Open In Colab

In [1]:
```
import sqlite3
from typing import Any, Tuple, Union

import matplotlib.pyplot as plt
import missingno as msno
import numpy as np
import pandas as pd
import seaborn as sns
from imblearn.over_sampling import SMOTE
from missmecha.analysis import MCARTest
from scipy.stats import chi2_contingency
from sklearn.feature_selection import (
    SelectKBest,
    SelectPercentile,
    mutual_info_classif,
)
from sklearn.impute import KNNImputer
from sklearn.metrics import normalized_mutual_info_score
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
```

!Note! If some graphs does not display, please run the whole jupyter notebook or specific cells for graphs to load

In [2]:
```
con = sqlite3.connect("../data/01_raw/bmarket.db")  # Connect to bmarket.db
cursor = con.cursor()
```

In [357…
```
cursor.execute("SELECT name FROM sqlite_master WHERE type = 'table';")
for row in cursor.fetchall():  # Check for all tables in database
    print(row)
```

```
('bank_marketing',)
```

In [3]:
```
query = "SELECT * FROM bank_marketing;"  # Retrieve data from bank_marketing
df = pd.read_sql_query(query, con)
df.head()
```

Out[3]:

	Client ID	Age	Occupation	Marital Status	Education Level	Credit Default	Housing Loan	Personal Loan	Cor Met
0	32885	57 years	technician	married	high.school	no	no	yes	
1	3170	55 years	unknown	married	unknown	unknown	yes	no	telepl
2	32207	33 years	blue-collar	married	basic.9y	no	no	no	cel
3	9404	36 years	admin.	married	high.school	no	no	no	Telepl
4	14021	27 years	housemaid	married	high.school	no	None	no	

1. Initiate Data Understanding and Insights

In [359…

```
df
```

Out[359…

	Client ID	Age	Occupation	Marital Status	Education Level	Credit Default	Housing Loan	Pe
0	32885	57 years	technician	married	high.school	no	no	
1	3170	55 years	unknown	married	unknown	unknown	yes	
2	32207	33 years	blue-collar	married	basic.9y	no	no	
3	9404	36 years	admin.	married	high.school	no	no	
4	14021	27 years	housemaid	married	high.school	no	None	
...	...	...	...	...	...	...	...	
41183	6266	58 years	retired	married	professional.course	unknown	no	
41184	11285	37 years	management	married	university.degree	no	no	
41185	38159	35 years	admin.	married	high.school	no	None	
41186	861	40 years	management	married	university.degree	no	None	
41187	15796	29 years	admin.	single	university.degree	no	yes	

41188 rows × 12 columns

In [360…

```
df.info()
print("\nTable Size:", df.shape)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 12 columns):
 #   Column                  Non-Null Count  Dtype 
---  ------                  --------------  ----- 
 0   Client ID               41188 non-null  int64 
 1   Age                     41188 non-null  object
 2   Occupation              41188 non-null  object
 3   Marital Status          41188 non-null  object
 4   Education Level         41188 non-null  object
 5   Credit Default          41188 non-null  object
 6   Housing Loan            16399 non-null  object
 7   Personal Loan           37042 non-null  object
 8   Contact Method          41188 non-null  object
 9   Campaign Calls          41188 non-null  int64 
 10  Previous Contact Days   41188 non-null  int64 
 11  Subscription Status     41188 non-null  object
dtypes: int64(3), object(9)
memory usage: 3.8+ MB

Table Size: (41188, 12)
```

In [361…

```
df.isna().sum()
```

Out[361…

```
Client ID                    0
Age                          0
Occupation                   0
Marital Status               0
Education Level              0
Credit Default               0
Housing Loan             24789
Personal Loan             4146
Contact Method               0
Campaign Calls               0
Previous Contact Days        0
Subscription Status          0
dtype: int64
```

In [362…

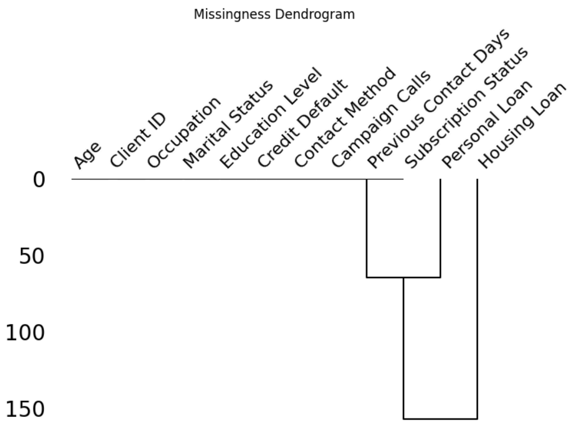
```
df.duplicated().sum()
```

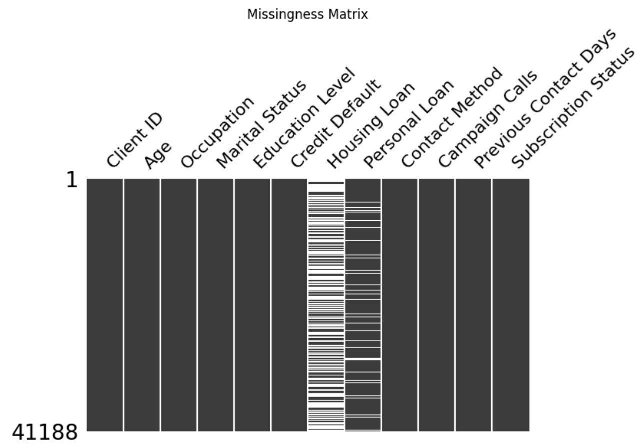
Out[362…

```
np.int64(0)
```

In [363…

```
fig, axes = plt.subplots(1, 2, figsize=(16, 6))

msno.dendrogram(df, ax=axes[0])
axes[0].set_title("Missingness Dendrogram")

msno.matrix(df, ax=axes[1], sparkline=False)
axes[1].set_title("Missingness Matrix")

plt.tight_layout()
plt.show()
```





> **OBSERVATION:**

- Reading the bank marketing table, the dataframe has **41188 rows** and **12 columns**.
- While observing the .info(), we can see that **`Client ID`**, **`Campaign Call`** and **`Previous Contact Days`** is assigned as *Integer* type. While the remaining columns are *Object* type.
- Furthermore, the .info() also shows that all of the columns has no empty values besides **Housing Loan (24789 missing data)** and **Personal Loan (4146 missing data)**.
- There is **no duplicated data** found.
- In addition, it is understandable that the `Personal Loan` and `Housing Loan` has a relationship in terms of missing values as shown in the dendrogram. Yet, they have a very far match to predict each other. Telling me that their missing values are not on the same row most of the time (Most likely due to the extreme sheer amount of missing data in Housing Loan).
- The `Subscription Status` column shows values of *yes* or *no* in string type instead of *True* or *False* in boolean type.
- Lastly, the values in `Age` column seems to **contains the text *years*** after all the numeric values, which is unnecessary. While `Education Level` column has a **two part format with a '.' between two key words** (e.g. high.school, univeristy.degree). The `Occupation` column has an **admin role that ended with '.'**.

> **THOUGHT PROCESS:**

---

1. A deeper observation into `Education Level` and `Occupation` columns is required to get a better understanding before cleaning.

2. I can remove *years* from the values in `Age` column and change the data type to *Integer*.

3. I can convert `Subscription Status` column into boolean type, with values of *True* or *False*, since the attribute says the column is defines as "Whether the client subscribed or not".

4. May consider dropping `Housing Loan` column since the missingno dendrogram and matrix shows an extremely high missingness.

Possible Hypothesis

- The table displayed shows signs of **missing data** in certain columns (e.g. `Occupation`, `Education Level`, `Credit Default`). These columns **were expected to have no empty values** based on previous statement. These missing values are refered to as *unknown*.

- If so, I need to replace all the *unknown* with *numpy NaN (np.nan)* to ensure all the missing data is captured.

Side Possibility 1a. Replace *unknown* and *None* with np.nan)

In [364…

```
df_unknown_to_none = df.copy()
replace_with_nan = ["unknown", None]
df_unknown_to_none.replace(replace_with_nan, np.nan, inplace=True)
df_unknown_to_none.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 12 columns):
 #   Column                  Non-Null Count  Dtype 
---  ------                  --------------  ----- 
 0   Client ID               41188 non-null  int64 
 1   Age                     41188 non-null  object
 2   Occupation              40858 non-null  object
 3   Marital Status          41108 non-null  object
 4   Education Level         39457 non-null  object
 5   Credit Default          32591 non-null  object
 6   Housing Loan            16006 non-null  object
 7   Personal Loan           36165 non-null  object
 8   Contact Method          41188 non-null  object
 9   Campaign Calls          41188 non-null  int64 
 10  Previous Contact Days   41188 non-null  int64 
 11  Subscription Status     41188 non-null  object
dtypes: int64(3), object(9)
memory usage: 3.8+ MB
```

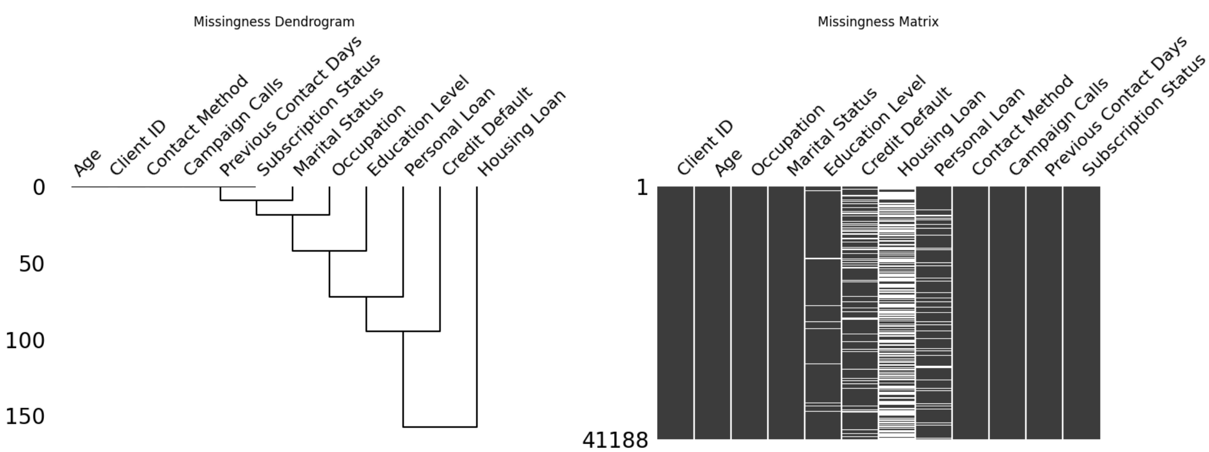
In [365…
```
df_unknown_to_none.isna().sum()
```

Out[365…
```
Client ID                  0
Age                        0
Occupation               330
Marital Status            80
Education Level         1731
Credit Default          8597
Housing Loan           25182
Personal Loan           5023
Contact Method             0
Campaign Calls             0
Previous Contact Days      0
Subscription Status        0
dtype: int64
```

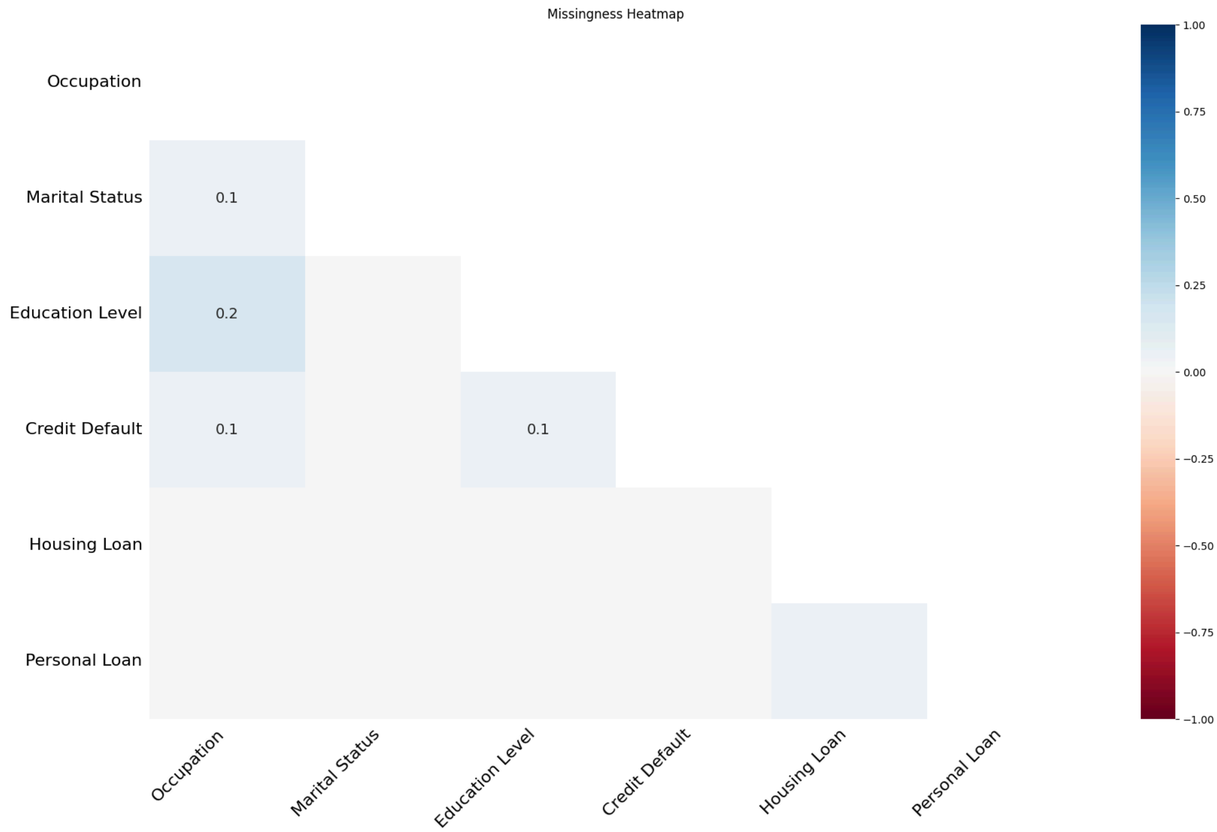
In [366…
```
df_unknown_to_none.duplicated().sum()
```

Out[366…
```
np.int64(0)
```

In [367…
```
fig, axes = plt.subplots(1, 2, figsize=(16, 6))

msno.dendrogram(df_unknown_to_none, ax=axes[0])
axes[0].set_title("Missingness Dendrogram")

msno.matrix(df_unknown_to_none, ax=axes[1], sparkline=False)
axes[1].set_title("Missingness Matrix")

plt.tight_layout()
plt.show()
```



In [368…
```
msno.heatmap(df_unknown_to_none)
plt.title("Missingness Heatmap")
plt.show()
```



> **Observation:**

- In this scenario of treating unknown as None, we can see that Housing Loan still has the furthest gap with the rest of columns in the dendrogram.
- Although in dendrogram, it shows a close relationship in missing values between some of the columns, the heatmap disagrees as all of them have a very low correlation
  - The highest correlation is 0.2 between Education Level and Occupation.
  - 3 of the correlation is 0.1
  - While the remaining are extremely close to 0.

> **Thought Process:**

---

1. This shows that methods like joint imputation or model-based imputation (if necessary) would not be helpful since there is very little correlation of the occurrence of missing values.
2. For very low missing values columns, we can drop the rows or impute them.
3. The ones with low missing values, will require independent imputation with techniques like simple imputation or random distribution imputation will suffice

4. High missing values may result in dropping the entire column.

Graph Plot Functions

In [31]:
```
def plot_bar_graph(
    df,
    col,
    y=None,
    kind="bar",
    figsize=(8, 5),
    top=None,
    title=None,
    ascending=False,
    x_rotation=0,
    legend=True,
    fontsize=9,
):
    """
    Plot a bar graph for the input data.

    Parameters
    ----------
    df    : DataFrame
    col   : name of column for x-axis
    y     : name of column for y-axis (only for 'bar')
    kind: 'bar' (Default) or 'count'
      bar:    plot bar graph
      count:  plot count graph
    """
    if kind == "count":  # Count plot to display frequencies of each unique
        counts = df[col].astype(str).value_counts(ascending=ascending).reset
        total = counts["count"].sum()
        # Calculate percentage of distribution of the values
        counts["label_text"] = counts.apply(
            lambda row: f"{row['count']} ({row['count'] / total * 100:.1f}%)
            axis=1,
        )

        # To display top frequent unique values
        plot_df = counts if top is None else counts.head(top)

        bars = plt.bar(
            plot_df[col],
            plot_df["count"],
            color=sns.color_palette("pastel", len(plot_df)),
        )
        for bar, label in zip(bars, plot_df["label_text"]):
            plt.text(
                bar.get_x() + bar.get_width() / 2,
                bar.get_height(),
                label,
                ha="center",
                va="bottom",
                fontsize=fontsize,
            )
```

```python
        if legend:
            plt.legend(
                bars,
                plot_df[col].astype(str),
                title=col,
                bbox_to_anchor=(1.05, 1),
                loc="upper left",
            )

    elif kind == "bar":
        if y is None:  # To ensure y is provided to compare
            raise ValueError("y must be provided for barplot")
        # To display top frequent unique values
        plot_df = df if top is None else df.head(top)

        bars = plt.bar(
            plot_df[col].astype(str),
            plot_df[y],
            color=sns.color_palette("pastel", len(plot_df)),
            label=y if legend else None,
        )
        for bar, val in zip(bars, plot_df[y]):
            plt.text(
                bar.get_x() + bar.get_width() / 2,
                bar.get_height(),
                f"{val}",
                ha="center",
                va="bottom",
                fontsize=9,
            )
        if legend:
            plt.legend(
                bars,
                plot_df[col].astype(str),
                title=col,
                bbox_to_anchor=(1.05, 1),
                loc="upper left",
            )

    else:
        raise ValueError("kind must be 'bar' or 'count'")

    plt.title(title if title else f"{kind.capitalize()} plot of {col}")
    plt.xlabel(col)
    plt.ylabel(y if kind == "bar" else "Frequency")
    plt.xticks(rotation=x_rotation)
    plt.show()


def plot_hist_graph(
    df,
    col,
    bins=None,
    shrink=0,
    figsize=(8, 5),
    title=None,
```

```python
    x_rotation=0,
):
    """
    Plot a histogram graph for the input data.

    Parameters
    ----------
    df    : DataFrame
    col   : name of column for x-axis
    bins  : number of bins for the historgram
    shrink: add gap between histogram bars
    """
    plt.figure(figsize=figsize)

    # Plot histogram
    sns.histplot(
        df[col],
        bins=bins,
        color="skyblue",
        edgecolor="black",
        linewidth=1.2,
        shrink=shrink,
    )

    plt.xticks(rotation=x_rotation)

    plt.title(title if title else f"Histogram of {col}")
    plt.xlabel(col)
    plt.ylabel("Frequency")
    plt.show()


def plot_box_graph(df, col, figsize=(8, 5), title=None, y_rotation=0):
    """
    Plot a box plot for the input data.

    Parameters
    ----------
    df    : DataFrame
    col   : name of column for x-axis
    """
    plt.figure(figsize=figsize)

    # Plot boxplot
    sns.boxplot(x=df[col])

    plt.title(title if title else f"Box Plot of {col}")
    plt.ylabel(col)
    plt.yticks(rotation=y_rotation)
    plt.show()
```

1b. Understanding Column data by Columns and insights

`Client ID` Column

In [370…

```
print("Number of unique values:", df["Client ID"].nunique())
```

```
Number of unique values: 41188
```

> **OBSERVATION:**

- All rows/entries are uniquely identified by the Client ID.
- No repeated Client ID throughout data.

> **THINKING PROCESS:**

---

1. `Client ID` column can be remove as it serves no predicting values and contribute to high dimensionality issue in input data.

