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DF-SCA: Dynamic Frequency Side Channel Attacks are Practical

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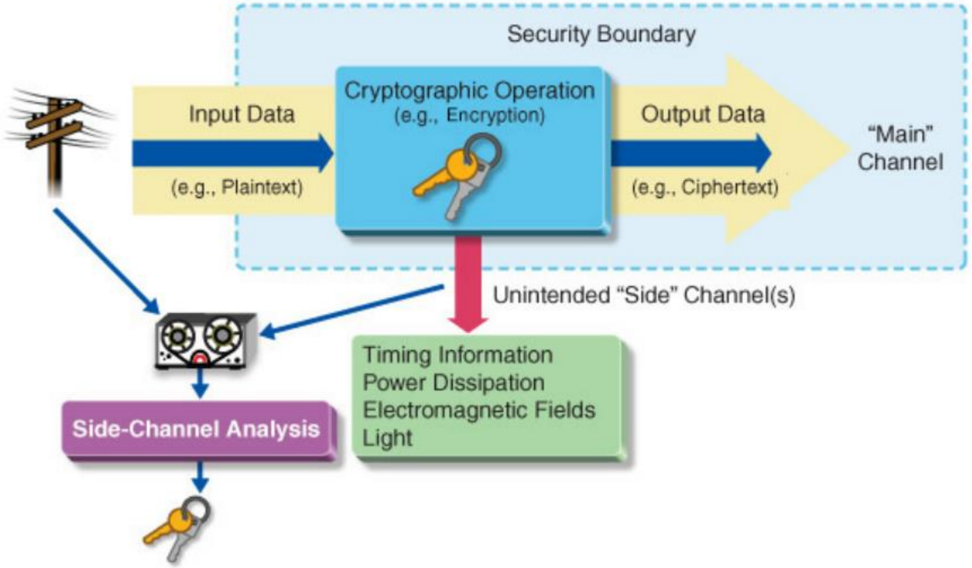
What is Side Channel Attack?

- Side-channel attacks use unintentional information leakage from secure chips to compromise their security

- **Compromising security:**
  - ✓ Cryptographic key recovery
  - ✓ Website fingerprinting
  - ✓ Keystroke detection

- These unintentional information can be of different types:
  - ✓ Timing information
  - ✓ Power dissipation
  - ✓ Electromagnetic fields
  - ✓ **Micro-architectural information**



Ref: Gamaarachchi, H. and Ganegoda, H., 2018. Power analysis-based side channel attack. *arXiv preprint arXiv:1801.00932*.

❑ Micro-architectural side-channel attacks refer to a side-channel attack that exploit information leakage from the hardware infrastructure itself

DF-SCA: Dynamic Frequency Side Channel

- Software-based dynamic frequency side-channel attack
- Applicable on Linux and Android OS devices
- Exploit unprivileged access to *cpufreq* interface

- Exploited in the context of covert channels and cryptographic attacks
- However, <u>it has not been investigated to infer user activity, e.g.,</u>
    - ➢ <u>Website fingerprinting</u>
    - ➢ <u>Keystroke detection</u>

CHALLENGE!

✓ **Noisy measurements**

✓ **Low resolution**

❑ Still dynamic frequency readings through Linux *cpufreq* interface provide sufficiently-detailed information on the user activity on Intel, AMD, and ARM architectures.

Dynamic Voltage and Frequency Scaling (DVFS)

- Allow switching between different frequency/voltage configurations based on the dynamic CPU resource demand.
- The rapid frequency changes are adjusted through different algorithms depending on the target application

CPUFreq Subsystem:

- Responsible for the performance scaling of the CPU in a Linux kernel-based operating system
- Comprises of three layers of code:
  - ✓ **Core:** Defines the layout of basic framework
  - ✓ **Scaling governor:** Defines different frequency scaling algorithms to predict the CPU latency
  - ✓ **Scaling driver:** Access a specific hardware interface to change the P-state based on the request set forth by the scaling governors

Dynamic Voltage and Frequency Scaling (DVFS)

PolicyX Interface:

- *CPUFreq* core generates a *sysfs* directory named *cpufreq*, under $/sys/devices/system/cpu$ path
- Within this directory a policyX sub-directory exists for all of the CPUs associated with the given policy
- policyX directories include policy-specific files to control *CPUFreq* behavior based on the corresponding policy objects.
- *CPUFreq* core generates several attributes dependent on the scaling governors and drivers, such as:

✓ *scaling_cur_freq*

✓ *scaling_min_freq*

✓ *scaling_max_freq*

✓ *scaling_available_governors*

✓ *scaling_governor*

✓ *scaling_driver*

Dynamic Voltage and Frequency Scaling (DVFS)

Scaling governor:

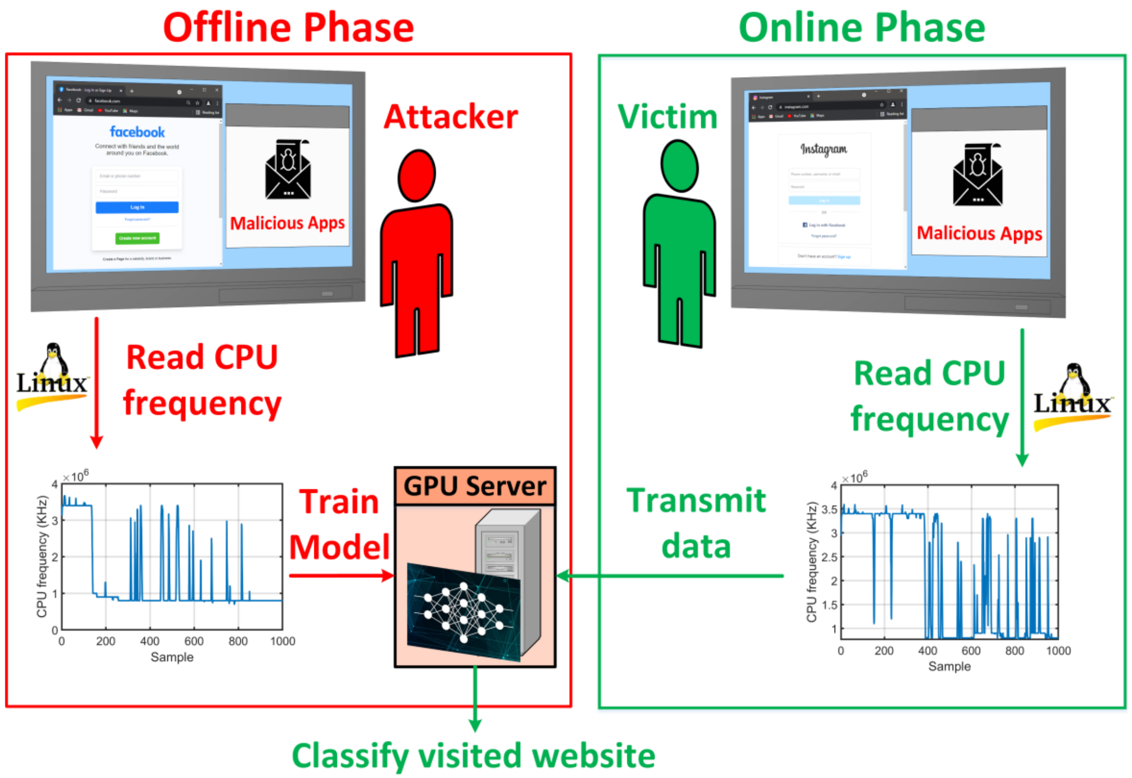
- ***Performance*** governor keeps the CPU around the highest frequency, within the *scaling_max_freq* policy limit
- ***Powersave*** governor keeps the core frequency low when there is no workload still within the *scaling_min_freq* policy limit.
- ***Userspace*** governor allows userspace application to set the CPU frequency for the associated policy
- ***Ondemand*** governor uses CPU load to determine the CPU frequency selection metric
- ***Conservative*** governor sets the CPU frequency selection metric based on the CPU load.
- ***Interactive*** governor is designed for latency-sensitive, interactive workloads
- ***Schedutil*** governor was designed to estimate the load based on the scheduler's Per-Entity Load Tracking (PELT) mechanism.

Scaling driver:

- Intel Core CPUs on Linux → Intel P-state driver
- AMD architecture → ACPI P-state driver
- Android systems → specialized frequency scaling driver called *msm*

Threat Model

- **Offline Phase:**
  - ✓ Attacker monitors the dynamic CPU frequency in his own system while rendering different websites.
  - ✓ A multi-class classification model is trained with the collected frequency measurements.
- **Online Phase:**
  - ✓ Attacker places a malicious code in a user-space application installed by the victim in his/her device
  - ✓ Monitor the current frequency in the victim's system.
  - ✓ Implement a cross-core side-channel attack through the current frequency readings
  - ✓ Attacker collects a single trace during the website rendering
  - ✓ Forward to the attacker's server in which the pre-trained model is located
  - ✓ Finally, the model is queried in the attacker server to classify the visited website



Assumptions:

- ❑ Victim's device is only running a particular browser instead of many applications at a time
- ❑ System Configuration (Attacker and Victim) needs to be matched.

