Data Fusion at Scale

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Situation awareness

“Situation awareness is the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future.” [emphasis added]

“Situation assessment... [is] the process of achieving, acquiring, or maintaining [situation awareness]”

Endsley’s model represents the analyst’s mental process as they construct a mental model of the world, i.e. their network and the actors in it and upon it. This doesn’t help us that much in building automated systems, however, except that some important considerations in designing a human-computer interface for situational awareness include:

* System capability - how to include all the necessary data and process it in an appropriate time frame?
* Interface design - how to design it to support awareness as an explicit goal?
* Automation - how much can we take off the analyst’s plate?
Fortunately, there is a related concept, Data Fusion, which is an automated situation assessment process. While we might not be able to automate all the levels (Perception, Comprehension, Projection) we can automate some and support others. Let’s explore the Data Fusion field to see what might be useful to us.
The JDL Data Fusion model describes an automated process that presents information through an HCI. Some previous work has applied this model to cybersecurity (see below). However, this model provides only a high-level roadmap for data fusion, we perhaps need some more guidance on what needs to be done.

Fortunately, there is a related model that uses somewhat different terminology to refer to the inputs/outputs of a data fusion process at the various levels of the JDL Data Fusion model.
Dasarathy's Functional Model (expanded)

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<td>Data</td>
<td>Features</td>
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An extended version of Dasarathy's Functional Model (first introduced in a simple form in Dasarathy (1994) but extended in Steinberg, A. and Bowman, C. (2001)) provides a detailed roadmap to the components of a full data and information fusion system. While the NorthWest quadrant is relatively familiar territory in the Multisensor Data Fusion world, with some forays into the SouthEast, the NorthEast and SouthWest quadrants are relatively unexplored even in that more mature field.

Here is a suggested flow for data fusion processes. From blue→red things become more abstract and require higher cognition, and the heavy arrows indicate the primary reasoning path, but there are interactions up and down the ladder. This is a fully connected graph of influences.
Viewed another way, we need to have extensive data collection and low-level fusion processes in the NorthWest quadrant, which can lead to making some higher-level inferences in the NorthEast quadrant, which is the primary area for deciding whether malicious activity is taking place, what the consequences are for the defended network, and possible responses.

Once there is some understanding of the situation, then in the SouthWest quadrant we can feed back into our lower-level processes, for example to save data for suspicious sessions longer, initiate new or more detailed data collection, or just modify our signatures and configurations.

In the SouthEast, quadrant we can use our situation assessment to decide what might happen in the near future, and to perform incident response.
It is useful to consider where some existing industry solutions fall in this model. Clearly the industry has been doing some higher-level work, but it’s important to realize that the forays into the NorthEast have been signature- and rule-driven. In other words, these areas represent the distilled understanding of human analysts rather than any kind of automated information fusion process.
The model suggests where automation is most appropriate. Clearly in the top left we can fully automate (data collection, protocol decoding for feature extraction). At the bottom right we probably never will be able to automate the response/counter-response process between human adversaries in this information space. However...
In the middle we need Daft Punk, part robot, part human. We need to be aggressive about applying machine learning appropriately to provide higher-level abstractions to the human analyst so that they can form correct situational awareness models more easily than poring over raw data, or waiting for alerts in their queue. This is both possible and necessary.

Daft Punk image by thedeviant426 at deviantart.com used under creative commons.
A quick detour: what about viewing security monitoring as a diagnostic process. We have a number of possible causes (C1, C2, … representing particular exploit kits, malware, human hacking techniques) each of which has a set of possible effects (E1, E2, …), and we have some belief about the chance of each effect occurring for a cause.

Now, if we observe some set of effects, there are ways to calculate, based on such a graph, the most likely cause(s).
Situation Assessment as Diagnosis

This type of graph is called a Bayesian Belief Network, and it’s an efficient representation of “abductive reasoning” which could be a way to automate how analysts think when they are doing security analysis. Unfortunately, while we are in some sense balancing such belief values implicitly, we rarely or never make such calculations explicit. (*) However, models have been applied to medical diagnostics with substantial success—could it be a way to automate certain mid-level data fusion tasks?

Here is an example calculation where we have observed effects E5 and E6. The result is that it’s three times more likely to be C2 than C3.

\[
P(C2|E5, E6) = \frac{P(C2) P(E5|C2) P(E6|C2)}{P(E5)P(E6)} \\
P(C3|E5, E6) = \frac{P(C3) P(E5|C3) P(E6|C3)}{P(E5)P(E6)}
\]

\[
P(C2|E5, E6) / P(C3|E5, E6) = (P(C2) / P(C3) which is assumed to be 1) * \\
[ P(E5|C2) P(E6|C2) ] / [ P(E5|C3) P(E6|C3) ]
\]

(*) In fact, Gary Klein et al. have shown that experienced people don’t actually decide anything, they just recognize situations that they have seen in the past, and as a result know what to do. This means we need to become much better at helping analysts recognize situations (situation awareness…). This is a larger subject beyond the scope of this presentation.
Situation Assessment as Diagnosis

This looks hard. However...

