Rosetta: Enabling Robust TLS Encrypted Traffic Classification in Diverse Network Environments with TCP-Aware Traffic Augmentation

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TLS Encryption Protocol

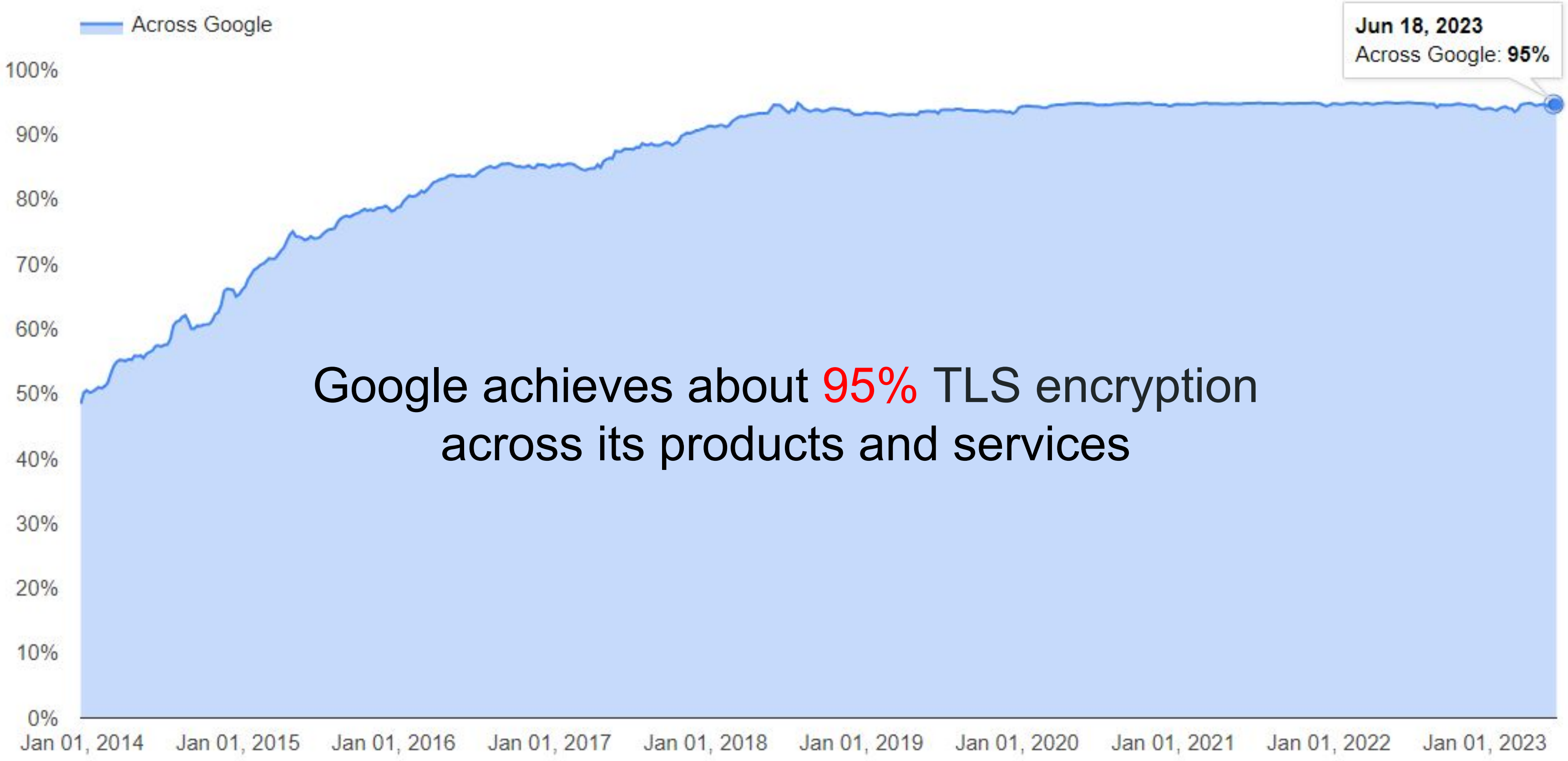
Website

Communications

Online Storage

TLS encryption is widely accepted by various applicaions

TLS Encryption Protocol



Google achieves about 95% TLS encryption across its products and services

Background

TLS encrypted traffic classification provides valuable information for

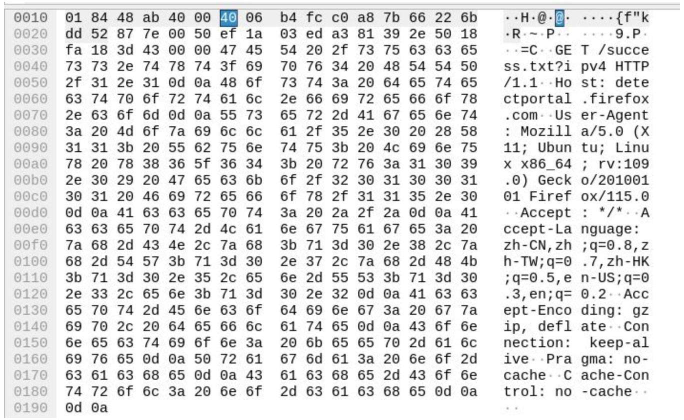
User Profiling

Intrusion Detection

Network Management

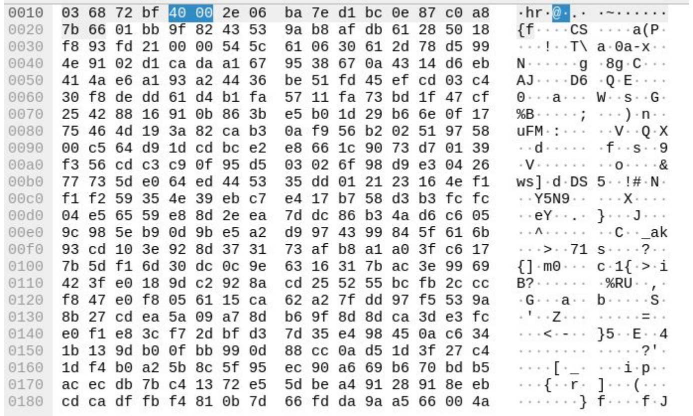
TLS Encryption

