Some Research Challenges for Big Data Analytics of Intelligent Security

Yuh-Jong Hu
hu at cs.nccu.edu.tw

Emerging Network Technology (ENT) Lab.
Department of Computer Science
National Chengchi University, Taipei, Taiwan

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OVERVIEW
Motivations
Research Challenges and Approaches

BACKGROUND
Big Data Analytics
Intrusion Detection Systems
Hybrid Intrusion Detection

COMPOSITE BIG DATA ANALYTICS MODELLING
Composite Big Data Analytics Modelling
Machine Learning with Domain Knowledge

PRELIMINARY CBDAM PROPOSAL
Ontology Learning
Rule Learning

CONCLUSION AND FUTURE WORKS
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2. Here, we are exploiting the *structured machine learning* for big data analytics.

3. We hope this might be helpful for the security intrusion detection problem.

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Research Challenges

1. How to apply the structured machine learning for big data?
2. Why collecting the security big datasets is hard?
3. What is the big data analytics lifecycle for intelligent security?
4. How do we extract the security features to model, classify, and detect the malicious (or outlier) behaviors?
5. Which modelling and analytics paradigms for recognizing intrusion patterns?
6. What are the possible core technologies?
   ▶ Knowledge representation and discovery (or query)?
   ▶ Machine learning algorithms?
   ▶ How to combine structured knowledge with machine learning?
   ▶ Which big data analytics platform? Spark vs. Hadoop
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Possible Approaches

1. Machine learning algorithms in inductive reasoning
2. Logic programming in deductive reasoning
3. Inductive with deductive reasoning? e.g. (probabilistic) inductive logic programming (ILP), statistical relational learning (SRL), structured machine learning.
4. Composite Big Data Analytics and Modelling (CBDAM)
5. Establishing CBDAM framework on Spark.
6. Verifying CBDAM for intelligent security and other domains.
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Big Data 6-Dimension Taxonomy

–Big Data Taxonomy, Big Data Working Group, CSA, Sep. 2014
Possible Data Domains for Analytics

- Big Data
  - Network security
    - Intrusion Detection
    - APTs
  - Social networking
    - Sentiment analysis
    - Social graphs
  - Visual media
    - Scene analysis
    - Image/audio understanding
  - Sensor data
    - Weather
    - Anomaly detection
  - Retail
    - Behavioral analysis
  - Finance
    - High frequency
  - Large scale science
    - Bioinformatics
    - High energy physics

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Mapping the Big Data Verticals

- VISUAL MEDIA
  (Video scene detection, image understanding)

- NETWORK SECURITY
  (Intrusion detection, APTs, malware, virus attacks)

- SENSOR DATA
  (Intrusion detection, long term trends, weather)

- SOCIAL NETWORKING
  (Trend analysis, query processing)

- RETAIL
  (Sentiment analysis, behavior analysis)

- LARGE SCALE SCIENCE
  (High-energy physics, bioinformatics)

- FINANCIAL
  (High-frequency trading)

- BATCH
- NEAR REAL-TIME
- REAL-TIME

--Big Data Taxonomy, Big Data Working Group, CSA, Sep. 2014
Big Data Computing Infrastructure

- Big Data Taxonomy, Big Data Working Group, CSA, Sep. 2014
**Spark in the Hadoop 2.0**

- Big Data Taxonomy, Big Data Working Group, CSA, Sep. 2014
Possible Machine Learning Algorithms

Big Data Learning Algorithms

- Supervised
- Classification
- Clustering
- Dimensionality reduction
- Unsupervised
- Semisupervised
- Reinforcement

Regression
- Polynomial
- MARS
- Decision trees
- Naive Bayes
- Support Vector machines
- K-means
- Gaussian Mixtures
- Principle Component analysis
- Active
- Co-training
- Markov Decision process
- Q-learning

Big Data Taxonomy, Big Data Working Group, CSA, Sep. 2014
Machine Learning Flow Chart

- Big Data Taxonomy, Big Data Working Group, CSA, Sep. 2014
Security and Privacy Research Problems

- Big Data Taxonomy, Big Data Working Group, CSA, Sep. 2014
Misuse Intrusion Detection

Misuse Intrusion Detection (Conti.)

- Signature rule-based SIEM systems on misuse detection
- Discovering attacks from intrusions *known features*
- Low false positive rate but cannot detect new attacks
- Zero-day and APTs are novel new attacks.

