Ensemble Approaches for Automatic Program Repair

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Background

Automatic Program Repair autonomously offers fixes to bugs/errors

- Through generation of patches
- Test-suite based

Difficult problem, even with assumptions-

- Bugs approximately correct,
- Fault localization, contextual information

```
    public static int bitcount(int n) {
        int count = 0;
        while (n != 0) {
-           n = (n ^ (n - 1));
+           n = (n & (n - 1));
            count++;
        }
        return count;
    }
```

QuixBugs: BITCOUNT.java

Background

Data

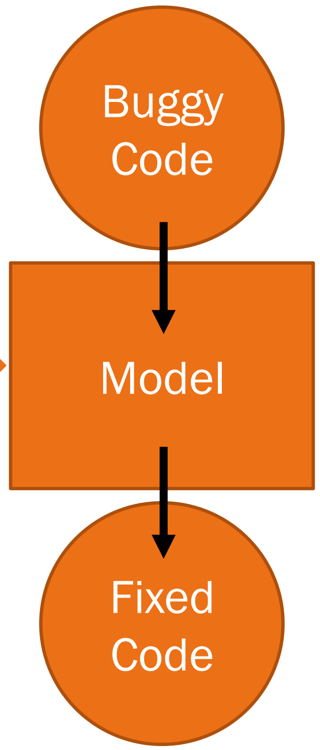
- Collection/Scraping
- Fault Localization
- Test Cases

Training

- Model Design
- Training
- Ensemble

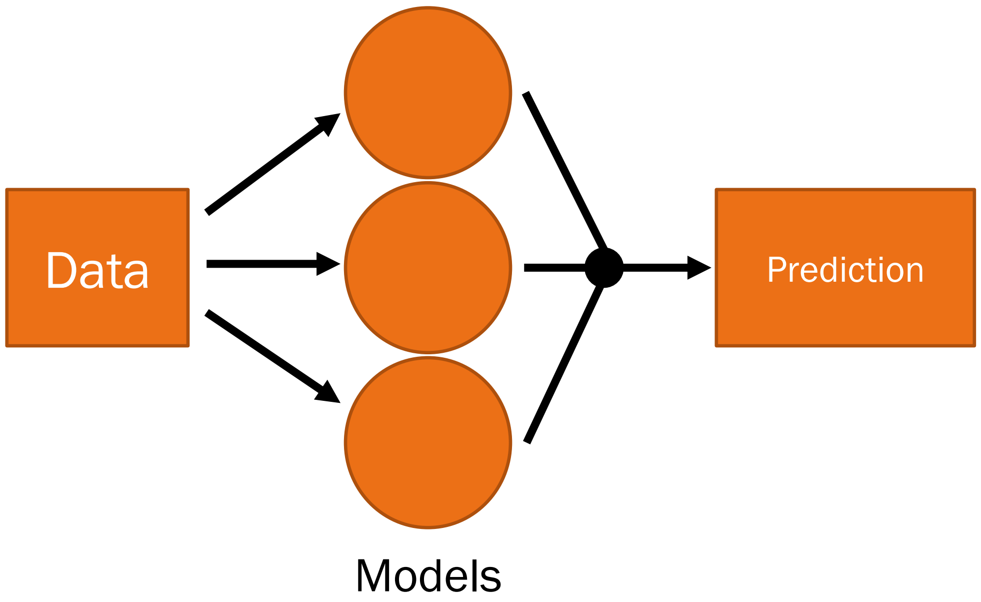
Inference

- <u>Patch Generation</u>
- Validation
- Time Concerns



Background

- Development of learning-based methods
  - Use neural networks and deep learning
  - Incremental improvements led to state-of-the art methodology
- Training: Learn/mimic fixing code
  - Ensemble improves by “wisdom of the crowd”

