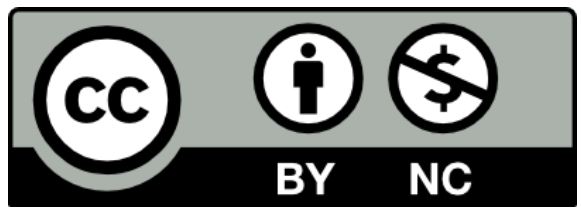
Business 4720 - Class 23

Managing Machine Learning Operations (MLOps)

Joerg Evermann

Faculty of Business Administration
Memorial University of Newfoundland
jevermann@mun.ca



MEMORIAL UNIVERSITY

This Class

What You Will Learn:

- MLOps Principles
- MLOps Challenges
- MLOps Lifecycle
- MLOps Participants
- MLOps Governance

MEMORIAL UNIVERSITY

Based On

Treveil, M. and the Dataiku Team (2020) *Introducing MLOps*, O'Reilly Media, Sebastopol, CA (T)

Gift, N. and Deza, Al. (2021) *Practical MLOps*, O'Reilly Media, Sebastopol, CA (GD)

MEMORIAL UNIVERSITY

Resources

Implementations are available on the following GitHub repo:

`https://github.com/jevermann/busi4720-mlops`

The project can be cloned from this URL:

`https://github.com/jevermann/busi4720-mlops.git`

MEMORIAL UNIVERSITY

MLOps Purpose

- Improve Operational Efficiency
  - Formalized and automated processes
  - Reliable and repeatable processes
  - Manageable, adaptable, and understandable processes
- Mitigate Risk
  - Availability of service
  - Model quality and model impacts
  - Prediction fairness
  - Skill loss
- Establish accountability, auditability, and traceability

MEMORIAL UNIVERSITY

ML Challenges

- Increasing number of machine learning models and applications
- Data is constantly changing
- Business needs can change rapidly
- Mixed teams of business professionals, data scientists, software engineers and IT staff
- Data scientists have little expertise in software engineering

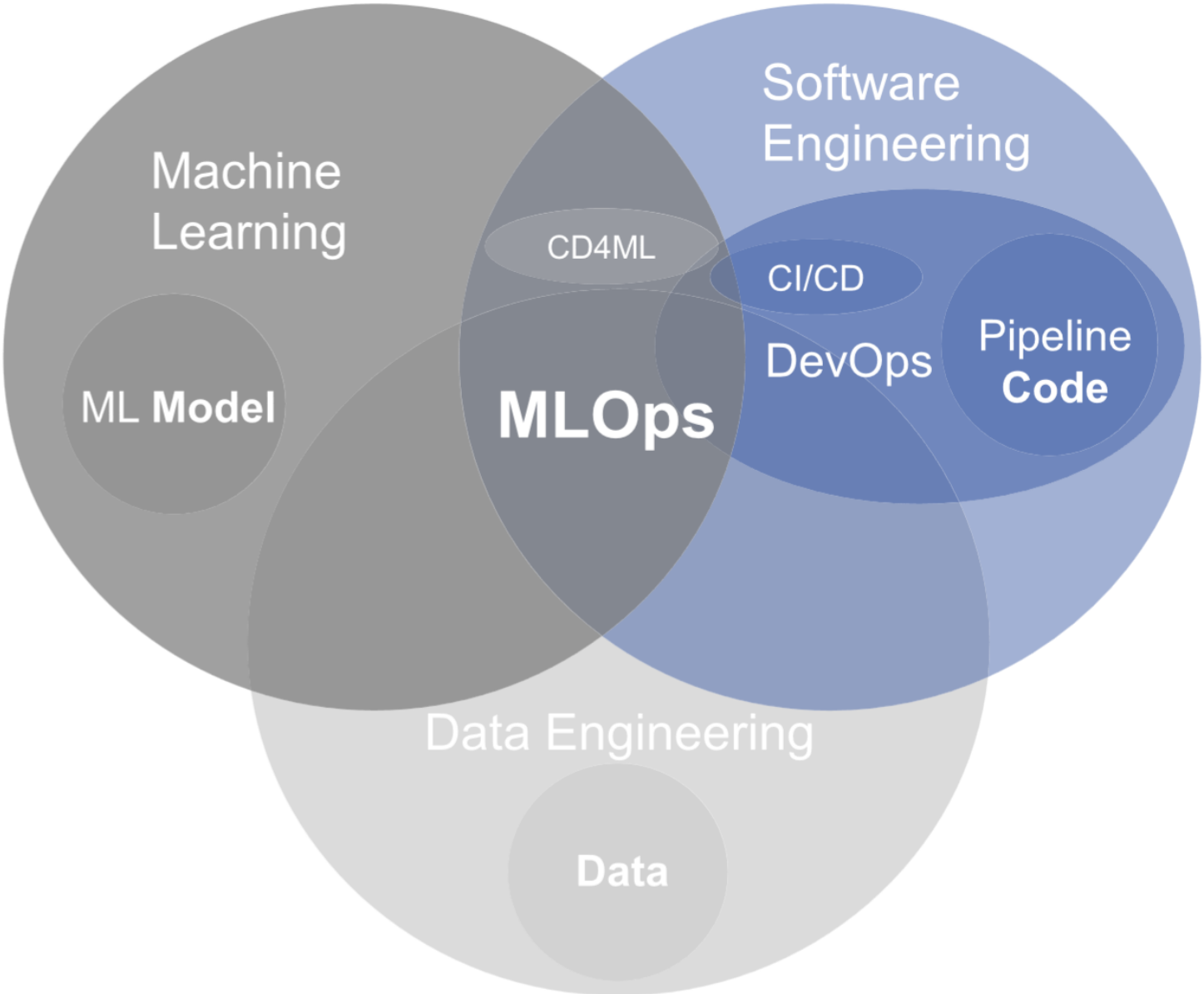
MEMORIAL UNIVERSITY

MLOps Principles

1. Reliability & Reproducability
2. Robust automation
3. Management and versioning of data and models
4. Continuous model (re-) development and continuous model delivery to production
5. Continuous monitoring in production

