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Introduction to Machine Learning Engineering and MLOps

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ML IN PRODUCTION

Today's Agenda

1. **About me, About Data Max**
   Bujar Bakiu, CEO Data Max
2. **Hidden Technical Debt in Machine Learning**
   Hidden Technical Debt in ML, and why it is an issue
3. **Modern ML Platforms, MLOps**
   Components of ML Platforms, their purpose, role of MLOps
4. **ML Model for Email Classification**
   A ML Model for NLP Classification
5. **Hands-on: Deploying ML Model in Kubernetes**
   Deploying and scaling an ML Model in k8s

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BUJAR BAKIU

Bujar Bakiu

- CEO & Machine Learning Engineer, Data Max
- Graduated 2016, MSc, RWTH Aachen University
- Passionate about Machine Learning, Software Engineering and running
- Find me in Twitter: @bujarbakiu
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Sadik Bakiu

PRINCIPAL ML ENGINEER

Bujar Bakiu

ML ENGINEER

Deni Myftiu

SYSTEMS ENGINEER

Igli Koxha

ML ENGINEER

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Also, we offer paid internship! 👩‍🎓👨‍🎓👨‍🎓

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Hidden Technical Debt in Machine Learning

- **Technical Debt**
- **Why is it hidden?**
- **How to mitigate?**

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MACHINE LEARNING

Machine Learning Workflow

How does a machine learning workflow look like?

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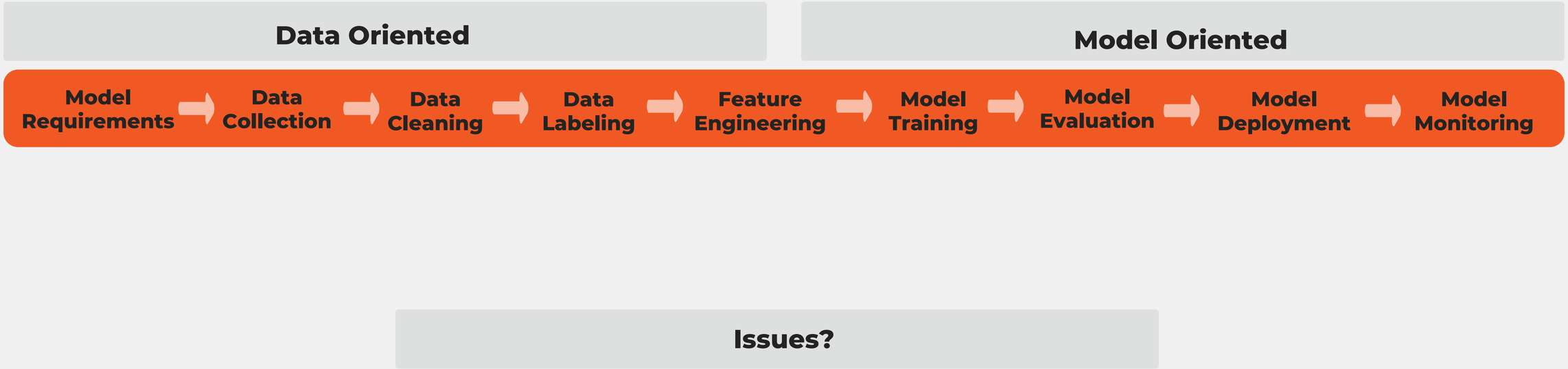
MACHINE LEARNING

Machine Learning Workflow

The nine stages of machine learning workflow.



