Going from Science to Product Development

An Overview of MLOps for I-Os

Eras of Workforce Science

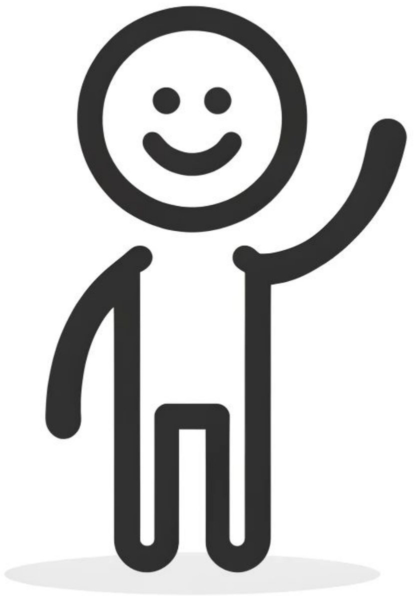
Traditional

Digitized

Productized

Impact of scaling science

Impact of one person



	Traditional 	Digitized 	Productized 
Output	Output of one person	10x Output	Output of hundreds of people
Error	Uncaught error	Uncaught errors spread	Uncaught errors compound dramatically
Bias	Bias of one person	Bias shared broadly	Bias systemically embedded

Introductions

Rob Stilson

HP

Employee Listening Program Manager

Derek Mracek

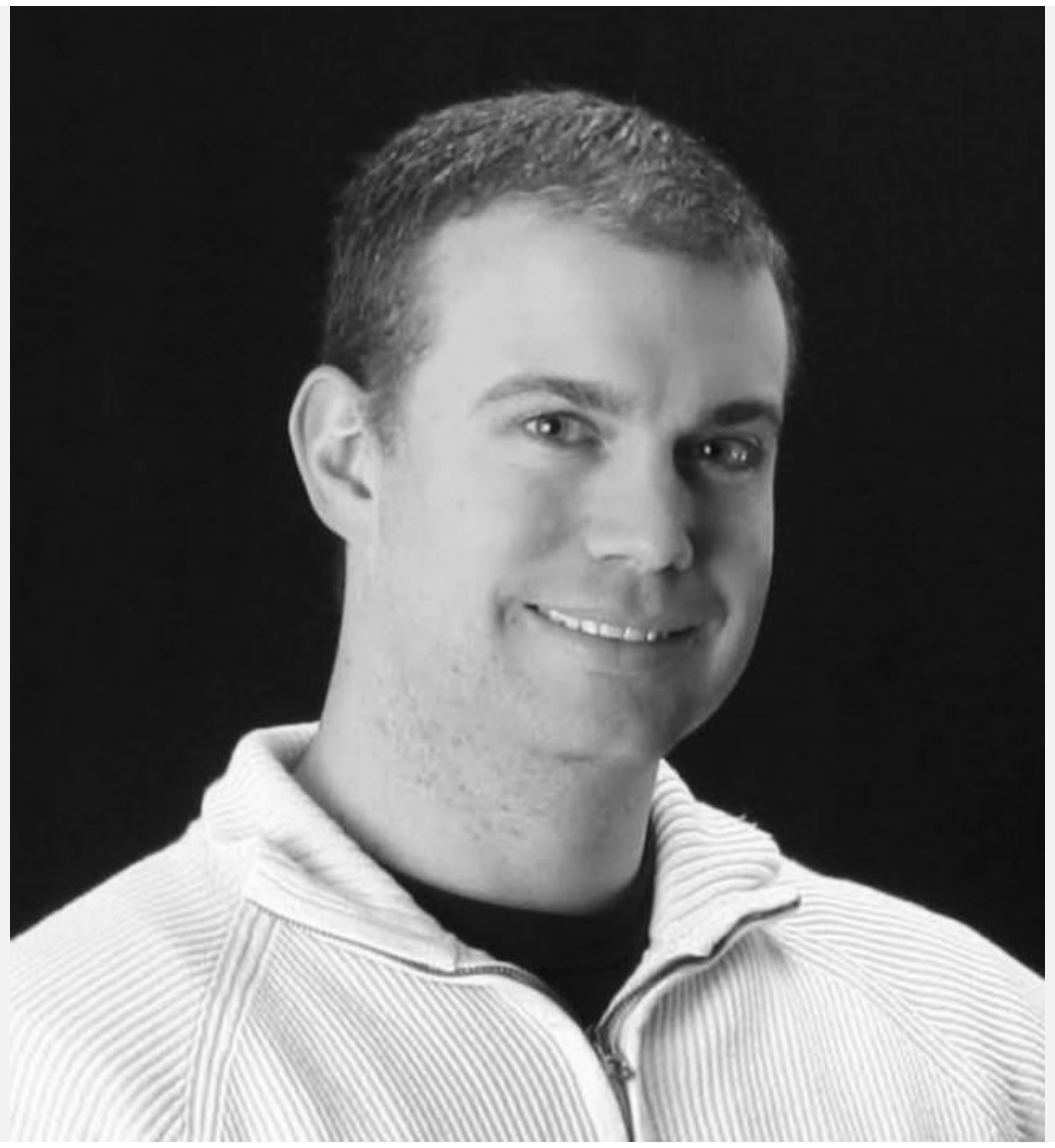
Association of American Medical Colleges

Manager, Analytics and Evaluation, R&D

Richard Rosenow

One Model

VP People Analytics Strategy

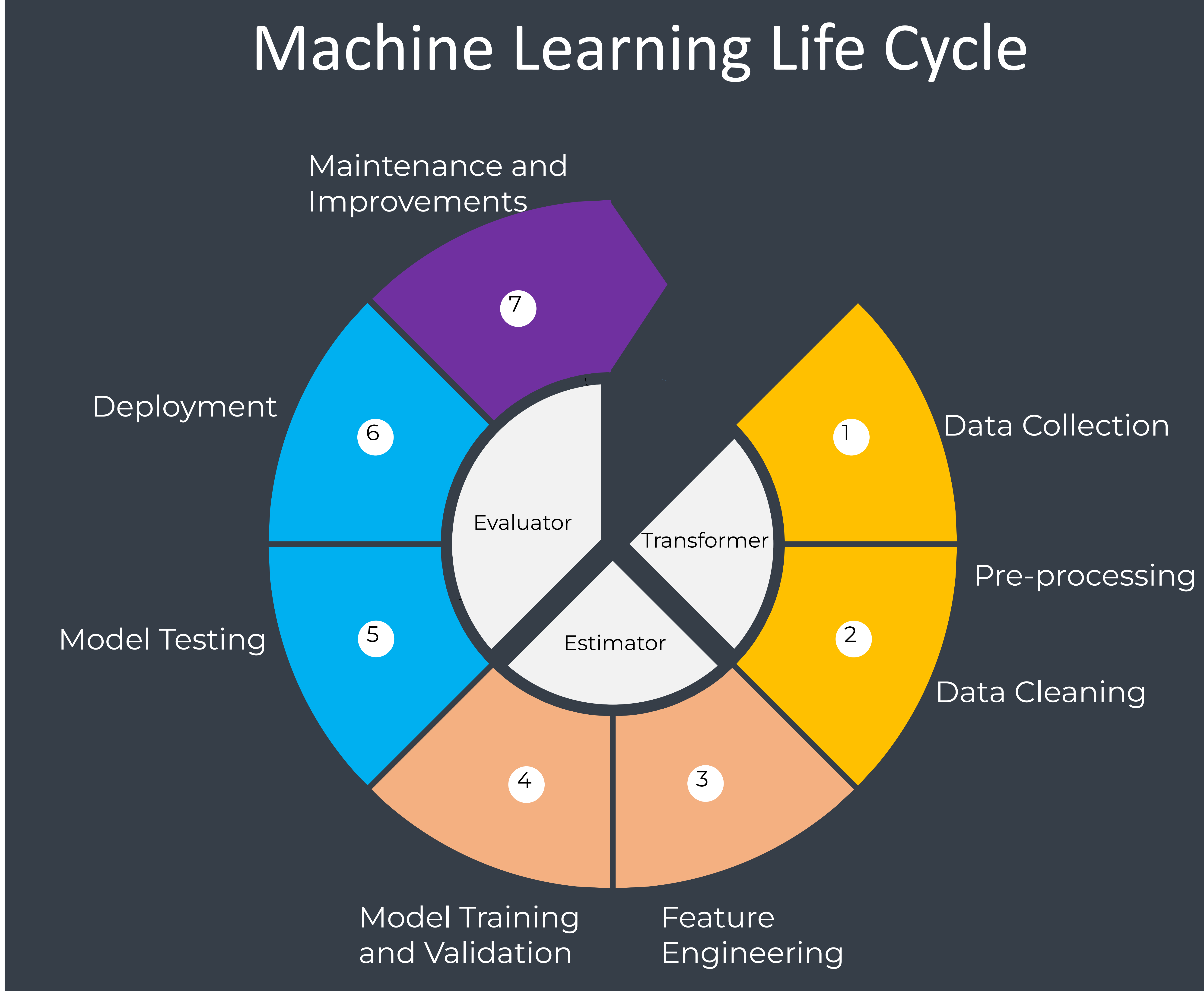


Overview

- Why do I-Os need to be involved in MLOps?
- Survey - Where are you currently on your journey?
- Machine Learning vs Machine Learning Operations
- 10 key definitions
- MLOps Lifecycle walk through
- Summary and wrap up
- Survey for future sessions

Why does MLOps need IO Psych?