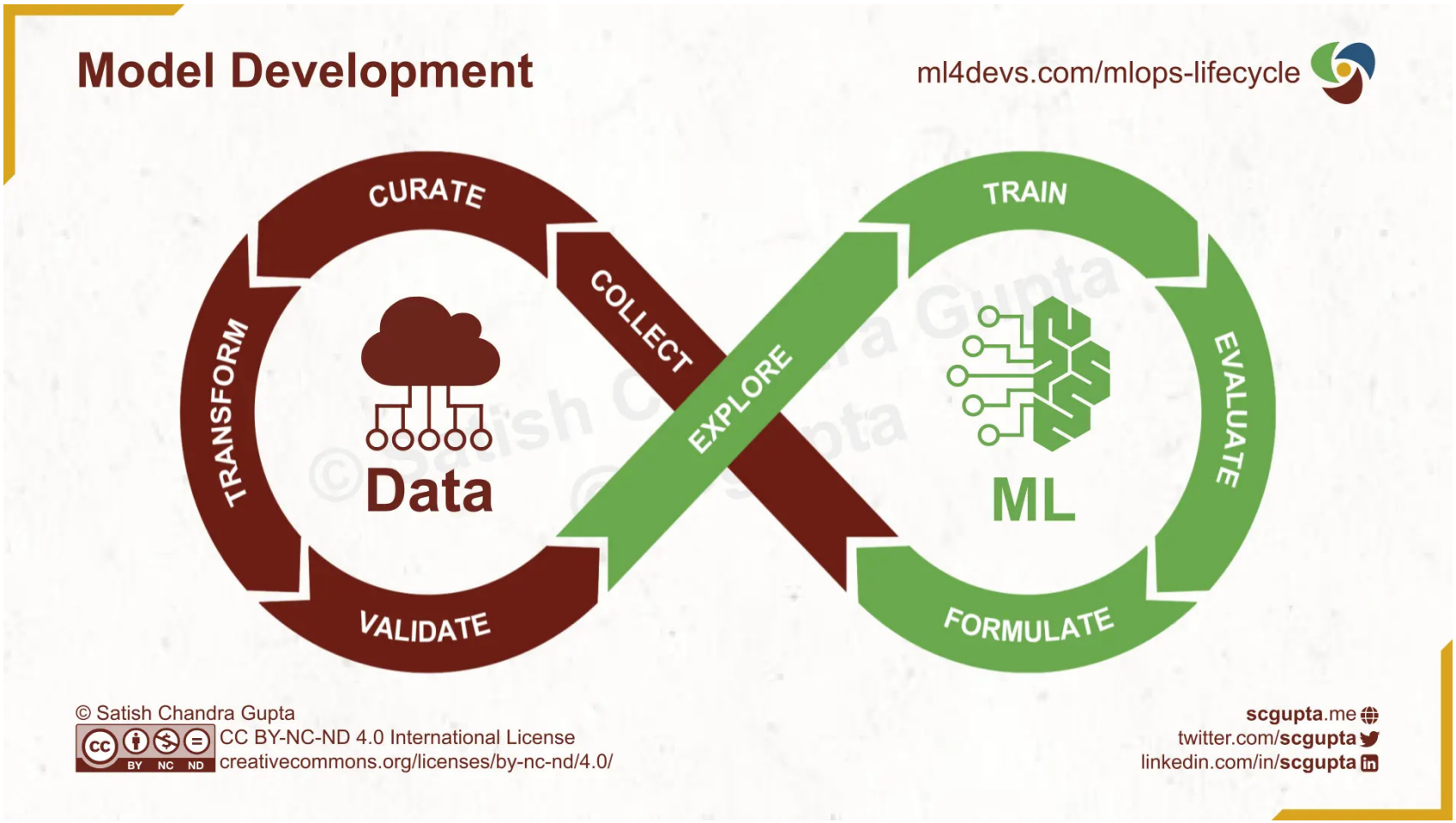
MEMORIAL UNIVERSITY

MLOps – Relationship to other disciplines

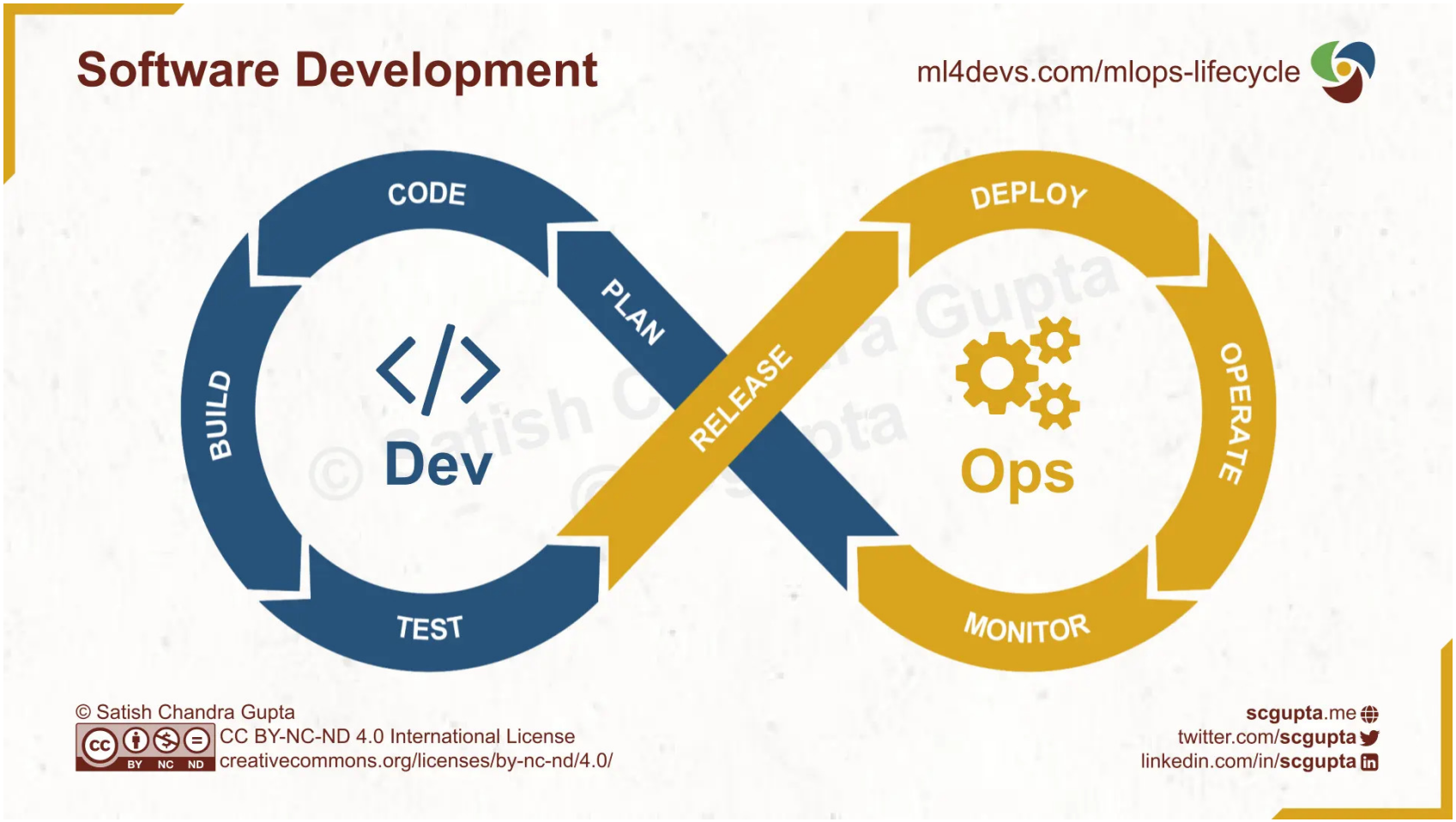


Source:
Kreuzberger, D., Kühl, N., & Hirschl, S. (2023). Machine learning operations (mlops): Overview, definition, and architecture. IEEE access, 11, 31866-31879.