HTTP



TLS Encryption

HTTPs



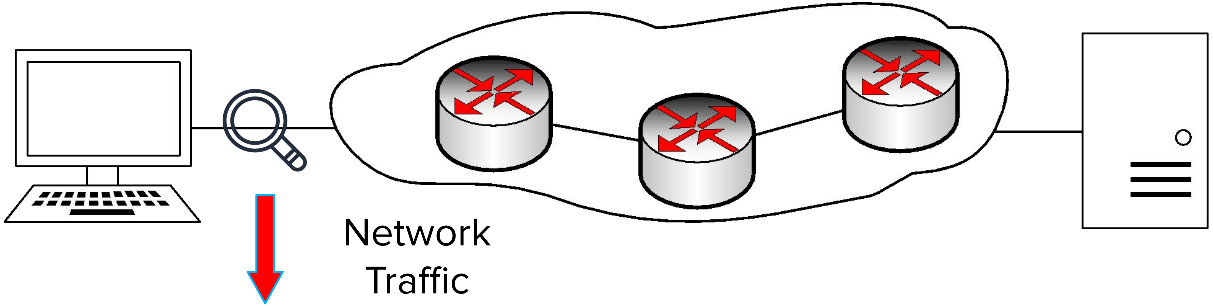
Classification based on Payload ✔

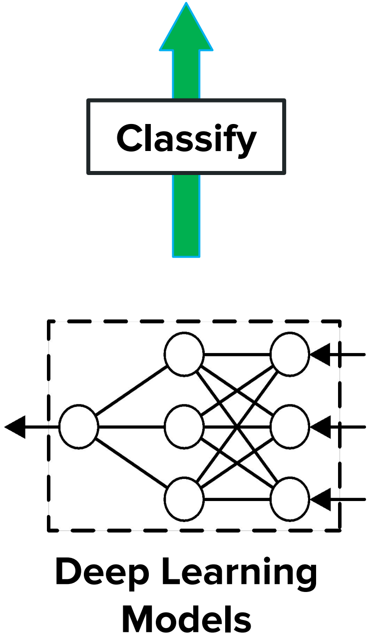
Classification based on Payload ✘

Payload become unrecognized after being encrypted by TLS

Deep Learning Models in TLS Traffic Classification

- TLS Traffic classification on **packet length sequence**

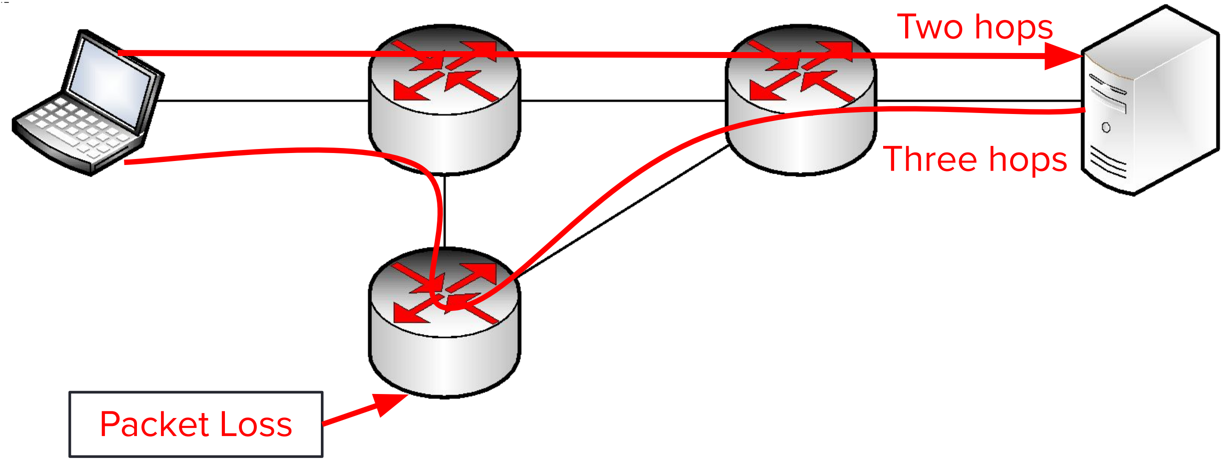




Amazon	517, 51, 163, 46, 86, 77, 168, ...
Facebook	517, 51, 163, 380, 161, 38, 46, ...
Google	190, 126, 485, 484, 485, 764, ...

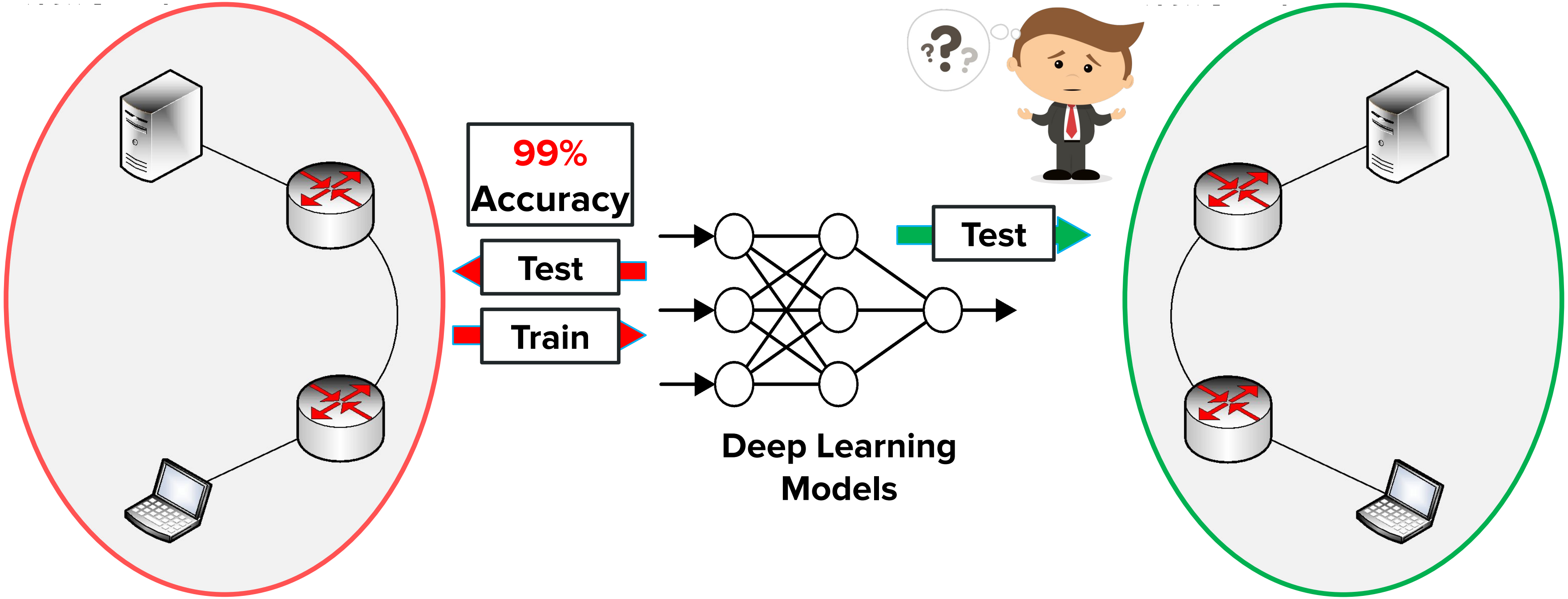
Diverse Network Environments

- Traffic may be affected by network environments in practice
  - Packet Loss
  - Routing Path



