



# Invisible Probe: Timing Attacks with PCIe Congestion Side-channel

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† Zhe Zhou is the corresponding author

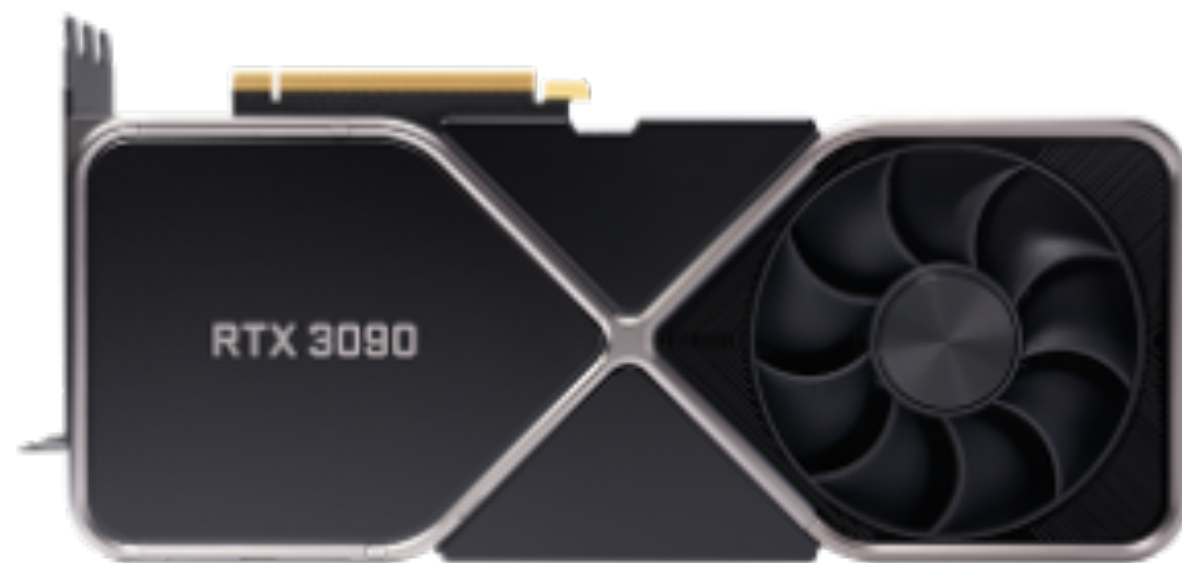
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- De facto protocol to connect CPU and peripheral devices

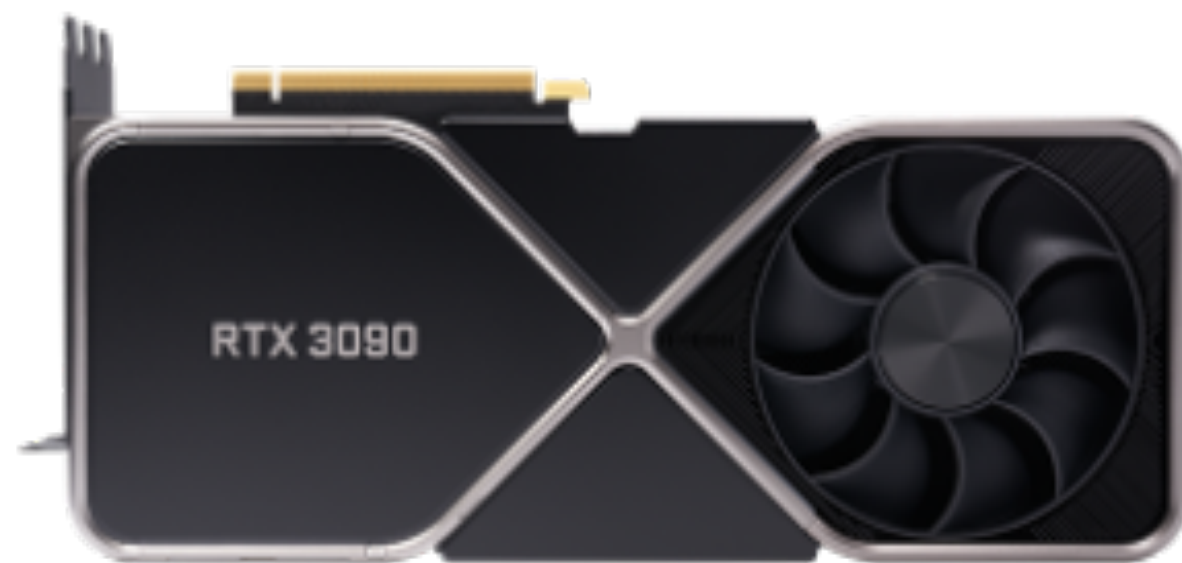
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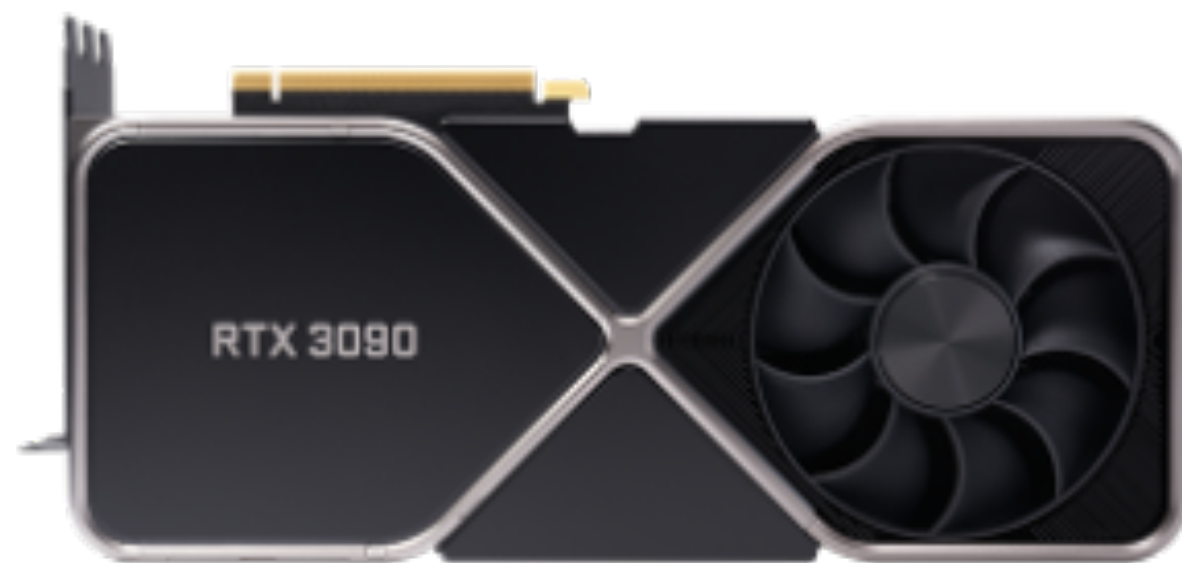
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**GAP!**

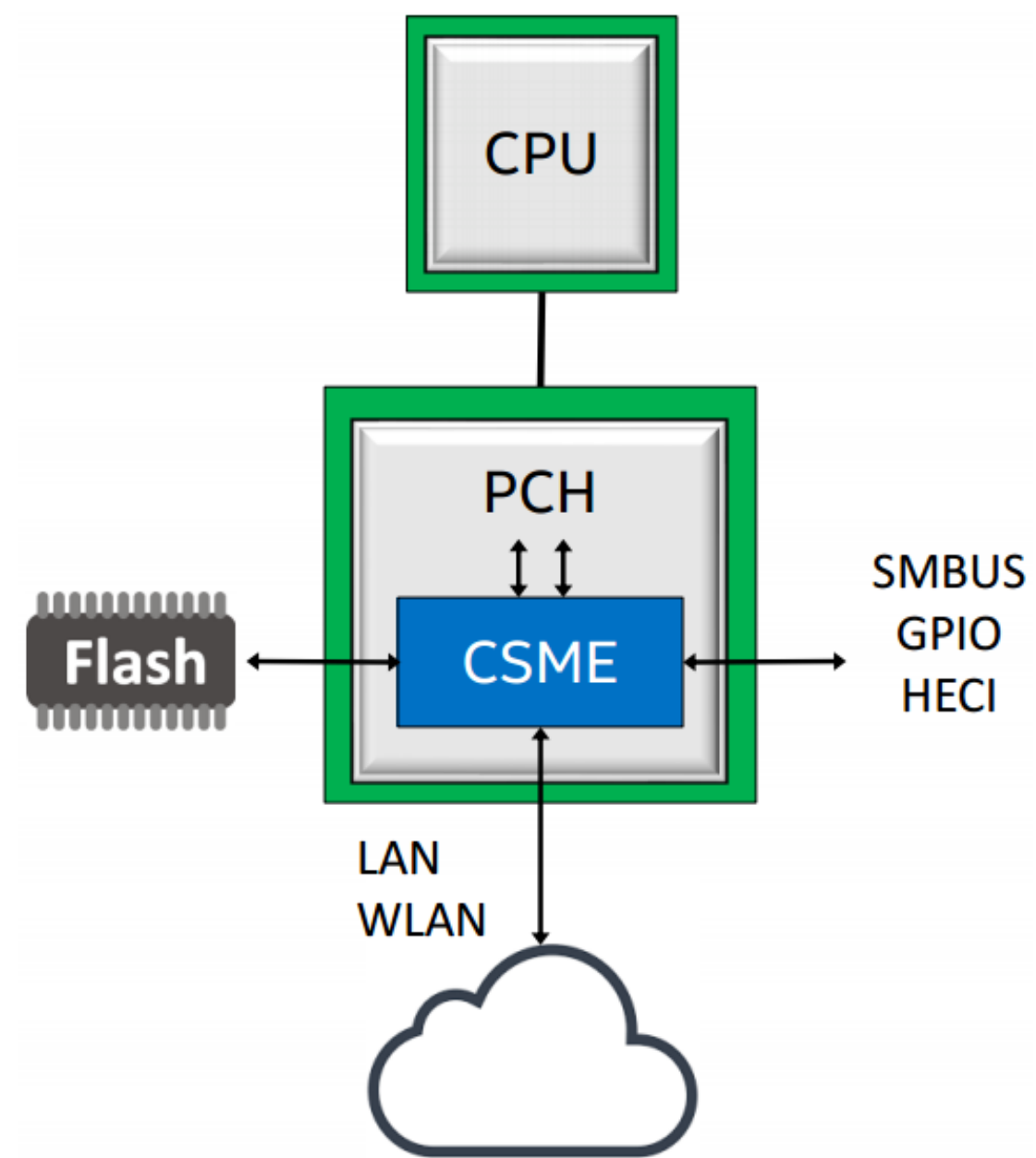


# **IO Switches to support more PCIe interfaces**



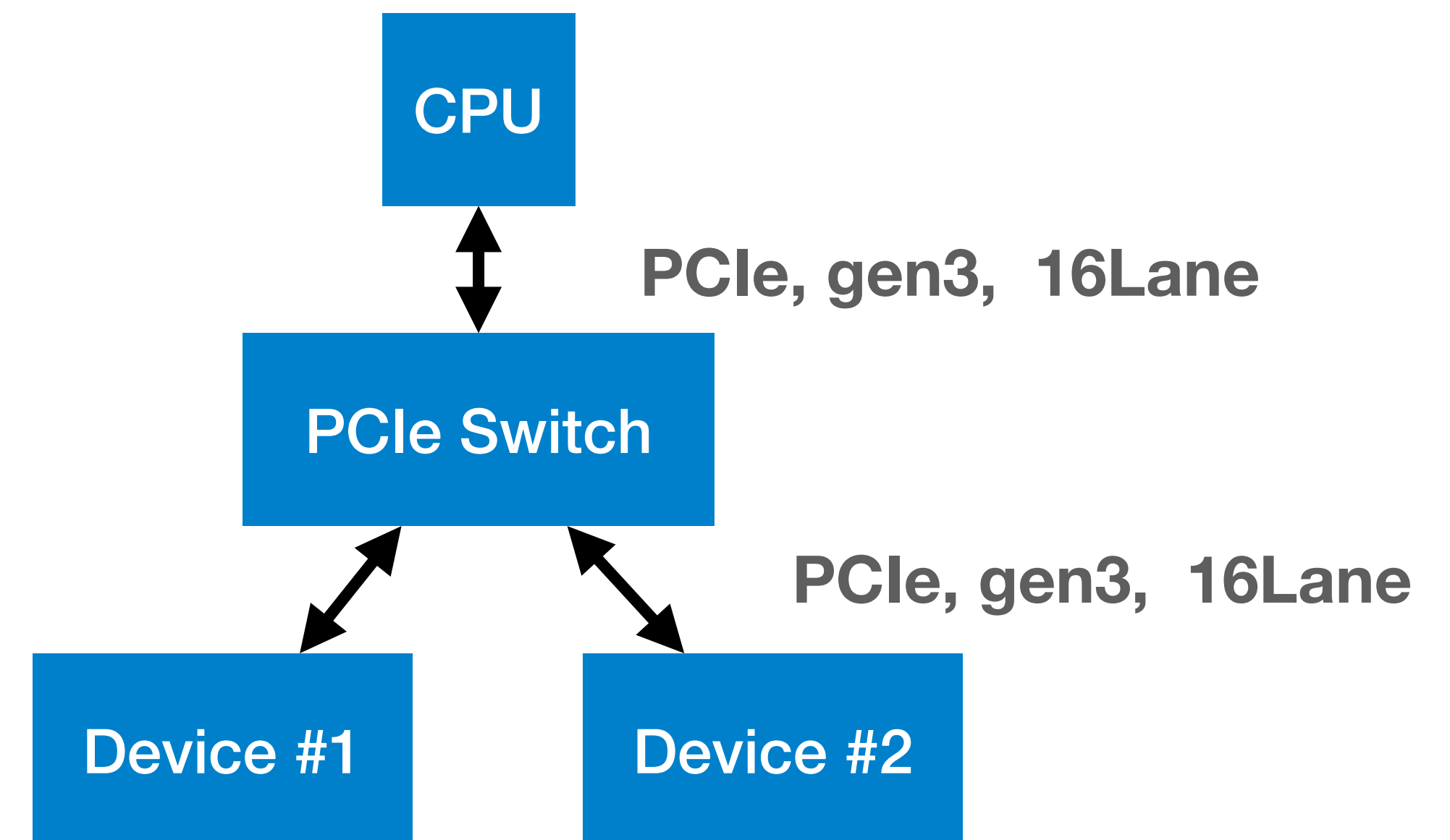
# IO Switches to support more PCIe interfaces

Platform Controller Hub (PCH)



[3]

PCIe Switch





# Problems of sharing channels

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- Throughput decrease

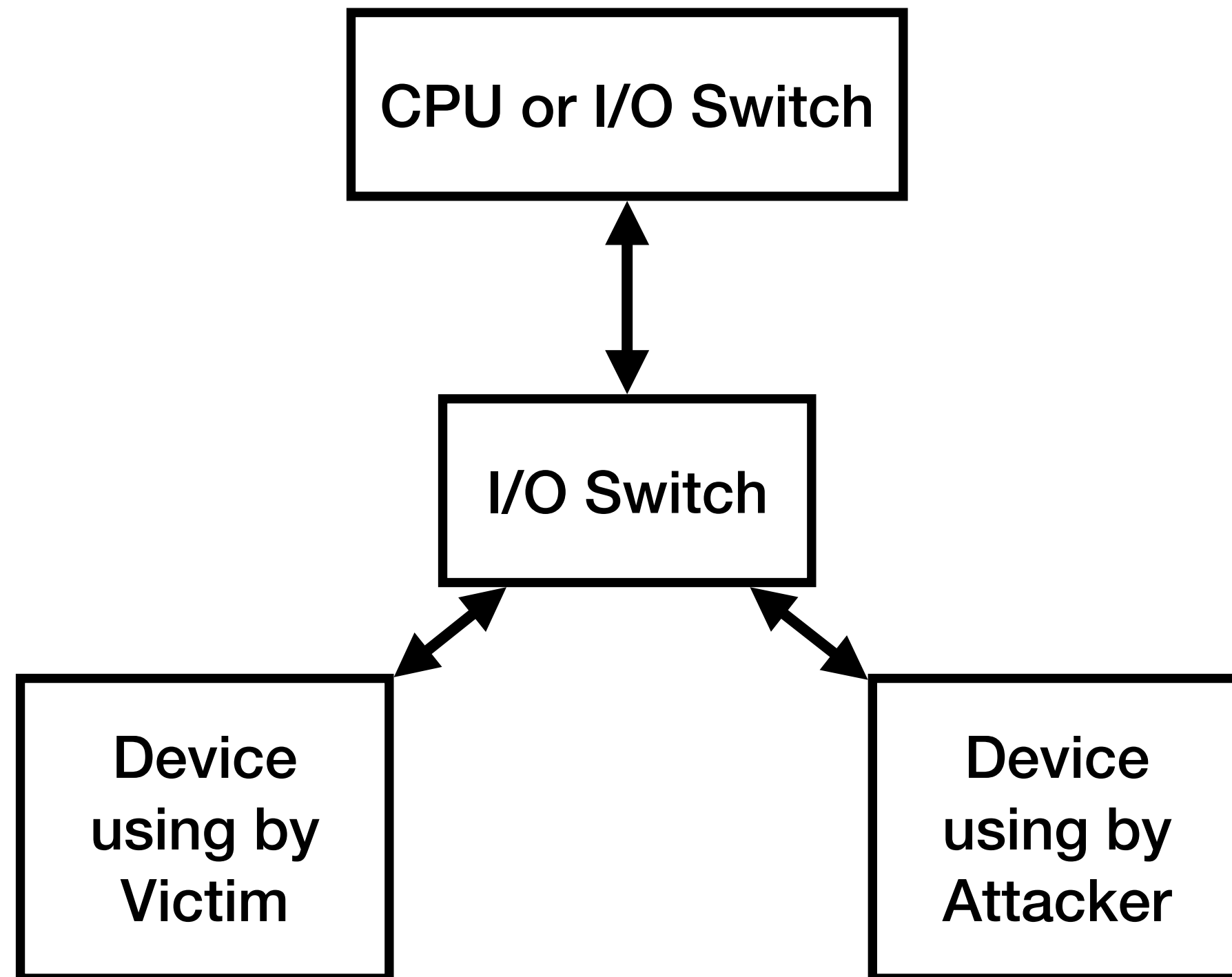
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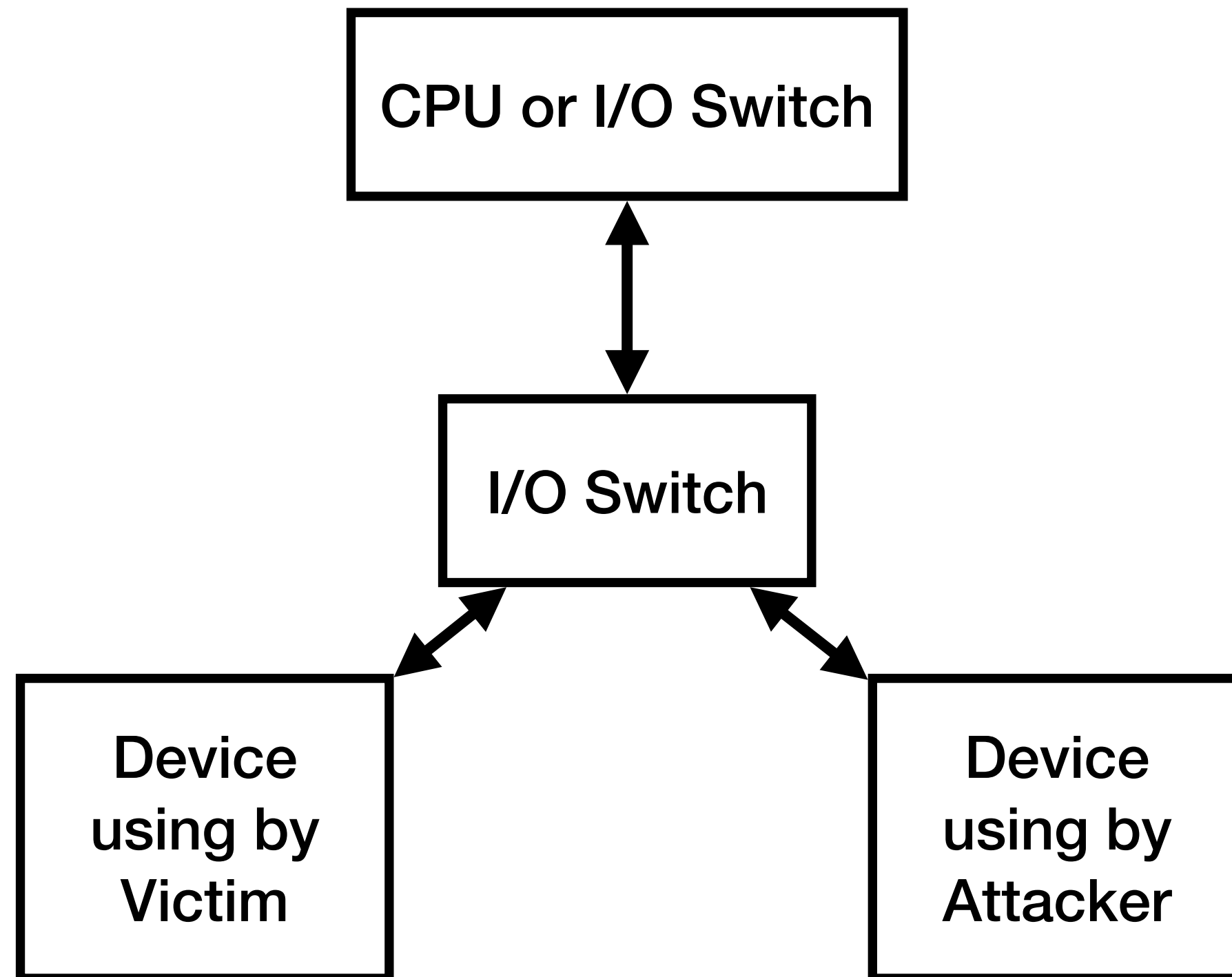
# Problems of sharing channels

- Throughput decrease
- Delays introduced
- Secrets leaking! (Side Channel Attack)

# Threat Model

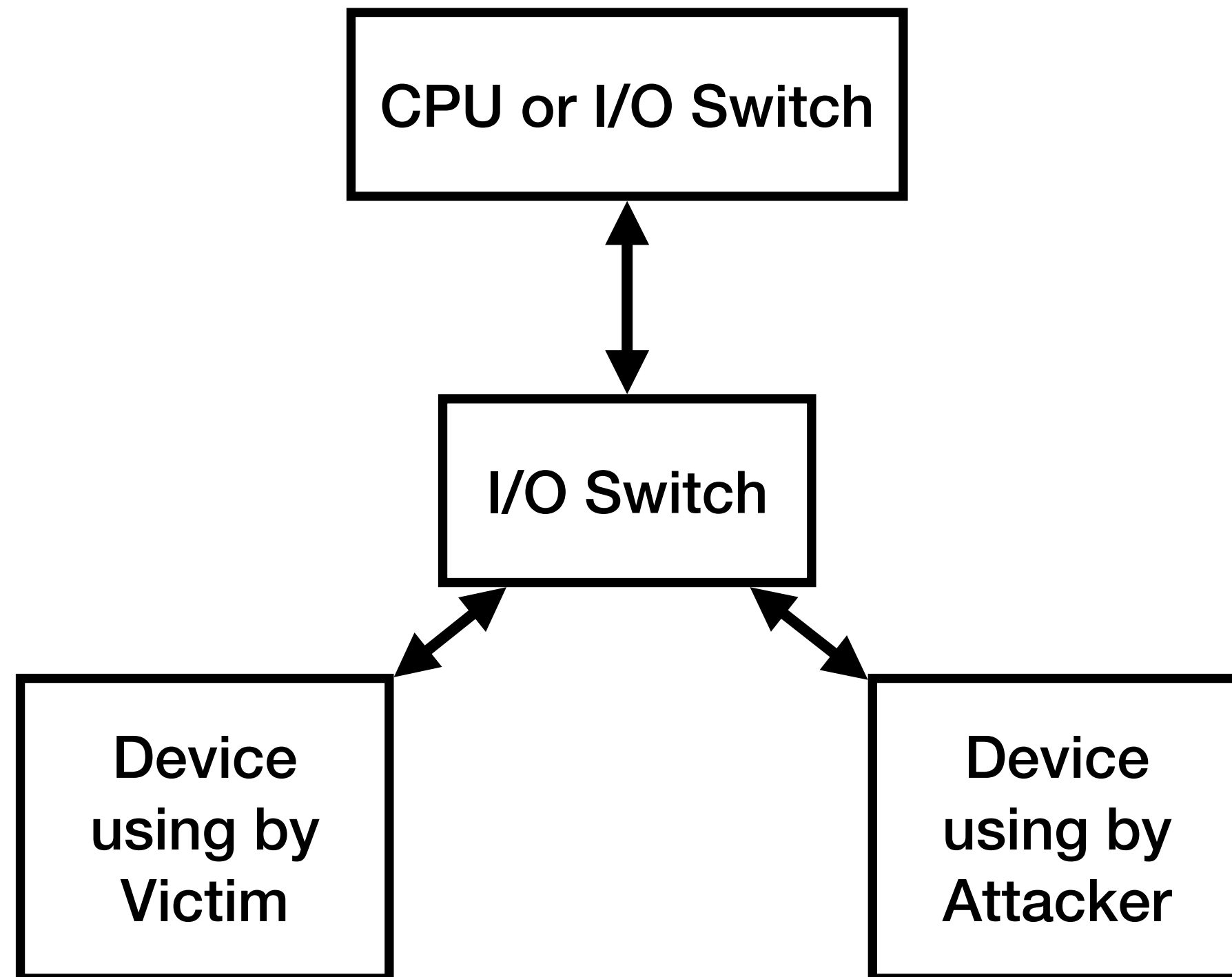


# Threat Model



- A pair of I/O devices:
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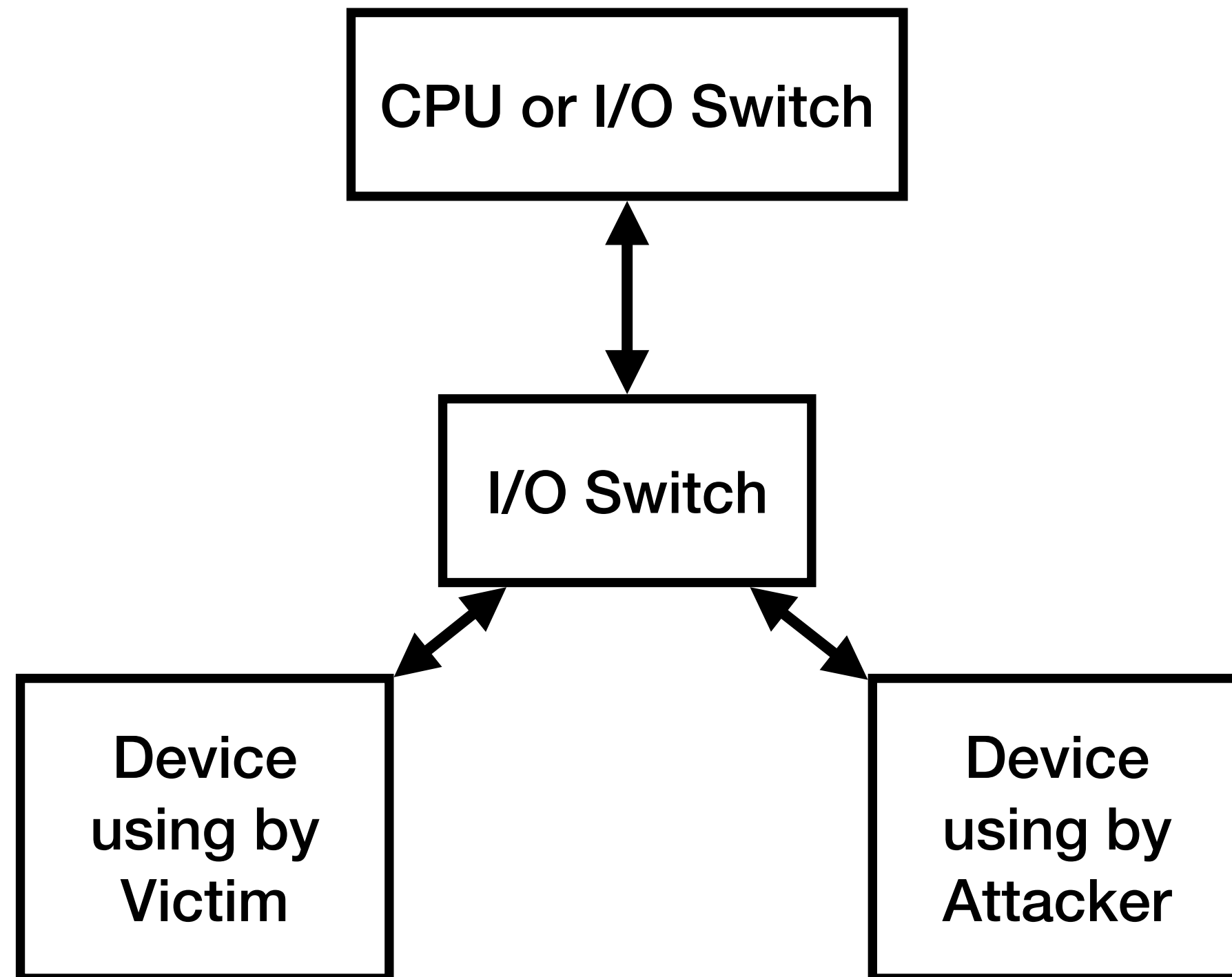
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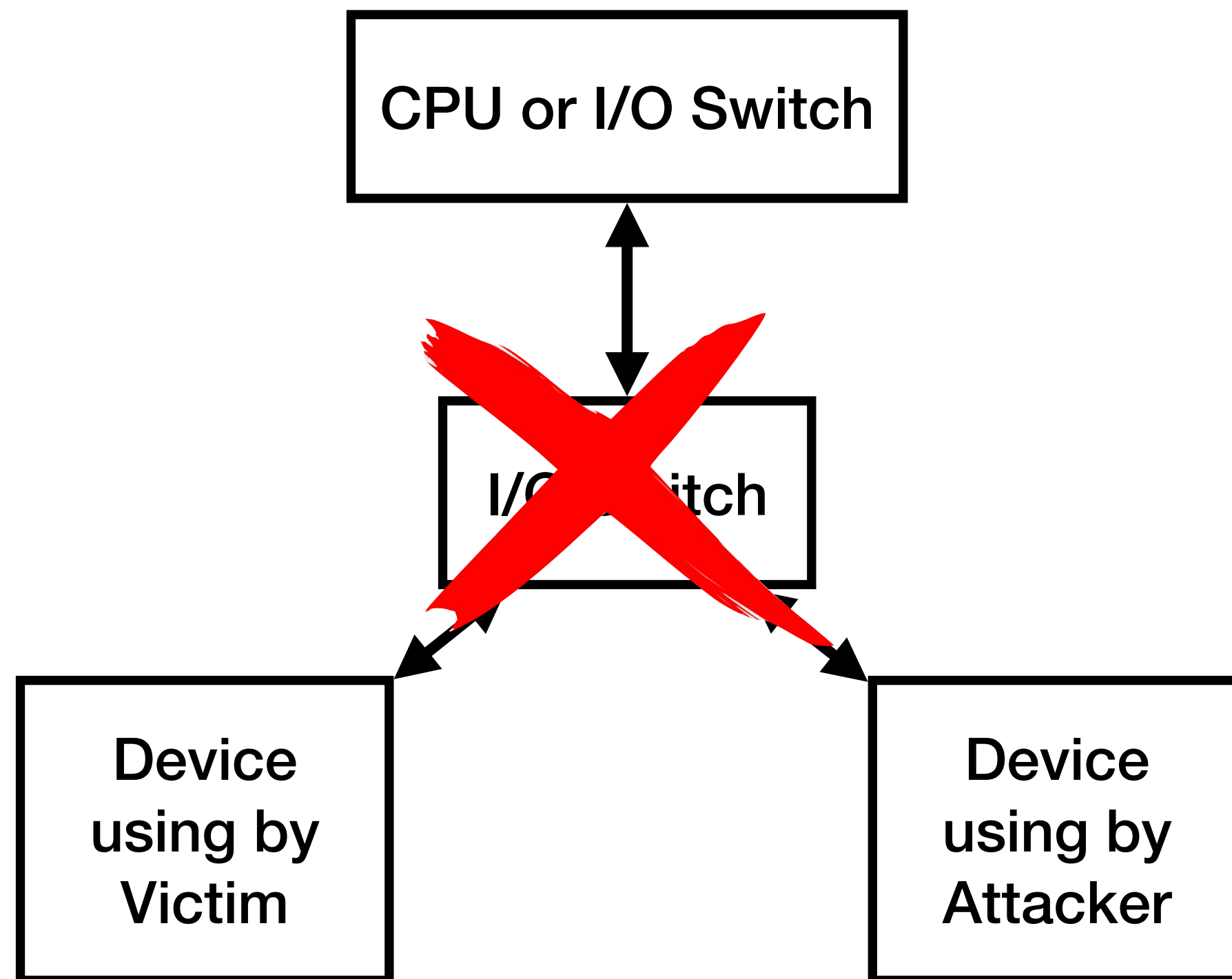


# Threat Model



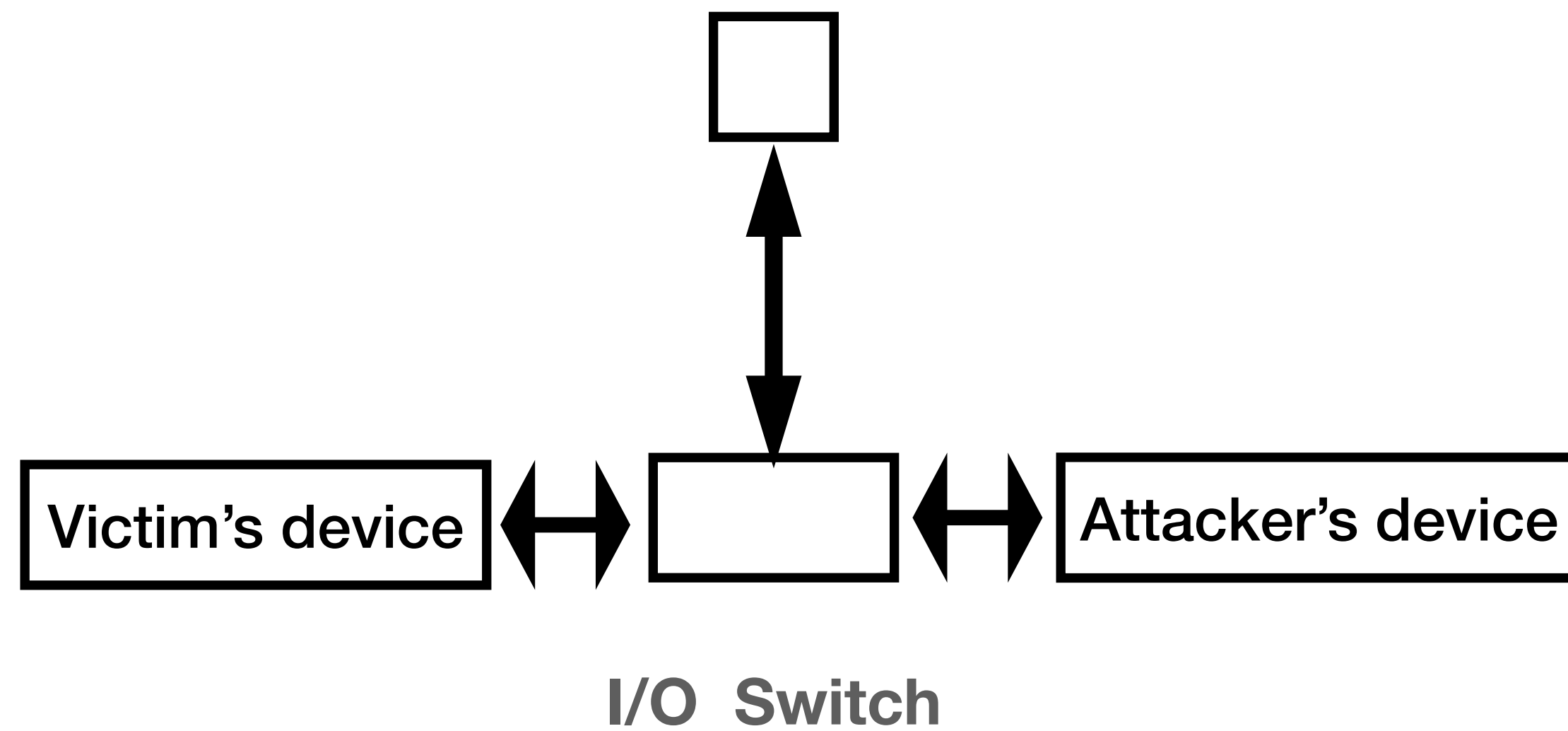
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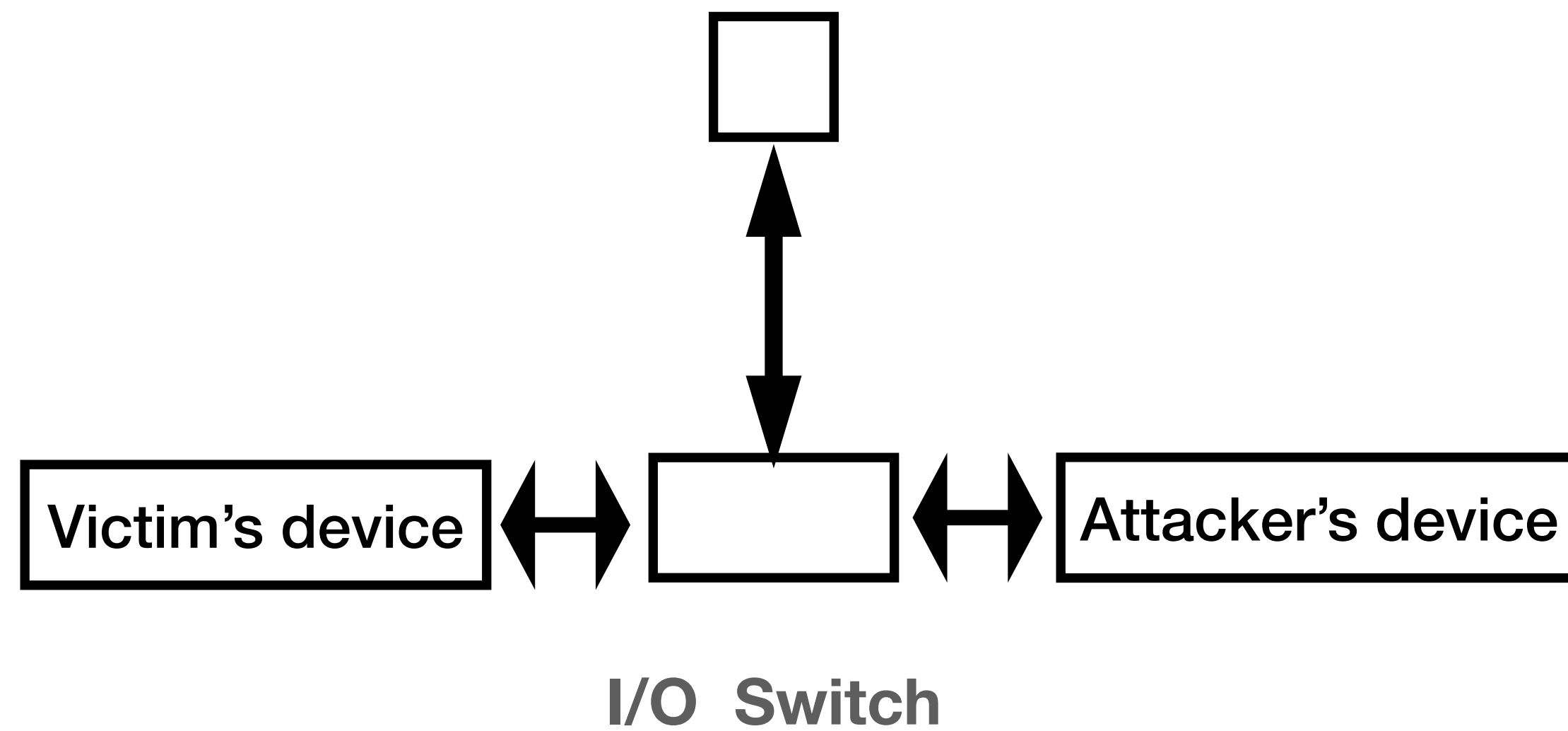
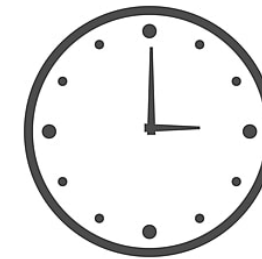


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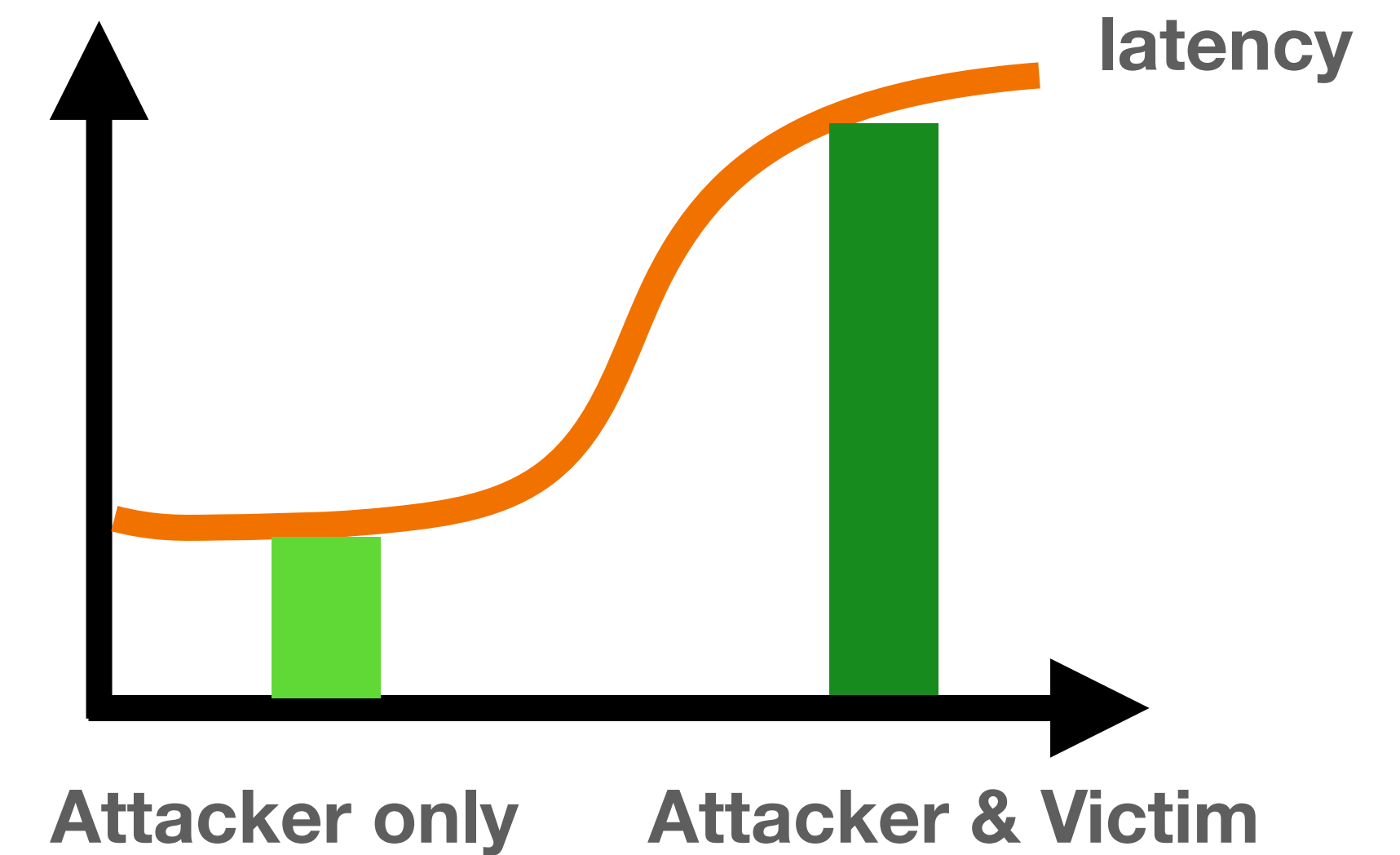
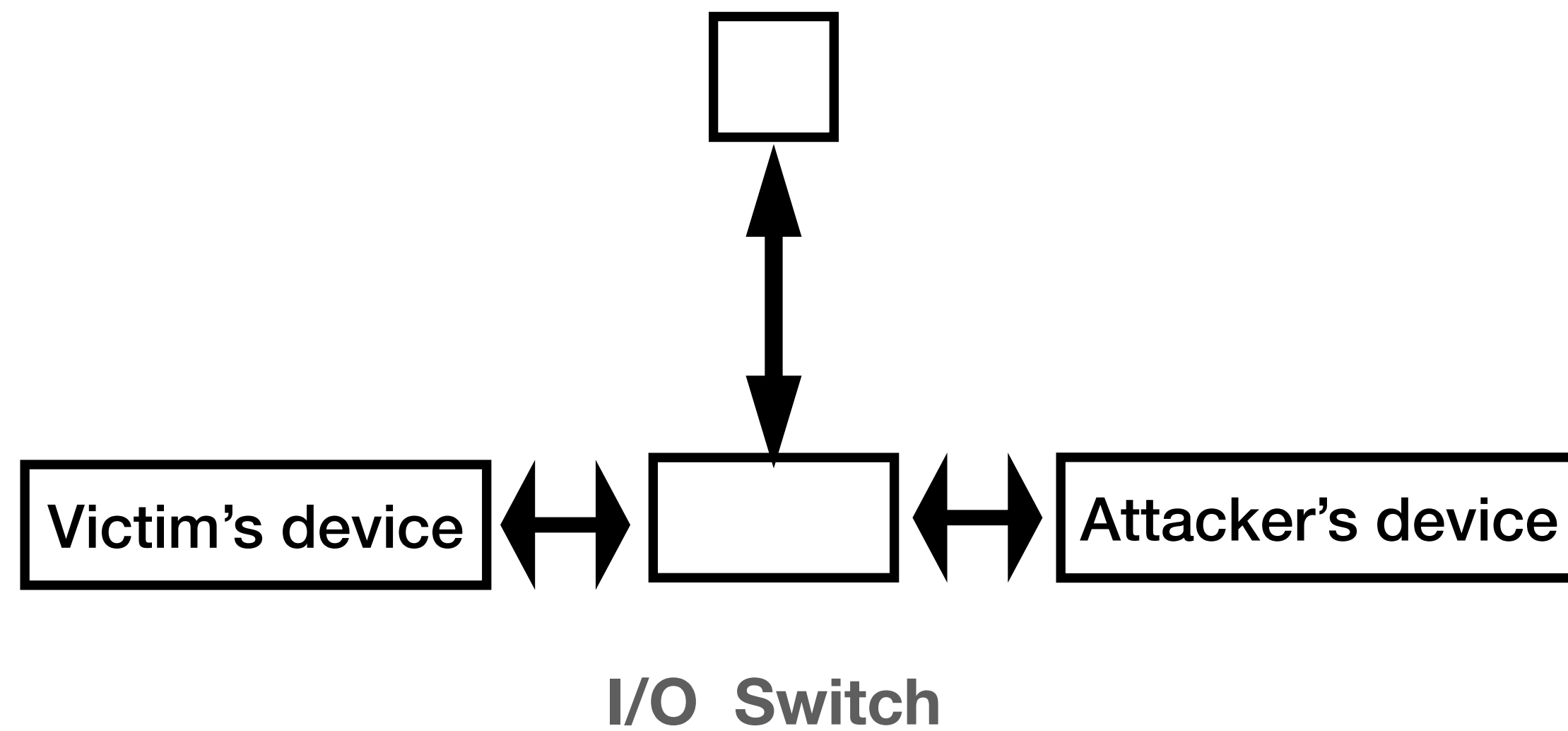
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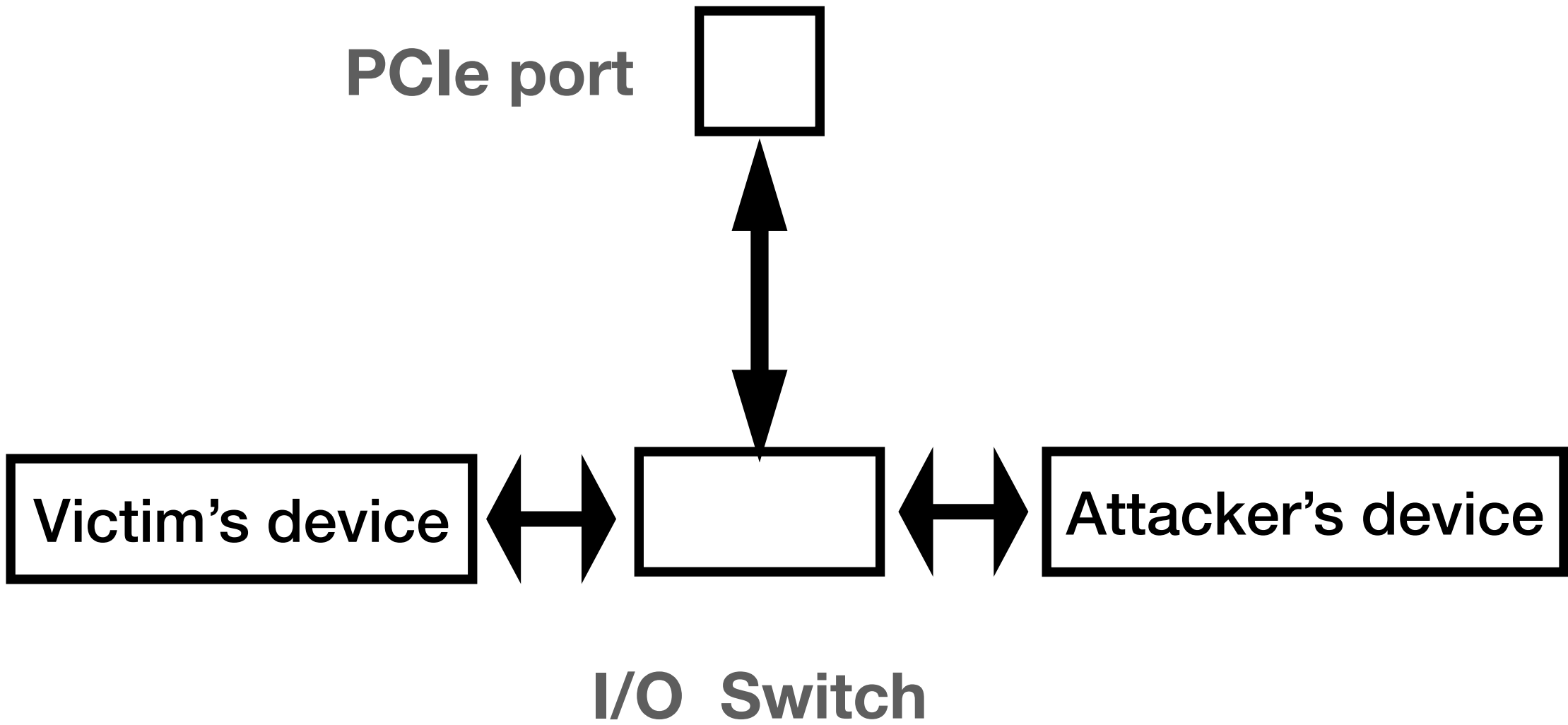
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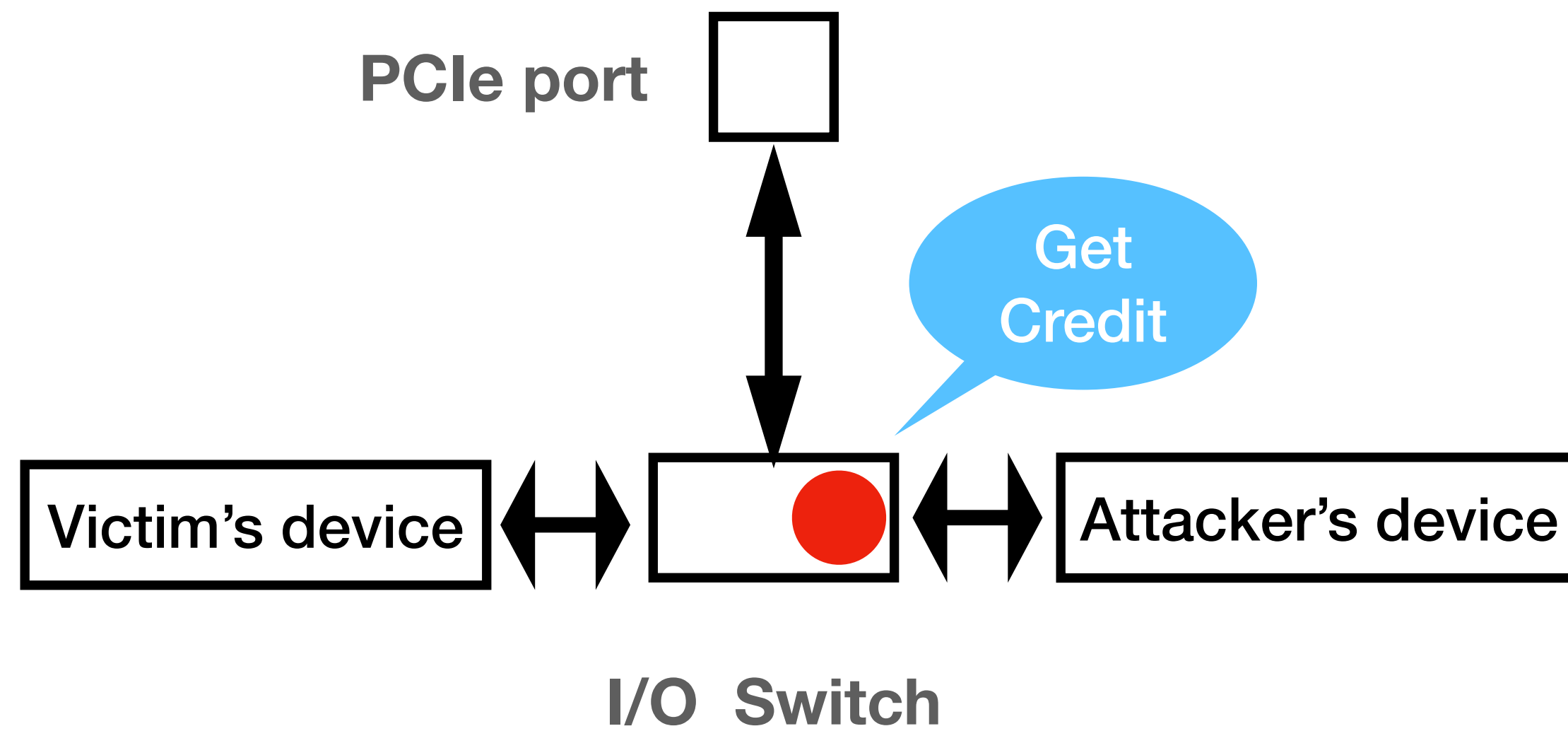
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$T=t_0$

