Feature Selection in Website Fingerprinting

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Advisor: Prof. Jasleen Kaur
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Website Fingerprinting

Goal: determine the visited website by inspecting network traffic on client side

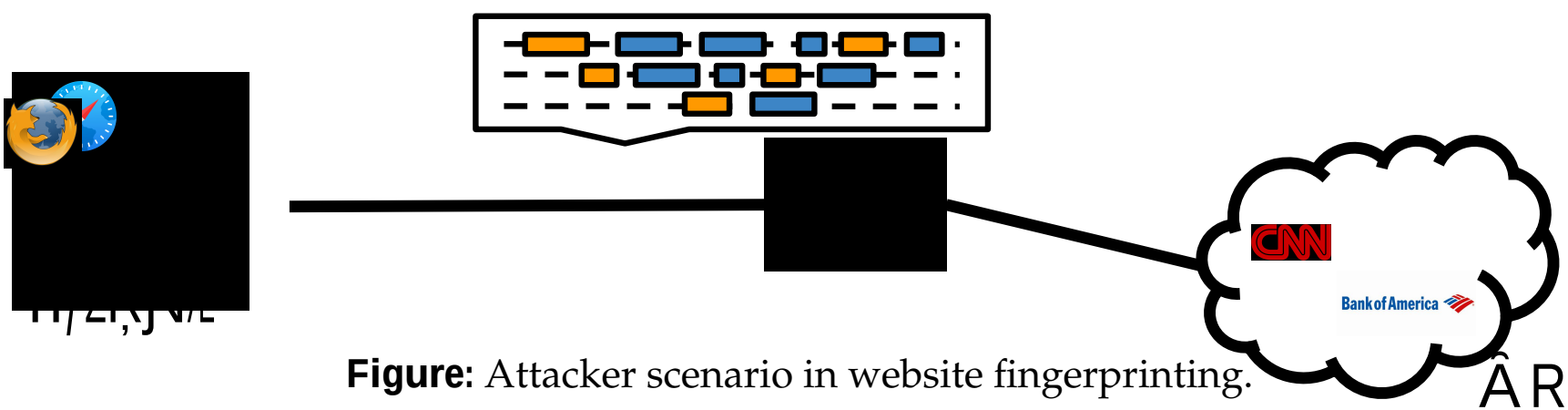

Figure: Attacker scenario in website fingerprinting.

Website Fingerprinting

Goal: determine the visited website by inspecting network traffic on client side

Application:

network manager: protect enterprise networks

Internet Service Providers: gauge user interests

malicious entities: exploit private user data

... ...

