Distinguishing Tor From Other Encrypted Network Traffic Through Character Analysis

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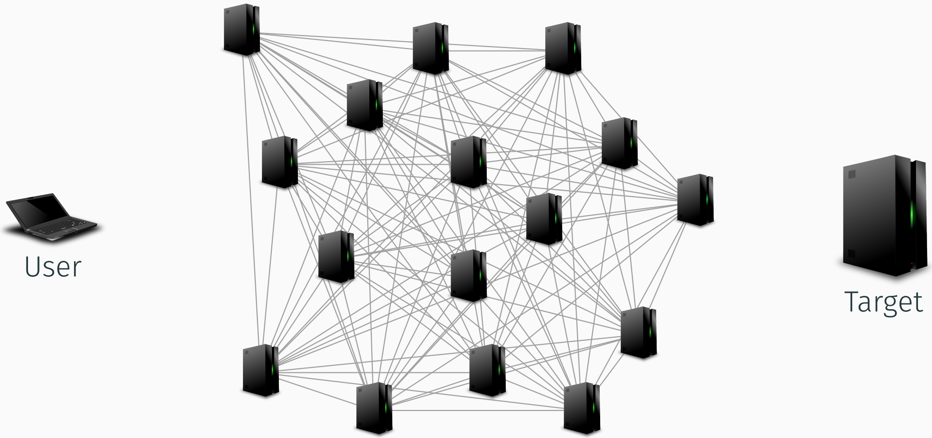
Outline

Anonymisation Using The Tor Network



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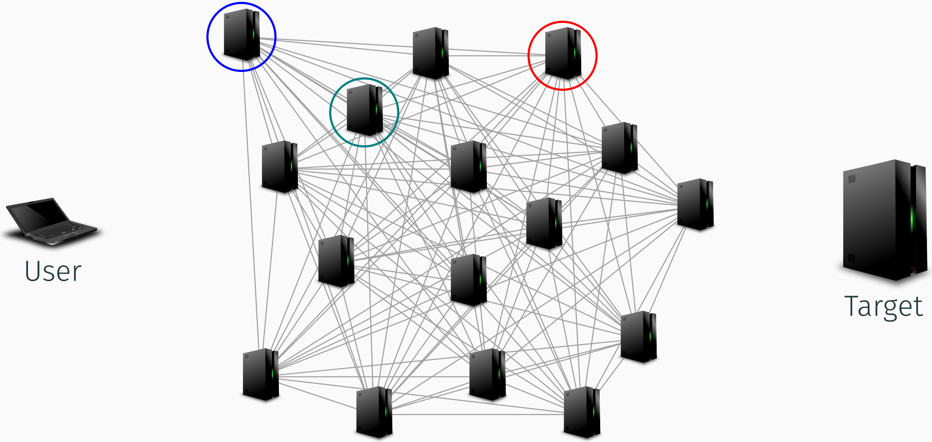

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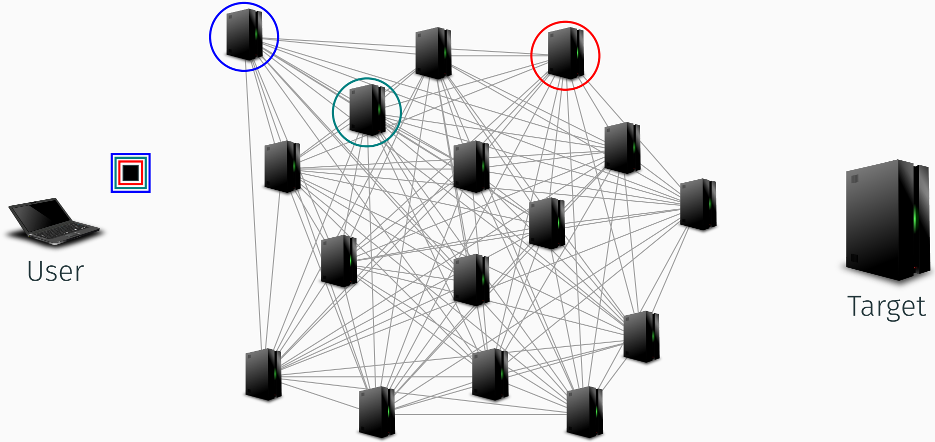

