Index

Symbols

- 1NF (first normal form), Relational Model
- 2NF (second normal form), Relational Model

A

- A/B testing, <u>A/B Testing-A/B Testing</u>, <u>Bandits</u>
- accuracy-related metrics, Monitoring accuracy-related metrics
- ACID (atomicity, consistency, isolation, durability), <u>Transactional and</u> <u>Analytical Processing</u>
- active learning, <u>Active learning</u>-<u>Active learning</u>
- ad hoc analytics, <u>Experiment tracking</u>
- adaptability, Adaptability
- adversarial attacks, <u>Evaluation challenge</u>
- adversarial augmentation, <u>Perturbation</u>
- AI (artificial intelligence), ethics, <u>Responsible AI</u>, <u>Discover sources for model biases</u>-<u>Discover sources for model biases</u>
 - data-driven approach limitations, <u>Understand the limitations of the data-driven approach</u>
 - irresponsible, case studies, <u>Irresponsible AI: Case Studies-Case</u> <u>study II: The danger of "anonymized" data</u>
 - mitigating biases, Establish processes for mitigating biases
 - model cards, <u>Create model cards</u>-<u>Create model cards</u>
 - trade-offs, <u>Understand the trade-offs between different desiderata</u>
- Airflow, <u>Data Science Workflow Management-Data Science Workflow</u>
 <u>Management</u>
- alert fatigue, Monitoring features, Alerts
- alert policies, Alerts
- algorithms
 - bandit algorithms, <u>Bandits</u>-<u>Contextual bandits as an exploration</u> <u>strategy</u>
 - continual learning and, <u>Algorithm challenge</u>-<u>Algorithm challenge</u>

- feature importance, <u>Feature Importance</u>
- analytical processing, Transactional and Analytical Processing
- Apache Iceberg, Transactional and Analytical Processing
- architectural search, <u>Hard AutoML</u>: <u>Architecture search and learned</u>
 <u>optimizer</u>
- Argo, <u>Data Science Workflow Management-Data Science Workflow</u>
 <u>Management</u>
- artifacts, Experiment Tracking and Versioning
- artificial intelligence (see AI)
- asynchronous prediction, <u>Batch Prediction Versus Online Prediction</u>
- automated retraining, <u>Stage 2: Automated retraining-Requirements</u>
- AutoML
 - architecture search, <u>Hard AutoML</u>: <u>Architecture search and</u>
 <u>learned optimizer-Hard AutoML</u>: <u>Architecture search and learned</u>
 <u>optimizer</u>
 - hard AutoML, <u>Hard AutoML</u>: <u>Architecture search and learned optimizer</u> <u>mizer-Hard AutoML</u>: <u>Architecture search and learned optimizer</u>
 - hyperparameter tuning, <u>Soft AutoML: Hyperparameter tuning-Soft</u>
 <u>AutoML: Hyperparameter tuning</u>
 - learned optimizer, <u>Hard AutoML</u>: <u>Architecture search and learned</u>
 <u>optimizer-Hard AutoML</u>: <u>Architecture search and learned</u>
 <u>optimizer</u>
 - soft AutoML, <u>Soft AutoML: Hyperparameter tuning-Soft AutoML:</u>
 <u>Hyperparameter tuning</u>
- autoscaling, <u>Scalability</u>

B

- bagging, ensembles, <u>Bagging</u>-<u>Bagging</u>
- bandit algorithms, <u>Bandits</u>-<u>Contextual bandits as an exploration</u>
 <u>strategy</u>
- BASE (basically available, soft state, and eventual consistency),
 Transactional and Analytical Processing
- base learners, <u>Ensembles</u>
- base model, fine tuning, <u>Transfer learning</u>
- baselines, offline model evaluation, **Baselines**
 - existing solutions, **Baselines**

- human, <u>Baselines</u>
- random, Baselines
- simple heuristic, **Baselines**
- zero rule, **Baselines**
- batch pipeline, <u>Unifying Batch Pipeline and Streaming Pipeline</u>
 <u>Unifying Batch Pipeline and Streaming Pipeline</u>
- batch prediction, <u>Batch Prediction Versus Online Prediction</u>-<u>Batch</u>
 <u>Prediction Versus Online Prediction</u>
 - moving to online prediction, <u>From Batch Prediction to Online</u>
 <u>Prediction-From Batch Prediction to Online Prediction</u>
- batch processing, <u>Batch Processing Versus Stream Processing-Batch</u>
 <u>Processing Versus Stream Processing</u>
- batches, overfitting, Versioning
- binary classification, Binary versus multiclass classification
- binary data, **Text Versus Binary Format**
- binary file size, **Text Versus Binary Format**
- boosting, ensembles, **Boosting-Boosting**
- Borg, Cron, Schedulers, and Orchestrators
- brand monitoring, Machine Learning Use Cases
- browsers, ML (machine learning) and, <u>ML in Browsers</u>
- building versus buying, <u>Build Versus Buy</u>-<u>Build Versus Buy</u>
- business analysis, **Iterative Process**
- business objectives, <u>Business and ML Objectives</u>-<u>Business and ML Objectives</u>

C

- calibration, <u>Model calibration</u>-<u>Model calibration</u>
- canary release, <u>Canary Release</u>
- cardinality, classification tasks and, <u>Binary versus multiclass</u>
 <u>classification</u>
- catastrophic forgetting, **Continual Learning**
- categorical features, <u>Encoding Categorical Features-Encoding</u>
 <u>Categorical Features</u>
- champion model, **Continual Learning**
- churn prediction, **Challenges of Class Imbalance**
- class imbalance, <u>Class Imbalance</u>

- algorithm-level methods, <u>Algorithm-level methods</u>
 - class-balanced loss, <u>Class-balanced loss</u>
 - cost-sensitive learning, Cost-sensitive learning
 - focal loss, <u>Focal loss</u>
- challenges, <u>Challenges of Class Imbalance-Challenges of Class</u>
 <u>Imbalance</u>
- evaluation metrics, <u>Using the right evaluation metrics</u>-<u>Using the right evaluation metrics</u>
- resampling, <u>Data-level methods: Resampling-Data-level methods:</u>
 <u>Resampling</u>
- class-balanced loss, <u>Class-balanced loss</u>
- classification
 - as regression problem, <u>Using the right evaluation metrics</u>
 - binary, <u>Binary versus multiclass classification</u>
 - hierarchical, <u>Binary versus multiclass classification</u>
 - high cardinality, Binary versus multiclass classification
 - multiclass, <u>Binary versus multiclass classification</u>, <u>Multiclass versus multilabel classification</u>
 - multilabel, Multiclass versus multilabel classification
 - sentiment analysis, <u>Learned Features Versus Engineered Features</u>
- classification models, <u>Classification versus regression</u>
- cloud computing, <u>ML on the Cloud and on the Edge</u>, <u>Public Cloud</u>
 <u>Versus Private Data Centers-Public Cloud Versus Private Data Centers</u>
 - elasticity, <u>Public Cloud Versus Private Data Centers</u>
 - multicloud strategy, <u>Public Cloud Versus Private Data Centers</u>
- code versioning, <u>Versioning</u>
- column deletion, **Deletion**
- column-major formats, <u>Row-Major Versus Column-Major Format-Row-Major Versus Column-Major Format</u>
 - pandas, <u>Row-Major Versus Column-Major Format</u>
 - Parquet, Row-Major Versus Column-Major Format
- Commuter, **IDE**
- compact convolutional filters, **Low-Rank Factorization**
- computational priorities, <u>Computational priorities</u>
- compute-intensive problems, When to Use Machine Learning
- concept drift, <u>Types of Data Distribution Shifts</u>, <u>Concept drift</u>
- confidence measurement, **Confidence measurement**

