METHODS FOR TESTING UNIFORMITY STATISTICS

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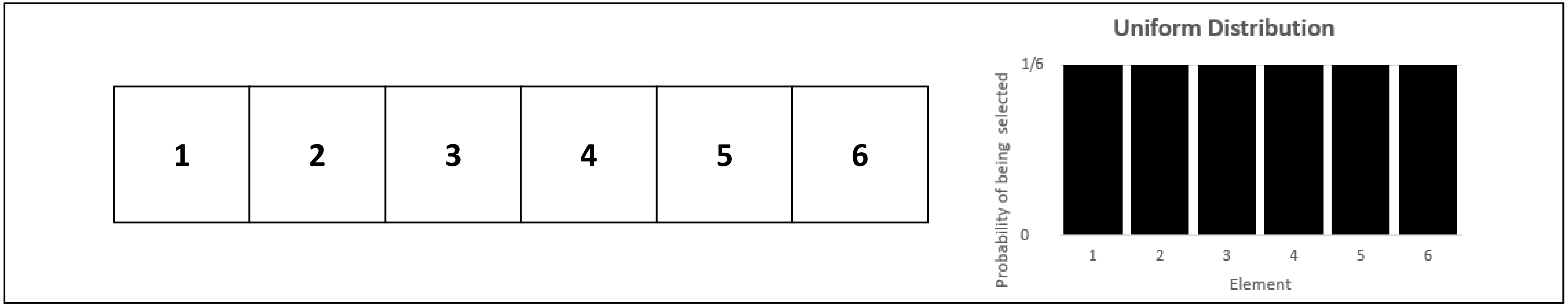
Definitions

- **Uniform Distribution:** A sample is said to adhere to a uniform distribution if every element in the sample has an equal chance of being randomly selected.



- **Uniformity Statistic:** A Uniformity Statistic is a means of measuring the extent to which a sample conforms to a uniform distribution.
    - The Uniformity Statistics considered in our research produce lower values for samples that adhere more strongly to a uniform distribution.

Problem Definition

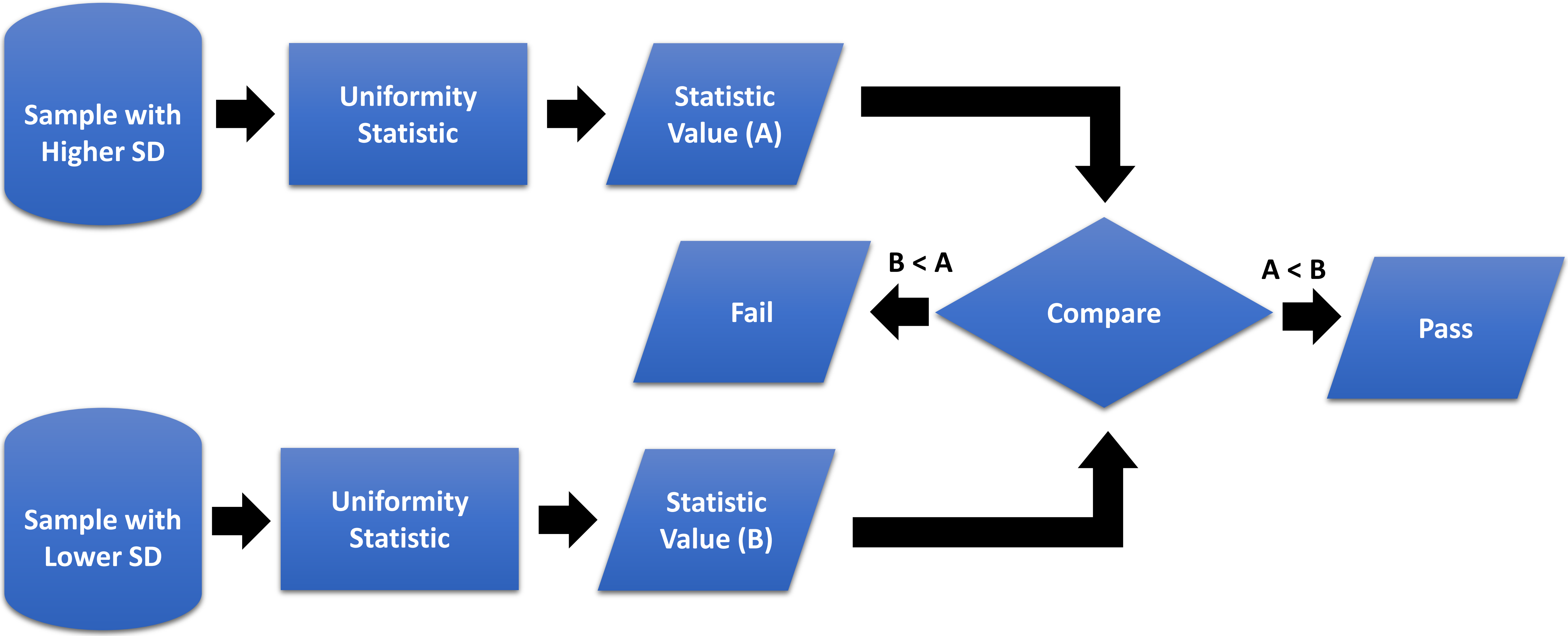
- Uniformity Statistics have the oracle problem, because it is very difficult to predict the outcome.

