# ML4SE + SE4ML

SEP592, Summer 2021

Shin Yoo

# Machine Learning

- "A field of AI that uses statistical techniques to give computer systems the ability to **learn** from data, without being explicitly programmed" (Wikipedia)

- Supervised Learning: examples + desired outcome

- Unsupervised Learning: find inherent structure in data

- Reinforcement Learning: learn from feedback given to the program's action in a changing environment

# ML4SE

- Broadly speaking, this course is AI4SE: we borrow from specific sub-domains of AI to solve SE problems.
    - At the highest level, GP can be thought of as supervised learning
    - Some applications of hyper-heuristic can be thought of as reinforcement learning

# Clustering

- Clustering is one of the representative form of unsupervised learning

- Whenever you suspect there are internal patterns in a problem, you can attempt clustering to reveal and exploit the pattern

# Maintenance & Reverse Engineering

- Module Clustering: assign modules to clusters based on their relationships
  - B. S. Mitchell and S. Mancoridis. On the automatic modularization of software systems using the bunch tool. IEEE Transactions on Software Engineering, 32(3):193–208, 2006.
- K. Praditwong, M. Harman, and X. Yao. Software module clustering as a multi-objective search problem. IEEE Transactions on Software Engineering, 37(2):264–282, March-April 2010.

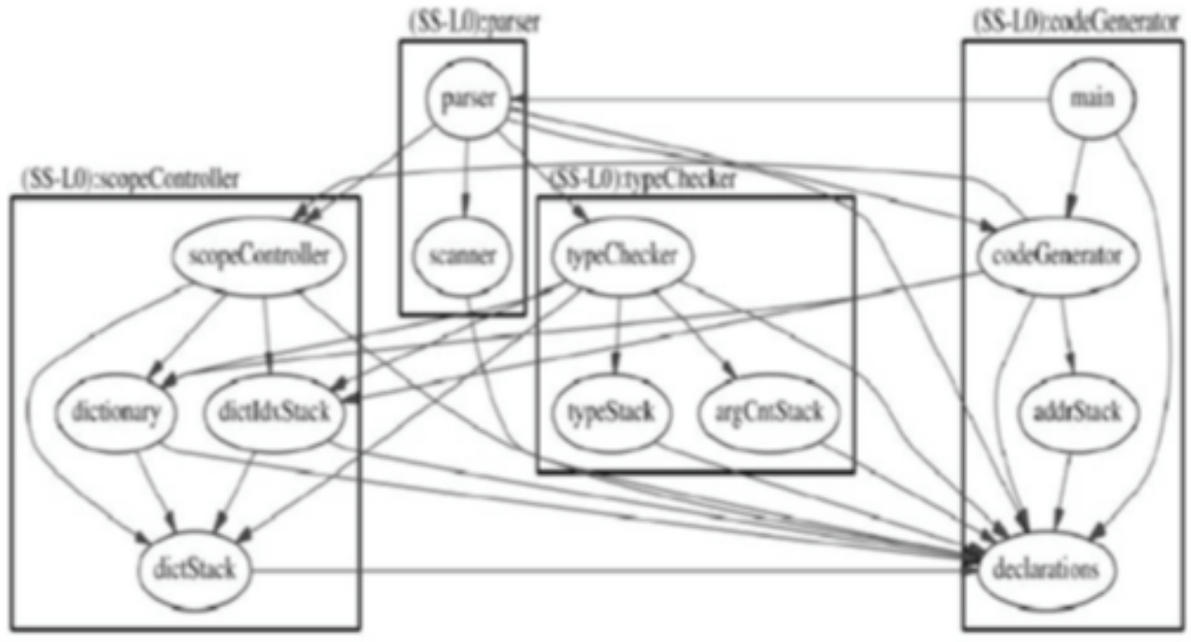
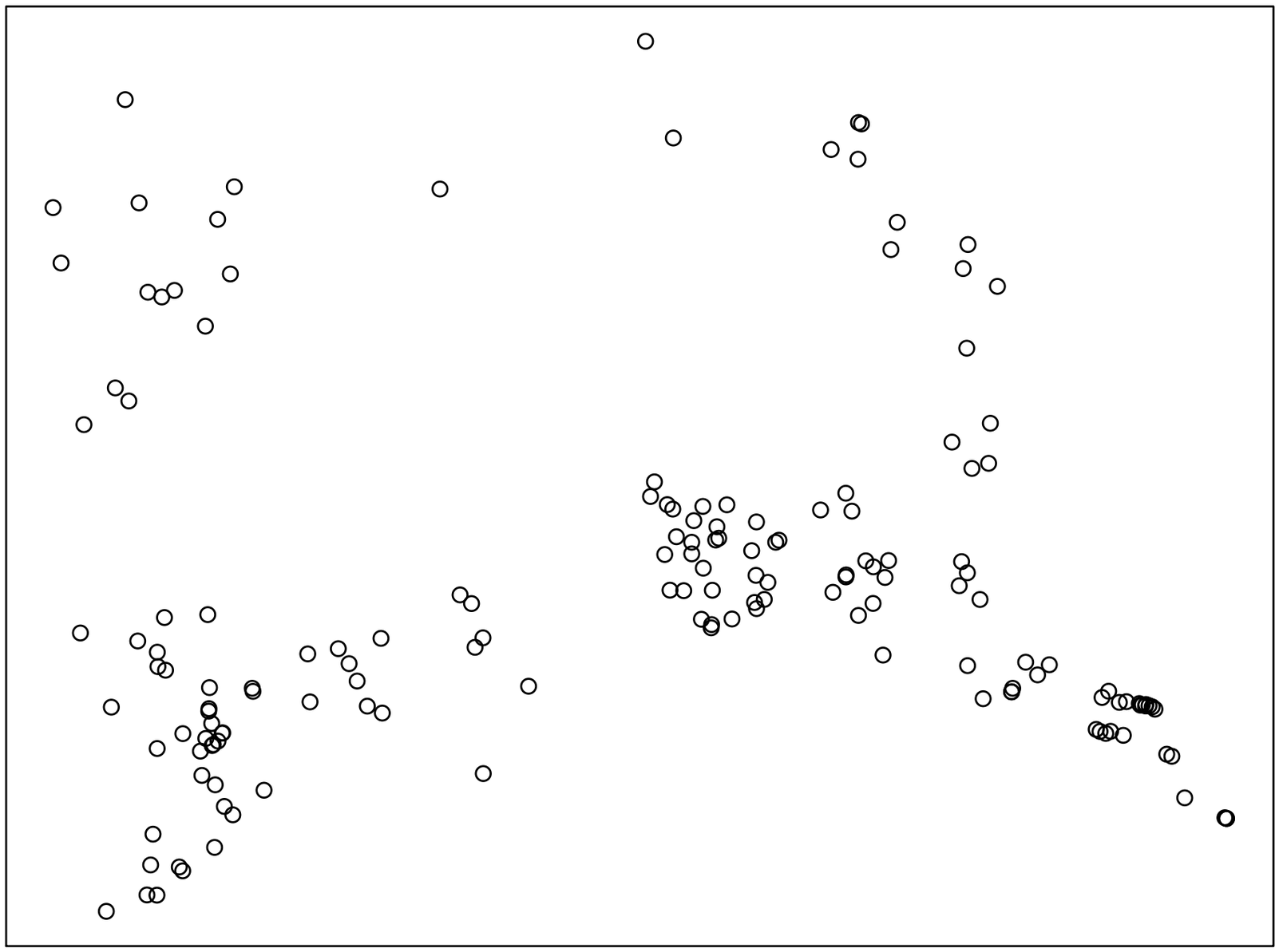



**Figure 3. A Module Dependency Graph and its Modularisation using Bunch, taken from [65]**

# Test Case Prioritisation




D. Leon and A. Podgurski. A comparison of coverage-based and distribution-based techniques for filtering and prioritizing test cases. In Proceedings of the IEEE International Symposium on Software Reliability Engineering (ISSRE 2003), pages 442–456. IEEE Computer Society Press, November 2003.

