Evaluating Security Against Rational Attackers

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Papers covered

- Ahto Buldas, Peeter Laud, Jaan Priisalu, Märt Saarepera, Jan Willemson, *Rational Choice of Security Measures via Multi-Parameter Attack Trees*, in CRITIS 2006, LNCS 4347, pp. 235–248
- Aivo Jürgenson, Jan Willemson, Processing Multi-parameter Attacktrees with Estimated Parameter Values, in IWSEC 2007, LNCS 4752, pp. 308–319

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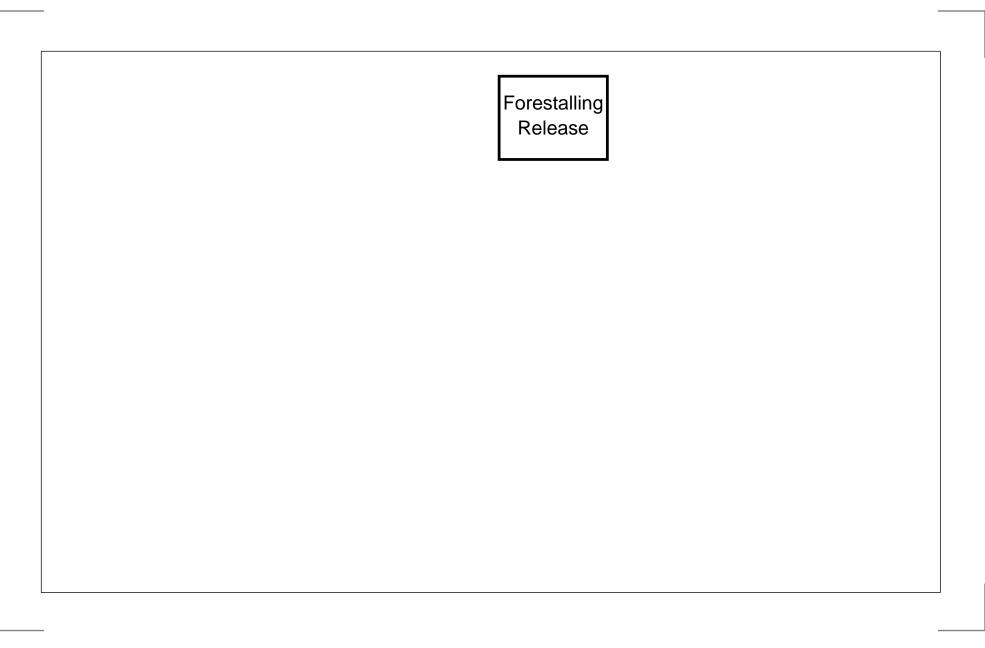
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 - sufficiently (i.e. achieving a satisfactory level), and
 - reasonably (i.e. not spending too much)
- Even if the losses associated with vulnerability exploits can be estimated, the corresponding probabilities are very difficult to evaluate
- This is especially true for targeted, company-specific attacks, since the required statistics does not exist or is difficult to get

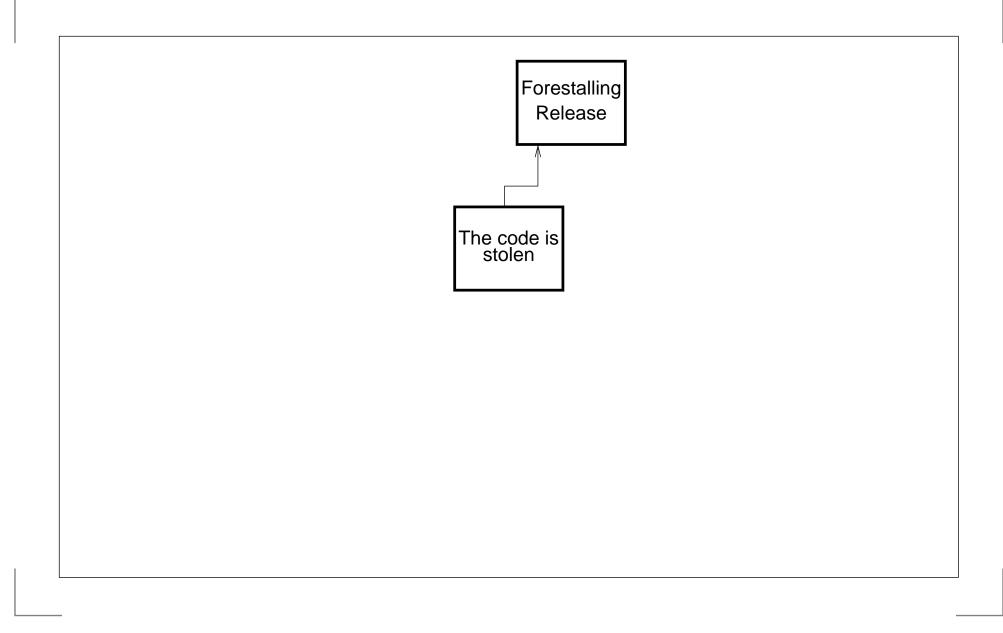
- Luckily, targeted attacks are often rational, i.e. the attackers
 - attack only if the attack is profitable, and
 - choose the attack with the highest outcome