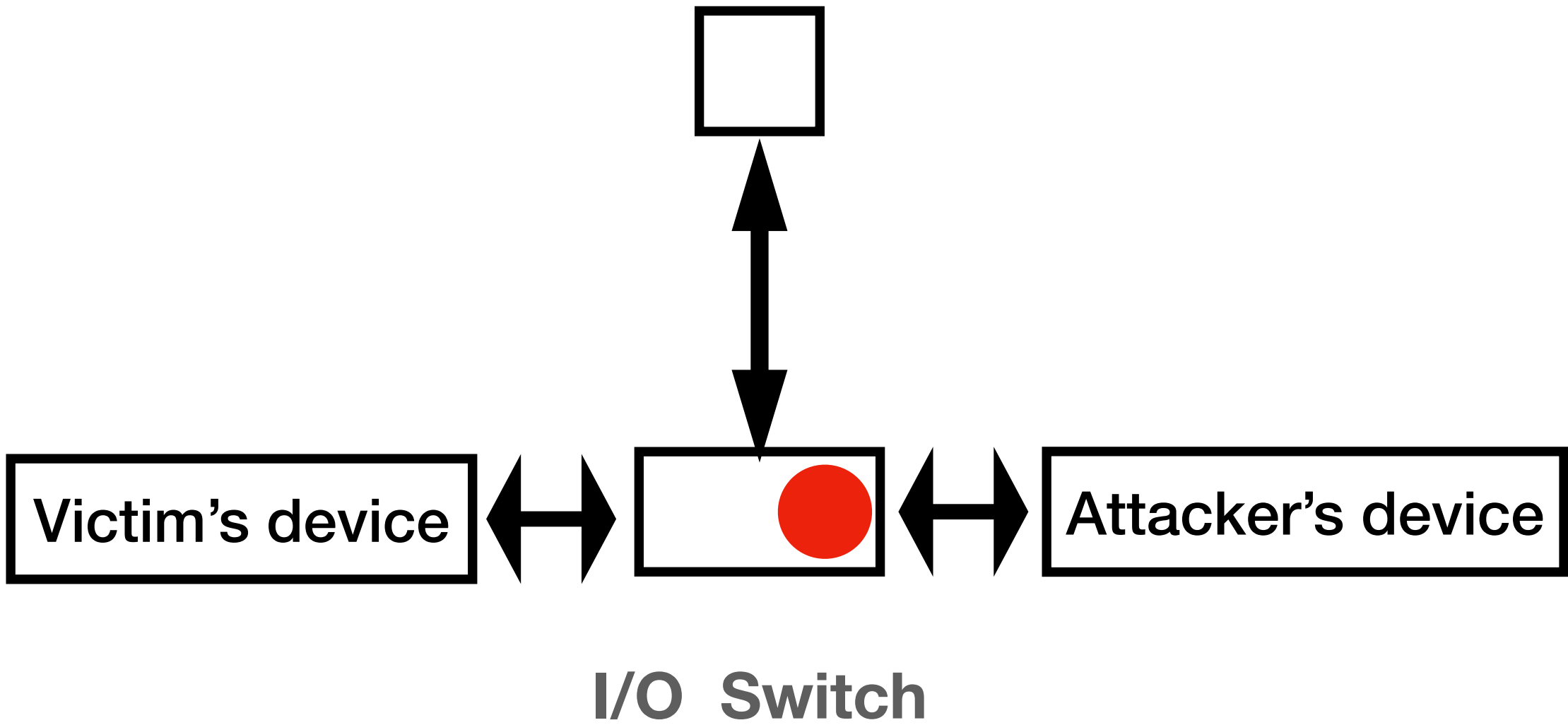




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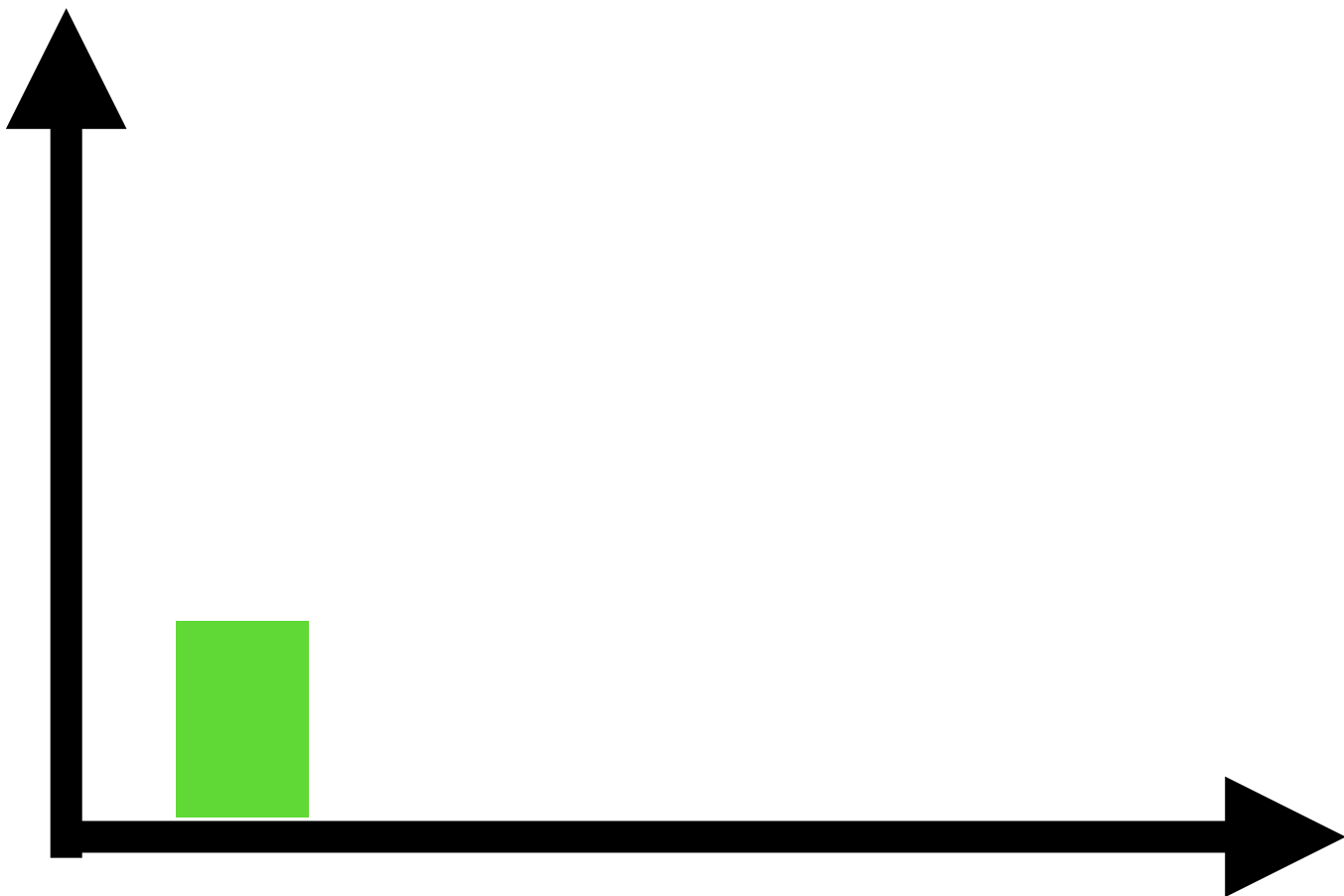
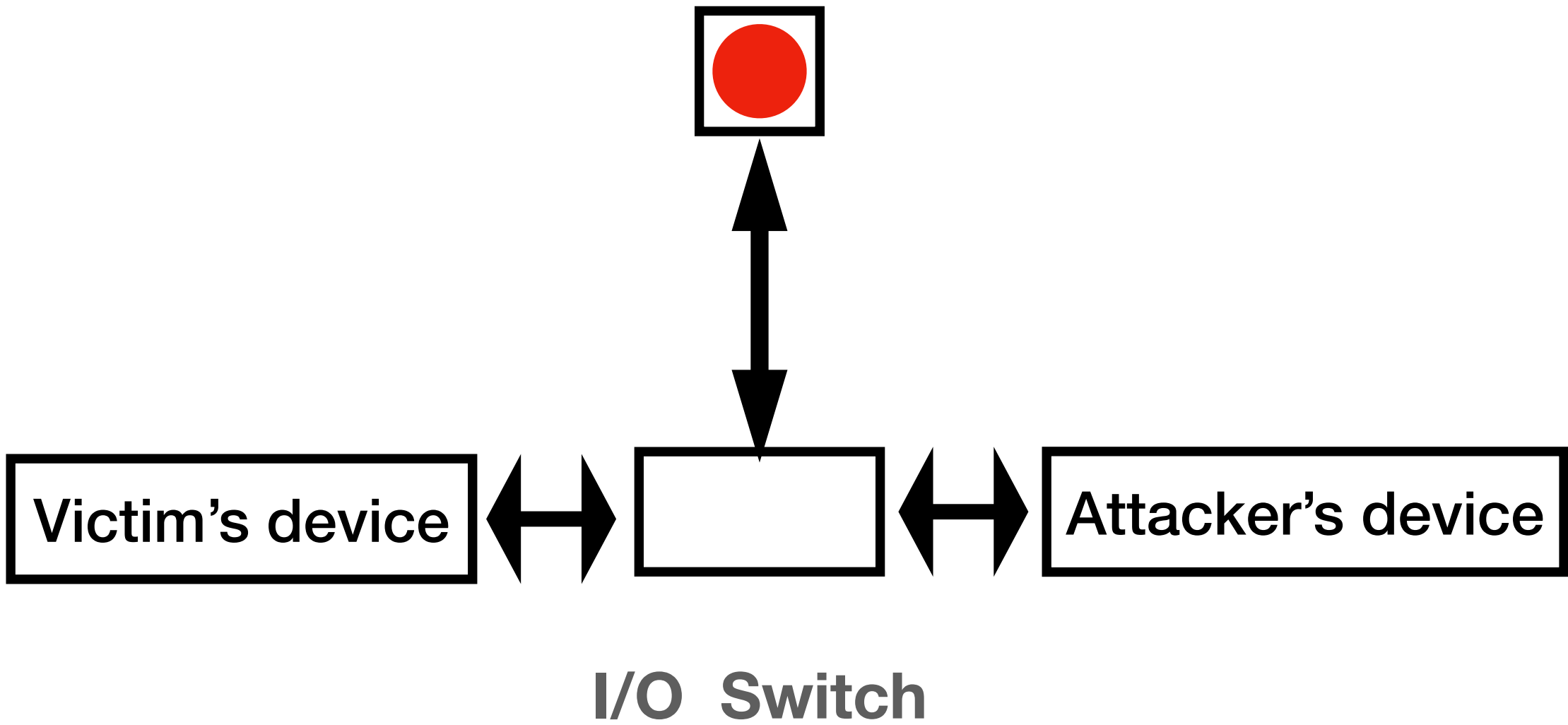
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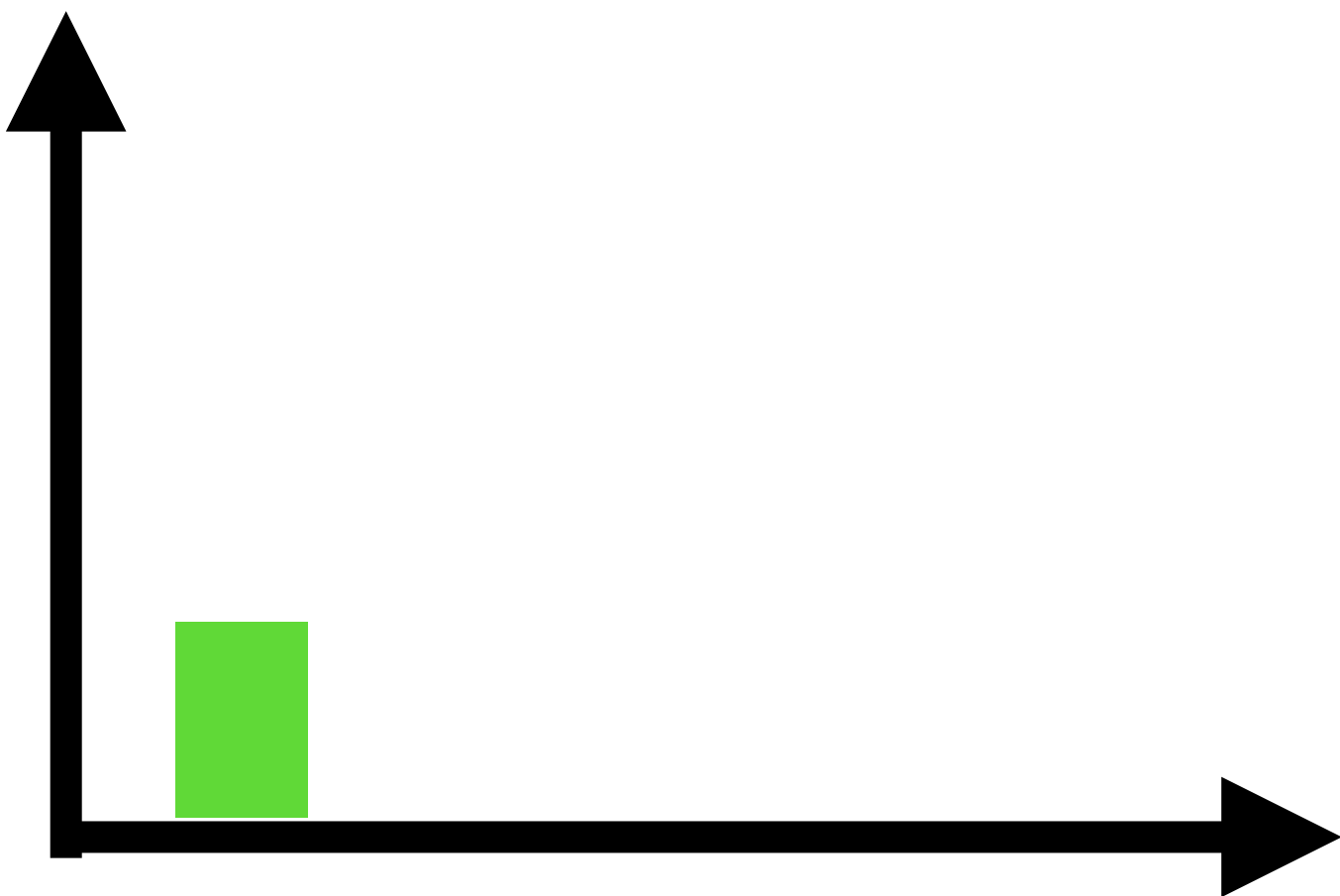
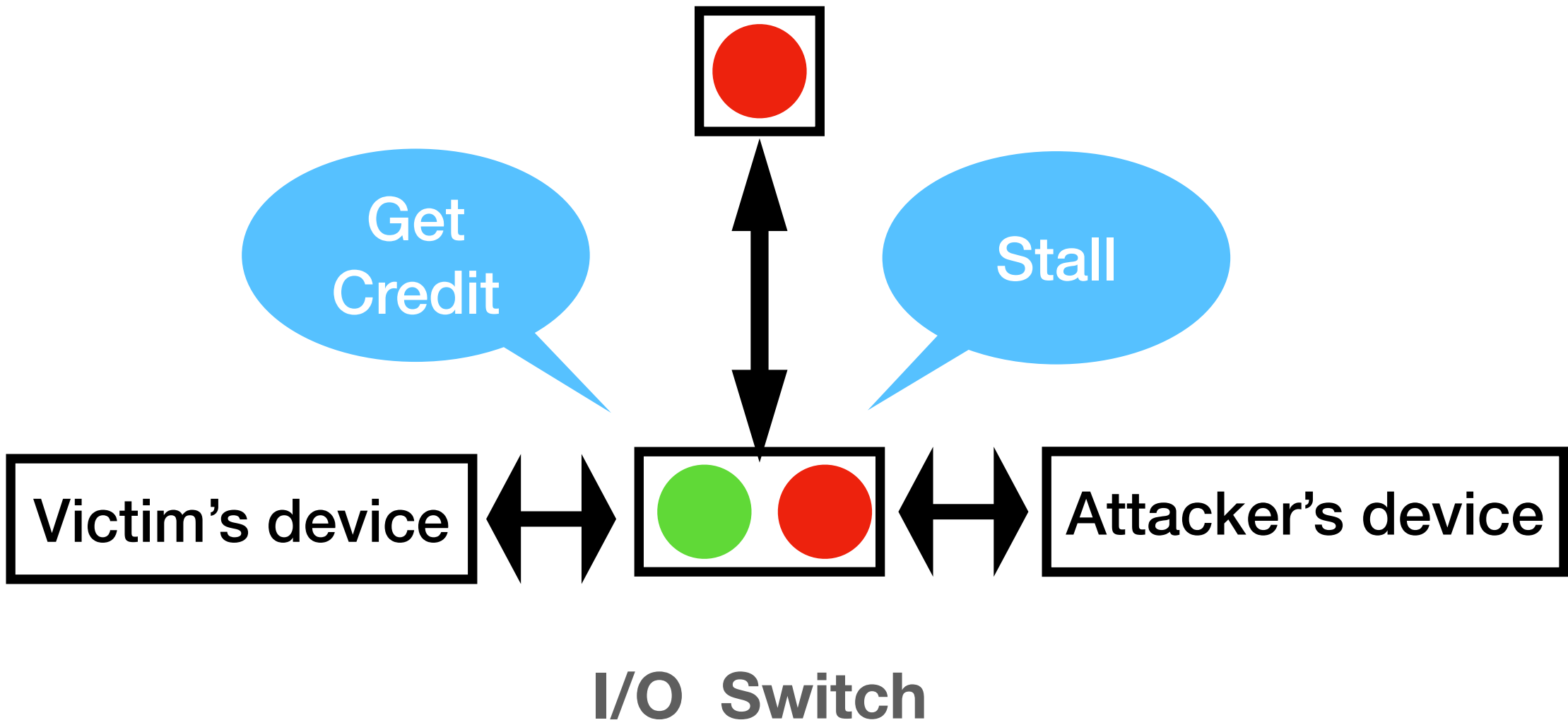
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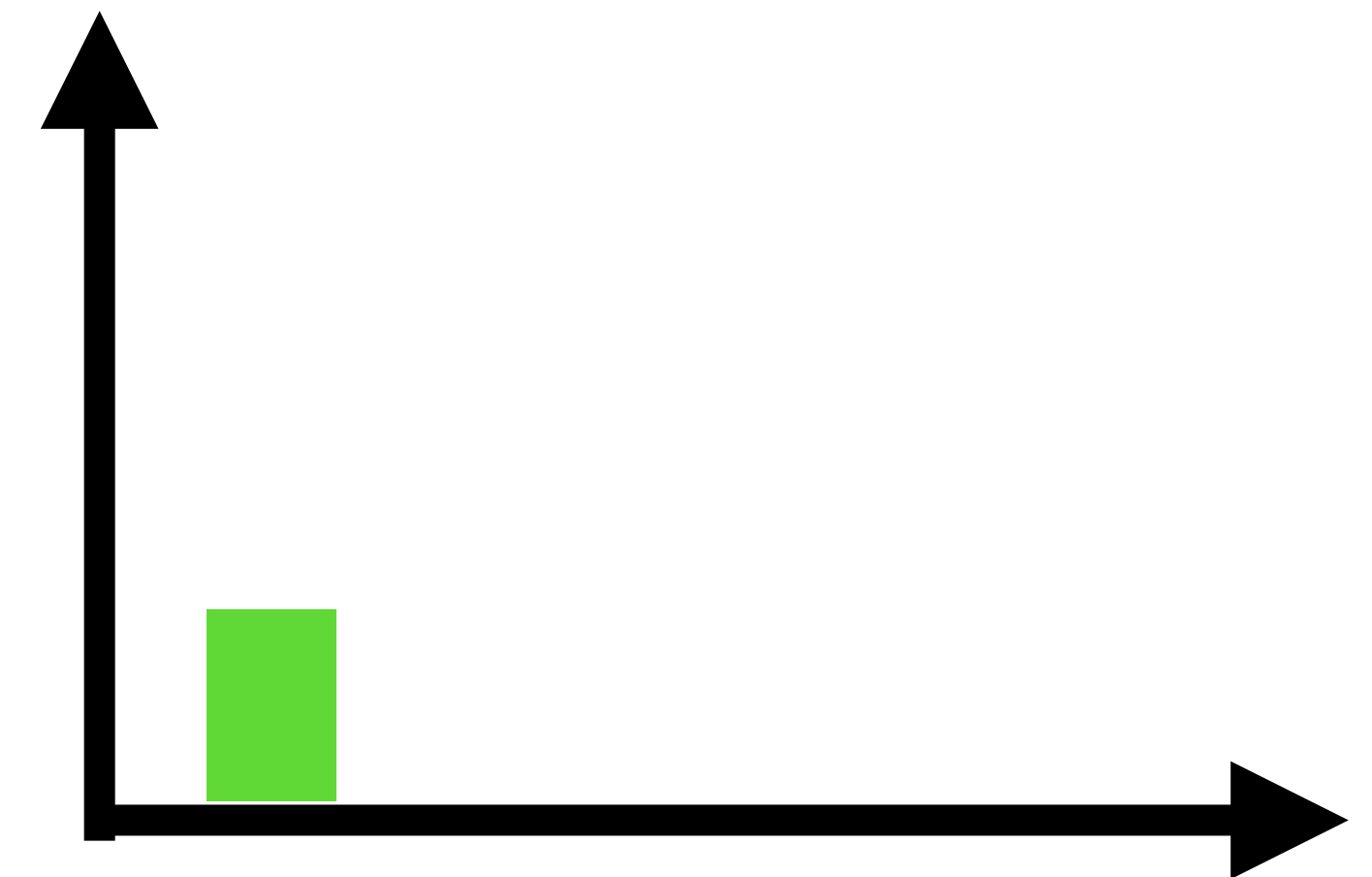
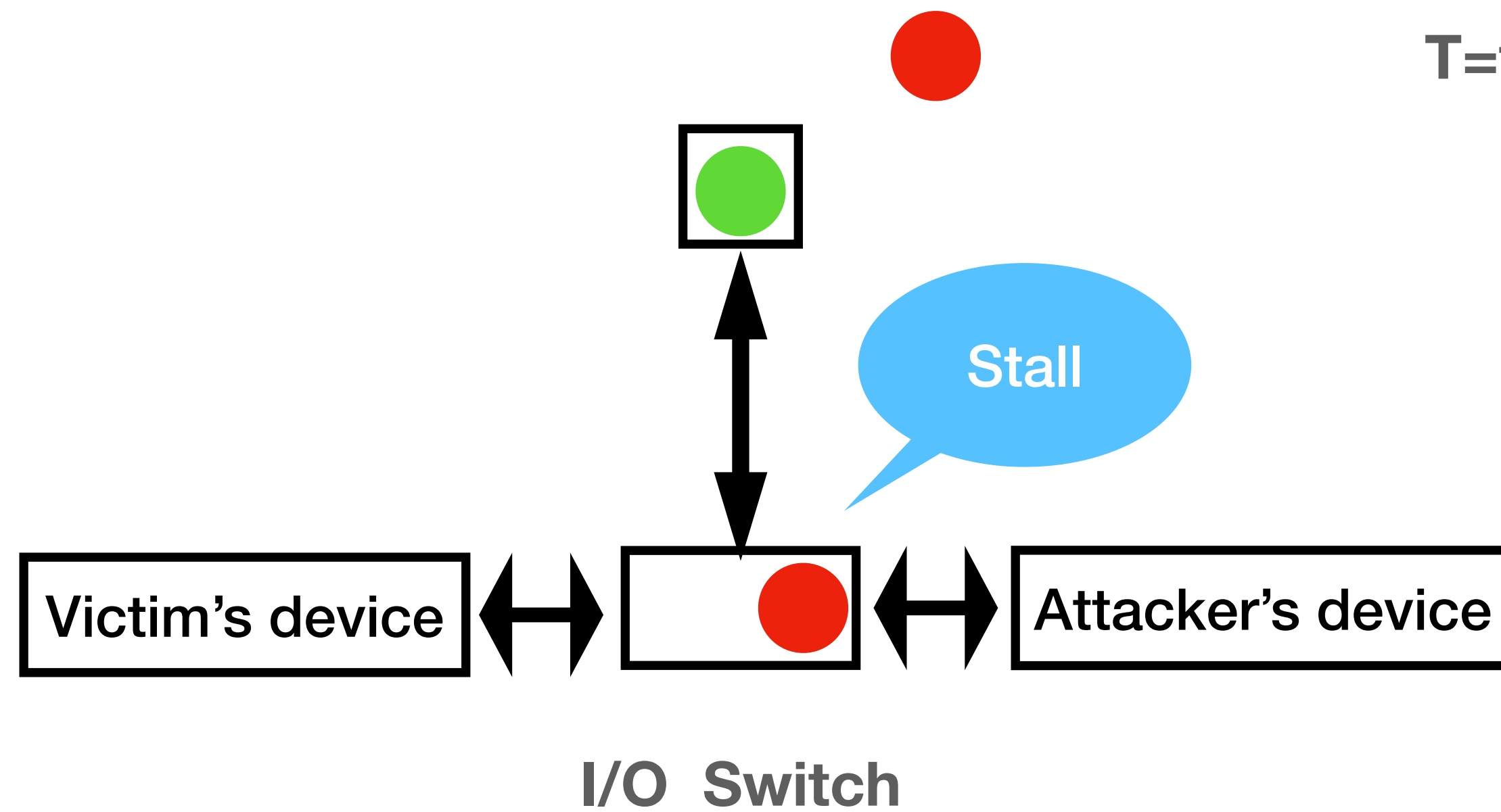
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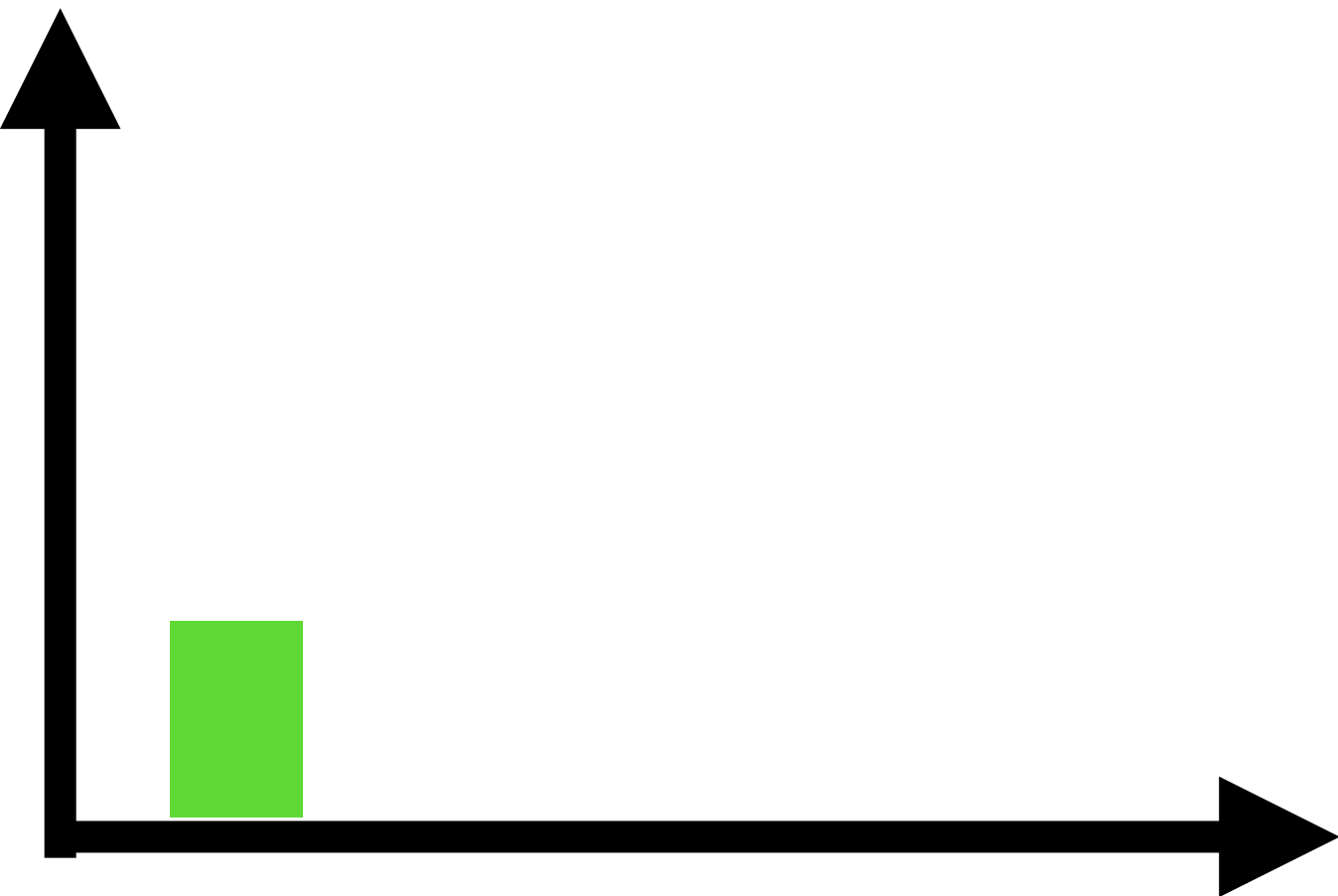
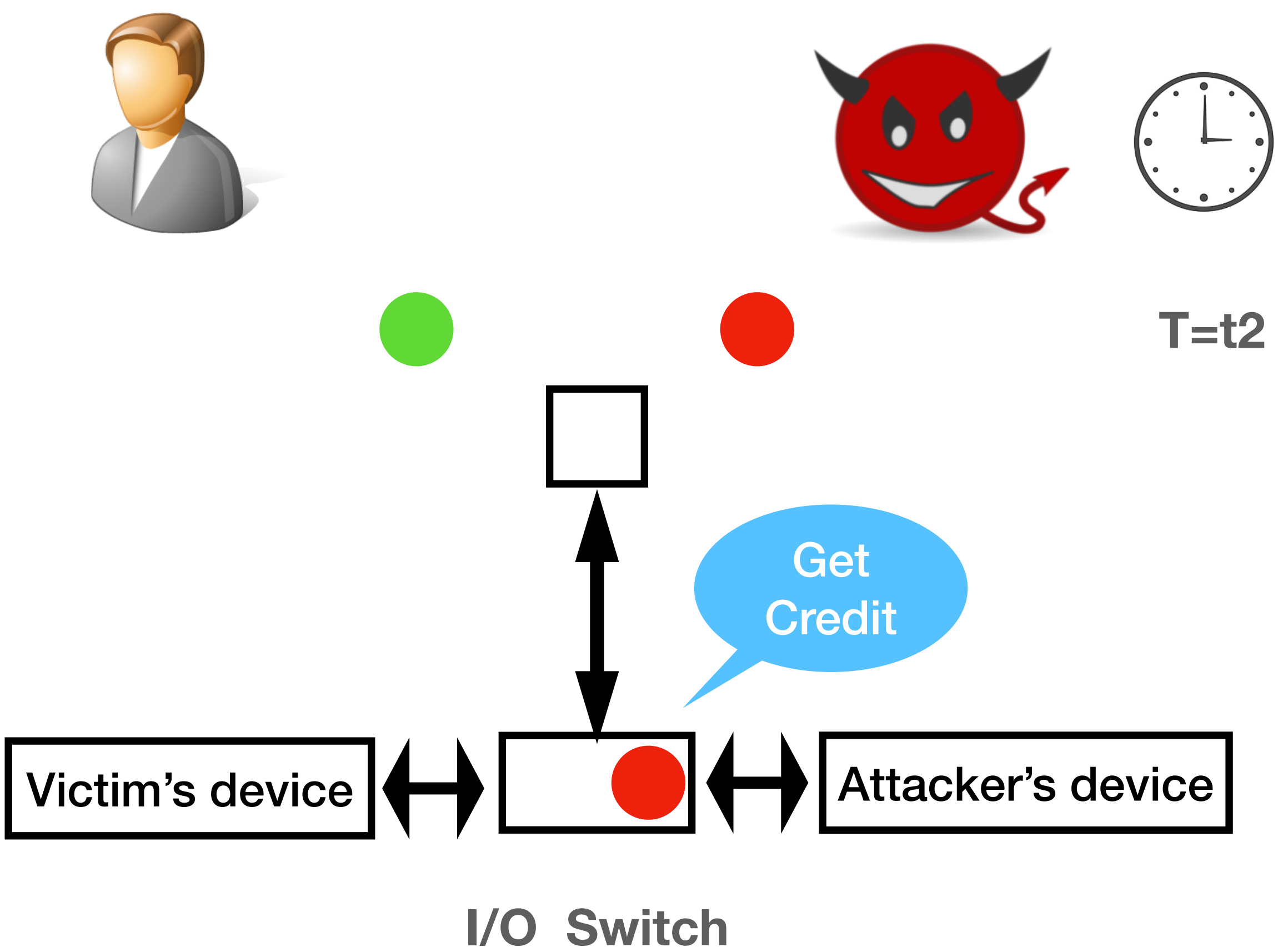
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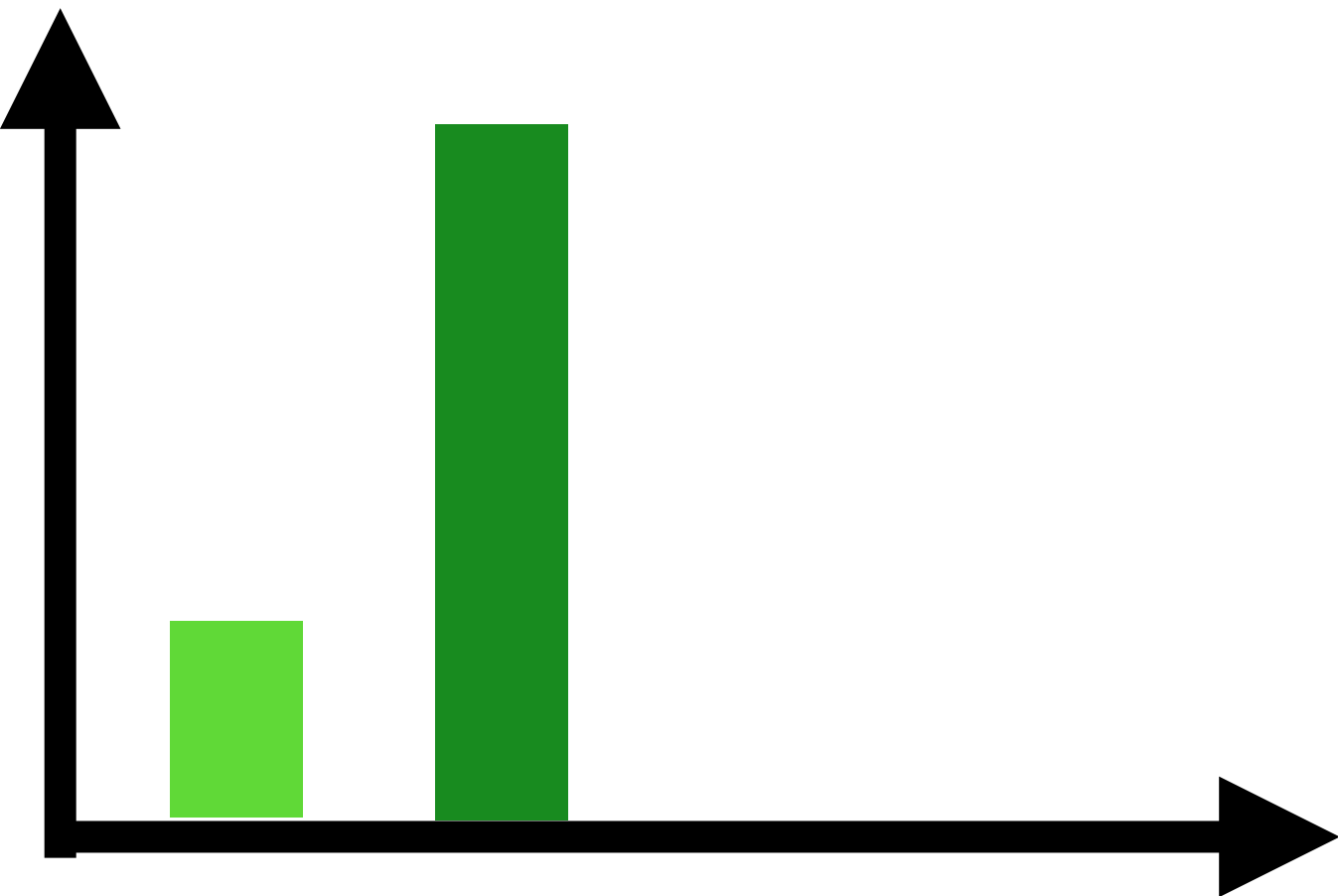
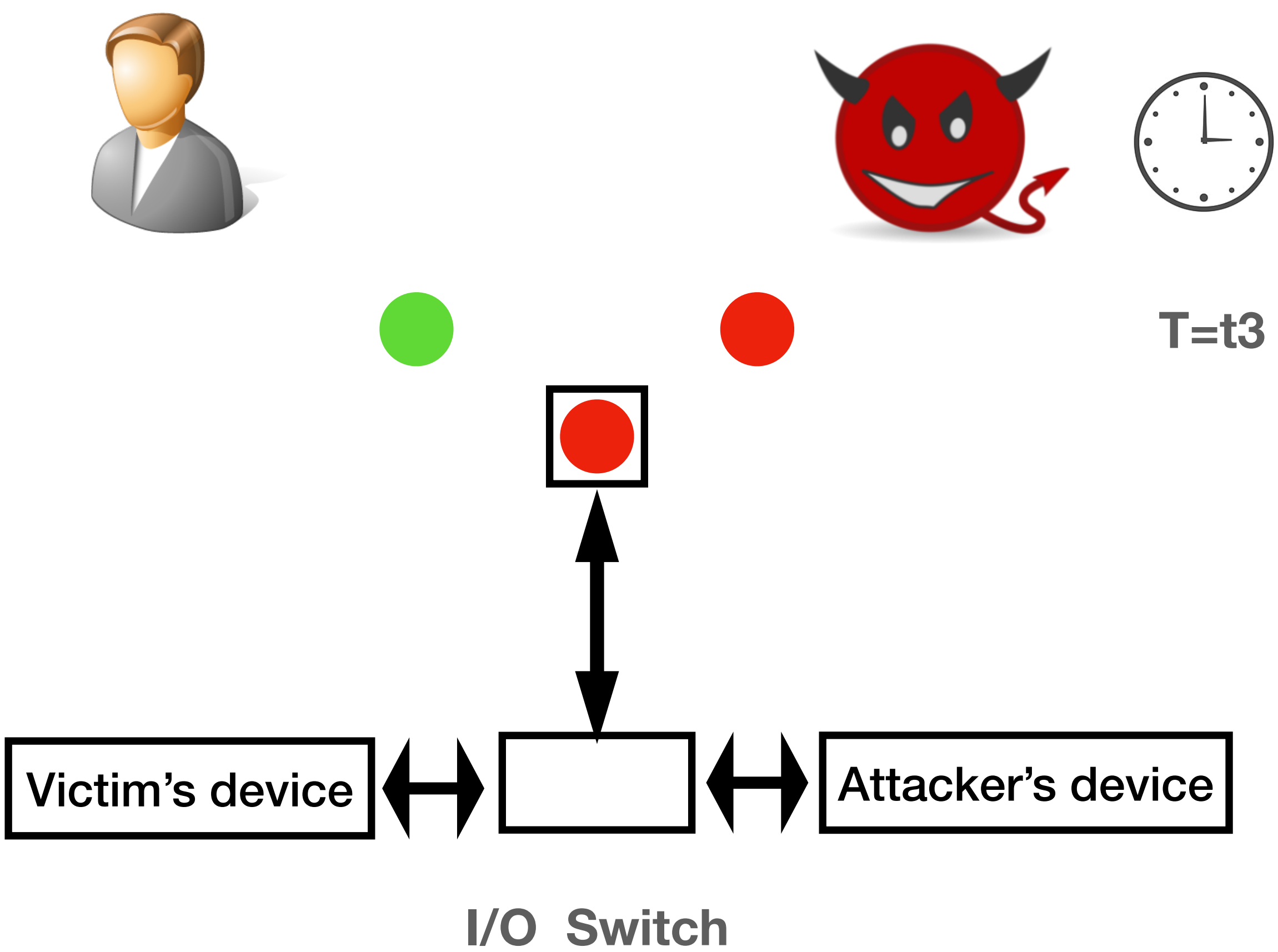
$T=t_2$