`Age` Column

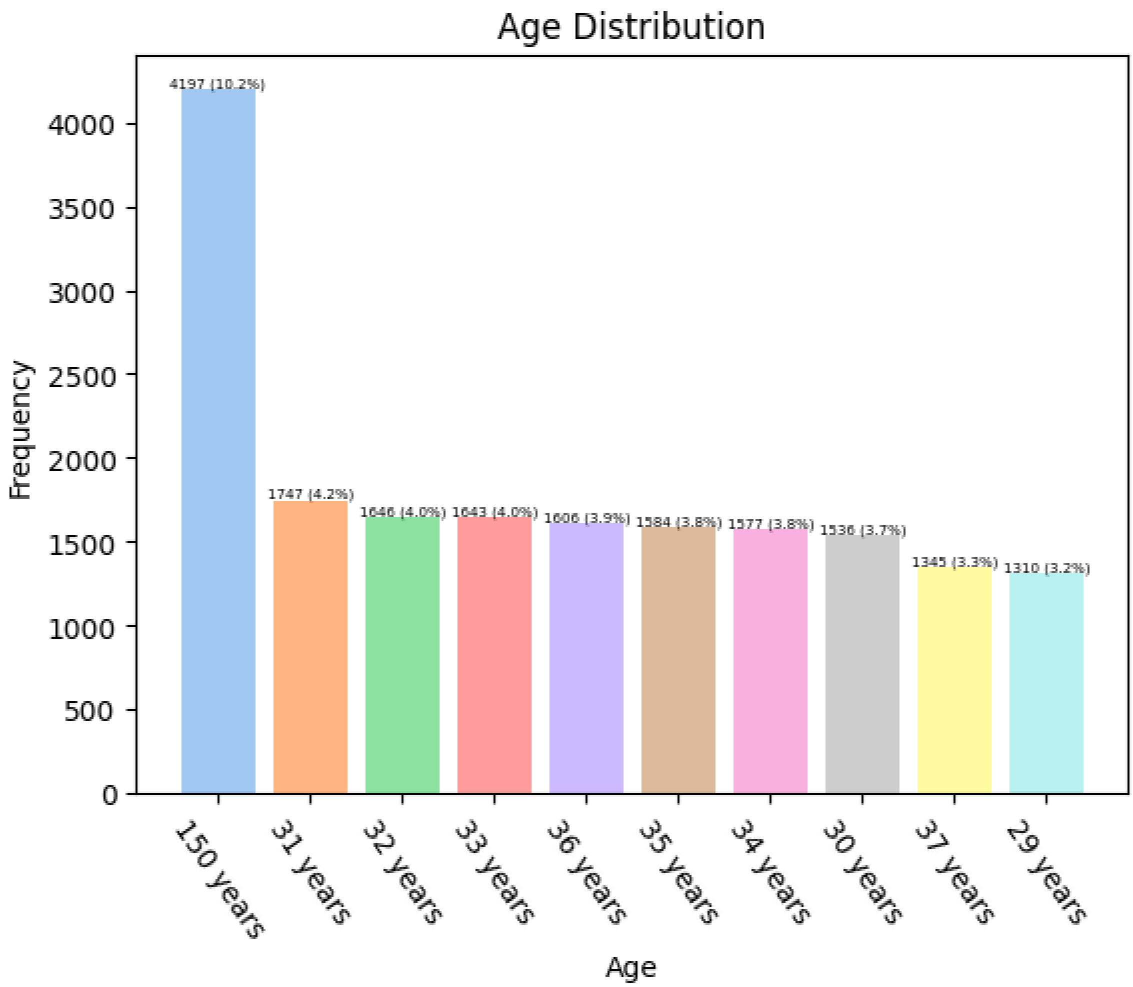
In [371…

```
display(df["Age"].describe())
print("List all unique values:\n", df["Age"].sort_values().unique())
```

```
count        41188
unique          77
top      150 years
freq          4197
Name: Age, dtype: object
List all unique values:
 ['150 years' '17 years' '18 years' '19 years' '20 years' '21 years'
 '22 years' '23 years' '24 years' '25 years' '26 years' '27 years'
 '28 years' '29 years' '30 years' '31 years' '32 years' '33 years'
 '34 years' '35 years' '36 years' '37 years' '38 years' '39 years'
 '40 years' '41 years' '42 years' '43 years' '44 years' '45 years'
 '46 years' '47 years' '48 years' '49 years' '50 years' '51 years'
 '52 years' '53 years' '54 years' '55 years' '56 years' '57 years'
 '58 years' '59 years' '60 years' '61 years' '62 years' '63 years'
 '64 years' '65 years' '66 years' '67 years' '68 years' '69 years'
 '70 years' '71 years' '72 years' '73 years' '74 years' '75 years'
 '76 years' '77 years' '78 years' '79 years' '80 years' '81 years'
 '82 years' '83 years' '84 years' '85 years' '86 years' '88 years'
 '89 years' '91 years' '92 years' '95 years' '98 years']
```

In [372…

```
plot_bar_graph(
    df,
    col="Age",
    y="Frequency",
    kind="count",
    title="Age Distribution",
    top=10,
    x_rotation=-55,
    legend=False,
    fontsize=5,
)
```



In [373…

```
print(
    "Percentage of 150 years old: {:.5f}%".format(
        df[df["Age"] == "150 years"].shape[0] / df.shape[0] * 100
    )
)
```

```
Percentage of 150 years old: 10.18986%
```

> **OBSERVATION:**

- This is an Ratio Numeric
- "150 years" !!! Most likely a recorded error.
- The value "150 years" has the highest frequency by a large margin compared to other ages.
- The values in `Age` column do **contains the text *years*** after all the numeric values, which is a data type issue.

> **THINKING PROCESS**

- I can remove *years* from the values in `Age` column.
- Convert the data type to *Integer*.

- Plot histogram to get better insights.
- Possibly impute the "150 years" with simple imputation (mean or median)

`Occupation` Column

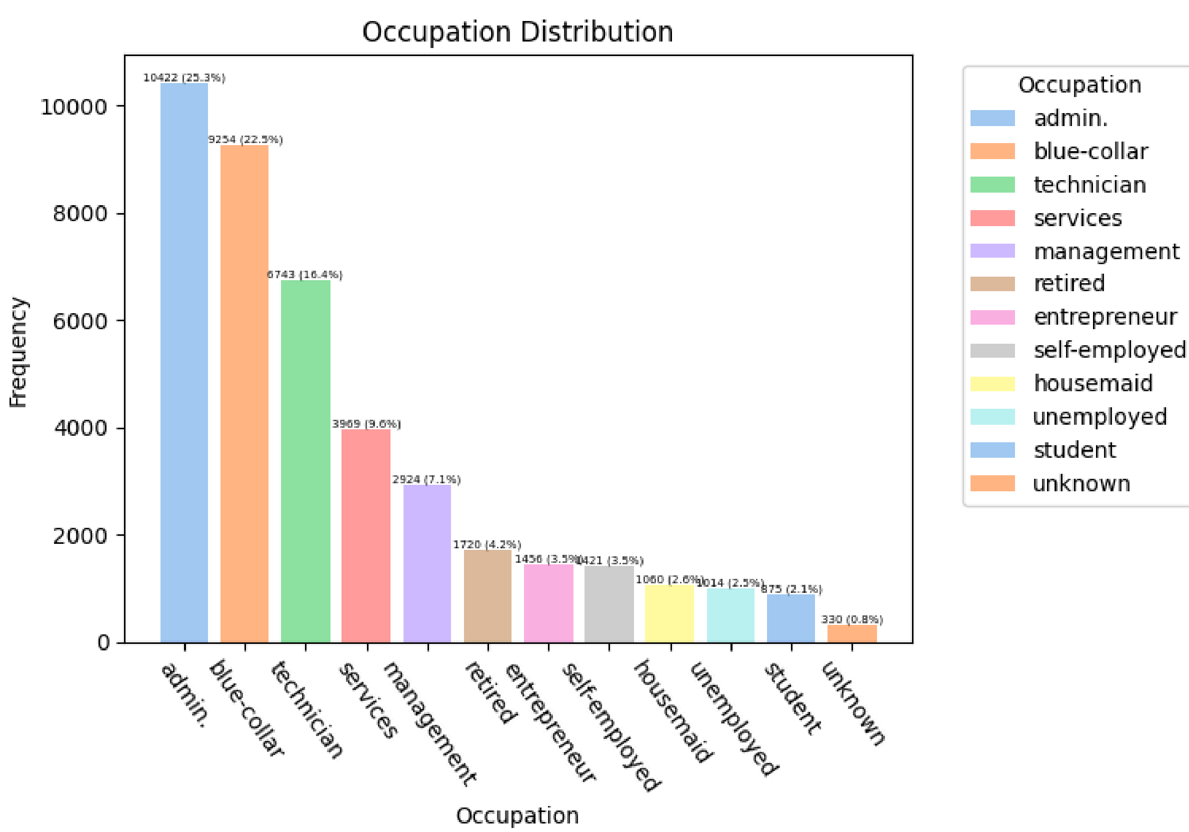
In [374…

```
display(df["Occupation"].describe())
print("List all unique values:\n", df["Occupation"].sort_values().unique())
```

```
count      41188
unique        12
top       admin.
freq       10422
Name: Occupation, dtype: object
List all unique values:
 ['admin.' 'blue-collar' 'entrepreneur' 'housemaid' 'management' 'retired'
 'self-employed' 'services' 'student' 'technician' 'unemployed' 'unknown']
```

In [375…

```
plot_bar_graph(
    df,
    col="Occupation",
    y="Frequency",
    kind="count",
    title="Occupation Distribution",
    x_rotation=-55,
    legend=True,
    fontsize=5,
)
```



In [376…
```
print(
    "Percentage of unknown: {:.2f}%".format(
        df[df["Occupation"] == "unknown"].shape[0] / df.shape[0] * 100
    )
)
```

```
Percentage of unknown: 0.80%
```

> **Observation:**

- It is a Nominal Category
- Possible to one-hot or integer encode to feed into machine learning
- unknown only made out of 0.8% of the column.

> **THINKING PROCESS**

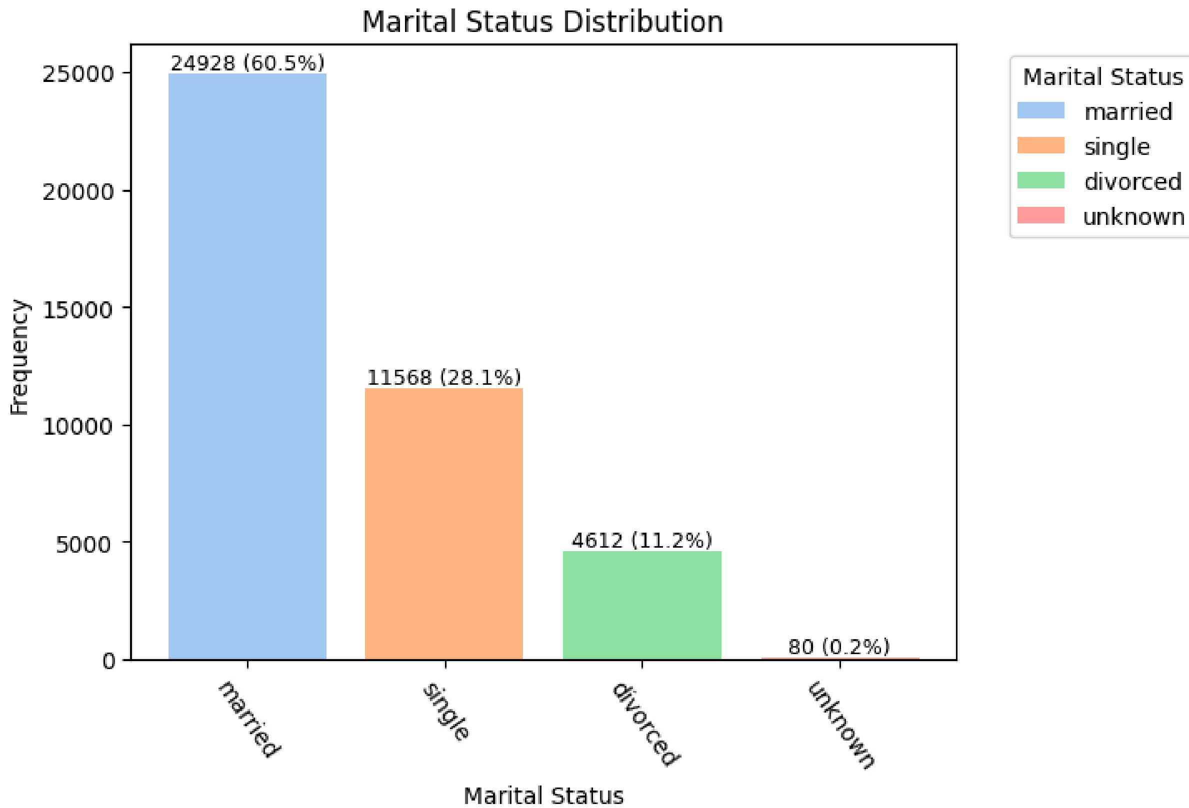
- unknown is only 0.8%, which is unlikely to give meaningful insights.
- Since it is small, we can afford to remove the row with the unknown in this column.

`Marital Status` Column

In [377…
```
display(df["Marital Status"].describe())
print("List all unique values:\n", df["Marital Status"].sort_values().unique
```

```
count       41188
unique          4
top       married
freq        24928
Name: Marital Status, dtype: object
List all unique values:
 ['divorced' 'married' 'single' 'unknown']
```

In [378…
```
plot_bar_graph(
    df,
    col="Marital Status",
    y="Frequency",
    kind="count",
    title="Marital Status Distribution",
    x_rotation=-55,
    legend=True,
)
```



In [379…

```
print(
    "Percentage of unknown: {:.2f}%".format(
        df[df["Marital Status"] == "unknown"].shape[0] / df.shape[0] * 100
    )
)
```

```
Percentage of unknown: 0.19%
```

> **Observation:**

- This is a Nominal Category
- Most client are Married, second most are Singles
- The third are Divorced
- unknown only made out of 0.19% of the column.

> **THINKING PROCESS**

- unknown is only 0.19%, which is unlikely to give meaningful insights.
- Since this is smalle, we can afford to remove the row with the unknown in this column.

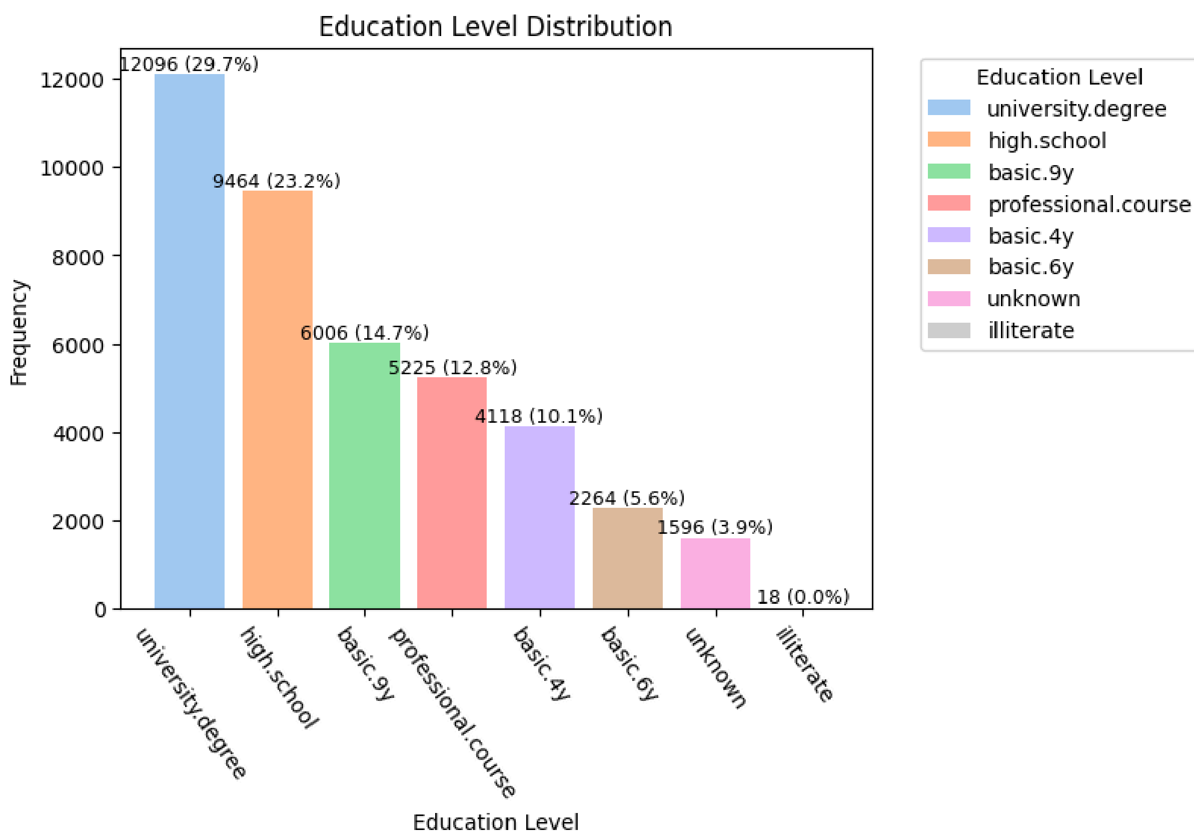
`Education Level` Column

In [380…

```
display(df["Education Level"].describe())
print("List all unique values:\n", df["Education Level"].sort_values().uniqu
```

```
count                   41188
unique                      8
top         university.degree
freq                    12168
Name: Education Level, dtype: object
List all unique values:
 ['basic.4y' 'basic.6y' 'basic.9y' 'high.school' 'illiterate'
 'professional.course' 'university.degree' 'unknown']
```

In [33]:
```
plot_bar_graph(
    df,
    col="Education Level",
    y="Frequency",
    kind="count",
    title="Education Level Distribution",
    x_rotation=-55,
    legend=True,
)
```



In [382…
```
print(
    "Percentage of unknown: {:.2f}%".format(
        df[df["Education Level"] == "unknown"].shape[0] / df.shape[0] * 100
    )
)
```

```
Percentage of unknown: 4.20%
```

> **Observation:**

- This is a Nominal Category
- Top are university, second highest is high school.
- Third is clients with 9 years of basic studies.
- unknown is made out of 4.2% in the column.

> **THINKING PROCESS**

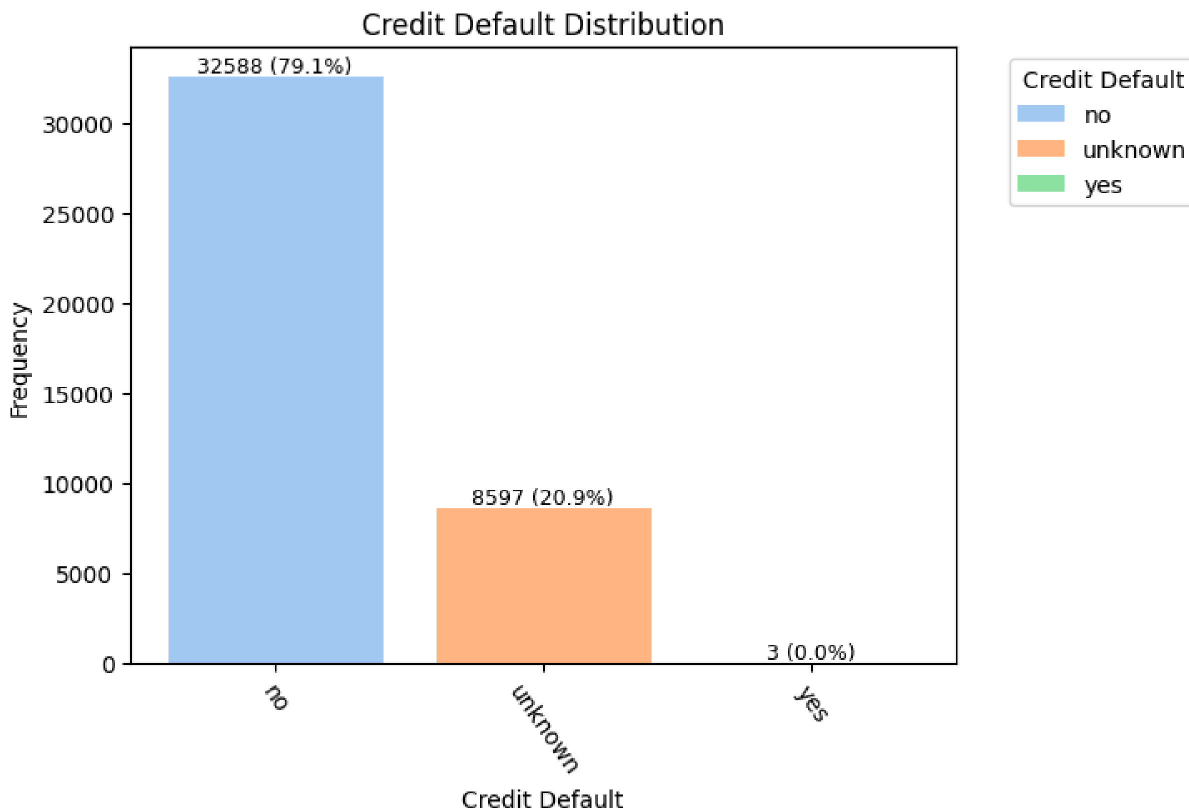
- unknown is 4.2%, which contribute relatively high to the dataset. Therefore, it cannot be drop as it will lose meaningful insights.
- Should be treated as a category since it may provide informative insights.

`Credit Default` Column

In [383…
```
display(df["Credit Default"].describe())
print("List all unique values:\n", df["Credit Default"].sort_values().unique
```

```
count      41188
unique         3
top           no
freq       32588
Name: Credit Default, dtype: object
List all unique values:
 ['no' 'unknown' 'yes']
```

In [384…
```
plot_bar_graph(
    df,
    col="Credit Default",
    y="Frequency",
    kind="count",
    title="Credit Default Distribution",
    x_rotation=-55,
    legend=True,
)
```



In [385…

```
print(
    "Percentage of yes: {:.5f}%".format(
        df[df["Credit Default"] == "yes"].shape[0] / df.shape[0] * 100
    )
)
print(
    "Percentage of unknown: {:.5f}%".format(
        df[df["Credit Default"] == "unknown"].shape[0] / df.shape[0] * 100
    )
)
print(
    "Percentage of no: {:.5f}%".format(
        df[df["Credit Default"] == "no"].shape[0] / df.shape[0] * 100
    )
)
```

```
Percentage of yes: 0.00728%
Percentage of unknown: 20.87258%
Percentage of no: 79.12013%
```

> **Observation:**

- This is a Nominal Category
- The amount of "yes" is way too little (only 3 rows) and most are "no" (80%).
- 20% is unknown, which shows no information.

> **THOUGHT PROCESS:**

- Can drop `Credit Default` column since majority disagree with credit default and only 0.007% agrees to it.
- Meaning it is severely imbalanced, where the column is unclassifiable.
- Especially, unknown made out of 20% which is also uninformative.

