Continuous location validation of cloud service components

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Introduction

Who we are and what we do

The Authors

- **Fraunhofer**-Institute for **A**pplied and **I**ntegrated **SEC**urity
- Research institute solely focused on IT security (~ 100 employees)
- Located in Munich (main office) and Berlin
- Part of the Fraunhofer Society, biggest applied research organization in Europe (~ 20.000 employees)

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Motivation

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- Service or data location is regarded as one of the key decision criteria for companies in choosing cloud providers
- It is incorporated into many certificates and regulations, especially in Europe (BSI C5, EU GDPR, …)
- Depending on the service model, a change of location is not in the control of the customer
- Service location might not always be transparent, especially if using SaaS

Main Contributions

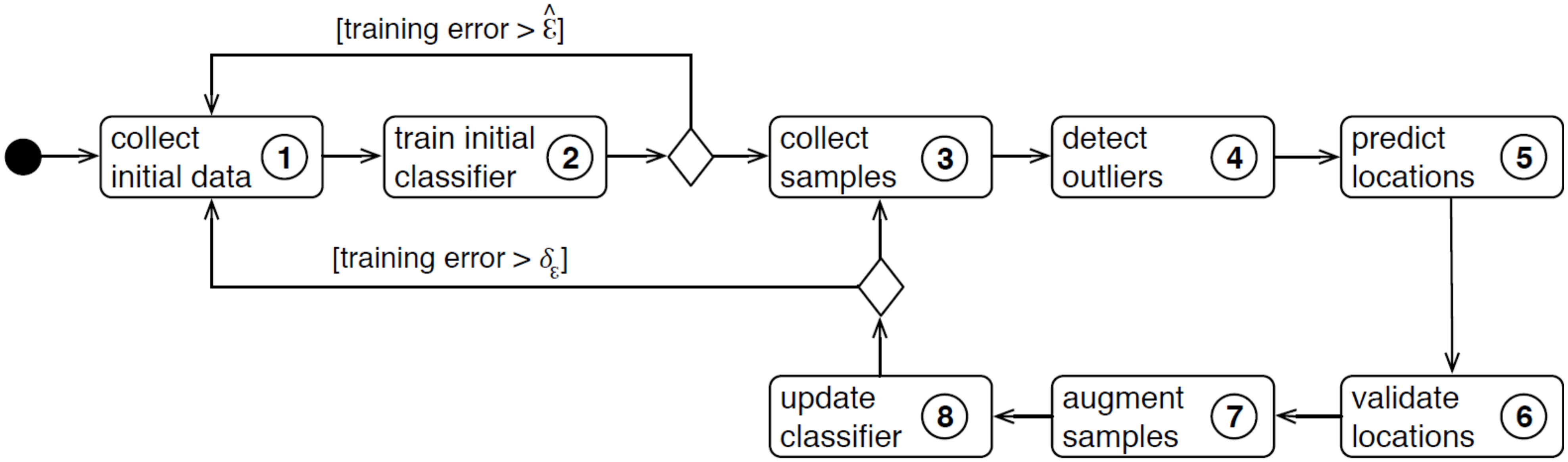
- Design of a process to classify geographical locations of virtual resources using Machine Learning ("location fingerprint")
- Continuous execution of process including measures to counter the "concept drift"
- Experimental evaluation of the process and method using 14 locations of Amazon Web Services (AWS)

