A New Approach to Evaluating Nullability Inference Tools

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    - Prior work has introduced **type inference techniques** to try to solve this problem

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  - Discussion of how the state-of-the-art can improve

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```
int x
```

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```
@Positive int x
```

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```
@Even int x
```

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```
@Nullable Object x
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  - Checker Framework Whole-Program Inference (ASE 2023)
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Next: a brief introduction to these three extant tools

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  - Implemented as intra-procedural **dataflow analysis**
  - Typically implemented at the **framework level**
- **Key idea**: iteratively run local inference and propagate results
  - Advantage: works with any typechecker built on a framework "for free" (no per-typechecker code required)

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Nima Karimipour, Justin Pham, Lazaro Clapp, and Manu Sridharan. *Practical Inference of Nullability Types.* In ESEC/FSE 2023.

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Implication: comparison has to be focused on nullability type systems, for now

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- Only NullGTN can possibly annotate **entrypoint parameters**
  - (Assuming no test cases)
  - In WPI's evaluation, this was the largest cause of missed human-written annotations (11%)
- All three tools were evaluated separately
  - 2/3 (WPI, NullGTN) use "**type reconstruction**" experiments
    - NullAway Annotator evaluation lacks ground truth

Type Reconstruction Experiments

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Major advantage: have ground truth: the human-written annotations

