Al beyond Al

Guido Van Humbeeck – VDAB guido.vanhumbeecl@vdab.be June 2020



Themes

- Positioning AI in de IT landscape
- Building AI artefacts
- Operationalize AI Artefacts
- MLOps



Types of Artificial Intelligence (AI)





Application Development





Data Management









Testing and Quality in Machine Learning





https://martinfowler.com/articles/cd4ml.html

Model Monitoring (Martin Fowler)

Model inputs: *what data is being fed to the models*, giving visibility into any training-serving skew. Model outputs: *what predictions and recommendations are the models making from these inputs*, to understand how the model is performing with real data.

Model interpretability outputs: metrics such as model coefficients, <u>ELI5</u>, or <u>LIME</u> outputs that allow further investigation to understand *how the models are making predictions to identify potential overfit or bias that was not found during training.*

decisions: what predictions our models are making given the production input data, and also which decisions are being made with those predictions. Sometimes the application might choose to ignore the model and make a decision based on pre-defined rules (or

to avoid future bias).

Model outputs and

User action and rewards: based on further user action. we can capture reward metrics to understand if the model is having the desired effect. For example, if we display product recommendations, we can track when the user decides to purchase the recommended product as a reward.



Model fairness: analysing input data and output predictions against known features that could bias, such as race, gender, age, income groups, etc



	Dev(Sec)Ops	DataOps Data starts with the same letter as Discipline	MLOps Creating value out of data Data kwaliteit is functie van de "purpose"				
Goal	Starts from Proce ss as & Requirements Design, build, integrate, run in ho use (eveloped applications and of the shelf packages in the most (cost) efficient way. C/C/D/CT (continuous testing) using mainstrain develop nen tools & environments (Java, C#, frameworks,) whereby Develo men t & Operations operate as one team with maximal automation of repe litive SDLC tasks.	Starts from Data & Information needs Deliver (real-time) qualitative data, fit for different purposes, through govermed and industrialized data pipelines starting from different sources like operational data, events, external data, open data,	Starts from challenges and data: what if we could ? Design, build, run (retrain) and deploy AI-models using • the data services of DataOps. • Specific tools and frameworks (e.g. Python, Tensorflow, BERT, Python Frameworks,) • Cl/CD/CT (Continuous Training) Every AI-model is accessible through API's.				
Roles & Skills Generic: Project leaders	Business Architect, Solutioner, Tichn cal Architect, Developer, Database Developer, Data Modelling, Operution ; Engineer	Data Guard Data Solutioner, Data Architect, Data Engineer, Data Modeller, DataOps Engineer	Data scientist, ML Expert, Data Engineer, MLOps Engineer				
QA	, utor vated testing Se surity testing Sc narcube	Test Data Pipelines Check Data Quality Test VDP Data Provisioning tp consumers	Check Data Quality – Check Bias in Data – Check Model quality – Check Bias in Model + robustness (monitoring)				
Governance	Resultments High ivel High ivel High ivel Detailed Unit Unit Unit Unit Unit Unit Unit Unit Viccroin LEGAC Implementation Services	 Data Guard role Data Architectural Rules & Policies No metadata = no data No Swamp rule 1 month rule Data solutioning Central management of business requestions Self service: controlled roll out of self-service tools Focus on Data Literacy Data Solutioning 	 Led by Digital Ethics Ethical Board Legal Constraints on data usage Automated Model Risk Management Model Monitoring Model interpretability outputs Model interpretability outputs User action and rewards Model fairness 				
SDLC	LDV(2)-ABT(2)-CBT-PRD 7?? Au omated QA CI/CD	2-layer model (Test/Development and Production) Industrialize Data Pipelines	Data Management Phase-Model Training Phase-Serving Management Experiment-Explore-Exploit(2) 2-layer model (Test/Development and 2 Production) Continuous Delivery for Machine Learning (CD4ML) Industrialize Data Pipelines				
Development Stack & Tooling	Technical Reference Architecture Codi ig gt idelines (enforced) J iva, Spring, Axon,	Data Vault, Python, S3, Glue, Dremio, Snowflake, Redshift,	R, Python, TensorFlow, Bert, Sagemaker, Java,				
Deploy	On premise: VMs, Cloud : Containers/Kubernetes Containers CD/Cl	On premise + Cloud Containers (sandboxes) Usage Monitoring	Deployes As A Service : MaaS (API driven) On premise + cloud: Containers CD4ML Model Technical Monitoring				
Infractructura	VMs, Containers	Cloud	High performance (CPU, Memory) (bullions, OBDA, Cloud)				
CLOUD OPERATIONS							

Environments: Interoperability. Who uses what?





