

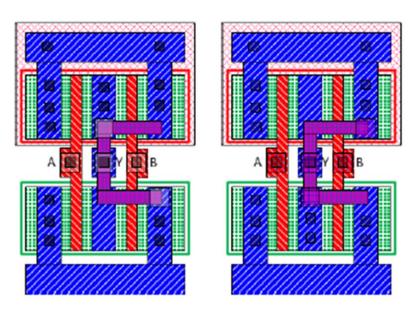
Improved Metrics for Obfuscated ICs

Mutian Zhu, Matthew French, and Peter A. Beerel

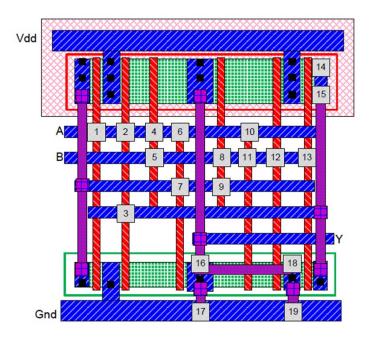


Introduction to Obfuscation





Obfuscated NAND and NOR gate



Can perform either as XOR, NAND, or NOR based on which contacts are true and dummy

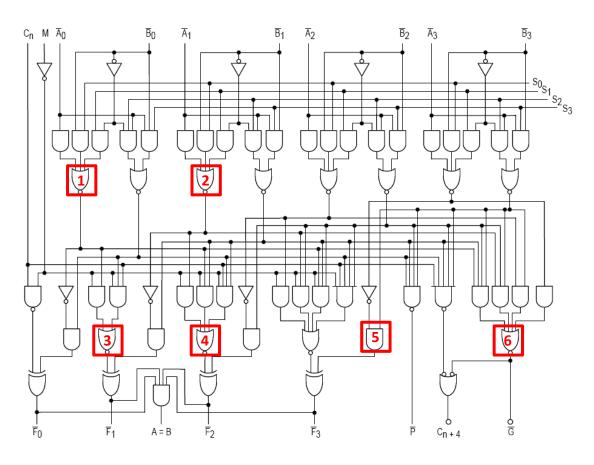
Cannot easily tell the function of an obfuscated element by observing its layout.

[J Rajendran, 2013]



Introduction to Obfuscation





Obfuscated elements

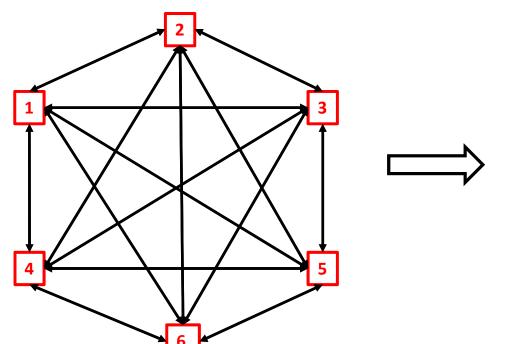
 Obfuscation elements can be put at the key part(s) of a circuit.

[Circuit from Wikipedia]



Our Assumption: Identities may be Correlated





 $\begin{bmatrix} 1 & \rho_{12} & \dots & \rho_{15} & \rho_{16} \\ \rho_{21} & 1 & \dots & \rho_{25} & \rho_{26} \\ \vdots & \ddots & & \vdots \\ \rho_{51} & \rho_{52} & \dots & 1 & \rho_{56} \\ \rho_{61} & \rho_{62} & \dots & \rho_{65} & 1 \end{bmatrix}$