# Case-Based Reasoning

- P. Tonella, P. Avesani, and A. Susi. Using the case-based ranking methodology for test case prioritization, ICSME 2006
- Human testers make pairwise comparison between test cases
- CBR learns to put priority scores to test cases, based on human examples
- Effective, but human comparison is extremely expensive

**Using the Case-Based Ranking Methodology for Test Case Prioritization**

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**Abstract**

*The test case execution order affects the time at which the objectives of testing are met. If the objective is fault detection, an inappropriate execution order might reveal most faults late, thus delaying the bug fixing activity and eventually the delivery of the software. Prioritizing the test cases so as to optimize the achievement of the testing goal has potentially a positive impact on the testing costs, especially when the test execution time is long.*

*Test engineers often possess relevant knowledge about the relative priority of the test cases. However, this knowledge can be hardly expressed in the form of a global ranking or scoring. In this paper, we propose a test case prioritization technique that takes advantage of user knowledge through a machine learning algorithm, Case-Based Ranking (CBR). CBR elicits just relative priority information from the user, in the form of pairwise test case comparisons. User input is integrated with multiple prioritization indexes, in an iterative process that successively refines the test case ordering. Preliminary results on a case study indicate that CBR overcomes previous approaches and, for moderate suite size, gets very close to the optimal solution.*

**1. Introduction**

Testing amounts for a large proportion of the software development and evolution effort. This is especially true for the system level testing, that typically occurs before each major release of the software. During system testing the whole application is exercised in a realistic setting. Correspondingly, the opportunities for automation are often inferior with respect to the previous testing phases (unit and integration). In fact, it might be hard to run the whole application unattended and to simulate any asynchronous input (e.g., interactive inputs) the application may receive. In such cases, system testing can last days or weeks and can involve substantial human effort.

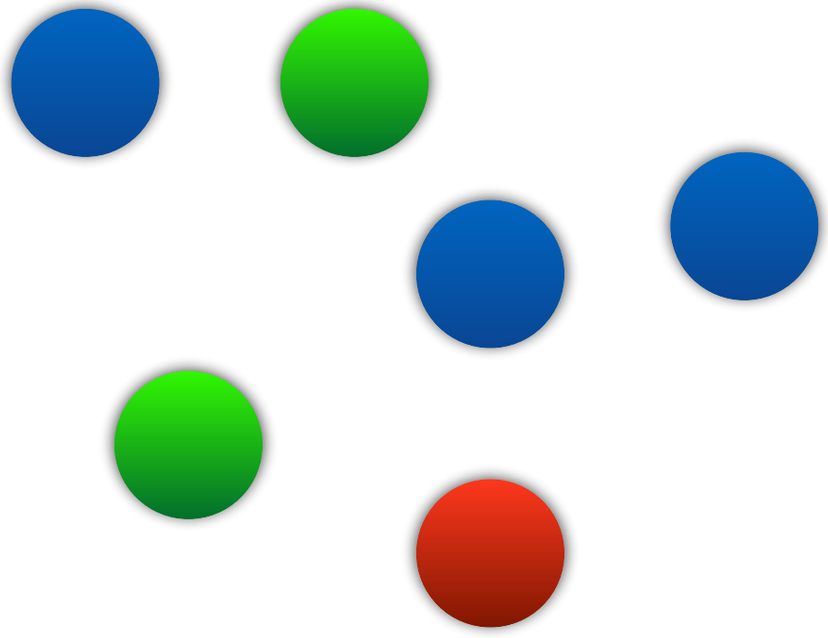
*Test case prioritization* aims at finding an execution order for the test cases which maximizes a given objective function. Among the others, the most important prioritization objective is probably discovering faults as early as possible, that is, maximizing the *rate of fault detection*. In fact, early feedback about faults allows anticipating the costly activities of debugging and corrective maintenance, with a related economical return. When the time necessary to execute all test cases is long, prioritizing them so as to discover most faults early might save substantial time, since bug fixing can start earlier.

Previous work on test case prioritization [6, 11, 13, 14, 15] is based on the computation of a prioritization index, which determines the ordering of the test cases (e.g., by decreasing values of the index). For example, the coverage level achieved by each test case was used as a prioritization index [13]. Another example is a fault proneness index computed from a set of software metrics for the functions exercised by each test case [6].

In this paper, we propose to incorporate user knowledge into the prioritization process and to integrate multiple prioritization indexes through the CBR (Case-Based Ranking) machine learning algorithm. CBR learns the target ranking from two inputs: a set of possibly partial indicators of priority and pairwise comparisons elicited from the user (cases). On one hand, all the information that can be gathered automatically about the test cases (coverage levels, fault proneness metrics, etc.) is used by CBR to approximate the target ranking. On the other hand, the user is involved in the prioritization process to resolve the cases where contradictory or insufficient data are available. The contribution required from the user consists of very local information and has the form of a pairwise comparison. Given two test cases, the user is requested to indicate the one that should be given higher priority. No quantification and no global evaluation is required. No consistency, such as transitivity, in the elicitation process is assumed. CBR operates iteratively and it produces a provisional ordering at each iteration. Thus, prioritization can be stopped at any time and CBR provides the user with the last ordering produced. Thus, the human effort dedicated to the prioritization process can be calibrated arbitrarily.

The main contributions of this paper over the state of the

# Interleaved Clusters Prioritisation



Cluster

Intra-cluster Prioritisation

Inter-cluster Prioritisation

Interleaving Clusters

S. Yoo, M. Harman, P. Tonella, and A. Susi. Clustering test cases to achieve effective & scalable prioritisation incorporating expert knowledge. In Proceedings of International Symposium on Software Testing and Analysis, ISSTA 2009, pages 201–211. ACM Press, July 2009.

# Classification/Prediction

- To identify to which of a set of categories a new example belongs
  - Defect Prediction / Fault Localisation: Is this statement/ method/file (likely to be) faulty or not?

- Hypotheses
  - “If a file goes through an unusually high number of changes, it is more likely to be faulty”
  - “If a file is modified by an unusually high number of developers, it is more likely to be faulty”

# Defect Prediction

- Collect past test history as well as various features leading up to the test results
- Train a classification model
- Before a large project moves into the testing stage, feed the collected data to see which file is more likely to be faulty

**Table 4. List of Change metrics used in the study.**

| Metric name | Definition |
|---|---|
| REVISIONS | Number of revisions of a file |
| REFACTORINGS | Number of times a file has been refactored[1] |
| BUGFIXES | Number of times a file was involved in bug-fixing[2] |
| AUTHORS | Number of distinct authors that checked a file into the repository |
| LOC_ADDED | Sum over all revisions of the lines of code added to a file |
| MAX_ LOC_ADDED | Maximum number of lines of code added for all revisions |
| AVE_ LOC_ADDED | Average lines of code added per revision |
| LOC_DELETED | Sum over all revisions of the lines of code deleted from a file |
| MAX_ LOC_DELETED | Maximum number of lines of code deleted for all revisions |
| AVE_ LOC_DELETED | Average lines of code deleted per revision |
| CODECHURN | Sum of (added lines of code – deleted lines of code) over all revisions |
| MAX_ CODECHURN | Maximum CODECHURN for all revisions |
| AVE_ CODECHURN | Average CODECHURN per revision |
| MAX_CHANGESET | Maximum number of files committed together to the repository |
| AVE_CHANGESET | Average number of files committed together to the repository |
| AGE | Age of a file in weeks (counting backwards from a specific release) |
| WEIGHTED_AGE | See equation (1) |

R. Moser, W. Pedrycz, and G. Succi. A comparative analysis of the efficiency of change metrics and static code attributes for defect prediction. In 2008 ACM/IEEE 30th International Conference on Software Engineering, pages 181–190, May 2008.

