Deep Information Retrieval for Malware Searching System

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Index

Part1

- Motivations - Malware retrieval systems
- Properties - Semantics awareness
- Methods - Metric learning

Part2

- Demo - Training and starting the system.
- Demo - Querying tests

Motivations

Q1. Why do we need malware retrieval systems?

Motivations

1. To help security experts
   - Categorize malicious codes.
   - Write reports of malware.
   - If they could search semantically similar malware samples, it’ll be useful for above tasks.

Motivations

2. Beyond a good feature extraction skills

- A lot of researches for getting good feature.
- We focused on how to solve the real problems using good features.

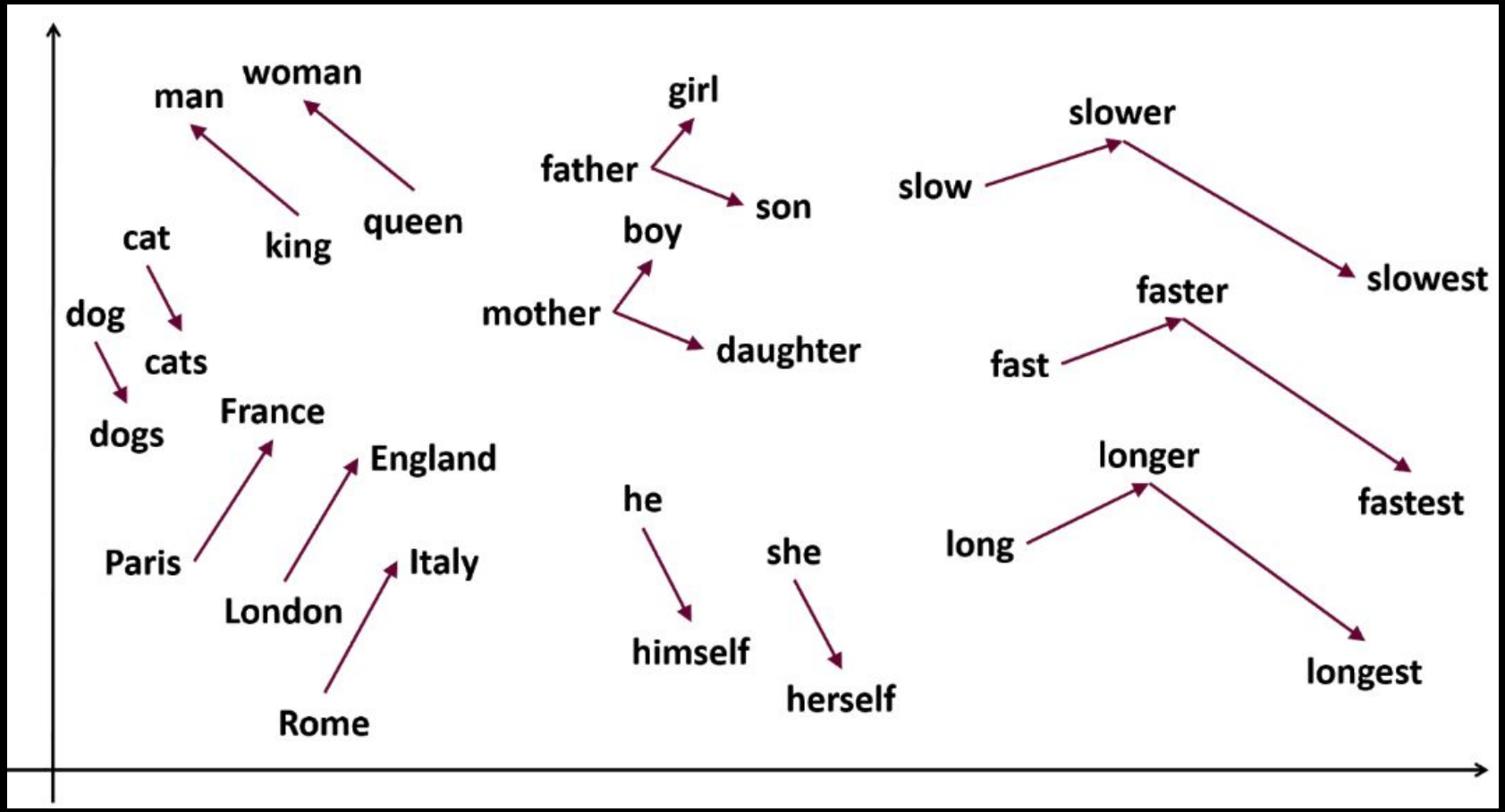
Properties

Q2. Why the malware retrieval system should be semantics-aware?

