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The Utility of Neural Network Test Coverage Measures

Rob Ashmore, Alec Banks

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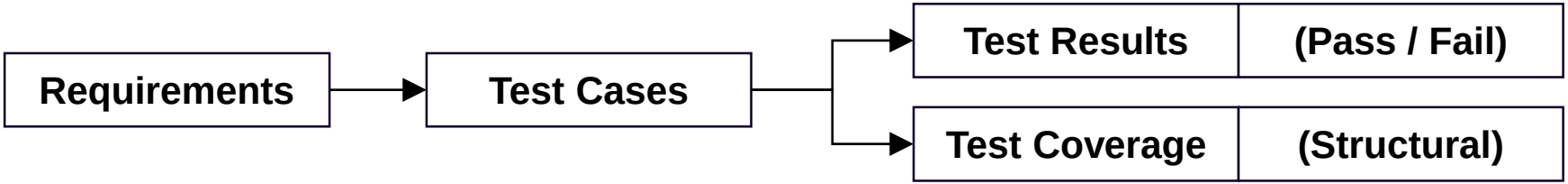


- We want assurance that the software behaviour is fully described by the requirements
- We use the ***Requirements*** to derive ***Test Cases***, which are executed dynamically
- We measure both the result of each test and how the collection of all tests covers the software structure
  - For example: Statement, Branch, Modified Condition / Decision Coverage [1]

- Incomplete code causes test failure; incomplete requirements may not be detected
- If tests pass, but do not achieve full coverage then, either:
  - Software behaviour is correct, requirements are incomplete
  - Requirements are correct, software includes additional unnecessary behaviour
  - Software behaviour and requirements are both correct, test set is incomplete

Requirements-Based Testing: Discussion

- 100% Requirements-Based Testing (RBT) for traditional software is based on:
  - A ***complete set of requirements***, which are (for example) accurate, consistent, unambiguous and verifiable
  - Which can be ***decomposed in a hierarchical, traceable manner***, so that low-level test results can confidently aggregate to high-level software behaviour
  - To “units”, where ***behaviour is closely linked to code structure***, behaviour that is strongly data-dependent should be captured as a specific requirement

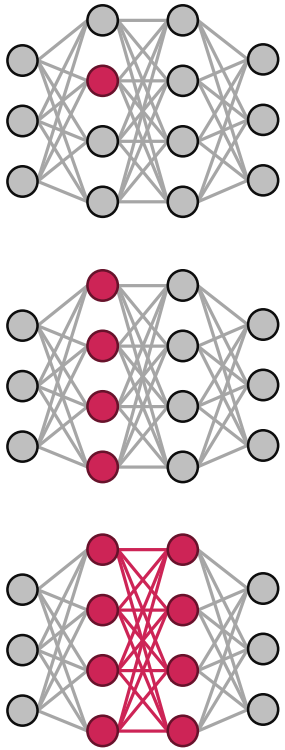
The combination of RBT and structural test coverage provides confidence that the requirements suitably describe the software's behaviour, both what it does and what it does not do

  - Note: 100% RBT and full structural coverage does not guarantee error free code

Neural Network Coverage Measures

Neural Network Coverage Measures

- Typical neural network coverage measures are related to neuron activations
- Historically, there has been a progression:
  - From measures that consider neurons in isolation [2]
  - Through measures that consider neurons within each layer [3], [4]
  - To measures that consider how neurons in one layer affect neurons in the subsequent layer [5]
- These approaches are reminiscent of traditional software coverage measures, with the neuron as the “low-level behavioural unit”



Towards Traditional Coverage for Neural Networks

Traditional Software -vs- Neural Networks

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Traditional Software Aspects	Neural Network Context
There is a complete set of requirements	Neural networks solve “open” problems; there is not a set of requirements that is accurate, complete, unambiguous and verifiable
Requirements can be hierarchically decomposed	Some level of decomposition may be possible, but requirements are not decomposed to a level that can directly be coded against
Behaviour is closely linked to code structure	The link between structure (i.e. neuron activation) and behaviour is indirect and not well-understood
Coverage can be measured efficiently	*Information on individual neuron activations may not be readily available from highly optimised hardware*

None of the aspects that make test coverage “work” for traditional software apply to neural networks

Partially Meeting the Test Coverage Aims

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Software satisfies requirements:

- Robustness to adversarial examples [6]
- Disciplined approach to requirements specification [7]
- Transformation of abstract domains through typical activation functions [8]
- Encoding logic constraints as part of the network training process [9]

Requirements cover behaviour:

- Tests cover input, operational, failure and adversarial domain spaces [10]
- Detection and mitigation of backdoor attacks [11]
- Automatic (formal) inference of network properties [12]

Current techniques allow the two main aims of requirements-based test coverage to be partially met for neural networks

Utility of Neural Network Coverage Measures

Utility of Neural Network Coverage Measures

- Neural network coverage measures provide additional utility, beyond the aims of requirements-based test coverage for traditional software:
  - They could be used to ***optimise training data*** (e.g. whether there is value in collecting additional training data)
  - They could be used to ***compare training and (independent) verification data sets***, specifically from the network's perspective
  - They could be used to ***generate additional inputs***, which could meaningfully extend the training data set
  - They could be used to ***choose between different neural networks***, for similar levels of performance, select the better covered network
  - They could be used to ***monitor runtime behaviour*** (e.g. by benchmarking activation patterns)

Conclusions

Conclusions

- Current neural network test coverage measures ***cannot provide the same level of confidence*** as requirements-based test coverage does for traditional software

- But, there are some approaches that ***can partially meet the aims of traditional coverage*** in the context of neural networks

- And, the neural network test coverage measures are ***valuable in other ways***

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