# **Data Preperation**

### Look at the attribute type; e.g., nominal, ordinal or quantitative.

In the Bank Marketing dataset, the attributes can be categorized into two types: Nominal (Categorical and Quantitative (Numerical). Below is a detailed classification:

## 1. Nominal (Categorical) Attributes

Nominal attributes represent categories without a specific order. They are qualitative and often describe characteristics or labels. In this dataset, the following attributes are nominal:

- Job: Type of job held by the customer.
- Marital: Marital status of the customer.
- Education: Level of education attained by the customer.
- Default: Indicates whether the customer has any credit in default.
- Housing: Indicates whether the customer has a housing loan.
- Loan: Indicates whether the customer has a personal loan.
- Contact: Method used for the last contact during the marketing campaign (e.g., telephone, cellular).
- Month: The month of the year when the customer was last contacted.
- Poutcome: Outcome of the previous marketing campaign for the customer.
- Y: Class attribute showing whether the customer has subscribed to a term deposit (binary outcome: 'yes' or 'no').

# 2. Quantitative (Numerical) Attributes

Quantitative attributes involve numerical values that can be measured or counted. They are key for statistical analysis and include:

- Age: Age of the customer (in years).
- Balance: Average yearly balance in the customer's account (in Euros).
- Day: Day of the month when the customer was last contacted.
- Duration: Duration of the last contact with the customer (in seconds).
- Campaign: Number of contacts performed during this marketing campaign.
- Pdays: Number of days since the customer was last contacted from a previous campaign. If the customer was not previously contacted, this value is set to 999.
- Previous: Number of contacts made before this campaign and for this customer.



# Find any missing values

### 1. Numerical Attributes

• Missing Values: None of the numerical attributes in the dataset have missing values, ensuring that all data points are complete and can be used for analysis without the need for imputation.



# 2. Categorical Attributes

- Unknown Values: For certain categorical attributes, there are instances where the value is labeled as 'unknown'. This often occurs when the information is not provided or recorded. The attributes with potential unknown values include:
  - o Job: Type of job held by the customer.

- o Education: Level of education attained by the customer.
- o Contact: Method used for the last contact during the marketing campaign.
- o Poutcome: Outcome of the previous marketing campaign for the customer.

Job	Frequency	Percent	Cumulative Frequency	Cumulative Percent
admin.	478	10.57	478	10.57
blue-collar	946	20.92	1424	31.50
entrepreneur	168	3.72	1592	35.21
housemald	112	2.48	1704	37.69
management	969	21.43	2673	59.12
retired	230	5.09	2903	64.21
self-employed	183	4.05	3086	68.26
services	417	9.22	3503	77.48
student	84	1.86	3587	79.34
technician	768	16.99	4355	96.33
unemployed	128	2.83	4483	99.16
unknown	38	0.84	4521	100.00

education	Frequency	Percent	Cumulative Frequency	Cumulative Percent
primary	678	15.00	678	15.00
secondary	2306	51.01	2984	66.00
tertlary	1350	29.86	4334	95.86
unknown	187	4.14	4521	100.00

contact	Frequency	Percent	Cumulative Frequency	Cumulative Percent
cellular	2896	64.06	2896	64.06
telephone	301	6.66	3197	70.71
unknown	1324	29.29	4521	100.00

poutcome	Frequency	Percent	Cumulative Frequency	Cumulative Percent
fallure	490	10.84	490	10.84
other	197	4.36	687	15.20
800088	129	2.85	816	18.05
unknown	3705	81.95	4521	100.00

# Find max, min, mean and standard deviation of attributes

### 1. Numerical Attributes

Variable	N	Mean	Std Dev	Minimum	Maximum
age	4521	41.1700951	10.5762110	19.0000000	87.0000000
balance	4521	1422.66	3009.64	-3313.00	71188.00
day	4521	15.9152842	8.2476673	1.0000000	31.0000000
duration	4521	263.9612917	259.8566326	4.0000000	3025.00
campaign	4521	2.7936297	3.1098067	1.0000000	50.0000000
pdays	4521	39.7666445	100.1211244	-1.0000000	871.0000000
previous	4521	0.5425791	1.6935624	0	25.0000000

