Using Squeezeness to test from Finite State Machines

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CREST Information Theory and Software Testing

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- Related to an expression? easy peasy lemon squeezy.

What's the meaning of Squeeziness in Information Theory?

- D. Clark & R. Hierons. *Squeeziness: An information theoretic measure for avoiding fault masking*, IPL, 2012.
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How bad is FEP?

- FEP can reduce testing effectiveness: we might fail to find a fault despite executing the faulty statement.
- Empirical studies show that many systems suffer from FEP.

What's this talk about?

The adaption of Squeeziness to a black box scenario.

This talk in a nutshell

Using Squeeziness to test from Finite State Machines

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Finite State Machines

Graphs with an initial state where transitions are labelled by a pair (input, output).

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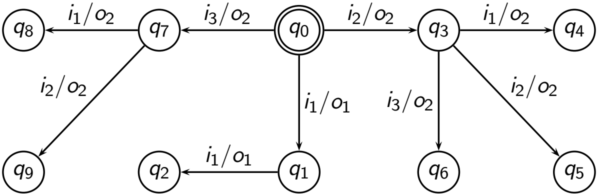
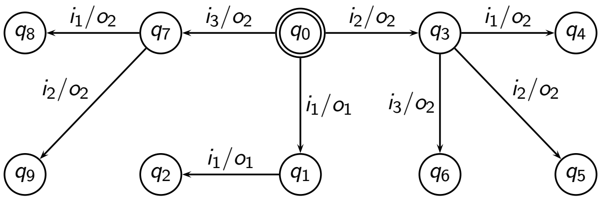


FSMs: assumptions

- FSMs are deterministic.
- FSMs representing SUTs are input-enabled.

FSMs as functions

An FSM M can be seen as a function $f_M : \texttt{dom}_M \longrightarrow \texttt{image}_M$ such that for all $\alpha \in \texttt{dom}_M$ (sequence of inputs performed by M) $f_M(\alpha) = \beta$ (sequence of outputs observed after applying α).



$$
\begin{aligned}
f_M(i_1) &= o_1 \\
f_M(i_3) &= o_2 \\
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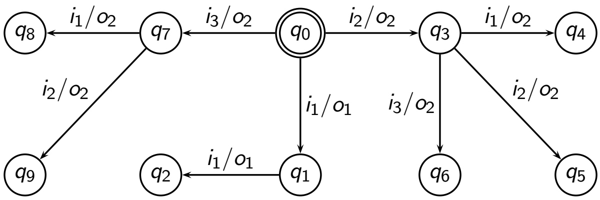

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Collisions

α_1 and α_2 collide for M if $\alpha_1 \neq \alpha_2$ and $f_M(\alpha_1) = f_M(\alpha_2)$.

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Squeeziness as difference of entropies

Entropy of the random variable ξ_A

$$\mathcal{H}(\xi_A) = -\sum_{a \in A} \sigma_{\xi_A}(a) \cdot \log_2(\sigma_{\xi_A}(a))$$

If $f : A \longrightarrow B$ then Squeeziness of f is the loss of information after applying f to A: $\mathcal{H}(A) - \mathcal{H}(B)$.

Squeeziness for FSMs

We need to define how to group inputs & outputs. Two alternatives:

- A unique random variable for the whole set of inputs/outputs.
- A random variable for each length of sequences of inputs/outputs.

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- A random variable for each length of sequences of inputs/outputs.

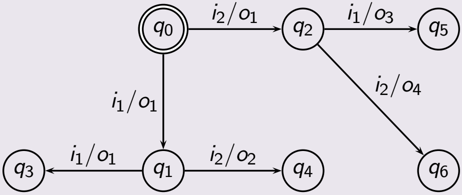
We choose the second one because it gives an incremental procedure to compute a sequence of *consecutive values* of Squeeziness.

Squeeziness as difference of entropies

Let FSM M, $k > 0$ and random variables $\xi_{\texttt{dom}_{M,k}}$ and $\xi_{\texttt{image}_{M,k}}$.

$$\texttt{Sq}_k(M) = \mathcal{H}(\xi_{\texttt{dom}_{M,k}}) - \mathcal{H}(\xi_{\texttt{image}_{M,k}})$$

Squeeziness is not monotonic



Squeeziness for $k = 1$ is $\log_2(2) = 1$ while for $k = 2$ is 0.
This is bad because we do not have an obvious stopping rule.

Squeeziness is null for bijective functions

If $f_{M,k}$ is bijective then $\mathtt{Sq}_k(M) = 0$.