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- These changes could **simplify inference**
  - We can check this empirically

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    - Via per-project historical investigation of git history
- **Manually categorize** changes
- **Run inference** on both version and compare results

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- We could identify before and after versions of **10 benchmarks**
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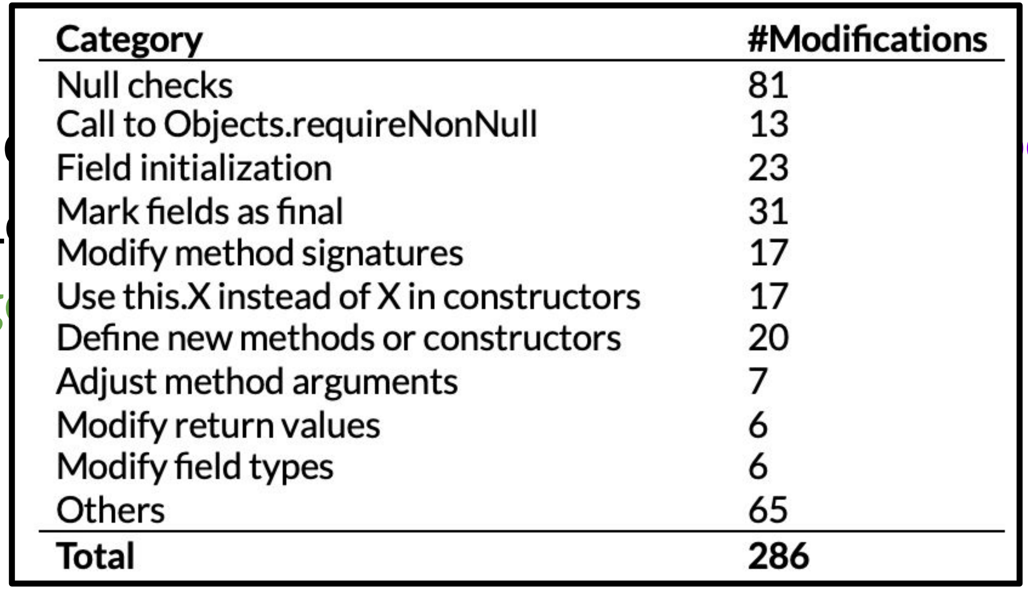

Category	#Modifications
Null checks	81
Call to Objects.requireNonNull	13
Field initialization	23
Mark fields as final	31
Modify method signatures	17
Use this.X instead of X in constructors	17
Define new methods or constructors	20
Adjust method arguments	7
Modify return values	6
Modify field types	6
Others	65
Total	**286**

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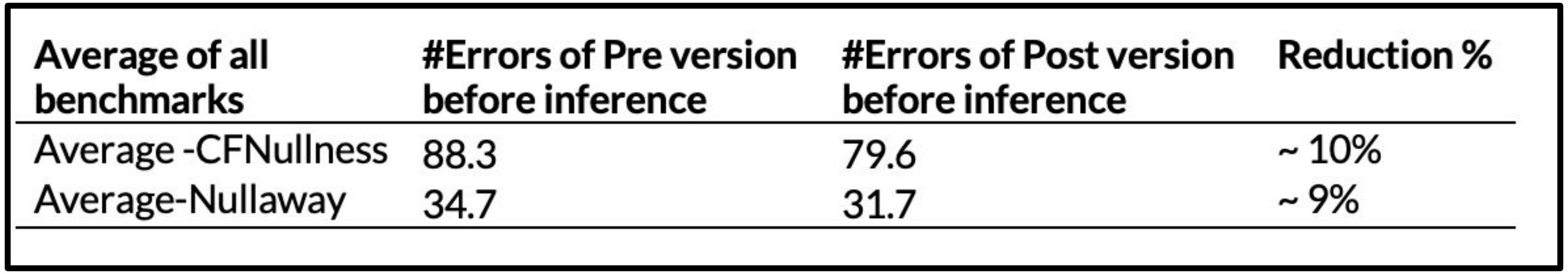

Average of all benchmarks	#Errors of Pre version before inference	#Errors of Post version before inference	Reduction %
