Information Leakage in Encrypted Network Traffic

Attacks and Countermeasures

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Joint work with:

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- Lucas Ballard (Google)
- Fabian Monrose (UNC)
- Gerald Masson (JHU)

Encrypted Network Traffic

<u>Problem</u>: How do we stop eavesdropping?

Cryptography to the rescue!

Encrypted Network Traffic

- Encrypt the payload contents
- What about features of the network traffic itself?
  - Port numbers, packet sizes, timing info

Network Traffic Features

- Traffic features may introduce a communications channel
  - Like a side-channel attack or covert channel

Source $\xrightarrow{X}$ Feature $\xrightarrow{Y}$ Network $\xrightarrow{Z}$ Observer

Network Traffic Features

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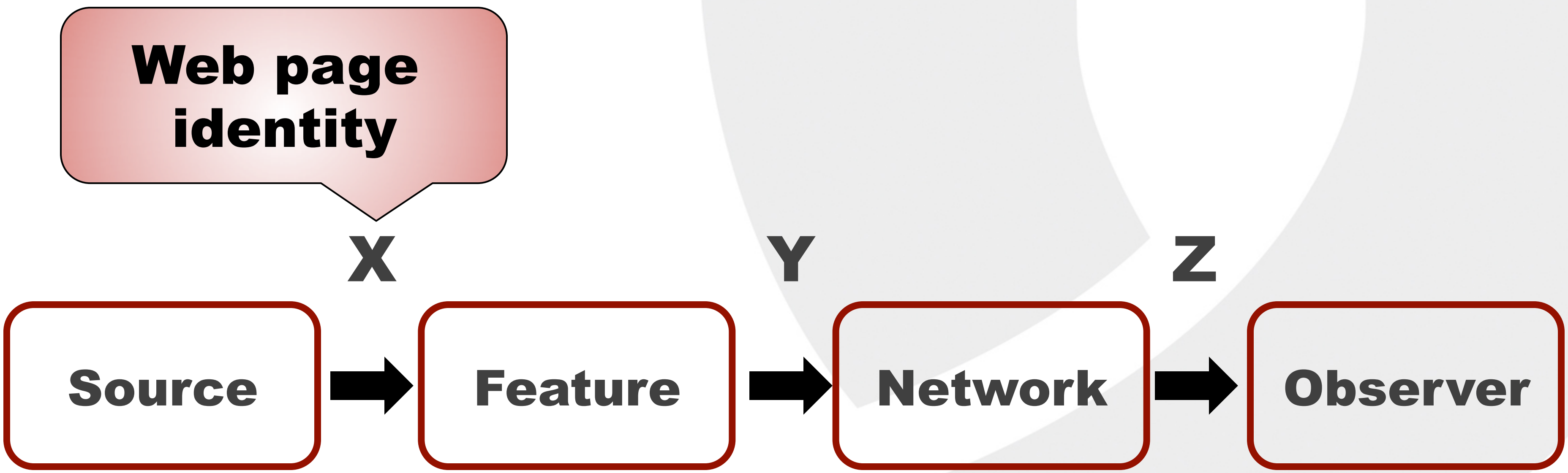
  - Like a side-channel attack or covert channel



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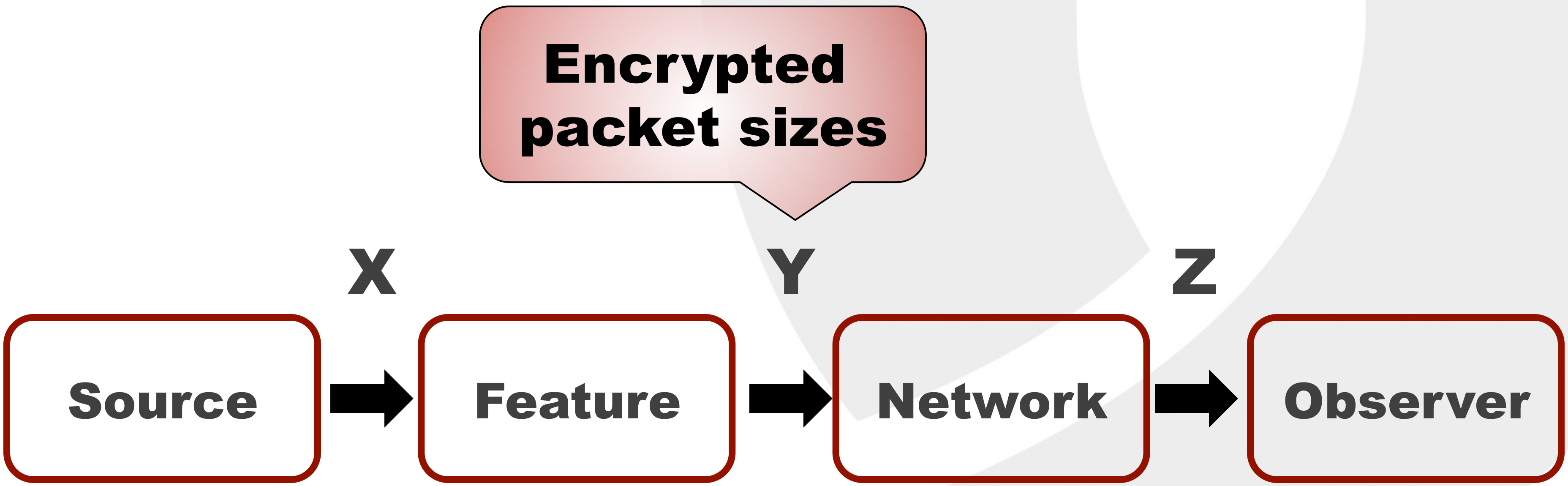

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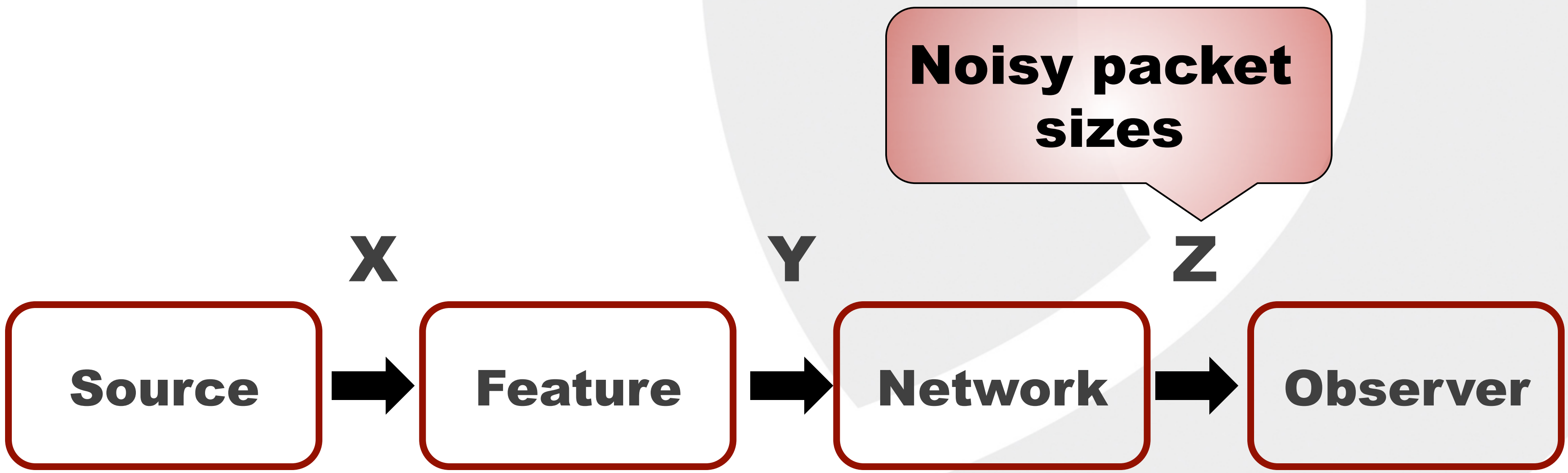


Preventing Information Leakage

- Information theory says we should make the distributions **uniform**
  - Quantize outputs to coarser levels
  - Ex: two vs. ten potential packet sizes
- What about performance?
  - Padding VoIP can introduce >42% overhead!!
  - Padding to 1500 bytes induces up to 150% overhead for HTTP!!