We are currently building these networks

- Implicitly, not explicitly
- Individually, not collectively
- Manually, not automatically

This is probably not a good model of higher-level reasoning, particularly Impact/Response...
These types of models are described in exhaustive detail in Daphne Koller’s book and free Coursera course (though it takes 20 hrs/week x 10 weeks to complete).
Here is an example of a way we can automate data fusion. It’s important to note that this is a rule-based procedure, which is not (strictly speaking) a machine learning approach, since such rule sets have to be constructed and maintained by experts. However, it can help to automate an otherwise manual process of identifying and labeling web servers on the network, which becomes more important the larger the network is.

Rules can also be a way to codify best practices, so that junior analysts can benefit from more experienced analysts’ work.
Rule-based: Entity-Relational Situation Assessment

Entities → Relations
User A owns host X
User A logs in, but not from host X
- Credentials compromised? (security)
- Using non-corp machine? (policy, risk)

Present to analyst as anomaly

Another rule-based example
What about machine learning?

Supervised learning
- Forget it, there’s never enough labeled data
- Even with labeled data, normal vs. malicious ratio of 1,000,000:1 = bad models

Unsupervised learning
- Careful feature selection
  - Protocol-aware
  - Threat-aware
- Identify clusters of known good traffic
- Multidimensional scaling for visualization
ML Example: Malware user-agents

1. HTTP Mozilla/5.0(compatible+MSIE)
2. Mozilla/4.0 (compatible; MSIE 6.0; Windows NT 5.0; NET CLR 1.1.4322)
3. Mozilla/5.0 (compatible; MSIE 7.0;Windows NT 5.1)
4. Mozilla /4.0(compatible; MSIE 6.0; Windows NT 5.1)
5. Mozilla/4.0 (compatible; MSIE 6.0 Windows NT 5.1; SV1; .NET CLR 2.0.50727)

These are User-Agent strings from actual malware command and control HTTP connections. Look closely to identify the errors in each.

Answers:
1. Just all wrong
2. NET instead of .NET
3. No space after semicolon
4. No space before parenthesis
5. No semicolon after MSIE 6.0

So 2-5 could be well-served by a feature that calculates the Levenshtein edit distance from known good browser strings. Small edit distances in this case would be bad.
These are recommendations for avoiding some of the pitfalls of earlier attempts to apply ML to the security problem. A naive, black box approach just doesn’t work. It’s especially important to construct models that make sense to analysts so that

1. The results are defensible, as otherwise the analysts won’t believe the results and thus the system will be ignored.

2. Error-prone models can be corrected, localized or updated based on the semantics of the threats and protocols involved.
Can we ever project?

Target tracking in physical space

Target tracking in information space?

What about projecting into the future? In physical space (tracking targets on radar) we are detecting physical objects that follow the laws of Physics, so we can predict future scenarios based on constraints such as force and velocity. What about in an abstract information space, though?
Can we ever project?

Target tracking in physical space

Target tracking in information space?

Some of the most principled work in this area is in attack graphs/scenario graphs. By understanding the vulnerabilities in the defended network, we can map out possible future actions by attackers. This state space can become large quite quickly, however. Also, these attack graphs don’t usually cover human vulnerability, which obviously plays an important role in modern intrusions.
There are some strategies for reducing the size of these graphs by emphasizing the most likely paths, for example (Wing, 2010):

1. Applying Google PageRank to identify the most likely nodes to be visited.
2. Allowing the analyst to decide which states are the most likely, or the most dangerous.

In practice, it's hard to build such attack graphs automatically in a way relevant to the particular environment.

Another problem is that this approach is that it includes only technical vulnerabilities, while human vulnerability (e.g. to social engineering) is a critical factor in overall system security.
An alternative approach?

Systems-Theoretic Accident Modeling and Processes (STAMP), Leveson MIT

• Safety/security are emergent properties
• What are the accidents/losses we want to prevent?
• What controls are needed to prevent the accident/loss?
• What are the failure conditions if a control
  ○ is not applied
  ○ is applied incorrectly
  ○ is applied too early/too late
  ○ stops too soon/continues too long
• What feedbacks are needed to ensure controls are appropriate? (→ detection) Modify design?
• Focus on prevention of accident/loss, shock resilience

STAMP is a process that has been proven effective in the safety realm (inadvertent actions by benevolent actors), and may be appropriate to the security realm (deliberate actions by malicious actors).

The focus is on controlling vulnerability, and since in detection we’re dealing with systems already in place, the focus has to be on risk mitigation (monitoring for violations of controls, and detection of accident/loss events). Security analysis systems could form part of the feedback, and hopefully can feed into an a continuous improvement process in the enterprise.

Projection becomes a process of estimating the most likely scenarios of accident/loss under the current situation, so we can adjust our actions to better protect against the most likely scenario. Development and discussion of enterprise and system vulnerability models based on STAMP is left for future work.
Conclusions

- Scale of network monitoring makes judicious automation necessary
- Dasarathy’s Functional Model provides a useful roadmap to data/information fusion
  - Low-level: automate
  - Mid-level: automate where possible, otherwise provide good tools
  - High-level: Good visualization, strong search and drill-down to assist the human analyst
- Structured data good (e.g. STIX, OpenIOC)

Structured data is good because we can incorporate it into our models in an automated way. Extracting indicators from human-written PDFs is just not desirable or scalable.