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360° Unsupervised Anomaly-based Intrusion Detection

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Presentation Outline

- Building a case for Anomaly Detection Systems
  - Bear with me if you already heard this rant :)
  - Intrusion Detection Systems, not Software !
  - Why do we need Anomaly Detection ?
- Network-based anomaly detection
  - Solving the curse of dimensionality
  - Clustering the payloads of IP packets
- Host-based anomaly detection
  - System call *sequence* analysis (done many times)
  - System call *argument* analysis (almost never)
  - Combining both, along with other ingredients
- Detecting 0-day attacks: hope or hype ?
- Conclusions

A huge problem, since 331 b.C.

- The defender's problem
  - The defender needs to plan for everything… the attacker needs just to hit one weak point
  - Being overconfident is fatal: King Darius vs. Alexander Magnus, at Gaugamela (331 b.C.)
- Acting *sensibly* is the key ("Beyond fear", by Bruce Schneier: a must read!)
- "The only difference between systems that can fail and systems that cannot possibly fail is that, when the latter actually fail, they fail in a totally devastating and unforeseen manner that is usually also impossible to repair" (Murphy's law on complex systems)
- a.k.a. "plan for the worst !!!" (and hope)

Tamper evidence and Intrusion Detection

- An information system must be designed keeping in mind that it *will* be broken into.
  - We must design systems to withstand attacks, and fail gracefully (failure-tolerance)
  - **We must design systems to be *tamper evident* (detection)**
  - We must design systems to be capable of recovery (reaction)
- An IDS is a *system* which is capable of detecting intrusion attempts on the *whole* of an *information system*
- We need *intrusion detection,* despite what Gartner's so-called analysts think or say
- The question is: which type of IDS components do we need to answer our requirements ?

The big taxonomy: Anomaly vs. Misuse

Anomaly Detection Model

- Describes **normal** behaviour, and flags deviations
- **Theoretically** able to recognize any attack, also 0-days
- Strongly dependent on the **model**, the **metrics** and the **thresholds**
- Generates statistical alerts: "Something's wrong"
- Difficult to use for automated reaction
- Has an ineliminable number of false positives
- Evaded by "mimicry"

Misuse Detection Model

- Uses a knowledge base to recognize the **attacks**
- Can recognize only attacks for which a "**signature**" exists
- Problems for **polymorphism** (e.g. ADMmutate), as well as signature expressiveness and canonicalization issues
- The alerts are precise: they recognize a specific attack, giving out many useful informations
- Can be easily used for automated reaction
- Usually no false positives, but "noncontextual alerts" to be tuned out
- Evaded by "strangeness"

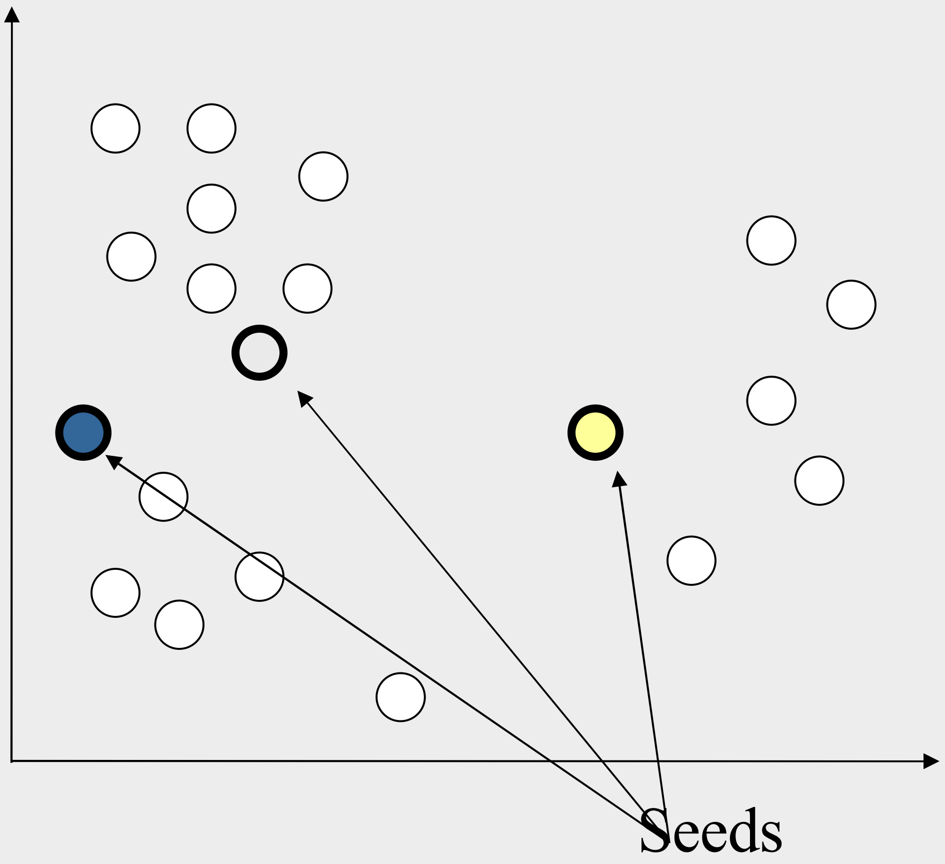
Unsupervised learning

- At the Politecnico di Milano Performance Evaluation lab we are working on anomaly-based intrusion detection systems capable of *unsupervised learning*
- What is a learning algorithm ?
  - It is an algorithm whose performances grow over time
  - It can extract information from training data
- Supervised algorithms learn on labeled training data
  - "This is a good event, this is not good"
  - Think of your favorite bayesian anti-spam filter
  - It is a form of generalized misuse detection
- Unsupervised algorithms learn on unlabeled data
  - They can "learn" the normal behavior of a system and detect variations (remembers something … ?) **[outlier detection]**
  - They can group together "similar things" **[clustering]**

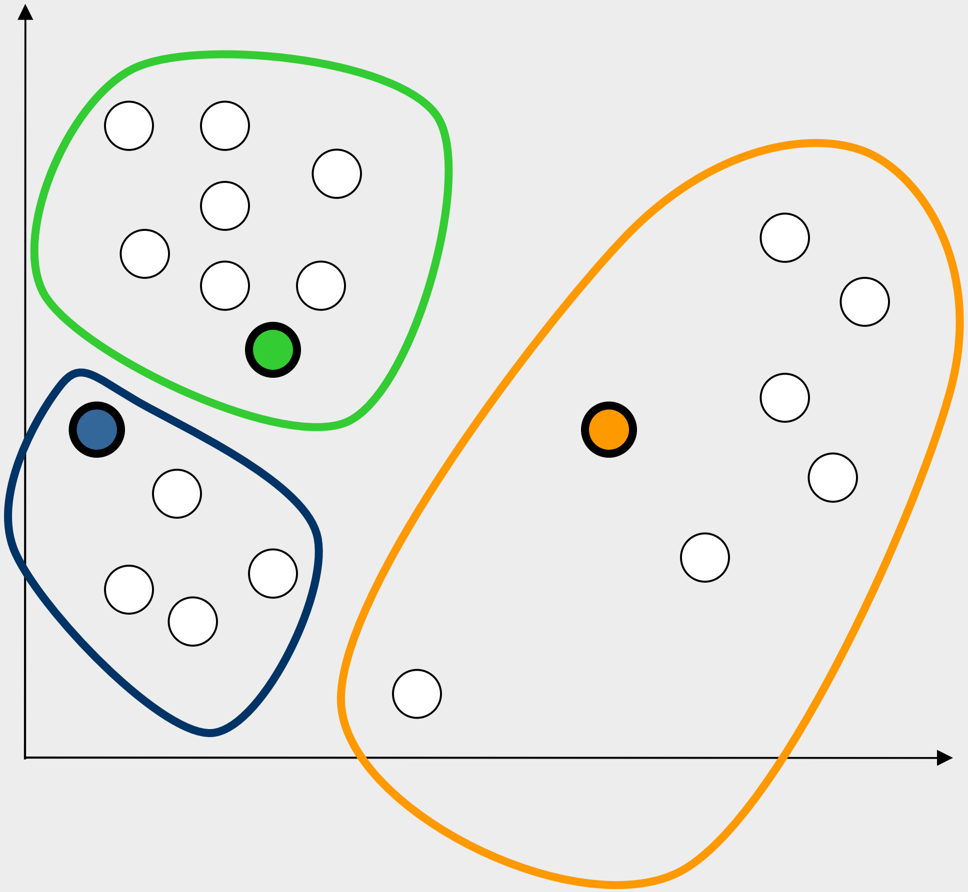
What is clustering ?

