The good 0(ld) days

Finding old bits of code in binaries in the hope of finding 0day

Thomas Dullien (“Halvar Flake”) -- Google Project Zero
thomasdullien@google.com
HITB Bejing 2018

Growing “old” with dignity

- G.C. Rota says that if you work in a field for long enough, you become an “institution”.
- You are expected to behave in a certain manner.

- What you do research-wise stops to matter:
  - If it is bad, people will say: He is old and slow.
  - If it is good, people will say: No wonder, he has been working on this for 20 years.

Talking about the good 0(Id) days

Memories.

- IDA Pro user since 1997
- 21 years of reverse engineering
- 19 years since I wrote my first exploit
- 17 years since I first worked on an IL for disassemblies
- 15 years since I wrote the first prototype of BinDiff
- 7 years since I joined Google

Software Supply Chains are complicated

- Including a third-party software component under liberal licenses is “free”
- Unprecedented economics:
  - You want to build X.
  - Many input parts for X are available, and for free!
  - Of course you will use them!
- Explosive innovation driven by vast quantities of high-quality libraries with liberal licenses.
- “Software is eating the world, and a good part of it is open-source.”

Software Supply Chains are complicated

- Dependencies have further dependencies.
- Your third-party library may contain code from another third-party library.
- Enumerating dependencies is nontrivial.

3rd party library security is hard

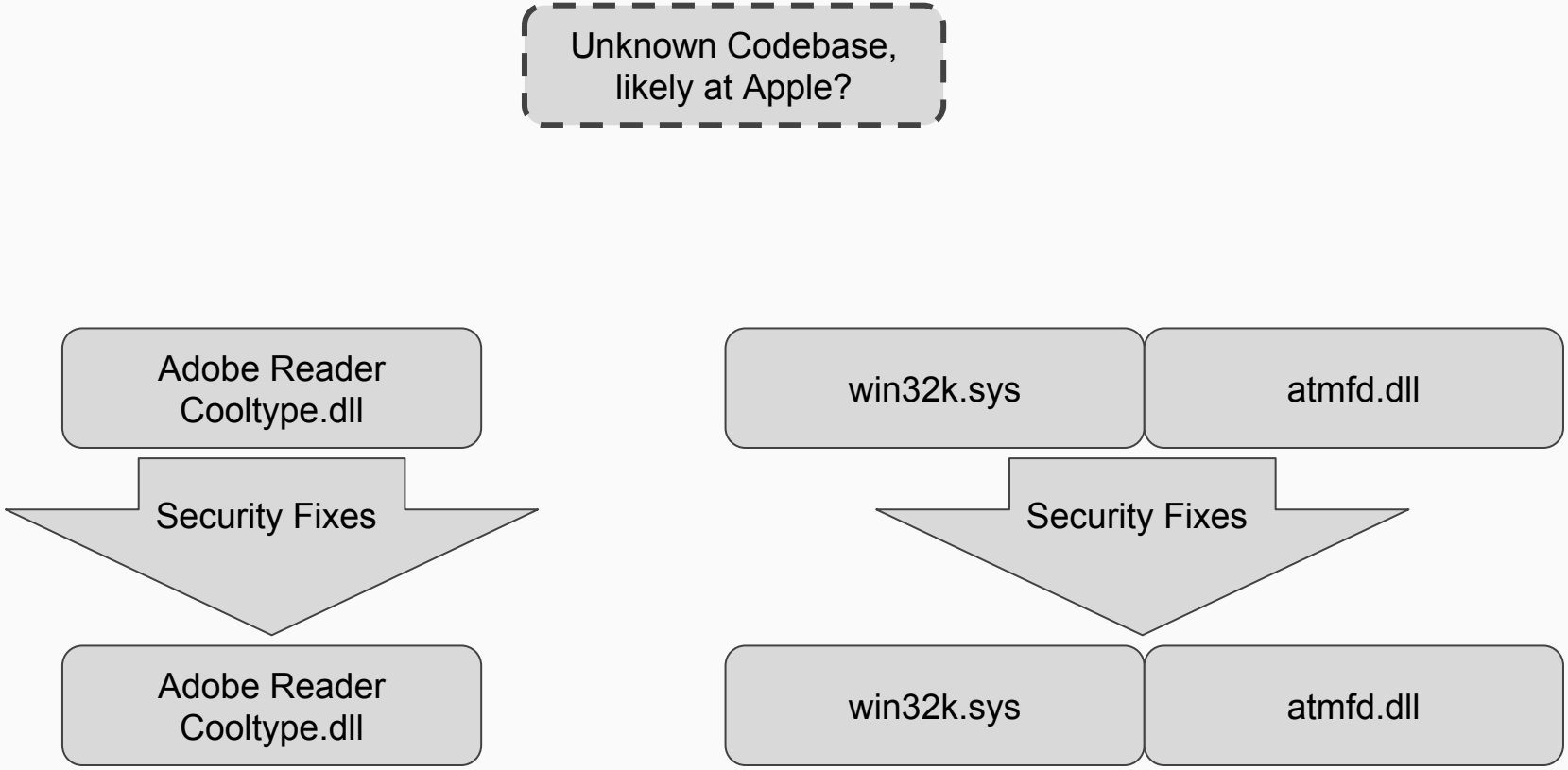
- How do you monitor 3rd-party libraries for security fixes?
- Does the 3rd-party library even distinguish between security and non-security fixes? If not, can you?
- How quickly can you update if a security flaw in a 3rd-party library is identified?

Centralized libraries are high-value targets

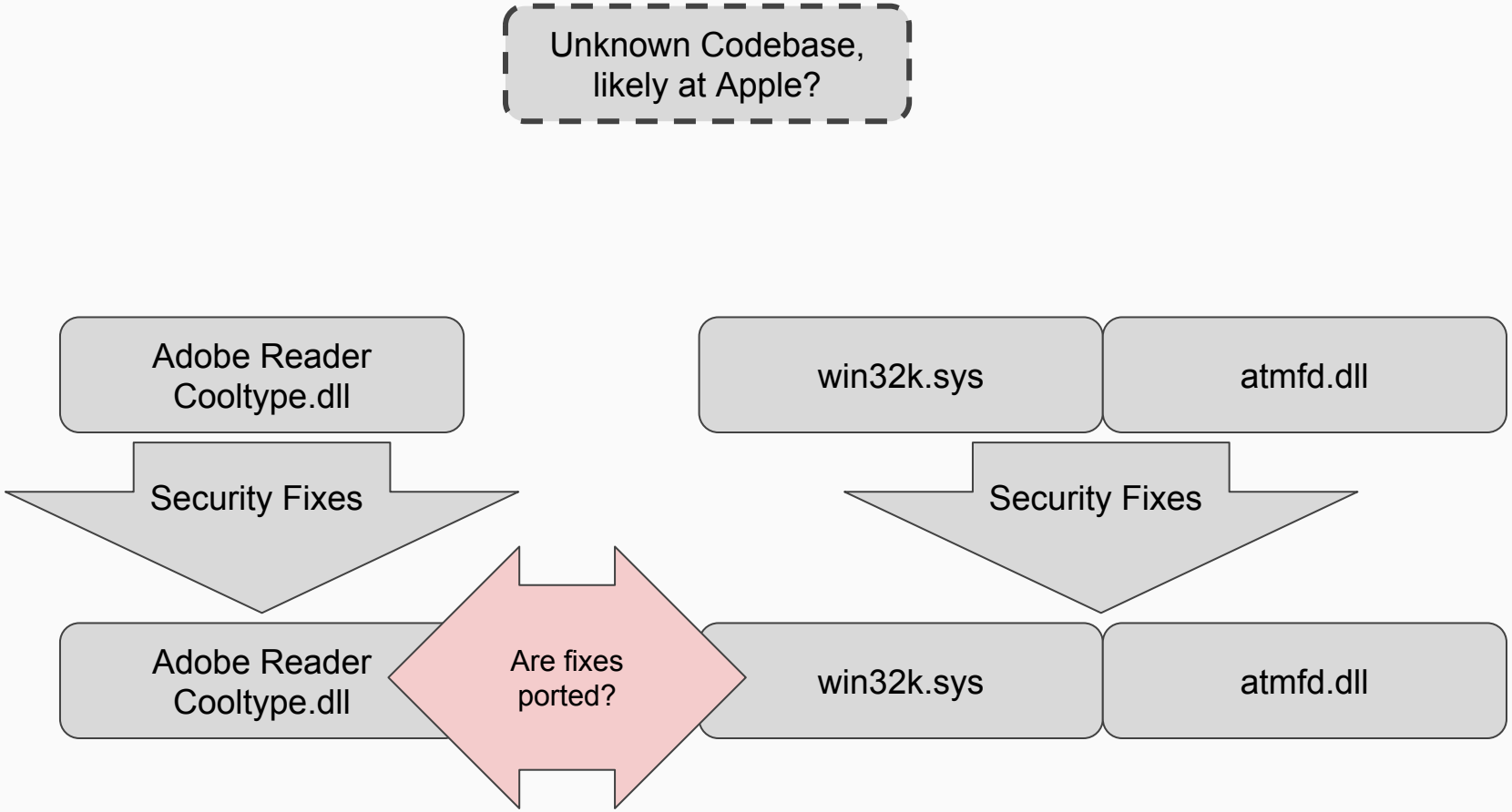
- A flaw in a single, well-chosen open-source library can affect dozens of products.
- Gold standard: Zlib (histrical example: CVE-2005-2096 - crash in zlib through decompressing a PNG)
- Other libraries with high centrality: Unrar (one bug gives compromise of almost all antivirus engines), libtiff (PDF rendering, browsers, thumbnailers), compression libraries (Brotli) etc. etc.