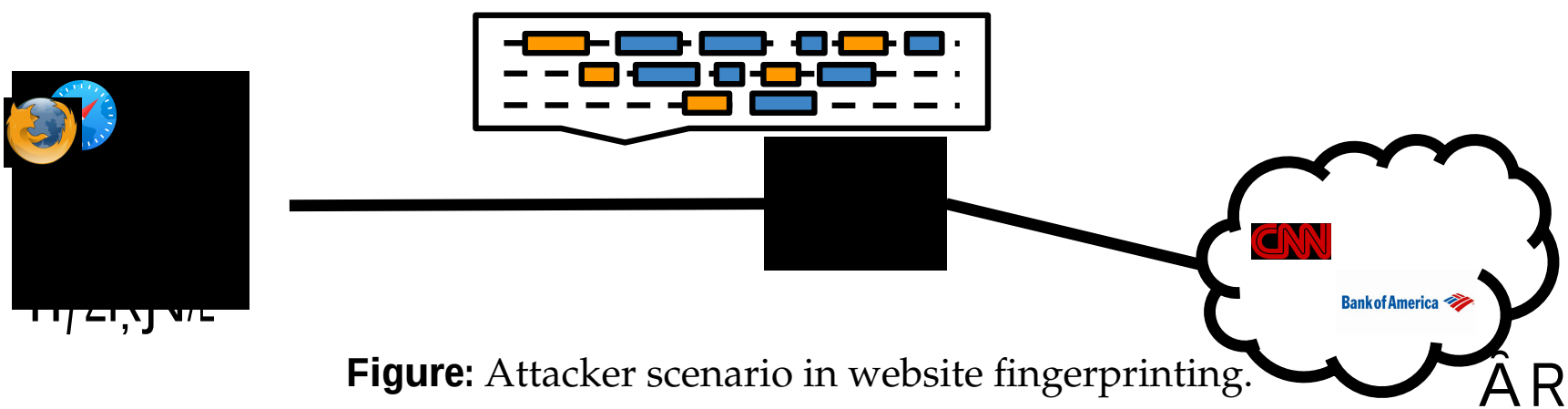

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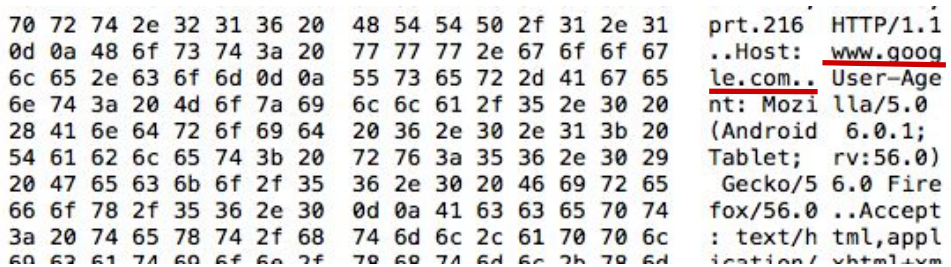
Figure: IP Packet

Figure: Attacker scenario in website fingerprinting.

Website Fingerprinting Methodology

1. Deep Packet Inspection



```
70 72 74 2e 32 31 36 20  48 54 54 50 2f 31 2e 31   prt.216 HTTP/1.1
0d 0a 48 6f 73 74 3a 20  77 77 77 2e 67 6f 6f 67   ..Host: www.goog
6c 65 2e 63 6f 6d 0d 0a  55 73 65 72 2d 41 67 65   le.com.. User-Age
6e 74 3a 20 4d 6f 7a 69  6c 6c 61 2f 35 2e 30 20   nt: Mozi lla/5.0
28 41 6e 64 72 6f 69 64  20 36 2e 30 2e 31 3b 20   (Android  6.0.1;
54 61 62 6c 65 74 3b 20  72 76 3a 35 36 2e 30 29   Tablet;  rv:56.0)
20 47 65 63 6b 6f 2f 35  36 2e 30 20 46 69 72 65    Gecko/5 6.0 Fire
66 6f 78 2f 35 36 2e 30  0d 0a 41 63 63 65 70 74   fox/56.0 ..Accept
3a 20 74 65 78 74 2f 68  74 6d 6c 2c 61 70 70 6c   : text/h tml,appl
```

Figure: Unencrypted payload over HTTP

Figure: IP Packet

Figure: Attacker scenario in website fingerprinting.

Website Fingerprinting Methodology

1. Deep Packet Inspection

```
eb 53 17 03 03 00 ac 00  00 00 00 00 00 00 01 a3   .S...... ........
99 71 07 49 71 49 62 49  01 43 f2 9b c4 fe db 37   .q.IqIbI .C.....7
da a4 f5 33 0b ab 0f df  55 2c 4f 70 37 ea 8c f7   ...3.... U,Op7...
f0 cc 26 a0 56 f9 05 2e  0c 1b 39 0c 66 db a6 42   ..&.V... ..9.f..B
20 5e 60 0a f6 31 3b fc  81 cf 09 7c f5 13 32 0c    ^`..1;. ...|..2.
c0 2b 54 9a 0c bb ed c2  e1 7b 1e ec 45 d6 2c 4a   .+T..... .{..E.,J
bf 64 65 ec a2 2e 42 d5  69 b7 b0 fb 82 b1 47 dc   .de...B. i.....G.
c8 3c e1 b5 2e 49 ea 1e  1e 71 7b 20 d9 6c 4c 42   .<...I.. .q{ .lLB
c3 66 79 bc a4 1a e2 7f  a9 fe 2e a9 2c 7e c4 8e   .fy..... ....,~..
9e 6f ba bc ff 3a 82 a6  d5 5c f3 d3 22 cd fb 1e   .o...:.. .\.."...
4f 31 b2 1f 60 52 18 0e  d3 ca db 7a a5 12 d3 7a   O1..`R.. ...z...z
f8 68 a2                                           .h.
```

