The Practical Assessment of Test Sets with Inductive Inference Techniques

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BACKGROUND

Test Adequacy

- Assessing the ability of a test set to identify faults
 - Successful execution of an adequate test set should imply that there are no faults in a tested program

- How do you know if a test set is adequate?
- Numerous adequacy criteria have been developed
 - Statement / branch / path / data-flow, ...

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Problem

 Criteria based on syntax are often a poor approximation for actual adequacy























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PROBLEM

Based on exact results - no flexibility

- The inferred model is either equivalent to the subject system or not.
 - The corresponding test set is either adequate or not.
- In reality, there is bound to be a certain degree of error.
 - A test set may result in a model that is 99% correct, with only small, trivial errors

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Setting

- There exists an *instance space* X
- The learning target is a *concept* $c \subset X$
 - For any element $x \in X$, c(x) = 1 or 0
- ► There is a *selection procedure EX*(*c*, *D*) that randomly selects elements in *X*
 - The probability of them belonging to *c* is determined by some static distribution *D* (not necessarily known)
- Given a labelled set of examples selected by *EX*, it is the goal of the learning procedure to infer *c*

Assessing a Learner

- Two problems
 - 1. Can only guarantee accurate result if supplied with every possible instance in *X*.
 - 2. Given that samples are a random subset, there is the chance that EX will supply a misleading sample.
- To address these issues, the success of a learner is characterised as follows:
 - δ probability that the hypothesis will meet the success conditions

• ε - allowable degree of error



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Assumptions

- Validity of final outcome must be interpreted with care
 - Test set is being evaluated against itself
 - Size of sets A and B must be sufficiently large and distinct

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 Test set generator must be capable of (eventually) exhaustively exercising the SUT

CONCLUSIONS

- Inferring models from tests gives us a 'test-eye view' of the system
- Test adequacy can be assessed by measuring model accuracy
- This can be achieved with established ML techniques
- For a given type of system (e.g. state-based) the PAC approach can be used to assess and compare the general performance of testing techniques.

Challenge

Find the best combination of machine-learner and test-set generator.

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