WEEK 1: Machine Learning System

1. What is Machine Learning (ML)?

- ML enables systems to **learn complex patterns from data** and make **predictions on unseen data**.
- Useful when:
    - The system has the capacity to learn.
    - Patterns are complex and repetitive.
    - Data exists or can be collected.
    - Predictions are needed at scale.
    - Wrong predictions are not costly.
    - It's repetitive (ซ้ำ)
    - Patterns constantly change.

When not to use ML:

- Simpler solutions do the tricks (แก้ปัญหาด้วยวิธีที่ง่ายกว่า)
- If the use case is unethical.
- It's not cost effective.

2. ML Use Cases and Requirements

- **Examples**: Recommender systems, predictive typing, machine translation, fraud detection, smart health.
- **System Requirements**:
  - **Reliability** - System should continue perform the correct function even in the face of adversity (ความทุกข์ยาก)
  - **Scalability** - Resource scaling
  - **Maintainability** - set up infra so contributors can work using tools that they're comfortable with.
  - **Adaptability** - Allowing updates without service interruption.

3. ML Project Life Cycle

- **Stages**:
  Dataset → Data Pipeline → Feature Engineering → Model Training → Evaluation → ML Model → Deployment.
- Development follows an **iterative and agile approach**.

4. ML Team Structure & Roles

- **Subject Matter Experts (SMEs)**: Define business questions/goals. (ผู้เชี่ยวชาญเฉพาะด้าน)
- **Data Scientists/ML Researchers**: Build and evaluate models. (Train prediction models) (Tensorflow, pytorch, Jupyter) (Report)
- **Data Engineers**: Manage data pipelines (ETL).
- **ML Engineers**: Handle CI/CD, scalability, deployment, and monitoring. (Train, deploy & maintain prediction models) (Tensorflow, Docker). (Real data)
- **ML Product Managers**: Work with ML team, business, users, data owner to prioritize & execute projects. (Jira)
- **MLOps / ML platform**: Build infrastructure to make the model easier to deploy, more scalable (AWS, Kafka, ML tooling vendors).

5. ML Systems vs Traditional Software

Traditional Software	**ML Systems**
Code and data are separated	Data and code are intertwined (ผสมกัน)
Stable data dependencies	Data dependencies are unstable (Data เปลี่ยนตลอดเวลา)
Focus on code logic	Focus on data patterns

6. Research vs Production in ML

Research	**Production**
Focus on model performance, Fast training, High throughput	Focus on stakeholder needs, low latency (ล่าช้า), Fast inference, fairness, interpretability
Static data	Constantly shifting data

7. Metrics and Problem Framing

- **Business Metrics**: Profit, sales, customer satisfaction.
- **ML Metrics**: Accuracy, F1-score, latency.
- Types of ML tasks: Regression, Binary Classification, Multiclass, Multilabel, Hierarchical Classification.

8. Key Features of MLOps

- Standardization and Streamlining.
- Automates the ML lifecycle (CI/CD).
- Ensures collaboration, governance, monitoring, reproducibility.
- Mitigates risks like model degradation, fairness issues, or loss of skilled personnel.
- Track of versioning with experiments in the design phase.

9. Data and Feature Engineering

- EDA leads to feature engineering and selection.
- Evaluate data availability, accuracy, and need for labeling.
- Perform feature engineering to improve model inputs.

10. Training, Evaluation & Deployment

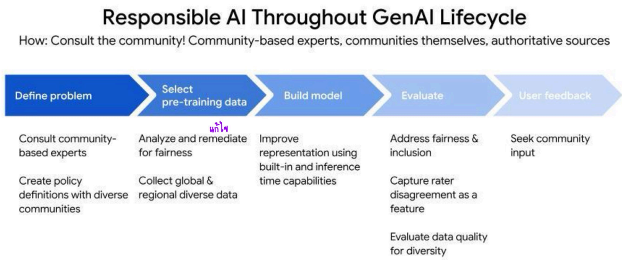
- Features can be automatically generated and hyperparameter tuned.
- Shapley values - Explain how the value of each feature contributes to a specific prediction.
- Track experiments and environment settings.
- Use reproducibility techniques.
- Deploy models via REST APIs, embedded models, or containerization (e.g., Docker).
- Model-as-a-service (Live score model) - Provide a REST API endpoint that responds to requests in real time.
- Embedded Model - Packaged into an application.

11. Monitoring and Feedback Loop

- **Monitoring focus**:
    - **DevOps**: Performance, resource usage.
    - **Data Scientists**: Input drift (1 of the most important components of an adaptable MLOps strategy), model accuracy over time.
    - **Business**: ROI, value delivery.
- Feedback mechanisms: Shadow testing, A/B testing.

12. Governance and Responsible AI

- Address **data governance**: data usage rights, PII protection, fairness.
- Ensure **process governance**: formalized steps for accountability.
- Incorporate **Responsible AI principles**:
    - Fairness, privacy, transparency, accountability.
    - Use tools like **Model Cards** for documenting model limitations and intended use.
    - **Model Card** - Provide information on how these model were trained and evaluated, Disclose (เปิดเผย) which models intend to be use.



13. The Feedback Loop

- Shadow Testing - The new model is deployed alongside the existing model.
- A/B Testing - Input requests split between two models.

