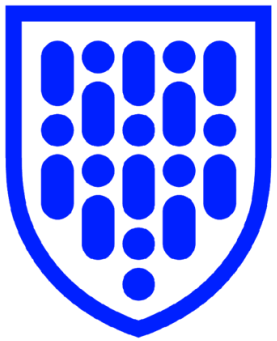

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2022

Data Science and AI

Module 10

Machine Learning Deployment and Cloud Computing

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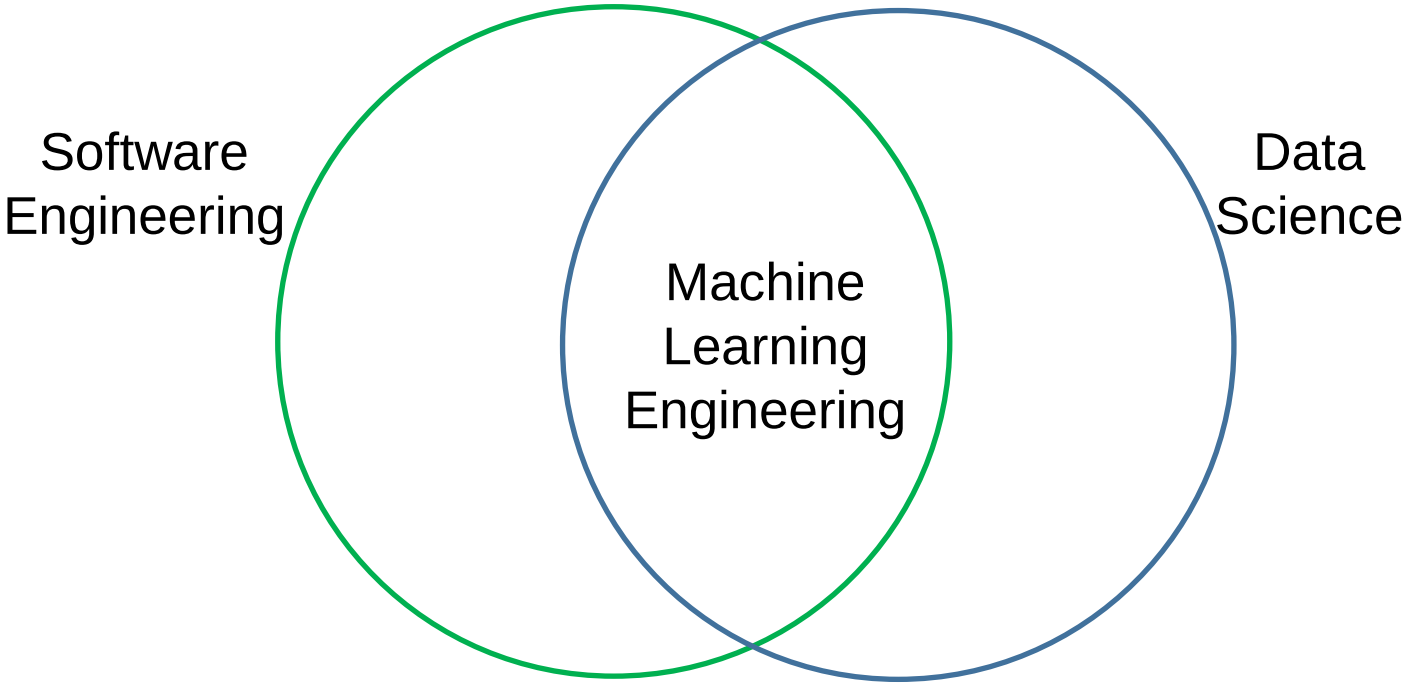
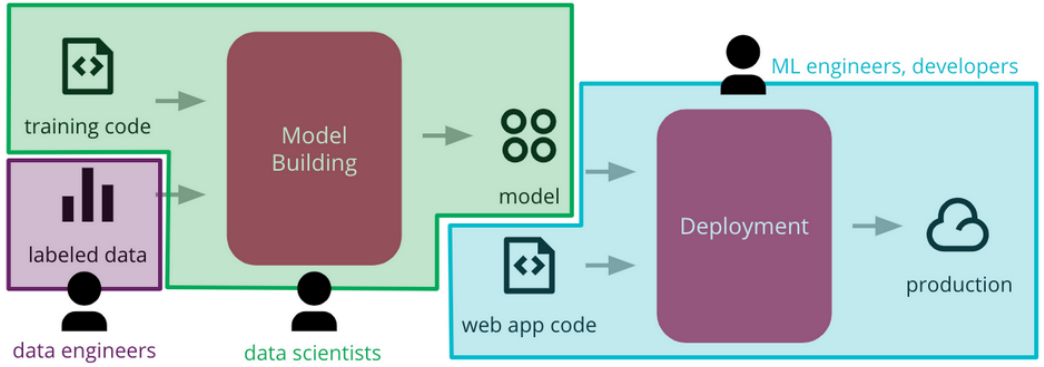
Agenda: Module 10 – Machine Learning Deployment and Cloud Computing

- Introduction
- Cloud computing
- Deployment
- DevOps, AutoML
- Cluster Computing
- Streaming Data

What is Machine Learning Deployment?

The process of making machine learning models and analyses easier to use and more accessible, bridging the gap between models and consumers





https://martinfowler.com/articles/cd4ml.html

Key Machine Learning Engineering Skills

- Well versed in Cloud Computing and Big Data technologies such as Hadoop or Spark
- Machine learning – knowledge of algorithms and how to code them using libraries (e.g. sklearn)
- Data engineering – automating the processes of feeding data in and feature engineering/selection
- Software engineering
  - scaling out models into a “production environment” where it is in operation for consumption by their intended users
  - optimising code for performance

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Cloud Computing

- Basics
- Virtualisation
- Cloud Computing Service Models
  - SaaS, PaaS, IaaS
- Introduction to AWS
  - S3
  - Machine Learning Services

The Challenges of Real-World Data and Computation

- "Big" Data is more than volume – it is about its complexity making it untenable to process using traditional means
  - **Volume** (requires multiple machines to store and process)
  - **Velocity** (data in motion)
  - **Variety** (often unstructured)
  - **Veracity** (often unreliable or incomplete)

- Challenge for data science – making models work in a dynamic real-time environment

  - Changes to data, algorithms, code

- Utilising a **cloud computing** environment addresses some of these challenges

Cloud Computing Basics

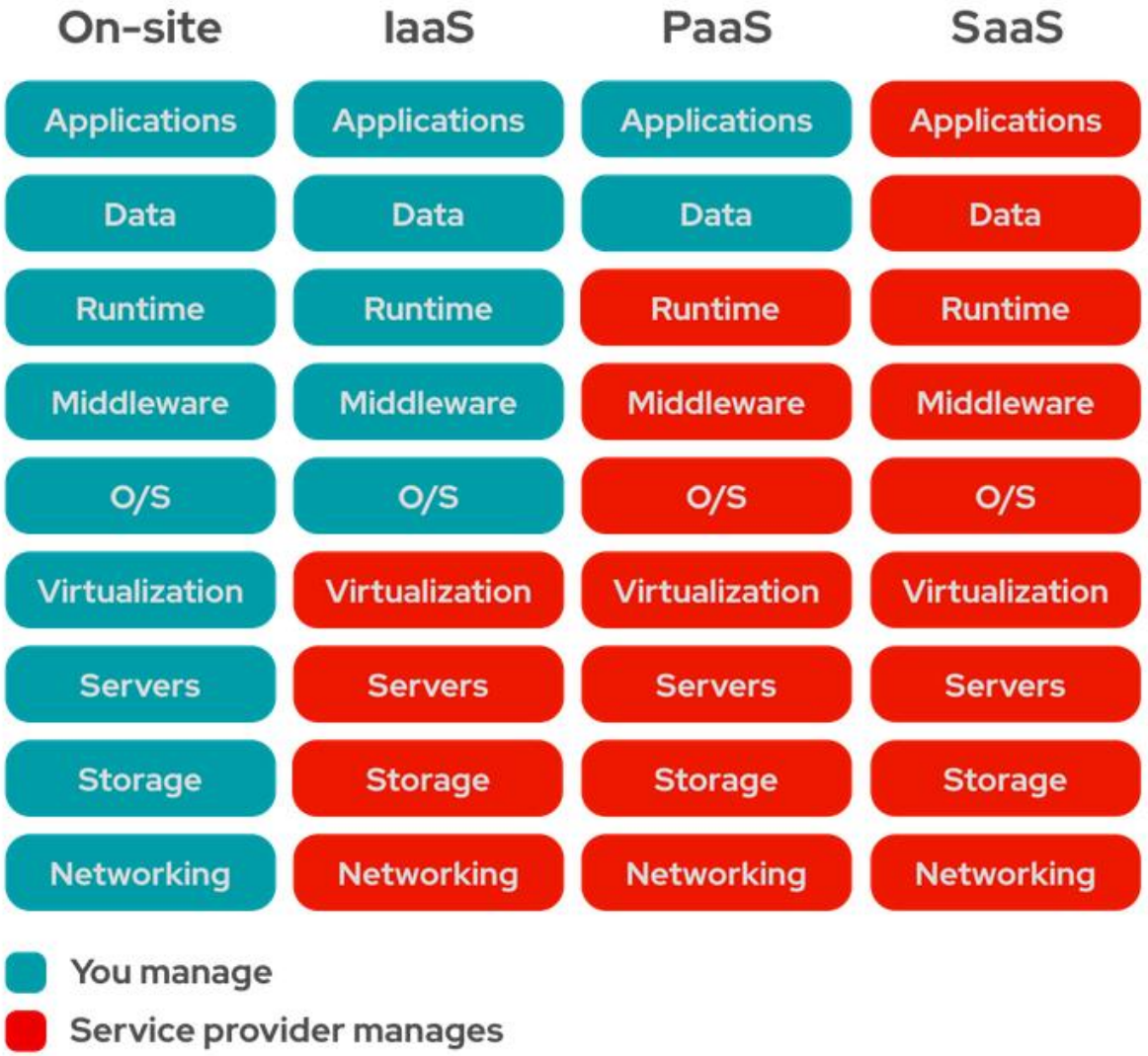
- **Cloud Computing** – the delivery of IT services (e.g. software, storage, computing processors) over a computer network (usually the Internet or Intranet)
- Characteristics (as per NIST – National Institute of Standards and Technology)
  - on-demand self-service provisioning of resources
  - broad network access
  - resource pooling (grouping together resources to improve the quality of service)
  - rapid elasticity (ability to scale up or down easily)
  - measured service (usage of resources is calculated and billed accordingly)
- Typically makes use of **virtualisation**

