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MLOps: Machine Learning Operationalization

ActiveState Webinar

Panelists

- **Nisha Talagala**, Co-Founder, CTO & VP Engineering, *ParallelM*
- **Boris Tvaroska**, Global Artificial Intelligence Solutions Lead, *Lenovo*

Housekeeping

- Webinar recording and slides will be available shortly
- Share questions with panelists using the Question panel
- Q&A session following presentations

MLOps: Machine Learning Operationalization

Capital One · Bank of America · American National · HSBC · Tesco Bank · Credit Suisse

Bombardier · GE Aviation · Northrop Grumman · NASA · Siemens · Cisco

intel · ca technologies · IBM · Microsoft · Hewlett Packard Enterprise · verizon

Track-record: 97% of Fortune 1000, 20+ years open source

Polyglot: 5 languages - Python, Perl, Tcl, Go, Ruby

Runtime Focus: concept to development to production

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Machine Learning Operationalization

Nisha Talaga, ParallelM

ParallelM

MLOps: Machine Learning Operationalization

Nisha Talagala

Co-Founder, CTO & VP Engineering
ParallelM

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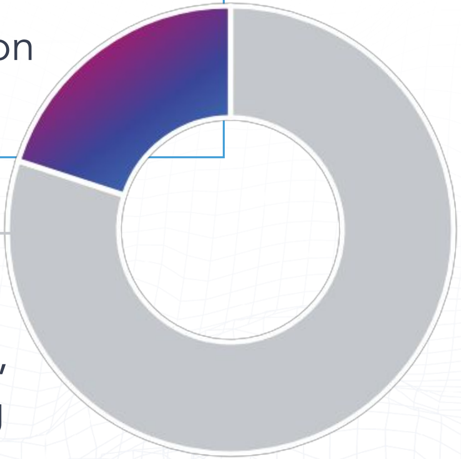
MLOps: The Last Mile

From Data Science to Business ROI

NISHA TALAGALA

CTO, ParallelM

Growing AI Investments; Few Deployed at Scale



20%

AI in Production

80%

Developing, Experimenting, Contemplating

Survey of 3073 AI-aware C-level Executives

Out of 160 reviewed AI use cases:

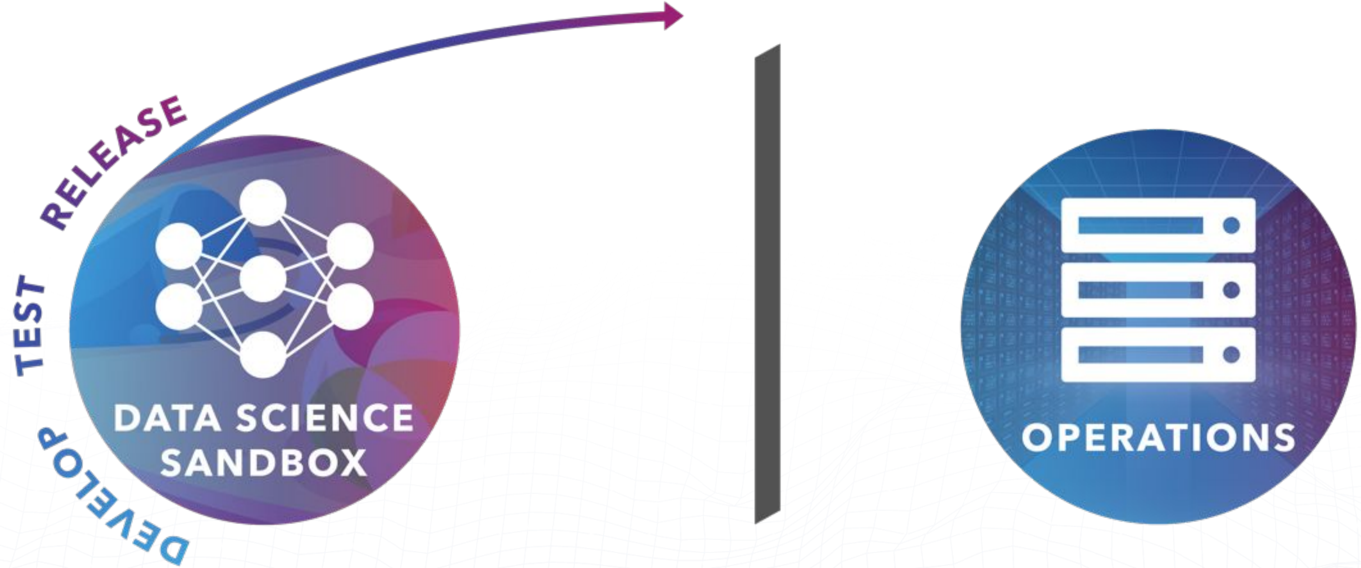
88% did not progress beyond the experimental stage

But successful early AI adopters report:

Profit margins **3–15%** higher than industry average

Source: "Artificial Intelligence: The Next Digital Frontier?", McKinsey Global Institute, June 2017

The ML Development and Deployment Cycle



Bulk of effort today is in the left side of this process (development)

- Many tools, libraries, etc.
- Democratization of Data Science
- Auto-ML

What makes ML uniquely challenging in production?