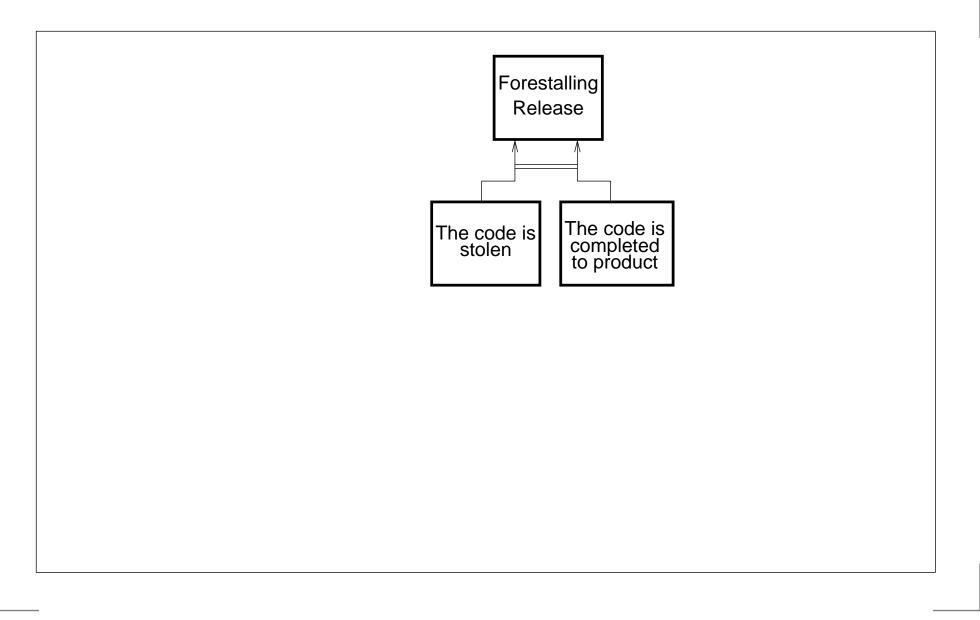
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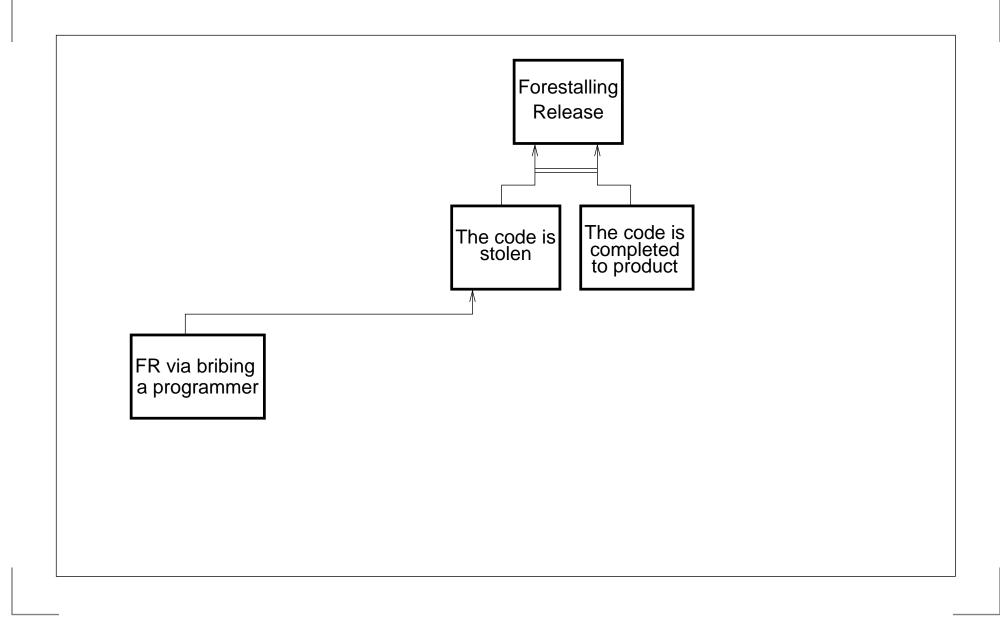
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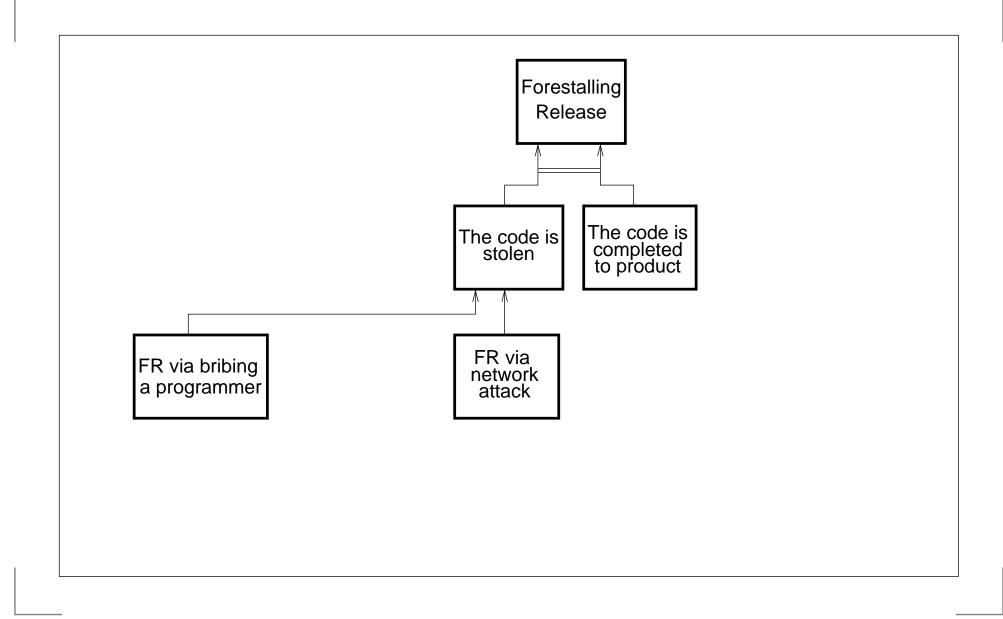
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- As a result, we obtain an attack tree