Adaptive Location Classification

Designing the process

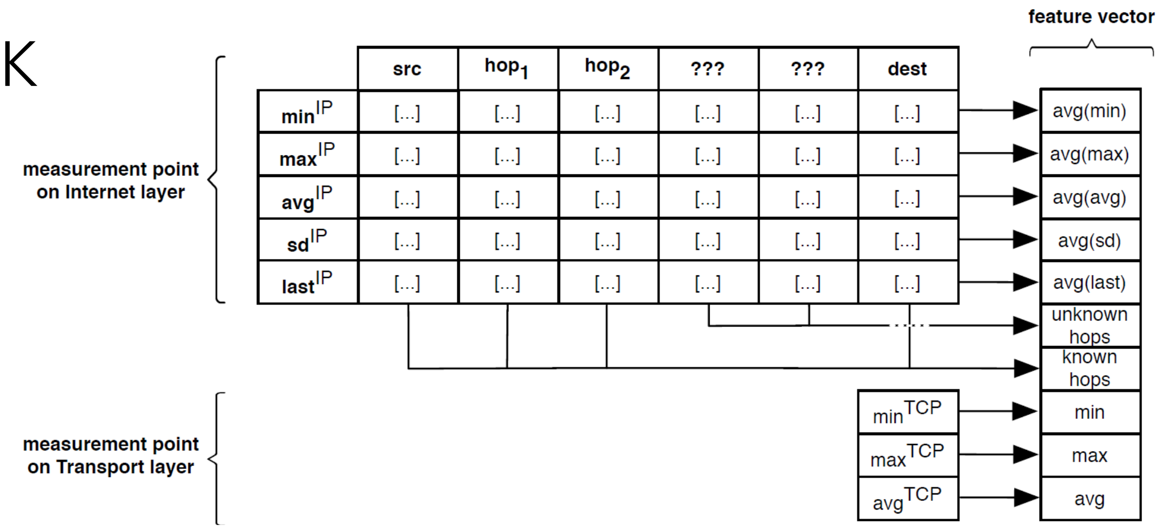
The process

- Goal: detect **changes** in a resource location
- Target: virtual resource with a (public) IPv4 address



Data Collection (Step 1)

- Internet layer
  - IPv4 traceroute (path + delay of hops)
  - Measurement is executed multiple times; *min*, *max*, *sd* are recorded
- Transport layer
  - Delay between SYN and SYN-ACK of the TCP three-way handshake
- Application layer
  - Not in scope of this paper; however we working on it



Training (Step 2)

- Input is the feature vector collected in the first step
- An appropriate supervised learning algorithm needs to be selected, i.e. k-NN or SVM (Linear SVM works good)
- We can calculate the training error ε to adjust parameters of the data collection, i.e. number of measurements (10 is good)
- Output: prediction model

Detection (Steps 5 and 6)

- To classify locations at a latter stage
  - Collect samples again (same as in the first step)
  - Apply the training model to let the classifier classify a location
- We do not want to rely on a single classification because of training errors
- Solution: Consider a sequence of location detections within a time interval by introducing an invalidation window size $|w_l^-| \geq \frac{\log v_l^-}{\log \varepsilon}$
  - Can be configured by a parameter v_l^-
  - Depends on the training error ε

Updating (Steps 4, 7 and 8)