Part I : Dataset dependency

- ML ‘black box’ into which many inputs (algorithmic, human, dataset etc.) go to provide output.
- Difficult to have reproducible, deterministically ‘correct’ result as input data changes
- ML in production may behave differently than in developer sandbox because live data ≠ training data

What makes ML uniquely challenging in production?

Part II : Simple to Complex Practical Topologies

- Multiple loosely coupled pipelines running possibly in parallel, with dependencies and human interactions
- Feature engineering pipelines must match for Training and Inference (CodeGen Pipelines can help here)
- Control pipelines, Canaries, A/B Tests etc.
- Further complexity if ensembles, federated learning etc are used

What makes ML uniquely challenging in production?

Part III : Heterogeneity and Scale

- Possibly differing engines (Spark, TensorFlow, Caffe, PyTorch, Sci-kit Learn, etc.)
- Different languages (Python, Java, Scala, R ..)
- Inference vs Training engines
  - Training can be frequently batch
  - Inference (Prediction, Model Serving) can be REST endpoint/custom code, streaming engine, micro-batch, etc.
  - Feature manipulation done at training needs to be replicated (or factored in) at inference
- Each engine presents its own scale opportunities/issues

What makes ML uniquely challenging in production?

Part IV : Compliance, Regulations…

- Established: Example: Model Risk Management in Financial Services
  - https://www.federalreserve.gov/supervisionreg/srletters/sr1107a1.pdf
- Emerging: Example GDPR on Reproducing and Explaining ML Decisions
  - https://iapp.org/news/a/is-there-a-right-to-explanation-for-machine-learning-in-the-gdpr/
- Emerging: New York City Algorithm Fairness Monitoring
  - https://techcrunch.com/2017/12/12/new-york-city-moves-to-establish-algorithm-monitoring-task-force/

What makes ML uniquely challenging in production?