Semantics-awareness

- Meaning
  - Property of system which uses our semantic relationships between objects.
- Examples
  - Word2Vec : Natural Language -> Vector space
  - Deep IR : Image -> Vector space
  - DCGAN, CVAE : Image <-> Vector space

Semantics-awareness



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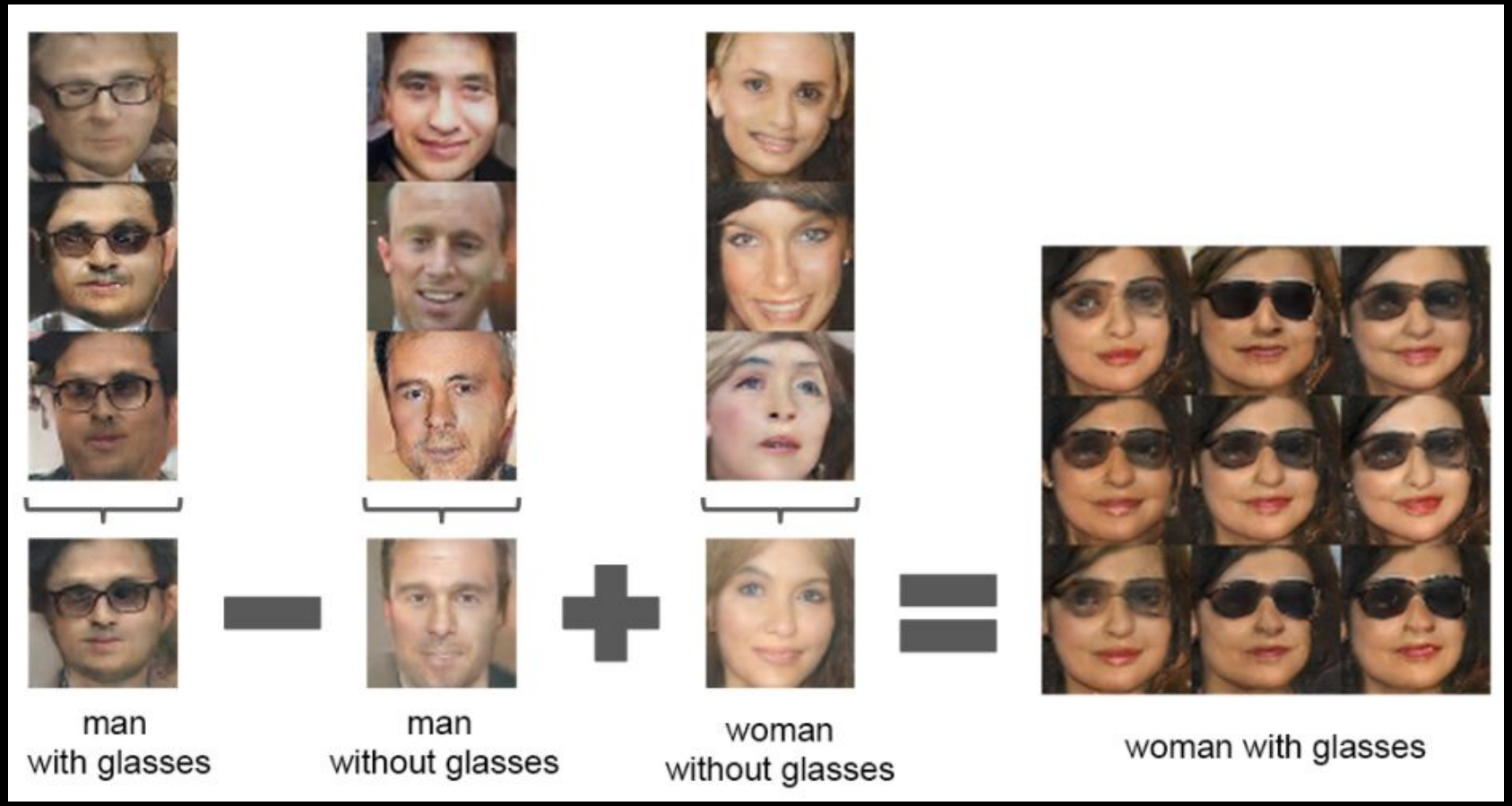
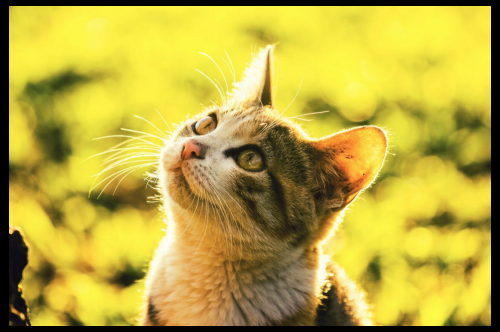
Semantics-awareness



Semantics-awareness

- If visual retrieval system is semantics-aware, then
  - It can find semantically similar images.