Performance in Diverse Network Environments

- DL-based classification in diverse network environments



Experimental Setup for Replayed TLS traffic

- Diverse Network Environments Construction
  - Location and Access mode
- Replayed Dataset
  - CIRA-CIC-DoHBrw-2020
- Models
  - CNN, LSTM, SDAE, DF, FS-Net, Transformer

Different Network Enviroments for **Replayed** Traffic

Network Type	Env. ID	Sender Loc.	Receiver Loc.	Access mode
Wired	θ_0	Local LAN	Local LAN	Ethernet
	θ_1	China	China	
	θ_2	Korea	China	
	θ_3	USA	China	
Wireless	θ_4	China	China	Wi-Fi
	θ_5	China	China	4G LTE
	θ_6	China	China	3G WCDMA

Evaluation on Various Deep Learning Models

- Mainstream deep learning models in Replayed Traffic (Trained in θ_0)

Model	Different Wired Network Environments								Different Wireless Access Network Environments					
	θ_0		θ_1		θ_2		θ_3		θ_4		θ_5		θ_6	
	AC	F1	AC	F1	AC	F1	AC	F1	AC	F1	AC	F1	AC	F1
CNN	99.89%	99.84%	98.21%	98.20%	53.16%	34.91%	57.04%	36.32%	87.47%	87.03%	74.42%	71.52%	53.26%	34.96%
SDAE	95.47%	95.46%	91.47%	91.47%	56.21%	43.40%	55.75%	36.04%	88.11%	88.03%	82.11%	81.42%	55.16%	41.73%
LSTM	95.26%	95.25%	87.68%	87.47%	53.05%	35.07%	57.04%	36.57%	82.00%	81.19%	70.84%	67.34%	53.58%	36.08%
DF	99.89%	99.84%	98.42%	98.41%	53.26%	34.75%	58.03%	36.72%	88.00%	87.57%	74.95%	72.17%	53.37%	35.00%
FS-Net	92.11%	92.10%	90.74%	90.71%	61.16%	52.11%	58.10%	39.66%	88.84%	88.76%	83.68%	83.30%	56.84%	44.50%
Transformer	99.56%	99.36%	98.28%	96.00%	62.22%	54.12%	57.04%	42.00%	93.74%	91.35%	85.62%	83.12%	54.27%	47.57%
On Average	**97.03%**	**96.98%**	**94.13%**	**93.71%**	**56.51%**	**42.39%**	**57.17%**	**37.89%**	**88.03%**	**87.32%**	**78.60%**	**76.48%**	**54.41%**	**39.97%**

Baseline

avg accuracy: -39.86%

avg accuracy: -42.68%

Experimental Setup for Real TLS Traffic

- Diverse Network Environments Construction
  - Location and Access mode
- Traffic datasets
  - Website traffic dataset:
    - 1.8 million TLS flows from 12 websites
- Models:
  - CNN, LSTM, SDAE, DF, FS-Net, Transformer

Different Network Enviroments for **Real** TLS Traffic

Network Type	Env. ID	Client Loc.	Access mode
Wired	τ_1	China	Ethernet
	τ_2	Korea	
	τ_3	USA	
Wireless	τ_4	China	Wi-Fi
	τ_5	China	4G LTE
	τ_6	China	3G WCDMA

Evaluation on Various Deep Learning Models

- Mainstream deep learning models in real website traffic (Trained in τ_1)

Model	Different Wired Network Environments						Different Wireless Access Network Environments					
	τ_1		τ_2		τ_3		τ_4		τ_5		τ_6	
	AC	F1	AC	F1	AC	F1	AC	F1	AC	F1	AC	F1
CNN	89.55%	89.28%	81.48%	80.88%	57.73%	52.29%	72.51%	68.51%	67.16%	60.15%	70.63%	68.73%
SDAE	82.37%	79.79%	78.13%	74.79%	70.04%	68.80%	68.04%	67.98%	64.57%	64.20%	69.94%	64.01%
LSTM	81.85%	77.39%	76.72%	74.08%	62.71%	57.26%	60.89%	60.04%	66.93%	63.60%	66.41%	61.67%
DF	91.27%	91.15%	83.95%	80.58%	83.59%	83.50%	79.90%	75.00%	70.67%	66.91%	73.03%	70.17%
FS-Net	85.81%	81.42%	73.02%	72.20%	64.42%	61.97%	70.14%	68.39%	64.84%	65.42%	67.65%	66.48%
Transformer	84.85%	82.13%	70.97%	69.57%	62.66%	58.46%	63.71%	62.14%	78.98%	75.38%	61.37%	59.74%
On Average	**85.95%**	**83.53%**	**77.38%**	**75.35%**	**66.86%**	**63.71%**	**69.20%**	**67.01%**	**68.86%**	**65.94%**	**68.17%**	**65.13%**

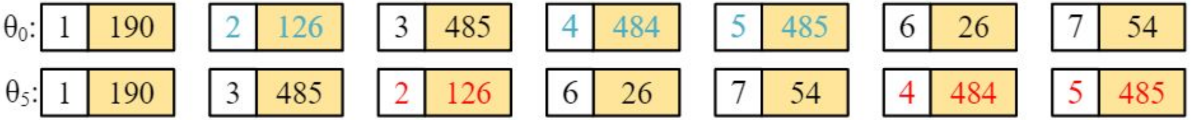
Baseline

avg accuracy: -19.09%

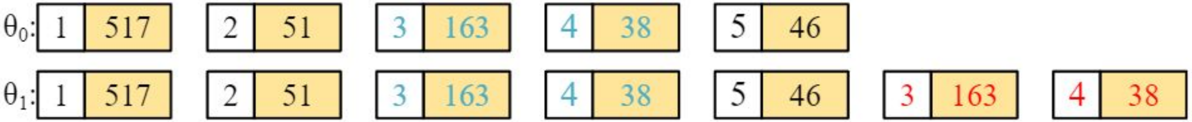
avg accuracy: -17.78%

Understanding Performance Degradation

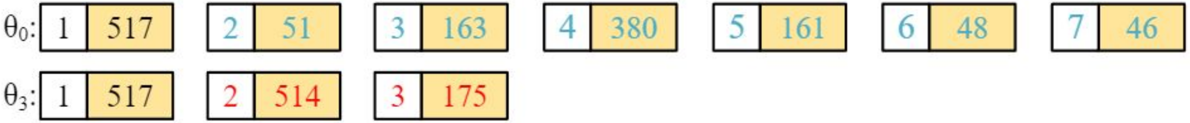
- Three phenomenons observed in diverse network environments
  - Phenomenon-I: packet subsequence shift (caused by packet loss)