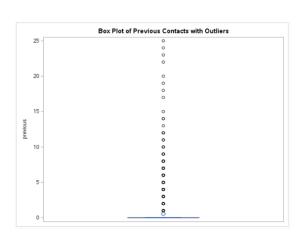
# 2. Categorical Attributes

Variable	N	Mean	Std Dev	Minimum	Maximum
Job_num	4521	2.5792966	0.6747373	1.0000000	3.0000000
Marital_num	4521	1.4981199	0.6954711	1.0000000	3.0000000
Education_num	4521	2.2313647	0.7487442	1.0000000	4.0000000
Default_num	4521	0.0168104	0.1285749	0	1.0000000
Housing_num	4521	0.5660252	0.4956763	0	1.0000000
Loan_num	4521	0.1528423	0.3598752	0	1.0000000
Contact_num	3197	1.0941508	0.2920840	1.0000000	2.0000000
Month_num	4521	6.1667773	2.3783802	1.0000000	12.0000000
Poutcome_num	4521	3.6540588	0.7838170	1.0000000	4.0000000
Y_num	4521	0.1152400	0.3193467	0	1.0000000

Determine any outlier values (records) for each of the attributes or attributes under consideration (min, max, std. dev, scatter plots, box plots or others can be used)

Below is a summary of the key findings:

- 1. Numerical Attributes
  - Previous Contacts (Previous)
    - o Outliers: 816 outliers are identified.
      - Details: Clients with a high number of previous contacts (up to 25 contacts) are considered extreme observations. These could represent persistent attempts to engage certain clients or cases where repeated contacts are necessary.

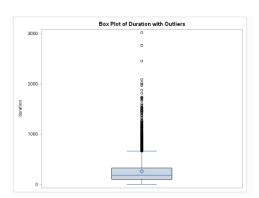




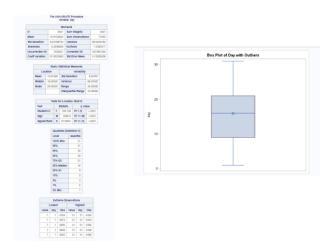
- Duration Since Last Contact (Pdays)
  - Outliers: 816 outliers are identified.

 Details: Extreme observations include values like -1 (likely a placeholder for missing or undefined data) and values up to 871 days. These extreme values could indicate significant delays between contacts or data entry issues.



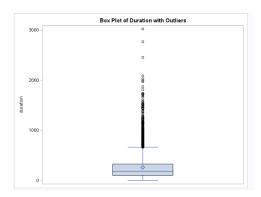


- Day of Month Contact was Made (Day)
  - Outliers: None detected.
    - Details: This attribute is well-distributed without any extreme observations, suggesting that contact days are evenly spread across the month.



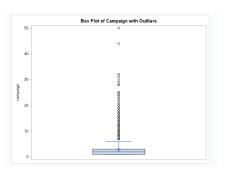
- Duration of Last Contact (Duration)
  - o Outliers: 330 outliers are identified from a total of 4521 observations.
    - Details: These longer durations might indicate successful engagements where clients were interested or required more time to discuss the term deposit offer. Notably, durations as long as 3025 seconds could highlight successful interactions, potentially leading to higher subscription rates.





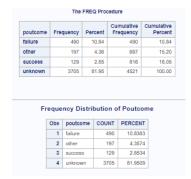
- Number of Contacts During This Campaign (Campaign)
  - o Outliers: 318 outliers are identified from a total of 4521 observations.
    - Details: These extreme values suggest instances where the number of contacts performed during the campaign is significantly higher than the majority of observations. Such cases could potentially skew the analysis or indicate specific conditions that warrant further investigation.





# 2. Categorical Attributes

- Outcome of Previous Marketing Campaign (Poutcome)
  - Unknown Values: 81.9509% of the values are labeled as 'unknown'.
    - Details: A high proportion of unknown outcomes can impact the analysis, as it limits the ability to draw meaningful insights from past campaign results.



- Month of Last Contact (Month)
  - Outliers: One significant outlier.
    - Details: The month of May accounts for 30.9224% of all contacts, making it a
      potential outlier. This suggests that a disproportionate number of contacts were
      made in May.





	Outli	ers in M	onth Base	d on Fre	quency	Distributio	n
Obs	month	COUNT	PERCENT	_TYPE_	_FREQ_	mean_freq	atd_freq
- 1	may	1398	30.9224	0	12	376.75	399.143

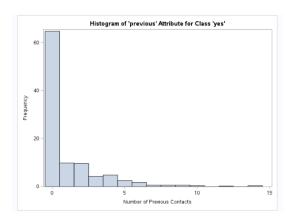
- Subscribed to Term Deposit (Y)
  - Class Imbalance: 88.4760% of the records are classified as "no".
    - Details: The target variable is highly imbalanced, with the majority of clients not subscribing to the term deposit. This imbalance may affect the performance of predictive models and should be addressed, potentially through resampling techniques.

