Detecting Automation of Twitter Accounts: Are You a Human, Bot, or Cyborg?

The Turtles Project: Design and Implementation of Nested Virtualization

Deepak Kumar

Detecting Automation of Twitter Accounts: Are You a Human, Bot, or Cyborg?

Zi Chu, Steven Gianvecchio, Haining Wang, Sushil Jajodia

IEEE Transactions in Dependable and Secure Computing August 2012

Twitter

- Online social networking and microblogging tool

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- Users post “tweets” - short, 280 character messages

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- Users post “tweets” - short, 280 character messages
- Users can be *followers* or *friends* of other users
- By end of Q4 2017, Twitter had ~330M monthly active users[1]

Automation on Twitter

- Automated programs, or ***bots,*** are prevalent on Twitter
    - In fact, integral to Twitter's design
    - "News bots"

Automation on Twitter

- Automated programs, or ***bots,*** are prevalent on Twitter
  - In fact, integral to Twitter's design
    - "News bots"
- However, bots can also be used in *malicious* ways

RUSSIAN BOTS ARE USING 2016 TACTICS TO HIJACK THE GUN DEBATE ON TWITTER

ERIN GRIFFITH SECURITY 02.15.18 02:00 PM

PRO-GUN RUSSIAN BOTS FLOOD TWITTER AFTER PARKLAND SHOOTING

After Florida School Shooting, Russian 'Bot' Army Pounced

By SHEERA FRENKEL and DAISUKE WAKABAYASHI FEB. 19, 2018

How can one determine if a Twitter user is automated?

Collecting Users + Tweets

Twitter Crawl

Timeline API

Collecting Users + Tweets

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Timeline API

Crawling Twitter

- Crawl Twitter with a Depth-First-Search

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Crawling Twitter

- Crawl Twitter with a Depth-First-Search
  - Select 5 users at random as a “seed”
  - For each user, record their tweets and their followers
  - Repeat for each follower…
  - In total, crawled **429,423** users

Collecting Users + Tweets

Twitter Crawl

Timeline API

Timeline API

- Twitter publishes the 20 most recent Tweets in global scope
  - Collected tweets and users during same timeframe as Twitter crawl
  - Added an additional **89,984** users

Twitter Dataset

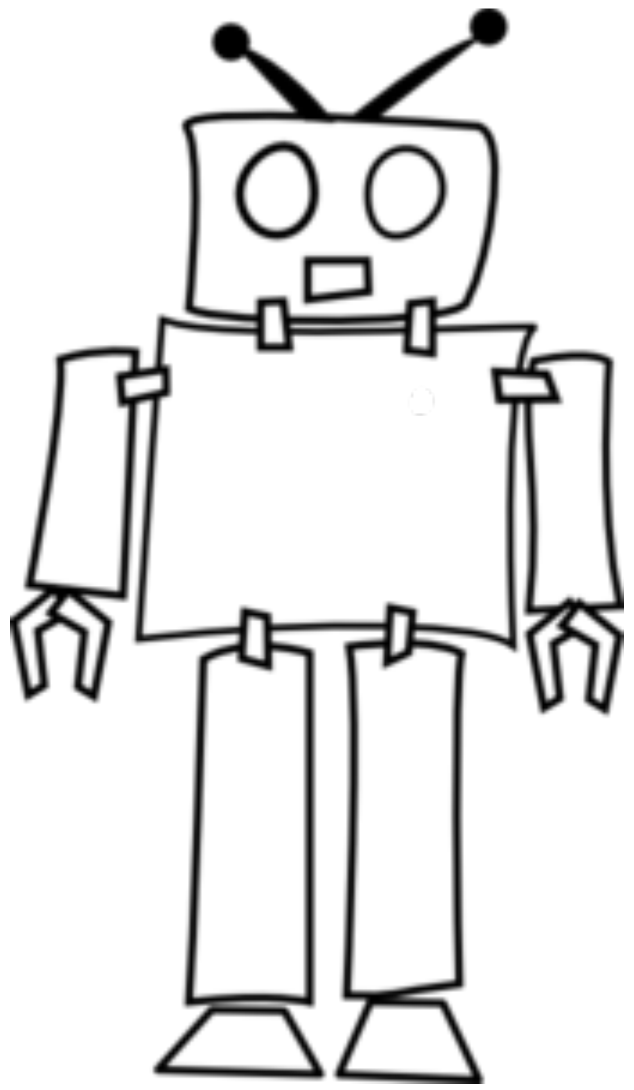
	Data Volume	Metadata Collected?
Users	512,407	username, followers, following, registration date, verified
Tweets	41,995,545	user, time, device

Types of Users on Twitter

Human

Types of Users on Twitter

Human



Bot

Types of Users on Twitter

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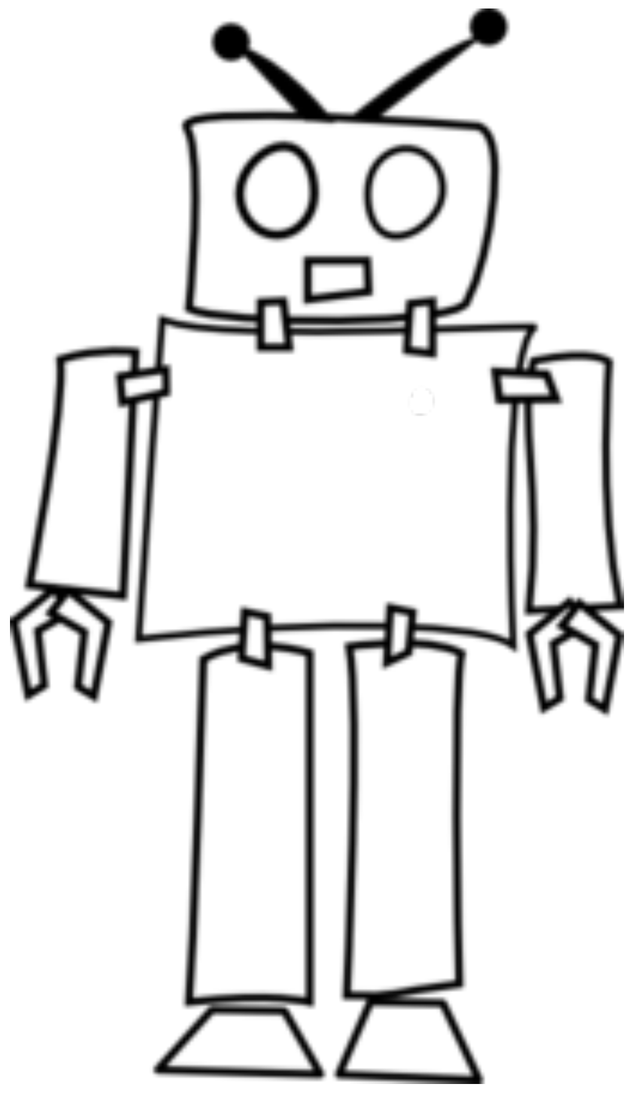
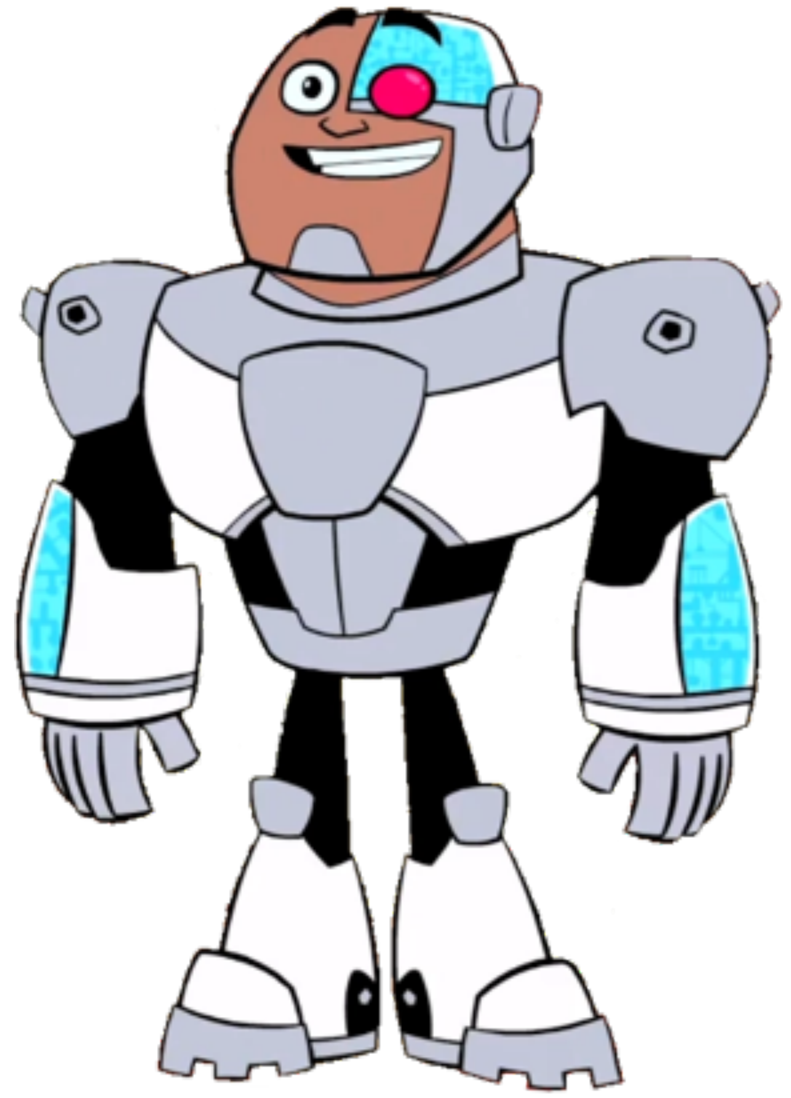


Bot



Cyborg

Classifying Users on Twitter: Ground Truth

- Select random sample of Twitter users from dataset
- Manually classify each user based on inspecting their profile
  - Follows the principle of “Turing Test” - 5 minutes to determine what class of user

Classifying Users on Twitter: Ground Truth

- Collected **2,000** unique users in each class
- Contributed **8,350,095** tweets

Classifying Users on Twitter: Ground Truth

- Collected **2,000** unique users in each class
- Contributed **8,350,095** tweets
- We can now investigate the *differences in behavior between user-classes*

Hypothesis: Each class of users exhibits unique behavior

Behavioral Patterns

Social Relationships

Tweeting Habits

Tweet Properties

Behavioral Patterns

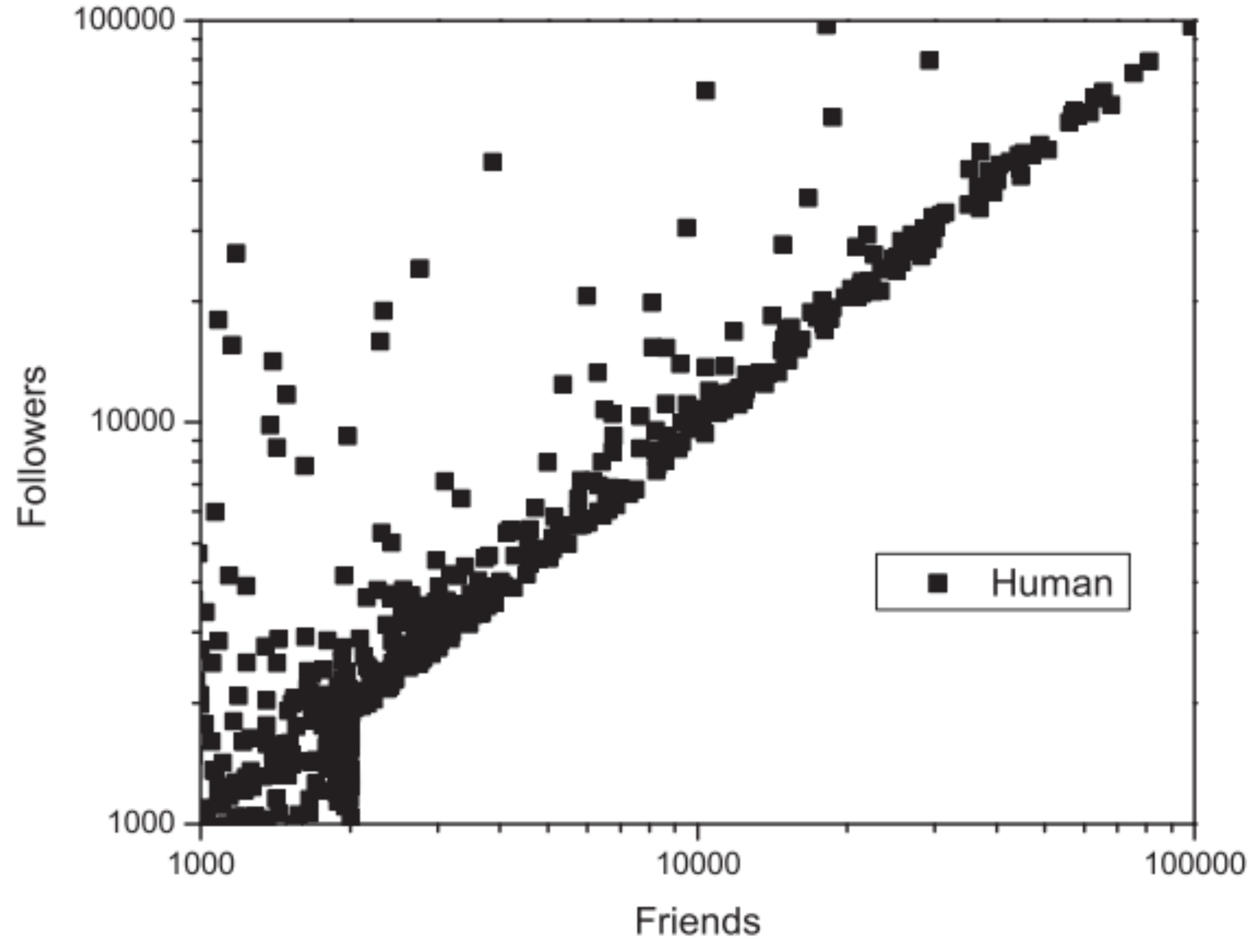
Social Relationships

Tweeting Habits

Tweet Properties

Social Relationships: Humans

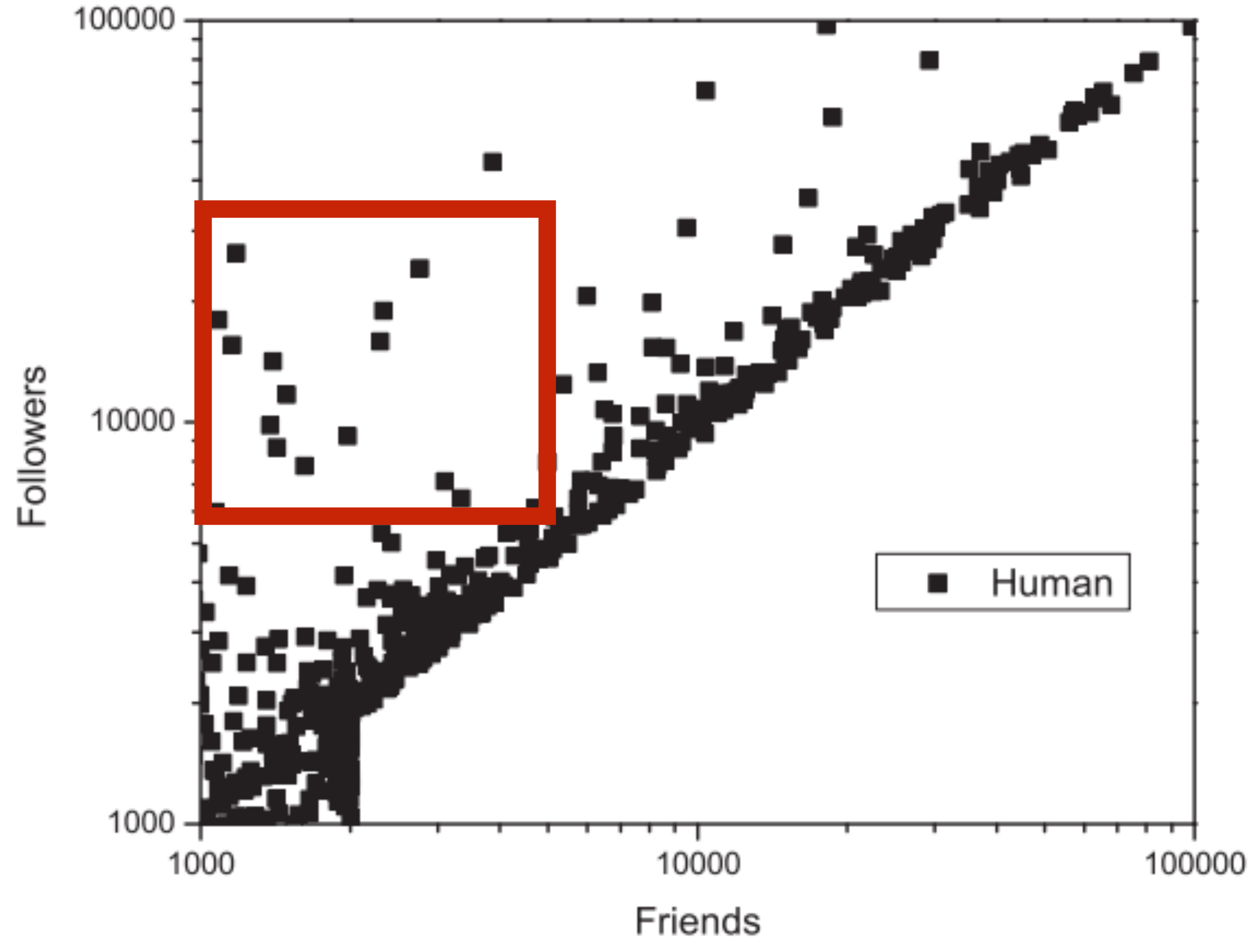
- Typically *reciprocal* relationships



(a) Human

Social Relationships: Humans

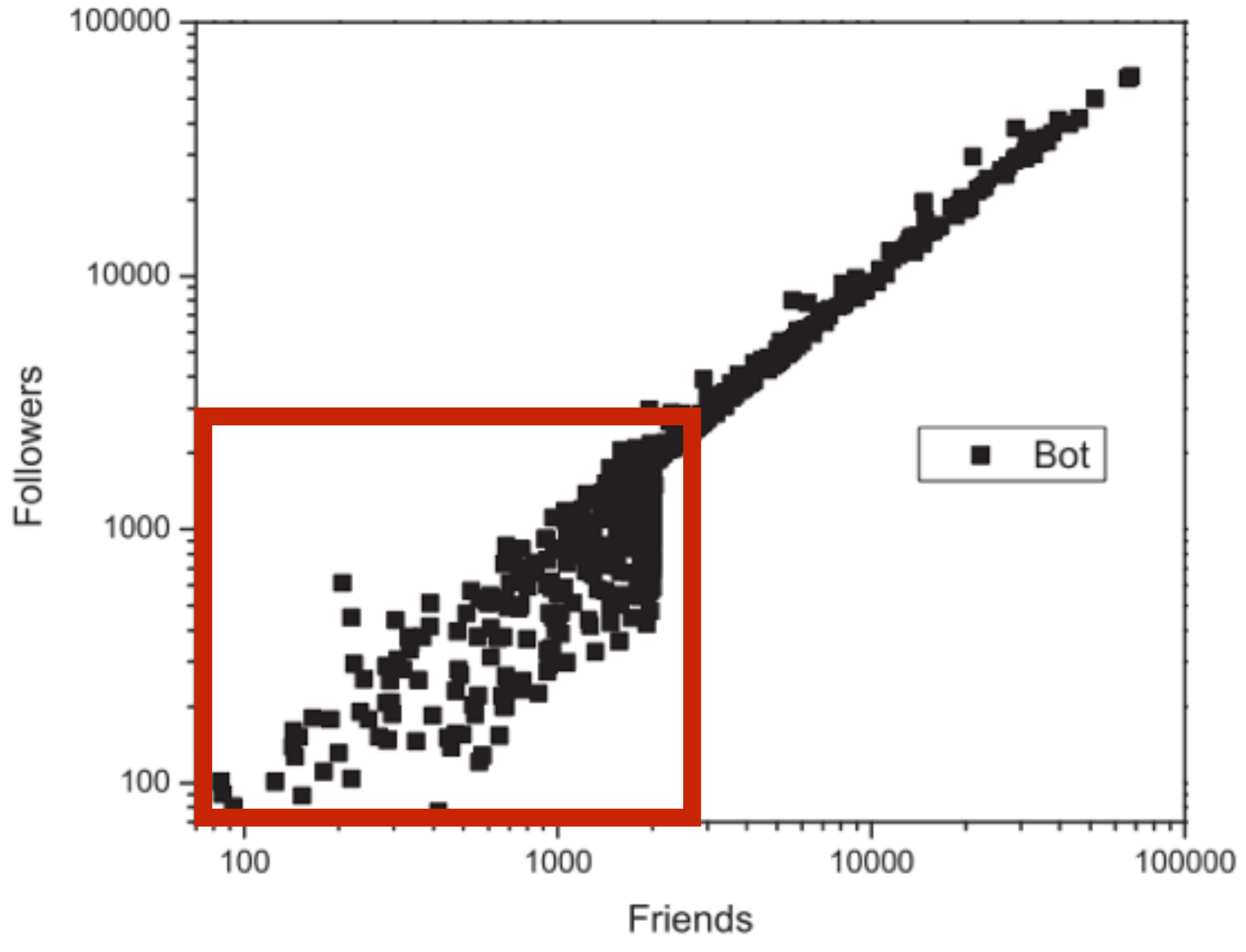
- Typically *reciprocal* relationships
- Handful of high follower/low friends, these are mainly celebrities and important human figures



(a) Human

Social Relationships: Bots

- Most bots have lots of friends (i.e., they follow many other accounts), but not followers

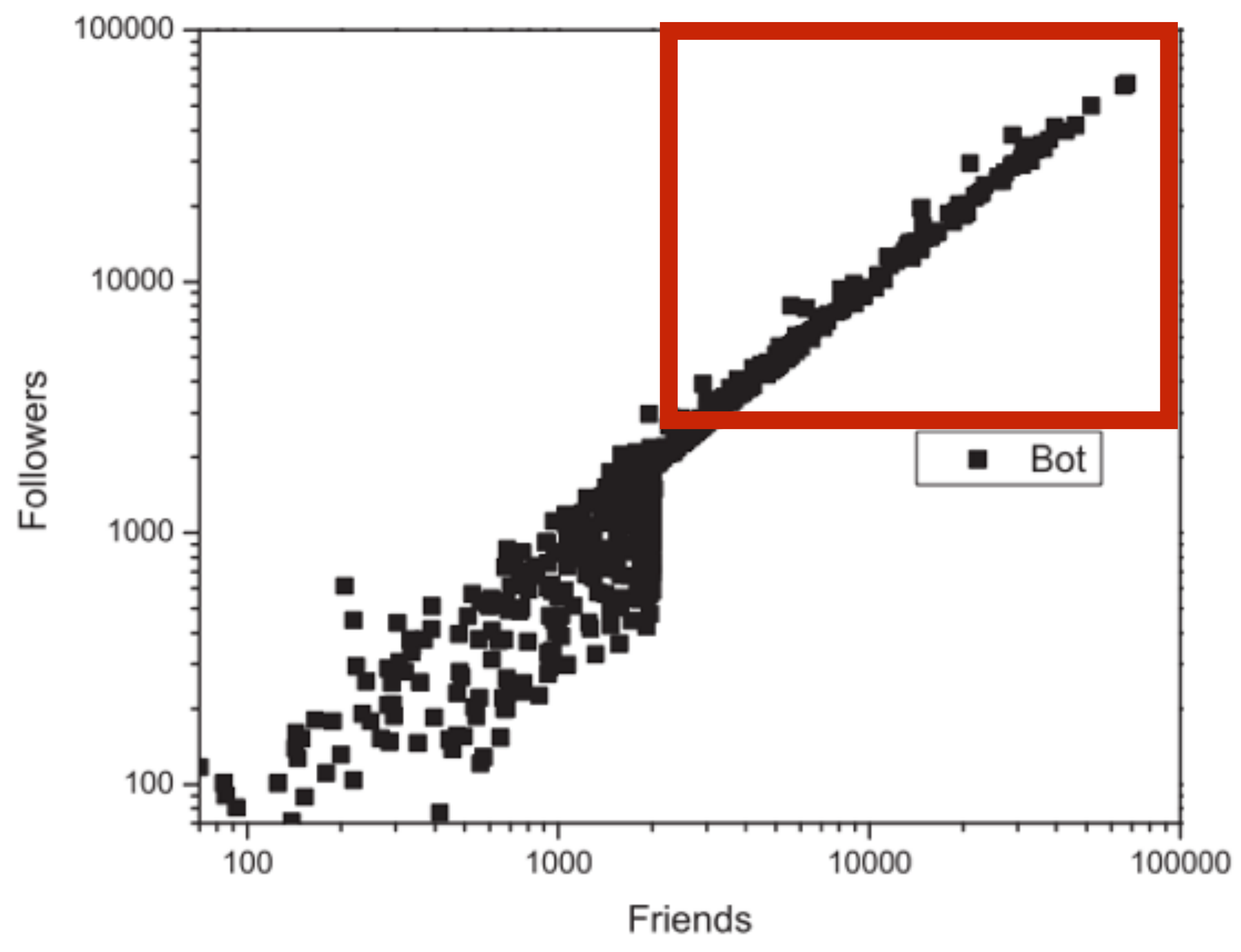


(b) Bot

Social Relationships: Bots

- Most bots have lots of friends (i.e., they follow many other accounts), but not followers

