Artificial Intelligence for banks

Presentation by

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Agenda

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AI in the current world

AI in the current world

Artificial Intelligence has been making great strides. It has shifted from an incomprehensible subject of a chosen few “Einsteins” to a daily used assistant. Companies invest enormous amounts of money in AI to revolutionize various aspects of their operations and gain a competitive edge in the market.

Why is it important to think about AI ?

- Cost Reduction and Process Optimization
- Improved efficiency
- Innovation and Competitive Advantage
- Enhanced customer experience
- Economic growth

PwC's support in achieving AI-powered business goals

How to effectively use AI to **build up** your company? How to transform your business to stay ahead?

PwC can help you to answer those questions as well as define the right AI vision and strategy of your company.

Clear path to the successful AI implementation

Our approach

Our proven approach contains a set of deliverables that help you to define a reasonable path of AI implementation for your business.

1. **Management awareness** - We will show the managers what the current and expected AI capabilities are and how they are used/can be used in banking sector. We will moderate unreasonably high expectations and challenge low expectations
2. **Use case ideation** - We will prepare a workshop to think up relevant AI use cases
3. **Vision** - We will help you to formulate the company AI vision
4. **Organization and team** - We will propose to you variants of organizational setup, services, competencies and roles to implement AI and benefit from AI
5. **Way of work** - We will define the changes in your way of working to include or enhance AI use
6. **Platform and tool** - We will define the main functionalities needed to use AI
7. **Regulation and risks** - We will articulate the main risks related to AI implementation in your company and explain the existing and emerging regulations
8. **Roadmap** - We will place all the main activities onto a roadmap

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Selected use cases

AI models | Use cases

AI deployment can benefit banks across various domains. Presented below are a exemplary use cases that illustrate how AI can impact internal processes and the customer service quality.

"Typical" models

Model	Description
Credit/risk scoring	Evaluate of creditworthiness of the company's clients / partners
Credit Score Monitoring	Continuously monitor changes in customers' credit profiles and take appropriate actions if needed
Real-Time Credit Decisioning	Analyze applicant data in real-time and make quicker lending decisions, reduce manual effort and streamline loan origination, providing a faster and more seamless experience for customers
Personalized Credit Offers	Analyze customer data, including income, spending patterns, and demographics, to customize credit offers that match individual needs and risk profiles
Fraud detection	Analyze patterns and anomalies within credit data to detect suspicious activities
Early Warning Systems	Monitor customer behavior, transaction patterns, and credit usage to identify early warning signs of financial distress
Portfolio Risk Analysis	Analyze the overall risk exposure of a bank's credit portfolio
Operational Efficiency	Optimize internal processes, reduce manual errors, improve operational efficiency, and lower costs

On top of that

Model	Description
Segmentation and Targeting	Incorporate external models to improve quality of decisions - e.g. telescoring for customer creditworthiness evaluation
Customer Service	Enhance customer satisfaction by using AI-powered chatbots and virtual assistants to handle customer inquiries
Customer Sentiment Analysis	Analyze customer feedback from various channels to understand sentiment, identify issues, and improve customer satisfaction
Segmentation and Targeting	Analyze customer data, including transaction history, spending patterns, and preferences to offer personalized product recommendations and targeted marketing campaigns, increasing cross-selling opportunities
Compliance Monitoring	Automate compliance monitoring, ensuring adherence to regulations and reducing human error
Market Analysis	Gather and analyze vast amounts of market data and use it to stay competitive in a rapidly evolving market
Automated Reporting and Insights	Automate the generation of reports, dashboards, and insights

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Our approach and capabilities

Data science team

Usually, at the center of AI implementation, there is a **data science team**. The team should not be composed only from data scientists, but also data engineers, analysts and DevOps engineers should be part of it.

These required roles are highly sought after in the job market, making **recruitment and retention** challenging. We will provide you with job descriptions and the proper mix of employees and contractors. To effectively attract and retain these experts, several critical factors must be considered: the specific use cases, the tools employed, the methodology applied, and the team's composition.

Not all AI development must be realized from scratch by the data science team.

A lot of ready-made AI solutions and knowledgeable suppliers are on the market. But it is important, data science team provides AI solutions to the company, and it should be their **right to decide** about developing the solution themselves or with the help of a supplier. We will address this situation in your case and bring the elements to decide on whether to **Make or Buy**.

