The AI in SE Applications Ladder:

Recommendations for an Organisational Strategy

Robert Feldt

Professor of Software Engineering

Chalmers University and Blekinge Inst of Tech

robert.feldt@gmail.com

Who am I?

Professor of Software Engineering (SE) in Sweden. Research is focused on Software Quality, Human factors in SE, and Applying AI.

Programmer since 38 years and consultant since 25 years. Sold my first program at age 13.

While doing research in academia I have worked with Tech and Software companies to apply AI to improve Software Engineering.

Main message

AI can be applied in many different ways in Software Engineering (SE)

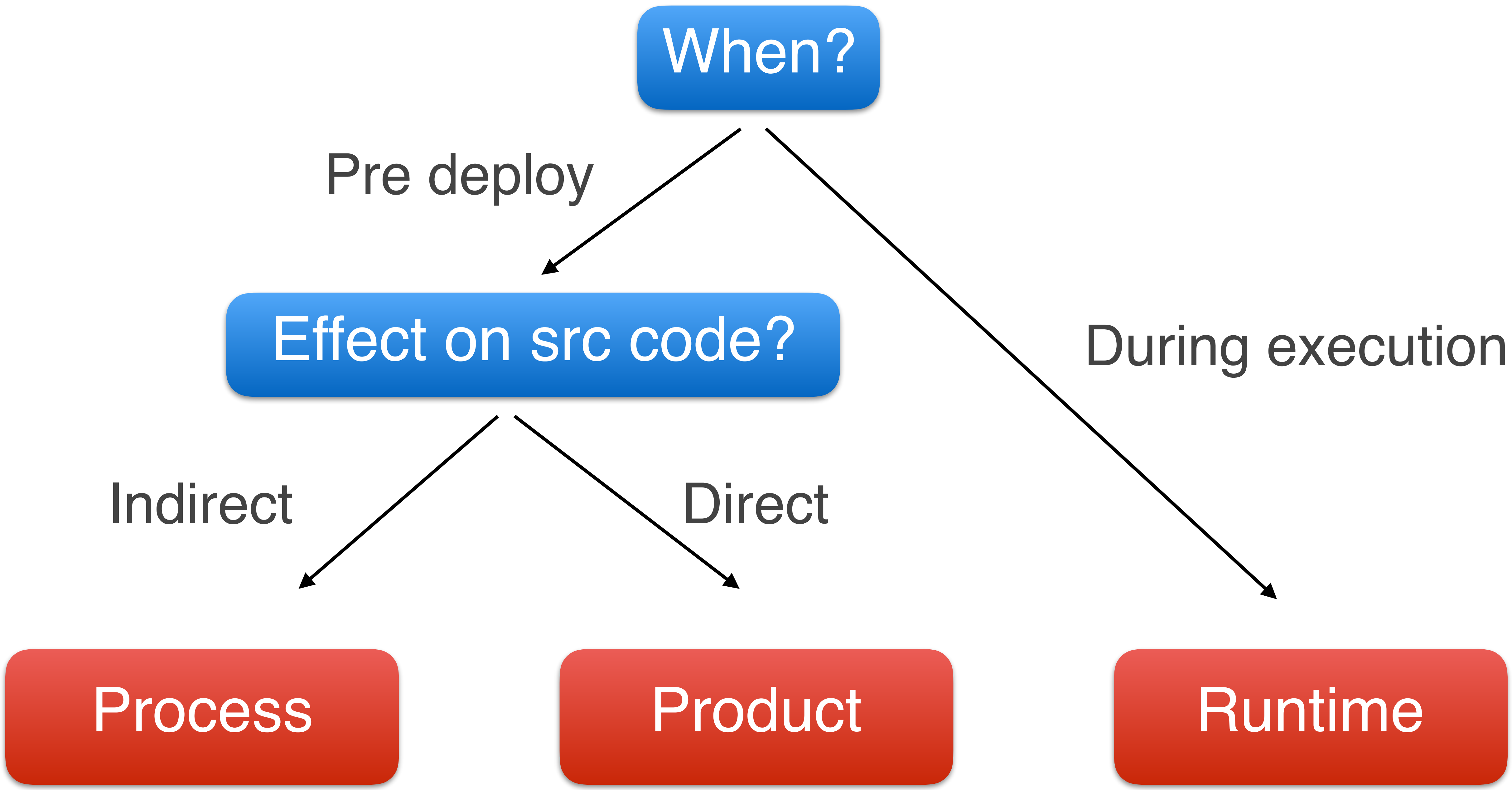
AI is not a single thing; it’s a “moving set” of advanced technologies.

A simple model of AI-in-SE applications help in analysis and for strategy

AI-SEAL Taxonomy: AI-in-SE Application Levels

- **Point** of AI application?
  - Determines how big an impact the AI and amount of control developers have on SW behaviour.
- **Type of AI** technology?
  - 5 main tribes + supporting technologies
- AI **Automation Level**?
  - From 1 (manual) to 10 (autonomous AI)
- Other and more detailed dimensions, for example:
  - **Shape** of artefact/software?
    - Traditional (Source code or Binary) or AI-specific (ANN)

Point of Application?



Type of AI technology?

So what is AI then?

Moving target definition of AI:

"How to make computers do things which, at the moment, people do better"
— Elaine Rich & Kevin Knight

Type of AI technology?

The Five Tribes of Machine Learning

Tribe	Origins	Master Algorithm
Symbolists	Logic, philosophy	Inverse deduction
Connectionists	Neuroscience	Backpropagation
Evolutionaries	Evolutionary biology	Genetic programming
Bayesians	Statistics	Probabilistic inference
Analogizers	Psychology	Kernel machines

[Domingos2015 “The Master Algorithm”]

Supporting technologies:

Advanced Statistics + Search/Optimisation

AI Automation level?

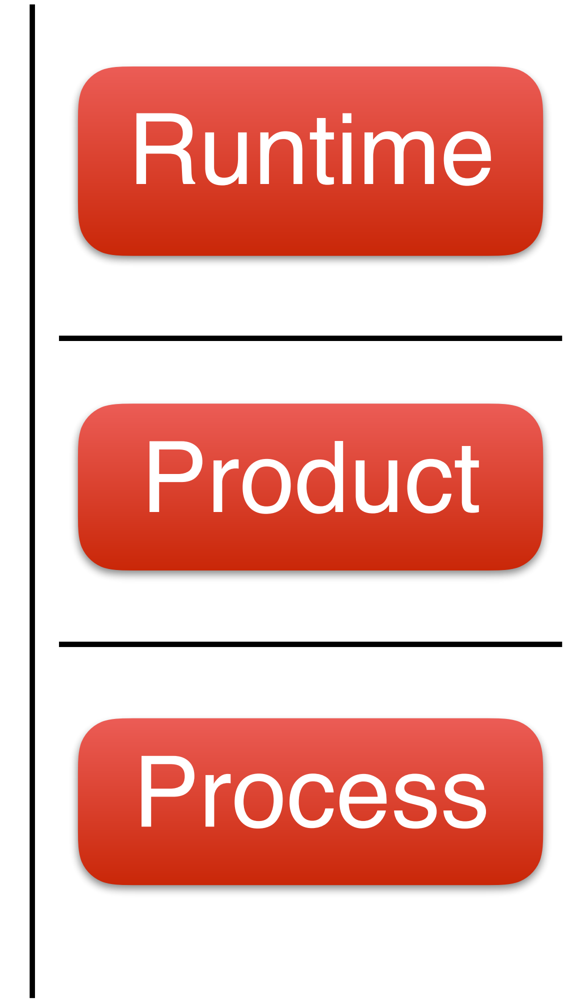
TABLE I
LEVELS OF AUTOMATION OF DECISION AND ACTION SELECTION

HIGH	10. The computer decides everything, acts autonomously, ignoring the human.
	9. informs the human only if it, the computer, decides to
	8. informs the human only if asked, or
	7. executes automatically, then necessarily informs the human, and
	6. allows the human a restricted time to veto before automatic execution, or
	5. executes that suggestion if the human approves, or
	4. suggests one alternative
	3. narrows the selection down to a few, or
	2. The computer offers a complete set of decision/action alternatives, or
LOW	1. The computer offers no assistance: human must take all decisions and actions.