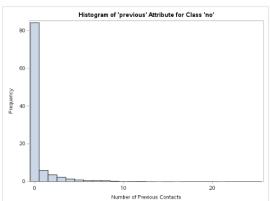


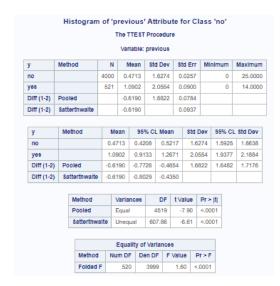
Analyze the distribution of numeric attributes (normal or other). Plot histograms for attributes of concern and analyze whether they have any influence on the class attribute.

Below is an analysis of key numeric attributes, along with histograms and insights on how they might influence the likelihood of subscription:

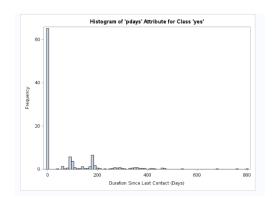
- Previous Contacts (Previous) Numerical
  - Distribution: The mean number of previous contacts for clients who subscribed (mean = 1.0902) is higher than for those who did not subscribe (mean = 0.4713).
  - Statistical Significance: Both the pooled and Satterthwaite t-tests show highly significant p-values (<.0001), indicating a statistically significant difference between the two groups.
  - Influence on Subscription:
    - Clients with more previous contacts are more likely to subscribe to a term deposit.
    - Marketing Strategy Insight: Previous contacts are an influential factor. Engaging clients multiple times may increase the likelihood of subscription.

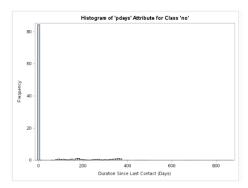






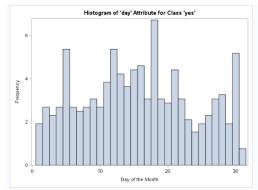
- Duration Since Last Contact (Pdays) Numerical
  - Distribution: The Pdays variable indicates a significant difference between clients who subscribed and those who did not. Higher Pdays (indicating longer time since last contact) is associated with a higher likelihood of subscription.
  - Statistical Significance: The difference is statistically significant, suggesting that the timing of the previous contact plays a role in the likelihood of subscription.
  - Influence on Subscription:
    - Clients contacted after a longer period are more likely to subscribe.
    - Marketing Strategy Insight: Consider the behavior of Pdays post-subscription.
       Adjusting the time between contacts might increase receptiveness to the marketing campaign.

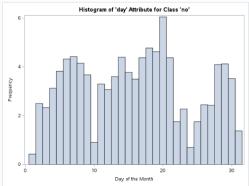






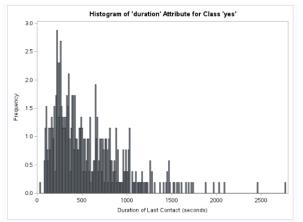
- Day of Month Contact was Made (Day) Numerical
  - Distribution: The Day variable shows no significant difference between those who subscribed and those who did not.
  - Statistical Significance: P-values for both the pooled and Satterthwaite methods are approximately 0.45, much higher than the typical significance level of 0.05.
  - Influence on Subscription:
    - The day of the month when contact was made does not significantly influence the likelihood of subscription.