- containers, <u>From Dev to Prod: Containers-From Dev to Prod:</u>
 Containers
- contextual bandits, Contextual bandits as an exploration strategy
- continual learning, <u>Iterative Process</u>, <u>Continual Learning</u>, <u>Why</u>

 <u>Continual Learning?-Why Continual Learning?</u>
 - algorithms and, <u>Algorithm challenge</u>-<u>Algorithm challenge</u>
 - evaluation and, <u>Evaluation challenge-Evaluation challenge</u>
 - feature reuse, **Requirements**
 - fresh data access, <u>Fresh data access challenge-Fresh data access</u>
 <u>challenge</u>
 - stateful training, <u>Stateless Retraining Versus Stateful Training</u>
 <u>Stateless Retraining Versus Stateful Training</u>
 - automated, <u>Stage 3: Automated, stateful training-Requirements</u>
 - stateless retraining, <u>Stateless Retraining Versus Stateful Training</u>
 <u>Stateless Retraining Versus Stateful Training</u>
 - manual, <u>Stage 1: Manual, stateless retraining</u>
 - training, automated retraining, <u>Stage 2: Automated retraining-Requirements</u>
 - versus online learning, <u>Stateless Retraining Versus Stateful</u>
 <u>Training</u>
- convenience sampling, Nonprobability Sampling
- cost-sensitive learning, Cost-sensitive learning
- covariate data distribution shift, Covariate shift-Covariate shift
- cron, schedulers, <u>Cron, Schedulers, and Orchestrators</u>-<u>Cron,</u>
 <u>Schedulers, and Orchestrators</u>
- cross-functional collaboration, teams, <u>Cross-functional Teams</u>
 <u>Collaboration</u>
- CSV (comma-separated values), row-major format, <u>Row-Major Versus</u>
 <u>Column-Major Format</u>

D

- DAG (directed acyclic graph), <u>Cron, Schedulers, and Orchestrators</u>
- dashboards, monitoring and, <u>Dashboards</u>
- data, <u>When to Use Machine Learning</u>, <u>Data</u>
 - mind versus data, Mind Versus Data-Mind Versus Data
 - training (see training data)

- unseen data, When to Use Machine Learning
- data augmentation, Data Augmentation
 - adversarial augmentation, Perturbation
 - data synthesis, <u>Data Synthesis</u>-<u>Data Synthesis</u>
 - perturbation, <u>Perturbation</u>-<u>Perturbation</u>
 - simple label-preserving transformations, <u>Simple Label-Preserving</u>
 Transformations
- data distribution shifts
 - addressing, <u>Addressing Data Distribution Shifts-Addressing Data</u>
 <u>Distribution Shifts</u>
 - detection
 - statistical methods, <u>Statistical methods</u>-<u>Statistical methods</u>
 - time scale windows, <u>Time scale windows for detecting shifts</u>-<u>Time scale windows for detecting shifts</u>
 - ML system failure, <u>Data Distribution Shifts</u>
 - concept drift, <u>Types of Data Distribution Shifts</u>, <u>Concept drift</u>
 - covariate shift, Covariate shift-Covariate shift
 - feature change, <u>General Data Distribution Shifts</u>
 - label schema change, General Data Distribution Shifts
 - label shift, <u>Types of Data Distribution Shifts</u>, <u>Label shift</u>
- data duplication, data leakage and, <u>Poor handling of data duplication</u>
 <u>before splitting</u>
- data engineering, **Iterative Process**
- data formats, **Data Formats**
 - binary, <u>Text Versus Binary Format</u>
 - column-major, <u>Row-Major Versus Column-Major Format-Row-Major Versus Column-Major Format</u>
 - JSON, <u>JSON</u>
 - multimodal data, <u>Data Formats</u>
 - relational model, NoSQL, <u>NoSQL</u>-<u>Graph model</u>
 - row-major, <u>Row-Major Versus Column-Major Format-Row-Major</u>
 <u>Versus Column-Major Format</u>
 - text, <u>Text Versus Binary Format</u>
- data freshness, model updates and, <u>Value of data freshness-Value of</u> data freshness
- data generation, data leakage and, <u>Leakage from data generation</u>
 <u>process</u>

- data iteration, Stateless Retraining Versus Stateful Training
 - model updates and, Model iteration versus data iteration
- data leakage, <u>Data Leakage</u>
 - data duplication prior to splitting, <u>Poor handling of data duplication before splitting</u>
 - data generation process and, <u>Leakage from data generation process</u>
 - detecting, <u>Detecting Data Leakage</u>
 - group leakage, Group leakage
 - Kaggle competition, **Data Leakage**
 - scaling before splitting, Scaling before splitting
 - statistics from test split, missing data and, <u>Filling in missing data</u>
 with statistics from the test split
 - time-correlated data, <u>Splitting time-correlated data randomly instead of by time</u>
- data models
 - relational, Relational Model-Relational Model
 - structured data, <u>Structured Versus Unstructured Data-Structured</u>

 Versus Unstructured Data
 - unstructured data, <u>Structured Versus Unstructured Data-Structured</u>
 Versus Unstructured Data
- data normalization, Relational Model
- data parallelism, distributed training and, <u>Data parallelism-Data</u>
 <u>parallelism</u>
- data scientists, teams, <u>Approach 2: Data scientists own the entire</u>
 <u>process-Approach 2: Data scientists own the entire process</u>
- data sources, <u>Data Sources</u>
 - databases, internal, <u>Data Sources</u>
 - logs, <u>Data Sources</u>
 - smartphones and, <u>Data Sources</u>
 - system-generated data, <u>Data Sources</u>
 - third-party data, **Data Sources**
 - user input, **Data Sources**
- data synthesis, <u>Data Synthesis</u>-<u>Data Synthesis</u>
- data-driven approach, AI ethics and, <u>Understand the limitations of the data-driven approach</u>
- databases and dataflow, <u>Data Passing Through Databases</u>
- dataflow, Modes of Dataflow

- message queue model, <u>Data Passing Through Real-Time Transport</u>
- passing through databases, <u>Data Passing Through Databases</u>
- passing through real-time transport, <u>Data Passing Through Real-</u> <u>Time Transport-Data Passing Through Real-Time Transport</u>
- passing through services, <u>Data Passing Through Services</u>-<u>Data</u>
 <u>Passing Through Services</u>
- request driven, <u>Data Passing Through Real-Time Transport</u>
- DataFrame, pandas and, Row-Major Versus Column-Major Format
- debugging, Versioning
- decision trees, pruning, Pruning-Pruning
- declarative ML systems, Relational Model
- deep learning
 - ML (machine learning) and, <u>Overview of Machine Learning</u>
 <u>Systems</u>
 - ML algorithms and, **Evaluating ML Models**
- degenerate feedback loops, ML system failure, <u>Degenerate feedback</u> <u>loops</u>
 - correcting, <u>Correcting degenerate feedback loops-Correcting degenerate feedback loops</u>
- dependencies, <u>Cron, Schedulers, and Orchestrators</u>
 - ML models, model store, Model Store
- dependency failure, Software System Failures
- deployment, <u>Iterative Process</u>, <u>Model Deployment and Prediction</u>
 Service
 - endpoints, exposing, <u>Model Deployment and Prediction Service</u>
 - failure, <u>Software System Failures</u>
 - ML models, Model Deployment
 - myths
 - limited models at once, <u>Myth 1: You Only Deploy One or Two ML</u>
 <u>Models at a Time-Myth 1: You Only Deploy One or Two ML</u>
 <u>Models at a Time</u>
 - model updating, <u>Myth 3: You Won't Need to Update Your Models</u> as Much
 - performance, <u>Myth 2: If We Don't Do Anything, Model</u>
 <u>Performance Remains the Same</u>
 - scale, <u>Myth 4: Most ML Engineers Don't Need to Worry About</u>
 <u>Scale</u>

