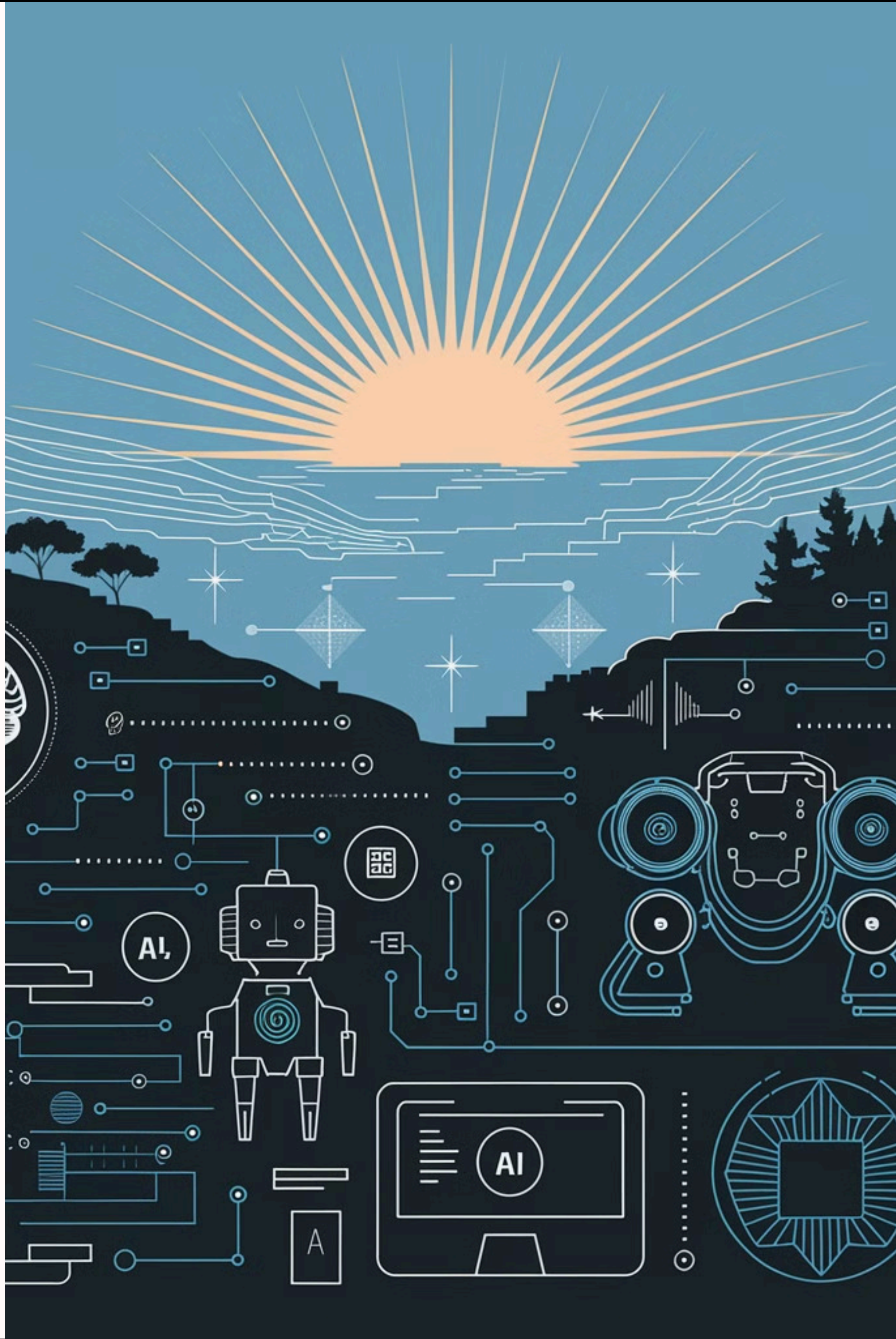
What is MLOps ?

How AI Success Demanded Operational Excellence

School of DevOps™

by Gourav Shah



The AI Revolution Begins

1. **2012**
   Deep learning breakthrough in ImageNet
2. **2015-2017**
   AI investment grows 300%
3. **2018-2020**
   Organizations rush to implement AI
4. **2021-Present**
   AI becomes business-critical

Great Expectations vs. Reality

The Dream

- Train a model
- Deploy it
- Watch magic happen
- Profit!

The Reality

- 87% of ML projects never reach production
- 9+ months from model to deployment
- 50%+ of models fail to deliver value