Examples

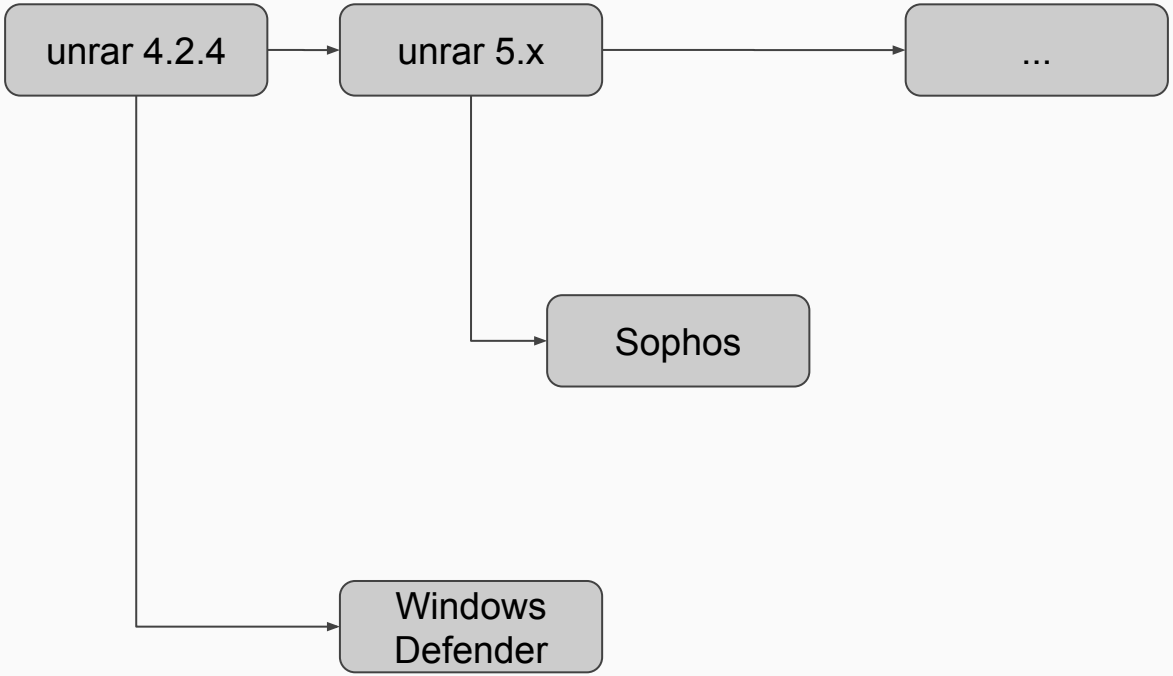
Example: Font parser codebase ancestry



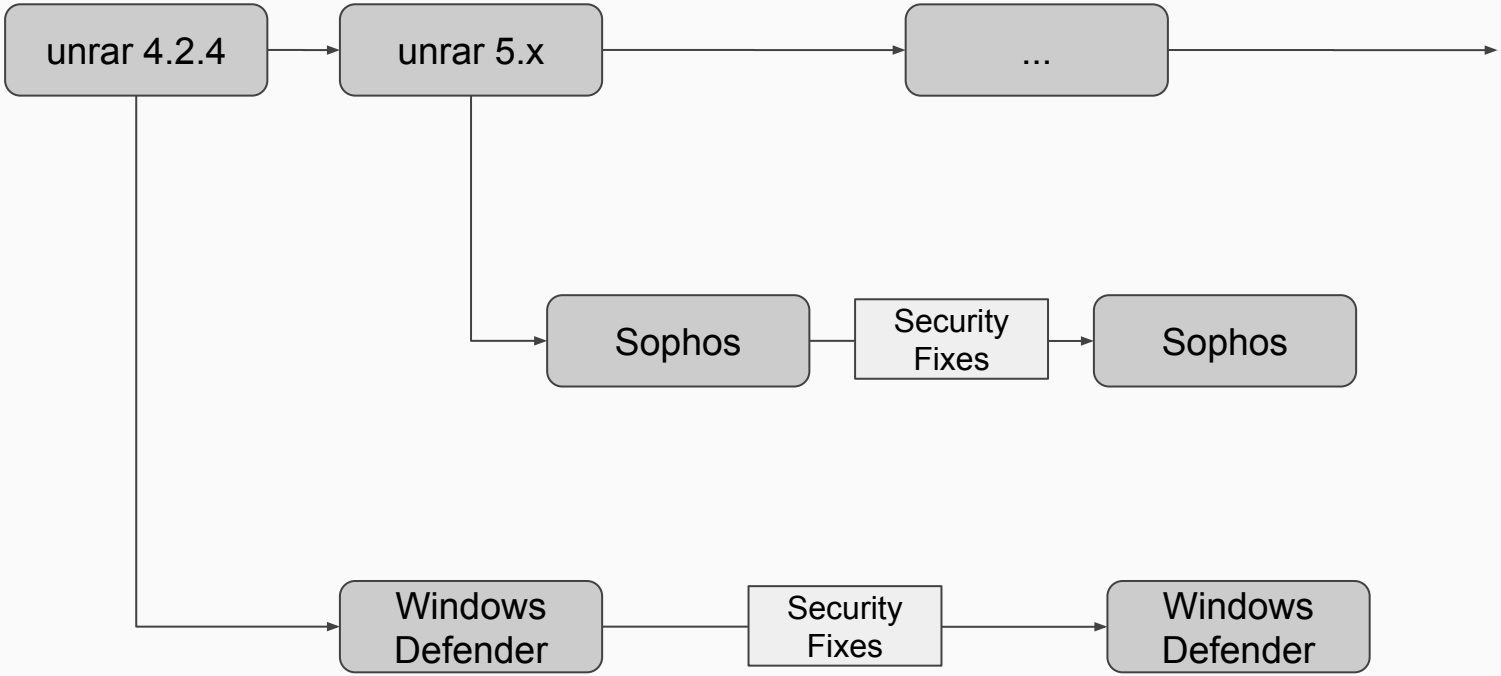
Example: Font parser codebase ancestry



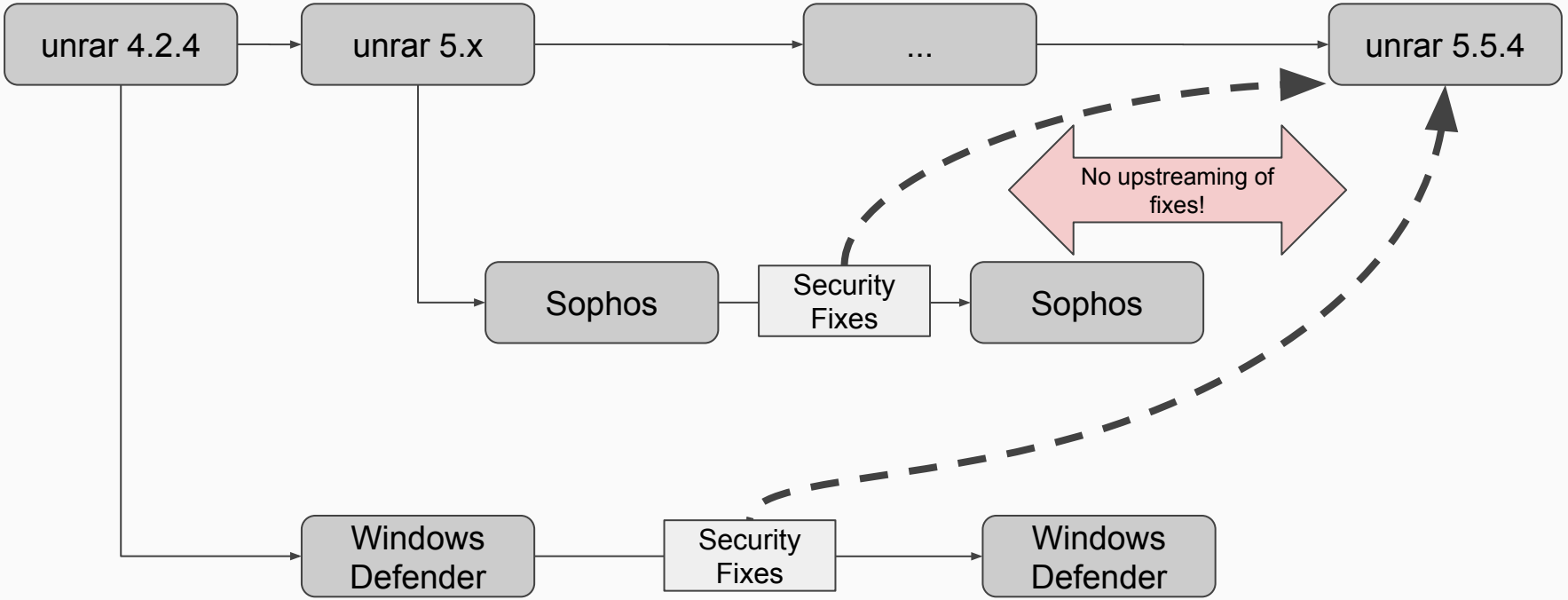
Example: UnRAR



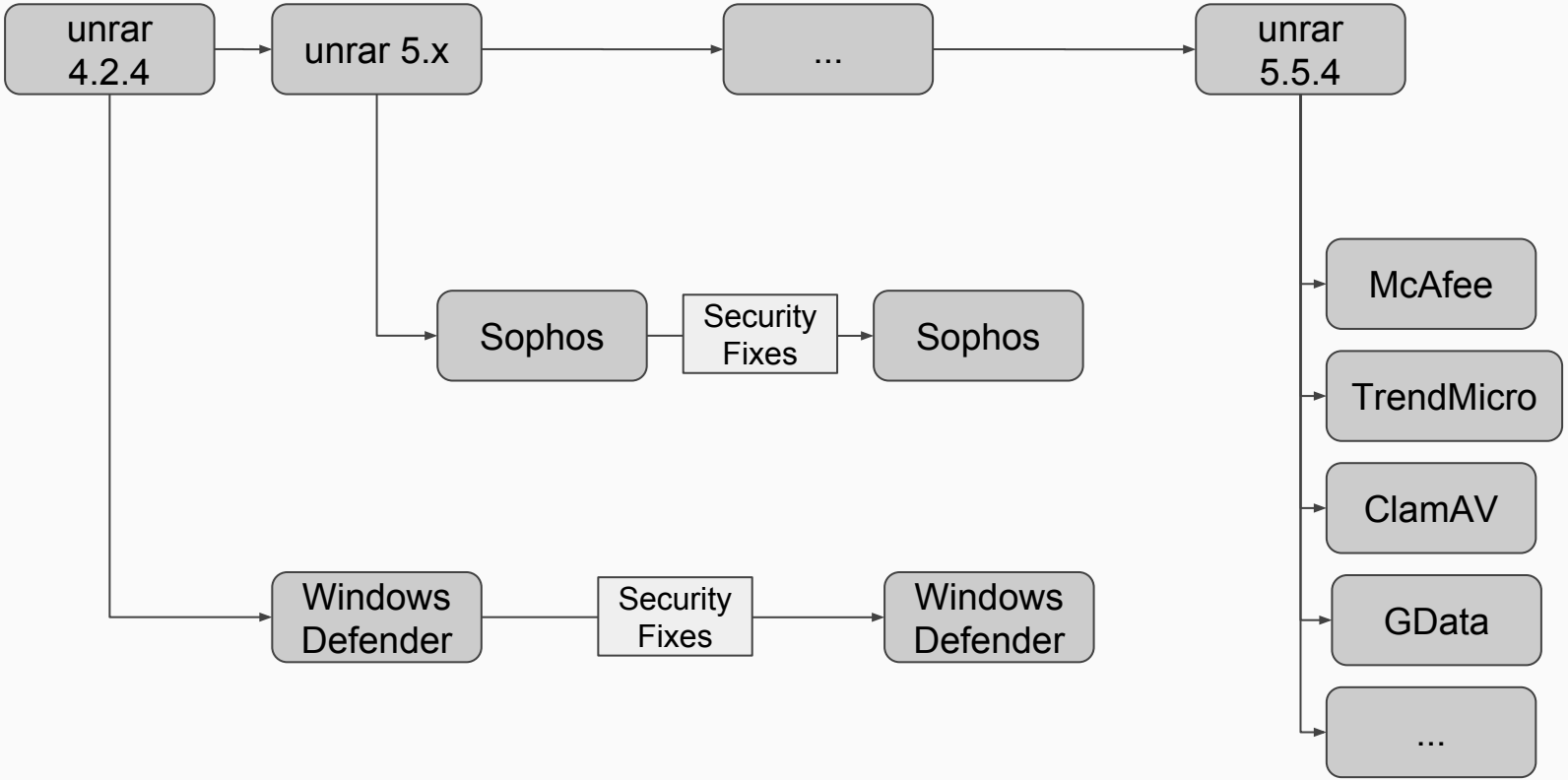
Example: UnRAR



Example: UnRAR



Example: UnRAR



Detection in binaries

Detection of libraries in binaries is difficult

- Compilers change over time
- The libraries themselves change over time
- Only “precise” way of detection: Common strings?

- Control-flow-graph & disassembly can change drastically …
  - due to compiler changes
  - due to compiler setting changes
  - due to library code changes
  - due to interaction of library code changes with compiler changes & settings changes

Related work

IDA’s FLIRT

- Byte signatures with wildcards & extra stack information.
- Fast, lightweight, but also brittle.

MACHOKE

- Serialize CFG into a canonical string.
- Apply Murmurhash3 on this string.

- No concept of “similar but not equal”.
- Tries to achieve fuzzyness by not taking instructions into account at all.

GENIUS [Paper]

- Operates on “ACFG” (CFGs annotated with extra data like # of calls, string constants etc.)
- Selects a “codebook” of representative graphs from groups of training graphs (e.g. implementations of the same function) via spectral clustering.
- Associates each codebook-graph with a high-dimensional vector.

GENIUS [Paper]

- Incoming graph is compared to each representative codebook graph (via calculating a bipartite graph matching), result vector in R^n is constructed from this.

- Similarity-search is performed using locality-sensitive hashing for approximate nearest neighbors using the R^n vector.

GEMINI [Paper]

- GENIUS suffers from …
  - expensive pre-clustering (for the codebook generation)
  - relatively expensive search (many bipartite graph matchings against codebook)
- GEMINI addresses these problems using Deep Learning.
- Uses “structure2vec” method to compute an R^n embedding from a graph.

GEMINI [Paper]

- Learn embedding from ACFGs to R^n using “structure2vec” (general graph-to-embedding model)
- “Siamese architecture” (2 parallel runs of the embedding, minimize / maximize resulting distance)
