What can be done with ML in Software Engineering research?

Paul Temple

ML and SE 2022-2023

Contact: paul.temple@irisa.fr

DiverSE
Diversity-Centric Software Engineering

About me

About me


MANCHE
Lannion
Saint-Malo
Morlaix
Guingamp
Brest
SAINT-BRIEUC
Dinan
Fougères
FINISTERE
29
CÔTES-D'ARMOR
22
ILLE-ET-VILAINE
35
RENNES
Pontivy
QUIMPER
MORBIHAN
56
Lorient
VANNES
Redon
OCEAN ATLANTIQUE

About me: Background

- 2008 – 2010: 1^{st} and 2^{nd} year study $\rightarrow$ computer science with an emphasis on data and image processing
- 2010 – 2013: Engineering school $\rightarrow$ computer science with an emphasis on data and image processing
- 2012 – 2013: Master's Degree on data and image processing

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- 2015 – 2018: PhD in Software Engineering $\rightarrow$ ML with software variability

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- 2015 – 2018: PhD in Software Engineering $\rightarrow$ ML with software variability
- 2019 – 2022: Post-doc in Namur $\rightarrow$ EoS VeriLearn project: SE for ML and ML for SE
- 2022 – ...: Associate Professor in DiverSE at UnivRennes $\rightarrow$ SE for ML and ML for SE

About me: Master's Internship

- February 2013 – May 2013
- Topic: Security of Machine Learning Processes applied to Multimedia
- Supervisors:

Laurent Amsaleg:

Ewa Kijak:

About me: PhD

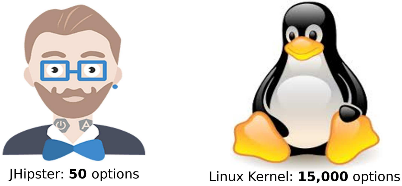
- Sept 2015 – Dec 2018
- Topic: Investigate the Matrix: Leveraging variability ...
- Supervisors:

Jean-Marc Jézéquel:

Mathieu Acher:

About me: PhD

Software Variability



$2^{15,000} \approx 10^{3,250} >> 10^{1,000} >>$ estimated # of particules

About me: PhD

options:

- no-mbtree (T or F)
- nr ([100..1000])
- qblur ([0; 1])

step = 0.0001

→ **18 millions** of configurations

⇒

About me: PhD

options:

- no-mbtree (T or F)
- nr ([100..1000])
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$\rightarrow$ **18 millions** of configurations

$\Rightarrow$

no-mbtree = T
qblur = 0.33
nr = 400

no-mbtree = F
qblur = 0.90
nr = 200

About me: PhD

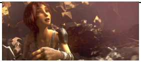
no-mbtree = F
qblur = 0.90
nr = 200

encoding time = 5 min

encoding time = 2 h

encoding time = 10 h

About me: PhD

	Program Variants				
				...	
Inputs		12	1	...	5
		1	348	...	10
	...				
		50	101	...	260

Can we and how to reduce either of those dimensions?

About me: current interests

Performance prediction of configurable systems

- Try to predict the performance based on the configuration
- Structure the configuration space for optimizing

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Testing ML models

- Testing in the SE sense (check the behavior)
- Various performance measures (fairness, energy consumption, etc.)

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ML models within systems

- ML models are part of systems
- ML models have a direct impact on the systems

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ML models within systems

- ML models are part of systems
- ML models have a direct impact on the systems

$\Rightarrow$ how to safely update ML models?

About DiverSE

Diversity-centric Software Engineering (DiverSE)

- Modeling (of systems)
- Languages
- Evolution and Maintenance of systems
- Testing
- Security (malware, web, DevOps, ...?)
- Privacy
- ...

`https://www.diverse-team.fr/`

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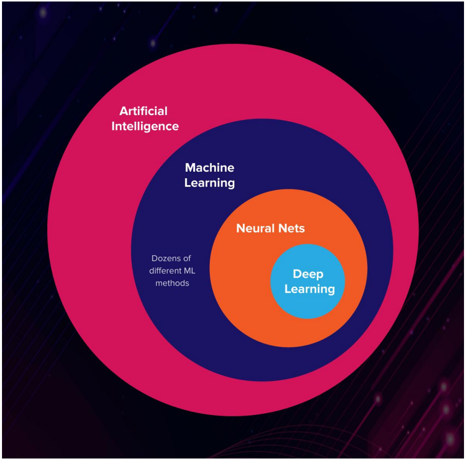
https://www.diverse-team.fr/team/
https://www.diverse-team.fr/positions/

Back to business
(ML and SE)

Intro: IA VS ML VS DL

Source: `https://serokell.io/blog/ai-ml-dl-difference`

Intro: IA VS ML VS DL



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A gentle introduction to DL by Patrick Pérez

Patrick Pérez in short

- DR Inria in Rennes

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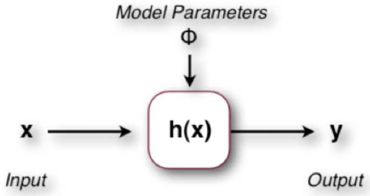

Source:

https://www.researchgate.net/publication/230691317_Gesture_Recognition_for_Musician_Computer_Interaction

Intro: Evaluate the performance of a ML model

How do you assess if your model performs well?