Average -CFNullness	88.3	79.6	~ 10%
Average-Nullaway	34.7	31.7	~ 9%

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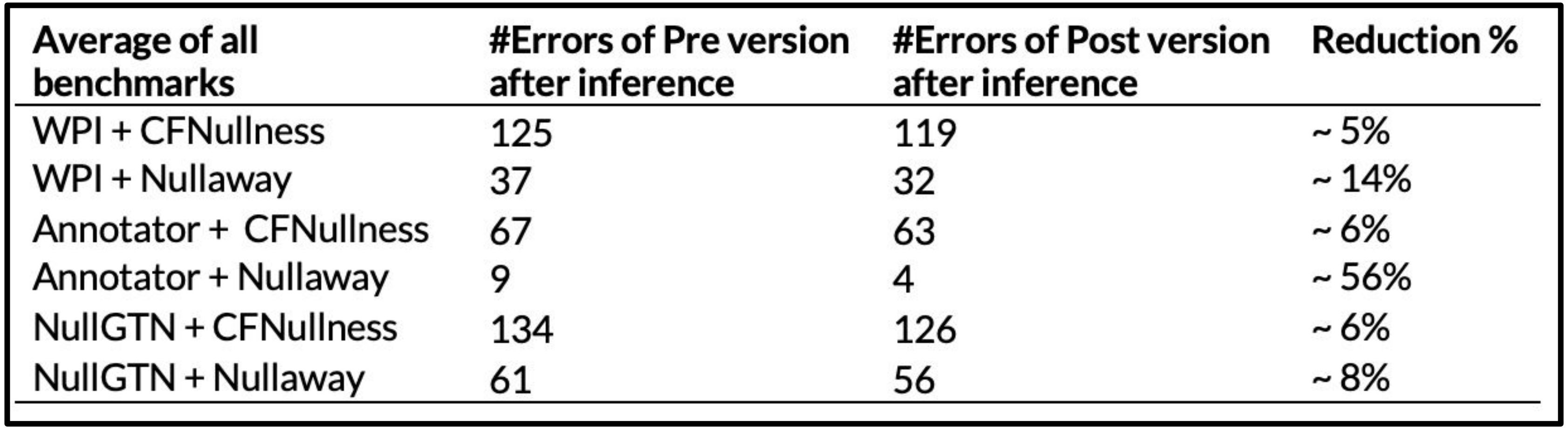

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WPI + CFNullness	125	119	~ 5%
WPI + Nullaway	37	32	~ 14%
Annotator + CFNullness	67	63	~ 6%
Annotator + Nullaway	9	4	~ 56%
NullGTN + CFNullness	134	126	~ 6%
NullGTN + Nullaway	61	56	~ 8%

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- Cannot fairly evaluate inference tools on pre-annotated code

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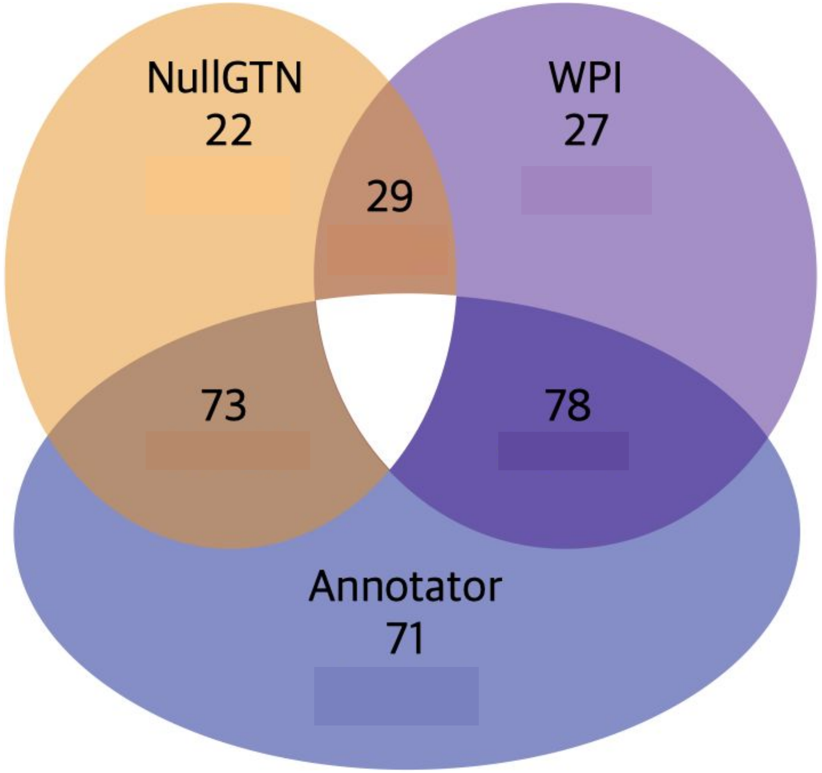
  - Definition for manual evaluation: a declaration should be marked as `@Nullable` if there exists a read of it that may observe a null value

Direct Comparison: Manual Analysis



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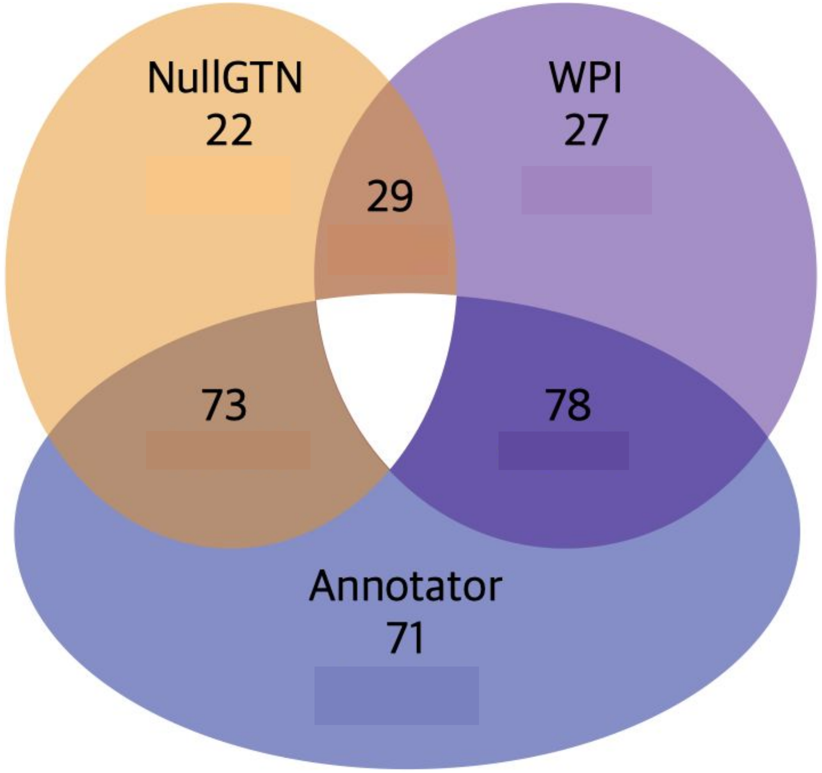

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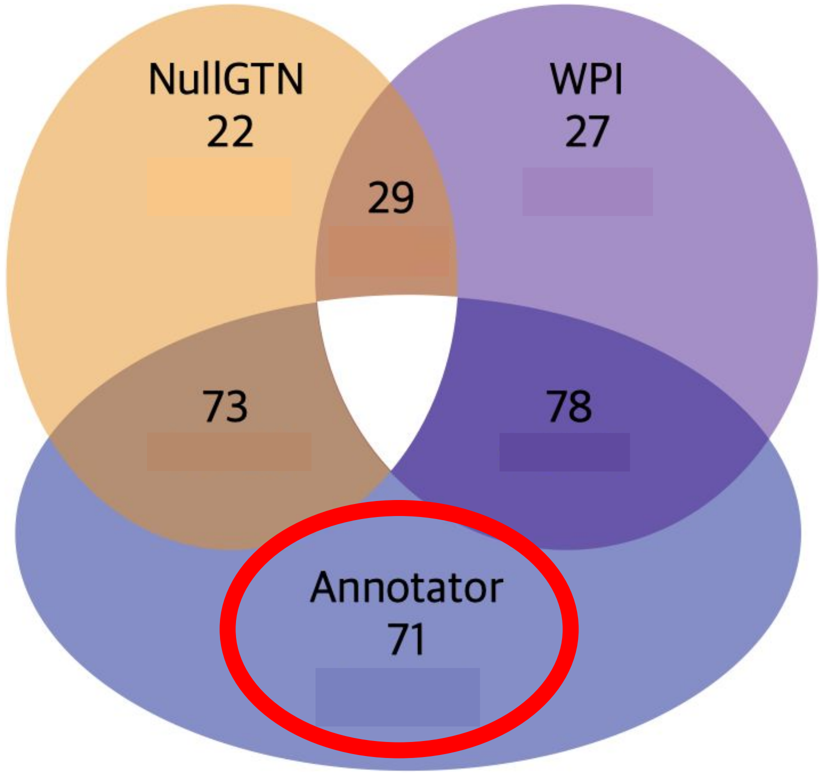
E.g., for 71 disagreements only NullAway Annotator is correct



