Thinking Like a Developer?

Comparing the Attention of Humans with Neural Models of Code

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Executive Summary

Direct comparison:

Developers vs. neural models of code

- Humans still (clearly) outperform models
- Partial agreement on what code to focus on
- Models ignore some tokens that developers deem important
- Human-model agreement correlates with prediction accuracy

Should try harder to mimic humans

Neural Software Analysis

Learning developer tools from large software corpora

Source code
Execution traces
Documentation
Bug reports
etc.

→ **Machine Learning** → **Predictive tool**

Neural Software Analysis

Learning developer tools from large software corpora

Source code
Execution traces
Documentation
Bug reports
etc.

→ **Machine Learning** →

New code, execution, etc.

Predictive tool

Information useful for developers

Common Tasks

Type prediction

Bug detection

Code summarization

Code completion

Program repair

Common Tasks

Type prediction

Bug detection

Code summarization

Code completion

Program repair

Humans could also do it.

$\rightarrow$ Added value: Automation

Understanding Models of Code

- **Emphasis of most papers: Accuracy**
- **Mostly unclear:**
  What do these models actually learn?
  - Intellectually unsatisfying
  - Risk of coincidental accuracy

Developers vs. Neural Models

Do neural models reason about code similarly to human developers?

- If yes: Good news
- If no: Should mimic developers more closely

Methodology

Idea: Compare Humans & Models

Developers

vs.

Machine Learning

Neural models of code

- Same task
- Same code examples
- Measure attention and effectiveness

Task 1: Code Summarization

```
{
  if (!prepared(state)) {
    return state.setStatus(MovementStatus.PREPPING);
  } else if (state.getStatus() == MovementStatus.PREPPING) {
    state.setStatus(MovementStatus.WAITING);
  }
  if (state.getStatus() == MovementStatus.WAITING) {
    state.setStatus(MovementStatus.RUNNING);
  }
  return state;
}
```

Input: Method body → **Output: Method name**

`updateState`

Dataset: 250 methods from 10 Java projects *

* *A Convolutional Attention Network for Extreme Summarization of Source Code*, ICML'16

Task 2: Program Repair

```
public double sqrt(double x, double epsilon) {
  double approx = x / 2d;
  while (Math.abs(x - approx) > epsilon) {
    approx = 0.5d * (approx + x / approx);
  }
  return approx;
}
```

Input: Method with a buggy line

↓

Output: Fixed line

```
while (Math.abs(x - approx * approx) > epsilon) {
```

Dataset: 16 bugs from QuixBugs (Java) *

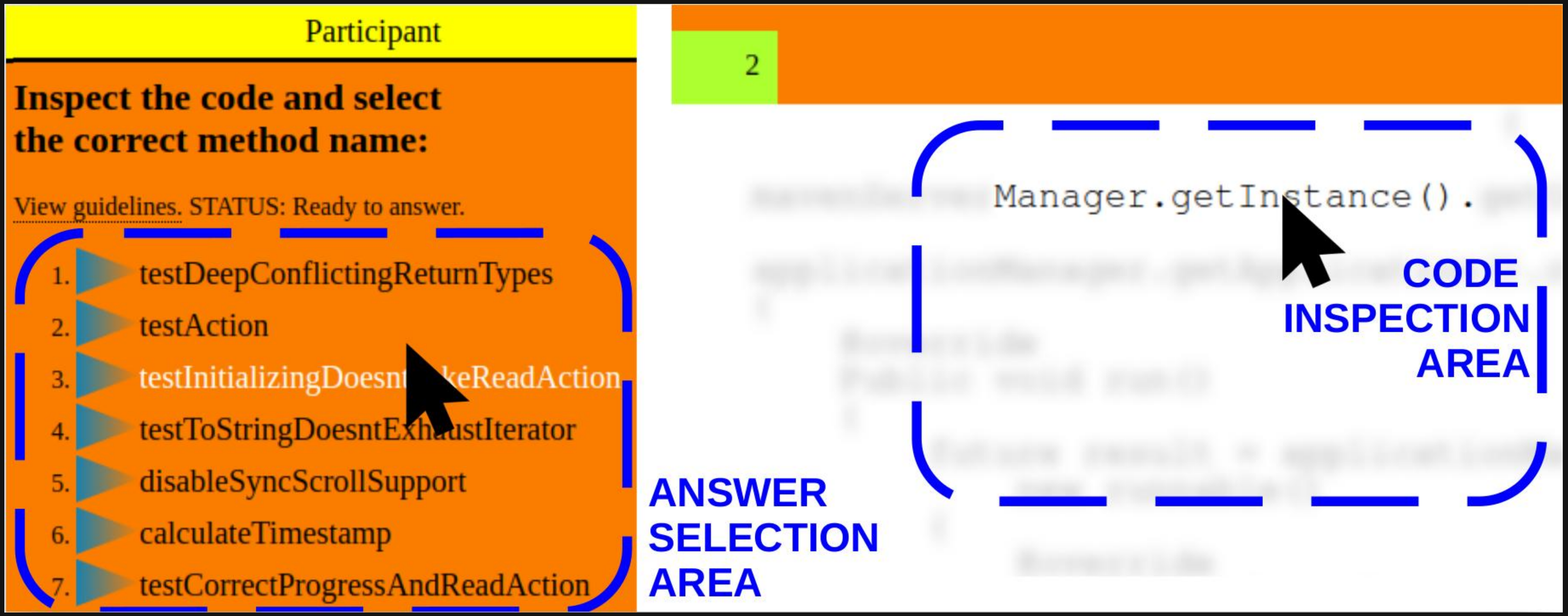
* *QuixBugs: A Multi-Lingual Program Repair Benchmark Set Based on the Quixey Challenge*, SPLASH'17 (Companion)

Capturing Human Attention

- **Goal: Track human attention while performing the task**
- **Approach: Unbluring-based web interface**
  - Initially, all code blurred
  - Moving mouse/cursor temporarily unblurs tokens