Intro: Evaluate the performance of a ML model

How do you assess if your model performs well?

Confusion matrix

		Oracle (Y)	
		0	1
Prediction ML model ($\hat{Y}$)	0	234 ($\pm$57.899)	69.5 ($\pm$26.973)
	1	141.1 ($\pm$60.440)	3566.2 ($\pm$25.804)

Intro: Feature descriptors

ML algorithms **does not work on raw data**

Tabular data

Explicit or Implicit? On Feature Engineering for ML-based Variability-intensive Systems, Temple and Perrouin, VaMoS'23

ML algorithms **does not work on raw data**

Tabular data

- Iris dataset → does not report pictures of irises
- Measure 4 characteristics

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Intro: Feature descriptors

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- Measure 4 characteristics
- Characteristics are defined by domain experts

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Image data

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Image data

- Describe images based on changes of textures and contrasts
- A few descriptors:

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- Describe images based on changes of textures and contrasts
- A few descriptors:
  - Harris corner

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  - Harris corner
  - SIFT
  - SURF

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- A few descriptors:
  - Harris corner
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  - Visual Bag of Words
- All aggregate different information

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Image data

- Describe images based on changes of textures and contrasts
- A few descriptors:
  - Harris corner
  - SIFT
  - SURF
  - Visual Bag of Words
- All aggregate different information
- Analyse (macro-)blocks of pixels

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ML algorithms **does not work on raw data**

Audio data

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Intro: Feature descriptors

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Audio data

- Ups and downs
- Composition of sinusoidal waves

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Intro: Feature descriptors

ML algorithms **does not work on raw data**

Audio data

- Ups and downs
- Composition of sinusoidal waves
- MFCC

$\rightarrow$ Change of representation space

Explicit or Implicit? On Feature Engineering for ML-based Variability-intensive Systems, Temple and Perrouin, VaMoS'23

Configurable systems? A few examples...

Intro: SPLs and Variability

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Intro: SPLs and Variability

What is variability?

- Software variability $\rightarrow$ ability to vary =)

Svahnberg *et al.*, A taxonomy of variability realization techniques: Research Articles, Soft. Pract. Exper. 2005

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- Ability to be efficiently extended, changed, customized, or configured for use in a particular context

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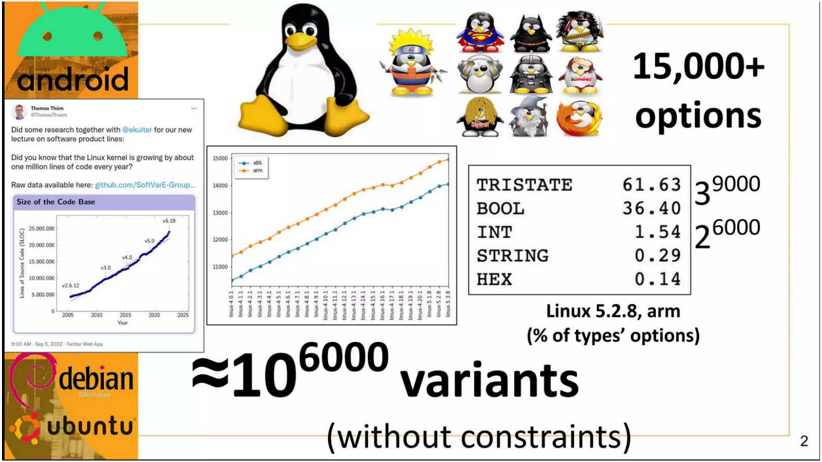
Intro: SPLs and Variability

What is variability?

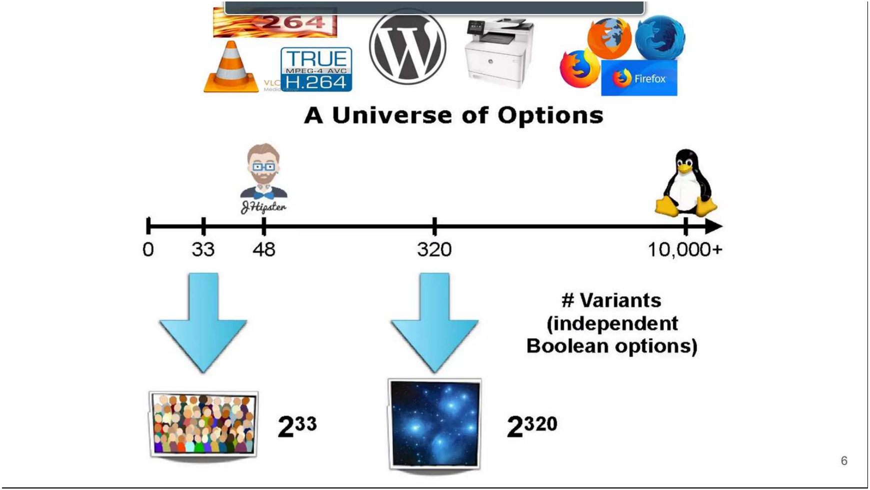
- Software variability $\rightarrow$ ability to vary =)
- Ability to be efficiently extended, changed, customized, or configured for use in a particular context
- Expected benefits
  - Lower production cost
  - Lower certification cost
  - Reduce time-to-market