- separation of responsibilities, <u>Model Deployment and Prediction</u>
 Service
- shadow deployment, Shadow Deployment
- development environment, infrastructure, <u>Infrastructure and Tooling</u>
 <u>for MLOps</u>, <u>Development Environment</u>
 - containers, <u>From Dev to Prod: Containers-From Dev to Prod:</u>
 <u>Containers</u>
 - setup, <u>Dev Environment Setup</u>
 - IDE, <u>IDE</u>-<u>IDE</u>
 - standardization, <u>Standardizing Dev Environments</u>-<u>Standardizing</u>
 Dev Environments
- directed acyclic graph (DAG), <u>Cron, Schedulers, and Orchestrators</u>
- directional expectation tests, <u>Directional expectation tests</u>
- discretization, feature engineering and, Discretization-Discretization
- distributed training, **Distributed Training**
 - data parallelism and, **Data parallelism**
 - model parallelism and, <u>Model parallelism-Model parallelism</u>
- Docker Compose, <u>From Dev to Prod: Containers</u>
- Docker images, <u>From Dev to Prod</u>: <u>Containers-From Dev to Prod</u>:
 <u>Containers</u>
- Dockerfiles, <u>From Dev to Prod: Containers-From Dev to Prod:</u>
 <u>Containers</u>
- document model, **Document model**
 - schemas, **Document model**
- downtime, <u>Software System Failures</u>
- driver management service, <u>Data Passing Through Services</u>
- dynamic sampling, Data-level methods: Resampling

E

- edge cases
 - failure and, **Edge cases**-**Edge cases**
 - outliers and, **Edge cases**
- edge computing, <u>ML on the Cloud and on the Edge</u>
 - model optimization, <u>Compiling and Optimizing Models for Edge</u>
 <u>Devices-Using ML to optimize ML models</u>
- EKS (Elastic Kubernetes Service), <u>Cron, Schedulers, and Orchestrators</u>

- embedding
 - positional embedding, <u>Discrete and Continuous Positional</u>
 <u>Embeddings-Discrete and Continuous Positional Embeddings</u>
 - word embeddings, <u>Discrete and Continuous Positional Embeddings</u>
- endpoint, exposing, Model Deployment and Prediction Service
- ensembles
 - bagging, <u>Bagging</u>-Bagging
 - base learners, **Ensembles**
 - boosting, **Boosting-Boosting**
 - spam classifiers, **Ensembles**
 - stacking, **Stacking**
- ethics in AI, <u>Responsible AI-Case study II: The danger of "anonymized"</u>
 data
- ETL (extract, transform, load), <u>ETL: Extract, Transform, and Load-ETL:</u>

 <u>Extract, Transform, and Load</u>
- evaluation, offline
 - confidence measurement, **Confidence measurement**
 - directional expectation tests, <u>Directional expectation tests</u>
 - invariation tests, **Invariance tests**
 - model calibration, <u>Model calibration</u>-<u>Model calibration</u>
 - perturbation tests, <u>Perturbation tests</u>-<u>Perturbation tests</u>
 - slice-based, <u>Slice-based evaluation</u>-<u>Slice-based evaluation</u>
- existing data, When to Use Machine Learning
- experiment artifacts, development and, Model Store
- experiment tracking, <u>Experiment tracking</u>-<u>Experiment tracking</u>
 - third-party tools, <u>Experiment tracking</u>
- exporting models, <u>Model Deployment and Prediction Service</u>

F

- F1 metrics, Using the right evaluation metrics
- factorization, low-rank, <u>Low-Rank Factorization</u>-<u>Low-Rank</u>
 Factorization
- fairness, <u>Fairness</u>
- feature change, <u>General Data Distribution Shifts</u>
- feature engineering, <u>Learned Features Versus Engineered Features</u>
 <u>Learned Features Versus Engineered Features</u>

- categorical features, <u>Encoding Categorical Features</u>-<u>Encoding</u>
 <u>Categorical Features</u>
- discretization, <u>Discretization</u>-<u>Discretization</u>
- feature crossing, <u>Feature Crossing</u>
- feature generalization, <u>Feature Generalization</u>-<u>Feature</u>
 Generalization
- feature importance, <u>Feature Importance</u>
- missing values and, **Handling Missing Values**
 - deletion, **Deletion**
 - imputation, Imputation-Imputation
 - MAR (missing at random), Handling Missing Values
 - MCAR (missing completely at random), <u>Handling Missing Values</u>
 - MNAR (missing not at random), <u>Handling Missing Values</u>
- NLP (natural language processing) and, <u>Learned Features Versus</u>
 <u>Engineered Features</u>
- positional embeddings, <u>Discrete and Continuous Positional</u>
 <u>Embeddings-Discrete and Continuous Positional Embeddings</u>
- predictive power of features, **Detecting Data Leakage**
- scaling, Scaling-Scaling
- useless features, <u>Engineering Good Features</u>
- feature scaling, <u>Scaling</u>-<u>Scaling</u>
- feature store, Feature Store-Feature Store
- features
 - computation, <u>Feature Store</u>
 - consistency, <u>Feature Store</u>
 - extracting, <u>Monitoring features</u>
 - failures and, **Versioning**
 - learned, <u>Learned Features Versus Engineered Features-Learned</u>
 <u>Features Versus Engineered Features</u>
 - management, <u>Feature Store</u>
 - monitoring, Monitoring features-Monitoring features
 - online, <u>Batch Prediction Versus Online Prediction</u>
 - reuse, <u>Requirements</u>
 - streaming, <u>Batch Prediction Versus Online Prediction</u>
- feedback loops, <u>Bandits</u>
 - ML system failure, <u>Detecting degenerate feedback loops</u>
- feedback, users, Feedback loop length

- fixed positional embeddings, <u>Discrete and Continuous Positional</u>
 <u>Embeddings</u>
- fixed-point inference, **Quantization**
- FLOPS (floating-point operations per second), Storage and Compute
- forecasting customer demand, Machine Learning Use Cases
- Fourier features, <u>Discrete and Continuous Positional Embeddings</u>
- fraud detection, <u>Machine Learning Use Cases</u>, <u>Challenges of Class</u>
 <u>Imbalance</u>

G

- GDPR (General Data Protection Regulation), Versioning
- generalization, features, <u>Feature Generalization</u>-<u>Feature</u> Generalization
- GKE (Google Kubernetes Engine), <u>Cron, Schedulers, and Orchestrators</u>
- Google Translate, Overview of Machine Learning Systems
- graph model, Graph model