  - Phenomenon-II: packet subsequence duplication (caused by packet loss)



  - Phenomenon-III: packet size variation (caused by delay variation)



How to enable robust traffic classification in various environments?

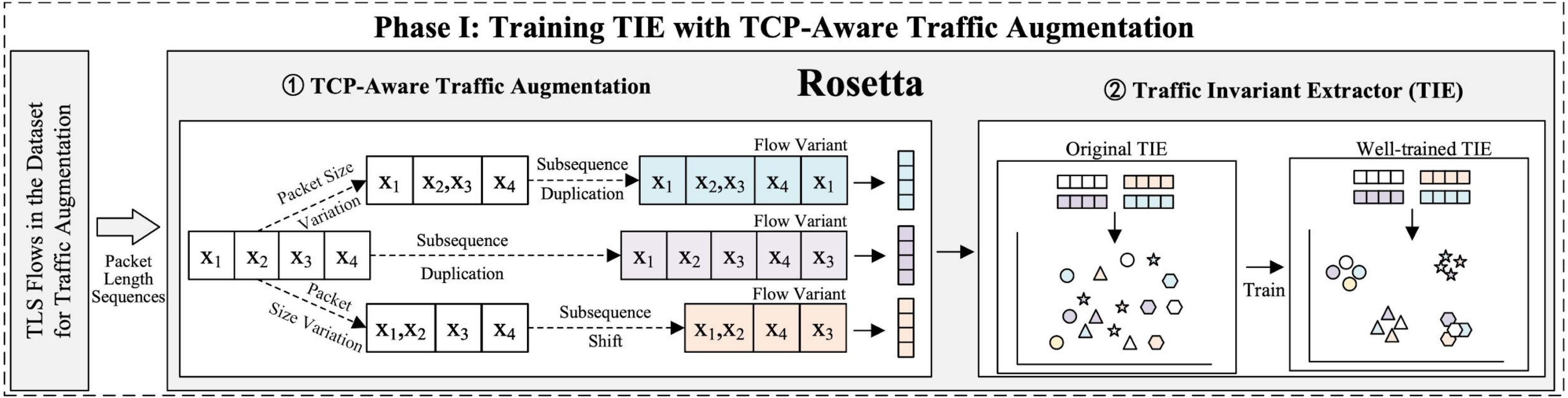
- Contribution I:

Make deep learning models aware of these regular packet sequence changes with TCP semantics.

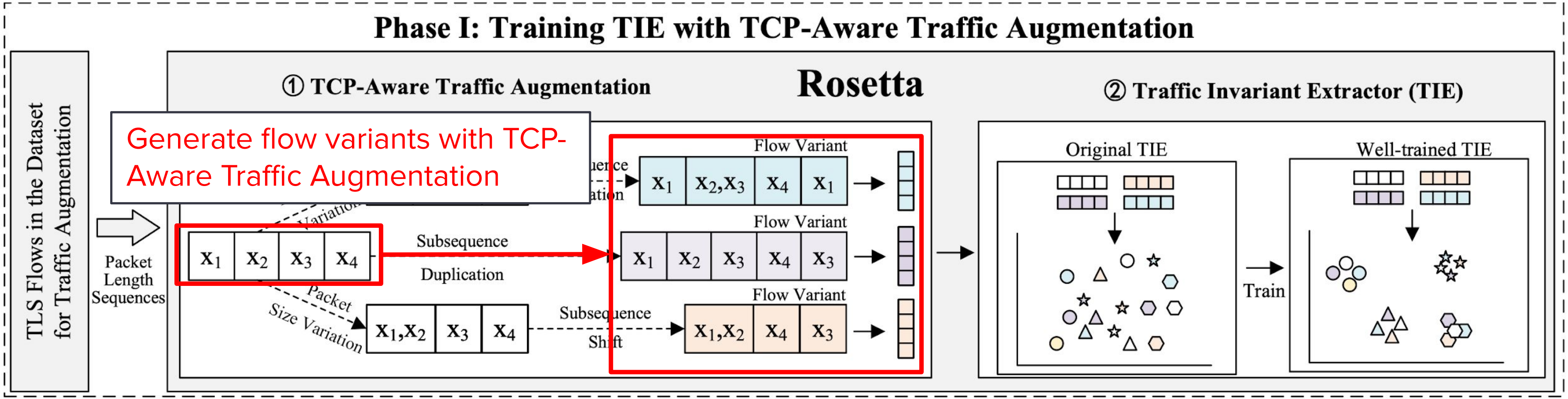
- Contribution II:

Extract robust features from flows for traffic classification.