Part V : Collaboration, Process

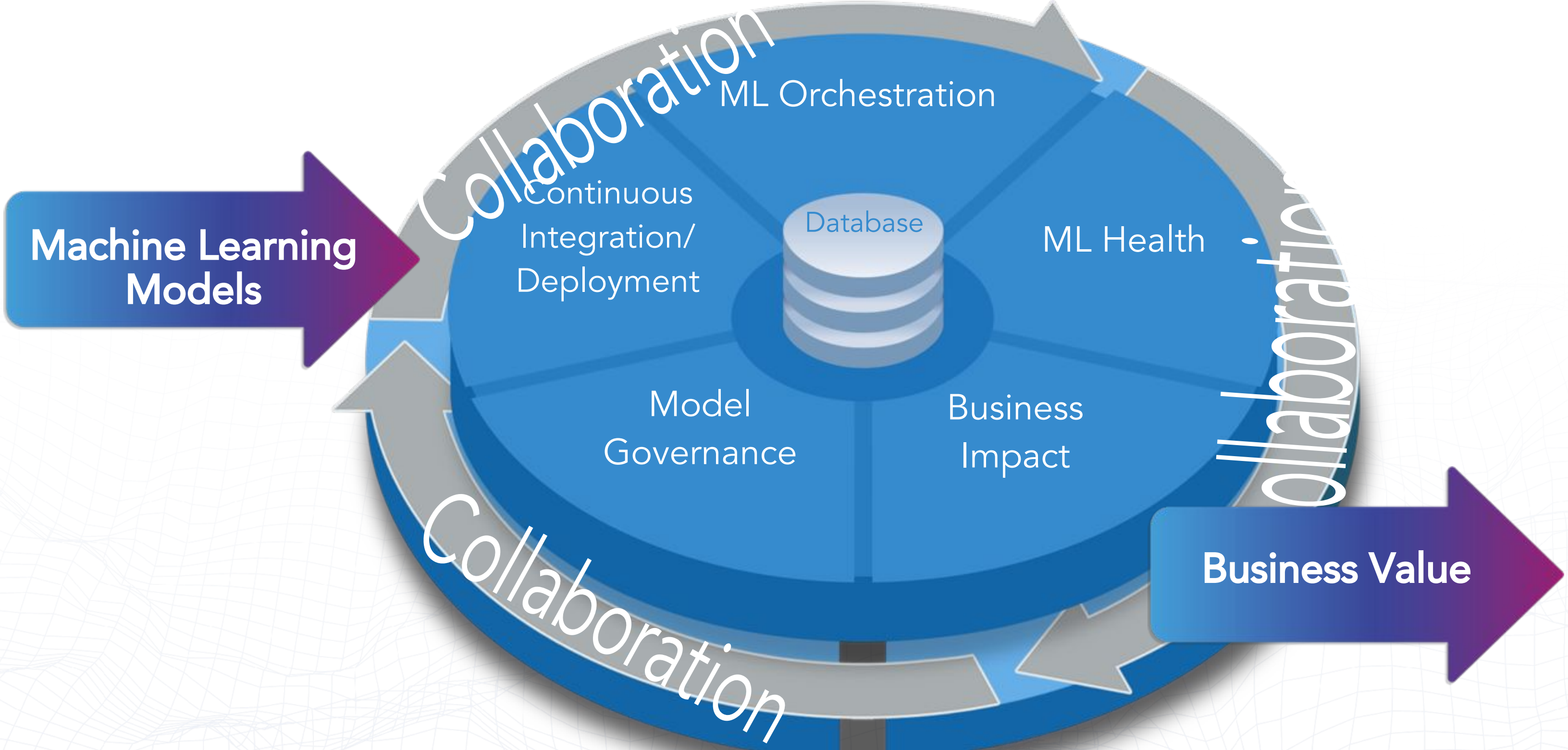
COLLABORATION

- Expertise mismatch between Data Science & Ops complicates handoff and continuous management and optimization

PROCESS

- Many objects to be tracked and managed (algorithms, models, pipelines, versions etc.)
- ML pipelines are code. Some approach them as code, some not
- Some ML objects (like Models and Human approvals) are not best handled in source control repositories

MLOps – Automating the Production ML Lifecycle



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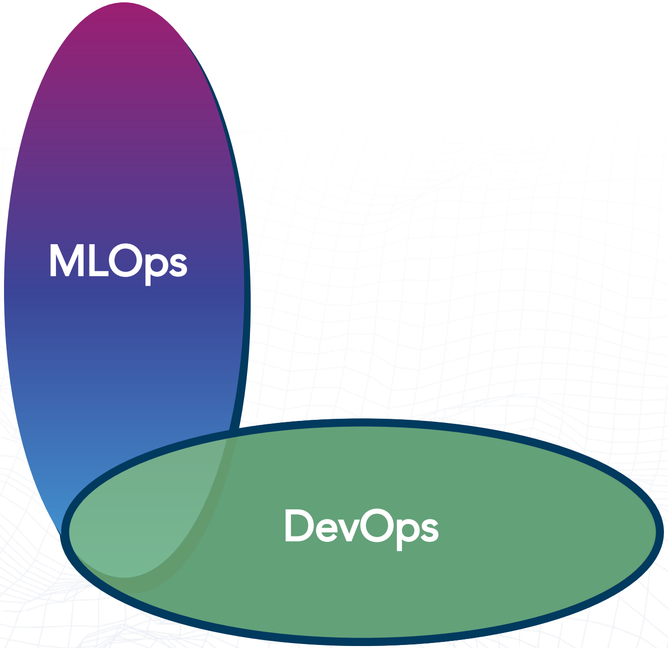
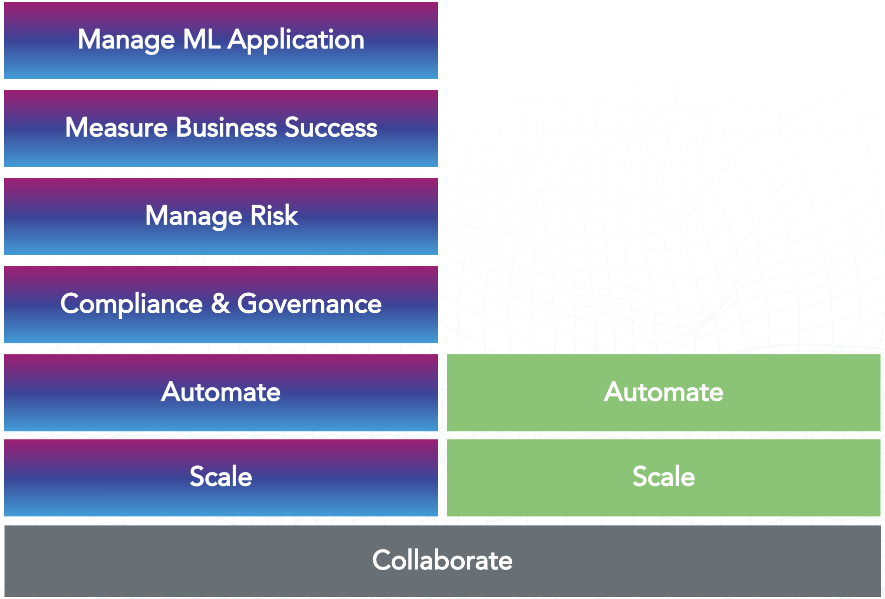
MLOps, DevOps and SDLC

- Integrate with SDLC (Source control repositories, etc.) for code
- Integrate with DevOps for Automation, Scale and Collaboration