Η

- H20 AutoML, Relational Model
- hand labels, **Hand Labels**
 - lineage, <u>Data lineage</u>
 - multiplicity, <u>Label multiplicity</u>-<u>Label multiplicity</u>
- hard AutoML, <u>Hard AutoML</u>: <u>Architecture search and learned optimizer</u>
- hardware failure, <u>Software System Failures</u>
- hashed functions, <u>Encoding Categorical Features</u>
- heuristics, LFs (labeling functions), <u>Weak supervision</u>
- heuristics-based slicing, Slice-based evaluation
- hierarchical classification, <u>Binary versus multiclass classification</u>
- human baselines, **Baselines**
- hyperparameters
 - failures and, <u>Versioning</u>
 - tuning, <u>Soft AutoML: Hyperparameter tuning-Soft AutoML:</u>

 <u>Hyperparameter tuning</u>
 - values over time, <u>Experiment tracking</u>

- IDE (integrated development environment), IDE
 - cloud dev environment, <u>Standardizing Dev Environments</u>
 - notebooks and, **IDE**
- importance sampling, <u>Importance Sampling</u>
- infrastructure, <u>Infrastructure and Tooling for MLOps</u>, <u>Infrastructure</u> and <u>Tooling for MLOps</u>
 - building versus buying, <u>Build Versus Buy-Build Versus Buy</u>
 - cloud computing and, <u>Public Cloud Versus Private Data Centers</u>
 <u>Public Cloud Versus Private Data Centers</u>
 - development environment layer, <u>Infrastructure and Tooling for</u>
 <u>MLOps</u>, <u>Development Environment</u>
 - setup, <u>Dev Environment Setup</u>-<u>IDE</u>
 - fundamental facilities, <u>Infrastructure and Tooling for MLOps</u>
 - ML platform layer, <u>Infrastructure and Tooling for MLOps</u>
 - requirements, <u>Infrastructure and Tooling for MLOps</u>
 - resource management layer, Infrastructure and Tooling for MLOps
 - storage and compute layer, <u>Infrastructure and Tooling for MLOps</u>,
 <u>Infrastructure and Tooling for MLOps</u>, <u>Storage and Compute</u>
 - compute resources, <u>Storage and Compute</u>
 - FLOPS, Storage and Compute
 - private data centers, <u>Public Cloud Versus Private Data Centers</u>
 Public Cloud Versus Private Data Centers
 - public cloud, <u>Public Cloud Versus Private Data Centers</u>-<u>Public Cloud Versus Private Data Centers</u>
 - units, Storage and Compute
- input, monitoring, Monitoring raw inputs
- instances on-demand, <u>Public Cloud Versus Private Data Centers</u>
- integrated development environment (see IDE)
- interleaving experiments, <u>Interleaving Experiments</u>-<u>Interleaving Experiments</u>
- internal databases, <u>Data Sources</u>
- interpretability, <u>Interpretability</u>
- invariation tests, **Invariance tests**
- IR (intermediate representation), <u>Compiling and Optimizing Models</u>
 <u>for Edge Devices</u>

- iterative processes
 - model development and, **Iterative Process**
 - performance check, Model Development and Offline Evaluation
 - model updates and, Model iteration versus data iteration
 - training the model and, <u>Iterative Process</u>-<u>Iterative Process</u>
 - data engineering, **Iterative Process**
 - project scoping, **Iterative Process**

J

- JSON (JavaScript Object Notation), JSON
- judgment sampling, Nonprobability Sampling

K

- k-means clustering models, **Evaluating ML Models**
- Kaggle, data leakage, Data Leakage
- knowledge distillation, **Knowledge Distillation**
- Kubeflow, Data Science Workflow Management
- Kubernetes (K8s), <u>From Dev to Prod: Containers</u>, <u>Cron, Schedulers, and</u>
 <u>Orchestrators</u>
 - EKS (Elastic Kubernetes Service), <u>Cron, Schedulers, and</u>
 <u>Orchestrators</u>
 - GKE (Google Kubernetes Engine), <u>Cron, Schedulers, and</u>
 <u>Orchestrators</u>

L

- label computation, Fresh data access challenge
- label schema change, General Data Distribution Shifts
- label shift, <u>Types of Data Distribution Shifts</u>, <u>Label shift</u>
- labeling, <u>Labeling</u>
 - class imbalance and, <u>Class Imbalance</u>
 - errors, class imbalance and, **Challenges of Class Imbalance**
 - hand labels, <u>Hand Labels</u>
 - lineage, <u>Data lineage</u>
 - multiplicity, <u>Label multiplicity</u>-<u>Label multiplicity</u>
 - lack of labels, <u>Handling the Lack of Labels</u>

- active learning, Active learning-Active learning
- semi-supervision, <u>Semi-supervision</u>-<u>Semi-supervision</u>
- transfer learning, Transfer learning-Transfer learning
- weak supervision, <u>Weak supervision</u>-<u>Weak supervision</u>
- ML algorithms, <u>Evaluating ML Models</u>
- natural labels, Natural Labels
 - feedback loop length, Feedback loop length
 - recommender systems, Natural Labels
- perturbation, <u>Perturbation</u>-<u>Perturbation</u>
- simple label-preserving transformations, <u>Simple Label-Preserving</u>
 <u>Transformations</u>
- language modeling, sampling and, Nonprobability Sampling
- latency, **Computational priorities**
- latency versus throughput, <u>Computational priorities</u>-<u>Computational priorities</u>
- learning, When to Use Machine Learning
- LFs (labeling functions), Weak supervision
 - heuristics, Weak supervision
- logs, <u>Data Sources</u>, <u>Data Sources</u>
 - experiment tracking, **Experiment tracking**
 - monitoring and, <u>Logs-Logs</u>
 - storage, <u>Data Sources</u>
- loop tiling, model optimization, Model optimization
- loss curve, **Experiment tracking**
- loss functions, <u>Objective Functions</u>
 - (see also objective functions)
- low-rank factorization, <u>Low-Rank Factorization-Low-Rank</u>
 <u>Factorization</u>

M

- maintainability, Maintainability
- Manning, Christopher, Mind Versus Data
- MAR (missing at random) values, <u>Handling Missing Values</u>
- MCAR (missing completely at random) values, <u>Handling Missing</u>
 <u>Values</u>
- merge conflicts, **Versioning**

- message queue, dataflow and, <u>Data Passing Through Real-Time</u>
 <u>Transport</u>
- Metaflow, <u>Data Science Workflow Management</u>
- metrics
 - monitoring and, Monitoring and Observability
 - accuracy-related metrics, <u>Monitoring accuracy-related metrics</u>
 - features, <u>Monitoring features</u>-<u>Monitoring features</u>
 - predictions, <u>Monitoring predictions</u>-<u>Monitoring predictions</u>
 - raw input, **Monitoring raw inputs**
 - performance metrics, **Experiment tracking**
 - system performance, **Experiment tracking**
- mind versus data, Mind Versus Data-Mind Versus Data
- missing at random (MAR), Handling Missing Values
- missing completely at random (MCAR), Handling Missing Values
- missing data, test split statistics and, <u>Filling in missing data with statistics</u>
 tics from the test split
- missing not at random (MNAR), <u>Handling Missing Values</u>
- ML (machine learning)
 - browsers and, ML in Browsers, ML in Browsers
 - cloud computing, <u>ML on the Cloud and on the Edge-ML in Browsers</u>
 - complex patterns, When to Use Machine Learning
 - deep learning and, <u>Overview of Machine Learning Systems</u>
 - edge computing, ML on the Cloud and on the Edge-ML in Browsers
 - existing data and, When to Use Machine Learning
 - learning, When to Use Machine Learning
 - model optimization, <u>Using ML to optimize ML models</u>-<u>Using ML to optimize ML models</u>
 - predictions and, When to Use Machine Learning
 - production and, <u>Machine Learning in Research Versus in</u>
 <u>Production-Discussion</u>
 - repetition, When to Use Machine Learning
 - research and, <u>Machine Learning in Research Versus in Production</u>-Discussion
 - scale, When to Use Machine Learning
 - smartphones and, <u>Machine Learning Use Cases</u>
 - unseen data, When to Use Machine Learning

