INTELLIGENCE ARTIFICIELLE

–

MYTHE OU RÉALITÉ

–

DÉFIS, OPPORTUNITÉS ET NOUVELLES COMPÉTENCES

20 JUIN 2019

MOT DE BIENVENUE

GEORGES KIOES

Partner, Deloitte

Administateur FEDIL & membre du Groupe de Haut Niveau sur la Transformation Digitale

INTELLIGENCE ARTIFICELLE DÉFIS ET OPPORTUNITÉS

FREDERIC ROBIN
Country General Manager
IBM Luxembourg

IBM – Artificial Intelligence

State of AI Development

Artificial Intelligence today

AI includes:

- Learning
- Reasoning
- Perceiving the environment
- Interacting with humans

Algorithms + Big data + Computing power

Where AI is:

- Web search
- Language translation
- Digital assistants
- Image understanding
- Text understanding and generation

Huge impact on all sectors:

- healthcare
- transportation,
- manufacturing,
- education
- …

The evolution of AI

General AI
Revolutionary

Broad AI
Disruptive and Pervasive

Narrow AI
Emerging

▼ We are here

2050 and beyond

We're at a Major Tipping Point for the Adoption of AI for Business

Businesses are now seeking to use AI broadly across their organizations to drive revenues, improve customer service, lower costs, and manage risk. According to our new Institute for Business Value study of 5,000 executives, while 82% of businesses are eager to move ahead with AI adoption, 60% fear liability issues and 63% lack the in-house talent to confidently manage the technology

Figure 1

Barriers in implementing AI: 2016 versus 2018

	2016	2018
Availability of skilled resources or technical skills	43%	63%
Regulatory constraints	29%	60%
Legal/security/privacy concerns about use of data and information	36%	55%
Degree of organizational buy-in/readiness/cultural fit	36%	44%
Data governance and policies	35%	43%
Availability of data to draw context for decision making	33%	43%
Availability of technology	46%	29%
Degree of executive support	30%	27%
Degree of customer readiness	28%	22%

Source: IBM Institute for Business Value surveys on AI/cognitive computing in collaboration with Oxford Economics. 2016 and 2018.

Not all AI is Created Equal: Enterprise v. Consumer AI

There are significant differences in business models, investment strategies and employee incentives between Consumer AI and Enterprise AI companies —advertising generated revenue v. revenue from the development, maintenance and support for the critical systems of the world.

With Enterprise AI Trust is an Imperative

IBM works hard to gain trust from our clients each and every day because we develop and deploy technology for the enterprises and organizations that run the most important systems on the planet: from transportation and financial services to healthcare and scientific discovery. Without trust, these organizations would not adopt, advance, and innovate with these new technologies.

AI – impact on jobs

La partie de l'image avec l'ID de relation rId2 n'a pas été trouvé dans le fichier.

IBM advocates for the net-positive impact AI will have on the global workforce by augmenting, not replacing, occupations and creating new economic and educational opportunities that benefit everyone.

Just as cars replaced horse-drawn wagons and email replaced fax machines, new technologies will change how we work.

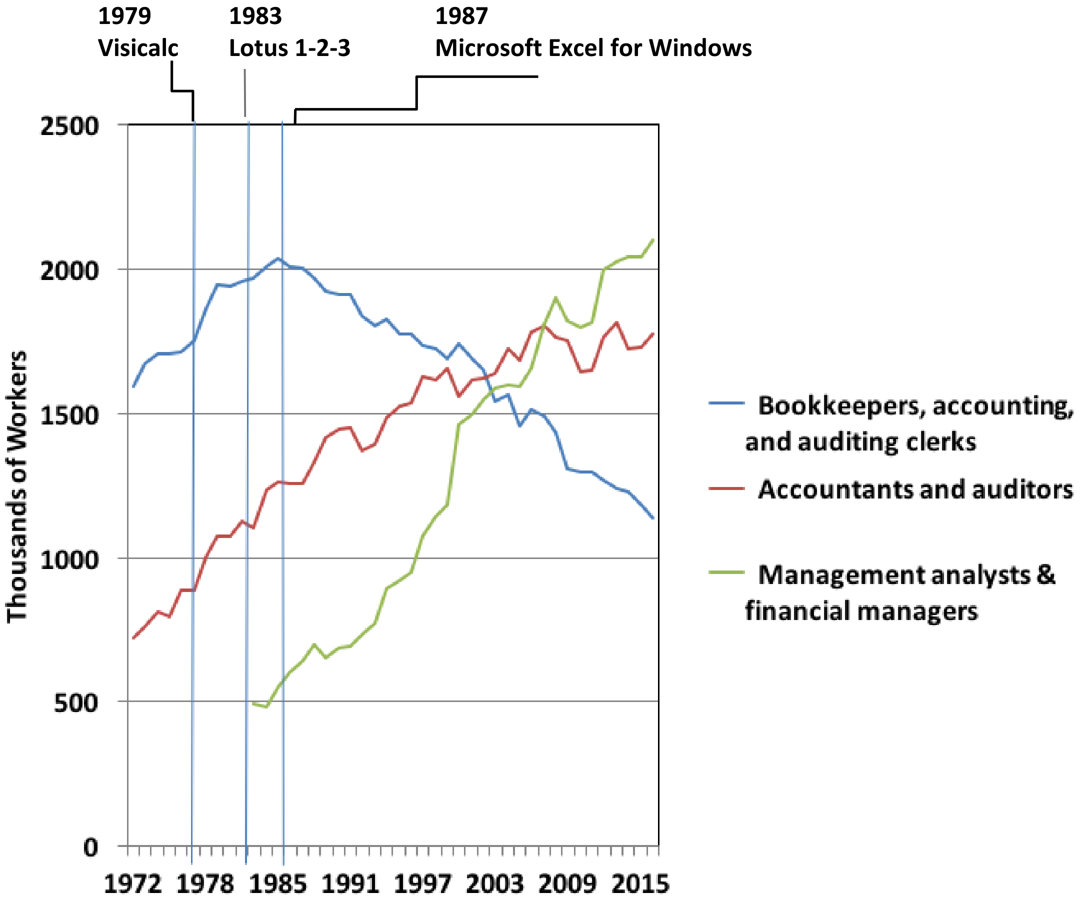
New technologies change the world – and how we work.

Significant new technologies have always created **new kinds of jobs** we couldn’t predict — electricity and the internet created entirely new industries, and we predict AI will do the same.

And new technologies have **changed how everyone works,** from the typewriter to the smartphone. AI will do the same — we will all need the skills to use analytics and artificial intelligence in our work.

Technological transformation leads to occupational transformation

New technology **pummeled demand for bookkeepers**, but the ranks of **accountants and auditors have grown.**



Source: Greg Ip, "We Survived Spreadsheets, and We'll Survive AI," *Wall Street Journal* August 2, 2017

The New Collar Worker

Many of these jobs, in areas such as cloud computing, cybersecurity, and digital design, do not necessarily require a four-year degree.

We must ensure workers have the skills they need for these "New Collar" jobs.

IBM is advocating for the future, investing in the next generation of New Collar workers, revolutionizing education, and training our employees for the AI Era.

New Collar Jobs:

- **Cloud engineering and network development**
- **Data science & analytics**
- **Cyber threat detection**
- **Design for digital experiences**

Pathways in Technology Early College High Schools (P-TECH) are innovative public schools spanning grades 9 to 14 that bring together the best elements of high school, college and career.

P-TECH has grown from 1 school in 2011 to more than 100 schools in 2018 and 200 schools in the coming years.

Within six years, students graduate with a no-cost associate degree in applied science, engineering, computers or other competitive STEM disciplines, along with the skills and knowledge they need to continue their studies or step easily into high-growth, “new collar” jobs.

QUESTION ÉTHIQUE DE L'INTELLIGENCE ARTIFICIELLE

NICHOLAS HODAC
Government and Regulatory Affairs Executive
IBM Europe

Artificial Intelligence

Ethics creates Trust

What does it take to trust a decision made by a machine?
“Trustworthy AI”

(Other than that it is 99 percent accurate)

Is it fair?