WEEK 2 : Machine Learning Fundamentals

1. What is Machine Learning (ML)?

- **Definition**: ML is a data analysis method that automates model building using algorithms that learn iteratively from data.
- **Purpose**: Allows computers to discover insights without explicit programming.

2. Why Machine Learning Matters

- **Automatic**: Once trained, models can operate autonomously.
- **Fast**: Handles big data faster than humans.
- **Accurate**: Improves prediction accuracy over manual methods.
- **Scalable**: Works effectively on large-scale datasets.

3. ML Development Workflow

1. **Data Acquisition**: Collecting data.
2. **Data Preparation**: Cleansing → Data Annotation (Ground Truth) , shaping, enrichment, annotation (labeling).
3. **Model Training**: Training with training/validation/test sets.
4. **Model Testing**: Performance evaluation, optimization.
5. **Deployment & Monitoring**: Includes out-of-bag (OOB) testing, shadow deployment, and iteration.

4. Types of Machine Learning

Learning Type	Description	Example
Supervised Learning	Learning from labeled data	Classification, Regression
Unsupervised Learning	Learning from unlabeled data	Clustering, Anomaly Detection
Advanced ML	Includes CNN, Transformers, LLMs	Image recognition, Translation,

5. Supervised Learning

- **Classification**: Predict categories (e.g., decision tree classifier).
- **Regression**: Predict continuous values (e.g., linear regression).
- **Examples**:
  - Gender prediction.
  - Loan customer lifetime value prediction.

6. Unsupervised Learning

- **Clustering**: Grouping similar data points.
- **Anomaly Detection**: Detecting outliers or abnormal cases.
- **Example Tools**:
  - Google Colab notebooks (links provided in the slides).
  - GitHub lecture materials (e.g., Decision Trees, Clustering, Anomaly Detection).

7. Common ML Issues

- **Overfitting**: Model performs well on training data but poorly on unseen data.
- **Unbalanced Data**: Disproportionate class distributions.
- **Noisy Data**: Unclean or irrelevant data.
- **Specialized vs. Generalized Learning**.
- **Optimization challenges**.

8. Foundations of Machine Learning

- **Mathematics & Statistics**: Regression, probability, Bayes theorem, entropy.
- **Computer Science**: Algorithms, data mining, HPC, optimization.
- **Artificial Intelligence**: Neural networks, reinforcement learning, computer vision, NLP.

WEEK 3 : Git and Version Control

- **Version Control Basics:**
  - Used for collaboration, tracking changes, and maintaining order in project files.
  - Two main types:
    - **Centralized Version Control (CVCS):** (e.g., CVS, Perforce, SVN) — developers pull from and push to a central server.
    - **Decentralized Version Control (DVCS):** (e.g., Git) — each developer has a full copy of the repository locally, allowing offline commits and branching.
- **Key Features of Good Version Control Systems:**
  - Store many versions.
  - Allow reverting to older versions.
  - Track the order of changes.
  - Manage reasonable version sizes.
  - Enable collaboration.
  - Help merge branched versions.
- **Git:**
  - Distributed version control system managing "commits" (snapshots) locally.
  - Stores old versions of files in a hidden folder (.git).
  - Tracks changes, allows reversion, and manages multi-developer work.
  - Handles merging (auto or manual).
- **Branching:**
  - Creates isolated "branches" for different work streams.
  - Commands include git checkout -b <branch> (Create new branch command), git add (Make changes), git commit (Make changes), git checkout (Switch between branches).
- **Pull Requests:**
  - Mechanism to safely propose and review changes before merging into the main branch.
  - Requires setting branch protection (e.g., requiring pull requests).
  - Pull requests are created after pushing changes from a new branch.
  - gh pr create to create a pull request (Create new branch, make your changes, push new branch, then run gh pr create)
- **GitHub:**
  - Web-based Git repository hosting service (owned by Microsoft).
  - Features: repository hosting, pull requests, issue tracking, project wikis, CI/CD actions, and collaboration tools.

To **push** your work to a new branch on GitHub, follow these steps:

✅ **1. Make sure you're on the right branch**
git checkout your-branch-name
✅ **2. Stage your changes**
git add .
✅ **3. Commit your changes**
git commit -m "Your commit message"
✅ **4. Push the branch to GitHub**
git push origin your-branch-name

WEEK 4 : Training Data

Data mixture used for pre-training.

1. Importance of Training Data in ML

- **Core foundation** for supervised learning.

- Data quality significantly impacts model performance.
- Data availability challenges:
  - Scarcity (ขาดแคลน) in low-resource languages.
  - Domain-specific data difficulties (e.g., healthcare, finance).
  - Ground truth acquisition issues.
  - Sampling/selection bias and labeling bias.

2. Labeling Strategies

Hand Labeling

- Done by humans (subject matter experts or crowdsourcing (External data annotators) platforms like Amazon Mechanical Turk).
- **Challenges**: Expensive, time-consuming, privacy concerns, slow iteration.
- **Label Multiplicity**: Different annotators may disagree.
  - Solution: Clear guidelines, training annotators, data lineage tracking.

Programmatic Labeling (Weak Supervision)

- Uses heuristics, keyword matching, regex, database lookups, and outputs of other models.
- Tools: **Snorkel** (Built around the concept of a labeling function (LF): a function that encodes heuristics).
- **Advantages**:
  - Cost-effective.
  - Scalable.
  - Better privacy control.

