CSE543 - Computer Security
Module: Intrusion Detection

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Intrusion

- An authorized action ...
- that exploits a vulnerability ...
- that causes a compromise ...
- and thus a successful attack.

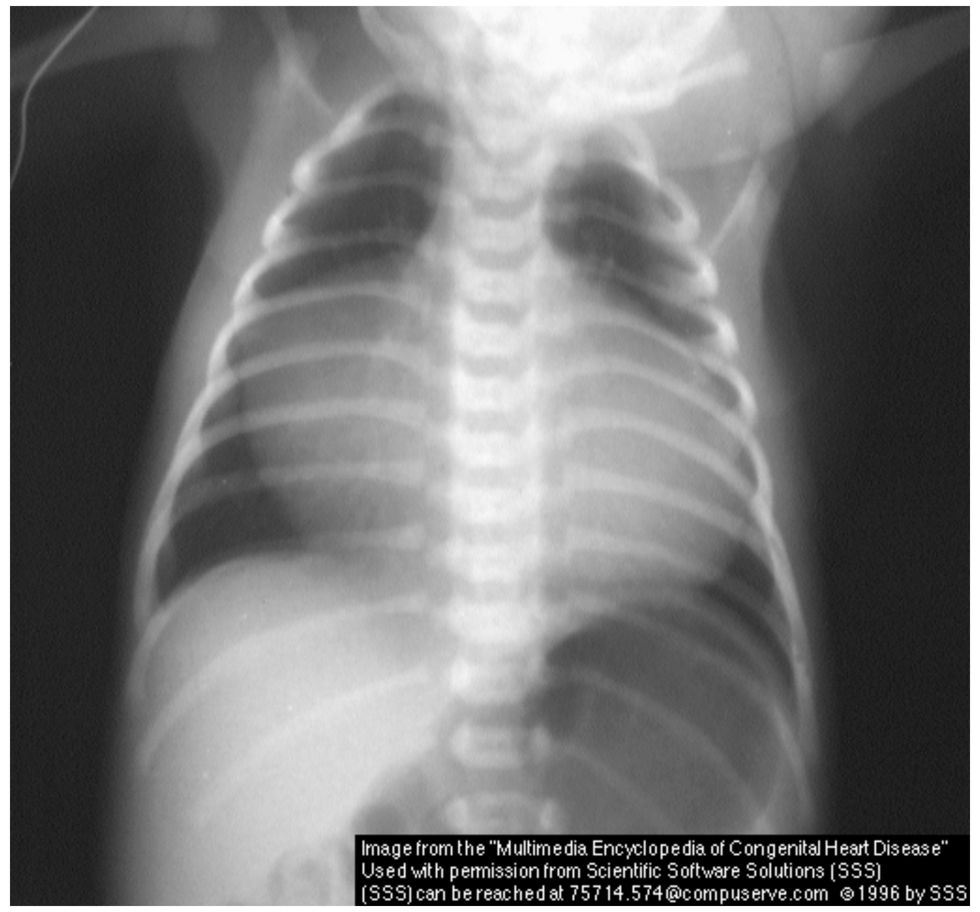
- *Authentication and Access Control Are No Help!*

Example Intrusions

- Network
  - Malformed (and unauthenticated) packet
  - Let through the firewall
  - Reaches the network-facing daemon
  - *Can we detect intrusions from packet contents?*
- Host
  - Input to daemon
  - Exploits a vulnerability (buffer overflow)
  - Injects attacker or reuses program code
  - Performs malicious action
  - *Can we detect intrusions from process behavior?*

Intrusion Detection (def. by Forrest)

- An IDS system finds intrusions
  - "The IDS approach to security is based on the assumption that a system will not be secure, but that violations of security policy (intrusions) can be detected by monitoring and analyzing system behavior." [Forrest 98]
  - However you do it, it requires
    - Training the IDS (*training*)
    - Looking for intrusions (*detection*)



- This is active area of computer security, that has led to lots of new tools, applications, and an entire industry

Intrusion Detection Systems

- IDS's claim to detect adversary when they are in the act of attack
  - Monitor operation
  - Trigger mitigation technique on detection
  - Monitor: Network or Host (Application) events
- A tool that discovers intrusions "after the fact" are called *forensic analysis* tools
  - E.g., from system logfiles
- IDS's really refer to two kinds of detection technologies
  - *Anomaly Detection*
  - *Misuse Detection*

