# New challenges for CISO: Artificial Intelligence, emerging technologies and regulations



COMMISSION DE SURVEILLANCE DU SECTEUR FINANCIER

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# **1. INTRODUCTION**

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- **3. RISKS AND RECOMMENDATIONS**
- 4. CONCLUSION & QUESTIONS

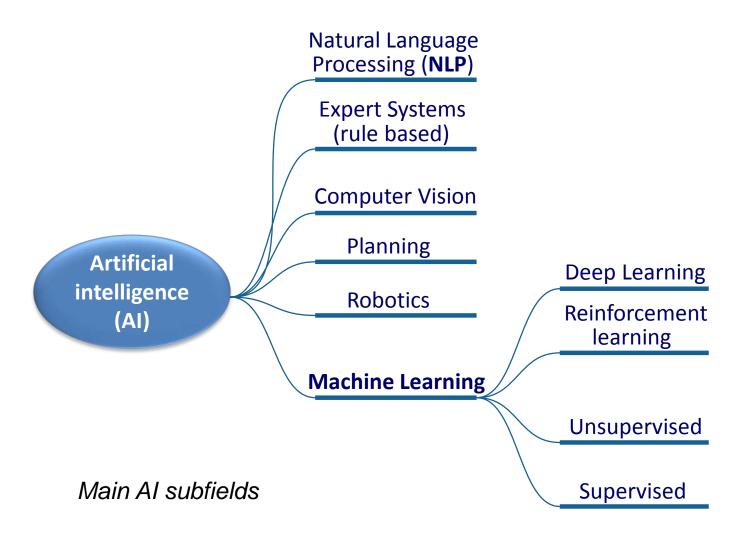
# **INTRODUCTION – WHAT IS AI?**

- What is AI?
  - "The theory and development of computer systems able to perform tasks that traditionally have required human intelligence."

Financial Stability Board

- Intelligent tasks:
  - Reasoning / Problem solving
  - Learning
  - Planning
  - Ability to understand language and speech
  - Ability to manipulate and move objects
  - etc...

# **INTRODUCTION – WHAT IS AI?**

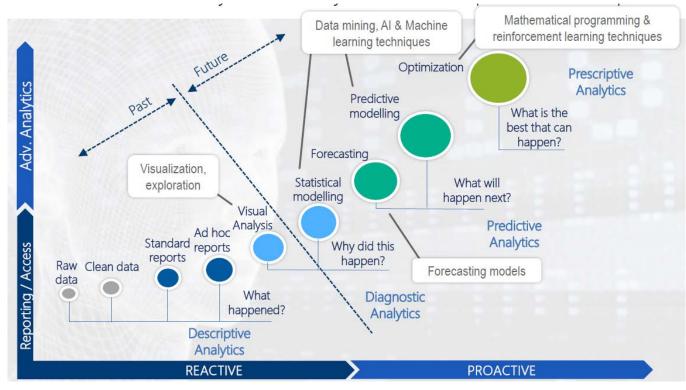


# GOVERNANCE EXPECTATIONS ON AI FOR SUPERVISED ENTITIES

- The common principle underlying the supervised machine learning algorithms is:
  - Machine learning algorithms are described as learning a target function (f) that best maps input variables (X) to an output variable (Y): Y = f(X)
  - In other words, the goal is to learn the mapping Y = f(X) in order to be able to make predictions of Y for a new X. This is called **predictive modeling** or **predictive analytics**.

