

KeyTAR: Practical Keystroke Timing Attacks and Input Reconstruction

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at CHAPEL HILL

Overview

🔑 Overview of Keystroke Timing Attack

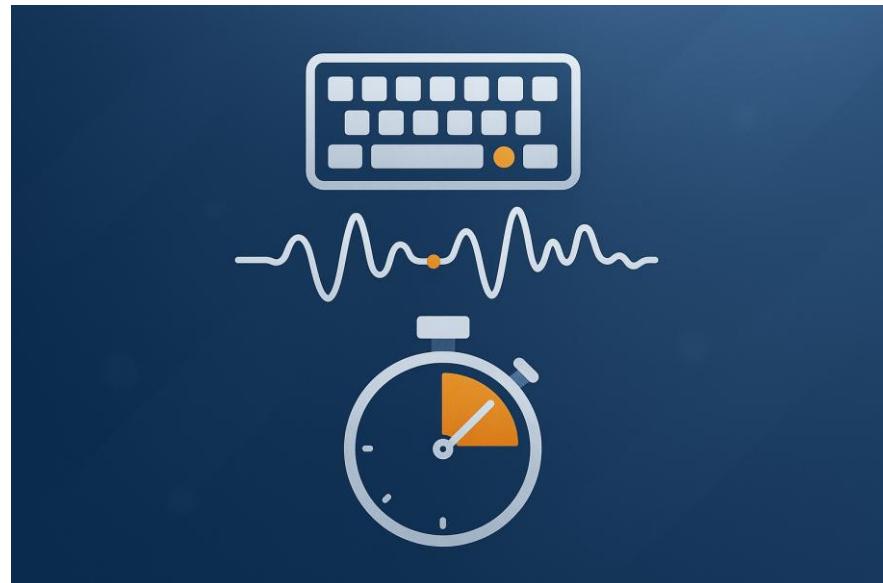
👁️ Keystroke Extraction

🏡 Trace Collection

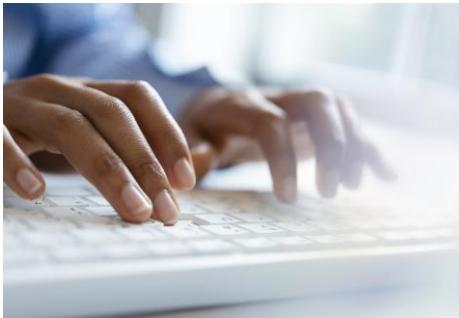
⚙️ Simulation Framework

📦 Input Reconstruction

📊 Results



Keystroke Timing Attack



Intervals: 74, 91, 108, 126, 143, 167, 182, 199, 214, 237, 255, 276, 289, 305, 328, 347, 362, 389, 421, 478

Keystroke Extraction

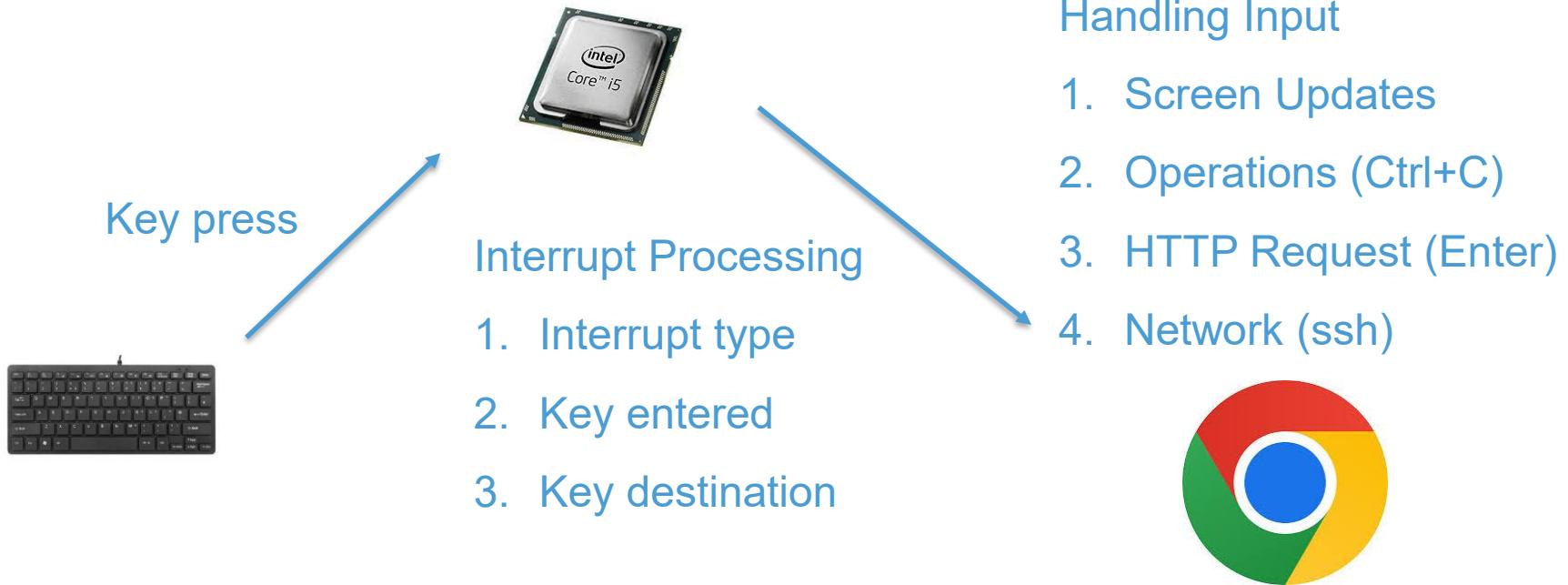
Lynn, got to the office OK.



Input Reconstruction



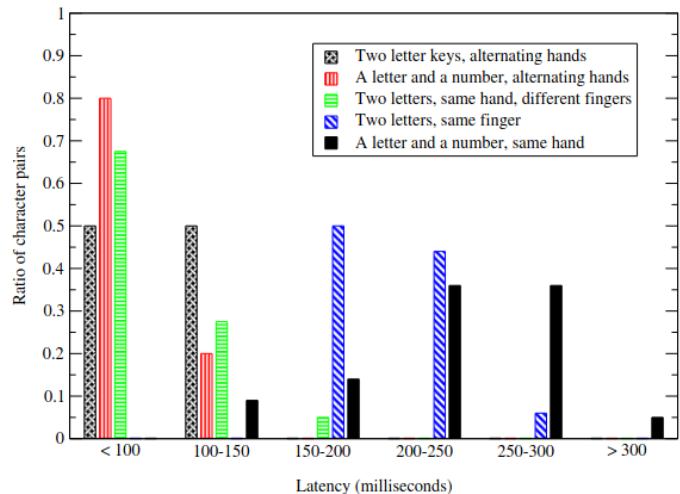
Keystroke Interrupt Handling



There are plenty of distinct executions unique to processing keystrokes

Why are these leaks dangerous?

Histogram of the latency of character pairs



Song, Dawn Xiaodong, David Wagner, and Xuqing Tian. "Timing analysis of keystrokes and timing attacks on {SSH}." 10th USENIX Security Symposium (USENIX Security 01). 2001.

