



Machine Learning in Production

Capability Testing of ML Models

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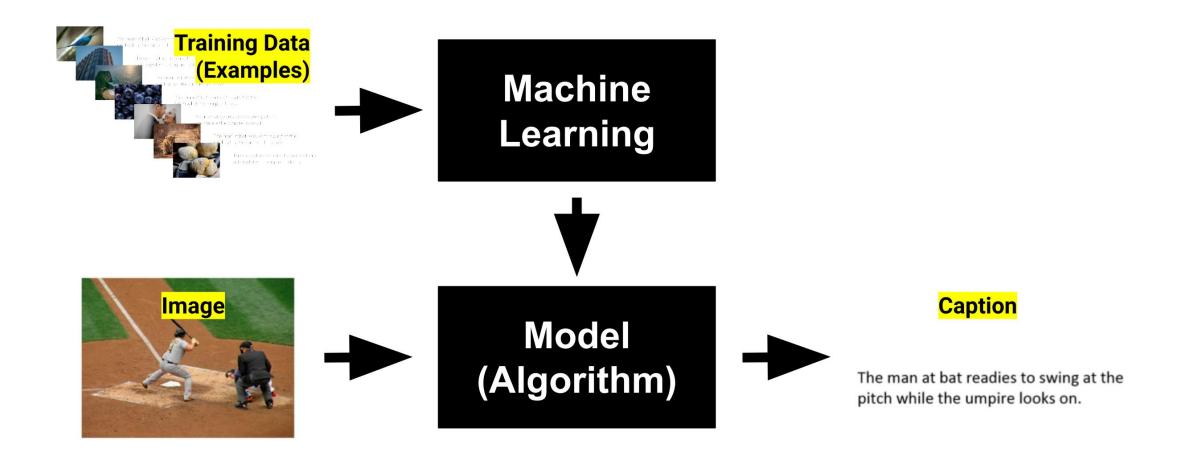
Intelligent Software Engineering Group
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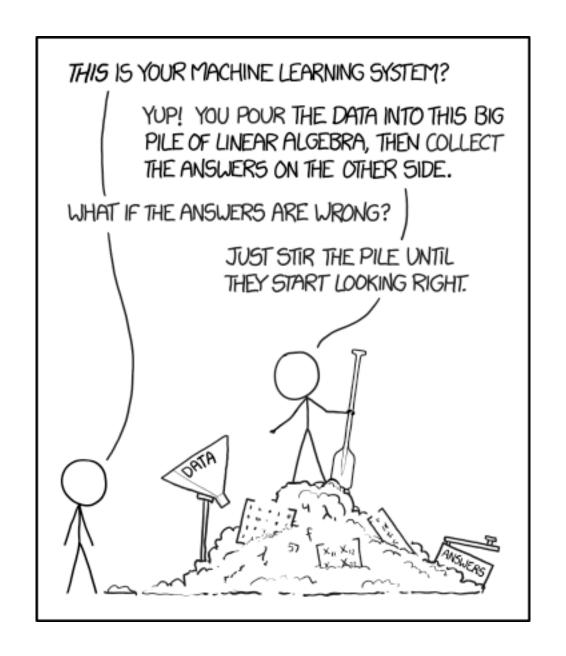
Programming vs Machine Learning

Programming vs Machine Learning



Programming vs Machine Learning







Evaluating Programs Evaluating Models

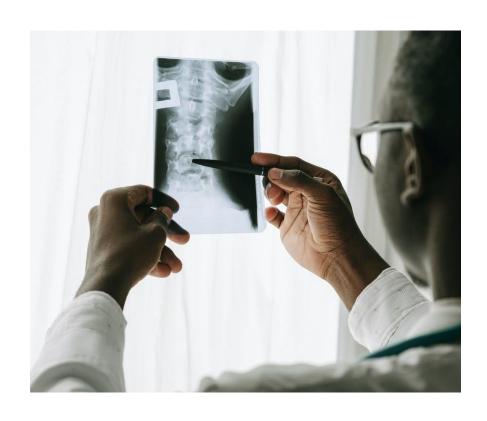


In software implementations, what is correctness?

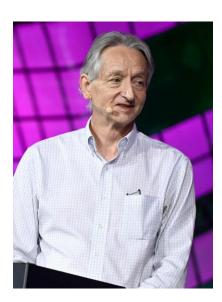
Programs' correctness?

```
/**
* Given a year, a month (range 1-12), and a day (1-31),
* the function returns the date of the following calendar day
* in the Gregorian calendar as a triple of year, month, and day.
* Throws InvalidInputException for inputs that are not valid dates.
def nextDate(year: Int, month: Int, day: Int) = ...
@Test
void testNextDate() {
       assert nextDate(2010, 8, 20) == (2010, 8, 21);
       assert nextDate(2024, 7, 15) == (2024, 7, 16);
       assert nextDate(2011, 10, 27) == (2011, 10, 28);
       assert nextDate(2024, 5, 4) == (2024, 5, 5);
       assert nextDate(2013, 8, 27) == (2013, 8, 28);
       assert nextDate(2010, 2, 30) throws InvalidInputException;
```

Case Study: Cancer Prognosis



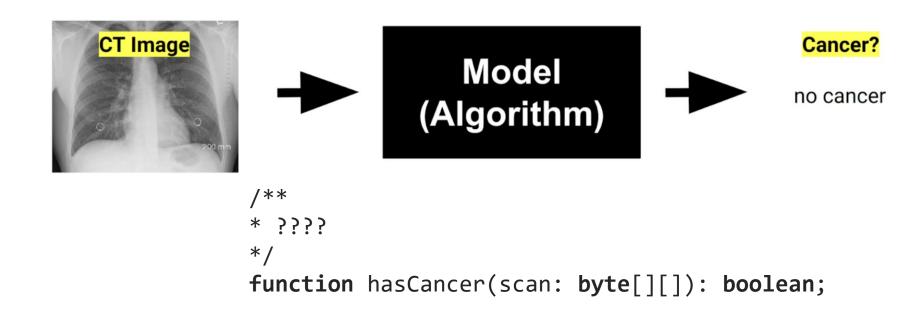
We should stop training radiologists now. It's just completely obvious that within five years, deep learning is going to do better than radiologists.