Manage ML Application

Measure Business Success

Manage Risk

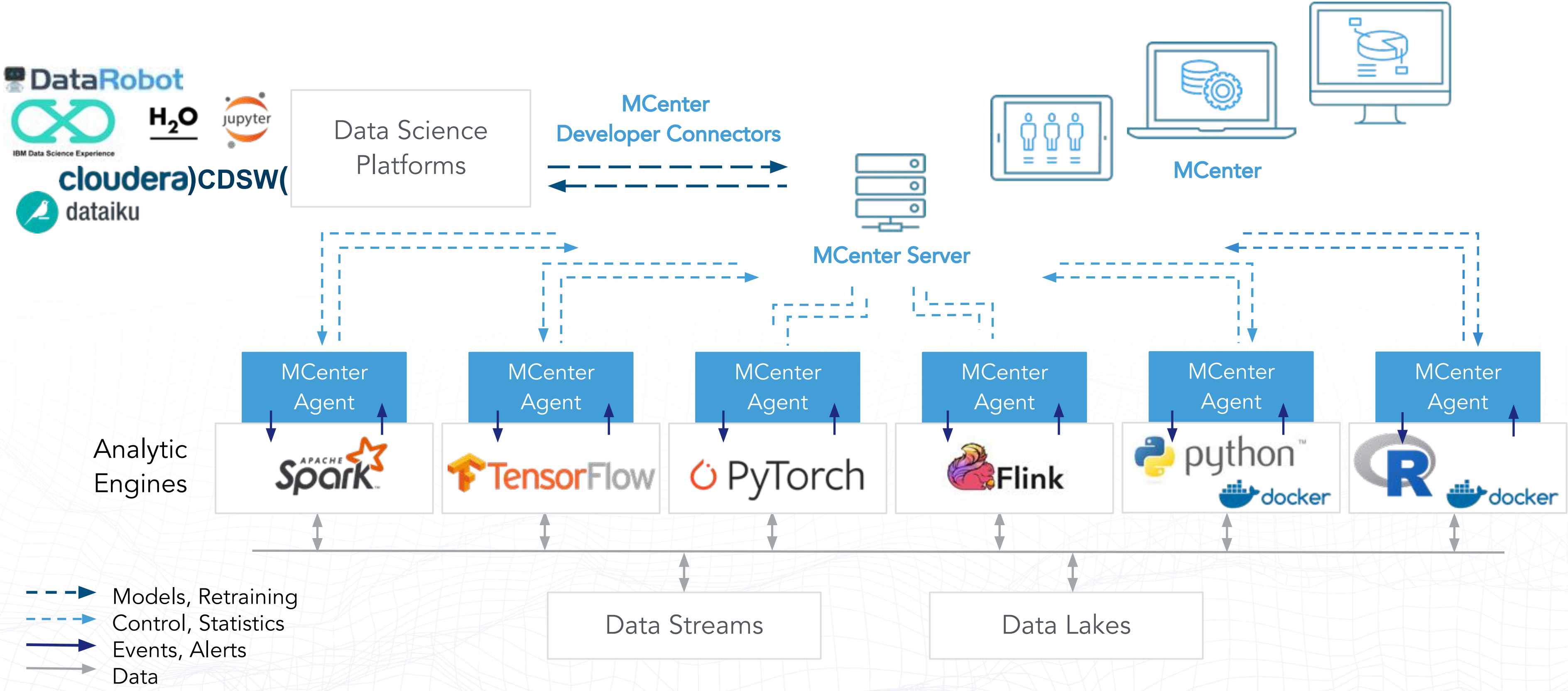
Compliance & Governance

Automate | Automate

Scale | Scale

Collaborate

How it Works – MCenter Architecture



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Summary

- We are at the beginnings of ML Operationalization
- Much like databases (backbone of production applications) need DBAs and software needs DevOps, ML needs MLOps (specialized operationalization practices, tools and training)
- For more information
  - https://www.mlops.org for MLOps resources
  - https://www.parallelm.com

Thank You

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Machine Learning Operationalization