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TECHNICAL DEBT

Hidden Tech Debt

- Entanglement
- Undeclared Consumer
- Unstable Data Dependency
- Underutilized Data Dependency
- Direct Feedback Loop
- Hidden Feedback Loop

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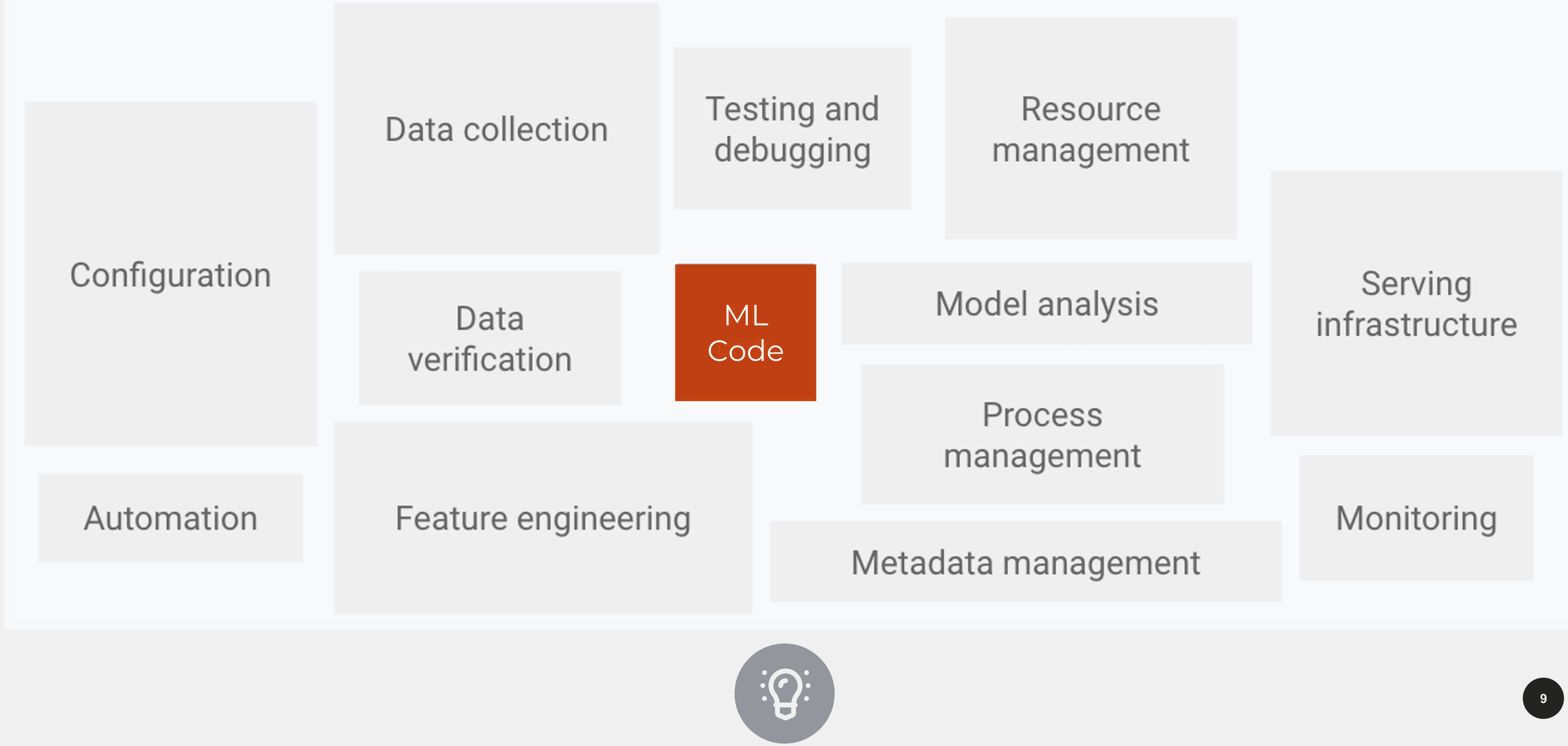
Configuration
Data collection
Testing and debugging
Resource management
Serving infrastructure
Data verification
ML Code
Model analysis
Process management
Automation
Feature engineering
Metadata management
Monitoring

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Software Engineering has been dealing with these for a while now.

Questions so far?