- *Clustering is the grouping of pattern vectors into sets that maximize the intra-cluster similarity, while minimizing the inter-cluster similarity*
- What is a pattern vector (tuple)?
  - A set of measurements or attributes related to an event or object of interest:
  - E.g. a persons credit parameters, a pixel in a multi-spectral image, or a TCP/IP packet header fields
- What is similarity?
  - Two points are similar if they are “close”
- How is “distance” measured?
  - Euclidean
  - Manhattan
  - Matching Percentage

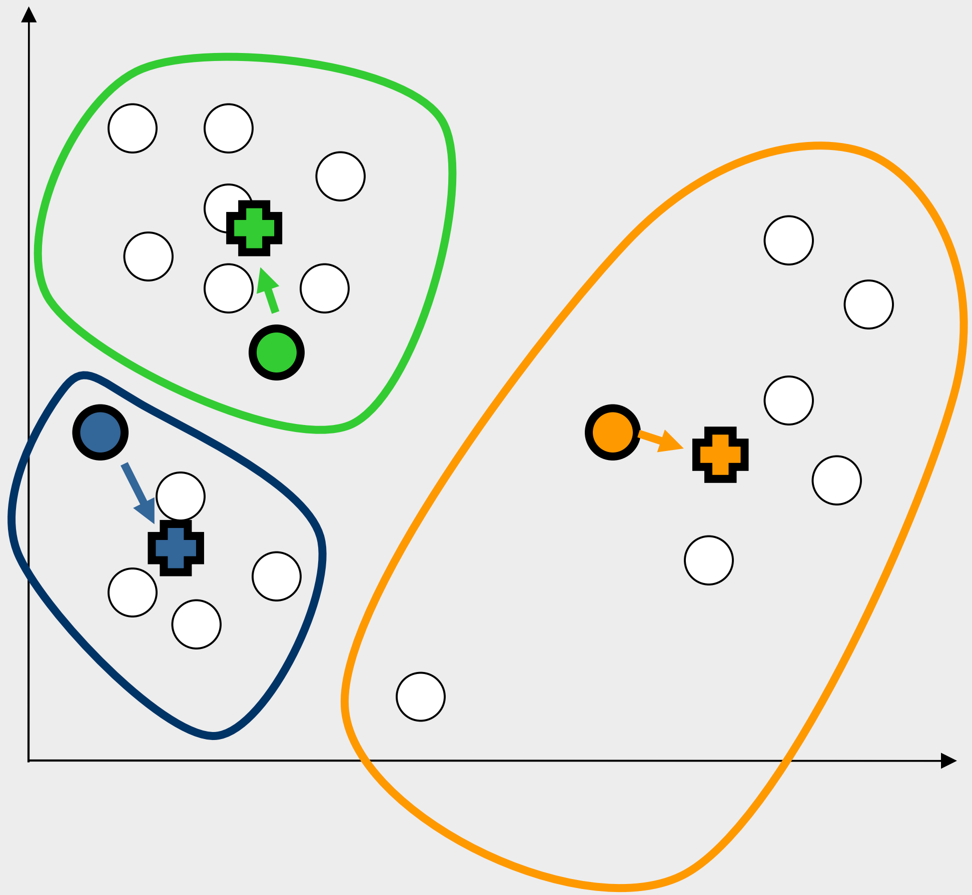
An example: K-Means clustering



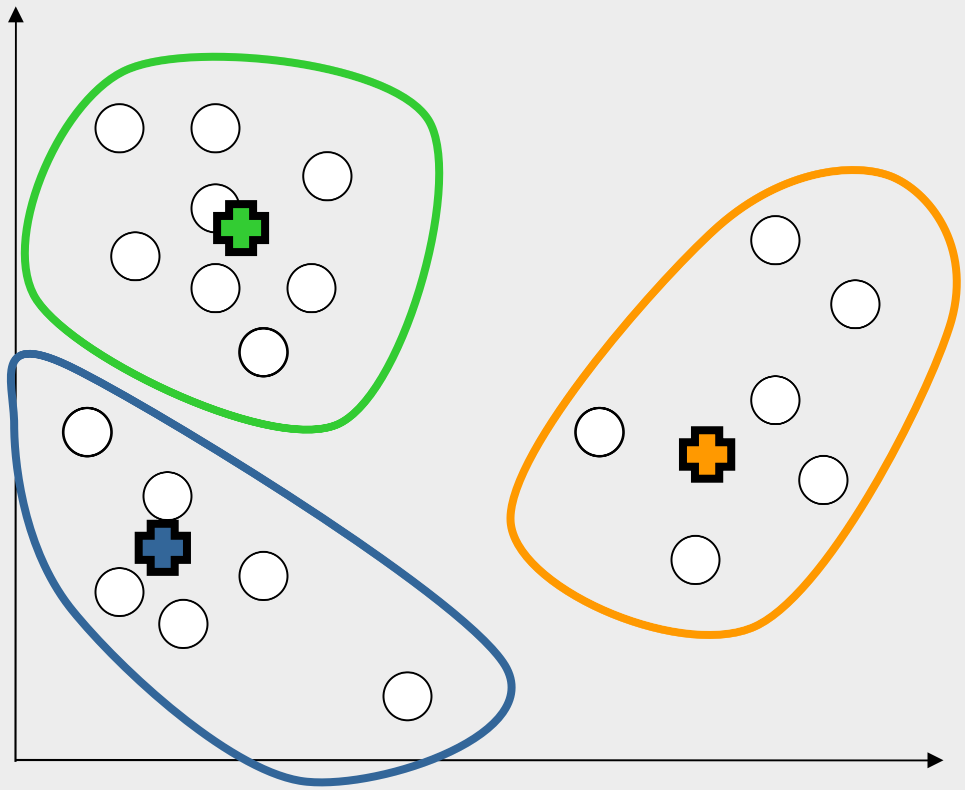
Assign Instances to Clusters



Find the new centroids



Recalculate clusters on new centroids



Which Clustering Method to Use?

