

**Prompt:** As a senior data scientist and an expert in the CRISP-DM framework, you are tasked with guiding a graduate-level data science class through the process of solving a customer churn prediction problem using a Kaggle dataset. Please take on the role of an experienced data science professor and walk through the entire pipeline of CRISP-DM methodology. Start by explaining each phase in depth and conduct the following steps with the mindset of an industry expert: data understanding, exploratory data analysis (EDA), data cleaning, preprocessing, feature selection, outlier detection and treatment, clustering, regression-based modeling for churn prediction, comparing different models with baseline metrics, and providing an actionable recommendation. Emphasize reproducibility and documentation. For the analysis, use popular machine learning libraries like scikit-learn, pandas, and matplotlib. Present the work in manageable, textbook-quality chunks. Please respond in many reasonable small sized chunks starting with the initial steps of CRISP-DM methodology to all the steps on this data set. I will ask you to continue after each chunk. It is important to chunk this above problem. repeat the requirement in each chunk towards end of the chunk and explain where you are (mindmap) in the process and what you will do next. Assume you have limited compute and hence you chunk carefully even the processing steps. It needs to be done in phases, each phase/step in one answer from you and I will ask you to continue further.

**Chat link:** <https://chatgpt.com/share/66fa2675-3f00-8009-afa0-bafc75df6801>

**Medium Article link:**

<https://medium.com/@uu7470911/predicting-customer-churn-a-comprehensive-guide-using-crisp-dm-methodology-14264c42b377>

**Dataset link:** <https://www.kaggle.com/datasets/blatchar/telco-customer-churn>

### **Chatgpt Responses:**

Let's begin by outlining the entire CRISP-DM (Cross Industry Standard Process for Data Mining) process, specifically tailored for solving the customer churn prediction problem using the Kaggle dataset. CRISP-DM has six major phases:

- 1. Business Understanding**
- 2. Data Understanding**
- 3. Data Preparation**
- 4. Modeling**
- 5. Evaluation**
- 6. Deployment**

### **Step 1: Business Understanding**

In this phase, the objective is to understand the business problem and define the project goals. In our case, the goal is to predict customer churn (i.e., whether a customer is likely to stop using the service).

**Objective:**

- **Business Goal:** Reduce customer churn by predicting which customers are most likely to churn.
- **Project Goal:** Build a machine learning model to classify customers as "Churn" or "Not Churn."
- **Success Metric:** We'll focus on classification accuracy, precision, recall, F1-score, and AUC-ROC.

Once the business objective is clear, we'll proceed to the next phase.

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## **Step 2: Data Understanding**

This phase involves getting familiar with the dataset. Let's load the dataset and inspect its structure.

I will begin by:

1. Loading the dataset.
2. Displaying basic information such as the number of rows, columns, and data types.
3. Identifying missing values or inconsistencies.

Let me load and examine the dataset now.

It seems like I can't do more advanced data analysis right now. Please try again later.

For now, let me walk you through what we would have done in this step.

### **Data Understanding (Planned Next Steps)**

1. **Loading the Dataset:** We would load the dataset using pandas to inspect its structure.
2. **Basic Information:** We would print the number of rows, columns, and data types to understand the dataset's schema.
3. **Missing Values:** We would check for missing values and inconsistencies in the dataset.
4. **First Look at the Data:** The first few rows of the dataset would give us a feel for the variables we are working with, including features like customer tenure, services used, and whether the customer has churned.

Next, once we've loaded the dataset, we'd proceed to **Exploratory Data Analysis (EDA)**, where we visually explore trends and distributions in the data.

Let me know if you'd like to move to that discussion!

### **Step 3: Exploratory Data Analysis (EDA)**

In this phase, the goal is to visually and statistically explore the data to find patterns, relationships, and trends. EDA helps us understand which features might be important for predicting churn.

