

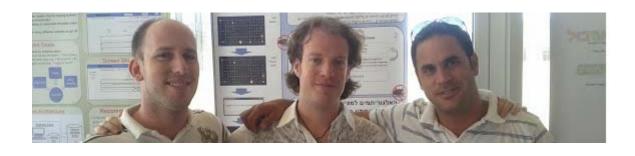






Integrating Artificial Intelligence in Software Testing

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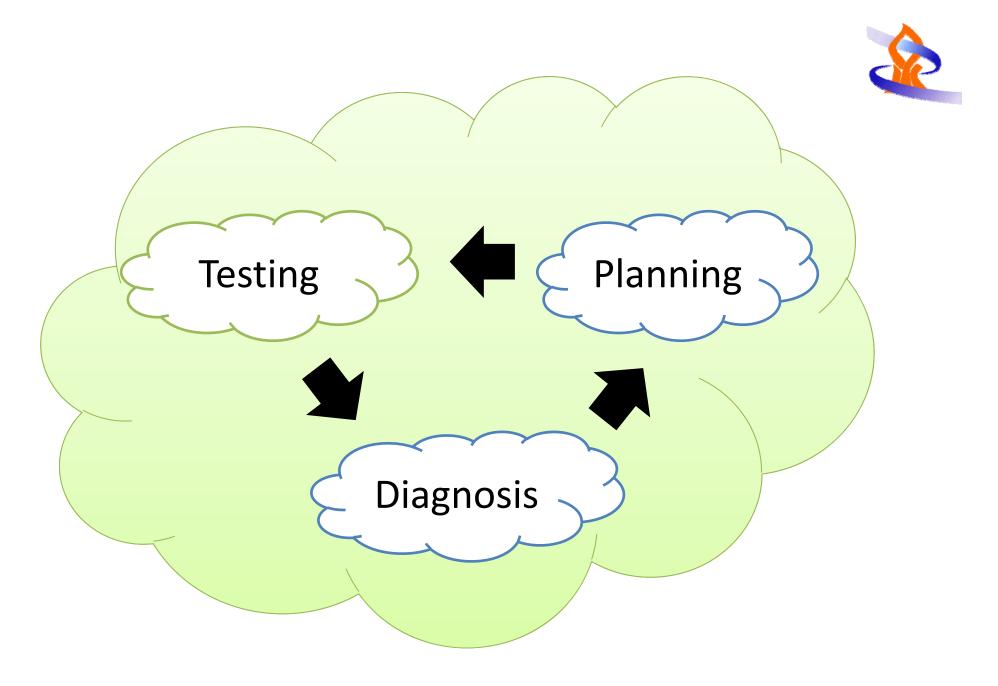
Artificial Intelligence

Planning

Diagnosis

Software Engineering

Testing



Testing is Important



- Quite a few software development paradigms
- All of them recognize the importance of testing
- There are several types of testing
 - E.g., unit testing, black-box (functional) testing





Programmer

- Write programs
- Follows spec.
- Goal: fix bugs!



- Runs tests
- Follows a test plan
- Goal: find bugs!





Handling a Bug

- 1. Bugs are reported by the tester
 - "Screen A crashed on step 13 of test suite 4..."
- 2. Prioritized bugs are assigned to programmers
- 3. Bugs are diagnosed
 - What caused the bug?
- 4. Bugs are fixed
 - Hopefully...





Why is Debugging Hard?

- The developer needs to reproduce the bug
- Reproducing (correctly) a bug is non-trivial
 - Bug reports may be inaccurate or missing
 - Software may have stochastic elements
 - Bug occurs only once in a while
 - Bugs may appear only in special cases

Let the tester provide more information!





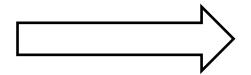


Introducing AI!