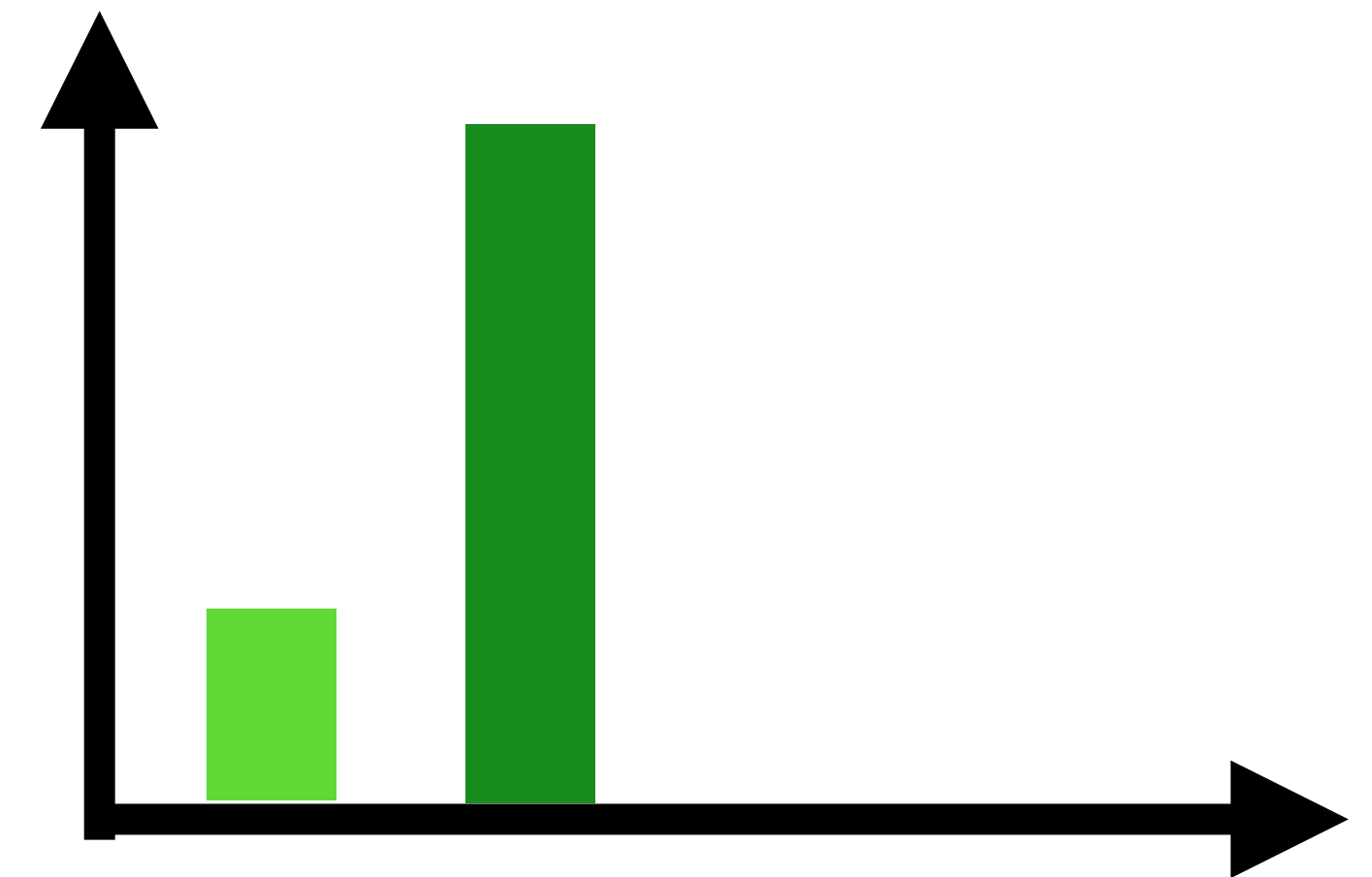
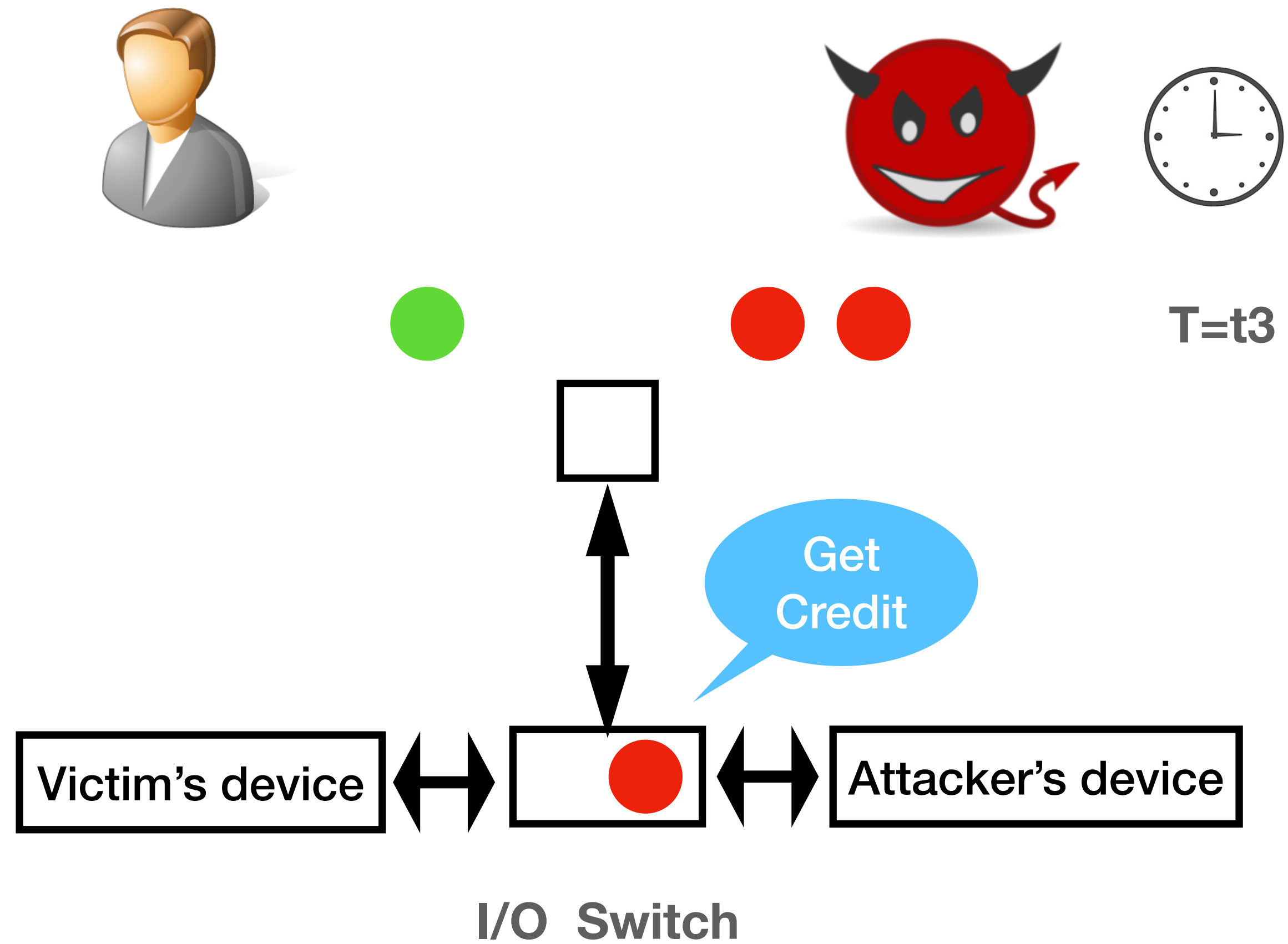
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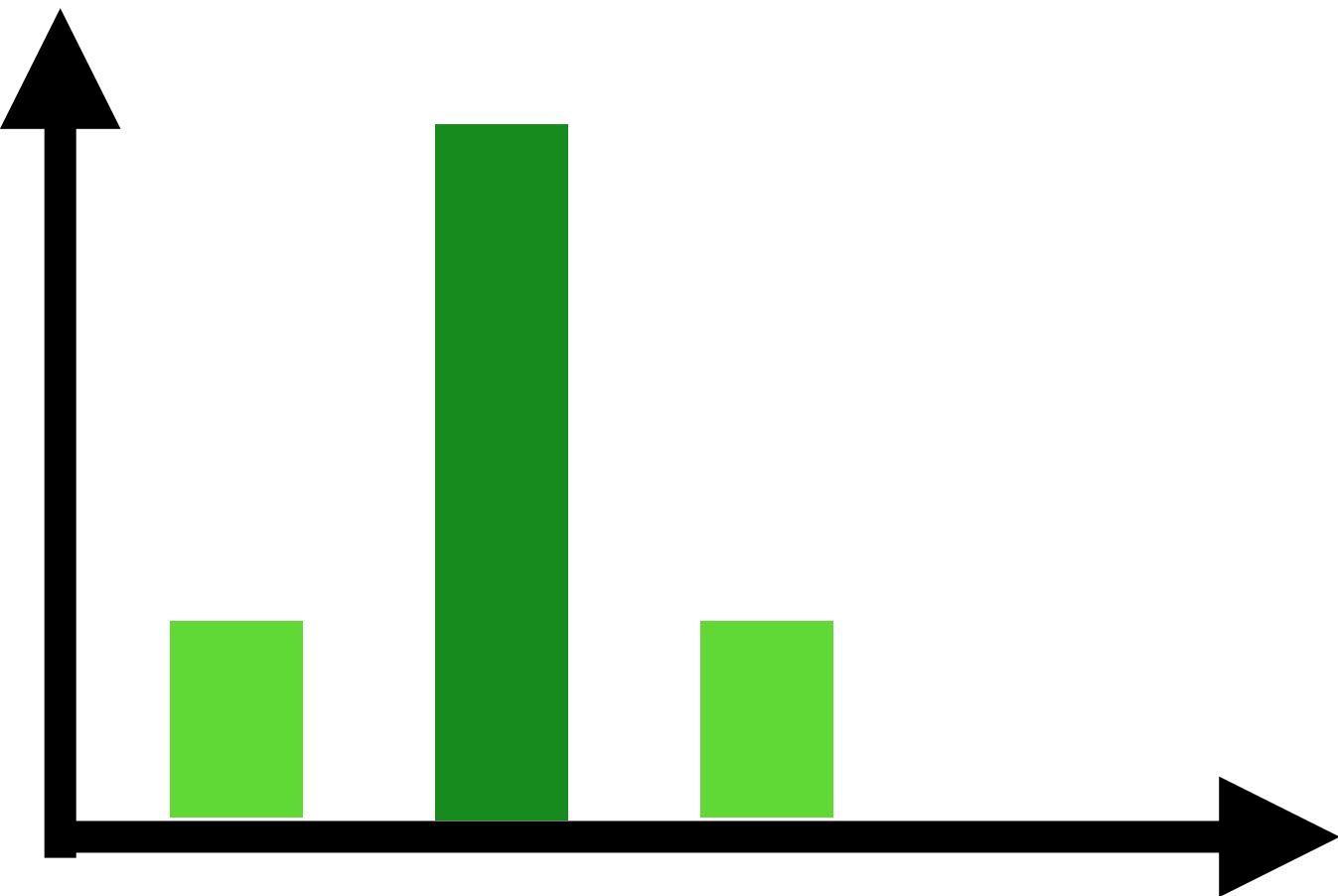
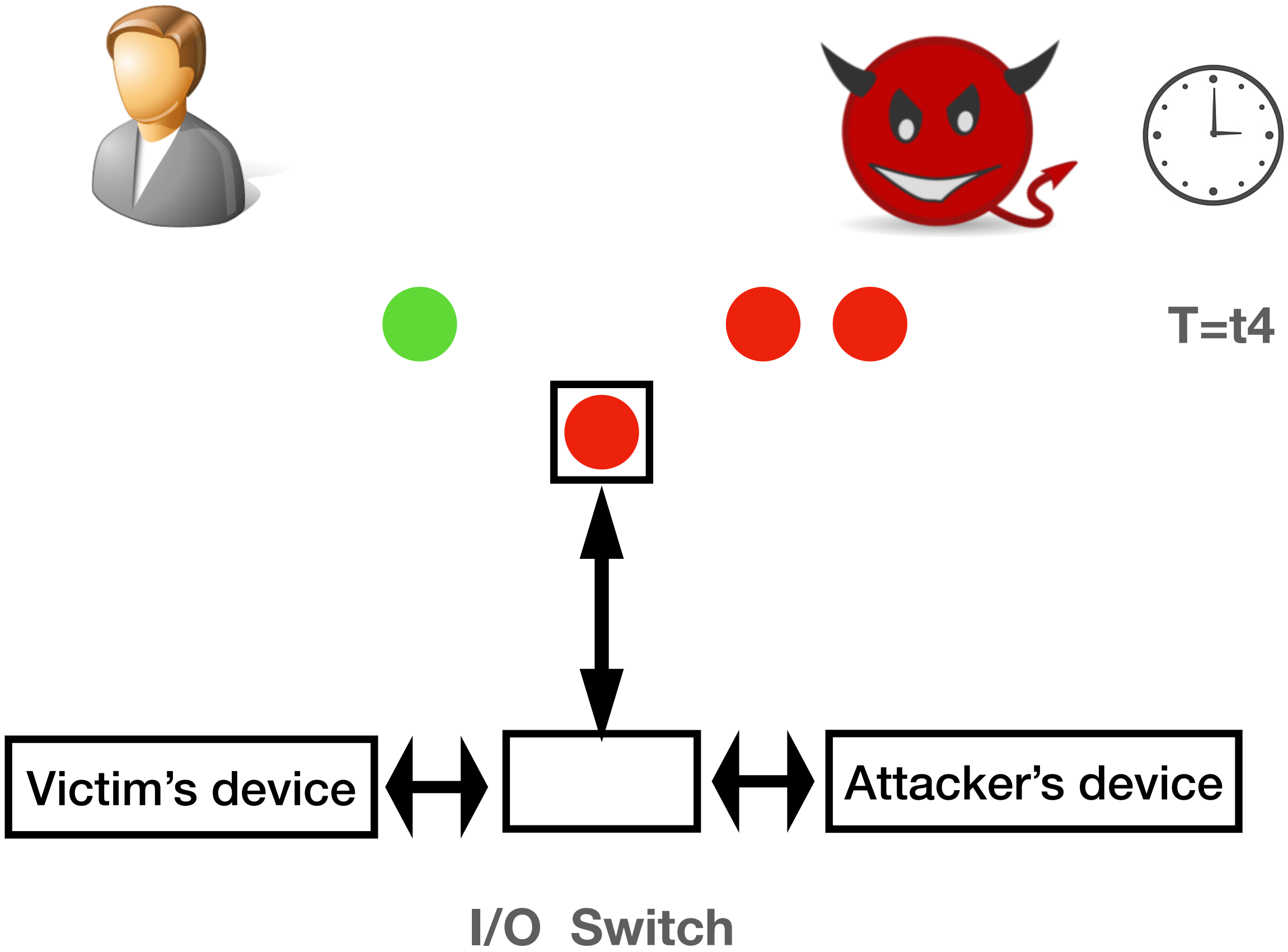


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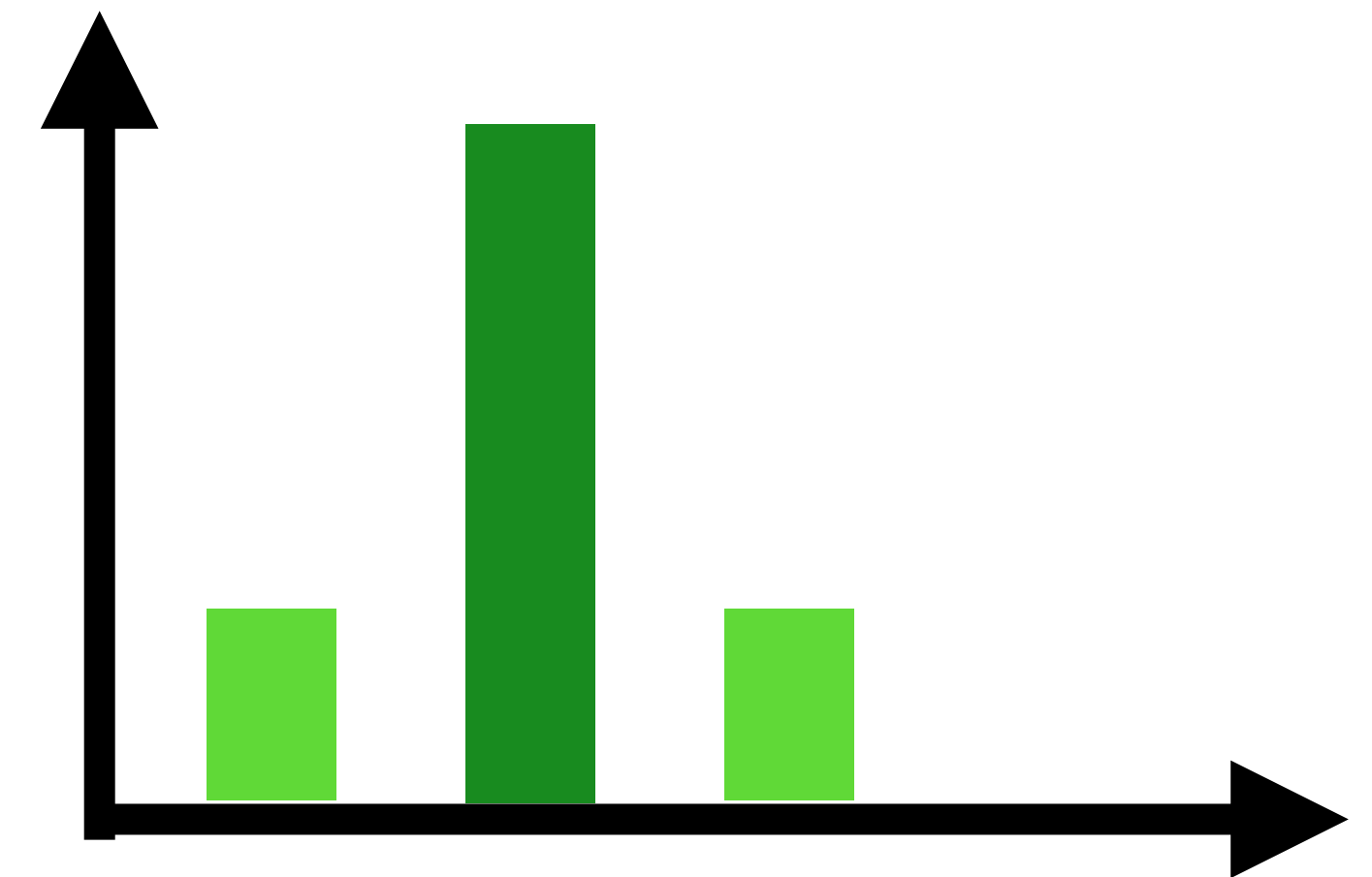




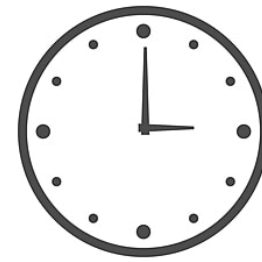
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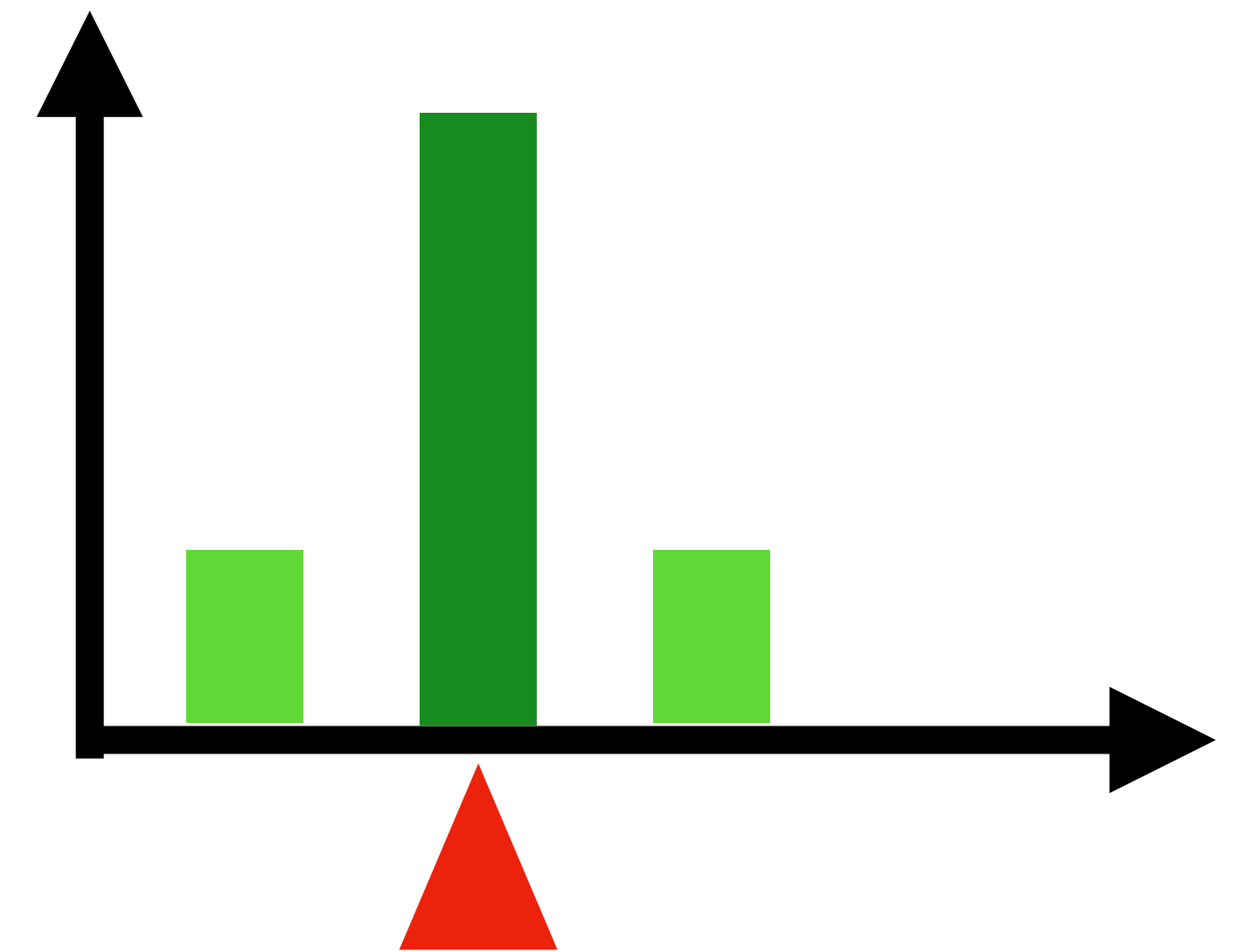
# Why are the data leaked?



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- Attacker knows when victim is active!



Data Movement

# How to monitor the victim behaviors?

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- Access data ceaselessly and make congestion

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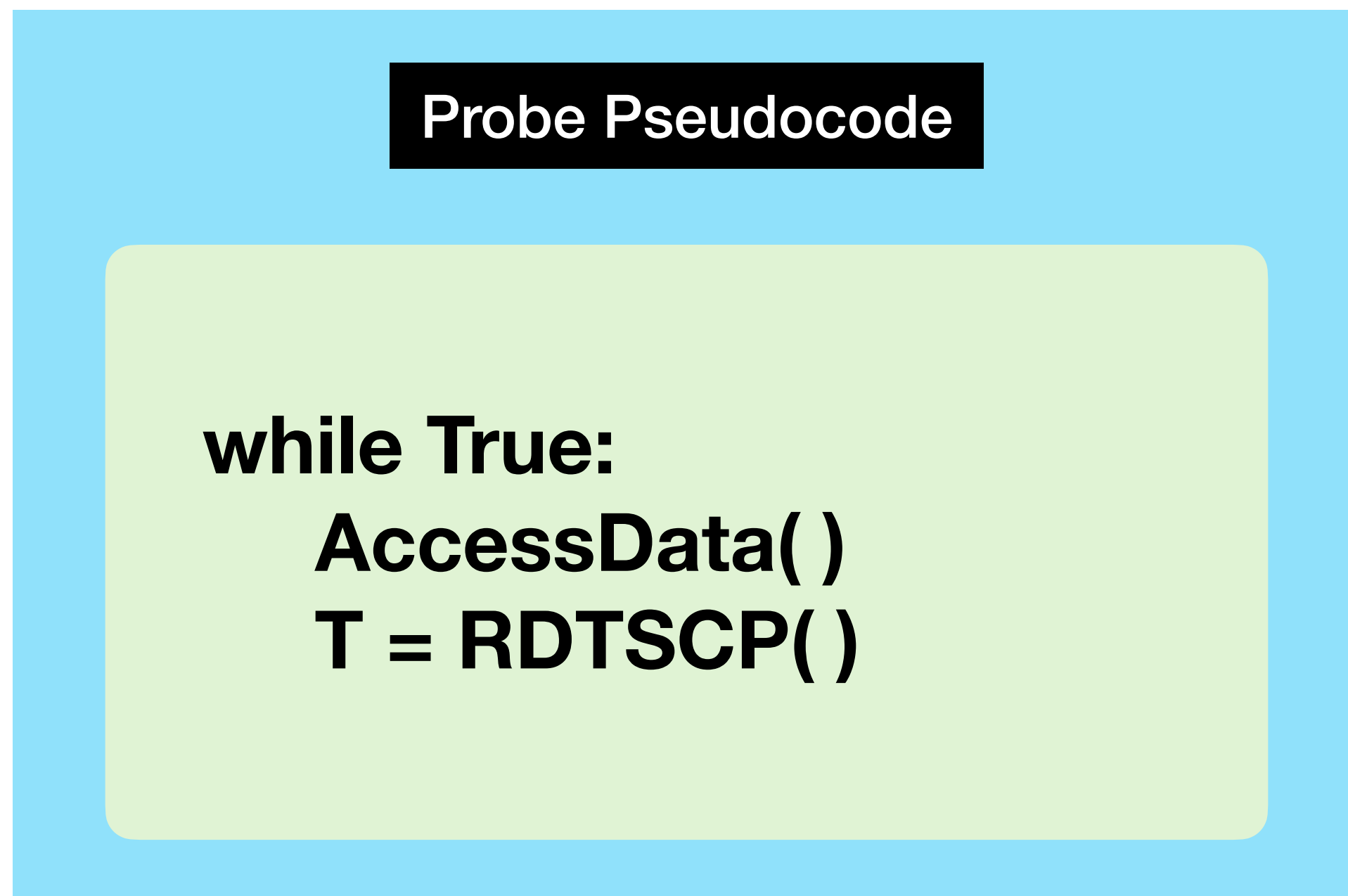
- Access data ceaselessly and make congestion
- Record latency between two operations

## Probe Pseudocode

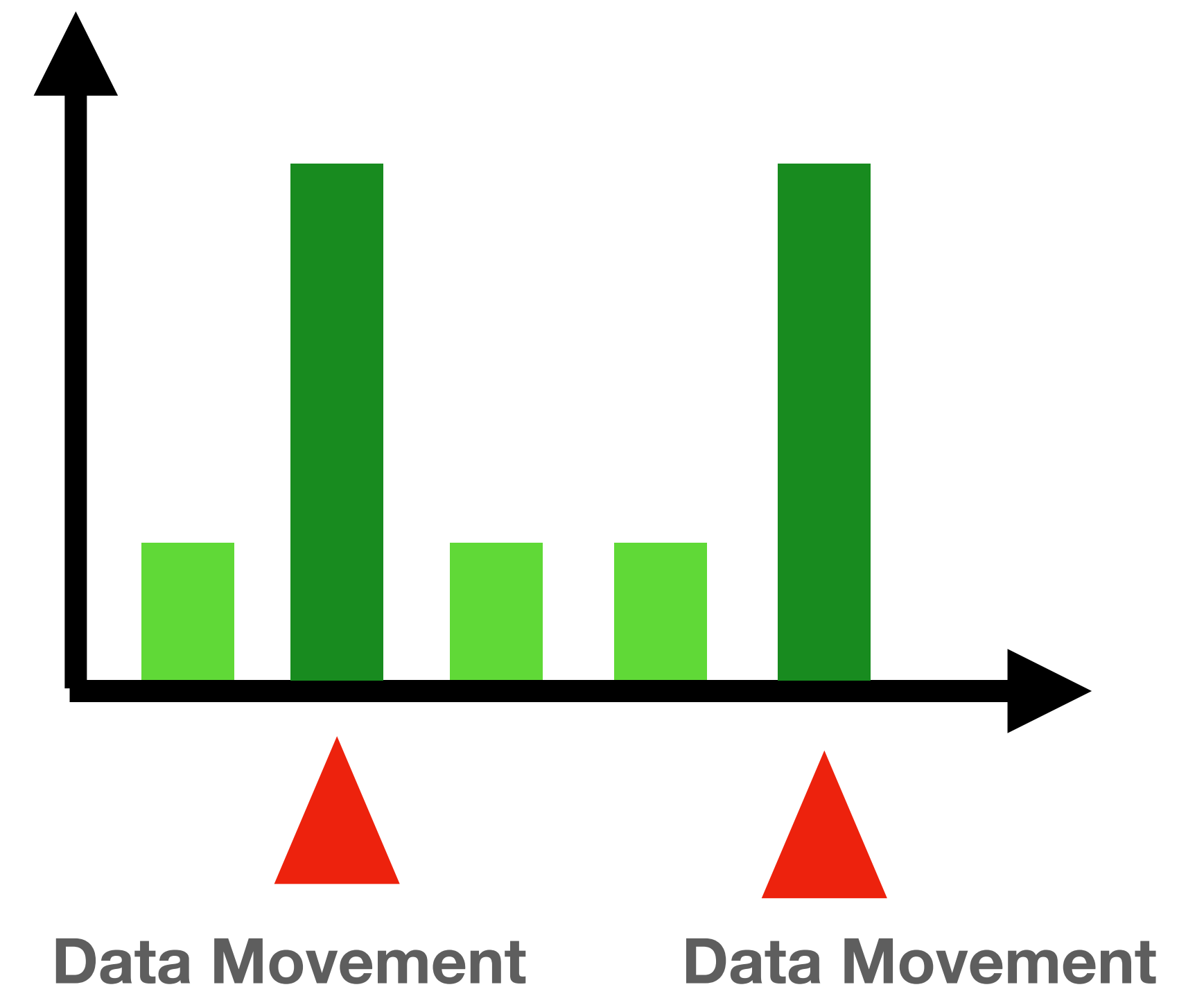
```
while True:  
    AccessData( )  
    T = RDTSCP( )
```

# How to monitor the victim behaviors?

- Access data ceaselessly and make congestion
- Record latency between two operations

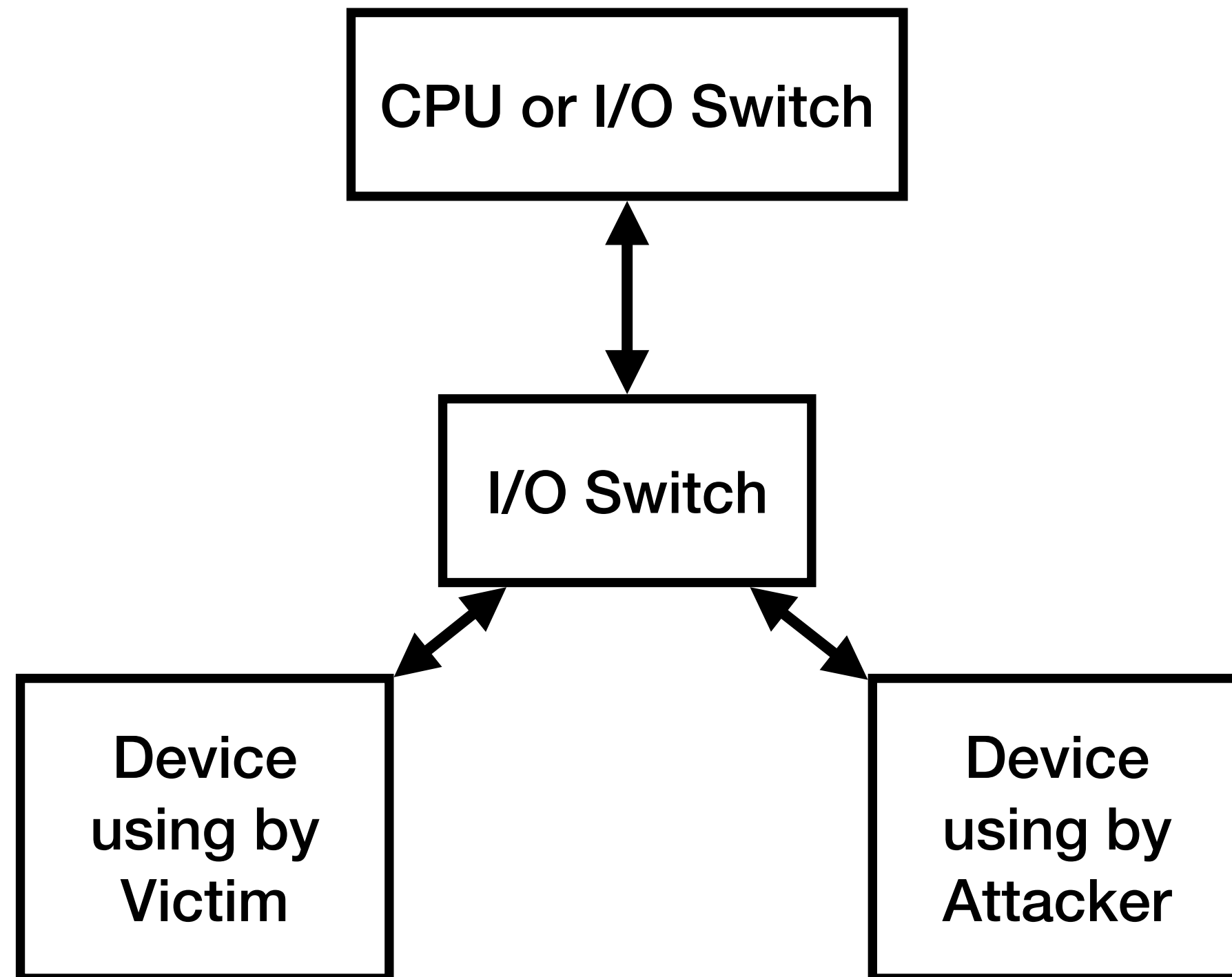


- A higher latency means data is transmitting

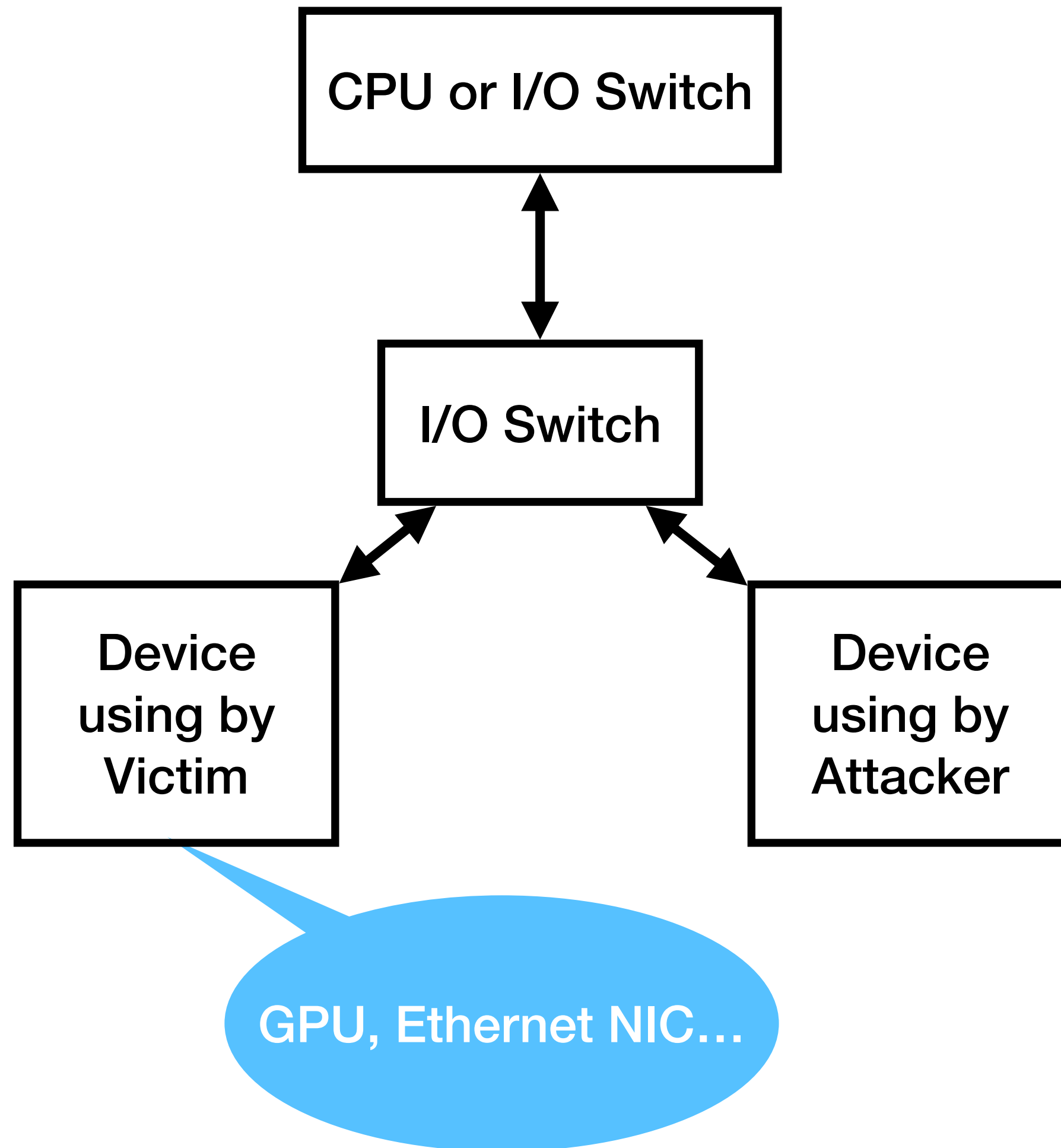




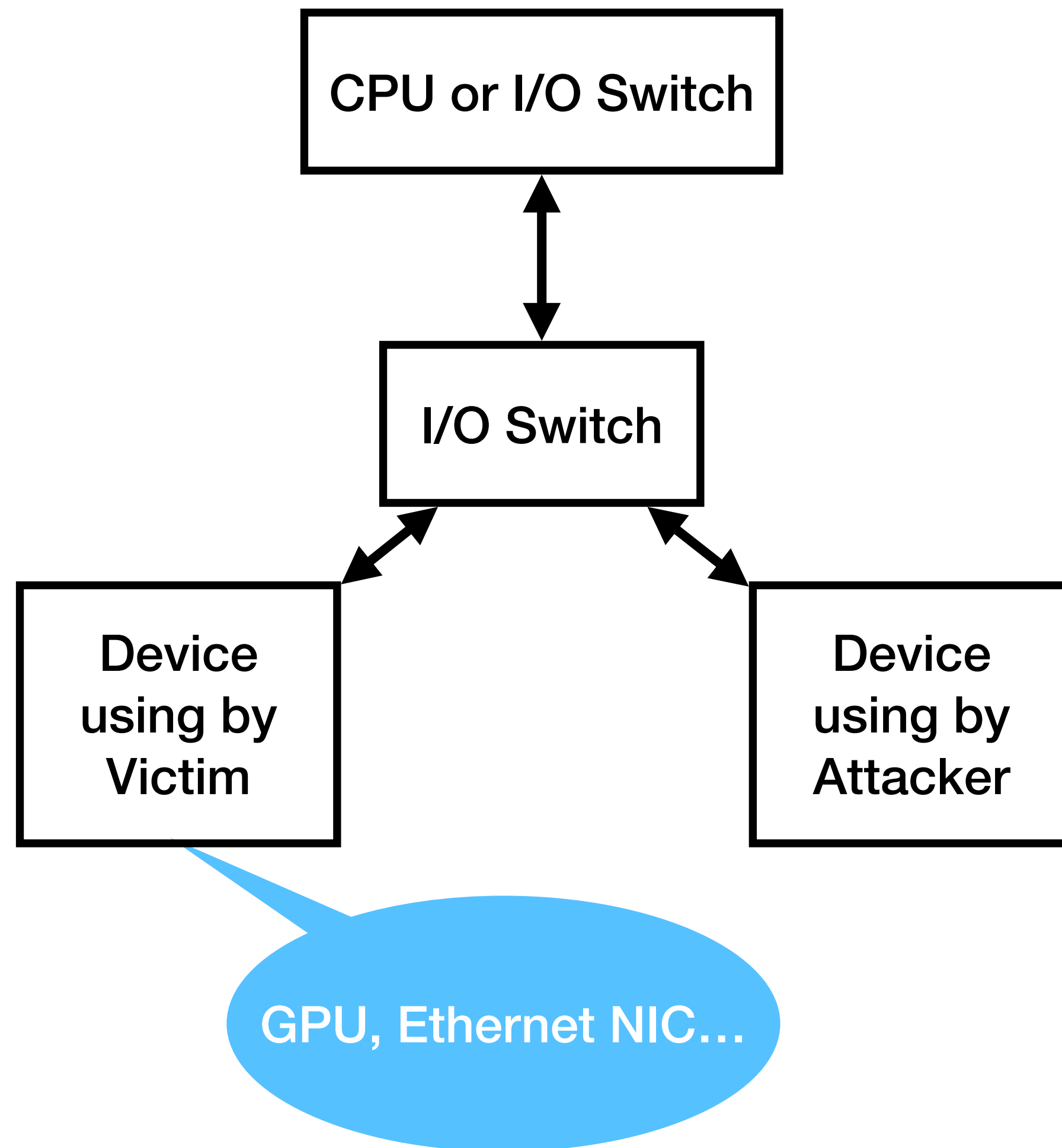
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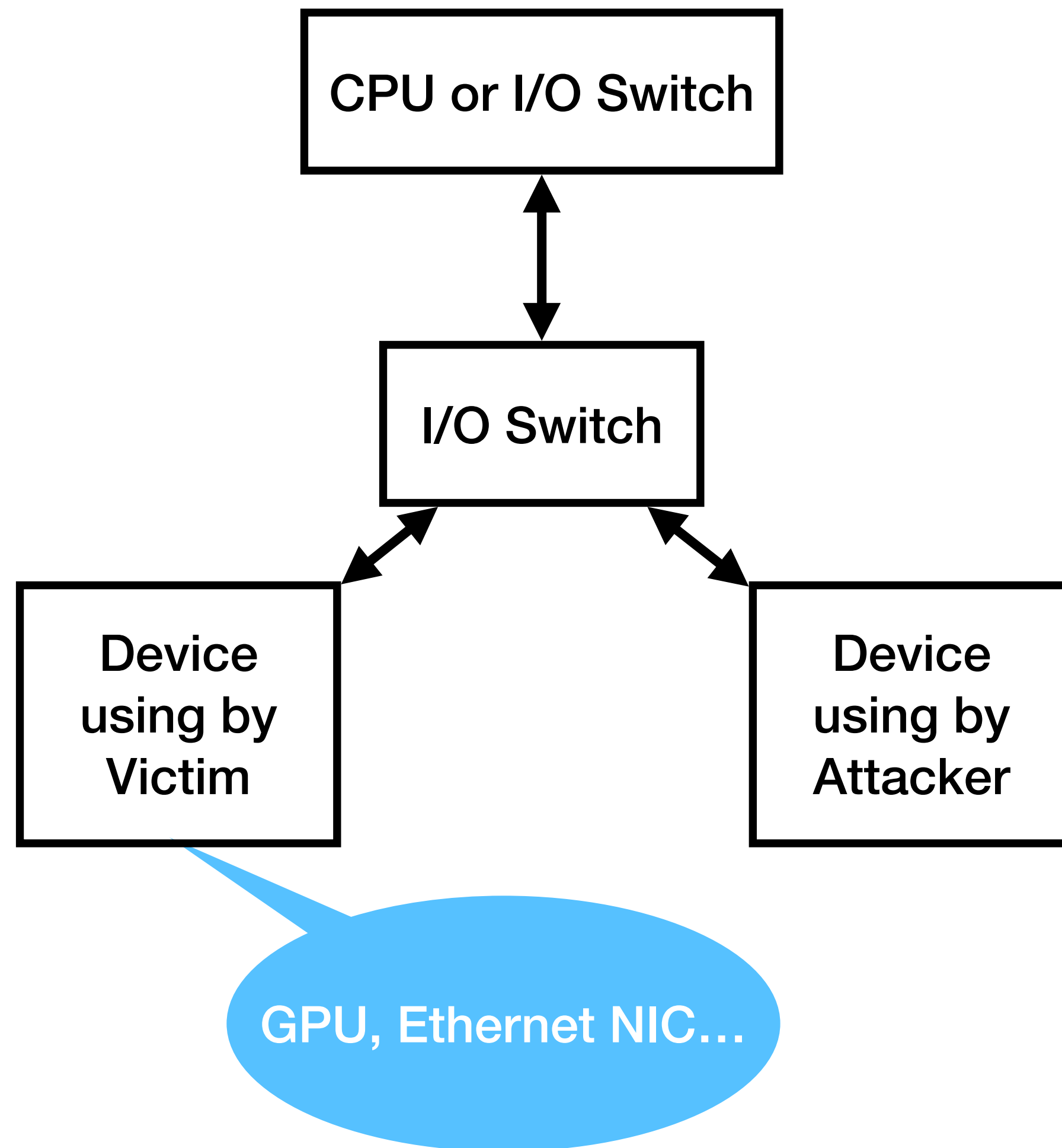


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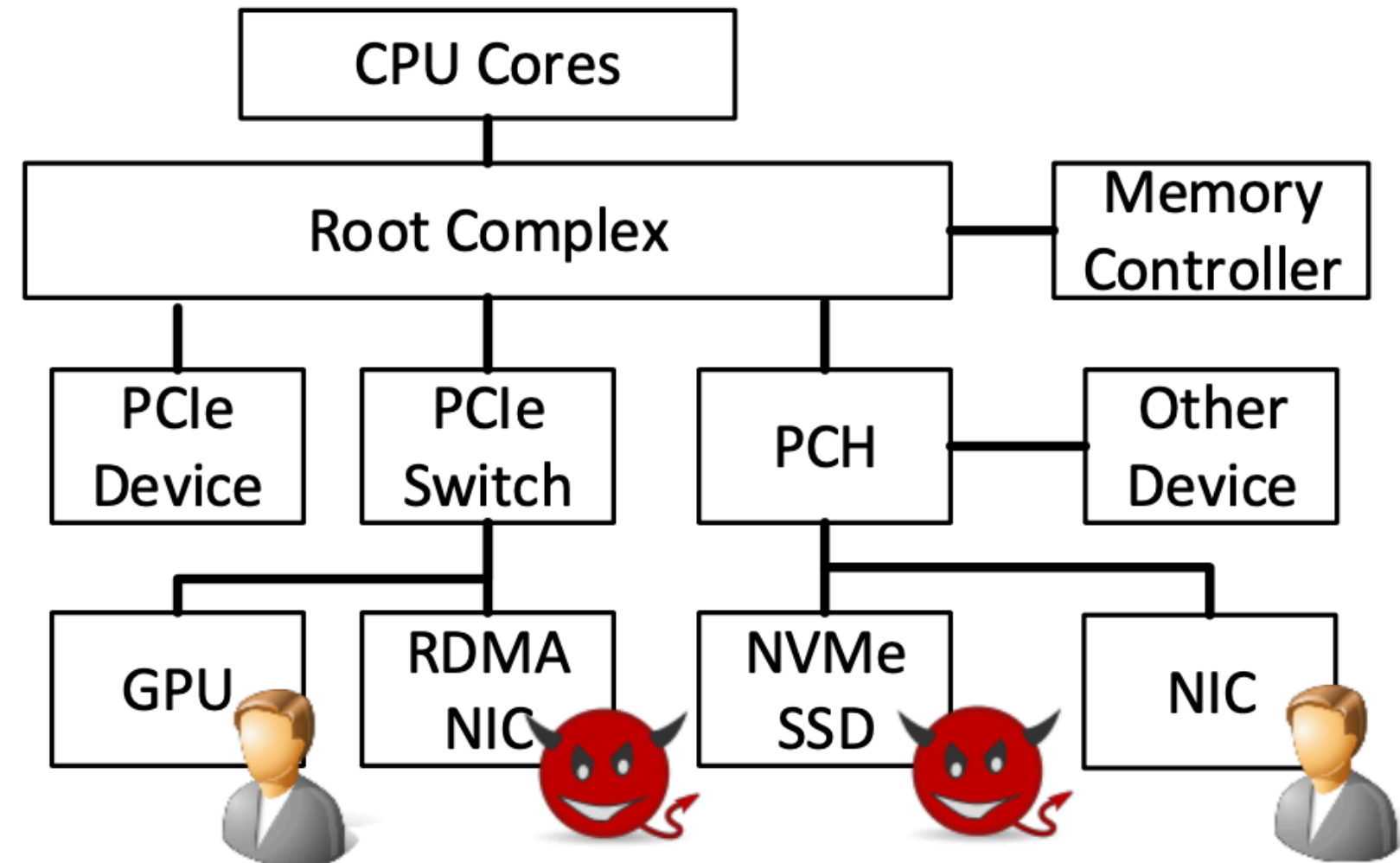
- GPU
  - password input in monitor
  - render webpages
  - machine Learning models trained