- Given input graph, calculating embedding into R^n is quick, lookup using locality-sensitive hashing for ANN.

GEMINI [Paper]

- Looks powerful.
- Not available publicly.
- Unclear how much the model learns beyond “string search”.

Practical considerations.

Motivation

- Reading MPEngine.dll, I recognized unrar code.
- Extensive experience with Adobe’s font parser & it’s heritage.
- “Can I build something that helps me find third-party libraries for my practical day-to-day-work?”

Design considerations

Automatically recognize & suggest libraries

- Given a function, I should be able to ask: “Does this look similar to anything in my library of 3rd-party-libs?”

- Search should be resilient to small changes in both graph and assembly.

Single-machine setup

- The system should not require extensive setup.
- Should run on a single machine without requiring big databases or distributed key-value stores in the background.
- The system should still allow quick lookup of O(million) stored library functions.

Easy integration with other RE tools

- Tools need to be integrated with RE workflows.
- Vulnerability researchers have heterogeneous setups: IDA, Binary Ninja, Radare2, Miasm, Hopper etc.

- Highly divergent extension APIs, philosophies etc.
- Solution: Compile to Python extension, should be easily accessible from all tools that have a Python Interpreter.

Learning from data

- “Machine Learning” (e.g. automated use of statistical estimation) can help extract useful information from lots of unstructured data.
- Both GENIUS and GEMINI use heavy-duty machine-learning algorithms.
- System under consideration should also allow improvement from data (“learning”).

Inspectability of learnt results

- When the ML algorithm learns something, the results should be “inspectable by an expert”.
- Initially: Happy to sacrifice accuracy in for interpretability of results.
- As confidence in the system grows, I am happy to move to more complicated/powerful ML models.

Easy sharing of results

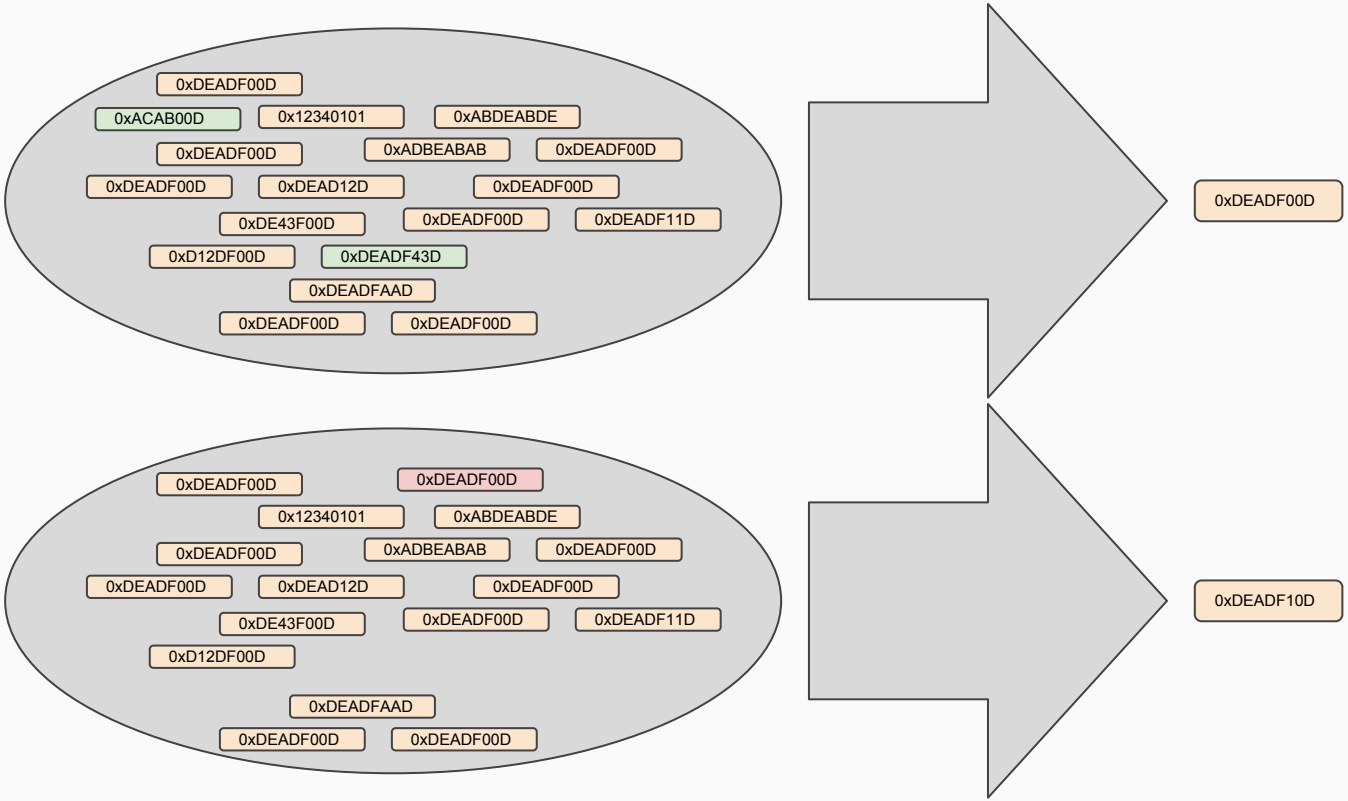
- The primary means of communication is still “email” or “chat”.
- It should be easy to send a friend the “fingerprint” of a given function via email or chat.