C-level support	Experiment	Explore	Exploit	
 Phase 1 BIAS Awareness Business Informed No business case 	 Purpose (look for challenges not use-cases) Data People (competences) Tools (e.g. Python, Neo4J, TensorFlow,) Computing power Data exploration 	X	X	
 Phase 2 Keep experimenting Start working on Data & AI Literacy Set up Digital Ethics/Ethical AI Business Consulted 	 Multiple simultaneous experiments Enrich internal data with external data People must spend 20% of their time in experimenting and exploring new technologies & data 	 API first Manually Set up (realtime) data pipelines Choice of tooling Manual Model Risk Mgmt First steps in MLOps 	 Integrate in operational systems Integrate with operational databases APIs published Data Pipelines run manually Manual deployment of model Manual Model Risk Management 	
 Phase 3 Keep experimenting Data & Literacy rolled out Ethical AI in place 	 Find solutions for new problems/challenges Identify new and better solutions for existing problems Keep looking for new ideas, technologies for the 	 Project oriented approach Several parallel projects Model Risk management set up for every new model Model inputs Model interpretability outputs 	 API first -versioned Industrialized Data Pipelines Regular retraining of Al- models Industrialized Model Risk Mgmt Version mgmt of data, 	

VDAB Ethical AI programma

Trust – Transparency – Benefit



"Technology is neither good nor bad; nor is it neutral."

First Law of Technology, Melvin Kranzberg (1917-1995), Professor, and Co-Founder, Society for the History of Technology



ETHICS GUIDELINES FOR TRUSTWORTHY AI

INDEPENDENT HIGH-LEVEL EXPERT GROUP ON ARTIFICIAL INTELLIGENCE SET UP BY THE EUROPEAN COMMISSION

Ethical Principles in the Context of AI Systems (i) Respect for human autonomy

- (ii) Prevention of harm
- (iii) Fairness
- (iv) Explicability

Trustworthy AI has three components, which should be met throughout the system's entire life cycle:

1. it should be **lawful**, complying with all applicable laws and regulations;

2. it should be **ethical**, ensuring adherence to ethical principles and values; and

3. it should be **robust, both from a technical and social perspective,** since, even with good intentions, AI systems can cause unintentional harm.

Requirements of Trustworthy AI

- 1. Human agency and oversight Including human control and human supervision
- 2. Technical robustness and safety

Including resilience to attack and security, fall back plan and general safety, accuracy, reliability and reproducibility

3. Privacy and data governance

Including respect for privacy, quality and integrity of data, and access to data

4. Transparency

Including traceability, explainability and communication

5. Diversity, non-discrimination and fairness

Including the avoidance of unfair bias, accessibility and universal design, and stakeholder participation

- 6. Societal and environmental wellbeing Including sustainability and environmental friendliness, social impact, society and democracy
- 7. Accountability

Including auditability, minimisation and reporting of negative impact, trade-offs and redress.



Fair or Equal





Experiment-Explore-Exploit



EXPERIMENT

- 1. Define Al use case
- 2. Initiate experiment and iterate
- 3. Define the sensitive variables
- 4. Perform qualitative assessment
- /* Milestone: Provide feedback to move to next phase

EXPLORE

- Select fairness metrics & define fairness for the use case
- 2. Perform qualitative assessment
- 3. Perform quantitative assessment
- 4. Create & share assessment results
- 5. /* Milestone: Review assessment results & provide feedback
- 6. Prepare for internal communication

EXPLOIT

- 1. Handovers (1. production ready Al systems to software factory 2. Usecase to Business Owner)
- 2. Share / update internal communication
- Perform qualitative assessment checks
- Monitor and assess data & model checks using the quantitative assessment asset
- 5. Create & Share assessment results
- 6. Review assessment results & provide feedback
- 7. Create & Share external communication material

Model Risk Mgmt Industrialization



A sustainable operating model 'Ethical board structure' There will be decisions to be made ...





Gartner Al Maturity Model

Level 1 Planning	Level 2 Experimentation	Level 3 Stabilization	Level 4 Expansion	Level 5 Transformation
 Early AI interest with risk of overhyping Pioneers explore available AI techniques and solutions First AI (speculative) use cases identified Agree upon use case success criteria, such as KPIs, with stakeholders Determine what AI means for your organization and define AI accordingly 	 Al experimentation: in a data science context, or with cloud AI APIs or with intelligent applications for predictive analytics Successful AI POCs, proving that a technology (e.g. computer vision, speech recognition, ML) can deliver business value First pilots, typically on revenue increase use cases (price optimization, product recommendations) AI lab. First recruitment of AI experts; identifying and upskilling your AI personnel 	 Several AI use cases in production, creating value with cost reduction use cases (e.g., process optimization or product/service innovations) Budget is assigned to corporate function(s) Mastering end-to- end AI development and implementation culminating in standardization on a platform for AI AI community of practice or (virtual) center of excellence 	 Al is pervasively used across the organization C-level ownership of Al Al ethics, governance and risk management Hybrid centralized/ decentralized Al organization Strategies and ongoing innovations with Al as a given Significant impact on workforce, roles and skills 	 Al is seamlessly integrated for digital process and chain transformation, and disruptive new business models Al is part of business DNA Shift from Al projects to Al products Synergy of human intelligence and Al in augmented intelligence A combination of in- house and external hiring Profound impact on people, culture and society at large
Select and prioritize Al use cases	Prove the business value of Al use cases	Stabilize infrastructure to access data and Al tools	Scale Al. Expand data sources.	Share your Al advantage with others by deliverin Al products



Thank you