- We investigated three different approaches for alleviating the oracle problem in uniformity statistics.

Intuition

- The standard deviation of a sample is a measure of the spread of values in that sample.
- Higher measures of standard deviations indicate that the values in the sample are more spread out, and thus the sample should adhere more strongly to a uniform distribution.
- Thus, the standard deviation is intrinsically linked to uniformity.
- All of our oracles are based on this observation.

Intuition Behind a Metamorphic Relation

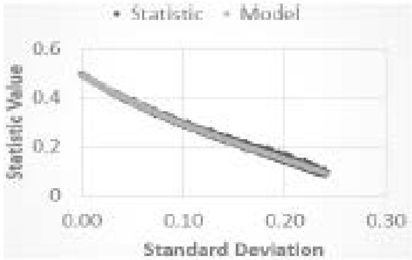


Intuition Behind Regression Model Oracles (1)

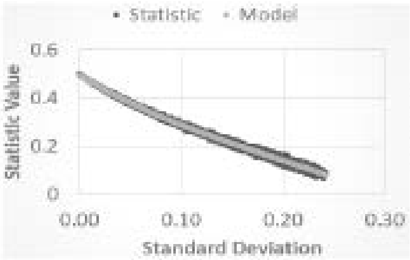
- For each uniformity statistic, we performed a Regression Analysis to learn the precise nature of the relationship between the standard deviation and test statistic value.
- For a given test statistic, the Regression Analysis enabled us to derive a mathematical formula that accepts a standard deviation value as input and outputs a predicted test statistic value.

Intuition Behind Regression Model Oracles (2)

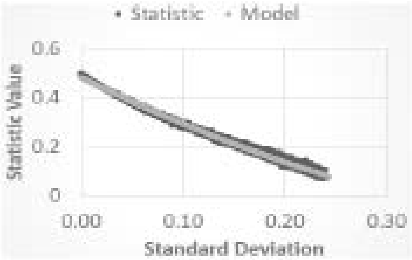
- Plot Statistic (Black) and Model (Grey), against standard deviation, based on 10000 samples.
- Applied one Mann-Whitney U Test per subject program to compare the statistic and model, and applied Benjamini-Hochberg correction to these tests. 14/18 of the statistics did not report a significant result.
- Most models are indistinguishable.