- use cases, <u>Machine Learning Use Cases</u>-<u>Machine Learning Use</u>
 Cases
- when to use, <u>When to Use Machine Learning-Machine Learning</u>
 Use Cases
- ML algorithms, <u>Overview of Machine Learning Systems</u>, <u>Model</u>
 <u>Development and Offline Evaluation</u>
 - deep learning and, **Evaluating ML Models**
 - labels, **Evaluating ML Models**
 - versus neural networks, **Evaluating ML Models**
- ML model logic, Model Deployment and Prediction Service
- ML models
 - continual learning, **Iterative Process**
 - data iteration, Stateless Retraining Versus Stateful Training
 - debugging, **Versioning**
 - deployment, Model Deployment
 - edge computing, optimization, <u>Compiling and Optimizing Models</u> <u>for Edge Devices-Using ML to optimize ML models</u>
 - ensembles, Ensembles, Ensembles
 - bagging, <u>Bagging</u>-Bagging
 - base learners, **Ensembles**
 - boosting, <u>Boosting</u>-<u>Boosting</u>
 - stacking, Stacking
 - evaluation, **Evaluating ML Models**
 - test in production, <u>Test in Production-Contextual bandits as an</u> <u>exploration strategy</u>
 - experiment tracking, <u>Experiment tracking</u>-<u>Experiment tracking</u>
 - exporting, Model Deployment and Prediction Service
 - failures
 - batches, overfitting, **Versioning**
 - components, <u>Versioning</u>
 - data problems, **Versioning**
 - feature choice, **Versioning**
 - hyperparameters and, **Versioning**
 - poor model implementation, **Versioning**
 - random seeds, **Versioning**
 - theoretical constraints, <u>Versioning</u>
 - iteration, Stateless Retraining Versus Stateful Training

- monitoring, Iterative Process
- offline evaluation, Model Offline Evaluation
 - baselines, Baselines-Baselines
 - methods, Evaluation Methods-Slice-based evaluation
- optimization, <u>Using ML to optimize ML models-Using ML to opti-</u> <u>mize ML models</u>
- parameters, model store, <u>Model Store</u>
- performance metrics, Experiment tracking
- selection criteria, Evaluating ML Models
 - human biases in, Avoid human biases in selecting models
 - model, <u>Understand your model's assumptions</u>
 - performance now and later, <u>Evaluate good performance now</u>
 <u>versus good performance later</u>
 - simple models, **Start with the simplest models**
 - state-of-the-art trap, Avoid the state-of-the-art trap
 - trade-offs, Evaluate trade-offs
- speed, Experiment tracking
- training, <u>Iterative Process-Iterative Process</u>
 - data engineering, **Iterative Process**
 - distributed, <u>Distributed Training-Model parallelism</u>
- update frequency, <u>How Often to Update Your Models</u>
 - data freshness and, <u>Value of data freshness-Value of data</u>
 <u>freshness</u>
 - data iteration and, Model iteration versus data iteration
 - model iteration and, Model iteration versus data iteration
- updates, <u>Stateless Retraining Versus Stateful Training</u>
- versioning, <u>Versioning</u>-<u>Versioning</u>
- ML platform, ML Platform
 - model deployment, <u>Model Deployment</u>
 - model store, <u>Model Store</u>-<u>Model Store</u>
- ML platform layer, infrastructure, <u>Infrastructure and Tooling for</u>
 <u>MLOps</u>
- ML system failures
 - data distribution shifts, <u>Data Distribution Shifts</u>
 - addressing, <u>Addressing Data Distribution Shifts-Addressing Data</u>
 <u>Distribution Shifts</u>
 - concept drift, Types of Data Distribution Shifts, Concept drift

- covariate, Covariate shift-Covariate shift
- detection, <u>Detecting Data Distribution Shifts-Time scale windows for detecting shifts</u>
- feature change, **General Data Distribution Shifts**
- label schema change, **General Data Distribution Shifts**
- label shifts, <u>Types of Data Distribution Shifts</u>, <u>Label shift</u>
- ML-system specific
 - degenerate feedback loops, <u>Degenerate feedback loops</u>
 <u>Correcting degenerate feedback loops</u>
 - edge cases, Edge cases
 - production data different from training data, <u>Production data</u> <u>differing from training data-Production data differing from</u> <u>training data</u>
- operational expectation violations, <u>Causes of ML System Failures</u>
- software
 - crashes, <u>Software System Failures</u>
 - dependency failure, <u>Software System Failures</u>
 - deployment failure, **Software System Failures**
 - downtime, <u>Software System Failures</u>
 - hardware failure, <u>Software System Failures</u>
- ML systems
 - declarative, Relational Model
 - failures, Causes of ML System Failures
 - iterative processes, <u>Iterative Process</u>-<u>Iterative Process</u>
 - requirements
 - adaptability, <u>Adaptability</u>
 - maintainability, Maintainability
 - reliability, <u>Reliability</u>
 - scalability, <u>Scalability</u>-<u>Scalability</u>
 - versus traditional software, <u>Machine Learning Systems Versus</u>
 <u>Traditional Software-Machine Learning Systems Versus Traditional</u>
 Software
- MLOPs, ML systems design and, <u>Overview of Machine Learning</u>
 <u>Systems-Overview of Machine Learning Systems</u>
- MNAR (missing not at random) values, <u>Handling Missing Values</u>
- model biases, AI ethics, <u>Discover sources for model biases</u>-<u>Discover sources for model biases</u>

- model calibration, Model calibration-Model calibration
- model cards, AI ethics, <u>Create model cards-Create model cards</u>
- model compression, Model Compression
 - knowledge distillation, Knowledge Distillation
 - low-rank factorization, <u>Low-Rank Factorization-Low-Rank</u>
 <u>Factorization</u>
 - pruning, **Pruning**-**Pruning**
 - quantization, **Quantization**-**Quantization**
- model development, **Iterative Process**
- model implementation, failures and, Versioning
- model parallelism, distributed training and, <u>Model parallelism-Model</u>
 <u>parallelism</u>
- model performance, business analysis, <u>Iterative Process</u>
- monitoring, <u>Monitoring and Observability</u>, <u>Continual Learning and</u>
 Test in Production
 - (see also test in production)
 - alerts and, Alerts
 - dashboards and, **Dashboards**
 - logs and, <u>Logs-Logs</u>
 - metrics and, Monitoring and Observability
 - accuracy-related metrics, <u>Monitoring accuracy-related metrics</u>
 - features, <u>Monitoring features-Monitoring features</u>
 - predictions, <u>Monitoring predictions</u>-<u>Monitoring predictions</u>
 - raw input, **Monitoring raw inputs**
- multiclass classification, <u>Binary versus multiclass classification</u>,
 <u>Multiclass versus multilabel classification</u>
- multilabel classification, Multiclass versus multilabel classification
- multimodal data, <u>Data Formats</u>

