Causes for the Failure of Machine Learning Projects in Productive Use

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MOTIVTION & OBJECTIVES

- Machine learning (ML) is one of the fastest-growing technology areas and is considered one of the most disruptive innovations for businesses today. Data availability and advances in computing power have enabled great growth in the research and practice of ML.
- Studies show that companies using ML models (i.e. using analytical tools in data analysis) increase their operational efficiency, develop new value propositions and perceive a significant competitive advantage. Consequently, the adoption of ML is reaching its inflection point as technological, societal, and competitive pressures push enterprises to transform and innovate.
- The real value of ML models can only be harnessed when they are actually deployed in a productive environment. Converting an algorithm into a business-valuable ML model is a time-consuming and complex task.
- Several studies conclude that 87% of ML projects ultimately do not make it into production

Research Questions

1. What factors impact the failure of ML projects in productive use?
2. Into which categories can the factors be divided?
3. What are the most critical factors impacting ML project failure?

METHODOLOGICAL APPROACH

Systematic Literature Review

The motivation for conducting a systematic literature review (SLR) is the ability to methodologically review previous literature and identify, summarize, evaluate and analyse all available research findings relevant to a particular subject area. The aim is to capture the current state of knowledge, identify gaps and controversies to be explored and to identify links to further fields of research.

- Search for suitable literature in scientific databases according to a defined procedure and selection criteria
- Evaluation of literature in several iterations according to quality criteria
- Extract relevant factors from each article

✓ Gather the scope of existing work and compile an initial overview and categorisation of factors influencing the failure of ML projects in productive use

Qualitative interviews

The reason for choosing a qualitative method is to capture subjective perspectives and experience-based knowledge that cannot be captured by pure literature search or quantitative data collection. Qualitative interviews with practitioners will be able to provide individual perspectives and experiences as it is possible to verbalize one's thoughts, beliefs, and opinions. The goal is to validate the findings obtained from literature and to capture additional factors causing ML projects to fail.

- Develop the interview guide based on the results of the SLR
- Choose participants deliberately from different companies and sectors to cover a wide range of influencing factors
- Conduct the interviews
- Transcription of interviews
- Analysis of the interviews according to Mayring's qualitative content analysis

✓ Validation and completion of previously developed factors through subjective experiences and perspectives

✓ Questioning the factors for their influence on the success of productive ML systems

Synthesis

In the synthesis all factors are consolidated and their relevance and dependencies are analysed. As a result, all factors impacting the failure of ML projects are recorded and categorised.

RESULTS

Technological Influences	Human/Organizational Influences	Economic Influences
Data ❖ Data availability ❖ Data quality ○ Data complexity ❖ Data handling ❖ Data drift **ML model** ○ Performance ❖ Monitoring ❖ Model drift ❖ Model update and maintenance ▪ Robustness ▪ Reproducibility **Infrastructure** ❖ Lacking infrastructure ○ Processing times ❖ Diverse requirements ▪ Interoperability **Standardization** ❖ Deployment ❖ Processes ❖ Evaluation metrics **Scalability** ❖ Scalability ❖ Size of data ❖ Moving from PoC to production **Reliability** ❖ Trust ❖ Explainability and transparency	**Knowledge and skill** ❖ ML knowledge and experience ❖ Wide set of skills ❖ ML professionals ❖ Gap between academia and practice **Goals and expectations** ❖ Expectation management ▪ Problem formulation ❖ Definition of success criteria **Organizational readiness** ❖ Organizational alignment ○ Strategy ❖ Management support ○ Acceptance **Project management** ○ Collaboration ❖ Communication ○ Risk management	**Business impact** ❖ Business impact **Costs** ❖ High costs ❖ Lack of funding **Compliance and ethics** ❖ Legal guidelines ❖ Ethical concerns Obtained from… ○ Interviews ▪ Literature ❖ Both

CONCLUSION

Summary

Based on how frequently factors were mentioned, what influence they have on other factors, and how they are evaluated in literature and interviews, it can be concluded that the following factors might be the most critical for the failure of machine learning projects in productive use:

- *ML knowledge, skills, and experience* appropriate to the role in a project team
- Efficient and effective communication and collaboration inside a project team but also with managers and users
- *Organizational alignment and strategy* on how ML models will ultimately be used and operated in production
- *Scalable infrastructure* that is appropriate for the diverse requirements of ML models

Critical Reflection

- *Methodological approach:* One of the limitations of this research is the limited amount of literature that was worked with in the SLR. In addition, all interviewees in the interviews work in similar professions with similar credentials and attitudes towards ML. Even though an attempt was made to gain an unbiased opinion on the topic when conducting the interviews, some subjectivity of the interviewees has to be taken into account.
- *General scope:* The aim was to draw a comprehensive picture of the causes of ML project failure based on the current state of research. During the work and in the results, it has been shown that the identified factors have different influence and depend on the particular use case and data. It is therefore difficult to draw concrete conclusions about specific industries and phases of the ML lifecycle.

Outlook

- Identification of further factors
- Restriction of the work to specific sectors
- Explicit differentiation of the phases of the ML lifecycle
- Deriving concrete measures on how ML projects can be carried out successfully

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