Machine Learning 441 Assignment 1

David Nicolay (26296918) 14 August 2025

Task 1: Analytics Base Table

1. 581012

2. 62

3. Fo continuous features see Table 1. For categorical features see Table 2.

Table 1: Data Quality Report for Continuous Features

Feature	Count	% Miss.	Card.	Min.	1^{st} Qrt.	Mean	Median	3^{rd} Qrt.	Max.	Std. Dev.
1	581012	0.00	1978	2054845.65	3104928.15	3271134.43	3311628.60	3496222.05	4264440.30	309481.13
2	581012	0.51	361	0.00	58.00	155.66	127.00	260.00	360.00	111.91
3	581012	0.00	576099	0.00	145.49	389.92	318.12	652.53	903.48	280.34
4	581012	0.05	67	0.00	9.00	14.10	13.00	18.00	66.00	7.49
5	581012	0.51	569	-691.00	108.00	269.42	218.00	384.00	1397.00	212.56
6	581012	0.00	581012	-173.07	6.99	46.42	29.91	68.97	600.95	58.30
7	581012	0.51	577988	-1.00	-0.50	-0.00	-0.00	0.50	1.00	0.58
8	581012	0.00	5811	0.00	1106.00	8158.11	1997.00	3328.00	510165098.00	1185156.02
9	581012	0.51	207	0.00	198.00	212.14	218.00	231.00	254.00	26.77
11	581012	0.00	255	0.00	119.00	142.53	143.00	168.00	254.00	38.27
12	581012	0.51	5826	0.00	1024.00	1980.43	1710.00	2550.00	7173.00	1324.25
61	581012	0.00	581012	1.00	145253.75	290506.50	290506.50	435759.25	581012.00	167723.86

Table 2: Categorical Data Quality Report

Feature	Count	%miss	Card.	Mode	Mode Freq.	Mode %	2^{nd} Mode	2^{nd} Mode Freq	2^{nd} Mode %
10	578069	0.51	186	231	13482	2.33	228	13474	2.33
13	578069	0.51	2	0.00	318579	55.11	1.00	259490	44.89
14	581012	0.00	2	0	551128	94.86	1	29884	5.14
15	581012	0.00	2	0	327648	56.39	1	253364	43.61
16	578069	0.51	1	0.00	578069	100.00		0	0.00
17	581012	0.00	1	0	581012	100.00		0	0.00
18	578069	0.51	3	0.00	538608	93.17	1.00	36589	6.33
19	581012	0.00	2	0	291278	50.13	1	289734	49.87
20	577566	0.59	2	0.00	574553	99.48	1.00	3013	0.52
21	173355	70.16	2	0.00	172455	99.48	1.00	900	0.52
22	581012	0.00	2	0	573487	98.70	1	7525	1.30
23	581012	0.00	2	0	576189	99.17	1	4823	0.83
24	581012	0.00	2	0	568616	97.87	1	12396	2.13
25	581012	0.00	2	0	579415	99.73	1	1597	0.27
26	581012	0.00	2	0	574437	98.87	1	6575	1.13
27	581012	0.00	2	0	580907	99.98	1	105	0.02
28	581012	0.00	2	0	580833	99.97	1	179	0.03
29	581012	0.00	2	0	579865	99.80	1	1147	0.20
30	581012	0.00	2	0	548378	94.38	1	32634	5.62
31	581012	0.00	2	0	568602	97.86	1	12410	2.14
32	581012	0.00	2	0	551041	94.84	1	29971	5.16
33	581012	0.00	2	0	563581	97.00	1	17431	3.00
34	581012	0.00	2	0	580413	99.90	1	599	0.10
35	581012	0.00	2	0	581009	100.00	1	3	0.00
36	581012	0.00	2	0	578167	99.51	1	2845	0.49
37	581012	0.00	2	0	577590	99.41	1	3422	0.59
38	581012	0.00	2	0	579113	99.67	1	1899	0.33
39	581012	0.00	2	0	576991	99.31	1	4021	0.69
40	581012	0.00	2	0	571753	98.41	1	9259	1.59
41	581012	0.00	2	0	580174	99.86	1	838	0.14
42	581012	0.00	2	0	547639	94.26	1	33373	5.74
43	581012	0.00	2	0	523260	90.06	1	57752	9.94
44	581012	0.00	2	0	559734	96.34	1	21278	3.66
45	581012	0.00	2	0	580538	99.92	1	474	0.08
46	581012	0.00	2	0	578423	99.55	1	2589	0.45
47	581012	0.00	2	0	579926	99.81	1	1086	0.19
48	581012	0.00	2	0	580066	99.84	1	946	0.16
49	581012	0.00	2	0	465765	80.16	1	115247	19.84
50	581012	0.00	2	0	550842	94.81	1	30170	5.19
51	581012	0.00	2	0	555346	95.58	1	25666	4.42
52	581012	0.00	2	0	528493	90.96	1	52519	9.04
53	581012	0.00	2	0	535858	92.23	1	45154	7.77
54	581012	0.00	2	0	579401	99.72	1	1611	0.28
55	581012	0.00	2	0	579121	99.67	1	1891	0.33
56	581012	0.00	2	0	580893	99.98	1	119	0.02
57	581012	0.00	2	0	580714	99.95	1	298	0.05
58	581012	0.00	2	0	565439	97.32	1	15573	2.68
59	581012	0.00	2	0	567206	97.62	1	13806	2.38
60	581012	0.00	2	0	572262	98.49	1	8750	1.51
62	581012	0.00	1	1	581012	100.00		0	0.00

