Sustainable Software Research @UNamur

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FREEDOM TO RESEARCH

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What about Namur (Namen, Nameur) ?

FR

Capital of the Walloon Region

55 Kms South-East of Brussels

Population: 110 000

What about UNamur?

Students: 7300
Personnel: 1500

Belgium: 1830
UNamur: 1831

Faculties: 7

Research Institutes: 11

Collaborations: >55 countries

Alliance: UNIVERSEH

Faculty of Computer Science

- Born in 1970, ***first in Belgium!***
- 19 professors
- 1 FNRS Research Associate (tenured scientist, me ☺)
- 18 Teaching assistants (PhD students)
- +/- 40 researchers (grantees, etc.)
- 650 students

NADI Namur Digital Institute

Digital World Challenges

Interdisciplinary Approach

150+ members

8 Research Directions

- Big Data & Artificial Intelligence
- Collaborative Economy
- Co-innovation & co-creation
- Security & Privacy
- Smart Cities & E-government
- Software & Systems
- Ethics & Technology
- Digital Education

UNIVERSEH

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Cyberwal by digital wallonia .be

INFORMATICS EUROPE

Since July 2025!

Research Topics…

- **Software Engineering** (Modelling, Variability & Configuration, Testing, Verification and Validation, Evolution of Data-intensive systems)
- **Security and Privacy** (network protocol, cybersecurity, …)
- **Machine Learning** (Trustworthy and Interpretable AI, AI Ethics, …)
- **Symbolic AI**
- **Formal Methods**
- **HCI** (Interaction, Augmented and Virtual reality, …)
- **Swarm Robotics**
- **Philosophy of Science, Ethics**

Several cross-disiplinary collaborations amongst these research topics!

Towards Greener Neural Architecture Search

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SoTA - Neural Architecture Search (NAS)

- Search for the ***optimal (performance)*** network via optimization algorithms
- Define and Explore a predefined space (neural architectures)
  - Based on enumerating "cells" in a skeleton architecture
- NasBenchX (101,201, ...)
  - Standardized benchmarks
  - Evaluate and compare NAS approaches