`Housing Loan` Column

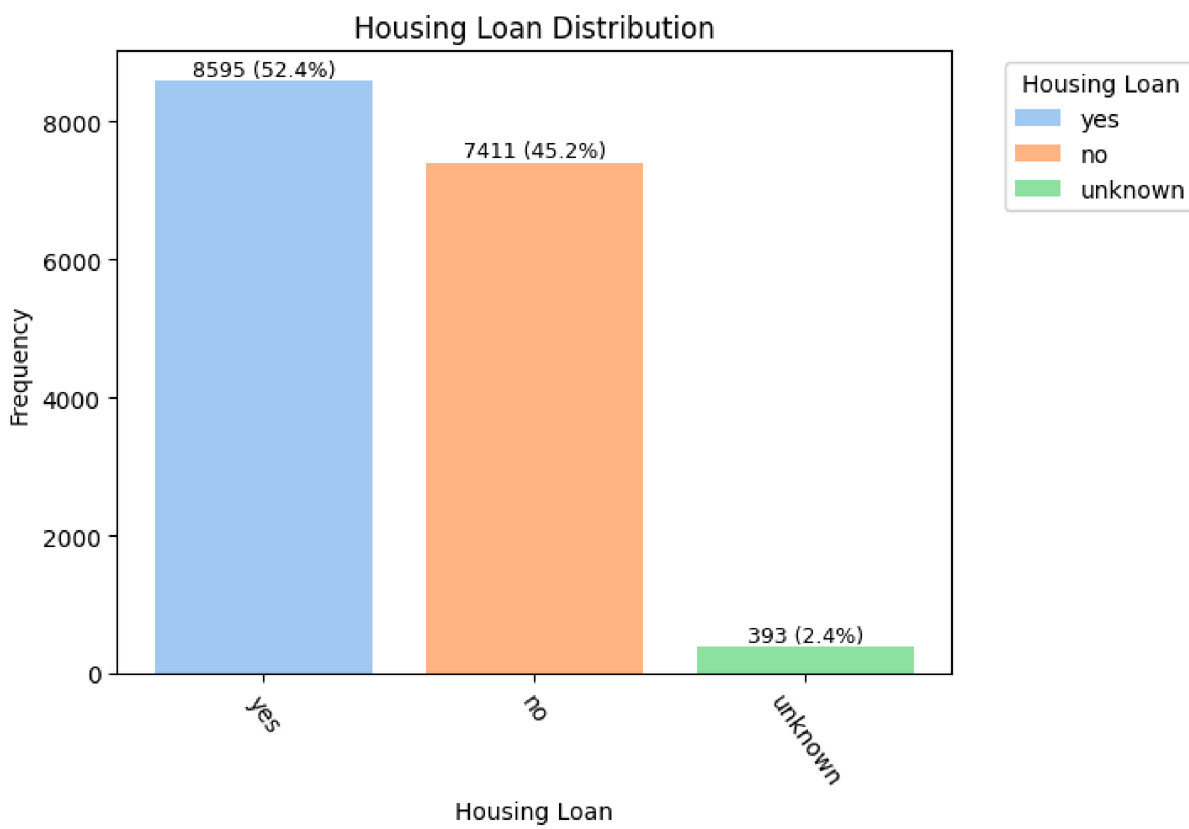
In [386…

```
display(df["Housing Loan"].describe())
print("List all unique values:\n", df["Housing Loan"].sort_values().unique()
```

```
count      16399
unique         3
top          yes
freq        8595
Name: Housing Loan, dtype: object
List all unique values:
 ['no' 'unknown' 'yes' None]
```

In [387…

```
plot_bar_graph(
    df,
    col="Housing Loan",
    y="Frequency",
    kind="count",
    title="Housing Loan Distribution",
    x_rotation=-55,
    legend=True,
)
```



In [388…

```
print(
    "Percentage of unknown (**include None in total frequency**): {:.5f}%".f
        df[df["Housing Loan"] == "unknown"].shape[0] / df.shape[0] * 100
    )
)
print(
    "Percentage of None: {:.5f}%".format(
        df[df["Housing Loan"].isna()].shape[0] / df.shape[0] * 100
    )
)
```

```
Percentage of unknown (**include None in total frequency**): 0.95416%
Percentage of None: 60.18501%
```

> **Observation:**

- This is a Nominal Category
- There is a very high percentage of missing values (60%) in the column.
- Excluding rows with None in Housing Loan column:
  - The number of "Yes" is the highest with 52.4% and "No" is second highest with 45.2%.
  - There is 2.4% of unknown which is the lowest.

> **THOUGHT PROCESS:**

- 60% is an extremely large gap for missing values.
- It may be the best to drop the entire column unless it can be imputed by other columns.

`Personal Loan` Column

In [389…

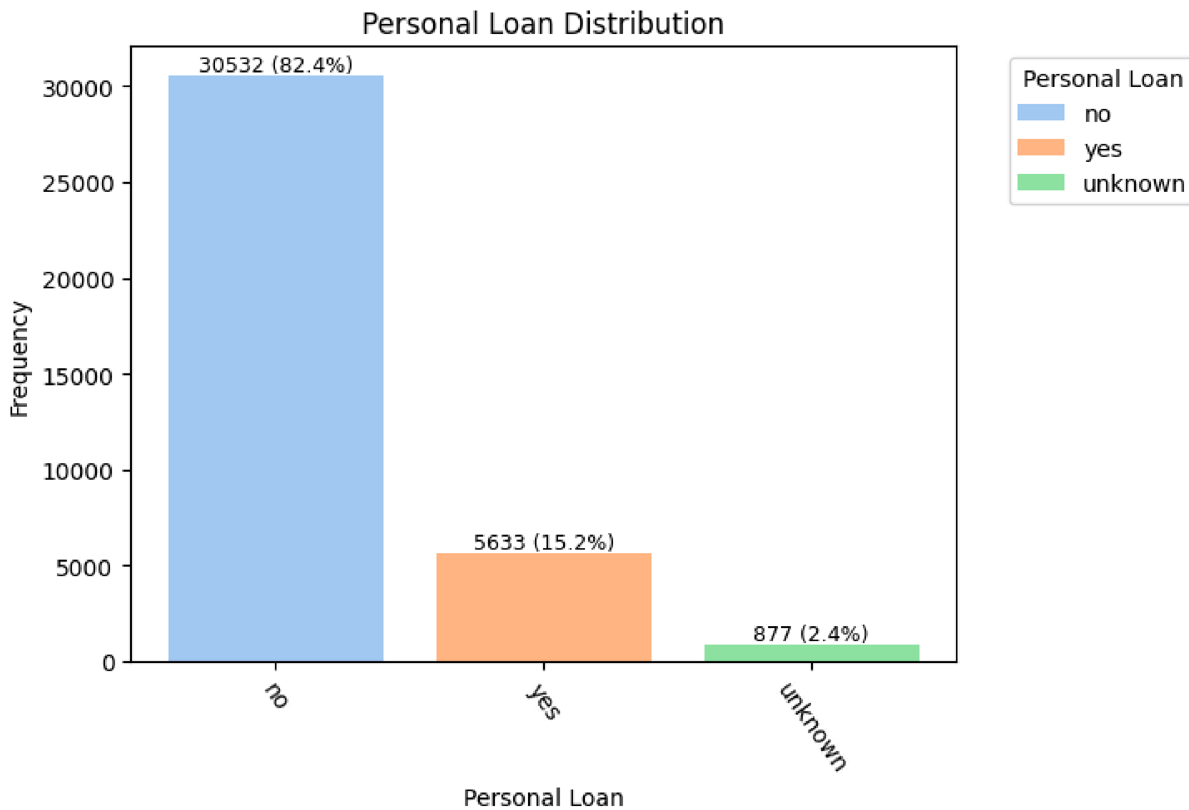
```
display(df["Personal Loan"].describe())
print("List all unique values:\n", df["Personal Loan"].sort_values().unique(
```

```
count      37042
unique         3
top           no
freq       30532
Name: Personal Loan, dtype: object
List all unique values:
 ['no' 'unknown' 'yes' None]
```

In [390…

```
plot_bar_graph(
    df,
    col="Personal Loan",
    y="Frequency",
    kind="count",
    title="Personal Loan Distribution",
    x_rotation=-55,
```

```
    legend=True,
)
```



In [391…

```
print(
    "Percentage of unknown (**include None in total frequency**): {:.5f}%".f
        df[df["Personal Loan"] == "unknown"].shape[0] / df.shape[0] * 100
    )
)
print(
    "Percentage of None: {:.5f}%".format(
        df[df["Personal Loan"].isna()].shape[0] / df.shape[0] * 100
    )
)
print("Number of rows of None: {}".format(df[df["Personal Loan"].isna()].sha
```

```
Percentage of unknown (**include None in total frequency**): 2.12926%
Percentage of None: 10.06604%
Number of rows of None: 4146
```

> **Observation:**

- This is a Nominal Category
- There is a relatively low percentage of missing values (10%) in the column.
- Excluding rows with None in Personal Loan column
  - The number of "No" is the highest with 82.4% and "Yes" is second highest with 15.2%.
  - There is 2.4% of unknown which is the lowest.

> **THOUGHT PROCESS:**

- Although missing values make up of only 10%, dropping them may not be ideal as it represents quite a significant number of rows.
- Imputation could be a better approach to retain as much data as possible while handling missing entries.

`Contact Method` Column

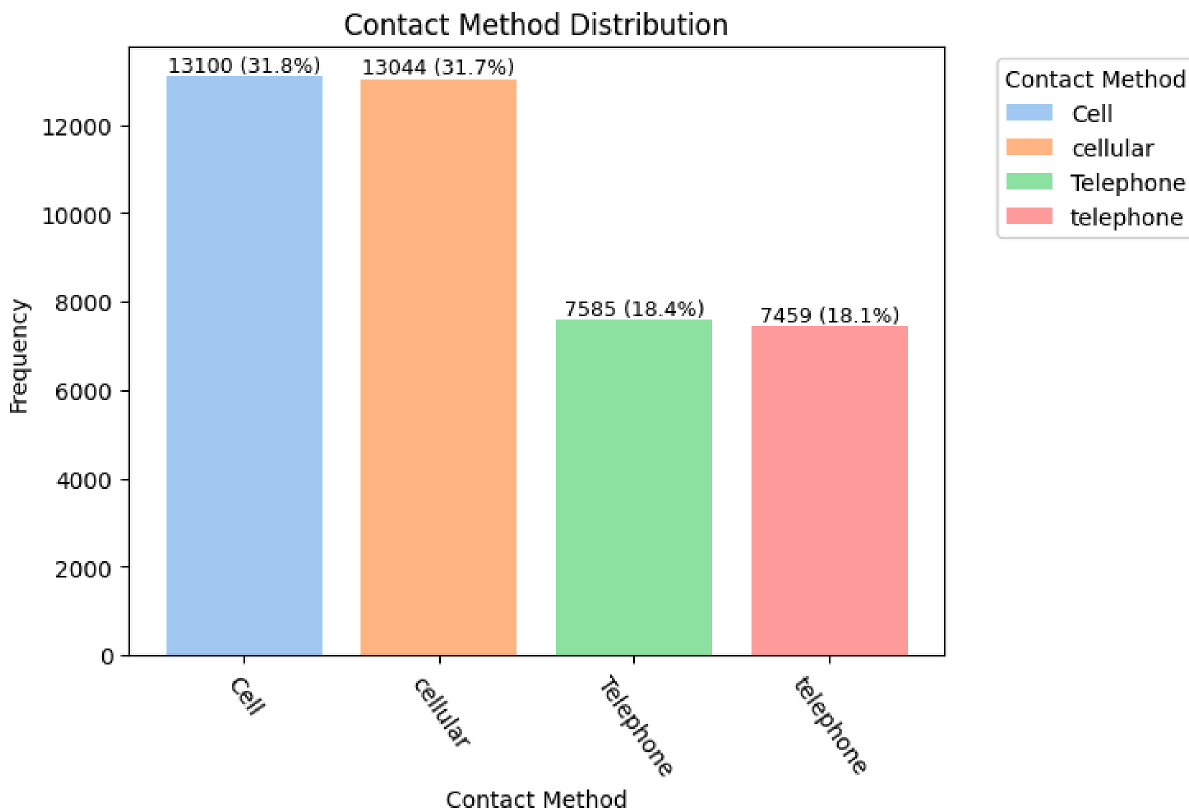
In [392…

```
display(df["Contact Method"].describe())
print("List all unique values:\n", df["Contact Method"].sort_values().unique
```

```
count     41188
unique        4
top        Cell
freq      13100
Name: Contact Method, dtype: object
List all unique values:
 ['Cell' 'Telephone' 'cellular' 'telephone']
```

In [393…

```
plot_bar_graph(
    df,
    col="Contact Method",
    y="Frequency",
    kind="count",
    title="Contact Method Distribution",
    x_rotation=-55,
    legend=True,
)
```



> **Observation:**

- This is a Nominal Category
- Repeated and inconsistent formats:
  - Cell and cellular
  - Telephone and telephone
- This is a Nominal category

> **THOUGHT PROCESS:**

- Replace all Cell with cellular
- Replace all Telephone with telephone

`Campaign Calls` Column

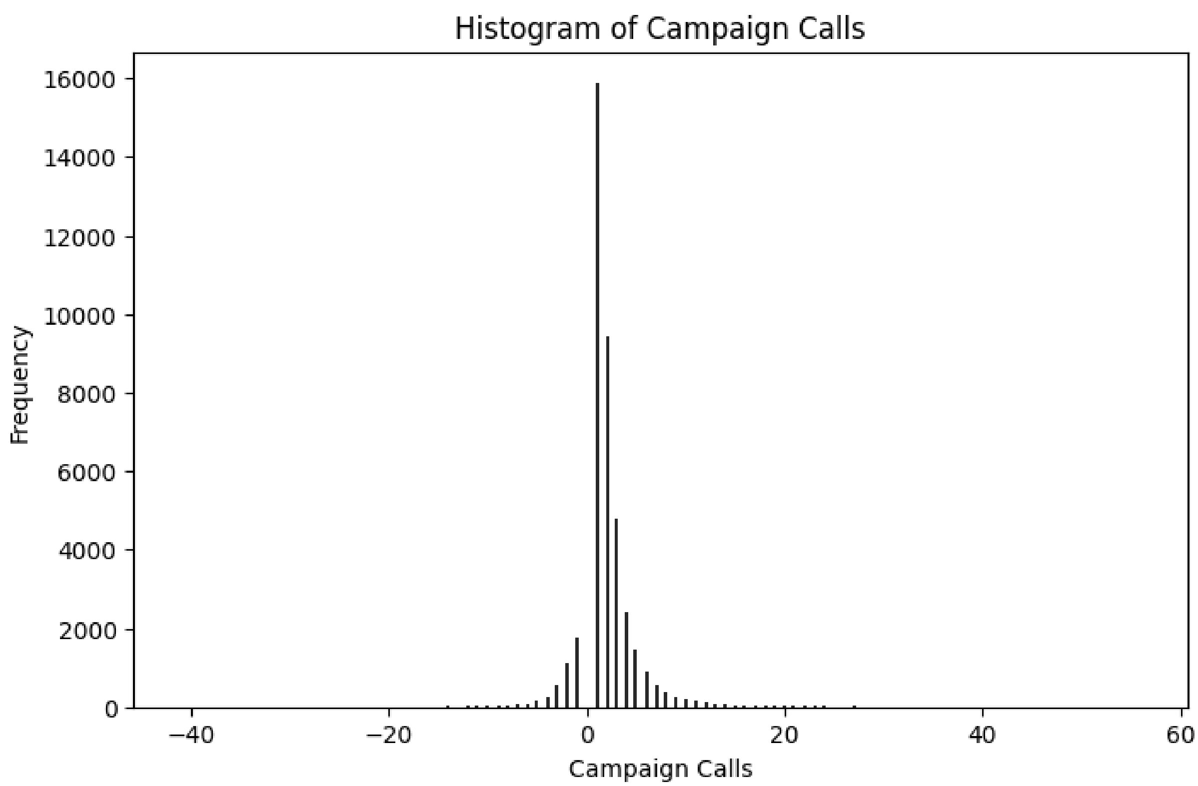
In [394…

```
display(df["Campaign Calls"].describe())
print("List all unique values:\n", df["Campaign Calls"].sort_values().unique
```

```
count    41188.000000
mean         2.051374
std          3.171345
min        -41.000000
25%          1.000000
50%          2.000000
75%          3.000000
max         56.000000
Name: Campaign Calls, dtype: float64
List all unique values:
 [-41 -35 -32 -29 -28 -25 -23 -22 -21 -20 -19 -18 -17 -16 -15 -14 -13 -12
 -11 -10  -9  -8  -7  -6  -5  -4  -3  -2  -1   1   2   3   4   5   6   7
   8   9  10  11  12  13  14  15  16  17  18  19  20  21  22  23  24  25
  26  27  28  29  30  31  32  33  34  35  37  39  40  42  43  56]
```

In [395…

```
# Freedman–Diaconis rule
q75, q25 = np.percentile(df["Campaign Calls"], [75, 25])
bin_width = 2 * (q75 - q25) * len(df) ** (-1 / 3)
bins = int((df["Campaign Calls"].max() - df["Campaign Calls"].min()) / bin_w

plot_hist_graph(df, col="Campaign Calls", bins=bins, x_rotation=0)
```



> **Observation:**

- This is a Ratio Numeric
- There is negative values in the column.
- There is a good and symmetric distribution from range -41 to 56, with a single peak at 1 calls.
- There is **No** 0 calls.

> **THOUGHT PROCESS:**

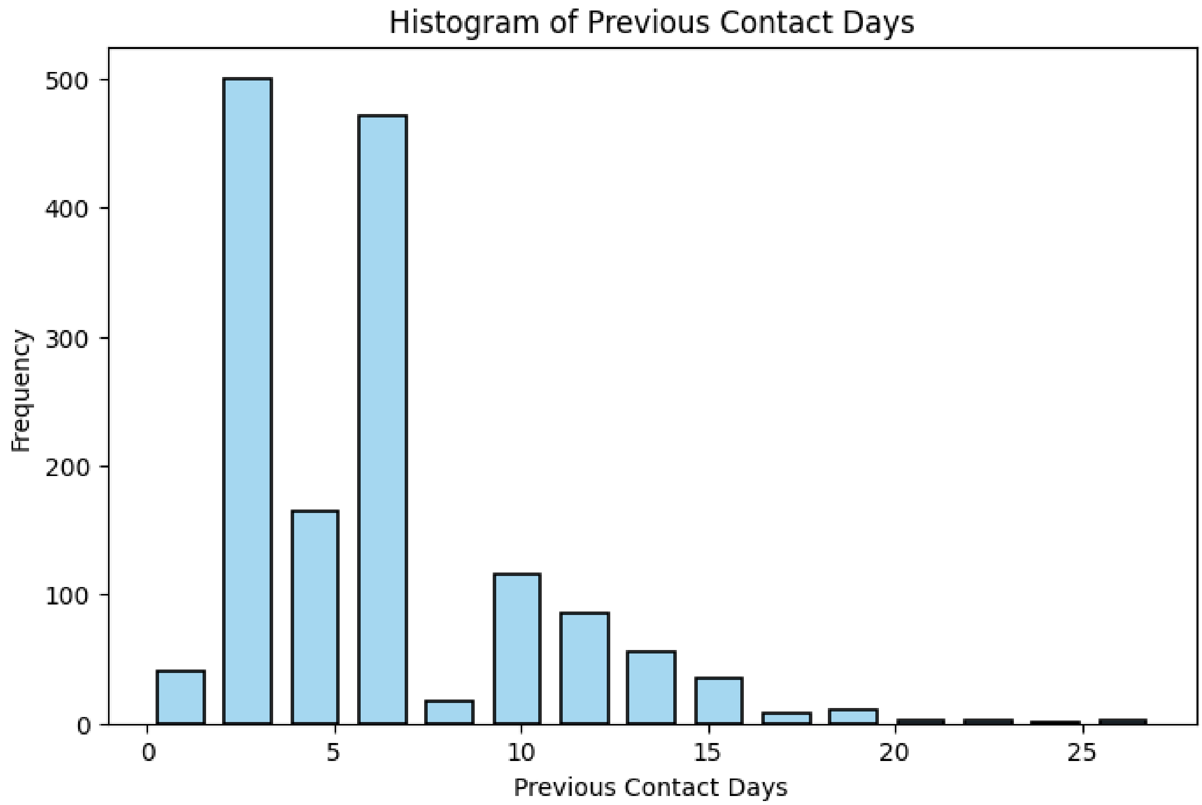
- Highly doubt that the negative values are valid:
  - The definition given is "*Total number* of contacts performed for this campaign and this client, including the last contact".
  - The calls are very evenly distributed, meaning that it is mirrored.
- Possible solution:
  1. Absolute the negative to turn to positive.
  2. Add another column to retain the negative meaning, together with Solution #1.