Figure: Encrypted payload over HTTPS

Figure: IP Packet

Figure: Attacker scenario in website fingerprinting.

Website Fingerprinting Methodology

1. Deep Packet Inspection
2. TCP/IP signature-based identi cation
   - Extract features from TCP/IP headers
   - Apply supervised machine learning algorithm

Figure: IP Packet

Figure: Attacker scenario in website ngerprinting.

Website Fingerprinting Methodology

TCP/IP Header Field	Function
Total Length	Total length of IP datagram
Source Address	The IP address of the original source of the IP datagram
Destination Address	The IP address of the nal destination of the IP datagram
Source Port	TCP port of sending host
Destination Port	TCP port of Destination host

Table: Five key elds in TCP/IP header.

1. Deep Packet Inspection
2. TCP/IP signature-based identi cation

   Extract features from TCP/IP headers
   Apply supervised machine learning algorithm

Figure: IP Packet

Figure: Attacker scenario in website ngerprinting.

Related Work & Limitations

Author	Scenario	Features	Classi er
Liberatore et al. 2006 (L)	SSH	packet size count	Naive Bayes
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Panchenko et al. 2011 (P)	SSH, Tor	burst markers, HTML markers, # of markers, ratio of incoming packets, occurring packet sizes, transmitted bytes, # of packets	SVM
Dyer et al. 2012 (Vng++)	SSH	per-direction bandwidth, transmission time, burst markers	Naive Bayes
Wang et al. 2013 (FLSVM)	Tor	Tor cell instances	Distance-based SVM
Feghhi et al. 2016 (DTW)	SSH	uplink timing information	Dynamic Time Warping
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Identify and analyze importance of features in each scenario

Feature Engineering

Packet direction

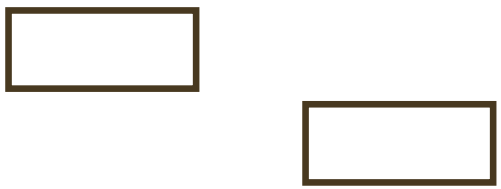
Outgoing Incoming

Packet length: length of rectangle

Packet timestamp

TCP connection : hIP address, port number i

Feature Engineering



Packet-level

e.g, # of incoming packets, packet size count, total incoming bytes, ...

Feature Engineering

Packet-level

Burst-level

Burst: a sequence of packets sent in one direction between two packets sent in the opposite direction

e.g.,packet seq.: (10, 10, -10, -10, 10) burst seq.: (20, -20, 10)

e.g, # of incoming bursts, burst size count,...

Feature Engineering

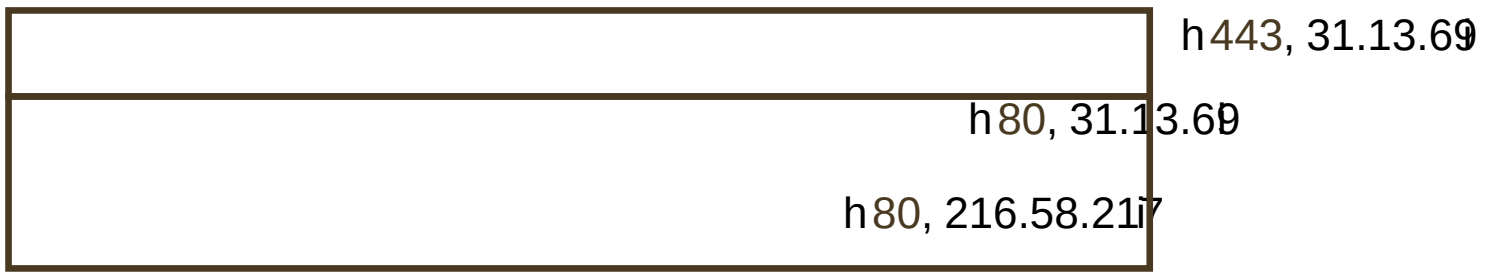
Packet-level

Burst-level

TCP-level

e.g, average # of incoming packets/TCP conn., average incoming bytes/TCP conn., ...

