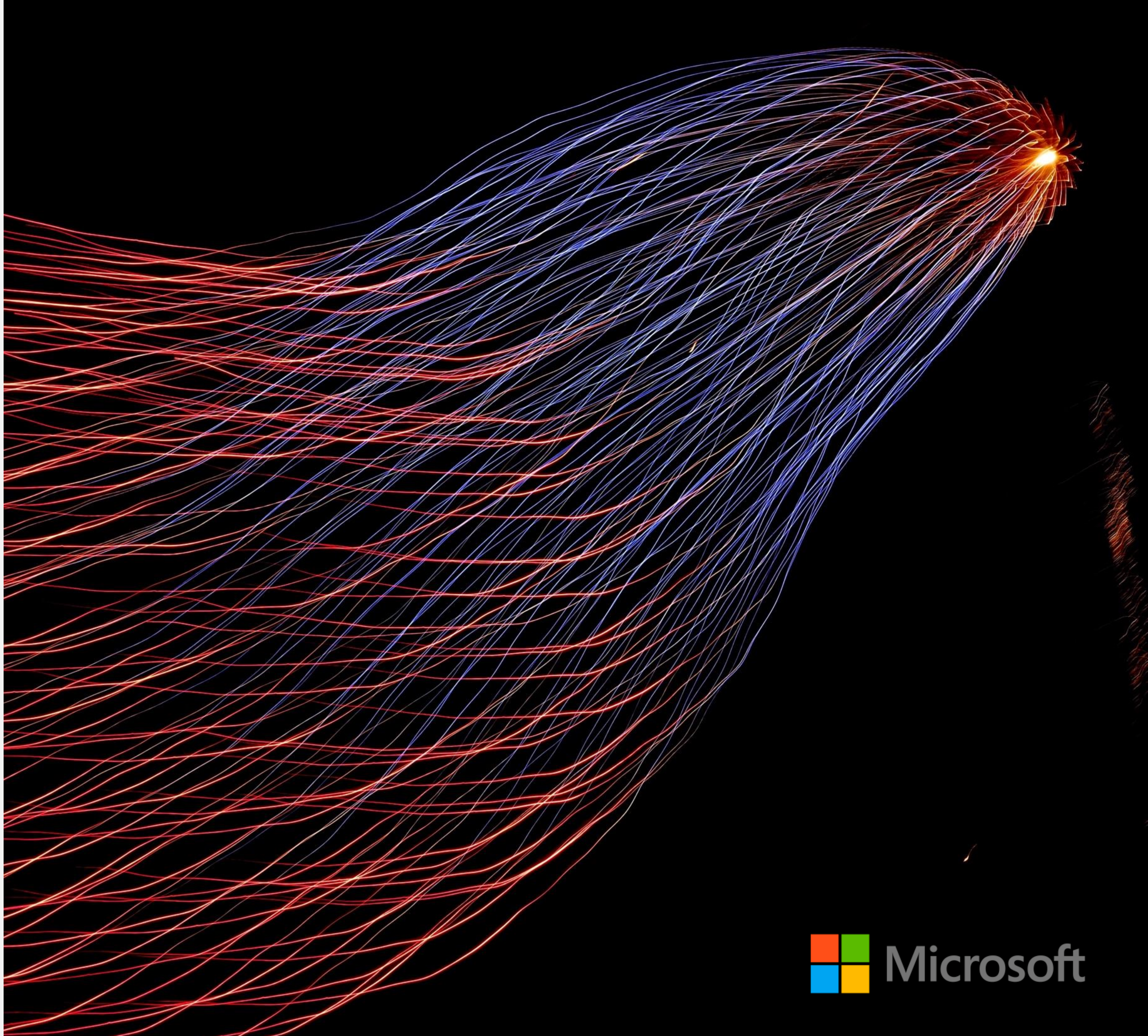
From Business Understanding to Value Realisation in Machine Learning



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Agenda

1. Idea Assessment
2. Feasibility study & value case
3. Proof of Concept
4. MVP Development & roll out
5. Maintenance & Governance