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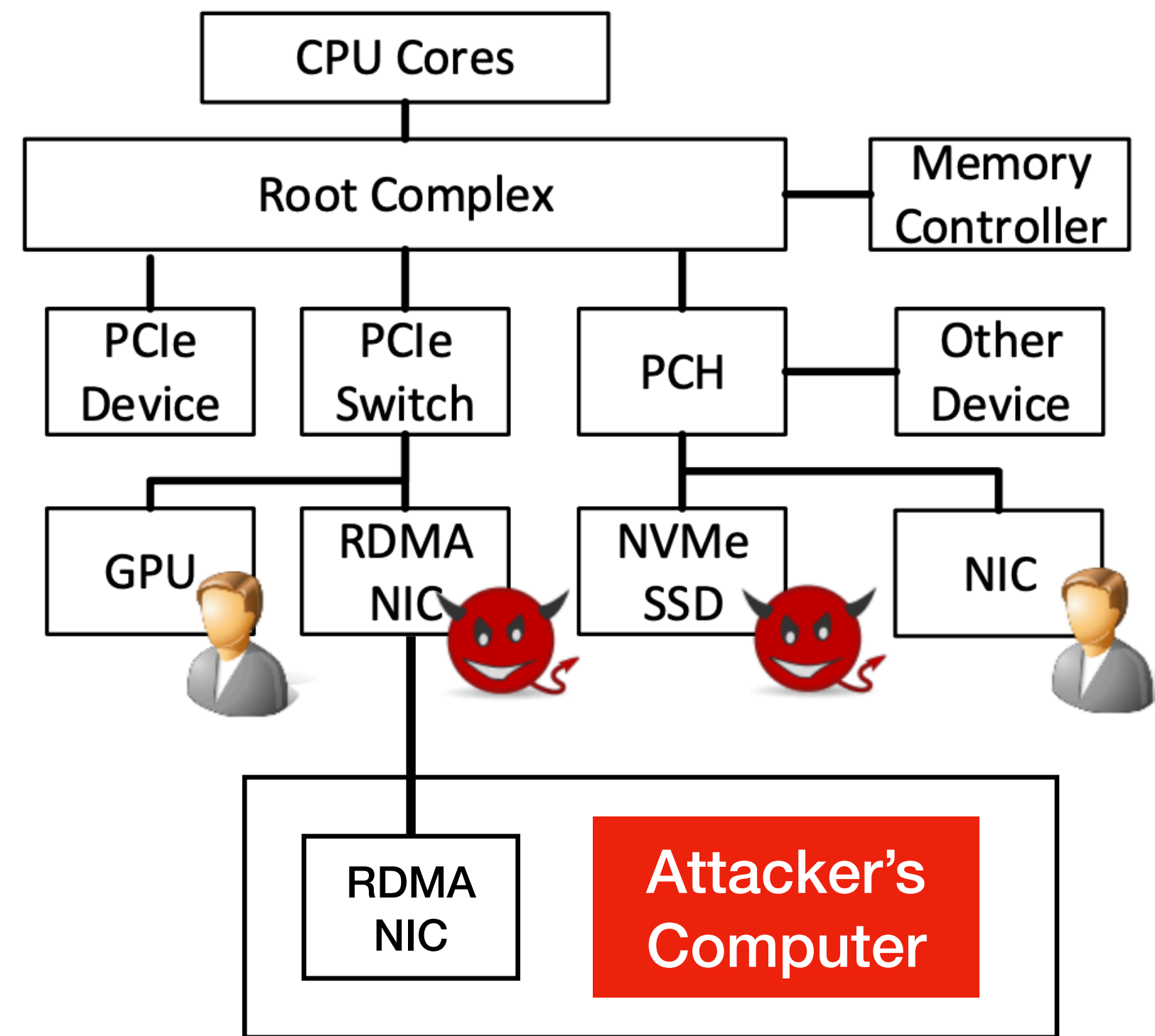


- GPU
  - password input in monitor
  - render webpages
  - machine Learning models trained
- Ethernet NIC
  - transmit webpages packets
  - SSH passwords or texts

# Attack scenarios and victim tasks

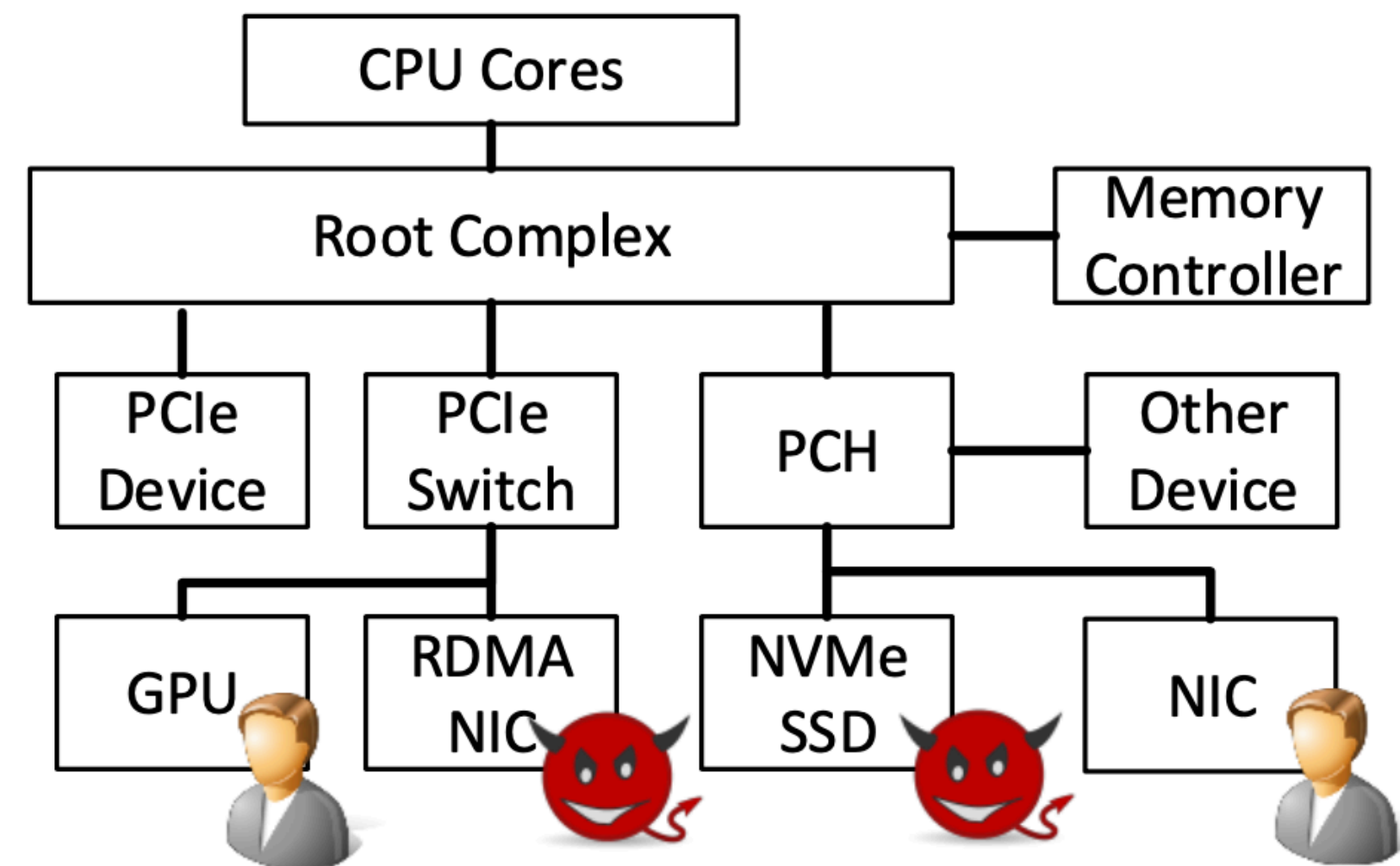


# Attack scenarios and victim tasks



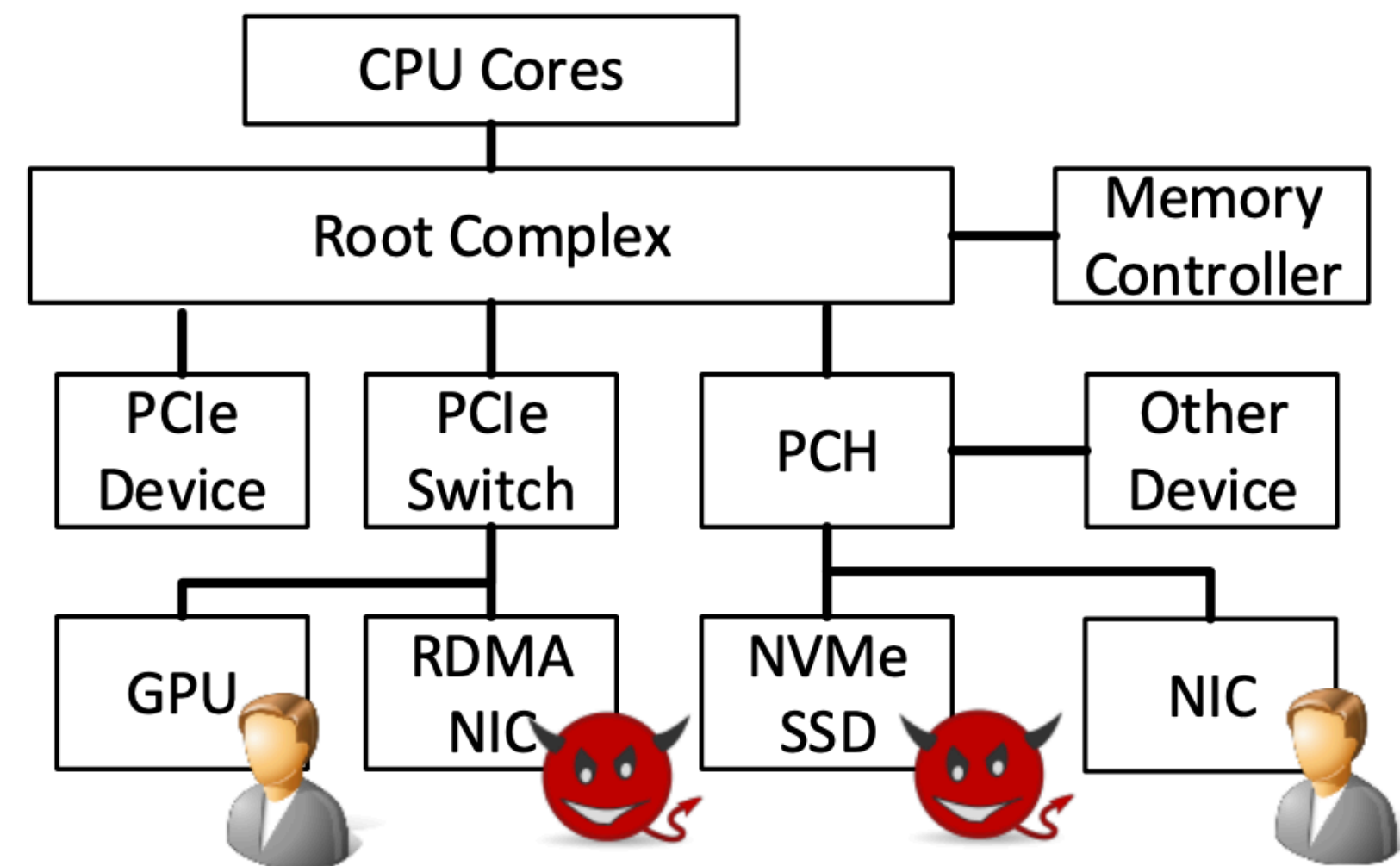
**S1 Control RDMA NIC to attack GPU**

# Attack scenarios and victim tasks



## S2 Control NVMe SSD to attack Ethernet NIC

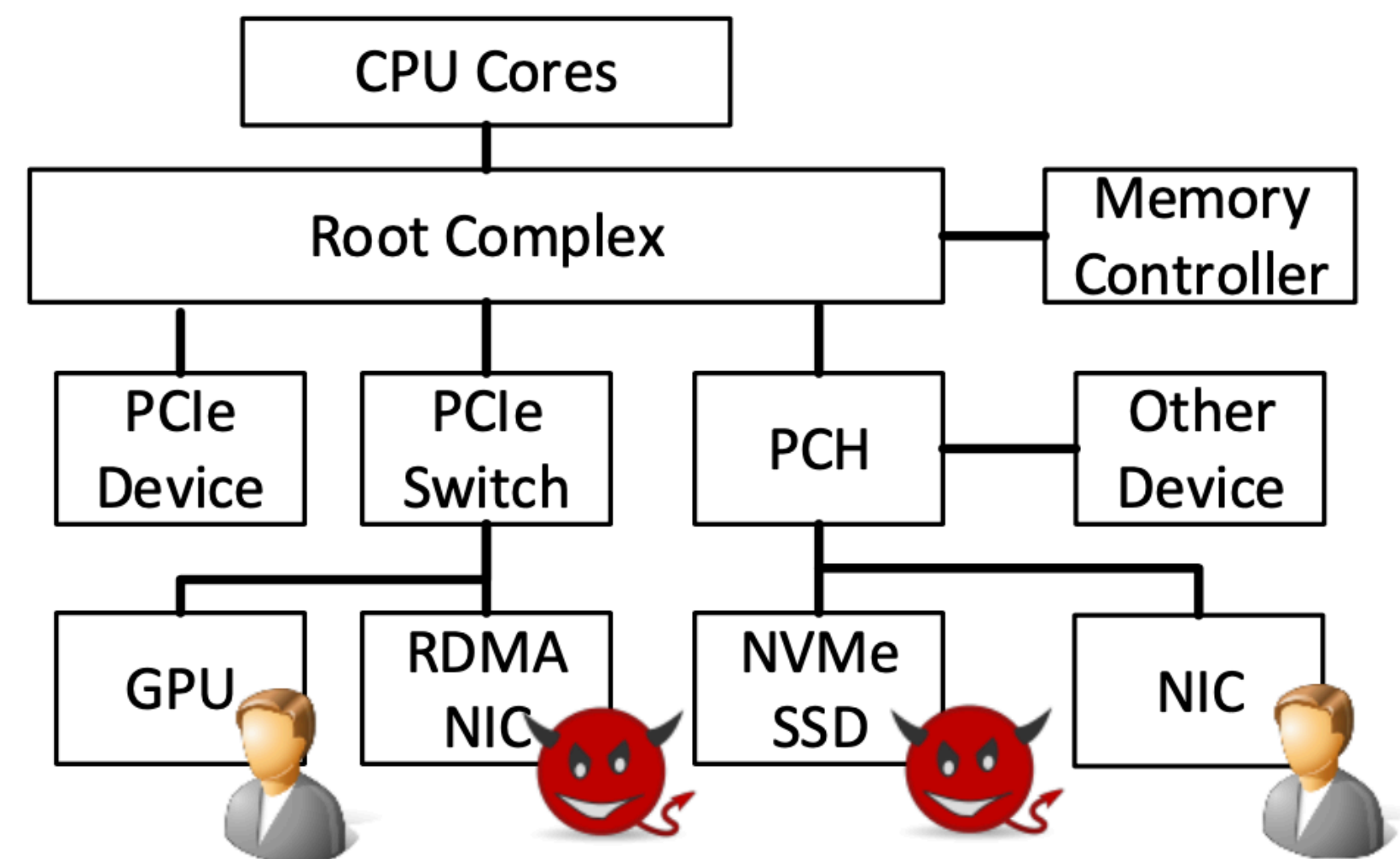
# Attack scenarios and victim tasks



- T1 User-input Inference
- T2 Webpage Inference
- T3 Machine-learning Model Inference



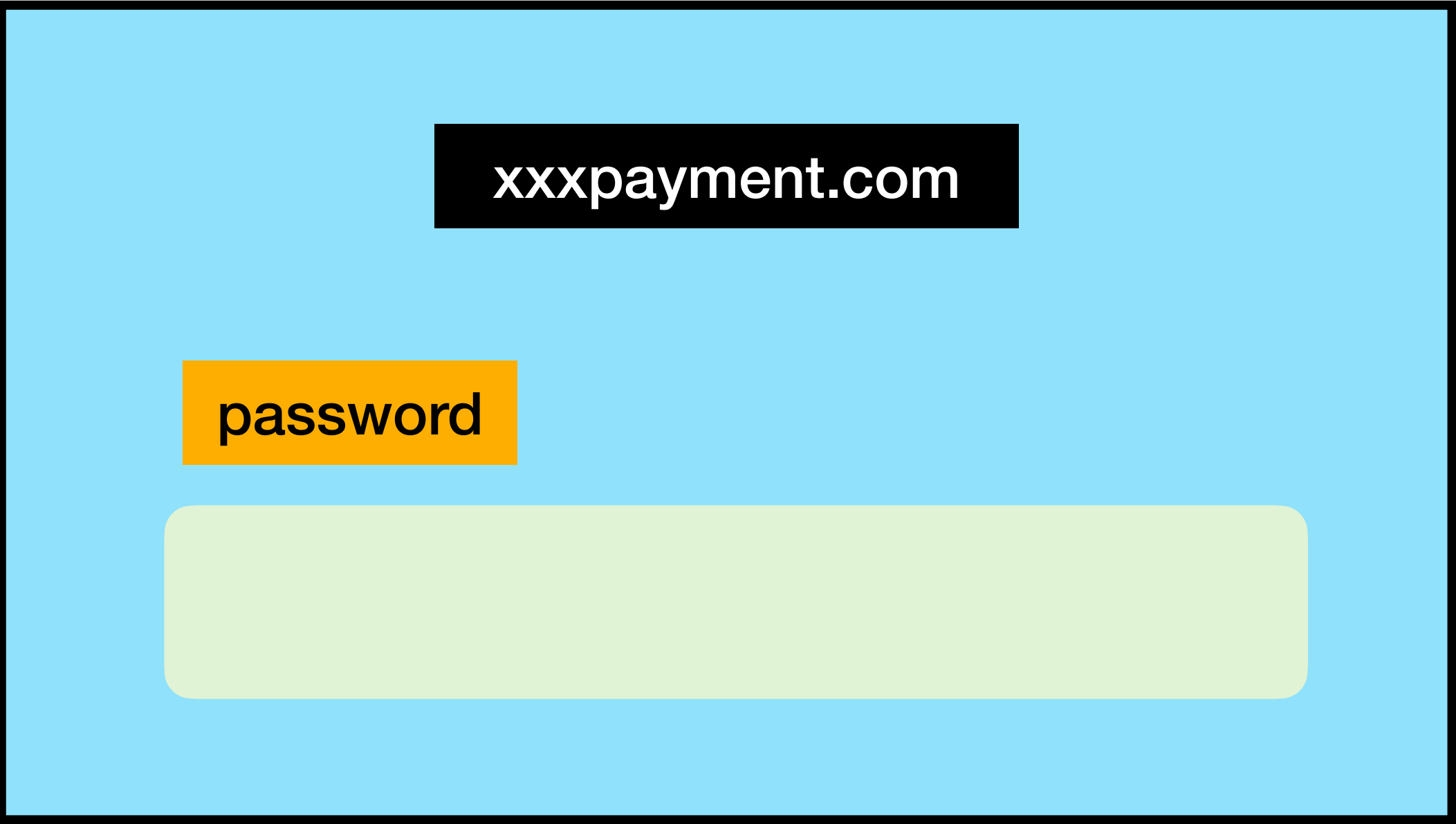
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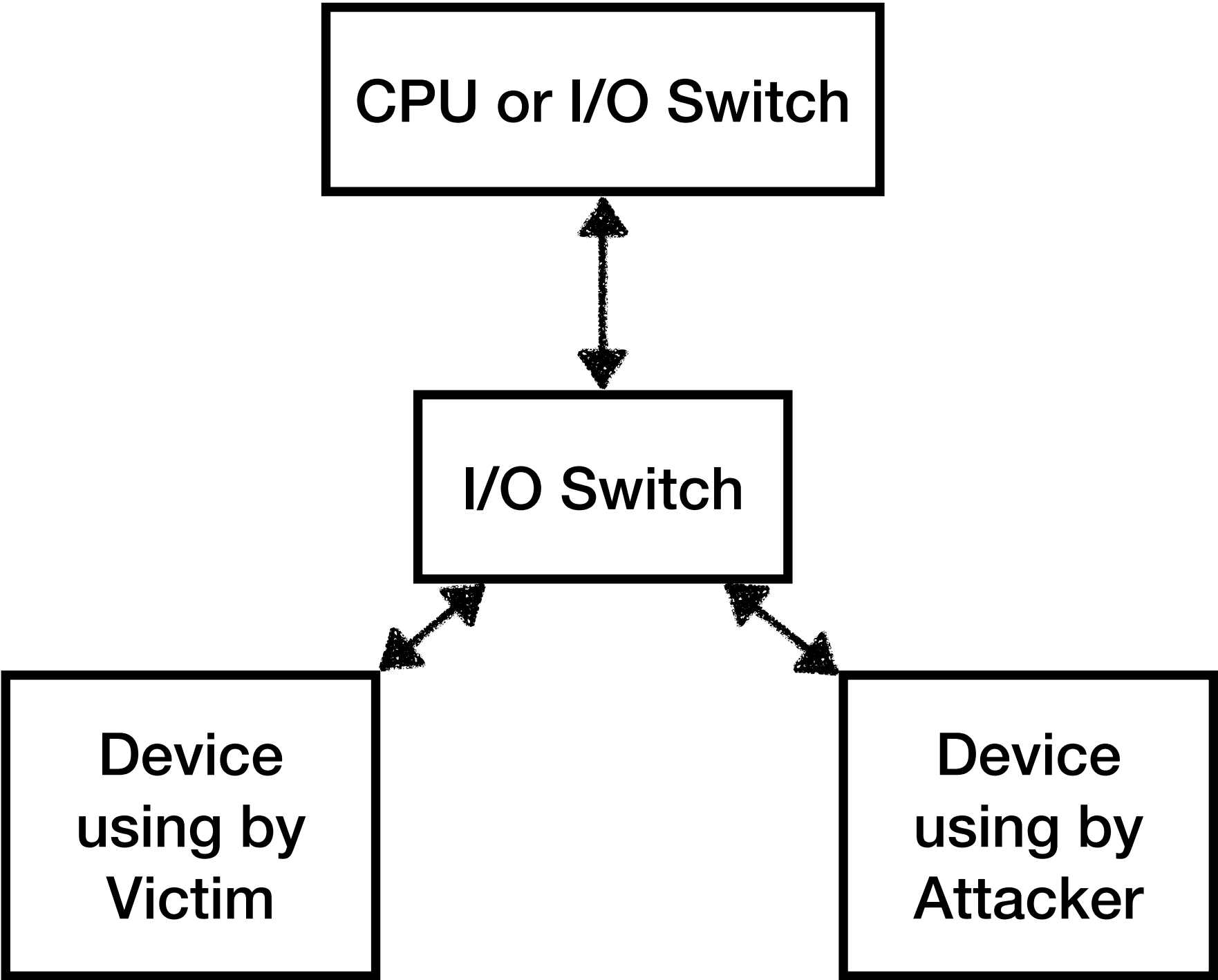
- T1 User-input Inference
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- T3 Machine-learning Model Inference