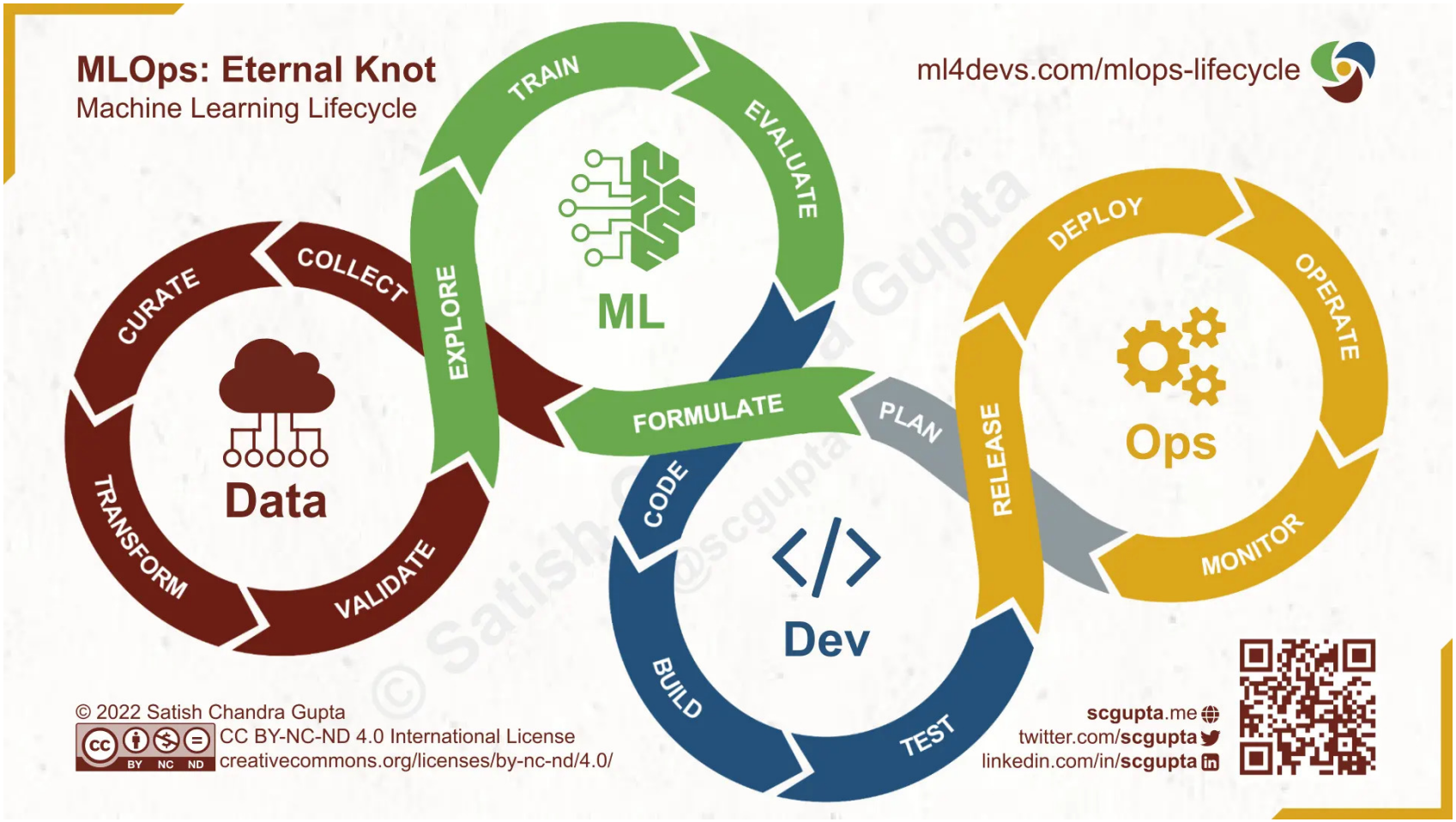
Model Development Lifecycle



Software Development Lifecycle



MLOps Lifecycle

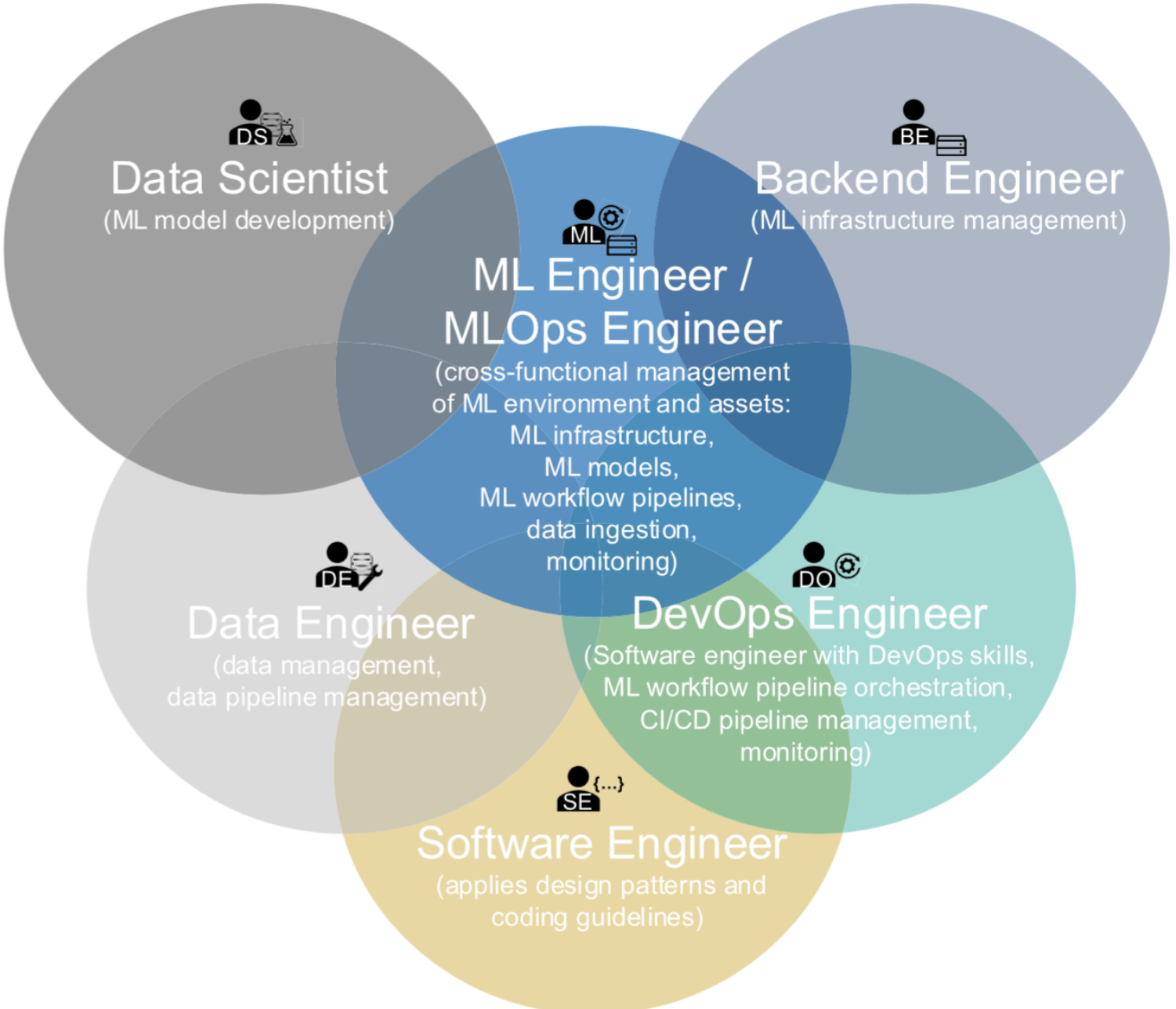


MLOps Participants

- Subject matter experts
  - Provide business questions, goals and KPIs for models
  - Evaluate model performance against business needs
- Data scientists
  - Develop and evaluate models
  - Deliver operationalizable models
- Data engineers
  - Optimize retrieval and use of data
- Software engineers
  - Integrate models into applications
- DevOps engineers
  - Build systems and test for security, performance, availability
  - CI/CD
- Model risk managers and model auditors
  - Minimize risk and ensure compliance
- ML engineer/ML architects
  - Ensure scalable and flexible environment

MEMORIAL UNIVERSITY

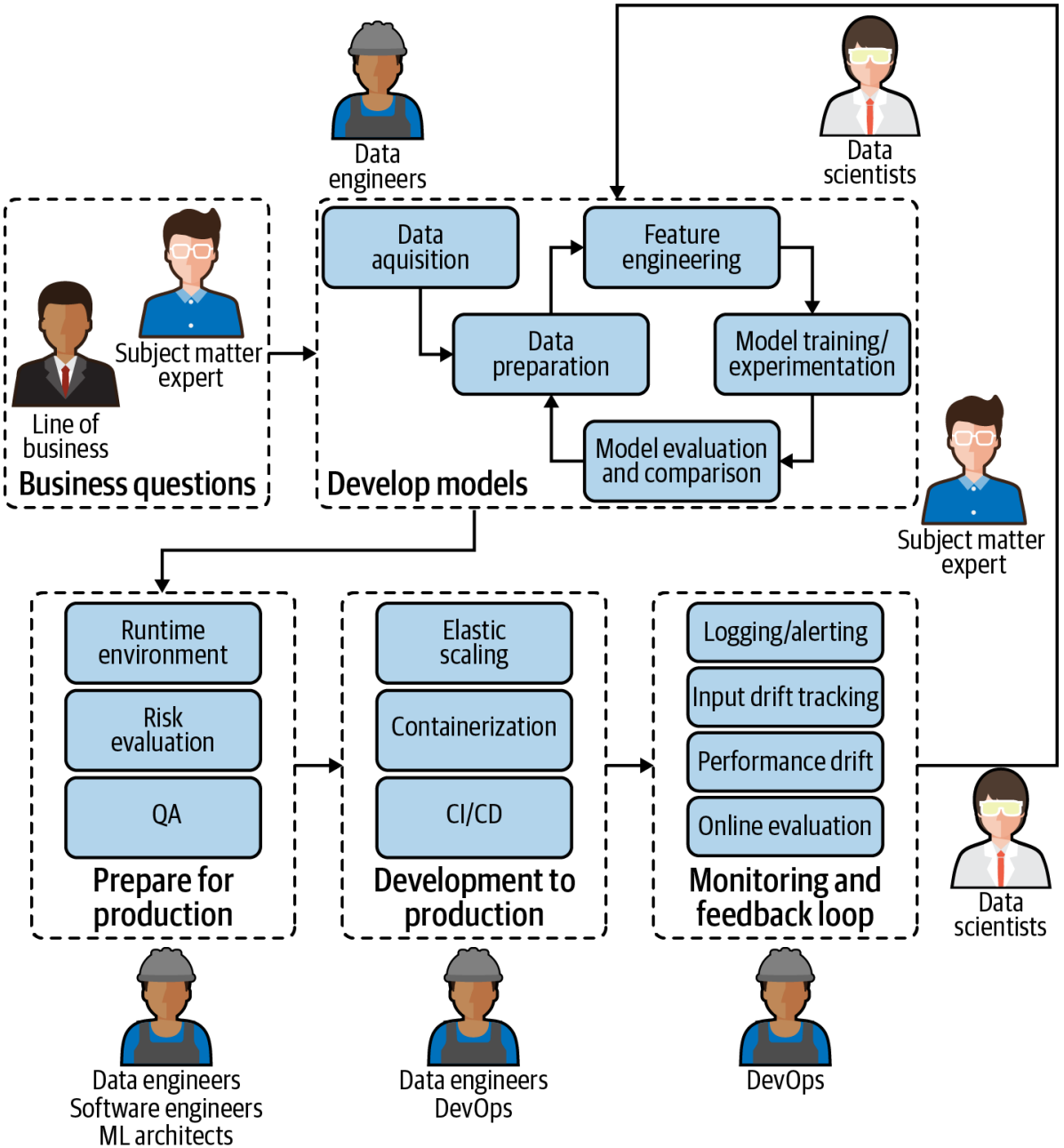
MLOps Participants – Overlapping Roles



Source:
Kreuzberger, D., Kühl, N., & Hirschl, S. (2023). Machine learning operations (mlops): Overview, definition, and architecture. IEEE access, 11, 31866-31879.