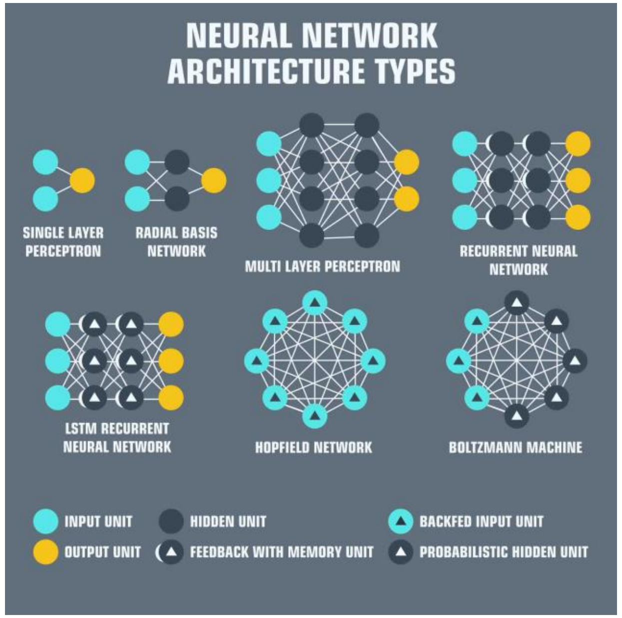


Motivation:

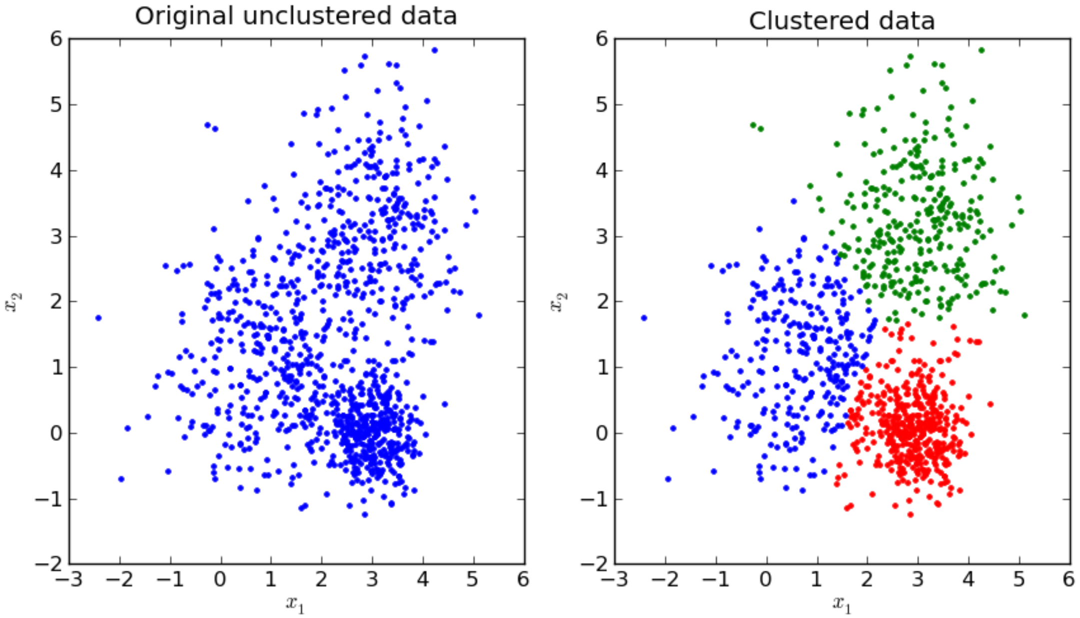
How can we characterize different clustering methods for training ensemble models?

Ensemble in Neural Networks:

1. Net Type   2. Data Clustering   3/4. Hyperparameters and Initial Weights



https://www.mygreatlearning.com/blog/cnn-model-architectures-and-applications/



https://towardsdatascience.com/k-means-data-clustering-bce3335d2203

Methods: Clustering

Fair comparison: Each method partitioned set into 4 clusters

- Addition of final "insertion" model to each method

Random Partitioning:

- Training and Evaluation evenly split into four "clusters"

Type Categorization:

- Training and Evaluation split via human-decided categories
- Statement, Return, If/While, Mixed

Machine Clustering:

- Use algorithms on machine understanding

Methods: Clustering

```
n = (n ^ (n - 1));  →  n = (n & (n - 1));
```

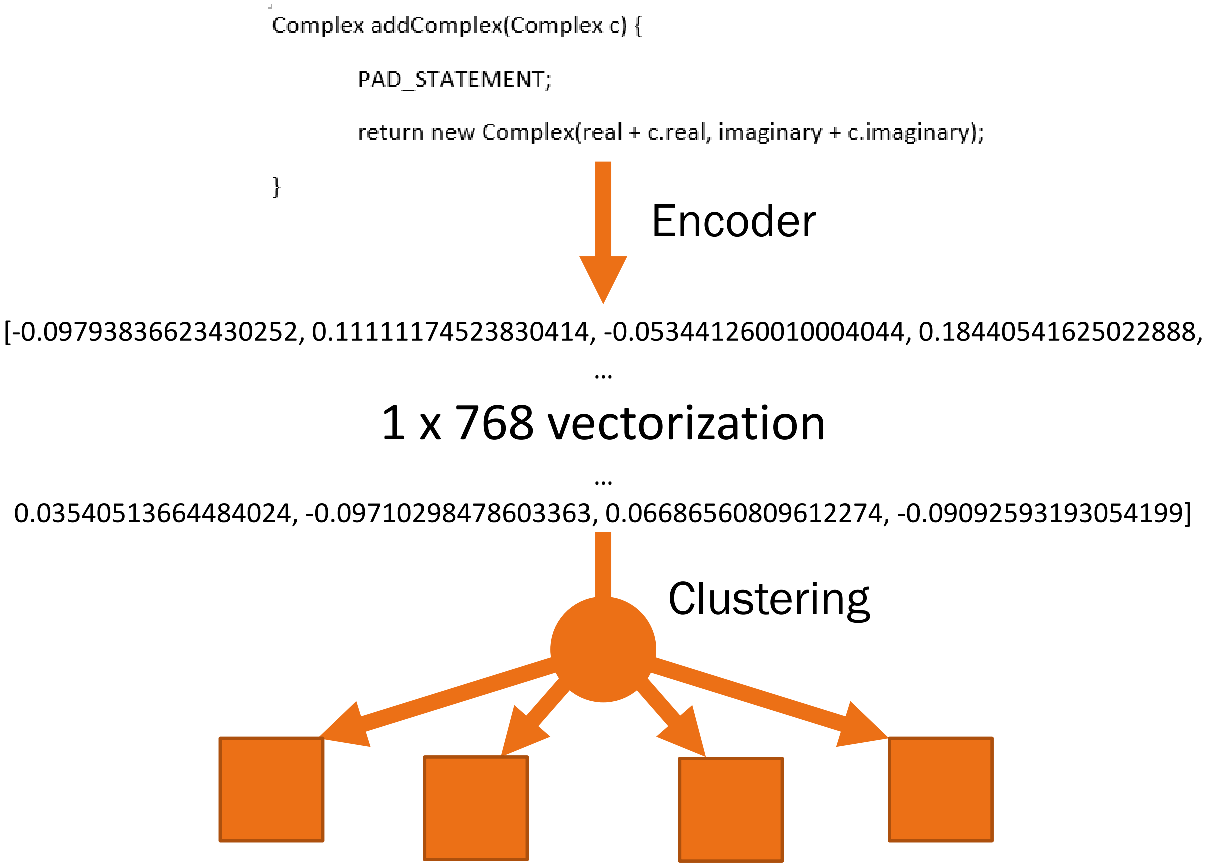
a) Statement Buggy Line Type

```
while (true) {  →  while (!queue.isEmpty()) {
```

b) If/While Buggy Line Type

```
return binsearch(arr, x, mid, end);
        → return binsearch(arr, x, mid+1, end);
```

c) Return Buggy Line Type



Methods: Training Data

Training data collected from GitHub

- Scrape source code from public projects
- Commits selected via messages: “fix”, “patch”
- JavaParser transforms into AST

