SEMANTIC ANOMALY DETECTION IN ONLINE DATA SOURCES

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This research was supported by the National Science Foundation under Grant ITR-0086003 and by the Sloan Software Industry Center at Carnegie Mellon University
The Register, March 19, 2001:

Reader Toby Doig nearly had a heart attack this morning when he visited Datek to check out his share portfolio and found that the Dow Jones Industrial Average (DJIA) had taken the full brunt of the stock market wobble and slumped just over 10,000 points to stand at 0.20 (down 99.999 percent, roughly)...
...clearly there had been a terrible computing error...
With anomaly detection

- Toby would be notified the data feed is behaving suspiciously
- Our results support semantic anomaly detection
  - by inferring invariants about normal behavior
  - that serve as proxies for missing specifications
Setting:
dynamic data feeds, incomplete specifications

Approach:
inferring invariants using multiple existing techniques

Feasibility results:
effective detection on stock quote data feeds, using 2 techniques
Everyday Software

Software people use for everyday purposes

- Not mission critical
- Must be dependable enough for practical use
  - Limited by dependability of elements
- Often incorporates elements maintained and developed by others
  - COTS (Commercial-Off-The-Shelf) components
  - Databases
  - Dynamic data feeds from online data sources
Dynamic data feeds

- A data source samples phenomena
  - Stock quotes, weather forecasts, airline ticket prices
- A data feed captures a particular usage of a data source via a view
  - KM (Kmart) quotes, Pittsburgh forecast, Pit–Tlv airfare
**Dependability of data feeds**

- Value increases by timely availability
- Evaluation/enhancement difficult
  - A priori validation insufficient
    - Data feed may change when being used
  - On-going failure detection and masking require specifications
    - Specifications are sketchy and incomplete
    - Free stock quote data feeds: at least 20min delay
- Semantic failures challenging
  - Results timely, well-formed BUT out-of-range, incorrect, inconsistent
- Availability under a semantic fault model needs to increase
  - Readiness for usage indicated by delivery of reasonable results
**Goal**

Long term: Increase the semantic availability of dynamic data feeds with **incomplete specifications**

This work: A first step

Results (this work):
- Can infer useful invariants about normal behavior of a data feed
  - By using/adapting statistical and machine learning techniques
- Can use as proxies for missing specifications
  - To effectively detect semantic anomalies
- Can do automatically, to a large extent
Setting:

dynamic data feeds, incomplete specifications

Approach:

- infer invariants using multiple existing techniques
- use as proxies for missing specifications for anomaly detection

Feasibility results:

effective detection on stock quote data feeds, using 2 techniques
**Goal (This Work)**

Given a sequence of observations
(time-ordered, with numeric attributes)
Build a (statistical) model to detect anomalies (outliers),
where a model is a set of invariants

...for example...

- \( \langle \text{attribute A value} \rangle \) within 2 standard deviations of estimated mean
- \( \langle \text{attribute A value} \rangle < \langle \text{attribute B value} \rangle \)
Invariant inference framework

Setup (human intervention required)

Data Feed $\rightarrow$ Gray Box $\rightarrow$ Suite of inference techniques tuned for the data feed

Usage (human intervention permitted but not required)

Data Feed $\rightarrow$ Infer invariants $\rightarrow$ Detect Anomalies
Example

Data feed: Datek stock quote for KM. \( \langle \text{cur}, \text{dhigh} \rangle \)

<table>
<thead>
<tr>
<th>time stamp</th>
<th>cur</th>
<th>dhigh</th>
</tr>
</thead>
<tbody>
<tr>
<td>1/10/2000 9:00am</td>
<td>34.5</td>
<td>49.8</td>
</tr>
<tr>
<td>1/10/2000 9:10am</td>
<td>29.1</td>
<td>49.8</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>1/10/2000 3:50pm</td>
<td>50.2</td>
<td>50.2</td>
</tr>
<tr>
<td>1/10/2000 4:00pm</td>
<td>46.3</td>
<td>50.2</td>
</tr>
</tbody>
</table>

Techniques

\( \Rightarrow \) Daikon [Ernst]: dynamically discover likely program invariants

\( \Rightarrow \) Mean: estimate confidence interval for mean of attribute distribution
Setup