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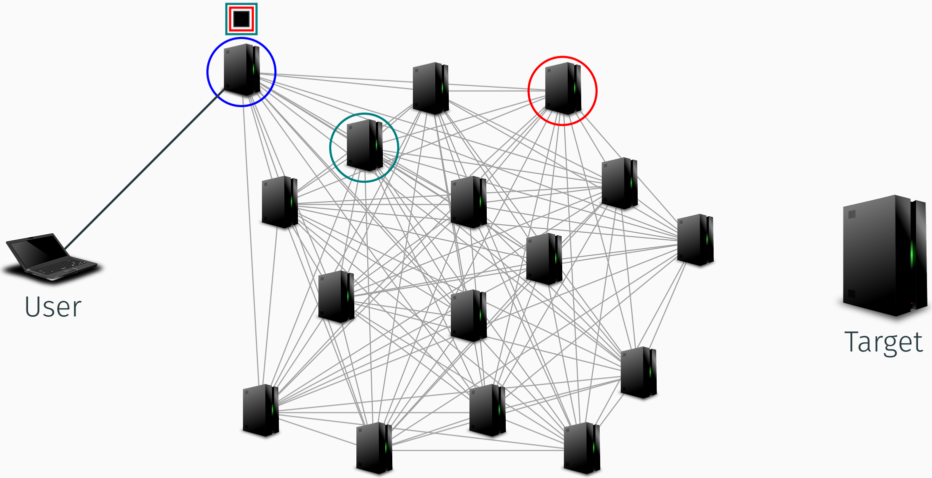

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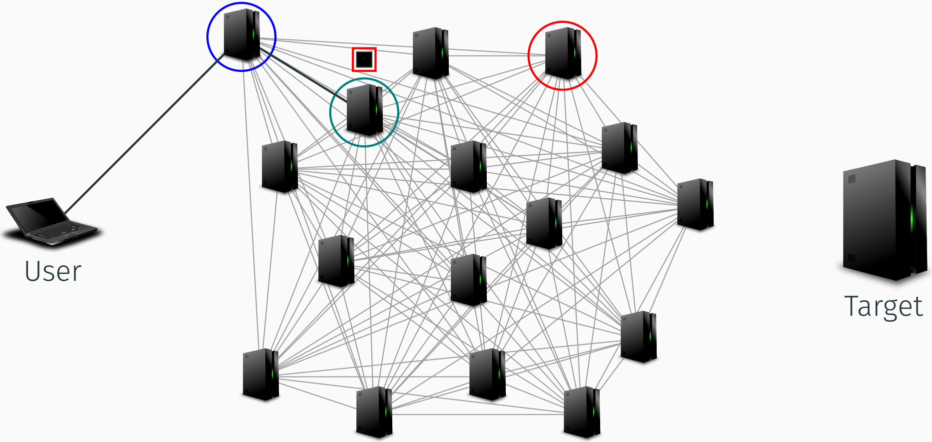

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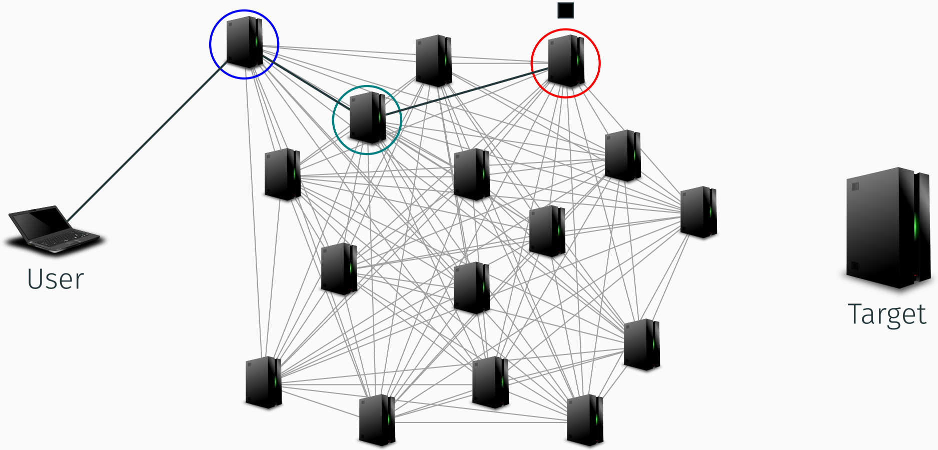