Feature Engineering



- Packet-level
- Burst-level
- TCP-level
- Port-level
  - TCP connections with different port numbers
  - e.g, average # of incoming packets sent over 443, ...
- IP address-level
  - TCP connections with different IP addresses
  - e.g, average incoming bytes transmitted with 216.58.217, ...

Feature Engineering

Packet-level
Burst-level
TCP-level
Port-level
IP address-level

109 feature categories, 35,683 features

** 61 feature categories have never been considered before

Communication Scenarios

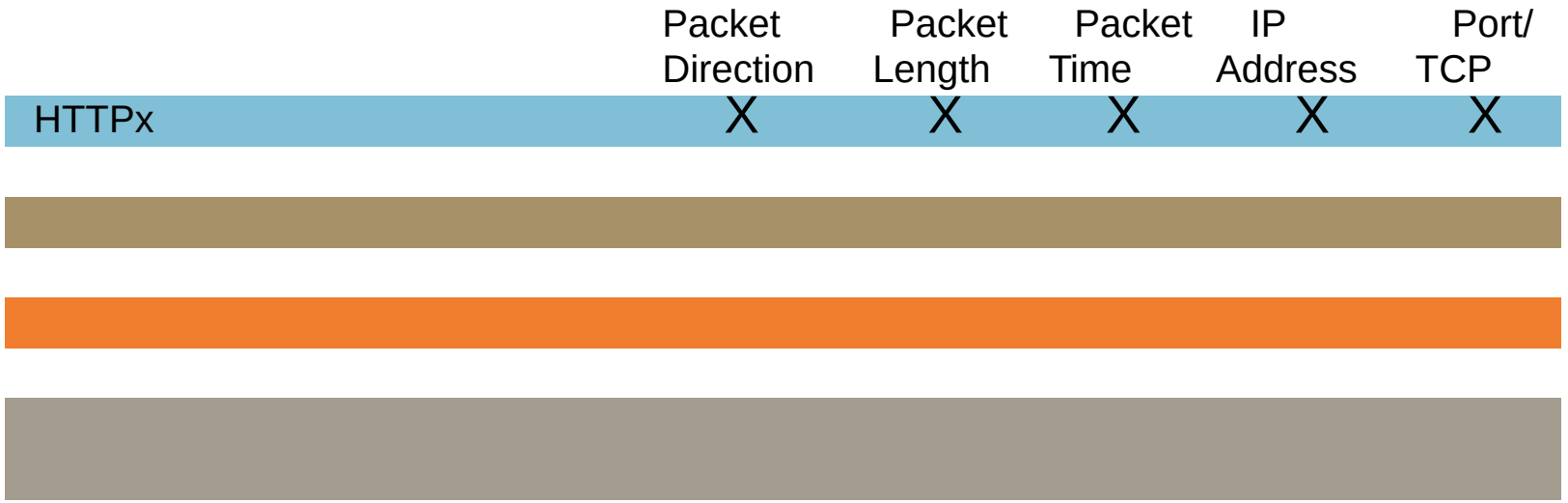


Table: Information available in each scenario.