The Cold, Hard Truth

$15.7T

AI Impact

Projected global economic impact by 2030

83%

Frustrated

Data scientists facing deployment challenges

90%

Struggling

Organizations having AI implementation issues

70%

Improvement

Reduction in time-to-value with proper practices

The 3AM Crisis

The Incident

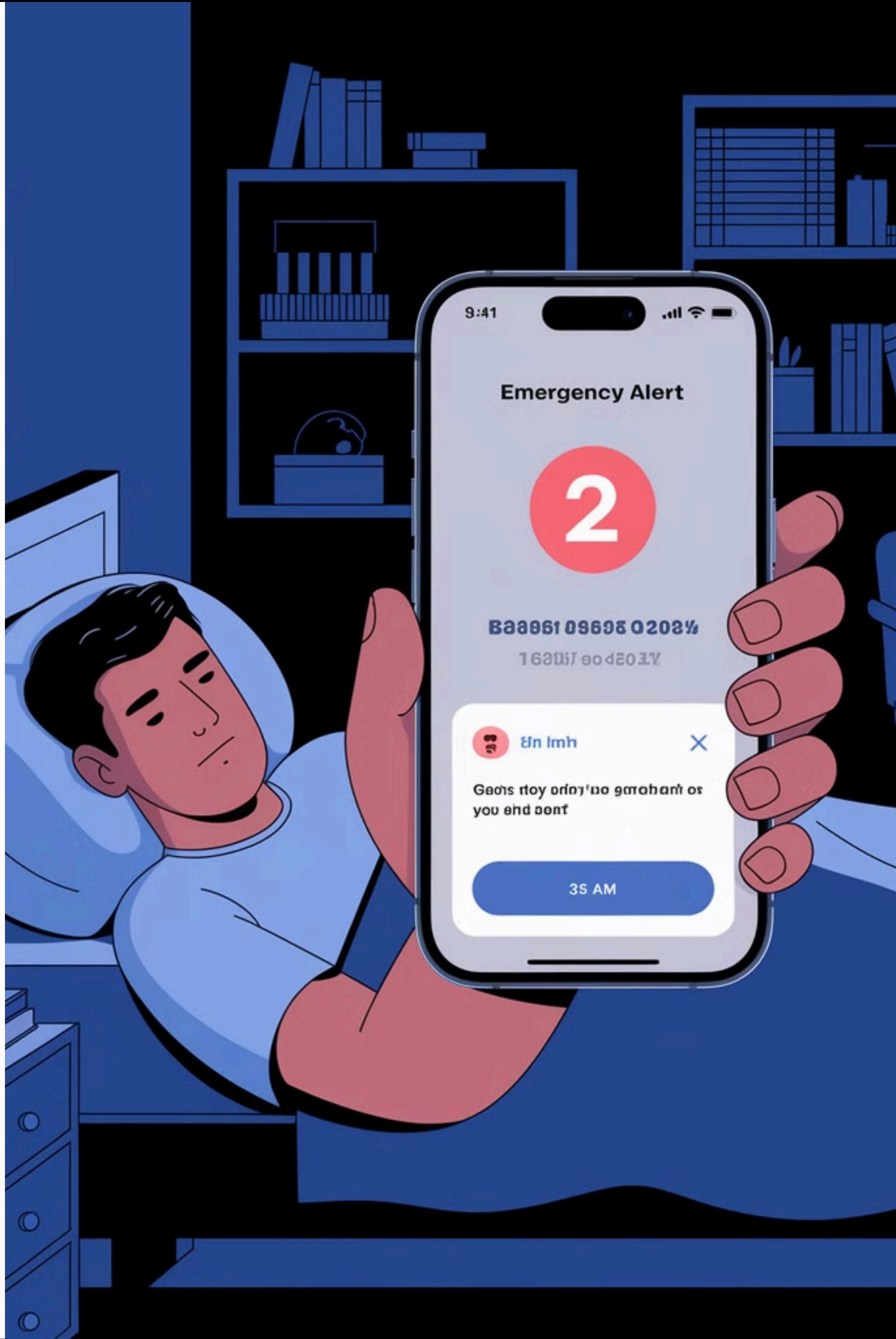
Recommendation engine suggesting winter coats to Australian users in summer

The Questions

Which model version? What training data? How did it pass testing?

The Problem

No systematic operational practices means no good answers



The Production Gap

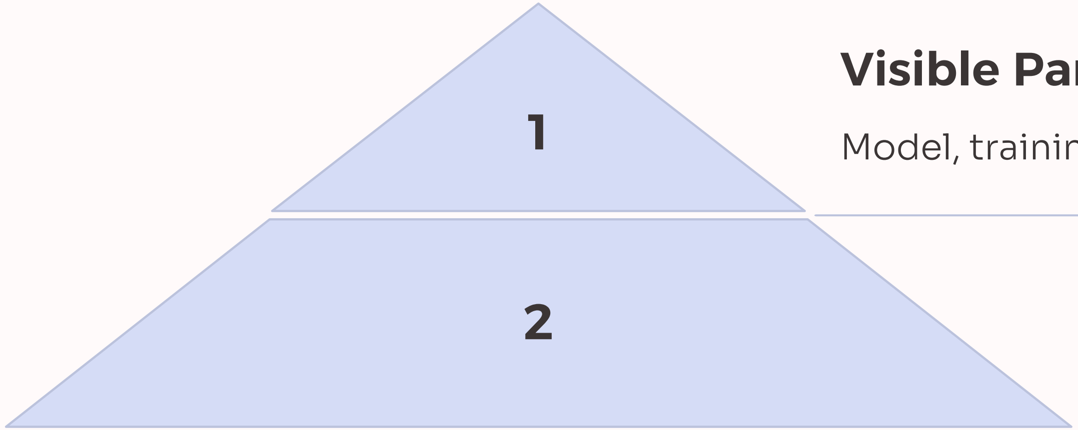
Data Science World

- Jupyter notebooks
- Experimentation focus
- Static datasets
- Academic metrics

Production World

- Scalable infrastructure
- Reliability requirements
- Dynamic data
- Business metrics

