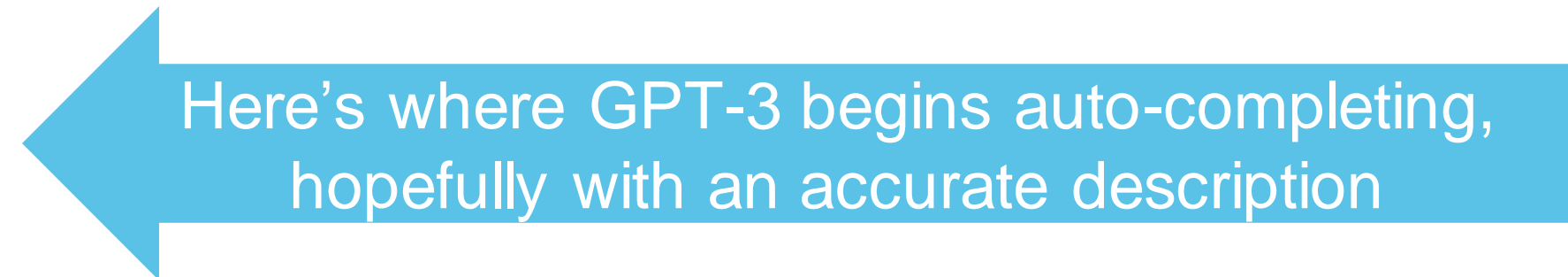
Command

```
cmd.exe /c copy C:\Windows\System32\rundll32.exe  
C:\Users\Pcs\AppData\Local\Temp\adobe.exe
```



Description

The above command will



An example auto-completion that describes a command line

```
1 ## Command
2 cmd.exe /c copy C:\Windows\System32\rundll32.exe
  C:\Users\Pcs\AppData\Local\Temp\adobe.exe
3 ## Description
4 The above command will copy rundll32.exe file and paste it in
  C:\Users\Pcs\AppData\Local\Temp\ folder.
```

Mode



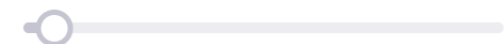
Model

code-davinci-002

Temperature 0.7



Maximum length 256



Stop sequences

Enter sequence and press Tab

×

Top P 0.95



Submit



73

Plain text



<https://beta.openai.com/playground>

Improving command line descriptions by using signature match context data



Sigma

Generic Signature Format for SIEM Systems
<https://github.com/SigmaHQ/sigma>



<https://virustotal.github.io/yara/>

```
cmd.exe /c copy C:\Windows\System32\rundll32.exe C:\Users\Pcs\AppData\Local\Temp\adobe.exe =>  
was detected by win_suspicious_copy_system32 signature.
```

Suspicious commands can be detected by signature-based rules and the signature names often provide useful context information.

Better prompts by adding in signature match information

Command

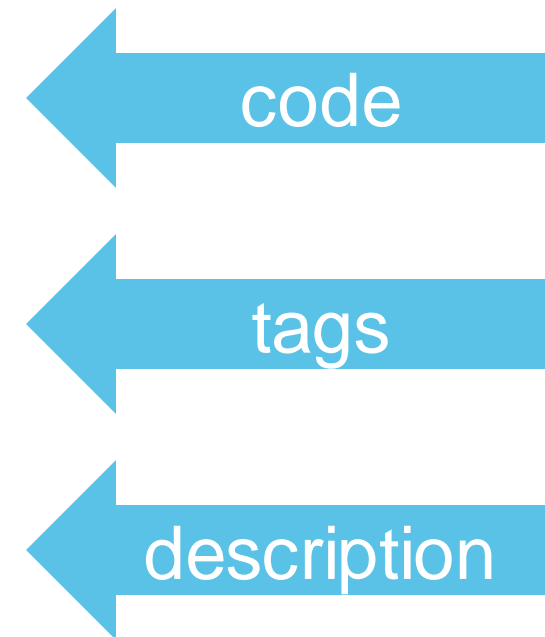
```
cmd.exe /c copy C:\Windows\System32\rundll32.exe  
C:\Users\Pcs\AppData\Local\Temp\adobe.exe
```

Tags

```
win_suspicious_copy_system32
```

Description

The above command will



Description from a command and tags

```
1 ## Command
2 cmd.exe /c copy C:\Windows\System32\rundll32.exe
  C:\Users\Pcs\AppData\Local\Temp\adobe.exe
3 ## Tags
4 win_suspicious_copy_system32
5 ## Description
6 The above command will copy rundll32.exe to
  "C:\Users\Pcs\AppData\Local\Temp\adobe.exe" where the attackers can use the
  rundll32.exe to perform malicious activity.
```