Communication Scenarios

	Packet Direction	Packet Length	Packet Time	IP Address	Port/ TCP
HTTPx	X	X	X	X	X
Anonymized IP address	X	X	X		X

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Tor	X		X		

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Tor	X		X		
Tor + Fixed Inter-arrival Time	X				

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HTTPx + PadToMTU	X		X	X	X
Tor	X		X		
Tor + Fixed Inter-arrival Time	X				
HTTPx + Incoming Packets Only	X	X	X	X	X
HTTPx + Outgoing Packets Only	X	X	X	X	X

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Tor

Murdoch et al. 2005, Panchenko et al. 2011, Yu et al. 2012, Cai et al. 2012, Wang et al. 2013, Wang et al. 2014, Panchenko et al. 2016, Abe et al. 2016, Rimmer et al. 2017

SSH/VPN

Bissias et al. 2005, Liberatore et al. 2006, Herrmann et al. 2009, Lu et al. 2010, Panchenko et al. 2011, Dyer et al. 2012, Feghhi et al. 2016,

HTTPx

Sun et al. 2002, Gong et al. 2010, Maciá-Fernández et al. 2010, Miller et al. 2014, Trevisan et al. 2016,

Feature Selection

Goal: select informative features in each scenario

Criterion : Mean Decrease Impurity (MDI) Importance derived from decision tree-based ensemble methods

Key Idea: compute the average decrease of entropy of each feature in multiple decision trees to measure their importance

Issue: biasin MDI Importance

MDI Importanceis biased with correlated features

Figure: Bias with correlated features on MDI importance.

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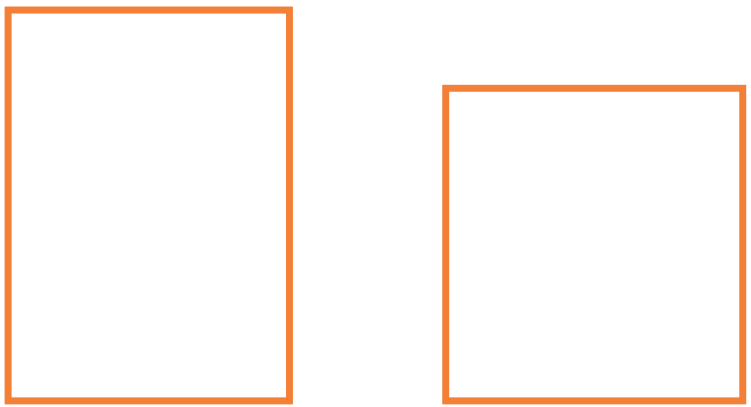

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Solution

1. Cluster correlated features
2. Choose one from each cluster as a representative
3. Calculate MDI Importance

Issue: biasin MDI Importance

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Figure: Bias with correlated features on MDI importance.

Solution

Complexity: $O(n^2)$
HTTPx: n 36; 000

1. Cluster correlated features
2. Choose one from each cluster as a representative
3. Calculate MDI Importance

Feature Selection Methodology

1. Reduce number of features
   - Calculate MDI importance
   - Filter out less important features
     - consider top n features that contribute to 99% of the total MDI importance
       e.g.,35,711! 5,852

Feature Selection Methodology

1. Reduce number of features

2. Remove correlated features

   Perform hierarchical clustering based on Euclidean distance

   Determine number of clusters based on silhouette scores

   Select one feature from each cluster

   e.g.,5,852! 2,512

Feature Selection Methodology

1. Reduce number of features

2. Remove correlated features

3: Select informative features

   Recalculate MDI Importance for selected features

   Group semantically-similar features

Dataset

Our Dataset

visit 3,000 websites listed in Alexa each 20 times with Google Chrome Version 61.0.3163.100
2,032 websites, each with at least 16 visits

Dataset

- Our Dataset
  - visit 3,000 websites listed in Alexa each 20 times with Google Chrome Version 61.0.3163.100
  - 2,032 websites, each with at least 16 visits
- Two other public datasets
  - SSH2000 Dataset[Liberatore et al. 2006]
    - 2,000 websites, each is visited 51 time over SSH
  - Tor Dataset [Wang et al. 2013]
    - 100 websites, each is visited 90 times with Tor browser

Evaluation Methodology

1. Select informative features in each scenario
2. Compare classi cation accuracy with feature sets proposed in previous work