Virtualisation

- **Virtualisation** allows multiple operating systems to be run on the same physical hardware of a computer
- A **virtual machine** (VM) is a software program or operating system running on hardware that behaves as though it were a single computer that runs its own applications
  - Multiple virtual machine **instances** may exist on the same physical host machine
  - If an application crashes on one VM it does not affect other applications on different VMs
- Allows for a more efficient use of computing resources

Cloud Computing Service Models

- **SaaS** – entire application made available over a web browser (e.g. Gmail, Office 365)
- **PaaS** – software development and deployment (e.g. AWS Elastic Beanstalk, Heroku, Google App Engine)
- **IaaS** – provides storage, networking, virtualised hardware (e.g. AWS, Microsoft Azure, Google Compute Engine)



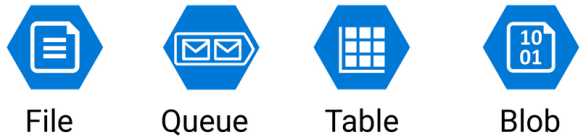
https://www.redhat.com/en/topics/cloud-computing/iaas-vs-paas-vs-saas

Instance Specifications

- Number and Type of processor (CPU vs GPU vs TPU)
- Memory (RAM or Storage)
- Type of Operating System (Linux/Unix, MacOS, Windows)
- Bandwidth
- Instances optimised for Compute, Memory (large datasets in memory) or Storage

- AWS Example: https://aws.amazon.com/ec2/instance-types/

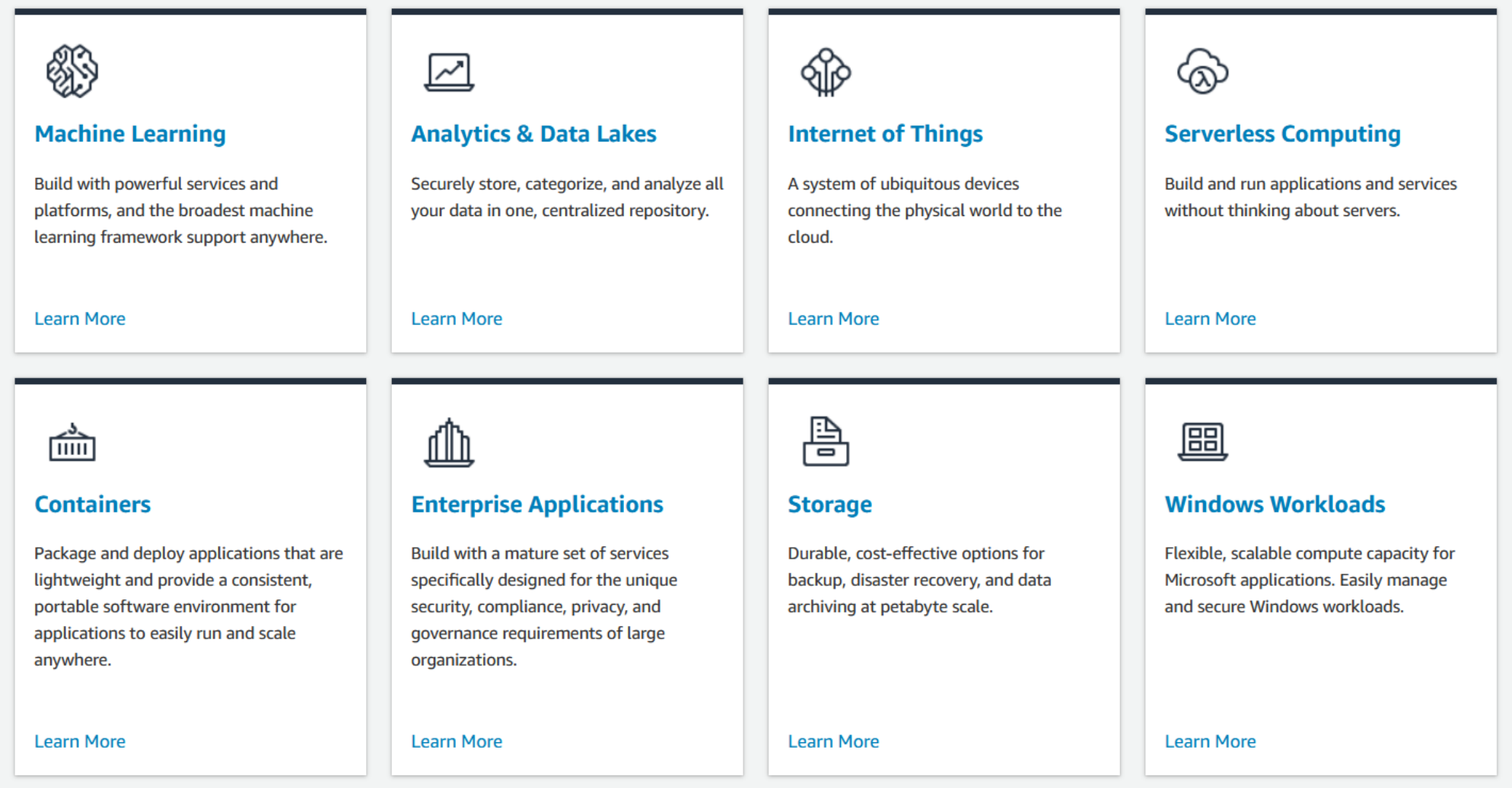
Leading Cloud Computing providers

	File storage	Computation	List of services
aws	 S3	 EC2	https://aws.amazon.com/products/
Azure	 File, Queue, Table, Blob — Storage Types	 Azure VM	https://azure.microsoft.com/en-au/services/
	 Google Cloud Storage	 Google Compute Engine	https://cloud.google.com/products

AWS S3 Buckets

- Simple Storage Service – does not provide computation
- **Buckets** store objects (data) and associated metadata
- Files are referenced as keys – there is no hierarchical structure
  - e.g. though dir/f1 and dir/f2 are allowed filenames, they do not share a common folder dir
- Its name should be globally unique
- Pricing: https://aws.amazon.com/s3/pricing/