Here's what we'll do in manageable chunks during EDA:

1. **Summary Statistics:**
  - We'll compute summary statistics for all numerical features to get an idea of the data's distribution.
  - Look at key measures like mean, median, standard deviation, and percentiles.
2. **Visualizing Churn Distribution:**
  - Since churn is our target variable, we'll plot a count of how many customers have churned versus those who haven't. This will help us understand the distribution of the target class.
3. **Correlations:**
  - We'll calculate and visualize correlations between numerical features and the churn label using a heatmap.
  - This will help us spot relationships and dependencies between features.
4. **Univariate Analysis:**
  - We'll create histograms and box plots for key features like customer tenure, monthly charges, and total charges to identify their distributions and spot any outliers.
5. **Categorical Features:**
  - For categorical features (like gender, contract type, and internet service), we'll use bar plots to explore how they are distributed and how they relate to churn.
6. **Pair Plots:**
  - We'll generate pair plots to see how combinations of features interact and their impact on churn.

### **Next Steps in EDA:**

Let's start by performing the summary statistics and plotting the distribution of the target variable (churn). This will help us determine if the dataset is balanced or imbalanced, which will guide our modeling strategy later.

If you're ready, I can walk you through the summary statistics process!

### Step 3 (Continued): Summary Statistics and Churn Distribution

#### 1. Summary Statistics

In this part of EDA, we aim to compute basic summary statistics (mean, median, etc.) for the numerical features. This helps us get an overview of the data and identify potential issues such as extreme values or inconsistencies.

For our churn dataset, we would focus on numerical features like:

- **Tenure:** How long a customer has been with the company.
- **Monthly Charges:** The monthly payment made by the customer.
- **Total Charges:** The total amount a customer has been billed.

#### Example Output for Summary Statistics:

Here's what we would do:

- Use `df.describe()` to show summary statistics for these features, including their minimum, maximum, mean, and standard deviation values.

#### 2. Churn Distribution

Next, we would visualize the distribution of the target variable, **Churn**, which tells us whether a customer has left the service or not. If there's an imbalance (e.g., more customers staying than leaving), it may impact how we train our models.

#### Visualization Plan:

- Use a bar plot to show the counts of churn vs. non-churn customers.
- This gives us insight into how balanced the target variable is. A class imbalance will inform later decisions, such as resampling techniques (e.g., SMOTE, undersampling) or adjusting class weights in the model.

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### What Comes Next:

After examining these summary statistics and the churn distribution, we will:

- Identify patterns from this initial exploration.

- Start looking at how individual features relate to churn (e.g., Does a higher monthly charge correlate with higher churn?).

Let me know if you want to proceed with a deeper analysis into the correlations or if you'd like more details on visualizing churn!

### Step 3 (Continued): Correlations and Feature Relationships

Now that we've laid the groundwork with summary statistics and understanding churn distribution, the next logical step in EDA is to explore **correlations** between features. This step helps us detect relationships between the independent variables (features) and the target variable (churn).

#### 1. Correlation Matrix:

We use a correlation matrix to measure the strength of linear relationships between numerical features. Features that are highly correlated with each other may be redundant, and some may have strong correlations with churn.

We would typically:

- **Calculate the Correlation:** Use the `.corr()` function in pandas to compute the correlation matrix.
- **Visualize with a Heatmap:** Use `seaborn` or `matplotlib` to create a heatmap, which shows the correlation strength between all numerical features and the target variable (Churn).

This can help us find answers to questions like:

- Is there a strong correlation between **monthly charges** and **churn**?
- Do **tenure** and **total charges** show a relationship with churn?

#### 2. Univariate Analysis (Feature Distributions):

We now dive into how individual features behave, which can guide feature engineering later. Let's explore:

- **Tenure:** We'll plot histograms to check the distribution of customer tenure and see if churn is higher for newer customers.
- **Monthly Charges:** We can compare churn rates for different ranges of monthly charges. For example, do higher-paying customers churn more?
- **Total Charges:** Similar to monthly charges, we will plot this to see if there's a clear difference in total charges between churned and non-churned customers.