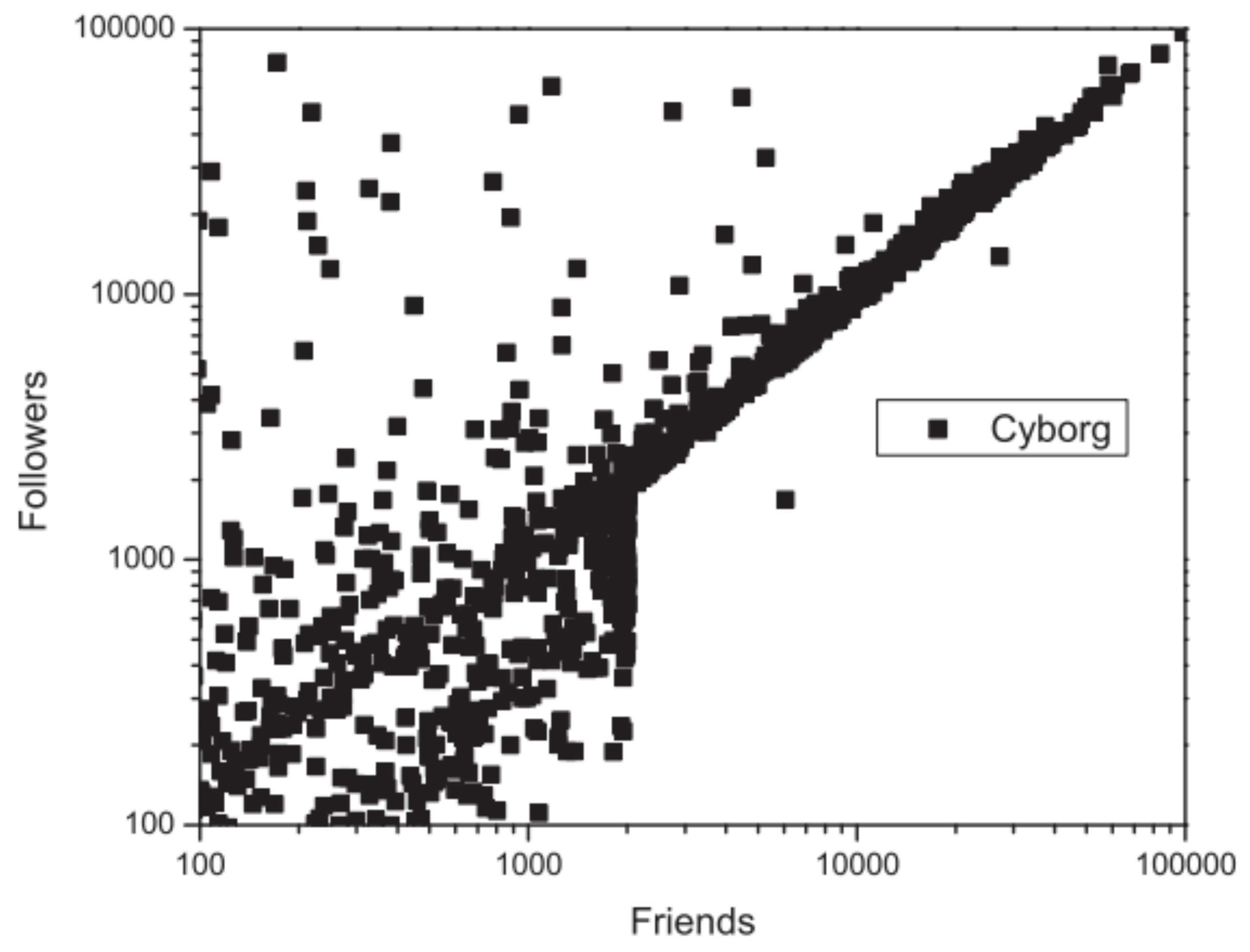
- Some bots are "smart" - they continually unfollow and follow to maintain a 1:1 ratio



(b) Bot

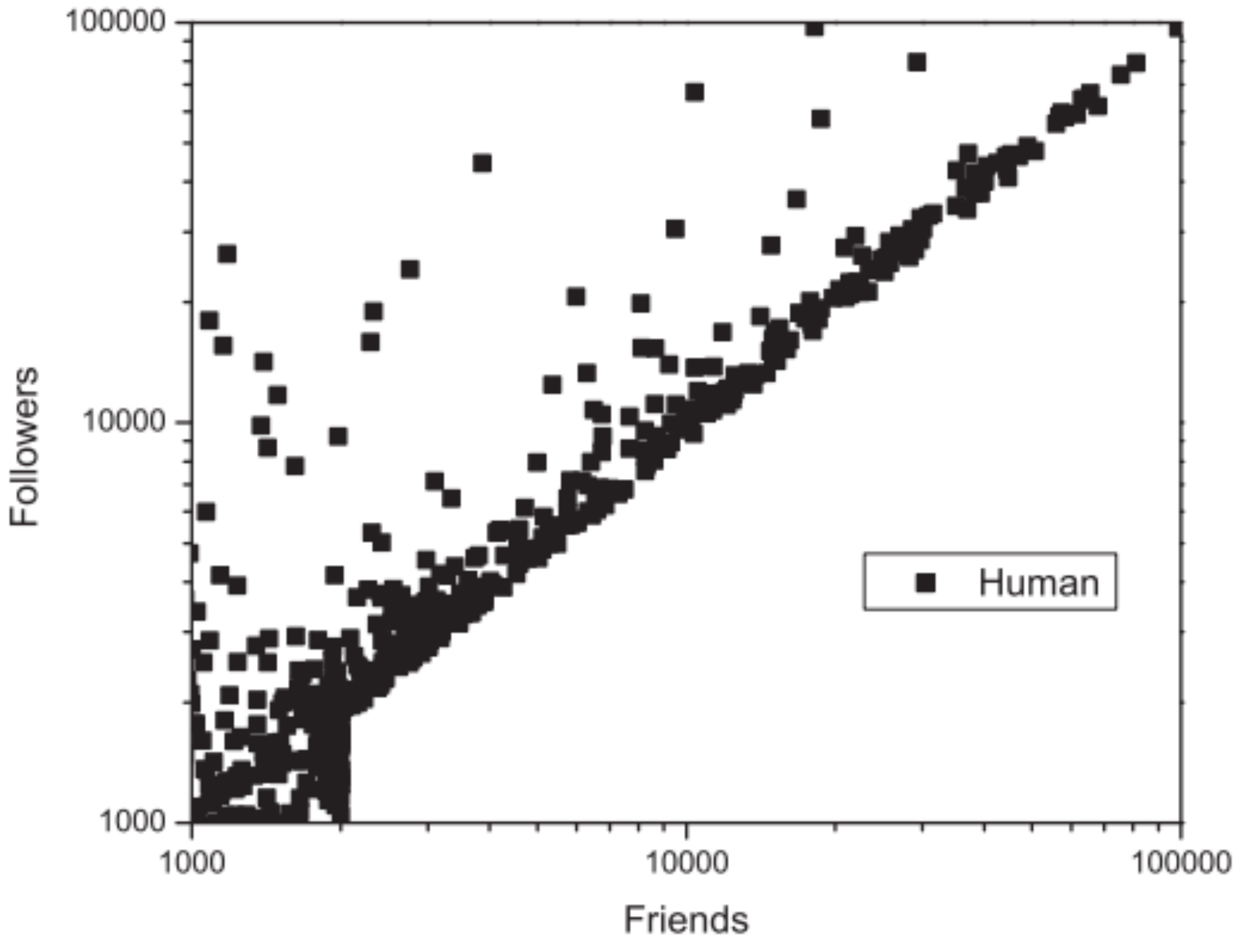
Social Relationships: Cyborgs

- Cyborgs exhibit a mix of human and bot social relationships



(c) Cyborg

Social Relationships



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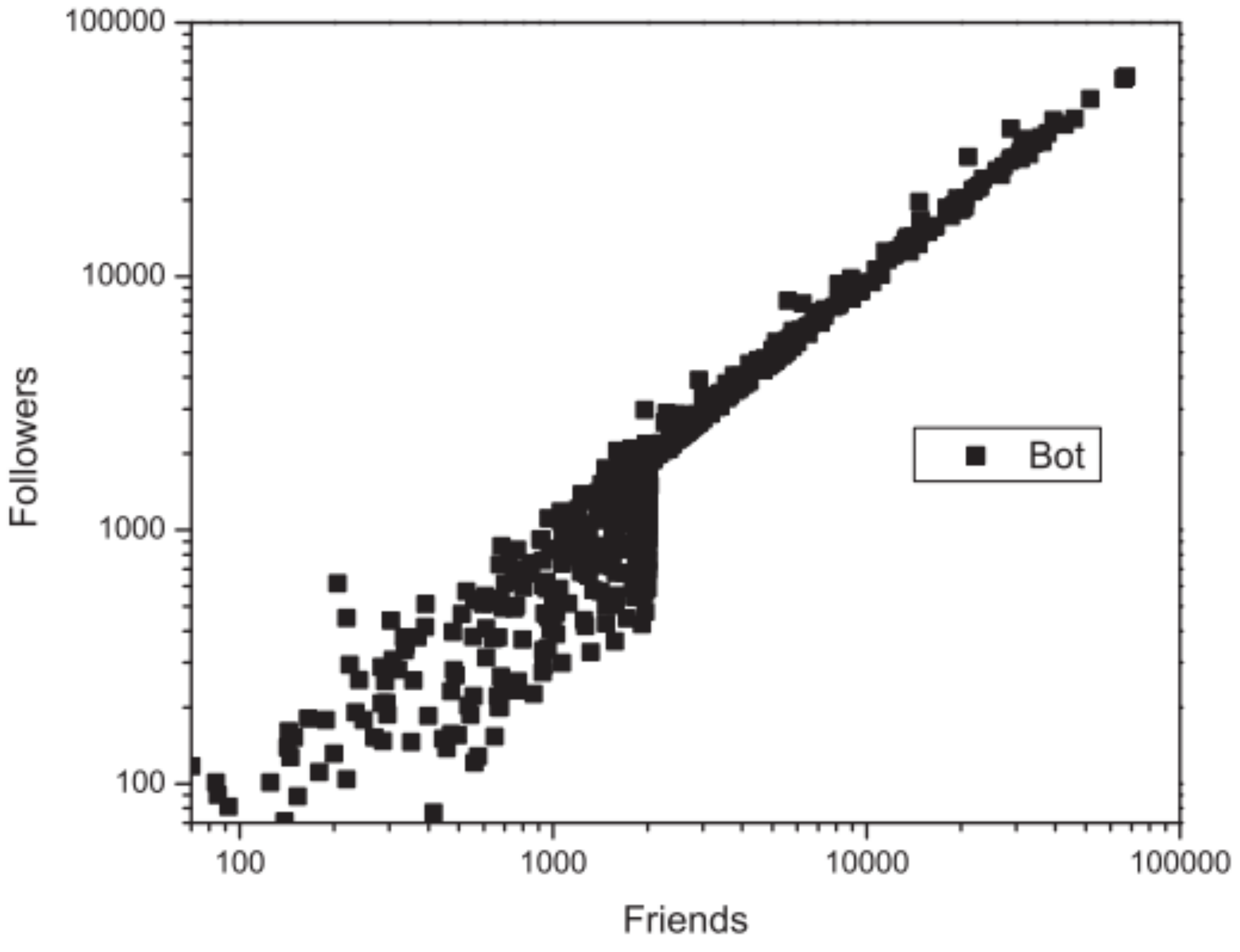
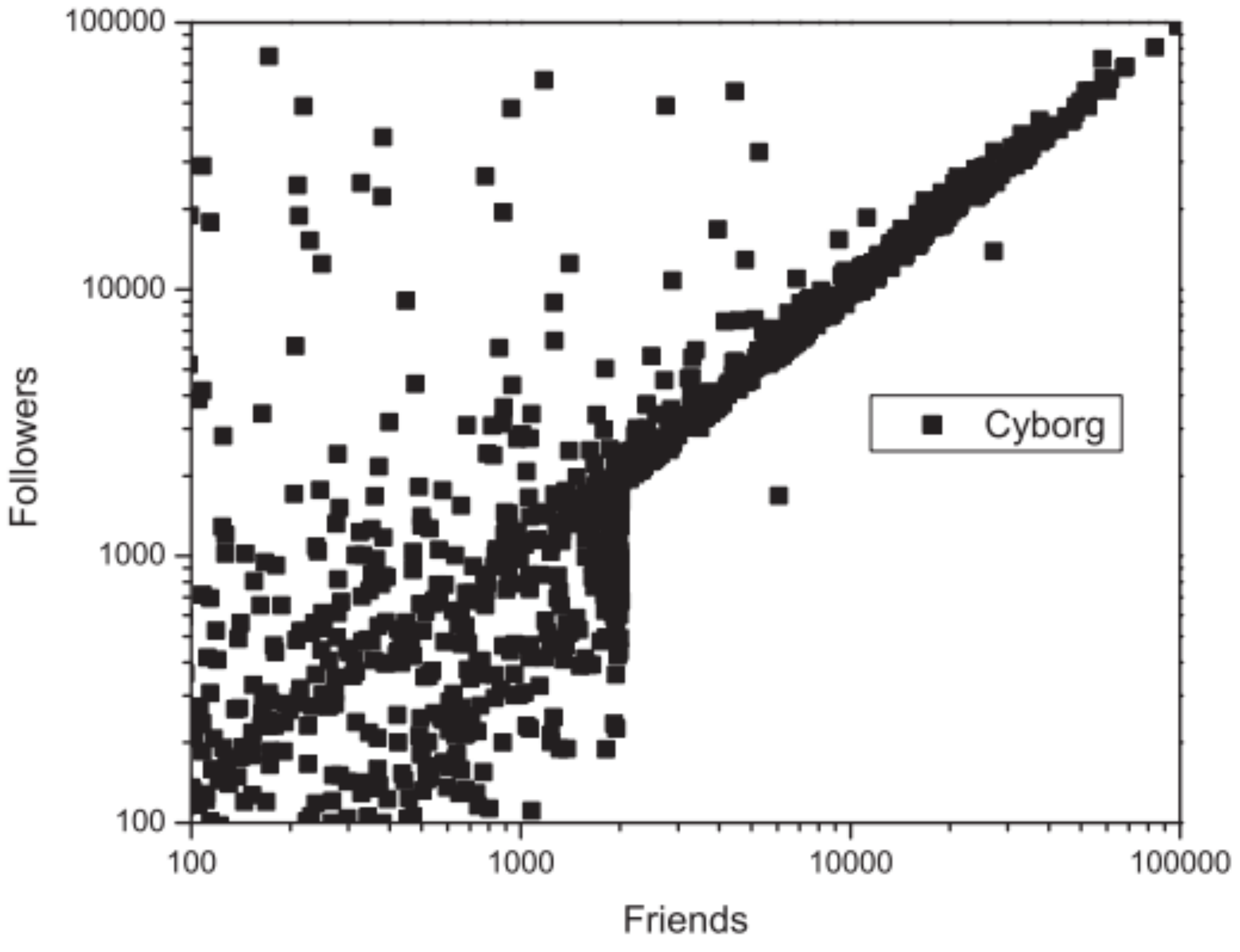


(b) Bot



(c) Cyborg

Takeaway: Automated users follow more users than those that follow them

Behavioral Patterns

Social Relationships

Tweeting Habits

Tweet Properties

Tweeting Habits: Entropy of Tweet Timing

- Entropy is the measure of *complexity* or *chaos* of a process
- In this context, the “process” is the *timing* of tweets

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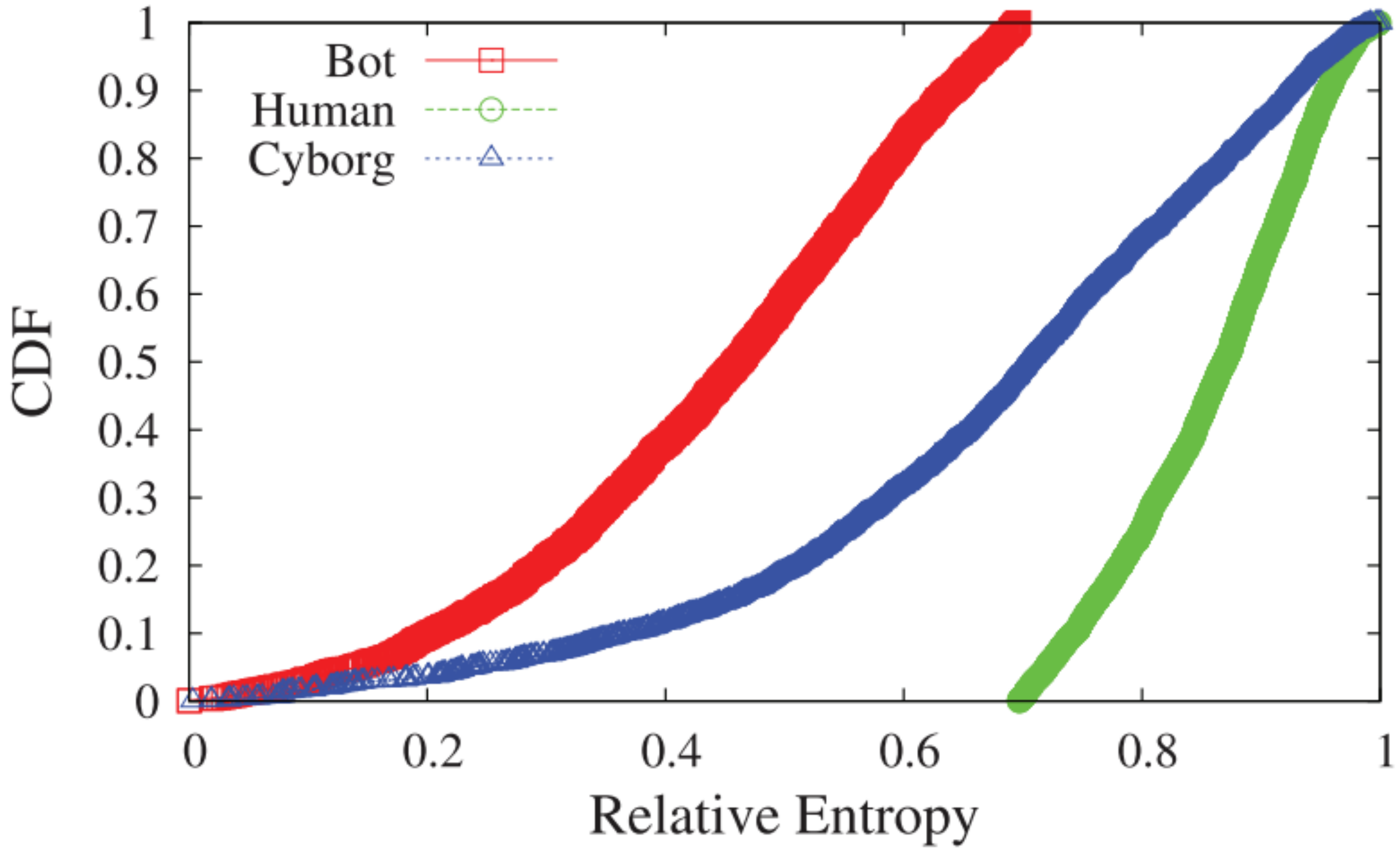
Key intuition: Automated accounts tweet at regular intervals, while humans do not

Tweeting Habits: Entropy of Tweet Timing

$$\frac{entropy(u_i)}{max(entropy(u_1), entropy(u_2), ..., entropy(u_n))}$$

- Normalize entropy of each account by largest entropy in the dataset



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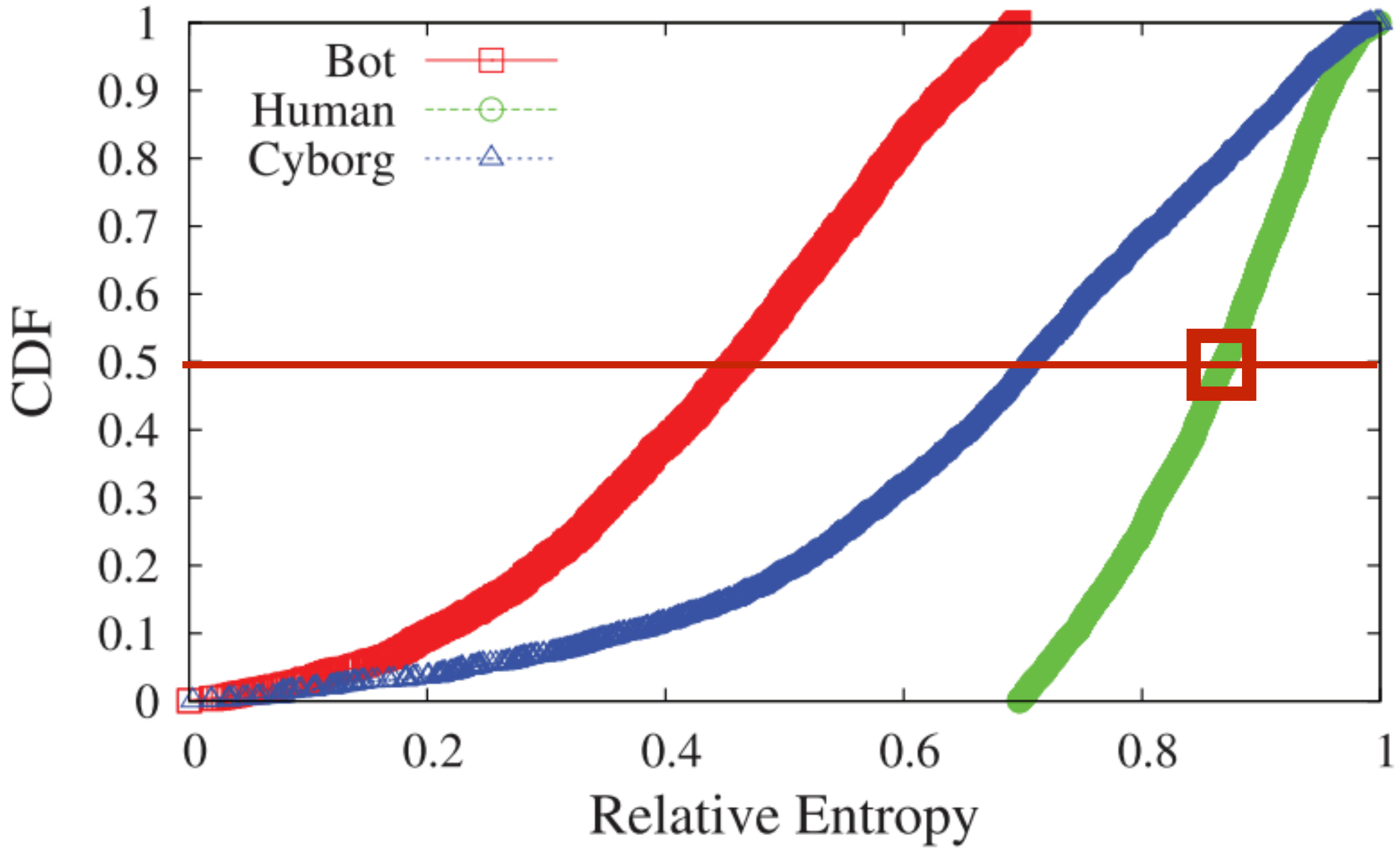