Run a test suite
Find a bug



Diagnose Fix the bug

Run a test suite
Find a bug

Plan next tests

Fix the bug
Plan next tests



Test, Diagnose and Plan (TDP)



- 1. The tester runs a set of planned tests (test suite)
- 2. The tester finds a bug
- 3. AI generates possible diagnoses
- 4. If there is only one candidate pass to programmer
- 5. Else, AI plans new tests to prune candidates



Diagnosis

Find the **reason** of a problem given observed **symptoms**

Requirement: knowledge of the diagnosed system

- Given by experts
- Learned by AI techniques



Model-Based Diagnosis

- Given: a model of how the system works
 - → Infer what went wrong
- Example:

```
IF ok(battery) AND ok(ignition)
THEN start(engine)
```

What if the engine doesn't start?



Where is MBD applied?

- Printers
 (Kuhn and de Kleer 2008)
- Vehicles
 (Pernestål et. al. 2006)
- Robotics

(Steinbauer 2009)



(Williams and Nayak, 1996; Bernard et al., 1998)











Software is Difficult to Model

- Need to code how the software should behave
 - Specs are complicated to model
- Static code analysis ignores runtime
 - Polymorphism
 - Instrumentation

• • •



Zoltar [Abrue et. al. 2011']

- Construct a model from the observations
- Observations should include execution traces
 - Functions visited during execution
 - Observed outcome: bug / no bug
- Weaker model
 - Ok(function1) → function1 outputs valid value
 - → A bug entails that at least one comp was not Ok



Execution Matrix

- A key component in Zoltar is the execution matrix
- It is built from the observed execution traces

- Observation 1 (BUG): F1→F5→F6

– Observation 2 (BUG): F2→F5

- Observation 3 (OK) : $F2 \rightarrow F6 \rightarrow F7 \rightarrow F8$

	F1	F2	F3	F4	F5	F6	F7	F8	Bug
Obs1	1	0	0	0	1	1	0	0	1
Obs2	0	1	0	0	1	0	0	0	1
Obs3	0	1	0	0	0	1	1	1	0

Diagnosis = Hitting Sets of Conflicts

In every BUG trace at least one function is faulty

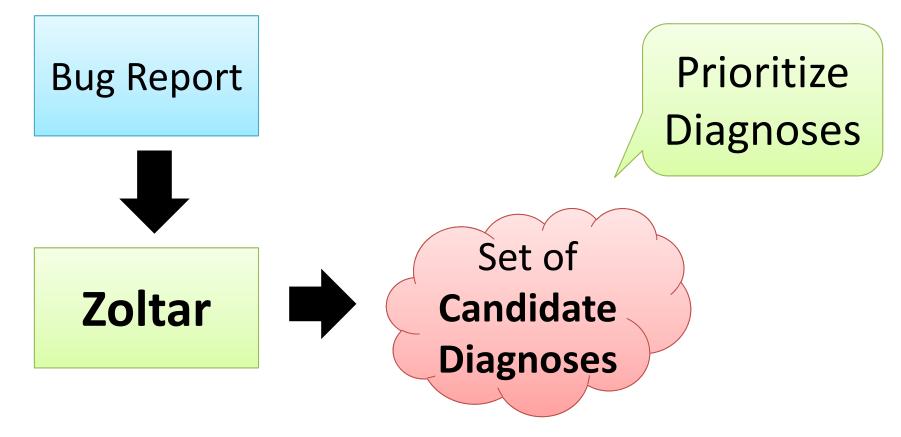
- Observations:
 - Observation 1 (BUG) : F1→F5→F6
 - Observation 2 (BUG) : F2→F5
- Conflicts:
 - Ok(F1) AND Ok(F5) AND Ok(F6)
 - Ok(F2) AND Ok(F5)

