LVForge: PE Malware Detection

Transformer + Deep Metric Learning

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Problem & Motivation

- Windows PE malware detection needs **high recall** at **low false-positive rate**.
- Standard accuracy alone is insufficient for deployment.
- Class imbalance (benign:malware $\approx 1:19$) makes threshold behavior critical.

Goal: build an operationally robust detector using a shared Transformer and compare objective functions.

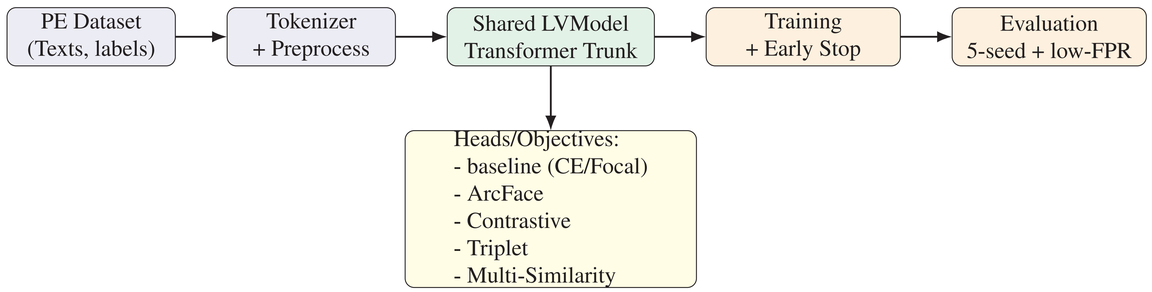
Contributions

- Unified Flax/JAX pipeline for baseline + DML variants.
- Controlled comparison of `baseline`, `arcface`, `contrastive`, `triplet`, `multi_similarity`.
- Multi-seed evaluation with operational metric: $\mathrm{TPR@FPR} = 10^{-2}$.
- Architecture-level extension of LVModel with metric-learning heads.

Data & Setup

- Dataset size: **34,370** PE samples.
- Input: text-like PE features, labels {benign, malware}.
- Backbone config: $d_{model} = 256$, heads$= 8$, FFN$= 512$, layers$= 2$, max seq len$= 380$.
- Training: batch$= 128$, epochs$= 5$, LR$= 2 \times 10^{-4}$, dropout$= 0.1$.

Unified Pipeline



LVModel Architecture Details

Base LVModel:

- Input shape: (B, T, d); token + positional embedding: $\mathbf{H}_0 = E_{tok}(\mathbf{X}) + E_{pos}(1{:}T)$.
- MHA uses one combined QKV projection: $\mathrm{QKV} = W_{qkv}\mathbf{H}$, reshaped to Q, K, V by heads.
- Scaled dot-product attention: $\mathrm{softmax}(QK^\top/\sqrt{d_h})$, then output projection.
- **Pre-norm** encoder layer: $x \leftarrow x + \mathrm{MHA}(\mathrm{LN}(x))$, $x \leftarrow x + \mathrm{FFN}(\mathrm{LN}(x))$.
- LVModel head: mean-pool $\rightarrow$ dense+tanh $\rightarrow$ dropout $\rightarrow$ LN $\rightarrow$ classifier logits.

Metric extensions:

- Shared trunk $\rightarrow$ projection to $d_{emb} = 256 \rightarrow$ LayerNorm + ℓ_2-norm embedding.

$n = 0.5, s = 64$).

Contrastive/Triplet/MS: linear logits + auxiliary metric losses.

Main Results (5-seed mean)

Variant	Accuracy	F1	ROC-AUC	PR-AUC	TPR@FPR=1e-2
baseline	0.9924	0.9960	0.9983	0.9999	0.9754
arcface	0.7979	0.7934	0.9704	0.9984	0.0000
contrastive	0.9931	0.9964	0.9971	0.9997	0.9533
triplet	0.9932	0.9964	0.9969	0.9998	0.9351
multi_similarity	**0.9946**	**0.9972**	0.9978	0.9999	**0.9851**

Runtime (single run): baseline 107.1s, arcface 93.6s, contrastive 130.8s, triplet 132.6s, multi_similarity 128.3s.

Discussion & Takeaways

- DML improves performance, but **objective selection matters**.
- **Multi-Similarity** is the best overall operating point.
- Baseline remains a strong competitor.
- ArcFace is unstable at strict low-FPR thresholds in this setup.

Deployment recommendation: Use Multi-Similarity as primary model, base-

Reproducibility

Code and paper assets are in: `/root/LVForge/docs/paper/`
Main paper: `IEEE-conference-template-062824/IEEE-conference-template-062824.tex`
All variants executed via: `scripts/run_all.py` with recorded logs and aggregated JSON metrics.