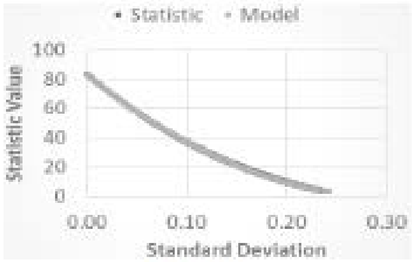
(a) C_n



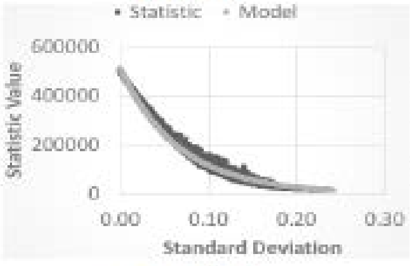
(b) C_n^-



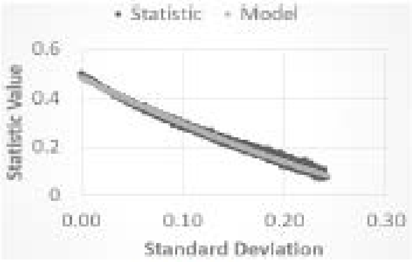
(c) C_n^+



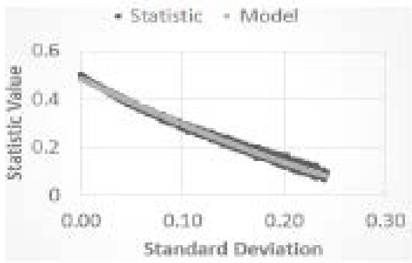
(d) W_n^2



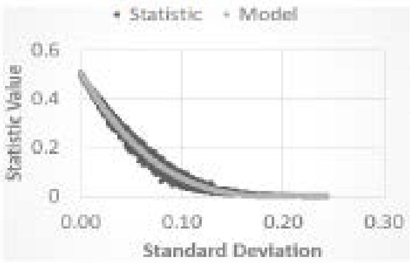
(e) $S_n^{(m)}$



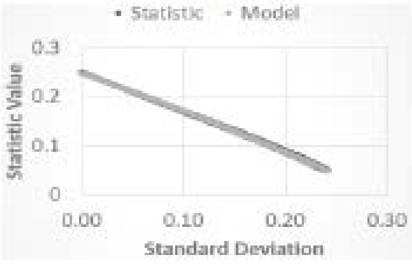
(f) D_n^-



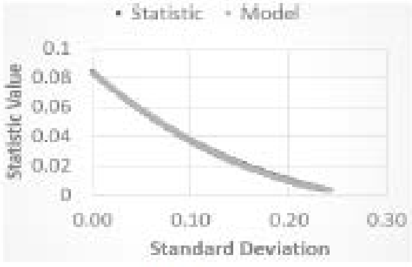
(g) D_n^+



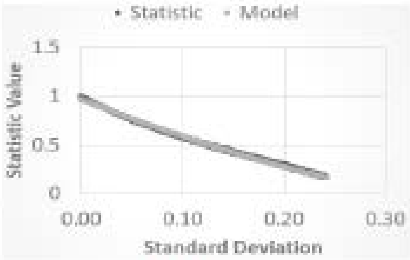
(h) $G(n)$



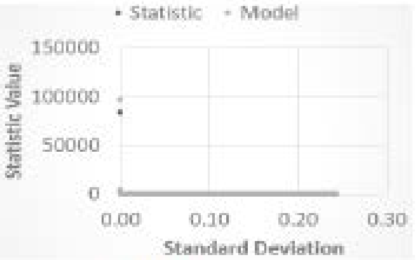
(i) T_1'



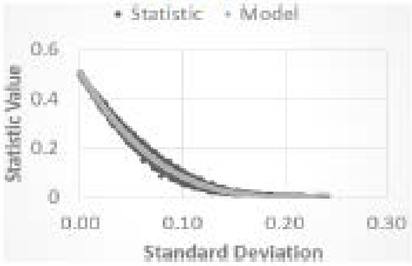
(j) T_2'