Anomaly Detection

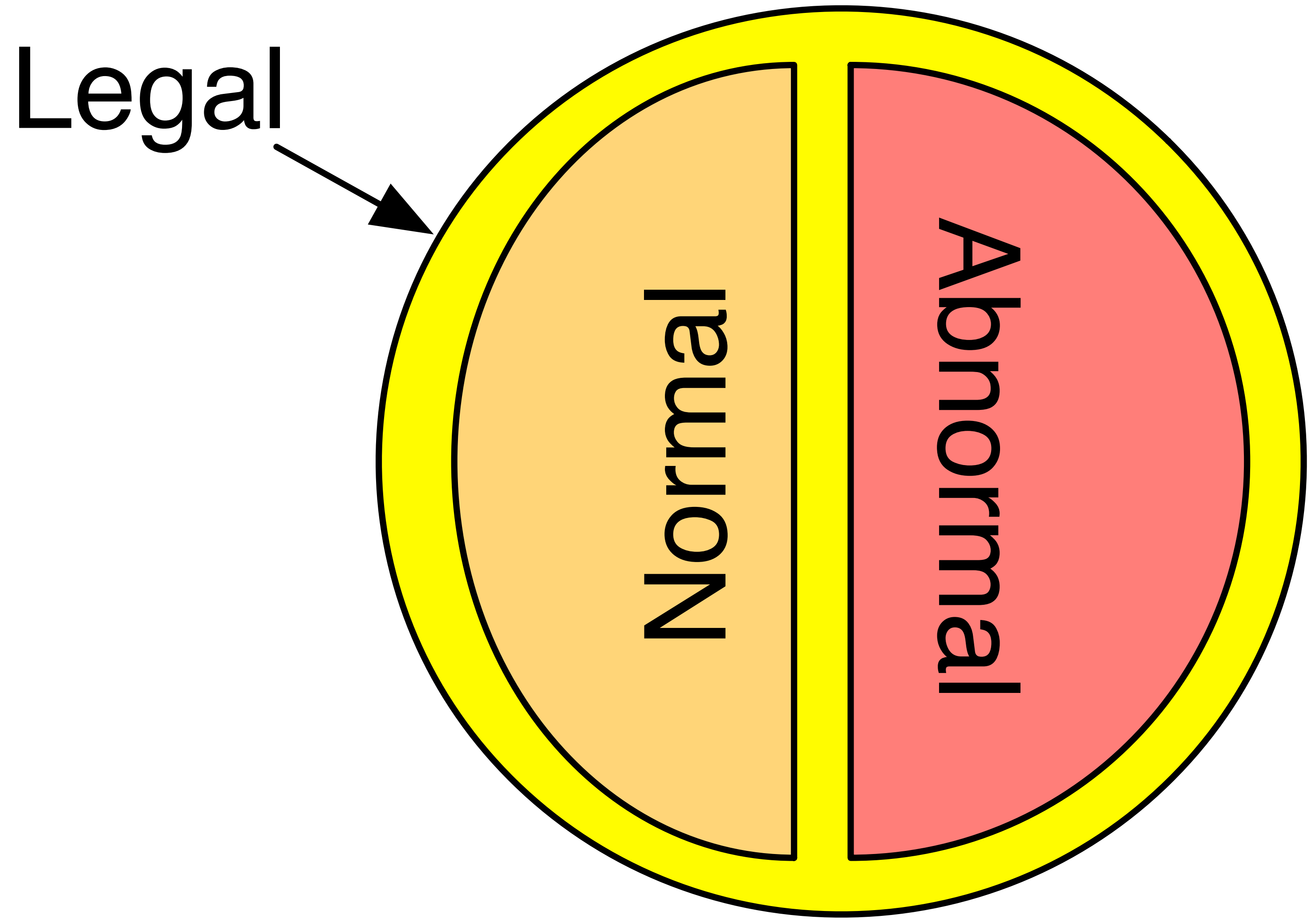
- Compares profile of normal systems operation to monitored state
  - Hypothesis: any attack causes enough deviation from profile (generally true?)
- Q: How do you derive normal operation?
  - AI: learn operational behavior from training data
  - Expert: construct profile from domain knowledge
  - Black-box analysis (vs. white or grey?)
- Q: Is normal the same for all environments?
- Pitfall: *false learning*