Implementation details

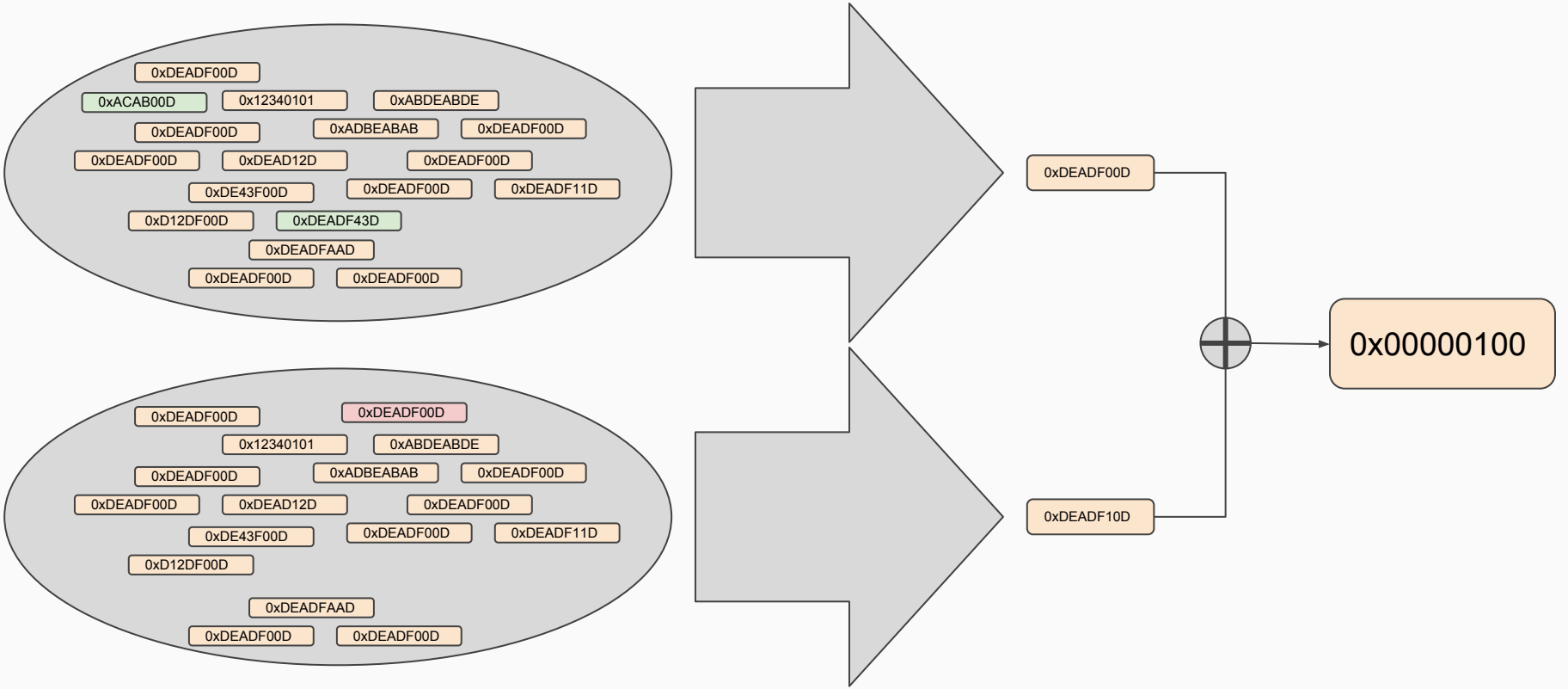
SimHash to obtain compact hashes

- SimHash provides a method to calculate a “similarity-preserving” hash from a set of feature hashes.
- Given two sets of features extracted from two functions, the SimHashes calculated from the two sets will have low hamming distance if the set similarity was high.
- Very nice properties: Our search index can be 128-bit hashes (compact!)

SimHash to obtain compact hashes



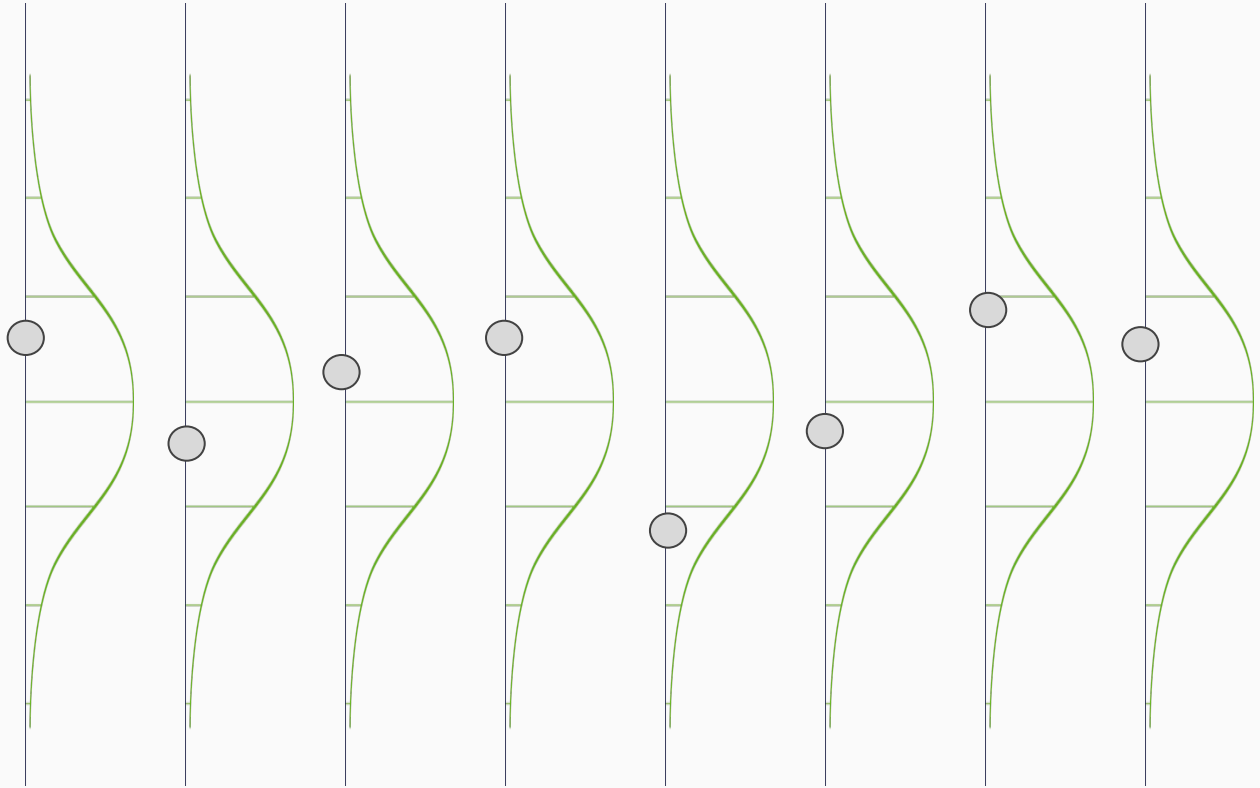
SimHash to obtain compact hashes



SimHash algorithm sketch

- Allocate array of N floats (if your input hashes have N bits)
- For every input hash, do:
  - If the bit input_hash[k] == 1, **in**crement the float[k] by 1.0
  - If the bit input_hash[k] == 0, **de**crement the float[k] by 1.0
- Convert floats to bits again by assigning positive floats to “1” bits and negative floats to “0” bits.

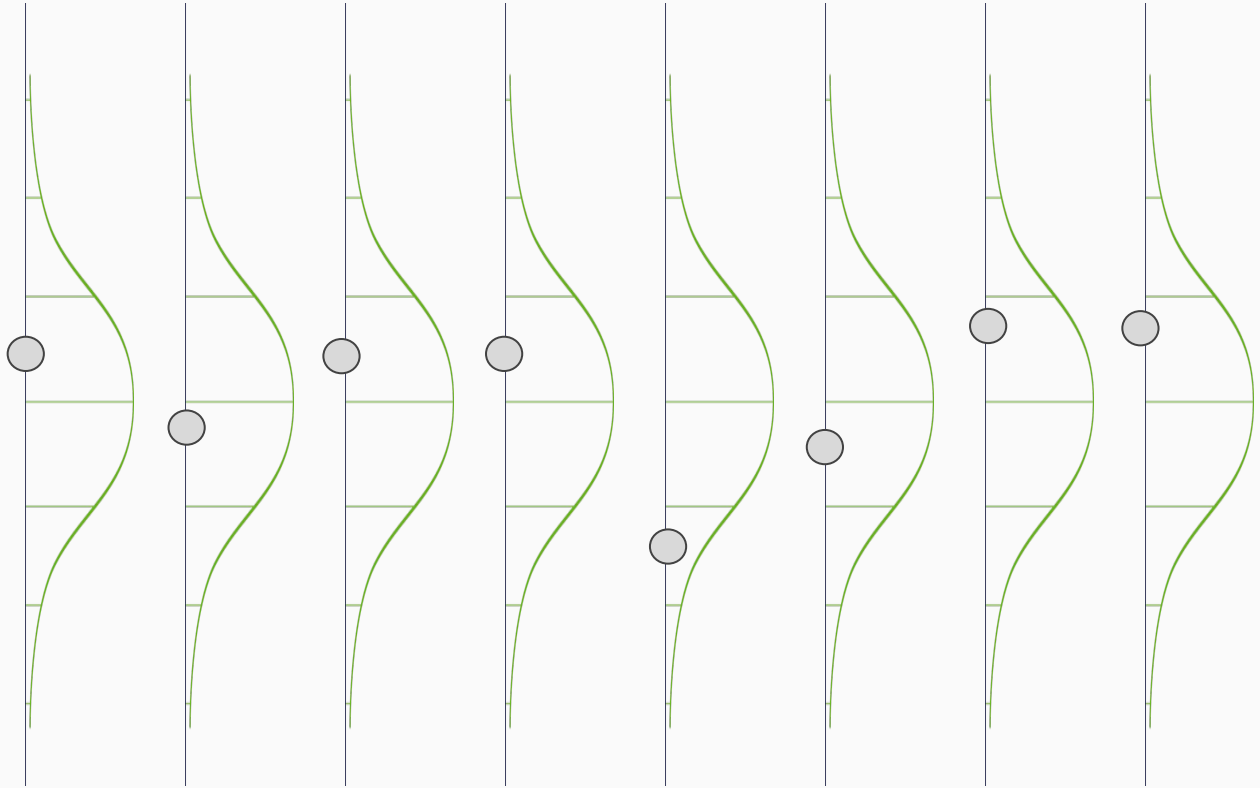
SimHash Illustration: Internal state after K steps



Floats are normally distributed around zero.

With every additional processed feature, they will wobble up or down a little bit.

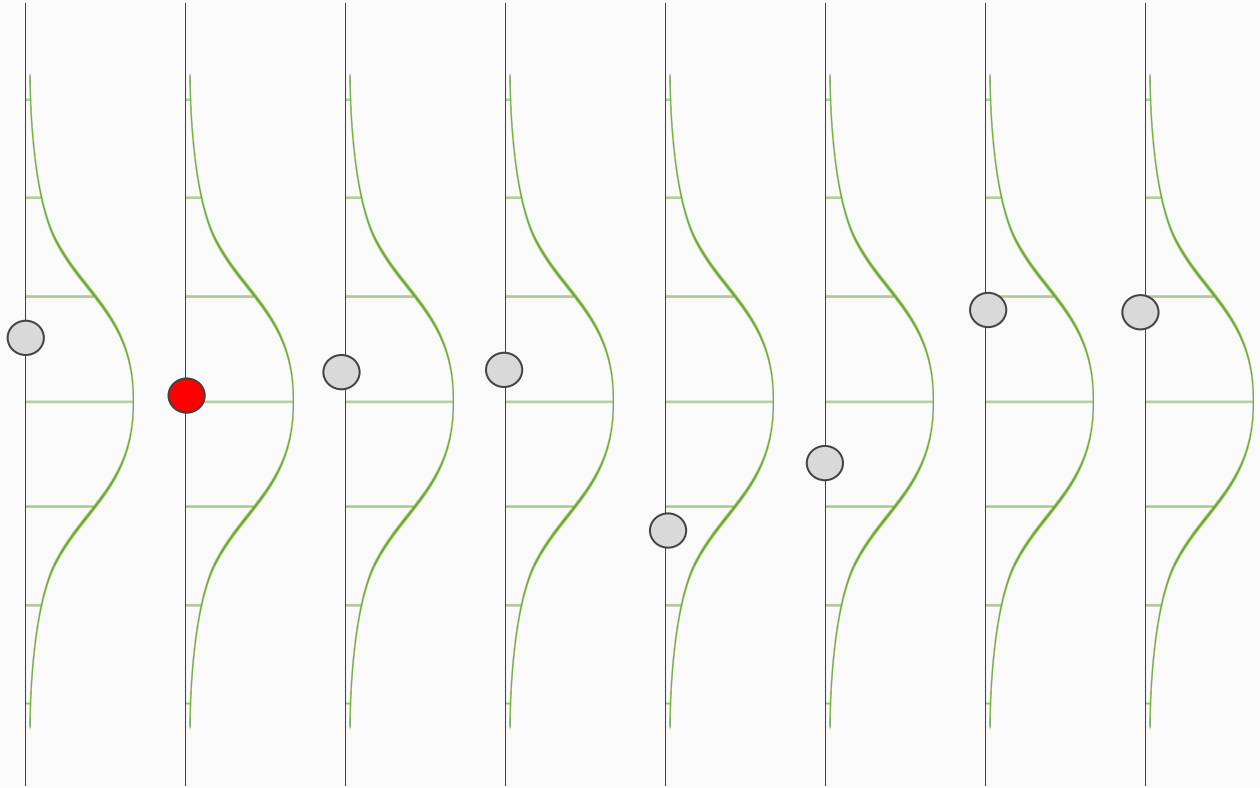
SimHash Illustration: Internal state after K steps