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Random variables for outputs are determined

Given FSM M, $k > 0$ and $\xi_{\mathtt{dom}_{M,k}}$, the probability distribution of $\xi_{\mathtt{image}_{M,k}}$ is completely determined.

$$\sigma_{\xi_{\mathtt{image}_{M,k}}}(\beta) = \sum_{\alpha \in f_M^{-1}(\beta)} \sigma_{\xi_{\mathtt{dom}_{M,k}}}(\alpha)$$

Maximum entropy principle

Maximum entropy is obtained with a uniform distribution $\xi_{\mathtt{dom}_{M,k}}$.

$$\mathtt{Sq}_k(M) = \frac{1}{|\mathtt{dom}_{M,k}|} \cdot \sum_{\beta \in \mathtt{image}_{M,k}} |f_M^{-1}(\beta)| \cdot \log_2(|f_M^{-1}(\beta)|)$$

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Maximum loss of information

Probability distribution maximising Squeeziness: uniformly distributed in the bigger inverse image of an element of the outputs β' and zero otherwise.

$$\sigma_{\xi_{\mathtt{dom}_{M,k}}}(\alpha) = \begin{cases} \frac{1}{|f_M^{-1}(\beta')|} & \text{if } \alpha \in f_M^{-1}(\beta') \\ 0 & \text{otherwise} \end{cases}$$

$$\mathtt{Sq}_k(M) = \log_2(|f_M^{-1}(\beta')|)$$

Probabilistic Squeeziness

We divide Squeeziness by its maximum value.

$$\mathtt{PSq}_k(M) = \frac{\mathcal{H}(\xi_{\mathtt{dom}_{M,k}}) - \mathcal{H}(\xi_{\mathtt{image}_{M,k}})}{\log_2(|f_M^{-1}(\beta')|)}$$

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Collisions and FEP

Let $m_i = |f_{M,k}^{-1}(\beta_i)|$ and $d = \sum_{i=1}^{n} m_i$. Assuming a uniform distribution, the probability of having a collision is:

$$\texttt{PColl}_k(M) = \sum_{i=1}^{n} \frac{m_i \cdot (m_i - 1)}{d \cdot (d-1)}$$

Relation between $\texttt{PColl}_k(M)$ and $\texttt{PSq}_k(M)$ is not monotonic

There exist M_1 and M_2 and $k > 0$ such that
$\texttt{PSq}_k(M_1) < \texttt{PSq}_k(M_2)$ but $\texttt{PColl}_k(M_1) > \texttt{PColl}_k(M_2)$.

Empirical Evaluation via simulations

Simulations to compute `PColl`, `PSq`, `Sq` assuming uniform distributions over the inputs (methodology similar to [CH12]).

- $d =$ size of the input space (ranging between 10^4 and $2 \cdot 10^9$).
- $m =$ maximum subdomain size (ranging between 10^2 and 10^4).

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- d = size of the input space (ranging between 10^4 and $2 \cdot 10^9$).
- m = maximum subdomain size (ranging between 10^2 and 10^4).
- Pearson & Spearman Rank correlation coefficient between `PColl` and `PSq`/ `Sq`. Similar results.
- Strong correlation between `PColl` and `PSq`. Values greater than 0.96 for input sets with $5 \cdot 10^6$ or more elements.

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- Pearson & Spearman Rank correlation coefficient between `PColl` and `PSq`/ `Sq`. Similar results.
- Strong correlation between `PColl` and `PSq`. Values greater than 0.96 for input sets with $5 \cdot 10^6$ or more elements.
- Standard Squeeziness has a better correlation. Still, `PSq` can be more useful because it is easier to compare results from different machines and lengths of inputs.

Empirical Evaluation via FSMs: Squeeziness and fault location

- 50 randomly generated FSMs (between 25 and 50 states).
- For each FSM we computed $\mathtt{Sq}$ and $\mathtt{PSq}$ for all $1 \leq k \leq 25$.
- We generated 100 valid mutants of M presenting FEP.

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- For each FSM we computed $\mathtt{Sq}$ and $\mathtt{PSq}$ for all $1 \leq k \leq 25$.
- We generated 100 valid mutants of M presenting FEP.
- No correlation between where the fault is produced and the Squeeziness and Probabilistic Squeeziness obtained for the length of the input sequence reaching the mutated transition.
- Negative result. We tried something less ambitious.

Empirical Evaluation via FSMs: Squeeziness and probability of FEP

Instead of *predicting* where the fault was, we consider the probability of FEP.

- Same 50 randomly generated FSMs.
- We generated 50 valid mutants of M (with and without FEP).
- We computed the probability of FEP, `Sq` and `PSq` for length 25.
- $p(FEP) = \frac{\#\text{ tests reaching wrong state but generating correct output}}{\#\text{ tests reaching wrong state}}$.

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- We computed the probability of FEP, $\mathtt{Sq}$ and $\mathtt{PSq}$ for length 25.
- $p(FEP) = \frac{\#\text{ tests reaching wrong state but generating correct output}}{\#\text{ tests reaching wrong state}}$.
- High correlations between probability of having FEP with sequences up to 25 and $\mathtt{Sq}$ and $\mathtt{PSq}$ for $k = 25$. All the values were greater than 0.75 and some close to 1.

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Application to testing

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We can choose a value of k such that $\mathtt{PSq}$ is low: this makes is less likely to have FEP.

Finally, if we have $\mathtt{PSq}= 0$ for a certain k, we can use this length of tests as a checkpoint (but remember that we do not have monotonicity).

Conclusions and future work

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- No correlation between Squeeziness for k (length of tests) and faults at length $k-1$.
- Correlation between Squeeziness and probability of FEP.
- Future work: Consider observable FSMs and experiments on *real* FSMs.

THANKS FOR YOUR ATTENTION!!
Questions? Comments?