- Human-Centric Design
- Bias Mitigation and Ethical AI
- Enhancing Team Dynamics
- Training and Development
- Change Management

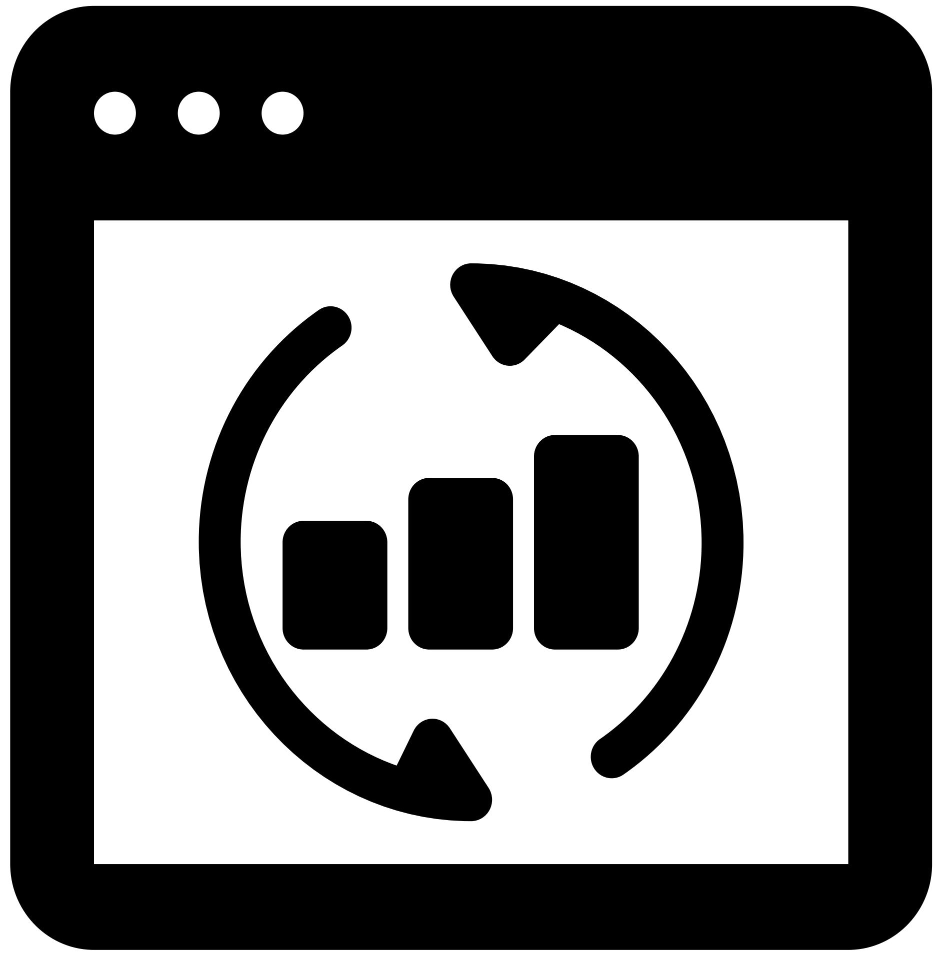


Where are you currently on your journey?