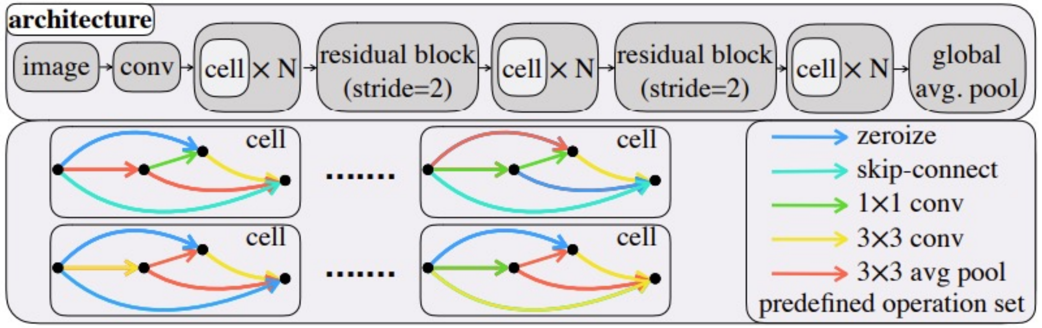
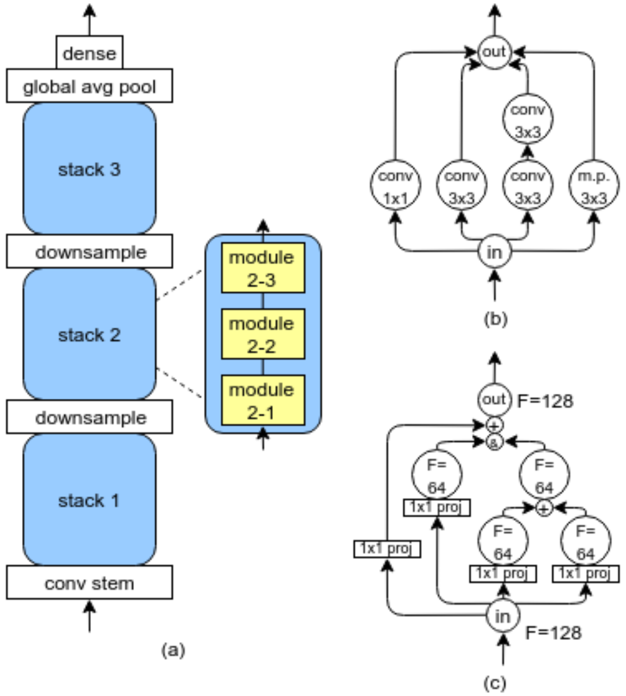
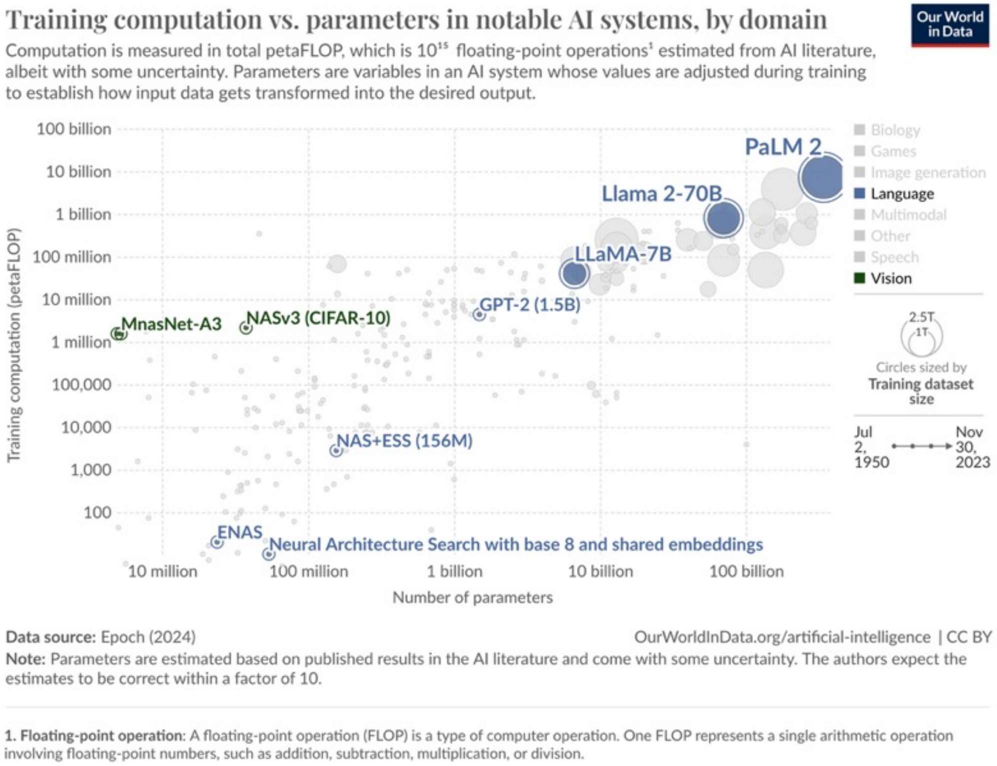


Figure 1: **Top**: the macro skeleton of each architecture candidate. **Bottom-left**: examples of neural cell with 4 nodes. Each cell is a directed acyclic graph, where each edge is associated with an operation selected from a predefined operation set as shown in the **Bottom-right**.