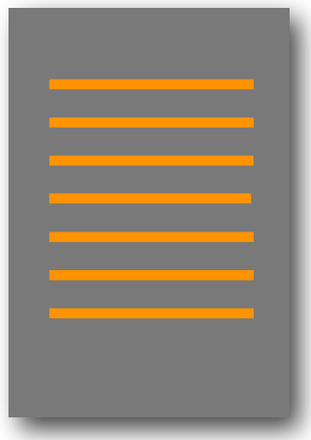
# Spectrum Based Fault Localisation

- Given some failing test case executions, fault localisation aims to automatically identify the program elements that are responsible for the observed failure

- One of the most widely studied technique is Spectrum-Based Fault Localisation

# Spectrum Based Fault Localisation

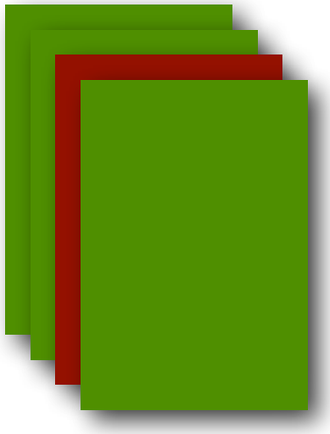
Program



Spectrum

$$e_f - \frac{e_p}{e_p + n_p + 1}$$

Risk Evaluation Formula



Tests

Higher ranking
=
Fewer statements
to check

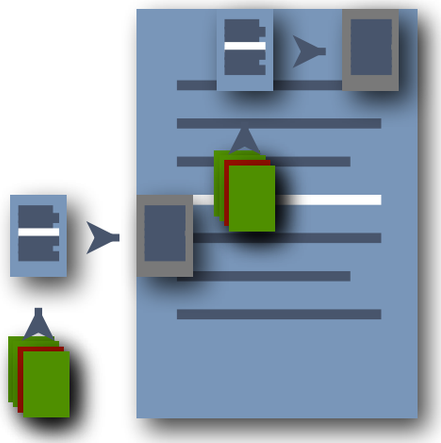
Ranking

# Spectrum Based Fault Localisation

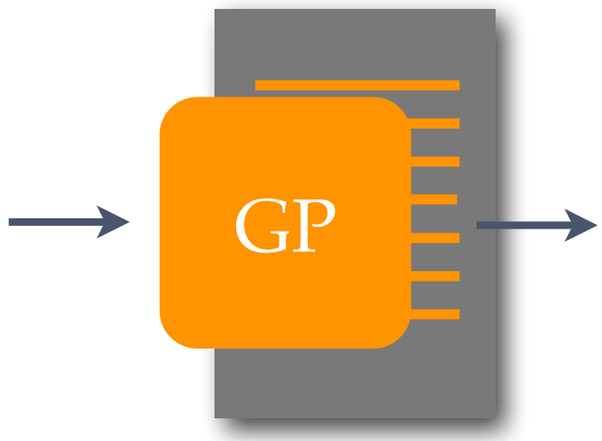
| Structural Elements | Test $t_1$ | Test $t_2$ | Test $t_3$ | Spectrum $e_p$ | $e_f$ | $n_p$ | $n_f$ | Tarantula | Rank |
|---|---|---|---|---|---|---|---|---|---|
| $s_1$ | • | | | 1 | 0 | 0 | 2 | 0.00 | 9 |
| $s_2$ | • | | | 1 | 0 | 0 | 2 | 0.00 | 9 |
| $s_3$ | • | | | 1 | 0 | 0 | 2 | 0.00 | 9 |
| $s_4$ | • | | | 1 | 0 | 0 | 2 | 0.00 | 9 |
| $s_5$ | • | | | 1 | 0 | 0 | 2 | 0.00 | 9 |
| $s_6$ | • | • | | 1 | 1 | 0 | 1 | 0.33 | 4 |
| $s_7$ (faulty) | | • | • | 0 | 2 | 1 | 0 | 1.00 | 1 |
| $s_8$ | • | • | | 1 | 1 | 0 | 1 | 0.33 | 4 |
| $s_9$ | • | • | • | 1 | 2 | 0 | 0 | 0.50 | 2 |
| Result | P | F | F | | | | | | |

$$\text{Tarantula} = \frac{\frac{e_f}{e_f+n_f}}{\frac{e_p}{e_p+n_p} + \frac{e_f}{e_f+n_f}}$$

# Evolving Formulæ



Program




Spectrum

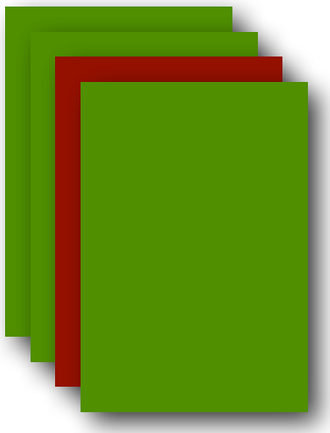
$$e_f^2(2e_p + 2e_f + 3n_p)$$

$$e_f^2\left(e_f^2 + \frac{e_p}{e_p\sqrt{n_p}}\right) + 1$$

$$\ldots$$

Risk Evaluation Formula

Training Data



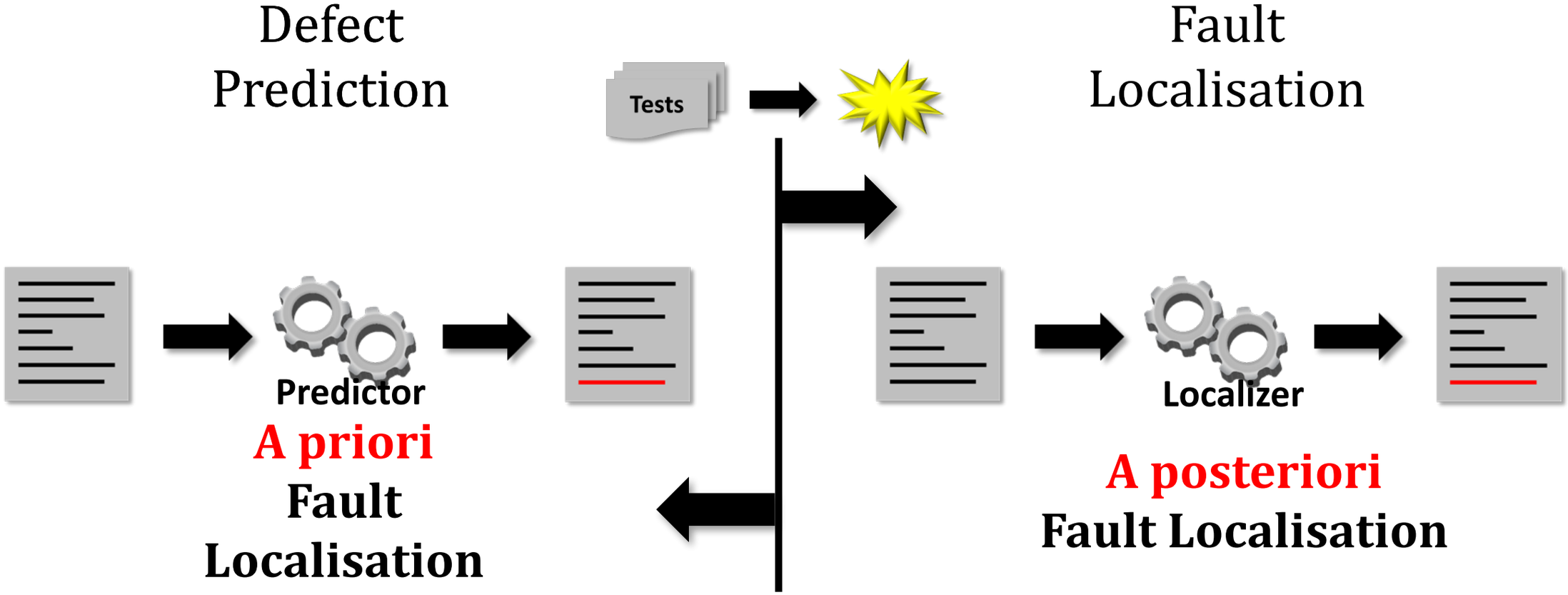
Tests

Fitness
(minimise)