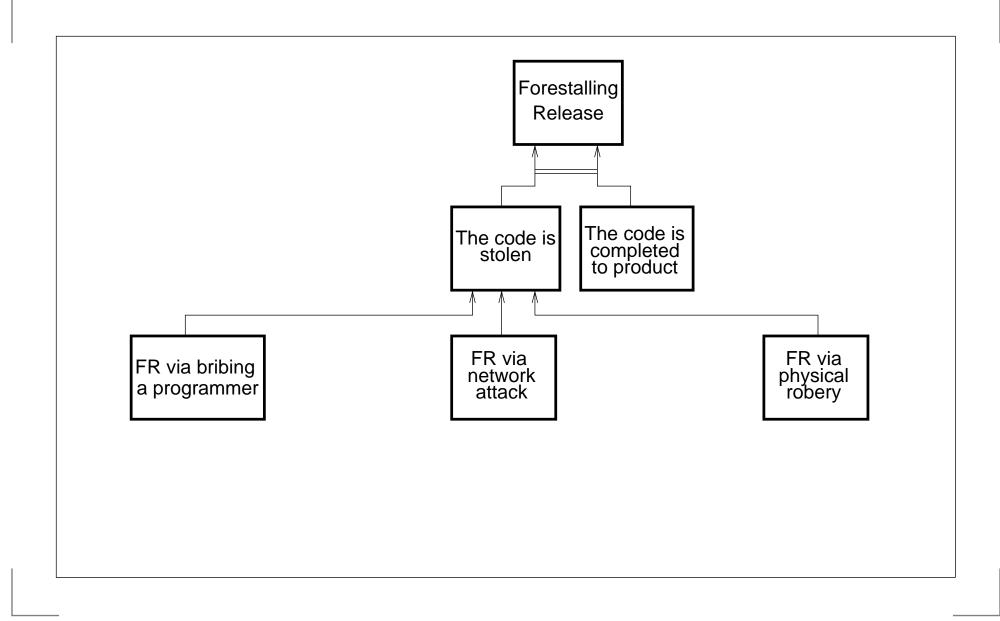


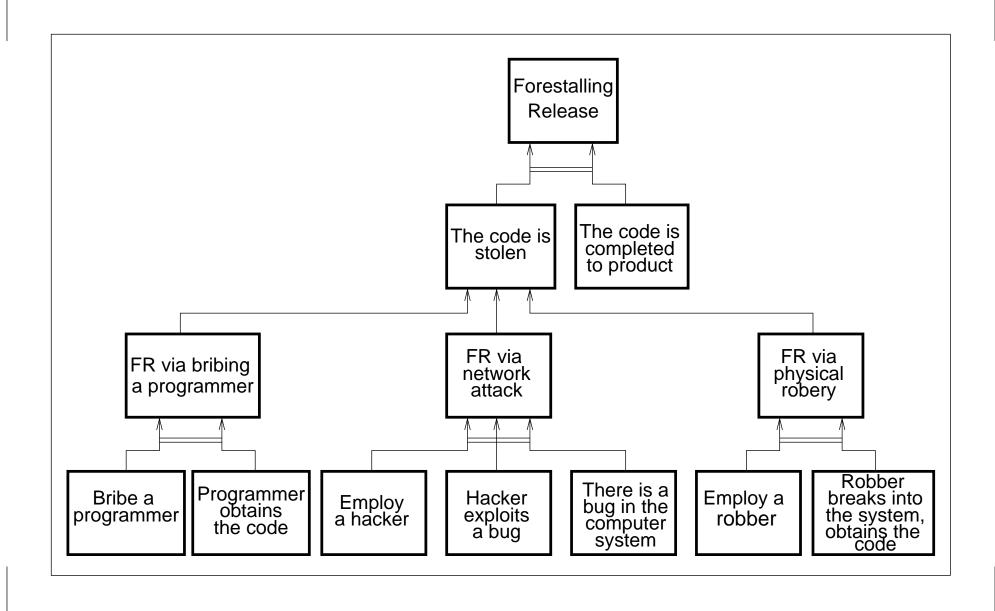










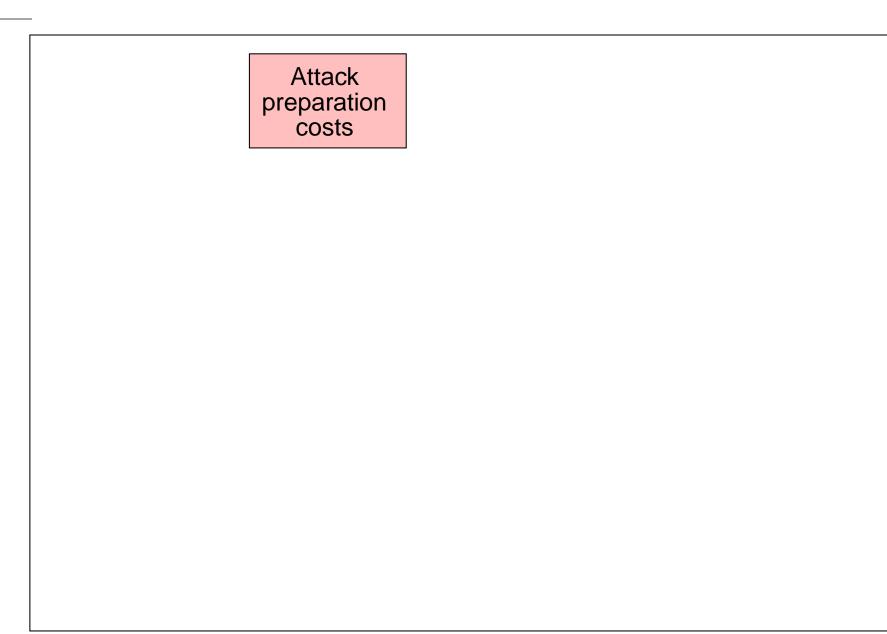


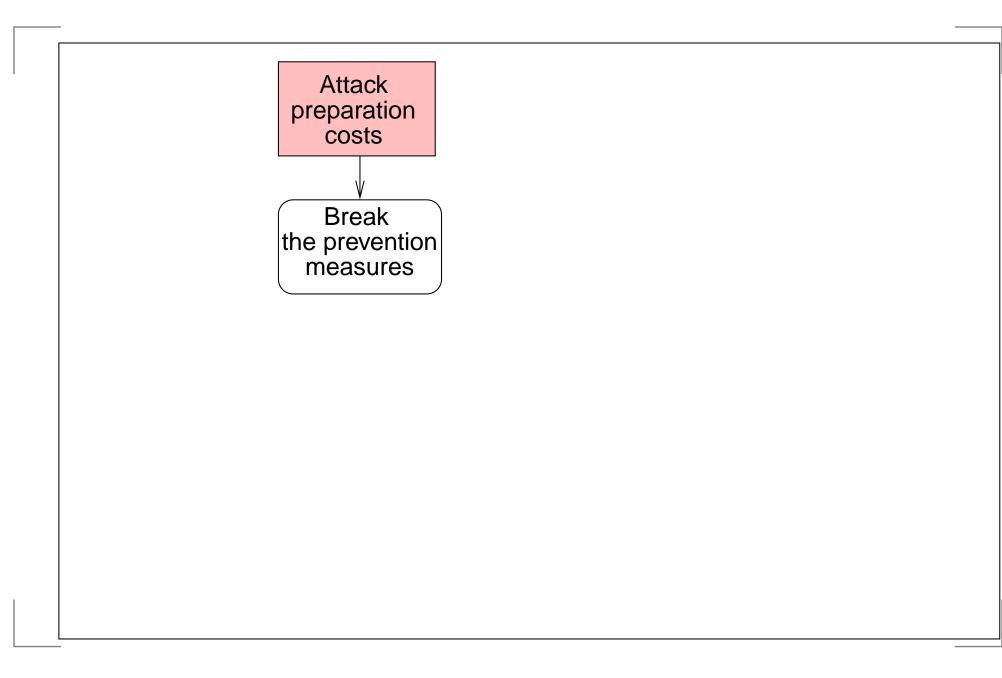
Parametrizing the Attack Tree

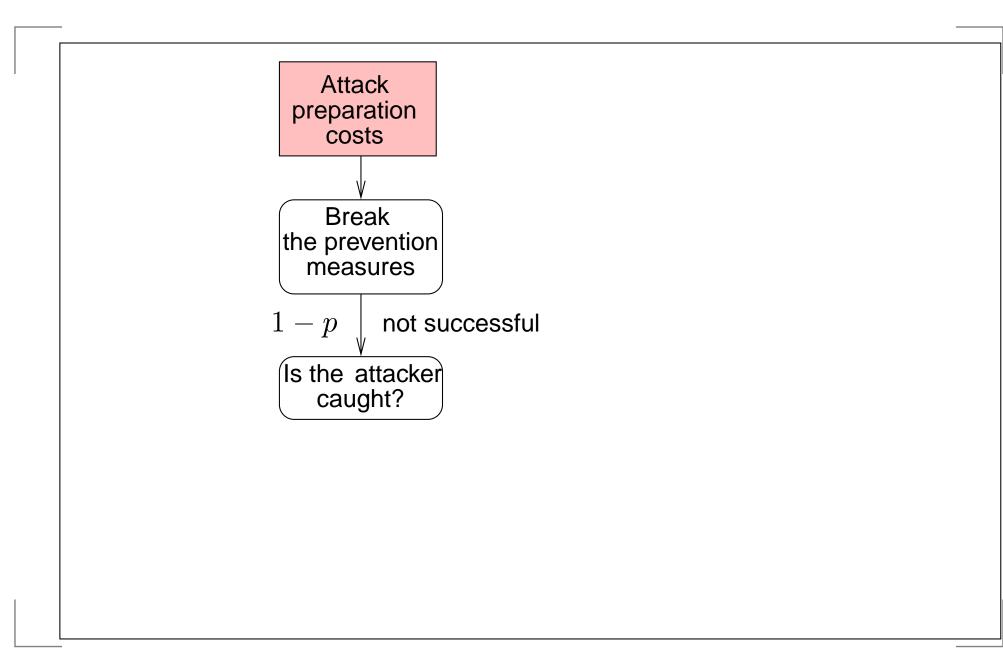
- When modelling the attack, we need to
 - set some parameter values to the leaves of the tree
 - define computation rules for parameter propagation