Experimental Setup

Intel Comet Lake

- CPU Model: Intel(R) Core (TM) i7-10610U CPU @1.80GHz
- Scaling Governors: powersave (default), performance
- Linux kernel version: 5.11.0-46-generic

Intel Tiger Lake:

- CPU Model: Intel(R) Core (TM) i7-1165G7 @ 2.80GHz
- Scaling Governors: powersave (default), performance
- Linux kernel version: 5.13.0-44-generic

Attribute	Micro-architecture			
	Intel Comet Lake	**Intel Tiger Lake**	**AMD Ryzen 5**	**ARM Cortex- A73**
base_freq	1.8 GHz	2.8 GHz	1.7 GHz	N/A
max_freq	4.9 GHz	4.7 GHz	4.06 GHz	2.36 GHz
min_freq	0.4 GHz	0.4 GHz	1.4 GHz	0.8 GHz
scaling_driv	intel_pstate	intel_pstate	acpi-cpufreq	msm
scaling_gov	powersave	powersave	ondemand	interactive
turbo_boost	✓	✓	✓	N/A

AMD Ryzen 5:

- CPU Model: AMD Ryzen 5 5500U CPU with Radeon Graphic
- Scaling Governors: ondemand (default), powersave, performance, conservative, userspace, schedutil
- Linux kernel version: 5.13.0-44-generic

ARM Cortex-A73:

- CPU Model: Four ARM Cortex-A53 and Four ARM Cortex-A73 cores
- Scaling Governors: interactive (default), powersave, performance, ondemand, conservative, userspace

Website Detection: Data Collection

Algorithm 1: Data Collection Algorithm for Each Website

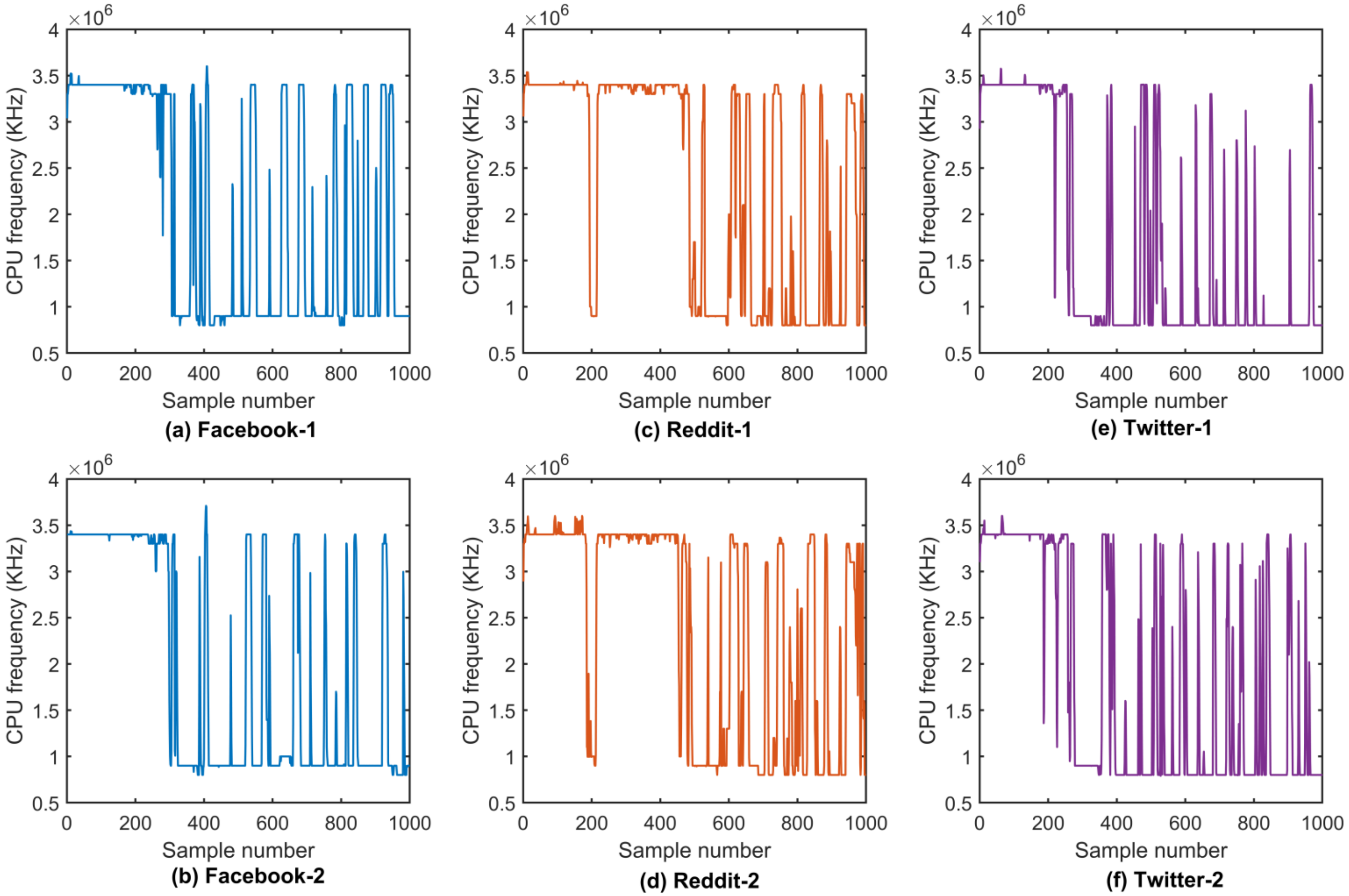
```
// T_i is the interval between each readings
// N_s is the number of samples
// N_M is the number of measurements per website
// url is the web-page address
// f is the CPU frequency
Input: T_i, N_s, N_M, url
Output: f
for i ← 1 to N_M do
    Run url in the browser ;
    for j ← 1 to N_s do
        f[i, j] ← Read scaling_cur_freq ;
        sleep T_i ;
    Close the browser ;
    sleep 1s ;
```