Geoffrey Hinton, 2016

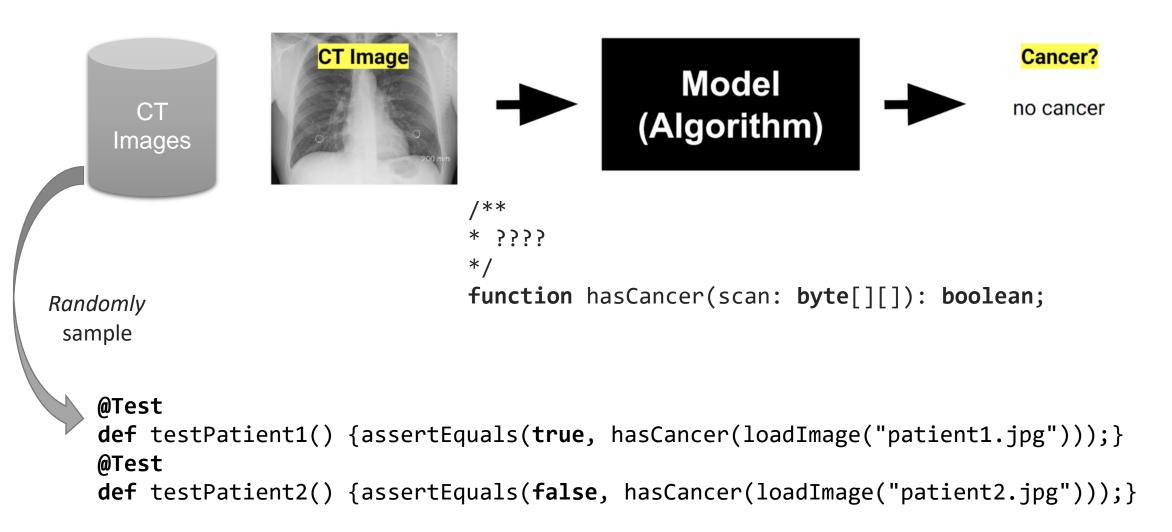
function hasCancer(image: byte[][], age: int, ...): boolean

What is models' correctness?



We have **no** such specifications!

In ML, what is correctness?



How should I think about evaluating models?

...as correct or wrong or buggy"?



It should be about whether they *fit* a problem!

"All models are wrong, but some are useful"

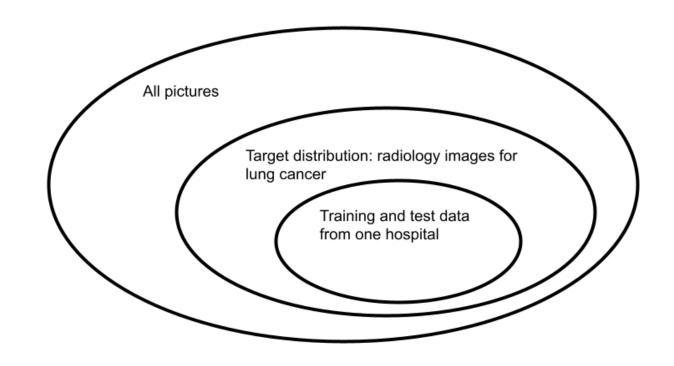
A model, 95% accuracy, may *fit* a problem quite well, 5% of mistakes may be acceptable for a *useful* solution to a problem



We accept a certain level of incorrect outputs

Key Assumption in ML Theory and Practice

Training and test data are independently drawn from the same target population



independent and identically distributed (i.i.d)

Our expectation...