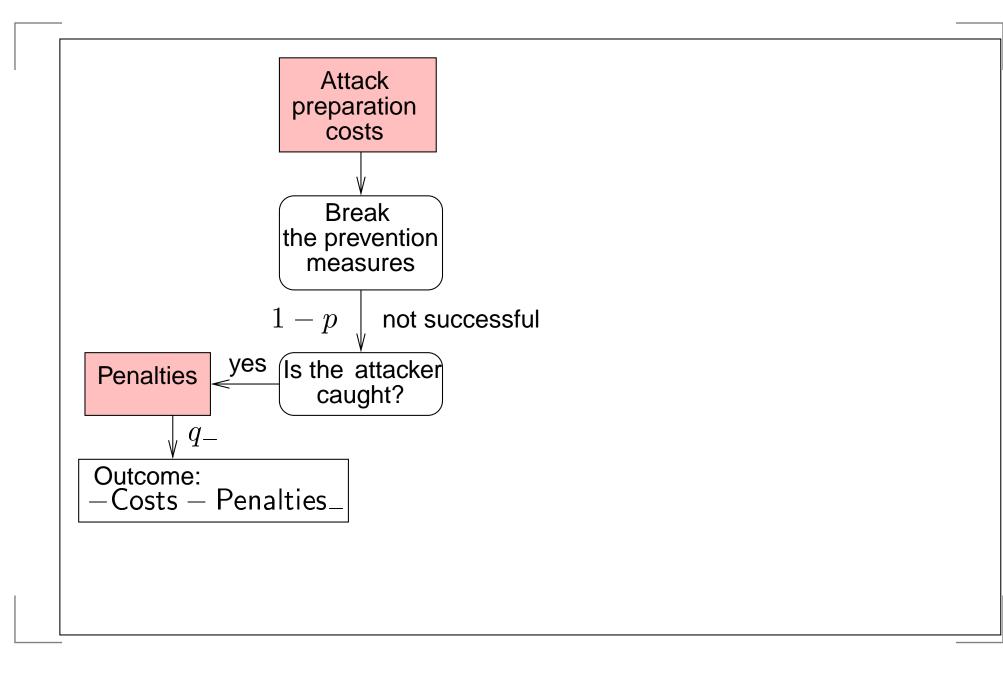
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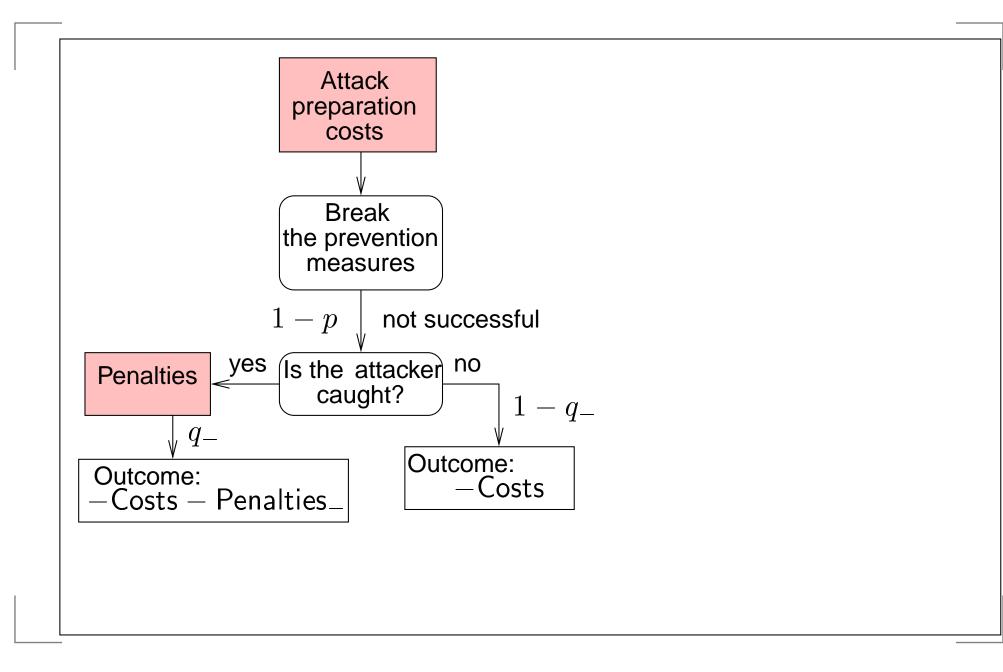
- When modelling the attack, we need to
 - set some parameter values to the leaves of the tree
 - define computation rules for parameter propagation
- In this framework we will consider the following parameters:
 - Gains the gains of the attacker if attack succeeds
 - Costs the cost of the attack
 - p the success probability of the attack
 - q, Penalties the probability of getting caught and penalties (if the attack was successful)
 - q_, Penalties_ the probability of getting caught and penalties (if the attack was unsuccessful)