Keystroke Extraction Techniques



SSH

Packet Arrival
SSH Keystroke
Routines



Network

Network Traffic
Encoding



Interrupts

Direct Monitor
Indirect Monitor



Cache

Flush+Reload
Prime+Probe

Keystroke Extraction with Cache Attacks

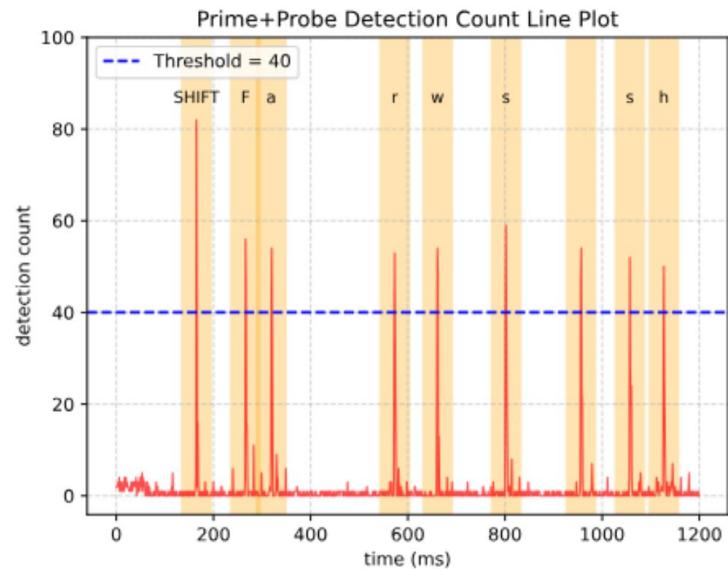
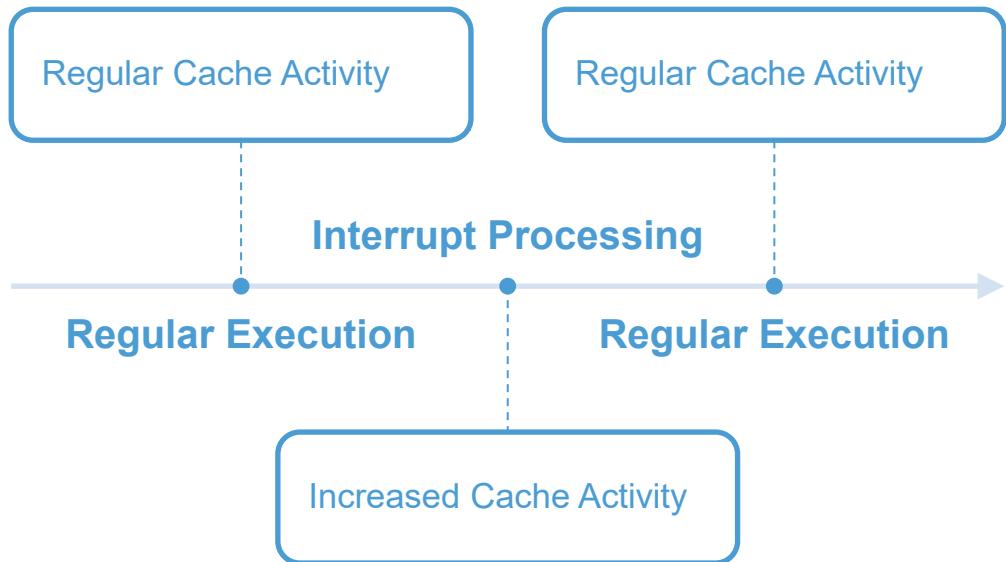
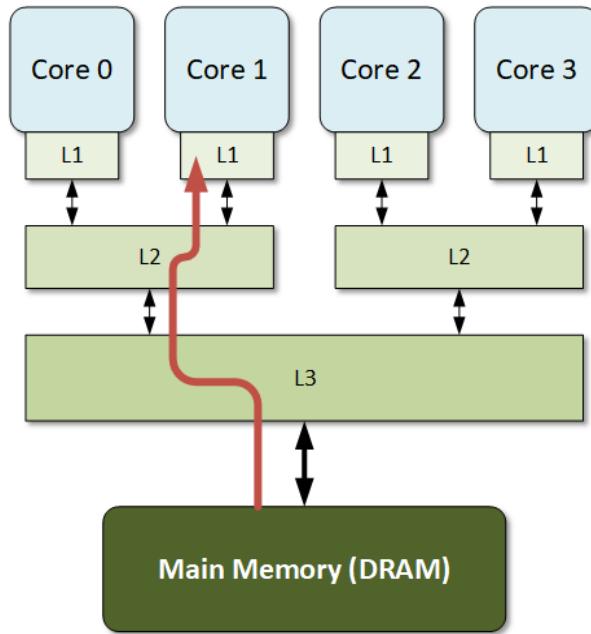
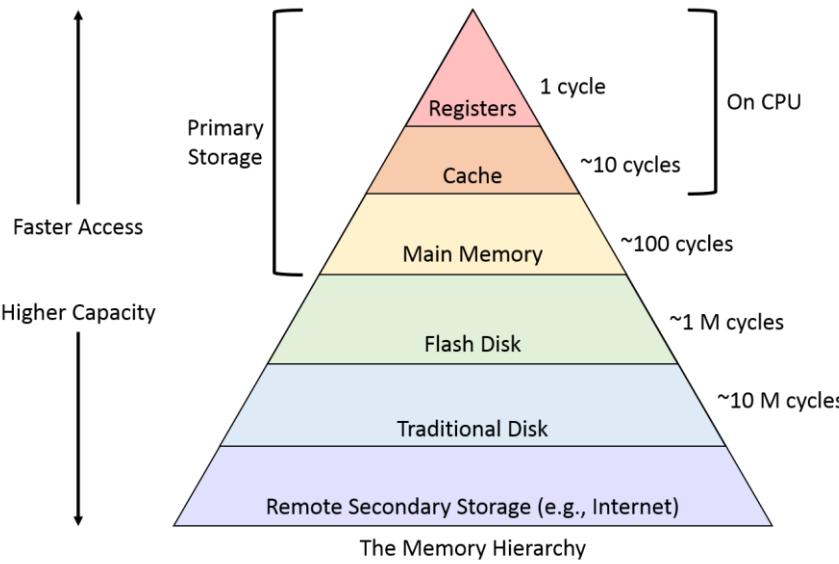


Figure 2. Keystroke Filtering from Aggregated Traces

Memory Hierarchy and The Cache



Flush / Evict + Reload Extraction



Keystroke Handling Function (KHF)

Flush(KHF)

Wait(10000);

Reload(KHF)



Type()

Cache

Flush / Evict + Reload Extraction

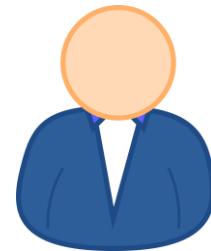


Keystroke Handling Function (KHF)

Flush(KHF)

Wait(10000);

Reload(KHF)



Type()

Cache

Flush / Evict + Reload Extraction

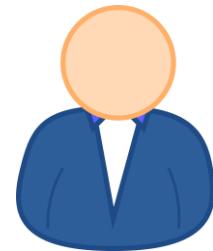


Keystroke Handling Function (KHF)

Flush(KHF)

Wait(10000);

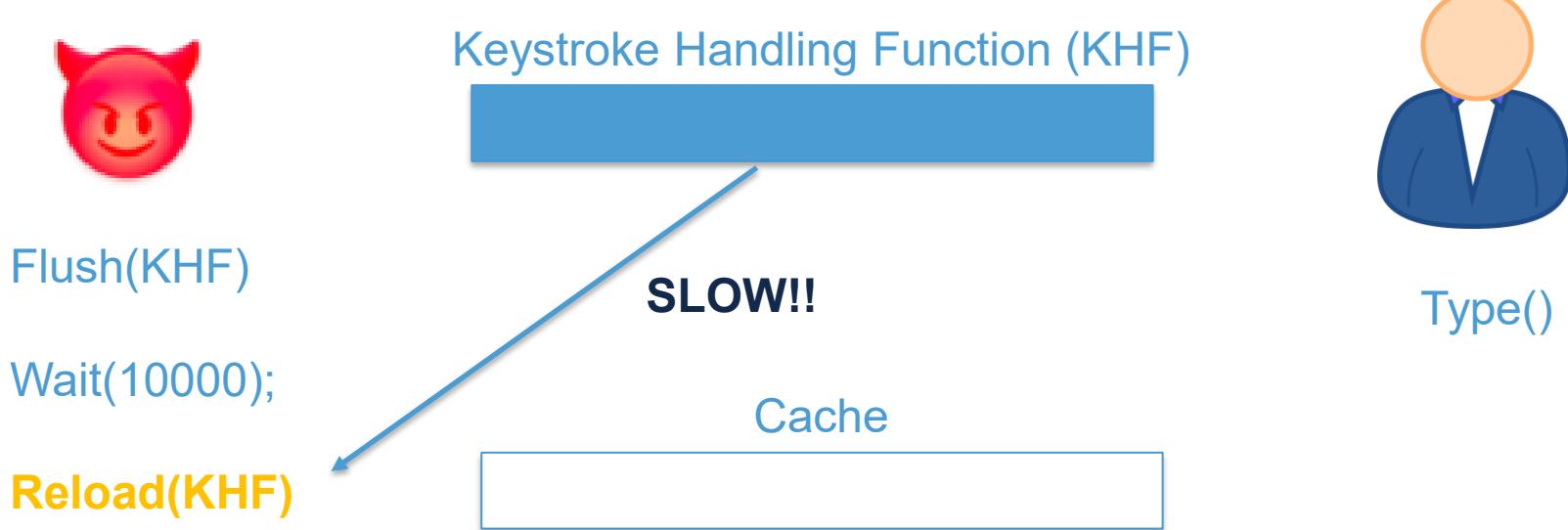
Reload(KHF)



Type()

Cache

Flush / Evict + Reload Extraction



Attacker infer that the victim did not type in the window.

