

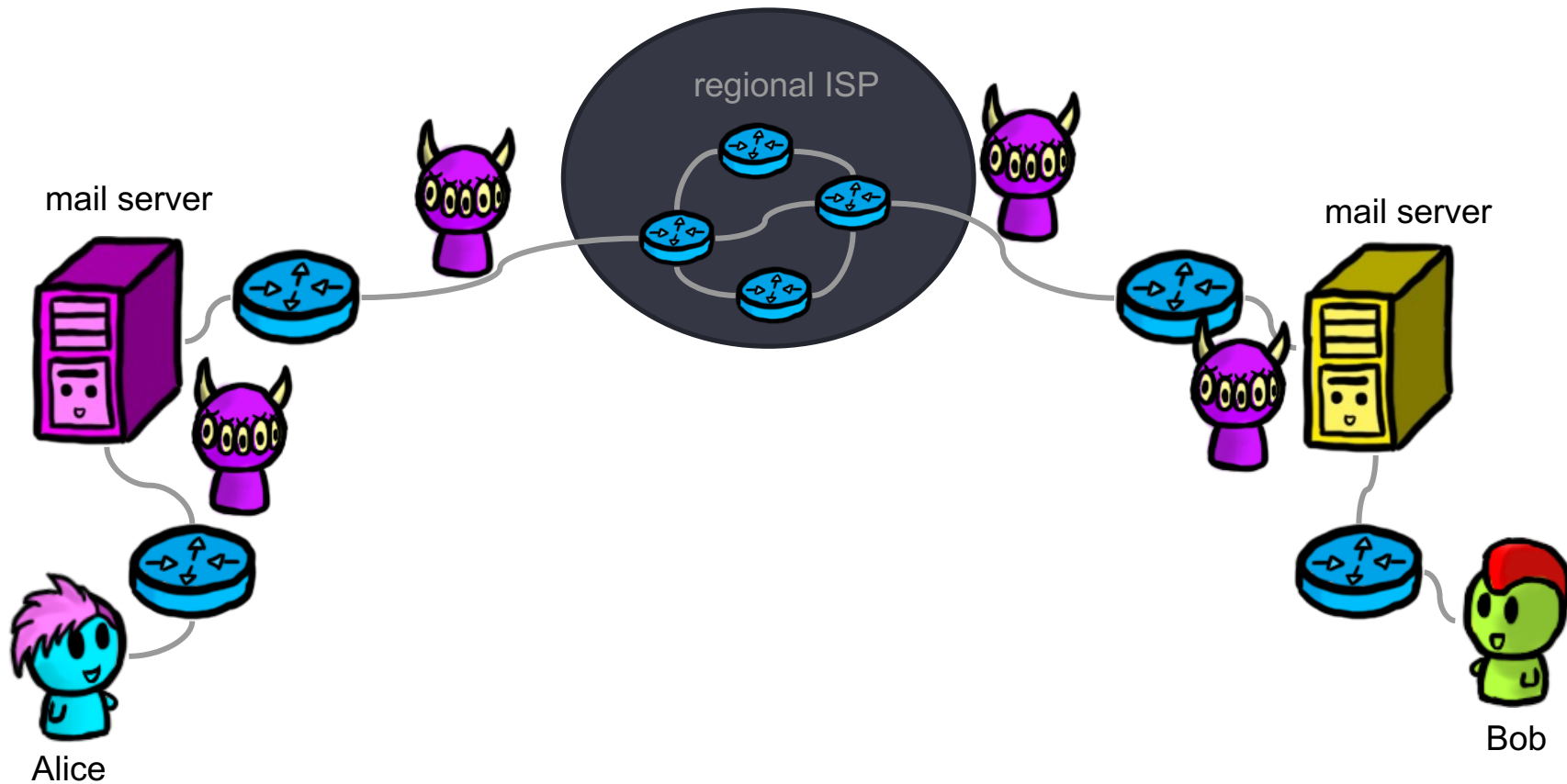
# CS489/698 Privacy, Cryptography, Network and Data Security

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Encrypted Traffic Analysis

Spring 2024, Monday/Wednesday 11:30am-12:50pm

# Traffic Analysis



# Easy attack surface:

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- Mallory has access to one of the many hops traffic takes on the internet

# Communication media (WiFi)

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- WiFi
  - Can be **easily intercepted** by anyone with a
- WiFi-capable (mobile) device
  - Don't need additional hardware, which would cause suspicion
- Maybe from kilometers away using a directed antenna
- WiFi also raises other security problems
  - Physical barriers (walls) help against random devices being connected to a wired network, but are (nearly) useless in case of wireless network

# Communication media

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- **Copper cable**
  - Inductance allows a physically close attacker to eavesdrop without making physical contact
  - Cutting cable and splicing in secondary cable is another option
- **Optical fiber**
  - No inductance, and signal loss by splicing is likely detectable
- **Microwave/satellite communication**
  - Signal path at receiver tends to be wide, so attacker close to receiver can eavesdrop
- **All these attacks are feasible in practice, but require physical expenses/effort**

# Traffic Analysis

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- TCP/IP has each packet include unique addresses for the packet's sender and receiver end nodes, which makes traffic analysis easy
- The attacker simply needs to sniff packets to determine what is going where and when.
  - Can be sensitive info such as two CEOs talking or a whistle blower.
- tcpdump is a text-based traffic analysis tool

# Tcpdump (1 of 3)

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```
·14:47:26.566195 IP 192.168.2.2.22 > 192.168.1.1.41916: Flags [P.], seq 196:568, ack 1, win 309,  
options [nop,nop,TS val 117964079 ecr 816509256], length 372
```

- 14:47:26.566195 the timestamp of the received packet
- IP is the network layer protocol (IPv4)
- 192.168.2.2.22 is the source IP address and port
- 192.168.1.1 is the destination IP address and port

# Tcpdump (2 of 3)

```
·14:47:26.566195 IP 192.168.2.2.22 > 192.168.1.1.41916: Flags [P.], seq 196:568, ack 1, win 309, options [nop,nop,TS val 117964079 ecr 816509256], length 372
```

- TCP Flag (Flags [P.]) fields include:

Value	Flag Type	Description
S	SYN	Start Connection
F	FIN	End (Finish) Connection
P	PUSH	Push data
R	RST	Reset connection
.	ACK	Acknowledgement



# Tcpdump (3 of 3)