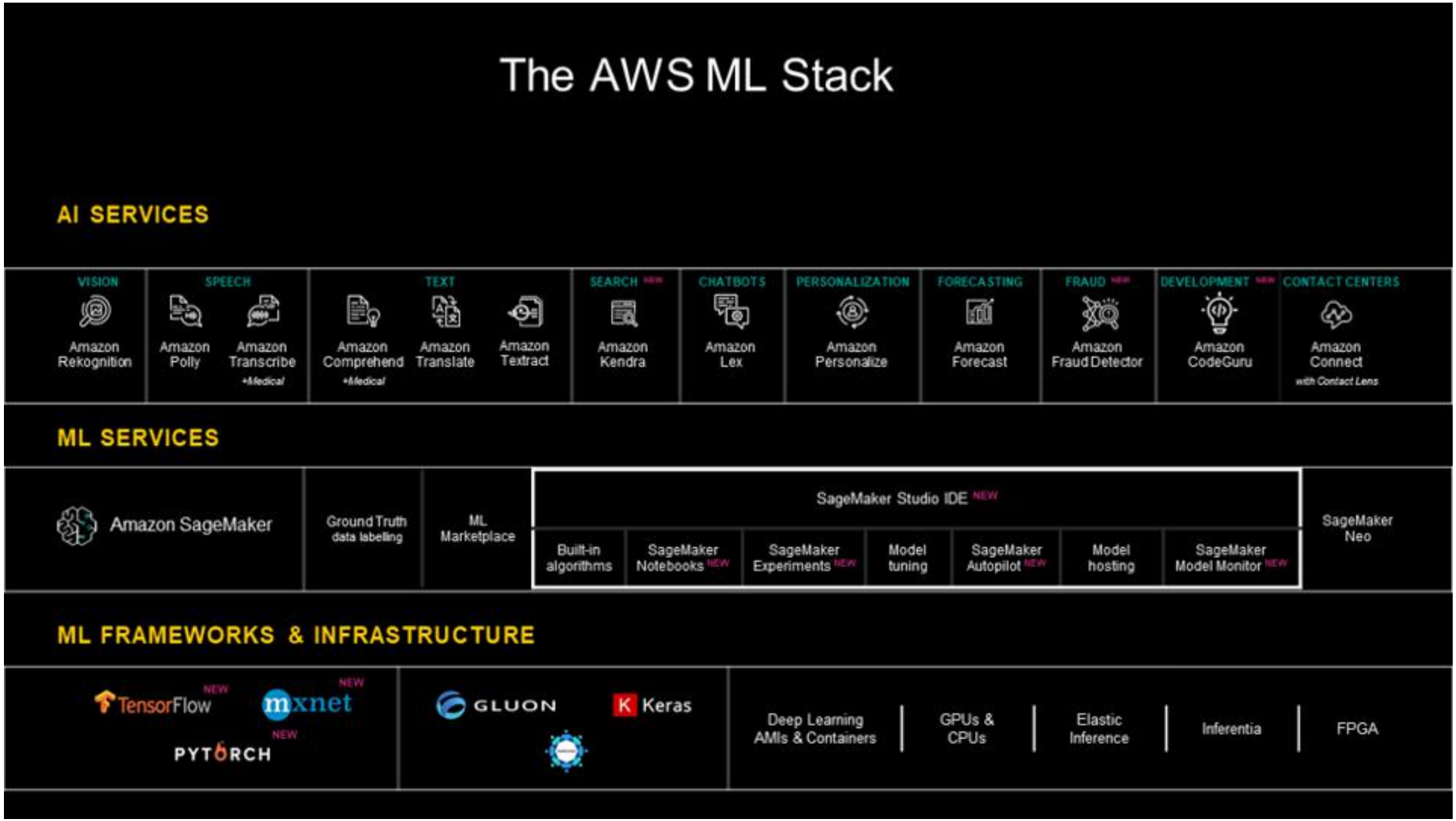
Amazon Web Services



https://aws.amazon.com/

AWS for Machine Learning

- **SageMaker** – notebooks (Jupyter and JupyterLab)
- **Amazon Rekognition** – image and video analysis such as facial recognition
- **Amazon Comprehend** – NLP
- **Amazon Textract** – text extraction from images or pdf files
- Amazon Lex – Building conversational interfaces (e.g. chatbots) into an application using voice and text
- Amazon Polly – text to speech
- Amazon Transcribe – speech to text
- AWS DeepLens – Deep-Learning-enabled video camera
- Amazon Personalize – individual recommendations
- Amazon Forecast – time series forecasting



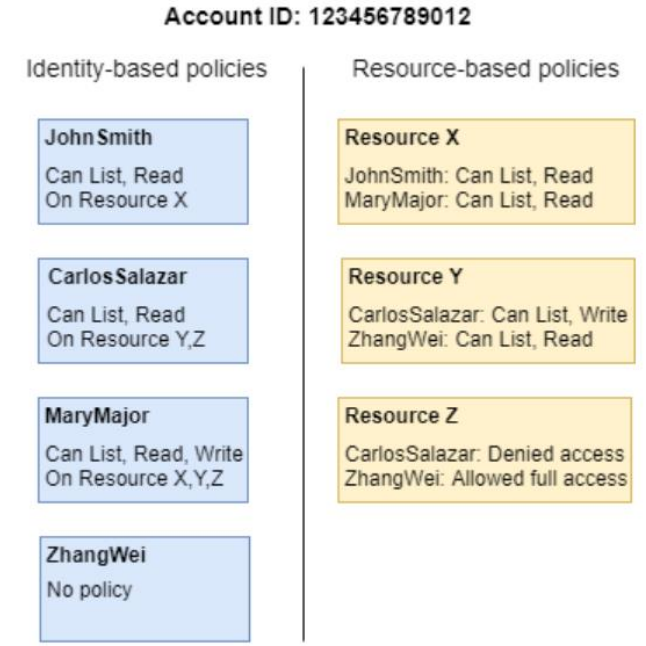
https://www.forbes.com/sites/moorinsights/2020/03/04/surprise-aws-leads-in-cloud-ai-services-ranking/

Identity and Access Management (IAM)

- Access in AWS is managed by creating policies and attaching them to IAM identities (users, groups of users, or roles) or AWS resources.

- **User** – an individual
- **Group** – a set of users sharing common roles and policies
- **Role** – a set of permissions for granting access to resources – not associated with any specific user or group and less permanent
- **Policy** – a document listing permissions (e.g. creating or updating a database table)

https://www.msp360.com/resources/blog/iam-identities/



https://docs.aws.amazon.com/IAM/latest/UserGuide/access_policies_identity-vs-resource.html

Lab 10.1: AWS SageMaker and Managed Services

Purpose

- Gain familiarity with AWS SageMaker and some Machine Learning Managed Services via the Console

Resources

- COCO Dataset (images)

Materials

- Jupyter Notebook (Lab-10_1)
- Sample image files

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Deployment

- Challenges
- Considerations
- Pipelining
- Small-scale deployment via a REST API
- DevOps and CI/CD
- Monitoring

Deployment

- **Deployment** refers to making models available in production environments, where they can provide exposure to more users or be consumed by other software systems.
- Only after this deployment do models add business value.
- Types of deployment depend on the frequency of model training:
- **Batch** – large amount of data is required for a prediction (e.g. a user's entire transaction history), latency does not matter
- **Real-time** – a small amount of data is required (e.g. choosing an online ad to show to a customer)

Challenges of Deployment

- Requires coordination between data scientists, IT teams, software developers, and business professionals to ensure a model works reliably in the organisation's production environment
- Sometimes a model is written in one language (e.g. R, Python) but is deployed in another (e.g. Java, C++)
- Incompatibility of code across different machines (operating systems, versions of libraries etc)
    - -> Containerisation

Challenges of Deployment

- Processing power (e.g. GPUs, TPUs) might be scarce and expensive for deployment at a large scale
- Scaling to accommodate a large number of users
- Data leakage or contamination – information about a target variable is present when it should not (e.g. information from the future, features depend on data from the holdout set)
- Reproducibility of results

Deployment Considerations

- Will the deployment deliver business value? Success metrics?
- What software tools to use?
- What are the dependencies (for code and data)?
- How will the results be consumed?
  - A dashboard?
  - Linked to an alert or triggering another software process?

Deployment Considerations

- Hosted on the cloud or on premise?
- How to scale it to more users?
- How to guarantee security?
- How often should the model be retrained?
- How to monitor performance?

Model pipelining

- To ensure reproducibility avoid transforming data manually (e.g. find/replace operations, editing a Spreadsheet in Excel)

- Make use of pipelines consisting of steps such as the following
  - Read in the data (possibly using a feature store)
  - Merge multiple sources
  - Completing missing values
  - Address class imbalance (e.g. resampling)
  - Feature selection/engineering
  - Dimension Reduction
  - Model training with optimised hyperparameters

- In Python: from sklearn.pipeline import Pipeline

Small-Scale Deployment

- Easiest way is to create a web REST API endpoint using a Web framework such as Flask
  - Enables real-time predictions but would not scale up to a large number of users

Basic steps:

- Set up a reproducible pipeline from data to prediction
- Save the model pipeline in binary format (pickle or joblib)
- Build an image (container) with model and library dependencies
- Have the image hosted on a Platform as a Service (e.g. Heroku, AWS Elastic Beanstalk)

Model as Data – what needs to be stored?