MEMORIAL UNIVERSITY

MLOps Participants – Roles in MLOps lifecycle



Source: Trevail et al. (2020), Figure 1-3

MLOps – Requirements

- Subject matter experts:
  - Understandability of deployed models in business terms
  - Feedback mechanism for models
- Data scientists and data engineers:
  - Automated model packaging and delivery
  - Ability to automatically test model quality
  - Visibility into model performance (dev, stage, production)
  - Visibility into data pipelines for each model
- Software engineers:
  - Versioning and automatic testing
- DevOps engineers:
  - Integration with wider DevOps strategies
  - Seamless deployment pipeline

MEMORIAL UNIVERSITY

MLOps Requirements [cont'd]

- Model risk managers and model auditors:
  - Automated reporting on all models (past and present), including data provenance
- ML engineer/architect:
  - Ability to assess and adjust infrastructure capacities

MEMORIAL UNIVERSITY

MLOps – Tooling

- Source Code Repository
  - Training, inference and application source code
  - Versioning
  - *Examples:* GitHub, GitLab
- CI/CD
  - Build, test, deploy
  - *Examples:* Jenkins, GitHub actions
- Workflow Orchestration
  - Defines execution and artifact usage
  - Data extraction, training, inference, deployment
  - *Examples:* Apache Airflow, AWS SageMaker Pipelines, Azure Pipelines
- Feature Store
  - Central storage of feature data
  - *Examples:* Google Feast, AWS Feature Store, Tecton.ai
- Model Training Infrastructure
  - CPU and GPU for training

MEMORIAL UNIVERSITY

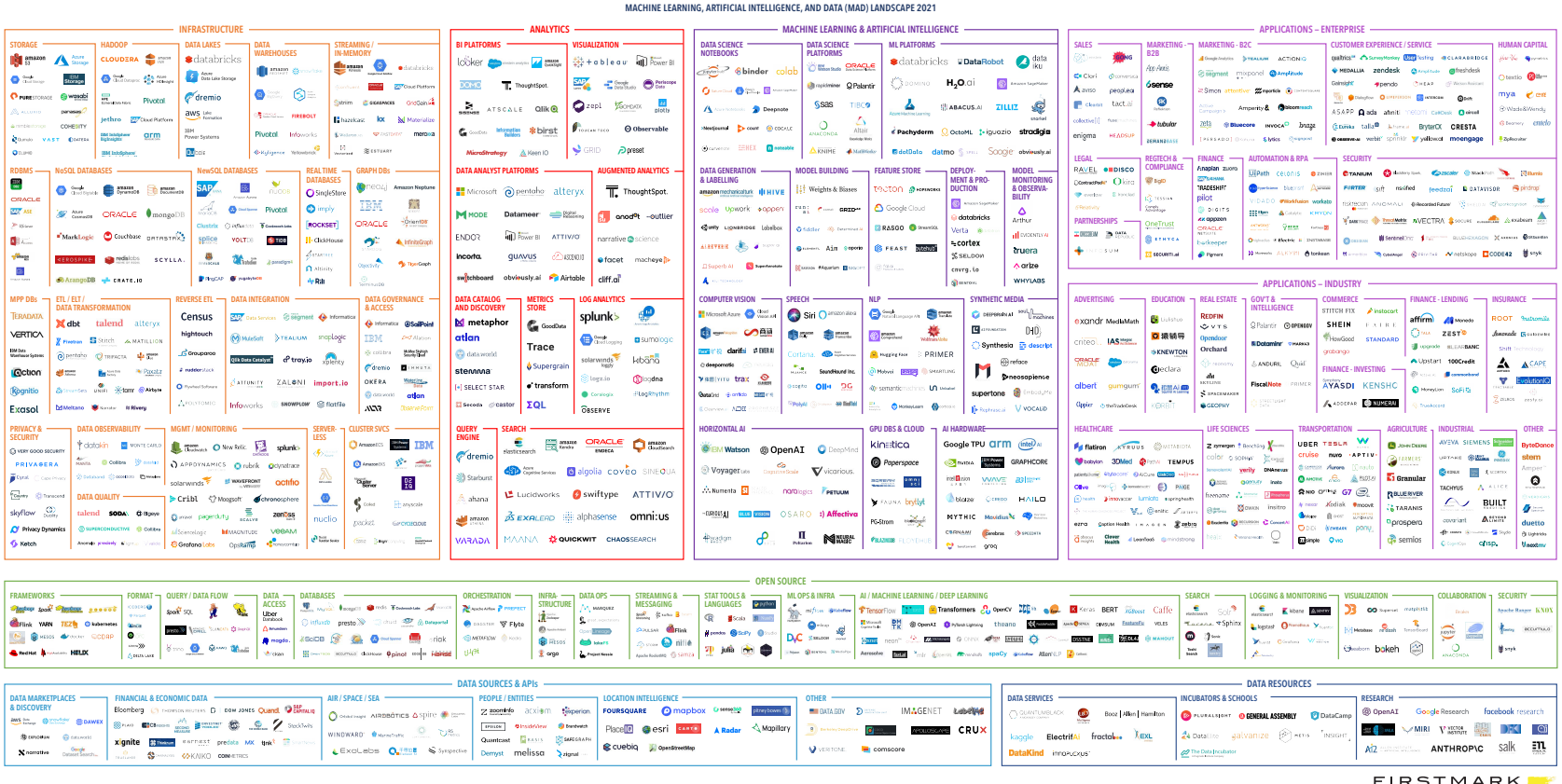
MLOps – Tooling [cont'd]

- Model Registry
  - Store trained model and metadata
  - Versioning
  - *Examples:* MLflow, AWS SageMaker Model Registry, Azure ML Model Registry
- ML Metadata Stores
  - ML Pipeline execution, model training, model lineage, etc.
  - *Examples:* MLFlow
- Model Serving
  - Online inference, real-time predictions
  - *Examples:* Flask, TensorFlow Serving, AWS SageMaker Endpoints
- Monitoring
  - Performance monitoring
  - Input drift detection
  - *Examples:* TensorBoard, AWS SageMaker model monitor