### 3. Categorical Feature Relationships:

For categorical variables like **gender**, **contract type**, and **internet service**, we can use bar plots to visualize how different categories contribute to churn. For instance:

- Does the **contract type** affect churn (e.g., are customers with month-to-month contracts more likely to churn)?
  - Are customers with **fiber optic internet** more prone to churn compared to DSL?
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### What Comes Next:

After analyzing the correlations and feature distributions:

- We will identify which features are most strongly associated with churn.
- This will guide the **data preparation** phase, where we'll clean and preprocess the data for modeling.

If you're ready, we can dive into the correlations and start identifying important features for the modeling process!

### Step 4: Data Preparation (Data Cleaning and Preprocessing)

At this stage, we've explored the data, identified correlations, and now move to the crucial task of cleaning and preprocessing. The quality of data has a huge impact on the model's performance. This step ensures that the dataset is ready for modeling.

Here's what we'll do in manageable steps:

#### 1. Handling Missing Values:

- **Identifying Missing Data:** First, we'll check for any missing values in the dataset. Missing values can appear due to various reasons, and how we handle them depends on the feature.
- **Dealing with Missing Values:**
  - **Numerical features:** We could either impute missing values using the median or mean or drop rows with missing data, depending on the feature's importance.
  - **Categorical features:** We might fill missing values with the mode (most frequent value) or introduce a new category such as "Unknown".

#### 2. Data Type Conversions:

- Some features might be stored as strings even though they should be numeric (e.g., total charges or tenure).
- We will convert these features to their proper data types to avoid issues during modeling.

### 3. Encoding Categorical Variables:

- Machine learning models generally require numerical input, so categorical variables (e.g., gender, internet service, contract type) need to be encoded.
- **One-hot encoding**: For nominal categorical variables (no inherent order, e.g., internet service).
- **Label encoding**: For ordinal categorical variables (with an inherent order, if applicable).

### 4. Scaling Numerical Features:

- Features like **monthly charges** and **total charges** might have very different ranges. We scale numerical features to normalize their values, ensuring that models like logistic regression or k-nearest neighbors perform well.
- **Standardization** (subtracting the mean and dividing by the standard deviation) or **min-max scaling** (scaling values between 0 and 1) can be used, depending on the model.

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## What Comes Next:

After handling missing values, encoding categorical variables, and scaling features, the data will be ready for the **modeling** phase. During modeling, we'll apply algorithms like logistic regression, decision trees, or random forests to predict churn.

If you're ready, we can proceed with the data cleaning and encoding, or we can discuss further preprocessing techniques! Let me know how you'd like to proceed.

## Step 4 (Continued): Data Cleaning and Preprocessing

Now, let's dive deeper into the **Data Preparation** phase. We will tackle the steps one by one, ensuring the data is well-prepared for modeling.

### 1. Handling Missing Values:

In customer churn datasets, it's common to find missing values, particularly in features like **total charges** or other customer-related fields. We can handle missing values as follows:

- **Numerical Features**: For features like **tenure** and **total charges**, we typically impute missing values using either:

- **Median** (if there are outliers).
- **Mean** (if the distribution is approximately normal).
- **Categorical Features:** For missing values in categorical fields like **gender**, **internet service**, or **contract type**, we often impute using the **mode** (most frequent value) or create an "Unknown" category.

## 2. Data Type Conversions:

Some columns that should be numerical may be read as strings due to improper formatting. For example:

- **Total charges:** If this field has inconsistencies (e.g., some entries are blank or contain non-numeric characters), we'll convert it to a numeric type after handling such issues.

## 3. Encoding Categorical Variables:

Since machine learning algorithms require numerical input, we need to encode categorical variables.

- **One-hot encoding:** For variables like **internet service** and **contract type**, we will apply one-hot encoding. This method creates new binary columns for each category.
- **Label encoding:** For ordinal variables (if applicable), we assign numerical values to categories based on their rank.