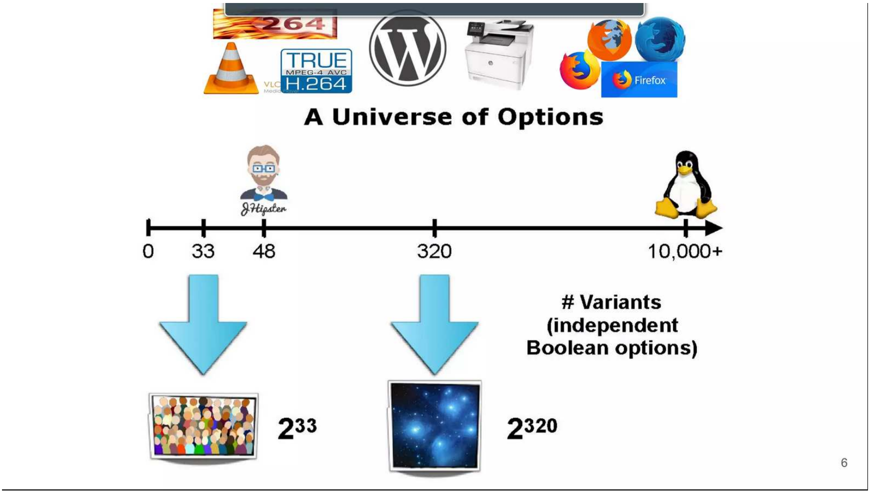
Svahnberg *et al.*, A taxonomy of variability realization techniques: Research Articles, Soft. Pract. Exper. 2005

Intro: SPLs and Variability



Intro: SPLs and Variability





Sébastien Mosser @petitroll · 25 févr.

"the number of atoms in the visible universe is 10^80. There are 2^15000 different versions of the Linux kernel. So astrophysicists works with things way simpler than software engineers". @jmjezequel options:

- no-mbtree (T or F)
- nr ([100..1000])
- qblur ([0; 1])

step = 0.0001

→ **18 millions** of configurations

⇒

no-mbtree = T
qblur = 0.33
nr = 400

no-mbtree = F
qblur = 0.90
nr = 200

Intro: SPLs and Variability

	no-mbtree	qbur	nr	exec time (s)
	T	0.33	400	24
	F	0.90	200	7

Intro: SPLs and Variability

	no-mbtree	qbur	nr	exec time (s)
	T	0.33	400	24
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	T	0.90	400	

How much time for the last configuration?

Intro: SPLs and Variability

	no-mbtree	qbur	nr	exec time (s)
	T	0.33	400	24
	F	0.90	200	7
	T	0.90	400	

How did we get the exeuction times?

Intro: SPLs and Variability

	no-mbtree	qbur	nr	exec time (s)
	T	0.33	400	24
	F	0.90	200	7
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How did we get the exeuction times?

- Select a value for each option
- Generate/Build the configuration
- Run the system with a (or several) inputs
- Measure time for the execution

Intro: SPLs and Variability

	no-mbtree	qbur	nr	exec time (s)
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$\Rightarrow$ How to **measure without measuring?**

...

Intro: SPLs and Variability

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- Select a value for each option
- Generate/Build the configuration
- Run the system with a (or several) inputs
- Measure time for the execution

$\Rightarrow$ How to **measure without measuring?**

...

(and **measure without building and running**)

Performance prediction

- Solely based on values of options
- "Guess" the value when executed

Intro: SPLs and Variability

Performance prediction

- Solely based on values of options
- "Guess" the value when executed
  - No builds
  - No executions

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  - No builds
  - No executions
- Generalize to unseen configurations

Performance prediction

- Solely based on values of options
- "Guess" the value when executed
  - No builds
  - No executions
- Generalize to unseen configurations

- Performance models
- Machine Learning (ML) models

Performance models

$Performance_{config}$ = 0.241 * no-mbtree - 0.316 * nr - 0.024 * qblur + 0.201 * no-mbtree x qblur + 0.129 no-mbtree x nr - ...