4. Target feature data quality report:

Table 3: Data Quality Report for target feature

Feature	Count	%miss	Card.	Mode	Mode Freq.	Mode %	2^{nd} Mode	2^{nd} Mode Freq	2^{nd} Mode %
T	581012	0.01	7	2.00	283269	48.75	1.00	211815	36.46

Task 2: Data Quality Issues

Table 4: Feature Quality Issues

Feature	**Data Quality Issue**	**Justification**
A1, A4, A6, A9, A11, A12	Outlier observations	It can be observed in Figure 8 that there are outliers present in these features. These box-plots were generated by first standardising the features the using the Interquartile Range (IQR) method to determine an outlier threshold. The IQR method determines the upper bound by calculating $Q3 + 1.5 \times IQR$ and the lower bound using $Q1 - 1.5 \times IQR$. Where $Q1$ is the 25th percentile (first quartile), $Q3$ is the 75th percentile (third quartile), and $IQR = Q3 - Q1$.
A2	Missing values	Many records have missing values for A2 as observed in Table 1. There are 0.51% of the observations with A2 missing.
A2, A3	Perfect correlation	The features A2 and A3 are perfectly correlated as observed in Figure 5. This means that they are an *exact* linear transformation of each other.
A4, A5, A7, A9, A10, A12, A13, A16, A18, A20, A21	Missing values	Testing revealed that there are a certain 2947 rows with all these features missing simultaneously.
A5	Outlier observations	Figure 4 raises concern surrounding some values of this feature being negative. Testing revealed that there are 26 outlier negative observations, whilst the rest of this feature contains positive values.
A8	Outlier observations	The maximum value of this feature is much higher than the mean and the 3rd quartile, indicating that there may be an error. The extreme nature of these outliers is shown in Figure 1. Through testing it was found that there are 18 observations greater than 50,000,000 with the 99.9th percentile sitting at 6699.0.
A9, A11	Strongly correlated features	Figure 5 indicates that A9 and A11 are strongly correlated with a coefficient of -0.78. After further investigation, we observed that there is likely a mathematical or physical constraint between the two features due to the relationship exhibited in Figure 6.
A10	Abnormal data type	There are 0.99% of the observations in feature A10 that have the value 'a' whilst all the other observations have numerical values.
A14, A18, A30, A32, A42, A43, A50, A52, A53	Class imbalance, $90\% < Mode\% < 95\%$	Table 2 indicates that these features have a class imbalance since their modal class consists of between 90% and 95% of the dataset.

