Comparing and Combining Analysis-Based and Learning-Based Regression Test Selection

Jiyang Zhang, Yu Liu, Milos Gligoric, Owolabi Legunsen, August Shi

The University of Texas at Austin, Cornell University

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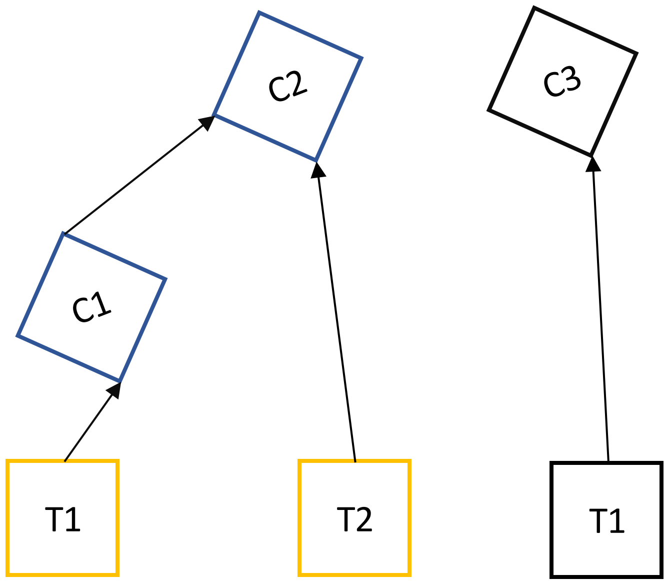
Regression Test Selection (RTS)

- Regression testing is widely practiced by software developers
- Regression test selection (RTS) optimizes regression testing by only rerunning a subset of tests that can be affected by changes.
- Evaluate RTS:
  - Safe
  - Precise
  - Efficient

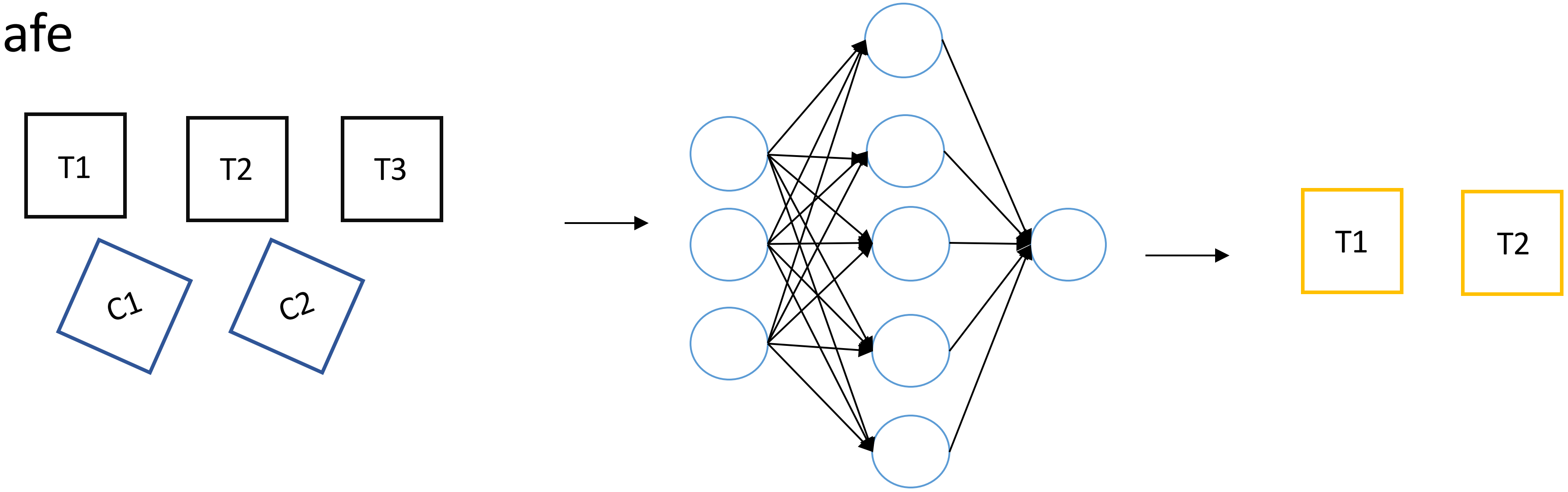
Analysis-based RTS

- RTS based on program analysis can save substantial testing time for (medium-sized) open-source projects.
  - Dynamic program analysis RTS (Ekstazi)
  - Static program analysis RTS (STARTS)
- Problems:
  - Costs
  - Imprecise
  - Large repository with multiple programming language