Siegmund *et al.*, Performance-influence models for highly configurable systems, ESEC/FSE 2015

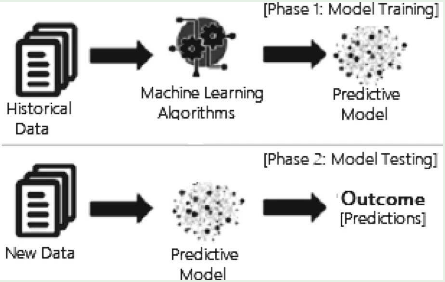
Performance models

$Performance_{config}$ = 0.241 * no-mbtree - 0.316 * nr - 0.024 * qblur + 0.201 * no-mbtree x qblur + 0.129 no-mbtree x nr - ...

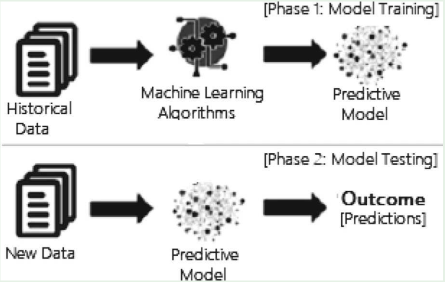
- Linear model
- More interactions → More precise
- Start with the minimal configuration and add influence of (tuple of) options

Siegmund *et al.*, Performance-influence models for highly configurable systems, ESEC/FSE 2015

ML models

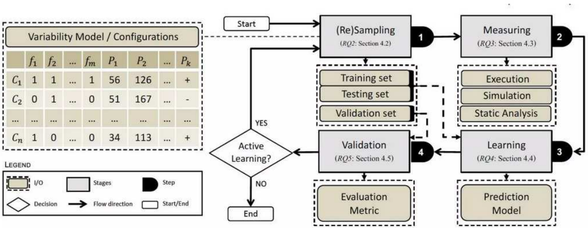

[Phase 1: Model Training]
Historical Data
Machine Learning Algorithms
Predictive Model
[Phase 2: Model Testing]
New Data
Predictive Model
Outcome
[Predictions]

ML models



- Can be more complex than a linear combination
- Start with a set of configurations (need to be measured)
- Can be interpretable (e.g., decision trees)

Sampling, Measuring, Learning



Learning Software Configuration Spaces: A Systematic Literature Review
Juliana Alves Pereira, Hugo Martin, Mathieu Acher, Jean-Marc Jézéquel, Goetz Botterweck, Anthony Ventresque https://arxiv.org/abs/1906.03018

Why performance prediction over configurable systems?

- Predict performance...

Martin *et al.*, Learning very large configuration spaces: What matters for linux kernel sizes, https://inria.hal.science/hal-02314830/, 2019

Martin *et al.*, Learning from thousands of build failures of Linux kernel configurations, https://inria.hal.science/hal-02147012/, 2019

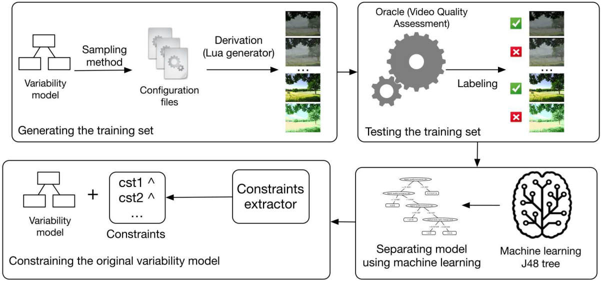
Why performance prediction over configurable systems?

- Predict performance... of unseen configurations
- Understand more things about the system (constraints, domain knowledge)
- Optimize
- Specialize the system
- ...

Martin *et al.*, Learning very large configuration spaces: What matters for linux kernel sizes, `https://inria.hal.science/hal-02314830/`, 2019

Martin *et al.*, Learning from thousands of build failures of Linux kernel configurations, `https://inria.hal.science/hal-02147012/`, 2019

Specialize the system



Temple *et al.*, Using machine learning to infer constraints for product lines, SPLC 2016

Martin *et al.*, A comparison of performance specialization learning for configurable systems, SPLC 2021

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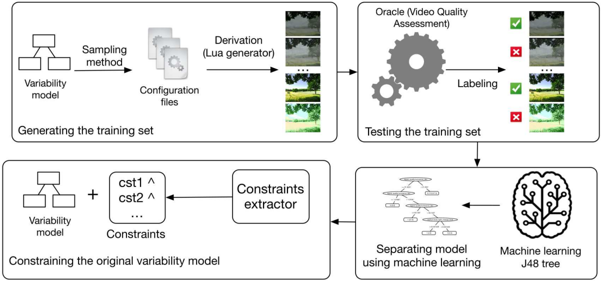

To keep or not to keep?

- (Binary) Classification problem

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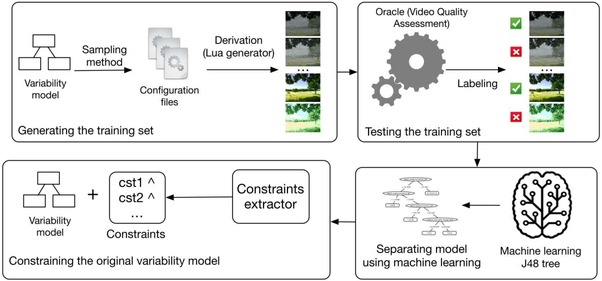

To keep or not to keep?