`Previous Contact Days` Column

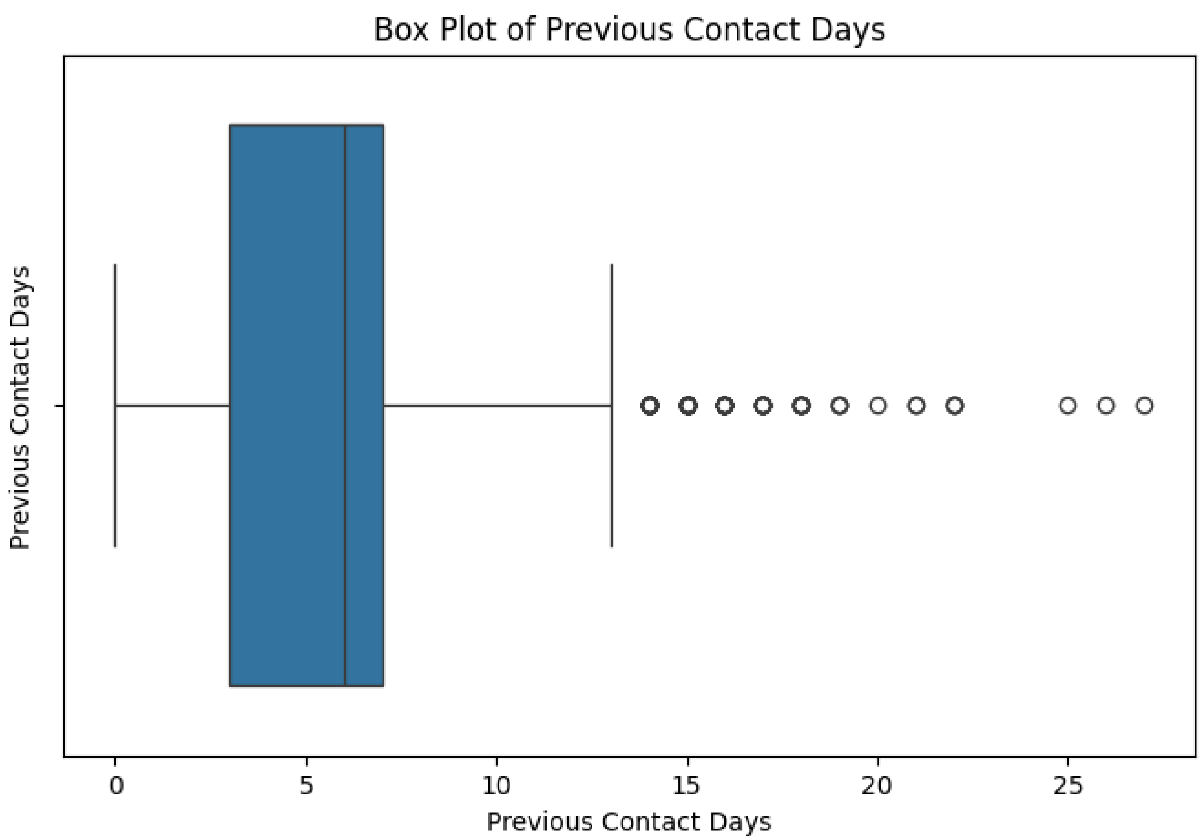
In [396…
```
display(df[df["Previous Contact Days"] != 999]["Previous Contact Days"].desc
print("List all unique values:\n", df["Previous Contact Days"].sort_values()
```

```
count    1515.000000
mean        6.014521
std         3.824906
min         0.000000
25%         3.000000
50%         6.000000
75%         7.000000
max        27.000000
Name: Previous Contact Days, dtype: float64
List all unique values:
 [  0   1   2   3   4   5   6   7   8   9  10  11  12  13  14  15  16  17
  18  19  20  21  22  25  26  27 999]
```

In [397…
```
plot_hist_graph(
    df[df["Previous Contact Days"] != 999],
    col="Previous Contact Days",
    bins=15,
    shrink=0.7,
    x_rotation=0,
)
```



In [398…
```
plot_box_graph(df[df["Previous Contact Days"] != 999], col="Previous Contact
```



In [399…
```
print(
    "Percentage of 999: {:.5f}%".format(
```

```
        df[df["Previous Contact Days"] == 999].shape[0] / df.shape[0] * 100
    )
)
```

```
Percentage of 999: 96.32174%
```

> **Observation:**

- This is a Ratio Numeric
- There has the highest number of occurences with 96%.
- 999 is way too big of a value to be plotted as well as for machine learning. Cannot be included into the histogram and box plot.
- Excluding 999:

> **THOUGHT PROCESS:**

- Replace 999 to -1 in order to maintain the no prior contact meaning.
- Add a boolean column for "got prior contact" or "no prior contact", as a feature, for AI model to understand meaning of -1 value. This prevents models, especially regression models, to treat -1 as a numeric value instead of category.

`Subscription Status` Column

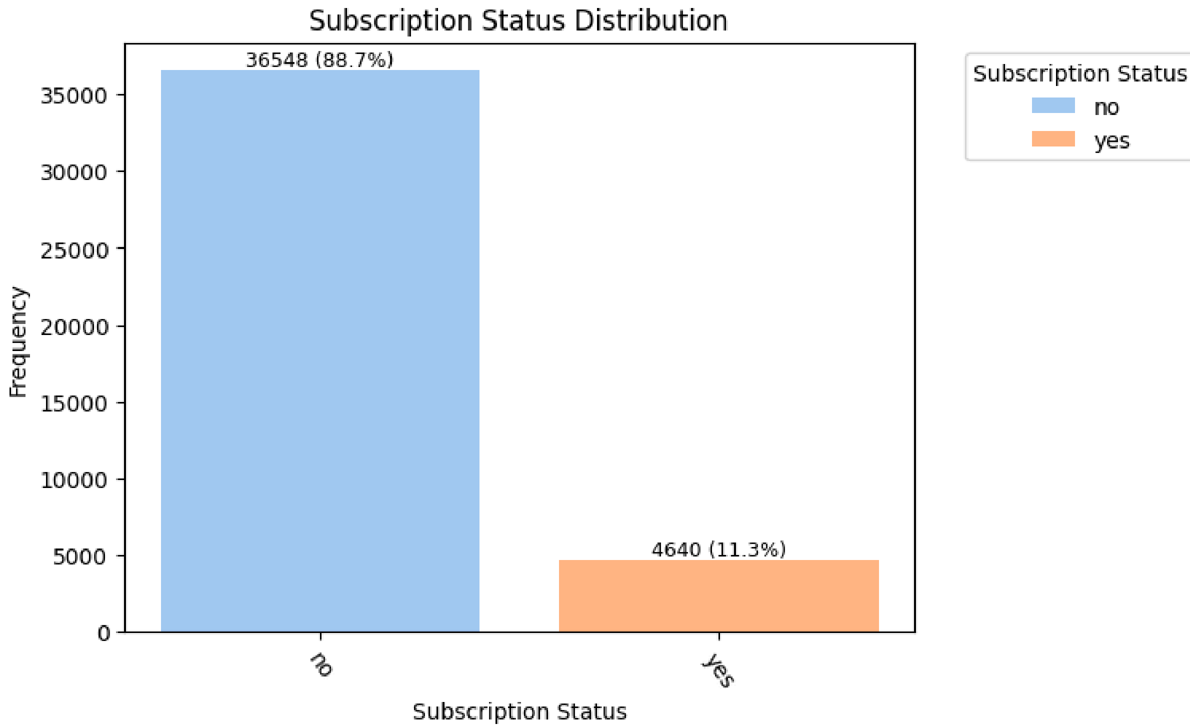
In [400…

```
display(df["Subscription Status"].describe())
print("List all unique values:\n", df["Subscription Status"].sort_values().u
```

```
count      41188
unique         2
top           no
freq       36548
Name: Subscription Status, dtype: object
List all unique values:
 ['no' 'yes']
```

In [401…

```
plot_bar_graph(
    df,
    col="Subscription Status",
    y="Frequency",
    kind="count",
    title="Subscription Status Distribution",
    x_rotation=-55,
    legend=True,
)
```



> **Observation:**

- This is a Nominal Category
- The column is very imbalance.

> **THOUGHT PROCESS:**

- Convert to Boolean data type
- Use Stratify when splitting the dataset for model training to ensure balance yes and no

Data Preparation

Data Cleaning

Data Cleaning on `Client ID` Column

In [6]:
```
df.drop("Client ID", axis=1, inplace=True)  # Drop Client ID
df.head()
```

Out[6]:

	Age	Occupation	Marital Status	Education Level	Credit Default	Housing Loan	Personal Loan	Contact Method	C
0	57 years	technician	married	high.school	no	no	yes	Cell	
1	55 years	unknown	married	unknown	unknown	yes	no	telephone	
2	33 years	blue-collar	married	basic.9y	no	no	no	cellular	
3	36 years	admin.	married	high.school	no	no	no	Telephone	
4	27 years	housemaid	married	high.school	no	None	no	Cell	

Data Cleaning on `Age` Column

In [7]:

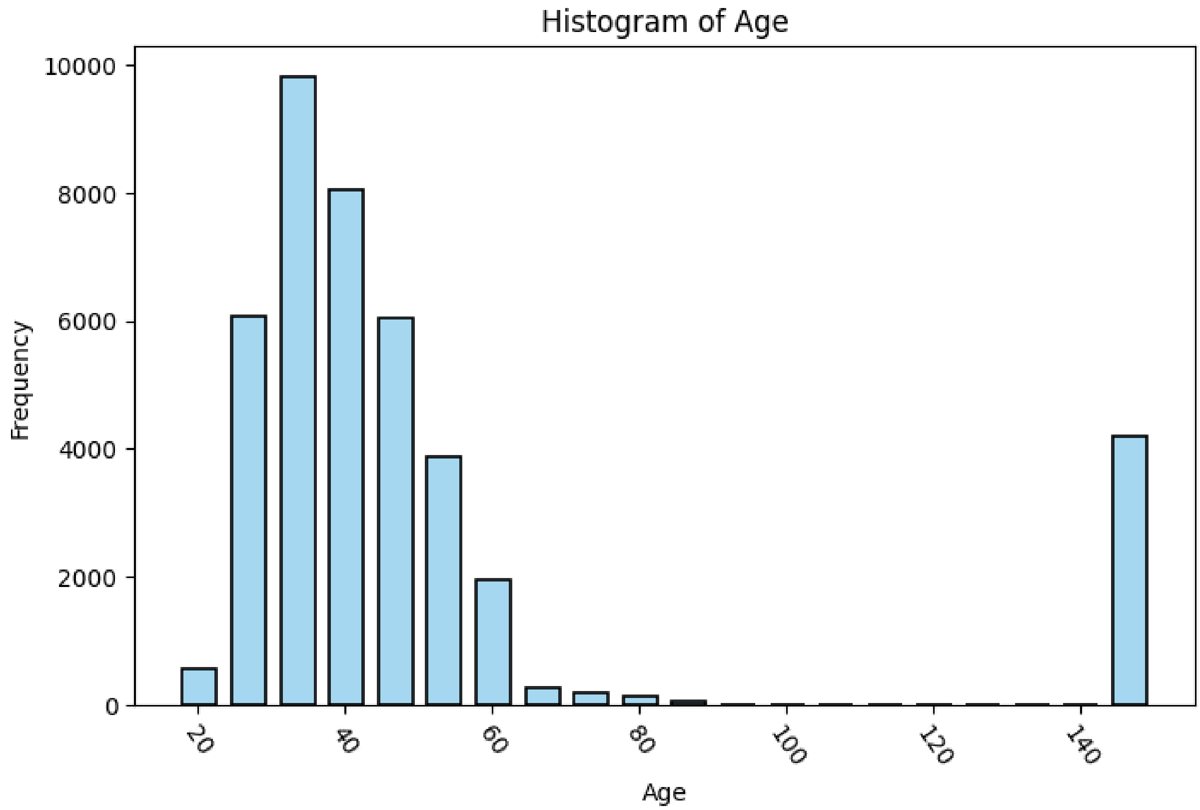
```
df["Age"] = df["Age"].map(lambda x: x.split()[0])  # Remove "years old" in A
df["Age"] = df["Age"].astype(int)
df["Age"]
```

Out[7]:

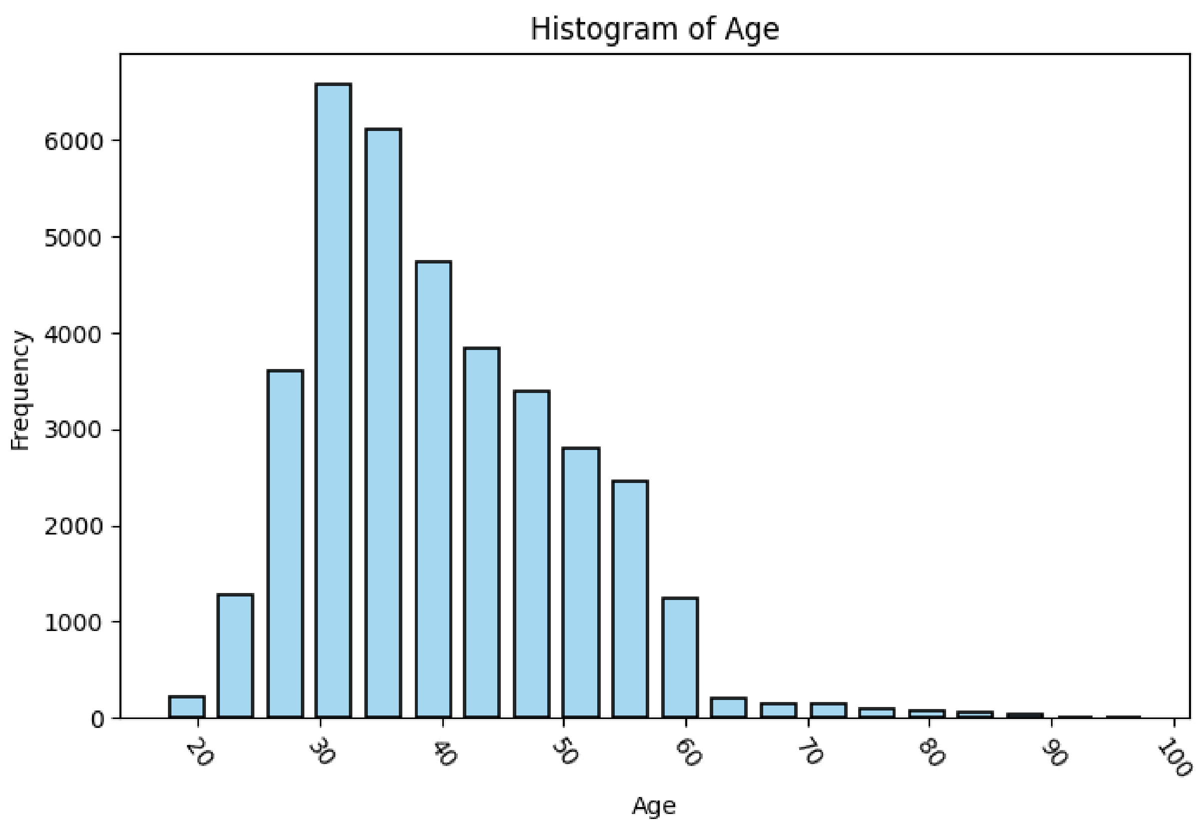
```
0        57
1        55
2        33
3        36
4        27
         ..
41183    58
41184    37
41185    35
41186    40
41187    29
Name: Age, Length: 41188, dtype: int64
```

In [8]:

```
plot_hist_graph(df, col="Age", bins=20, shrink=0.7, x_rotation=-55)
```



In [9]:
```
plot_hist_graph(df[df["Age"] != 150], col="Age", bins=20, shrink=0.7, x_rota
```



> **Observation:**

- There is a skew distribution of Age column (To the left).
- The outlier is 150, which is most likely an error, it also make up of about 4000 clients in the dataset.

> **THOUGHT PROCESS:**

- With large number of 150 in Age column, imputation need to be carried out instead of dropping.

Data Cleaning on `Occupation` Column

In [10]:
```
# Remove rows with unknown in Occupation column
df.drop(df[df["Occupation"] == "unknown"].index, axis=0, inplace=True)

# Display unique values in Occupation column
print("List all unique values:\n", df["Occupation"].sort_values().unique())
print("New Shape: ", df.shape)
```

```
List all unique values:
 ['admin.' 'blue-collar' 'entrepreneur' 'housemaid' 'management' 'retired'
 'self-employed' 'services' 'student' 'technician' 'unemployed']
New Shape:  (40858, 11)
```

Data Cleaning on `Marital Status` Column

In [11]:
```
# Remove rows with unknown in Marital Status column
df.drop(df[df["Marital Status"] == "unknown"].index, axis=0, inplace=True)

# Display unique values in Marital Status column
print("List all unique values:\n", df["Marital Status"].sort_values().unique
print("New Shape: ", df.shape)
```

```
List all unique values:
 ['divorced' 'married' 'single']
New Shape:  (40787, 11)
```

Data Cleaning on `Credit Default` Column

In [12]:
```
df.drop("Credit Default", axis=1, inplace=True)  # Drop Credit Default colum
df.head()
```

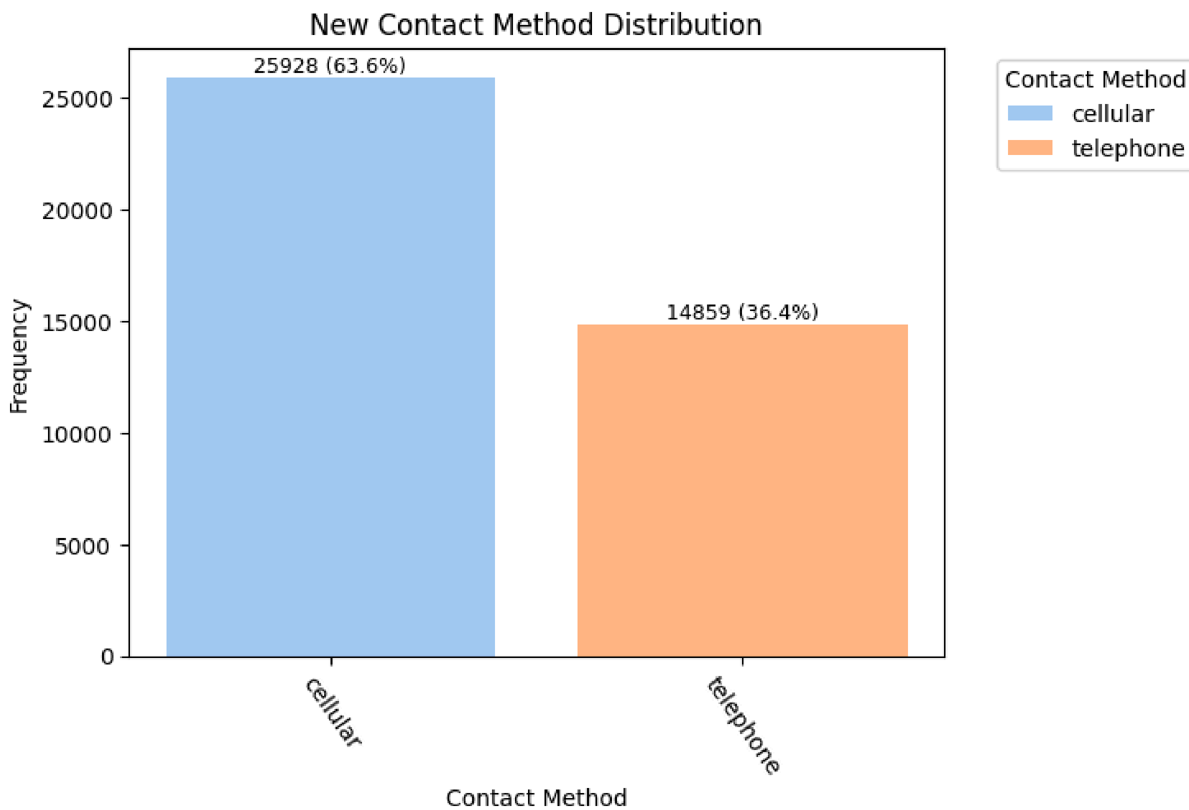
Out[12]:

	Age	Occupation	Marital Status	Education Level	Housing Loan	Personal Loan	Contact Method	Camp
0	57	technician	married	high.school	no	yes	Cell	
2	33	blue-collar	married	basic.9y	no	no	cellular	
3	36	admin.	married	high.school	no	no	Telephone	
4	27	housemaid	married	high.school	None	no	Cell	
5	58	retired	married	professional.course	None	yes	Cell	

Data Cleaning on `Contact Method` Column

In [13]:
```
# Replace Cel with cell and Telephone with telephone
df["Contact Method"] = df["Contact Method"].map(
    lambda x: "cellular" if x[0].lower() == "c" else "telephone"
)
```

In [14]:
```
plot_bar_graph(
    df,
    col="Contact Method",
    y="Frequency",
    kind="count",
    title="New Contact Method Distribution",
    top=10,
    x_rotation=-55,
    legend=True,
)
```



> **Observation:**

- There is a higher number of client contacted by cellular (63.6%)
- The remaining are through telephone (36.4%)

> **THOUGHT PROCESS:**

- The dataset provided a good distribution of contact methods.