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Table 4 – continued from previous page

Feature	**Data Quality Issue**	**Justification**
A16	Cardinality of 1	This categorical variable is redundant since all the observations have the same value. This is observed in the cardinality column of Table 2.
A17	Cardinality of 1	This categorical variable is redundant since all the observations have the same value. This is observed in the cardinality column of Table 2.
A20, A21, A22, A23, A24, A25, A26, A27, A28, A29, A31, A33, A34, A35, A36, A37, A38, A39, A40, A41, A44, A45, A46, A47, A48, A51, A54, A55, A56, A57, A58, A59, A60	Severe class imbalance, $95\% \leq Mode\% < 100\%$	Table 2 indicates that these features have a severe class imbalance since their modal class consists of between 95% and 100% of the dataset.
A21	Missing values	Many records, specifically 70.16%, have missing values for A21 as observed in Table 2.
A35	Extremely high class imbalance	The 2nd class for this feature only has three observations. This rounds to 0.01% shown in Table 2.
A61	ID Feature	This feature has a perfectly uniform distribution observed in Figure 2. Testing revealed that the feature value is exactly the same as the row number for all observations.
A61, A1	Strongly correlated features	The features A1 and A61 are strongly correlated, as observed in Figure 5 with a correlation coefficient of -0.95.
A62	Cardinality of 1	This categorical variable is redundant since all the observations have the same value.
T	Target class imbalance	It can be observed in Figure 7b that there is a severe target class imbalance, with only 2747 observations in class 4. This means that certain classes are better represented in the dataset and can lead to machine learning model bias.
T	Target variable missing values	Testing revealed that there are 60 missing observations in the target variable. This rounds to 0.01% of the data seen in Table 3.