Semi-Supervised Learning (Self Training)

- Train model on a small set of labeled data
- Use this model to generate predictions for unlabeled data.
- Use predictions with high raw probabilities as labels.
- Repeat step 1 with new labeled data

Transfer Learning

- Zero-shot, One-shot, Few shot
- Apply pre-trained models to new tasks with fine-tuning or prompt-based adjustments.

3. Class Imbalance Problem

- **Definition**: One class dominates the dataset (e.g., 99.99% normal vs. 0.01% cancer).
- **Challenges**:
  - Poor learning in rare classes.
  - Asymmetric (ไม่สมมาตร) error costs.
- **Solutions**:
  - Choosing proper evaluation metrics (Precision, Recall, F1-score).
  - Data-level approaches (e.g., data augmentation).
  - Algorithm-level approaches (e.g., cost-sensitive learning using cost matrices).

4. Choosing the Right Metrics

Accuracy	Not suitable for imbalanced data.
Precision	Important when **false positives** are costly (e.g., spam detection). Actually positive.
Recall	Important when **false negatives** are costly (e.g., cancer detection). Find rare cases. Correctly predicted.
F1-score	Balances precision and recall; best for imbalanced datasets.

5. Data Augmentation Techniques

- **For NLP**: Synonym replacement (e.g., using GloVe embeddings).
- **For Computer Vision**: Image transformations (rotation, flipping, scaling).
-

6. Algorithm-Level Method

- If predicted correctly i = j has cost = 0, if not has some costs.
- If i != j cost in ij = 2ji or ji = 2ij.

7. Non-probabilistic sampling

- **Convenience sampling**: Samples of data are selected based on their availability.
- **Snowball sampling**: future samples are selected based on existing samples. (เริ่มจากที่มีอยู่แล้วขยายไปเรื่อยๆ)
- **Judgment sampling**: Experts decide what samples to include.
- **Quota sampling**: Select samples based on quota.

8. Sampling Techniques for Data Selection

Method	Description	Pros/Cons
Random Sampling	Equal chance for each data point.	Rare events may be missed.
Stratified Sampling (แบ่งชั้น)	Ensures subgroup representation.	Better for class balance.
Weighted Sampling	Higher chance for important samples.	Useful for emphasizing critical groups.
Non-Probabilistic Sampling	Convenience, snowball, judgment, quota sampling.	May introduce selection bias.

9. Handling Rare Events (e.g., Fraud Detection Case Study)

- If the fraud rate is low (0.2%), random sampling might miss fraud cases.
- Use **stratified** or **weighted sampling** to ensure coverage of rare but critical fraud patterns.

WEEK 5 : Containerization

1. The Problem with Traditional Software Deployment

- **Issues before containerization**:
  - Dependency conflicts (ขัดแย้ง) (different software components need different library versions).
  - Environment inconsistencies (code works on one machine but not another).
  - Resource inefficiency when running multiple applications on the same machine.
  - Difficult scalability due to complex configurations.

2. Virtual Machines (VMs) as a Traditional Solution

- **How VMs work**:
  - Each VM runs its own full operating system.
  - High resource consumption (RAM, CPU, storage).
  - Slow startup (OS boot time).
  - Duplication of dependencies even when apps share libraries. (ต้องลง library ใหม่ แม้ว่าจะ share ร่วมกัน)
- **VM analogy**: Like building separate houses for each application.

3. Containerization Technology

- **What is a Container?**
  - Tool to produce reproducible environments by isolating and packaging everything that program needs.
  - A process that is isolated from the host system.
  - Packages all dependencies needed for an application.
  - Much lighter and faster than VMs (no full OS required).

- **Benefits**:
    - Portability across environments.
    - Reproducibility and reduced incompatibility issues.
    - Faster startup, more efficient resource use.
- **Popular Tool**: Docker (used throughout this course).
- **Container analogy**: Like apartments in the same building (shared foundation, isolated setup).

4. VMs vs. Docker (Comparison)

Feature	**Virtual Machines**	**Docker Containers**
OS Overhead	Full OS per VM	Shares host OS
Resource Usage	High (RAM, CPU, storage)	Low
Startup Time	Minutes (OS boot required)	Seconds
Scalability	Less efficient	Highly efficient
Portability	Limited to VM environment	Easy to run anywhere Docker is available

5. Docker Basics

Installation and Check

- Verify with: docker --version

Running Your First Docker Container

docker run hello-world

- Docker pulls the image from Docker Hub and runs a test script to confirm the setup.

6. Docker Desktop

- Docker Desktop provides a GUI interface to manage containers.

7. Shell Scripting with Docker

- Steps:
    - Fork the repo.
    - Clone it locally for your work.

8. Understanding the Dockerfile

What is a Dockerfile?

- A **Dockerfile** is a **text file** that contains a series of **instructions** on how to build a Docker image.
- It **automates** the creation of Docker images, ensuring consistency and reproducibility.
- Think of it like a **recipe**: each line tells Docker **how to assemble** the environment for your application.

How a Dockerfile Works

- When you run the command docker build, Docker reads the Dockerfile **line-by-line** and executes each instruction.
- Each instruction creates a **layer** in the final image.
    - Layers make building faster by caching unchanged steps.