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Modern Machine Learning Platforms

- **Components**
- **Deployment/Scaling**
- **Monitoring**

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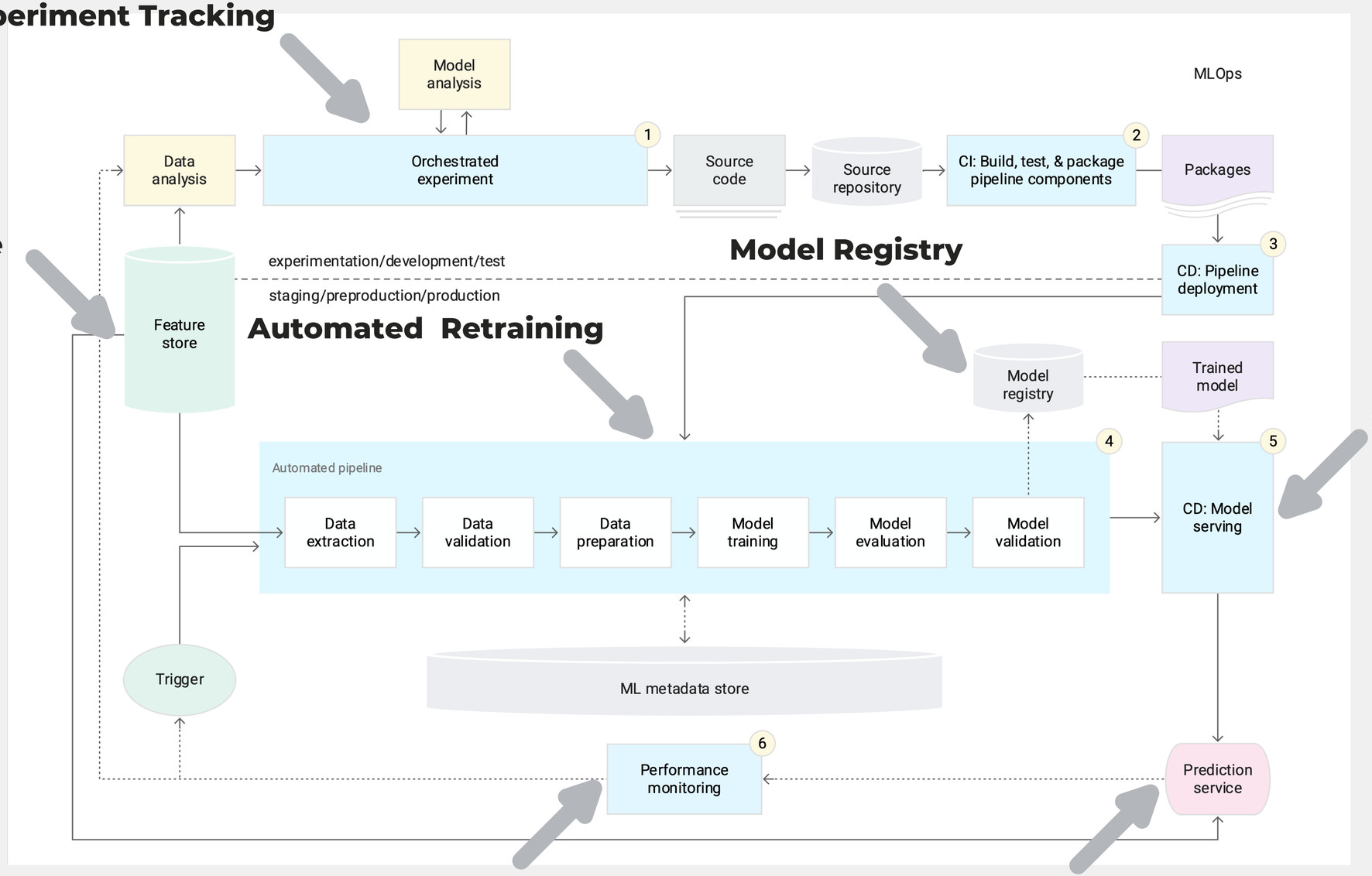
Experiment Tracking