- (Binary) Classification problem
- Regression → discretize → n-class problem

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How to represent configurations for ML?

	no-mbtree	qbur	nr	exec time (s)
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	T	0.90	400	

- Need a **homogeneous representation**

How to represent configurations for ML?

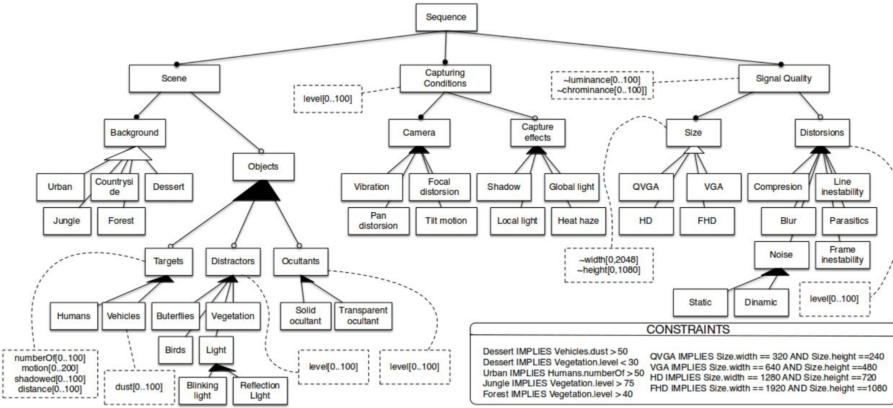

Figure 5: Feature model, excerpt of the model used in the MOTIV project, to represent variability (through feature attributes) of a video sequence.

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- Configuration $\rightarrow$ set of options $\rightarrow$ vector
  Need all options (selected or not)

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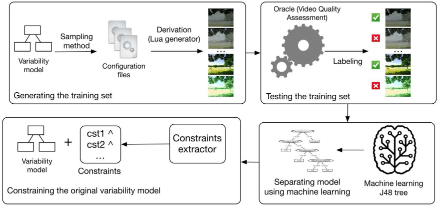
- Need a **homogeneous representation**
- Configuration $\rightarrow$ set of options $\rightarrow$ vector
  Need all options (selected or not)
- Heterogenous features in a homogeneous representation
  Feature importance?

Maybe we are wrong?

Are ML models good enough?



Results: more than 80% correctly classified

Temple *et al.*, Towards quality assurance of software product lines with adversarial configurations, SPLC 2019

Temple *et al.*, Empirical assessment of generating adversarial configurations for software product lines, EMSE 2021

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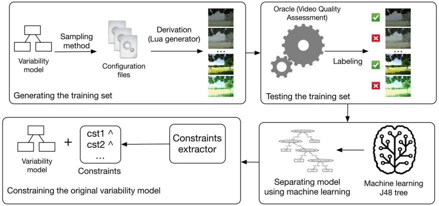

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Can we do better?

- Generate more configs that are 'difficult"

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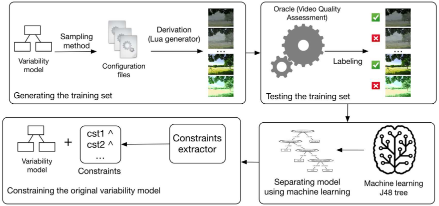

Results: more than 80% correctly classified

Can we do better?

- Generate more configs that are ‘difficult”
- Use Adversarial Machine Learning

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Are ML models good enough?

About advML

- Went off around 2015
- Better understand ML models and their weaknesses
- 2 main directions: GANs, Evasion/Poisoning

Biggio and Roli, Wild Patterns: Ten Years After the Rise of Adversarial Machine Learning, Pattern Recognition 2018

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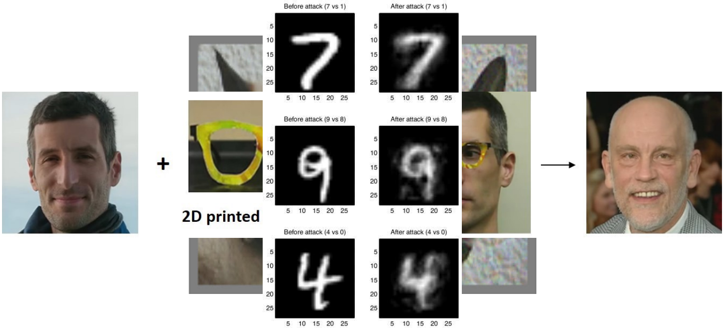

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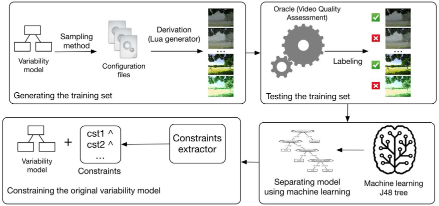

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Use Adversarial Machine Learning (to get new configurations)