Capturing Human Attention

Task 1: Code Summarization

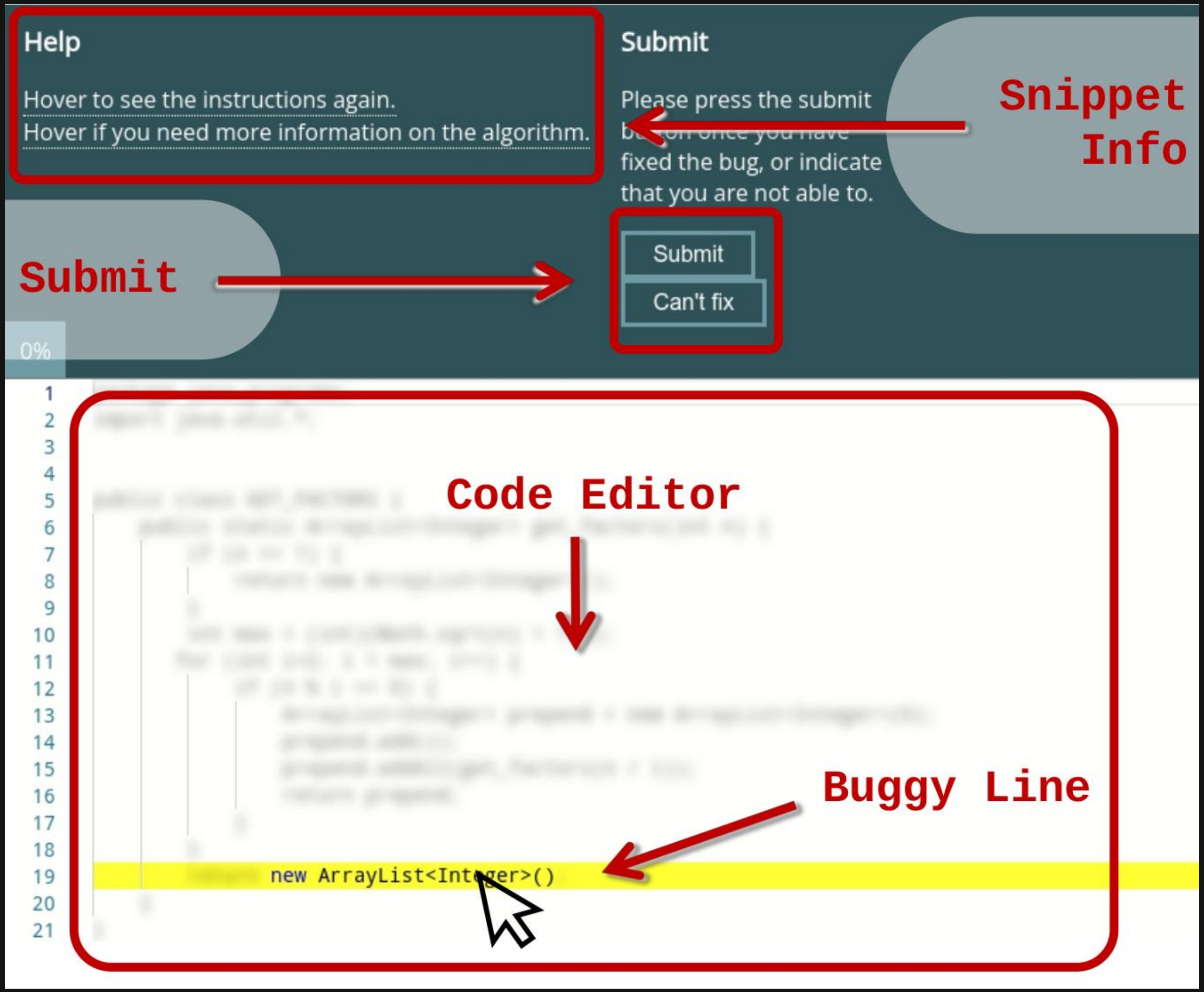


Capturing Human Attention

- **91 participants**: Undergrads, graduate students, crowd workers
- **1,508 human attention records**
- 5+ records for each of 250 methods
- On average per record:
  1,271 mouse-token events

Capturing Human Attention

Task 2: Program Repair

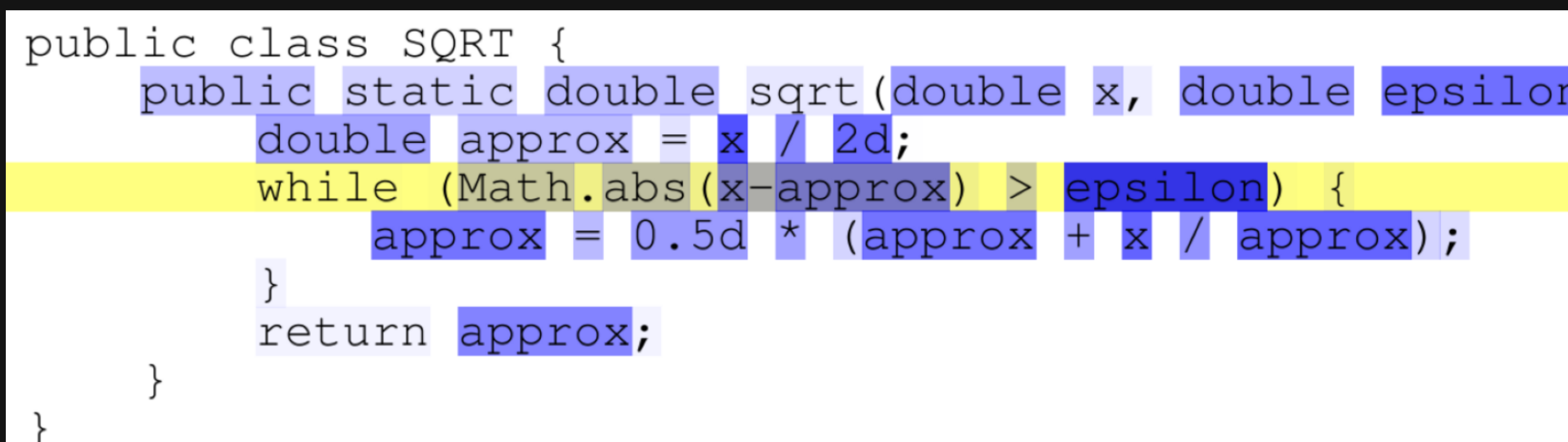


Capturing Human Attention

- **27 participants**: Software engineers, graduate students
- **98 bug fixing records**
- 5–7 records for each of 16 bugs
- On average per record: 983 unblur events and 13 edit events

Capturing Human Attention

Summarize fine-grained attention record into attention map:



Model Attention

Task 1: Code summarization

- Convolutional sequence-to-sequence (CNN)
  A Convolutional Attention Network for Extreme Summarization of Source Code, ICML'16
- Transformer-based, sequence-to-sequence model
  A Transformer-based Approach for Source Code Summarization, ACL'20
- Both models:

  Regular attention and copy attention

Model Attention

Task 2: Program repair

- LSTM-based, sequence-to-sequence: SequenceR
  SequenceR: Sequence-to-Sequence Learning for End-to-End Program Repair, TSE'21
  - Regular attention and copy attention
- AST-based transformer: Recoder
  A Syntax-Guided Edit Decoder for Neural Program Repair, FSE'21
  - Regular attention only

Results

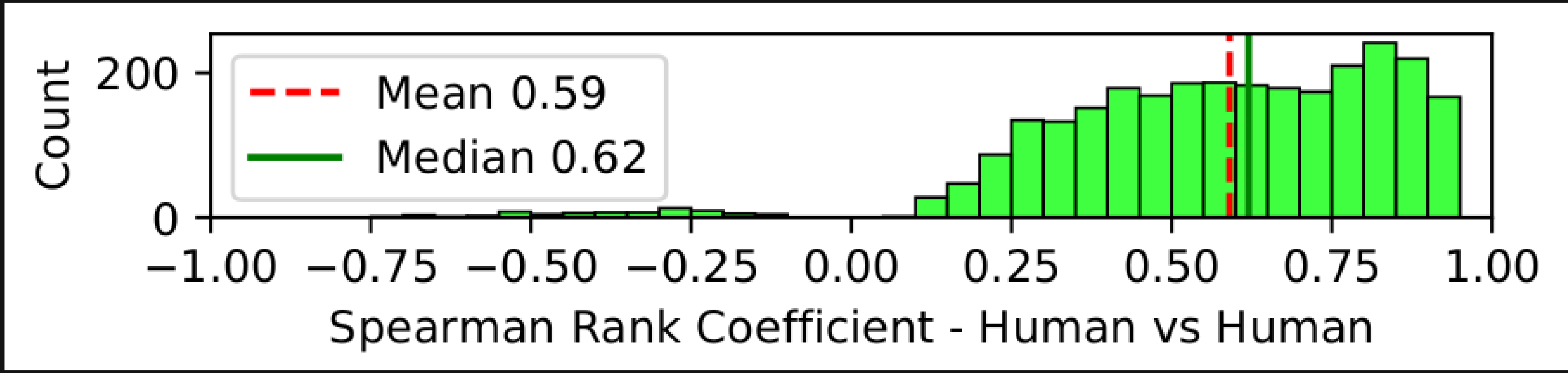
Human-Model Agreement

Do developers and models focus on the same tokens?

- Given for each code example
  - Human attention vector $\vec{h}$
  - Model attention vector $\vec{m}$
- Measure agreement between them
  - Spearman rank correlation: $\frac{cov(rg_{\vec{h}}, rg_{\vec{m}})}{\sigma_{rg_{\vec{h}}}, \sigma_{rg_{\vec{m}}}}$

Results: Summarization

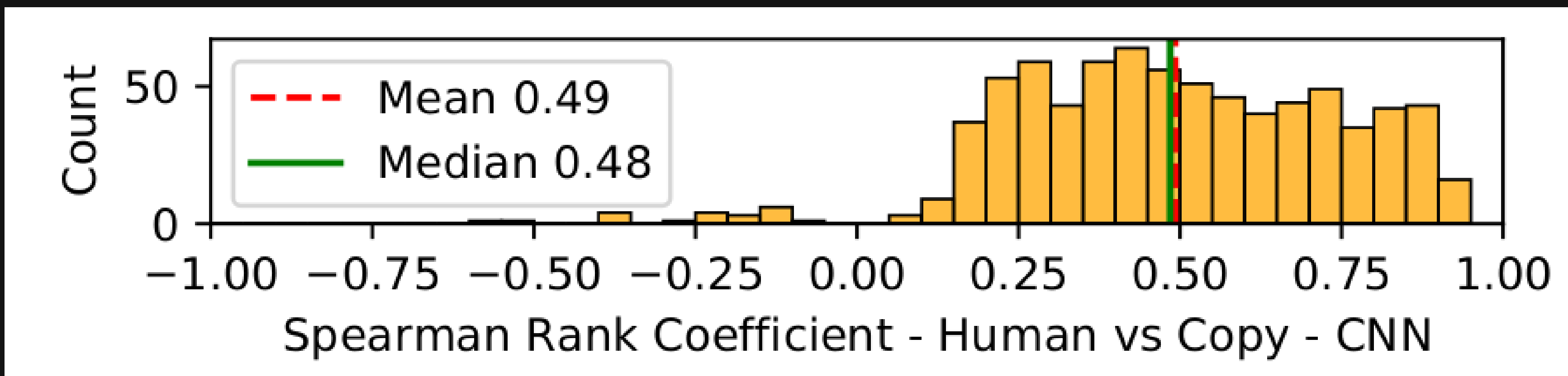
Human-human agreement:

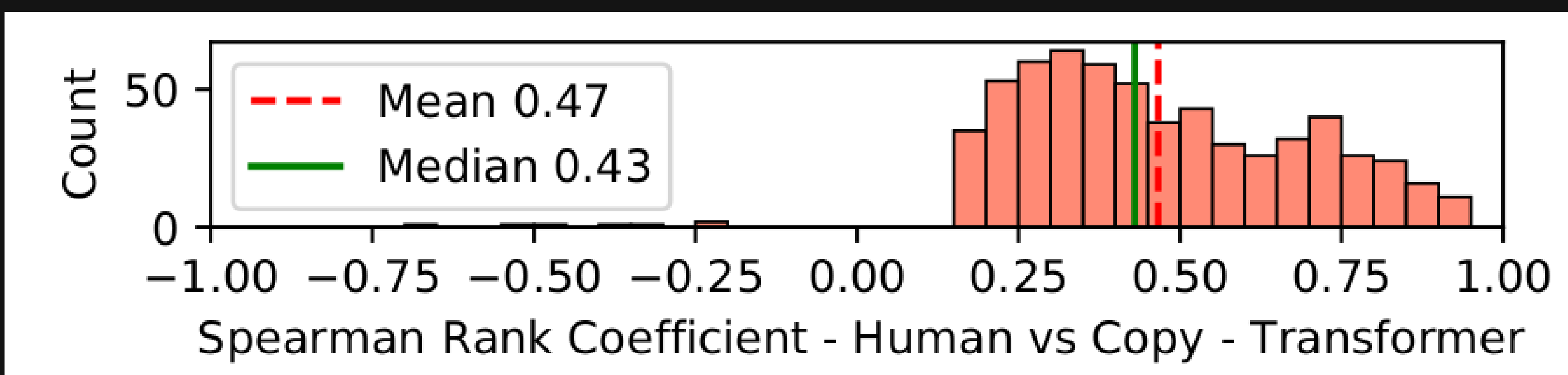


Developers mostly agree on what code matters most

Results: Summarization

Human vs. copy attention:

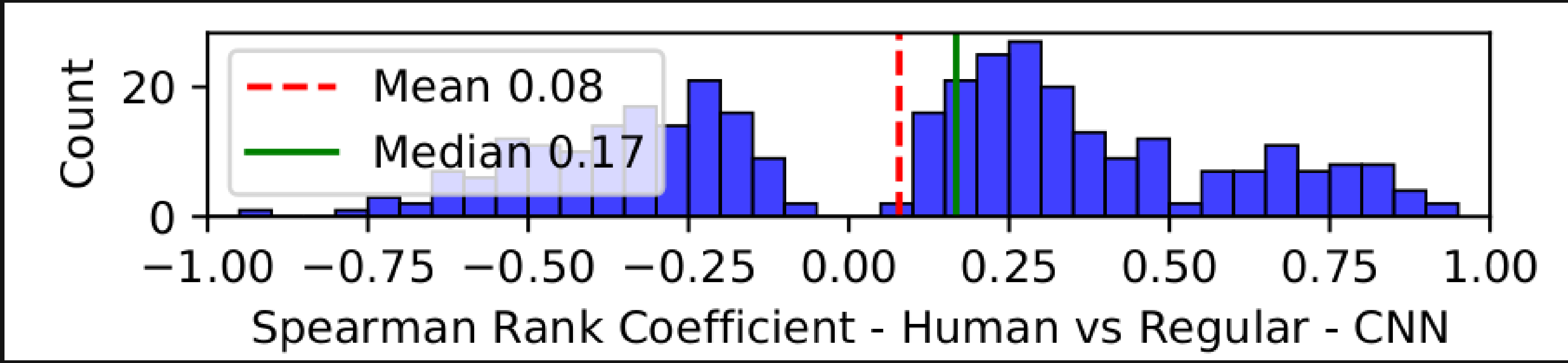


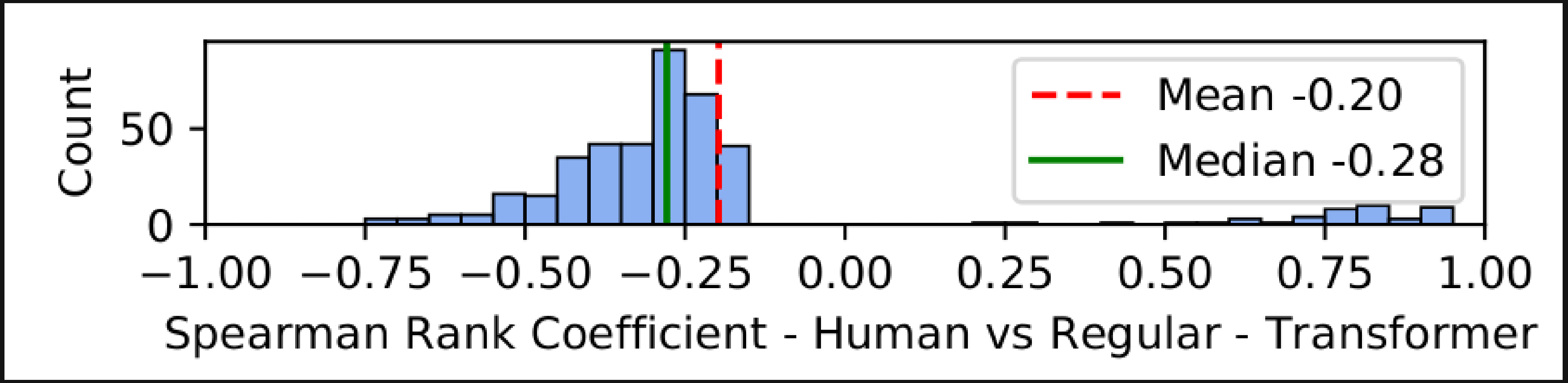


Empirical justification for copy attention

Results: Summarization

Humans vs. regular attention:

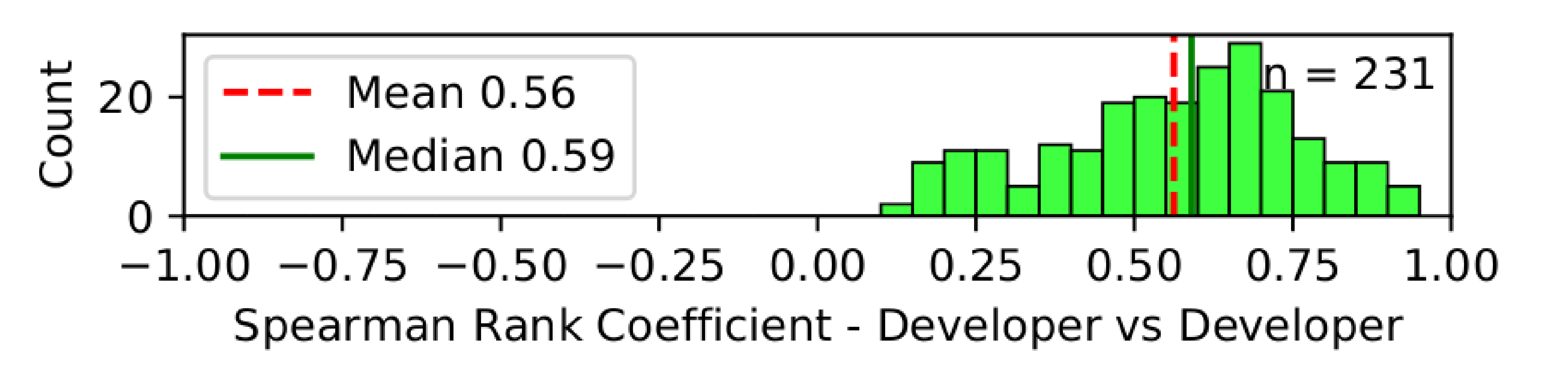




Lots of room for improvement!