- There are a number of clustering algorithms, K-means is just one of the easiest to grasp
- How do we choose the proper clustering algorithm for a task ?
  - Do we have a preconceived notion of how many clusters there should be?
    - K-means works well only if we know K
    - Other algorithms are more robust
  - How strict do we want to be?
    - Can a sample be in multiple clusters ?
    - Hard or soft boundaries between clusters
  - How well does the algorithm perform and scale up to a number of dimensions ?
- The last question is important, because data miners work in an offline environment, but we need speed!
  - Actually, we need speed in classification, but we can afford a rather long training

Outlier detection

- What is an outlier ?
  - It's an observation that deviates so much from other observations as to arouse suspicions that it was generated from a different mechanism
- If our observations are packets… attacks probably are outliers
  - If they are not, it's the end of the game for unsupervised learning in intrusion detection
- There is a number of algorithms for outlier detection
- We will see that, indeed, many attacks are outliers

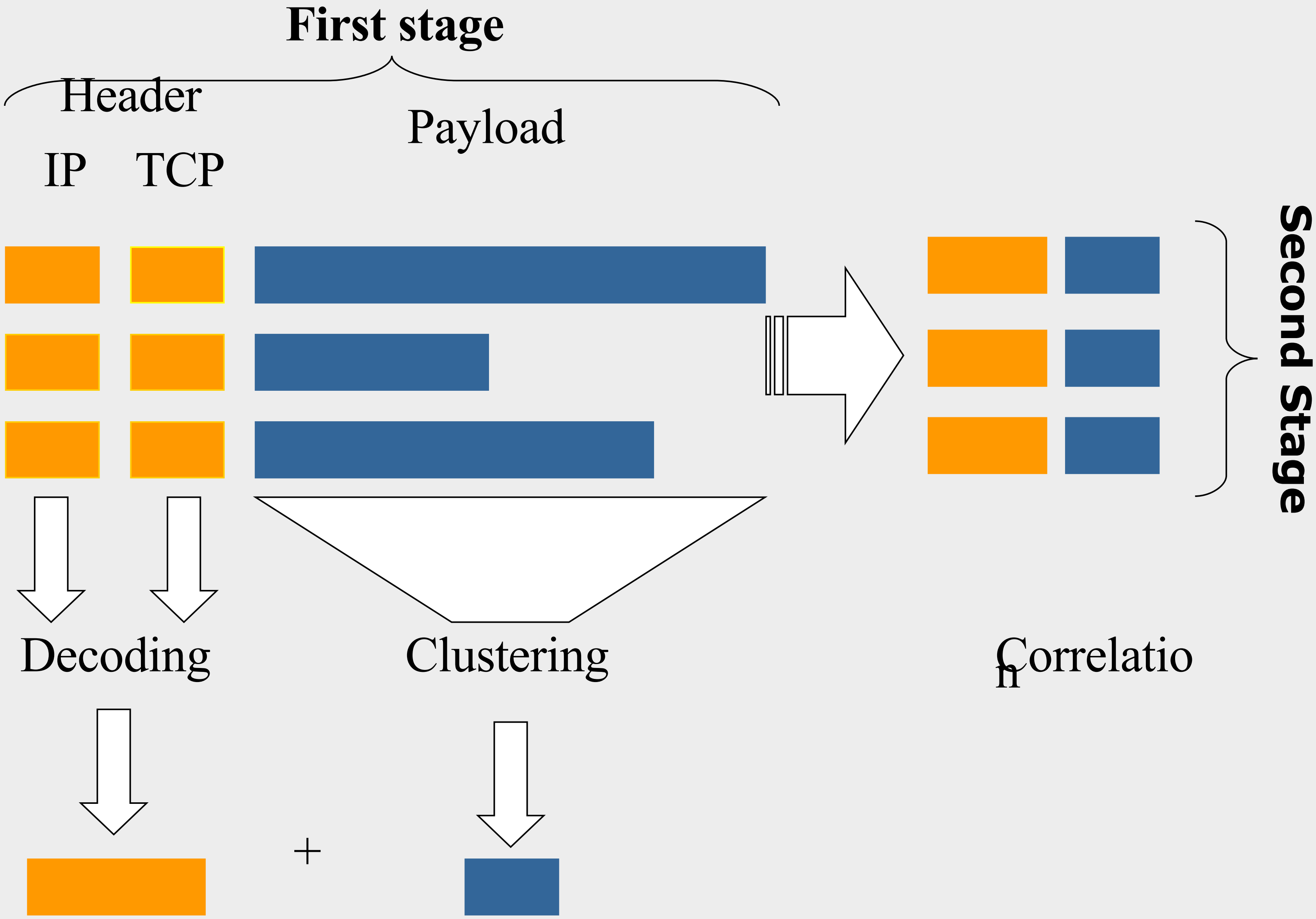
Multivariate time series learning

- A time series is a sequence of observations on a variable made over some time
- A multivariate time series is a sequence of vectors of observations on multiple variables
- If a packet is a vector, then a packet flow is a multivariate time series
- What is an outlier in a time series ?
  - Traditional definitions are based on wavelet transforms but are often not adequate
- Clustering time series might also be an approach
  - We can transform time series into a sequence of vectors by mapping them on a rolling window

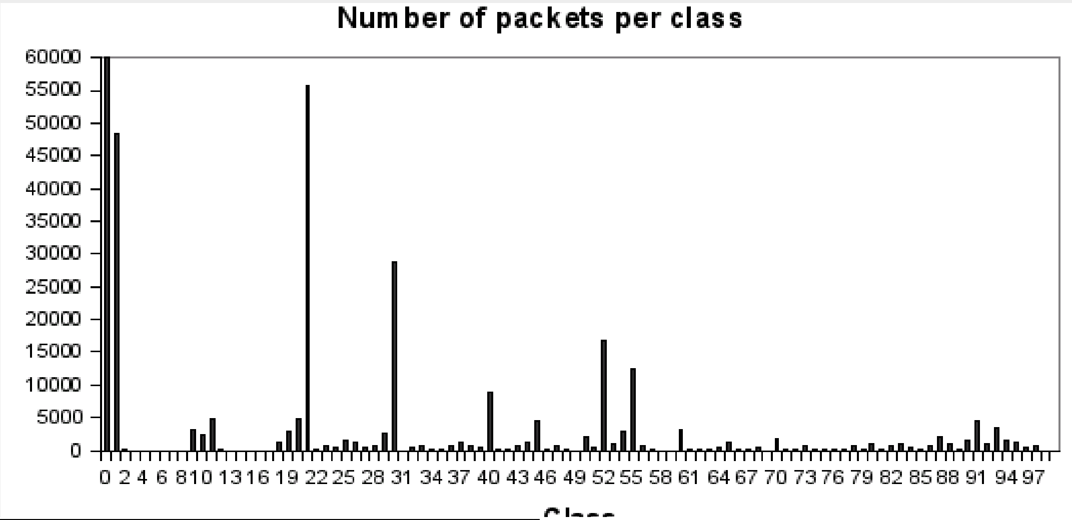
A hard problem, then…

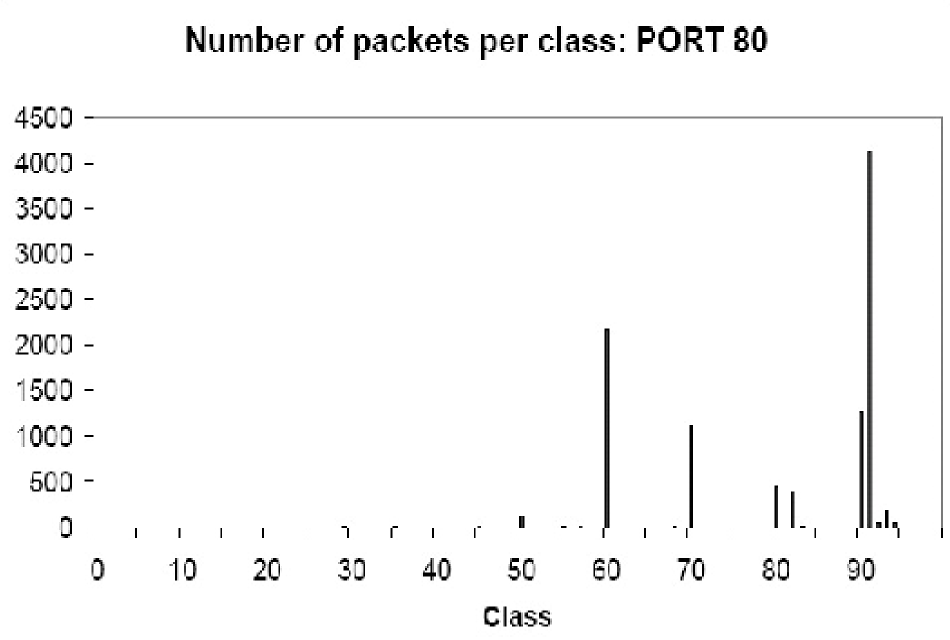
- A network packet carries an unstructured payload of data of varying dimension
- Learning algorithms like structured data of fixed dimension since they are vectorized
- A common solution approach was to *discard the packet contents.* Unsatisfying because many attacks are right there.
- We used **two** layers of algorithms, prepending a clustering algorithm to another learning algorithm
- After much experimentation we found that a Self Organizing Map (with some speed tweaks) was the best overall choice