The Hidden Complexity of ML Systems



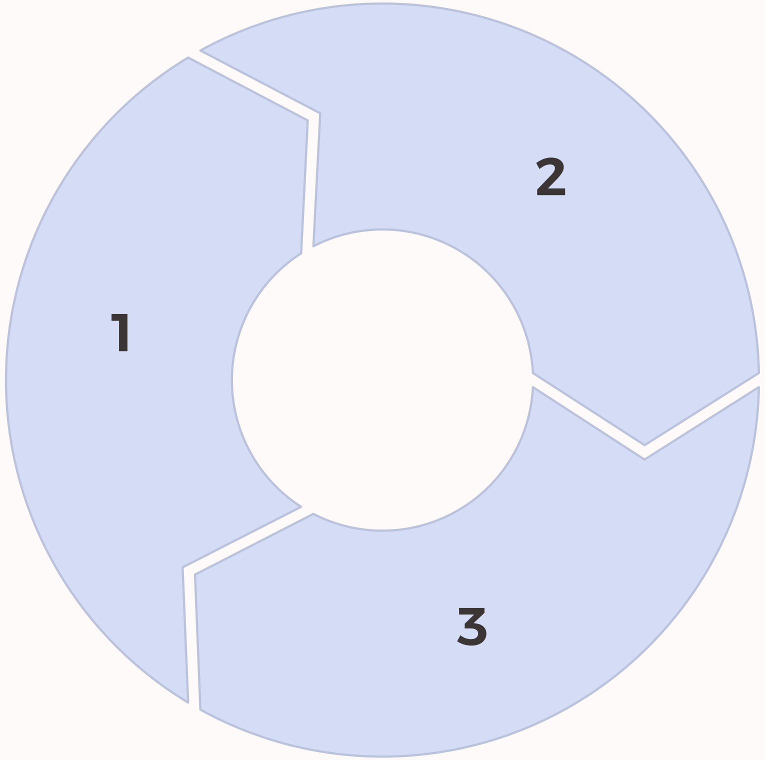
Visible Part (10%)

Model, training code, metrics

Hidden Complexity (90%)