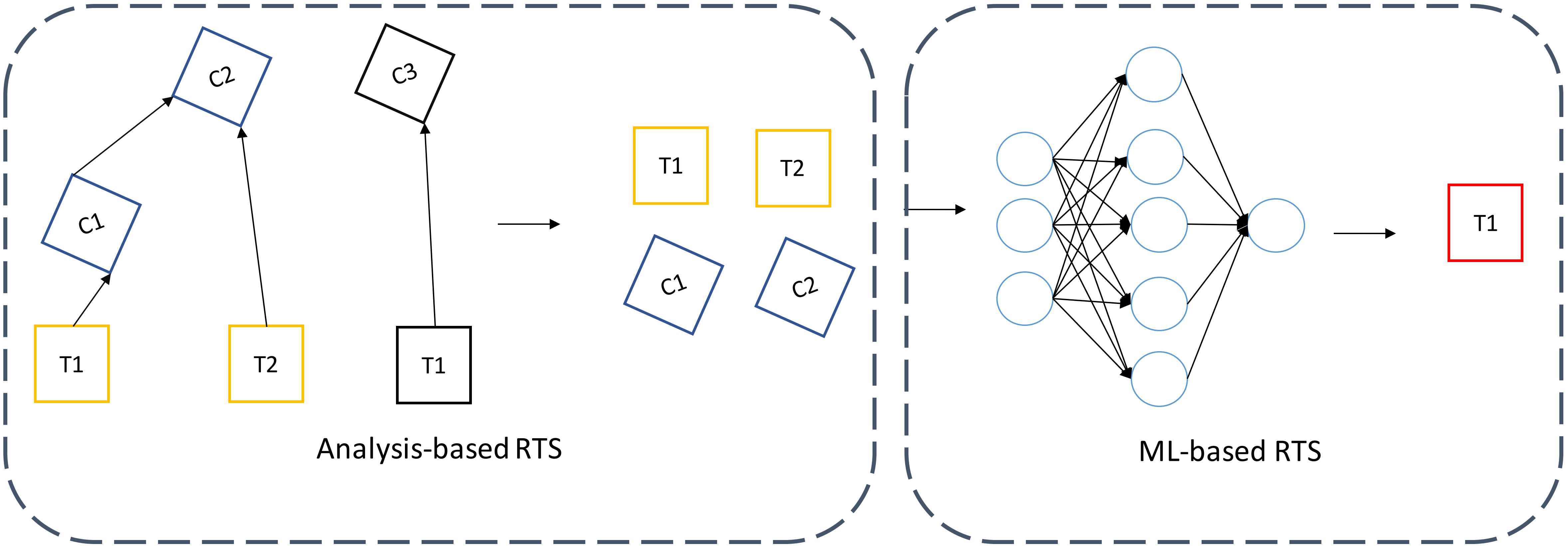


Machine Learning (ML) RTS

- ML-based RTS model learns from designed features
  - Predictive Test Selection (Machalica et al.)
- Problems:
  - Requires large training data
  - Unsafe



Combining



Our contributions

- Design and implement novel ML-based RTS models
  - Use mutation analysis to build training dataset
- Combine ML-based RTS with analysis-based RTS to improve precision
- Compare our approaches with prior analysis-based RTS and rule-based RTS

Outline

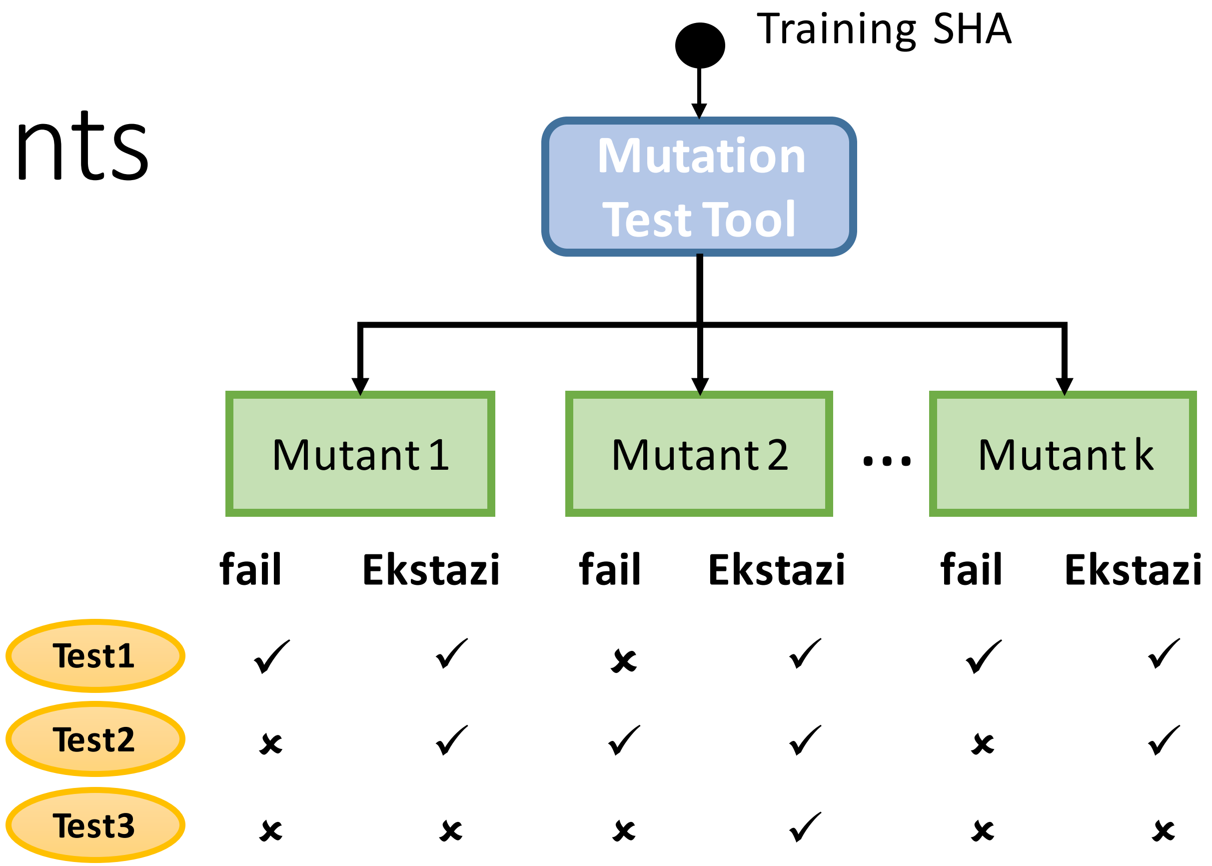
- Technique
  - Training Dataset from Mutans
  - Feature Extraction
  - Model Design
  - Model Variations
  - Combining Analysis-based RTS and ML-based RTS
- Empirical Study
  - Dataset
  - Experiments set up
  - Results and findings