Intriguing properties https://arxiv.org/pdf/1312.6199.pdf

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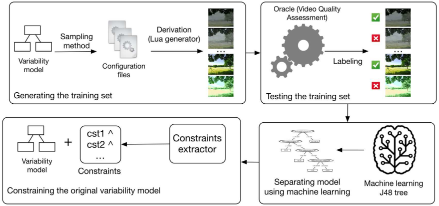

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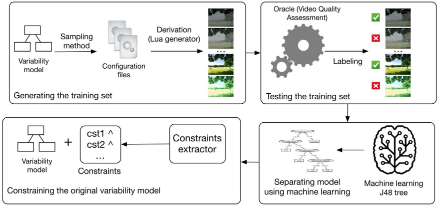

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Use Adversarial Machine Learning (to get new configurations)

- NDSS'13: Intriguing properties of neural networks
- Present the notion of natural adversarial examples
- Data that are difficult to classify (*i.e.*, lay in between two classes)

Intriguing properties https://arxiv.org/pdf/1312.6199.pdf

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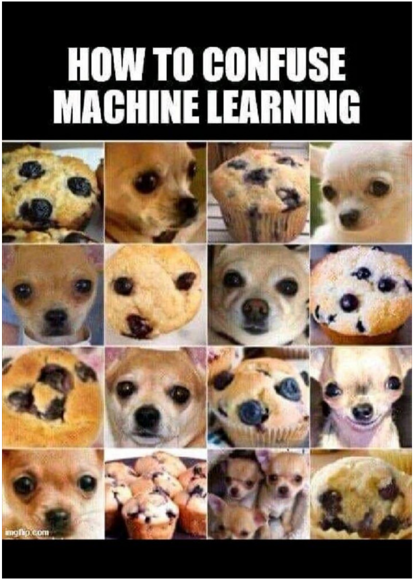
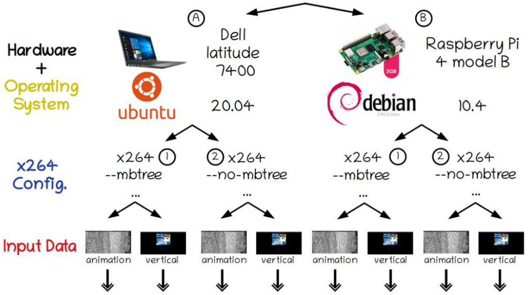


Source: `https://www.kaggle.com/datasets/samuelcortinhas/muffin-vs-chihuahua-image-classification/data`

Are we done?

	no-mbtree	qbur	nr	exec time (s)
	T	0.33	400	24
	F	0.90	200	7
	T	0.90	400	

Deep Software Variability



Duration (s)	6	22	6	25	73	351	72	359
Size (MB)	33	28	21	34	33	28	21	34

Martin *et al.*, Transfer learning across variants and versions: The case of linux kernel size, TSE 2021

Lesoil, Deep Software Variability, PhD thesis, `https://inria.hal.science/tel-04055573/`, 2023

Wrap-up Performance Prediction

- Configuration options quickly increase the complexity of a system
- Building/Executing all the different variants is not possible
- An example: the Linux Kernel and its 15,000 options

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  - Prediction models (linear and need to state all the interactions)
  - ML models (learn by themselves and co-occurence)

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- We can improve the model via adversarial retraining

ML and SE

(VaryMinions)

ML and SE

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Sophie Fortz's PhD

ML and SE

(VaryMinions)

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(thanks for the slides)

VaryMinions: Context

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- Different evolutions came out
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What can you do to know which instances are impacted?
What can you do to know where the bug comes from? (which feature or part of the process)

VaryMinions: Research Problem

Multiple instances of the same process

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- Multiple logs per instance of the process
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Combinatorial explosions

- Lot of information per log
- Many variants
- Many logs per variants

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Need for automation

- Can ask domain expert which logs correspond to which variant(s)

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Representation of logs?

- Logged information follow the steps of the process
- Can be seen as an ordered sequence of events
- A sentence is an ordered sequence of words

Can we make as if logs are text?

VaryMinions: ML to the rescue

Log annotation

- Let experts annotate a few logs
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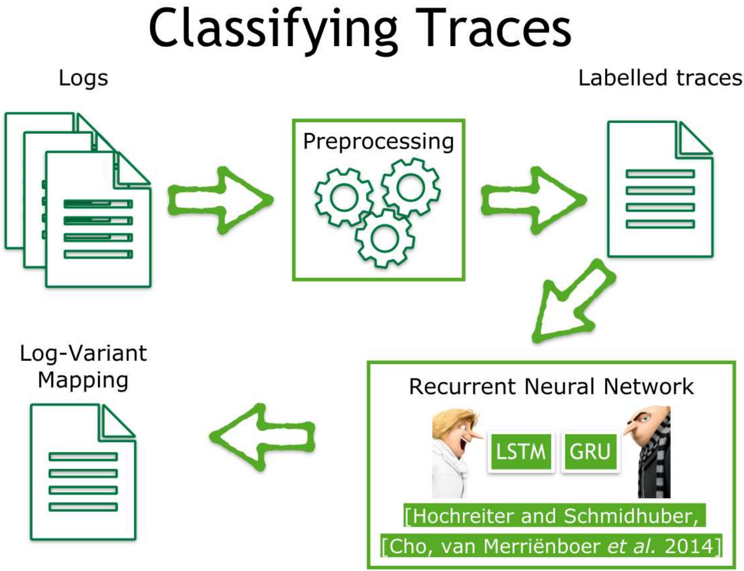
  - LSTM