Generalizing beyond the training distribution























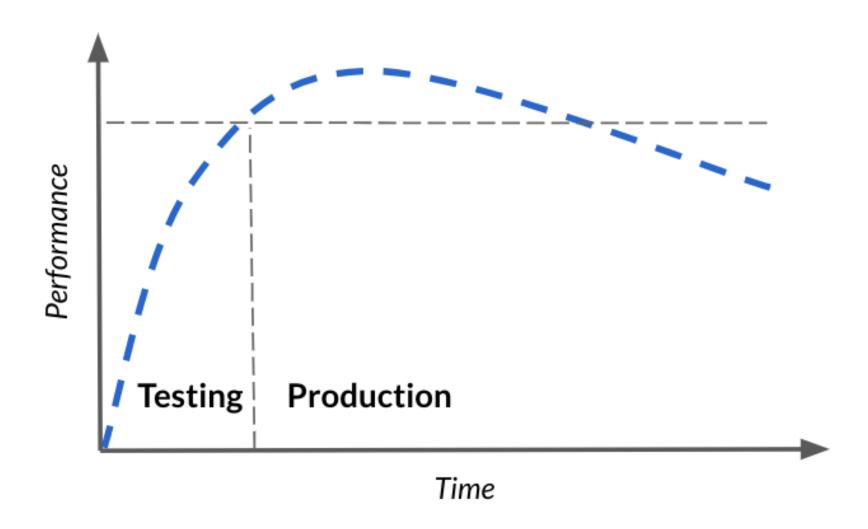






HOSPITAL

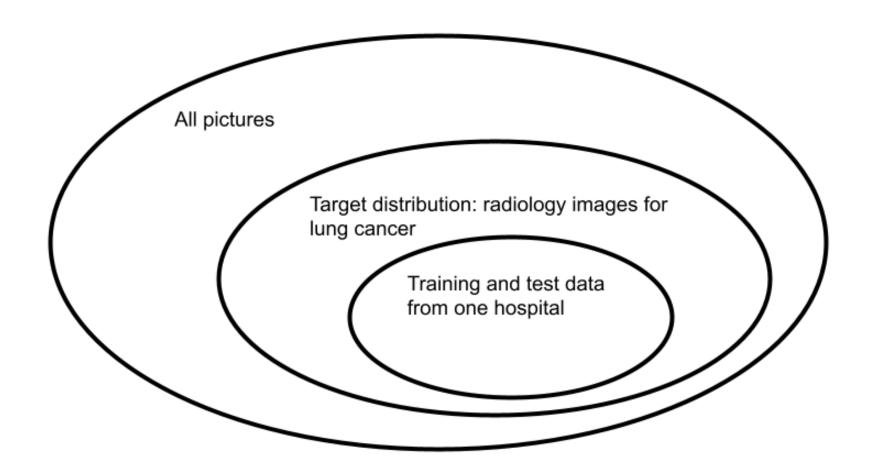
Model Performance Drifts over Time

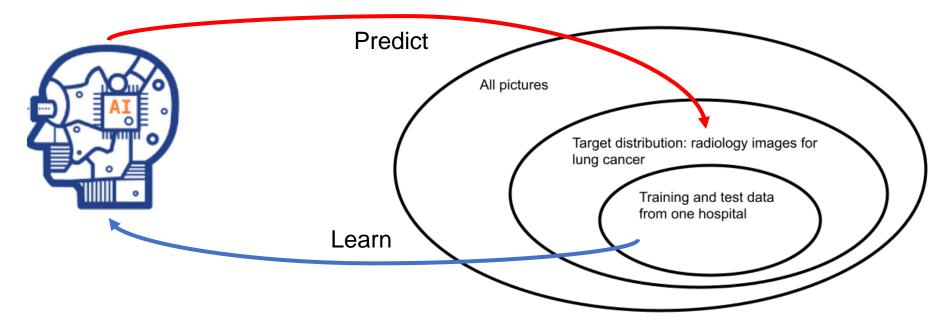




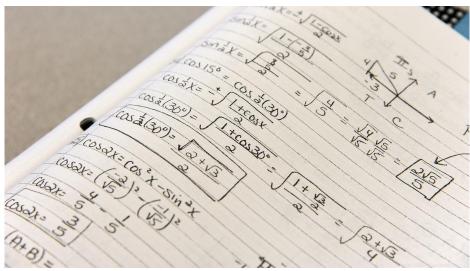
NeuralTalk2: A flock of birds flying in the air Microsoft Azure: A group of giraffe standing next to a tree

Out-of-distribution Problem





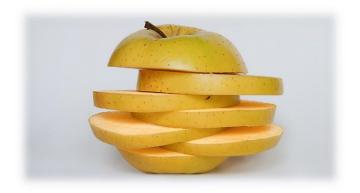




Our reactions?

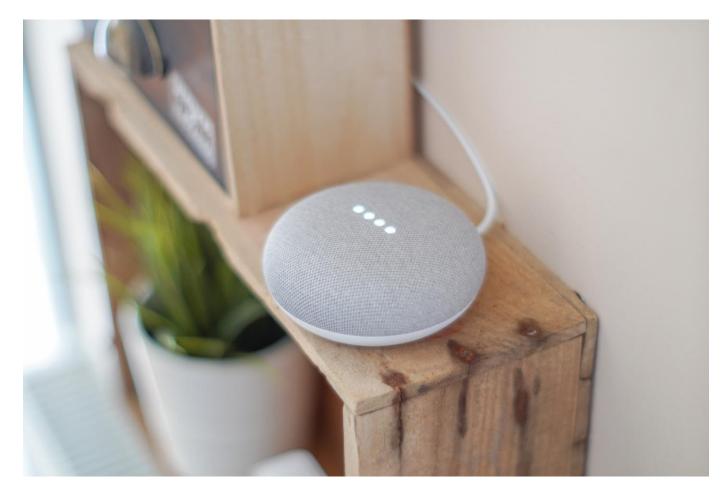
Generalizing beyond the training distribution





Slicing test data

Not All Inputs are Equal: Frequent Cases



"Call mom" "What's the weather tomorrow?" "Add asafetida to my shopping list"

Not All Inputs are Equal: Edge Cases





How do you identify Important Inputs?