Training Data from Mutants

- It is hard to obtain large data from open-source projects for training
- Utilize Mutation Testing (Pitest) to create Dataset

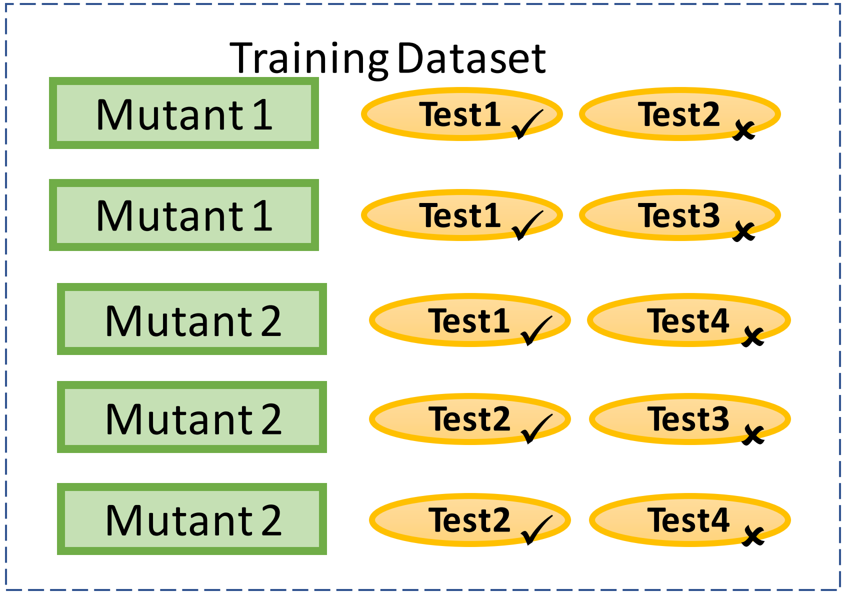
Training Data from Mutants

- Labeling the data in two ways:
  - A) Model predicts test failure:
    - Positive labels: test-mutants that are killed
  - B) Model predicts what Ekstazi selects
    - Positive labels: test-mutants that are selected by Ekstazi



Training Data from Mutants

- To overcome the data imbalance, training dataset instances are pairs of $\langle c, t^+, t^- \rangle$



Machine Learning Model

Feature Extraction

Feature Representation Learning

Likelihood Prediction

Feature Extraction

- Test:
  - split the test class name into tokens via *camelCase* and *snake_case*
  - convert to lower case

StrTokenizerTest.java → str | tokenizer | test

Feature Extraction

- Code diff:
  - Basic
    - Split changed class name into tokens via camelCase and snake_case and convert to lower case

StrTokenizer.java → str | tokenizer

  - Code
    - the sequence of tokens on added and modified lines

if (pos > 0) return true; → if | (| pos | > | 0 |) | return | true | ;