	T1	T2	T3
S1	✓	✓	✓
S2		✓	

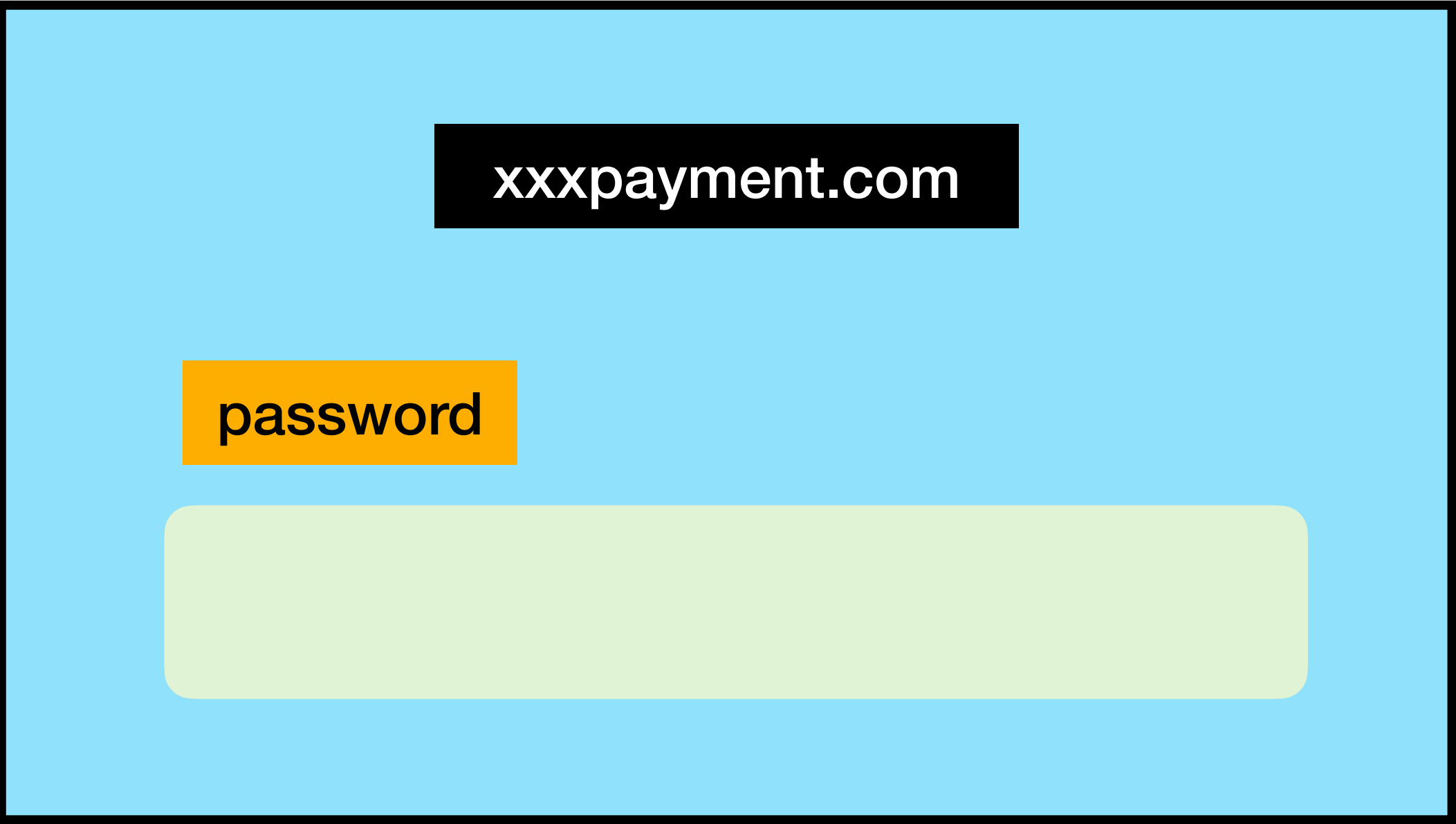
# User-input Inference



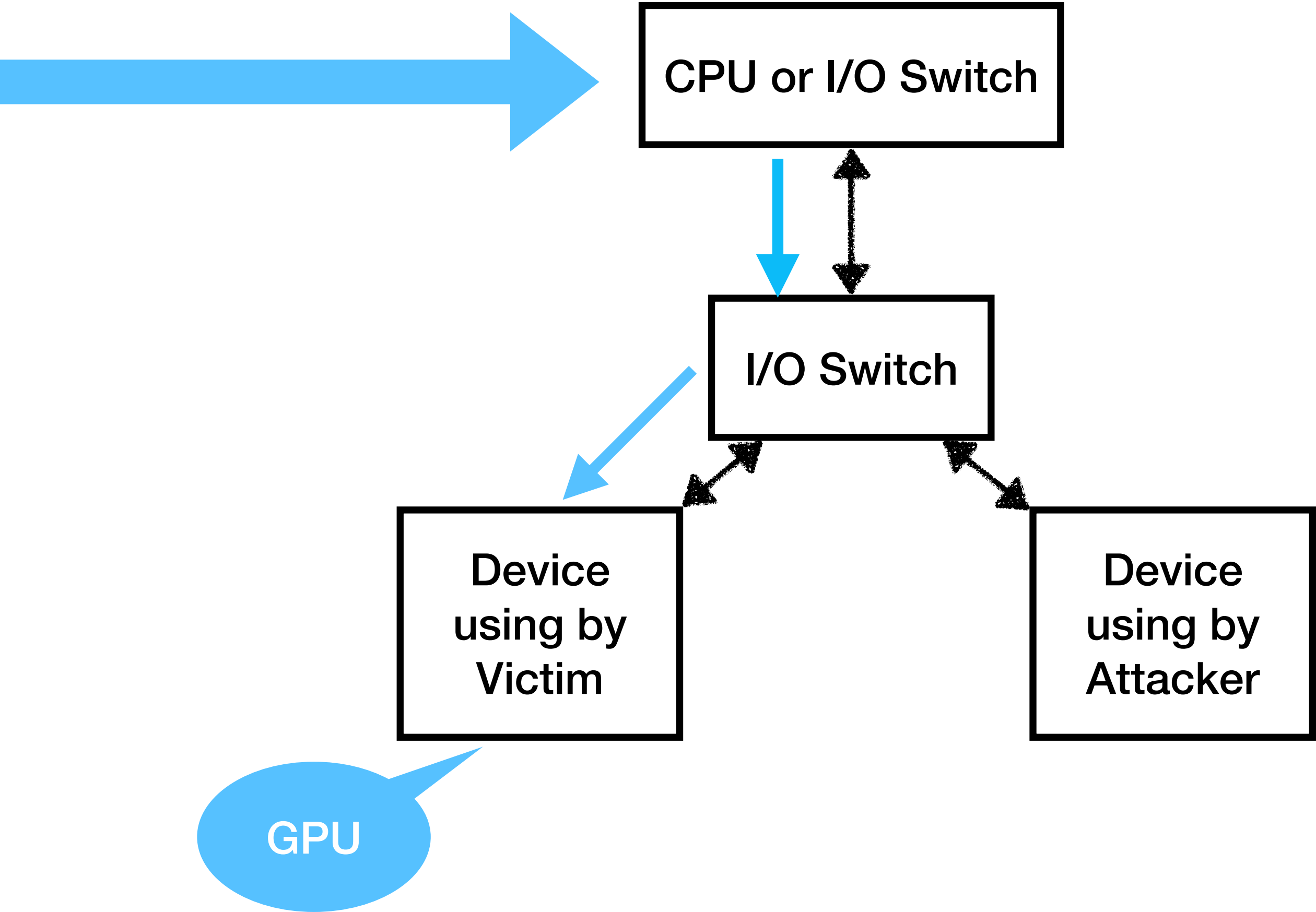
Delay Sequence



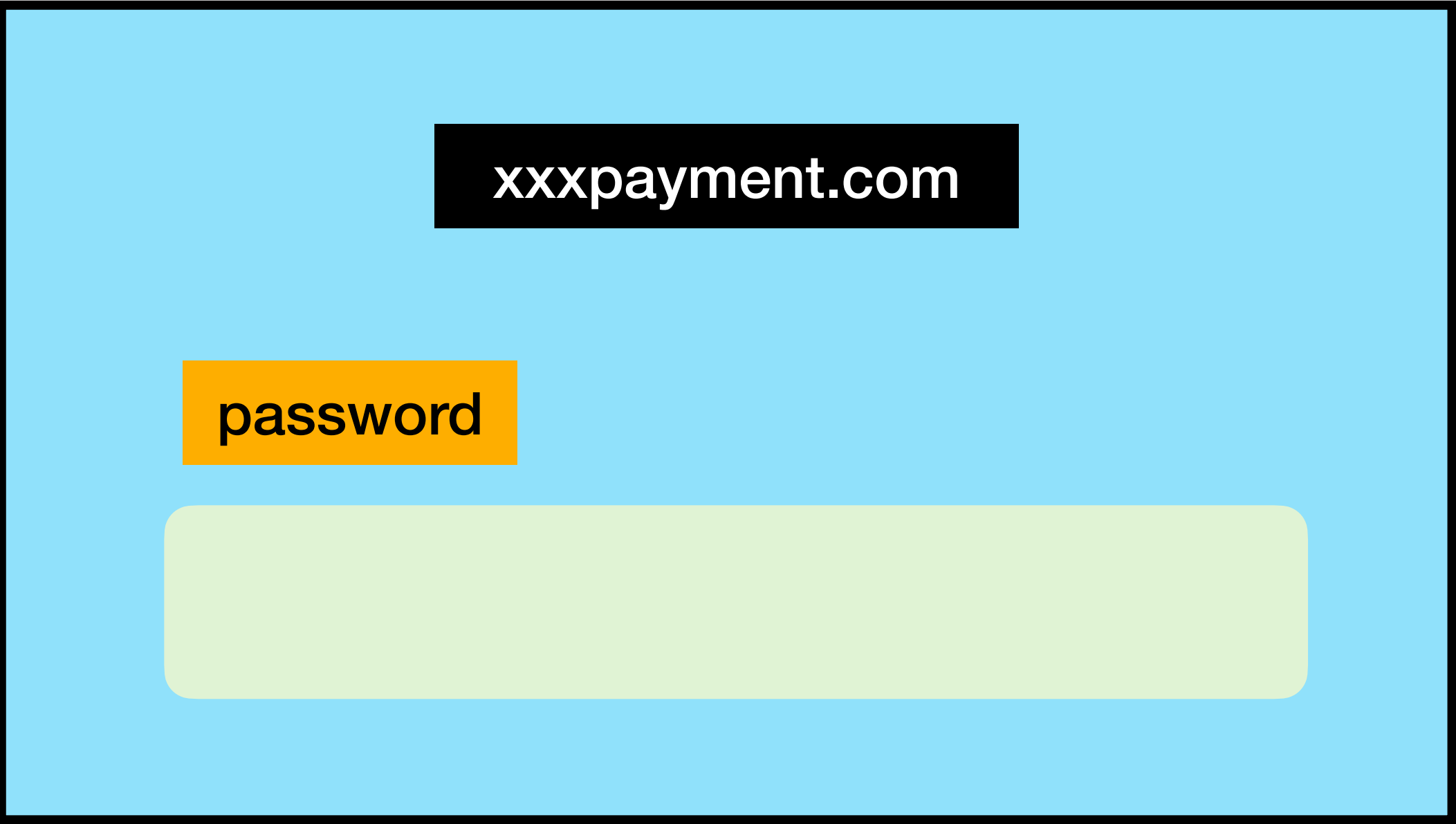
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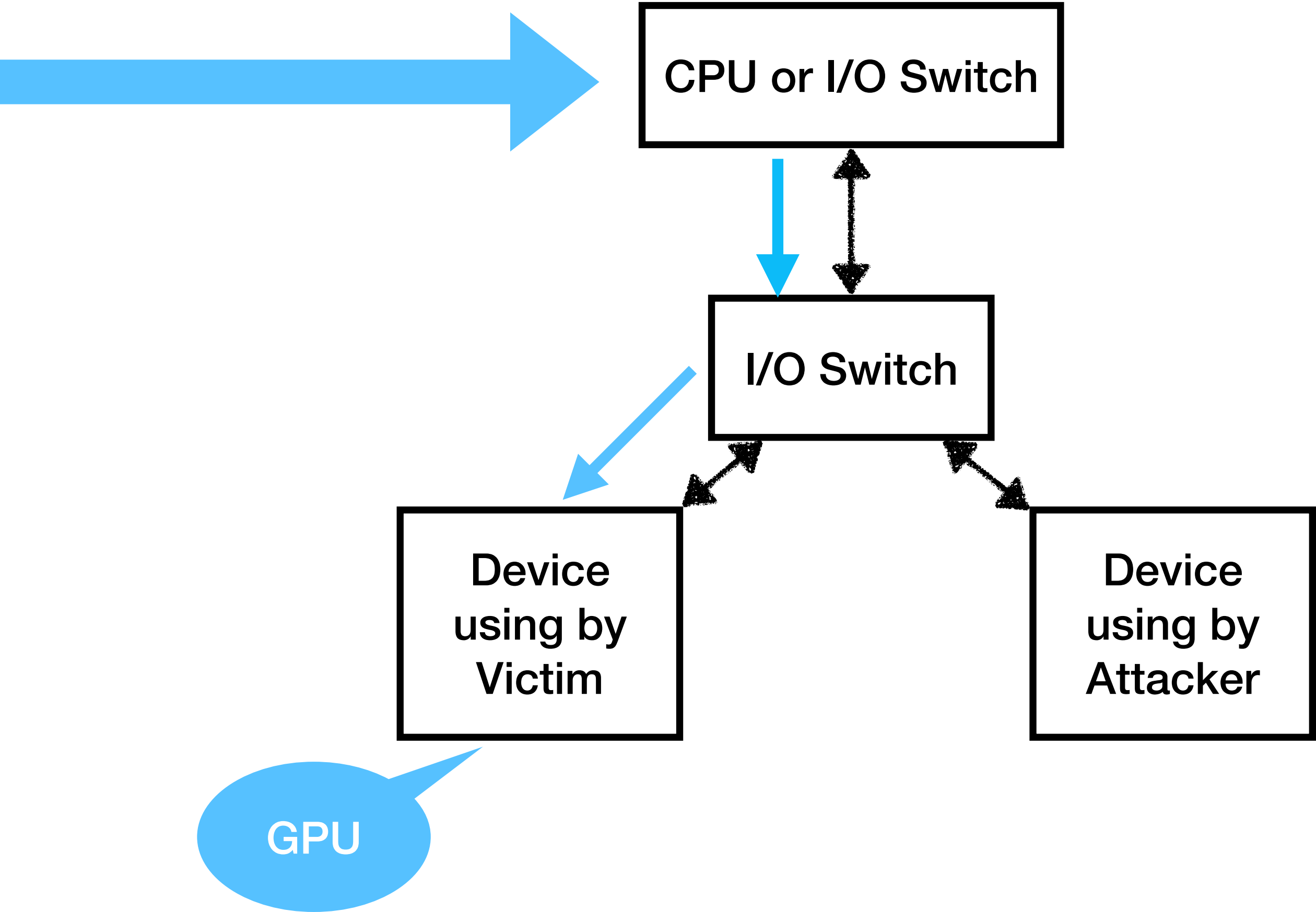
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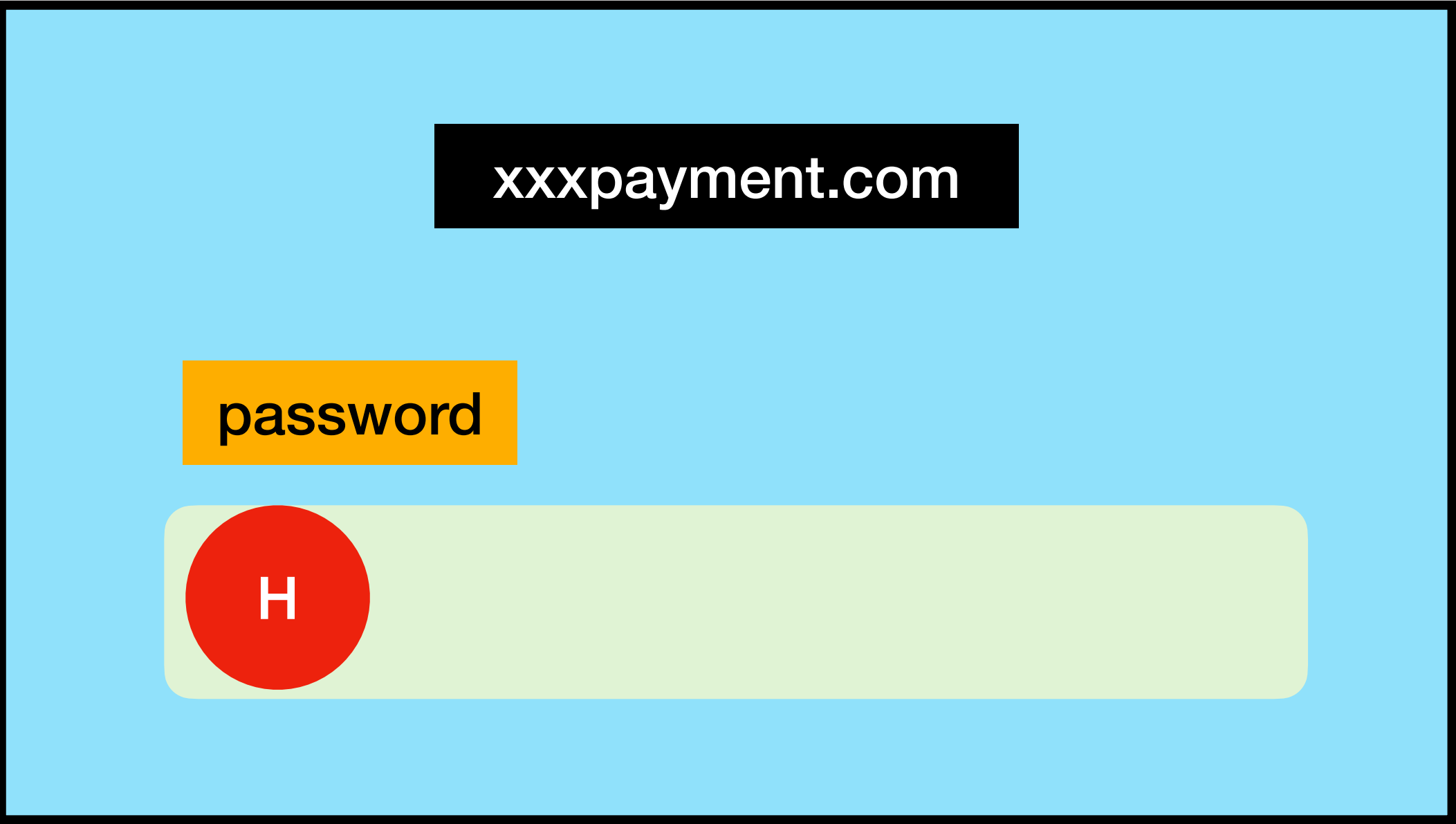
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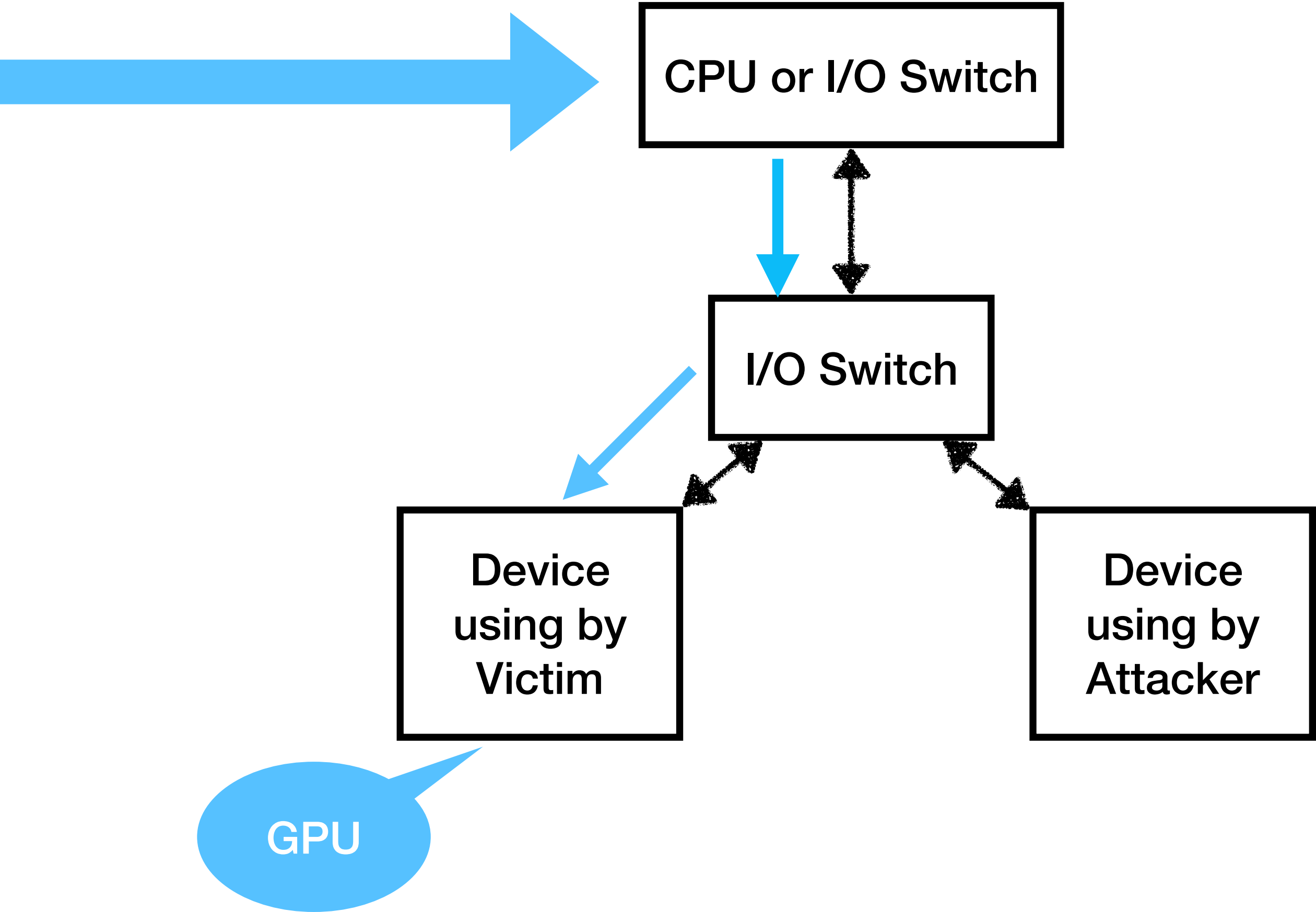
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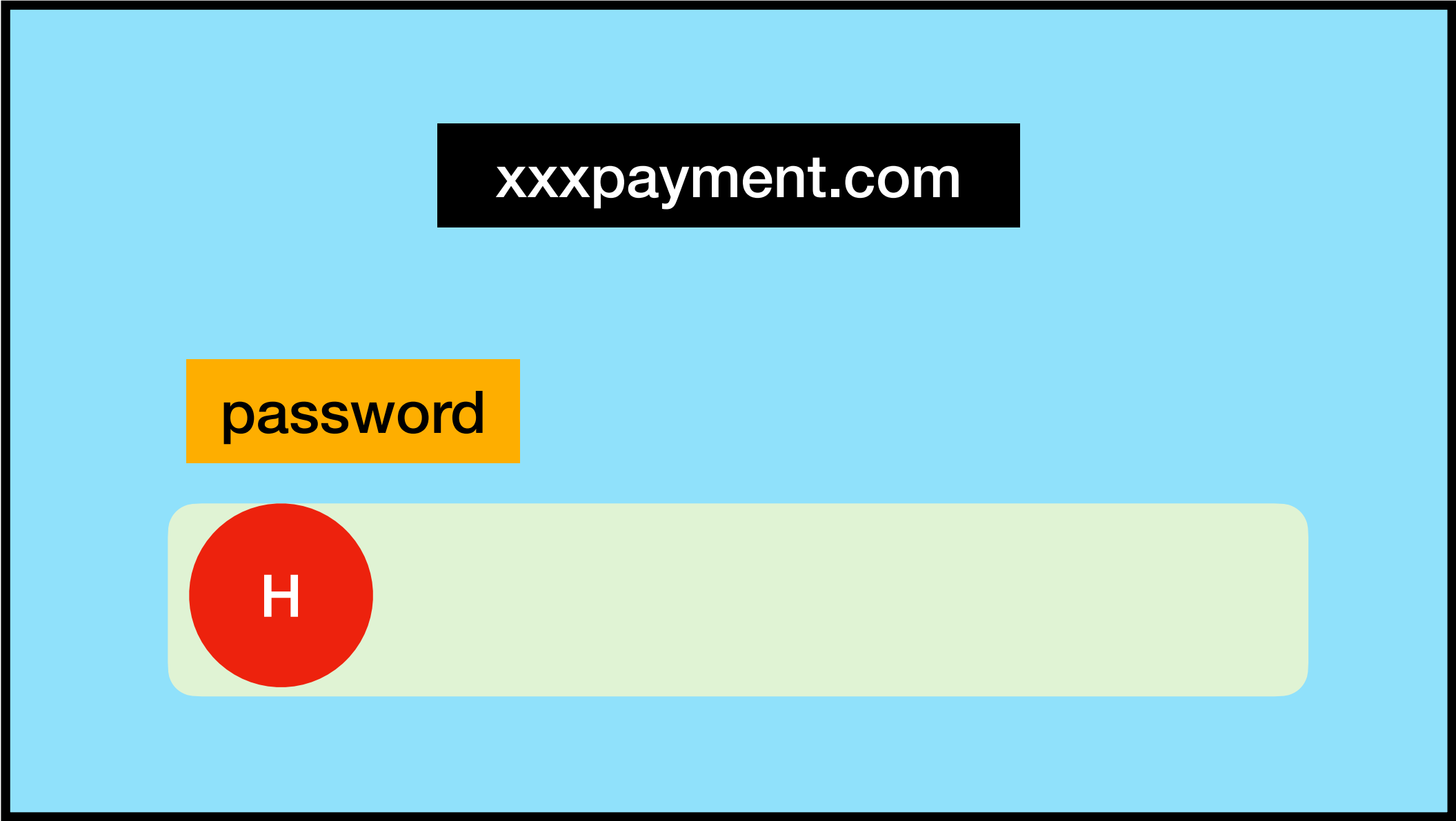
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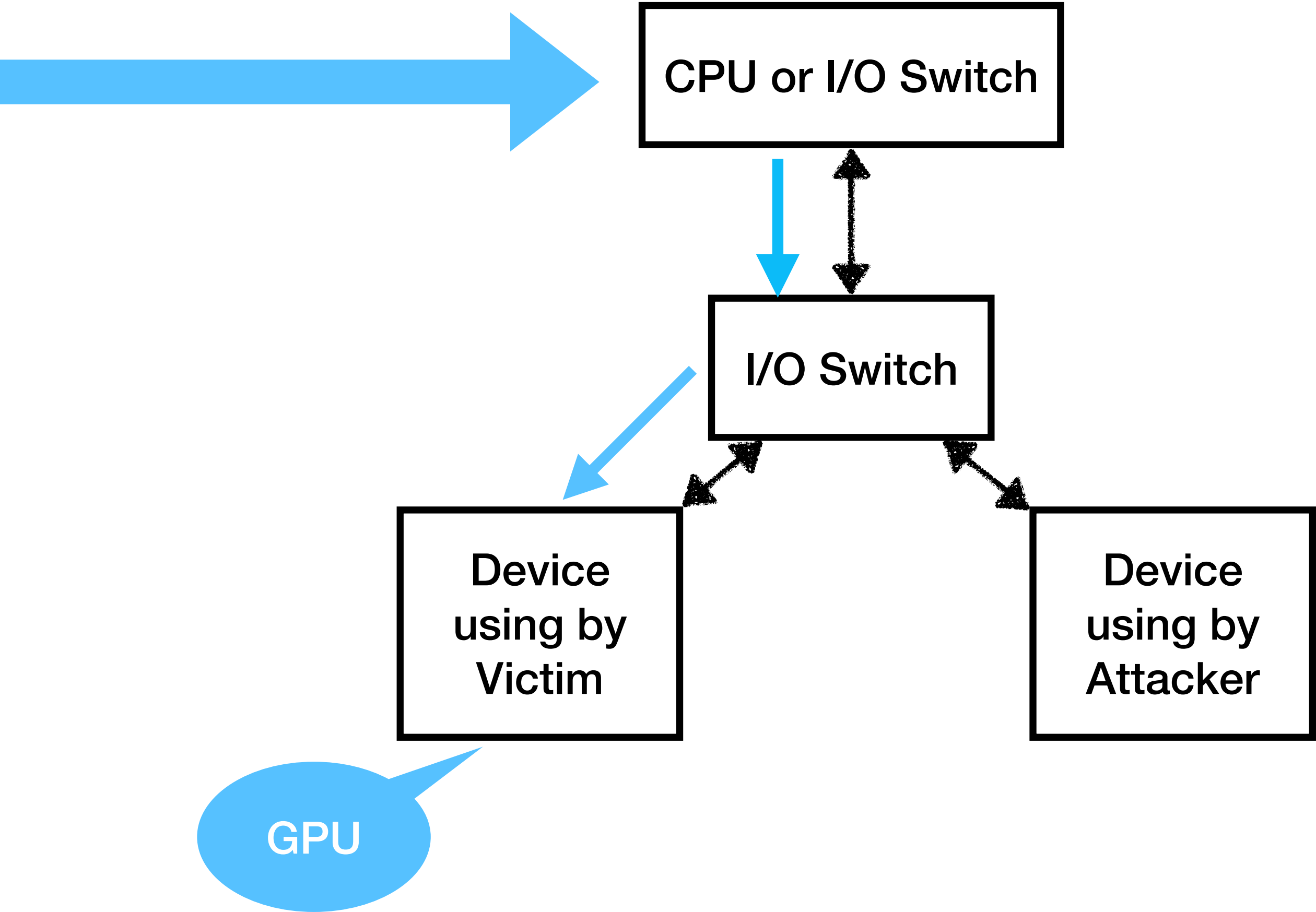
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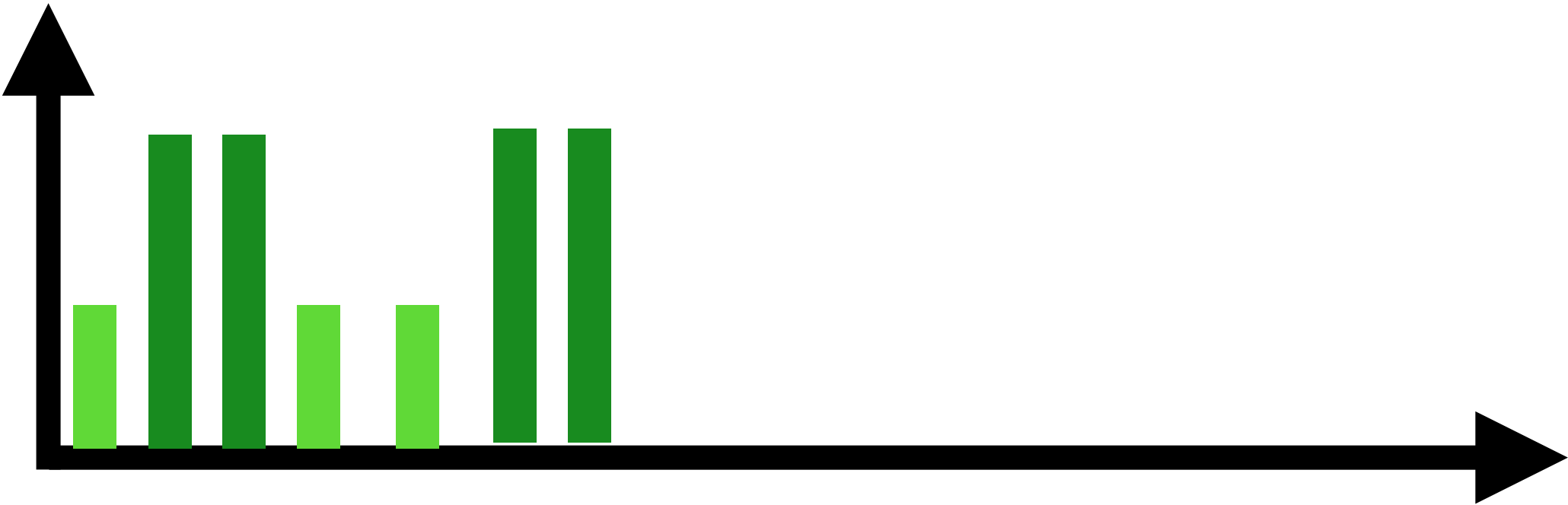
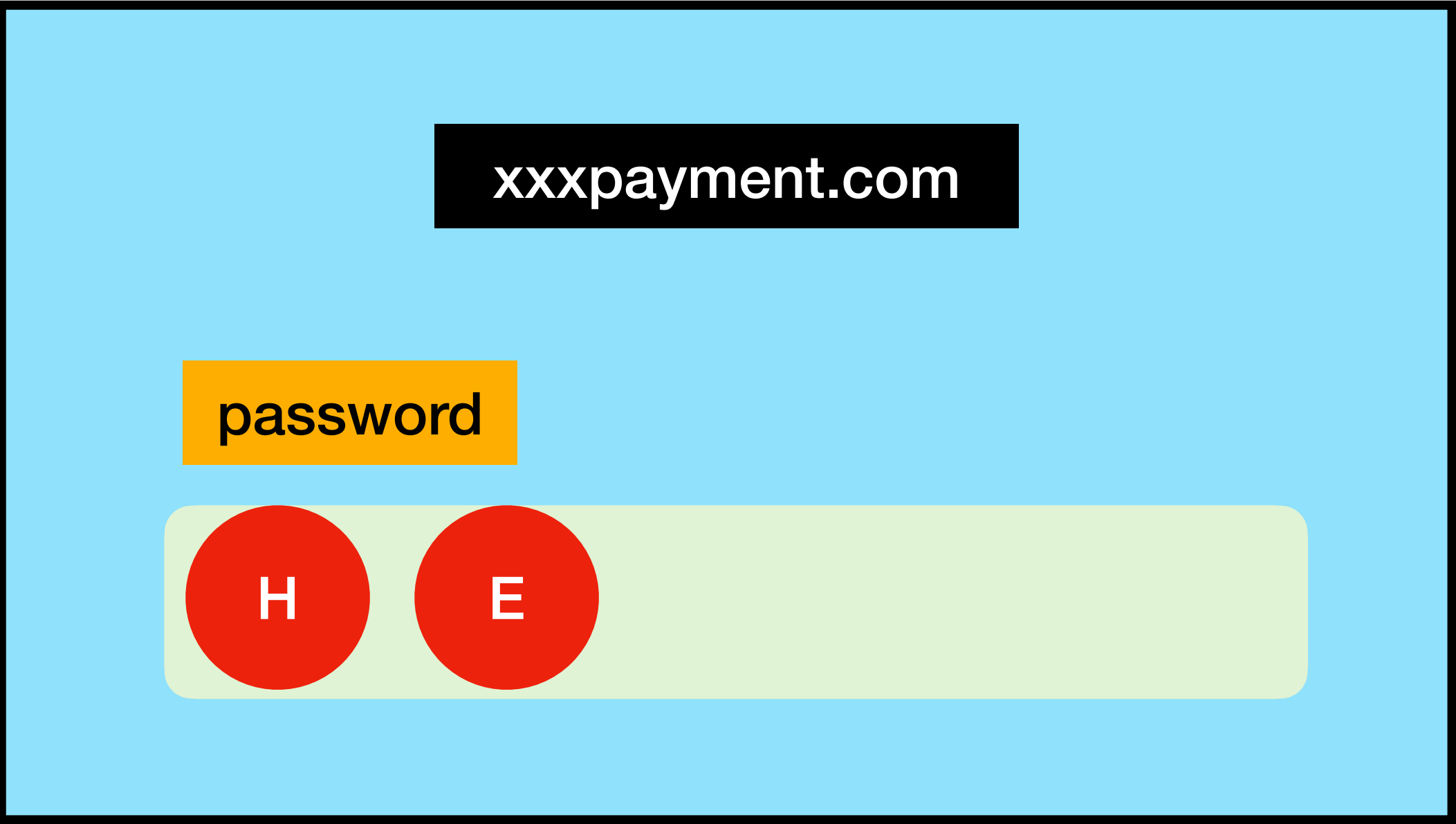
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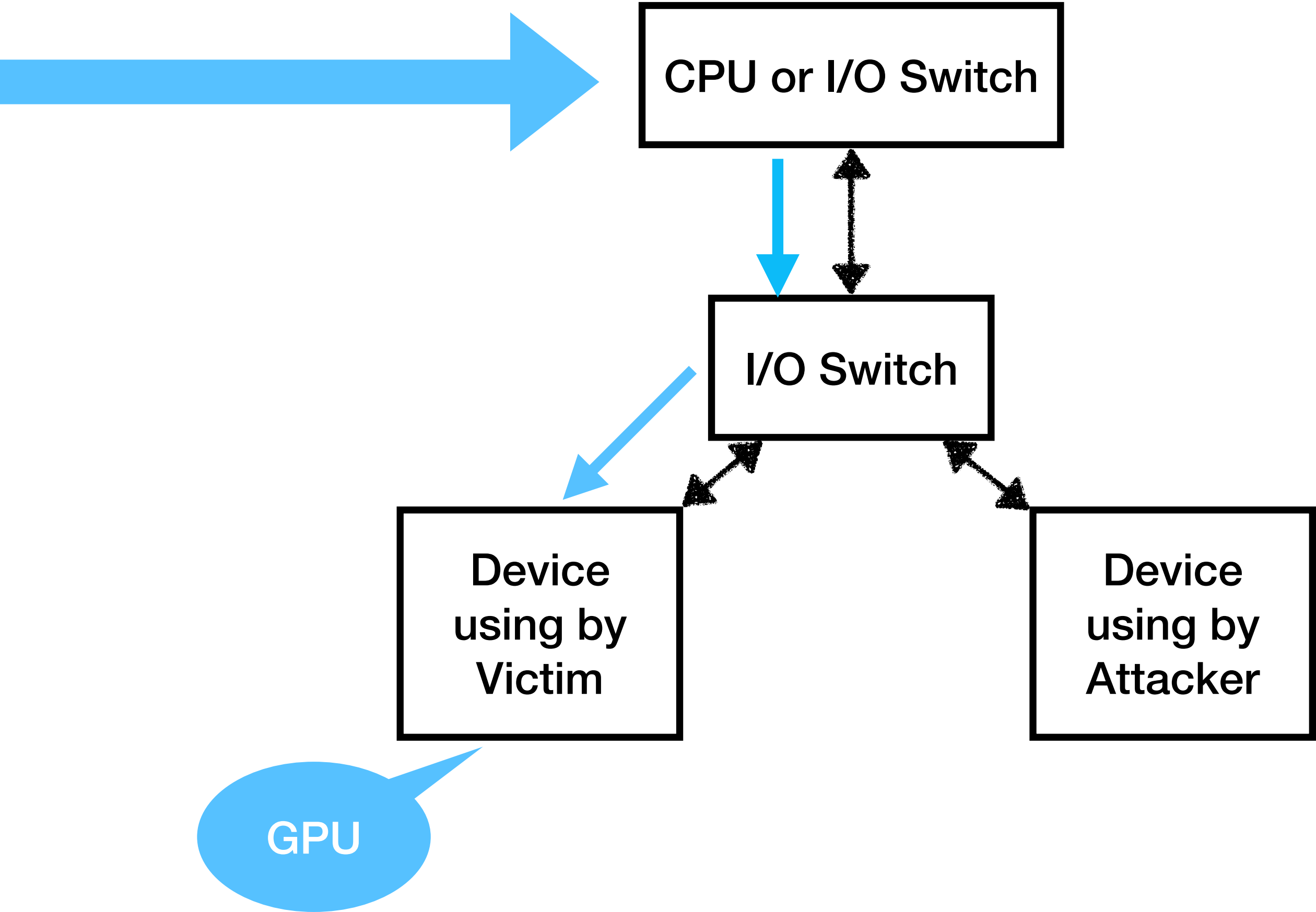
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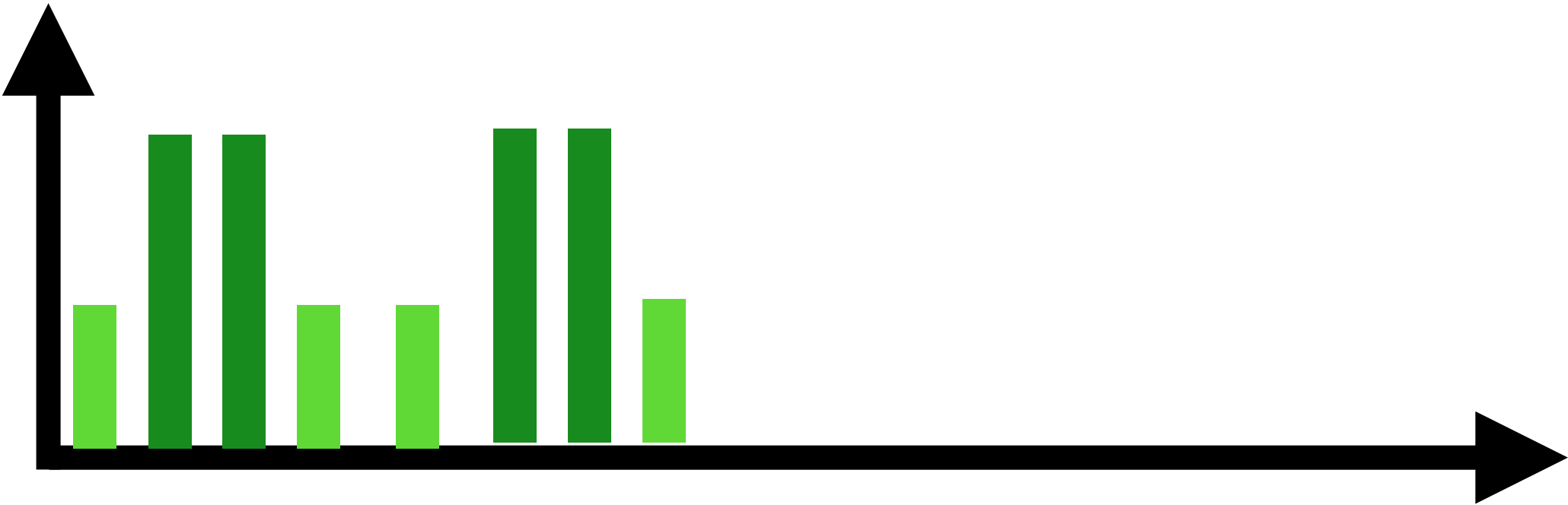
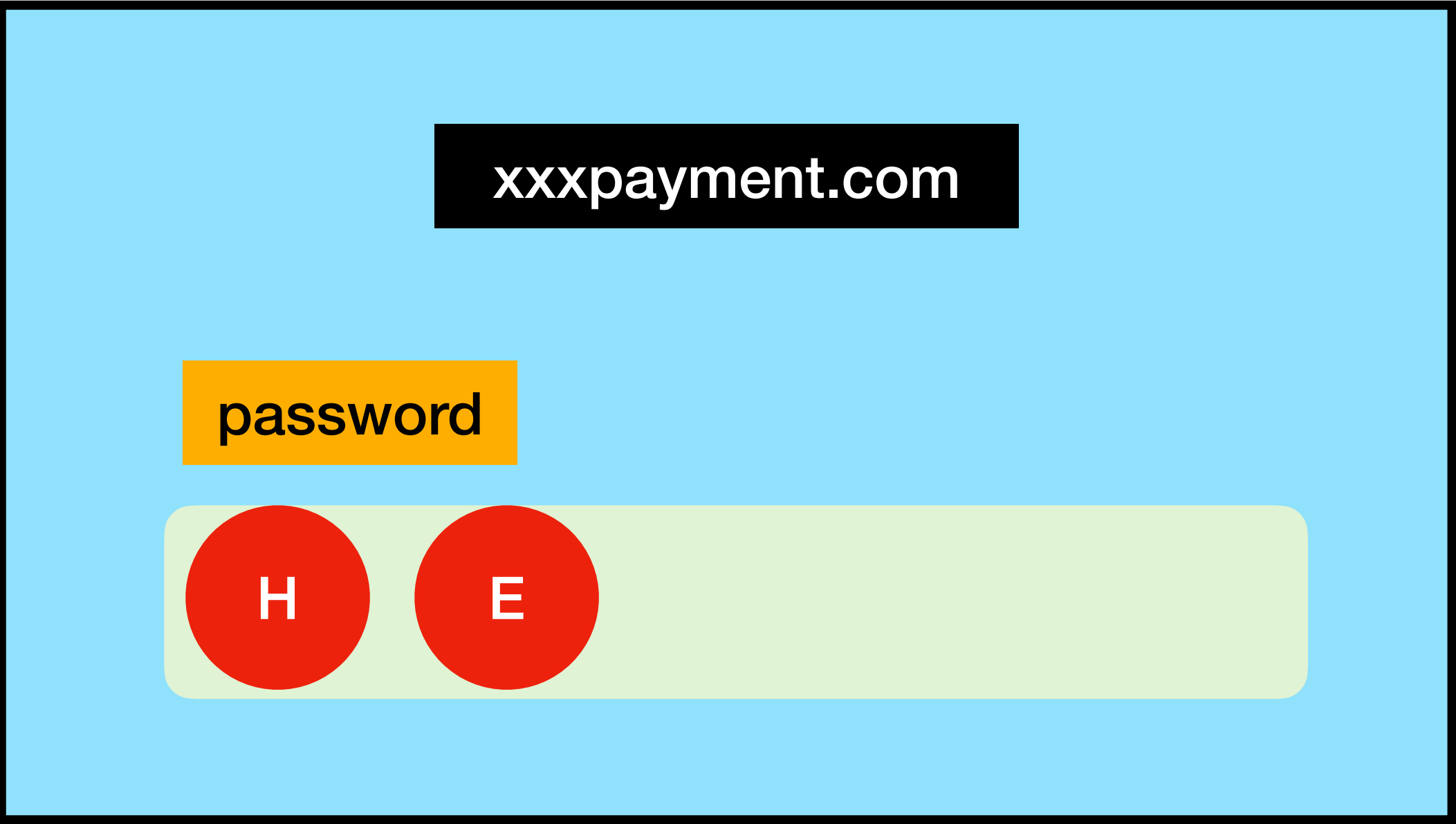
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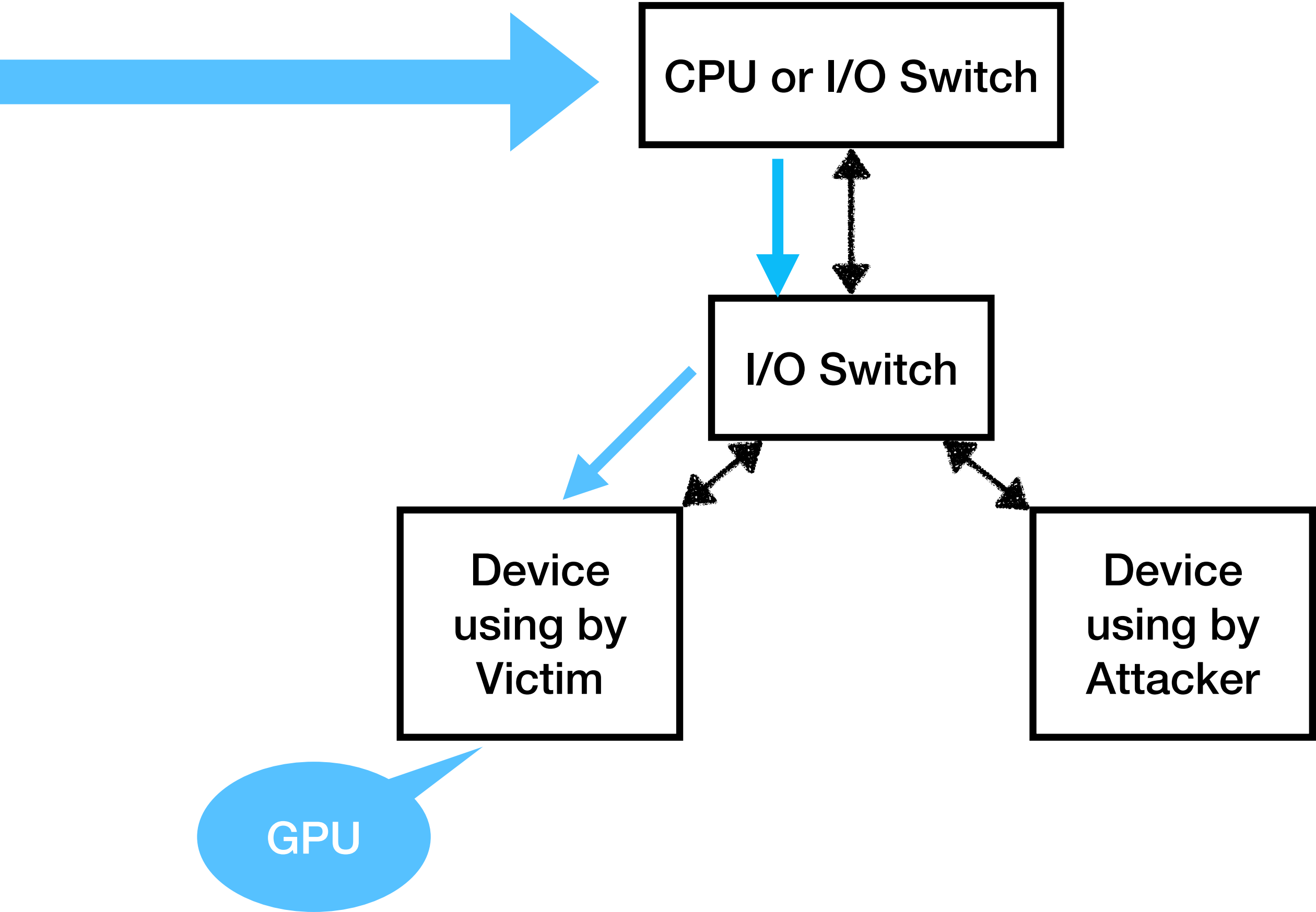
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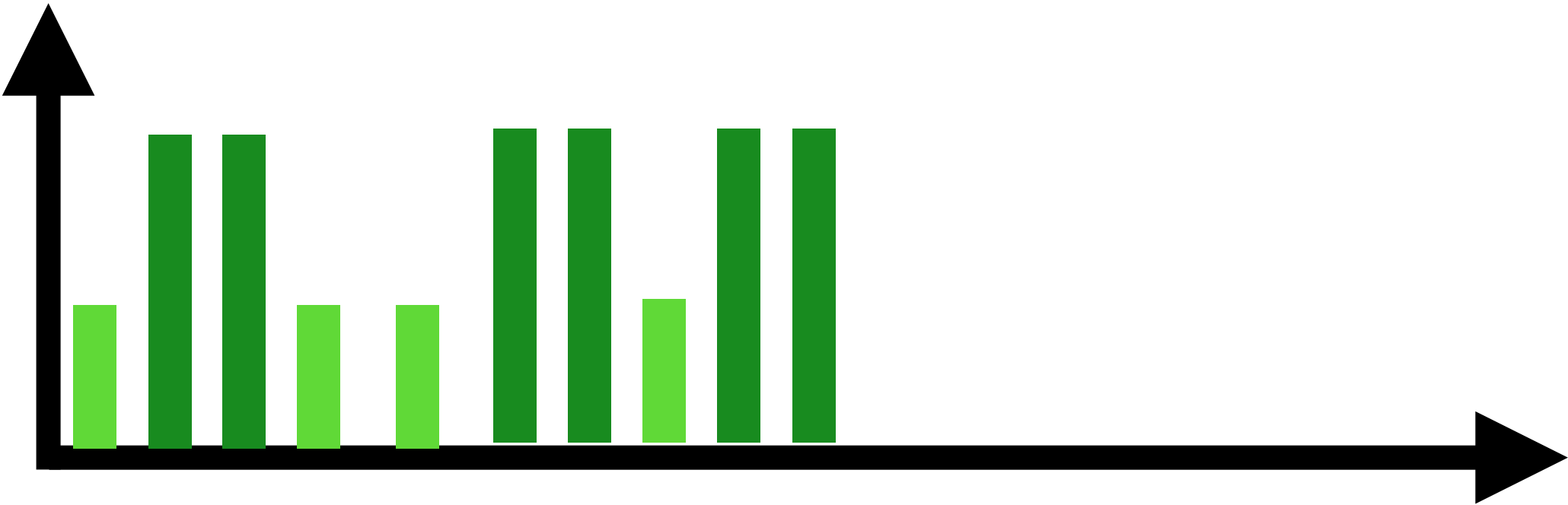
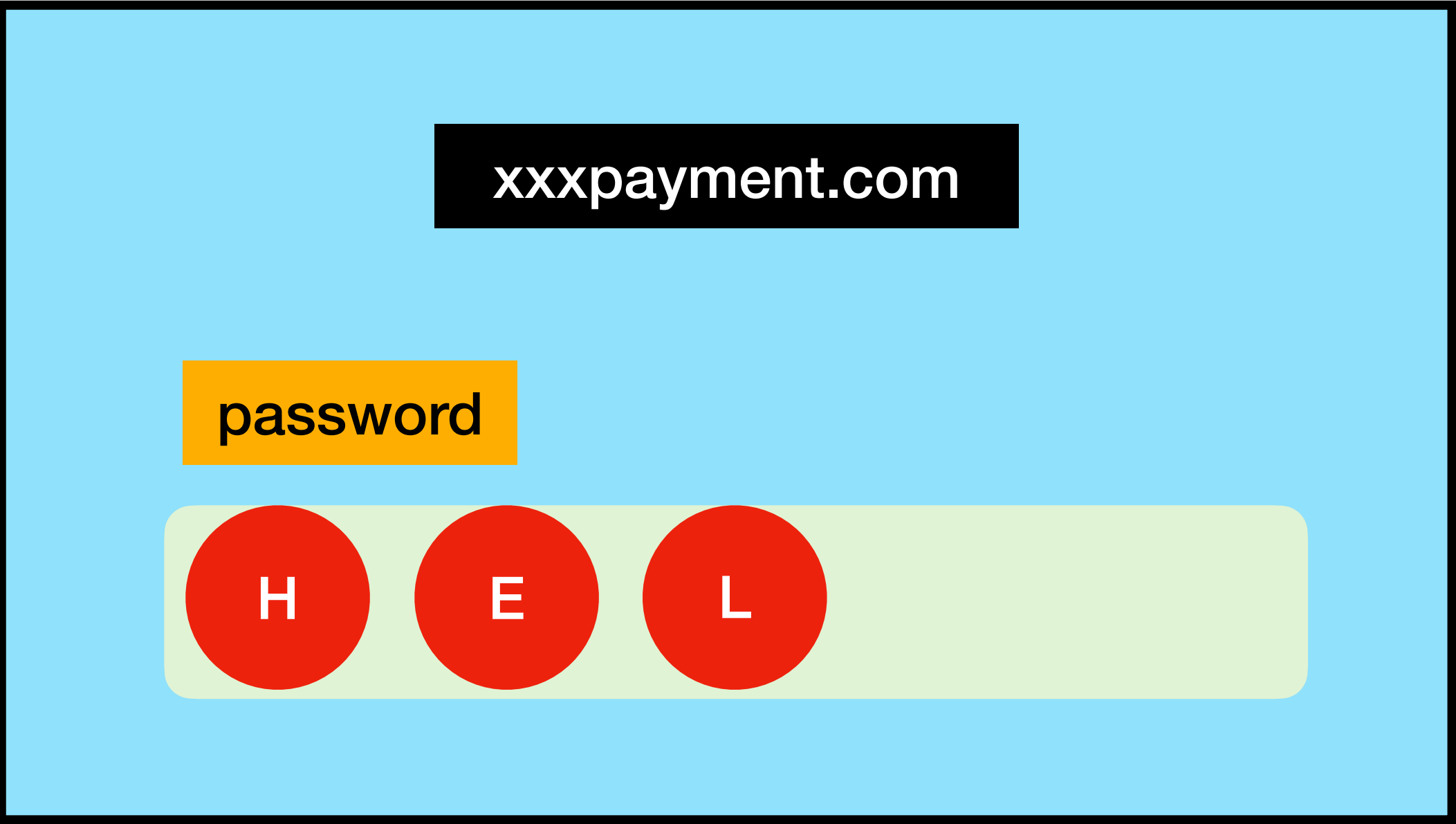


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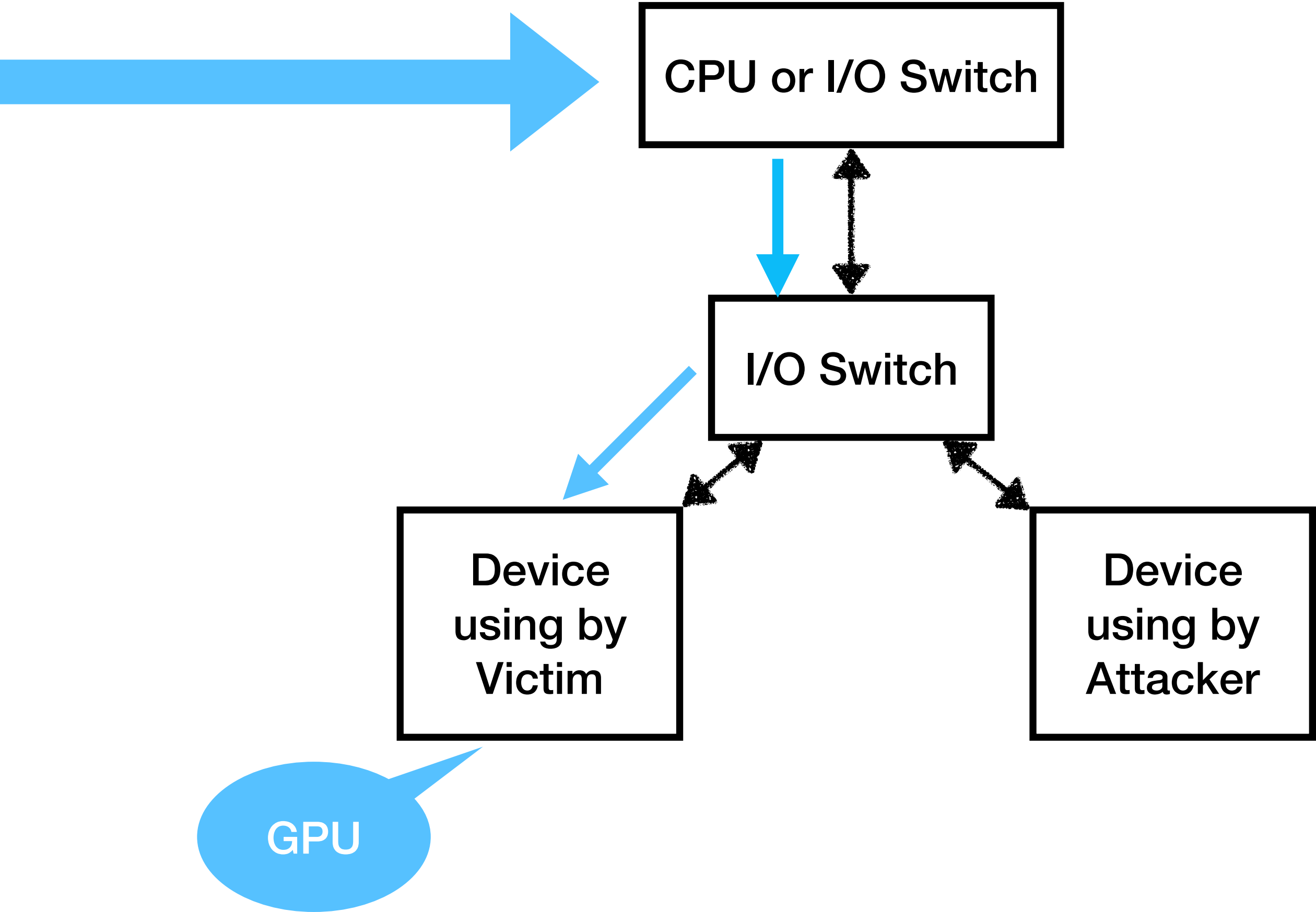