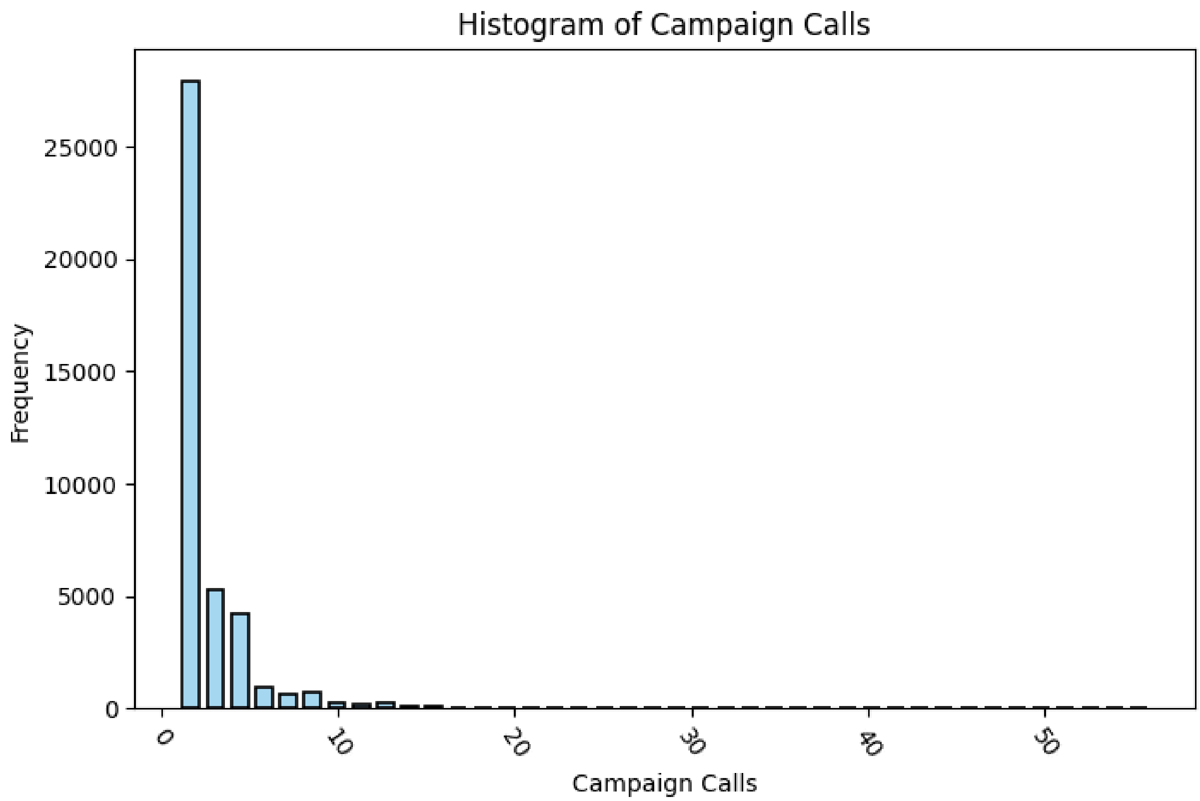
Data Cleaning on `Campaign Calls` Column

In [15]:
```
# Convert all negative values to positive
df["Campaign Calls"] = df["Campaign Calls"].apply(lambda x: abs(x))
display(df["Campaign Calls"].describe())
print("List all unique values:\n", df["Campaign Calls"].sort_values().unique
```

```
count    40787.000000
mean         2.566112
std          2.768103
min          1.000000
25%          1.000000
50%          2.000000
75%          3.000000
max         56.000000
Name: Campaign Calls, dtype: float64
```

```
List all unique values:
 [ 1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
 25 26 27 28 29 30 31 32 33 34 35 37 39 40 41 42 43 56]
```

In [16]:
```
plot_hist_graph(df, col="Campaign Calls", bins=40, shrink=0.7, x_rotation=-5
```



> **Observation:**

- The distribution of calls is extremely skew to the left.
- There is a outlier of 56 calls.

> **THOUGHT PROCESS:**

- Scaling may be needed for regression models in **model training** stage.

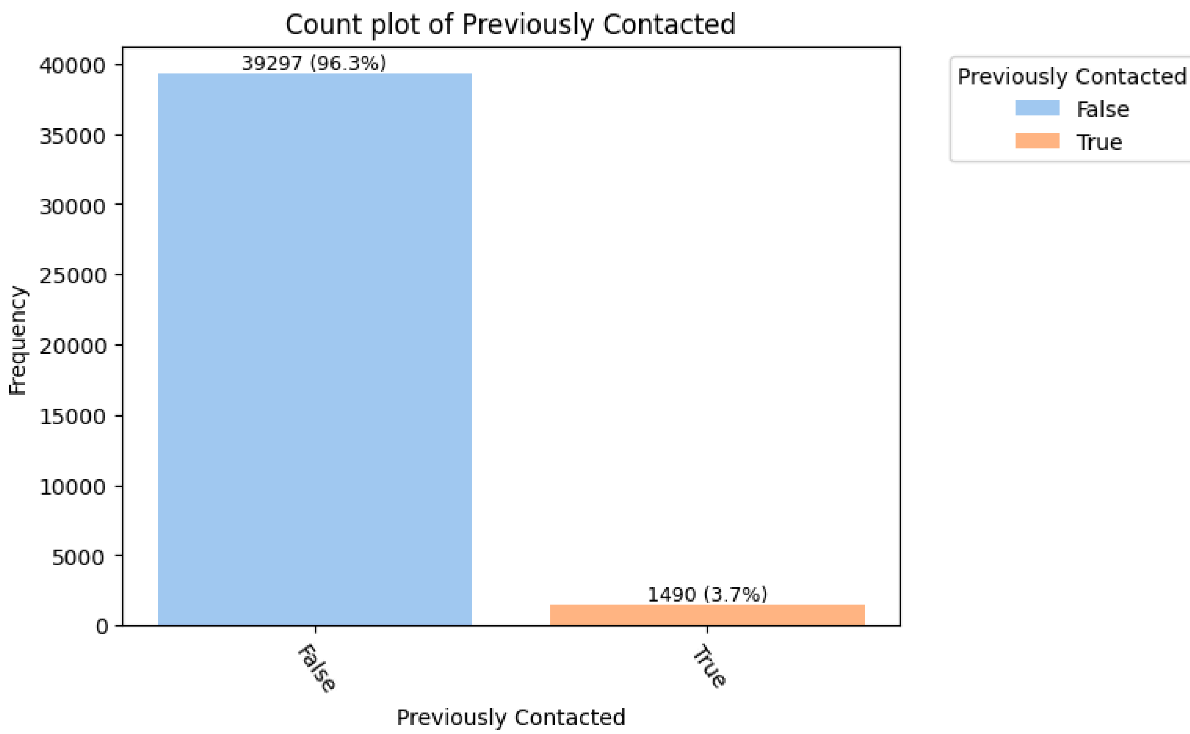
Data Cleaning on `Previously Contacted` Column

In [17]:
```
# Create Previously Contacted column where no prior call (999) means False a
df["Previously Contacted"] = df["Previous Contact Days"] != 999

# Replace no prior (999) with -1
df["Previous Contact Days"] = df["Previous Contact Days"].map(
    lambda x: -1 if x == 999 else x
)
df.head()
```

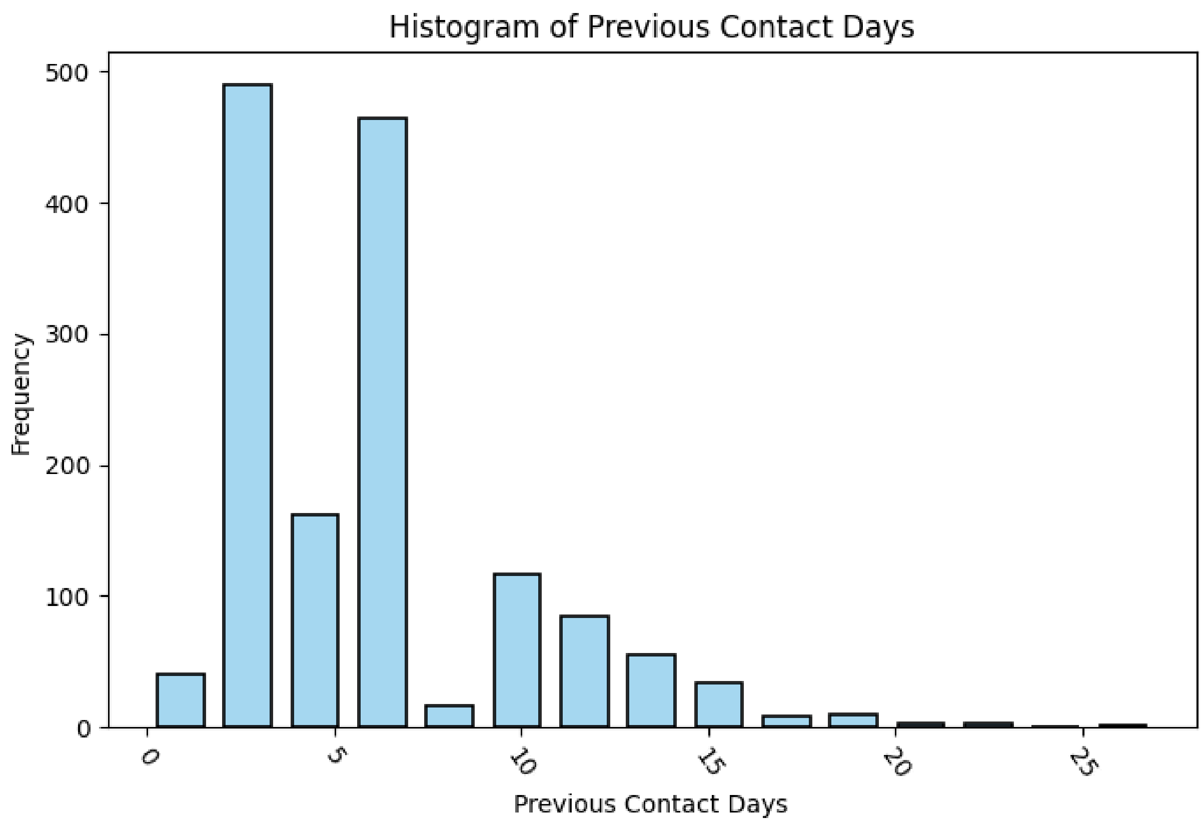
Out[17]:

	Age	Occupation	Marital Status	Education Level	Housing Loan	Personal Loan	Contact Method	Campa C
0	57	technician	married	high.school	no	yes	cellular	
2	33	blue-collar	married	basic.9y	no	no	cellular	
3	36	admin.	married	high.school	no	no	telephone	
4	27	housemaid	married	high.school	None	no	cellular	
5	58	retired	married	professional.course	None	yes	cellular	

In [32]:
```
plot_bar_graph(df, col="Previously Contacted", y="Frequency", kind="count",
```



In [19]:
```
plot_hist_graph(
    df[df["Previous Contact Days"] != -1],
    col="Previous Contact Days",
    bins=15,
    shrink=0.7,
    x_rotation=-55,
)
```



In [20]:
```
columns = df.columns.tolist()
columns.remove("Subscription Status")
columns.append("Subscription Status")
df = df.reindex(columns=columns)
df.head()
```

Out[20]:

	Age	Occupation	Marital Status	Education Level	Housing Loan	Personal Loan	Contact Method	Campa(
0	57	technician	married	high.school	no	yes	cellular	
2	33	blue-collar	married	basic.9y	no	no	cellular	
3	36	admin.	married	high.school	no	no	telephone	
4	27	housemaid	married	high.school	None	no	cellular	
5	58	retired	married	professional.course	None	yes	cellular	

`Previously Contacted` : False means no prior contact (999) | True means there is contact

`Previous Contact Days` : 999 converted to -1

> **Observation:**

- There is a huge imbalance of Previously Contacted column, where very low numbers of clients have prior contact.
- The Previous Contact Days columns show a bimodel distribution.
- Highest is 3 calls with 431 rows and second highest is 6 calls with 404 rows.

> **THOUGHT PROCESS:**

- Although it seems like there is only 3.7% with prior contact, dropping the column may not be an ideal choice since it can still give meaningful insights.

Data Cleaning on `Subscription Status` Column

In [21]:
```
# Convert yes to True and no to False
df["Subscription Status"] = df["Subscription Status"].map(
    lambda x: True if x == "yes" else False
)
df.dtypes
```

Out[21]:
```
Age                        int64
Occupation                object
Marital Status            object
Education Level           object
Housing Loan              object
Personal Loan             object
Contact Method            object
Campaign Calls             int64
Previous Contact Days      int64
Previously Contacted        bool
Subscription Status         bool
dtype: object
```

In [22]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 40787 entries, 0 to 41187
Data columns (total 11 columns):
 #   Column                 Non-Null Count  Dtype 
---  ------                 --------------  ----- 
 0   Age                    40787 non-null  int64 
 1   Occupation             40787 non-null  object
 2   Marital Status         40787 non-null  object
 3   Education Level        40787 non-null  object
 4   Housing Loan           16243 non-null  object
 5   Personal Loan          36679 non-null  object
 6   Contact Method         40787 non-null  object
 7   Campaign Calls         40787 non-null  int64 
 8   Previous Contact Days  40787 non-null  int64 
 9   Previously Contacted   40787 non-null  bool  
 10  Subscription Status    40787 non-null  bool  
dtypes: bool(2), int64(3), object(6)
memory usage: 3.2+ MB
```

Simple Data Imputation Analysis

Simple Imputation on `Age` Column

In [419…

```
df_mean_rp = df.copy()
df_not_150 = df[df["Age"] != 150]["Age"]  # Retrieve rows without 150 to cal
# impute 150 with the average age
df_mean_rp["Age_mean"] = df["Age"].apply(
    lambda x: df_not_150.agg("mean") if x == 150 else x
)
df_mean_rp["Age_mean"].head()
```

Out[419…

```
0    57.0
2    33.0
3    36.0
4    27.0
5    58.0
Name: Age_mean, dtype: float64
```

In [420…

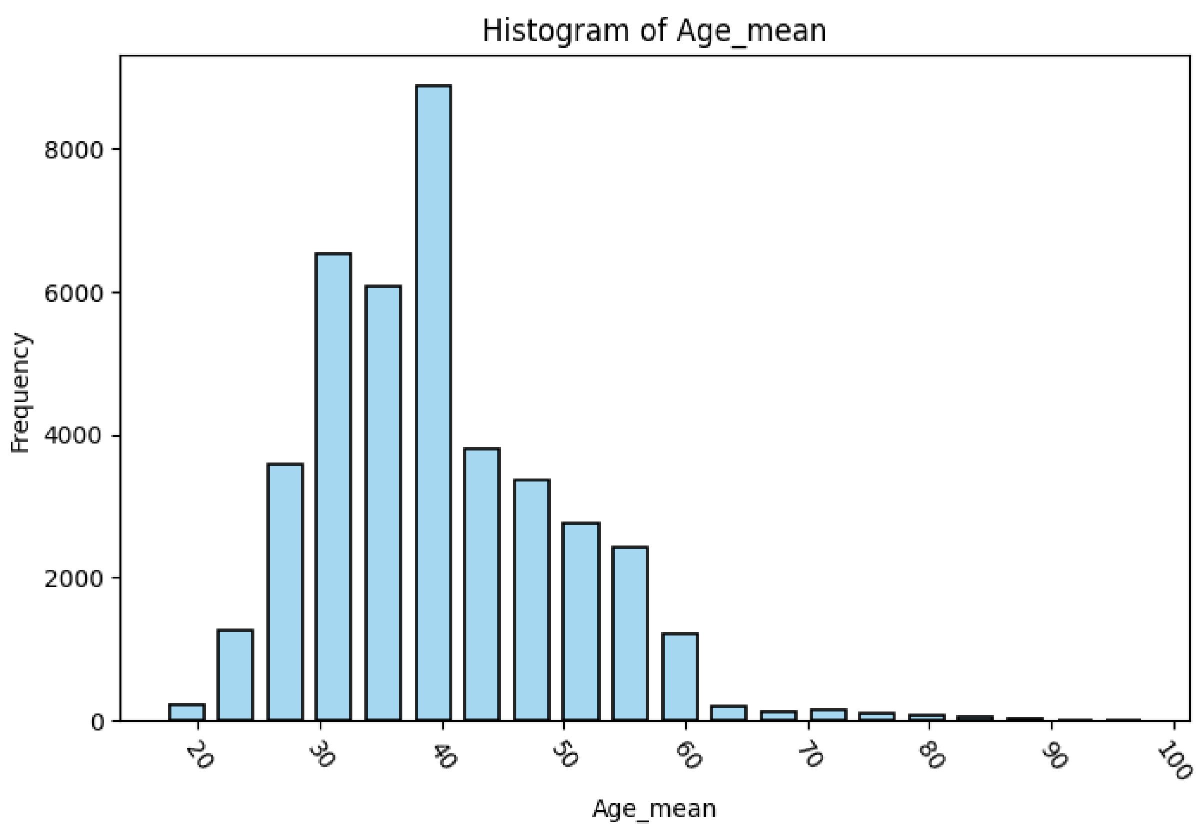
```
df_not_150.agg("mean")
```

Out[420…

```
np.float64(39.97881517881518)
```

In [421…

```
plot_hist_graph(df_mean_rp, col="Age_mean", bins=20, shrink=0.7, x_rotation=
```



In [422…

```
df_median_rp = df.copy()

# Retrieve rows without 150 to calculate median
df_not_150 = df[df["Age"] != 150]["Age"]
df_median_rp["Age_median"] = df["Age"].apply(
```

```
    lambda x: df_not_150.agg("median") if x == 150 else x
)

# impute 150 with the middle age
df_median_rp["Age_median"].head()
```

Out[422…

```
0    57.0
2    33.0
3    36.0
4    27.0
5    58.0
Name: Age_median, dtype: float64
```

In [423…

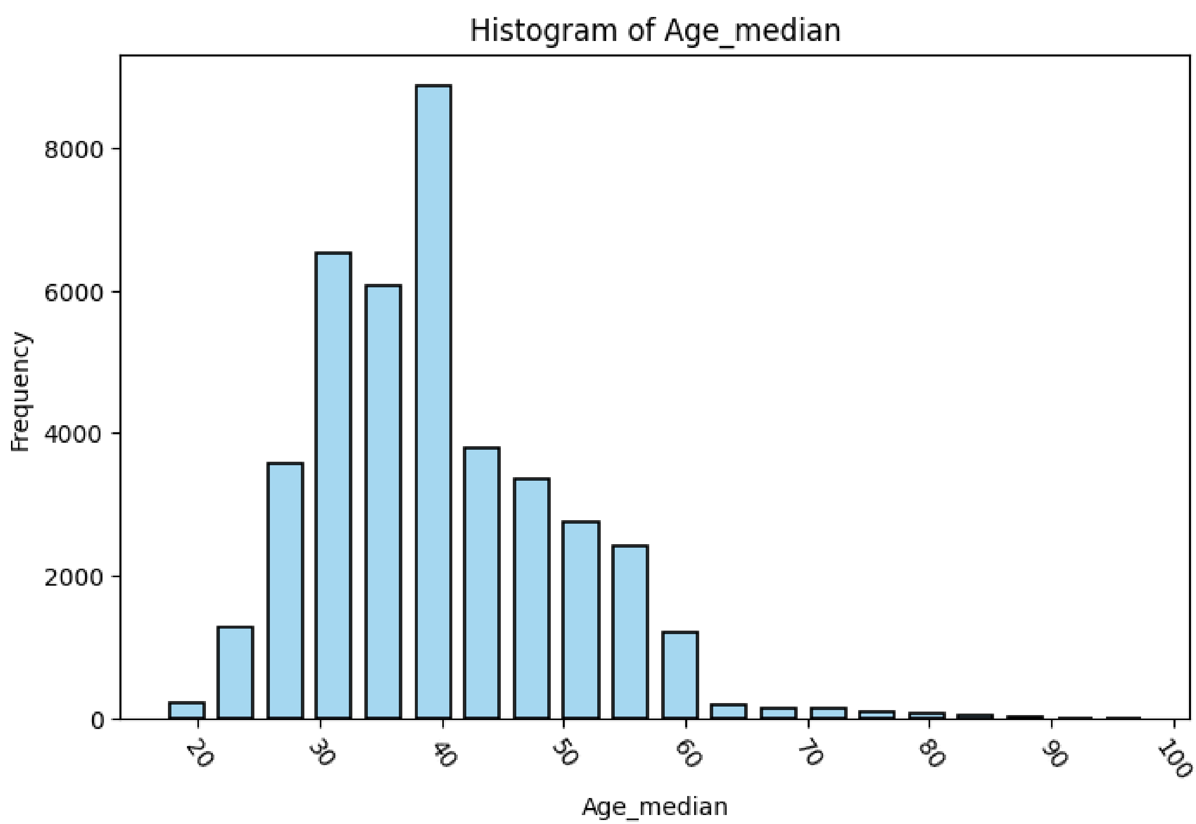
```
df_not_150.agg("median")
```

Out[423…

```
np.float64(38.0)
```

In [424…

```
plot_hist_graph(df_median_rp, col="Age_median", bins=20, shrink=0.7, x_rotat
```



> **Observation:**

- Both mean and median imputation were able to derive to the same distribution since both are approximately 38 to 39 years old.
- This shifted the distribution slightly to the center, distorting its original shape.

> **THOUGHT PROCESS:**

---

1. In order to maintain the original shape of distribution, I decided that mean and median may not be the best so I may utilize random distribution imputation instead.

Check relationships

In [5]:
```
def ohe_encode(df: pd.DataFrame) -> pd.DataFrame:
    """
    One hot encode all object type columns in input DataFrame

    parameters:
    -----------
    df: pd.DataFrame
      Input DataFrame
    """
    encoder = OneHotEncoder(sparse_output=False)
    df_copy = df.copy()

    # Initiate Dataframe with same number of rows
    df_encode = pd.DataFrame(index=df_copy.index)

    for col in df_copy.columns:
        if df_copy[col].dtype == "object":
            encoded = encoder.fit_transform(df_copy[[col]])

            # Get ohe column value names
            value_col = encoder.get_feature_names_out([col])
            encoded_columns = pd.DataFrame(
                encoded, columns=value_col, index=df_copy.index
            )
            df_encode = pd.concat([df_encode, encoded_columns], axis=1)
        else:
            df_encode[col] = df_copy[col]
    return df_encode


def int_encode(df):
    encoder = LabelEncoder()
    df_copy = df.copy()

