EDA Presentation

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Initialization

```
#reading in necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
#loading in data
bank_data = pd.read_csv('bank-additional-full.csv', sep=';')
#displaying first several rows
bank_data.head()
```

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	...	campaign	pdays	previous	poutcome	emp.var.rate	cons
0	56	housemaid	married	basic.4y	no	no	no	telephone	may	mon	...	1	999	0	nonexistent	1.1	
1	57	services	married	high.school	unknown	no	no	telephone	may	mon	...	1	999	0	nonexistent	1.1	
2	37	services	married	high.school	no	yes	no	telephone	may	mon	...	1	999	0	nonexistent	1.1	
3	40	admin.	married	basic.6y	no	no	no	telephone	may	mon	...	1	999	0	nonexistent	1.1	
4	56	services	married	high.school	no	no	yes	telephone	may	mon	...	1	999	0	nonexistent	1.1	

5 rows × 21 columns

We can see that our dataset is made up of 20 features columns and a single target column. The columns are a mix of numeric and categorical variables. We can now examine our data for cleaning and preparation for use in models.

Data Understanding and Preparation

```
#viewing overall dataset info
bank_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 21 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             41188 non-null  int64
 1   job             41188 non-null  object
 2   marital         41188 non-null  object
 3   education       41188 non-null  object
 4   default         41188 non-null  object
 5   housing         41188 non-null  object
 6   loan            41188 non-null  object
 7   contact         41188 non-null  object
 8   month           41188 non-null  object
 9   day_of_week     41188 non-null  object
 10  duration        41188 non-null  int64
 11  campaign        41188 non-null  int64
 12  pdays           41188 non-null  int64
 13  previous        41188 non-null  int64
 14  poutcome        41188 non-null  object
 15  emp.var.rate    41188 non-null  float64
 16  cons.price.idx  41188 non-null  float64
 17  cons.conf.idx   41188 non-null  float64
 18  euribor3m       41188 non-null  float64
 19  nr.employed     41188 non-null  float64
 20  y               41188 non-null  object
dtypes: float64(5), int64(5), object(11)
memory usage: 6.6+ MB
```

It appears that we have a total of 41188 rows, with no apparent missing values. Our data types appear to match the column expectations. We will now confirm that there are no missing values by counting null values.

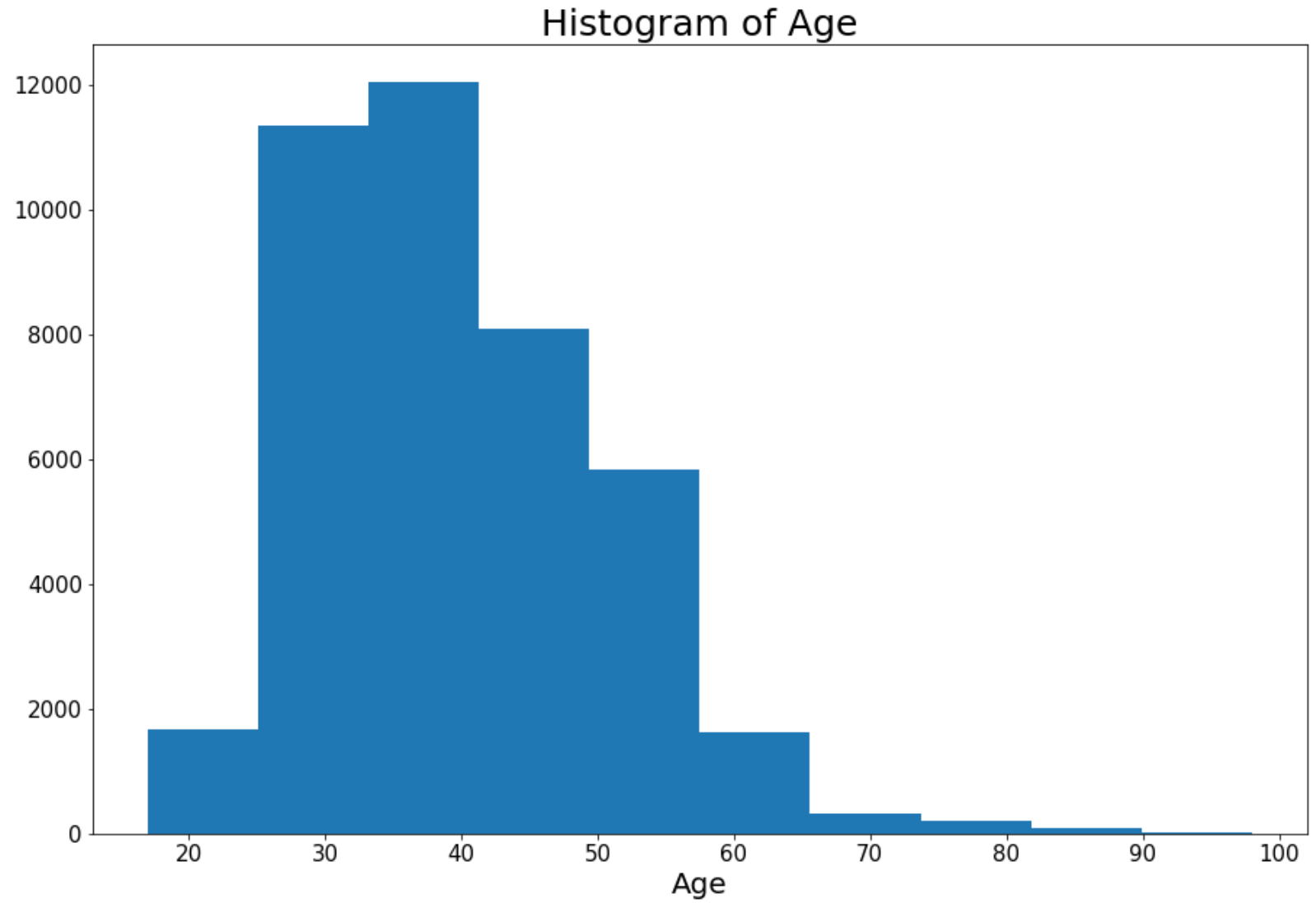
```
#finding count of all null values by column.
bank_data.isnull().sum()
```

```
age               0
job               0
marital           0
education         0
default           0
housing           0
loan              0
contact           0
month             0
day_of_week       0
duration          0
campaign          0
pdays             0
previous          0
poutcome          0
emp.var.rate      0
cons.price.idx    0
cons.conf.idx     0
euribor3m         0
nr.employed       0
y                 0
dtype: int64
```

We can see that there are no missing values which will need to be addressed at this time. We will now begin our column-based examination of our data for skew and potential outliers.

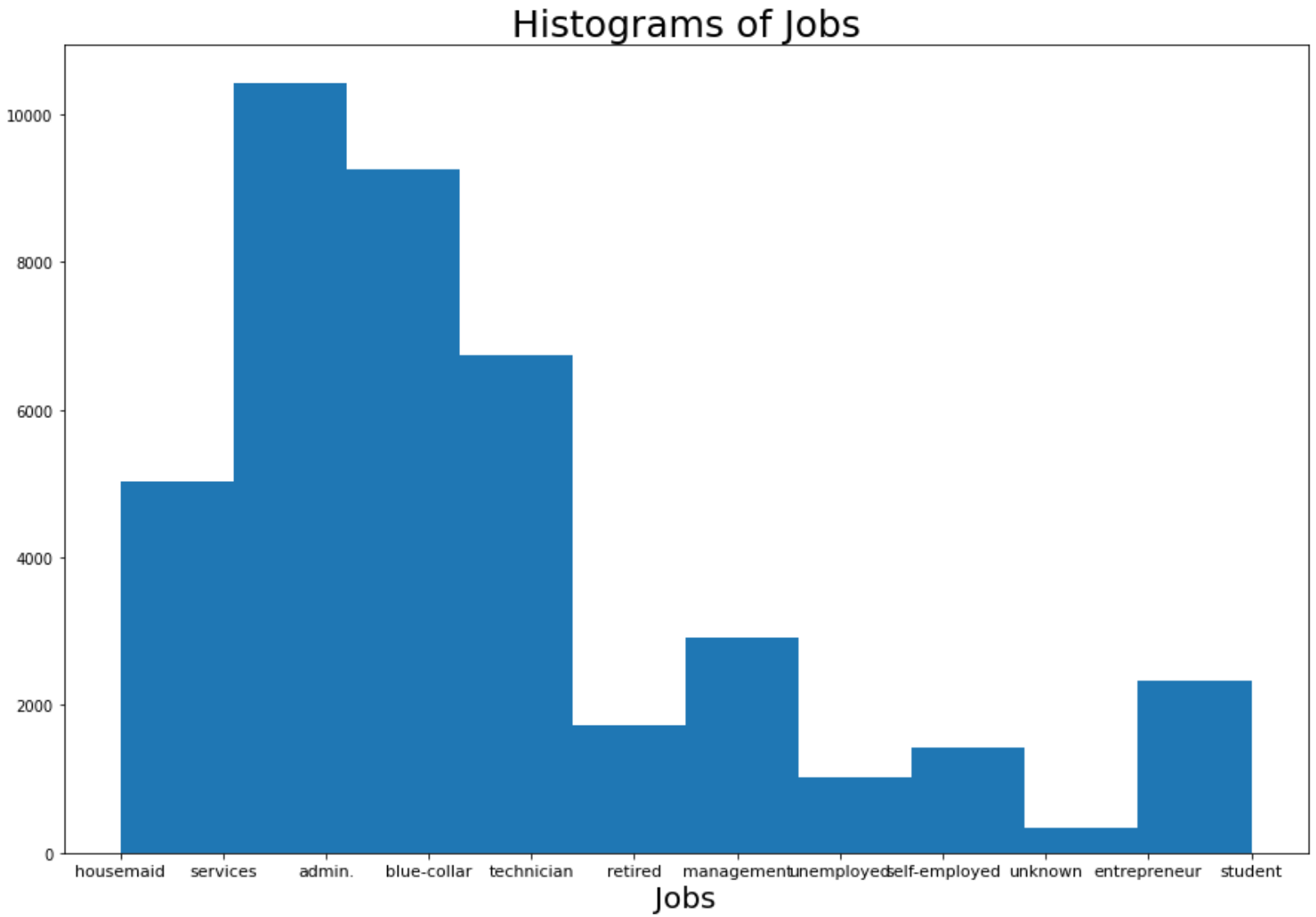
Age

```
plt.figure(figsize=(15,10))
plt.hist(bank_data['age'])
plt.title('Histogram of Age', fontsize=25)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
plt.xlabel('Age', fontsize=20)
plt.show()
```



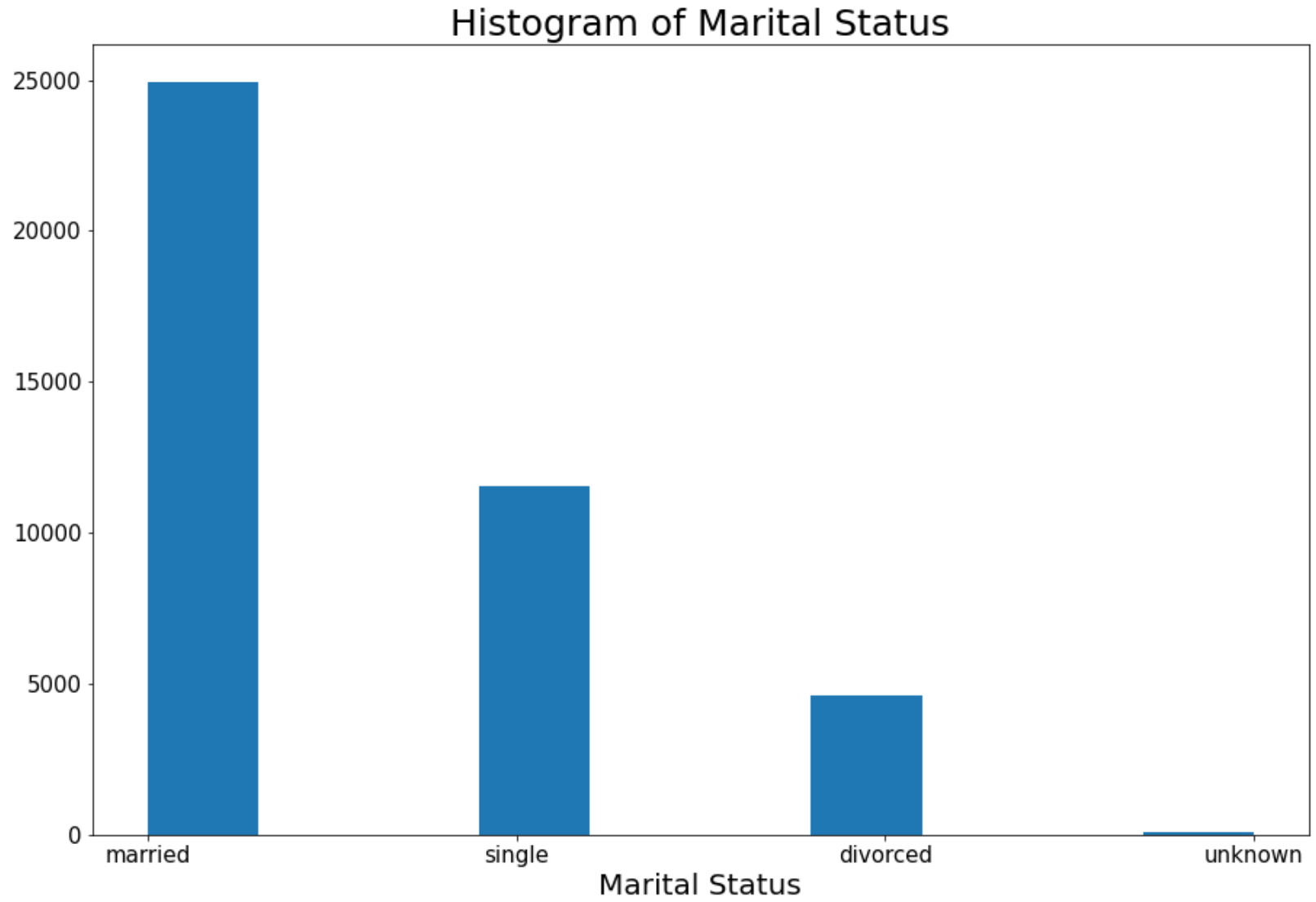
Job

```
plt.figure(figsize=(15,10))
plt.hist(bank_data['job'])
plt.title('Histograms of Jobs', fontsize=25)
plt.xlabel('Jobs', fontsize=20)
plt.xticks(fontsize=11)
plt.show()
```