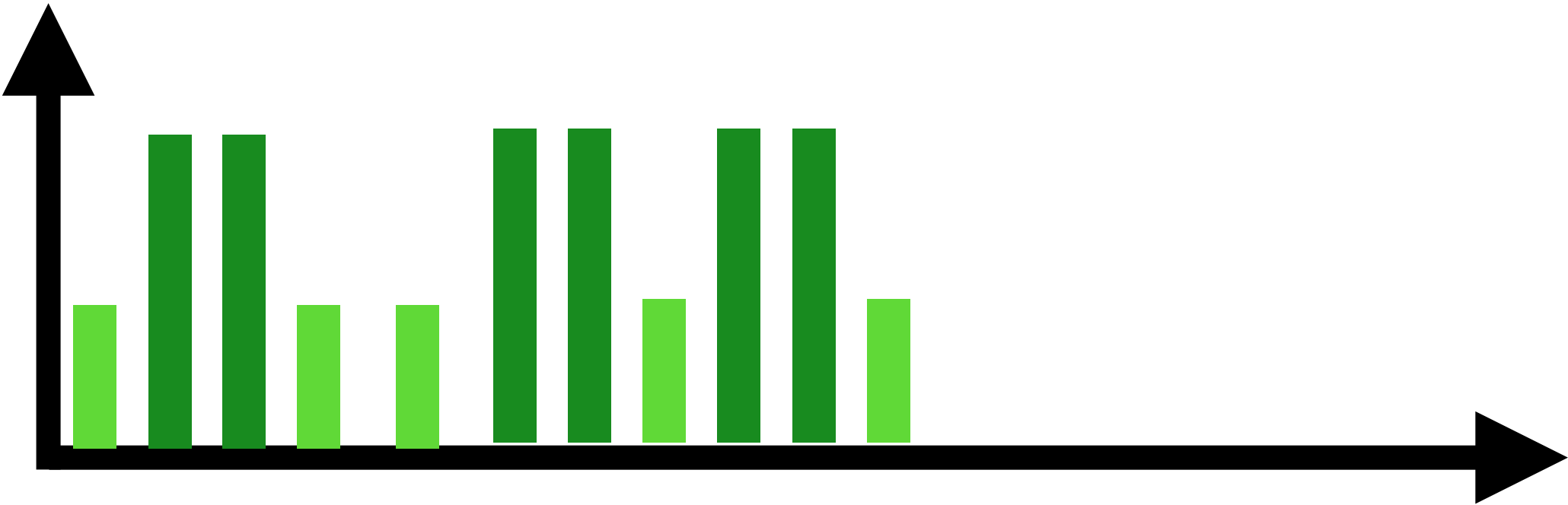
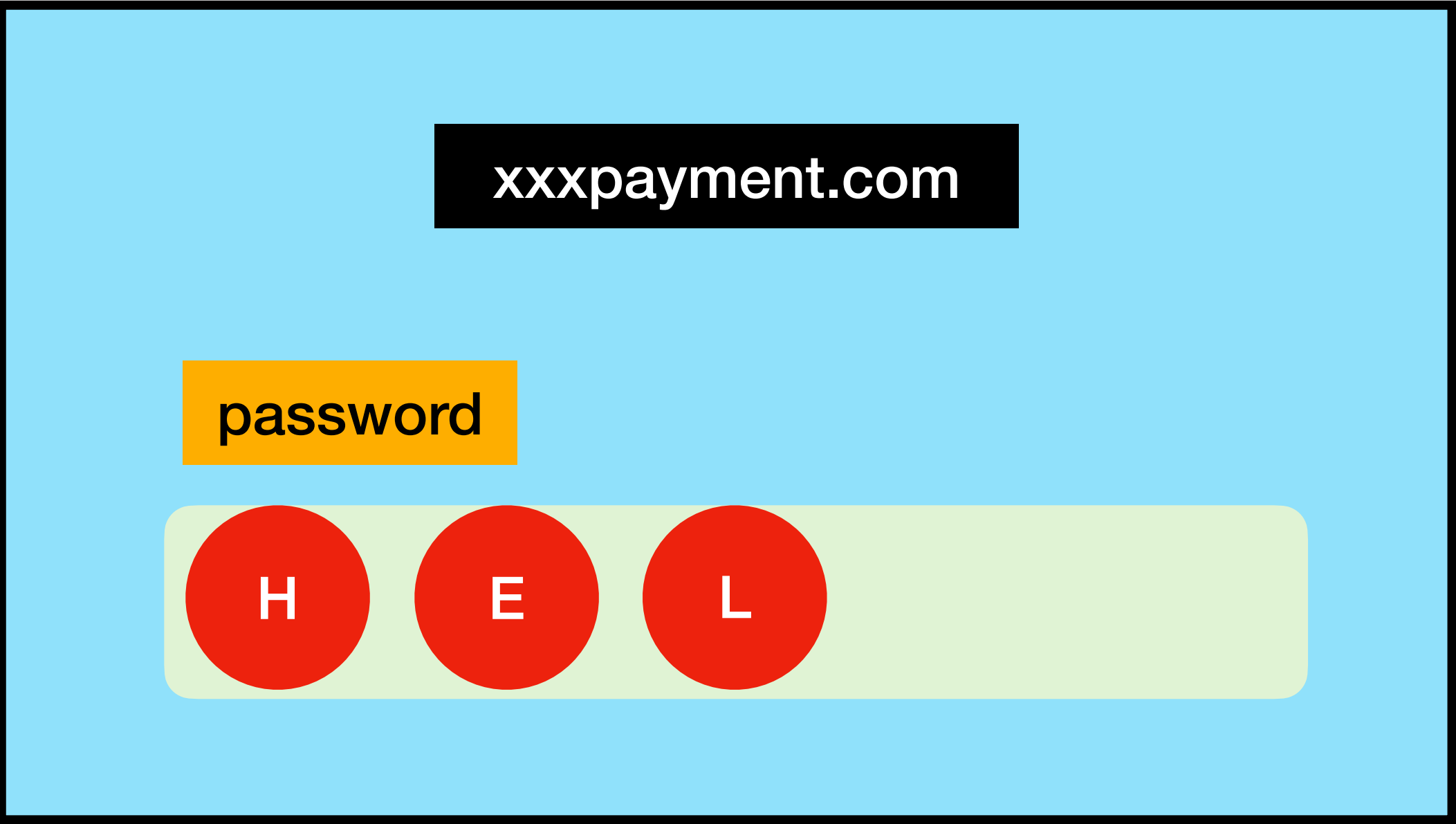
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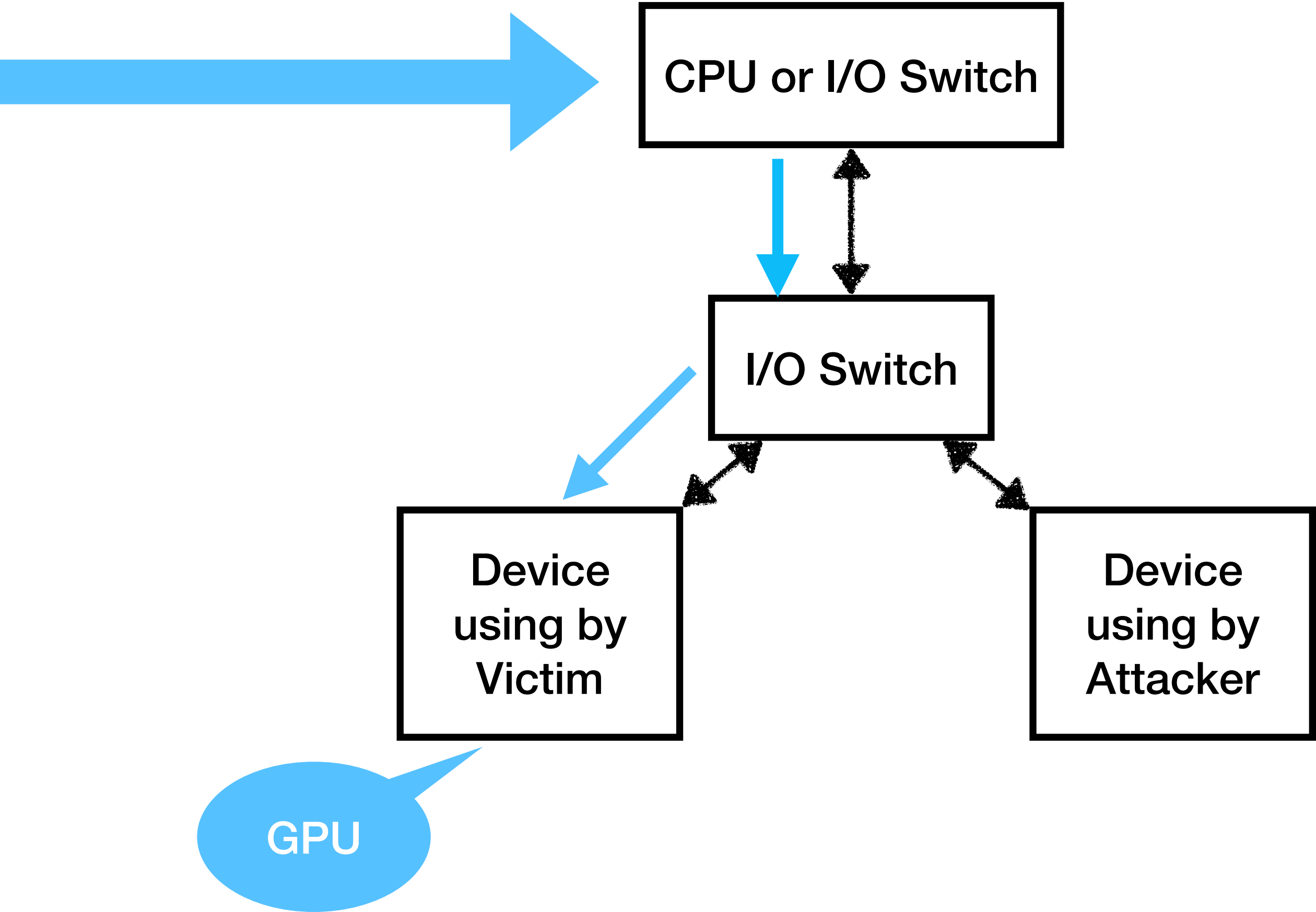
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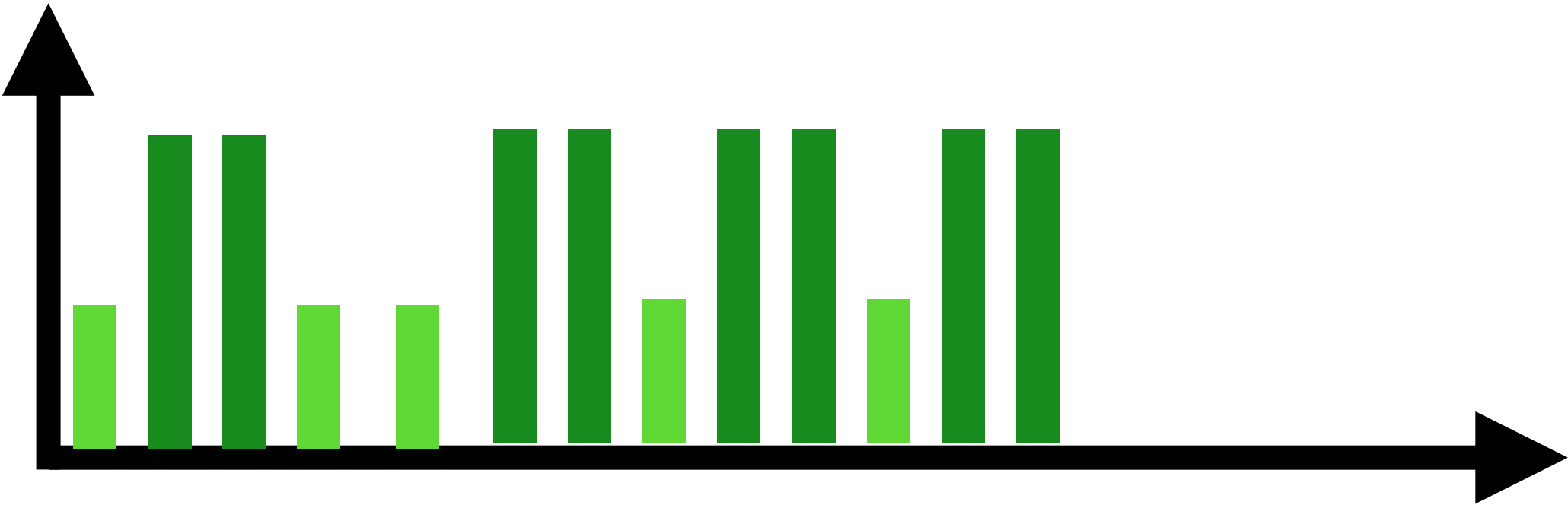
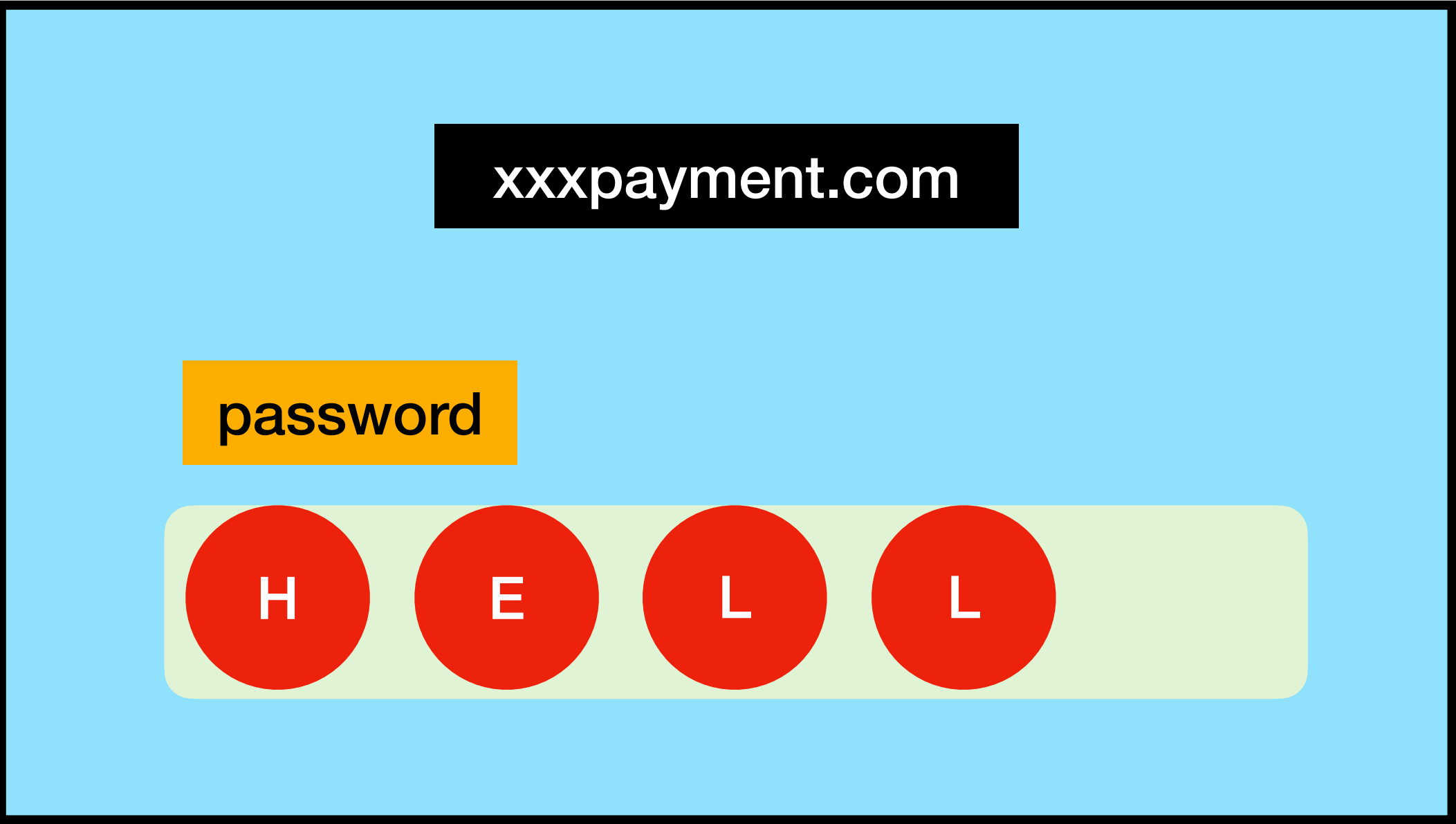
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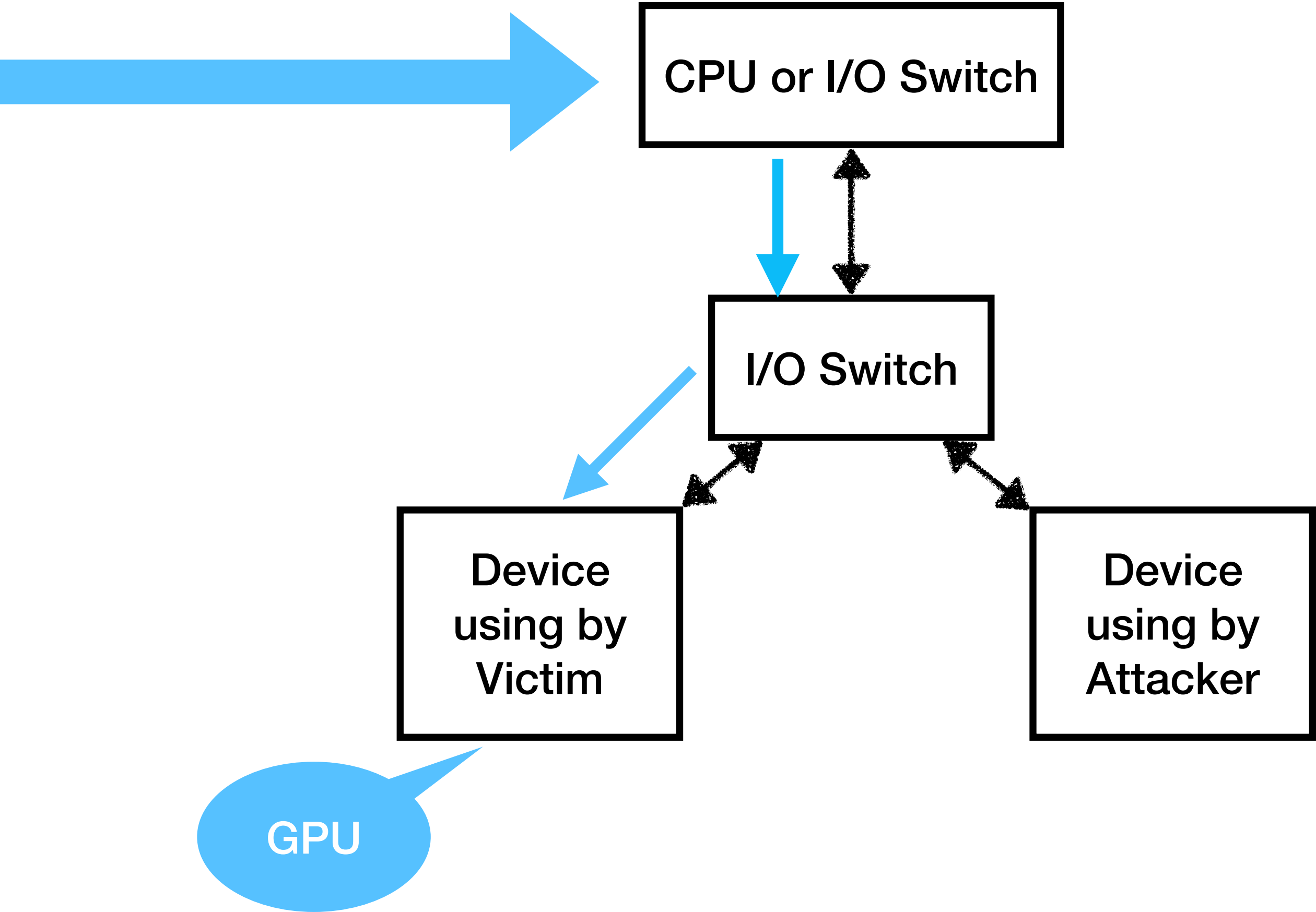
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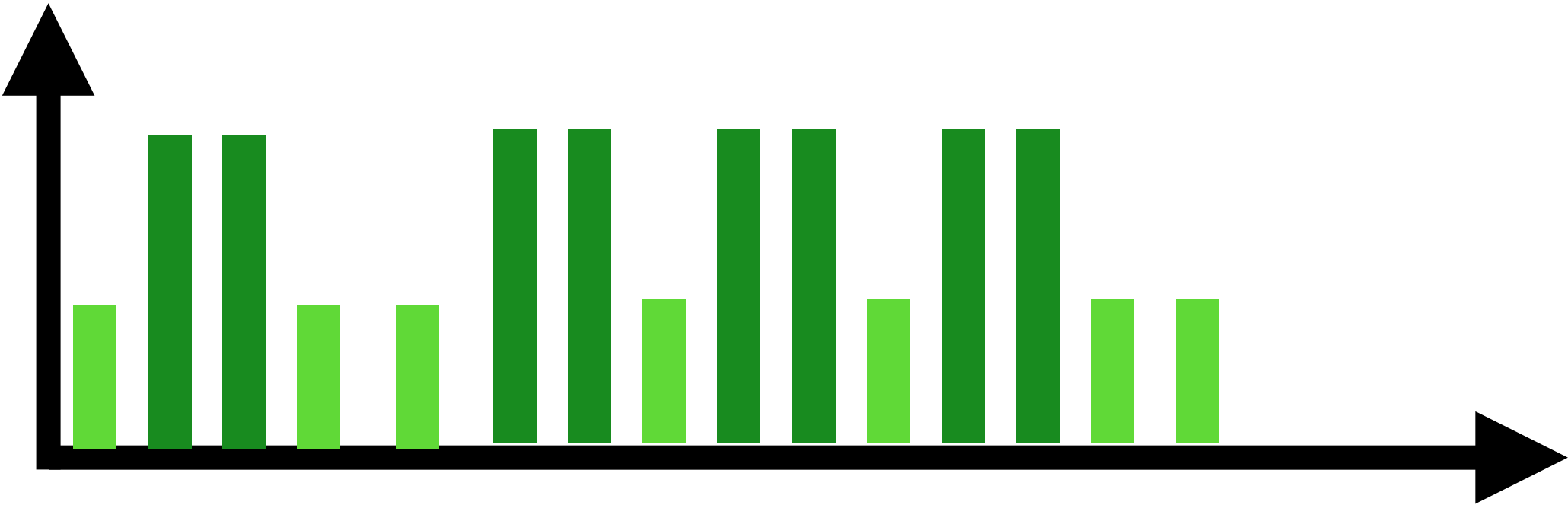
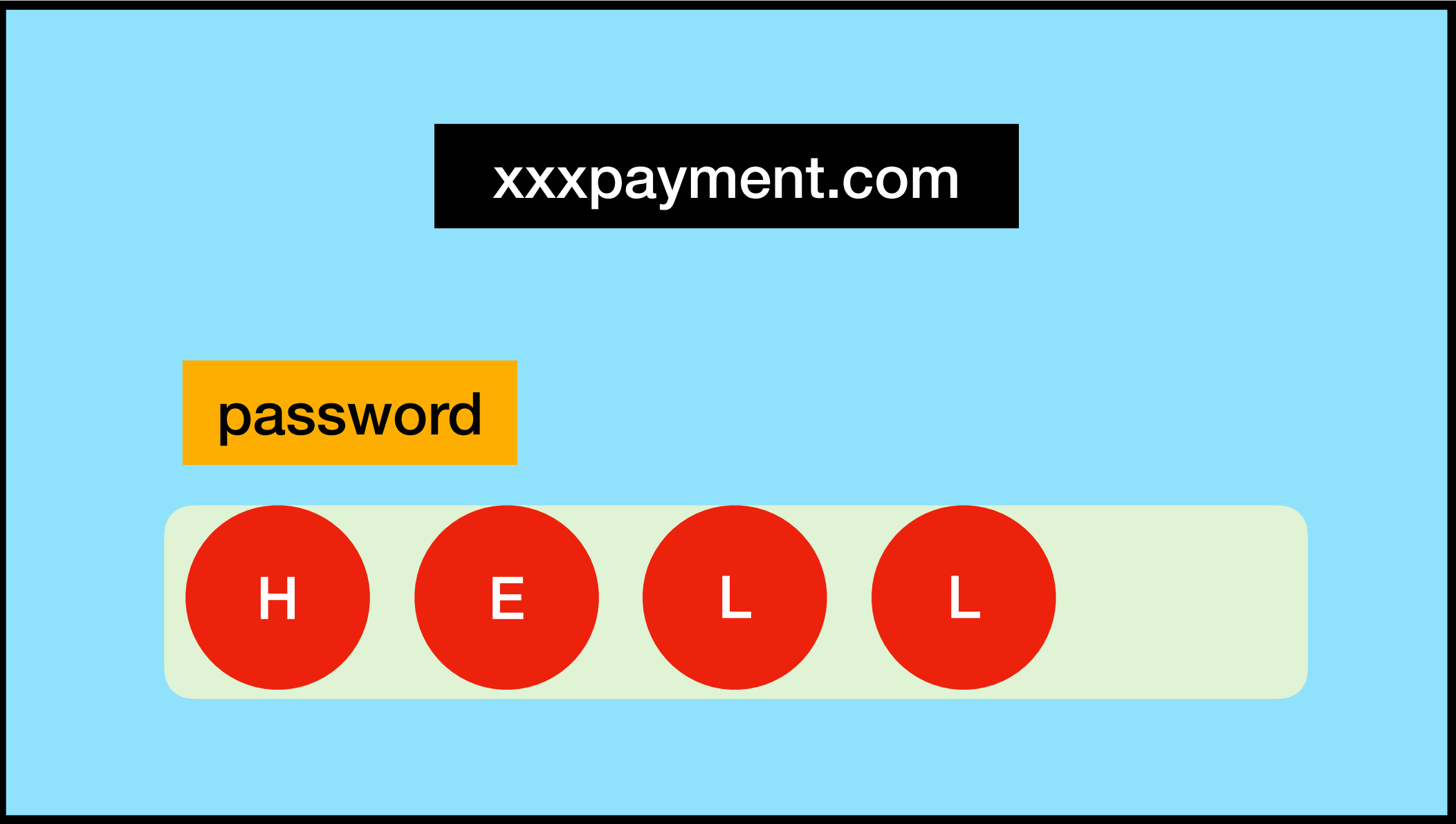
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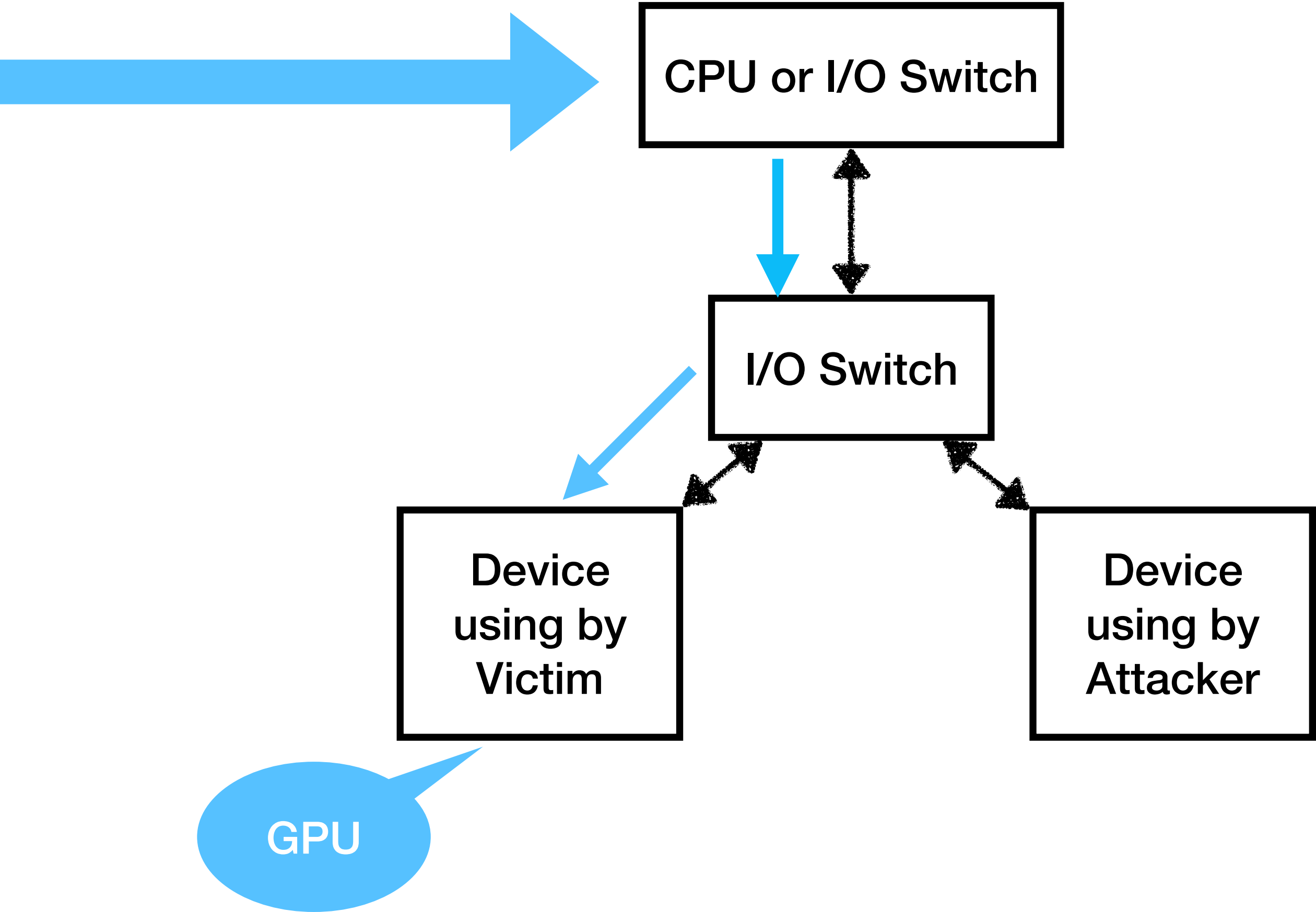
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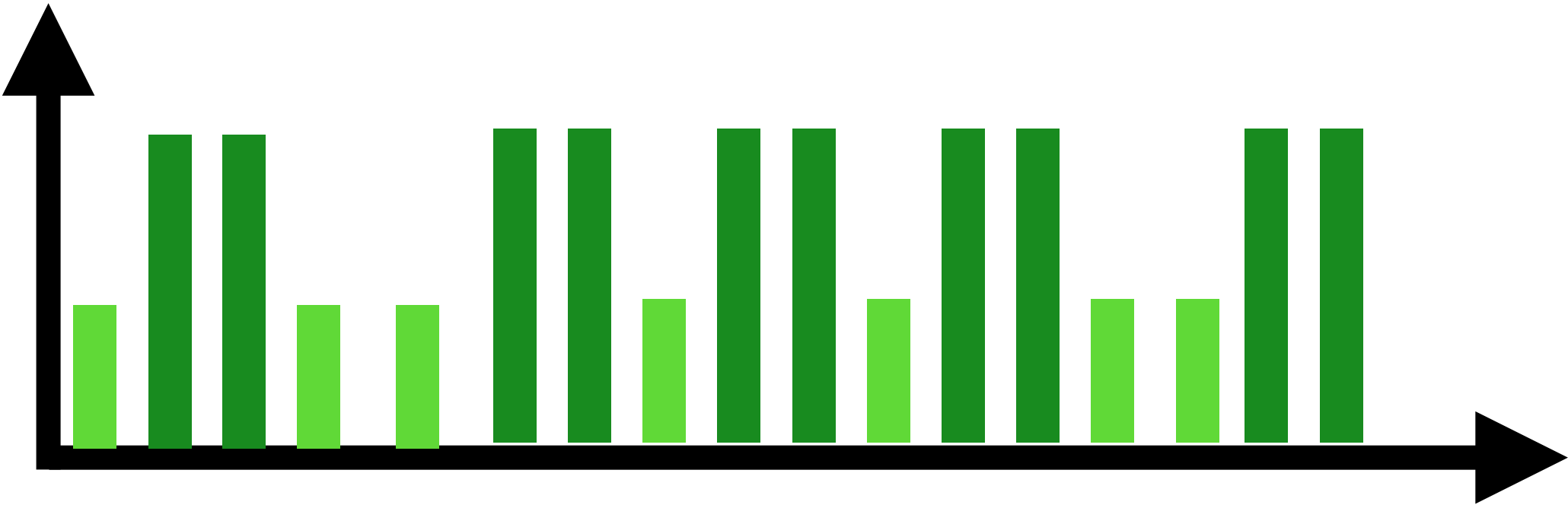
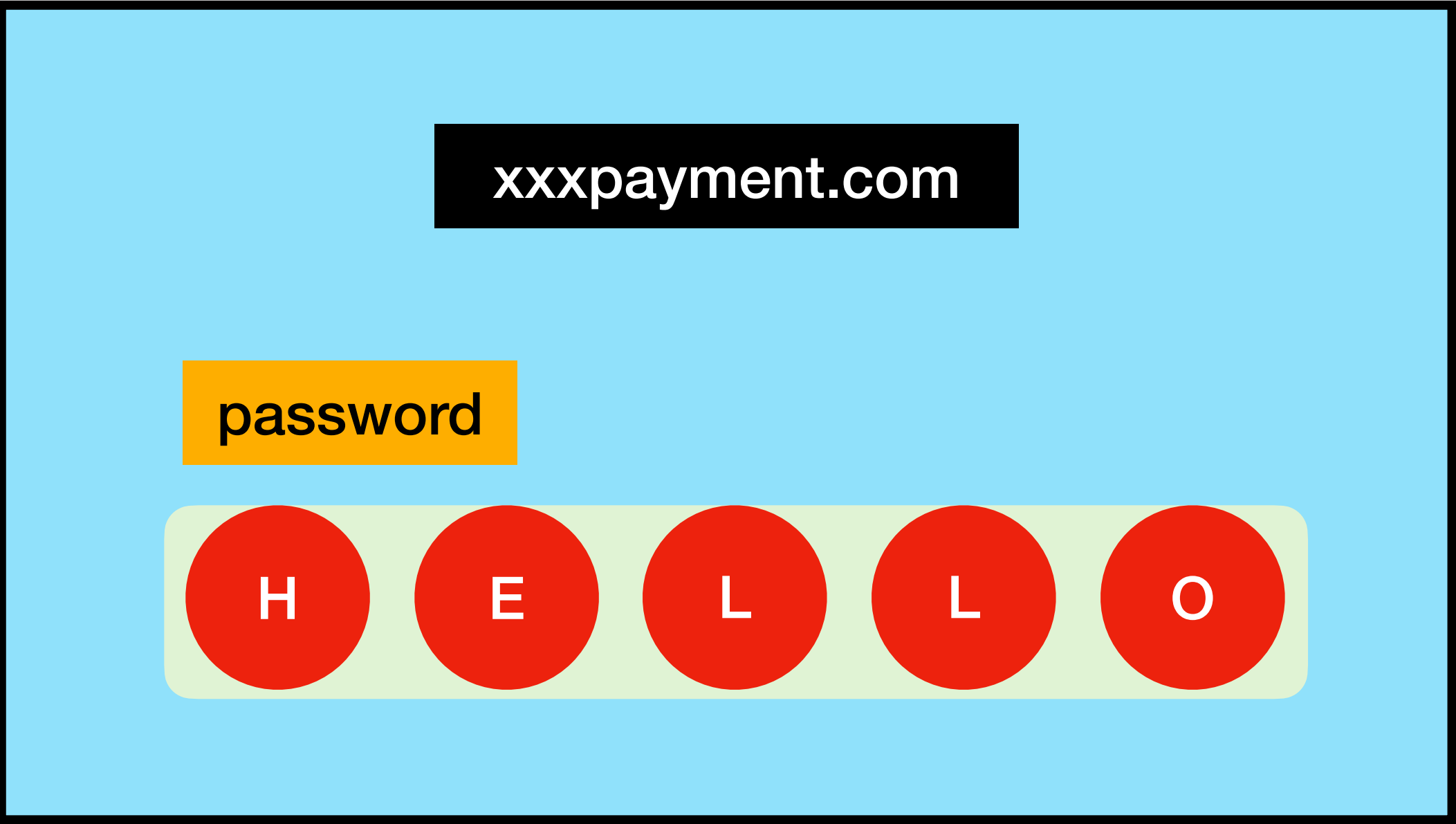
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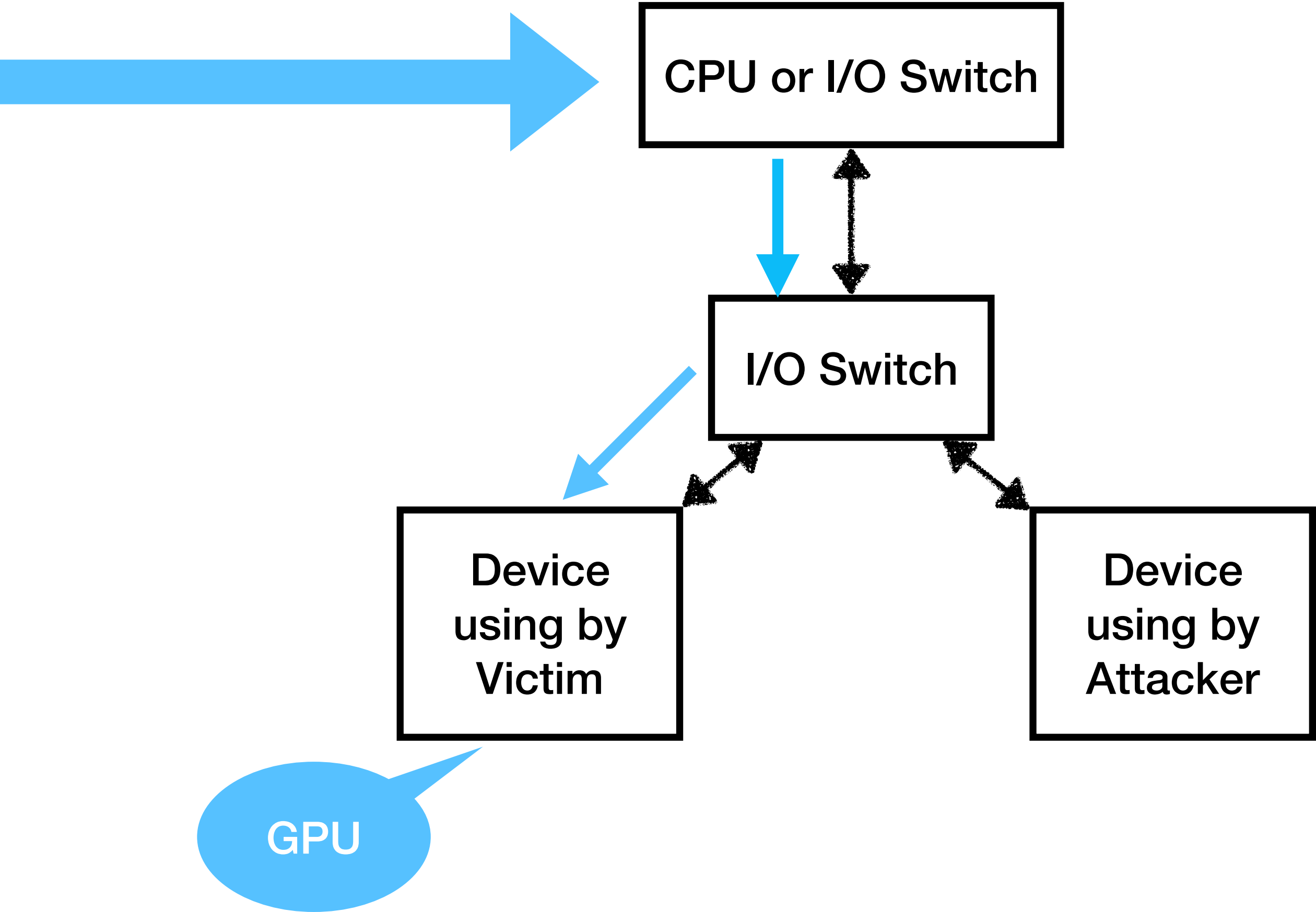
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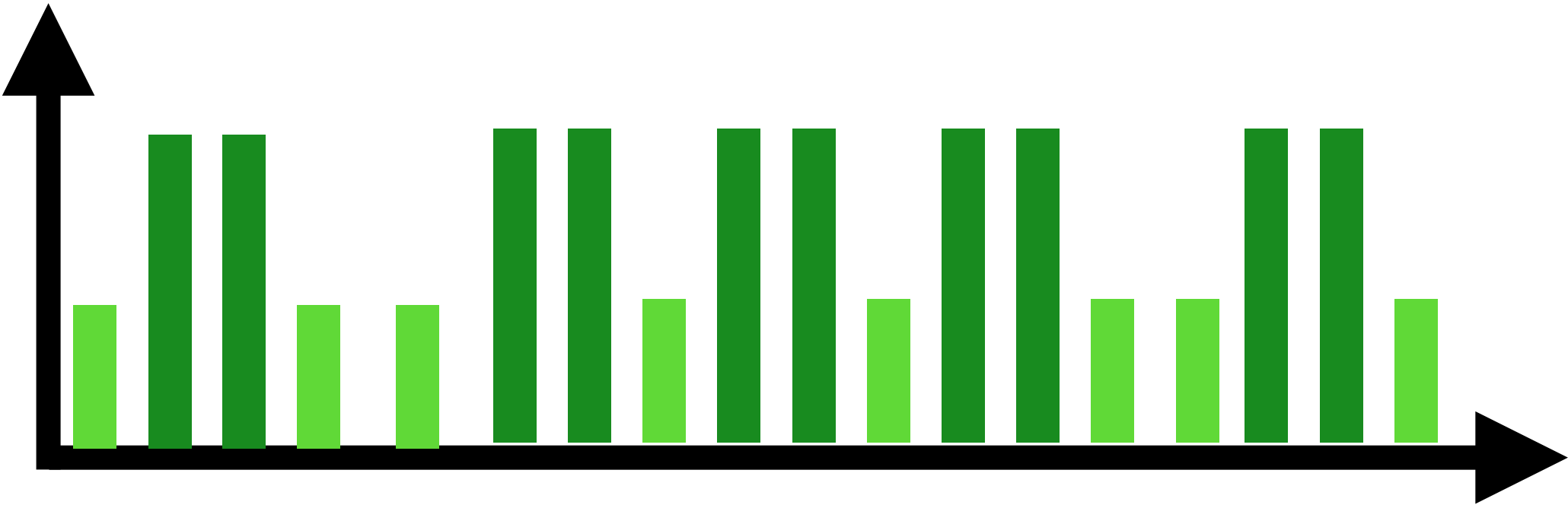
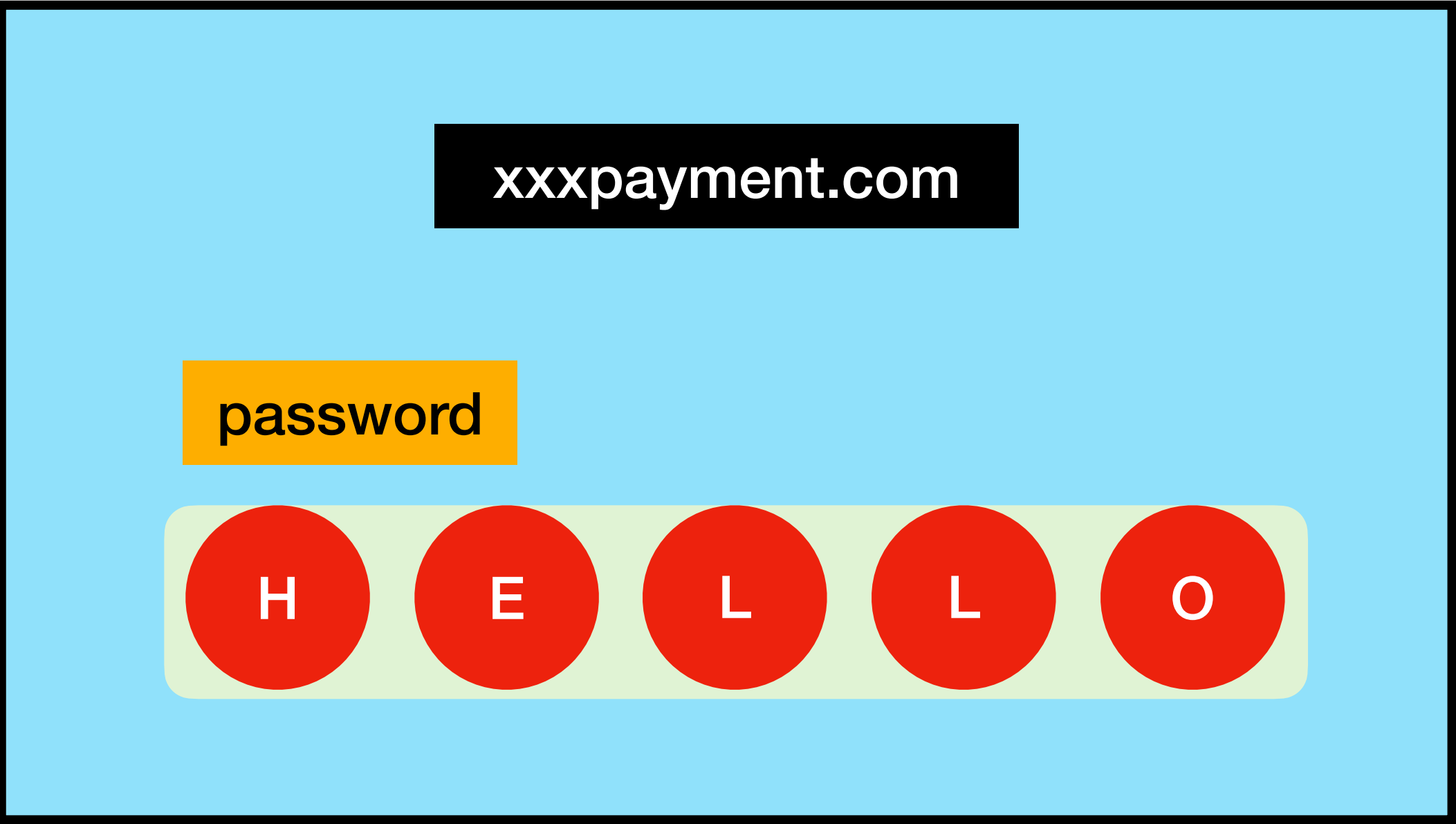
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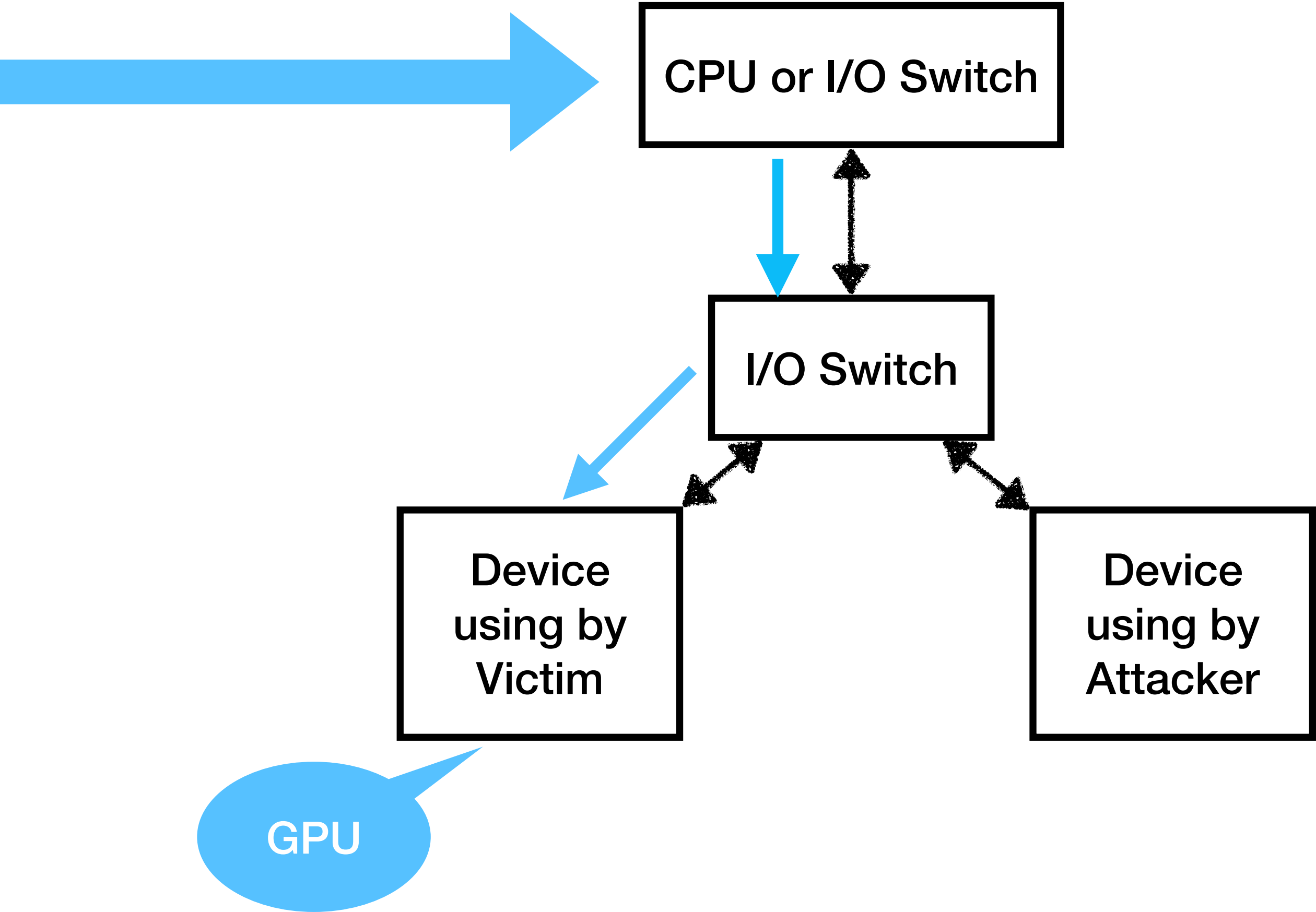
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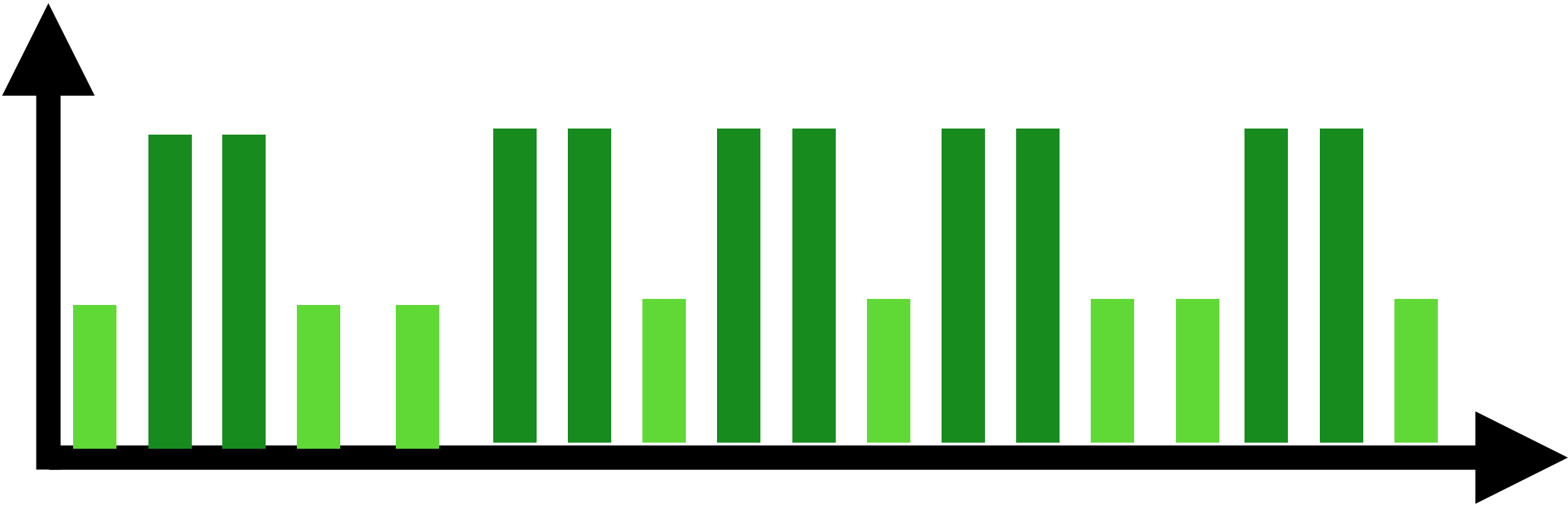
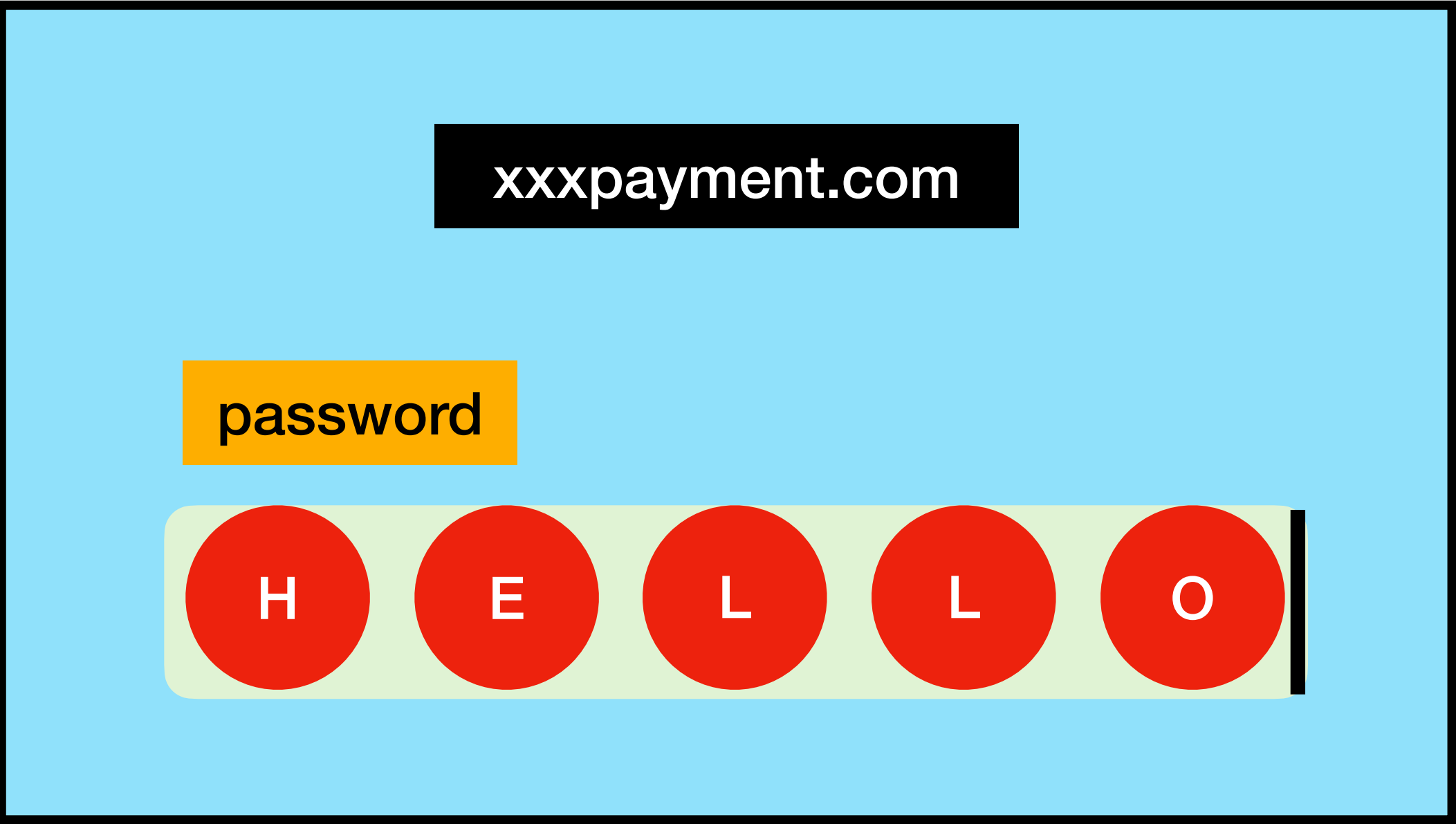
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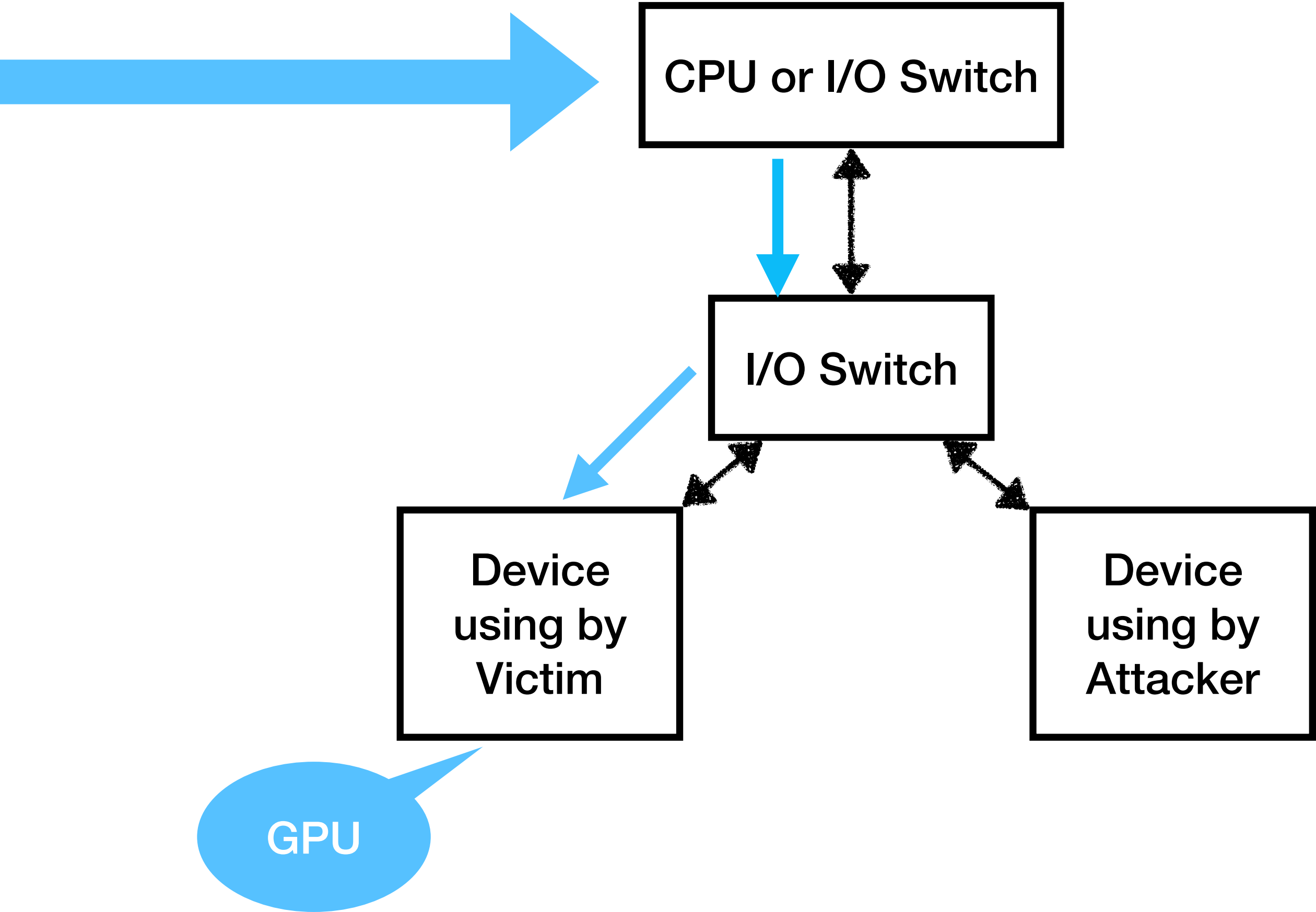
Delay Sequence