Feature Store



Monitoring

Inference

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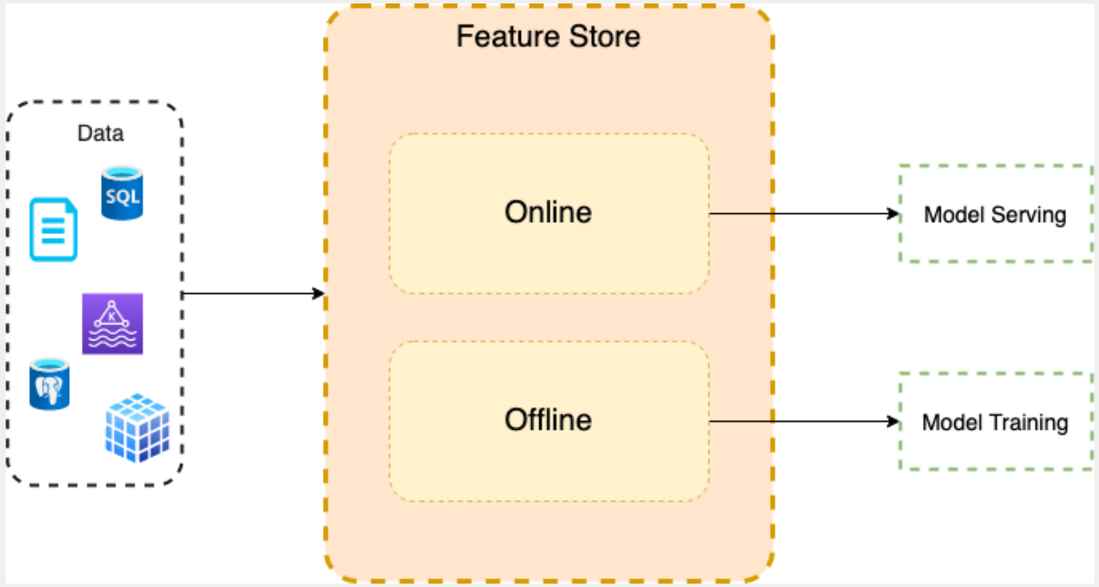

ML WORKOFLOW

Feature Store

- Stores transformed data
- Offline, stored in big warehouse/database. Historic data used for batch processing and training
- Online, fast, responsive and usually only a small subset of all data. Used for data augmentation
- Data can be of different formats, or sources.

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Example Feature

```python
@new_feature_name(
    inputs={'name': 'input_table_name'},
    online=True,
    offline=True,
    feature_start_time=datetime(2021, 5, 20),
    batch_schedule='1d',
    ttl='30days',
    owner="name@email.ai",
    family='feature_family',
    description='A helpful description for the feature'
)
def new_feature_name_sql(inputs):
    return f'''
        SELECT
            colA,
            colB as col_B,
            colC
        FROM
            {inputs.name}
        '''
```

ML WORKOFLOW

Experiment Tracking

- Keep track of models and hyperparameters used
- Keep track of training and evaluation data used
- Environment configuration files
- Model weights, evaluation metrics