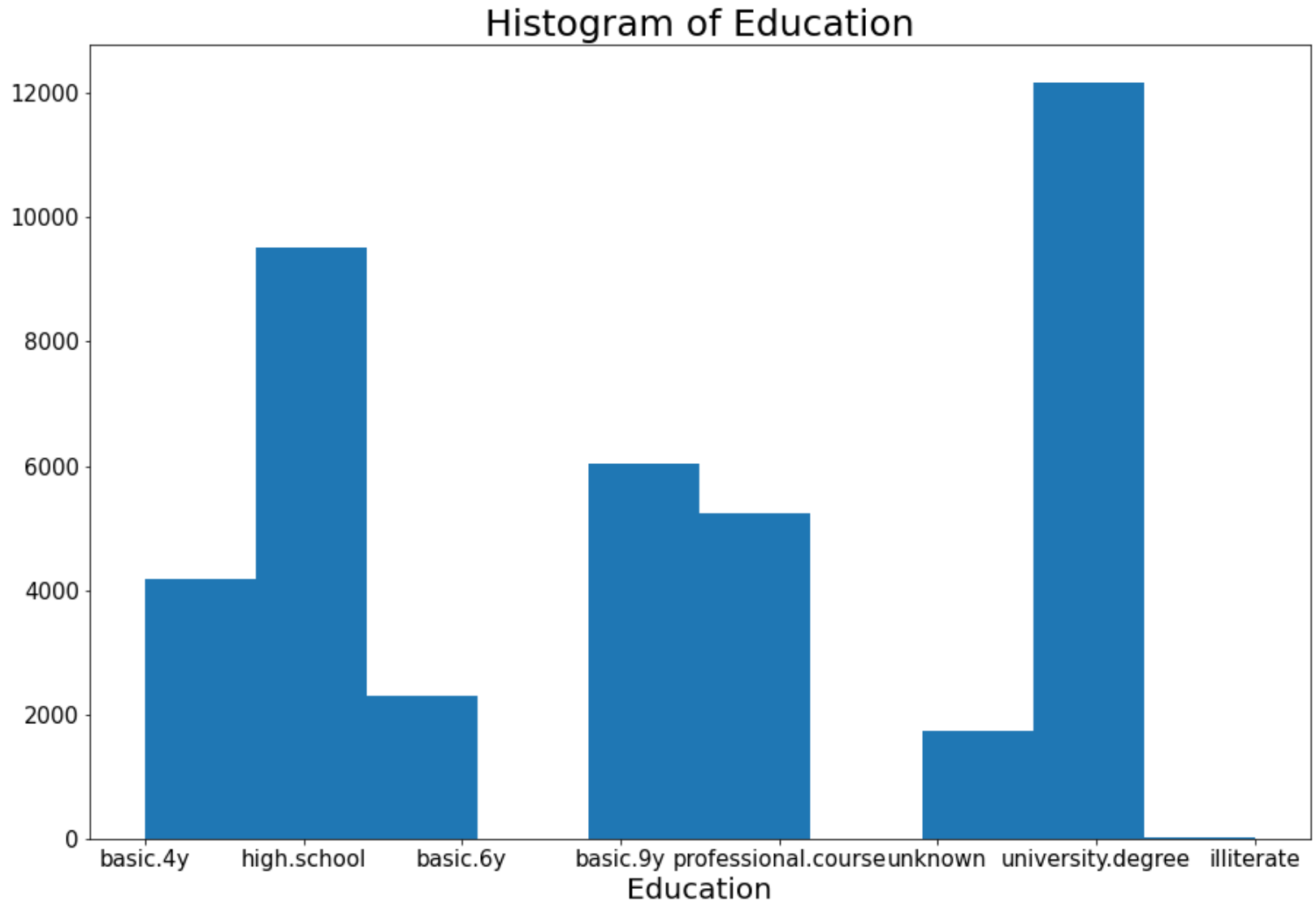
Marital

```
plt.figure(figsize=(15,10))
plt.hist(bank_data['marital'])
plt.title('Histogram of Marital Status', fontsize=25)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
plt.xlabel('Marital Status', fontsize=20)
plt.show()
```



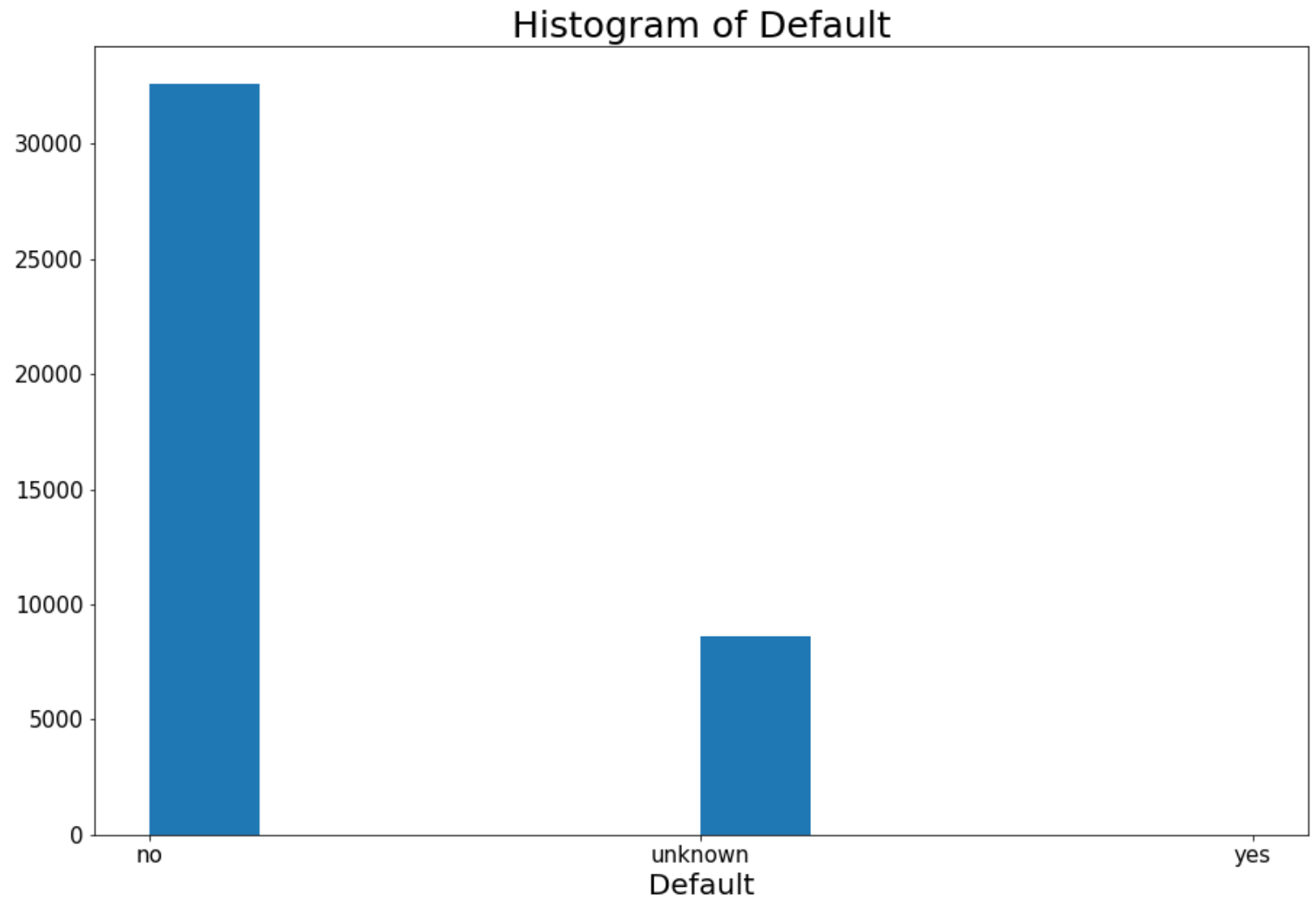
Education

```
plt.figure(figsize=(15,10))
plt.hist(bank_data['education'])
plt.title('Histogram of Education', fontsize=25)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
plt.xlabel('Education', fontsize=20)
plt.show()
```



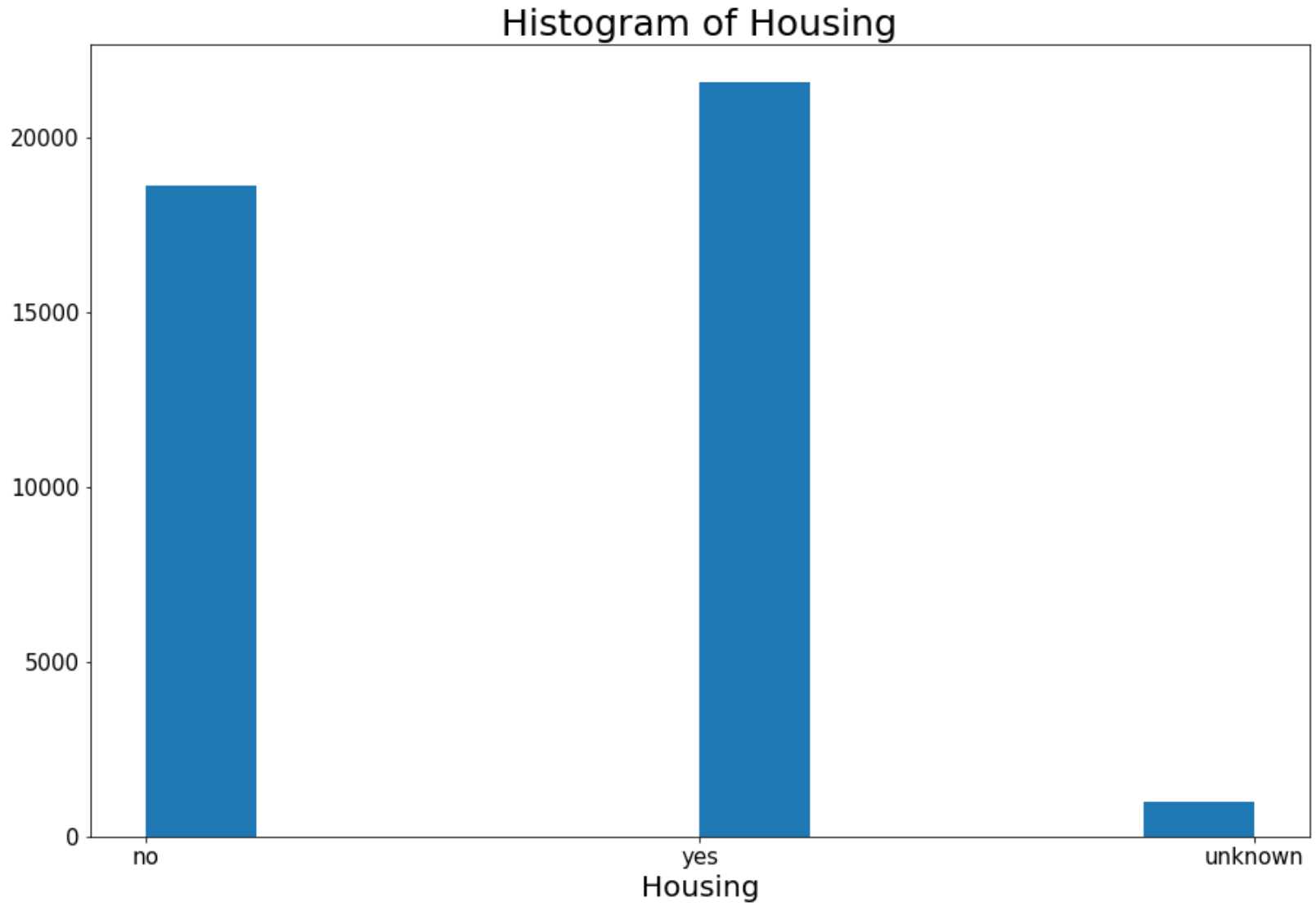
Default

```
plt.figure(figsize=(15,10))
plt.hist(bank_data['default'])
plt.title('Histogram of Default', fontsize=25)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
plt.xlabel('Default', fontsize=20)
plt.show()
```