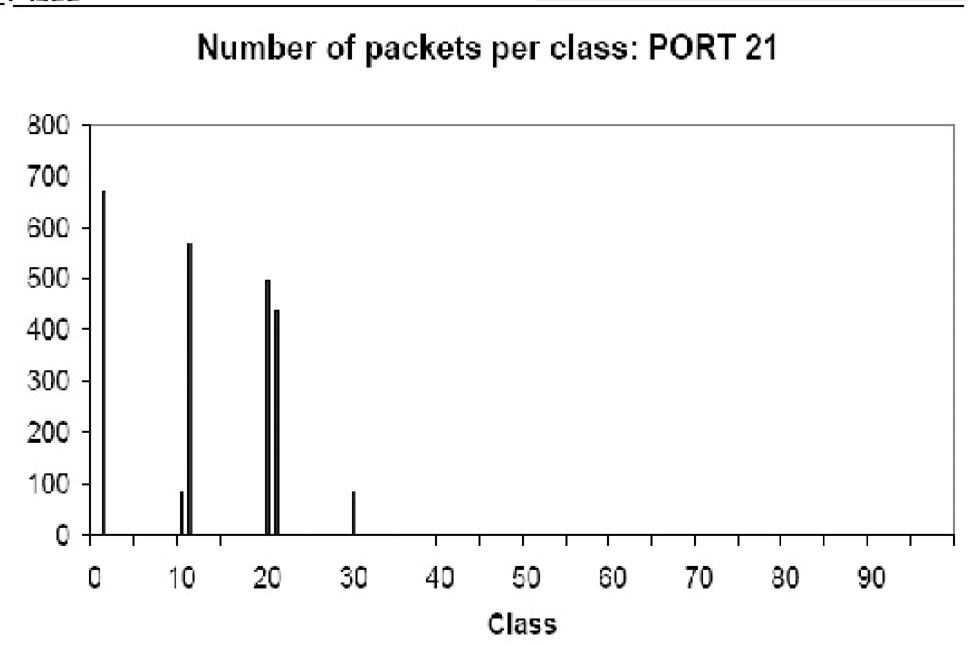
The overall architecture of the IDS



Recognising the protocols...