Selected Features in Tor
Overview

- TCP/IP header information
  - packet direction and timestamp
- No. of feature categories:
  - new/ all: 15/38
- Sum. of importance:
  - new/ all: 22.18/100

1	preposition of rst 300 incoming packets	24.039
2	concentration of outgoing packets in rst 2,000 packets	7.417
3	initial 30 incoming packets	5.906
4	alternative concentration of outgoing packets	5.673
5	** cumulative size with direction of rst 100 packets	5.65
6	initial 30 packets	5.611
7	position of rst 300 outgoing packets	5.424
8	position of rst 300 incoming packets	4.413
9	initial 30 outgoing packets	4.197
10	preposition of rst 300 outgoing packets	4.196
11	** inter-arrival time of rst 20 packets	2.38
12	unique burst size	1.978
13	** inter-arrival time of rst 20 incoming packets	1.896
14	** inter-arrival time of rst 20 outgoing packets	1.824
15	** initial 30 outgoing bursts	1.761
16	** initial 30 bursts	1.3
17	number of outgoing packets per second	1.205
18	** # of packets in incoming burst count	1.163
19	** # of packets in a burst count	1.108
20	alternative outgoing packets per second	0.934
21	** outgoing burst duration	0.878
22	# of outgoing packets per TCP conn.	0.864
23	** initial 30 incoming bursts	0.862
24	ratio of incoming packets # per TCP conn.	0.842
25	concentration of rst 30 outgoing packets	0.815
26	** burst duration	0.812
27	burst size count	0.785
28	** # of packets in outgoing burst	0.65
29	size of incoming bursts	0.591
30	alternative packets per second	0.558
31	concentration of last 30 incoming packets	0.463
32	interpolant of cumulative packet size	0.438
33	** # of packets in each burst	0.432
34	concentration of last 30 outgoing packets	0.428
35	number of packets per second	0.428
36	number of incoming packets per second	0.372
37	** # of packets in outgoing burst count	0.358
38	** incoming burst duration	0.34

Table: Most informative features in Tor.

Selected Features inTor

Example features

Cumulative packet size with direction

captures incoming/ outgoingpacket ordering

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Example features

Inter-arrival time between packets

interleaving of packets from parallel TCP connections

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- Eight feature sets proposed in previous research

Classi er: Extra-Trees, 10-fold validation

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- Our dataset: 82.78% vs. 96.83%

Classi cation Performance in Tor

Features:

- Informative features identi ed in Tor (Ours)
- Eight feature sets proposed in previous research

Classi er: Extra-Trees, 10-fold validation

2,000 websites, each with 16 instances

- Our dataset: 82.78% vs. 96.83%
- SSH2000: 63.13% vs. 80.29%

Classi cation Performance
in Other Communication Scenarios

Conclusion

Extract a comprehensive list of features from TCP/IP headers for website ngerprinting

Study eight different communication scenarios

Identify and select informative features in each scenario

Limitation & Future Work

Practical issues in website ngerprinting

- impact of caching
- geographic location
- client browser platform
- network segmentation
- ...

Thanks

Feature Selection Approaches

- Filters
  - Select features based on their correlation with the predict
    Pearson correlation coef cient, mutual information, ...
- Wrappers & Embedded
  - Measure the relative usefulness of feature subsets
    Wrappers
    - search the space of all feature subsets
      forward selection, backward selection, ...
    - Embedded
      - search guided by the learning process
        Decision tree

	Computation Ef ciency	Feature Correlation
Filters	X	7
Wrappers	7	X
Embedded	X	X

Table: Comparison of feature selection approaches.

Feature Selection

Goal: select informative features in each scenario

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Criterion : Mean Decrease Impurity (MDI) Importance derived from decision tree-based ensemble methods

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Decision Tree

Figure: A decision tree to differ website A, B and C.

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Entropy

measure impurity based on probability of each possible output

A	B	C	Entropy
10	0	0	0
5	5	0	$\frac{1}{2}\log 2 + \frac{1}{2}\log 2 + 0$ 0:301

Table: Entropy with different probabilities.