N

- n-grams, <u>Learned Features Versus Engineered Features</u>
- NAS (neural architecture search), <u>Hard AutoML: Architecture search</u> and learned optimizer
- natural labels, <u>Natural Labels</u>
 - feedback loop length, Feedback loop length
 - recommender systems, Natural Labels

- natural language processing (NLP) (see NLP)
- neural architecture search (NAS), <u>Hard AutoML</u>: <u>Architecture search</u>
 and learned optimizer
- neural networks, **Evaluating ML Models**
 - positional embedding, <u>Discrete and Continuous Positional</u>
 <u>Embeddings</u>
- newsfeeds
 - ranking posts, **Decoupling objectives**
 - user engagement and, **Decoupling objectives**
- NLP (natural language processing), <u>Simple Label-Preserving</u>
 Transformations
 - data augmentation and, **Data Augmentation**
 - feature engineering, <u>Learned Features Versus Engineered Features</u>
- nonprobability sampling, Nonprobability Sampling
 - biases, Nonprobability Sampling
- Norvig, Peter, Mind Versus Data
- NoSQL, NoSQL
 - document model, **Document model**
 - graph model, Graph model
- notebooks, IDE and, <u>IDE</u>
- NSFW (not safe for work) content filtering, <u>Decoupling objectives</u>
- NumPy, <u>Row-Major Versus Column-Major Format</u>

0

- objective functions, **Objective Functions**-**Decoupling objectives**
- observability, <u>Monitoring and Observability</u>, <u>Observability</u>
 <u>Observability</u>
- offline evaluation of models, <u>Model Offline Evaluation</u>
 - baselines, <u>Baselines</u>
 - existing solutions, **Baselines**
 - human, Baselines
 - random, <u>Baselines</u>
 - simple heuristic, <u>Baselines</u>
 - zero rule, <u>Baselines</u>
- OLAP (online analytical processing), <u>Transactional and Analytical</u>
 <u>Processing</u>

- OLTP (online transaction processing) system, <u>Transactional and</u> <u>Analytical Processing</u>
- on-demand instances, <u>Public Cloud Versus Private Data Centers</u>
- on-demand prediction, <u>Batch Prediction Versus Online Prediction</u>
- One Billion Word Benchmark for Language Modeling, <u>Mind Versus</u>
 <u>Data</u>
- online features, <u>Batch Prediction Versus Online Prediction</u>
- online learning, Stateless Retraining Versus Stateful Training
- online prediction, <u>Batch Prediction Versus Online Prediction</u>-<u>Batch</u>
 <u>Prediction Versus Online Prediction</u>, <u>Bandits</u>
 - moving to from batch prediction, <u>From Batch Prediction to Online</u>
 <u>Prediction-From Batch Prediction to Online Prediction</u>
 - streaming pipeline, <u>Unifying Batch Pipeline and Streaming</u>
 <u>Pipeline-Unifying Batch Pipeline and Streaming Pipeline</u>
- operation expectation violations, <u>Causes of ML System Failures</u>
- operator fusion, model optimization and, Model optimization
- orchestrators
 - HashiCorp Nomad, Cron, Schedulers, and Orchestrators
 - Kubernetes (K8s), <u>Cron, Schedulers, and Orchestrators</u>
- outliers, edge cases and, <u>Edge cases</u>
- oversampling
 - overfitting, **Data-level methods: Resampling**
 - SMOTE, Data-level methods: Resampling

P

- pandas, Row-Major Versus Column-Major Format
- Papermill, <u>IDE</u>
- parallelization, model optimization and, <u>Model optimization</u>
- parameter values over time, Experiment tracking
- Pareto optimization, **Decoupling objectives**
- Parquet, <u>Row-Major Versus Column-Major Format</u>, <u>Text Versus Binary</u>
 Format
 - binary files, Text Versus Binary Format
- patterns
 - changing, When to Use Machine Learning
 - complex, When to Use Machine Learning

- Pearl, Judea, Mind Versus Data
- performance metrics, **Experiment tracking**
 - system performance, Experiment tracking
- perturbation, Perturbation-Perturbation
- perturbation method of semi-supervision, <u>Semi-supervision</u>
- perturbation tests, <u>Perturbation tests</u>-<u>Perturbation tests</u>
- positional embedding, <u>Discrete and Continuous Positional</u>
 <u>Embeddings-Discrete and Continuous Positional Embeddings</u>
 - fixed, <u>Discrete and Continuous Positional Embeddings</u>
- precision metrics, <u>Using the right evaluation metrics</u>
- prediction, <u>When to Use Machine Learning</u>, <u>Multiple ways to frame a problem</u>
 - asynchronous, <u>Batch Prediction Versus Online Prediction</u>
 - batch prediction, <u>Batch Prediction Versus Online Prediction</u>-<u>Batch</u>
 Prediction Versus Online Prediction
 - moving to online prediction, <u>From Batch Prediction to Online</u>
 <u>Prediction-From Batch Prediction to Online Prediction</u>
 - "mostly correct," user experience, <u>Combatting "Mostly Correct"</u>

 <u>Predictions-Combatting "Mostly Correct" Predictions</u>
 - on-demand prediction, <u>Batch Prediction Versus Online Prediction</u>
 - online, <u>Batch Prediction Versus Online Prediction</u>-<u>Batch Prediction</u>
 <u>Versus Online Prediction</u>
 - streaming pipeline, <u>Unifying Batch Pipeline and Streaming</u>
 <u>Pipeline-Unifying Batch Pipeline and Streaming Pipeline</u>
 - synchronous, <u>Batch Prediction Versus Online Prediction</u>
- predictions, monitoring, <u>Monitoring predictions-Monitoring</u>
 <u>predictions</u>
- predictive power of features, <u>Detecting Data Leakage</u>
- price optimization service, <u>Data Passing Through Services</u>
- problem framing, <u>Framing ML Problems</u>-<u>Decoupling objectives</u>
- processing
 - analytical, Transactional and Analytical Processing
 - batch processing, <u>Batch Processing Versus Stream Processing-Batch</u>
 <u>Processing Versus Stream Processing</u>
 - ETL (extract, transform, load), <u>ETL: Extract, Transform, and Load</u> <u>ETL: Extract, Transform, and Load</u>

- stream processing, <u>Batch Processing Versus Stream Processing</u>
 Batch Processing Versus Stream Processing
- transactional, Transactional and Analytical Processing
 - ACID and, Transactional and Analytical Processing
- production environment, <u>Model Deployment and Prediction Service</u>
- production, ML and, <u>Machine Learning in Research Versus in</u>
 <u>Production-Discussion</u>
- project objectives, <u>Business and ML Objectives</u>-<u>Business and ML</u>
 <u>Objectives</u>
- project scoping, **Iterative Process**
- prototyping, batch prediction and, <u>From Batch Prediction to Online</u>
 Prediction
- pruning, <u>Pruning</u>-<u>Pruning</u>
- public cloud versus private data center, <u>Public Cloud Versus Private</u>
 Data Centers-Public Cloud Versus Private Data Centers

