Why security data science matters and how it’s different: pitfalls and promises of data science based breach detection and threat intelligence

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Work presented in this talk contains significant contributions from Alex Long, David Slater, Giacomo Bergamo, Konstantin Berlin, and Robert Gove
Background on Invincea

- **Invincea**
  - Security startup with ~80 staff focused on creating endpoint security solutions

- **Invincea Labs**
  - ~40 researchers working on a dozen or so research programs, some of which generate new products for Invincea as a whole

- **Invincea Labs-Data Science team**
  - 8 researchers working on a handful of machine learning, visualization, and data mining projects mostly applied to security
Presentation Overview

Session 1:
- What is data science and why does it matter for defending our networks?
- Data science at a glance – machine learning and visualization
- Unique problems in security data science

Session 2:
- Three case studies from Invincea Labs
  - Machine learning based malware detection – going beyond signatures
  - Machine learning based prediction of malware family “hockey stick” growth – predicting malware’s future
  - Visualization and machine learning for threat intelligence – malware clustering and automated profiling
What is data science?
Data science consists of three technical areas …

<table>
<thead>
<tr>
<th>1. Scalable data storage technologies</th>
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<td>2. Machine learning / scalable analytics</td>
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<td>3. Data visualization / decision support</td>
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... and involves potentially limitless applications

- Computer vision
- Voice recognition / natural language processing
- Social network analysis
- Robotics
Data science projects often involve *all three data science areas*.
Why security needs data science
We have access to the signals needed to detect attackers, but they are currently the “dark matter” of our field.
The “dark matter” of information security is where attackers hide

Terabytes of logs generated by enterprise networks that are never examined …

Reams of user behavioral data that could hold information about threats …

… the 400 million+ malware samples seen in the Internet, most of which have never been analyzed
Evidence we can be successful: data science breakthroughs in adjacent domains

TIMIT Speech Recognition

- Traditional
- Deep Learning

Error Rate

Years: 1998 to 2014
Evidence we can be successful: data science breakthroughs in adjacent domains
The big question: Can data science produce analogous breakthroughs to problems that seem intractable in the security space?
A lightning overview of machine learning
Some definitions: training data, test data, prediction, generalization

- Training data: data that we show to machine learning algorithms to “teach them”
- Labeled training data: data that we show to machine learning algorithms that alongside answers to questions
- Unlabeled training data: data that we show to machine learning algorithms without answers to questions
- Test data: data that we show to machine learning algorithms to evaluate their accuracy
Some definitions: types of machine learning

- Supervised learning: algorithms that require *labeled training data*
- Unsupervised learning: algorithms that do not require *labeled training data*
Definition of a “feature space”

<table>
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<tr>
<th>File size</th>
<th>File compression level</th>
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<tr>
<td>2342315</td>
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<tr>
<td>2343909</td>
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<tr>
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<tr>
<td>1456145</td>
<td>0.14</td>
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Feature extraction code

Raw files …
/malware/file1
/malware/file2
/malware/file3
…
Visualization of the two-dimensional “file” feature space
Clustering algorithms focus on identifying like-groups without any prior knowledge about the data.

It is likely there are two families of malware in this dataset!
Why clustering matters

- Group together similar security events
- Group together similar malware
- Group together similar network streams
- Group together similar (malicious) domain names
Machine learning problem is to “learn” a good location for a boundary that separates the classes.
A real-world classification algorithm in action (credit: Andrej Karpathy)
Why classification matters

- Detect malware and malicious behavior by classifying good vs. bad
- Detect suspicious network streams by classifying good vs. bad
- Detect *types* of network streams based on their contents
- ...
Machine learning problem is to learn a function that predicts the correct number of attacks for the next year.
Why regression matters

- Predict future growth of malware families
- Identify security incident trends
- Identify growth of botnets
- ...

![Image of a graph showing cumulative unique samples over months with labels for 'Late adopters', 'Rapid growth', and 'R&D'.]
Adding dimensions:
A classifier in three dimensions
What would ten dimensions look like?

- Impossible to truly visualize
- If we could actually see this ten dimensional cube, all angles would be 90 degrees
- And, all lines would be equal length
- *And yet, machine learning algorithms operate in such high-dimensional spaces*

*A ten dimensional cube!*
Thinking about dimensionality

- In security data science, for most problems we care about, data have not 2-dimensions, but *thousands* or *millions* of dimensions.