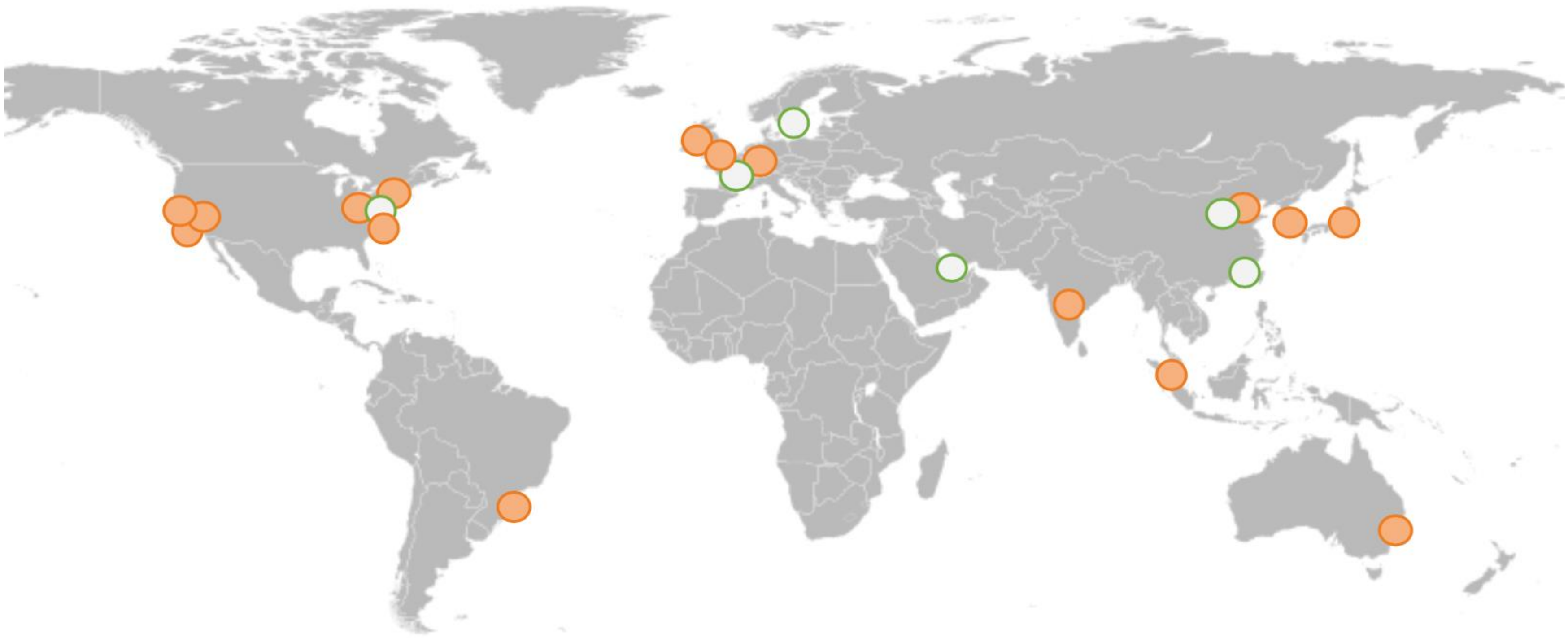
- After detection, we update the training model using the data fed into the classifier
- Before adding, we remove potential outliers using appropriate algorithms, i.e. one-class SVM
- Stop condition: We define a maximum training error *after* updating δ_ε, if the training error ε exceeds this, the process is stopped
- The new training error automatically configures the invalidation window size w_l^- (the higher the error, the larger the window)

Evaluation

Trying it out…

Setup in AWS

At the time of the experiment, 16 geographic *regions* in AWS
1 *region* = multiple *availability zones* (usually 2-3)



Setup in AWS

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- 14 EC2 instances in 14 regions (excluding Beijing and AWS Gov Cloud)
- Instances with public IPv4 address with security groups that enable ICMP and SSH
- Origin of measurement was also in AWS, Frankfurt

Data Collection

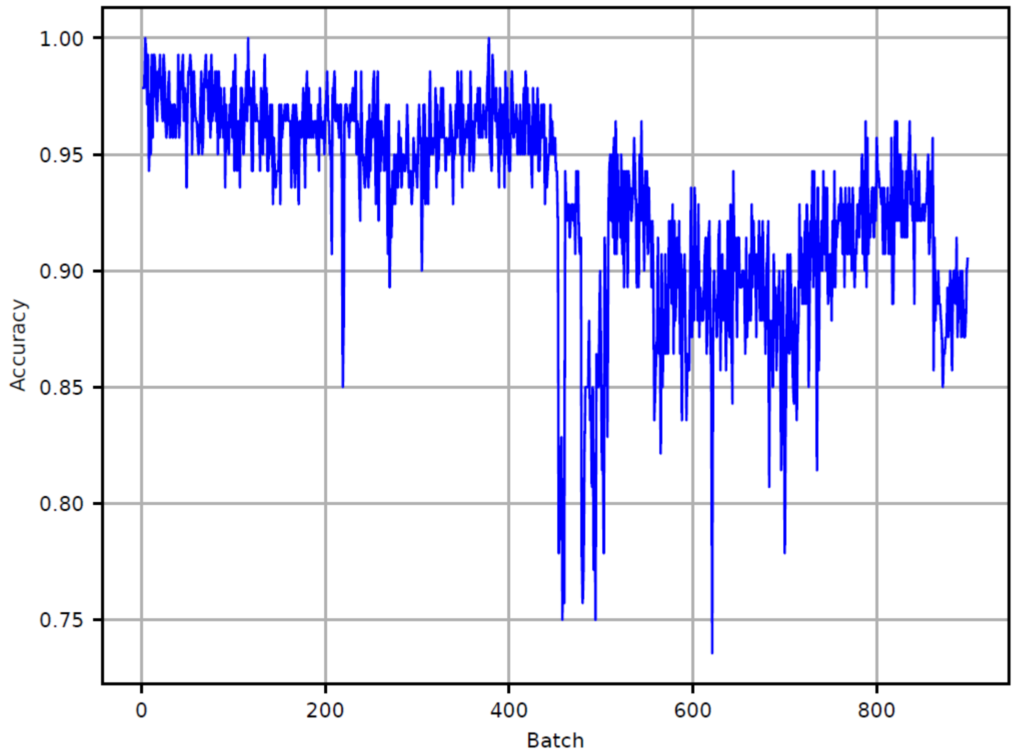
- *mtr* to gather traceroute and *nping* to collect TCP delay (port 22)
- Experiment duration
  - 17th December 2016 – 23rd December 2016
  - 15th December 2016 – 3rd January 2017
- In total 139699 delay measurements