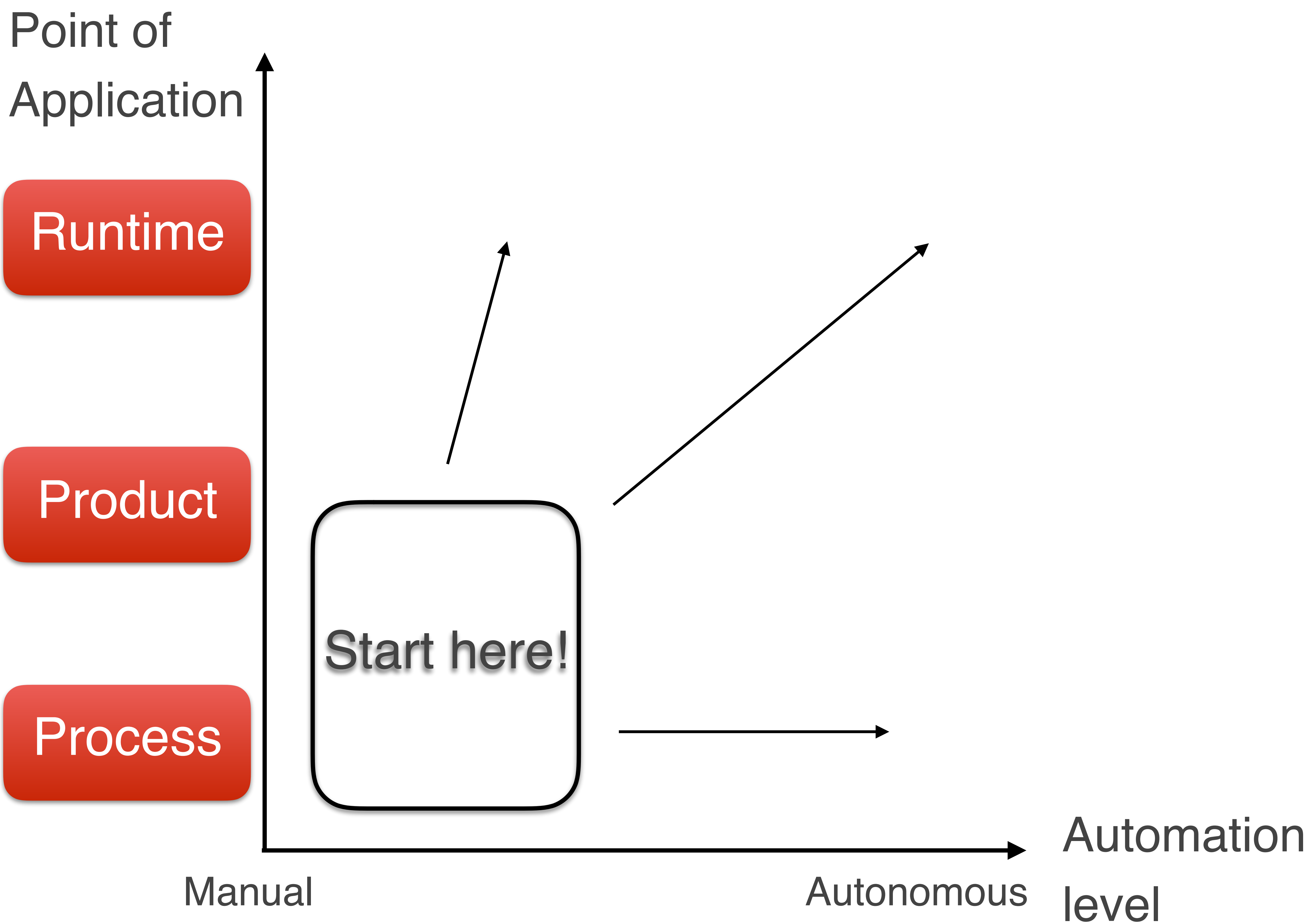
Sheridan1980 from [Frohm2008]

AI-in-SE applications have different levels of risk

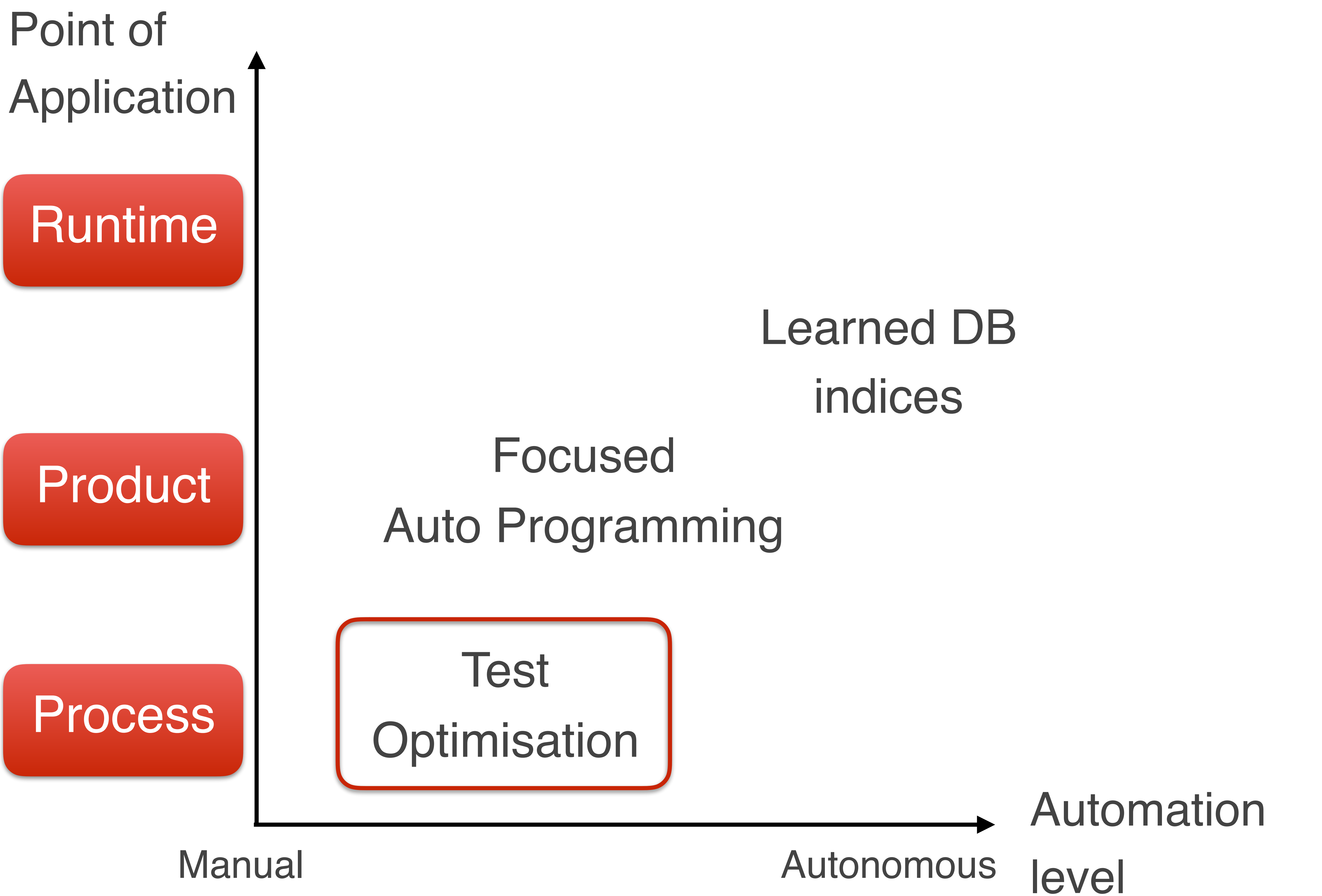
- A ladder of increasing risk:
  - Product more risky than Process
  - Runtime more risky than Product
- Higher levels of automation have higher levels of risk
  - Less time to “reverse” decisions
- Thus:
  - If an AI technology is new to your company, start at low level of automation & at a “lower” point of application.
  - Build more experience then expand “out and up”