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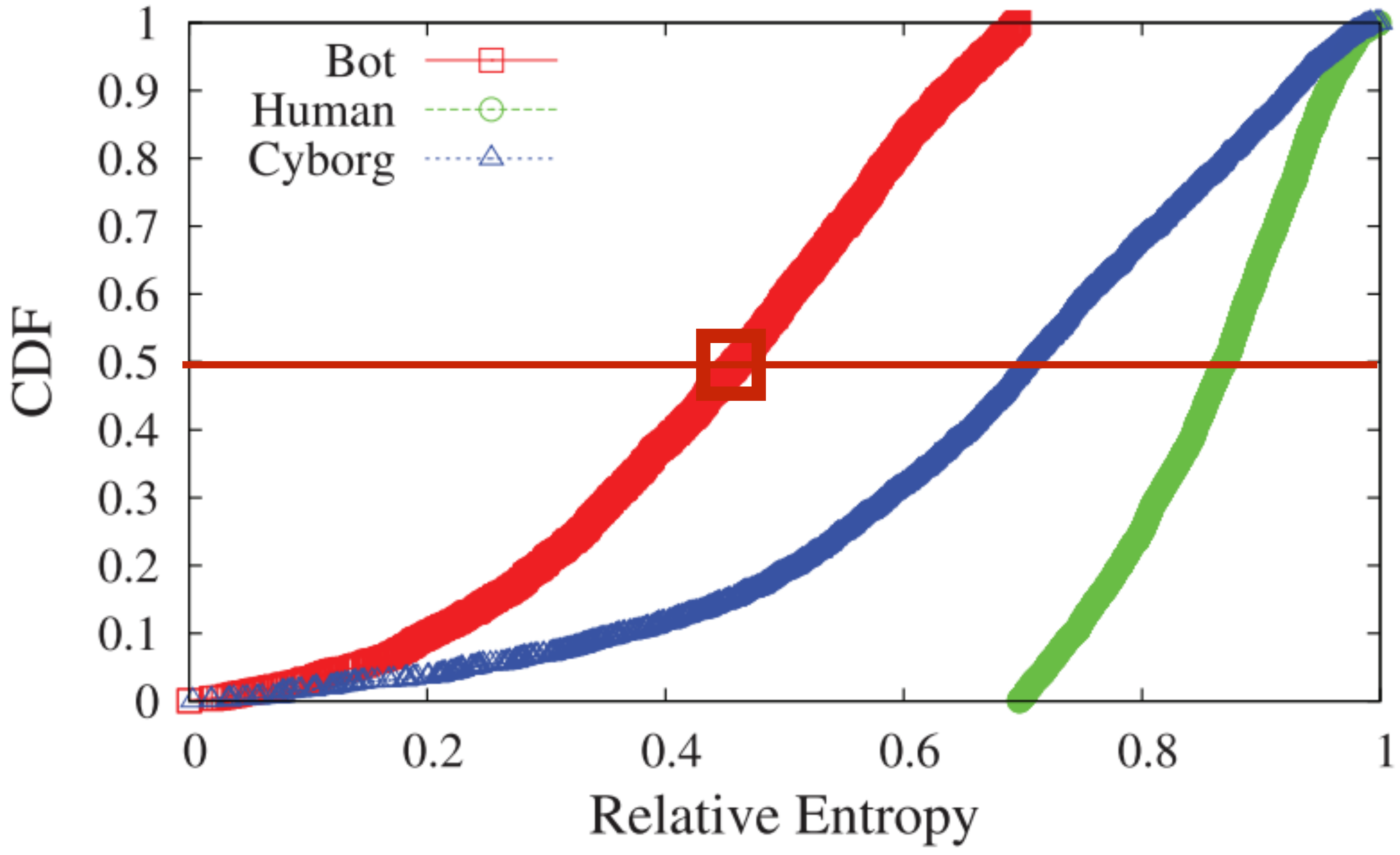

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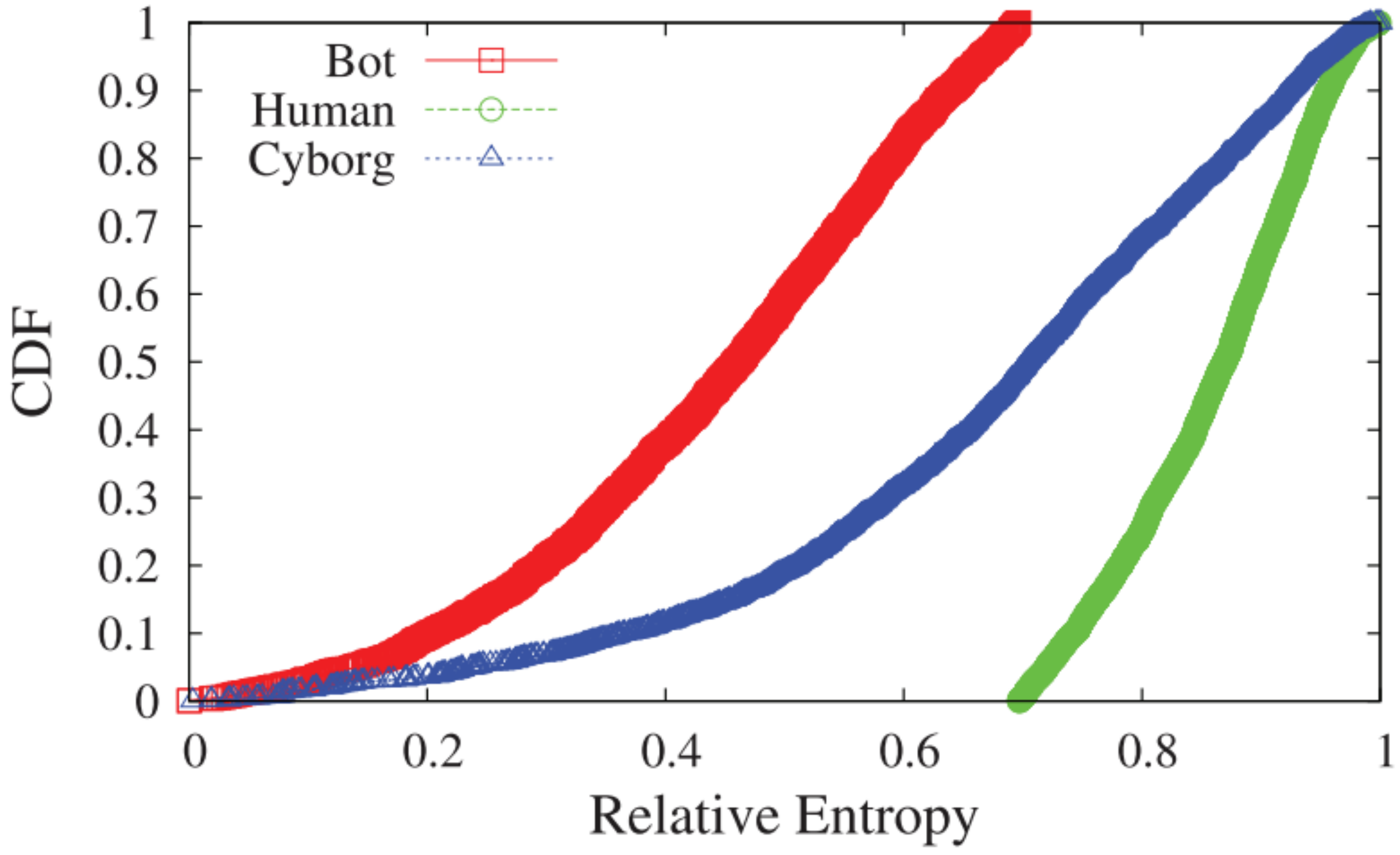
Takeaway: Human tweeting behavior is more random than bot tweeting behavior



Tweeting Habits: What tools are used to Tweet?

- Users can Tweet via a wide-array of channels
  - Web
  - Mobile
  - Third party applications
  - APIs

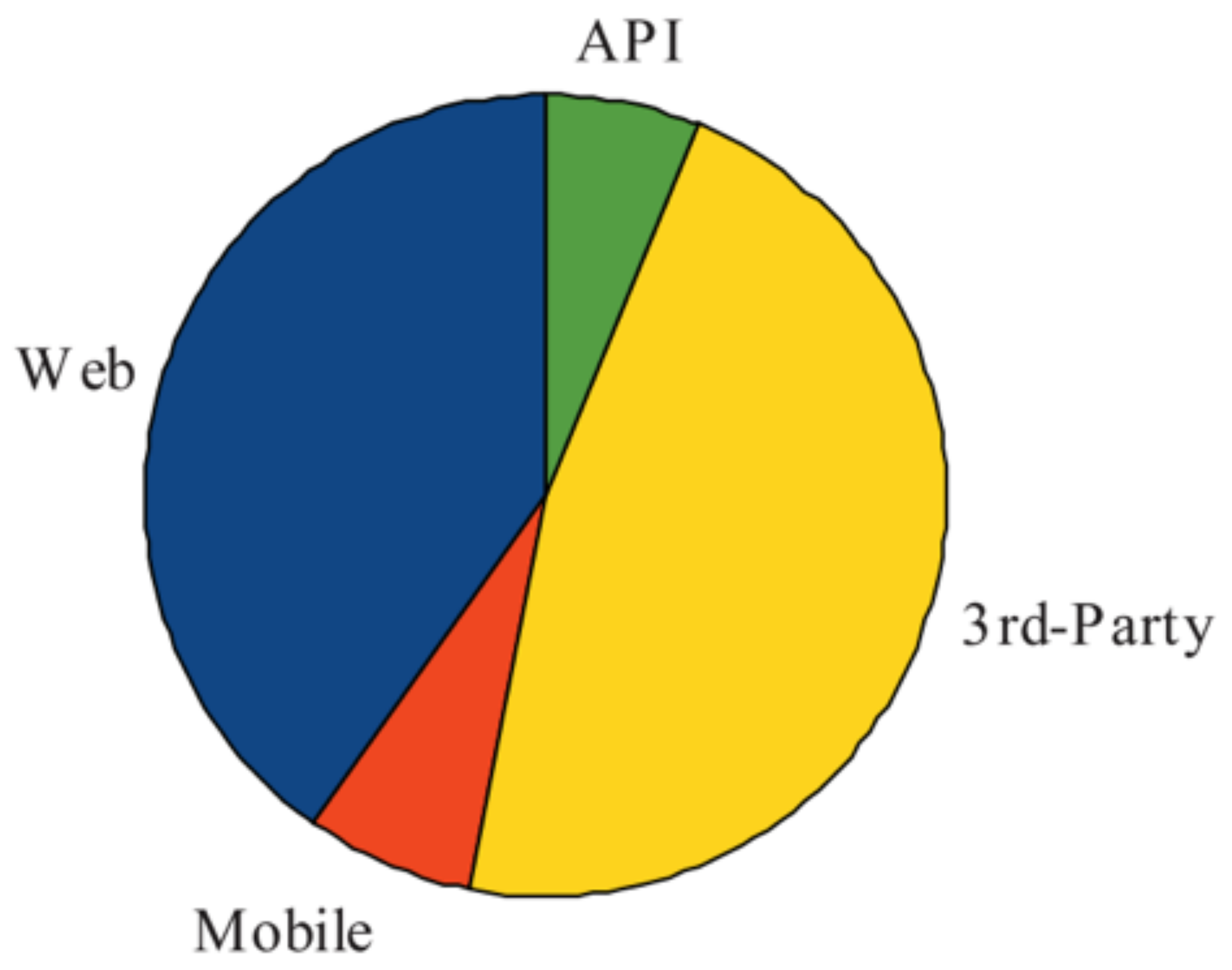


Fig. 6. Tweeting device makeup.

Tweeting Habits: What tools are used to Tweet?

Human	Bot	Cyborg
Web (50.53%)	API (42.39%)	Twitterfeed (31.29%)
TweetDeck (9.19%)	Twitterfeed (26.11%)	Web (23%)
Tweetie (6.23%)	twitRobot (13.11%)	API (6.94%)
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Takeaway: Humans tweet via manual tools

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Takeaway: Bots largely use APIs and automatic tools to tweet

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Takeaway: Cyborgs use a mixture of bot + human tools

Behavioral Patterns

Social Relationships

Tweeting Habits

Tweet Properties

Tweet Properties: URLs

- The # of URLs in bot tweets is higher than those of human + cyborg
- Some bots tweet more than one URL per tweet!

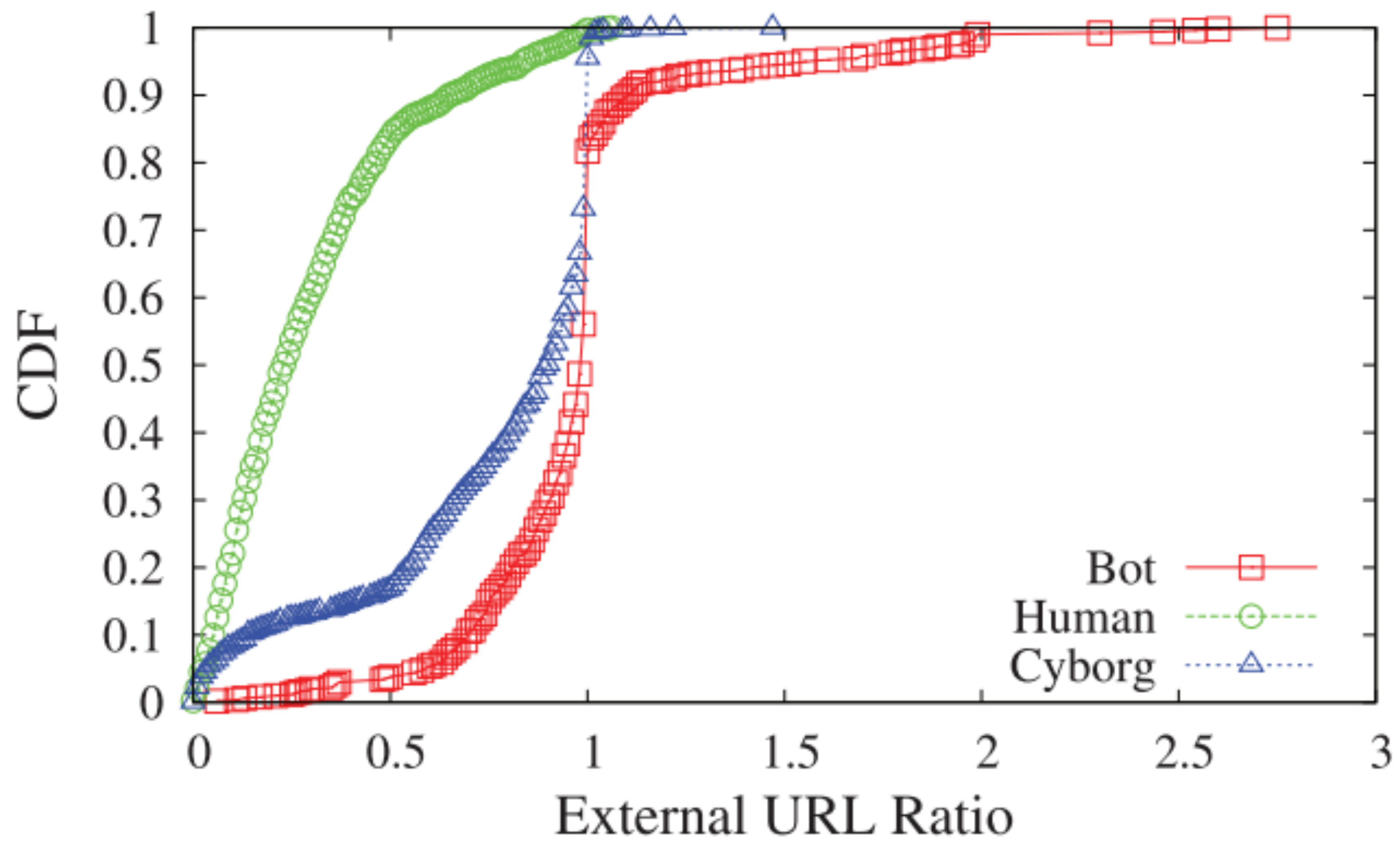


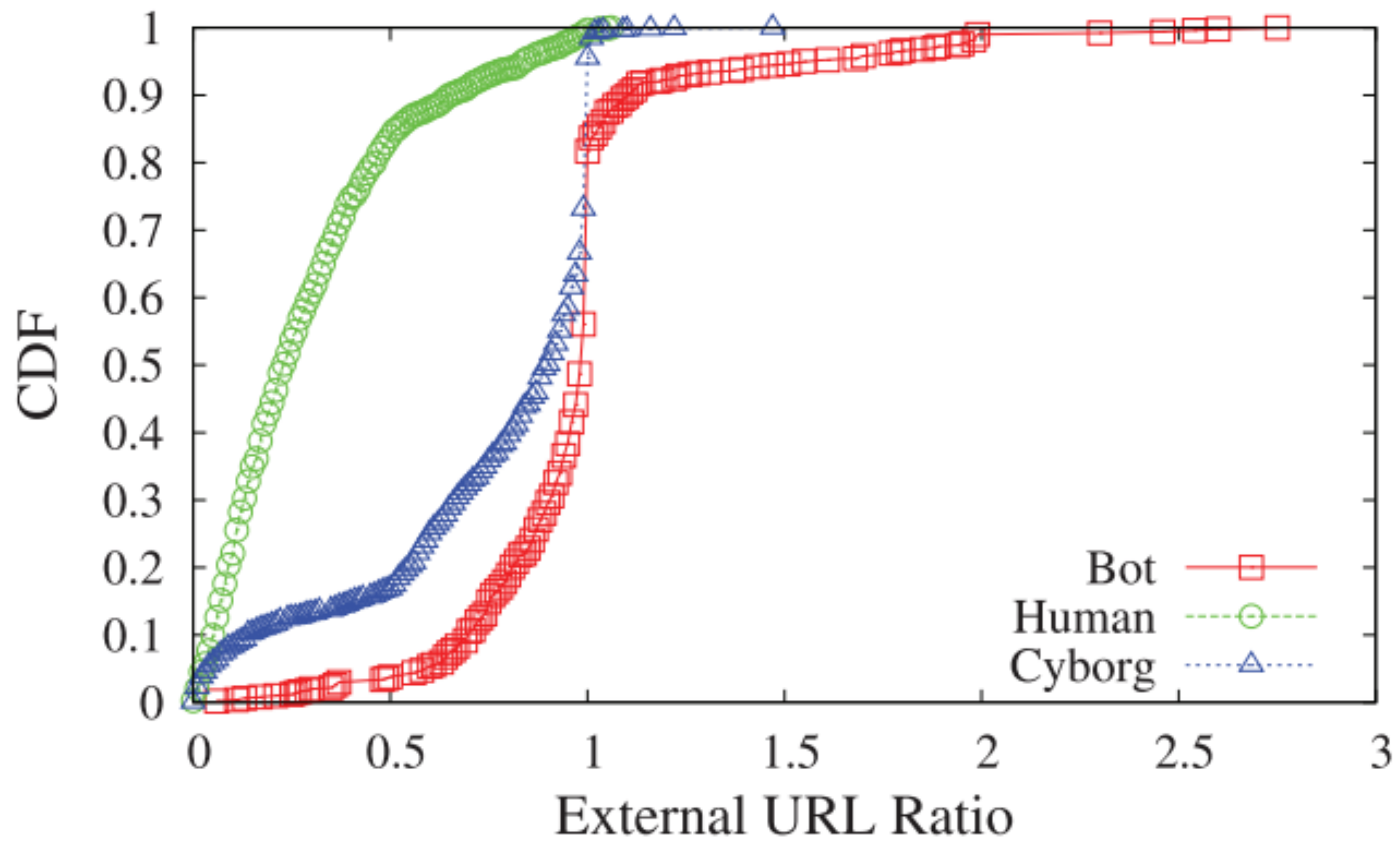
Fig. 7. External URL ratio in tweets.

Tweet Properties: URLs

- The # of URLs in bot tweets is higher than those of human + cyborg

- Some bots tweet more than one URL per tweet!

- Another useful property of URLs: appearing in **blacklists**



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Tweet Properties: Spam

- Intuition: Use **spam** as a mechanism for identifying automation

Tweet Properties: Spam

- Intuition: Use **spam** as a mechanism for identifying automation
- How? Naive Bayes for Spam Classification

Identifying Spam via Naive Bayes

- Simple classification model built off of conditional probabilities
  - "What is the likelihood a message is spam given previous spam messages?"
  - Treat each word (or set of words!) as *independent events*
- Researchers labeled tweets as "spam" in ground-truth collection

$$\Pr(S|W) = \frac{\Pr(W|S) \cdot \Pr(S)}{\Pr(W|S) \cdot \Pr(S) + \Pr(W|H) \cdot \Pr(H)}$$

Takeaway: Humans, Bots, and Cyborgs exhibit different behavioral patterns

Can a standard machine learning classifier use these differences to detect bots?

Classifying Automation: Features

Features
Timing Entropy
URL Ratio
Automated Device %
Bayesian Spam Detection
Manual Device %
Registration Date
Mention Ratio
Link Safety
Hashtag Ratio
Followers to Friends Ratio
Account Verification

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Classifying Automation: Training and Testing

- Use a *random forest*, popular ML algorithm for labeled classification
- Use 10-fold cross validation to determine accuracy of the model
- Split ground-truth data randomly into 10 partitions
    - Train on 9, test on 1
    - Repeat and average results

Classifying Automation: Training and Testing

		Classified			
		Human	Cyborg	Bot	True Positive
Actual	Human	1972	27	1	98.6%
	Cyborg	65	1833	102	91.7%
	Bot	2	46	1952	97.6%
	Total				96.0%

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Twitter Composition

- Apply classification algorithm to set of 500,000 users
- 53.2% Human
- 36.2% Cyborg
- 10.5% Bot
- 5:4:1 Ratio on Twitter in 2012

My Takeaways

- Good first step towards automation detection (96% TP!), but shelf life of technique is limited
  - Behavioral properties are the easiest to change
  - In 2018, bots behave just like humans

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- We still don’t understand how effective bots are at their tasks

My Takeaways

- Good first step towards automation detection (96% TP!), but shelf life of technique is limited
    - Behavioral properties are the easiest to change
    - In 2018, bots behave just like humans
- We still don't understand how effective bots are at their tasks
- **Paper: Understanding the network infrastructure behind automation**
- **Paper: Attribution of bot effectiveness through network analysis**

Classifying Users on Twitter: Ground Truth

	Human	Bot	Cyborg
Criteria	• Original, intelligent, specific content	• Unoriginal content • *Clearly* automated (i.e., RSS feed) • Spammy, filled with shady URLs	• Evidence of both bot and human participation

Classifying Automation: Feature Importance

Features	Accuracy
Timing Entropy	82.8%
URL Ratio	74.9%
Automated Device %	71.0%
Bayesian Spam	69.5%
Manual Device %	69.2%
Registration Date	62.9%
Mention Ratio	56.2%
Link Safety	49.3%
Hashtag Ratio	47.0%
Followers to Friends	45.3%
Account Verification	35.0%

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Account Verification	35.0%

Takeaway: No one feature tells the whole picture

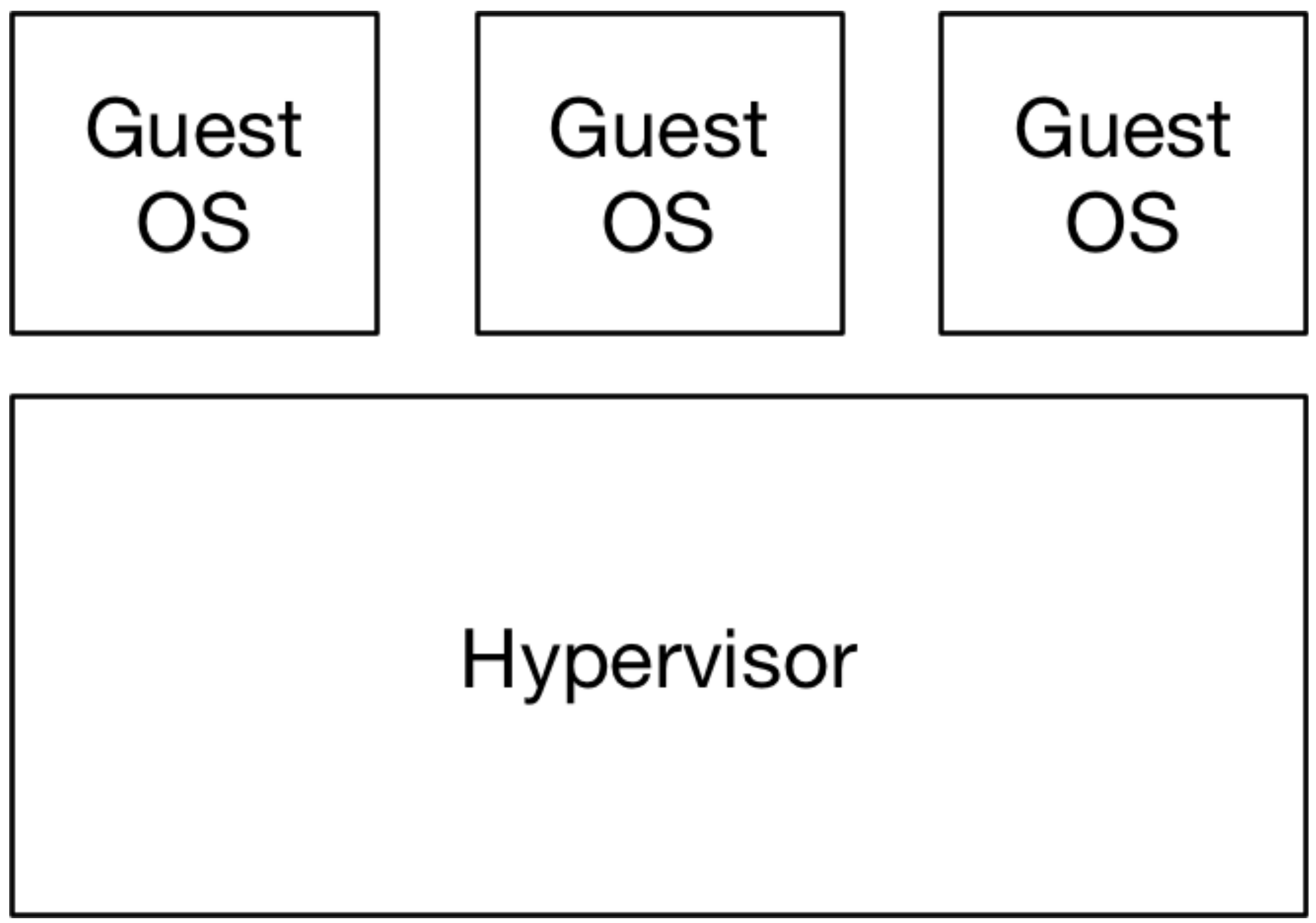
The Turtles Project: Design and Implementation of Nested Virtualization