Please respond to the survey to let us know where you are in your MLOps journey

CHECK IN SURVEY

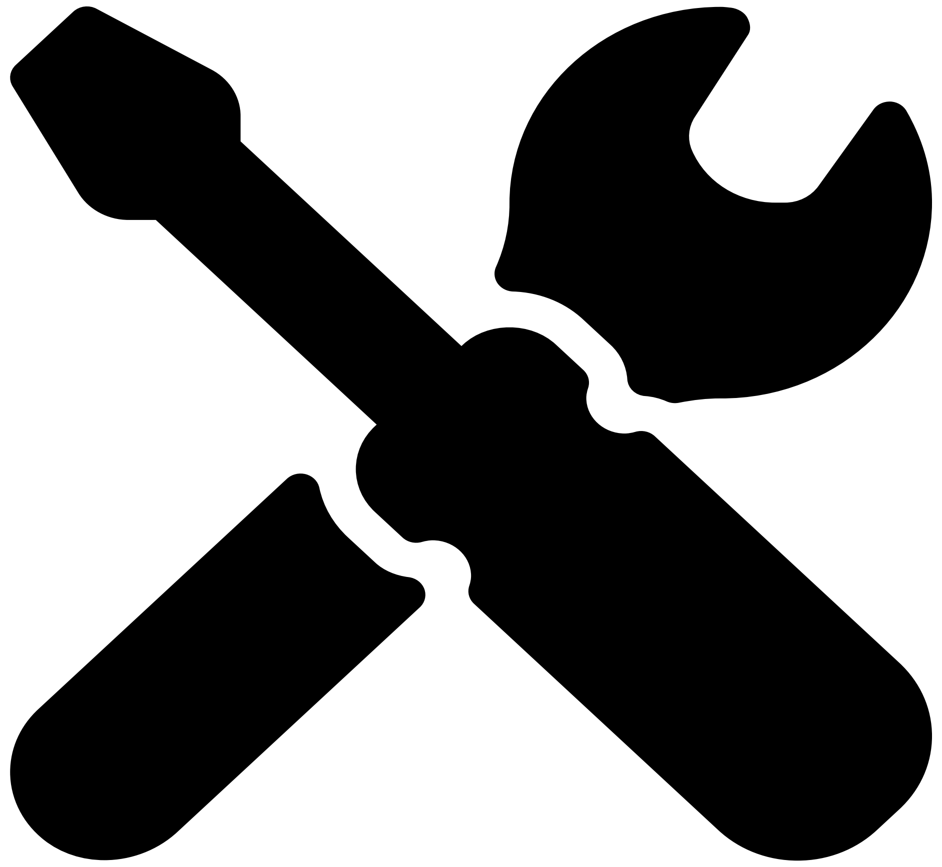
Machine Learning



Definition
Building and testing models

VS

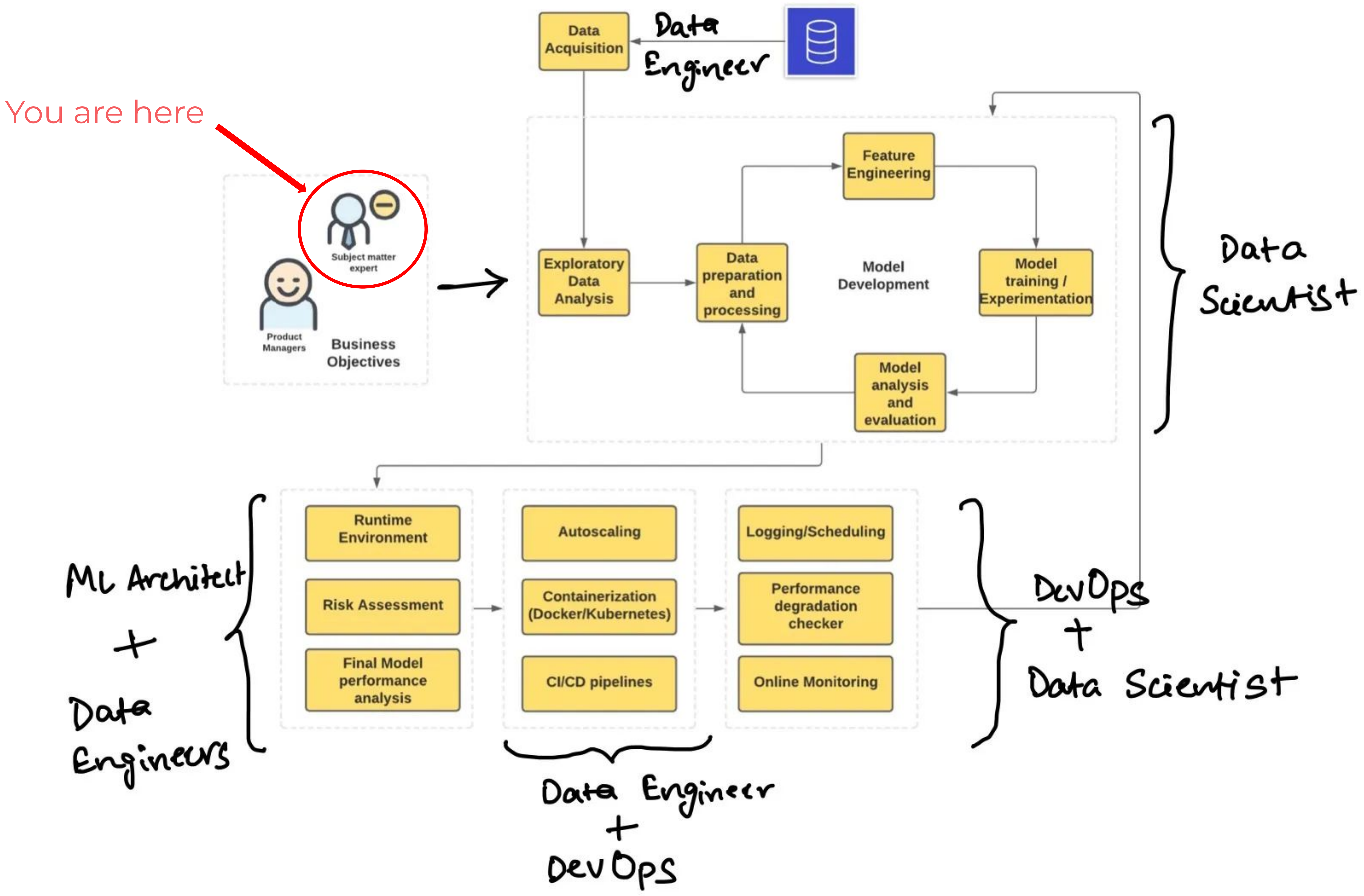
Machine Learning Operations



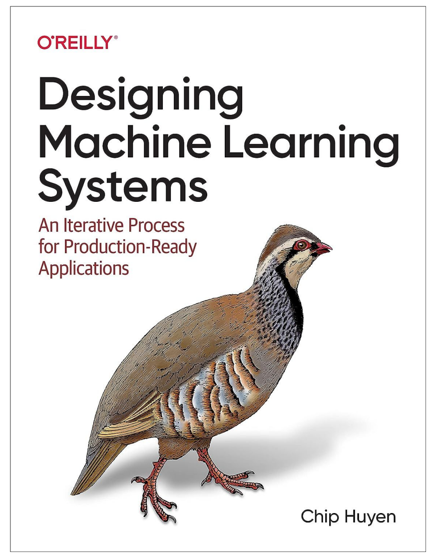
Definition
Deploying and maintaining models

Where in the world is the IO Psychologist?

ML Engineering & Operations



From: https://towardsdatascience.com/what-is-mlops-everything-you-must-know-to-get-started-523f2d0b8bd8



80/20 LIST OF TERMS AND TECH

1 MLOPS
Lifecycle of an ML project

2 ML Platform
Data | Model version control

3 Git
Code version control

4 CI/CD
Automate ML model integration and delivery, ensuring robust, efficient deployment and updates

5 Monitoring
Tracks model performance and health in production, enabling timely updates and adjustments

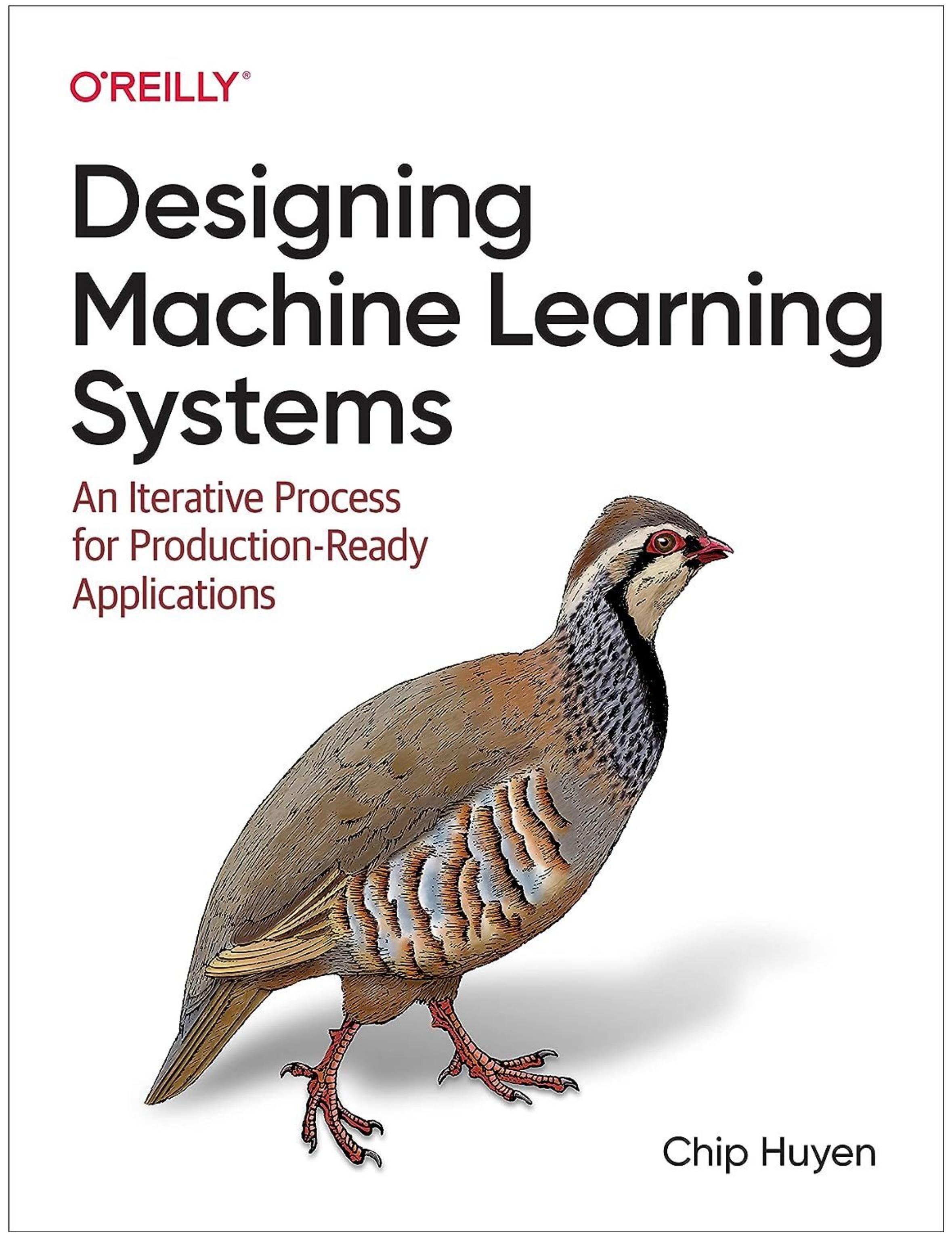
6 Concept Drift
"Same input, different output"

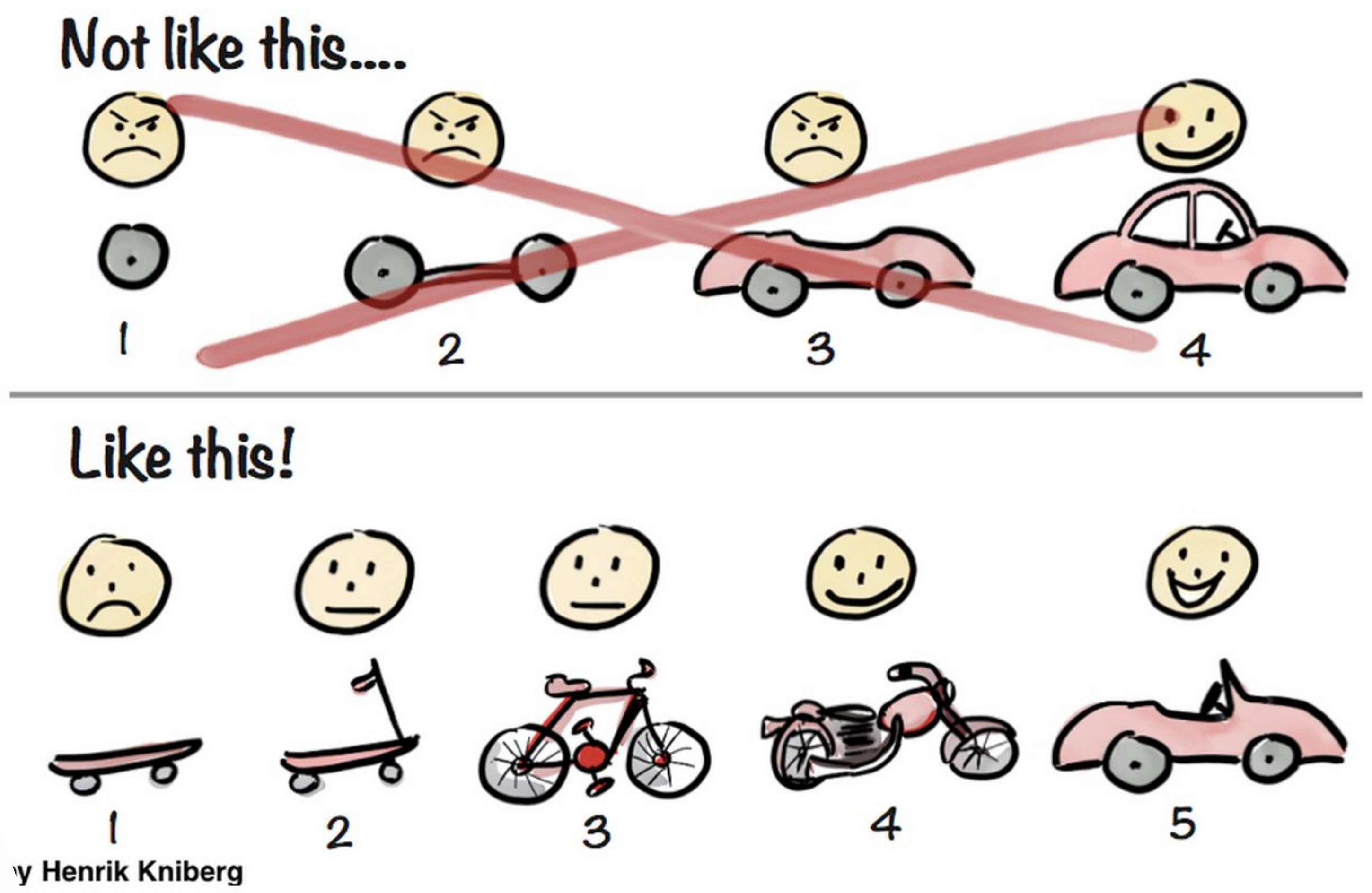
7 Containerization
Consistent environments