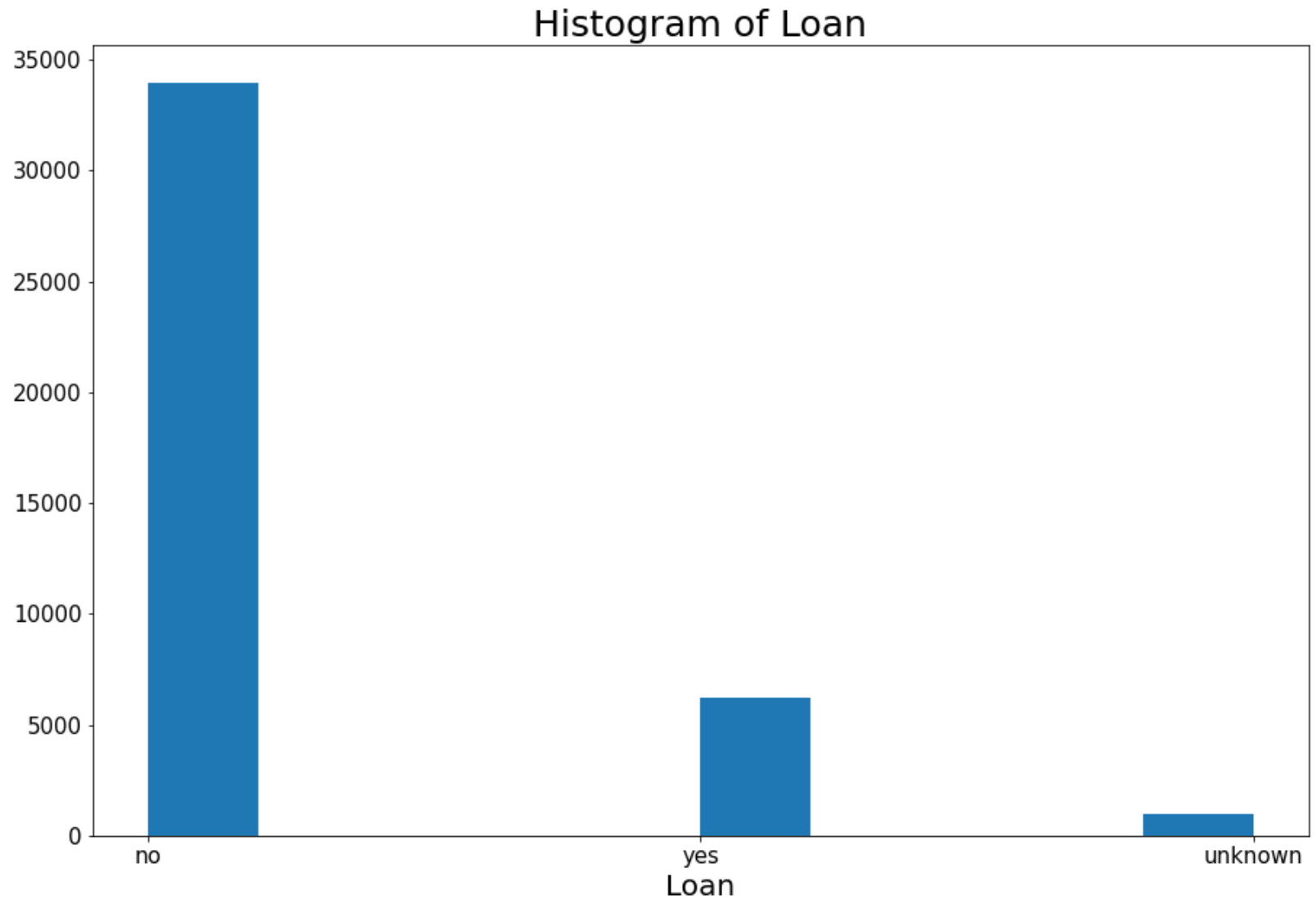
Housing

```
plt.figure(figsize=(15,10))
plt.hist(bank_data['housing'])
plt.title('Histogram of Housing', fontsize=25)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
plt.xlabel('Housing', fontsize=20)
plt.show()
```



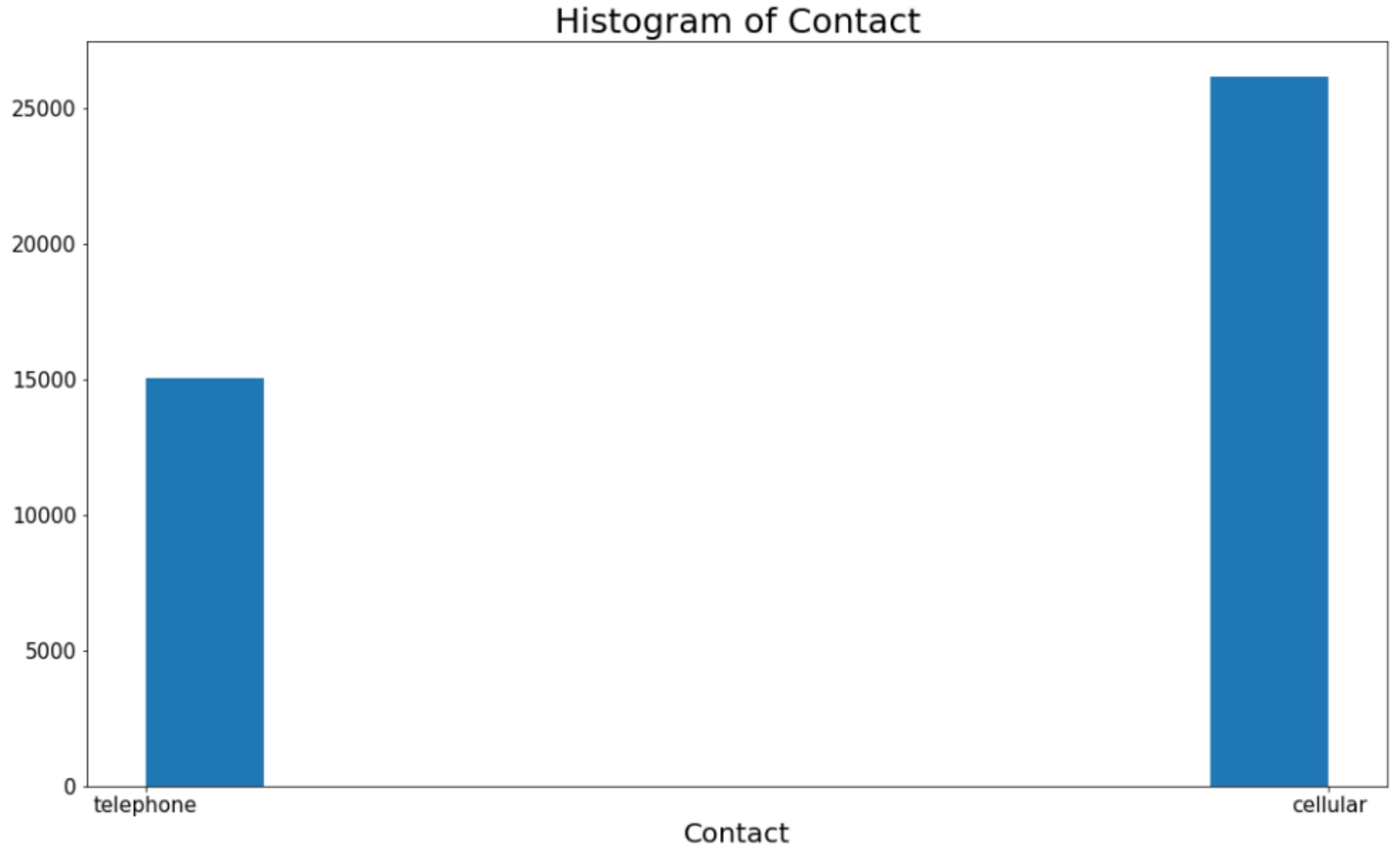
Loan (history of having a loan)

```
plt.figure(figsize=(15,10))
plt.hist(bank_data['loan'])
plt.title('Histogram of Loan', fontsize=25)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
plt.xlabel('Loan', fontsize=20)
plt.show()
```



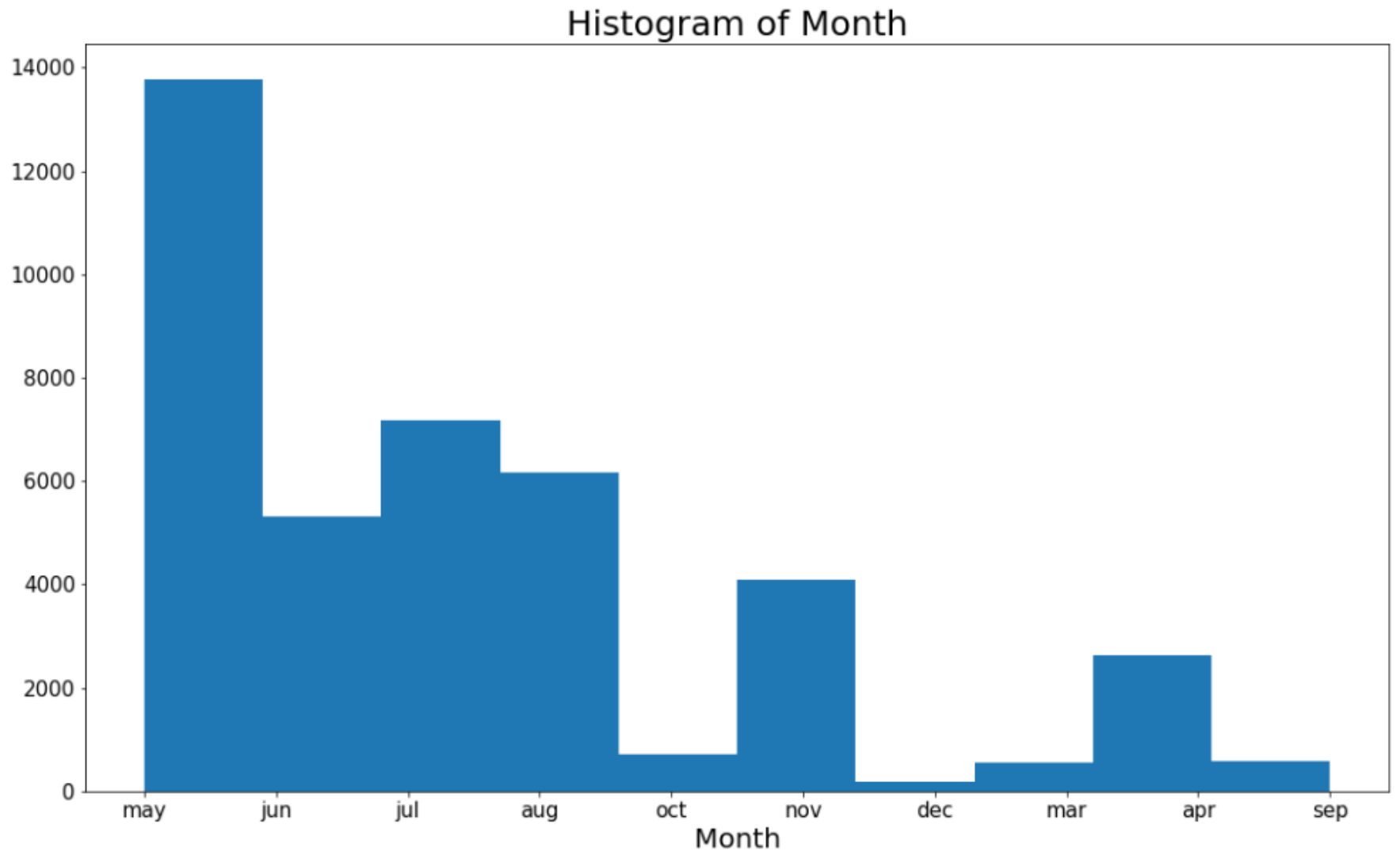
Contact (cell vs telephone)

```
plt.figure(figsize=(17,10))
plt.hist(bank_data['contact'])
plt.title('Histogram of Contact', fontsize=25)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
plt.xlabel('Contact', fontsize=20)
plt.show()
```



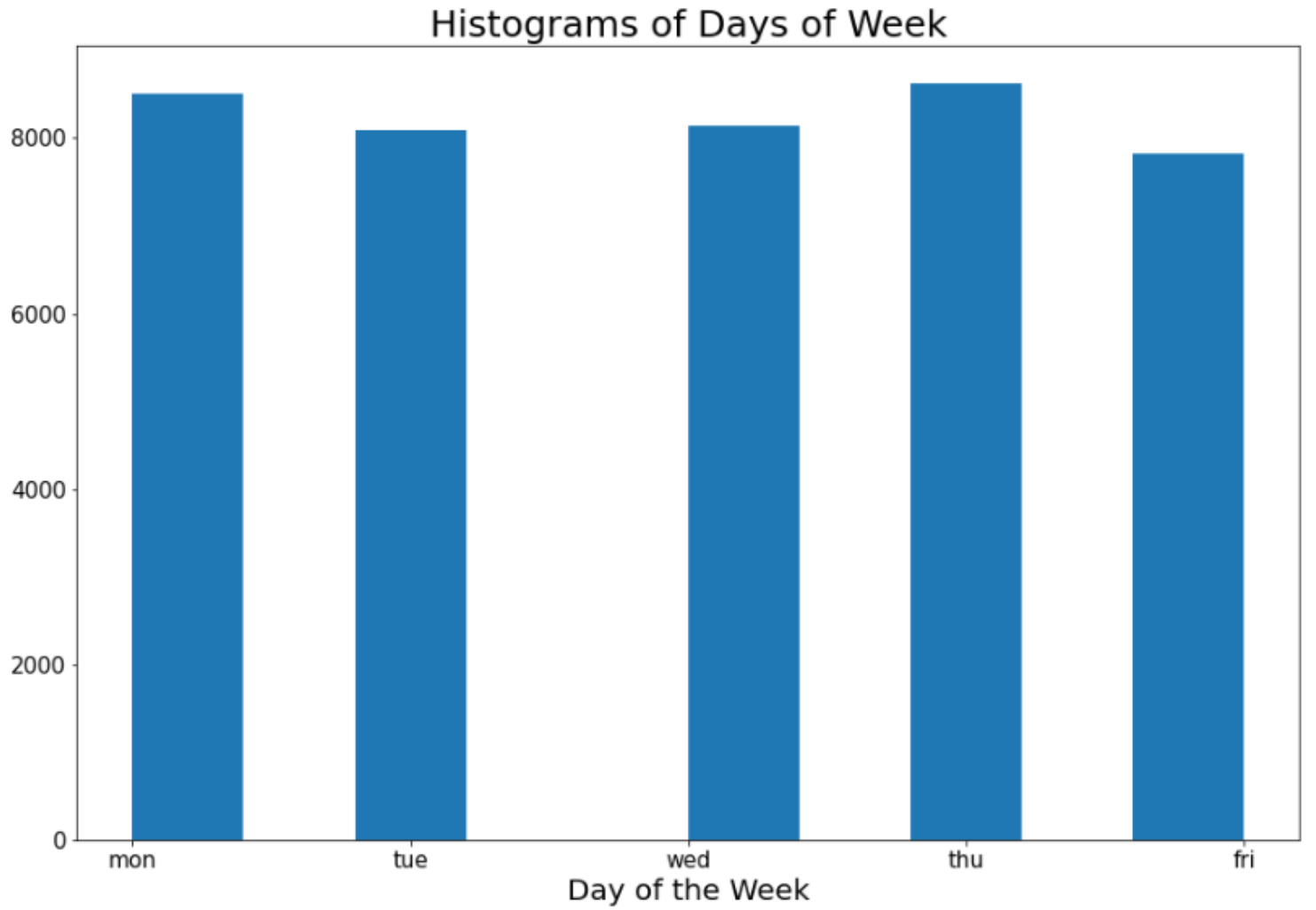
Month

```
plt.figure(figsize=(17,10))
plt.hist(bank_data['month'])
plt.title('Histogram of Month', fontsize=25)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
plt.xlabel('Month', fontsize=20)
plt.show()
```



