Week #9 Deliverables

Team member details:

Group Name: Intern_Project

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Problem Description

ABC Bank wants to sell its term deposit product to customers and before launching the product they want to develop a model which help them in understanding whether a particular customer will buy their product or not (based on customer's past interaction with bank or other Financial Institution).

Github Repo link:

https://github.com/1Sophani/DataGlacier-Internship/tree/main/Week%209

Data cleansing and transformation

```
# Reload the data with the correct delimiter and handling of quotes
df = pd.read_csv("bank-full.csv", delimiter=';', quotechar='"')

# Check the first few rows to confirm it loads into the expected 17 columns
df.head(10)
```

	age	job	marital	education	default	balance	housing	loan	contact	day	month	duration
0	58	management	married	tertiary	no	2143	yes	no	unknown	5	may	261
1	44	technician	single	secondary	no	29	yes	no	unknown	5	may	151
2	33	entrepreneur	married	secondary	no	2	yes	yes	unknown	5	may	76
3	47	blue-collar	married	unknown	no	1506	yes	no	unknown	5	may	92
4	33	unknown	single	unknown	no	1	no	no	unknown	5	may	198
5	35	management	married	tertiary	no	231	yes	no	unknown	5	may	139
6	28	management	single	tertiary	no	447	yes	yes	unknown	5	may	217
7	42	entrepreneur	divorced	tertiary	yes	2	yes	no	unknown	5	may	380
8	58	retired	married	primary	no	121	yes	no	unknown	5	may	50
9	43	technician	single	secondary	no	593	yes	no	unknown	5	may	55

```
#Check for null values
df.isnull().sum()
```

```
age          0
job          0
marital      0
education    0
default      0
balance      0
housing      0
loan         0
contact      0
day          0
month        0
duration     0
campaign     0
pdays        0
previous     0
poutcome     0
y            0
dtype: int64
```

```
df['y']
```

```
0        no
1        no
2        no
3        no
4        no
        ...
45206    yes
45207    yes
45208    yes
45209     no
45210     no
Name: y, Length: 45211, dtype: object
```

Solution:

```
# Change categorical to numerical values by encoding
df['y']= df['y'].map({'yes':1, 'no':0})
```

```
print(df['y'])
```

```
0        0
1        0
2        0
3        0
4        0
        ..
45206    1
45207    1
45208    1
45209    0
45210    0
Name: y, Length: 45211, dtype: int64
```

```
# Count the values in the last column
```