Flush / Evict + Reload Extraction

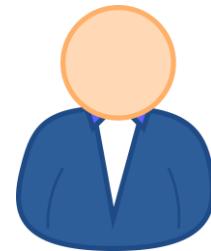


Keystroke Handling Function (KHF)

Flush(KHF)

Wait(10000);

Reload(KHF)



Type()

Cache

Flush / Evict + Reload Extraction

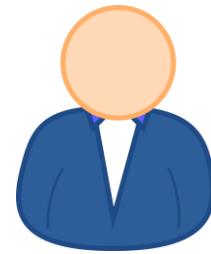


Keystroke Handling Function (KHF)

Flush(KHF)

Wait(10000);

Reload(KHF)



Type()

Cache

Flush / Evict + Reload Extraction



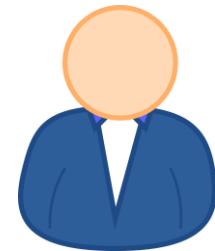
Keystroke Handling Function (KHF)

Flush(KHF)

Wait(10000);

Reload(KHF) ←

FAST!!



Type()

Cache

Attacker infer that the victim typed in the window.

Problems with Flush+Reload



Memory

Requires shared memory



Target

Requires knowledge and access



Speed

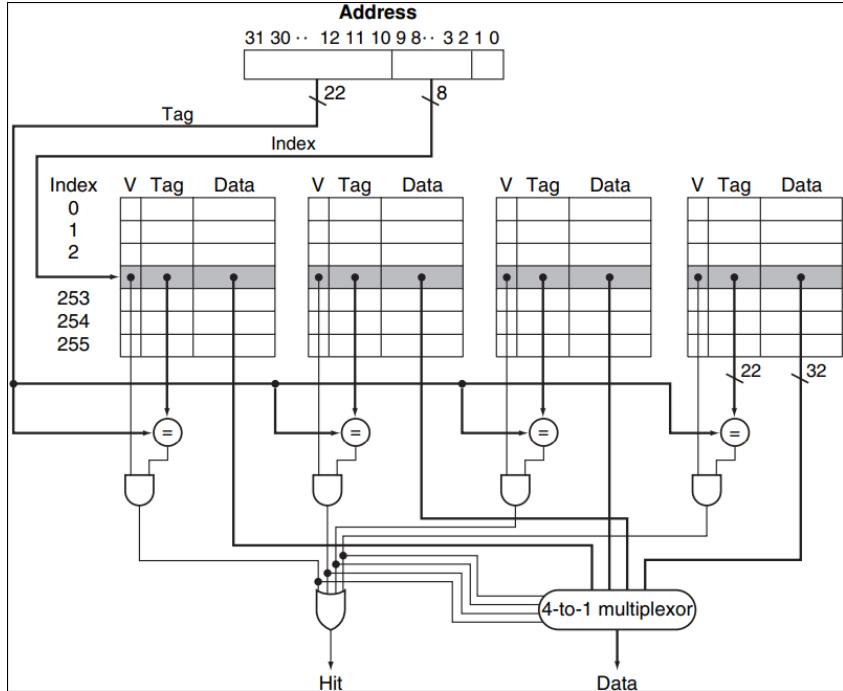
Slow execution and blind spots



Generality

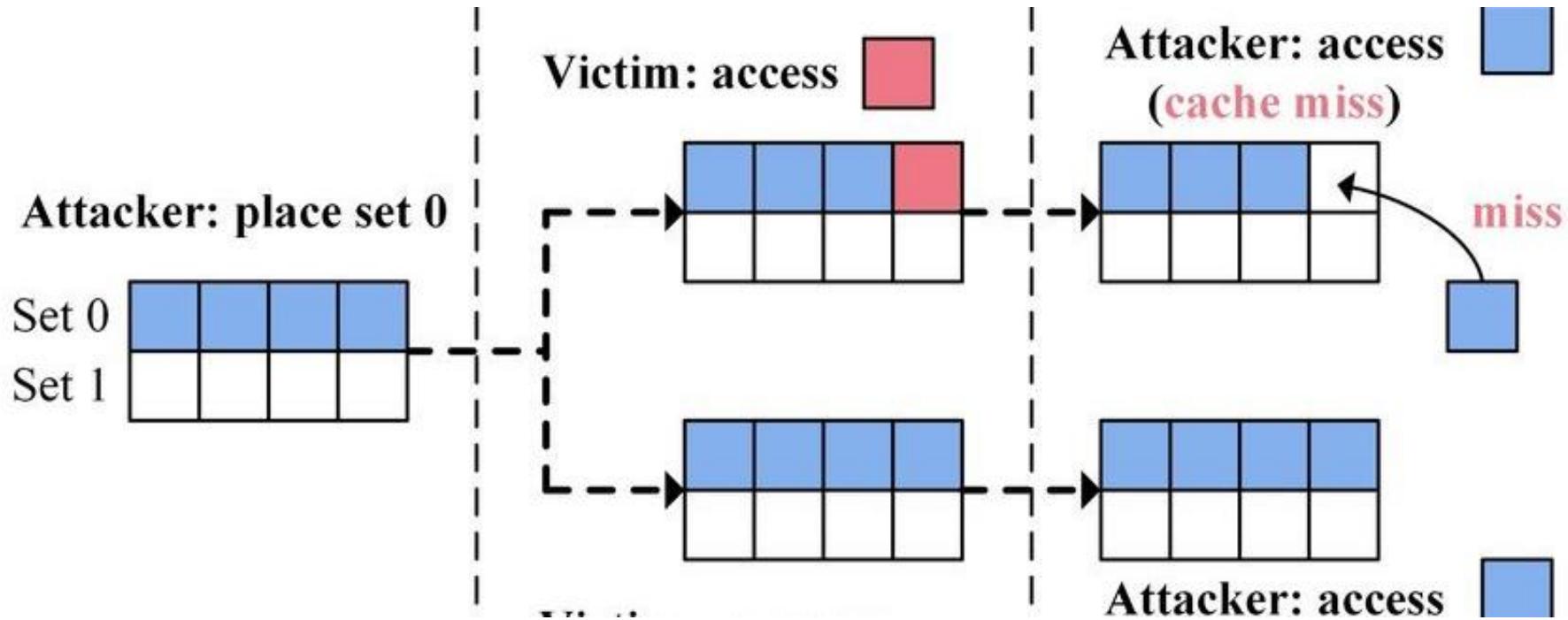
Unable to create a general exploit

Simplified Eviction Set Construction Example



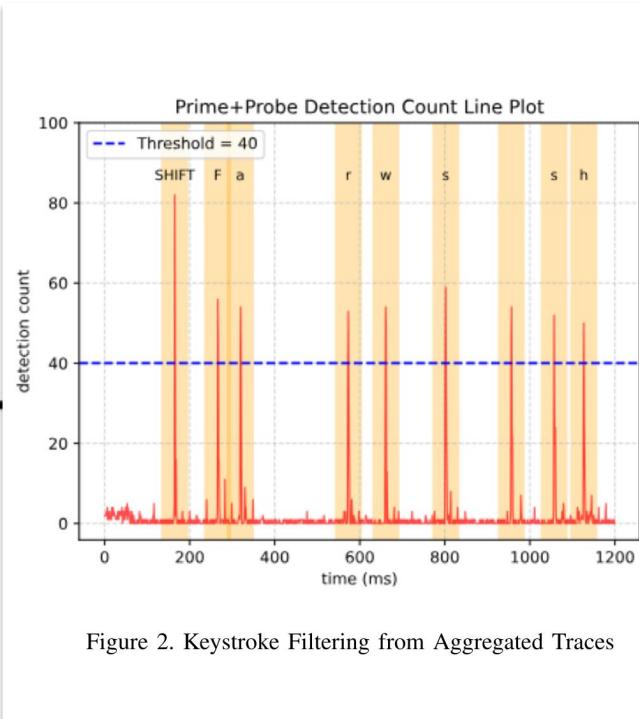
- 4-way set-associative cache
- 4-byte cache lines (2 bits)
- 256 sets (8 bits)
 - Usually computed by `CACHE_SZ / WAYS / LINE_SZ`
- Generate an eviction set with 4 lines with identical bits 2-9