```
·14:47:26.566195 IP 192.168.2.2.22 > 192.168.1.1.41916: Flags [P.], seq 196:568, ack 1, win 309,  
options [nop,nop,TS val 117964079 ecr 816509256], length 372
```

- `seq 196:568` is the sequence number of the data contained in the packet (196 bytes to 568 bytes)
- `ack 1` is the ack number, which is 1 (sender) or the next expected byte (receiver)
- `win 309` is the number of bytes available in the receiving buffer
- `options [nop,nop,TS val 117964079 ecr 816509256]`, are the TCP options
- `length 372` is the length, in bytes, of the payload data (the difference between the first and last byte in the sequence number)

# Encrypted Traffic Analysis

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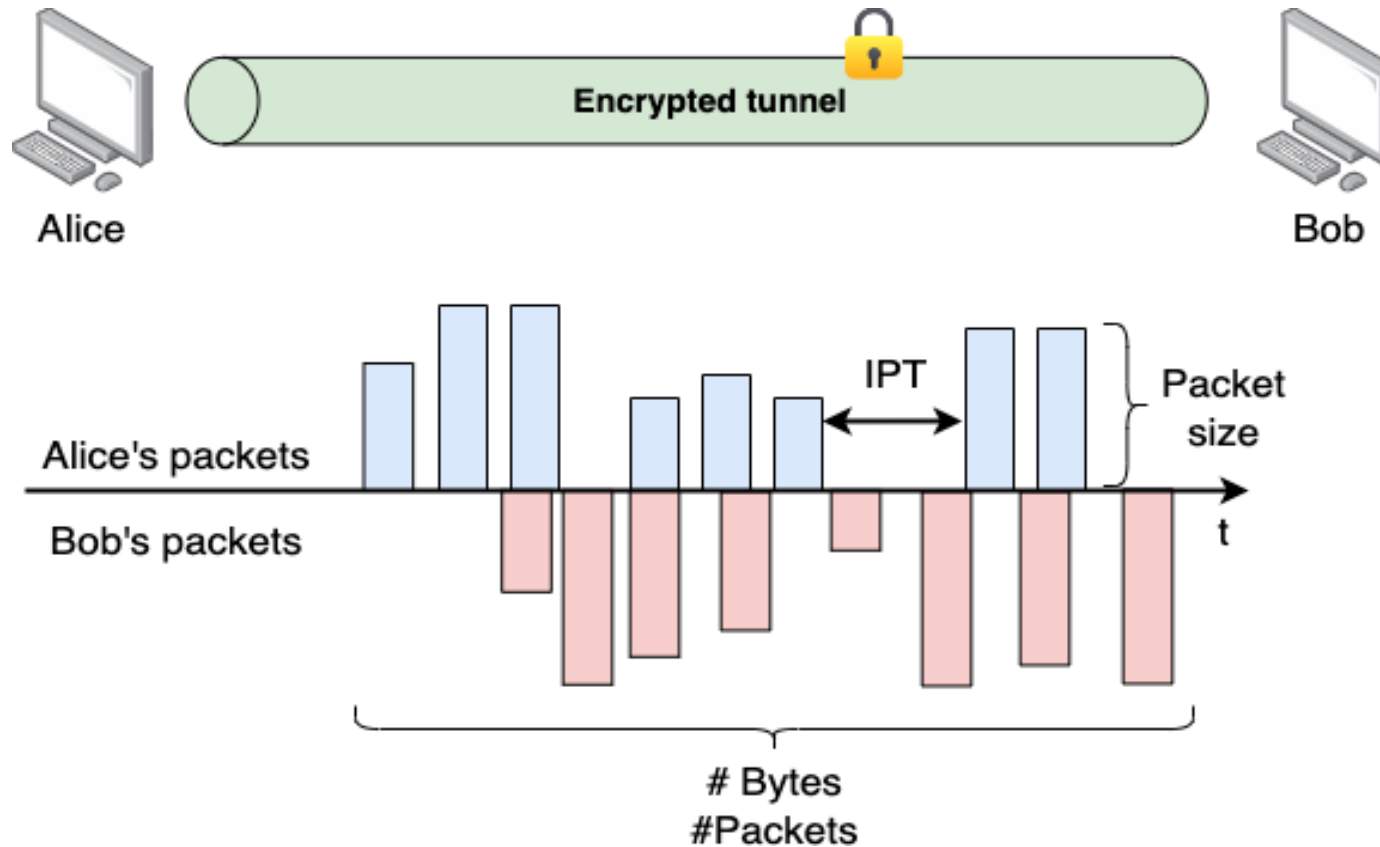
# Encryption reduces visibility over network traffic

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- TLS and other PETs significantly improved security and privacy for Internet users
  - Plaintext is no longer visible
  - Traffic monitoring capabilities are significantly reduced
- But one should not assume that traffic encryption provides absolute protection
  - e.g., against behavioural analysis
- There are strong incentives to “see” beyond encryption
  - Both for network adversaries and network administrators

# Encrypted traffic analysis (ETA)

- Let's look at an encrypted tunnel between Alice and Bob:



# Network flows and metadata

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- What is a network flow?
  - A flow is typically represented by a five-tuple
  - <Src. IP, Dest. IP, Src. port, Dest. port, Proto>
- One can extract additional metadata tied to a flow:
  - Flow duration
  - Amount of packets exchanged Packet sizes
  - Packet inter-arrival times
  - Payload byte entropy And more...
- What is this good for?

# Encrypted traffic analysis (ETA) as a side channel

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- Think of ETA as a sort of network side channel!
- ETA can be used to infer information about encrypted traffic