Implementation Problems

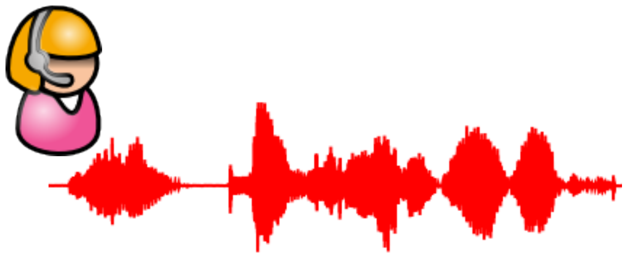
- Performance almost always wins over security for consumer implementations
- Results in attacks that infer contents of encrypted network traffic
  - Login passwords for SSH → packet timing
  - Web page identities for SSL/TLS → packet size
  - Language and phrases for VoIP → packet size

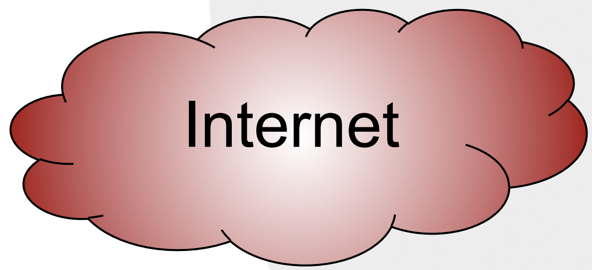
Overview

- Illustrate potential privacy problems introduced by network traffic features:
  - Uncovering Spoken Phrases in Encrypted Voice over IP Conversations
- Present efficient countermeasure by moving from information theoretic model:
  - Traffic Morphing: An Efficient Defense Against Statistical Traffic Analysis

How Does VoIP Work?

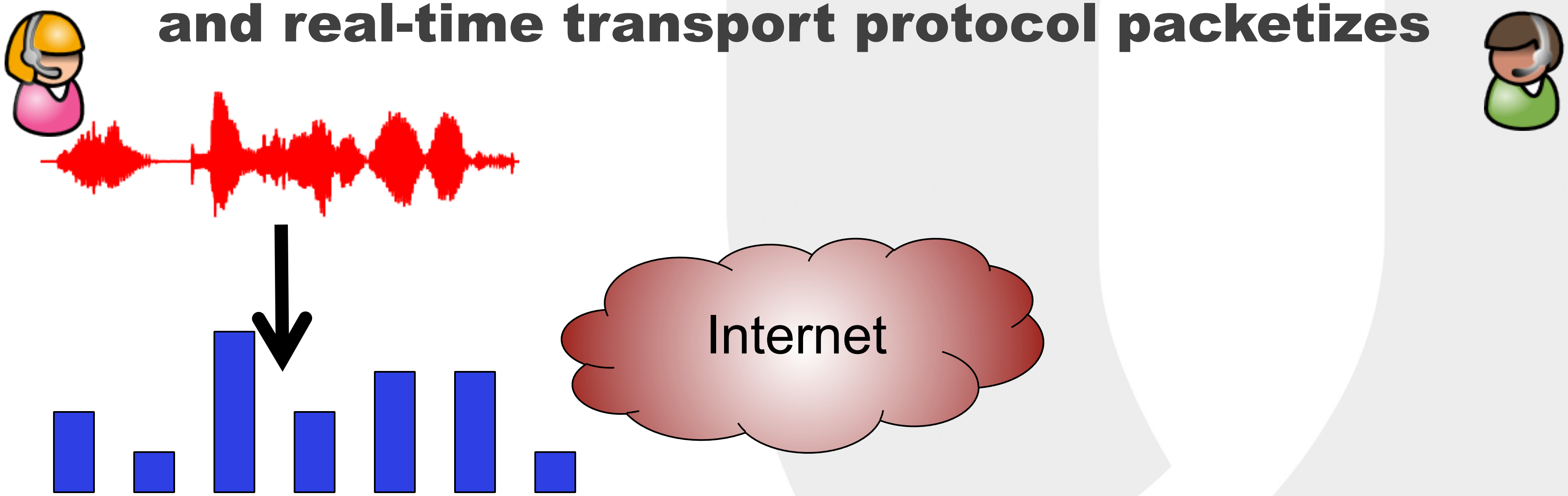
Alice speaks into her microphone to produce an audio waveform





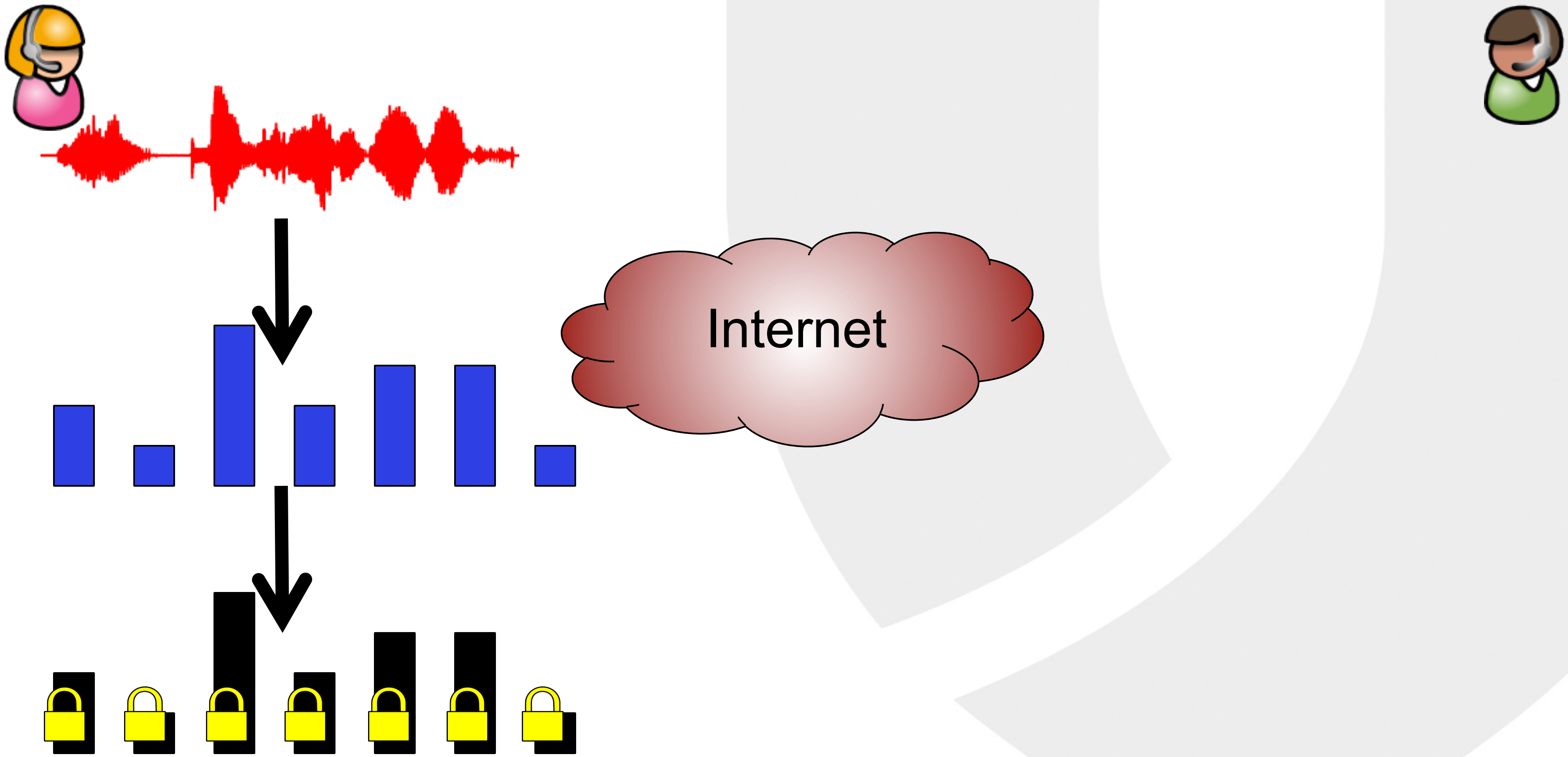
How Does VoIP Work?

Variable Bit-Rate audio codec compresses waveform and real-time transport protocol packetizes