Obfuscated elements

 ρ_{ij} Correlation coefficient between elements i and j

Pair-wise correlation between identifies of obfuscation elements exist



Expected Number of Attacks

A. Brute Force Attack

$$E[N] = 2^{n-1} + 0.5$$

n: Number of obfuscation elements

B. Correlation Driven Attack

$$E[N] = \sum_{i=1}^{2^n} i \times P_{si}$$

i: Success with i attacks, P_{si} : Probability of success with the ith attack

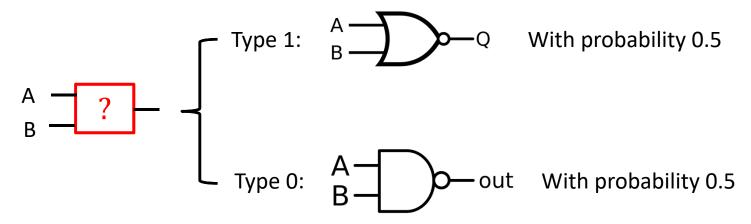
C. Entropy Lower Bound [James L. Massey, 1994]

$$E[N] \ge \left(\frac{1}{4}\right) 2^{H(P)} + 1$$

P: Joint distribution of all possible key combinations. H(P): The entropy of P

Constraints on the Joint Distribution





• Then the mathematical definition of ho_{ij} gives:

$$P_{ij}(1,1) = \frac{1}{4} + \frac{\rho_{ij}}{4}$$

 $P_{ij}(1,1)$: Probability of obfuscation element i and j both taking type one.

Constraints on the Joint Distribution

The definition of marginal distribution gives the system of equations:

$$\begin{cases} P_i(1) = P_{ij}(1,0) + P_{ij}(1,1) = 0.5 \\ P_j(0) = P_{ij}(0,0) + P_{ij}(0,1) = 0.5 \\ P_i(1) = P_{ij}(0,1) + P_{ij}(1,1) = 0.5 \end{cases}$$

By solving them gives us:

$$P_{ij}(0,0) = P_{ij}(1,1) = \frac{1}{4} + \frac{\rho_{ij}}{4}$$

$$P_{ij}(1,0) = P_{ij}(0,1) = \frac{1}{4} - \frac{\rho_{ij}}{4}$$

• Each $P_{ij}(u, v)$ also satisfies

$$\sum_{k=1}^{2^n} a_k P_{12...n}(x_1, ..., x_n) = P_{ij}(u, v) , a_k \in \{0, 1\}$$

where a_k equals one if and only if $x_i = u$ and $x_j = v$ and $u, v \in \{0,1\}^2$

Constraints on the Joint Distribution



This yilds system of linear equations:

: Obfuscated elements

$$\sqrt{}$$

$$A \times \underline{P} = b$$

$$A : \text{Boolean parameter} \quad \underline{P} = \begin{bmatrix} P_{12\dots n}(0,\dots,0) \\ \vdots \\ P_{12\dots n}(1,\dots,1) \end{bmatrix} \qquad b = \begin{bmatrix} P_{12}(0,0) \\ \vdots \\ P_{n-1n}(1,1) \end{bmatrix}$$

$$b = \begin{bmatrix} P_{12}(0,0) \\ \vdots \\ P_{n-1n}(1,1) \end{bmatrix}$$



Choosing the Joint Distribution

Choose the solution with maximum entropy:

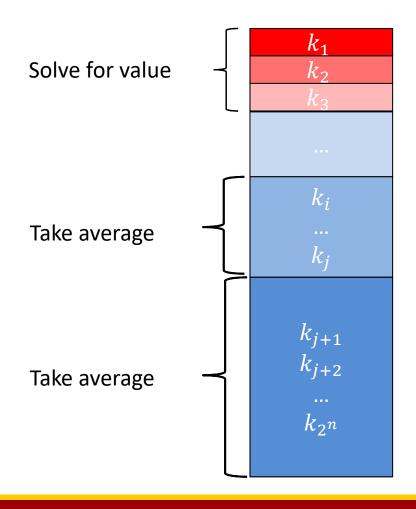
$$argmin \sum_{i=1}^{2^n} P(i) \log[P(i)]$$

subject to
$$P(i) \ge 0$$
, $i = 1, 2, ..., 2^n$
 $A \times \underline{P} = b$

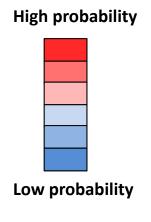
- Yields the largest number of expected guesses
- Can be implemented using known optimization algorithms
 - Easily implemented
 - But limited to small *n* due to exponential number of constraints



Complexity Reduction: Approximation Algorithm



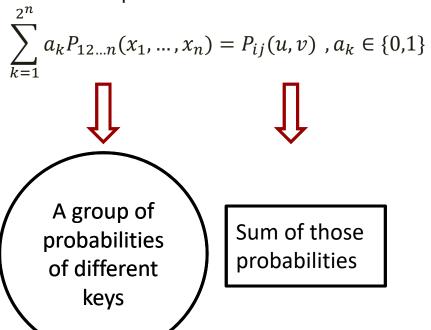
• k_i : The key with i-th highest probability to be correct.