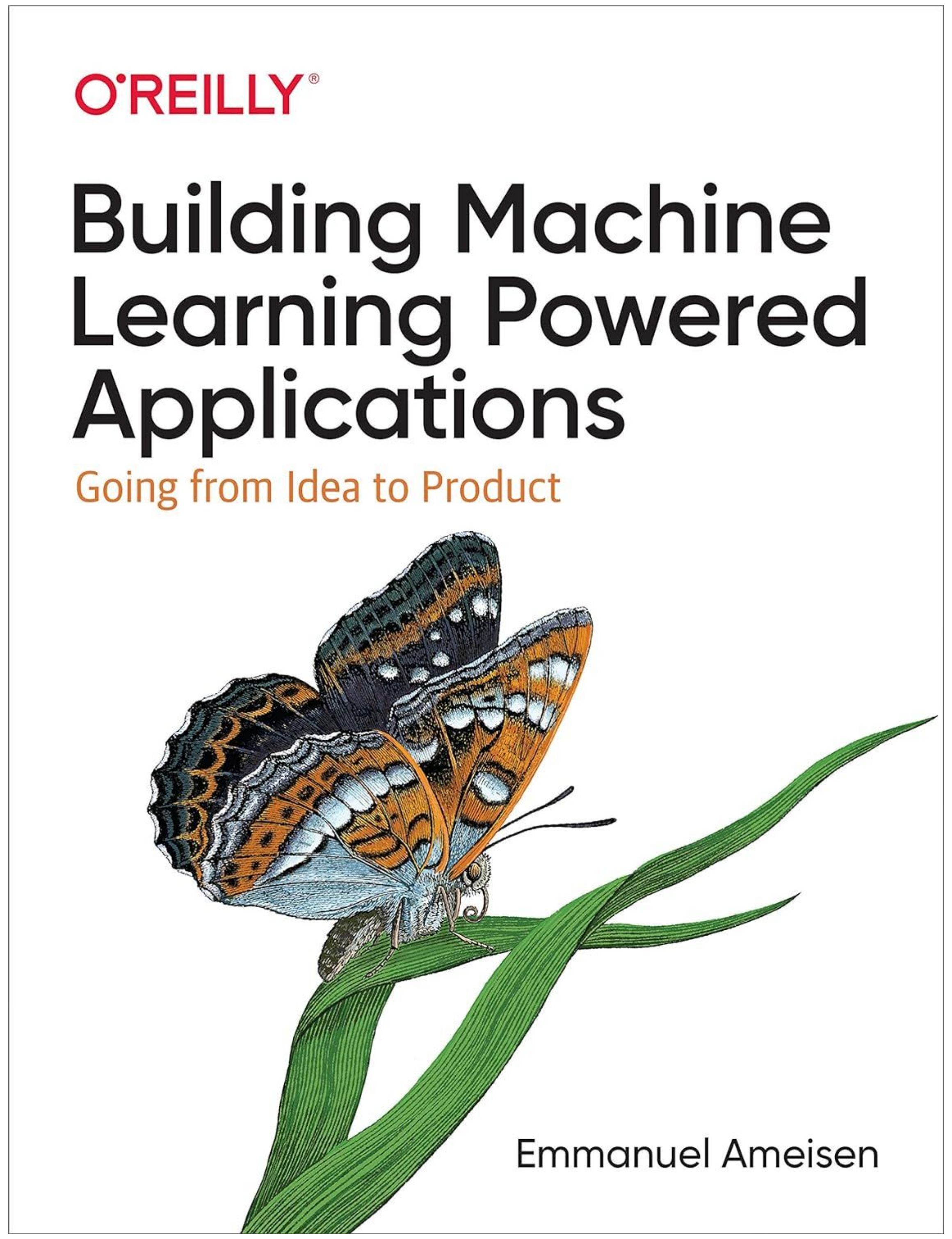
8 Config Files
YAML
TOML
JSON

9 FastAPI
Modern, fast web framework for building APIs with Python, emphasizing performance and ease of use

10 Pydantic
Data validation and settings management using Python type annotations, ensuring data quality and error handling







Chip is the leading voice on MLOPs

Skateboard Mindset in Product Development

2 ML Platform

MLOPs

- **Streamlined Workflow:** ML platforms integrate various stages of the ML lifecycle, from data preprocessing and model training to deployment and monitoring.
- **Data/Model/Version Control -** With built-in version control, experiment tracking, and model registries, these platforms simplify model management, allowing teams to track the evolution of their models, reproduce results, and adhere to governance standards.
- **Scalability -** These platforms are built to handle workloads of varying sizes, from small datasets and models to large-scale, enterprise-level applications. GPU vs CPU.
- **Collaboration across technical functions -** ML platforms often come with collaborative features that enable teams to work together seamlessly, sharing datasets, models, and insights. This enhances productivity and ensures a cohesive approach to model development and deployment.
- **Improved Deployment and Monitoring Capabilities -** ML platforms offer tools for easy model deployment and robust monitoring of model performance and health in production environments.

Science Product Development

- **Streamlined Workflow:** Less time spent on technical hurdles and more on applying our expertise to enhance model relevance and impact.
- **Data/Model/Version Control -** ML platforms can help provide evidence, now and later, to ensure that models are both scientifically robust and ethically sound.
- **Scalability -** As science-based models grow in sophistication, ML platforms ensure these can be deployed and managed efficiently, regardless of scale.
- **Collaboration across technical functions -** User-friendly interfaces lower the barrier for entry, ensuring models are accessible and understandable to all stakeholders, fostering a more inclusive approach to product development.
- **Improved Deployment and Monitoring Capabilities -** These tools not only facilitate the initial deployment of models but also support their ongoing evaluation and refinement in production environments, ensuring they continue to deliver real-world value over time.

METAFLOW

3 Git

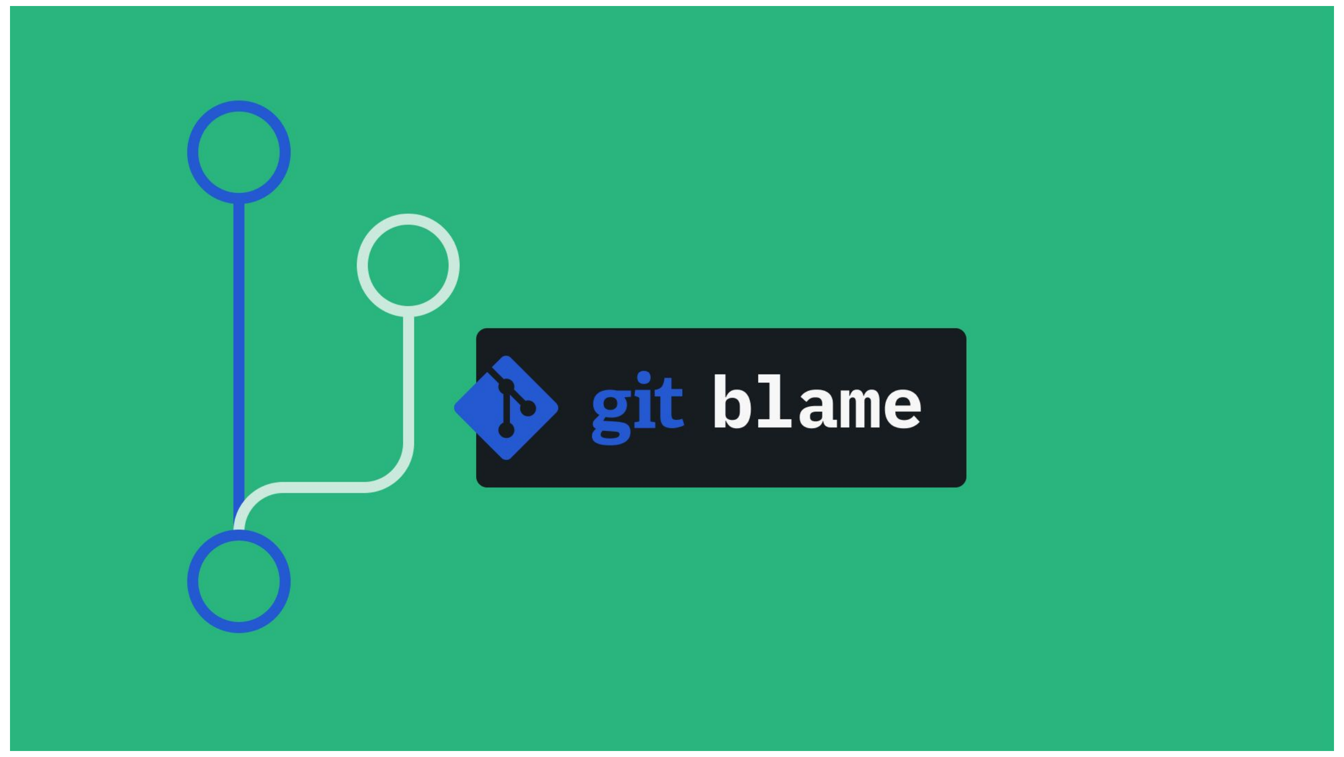
Version control software

MLOPs

- **Version Control and Collaboration-** It keeps track of changes in a repository, enabling teams to collaborate more efficiently by merging changes, resolving conflicts, and maintaining a comprehensive history of who did what and when.
- **Branching and Merging -** Peer review and visibility into what's going on with data scientists, and engineers.
- **Rollback Features -** Revert to previous versions of a project, making it easier to undo mistakes and recover from errors. This rollback feature is crucial for maintaining the stability and integrity of the codebase over time
- **Integration -** Allows for CI/CD
- **Enhanced Security -** Hashing tech ensures code integrity.