Hitting sets of Conflicts

Possible diagnoses: {F5} ,{F1,F2},{F6,F2}



Software Diagnosis with Zoltar





Plan More Tests

Bug Report

AlEngine



Set of
Possible
Diagnoses

Suggest New Test to Prune Candidates



Plan More Tests

Bug Report



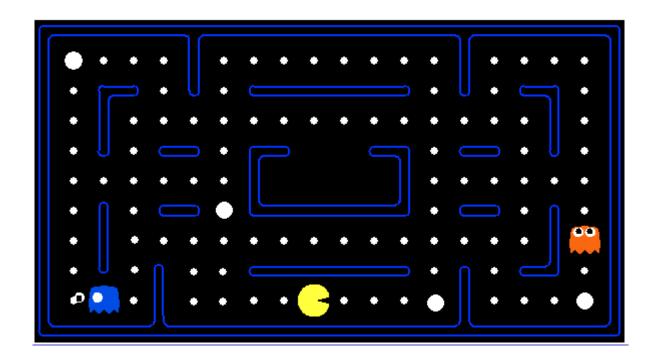
AlEngine



A single diagnosis

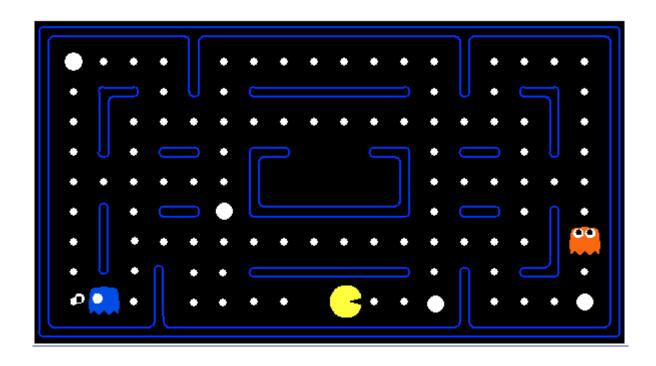
Suggest New Test to Prune Candidates





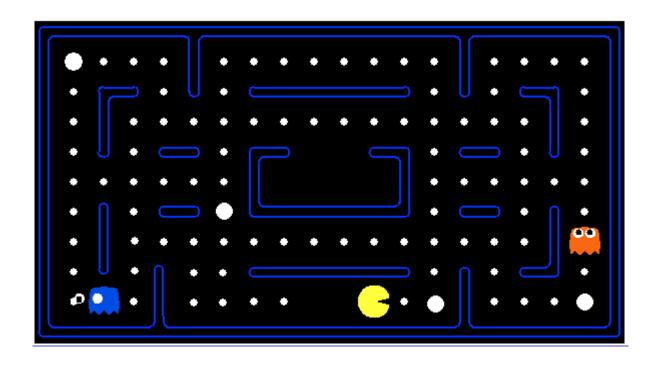






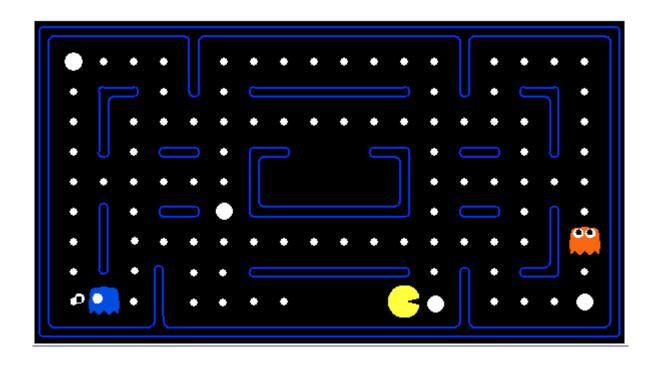






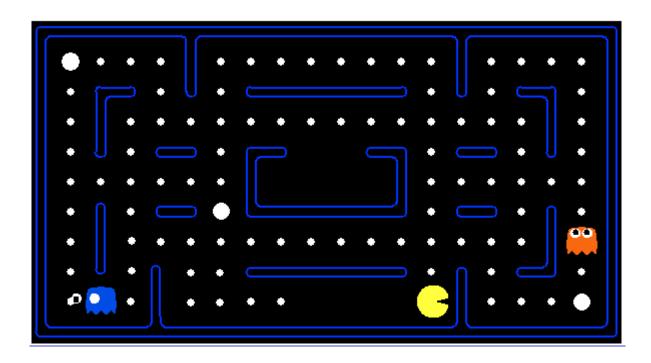






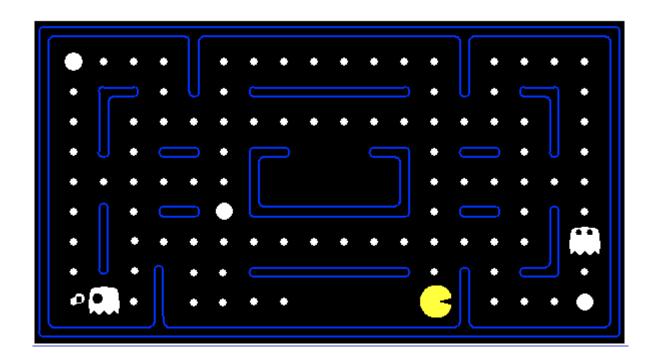














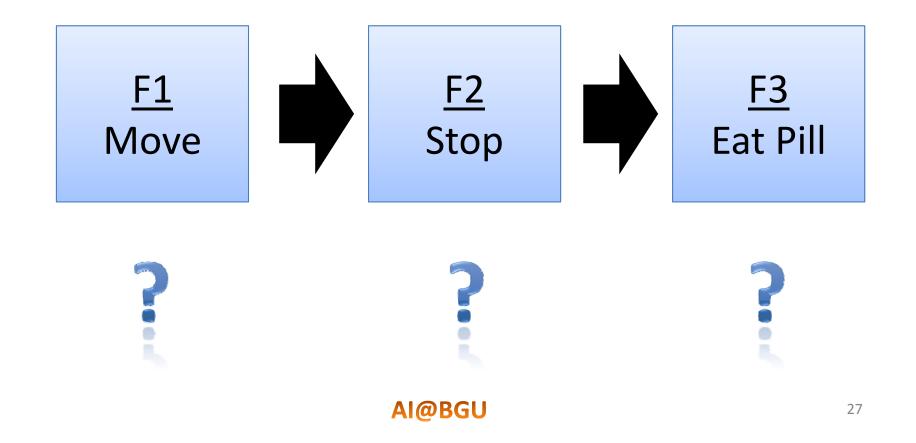


```
C:\Windows\system32\cmd.exe
                           0/1 (0.00)