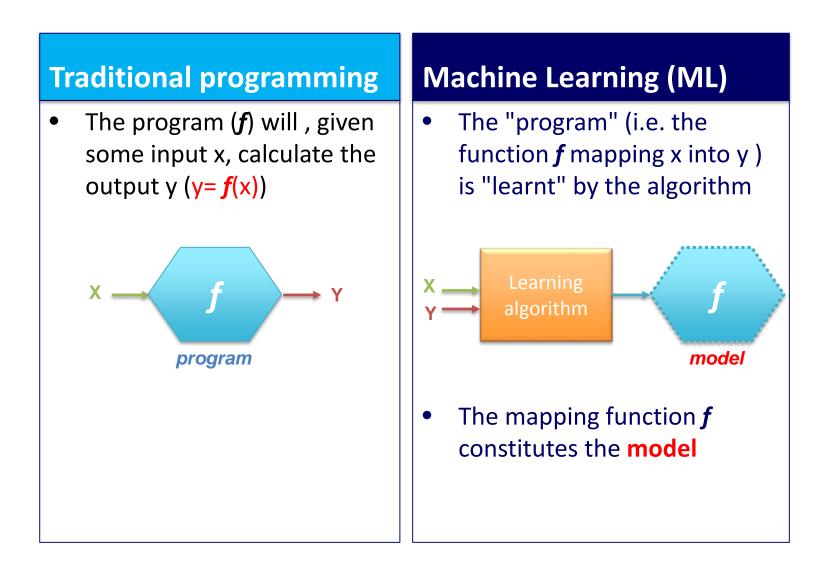
# **INTRODUCTION – WHAT IS AI?**

# • Data Analytics



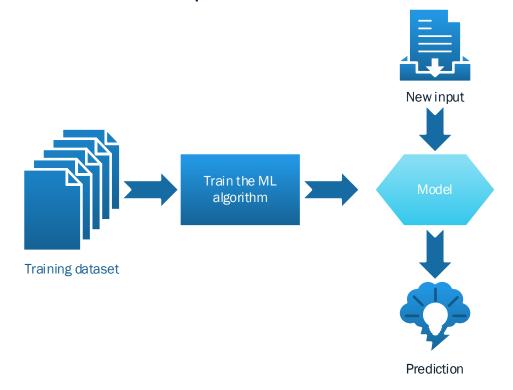
#### Source: SAS (AI Luxembourg Summit 2018)

# **INTRODUCTION – WHAT IS AI?**



# **INTRODUCTION – MACHINE LEARNING**

• A **model** is a representation of what the algorithm has learnt from the training data and is used to make prediction on new input data



# **AI OPPORTUNITIES**

# AI OPPORTUNITIES – AI DEMOCRATIZATION

- Al is not new, but is now more accessible due to several factors:
  - More powerful and dense processors (GPU)
  - Lower storage cost
  - Cloud computing
  - Big data: large data sets available for "learning"
  - AI tools and platforms (e.g. DataRobot, DataIKU, Microsoft, Google, Amazon, etc..)

# AI OPPORTUNITIES – USE CASES

- RPA (Robotic Process Automation) and IPA (*Intelligent* Process Automation)
- Chatbots
- Robo-advisors
- Fraud detection
- Terrorism Financing detection
- Credit scoring
- Other (NLP/text mining, algorithmic trading, facial recognition in KYC processes, IT security, etc...)

- Key Risk areas:
  - Data
  - Governance
  - Ethics
  - Technology
  - External providers

# **RISKS AND RECOMMENDATIONS - DATA**

## **Risks**

- Difficult to find the right data
- Data quality issues
- External data not appropriate/ not reliable

# Recommendations

#### • Data governance:

- clear roles & responsabilities for data ownership;
- data dictionaries,
- data quality management,
- etc...
- Involve business data owners
- Due diligence of data source providers
- Verify adequacy of data for the target context

# **RISKS AND RECOMMENDATIONS - GOVERNANCE**

# **Risks**

- No human in the loop / uncontrolled automated actions
- Lack of AI specific skills (e.g. data scientists; AI auditor,...) or over-reliance on few key staff
- Fear of change/ lack of adoption by business users
- Lack of understanding of AI results

- Never leave a machine to decide on critical tasks alone (human oversight / dual validation)
- Involve Internal Audit, Risk and Compliance functions in AI projects since the beginning (+ training)
- Use external AI experts and ensure knowledge transfer
- Involve business users from the start (key success factor)

# **RISKS AND RECOMMENDATIONS - ETHICS**

## **Risks**

- **Bias** (within training/validation datasets, algorithms,...)
- Discrimination (e.g. populations not fairly represented in the training data)
- Personal data collected/processed without consent (e.g. behavioral data)
- Accountability of AI actions

- Al code of conduct (incl. fairness)
- Identify and remove bias (during data preparation)
- Active inclusion: seek for diversity in training / validation data
- Create specific datasets to test against discrimination
- Challenge the need for personal data/ data privacy by design
- Accountability cannot be delegated to a machine: ultimate responsibility relies with senior management

# **RISKS AND RECOMMENDATIONS - ETHICS**

## **Risks**

- Lack of **explainability**/ «black box» models
- Lack of auditability

- **Document the data preparation** process (model blueprint)
- Document the choice of the algorithm; choose more interpretable algorithms (e.g. decision trees) depending on the criticality of the system
- Use **explainable AI** techniques (e.g. interpreter) when required
- Implement detailed **audit logs**
- Implement technical means to simulate the input data into the AI to perform investigations in case of need

# **RISKS AND RECOMMENDATIONS - TECHNOLOGY**

# **Risks**

- Change management:
  - Lack of involvement of business users
  - **data leakage** (output information in input data)
  - Lack of documentation/ traceability
- Poor results/ model not accurate
- Predictive power of ML is limited to what can be learnt from past observations: cannot predict something never seen before!