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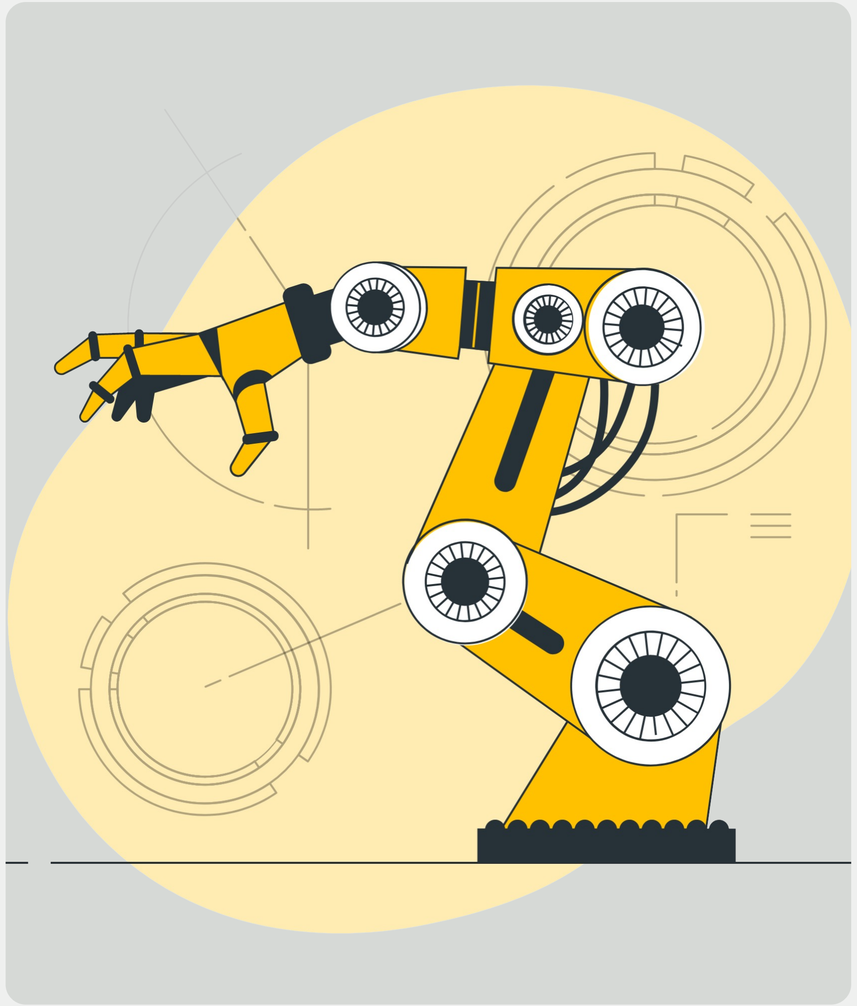
ML WORKOFLOW

Automated Retraining

- Train and retrain models on trigger
- Metadata stored for each step in the process
- Artifacts of each step documented
- Automated checks before going in production/next stage



ML WORKOFLOW

Model Registry

- Trained model artifacts are stored
- Centralized storage
- Metadata of model
- Source for production model deployment

ML WORKOFLOW

Model Serving

- Serve model as API
- Take the latest version without downtime
- Automated scaling

ML WORKOFLOW

Model Monitoring

- Check for Drift
  - Training data not representing reality
  - Relationship between input and prediction changes
- Check for performance issues
- Monitor for bugs
- Monitor for fairness

Questions so far?

What was this all about?

Let’s go back to the diagram!

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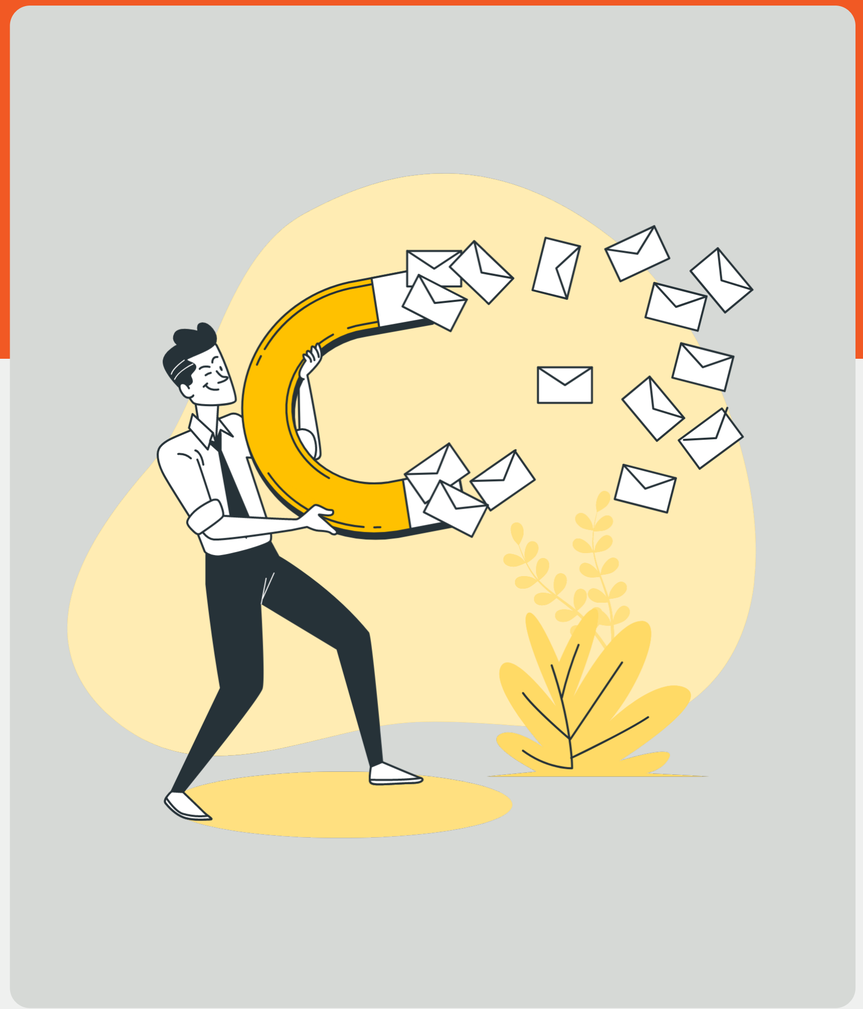

