

## **Case 1: Customer Churn Prediction**

#### **Question:**

You are provided with customer data for a telecom company, including demographic information, service usage, and whether the customer has churned or not. How would you build a model to predict customer churn?

- 1. Data Exploration: Understand the data, check for missing values, and explore patterns.
- 2. Feature Engineering: Create relevant features like usage patterns, duration of service, and interaction with support.
- 3. Model Selection: Use models like logistic regression, decision trees, or ensemble methods like random forests or XGBoost.
- **4. Evaluation:** Use metrics like accuracy, precision, recall, and AUC-ROC.
- 5. Deployment: Implement the model in a production environment and monitor performance.

# Case 2: A/B Testing

#### **Question:**

An e-commerce company wants to test a new recommendation algorithm. How would you design an A/B test to measure its effectiveness?

- 1. Hypothesis Definition: Clearly state the null and alternative hypotheses.
- 2. Sample Size Calculation: Determine the required sample size to achieve statistical significance.
- 3. Randomization: Randomly assign users to the control (current algorithm) and treatment (new algorithm) groups.
- 4. Metrics: Define success metrics such as click-through rate, conversion rate, and average order value.
- **5. Analysis:** Use statistical tests to compare the performance of both groups.
- **6. Conclusion:** Draw conclusions based on the results and make recommendations.



### **Case 3: Fraud Detection**

#### **Question:**

You are tasked with detecting fraudulent transactions for a credit card company. How would you approach this problem?

- 1. Data Understanding: Analyze transaction data to identify patterns indicative of fraud.
- 2. Feature Engineering: Create features such as transaction amount, frequency, location, and time of day.
- 3. Modeling: Use supervised learning models like logistic regression, decision trees, and anomaly detection methods like isolation forests.
- 4. Evaluation: Evaluate using metrics like precision, recall, F1 score, and confusion matrix.
- 5. Monitoring: Continuously monitor model performance and update the model as fraud patterns evolve.

# **Case 4: Sales Forecasting**

### **Question:**

A retail company wants to forecast sales for the next quarter. How would you approach this task?

- 1. Data Collection: Gather historical sales data, including seasonal trends and external factors like holidays.
- 2. Exploratory Data Analysis (EDA): Identify patterns, trends, and anomalies in the data.
- 3. Feature Engineering: Create features such as moving averages, lagged values, and external indicators.
- **4. Model Selection:** Use time series models like ARIMA, exponential smoothing, or machine learning models like random forests and gradient boosting.
- **5. Evaluation:** Validate model performance using metrics like RMSE, MAE, and MAPE.
- 6. Forecasting: Generate forecasts and provide actionable insights.



# **Case 5: Recommender Systems**

### **Question:**

You need to build a recommendation system for an online streaming service. How would you approach it?

- 1. Data Understanding: Analyze user behavior data, including watch history, ratings, and preferences.
- 2. Collaborative Filtering: Implement user-based or item-based collaborative filtering.
- 3. Content-Based Filtering: Use metadata like genre, actors, and directors to recommend similar content.
- 4. Hybrid Approach: Combine collaborative and content-based filtering for better recommendations.
- **5. Evaluation:** Use metrics like precision, recall, and mean reciprocal rank (MRR) to evaluate the recommender system.
- **6. Personalization:** Continuously update the model based on user interactions to improve recommendations.



# **Case 6: Sentiment Analysis**

#### **Question:**

A company wants to analyze customer reviews to understand their sentiments about its new product. How would you proceed?

- 1. Data Collection: Gather customer reviews from various sources like social media, websites, and surveys.
- 2. Preprocessing: Clean and preprocess the text data, including tokenization, stop-word removal, and stemming/lemmatization.
- 3. Feature Extraction: Use techniques like TF-IDF, word embeddings, or BERT for feature extraction.
- **4. Modeling:** Use machine learning models like logistic regression, SVM, or deep learning models like LSTM and BERT.
- **5. Evaluation:** Evaluate model performance using metrics like accuracy, precision, recall, and F1 score.
- **6. Insights:** Analyze the results to provide actionable insights to the company.



# **Case 7: Anomaly Detection**

#### **Question:**

You are provided with server logs and need to detect anomalies in server performance. How would you approach this problem?

- 1. Data Understanding: Analyze the server logs to identify normal and abnormal behavior patterns.
- 2. Feature Engineering: Create features like CPU usage, memory usage, request count, and error rates.
- 3. Modeling: Use unsupervised learning methods like clustering (e.g., DBSCAN), isolation forests, or autoencoders for anomaly detection.
- **4. Evaluation:** Validate the model using techniques like ROC curve and precision-recall curves.
- **5. Deployment:** Implement the model in a monitoring system to detect anomalies in real-time and alert the relevant teams.



# **Case 8: Image Classification**

### **Question:**

A healthcare company needs to classify X-ray images to detect pneumonia. How would you approach this problem?

- 1. Data Collection: Gather a dataset of labeled X-ray images.
- 2. Preprocessing: Preprocess the images by resizing, normalization, and augmentation to increase the dataset size.
- 3. Model Selection: Use convolutional neural networks (CNN) architectures like ResNet, VGG, or transfer learning models.
- 4. Training: Train the model using cross-validation to avoid overfitting.
- **5. Evaluation:** Use metrics like accuracy, precision, recall, F1 score, and AUC-ROC.
- **6. Deployment:** Implement the model in a clinical setting, ensuring it integrates with existing systems and provides explainable results.



# Case 9: Natural Language Processing (NLP)

### **Question:**

A customer support system needs to automatically categorize incoming support tickets. How would you approach this problem?

- 1. Data Collection: Gather a dataset of historical support tickets and their categories.
- 2. Preprocessing: Clean and preprocess the text data, including tokenization, stop-word removal, and stemming/lemmatization.
- 3. Feature Extraction: Use techniques like TF-IDF, word embeddings, or BERT for feature extraction.
- **4. Modeling:** Use classification models like logistic regression, SVM, or deep learning models like LSTM and BERT.
- **5. Evaluation:** Evaluate model performance using metrics like accuracy, precision, recall, and F1 score.
- 6. Deployment: Integrate the model into the support system to automatically categorize new tickets and continuously improve based on user feedback.



# **Case 10: Market Basket Analysis**

## Question:

A grocery store wants to analyze customer purchase patterns to increase sales. How would you approach this problem?

- 1. Data Collection: Gather transaction data, including items purchased and transaction timestamps.
- 2. Preprocessing: Clean the data, removing any inconsistencies or missing values.
- **3. Association Rule Mining:** Use algorithms like Apriori or FP-Growth to find frequent itemsets and generate association rules.
- **4. Evaluation:** Evaluate the rules using metrics like support, confidence, and lift.
- **5. Insights:** Analyze the results to identify patterns and provide recommendations to increase cross-selling and up-selling.
- 6. Implementation: Implement changes in the store layout, promotions, and marketing strategies based on the insights.