Is it easy to understand?

Did anyone tamper with it?

Is it accountable?

IBM **FAIRNESS** **EXPLAINABILITY** **ROBUSTNESS** **ACCOUNTABILITY**

18

EU HLEG Ethics Guidelines for AI – Principles

4 Ethical Principles based on fundamental rights

Respect for human autonomy

Prevention of harm

Fairness

Explicability

Ethics, Diversity & Inclusion in AI

Ethics in AI is a topic that every company is concerned about. Core to this is creating fair AI systems and also **ensuring that AI systems are aligned to the values of humans**. Creation of fair systems requires unbiased data and **a spirit of diversity and inclusion and multi-stakeholder engagement**.

We believe that AI has the ability to mitigate, rather than accelerate, our existing prejudices.

The quest for unbiased AI

The Guardian US edition

Rise of the racist robots – how AI is learning all our worst impulses

FAST COMPANY

02.28.18

Now Is The Time To Act To End Bias In AI

As decisions made by algorithms come to control more and more aspects of modern life, we need to act swiftly to make sure those decisions are actually fair. As of right now, they're often not.

Forget Killer Robots—Bias Is the Real AI Danger

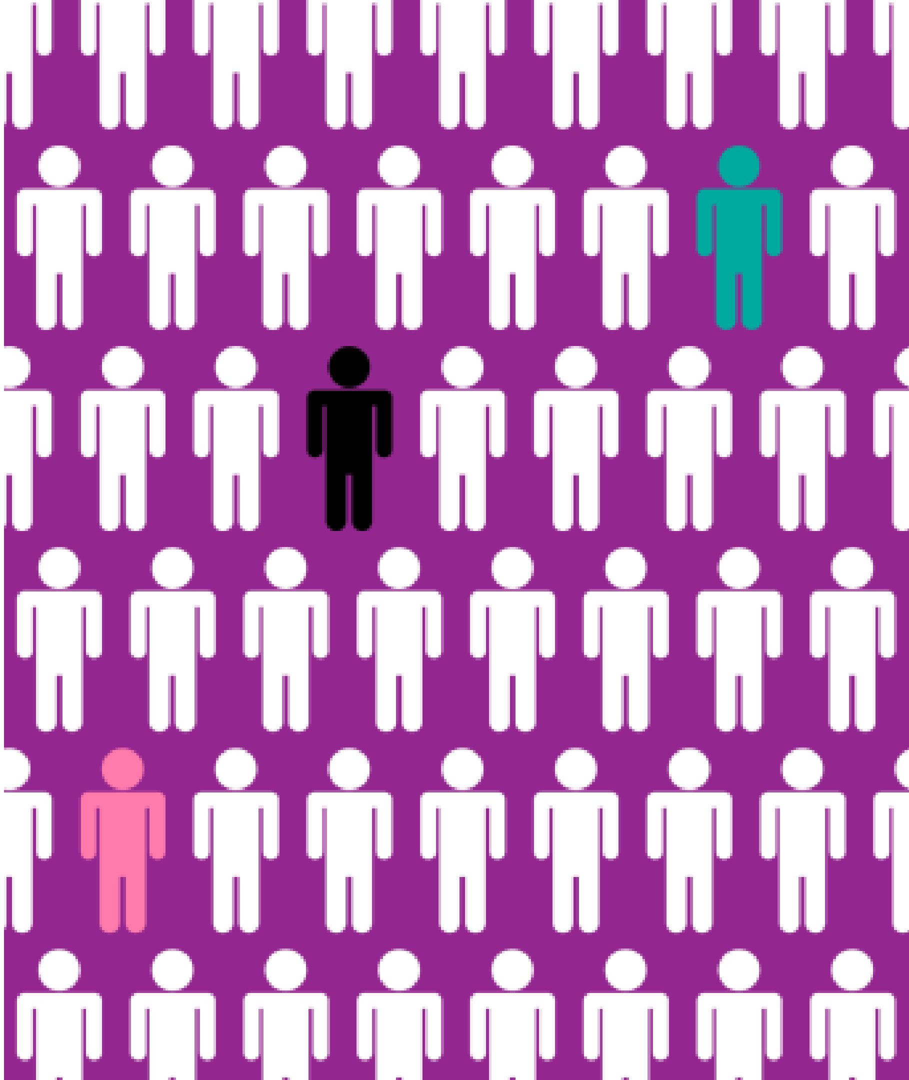
Harvard Business Review

TECHNOLOGY

Can We Keep Our Biases from Creeping into AI?

by Kriti Sharma

FEBRUARY 09, 2018



Unwanted bias and algorithmic fairness

Machine learning, by its very nature, is always a form of statistical discrimination.

Discrimination becomes objectionable when it places certain privileged groups at systematic advantage and certain unprivileged groups at systematic disadvantage.

It is illegal in certain contexts (e.g., Equal Credit Opportunity, The Equal Pay Act, The Americans With Disabilities Act), but not well understood in others.

Unwanted bias in training data yields models that scale that bias, including prejudice in labels and undersampling or oversampling, but bias can creep in due to incorrect model build, selection or deployment.

AI Fairness 360

An extensible toolkit for detecting, understanding, and mitigating unwanted algorithmic bias

IBM Research Trusted AI

Home | Demo | Resources | Community

AI Fairness 360 Open Source Toolkit

This extensible open source toolkit can help you examine, report, and mitigate discrimination and bias in machine learning models throughout the AI application lifecycle. Containing over 30 fairness metrics and 9 state-of-the-art bias mitigation algorithms developed by the research community, it is designed to translate algorithmic research from the lab into the actual practice of domains as wide-ranging as finance, human capital management, healthcare, and education. We invite you to use it and improve it.

API Docs ↗ | Get Code ↗

Not sure what to do first? Start here!

Read More
Learn more about fairness and bias mitigation concepts, terminology, and tools before you begin.

→

Try a Web Demo
Step through the process of checking and remediating bias in an interactive web demo that shows a sample of capabilities available in this toolkit.

→

Watch a Video
Watch a video to learn more about AI Fairness 360.

→

Read a paper
Read a paper describing how we designed AI Fairness 360.

→

Use Tutorials
Step through a set of in-depth examples that introduces developers to code that checks and mitigates bias in different industry and application domains.

→

Ask a Question
Join our AIF360 Slack Channel to ask questions, make comments and tell stories about how you use the toolkit.

→

View Notebooks
Open a directory of Jupyter Notebooks in GitHub that provide working examples of bias detection and mitigation in sample datasets. Then share your own notebooks!

→

Contribute
You can add new metrics and algorithms in GitHub. Share Jupyter notebooks showcasing how you have examined and mitigated bias in your machine learning application.

→

Learn how to put this toolkit to work for your application or industry problem. Try these tutorials.

Credit Scoring
See how to detect and mitigate age bias in predictions of credit-worthiness using the German Credit dataset.

→

Medical Expenditure
See how to detect and mitigate racial bias in a care management scenario using Medical Expenditure Panel Survey data.

→

Gender Bias in Face Images
See how to detect and mitigate bias in automatic gender classification of face images.