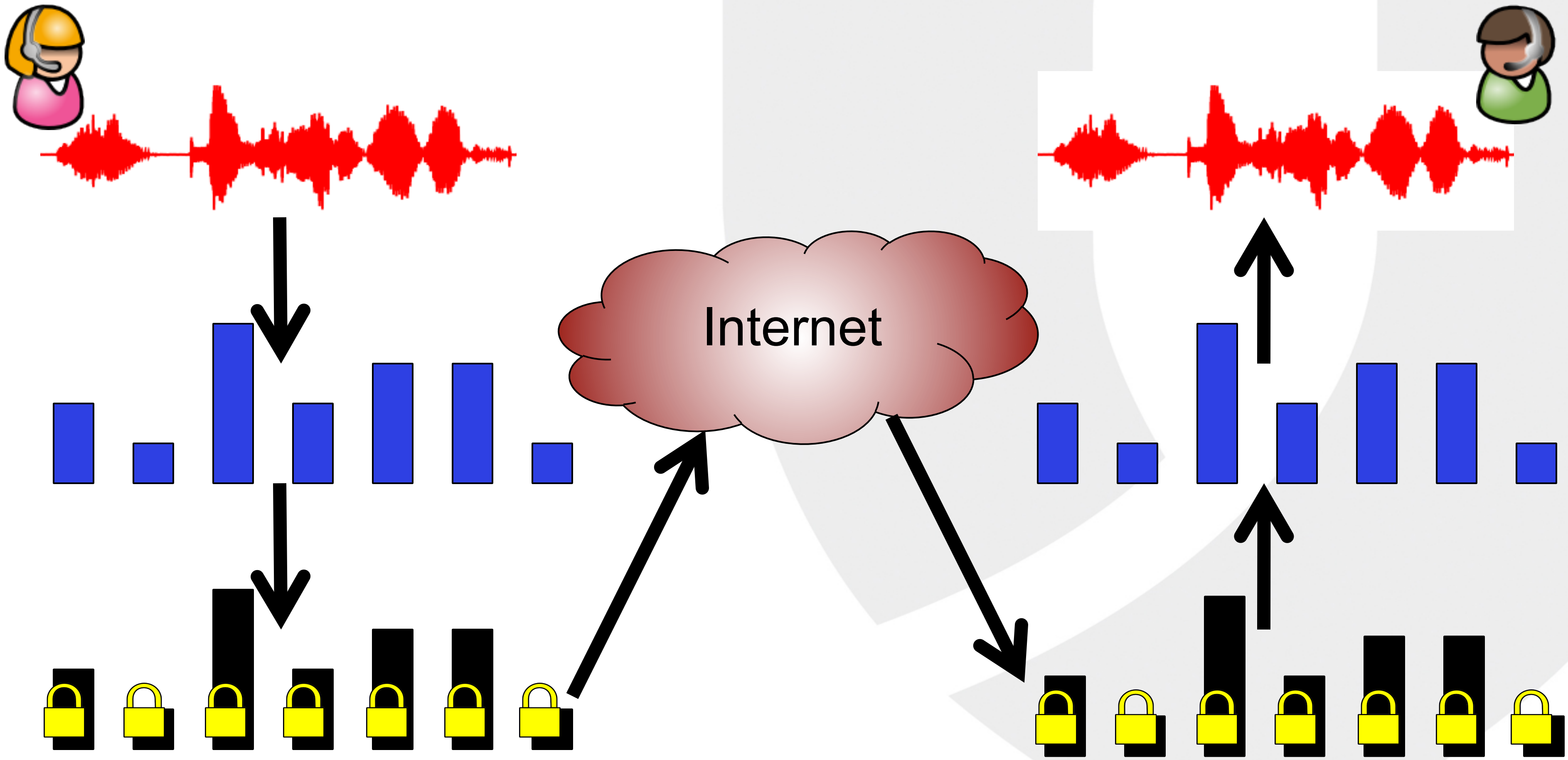
How Does VoIP Work?

Stream cipher used to efficiently encrypt packets



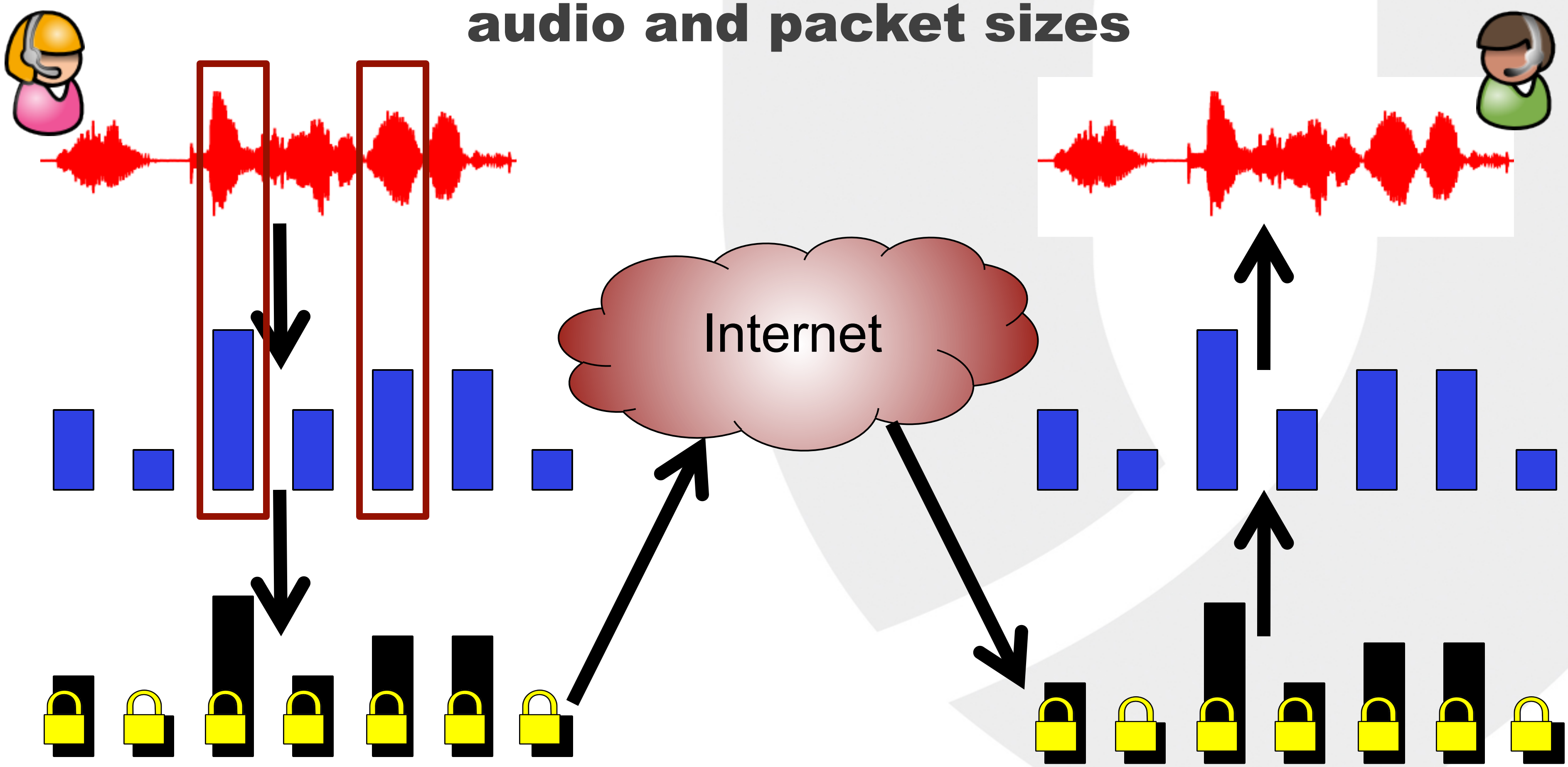
How Does VoIP Work?