450,000 data points in Training

50,000 data points in Evaluation

```
Complex addComplex(Complex c) {
        PAD_STATEMENT;
        return new Complex(real + c.real, imaginary + c.imaginary);
}
```

Parser


```
{'id': 1, 'mappings': {'imaginary': 'VAR_1', 'real': 'VAR_2', 'PAD_STATEMENT': 'VAR_3', 'Complex': 'TYPE_1', 'complexAdd': 'METHOD_1', 'NaN': 'VAR_<UNK>', '
isNaN': 'VAR_<UNK>'}, 'nodes': ['MethodDeclaration', 'ReferenceType', 'Complex', 'complexAdd', 'FormalParameter', 'ReferenceType', 'Complex', 'c', 'Statemen
tExpression', 'MemberReference', 'PAD_STATEMENT', 'ReturnStatement', 'ClassCreator', 'ReferenceType', 'Complex', 'BinaryOperation', 'MemberReference', 'real
', '+', 'MemberReference', 'c', 'real', 'BinaryOperation', 'MemberReference', 'imaginary', '+', 'MemberReference', 'c', 'imaginary'], 'edges': [[0, 1, 'retu
rn_type'], [1, 2, 'name'], [0, 3, 'name'], [0, 4, 'parameters'], [4, 5, 'type'], [5, 6, 'name'], [4, 7, 'name'], [0, 8, 'body'], [8, 9, 'expression'], [9, 1
0, 'member'], [0, 11, 'body'], [11, 12, 'expression'], [12, 13, 'type'], [13, 14, 'name'], [12, 15, 'arguments'], [15, 16, 'operandl'], [16, 17, 'member'],
[15, 18, 'operator'], [15, 19, 'operandr'], [19, 20, 'qualifier'], [19, 21, 'member'], [12, 22, 'arguments'], [22, 23, 'operandl'], [23, 24, 'member'], [22,
 25, 'operator'], [22, 26, 'operandr'], [26, 27, 'qualifier'], [26, 28, 'member']], 'rem_roots': [8], 'add_roots': [{'nodes': ['IfStatement', 'BinaryOperati
on', 'MemberReference', 'isNaN', '||', 'MemberReference', 'c', 'isNaN', 'ReturnStatement', 'MemberReference', 'NaN'], 'edges': [[0, 1, 'condition'], [1, 2,
'operandl'], [2, 3, 'member'], [1, 4, 'operator'], [1, 5, 'operandr'], [5, 6, 'qualifier'], [5, 7, 'member'], [0, 8, 'then_statement'], [8, 9, 'expression']
, [9, 10, 'member']]}]}
```

Methods: Training

Training order randomized: Cycle through all data = epoch

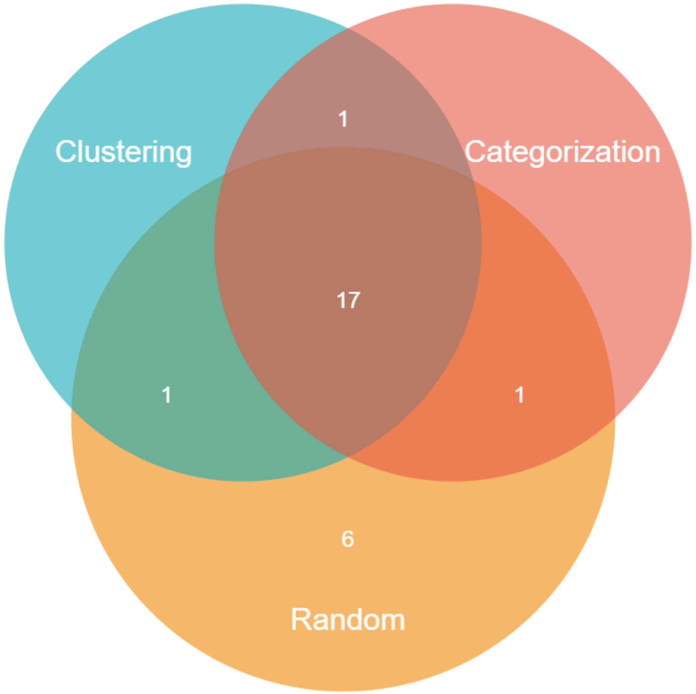
Training length approximately based on number of data points in cluster