All images used in this presentation are from www.unspalsh.com

WILL KNIGHT BUSINESS 10.20.2020 12:00 AM

Wired Magazine

Companies Are Rushing to Use AI—but Few See a Payoff

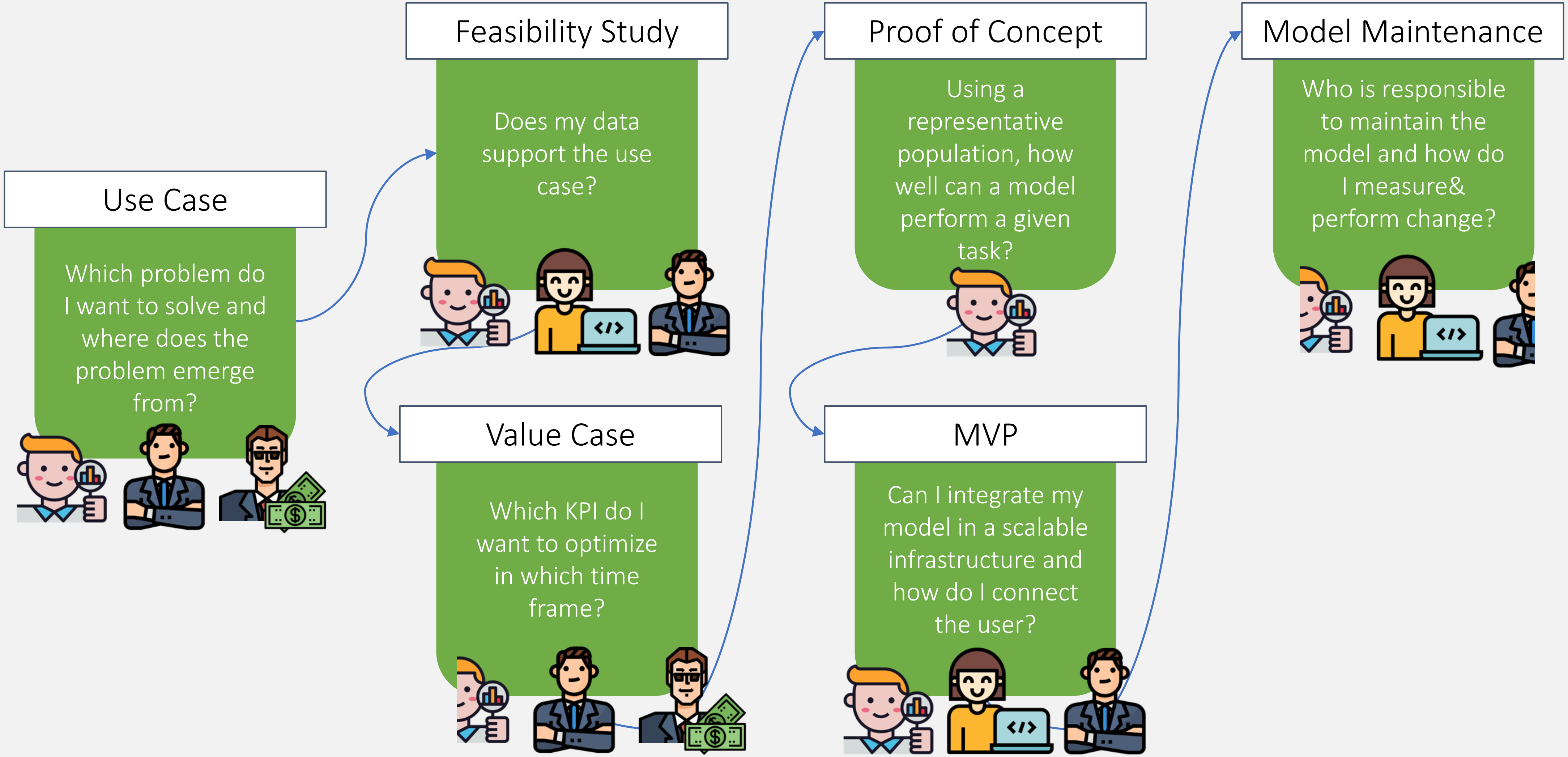
1. 26% of companies have AI systems in widespread production — more than double the 12% in last year's survey. However, and 26% said they consider themselves data driven. source

2. "AI implementation, whilst following the various ethics of AI, does not automatically translate into profitability for businesses" source

3. "7 out of 10 companies reported minimal or no value from their AI investments. One of the reasons for poor returns was that relatively few projects were deployed into production source