Neural Architecture Search Environmental Costs





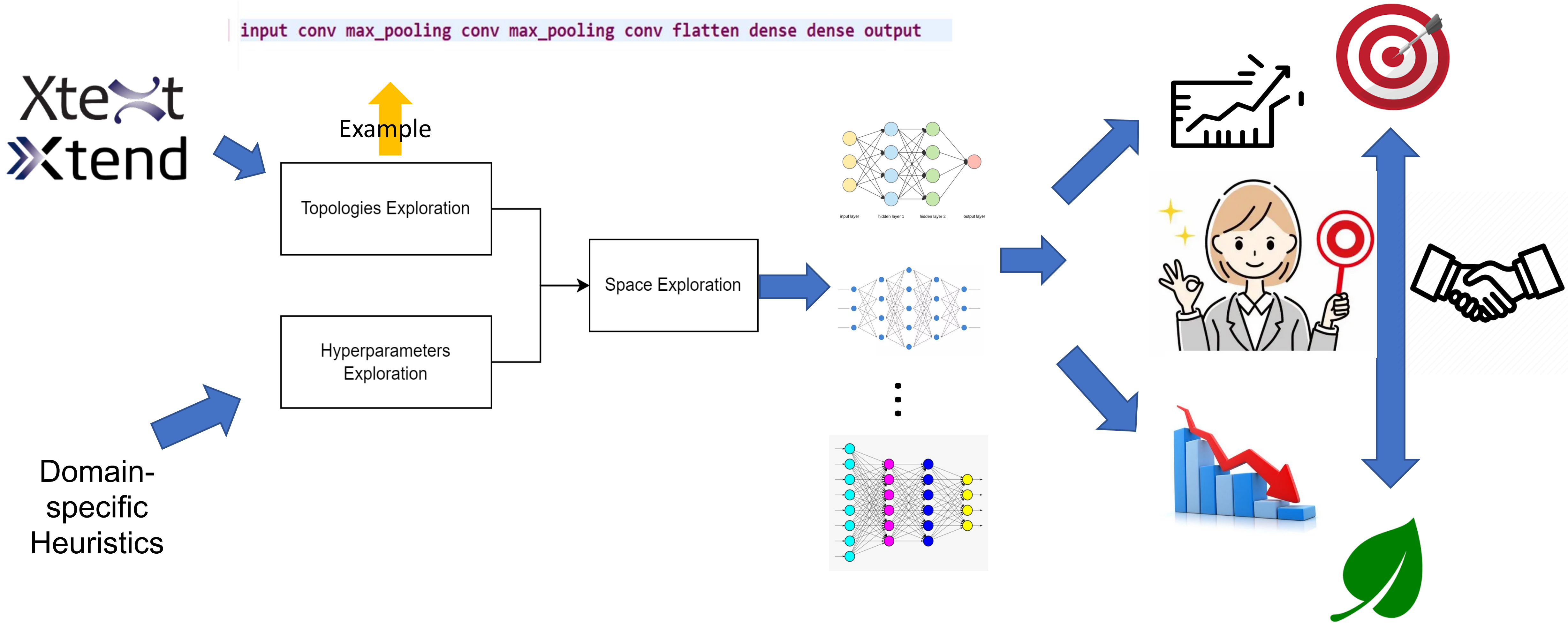
Neural Architecture Search => 400K trained CNNs for benchmarking/optimization research

Training 10K Models (CIFAR-10) ≈ ***Annual*** Consumption of ***600*** Chinese Households

Motivation – A. Gratia’s PhD Thesis

- **More diversified design spaces**
- **More sustainable search strategies**
- **Energy-performance trade-off awareness** (instead of blindly optimising structure)

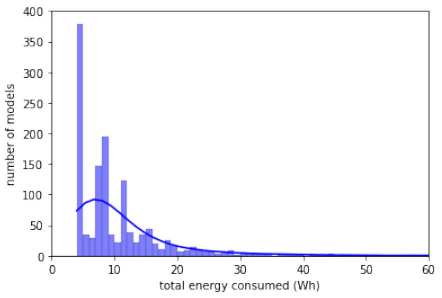
CNNGEN



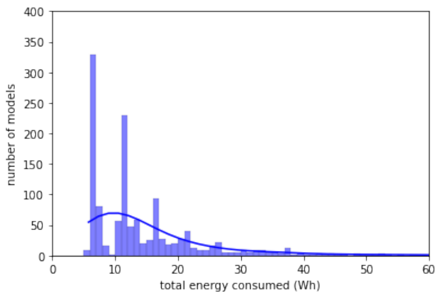
input conv max_pooling conv max_pooling conv flatten dense dense output
Example
Xtext
Xtend
Topologies Exploration
Hyperparameters Exploration
Space Exploration
Domain-specific Heuristics
input layer
hidden layer 1
hidden layer 2
output layer

A more Diverse Search Space

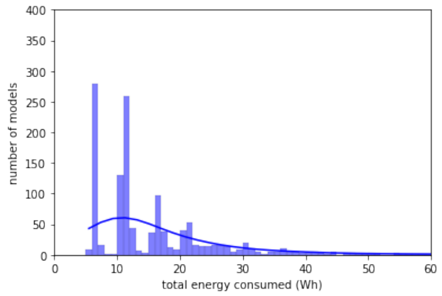
- **Models:**
  - **CNNGen:** Generated models range from **9 to 270 layers** (1,300 random models).
  - **NASBench:** Covers **15 to 85 layers** across a larger set.
- **Accuracy Distribution:**
  - CNNGen's average accuracies are lower than NASBench's.
  - However, the **high variance** indicates opportunities for targeted optimisation.
- **Energy Distribution:**
  - CNNGen's energy consumption spans a wide range.
  - Useful for building robust **energy-prediction models**.