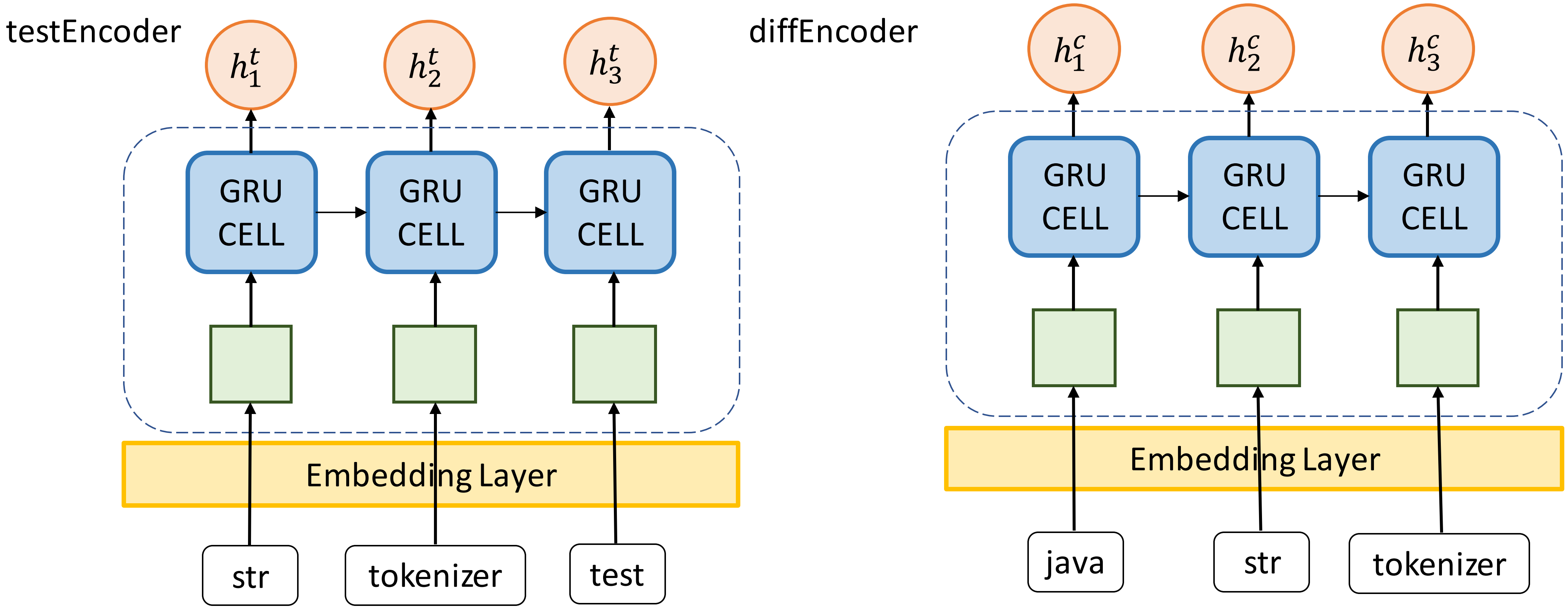
  - ABS
    - map parts of the changed lines of code to general operators

if (pos > 0) return true; → ConditionalBoundaryMutator | BooleanReturnValsMutator