Semantics-awareness

Semantics-awareness

For the malwares,

- We can find samples which are semantically similar with a queried sample.
- We can find samples which have properties like “ransom, smspay, dropper”.
- We can find samples which have properties that “dropper” is removed from a queried sample.

Methods

Q3. Why do we use Metric learning?

Metric Learning

- Metric is a distance function.
  - Examples
    - Euclidean distance
    - Cosine similarity
- Learn how similar two objects are.

Similarities between Malwares

- Structural similarity
  - Static features (size, libraries, permissions, entropy, …)
- Semantic similarity
  - Static + Dynamic features (behaviors, logs, packets…)

Metric Learning

- Objectives
  - Embed malware samples on vector space.
  - Each embedded vector is made up of property vectors and some noise that includes the other informations.
  - Semantically similar samples should be embedded nearly in the vector space.

Metric Learning

- Parameterized distance function
  - $D(s_1, s_2; \theta) = d$
- Deep neural network
  - Universal function approximator
  - Examples of metric learning by deep learning
    - Siamese network, triplet loss
    - Center loss

Objective Function

- Objective Function
  - Multi-label Center Loss

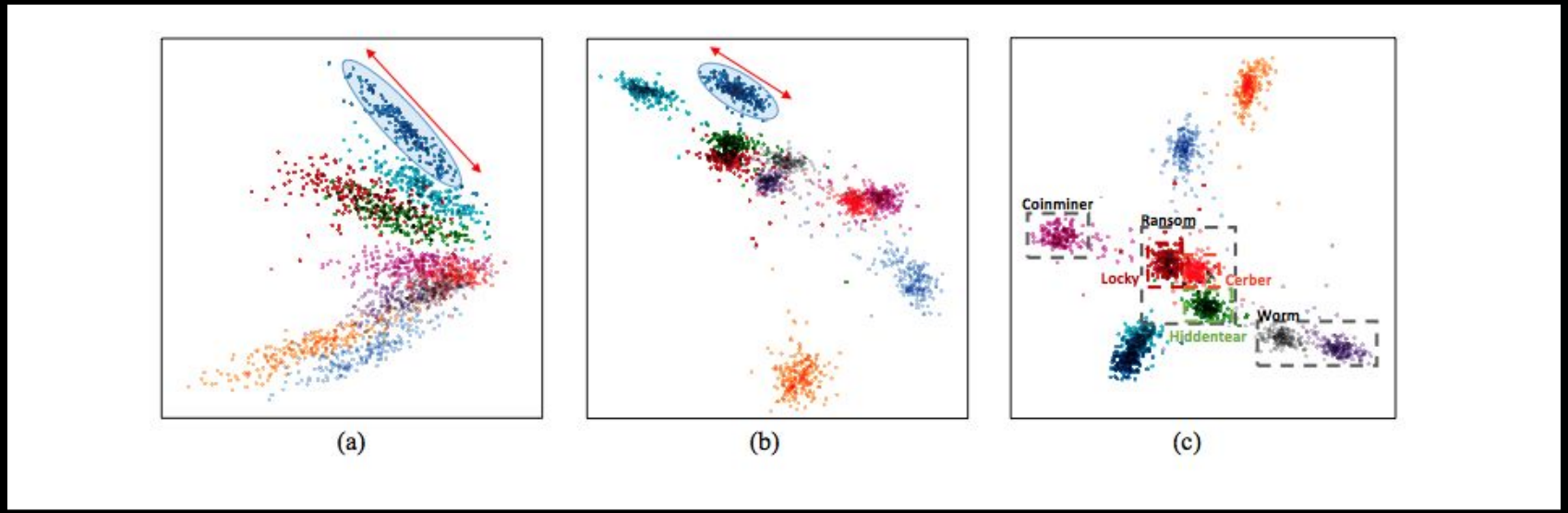
$$L = L_s + \lambda L_c$$

$$= -\frac{1}{N}\sum_i \sum_j y_{mij} \log \hat{y_{ij}} + \lambda \frac{1}{N} \sum_i (\mathbf{s}_{\text{target}} - h(v_i; \theta))^2$$

where

$$\hat{y_{ij}} = \frac{\exp(Wh(v_i; \theta) + \mathbf{b})}{1 + \exp(Wh(v_i; \theta) + \mathbf{b})}$$