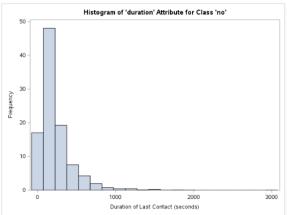


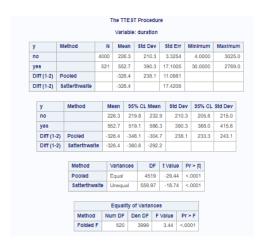


				rTEST Varlabi			•					
у	Method		N I	Mean	Std	Dev	Sto	Err	Minimum		M	aximum
по		400	0 15.	9488	8.2497		0.1	304	1	.0000	т	31.0000
уев		52	521 15.6583		8.3	2351	351 0.3		8 1.0000			31.0000
DIff (1-2)	Pooled		0.	2904	8.3	2481	0.3	0.3842				
DIff (1-2)	Satterthwalte		0.	2904			0.3	836				
у	Method		Mean	95	% CL	Mea	n	std	Dev	95%	CL S	td Dev
no		15.	9488	15.6930 1		16.2	045	45 8.2		7 8.072		8.4346
yes		15.	6583	14.9496 1		16.3	8.2		351	7.763	16	8.7681
Diff (1-2)	Pooled	0.	0.2904		0.4628 1		0436 8.3		481	8.081	15	8.4217
Diff (1-2)	Satterthwalte	0.	0.2904 -0.4		629 1.043		437				П	
	Method Pooled Satterthy	unite.	Varia Equa			DF 519		<b>ue</b> 76	Pr >   0.449	17		
	Sattertin	valte	Uneq	uai	003	.35	U.	/6	0.445	13		
			Equa	ality of	Vari	ance	8			1		
	Metho	d I	Num D	F De	n DF	F	Value	P	r×F			
	Folded	I F	399	9	520		1.00	0.	9707			

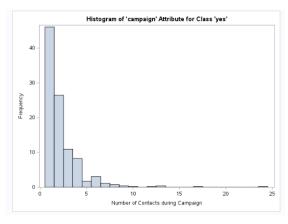
- Duration of Last Contact (Duration) Numerical
  - Distribution: The mean call duration is significantly longer for clients who subscribed (mean = 552.7 seconds) compared to those who did not subscribe (mean = 226.3 seconds).
  - Statistical Significance: P-values for both the pooled and Satterthwaite methods are less than 0.0001, indicating a statistically significant difference between the two groups.
  - o Influence on Subscription:
    - Longer call durations are associated with a higher likelihood of subscription.
    - Marketing Strategy Insight: Emphasize strategies that promote longer and more engaging interactions with potential customers.

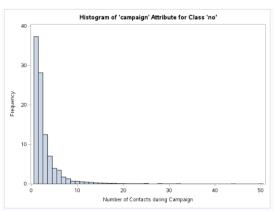






- Number of Contacts During This Campaign (Campaign) Numerical
  - Distribution: Clients who subscribed had a lower mean number of contacts compared to those who did not subscribe.
  - Statistical Significance: Both the Pooled and Satterthwaite methods show highly significant p-values (<0.0001).</li>
  - Influence on Subscription:
    - Fewer contacts during the campaign are associated with higher subscription
    - Marketing Strategy Insight: Focus on a strategic number of contacts. Excessive contacts may not lead to higher subscription rates, and tailoring the number of contacts could improve outcomes.





у	Me	thod		N	Me	ean	Sto	Dev	Si	td E	rr M	InImi	ımı	Maximum				
no								00	2.86	623	3.	2126	0	.050	8	1.00	00	50.0000
yes			5	21	2.26	868	2.	0921	21 0.091		7	1.0000		24.0000				
DIff (1-2)	Po	oled			0.59	955	3.	1043	0	.144	6							
DIff (1-2)	Sa	tterthwalte			0.59	955			0	.104	8							
у		Method		Me	an	959	6 CI	Mear	1	Std	Dev	959	6 CL	Std Dev				
no	Т			2.86	23	2.76	27	2.96	18	3.	2126	3.1	437	3.2846				
уев				2.26	68	2.08	67	2.44	39	2.	0921	1.9	723	2.2275				
DIff (1-2	)	Pooled	0.59		955 0.31	20	0.878	789 3.1		1043	3.0416		3.1697					
DIff (1-2	)	Satterthwalt	9 (	0.59	155	0.38	98	0.80	11									
		Method		٧	arlan	1098		DF	t٧	alue	Pr	>  t						
		Pooled		E	qual		- 4	519		4.12	<.0	001						
		Satterthw	alte	U	Inequ	al	87	7.72		5.68	<.0	001						
				E	qual	Ity of	Var	lance	8									
		Method		Nu	n DF	De	n D	FF	Valu	ue eu	Pr>	F						

# Which attributes seem to be correlated? Which attributes seem to be most linked to the class attribute?

### <u>Previous Contacts (Previous) vs. Duration Since Last Contact (Pdays)</u>

- Correlation Coefficient: 0.57756 (Moderate positive linear relationship)
- p-value: < 0.0001 (Statistically significant)

- There is a moderate positive correlation between the number of previous contacts (Previous) and the number of days since the last contact (Pdays).
- As the number of previous contacts increases, the duration since the last contact tends to increase.
- The statistically significant p-value suggests that this relationship is not due to random chance. It implies that clients who were contacted more frequently in the past tend to have longer periods since their last contact.