AI-in-SE applications have different levels of risk/gain



AI-in-SE applications have different levels of risk/gain



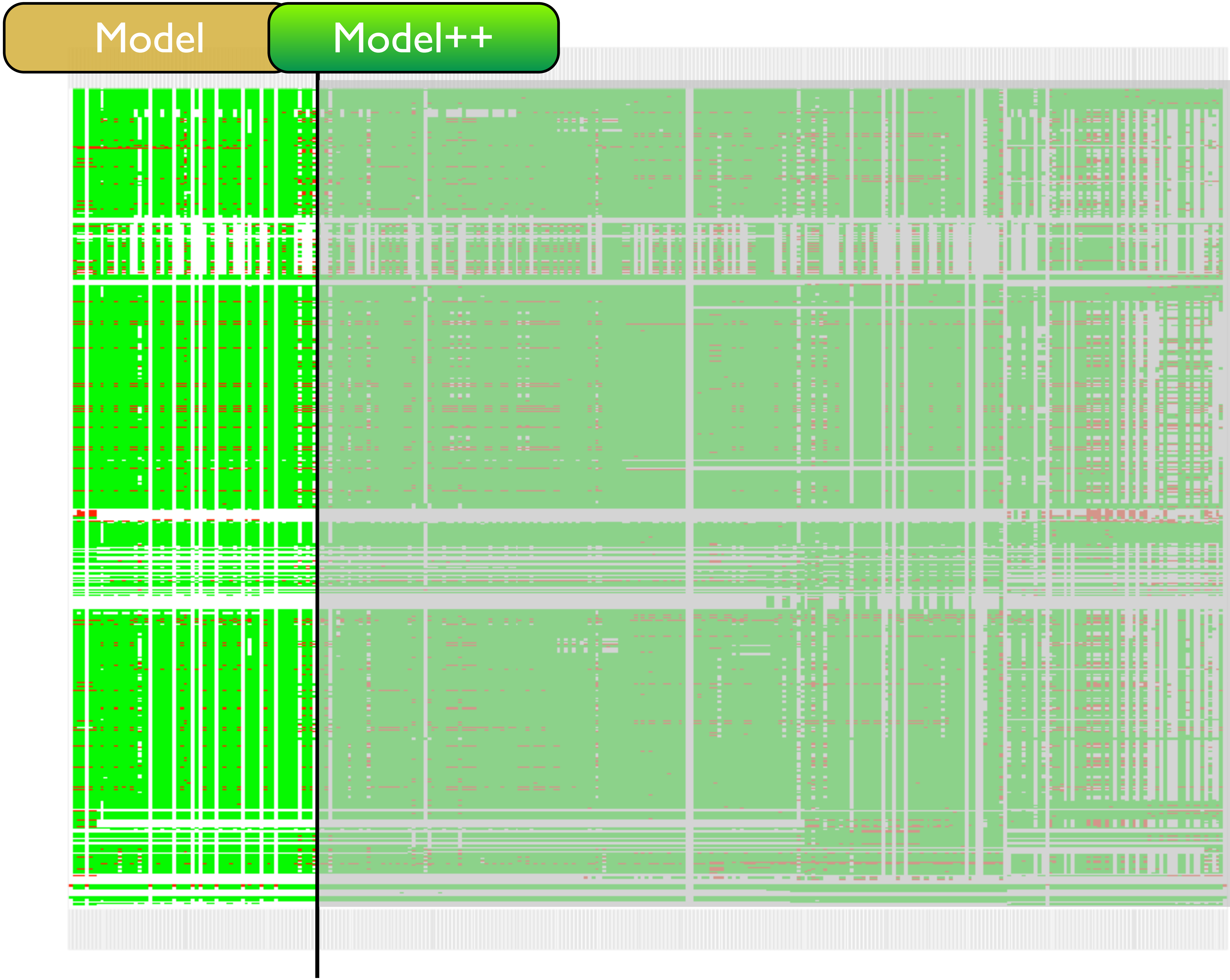
RUAG

Aerospace

HUAWEI

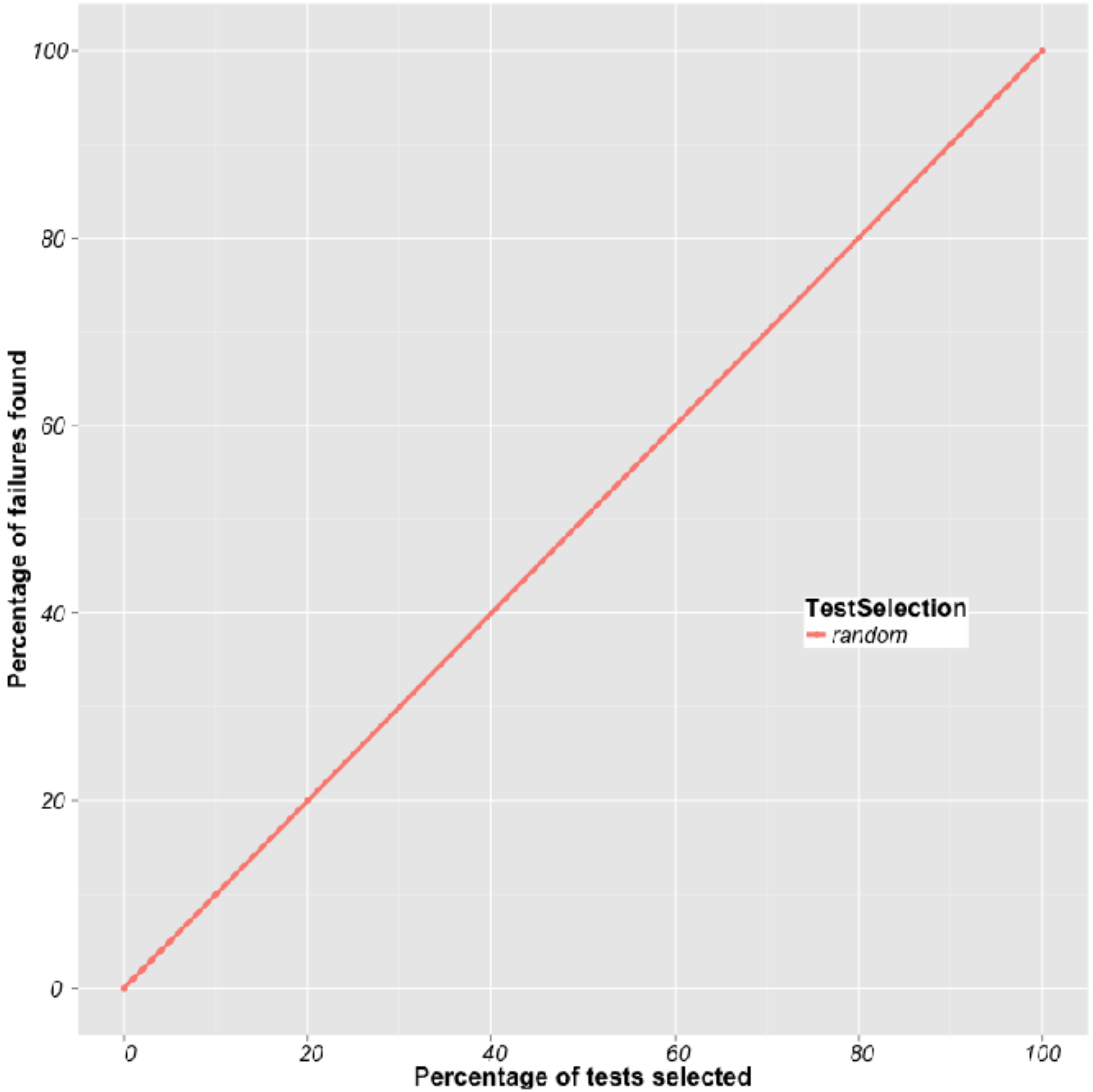
Technologies Sweden AB

Per Vollmer’s Team

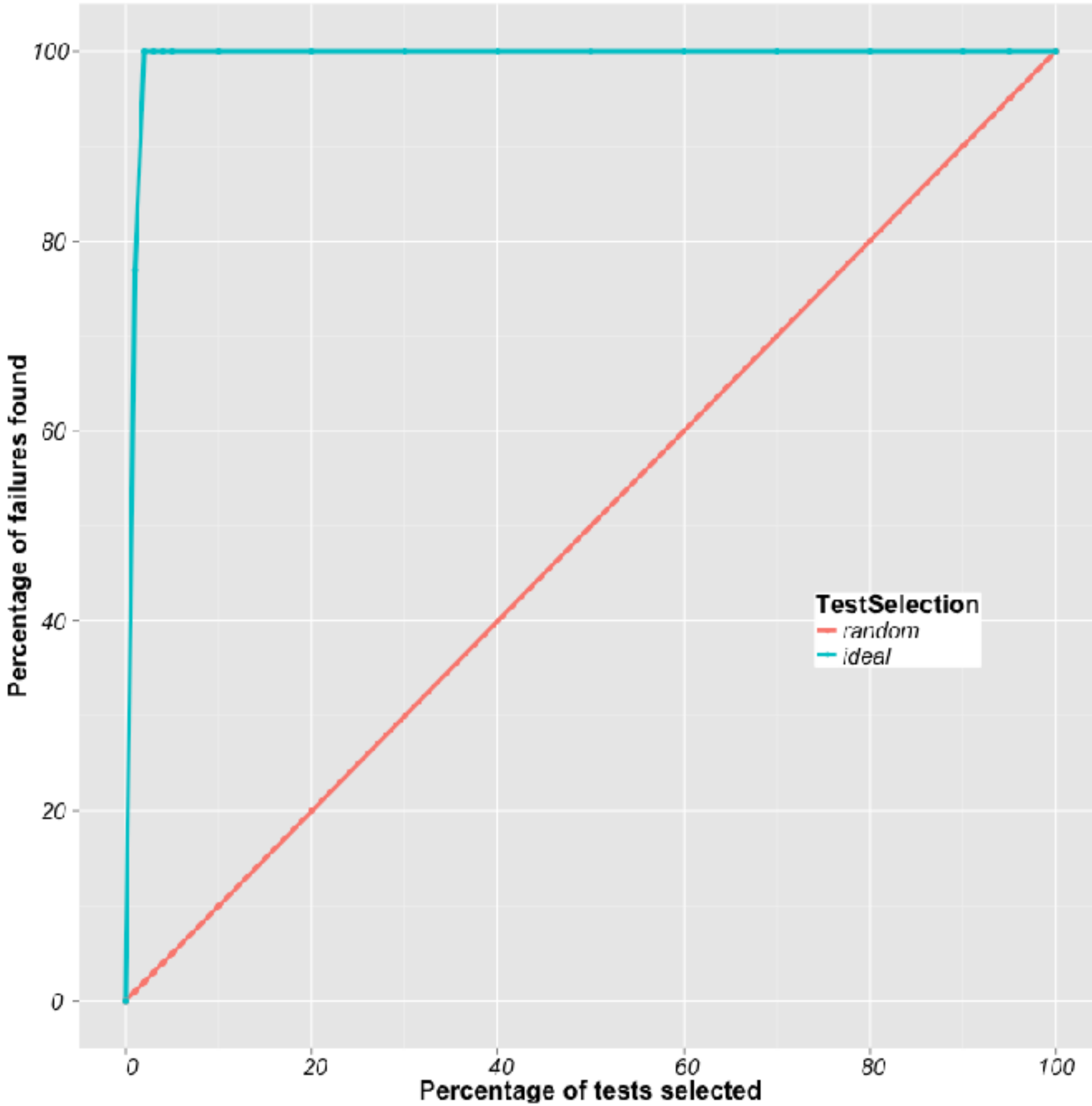


Model
Model++

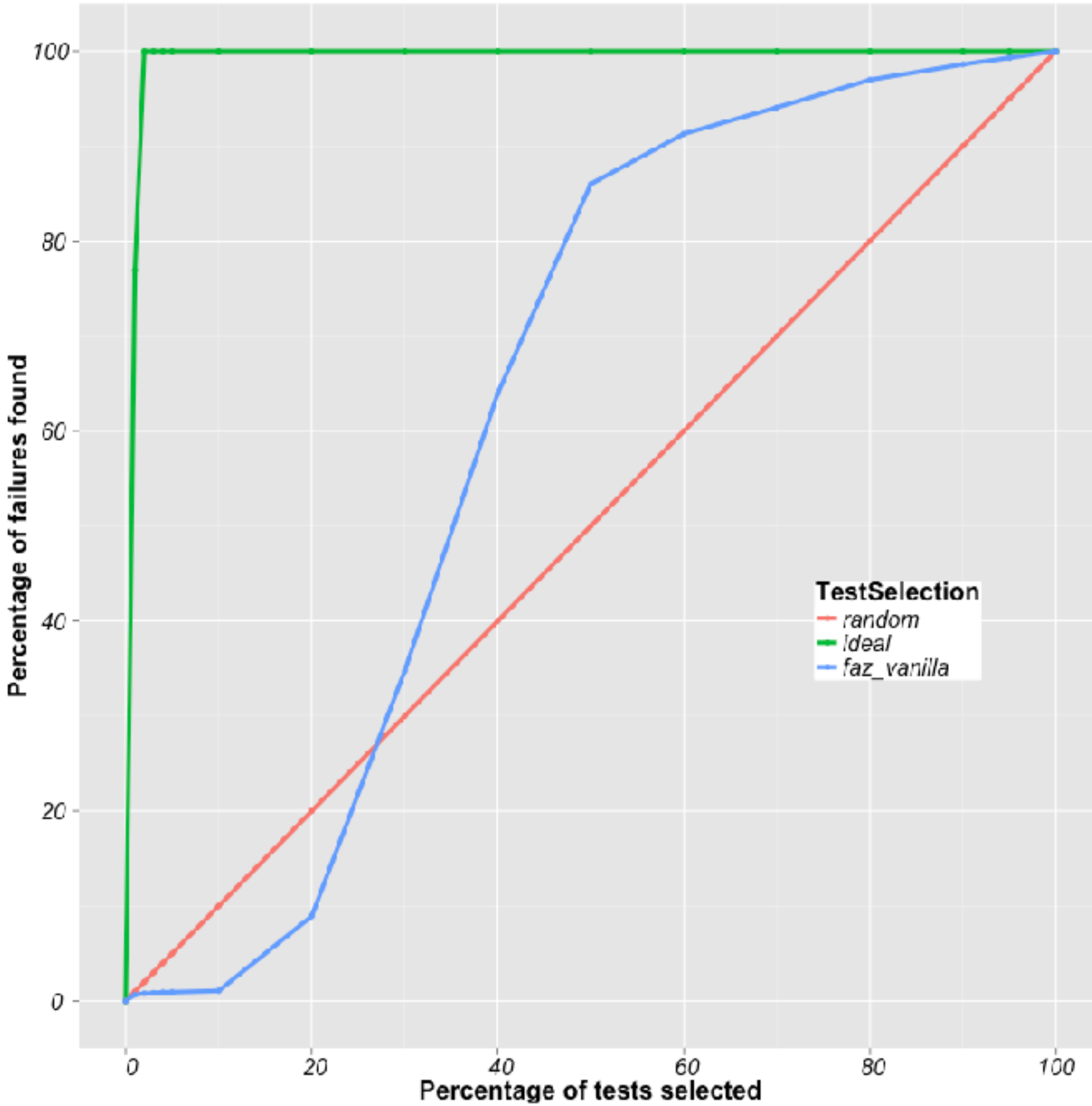
Testing only what is likely to fail



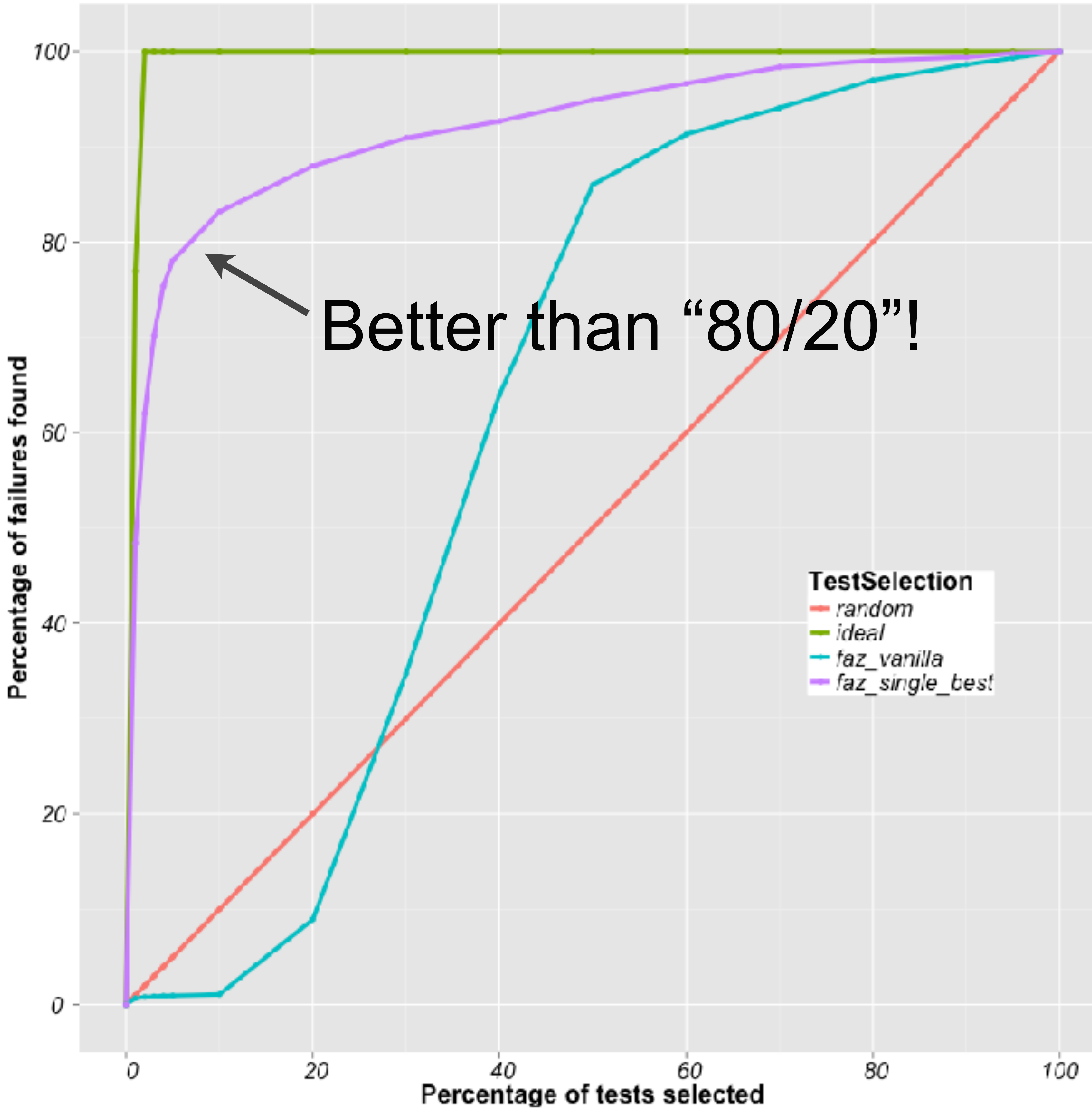
Testing only what is likely to fail



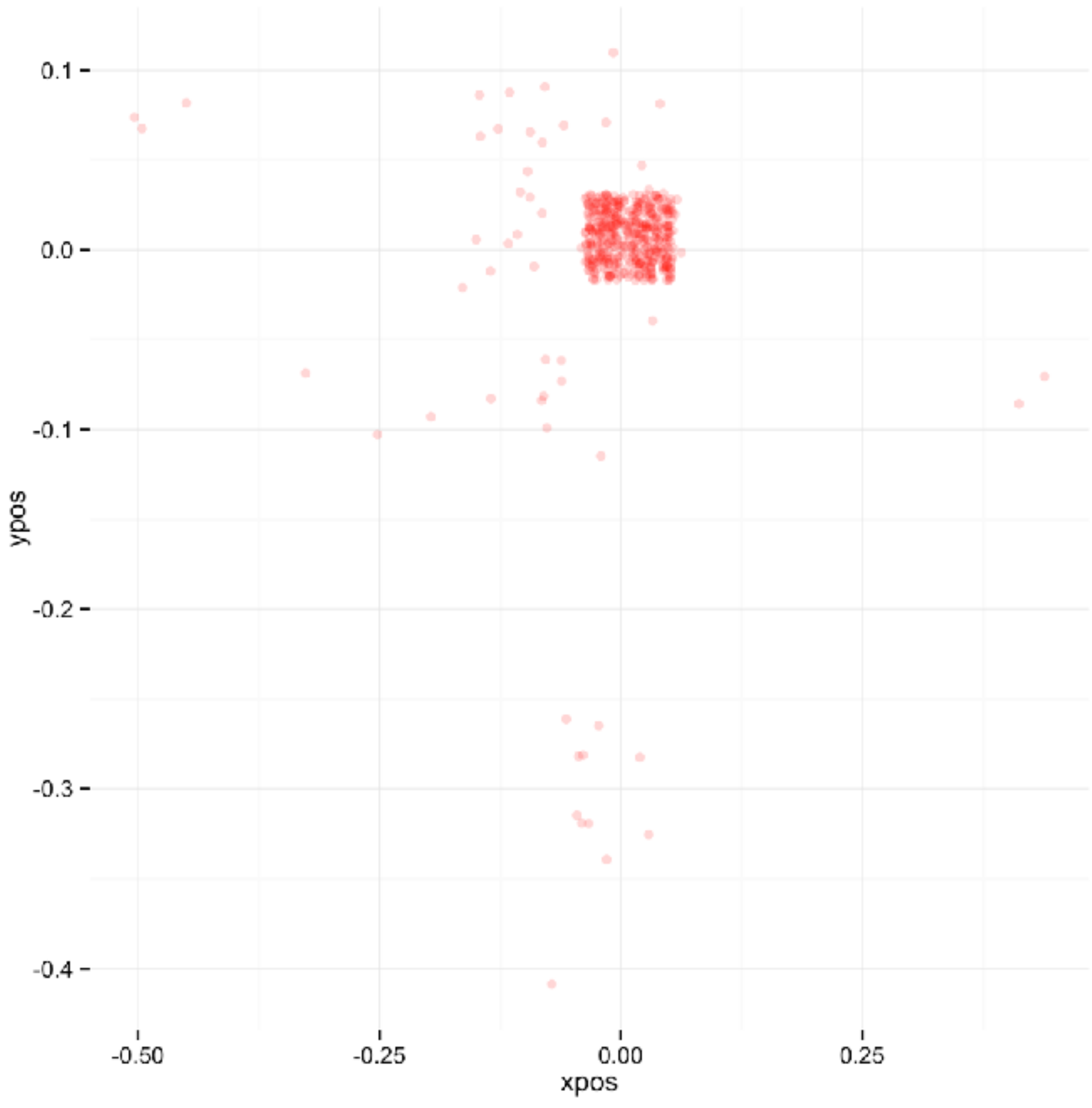