Science Product Development

- **Version Control and Collaboration -** Interdisciplinary collaboration as a cornerstone of successful MLOps implementation.
- **Branching and Merging -** Iterative model development and deployment, where new scientific insights or model improvements can be tested and refined without disrupting the ongoing operations.
- **Rollback Features -** Maintaining model accuracy and reliability in production is paramount
- **Integration -** Iterative model development and deployment
- **Enhanced Security -** Security is vital for ensuring that the transition from science to product development upholds the integrity and accountability standards necessary in I-O psychology applications.



Bitbucket

4 CI/CD

Automate ML model integration and delivery, ensuring robust, efficient deployment and updates

MLOPs

- **Automated Workflows -** Enhance collaboration and product development cycles.
- **Continuous Testing -** Don't break the software/product.
- **Consistent Deployments -** Spend time building features not troubleshooting why things are breaking.
- **Collaboration -** CI/CD promotes collaboration between developers and non-technical stakeholders.
- **Faster Feedback Loops -** Move fast. Users get access to new features and updates sooner. Agile mindset. Customer/stakeholder obsession.
- **Accelerate Innovation** - CI/CD can be your friend to test hypotheses and iterate much faster.

Science Product Development

- **Automated Workflows -** Have a seat at the table baking people science into products.
- **Continuous Testing -** Maintain the reliability and validity of models as they are deployed and updated in production environments.
- **Consistent Deployments -** Prioritize the development of impactful, science-driven features.
- **Collaboration -** Products are not only technically sound but can meet IO science.
- **Faster Feedback Loops -** Velocity in integrating new I-O psychology findings into products, ensuring that users benefit from the latest research.
- **Accelerate Innovation** - Reduce the time going from science to product.

5 Monitoring

Tracks model performance and health in production, enabling timely updates and adjustments

MLOPs

- **Performance Metrics Tracking -** Continuously tracking various performance metrics of, such as accuracy, precision, recall, and F1 score.
- **Resource Utilization and System Health -** System health where the model is deployed, including CPU and GPU utilization, memory consumption, disk I/O, and network bandwidth.
- **Latency and Throughput Measurements -** UX Metrics.
- **Error Rates and Exception Logging -** Exception logging helps in diagnosing and rectifying issues promptly.
- **Data Quality and Volume -** Checks for missing values, outliers, or changes in data distribution that fall within expected norms.

Science Product Development

- **Performance Metrics Tracking -** Maintaining the scientific integrity and applicability of the science in production.
- **Resource Utilization and System Health -** Efficient resource management to ensure the Science is both cost-effective and high-performing.
- **Latency and Throughput Measurements -** Tools meet the expectations of end-users.
- **Error Rates and Exception Logging -** Quickly troubleshoot minimizing impact on users and maintaining the credibility of the Science.
- **Data Quality and Volume -** Models deployed continue to reflect organizational realities accurately.

6 Concept Drift

"Same input, different output"

MLOPs

- **Necessitates Continuous Monitoring and Updating -** Continuously monitor for changes in data patterns and update accordingly to maintain their accuracy and reliability in real-world applications.
- **Underlines the Importance of Data Management -** Robust data management practices, allowing for the identification and integration of new data patterns into model retraining processes.
- **Emphasizes Agile Development and Deployment -** ML models may need to be updated frequently to respond to new data.
- **Highlights the Role of Cross-disciplinary Collaboration -** Addressing concept drift effectively requires expertise in data science, software engineering, and the specific domain, i.e., I-O psychology.
- **Advocates for Ethical Considerations and Fairness-** Concept drift can introduce or exacerbate biases in ML models, making the continuous evaluation of model fairness and ethical considerations essential.

Science Product Development

- **Necessitates Continuous Monitoring and Updating -** Ongoing vigilance for data changes and timely model updates to preserve model accuracy and applicability in dynamic organizational contexts.
- **Underlines the Importance of Data Management -** Models need to adapt to evolving organizational and workforce dynamics, necessitating sophisticated data management to identify and incorporate new data trends for model retraining.
- **Emphasizes Agile Development and Deployment -** Tools remain relevant and effective in the face of changing data landscapes.
- **Highlights the Role of Cross-disciplinary Collaboration -** Interpreti data changes and adjust models, ensuring that I-O principles are seamlessly integrated into the technical response to evolving data patterns.
- **Advocates for Ethical Considerations and Fairness-** Guide the ethical deployment and adjustment of models in response to changing data environments.

Drift Detectors from `Alibi Detect` Github Repo

Drift Detection

Detector	Tabular	Image	Time Series	Text	Categorical Features	Online	Feature Level
Kolmogorov-Smirnov	✔	✔		✔	✔		✔
Cramér-von Mises	✔	✔				✔	✔
Fisher's Exact Test	✔				✔	✔	✔
Maximum Mean Discrepancy (MMD)	✔	✔		✔	✔	✔	
Learned Kernel MMD	✔	✔		✔	✔		
Context-aware MMD	✔	✔	✔	✔	✔		
Least-Squares Density Difference	✔	✔		✔	✔	✔	
Chi-Squared	✔				✔		✔
Mixed-type tabular data	✔				✔		✔
Classifier	✔	✔	✔	✔	✔		
Spot-the-diff	✔	✔	✔	✔	✔		✔
Classifier Uncertainty	✔	✔	✔	✔	✔		
Regressor Uncertainty	✔	✔	✔	✔	✔		

7 Containerization

MLOPs

- **Ensures Consistency Across Environments -** Containerization encapsulates the model and its dependencies in a single package, ensuring that it runs consistently across different computing environments.
- **Simplifies Model Deployment -** Containers can be easily moved, started, stopped, and managed across environments.
- **Facilitates Collaboration and Version Control: -** See Git
- **Enhances Scalability and Performance -** Containers can be quickly scaled up or down based on demand, offering a practical solution to scalability challenges.
- **Promotes Reproducibility of Research -** Containers promote reproducibility in transitioning from scientific models to products by providing a standardized environment that precisely replicates the setup in which the original model was developed and validated.

Science
Product Development

- **Ensures Consistency Across Environments -** This helps with the challenge of moving a validated scientific model into a production environment without performance degradation or unexpected behavior
- **Simplifies Model Deployment -** By containerizing ML models, scientists and technologists can simplify the deployment process.
- **Facilitates Collaboration and Version Control: -** See Git
- **Enhances Scalability and Performance -** Thus, ML models can handle varying loads efficiently, a key consideration for scientists looking to deploy robust and responsive applications.
- **Promotes Reproducibility of Research -** This ensures that the scientific integrity of the model is maintained when moving to production, addressing potential concerns about the fidelity and effectiveness of the deployed model.

8 Config Files

YAML | TOML | JSON

MLOPs

- **Facilitates Model Configuration and Deployment -** Config files enable easy setup and management of model parameters, environments, and deployment settings. This simplifies the process of moving machine learning models from the development phase to production.
- **Enhances Reproducibility and Scalability -** By standardizing model configurations and environment setups, config files contribute to the reproducibility of machine learning experiments.
- **Promotes Collaboration Across Disciplines -** The use of config files can demystify the operational aspects of machine learning models for non-technical stakeholders, including I-O psychologists.
- **Streamlines Model Tuning and Experimentation -** Config files allow for easy adjustments to model parameters and experimentation setups, enabling rapid iteration and tuning of models.
- **Supports Best Practices in MLOps Pipelines -** The use of config files is a best practice in MLOps for managing complex workflows, from data preprocessing to model deployment and monitoring. They help in codifying and automating MLOps pipelines, ensuring that the transition from science to product development is as smooth and efficient as possible.

Science
Product Development

- **Facilitates Model Configuration and Deployment -** Adjust model configurations without diving deep into the code, thus bridging the gap between research and operational deployment.
- **Enhances Reproducibility and Scalability -** This is crucial for maintaining the integrity and reliability of scientific findings as they are translated into products. Moreover, they support scalability by facilitating the deployment of models across different environments and platforms.
- **Promotes Collaboration Across Disciplines -** Demystification fosters cross-disciplinary teamwork between data scientists, engineers, and scientists, ensuring that everyone can contribute to and understand the model's deployment and operation,
- **Streamlines Model Tuning and Experimentation -** This agility is essential for translating scientific research into effective products, as iterative improvements based on real-world feedback and data are key to the development process.
- **Supports Best Practices in MLOps Pipelines -** Config files act as a bridge, enabling I-O psychologists to apply their scientific expertise within the operational framework of MLOps to develop impactful, data-driven products.