Reading CPU frequency:
$/sys/devices/system/cpu/cpu1/cpufreq/scaling\_cur\_freq$

Selected parameters in the Algorithm:

- $T_i = 10\ ms$
- Google-chrome: $N_s = 1000$
- Tor browser: $N_s = 3000$
- $N_M = 100$

Website Detection: Data Collection



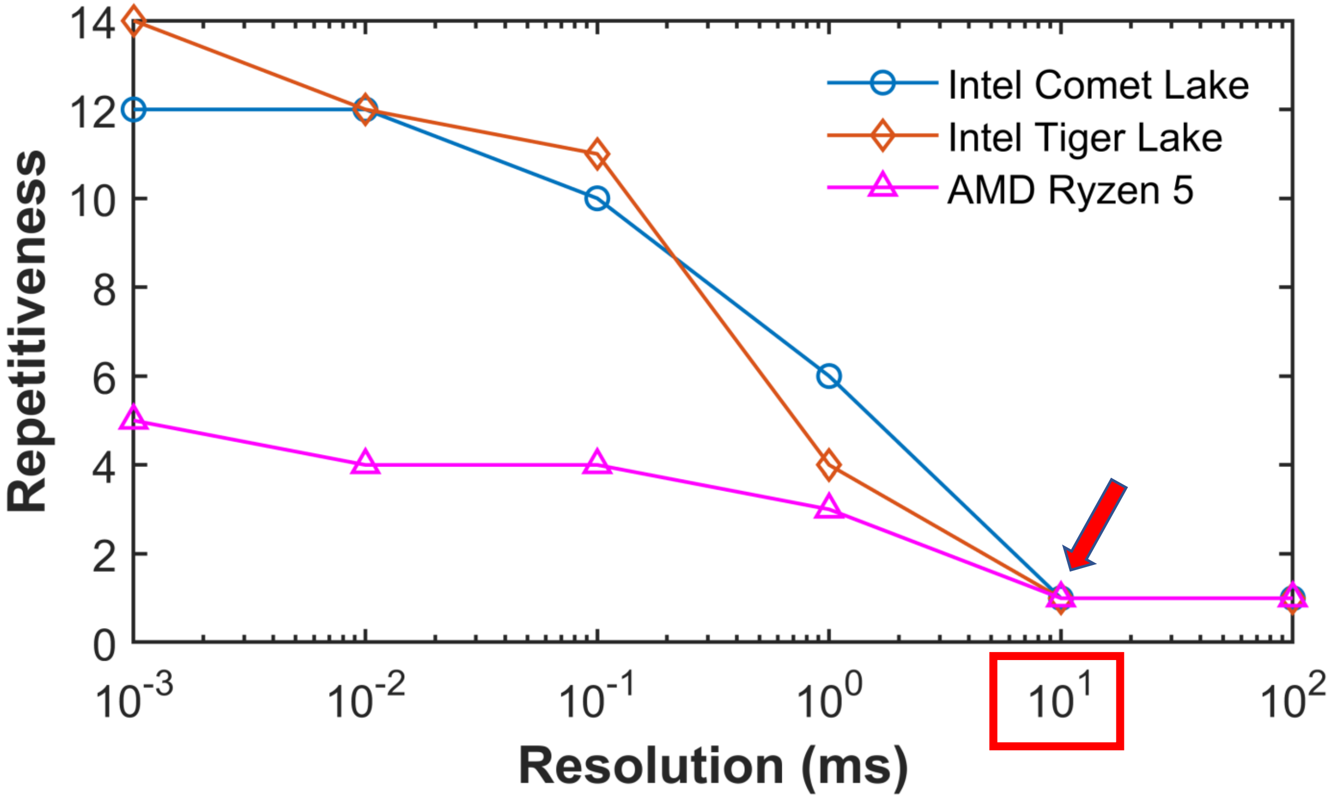
- Each website has a distinct pattern as the contents of these websites include different JS scripts, images, HTML documents, and plug-in objects.
- CPU workload generates a unique fingerprint on the frequency readings for individual website.