Moving artificial-intelligence projects from proof of concept to production remains a struggle, with companies failing almost half of the time, according to a recent report source

Data Science projects require multiple disciplines involved at different stages yield successful results



1. Idea Assessment

Impulses to begin a data science use case are numerous and require similar assessment steps but in different orders

	Bottom Up Approach	Top Down Approach	Inside Out
Assumptions	• Data • infrastructure that supports deployment of AI • “Data literate talent“	• Data • infrastructure that supports deployment of AI • Buy-in from departments affected by use-cases	• Data • infrastructure that supports deployment of AI • Business process knowledge
Impulse	• Business process knowledge • Data knowledge	• Strategic initiative that can be supported with data science	• Pain point or innovation trigger within department/industry/domain
Initial Actions	• Use case definition • Feasibility assessment • Value case • Business buy-in • Budget & talent allocation • ….	• Use case identification • Value case • Feasibility assessment • Budget & talent allocation • …	• Use case definition • Feasibility assessment • Value case • Budget & talent allocation • …

2. Feasibility study & value case

A feasibility study combined with a value case determines if your AI project is technically & economically viable

Feasibility Study

- Where is my data?
- How do I gather my data?
- Who will process my data?
- What are the targets of my analysis and which methods can be used
    - *Start with easier methods*
- What is the state-of-the-art in solving my problem?
    - *Introduce more complex methods*
- Who are the end-users of Data Science product?
- Are there data protection requirements?

<u>Outcome</u>: Yes/no indication if use case is technically & legally possible

Value Case

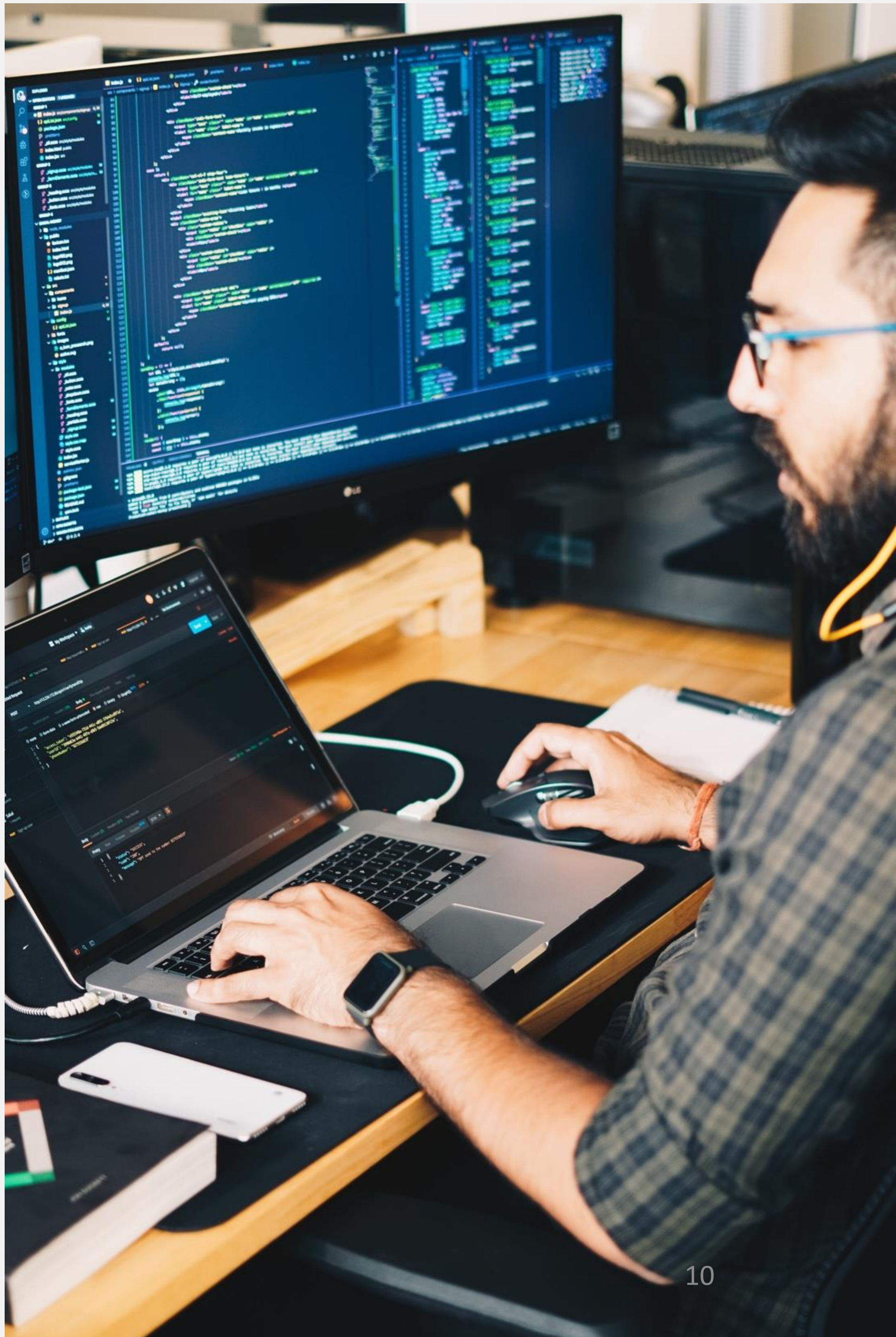
- How does my model target translate into a business KPI?
- How will my KPI be affected?
    - Cost/Revenue impact
    - Faster servicing of clients/patients
    - Etc.
- What is the timeframe my sponsor demands for value realization?
    - Is it a feasible horizon and do I need to manage expectations, seek further sponsors?