Identify Important Inputs

- Curate Validation Data for Specific Problems and Subpopulations:
 - Important inputs ("call mom") -- expect very high accuracy
 - closest equivalent to unit tests
 - Different subpopulations (e.g., accents) -- expect comparable accuracy
 - Challenging cases or stretch goals -- accept lower accuracy
- Derive from requirements, experts, user feedback, expected problems etc.
- Guide testing by identifying groups and analyzing accuracy of subgroups
- Slice test data by population criteria, also evaluate interactions

IBM work: sentiment analysis on reviews from IMDB

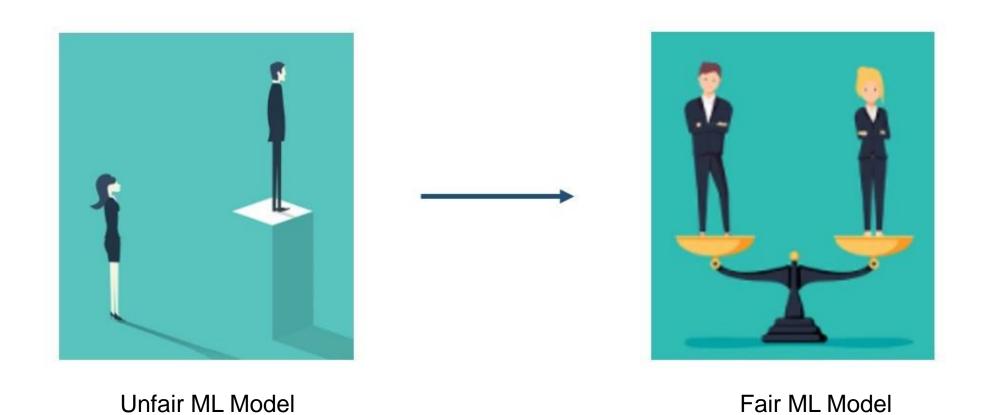
SUPPORT	ACC
38	78.94
338	87.87
3007	90.95
6192	91.40
	38 338 3007

MAIN_GENRE	RAT_CAT	LEN_CAT	SUPPORT	ACC
Mystery	OK	long	11	72.72
Fantasy	OK	short	36	77.77
Crime	OK	long	100	81.00
Comedy	GOOD	long	55	96.36

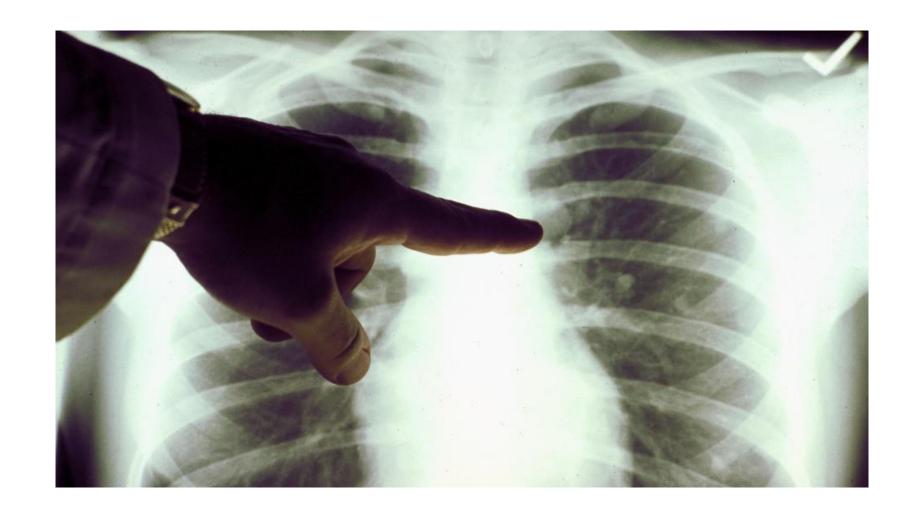
Voice Assistants?



Slicing data: Fairness in ML

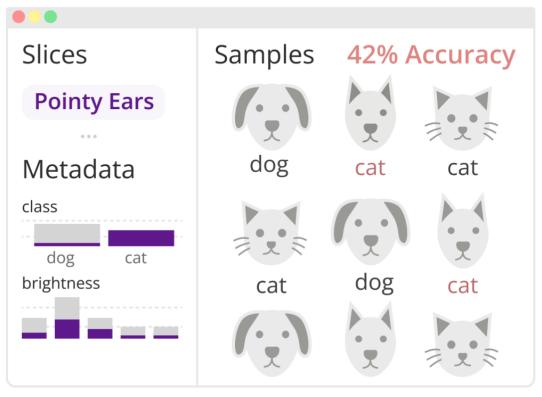


How to slice evaluation data for cancer prognosis?