Pipelines, versioning, monitoring

MLOps: A New Discipline Emerges



Machine Learning

Science of creating predictive models

DevOps

Practices for reliable software delivery

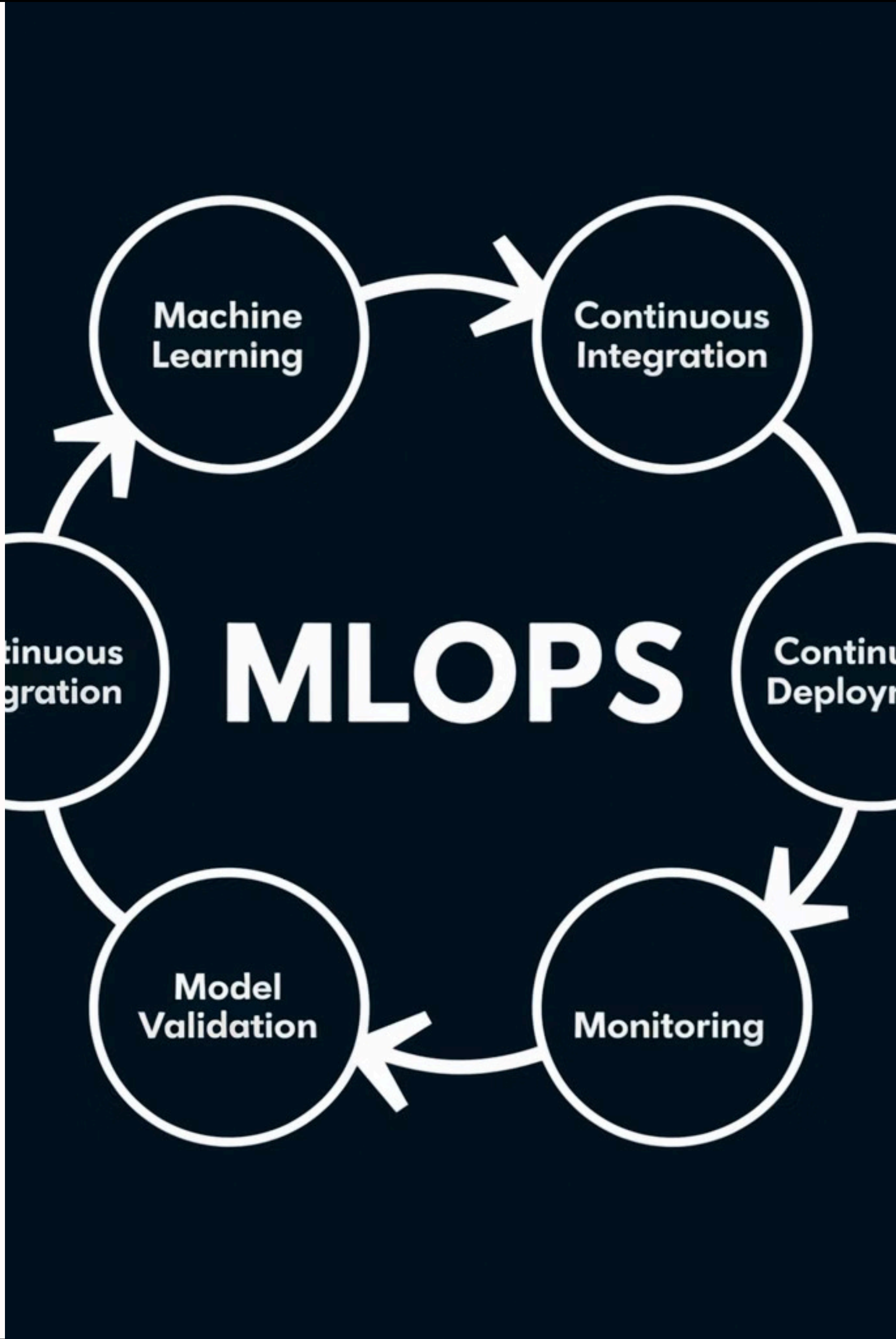
Data Engineering

Systems for data processing and management

What is MLOps?

MLOps is a set of practices at the intersection of Machine Learning, DevOps, and Data Engineering aimed at deploying and maintaining ML systems in production reliably and efficiently.

1. **Bridges development and operations**
2. **Standardizes the ML lifecycle**
3. **Automates repetitive processes**
4. **Enables reproducibility and governance**



If ML Were a Restaurant...

Without MLOps

- No standardized recipes
- No ingredient tracking
- Inconsistent meals
- Can't scale successful dishes

With MLOps

- Recipe versioning
- Ingredient quality control
- Consistent preparation
- Scalable kitchen operations