(a) Distribution of energy of 1,300 models generated with CNNGen on CIFAR-10.



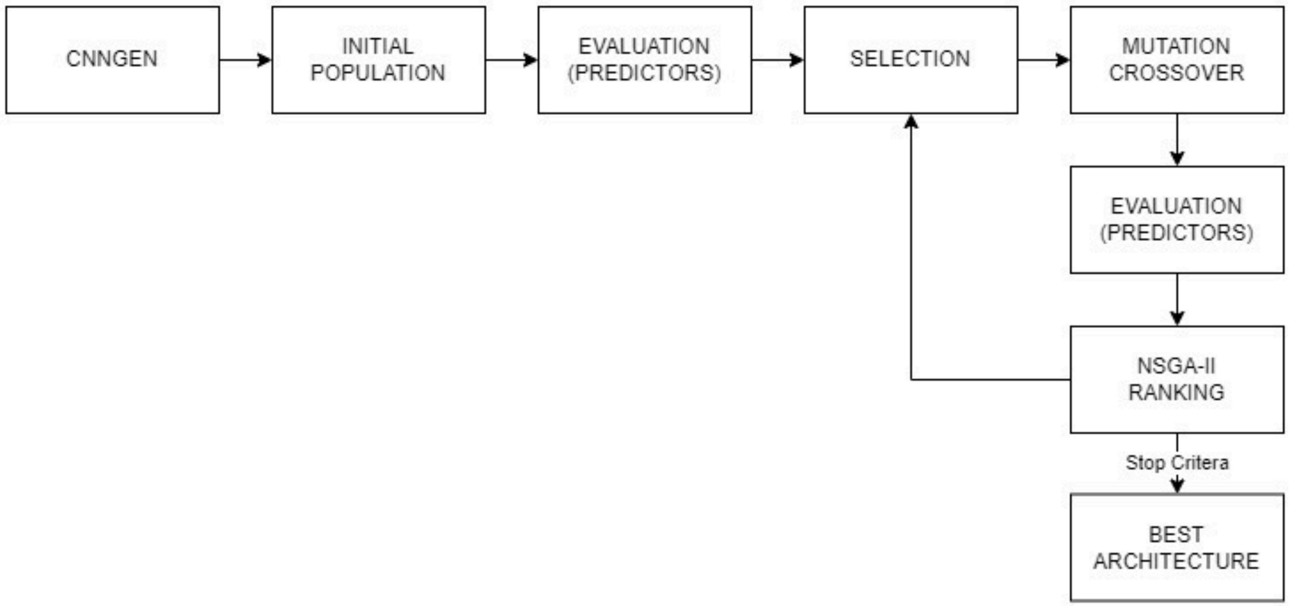
(b) Distribution of energy of 1,300 models generated with CNNGen on CIFAR-100.



(c) Energy distribution of 1,300 models generated with CNNGen on the Fashion-MNIST.

Greener Neuroevolution via Prediction

- Evolving the population with NSGA-II
- Fitness function based on ML predictors (energy & accuracy)
    - No need to train individuals (saves energy)
    - Faster (6x)
    - But at the initial cost of predictor training on 40k models



Energy consumption halved for a 2% performance decrease

Contributions & Collaborators

Antoine Gratia

Paul Temple

Pierre-Yves Schobbens

Shin'ichi Satoh

- Antoine Gratia, Hong Liu, Shin'Ichi Satoh, Paul Temple, Pierre-Yves Schobbens, Gilles Perrouin, "*CNNGen: A Generator and a Dataset for Energy-Aware Neural Architecture Search*". ESANN 2024, Oct 2024, Bruges, Belgium. pp.173-178.
- Gratia, A., Temple, P., Schobbens, PY., Perrouin, G. (2025). *Energy-Aware Neural Architecture Search: Leveraging Genetic Algorithms for Balancing Performance and Consumption*. Artificial Life and Evolutionary Computation Springer, 2025.
- Antoine Gratia, Topological Architecture Exploration and Neuroevolution for Energy-aware Neural Architecture Search, PhD Thesis, September 2025.