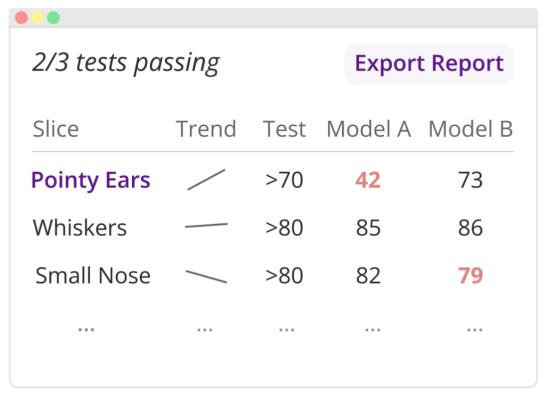


Multiple slices on image recognition, and model comparison

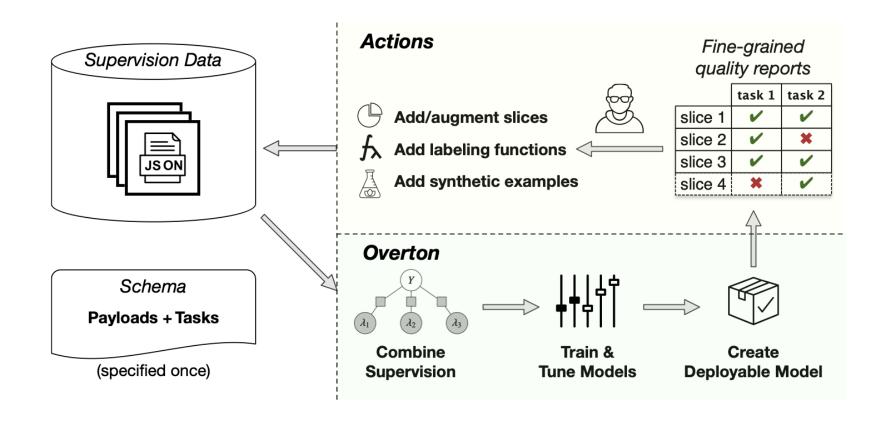
Exploration



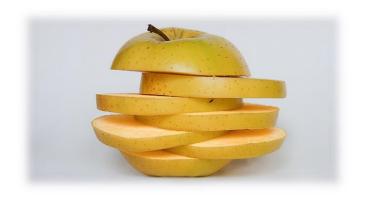
≡ Analysis



Overton system at Apple



Slicing test data: Why?

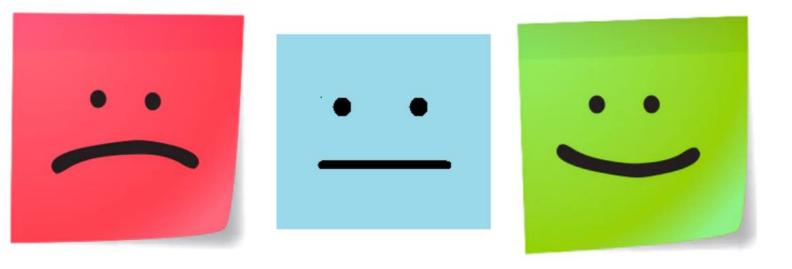


- Identifying problems and anticipating potential problems
 - More tractable problem of improving accuracy for individual slices, rather than trying to improve for the entire input space at once.
- Encourage a team to plan for mitigations:
 - Collecting more training and test data for neglected subpopulations
 - Adjusting how the system uses predictions for these subpopulations to compensate for the reduced confidence

Capability Testing

Capability testing

- Capability testing: test whether model can learn key capabilities that humans found essential for solving a task
 - → Better mirror human strategies for solving a problem
- Capabilities are inherently domain-specific



Sentiment Analysis

This course is quite fantastic



"Oh great, the battery life on this phone is amazing! It lasts a whole 5 minutes."