Results: Program Repair

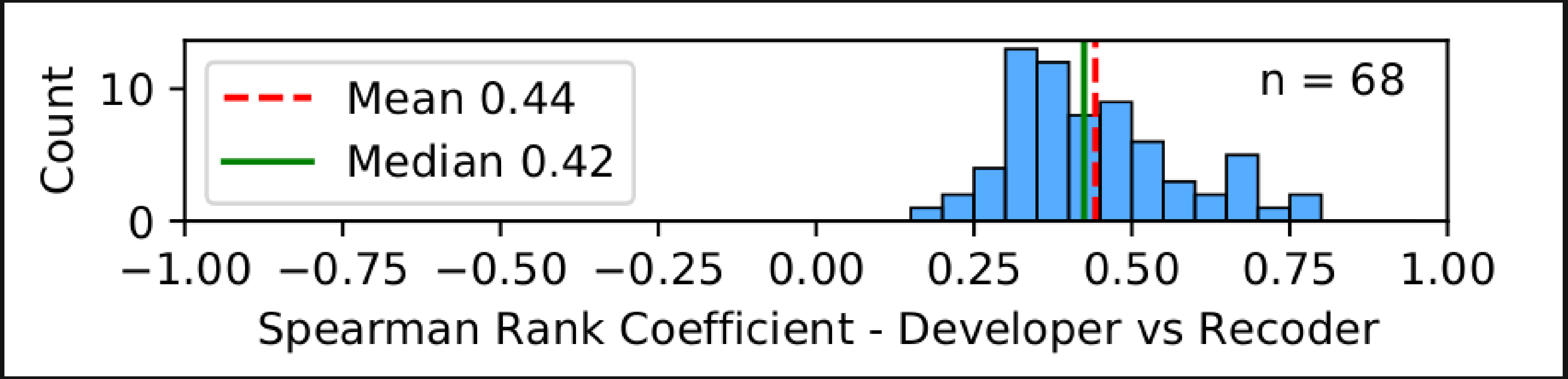
Human-human agreement:

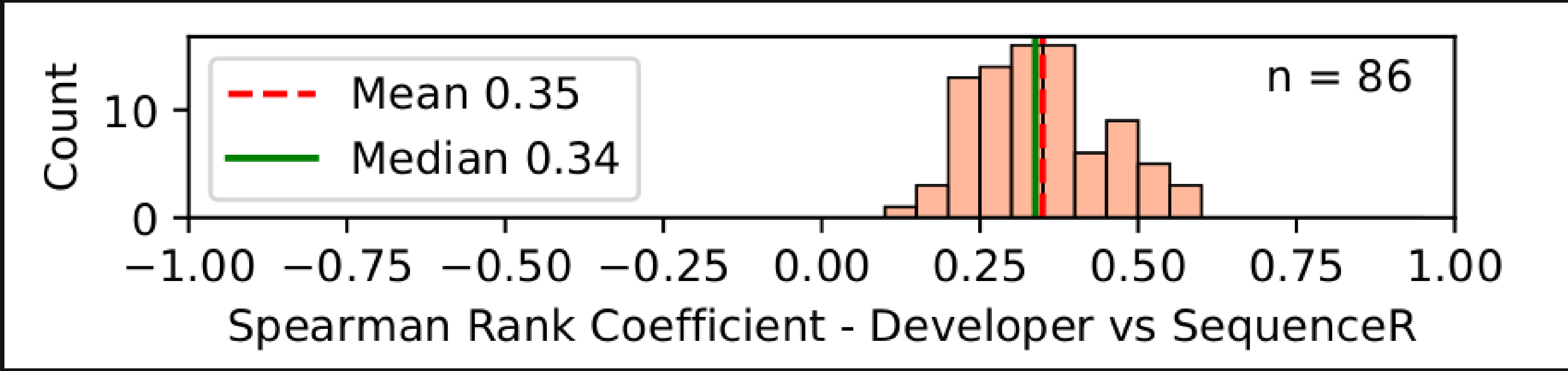


Developers mostly agree on what code matters most

Results: Program Repair

Human-model agreement:





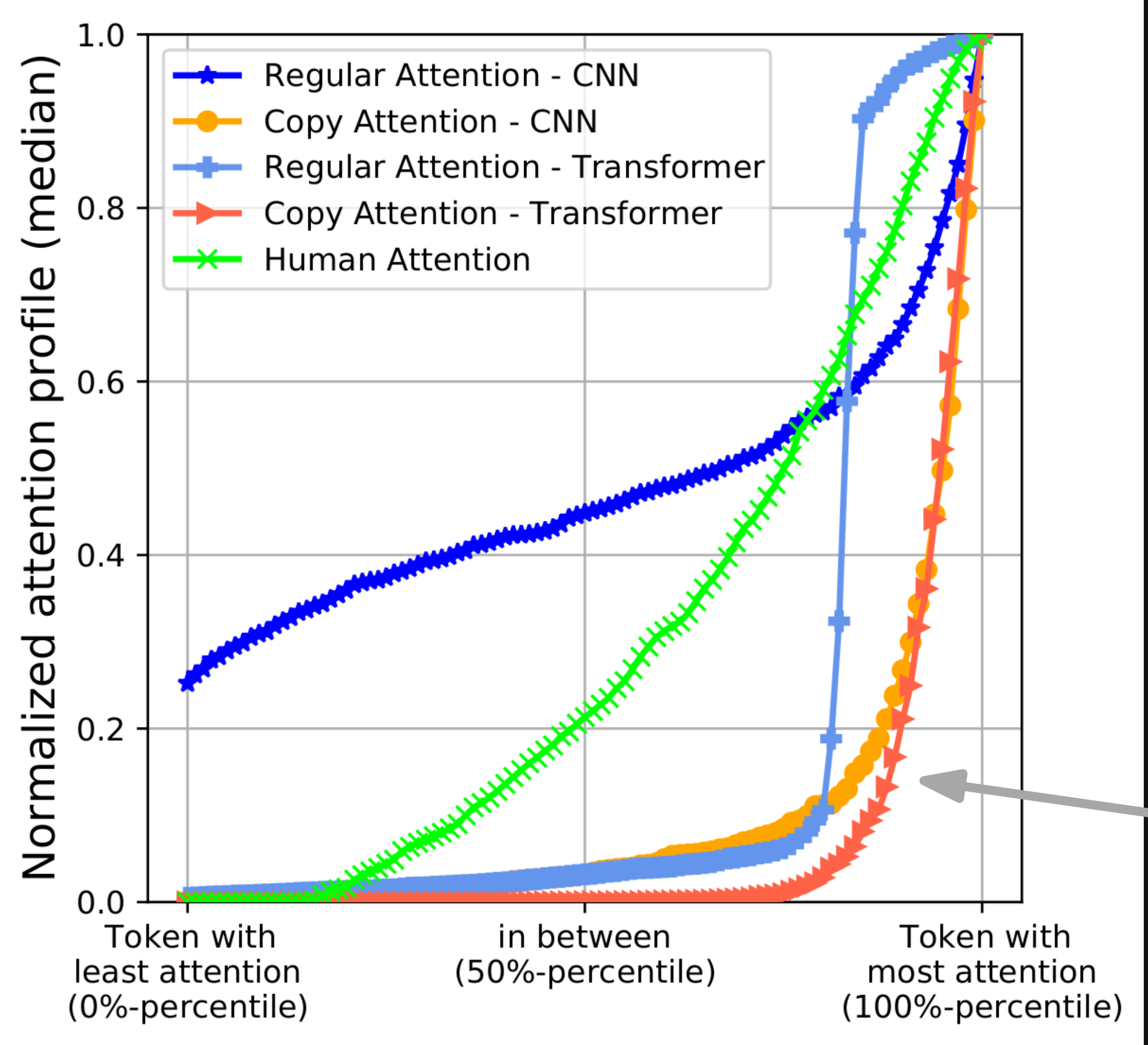
Some room for improvement

Divided vs. Selective Attention

How to distribute attention over the given code?