- We'll look at three particular ETA applications for:
  - network analytics
  - network security
  - privacy breaches
- We'll also discuss potential countermeasures

# Network Analytics

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# Network Analytics

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- Traffic Engineering
  - Prioritize application traffic (e.g., WhatsApp, Skype)
    - e.g., for non-neutral Internet ISPs
  - Throttle selected protocols (e.g. BitTorrent)
    - e.g., for “traffic management” purposes
- Quality-of-Service
  - Derive quality metrics from encrypted flows
    - e.g. videoconferencing and video streaming QoE
    - e.g. websites’ page load time, speed index



# Use case: Identification of mobile applications

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- Mobile applications' traffic leaves a fingerprint
  - Network observers can understand which apps you are using
- Build a classifier based on summary statistics from each flow
  - Look at the packet size/timing distributions
  - Minimum, maximum, mean, standard deviation, variance, skew, kurtosis, percentiles, etc.
- May need to separate traffic bursts
  - Network packets occurring together within a threshold of time
  - Traffic bursts may encompass multiple flows

# Let's classify some apps!

## Feature set

Total Packets	Total Bytes	Max Size	Min Size	Mean Size	Std. Dev Size	Percentile 10th	.....	Percentile 90th	CLASS
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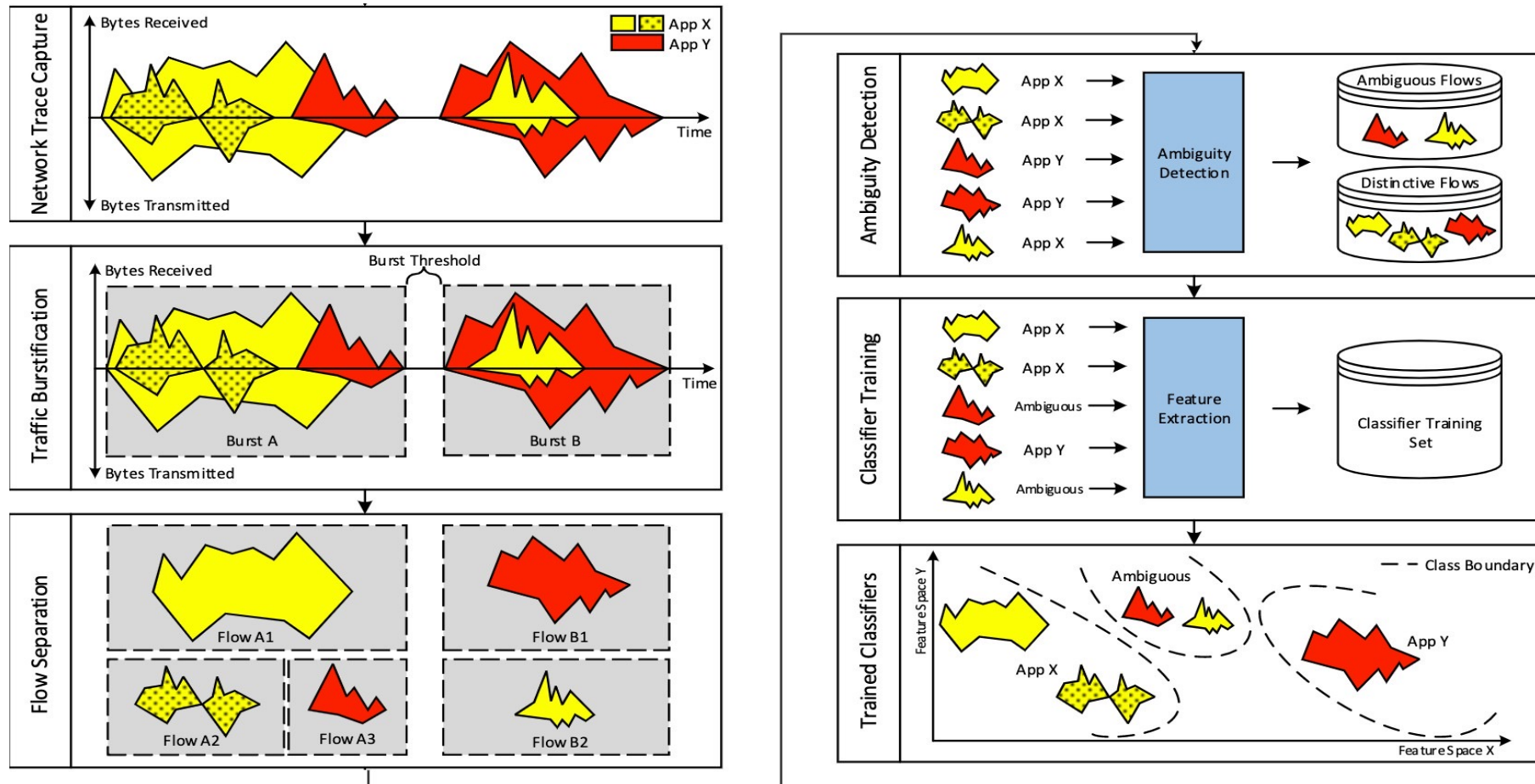
## Training data

$S_{T1}$	1405	123400	980	60	700	43	125	.....	948	Twitter
$\vdots$										
$S_{Tn}$	1566	134050	1250	60	842	54	143	.....	1014	Twitter
$\vdots$										
$S_{I1}$	2864	236544	1204	60	1024	64	92	.....	1140	Instagram
$\vdots$										
$S_{In}$	3264	286458	1280	60	1120	82	104	.....	1220	Instagram

## New data sample

	1479	125382	1240	60	792	56	142	.....	1002	???
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# Use case: Identification of mobile applications