- High dimensional data make physical intuition more difficult, but it nonetheless is how most data scientists reason about their models.
Data visualization
Real world data visualization: Some visualizations reveal “unknown unknowns” about data

Credit: Aaron Koblin
Others answer hard questions in a visually intuitive way

Credit: Charles Joseph Minard
Visualizations are not necessarily static
Data processing capabilities of the human visual system

### Preattentive attributes of visual perception

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<th>Length</th>
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<td>Enclosure</td>
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<th>Intensity</th>
<th>Position</th>
<th>Motion</th>
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<tr>
<td></td>
<td></td>
<td></td>
<td>2-D position</td>
<td>Spatial Grouping</td>
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<td>Direction of Motion</td>
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More preattentive reasoning

Visual search
A human visual system “fail”
Visualization design principles

❖ Overview first, details on demand
❖ Visualizations should answer questions, or should be explicitly exploratory
❖ Design with a user in mind, and a user workflow in mind
❖ Don’t overload the user with too many visual channels
Questions?
What makes security data science different?
The presence of an adversary

- Attackers are deliberately trying to evade detection systems.
- This makes applying classification, regression, and clustering a far different problem than, for example, classifying news articles into categories.
- Attackers' techniques are constantly changing.
- This makes applying data science methods to security different from, say, voice recognition.

A decision boundary decided on at training time might be invalid when we deploy the system because attackers’ tools may have changed!
Addressing the “evolving adversary” problem: Adversarial evolution should be addressed by modeling attacker behavior in the way we evaluate our data science tools.

Degradation of machine learning based malicious behavior detection due to adversary evolution

Figure from work by Konstantin Berlin, David Slater, Joshua Saxe
The false positive problem

Many of the things we look for in security are extremely rare

- Exploitable vulnerabilities are rare
- On an enterprise network, malware is rare relative to benignware
- Insider threat behavior is rare
- False positives rates (the percentage of false cases mislabeled as true) have to be extremely low in security for approaches to be useful
A machine learning based detection “fail” due to false positives

Our detection system achieved a 75% detection rate at a 0.4% false positive rate

BUT, when we do the math, we see that:

- 34% of our alarms will be false positives if we assume 1/100 malware to benign ratio
- 84% of our alarms will be false positives if we assume a 1/1,000 malware to benign ratio
- 98% of our alarms will be false positives if we assume a 1/10,000 malware to benign ratio
Addressing the false positive problem

- Focus on measurement of system detection rate in the ultra-low false positive region
- Emphasize collection of huge volumes of benign examples so the false positive rate can be accurately measured in low-FPR region
- Pick models that predict accurate probabilities – calibrate these models
- Learn the dark art of designing systems that operate well at low false positive rates!
The need for interpretability

- In other areas of data science, all we care about are correct detections.
- In security correct detections are only part of the story, we also need explanations (if a data science tool tells me I’ve been compromised, I want to see all of the evidence it is using to make that claim so I can follow up).
Building interpretability into the data science workflow

Throughout the data science workflow, think about how you’re building interpretability into your data science product.

Presentation is often just as important as model accuracy, because it means people can actually use your results.
The lack of labeled data

In other data science areas, the research community has millions of labeled examples to train their models on.

Not so when it comes to zero-day attack data!
One potential mitigation

- Use crowdsourced data in auxiliary domains to build data science approaches

Figure 1. An illustration of the intuition that we can correlate terms found in malware binaries and terms found in StackExchange documents to identify high-level software capabilities within malware.
Another potential mitigation

- Build approaches that don’t require any ground truth

Rainbow colored but equal length bands depict variation in sample behavior.

A cluster of malware samples. Surprisingly, menti and jorik.fraud families appear similar.

Surprisingly, these jorik.fraud samples appear quite different from the others.
Questions, discussion?