Q

- quantization, <u>Quantization</u>-<u>Quantization</u>
- query languages, <u>Relational Model</u>
- quota sampling, <u>Nonprobability Sampling</u>

R

- random baselines, **Baselines**
- real-time transport
 - dataflow and, <u>Data Passing Through Real-Time Transport-Data</u>

 <u>Passing Through Real-Time Transport</u>
 - streaming data and, <u>Batch Processing Versus Stream Processing</u>
- reasonable scale, <u>Infrastructure and Tooling for MLOps</u>
- recall metrics, <u>Using the right evaluation metrics</u>
- recommender systems, labels, Natural Labels
- regression
 - class imbalance and, Class Imbalance
 - tasks, Multiple ways to frame a problem
- regression models, <u>Classification versus regression</u>
- relational databases, <u>Relational Model</u>

- relational models, Relational Model-Relational Model
 - data normalization, Relational Model
 - NoSQL, NoSQL
 - document model, **Document model**
 - graph model, Graph model
 - tables, <u>Relational Model</u>
- reliability, **Reliability**
- repetition, When to Use Machine Learning
- repetitive jobs, scheduling, Cron, Schedulers, and Orchestrators
- request-driven data passing, <u>Data Passing Through Real-Time</u>
 <u>Transport</u>
- resampling, Data-level methods: Resampling
 - dynamic sampling, Data-level methods: Resampling
 - oversampling
 - overfitting and, <u>Data-level methods: Resampling</u>
 - SMOTE, <u>Data-level methods: Resampling</u>
 - two-phase learning, <u>Data-level methods: Resampling</u>
 - undersampling, Data-level methods: Resampling
- reservoir sampling, <u>Reservoir Sampling-Reservoir Sampling</u>
- resource management, Resource Management
- resource management layer, infrastructure, <u>Infrastructure and</u>
 <u>Tooling for MLOps</u>
- REST (representational state transfer), <u>Data Passing Through Services</u>
- ride management service, <u>Data Passing Through Services</u>
- ROC (receiver operating characteristics) curve, <u>Using the right evaluation metrics</u>
- Rogati, Monica, Mind Versus Data
- ROI (return on investment), maturity stage of adoption, <u>Business and</u>
 <u>ML Objectives</u>
- row deletion, <u>Deletion</u>
- row-major format, <u>Row-Major Versus Column-Major Format-Row-Major Versus Column-Major Format</u>
 - CSV (comma-separated values), <u>Row-Major Versus Column-Major</u>
 Format
 - NumPy, <u>Row-Major Versus Column-Major Format</u>
- RPC (remote procedure call), <u>Data Passing Through Services</u>

- sampling, <u>Sampling</u>
 - importance sampling, Importance Sampling
 - nonprobability, Nonprobability Sampling
 - biases, Nonprobability Sampling
 - reservoir sampling, Reservoir Sampling-Reservoir Sampling
 - simple random sampling, Simple Random Sampling
 - stratified sampling, **Stratified Sampling**
 - weighted sampling, Weighted Sampling
- scalability, <u>Scalability</u>-<u>Scalability</u>
 - autoscaling, <u>Scalability</u>
- scale, When to Use Machine Learning
 - deployment myths, <u>Myth 4: Most ML Engineers Don't Need to</u> <u>Worry About Scale</u>
- schedulers, <u>Cron, Schedulers, and Orchestrators-Cron, Schedulers, and</u>
 Orchestrators
 - Borg, Cron, Schedulers, and Orchestrators
 - Slurm, Cron, Schedulers, and Orchestrators
- schemas, document model, <u>Document model</u>
- scoping a project, <u>Iterative Process</u>
- self-training, Semi-supervision
- semi-supervision, <u>Semi-supervision</u>-<u>Semi-supervision</u>
- sentiment analysis classifier, <u>Learned Features Versus Engineered</u>
 <u>Features</u>
- serialization, Model Deployment and Prediction Service
- services
 - dataflow and, <u>Data Passing Through Services</u>-<u>Data Passing Through</u>
 <u>Services</u>
 - driver management, <u>Data Passing Through Services</u>
 - price optimization, <u>Data Passing Through Services</u>
 - ride management, <u>Data Passing Through Services</u>
- SGD (stochastic gradient descent), <u>Data parallelism</u>
- shadow deployment, **Shadow Deployment**
- SHAP (SHapley Additive exPlanations, <u>Feature Importance</u>
- simple heuristic, offline evaluation, **Baselines**

- simple label-preserving transformations, <u>Simple Label-Preserving</u>
 Transformations
- simple random sampling, Simple Random Sampling
- Simpson's paradox, Slice-based evaluation
- skewed distribution, feature scaling and, Scaling
- slice-based evaluation, <u>Slice-based evaluation</u>-<u>Slice-based evaluation</u>
- slicing
 - error analysis, <u>Slice-based evaluation</u>
 - heuristics based, Slice-based evaluation
 - slice finders, Slice-based evaluation
- Slurm, Cron, Schedulers, and Orchestrators
- smartphones
 - data sources and, **Data Sources**
 - ML (machine learning) and, Machine Learning Use Cases
- smooth failing, user experience, **Smooth Failing**
- SMOTE (synthetic minority oversampling technique), <u>Data-level meth-ods: Resampling</u>
- Snorkel, Weak supervision
- snowball sampling, Nonprobability Sampling
- soft AutoML, <u>Soft AutoML: Hyperparameter tuning-Soft AutoML:</u>
 <u>Hyperparameter tuning</u>
- software system failure
 - crashes, <u>Software System Failures</u>
 - dependency, Software System Failures
 - deployment, <u>Software System Failures</u>
 - hardware, <u>Software System Failures</u>
- spam filtering, **Decoupling objectives**
- splitting
 - data duplication, <u>Poor handling of data duplication before splitting</u>
 - data leakage and, Scaling before splitting
- SQL, Relational Model
- SQL databases, Relational Model
- SSD (solid state disk), Storage and Compute
- stacking, ensembles, **Stacking**
- stakeholders, research projects, <u>Different stakeholders and requirements</u>

 ments-<u>Different stakeholders and requirements</u>
- state-of-the-art models, Avoid the state-of-the-art trap

- stateful training, <u>Stateless Retraining Versus Stateful Training-Stateless</u>
 <u>Retraining Versus Stateful Training</u>
 - automated, <u>Stage 3: Automated</u>, <u>stateful training-Requirements</u>
- stateless retraining, <u>Stateless Retraining Versus Stateful Training</u>
 <u>Stateless Retraining Versus Stateful Training</u>
 - manual, Stage 1: Manual, stateless retraining
- stochastic gradient descent (SGD), Data parallelism
- storage and compute layer, infrastructure, <u>Infrastructure and Tooling</u>
 <u>for MLOps</u>, <u>Infrastructure and Tooling for MLOps</u>, <u>Storage and</u>
 <u>Compute</u>
 - compute resources, Storage and Compute
 - FLOPS (floating-point operations per second), Storage and Compute
 - private data centers, <u>Public Cloud Versus Private Data Centers</u>
 <u>Public Cloud Versus Private Data Centers</u>
 - public cloud, <u>Public Cloud Versus Private Data Centers</u>-<u>Public Cloud</u>
 Versus Private Data Centers
 - units, Storage and Compute
- storage engines, Data Storage Engines and Processing
- stratified sampling, Stratified Sampling
- stream processing, <u>Batch Processing Versus Stream Processing-Batch</u>
 <u>Processing Versus Stream Processing</u>
- streaming data, real-time transport, <u>Batch Processing Versus Stream</u>
 <u>Processing</u>
- streaming features, <u>Batch Prediction Versus Online Prediction</u>
- streaming pipeline, <u>Unifying Batch Pipeline and Streaming Pipeline</u> <u>Unifying Batch Pipeline and Streaming Pipeline</u>
- structured data, <u>Structured Versus Unstructured Data-Structured</u>

