Project 4 Report

Aaron Gonzales

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1 Metadata

(a) Team Name: we_are_not_scientists

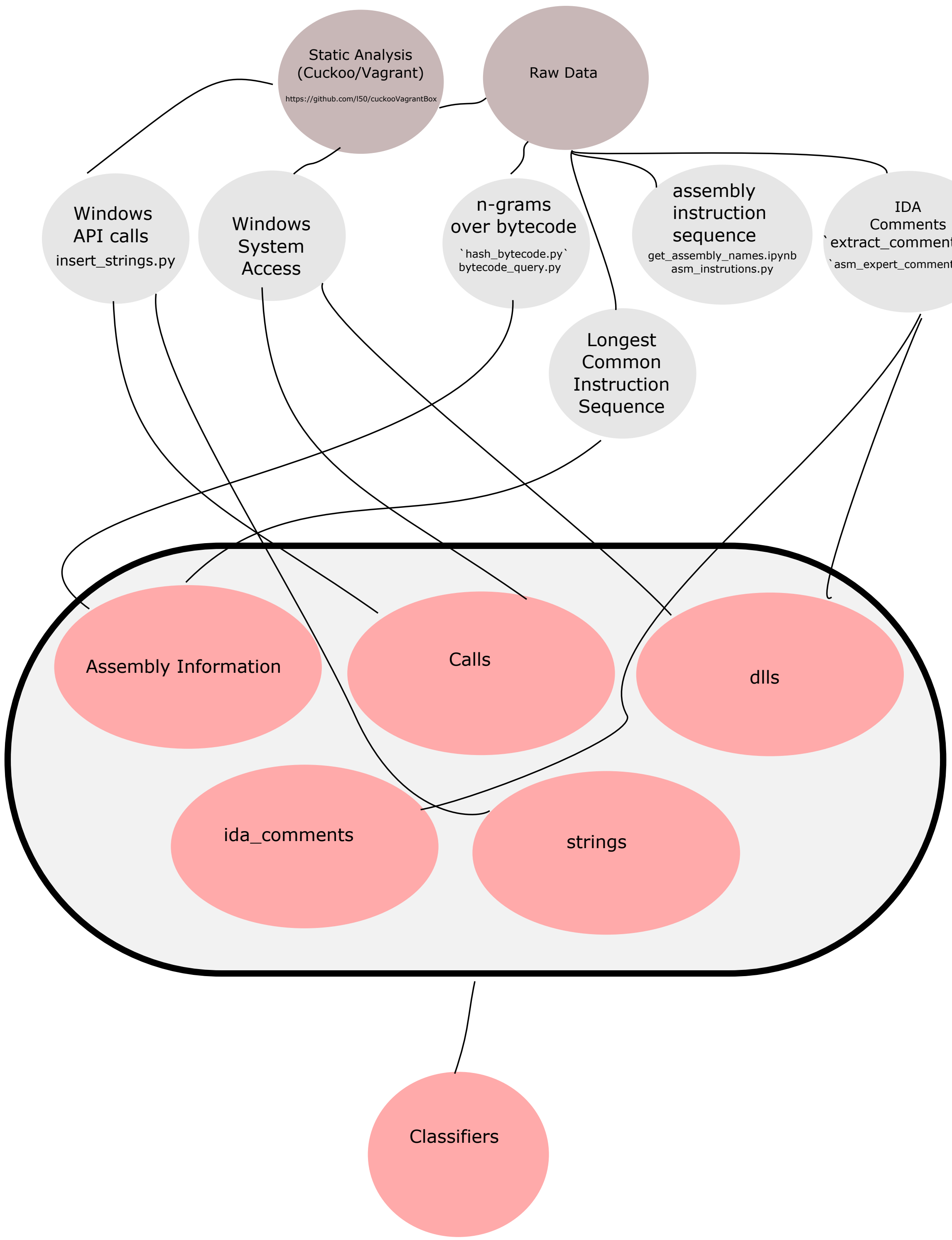
Teammates:

- Aaron Gonzales
- Andres Ruiz
- Mike Wyatt
- Adam Delora
- Jayson Grace
- Geoff Alexander

Score:

256	↓1	we_are_not_scientists	0.212410090	13	Fri, 10 Apr 2015 00:11:04 (-29.6h)

Workflow



Static Analysis (Cuckoo/Vagrant)
https://github.com/l50/cuckooVagrantBox
Raw Data
Windows API calls
insert_strings.py
Windows System Access
n-grams over bytecode
`hash_bytecode.py`
bytecode_query.py
assembly instruction sequence
get_assembly_names.ipynb
asm_instrutions.py
IDA Comments
`extract_comments.py`
`asm_expert_comments.py`
Longest Common Instruction Sequence
Assembly Information
Calls
dlls
ida_comments
strings
Classifiers

2 Methods used

(a) feature engineering and extraction

Summary

We focused heavily on generating features for our classifiers. Those features were broken down into several broad categories, relating to information about the assembly code itself, any files or function calls the program made during runtime, the comments that the disassembler made, and results from a secondary dynamic analysis performed by Geoff. Malware can be analyzed statically or dynamically, where static analysis represents more structure or summary information about the program and dynamic analysis is where you watch what a program does under execution in a safe environment and record the outcome.

All data was stored in a centralized MongoDB (NoSQL) database to which every team member had access.

Methods used:

Dynamic Analysis

Geoff and Jayson set up environments to analyze the malware's behavior, which is mostly hosted in Jayson's github repository at `https://github.com/l50/cuckooVagrantBo`. Some of this data was spit out in JSON format, which was fed directly to Mongo, and some of it required further processing (Windows API calls / insert_strings.py).