√in Rate:
Record:
                            \mathbf{hoss}
D:\projects\scarch\python pacman.py
Pacman dicd! Scorc: -537
Nucrayo Scorc: -537.0
Scorcs: -537
Win Rate:
                           0/1 (0.00)
Record:
                            ross.
D:\projects\search\python pacman.py
Pacman died! Score: -535
Nucrage Score: -535.0
Scores: -535
Win Rate:
Record:
                           0/1 (0.00)
D:\projects\search\python pacman.py
Pacman died! Score: -525
Nucrage Score: -525.0
Scores: -525
Win Rate: 0/1 (0.00)
Record:
                            Loss
D:\projecta\scarch}_
```



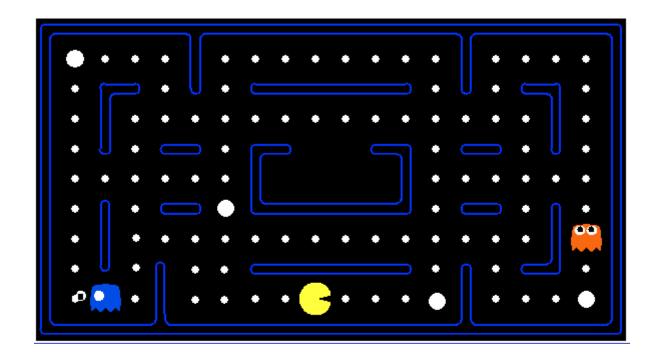


Execution Trace





Which Diagnosis is Correct?