Energy-efficient Neural Networks

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Green ML / DL

Parcimonious IA / green AI

- challenge = AI is a huge consumer of data and energy
- goal = reduce this consumption with no/small performance loss
- research ideas
  - approximate the true objective function with something that is easier
  - create new architectures (e.g., based on conditional computation)
  - simplify models / focus on small models (e.g., SLMs)
  - create new, more efficient learning algorithms (w.r.t. data and energy)
- links with practical applications (astronomy, sign language recognition, time series analysis, industry 4.0, etc.)

Application to CNNs

Energy efficiency in Convolutional Neural Networks : A method built on Squeeze-and-Excitation mechanisms

Draguet Noémie

Making Convolutional Neural Networks Energy-Efficient: An Introduction

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Abstract. As convolutional neural networks (CNNs) have become mainstream for object recognition and image classification, the environmental impact caused by their high energy consumption (EC) is non negligible. This paper examines techniques that have the ability to reduce the EC of CNNs. It also highlights the inconsistency of metrics that are used for estimating or measuring EC, which reduces the comparability of these techniques. This review aims to shed light on the current situation and to provide a basis for future research in green machine learning.

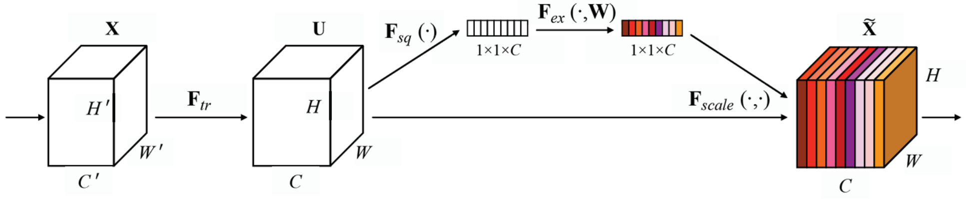
1 Introduction

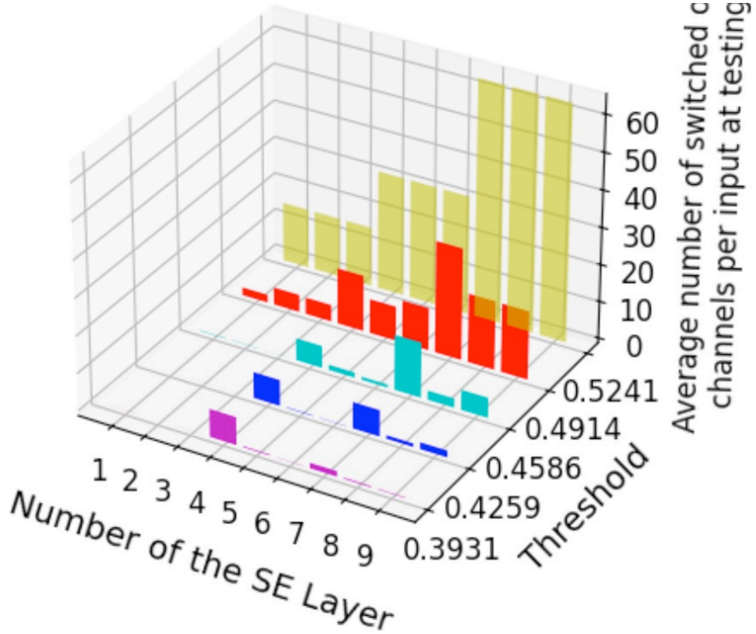
As machine learning and artificial intelligence become increasingly popular, these technologies start having growing consequences on the environment due to their substantial energy consumption (EC). Among various models are convolutional neural networks (CNNs) that perform well in object recognition and image classification. However, they usually require a lot of computational power to achieve satisfying results given their high dimensional inputs, their large size and their substantial number of parameters. For example, 0.19 joules are necessary for making an inference with ResNet50 on Nvidia RTX 2080 Ti [1]. So far, the literature has focused on improving the accuracy of those models, or on decreasing their size [2], inference time [3] and EC for performance or portability purposes [4]. Furthermore, the decrease in energy resulting from the proposed methods is usually not measured with a same metric, which makes the comparison of different techniques difficult and the literature inconsistent regarding EC. This paper gives an overview of existing methods that have for purpose or side effect to reduce the EC of CNNs, which can help introducing junior researchers to this subject and might open doors for future research in this area.

Section 2 discusses metrics to measure or approximate the EC of a model and gives recommendations about their use. Section 3 introduces families of methods that reduce the EC of CNNs and shows the results obtained with these methods. Finally, Section 4 concludes and gives perspectives for future research.