Floats are normally distributed around zero.

With every additional processed feature, they will wobble up or down a little bit.

SimHash Illustration: Internal state after K steps



Floats are normally distributed around zero.

With every additional processed feature, they will wobble up or down a little bit.

Only those that cross the “zero” line will change the resulting hash.

Locality-sensitive hashes via permutation

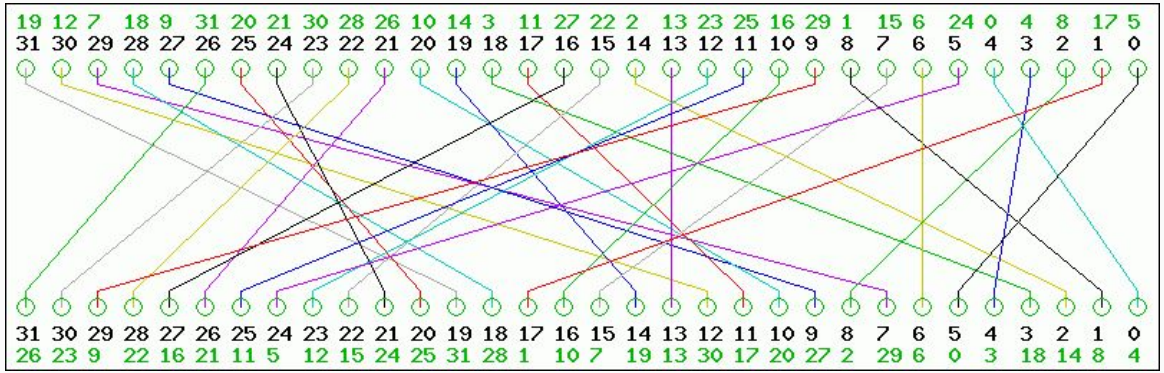
- Similarity search in O(million) of hashes is doable, but O(million) sounds like it would be slow.
- Approximate nearest-neighbor search can be achieved using locality-sensitive hashing.
- LSH: A family of hash functions where nearby points have a higher probability of landing in the same hash bucket than far-away points.

Locality-sensitive hashes via permutation

- Easy for hashes (~bit-vectors): Simply take a random subset of bits.
- Pick random permutation. Permute all the bits, then take first N bits as hash.
- Permute & take first N bits again for the next hash.

Locality-sensitive hashes via permutation

- 128-bitwise permutation can be had for ~65 cycles. (I used a cool generator that generates C code for a given bitwise permutation: http://programming.sirrida.de/calcperm.php)



Learning good weights from example data.

SimHash with learnt weights

- SimHash uses +1 and -1 as weights.
- Not every feature has the same relevance - function prologues etc.
- How can we best “learn” good weights from examples?
- First, generate labeled examples: Lots of versions of the same function.

SimHash with learnt weights

- Can we optimize weights so that …
  - … pairs of similar functions get closer together and
  - … pairs of dissimilar functions get moved to be further apart?
- SimHash distance is Hamming Distance, which is discrete.
- Supervised Machine Learning usually means running optimization algorithms on a differentiable loss function.
- We need something continuous to differentiate so we can “learn weights”.

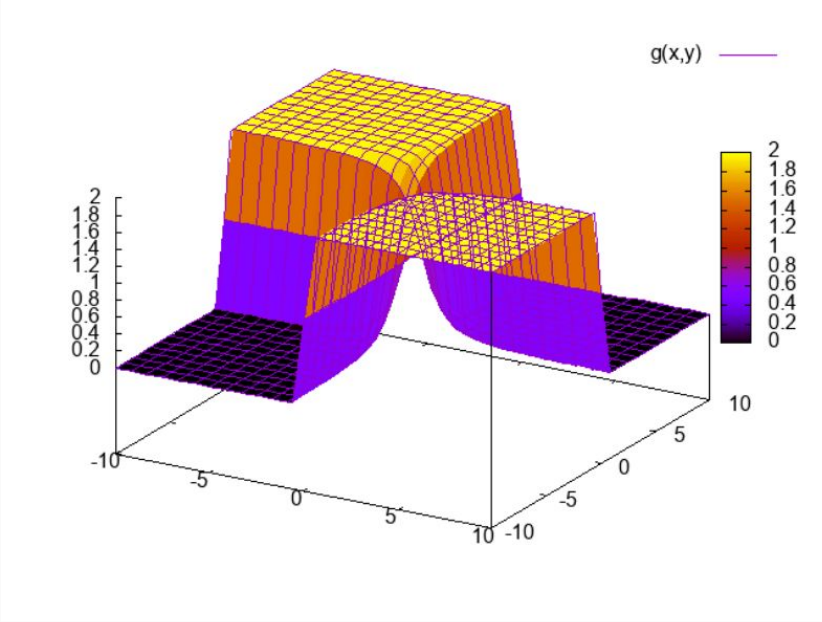
SimHash with learnt weights

- Before we convert floats to bits again, we have float values for every k
- We can take two vectors of floats and run them component-wise through a function that punishes “same sign” or “different sign”.

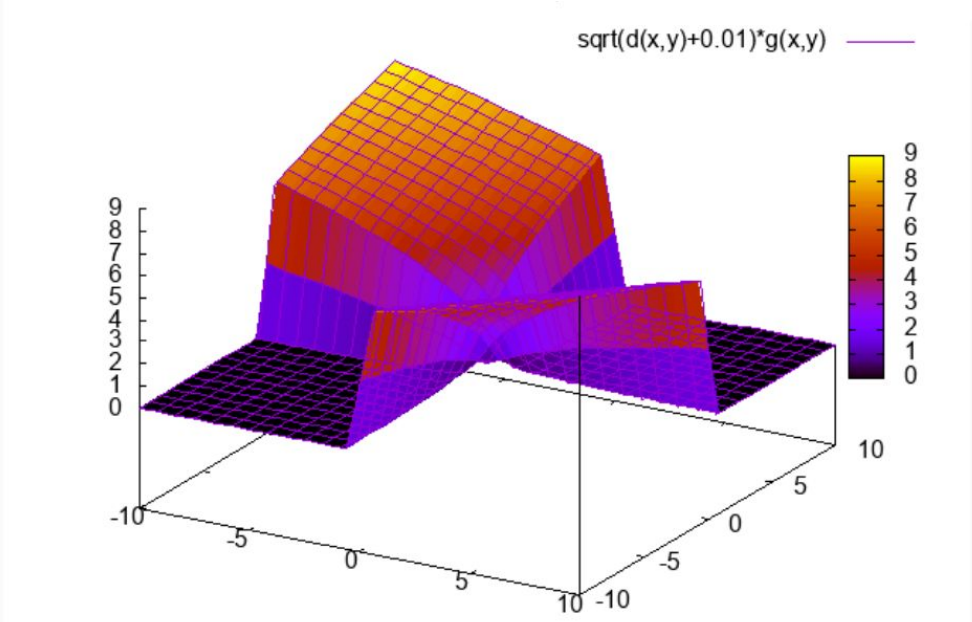
SimHash with learnt weights

$$g(x,y) := -\frac{xy}{\sqrt{x^2y^2+1.0}} + 1.0$$

$$d(x,y) := \sqrt{(x-y)^2 + 0.01}$$



Smooth step function: No gradient in the flats.



Multiply with d(x,y) to slope the flat sections.

Automatic differentiation & minimization

- Many libraries exist to perform automatic differentiation & minimization.
- I wanted a pure C++ codebase, so instead of Python/TensorFlow or Python/Keras or Julia I used a C++ library (SPII) for it.
- This makes using GPUs for training hard, so was probably not a great decision.

Evaluating the training results.