9

FastAPI

Modern, fast web framework for building APIs with Python, emphasizing performance and ease of use

MLOPs

- **High Performance -** FastAPI's high performance ensures that ML models can handle high volumes of requests efficiently – and in PYTHON.
- **Rapid Development -** FastAPI facilitates quick development of RESTful APIs, crucial for deploying machine learning models developed by I-O psychologists.
- **Data Validation and Serialization -** FastAPI uses Pydantic for data validation and serialization, ensuring the integrity and security of data being processed and served by ML models.
- **Ease of Learning and Collaboration -** Extensive documentation and community support.
- **Automatic Interactive Documentation -** The automatic documentation with Swagger UI and ReDoc, simplifies the process of testing, understanding, and interacting with the ML models.

Science
Product Development

- **High Performance -** FastAPI applications can serve organizational needs without latency or downtime – and in PYTHON.
- **Rapid Development -** This helps to move from analytical or scientific models to tangible products that impact organizational outcomes.
- **Data Validation and Serialization -** This is key for scientists who are concerned with the ethical and accurate application of their models.
- **Ease of Learning and Collaboration -** This encourages scientists to directly engage with the deployment process, facilitating a better understanding of how our scientific work translates into operational products.
- **Automatic Interactive Documentation -** This supports clear communication and collaboration between scientists, developers, and stakeholders, ensuring the deployed models are easily accessible and usable.

10 Pydantic

Data validation and settings management using Python type annotations, ensuring data quality and error handling

MLOPs

- **Type Hint Integration -** Ensures strict data validation and compatibility with static typing tools like mypy. This integration is pivotal for maintaining data integrity throughout the MLOps lifecycle, from model training to deployment.
- **High Performance -** Enables fast apps and deployments of ML models.
- **Flexible Serialization -** Easily convert complex data structures into a format suitable for ML workflows with Pydantic aids in the seamless training, evaluation, and deployment of models.
- **Strict Mode and Data Coercion -** Ensure the consistency and quality of data, a cornerstone for the reproducibility and reliability of ML experiments and deployments.
- **Ecosystem-** Sequoia.

Science Product Development

- **Type Hint Integration -** Bridge the gap between scientific models and operational products. Ship it!
- **High Performance -** It's in Python and is performant. Scientists love Python.
- **Flexible Serialization -** This flexibility is crucial for operationalizing scientific models and creating practical, impactful tools within organizations.
- **Strict Mode and Data Coercion -** Science can withstand scrutiny in diverse operational environments.
- **Ecosystem-** Scientists can use the best available technologies going from science to product(ion).

1. DATA PREPARATION

Overview:

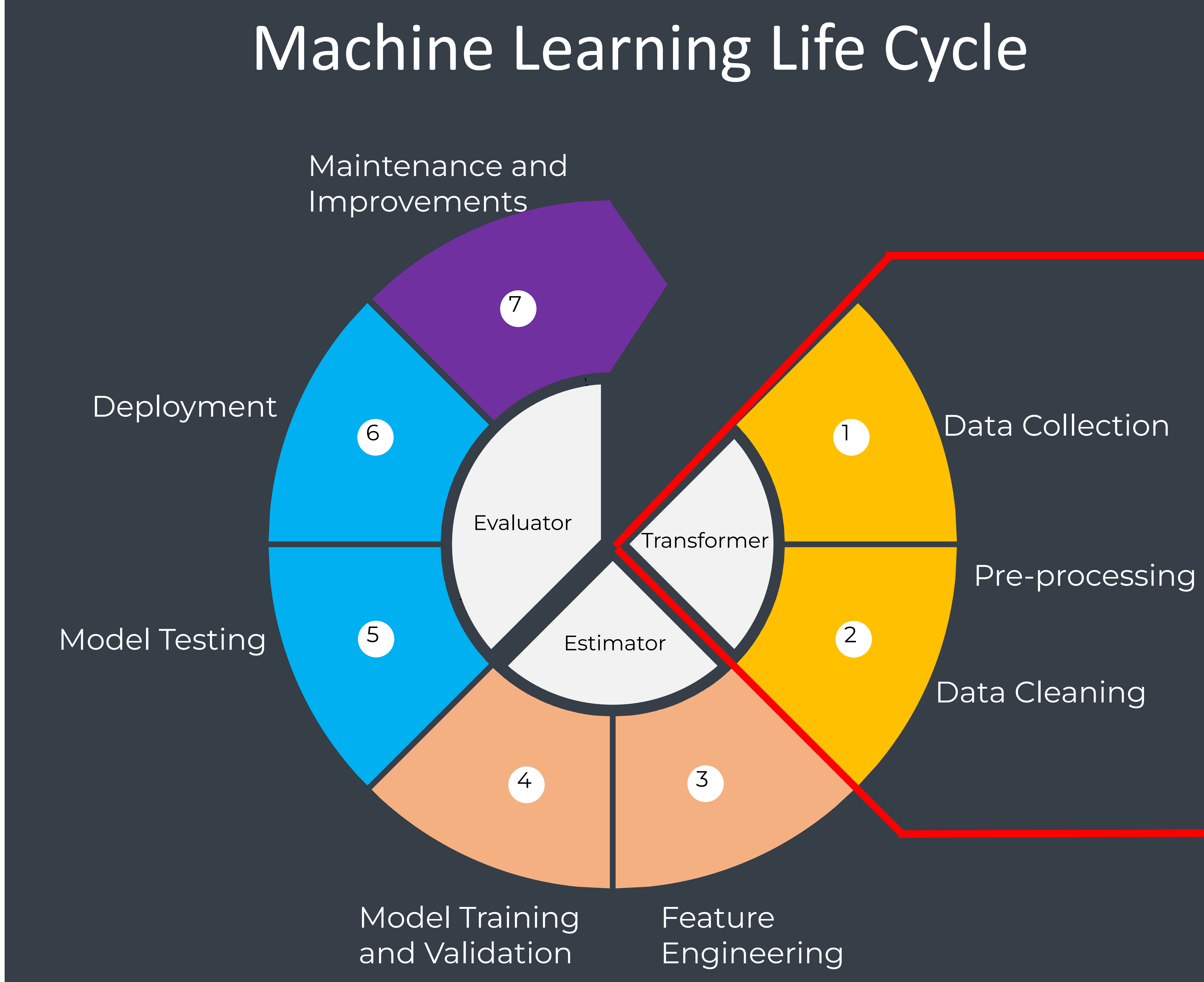
Data preparation involves collecting, cleaning, and transforming raw data into a format suitable for modeling

Example:

Consolidating survey responses and demographic information for predictive employee turnover models

Where the I-O fits in:

I-Os apply psychological principles to ensure data relevance and mitigate biases in workforce analytics



2. MODEL TRAINING

Overview:

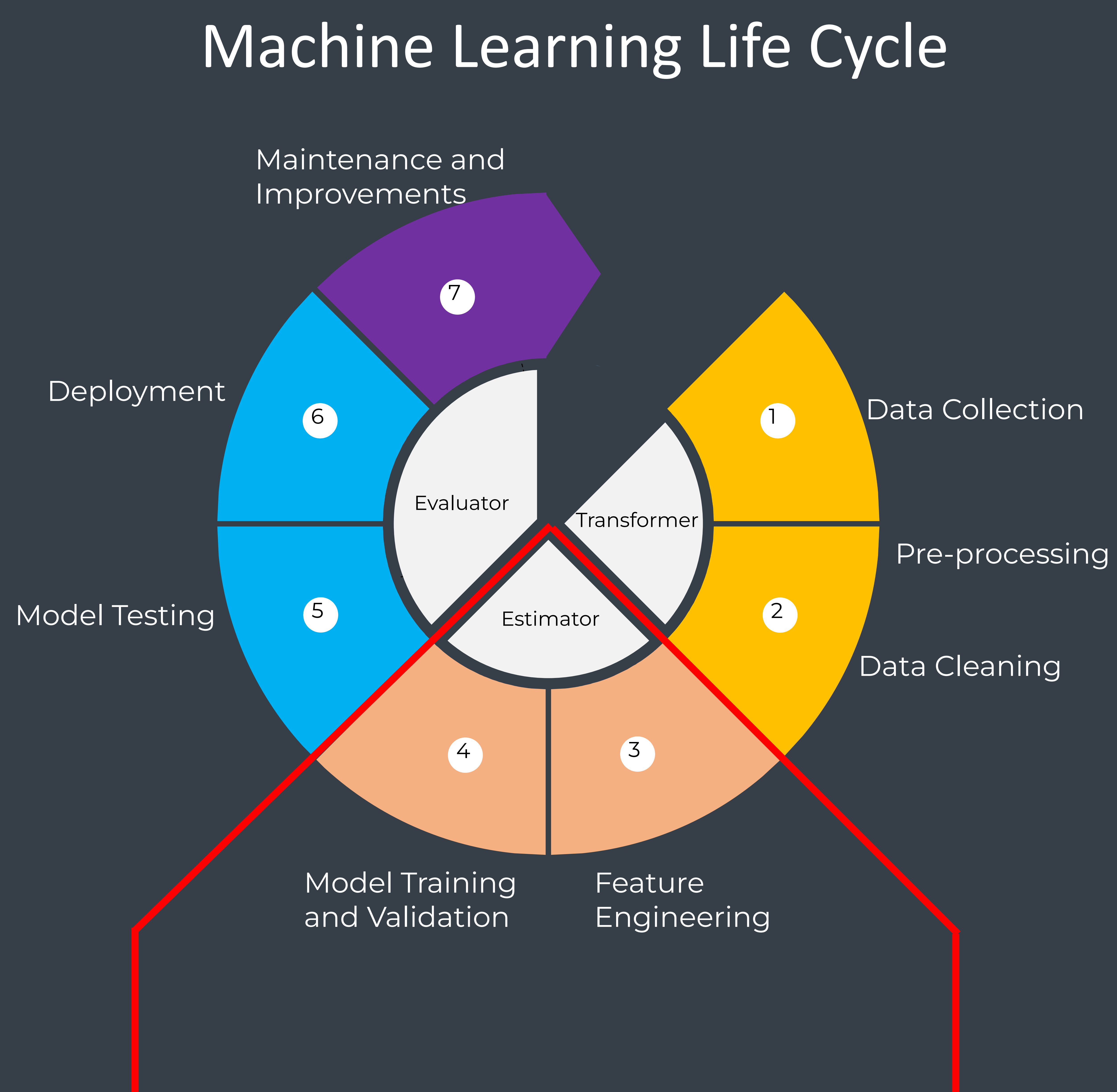
Training involves using prepared data to teach models to make predictions or decisions