Boris Tvaroska, Lenovo

Lenovo

MLOps: Machine Learning Operationalization

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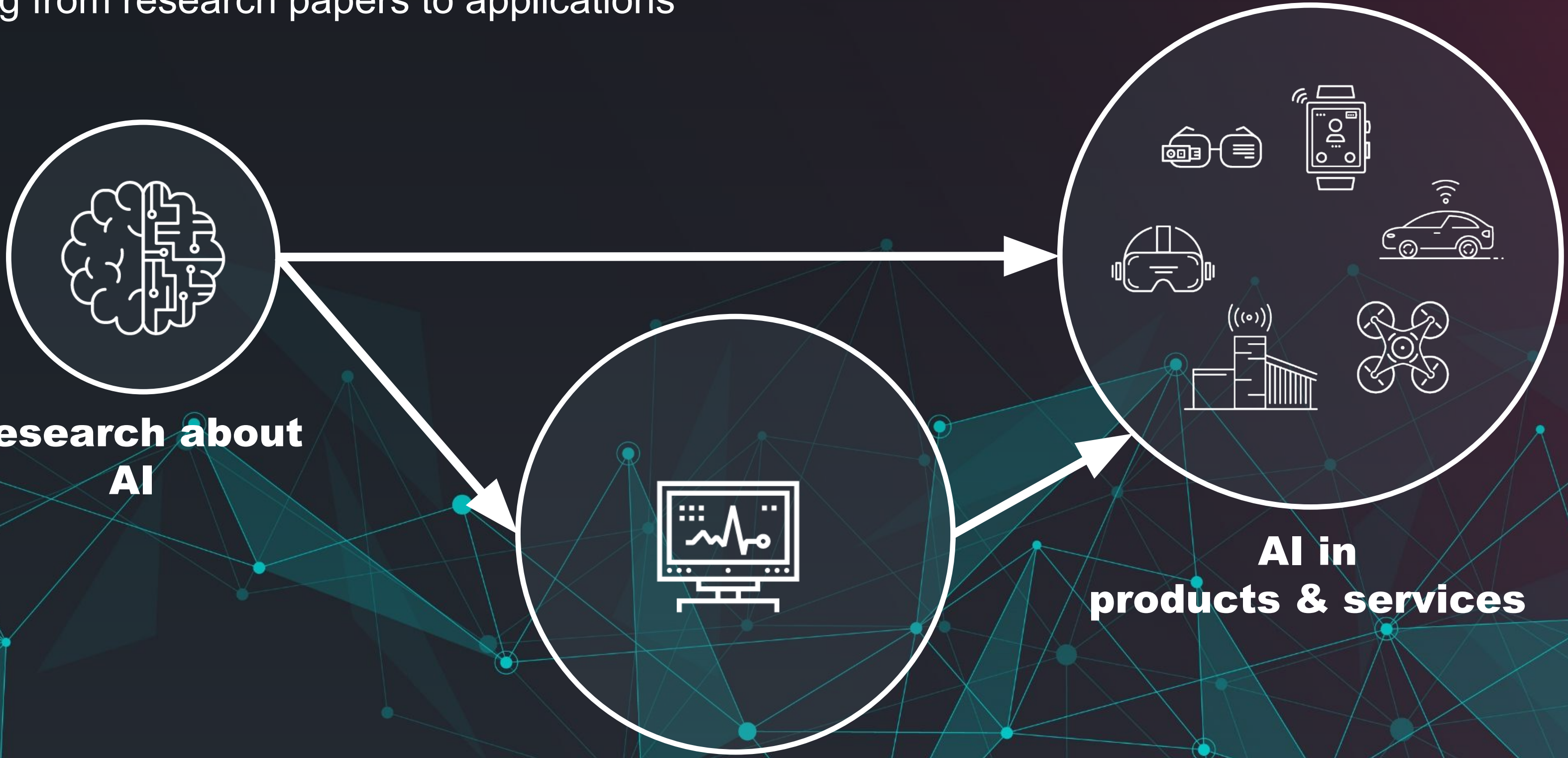
Integrating data science into SDLC

Boris Tvaroska

September 2018

Evolution of AI

Moving from research papers to applications



Research about AI

Reports using ML/DL

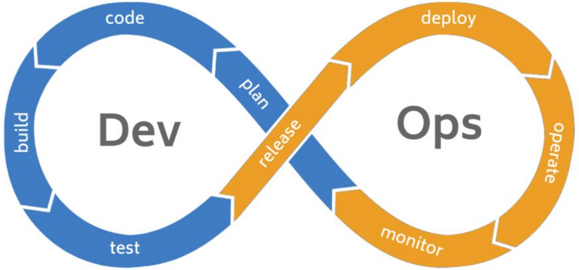
AI in products & services

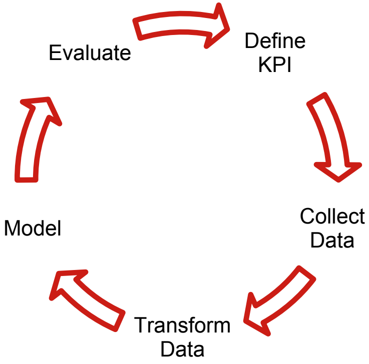
What can happen?

I did not change a single line of code.

Junior Software Engineer after breaking the build

Different lifecycles





- Starts with change in code
- Established practice
- Iterations in days / weeks

- Starts which change in code, data or metrics
- Emerging practice
- Iterations as fast as possible, several times per day

Main challenges

Test

- The wrong result is acceptable
- Need to test for False Positives
- Need to test for False Negatives

- Longer test times
- More test cases needed

Build & Deploy

- More artifacts to work with
- Frequent changes
- Versioning of artifacts and source data