Anomaly Intrusion Detection

Anomaly Intrusion Detection (Conti.)

(a) Multi-class Anomaly Detection

(b) One-class Anomaly Detection

Anomaly Intrusion Detection (Conti.)

Network Traffic → Pre-Processing → Dataset → Pattern Building → Outlier Detection → Alerts

Identifying attacks with significant deviations from normal.

Extracting features to represent normal activity is hard.

Can detect new attacks, but a high false positive rate.

Use attack free training datasets to learn.

How about hybrid intrusion detection?

Hybrid Intrusion Detection

Hybrid Intrusion Detection (Conti.)

Hybrid Intrusion Detection (Conti.)

- How to combine misuse with anomaly intrusion detection?
- High performance online *misuse* detection engine runs with offline *anomaly* system.
- How to extracting security features to model abnormal signatures and normal behaviors?
- Possible network security features are *packet size*, *IP addresses*, *ports*, *header fields*, *time stamps*, *inter-arrival time*, *session duration*, *session volume*, etc.
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Big Data Analytics Lifecycle for Intelligent Security

1. Acquisition and Recording
2. Cleaning and Extracting
3. Aggregation and Semantic Annotation
4. Query and Analytics
5. Modelling and Verification
6. Reactive and Proactive Actions

Dataset Processing Layer
- Load
  - Transform
  - Extraction

Structured Knowledge Modelling Layer
- RDF(S)
  - SPARQL

Machine Learning Analytics Layer
- Training
  - Testing
  - Attack Behaviors

Optimize

7. Intrusions Detected and Alert
END
Composite Big Data Analytics and Modelling (CBDAM) (Conti.)

**Figure:** CBDAM Architecture
Composite Big Data Analytics and Modelling (CBDAM) (Conti.)

**Figure:** Dataset Processing (DAP) layer
Composite Big Data Analytics and Modelling (CBDAM) (Conti.)

Figure: Structured Knowledge Modelling (SKM) layer
Composite Big Data Analytics and Modelling (CBDAM) (Conti.)

**Figure:** Machine Learning and Analytics (MLA) layer
Machine Learning with Perfect Domain Knowledge

**Figure:** Security domain knowledge aids machine learning

Research issues and challenges:

1. What are the important features should be extracted from the big datasets $D$ and model the initial security domain knowledge $K$ to further learn the intrusion behaviors $B$?
2. What algorithms exist to learn the security target function $f(x)$ from training instances $x_i \in D_l$, where $D = D_l \cup D_u$,?
3. How many training datasets $D_l$ are sufficient to offer an acceptable target function $f(x)$ to approximate the true intrusion behaviors $B_t$?
4. How to provide and use a minimum amount of labelled training instances $x_l \in D_l$ to learn and classify the intrusion behaviors correctly?
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2. The learner is provided with a perfect security domain knowledge $K_p$ to satisfy the correct and complete criteria.

3. What do you mean the learner has the correct and complete intrusion detection criteria?
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Machine Learning with Perfect Domain Knowledge (Conti.)

- \( K_p \) can be shown as a combination of ontologies \( O \) and rules \( R \) to explain the labelled training instances \( D_l \).
- The desired output is a hypothesis \( h \in H \) consistent with the labelled training instances \( x_i \in D_l \) and the security domain knowledge \( K_p \) with acceptable detection capability for unknown instances \( x_j \in D_u \).
- Why we need a perfect domain knowledge \( K_p \) to model our hypothesis \( h_p \in H \)?
- However, a perfect domain knowledge \( K_p \) with sound and complete criteria is hard to obtain.

Seminar at CS&E, Yuan Ze Univ.

Composite Big Data Analytics Modelling

Machine Learning with Domain Knowledge

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Inductive Learning System (ILS)

\[ ILS = (\forall < x_i, f(x_i) > \in D_l)(K'_p \land h_p \land x_i) \vdash f(x_i) \]

- \( K'_p \): background knowledge for security
- \( D_l \): training datasets
- A hypothesis \( h_p \in H \)
- \( f \): target function
- \( f(x_i) \): target value
- \( x_i \): the \( i^{th} \) training instance.