Muli Ben-Yehuda, Michael D. Day, Zvi Dubitzky, Michael Factor, Nadav Har'El, Abel Gordon, Anthony Liguori, Orit Wasserman, Ben-Ami Yassour

OSDI 2010

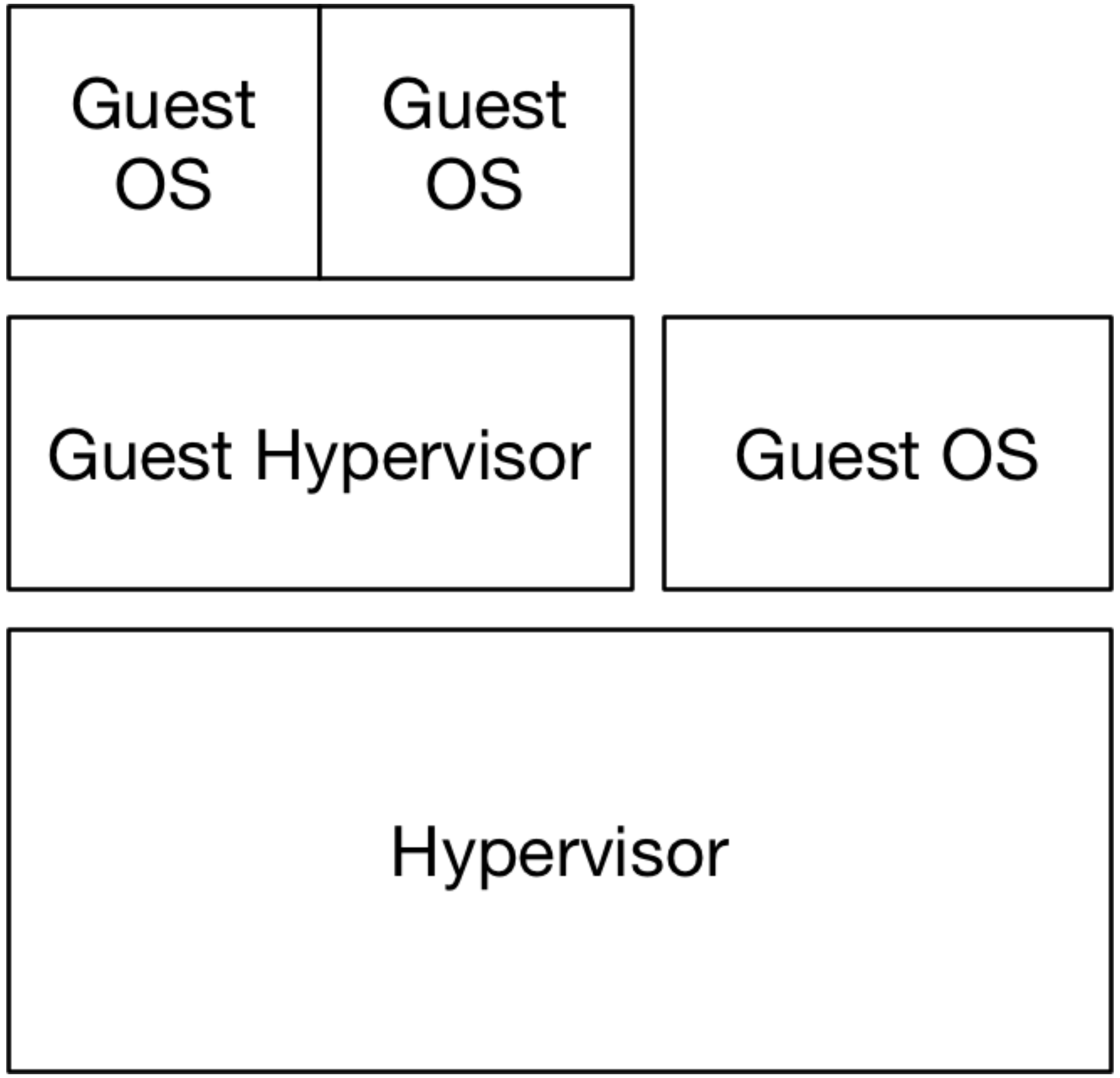
Classic Virtualization

- One hypervisor
  - Runs multiple guest operating systems
  - Hardware support from Intel (Intel VMX), AMD (AMD SVM) for x86



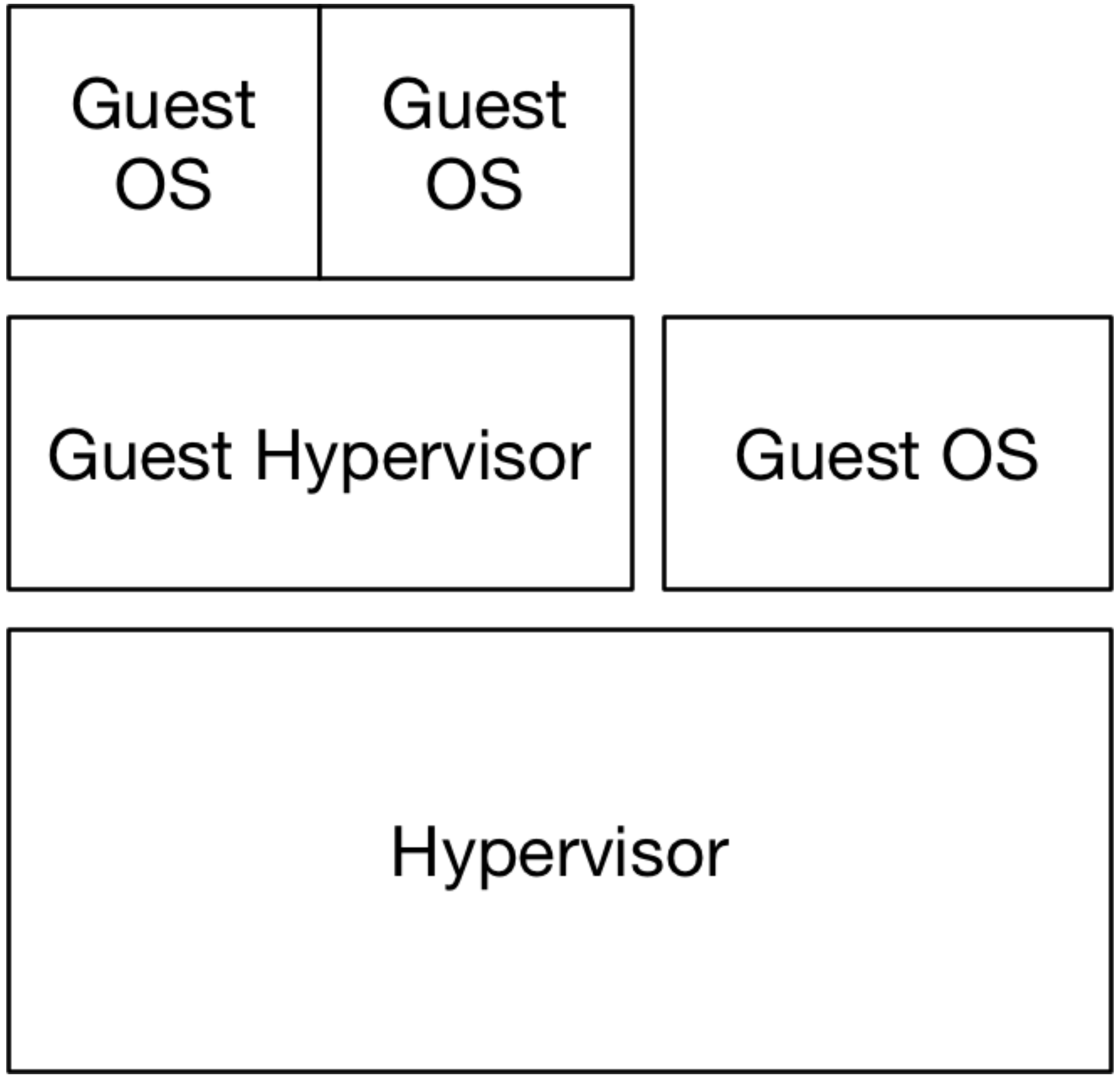
Nested Virtualization

- Run multiple *unmodified* hypervisors
  - Unmodified guest operating systems



Nested Virtualization

- Run multiple *unmodified* hypervisors
  - Unmodified guest operating systems
- Nested virtualization increasing in importance
  - Many commodity OSes make use of virtualization already



Why Nested Virtualization?

- Cloud
  - Expose user-controlled hypervisor as a virtual machine

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Problem: No x86 support for nested virtualization!

Why Nested Virtualization?

- Cloud
  - Expose user chine
  - Scale infrast isors on single host
- Security
  - Hypervisor-le l intrusion detection

The Turtles Project

- *Single-level architectural support for nested virtualization*

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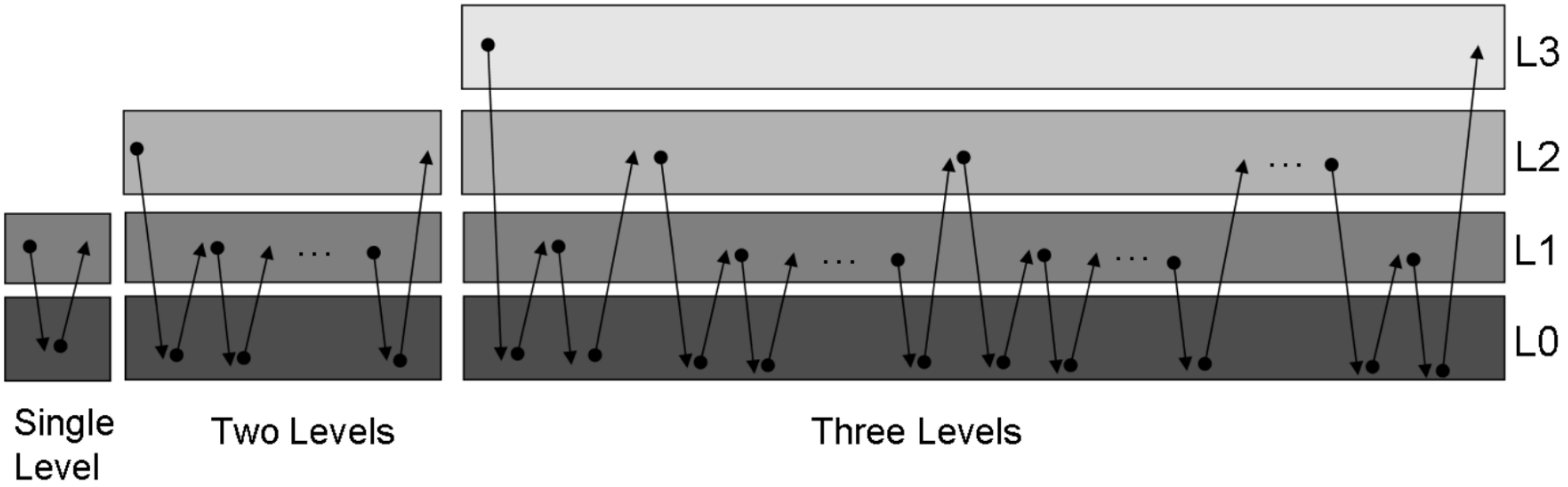
The Turtles Project

- *Single-level architectural support for nested virtualization*
  - Single hypervisor mode
  - Any trap at a nested level is handled by the “base” hypervisor, called L_0
  - Traps are then *forwarded* by L_0 to the appropriate level
  - L_0 thus *multiplexes* hardware between higher level hypervisors and OSes

Turtles Theory



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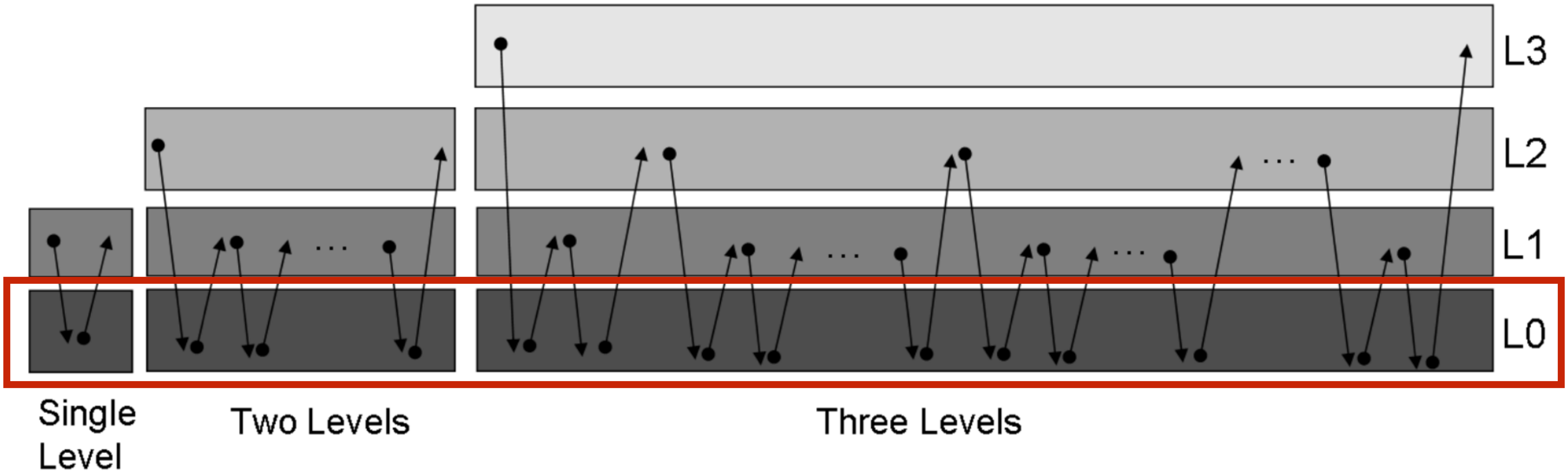

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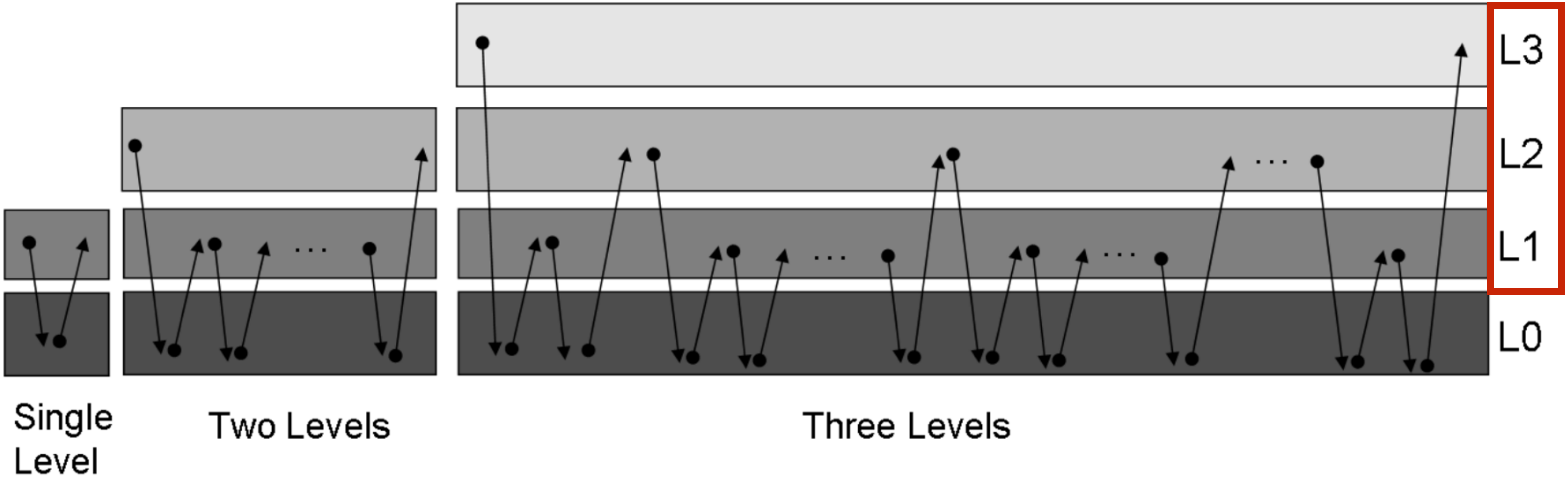

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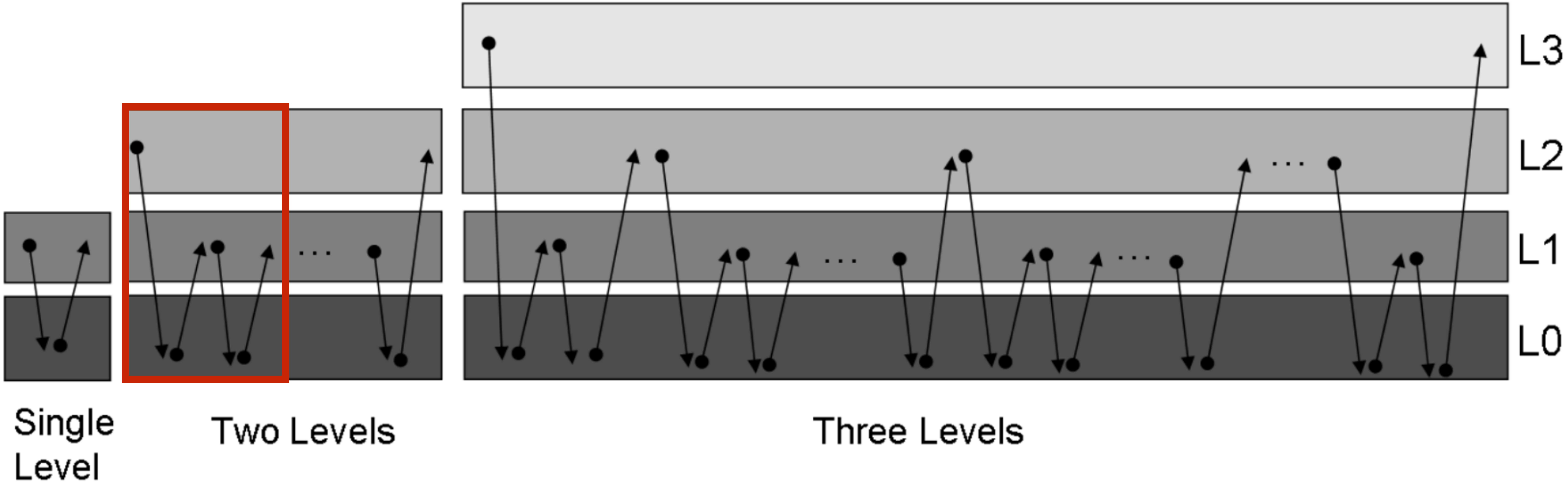


Implementing Turtles

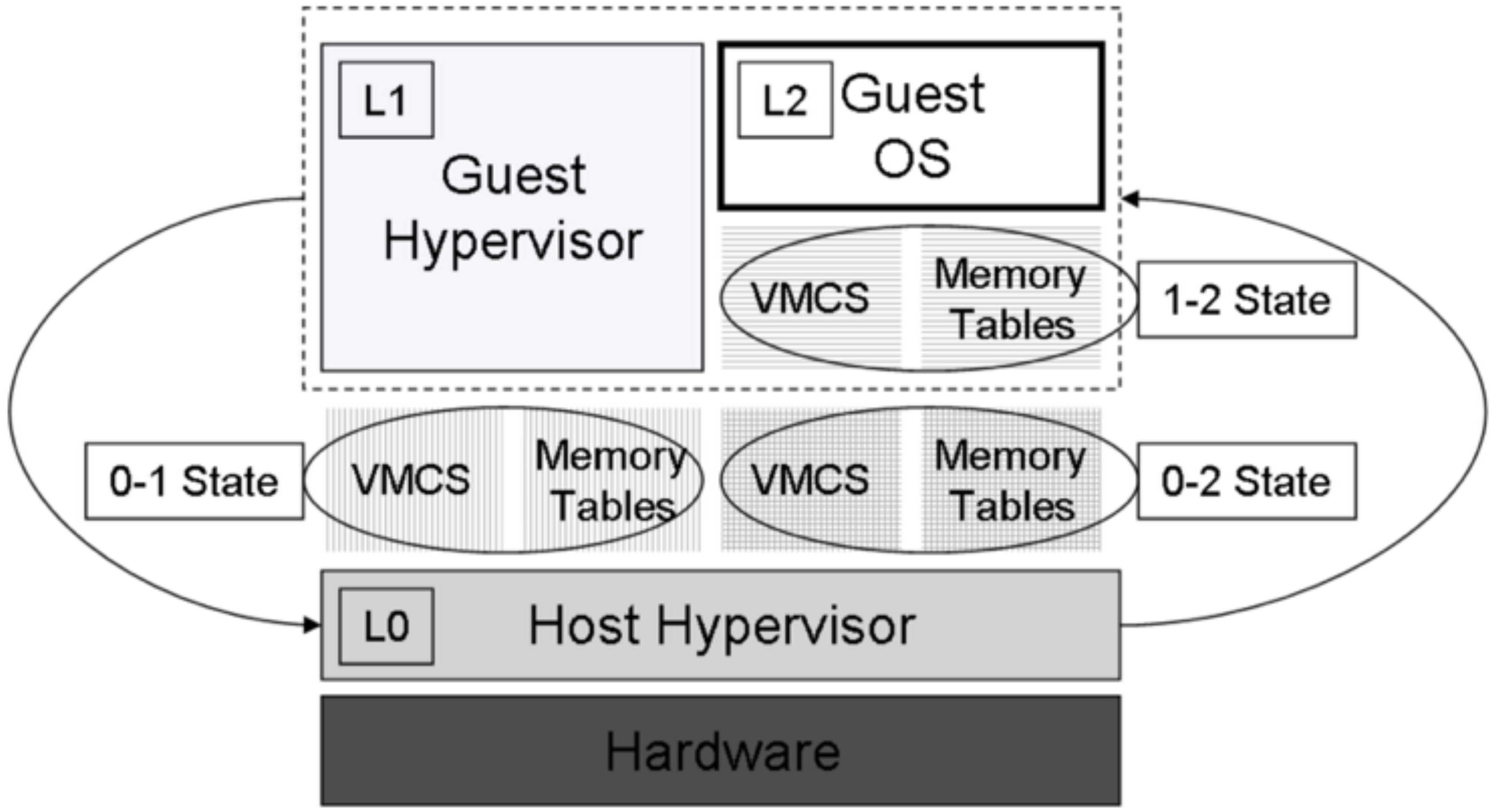
- Nested VMX Virtualization for CPUs
- Multidimensional Paging for MMUs
- Multi-level Device Assignment for I/O

Implementing Turtles

- **Nested VMX Virtualization for CPUs**
- Multidimensional Paging for MMUs
- Multi-level Device Assignment for I/O