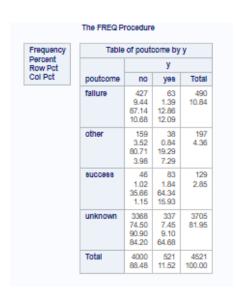


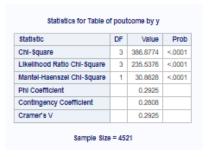
# Outcome of Previous Marketing Campaign (Poutcome) vs. Subscribed

p-value: < 0.0001 (Statistically significant)</li>

# Interpretation:

- There is a significant association between the outcome of the previous campaign (Poutcome) and whether the client subscribed to a term deposit (Subscribed).
- Clients with a 'success' outcome in the previous campaign have a much higher likelihood of subscribing (64.34%) compared to those with other outcomes. Conversely, clients with 'unknown' or 'failure' outcomes are less likely to subscribe.
- This suggests that the outcome of the previous campaign is a strong predictor of the likelihood of a client subscribing to a term deposit, with a 'success' outcome being particularly indicative of a positive response.



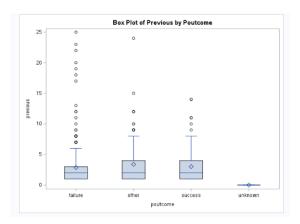


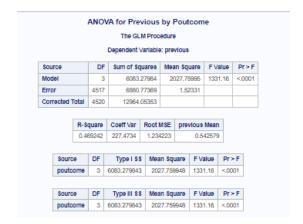
# Number of Previous Contacts (Previous) vs. Outcome of Previous Marketing Campaign (Poutcome)

p-value: < 0.0001 (Statistically significant)</li>

#### Interpretation:

- The ANOVA results indicate a strong relationship between the number of previous contacts (Previous) and the outcome of the previous marketing campaign (Poutcome).
- The significant p-value suggests that the differences in mean Previous values across different Poutcome categories are unlikely due to random chance.
- The high R-Square value indicates that Poutcome plays a crucial role in predicting the number of previous contacts made with clients.

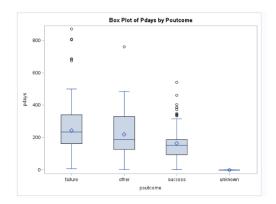


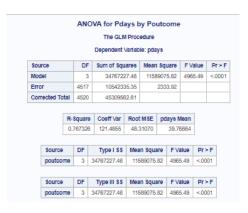


### Duration Since Last Contact (Pdays) vs. Outcome of Previous Marketing Campaign (Poutcome)

p-value: < 0.0001 (Statistically significant)</li>

- There is a significant association between Poutcome and Pdays, suggesting that knowing the outcome of the previous marketing campaign allows for a high degree of accuracy in predicting the number of days since the last contact.
- Poutcome is a strong predictor of Pdays, indicating that the success or failure of a previous campaign has a substantial impact on the duration since the last contact.





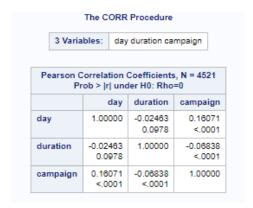
# Day of Month Contact was Made (Day) vs. Duration of Last Contact (Duration)

• Correlation Coefficient: -0.02463 (Very weak negative correlation)

p-value: 0.0978 (Not statistically significant)

#### Interpretation:

• There is a very weak negative correlation between the day of the month (Day) and the duration of the call (Duration), which is not statistically significant. This suggests that the timing of the contact during the month has no meaningful relationship with the duration of the calls.



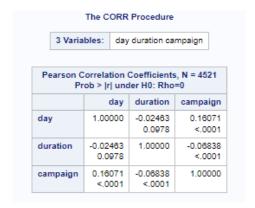
# Day of Month Contact was Made (Day) vs. Number of Contacts (Campaign)

Correlation Coefficient: 0.16071 (Weak positive correlation)

p-value: < 0.0001 (Statistically significant)</li>

# Interpretation:

• There is a weak positive correlation between the day of the month (Day) and the number of contacts (Campaign), which is statistically significant. This indicates a slight tendency for the day of the month to be associated with the number of contacts made to the customer.