- Taylor et al., IEEE TIFS '17

# Use case: Measuring video QoE

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- Majority of video traffic is delivered over adaptive bitrate
  - A video is encoded in multiple resolutions and split into chunks of variable length
  - Clients continuously fill a buffer of chunks, where ensuing chunks are based on network conditions
- DPI solutions can no longer be used to extract meaningful QoE metrics
  - e.g., initial delays, playback stalls frequency, resolution switch

# Use case: Measuring video QoE (cont)

- Features extracted from encrypted traffic guide the models to detect quality impairments
  - Able to detect stalls, average quality, and video quality adjustments

Network Features	Ground Truth (URI)
minimum RTT	chunk resolution
average RTT	stall count
maximum RTT	stall duration
Bandwidth-delay product	video session ID
average bytes-in-flight	
maximum bytes-in-flight	
% packet loss	
% packet retransmissions	
chunk size	
chunk time	

- Dimopoulos et al., IMC '16

# Network Security

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# Malware Detection

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- Traditional network-based malware detection relies on unencrypted data
  - Heavy use of deep packet inspection
  - e.g., for signature-based detection over packet payloads
- No longer useful to detect viruses or data exfiltration
- Encrypted traffic analysis helps us to identify:
  - Malware communications towards C&C servers
  - Unusual network traffic patterns in the network

# Malware Detection

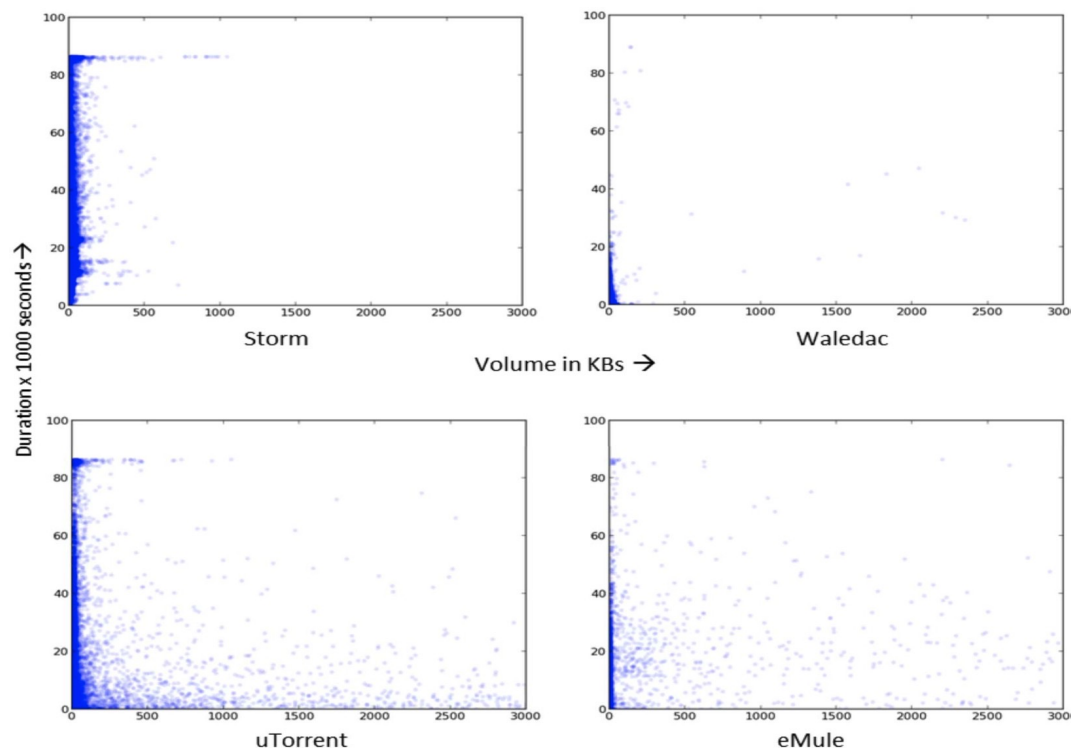
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- Malware classification:
  - Build a model out of legitimate / malicious network activity
  - Leverage “fingerprints” of legitimate / malicious behaviour
  - What if a **new** malware stream emerges?
  
- Anomaly detection:
  - Build a model for legitimate traffic and flag strange behavior