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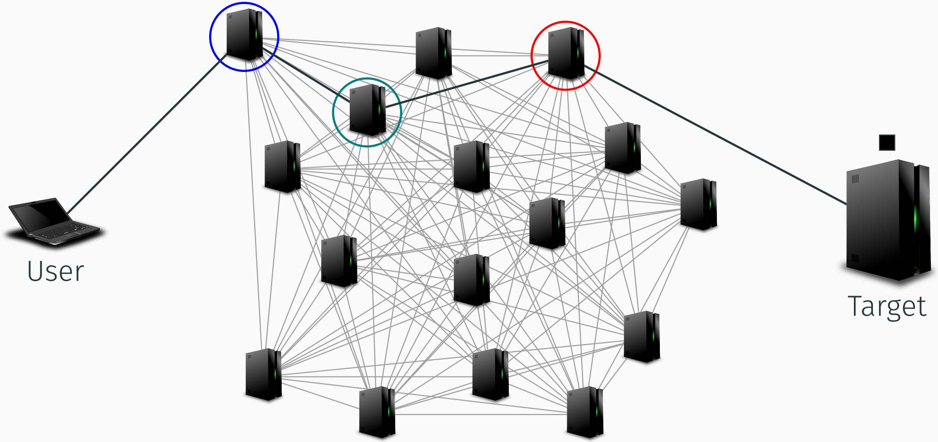
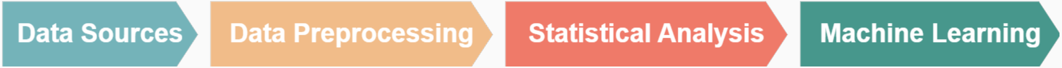


Results From Pitpimon's PhD Thesis

Methodology



1. **Data Sources:** Utilized two distinct datasets:
   a) A **public Tor dataset** from UNB-CIC, encompassing eight application types: audio, browsing, chat, email, FTP, P2P, video, and VoIP.
   b) A **private dataset** focusing on browsing applications.
2. **Data Preprocessing:** Clean and prepare the raw data for analysis.
3. **Statistical Analysis:** Conducted using the Mann-Whitney U Test to identify significant differences and patterns.
4. **Machine Learning Models:** Implemented and evaluated three models—J48, Random Forest, and KNN.

Results From Pitpimon’s PhD Thesis

Analysis of Tor vs. Non-Tor Traffic

Table 1: Number of balanced Tor and non-Tor instances for nine applications

Audio	26,082	**Email**	12,300	**Video**	32,154
Browsing	71,950	**FTP**	514,952	**VoIP**	737,382
Chat	6,504	**P2P**	433,770	**Private**	29,600

Statistical Analysis

- The **Mann-Whitney U test** showed significant differences in traffic, with differentiation rates of ***95.42%*** for the public dataset and ***100%*** for the private dataset.

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Machine Learning Analysis

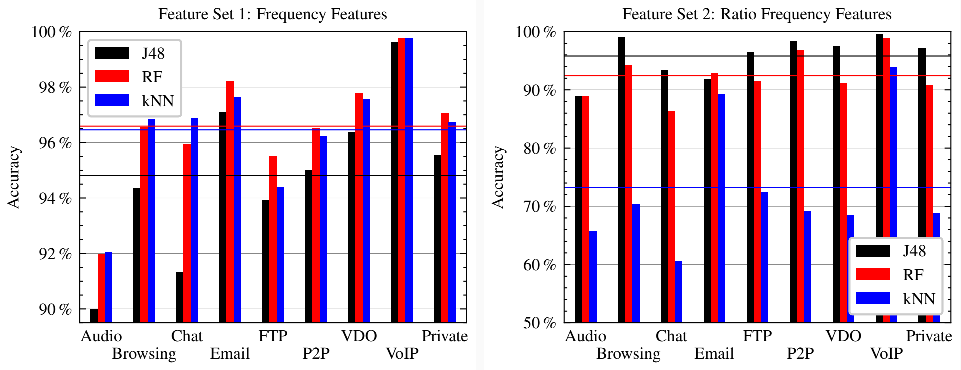

Figure 1: Results of the approach proposed.

Why Are These Results That Remarkable?

Adversarial Indistinguishability Experiment

1. An attacker $\mathcal{A}$ chooses two messages m_0 and m_1 of the same length for a given encryption scheme with security parameter N. The security parameter may be viewed as corresponding to the length of the key.
2. A random key k is generated (depending on N) and a bit $b \in \{0, 1\}$ is chosen at random. $\mathcal{A}$ receives the so-called challenge ciphertext $c \leftarrow \mathsf{Enc}_k(m_b)$.
3. $\mathcal{A}$ outputs a bit $b' \in \{0, 1\}$.
4. The result of the experiment is 1 if $b = b'$, otherwise 0.