    # Initiate Dataframe with same number of rows
    df_encode = pd.DataFrame(index=df_copy.index)

    for col in df_copy.columns:
        if df_copy[col].dtype == "object":
            df_encode[col] = encoder.fit_transform(df_copy[col])
        else:
            df_encode[col] = df_copy[col]
    return df_encode
```

Little MCAR Test

In [24]:
```
columns_na = df.columns[df.isna().any()]
for col in columns_na:
    print(f"{col}'s NaN no.: {df[col].isna().sum()}")
```

```
Housing Loan's NaN no.: 24544
Personal Loan's NaN no.: 4108
```

In [25]:
```
df_encode_mcar = int_encode(df)
columns_na = df_encode_mcar.columns[df.isna().any()]
for col in columns_na:
    # Convert 3 back to nan since nan was converted
    df_encode_mcar[col] = df_encode_mcar[col].map(lambda x: np.nan if x == 3

    # Check if number of nan is correct
    print(f"{col}'s nan no.: {df_encode_mcar[col].isna().sum()}")
```

```
Housing Loan's nan no.: 24544
Personal Loan's nan no.: 4108
```

In [26]:
```
mcar_test = MCARTest()
results = mcar_test.little_mcar_test(df_encode_mcar)
results
```

```
Method: Little's MCAR Test
Test Statistic p-value: 0.129272
Decision: Fail to reject the null hypothesis (α = 0.05)
→ There is insufficient evidence to reject MCAR.
```

Out[26]:
```
np.float64(0.129272233398945)
```

In [ ]:
```
results = mcar_test.little_mcar_test(df_encode_mcar.drop("Housing Loan", axi
results
```

```
Method: Little's MCAR Test
Test Statistic p-value: 0.853363
Decision: Fail to reject the null hypothesis (α = 0.05)
→ There is insufficient evidence to reject MCAR.
```

Out[ ]:
```
np.float64(0.8533634300872586)
```

In [28]:
```
df_encode_mcar_age_150_to_nan = df_encode_mcar.copy()
df_encode_mcar_age_150_to_nan["Age"] = df_encode_mcar_age_150_to_nan["Age"].
    lambda x: np.nan if x == 150 else x
)
```

In [29]:
```
results = mcar_test.little_mcar_test(df_encode_mcar_age_150_to_nan)
results
```

```
Method: Little's MCAR Test
Test Statistic p-value: 0.124373
Decision: Fail to reject the null hypothesis (α = 0.05)
→ There is insufficient evidence to reject MCAR.
```

Out[29]:
```
np.float64(0.12437348127431758)
```

> **Observation:**

- Using little MCAR Test, the p value is significantly large (> 0.05), indicating that the data are consistent with missing completely at random (MCAR)
- Even with replacing 150 to na in Age column, the p value is still high.

> **THOUGHT PROCESS:**

---

1. This means that the missingness patterns is independent.
2. Suggesting to utilize simple imputation such as mean, median or random distribution.

Mutual Information (MI) of Personal Loan

In [34]:
```
def bin_numeric(df, bins=10):
    df_bin = df.copy()

    # Select columns that are numbers
    numeric_cols = df.select_dtypes(include=["number"]).columns
    for col in numeric_cols:
        # Apply binning
        df_bin[col] = pd.qcut(df_bin[col], q=bins, duplicates="drop").astype
    return df_bin

def mutual_information_compare(df, target_col):
    bin_num_df = bin_numeric(df.dropna(subset=[target_col]))
    df_encode_temp = int_encode(bin_num_df)
    # Convert continuous number to discrete values
    X_df_temp, y_temp = (
        df_encode_temp.drop(["Personal Loan", "Housing Loan", "Age"], axis=1
        df_encode_temp[target_col],
    )
    nmi_scores = []

    for col in X_df_temp.columns:  # Compare each column with target column
        X = X_df_temp[col]
        nmi_score = normalized_mutual_info_score(X, y_temp)
        nmi_scores.append(nmi_score)

    nmi = pd.Series(nmi_scores)
    nmi.index = X_df_temp.columns
    nmi = nmi.rename(target_col).sort_values(ascending=False).round(4).reset
    return nmi
```

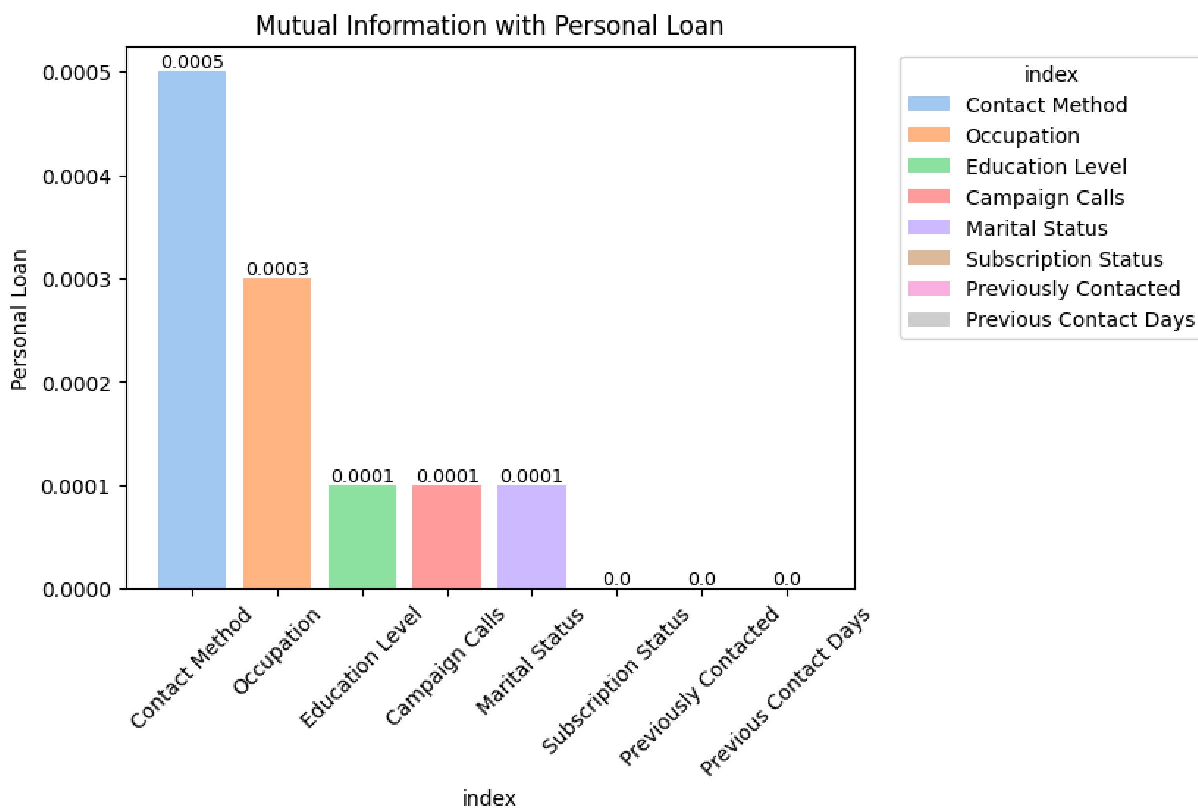
In [35]:
```
target = "Personal Loan"

nmi = mutual_information_compare(df, target_col=target)
nmi
```

Out[35]:

	index	Personal Loan
0	Contact Method	0.0005
1	Occupation	0.0003
2	Education Level	0.0001
3	Campaign Calls	0.0001
4	Marital Status	0.0001
5	Subscription Status	0.0000
6	Previously Contacted	0.0000
7	Previous Contact Days	0.0000

In [436…

```
plot_bar_graph(
    nmi,
    col="index",
    y=target,
    kind="bar",
    title=f"Mutual Information with {target}",
    x_rotation=45,
)
```



> **Observation:**

- All the normalized mutual information values are very low.
- The highest correlation is only 0.0005 between Personal Loan and Previous Contact Days.
- While the remaining are less than 0.0003.
- Especially, correlation between Personal Loan and Subscription Status is very low.

> **THOUGHT PROCESS:**

---

1. Although, the correlation with Previous Contact Days is highest with 0.0005.

2. The remaining are all very little correlation, meaning the other columns carry minimal information about Personal Loan, model based imputation may not be an ideal choice.

3. The normalized MI tells me that Personal Loan can only be impute independently, so possibly usage of random distribution.

4. Since Personal Loan is also surprisingly low correlation with Subscription Status, it is also a choice to drop the column for feature selection if the team decides to.

Mutual Information (MI) of Housing Loan

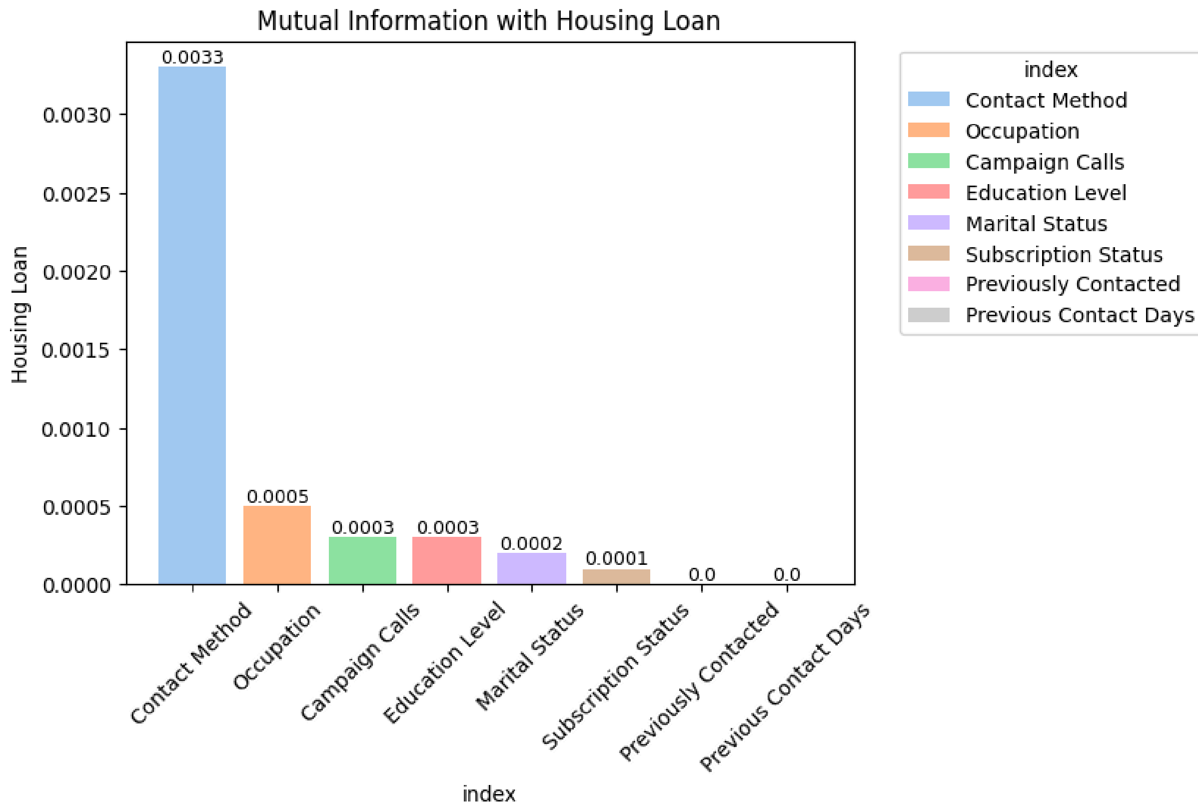
In [36]:
```
target = "Housing Loan"

nmi = mutual_information_compare(df, target_col=target)
nmi
```

Out[36]:

	index	Housing Loan
0	Contact Method	0.0033
1	Occupation	0.0005
2	Campaign Calls	0.0003
3	Education Level	0.0003
4	Marital Status	0.0002
5	Subscription Status	0.0001
6	Previously Contacted	0.0000
7	Previous Contact Days	0.0000

In [440…
```
plot_bar_graph(
    nmi,
    col="index",
    y=target,
    kind="bar",
    title=f"Mutual Information with {target}",
```

```
    x_rotation=45,
)
```



> **Observation:**

- All the normalized mutual information values are very low.

> **THOUGHT PROCESS:**

---

1. Although, the correlation with Previous Contact Days is highest with 0.0033.
2. The remaining are all very little correlation, meaning the other columns carry minimal information about Personal Loan, model based imputation may not be an ideal choice.
3. The normalized MI tells me that Housing Loan can only be impute independently, so possibly usage of random distribution.
4. Since Housing Loan also has very low correlation with Subscription Status, it is a choice to drop the column for feature selection if the team decides to.

Mutual Information (MI) of Age

In [37]:
```
target = "Age"
```

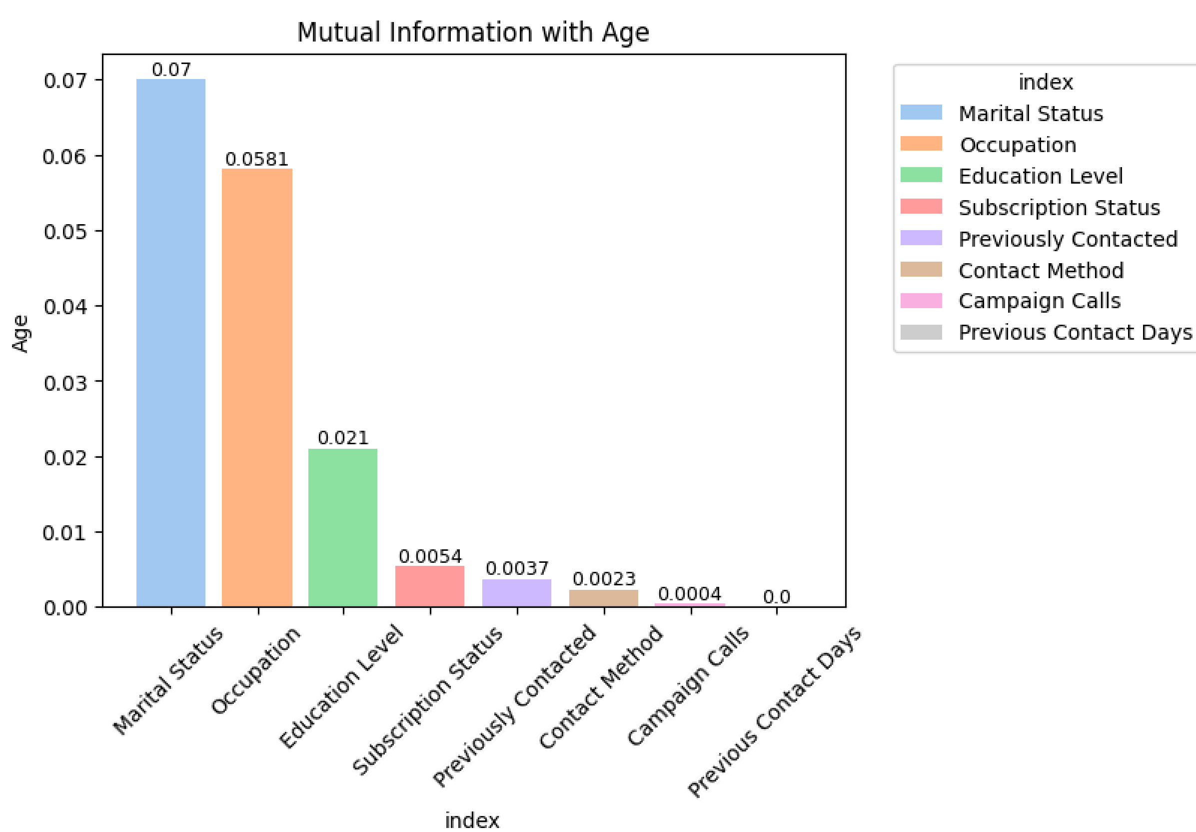
```
nmi = mutual_information_compare(df[df["Age"] != 150], target_col=target)
nmi
```

Out[37]:

	index	Age
0	Marital Status	0.0700
1	Occupation	0.0581
2	Education Level	0.0210
3	Subscription Status	0.0054
4	Previously Contacted	0.0037
5	Contact Method	0.0023
6	Campaign Calls	0.0004
7	Previous Contact Days	0.0000

In [445…

```
plot_bar_graph(
    nmi,
    col="index",
    y=target,
    kind="bar",
    title=f"Mutual Information with {target}",
    x_rotation=45,
)
```



> **Observation:**

- All the normalized mutual information values are also low.

> **THOUGHT PROCESS:**

---

1. The normalized MI tells me that Age may require to impute independently.
2. With support of previous analysis like simple imputation and little MCAR test random distribution may be the solution.
3. Imputing with KNN may also be an available choice, however, due to the low MI score, the output may be weak.

Decided Missing Data Solution for Age, Housing Loan & Personal Loan

In [446…

```
df_new = df.drop("Housing Loan", axis=1)  # Drop Housing Loan
df_new.head()
```

Out[446…

	Age	Occupation	Marital Status	Education Level	Personal Loan	Contact Method	Campaign Calls	Prev Con I
0	57	technician	married	high.school	yes	cellular	1	
2	33	blue-collar	married	basic.9y	no	cellular	1	
3	36	admin.	married	high.school	no	telephone	4	
4	27	housemaid	married	high.school	no	cellular	2	
5	58	retired	married	professional.course	yes	cellular	1	

In [447…

```
def random_distribution(df):
    df_temp = df.copy()
    targets = {"Age": 150, "Personal Loan": "none"}
    rng = np.random.default_rng(42)

    if not isinstance(df, pd.DataFrame):
        raise TypeError("Submitted dataframe is not a pd.DataFrame")

    for target, val in targets.items():
        col = df_temp[target]

        if val == "none":  # When the goal is to impute nan
            temp_col = col[~col.isna()]
            tobe_fill = col.isna()

        else:  # When the goal is to impute specific value
            temp_col = col[col != val]
            tobe_fill = col == val
```

```
        # Retrieve distribution of values
        distribution = temp_col.value_counts(normalize=True).tolist()
        labels = temp_col.value_counts().index.tolist()
        fill_mask = tobe_fill

        # Randomly assign target values with other unique values based on di
        fill = rng.choice(labels, size=fill_mask.sum(), p=distribution)
        df_temp.loc[fill_mask, target] = fill

    return df_temp
```

In [448…

```
df_new = random_distribution(df_new)
df_new.head()
```

Out[448…

	Age	Occupation	Marital Status	Education Level	Personal Loan	Contact Method	Campaign Calls	Prev Con I
0	57	technician	married	high.school	yes	cellular	1	
2	33	blue-collar	married	basic.9y	no	cellular	1	
3	36	admin.	married	high.school	no	telephone	4	
4	27	housemaid	married	high.school	no	cellular	2	
5	58	retired	married	professional.course	yes	cellular	1	

In [449…

```
df_new["Age"][df_new["Age"] == 150].sum()
```

Out[449… np.int64(0)

In [450…

```
df_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 40787 entries, 0 to 41187
Data columns (total 10 columns):
 #   Column                 Non-Null Count  Dtype 
---  ------                 --------------  ----- 
 0   Age                    40787 non-null  int64 
 1   Occupation             40787 non-null  object
 2   Marital Status         40787 non-null  object
 3   Education Level        40787 non-null  object
 4   Personal Loan          40787 non-null  object
 5   Contact Method         40787 non-null  object
 6   Campaign Calls         40787 non-null  int64 
 7   Previous Contact Days  40787 non-null  int64 
 8   Previously Contacted   40787 non-null  bool  
 9   Subscription Status    40787 non-null  bool  
dtypes: bool(2), int64(3), object(5)
memory usage: 2.9+ MB
```

In [451…

```
# Old Personal Loan
print(df["Personal Loan"].unique())
df["Personal Loan"].value_counts(normalize=True)
```

```
['yes' 'no' None 'unknown']
```

Out[451…

```
Personal Loan
no         0.824150
yes        0.152076
unknown    0.023774
Name: proportion, dtype: float64
```

In [452…

```
# New Personal Loan
print(df_new["Personal Loan"].unique())
df_new["Personal Loan"].value_counts(normalize=True)
```