→

Bias Detection and Mitigation

Detect when AI is delivering unfair outcomes

The Quest for "Explainable AI"

CIO JOURNAL

Companies Grapple With AI's Opaque Decision-Making Process

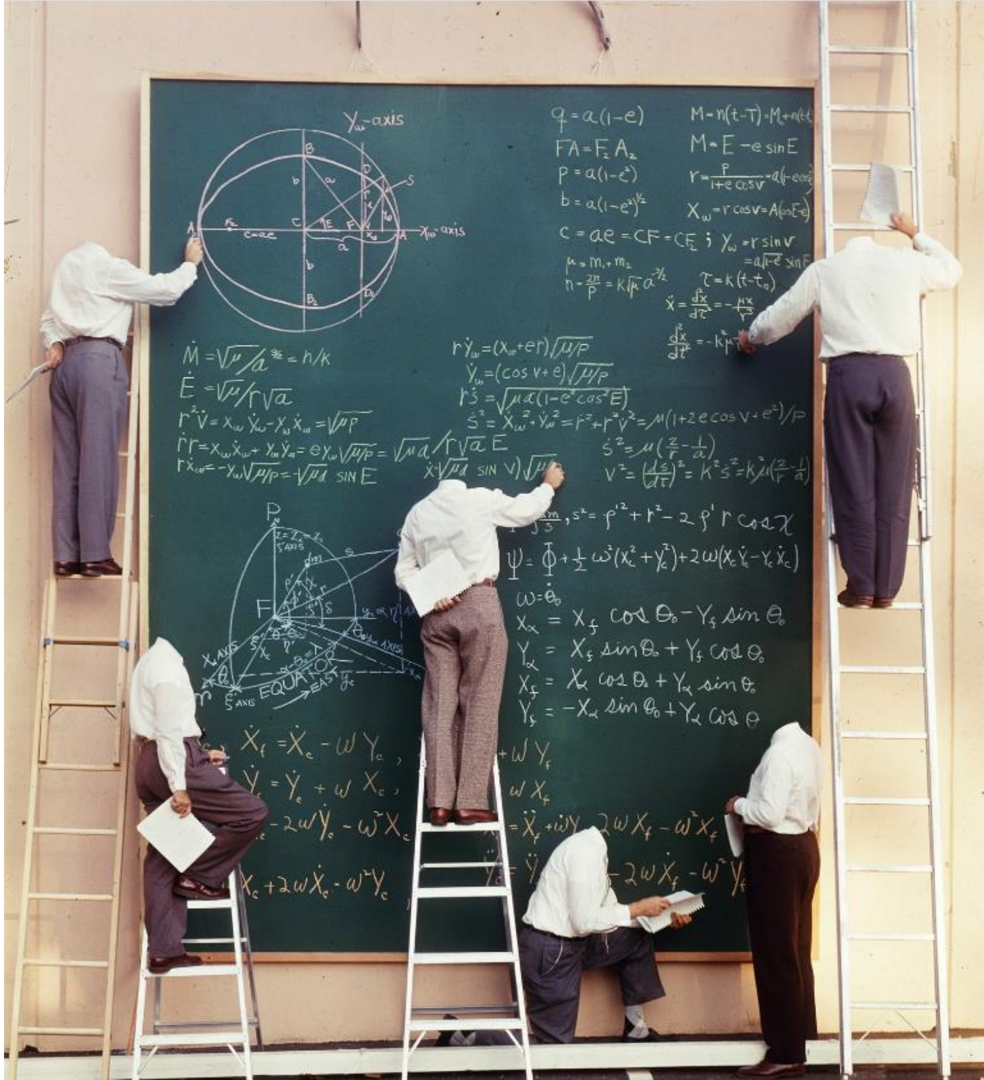
THE WALL STREET JOURNAL

Why Explainable AI Will Be the Next Big Disruptive Trend in Business

AlleyWatch

When a Computer Program Keeps You in Jail

Don't Trust Artificial Intelligence? Time To Open The AI 'Black Box'



One explanation does not fit all

Different stakeholders require explanations for different purposes and with different objectives, and explanations will have to be tailored to their needs.

End users

"Why did you recommend this treatment?"

Who: Physicians, judges, loan officers, teacher evaluators
Why: trust/confidence, insights

Affected users

"Why was my loan denied? How can I be approved?"

Who: Patients, accused, loan applicants, teachers
Why: understanding of factors

Regulatory bodies

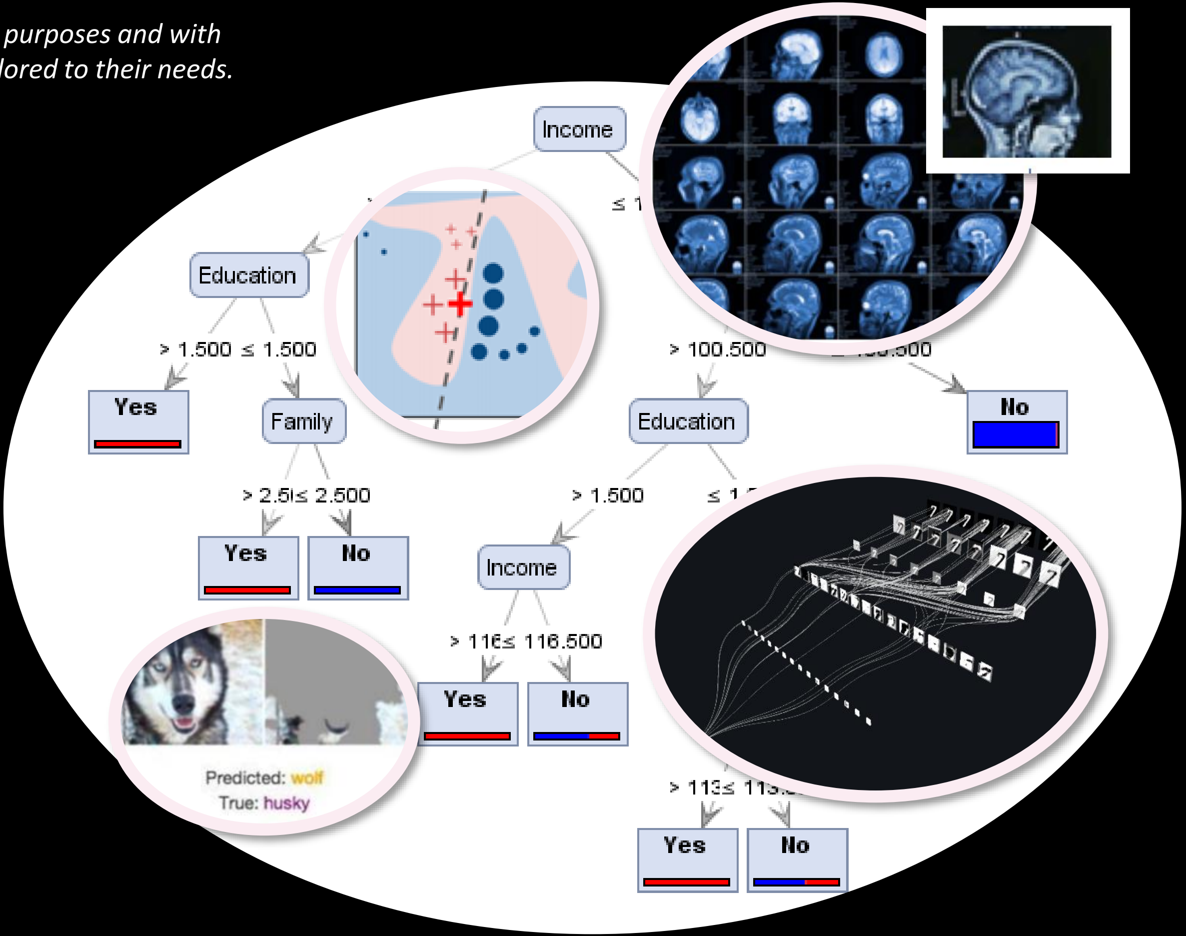
"Prove that your system didn't discriminate."

Who: EU (GDPR), NYC Council, US Gov't, etc.
Why: ensure fairness for constituents

AI system builders/stakeholders

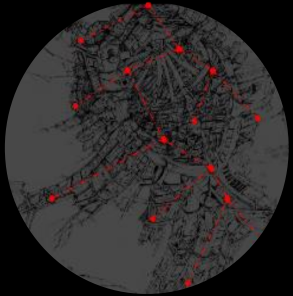
"Is the system performing well? How can it be improved?"