- Persistence – saving a model for future use without having to retrain

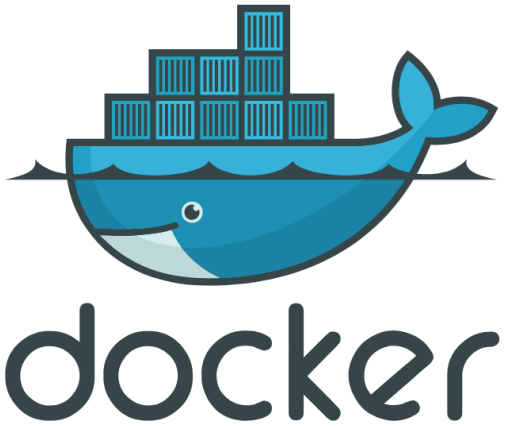
- Linear regression – a list of coefficients
  - Predict by applying a linear combination of the inputs
- KNN – the entire dataset
  - Predict by finding the k nearest neighbours to a given input
- Decision tree – the set of decisions at each node
  - Predict by traversing the tree according to the outcome of each decision
- Neural network – all weights and activation functions between neurons
  - Predict by applying the linear combinations and activation functions to a given input

Containers

- A container is a set of software processes isolated from the rest of an operating system
- It contains all the files necessary to support the processes (model + library dependencies)
- Different from a virtual machine in that they do not require a full operating system – a single operating system may run separate container instances
- Programs inside a container only have visibility to contents of the container and devices connected to it

Containers

- Advantage: avoiding environment related issues - if containerised code works on one machine, it will run on another irrespective of the characteristics of the machine
- Docker is the most popular containerization service
- Docker Tutorial: docker-curriculum.com



Deployment via Flask

- Flask is a web framework allowing one to create small-scale web apps in Python
- Allows one to create a REST API service that is deployed on a web server

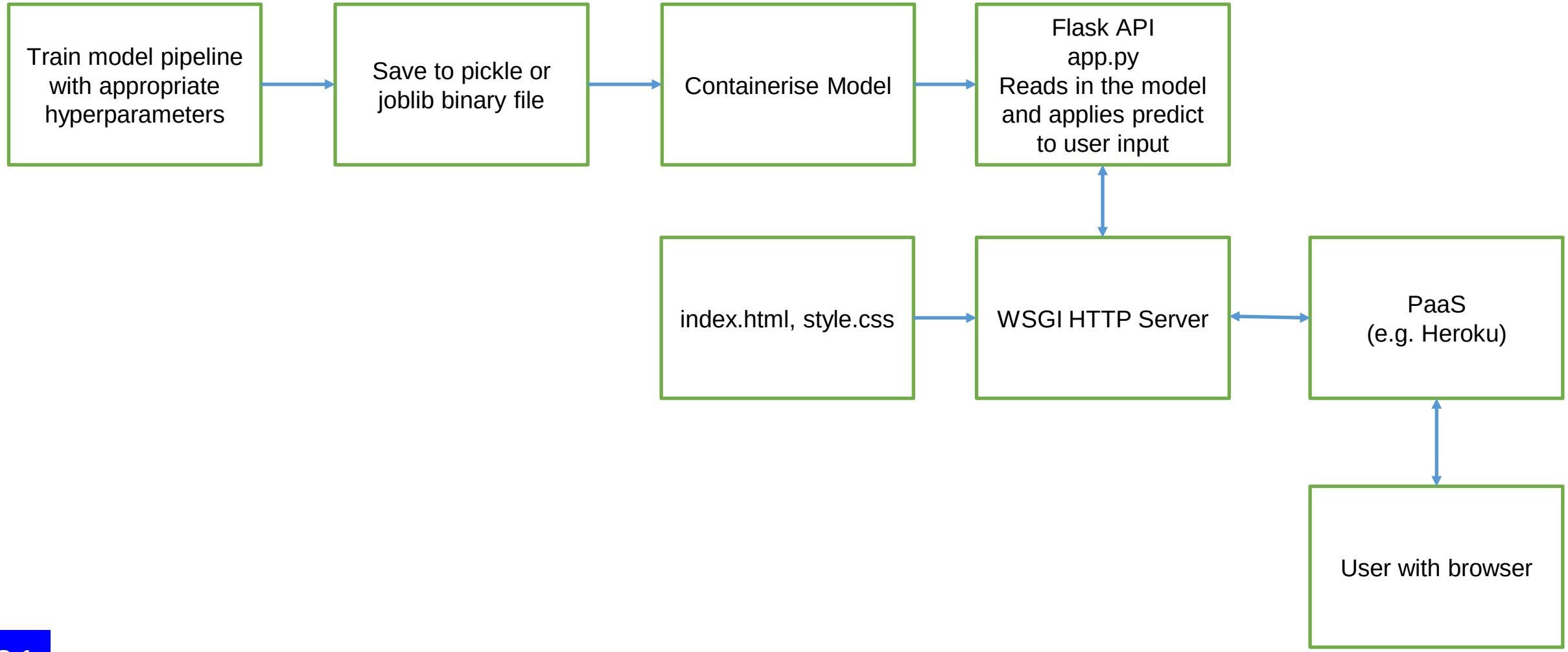
- For larger applications one can use Gunicorn with Nginx as the web server

```
@app.route('/')
def home():
    return render_template('index.html')

@app.route('/predict',methods=['POST'])
def predict():
    …
```

@app.route allows Flask to assign functions to URLs

Deployment via Flask



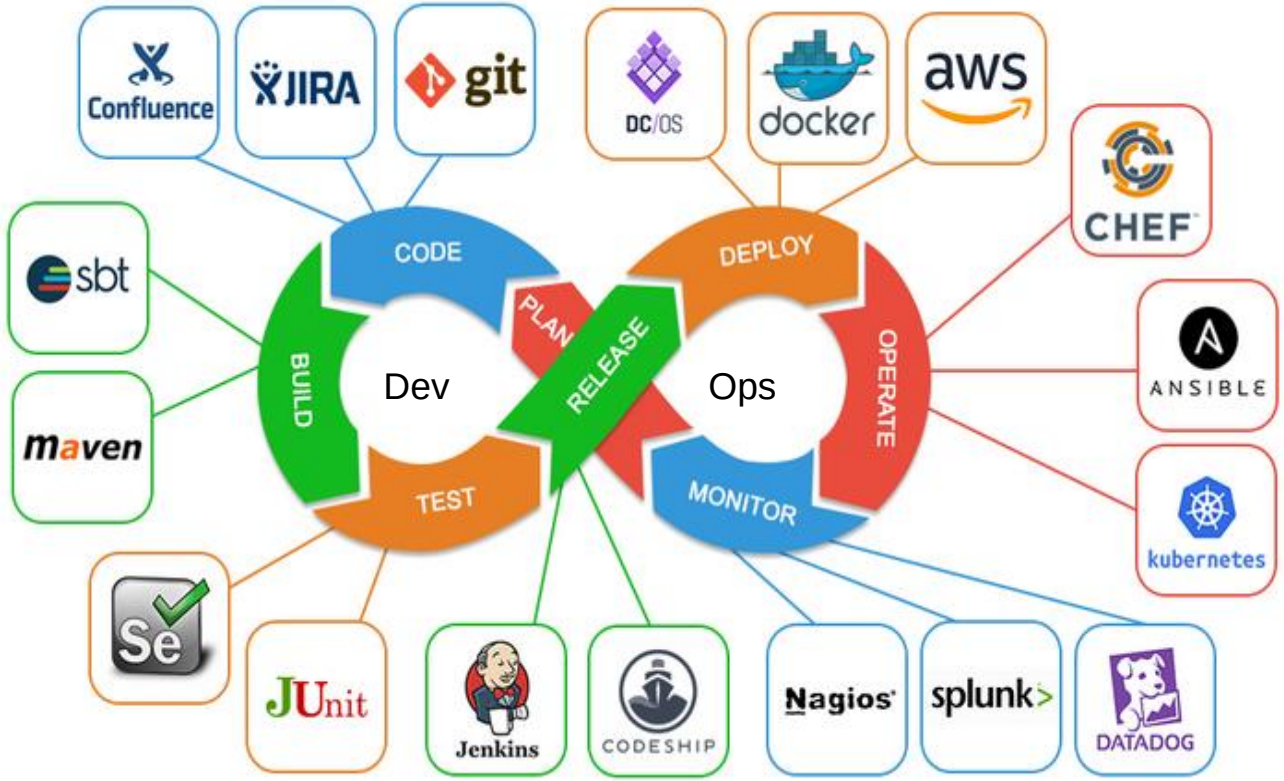
Model Monitoring and Maintenance

- Monitoring and scoring models while in production ensures they are behaving as intended
- Model/data drift – the statistics of input data no longer match the training data – hence the need to retrain
  - Statistical tests can check for the closeness between distributions of training data and data observed in production
- Concept drift – change in the meaning/interpretation of the target variable over time
  - e.g. in detecting rare events the definition of an anomaly changes over time
- Usually the remedy is more frequent training but on occasions the model needs to be redesigned

Larger scale: DevOps and CI/CD

- DevOps is a combination of Software Development (Dev) and IT Operations (Ops)
- IT Operations – services provided by an IT department for its customers
- DevOps aims to shorten the systems development life cycle and provide continuous delivery while maintaining high software quality
- CI/CD (Continuous Integration/Continuous Deployment) automates the process of building-testing-deploying (e.g in Dev/Test/Prod environments), shortening the life cycle of software development while maintaining quality
- New ideas can be deployed in production more rapidly, providing value to the user