Traditional Prime+Probe

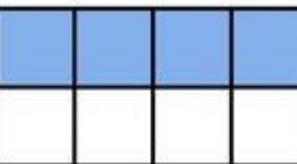
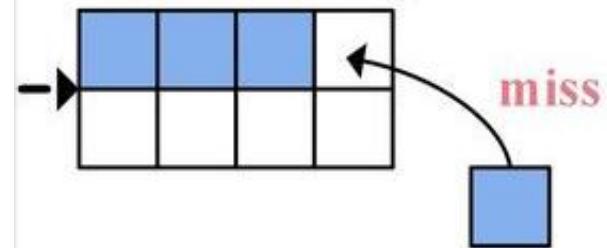


Windowless Prime+Probe

Attacker: place set 0



Attacker: access
(cache miss)



Attacker: access

Resolving Problems with Flush+Reload



Memory

Requires no shared memory



Target

Requires no knowledge or access



Speed

Fast execution and no blind spots



Generality

Monitor general activity of the cache

Threat Model

Native Extraction

- User-level attacker
- Execute arbitrary programs
- No software vulnerabilities

Web Extraction

- Server + Frontend Webpage
- Up-to-date browser with proper sandbox protection

Capability: Detect all keystrokes issued to the same device

Trace Collection



Dataset: Observations on Typing from 136 Million Keystrokes (Dhakal et. al. CHI 2018)



Simulate Keystroke Replays with IOCTL Interface



Trace Collection with Simultaneous Cache Attack

Simulation Framework

- **Generate side-channel traces for each typing sample**
- **Measuring Thread:**

Trace collection from interrupts

- **Simulating Thread:**

Replays typing samples

```
"test_id": "0-0-0",
"keystrokes": "[[SHIFT]", "t", "h", "e"],
"intervals_ms": [ 163, 254, 91, 143 ]
```

Figure: Example Simulation Input Data

Sequential Consistency (SC) Model

The result of any execution is the same as if the operations of all the processors were executed in some sequential order, and the operations of each individual processor appear in this sequence in the order specified by its program.

1. All instructions are executed in some order
2. Instructions within each program are executed in sequential order

Lamport, "How to Make a Multiprocessor Computer That Correctly Executes Multiprocess Programs," in IEEE Transactions on Computers, vol. C-28, no. 9, pp. 690-691, Sept. 1979, doi: 10.1109/TC.1979.1675439.

Sequential Consistency Execution Example

Process 1	$X = 0, Y = 0$	$X = 0, Y = 1$	$X = 1, Y = 0$	$X = 1, Y = 1$
A: $X = 1$	A: $X = 1$	A: $X = 1$	A: $X = 1$	A: $X = 1$
B: $Y = 1$	B: $Y = 1$	D: $X = 0$	D: $X = 0$	B: $Y = 1$
C: Print(Y)		D: $X = 0$	E: $Y = 0$	D: $X = 0$
			B: $Y = 1$	
Process 2	E: $Y = 0$	B: $Y = 1$	E: $Y = 0$	E: $Y = 0$
D: $X = 0$				
E: $Y = 0$	C: Print(X)	C: Print(X)	C: Print(X)	C: Print(X)
F: Print(X)	F: Print(Y)	F: Print(Y)	F: Print(Y)	F: Print(Y)

Synchronization with Sequential Consistency

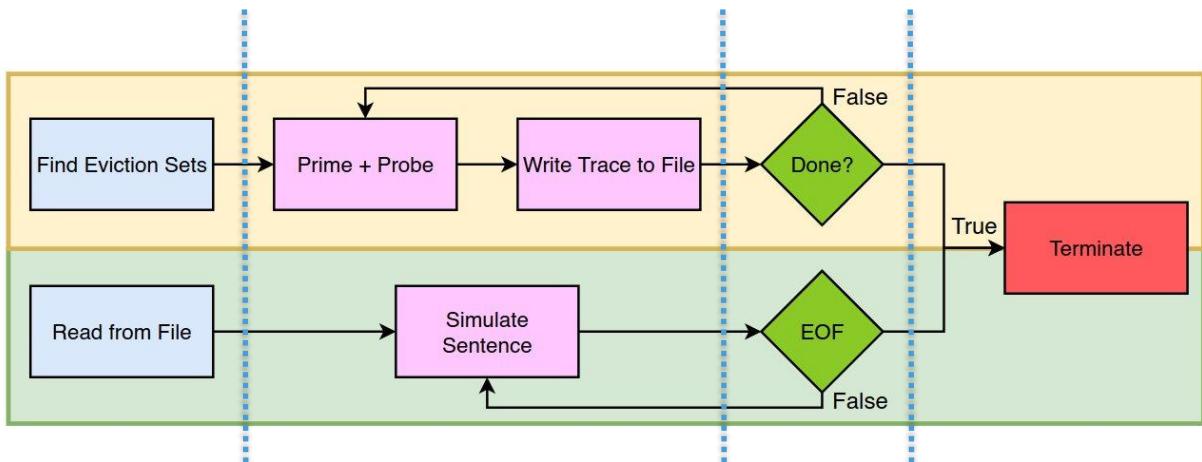


Figure 3. Simplified Keystroke Simulation System Workflow

- Concurrent attack and simulation
- Sync variables
 - EVSET_RDY
 - RD_FILE_DONE
 - IS_EOF
 - PP_RDY
- Shared Memory

Work in Progress: Attacking M2 on AVP



Cache flush
instructions



Low-level memory
interfaces



Fine-Grained Timer



Unique cache
architectures



Special optimizations
(LSDP/MDP, DMP,
LAP, LVP)



Remote Keylogging with Large Language Model

- Background: GPT Keylogger
 - What was your prompt? A Remote Keylogging Attack on AI Assistants (2024, USENIX)

rate tokens. For example, consider the text “*Oh no! I’m sorry to hear that. Try applying some cream.*” The tokenizer of GPT-3.5 and 4 would tokenize it as

Oh no! I’m sorry to hear that. Try applying some cream.
and the tokenizer of LLAMA-1 and 2 would tokenize it as

Oh no! I’m sorry to hear that. Try applying some cream.

LLM_B Training Prompt

Translate the Special Tokens to English, given the context.

Context: I need more details about your rash.

Special Tokens: _5 _3 _3 _1 _4 _5 _5 _3 _5 _5 _1

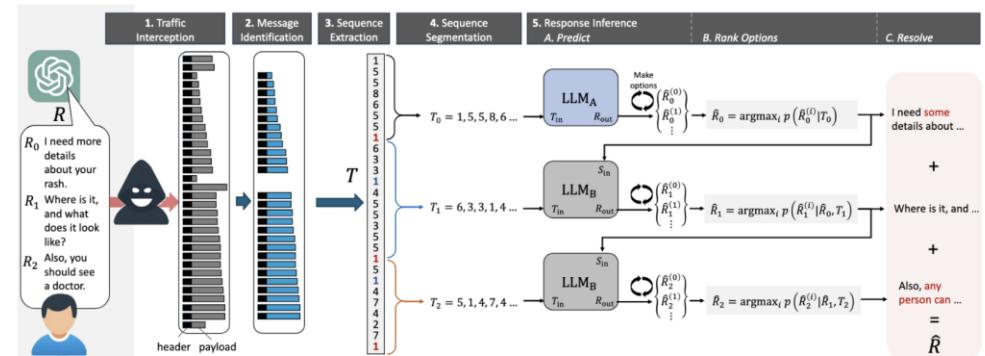


Figure 2: An overview of the attack framework: (1) Encrypted traffic is intercepted and then (2) the start of the response is identified. Then (3) the token-length sequence T is extracted and (4) a heuristic is used to partition T into ordered segments (T_0, T_1, \dots). Finally, (5) each segment is used to infer the text of the response. This is done by (A) using two specialized LLMs to predict each segment sequentially based on prior outputs, (B) generating multiple options for each segment and selecting the best (most confident) result, and (C) resolving the predicted response \hat{R} by concatenating the best segments together.