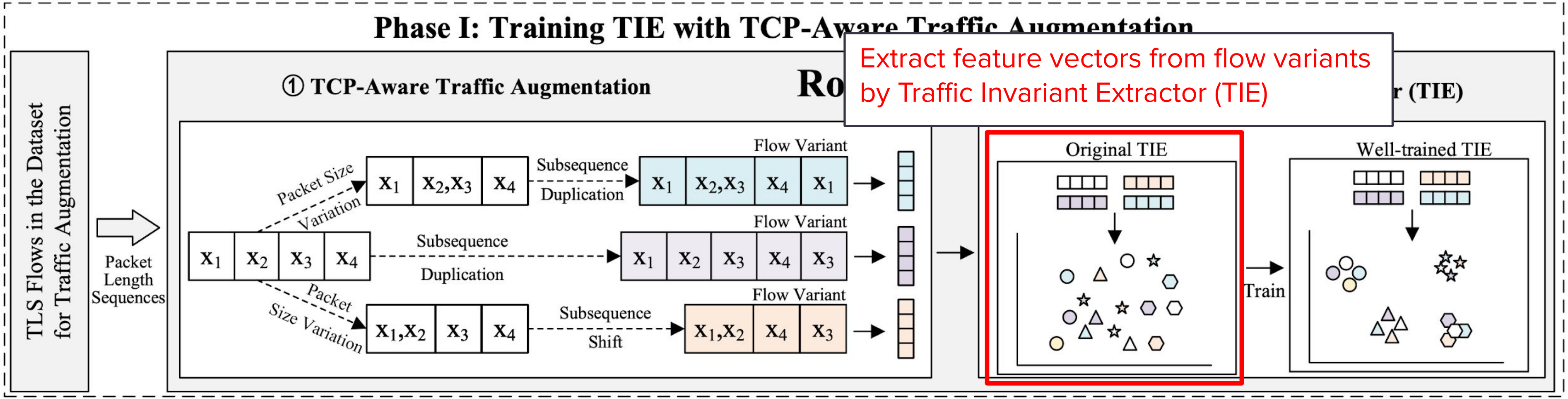
Rosetta Overview



Rosetta Overview

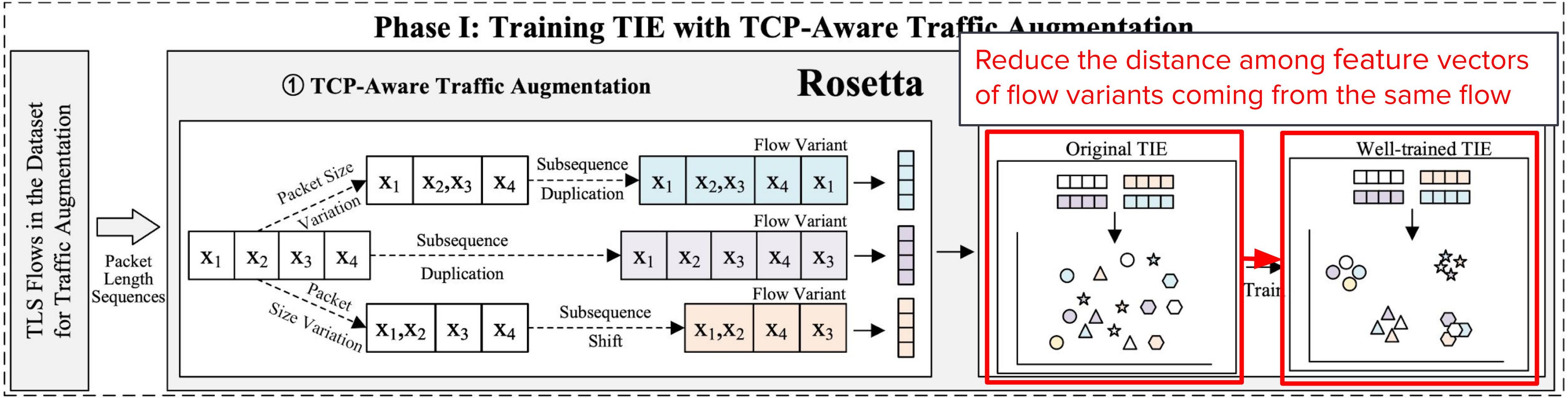


Rosetta Overview



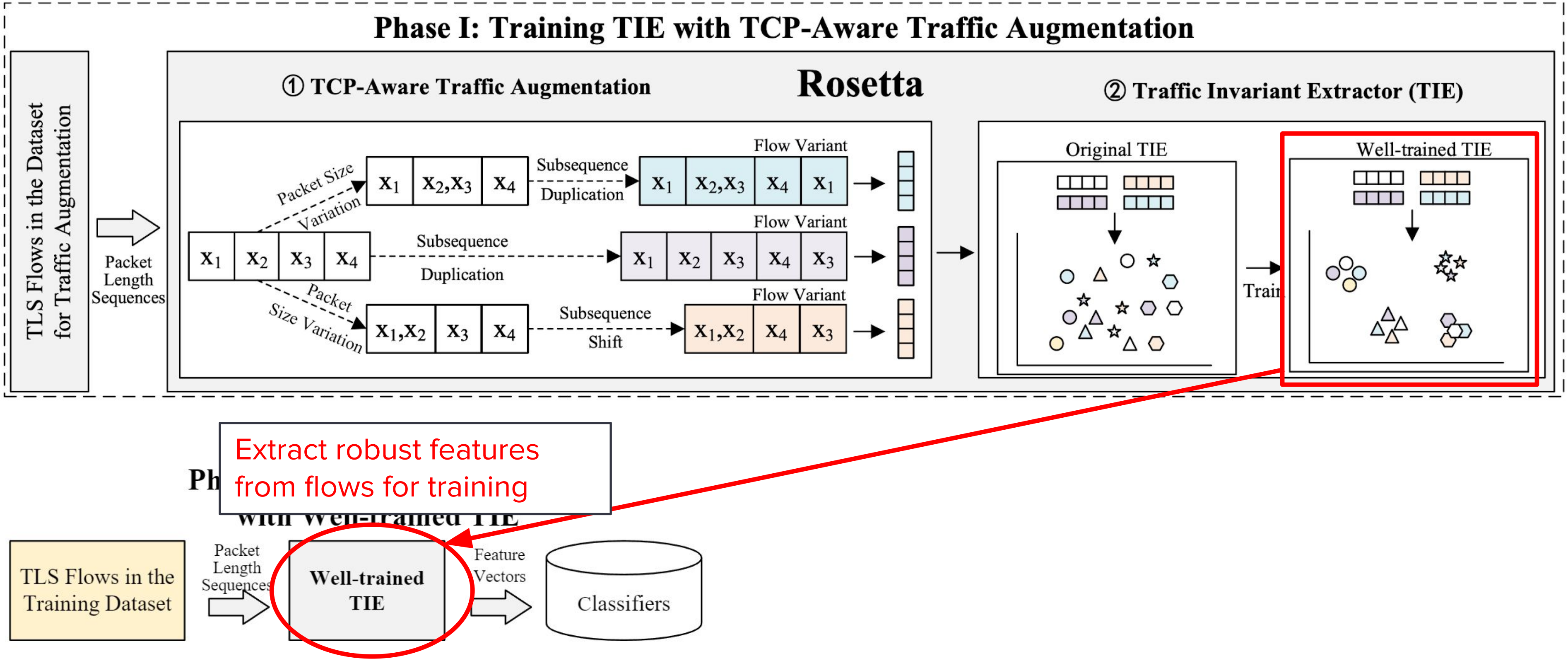
Extract feature vectors from flow variants by Traffic Invariant Extractor (TIE)