  - Via one-class learning or clustering
  - What if legitimate behavior **changes** over time?



# Use case: P2P botnet detection

- Can we pinpoint interactions between bots and C&Cs?
  - Tend to be low-volume and long-standing vs. benign P2P apps



Narang et al., IEEE SPW '14

# Use case: P2P botnet detection

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- Flows

- P2P applications (including botnets) randomize port numbers
- The usual flow definition leads to the generation of multiple flows out of what can be a continued interaction between two peers

- Super-flows

- Aggregate multiple flows between two IPs into a super-flow
  - What if two IPs have benign and malicious flows between them?

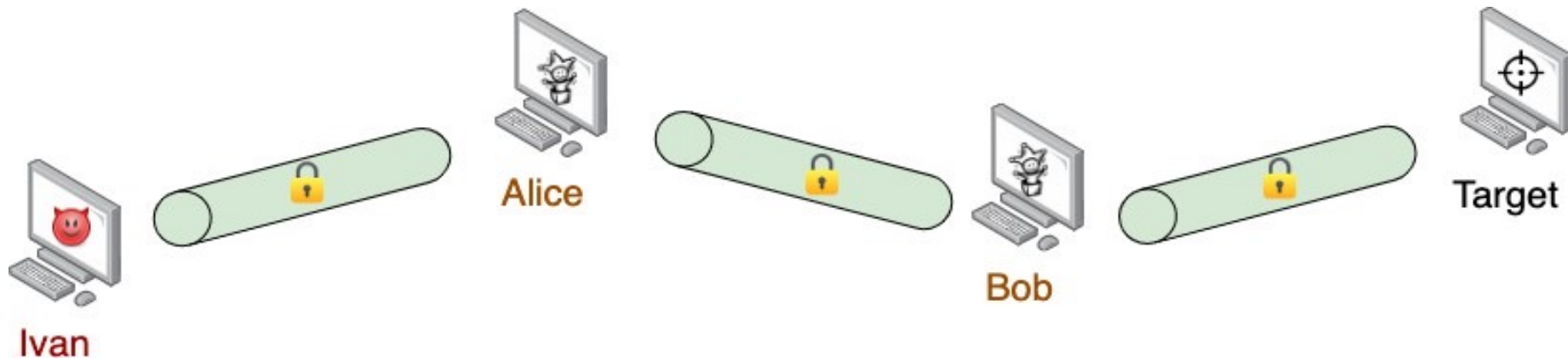
# Use case: P2P botnet detection

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- Conversations
  - Start by clustering flows:
    - Protocol, packets per second, avg. payload size
  - Create conversations from flows placed within the same clusters
  - Finally, classify conversations as malicious or benign based on:
    - Duration of the conversation
    - Number of packets exchanged
    - Volume of data exchanged
    - Median of packet inter-arrival times
- This approach was also shown effective for detecting previously unseen botnets!

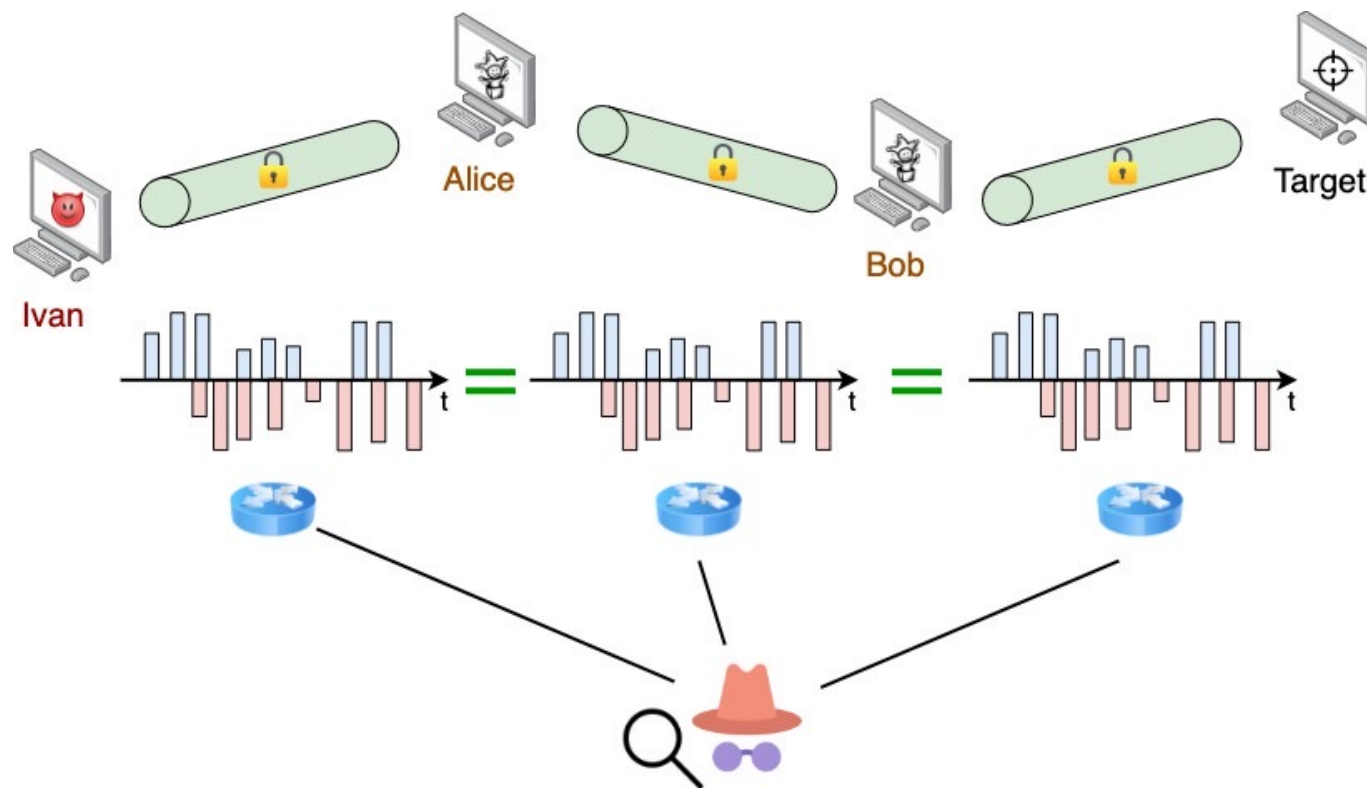
# Stepping stones

- An attacker can hide its identity by using other machines as intermediaries (i.e., stepping-stones)
  - e.g., by hopping through compromised machines or by using Tor



# Traffic Correlation

- Detection of stepping-stones
  - Attempt to match (roughly) the same sequence of packets at different network vantage points



# Difficulties in Performing Traffic Correlation

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- In practice, flow observations will not be an exact match
  - Due to network imperfections
    - Packet delays, jitter, loss
- Due to countermeasures
  - Chaff and delay injection at intermediate nodes, padding