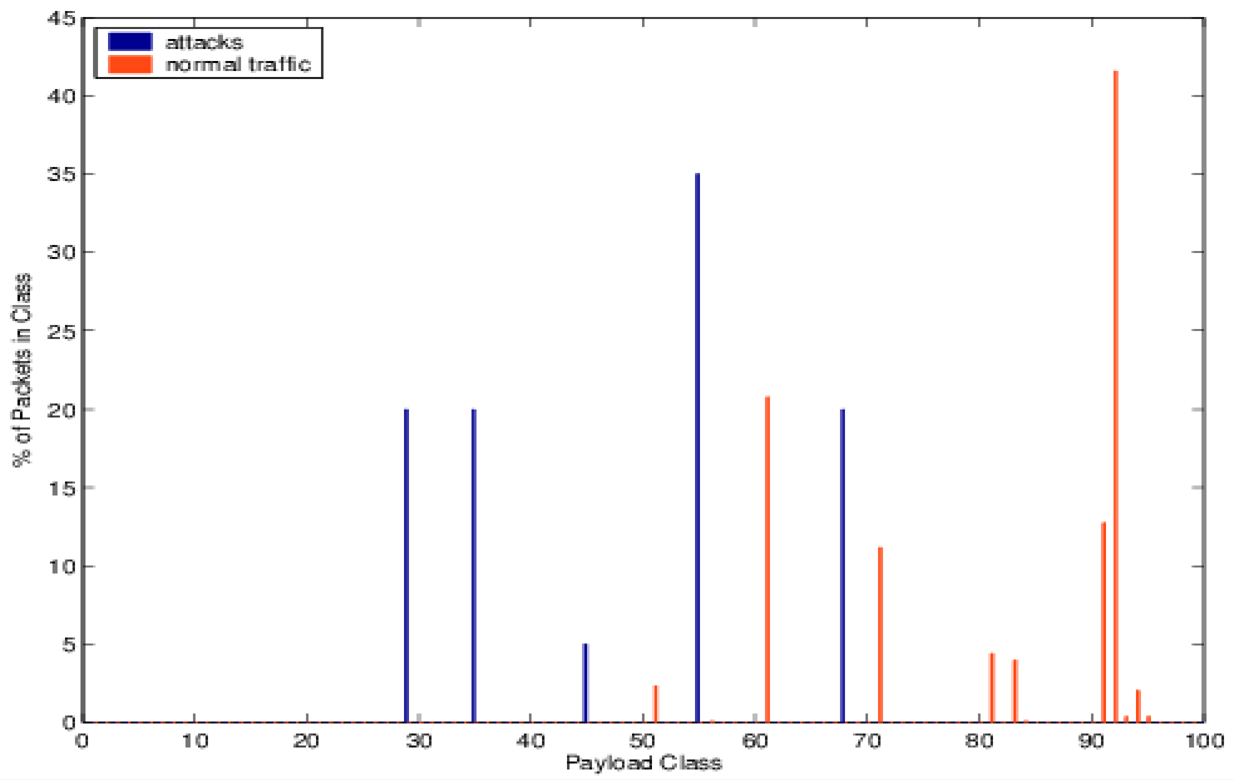






Recognising the attacks

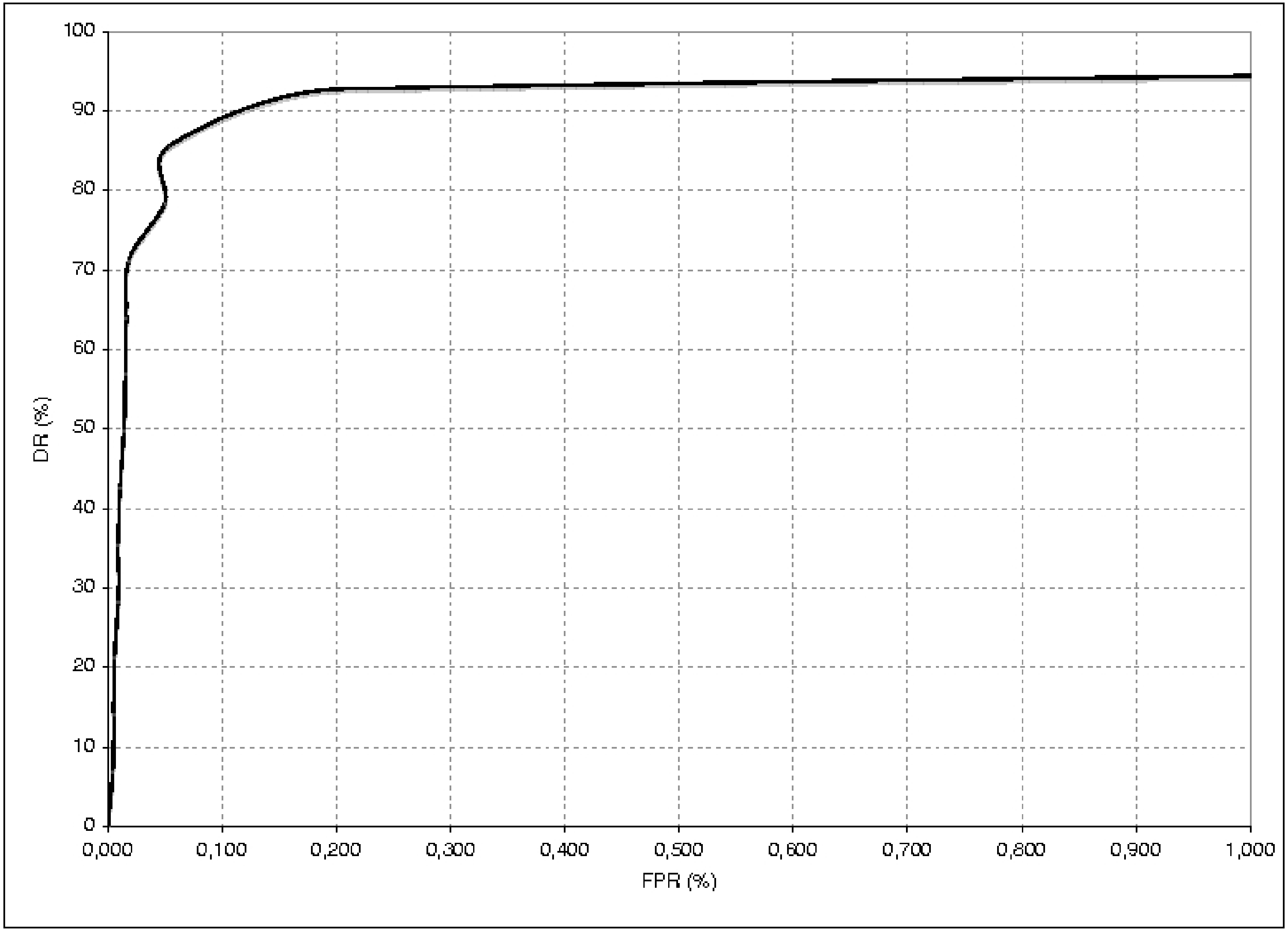
- Let us look at HTTP (DPORT=80)
- Attack packets are in blue, normal packets in orange
- The characterization makes attacks outliers !



Outlier detection & results

- Using the Smart Sifter outlier detection algorithm
  - Detection Rate well above 70%
  - False Positive Rate around 0,03%
- Some thousands of false alerts per day
  - An order of magnitude better than other systems
  - Still, too much: we are working on it
- We will release the tool as a GPL Snort plug-in... I know, I've been promising for two years, but I'm just never satisfied...

ROC curve of our NIDS



HIDS: state of the art

- Host-based, anomaly based IDS have a long academic tradition, and there's a gazillion papers on them
- Let us focus on one observed *feature*: the sequence of system calls executed by a process during its life
- Assumption: this sequence can be characterized, and abnormal deviations of the process execution can be detected
- Earlier studied focused on the sequence of calls
  - Used markovian algorithms, wavelets, neural networks, finite state automata, N-grams, whatever, but just on the sequence of calls
  - Markov models comprise other models
- An interesting and different approach was introduced by Vigna et al. with "SyscallAnomaly/LibAnomaly", but we'll see that in due time

Time series learning (again)

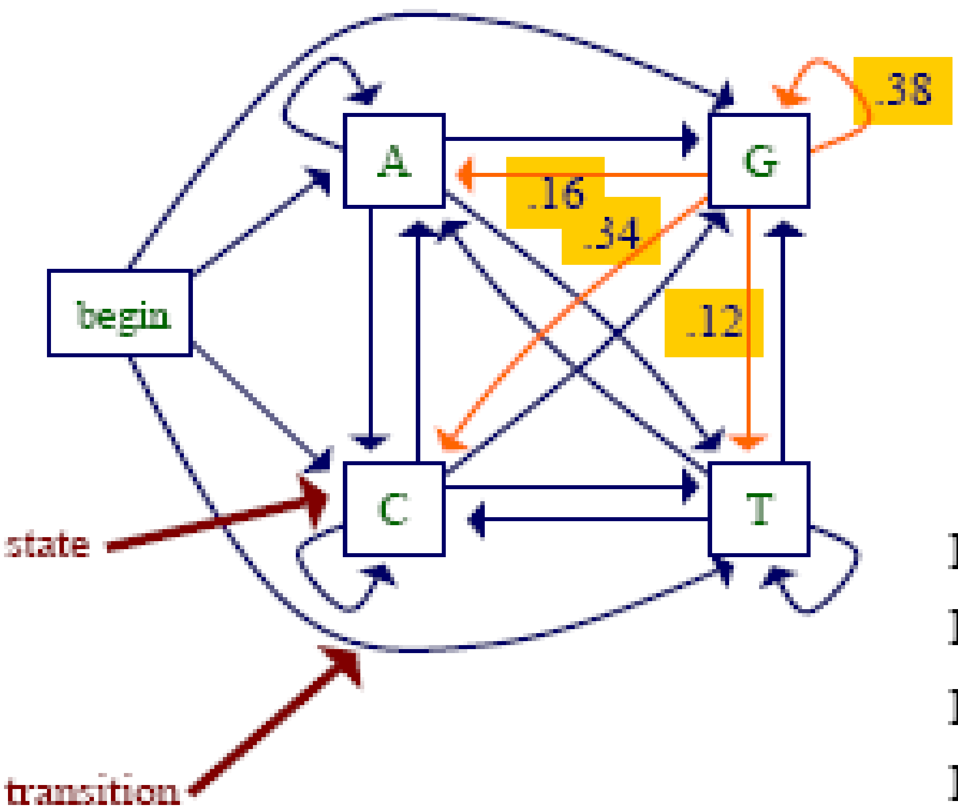
- If a syscall is an observation, then a program is a time series of syscalls
- If our observations are descriptive of the behavior of systems… attacks probably are outliers
- Once again, definitions based on wavelet transforms are not adequate
- Markov chains give us an approach to model the SEQUENCE of system calls
  - Has been done a number of times

What is a Markov chain ?

- A stochastic process is a finite-state, k-th order Markov chain if it has:
  - A finite number of states
  - The Markovian property (probability of next state depends only on *k* most recent states)
  - Stationary transition probabilities (not variable w/time)
- Probabilities, in a first-order chain with s states can be expressed as a square matrix of order s
  - In n-th order, with a order s^n
- They comprise other models
  - N-grams are simplified n-th order markov chains
  - FSA are simplified markov chains (almost ;)
  - Probabilistic grammars are Markov chains (probably)

An example of Markov chain

Markov Chain Models



transition probabilities

$$\Pr(x_i = a \mid x_{i-1} = g) = 0.16$$

$$\Pr(x_i = c \mid x_{i-1} = g) = 0.34$$

$$\Pr(x_i = g \mid x_{i-1} = g) = 0.38$$

$$\Pr(x_i = t \mid x_{i-1} = g) = 0.12$$

Training a Markov chain

- We can compute the *likelihood* of a sequence in a model with a simple conditional probability
- We can build the model which fits a given sequence or set of sequences by calculating the *maximum likelihood* model, the one which gives the various observations the maximum probability
- Can be done through simple calculations (problem of null probabilities), or through Bayesian ones
- Comparison of probability of sequences of different length is difficult (can use the logarithm or other tricks to smooth)

Which Markov chain does this fit ?

