How Machine Learning Is Solving the Binary Function Similarity Problem

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The binary function similarity problem

Binary function similarity is the problem of **taking as input the binary representation** of a pair of functions, and **producing as output a numeric value** that captures the similarity between them

Two functions are similar if they are compiled from **the same source code**

Several **practical applications** (e.g., reverse engineering, detect vulnerabilities, malware clustering).

Research motivation

Researchers have published an astonishing number of papers:

- Different communities publish in different venues
- The field is extremely fragmented

Main challenges:

- Inability to neither reproduce nor replicate previous results
    - Artifacts are often incomplete or incorrect
- Evaluation results are often opaque
    - Different objectives, settings, concept of similarity, and granularities
    - Different datasets, metrics, and implementations

It is unclear in which direction binary similarity research is heading and why.

Our contribution

Perform the first measurement study on the state of the art of binary function similarity:

- We **explore existing research** and group each solution based on the adopted approach
  - We particularly focus on recent successful techniques based on machine learning
- We select, compare, and implement **the ten most representative approaches** and their variants
  - Approaches vs. papers
  - Our implementations are built on top of a common framework
- We build a new dataset that we use as a **common benchmark.**

Measuring function similarity

Direct vs. indirect comparison:

- Direct comparison methods always require two functions in input
- Indirect comparison methods map the input features to a low-dimensional representation

Indirect comparison methods include:

- Fuzzy hashes intentionally map similar input values to similar hashes
- Code embeddings take in input a stream of tokens (e.g., Word2vec, Seq2seq, Transformer)
- Graph embeddings take in input the function control flow graph (e.g., Graph Neural Network).