Common Dockerfile Instructions

Command	**Purpose**	**Example**
FROM	Set the base image	FROM python:3.10
COPY	Copy files from host to container	COPY . /app
RUN	Execute a command in the container	RUN pip install -r requirements.txt
CMD	Set the default command to run	CMD ["python", "app.py"]
EXPOSE	Inform Docker which port to listen on	EXPOSE 5000
WORKDIR	Set the working directory inside the container	WORKDIR /app
ENV	Set environment variables	ENV ENVIRONMENT=production

Simple Example of a Dockerfile

```
# Use an official Python runtime as a parent image
FROM python:3.10

# Set the working directory
WORKDIR /app

# Copy the directory contents into the container
COPY . .

# Install dependencies
RUN pip install -r requirements.txt

# Expose port 5000
EXPOSE 5000

# Run app.py when the container launches
CMD ["python", "app.py"]
```

WEEK6: Building Data Pipeline (Airflow)

1. Overview of the Module

- Focus: **Apache Airflow**, building data pipelines, and error analysis.
- Goal: Understand how to automate, schedule, and monitor ML workflows effectively.

2. The Need for Workflow Management

- **Challenges without Workflow Management**:
    - Manual script scheduling with CRON (Command Run ON) lacks scalability and maintainability.
    - Difficult to manage hundreds of workflows, dependencies, and environment configurations.
    - Poor monitoring and troubleshooting of failed jobs.

3. Apache Airflow: A Solution for Workflow Management

- **What is Airflow?**
    - Open-source platform for authoring, scheduling, and monitoring workflows.
    - Defines workflows as **DAGs (Directed Acyclic Graphs)**.
    - Written in Python, supports distributed execution, and provides a friendly UI.
- **Airflow Features**:
    - Scalable, distributed task execution.
    - Workflow visualization (Grid View, Graph View, Calendar View, Gantt View).
    - Re-run specific steps, monitor failures, and track dependencies.

CRON */5 means every 5 …

4. Airflow summary

- **Scheduler** reads the DAG folder.
- DAG is parsed by a process to create a DagRun based on the scheduling parameters of DAG. (Create a DagRun in DB from Scheduler)
- **Taskinstance** is instantiated for tasks that need to be executed and flagged to **Scheduled** in the metadata DB. (Send by Scheduler to DB)
- **Scheduler** gets all TaskInstances flagged **Scheduled** from the metadata DB, changes the state to **Queued** and sends them to the executors to be executed.

- **Executors** pull out Tasks from the Queueing system, change the state from **Queued** to **Running** and workers start executing the **TaskInstances**.
- Task is finished, Executor changes the state of that task to its final state in the DB. **DagRun** is updated by the **Scheduler** with the state **Success** and **Failed**.

5. Core Concepts in Airflow (Next Column)

Concept	Description
DAG	Collection of tasks with dependencies, written as Python code.
Task	A node in the DAG representing a unit of work.
Operators	Define the type of work (e.g., PythonOperator, BashOperator, Sensor). Building block of Airflow, determining the actual work gets done, defines how that task will be run.
Hooks & Providers	Interface with external systems (e.g., MySQL, AWS, HDFS). Allow connection to external API and DB. Act as building blocks for operators.
Connections	Store information that allows you to connect to external systems (Authentication credentials or API tokens). Managed directly from UI and the actual information is encrypted and stored as metadata in Airflow's underlying Postgres or MySQL DB.

DAG properties:
- Directed: If multiple tasks with dependencies exist, each must have at least one defined upstream or downstream.
- Acyclic: Tasks are not allowed to self-reference or loop.
- Graph: All tasks are laid out with a set relationship with other tasks.

6. Types of Operators

Operator Type	Function
Action Operators	Execute a function (e.g., PythonOperator, BashOperator).
Transfer Operators	Move data between systems (e.g., MySqlToHiveOperator).
Sensor Operators	Wait for conditions (e.g., HttpSensor, SqlSensor).

Operators are defined individually, they pass information to other operations using **XComs**.

7. Airflow Architecture and Workflow Execution
- **Scheduler** reads DAGs → creates DagRun → instantiates TaskInstances.
- **Executor/Workers** pull queued tasks → execute them → update task status (success, failed).
- **Web Server/UI** displays DAG status, task runs, logs, and execution history.

8. Monitoring and Visualization in Airflow
- **Grid View**: Task list with status.
- **Graph View**: Workflow graph with task relationships.
- **Calendar View**: Execution calendar.
- **Gantt View**: Task timing and overlap.
- **Logs**: Detailed execution logs per task.
- **Landing Time = Job complete time - Scheduled start time**
- **Xcom**: View cross-task communication

9. Example Operators

Operator	Purpose
EmptyOperator (DummyOperator)	Placeholder, does nothing (used for grouping tasks). Evaluated by scheduler but never processed by the executor.
BashOperator	Executes bash commands. If **BaseOperator.do_xcom_push** is **True**, the last line written to stdout will also be pushed to an XCom when the bash command completes.
PythonOperator	Runs Python functions.
BranchPythonOperator	Enables conditional branching in workflows.
HttpSensor	Waits for HTTP response. Executes HTTP GET and returns False on **404 Not Found** or **response_check** returning False. Other than 404 would raise an exception and fail the sensor. To avoid **extra_option** can be passed with value {'**check_response: False**} It will make the **response_check** be executed for any http status code.
SqlSensor	Waits for SQL conditions to be met. (**Success of Failure**) or if the cell is not in (**0, '0', '', None**).