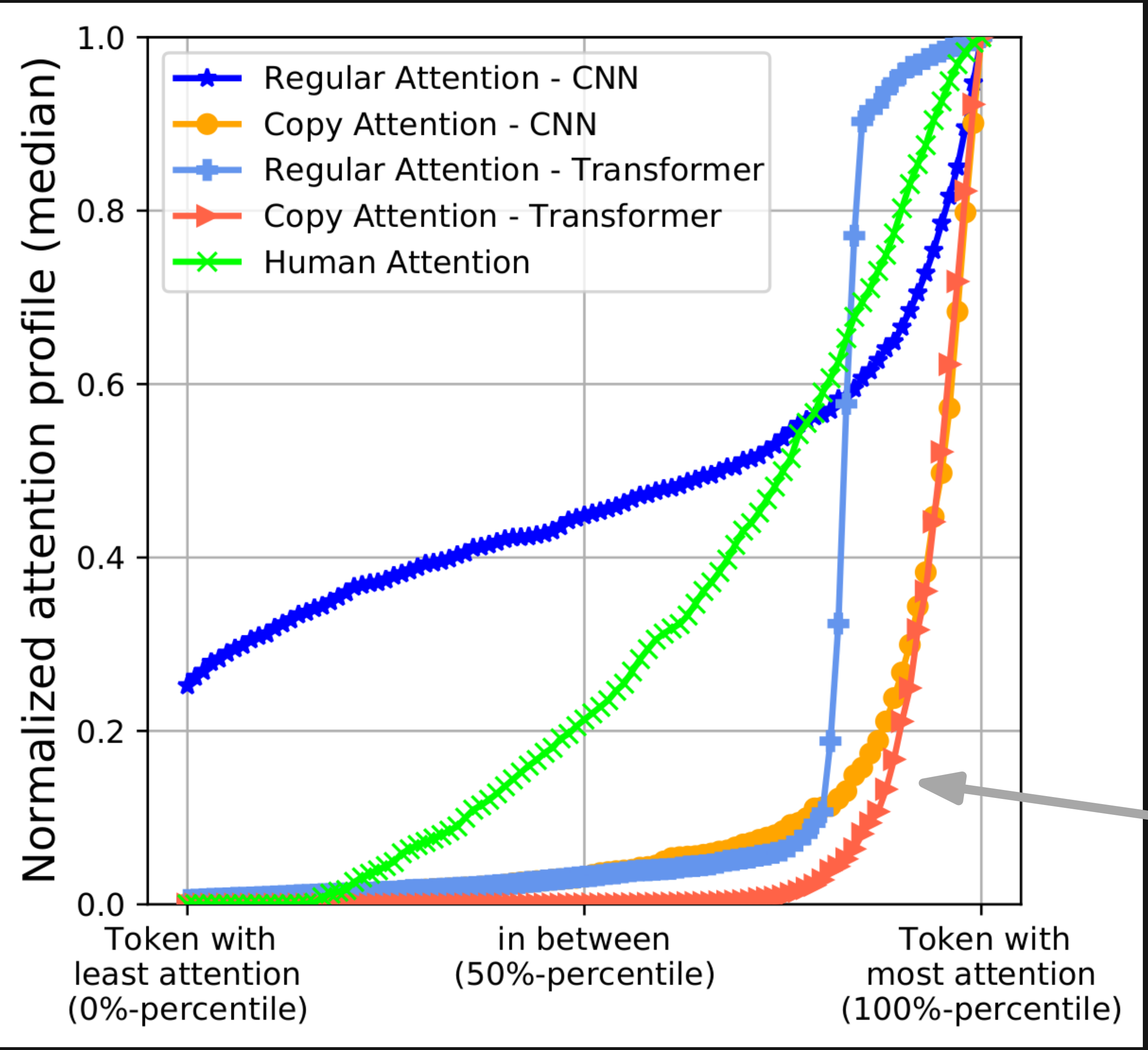
- One extreme: Equally distribute over all tokens
- Other extreme: Focus on a few tokens only

Results: Summarization



More dented curve: Focus on few tokens only

Results: Summarization



No model closely matches developers

Overspecial-ization to a few tokens

More dented curve: Focus on few tokens only

Results: Program Repair

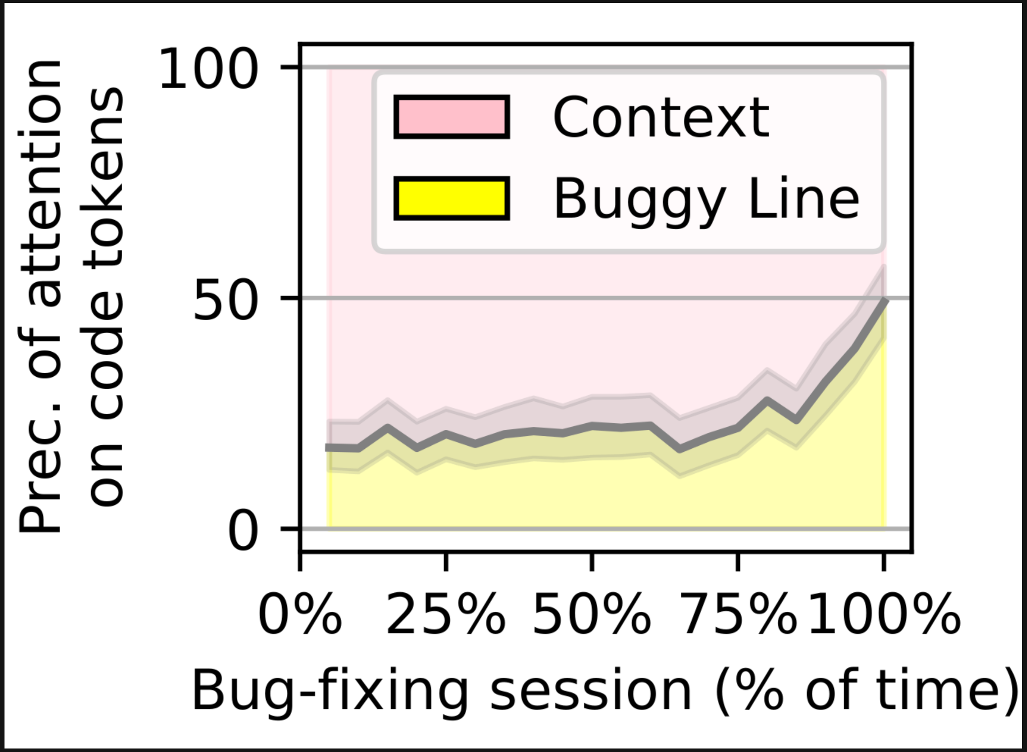
Focus on buggy line vs. code context:

	Buggy line	Context
Developers	37%	63%
SequenceR	67%	33%
Recoder	13%	87%

Again, no model closely matches developers

Results: Program Repair

Human attention evolves over time:



Models could mimic human behavior:

First understand, then fix

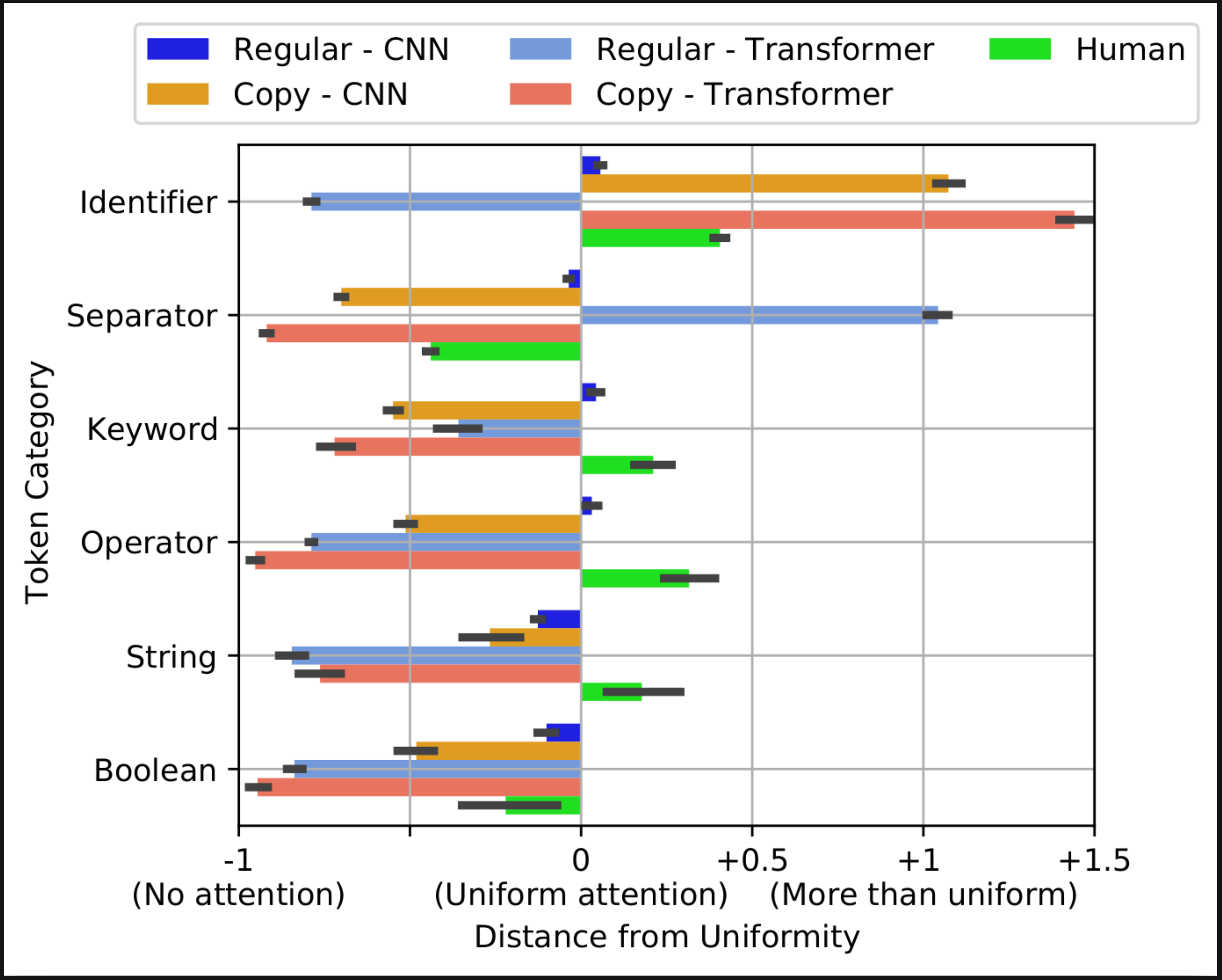
Tokens to Focus On

What kind of tokens to focus on?