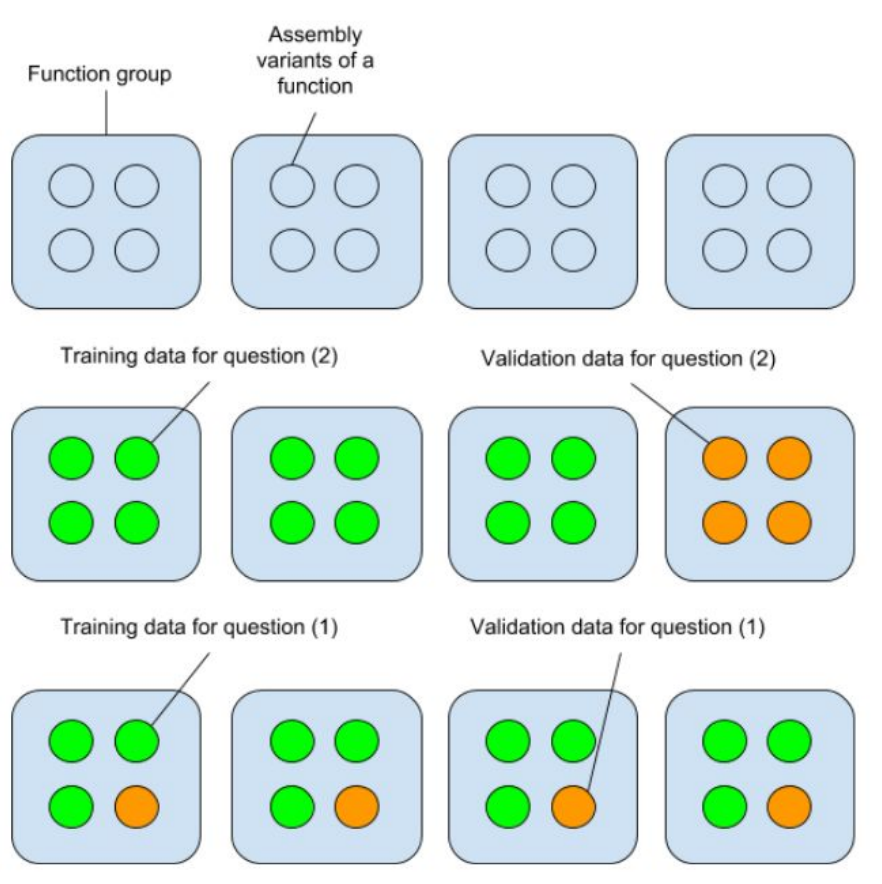
Questions we have:

1. Does the learning process improve our ability to detect variants of a function we have trained on?

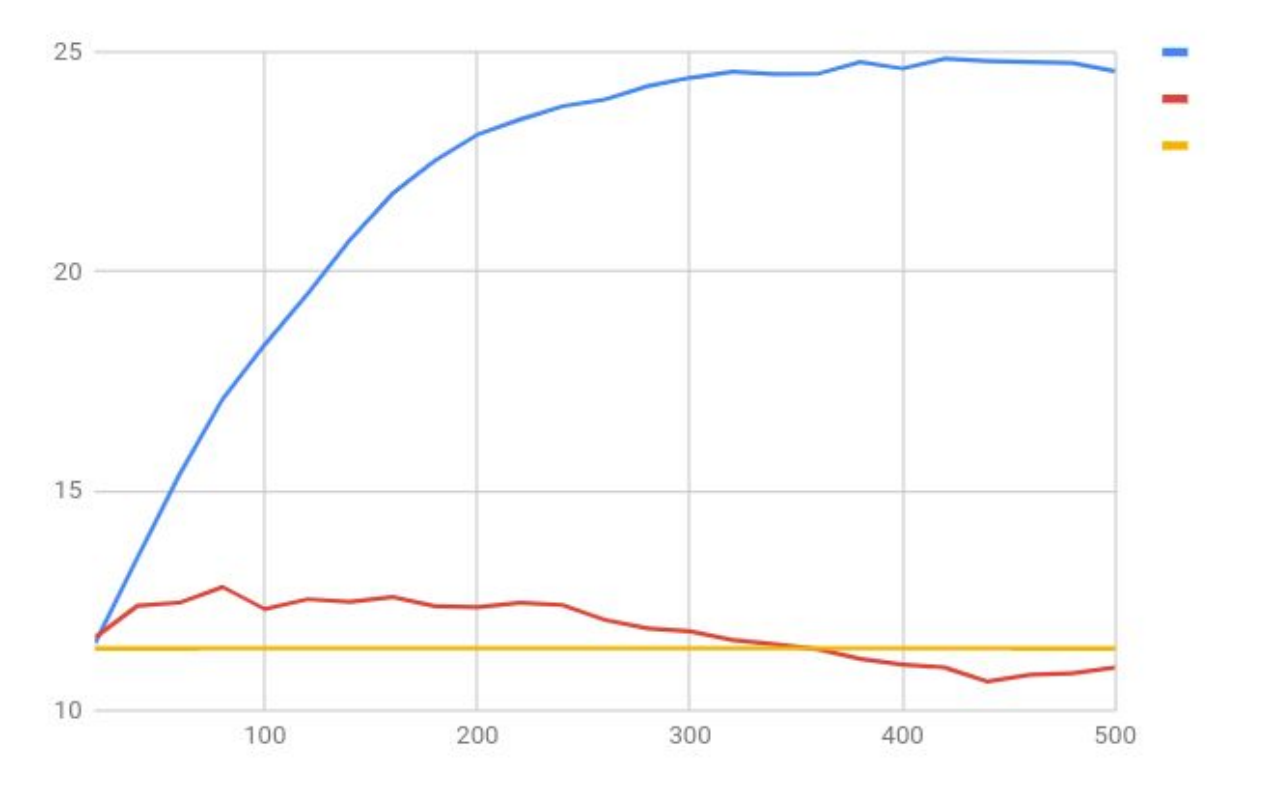
2. Does the learning process improve our ability to detect variants of a function **even if we have not seen** a variant of it before?

3. Are the results we get for (1) or (2) practically useful yet?

Different ways of splitting data for question 1 and 2



Difference in average distance for between similar and dissimilar pairs after N steps



Data split for Question 1

Data split for Question 2

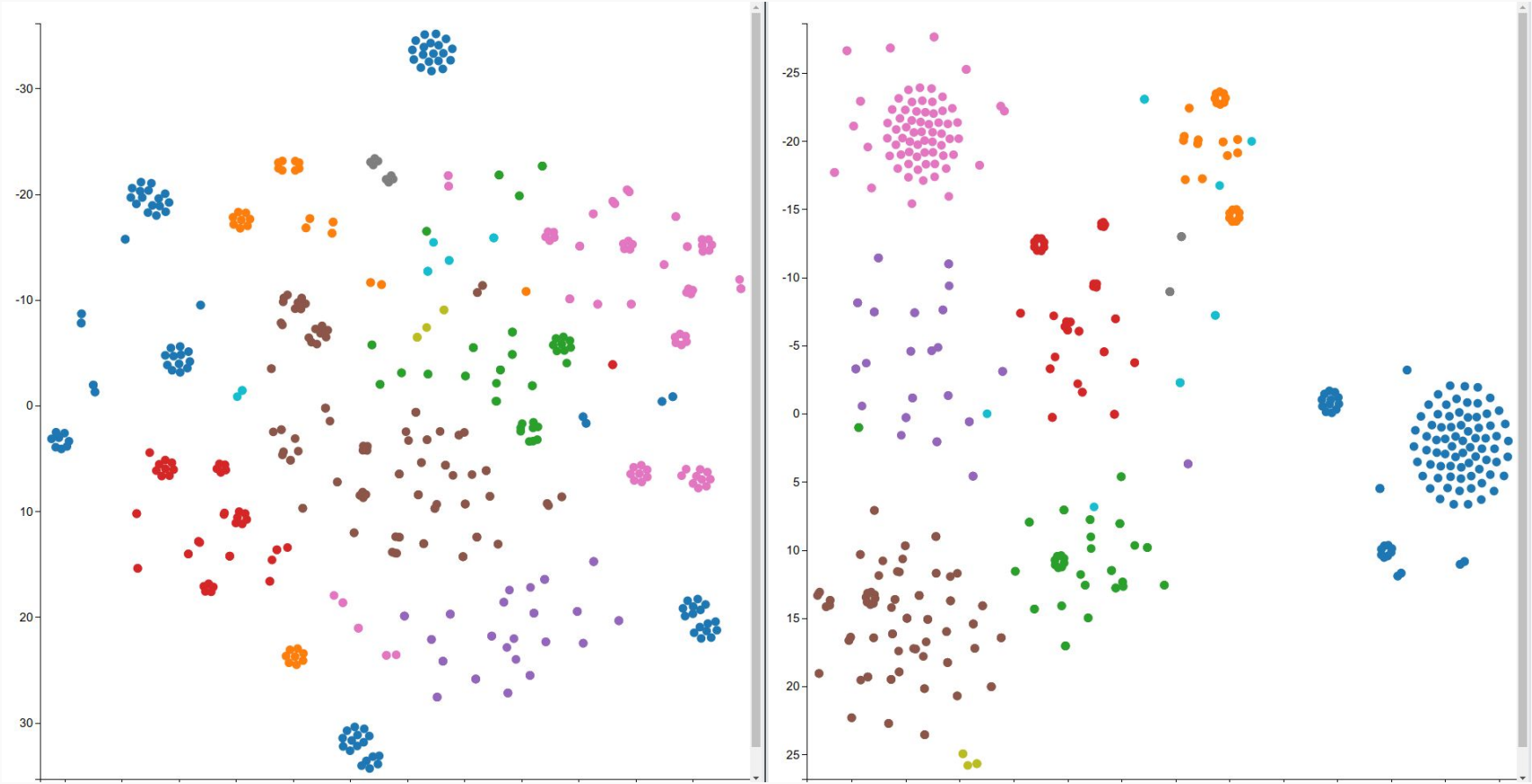
No training

Current state

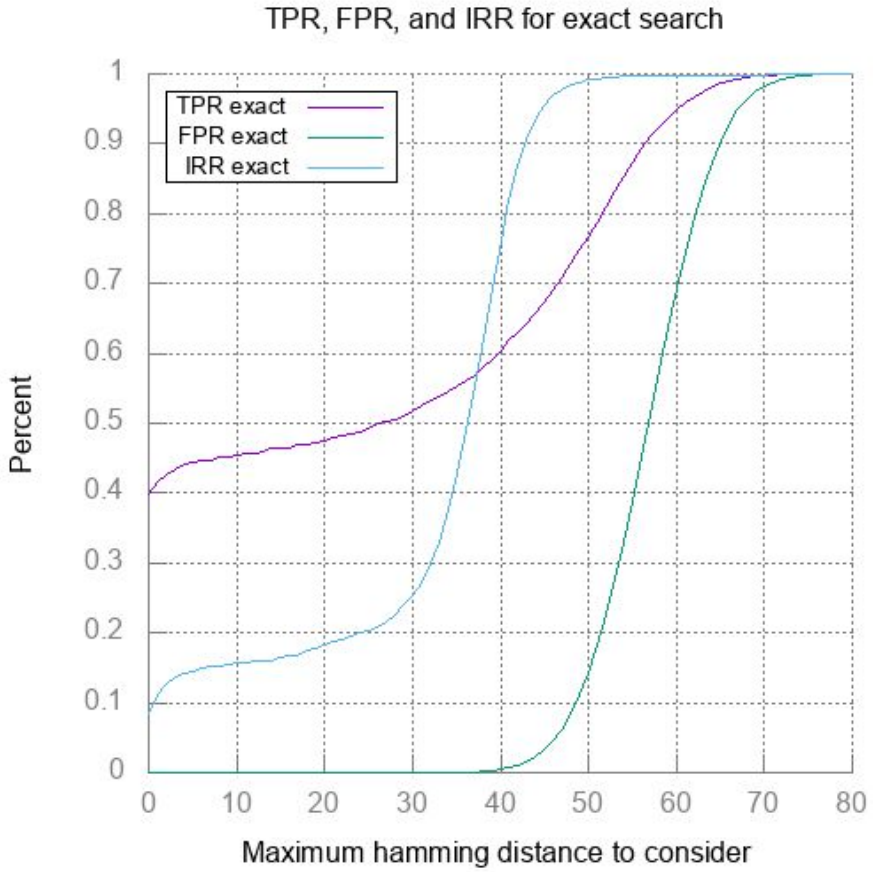
1. Mean-difference-between-good-and-bad-pairs goes up significantly for functions that we had variants for -- see graph (better separation).