Rosetta Overview

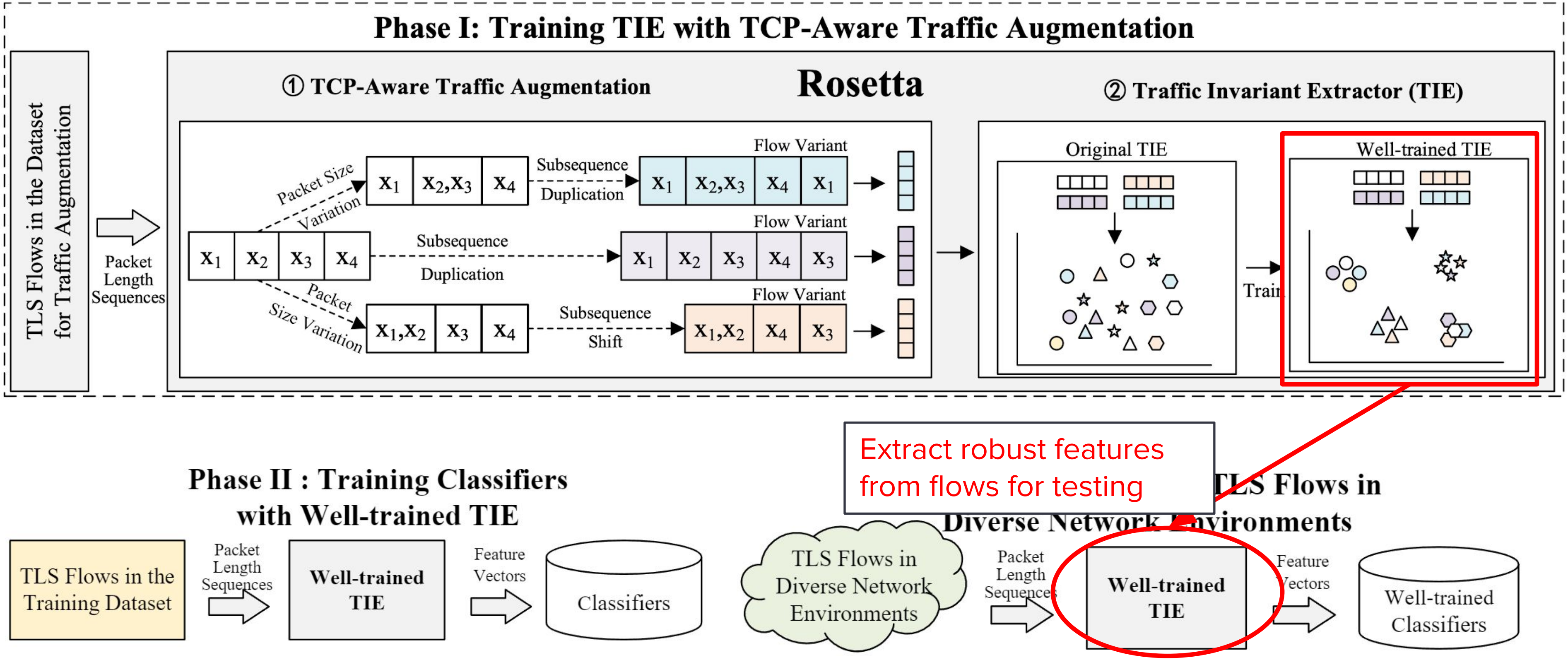


Reduce the distance among feature vectors of flow variants coming from the same flow

Rosetta Overview



Rosetta Overview



TCP-Aware Traffic Augmentation

- Three types of traffic augmentation algorithms
    - Packet Subsequence Duplication Augmentation
        - Fast retransmit and RTO
    - Packet Subsequence Shift Augmentation
        - Fast retransmit and RTO
    - Packet Size Variation Augmentation

TCP-Aware Traffic Augmentation

An example of Packet Subsequence Duplication Augmentation via Fast Retransmit

Original sequence: 100 200 300 400 500 600

Augmented sequence: 100 200 300 200 400 500 600

TCP-Aware Traffic Augmentation

An example of Packet Subsequence Duplication Augmentation via RTO

Original sequence: 100 | 200 | 300 | 400 | 500 | 600

Augmented sequence: 100 | 200 | 300 | 400 | 200 | 300 | 500 | 600

TCP-Aware Traffic Augmentation

An example of Packet Subsequence Shift Augmentation via Fast Retransmit

Original sequence: 100 200 300 400 500 600

Augmented sequence: 100 300 200 500 600 400

TCP-Aware Traffic Augmentation

An example of Packet Subsequence Shift Augmentation via RTO

Original sequence:	100	200	300	400	500	600
Augmented sequence:	100	400	200	300	500	600

TCP-Aware Traffic Augmentation

An example of Packet Size Variation Augmentation

Original sequence:	100	200	300	400	500	600
Augmented sequence:	100	500	400	500	600	

Traffic Invariant Extractor (TIE)

- Loss Function of TIE

$$\mathcal{L}_{\alpha,\zeta} = \| \overline{p_\alpha}(m_\alpha) - \overline{m'_\zeta} \|_2^2 = 2 - 2 \cdot \frac{< p_\alpha(m_\alpha), m'_\zeta >}{\| p_\alpha(m_\alpha) \|_2 \cdot \| m'_\zeta \|_2}$$

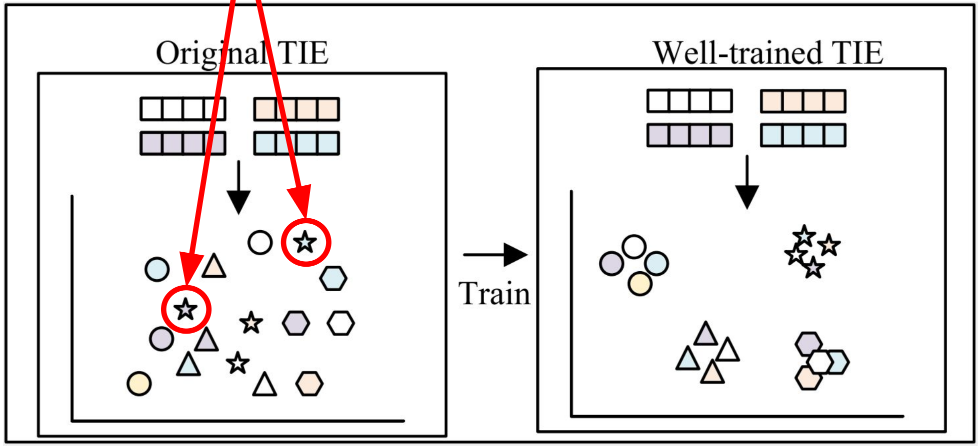
Traffic Invariant Extractor (TIE)