Who: EU (GDPR), NYC Council, US Gov't, etc.
Why: ensure or improve performance

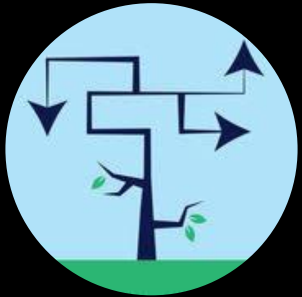


Our research focuses on tackling different ways to explain

Selected 2018 explainability innovations from IBM Research



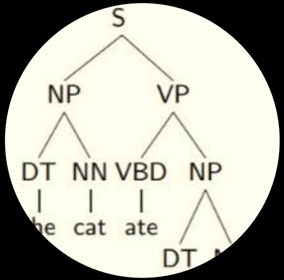
<u>Global, Post-Hoc</u>
Improving Simple Models with Confidence Profiles
NIPS 2018



<u>Global, Directly Interpretable</u>
Boolean Decision Rules via Column Generation
NIPS 2018

Variational Inference of Disentangled Latent Concepts from Unlabeled Observations
ICLR 2018

<u>Local, Post-Hoc</u>
Explanations Based on the Missing: Towards Contrastive Explanations with Pertinent Negatives
NIPS 2018



<u>Interactive Model Visualization</u>
Seq2Seq-Vis: A Visual Debugging Tool for Sequence-to-Sequence Models
IEEE VAST 2018

The quest for safe and robust AI

INFOSEC INSTITUTE How Criminals Can Exploit AI

SecurityIntelligence

How Can Companies Defend Against Adversarial Machine Learning Attacks in the Age of AI?

Home > Security

NEWS

Hackers get around AI with flooding, poisoning and social engineering

Many defensive systems need to be tuned, or tune themselves, in order to appropriately respond to possible threats.

OPINION

The rise of artificial intelligence DDoS attacks

The leaves may change color, but the roots are the same. Are you ready for AI-based DDoS attacks?

IBM ART

Adversarial Robustness

- Metrics
- Adversarial Sample Detection
- Input Preprocessing
- Model Hardening

Model Theft

- Prevention of theft via APIs
- Detection of model theft attacks
- Deterring theft through model watermarking

Model and Data Privacy

- Provable privacy guarantees for training data (local differential privacy)
- Secure federated learning

Poisoning Attacks

- Detect poisoned training and models
- Poison can degrade performance or insert backdoors

IBM **ART**
Adversarial Robustness Toolbox
a.k.a. Nemesis

Model Robustness for AI DevOps

- Develop ART as platform agnostic library
- Modular framework to evaluate robustness, generate adversarial samples, and harden models
- Integration into IBM offerings to build secure model building pipelines

Accountability - The quest for Value alignment

- Most AI systems learn to perform a task from data
  - Positive and negative training examples (supervised learning)
  - Feedback during the online use of the system (reinforcement learning, RL)
  - This allows humans to specify an objective without having to say how to achieve it, and AI to learn creative strategies that humans may not think of

- However, it also may bring AI to do unexpected and undesired actions

- We must combine the creativity of AI with constraints, guidelines, or priorities derived from values, ethics, morals, business process, guidelines, laws, etc.
  - IBM Research explored two approaches, for RL and for preference-based AI systems

- But who decides the values? How do we make sure that they are the right values? How do we define values that consider all dimensions of the problem to be solved?
  - Diversity and inclusion is key

Accountability - “Fact Sheets” for transparency

Increasing Trust in AI Services through Supplier’s Declarations of Conformity

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[1]Yorktown Heights, New York, [2]Bengaluru, Karnataka

Abstract

The accuracy and reliability of machine learning algorithms are an important concern for suppliers of artificial intelligence (AI) services, but considerations beyond accuracy, such as safety, security, and provenance, are also critical elements to engender consumers' trust in a service. In this paper, we propose a supplier's declaration of conformity (SDoC) for AI services to help increase trust in AI services. An SDoC is a transparent, standardized, but often not legally required, document used in many industries and sectors to describe the lineage of a product along with the safety and performance testing it has undergone. We envision an SDoC for AI services to contain purpose, performance, safety, security, and provenance information to be completed and voluntarily released by AI service providers for examination by consumers. Importantly, it conveys product-level rather than component-level functional testing. We suggest a set of declaration items tailored to AI and provide examples for two fictitious AI services.

1 Introduction

Artificial intelligence (AI) services, such as those containing predictive models trained through machine learning, are increasingly key pieces of products and decision-making workflows. A service is a function or application accessed by a customer via a cloud infrastructure, typically by means of an application programming interface (API). For example, an AI service could take an audio waveform as input and return a transcript of what was spoken as output, with all complexity hidden from the user, all computation done in the cloud, and all models used to produce the output pre-trained by the supplier of the service. A second more complex example would provide an audio waveform translated into a different language as output. The second example illustrates that a service can be made up of many different models (speech recognition, language translation, possibly sentiment or tone analysis, and speech synthesis) and is thus a distinct concept from a single pre-trained machine learning model or library.

In many different application domains today, AI services are achieving impressive accuracy and other similar performance metrics. Accuracy, however, is only a consumer's very basic need. Taking Maslow's hierarchy of needs as a metaphor [1], accuracy is a physiological need like food and shelter. Once this need is met, consumers seek the higher-level need of safety and security. Safety is the prevention of unintentional harms and security is the prevention of deliberate harms. Methods for safe and secure machine learning are currently active areas of research [2, 3] and are already making their way into AI services.

At the next level up in the hierarchy of needs is *trust*. Transparency about the performance and reliability of the service, the safety and security measures instituted in the service (including operating conditions under which it was tested), and the lineage of the datasets, training algorithms, and models that go into the service all lend trust to the consumer. Trusted AI services, thus, need good task performance, good safety and security measures, accountability via lineage, with supporting evidence for each of these aspects.

Toward this final end of transparency, we propose a *supplier's declaration of conformity* (SDoC) for AI services. An SDoC is a document to "show that a product, process or service conforms to a standard or technical regulation, in which a supplier provides written assurance [and evidence] of conformity to the specified requirements," and is used in many different

1

- What is the **intended use** of the service output?
- What **algorithms** or techniques does this service implement?
- Which datasets was the service **tested** on?
- Describe the **testing methodology** and **test results**.
- Are you aware of possible examples of **bias**, **ethical** issues, or other **safety risks** as a result of using the service?
- Are the service outputs **explainable** and/or interpretable?
- For each dataset used by the service:
  - Was the dataset checked for **bias**?
  - What efforts were made to ensure that it is **fair** and **representative**?
  - Does the service implement and perform any **bias detection and remediation**?
- What is the **expected performance** on unseen data or data with different distributions?
- Was the service checked for **robustness against adversarial attacks**?
- When were the models last updated?