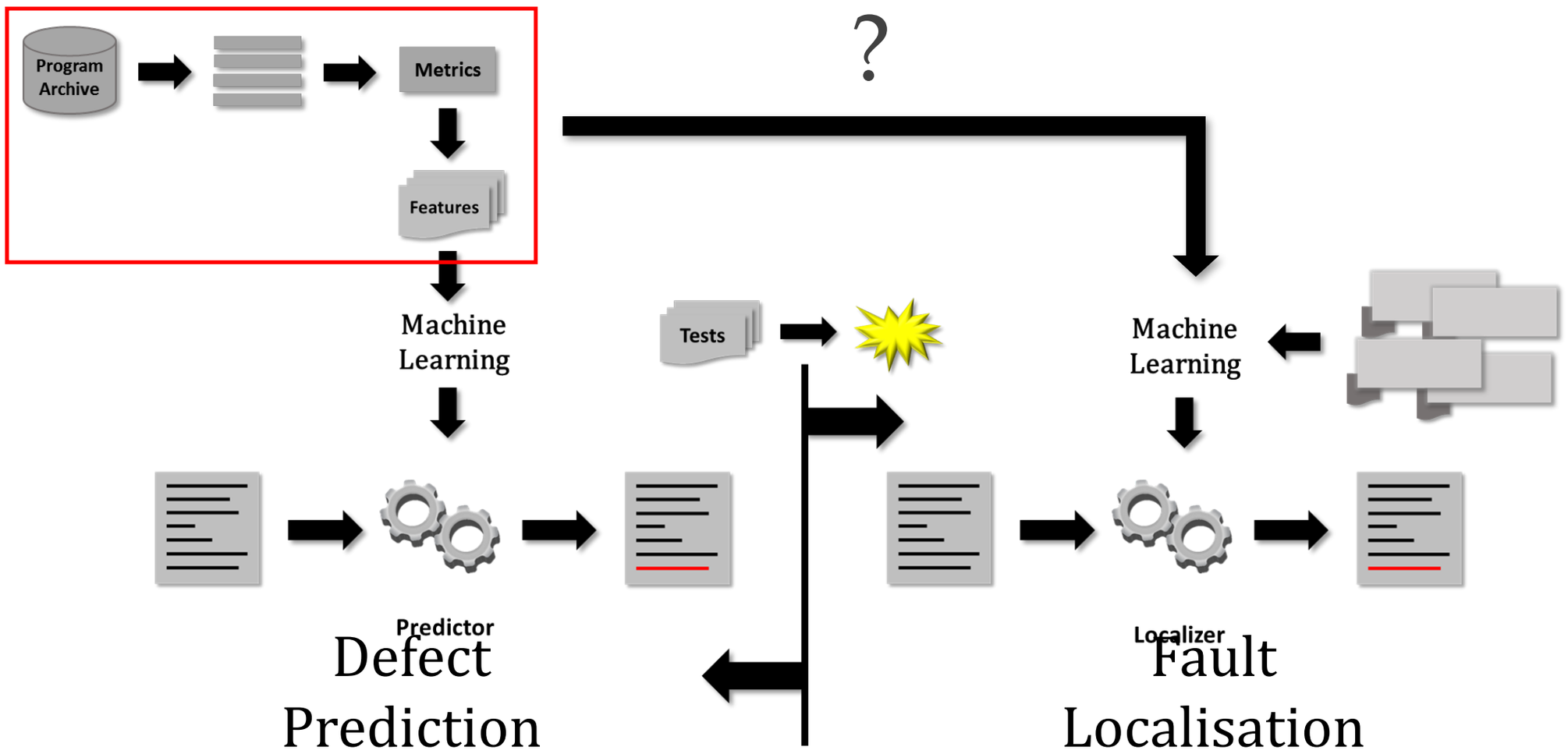
Ranking

S. Yoo. Evolving human competitive spectra-based fault localisation techniques. SSBSE 2012, volume 7515 of Lecture Notes in Computer Science, pages 244–258. Springer, 2012.

# Defect Prediction and Fault Localisation: the ML perspective



# Defect prediction and Fault Localisation




J. Sohn and S. Yoo. Fluccs: Using code and change metrics to improve fault localisation. In Proceedings of the International Symposium on Software Testing and Analysis, ISSTA 2017, pages 273–283, 2017.

# Ranking Suspicious Program Elements

- Genetic Programming: we know the real faulty element in the training data. We evolve a score formula that takes input features and returns suspiciousness scores: rank the elements, and take the ranking of the real faulty element as the fitness to minimise

- Linear RankSVM: learns the ranking score function, which is linear sum of individual features

- Gaussian Process / Random Forrest: use the faulty/non-faulty labels in the training data to train classifiers - take the classification scores to rank program elements

# Information Retrieval

- IR is also used to perform fault localisation

- Given a bug report, the program element responsible for the observed failure is the part of the source code that is lexically the most similar to the bug report

- See for example: R. K. Saha, M. Lease, S. Khurshid, and D. E. Perry. Improving bug localization using structured information retrieval. In Automated Software Engineering (ASE), 2013.

# Recommendation System

- You buy X from Amazon, and give it five star. Amazon gives you “people who bought (and liked) this also bought…”