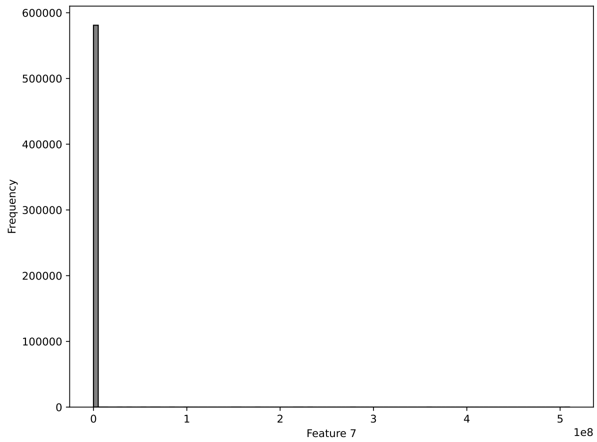


Figure 1: Feature 8 distribution with 100 bins

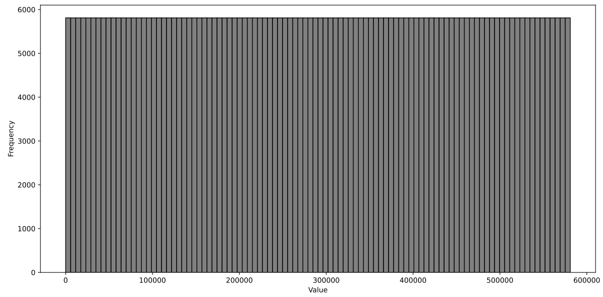


Figure 2: Feature 61 distribution with 100 bins

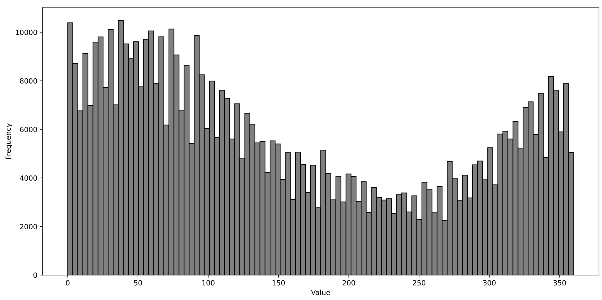


Figure 3: Feature 2 distribution with 100 bins

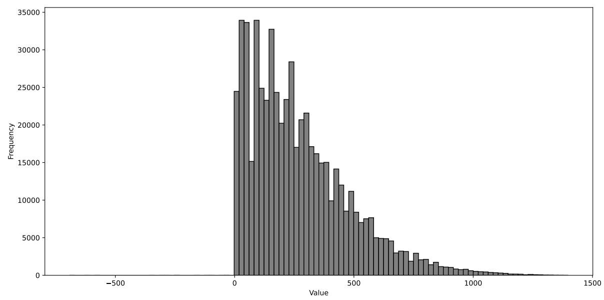


Figure 4: Feature 5 distribution with 100 bins

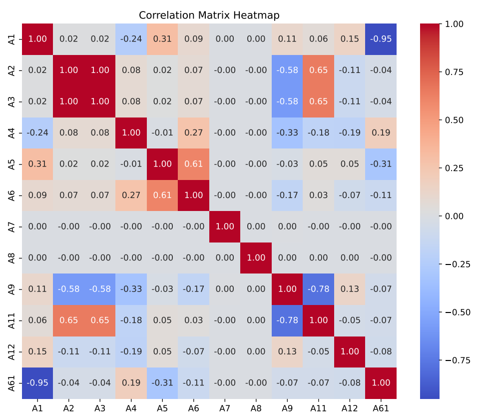


Figure 5: Correlation heatmap

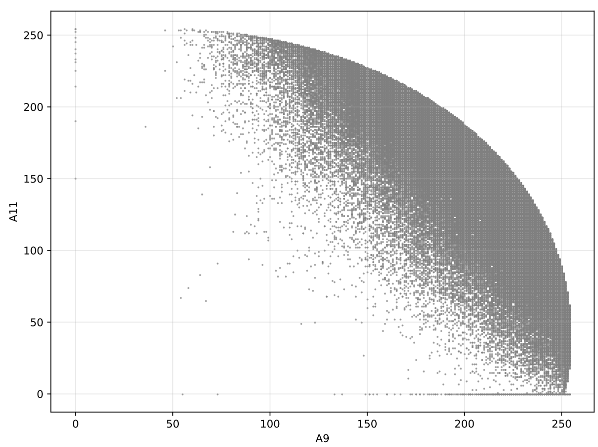


Figure 6: A9 vs A11 scatter plot

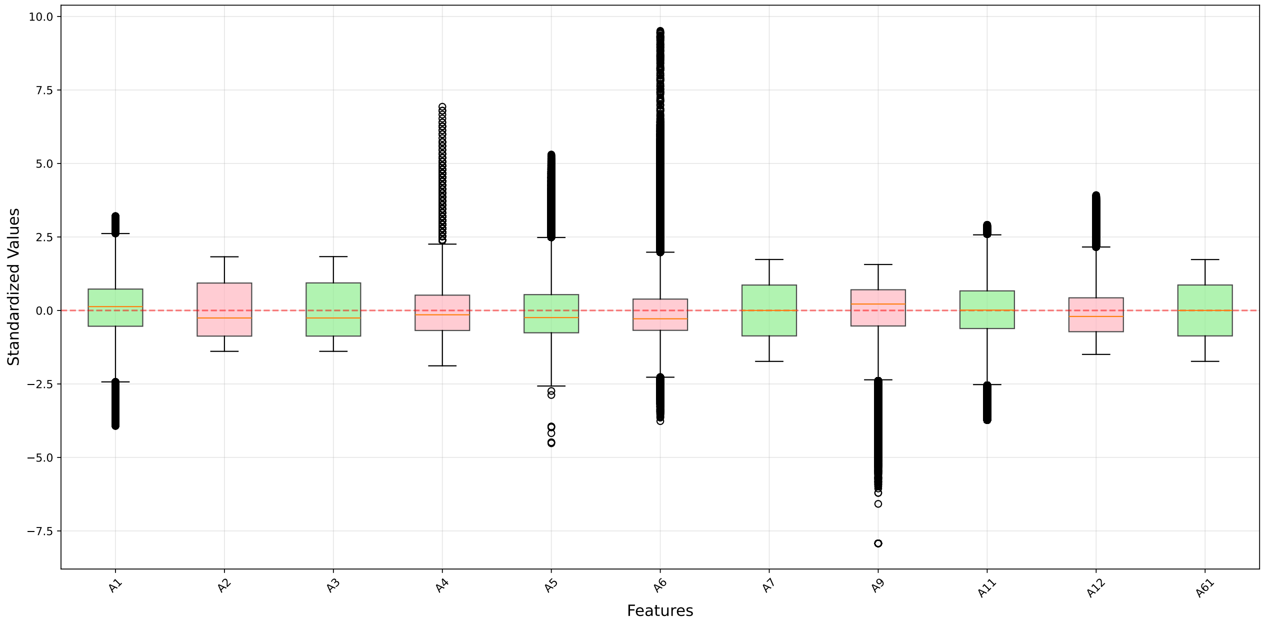
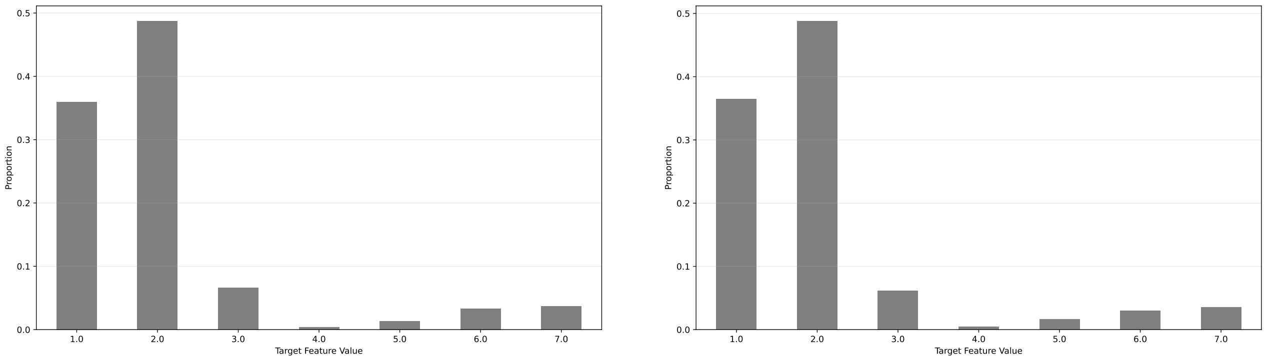