A common pattern exists while visiting the same websites for multiple measurements

Website Detection: Data Collection

cpufreq Resolution:

- Higher resolution enables attackers to capture a more detailed fingerprint
- We observe that the number of repeated values increases with the decreasing amount of delay between each reading
- The optimal delay is **10 ms** for Intel and AMD architectures
- The speed of querying the *cpufreq* interface on Android devices is different than Intel and AMD architectures
- This value is defined by the *min_sample_time* in the *interactive* governor, which is set to **20 ms** by default.



Website Detection: Performance Evaluation

Table 2: Test accuracy for different setups with their default scaling governor mode explored with four ML models

Micro-architecture	Governor	Browser	Test Accuracy			
			CNN	SVM	KNN	RF
Intel Comet Lake	*powersave*	Chrome	94.5%	92.0%	74.6%	93.7%
		Tor	73.7%	64.9%	33.6%	63.6%
		Tor (Top 5 score)	93.0%	86.6%	54.0%	86.2%
Intel Tiger Lake	*powersave*	Chrome	97.6%	95.8%	84.3%	93.0%
		Tor	68.7%	51.9%	16.2%	30.4%
		Tor (Top 5 score)	86.1%	78.7%	30.9%	55.0%
AMD Ryzen 5	*ondemand*	Chrome	93.1%	90.4%	78.4%	84.9%
		Tor	60.3%	50.8%	24.7%	29.8%
		Tor (Top 5 score)	87.0%	83.2%	46.5%	58.2%
ARM Cortex-A73	*interactive*	Chrome	87.3%	71.7%	38.6%	69.6%

Website Detection: Related Work

Table 3: Previous works based on different side-channel profiling techniques for website fingerprinting. For each work, attack vector, resolution, targeted browser, classification accuracy, and number of websites profiled are given.