The 3 Pillars of MLOps

CI/CD

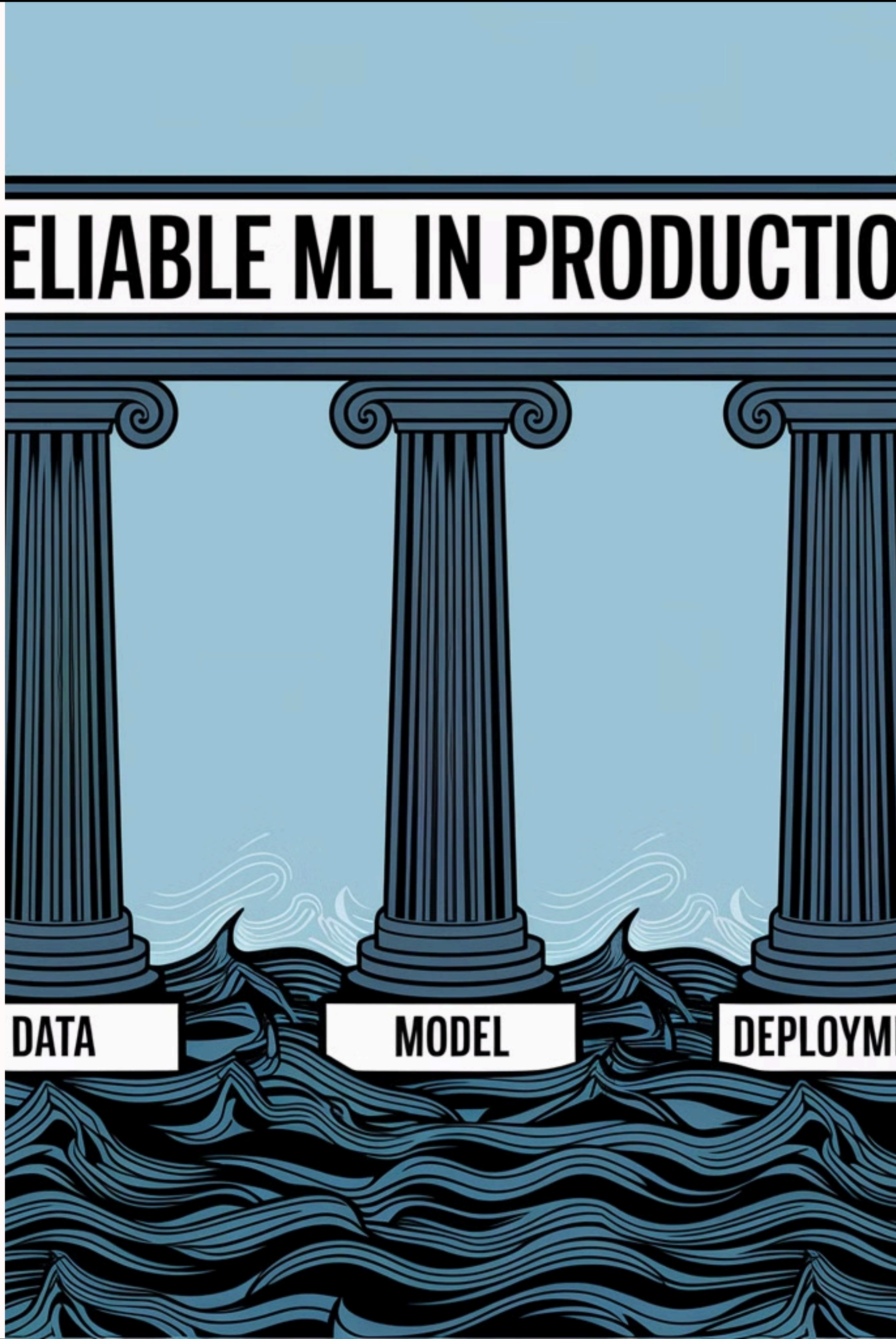
Automated testing, building, deployment

Orchestration & Automation

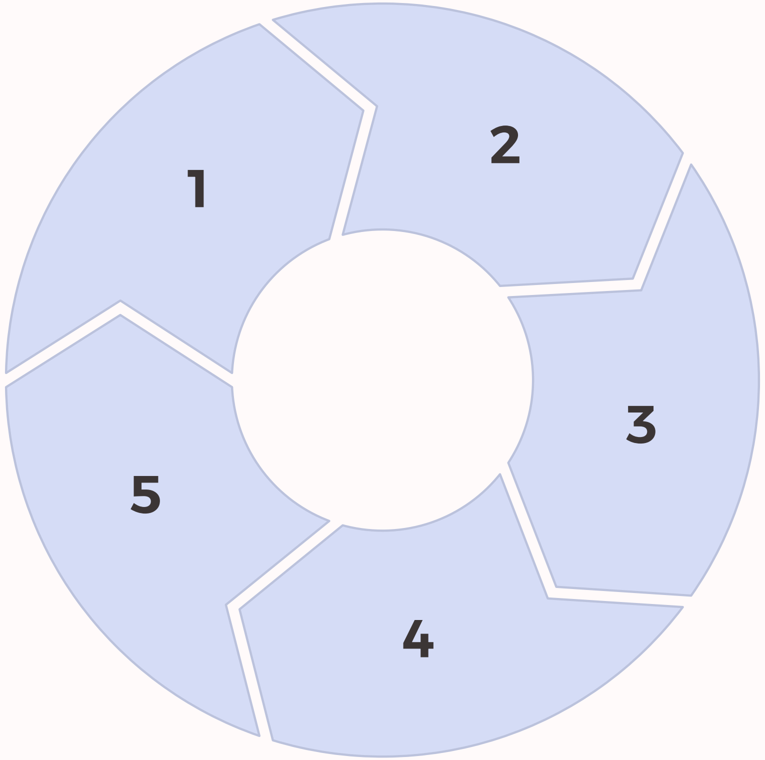
End-to-end workflow management

Monitoring & Management

Performance tracking, drift detection



MLOps Core Practices



Version Everything

Code, data, models, configs

Automate Pipelines

Training, testing, deployment