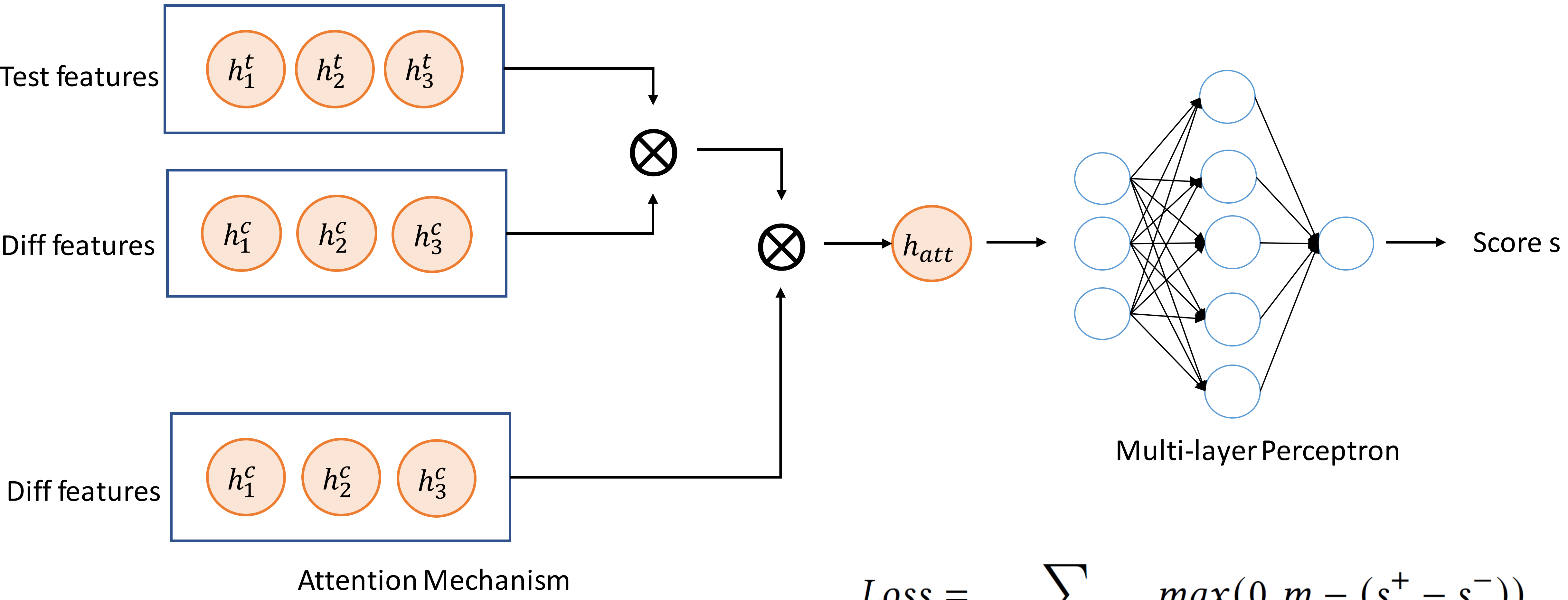
Feature Representation Learning

- Two Bi-drectional Gated Recurrent Unit encoders:
  - diffEncoder: encodes features from the code diff
  - testEncoder: encodes features from the tests

Feature Representation Learning

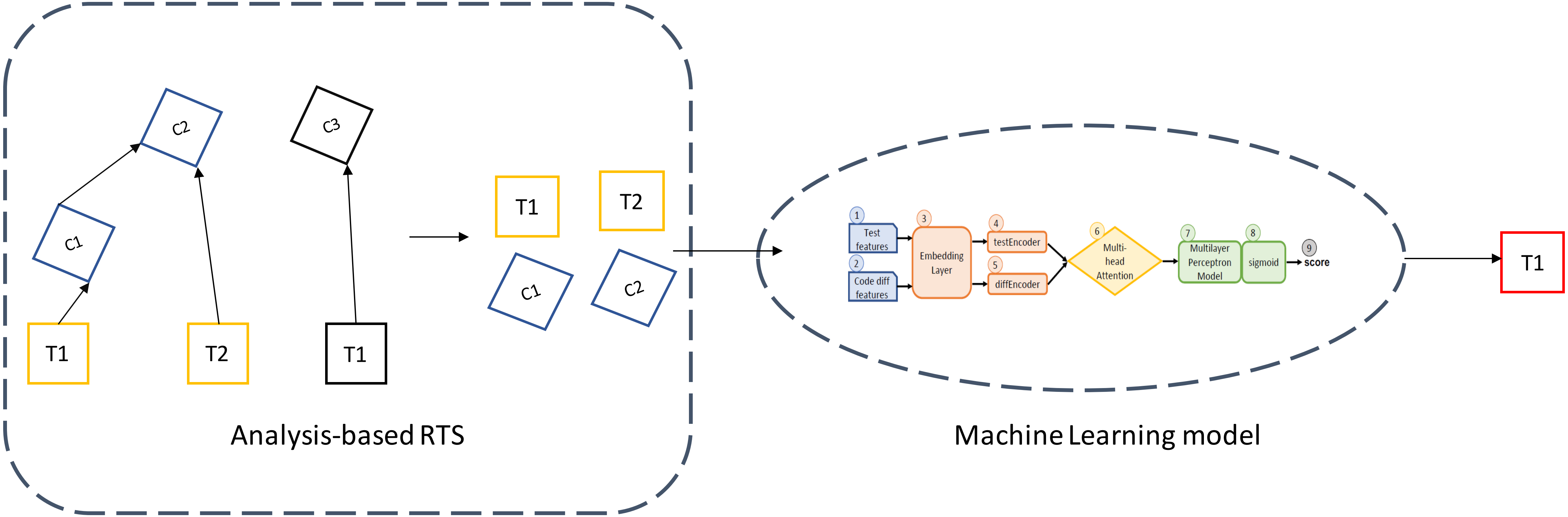


Feature Representation Learning



$$Loss = \sum_{\langle c, t^+, t^- \rangle \in D} max(0, m - (s^+ - s^-))$$

Combining Analysis-based RTS and ML-based RTS



Outline

- Technique
  - Overview
  - Training Dataset from Mutans
  - Feature Extraction
  - Model Design
  - Combining Analysis-based RTS and ML-based RTS
- Empirical Study
  - Baselines
  - Dataset
  - Experiments setup
  - Results and findings