Day of the Week

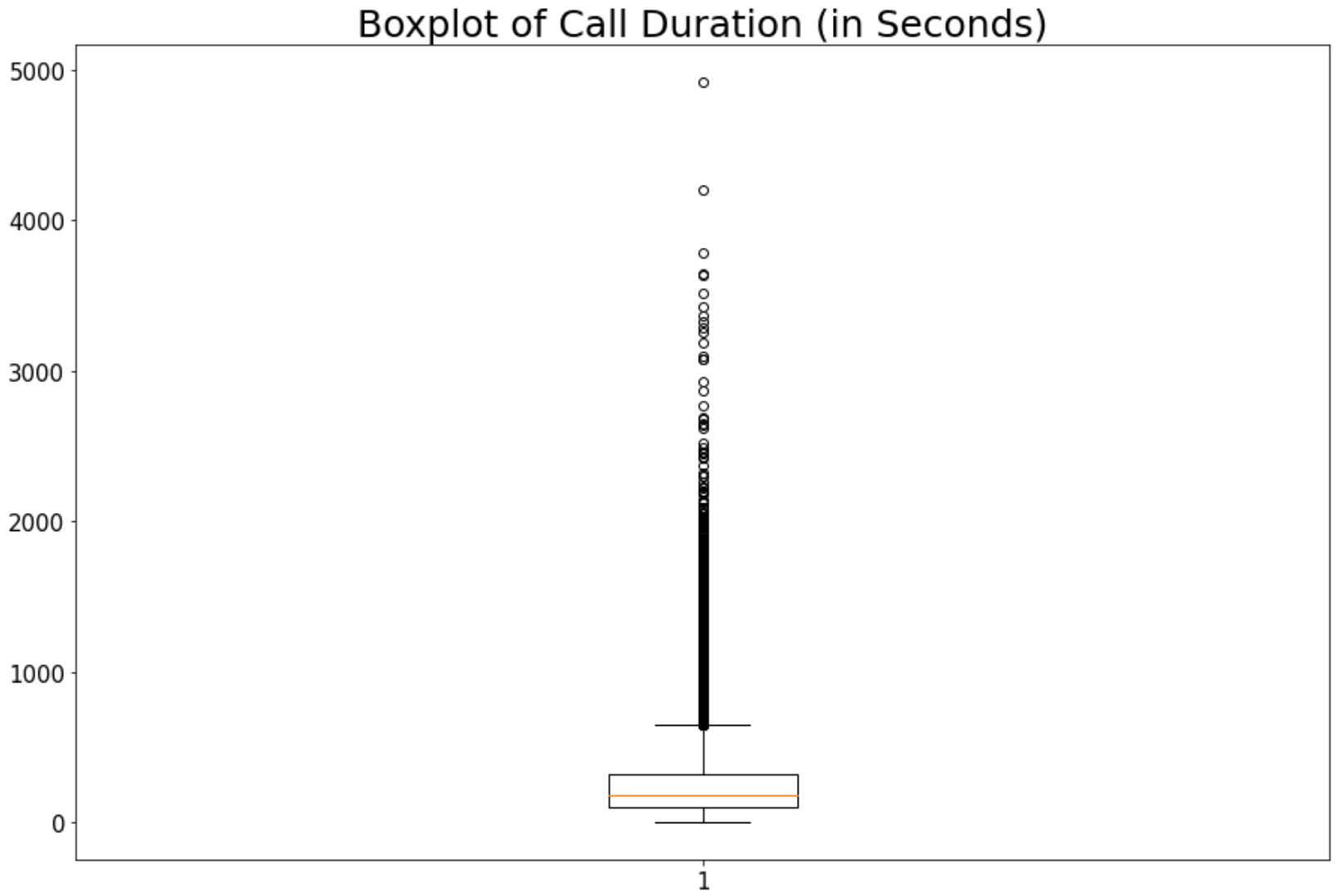
```
#examination of day_of_week column
plt.figure(figsize=(15,10))
plt.hist(bank_data['day_of_week'])
plt.title('Histograms of Days of Week', fontsize=25)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
plt.xlabel('Day of the Week', fontsize=20)
plt.show()
```



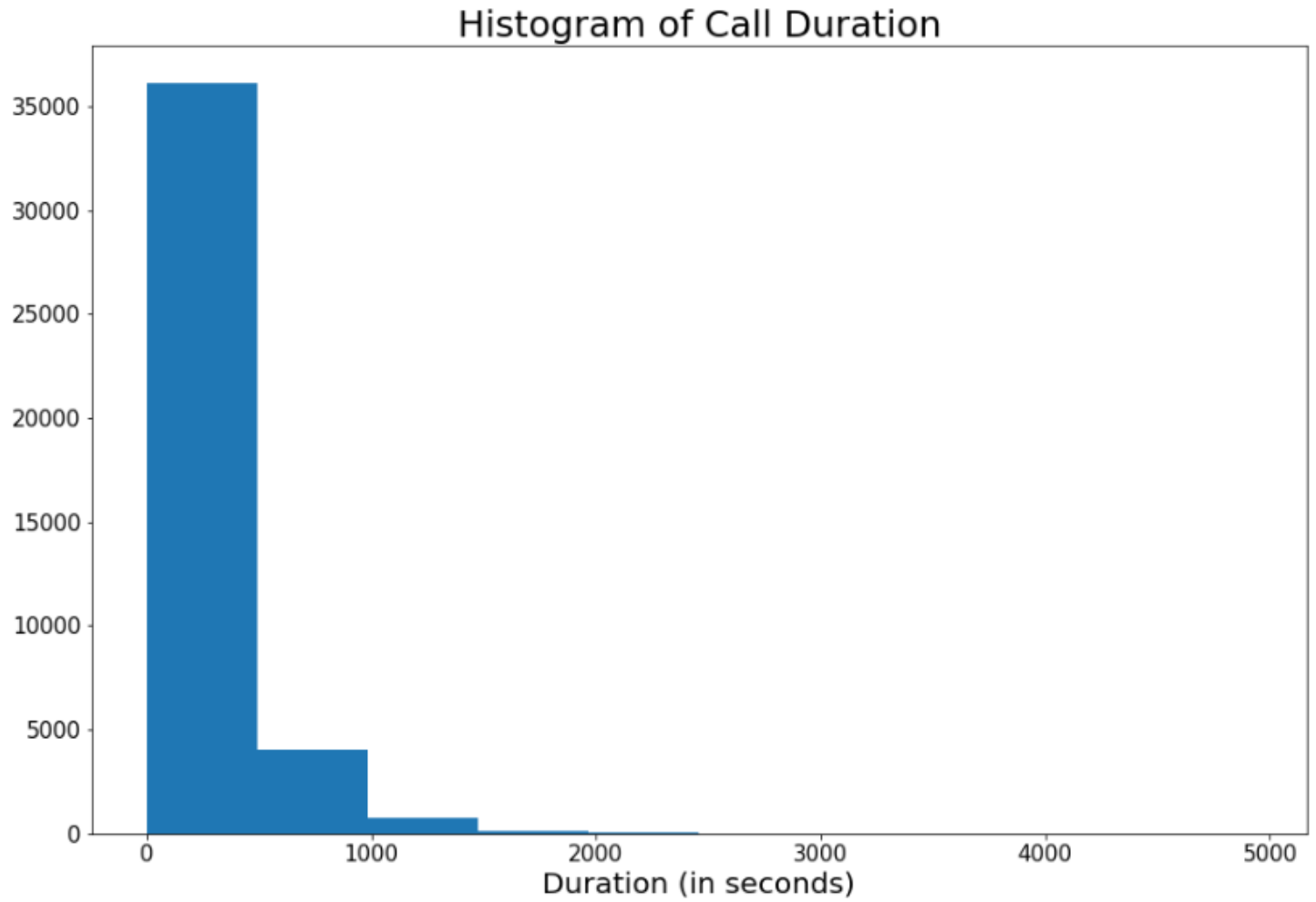
It appears that there each day of the week has a relatively similar number of calls; there is not a single day of the week which outperforms the others.

Call Duration

```
#creating boxplot of call duration
plt.figure(figsize=(15,10))
plt.boxplot(bank_data['duration'])
plt.title('Boxplot of Call Duration (in Seconds)', fontsize=25)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
plt.show()
```



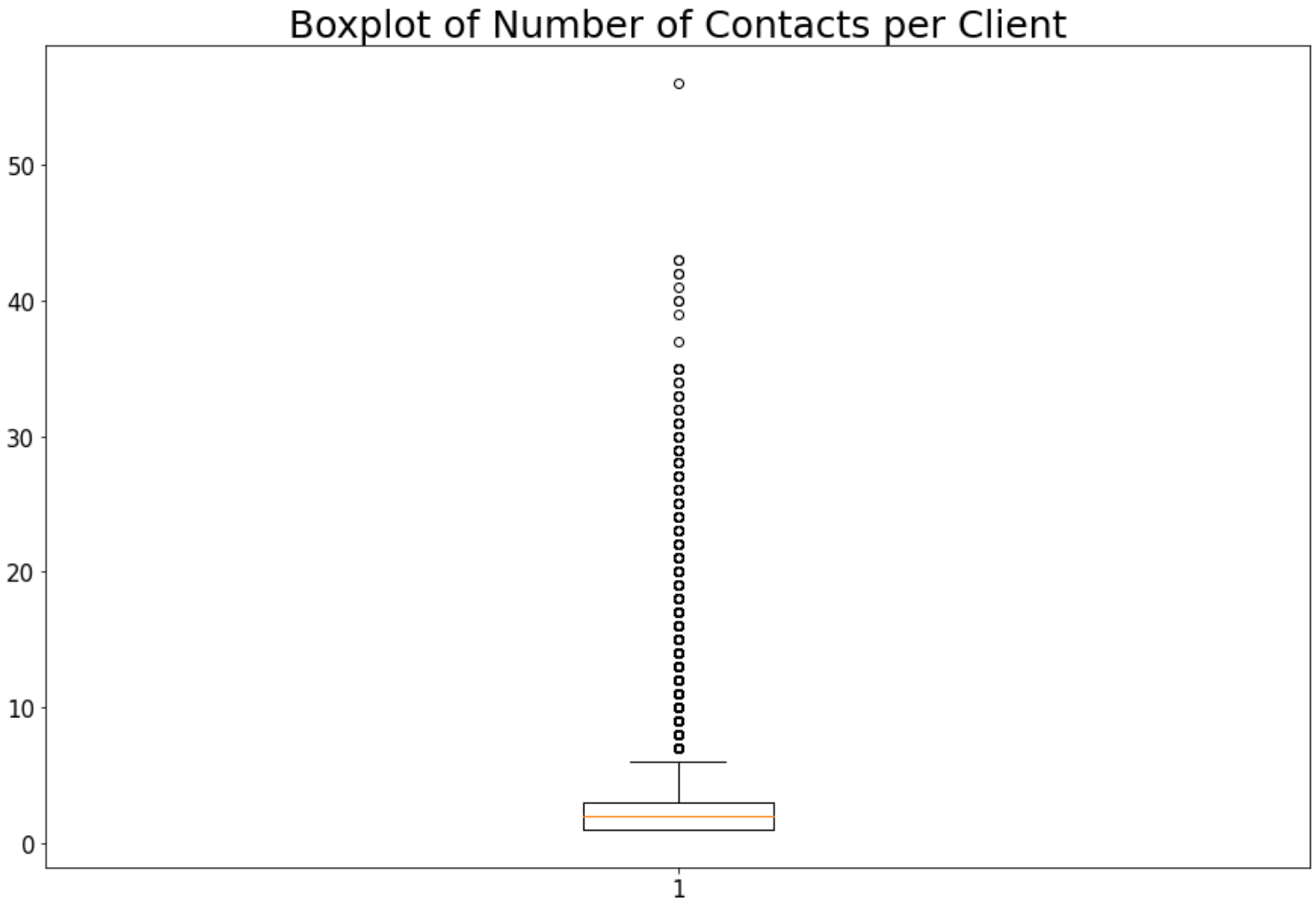
```
#creating histogram of call duration
plt.figure(figsize=(15,10))
plt.hist(bank_data['duration'])
plt.title('Histogram of Call Duration', fontsize=25)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
plt.xlabel('Duration (in seconds)', fontsize=20)
plt.show()
```