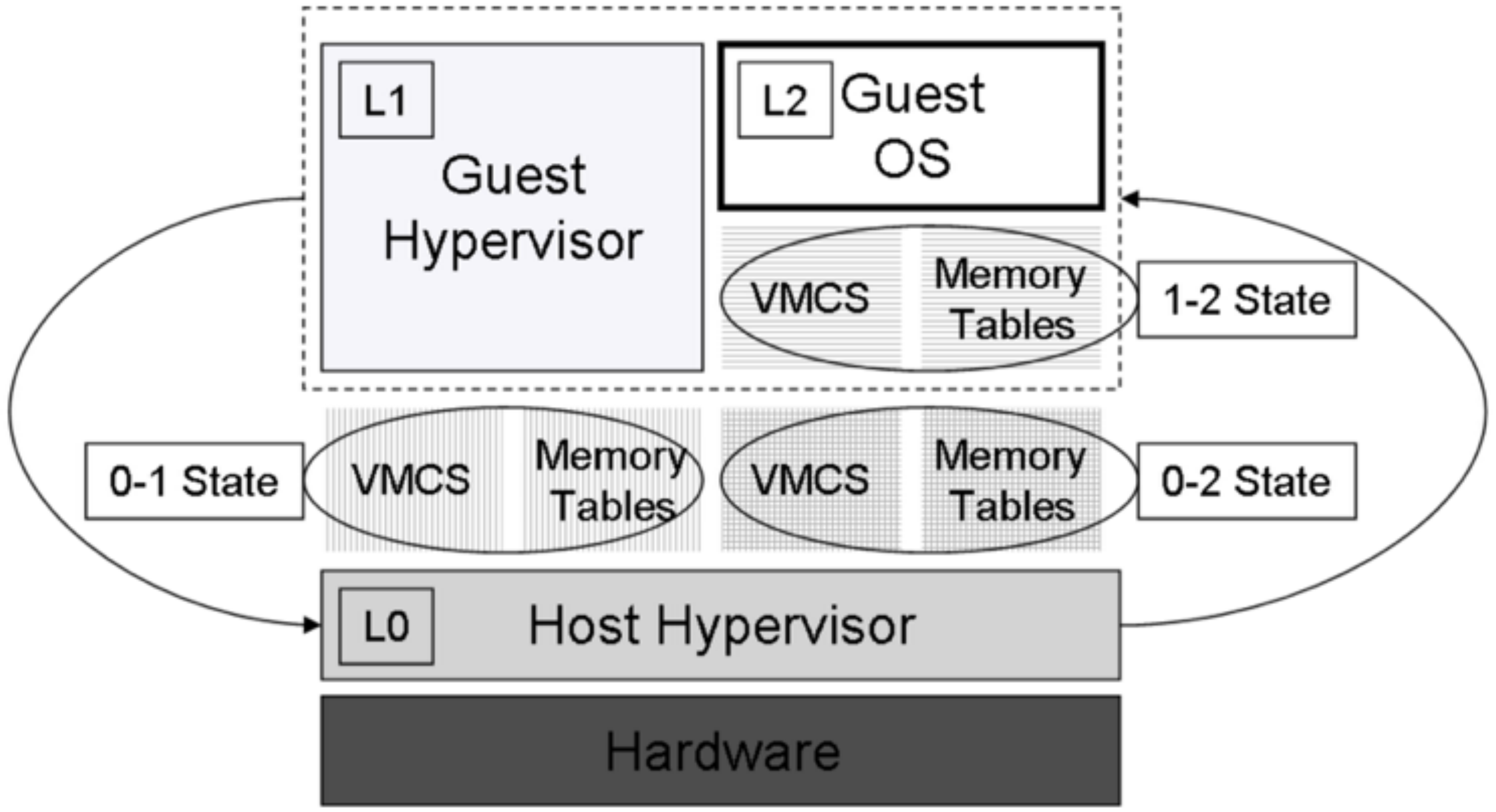
Nested CPU Virtualization: Design

- L_0 can leverage virtualization support from hardware (VMX)
  - Supports *guest mode* and *host mode* for CPUs



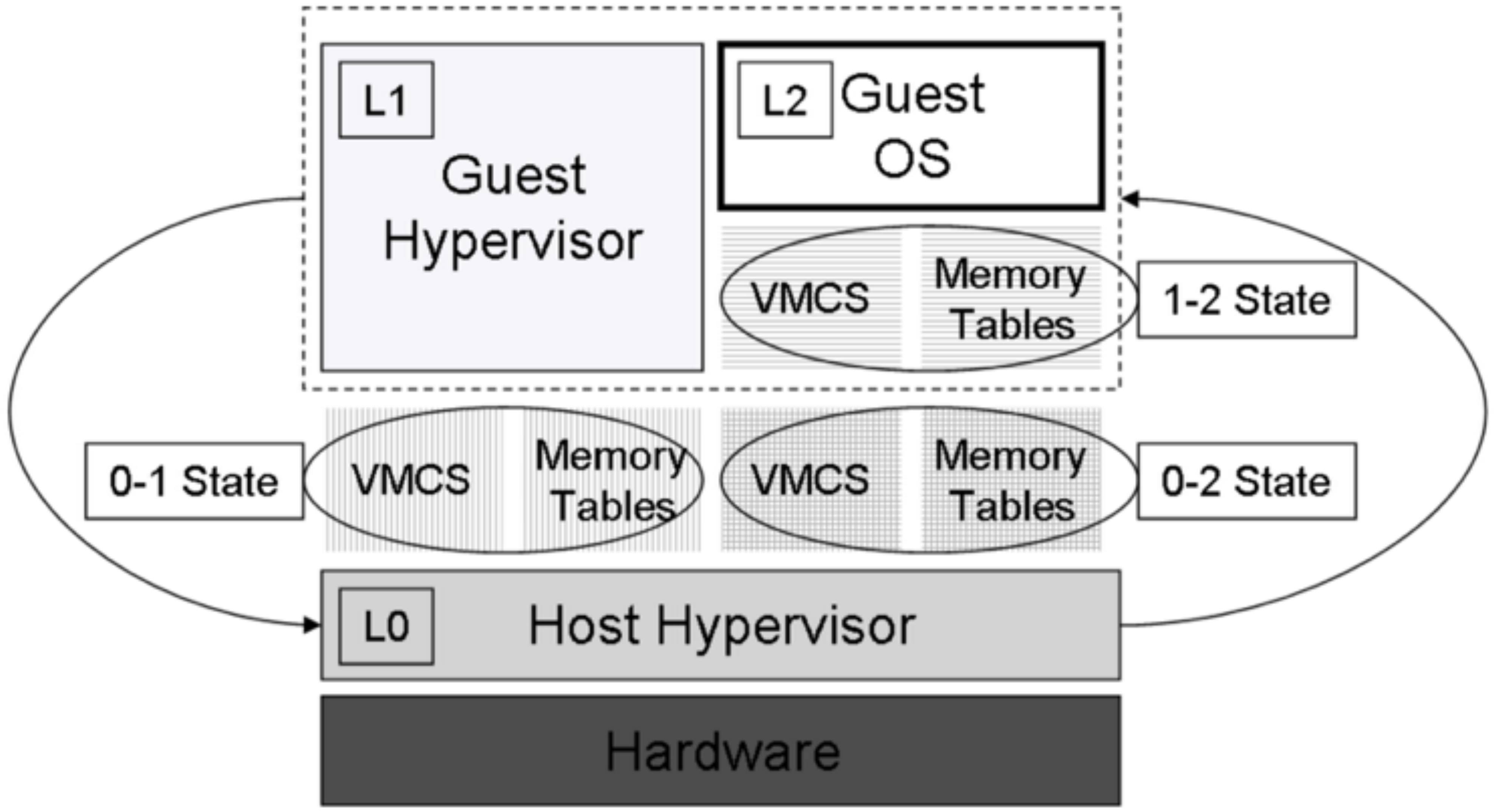
Nested CPU Virtualization: Design

- L_0 can leverage virtualization support from hardware (VMX)
    - Supports *guest mode* and *host mode* for CPUs
    - VMCS: Control structures for defining virtual machines environments
        - Defines traps, CPU registers, host state, guest state



Nested CPU Virtualization: Design

- Recursive VMX emulation



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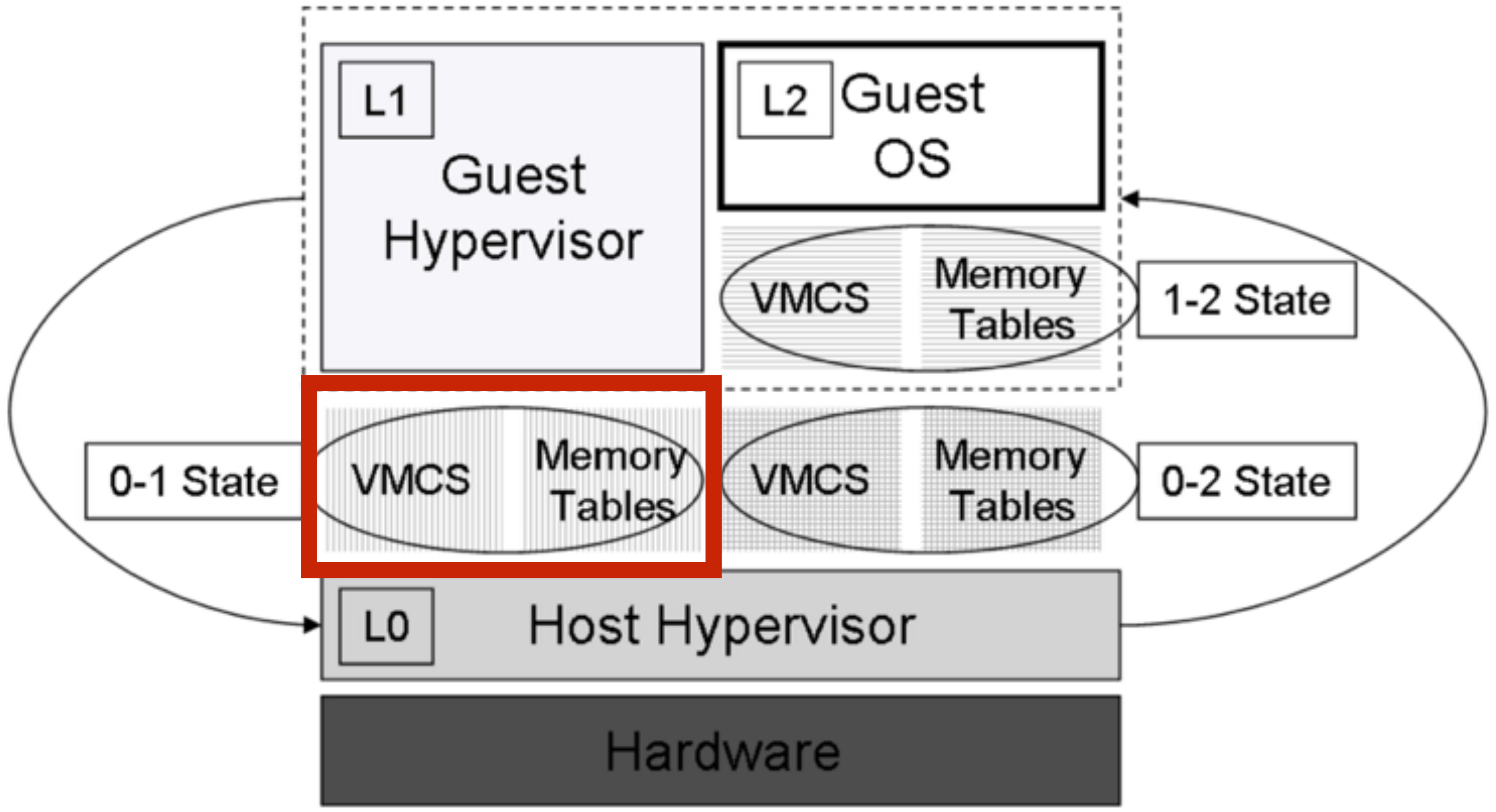

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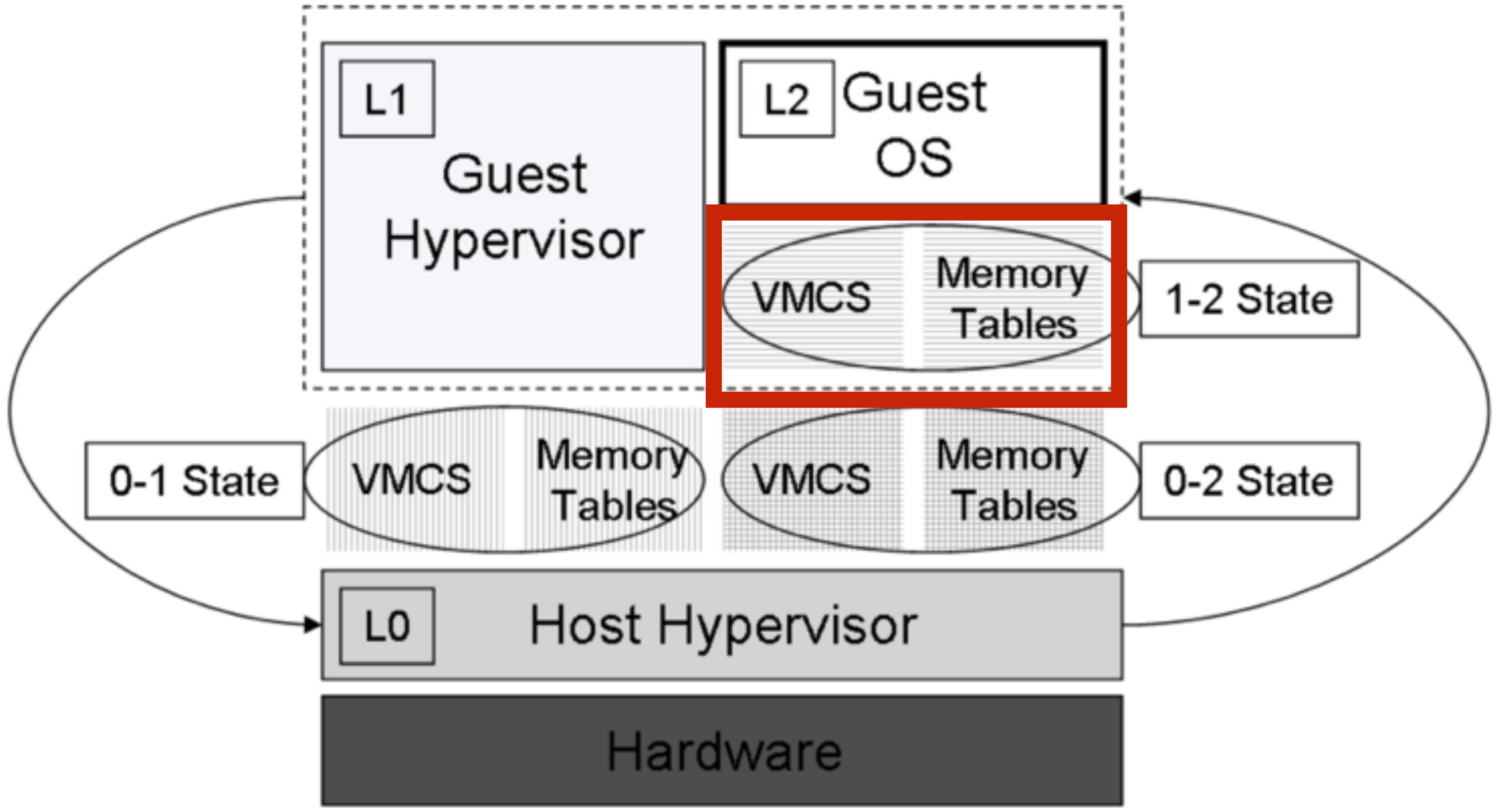

Nested CPU Virtualization: Design

Key point: L_0 must maintain state (VMCS) about L_2 to actually run L_2 on the hardware

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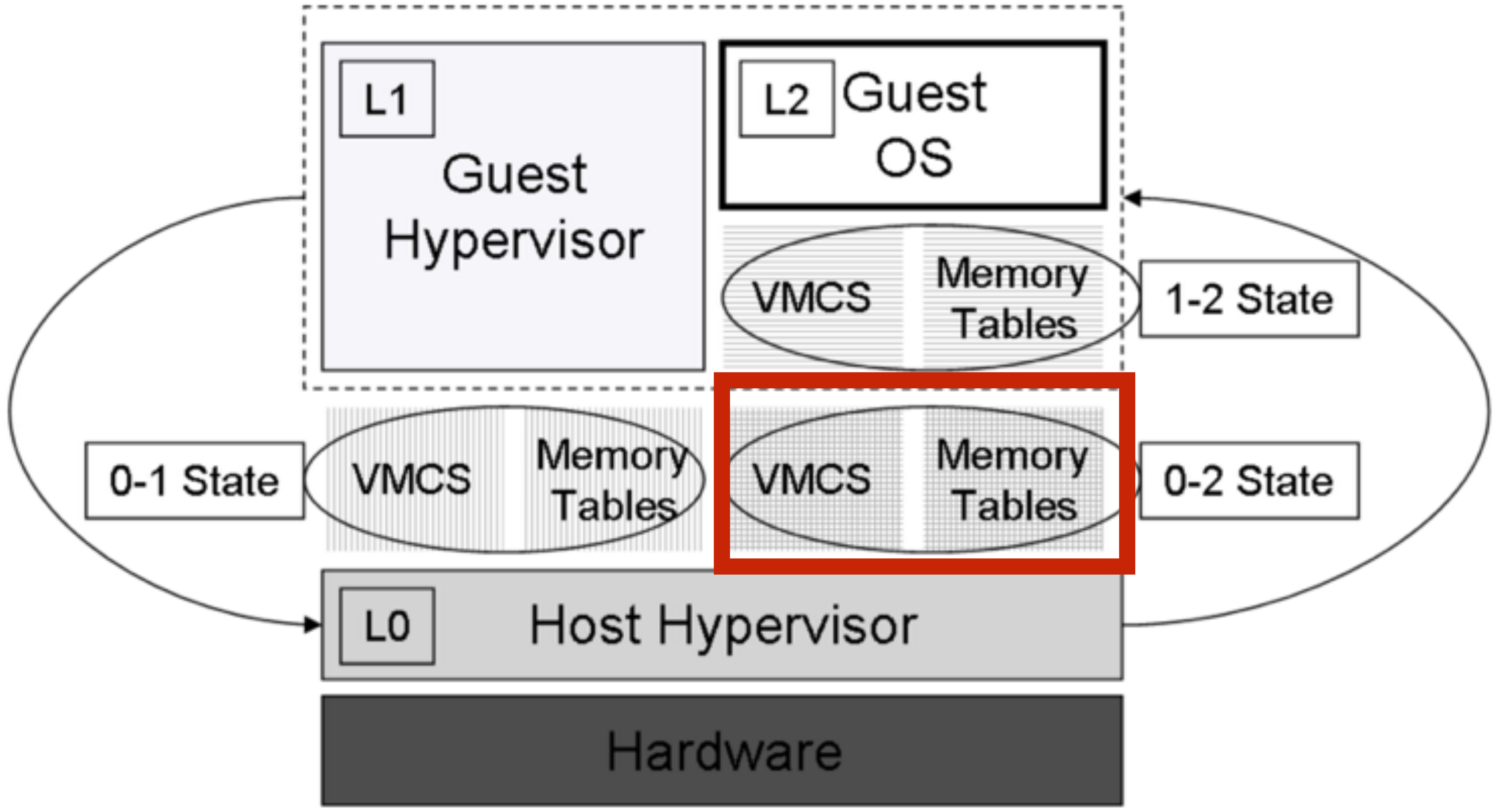

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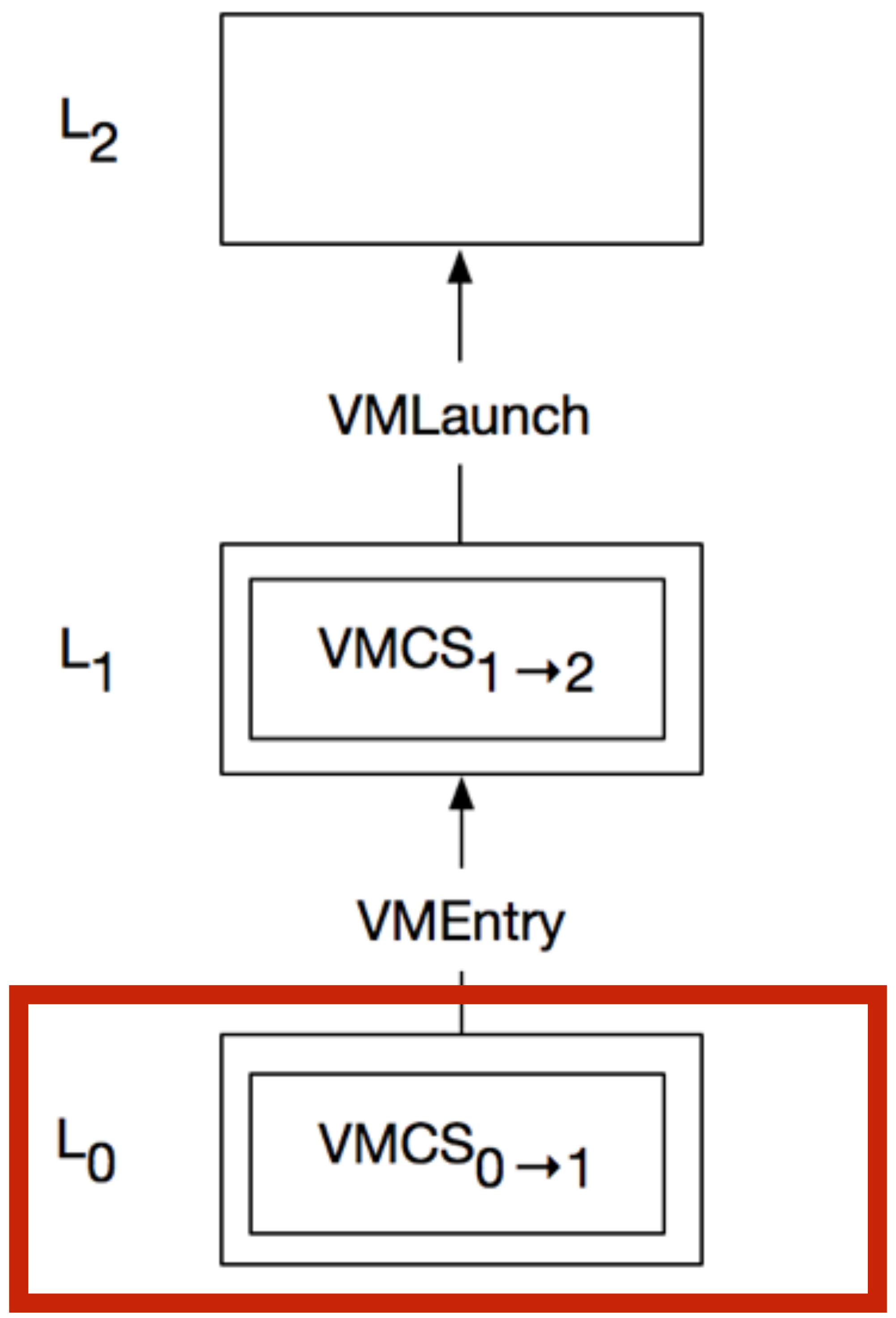
- L_0 runs L_1 using $VMCS_{0 \to 1}$



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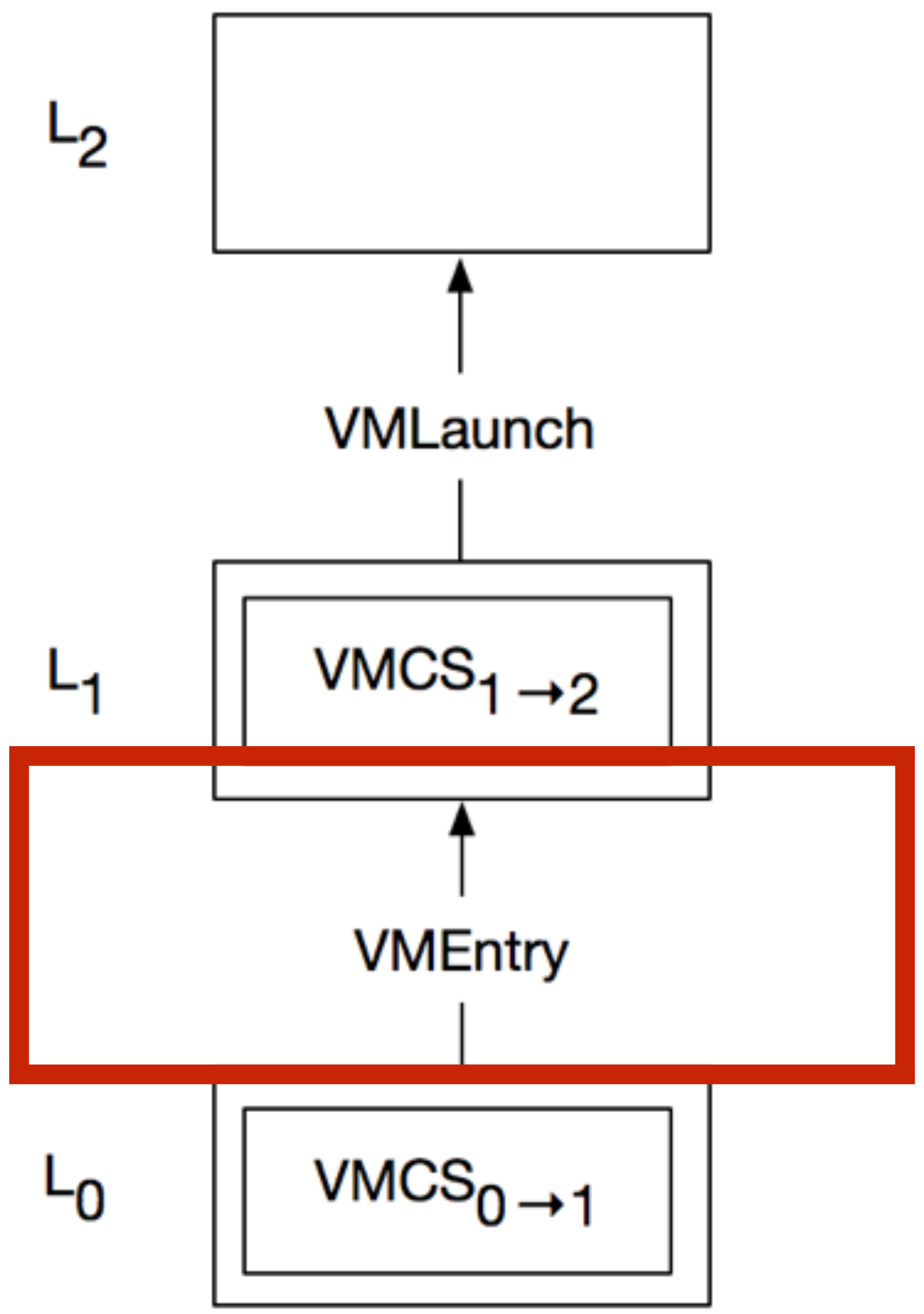