**Augmented Daikon**
- Augment to handle noise
- Pre-process data

**Mean**
- Tune parameter

**Both**
- Find training set size

*Stock quotes* → **Augmented Daikon** → **Mean**
### Usage

1. **Infer invariants**
   - Infer invariants over a moving window of observations

2. **Detect anomalies**
   - Evaluate each invariant over fresh observations
   - Report when false

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### Stock quotes

<table>
<thead>
<tr>
<th>Time</th>
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</tr>
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#### Infer invariants

- **Daikon**
  - $\text{cur} \leq \text{dhigh}$
  - $\text{dhigh} = 49.8 \mid 50.2$

- **Mean**
  - $19.7 \leq \text{cur} \leq 59.8$
  - $49.4 \leq \text{dhigh} \leq 50.6$

#### Detect Anomalies

- Time | Cur  | Dh high |
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>10:40am</td>
<td>102.3</td>
<td>49.8</td>
</tr>
</tbody>
</table>

- $\text{dhigh} = 49.8 \mid 50.2$
- $19.7 \leq \text{cur} < 59.8$
- $49.4 \leq \text{dhigh} < 50.6$
Appropriate for

- Everyday usage (non-critical), incomplete specifications
- Dynamic data, truth unknown before data used
- Ordered observations, numeric attributes
- Failures that result from
  - Faulty sensors
  - Human error when entering information
- Single feed, multiple feeds with a semantic relation
  - Redundancy
  - Correlation

stock quotes: Datek, Yahoo!Finance
rainfall amounts, river level
Setting:
   dynamic data feeds, incomplete specifications

Approach:
   inferring invariants using multiple existing techniques

Feasibility results:
   effective detection on stock quote data feeds, using 2 techniques
**Data and methodology**

- **Techniques**: Daikon, Mean
- **Data**: 3 stock-quote data sources; each viewed for 3 stock tickers
  1. Infer invariants over a training set
  2. Detect anomalies (evaluate invariants) over a disjoint validation set
    - With and without a voting heuristic

Diagram:

- Data Feed → Training (2.5w) → Validation (1w) → Infer invariants → Detect Anomalies
Voting heuristic

- Cross checks data with a redundant data feed
  - Multi version comparison; independence required
- Eliminate false positives: invariant breaks over both
- Identify false negatives: invariant breaks only over redundant

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Results (example)

...Daikon...

A data feed
Best detection
Pointing to worst detection

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Results

- Misclassification: \( \frac{\text{False positives} + \text{False negatives}}{\text{anomalies} + \text{normal}} \)
  - <30% (due to 1 to 2 invariants; remove manually during setup)
  - <15%, usually <2% with voting heuristic
- Daikon and Mean complementary
- Detected anomalies helped us expose implicit specs of data source
### Examples of Implicit Spec

1. DS2 immediately updates $w_{52l}, w_{52h}$ when exceeded by $d_{low}, d_{high}$
2. DS1 does not

<table>
<thead>
<tr>
<th>Time Stamp</th>
<th>$d_{high}$</th>
<th>$w_{52h}$</th>
<th>$d_{high}$</th>
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</tr>
</tbody>
</table>

- $w_{52h}$ values inconsistent
- $d_{high} \nless w_{52h}$

- DS2 updates $w_{52l}, w_{52h}$ infrequently if not exceeded by $d_{low}, d_{high}$
- DS0 updates $w_{52l}, w_{52h}$ frequently (about once a week)
- DS1, DS2 calculate volume differently for a particular stock
Feasibility demonstrated

...in the context of stock market tickers...

...for a single data feed with numeric attributes...

A first step in increasing the semantic availability of dynamic data feeds with incomplete specifications

...because raises a flag that will trigger repair...

➤ Can infer useful invariants about normal behavior of a data feed

➤ Can use as proxies for missing specifications
   ➢ To effectively detect semantic anomalies

➤ Can do automatically, to a large extent
   ➢ Training set size; parameter (for Mean)
Ongoing Work

- Level of automation
  - Training set size; handling normal changes in data (concept drift)
  - Adjusting parameters of techniques
  - Attribute selection

- Generality
  - Multiple data feeds
  - Existing specifications
  - Techniques
  - Types of data feeds (categorical, text is beyond our scope)
Questions