Figure: A decision tree to differ website A, B and C.

Feature Selection

Goal: select informative features in each scenario

Criterion: *Mean Decrease Impurity (MDI) Importance* derived from decision tree-based ensemble methods

Decision Tree
Entropy
Information Gain

measure *the total decrease of impurity*
when consider a feature as a split n

A	*B*	*Entropy*
5	5	0.301

	A	*B*	*Entropy*
20	5	0	0
> 20	0	5	0

$$\textit{Information Gain} = 0{:}301 - (\frac{5}{10}\ 0 + \frac{5}{10}\ 0) = 0{:}301 \quad (1)$$

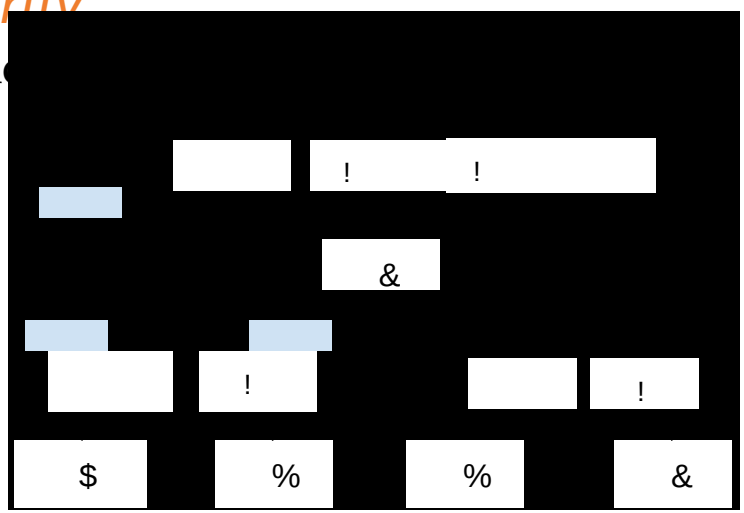

Figure: A decision tree to differ website *A*, *B* and *C*.

Mutual Information & Gini Index

In Extra-Trees, using mutual information/entropy or gini index as impurity measure has been demonstrated to achieve comparable stability score and performance (Haralampieva and Brown 2016).

Hierachical Clustering

Average Linkage

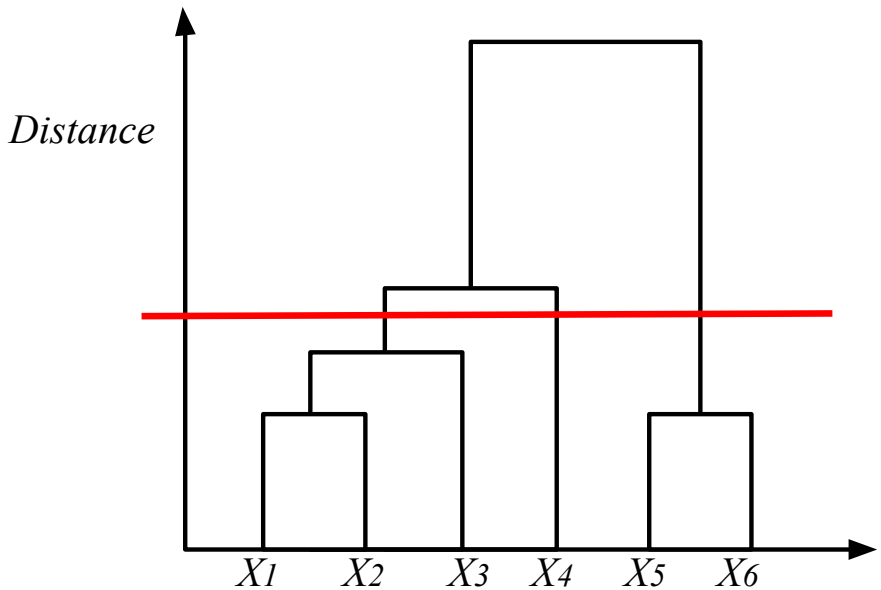

Figure: Hierarchical Clustering