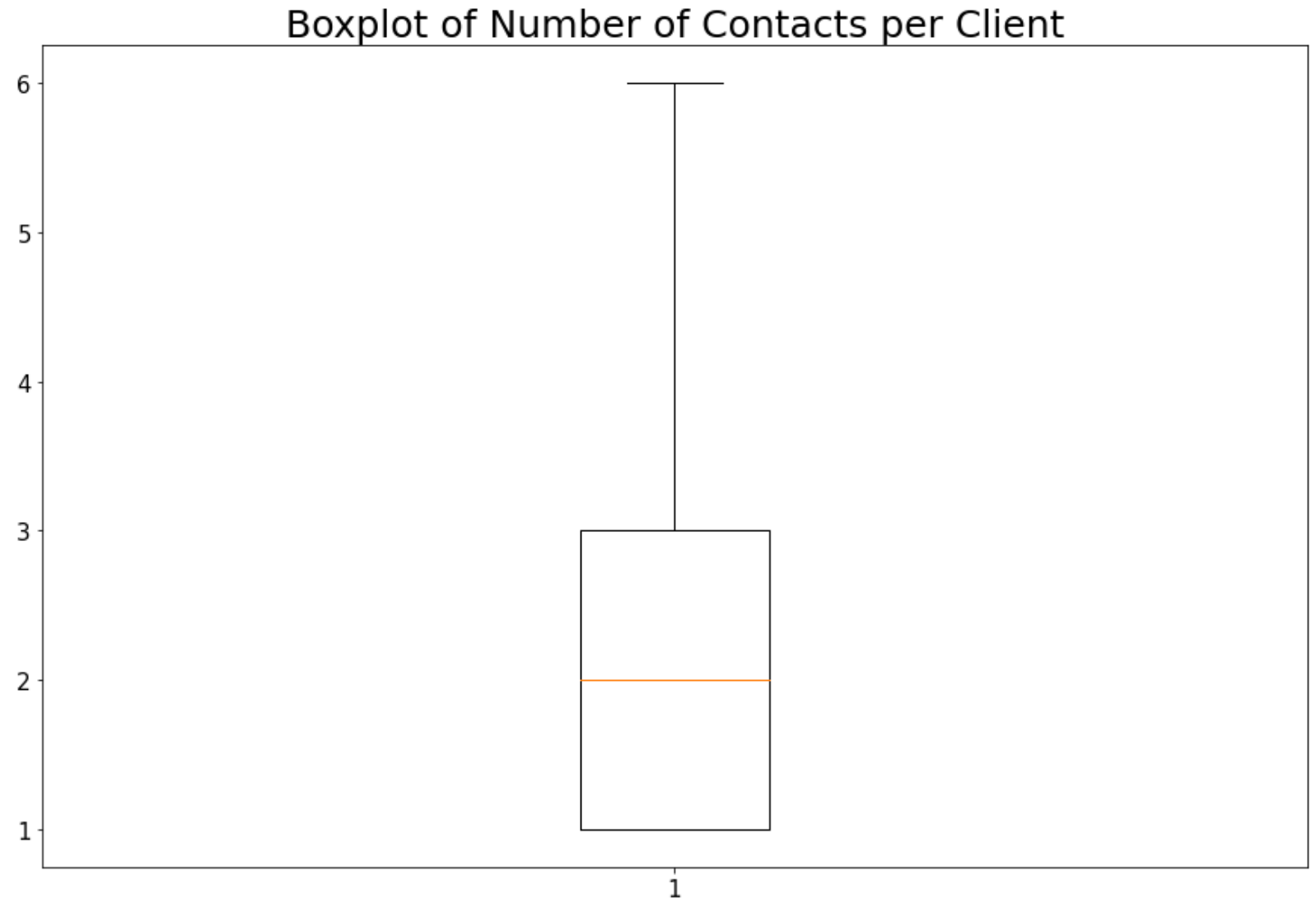
There are a significant number of outliers related to this column and it is right skewed. This is likely due to the majority of calls resulting in no term deposit subscription being close to zero, bringing down the average call time. This would typically need to be addressed prior to model creation, but due to the fact this variable is not known until after the call is completed, it will not be helpful in creating a accurate predictive model. Therefore this feature will be dropped from the dataset after exploration prior to model creation.

Campaign (Number of contacts per client)

```
#creating boxplot of campaign
plt.figure(figsize=(15,10))
plt.boxplot(bank_data['campaign'])
plt.title('Boxplot of Number of Contacts per Client', fontsize=25)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
plt.show()
```

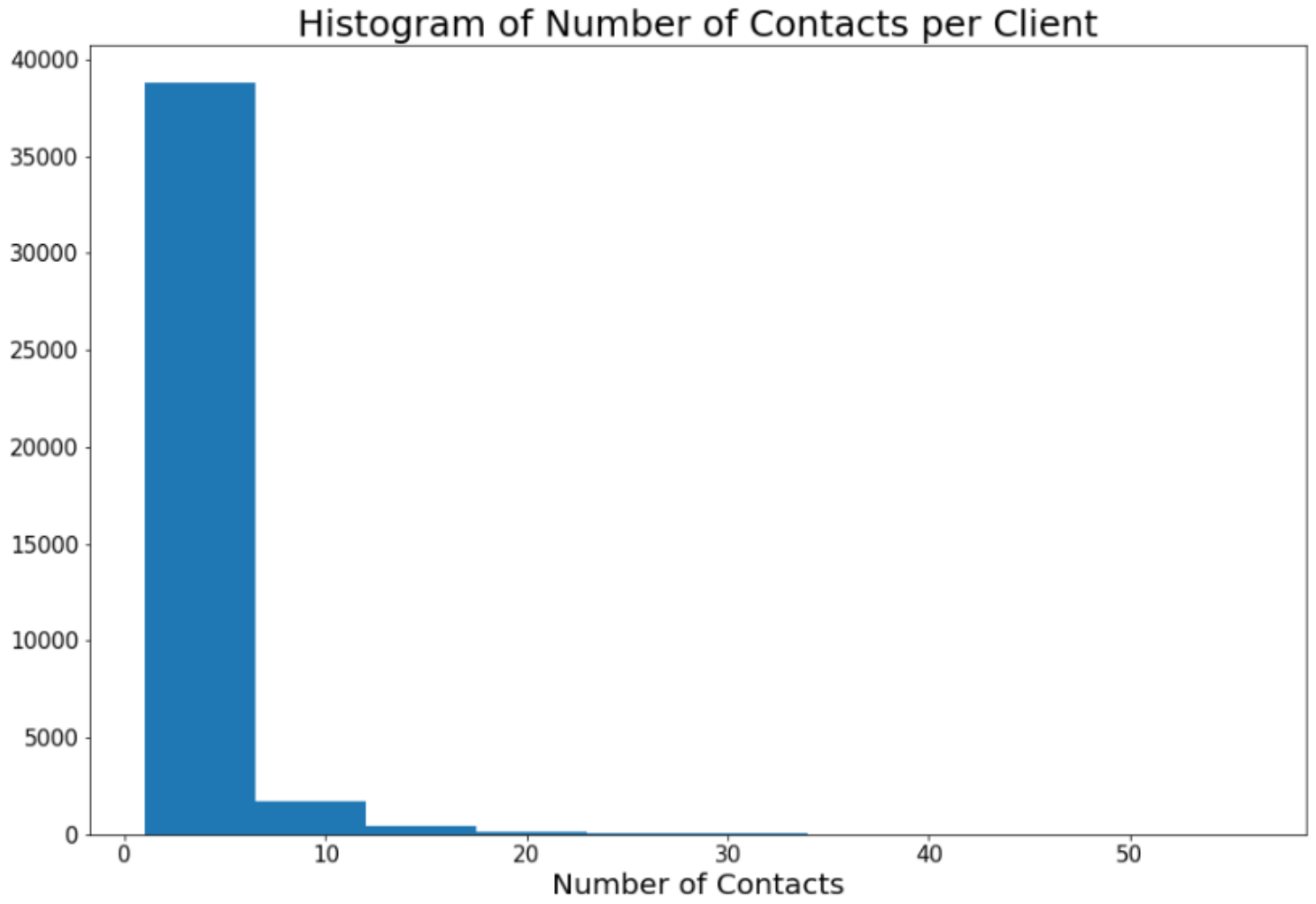


```
plt.figure(figsize=(15,10))
plt.boxplot(bank_data['campaign'], showfliers=False)
plt.title('Boxplot of Number of Contacts per Client', fontsize=25)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
plt.show()
```



The median number of contacts are 2 while 75% of contacts were 3 or under.

```
#creating histogram of campaign
plt.figure(figsize=(15,10))
plt.hist(bank_data['campaign'])
plt.title('Histogram of Number of Contacts per Client', fontsize=25)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
plt.xlabel('Number of Contacts', fontsize=20)
plt.show()
```

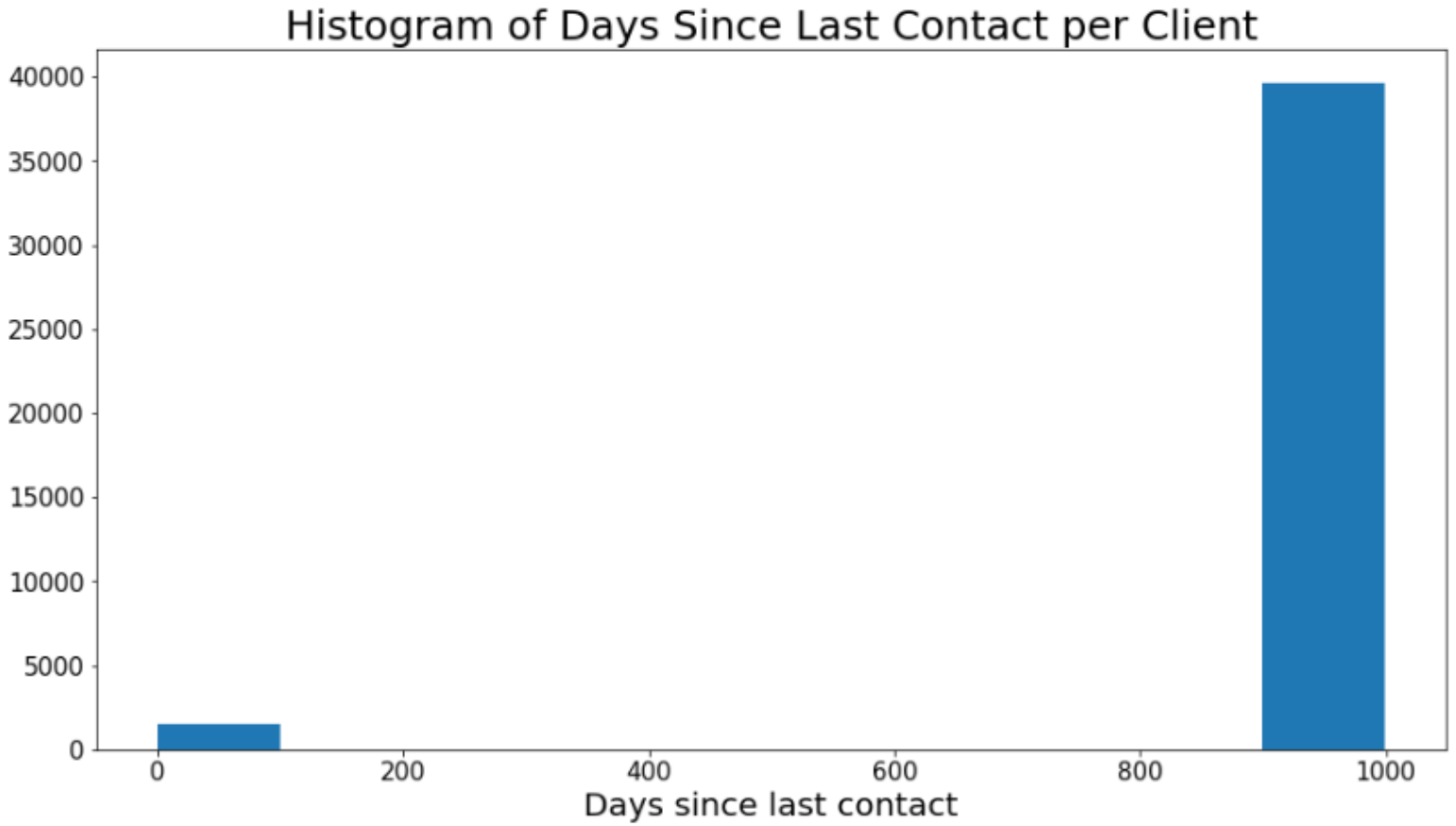


We can see a similar issue, with large numbers of outliers and righ-skewed data. It can be assumed that since this is likely due to the majority of customers being relatively new, since the values are a count of every time the client has been contacted. It may be worth further exploration into length of time a client has been with the company to see if this has a greater effect on our predictions.