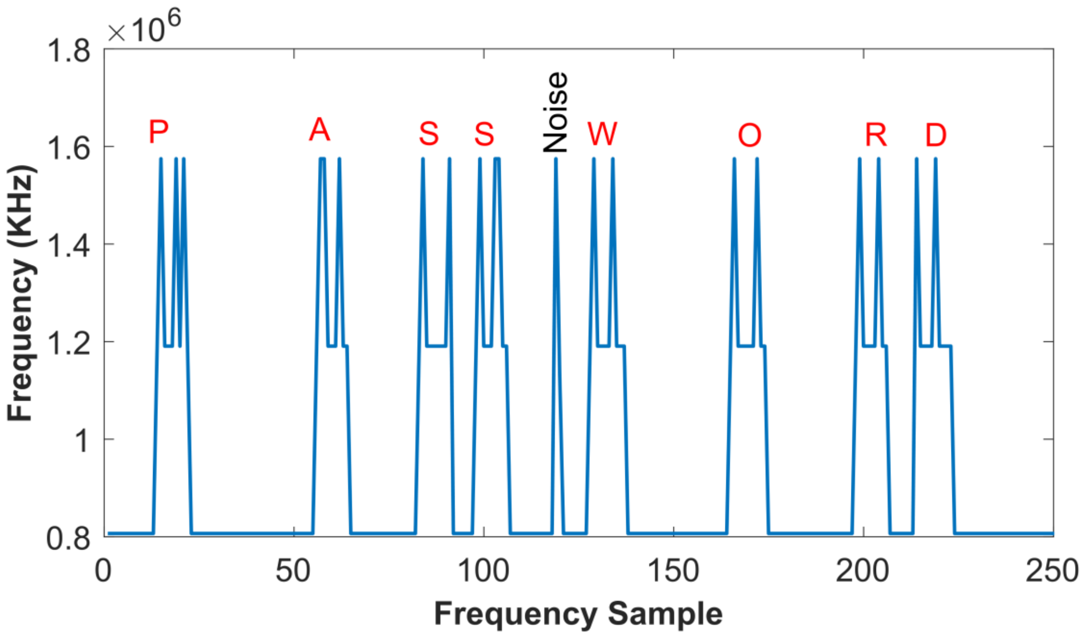
Work	Attack Vector	Resolution	Browser	Accuracy (%)	# of Websites
DF-SCA	Frequency scaling	**10 ms**	Chrome/Tor	**97.6**	100
Rendered Insecure [32]	GPU memory API	60 μs	Chrome	90.4	200
PerfWeb [13]	Performance counters	40 μs	Chrome/Tor	86.4	30
RedAlert [53]	Intel RAPL	1 ms	Chrome	99	37
Shusterman et al. [43]	Last-level cache	2 ms	Firefox/Chrome/Tor	80	100
Spreitzer et al. [47]	Data-usage	20 ms	Tor	95	100
Zhang et al. [52]	iOS APIs	1 ms	Safari	68.5	100
Memento [18]	procfs	10 μs	Chrome	78	100
Loophole [48]	shared event loop	25 μs	Chrome	76.7	500

Keystroke Detection

- We assume that a phone user enters her password to log into his account in a banking application
- Considered Banking Application: Bank of America (BoA)
- Sampling rate: **20 ms**

- The collected keystrokes have three common properties
  - ✓ A single keystroke length changes between 8 and 12 samples
  - ✓ The big cores' frequency increases up to 1.6GHz
  - ✓ If two consecutive keystrokes are close to each other, the length of a keystroke pattern is higher than 12 samples.

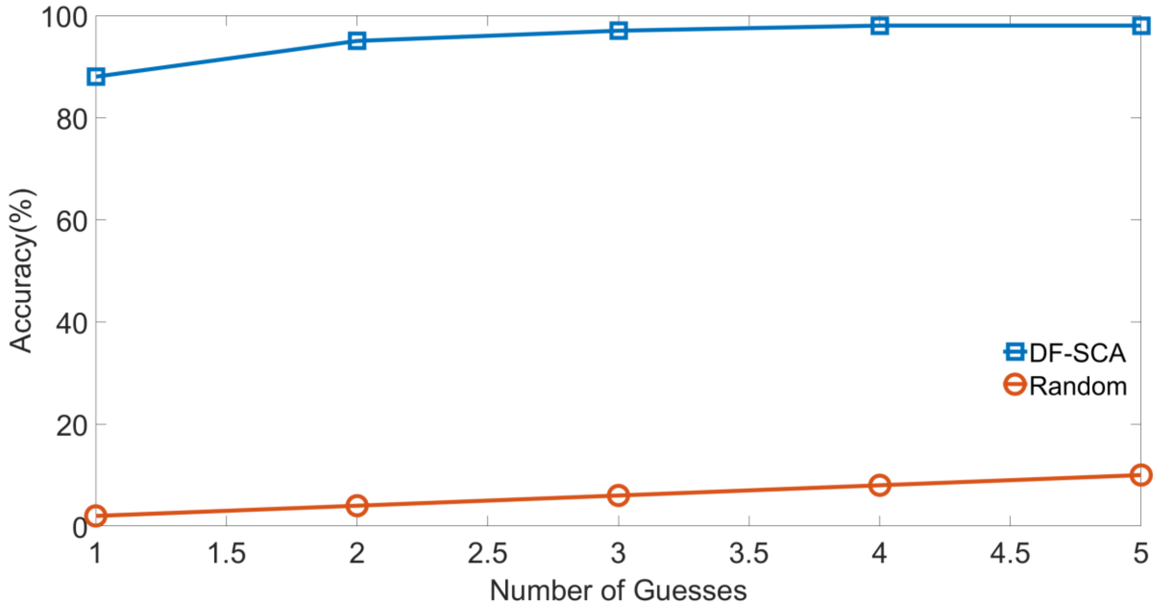
- It takes 200 ms in average to decrease the frequency from peak to idle frequency level
- Hence, an attacker is able to distinguish the keystrokes that have at least 200 ms between each key press with DF-SCA.