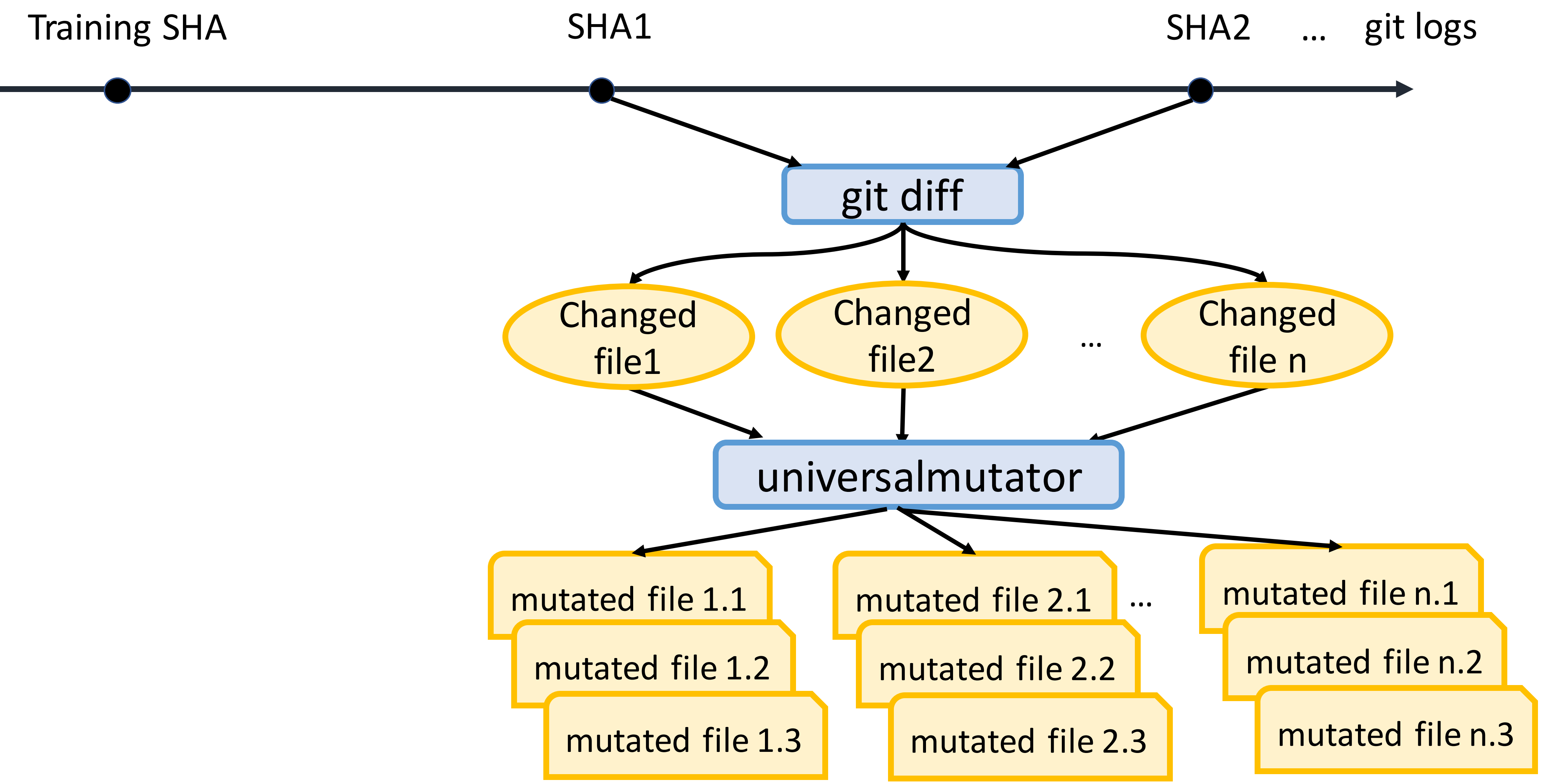
Baselines

- Information Retrieval-based RTS model: BM25
    - Rank tests based on their relevance to code changes by treating each test file as a document and the code changes as a query
    - The ranking is based on assigned scores to each test
- EALRTS
    - Features from a dependency graph extracted by STARTS and the project's Git commit history
    - Random Forest machine learning model

Dataset

- Training data
  - 10 open-source Java projects
  - Select a training commit without failures and can be run by Analysis-based RTS (Ekstazi, STARTS)
- Evaluation dataset:
  - The evaluation dataset for each project are collected by leveraging its real code evolution
  - Select commits that are after the training commit for evaluation
  - Failing tests are introduced by mutating the code at the evaluation commits