Object detection



(A) Cow: 0.99, Pasture: 0.99, Grass: 0.99, No Person: 0.98, Mammal: 0.98

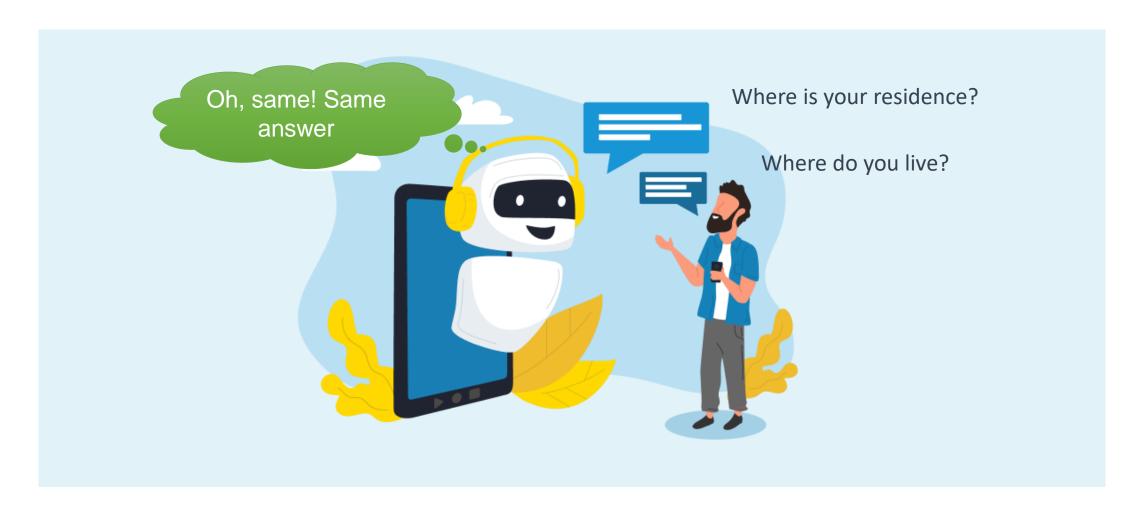


(B) No Person: 0.99, Water:0.98, Beach: 0.97, Outdoors:0.97, Seashore: 0.97

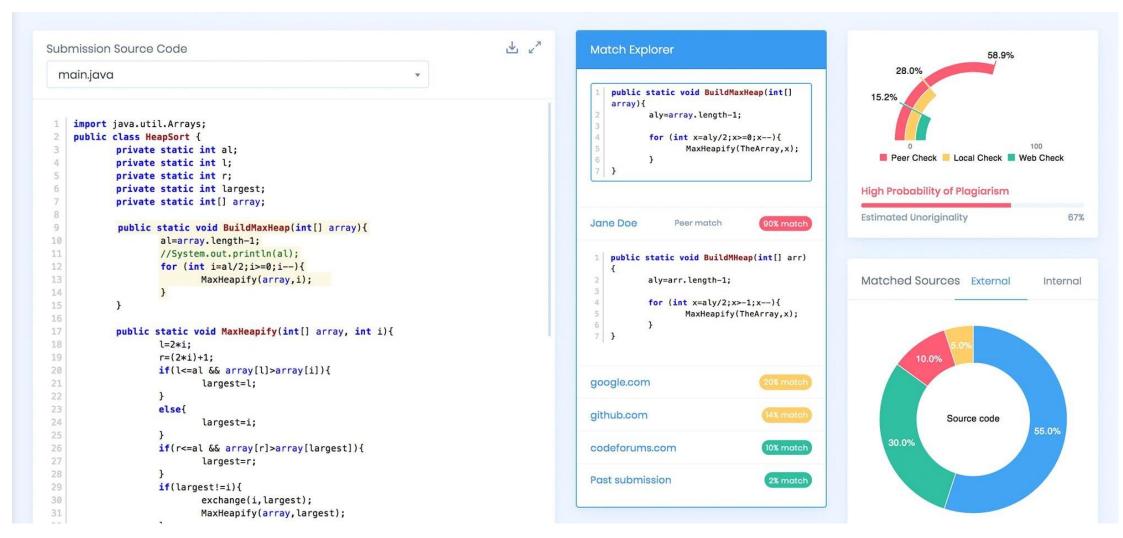


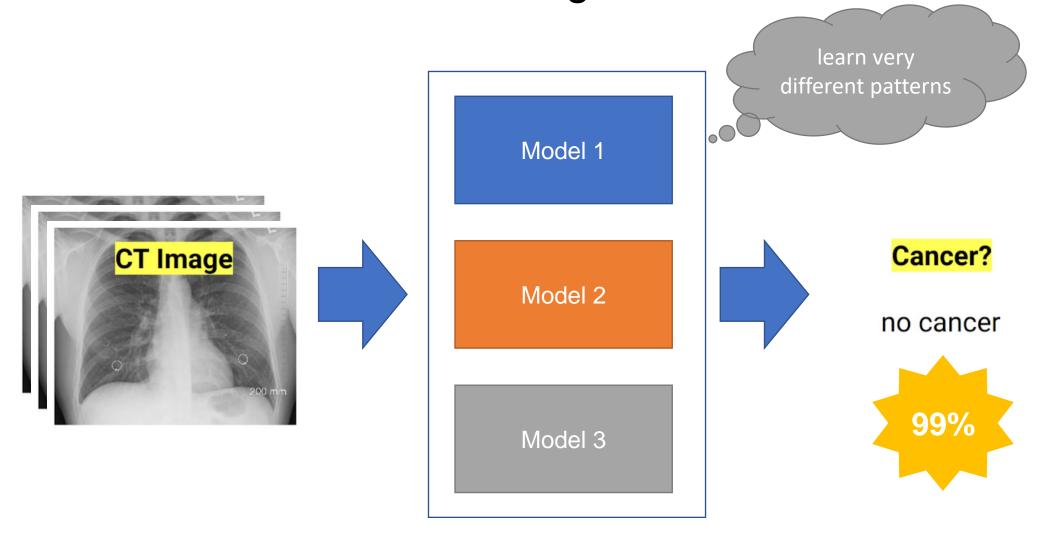
(C) No Person: 0.97, Mammal: 0.96, Water: 0.94, Beach: 0.94, Two: 0.94