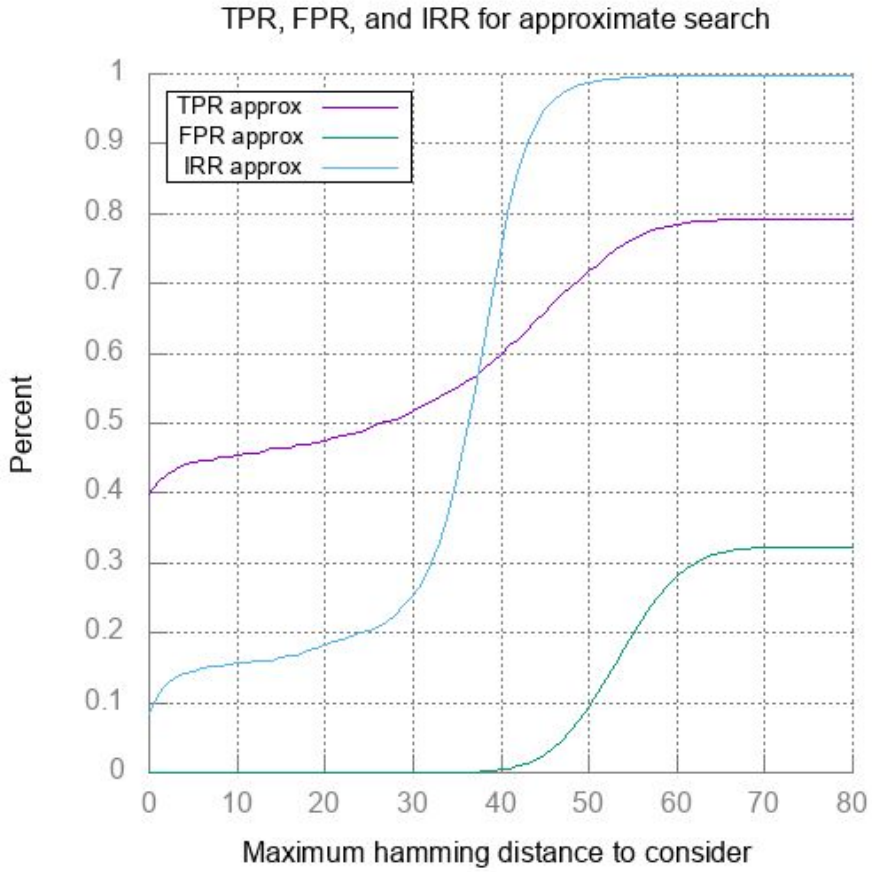
2. Mean-difference-between-good-and-bad-pairs goes up very slightly for functions that we had no variants for (very slightly better separation). Something about compilers is being learnt, but the signal is weak (better models?).

T-SNE of untrained (left) and trained (right) hash distances (Question 1)

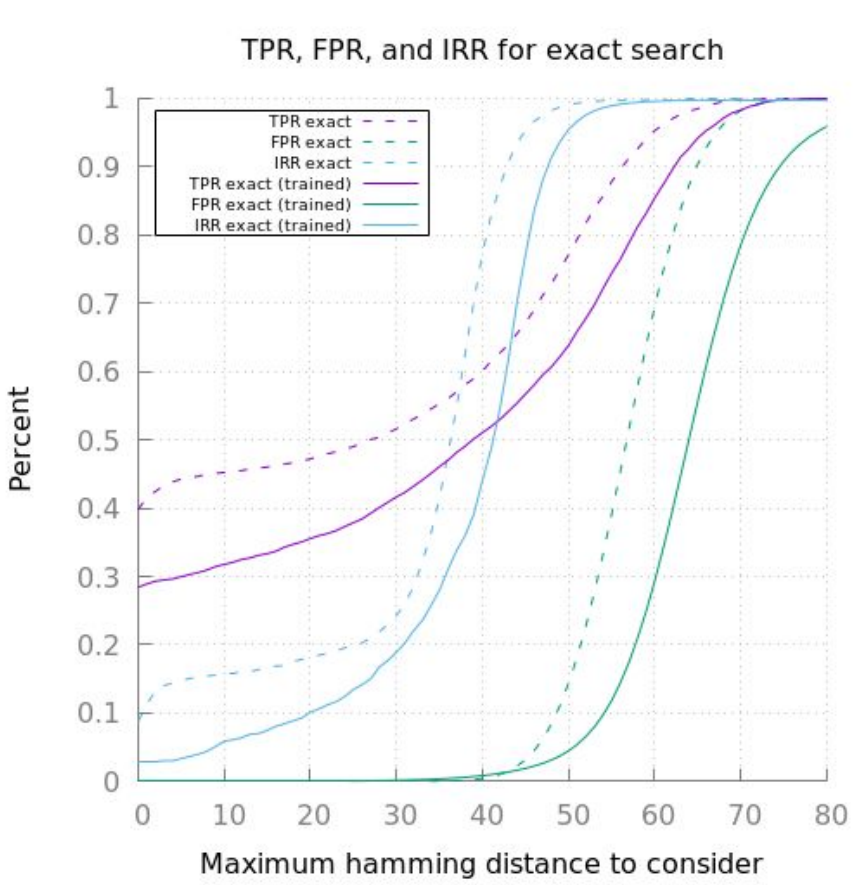


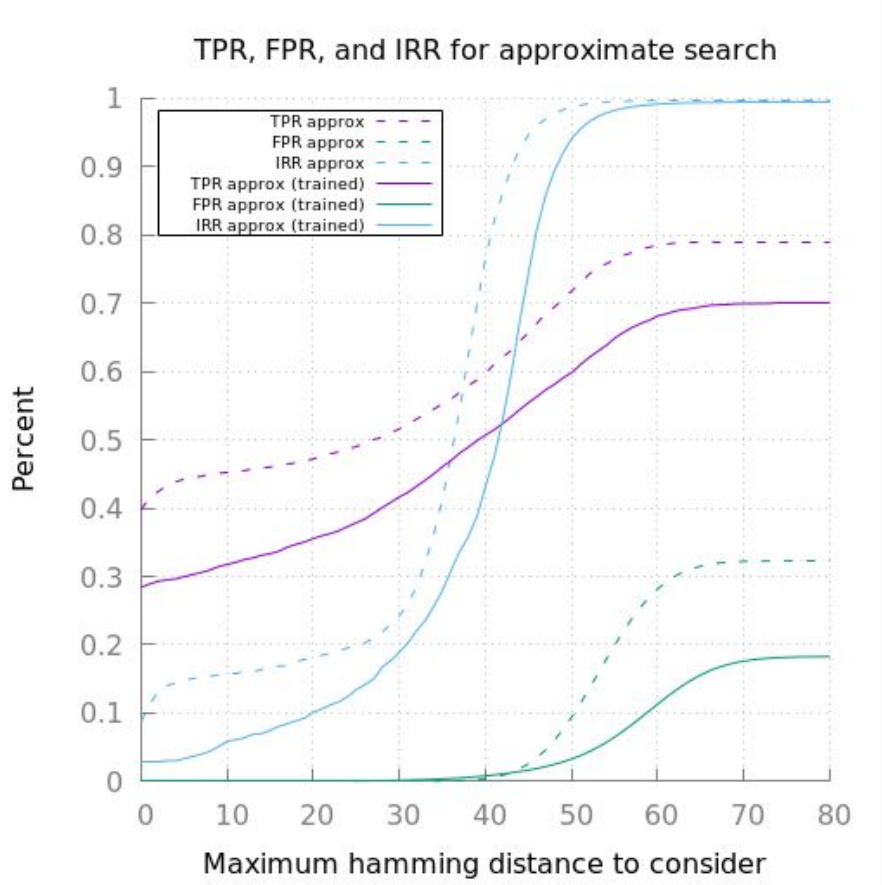
True positive rate, False positive rate, and Irrelevant results rate





True positive rate, False positive rate, and Irrelevant results rate: Training





Interfacing with Python, IDA, Binja

Python Interface is very simple

```
git clone https://github.com/googleprojectzero/functionsimsearch
# install only the python bindings
cd functionsimsearch
python ./setup.py install --user

Python
>>> import functionsimsearch
>>> fg = functionsimsearch.FlowgraphWithInstructions()
>>> fsh = functionsimsearch.SimHasher()
>>> fg.add_node(0x401000)
>>> fg.add_instructions(0x401000, (("push", ("ebp","")), ("mov", ("ebp", "esp")), ("sub", ("esp", "0x20"))))
>>> fg.to_json()
u'{"edges":[],"name":"CFG","nodes":[{"address":4198400,"instructions":[{"mnemonic":"push","operands":["ebp",""]},{"
mnemonic":"mov","operands":["ebp","esp"]},{"mnemonic":"sub","operands":["esp","0x20"]}]}]}'
>>> fsh.calculate_hash(fg)
(7763007128511167962L, 7763007128511167962L)
```

Python Interface is very simple

```
>>> index = functionsimsearch.SimHashSearchIndex("/home/thomasdullien/searchindex", False)
>>> # Add a function with a given SimHash to the index.
>>> index.add_function(hash[0], hash[1], file_id, address)

>>> # Query for the best 5 matches for a given function.
>>> results = index.query_top_N(hash[0], hash[1], 5)
>>> for r in results:
>>>    number_of_identical_bits = r[0]
>>>    file_id_of_result = r[1]
>>>    address_of_result = r[2]
```

Experimental plugins for IDA and Binja exist

- Tiny and proof-of-concept-y
- Only allow saving & search
- Only text output as UI at the moment

Problems & Challenges

False positive requirements

- Scanning a single large binary can easily involve 60k+ queries.
- False positives are very wasteful of vuln-researcher time.
- False-discovery-rate needs to be somewhere below 0.0001 or even 0.00001.
- We are **not** there yet.

Small graphs

- Method fails spectacularly on small graphs.
- If a change in the graph is only 4 edges away from most other nodes, the graphlets all change and mess up results.
- Different methods will be needed for small functions (context?)