```
['yes' 'no' 'unknown']
```

Out[452…

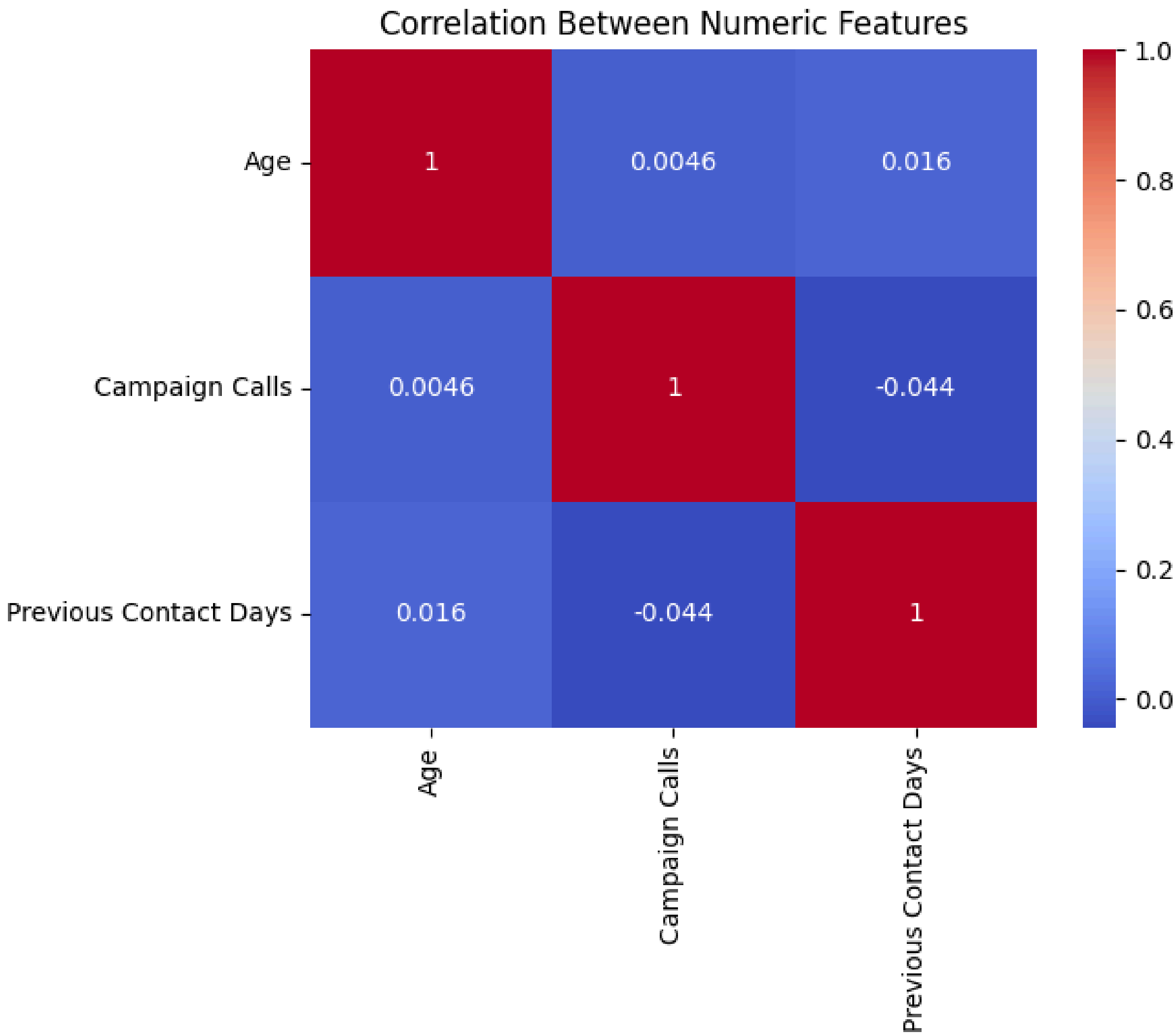
```
Personal Loan
no         0.824650
yes        0.151494
unknown    0.023856
Name: proportion, dtype: float64
```

Numeric Correlation

In [453…

```
numeric_cols = ["Age", "Campaign Calls", "Previous Contact Days"]

# Using pairwise heatmap
corr_matrix = df_new[numeric_cols].corr()
print(corr_matrix)

sns.heatmap(corr_matrix, annot=True, cmap="coolwarm")
plt.title("Correlation Between Numeric Features")
plt.show()
```

```
                            Age  Campaign Calls  Previous Contact Days
Age                    1.000000        0.004586               0.016419
Campaign Calls         0.004586        1.000000              -0.043937
Previous Contact Days  0.016419       -0.043937               1.000000
```



> **Observation:**

- Overall, the numeric columns have are very low correlation.
- Age compared to Campaign Calls and Previous Contact Days have a slight positive correlation, with 0.0033 and 0.022 repsectively.
- Campaign Calls and Previous Contact Days have a slight negative correlation with -0.044

> **THOUGHT PROCESS:**

---

1. This shows that the numeric columns have non-linear relationship between them.
2. The columns are mostly independent of one another.

Mutual Information

In [454…

```
def bin_numeric(df, bins=10):
    df_bin = df.copy()

    # Select columns that are numbers
    numeric_cols = df.select_dtypes(include=["number"]).columns
    for col in numeric_cols:
        # Apply binning
        df_bin[col] = pd.qcut(df_bin[col], q=bins, duplicates="drop").astype
    return df_bin


def mutual_information_matrix(df, figsize=(12, 10)):
    cols = df.columns
    n = len(cols)

    # Initialize matrix
    nmi_matrix = pd.DataFrame(np.zeros((n, n)), columns=cols, index=cols)

    # Compute normalized MI for each pair
    for i in range(n):
        for j in range(i, n):
            x = df[cols[i]]
            y = df[cols[j]]

            nmi = normalized_mutual_info_score(x, y, average_method="arithme

            nmi_matrix.iloc[i, j] = nmi
            nmi_matrix.iloc[j, i] = nmi

    plt.subplots(figsize=figsize)
    sns.heatmap(nmi_matrix, annot=True, fmt=".4f", cmap="viridis", square=Tr
    plt.title("Mutual Information Heatmap")

    plt.show()

    return nmi_matrix
```

In [455…

```
bin_num_df = bin_numeric(df_new)
encode_df = int_encode(bin_num_df)
mi_matrix = mutual_information_matrix(encode_df)
print(mi_matrix)
```


Mutual Information Heatmap
Age
Occupation
Marital Status
Education Level
Personal Loan
Contact Method
Campaign Calls
Previous Contact Days
Previously Contacted
Subscription Status
1.0000 0.0468 0.0560 0.0169 0.0002 0.0018 0.0003 0.0000 0.0031 0.0045
0.0468 1.0000 0.0342 0.2126 0.0003 0.0060 0.0005 0.0000 0.0072 0.0084
0.0560 0.0342 1.0000 0.0165 0.0000 0.0034 0.0001 0.0000 0.0015 0.0022
0.0169 0.2126 0.0165 1.0000 0.0001 0.0063 0.0001 0.0000 0.0017 0.0022
0.0002 0.0003 0.0000 0.0001 1.0000 0.0004 0.0001 0.0000 0.0000 0.0000
0.0018 0.0060 0.0034 0.0063 0.0004 1.0000 0.0029 0.0000 0.0211 0.0231
0.0003 0.0005 0.0001 0.0001 0.0001 0.0029 1.0000 0.0000 0.0039 0.0038
0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 0.0000 1.0000 0.0000 0.0000
0.0031 0.0072 0.0015 0.0017 0.0000 0.0211 0.0039 0.0000 1.0000 0.1220
0.0045 0.0084 0.0022 0.0022 0.0000 0.0231 0.0038 0.0000 0.1220 1.0000
1.0
0.8
0.6
0.4
0.2
0.0

```
                         Age  Occupation  Marital Status  Education Level  \
Age                   1.000000    0.046783        0.055965         0.016941
Occupation            0.046783    1.000000        0.034160         0.212573
Marital Status        0.055965    0.034160        1.000000         0.016468
Education Level       0.016941    0.212573        0.016468         1.000000
Personal Loan         0.000166    0.000254        0.000023         0.000118
Contact Method        0.001830    0.006033        0.003431         0.006278
Campaign Calls        0.000300    0.000545        0.000119         0.000134
Previous Contact Days 0.000000    0.000000        0.000000         0.000000
Previously Contacted  0.003101    0.007153        0.001543         0.001723
Subscription Status   0.004477    0.008366        0.002192         0.002218

                       Personal Loan  Contact Method  Campaign Calls  \
Age                         0.000166        0.001830        0.000300
Occupation                  0.000254        0.006033        0.000545
Marital Status              0.000023        0.003431        0.000119
Education Level             0.000118        0.006278        0.000134
Personal Loan               1.000000        0.000378        0.000076
Contact Method              0.000378        1.000000        0.002910
Campaign Calls              0.000076        0.002910        1.000000
Previous Contact Days       0.000000        0.000000        0.000000
Previously Contacted        0.000048        0.021120        0.003876
Subscription Status         0.000022        0.023085        0.003822

                       Previous Contact Days  Previously Contacted  \
Age                                      0.0              0.003101
Occupation                               0.0              0.007153
Marital Status                           0.0              0.001543
Education Level                          0.0              0.001723
Personal Loan                            0.0              0.000048
Contact Method                           0.0              0.021120
Campaign Calls                           0.0              0.003876
Previous Contact Days                    1.0              0.000000
Previously Contacted                     0.0              1.000000
Subscription Status                      0.0              0.121985

                       Subscription Status
Age                               0.004477
Occupation                        0.008366
Marital Status                    0.002192
Education Level                   0.002218
Personal Loan                     0.000022
Contact Method                    0.023085
Campaign Calls                    0.003822
Previous Contact Days             0.000000
Previously Contacted              0.121985
Subscription Status               1.000000
```

> **Observation:**

- The normalized mutual information (NMI) between the columns are mostly less than 0.01 correlation, meaning that the features are independent of one another.

- With one exception, where the NMI between Education Level and Occupation is 0.2165, which stands out, meaning both columns have higher correlation.

> **THOUGHT PROCESS:**

---

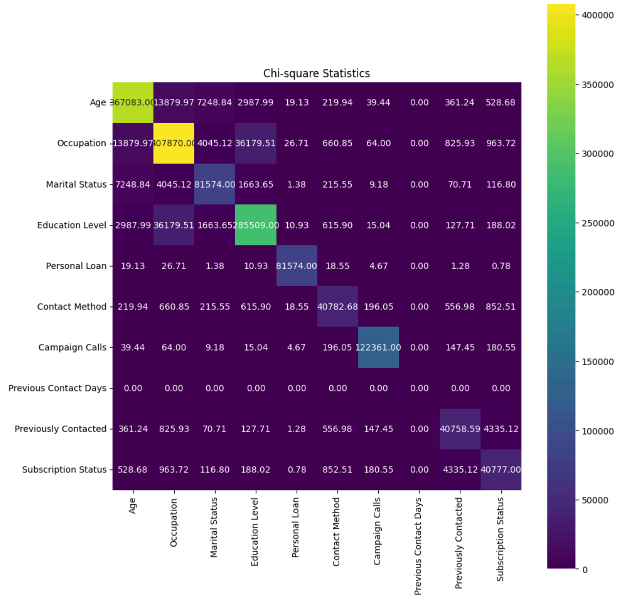
1. Overall, the columns are mostly independent of one another.
2. It makes sense for Occupation and Education Level to have higher correlation since they are similar in real world context.
3. Surprisingly, Previously Contacted has highest dependency with Subscription Status.
4. Previous Contact Days has no dependency with Subscription Status.

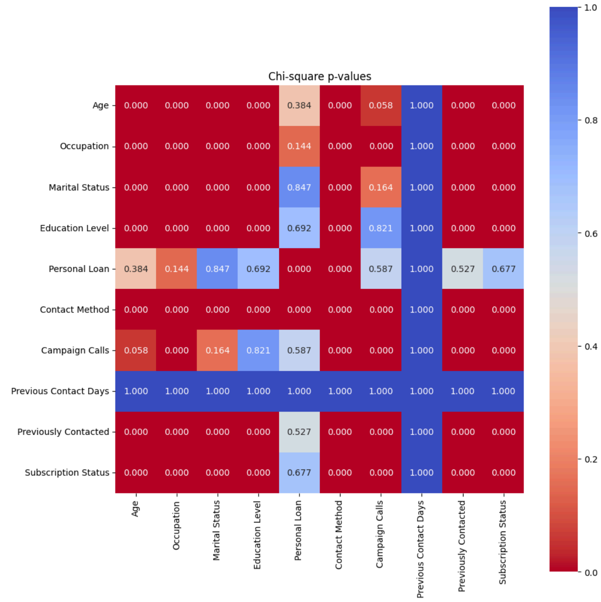
Chi Square Test

In [456…

```
def chi2_matrix(df):
    # Ensure only categorical columns
    cat_cols = df.select_dtypes(include=["object", "bool"]).columns
    n = len(cat_cols)

    chi2_matrix = pd.DataFrame(np.zeros((n, n)), index=cat_cols, columns=cat
    p_matrix = pd.DataFrame(np.zeros((n, n)), index=cat_cols, columns=cat_cc

    # Compute chi square for each pair
    for i in range(n):
        for j in range(i, n):
            # contingency table
            table = pd.crosstab(df[cat_cols[i]], df[cat_cols[j]])
            chi2, p, dof, expected = chi2_contingency(table)

            chi2_matrix.iloc[i, j] = chi2
            chi2_matrix.iloc[j, i] = chi2
            p_matrix.iloc[i, j] = p
            p_matrix.iloc[j, i] = p

    fig, axes = plt.subplots(1, 2, figsize=(20, 10))
    sns.heatmap(
        chi2_matrix, annot=True, fmt=".2f", cmap="viridis", square=True, ax=
    )
    axes[0].set_title("Chi-square Statistics")

    sns.heatmap(
        p_matrix, annot=True, fmt=".3f", cmap="coolwarm_r", square=True, ax=
    )
    axes[1].set_title("Chi-square p-values")

    plt.tight_layout()
    plt.show()

    return chi2_matrix, p_matrix
```

```
bin_num_df = bin_numeric(df_new)
chi2_matrix(bin_num_df)
```





```
Out[456… (                           Age     Occupation  Marital Status  \
 Age                     367083.000000   13879.973705     7248.841217
 Occupation               13879.973705  407870.000000     4045.117713
 Marital Status            7248.841217    4045.117713    81574.000000
 Education Level           2987.994996   36179.505595     1663.647637
 Personal Loan               19.134928      26.711664        1.383333
 Contact Method             219.939660     660.851162      215.549365
 Campaign Calls              39.437752      63.995285        9.183562
 Previous Contact Days        0.000000       0.000000        0.000000
 Previously Contacted       361.238867     825.933649       70.714195
 Subscription Status        528.677914     963.723715      116.802253

                        Education Level  Personal Loan  Contact Method  \
 Age                        2987.994996      19.134928      219.939660
 Occupation                36179.505595      26.711664      660.851162
 Marital Status             1663.647637       1.383333      215.549365
 Education Level          285509.000000      10.926242      615.903137
 Personal Loan                10.926242   81574.000000       18.554607
 Contact Method              615.903137      18.554607    40782.682092
 Campaign Calls               15.036754       4.671236      196.052075
 Previous Contact Days         0.000000       0.000000        0.000000
 Previously Contacted        127.710883       1.281740      556.980081
 Subscription Status         188.017680       0.778750      852.509997

                        Campaign Calls  Previous Contact Days  \
 Age                         39.437752                    0.0
 Occupation                  63.995285                    0.0
 Marital Status               9.183562                    0.0
 Education Level             15.036754                    0.0
 Personal Loan                4.671236                    0.0
 Contact Method             196.052075                    0.0
 Campaign Calls          122361.000000                    0.0
 Previous Contact Days        0.000000                    0.0
 Previously Contacted       147.446661                    0.0
 Subscription Status        180.545638                    0.0

                        Previously Contacted  Subscription Status
 Age                              361.238867           528.677914
 Occupation                       825.933649           963.723715
 Marital Status                    70.714195           116.802253
 Education Level                  127.710883           188.017680
 Personal Loan                      1.281740             0.778750
 Contact Method                   556.980081           852.509997
 Campaign Calls                   147.446661           180.545638
 Previous Contact Days              0.000000             0.000000
 Previously Contacted           40758.593206          4335.115693
 Subscription Status             4335.115693         40776.995363  ,
                                  Age     Occupation  Marital Status  \
 Age                     0.000000e+00   0.000000e+00    0.000000e+00
 Occupation              0.000000e+00   0.000000e+00    0.000000e+00
 Marital Status          0.000000e+00   0.000000e+00    0.000000e+00
 Education Level         0.000000e+00   0.000000e+00    0.000000e+00
 Personal Loan           3.835593e-01   1.435727e-01    8.470865e-01
 Contact Method          2.154956e-42  1.582524e-135    1.563328e-47
 Campaign Calls          5.777810e-02   2.944623e-04    1.635148e-01
 Previous Contact Days   1.000000e+00   1.000000e+00    1.000000e+00
```

```
Previously Contacted    2.508756e-72  5.475868e-171    4.411717e-16
Subscription Status    4.137481e-108  1.216594e-200    4.332245e-26

                       Education Level  Personal Loan  Contact Method  \
Age                       0.000000e+00       0.383559    2.154956e-42
Occupation                0.000000e+00       0.143573   1.582524e-135
Marital Status            0.000000e+00       0.847087    1.563328e-47
Education Level           0.000000e+00       0.691820   9.151481e-129
Personal Loan             6.918203e-01       0.000000    9.352295e-05
Contact Method           9.151481e-129       0.000094    0.000000e+00
Campaign Calls            8.211031e-01       0.586616    3.007163e-42
Previous Contact Days     1.000000e+00       1.000000    1.000000e+00
Previously Contacted      1.889812e-24       0.526834   3.815541e-123
Subscription Status       3.939163e-37       0.677480   2.069610e-187

                       Campaign Calls  Previous Contact Days  \
Age                      5.777810e-02                    1.0
Occupation               2.944623e-04                    1.0
Marital Status           1.635148e-01                    1.0
Education Level          8.211031e-01                    1.0
Personal Loan            5.866161e-01                    1.0
Contact Method           3.007163e-42                    1.0
Campaign Calls           0.000000e+00                    1.0
Previous Contact Days    1.000000e+00                    1.0
Previously Contacted     9.365650e-32                    1.0
Subscription Status      6.724069e-39                    1.0

                       Previously Contacted  Subscription Status
Age                            2.508756e-72        4.137481e-108
Occupation                    5.475868e-171        1.216594e-200
Marital Status                 4.411717e-16         4.332245e-26
Education Level                1.889812e-24         3.939163e-37
Personal Loan                  5.268338e-01         6.774803e-01
Contact Method                3.815541e-123        2.069610e-187
Campaign Calls                 9.365650e-32         6.724069e-39
Previous Contact Days          1.000000e+00         1.000000e+00
Previously Contacted           0.000000e+00         0.000000e+00
Subscription Status            0.000000e+00         0.000000e+00  )
```

> **Observation:**

- There is a similarity between chi square result and mutual information.
- Additionally, the p values of each pair of columns are mostly 0, meaning the columns are detected to have some dependency to each other.
- Previous Contact Days is 1 compared with other columns, especially with Subscription Status, meaning no evidence of association between columns.

> **THOUGHT PROCESS:**

---

1. The p values just shows whether any dependencies exist for the columns (p value < 0.05, rejecting null hypothesis), while mutual information and chi square shows

the strength of those dependencies.

2. Both mutual information and p values are suggesting to drop Previous Contact Days since they are > 0.05, which fails to reject the null hypothesis, saying Previous Contact Days has insufficient evidence of relating with other columns, especially Subscription Status.
3. Though Personal Loan has high p values (0.7) suggesting that there is less evidence of association with Status Subscription. However, there is still some association and since other columns already have a low dependencies, it would be best to continue keeping Personal Loan to predict Subscription Status.

In [457…
```
# Decided to drop Previous Contact Days
df_new.drop("Previous Contact Days", axis=1, inplace=True)
```

Potential feature selection method

In [458…
```
def my_train_test_split(
    df: pd.DataFrame, val_sample: bool = False, test_size: int = 0.2, rs: ir
) -> Union[
    Tuple[pd.DataFrame, pd.DataFrame, pd.Series, pd.Series],
    Tuple[pd.DataFrame, pd.DataFrame, pd.DataFrame, pd.Series, pd.Series, pc
]:
    """
    Split input DataFrame into train, test and val(optional)

    parameters:
    -----------
    df: pd.DataFrame
      Input DataFrame

    val_sample: bool
      State whether to generate validation data sample

    test_size: int
      State the size of test dataset

    rs: int
      Set random state for randomness
    """
    label = "Subscription Status"
    X, y = df.drop(label, axis=1), df[label]
    if val_sample:
        X_train, X_temp, y_train, y_temp = train_test_split(
            X, y, test_size=test_size, random_state=rs, stratify=y
        )
        X_val, X_test, y_val, y_test = train_test_split(
            X_temp, y_temp, test_size=0.5, random_state=rs, stratify=y_temp
        )
        return X_train, X_val, X_test, y_train, y_val, y_test

    else:
        X_train, X_test, y_train, y_test = train_test_split(
            X, y, test_size=test_size, random_state=rs, stratify=y
```

```
        )
        return X_train, X_test, y_train, y_test
```

MI feature selection

In [459…
```
X_train, X_test, y_train, y_test = my_train_test_split(df_new, test_size=0.3
int_encoded_X = int_encode(X_train)
int_encoded_X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 28550 entries, 38914 to 39273
Data columns (total 8 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   Age                  28550 non-null  int64
 1   Occupation           28550 non-null  int64
 2   Marital Status       28550 non-null  int64
 3   Education Level      28550 non-null  int64
 4   Personal Loan        28550 non-null  int64
 5   Contact Method       28550 non-null  int64
 6   Campaign Calls       28550 non-null  int64
 7   Previously Contacted 28550 non-null  bool
dtypes: bool(1), int64(7)
memory usage: 1.8 MB
```

In [460…
```
discrete_mask = [False, True, True, True, True, True, False, True]

target_mi_scores = mutual_info_classif(
    int_encoded_X, y_train, random_state=42, discrete_features=discrete_mask
)
```

In [461…
```
target_mi = pd.Series(target_mi_scores)
target_mi.index = int_encoded_X.columns
target_mi = (
    target_mi.rename(y_train.name).sort_values(ascending=False).round(4).res
)
target_mi
```

Out[461…

	index	Subscription Status
0	Previously Contacted	0.0318
1	Contact Method	0.0109
2	Age	0.0103
3	Occupation	0.0093
4	Campaign Calls	0.0039
5	Education Level	0.0023
6	Marital Status	0.0010
7	Personal Loan	0.0000

In [462…

