1 APPENDICES

1.1 Appendix 1 - Summary of Well-known Data Quality Issues and the Data Quality Dimension Violations Associated

Table 1 - Data Quality Issues and Data Quality Dimension Violations [Adapted from Visengeriyeva and Abedjan, 2020]

#	Data Quality Issue	sues and Data Quality Dimension Violations [Adapted from Visengeriyeva and Abedja Description	Data Quality
"	Data Quanty Issue	Description	Dimensions
1	Missing data	Comprises missing tuples and missing values. Tuple completeness requires that all tuples are present in the table. Missing value issue consists of either null values or disguised values. Value completeness requires that all values are present in the table, while null values indicate that the value is unknown or non-existent.	Accuracy, Completeness
2	Incorrect data	Data that differ from the values of the real-world entity (e.g., wrong date of birth).	Accuracy
3	Misspellings	Syntactic deviation of the data value from its ground truth (e.g., "Smiht" instead of "Smith").	Accuracy
4	Ambiguous data	Data values which might be interpreted in several ways (e.g., abbreviations or cryptic values).	Accuracy, Consistency
5	Extraneous data	Presence of additional data in the attribute value (e.g., the address column contains a person's name in addition to the address).	Consistency, Uniqueness
6	Outdated temporal data	Values that are obsolete or outdated.	Timeliness
7	Misfielded values	Values that are placed inside the wrong attribute.	Accuracy, Consistency, Completeness
8	Incorrect references	Entities that contain wrong information concerning the reference relation (e.g., the employee is associated with a wrong department).	Accuracy
9	Duplicates	Tuples/values that represent the same real-world entity.	Uniqueness
10	Structural conflicts	Conflicting duplicates in different sources.	Consistency, Uniqueness
11	Different word orderings	Values that violate the expected word order (e.g., first name precedes last name).	Consistency, Uniqueness
12	Different aggregation levels	Entities produced by applying different aggregation methods (e.g., entries per quartal vs. entries per year).	Accuracy, Consistency
13	Temporal mismatch	Refers to erroneous data that arise due to non-enforcement of integrity constraints for temporal data.	Accuracy, Timeliness
14	Different units/representations	Occurrence of multiple representations for the same concept (e.g., Price in different currencies).	Consistency
15	Domain violation	Values that violate semantic rules defined on the specific attribute.	Accuracy
16	FD violation	Values that violate previously specified functional dependencies.	Accuracy, Consistency
17	Wrong data type	Values that violate the data type specification of the corresponding attribute, i.e., data type constraint violation.	Consistency
18	Referential integrity violation	Tuples that violate the referential integrity constraints defined on multiple relations (e.g., missing foreign key).	Accuracy, Consistency, Completeness
19	Uniqueness violation	Duplication of values under the uniqueness constraint.	Uniqueness
20	Use of synonyms	Occurrence of synonymous representations for the same concept inside the same column (e.g., "lecturer" and "professor").	Uniqueness

21	Use of special	Refers to different representations of compound data, such as Social Security Number or	Consistency
	characters (space, no space,	phone number.	
	dash, parentheses)		
22	Different encoding	Inconsistent usage of encodings for values within a dataset (e.g., ASCII or EBCDIC).	Consistency
	formats		

1.2 Appendix 2 - Spreadsheet with first selection of ten datasets from the UCI Catalogue

The decision to choose these ten datasets was the following:

- The top two datasets from each of the areas: Life, Social, Physical, Computer and Financial.
- This is how the top two datasets were chosen for each area:
- 1) Sorting from top to bottom of the 'web_hits' column that showed how many web hits each dataset obtained.
- 2) Sorting from top to bottom of the 'num_papers' column, which showed the number of research papers that cited each dataset.
- 3) Ranking from 1 to the lowest amount for the 'web_hits' column. The top one is number 1
- 4) Ranking from 1 to the lowest amount for the 'num_papers' column. The top one is number 1
- 5) Addition of the two rankings.
- 6) Ranking from 1 to the lowest amount for the sum of rankings.
- 7) Only the first 2 top in each area were chosen, and they are presented in green below:



Figure 1 – Definition of ten datasets chosen from 5 areas

1.3 Appendix 3 – Definition of datasets for the second selection

In the second selection 40 more datasets from the UCI Catalogue were analysed. The definition was determined based on a proportional representation of each domain, considering the total number of datasets available in each. This was executed while excluding the datasets adopted in the first iteration from the initial five chosen domains. This iteration introduced two additional domains: the "Business" domain and an untitled category encompassing areas not specified in the UCI Catalogue.