❑ Our goal is not to outperform the existing works in the keystroke attack literature, but rather demonstrates DF-SCA attack has sufficient resolution and accuracy to perform a password detection attack.

Keystroke Detection

- Selected password: **50 out of 200** most used passwords on web
- Length of the password varies from **6 to 9 characters**.
- The phone user entered **50** distinct passwords for at least **10 times**
- In total, **1252 password measurements** were collected from **50 distinct passwords**
- The achieved keystroke detection rate is **95%**
- The inter-keystroke timings are determined
- **10 measurements** for each password are selected to evaluate the password detection accuracy
- A Kth-nearest neighbor (KNN) model is trained with the measurements.



- ❑ The model can guess the correct password with **88%** success rate with one guess
- ❑ With only **3 guesse**s, the success rate is **97%**

Countermeasures

- **Restricting Access Privilege** for *cpufreq* interface from userspace applications in Linux OS.
- **Decreasing the update interval** of the *cpufreq* interface
  - ✓ With lower resolution, the amount of information leaked by DF-SCA can be diminished significantly
- **Artificial noise** can be introduced by the system to mask the rapid frequency changes in the system
  - ✓ Example: by randomly inserting workloads in the system
  - ✓ Since side-channel analysis takes advantage of Deep Learning algorithms frequently, **adversarial obfuscation techniques** can also be implemented to **fool the Deep Learning models**
- Similarly, keystroke attacks can be eliminated by **introducing additional keystrokes** to make the distribution more uniform

Impact of Different Scaling Governors

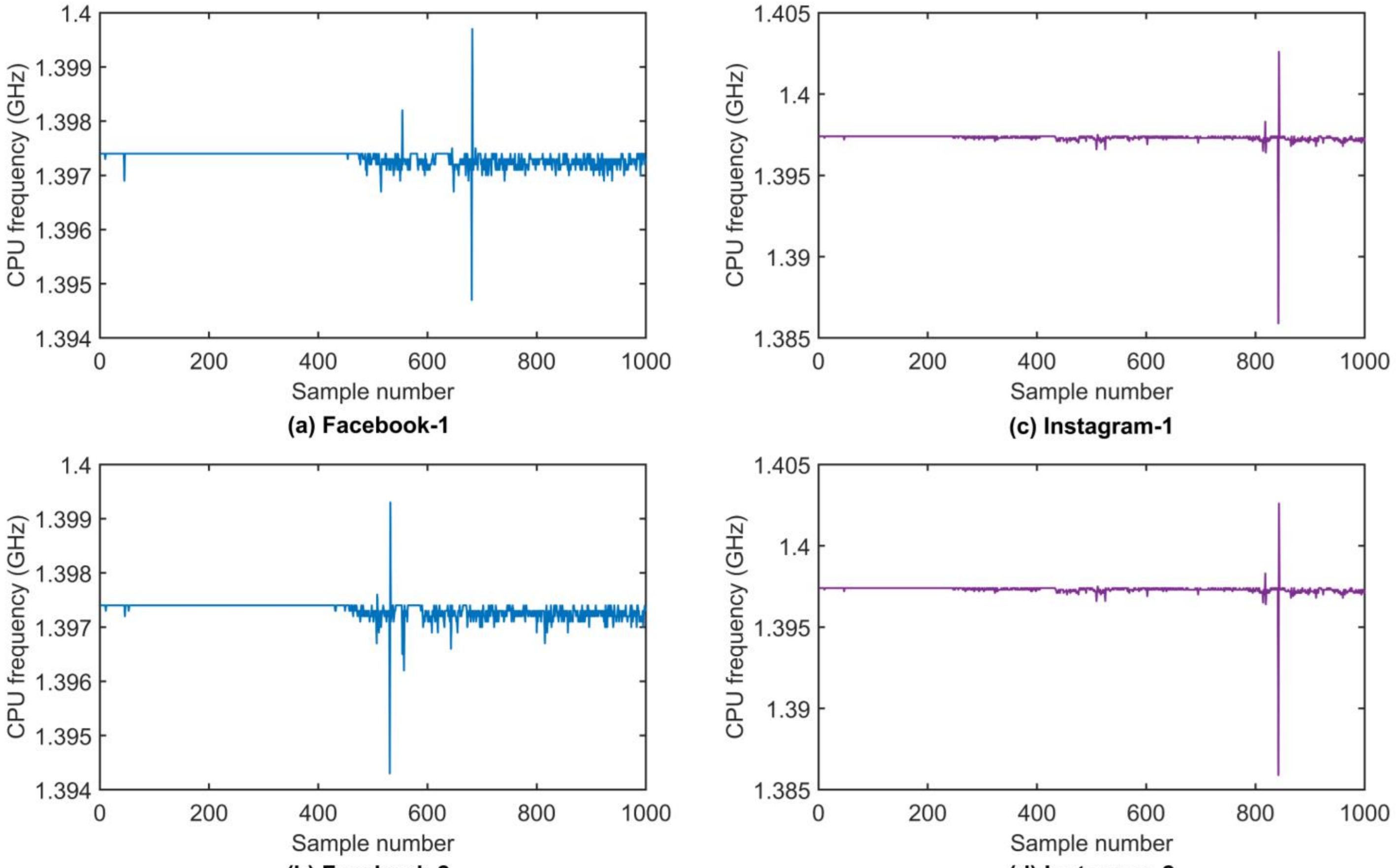
- **Intel Tiger Lake:**
  - Accuracy improves slightly when the scaling governor is changed to *performance* from *powersave*
- **AMD Ryzen 5:**
  - The default scaling governor *ondemand* gives the highest website classification accuracy.
  - The *performance* and *powersave* governors drop the classification.