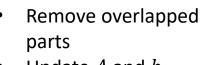
Approximation Algorithm

Take another look at the equation:

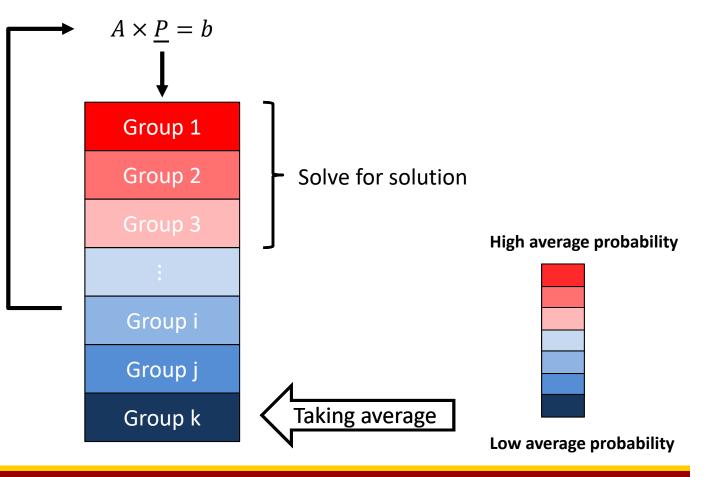




Approximation Algorithm



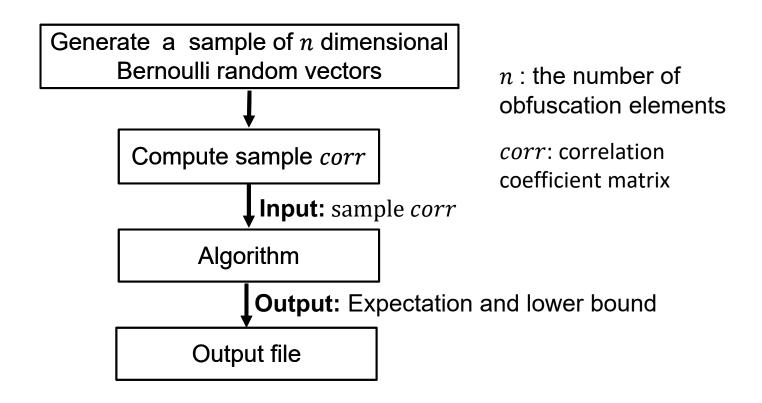
• Update A and b







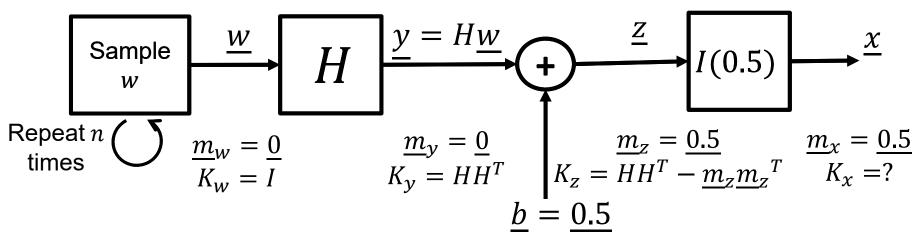
Experimental Results: Simulation





Generate a Bernoulli Random Vector





- w: follows elementary Gaussian distribution N(0,1)
- \underline{m} : mean vector
- *K* : covariance matrix.
- *H*: A random matrix used to create the correlations
- *I*(0.5): Indicator function with threshold 0.5.
- x : Sampled Bernoulli random vector with non-identity covariance matrix.