WEEK7: Data Cleansing + Feature Engineering

Section 1: Data Cleansing (Data Wrangling)

1. Why Dirty Data Happens
- Causes:
  - Lack of input validation.
  - Software miscalculations or incomplete calculations.
  - Direct database manipulation.
  - Poor schema design.

2. Data Quality Dimensions
- **Accuracy (ข้อมูลถูกต้อง), Validity (ข้อมูลถูก format e.g. email ต้องมี @), Reliability, Timeliness,**

Relevance, Completeness, Compliance (ปฏิบัติตามข้อกำหนด)

3. Common Data Quality Problems

Problem Type	Single Source	Multi Source
Schema Level	Poor design, lack of integrity	Naming conflicts, structural issues
Instance Level	Misspellings, duplication	Inconsistent aggregating / timing

4. Topics in Data Cleansing

Problem Type	Example	Solution Approach
Missing Data	Missing departure time	Remove rows/columns, fill with zero or estimated values
Wrong Data	Negative ATM amounts	Remove or correct based on logic
Fragmented Data	Name split across fields	Merge into a common group
Outliers	Extremely high incomes	Clip or remove outliers based on analysis

Section 2: Feature Engineering

1. Common Techniques

Task	Purpose
Scaling	Normalize data for clustering/similarity analysis
Encoding Categorical Variables	Prepare non-numeric data for models
Dealing with Non-Linearity	Normalize skewed data distributions
Trend Calculation	Capture long-term and short-term patterns

2. Scaling Methods

Method	Range	Use Case
MinMaxScaler	0 to 1	Standard normalization
MaxAbsScaler	-1 to 1	Centered around zero

3. Encoding Categorical Variables

Encoding Type	Example
Binary Encoding	Yes/No → 1/0
Ordinal Encoding	Low, Medium, High → 0, 1, 2
Nominal Encoding	One-hot encoding (dummy variables)

4. Dealing with Non-Linearity

- Use **log transformation** or similar methods to handle skewed distributions or outliers.
- Ensure better visualization, clustering, or regression analysis.

5. Trend Analysis

Trend Type	Method
Long-term Trend	Slope from regression analysis
Short-term Trend	$T = M_0 - (M_1 + M_2)/2$, where M's are recent data points

1. Dealing with Missing Data

```
# Check missing values
print(df.isnull().sum())

# Option 1: Drop rows with missing values
df_cleaned = df.dropna()

# Option 2: Fill missing values with 0
df_filled = df.fillna(0)

# Option 3: Fill missing values with mean (for numerical columns)
df['age'] = df['age'].fillna(df['age'].mean())
```

2. Handling Outright Wrong Data

```
# Check distributions
pd.crosstab(df['age'], columns = 'N')

# Detect negative values in 'amount' column
wrong_data = df[df['amount'] < 0]
print(wrong_data)

# Remove rows with wrong values
df = df[df['amount'] >= 0]
```

3. Fixing Fragmented Data (การกระจายตัว / การแบ่งข้อมูล)

- Fix by merging the value to the bigger group.
- Can be caused by the poor design of DB.

```
# Merge fragmented categorical fields

# Example: merging similar job titles
df.replace(to_replace = 'Marketing and Advertising' (Original Data), value = 'Marketing' (New Data), inplace = True)
```

4. Handling Outliers

- Occurs when the data point is exceptionally different from the main distribution.
- Detected by distribution plot.

```
# Visualize distribution


# Clip outliers
P99 = df[df['JobRole'] == 'Research']['Income'].quantile(0.99)
df.loc[df['JobRole'] == 'Research', 'Income'] = df.loc[df['JobRole'] == 'Research', 'Income'].clip(upper = P99)
```

Section 3: Coding

1. Scaling Features

```
from sklearn.preprocessing import MinMaxScaler, MaxAbsScaler

scaler = MinMaxScaler()  # or MaxAbsScaler()

# Assume numerical columns
numerical_cols = ['age', 'income', 'years_experience']

df[numerical_cols] = scaler.fit_transform(df[numerical_cols])
```

2. Encoding Categorical Variables

Binary Encoding: 0/1

df['is_married'] = df['marital_status'].map({'Married': 1, 'Single': 0})

df[['default', 'housing', 'loan', 'y']].apply(lambda x: x.map({'yes' :1, 'no': 0}))

Ordinal Encoding: Integer sequence

from sklearn.preprocessing import OrdinalEncoder

ordinal_scaler = OrdinalEncoder

ordinal_scaler.fit([['unknown', 0], ['primary', 1]])

ordinal_scaler.transform(df['education'].values.reshape(-1,1))

education_mapping = {'High School': 1, 'Bachelor': 2, 'Master': 3, 'PhD': 4}

df['education_level'] = df['education'].map(education_mapping)

One-Hot Encoding (Nominal Encoding: dummies)

df = pd.get_dummies(df, columns=['city'])

3. Dealing with Non-Linearity (Log Transformation)

Log transform skewed data
df['log_income'] = np.log1p(df['income']) # log(1 + income) to handle zero values

4. Feature: Trend Calculation (for Time Series)

Example: Short-term trend (simple version)
df['short_term_trend'] = df['sales_today'] - (df['sales_yesterday'] + df['sales_day_before']) / 2

WEEK8: Model Parameter Tuning

2. Overfitting and Model Evaluation

- **Overfitting Case 1**: Testing on the training data gives misleadingly perfect results.
- **Overfitting Case 2**: Too complex models memorize training data, fail on unseen data.
- **Solution**: Use separate data for training and testing to evaluate model generalization.