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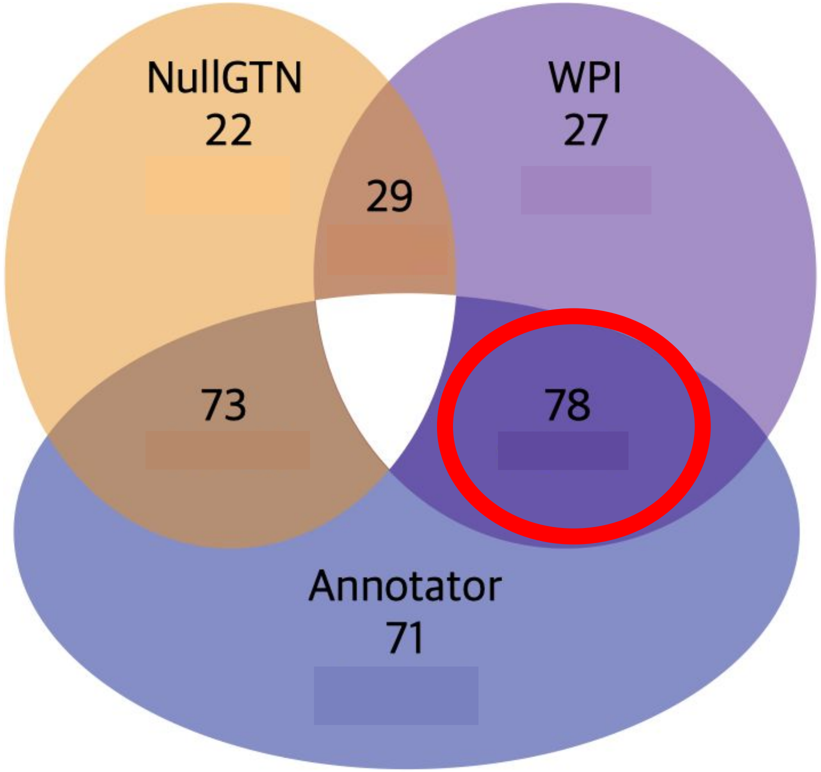
And for 78 disagreements, both WPI and Annotator are correct (and NullGTN is wrong)



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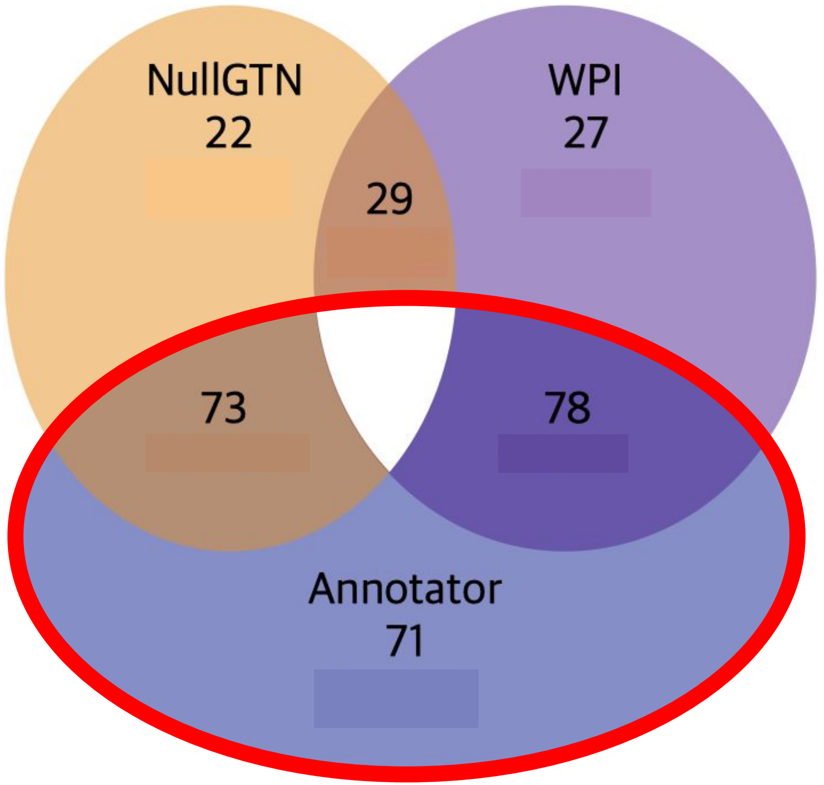
- Each number represents the number of times that the tool handles a disagreement correctly
- Overall conclusion: Annotator makes the **fewest mistakes**, but it doesn't strictly dominate the other tools



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- WPI is hampered by internal consistency
  - Inherits **dataflow imprecision** from the typechecker
    - Causes errors to **cascade**
- NullGTN overgeneralizes
  - We also observed that it handles “poorly-written” code especially badly

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  - Lots of **room for improvement**
- Can we combine the strengths of different tools? E.g.:
  - Use NullGTN **only** for entrypoint parameters?
  - Could **warning fitness** stop imprecision cascades in WPI?