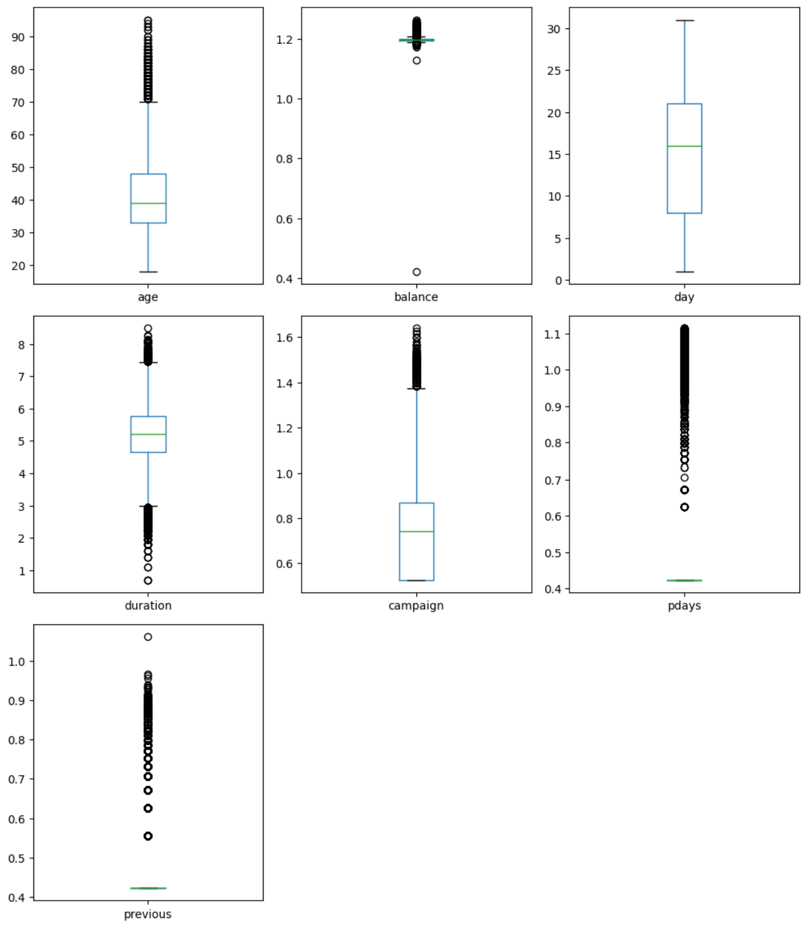
```python
# Count the values in the last column
value_counts = df.iloc[:, -1].value_counts()

# Calculate percentages
total = value_counts.sum()
percentages = (value_counts / total) * 100

print("\nPercentages:")
for value, count in value_counts.items():
    percentage = percentages[value]
    print(f"{value}: {count} ({percentage:.2f}%)")
```

```
Percentages:
no: 39922 (88.30%)
yes: 5289 (11.70%)
```

```python
#balance the data
def balance_csv(input_file, output_file, sample_size=None):
    # Read the CSV file
    df = pd.read_csv(input_file, sep=';')

    # Get the target column (last column)
    target_col = df.columns[-1]

    # Group by the target column
    grouped = df.groupby(target_col, group_keys=False)  # Exclude grouping keys from being 

    # Determine the sample size for each group
    if sample_size is None:
        sample_size = grouped.size().min()
    else:
        sample_size = min(sample_size // 2, grouped.size().min())

    # Take a random sample from each group
    sampled = grouped.apply(lambda x: x.sample(n=sample_size, random_state=42))

    # Shuffle the DataFrame to mix 'yes' and 'no' rows
    df_balanced = sampled.sample(frac=1, random_state=42).reset_index(drop=True)

    # Write to output file
    df_balanced.to_csv(output_file, sep=';', index=False)

    # Print statistics
    value_counts = df_balanced[target_col].value_counts()
    print(f"Output file created: {output_file}")
    print(f"Yes count: {value_counts.get('yes', 0)}")
    print(f"No count: {value_counts.get('no', 0)}")

# Usage
balance_csv('bank-full.csv', 'bank_balanced.csv')
```

```
Output file created: bank_balanced.csv
Yes count: 5289
No count: 5289
```

```
Outliers in column 'age':
Number of outliers: 487
Percentage of outliers: 1.08%

Outliers in column 'balance':
Number of outliers: 4729
Percentage of outliers: 10.46%

Outliers in column 'duration':
Number of outliers: 3235
Percentage of outliers: 7.16%

Outliers in column 'campaign':
Number of outliers: 3064
Percentage of outliers: 6.78%

Outliers in column 'pdays':
Number of outliers: 8257
Percentage of outliers: 18.26%

Outliers in column 'previous':
Number of outliers: 8257
Percentage of outliers: 18.26%
```




```python
#Impute the mean to diminish outliers
def impute_outliers(df):
    for column in ["balance","campaign", "duration", "pdays", "previous"]:
        if column == "pdays":
            valid_data = df[df[column] != -1][column]
        elif column == "previous":
            valid_data = df[df[column] != 0][column]
        else:
            valid_data = df[column]

        mean = valid_data.mean()
        std = valid_data.std()
        lower_limit = mean - std
        upper_limit = mean + std

        # Only impute values that are not -1 for pdays or 0 for previous
        if column == "pdays":
            df.loc[(df[column] < lower_limit) & (df[column] != -1), column] = mean
            df.loc[(df[column] > upper_limit) & (df[column] != -1), column] = mean
        elif column == "previous":
            df.loc[(df[column] < lower_limit) & (df[column] != 0), column] = mean
            df.loc[(df[column] > upper_limit) & (df[column] != 0), column] = mean
        else:
            df.loc[df[column] < lower_limit, column] = mean
            df.loc[df[column] > upper_limit, column] = mean

    return df
```

```python
# Impute outliers
df_imputed = impute_outliers(df)

def check_outliers(df):
    def find_outliers(series, ignore_value=None):
        if ignore_value is not None:
            series = series[series != ignore_value]
        Q1 = series.quantile(0.25)
        Q3 = series.quantile(0.75)
        IQR = Q3 - Q1
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR
        return series[(series < lower_bound) | (series > upper_bound)]

    for column in df.select_dtypes(include=[np.number]).columns:
        if column == "pdays":
            outliers = find_outliers(df[column], ignore_value=-1)
        elif column == "previous":
            outliers = find_outliers(df[column], ignore_value=0)
        else:
            outliers = find_outliers(df[column])

        print(f"\nOutliers in column '{column}':")
        print(f"Number of outliers: {len(outliers)}")
        print(f"Percentage of outliers: {(len(outliers) / len(df[column])) * 100:.2f}%")

df = pd.read_csv('bank-full.csv', delimiter=';')

print("Check outliers for original df & imputed df: ")
check_outliers(df)
print('-------------------------')
check_outliers(df_imputed)
```

```
Outliers in column 'age':
Number of outliers: 487
Percentage of outliers: 1.08%

Outliers in column 'balance':
Number of outliers: 4729
Percentage of outliers: 10.46%

Outliers in column 'day':
Number of outliers: 0
Percentage of outliers: 0.00%

Outliers in column 'duration':
Number of outliers: 3235
Percentage of outliers: 7.16%

Outliers in column 'campaign':
Number of outliers: 3064
Percentage of outliers: 6.78%

Outliers in column 'pdays':
Number of outliers: 49
Percentage of outliers: 0.11%

Outliers in column 'previous':
Number of outliers: 453
Percentage of outliers: 1.00%
-------------------------

Outliers in column 'age':
Number of outliers: 487
Percentage of outliers: 1.08%

Outliers in column 'balance':
Number of outliers: 1381
Percentage of outliers: 3.05%

Outliers in column 'day':
Number of outliers: 0
Percentage of outliers: 0.00%

Outliers in column 'duration':
Number of outliers: 0
Percentage of outliers: 0.00%

Outliers in column 'campaign':
Number of outliers: 9043
Percentage of outliers: 20.00%

Outliers in column 'pdays':
Number of outliers: 8257
Percentage of outliers: 18.26%

Outliers in column 'previous':
Number of outliers: 8257
Percentage of outliers: 18.26%

Outliers in column 'y':
Number of outliers: 5289
Percentage of outliers: 11.70%
```

```
Column: age
Skewness: 0.6848
Interpretation: Moderately Positively Skewed

Column: balance
Skewness: 8.3600
Interpretation: Highly Positively Skewed

Column: day
Skewness: 0.0931
Interpretation: Approximately Symmetric (Slightly Positive)

Column: duration
Skewness: 3.1442
Interpretation: Highly Positively Skewed

Column: campaign
Skewness: 4.8985
Interpretation: Highly Positively Skewed

Column: pdays
Skewness: 2.6156
Interpretation: Highly Positively Skewed

Column: previous
Skewness: 41.8451
Interpretation: Highly Positively Skewed
```