The DevOps Lifecycle with Sample Tools

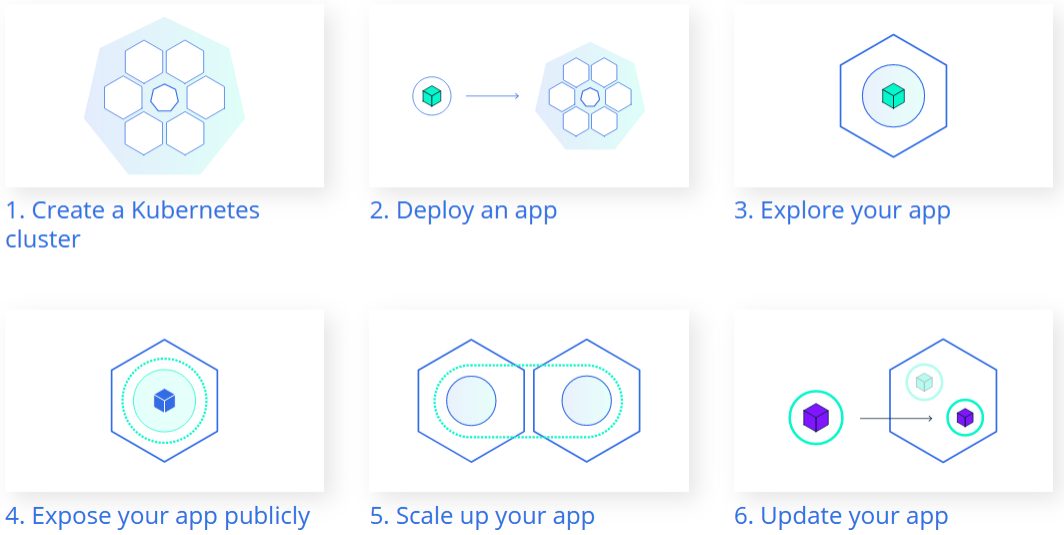


https://dzone.com/articles/why-should-i-learn-devops

See also: https://i.redd.it/92ja1d3v0x141.jpg

Orchestration

- A web service can scale by orchestration – a cluster of containers can be created on demand based on a copy of the original image container
- This also ensures fault tolerance should one container fail
- Kubernetes and Amazon ECS (Elastic Container Service) are well known orchestration systems



https://kubernetes.io/docs/tutorials/kubernetes-basics/

Enabling Security

Ways to ensure secure model deployment include

- Cryptographically encrypting the model
- Hosting with a secure protocol (https vs http)
- Providing access control (e.g. token-based API)
- Including password protections

Machine Learning Platforms

Developed internally

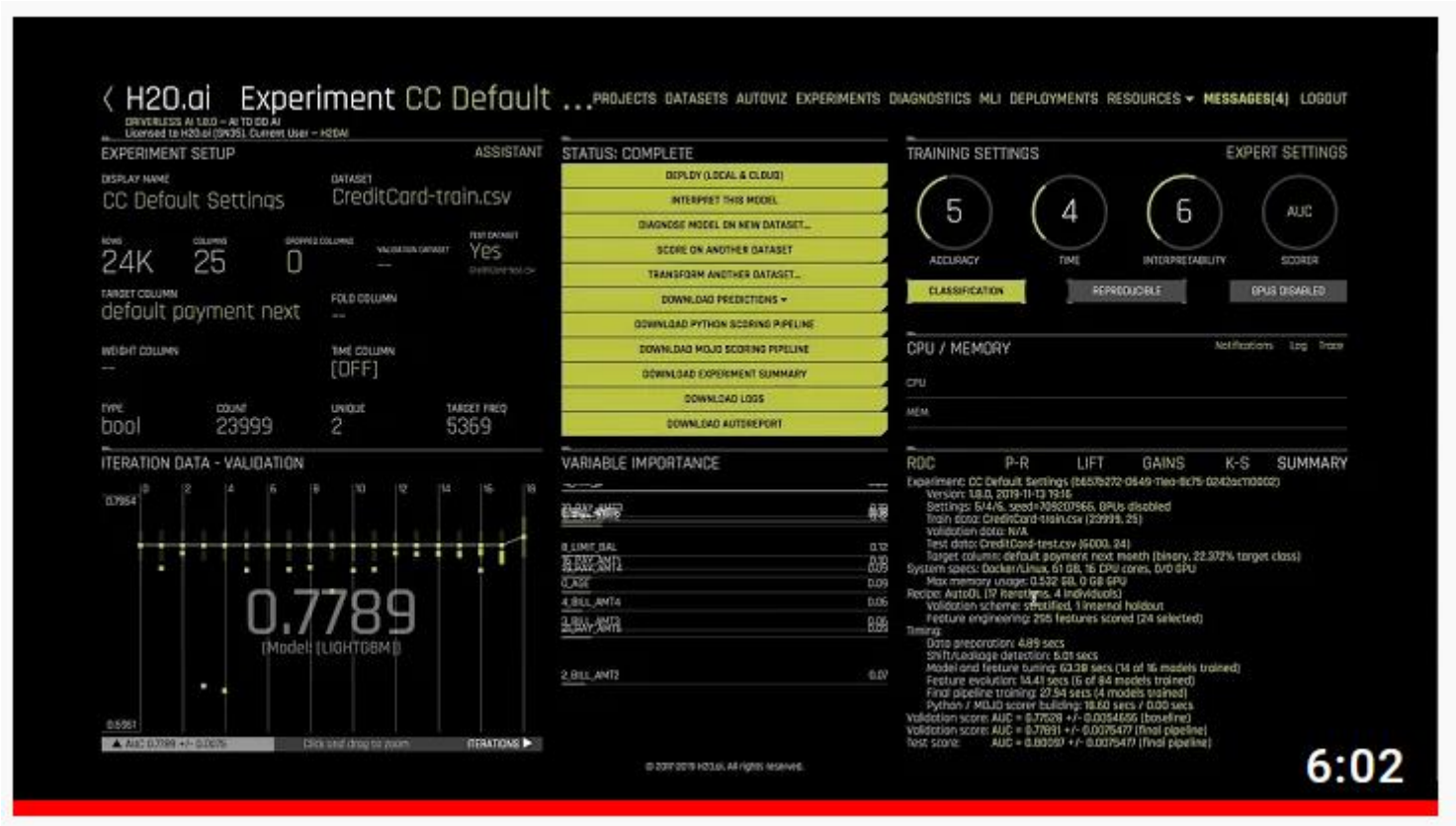
- Google: TFX (TensorFlow Extended)
- Uber: Michelangelo
- Databricks: MLFlow
- Facebook: FBLearner Flow

AutoML

- Tools exist to automate the process from data ingestion to deployment
  - Most useful for data clean-up and hyperparameter tuning
- Data scientists are still needed for problem definition, appropriate feature engineering requiring domain knowledge

- Google Cloud AutoML
- Microsoft Azure AutoML
- AWS SageMaker Autopilot
- DataRobot
- H20.ai
- TPOT
- Auto-Sklearn

One example of AutoML - H2O.ai demo



https://www.youtube.com/watch?v=ZqCoFp3-rGc

Lab 10.2: Model Deployment

- Purpose
  - Learn how to deploy a simple app on a cloud platform
- Resources
  - Reviews Data – sentiments.csv
- Materials
  - Jupyter Notebook (Lab 10_2)
  - Several Python scripts and text files