Function representations

CODE /DATA

Raw bytes
Assembly
Normalized assembly
Intermediate Representations

higher abstraction

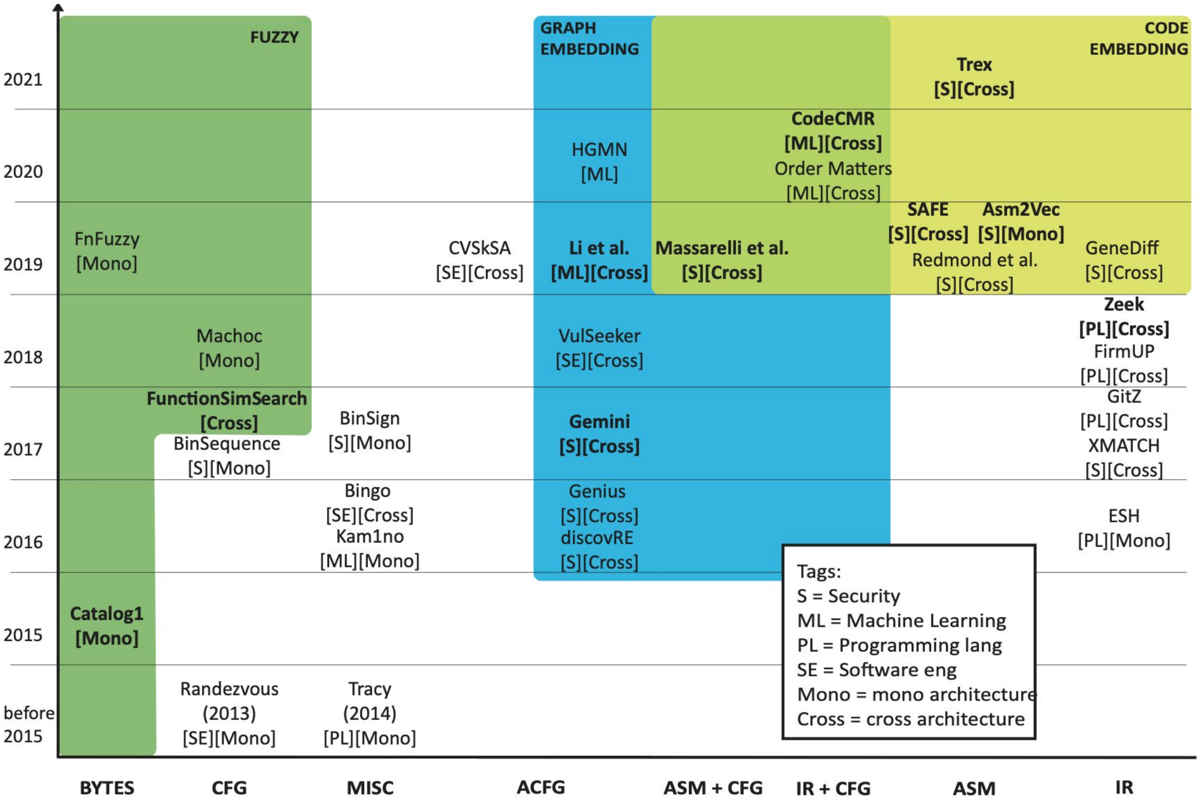
STRUCTURE

Control Flow Graph
Annotated Control Flow Graph

OTHERS

Data flow analysis
Dynamic analysis
Symbolic execution and analysis

Timeline of publication



Implementation and Dataset

We implemented each phase of the evaluation in an uniform way:

- IDA Pro 7.3 for the **binary analysis**, IDA Pro scripts for the **feature extraction**
- Tensorflow 1.14 for the **neural network models** in (except for Trex)
- Gensim 3.8 for the **word2vec models** (including Asm2vec)

We created two new datasets, Dataset-1 and Dataset-2. They include:

- Multiple compiler families and versions (GCC and `Clang`)
- Multiple compiler optimizations (`O0`, O1, O2, O3, and `Os`)
- Multiple architectures and bitnesses (x86-64, ARM, and MIPS, in 32 and 64 bit versions)
- Software of different nature (command line utilities vs. GUI applications)

Experiments

Selected approaches are evaluated on six tasks: XO, XC, XC+XB, XA, XA+XO, XM

- E.g., **XC**: the function pairs have different compiler, compiler versions, and optimizations, but same architecture and bitness.

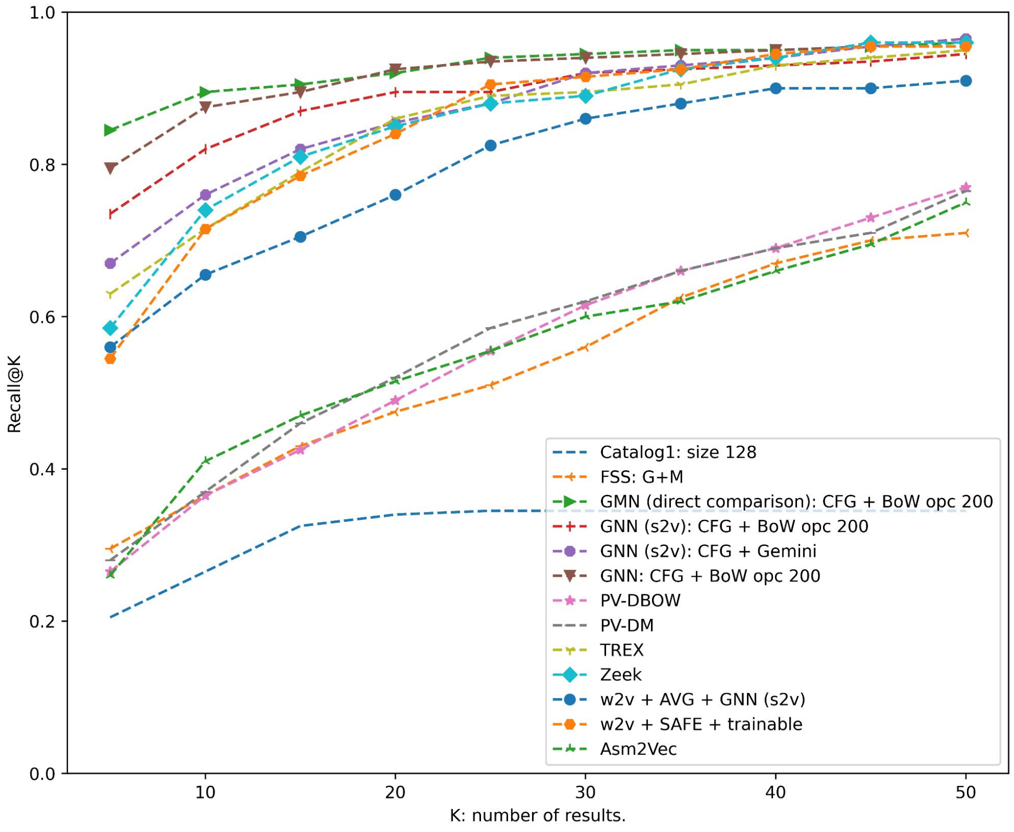
Each task is evaluated according to two different tests:

- The **area under curve** (AUC)
- The **mean reciprocal rank** (MRR) and the **recall** (Recall@K) at different K thresholds

The **function pair selection** aspect is crucial for a proper evaluation.