Bias vs Variance Trade-off

- **Bias**: Error from assumptions in the model.
- **Variance**: Error from sensitivity to small fluctuations in the training set.

---

3. Hold-Out and Cross-Validation

- **Hold-Out Method**: Reserve part of data as test set (X_test, y_test).
- **Cross-Validation (CV)**:
  - Reduces overfitting risk on the test set.
  - Solve parameters can be tweaked until the estimator.
  - **K-Fold CV**: Splits data into K parts, trains on K-1 parts, tests on the remaining part, rotates through all folds.

4. Hyperparameter Tuning

- **Hyperparameters**: Settings not learned from data (e.g., C, gamma in SVM, alpha in Lasso).
- Adjusted manually or via search to improve model performance.
- Not directly learnt within estimators.

5. Parameter Tuning Approaches

Method	Description
GridSearchCV	Exhaustively tries all parameter combinations.
RandomizedSearchCV	Samples random parameter combinations from a defined distribution.

6. Parameter Tuning Workflow

Parameters provided when constructing an estimator may be optimized in this manner.

1. Define estimator (model).
2. Define parameter space.
3. Choose the search method (GridSearchCV / RandomizedSearchCV).
4. Apply cross-validation.
5. Evaluate using scoring metrics (e.g., accuracy, RMSE).
6. Use estimator.get_params() to view tunable parameters.

7. Nested Cross-Validation

- Combines two layers of cross-validation:
  - **Inner loop**: Parameter tuning.
  - **Outer loop**: Model evaluation.
- Avoids bias from selecting parameters based on the test set.

8. Example with Python (Scikit-Learn)

- **Loading data, splitting X and y.**
- Use of cross_validate, GridSearchCV, and evaluation metrics.
- Recommended practice: After tuning, validate the model with another unseen test set.

9. Evaluation Metrics

Metric	Purpose
Accuracy	Classification performance.
RMSE	Regression error measurement.

10. Example Use Case: Recommender System

- Tune hyperparameters to minimize RMSE.
- Select the algorithm with the best cross-validation performance

1. Basic Train/Test Split

```
from sklearn.model_selection import train_test_split

# Assume you have loaded your dataset
X = df.drop('target', axis=1)
y = df['target']

# Split into training and testing
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

2. K-Fold Cross-Validation

```
from sklearn.model_selection import cross_validate
from sklearn.ensemble import RandomForestClassifier

model = RandomForestClassifier()

# Perform cross-validation
cv_results = cross_validate(model, X_train, y_train, cv=5, return_train_score=True)

print(cv_results)
```

3. Hyperparameter Tuning with GridSearchCV

```
from sklearn.model_selection import GridSearchCV
from sklearn.svm import SVC

# Define model
svc = SVC()

# Define parameter grid
param_grid = {
    'C': [0.1, 1, 10],
```

```
    'kernel': ['linear', 'rbf'],
    'gamma': ['scale', 'auto']
}

# Setup GridSearchCV
grid_search = GridSearchCV(svc, param_grid, cv=5,
scoring='accuracy')

# Fit model
grid_search.fit(X_train, y_train)

# Best parameters and score
print("Best Parameters:", grid_search.best_params_)
print("Best Cross-Validation Score:", grid_search.best_score_)
```

4. Hyperparameter Tuning with RandomizedSearchCV

```
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import uniform

# Define model
svc = SVC()

# Define parameter distribution
param_dist = {
    'C': uniform(0.1, 10),
    'gamma': ['scale', 'auto'],
    'kernel': ['linear', 'rbf']
}

# Setup RandomizedSearchCV
random_search = RandomizedSearchCV(svc,
param_distributions=param_dist, n_iter=10, cv=5,
random_state=42)

# Fit model
random_search.fit(X_train, y_train)

# Best parameters and score
print("Best Parameters:", random_search.best_params_)
print("Best Cross-Validation Score:",
random_search.best_score_)
```

5. Evaluate the Best Model on the Test Set