2 Metrics for Energy Consumption

Before introducing techniques that can reduce the EC of CNNs, it is essential to first discuss how to measure it. Indeed, works in the literature use multiple





DRAGUET, Noémie ; Frénay, Benoît. **Making Convolutional Neural Networks Energy-Efficient : An Introduction**. Proc. ESANN. 2025.

Understanding Software Energy Consumption

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SNAIL
TEAM@UNAMUR

"We research emerging software quality properties through the lenses of software reliability and developers' experience"

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Jérôme Maquoi

Software Testing, Sustainability, Energy Consumption

- Green coding
- Monitoring code energy consumption
- Raising developers' awareness
- Studying the impact of a code change
- https://snail.info.unamur.be/tag/energy-consumption/

Energy Codesumption (DevOpsSustain'25)

Energy Codesumption, Leveraging Test Execution for Source Code Energy Consumption Analysis

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Abstract

The software engineering community has increasingly recognized sustainability as a key research area. However, developers often have limited knowledge of effective strategies to reduce software energy consumption. To address this, we analyze energy consumption in software execution, aiming to raise developer awareness by linking energy consumption with each line of code. We rely on unit test executions to identify energy-intensive executions and manually analyze five hot and five cold spots to identify potentially energy-intensive source code constructs. Our findings suggest a link between the energy consumption of the source code and the number of objects' attributes created within that code. These results lay the groundwork for further analysis of the relationship between object instantiation and energy consumption in Java.

CCS Concepts

• **Hardware → Power estimation and optimization**; • **Software and its engineering** → *Software testing and debugging*.

Keywords

energy consumption, source code analysis, test execution, java

ACM Reference Format:
Jérôme Maquoi, Maxime Cauz, Benoît Vanderose, and Xavier Devroey. 2025. Energy Codesumption, Leveraging Test Execution for Source Code Energy Consumption Analysis. In *33rd ACM International Conference on the Foundations of Software Engineering (FSE Companion '25), June 23–28, 2025, Trondheim, Norway*. ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3696630.3728707

1 Introduction

Reducing the environmental impact of all aspects of IT, including energy consumption of running software, is becoming crucial to achieving a more sustainable society. In recent years, various aspects of software sustainability and green software engineering have been investigated by the research community [4, 20, 22–24, 27]. In particular, [17] has shown that developers recognize, to a certain extent, the challenges associated with software energy consumption. However, they often lack knowledge of effective strategies to reduce their software's energy footprint. To bridge this gap, we need (i) methods to measure and report source code energy consumption and (ii) identify code constructs that increase energy usage to develop appropriate tooling.

This short paper lays the foundations for our research objective: gaining a deeper understanding of the underlying causes of energy consumption from the source code. More specifically, we answer the following research question (**RQ**): *how does the source code of a Java project impact its energy consumption?* For that, we rely on JoularJX [16], a state-of-the-art tool, to measure energy consumption at the source code level of Java projects (i.e., each execution branch is associated with its energy consumption). Based on the measurements, we identified high- and low-energy-intensive parts of the code and performed a manual analysis to identify recurring code constructs.