MEMORIAL UNIVERSITY

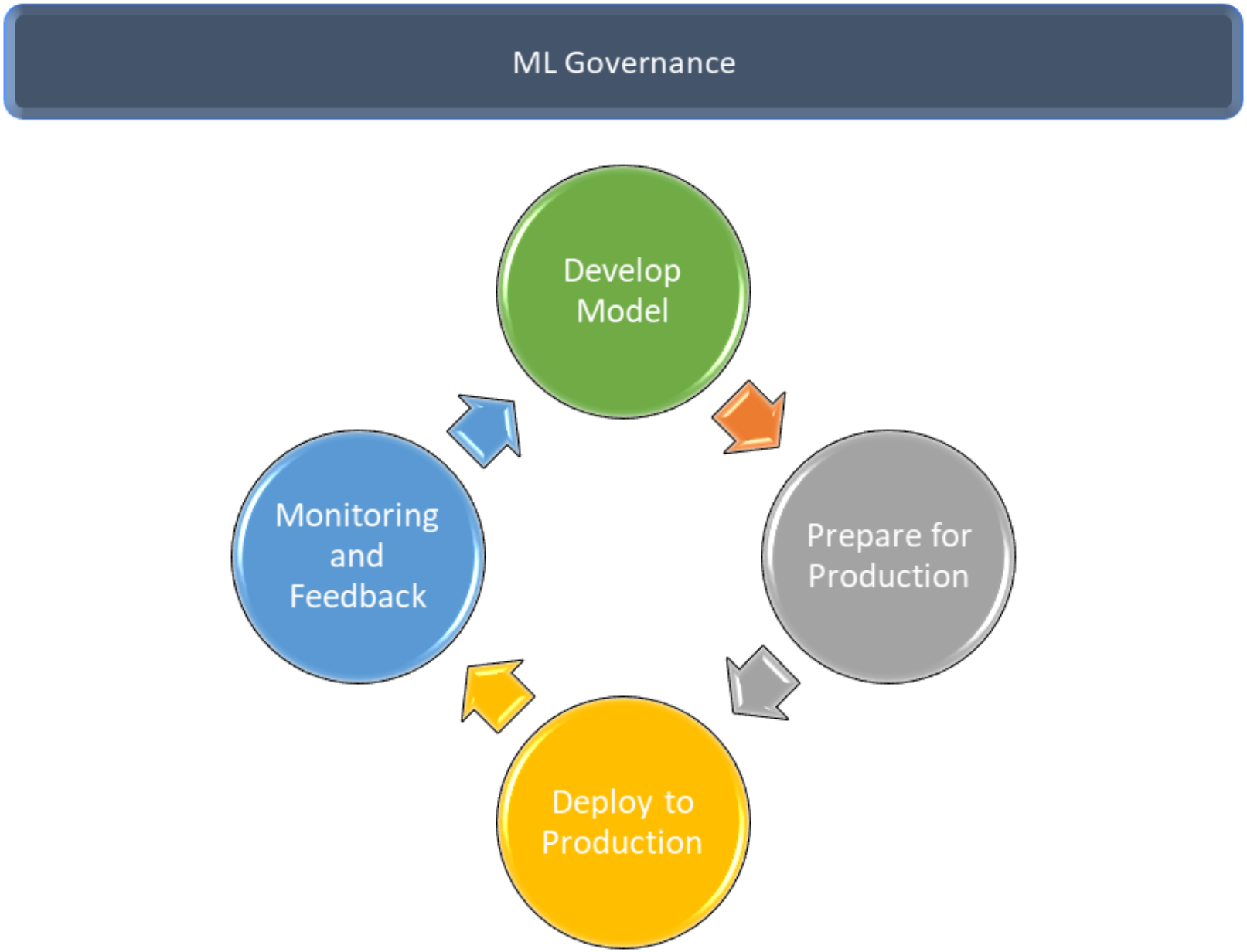
MLOps Tooling [cont'd]

Commercial Offerings

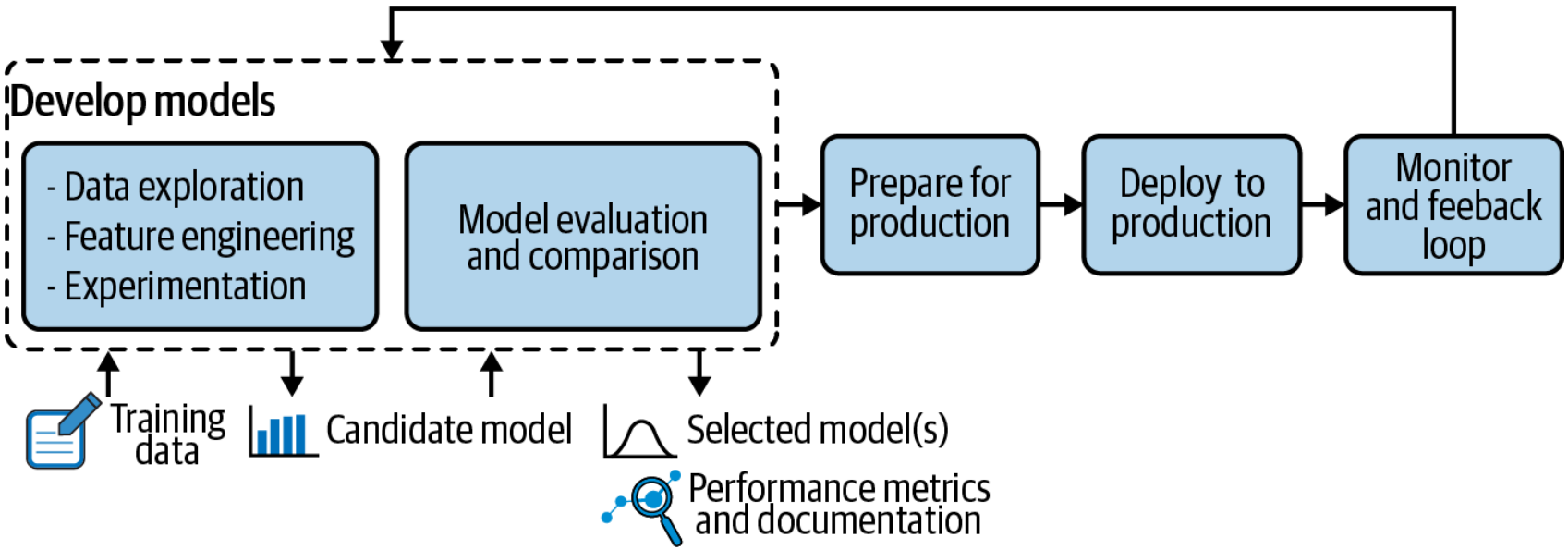


Source: Turck, Matt. *Red Hot – The 2021 Machine Learning, AI and Data (MAD) Landscape*. September 28, 2021. `https://mattturck.com/data2021/` (last accessed July 22, 2024)

MLOps Lifecycle



Develop Models



Source: Treveil et al. (2020), Figure 4-1

Develop Models [cont'd]

Data

- What data are available? What is the quality of that data?
- Can the data legally be used for this purpose? What are the terms of use of the data?
- How can the data be accessed?
- What features can be created by combining data sets?
- Must the data be redacted or anonymized?
- Are there features that cannot be used legally (age, gender, race, etc.)?
- Is the data representative of minority classes/populations?

Automation and Tools

- ETL Pipelines (extraction from source)
- Data Lakes (centralized storage)
- Feature Stores (engineered features)

Develop Models [cont'd]

Model Training

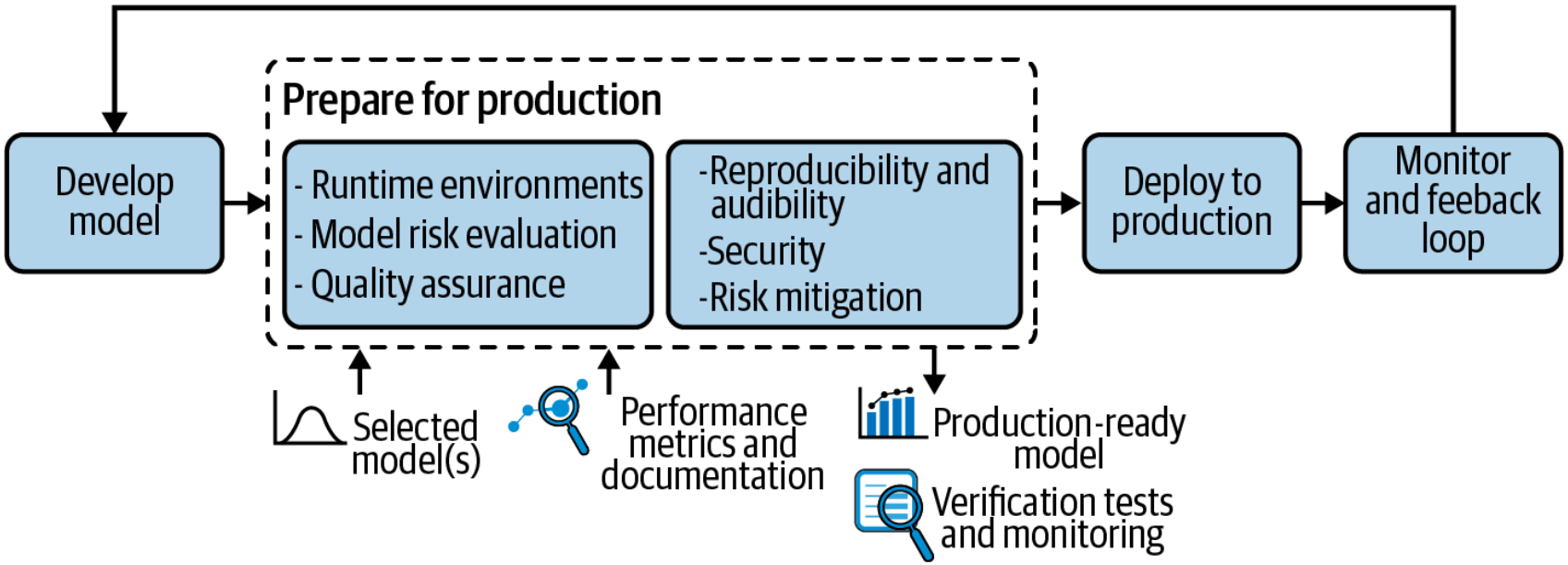
- What are appropriate evaluation metrics?
- Is the model performance acceptable for sub-populations?
- Does the model need to be interpretable or explainable?
- Are the model outcomes fair?