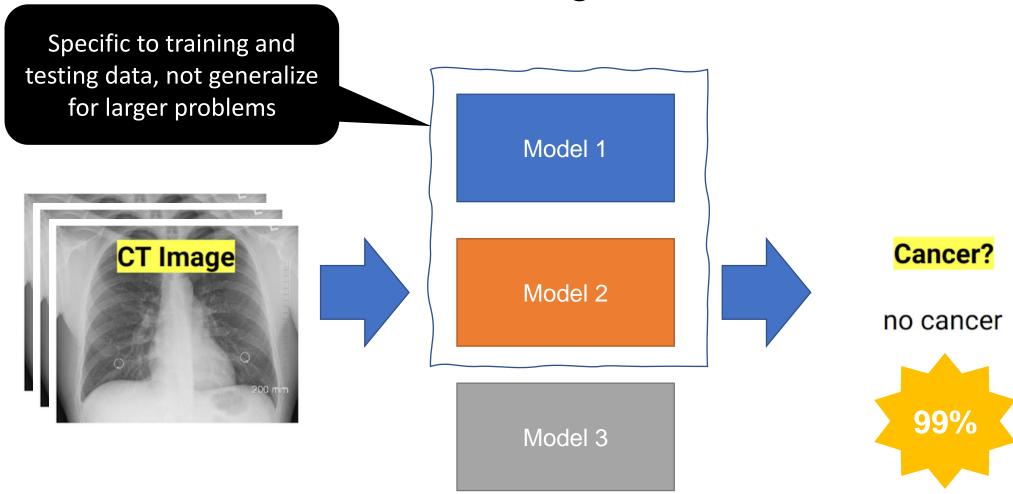
Question-Answering

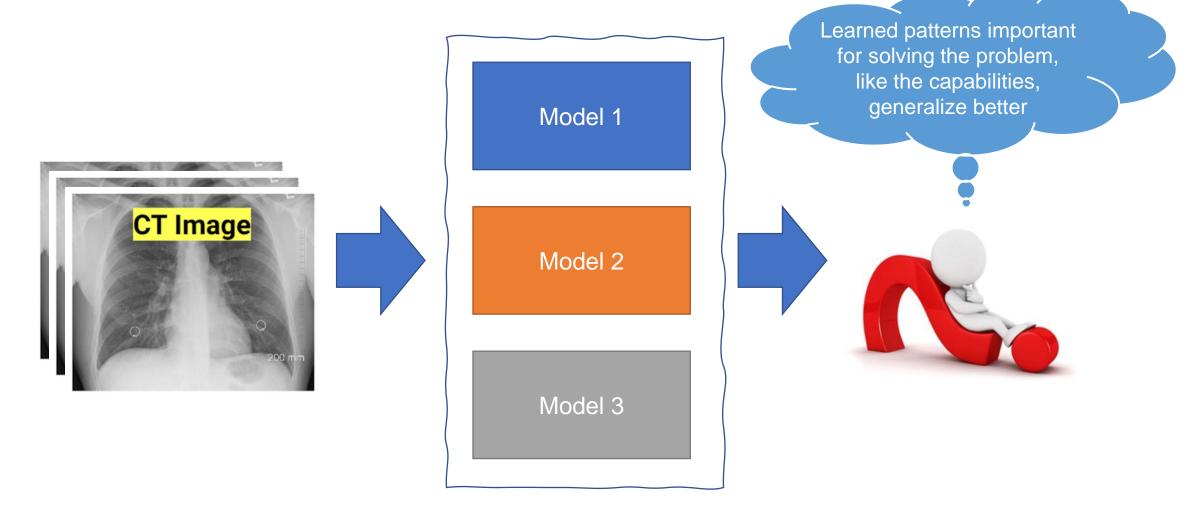


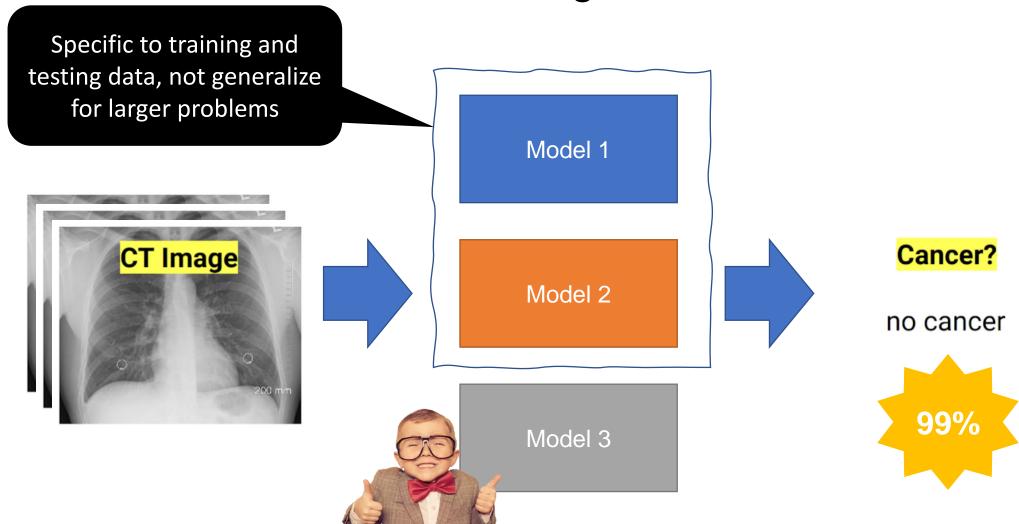
Capabilities of Code Plagiarism Checker?











Capability Testing Strategies

Domain-specific example generators

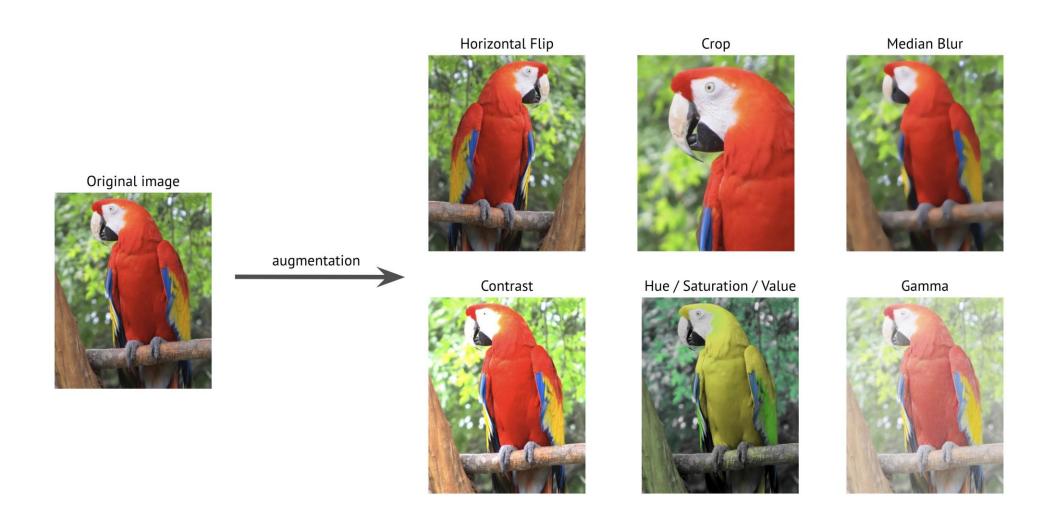


"I love the food"

