

Addressing Malware Family Concept Drift with Triplet Autoencoder

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INTRODUCTION Machine Learning in Cybersecurity

- Machine learning has become a key tool in cybersecurity. These systems, when well-trained, are highly effective at identifying threats.
- However, ML models quickly become **outdated** as thousands of **new malware** are created daily, and existing ones **evolve**.
- This constant change, known as **concept drift**, significantly impacts model performance over time.

INTRODUCTION **Concept Drift in Malware Analysis**

- There are 2 types of concept drift in the field of malware classification.
 - Emerging malware families: New, previously unseen malware families.
 - Evolving malware families: Variants within existing families.
- In this work, we focus on the first one, and develop an adaptive model that differentiates between known and new malware families.

METHOD Overview



METHOD Autoencoder

- High-dimensional data makes distances hard to define; known as the **curse of dimensionality**.
- As dimensionality increases, distances between data points become less informative, making it difficult to distinguish clusters.
- Autoencoders address this by reducing data to a lowerdimensional space while retaining essential features.



METHOD Metric Learning

- Metric learning focuses on defining a distance metric to distinguish data points.
- It enables the grouping of similar samples while clearly separating distinct classes.



METHOD **Triplet Loss**

- Optimizes the distance between data points to create distinct clusters.
- Uses three points (triplets) for training:
 - Anchor: A sample from a known malware family.
 - **Positive**: Another sample from the same family.
 - **Negative**: A sample from a different family.
- Ensures that the anchor-positive distance is smaller than the **anchor-negative** distance by a specified margin.



METHOD DBSCAN

- DBSCAN (Density–Based Spatial Clustering of Applications with Noise) is a clustering algorithm that groups data points based on their density.
- Why use DBSCAN?
 - To detect sub-clusters: Identifies distinct clusters within a single malware family, allowing differentiation between multiple variants.
 - To detect outliers: Flags low-density points as outliers, capturing mislabelled samples or anomalies.









family	sample size	family
FakeInstaller	925	berk
DroidKungFu	667	dinv
Plankton	625	gane
GingerMaster	339	mira
BaseBridge	330	sfon
lconosys	152	silly
Kmin	147	sma
FakeDoc	132	

nily	sample size	
erbew	1741	
linwod	1942	
anelp	1413	
nira	1526	
fone	3218	
illyp2p	3012	
mall	3606	

EVALUATION t-SNE Plot of Feature Spaces



vanilla autoencoder

triplet autoencoder

EVALUATION **Distances From Centroids**







vanilla autoencoder





evaluation Results



family selected as unknown	f1 score
FakeInstaller	0.95
DroidKungFu	0.90
Plankton	0.87
GingerMaster	0.85
BaseBridge	0.98
lconosys	0.65
Kmin	0.62
FakeDoc	0.66



amily selected as unknown	f1 score
berbew	0.99
dinwod	0.96
ganelp	0.97
mira	0.58
sfone	0.51
sillyp2p	0.83
small	0.96

Takeaways

- The triplet autoencoder combined with DBSCAN clustering significantly improves accuracy in identifying previously unseen malware families.
- DBSCAN improves clustering quality by effectively handling outliers and ensuring clear separation of different malware variants.
- The method demonstrates strong generalizability across diverse datasets (Android and Windows PE), confirming its effectiveness in various environments.