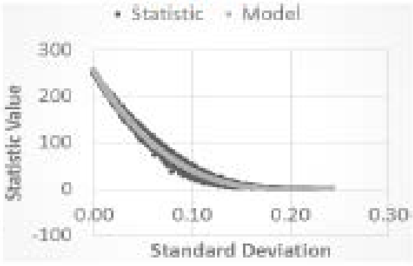
(k) K_n



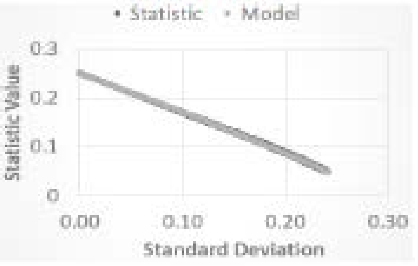
(l) $E_{m,n}$



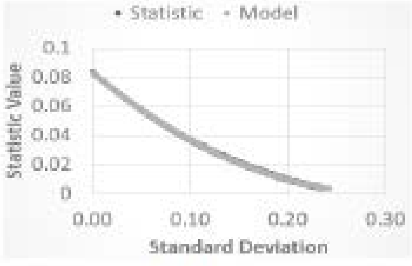
(m) Q



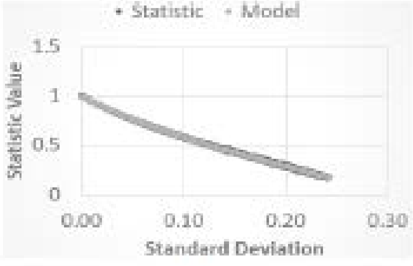
(n) $A^*(n)$



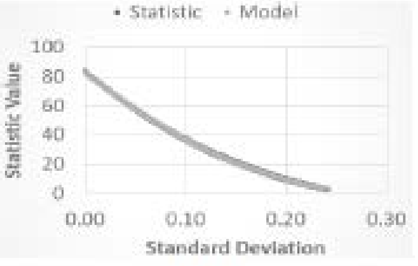
(o) T_1



(p) T_2

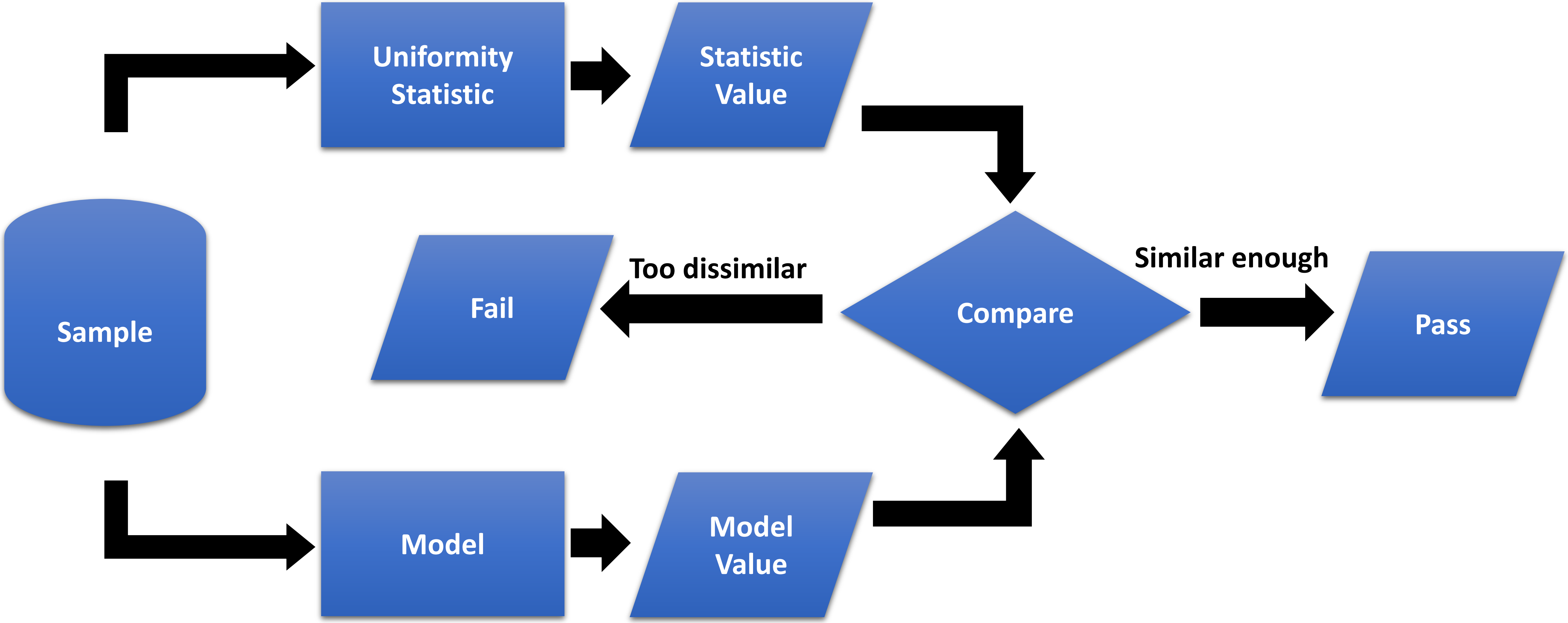


(q) V_n

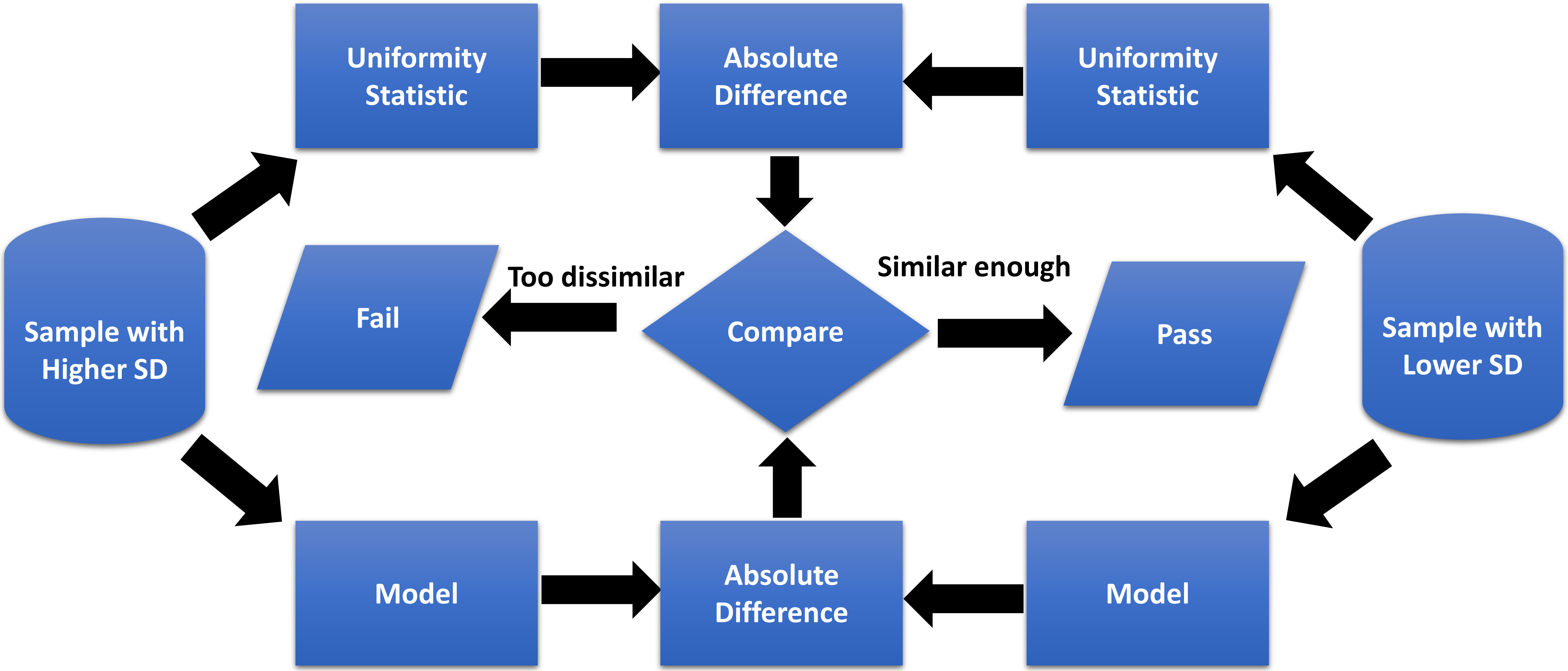


(r) U_n^2

Intuition Behind Regression Model Oracles (3)



Intuition behind Metamorphic Regression Model Oracles



Experimental Design – Subject Programs

- **Subject Programs:** 18 Uniformity Statistics – D_n^+, D_n^-, V_n, W_n^2, U_n^2, C_n^+, C_n^-, C_n, K_n, T_1, T_2, T_1', T_2', $G(n)$, Q, $S_n^{(m)}$, $A^*(n)$, $E_{m,n}$

- **Code Reuse:**
  - V_n reuses D_n^+ and D_n^-
  - U_n^2 reuses W_n^2
  - C_n reuses C_n^+ and C_n^-
  - K_n reuses C_n^+ and C_n^-
  - Q reuses G(n)

Experimental Design – Mutants

- Mutmut mutation testing tool.
- Removed equivalent mutants.
- Removed crashed mutants.
- 196 mutants in total.

Statistic	Number Of Mutants
$E_{m,n}$	19
$G(n)$	14
K_n	1(+9+8)
Q	12(+14)
$S_n^{(m)}$	14
T_1	12

Statistic	Number Of Mutants
$T_1^{'}$	14
T_2	14
$T_2^{'}$	16
U_n^2	6(+20)
V_n	1(+7+5)
W_n^2	20