Example:

Utilizing regression analysis on employee data to forecast performance outcomes

Where the I-O fits in:

I-Os refine training criteria to align with organizational psychology metrics and outcomes



3. DEPLOYMENT

Overview:

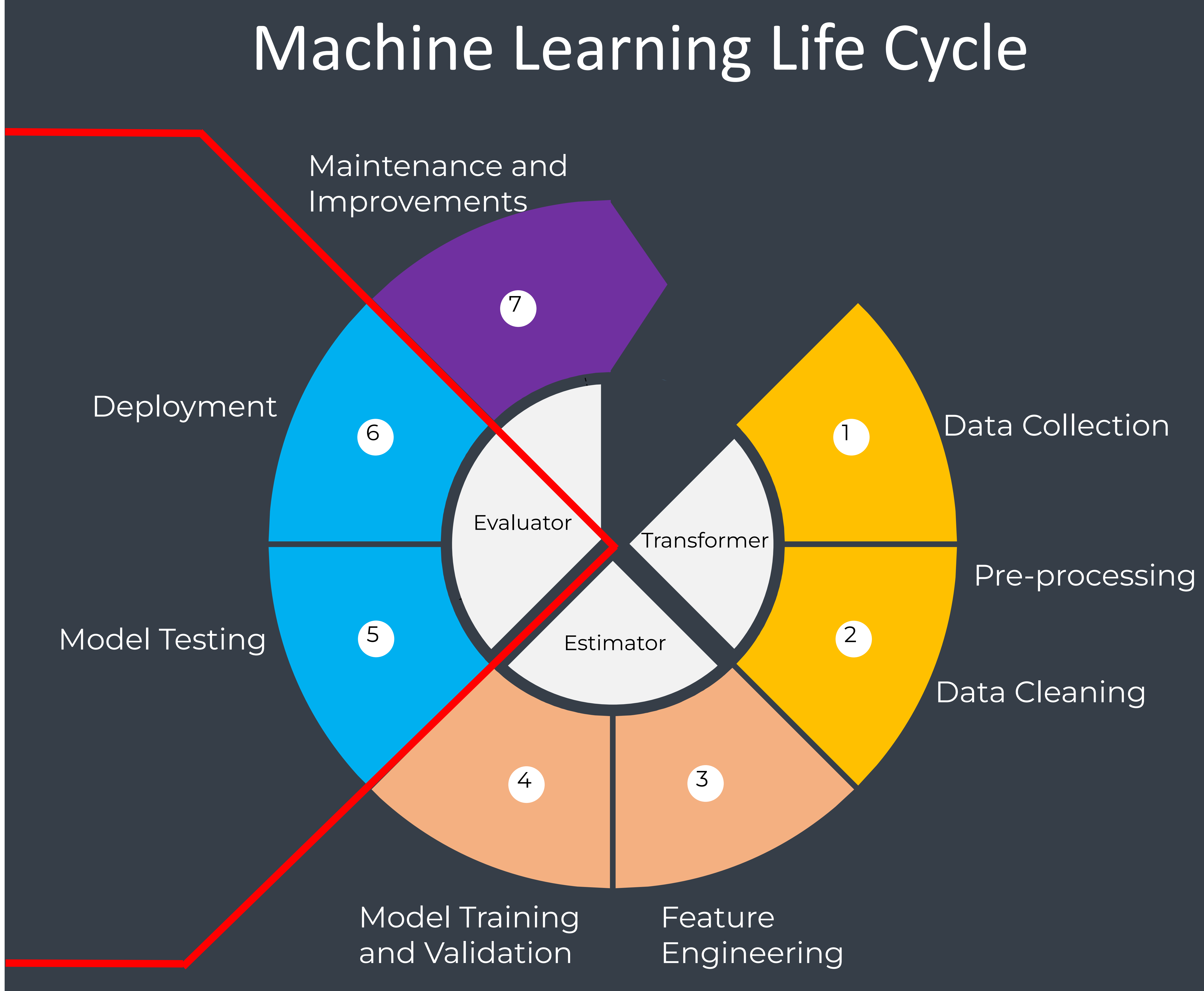
Deployment is launching a trained model into production for practical use

Example:

Implementing a churn prediction model into HR systems for real-time analysis

Where the I-O fits in:

I-Os evaluate long-term impact on workforce dynamics, suggesting improvements for sustained effectiveness



4. MONITORING & MAINTENANCE

Overview:

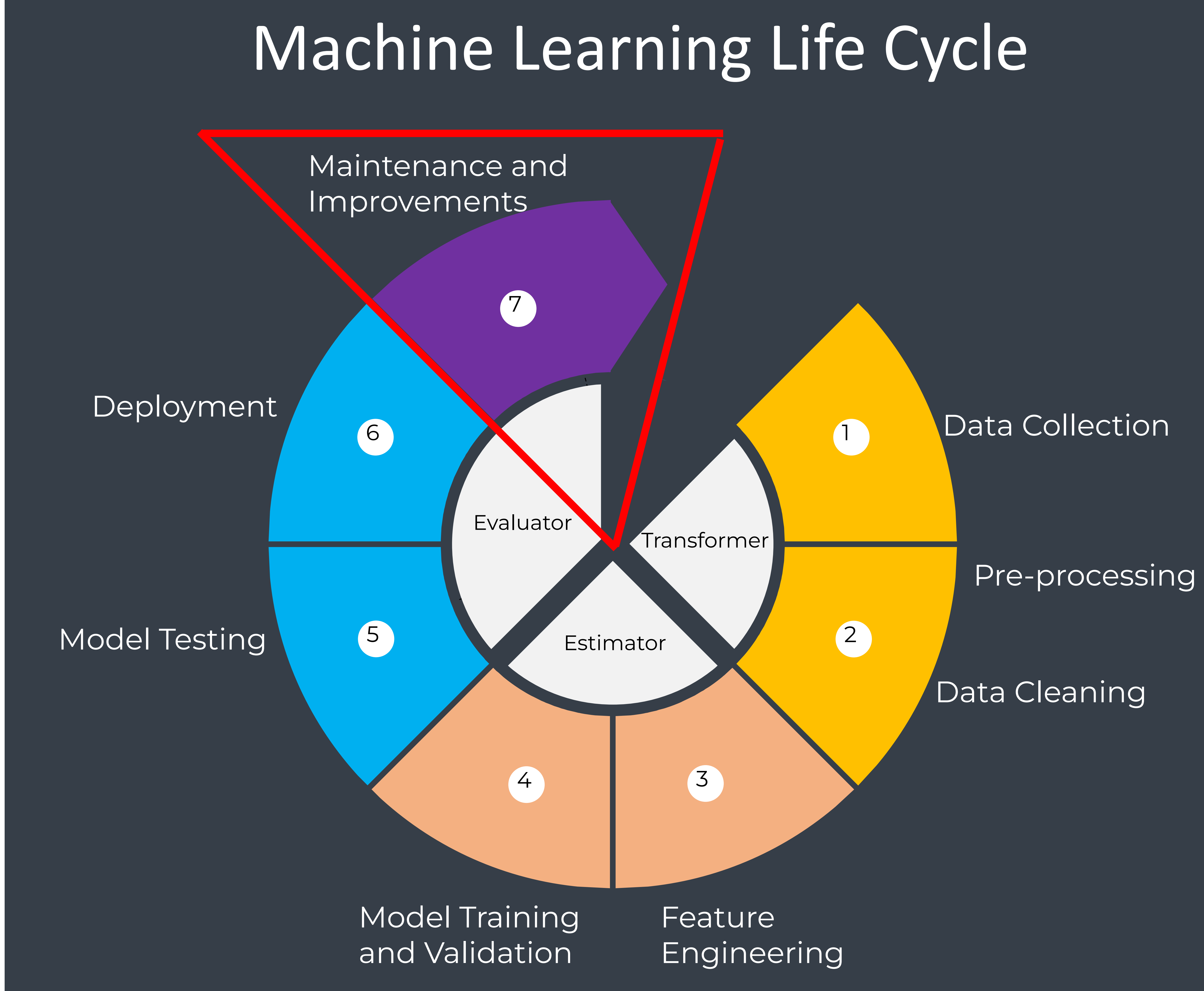
Continuous oversight of model performance post-deployment, with updates as needed

Example:

Tracking model accuracy of employee engagement predictions over time

Where the I-O fits in:

I-Os evaluate long-term impact on workforce dynamics, suggesting improvements for sustained effectiveness



ADDITIONAL RESOURCES

1 Step-by-step model deployment example

ETA estimator project for Uber

2 Overall MLOps

- Swirl AI Newsletter
- Highlights
  - Evolving Maturity of MLOps Stack in your Organisation
  - CI/CD for Machine Learning
  - Building efficient Experimentation Environments for ML Projects

3 Environment

- Docker
  - Docker in 1 hour (shout out to Albert Rapp)

4 Making Friends with Machine Learning

- Entire Course
- Broken out by snippets

CONVERSATION STARTERS

Use these examples to get the conversation going with others in your organization

What conversation starters have you had success with?

