Towards Quality Assurance of SPLs with Adversarial Configurations

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Configurable systems

Linux Kernel: **15,000** options

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

JHipster

JHipster: **50** options

- Generate web app
- Micro-services

Halin *et al.*, https://doi.org/10.1007/s10664-018-9635-4
https://www.jhipster.tech/microservices-architecture

JHipster

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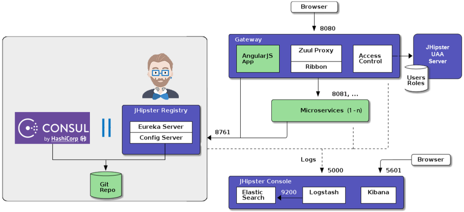
- Generate web app
- Micro-services
- 26,000+ configurations



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JHipster: **50** options

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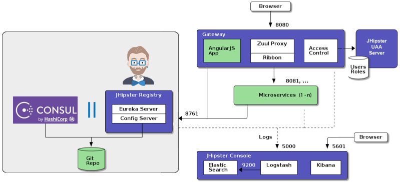
NETFLIX OSS + + docker



elastic + logstash + kibana

Problem:

- Which variants can be build under X seconds?
- Which variants can run with limited resources? (less than Y Watts)

Reducing configuration space with ML

JHipster → 26,000+ configurations

- **Exploring** all configurations is **impossible**
- **Measuring** performances is **costly**
- **Few** configurations are **acceptable** (meet performances)

→ How to find the few interesting one?

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Performance predictions

- Assumption: similar configuration → similar performances
- **Train** a model on **few** configurations
- **Predict** on **all** the others

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Performance predictions

- Assumption: similar configuration $\rightarrow$ similar performances
- **Train** a model on **few** configurations
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$\rightarrow$ **Filter** to retrieve the interesting ones

Reducing configuration space with ML

Scope the configuration space

- User: "I want technology X and Y but the system should run under S seconds"
- Learn which configurations are ok with that

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

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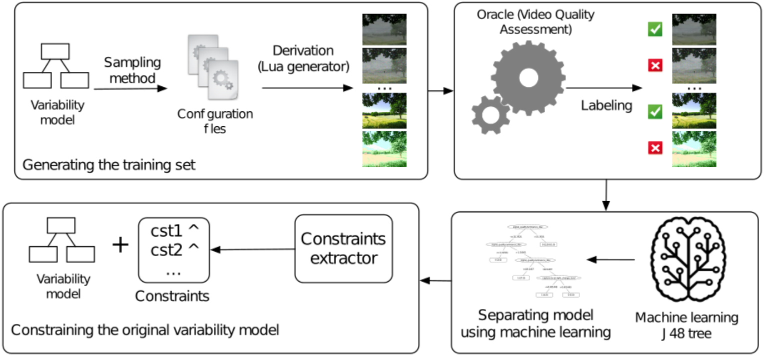

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Improving the classification of software configurations

Impacts

Machine Learning is based on statistics $\rightarrow$ errors

- Over-constraining
- Under-constraining

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Over-constraining

- Forbid more configurations than necessary
- Lack of flexibity

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Over-constraining

- Forbid more configurations than necessary
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Under-constraining

- Allow more configurations than necessary
- Waste of resources

Improve the quality of the classifier

Robustifying the model

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

Goodfellow *et al.*, https://arxiv.org/pdf/1412.6572.pdf

Elsayed *et al.*, https://proceedings.neurips.cc/paper/2018/file/8562ae5e286544710b2e7ebe9858833b-Paper.pdf

Sharif *et al.*, https://dl.acm.org/doi/pdf/10.1145/2976749.2978392

YT: https://www.youtube.com/watch?v=6Xh1vuwnVhU

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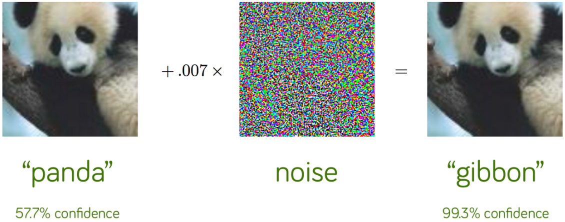

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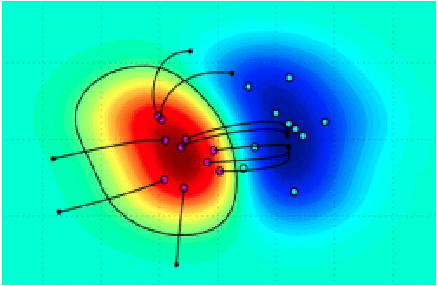
Sharif *et al.*, https://dl.acm.org/doi/pdf/10.1145/2976749.2978392
YT: https://www.youtube.com/watch?v=6Xh1vuwnVhU

Improve the quality of the classifier

Adv. configurations, how does it work?

- Configurations of a system = **vector of (Binary) options**
- Model is trained on few configurations
- Choose a (known) configuration
- Apply gradient descent → **modifications** on the values of options
- **Repeat** gradient descent until happy



Biggio *et al.*, `https://arxiv.org/pdf/1708.06131.pdf`

Adv. ML and software systems

Adv ML allows for:

- Automatic generation of new configurations → iterative modifications
- prediction error mitigation → adversarial retraining
- enhanced design space coverage → adversarial configurations

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Future works

- Need for better support for domain constraints
- Integration with constraint solvers
- Can adv ML be used as a new sampling strategy?

Sum-up

- Introduce adv ML to variability
- ML models useful to deal with configurable design spaces
- Generate configurations with high risk of misclassification
- Open directions for new sampling strategies?
- Need for better constraint support

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Contact us:

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