Reconstruction on Clean Time Intervals

- Dataset:
 - Observations on Typing from 136 Million Keystrokes
- Method:
 - Machine translation task
- Metrics:
 - Treat edit distance < 0.1 as successful reconstruction
 - Dataset split
 - Within/Across Participants
 - Within/Across Sentences

Model	Top-1 Recon. Acc. \uparrow	Top-5 Recon. Acc. \uparrow
KREEP [25]	0.10%	0.20%
T5 (Ours) [50]	16.84%	33.53%
OLMo 1B (Ours)	21.09%	34.92%

LLM_A Training Prompt

User: Translate the Time intervals to Keystrokes.
Time intervals: 516 222 165 294 141 159 144 162 75 123
81 639 105 87 774 84 90 183 498 111 102 93 399 78 645
144 459
Assistant: Lynn, got to the office OK.

Representative Reconstruction Examples

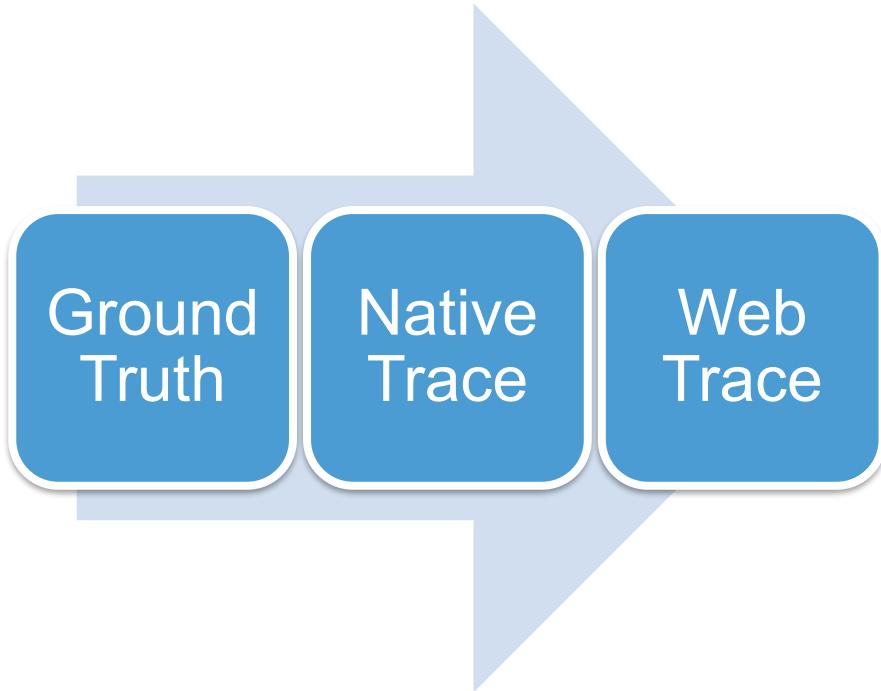
Edit distance ≈ 0.06
Input: Hope that all is well in Denver.
Prediction: Hope that all is well in Denver

Edit distance ≈ 0.07
Input: Crestone won't have final measurement until this week.
Prediction: crestone won't have final measurement until next week.

Edit distance ≈ 0.08
Input: Taka has to be completed.
Prediction: Task has to be completed.

Edit distance ≈ 0.17
Input: Let Gary Smith know if you want him.
Prediction: Let Gary Smith know today if you want him.

Reconstruction with Curriculum Learning



- Curriculum Learning: ML with tasks of increasing difficulty
- Noise determines the difficulty of input reconstruction

Reconstruction on Cache Time Intervals

- Dataset:
 - Observations on Typing from 136 Million Keystrokes
 - **Replayed and extract time intervals from cache**
- Method:
 - Modeling as machine translation task
 - **Curriculum Learning**
- Metrics:
 - Treat edit distance < 0.1 as successful reconstruction
 - Dataset split
 - Within/Across Participants
 - Within/Across Sentences

TABLE 3. ABLATION STUDY: TOP-5 RECONSTRUCTION ACCURACY (%) ON CACHE-EXTRACTED DATA

Training Strategy	APAS	APWS	WPAS	WPWS
Ground Truth Only	11.40%	25.05%	11.01%	25.39%
Cache Only	3.71%	19.41%	4.35%	19.14%
Curriculum Learning (Ours)	16.94%	42.92%	20.21%	41.89%

TABLE 2. RECONSTRUCTION PERFORMANCE OF THE CURRICULUM LEARNING MODEL ON CACHE-EXTRACTED TIME INTERVALS

Setting	Top-1 Recon. Acc. \uparrow	Top-5 Recon. Acc. \uparrow	Top-1 Mean Edit Dist. \downarrow	Top-5 Mean Edit Dist. \downarrow
APAS	8.84%	16.94%	0.7635	0.6251
APWS	26.78%	42.92%	0.6070	0.4294
WPAS	9.25%	20.21%	0.7437	0.5928
WPWS	27.15%	41.89%	0.6077	0.4382

Extend to Vision Pro Input Traces

- Challenge:
 - Dataset is much smaller
 - Distribution shift

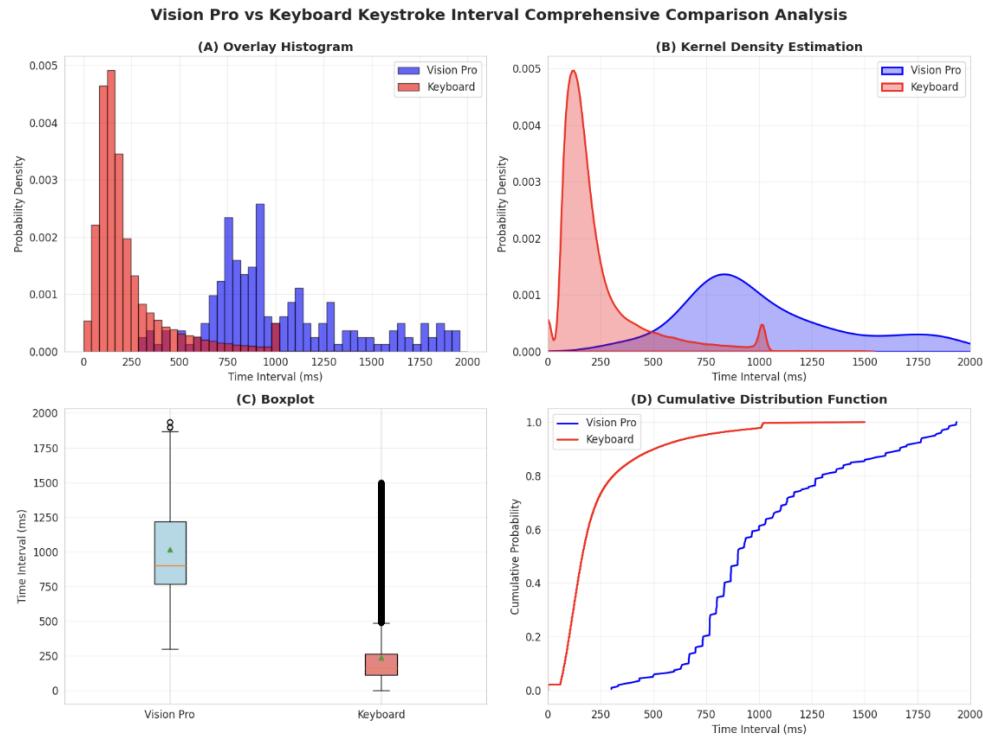
Vision Pro keystroke interval data points: 229
Keyboard keystroke interval data points: 479107