Results

Recall at different K for different models on the **XM** task (Dataset-1)



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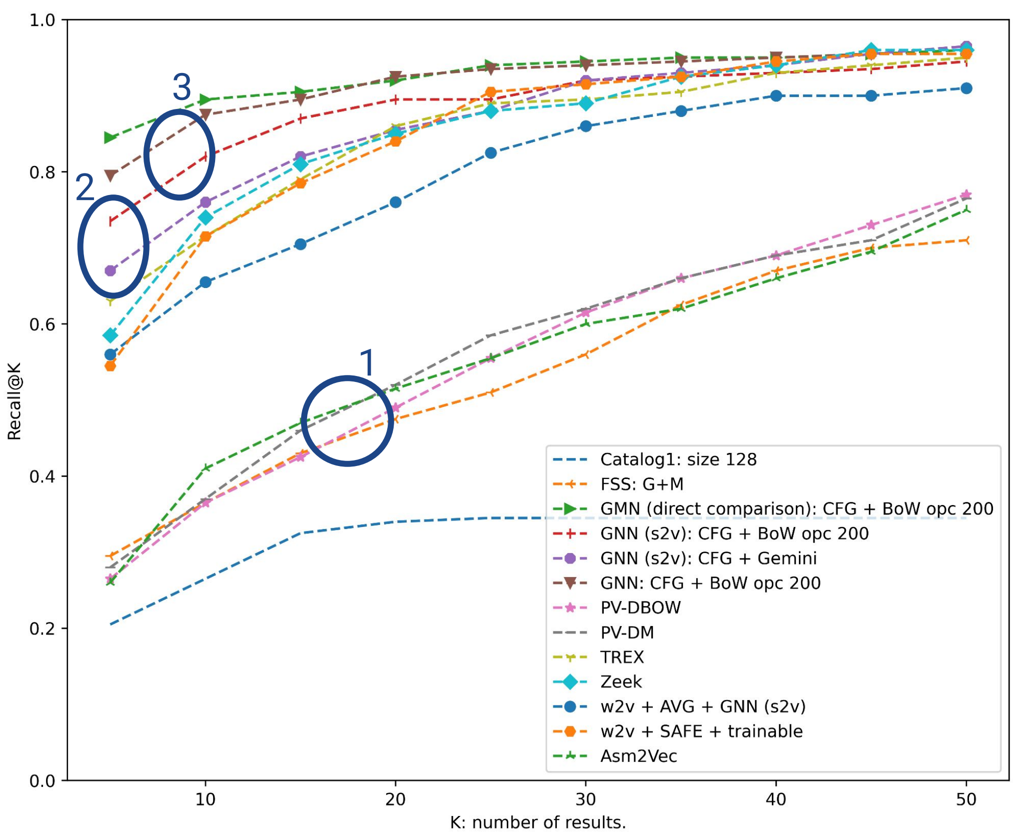

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Takeaways

Main contribution of the novel machine learning solutions

Deep-learning models provide **an effective way of learning** a function representation

The **Siamese architecture** in combination with a **margin based loss** introduced significant improvements

GNNs are effective encoders and can be used in combination with others.

Takeaways (2)

The role of different set of features

Using basic block features (e.g., **ACFG**) provides better results

Minimal difference between manually engineered features and simpler ones (e.g., BoW opcodes)

Dataflow information can boost the results, especially for large functions.

Takeaways (3)

Cross-architecture vs single architecture

Most of the machine-learning models **perform very similarly on all the evaluated tasks**

Training on generic task data allows to achieve performances close to the best for each task

Asm2Vec and Catalog1 are limited to comparisons to a single architecture.

Takeaways (4)

Future directions of research

GNN models provide the best results, but there are tens of different variants that need to be tested

Combining GNNs with **intermediate representations** and **data flow information** must be studied

Training strategy and **loss functions** have been barely discussed in the past and only recently explored.

Thank You

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https://github.com/Cisco-Talos/binary_function_similarity/