## How to improve DL for SE

A case study with code smell detection

## Code smells

- "Certain structures in the code that suggest (sometimes they scream for) the possibility of refactoring." Beck et al. (2019)
- Feature envy: Class A is "envious" of class B.
- Large class: A do-it-all class.
- Long method: "What does this do??"
- Misplaced class: Classes that are misplaced (obviously).

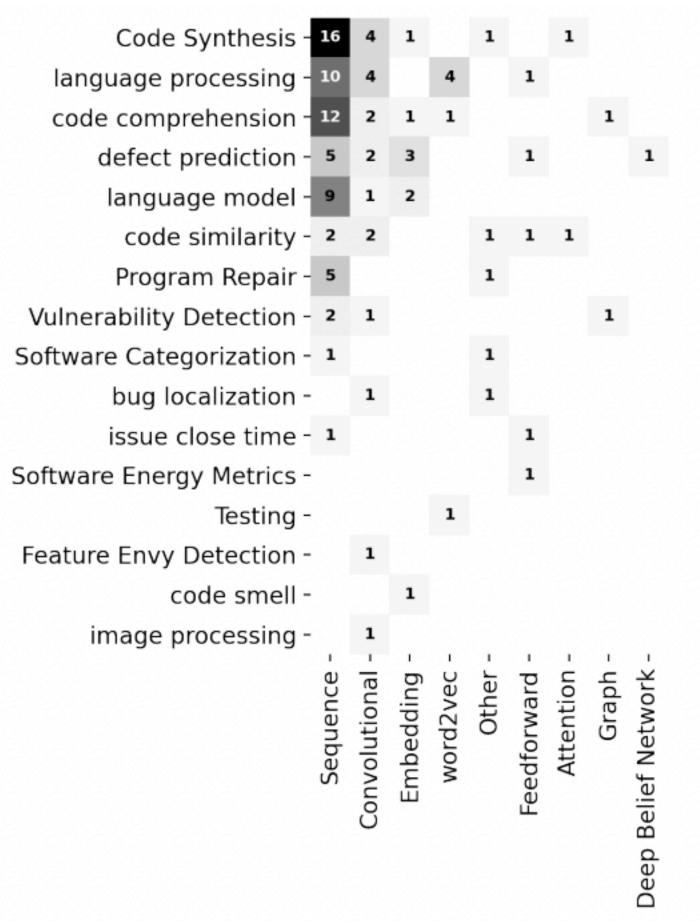
## Data

- Smell-inducing refactoring (Liu et al., 2019)
- Example: move a method from one class to another to induce feature envy



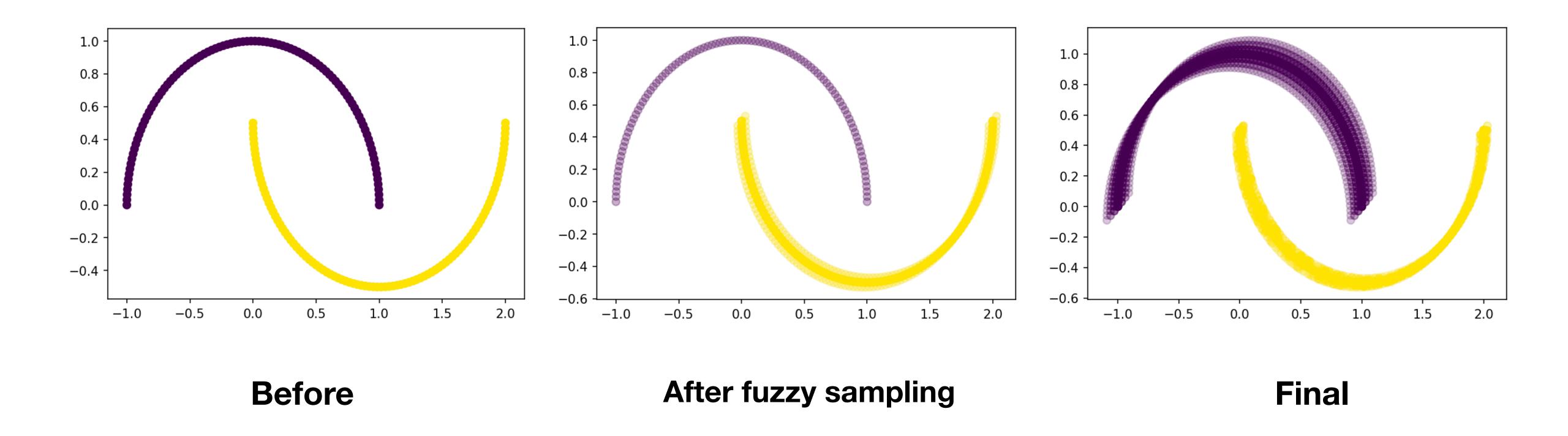
# What's wrong with prior work? Complexity