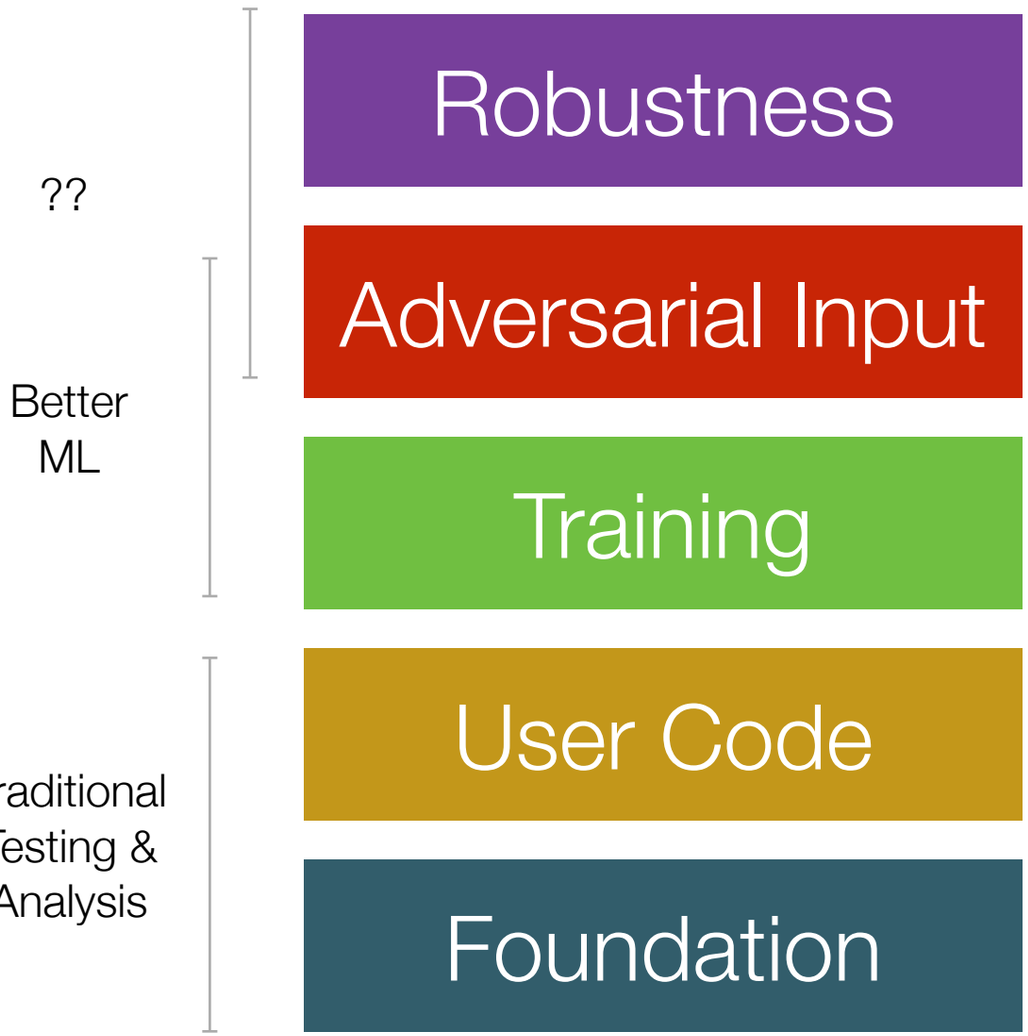
- Similarly, we can think of bug-triaging (i.e., the question of who should handle the new bug report) as:

- You fix bug X from Project Z, and does the job well. The project gives you “people who successfully fixed bugs like this may also do well on…”

# SE4ML

- We will see ML components as part of larger systems
    - Autonomous driving, photography manager, machine translation…
- ML research may deal with the core precision issues, but SE research has to deal with the larger system, especially in terms of quality assurance.
- But what is a fault in machine learning?

# What are the faults?




Input is not malicious but learner fails anyway

Malicious inputs that trick the learner

Mis-training, biased training data, etc

Faults in YOUR TensorFlow Code

Faults in TensorFlow, for example

# What is the test oracle?

- For many practical ML/Deep Learning systems, inputs are raw, real-world perceptions (such as photography/ video, voice, etc)

- Currently human judgement (a.k.a. data labelling) is often the only effective test oracle, but this is extremely expensive

# Metamorphic Testing

- In testing, there is a widely known technique that focuses on metamorphic relationships between inputs and outputs

- Given an IO pair for program P, y=P(x), if metamorphic relation f and g hold for input and output, it has to follow that g(y) = P(f(i))

  - For example: if P is the sine function, f(x) = π - x, g(y) = y. That is, if $y_0 = P(x_0)$, y1 = $y_0 = P(\pi - x_0) = P(x_1)$

- MT cannot replace a full oracle, but if a program violates its own metamorphic properties, **something** is wrong

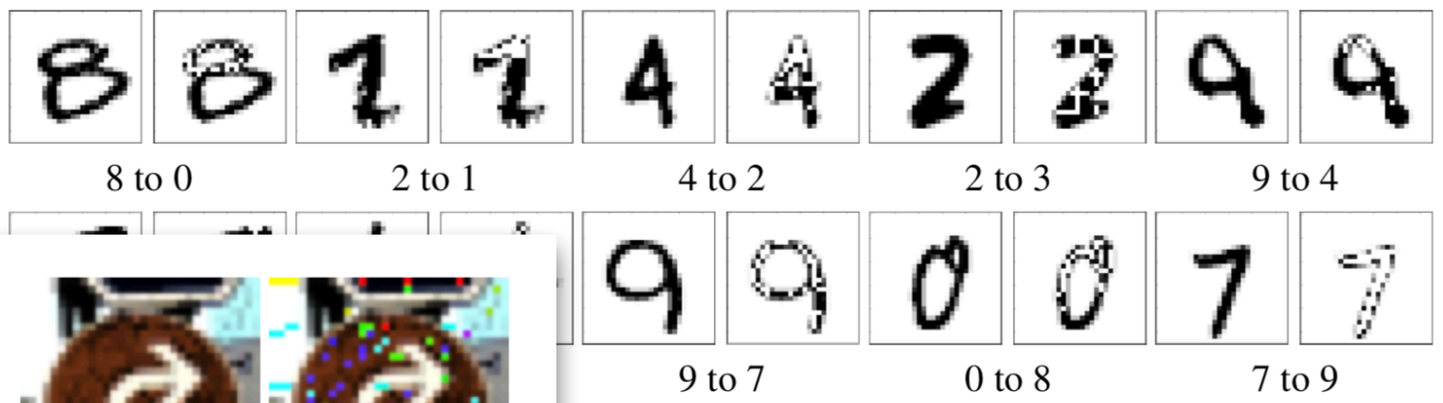
# Metamorphic Testing for DL

- MT has been applied to test DL robustness
  - If we apply negligible (i.e., bearable by humans) perturbation to the input, the output of the DL system should be the same
- Again, if a DL system violates this, **something** is wrong

# Adversarial Examples

automobile to bird  automobile to frog  automobile to airplane  automobile to horse

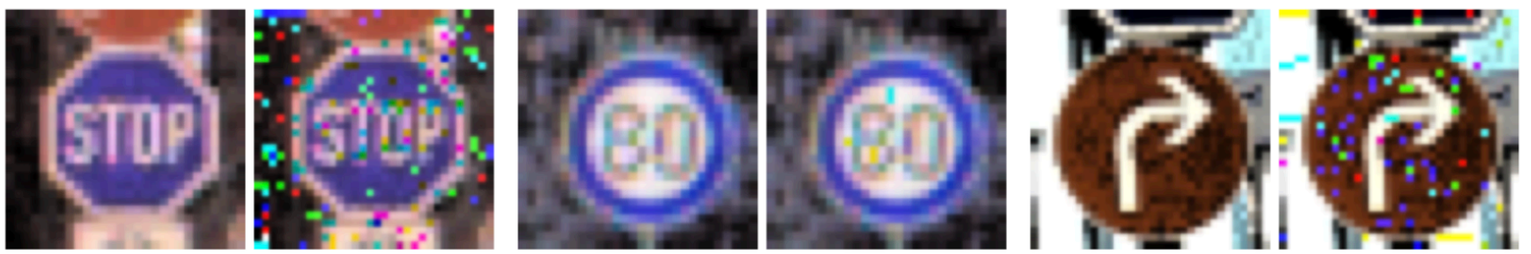
**Fig. 1.** Automobile images (classified correctly) and their perturbed images (classified wrongly)



8 to 0  2 to 1  4 to 2  2 to 3  9 to 4

9 to 7  0 to 8  7 to 9

ples for a neural network trained on MNIST



"stop" to "30m speed limit"  "80m speed limit" to "30m speed limit"  "go right" to "go straight"

**Fig. 11.** Adversarial examples for the network trained on the GTSRB dataset by multi-path search

Safety verification of deep neural networks,
Xiaowei Huang, Marta Kwiatkowska, Sen Wang, Min Wu (https://arxiv.org/abs/1610.06940)