- **Document** the choices made at each step of the development process (e.g. feature selection, choice of algorithm,...)
- Prefer using integrated platforms
- Monitor model performance (via accuracy metrics and business KPIs, etc.) and update the model (re-training) when needed
- Perform **parallel runs** (old Vs new AI model)

# **RISKS AND RECOMMENDATIONS - TECHNOLOGY**

# **Risks**

- Insufficient error and incident management
- Technical operational issues (e.g. interfaces with legacy systems)
- Security vulnerabilities/ robustness to attacks

- Plan for error and incident management (e.g. RPA processes can generate frequent operational errors)
- Apply security by design
- Test model robustness
- Perform independent security reviews according to the criticality of the system
- Technological watch: monitor improvements in the attack and defense techniques (remember that attackers are also using AI to improve their attacks!)

# RISKS AND RECOMMENDATIONS – EXTERNAL PROVIDERS

# Risks

- Dependency on few providers
- General outsourcing risks
- Systemic risks: if the same model is used by many institutions, market movements and errors may be amplified

- Plan for the maintenance of the AI solution (e.g. have the right AI staff internally Vs SLA with external provider)
- Apply best practices and regulatory recommendations on IT outsourcing (e.g. circular CSSF 12/552)
- Customize the AI product
- Monitor systemic effects

# **KEY SECURITY ISSUES**

- Why should someone hack an AI?
  - To stop the service based on AI
  - To hijack the AI
    - For personal needs
      - To bypass the analysis (i.e. KYC/AML, biometrics)
      - To Influence the outcome in favor of the hacker (i.e. Asset management, credit scoring, political elections)
    - To harm the provider
      - To influence the outcome used by the provider (i.e. wrong investments)
      - To fuzz the results in an random way that it will lead to a loss of trust

# **KEY SECURITY ISSUES**

- How could a hacker corrupt an AI?
  - By acting on the data
    - Initial data
    - Learning process
  - By acting on the model
    - Tuning parameters
    - Mathematical model substitution
    - Code modification
  - By acting on the explainability tools
    - Hiding the biais

Risks	Threats
<ul> <li>Data quality issues</li> <li>External data not appropriate/ not reliable</li> <li>No human in the loop / uncontrolled automated actions</li> <li>Lack of AI specific skills (e.g. data scientists; AI auditor,) or over-reliance on few key staff</li> <li>Bias (within training/validation datasets, algorithms,)</li> </ul>	<ul> <li>Corruption of data</li> <li>Security threats on external data providers</li> <li>External data providers phishing (MITM, fake data provider by redirection)</li> <li>Undetected corruption (no human, no audit)</li> <li>Modified datasets, algorithms</li> <li>Traceability of AI actions</li> </ul>

Risks	Threats
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## **Risks**

- Change management:
  - Lack of involvement of business users
  - data leakage (output information in input data)
  - Lack of documentation/ traceability
- Predictive power of ML is limited to what can be learnt from past observations: cannot predict something never seen before!

# Threats

- Corruption of data
  - Security threats on external data providers
  - External data providers phishing (MITM, fake data provider by redirection)
  - Undetected corruption (no human, no audit)
- Modified datasets, algorithms

# CONCLUSION

# CONCLUSION

- Plan for error and incident management
- Apply security by design
- Test model robustness
- Perform **independent security reviews** according to the criticality of the system
- Technological watch: monitor improvements in the attack and defense techniques (remember that attackers are also using AI to improve their attacks!)
- Use only the necessary data
- Key controls: data governance, human in the loop
- Key challenges: fairness, explainaibility, auditability

# **CONCLUSION**

#### Reference:

 CSSF whitepaper "Artificial Intelligence: opportunities, risks and recommendations for the financial sector" www.cssf.lu/fileadmin/files/Publications/Rapports\_ponc tuels/CSSF\_White\_Paper\_Artificial\_Intelligence\_201218. pdf

# **QUESTIONS ?**