<u>Outcome</u>: Estimation of KPI evolution and time to value

3. Proof of Concept

PoCs should be rapidly delivered and provide a solid indication of how well your data science product could perform

1. Estimate tasks & budget and prepare backlog for PoC
2. Mobilize team
3. Start data science activities & document results
4. Appreciate the need to iterate AI systems
5. Present results to relevant stakeholders with performance and purpose of your solution
6. Fail/Go decision to move into MVP
7. If Go: set up an implementation plan



4. Minimal Viable Product

MVPs aim at integrating the POC into a scalable environment and test it with the user

A Data Science MVP "marries" several engineering disciplines and has the following responsibilities:

- Data Scientist to transfer PoC and make code available that can be scaled
- Developer to set up DevOps toolchain and set testing practices in place
- Architect to integrate solution into existing IT infrastructure / cloud environment
- Domain / business stakeholder to integrate solution into business process and drive change

Engineer

- Modeling & Evaluation
- Governance
    - Reproducibility, Standards, Regulatory Requirements
- Holistic Architecture
    - Application. Logic
    - Technical Integration
- User testing

Deploy

- Pipeline automatization
- Dataset Dependency (Live Data not equal to Training Data)
- Feature Engineering Pipelines must match for Training and Inference
- Control Pipelines, Canaries, A/B Testing

Monitor

- Technical Monitoring
- Model Monitoring
- Model Management (Dynamic Model Selection & Retraining)
- Tracing, Logging,
- Metrics and KPI's defined
- Dataset Dependency

Trust, Transparency, Fairness

- Model Risk Management
- Reproduce and Explain ML Decision
- Fairness Monitoring (Measuring Bias)
- Methods & Tools for Decision Making

Source: IBM AI@Scale offering, AI/ML Ops

5. Model Maintenance

A model maintenance & governance framework makes sure that risks are managed, and change protocols are followed

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Deploy

- Version training data
  - Azure Machine Learning versioned datasets
- Version trained models
  - Models within AzureML model registry
- CI/CD pipeline to test new releases
  - GitHub, ADO, Bitbucket combined with AzureML Pipelines
- GDPR considerations for data storage & processing
  - E.g. hybrid cloud approaches when dealing with PII
- A/B testing
  - Green/Blue deployment via AzureML managed endpoints

Trust, Transparency & Fairness

- Risk control model governing the process of releasing models with owners & sign-offs
- Explainability features
  - E.g. SHAP, LIME to enable user to understand model decision when in doubt
- Fairness monitoring to uncover training biases
  - Fairlearn & AI Fairness Dashboard
  - Microsoft Office of Responsible AI
- Model & data drift detection
  - Pipeline based approach measuring drift between reference & current dataset

Thank you for your attention and much success with your next AI project ☺!