Track Experiments

Parameters, metrics, artifacts

Monitor Continuously

Performance, drift, resources

Enable Governance

Lineage, documentation, compliance

The Technical Debt Monster

Machine learning systems have a special capacity for incurring technical debt.

1. **ML-Specific Debt**

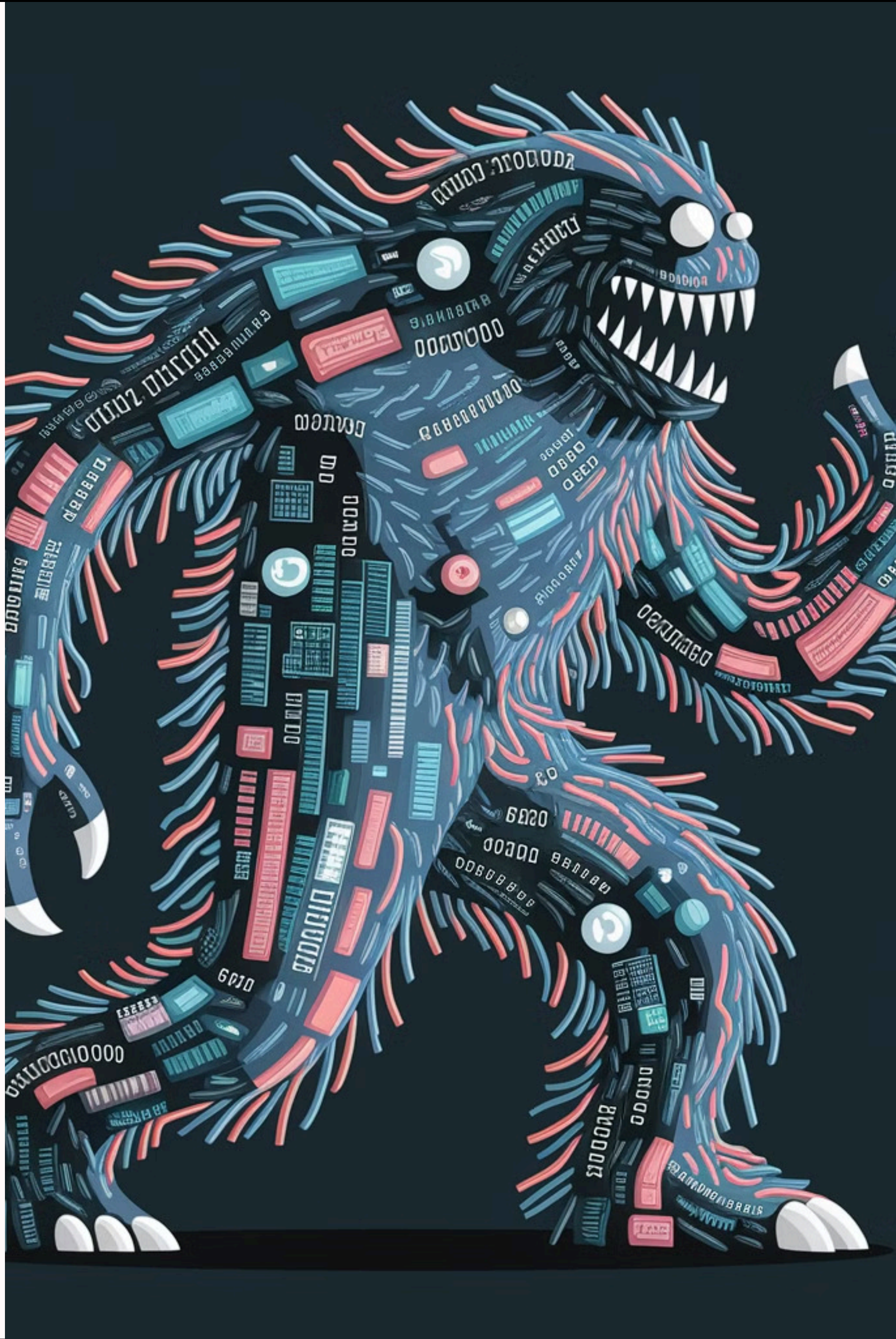
   Data dependencies, configuration complexity