- Different kinds: Identifiers, separators, etc.
- For each kind, compute distance from uniformity
  - $= 0$ means uniform attention
  - -1 means no attention at all
  - > 0 means more than uniform attention

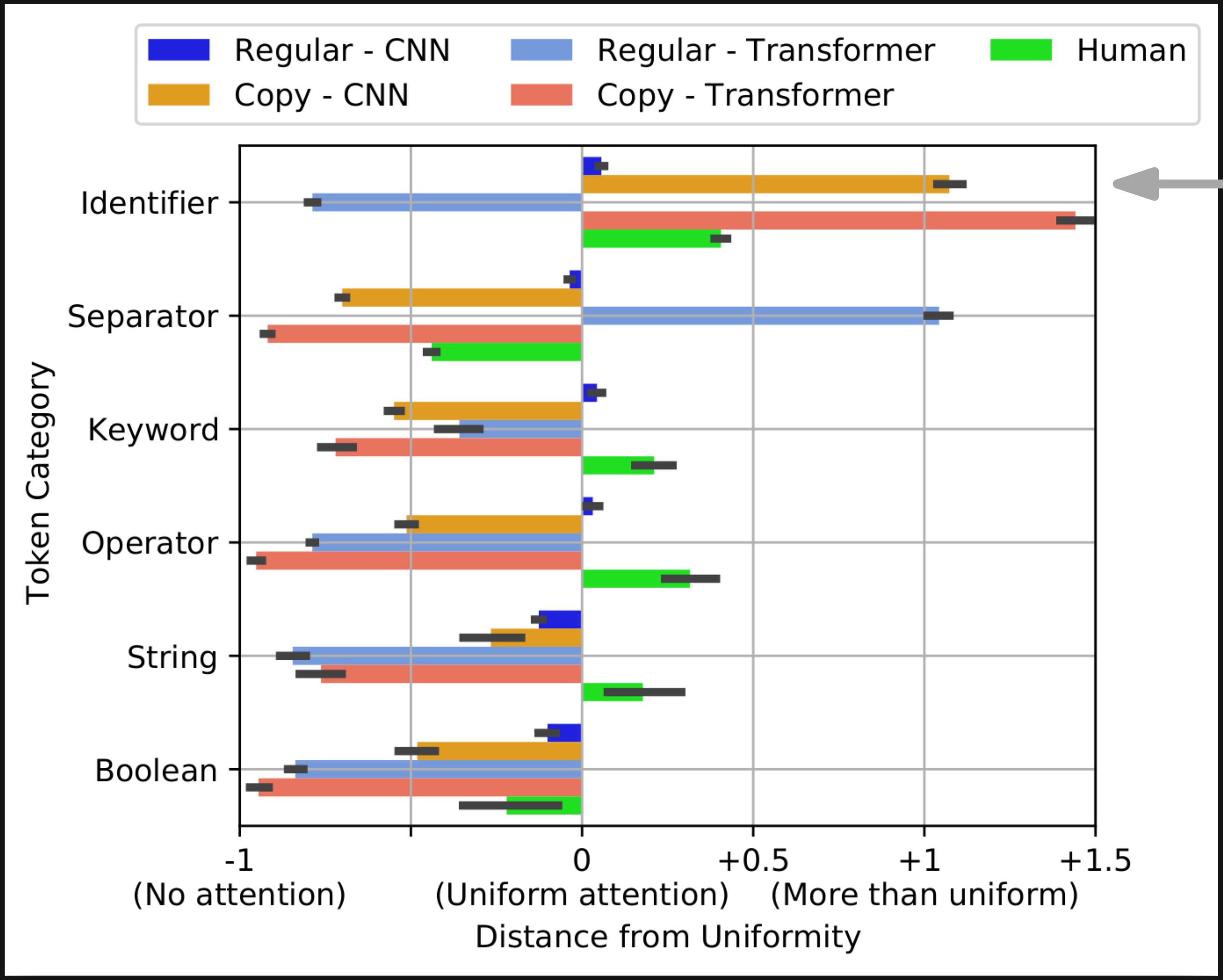
Results: Summarization

Distance from uniformity:



Results: Summarization

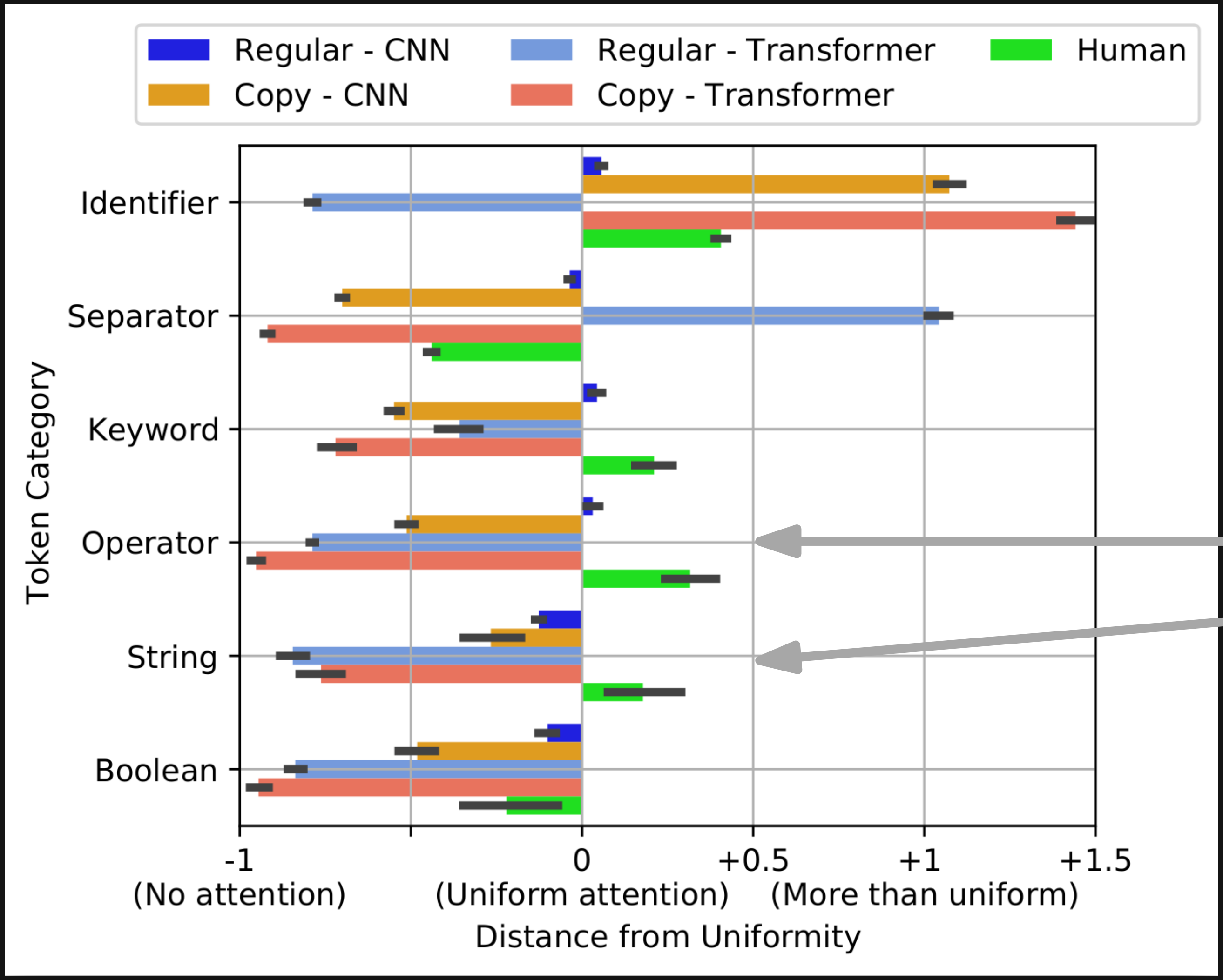
Distance from uniformity:



Identifiers are deemed important

Results: Summarization

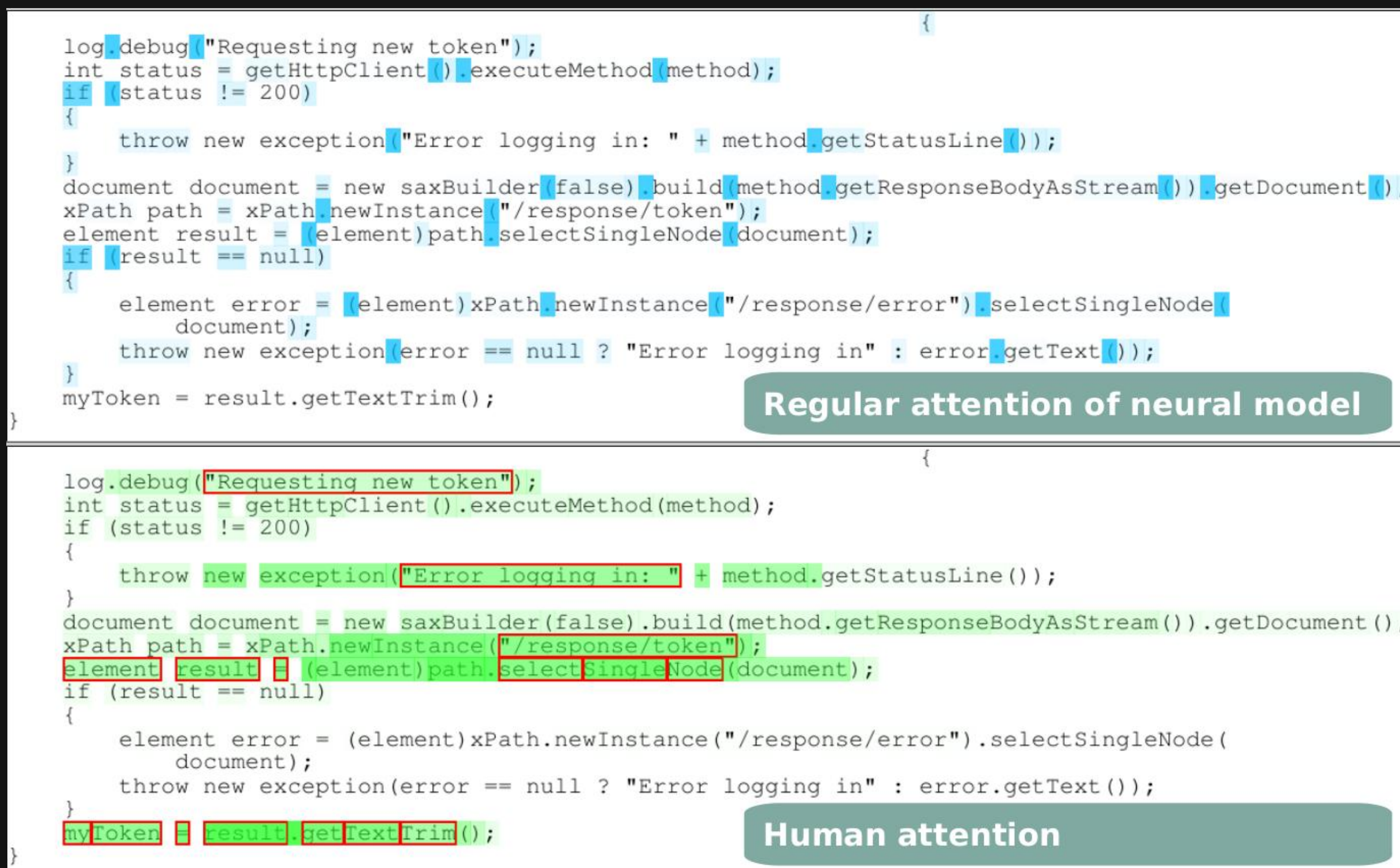
Distance from uniformity:



Models mostly ignore some kinds of tokens

Results: Summarization

Example from Transformer model:



Results: Summarization

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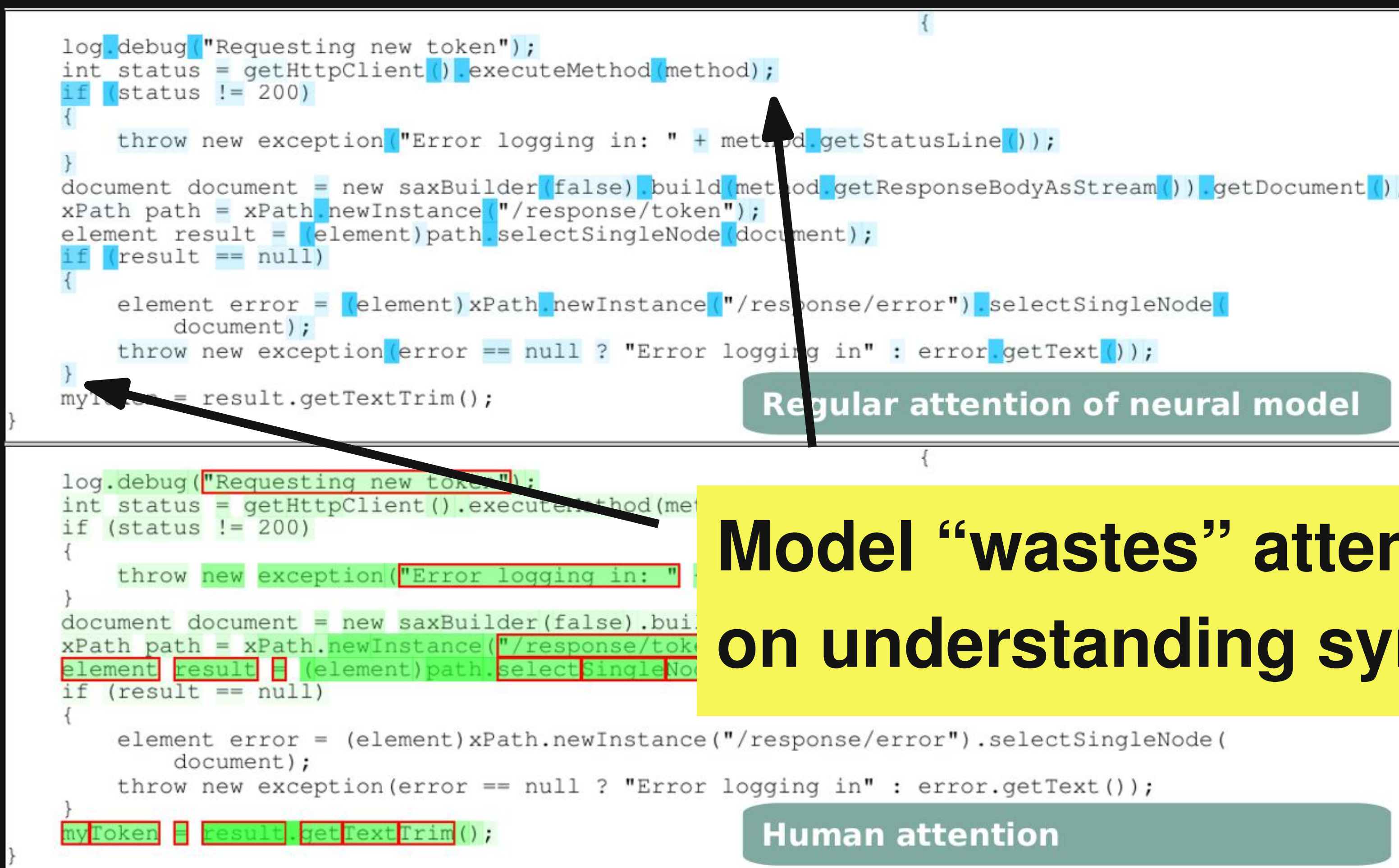
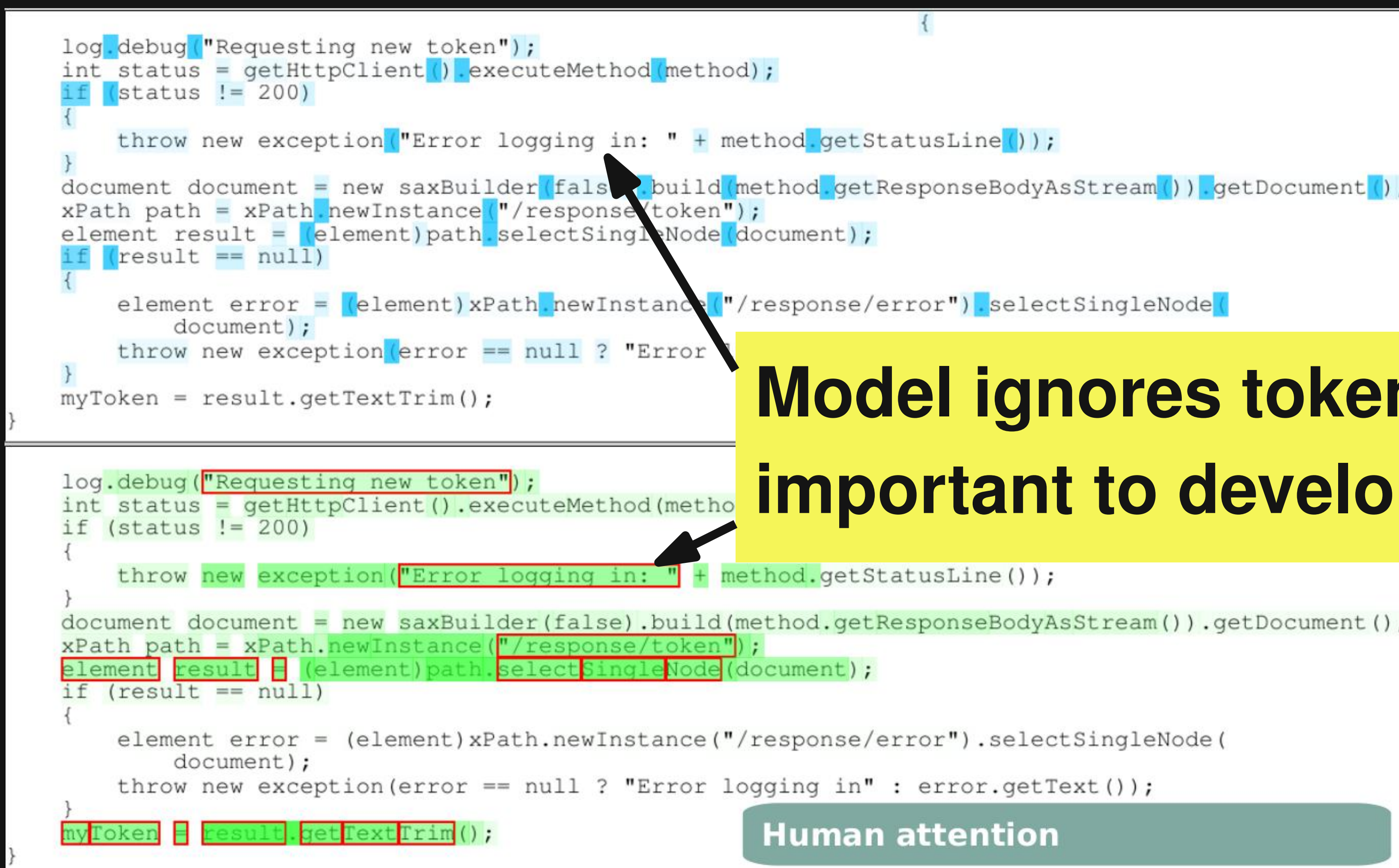