Pdays (Number of days since last contact of previous campaign)

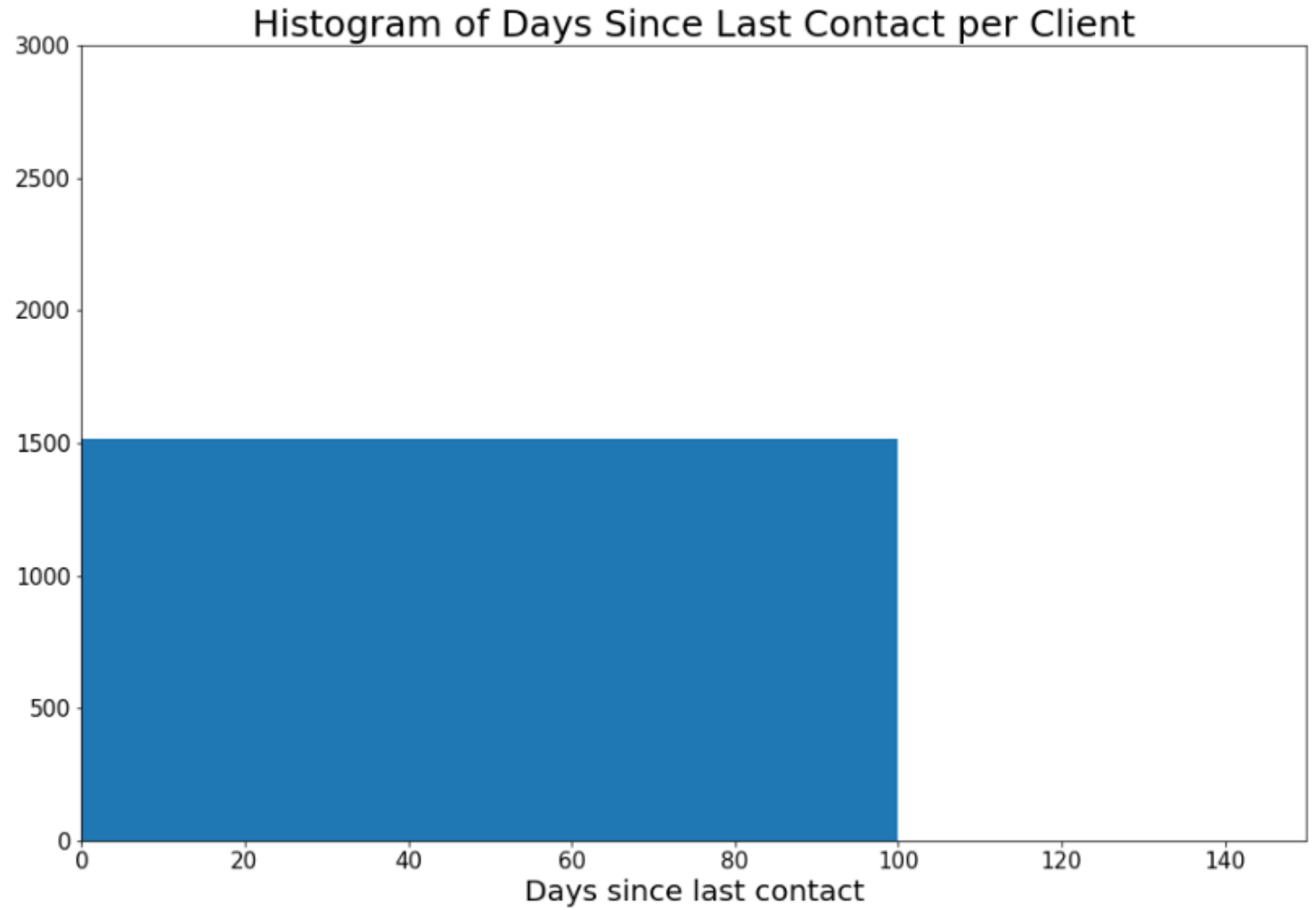
It is important to note that a client which has not been contacted previously will have a pday value of 999. This will make it difficult to interpret a boxplot due to the large spread. Therefore a histogram will be utilized to better examine the data.

```
#creating histogram of pdays
plt.figure(figsize=(15,8))
plt.hist(bank_data['pdays'])
plt.title('Histogram of Days Since Last Contact per Client', fontsize=25)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
plt.xlabel('Days since last contact', fontsize=20)
plt.show()
```



As expected, the majority of clients fall into the category of never being contacted, and thus have a value of 999. We will take a closer look at those who have been contacted previously by adjusting our limits.

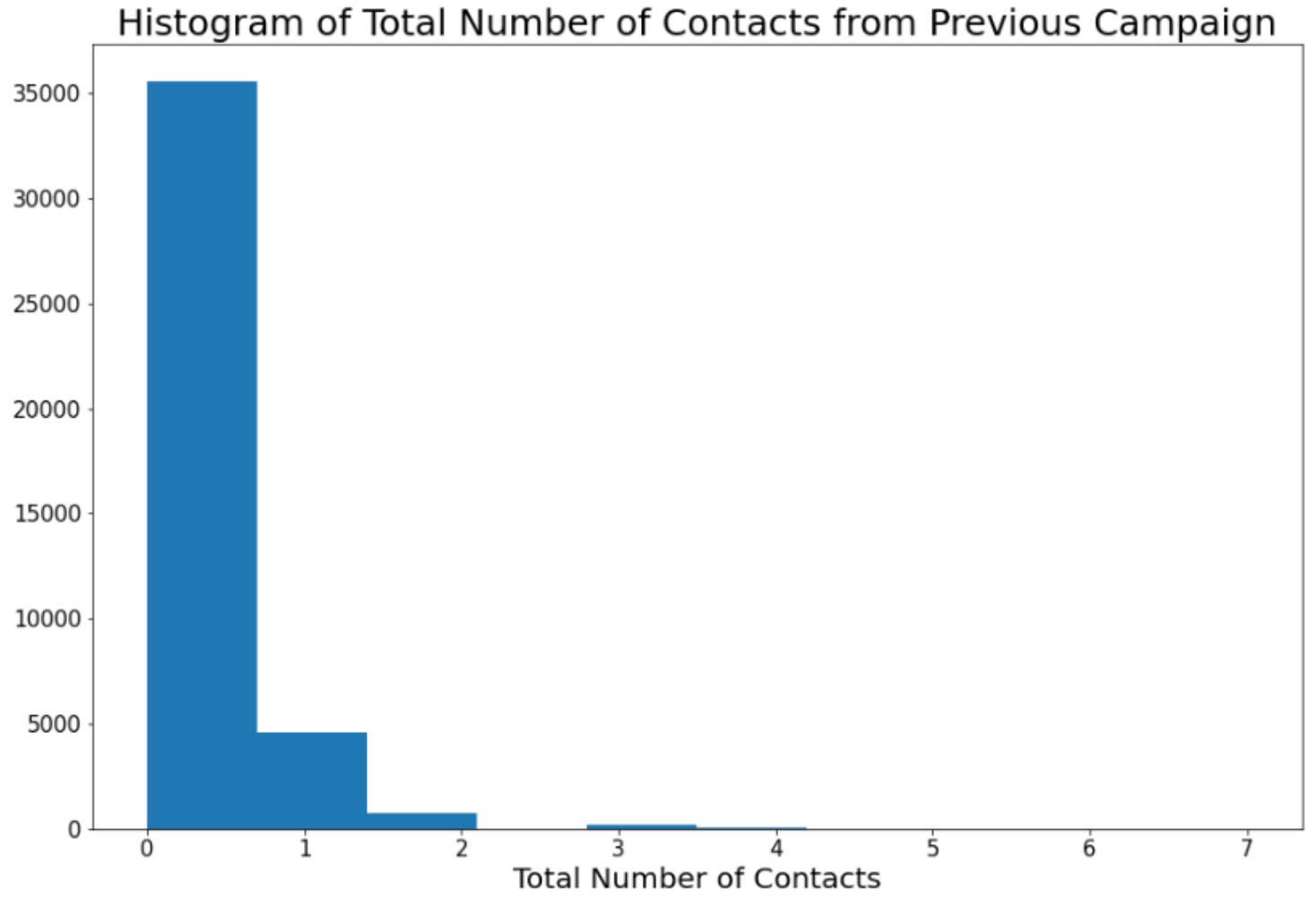
```
#creating histogram of pdays -previously contacted
plt.figure(figsize=(15,10))
plt.hist(bank_data['pdays'])
plt.title('Histogram of Days Since Last Contact per Client', fontsize=25)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
plt.xlabel('Days since last contact', fontsize=20)
plt.xlim(0,150)
plt.ylim(0, 3000)
plt.show()
```



It appears that all the customers that have been contacted fall within the previously 100 days.

Previous (Total number of contacts from previous campaign)

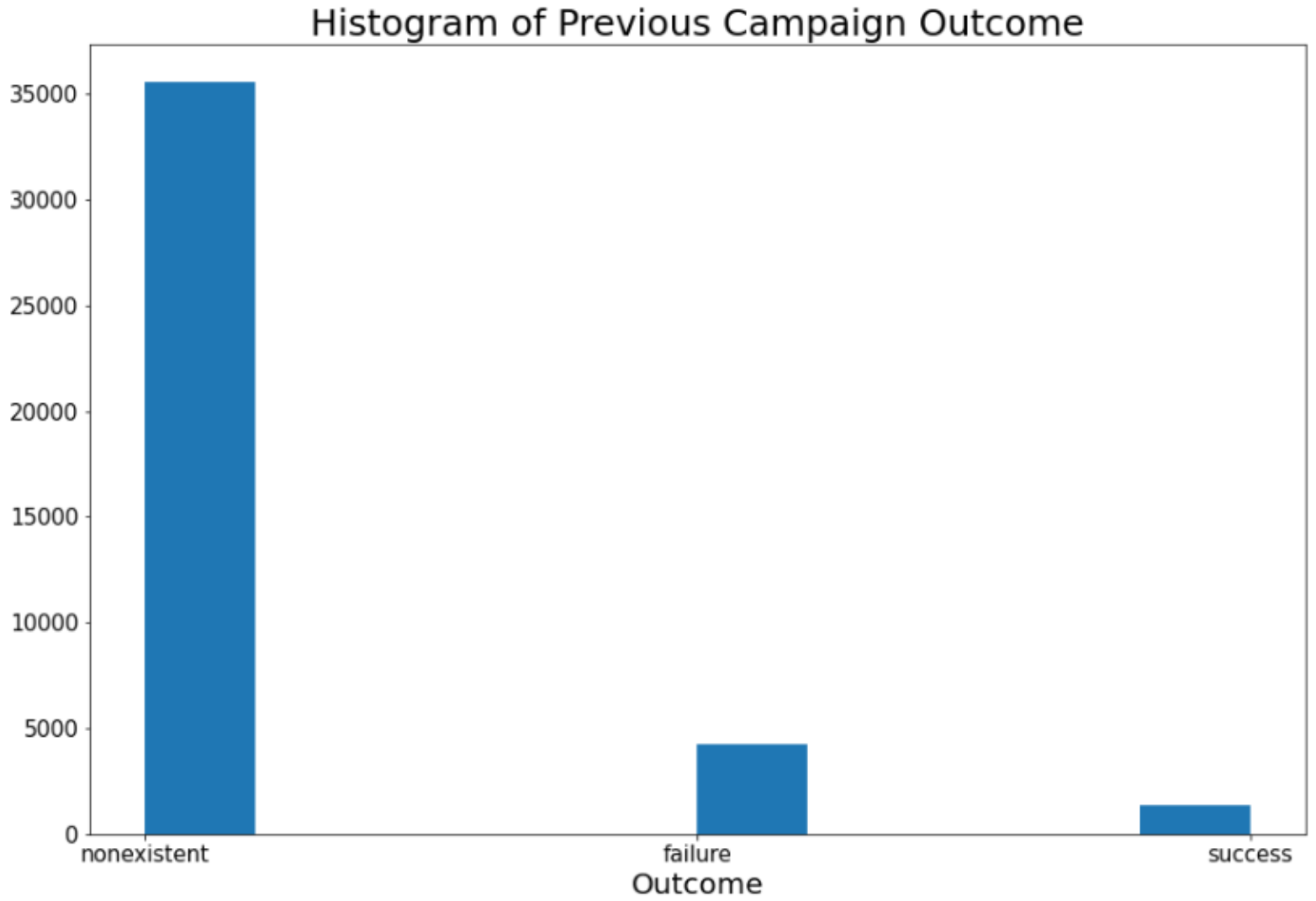
```
#creating histogram of previous
plt.figure(figsize=(15,10))
plt.hist(bank_data['previous'])
plt.title('Histogram of Total Number of Contacts from Previous Campaign', fontsize=25)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
plt.xlabel('Total Number of Contacts', fontsize=20)
plt.show()
```



As expected based on our previous column, there are a large number of clients which have never been contacted prior, resulting in a right-skewed data set.

POutcome (Outcome of previous campaign)

```
#creating histogram of poutcome
plt.figure(figsize=(15,10))
plt.hist(bank_data['poutcome'])
plt.title('Histogram of Previous Campaign Outcome', fontsize=25)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
plt.xlabel('Outcome', fontsize=20)
plt.show()
```



```
bank_data['poutcome'].value_counts()
```