What are the sources of **dissatisfaction among data scientists**, and what factors could erode their loyalty and enthusiasm? One critical aspect is investing time and effort into developing an AI solution that ends up unused by the company. Surprisingly, this situation is quite common. Another demotivating factor is navigating through bureaucratic processes involving multiple levels of approval beyond their control, often leading to extended delays and inefficiencies in project progression. Additionally, the extended duration needed for data preparation can be discouraging; although they're keen to create AI models, the necessary data isn't readily available. Lastly, the presence of low-quality data makes it difficult for data scientists to perform their tasks effectively.

Functions of modern data science framework

Modeling data availability

- Data easily accessible from modeling environment
- Data science team in control of data extraction
- Long-term data storage and versioning

- Data storage separate from modeling environment
- Data extraction controlled by a different team
- Data provided in flat files without any version control

Modeling environment

- Modern programming language (e.g., Python)
- Collaboration tools for smooth cooperation inside team
  - Shared virtual storage
  - Code version control (e.g., GIT)
  - Libraries version control (e.g., conda, poetry)
  - Experiments and models version control (e.g., What does this mean?)
- Virtual machines for computation / memory-intensive tasks

- Outdated programming languages (e.g., SAS)
- Complicated and messy collaboration inside the team
  - File sharing through emails
  - No code version control
  - Different version of libraries on local machines
  - No control over experiments and models
- Only local machines with limited computation power

Functions of modern data science framework

Documentation and outputs

- Versioning of outputs (model registry)
- Documentation integrated in the data science framework

- No systematic control over model versions
- Documentation in separate files without versioning

Deployment to production

- Production code in the same framework as development environment
- Project structure created taking deployment into consideration
- Integrated testing
- Containerization and CI/CD pipeline
- Scheduling and automation of tasks (e.g., monthly scoring)
- Data science team in charge of production settings

- Production system separated from development environment (or in different programming language)
- No consideration of deployment during modeling
- Complicated testing procedure
- Difficult integration (and updates) in production systems
- Manual running of production scripts
- Separate DevOps / MLOps team in charge of production

Functions of modern data science framework

Monitoring and validation

- Real-time monitoring / validation of model performance
- Monitoring / validation integrated in data science platform
- Alerts and early warnings in case of unexpected behavior
- Fully automated reporting interface

- Ad hoc one-time monitoring / validation reports
- Reports has to be created outside data science platform
- No real-time information about potential problems
- Requiring manual effort, consuming time and human resources

Planning and project management

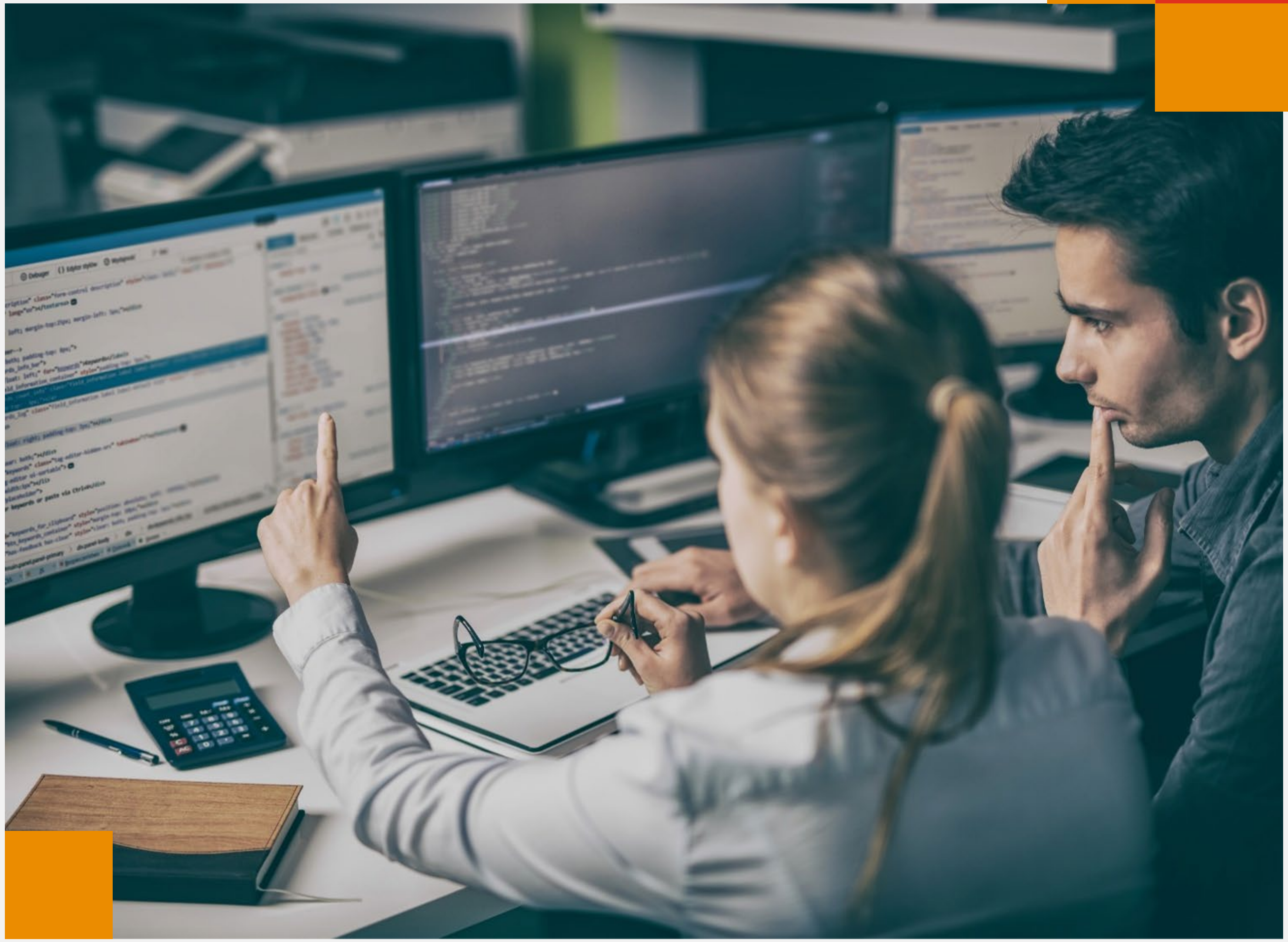
- Modern project management tools (e.g., Jira, Azure DevOps)
- Time estimation and real-time tracking for individual tasks
- Integration with documentation, code, and outputs