Figure 8: Boxplots of standardised continuous variables



(a) Target value distribution (missing)

(b) Target value distribution (entire dataset)

Figure 7: Comparison of target value distribution for missing data observations vs entire dataset

Task 3: Addressing The Data Quality Issues

Table 5: Data Quality Fixes

Feature	**Data Quality Issue**	**Handling Strategy**	**Justification**
A1, A4, A6, A9, A11, A12	Outlier observations	Nothing	These outliers can be considered *valid* outliers and should not be removed. This is due to the outliers not appearing to be out of line with the distributions of the feature overall.
A2	Missing values	Remove feature	See below.

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Table 5 – continued from previous page

Feature	Data Quality Issue	Handling Strategy	Justification
A2, A3	Perfect correlation	Remove feature A2	Since the features are perfectly correlated, we are essentially storing the same information twice which provides no value to a machine learning model. Since A2 has missing values we might as well remove it to deal with two quality issues at the same time.
A4, A5, A7, A9, A10, A12, A13, A16, A18, A20, A21	Missing values	Remove observations	Since testing revealed that there are a certain 2947 rows with all these features missing simultaneously, it makes sense to simply remove all these observations since they have a large amount of missing information. It is useful to note that the distribution of the target variable in these observations matches the overall distribution of the target variable for the whole dataset observed in Figure 7. This means that we are not likely to lose any useful information about a certain target category when removing these observations.
A5	Outlier observations	Remove observations	Since there are only 26 negative observations, we can safely drop these as they make up only a minute part of the dataset.
A8	Outlier observations	Remove observations	There must be an error with the observations in question because the outliers are so incredibly skewed. Through testing it was found that there are 18 observations greater than 50,000,000 with the 99.9th percentile sitting at 6699.0.
A9, A11	Strongly correlated features	Nothing	Despite these features being strongly correlated, there is still a chance that the features' relationship makes sense in the domain context. Therefore we elect to not remove either feature.

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Feature	Data Quality Issue	Handling Strategy	Justification
A10	Abnormal data type	Remove observations	Testing revealed that the levels of this suspected categorical variable range from 100–254 predominantly. Since many observations have the value 'a', we can guess this error is not at random and the character 'a' could be replaced with 255. This fits the distribution seen in Figure 9. Despite these facts, one would need to consult a domain expert before replacing it by 255, therefore the safer option is to remove the observations.
A14, A18, A30, A32, A42, A43, A50, A52, A53	Class imbalance, $90\% < Mode\% < 95\%$	Under-sample majority classes	Due to the large number of observations in this dataset, we can safely under-sample the majority class to reduce the class imbalances. If this reduces the dataset's size too much, we can always consider oversampling the minority classes.
A16	Cardinality of 1	Drop feature	This categorical variable can be removed since it will have no effect on a model's performance.
A17	Cardinality of 1	Drop feature	This categorical variable can be removed since it will have no effect on a model's performance.
A20, A21, A22, A23, A24, A25, A26, A27, A28, A29, A31, A33, A34, A35, A36, A37, A38, A39, A40, A41, A44, A45, A46, A47, A48, A51, A54, A55, A56, A57, A58, A59, A60	Severe class imbalance, $95\% \leq Mode\% < 100\%$	Under-sample majority classes	Due to the large number of observations in this dataset, we can safely under-sample the majority class to reduce the class imbalances. If this reduces the dataset's size too much, we can always consider oversampling the minority classes.