Vision Pro statistics:

Mean: 1227.63 ms
Median: 965.00 ms
Std Dev: 687.39 ms
Min: 301.00 ms
Max: 5205.00 ms

Keyboard statistics:

Mean: 235.24 ms
Median: 162.00 ms
Std Dev: 211.77 ms
Min: 0.00 ms
Max: 1500.00 ms



Extend to Vision Pro Input Traces

- Reasoning with question:
 - Step 1: Hard Constraint – Keystroke Counting
 - Step 2:
 - Soft Constraint – Rhythm and Timing Analysis
 - Work Boundaries (Pauses)
 - Complexity & Speed
 - Step 3: Final Selection

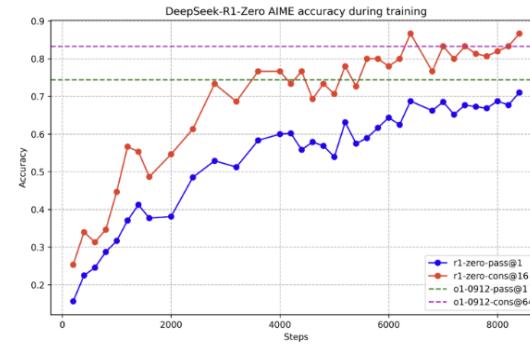


Figure 2 | AIME accuracy of DeepSeek-R1-Zero during training. For each question, we sample 16 responses and calculate the overall average accuracy to ensure a stable evaluation.

Step 2: Soft Constraint – Rhythm and Timing Analysis

1. Word Boundaries (Pauses):

- Typists often pause slightly longer between words (before hitting Space) or at the start of a new word.
- Look at the sequence of intervals. Are there distinct "spikes" or larger values (e.g., > 200–300ms)?
- Count the number of significant pauses. Does this count roughly match the number of words (spaces) in the option?

2. Complexity & Speed:

- Short intervals (e.g., < 100ms) often correspond to easy bigrams (e.g., 'th', 'er', 'in') or alternating hands.
- Long intervals might correspond to Shift key presses, difficult reaches, or punctuation.
- Does the "texture" of the intervals match the complexity of the sentence? (e.g., a simple sentence should have smooth intervals; a complex one with symbols should be choppier).

Extend to Vision Pro Input Traces

- Baseline: 1B LLM Model Finetuned on 1.3M time interval and sentence pairs
- Performance: 22% Top-1 reconstruction success rate on clean time interval and sentence pairs
- Experiment:
 - Synthesis 3000 output templates and retrain the baseline model with mixed outputs to preserve the language ability and enable the reasoning ability
 - 0.2M template outputs:
 - "<think> </think> Based on the inter-keystroke timings, the user appears to be typing <answer>...</answer>"
 - "<think> </think> These keystroke intervals likely correspond to the input <answer>...</answer>"
 - 10K Reasoning outputs generated by DeepSeek R1:
 - "<think> Follow step 1, I should...</think> User inputs <answer>...</answer>"
 - Performance: 24% successful reconstruction rate and model learns to follow the format
- Future Steps: reinforcement learning.

KEYTAR2.0 : APPLE VISION PRO

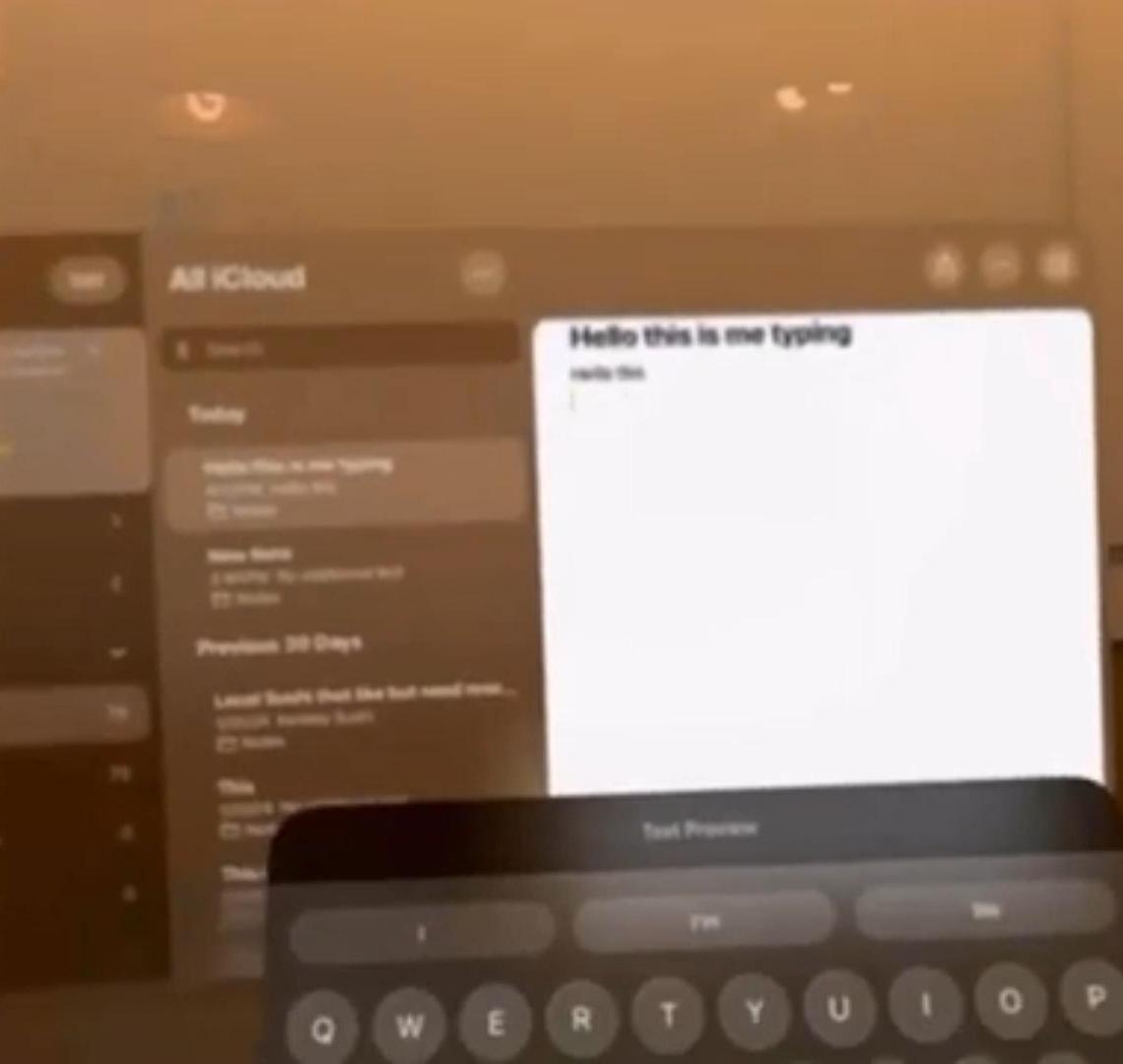
Background: Apple Vision Pro



Productivity

A workspace with infinite space.