Testing only what is likely to fail



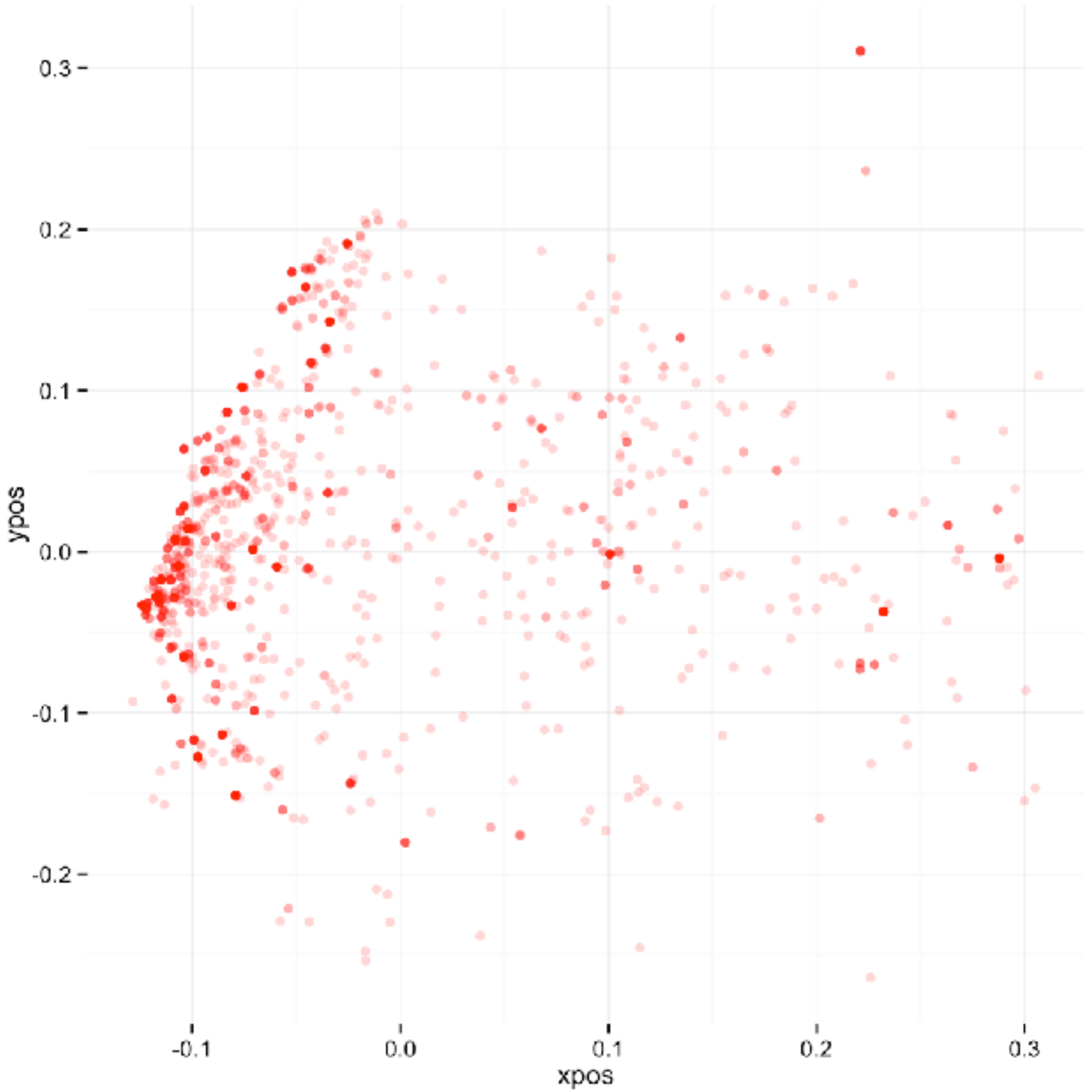
Testing only what is likely to fail



System A

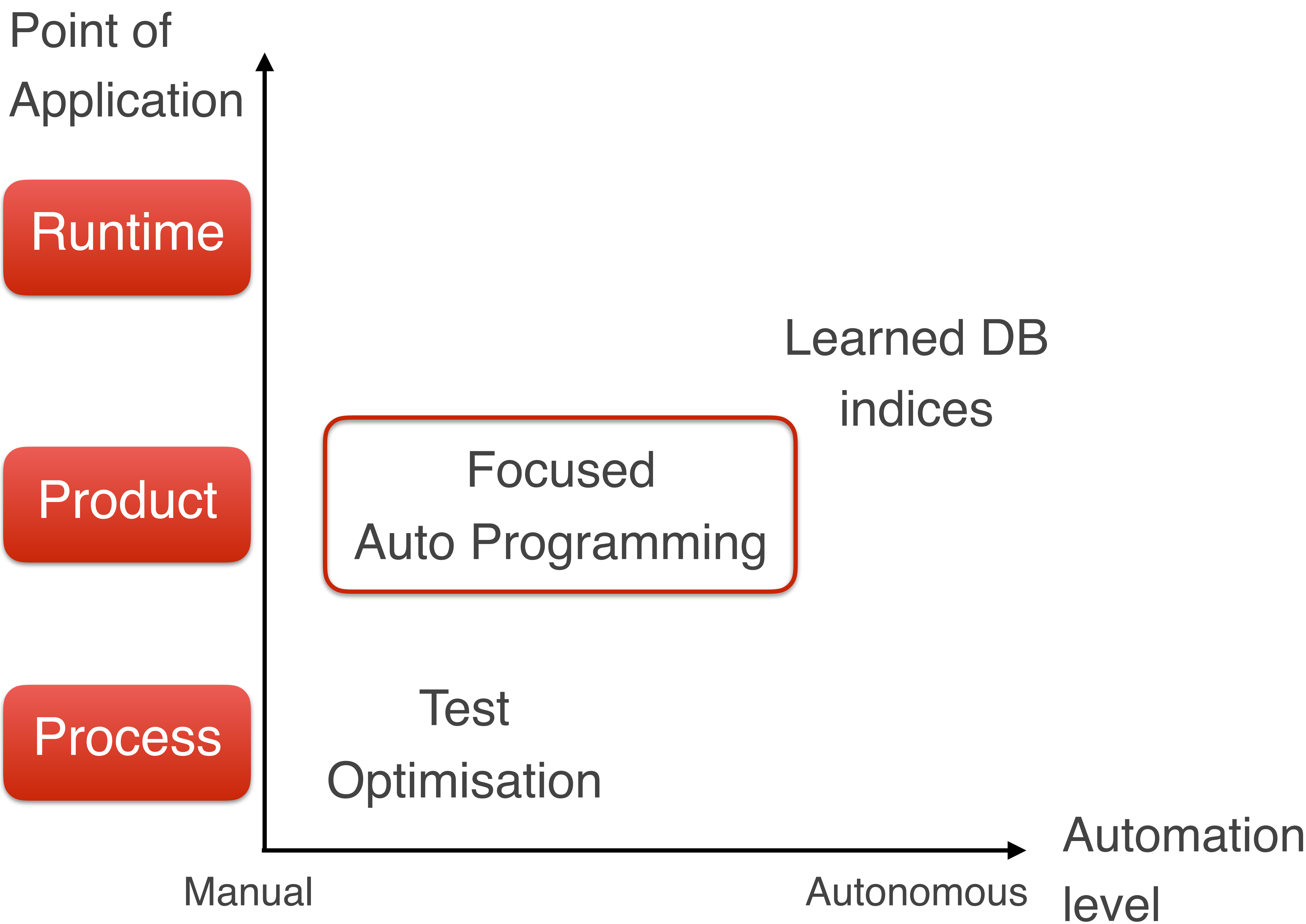


System B



Lessons learned: AI in SE Analytics/Optimization

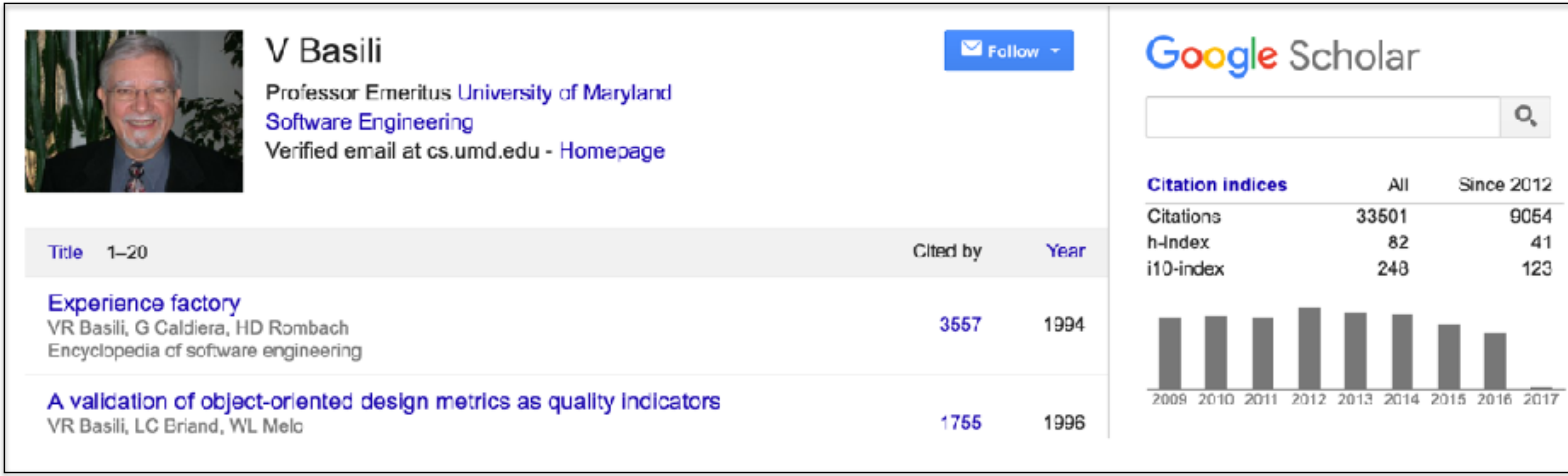
- Quality of data more important than advanced AI/ML
  - How much data do you have?
  - Do the data represent all important aspects?
- Simple statistical models often almost as good as advanced AI/ML