Training

- Implemented using *scikit-learn* using the *LinearSVC* classifier
- 10% of the data used as the training set
  - Upper bound on the training error of $\hat{\varepsilon} = 0.0327$
  - We tolerate training error after updating $\delta_\varepsilon < 0.35$

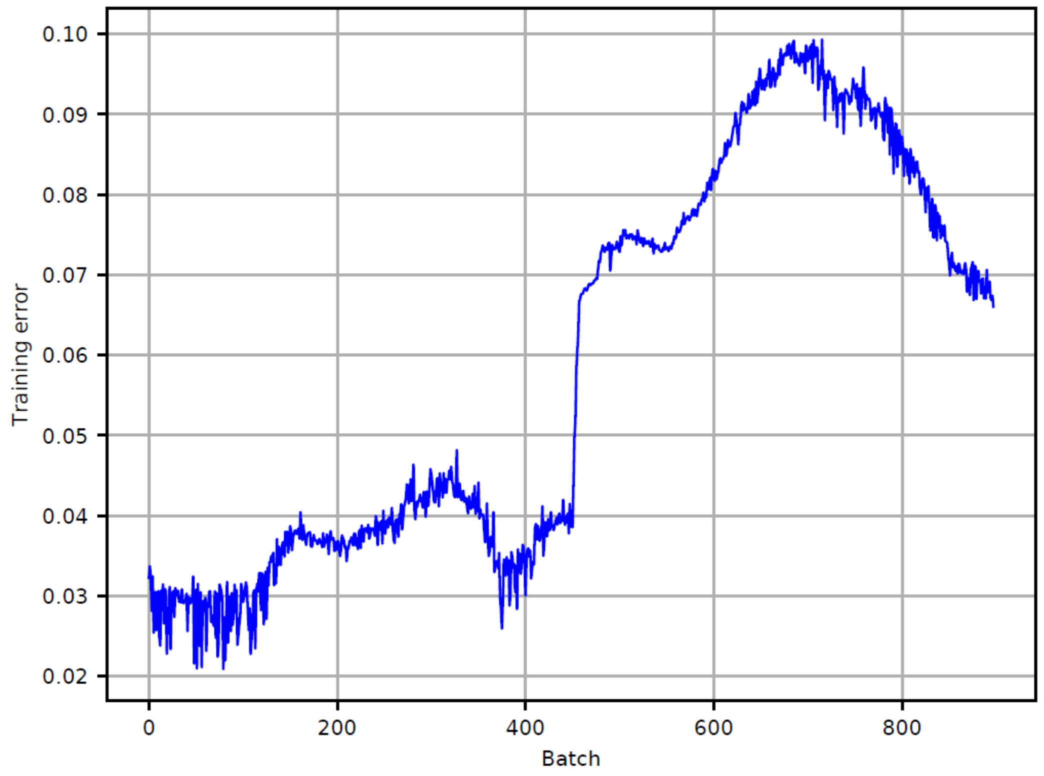
Detection

- Remaining 90 % of the dataset are used as the test set
- Split up in 898 successive batches
- Each batch simulates the Collect new samples step of the process
- Location is predicted and compared to the expected value