Plug for next half of the talk:

- Deep learning based malware detection producing unprecedented accuracy!
- Predicting which malware families are going to go “viral” using autoregression!
- Automatically detecting malware capabilities and “social network” relationships using a suite of machine learning, data storage and visualization tools!
Three security machine learning cases studies
Agenda

- Deep neural network based malware detection *(Joshua Saxe, Konstantin Berlin)*

- Predicting the explosive growth of malware families *(Giacomo Bergamo, Joshua Saxe)*

- Cynomix: A machine learning driven workbench for malware analysis and malware relationship analysis *(Alex Long, Giacomo Bergamo, Joshua Saxe, Robert Gove, Sigfried Gold)*
Case study 1:
Deep neural network-based malware detection
Joint work by Joshua Saxe and Konstantin Berlin
Motivation

- On average, anti-virus sensors have a 40% chance of missing zero-day malware.
- The data seem to suggest that it takes almost a year before anti-virus sensors start detecting the hardest-to-detect zero-day malware.
- Machine learning holds the promise of providing an orthogonal detection methodology that can significantly increase our overall detection rate.
Results in an operational setting

- 60% detection rate on new malware as false positives converge on 0 (in contrast to anti-virus engines’ 40%)
- 95% detection rate on new malware as false positives approach five per day
- *Test performed on feed of new binaries obtained from multiple customer networks compromising on the order of thousands of individual machines*
How we accomplished this, starting with intuition behind our system
Intuition about inputs:
Exploit shared code relationships

If we **train** on a malware sample with code component A, and then **test** on a sample with component A and previously unseen component B, and component A occurs rarely or never in *benignware*, we should classify the sample as malware.
If we train on a malware sample with data component A, and then test on a sample with data component A and previously unseen data component B, and component A rarely or never occurs in benignware, we should classify the test sample as malware.
Learn general heuristics about what constitutes malware

Anti-virus analysts identify PE metadata that’s abnormal or suspicious and use heuristics defined over these data to detect suspicious files

A machine learning method should automatically learn such rules as well
The overall design of our feature space and how it supports these modeling goals

- **Contextual byte features**: Capture shared component relationships
- **PE import features**: Capture functionality to support generalization
- **String 2d histogram features**: Capture literal strings to support automatic formulation of signatures
- **PE metadata features**: Capture both signature-like patterns and general anomalous packaging information

1024 dimensions
Our overall architecture

Feature extraction (1-2 seconds) populates a 1024 fixed-dimensional feature space via the feature hashing trick.

- Contextual byte features
- PE import features
- String 2d histogram features
- PE metadata features

Neural network (30 minutes to train on 400k files), can be trained in streaming fashion.

Bayesian calibration model: convert neural network output to principled probability that a given file is malware.

Model operationalization: 80MB model data stored in memory representing 400k training samples, supporting streaming, parallel evaluation of files’ P(malware)
Contextual byte histogram features: a key component of our feature space

- Feature extraction algorithm:
  - Slide a 1024 byte window over the target binary, taking 256 byte steps
  - Compute the entropy of each 1024 byte window
  - For each byte in the window, store a tuple (byte, entropy)
  - Create a 2d histogram with byte values on one axis and entropy on another axis
Byte/entropy histograms: a key component of our feature space
Byte/entropy representation of a binary file (benign in this example)
Byte/entropy representation of a binary file with a simulated component added
Visualizing what our neurons “learn” about the byte/entropy features
Building a neural network that uses our features to detect malware

Feature extraction (1-2 seconds) populates a 1024 fixed-dimensional feature space via the feature hashing trick

- Contextual byte features
- PE import features
- String 2d histogram features
- PE metadata features

Neural network (30 minutes to train on 400k files), can be trained in streaming fashion

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Model operationalization: 80MB model data stored in memory representing 400k training samples, supporting streaming, parallel evaluation of files’ P(malware)
What are neural networks?

- A set of inputs
- A set of nonlinear transforms to those inputs
- A set of outputs
- This simple setup can approximate any function, given the right parameters

Learned decision boundary

Attribute 1

Attribute 2
What kinds of functions can neural networks represent?

- Anything!
- This is even true for a simple three-layer feed forward neural network.
- To get an intuition for this, think about what you can do when you add up the trigonometric wave forms.
Training a neural network on 2-dimensional inputs (credit: Andrej Karpathy)
Deep networks

- In theory these are no more expressive than a three-layer network
- However, they seem to provide better models of the world in terms of layered abstractions
How do we train neural networks?

- “Backpropagation”: errors at the output propagate backward through all weights and biases in the network.

- In practice more modern techniques are layered on top of backpropagation now (stochastic gradient descent).