  - Data often unreliable => simple models give (at least) 80% of value for 20% of complexity
  - Statistical models easier to understand => robust
- Online algorithms almost always worth it => scalability
- Visualising results important for impact, Human + AI > AI
- An AI system is not enough, people need training + understanding to change their behaviour


Point of
Application
Runtime
Product
Process
Learned DB
indices
Focused
Auto Programming
Test
Optimisation
Automation
level
Manual
Autonomous

Focused Automated Programming

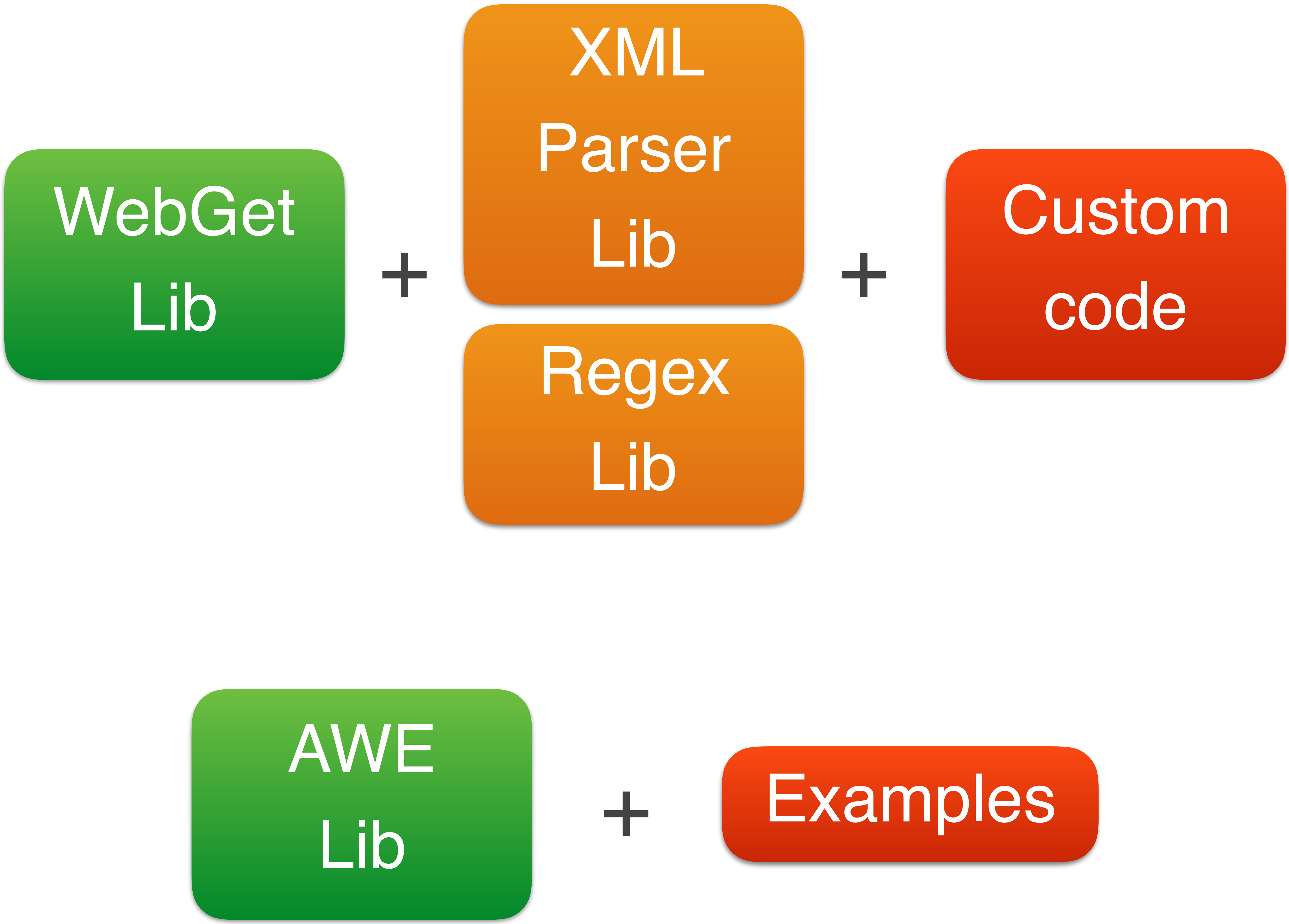
- I propose we should study FAP! aka…
  - Domain-specific Automated Programming (DAP)
  - Task-specific Automated Programming (TAP)
- Defined as: *“Focused application of search and optimisation to create/adapt/tune (parts of) program code during its development, setup and/or execution”*
- Focused here essentially means “human-guided”, i.e. it is a hybrid/interactive development philosophy

Example: Web extraction library




```
{
   "name": "V Basili",
   "citations": 33501,
   "h-index": 82
}
```