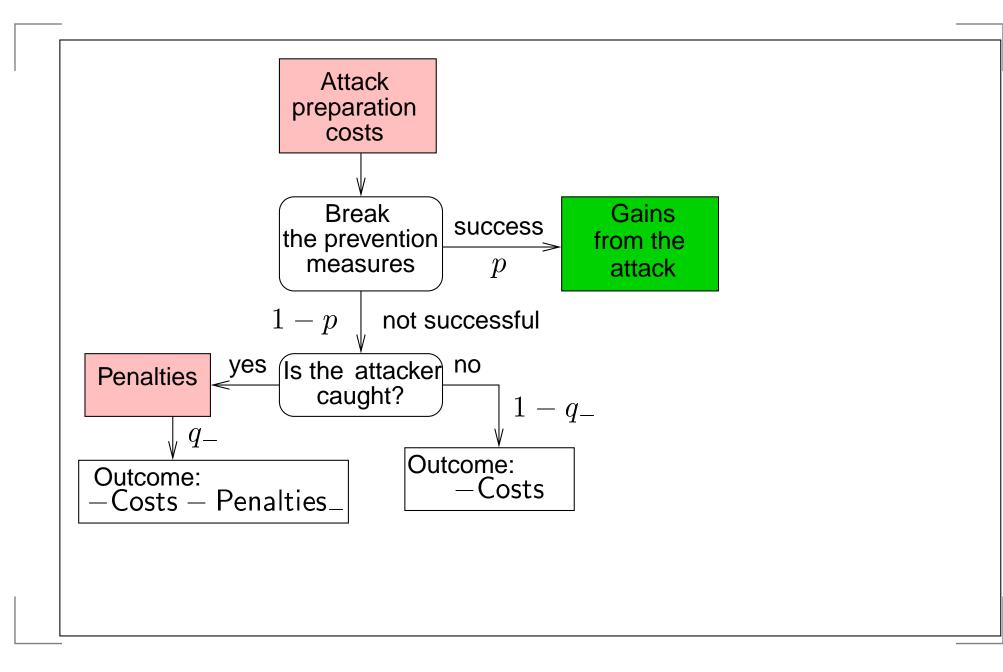


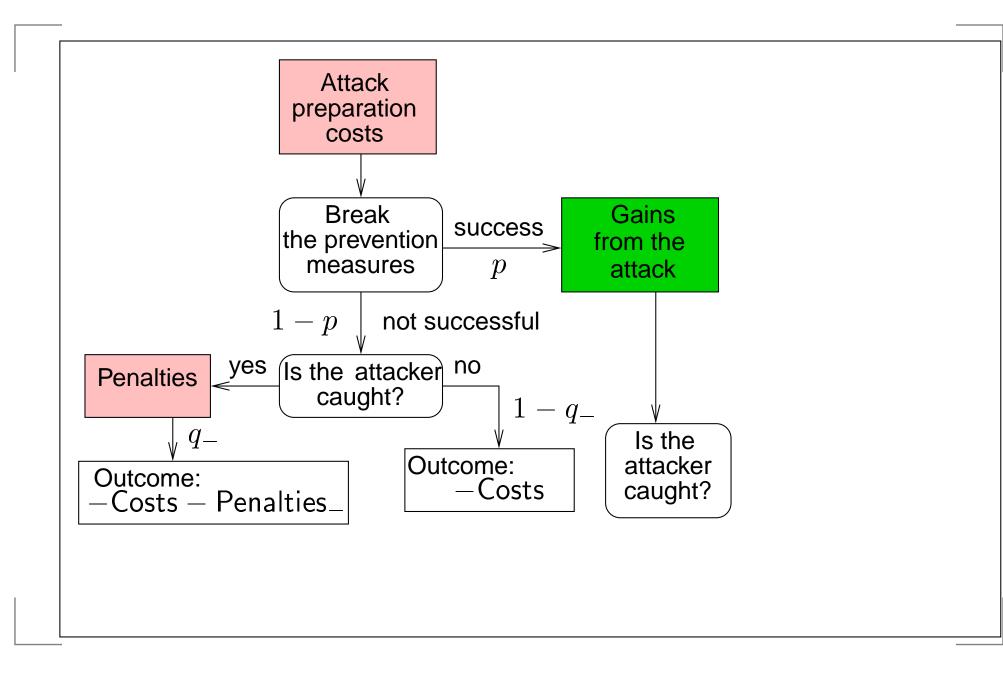


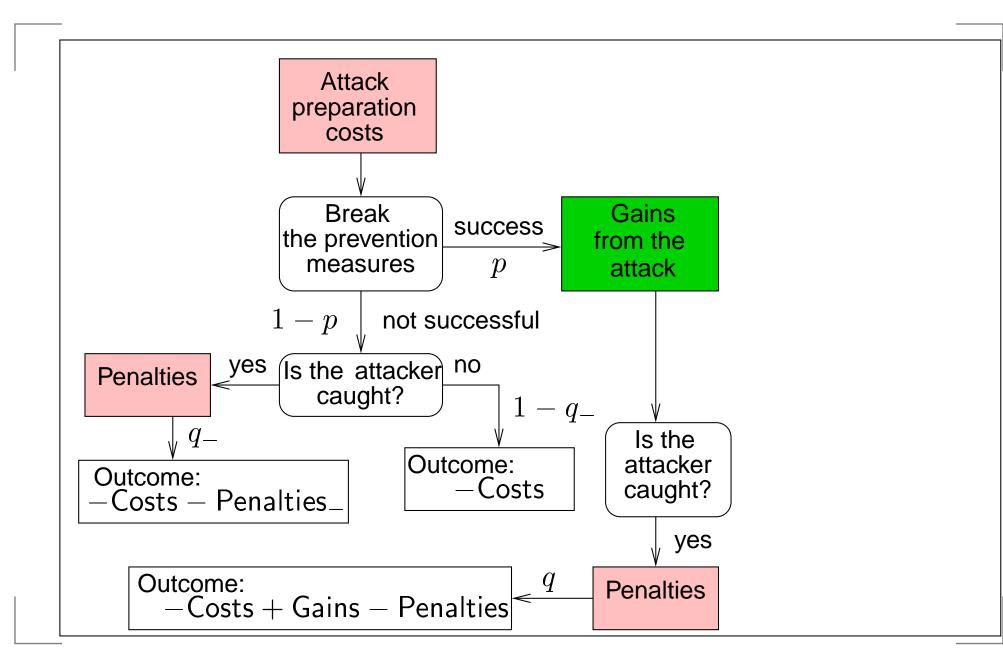


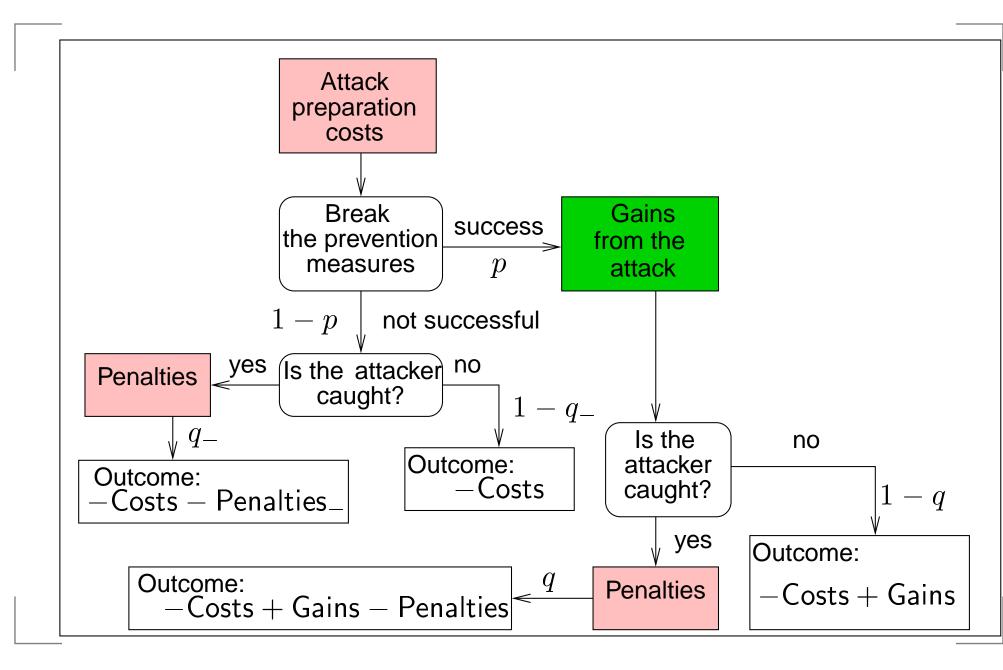


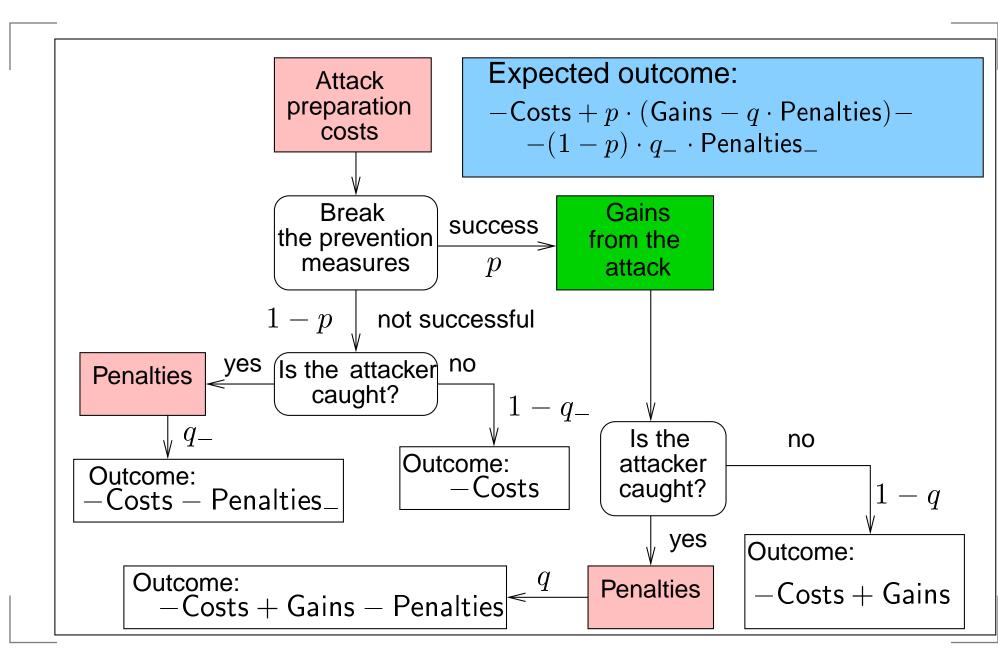












Tree Computations (I)

Denoting $\pi = q \cdot \text{Penalties}$ and $\pi_- = q_- \cdot \text{Penalties}_$, we set the parameters (Costs, p, π, π_-) for every leaf node. Then we have

 $\mathsf{Outcome} = -\mathsf{Costs} + p \cdot \mathsf{Gains} - p \cdot \pi - (1-p) \cdot \pi_{-}$

• For an OR-node with child nodes with parameters $(\text{Costs}_1, p_1, \pi_1, \pi_{1-})$ and $(\text{Costs}_2, p_2, \pi_2, \pi_{2-})$ the parameters $(\text{Costs}, p, \pi, \pi_-)$ are computed as:

$$(\mathsf{Costs}, p, \pi, \pi_{-}) =$$

 $\begin{cases} (\text{Costs}_1, p_1, \pi_1, \pi_{1-}), & \text{if } \text{Outcome}_1 > \text{Outcome}_2 \\ (\text{Costs}_2, p_2, \pi_2, \pi_{2-}), & \text{if } \text{Outcome}_1 \leq \text{Outcome}_2 \end{cases} \end{cases}$

Tree Computations (II)