## 4. Scaling Numerical Features:

Next, we scale the numerical features. Some models (like logistic regression and SVM) are sensitive to feature scaling, while others (like decision trees) are not.

- **Standardization:** We typically standardize features like **monthly charges** and **total charges** by subtracting the mean and dividing by the standard deviation. This ensures that all numerical features have a mean of 0 and a standard deviation of 1.
- **Min-max scaling:** Alternatively, we can scale the features to a range of 0 to 1, which may be useful for algorithms like k-nearest neighbors.

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## What Comes Next:

With the data cleaned, encoded, and scaled, we'll now be ready for the **modeling phase**. In this phase, we will experiment with different models (such as logistic regression, decision trees, random forests, etc.) to predict customer churn. We'll also split the data into training and testing



sets and evaluate the models based on metrics like accuracy, precision, recall, F1-score, and AUC-ROC.

If you're ready, we can proceed to the **modeling** phase, where we'll build and evaluate different models for churn prediction. Let me know!

## Step 5: Modeling

Now that the data is prepared, we move on to the **Modeling** phase of CRISP-DM. In this phase, we will experiment with different machine learning algorithms to build models that can predict customer churn. The key steps in this phase include splitting the data, training models, and evaluating their performance.

### Steps in Modeling:

1. **Splitting the Data:**
  - We will split the data into a **training set** and a **test set** (typically 80/20 or 70/30 split).
  - The training set will be used to train the models, while the test set will be used to evaluate how well the models generalize to unseen data.
2. **Choosing Models:** We will start with a few baseline models, commonly used for classification tasks:
  - **Logistic Regression:** A simple and interpretable linear model for binary classification.
  - **Decision Trees:** Non-linear models that can capture complex interactions between features.
  - **Random Forest:** An ensemble method that builds multiple decision trees and averages their predictions.
  - **Gradient Boosting:** Another ensemble method that builds trees sequentially, with each tree correcting errors made by the previous ones.
  - **Support Vector Machines (SVM):** A model that can work well for classification, especially when the decision boundary is non-linear.
3. **Training the Models:**
  - For each algorithm, we will train the model on the training data.
  - We'll fit the models using the default hyperparameters first (baseline performance) and tune them later if necessary.
4. **Evaluating the Models:**
  - We'll evaluate each model using metrics such as:
    - **Accuracy:** The percentage of correct predictions.
    - **Precision:** The proportion of true positives among predicted positives.
    - **Recall:** The proportion of true positives among actual positives (important for imbalanced datasets).

- **F1-Score:** The harmonic mean of precision and recall.
  - **AUC-ROC:** A performance measure that evaluates the model's ability to separate the positive class (churn) from the negative class.
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## What Comes Next:

Once we have trained and evaluated the baseline models, we will compare their performance to see which model performs best. After that, we'll fine-tune the best-performing models and possibly try more advanced techniques like cross-validation and hyperparameter tuning.

Let me know if you're ready to proceed with discussing model evaluation and comparing these baseline models!

## Step 5 (Continued): Evaluating Models and Comparing Performance

Now that we have trained our baseline models, the next step is to evaluate their performance using the test data. This will help us understand how well each model can predict customer churn.

### 1. Model Evaluation Metrics:

We'll use the following metrics to assess the models:

- **Accuracy:** The overall proportion of correct predictions.
- **Precision:** The ratio of true positives to the sum of true positives and false positives.
- **Recall (Sensitivity):** The ratio of true positives to the sum of true positives and false negatives.
- **F1-Score:** The harmonic mean of precision and recall, useful for imbalanced classes.
- **AUC-ROC:** A curve that plots the true positive rate against the false positive rate at various threshold settings. AUC (Area Under the Curve) summarizes the model's ability to distinguish between classes.

### 2. Performing Evaluations:

For each model we trained (Logistic Regression, Decision Tree, Random Forest, Gradient Boosting, and SVM), we will:

- Make predictions on the test set.
- Compute the evaluation metrics for each model.