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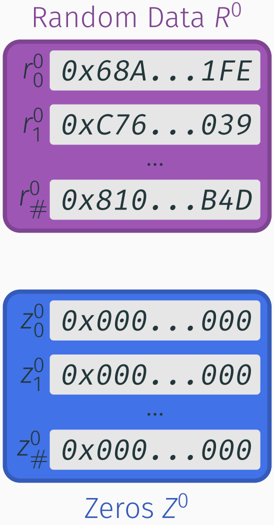
In a perfect crypto world, distinguishing Tor-encrypted traffic from other encrypted traffic should not be possible!

New Experiments: Data Generation and Feature Engineering



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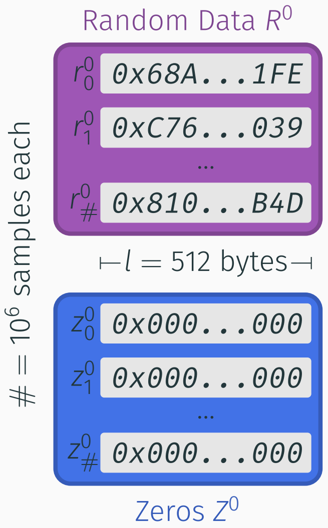

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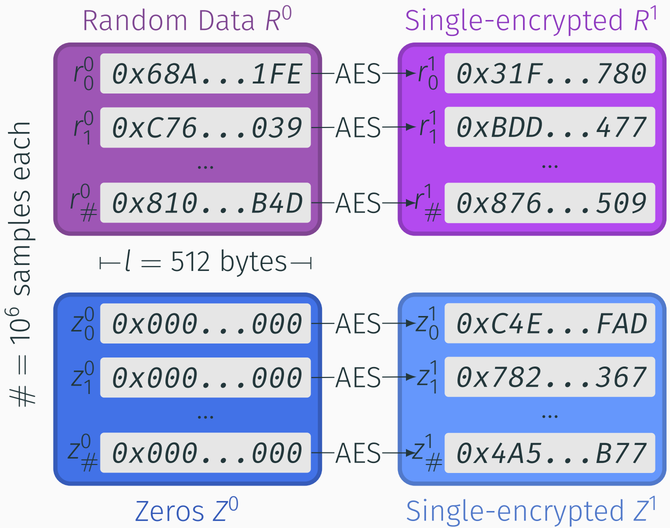

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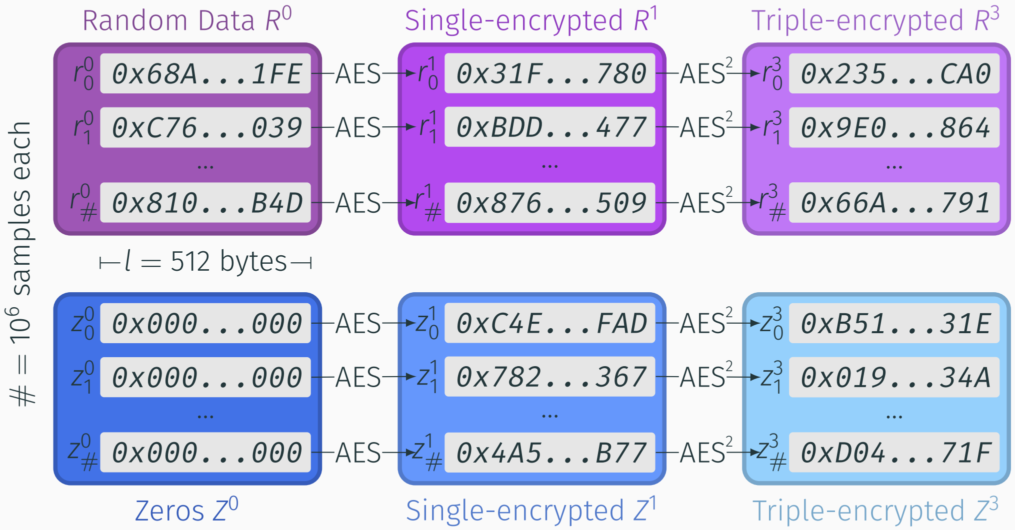