Web extraction, traditional solution vs AdaptiLib



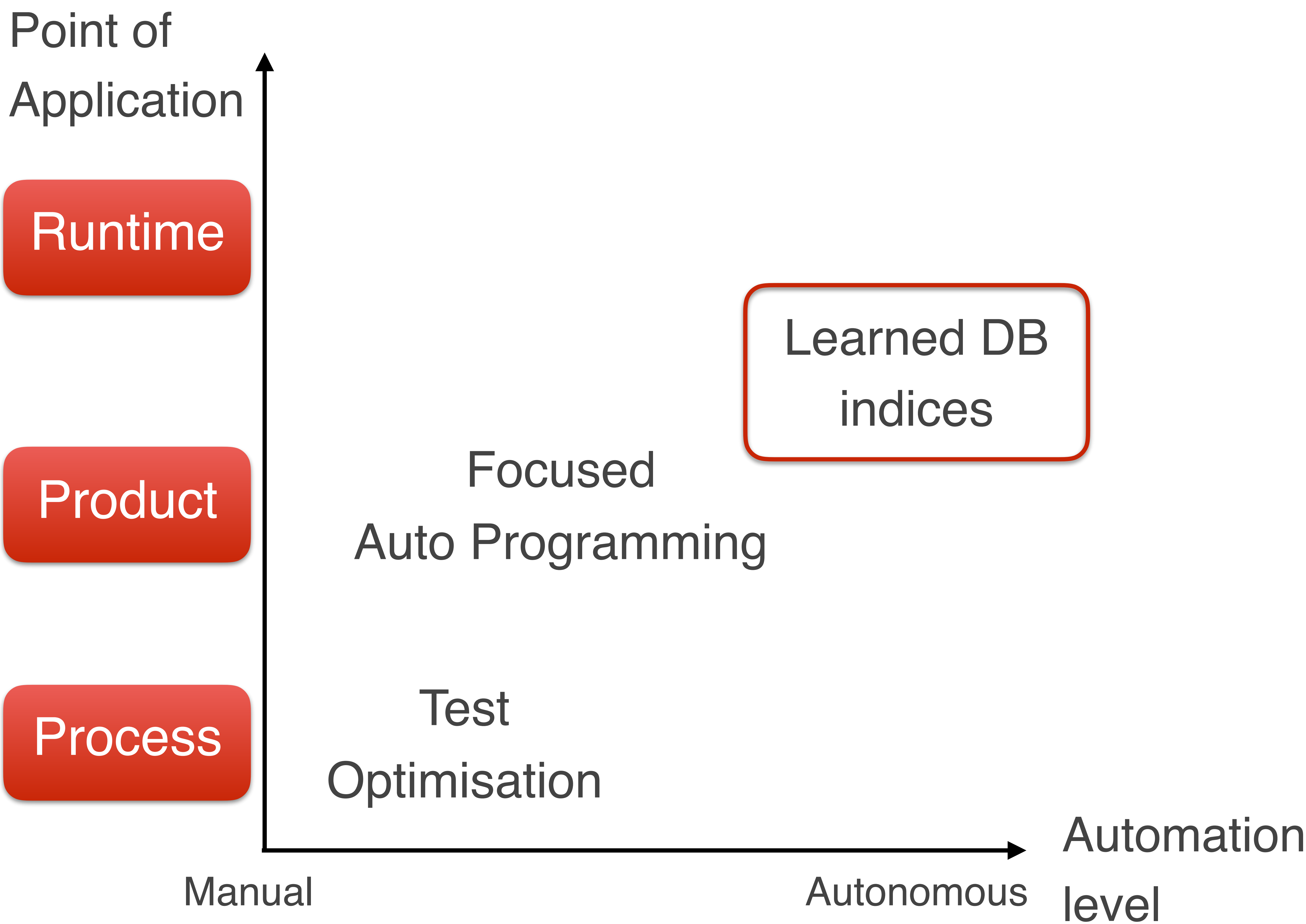
Example: Adaptive Web Extraction (AWE!) library, in practice

```
examples = [
("scholar.google.se/citations?user=B3C4aY8AAAAJ&hl=en",
{"name": "V Basili",
   "citations": 38599,
   "h-index": 83}),
("scholar.google.se/citations?user=Zj897NoAAAAJ&hl=en",
{"name": "Lionel Briand",
   "citations": 23720,
   "h-index": 71})]

gscholar_ex = create_extractor(examples)

extract(gscholar_ex, "scholar.google.se/citations?
user=CQDOm2gAAAAJ&hl=en")

# returns:
# {"name": "Barbara Ann Kitchenham",
#  "citations": 24122,
#  "h-index": 66})]
```



Point of Application
Runtime
Product
Process
Learned DB indices
Focused Auto Programming
Test Optimisation
Automation level
Manual
Autonomous

Product/NeuralNet/10 AI-in-SE: Learned DB Indices

The Case for Learned Index Structures

Tim Kraska*
MIT
Cambridge, MA
kraska@mit.edu

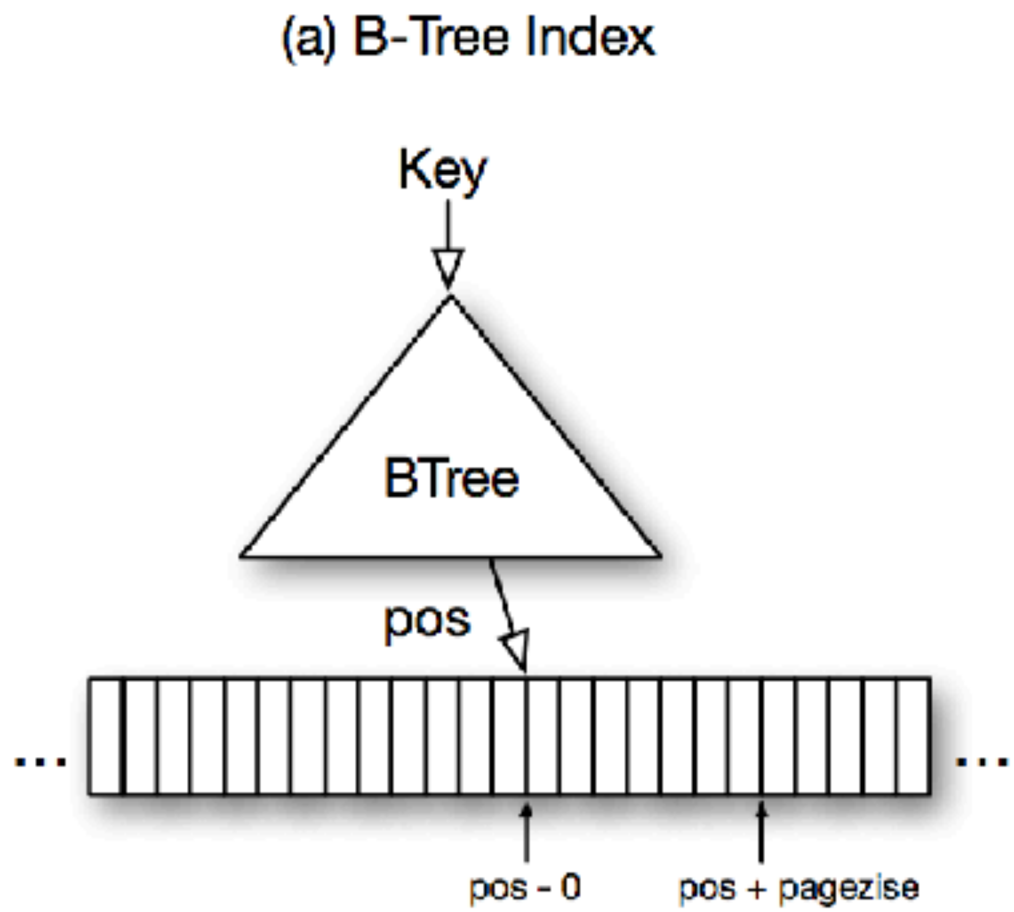
Alex Beutel
Google, Inc.
Mountain View, CA
alexbeutel@google.com

Ed H. Chi
Google, Inc.
Mountain View, CA
edchi@google.com

Jeffrey Dean
Google, Inc.
Mountain View, CA
jeff@google.com

Neoklis Polyzotis
Google, Inc.
Mountain View, CA
npolyzotis@google.com

[https://arxiv.org/pdf/1712.01208.pdf]



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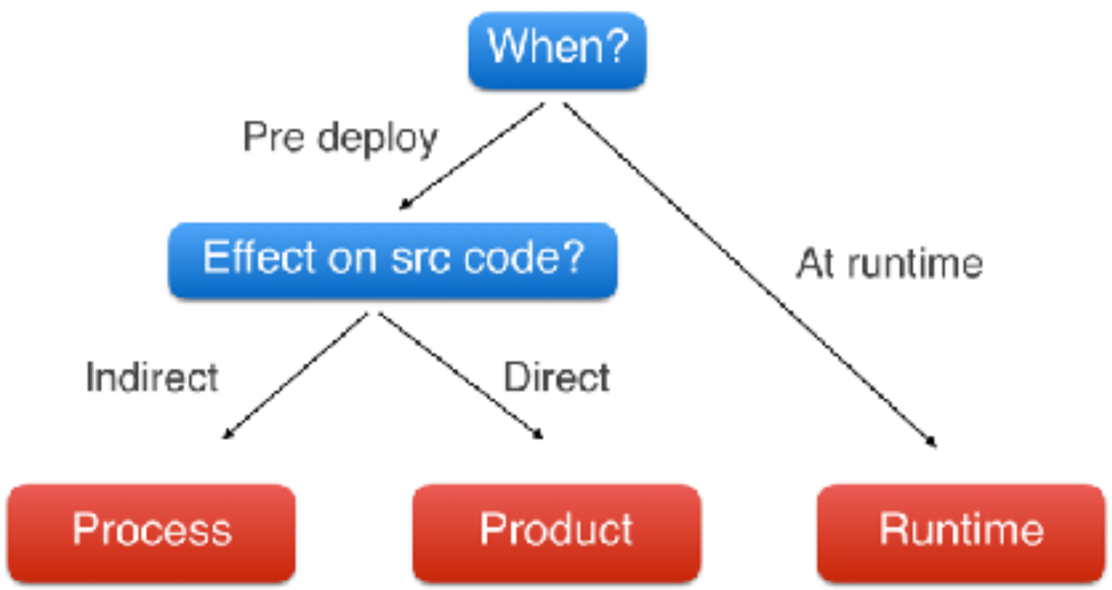
Product/NeuralNet/10 AI-in-SE: Learned DB Indices