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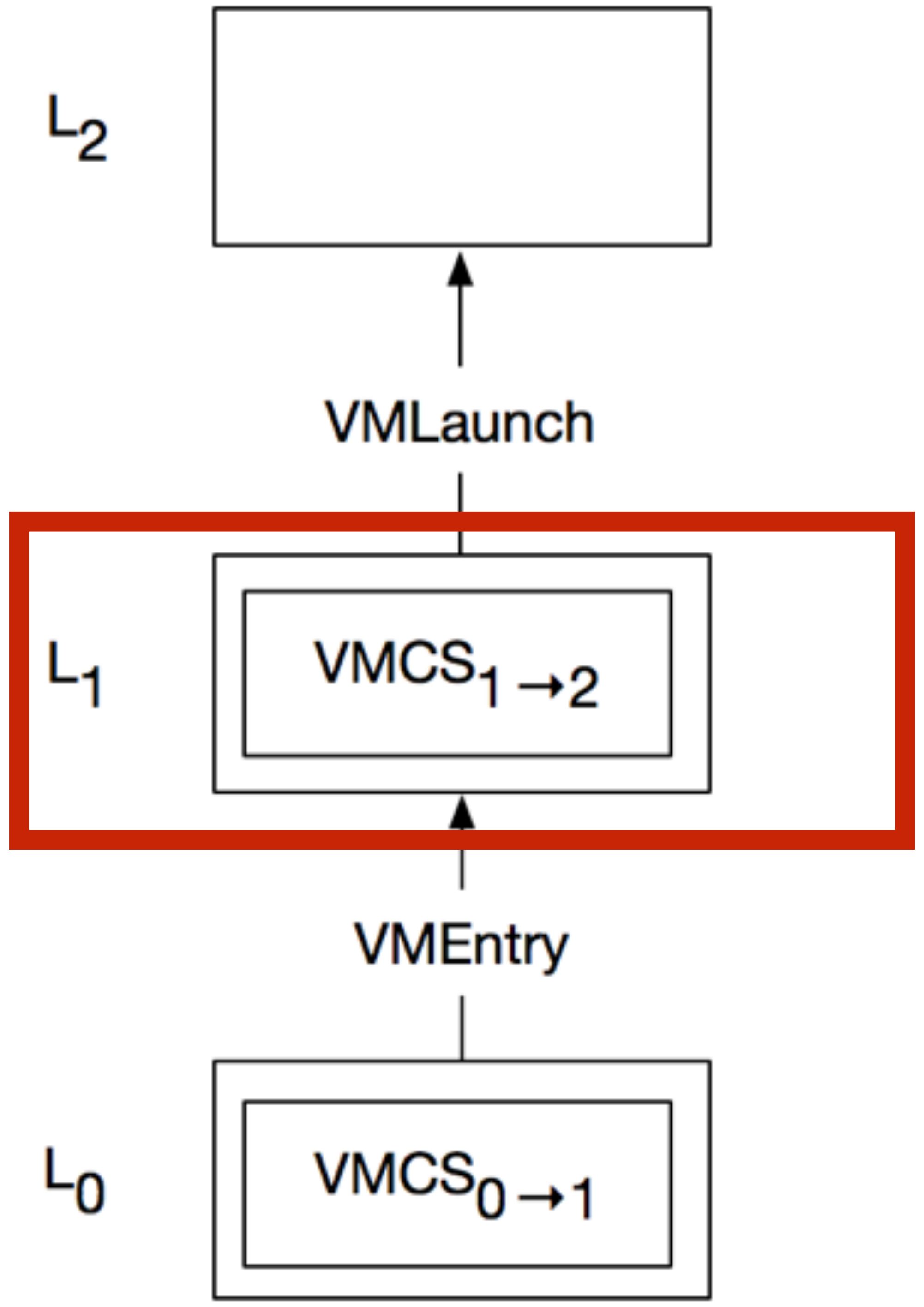

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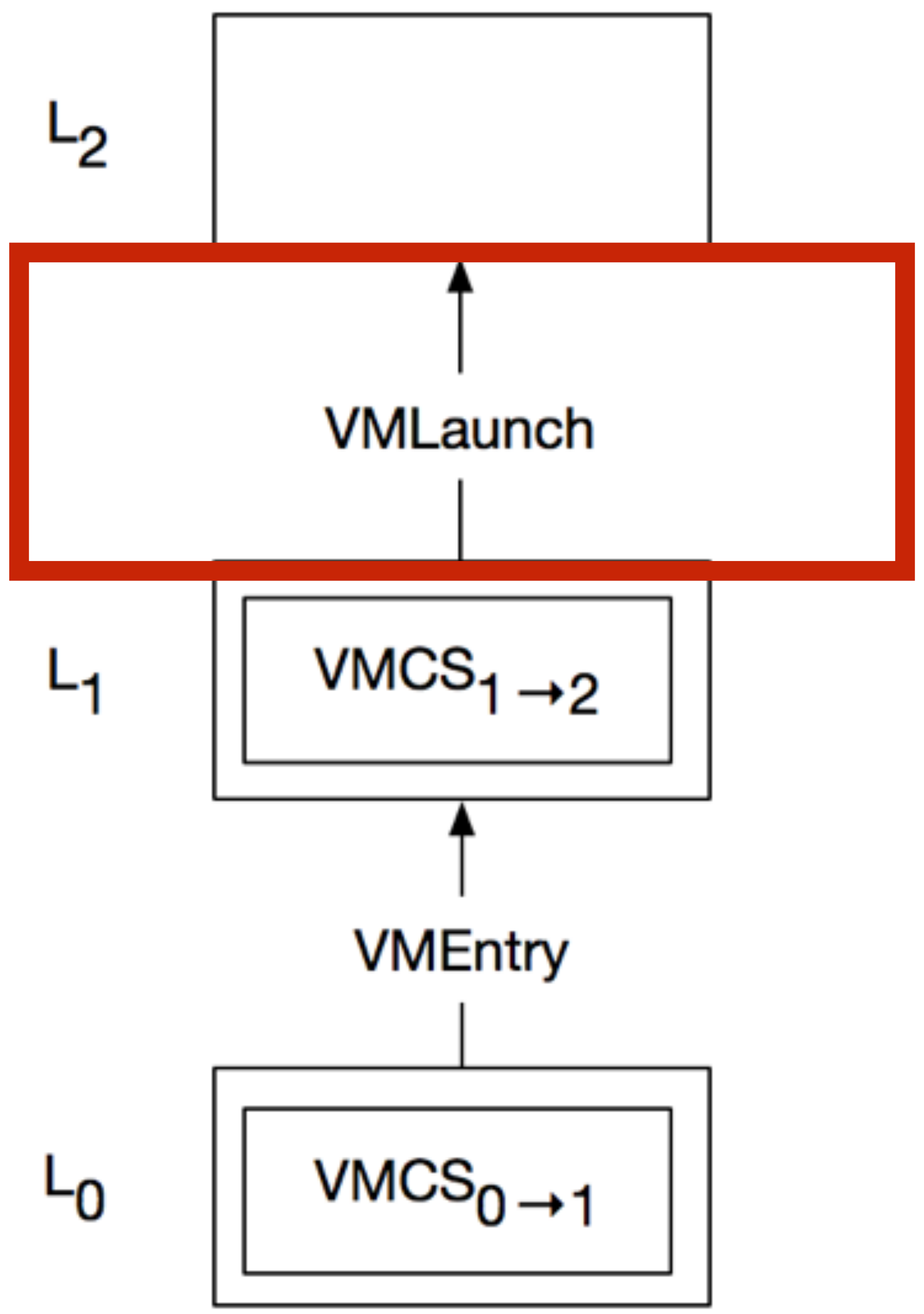

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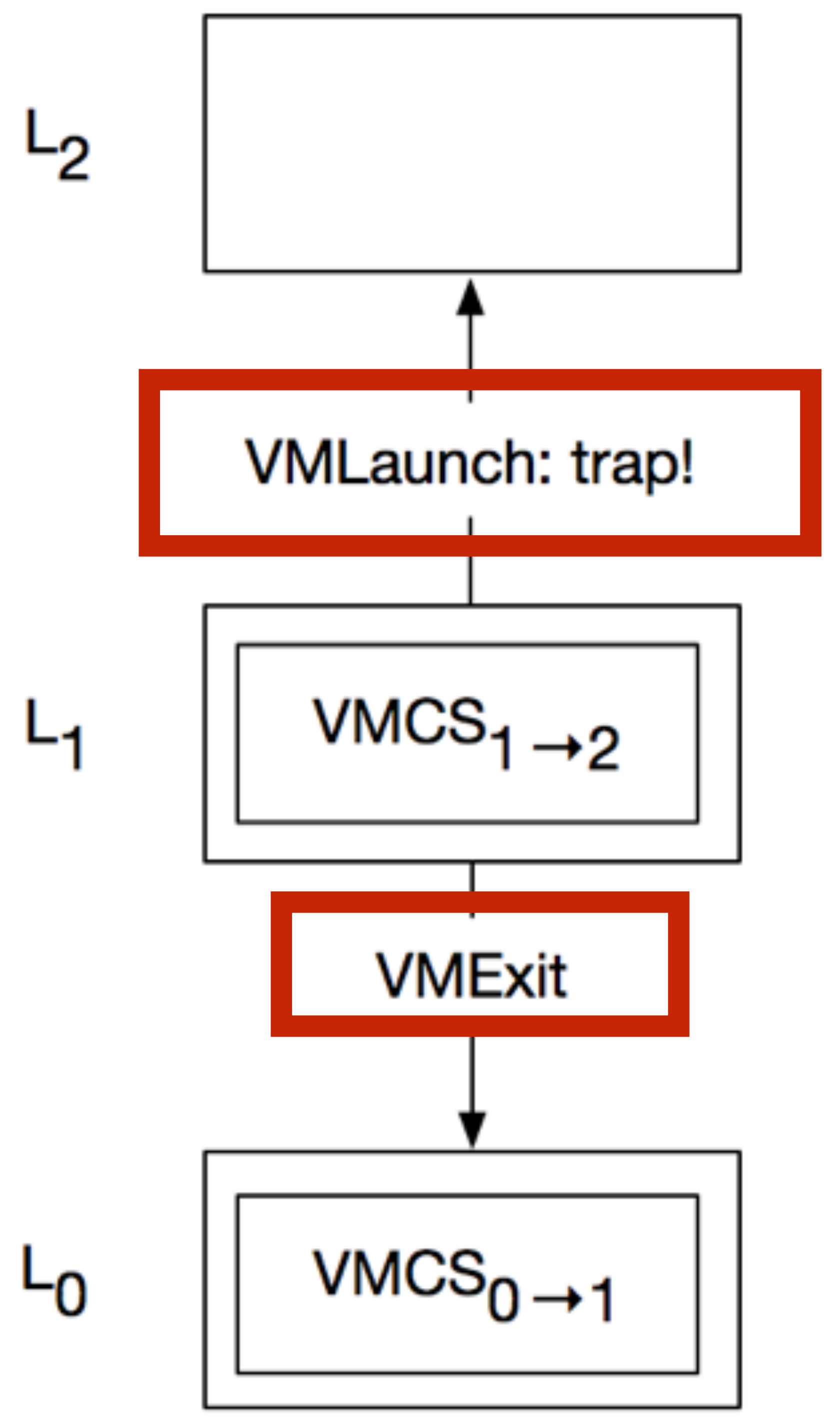

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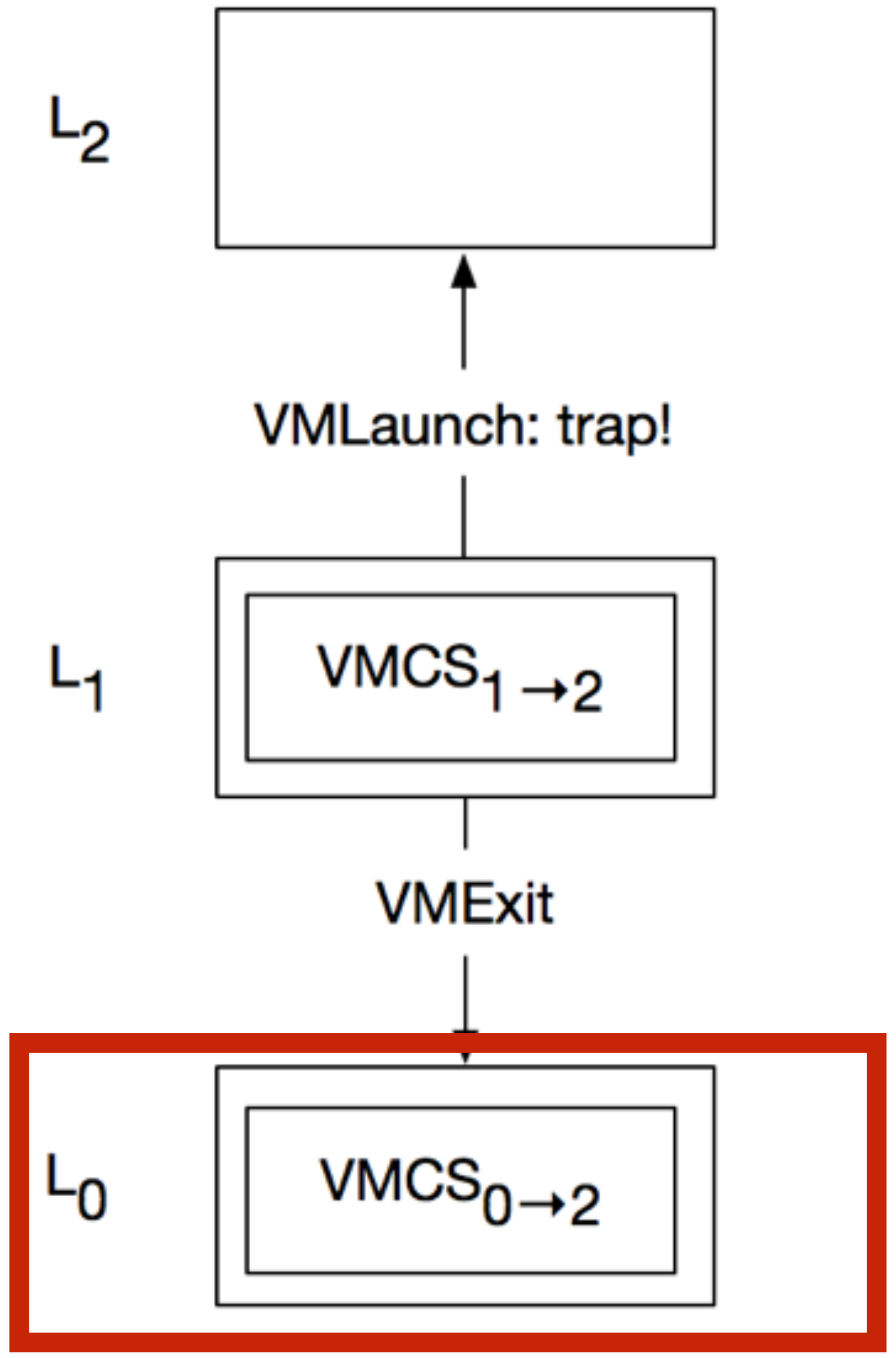

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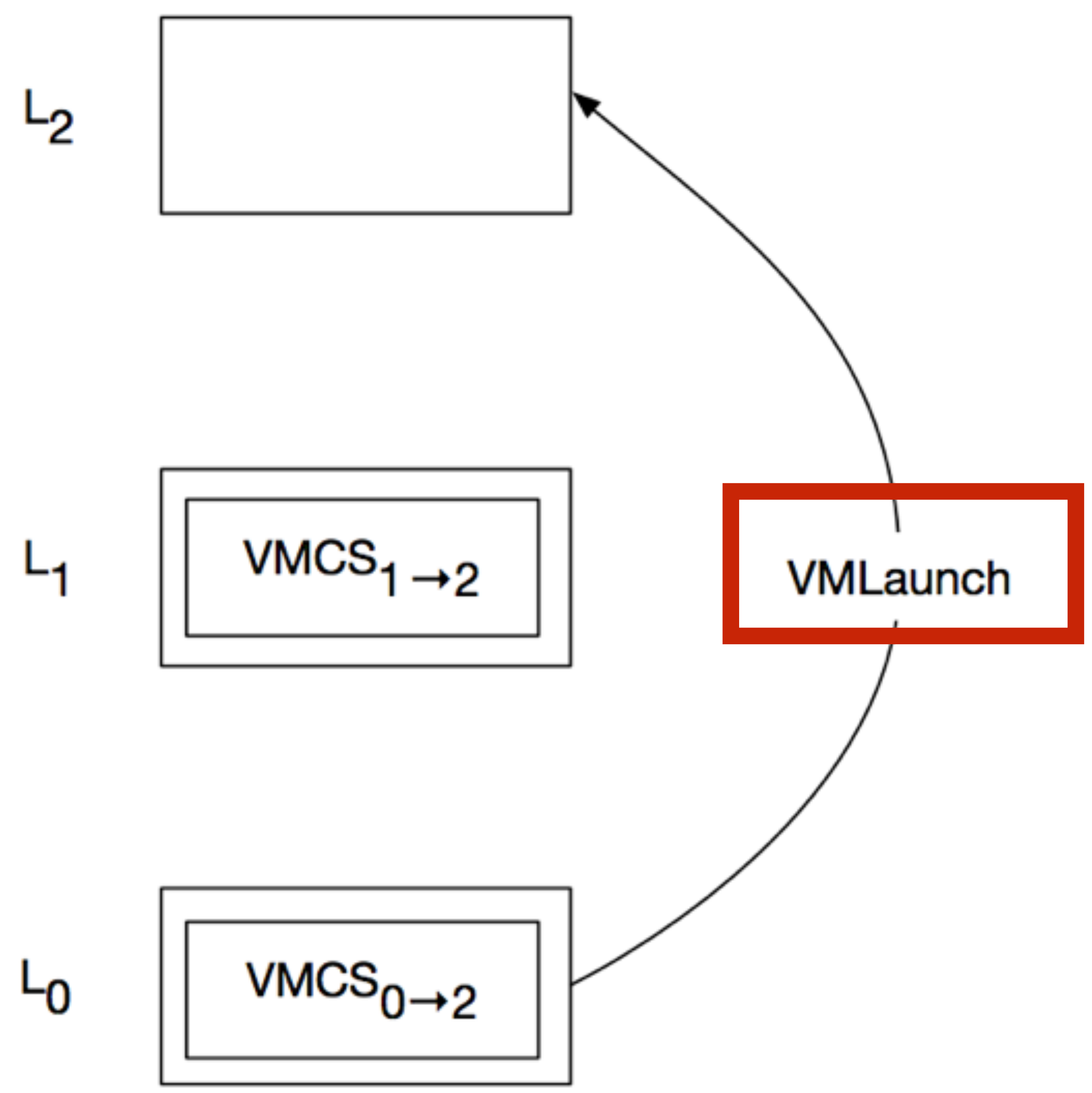

Implementing Turtles

- Nested VMX Virtualization for CPUs
- **Multidimensional Paging for MMUs**
- Multi-level Device Assignment for I/O

MMU Virtualization

- With nested virtualization, we have to make n translations for n levels $L_{2virtual} \rightarrow L_{2physical}$, $L_2 \rightarrow L_1$, $L_1 \rightarrow L_0$

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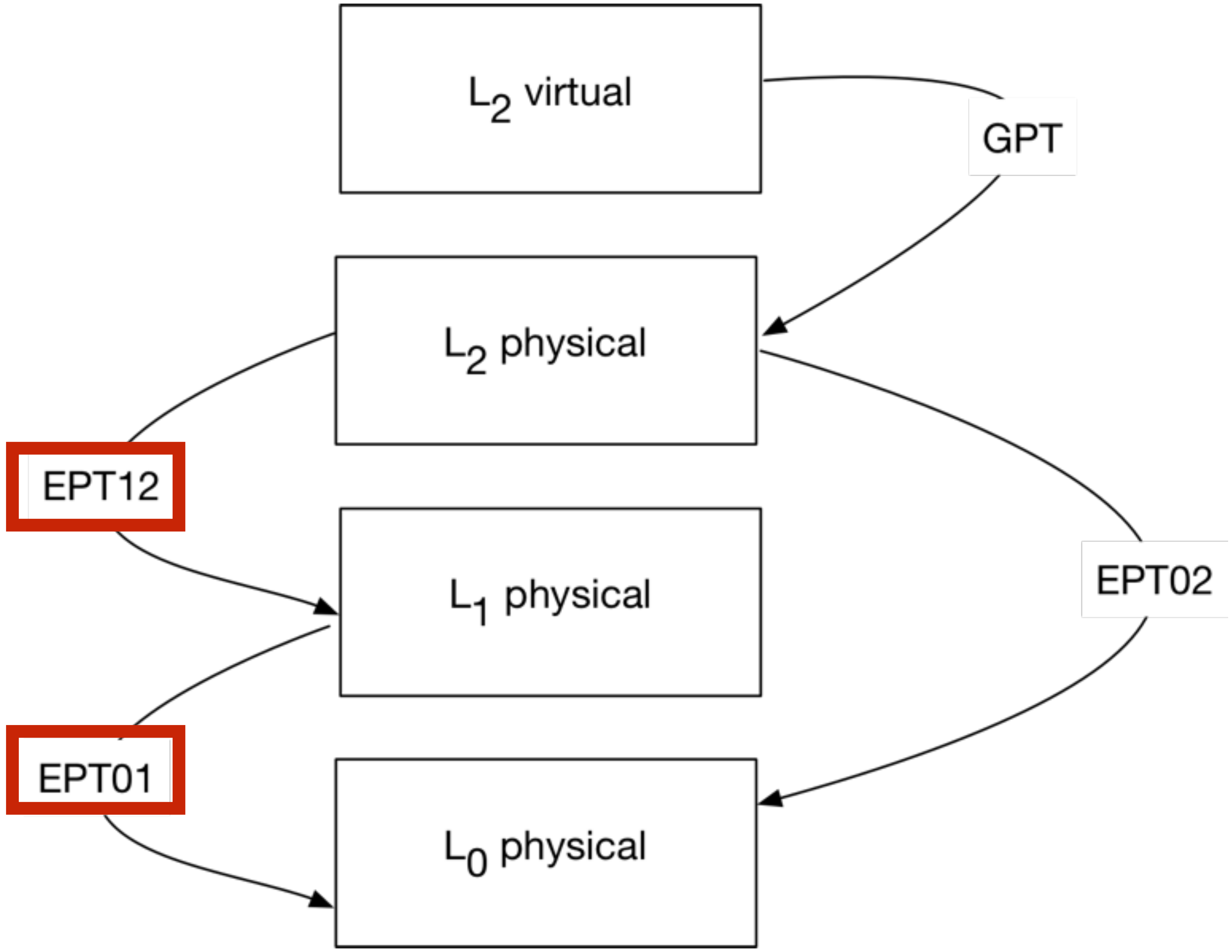
- Unfortunately, only **two dimensions** of hardware support
  - EPT (extended page table) provides translation from guest physical to host physical