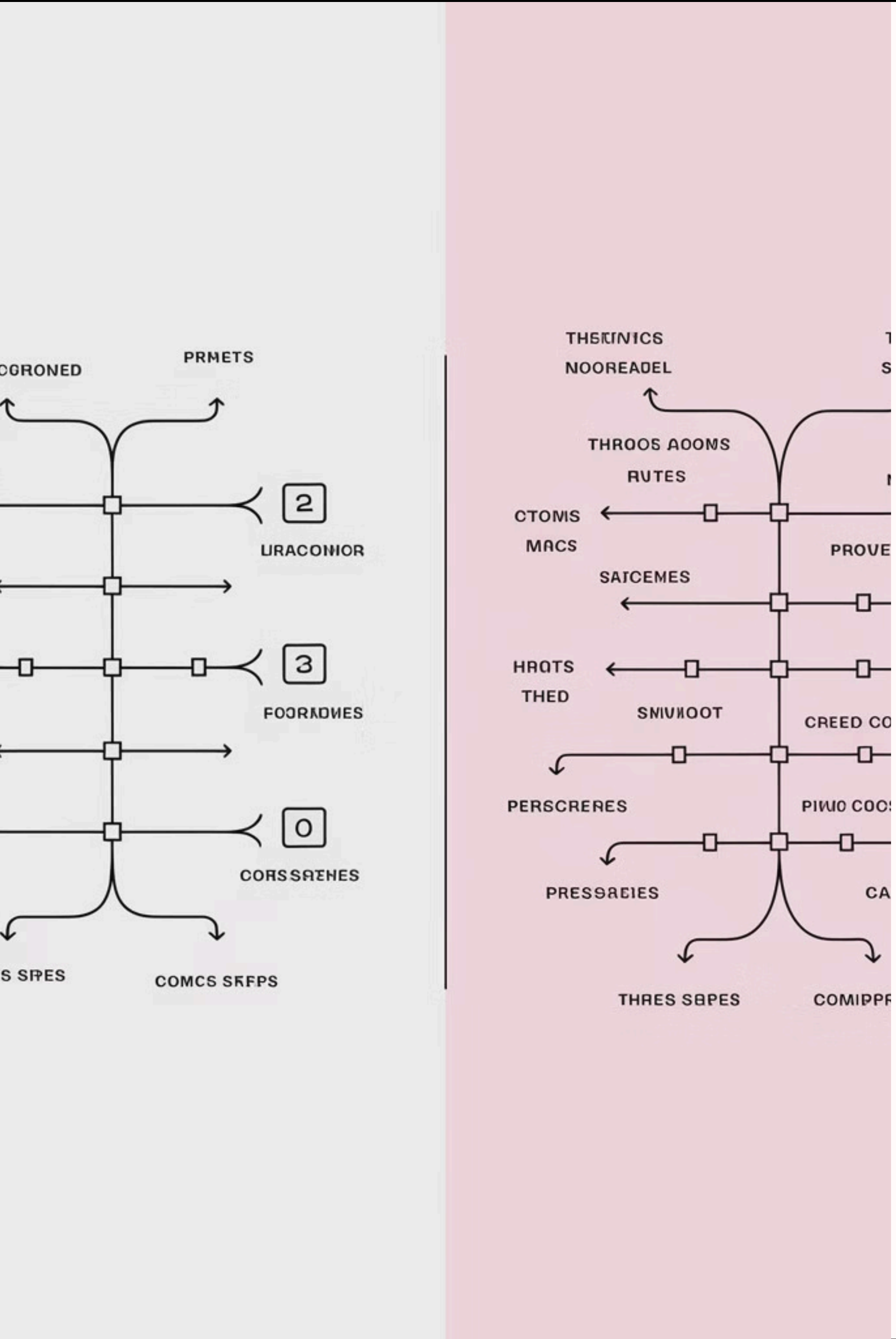
2. **Experimentation Issues**

   No tracking, undocumented features

3. **Operational Problems**

   Manual deployment, lack of monitoring





ML Lifecycle vs. Software Development

1

Traditional Software

Requirements → Design → Implementation → Testing → Deployment → Maintenance

2

ML Development

Problem framing → Data prep → Feature engineering → Training → Evaluation → Deployment → Monitoring

3

Key Differences

Data dependency, non-deterministic behavior, continuous retraining

The Bottom Line: Business Value

70%

Faster

Reduction in time-to-deployment

40%

Better

Improvement in model performance

65%

Reliable

Fewer production incidents

4x

Scalable

More models in production

The MLOps Maturity Journey

Level 0: Manual Process

Manual preparation, no versioning

Level 1: Pipeline Automation

Automated training, basic versioning

Level 2: CI/CD Automation

Automated testing, inference deployment, basic monitoring

Level 3: Automated Operations

Drift detection, on-demand retraining

Level 4: Full Automation

Auto-triggered retraining, self-healing

The Pioneers' Advantage

Netflix

Created Metaflow, reduced deployment time by 60%

Uber

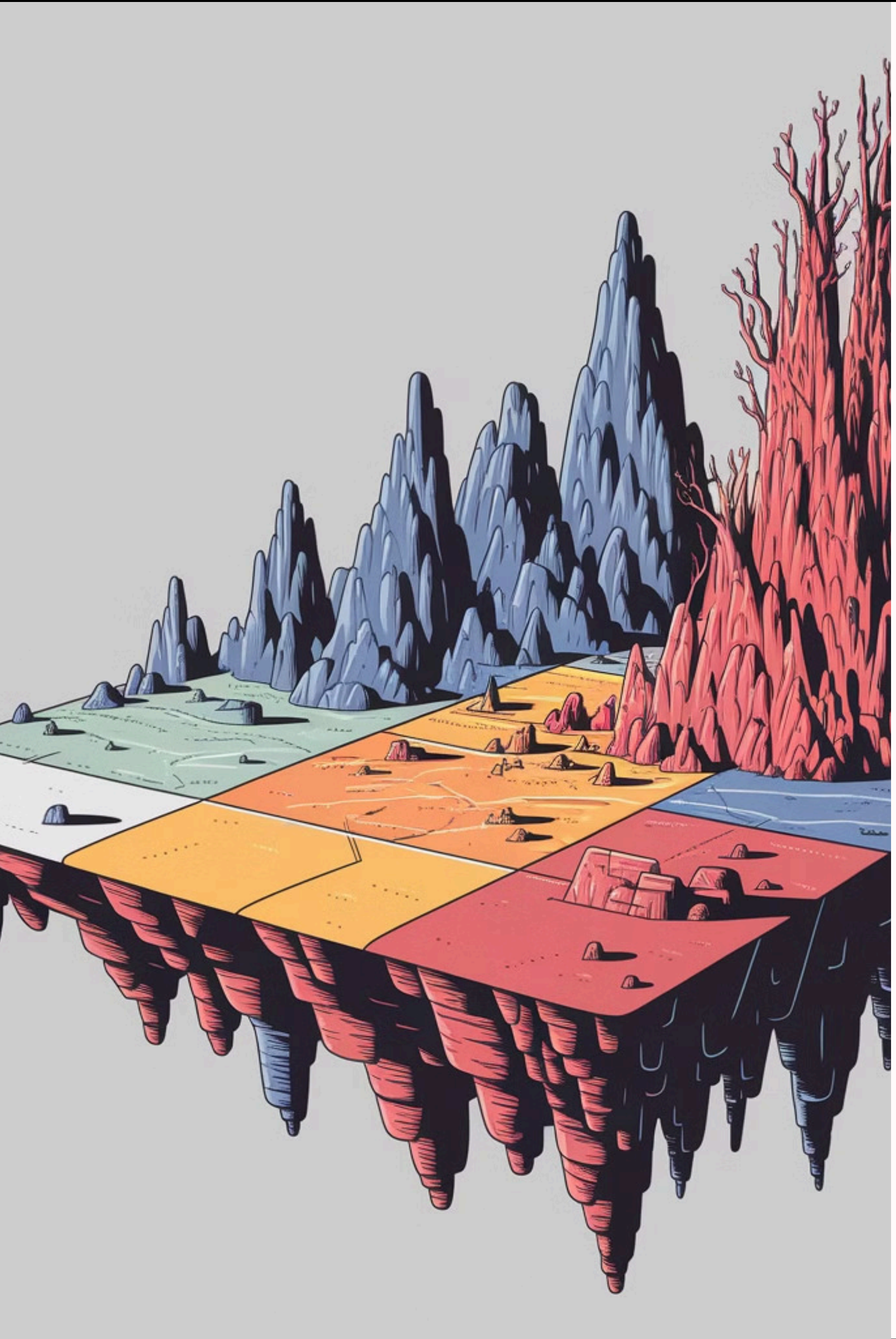
Built Michelangelo, enabling millions of daily predictions