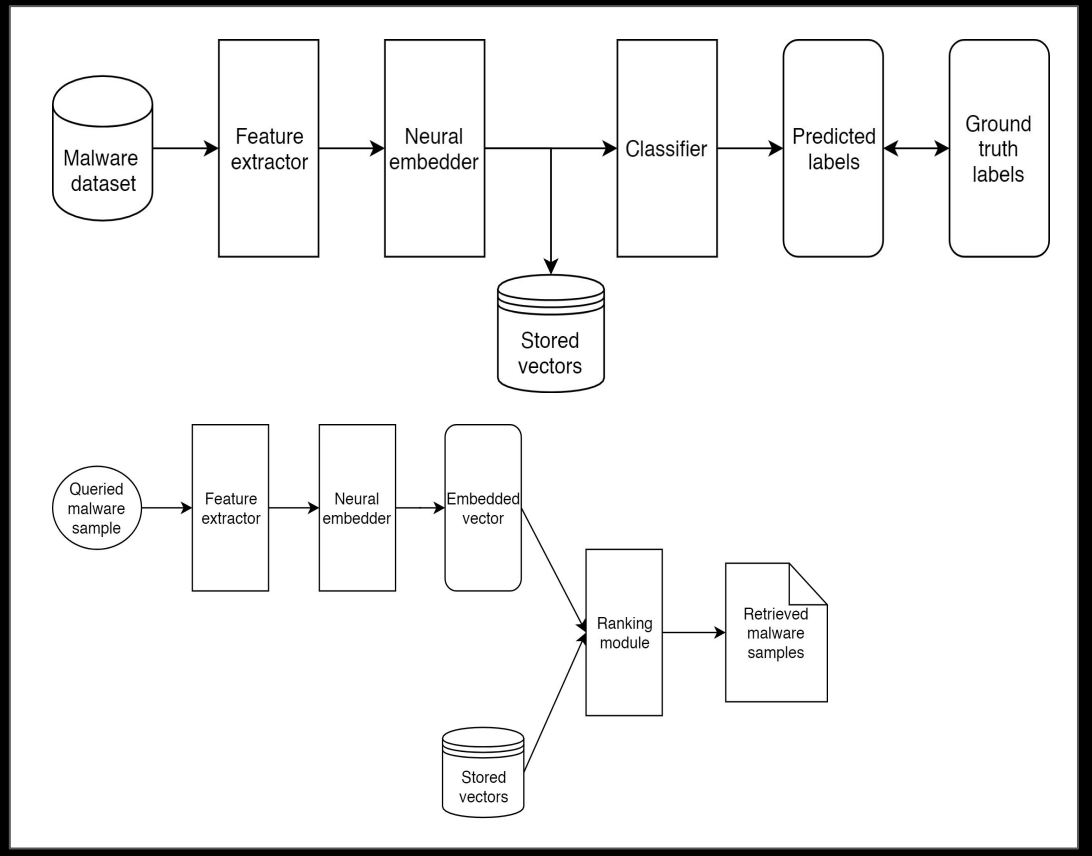
Objective Function



- Decrease inner class variance and increase inter class variance.
- If samples share properties, then they are located nearly.

Structure

- Structure of our proposed system.
  - Feature extractor
  - Neural embedder
  - Classifier
  - Ranking module



More Specifically

- Preparing dataset
  - Multi-tagged malware samples
  - Attach multi-tags to malware samples based on their properties.

Qualitative Results

Dataset	Querying trainset						Querying validset					
Metric	Precision			Weighted precision			Precision			Weighted precision		
k	top1	top10	top100	top1	top10	top100	top1	top10	top100	top1	top10	top100
Weighted centerloss (sum)	0.9846	0.9743	0.9374	0.9869	**0.9802**	**0.955**	0.8717	0.862	0.8272	0.8808	0.8746	0.8534
Weighted centerloss (avg)	**0.9856**	0.9772	**0.9481**	0.9855	0.9779	0.9528	**0.8929**	**0.8837**	0.8559	**0.8893**	0.8815	0.8591
Centerloss (sum)	0.9843	0.9737	0.9358	0.984	0.9733	0.9388	0.8736	0.8676	0.8373	0.8752	0.872	0.8462
Centerloss (avg)	0.987	**0.9776**	0.9474	0.9872	**0.9776**	0.9472	0.8845	0.8779	**0.8562**	0.8892	**0.8829**	**0.8631**
Multi-label (baseline2)	0.9764	0.9617	0.9115	0.9752	0.9593	0.9094	0.8871	0.8713	0.8184	0.8869	0.8704	0.8236
Single-label (baseline1)	0.9035	0.8727	0.8061	0.9004	0.8667	0.7946	0.8489	0.8231	0.7446	0.8434	0.8151	0.733