- Simple answer: you compute the likelihood
- If you need to compare multiple models, this is more complex
  - You need to take into account the prior probability, or probability of the model, since:
    $P(M|O) = P(O|M)\ P(M) / P(O)$
  - P(O) is fixed and cancels out, but you usually don't know P(M): depending on the choice, you can have varying results
- S. Zanero, “Behavioral Intrusion Detection” explains the mathematical trick

SyscallAnomaly: analyzing the variables

- SysCall Anomaly, proposed by Vigna et al.
  - Each syscall separately evaluated on 4 separated models
    - (maximum) string length
    - Character distribution
    - Structural inference
    - Token search
- Each model is theoretically interesting, but exhibits flaws in real-world situations
  - Structural inference
    - Realized as a markov model with no probabilities...
    - Too sensitive !
  - Token search
    - No “search”, really: you must predefine what is a token
    - Again, no probabilities

Our proposal

- We evolved the models
  - Structural inference: abolished (halving false positives...)
  - Implemented a model for filesystem paths (depth – structural similarities, e.g. elements in common)
  - Token Search: probabilistic model
    - UID/GID specialization, considering three categories: superuser, system id, regular id
- Now, we wanted to add
  - Correlation among the arguments of a single syscall
    - Hierarchical clustering algorithm to create classes of use
  - Correlation among system calls over time
    - Through a proven, reliable Markov chain

Clustering system calls

- *Clustering is the grouping of pattern vectors into sets that maximize the intra-cluster similarity, while minimizing the inter-cluster similarity*
- Here “pattern vectors” are the values of various models
- We used a hierarchical agglomerative algorithm
  - Pick up the two most similar items
  - Group them
  - Compute distance from the new group to other groups
  - Repeat
- What is similarity?
  - Two patterns are similar if they are “close”
  - We had to define similarity for each model type
    - e.g. is /usr/local/lib similar to /usr/lib? And to /usr/local/doc?

Results of clustering

- The clustering process aggregates *similar uses* of a same system call
  - E.g.: let us take the `open` syscalls in fdformat:

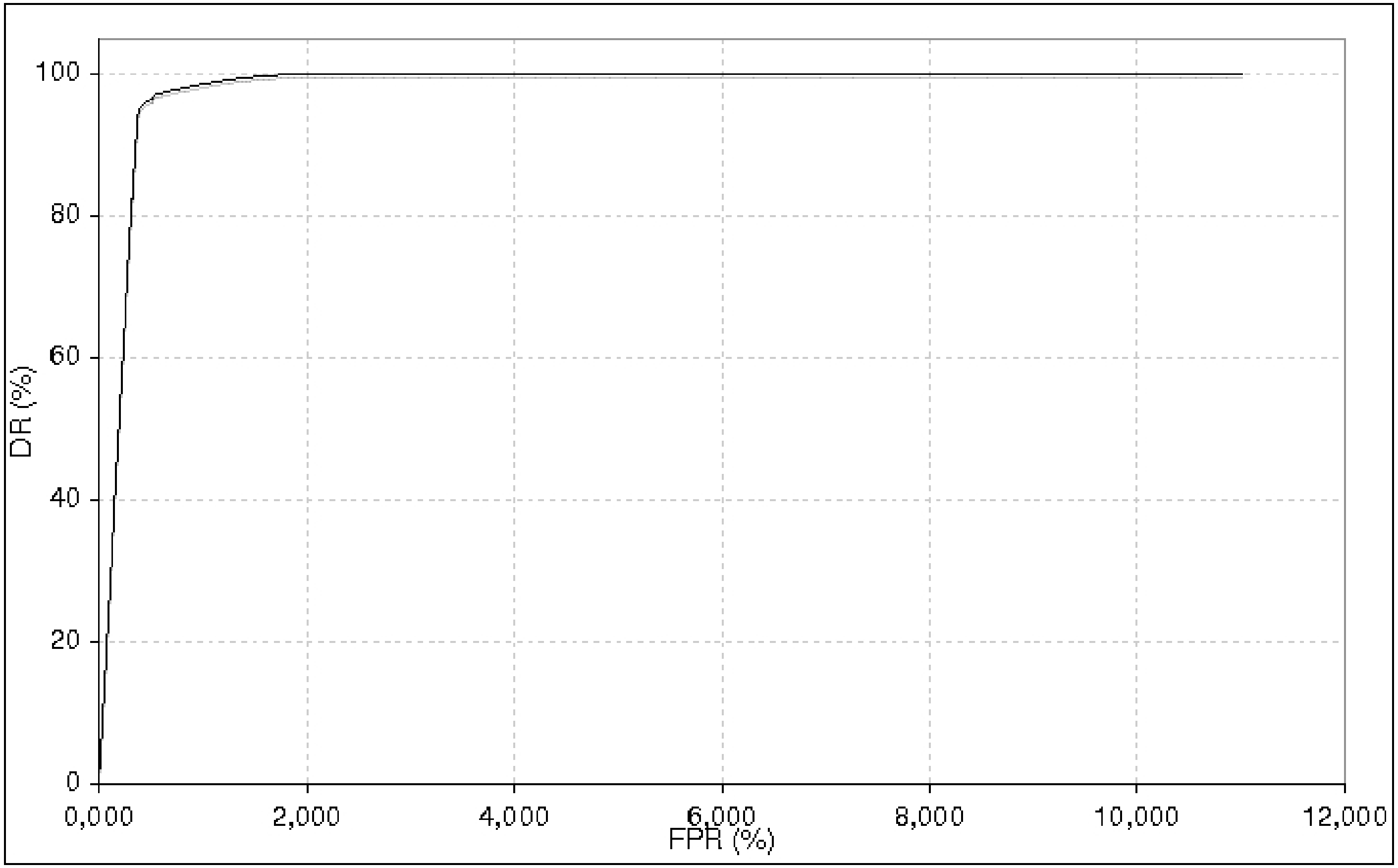
```
/usr/lib/libvolmgt.so.1, -rwxr-xr-x
/usr/lib/libintl.so.1, -rwxr-xr-x
/usr/lib/libc.so.1, -rwxr-xr-x
/usr/lib/libadm.so.1, -rwxr-xr-x
/usr/lib/libw.so.1, -rwxr-xr-x
/usr/lib/libdl.so.1, -rwxr-xr-x
/usr/lib/libelf.so.1, -rwxr-xr-x
/usr/platform/sun4u/lib/libc_psr.so.1, -rwxr-xr-x
/devices/pseudo/mm@0:zero, crw-rw-rw-
/devices/pseudo/vol@0:volctl, crw-rw-rw-
/usr/lib/locale/iso_8859_1/LC_CTYPE/ctype,-r-xr-
  xr-x
```

- Each of the clusters is a separate *type* of syscall (e.g. “open_1”, “open_2”, “open_3”)

A matter of sequence

- We can now build a Markov chain which uses as states the *clusters* of syscalls, as opposed to the syscalls per se
- We can train the model easily on normal program executions
  - Not static analysis, we would include bugs
- At runtime we will have three “outlier indicators”:
  - The likelihood of the sequence so far
  - The likelihood of this syscall in this position
  - The “similarity” of this syscall arguments to the best-matching cluster
- 1) indicates likely deviation of program course
- 2) and 3) punctual indicators of anomaly