```
# Utilize a feature selection technique to keep top k highest scoring featur
select_cols = SelectKBest(k=5)
select_cols.scores_ = target_mi  # Pass Mutual Information score
select_cols.pvalues_ = None  # Reset P values
select_cols.fit(int_encoded_X, y_train)
int_encoded_X.columns[select_cols.get_support()]
```

Out[462…

```
Index(['Marital Status', 'Education Level', 'Contact Method', 'Campaign Cal
ls',
       'Previously Contacted'],
      dtype='object')
```

In [463…

```
# Utilize a feature selection technique to keep top percentage of features
select_cols = SelectPercentile(percentile=70)
select_cols.scores_ = target_mi  # Pass Mutual Information score
select_cols.pvalues_ = None  # Reset P values
select_cols.fit(int_encoded_X, y_train)
int_encoded_X.columns[select_cols.get_support()]
```

Out[463…

```
Index(['Marital Status', 'Education Level', 'Contact Method', 'Campaign Cal
ls',
       'Previously Contacted'],
      dtype='object')
```

> **Observation:**

- With a clean dataset, I can proceed with a pre-feature selection making full use of mutual information.
- These are some features selected that can possibly maintain accuracy while reducing dimensionality.

MI feature selection (One Hot Encoded)

In [464…

```
ohe_encoded_X = ohe_encode(X_train)
ohe_encoded_X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 28550 entries, 38914 to 39273
Data columns (total 30 columns):
 #   Column                              Non-Null Count  Dtype
---  ------                              --------------  -----
 0   Age                                 28550 non-null  int64
 1   Occupation_admin.                   28550 non-null  float64
 2   Occupation_blue-collar              28550 non-null  float64
 3   Occupation_entrepreneur             28550 non-null  float64
 4   Occupation_housemaid                28550 non-null  float64
 5   Occupation_management               28550 non-null  float64
 6   Occupation_retired                  28550 non-null  float64
 7   Occupation_self-employed            28550 non-null  float64
 8   Occupation_services                 28550 non-null  float64
 9   Occupation_student                  28550 non-null  float64
 10  Occupation_technician               28550 non-null  float64
 11  Occupation_unemployed               28550 non-null  float64
 12  Marital Status_divorced             28550 non-null  float64
 13  Marital Status_married              28550 non-null  float64
 14  Marital Status_single               28550 non-null  float64
 15  Education Level_basic.4y            28550 non-null  float64
 16  Education Level_basic.6y            28550 non-null  float64
 17  Education Level_basic.9y            28550 non-null  float64
 18  Education Level_high.school         28550 non-null  float64
 19  Education Level_illiterate          28550 non-null  float64
 20  Education Level_professional.course 28550 non-null  float64
 21  Education Level_university.degree   28550 non-null  float64
 22  Education Level_unknown             28550 non-null  float64
 23  Personal Loan_no                    28550 non-null  float64
 24  Personal Loan_unknown               28550 non-null  float64
 25  Personal Loan_yes                   28550 non-null  float64
 26  Contact Method_cellular             28550 non-null  float64
 27  Contact Method_telephone            28550 non-null  float64
 28  Campaign Calls                      28550 non-null  int64
 29  Previously Contacted                28550 non-null  bool
dtypes: bool(1), float64(27), int64(2)
memory usage: 6.6 MB
```

In [465…

```
target_mi_scores_ohe = mutual_info_classif(
    ohe_encoded_X, y_train, random_state=42, discrete_features="auto"
)
```

In [466…

```
target_mi_ohe = pd.Series(target_mi_scores_ohe)
target_mi_ohe.index = ohe_encoded_X.columns
target_mi_ohe = (
    target_mi_ohe.rename(y_train.name)
    .sort_values(ascending=False)
    .round(4)
    .reset_index()
)
target_mi_ohe
```

Out[466...

	index	Subscription Status
0	Previously Contacted	0.0315
1	Contact Method_cellular	0.0159
2	Contact Method_telephone	0.0117
3	Age	0.0116
4	Occupation_blue-collar	0.0056
5	Education Level_university.degree	0.0048
6	Occupation_retired	0.0044
7	Campaign Calls	0.0043
8	Marital Status_divorced	0.0038
9	Occupation_student	0.0031
10	Education Level_basic.4y	0.0028
11	Education Level_basic.9y	0.0025
12	Personal Loan_no	0.0020
13	Personal Loan_yes	0.0019
14	Education Level_basic.6y	0.0016
15	Marital Status_married	0.0014
16	Occupation_admin.	0.0012
17	Occupation_self-employed	0.0007
18	Education Level_professional.course	0.0002
19	Occupation_unemployed	0.0000
20	Occupation_entrepreneur	0.0000
21	Occupation_management	0.0000
22	Occupation_technician	0.0000
23	Occupation_services	0.0000
24	Occupation_housemaid	0.0000
25	Marital Status_single	0.0000
26	Education Level_high.school	0.0000
27	Education Level_illiterate	0.0000
28	Personal Loan_unknown	0.0000

	index	Subscription Status
29	Education Level_unknown	0.0000

In [467…
```
select_cols = SelectKBest(k=15)
select_cols.scores_ = target_mi_ohe
select_cols.pvalues_ = None
select_cols.fit(ohe_encoded_X, y_train)
ohe_encoded_X.columns[select_cols.get_support()]
```

Out[467…
```
Index(['Age', 'Occupation_admin.', 'Occupation_blue-collar',
       'Occupation_retired', 'Occupation_services', 'Occupation_student',
       'Marital Status_married', 'Marital Status_single',
       'Education Level_basic.6y', 'Education Level_basic.9y',
       'Education Level_university.degree', 'Contact Method_cellular',
       'Contact Method_telephone', 'Campaign Calls', 'Previously Contacte
d'],
      dtype='object')
```

In [468…
```
select_cols = SelectPercentile(percentile=70)
select_cols.scores_ = target_mi_ohe
select_cols.pvalues_ = None
select_cols.fit(ohe_encoded_X, y_train)
ohe_encoded_X.columns[select_cols.get_support()]
```

Out[468…
```
Index(['Age', 'Occupation_admin.', 'Occupation_blue-collar',
       'Occupation_entrepreneur', 'Occupation_retired', 'Occupation_service
s',
       'Occupation_student', 'Occupation_unemployed',
       'Marital Status_divorced', 'Marital Status_married',
       'Marital Status_single', 'Education Level_basic.4y',
       'Education Level_basic.6y', 'Education Level_basic.9y',
       'Education Level_illiterate', 'Education Level_university.degree',
       'Education Level_unknown', 'Contact Method_cellular',
       'Contact Method_telephone', 'Campaign Calls', 'Previously Contacte
d'],
      dtype='object')
```

> **Observation:**

- In the scenario when one hot encoded is used on the dataset for model training.
- These are some features selected that can possibly maintain accuracy while reducing dimensionality as well.

Pipeline function preparation

Preparing code to be added to Kedro pipeline

Clean data

In [469…

```
def random_distribution(
    df: pd.DataFrame, target_col: str, target_val: Any = "none"
) -> pd.DataFrame:
    """
    Apply random distribution imputation to selected column

    parameters:
    -----------
    df: pd.DataFrame
      Input DataFrame

    target_col: str
      Selected column to impute

    target_val: Any
      Selected value (data) to be impute
      input: "none" (default) or specific value from column
      example:
        "none"    : imputes all the np.nan or None in specified column
        150       : imputes all values with 150 in the specified column
        "unknown" : imputes all values with unknown in the specified column
    """
    df_temp = df.copy()
    rng = np.random.default_rng(42)
    col = df_temp[target_col]
    if target_val == "none":
        temp_col = col[~col.isna()]
        tobe_fill = col.isna()
    else:
        temp_col = col[col != target_val]
        tobe_fill = col == target_val
    distribution = temp_col.value_counts(normalize=True).tolist()
    labels = temp_col.value_counts().index.tolist()
    fill_mask = tobe_fill
    fill = rng.choice(labels, size=fill_mask.sum(), p=distribution)
    df_temp.loc[fill_mask, target_col] = fill
    return df_temp


def reindex_target_col(df: pd.DataFrame) -> pd.DataFrame:
    """
    Move position of Subscription Status column (target/label) to the back

    parameters:
    -----------
    df: pd.DataFrame
      Input DataFrame
    """
    cols = df.columns.tolist()
    cols.remove("Subscription Status")
    cols.append("Subscription Status")
    df_reorganized = df.reindex(columns=cols)
    return df_reorganized
```

```python
def clean_clientId(df: pd.DataFrame) -> pd.DataFrame:
    """
    Data cleaning on Client ID column
    Function action: Drop Client Id column

    parameters:
    -----------
    df: pd.DataFrame
      Input DataFrame
    """
    df_new = df.drop("Client ID", axis=1)
    return df_new


def clean_age(df: pd.DataFrame) -> pd.DataFrame:
    """
    Data cleaning on Age column
    Function actions: Remove 'years' and keep the age number as integer,
    then apply random distribution imputation to Age column.

    parameters:
    -----------
    df: pd.DataFrame
      Input DataFrame
    """
    df_temp = df.copy()
    df_temp["Age"] = df_temp["Age"].map(lambda x: x.split()[0])
    df_temp["Age"] = df_temp["Age"].astype(int)
    df_new = random_distribution(df_temp, target_col="Age", target_val=150)
    return df_new


def clean_occupation(df: pd.DataFrame) -> pd.DataFrame:
    """
    Data cleaning on Occupation column
    Function action: Drop rows with 'unknown'

    parameters:
    -----------
    df: pd.DataFrame
      Input DataFrame
    """
    df_new = df.drop(df[df["Occupation"] == "unknown"].index, axis=0)
    return df_new


def clean_maritalStatus(df: pd.DataFrame) -> pd.DataFrame:
    """
    Data cleaning on Marital Status column
    Function action: drop rows with 'unknown'

    parameters:
    -----------
    df: pd.DataFrame
```

```
      Input DataFrame
    """
    df_new = df.drop(df[df["Marital Status"] == "unknown"].index, axis=0)
    return df_new


def clean_creditDefault(df: pd.DataFrame) -> pd.DataFrame:
    """
    Data cleaning on Credit Default column
    Function action: 'Drop Credit Default Column

    parameters:
    -----------
    df: pd.DataFrame
      Input DataFrame
    """
    df_new = df.drop("Credit Default", axis=1)
    return df_new


def clean_housingLoan(df: pd.DataFrame) -> pd.DataFrame:
    """
    Data cleaning on Housing Loan column
    Function action: Drop Housing Loan Column

    parameters:
    -----------
    df: pd.DataFrame
      Input DataFrame
    """
    df_new = df.drop("Housing Loan", axis=1)
    return df_new


def clean_personalLoan(df: pd.DataFrame) -> pd.DataFrame:
    """
    Data cleaning on Personal Loan column
    Function action: Apply random distribution imputation to Personal Loan c

    parameters:
    -----------
    df: pd.DataFrame
      Input DataFrame
    """
    df_temp = df.copy()
    df_new = random_distribution(df_temp, target="Personal Loan")
    return df_new


def clean_contactMethod(df: pd.DataFrame) -> pd.DataFrame:
    """
    Data cleaning on Contact Method column
    Function action: Rename 'Cell' value with 'cellular' and 'Telephone' wit

    parameters:
    -----------
```

```
    df: pd.DataFrame
      Input DataFrame
    """
    df_new = df.copy()
    df_new["Contact Method"] = df_new["Contact Method"].map(
        lambda x: "cellular" if x[0].lower() == "c" else "telephone"
    )
    return df_new


def clean_campaignCalls(df: pd.DataFrame) -> pd.DataFrame:
    """
    Data cleaning on Campaign Calls column
    Function action: Absolute/Convert all negative values to positive

    parameters:
    -----------
    df: pd.DataFrame
      Input DataFrame
    """
    df_new = df.copy()
    df_new["Campaign Calls"] = df_new["Campaign Calls"].apply(lambda x: abs(
    return df_new


def clean_previousContactDays(df: pd.DataFrame) -> pd.DataFrame:
    """
    Data cleaning on Previous Contact Days column
    Function action: Rename 999 to -1 and added a Previously Contacted colum
                     as boolean:
                     False = no prior contact
                     True = got prior contact

    parameters:
    -----------
    df: pd.DataFrame
      Input DataFrame
    """
    df_new = df.copy()
    df_new["Previously Contacted"] = df_new["Previous Contact Days"] != 999
    df_new.drop("Previous Contact Days", axis=1, inplace=True)
    df_new = reindex_target_col(df_new)
    return df_new


def clean_subscriptionStatus(df: pd.DataFrame) -> pd.DataFrame:
    """
    Data cleaning on Subscription Status column
    Function action: Rename 'yes' with 1 and 'no' with 0 and convert to bool

    parameters:
    -----------
    df: pd.DataFrame
      Input DataFrame
    """
    df_new = df.copy()
```

```
    df_new["Subscription Status"] = df_new["Subscription Status"].map(
        lambda x: True if x == "yes" else False
    )
    df_new["Subscription Status"] = df_new["Subscription Status"].astype(boo
    return df_new
```

Encode data

In [470…

```
def encoder_selection(encoder: str = "ohe") -> Union[OneHotEncoder, LabelEnc
    """
    Select One Hot Encoding or Integer Encoding method

    parameters:
    -----------
    encoder: "ohe" (default) or "int"
      ohe: one hot encoding
      int: integer encoding
    """
    match encoder:
        case "ohe":
            encoder = OneHotEncoder()
        case "int":
            encoder = LabelEncoder()
        case _:
            raise ValueError("encoder must be 'ohe' or 'int'")
    return encoder


def ohe_encode(df: pd.DataFrame) -> pd.DataFrame:
    """
    One hot encode all object type columns in input DataFrame

    parameters:
    -----------
    df: pd.DataFrame
      Input DataFrame
    """
    encoder = encoder_selection("ohe")
    df_copy = df.copy()
    df_encode = pd.DataFrame(index=df_copy.index)

    for col in df_copy.columns:
        if df_copy[col].dtype == "object":
            encoded = encoder.fit_transform(df_copy[[col]])
            value_col = encoder.get_feature_names_out([col])
            encoded_df = pd.DataFrame(encoded, columns=value_col, index=df_c
            df_encode = pd.concat([df_encode, encoded_df], axis=1)
        else:
            df_encode[col] = df_copy[col]
    return df_encode


def int_encode(df: pd.DataFrame) -> pd.DataFrame:
    """
    Integer encode all object type columns in input DataFrame
```

```
    parameters:
    -----------
    df: pd.DataFrame
      Input DataFrame
    """
    encoder = encoder_selection("int")
    df_copy = df.copy()
    df_encode = pd.DataFrame(index=df_copy.index)

    for col in df_copy.columns:
        if df_copy[col].dtype == "object":
            df_encode[col] = encoder.fit_transform(df_copy[col])
        else:
            df_encode[col] = df_copy[col]
    return df_encode
```

Split Data

In [471…

```
def my_train_test_split(
    df: pd.DataFrame, val_sample: bool = False, test_size: int = 0.2, rs: ir
) -> Union[
    Tuple[pd.DataFrame, pd.DataFrame, pd.Series, pd.Series],
    Tuple[pd.DataFrame, pd.DataFrame, pd.DataFrame, pd.Series, pd.Series, pc
]:
    """
    Split input DataFrame into train, test and val(optional)

    parameters:
    -----------
    df: pd.DataFrame
      Input DataFrame

    val_sample: bool
      State whether to generate validation data sample

    test_size: int
      State the size of test dataset

    rs: int
      Set random state for randomness
    """
    label = "Subscription Status"
    X, y = df.drop(label, axis=1), df[label]
    if val_sample:
        X_train, X_temp, y_train, y_temp = train_test_split(
            X, y, test_size=test_size, random_state=rs, stratify=y
        )  # Use stratify for imbalance target values
        X_val, X_test, y_val, y_test = train_test_split(
            X_temp, y_temp, test_size=0.5, random_state=rs, stratify=y_temp
        )
        return X_train, X_val, X_test, y_train, y_val, y_test

    else:
        X_train, X_test, y_train, y_test = train_test_split(
```

```
            X, y, test_size=test_size, random_state=rs, stratify=y
        )
        return X_train, X_test, y_train, y_test
```

Variation of data preparation

In [472…

```
# Use SMOTE to balance training dataset
def smote(
    X_train: pd.DataFrame, y_train: pd.Series, rs: int = 42
) -> Tuple[pd.DataFrame, pd.Series]:
    """
    Apply SMOTE to training dataset

    paramters:
    ----------
    X_train: pd.DataFrame
      Input features training dataset

    y_train: pd.Series
      Input label training dataset

    rs: int
      Set random state for randomness
    """
    smote = SMOTE(random_state=rs)
    X_train_res, y_train_res = smote.fit_resample(X_train, y_train)
    X_train_res, y_train_res = pd.DataFrame(X_train_res), pd.Series(y_train_
    return X_train_res, y_train_res


# Utilize KNNImputer
def my_knnimputer(
    df: pd.DataFrame,
    target_col: str,
    target_val: Any = None,
    corr_cols: list = None,
    n_neighbors: int = 5,
):
    """
    Impute target values such as missing data with KNN
    Ensure all columns in corr_cols are encoded or numeric

    paramters:
    ----------
    df: pd.DataFrame
      Input DataFrame

    target_col: str
      Column to be impute

    target_val: Any
      Value in target column to be impute

    corr_cols: list
      Correlated columns to assist in KNN imputation
```

```
    n_neighbors: int
      Set the number of similar groups (nearest neighbours) to look
      at when estimating a missing value.
    """
    df_copy = df.copy()
    imputer = KNNImputer(n_neighbors=n_neighbors)

    if target_val is not None:
        df_copy[target_col] = df_copy[target_col].map(
            lambda x: np.nan if x == target_val else x
        )

    if corr_cols is not None:
        final_corr_cols = (
            corr_cols if target_col in corr_cols else corr_cols.append(targe
        )
        df_copy[final_corr_cols] = imputer.fit_transform(df_copy[final_corr_
    else:
        df_copy[target_col] = imputer.fit_transform(df_copy[[target_col]])

    return df_copy


# Vairant of clean age function (with knn)
def clean_age_with_knn(df: pd.DataFrame) -> pd.DataFrame:
    """
    Data cleaning on Age column
    Function actions: Remove 'years' and keep the age number as integer,
    then apply KNN imputation to Age column.

    ! Correlated features selected to assist with imputation are (based on E
      ['Occupation', 'Marital Status', 'Education Level',
      'Subscription Status','Previous Contact Days']

    !! Ensure cleaning for other columns are done, excluding the clean_age f
    before using this function

    !!! This function auto encode the cleaned data with int_encode before im

    parameters:
    -----------
    df: pd.DataFrame
      Input DataFrame
    """
    df_temp = df.copy()
    df_temp["Age"] = df_temp["Age"].map(lambda x: x.split()[0])
    df_temp["Age"] = df_temp["Age"].astype(int)

    corr_cols = ["Marital Status", "Occupation", "Education Level"]

    encoded_df = int_encode(df_temp[corr_cols].append("Age"))
    df_new["Age"] = my_knnimputer(
        encoded_df, target_col="Age", target_val=150, corr_cols=corr_cols
    )
    return df_new
```

Conclusion

Null Values Handling

- Missing Completely At Randome (MCAR) Test:
  - MissingNo
    - Dendrogram
    - Missing Matrix
    - Heatmap
  - Little MCAR Test
  - Mutual information on each column to be impute

These methods have been used to check whether they can be imputed using values from other columns. Therefore, I was able to pinpoint that the columns to be impute are considered as MCAR, has to be imputed independently

- Finalized techniques suggested to impute are:
  - Random Distribution
  - KNN

Data Cleaning & Preparation on columns

- Dropped Columns:
  - Client ID
  - Credit Default
  - Housing Loan
  - Previous Contact Days
- Removed "unknown" values:
  - Occupation
  - Marital Status
- Feature Engineering:
  - Age (remove ‘years old’)
  - Campaign Calls (absolute negative values)
- Impute/Replace Values:
  - Age (150)
  - Personal Loan (nan)
  - Contact Method (cel & Telephone)
  - Subscription Status (yes & no)

- Split column to cretae new feature
    - Previous Contact Days

Dependencies Analysis

- Pairwise Heatmap on numeric columns
- Mutual Information
- Chi Square Test with p values

Additional Suggested Techniques that may help model training

- Feature Selection
    - Mutual information
        - selectKBest: ['Marital Status', 'Education Level', 'Contact Method', 'Campaign Calls', 'Previously Contacted']
        - selectPercentile: ['Marital Status', 'Education Level', 'Contact Method', 'Campaign Calls', 'Previously Contacted']
    - Mutual information for One Hot Encoded scenario:
        - selectKBest: ['Age', 'Occupation_admin.', 'Occupation_blue-collar', 'Occupation_retired', 'Occupation_services', 'Occupation_student', 'Marital Status_married', 'Marital Status_single', 'Education Level_basic.6y', 'Education Level_basic.9y', 'Education Level_university.degree', 'Contact Method_cellular', 'Contact Method_telephone', 'Campaign Calls', 'Previously Contacted']
        - selectPercentile: ['Age', 'Occupation_admin.', 'Occupation_blue-collar', 'Occupation_entrepreneur', 'Occupation_retired', 'Occupation_services', 'Occupation_student', 'Occupation_unemployed', 'Marital Status_divorced', 'Marital Status_married', 'Marital Status_single', 'Education Level_basic.4y', 'Education Level_basic.6y', 'Education Level_basic.9y', 'Education Level_illiterate', 'Education Level_university.degree', 'Education Level_unknown', 'Contact Method_cellular', 'Contact Method_telephone', 'Campaign Calls', 'Previously Contacted']

- Counter imbalance dataset:
    - SMOTE