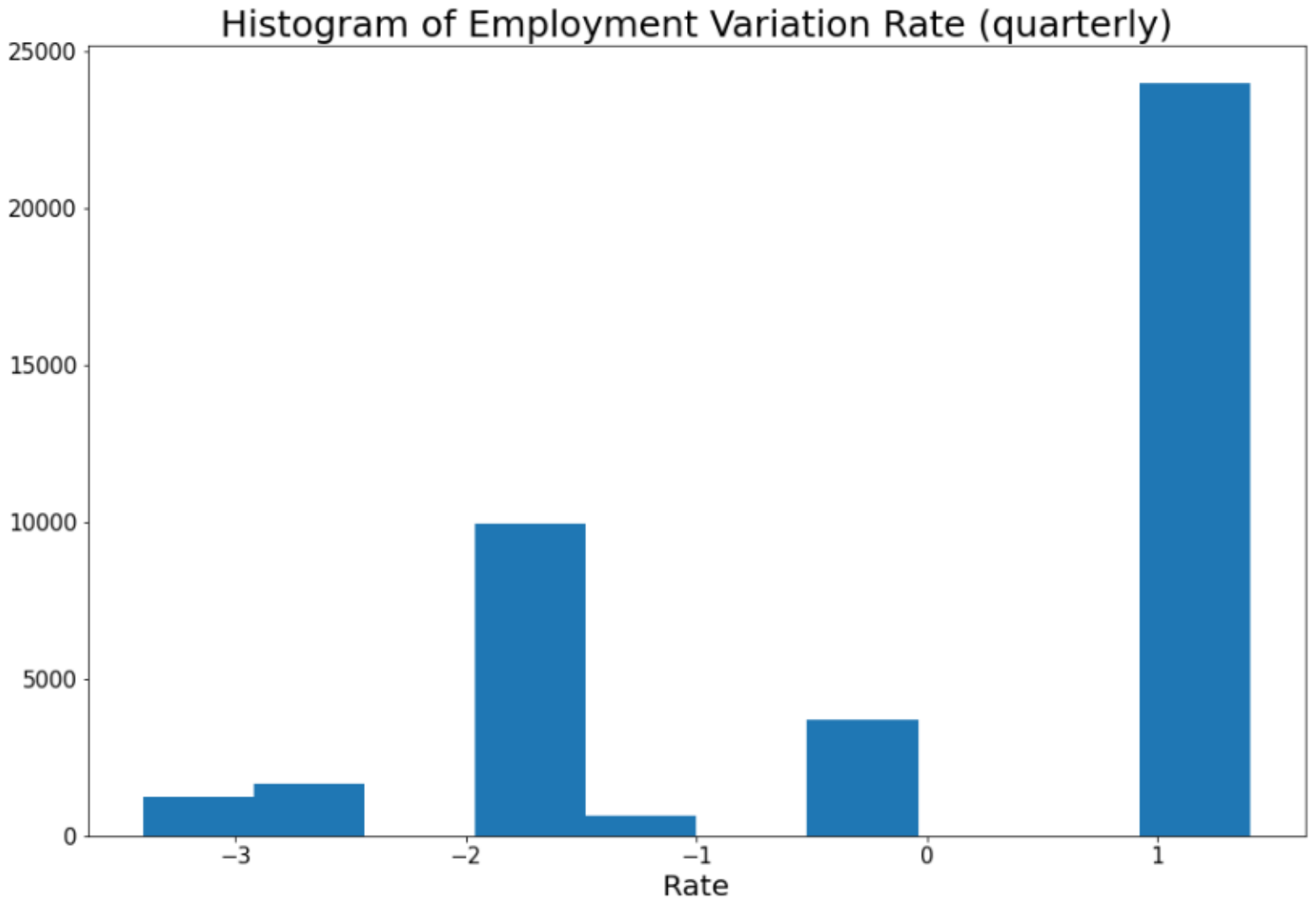
```
nonexistent    35563
failure         4252
success         1373
Name: poutcome, dtype: int64
```

As we have so many new clients in this dataset, the majority of this column is nonexistent. However, we can see that the majority of the contacts were a failure, at 4252 failures compared to only 1373 successes.

We will now examine the social and economic context attributes

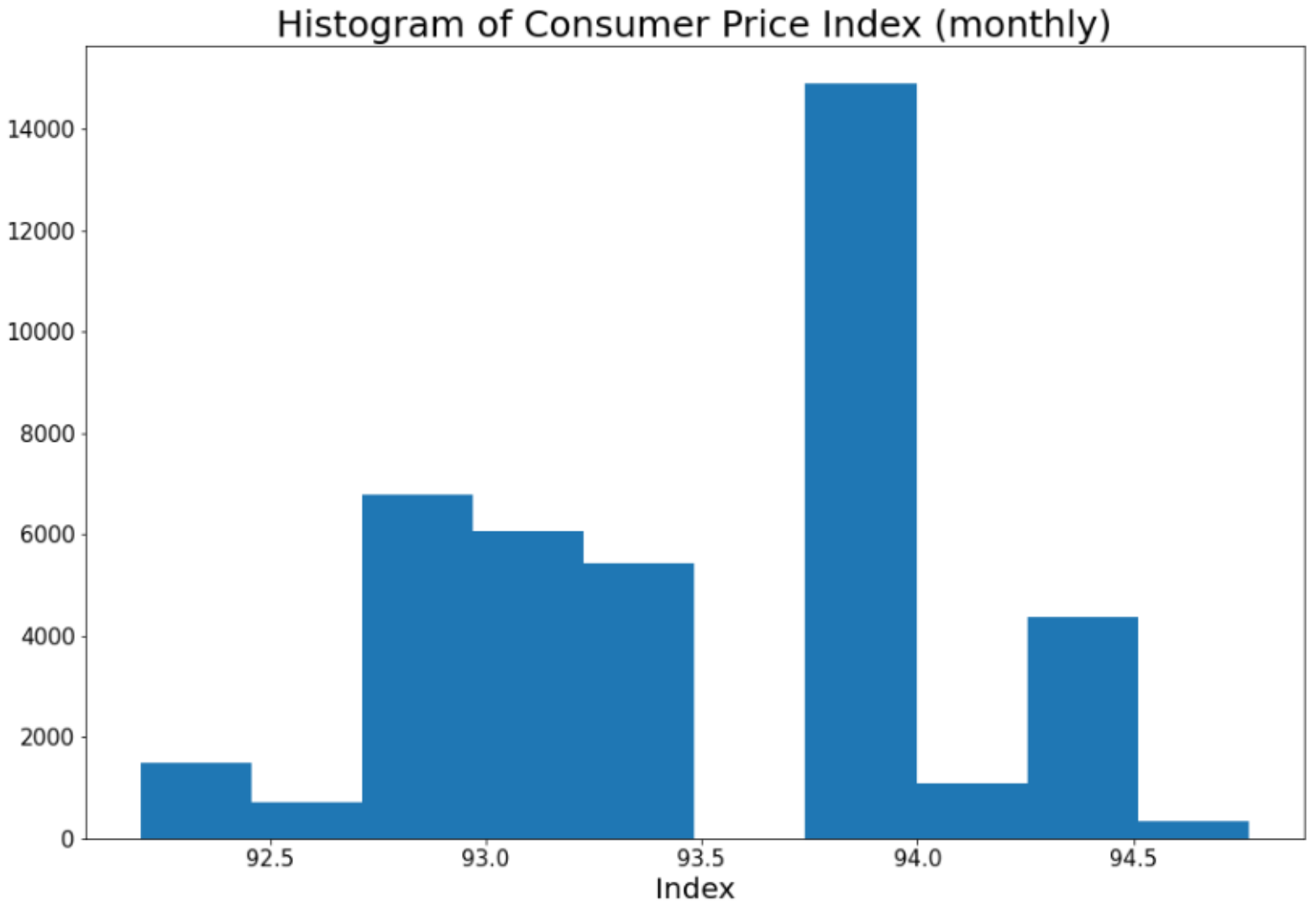
Emp.Var.Rate (employment variation rate - quarterly indicator)

```
#creating histogram of emp.var.rate
plt.figure(figsize=(15,10))
plt.hist(bank_data['emp.var.rate'])
plt.title('Histogram of Employment Variation Rate (quarterly)', fontsize=25)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
plt.xlabel('Rate', fontsize=20)
plt.show()
```



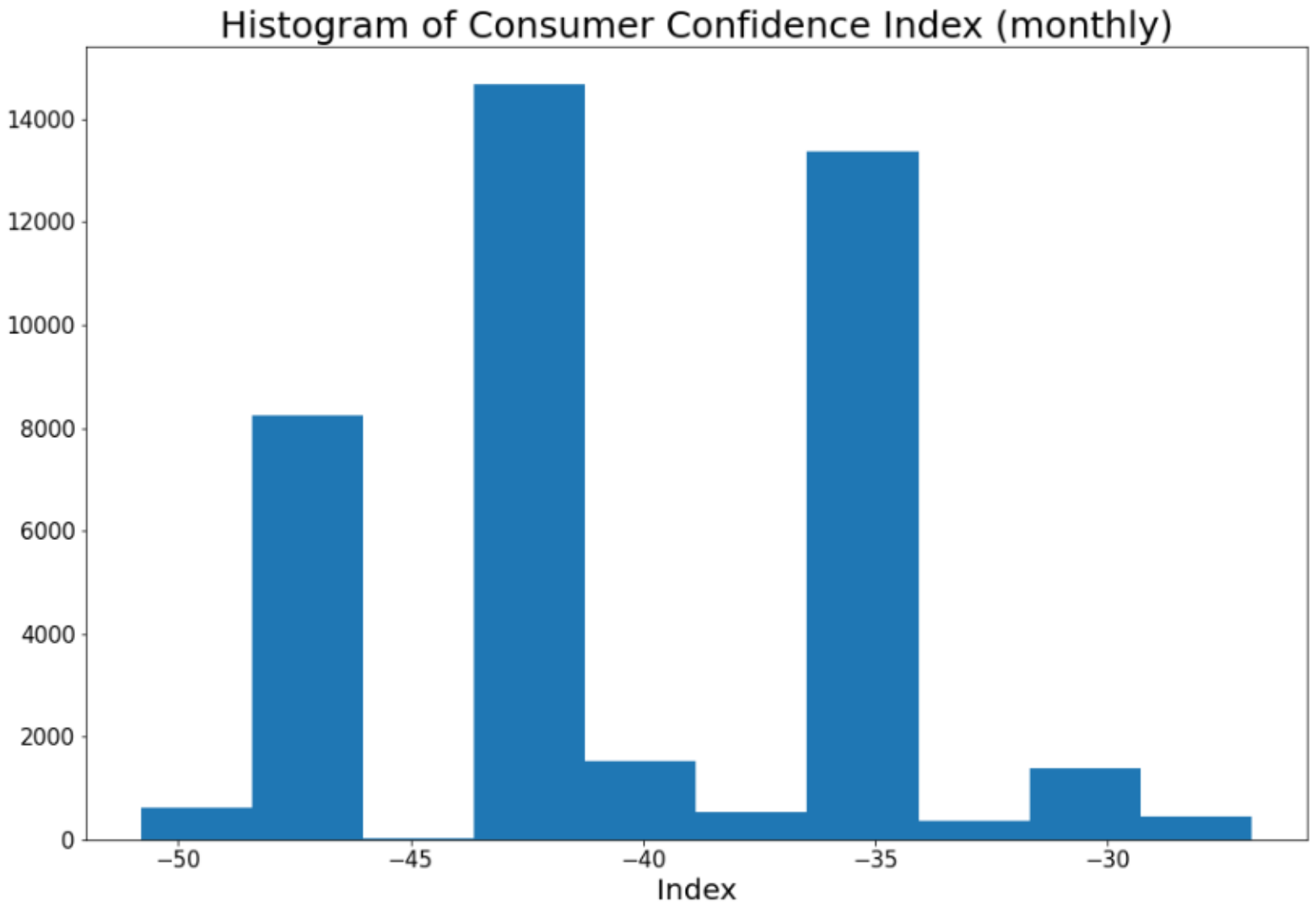
Cons.Price.Idx (consumer price index - monthly indicator)

```
#creating histogram of cons.price.idx
plt.figure(figsize=(15,10))
plt.hist(bank_data['cons.price.idx'])
plt.title('Histogram of Consumer Price Index (monthly)', fontsize=25)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
plt.xlabel('Index', fontsize=20)
plt.show()
```



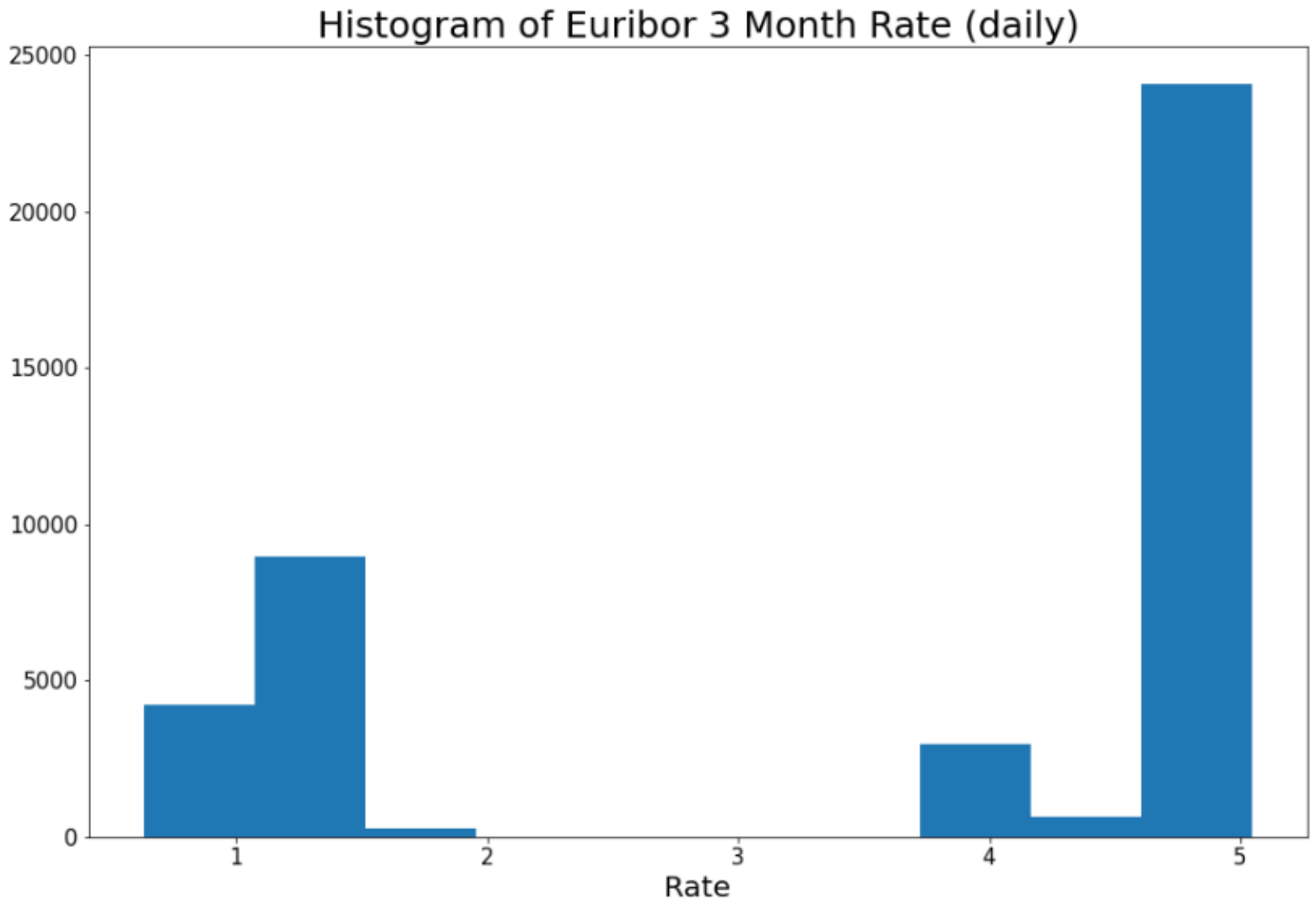
Cons.Conf.Idx (consumer confidence index - monthly indicator)

```
#creating histogram of cons.conf.idx
plt.figure(figsize=(15,10))
plt.hist(bank_data['cons.conf.idx'])
plt.title('Histogram of Consumer Confidence Index (monthly)', fontsize=25)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
plt.xlabel('Index', fontsize=20)
plt.show()
```