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    - 255 Java programs, ~1.4 million LoC

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- Two proxies for quality:
  - Manual analysis of 300 sampled disagreements
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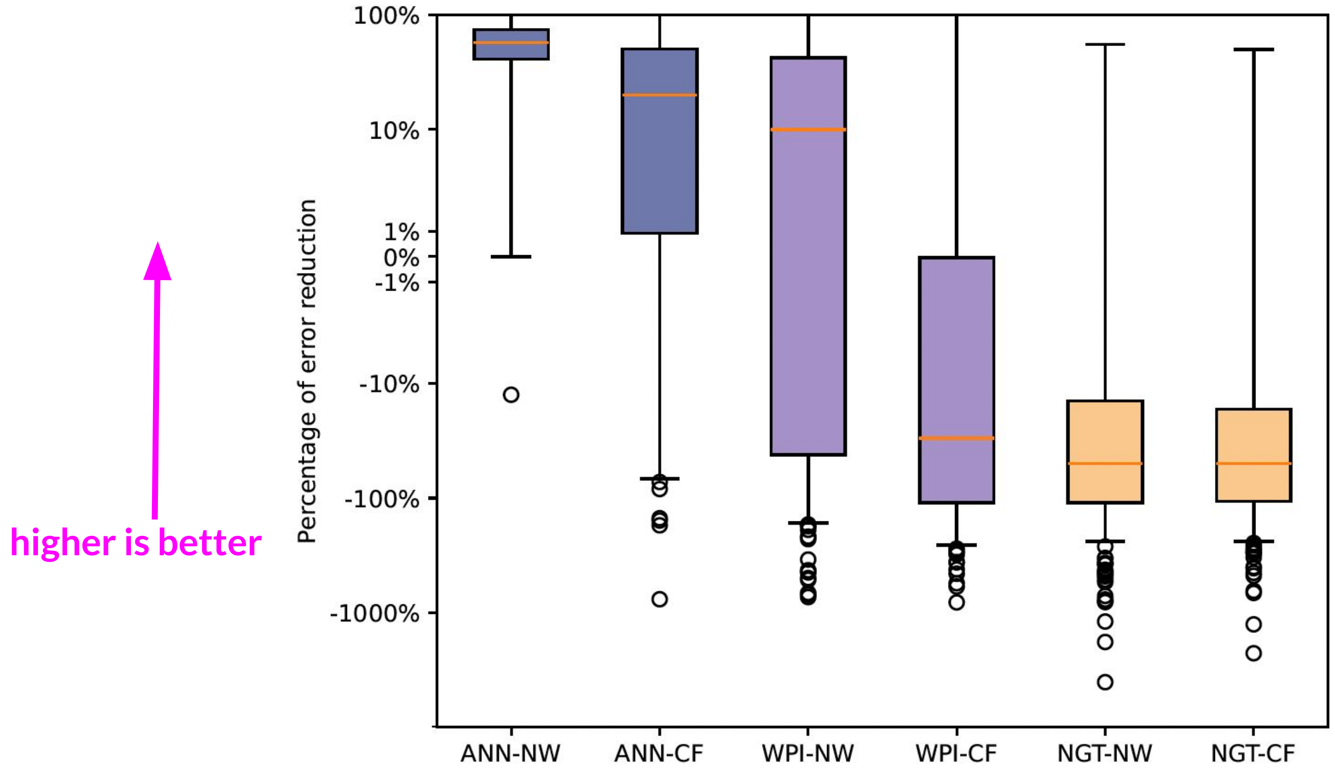

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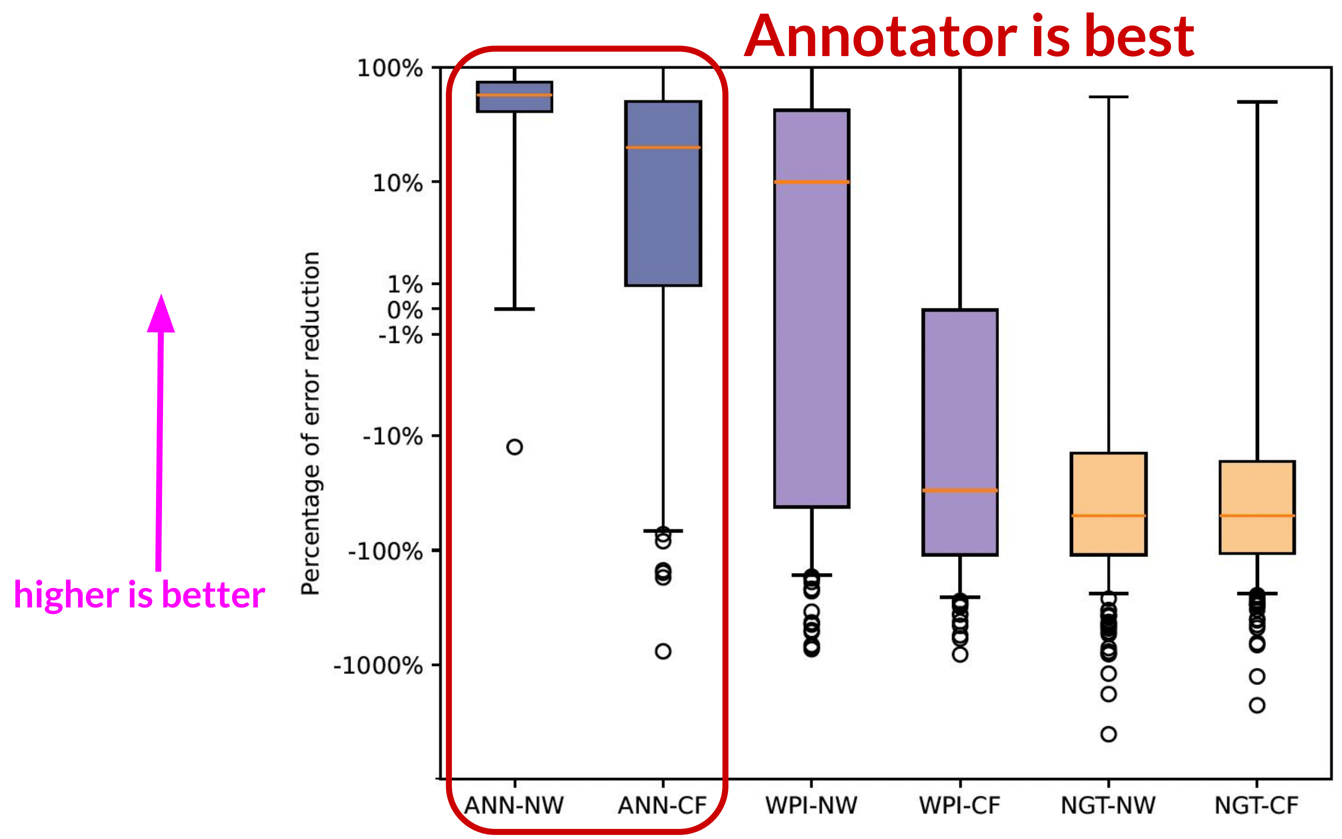

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WPI has a wide range