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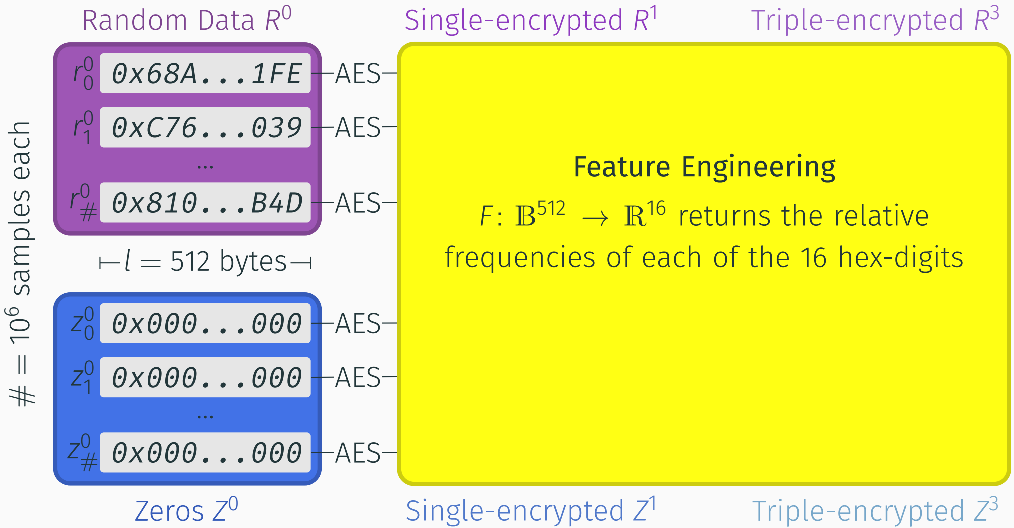

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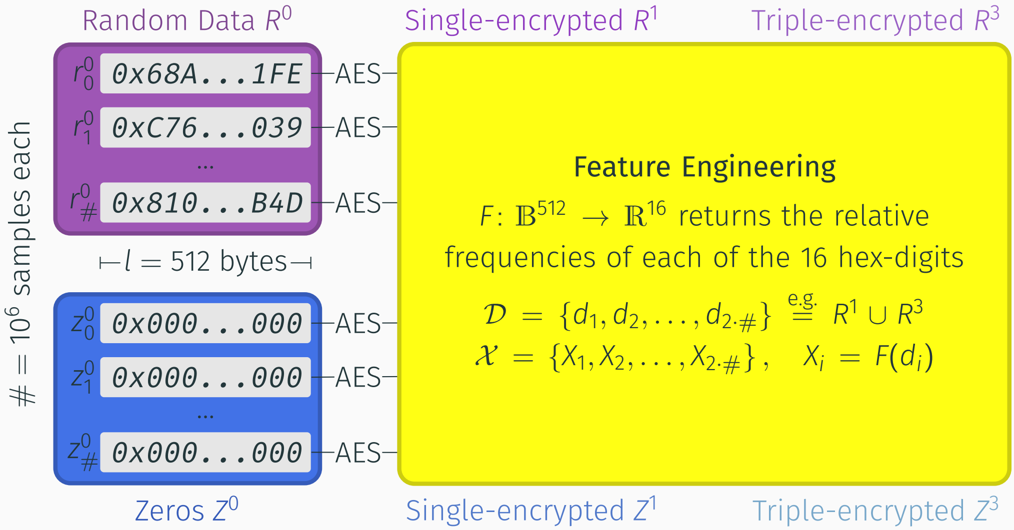

Feature Engineering

$F\colon \mathbb{B}^{512} \to \mathbb{R}^{16}$ returns the relative frequencies of each of the 16 hex-digits

$$\mathcal{D} = \{d_1, d_2, \ldots, d_{2\cdot\#}\} \overset{\text{e.g.}}{=} R^1 \cup R^3$$

$$\mathcal{X} = \{X_1, X_2, \ldots, X_{2\cdot\#}\}, \quad X_i = F(d_i)$$

New Experiments: Algorithms and Experiments

AES Modes of Operation

- Cipher Block Chaining (CBC)
- Counter (CTR)
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Train-Test-Split

- Split $(\mathcal{X}, \mathcal{Y})$ into $(\mathcal{X}_{\text{tr}}, \mathcal{Y}_{\text{tr}})\,;(\mathcal{X}_{\text{te}}, \mathcal{Y}_{\text{te}})$
- Ratio: 75 % training, 25 % test

A total of 18 experiments were conducted

New Experiments: Results (CBC)

RF (49.90 %)