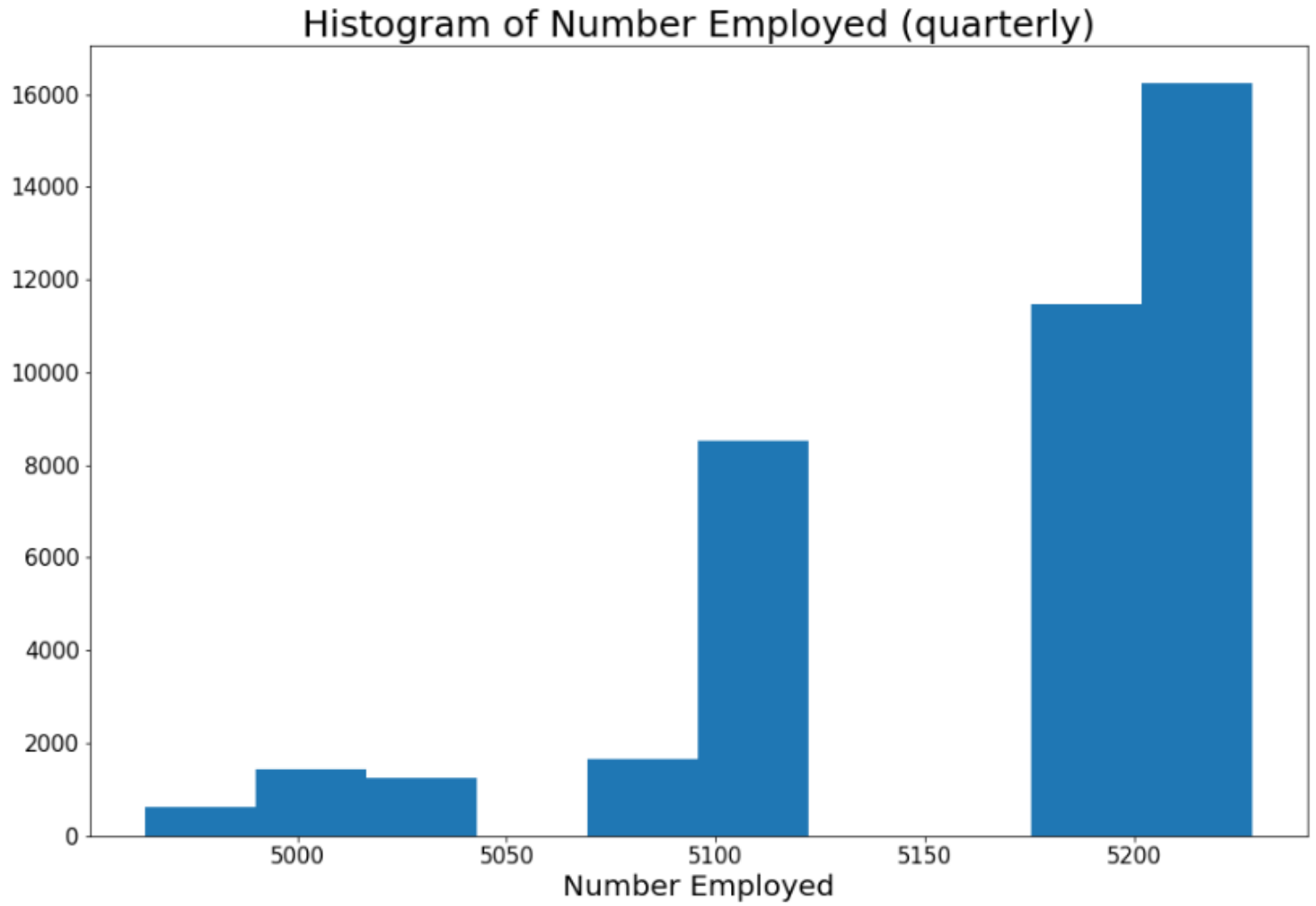
Euribor3m (euribor 3 month rate - daily indicator)

```
#creating histogram of euribor3m
plt.figure(figsize=(15,10))
plt.hist(bank_data['euribor3m'])
plt.title('Histogram of Euribor 3 Month Rate (daily)', fontsize=25)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
plt.xlabel('Rate', fontsize=20)
plt.show()
```



Nr.Employed (number of employees - quarterly indicator)

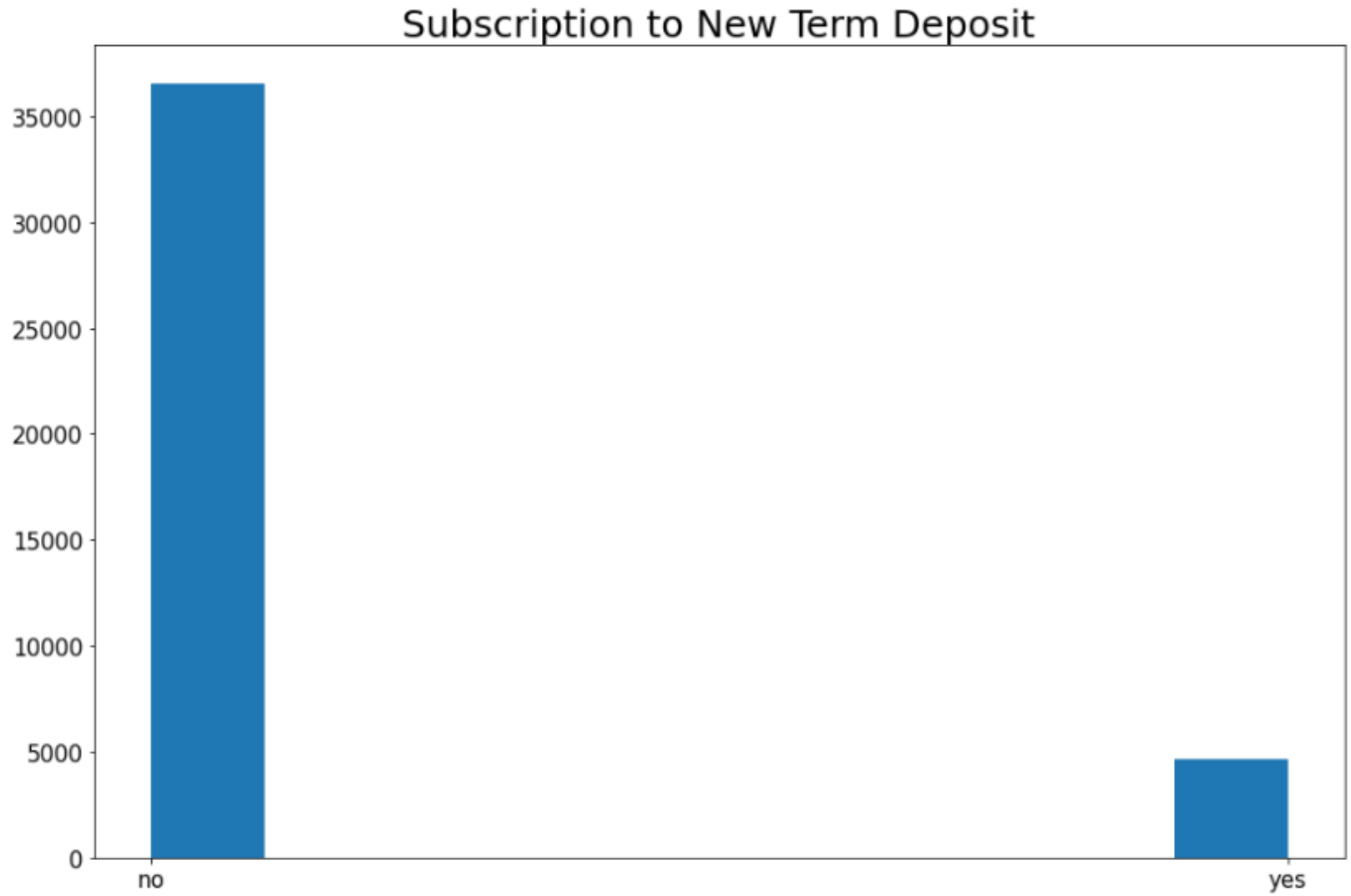
```
#creating histogram of nr.employed
plt.figure(figsize=(15,10))
plt.hist(bank_data['nr.employed'])
plt.title('Histogram of Number Employed (quarterly)', fontsize=25)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
plt.xlabel('Number Employed', fontsize=20)
plt.show()
```



Overall, all of our social and economic data shows no significant evidence for skew or outliers which will need to be addressed.

Y (Whether client subsribed to new term deposit)

```
#creating histogram of y
plt.figure(figsize=(15,10))
plt.hist(bank_data['y'])
plt.title('Subscription to New Term Deposit', fontsize=25)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
plt.show()
```

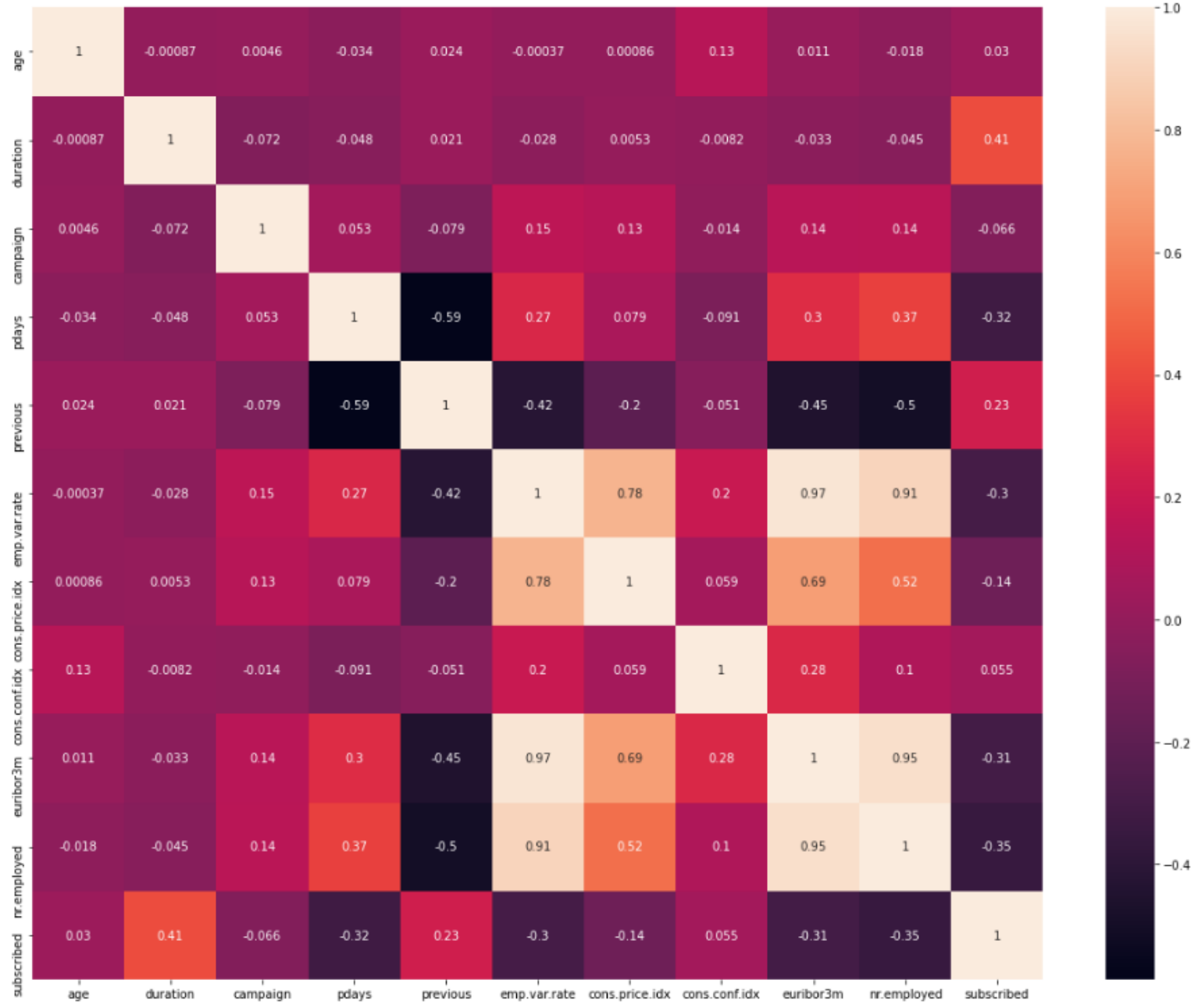


```
bank_data['y'].value_counts()
```

```
no      36548
yes      4640
Name: y, dtype: int64
```

Our value count shows a clear class imbalance with approximately 89% of users not subscribing to the term deposit. This may result in issues later on in our model creation, and will need to be addressed. First, we will change this column to a bool value, and change the name to a more recognizable column name of "subscribed".

```
corr_matrix = bank_data.corr()
plt.figure(figsize=(19,15))
sns.heatmap(corr_matrix, annot=True)
plt.show()
```



```
pd.plotting.scatter_matrix(bank_data, alpha=0.2, figsize=(15,15))
plt.show()
```