Windows API calls

Geoff did not upload this code to the repository, but it consisted of a semi-dynamic analysis of malware samples and gave us the dynamically-linked libraries and windows API function calls accessed by a piece of malware. The output from this program was very dirty, so a good deal of parsing had to be done. Aaron built a scraper to get the proper list of function names from Microsoft's website and used that to help extract some of the names correctly (and in another area of the project).

Cuckoo

Jayson built the analysis pipeline for running a more complete dynamic analysis. This code lives in the repo mentioned above. Data was organized in batches to run on several machines, as there were 10,000 samples and each sample took 90-240 seconds to run.

n-grams over bytecode

Following a suggestion on Kaggle, Aaron built methods to extract uni and bigrams from valid hexidecimal representation of the "raw" bytecode and to build a bag-of-words model from there, as Scikit-Learn's dict_vectorizer didn't handle the data well. The code for these things lives mostly in bytecode_query.py.

assembly instruction sequence

This was parsed out from the raw files as a starting point for further feature engineering. A list of x86 assembly instructions was parsed from the web and matched against lines in the file. The raw instruction sets were very messy and difficult to parse without doing this, though it didn't take all that long to do. The relevant files are get_assembly_names.ipynb and asm_instrutions.py. Long n-grams (3-8) were generated over this sequence to look for common patterns (loops) within the code across families, which became a reasonable feature on its own later.

Longest common instruction sequence

Andres built methods to extract the longest common instruction subsequence between all pairs of files, but this didn't work out due to the computation time involved (10,000 sequences, 200-500 instructions per sequence, compared to many other sequences in a class. It was mostly wishful thinking and we moved on to more cohesive ideas).

Ida comments

IDA is the Interactive Dissembler that the malware community uses to generate human-readable code. It can give valuable annotations in the generated files and we parsed out the comments to use them as a text feature. This was a tip from a Mandiant employee. The relevant files are extract_comments.py and asm_expert_comments.py.

Assembly statistics

Our security people recommended doing frequency counts over various types of actions, which were computed and stored as a set of data within the assembly code. This included types and numbers of system calls and their subtypes.

(b) Classifiers

Random Forests

We had strong cross validation scores (or so we thought; they never broke into the top scores when submitted to the leaderboard but would achieve roughly 85-92% cross validated accuracy). Mike mainly ran initial models with these and did some parameter sweeps over them to eek out more accuracy from the RFs.

SVM

SVMs were ran over several of the text representations (TFIDF over long ngrams, IDA comments, etc.). Reasonable accuracy was obtained, but again, nothing great compared to the leaderboard. An SVM with the bytecode uni and bigrams reached 97% CV accuracy but overfit heavily on the leaderboard score.

3 What we could have done

We had several glaring issues with our project. First, as this was purely extracurricular, not everyone devoted much time to it and several teammates dropped out before too long (or didn't contribute all that much for various reasons). As such, most of the work specified up front had to be radically changed and redistributed. Lots of features were generated as Andres and Aaron were the members mostly in charge of that, and very few models were ran because not many people had time or desire to run them. We also wasted an incredible amount of effort up front (several weeks worth of planning and execution) trying to use Cuckoo/Vagrant to do some dynamic analysis, only to have one of the security people on our team realize that we were getting garbage out because some key features were missing from the malware files themselves, invalidating this huge source of work. If it had worked, we might have had a golden set of features and we could focus our efforts on combining features and building ensembles to increase our score.

We could have also just ran more models more quickly. The top-placing teams are also the teams with huge numbers of models ran and submitted. It would have been simple to run several models on our data nearly every day and see if small tweaks or improvements to the features would have helped more. By the last week of the competition, we were stuck with having comparatively low scores and not many more chances of getting a great model made and run.

We also, for some reason, had issues organizing the data centrally from the outset. It's possible that during unpacking of the large datasets, some files were corrupted or did not finished unpacking, resulting in some early discrepancies between extractions and runs. We had issues getting resources from the department for this as well, and some work was delayed due to a both a lack of provisioning them and a lack of properly supporting them. These are not primary reasons for getting a low score, but they are worth noting.

For a first attempt, I'd say that those of us who really worked at this leaned a great deal, including how to work at a different pace than in academia, how to collaborate using github (some had never really used it extensively), centralized databases (the DB was hosted on a department VM or Andres' machine and could be access outside the department), how to use effective new toolkits (learning scikit-learn, ipython notebook, multiprocessing, etc.), and so on. We are disappointed in our score, but we will learn from this and hopefully do much better in future competitions.

4 Participation

Aaron Gonzales

Score: 10.

Helped every aspect of the project, from feature engineering to setting up the database to helping automate the (failed) dynamic analysis. Generated lots of features and helped people learn how to use the new tools.

Andres Ruiz

Score: 10 Maintained the database on his personal machine for some time. Worked a great deal with Aaron to help with feature extraction and also ran / submit a number of models.

Mike Wyatt

Score: 9 Ran models, did some parameter sweeping.

Adam Delora

Score: 7 Ran several models.

Jayson Grace

Score: 10 Put in incredible effort getting the dynamic pipelines to work, even though they were not useful in the end. One of the security experts on the team.

Geoff Alexander

Score: 9 Primary malware consultant. Set up tools to help extract strings and dll calls in a semi-dynamic way after our primary method failed.

Additional

We also started with more people, including Amanda Minnich, Pravallika Devineni, and Abdullah Mueen. Mueen was our primary adviser on the project and we brainstormed with him. Amanda had worked last year doing some of this for Mandiant, but was mostly unavailable to help and remained a commentator and source of consulting, but not a main contributor. Pravallika dropped out fairly early on.