Automation and Tools

- Model registries and repositories (weights, biases, hyperparameters, random seeds, results, etc.)
- Container makefiles and container registries (fixing software versions and environment)
- Feature Stores (training and test data versioning and update processes)

MEMORIAL UNIVERSITY

Prepare for Production



Source: Treveil et al. (2020), Figure 5-1

Prepare for Production [cont'd]

Technical Questions

- What is the runtime environment? (e.g. Flask containers, Tensorflow Serving, Kubernetes Clusters, Edge Devices, JavaScript)
- Does the model need to be adapted? (e.g. transformation, quantization, pruning)
- How are data features accessed or provided?

Risk Assessment Questions

- What if the model acts in the worst possible way?
- What if a client extracts training data or model details?
- What are financial, business, legal, and reputational risks?

MEMORIAL UNIVERSITY

Prepare for Production [cont'd]

Sources of Risk

- Errors in model design or training (incl. data prep)
- Errors in runtime environment
- Data quality problems
- Differences btw training & production data ("input drift")
- Abuse of model or misuse of outputs
- Adversarial attacks
- Legal risk from training data use or model results
- Reputational risk

MEMORIAL UNIVERSITY

Prepare for Production [cont'd]

Risk Mitigation

- Shadow testing
- Progressive rollouts
- Continuous logging and monitoring
- Input and output checks
- Failover to simpler model
- Periodic retraining

MEMORIAL UNIVERSITY

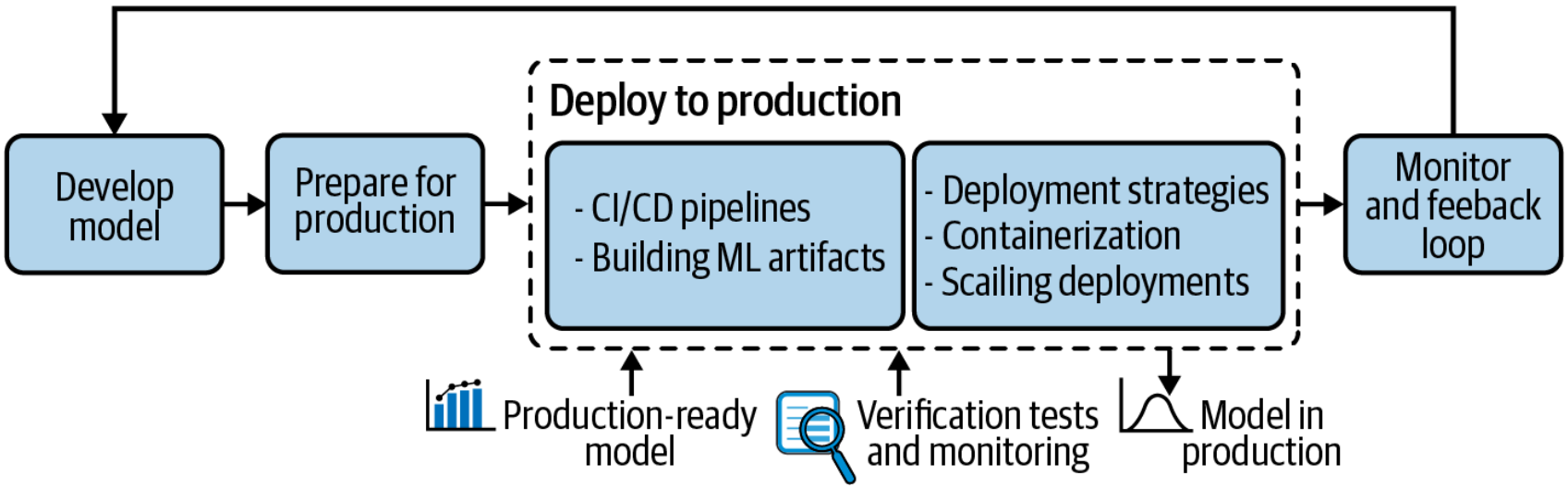
Prepare for Production [cont'd]

Automation and Tools

- Continuous integration and automated testing
- Model registries to document artifact
  - Input data sources and provenance
  - Model assumptions
  - Software dependencies
  - Test results (incl. explanations and bias evaluation)
  - Training and test logs

MEMORIAL UNIVERSITY

Deploy to Production



Source: Treveil et al. (2020), Figure 6-1

Deploy to Production [cont'd]

Automated CI/CD Pipeline

1. Build model
   - 1.1 Build model artifacts (model code, configuration, data, trained model, environment, documentation, test code and test data)
   - 1.2 Archive and register model
   - 1.3 Basic checks
   - 1.4 Evaluate bias and interpretability
2. Deploy to test environment
   - 2.1 Evaluate predictive performance
   - 2.2 Evaluate computational performance
3. Deploy to production environment
   - 3.1 Limited deployment (parallel or "canary")
   - 3.2 Full deployment

Adapted from Trevail et al. (2020) (pg. 74, 75)

MEMORIAL UNIVERSITY

Deploy to Production

Scalability and Reliability

- Deployment targets (models to servers)
- Automatic Workload balancing
- Automatic Failover (detection, reprovisioning)
- Model upgrades

Maintenance

- Continuous Resource monitoring
- Continuous Health checks
- Continuous ML metrics monitoring

MEMORIAL UNIVERSITY

Deploy to Production

Automation and Tools

- Source code repositories (e.g. GitHub)
- Continuous integration (e.g. Jenkins)
- Model registries (e.g. MLflow)
- Model serving (e.g. Flask, Tensorflow Serving)
- Log data storage and analysis

MEMORIAL UNIVERSITY

Deployment Options

- Microservice (e.g. Flask)
- Tensorflow TFX and Tensorflow Serving
- Tensorflow JS (for browser deployment)
- Tensorflow Lite (for edge devices and mobile apps)

MEMORIAL UNIVERSITY

Flask Example – Step 1: Create a Trained Model

Complete file is available on GitHub.

Define the model and train it:

```
import keras.utils
import pandas as pd
import tensorflow as tf
import tensorflowjs as tfjs

keras.utils.set_random_seed(42)
boston_data = \
 pd.read_csv("https://evermann.ca/busi4720/boston.csv")

boston_features = boston_data[['rm', 'tax', 'age']]
boston_labels = boston_data['medv']

# Linear regression model
norm_boston_model=keras.models.Sequential([
    keras.layers.Input(shape=(3,), dtype=tf.float32),
    keras.layers.Dense(1, activation=None) ])
```

MEMORIAL UNIVERSITY

Flask Example [cont'd]

Fit the model and save it:

```
stop_callback = keras.callbacks.EarlyStopping()
norm_boston_model.compile(
    loss = tf.keras.losses.MeanSquaredError())
norm_boston_model.fit(
    boston_features, boston_labels,
    epochs=100, validation_split=0.33,
    callbacks=[stop_callback])

# Save model for use in Keras
norm_boston_model \
    .save('norm.boston.model.trained.save')
# Export model for use in TF Serving
norm_boston_model \
    .export('norm.boston.model.trained.export')
# Convert model for use in TFJS
tfjs.converters.save_keras_model(norm_boston_model, \
    'norm.boston.model.trained.tjfs')
```

MEMORIAL UNIVERSITY

Flask Example – Step 2: Serve the Model

Complete file is available on GitHub.