Packets sent over IP network and decoded



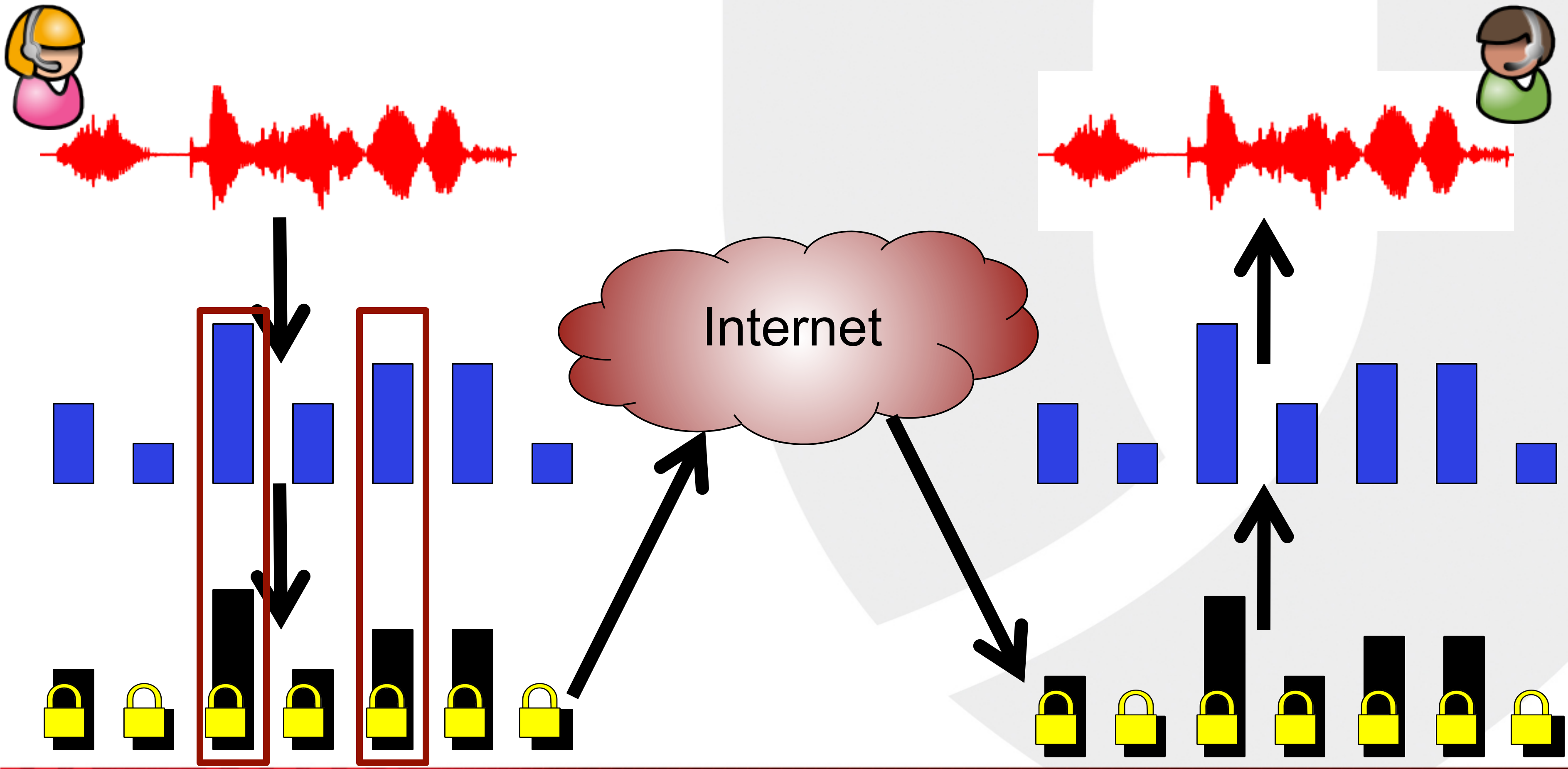
Attack Intuition

Variable Bit-Rate **codec allows correlation between audio and packet sizes**



Attack Intuition

Length-preserving **stream cipher keeps correlation**



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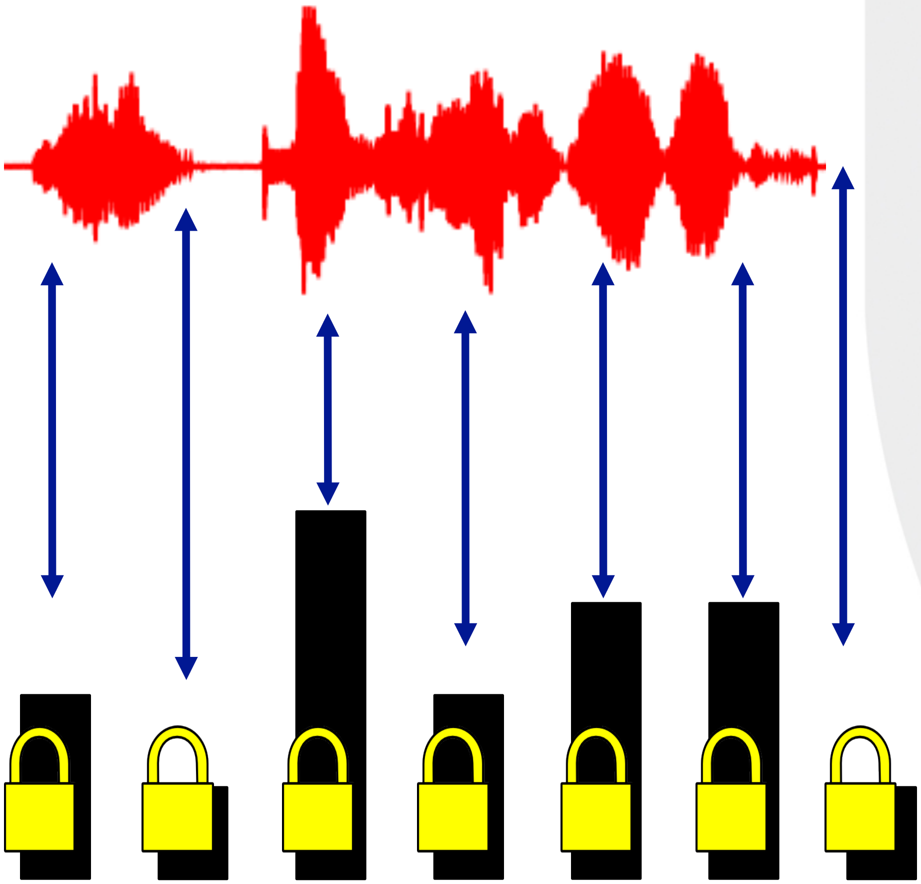
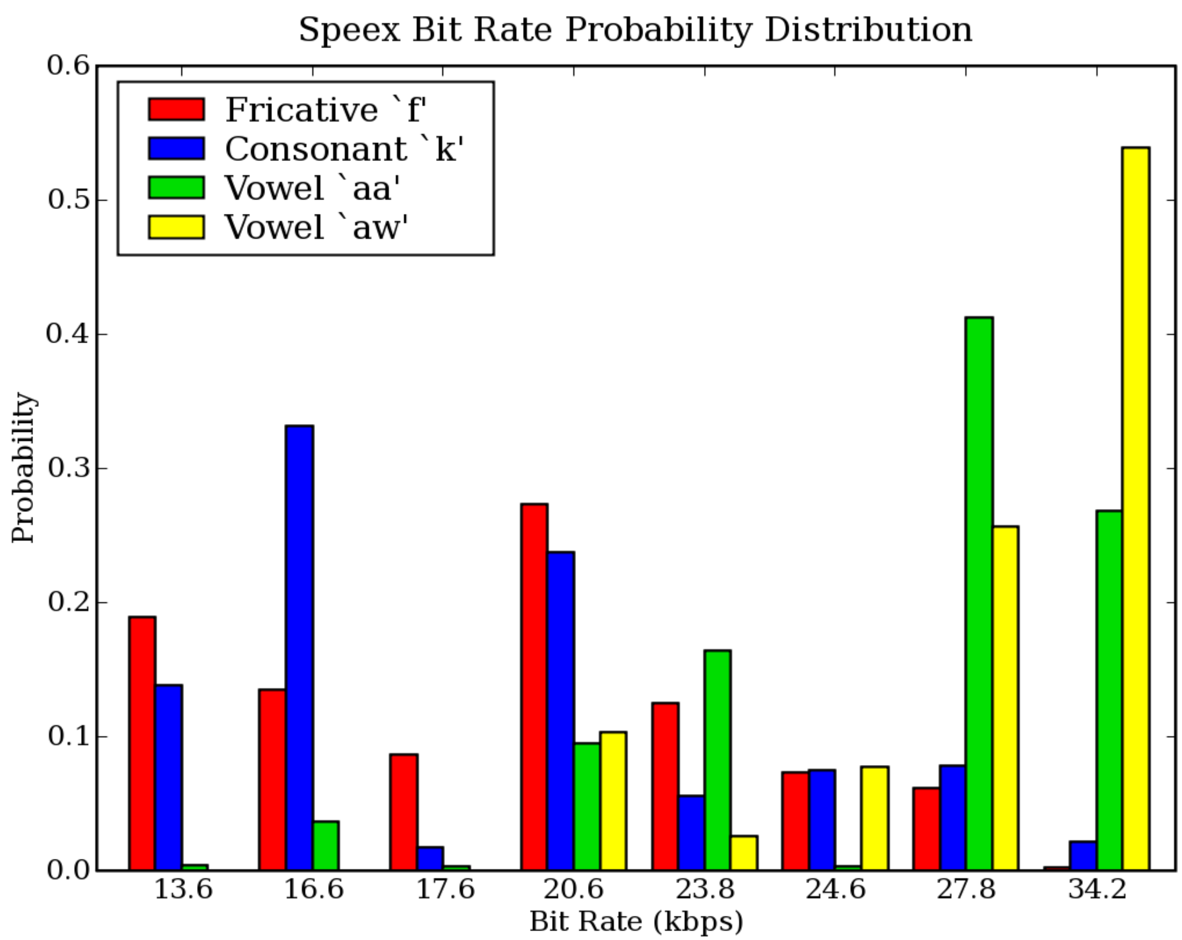


Packet sizes carry information about the original audio

Original audio is made up of the building blocks of language called phonemes

Attack Intuition



Phrase Spotting

- How do we use the correlation between packet size and audio?
  - Build a **statistical model** for the sequence of packet sizes in phrase
  - Use the model to detect when a phrase of interest has occurred

- Known as **phrase spotting**

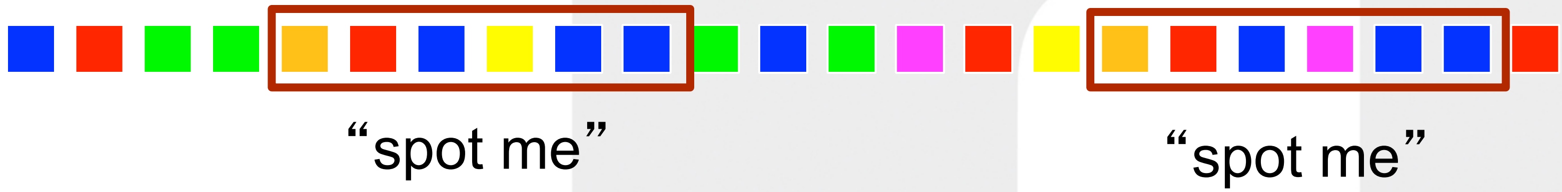
Phrase Spotting

Packets: 