- Seed: Watson (2020)
- Search: "deep learning AND software", "deep learning AND defect prediction", and "deep learning AND bug"
- Filter: Published in top venues, highly cited, etc.
- Backward snowballing: Wohlin (2014)



### ...and how do we fix it?

### **Fuzzy sampling**



# GHOST Fuzzy sampling + ...

- Fuzzy sampling (twice)
- SMOTE
- Hyper-parameter optimization
- Weighted loss functions

## But does it work?

### Yes (that's why we're here)

SOT	A (repro	duced)		Fuzzy sampling (with GHOST)			
Precision	Recall	F1	AUC	Precision	Recall	F1	AUC
79.5	80	79.7	88	98	98	98	99.3
79.2	79.2	79.2	87.3	97.7	97.7	97.7	99.1
80.1	79.9	80	88.3	98	98	98	99.3
80.6	80.4	80.5	88.8	98.2	98.2	98.2	99.3
80	80.1	80	88.1	97.7	97.7	97.7	99.1
78.7	78.5	78.6	87	97.8	97.8	97.8	99.2
78.5	78.2	78.3	86.3	97.7	97.7	97.7	99.2
80.3	80.2	80.2	88	97.7	97.7	97.7	99.1
79.8	79.6	79.7	87.8	97.8	97.8	97.8	99.2
77.9	77.5	77.7	85.8	97.8	97.8	97.8	99.1

SOT	A (repro	duced)		Fuzzy sampling (with GHOST)				
Precision	Recall	F1	AUC	Precision	Recall	F1	AUC	
41.7	77.8	52.5	72.2	41.7	70	51.5	71.2	
44.6	78.2	55.6	70.3	45.8	76.7	57	71.1	
53.4	82.5	63.4	71.3	54.1	80.5	62.2	70.4	
51.7	67.1	56	66.1	51.3	64.9	54.1	61.6	
35.2	84.8	47.6	73.6	35.4	77.8	47.1	72.9	
49.9	83.9	62.3	76.7	47.7	86.3	61.2	76.1	
39.1	73.5	50.7	73.4	38.9	73.6	50.5	73.2	
36.1	66.3	47.5	65.9	38	73.9	46.2	64.8	
38.4	81.2	51.8	72.6	38.2	81.5	52.2	72.7	
38.5	81.5	52.1	80.3	37.3	81.1	50.9	79.8	

#### Feature envy

SOTA (reproduced)				Fuzzy sampling (with GHOST)			
Precision	Recall	F1	AUC	Precision	Recall	F1	AUC
33.7	78.3	47.1	50	82.9	77.5	80.1	89.5
6.1	100	11.5	50	0	0	0	68.8
61.5	100	76.2	50	76.8	81.8	79.2	75
11.9	100	21.3	50	32.2	71.4	44.4	74.6
11.4	100	20.5	50	23.8	23.6	23.7	63.1
0	0	0	50	42.9	71.4	53.6	70.7
9.1	14.3	11.1	50	27.9	28.6	28.2	65.3
0	0	0	50	0	0	0	50
30	100	46.2	50	53.8	80	64.3	75.7
15.7	100	27.1	50	57.7	73.5	64.6	80.4

Long method

SOTA (reproduced)				GHOST			
Precision	Recall	F1	AUC	Precision	Recall	F1	AUC
34.1	100	50.9	98.6	44.7	100	61.8	100
32.7	100	49.3	96.3	43.3	99.4	60.3	99.4
32.6	100	49.2	98.7	36	100	53	100
35.2	96.1	51.6	93.4	36.3	96.3	52.7	97.3
41.2	96.8	57.7	92	53.8	99.3	69.8	99.6
48.5	99.8	65.3	99.7	48.4	99.9	65.2	99.8
44.5	99.7	61.6	99.5	43.8	100	60.9	99.8
18.2	90.6	30.4	85.6	24.5	100	39.4	100
43.6	100	60.7	92.2	44	100	61.8	100
21.6	86.4	34.6	74.3	32.6	96.1	48.6	96.3

Large class

Misplaced class

## Lessons learned

- Simpler learners with adequate preprocessing can outperform more complex learners, faster.
- Try simpler baselines before moving to more complex learners.
- Use GHOST as one such baseline.

## Thank you!

GHOST paper <u>bit.ly/msr-ghost</u>

Fuzzy sampling <u>bit.ly/fuzzy-sampling</u>

These slides <u>bit.ly/msr-ghost-slides</u>

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