https://arxiv.org/abs/1808.07261

LE PROJET „AISE“: UNE FABRIQUE DE TALENTS POUR LES ENTREPRISES DU LUXEMBOURG

NICOLAS GUELFI

Professeur

Université du Luxembourg

MADE IN LUXEMBOURG

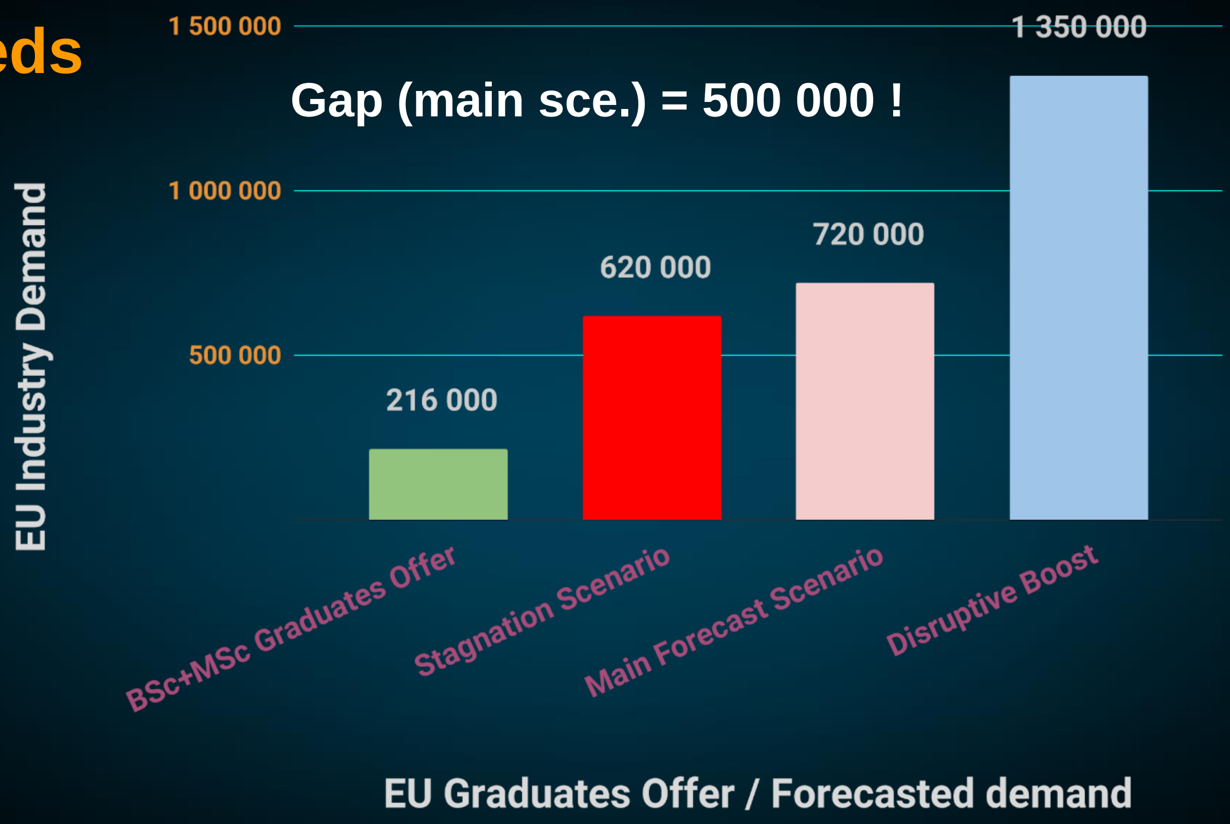
Luxembourg Academy in Artificial Intelligence and Software Engineering

Do you, will you need Talents in Data Science, AI DevOps, Agile, ...

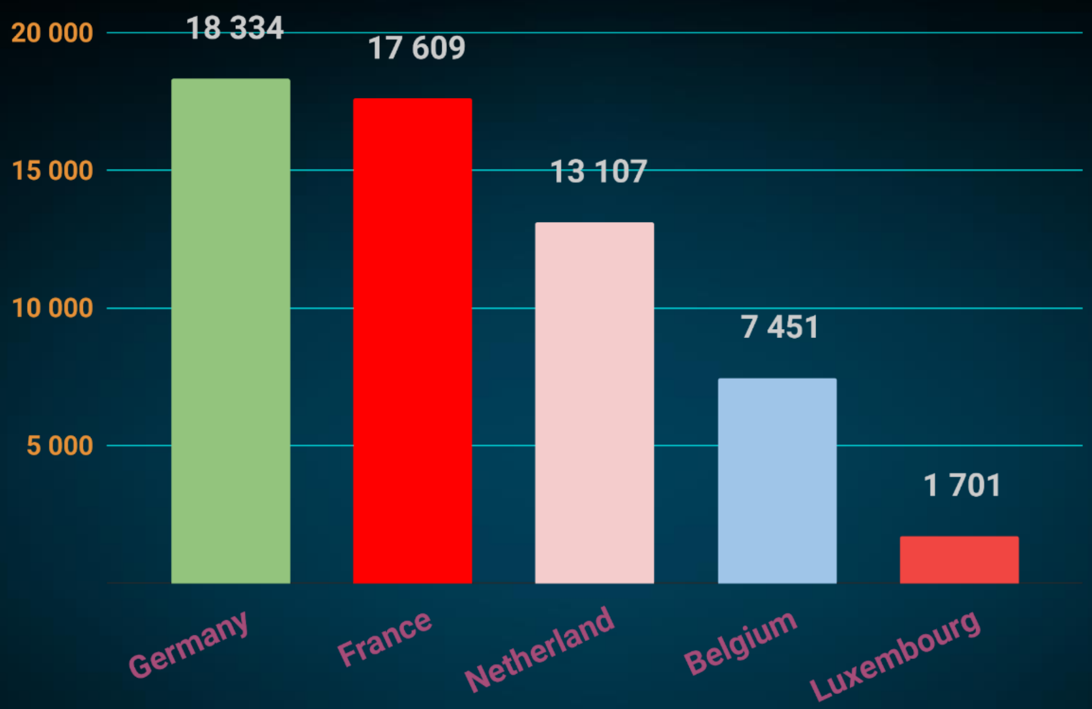
?

Talent in EU

Offer / Needs

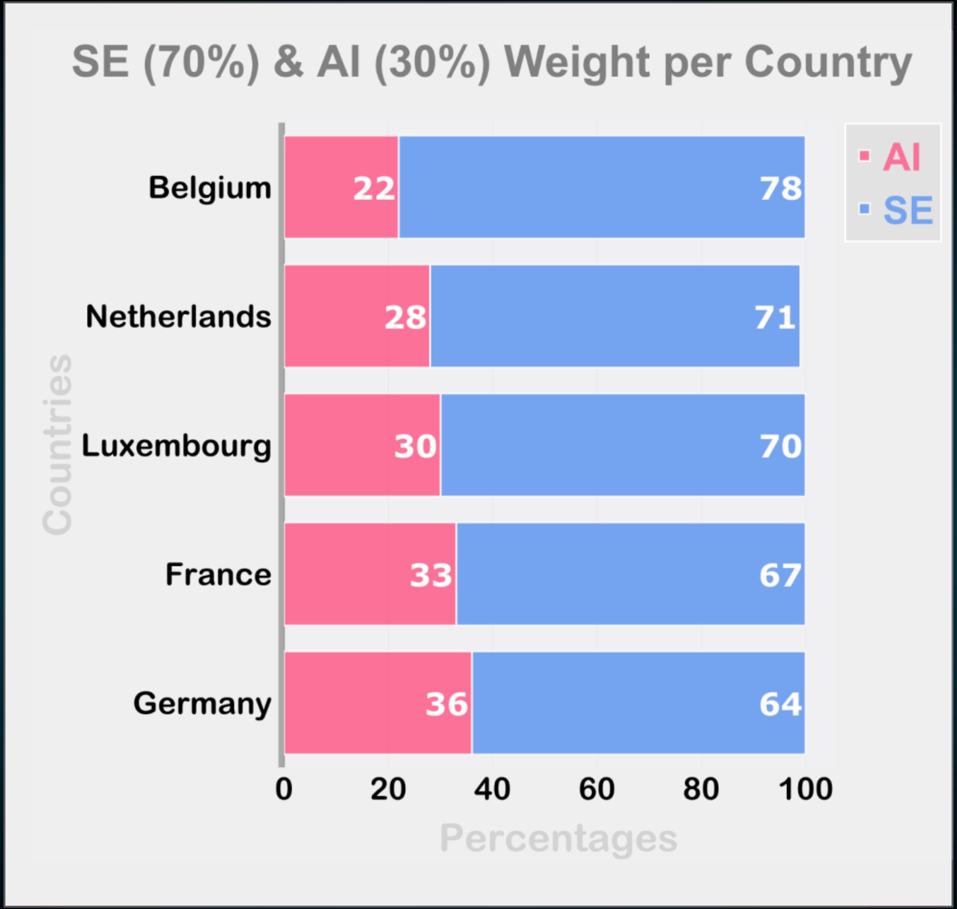


[Empirica 2015-2020]



Job Offers / Country (58202 over last 6 months)

[Guelfi 2019]


SE (70%) & AI (30%) Weight per Country
Countries
Belgium
22
78
Netherlands
28
71
Luxembourg
30
70
France
33
67
Germany
36
64
0
20
40
60
80
100
Percentages
AI
SE

[Guelfi 2019]

Hits per SE Concepts
(top ones)