VaryMinions: Overview



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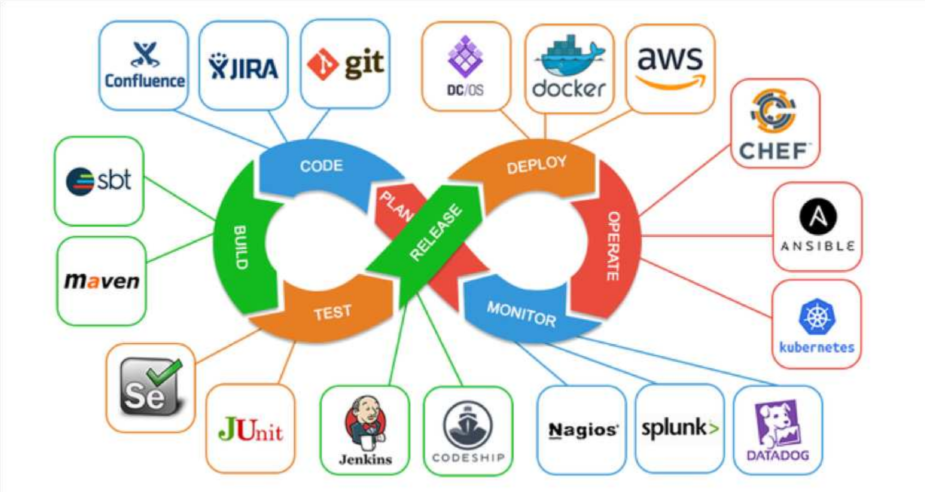
- potential evolutions: custom losses, bigger models?, much more

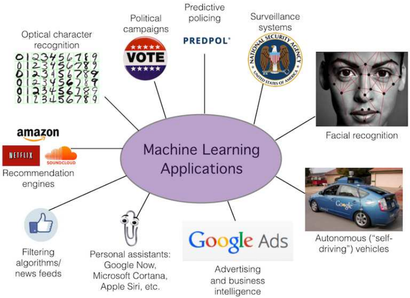
ML and SE

(When ML meets DevOps)

Overview of DevOps



ML in DevOps



Source:https://www.redshiftzero.com/img/ml_applications.png

- Modern system are complex (multiple components, configurable, etc.)
- Need to adapt to the environment
- ML decisions impact the system (adaptations, outputs, etc.)

ML in DevOps

ML Assumptions

- Training(, validation,) and test sets $\rightarrow$ same distribution
- Distributions do not evolve

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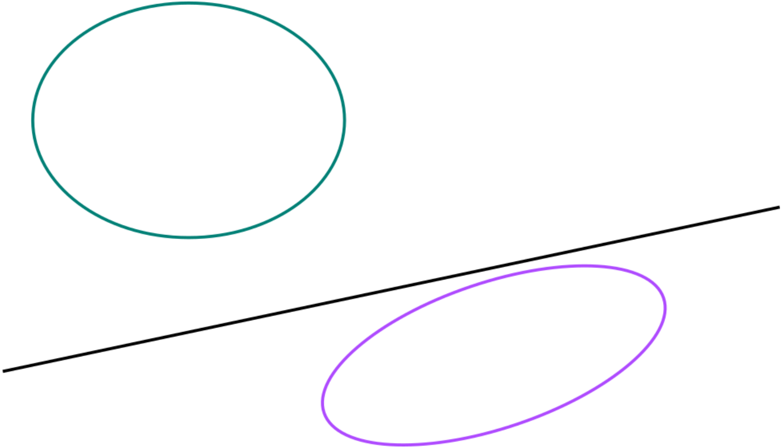