- Loss Function of TIE

$$\frac{< p_\alpha(m_\alpha), m'_\zeta >}{\cdots \parallel m'_\zeta \parallel_2}$$

Large distance among feature vectors of flow variants coming from the same flow

- Robust Feature Extraction



Traffic Invariant Extractor (TIE)

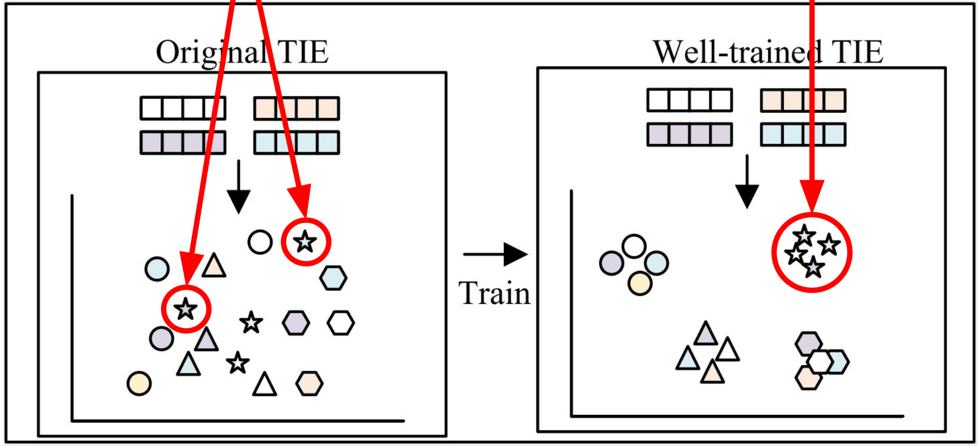
- Loss Function of TIE

$< p_\alpha(m_\alpha), m'_\gamma >$

Large distance among
variants coming fr

Small distance among feature vectors of flow
variants coming from the same flow

- Robust Feature Extraction



Evaluation with Rosetta

- Improvement on replayed traffic

Model	Different Wired Network Environments					
	θ_1		θ_2		θ_3	
	AC	F1	AC	F1	AC	F1
CNN + Rosetta	93.05% (↓5.16%)	93.03%(↓5.17%)	82.00% (↑28.84%)	81.78%(↑46.87%)	83.72% (↑26.68%)	82.85%(↑46.53%)
SDAE + Rosetta	91.89% (↑0.42%)	91.77%(↑0.30%)	86.63% (↑30.42%)	86.63%(↑43.23%)	84.17% (↑28.42%)	83.69%(↑47.65%)
LSTM + Rosetta	86.63% (↓1.05%)	84.03%(↓3.44%)	79.89% (↑26.84%)	78.32%(↑43.25%)	82.00% (↑24.96%)	78.98%(↑42.41%)
DF + Rosetta	94.42% (↓4.00%)	94.39%(↓4.02%)	86.63% (↑33.37%)	86.63%(↑51.88%)	86.01% (↑27.98%)	85.83%(↑49.11%)
FS-Net + Rosetta	89.26% (↓1.48%)	89.12%(↓1.59%)	84.63% (↑23.47%)	84.47%(↑32.37%)	84.17% (↑26.07%)	83.50%(↑43.84%)
Transformer + Rosetta	94.11%(↓4.17%)	93.74%(↓2.26%)	84.11% (↑21.89%)	83.60%(↑29.48%)	83.37% (↑26.33%)	80.38%(↑38.38%)
On Average	**91.56%(↓2.57%)**	**91.01%(↓2.70%)**	**83.98%(↑27.47%)**	**83.57%(↑41.18%)**	**83.91%(↑26.74%)**	**82.54%(↑44.65%)**

Significant improvement

Model	Different Wireless Access Network Environments					
	θ_4		θ_5		θ_6	
	AC	F1	AC	F1	AC	F1
CNN + Rosetta	89.05% (↑1.58%)	88.93%(↑1.90%)	85.37% (↑10.95%)	85.08%(↑13.55%)	80.42% (↑27.16%)	80.37%(↑45.41%)
SDAE + Rosetta	89.89% (↑1.78%)	89.74%(↑1.71%)	83.47% (↑1.36%)	82.95%(↑1.52%)	81.89% (↑26.73%)	81.88%(↑40.15%)
LSTM + Rosetta	85.37% (↑3.37%)	82.34%(↑1.15%)	82.53% (↑11.69%)	78.22%(↑10.87%)	76.53% (↑22.95%)	73.42%(↑37.33%)
DF + Rosetta	86.84% (↓1.16%)	86.53%(↓1.05%)	82.11% (↑7.16%)	81.31%(↑9.14%	82.63% (↑29.26%)	82.57%(↑47.57%)
FS-Net + Rosetta	85.58% (↓3.26%)	85.16%(↓3.60%)	84.42% (↑0.74%)	83.89%(↑0.60%)	77.26% (↑20.42%)	76.97%(↑32.47%)
Transformer + Rosetta	90.74% (↓3.00%)	89.81%(↓1.54%)	89.16% (↑3.54%)	88.20%(↑5.08%)	81.47% (↑27.20%)	79.63%(↑32.06%)
On Average	**87.91%(↓0.12%)**	**87.09%(↓0.24%)**	**84.51%(↑5.91%)**	**83.27%(↑6.79%)**	**80.03%(↑25.62%)**	**79.14%(↑39.17%)**