- Project management outside the data science framework
- Complicated tracking and governance
- No integration with documentation, codes, or outputs

Functions of modern data science framework

Modeling environment

- Faster project delivery
- Increased quality of delivery
- Higher effectiveness and costs savings
- Reduction of risk of error / miscommunication
- More extensive control over the product
- Improved project management
- Flexibility and ability to quickly react to new situations
- Support experimentation and innovation



Building data science framework/platform

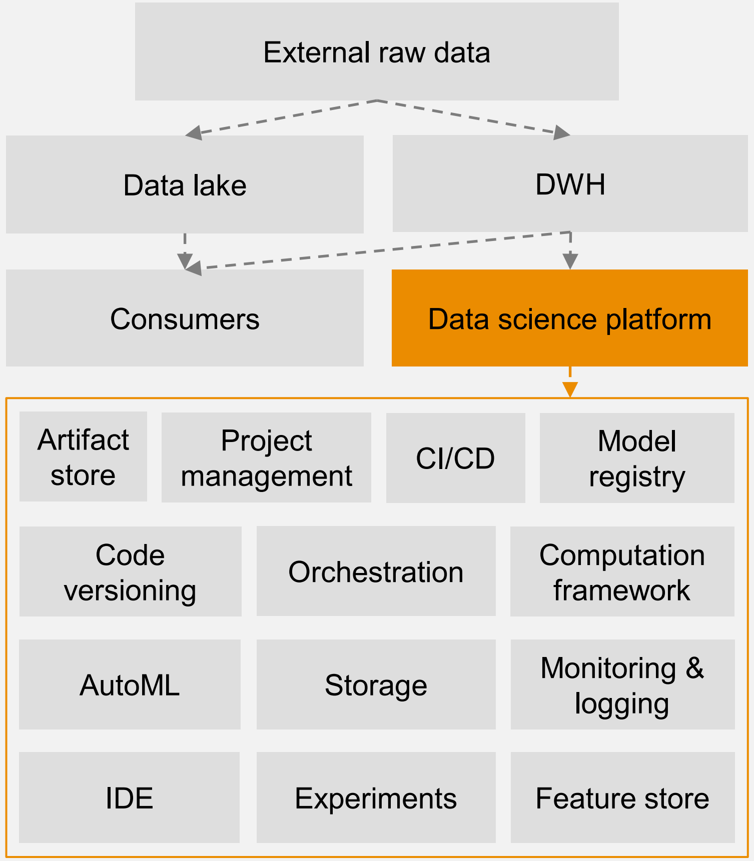
On top of traditional data solutions, we implement a platform dedicated to machine learning and AI use cases. The platform consists of all the tools data scientists would need to accomplish their tasks.