- Traffic correlation algorithms must account for small differences between each flow observation

$$\delta_t(C, C') = \log \left( \prod_{k=1}^K |T_k(C', t) - T_k(C, t)| \right)$$

Staniford-Chen and Heberlein, IEEE S&P '95

# Privacy Breaches

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# Nefarious uses of encrypted traffic analysis

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- One would assume that encryption is all that is needed to securely communicate over the Internet
- Unfortunately, encryption does not hide traffic patterns
- Traffic analysis can be weaponized to breach users' privacy



# Metadata is not your data. Or is it?

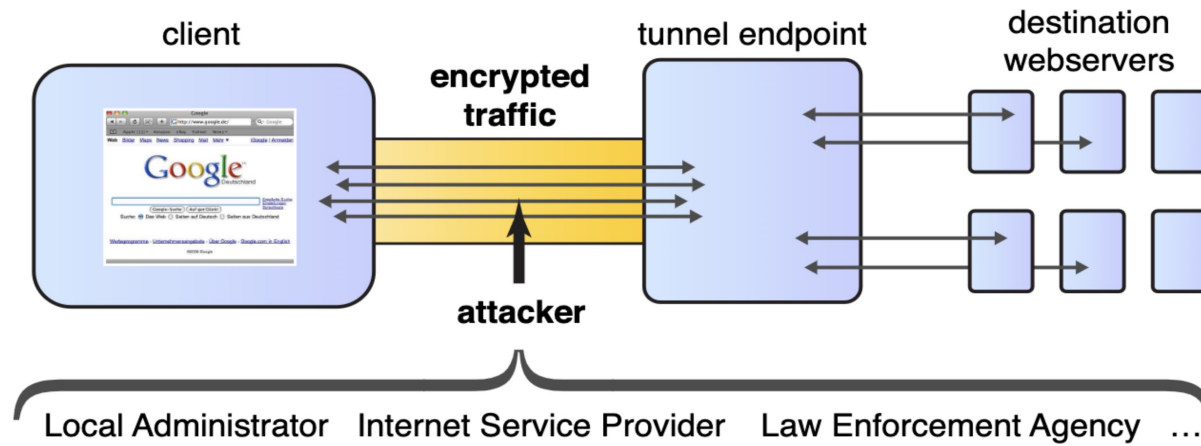
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(Dr. Evil making you think metadata is useless)

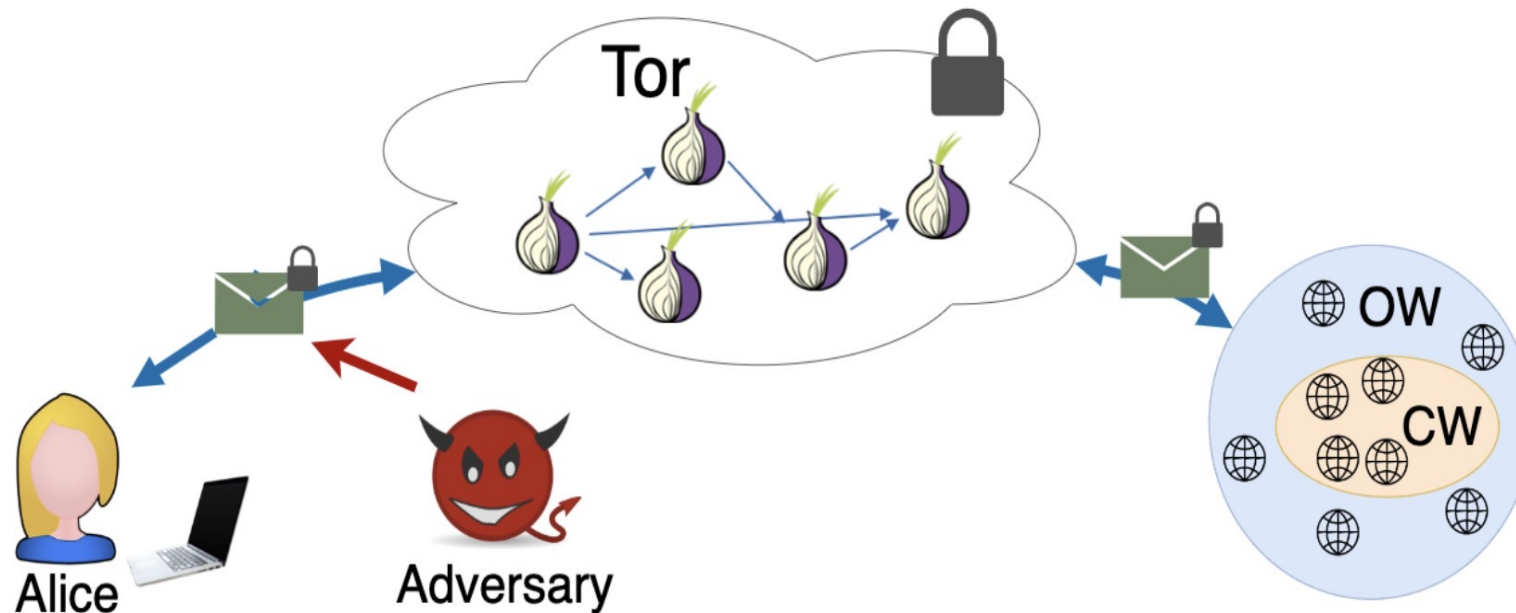
# Website fingerprinting over VPNs

- VPNs are advertised as the “holy-grail” of Internet security
  - Passive adversaries can uncover which website is being visited
  - By building traffic fingerprints and using a classifier
- The attack can be launched in two settings:
  - Closed-world Open-world



# Website fingerprinting over Tor

- The Tor network can be seen as one “big VPN node”
  - Tor exchanges data in fixed-size cells
  - But packet direction and timing still leaks information



# Website fingerprinting over Tor

- Features based on different traffic representations have been used to launch website fingerprinting attacks on Tor
  - Directional representation - Rimmer et al., NDSS '18
  - Directional + timing representation - Saidur Rahman et al., PoPETs '20

Rimmer et al. (Directional representation)

+1	-1	+1	+1	-1	-1	-1	+1	+1	yahoo.com
+1	+1	-1	-1	-1	-1	+1	-1	+1	google.com

Saidur Rahman et al. (Directional + timing representation)

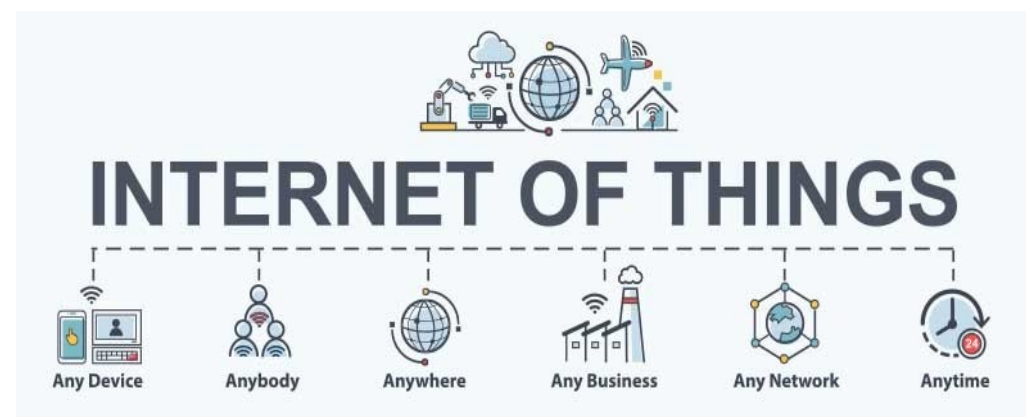
+0.02	-0.01	+0.03	+0.01	-0.03	-0.04	-0.01	+0.01	+0.02	yahoo.com
+0.01	+0.04	-0.02	-0.01	-0.01	-0.01	+0.02	-0.01	+0.02	google.com

Fixed-size input to neural network