Evaluation Dataset Construction

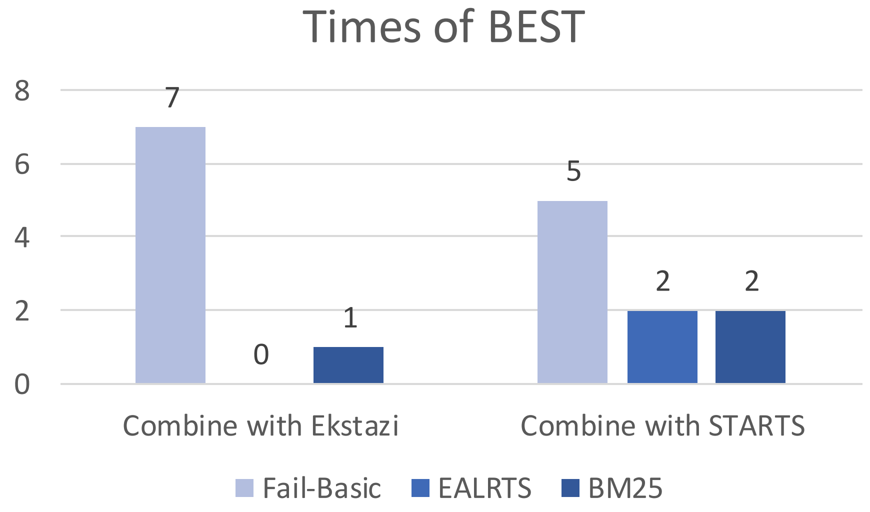


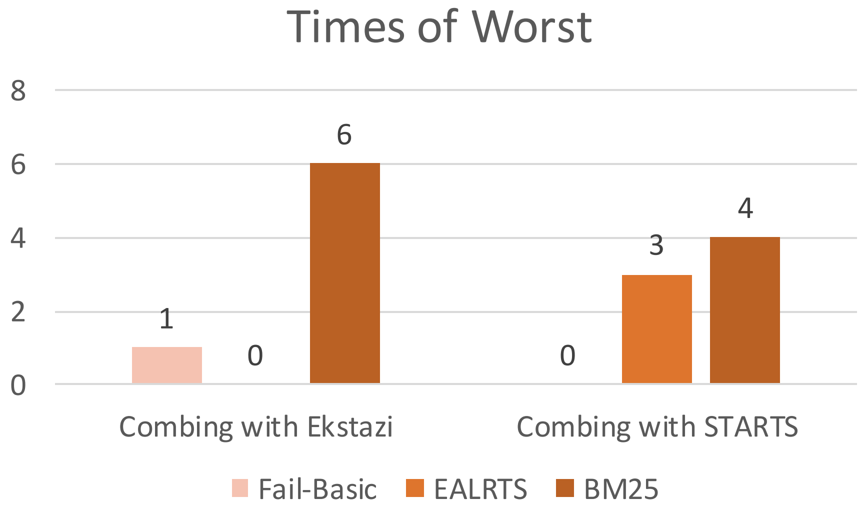
Experiments Setup

- Evaluation Setup
  - Run models to select the failing tests from the tests selected by analysis-based RTS tool
  - Compute the percentage of tests that the model would need to select to run all failing tests
  - Measure the overhead of combining Analysis-based RTS tool with ML-based RTS models
- Metrics
  - **Best safe selection rate:**
    - the largest selection rate needed to select all failing tests across all pairs of mutants and commits in each project (ensuring safe selection)
  - **End-to-end testing time:**
    - summation of the time to select tests and the time for running the selected tests such that all the failing tests are included in the selected test set

Results (1/3)

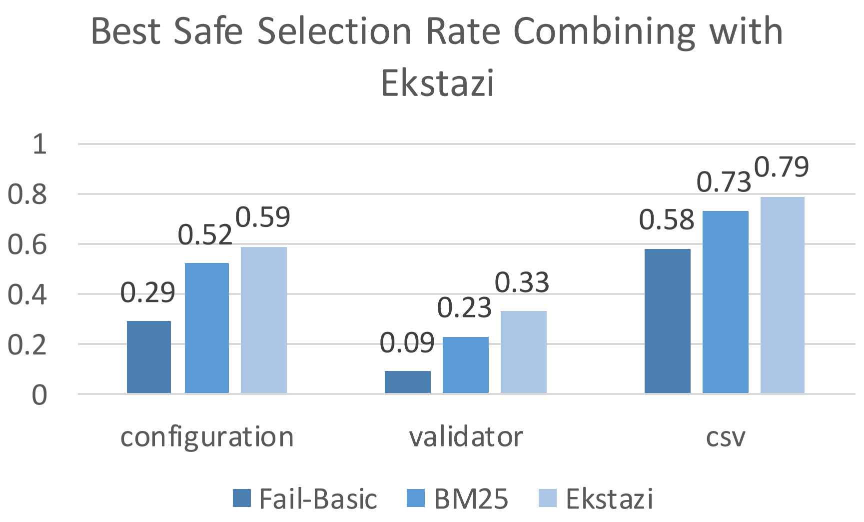
- There is no single ML-based RTS model that consistently outperforms or underperforms the rest
- Fail-Basic is the model with the highest number of **BEST**, better than all other ML-based RTS models and baselines when combining with analysis-based RTS models

