Audition CRCN CNRS 2022
Efficient Exploration of Colossal Configurable Spaces

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March 2022

Equipes : Spirals (Lille) ; ProGresS (Bordeaux) ; NaoMod (Nantes)

Software variability & system complexity

Linux Kernel: **15,000** options

Software variability & system complexity

Linux Kernel: **15,000** options

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

Software variability & performances

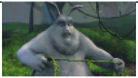
no-mbtree = F
qblur = 0.90
nr = 200

processing time $= 5$ min

processing time $= 2$ h

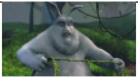
processing time $= 10$ h

Evaluating performance is complex

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

Link to PhD manuscript and slides for defense

Evaluating performance is complex

	Program Variants				
				...	
Inputs		12	1	...	5
		1	348	...	10
	...				
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Investigate the Matrix

- **Multimorphic** Testing → **reduce inputs** based on capability to observe different performances
- **Reduce variants** with ML

Link to PhD manuscript and slides for defense

Do we need to measure?

Assumptions

- Exploring all configurations is **impossible**
- Measuring performances is **costly**

Siegmund *et al.*, Perf. Prediction with feature interaction, ICSE'12
Siegmund *et al.*, Perf.-Influence models for config. systems, FSE'15
Guo *et al.*, Var.-aware perf. prediction, ASE'13

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Assign a measure without measuring

- Similar configurations produce similar performances
- Performance prediction

		Program Variants			
		264	264	...	264
Inputs		12	1	...	5
		1	348	...	10
			...		
		50	101	...	260

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Do we need to measure?

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Users know what they want

- Technically & performance-wise
- **Few** configurations are **acceptable**

→ **Scope** the configuration space

		Program Variants			
		264	264	...	264
Inputs		12	1	...	5
		1	348	...	10
		...			
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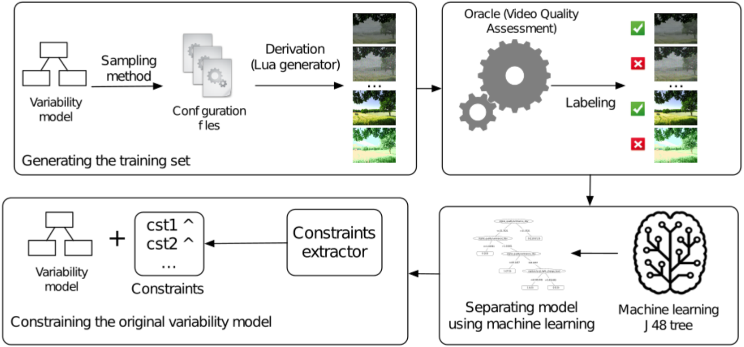
Temple *et al.*, Using machine learning to infer constraints for product lines, SPLC'16

Reducing configuration space with ML



Temple *et al.*, Using machine learning to infer constraints for product lines, SPLC'16

Adversarial configurations

Temple *et al.*, Adv. Configs for config. systems, EMSE'21
Link to PRALab website

Adversarial configurations

- 1^{st} **use** of adversarial ML techniques for configurable systems
- Collaboration between:
  - Battista Biggio and Fabio Roli, PRALab, Sardinia
  - Mathieu Acher and Jean-Marc Jézéquel, IRISA, Rennes
  - Gilles Perrouin and myself, Namur
- Published at SPLC'19 $\rightarrow$ extended in EMSE'21

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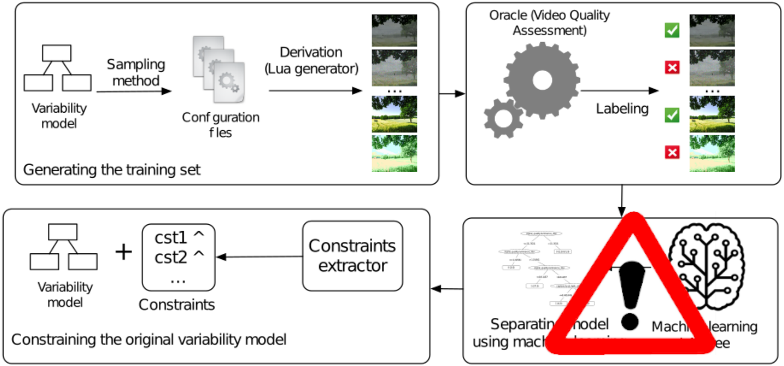
Reducing configuration space with ML