Facebook

Developed FBLearner, supporting 1M+ model runs daily

Airbnb

Implemented Bighead, increased experiment velocity 4x



The Evolving AI Landscape

1. **2015-2018: Traditional ML Focus**

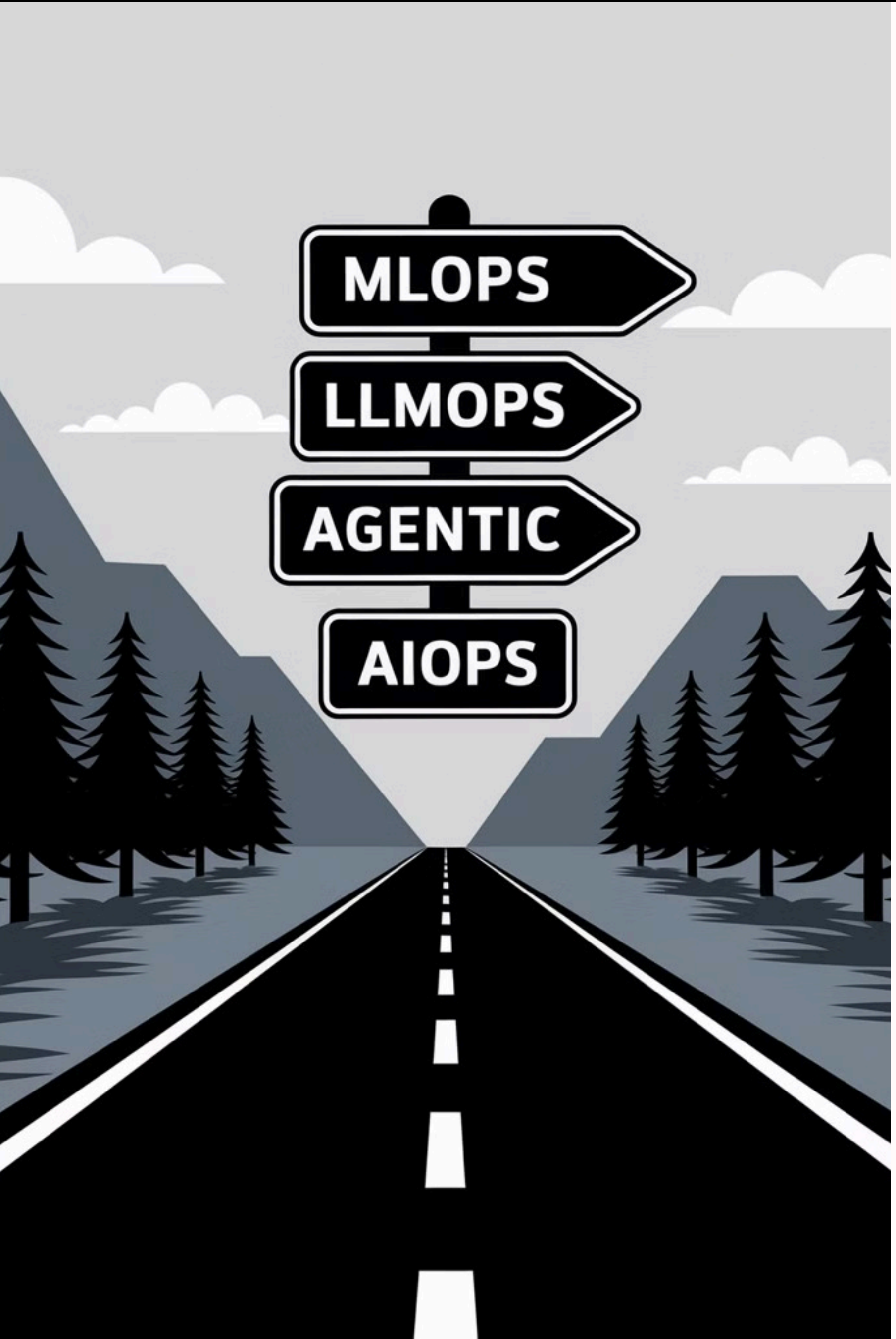
   Custom models, structured data, centralized development

2. **2018-2021: Deep Learning Expansion**

   Neural networks, unstructured data, model ensembles

3. **2021-Present: Foundation Models & Agents**

   Large language models, multimodal systems, agentic capabilities



The Evolution Continues

1

MLOps

Traditional machine learning operations

2

LLMOps

Foundation model operations

3

AgenticAIOps

Autonomous agent operations

Reflections

1 **Maturity Assessment**

Where are you on the MLOps journey?

2 **Pain Points**

Biggest challenge moving ML to production?

3 **Time Savings**

How much time could proper MLOps save?

4 **Business Impact**

Value of deploying models twice as fast?