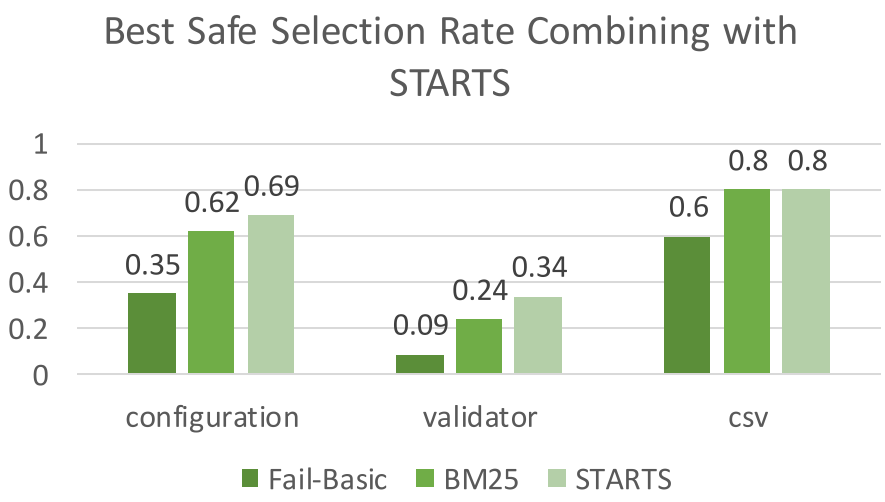




Results (2/3)

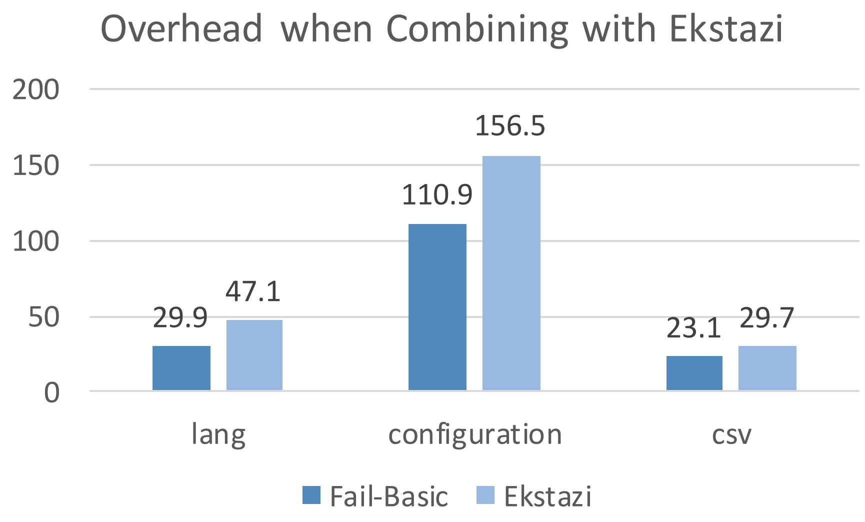
- Combining ML-based RTS with analysis-based RTS improves the precision of Ekstazi and STARTS

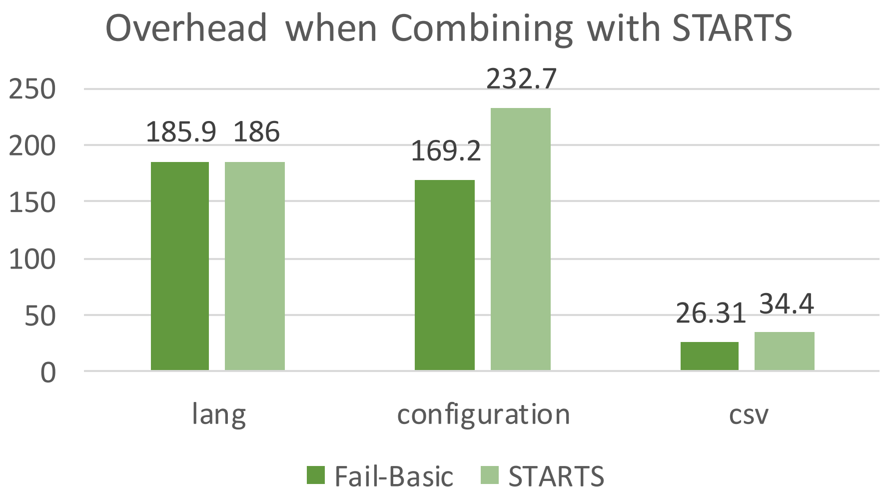




Results (4/4)

- ML-based RTS models combined with an analysis-based RTS technique for the most part outperform the corresponding analysis-based RTS technique





Conclusion

- Combining ML-based RTS and Analysis-based RTS improves the precision of analysis-based RTS
    - Our best ML-based RTS model reduces the average selection rate of two analysis-based RTS techniques, Ekstazi and STARTS by 25.34% and 21.44%
- Combining ML-based RTS models with an analysis-based RTS technique results in reduced end-to-end testing time
    - Overhead of the ML-based RTS models are small compared with the analysis-based RTS techniques
    - Substantial time savings result from running fewer tests than what the analysis-based RTS technique selects

Thank you!

Jiyang Zhang <jiyang.zhang@utexas.edu>