[83]: ['balance', 'duration', 'campaign', 'pdays', 'previous']

```
def apply_log_transformations(df, log_columns):
    df_transformed = df.copy()

    for col in log_columns:
        if col in df_transformed.columns:
            min_value = df_transformed[col].min()
            if min_value <= 0:
                df_transformed[col] = df_transformed[col] - min_value + 1
            df_transformed[col] = np.log1p(df_transformed[col])

    return df_transformed

df = pd.read_csv('bank-full.csv', delimiter=';')
log_columns = check_skewness(df, printing=False)
prev_len = 0
while len(log_columns) != prev_len:
    prev_len = len(log_columns)
    df = apply_log_transformations(df, check_skewness(df, printing=False))
    log_columns = check_skewness(df, printing=False)
check_skewness(df)
```

```
Column: age
Skewness: 0.6848
Interpretation: Moderately Positively Skewed

Column: balance
Skewness: -28.1249
Interpretation: Highly Negatively Skewed

Column: day
Skewness: 0.0931
Interpretation: Approximately Symmetric (Slightly Positive)

Column: duration
Skewness: -0.4055
Interpretation: Approximately Symmetric (Slightly Negative)

Column: campaign
Skewness: 0.7709
Interpretation: Moderately Positively Skewed

Column: pdays
Skewness: 1.6679
Interpretation: Highly Positively Skewed

Column: previous
Skewness: 2.2532
Interpretation: Highly Positively Skewed
```

: ['balance', 'pdays', 'previous']

Tabular data details:

Total number of observations	42511
Total number of files	3
Total number of features	17
Base format of the file	.csv and .ipynb
Size of the data	5.37 MB

Submitted by: Sophonie Sidrac
Submitted to: Data Glacier