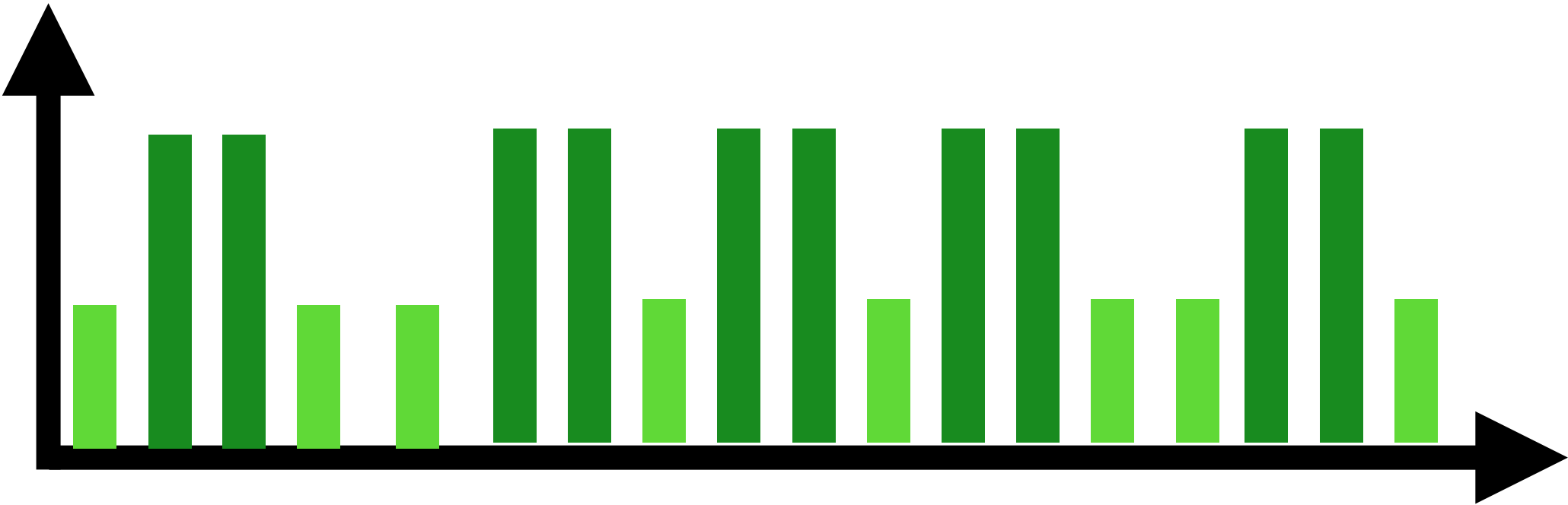
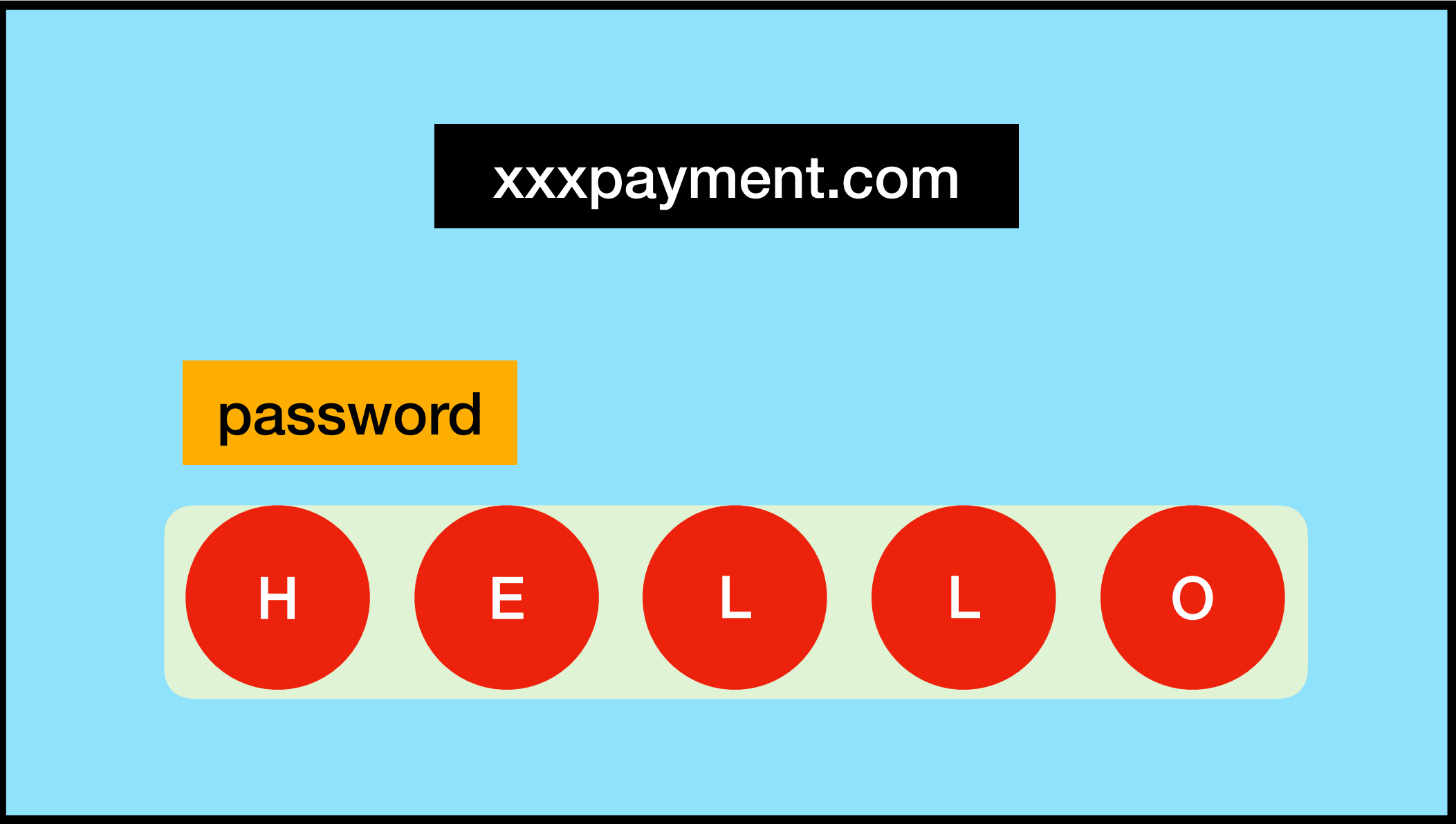
# User-input Inference



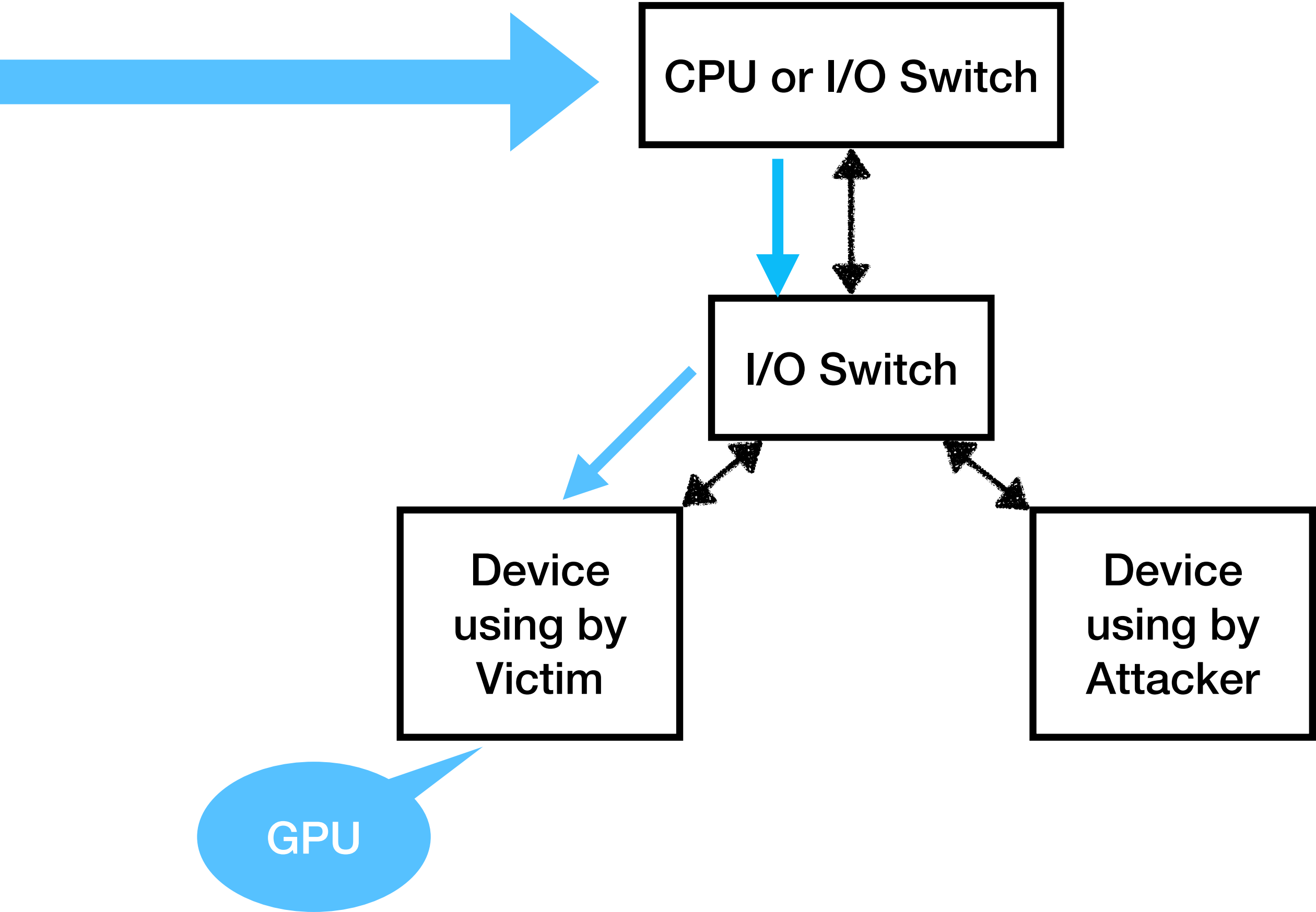
Delay Sequence



# User-input Inference

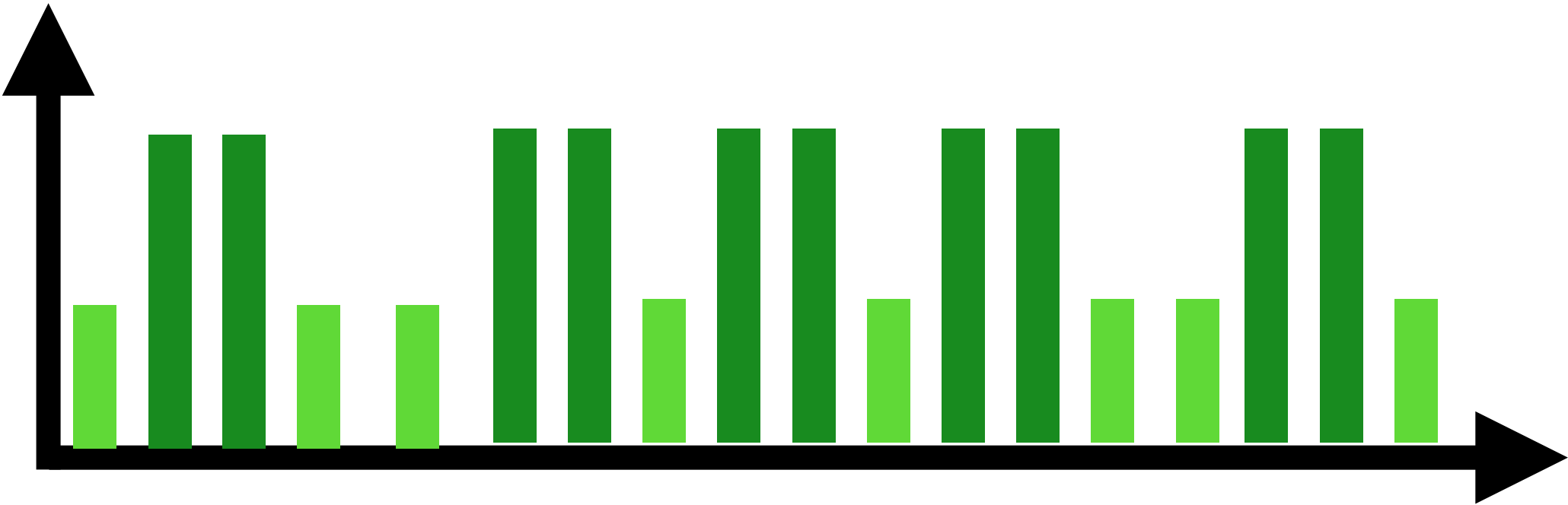
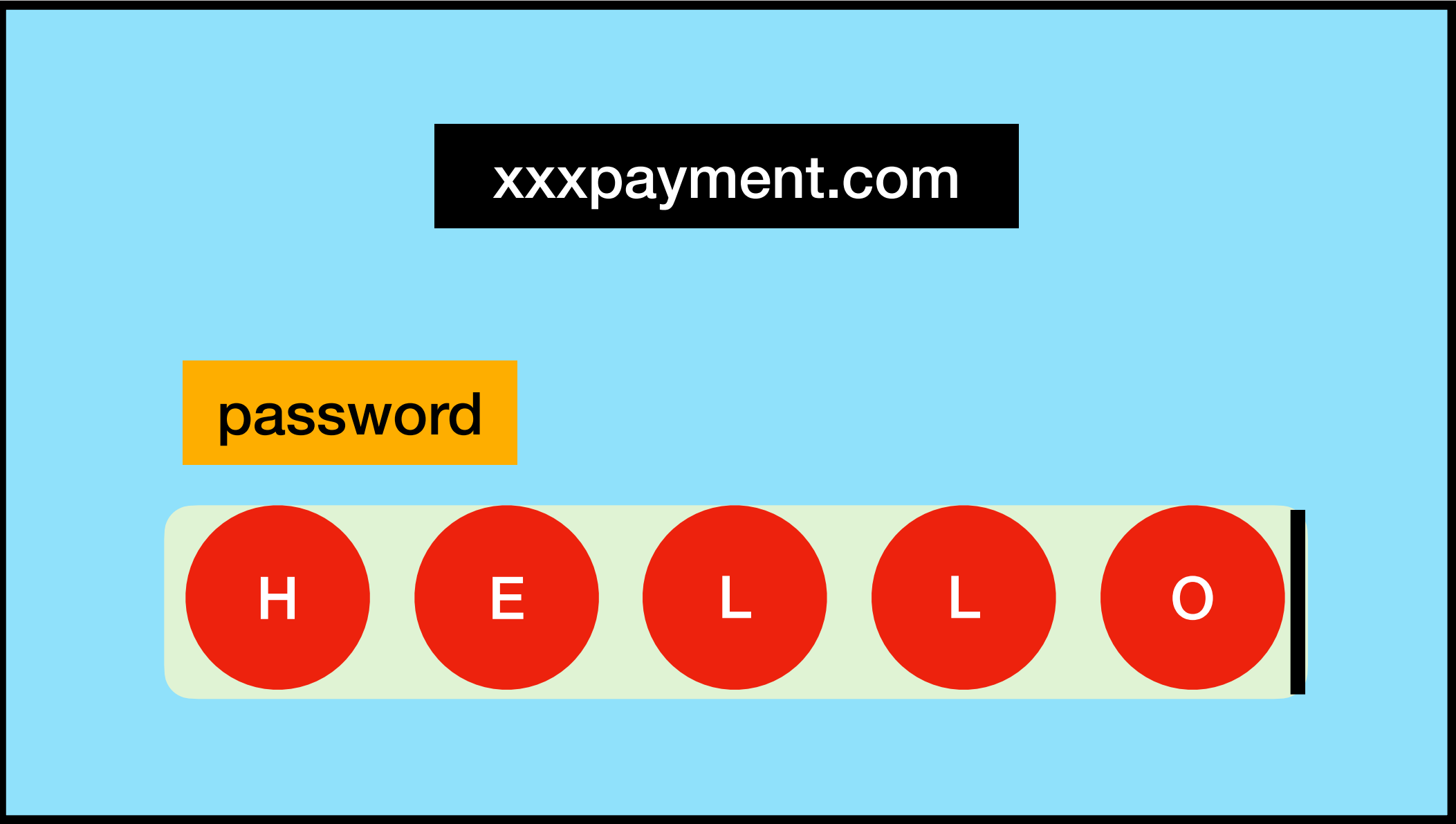


Delay Sequence

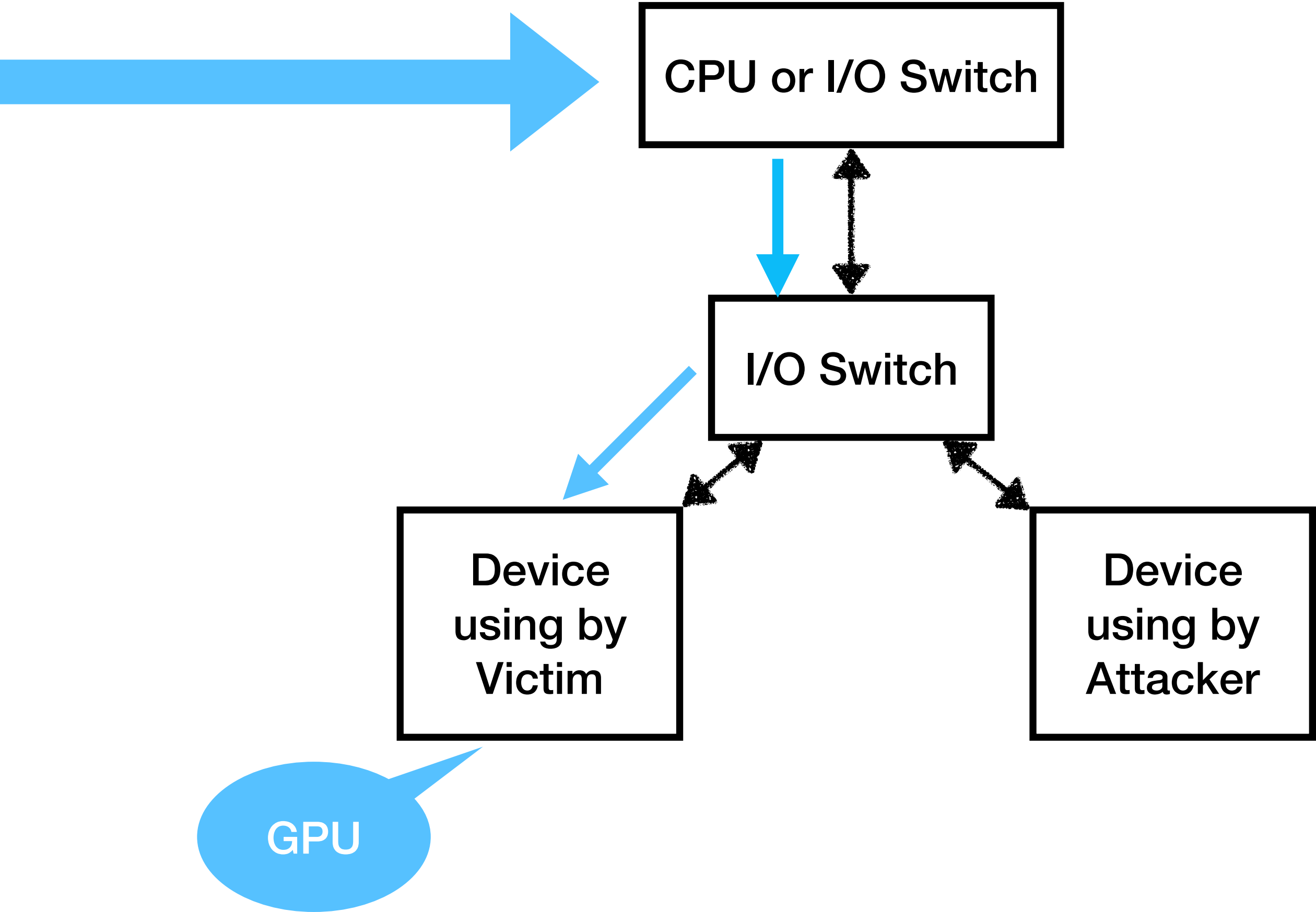




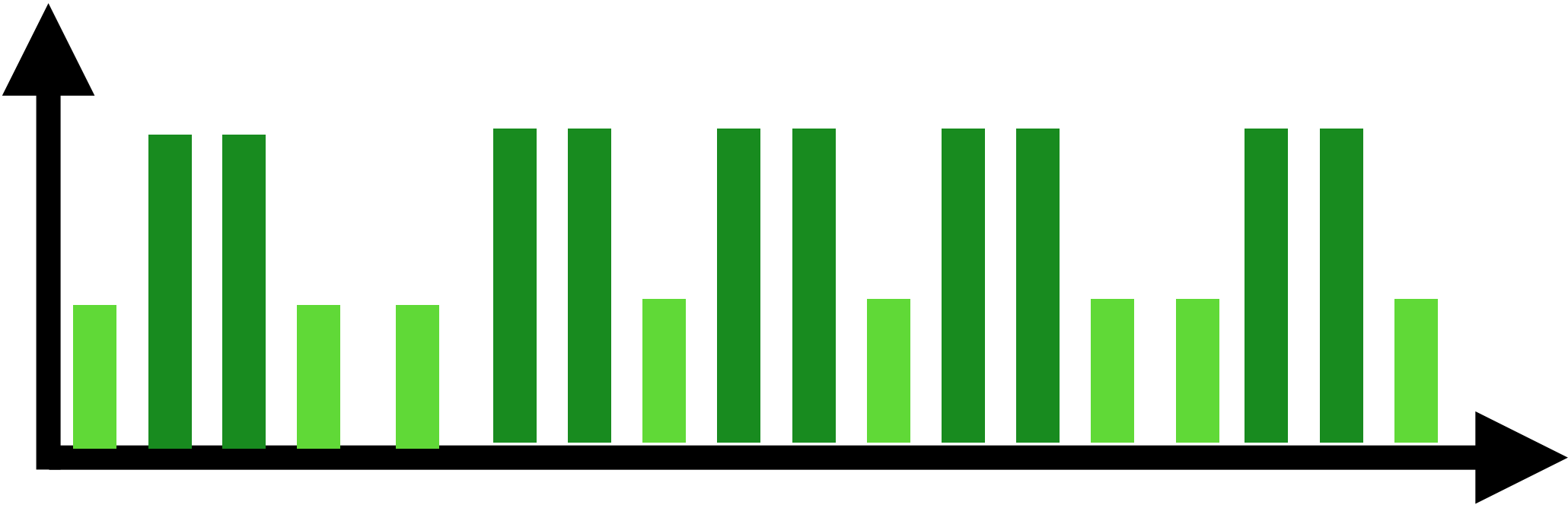
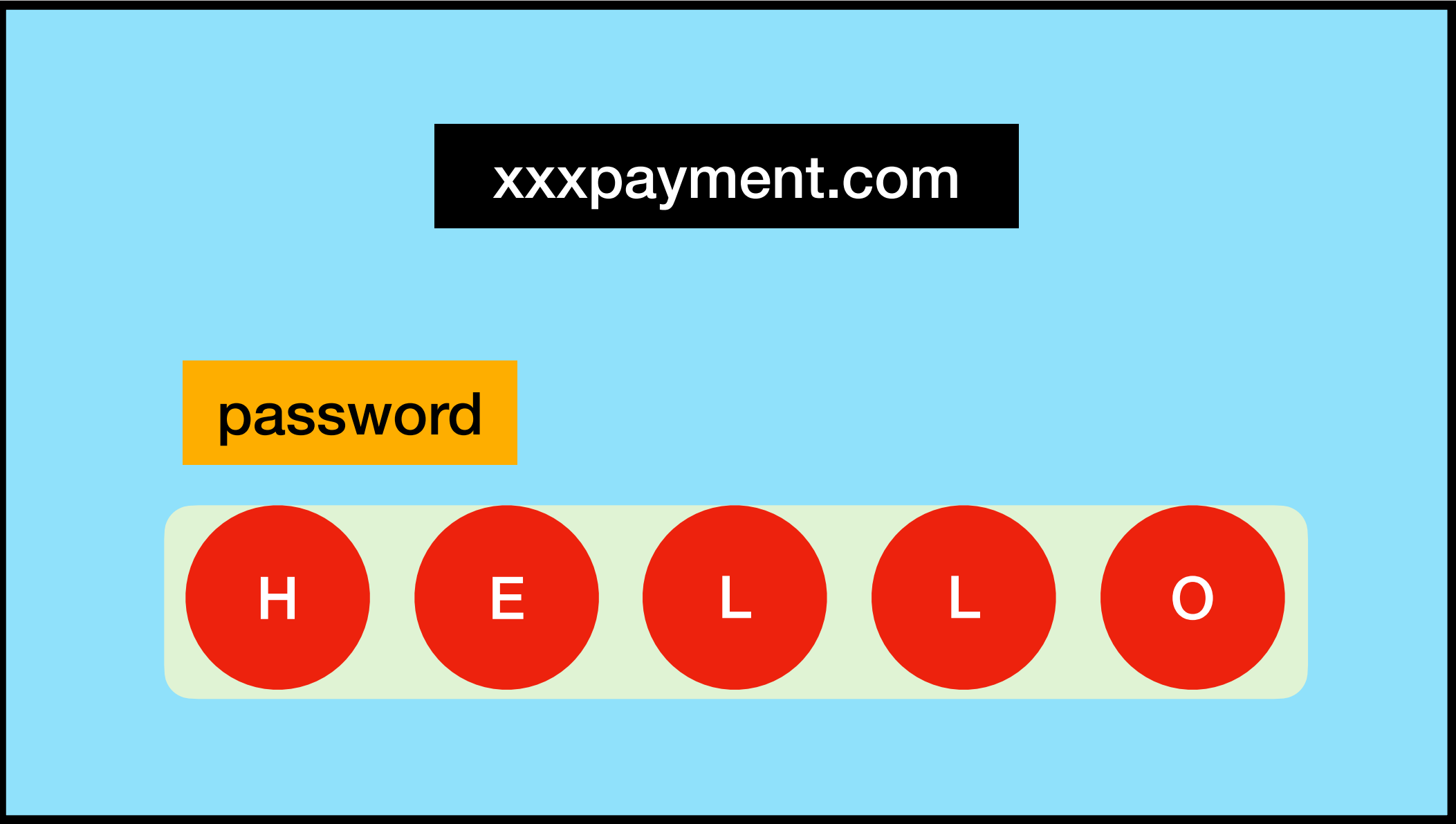
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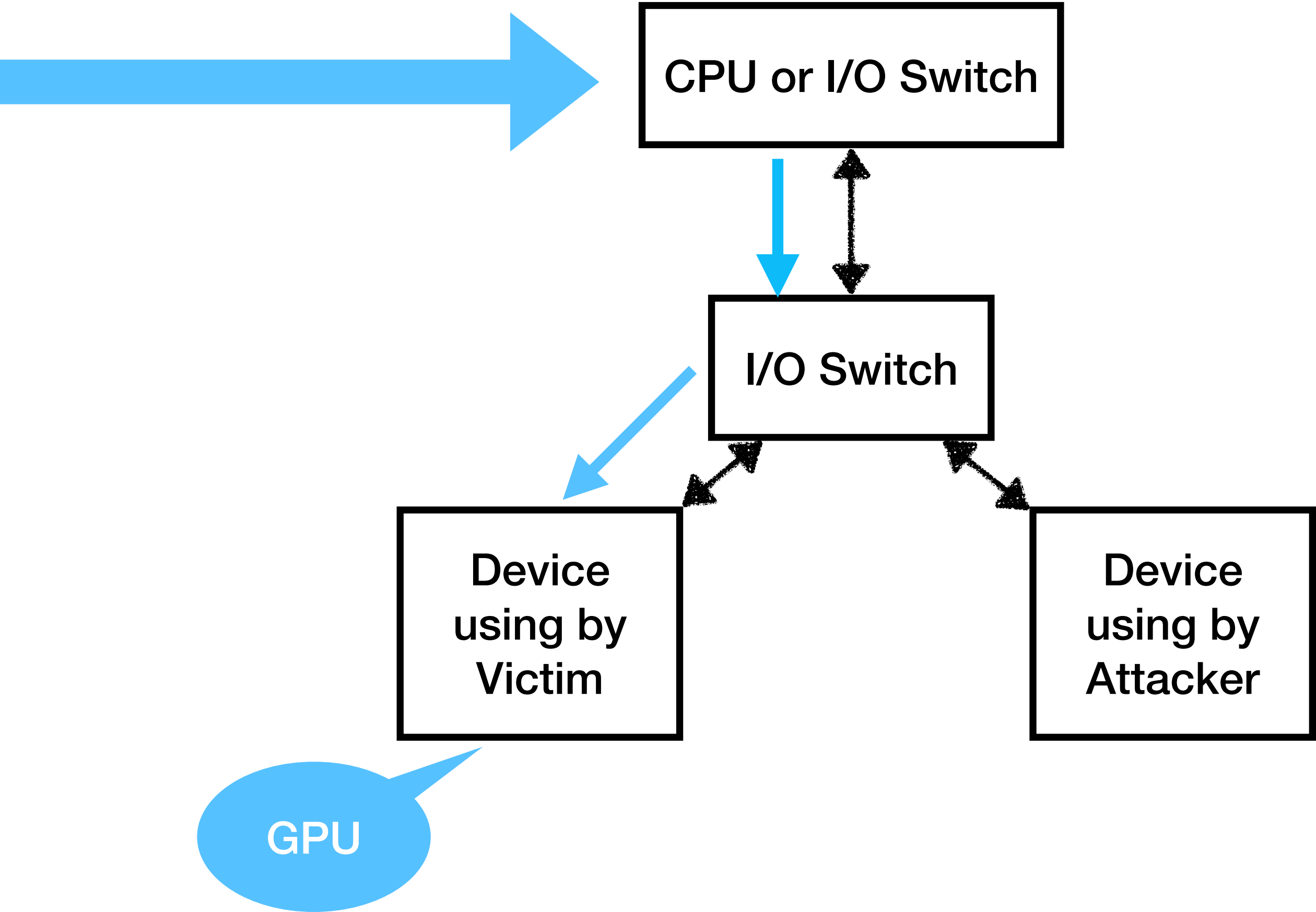
Delay Sequence



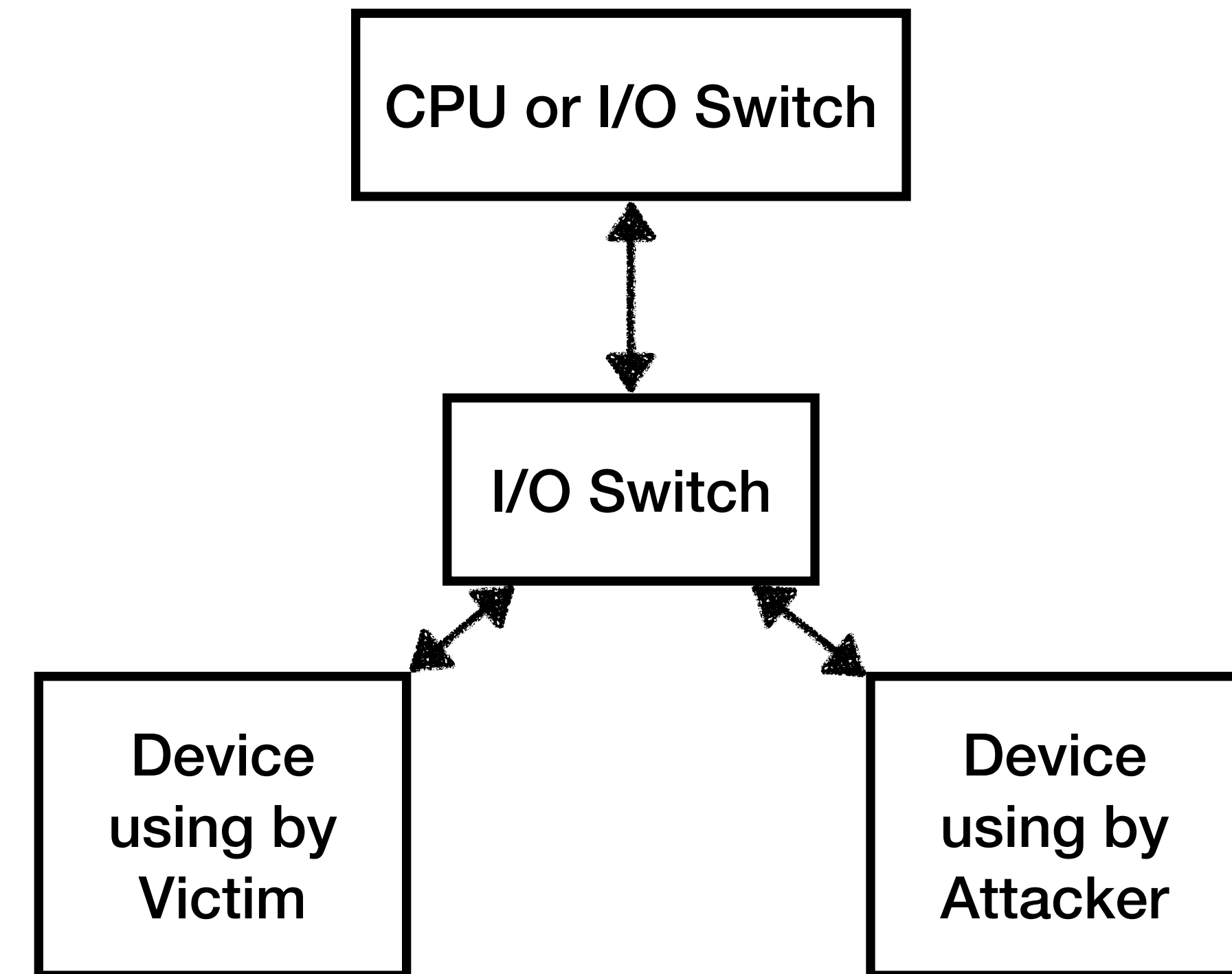
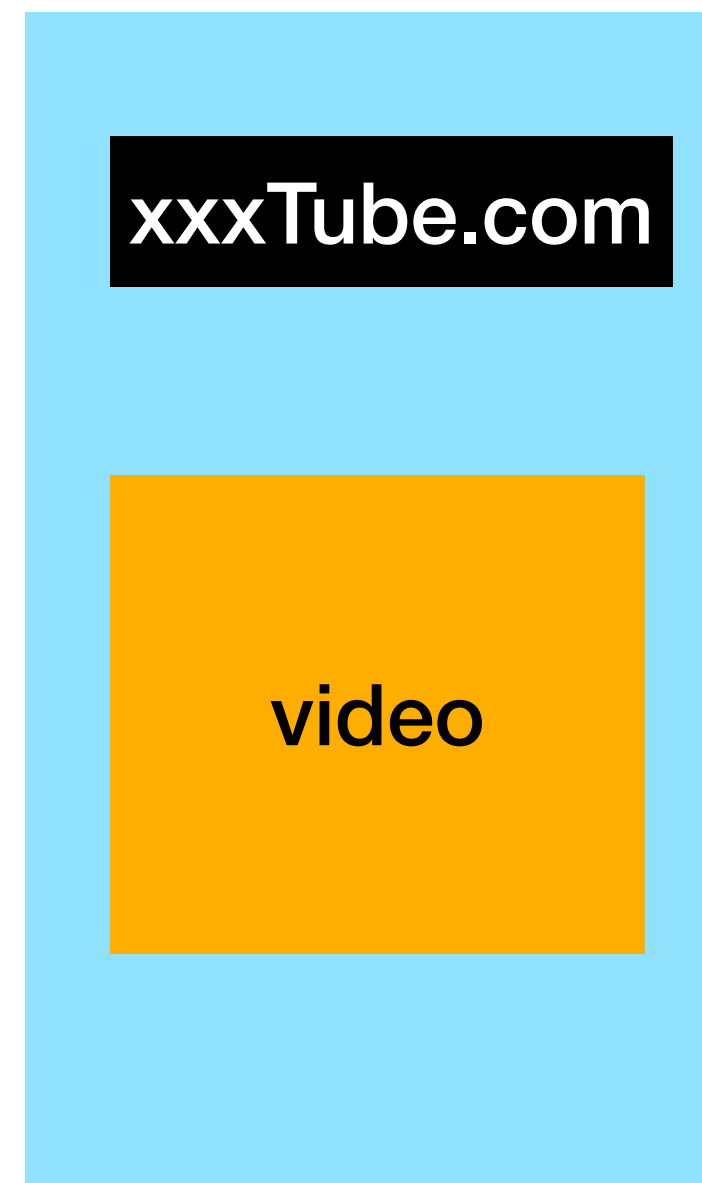
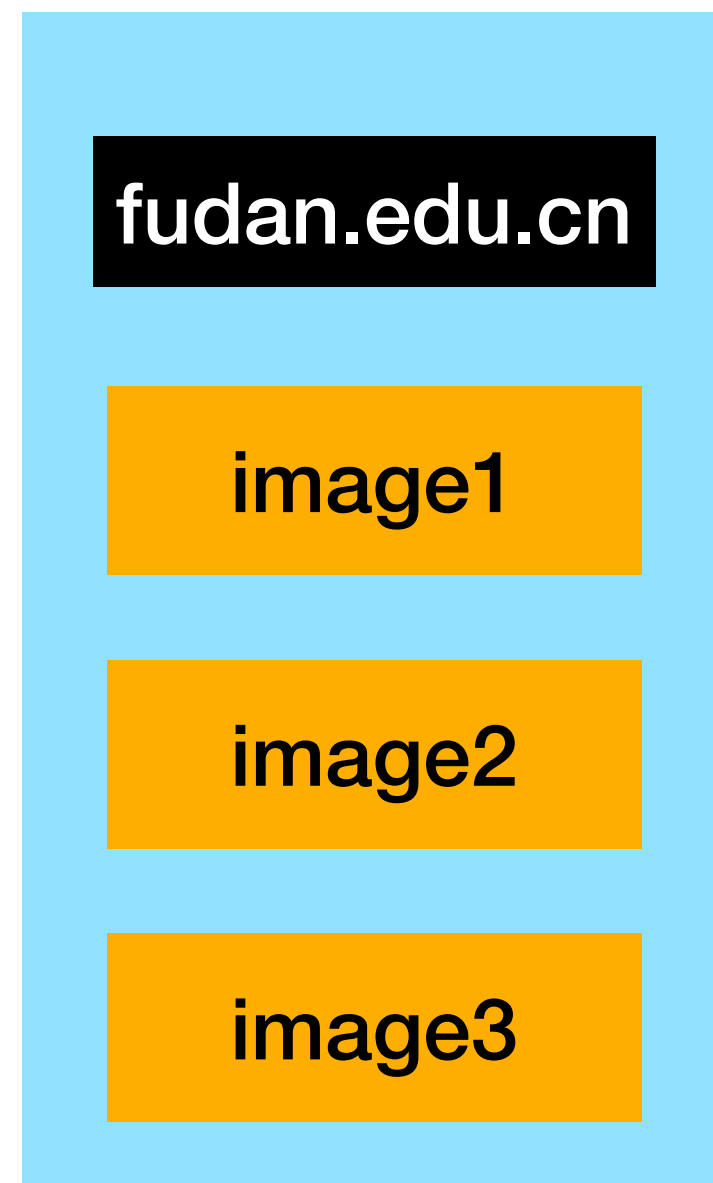
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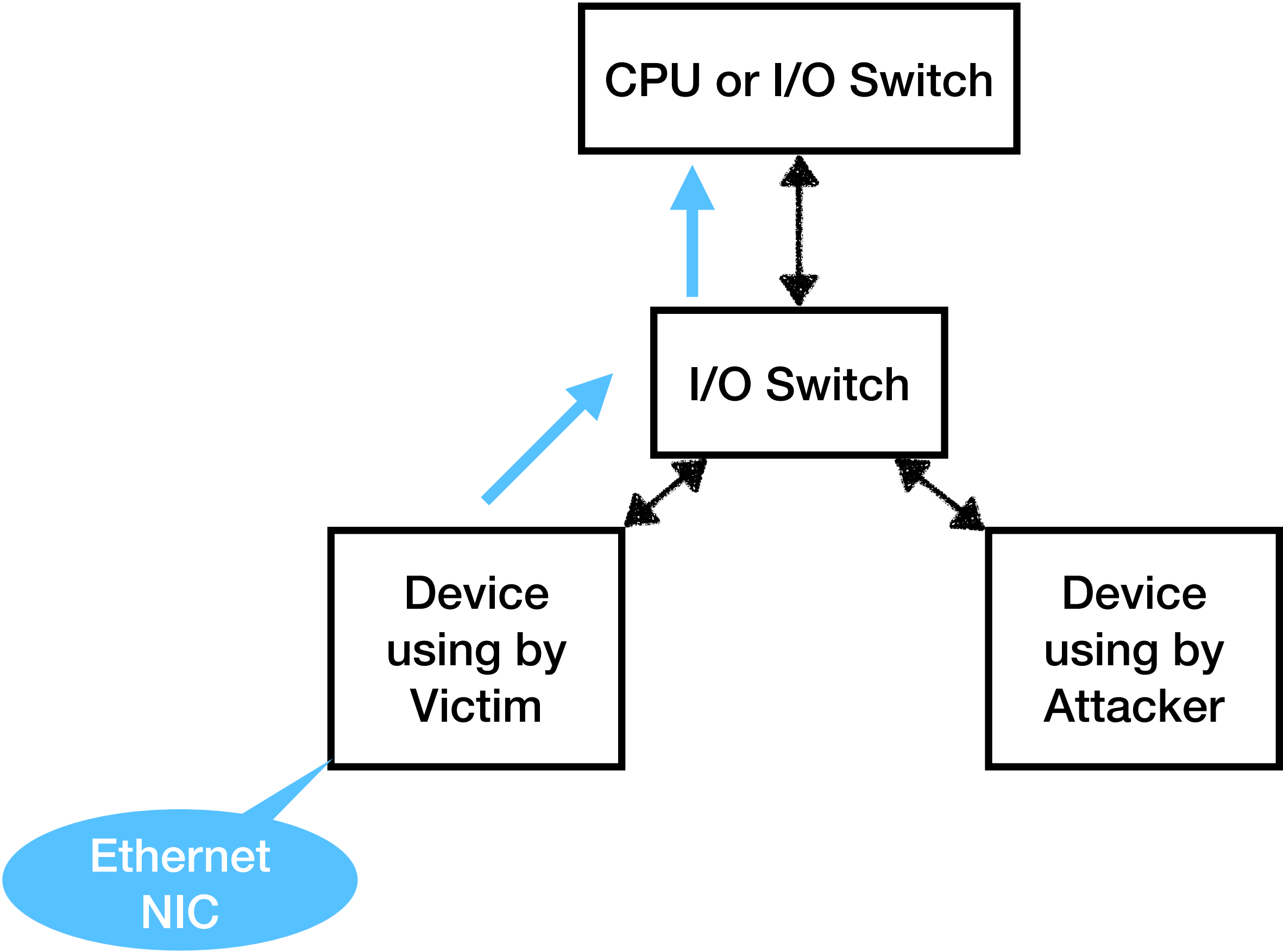
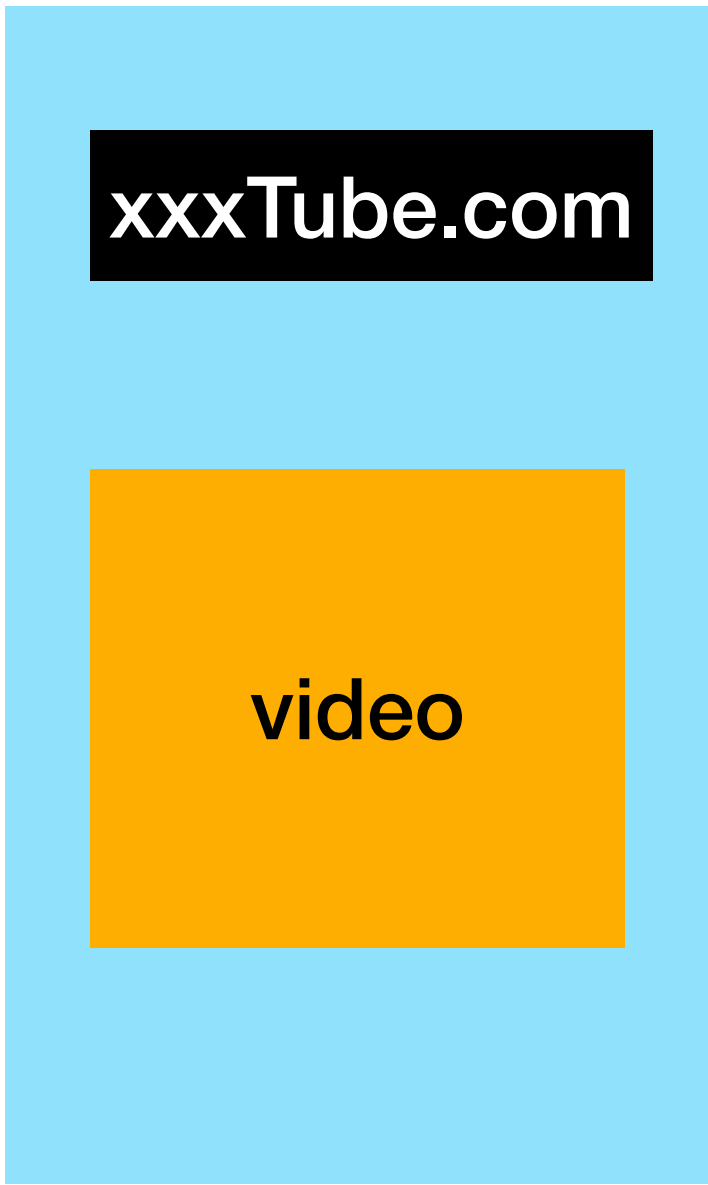
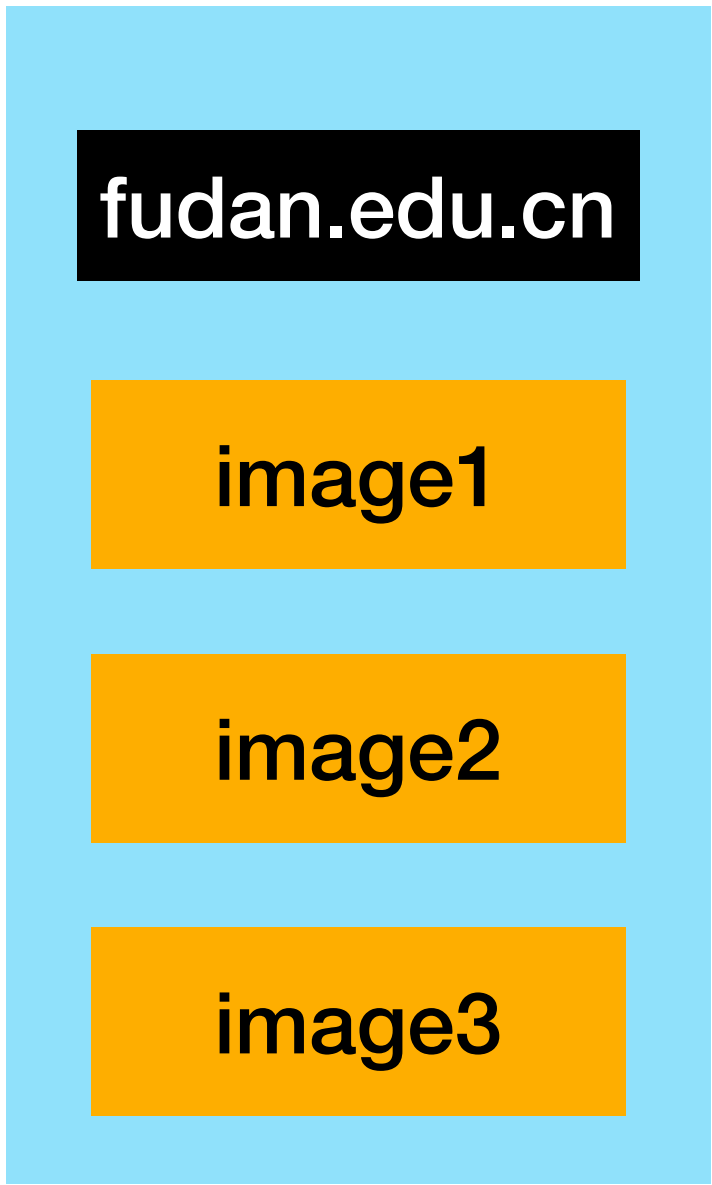
Delay Sequence