Deductive Learning System (DLS)

\[
DLS = \begin{cases} 
(\forall < x_i, f(x_i) > D_l)(h_p \land x_i \vdash f(x_i)) \\
D_l \land K_p \vdash h \\
(\forall < x_i, f(x_i) >) \in D_l)(K_p \land x_i) \vdash f(x_i)
\end{cases}
\]

- \(K_p\): domain knowledge for security
- \(D_l\): training datasets
- A hypothesis \(h_p \in H\)
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How about an imperfect domain knowledge $K_{ip}$?

**This is an optimization problem**

Minimize $\arg\min_{h \in H} \alpha_{D_{ip}} \text{error}_{D_{ip}}(h) + \beta_{K_{ip}} \text{error}_{K_{ip}}(h)$

where

- $\alpha_{D_{ip}}$ and $\beta_{K_{ip}}$: tunable parameters
- $\text{error}_{D_{ip}}(h_{ip})$: the ratio of instances misclassified by $h_{ip}$
- $\text{error}_{K_{ip}}(h_{ip})$: the probability that $h_{ip}$ disagrees with $K_{ip}$ on the classification of an instance.

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Ontology Learning

Ontology Representation

▷ What do you mean ontology?
▷ What ontology languages are available?
▷ How ontology can use security features to describe the concepts of intrusions?
▷ Why we need SPARQL query in the ontology learning process?
Ontology Learning (Conti.)

Feature Extraction and Representation

- Feature is a basic element of a recognized intrusion pattern.
- Possible feature types are:
  - Selector features
  - Order features
  - Hierarchical features
  - Relational features
  - Set-value features
- Above features should be combined with time, spatial, sequence order’s contextual features to classify intrusion types.

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Ontology Learning (Conti.)

Ontology Learning

- Ontology learning is a concept with instance learning to create, revise, and update the previous ontologies to reflect the status changes.
- Ontology learning is achieved by ontology matching, alignment, and merging from multiple ontologies.
- Ontology learning is an iterative process to reflect and adapt for new datasets.
- Ideally, we need an (semi-)automated ontology learning.
Ontology Learning for Intelligent Security
Rule Learning

**Rule Representation**

- Rule can be represented as: **If body then head**
  - a **body** contains a conjunction of conditions
  - each condition is a feature satisfaction constraint
  - a **head** contains a prediction with a classification label

- A rule is said to **cover** an positive (or negative) instance if the instance satisfies the conditions of the rule.

- A rule’s head is predicted class label or prediction values for an instance if a rule covers this instance.

- If a rule’s head only covers the positive instance, so NAF for CWA is assumed.

Rule Learning (Conti.)

Rule Learning

- A rule learning is (probabilistic) inductive logic program (ILP), statistical relational learning, structured machine learning, etc.
- A single rule learning is for a general to specific principle.
- A ruleset learning is for a specific to general principle.
- How to combine the deductive with inductive reasoning?
- This can be achieved by structured machine learning, how?
**Rule Learning (Conti.)**

**FROM ONTOLOGY TO RULE LEARNING AND VICE VERSA**

- On ontology learning, the RDF(S)-based ontology schema and instances are imported to the rule module by using SPARQL for classification.
- On rule learning, the rules (or SPARQL queries) enable the ontology module to reformulate the ontologies through approximate query to enable new predicate features.
- RDF(S) graph ontologies with approximate SPARQL query with time and error bounds can learn the new evolving ontologies.
Rule Learning (Conti.)

FROM ONTOLOGY TO RULE LEARNING AND VICE VERSA

▶ Later, we will upgrade to the logic-based ontologies with Datalog rules.

▶ The evolving ontologies with schema and relationships dynamic creation and removing.

▶ The rule (or query) learning allows approximate query to discover potential predicate relationships of features with a certain confidence.
Rule Learning for Intelligent Security Enforcement
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Conclusion and Future Works
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- Preliminary Results:
  1. Structured machine learning in inductive logic program (ILP), since 1990+, has been established at least 20+ years.
  2. Big data analytics is a driving force to rethink about the research challenges.
  3. A combination of ontology with rule learning creates a specific research avenue.
  4. A hybrid intrusion detection application domain is the first problem to verify this concept.
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Future Works:

1. The RDF(S) graph ontology learning with SPARQL rule learning for supervised machine learning, e.g., random forest and boosting, are considered first to verify the intelligent security problem.
2. The SPARK with RDF(S) and SPARQL platform have been establishing for the CBDAM platform.
3. Using the logic-based ontology and rules to verify structured machine learning concepts will be the next research challenge.
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