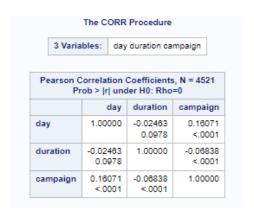
# <u>Duration of Last Contact (Duration) vs. Number of Contacts (Campaign)</u>

Correlation Coefficient: -0.06838 (Weak negative correlation)

• p-value: < 0.0001 (Statistically significant)

#### Interpretation:

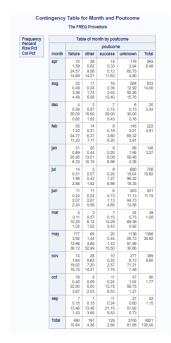
• There is a weak negative correlation between the duration of the call (Duration) and the number of contacts (Campaign), which is statistically significant. This suggests that as the number of contacts increases, the duration of each individual contact tends to slightly decrease.

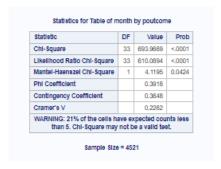


### Month of Contact vs. Outcome of Previous Marketing Campaign (Poutcome)

• p-value: < 0.0001 (Statistically significant)

- There is a significant association between the month of contact (Month) and the outcome of the previous marketing campaign (Poutcome). This suggests that the outcomes of previous campaigns are not independent of the month in which contacts are made.
- The month of contact influences the likelihood of different outcomes, indicating potential seasonal trends in marketing campaign outcomes.





### Month of Contact vs. Subscribed

p-value: < 0.0001 (Statistically significant)</li>

#### Interpretation:

• There is a significant association between the month of contact (Month) and whether the client subscribed to a term deposit (Subscribed). Certain months, such as May and August, have higher subscription rates, suggesting optimal timing for contacting potential clients.



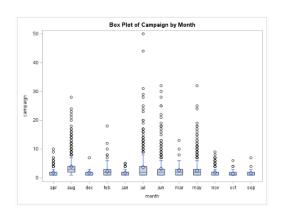
Statistic	DF	Value	Prob
Chi-Square	11	250.5001	<.0001
Likelihood Ratio Chi-Square	11	187.4051	<.0001
Mantel-Haenszel Chl-Square	1	7.5732	0.0059
Phi Coefficient		0.2354	
Contingency Coefficient		0.2291	
Cramer's V		0.2354	

# Month of Contact vs. Number of Contacts (Campaign)

p-value: < 0.0001 (Statistically significant)</li>

#### Interpretation:

• The timing of the campaign within the year has a statistically significant effect on the number of contacts made. However, the R-Square value indicates that the month alone explains a small portion of the variability in Campaign, suggesting other factors also play a role.

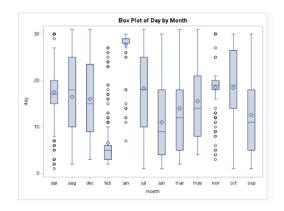




# Month vs. Day of Contact

p-value: < 0.0001 (Statistically significant)</li>

Interpretation: There is a statistically significant relationship between the month in which the contact was made and the day of the month when the contact occurred. The R-Square value indicates that approximately 20.16% of the variance in the day of contact can be explained by differences between month categories. This suggests that the month has a notable impact on the specific day within the month when contacts are made.

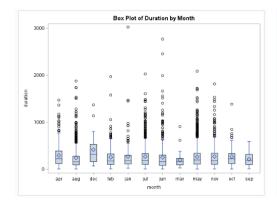




### Month vs. Duration of Contact

• p-value: < 0.0001 (Statistically significant)

Interpretation: There is a statistically significant relationship between the month in which the contact was made and the duration of the contact. The R-Square value of 15.08% indicates that the month of contact can explain a moderate portion of the variance in contact duration, suggesting that the month does influence how long a contact lasts.

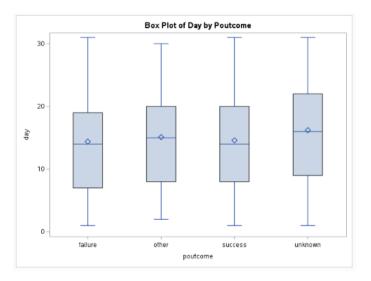




### Outcome of Previous Marketing Campaign (Poutcome) vs. Day of Contact

p-value: < 0.0001 (Statistically significant)</li>

• Although Poutcome has a statistically significant effect on the day of the month (Day), the effect size is very small, indicating limited practical significance.