Extending to Apple Vision Pro: Pinch Typing



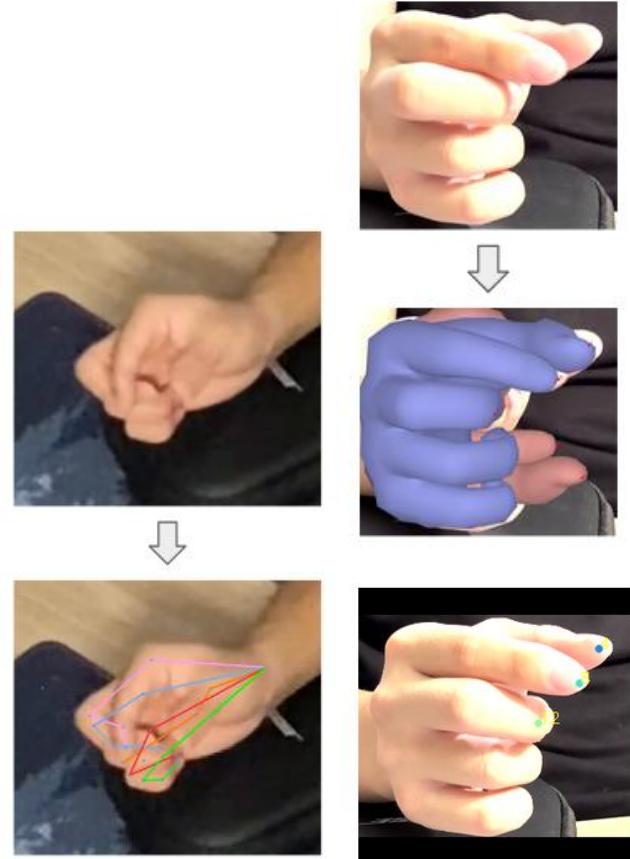
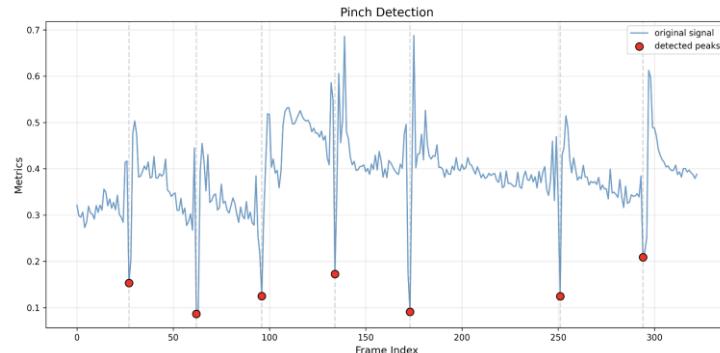
No existing traces available

Replay framework does not exist

Goal: Generate a similar dataset
for typing on the Apple Vision Pro

Background: Pose Estimation

- Pose estimation task is a well-established field with strong models
- Models can track each finger and map them onto a 3D Cartesian plane



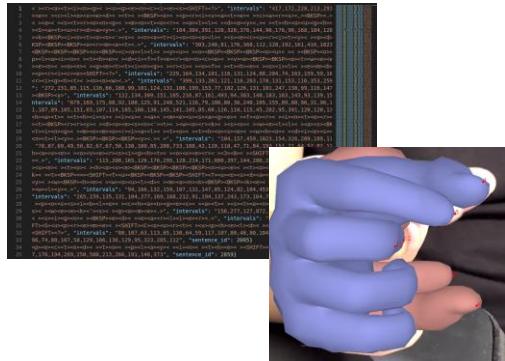
Motivation

- Head-mounted devices (i.e. Apple Vision Pro) have been growing in popularity for productive use
- Preliminary studies show significant difference in regular and AVP keystroke timings due to its unique input method
- Preliminary studies show strong results in detecting typing gesture

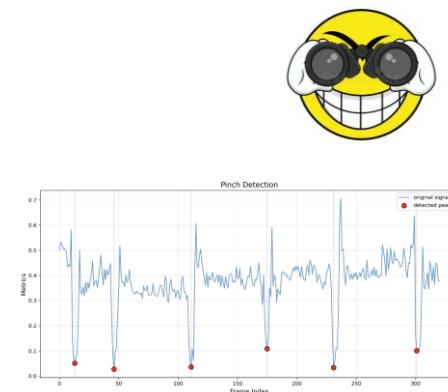
KEYTAR2.0 : APPLE VISION PRO

KeyTAR2.0 Workflow

Dataset Creation/ Model Training



Attack via P-P/Vision or Keystroke Timings



Typed Content Inference with LLM

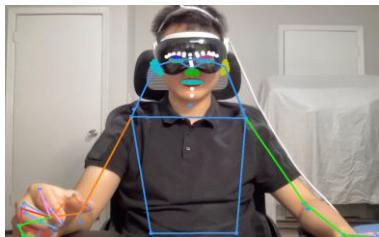
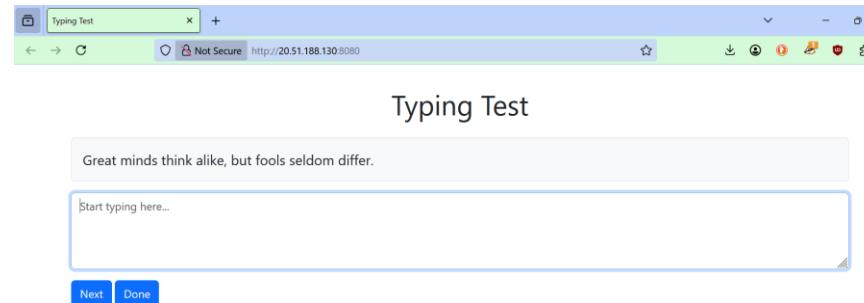
LLM_A Training Prompt

User: Translate the Time intervals to Keystrokes.
Time intervals: 516 222 165 294 141 159 144 162 75 123
81 639 105 87 774 84 90 183 498 111 102 93 399 78 645
144 459
Assistant: Lynn, got to the office OK.

KEYTAR2.0: APPLE VISION PRO

Methodology: Collection

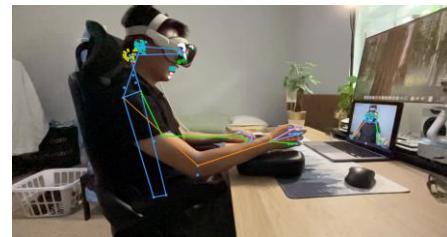
- 4 Perspectives
- Typing test on website
- Changed prompts to lowercase, no special characters
- Simultaneously run prime+probe to collect noisy traces



Front



Hand



Side



Top

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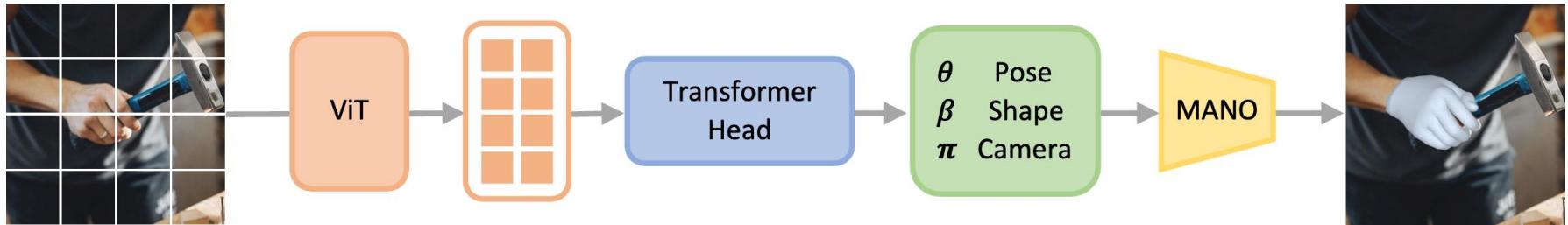
KEYTAR2.0: APPLE VISION PRO

Methodology: Collection

- 4 * BU505MCF
 - 2,448 x 2,048, 75fps, USB3.1
- Sync four perspective through integrated controller (< 1ms)
- Sync videos with ground truth by server time request (< 30ms)



Methodology: Pinch Detection



1. Pose estimation model is used to locate and crop out the hand region
2. Use a ViT backbone to extract the visual feature from the hand image
3. Transformer-based decoder is applied to predict the parameters
4. The model is trained on a mixture of multiple datasets

KEYTAR2.0: APPLE VISION PRO

Methodology: Pinch Detection

	170001	i_am_a_student	it_is_a_good_day	panzer	uzumymw
GT	6	14	16	6	7
front	6	14	16	6	7
hand	6	14	16	6	7
side	6	7	12	4	5
top	6	14	16	6	7

- The detection pipeline could accurately capture all the pinches in all the angles
- Except the very challenging side view, where the thumb is usually invisible