Random Partitioning	Type Categorization				Machine Clustering*			
All Clusters	Return	If/While	Statement	Mixed	0	1	2	3
113,000	48,000	47,000	252,000	106,000	136,000	92,000	67,00	46,000

Random Partitioning	Type Categorization			Machine Clustering*		
All Clusters	Return & If/While	Statement	Mixed	0/1	2	3
10 Epochs	20 Epochs	15 Epochs	10 Epochs	10 Epochs	15 Epochs	20 Epochs

Results: Overview

Random Partitioning	Type Categorization	Machine Clustering	State-of-the Art
25	19	19*	26



Model trained on randomly partitioned data performed best

Generate very similar patches

- Model type and data the same

Differences in Generation-

- Differing Parameters
- Patch Ranking

Results: Generation

QuixBug: LEVENSHTEIN

Original

- return 1 + levenshtein(source.substring(1), target.substring(1))

Random

- return 0 + levenshtein(source.substring(1), target.substring(1))

Cluster

- return levenshtein(source.substring(1), target.substring(1))

Category

- return 1 * levenshtein(source.substring(1), target.substring(1))

Results: Generation

QuixBug: FIND_IN_SORTED

Original

- Return binsearch(arr, x, mid, end)

Random

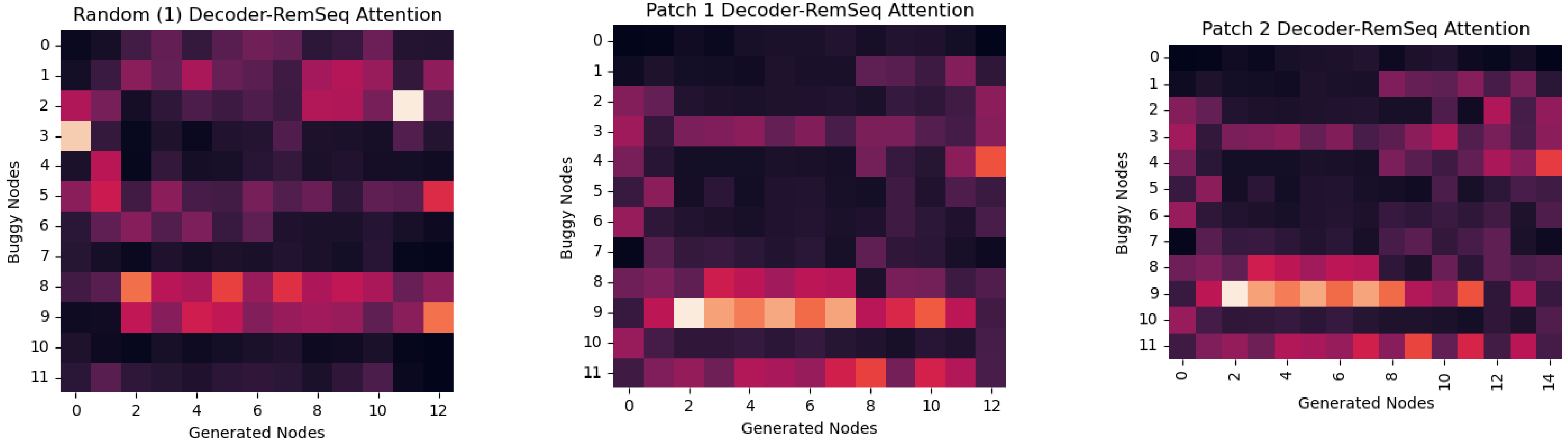
- return binsearch(arr, x, mid + 1, end)