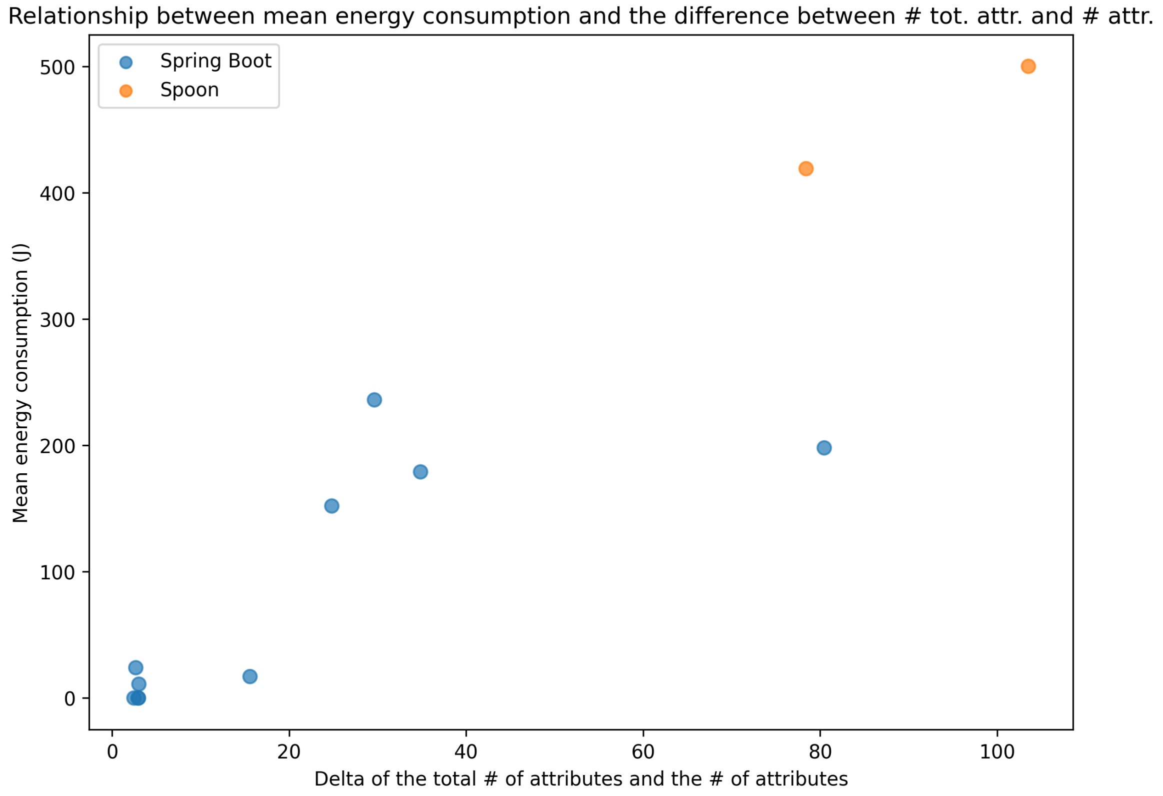
FSE Companion '25, Trondheim, Norway

ACM ISBN 979-8-4007-1276-0/2025/06
https://doi.org/10.1145/3696630.3728707

2 Background and related work

A recent survey [13] highlights the need for improved skills among developers in energy-aware development. Developing such skills should be paired with raising developer awareness about the energy consumption of their code, which requires tools that can assess the energy consumption associated with the source code.

Energy consumption assessment. The first method relies on theoretical models to estimate consumption without direct measurements. For example, the TEEC model estimates CPU, memory, and disk power usage during application execution through established mathematical expressions [1]. Alternatively, physical measurement utilizes a power meter connected to the hardware. This approach provides the most accurate representation of energy consumption during software execution. For instance, a framework that detects energy hotspots in Android applications employs a physical power meter for accurate detection of these energy-intensive areas [3]. More recently, hardware sensors with software interfaces have been able to measure components like CPUs, GPUs, RAMs, and disks. Manufacturers provide interfaces for power data, such as Intel's