Load the model for prediction:

```
import keras
import flask
from flask import request
import pandas as pd

# Load the trained model
norm_boston_model = keras.saving. \
    load_model('norm.boston.model.trained.save')

# A predict function for the model
def predict(inputs):
    return norm_boston_model. \
        predict_on_batch(inputs)[0][0]

app = flask.Flask(__name__)
```

MEMORIAL UNIVERSITY

Flask Example [cont'd]

Define the URL handler and run app:

```
@app.route("/predict_json", methods=["POST"])
def predict_json():
    reply = {}
    # TODO: Input checking goes here
    # TODO: Input logging goes here
    inputs = pd.DataFrame \
                .from_dict(request.json) \
                .transpose()
    prediction = predict(inputs)
    # TODO: Output checking goes here
    # TODO: Output logging goes here
    reply["prediction"] = str(prediction)
    reply["success"] = True
    return flask.jsonify(reply)

app.run()
```

MEMORIAL UNIVERSITY

Flask Example – Step 3: Access the Service

Complete file is available on GitHub.

Access the prediction with JSON POST request:

```
#!/usr/bin/bash
curl -X POST \
     -H "Content-Type: application/json" \
     --data '[6, 250, 66.5]' \
     http://localhost:5000/predict_json
```

MEMORIAL UNIVERSITY

Flask Example – Web Forms

Complete file is available on GitHub.

Access using a JSON POST request from a Web Form:

```
<!DOCTYPE html>
<html lang="en">
 <head>
  <meta charset="UTF-8">
   <title>Boston Housing Data Prediction Service</title>
   <script>
    async function predict() {
     // Get the values from the text inputs
     const rooms =
      parseFloat(document.getElementById('rooms').value);
     const tax =
      parseFloat(document.getElementById('tax').value);
     const age =
      parseFloat(document.getElementById('age').value);
     // Create a JSON payload
     const payload = JSON.stringify([rooms, tax, age]);
```

MEMORIAL UNIVERSITY

Flask Example [cont'd]

```
    // Make a POST request to the server
    const response = await fetch('/predict_json', {
      method: 'POST',
      headers: {
        'Content-Type': 'application/json'
      },
      body: payload
    });
    // Parse the JSON response
    const result = await response.json();
    // Display the result
    document.getElementById('output-div').textContent
      = result.prediction;
  }
 </script>
</head>
```

Flask Example [cont'd]

```
 <body>
  <h1>Boston Housing Data Inputs</h1>
  <form onsubmit="event.preventDefault(); predict();">
   <p>
    <label for="rooms">Number of Rooms</label>
    <input name="rooms" id="rooms" required>
   </p>
   <p>
    <label for="tax">Tax Rate per $10,000</label>
    <input name="tax" id="tax" required>
   </p>
   <p>
    <label for="age">Prop bldg older than 1940</label>
    <input name="age" id="age" required>
   </p>
   <input type="submit" value="Submit">
  </form>
  <p>Prediction is: <div id="output-div">...</div></p>
 </body>
</html>
```

MEMORIAL UNIVERSITY

Tensorflow JS Example

Complete file is available on GitHub.

```
<!DOCTYPE html>
<html>
 <head>
  <script src="https://cdn.jsdelivr.net/npm/\
     @tensorflow/tfjs@latest/dist/tf.min.js"></script>
  <script>
   async function predict() {
    // Load the model
    const model = await \
     tf.loadLayersModel('https://raw.githubusercontent.\
      com/jevermann/busi4720-mlops/main/model.json');
    // Get the values from the text inputs
    const rooms =
     parseFloat(document.getElementById('rooms').value);
    const tax =
     parseFloat(document.getElementById('tax').value);
    const age =
     parseFloat(document.getElementById('age').value);
```

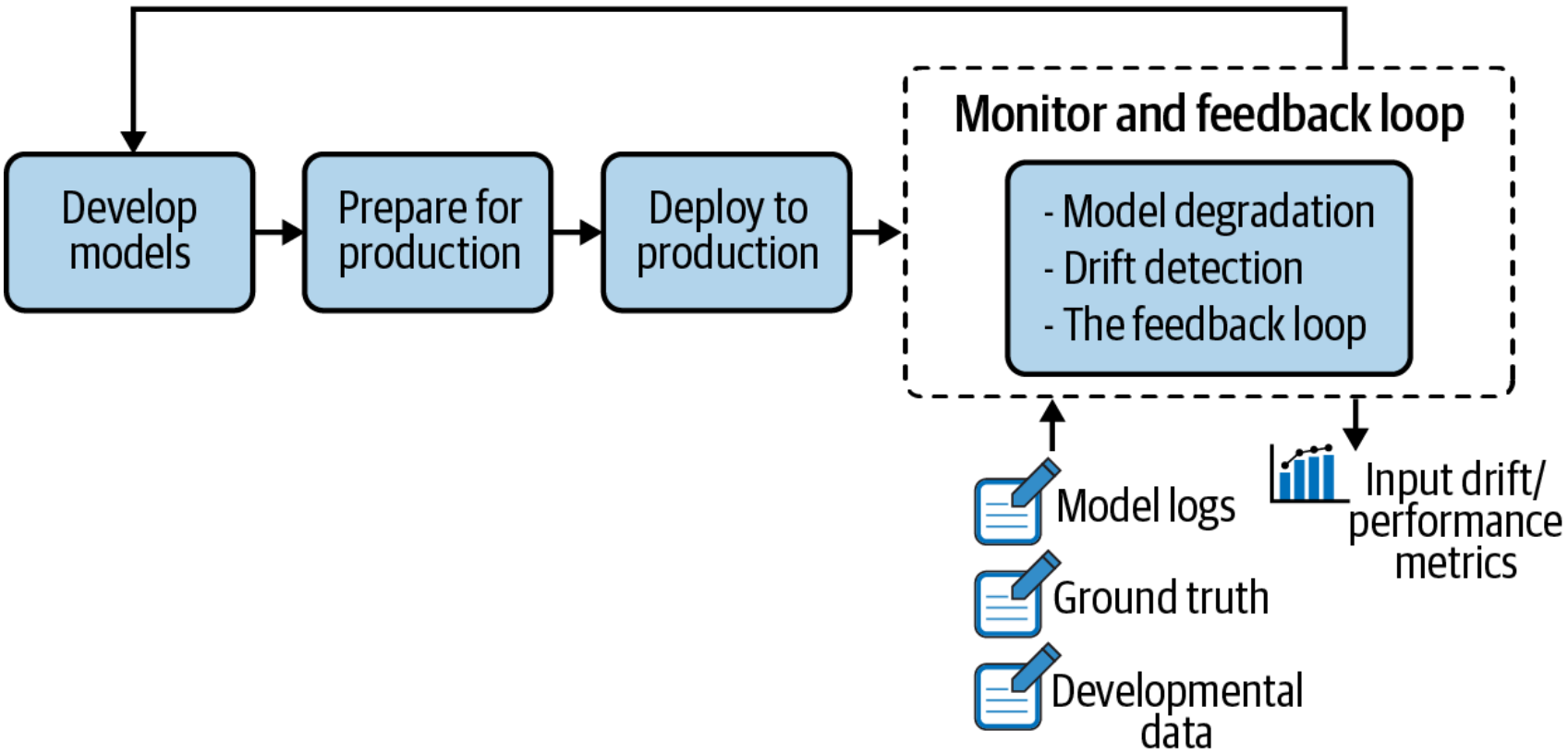
MEMORIAL UNIVERSITY

Tensorflow JS Examples [cont'd]

```
    // Package the values into a Tensor
    const inputs = tf.tensor2d([rooms, tax, age],[1, 3]);
    // Get the prediction from the model
    document.getElementById('output-div').innerText =
     model.predict(inputs).dataSync();
   }
  </script>
</head>
```

Remainder of the Web form as above.

Monitoring and Feedback



Source: Treveil et al. (2020), Figure 7-1

Monitoring and Feedback [cont'd]

Model Retraining Considerations

- Domain changes
- Training cost
- Model performance
- Ground truth availability

Ground Truth for Monitoring and Retraining

- Not always immediately or imminently available (e.g. loan repayment)
- Ground truth and prediction are decoupled (e.g. missing or mismatched identifiers)
- Ground truth not available for all classes (e.g. fraud detection)

MEMORIAL UNIVERSITY

Monitoring and Feedback [cont'd]

Input Drift Causes

- Selection bias
- Non-stationary environment

Input Drift Detection

- Univariate statistical tests (e.g. χ^2 or Kolmogorov-Smirnov)[a] [b]
- Domain classifier approach (train classifier to predict old or new sample domain)

[a] https://en.wikipedia.org/wiki/Chi-squared_test
[b] https://en.wikipedia.org/wiki/Kolmogorov-Smirnov_test

MEMORIAL UNIVERSITY

Monitoring and Feedback [cont'd]

Feedback Loop Requirements

- Logging (metadata, inputs, outputs, actions taken, explanations)
- Model store (features, preprocessing, train and test data, algorithm, eval metrics)
- Online evaluation (shadow testing or A/B testing)

MEMORIAL UNIVERSITY

Basic Python Logging

Complete file is available on GitHub.