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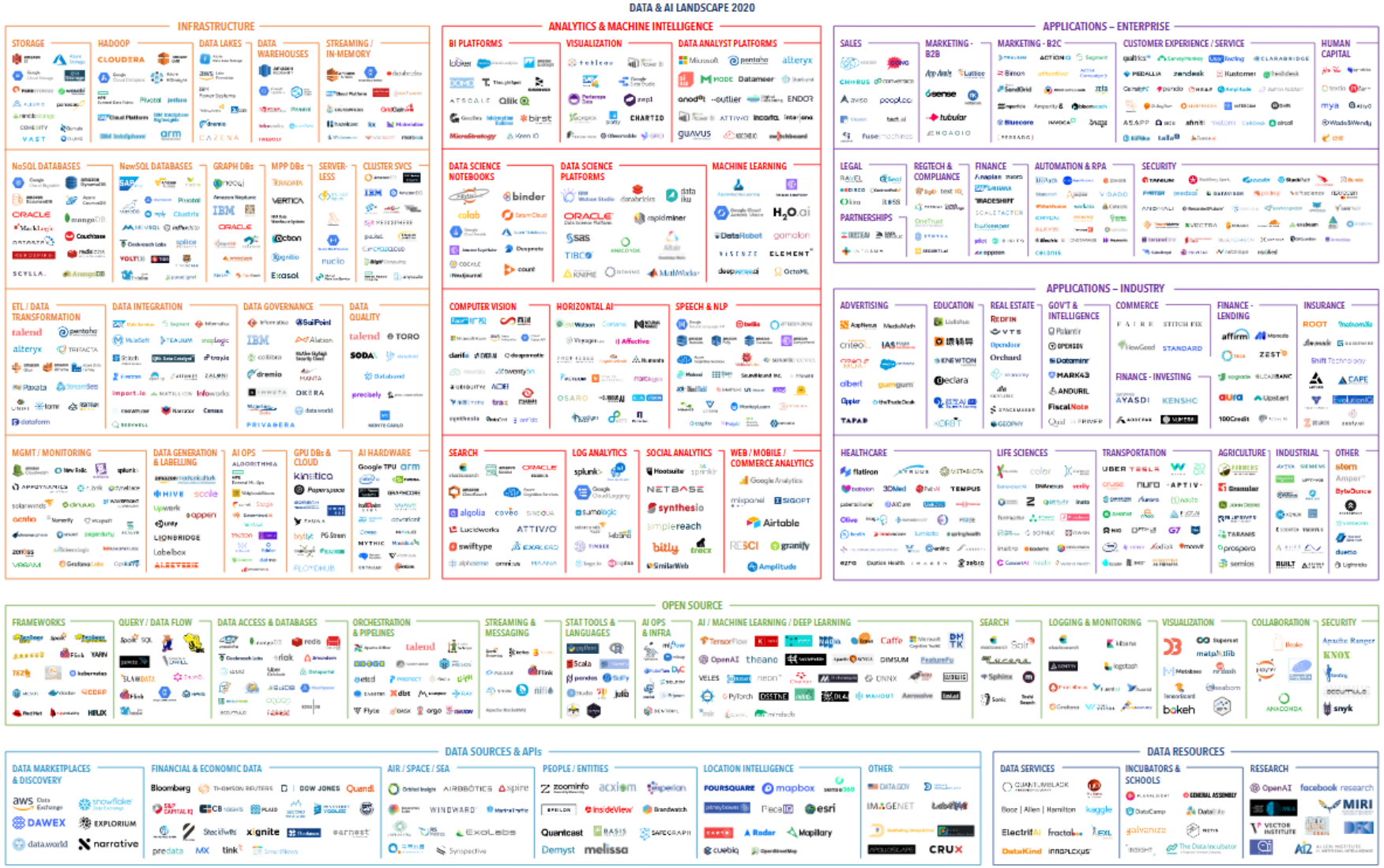
Cluster Computing

- Introduction
- Hadoop
- Spark
- PySpark
- Amazon EMR

The Data & AI Landscape is vast!



https://mattturck.com/data2020/

Introduction

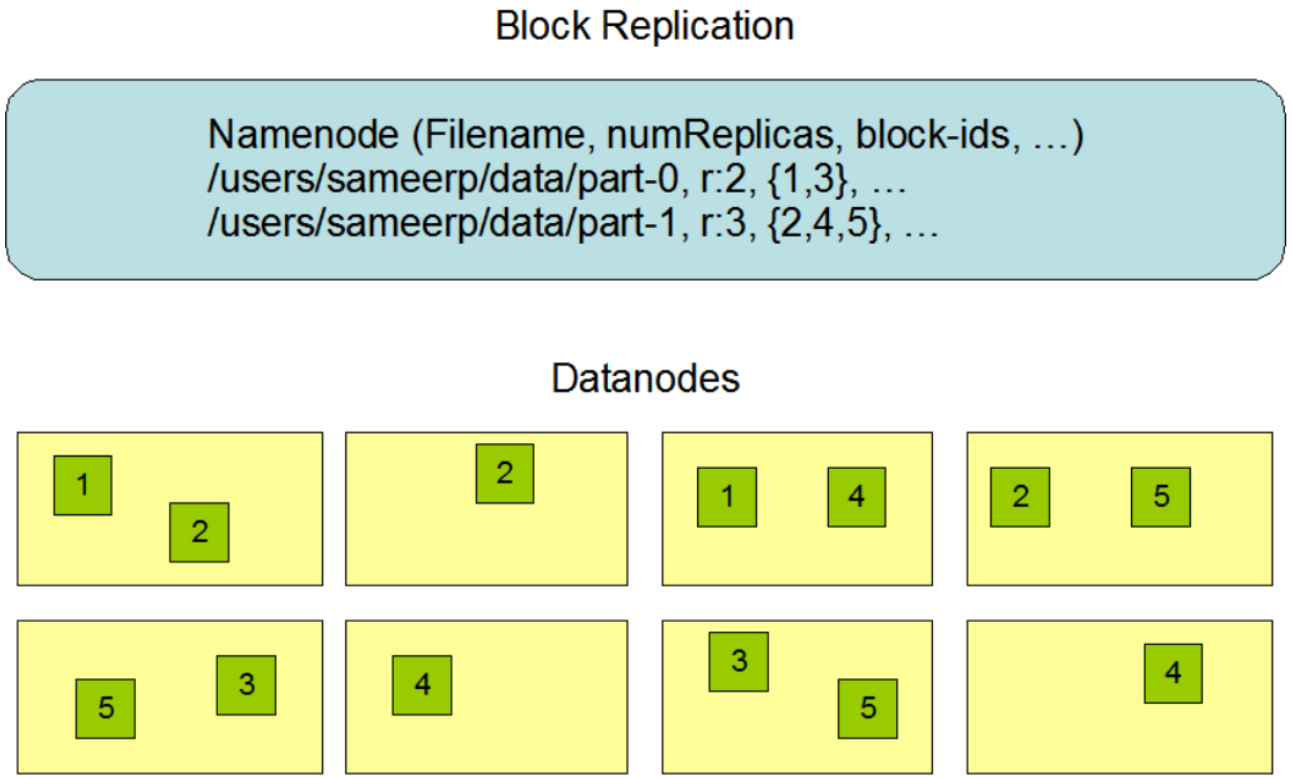
- **Cluster computing** – two or more computing nodes (servers) connected via a Fast Area Network, usually performing the same task
- Chief benefits – speed, scalability, flexibility over traditional mainframe solutions
- A **load balancer** may be used to spread the computing load evenly across the cluster for better overall performance
- Applications in Machine Learning
  - Working with large datasets
  - Deep learning (often nodes will have GPUs or TPUs)

Parallel Computation

- MapReduce: splits a large task into multiple map and reduce tasks that can be distributed across a cluster
  - **Map**: Process chunks (splits) of data in parallel creating intermediate results as key-value pairs
  - **Shuffling**: Pairs with the same key are sent to the same reducer
  - **Reduce**: Process in parallel each of the pairs having the same key
- Hadoop: Apache's implementation of MapReduce
- YARN: Performs resource management and job scheduling for Hadoop
- Apache Spark: For in-memory data processing

HDFS – Hadoop Distributed File System (Big Data Storage)

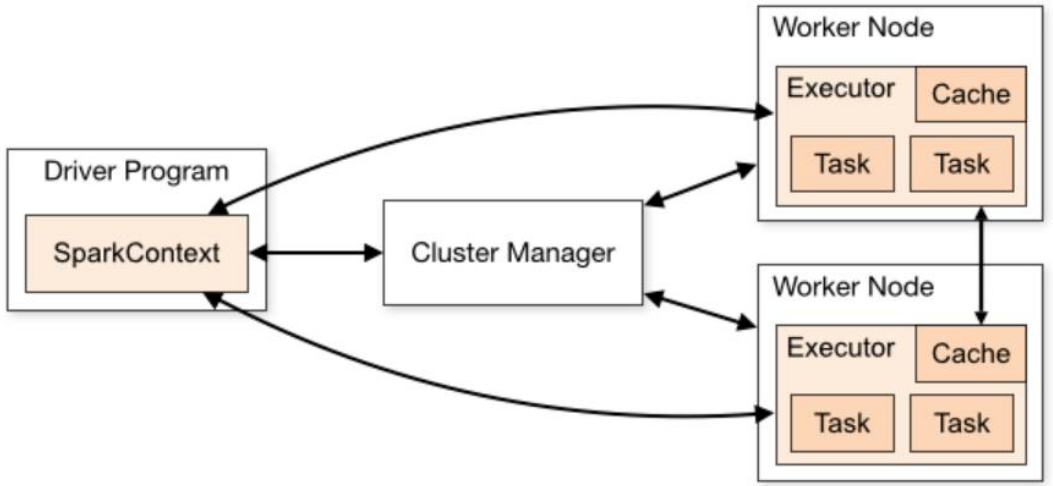
- Inputs and outputs of a map-reduce operation are stored in HDFS
- **Namenode** is a master node that contains metadata about how data is to be distributed in the cluster
- Here a large single file is split into five parts indicated by block-ids 1 to 5. Blocks 1 and 3 have two copies while 2, 4, 5 are replicated three times among the Datanodes
- Replication of data ensures fault-tolerance (default replication value is 3 in Hadoop)