Multi-dimensional Paging

- Each level creates a virtual EPT that it exposes to higher levels



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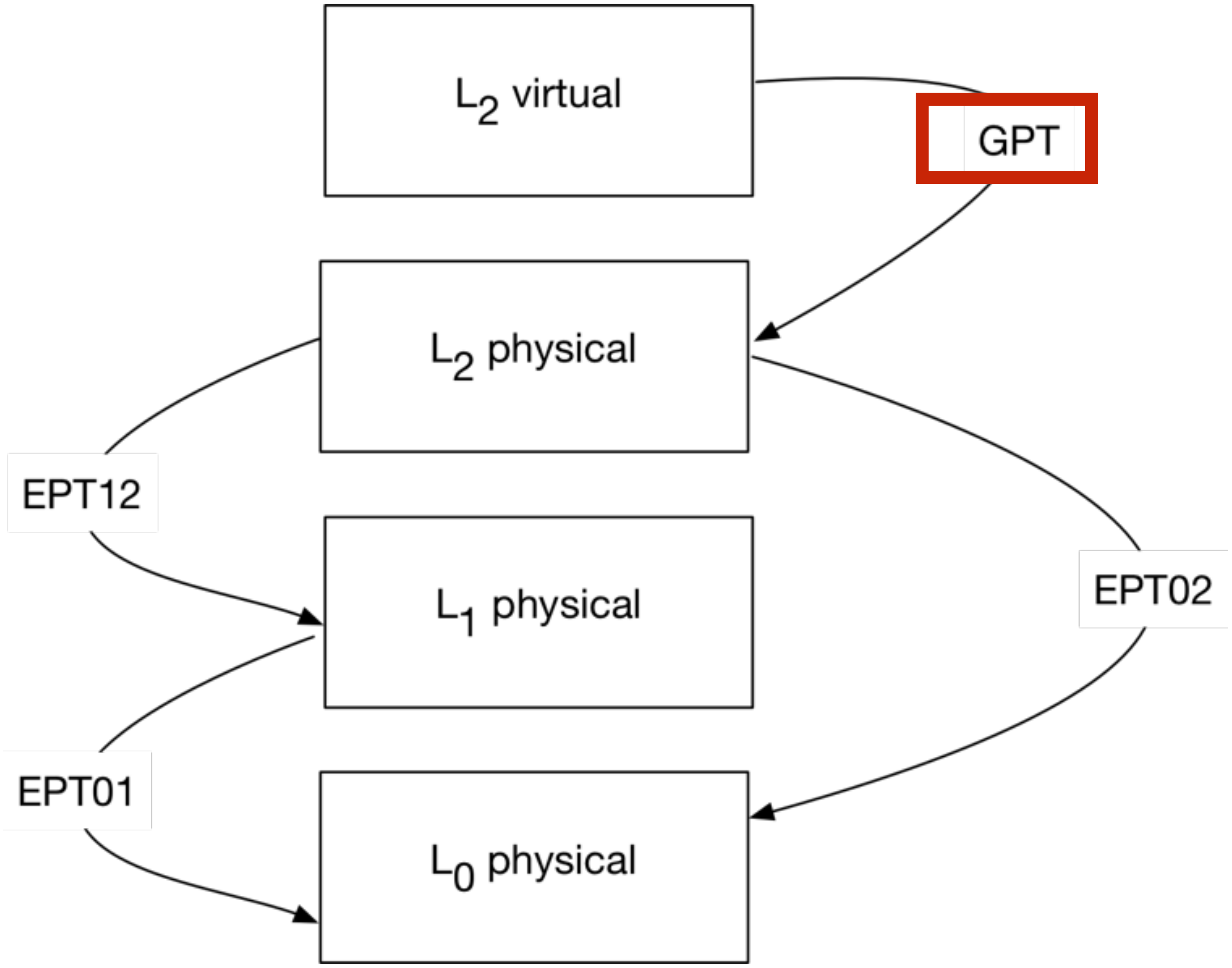
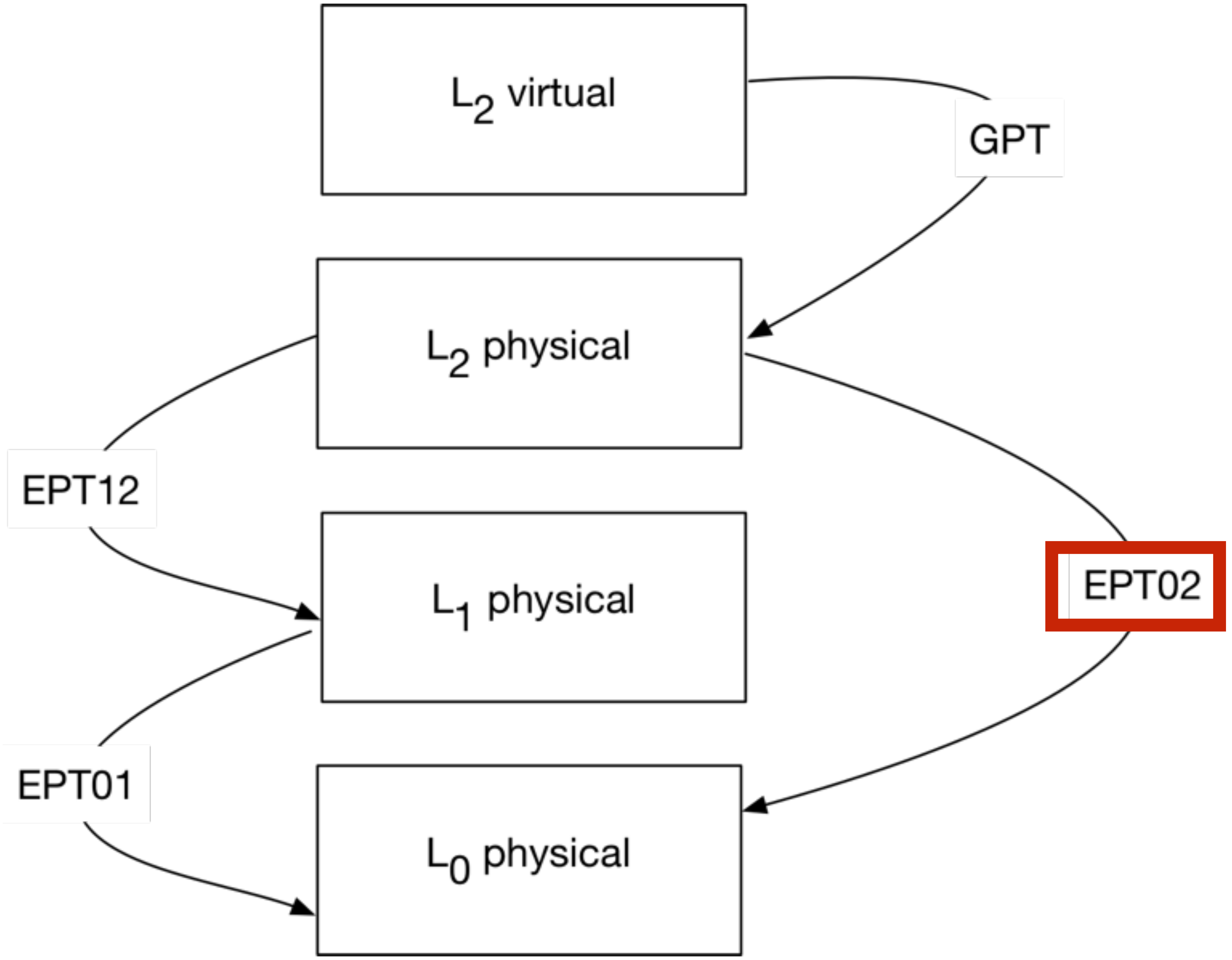


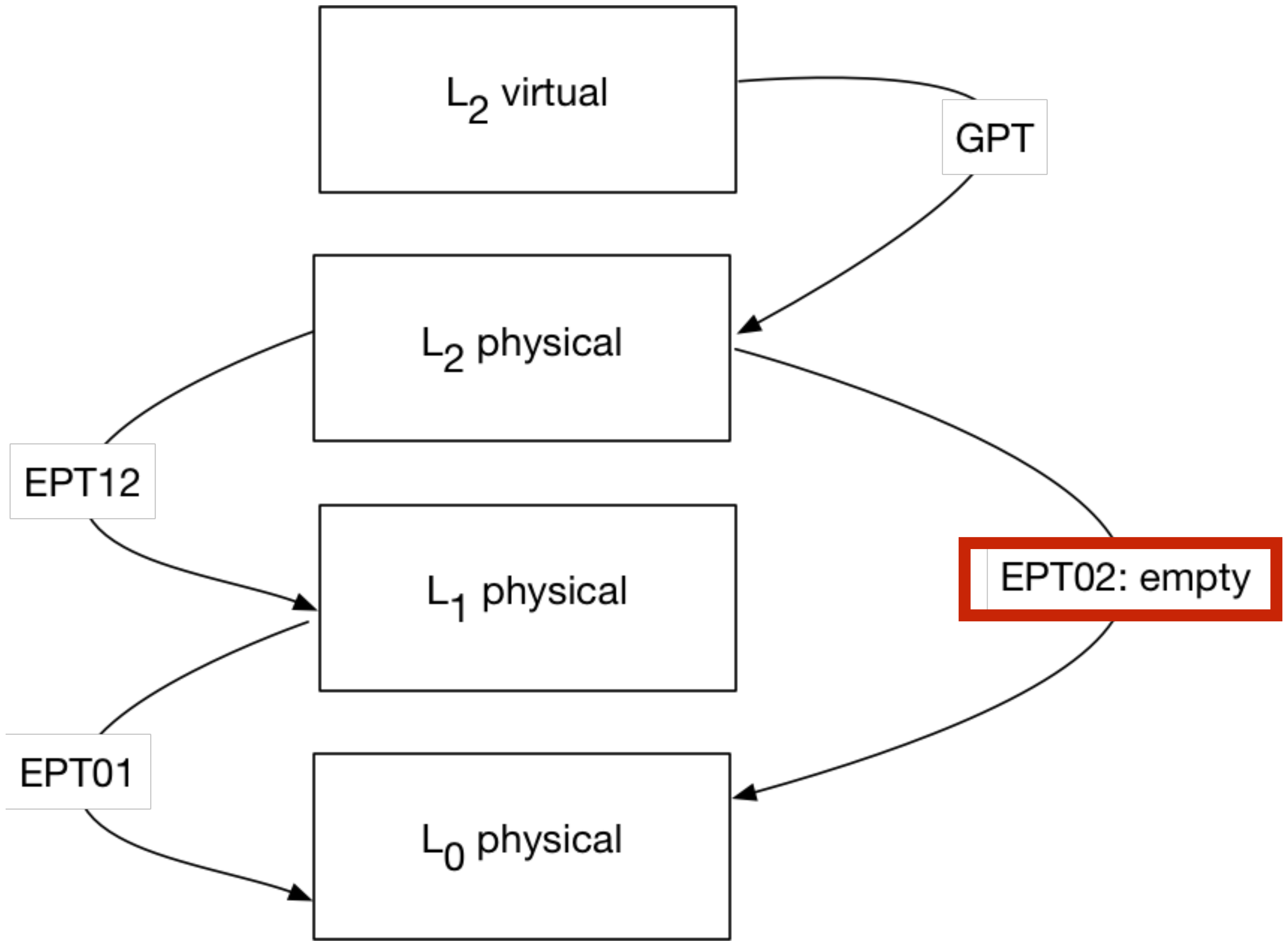
Multi-dimensional Paging

- Each level creates a virtual EPT that it exposes to higher levels
- Guest handles their own page table
- “Base” hypervisor translates address using *compressed* EPT



Building the Compressed EPT

- Start with empty $EPT_{0 \to 2}$



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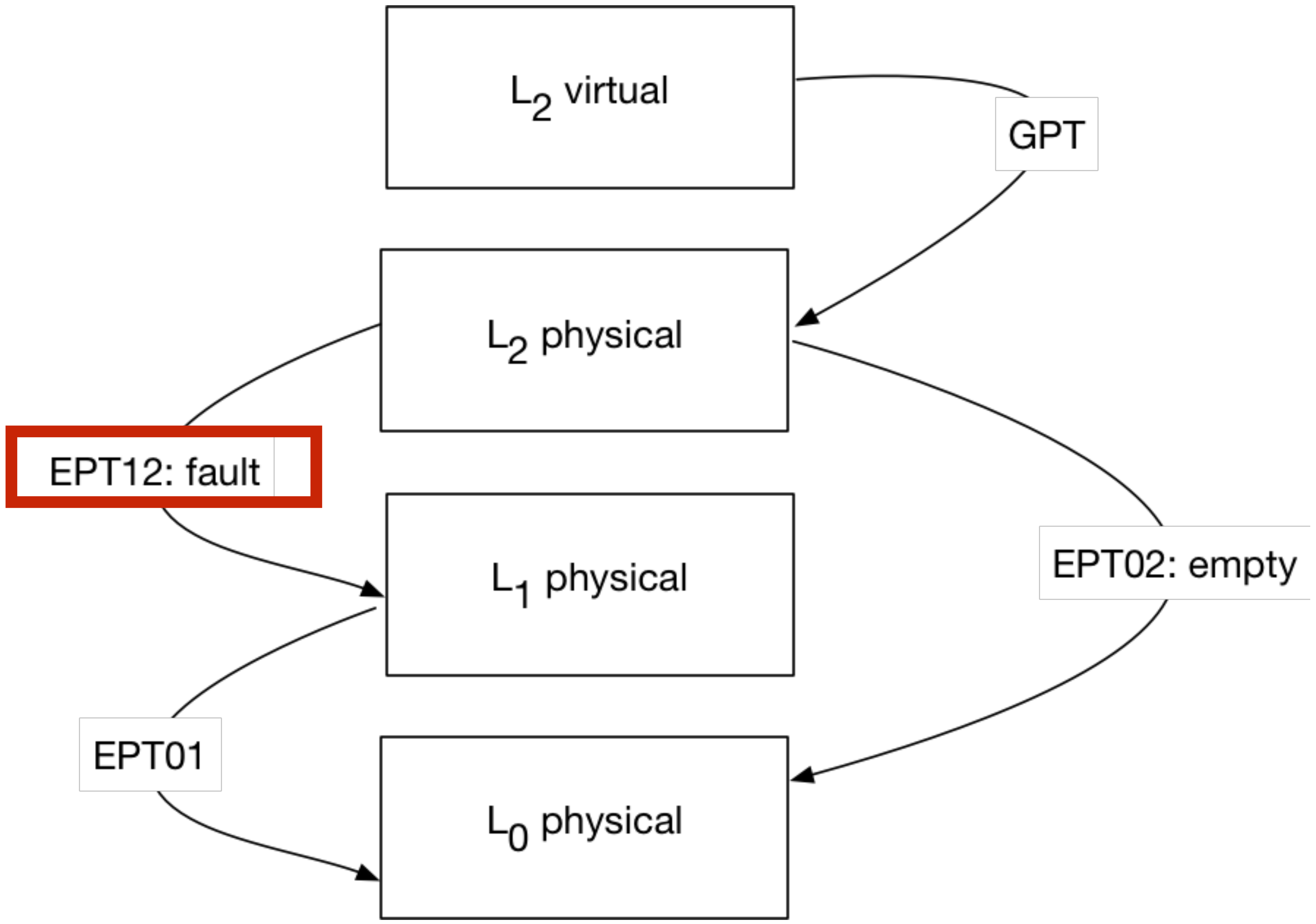

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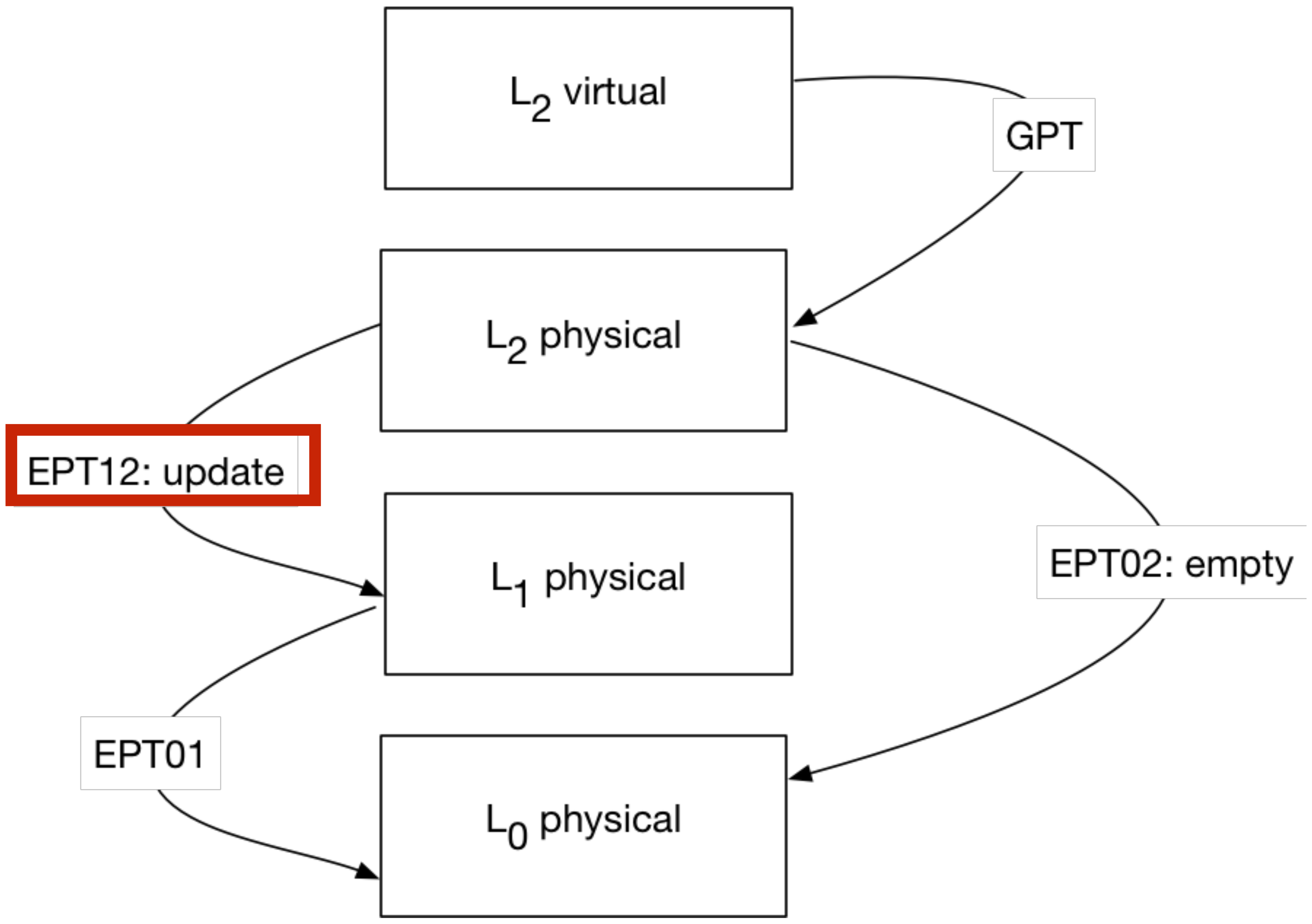

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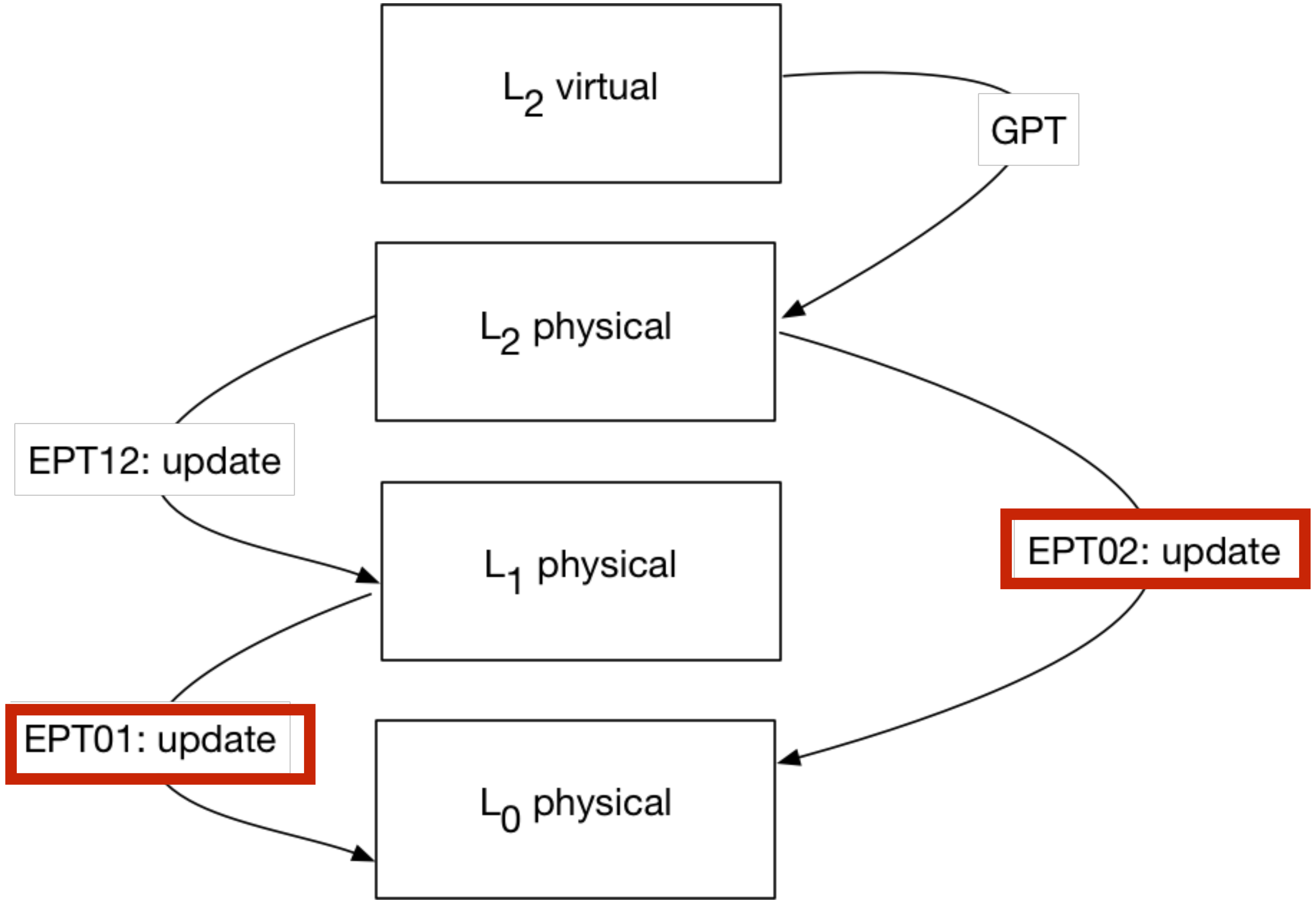

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- I/O remains an outstanding challenge
  - *Emulate* known devices
  - Para-virtual drivers (hypercalls to base hypervisor)
  - **Direct device assignment**
- We have hardware support for virtual devices DMA via IOMMU
  - Translates guest physical addresses for I/O

Emulating the IOMMU

- L_0 emulates an IOMMU for L_1

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Emulating the IOMMU

- L_0 emulates an IOMMU for L_1
- L_1 sets up $IOMMU_{2 \rightarrow 1}$ mapping
- L_0 builds the $IOMMU_{2 \rightarrow 0}$ mapping

"It's turtles all the way down!"