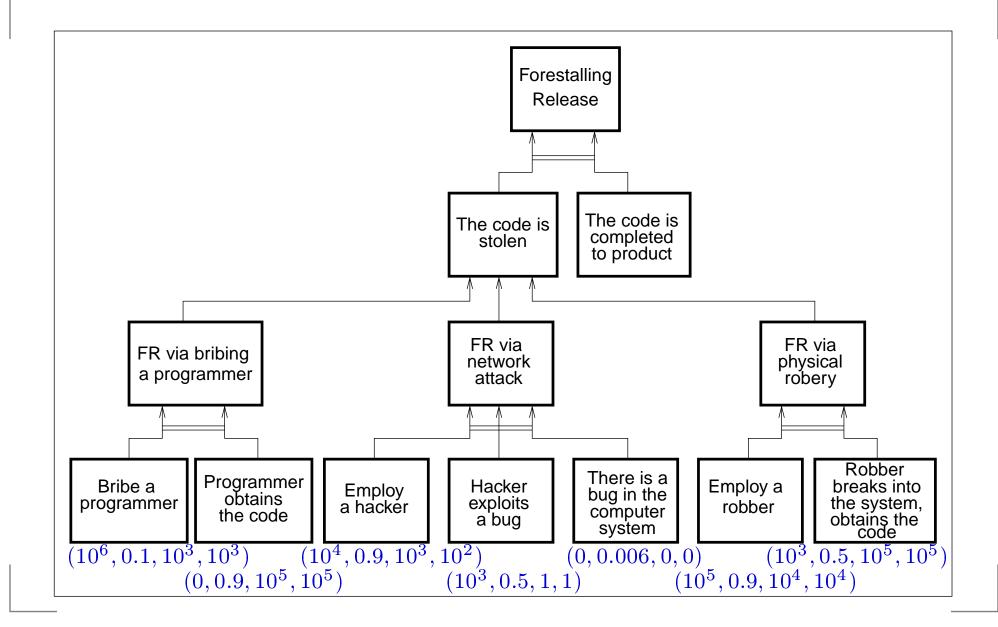
• For a AND-node with child nodes with parameters $(Costs_1, p_1, \pi_1, \pi_{1-})$ and $(Costs_2, p_2, \pi_2, \pi_{2-})$ the parameters $(Costs, p, \pi, \pi_-)$ are computed as follows:

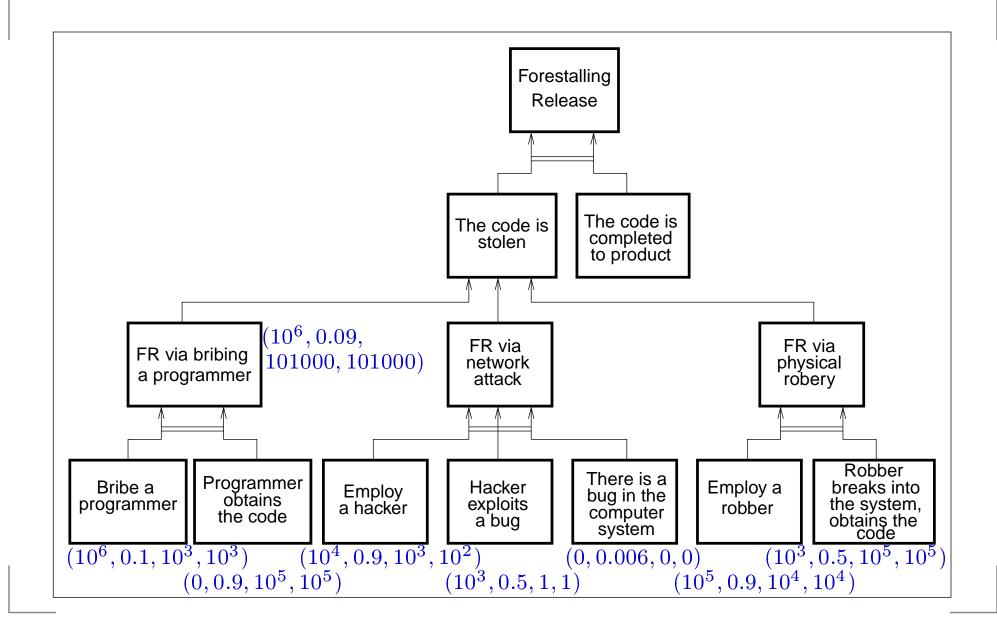
Costs = Costs₁ + Costs₂

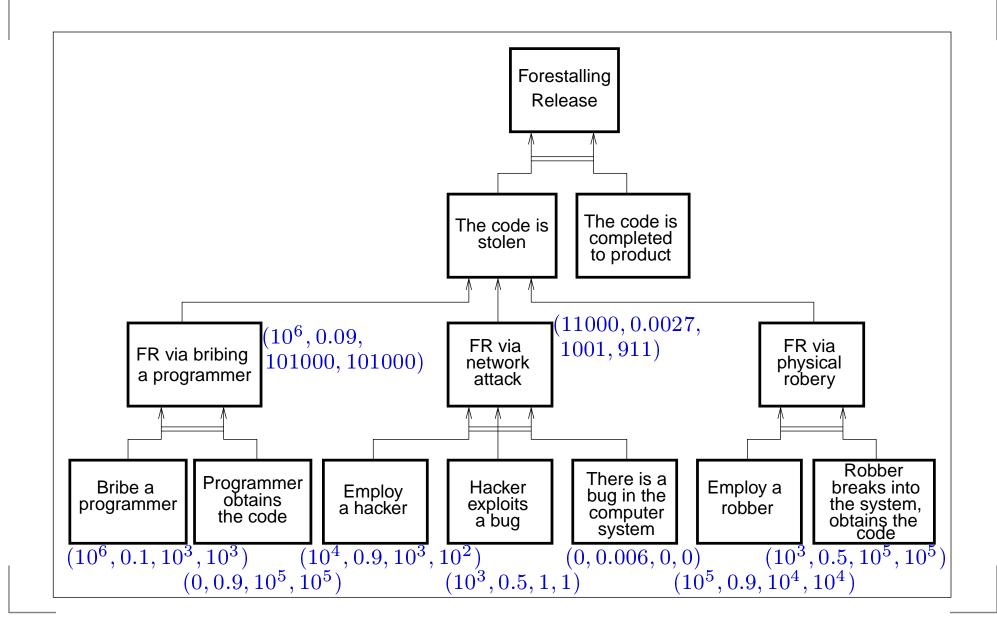
$$p = p_1 \cdot p_2$$

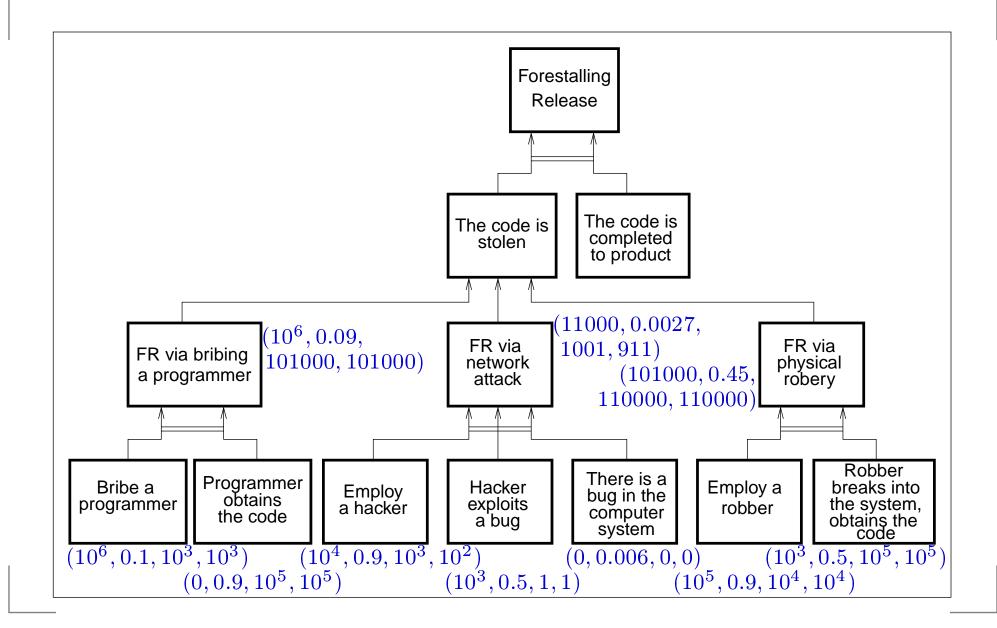
 $\pi = \pi_1 + \pi_2$
 $\pi_- = \frac{p_1(1-p_2)(\pi_1 + \pi_{2-}) + (1-p_1)p_2(\pi_{1-} + \pi_2)}{1-p_1p_2} + \frac{(1-p_1)(1-p_2)(\pi_{1-} + \pi_{2-})}{1-p_1p_2}$