ROC curve of our HIDS

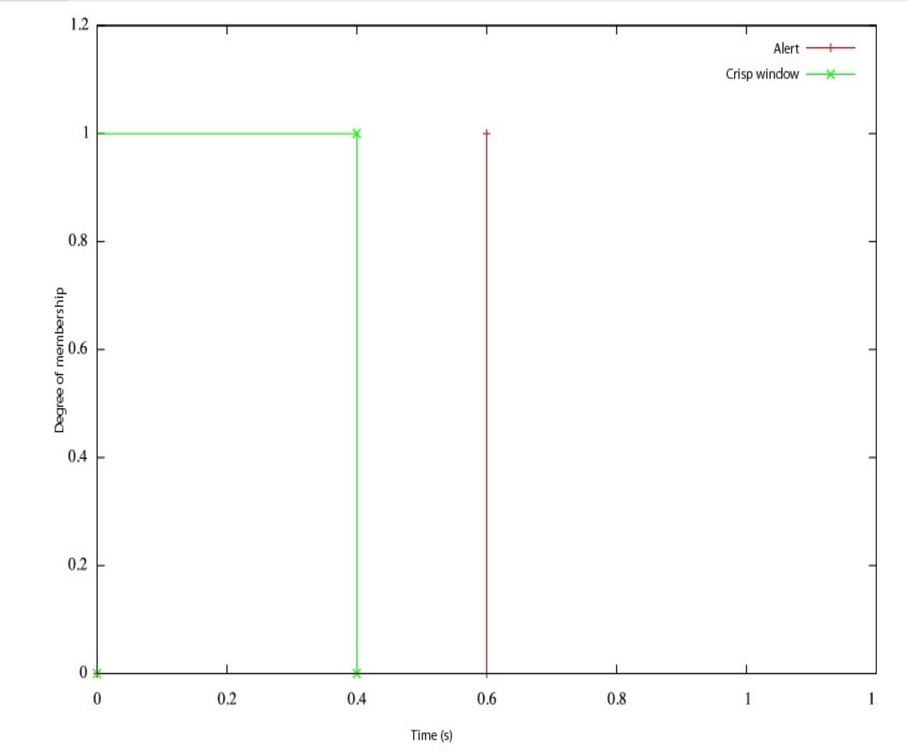


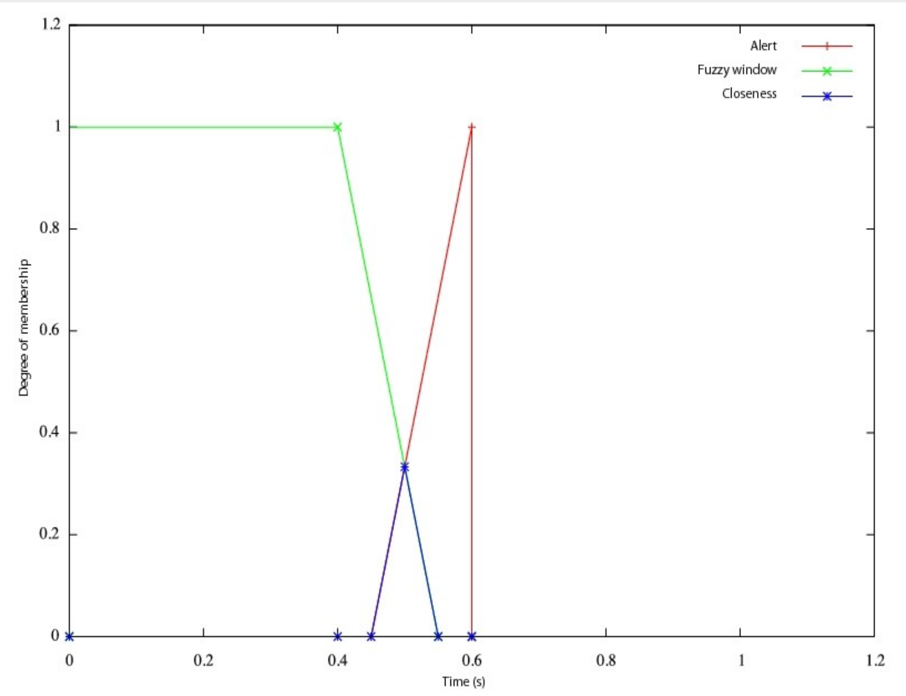
Putting it all together !

- What do we have so far ?
  - A system which flags anomalous packets with an "outlier factor"
  - A system which flags anomalous syscalls on a host with a (set of) outlier factor(s)
- How can we correlate these alerts, maybe even along with others ?
- A process of *alert stream fusion*
  - *Aggregation* of alerts referring to the same event
  - *Correlation* of events likely to be related
  - *Scenario awareness* and high-level analysis
- We addressed 1) and 2) until now

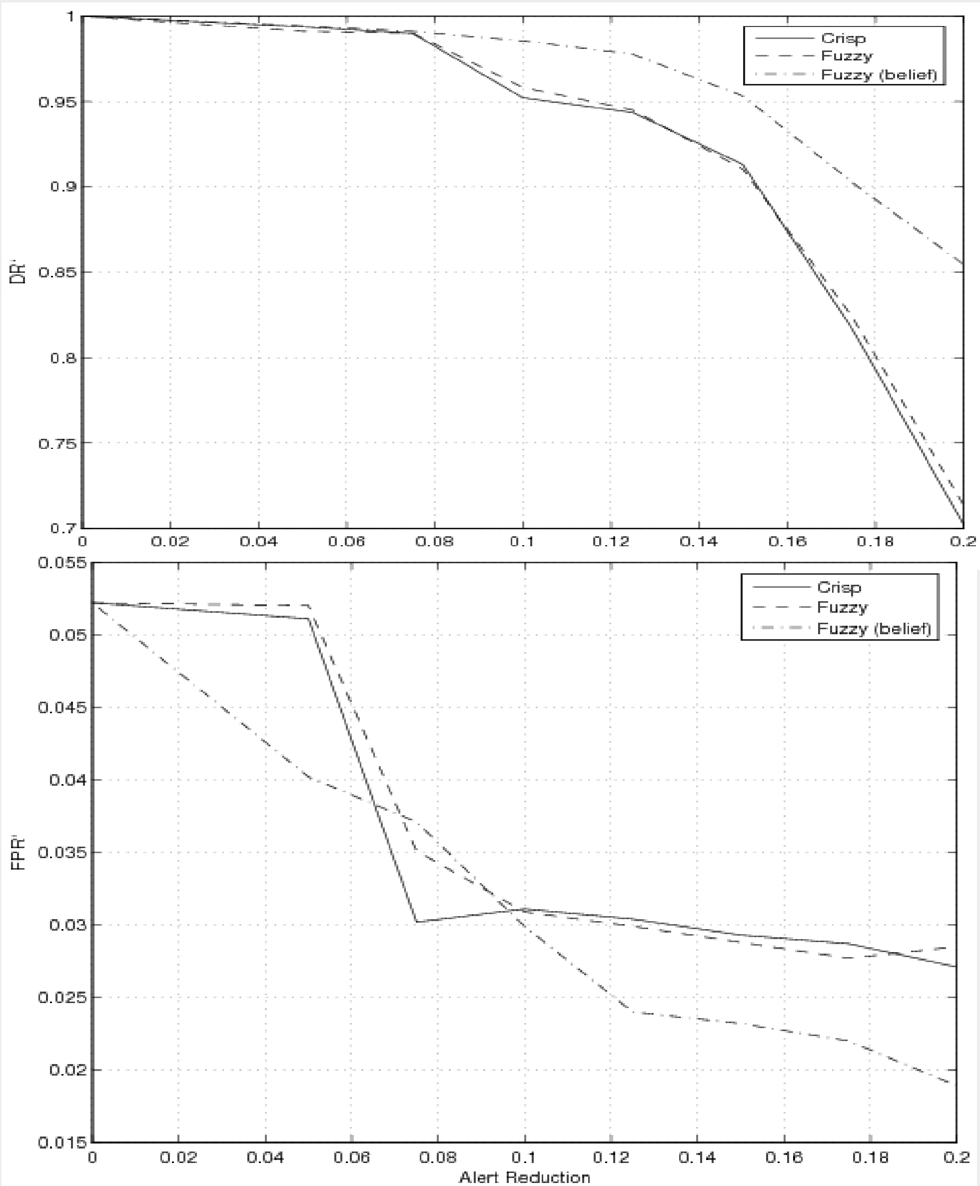
Aggregating alerts

- Putting together alerts with common features (attacker, target, service...) and “near” in time
- Near = fuzzy concept
  - More robust. Models uncertainty and errors as well!