Type	Config	Search	Total (ns)	Model (ns)	Search (ns)	Speedup	Size (MB)	Size Savings	Model Err ± Err Var.
Btree	page size: 16	Binary	280	229	51	6%	104.91	700%	4 ± 0
	page size: 32	Binary	274	198	76	4%	52.45	300%	16 ± 0
	page size: 64	Binary	277	172	105	5%	26.23	100%	32 ± 0
	page size: 128	Binary	265	134	130	0%	13.11	0%	64 ± 0
	page size: 256	Binary	267	114	153	1%	6.56	-50%	128 ± 0
Learned Index	2nd stage size: 10,000	Binary	98	31	67	-63%	0.15	-99%	8 ± 45
		Quaternary	101	31	70	-62%	0.15	-99%	8 ± 45
	2nd stage size: 50,000	Binary	85	39	46	-68%	0.76	-94%	3 ± 36
		Quaternary	93	38	55	-65%	0.76	-94%	3 ± 36
	2nd stage size: 100,000	Binary	82	41	41	-69%	1.53	-88%	2 ± 36
		Quaternary	91	41	50	-66%	1.53	-88%	2 ± 36
	2nd stage size: 200,000	Binary	86	50	36	-68%	3.05	-77%	2 ± 36
		Quaternary	95	49	46	-64%	3.05	-77%	2 ± 36
Learned Index Complex	2nd stage size: 100,000	Binary	157	116	41	-41%	1.53	-88%	2 ± 30
		Quaternary	161	111	50	-39%	1.53	-88%	2 ± 30

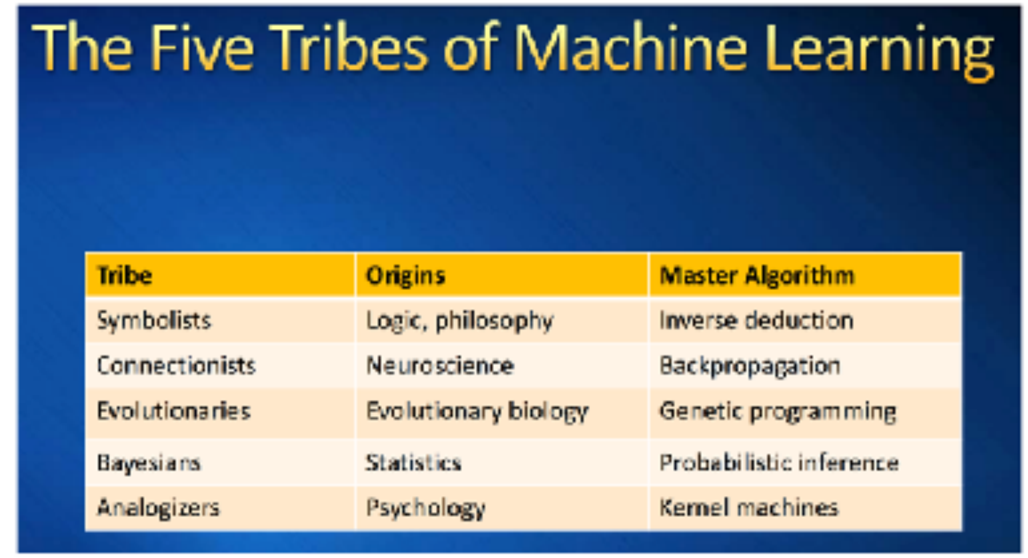
Figure 4: Map data: Learned Index vs B-Tree

[https://arxiv.org/pdf/1712.01208.pdf]

Point of Application?



Type of AI technology?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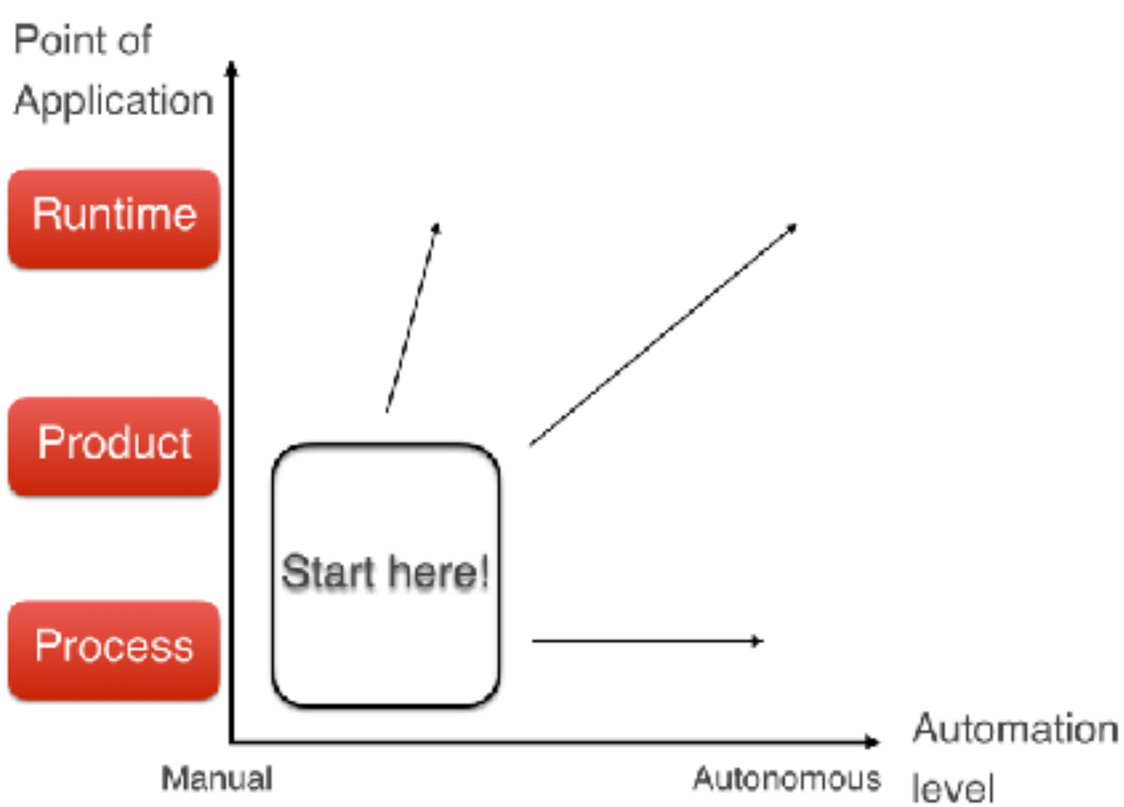
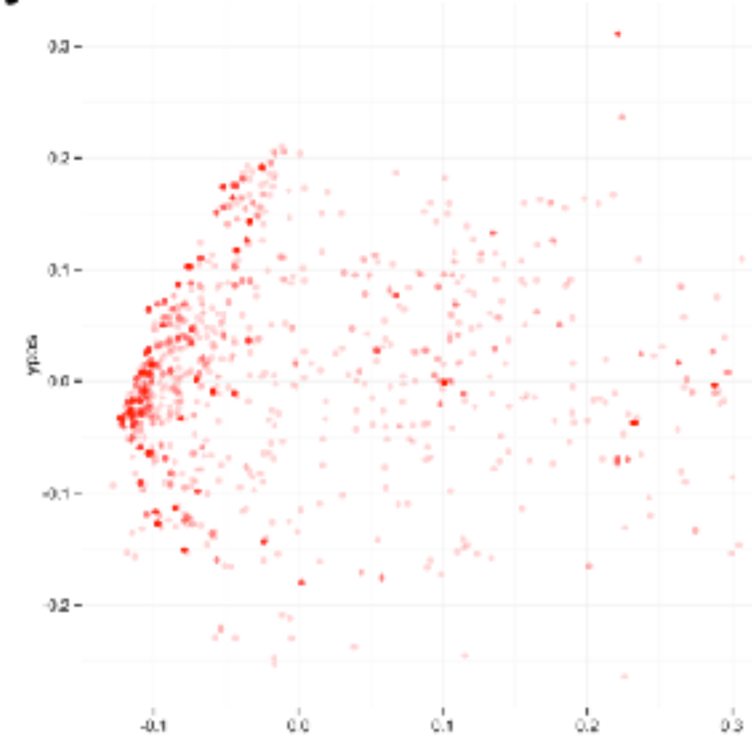


System B

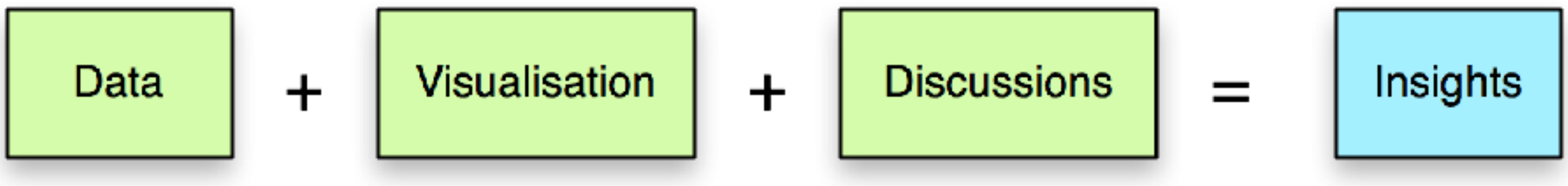


Contact

robert.feldt@gmail.com

robert.feldt@chalmers.se

http://www.robertfeldt.net


Data
+
Visualisation
+
Discussions
=
Insights

Test case **Half life**