Concept	Hits
Software Engineering (SE, Agile Method)	80 202
DevOps + Cloud Computing	62 858
Java, JavaEE, JavaScript	36 559
Testing	27 102
Python	18 924
Linux	12 003
C++	9 008
Docker	8 394
Jenkins	6 081
Oracle	5 359
Spring	5 298
GIT	4 771
Kubernetes	4 652
Angular	4 446
Ansible	4 091
Windows	3 808
REACT	2 991

Hits per AI Concepts
(top ones)

Concept	Hits
Data Science	55 517
Artificial Intelligence (AI, Machine learning, Neural Network, Machine intelligence)	50 187
Hadoop	6 726
Spark	6 239
Scala	5 045
Autonomous	4 953
Business intelligence	3 705
NoSQL	3 451
Robotics	2 437
Tensorflow	2 249
Cassandra	1 842
Computer vision	1 745
Natural Language Processing	954
Keras	893
PyTorch	527
Caffe	381

[Guelfi 2019]

YOU

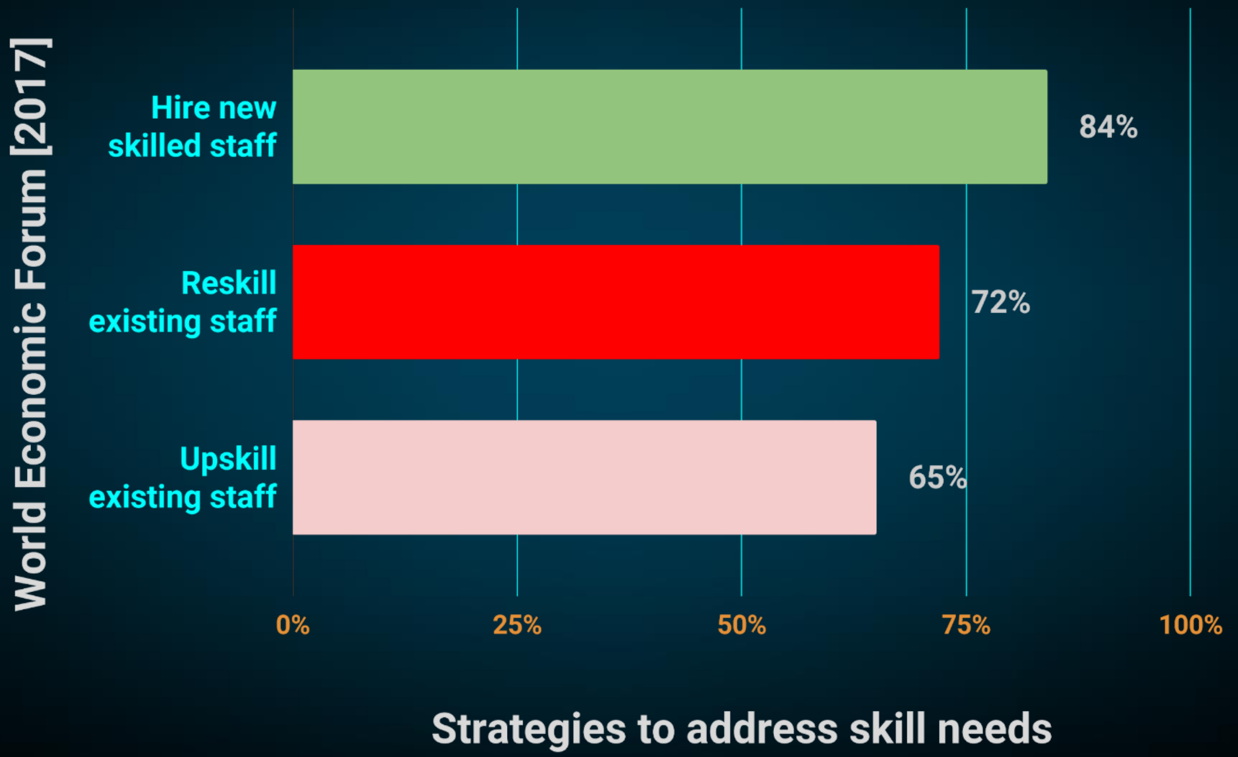
need Talents in

Data Science, AI

DevOps, Agile, ...

!

Facing New Skills Demand



You are/will be
SEARCHING for
Talents in
Data Science, AI
DevOps, Agile, ...
!

Recruitment Real Costs

- **Hypothesis:**
  - **80 k€ employee full cost**
  - Time from job opening to 1st work day (4/11/16 weeks)

- **Cost lines to consider**
  - Productivity loss
  - Contractor cover
  - Company activities dislocation due to hiring time
  - Management time
  - Impact of higher/lower quality hires on salary and productivity
  - Attrition (half of new hires leave within the first twelve months)

Approach	*Min.*	*Average*	*Max.*
In-House Solution or Agency Led Solution	**58 k€**	**180 k€**	**230 k€**
Recruitment Process Outsourcing	**47 k€**	**142 k€**	**190 k€**
Talent Warehousing Outsourced Solution	**26 k€**	**80 k€**	**103 k€**

[Quarsh 2018]

YOU need Talents ...

Let's build a solution together

!

Solution

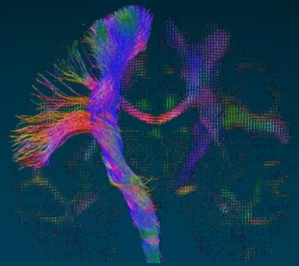
- **Local Talent Factory**
  - AISE Academy
    - **online / onsite**
  - **Hiring, Reskilling, Upskilling**

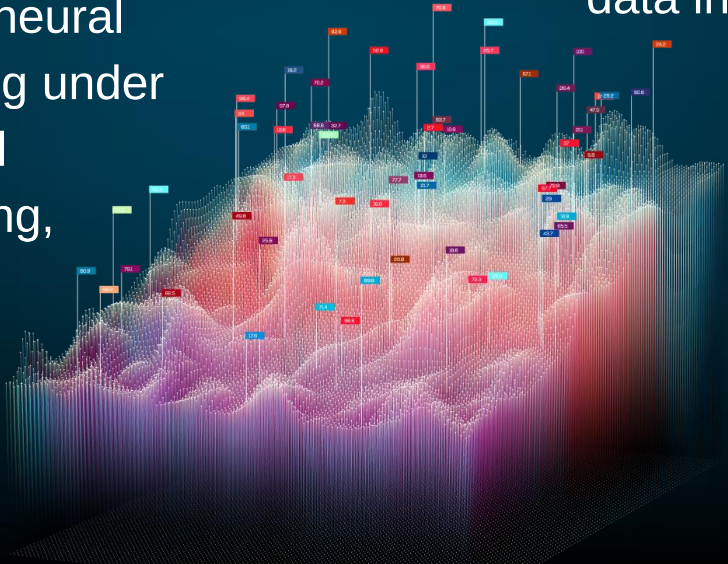
- **Advantages**
  - Secured
  - Tailored
  - Flexible
  - Durable
  - Profitable

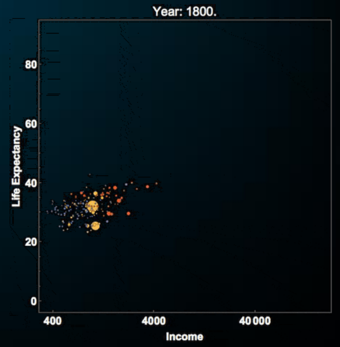
AISE Domains

- **Artificial Intelligence**
  - knowledge representation and reasoning, perception and computer vision, machine learning, neural networks, reasoning under uncertainty, natural language processing, robotics.

- **Data Science**
  - statistical methods for data analysis, predictive analytics, infrastructure and platforms for data science applications, data management and enterprise data infrastructure.







AISE Domains

- **Software Engineering**
  - agile methods, requirements, testing, maintenance, quality, engineering professional practice, standards.

- **DevOps**
  - continuity and automated support of planning, coding, testing, code review, integration, deployment, delivery, performance measurement, monitoring, configuration management, improvement, communication.