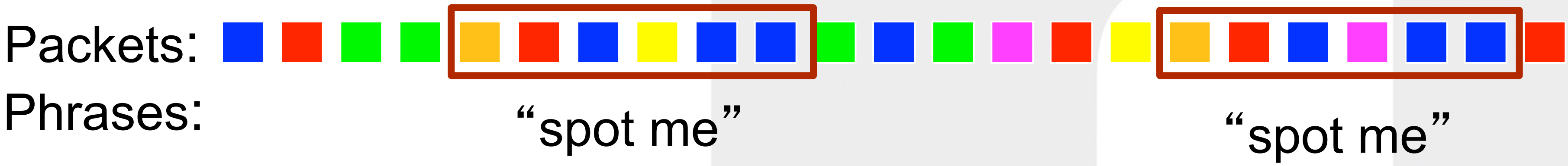
Phrase Spotting

Packets:

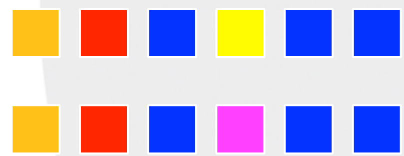
Phrases:



Phrase Spotting



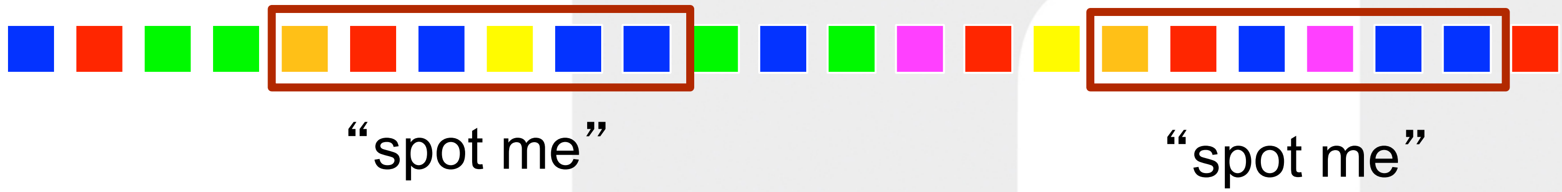
Extract Training Data



Phrase Spotting

Packets:

Phrases:



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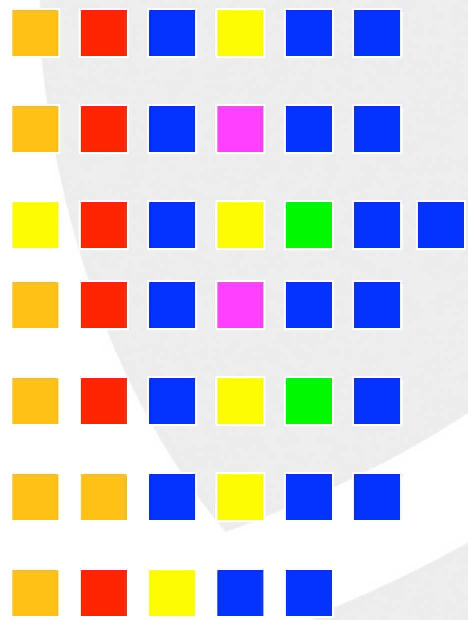

Phrase Spotting

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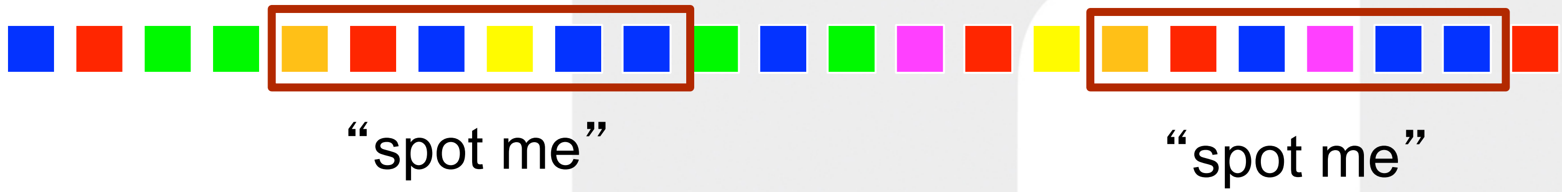
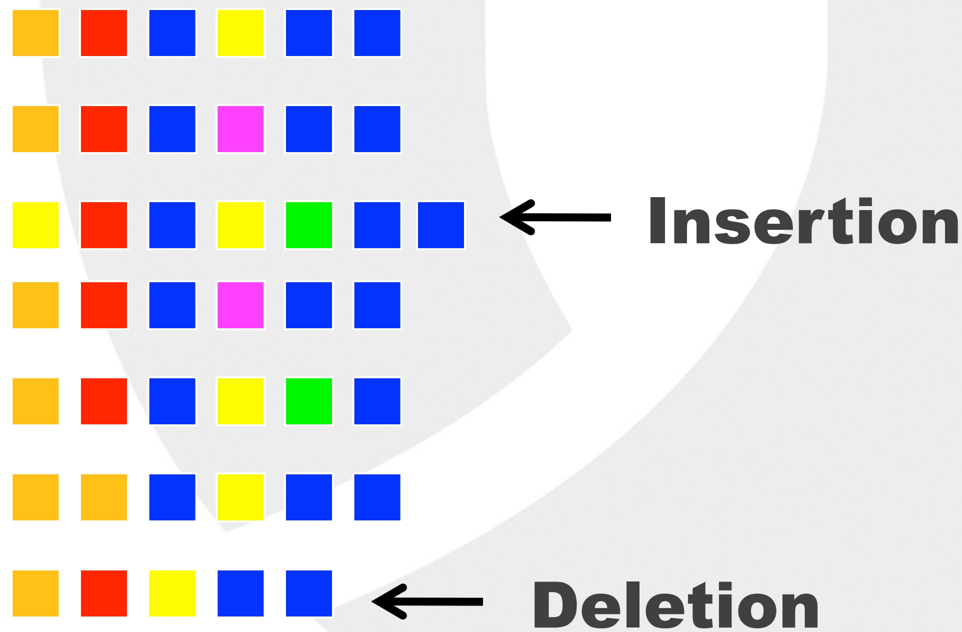
Packets:

Phrases:



Multiple Sequence Alignment



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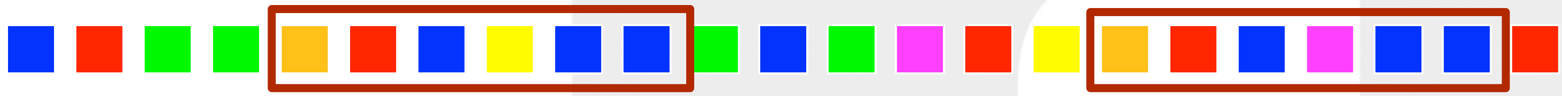
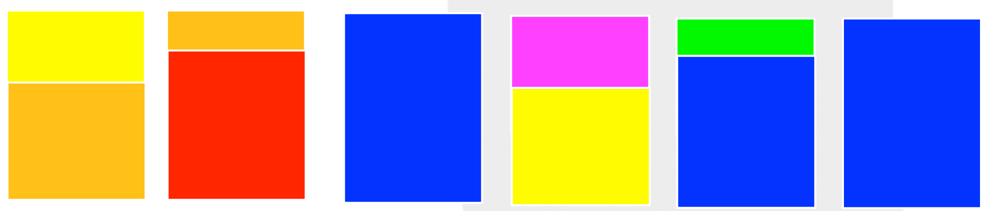
Packets: 

Phrases: “spot me” “spot me”



Aligned columns known as the consensus sequence for the phrase

Represented with a Profile Hidden Markov Model (HMM)

Synthesizing Training Data

- How do we train our phrase HMM without speaker-specific data?
- What if we do not have examples of the phrase we are looking for?
- Use **concatenative synthesis**!
  - Break phrase pronunciation into phonemes
  - Concatenate available phonemes together

Synthesizing Training Data

1. Split phrase into words

the bike is red

Synthesizing Training Data

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2. Break words into phonemes

   dh ah   b ay k   ih z   r eh d

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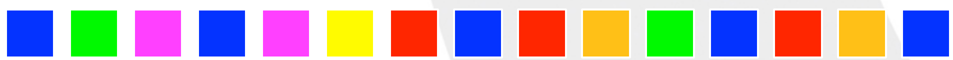

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   the bike is red

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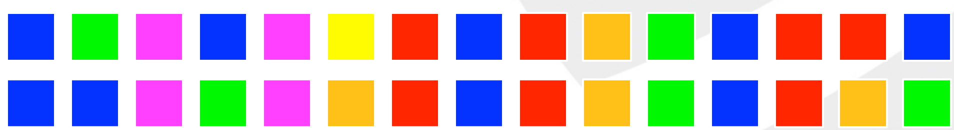
3. Replace phonemes with packet sizes