Compute Sample Correlation Coefficient Matrix

Repeatedly perform sampling procedure: $X = [\underline{x_1}, \underline{x_2} \dots \underline{x_S}]$



Sample Correlation matrix: $\widehat{R_x} = \frac{XX^T}{S}$, Sample mean: $\underline{\widehat{m_x}} = \frac{\sum_{i=1}^S \underline{x_i}}{S}$



Sample covariance matrix: $\widehat{K_x} = \widehat{R_x} - \underline{\widehat{m_x}} \widehat{m_x}^T$



Sample correlation coefficient: $\widehat{\rho_{ij}} = \frac{\widehat{K_{\chi}}(i,j)}{\sqrt{\widehat{K_{\chi}}(i,i)}\sqrt{\widehat{K_{\chi}}(j,j)}}$

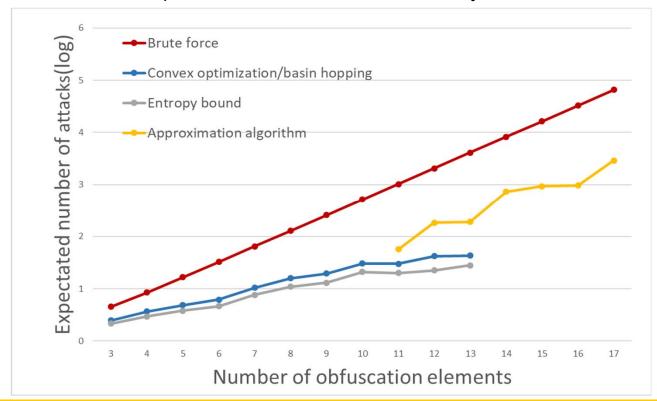


Sample correlation coefficient matrix: corr

Simulation Results



- Tested two built-in python functions to directly find the arg-min
 - Basin hopping algorithm and convex optimization solver
- Implemented approximation algorithm in python using numPy
 - Use convex optimization to solve for critical keys

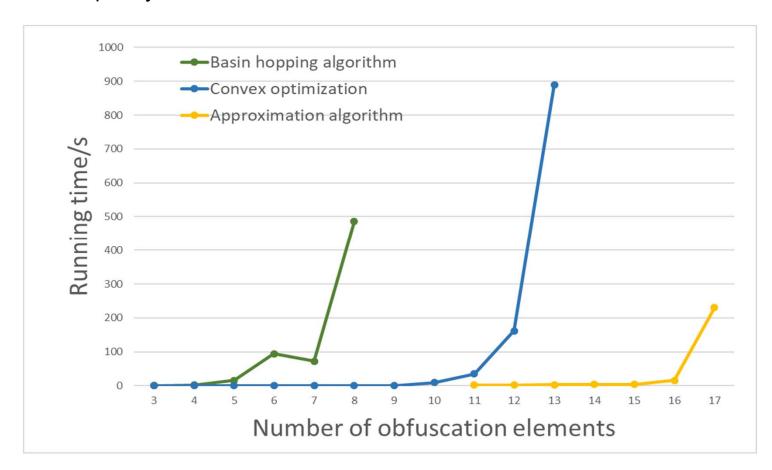




Simulation Results



The complexity is still a concern.







Summary and Conclusions

- Our metric shows that correlation information can reduce the number of attacks needed to reverse engineer a chip dramatically.
- If an attacker follows the strategy in our paper, the proposed metric represents an upper bound on the expected number of guesses.
- Complexity scaling exponentially with number of obfuscated elements is a challenge to both us and attackers.
- Addressing this complexity scaling problem is future work





Key References

- Massey, James L. "Guessing and entropy." Information Theory, 1994.
 Proceedings., 1994 IEEE International Symposium on. IEEE, 1994.
- Rajendran, Jeyavijayan, et al. "Security analysis of integrated circuit camouflaging." Proceedings of the 2013 ACM SIGSAC conference on Computer & communications security. ACM, 2013.