https://hadoop.apache.org/docs/r1.2.1/hdfs_design.html

Spark and PySpark

- Spark accesses data from HDFS but avoids MapReduce processing, instead performing in-memory computing instead of on disk.
  - hence a faster alternative
- PySpark is a Spark API for Python
- A SparkContext represents the connection to a Spark cluster
- Subpackages:
  - pyspark.sql module
  - pyspark.streaming module
  - pyspark.ml package
  - pyspark.resource module



https://spark.apache.org/docs/latest/cluster-overview.html

pyspark.sql

- This provides SQL-like functions for Spark DataFrames
  - SparkSession – create this to start working with a DataFrame
  - createDataFrame – via a variety of file formats such as csv, JSON, ORC, Parquet, Hive tables, Avro

```
data = [('John','','Smith','1993-03-06','M',4000),
  ('Gareth','Smart','','2002-07-29','M',5000),
  ('Linda','','Carey','1988-05-06','F',5000),
]

from pyspark.sql import SparkSession
spark = SparkSession.builder.appName('Name of App').getOrCreate()
columns = ["firstname","middlename","lastname","dob", "gender","salary"]
df = spark.createDataFrame(data=data, schema = columns)
```

pyspark.sql

Note that Spark Dataframes are immutable, so any modification needs to be written to a new dataframe

```
#update a column
dfnew = df.withColumn("salary",col("salary")*100)

#show all rows
dfnew.show(truncate=False)

#use select for column subsetting, filter for row subsetting
dfnew.select("salary")
dfnew.filter(dfnew."salary" > 2000)
```

Big Data – Example tools

- Hue, Apache Impala – real-time SQL for data warehouses (the latter for Hadoop)
- Pig/Hive: SQL-like scripting and querying tools for data processing that simplify MapReduce programs.
- HBase, MongoDB, Elasticsearch: Examples of a few NoSQL databases.
- Mahout, Spark ML: Tools for running scalable machine learning algorithms in a distributed fashion.
- Flume, Sqoop, Logstash: Data ingestion and integration (e.g. transfer of data between databases)
- Splunk, Elastic Stack: Monitoring of log files

Amazon EMR

- Amazon Elastic Map Reduce – distributes processing over EC2 clusters
- Master node – manages the cluster
- Core nodes – run tasks and store results in HDFS
- Task nods (optional) – run computation but do not make use of HDFS storage
- Spark Livy – a web service that connects with Spark over a REST interface enabling one to connect SageMaker to a cluster

Node type	Instance type	Instance count	Purchasing option
Master Master - 1	**m4.large** 2 vCore, 8 GiB memory, EBS only storage EBS Storage: 32 GiB Add configuration settings	1 Instances	**On-demand** **Spot** Use on-demand as max price
Core Core - 2	**m4.large** 2 vCore, 8 GiB memory, EBS only storage EBS Storage: 32 GiB Add configuration settings	2 Instances	**On-demand** **Spot** Use on-demand as max price
Task Task - 3	**m5.xlarge** 4 vCore, 16 GiB memory, EBS only storage EBS Storage: 64 GiB Add configuration settings	0 Instances	**On-demand** **Spot** Use on-demand as max price

Lab 10.3: Big Data Computing

- Purpose
  - Learn how to use PySpark to analyse a large dataset
- Resources
  - A population dataset from Population Division, United Nations
- Materials
  - Jupyter Notebook (Lab 10_3) in Google Colab

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Stream Computing

- Data Stream Processing
- The Pub/Sub Model
- Apache Kafka
- Amazon Kinesis
- Amazon Kinesis Analytics (SQL)
  - Windowed queries

Data Streams are everywhere

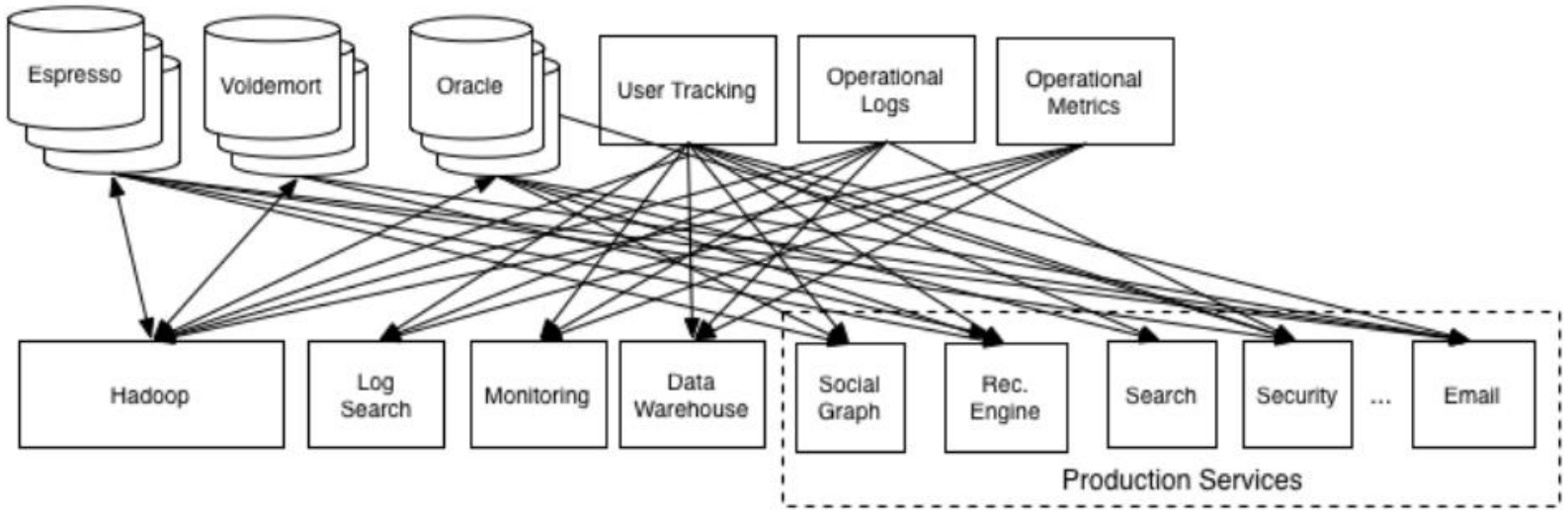
- Sensor data
- Video
- News feeds
- Financial data
- Online gaming
- Network Traffic data
- Clickstreams or App activity tracking
- Social media
- Location tracking
- Machine logs

Data Stream Processing

- Typically a solution comes from the use of multiple tools
- A stream process can be thought of as a directed acyclic graph composed of **sources**, **operators** and **sinks**
- **Sources** – where streams enter the streaming system
- **Operators** – functions of streams producing an output stream
- **Sinks** – places where streams flow out of the streaming system (e.g. a dashboard or database)
- Sources, sinks, operators combined into directed acyclic graph
- No batch processing, outputs constantly produced
- Event time and processing time generally differ
- Computation performed upon every event or within time windows

The Pub/Sub Model

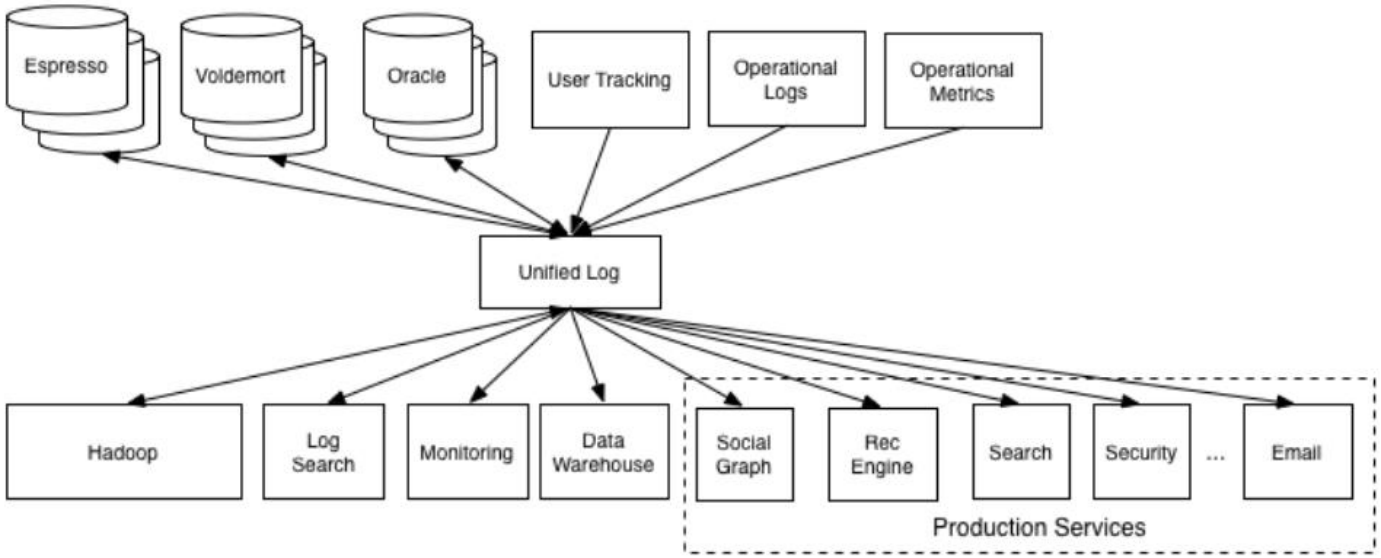
- Traditionally data systems and repositories are connected in the following manner, with a separate pipeline needed for each connection



https://engineering.linkedin.com/distributed-systems/log-what-every-software-engineer-should-know-about-real-time-datas-unifying