True \ Prediction	Z^1	Z^3
Z^1	120,550 (24.11 %)	129,450 (25.89 %)
Z^3	121,055 (24.21 %)	128,945 (25.79 %)

DT (49.92 %)

True \ Prediction	Z^1	Z^3
Z^1	131,716 (26.34 %)	118,284 (23.66 %)
Z^3	132,124 (26.42 %)	117,876 (23.58 %)

kNN (50.10 %)

True \ Prediction	Z^1	Z^3
Z^1	156,050 (31.21 %)	93,950 (18.79 %)
Z^3	155,546 (31.11 %)	94,454 (18.89 %)

RF (49.98 %)

True \ Prediction	R^1	R^3
R^1	121,993 (24.40 %)	128,007 (25.60 %)
R^3	122,116 (24.42 %)	127,884 (25.58 %)

DT (50.04 %)

True \ Prediction	R^1	R^3
R^1	113,512 (22.70 %)	136,488 (27.30 %)
R^3	113,320 (22.66 %)	136,680 (27.34 %)

kNN (50.01 %)

True \ Prediction	R^1	R^3
R^1	155,438 (31.09 %)	94,562 (18.91 %)
R^3	155,387 (31.08 %)	94,613 (18.92 %)

New Experiments: Results (CTR)

RF (50.07 %)

True \ Prediction	Z^1	Z^3
Z^1	110,909 (22.18 %)	139,091 (27.82 %)
Z^3	110,566 (22.11 %)	139,434 (27.89 %)

DT (49.88 %)

True \ Prediction	Z^1	Z^3
Z^1	139,964 (27.99 %)	110,036 (22.01 %)
Z^3	140,569 (28.11 %)	109,431 (21.89 %)

kNN (50.11 %)

True \ Prediction	Z^1	Z^3
Z^1	155,935 (31.19 %)	94,065 (18.81 %)
Z^3	155,368 (31.07 %)	94,632 (18.93 %)

RF (50.06 %)

True \ Prediction	R^1	R^3
R^1	104,927 (20.99 %)	145,073 (29.01 %)
R^3	104,634 (20.93 %)	145,366 (29.07 %)

DT (50.04 %)

True \ Prediction	R^1	R^3
R^1	126,658 (25.33 %)	123,342 (24.67 %)
R^3	126,479 (25.30 %)	123,521 (24.70 %)

kNN (49.90 %)

True \ Prediction	R^1	R^3
R^1	155,333 (31.07 %)	94,667 (18.93 %)
R^3	155,848 (31.17 %)	94,152 (18.83 %)

New Experiments: Results (ECB)

RF (49.99 %)

True \ Prediction	Z^1	Z^3
Z^1	129,216 (25.84 %)	120,784 (24.16 %)
Z^3	129,249 (25.85 %)	120,751 (24.15 %)

DT (49.97 %)

True \ Prediction	Z^1	Z^3
Z^1	125,043 (25.01 %)	124,957 (24.99 %)
Z^3	125,205 (25.04 %)	124,795 (24.96 %)

kNN (49.95 %)

True \ Prediction	Z^1	Z^3
Z^1	155,541 (31.11 %)	94,459 (18.89 %)
Z^3	155,771 (31.15 %)	94,229 (18.85 %)

RF (49.91 %)

True \ Prediction	R^1	R^3
R^1	127,775 (25.55 %)	122,225 (24.45 %)
R^3	128,250 (25.65 %)	121,750 (24.35 %)

DT (49.83 %)

True \ Prediction	R^1	R^3
R^1	120,618 (24.12 %)	129,382 (25.88 %)
R^3	121,479 (24.30 %)	128,521 (25.70 %)

kNN (50.03 %)

True \ Prediction	R^1	R^3
R^1	155,696 (31.14 %)	94,304 (18.86 %)
R^3	155,553 (31.11 %)	94,447 (18.89 %)

Conclusion and Outlook

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Pitpimon's PhD Thesis shows distinguishability of Tor and non-Tor packets

Q: Is this due to the different number of encryption passes?
I.e.: Can *single-encrypted* data be distinguished from *triple-encrypted* data via analysis of hex characters?

A: All three ML models failed to do so regardless of the type of encrypted data.
The accuracy is $\approx 50\,\%$, which is the guess probability.

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A: All three ML models failed to do so regardless of the type of encrypted data.
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Outlook

Further experiments needed to gradually rule out possible explanations for the distinguishability and to identify the actual cause.

Thank you!