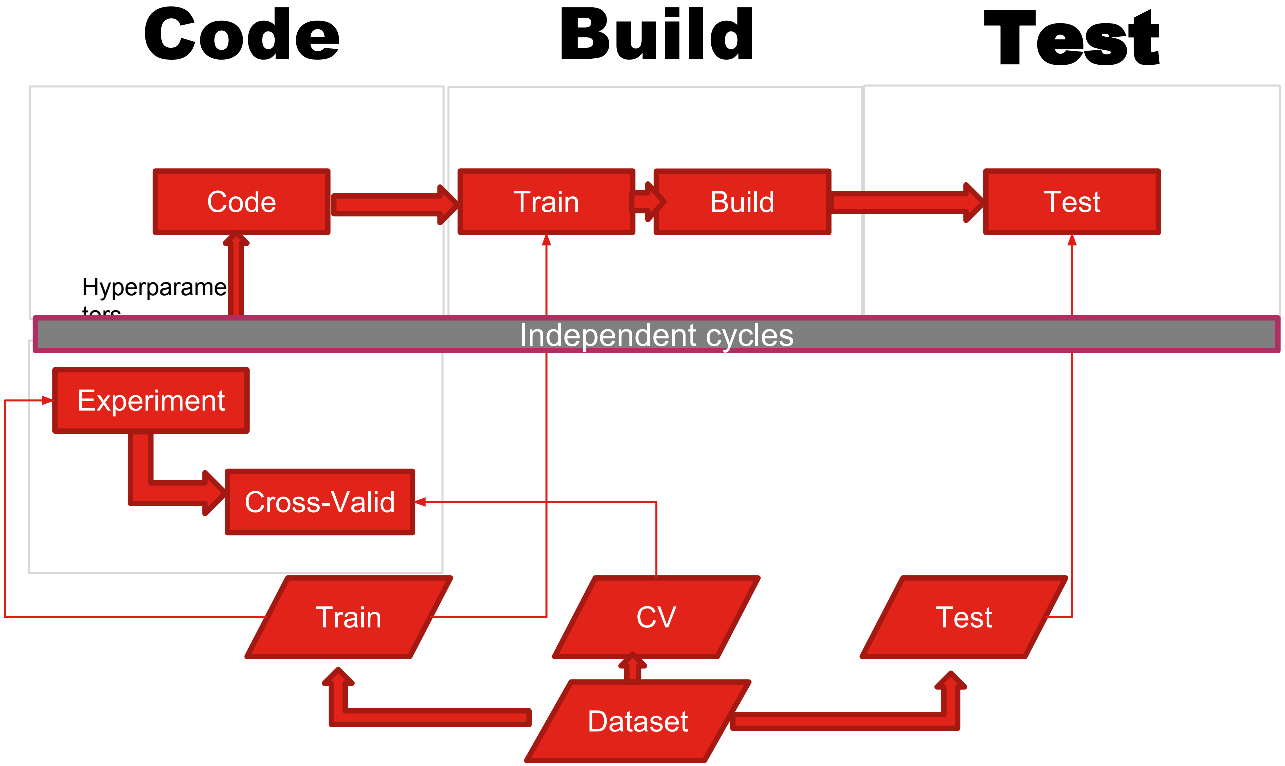
Training in test/build cycle

Possible for simple models with small amount of data

Existing toolset

Risks:

- Slow CI/CD cycle
- More failing builds



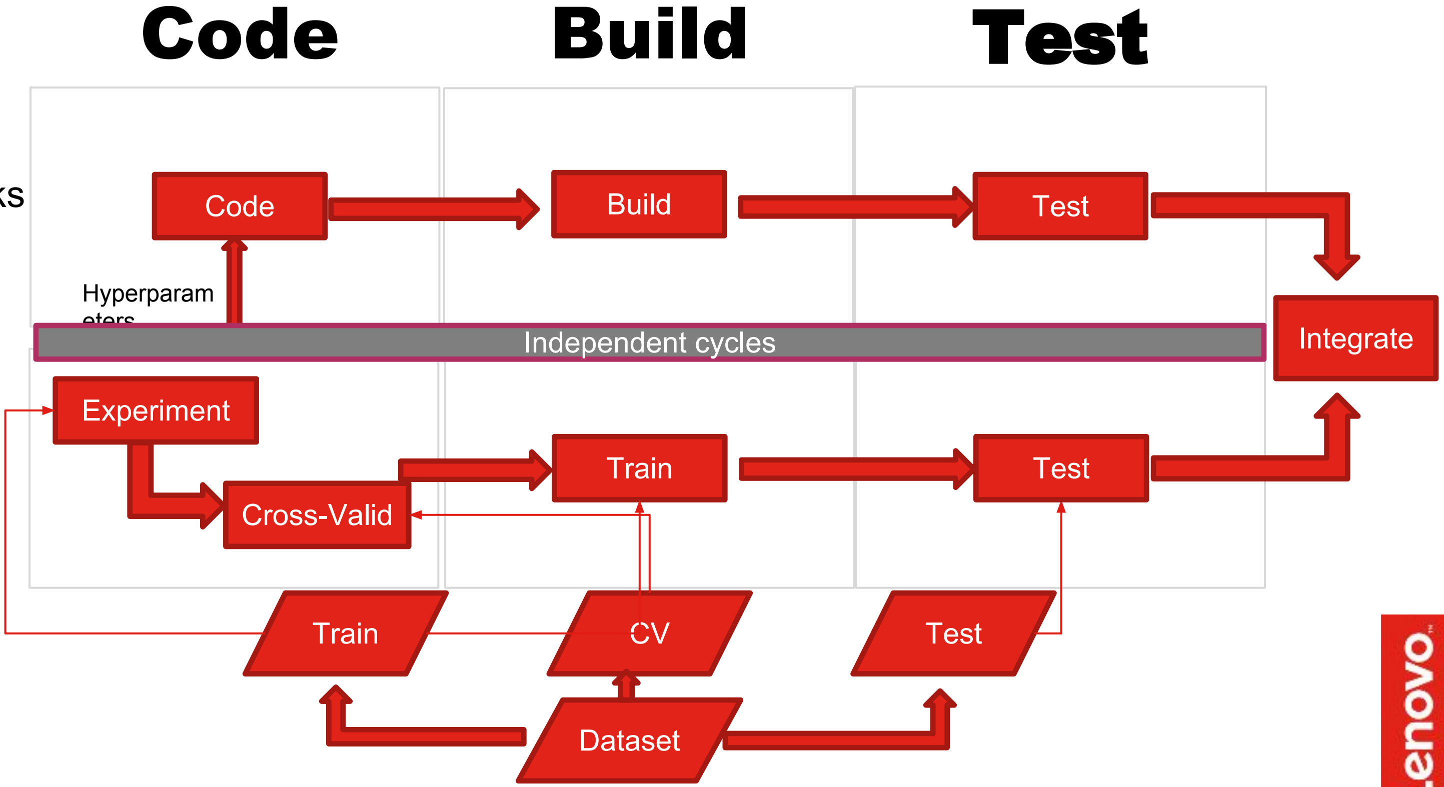
Model as a service

Model is independent

Fit languages/frameworks

Risks:

- Interface is vector
- Pre-mature service boundaries
- Multi-step application

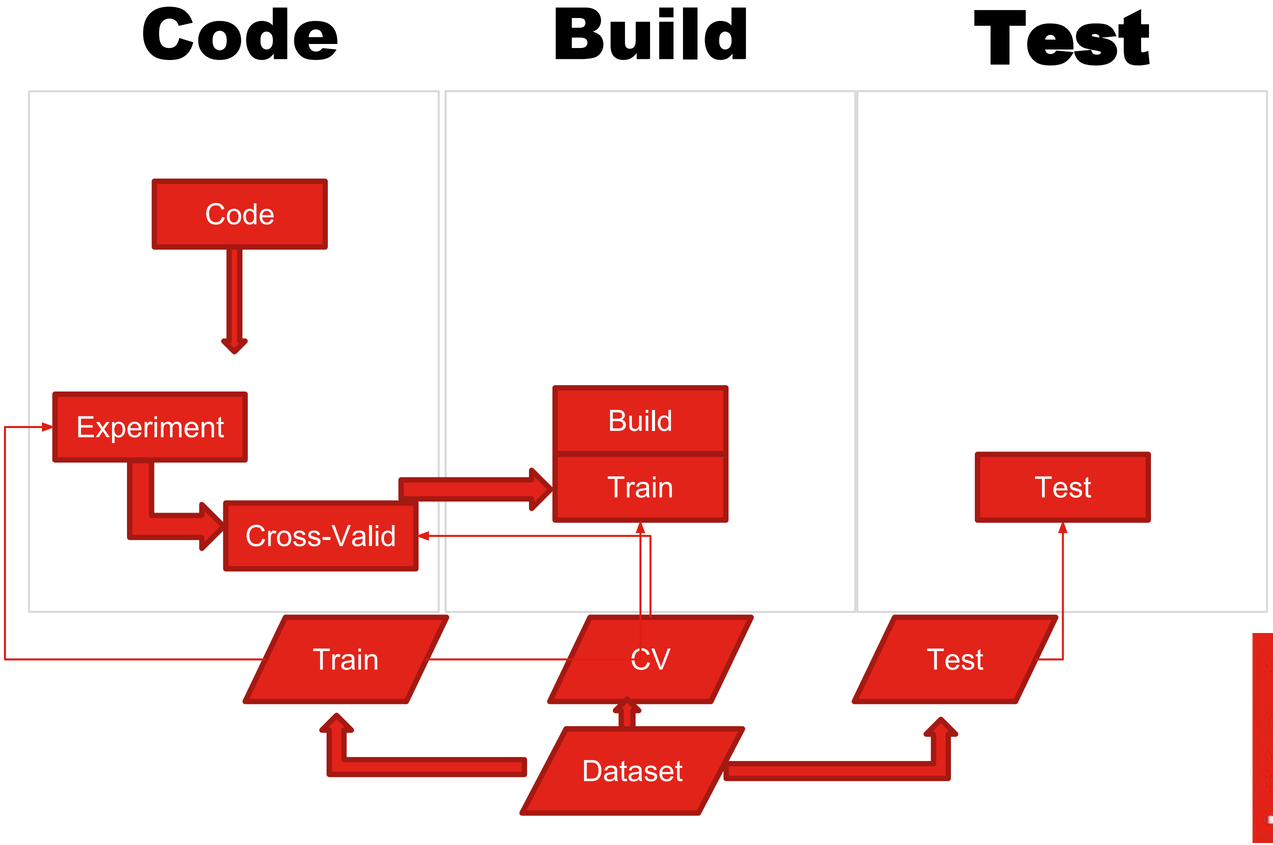


SW emerged in Data Science

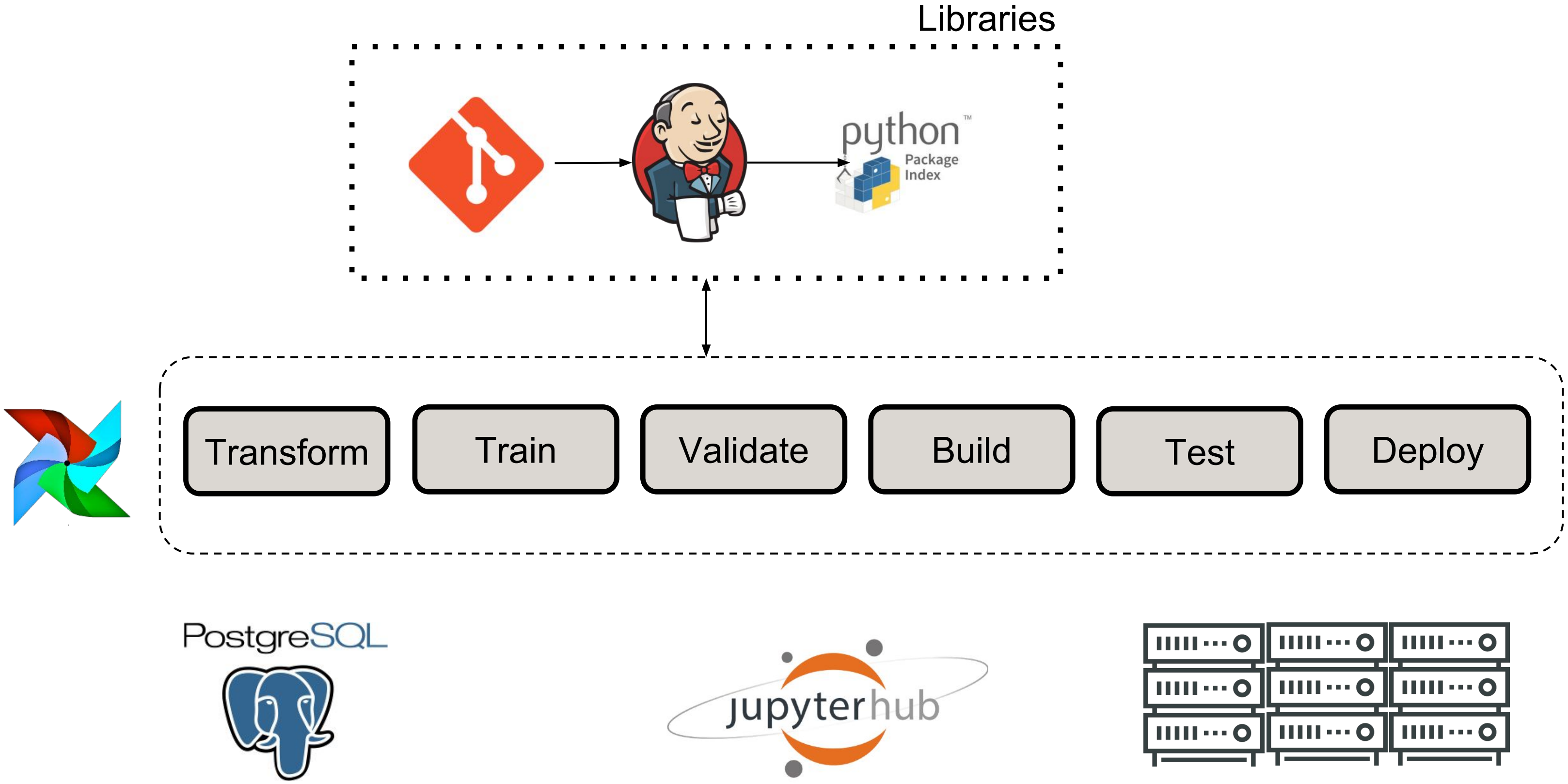
Clearly defined service

Data Science toolset
Data Science framework

Risks:
- Culture clash



Practical example



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Q & A

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Thank you to our panelists

- **Nisha Talagala**, Co-Founder, CTO & VP Engineering, *ParallelM*
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What’s Next

- Learn more about our Platform: https://www.activestate.com/platform

- Watch a demo: https://www.youtube.com/watch?v=c5AIxN9ehrI

- Contact platform@activestate.com for more information.

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Where to find us

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