4. Repeat to capture variations in speech



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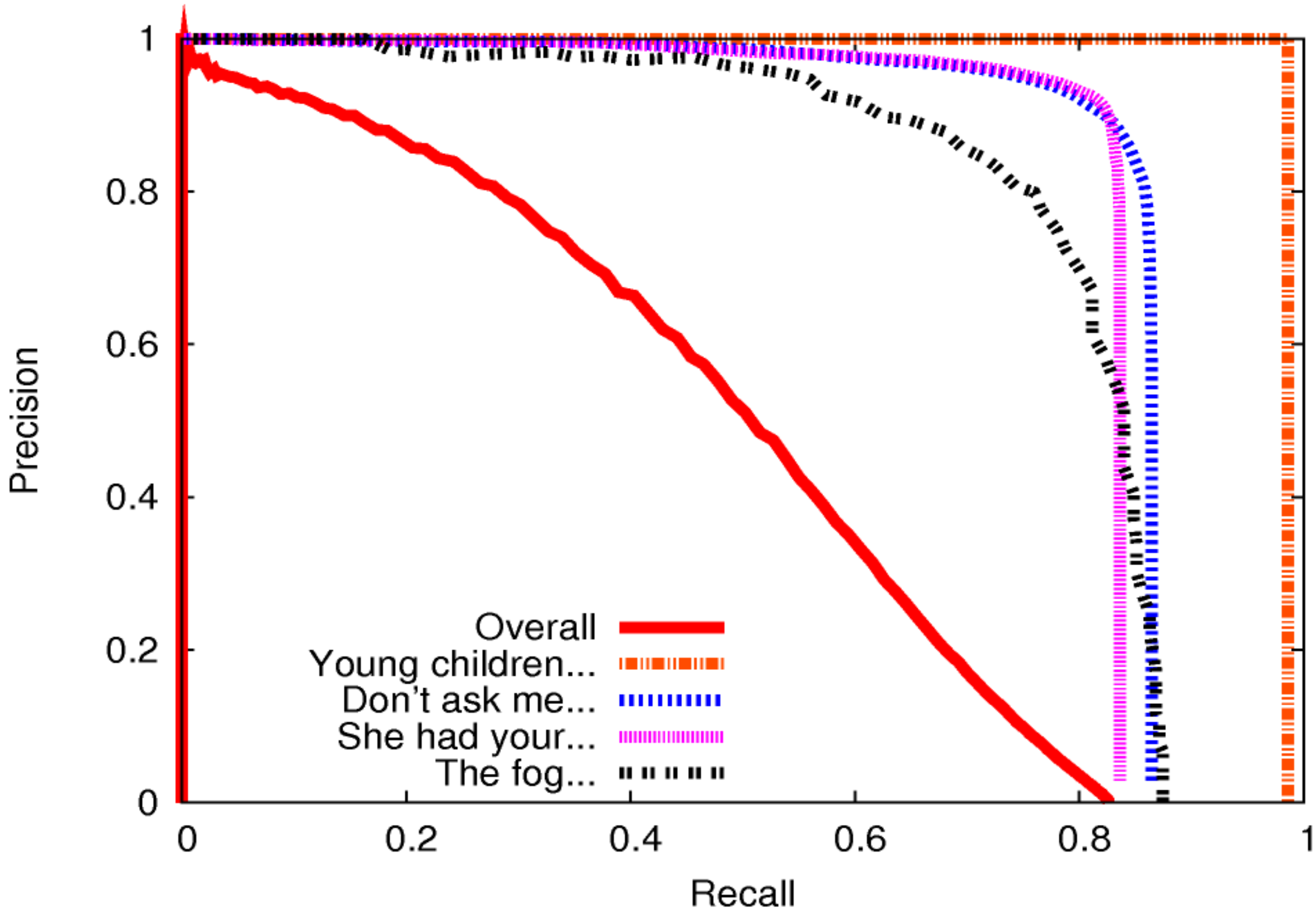
Evaluation

- **TIMIT Dataset:**
  - 462 training speakers, 168 testing speakers
  - 122 distinct phrases
  - Diverse set of dialects, pronunciations, etc.
- **Use information retrieval metrics:**
  - Recall = TP / (TP+FN)
  - Precision = TP / (TP+FP)

Results



Precision
Recall
1
0.8
0.6
0.4
0.2
0
0
0.2
0.4
0.6
0.8
1
Overall
Young children...
Don't ask me...
She had your...
The fog...

Results

- Method is **robust** to variations in the audio
  - Noise
  - Gender
  - Dialect
  - Wide-band vs. Narrow-band
- Surprising amount of information leakage from encrypted VoIP traffic
  - More recent work produces transcripts

Countermeasures

- Padding can be effective for some types of information, but not others
- Can we do better?

Protocol	Leaked Info.	Block Size	Accuracy	Overhead
VoIP	Phrases	256-bit	0.4%	16.5%
	Language	512-bit	6.9%	42.2%
HTTP	Web Pages	1500 bytes	35.9%	140.8%

Traffic Morphing

- What if we could **morph** one class of traffic to look like another?
  - Ex: Farsi appears to be English
- Use **convex optimization** to stochastically change packet sizes to:
  - Minimize overhead
  - Ensure distribution “looks” like the target

How to Morph Traffic

Source Distribution

(Packet Sizes for Farsi)

$$X = \begin{bmatrix} x_1 \\ x_2 \\ \dots \\ x_n \end{bmatrix}$$

Target Distribution

(Packet Sizes for English)

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{bmatrix}$$

How to Morph Traffic

Find morphing matrix A such that:

$$\begin{bmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ & & \dots & \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \dots \\ x_n \end{bmatrix}$$

How to Morph Traffic

Treat each column as a probability distribution for morphing source packet size s_j to target

$$\begin{bmatrix} y_1 \\ y_2 \\ \cdots \\ y_n \end{bmatrix} = \begin{bmatrix} a_{11} & \boxed{a_{12}} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ & & \cdots & \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \cdots \\ x_n \end{bmatrix}$$

$$a_{ij} = \Pr[Y=s_i \mid X=s_j]$$

How to Morph Traffic

- Underspecified system of equations:
  - n^2 unknowns and 2n equations
  - Infinitely many solutions
- Choose one that minimizes the cost:

$$
\begin{array}{lll}
\text{minimize} & f_0(A) & \\
\text{subject to} & \sum_{j=1}^{n} a_{ij} x_j = y_i, & \forall i \in [1, n] \\
 & \sum_{i=1}^{n} a_{ij} = 1, & \forall j \in [1, n] \\
 & a_{ij} \geq 0, & \forall i, j \in [1, n]
\end{array}
$$

How to Morph Traffic

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Overhead

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\end{array}
$$

How to Morph Traffic

- To morph source packet with size s_j:
  - Find j^{th} column of morphing matrix A
  - Sample from column according to distribution
  - Alter packet size to match sampled size s_i

$$\begin{bmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ & & \dots & \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \dots \\ x_n \end{bmatrix}$$

Real-world Challenges

- Many issues arise in the real-world:
  - Reducing packet sizes?
  - Large sample spaces?
  - Slight changes in distribution?
  - Not enough packets?

VoIP Morphing Results

- Apply morphing to VoIP language identification work of Wright et al.
  - Nearest-neighbor classifier
  - n-gram distributions of packet sizes
  - Can the classifier distinguish morphed from real?

Strategy	Overhead	Bigram Accuracy
No Padding	0.0%	71%
512-bit Padding	42.2%	50%
Morphing	15.4%	54%

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VoIP Morphing Results

- Morpher must be at least as **"powerful"** as the classifier to reduce accuracy
  - Trigram classifier beats bigram morphing
  - ...but we can make a trigram morpher...

Strategy	Bigram Accuracy	Trigram Accuracy
No Padding	71%	76%
512-bit Padding	50%	50%
Morphing	54%	76%