# Robustness Testing

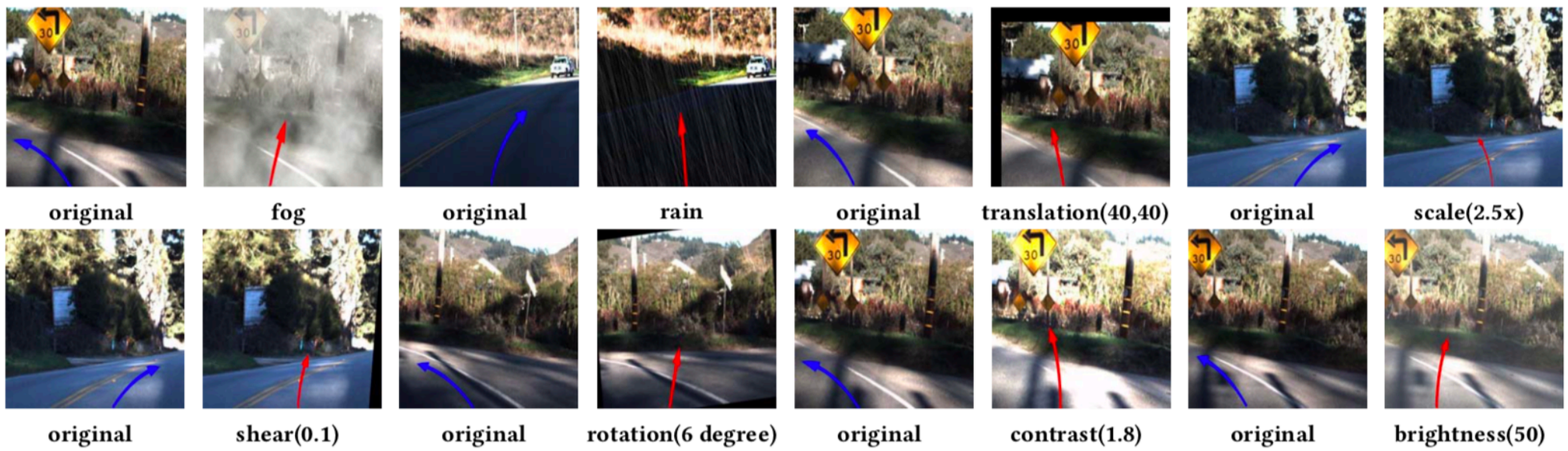



**Figure 7: Sample images showing erroneous behaviors detected by DeepTest using synthetic images. For original images the arrows are marked in blue, while for the synthetic images they are marked in red. More such samples can be viewed at https://deeplearningtest.github.io/deepTest/.**

Y. Tian, K. Pei, S. Jana, and B. Ray. Deeptest: Automated testing of deep-neural-network-driven autonomous cars. In Proceedings of the 40th International Conference on Software Engineering, ICSE '18, pages 303–314, New York, NY, USA, 2018. ACM.

# Coverage for Deep Learning Systems

- Various coverage criteria have been suggested:
  - Neuron Coverage: given a set of test input, NC measures % of neutrons that have been activated above a given threshold (e.g., 0.6)
  - k-Multisection Neuron Coverage: mark the range of neuron activation during training, divide the range into k buckets, and count the number of buckets checked during execution of the given input set
  - Strong Neuron Activation Coverage: mark the range of neuron activation during training, and count the number of neutrons that are activated beyond the maximum observed activation value
- All designed to diversify neuron activation patterns

# A Big Challenge

- For traditional software, inputs can be either randomly sampled, searched, or synthesised
- For DL systems that interface with the real physical world, inputs have to be collected from the real world
- You can try random sampling or search, but would it be relevant?

# Fooling DNNs with Genetic Algorithm

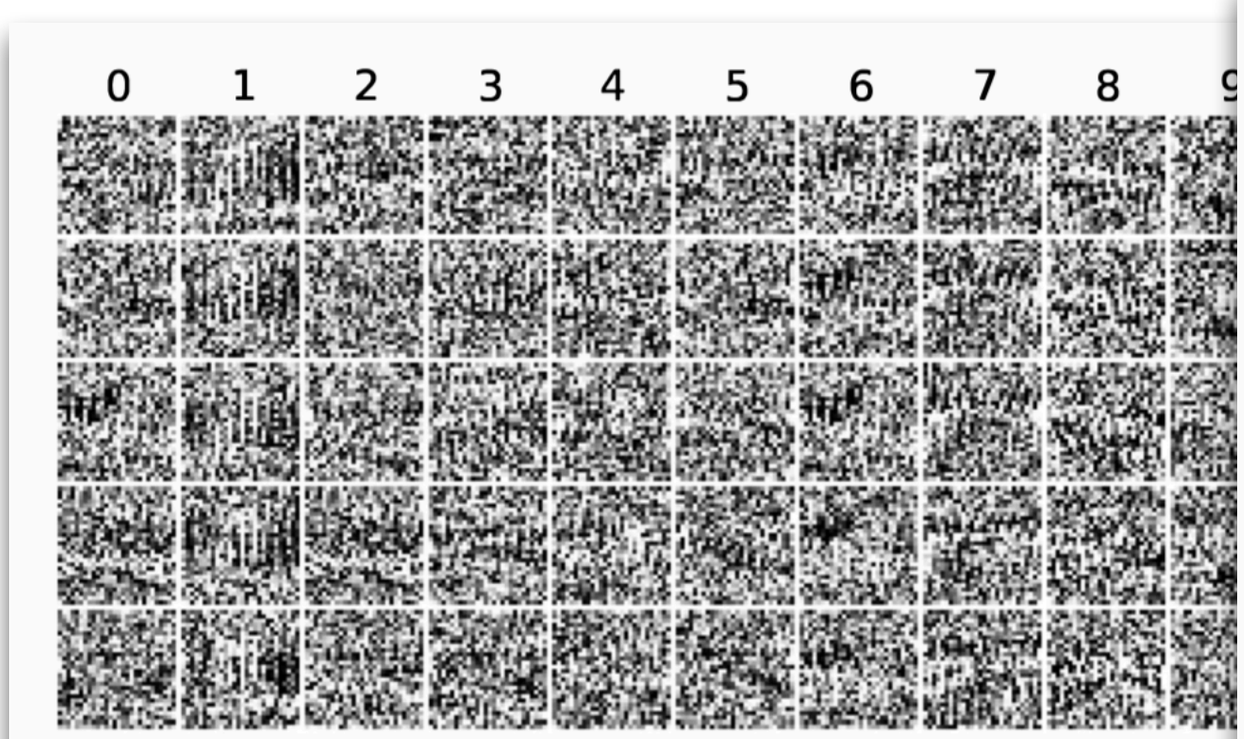



Figure 4. Directly encoded, thus irregular, images that MNI
DNNs believe with 99.99% confidence are digits 0-9. Each c
umn is a digit class, and each row is the result after 200 generatic
of a randomly selected, independent run of evolution.