Optimizing Exit Handling

- Handling VMExits is slower in L_1 than in L_0
  - Updates to VMCS in exit handling is privileged
- Solution: Trap the first time privileged exit code occurs, then replay in non-trapping environment
  - L_1 directly write to $VMCS_{1\rightarrow 2}$
  - Called DRW (direct read + write)

Overall Evaluation

- Two nested layers (L_1 and L_2)
- Macro and Microbenchmarks to identify general and worst cases
- KVM as base hypervisor (L_0)
  - Running KVM (L_1)
  - Running Ubuntu 9.04 (L_2)

Overall Evaluation

Kernbench

	Host	Guest	Nested	$\text{Nested}_{\text{DRW}}$
Runtime	324.3	355	406.3	391.5
% overhead vs. host	-	9.5	25.3	20.7
% overhead vs. guest	-	-	14.5	10.3
%CPU	93	97	99	99

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	Host	Guest	Nested	Nested_{DRW}
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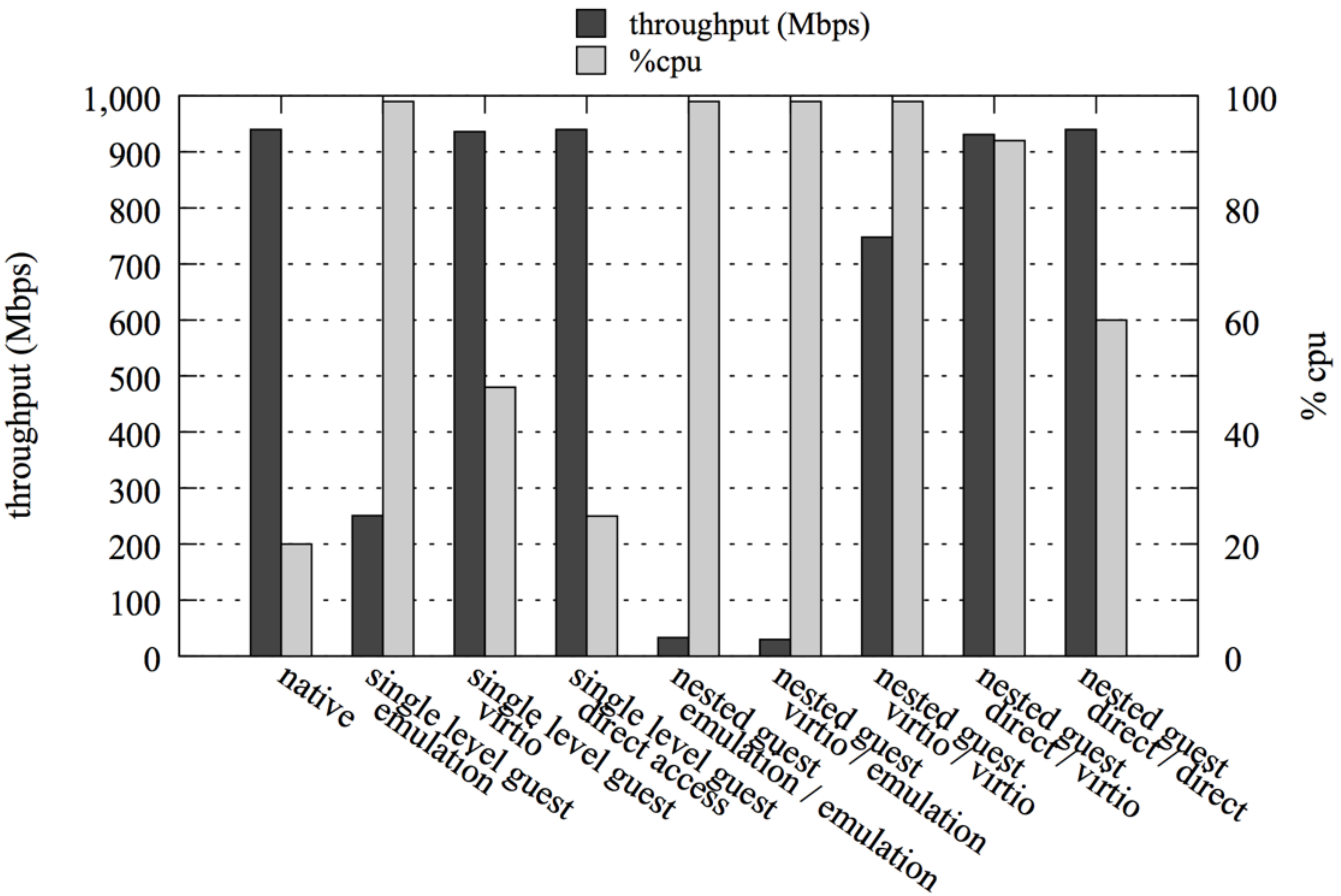
Takeaway: Can achieve nested virtualization with 6 - 10% overhead

I/O Intensive Workloads



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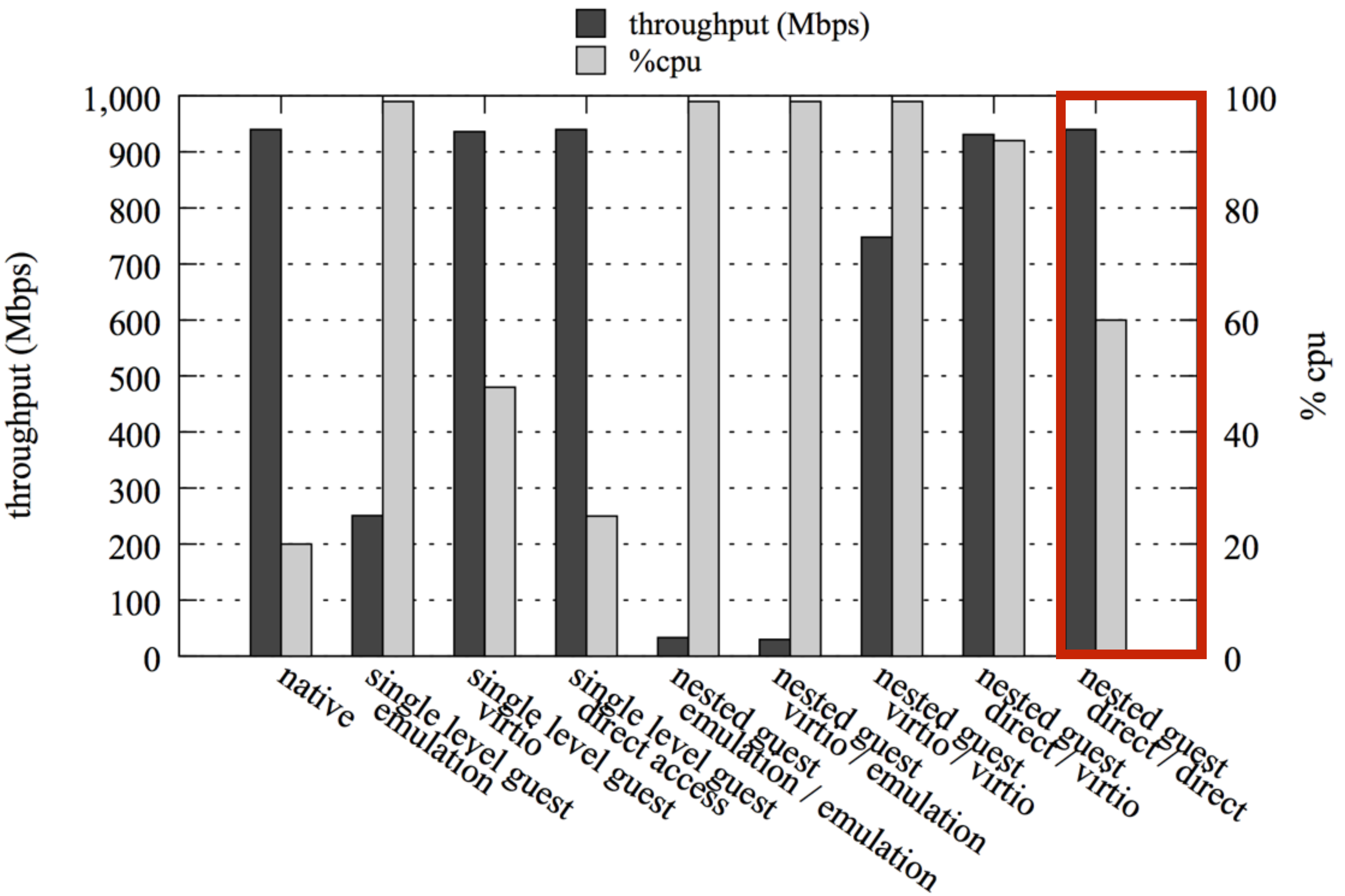

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- Run “cpuid” in a loop to generate exits
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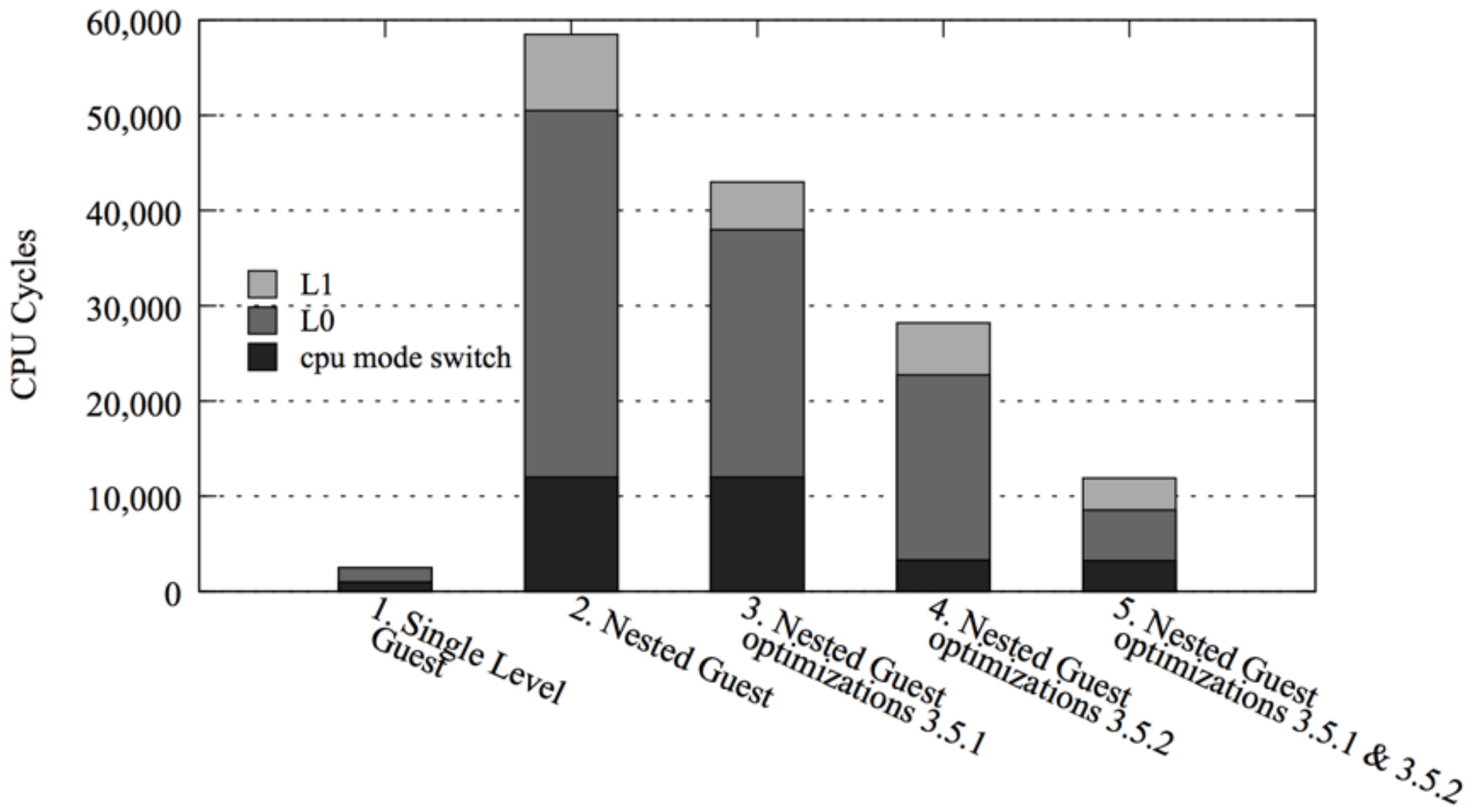

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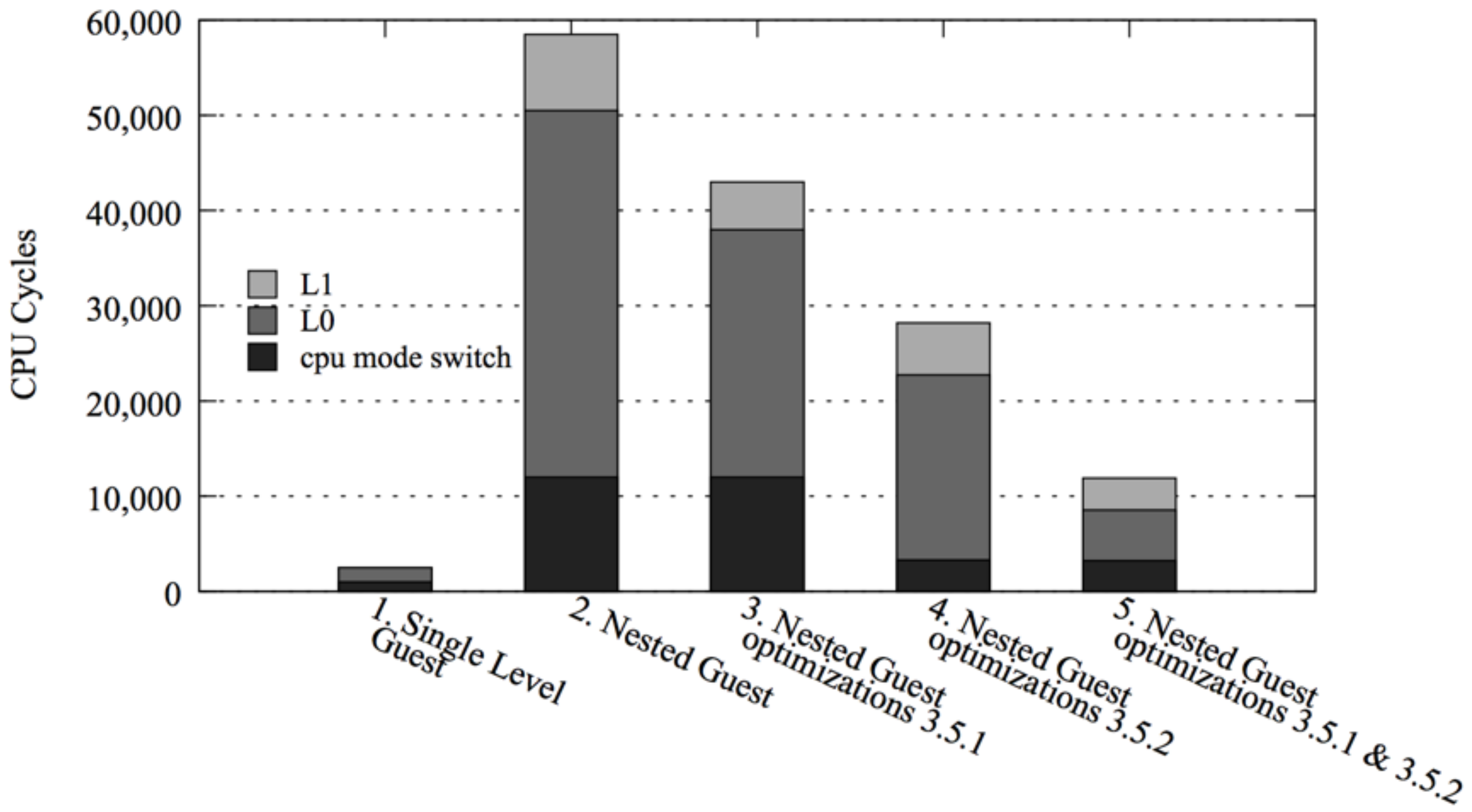

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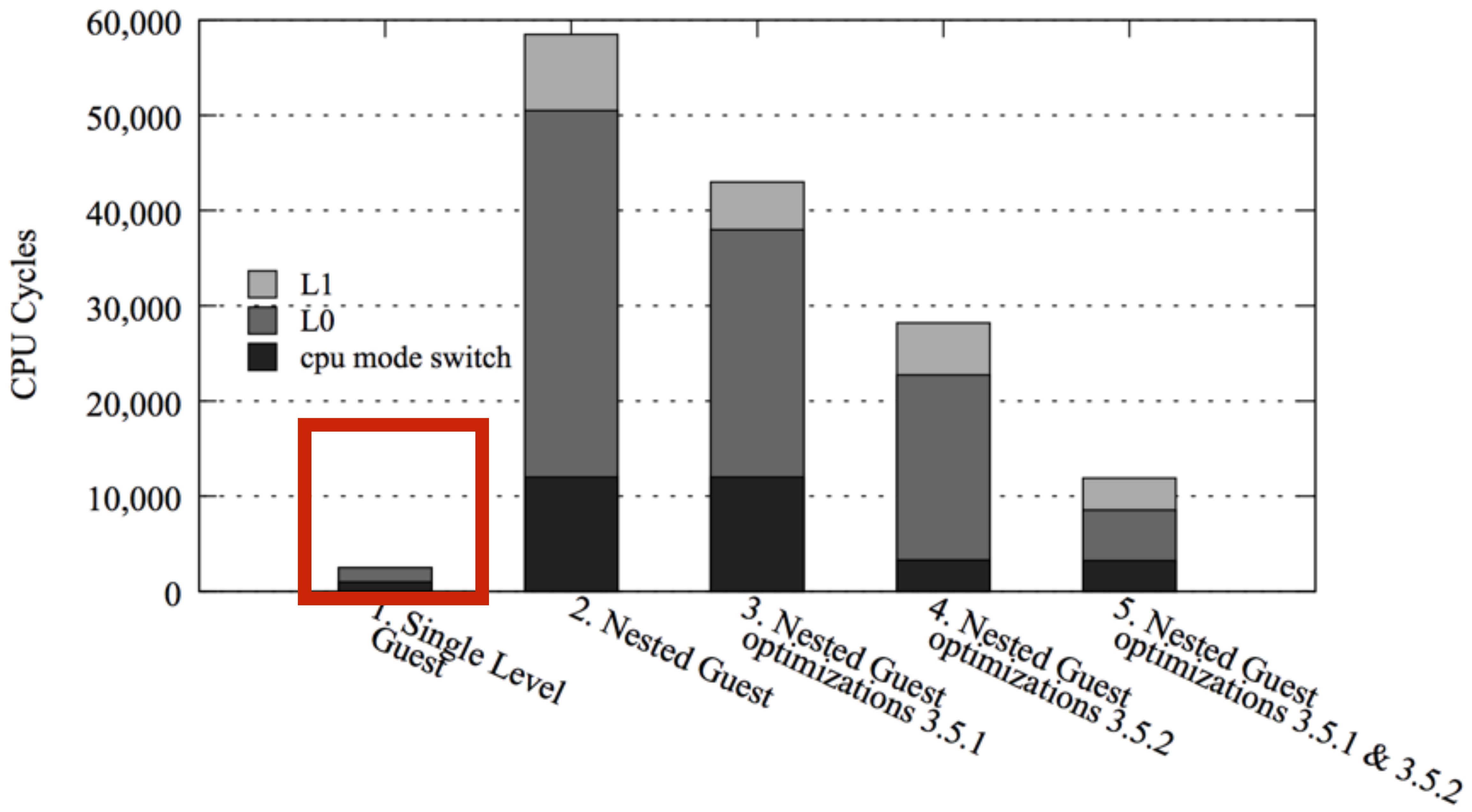

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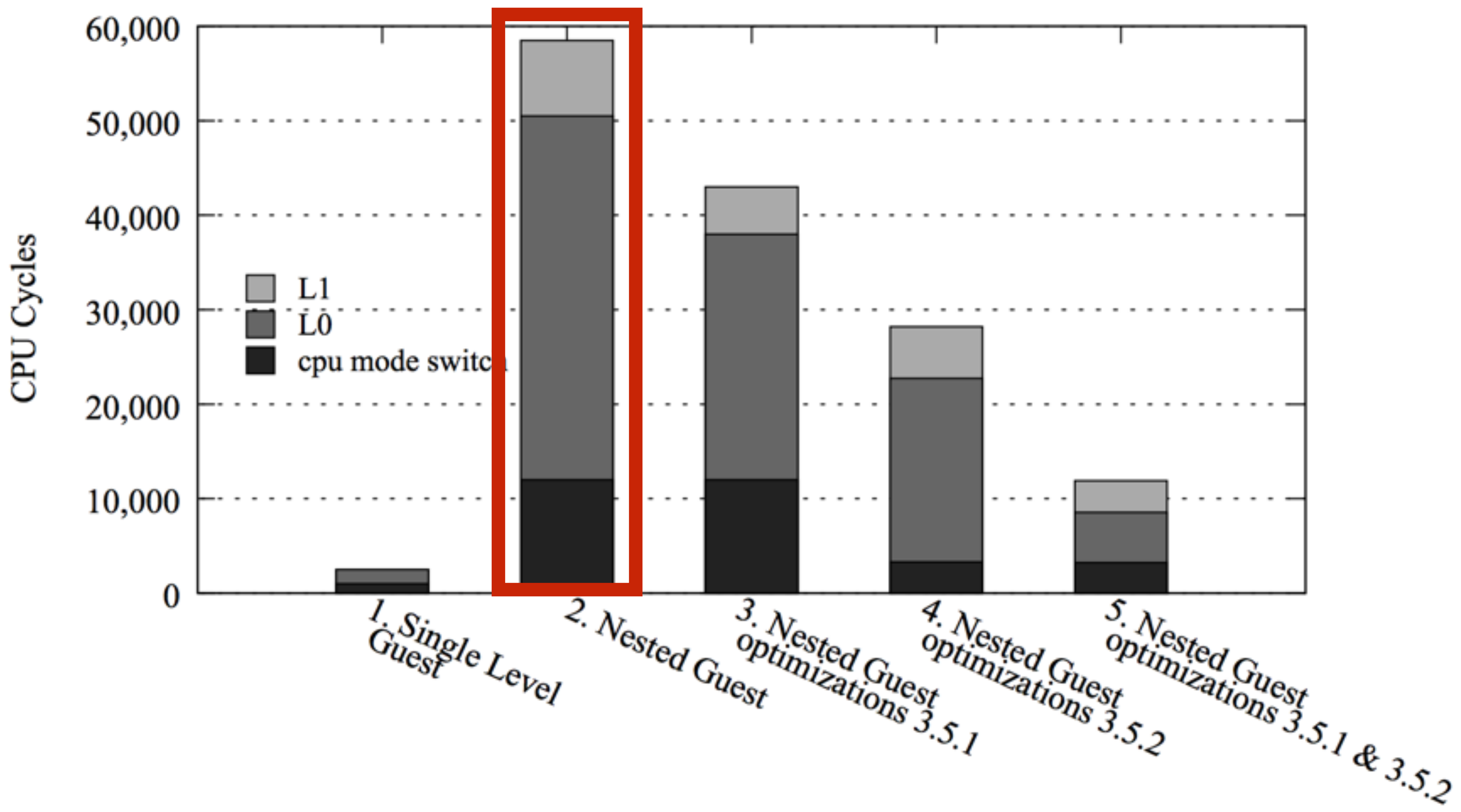

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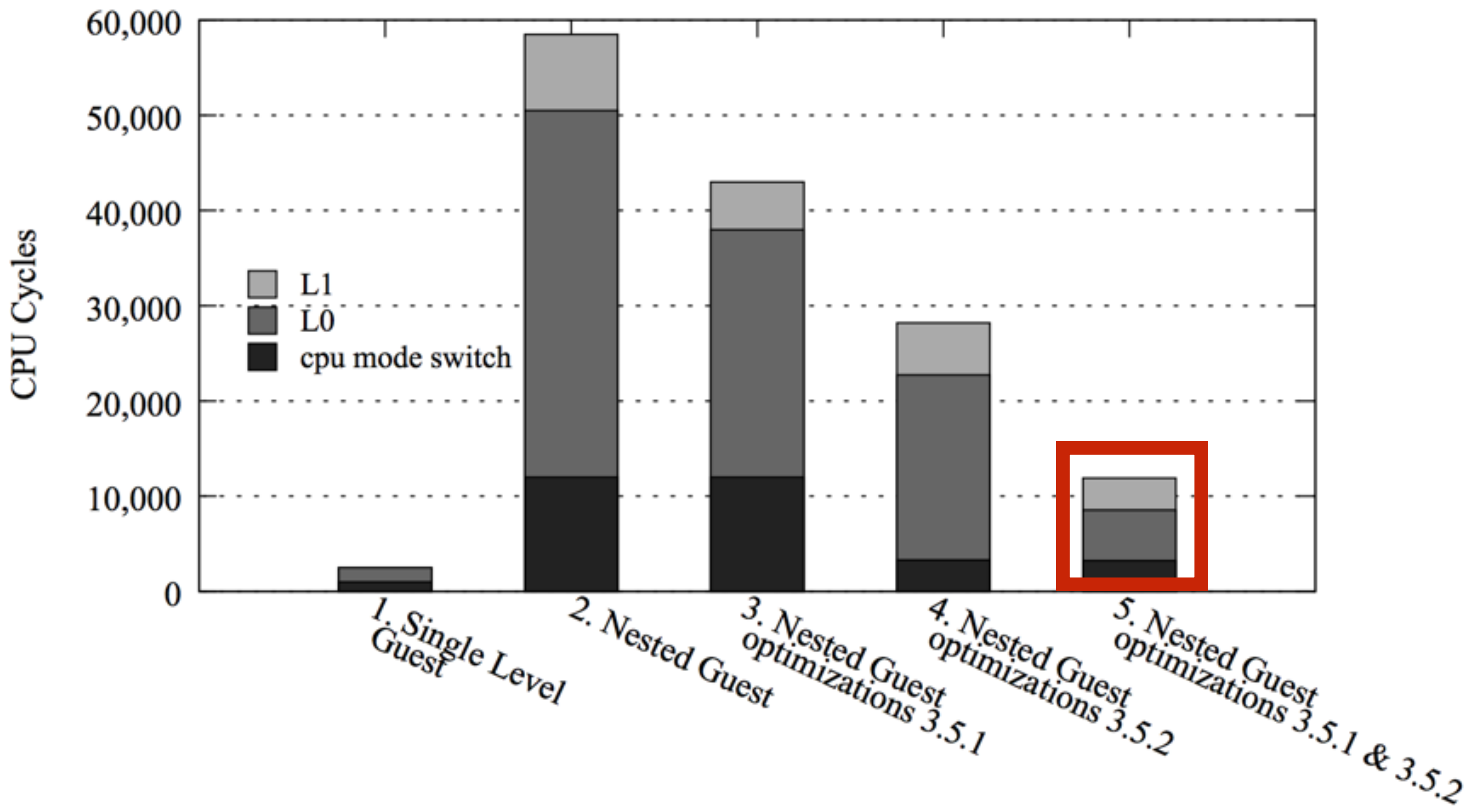

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Takeaway: Worst case is 580x worse, but can be optimized

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References

- [1] https://www.statista.com/statistics/282087/number-of-monthly-active-twitter-users/