Use Case – Email Classification

- **Enron Data Set**
- **Supervised Learning**
- **Naïve Bayes**

Email Classifier

Based on the content of an e-mail define on which department to forward it.

- CountVectorizer & Tfidf Transformation
- Manually labeled data from Enron dataset
- Naïve Bayes Estimator
- Not great accuracy but that is not the point

```
pipeline = Pipeline([
    ("vect", CountVectorizer()),
    ("tfidf", TfidfTransformer()),
    ("clf", MultinomialNB())
])

model = pipeline.fit(X_train, y_train)
```

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Email Classifier

- Serve model in a service with API

```python
model = pickle.load(open('model.pkl', 'rb'))

@app.route('/predict', methods=['POST'])
def predict():
    message = req.get("message")
    logging.info(f"Received message: {message}")

    prediction = model.predict(message)
    logging.info(f"prediction: {prediction}")

    return {"label": prediction}
```

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Email Classifier

- Containerize the service

```
FROM python:3.8.10

WORKDIR /app

COPY requirements.txt requirements.txt
RUN pip install -r requirements.txt

COPY app.py app.py
COPY model.pkl model.pkl

EXPOSE 5000

ENV FLASK_APP=app.py
ENV FLASK_RUN_HOST=0.0.0.0

CMD ["flask", "run"]
```

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Email Classifier

- Build image
- Add to cluster
- Deploy and scale

```
# Build Docker image
docker build -t email_classifier_image .
# Add image to cluster
minikube image load email_classifier_image

# create kubernetes resources
kubectl apply -f deployment.yaml

# scale deployment
kubectl scale deploymemnt email-classifier-deployment
-n email-classifier-namespace --replicas=3
```

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Email Classifier

- Kubernetes resources

```
# Build Docker image
docker build -t email_classifier_image .
# Add image to cluster
minikube image load email_classifier_image

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```

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Email Classifier

- Kubernetes resources

```yaml
kind: Namespace
apiVersion: v1
metadata:
  name: email-classifier-namespace
  labels:
    name: email-classifier
---
apiVersion: v1
kind: Service
metadata:
  name: flask-service
  namespace: email-classifier-namespace
spec:
  selector:
    app: email-classifier
  ports:
    - protocol: "TCP"
      port: 5000
      targetPort: 5000
  type: ClusterIP

```

```yaml
---
apiVersion: apps/v1
kind: Deployment
metadata:
  name: email-classifier-deployment
  namespace: email-classifier-namespace
spec:
  selector:
    matchLabels:
      app: email-classifier
  replicas: 1
  template:
    metadata:
      labels:
        app: email-classifier
    spec:
      containers:
        - name: email-classifier
          image: email-classifier:latest
          imagePullPolicy: Never
          ports:
            - containerPort: 5000
```

THANK YOU!

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