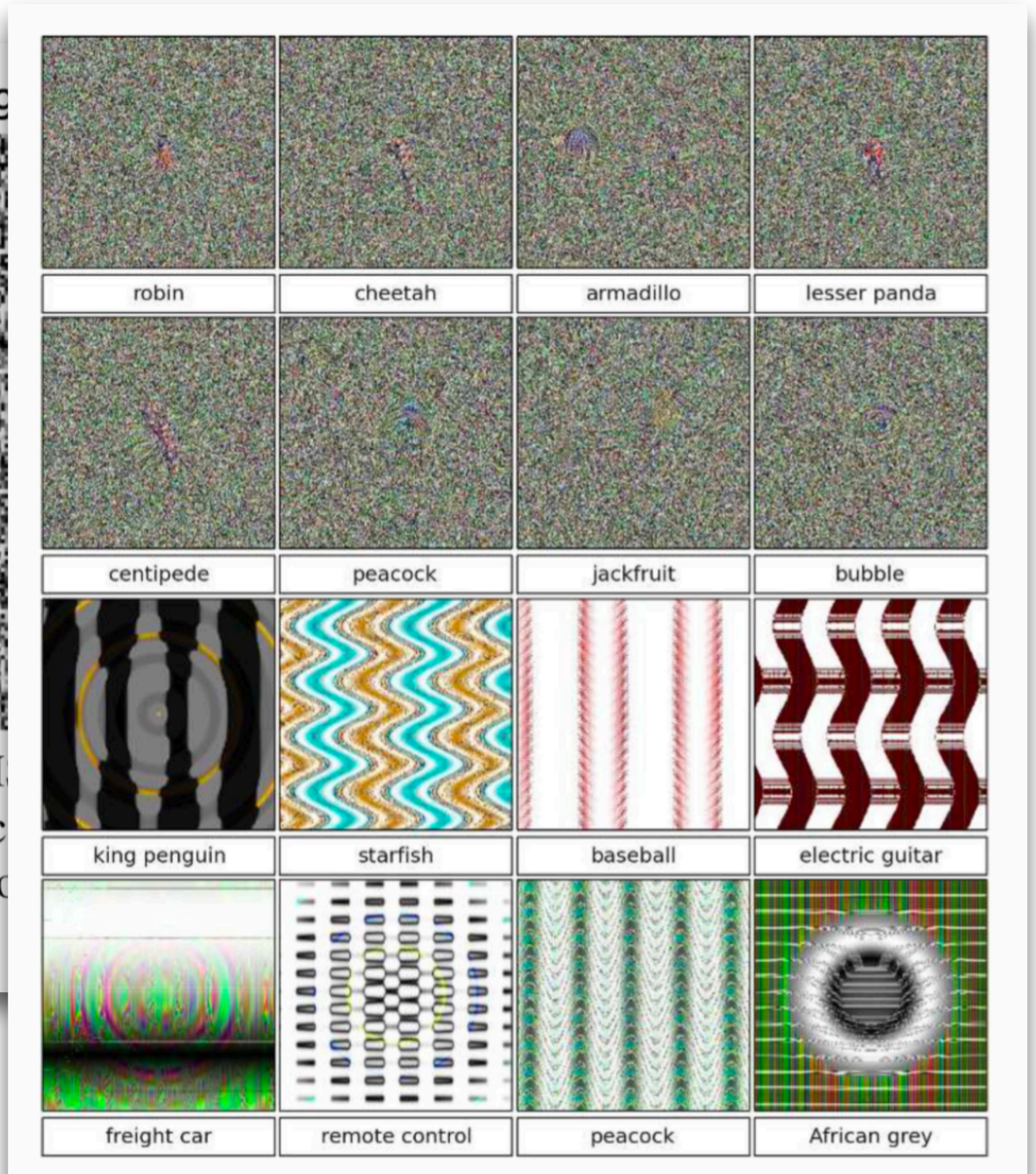
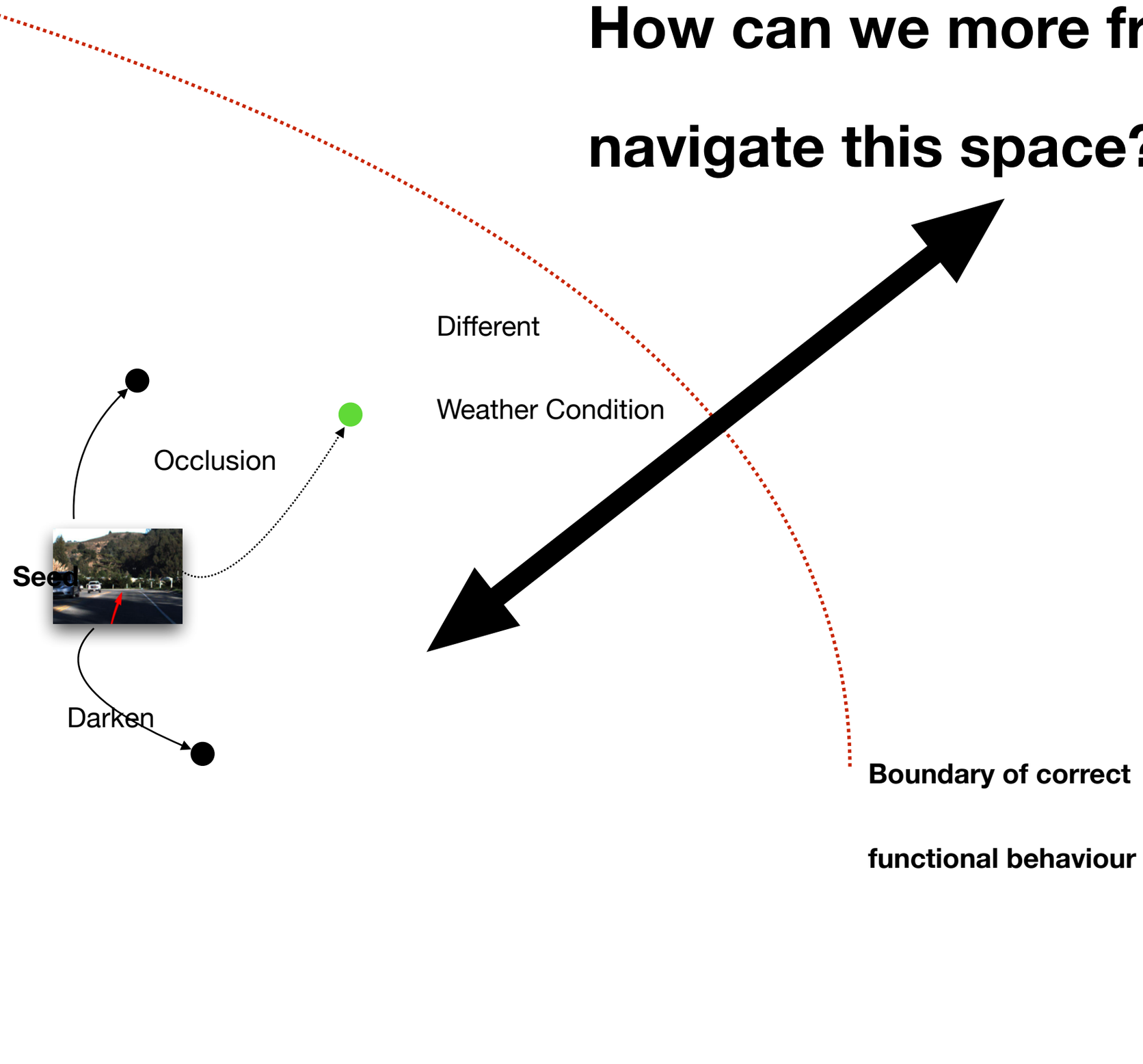