AISE in Practice

Business Cases

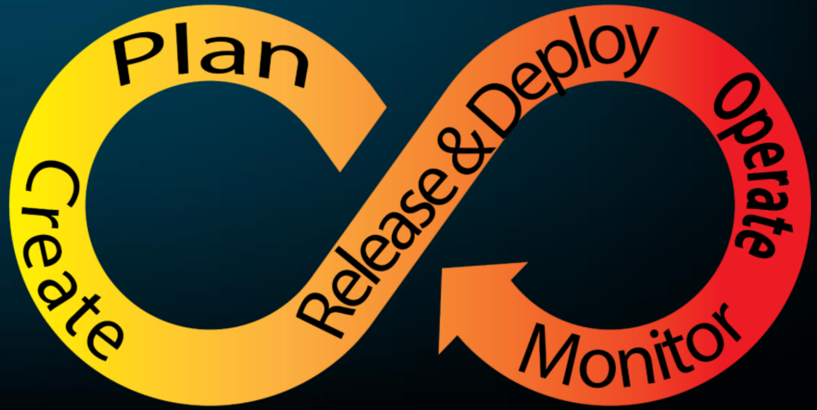
TGP

-

The Great Partner

Process - Overview

1. Plan "Skills Strategy"
   a. AISE/Partner contact
   b. Knowledge acquisition strategy
      i. Hiring, Reskilling, Upskilling
   c. Individualized study plan(s) inception
2. Create "Study Plan"
3. Deploy "Study Plan"
4. Operate "Study Plan"
5. Monitor "Study Plan"



Process - Schedule

- **Academy Schedule**
  - flexibility
  - complete
  - **Onsite & Online**
- **Activities**
  - Personal Work
  - Engineering Tutoring
  - Scientific Tutoring
  - Peer Tutoring
  - Certification
  - Seminars

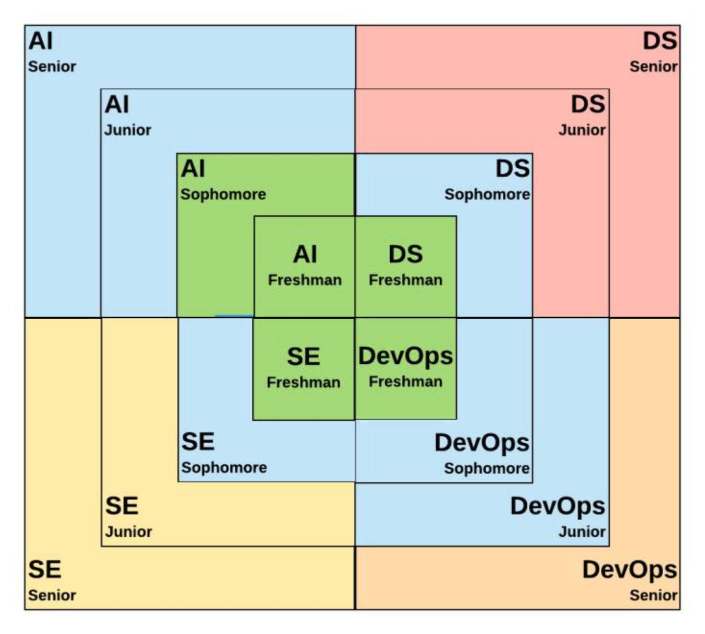
	Day	Mo	Tu	We	Th	Fr	Sat
Time							
		Study Plan Management					
8							
9	Seminar Sessions	Personal Work Slot A		Engineering Tutoring sessions			
				Scientific Tutoring sessions			
				Peer Tutoring sessions			
				Certification sessions			
13							
14	Seminar Sessions	Personal Work Slot B		Engineering Tutoring sessions			
				Scientific Tutoring sessions			
				Peer Tutoring sessions			
17				Certification sessions			
18							
19	Seminar Sessions	Personal Work Slot C		Engineering Tutoring sessions			
				Scientific Tutoring sessions			
				Peer Tutoring sessions			
				Certification sessions			
23							


New Talents Recruitment
AiSE
The Great Partner
New Talents
Henri
Alexandra

The Great Partner - New Talent - Study Plan

Alexandra

- **1 year full time education**
- Certificates validated by **VPE**
  (Validation of Prior Experience)
  - **DS/DevOps/SE** (Freshman / Master 1)
  - **AI** (Sophomore / Master 1)
- Study plan defined with partner
- **Practical Projects defined with and for partner**
- **Liability contract with partner**



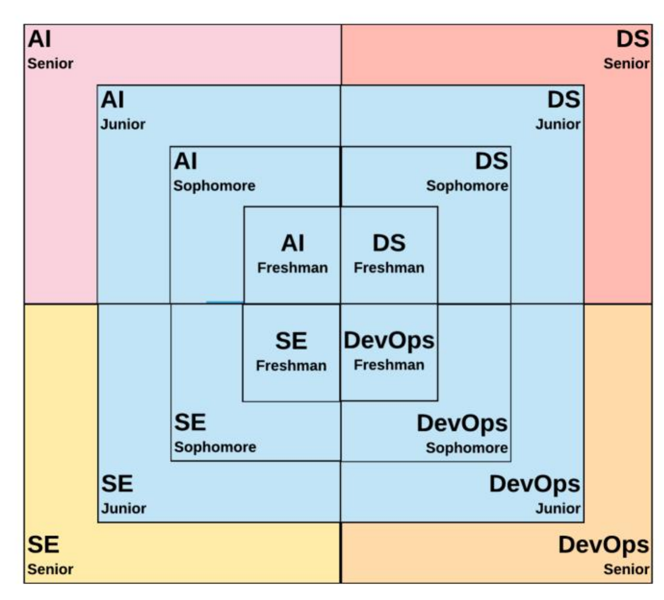
- **Certificates Targeted**
  - **AI** (Senior / Master 2) + **DevOps** (Junior / Master 2) + **DS** (Sophomore / Master 2) + **SE** (Sophomore / Master 2)

The Great Partner - New Talent - Study Plan

Henri

- **2 years full time education**
- Study plan defined with partner
- **Practical Projects defined with and for partner**
- **Liability contract with partner**

- **Certificates Targeted**
  - **AI** (Junior / Master 2) + **DS** (Junior / Master 2)
  - **DevOps** (Junior / Master 2) + **SE** (Junior / Master 2)