Mode



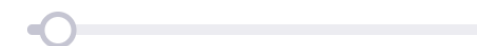
Model

code-davinci-002

Temperature 0.7



Maximum length 256



Stop sequences

Enter sequence and press Tab

##

Top P 0.95



Submit

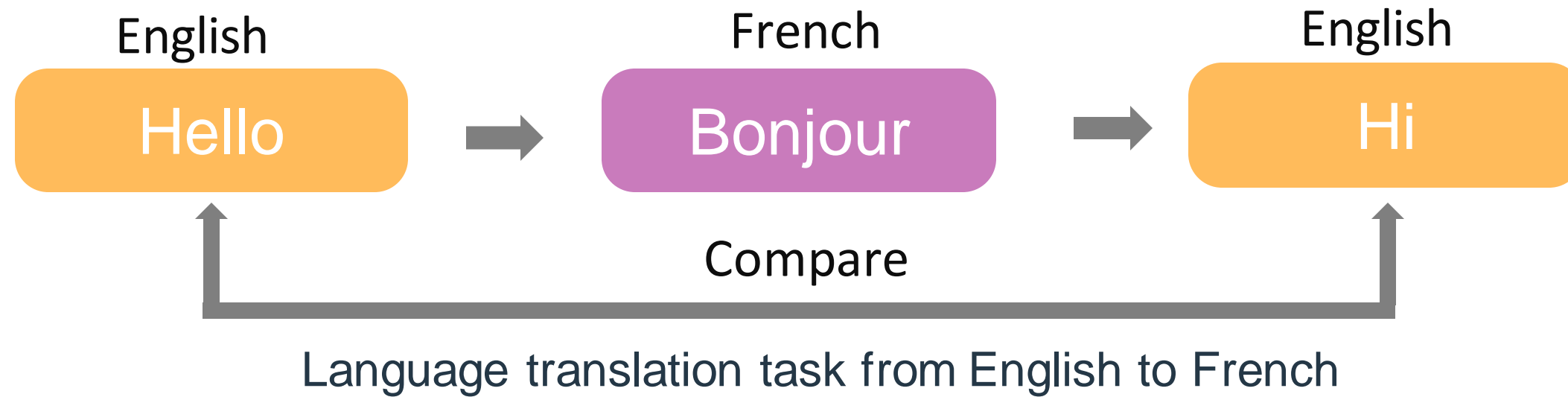


104

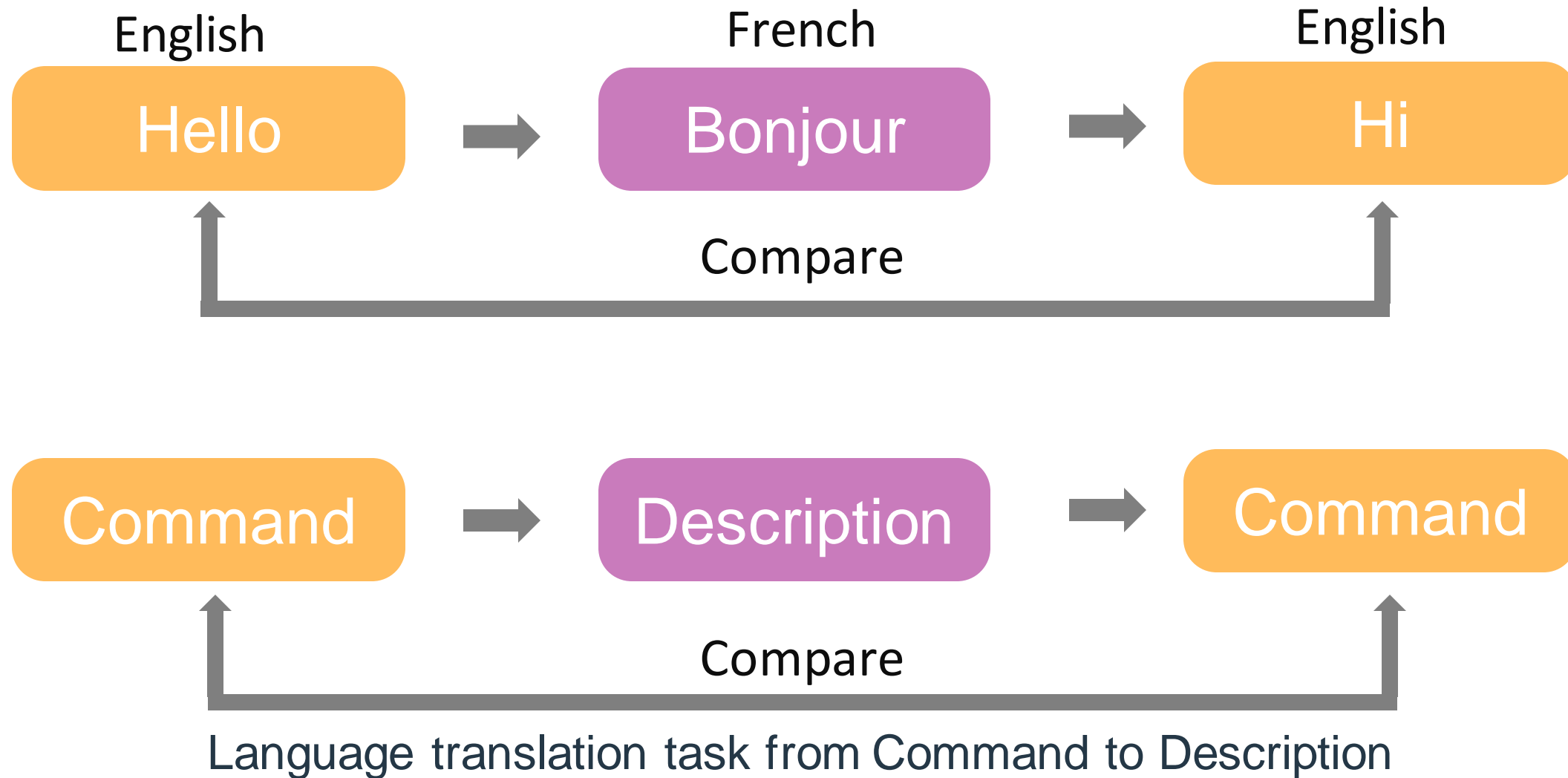
Plain text

<https://beta.openai.com/playground>

Our clever idea: evaluating descriptions for quality using “back-translation”



Our clever idea: evaluating descriptions for quality using “back-translation”



Steps to choose the best description

Generating descriptions

- input: a command, tags

Back-translating commands

- input: a description, tags

Ranking descriptions by similarity scores

- input: the query and back-translated commands

Prompt design for Back-translation

Tags

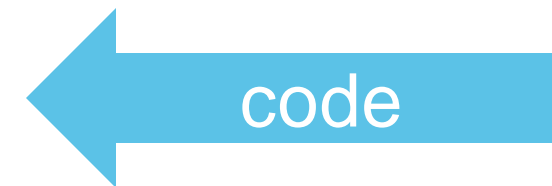
win_suspicious_copy_system32

Description

The command below will copy the rundll32.exe file from the C:\Windows\System32 folder to the C:\Users\PCs\AppData\Temp\ folder.

Command

cmd.exe



The first word, *cmd.exe* in Command is provided from the query code to guide GPT-3 to generate relevant code.

Improved description with Back-translation

```
## Description
The command below will copy rundll32.exe to "C:\Users\Pcs\AppData\Local\Temp"
where the attackers can use the rundll32.exe to perform malicious activity.
## Command
cmd.exe /c copy C:\Windows\System32\rundll32.exe