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Feature	**Data Quality Issue**	**Handling Strategy**	**Justification**
A21	Missing values	Drop feature	Testing revealed that the correlation between missingness of A21 and the target is -0.0004. This only means that there is not a linear relationship. It is possible that the missingness is still related to the target feature. Plotting the confusion matrix Figure 10 indicates that A21 has the same values as A20 for every observation. This makes it redundant. Due to the high number of missing values we should remove the feature. It still is worth investigating adding the missingness as an extra category.
A35	Extremely high class imbalance	Drop feature	Since there are only three observations in the second class for this feature, it should be removed without affecting model performance.
A61	ID Feature	Drop feature	It was confirmed that this feature perfectly fits the description of an ID column, meaning it has no predictive power and can be removed.
A61, A1	Strongly correlated features	Drop feature	Since we have already established that A61 is a redundant ID feature and have determined to remove it, we have solved the issue.
A62	Cardinality of 1	Drop feature	This categorical variable can be removed since it will have no effect on a model's performance.
T	Target class imbalance	Synthetic minority oversampling technique	Since we have so few observations for classes 3, 4, 5, 6 and 7; using SMOTE will help resolve our issue by creating new instances to balance out the classes.
T	Target variable missing values	Remove observations	Since such an insignificant number of observations are missing, we can safely drop these observations without affecting the size of our dataset much as all.