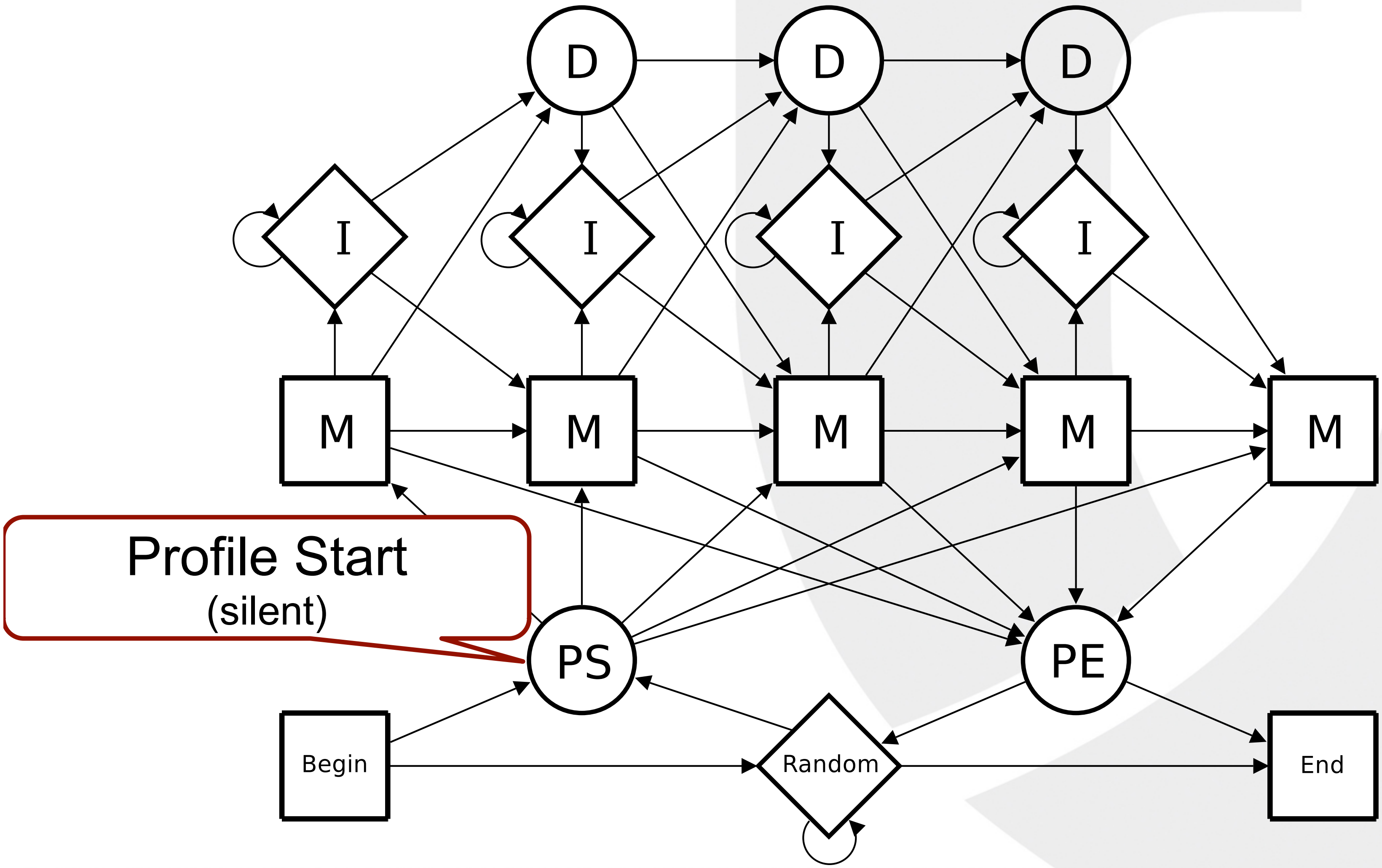
Open Questions

- How do we determine security of morphing-like countermeasures?
  - No obvious proof since we are not working in an information theoretic model
- Is there a way to tell if a classifier can ever win?
  - Certain natural limitations and costs may prevent morphing in some scenarios
  - Ex: Cannot buffer packets indefinitely

Summary

- Most users assume contents are secure with well-known cryptographic protocols
- Performance considerations lead to information leakage from traffic features
- Explored security/performance trade-off:
  - Phrase spotting in encrypted VoIP
  - Countermeasures using traffic morphing

Search Hidden Markov Model



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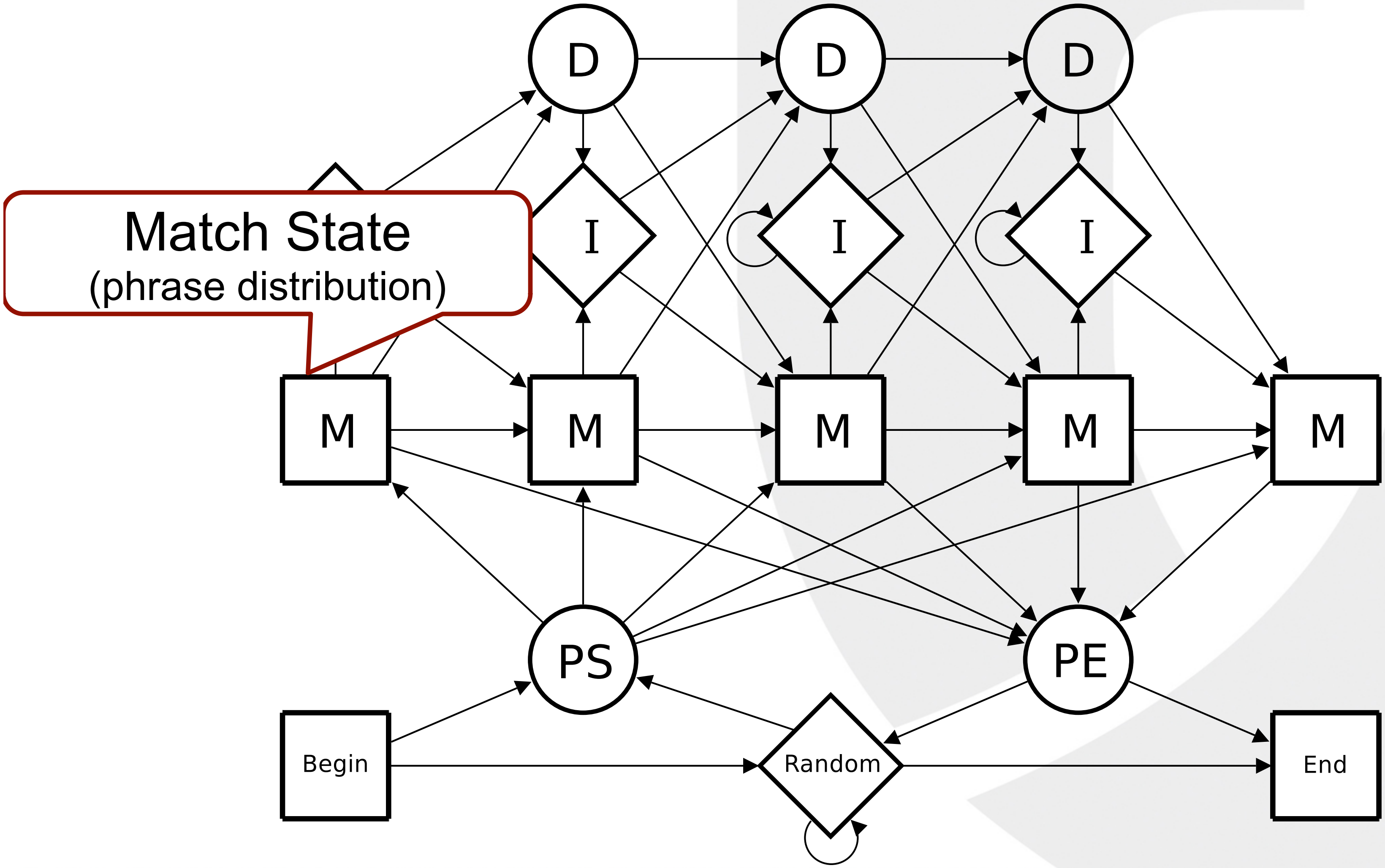

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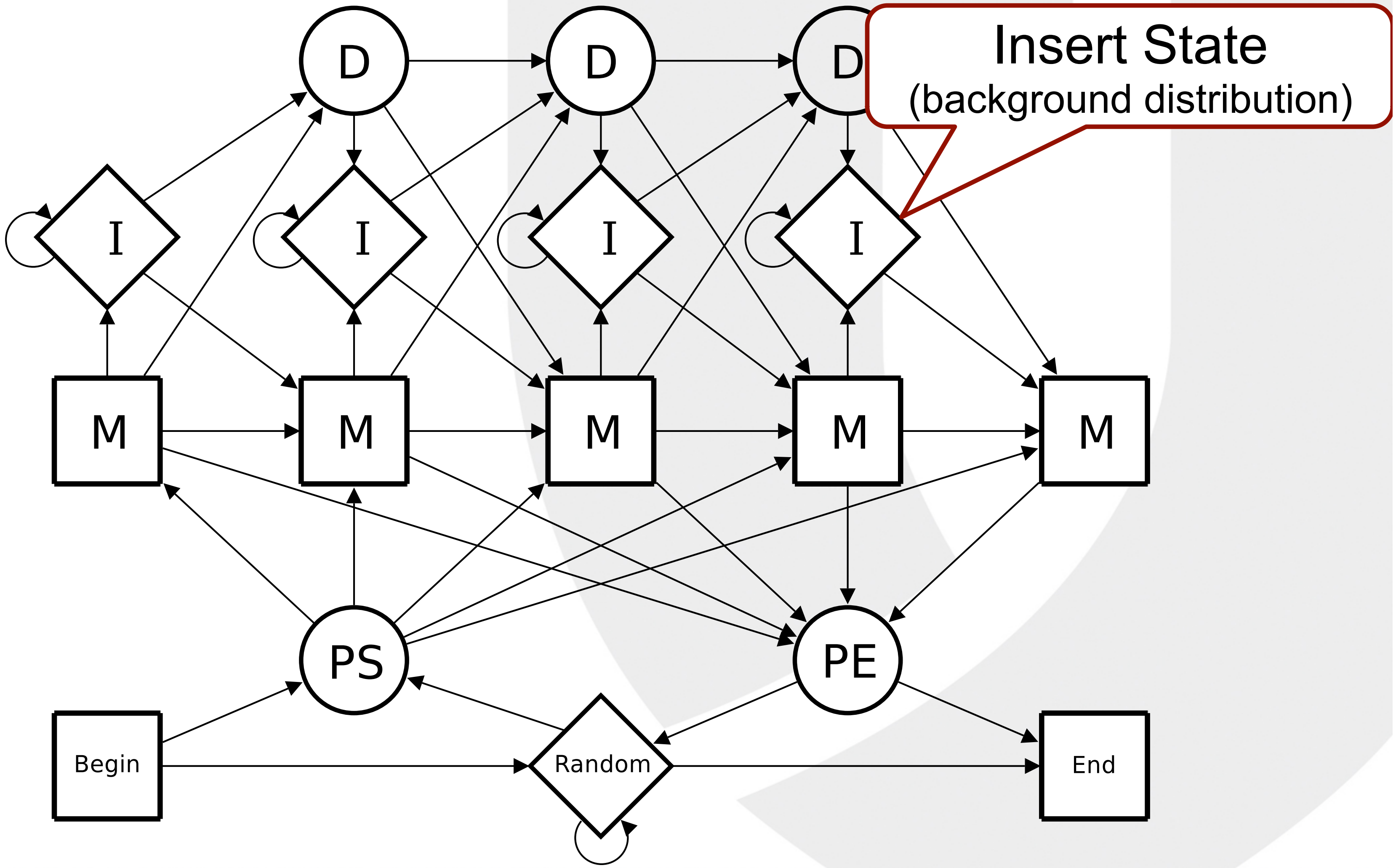