```
from sklearn.metrics import accuracy_score

# Use the best model from grid search
best_model = grid_search.best_estimator_

# Predict and evaluate
y_pred = best_model.predict(X_test)
test_accuracy = accuracy_score(y_test, y_pred)

print("Test Accuracy:", test_accuracy)
```

- Split → Cross-validate → Tune hyperparameters (GridSearchCV or RandomizedSearchCV) → Test best model.

WEEK9: Models and Experiment Tracking

2. Choosing an ML Model

- **Avoid the (State Of The Arts) SOTA Trap**: SOTA models may not suit your use case due to resource, speed, or data differences.
- **Start Simple**: Use simpler models as baselines.
- **Avoid Bias in Evaluation**:
  - Equal experiment effort for all architectures.
  - Consider future scalability and data growth.
- **Balance Trade-offs**:
  - False positives vs false negatives.
  - Compute cost vs accuracy.
  - Interpretability vs accuracy.

3. Model Interpretability

- Importance of understanding **why** models make decisions.
- Use techniques like **Random Forest Feature Importance** to explain models.

Ensemble models are mostly useful for leaderboards.

4. Ensemble Methods Overview

Method	Description	Example
Bagging	Sample with replacement, aggregate predictions.	Random Forest
Boosting	Focus on misclassified samples in each iteration.	XGBoost, LightGBM
Stacking	Combine multiple models via a meta-model.	Model stacking (meta-learning)

Command Crawl is an organization that crawls the web and provides snapshots that are free to the public.

5. Foundation Models and Transformers

- **Language Models (LMs)**: Probability distribution over token sequences.
- **Tokenizer Unfairness**: Tokenizer designs may introduce language biases.
- **Transformer Architecture**: Attention mechanism (key, query, value) enables contextual understanding.
- **Training Data Challenges**:
  - Underrepresentation of low-resource languages.
  - Consent and data privacy issues (e.g., Common Crawl concerns).
- **Research Directions**
  - **Data collection methods** for low resource data (e.g. SEACrowd, AYA Model from Cohere)
  - **Synthetic data generation** using AI generates data to train the model.

6. Training Compute Cost

- Large models require significant compute (e.g., GPT-3, Llama series).
- FLOPs floating point operations measure the number of floating point operations performed for a certain task and GPU requirements estimate cost and training time.

7. Experiment Tracking: Why and How

- **Purpose**:
  - Organize: Organize experiments systematically.
  - Reproduce: Enable reproducibility.
  - Log: Track parameters, metrics, models, and metadata.

Experiment Tracking Tools

Tool	Key Features
MLflow	Experiment tracking of any variable that may affect the model, model registry, deployment.
Weights & Biases	Experiment monitoring and collaboration.

8. MLflow Essentials

- **Four Modules**:
  - Tracking (experiments, runs, metrics).
  - Models (save, load models).
  - Model Registry (manage production stages).
  - Projects (standardize reproducible code packaging).

9. Automated Logging

- Automatic logging allows logging metrics, parameters, and models without the need for explicit log

statements. (Support e.g Scikit-learn, Keras, Gluon, XGBoost, LightGBM, Statsmodels, Spark, Fastai, Pytorch)
- **mlflow.xgboost.autolog()**

UI Commands:
mlflow server --host 127.0.0.1 --port 8080
mlflow ui --backend-store-uri sqlite:///mlflow.db

- **Autologging Supported Libraries**: scikit-learn, XGBoost, LightGBM, PyTorch, etc.

WEEK10: Model Deployment

1. What is Model Deployment?

- The process of making a trained ML model available for **real-world use**.
- Allows:
  - **Real-time or batch predictions**.
  - Integration into business workflows.
  - Scalability across multiple users and devices.

2. Types of Deployment

Type	Description	Tools/Platforms
Local Deployment	Offline testing or small-scale applications.	Local machines.
Cloud Deployment	Scalable, online applications.	AWS SageMaker, Google AI Platform, Azure ML.
Edge Deployment	For IoT/mobile devices; optimized models for limited hardware.	TensorFlow Lite, ONNX.
Containers & APIs	Package models using Docker and exposed via Flask, FastAPI, TensorFlow Serving.	Docker, REST APIs.

3. Prediction Pipelines

Pipeline Type	Description	Example Scenario
Batch Prediction	Predict periodically before requests arrive, store results and retrieve them when requests arrive.	Retail sales forecast done weekly.
Online Prediction	Predict in real-time after requests arrive, Prediction returned as responses, sync when using requests like REST/ RPC (e.g. HTTP prediction).	Fraud detection on credit card transactions.

4. Real-World Use Cases

Scenario	Use of Prediction
Retail	Sales forecasting using batch prediction.
Banking	Fraud detection via real-time predictions.
Ride-sharing	Real-time matching of drivers and riders.

5. Model Optimization for Deployment (Inference Optimization Techniques)

Technique	Purpose	Tools/Examples
Quantization	Reduce model size by converting weights (float32 → int8/float16).	TensorRT, PyTorch Quantization, ONNX Runtime.
Pruning	Remove less important neurons/filters.	Trade-off: size vs. accuracy.
Distillation	Train a small model to mimic a large one.	Student-teacher model setup.

6. ONNX: Open Neural Network Exchange

- Universal format for deploying models across frameworks.
- Supports transferring models from **PyTorch, TensorFlow** to environments like **C++, mobile, web**.
- Enables efficient inference with engines like ONNX Runtime and TensorRT.
- import torch
- import torchvision.models as models

7. TensorRT for Efficient Inference