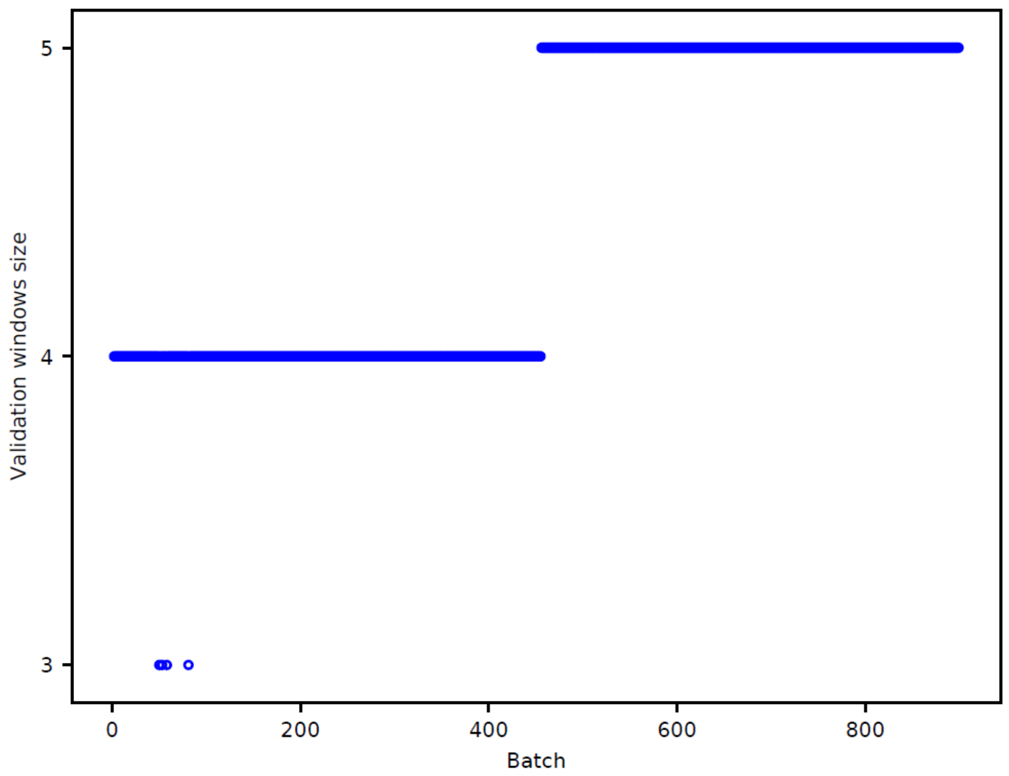


Training error vs. window size

Observed training error



Invalidation window size



Result

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- Test accuracy varies between 73.57 % and 100 %
- However, during the experiment, the invalidation window size was never exceeded
- As expected, no location change was observed during the experiment

Parameter	$\bar{x}$ (%)	$\hat{x}$ (%)	sd (%)	max (%)	min (%)
Test accuracy per batch	92.96	94.28	4.35	100	73.57

Conclusions

… and Future Work

Conclusions

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- Introduction of an adaptive process to detect changes in the location of virtual resources
- Demonstration of feasibility by evaluating 14 AWS regions
- SVM classifier performed very well during evaluation (avg 92.96 %)

Limitations and Future Work

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- We need to further study the affect of L2/L3 load balancers on the measurements
- Extend research from *service* location to *data* location
- Investigate performance of other classifiers, such as Random Forest
- Apply more sophisticated methods to detect concept drifts

Questions?