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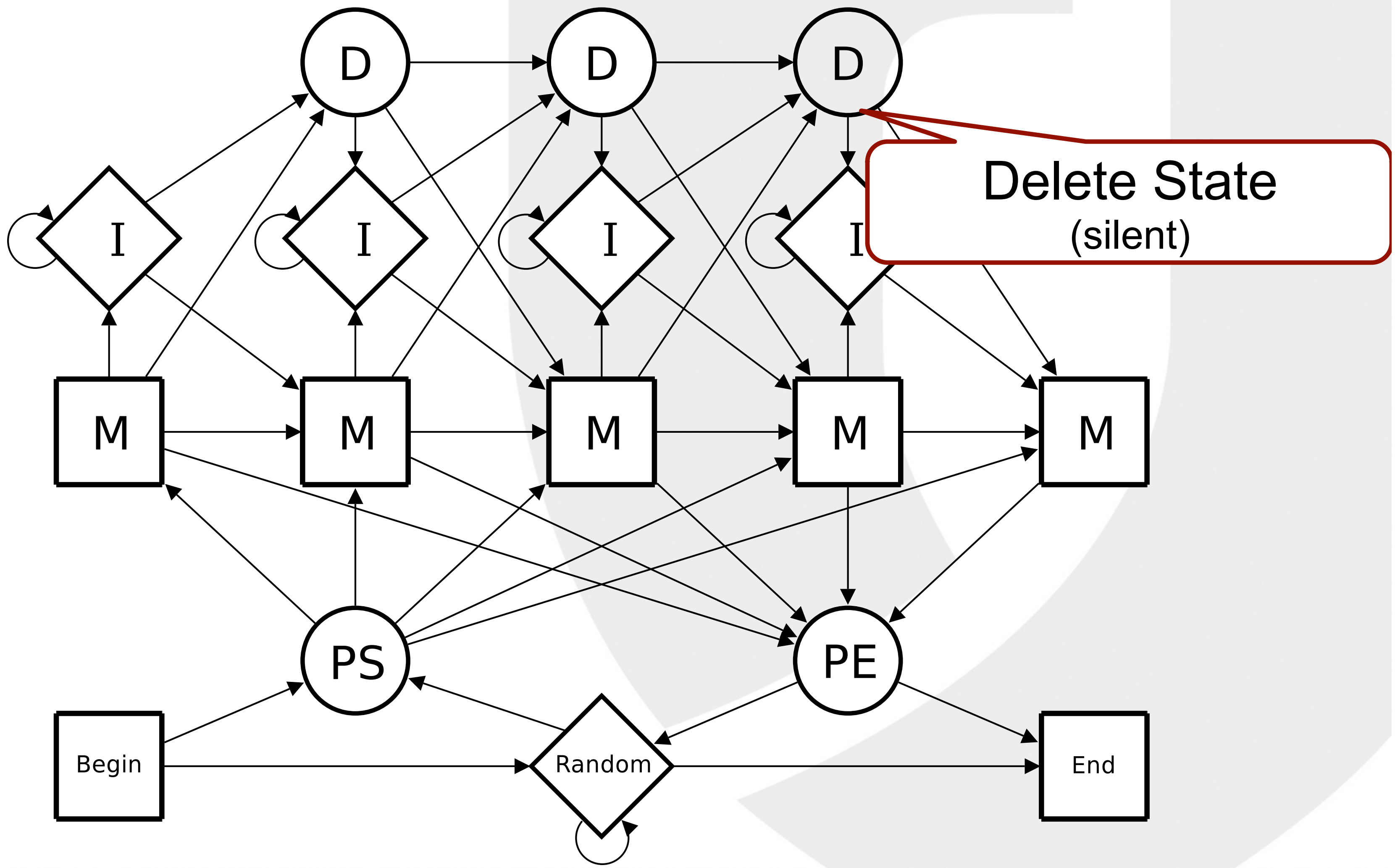

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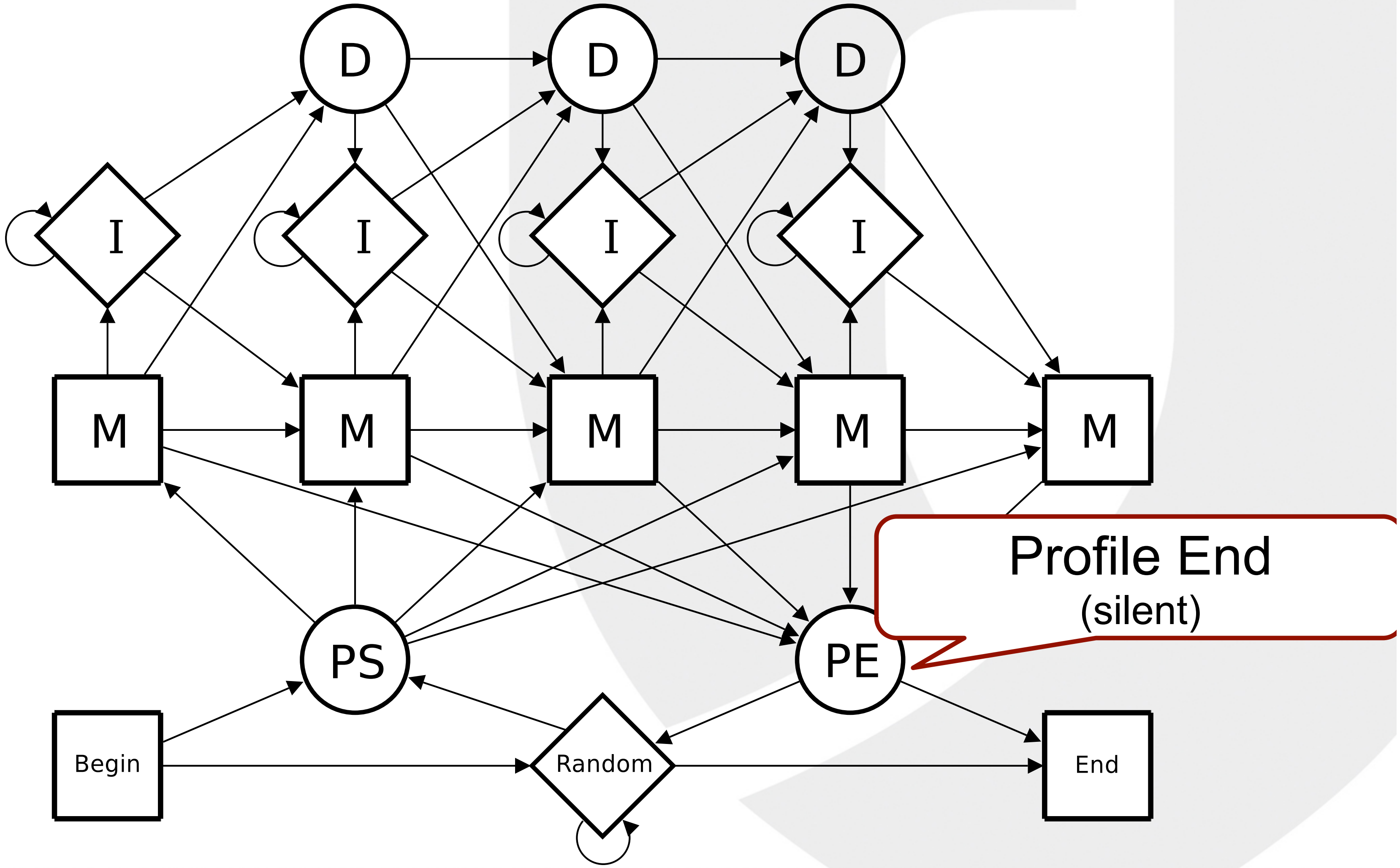

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