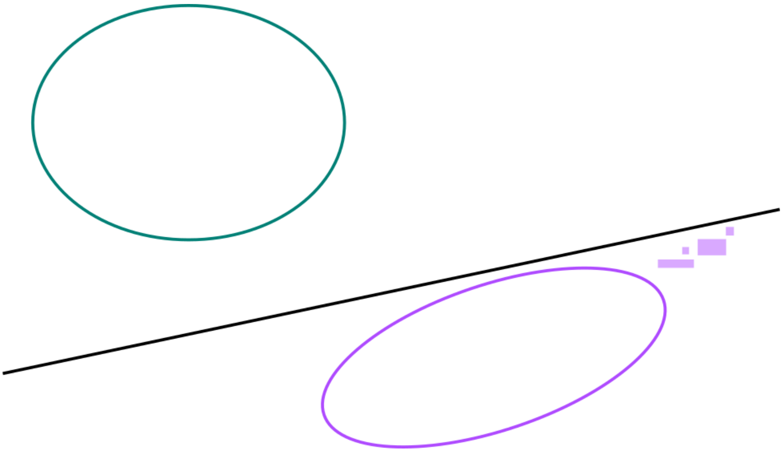

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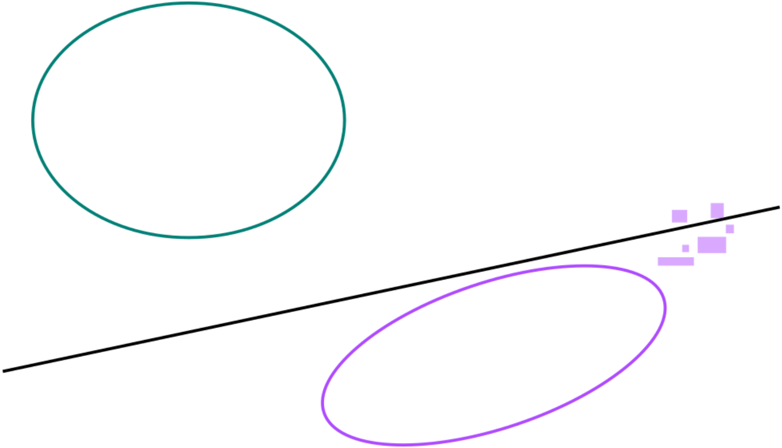

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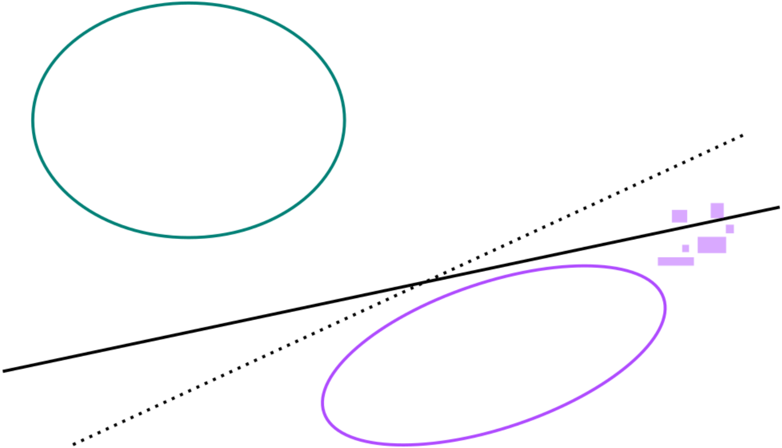

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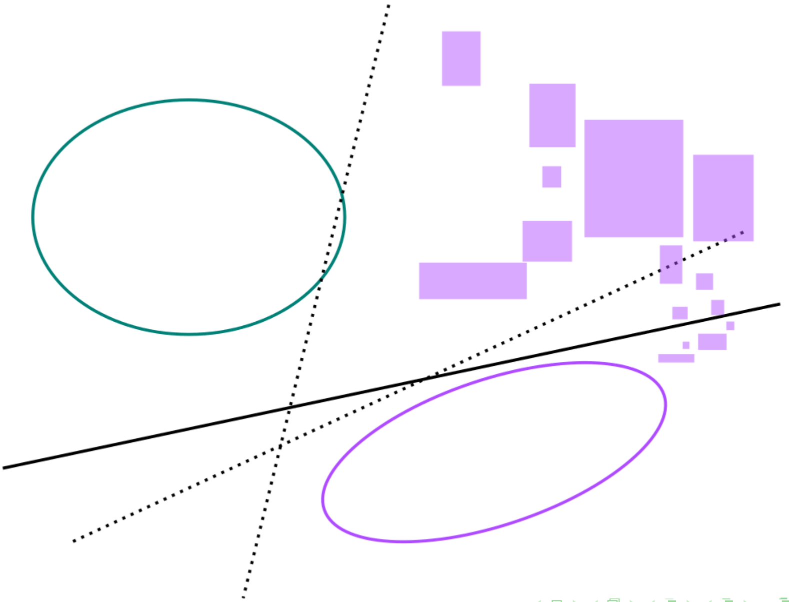

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retraining from scratch

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→ Compliant with DevOps?
How often should we retrain?

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Update the model

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Problems

- Check and relabeling can be tedious
- Lot of data might be necessary to have an impact
- Consecutive changes over time $\Rightarrow$ **model shifting**

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Federated learning?

- Keep a "master" version
- Deploy customized versions for customers
- customized versions are upgraded & "master" version is retrained

Extremely hot topic in research

Wrap-up DevOps and ML

ML models are part of systems

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- Problem: How often updating is needed?
- Problem: Consequences on Federated learning?