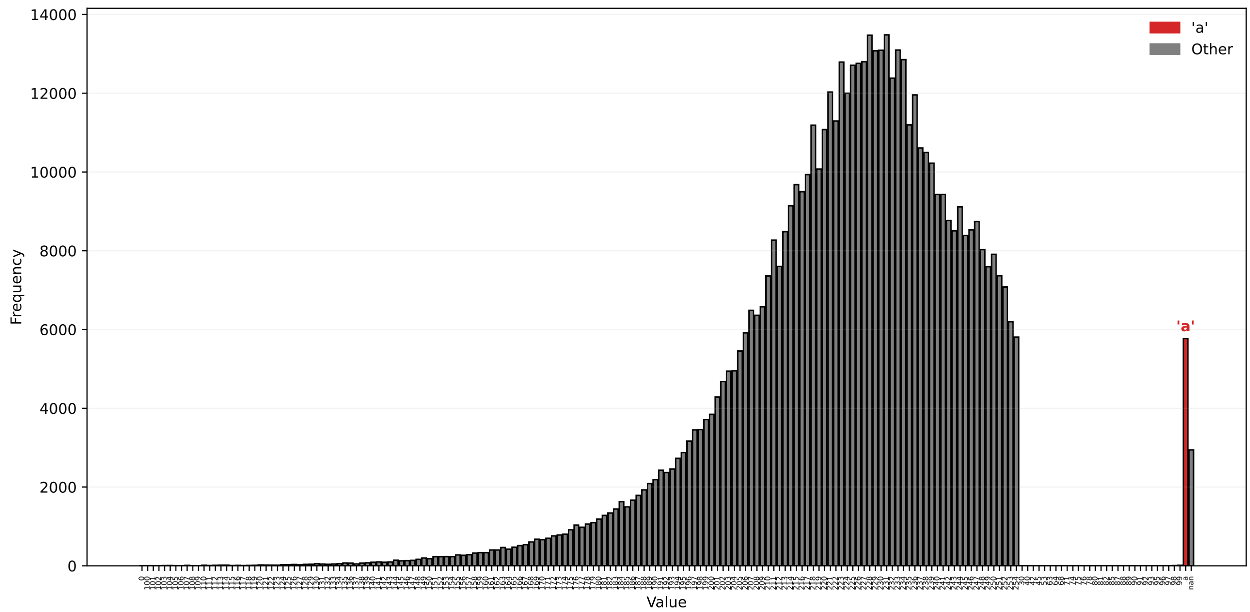

Figure 9: Feature 10 distribution ordered by value

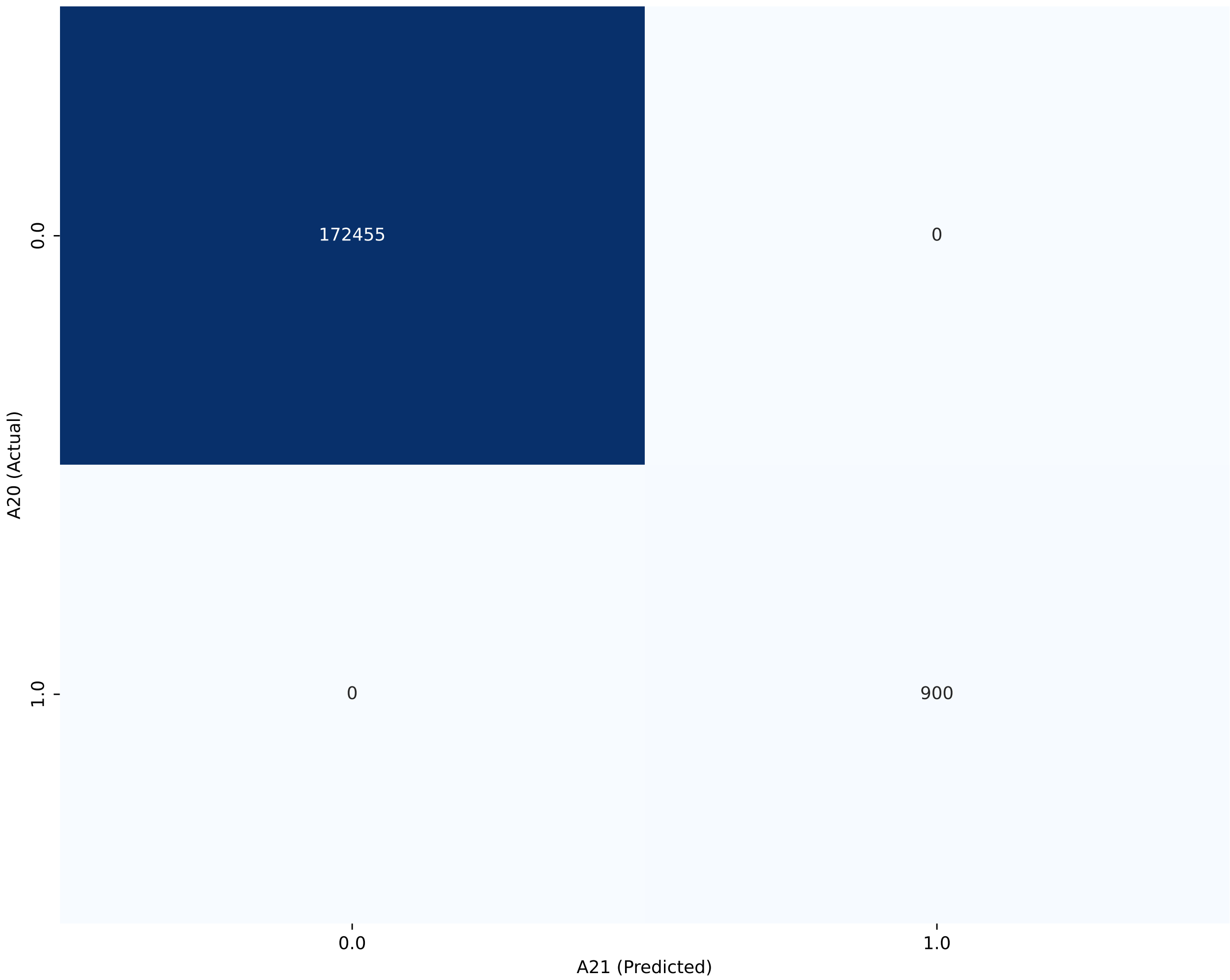

Figure 10: Confusion matrix of A20 vs A21