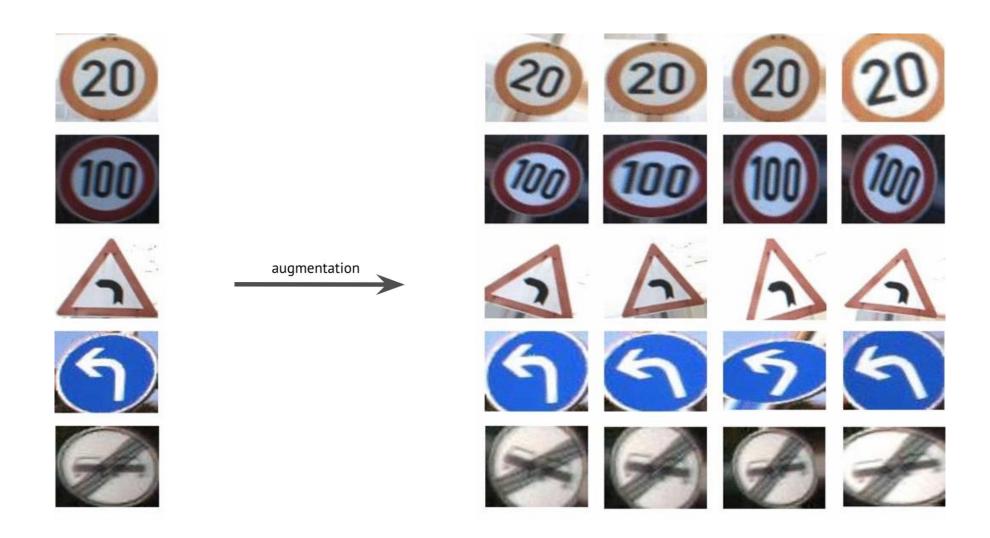
Templates:
"I {NEGATION} {POS_VERB}
the {THING}."

"I didn't love the food"
...

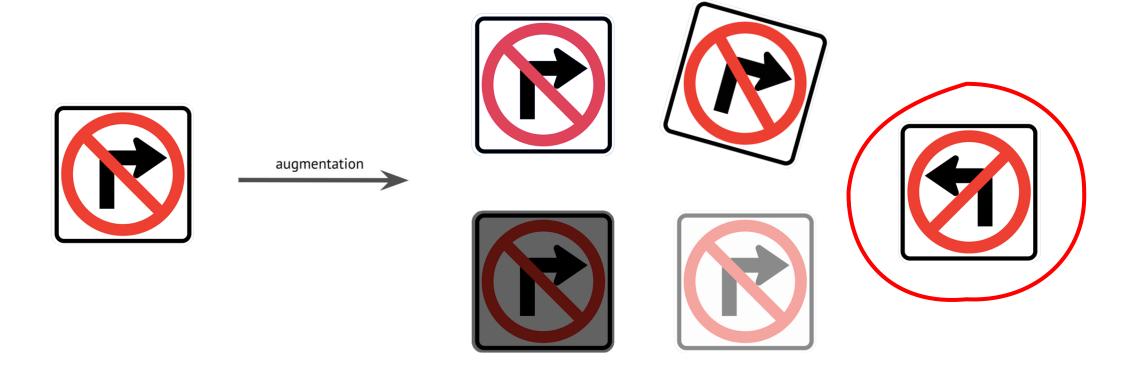
Mutating existing inputs



Mutating existing inputs



Mutating existing inputs



Mutated

Original

Mutated

50

Crowd-sourcing test creation

"The battery life on this phone is amazing! It easily lasts all day."



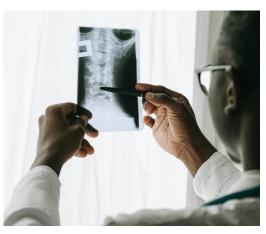
"Oh great, the battery life on this phone is amazing! It lasts a whole 5 minutes."



Identifying capabilities

- Analyzing common (known) mistakes --> making clear candidates for capabilities
 - NLP models using word overlap rather than understanding a text's content
 - Computer vision models focusing on texture over shape
- Using existing knowledge about the problem
 - In NLP, some partial understanding: synonyms, anonyms, identifying named entities, semantic role labeling, negation, and coreference.
- Observe humans
 - Where we do not have domain knowledge, we can study how humans solve a problem
- Derived from requirements (typically invariants)
 - E.g., Fairness requirements
 - Credit risk prediction shall not differ depending on gender/color
 - Changing person names should not affect the sentiment of the text

One final look...



- Analyzing model mistakes: The model performs poorly when brightness is not calibrated across multiple scanners
 - Capabilities: ???
- Observing humans: Ask radiologists why they disagree with a model
 - Capabilities experts use that the model may be missing
- Existing knowledge: Look into non-ML literature on cancer diagnosis
 - Capabilities that radiologists use when looking for cancer in training material for radiologists

Wrap this up...

- Identifying capabilities and then creating test data is not that different selecting inputs for unit tests.
- We have no a strong specification for ML problems, we have some knowledge about the problem and past mistakes.
- Identifying capabilities is not unlike selecting test inputs for a program without looking at code (black-box testing)