- The beauty of these algorithms is that millions of algorithms can be estimated within hours.
Our neural network architecture

Unbounded number of features (millions) compressed to 1024

Contextual byte features
PE import features
String 2d histogram features
PE metadata features

1024 neurons
1024 neurons
1 neuron
Visualizing neurons...
Visualizing what our neurons “learn” about the byte/entropy features
In-lab accuracy evaluation on 400k files

We can detect about 75% of malware samples our neural network has *never seen before* at a 0.01% false positive rate.

We can detect 95% of malware samples that our neural network has *never seen before* at a 0.1% false positive rate.

*Takeaway*: these results model the zero-day malware detection problem (showing detection of previously unseen malware) and are the best publicized results we know of.
Simulating concept drift

On this test we *train* on malware with compile timestamps between 2000 and July 31\textsuperscript{st} 2014

Then we evaluate our ability to *detect* malware received in our lab over the last year

The results, as you’d expect, are noticeably worse, but still pretty good!
Results in an operational setting

- 60% detection rate on new malware as false positives converge on 0 (in contrast to anti-virus engines’ 40%)
- 95% detection rate on new malware as false positives approach five per day
- Test performed on feed of new binaries obtained from multiple customer networks compromising on the order of thousands of individual machines
Case study 2. Predicting the future “success” of malware families

*Joint work, Joshua Saxe and Giacomo Bergamo*
Project overview

The problem: predict which malware families will grow explosively

- New malware families (such as Koobface, Storm and Zeus) become targets for robust detection and disruption after they have achieved widespread criminal adoption

- Can we predict this in advance?

Payoff:
- Focus our reversing and countermeasure efforts on malware likely to achieve breakaway success

Our approach: adapt models of technology diffusion to predicting explosive malware
Exemplar malware family: Zbot / Zeus

Rapid growth

Late adopters

R&D

Creator “retires”: Late 2010

Media notoriety, 2009

First identified July 2007
Bird’s eye view of 20 malware families ‘goodness of fit’

- Considerable variation in shape of data
- Still tends to fit a parametric ‘S-shape’
- Given this variation how well can we predict explosion and taper?
Predictive modeling approach

Key modeling points:

- We want to observe how many new variants we’re observing for each family in each discrete time bin (say, per-month).

- Use linear regression to calculate month by month speed of new variant production.

- Second order regression measures acceleration / deceleration in this process.

- Threshold on acceleration determines if takeoff has been entered.
A good case and a bad case: Lmir and Zbot
Results on all 20 of our malware families
Case study 3: A machine learning-aided malware analysis workbench

*Alex Long, Robert Gove, Joshua Saxe, Sigfried Gold, Giacomo Bergamo, Aaron Liu*
Capabilities of our research prototype ("Cynomix")

- Performs automatic capability recognition by “learning” from StackOverflow
- Builds a “social network” of malware samples based on shared code relationships
The Internet is rife with text that combines example code with natural language description of its functionality.

It might be possible to piggyback on the expert knowledge of the web “crowd,” which holds more knowledge than the mind of any one malware subject matter expert.
Overall, we found the approach works

- Detecting malware capabilities based on a text mining approach leveraging crowdsourced data yields good results some of the time
- Requires unpacked malware
- Detections are still somewhat noisy
- But, good enough to be adopted by and benefit practitioners

Rest of this talk adds more detail, describing methods and results
Document datasets we used

- Four textual datasets including ~6 million Q&A threads
- This Q&A data is made publicly available as an XML dump by StackExchange
- Approach could accommodate new datasets such as malware technical reverse engineering reports, malware forums
Our approach to capability-detection

1. CrowdSource config file
   - Full text queries retrieve capability-relevant document sets

2. StackExchange
   - Full text index of web technical documents
   - Capability-term associations computed

3. Terms extracted from malware printable strings

4. Bayesian inference on associations produces capability detections
   - Capability report for malware generated
Using Bayesian networks with “Noisy-OR” to infer capabilities