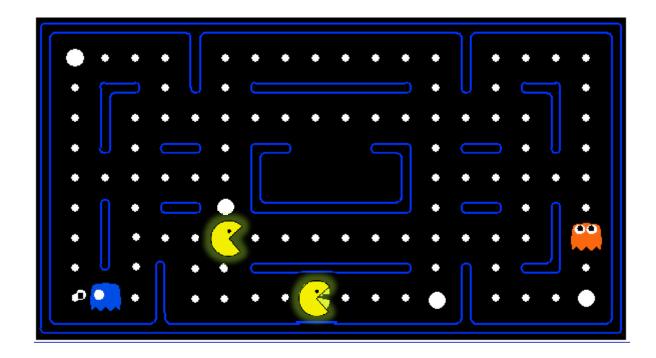






Knowledge

Most probable cause: Eat Pill

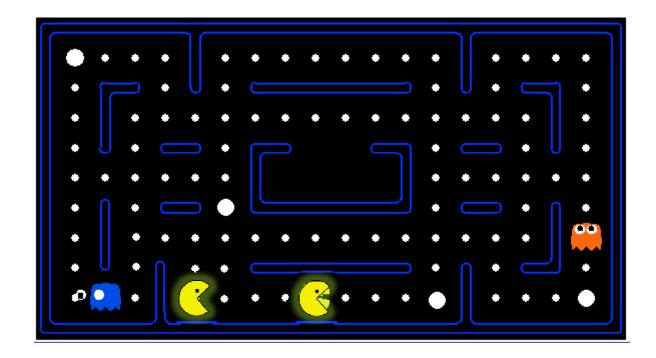






Knowledge

- Most probable cause: Eat Pill
- Most easy to check: Stop





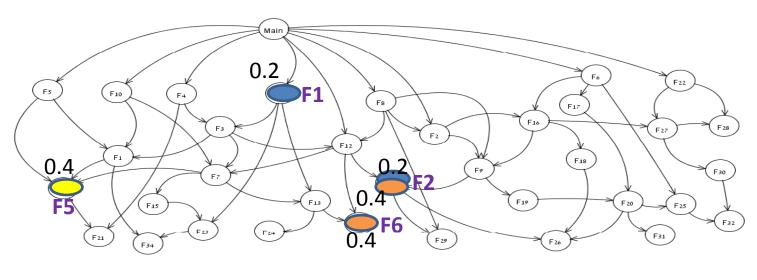
Objective

Plan a sequence of tests
to find the best diagnosis
with minimal tester actions



1. Highest Probability (HP)

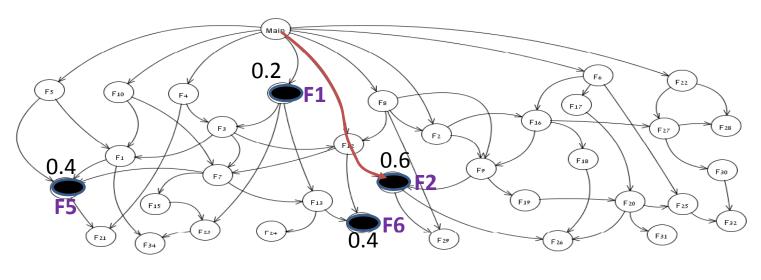
- Compute the prob. of every function C_i
 - = Sum of prob. of candidates containing C_i
- Plan a test to check the most probable function





1. Highest Probability (HP)

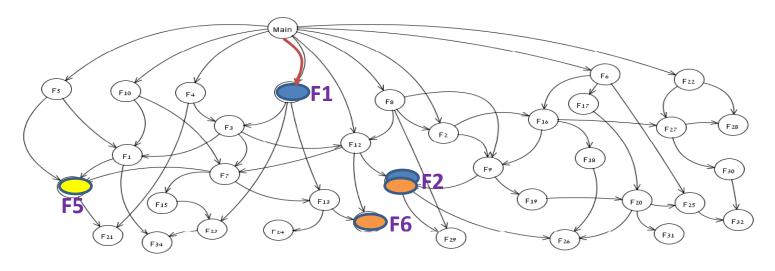
- Compute the prob. of every function C_i
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2. Lowest Cost (LC)

- Consider only functions C_i with 0<P(C_i)<1
- Test the closest function from this set