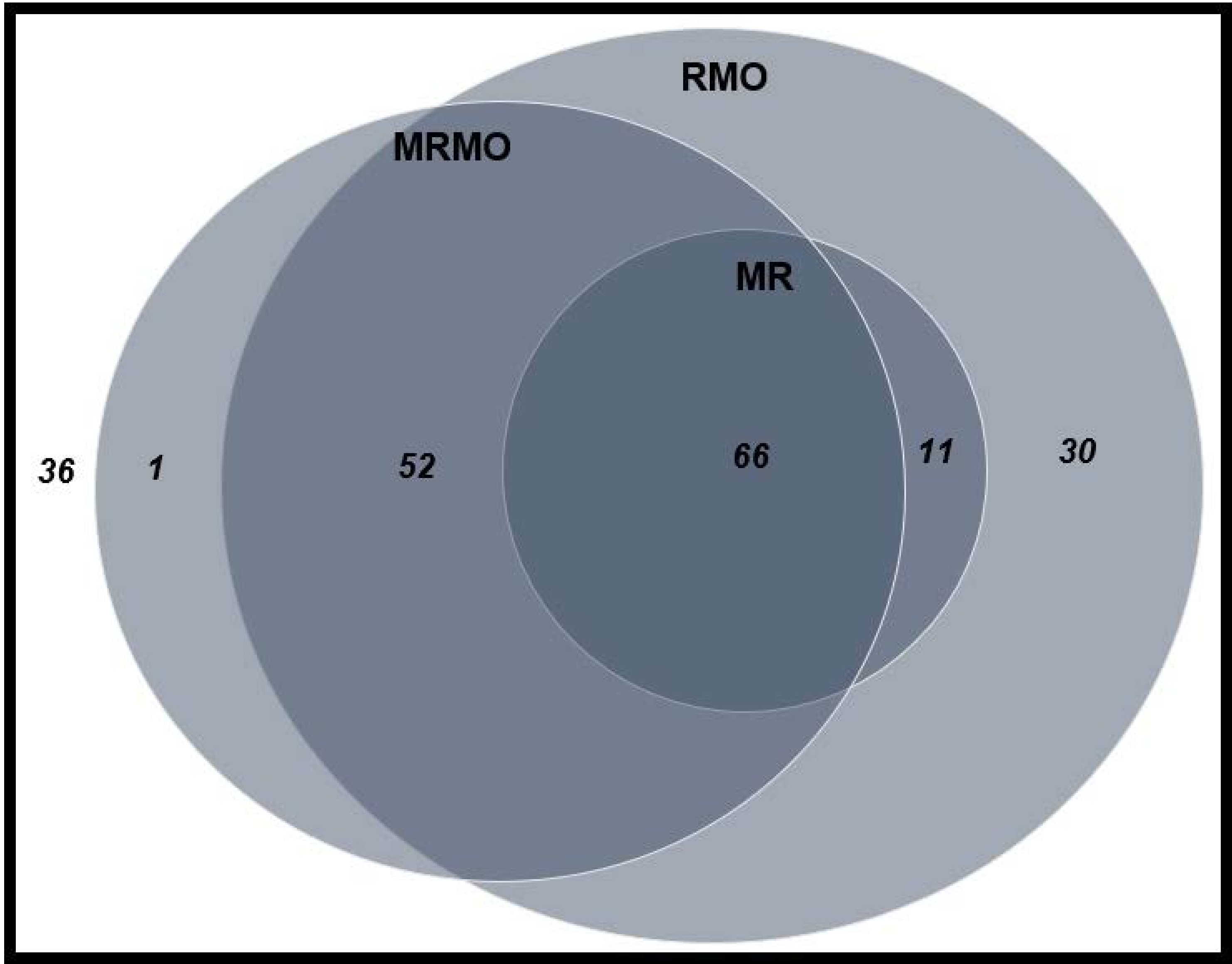
Statistic	Number Of Mutants
$A^*(n)$	24
C_n	0(+9+8)
C_n^-	9
C_n^+	8
D_n^-	7
D_n^+	5

Experimental Design – Test Suites

- **Mutation Testing Test Suites:**
  - We generated one test suite per oracle, by random testing.
  - These test suites consist of 100 test cases
  - Test cases in these test suites could either deterministically report false positives, or deterministically not report false positives.
    - Metamorphic Regression Model Oracle had one such test case – this was replaced to prevent false positives from confounding the results.
- **False Positive Rate Test Suites:**
  - We generated one test suite per oracle, by random testing.
  - Each test suite consisted of 1000 test cases.