# IoT device fingerprinting

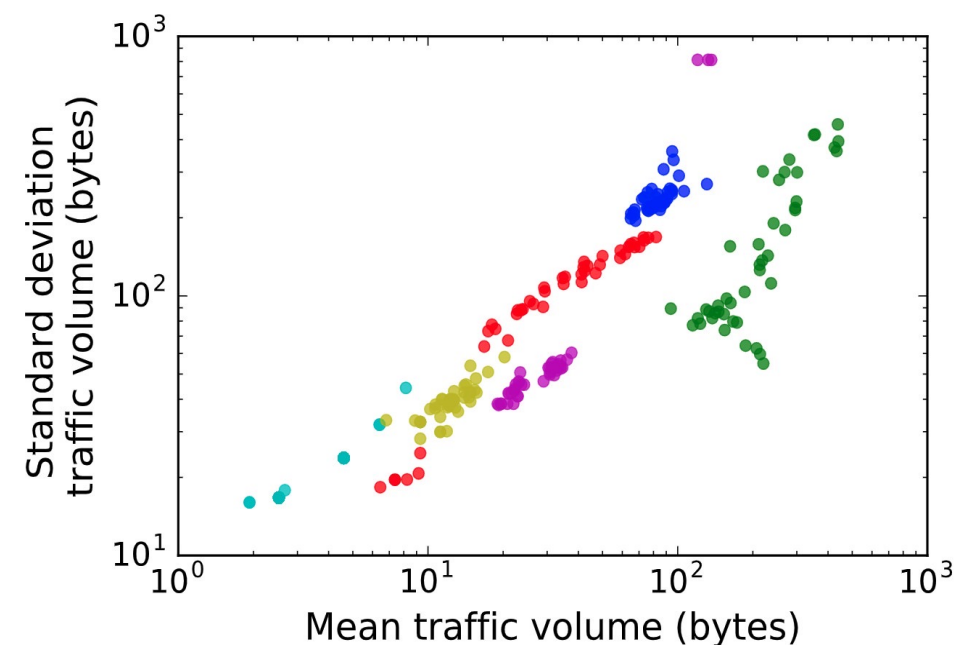
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- Passive network observers can potentially analyze IoT network traffic to infer sensitive details about users
  - Does this user have a blood monitor? A security camera? A sex toy?
- DNS queries associated with each encrypted flow often contain the device manufacturer name
  - We can even pinpoint the exact device



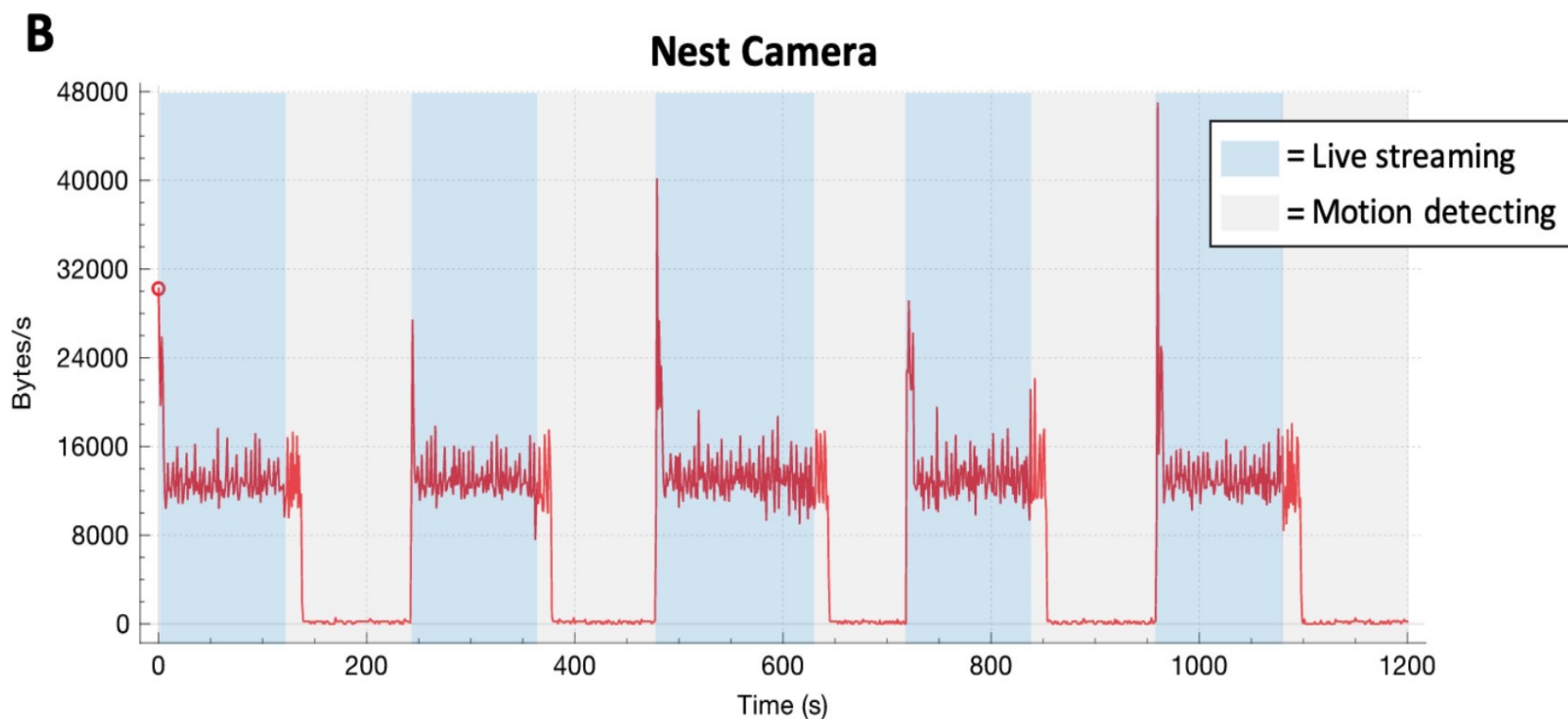
# Distinguishing devices through traffic volume

- Rather simple volumetric features allow us to identify IoT devices (Apthorpe et al., ConPro '17)
  - Once a device is identified, one can also infer its state



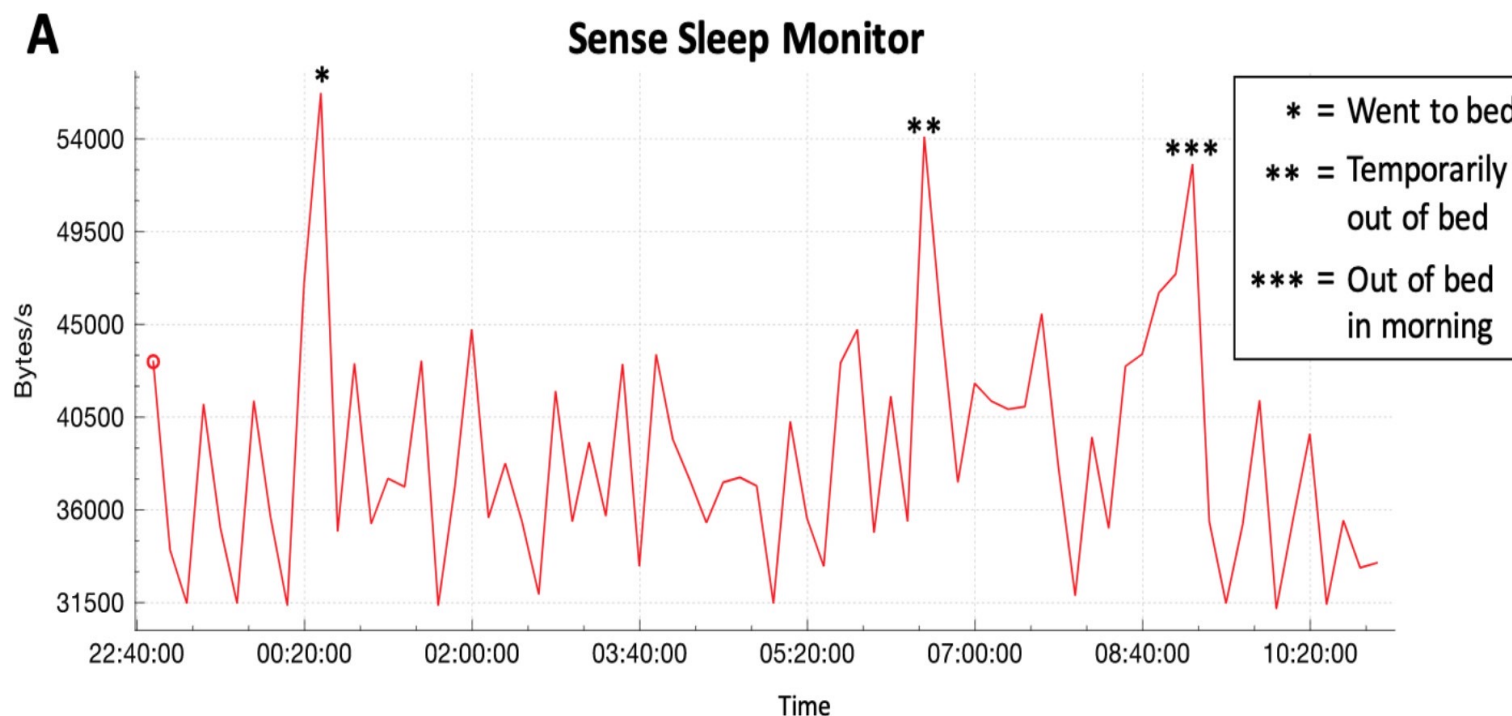
# Motion sensor - Nest indoor security camera

- Easy to discern when the camera picks up movement
  - Easy to discern when nobody's home?



# Sleep tracker example - Sense sleep monitor

- Easy to discern when a user goes to bed and wakes-up
  - Easy to discern if a burglar should leave the crime scene?

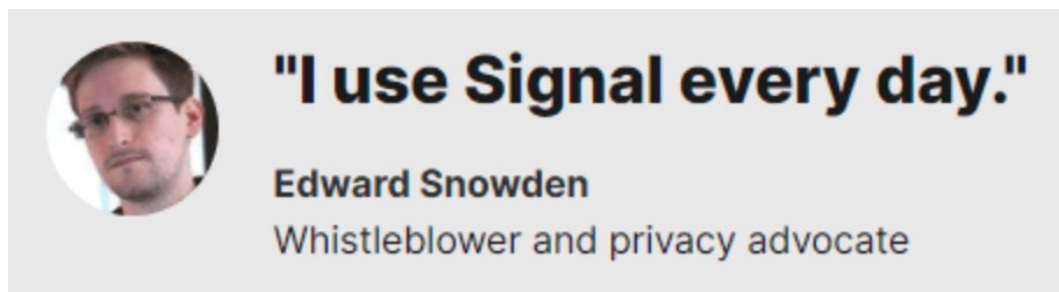




# Practical attacks against IM applications

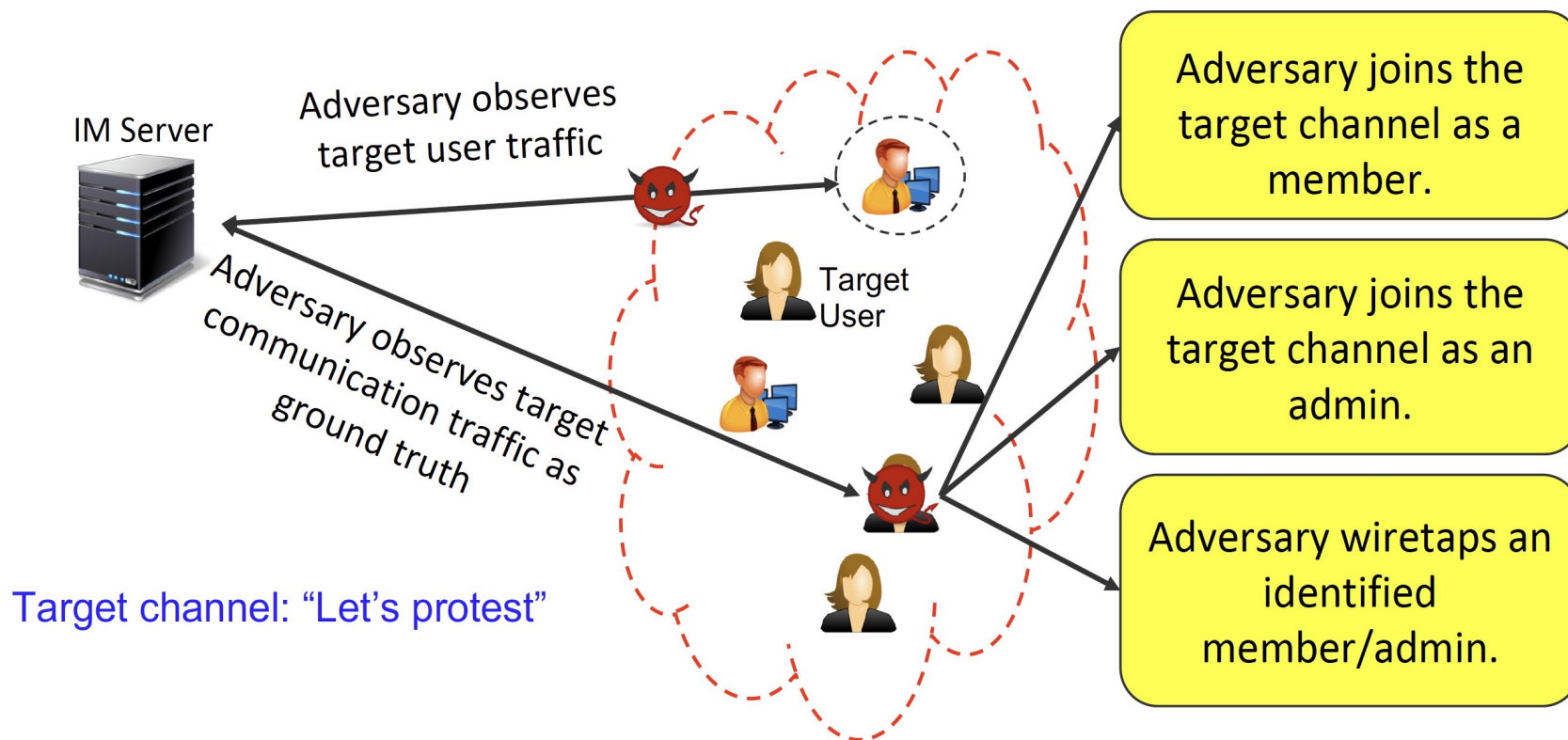
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- IM applications are extensively used to exchange potentially sensitive content securely
  - Remember OTR and Signal
  - Oftentimes used to exchange politically and socially sensitive content
  - Governments and corporations may be interested in identifying participants of IM conversations
    - e.g., target whistleblowers or dissidents



# Adversary aims to uncover group membership

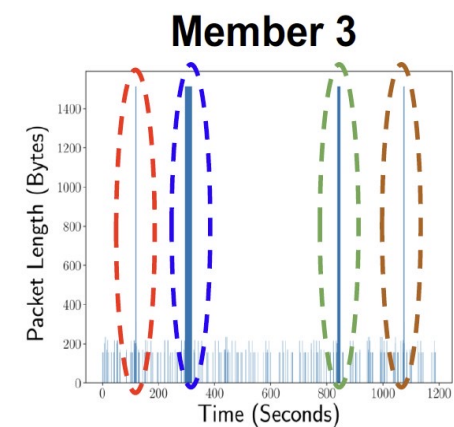
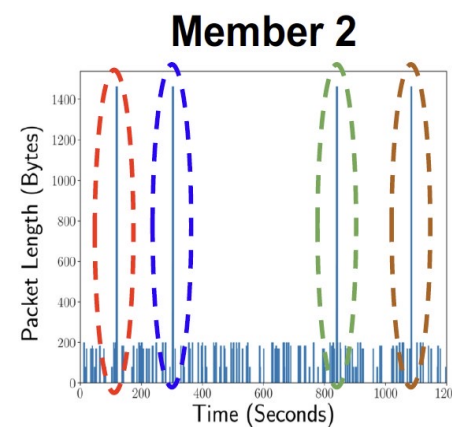
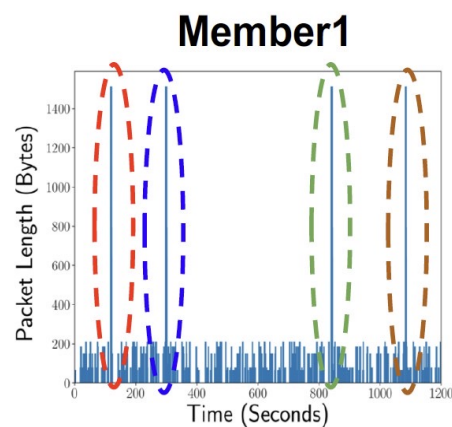
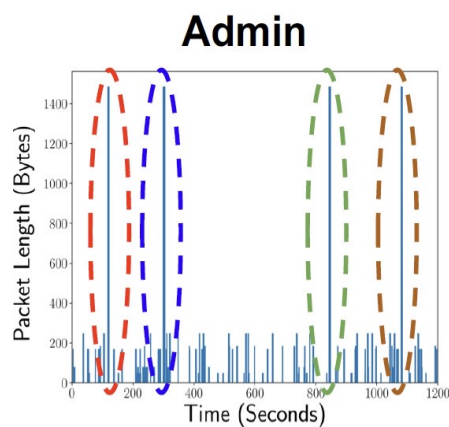
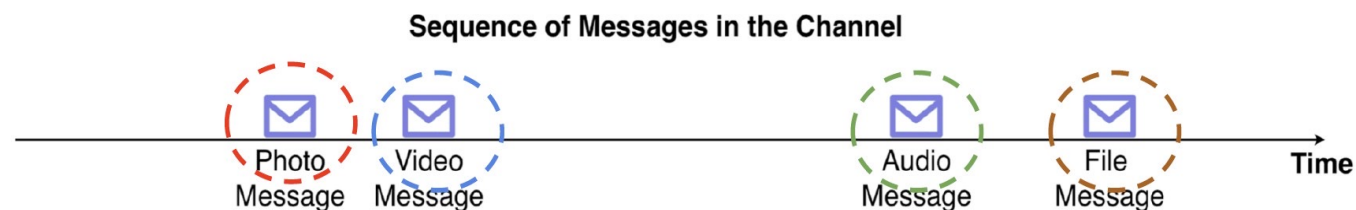
- How can the adversary set up the attack?



Bahramali et al., NDSS '20

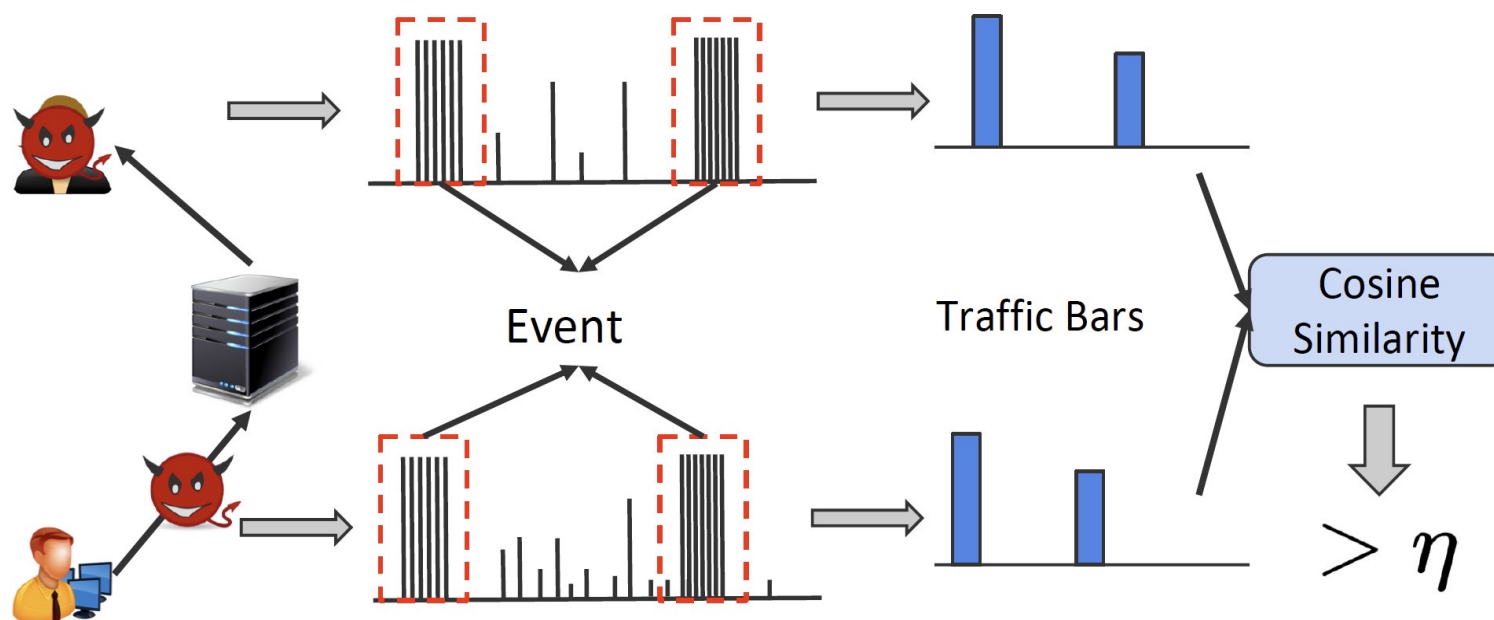
# Looking for messaging events

- Messaging events have different fingerprints