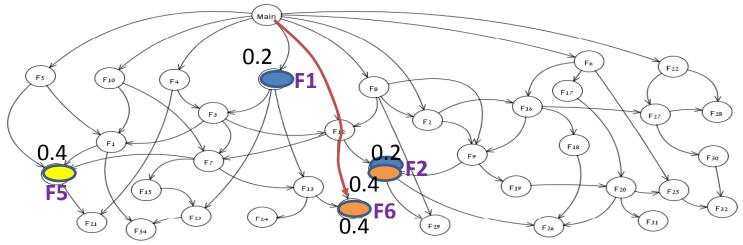




3. Entropy-based

- A test α = a set of components
 - $-\Omega_{+}$ = set of candidates that assume α will pass
 - $-\Omega_{\perp}$ = set of candidates that assume α will fail
 - $-\Omega_2$ = set of candidates that are indifferent to α
- Prob. α will pass = prob. of candidates in Ω_+
- Choose test with lowest Entropy $(\Omega_+, \Omega_-, \Omega_-, \Omega_-)$

= highest information gain





4. Planning Under Uncertainty

- Outcome of test is unknown
 - → we would like to minimize expected cost
- Formulate as Markov Decision Process (MDP)
 - States: set of performed tests and their outcomes
 - Actions: Possible tests
 - Transition: $Pr(\Omega_+)$, $Pr(\Omega_-)$ and $Pr(\Omega_?)$
 - Reward (cost): Cost of performed tests
- Current solver uses myopic sampling



Preliminary Experimental Results

- Synthetic code
- Setup
 - Generated random call graphs with 300 nodes
 - Generate code from the random call graphs
 - Injected 10/20 random bugs
 - Generate 15 random initial tests
- Run until a diagnosis with prob.>0.9 is found
 - Results on 100 instances



Preliminary Experimental Results

	MDP		LC		Entropy		HP	
Prob.	10	20	10	20	10	20	10	20
0.1	7.5	10.1	11.0	10.6	24.3	63.0	29.4	87.4
0.2	13.2	15.7	16.9	20.4	39.3	92.7	38.5	115.7
0.3	15.7	19.4	20.2	24.8	43.2	99.4	44.7	118.8
0.4	17.2	22.1	22.6	30.0	49.2	103.3	52.7	120.7
0.5	20.1	24.9	27.5	35.8	56.2	107.0	71.3	130.8
0.6	23.8	25.6	31.1	37.7	57.8	111.0	71.8	132.7
0.7	25.8	26.8	31.2	38.7	65.1	111.9	74.3	133.9
0.8	26.0	32.2	32.4	39.9	69.9	115.3	77.6	135.3
0.9	26.9	33.0	35.0	42.2	73.0	143.9	79.0	136.4

- HP and Entropy perform worse than (LC) and MDP
- probability based (HP and Entropy) perform worse than the cost based approach.
- MDP which considers cost and probability outperforms the others
- 20 bugs is more costly for all algorithms than 10 bugs



Preliminary Experimental Results - NUnits

- Real code
- Well-known testing framework for C#
- Setup
 - Generated call graphs with 302 nodes from NUnits
 - Injected 10,15,20,25,30 random bugs
 - Generate 15 random initial tests
- Run until a diagnosis with prob.>0.9 is found
 - Results on 110 instances



Preliminary Experimental Results - NUnits

Prob.	MDP	LC	Entropy	HP
0.1	2.34	1.92	4.00	5.15
0.2	3.16	2.50	5.79	7.06
0.3	4.18	3.54	15.42	17.47
0.4	4.88	7.00	50.70	66.58
0.5	5.08	7.00	50.75	66.75
0.6	6.45	8.06	53.85	70.14
0.7	6.45	8.06	53.85	70.14
0.8	6.45	8.09	53.85	70.14
0.9	6.45	8.17	55.69	70.41

- Similar results
- The cost increases with the probability bound
- MDP which considers cost and probability outperforms the others



Conclusion

- The test, diagnose and plan (TDP) paradigm:
 - AI diagnoses observed bug with MBD algorithm
 - AI plans further tests to find correct diagnosis
- Empowers tester using Al
 - Bug diagnosis done by tester+Al