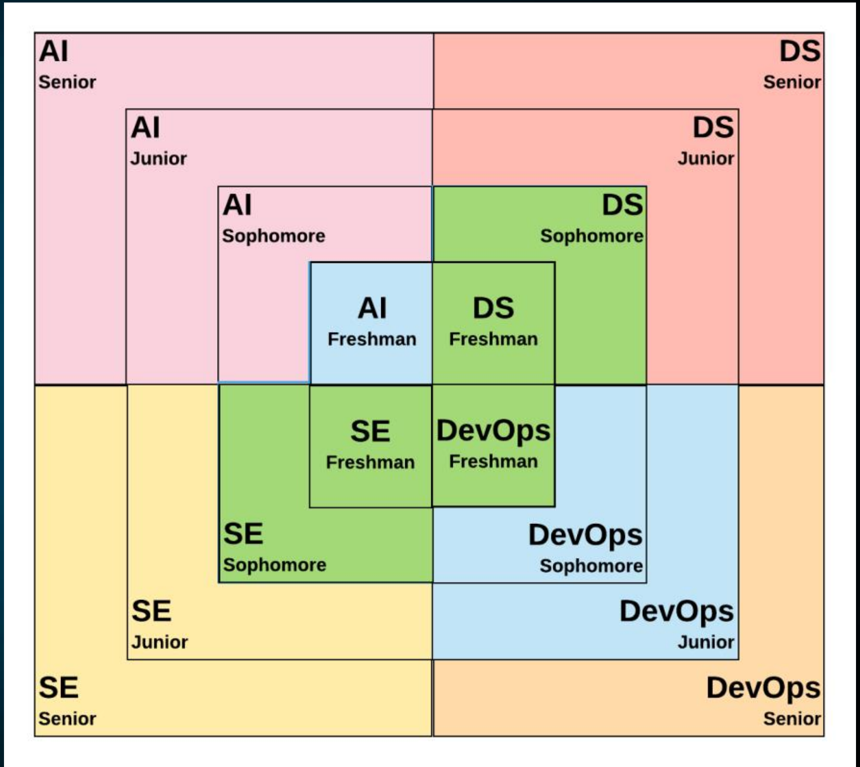
Upskilling - Reskilling

Alan

Barbara

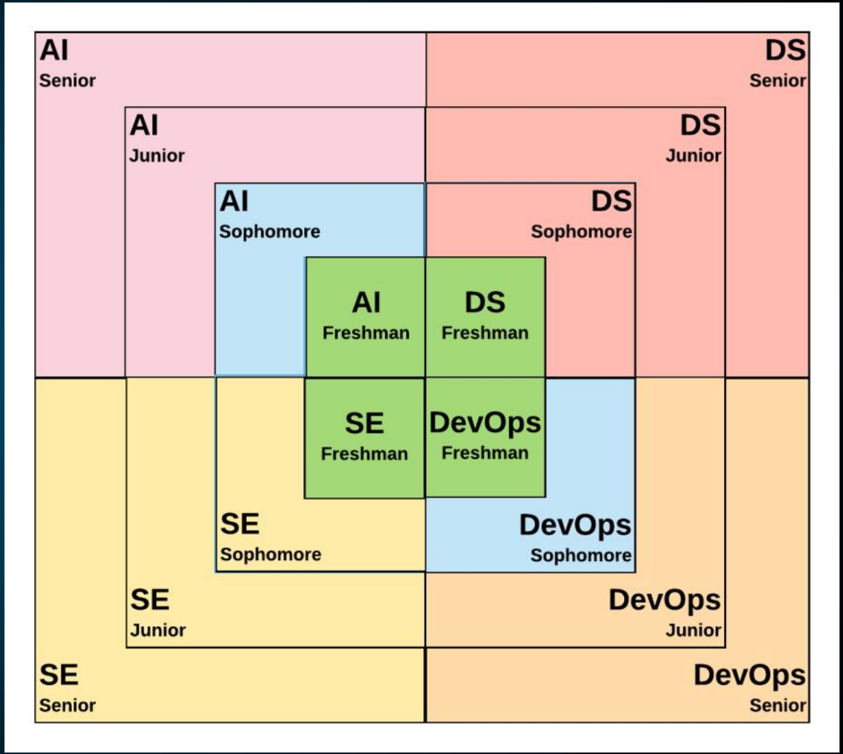
AISE in Practice - *The Great Partner* - Plan "Study Plan"

- ***Alan Turing***
  - **100 work days** over **2020 and 2021**
  - Certificates validated by VPE
    (Validation of Prior Experience)
    - **DS** (Sophomore / Insider)
    - **DevOps** (Freshman / Master 1)
    - **SE** (Sophomore / Insider)
  - Certificates Targeted
    - **AI** (Freshman / Insider)
    - **DS** (Sophomore / Master 1)
    - **DevOps** (Junior / Master 1)
    - **SE** (Sophomore / Insider)



AISE in Practice - *The Great Partner* - Plan "Study Plan"

- ***Barbara Liskov***
  - **60 work days** over **2020 and 2021**
  - Certificates validated by VPE
    (Validation of Prior Experience)
    - **AI** (Freshman / Master 1)
    - **DS** (Freshman / Master 1)
    - **DevOps** (Freshman / Master 1)
    - **SE** (Freshman / Master 1)
  - Certificates Targeted
    - **AI** (Sophomore / Master 1)
    - **DevOps** (Sophomore / Master 1)



Process - Work Days *(Alan Turing)*

		2020						2021					
Alan Turing (TGP)	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Total
VPE *(Validation of Prior Experience)*													
WorkDays			10	10	10	10	5	20	10	10	10	5	100
Engineering Tutoring sessions			10	10	10	10	5	20	10	10	10	5	100
Scientific Tutoring sessions			2	2	2	2	1	4	2	2	2	1	20
Peer Tutoring sessions			5	15	15	5		5	5	10	15		75
Seminar Sessions			2		4			4	2	3			15
Certification sessions					5				10			10	25

Process - Work Days *(Barbara Liskov)*

2020 2021

Barbara Liskov (TGP)	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Total
VPE *(Validation of Prior Experience)*													
WorkDays						20	20	20					60
Engineering Tutoring sessions						20	20	20					60
Scientific Tutoring sessions						4	4	4					12
Peer Tutoring sessions						5	15	10					30
Seminar Sessions						4	2	2					8
Certification sessions							2			2			4

Costs

TGP - Costs

Academy

40 k€ / year

The Great Partner

Partner Cost (k€/year)	*Talent Cost (k€/year)*
40	0
20	20
0	40

New Talent

*Annual full cost / talent = **80 k€***

Upskilling - Reskilling

Academy

320 € / workday

The Great Partner

New Talent

Coverage	***Partner*** ***Cost (€/workday)***
Membership **Validation of Prior Experience** **Work Days** **Certification**	**320 €**

Barbara: 60 days

Alan: 100 days

Total full cost / workday = 640 € / Workday

Financial Settings

Companies (Loi du 29 août 2017 portant modification du Code du travail)

Co-financing of the education programme with the following eligible costs;

Participants

- **Participants' salary**
- Travel expenses
- Accommodation and food services

External professor/mentor/trainer:

- **Invoice for fees**
- Travel, accommodation and catering expenses

Students/Learners

Co-financing of the education programme with the following eligible costs:

Full-time students:

- CEDIES grants, with conditions

Continuous learner/student:

- Training leave (80days: 20 days/2 years)
- Reimbursement of the employer
- Tax deduction for the employee (conditions)

Statutes

Statutes

- **Company**
  - Spin-off
  - Start-up
- **Non profit structure**
  - ASBL / Foundation
- **PPP**

MADE IN LUXEMBOURG

Towards an International Academy

Local Academic Experts

- **University of Luxembourg**
  - Prof. Dr. Guelfi Nicolas (**SE**, **AI**)
  - Prof. Dr. Bouvry Pascal (**AI**)
  - Prof. Dr. Van der Torre Leon (**AI**)
  - Prof. Dr. le Traon Yves (**SE**,**DS**)
  - Prof. Dr. Navet Nicolas (**SE**)
  - Prof. Dr. Theobald Martin (**DS**)





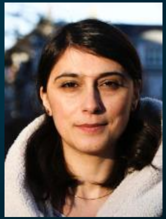

International Academic Collaborations

- **Carnegie Mellon University** *(CA, USA) Silicon Valley*
  - Prof. Dr. Péraire Cécile (**SE**)
- **McGill University** *(Canada)*
  - Prof. Dr Kienzle Jorg (**SE**)
- **Universidad Nacional del Sur** (Argentina)
  - Prof. Guillermo R. Simari (**AI**)
- **INRIA** (Grenoble, France)
  - Prof. Dr. El-Ghazali Talbi (**SE**,**AI**)
- **Utrecht University** *(Netherland)*
  - Prof. Dr Jan Broersen (**AI**)
- **Zhejiang University** *(China)*
  - Prof. Dr Beishui Liao (**AI**)
- **University of Bergen** *(Norway)*
  - Prof. Dr Marija Slavkovik (**AI**)
- **DFKI** (Germany)
  - Prof. Dr.-Ing. Philipp Slusallek









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International Industry Collaborations

- **John Micco**
  - **VMWare** *(CA Silicon Valley, USA)*
  - Cloud Transformation Architect (**SE**)
- **Vladimir Bacvanski**
  - **Paypal** *(CA Silicon Valley, USA)*
  - Principal MTS, Architect (SE)
- **Damien Octeau**
  - **Google** *(CA Silicon Valley, USA)*
  - Senior Software Engineer (**AI,SE**)
- **John Penix**
  - **Google** *(CA Silicon Valley, USA)*
  - Senior Software Engineer (**SE**)




Support Video Messages

aiseacademy.lu/survey

Founding Partners ...

- Prof. Dr. Nicolas Guelfi
- Prof. Dr. Pascal Bouvry
- Prof. Dr. Eric Tschirhart

FEDIL

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