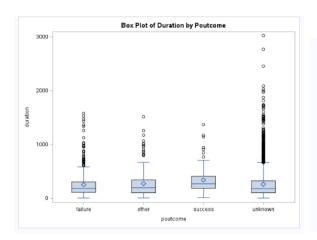
	Al	NO	VA for Da The GLM Dependent	Proc	edure					
Source	DF	•	Sum of Squ	aree Mean Square			F۱	/alue	Pr > F	
Model		3	1804.1	1278 601		1.3759		8.89	<.0001	
Error	4517	7	305664.426		67.6698					
Corrected Total	al 4520	)	307468.5	539						
	0.0058		51.68720		ot MSE 226165	day N	_			
Source	DF		Type I SS	Mea	n Squar	e FV	'alue	Pr	• F	
dource	me 3 1		804.127765 6		601.375922		8.89		01	
poutcom	9 3	18	804.127765	60	1.37592	2	0.00			
	DF		7ype III \$\$		n Squar		alue	Pr		

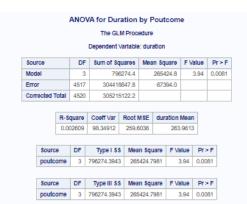
# Outcome of Previous Marketing Campaign (Poutcome) vs. Duration of Last Contact

p-value: 0.0081 (Statistically significant)

## Interpretation:

• The relationship between Poutcome and Duration is statistically significant, but the small R-Square value indicates that Poutcome explains only a very small proportion of the variance in Duration.

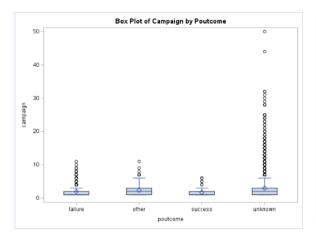


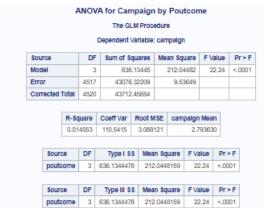


# Outcome of Previous Marketing Campaign (Poutcome) vs. Number of Contacts (Campaign)

• p-value: < 0.0001 (Statistically significant)

• There is a statistically significant association between Poutcome and Campaign, but the low R-Square value suggests that the relationship is not strong in terms of explaining the variation in Campaign.





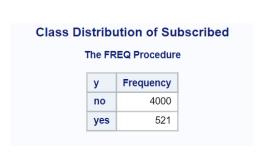
Which attributes do you think can be eliminated or included in the analysis? This can be a subjective decision or an objective decision based on statistical method

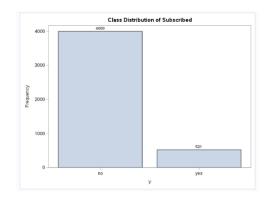
• Selection strategy included in Decision Tree and Naïve Bayes report

Determine whether the dataset has an imbalanced class distribution (same proportion of records of different types or not) and do you need to balance the dataset.

The analysis of the class distribution for the target variable "y" (representing whether clients subscribed to a product or not) reveals a significant imbalance:

- Yes (Subscribed): 521 out of 4521 records (11.5%)
- No (Not Subscribed): 4000 out of 4521 records (88.5%)





### Interpretation:

• The "Yes" class, which represents clients who subscribed, constitutes only 11.5% of the total dataset, while the "No" class, representing clients who did not subscribe, makes up a substantial 88.5%. This significant disparity indicates that the dataset is imbalanced, with the "Yes" class being underrepresented.

In the predictive modeling section of this assignment, we have balanced the class attribute "y" (which represents whether clients subscribed or not) accordingly.

# Reason for Balancing:

Given the significant class imbalance in the dataset—where the "Yes" class (subscribed) constitutes only 11.5% of the data, while the "No" class (not subscribed) makes up 88.5%—balancing the dataset was necessary. This imbalance could lead to a model that is biased towards the majority class, resulting in poor performance when predicting the minority class.

# Impact of Balancing:

 Balancing the dataset helps the model to better learn and predict the minority class ("Yes"), improving key performance metrics such as precision, recall, and F1-score for the subscribed class. This approach ensures that the model is more reliable and effective in making accurate predictions across all classes, particularly in identifying clients who are likely to subscribe.