Answer we have so far:

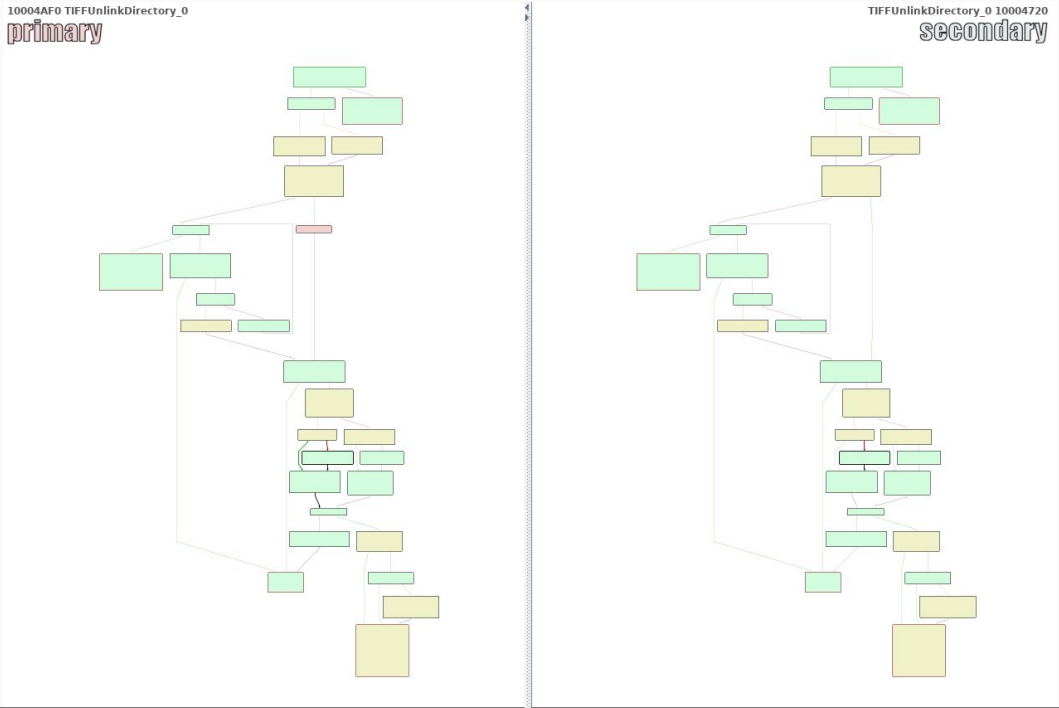
1. Does the learning process improve our ability to detect variants of a function we have trained on? **Yes, measurably.**

2. Does the learning process improve our ability to detect variants of a function **even if we have not seen** a variant of it before? Yes, but only slightly. So not yet in practice.

3. Are the results we get for (1) or (2) practically useful yet? Not yet, due to extremely strict false-positive / false-discovery requirements.

Some example functions and their distances.

TIFFUnlinkDirectory: VS2017 vs VS2013



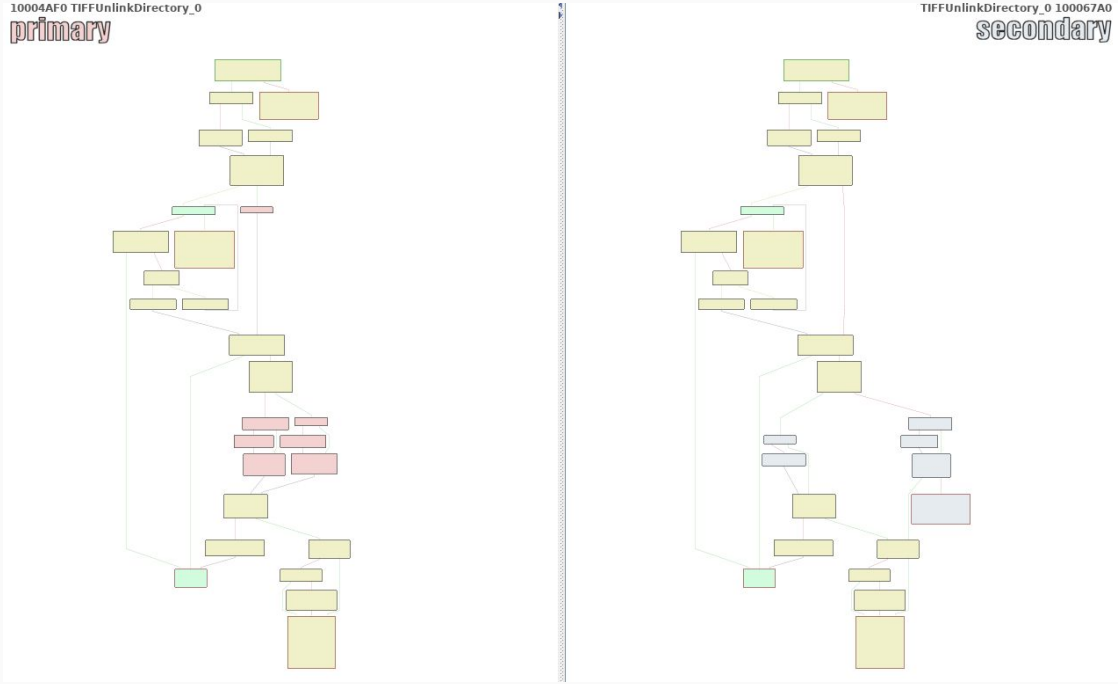
e6ae12282450f4bafbbdf80d0e8965e4

e0ff52282c10f1baabf8f80f4e8965c4

11001010001010000000000000000001000010000000000010100000000010100000100010100000000000001001000000000000000000000000010000000

18 bits difference

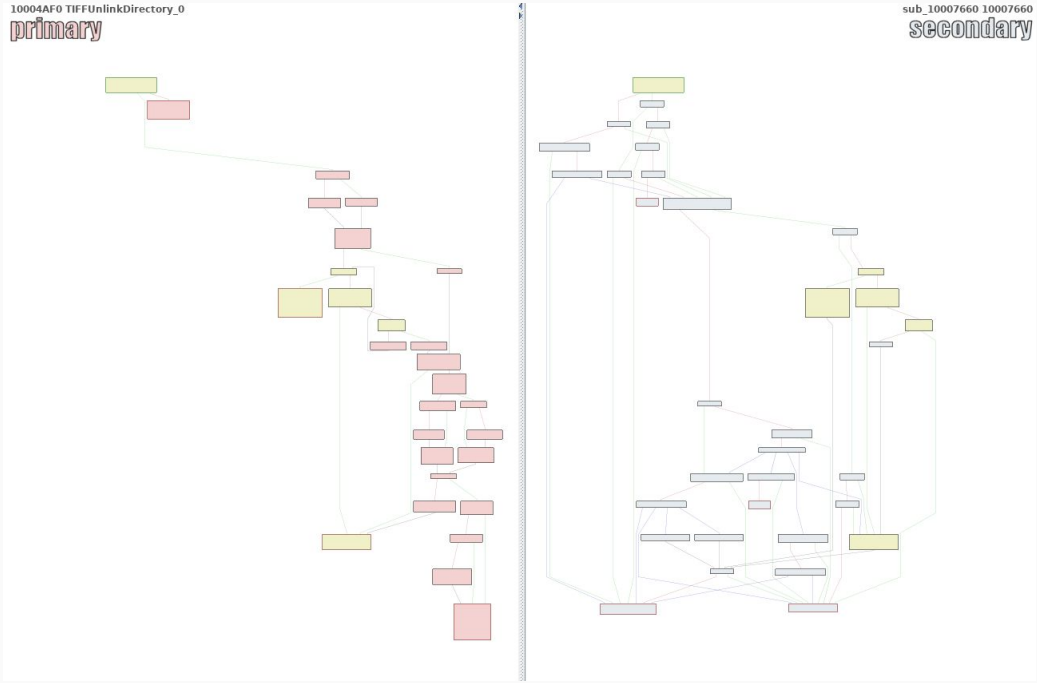
TIFFUnlinkDirectory: VS2017 vs VS2010



e6ae12282450f4bafbbdf80d0e8965e4	a4ef166c6088f61a93b9f81d0e0b5544

```
10000100100000100000100010001000100010011011000000000101010000001101000000001000000000000010000000000001000001000110000101000000
                                                27 bits difference
```

TIFFUnlinkDirectory: VS2017 vs. random function



e6ae12282450f4bafbbdf80d0e8965e4	9aeba2a166b67d98ebb1b3bde6950a89

```
11111000100010110110000100010010100001011100110100010010010001000010000000011000100101110110000111010000001110001101111011011015
                                54 bits difference (expectation for random matches is 64 bits)
```

Amusing results

Some amusing results:

1. We can detect UnRAR code in mpengine reasonably well. **Not very exciting, we knew this already.**

2. We can detect libTIFF code in Adobe Reader pretty well. **Not very exciting; we knew this already.**

3. We found Microsoft forked **libTIFF 3.9.x** into WinCodec.DLL and then rewrote it significantly. There is also a forked libJPEG in there. No bugs found yet, though.

Other lessons learned:

- Linear search is very very fast.
- We can easily sweep through 200m hashes in 200 milliseconds on a laptop core.
- Fancy LSH-search-index only starts paying off for billions of hashes.

Other lessons learned:

- String search is very very effective. Finds 95% of the libraries.
- Graph similarity & machine learning is a lot of effort for the last 5%.

Future directions

Reimplement the “learning” code

- Current learning code is implemented in C++.
- Auto-parallelization and GPU offload is made complicated.

- Great libraries for learning exist. This code needs to be rewritten.
  - TensorFlow
  - Keras
  - Most likely: Julia v1.0 (because I like the language)

Better features to go into the hash

- Current feature input is subgraphs (“graphlets”) and mnemonic tuples.
- Operands are discarded, string references too.

- Both should be included (they carry a lot of signal !)
- Only obstacle: A clean, cross-disassembler way of parsing constants out of operands.

- Joint graphlet + instruction features will also be very helpful.

More powerful ML models

- Our model is extremely simple.
- Features are never considered in their “interaction”, simple linear weights for all features.
- Much stronger models exist:
  - DNN approach from Gemini.
  - Graph NN’s to learn graph structure.
  - RNN’s to learn better embeddings for instruction sequences.

Better training methods

- Current code “trains in pairs”.
- Learning of distances can often benefit from “triplet learning” and “quadruplet learning”.

Questions?

https://github.com/googleprojectzero/functionsimsearch