KEYTAR2.0: APPLE VISION PRO

Methodology: Data Collection

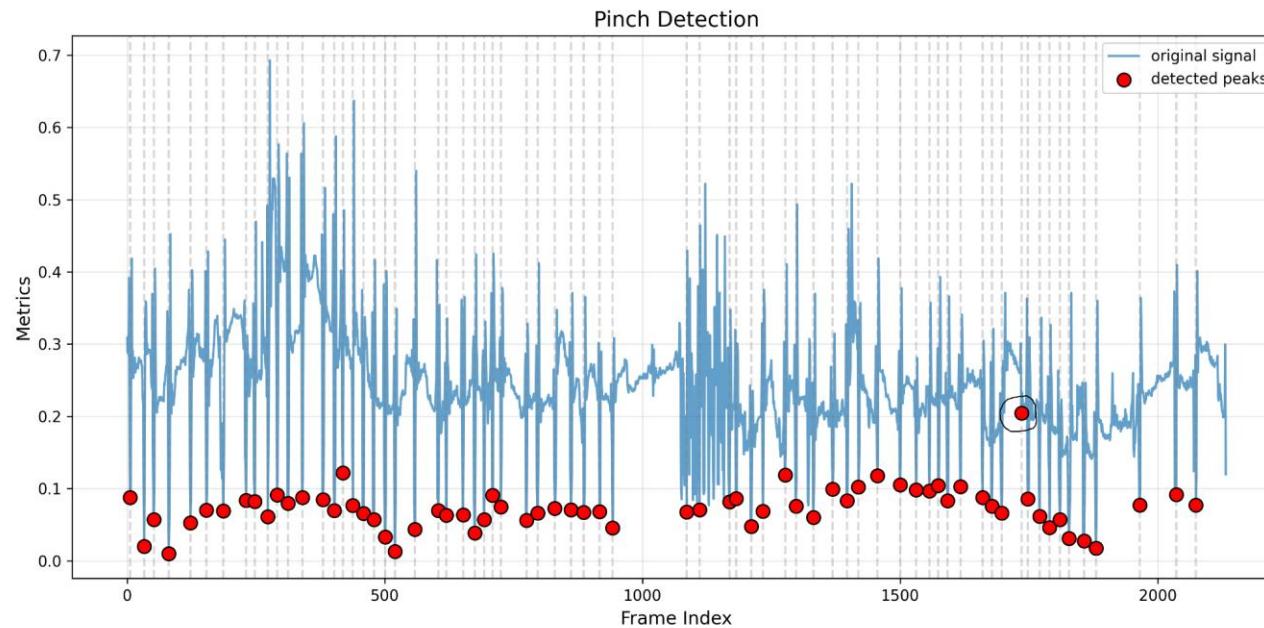
We first work on long sentences, but this poses challenges:

- High incorrect typing rate due to the inaccurate eye tracking
- Mismatch between actual pinches and collected ground truth pinches



```
predicted time interval:1480.3987816307406, gt time interval:1000  
predicted time interval:1760.4742268041236, gt time interval:366  
predicted time interval:1240.334114339269, gt time interval:1534  
predicted time interval:1040.2802249297094, gt time interval:938  
predicted time interval:680.1832239925023, gt time interval:1062  
predicted time interval:720.1940018744143, gt time interval:1433  
predicted time interval:1000.2694470477976, gt time interval:1767  
predicted time interval:1720.4634489222117, gt time interval:1599  
predicted time interval:720.1940018744143, gt time interval:668  
predicted time interval:760.2047797563263, gt time interval:735  
predicted time interval:1560.420337394564, gt time interval:698  
predicted time interval:480.1293345829428, gt time interval:1000  
predicted time interval:920.2478912839738, gt time interval:1700  
predicted time interval:760.2047797563263, gt time interval:733  
predicted time interval:800.215557638238, gt time interval:767  
predicted time interval:720.1940018744143, gt time interval:2065.000000000233  
predicted time interval:1160.312558575445, gt time interval:867.9999999997672  
predicted time interval:920.2478912839738, gt time interval:766  
predicted time interval:3400.9161199625114, gt time interval:801  
predicted time interval:2840.7652296157453, gt time interval:733  
predicted time interval:1520.4095595126525, gt time interval:2066  
未检测出pinch time如下:[1613755]  
detect 69 peaks, index: [ 6 33 52 81 123 154 187 231 248 273 291 312 340 380  
402 419 438 459 479 501 520 558 604 619 652 675 693 709  
725 775 797 830 861 886 917 942 1086 1111 1169 1182 1211 1234  
1277 1298 1332 1369 1397 1419 1456 1500 1531 1557 1574 1592 1617 1660  
1678 1697 1736 1748 1771 1790 1810 1828 1857 1880 1965 2036 2074]
```

Methodology: Data Collection



KEYTAR2.0: APPLE VISION PRO

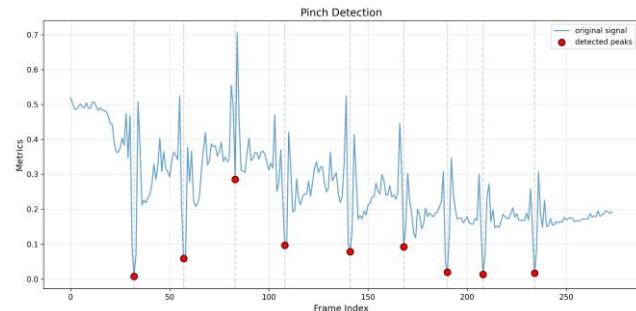
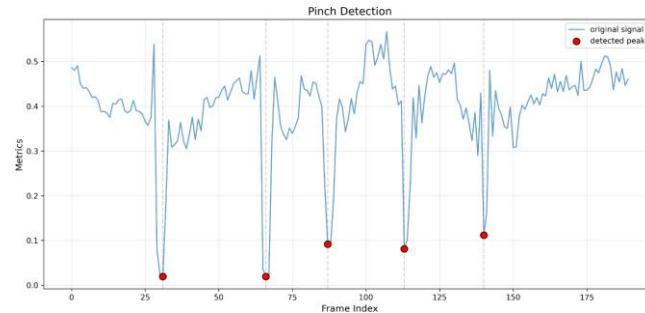
Methodology: Data Collection

If we use simpler sentences and only considers keystrokes that can be captured on the Vision Pro keyboard

- Our method is pretty accurate in the time interval

```
/root/autodl-tmp/VR/data_new/IMG_7656.mp4
6378
predicted time interval:1168.7434554973822, gt time interval:1200
predicted time interval:701.2460732984293, gt time interval:698.999999999709
predicted time interval:868.2094240837697, gt time interval:866
predicted time interval:901.6020942408378, gt time interval:867
detect 5 peaks, index: [ 31 66 87 113 140]
```

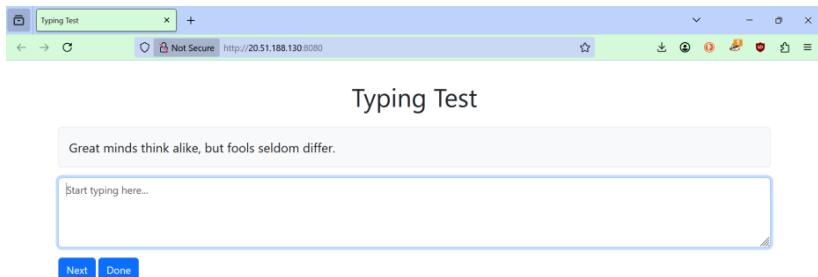
```
/root/autodl-tmp/VR/data_new/IMG_7655.mp4
9172
predicted time interval:833.81818181819, gt time interval:835.000000000291
predicted time interval:867.170909090909, gt time interval:835.999999999709
predicted time interval:833.81818181819, gt time interval:864
predicted time interval:1100.639999999999, gt time interval:1100
predicted time interval:900.52363636363, gt time interval:900
predicted time interval:733.76, gt time interval:734.000000000291
predicted time interval:600.3490909090909, gt time interval:629.999999999709
predicted time interval:867.170909090909, gt time interval:834.000000000291
detect 9 peaks, index: [ 32 57 83 108 141 168 190 208 234]
```



KEYTAR2.0: APPLE VISION PRO

Full Scale Data Collection

- ~15 Min
- Typing test on Apple Vision Pro
- Experienced vs Unexperienced typists
- Chance to play around and experience new tech!
- 2 Class bonus points!!!



Help us out!



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