Category/Cluster

- (insert) mid++

Results: Attention

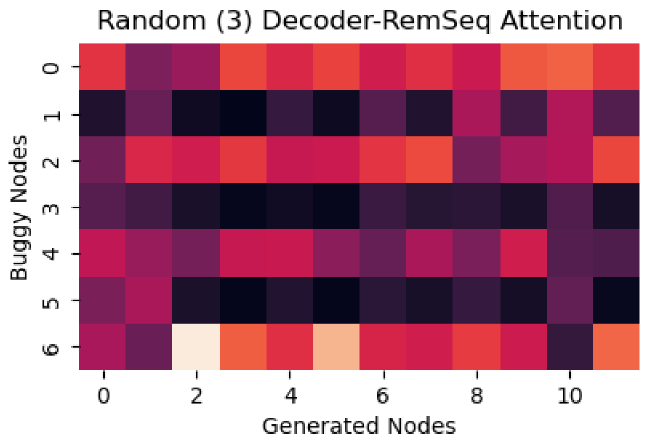
Differences in Attention:

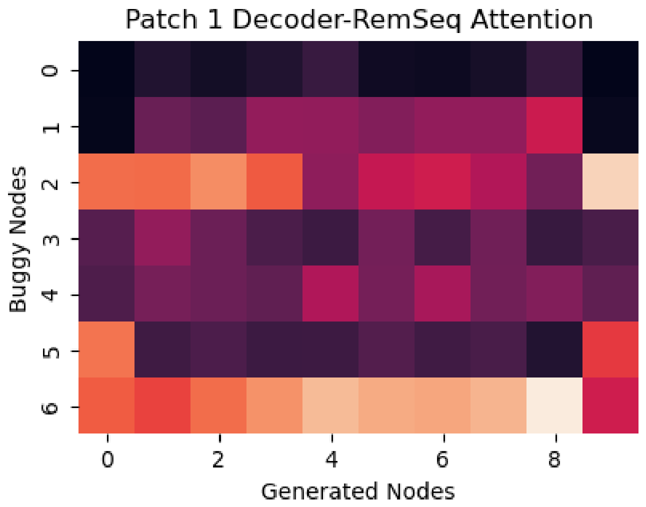


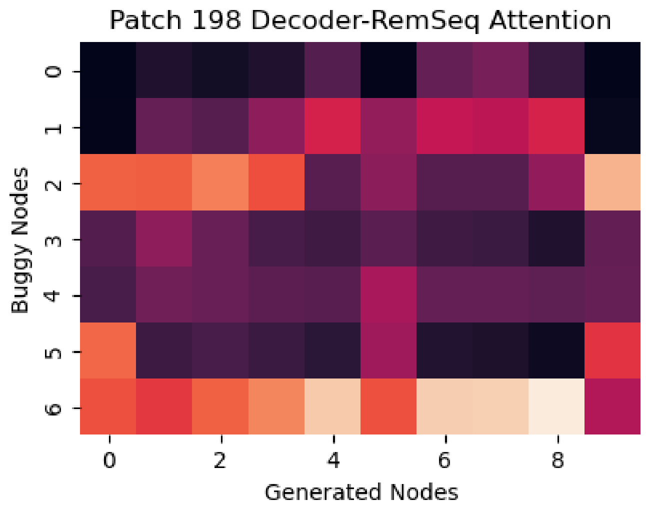
QuixBugs bug NEXT_PALINDROME

Results: Attention

Differences in Attention:







QuixBugs bug KTH

Results: Categorization Efficiency

"Ablation Study": Compare index of perfect match

- Ranking with all models/only specific category

QuixBugs ID:	1	2	3	6	9	11	12	14
Category	StateEx	If	Mixed	If	Return	StateEx	Return	If
Class Rank	0	669	10	27	N/A	5	N/A	6
All Rank	0	1187	54	10	484	25	70	13

QuixBugs ID:	17	20	23	24	27	29	33
Category	Return	StateEx	StateEx	If	If	StateEx	Mixed
Class Rank	N/A	0	3	1	0	192	N/A
All Rank	2834	0	15	3	0	881	109

Conclusions

Ensemble trained on randomly partitioned data performed best:

- Machine Clustering ~ Human Categorization

General vs Specific domain knowledge

Class imbalances

Model convergence and metrics

Extensions:

- Apply to wider variety of model types
- Additional ensemble methods

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