Dataset	APK19000			PE1300		
Variance	Intra-class	Inter-class	Inter/Intra	Intra-class	Inter-class	Inter/Intra
Weighted centerloss (sum)	0.0473	2.793	59.0486	0.129	2.169	16.8140
Weighted centerloss (avg)	**0.0101**	**1.1906**	**117.8812**	**0.0361**	**1.2698**	**35.1745**
Centerloss (sum)	0.2268	5.2967	23.3541	0.1748	1.8299	10.4685
Centerloss (mean)	0.0258	1.2785	49.5543	0.1332	1.6826	12.6321
Multi-label (baseline2)	2.4956	21.8435	8.7528	25833.582	840.54	0.0325
Single-label (baseline1)	1.2103	15.18	12.5423	2310.7649	267.683	0.1158

Demo - Training MR System

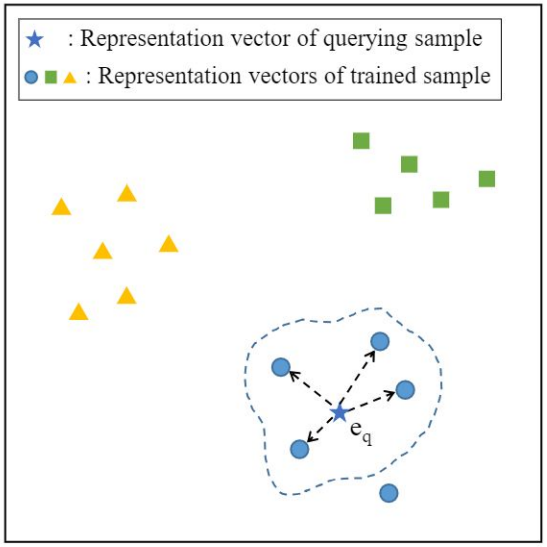
https://github.com/est-ai/malware-retrieval

Demo - Querying test

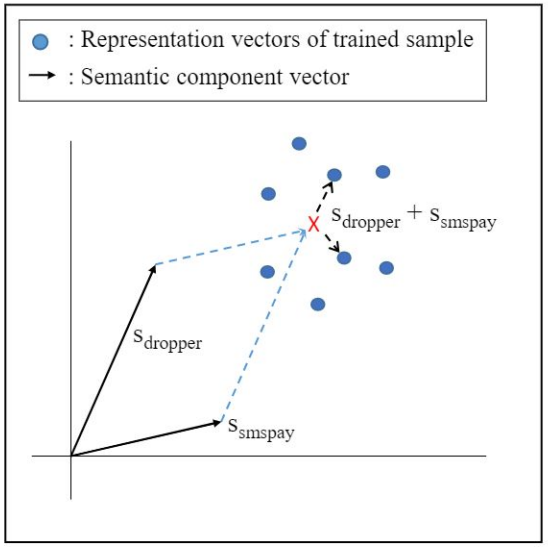
Sample Analysis

- Statistical Analysis - Probabilities of tags

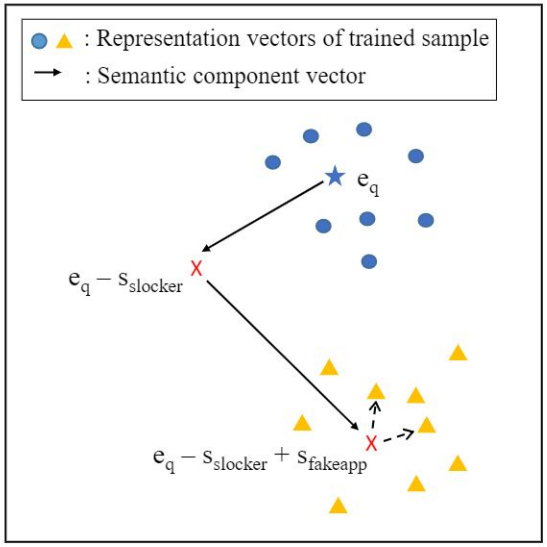
Verify Semantics-awareness



(a)



(b)



(c)

Querying by sample

Querying by tags

Querying by sample + tags

Issues

- Generalization
- Tagging

Demonstration

Thank you