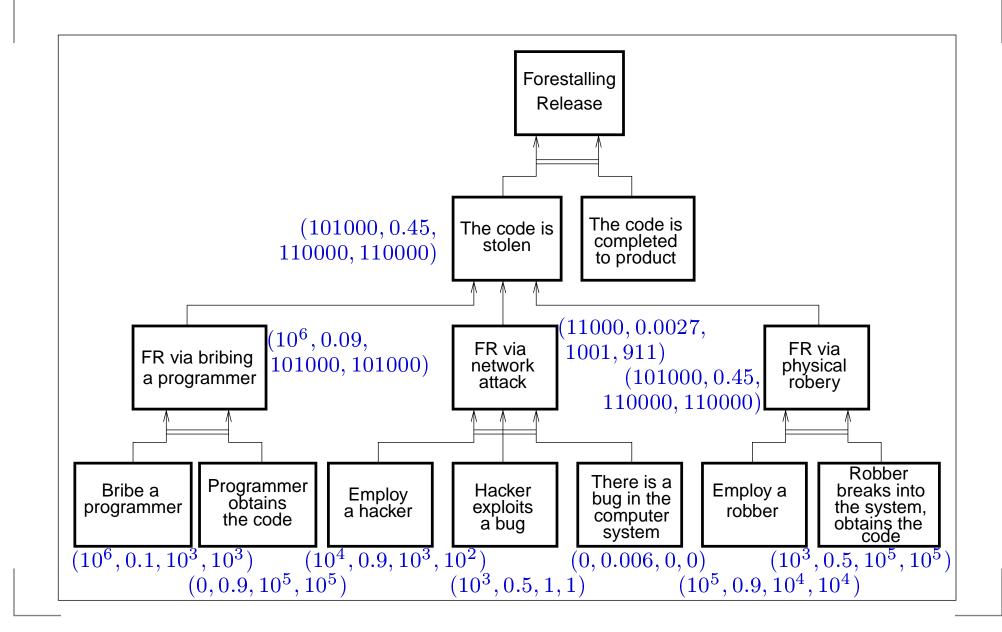
The last formula represents the average penalty of an attacker, assuming that at least one of the two child-attacks was not successful