- NVIDIA's optimization toolkit for faster and more efficient inference.
- Supports quantization, pruning, and high-performance deployment.
- **TensorRT:** Trained DNN → ONNX Conversion → TensorRT Optimizer → TensorRT runtime
- **TensorRT Framework Integrations:** Pytorch (Trained DNN) → One Line TensorRT Framework Integrations API (TensorRT Optimizer → TensorRT Runtime) → Pytorch (TorchScript) (In-framework Inference)

8. Deployment with Docker

- Containerize your ML model and serve via REST APIs.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}|$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2$$

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2}$$

$$R^2 = 1 - \frac{\sum(y_i - \hat{y})^2}{\sum(y_i - \bar{y})^2}$$

Where,
$\hat{y}$ – predicted value of y
$\bar{y}$ – mean value of y

7. A classifier's confusion matrix for the classes "Normal" and "Disease" is shown below. (10 points)

Predicted class

	Class	Disease	Normal	Total
Actual class	Disease	270 =TP	280 = FN	550 = P
	Normal	2000 = FP	12000 = TN	14000 = N
	Total	2270	12280	14550 =ALL

7.1) What is the accuracy of this classifier? What is the accuracy of each class? (3 point)

ACCURACY = (270 +12000) / 14550 = 0.8433

7.2) What are the precision, recall and specificity of this classifier? (3 point)

SENSITIVTY = TP/ P = 270 / 550 = 0.4909,
SPECIFICITY = TN/ N = 12000 / 14000 = 0.8571
PRECISION = TP / (TP +FP) = 270/ (270 +2000) = 0.1189
RECALL = TP/ (TP+FN) = 270 /(270+280) = 0.4909

7.3) What is the F1-score of this classifier? (2 points)

F1-score = 2 (PRECISION)(RECALL) / (PRECISION + RECALL)
= 2 (0.1189)(0.4909) / (0.1189+0.4909) = 0.1914

7.4) Should we use this classifier with patients in the hospital? Why or why not? (2 points)

NO, because the sensitivity, specificity and f-measure are too low. The classifier is not reliable.

WEEK11: Model Monitoring

1. Software Failures

- Dependency Failure, Deployment failure, Hardware failure, Downtown or crashing.

2. Monitoring and Observability

- Monitoring accuracy-related metric - track model prediction performance.
  - Real time ground truth such as upvote, downvote, purchase click.
  - Human-in-the-loop - let users evaluate and provide feedback.
- Monitoring prediction
  - For distribution shifts
  - Spam email classifier.

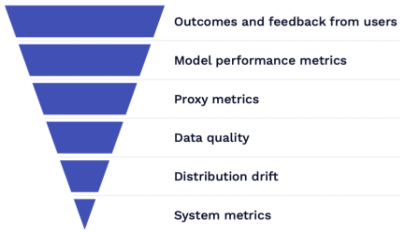
3. Model Monitoring Method

- Data pipelines: Automated scripts that analyze the model prediction, data quality, drift, and the result are stored in DB.
- Batch monitoring - Scheduled jobs that run model evaluation and log metric to DB.
- Real-time monitoring: Metrics are sent from live ML models to a monitoring service for tracking.
- Alert: Get notification when metric values are below thresholds without even the need of a dashboard
- Reports: Static reports for one-time sharing
- Dashboard: Live dashboards to interactively visualize model and data metric over time

4. Beyond standard metric

- Standard Metrics (Precision, Recall) are not enough
  - Limited in real-world setting
  - Often rely on delayed ground truth feedback
- Challenge in production
  - Delayed feedback, past performance != future performance
  - Target variable may shift frequently
- Customer Metric Matter
  - Require deep business understanding,
  - One-size-fits-all metrics (Like Aggregates) miss critical issues.
  - Different segments need tailored (ปรับแต่ง) evaluation.
- Early monitoring is key
  - Monitor input data & model behavior before feedback arrives, identify drift and anomalies early, stay responsive in fast-changing environments.

Metric to monitor



- **Proxy metric (Business metric)**
- **Data Quality -** a set of rules you apply to measure the quality of data.
- **Type of drifts**
  - **Instantaneous drift** - happens when a model is deployed in a new domain, bug introduced in the pre-processing pipeline.
  - **Gradual drift** - happens when users' preference change or new concepts get introduced to the corpus (คลังข้อมูล) over time.
  - **Periodic drift** - happens when users' preferences are seasonal or people in different time zones use your model differently.
  - **Temporary drift** - happens when a malicious (เป็นอันตราย) user attacks your model, a new user tries product and churns (ฟอง), someone uses product in an unintended way.
- **Measuring distribution shift** - To calculate how different a new data distribution is from a reference (expected) distribution using **KL Divergence**.

from scipy.stats import entropy
 # Reference distribution (e.g., training set)
Q = np.array([0.4, 0.3, 0.2, 0.1])

 # Actual/Observed distribution (e.g., current incoming data)
P = np.array([0.1, 0.2, 0.3, 0.4])
 kl_divergence = entropy(P, Q)

  - KL Divergence = 0 → Both distributions are identical
  - Higher KL Divergence → Larger discrepancy (ความคลาดเคลื่อน) between current and reference distribution.
- **System Metrics**
  - CPU Usage - Commands(top, mpstat) - Output Format(Live, Loggable)
  - Memory Usage - Command(free, vmstat) - Output Format(Text, Tabular)
  - Disk Usage - Command(df -h, iostat) - Output Format(Text, Tabular)
  - GPU Usage (NVIDIA) - Command(nvidia-smi) - Output Format(Text/CSV)
  - Network Usage - Command(ifstat, vnstat) - Output Format(Text/CSV)

- Nohup ./log_metrics,sh (running background)
- all_features_stattest: Defines a custom drift detection method for all features
- num_features_stattest: Defines a custom drift detection method for numerical features only
- cat_features_stattest: Defines a custom drift detection method for categorical features only
- per_feature_stattest: Defines a custom drift detection method per feature