Significant improvement

Evaluation with Rosetta

- Improvement on real website traffic

Model	Different Wired Network Environments					
	τ_1		τ_2		τ_3	
	AC	F1	AC	F1	AC	F1
CNN + Rosetta	86.63%(↓2.92%)	86.06%(↑4.19%)	84.83%(↑3.35%)	81.33%(↑0.45%)	91.04%(↑33.31%)	91.04%(↑38.75%)
SDAE + Rosetta	84.67%(↑2.30%)	81.54%(↑12.50%)	85.54%(↑7.41%)	84.49%(↑9.70%)	89.47%(↑19.43%)	85.87%(↑17.07%)
LSTM + Rosetta	84.17%(↑2.32%)	82.07%(↑5.48%)	76.01%(↓0.71%)	74.13%(↑0.05%)	88.52%(↑25.81%)	88.14%(↑30.89%)
DF + Rosetta	90.37%(↓0.90%)	90.10%(↑5.43%)	85.19%(↑1.24%)	81.00%(↑0.42%)	90.15%(↑6.56%)	90.14%(↑6.64%)
FS-Net + Rosetta	86.99%(↑1.18%)	86.47%(↑6.66%)	84.83%(↑11.81%)	76.24%(↑4.04%)	88.41%(↑23.99%)	88.40%(↑26.43%)
Transformer + Rosetta	90.02%(↑5.17%)	87.93%(↑1.74%)	85.36%(↑14.39%)	81.37%(↑11.80%)	89.70%(↑27.04%)	89.69%(↑31.23%)
On Average	**87.14%(↑1.19%)**	**85.69%(↑2.17%)**	**83.63%(↑6.25%)**	**79.76%(↑4.41%)**	**89.55%(↑22.69%)**	**88.88%(↑25.17%)**

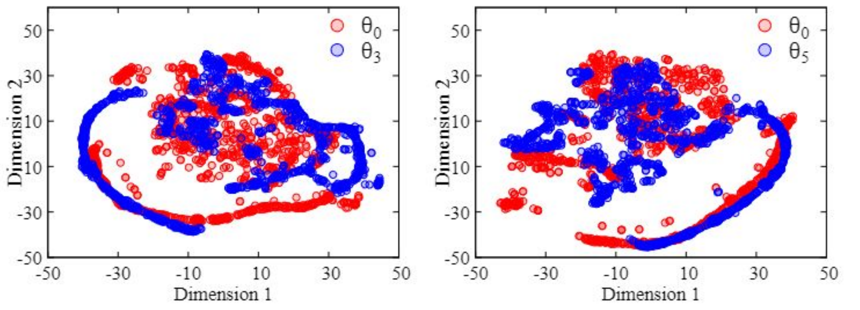
Significant improvement

Improved in all the wired networks

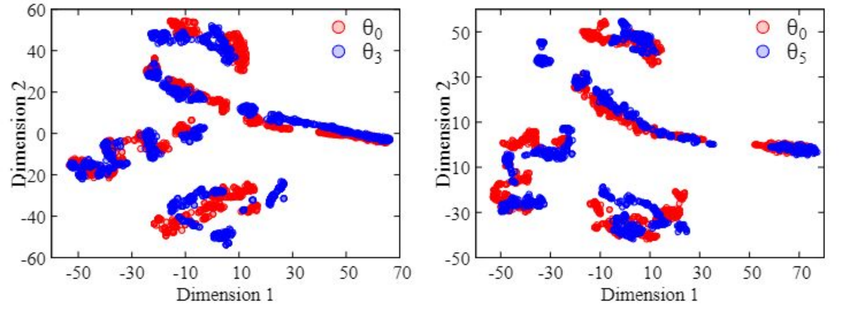
Model	Different Wireless Access Network Environments					
	τ_4		τ_5		τ_6	
	AC	F1	AC	F1	AC	F1
CNN + Rosetta	77.24%(↑4.73%)	75.02%(↑6.51%)	83.58%(↑16.42%)	82.38%(↑22.23%)	75.92%(↑5.29%)	70.66%(↑1.93%)
SDAE + Rosetta	79.10%(↑11.06%)	77.54%(↑9.56%)	74.31%(↑9.74%)	71.18%(↑6.98%)	71.95%(↑2.01%)	65.80%(↑1.79%)
LSTM + Rosetta	69.28%(↑8.39%)	79.53%(↑19.49%)	75.16%(↑8.23%)	74.37%(↑10.77%)	69.59%(↑3.18%)	62.84%(↑1.17%)
DF + Rosetta	84.13%(↑4.23%)	81.67%(↑6.67%)	84.19%(↑13.52%)	80.48%(↑13.56%)	77.58%(↑4.55%)	76.10%(↑5.93%)
FS-Net + Rosetta	77.95%(↑7.81%)	74.79%(↑6.40%)	75.95%(↑11.11%)	72.87%(↑7.45%)	72.83%(↑5.18%)	67.44%(↑0.96%)
Transformer + Rosetta	76.84%(↑13.13%)	74.80%(↑12.66%)	75.66%(↓3.32%)	72.60%(↓2.78%)	76.60%(↑15.23%)	70.23%(↑10.49%)
On Average	**77.42%(↑8.23%)**	**77.22%(↑10.21%)**	**78.14%(↑9.28%)**	**75.64%(↑9.70%)**	**74.08%(↑5.91%)**	**68.85%(↑3.71%)**

Improved in all the wireless networks

Feature visualization in 2D space



(a) Distribution between θ_0 and θ_3. (b) Distribution between θ_0 and θ_5.



(a) Distribution between θ_0 and θ_3. (b) Distribution between θ_0 and θ_5.

Feature vectors extracted by DF

Feature vectors extracted by Rosetta

Evaluation on Traffic Augmentation Algorithms

- Compare with other data augmentation methods
  - Random Mask (RM) and Random Shift (RS) in NLP
  - Model: DF

Data Aug.	Different Wired Network Environments								Different Wireless Access Network Environments						On Average	
	θ_0		θ_1		θ_2		θ_3		θ_4		θ_5		θ_6			
	AC	F1	AC	F1	AC	F1	AC	F1	AC	F1	AC	F1	AC	F1	AC	F1
RM [17]	97.89%	97.80%	89.47%	88.12%	53.26%	11.56%	58.03%	16.47%	78.00%	71.72%	61.58%	34.00%	52.84%	14.44%	70.15%	47.73%
RS [60]	99.79%	99.77%	86.42%	83.09%	56.26%	16.16%	56.13%	21.84%	77.47%	68.53%	58.53%	20.88%	53.16%	16.74%	69.68%	46.72%
Ours	95.16%	95.14%	94.42%	94.39%	86.63%	86.63%	86.01%	85.83%	86.84%	86.53%	82.11%	81.31%	82.63%	82.57%	**87.69%**	**87.49%**

Better than other data augmentation methods in most networks

Conclusion

- Mainstream DL models cannot robustly classify TLS encrypted traffic in different network environments.

- Rosetta enables robust TLS encrypted traffic classification by
  - TCP-aware traffic augmentation
  - Traffic invariant extractor

- We improve the encrypted traffic classification performance of existing DL models for replayed and real network traffic.

Thank you and Questions?

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