False positive reduction

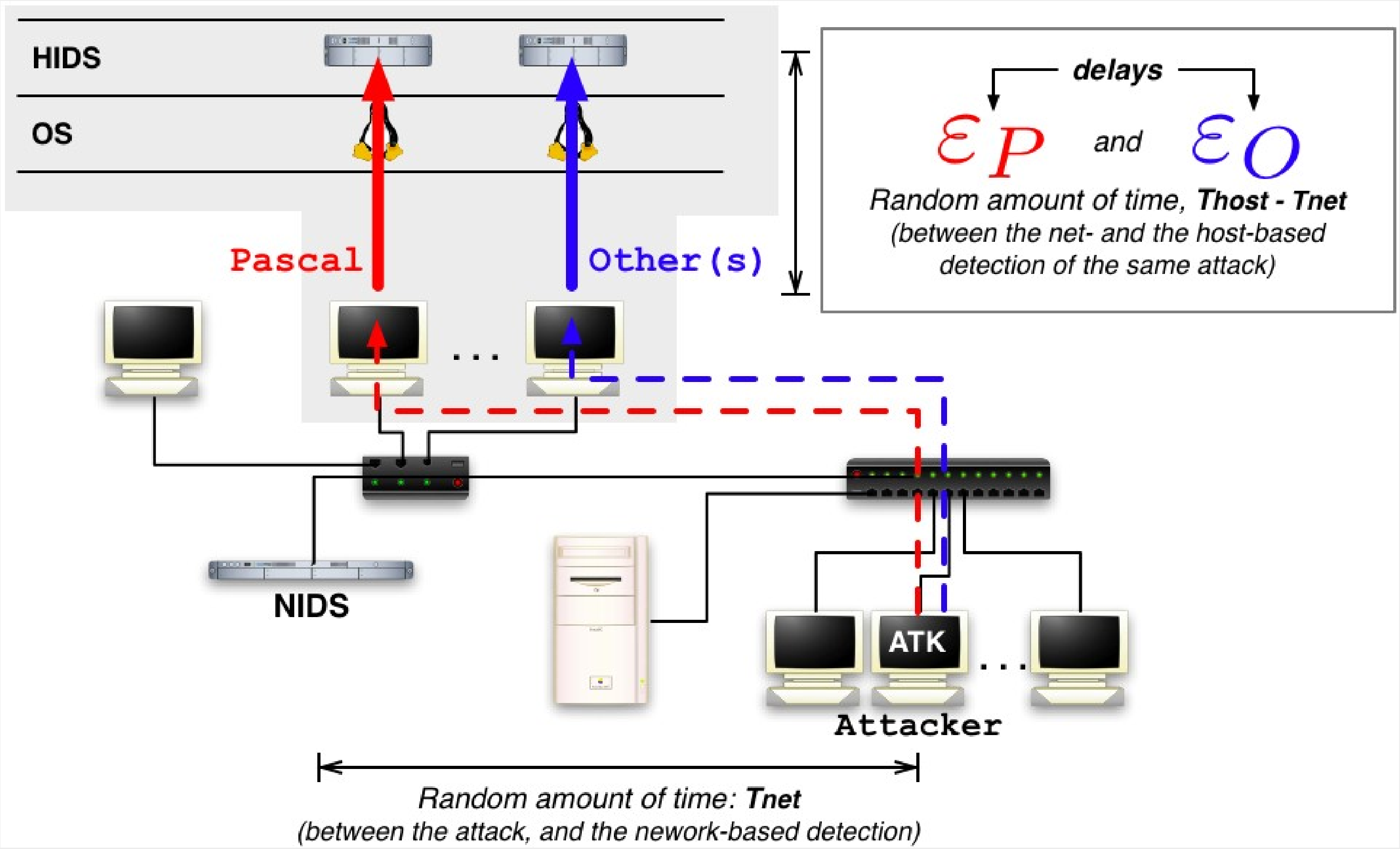


- We compare FPR and DR reduction while incrementing aggregation and suppression of alerts
- Belief correction preserves from suppression alerts with high support

Using “causality” to study correlation

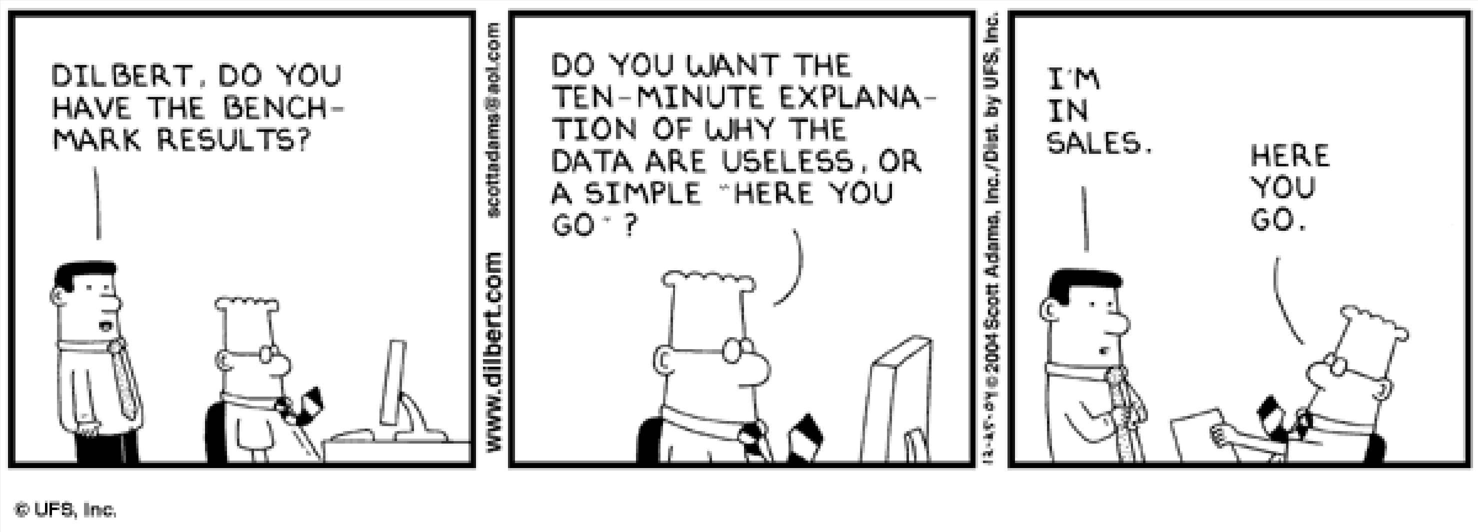
- Granger test for causality
  - If *some_data* is better explained with *some_other_data* in input than it is by itself, then *other_data* causes *data*
  - More formally, if an AR model on the output fits worse than an ARX model with the input, then the input “causes” the output
  - ... Nobel prize for Economy.
- Some early researchers proposed it for correlation, and we tried
  - Dependent on the order of the model, i.e. the time frame over which correlation makes sense
- Results are not good, but the *general category* of the approach seems reasonable: if only we could create a non-parametric version of it...

Non parametric statistical approach



This will be disclosed today at the RAID symposium in Australia ;)

A word of caution about "results"



- Look up my presentation at BH Fed on why the evaluation of intrusion detection systems is mostly useless as of now
- Additionally, testing "correlation" would need us to know what we are looking for, but that's matter for another presentation in the future...

Conclusions & Future Work

- Conclusions:
  - IDS are going to be needed as a complementary defense paradigm (detection & reaction vs. prevention)
  - In order to detect unknown attacks, we need better anomaly detection systems
  - We can successfully use unsupervised learning for anomaly detection in an host based environment using
    - System call sequence
    - System call arguments
  - We can successfully aggregate alerts in an unsupervised fashion. Correlation needs more work!
- Future developments:
  - (more) correlation
  - Integrating the host based solution to become an IPS, maybe using CORE FORCE?
  - Real-world evaluation, perhaps in the framework of the European FP7 project WOMBAT

Thank you!

Any question?

I would greatly appreciate your feedback !

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