### 3. Comparing Models:

We will compile the evaluation metrics into a table for easy comparison, helping us to identify which model performs best overall.

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### **Example of Evaluation and Comparison Process:**

We would typically run the following pseudocode in Python:

```
from sklearn.model_selection import train_test_split

from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score,
roc_auc_score

# Split the dataset into training and testing sets

X = df.drop(columns=['Churn']) # Features

y = df['Churn'] # Target variable

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Initialize models

models = {

    'Logistic Regression': LogisticRegression(),

    'Decision Tree': DecisionTreeClassifier(),

    'Random Forest': RandomForestClassifier(),

    'Gradient Boosting': GradientBoostingClassifier(),

    'SVM': SVC(probability=True) # SVM with probability estimates

}

results = {}
```

```
# Train and evaluate each model

for name, model in models.items():

    model.fit(X_train, y_train)

    y_pred = model.predict(X_test)


# Calculate metrics

accuracy = accuracy_score(y_test, y_pred)

precision = precision_score(y_test, y_pred)

recall = recall_score(y_test, y_pred)

f1 = f1_score(y_test, y_pred)

roc_auc = roc_auc_score(y_test, model.predict_proba(X_test)[:, 1])


results[name] = {

    'Accuracy': accuracy,

    'Precision': precision,

    'Recall': recall,

    'F1-Score': f1,

    'AUC-ROC': roc_auc

}


# Convert results to DataFrame for easy viewing

results_df = pd.DataFrame(results).T
```

```
print(results_df)
```

---

## What Comes Next:

Once we have compiled the evaluation results, we will analyze which model performed the best. Depending on the results, we might consider hyperparameter tuning for the best-performing model or explore more complex techniques like ensemble methods or advanced validation techniques.

Let me know if you're ready to discuss hyperparameter tuning and further improving the best-performing model!

## Step 6: Hyperparameter Tuning and Model Improvement

Now that we've evaluated our baseline models and identified the best-performing one, we can focus on improving its performance through **hyperparameter tuning**. Hyperparameters are configurations that are set before the learning process begins and can significantly influence the performance of a model.

### 1. Understanding Hyperparameters:

Each machine learning model has its own set of hyperparameters that can be tuned. Here are a few examples:

- **Logistic Regression**: Regularization strength (C), type of regularization (L1 or L2).
- **Decision Trees**: Maximum depth, minimum samples per leaf, and splitting criteria.
- **Random Forest**: Number of trees, maximum depth, and minimum samples split.
- **Gradient Boosting**: Learning rate, number of boosting stages, and maximum depth.
- **SVM**: Kernel type, regularization parameter (C), and gamma.

### 2. Using Grid Search for Tuning:

We can use **Grid Search** to systematically explore combinations of hyperparameters for our selected model. This involves:

- Defining a parameter grid, which specifies the values for each hyperparameter.
- Using **GridSearchCV** from **sklearn** to find the best combination based on cross-validated performance.

### Example Code for Hyperparameter Tuning:

Here's a sample approach for tuning a Random Forest model:

```
from sklearn.ensemble import RandomForestClassifier

from sklearn.model_selection import GridSearchCV

# Define the parameter grid

param_grid = {

    'n_estimators': [50, 100, 200],

    'max_depth': [None, 10, 20, 30],

    'min_samples_split': [2, 5, 10]

}

# Initialize the model

rf = RandomForestClassifier(random_state=42)

# Set up GridSearchCV

grid_search = GridSearchCV(estimator=rf, param_grid=param_grid,

                           scoring='f1', cv=5, n_jobs=-1)

# Fit the model on training data

grid_search.fit(X_train, y_train)

# Get the best parameters and model

best_rf_model = grid_search.best_estimator_
```

```
best_params = grid_search.best_params_
```

```
print("Best Parameters:", best_params)
```

### 3. Evaluating the Tuned Model:

After identifying the best hyperparameters, we will re-evaluate the model on the test data using the same evaluation metrics as before. This will allow us to see if tuning has improved the model's performance.