The platform could be implemented on-premise or in-cloud - e.g., Microsoft Azure.

Example technical solution implemented in MS Azure:

- **IDE**: Jupyter notebooks*
- **Computation framework**: Azure Machine Learning Studio
- **AutoML**: Azure Machine Learning**
- **Model registry**: Azure Machine Learning** (MLFlow)
- **Experiments**: Azure Machine Learning** (MLflow)
- **Feature store**: Azure Machine Learning** (MLFlow)
- **Monitoring & logging**: Azure Machine Learning** (MLflow) + Azure Monitor
- **Orchestration**: Azure Data Factory (Airflow), Azure Databricks* Workflows
- **Artifact store**: Azure DevOps Artifacts
- **Project management**: Azure DevOps Boards + Wiki
- **Code versioning**: Azure DevOps Repos
- **CI/CD**: Azure DevOps Pipelines
- **Storage**: Azure Data Lake Storage + Delta Lake + Azure SQL Database

  * or other open source IDE (e.g., VS Code)
  ** or Azure Databricks (Spark)



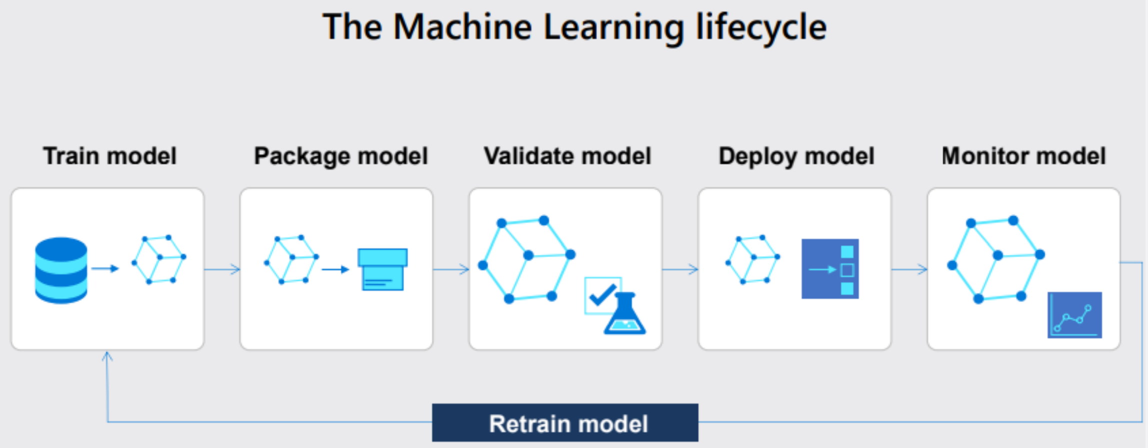
Building data science framework/Way of working

The ultimate goal of data scientists is to prepare solutions that automatically provide **smart advice from data** or that automatically **answer questions** or can just conversate.

The important role to benefit from data science is the **business or product owner**. They are atheperson who can connect business opportunities with data science capabilities and has the power to decide where to use data science.

There are 3 related processes to achieve the goal:

1. **Business delivery -** from idea, through cost/benefit analysis, objective specification, changes in the organization, product and client service up to business monitoring
2. **Data science delivery -** from data preparation, through model training and deployment up to model monitoring
3. **DevOps delivery -** automation of data processing for the model, creation of CI/CD pipelines, encapsulation of the model to an application, operation and technical support



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Summary

Data culture strategy

Having the best of breed data platforms and excellent data specialists does not mean the company will succeed in gaining **maximum value from data**. Something that is required to win in the competitive fight in the digital world.

No endeavors by data specialists can cover all the company's and the employees' needs to get responses from data.

The employees must learn how to understand and use data to find answers to their basic questions: so-called **BI self service**. There are effective tools in the market powered by AI, which can help them in this effort. It is also important the employee experience the difference between a decision based on data and a decision based on their intuition. In addition, the employees should recognize and understand the problem when using low-quality data.

Another part of data culture lies in the employees' understanding how they can **benefit from and work with data specialists**, mainly data scientists and what AI can bring to them.

PwC has the experience and know-how to focus and structure **data education** and how to use the tools to achieve a steep learning curve and the best results.

Interested?
Contact us.

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Thank you

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