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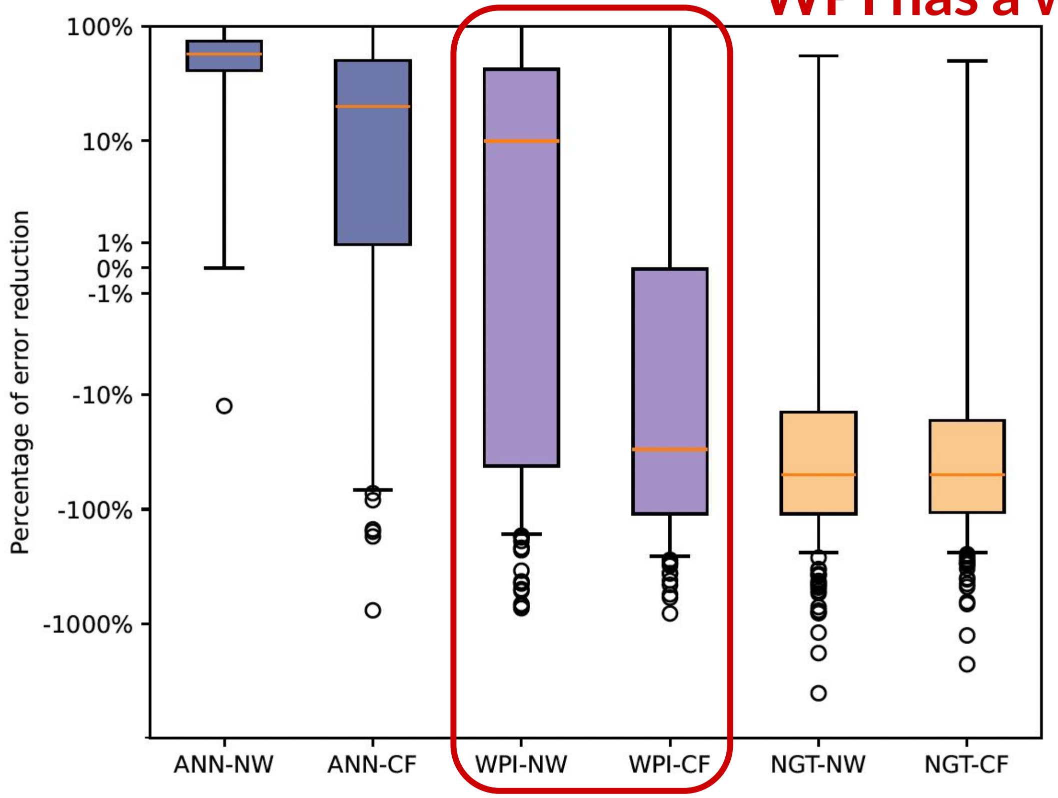

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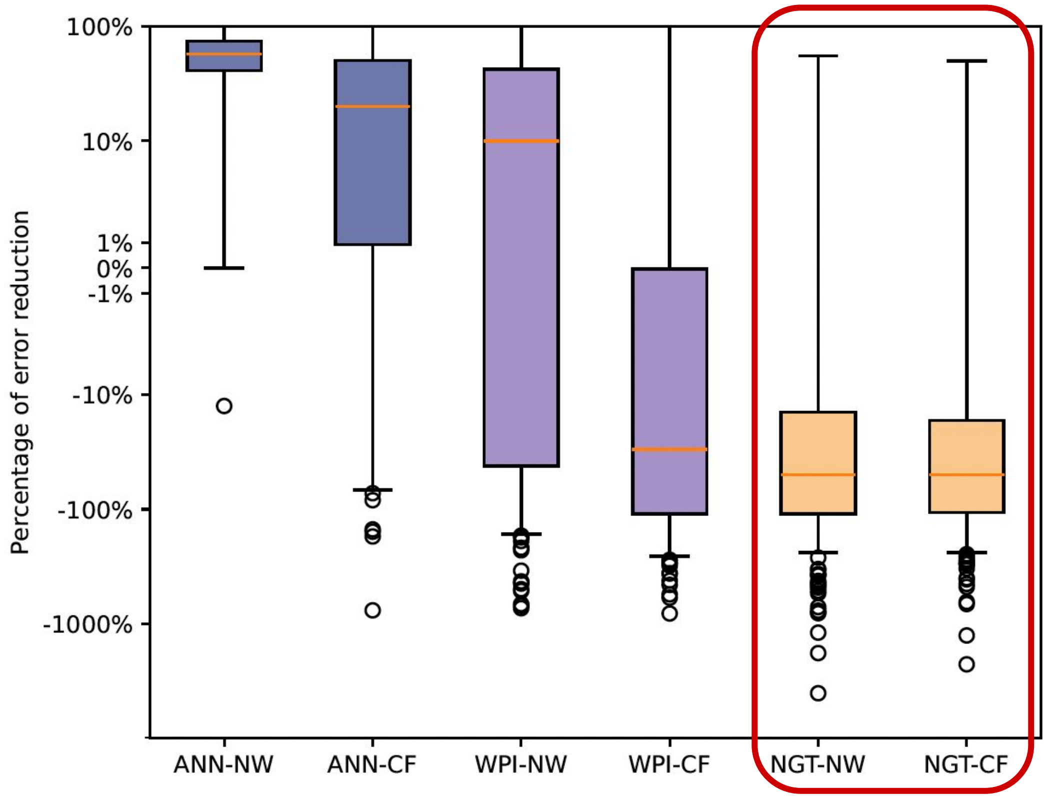

NullGTN is consistently worst