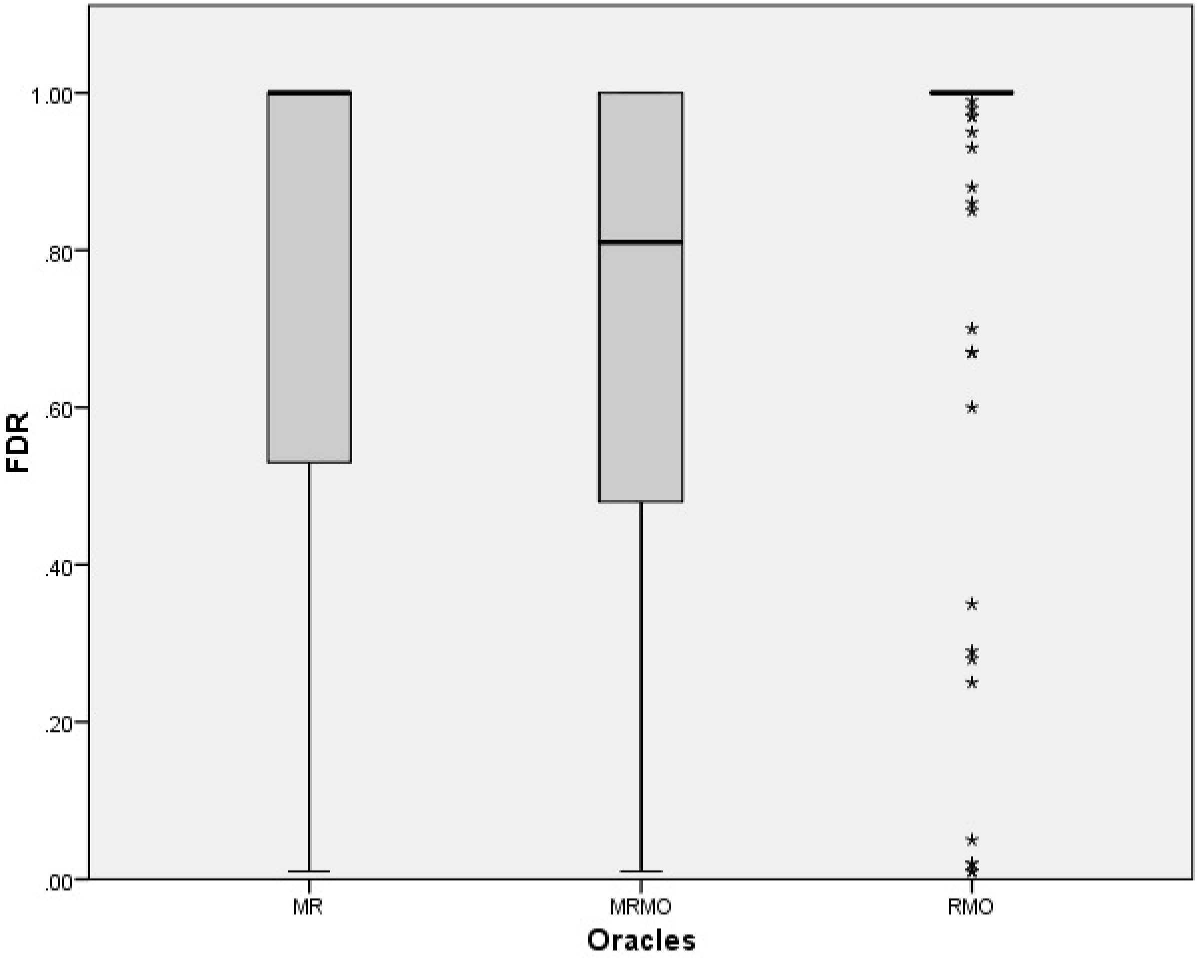
Results and Discussion – Mutation Score

- MR – 77/196, RMO – 159/196, and MRMO – 119/196
- Fisher's Exact Tests + Benjamini-Hochberg Correction = Significant Difference
- MRMO is probably more effective than MR because of tightness
- RMO is probably more effective than MRMO because:
  - RMO was less aggressively tuned
  - MRMO is blind to faults that cause the same level of difference between the source and follow-up test case, whilst RMO is not



Results and Discussion – Failure Detection Rate

- RMO obtained an FDR of 100% for 137/159 killed mutants
- MR obtained an FDR of 100% in 52/77 killed mutants
- MRMO obtained an FDR of 100% for 40/119 killed mutants
- Mann-Whitney U Tests + Benjamini-Hochberg Correction = Significant
- Interesting: MR is more effective than MRMO in terms of FDR



Results and Discussion – False Positive Rate

- False positives arise from:
  - Statistics can make errors and this could result in false positives
  - The models used in the RMO and MRMO oracles could make inaccurate predictions
- MR reports 0 false positives in all subject programs
- The largest false positive rates that were observed for RMO and MRMO across all subject programs is:
  - MRMO: 0.40%
  - RMO: 0.40%

Future Work

- A Genetic Algorithm based test case selection methodology that attempts to maximise the difference between the statistic and the models for the RMO oracle.
- The RMO and MRMO oracles both require tuning before they can be used. A method that circumvents this requirement would improve the usability of these techniques.

Thank you for listening. Are there any questions?