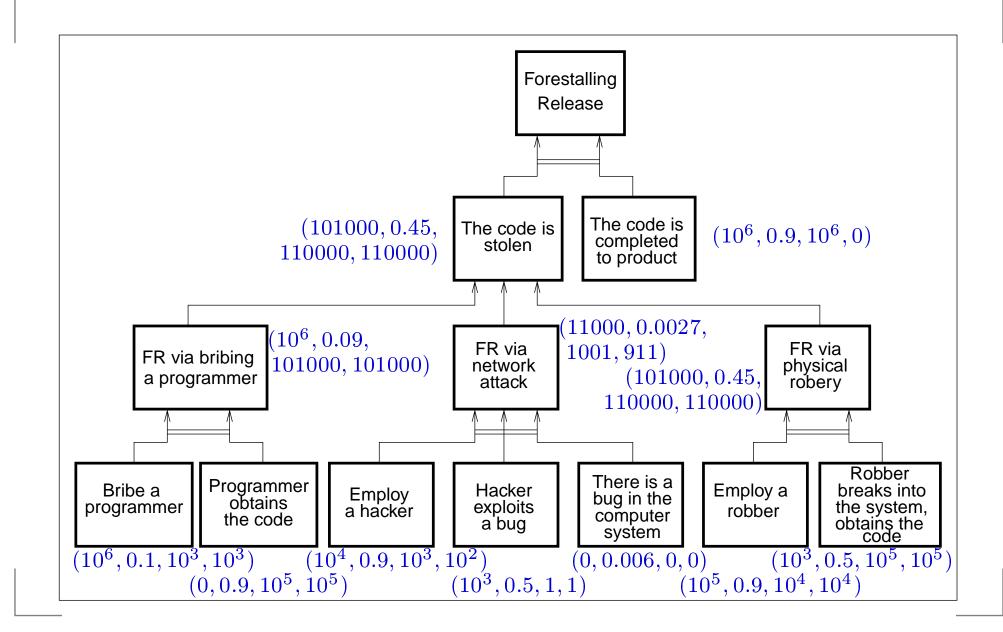




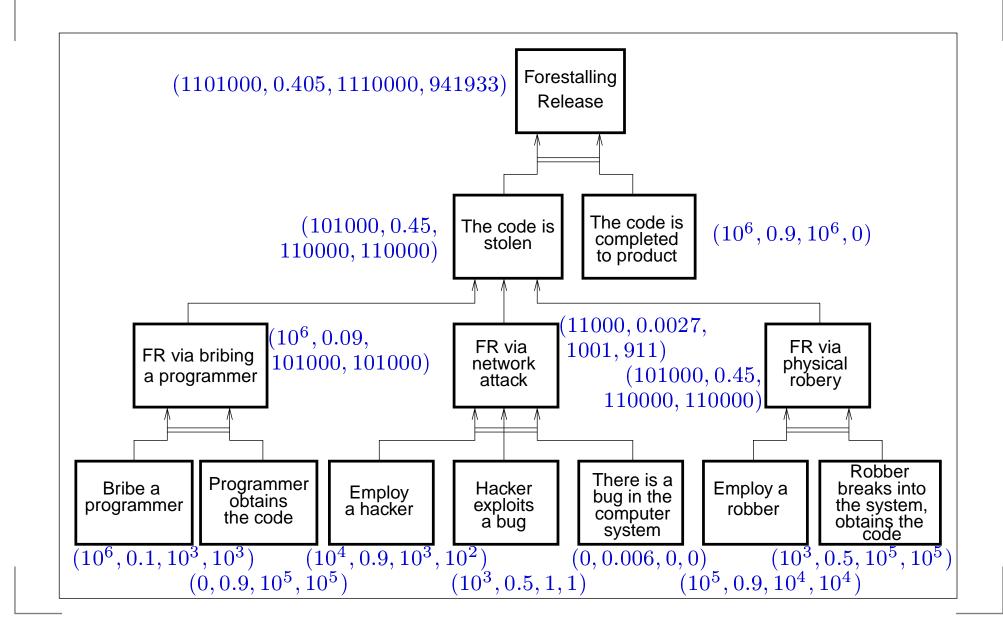




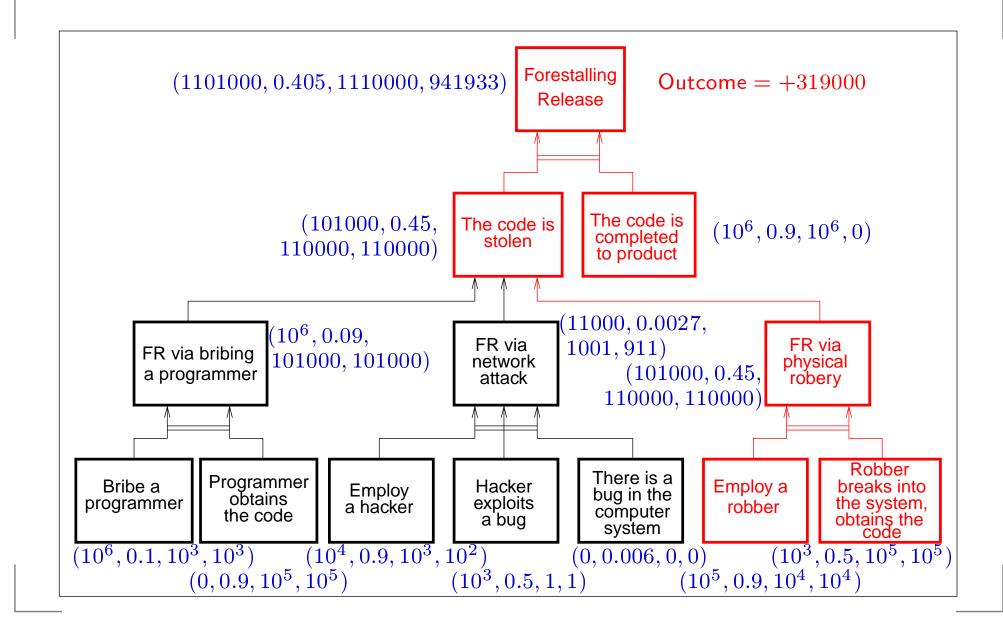




Tree Computations: Example



Tree Computations: Example



Evaluating Security Measures

- After building the attack tree, we can evaluate and compare potential security measures
- Security measures may
 - increase detection probability, hence increasing π and/or $\pi_-,$
 - increase Costs of the attack,
 - reduce the probability p of the attack success.

etc

We can then change the respective parameters, make the tree computations again and see, whether the Outcome has become negative

Modeling Parameter Estimations

- Usually, when an expert evaluates some parameter, his estimation is not absolute, but holds with some confidence
- Thus, we can consider estimated values of the form

$$p_X = \Pr[k_1 \le X \le k_2] \quad ,$$

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- How does one compute with estimated values?

Estimation Arithmetic – Operations

Our tree computations need the following arithmetic primitives:

- Adding a fixed real number
- Multiplying by a fixed real number
- Adding/subtracting two estimated values
- Multiplying two estimated values
- Dividing two estimated values
- Comparing two estimated values

Estimation Arithmetic – Basic Pattern

The basic pattern of all the estimation arithmetic operations is the following:

- Convert the estimations to normally distributed random variables
 - If needed, centralize them to mean value 0
- Compute with the random variables
- Convert the resulting random variable back to an estimation
 - If needed, de-centralize

$\textbf{Estimation} \rightarrow \textbf{Random Variable}$

• To convert the estimation \mathcal{X} to a random variable X, we have to find out the mean a_X and standard deviation σ_X :

$$a_X = \mathbf{E}X = \frac{k_1 + k_2}{2} \quad ,$$

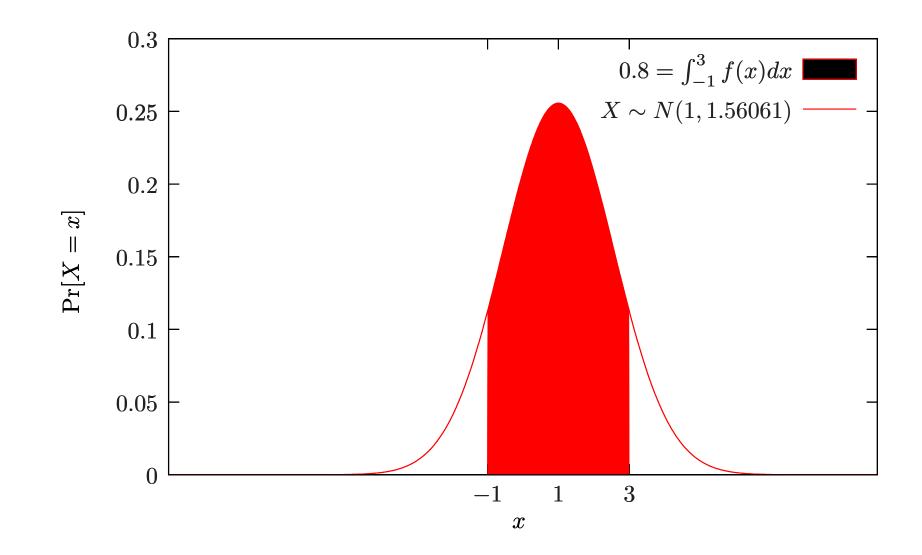
$$p_X = \Pr(k_1 \le X \le k_2) = \Phi\left(\frac{k_2 - a_X}{\sigma_X}\right) - \Phi\left(\frac{k_1 - a_X}{\sigma_X}\right)$$

where the $\Phi(x)$ is the Laplace's function

• We denote conversion of estimation \mathcal{X} to normally distributed random variable X as $\mathcal{X} = (p_X, k_1, k_2) \rightarrow X \sim N(a_X, \sigma_X)$

,

 $\mathcal{X} = (p_X, k_1, k_2) \to X \sim N(a_X, \sigma_X)$



Random Variable \rightarrow **Estimation**

- To convert the probabilistic variable X back to an estimation \mathcal{X} , we need to specify the confidence p'_X
- To simplify the operations with our estimations of the attack-tree node parameters, we will convert all estimations to the same global confidence level p_T
- In effect, p_T defines the confidence level or the margin of error at which we would like to have the answer of our attack-tree analysis given
- If the original estimation \mathcal{X} of an expert is given using some other confidence level p_X , we first convert $\mathcal{X} = (p_X, k_1, k_2) \rightarrow X \sim N(a_X, \sigma_X)$ and then find the new interval $[k'_1, k'_2]$ by $X \sim N(a_X, \sigma_X) \rightarrow \mathcal{X} = (p_T, k'_1, k'_2)$

Soundness of Computations

- Most parameters of the nodes have a limited value domain, e.g. Cost ≥ 0 and $p \in [0, 1]$
- However, as a result of conversions and tree computations, some values may drop out of this domain
- Generally, such a situation indicates that no sound conclusions can be drawn on the given confidence level p_T. This problem can be solved in a number of ways:
 - The global confidence level p_T can be decreased. It is possible to find the largest value p_T ensuring sound conclusions and this value can be considered as the confidence level of the whole tree
 - It is possible to define the required confidence level locally for each node

Result Interpretation

- As a result of the computations, Outcome of the root node is found as an estimation $\mathcal{X} = (p_X, k_1, k_2)$. There are three possible major cases:
 - $0 < k_1 < k_2$ the vulnerability level is *high*;
 - $k_1 < k_2 < 0$ the vulnerability level is *low*;
 - $k_1 \leq 0 \leq k_2$ the vulnerability level is *medium*
 - $\frac{k_1+k_2}{2} < 0$ the vulnerability level is *lower medium*
 - $\frac{k_1+k_2}{2} > 0$ the vulnerability level is *higher medium*

Further directions

- More case studies
- An analysis tool
- Tree computations are known to be imprecise
 - We use Gains in every internal node, even though the attacker gets the whole gain after the primary threat has been materialized
 - Precise computations can not be done as tree computations – we would need to consider all the subsets of the leaf set
 - Can this work be optimized?

Thank You!

Questions?