Misuse Detection

- Profile known attacks
  - Monitor operational state for known attack behaviors
  - Hypothesis: attacks of the same kind has enough similarity to distinguish from normal behavior
  - This is largely *pattern matching*
- Q: Where do "known attack patterns" come from?
  - Record: examples of known attacks
  - Expert: domain knowledge
  - AI: Learn by negative and positive feedback

The “confusion matrix”

- What constitutes a intrusion is really just a matter of definition
  – A system can exhibit all sorts of behavior

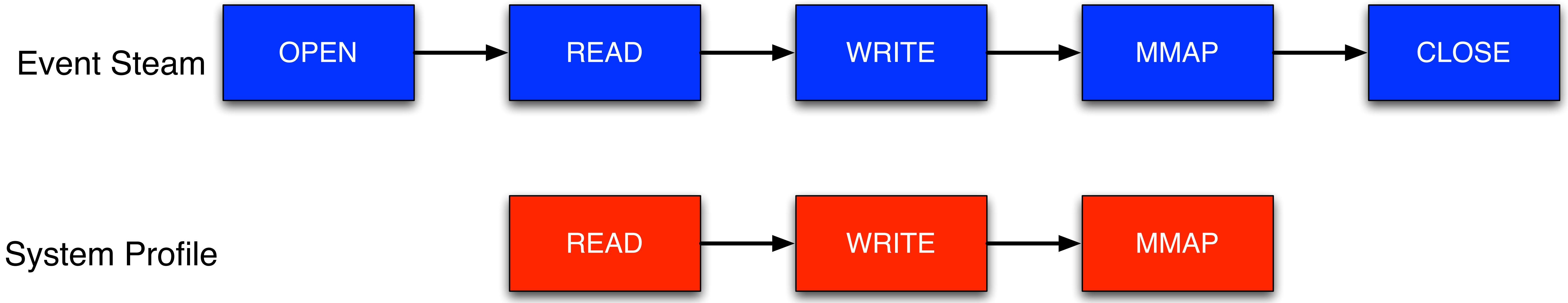


		Detection Result	
		T	F
Reality	T	True Positive	False Negative
	F	False Positive	True Negative

- Quality determined by consistency with a given definition
  – *context sensitive*

Sequences of System Calls

- Forrest et al. in early-mid 90s, attempt to understand the characteristics of an intrusion



- Idea: match sequence of system calls with profiles
  - *n-grams* of system call sequences (learned)
    - Match sliding windows of sequences
    - Record the number of mismatches
    - Use n-grams of length ***5, 6, 11***.
- If found, then it is normal (w.r.t. learned sequences)

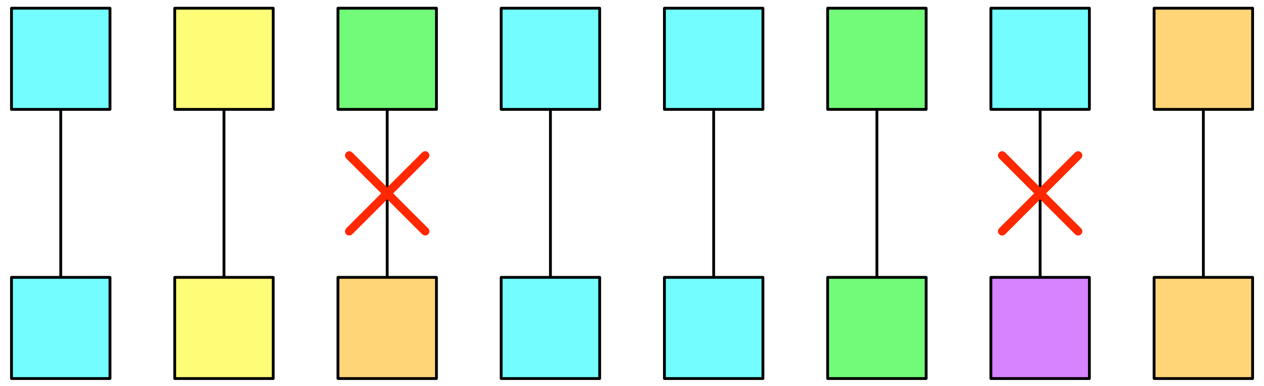
Evaluating Forrest et al.