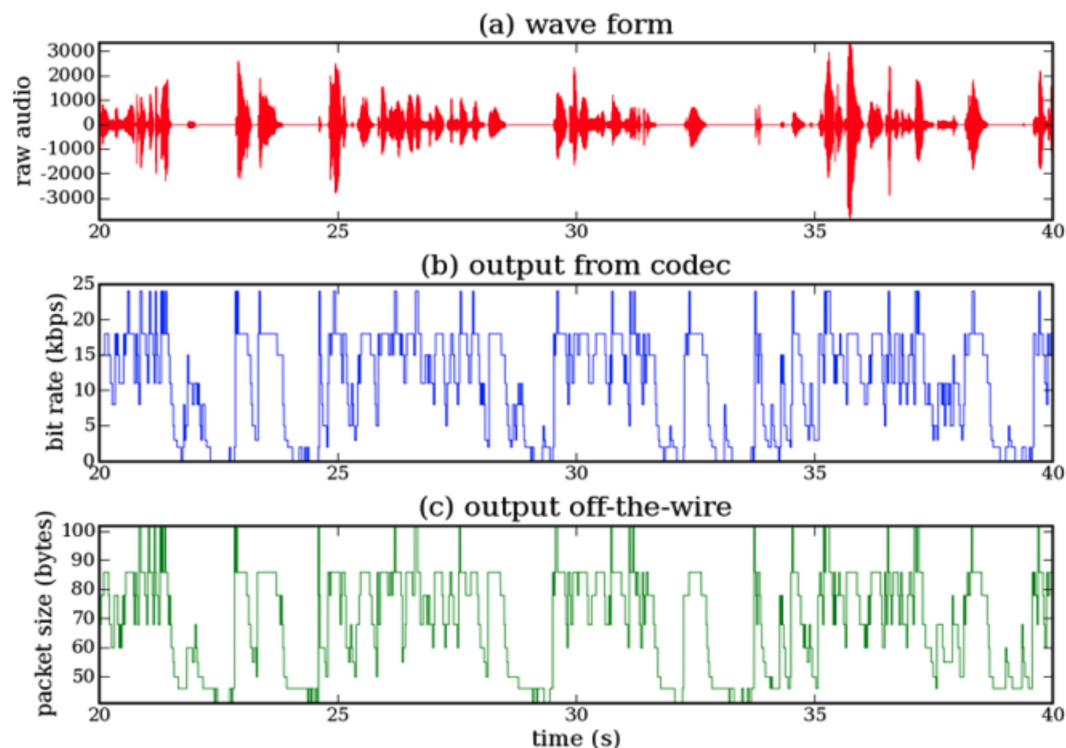
# Matching messaging events fingerprints

- Extract meaningful events and compare similarity
- Attack succeeded against Signal, Telegram, and WhatsApp!



# VoIP eavesdropping

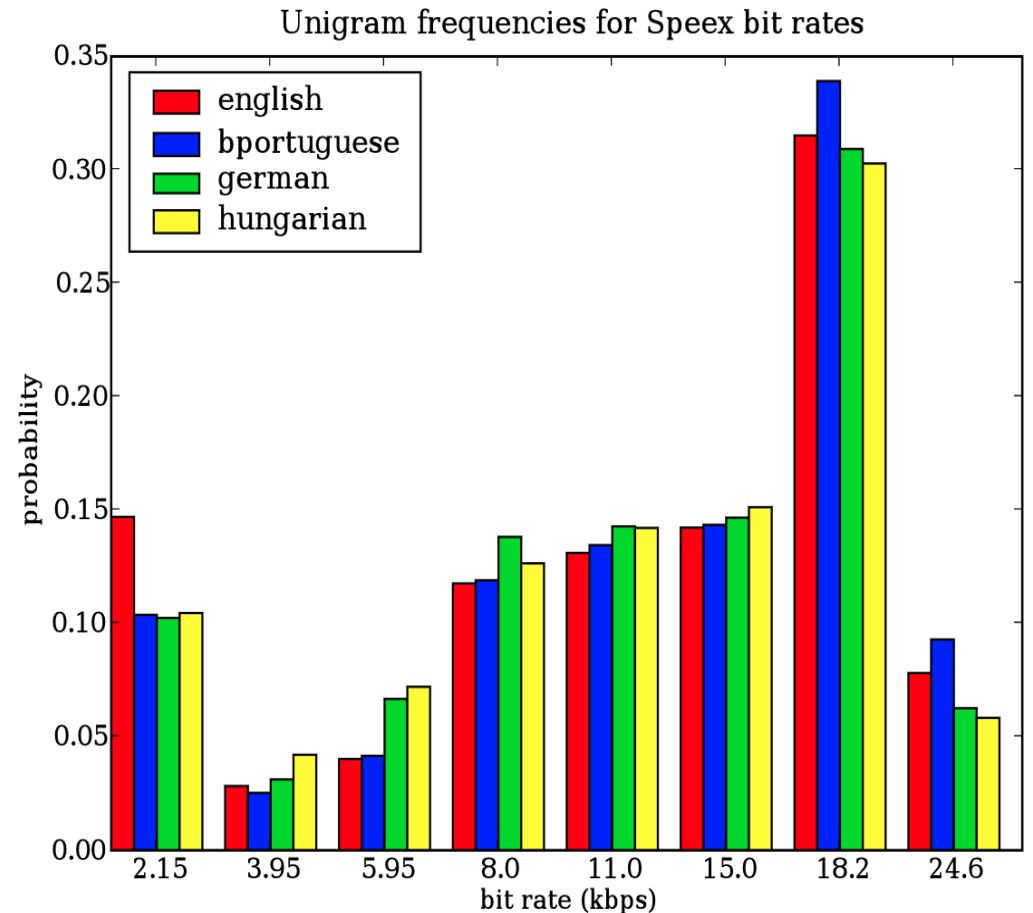
- Encrypted packet patterns resemble VBR codec bitrates
  - Can we infer meaningful semantics from the transmission of encrypted audio frames?



Wright et al., USENIX SEC '07

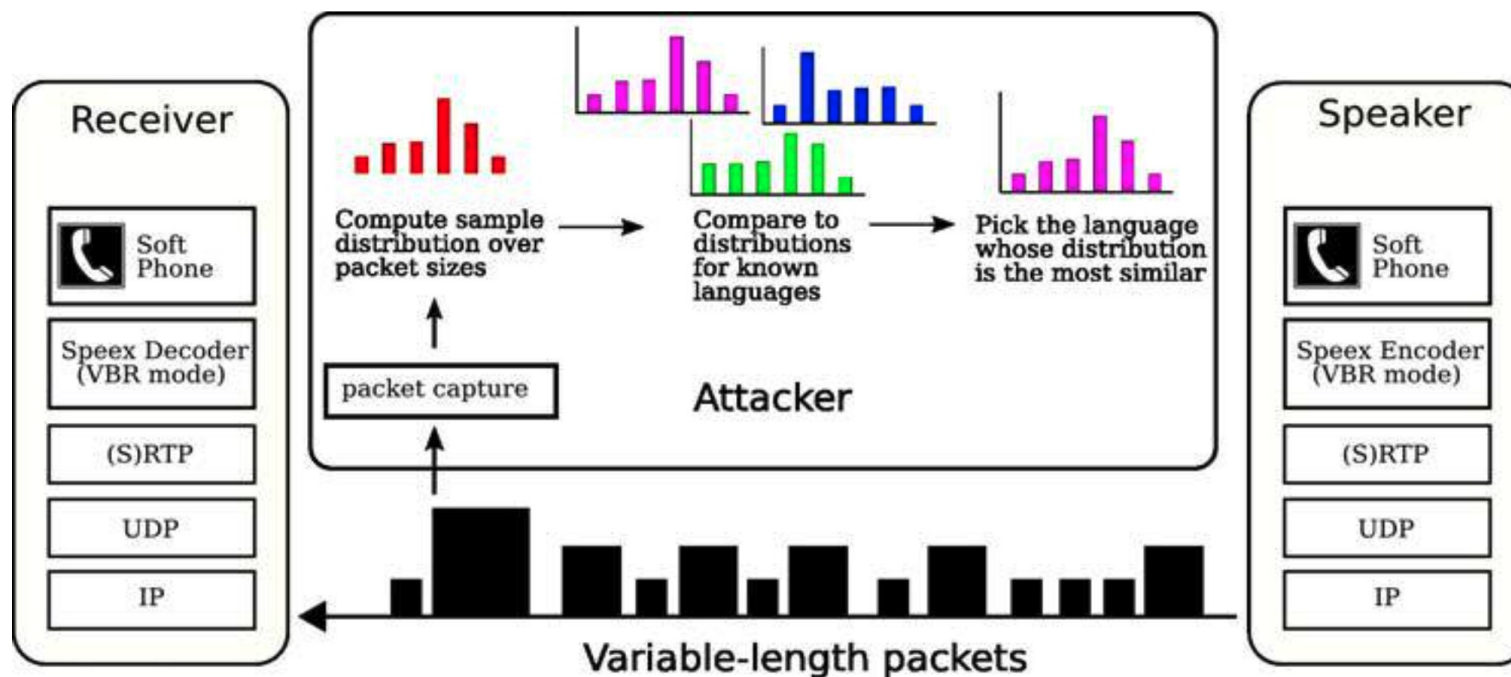
# Noticeable (coarse-grained) differences

- Maybe we can identify the language being spoken?
  - Languages have different bitrate frequencies



# How to distinguish different languages?

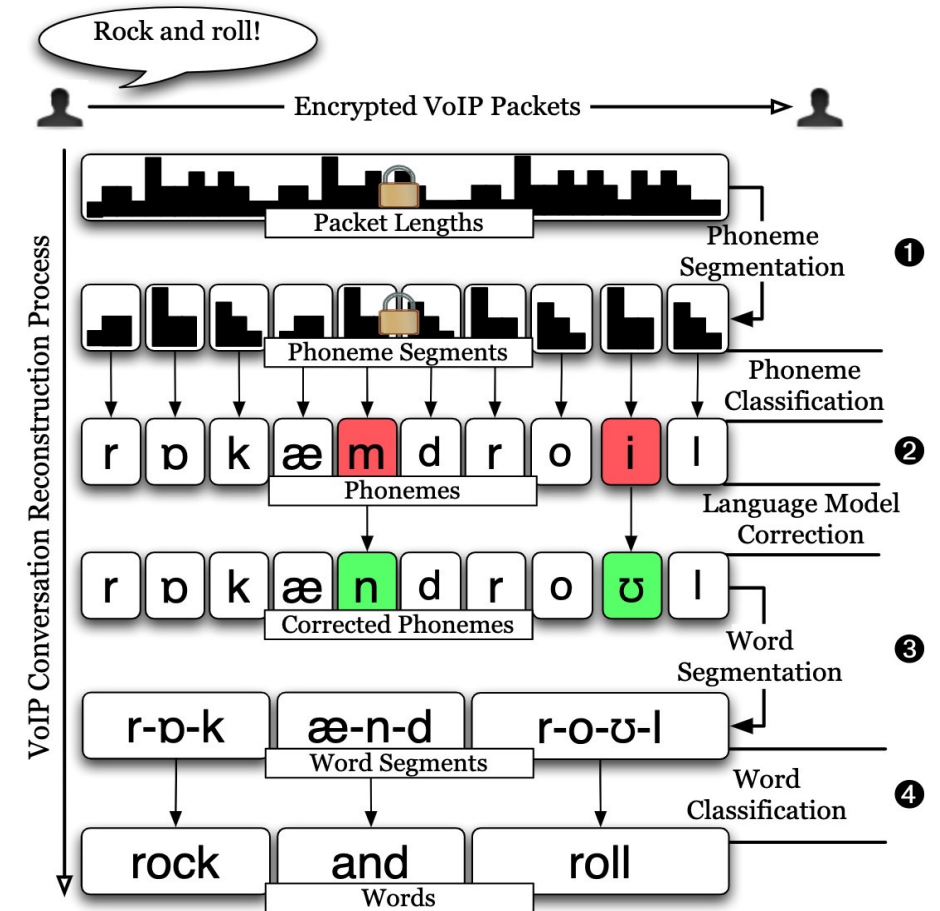
- Compute distance between probability distributions
  - Samples from same language have similar distribution
  - Compute packet size n-grams for even better results
    - Given sequence 10, 20, 30, 15  $\rightarrow \{(10, 20), (20, 30), (30, 15)\}$





# Noticeable (fine-grained) differences

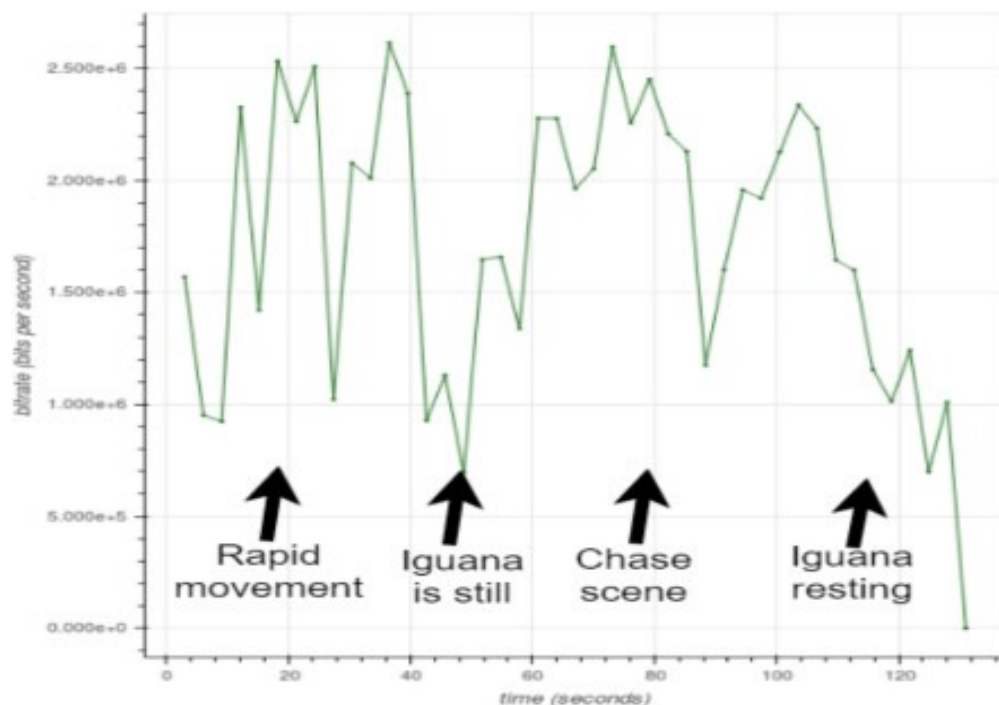
- Can we segment packet size sequences into phonemes?
  - If so, we can recover approximated transcripts





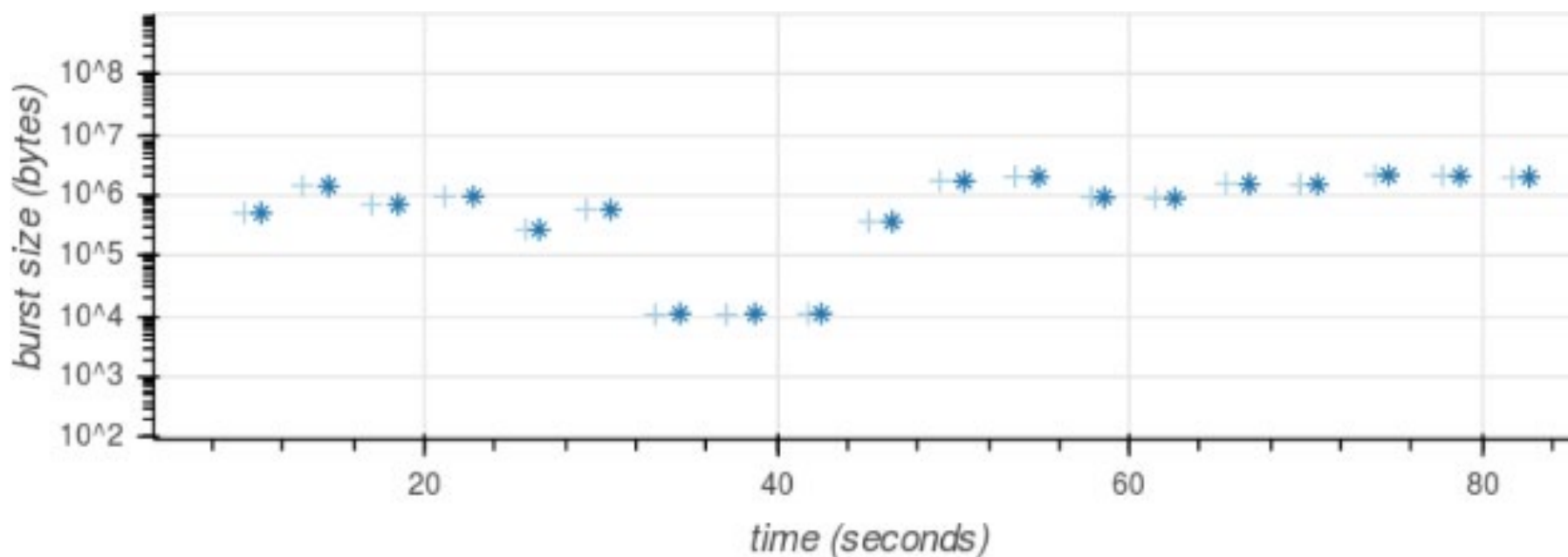
# Video re-identification

- At this point, you've probably guessed it, traffic analysis can also be used to uncover which videos you are streaming
  - The bitrate of VBR video sequences also leaks some information



# Re-identification of Netflix video streaming

- Burst sizes of a streamed scene of “Reservoir Dogs”
  - Very similar, even when watched over different networks



Schuster et al., USENIX SEC '17

# Countermeasures to traffic analysis

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- Introduce padding
- Add chaff traffic
- Shape traffic (look like something)
- Aggregate traffic (e.g, multiplex over single connection)
- Split a single connection across multiple networks
  
- Main trade-off to consider is overhead
  - Achievable throughput
  - Spent bandwidth

Schuster et al., USENIX SEC '17