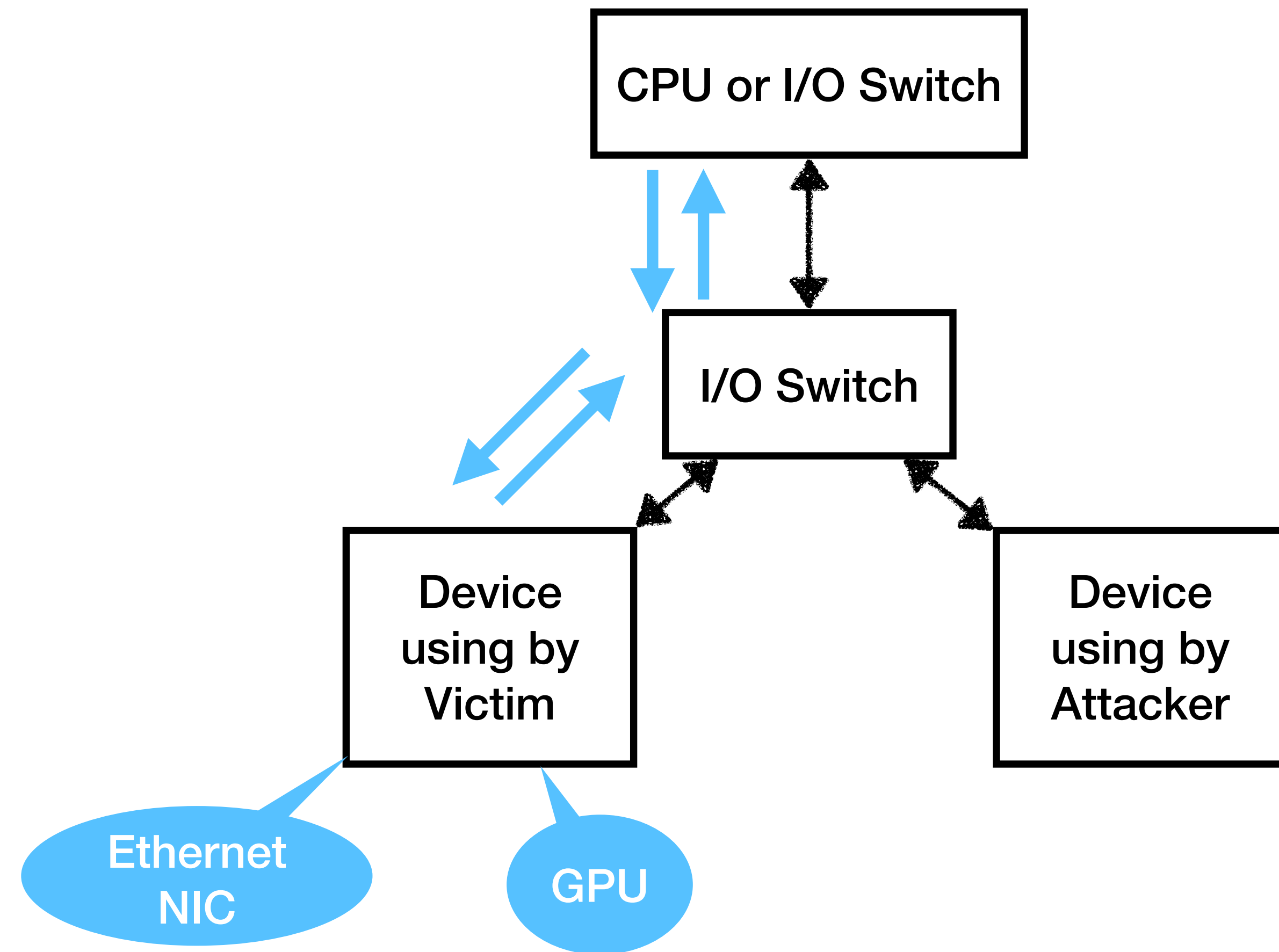
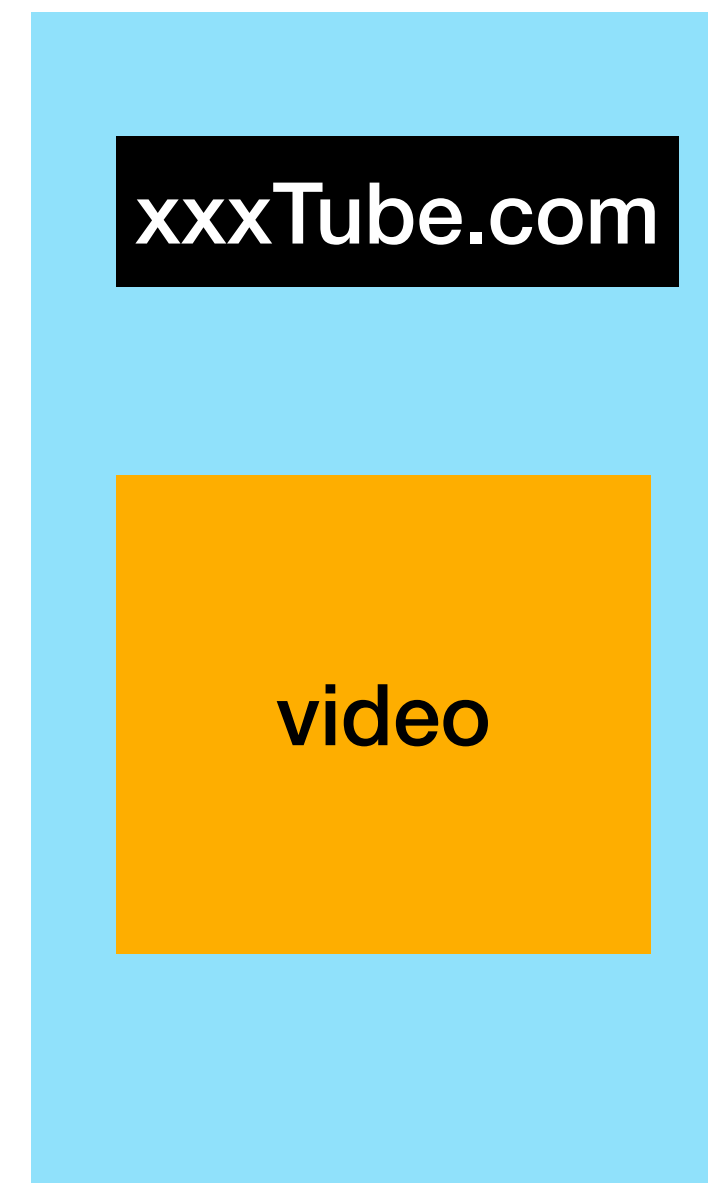
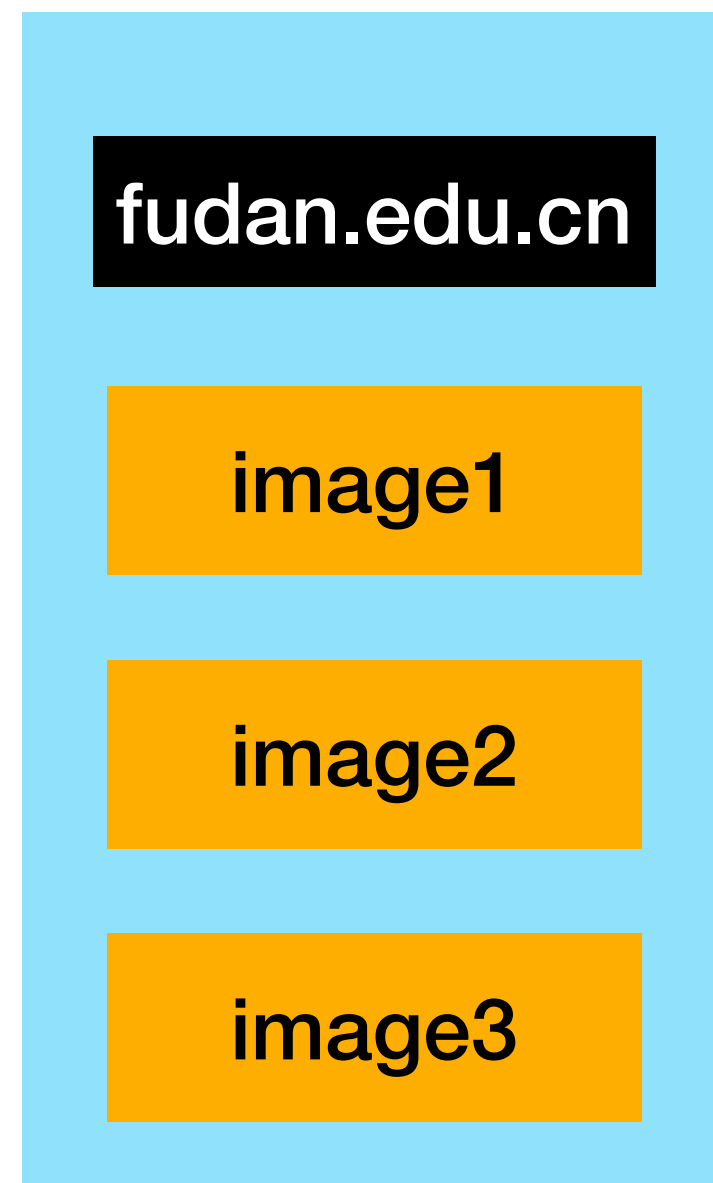
# Webpage Inference



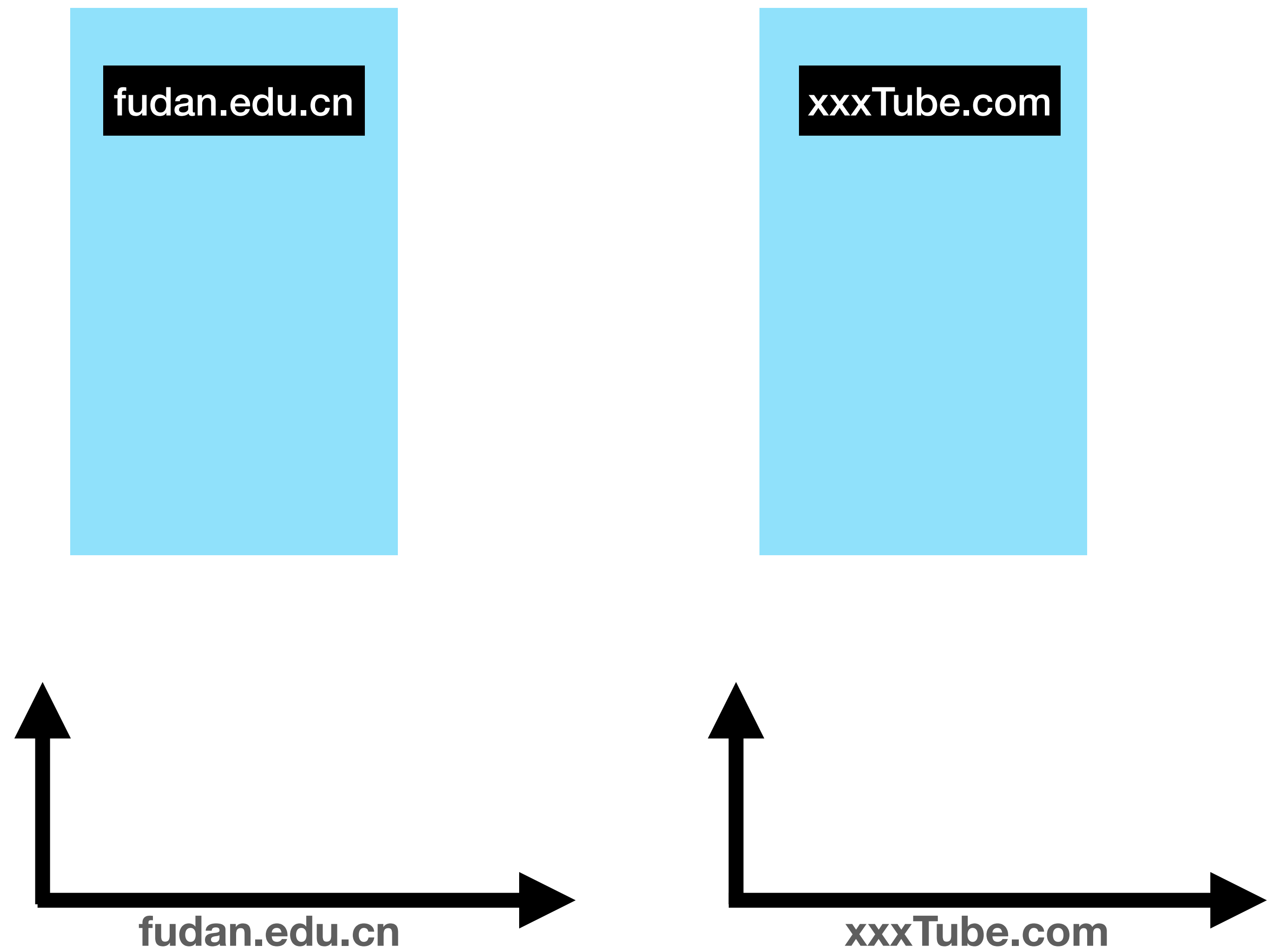
# Webpage Inference



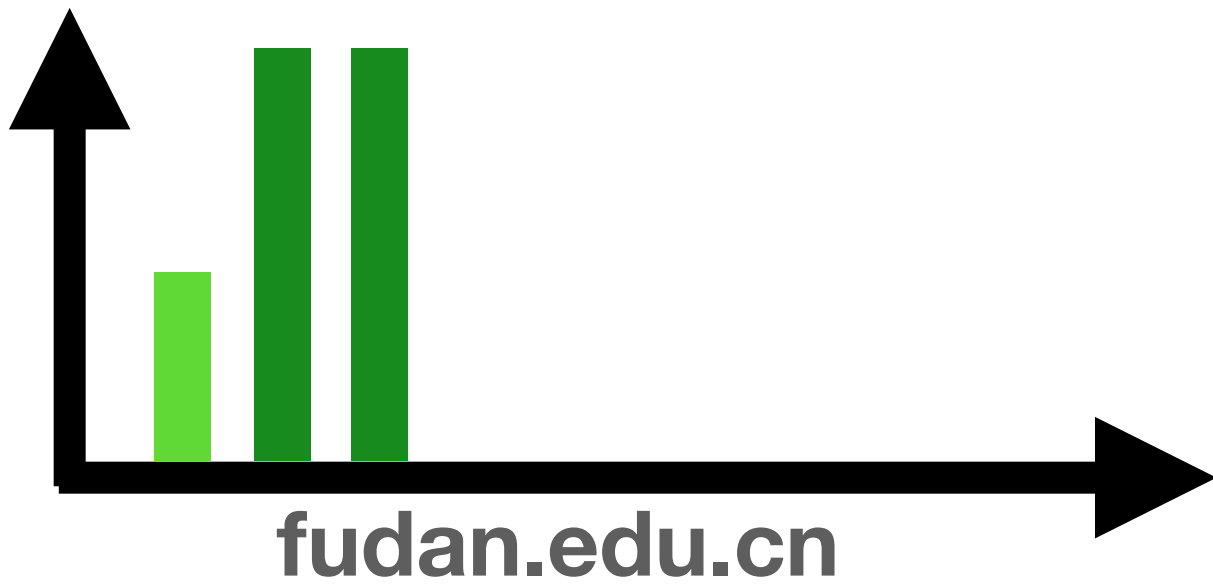
# Webpage Inference



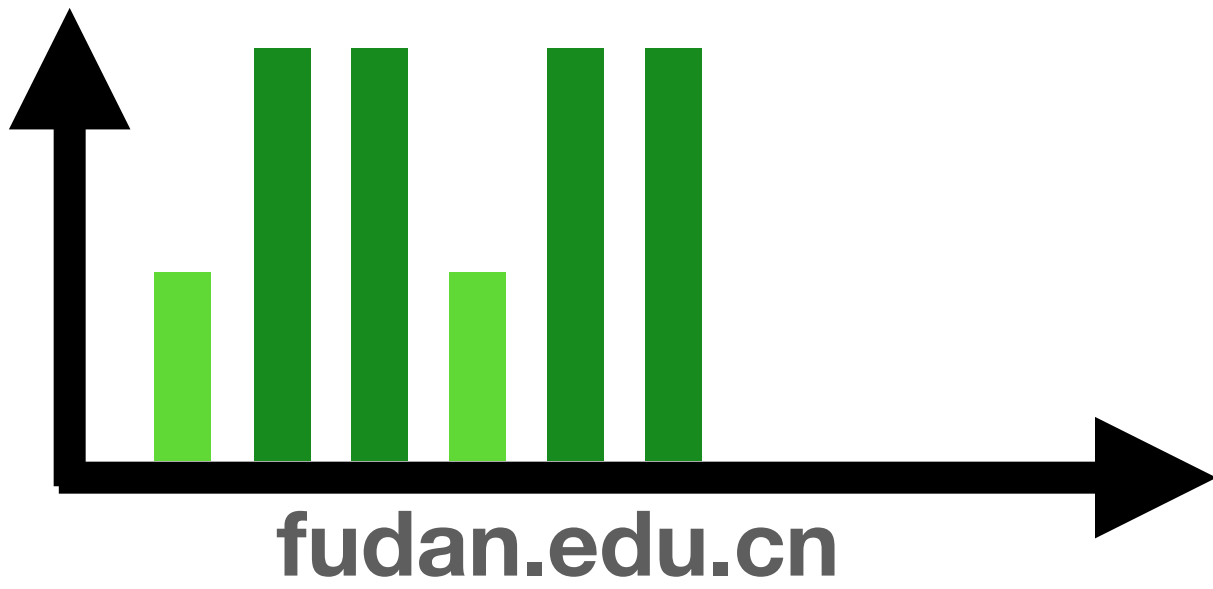
# Webpage Inference



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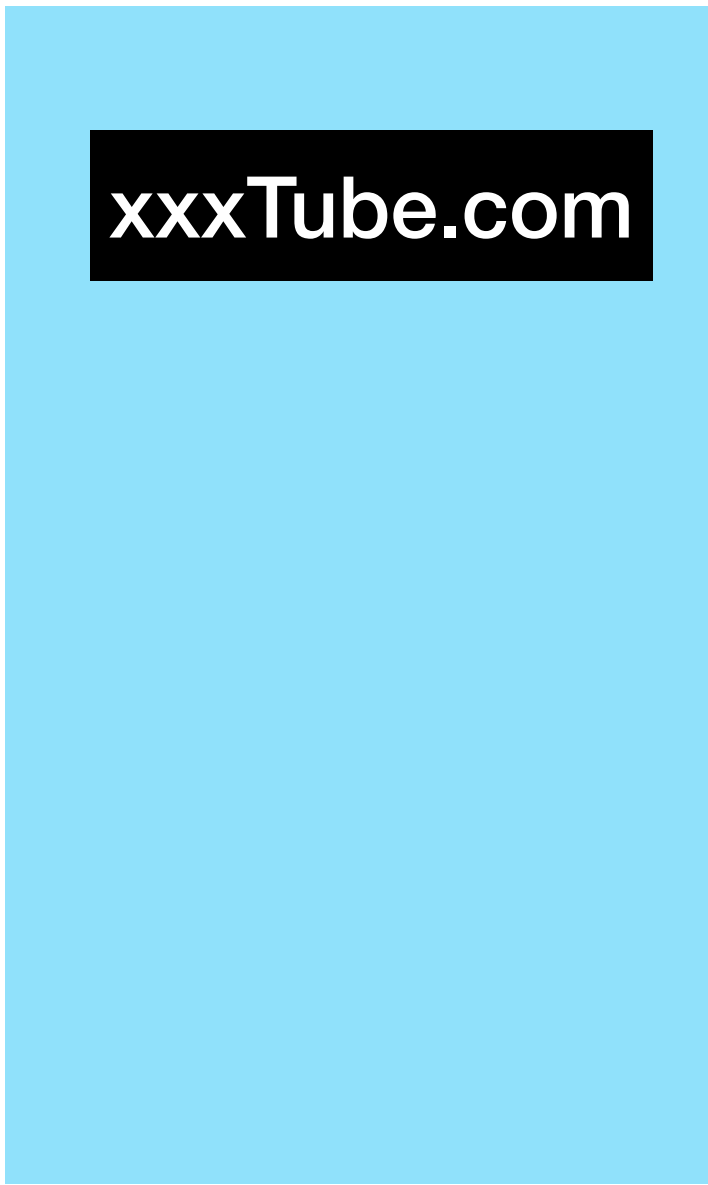
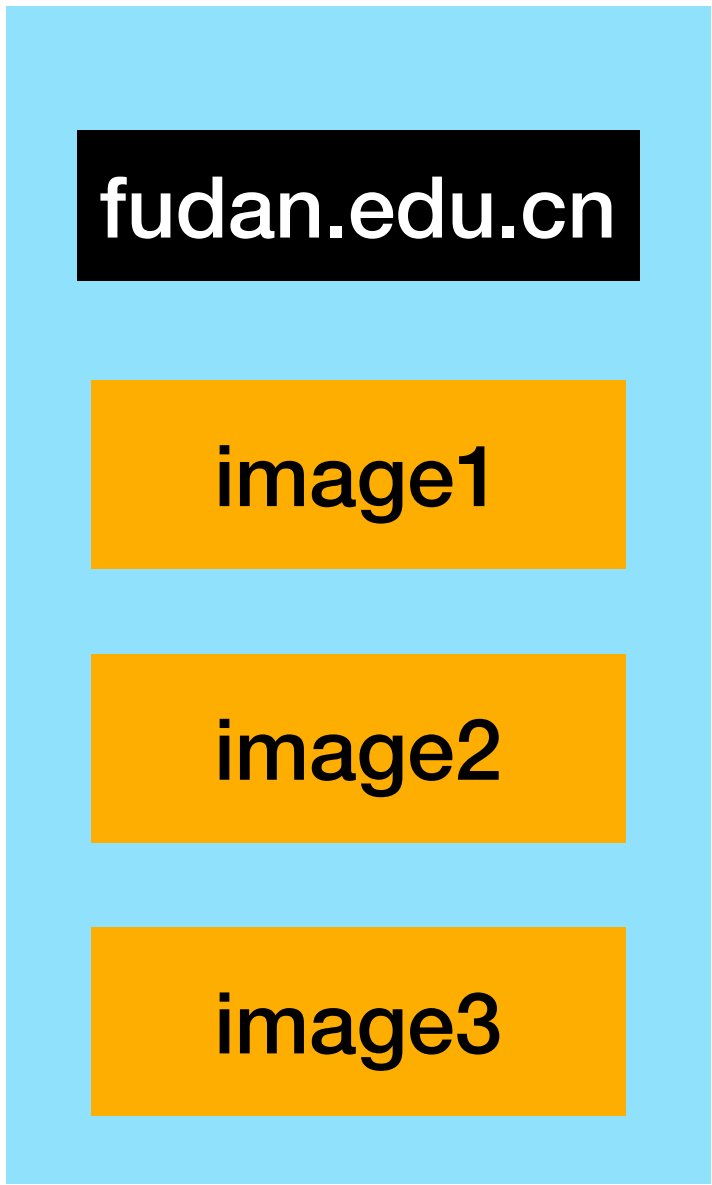


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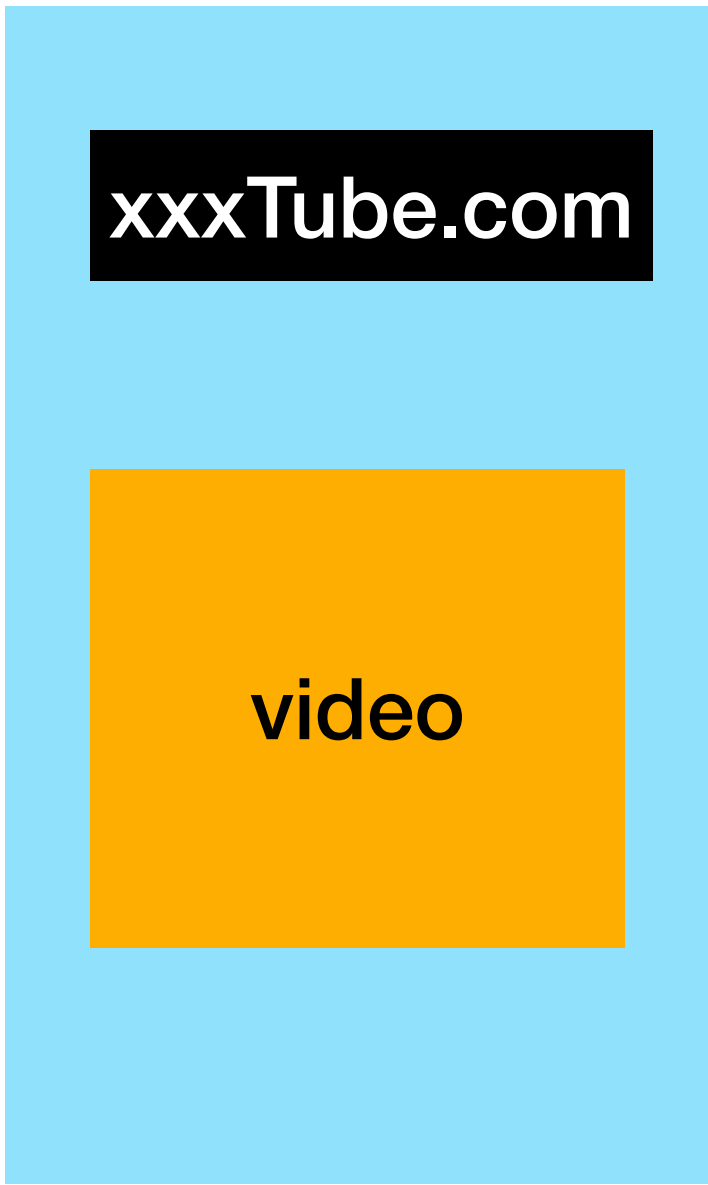
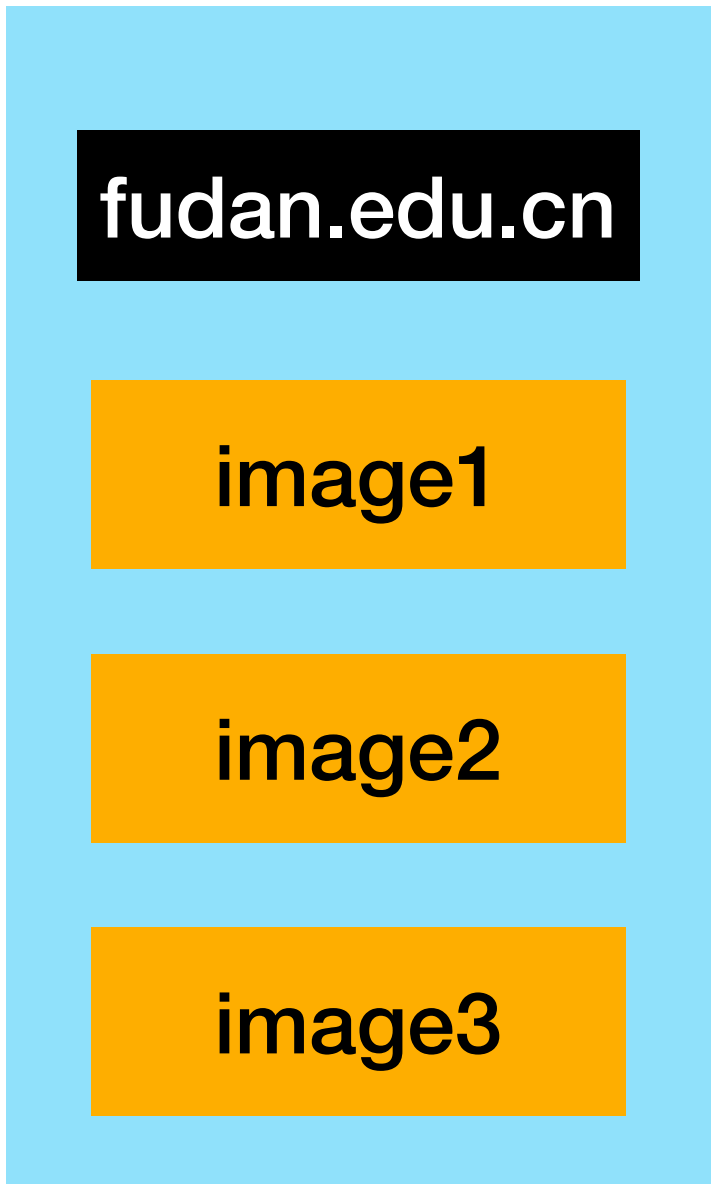




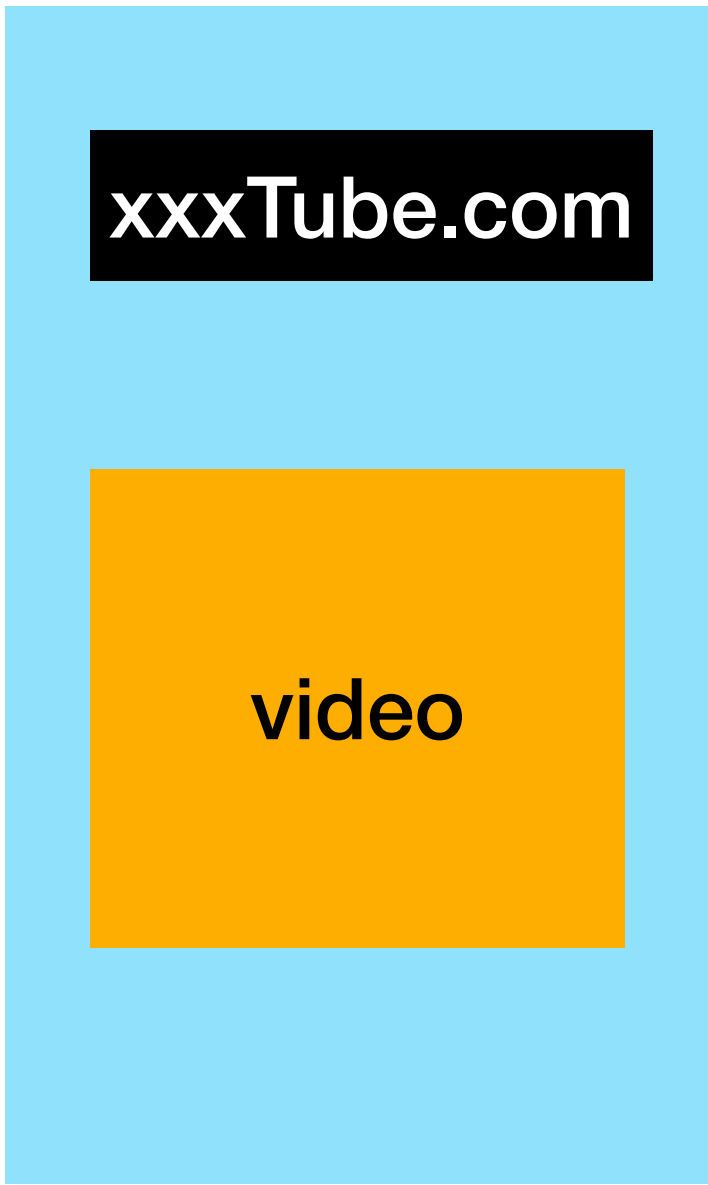
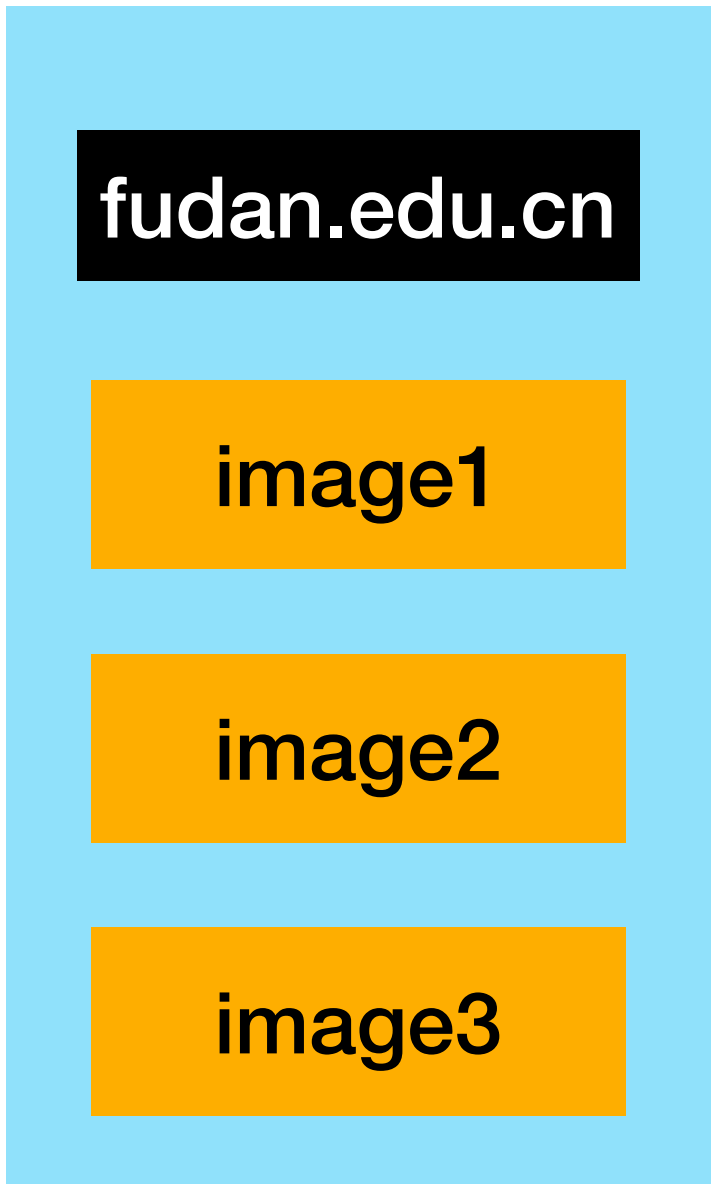
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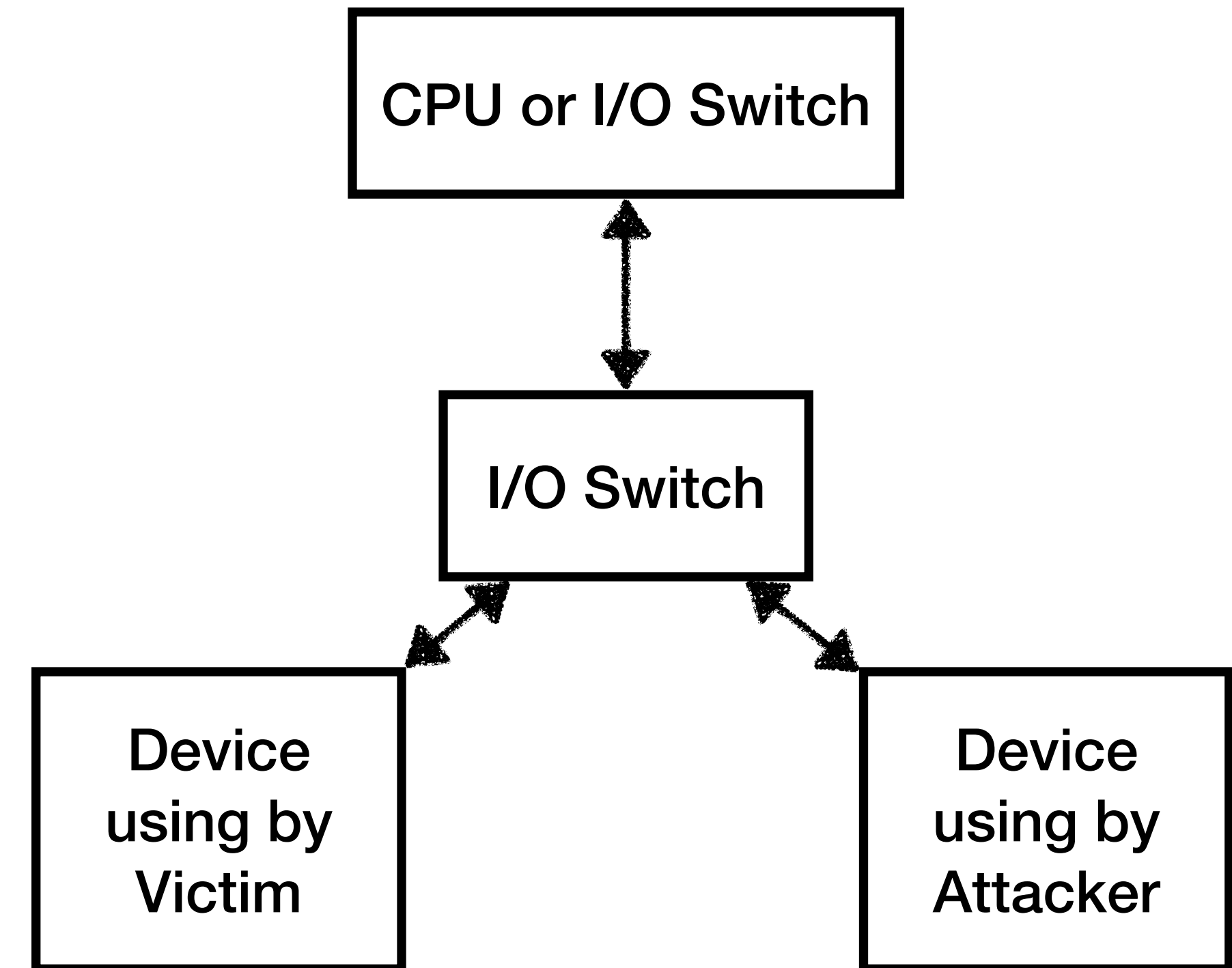
# Webpage Inference



The actual situation will be more complicated

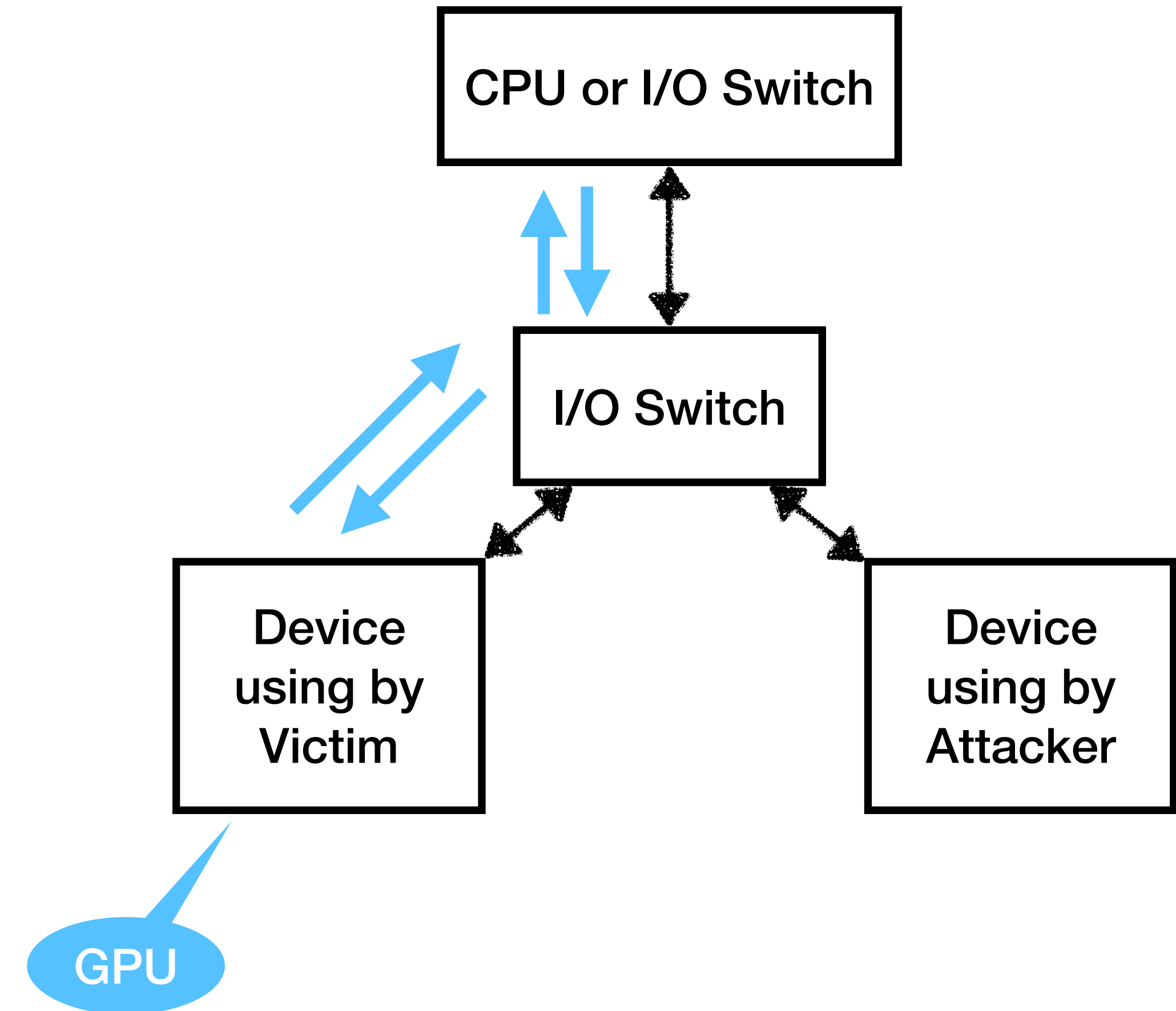


# Machine-learning Model Inference



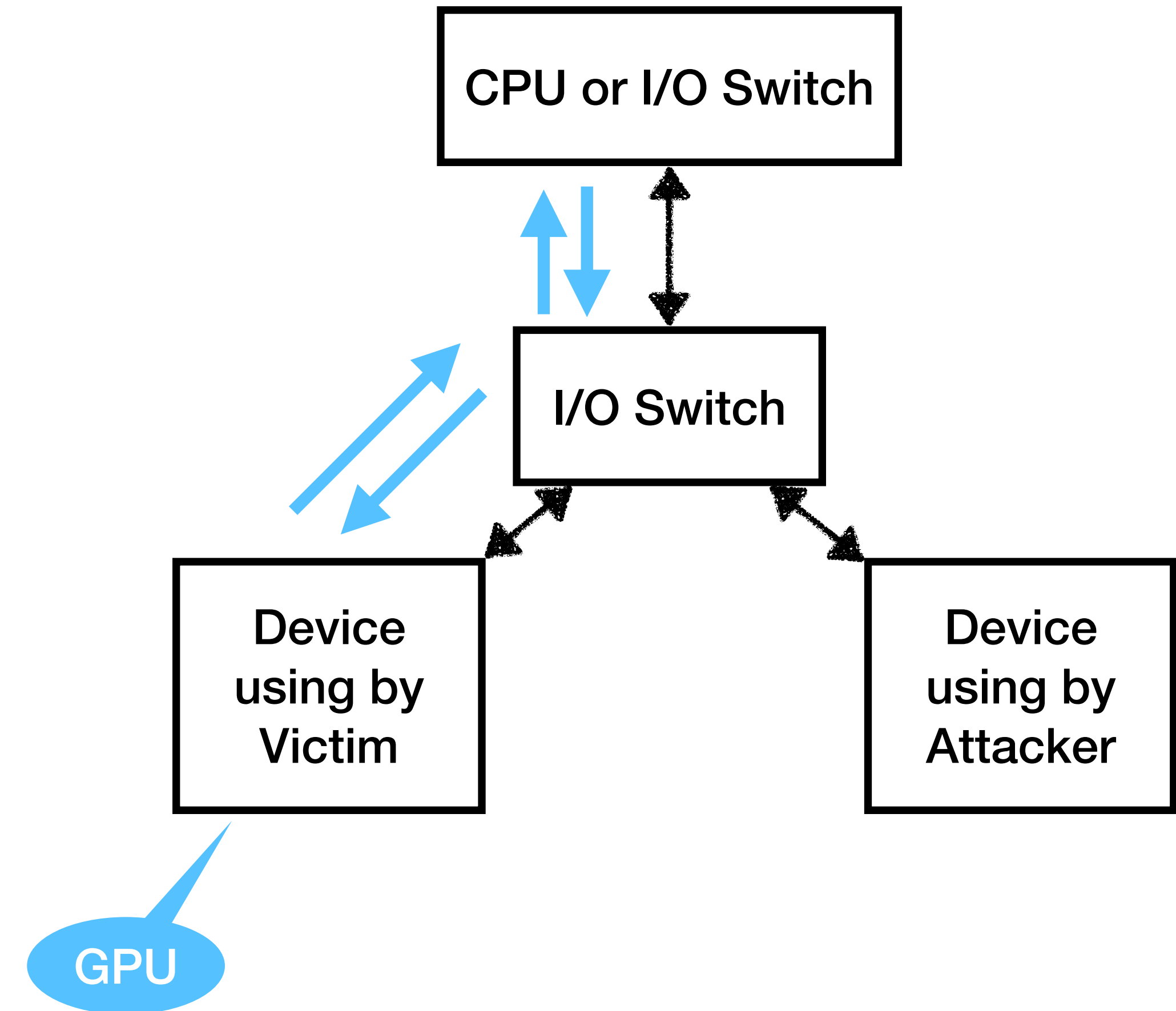
# Machine-learning Model Inference

- Data transferred in and out of the GPU



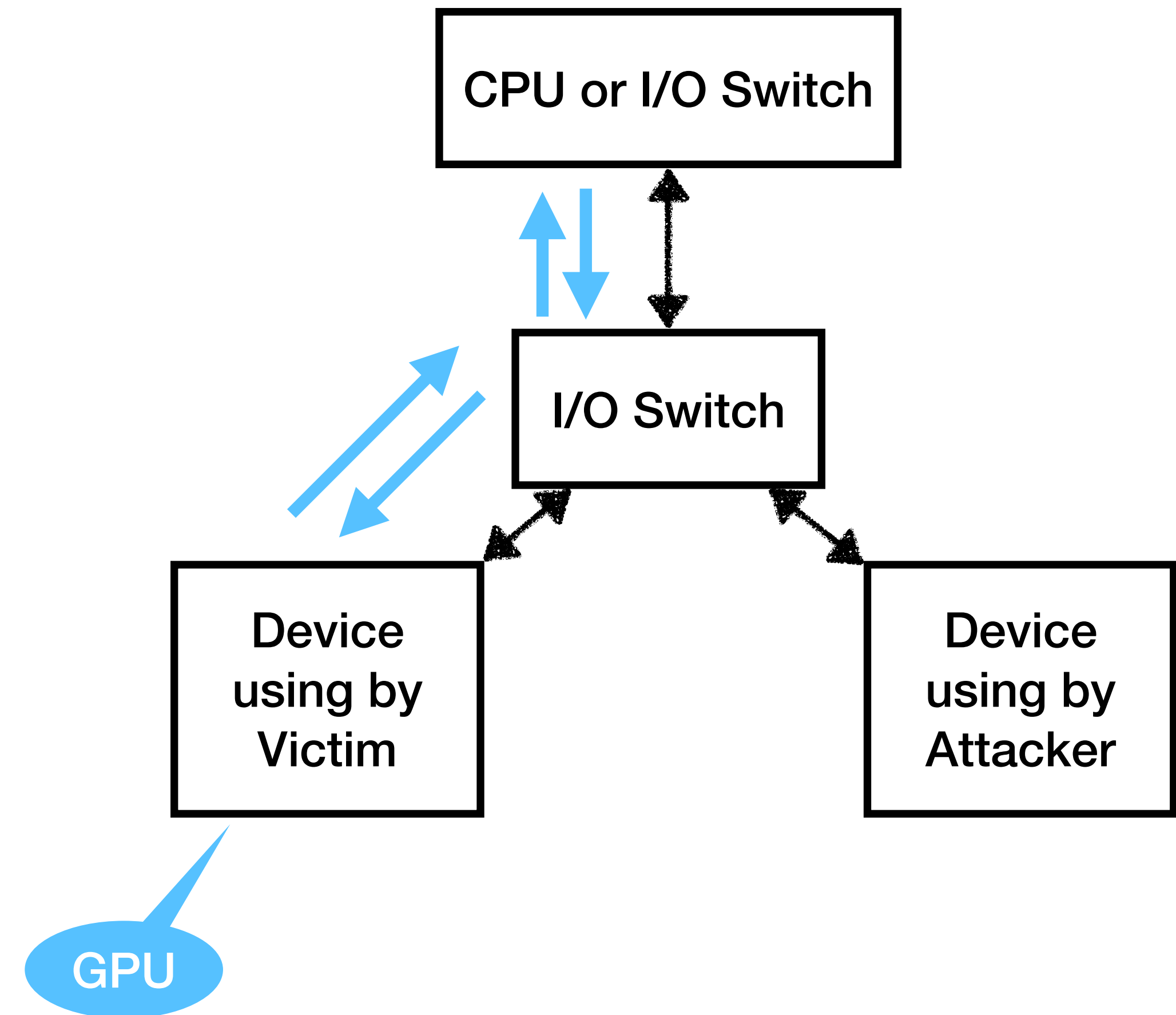
# Machine-learning Model Inference

- Data transferred in and out of the GPU
- Different layers transfer different size of data at different frequency



# Machine-learning Model Inference

- Data transferred in and out of the GPU
- Different layers transfer different size of data at different frequency
- Delay sequences of models significantly different



# Experiments and results



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  - Extract keystrokes from delay sequences
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  - Accuracy: above 96% in S1, above 93% in S2
- Machine-learning Model Inference
  - Probe 10 machine-learning models, collect delay sequence, and train the same classifier
  - All the models are correctly classified

# Potential Mitigation



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- Develop two attack strategies:
  - using RDMA NIC to attack GPU
  - using NVMe SSD to attack Ethernet NIC
- Evaluate them under three tasks:
  - keystroke typing
  - webpage browsing
  - training machine-learning model

**Thank you for listening!**  
**Questions?**

# References

- [1] D.X.Song,D.A.Wagner,and X.Tian,“Timing analysis of keystrokes and timing attacks on ssh.” in USENIX Security Symposium, vol. 2001, 2001.
- [2] P. Zhou, W. Shi, J. Tian, Z. Qi, B. Li, H. Hao, and B. Xu, “Attention- based bidirectional long short-term memory networks for relation classification,” in Proceedings of the 54th annual meeting of the association for computational linguistics (volume 2: Short papers), 2016, pp. 207–212.
- [3] <https://hakk.me/windows-secure-boot-process-enumeration-detailed-mechanism-and-overview-a156b57f4f98>