- Most clearly interpreted as a one-layer Bayesian network with Noisy-OR gate edges
- Parameters can be quickly estimated in closed form using document frequencies combined with prior belief; we use the Beta-Bernoulli model
- For equations, read the paper!
Our model “learns” what symbols are associated with what malware capabilities, using these associations to explain its detections to analysts.

```plaintext
[[ ]] category: gui
[*] low level GUI calls / screenshot (somewhat likely)
[*] Extracted from sample: Post title on StackOverflow

[-] 'BitBlt'
[-] 'CreateCompatibleDC'
[-] 'CAPTURE': Screen
[-] 'DeleteDC'
[-] 'SelectObject'
[-] 'screen. [CAPTURE, screen capture, Screen'
[-] 'gdi32, Gdi32'
[-] 'GetDeviceCaps'
[-] 'Gdi32.dll, gdi32.dll'
[-] 'CreateDIBSection'
[-] 'CloseClipboard'
[-] 'frame [CAPTURE'
[-] 'GetForegroundWindow'
[-] 'OpenClipboard'
[-] 'GetClipboardData'
[-] 'User32'
[-] 'Screen'
[-] 'capturing'
```

Capturing screenshot
Capturing screenshot
C: take screenshot
C# Code for capturing Full ScreenShot
Capturing screenshot
Capturing screenshot
C# rectangle drawing and screenshot
C# Code for capturing Full ScreenShot
Desktop screenshot in WPF
Capturing screenshot
Screenshot program not working
Kinect take screenshot with pictures overlayed
C# - Capture screenshot of active window
Screenshot program not working
Screenshot program not working
Window screenshot using WinAPI
Sending screenshot via C#
Capturing screenshot
Our approach can also explain to analysts where in the web technical documents it found evidence for a prediction

[*] low level GUI calls / screenshot (somewhat likely)
[*] Extracted from sample: Post title on StackOverflow

[-] 'capturing screen'

Capturing screenshot in iphone?

s code but it not working for me .... it gave me same result. :( update - hello RRB:
this code is working into my application for capture the screenshot of a iphone. -
can i give the demo for that - actually i want to create video of game play using
"capturing screen" shots along with sound. I want functionality like talking
tom application. - you should probably take a look at AVFoundation and specifically
AVAssetWriter as a way of creating videos of your screen content. - Take the
screenshot of yo

[-] 'BitBlt'

Capturing screenshot

// bitmap handle HBIMAP hbitmap = CreateCompatibleBitmap(hdc_screen, bounds.width,
bounds.height); // select the bitmap handle SelectObject(hdc_memory, hbitmap); //
paint onto the bitmap BitBlt(hdc_memory, bounds.x, bounds.y, bounds.width,
bounds.height, hdc_screen, bounds.x, bounds.y, SRCPAINT); // release the screen DC
ReleaseDC(NULL, hdc_screen); // get the pixel data from the bitmap handle and put it

[-] 'CreateCompatibleDC'

Capturing screenshot

void get_screenshot(COLORREF** img, const Rectangle &bounds) { // get the screen DC
HDC hdc_screen = GetDC(NULL); // memory DC so we don't have to constantly poll the
screen DC HDC hdc_memory = CreateCompatibleDC(hdc_screen); // bitmap
handle HBIMAP hbitmap = CreateCompatibleBitmap(hdc_screen, bounds.width,
Results analysis on 14 capabilities

Accuracy at Decision Threshold of 0.37

- normalized precision
- recall
Results analysis on 14 capabilities

Running time on the order of ~200ms per sample

CrowdSource runtimes per sample (839 samples)
Building the malware “social network”: identifying shared code between malware samples

The approaches we have developed discover genealogical relationships between millions of malware samples based on identification of shared attributes.
Dynamic similarity analysis

Rainbow colored but equal length bands depict variation in sample behavior.

A cluster of malware samples. Surprisingly, menti and jork.fraud families appear similar.

Surprisingly, these jork.fraud samples appear quite different from the others.
Demonstration / guided tour of malware “social network” visualization and malware capability recognition interface
Conclusion
Takeaways / Sound Bytes

- Security data science holds the promise of shining a spotlight into the reams of “dark matter” security data that we’re currently not exploiting, thereby changing the game in network defense.

- Security data science is different: it requires ultra-low false positive rates, interpretability, and adversarial modeling.

- As data science advances, security will not be unaffected – there is every reason to think that data science will disrupt security just as it has advertising, human computer interface design, and computer vision.
Get involved!

- Security data science is a new field in which security professionals of all backgrounds can make an impact.
- If you’re new to data science, pick up scikit-learn, networkx, numpy, theano, R, or any of the other open source tools, along with a good data mining textbook, and start hacking.
- If you’re new to security, work with security professionals to find data science applications that make sense.