Model “wastes” attention on understanding syntax

Results: Summarization

Example from Transformer model:



Model ignores tokens important to developers

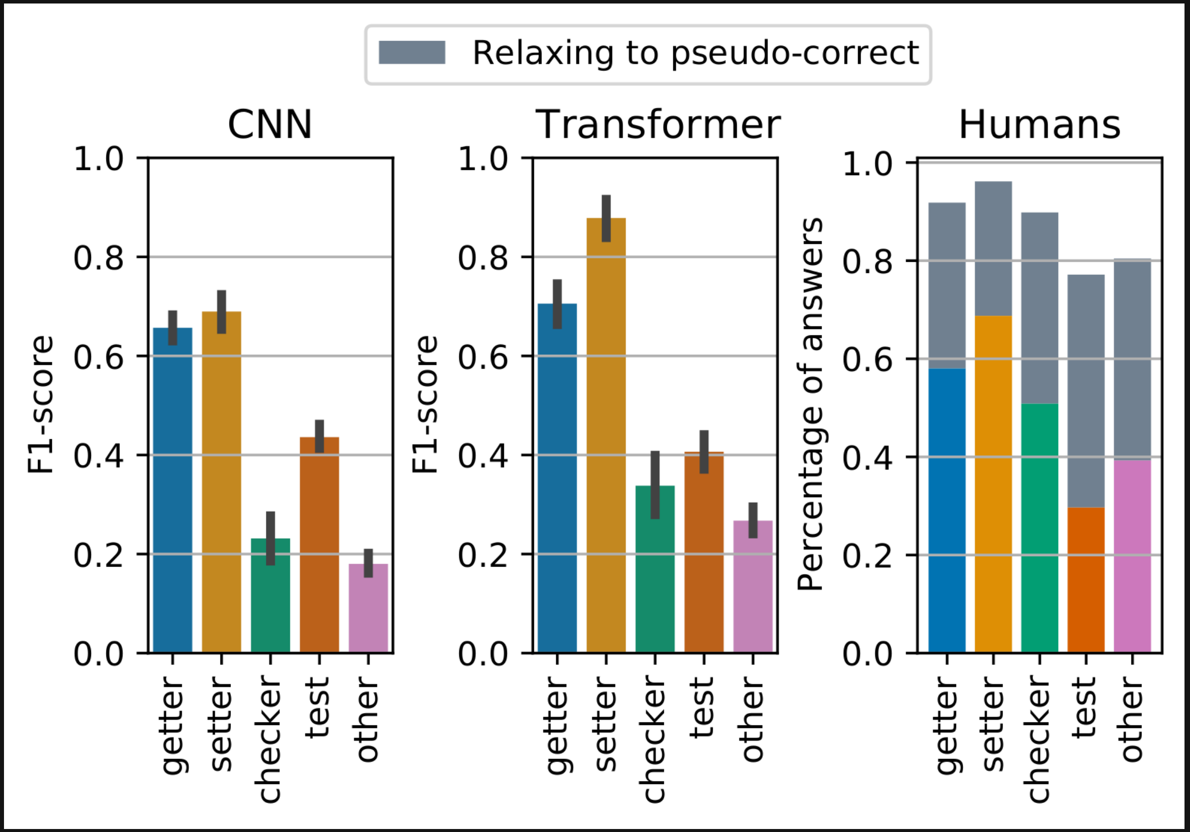
Effectiveness

Comparing developers and models w.r.t. their effectiveness at solving the task

- Strengths and weaknesses?
- Can current models compete with developers?

Results: Summarization

Comparing different kinds of methods:



Models underperform on non-trivial methods

Results: Program Repair

Success rate during program repair:

	Plausible patch ratio	
	Top-5	Top-100
SequenceR	2/80 (2.5%)	17/1395 (1.2%)
Recoder	2/80 (2.5%)	10/908 (1.1%)

Results: Program Repair

Success rate during program repair:

	Plausible patch ratio	
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SequenceR	2/80 (2.5%)	17/1395 (1.2%)
Recoder	2/80 (2.5%)	10/908 (1.1%)
	5-7 developers/bug	
Developers	68/98 (69.4%)	

Models are far from human effectiveness

Effectiveness vs. Agreement

Are models more effective when they agree more with developers?

Results: Summarization

Human-model agreement for all vs. accurate predictions:

	Spearman rank correl.	
	All methods	Methods with F1 $\geq$ 0.5
CNN (regular)	0.08	0.24
CNN (copy)	0.49	0.55
Transformer (reg.)	-0.20	0.02
Transformer (copy)	0.47	0.55

More human-like predictions are more accurate

Implications

- **Direct human-model comparison**
  - Helps understand why models (do not) work
- **Should create models that mimic humans**
  - Use human attention during training
  - Design models that address current weaknesses
    - E.g., understanding string literals

Conclusions

- **Available for future research:**
  - Interface for capturing human attention
  - Datasets of human attention records
- **More details:**

  Thinking Like a Developer? Comparing the Attention of Humans with Neural Models of Code, ASE'21