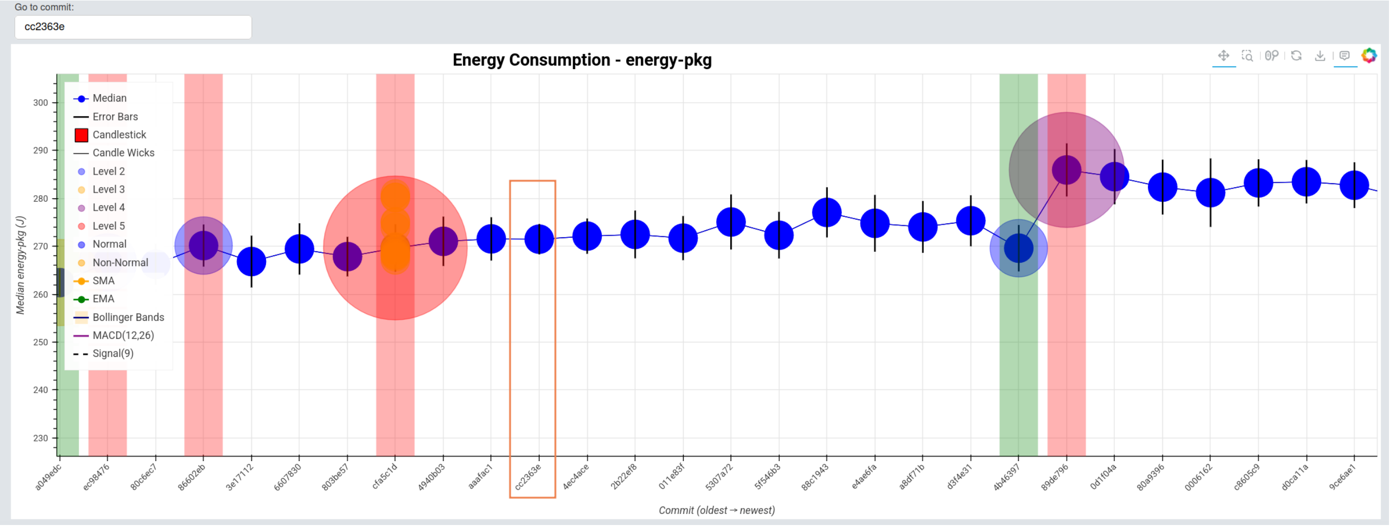


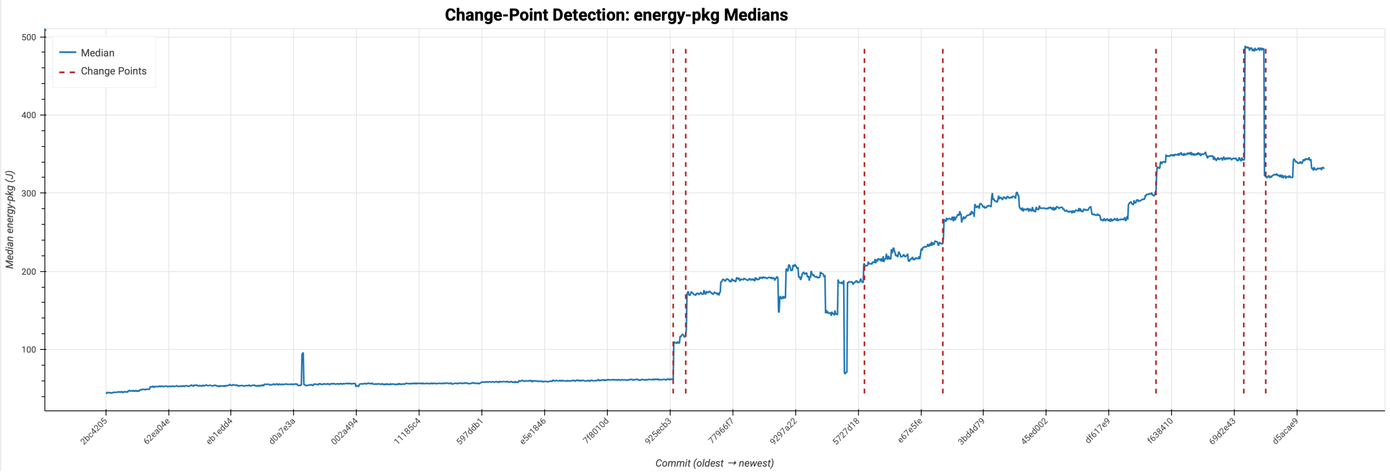
Energy costs may be caused by the quantity and complexity of generated attributes inside constructors

https://snail.info.unamur.be/publication/maquoi-2025/

EnergyTrackr: Energy Regressions Detection

- A modular and automated tool to detect energy regression commits
- Executes the project’s tests
- Relies on statistical methods to detect energy consumption changes
- Different visualisations





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Teaching: JEDDT

- Sustainable Development and Transition Education Days
- Guest lecture (2h)
  - Prof. Benoît Vanderose
  - Prof. Xavier Devroey
- Impact of IT
  - Hardware / Software
  - Internet
  - AI and LLMs

https://www.unamur.be/en/institution/sustainable/education/jeddt

Conclusions

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Summary & Future Work

- Growing green software research across all informatics fields : SE, AI, …
- Transfer this in the curriculum
- Global awareness is rising, but it is easier for some communities to accept tradeoffs…

- Energy-aware scheduling for micro-controllers
- Energy Consumption of AI-generated code
- Assessing (data) distillation energy costs

Contacts


Profs. Xavier Devroey & Benoît Vanderose
Topic: GREEN SE, Teaching

Dr. Gilles Perrouin
Topic: SE 4 GREEN AI

Prof. Benoît Frénay
Topics: GREEN AI


e-peas
semiconductors

Profs. Pierre-Yves Schobbens & Laurent Schumacher
Topics: Energy-aware micro-controllers

Research Track Round 1: **Dec 4, 2025**

Other tracks: Industry, doctoral symposium, Projects, …

SCAN ME