 Versus Unstructured Data
- Sutton, Richard, Mind Versus Data
- synchronous prediction, <u>Batch Prediction Versus Online Prediction</u>
- synthetic minority oversampling technique (SMOTE), <u>Data-level methods: Resampling</u>
- system performance metrics, **Experiment tracking**
- system-generated data, <u>Data Sources</u>

- tags, model store, Model Store
- tasks
 - classification, <u>Classification versus regression</u>
 - binary, Binary versus multiclass classification
 - high cardinality, Binary versus multiclass classification
 - multiclass, <u>Binary versus multiclass classification</u>, <u>Multiclass versus multilabel classification</u>
 - multilabel, <u>Multiclass versus multilabel classification</u>
 - labels, Natural Labels
 - regression, <u>Classification versus regression</u>, <u>Multiple ways to frame</u>
 <u>a problem</u>
- teams
 - cross-functional collaboration, <u>Cross-functional Teams</u>
 <u>Collaboration</u>
 - data scientists, <u>Approach 2: Data scientists own the entire process</u>
 <u>Approach 2: Data scientists own the entire process</u>
 - production management, <u>Approach 1: Have a separate team to</u> <u>manage production</u>
- telemetry, Observability
- test in production, <u>Continual Learning and Test in Production</u>, <u>Test in Production</u>
 - A/B testing, A/B Testing-A/B Testing
 - bandits, Bandits-Contextual bandits as an exploration strategy
 - canary release, <u>Canary Release</u>
 - interleaving experiments, <u>Interleaving Experiments</u>-<u>Interleaving Experiments</u>
 - shadow deployment and, <u>Shadow Deployment</u>
- text data, <u>Text Versus Binary Format</u>
- text file size, <u>Text Versus Binary Format</u>
- theoretical constraints, failures and, <u>Versioning</u>
- third-party data, <u>Data Sources</u>
- time-correlated data, data leakage and, <u>Splitting time-correlated data</u> randomly instead of by time
- training
 - automated retraining, <u>Stage 2: Automated retraining-Requirements</u>
 - distributed, **Distributed Training**
 - data parallelism and, <u>Data parallelism</u>-<u>Data parallelism</u>

- model parallelism and, Model parallelism-Model parallelism
- stateful, <u>Stateless Retraining Versus Stateful Training-Stateless</u>

 <u>Retraining Versus Stateful Training</u>
 - automated, <u>Stage 3: Automated, stateful training-Requirements</u>
- stateless retraining, <u>Stateless Retraining Versus Stateful Training</u>
 <u>Stateless Retraining Versus Stateful Training</u>
 - manual, Stage 1: Manual, stateless retraining
- training data, <u>Training Data</u>
 - class imbalance, Class Imbalance
 - algorithm-level methods, <u>Algorithm-level methods-Focal loss</u>
 - challenges, <u>Challenges of Class Imbalance-Challenges of Class</u>
 Imbalance
 - evaluation metrics, <u>Using the right evaluation metrics-Using the</u>
 <u>right evaluation metrics</u>
 - resampling, <u>Data-level methods: Resampling-Data-level methods: Resampling</u>
 - data augmentation, <u>Data Augmentation</u>
 - perturbation, <u>Perturbation</u>-<u>Perturbation</u>
 - simple label-preserving transformations, <u>Simple Label-Preserving Transformations</u>
 - data distributions, <u>Production data differing from training data</u>
 - data leakage, Data Leakage
 - labeling, **Labeling**
 - hand labels, <u>Hand Labels</u>-<u>Data lineage</u>
 - lack of labels, <u>Handling the Lack of Labels-Active learning</u>
 - natural labels, <u>Natural Labels</u>-<u>Feedback loop length</u>
 - user feedback, <u>Feedback loop length</u>
 - n-grams, <u>Learned Features Versus Engineered Features</u>
 - noisy samples, <u>Perturbation</u>
 - sampling, <u>Sampling</u>
 - importance sampling, Importance Sampling
 - nonprobability, <u>Nonprobability Sampling-Nonprobability</u>
 <u>Sampling</u>
 - reservoir sampling, <u>Reservoir Sampling</u>-<u>Reservoir Sampling</u>
 - simple random sampling, Simple Random Sampling
 - stratified sampling, Stratified Sampling
 - weighted sampling, Weighted Sampling

- training the model, iteration and, <u>Iterative Process-Iterative Process</u>
 - data engineering, **Iterative Process**
 - project scoping, **Iterative Process**
- transactional processing, Transactional and Analytical Processing
 - ACID and, <u>Transactional and Analytical Processing</u>
- transfer learning, Transfer learning-Transfer learning
- two-phase learning, Data-level methods: Resampling

U

- undersampling, **Data-level methods: Resampling**
- unseen data, When to Use Machine Learning
- unstructured data, <u>Structured Versus Unstructured Data-Structured</u>
 Versus Unstructured Data
- updates, deployment myths, <u>Myth 3: You Won't Need to Update Your</u>
 <u>Models as Much</u>
- use cases, Machine Learning Use Cases-Machine Learning Use Cases
- user experience, User Experience
 - consistency, **Ensuring User Experience Consistency**
 - predictions, mostly correct, <u>Combatting "Mostly Correct"</u>
 <u>Predictions-Combatting "Mostly Correct" Predictions</u>
 - smooth failing, Smooth Failing
- user feedback, Feedback loop length
- user input data, <u>Data Sources</u>

\mathbf{V}

- vCPU (virtual CPU), <u>Storage and Compute</u>
- vectorization, model optimization, <u>Model optimization</u>
- versioning, <u>Versioning</u>-<u>Versioning</u>
 - code versioning, **Versioning**

W

- WASM (WebAssembly), ML in Browsers
- weak supervision, <u>Weak supervision</u>-Weak supervision
 - Snorkel, <u>Weak supervision</u>
- weighted sampling, Weighted Sampling

- word embeddings, <u>Discrete and Continuous Positional Embeddings</u>
- workflow management, <u>Data Science Workflow Management</u>
 - Airflow, <u>Data Science Workflow Management-Data Science</u>
 <u>Workflow Management</u>
 - Argo, <u>Data Science Workflow Management-Data Science Workflow Management</u>
 - DAG (directed acyclic graph), <u>Cron, Schedulers, and Orchestrators</u>
 - Kubeflow, <u>Data Science Workflow Management</u>
 - Metaflow, <u>Data Science Workflow Management</u>

 \mathbf{X}

• XGBoost, <u>Feature Importance</u>

Z

- zero rule baselines, **Baselines**
- zero-shot learning, **Transfer learning**

Support Sign Out

©2022 O'REILLY MEDIA, INC. TERMS OF SERVICE PRIVACY POLICY