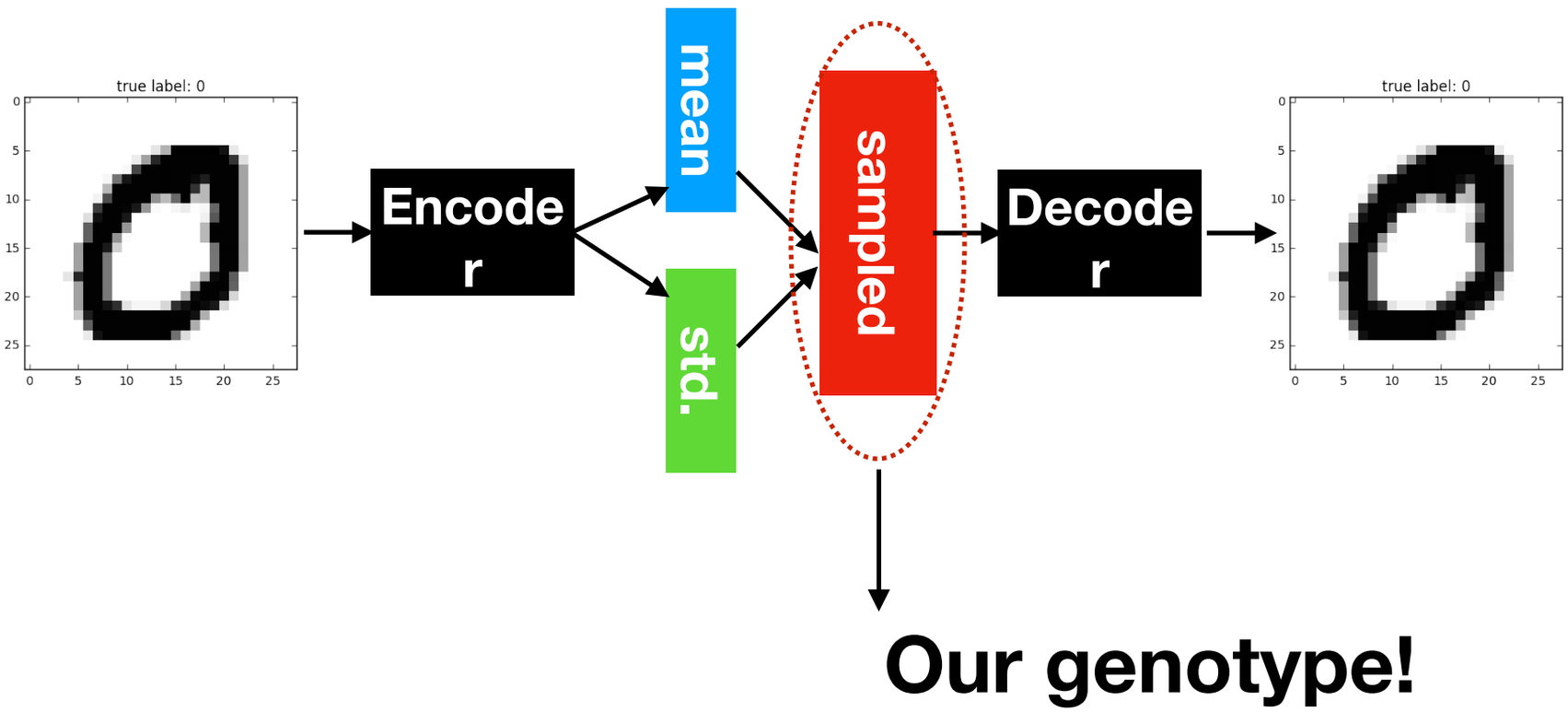

Figure 1. Evolved images that are unrecognizable to humans, but that state-of-the-art DNNs trained on ImageNet believe with $\geq$ 99.6% certainty to be a familiar object. This result highlights differences between how DNNs and humans recognize objects. Images are either directly (*top*) or indirectly (*bottom*) encoded.

A. M. Nguyen, J. Yosinski, and J. Clune. Deep neural networks are easily fooled: High confidence predictions for unrecognizable images. 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 427–436, 2015.

**How can we more freely navigate this space?**

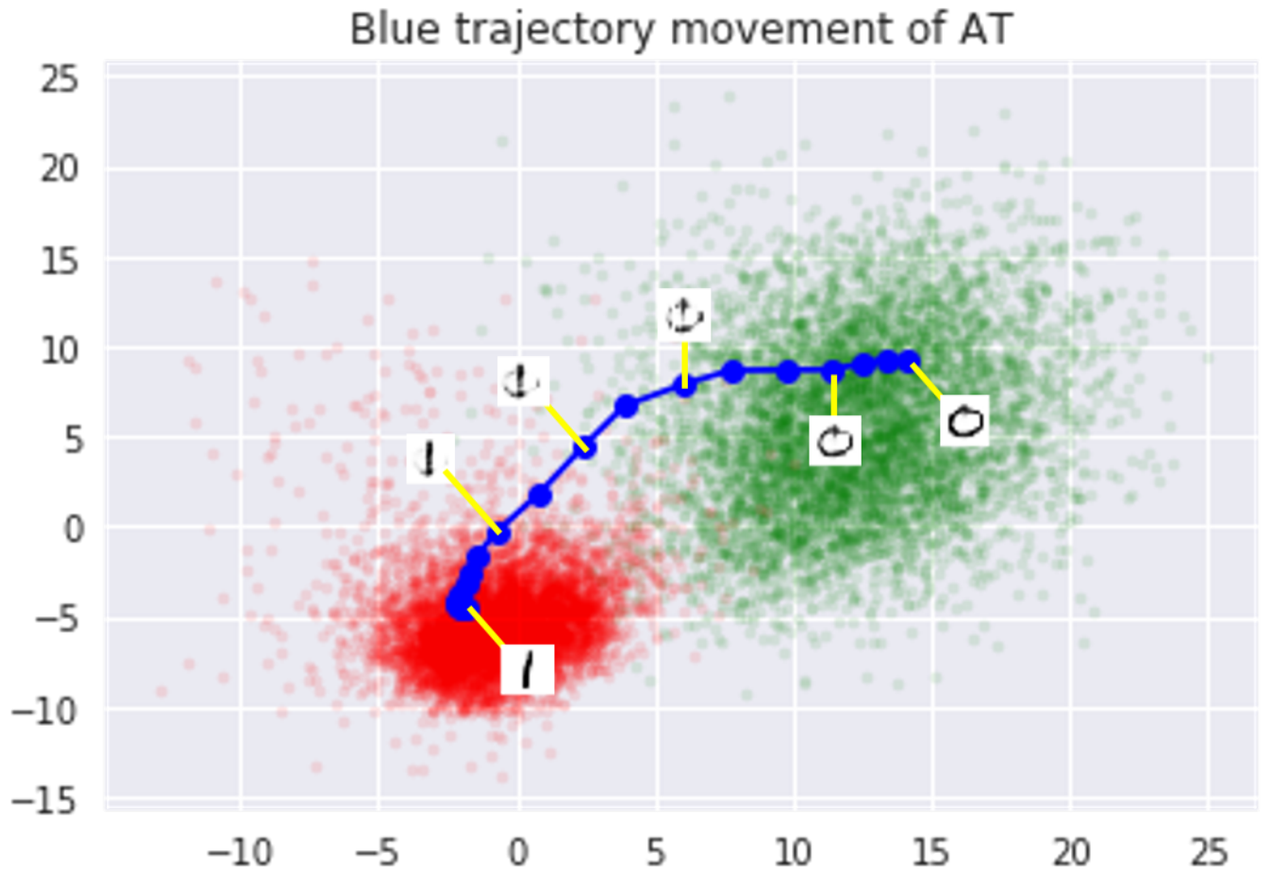


# Variational Auto-Encoders (VAEs)



# VAE + GA = Search Based Input Data Generation

- Representation: a latent vector that fits our VAE
- Fitness: Surprise Adequacy of the image decoded from a candidate solution (i.e., a latent vector)
- We visualise the search trajectory using Activation Trace (i.e., the output of a specific layer of the DNN) and PCA



# Many Open Questions

- DL systems have continuous quality measure (precision/recall/accuracy); traditional systems have discontinuous quality measure (test pass/fail) - how do we connect these two worlds, when a DL system is part of a larger, conventional SW system?

- How do we automatically generate test inputs for a DL system, without going into the real world?

- How can search help? :)