C:\Users\Pcs\AppData\Local\Temp\rundll32.exe
```

```
## Description
The command below will copy rundll32.exe to
"C:\Users\Pcs\AppData\Local\Temp\adobe.exe" where the attackers can use the
rundll32.exe to perform malicious activity.
## Command
cmd.exe /c copy "C:\Windows\System32\rundll32.exe"
"C:\Users\Pcs\AppData\Local\Temp\adobe.exe"
```

GPT-3 can generate multiple descriptions but **the second one is better** as it has higher information coverage. Back-translation step allows us to choose the best candidate.

Description from Command and Tags

Command

```
cmd.exe dir /b /s \"C:\\Users\\Pcs\\Desktop\\*.*)" | findstr /i password
```

Tags

```
win_pc_suspicious_dir,win_suspicious_findstr
```

Description

The command will recursively list all files in the "C:\Users\Pcs\Desktop" directory and all subdirectories and will search the output for files containing the word "password".

Source code

Source code is available in <https://github.com/sophos/gpt3-and-cybersecurity>.

Spam detector

Invoke the following command to identify a message as spam or ham.

```
python spam_detector.py --message="test message"
```

Command analyzer

Invoke the following command to translate a command line into a natural language description.

```
python command_analyzer.py --cmd="command line" --tags=="comma seperated tags"
```



Q&A