Set up the logger:

```
import logging.handlers

req_logger=logging.getLogger(model_name+'.requests')
req_logger.setLevel(logging.INFO)
req_logger.addHandler(
    logging.FileHandler(
        model_name+'.requests.log'))
# req_logger.addHandler(
#     logging.handlers.RotatingFileHandler(
#         model_name+'.requests.log',
#         maxBytes=1000000,
#         backupCount=5))
```

MEMORIAL UNIVERSITY

Basic Python Logging [cont'd]

Use the logger:

```
@app.route("/predict_json", methods=["POST"])
def predict_json():
    req_logger.info('%s TIME %s IP %s JSON %s',
                    model_name,
                    time.ctime(),
                    request.remote_addr,
                    request.json)
...
def predict_form():
    req_logger.info('%s TIME %s IP %s FORM %s',
                    model_name,
                    time.ctime(),
                    request.remote_addr,
                    request.form)
...
```

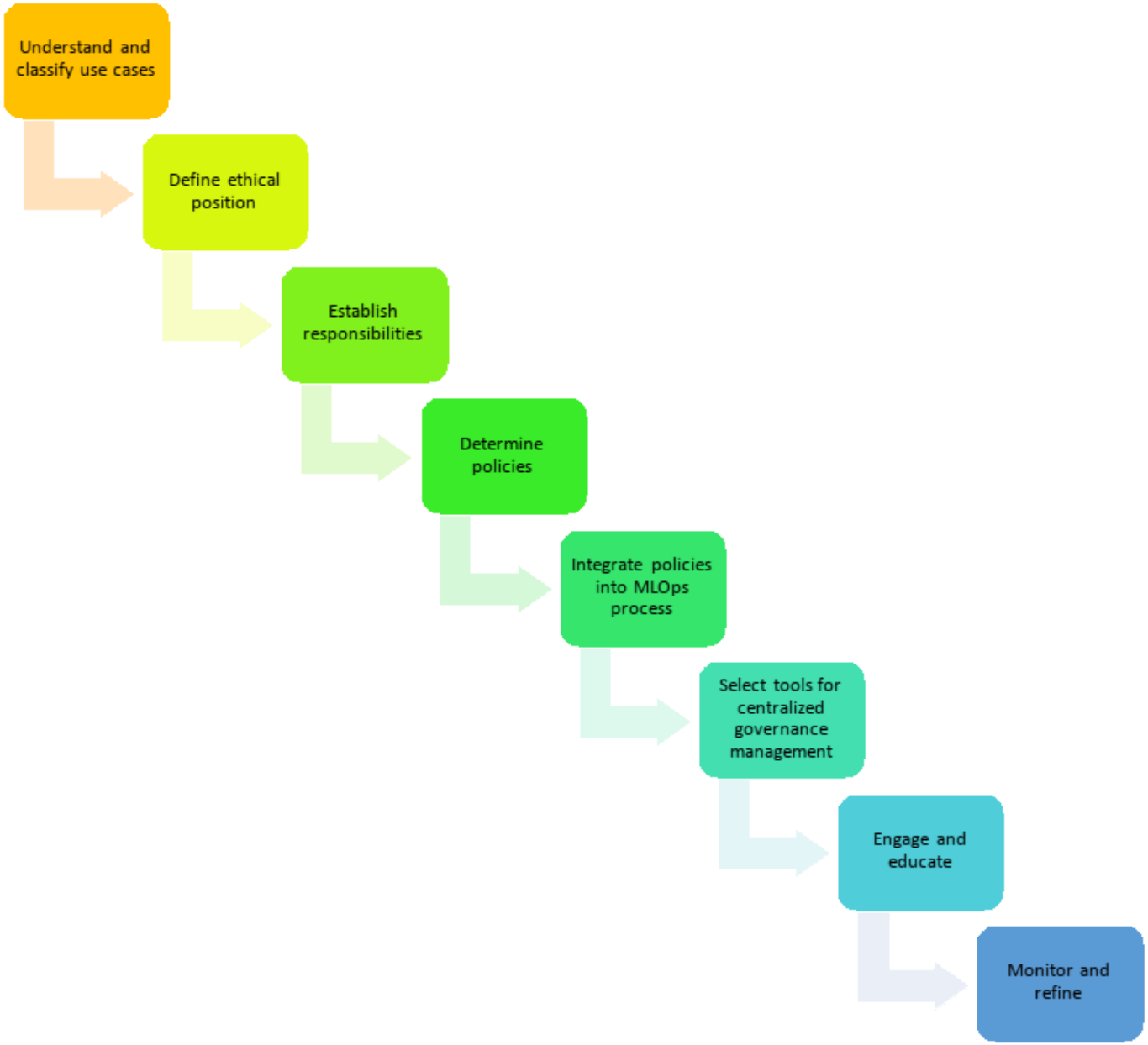
MEMORIAL UNIVERSITY

Hands-On Exercise

1. Download the complete file from GitHub.
2. Define a second logger that writes to a different log file
   - You do not need to rotate this log file
   - The definition of the second logger is analogous to that of the request logger
3. Add logging to the `predict_json()` and the `predict_form()` functions to capture the time, the three inputs, and the prediction in the log.
   - Replace the `# TODO: Output logging goes here` comments with your code
   - To make the log easy to analyze, write the information in CSV format. Make sure you quote the fields that need quoting.

MEMORIAL UNIVERSITY

MLOps Governance



MEMORIAL UNIVERSITY

MLOps Governance

1. Understand ML Uses

- Who is the consumer of the model output?
- What regulations and legal constraints apply?
- What are the legal, financial, reputational risks of errors?
- What is need for explainability or interpretability?
- What are the availability requirements?
- What is the model lifetime and likely rate of model decay?

2. Define Ethical Position

- How important are aspects like equality, privacy, human rights, democracy, bias?
- How transparent should decision making be?
- What level of responsibility for errors will the business assume?
- What is the potential for deception, manipulation, exploitation?

Adapted from Treveil et al. (2020), Chapter 8

MEMORIAL UNIVERSITY

3. Establish Responsibilities ("Who will do what?")

- Strategic, tactical, and operational
- Senior management sponsorship
- Integrate into existing governance mechanisms

Tasks	Business stakeholders	Business analysis/ citizen DS	Data scientists	Risk/ audit	Data ops	Production/ exploitation	Resources admin/ architect
Identification	A/R	C		I			
Data preparation	C	A/R	C				
Data modeling	C	A	R				
Model acceptance	I	C	C	A/R			
Productionalization		C	A/R	I	C		
Capitalization			R		R		A
Integration to external systems					A/R		
Global orchestration		C			R	A	
User acceptance tests	A/R	R	C		I		
Deployments					R	A	I
Monitoring	I	C				A/R	I

A: accountable R: responsible C: consulted I: informed

Source: Treveil et al. (2020), Figure 8-4

MLOps Governance [cont'd]

4. Define Policies ("How will we do this?")

Establish rules for:

- Reproducibility and traceability
- Auditability and documentation
- Sign-off between stages
- Model verification
- Model explainability
- Model bias and bias testing
- Model deployment mechanisms
- Model monitoring
- Data quality and data compliance

Adapted from Treveil et al. (2020), Chapter 8

MEMORIAL UNIVERSITY

MLOps Governance [cont'd]

5. Integrate Policies into MLOps Process ("When will we do this?")

- Formalize and automate MLOps processes
- Define controls
- Define monitoring of controls

6. Implement Governance Tools

- Automate controls
- Logging of control violations
- Auditing of control effectiveness
- Policy and procedure maintenance

MEMORIAL UNIVERSITY

MLOps Governance [cont'd]

7. Engage and Educate

- Communicate
- Awareness
- Training
- Buy-in & commitment
- Culture

8. Monitor and Refine

- Evaluate risk exposure
- Evaluate policy adequacy
- Evaluate control effectiveness
- Evaluate MLOps process performance

MEMORIAL UNIVERSITY