CONVERSATION STARTER ONE

"How do we address ethical considerations, like bias and fairness, in our machine learning models?"

CONVERSATION STARTER TWO

"In what ways do our machine learning initiatives align with the broader organizational goals and values?"

What areas would you like to see at future SIOPs?

Please let us know what areas you would like to learn more about at future SIOPs

FUTURE SIOP SESSIONS

QUESTIONS?

THANK YOU!

APPENDIX

POPULAR MLOPS TOOLS

1. Domino Enterprise MLOps Platform
2. AWS Sagemaker
3. Azure Machine Learning
4. MLflow
5. Run:ai
6. Kuberflow

CONVERSATION STARTERS

Use these examples to get the conversation going with others in your organization

What conversation starters have you had success with?

CONVERSATION STARTER ONE

"What are the key challenges you face when deploying machine learning models into production?"

CONVERSATION STARTER TWO

"How do we monitor the performance of deployed models, and what steps are taken if a model's performance degrades over time?"

CONVERSATION STARTERS

Use these examples to get the conversation going with others in your organization

What conversation starters have you had success with?

CONVERSATION STARTER ONE

"How do you ensure the quality and relevance of data used in our machine learning models?"

CONVERSATION STARTER TWO

"Could you describe the process of feature engineering and its importance in building effective models?"

CONVERSATION STARTERS

Use these examples to get the conversation going with others in your organization

What conversation starters have you had success with?

CONVERSATION STARTER ONE

"How can the I-O team collaborate more effectively with the MLOps team to enhance model development and deployment?"

CONVERSATION STARTER TWO

"What are some common misunderstandings or communication gaps you've observed between technical and non-technical teams regarding MLOps?"

CONVERSATION STARTERS

Use these examples to get the conversation going with others in your organization

What conversation starters have you had success with?

CONVERSATION STARTER ONE

"What are the primary tools and technologies we use in our MLOps pipeline, and why were they chosen?"

CONVERSATION STARTER TWO

"How do we handle version control and documentation for our machine learning projects?"

CONVERSATION STARTERS

Use these examples to get the conversation going with others in your organization

What conversation starters have you had success with?

CONVERSATION STARTER ONE

"What skills or knowledge do you think are crucial for someone in my role to better understand MLOps?"

CONVERSATION STARTER TWO

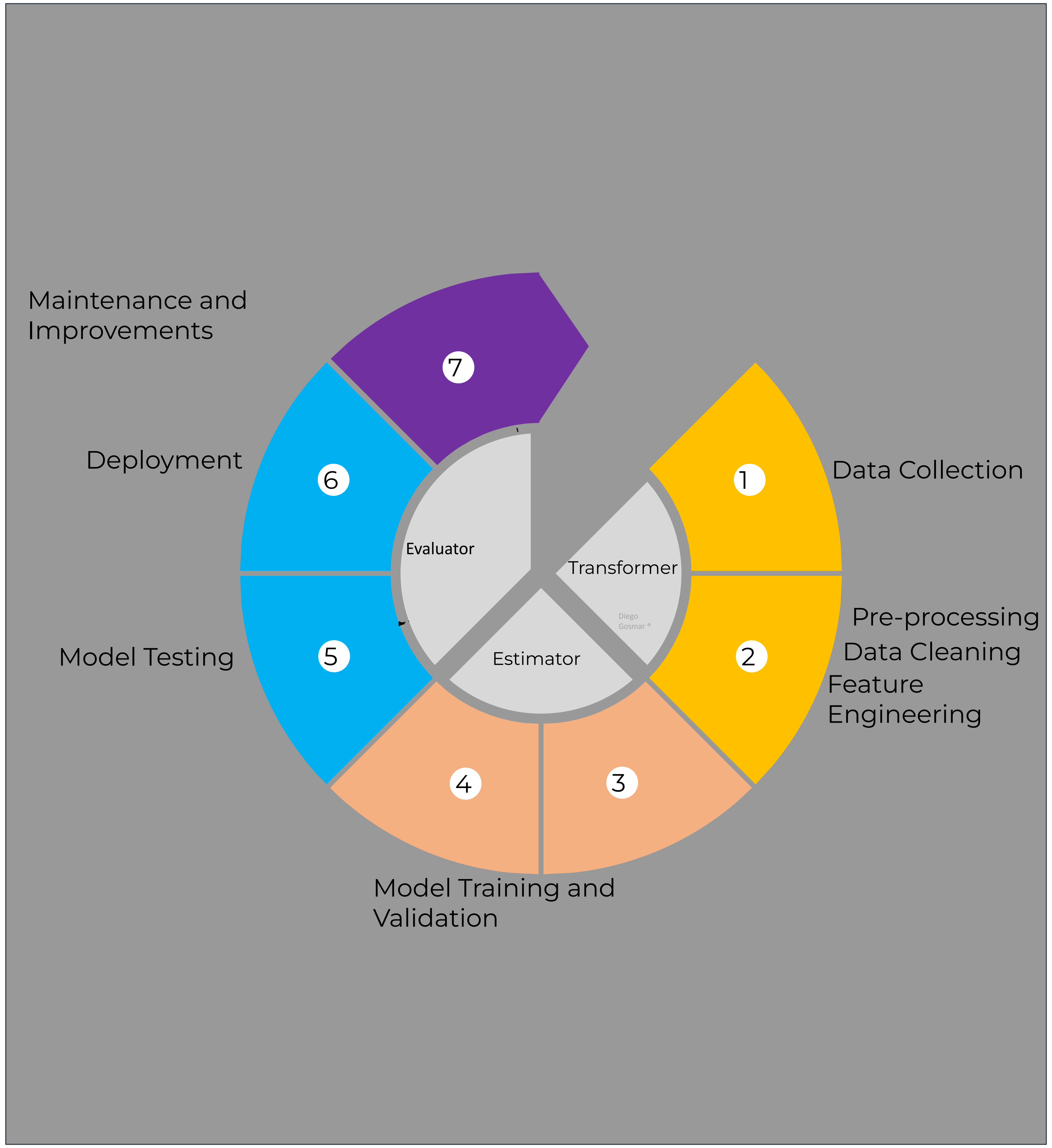
"Are there any resources or learning paths you would recommend for someone new to MLOps?"

ALTERNATE SLIDES

Why do I-Os need to be involved in MLOps?

- **Human-Centric Design -** I-Os ensure that ML models and AI systems are designed with a deep understanding of human behavior, work dynamics, and organizational culture, promoting user acceptance and ethical usage
- **Bias Mitigation and Ethical AI -** Expertise in psychometrics and organizational behavior is critical in identifying and mitigating biases in datasets and algorithms, fostering fairness, and ethical decision-making in automated processes
- **Enhancing Team Dynamics -** As MLOps involves cross-functional collaboration, I-Os can optimize team structures, communication, and workflows, facilitating smoother integration of ML projects into organizational processes
- **Training and Development -** They play a key role in developing training programs that bridge the gap between AI capabilities and workforce skills, ensuring employees are equipped to work effectively with emerging technologies
- **Change Management-** I-Os are adept at managing change, crucial for organizations adopting MLOps practices. They ensure that technological changes align with organizational goals and employee well-being, easing the transition and fostering a culture of innovation

MACHINE LEARNING LIFE CYCLE



While ML (a subset of AI) is centered on developing predictive models from data, MLOps focuses on the lifecycle management of these models, ensuring they can be deployed at scale and with high reliability in real-world applications. MLOps bridges the gap between the creation of ML models and their practical, operational use within organizations, emphasizing efficiency, collaboration, and continuous improvement.

Machine Learning vs Machine Learning Operations

Machine Learning

- Develop and implement ML models and algorithms
- Collaborating with Data Scientists to fine-tune and optimize models
- Integrating ML models into existing software systems or creating new applications

Machine Learning Ops

- Implementing Continuous Integration/Continuous Development (CI/CD) pipelines for machine learning projects
- Ensuring scalability and reliability of ML infrastructure
- Monitoring model performance and implementing strategies to maintain accuracy
- Collaborating with data scientists and ML engineers to deploy models efficiently and securely