- The qualitative measure of detection is the departure of the trace from the database of n-grams
- They measure how far a particular n-gram *i* departs by computing the minimum Hamming distance of the sample from the database (really pairwise mismatches)

d_{min} = min(d(i,j) | for all normal j in n-gram database)

this is called the *anomaly signal*.

- Result: on lpr (print files), sendmail, etc.
  - About 1 in 100 false positive rate for lpr
  - % abnormal seqs - 1-2% for lpr attack
- Is this good?



Can You Evade Forrest?

- Can you devise a malware program that performs its malicious actions and cannot be detected by Forrest?
  - How would you do that?

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- Mimicry - Wagner and Soto - ACM CCS 2002

"gedanken experiment”

- Assume a very good anomaly detector (99%)
- And a pretty constant attack rate, where you can observe 1 out of 10000 events are malicious

- Are you going to detect the adversary well?

Bayes' Rule

- Pr(x) function, probability of event x
  - Pr(sunny) = .8 (80% of sunny day)
- Pr(x|y), probability of x given y
  - Conditional probability
  - Pr(cavity|toothache) = .6
    - 60% chance of cavity given you have a toothache
  - Bayes' Rule (of conditional probability)

$$\Pr(B|A) = \frac{\Pr(A|B)\Pr(B)}{\Pr(A)}$$

The (base-rate) Bayesian Fallacy

- Setup
  - Pr(T) is attack probability, 1/10,000
    - Pr(T) = .0001
  - Pr(F) is probability of event flagging, unknown
  - Pr(F|T) is 99% accurate (higher than most techniques)
    - Pr(F|T) = .99, Pr(!F|!T) = .99 , Pr(!F|T) = .01, Pr(F|!T) = .01
- Deriving Pr(F)
  - Pr(F) = Pr(F|T)*Pr(T) + Pr(F|!T)*Pr(!T)
  - Pr(F) = (.99)(.0001) + (.01)(.9999) = .010098
- Now, what's Pr(T|F)?

The Bayesian Fallacy (cont.)

- Now plug it in to Bayes Rule

$$\Pr(T|F) = \frac{\Pr(F|T)\ \Pr(T)}{\Pr(F)} = \frac{\Pr(.99)\ \Pr(.0001)}{\Pr(.010098)} = .0098$$

- So, a 99% accurate detector leads to …
  - 1% accurate detection.
  - With 99 false positives per true positive
  - This is a central problem with IDS
- Suppression of false positives real issue
  - Open question, makes some systems unusable

Where is Anomaly Detection Useful?

System	Attack Density P(T)	Detector Flagging Pr(F)	Detector Accuracy Pr(F|T)	True Positives P(T|F)
A	0.1		0.65	
B	0.001		0.99	
C	0.1		0.99	
D	0.00001		0.99999	