Table 4: The impacts of different scaling governors on website fingerprinting accuracy for Intel Tiger Lake and AMD Ryzen 5 architectures

Scaling governor	Test Accuracy (%)	
	Intel Tiger Lake	AMD Ryzen 5
performance	**97.8**	68.1
powersave	97.6	75.3
userspace	N/A	80.1
ondemand	N/A	**97.6**
conservative	N/A	96.7
schedutil	N/A	**97.6**

Impact of Different Scaling Governors

- Unlike other scaling governors, for ***userspace*** governor the CPU <u>keeps the core frequency below it's base frequency</u>.
- Although the variation is quite low, a similar pattern for the same web page can still be noticeable from this figure.



(a) Facebook-1
(b) Facebook-2
(c) Instagram-1
(d) Instagram-2

Universal ML Model for different microarchitectures

- Previously, we trained separate ML models for Intel, AMD, and ARM architectures to obtain the highest website fingerprinting accuracy.
- We are interested to know whether it is possible to replace the individual ML models with a universal ML model.
- This will facilitate the attacker to perform website fingerprinting without requiring to know the exact targeted microarchitecture.

Table 5: The universal ML Model training and evaluation for Intel Tiger Lake, Intel Comet Lake, and AMD Ryzen 5 architectures

Micro-architecture	Test Accuracy (%)
Intel Comet Lake + Intel Tiger Lake	95.9
Intel Comet Lake + Intel Tiger Lake + AMD Ryzen 5	92.3

- Combined the CPU frequency traces of the Intel microarchitectures to train one CNN model and achieved test accuracy of **95.9%**
- Later, combined both Intel and AMD frequency traces, which leads to **92.3%** accuracy with one CNN model

Outcomes

- The attacker only needs to collect 10 seconds of the frequency values to detect the websites in Google Chrome browser applicable to Intel, AMD, and ARM devices.
- Even though DF-SCA's resolution is significantly lower than many previous attacks, it is still possible to detect the visited websites with a high accuracy.
- Moreover, victim keystrokes can be detected with 95% success rate which yields to a successful password recovery attack with a simple ML classification.
- As a result, DF-SCA is a potential threat for all the components that take advantage of DVFS technology.
- The access privilege restriction or artificial noise injection might become fruitful countermeasures against such a threat.

❑ The dataset and the code are made available in GitHub:
https://github.com/Diptakuet/DF-SCA-Dynamic-Frequency-Side-Channel-Attacks-are-Practical.git

THANK YOU

QUESTIONS?