The Pub/Sub Model

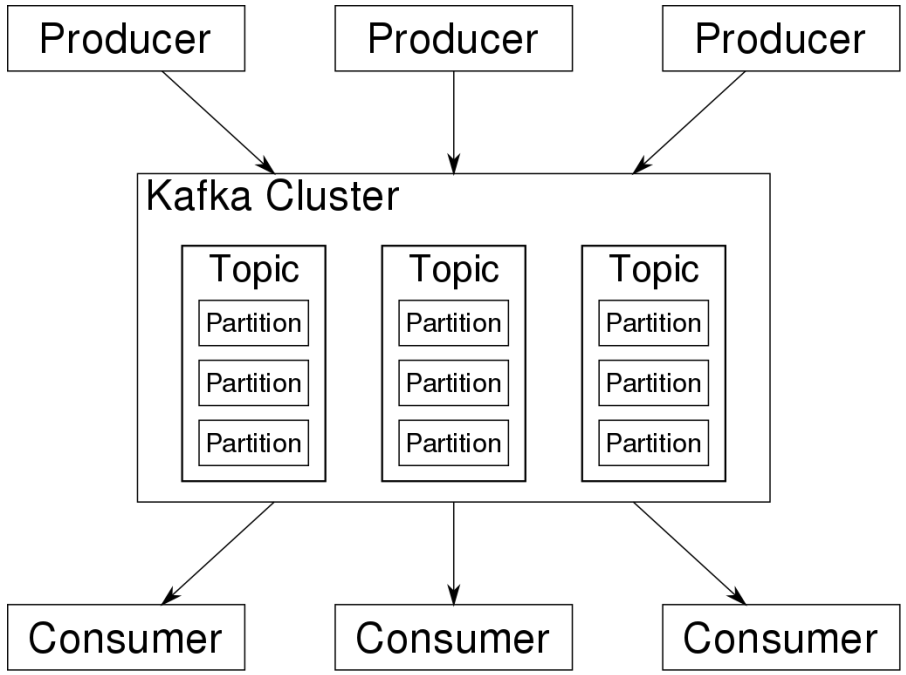
- Connections can be greatly reduced by separating the **producers** and **consumers** of data, each publishing to/subscribing from a messaging system
- **Apache Kafka** is one such model employing distributed stream processing



https://engineering.linkedin.com/distributed-systems/log-what-every-software-engineer-should-know-about-real-time-datas-unifying

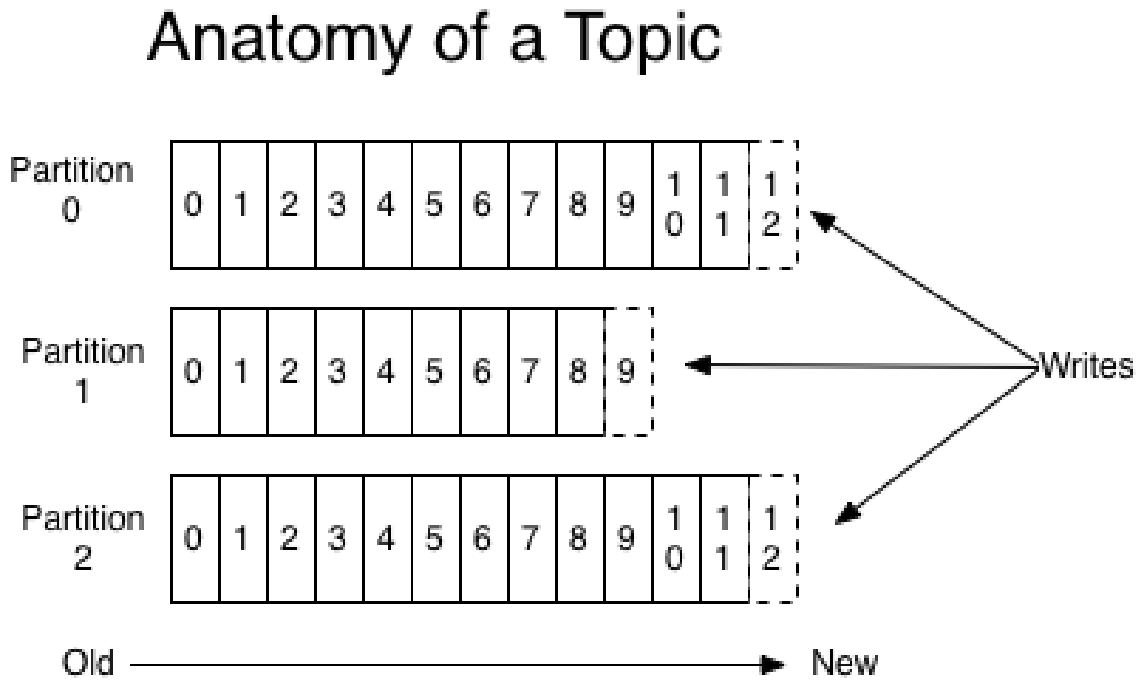
Apache Kafka

- **Broker** - handles all requests from clients (producers, consumers and metadata) and keeps data replicated within the cluster.
- **Topics** (categories) are divided into **partitions** containing records each with a unique offset in a fixed sequence. Partitions may be replicated across the cluster.



Apache Kafka

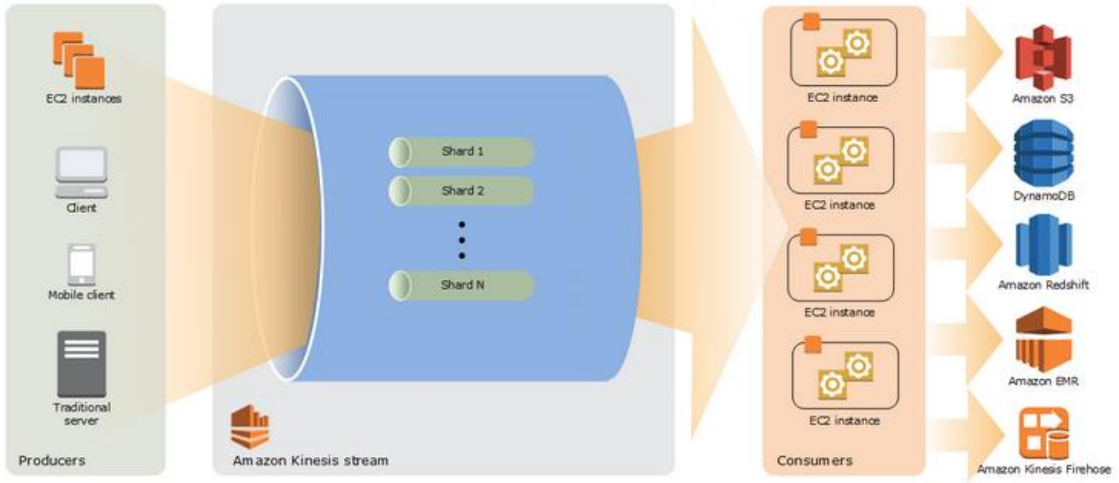
- **Message (record)** - a key / value pair – the key assigns records to a specific partition (the publisher can also specify a partition directly)
- A record inside a partition has an **offset**, used to identify the order in which records are published to a partition – hence messages can either be read from the beginning or a specified offset
- **Zookeeper** – used for service synchronisation, tracking the status of nodes (brokers) in the Kafka cluster and maintaining a list of Kafka topics and messages (metadata)



https://sookocheff.com/post/kafka/kafka-in-a-nutshell/log-anatomy.png

Amazon Kinesis

- AWS platform for streaming data
- The throughput is in units of **shards**
- To put data into the stream, one specifies the **name** of the stream, a **partition key**, and the **data blob** to be added to the stream
- The partition key is used to determine which shard in the stream the data record is added to.



- 1 shard can support up to 5 transactions per second for reads, up to a maximum total data read rate of 2 MB per second and up to 1,000 records per second for writes, up to a maximum total data write rate of 1 MB per second (typically consumers are slower in transactions than producers)

Lab 10.4 (Optional)

- Purpose
  - Learn how to use Apache Kafka in data streaming applications
- Resources
  - fraud_data.csv
- Materials
  - Jupyter Notebook (Lab 10_4) in Google Colab

Questions?

Appendices

End of Presentation!