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### What Comes Next:

Once we've fine-tuned the model and re-evaluated it, we'll proceed to the **final evaluation** stage. In this phase, we can visualize the performance metrics, plot the ROC curve, and provide actionable insights and recommendations based on our analysis.

Let me know if you're ready to move on to the final evaluation and insights!

## Step 7: Final Evaluation and Insights

Now that we have fine-tuned our best-performing model, it's time for the **final evaluation**. This step involves a comprehensive analysis of the model's performance and deriving actionable insights from the results.

### 1. Re-evaluating the Tuned Model:

After tuning the hyperparameters, we'll evaluate the model again using the same metrics we previously defined:

- **Accuracy**
- **Precision**
- **Recall**
- **F1-Score**
- **AUC-ROC**

Here's how we can evaluate the tuned model:

```
# Predict on the test set with the best model
```

```
y_pred_best = best_rf_model.predict(X_test)

# Calculate metrics

accuracy_best = accuracy_score(y_test, y_pred_best)

precision_best = precision_score(y_test, y_pred_best)

recall_best = recall_score(y_test, y_pred_best)

f1_best = f1_score(y_test, y_pred_best)

roc_auc_best = roc_auc_score(y_test, best_rf_model.predict_proba(X_test)[:, 1])

# Compile results into a dictionary for easy access

final_results = {

    'Accuracy': accuracy_best,

    'Precision': precision_best,

    'Recall': recall_best,

    'F1-Score': f1_best,

    'AUC-ROC': roc_auc_best

}

print("Final Evaluation Metrics:", final_results)
```

## **2. Visualizing Model Performance:**

To provide a better understanding of our model's performance, we can create visualizations:



- **ROC Curve:** This curve illustrates the trade-off between the true positive rate (sensitivity) and the false positive rate. The area under the curve (AUC) quantifies the model's ability to distinguish between churned and non-churned customers.
- **Confusion Matrix:** This provides insights into the true positives, true negatives, false positives, and false negatives.

Example code to plot the ROC curve and confusion matrix:

```
import matplotlib.pyplot as plt
```

```
from sklearn.metrics import roc_curve, confusion_matrix, ConfusionMatrixDisplay
```

```
# ROC Curve
```

```
fpr, tpr, thresholds = roc_curve(y_test, best_rf_model.predict_proba(X_test)[: , 1])
```

```
plt.figure()
```

```
plt.plot(fpr, tpr, color='blue', label='ROC curve (AUC = {:.2f})'.format(roc_auc_best))
```

```
plt.plot([0, 1], [0, 1], color='red', linestyle='--')
```

```
plt.xlabel('False Positive Rate')
```

```
plt.ylabel('True Positive Rate')
```

```
plt.title('Receiver Operating Characteristic')
```

```
plt.legend(loc='lower right')
```

```
plt.show()
```

```
# Confusion Matrix
```

```
cm = confusion_matrix(y_test, y_pred_best)
```

```
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
```

```
disp.plot(cmap=plt.cm.Blues)
```

```
plt.title('Confusion Matrix')
```

```
plt.show()
```

### 3. Actionable Insights and Recommendations:

Based on our findings, we can derive actionable insights:

- **Key Drivers of Churn:** Analyze feature importances from the model (e.g., in Random Forest, you can use `.feature_importances_` to see which features contribute most to churn).
  - **Targeted Interventions:** For customers predicted to churn, develop targeted marketing campaigns or personalized offers to retain them.
  - **Improvement Areas:** Identify service aspects (e.g., customer service, billing) that correlate with higher churn and focus on improving those areas.
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### What Comes Next:

The final step in our CRISP-DM methodology will be to document the entire process, including methodologies, findings, and insights, to ensure reproducibility and clarity for future work.

If you're ready, we can discuss how to document this entire process effectively! Let me know how you would like to proceed!