$$\Pr(B|A) = \frac{\Pr(A|B)\Pr(B)}{\Pr(A)}$$

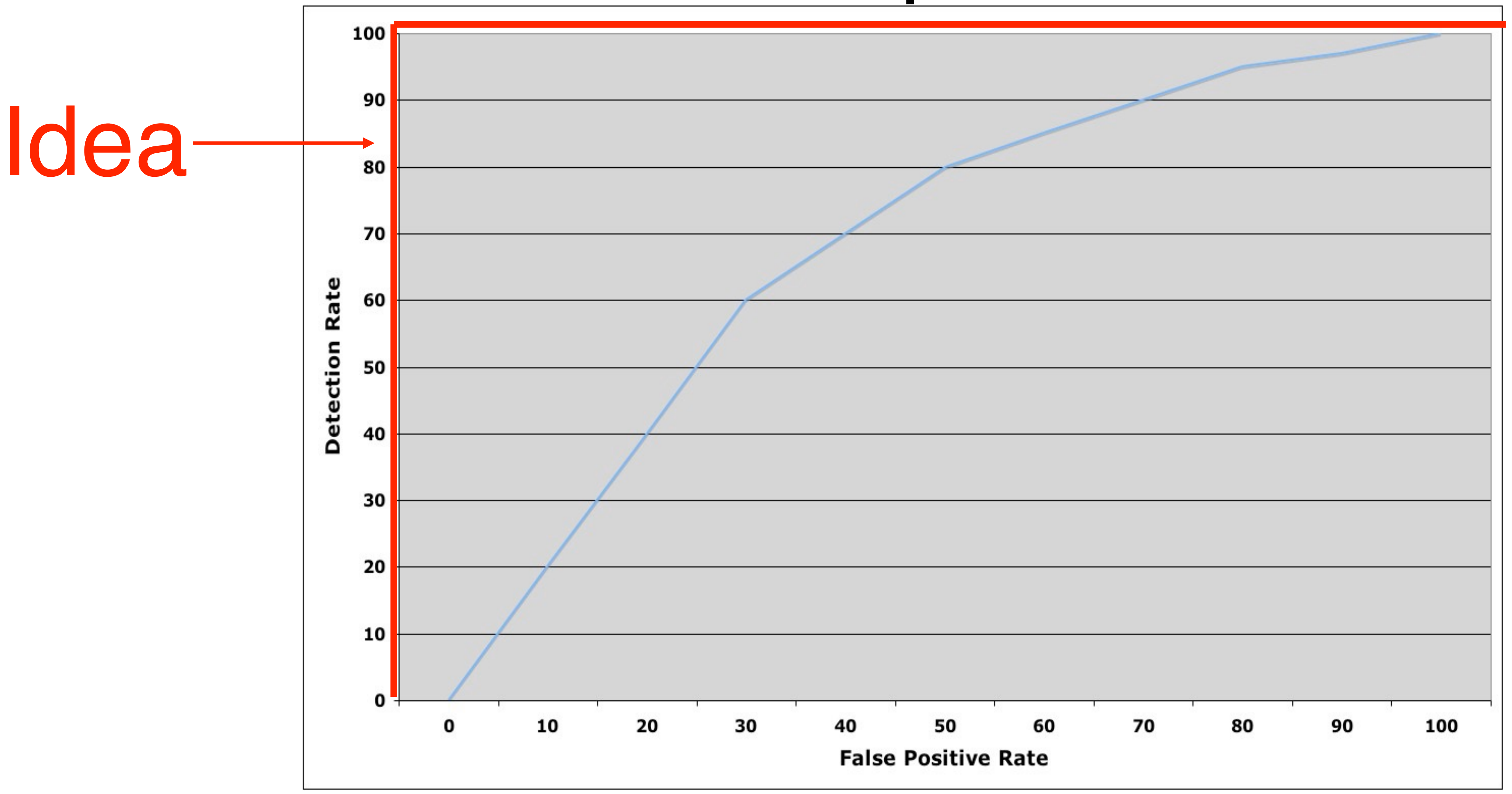
Where is Anomaly Detection Useful?

System	Attack Density P(T)	Detector Flagging Pr(F)	Detector Accuracy Pr(F|T)	True Positives P(T|F)
A	0.1	0.38	0.65	0.171
B	0.001	0.01098	0.99	0.090164
C	0.1	0.108	0.99	0.911667
D	0.00001	0.00002	0.99999	0.5

$$\Pr(B|A) = \frac{\Pr(A|B)\Pr(B)}{\Pr(A)}$$

The ROC curve

- Receiver operating characteristic
  - Curve that shows that detection/false positive ratio



- Axelsson talks about the real problem with some authority and shows how this is not unique to CS
  - Medical example

Example ROC Curve

- You are told to design an intrusion detection algorithm that identifies vulnerabilities by solely looking at transaction length, i.e., the algorithm uses a packet length threshold T that determines when a packet is marked as an attack. More formally, the algorithm is defined:

$$\mathrm{D}(\mathrm{k}, \mathrm{T}) \rightarrow [0, 1]$$

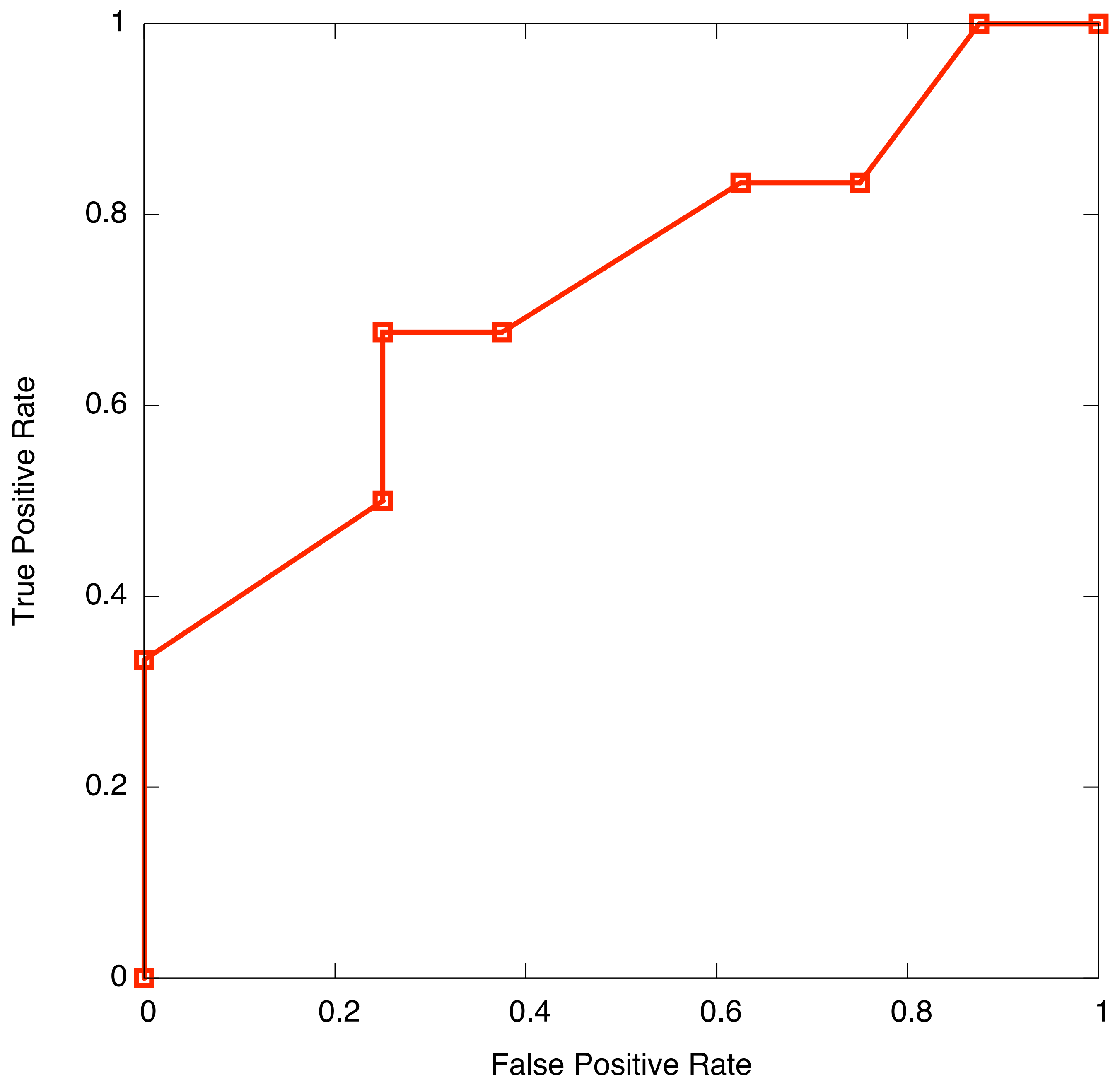
- where k is the packet length of a suspect packet in bytes, T is the length threshold, and (0,1) indicate that packet should or should not be marked as an attack, respectively. You are given the following data to use to design the algorithm.

➡ attack packet lengths: 1, 1, 2, 3, 5, 8

➡ non-attack packet lengths: 2, 2, 4, 6, 6, 7, 8, 9

- Draw the ROC curve.

Solution



T	0	1	2	3	4	5	6	7	8	9
TP	0	2	3	4	4	5	5	5	6	6
TP%	0.00	33.33	50.00	66.67	66.67	83.33	83.33	83.33	100.00	100.00
FP	0	0	2	2	3	3	5	6	7	8
FP%	0.00	0.00	25.00	25.00	37.50	37.50	62.50	75.00	87.50	100.00

The reality …

- Intrusion detections systems are good at catching demonstrably bad behavior (and some subtle)
- Alarms are the problem
  - How do you suppress them?
  - and not suppress the true positives?
  - This is a limitation of *probabilistic pattern matching*, and nothing to do with bad science
- Beware: the fact that an IDS is not alarming does not mean the network is safe
- All too often: used as a tool to demonstrate all safe, but is not really appropriate for that.