;

Machine Learning is based on statistics → errors

- Over-constraining: lack of flexibity
- Under-constraining: waste of resources

Improving the pipeline

Robustifying the model

- Show new configurations
- Configurations with **high risk** of misclassification

Goodfellow *et al.*, Adversarial examples, ICLR'15
Elsayed *et al.*, Fool both humans and computers, NeurIPS'18
Sharif *et al.*, Accessorize to crime, CCS'16

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predict.: acceptable

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no-mbtree = F
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predict.: acceptable

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Robustifying the model

no-mbtree = F
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predict.: non-acceptable

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predict.: non-acceptable

Adversarial Configurations

- Adversarial retraining
- Analyze them to understand what is wrong

Biggio *et al.*, Evasion attacks against SVMs, ECML'13

Research project

- ML for SPLs
  - Adversarial configurations for improvement
  - Find a more efficient representation for configurations
- ML models exploration with SPLs

Adversarial configurations for improvement

Adversarial configurations

- Can be used to improve fairness aspects

Delobelle *et al.*, Ethical Adversaries, SIGKDD Exploration NewsLetters

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Support for constraints

- Constraints on feature values and combinations → forbidding exploring subspaces
- Constraints may be complex → involve several features
- Generation process is iterative → constraint checking strategy

Delobelle *et al.*, Ethical Adversaries, SIGKDD Exploration NewsLetters

Research Project: Find an efficient representation for configurations

What is wrong?

- Similar configurations $\rightarrow$ similar performances
- options as a feature vector $\rightarrow$ interactions?

Iscen *et al.*, Metric Learning, CVPR'19

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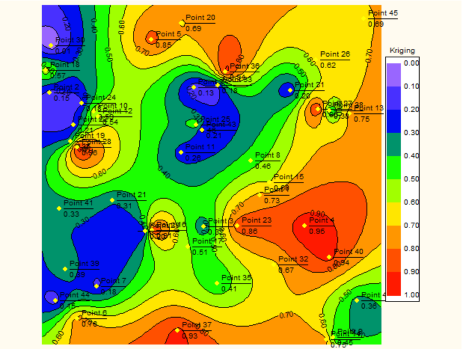

Iscen *et al.*, Metric Learning, CVPR'19

Research Project: ML models design with variability management tools

Modern ML models

- 100 epochs ImageNet to train AlexaNet in 24*minutes* for **only 1.2M dollars**

$\Rightarrow$ Impossible if you are not GAFAM

Research Project: ML models design with variability management tools

Modern ML models

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⇒ Impossible if you are not GAFAM

Explicitly managing variability

- Defining a model is complex
- Many models exist (and they can be combined)

→ PhD Antoine Gratia: manage the exploration of DL design space

Research Project: ML models design with variability management tools

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$\rightarrow$ PhD Antoine Gratia: manage the exploration of DL design space

Goal of variability management

- Reducing costs to make it accessible
- Green computing
- Reduce complexity of models $\rightarrow$ explainability

Integration

- Spirals, Lille
- ProGresS, Bordeaux
- NaoMod, Nantes

Teams

- Software Engineering teams with lack of ML background
- centered around variability

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- centered around variability

Spirals

- Great work environment
- run-time adaptation // performance

ProGresS

- Want to develop collaborations with the BKB team
- evolution

NaoMod

- Projects in collaboration with companies
- architecture

Efficient Exploration of Colossal Configurable Spaces

- Software variability; Machine learning; Performance
- Testing performances of configurable systems is difficult
- Adversarial configurations
- Research Project:
  - representation problem
  - adversarial for improvement $\rightarrow$ fairness; adversarial sampling
  - var. management for models $\rightarrow$ green computing, reducing complexity
- teams:
  - Spirals, Lille
  - ProGresS, Bordeaux
  - NaoMod, Nantes