Area	Count	Frequency (%)	Count for the second iteration	New frequency	Distribution for 40 datasets	Final count for 40 datasets
Computer	232	37.3%	230	37.6%	15.03	15
Life	145	23.3%	143	23.4%	9.35	9
Physical	57	9.2%	55	9.0%	3.59	4
Social	41	6.6%	39	6.4%	2.55	3
Business	40	6.4%	40	6.5%	2.61	3
Game	12	1.9%	12	2.0%	0.78	0
Financial	5	0.8%	3	0.5%	0.20	0
Computer Security	1	0.2%	1	0.2%	0.07	0
(Missing)	89	14.3%	89	14.5%	5.82	6
Total	622	1	612	1	40	40

Figure 2 – Determination of 40 new datasets to be analysed.

The datasets were chosen based on their number of web hits, as a significant portion of the datasets in the UCI Catalog do not provide information on the number of papers that used them.

See below the final list of the datasets chosen according to the rule from above:

index name	area	instances	attribute	year	#webhits	Order	date_donate	web_hits	dataset_file_format	This shoot is audomed l
186 Wine Quality	Business	4898	12	2009	6	1	7/10/2009	2160922	csv	This sheet is ordered by area.
222 Bank Marketing	Business	45211	17	2012	7	2	14/02/2012	2056977	zip	Here are the 3 datasets from
352 Online Retail	Business	541909	8	2015	20	3	6/11/2015	832562	xls	Business area and 15 from
602 Dry Bean Dataset	Computer	13611	17	2020	3	1	14/09/2020	2213938	zip	Business area and 13 from
545 Rice (Cammeo and Osn	Computer	3810	8	2019	9	2	6/10/2019	1969142		Computer area as previously
232 Human Activity Recogn	Computer	10299		2012	14		10/12/2012	1314591		defined. It is easy to see that
360 Air quality	Computer	9358		2016	27	3	23/03/2016	725672		,
346 Air Quality	Computer	9358		2016	28		23/03/2016	725671		the order in each area is done
228 SMS Spam Collection	Computer	5574		2012	34		22/06/2012	479991	•	by #webhits. There are many
242 Energy efficiency	Computer	768	_		38	4	30/11/2012	462717		,
267 banknote authenticatio		1372		2013	39	5	16/04/2013	460121		cases in red that were not
29 Computer Hardware	Computer	209		1987	46	6	1/10/1987	414194		chosen. Some cases are due
80 Optical Recognition of		5620		1998	52		1/07/1998	389787		
6 Artificial Characters	Computer	6000		1992	61 69		1/07/1992	313031		to high quantity of attributes
294 Combined Cycle Power 81 Pen-Based Recognition		9568 10992		2014 1998	73	,	26/03/2014 1/07/1998	292540 283022		(561 in ID 232, 513 in ID
342 Detect Malacious Exec		373			73 77		3/03/2016	273969		242 5625 : ID 256 1559 :
229 Skin Segmentation	Computer	245057		2012	86	Q	17/07/2012	255159		342, 5625 in ID 256, 1558 in
256 Daily and Sports Activit		9120		2012	88	Ů	8/07/2013	251575		ID 51 and 294 in ID 4); or
246 3D Road Network (Nor		434874			98	9	16/04/2013	235945		
51 Internet Advertisemen		3279		1998	45	Ĩ	1/07/1998	416162		repeated datasets (ID 360 and
4 Anonymous Microsoft		37711		1998	108		1/11/1998	221962	•	346); or just have one or two
374 Appliances energy pre-		19735			109	10	15/02/2017	221573		columns (ID 228); or are
248 Buzz in social media	Computer	140000	77	2013	115		27/05/2013	206018	gz	` ''
343 Occupancy Detection	Computer	20560	7	2016	121		29/02/2016	200819	0	basically just numbers in
128 KDD Cup 1999 Data	Computer	4000000	42	1999	127	13	1/01/1999	193028	gz	character recognition
303 Perfume Data	Computer	560	2	2014	131	14	22/07/2014	189180	xls	
225 Restaurant & consume	Computer	138	47	2012	132	15	4/08/2012	186722	zip	datasets (IDs 80, 6 and 81).

Below you see the continuation.

										•	
index i		area	instances		•					dataset_file_format	And here are the 9 datasets
	Breast Cancer Wisconsir		569		1995			1/11/1995			from Life, 6 from N/A, 4
		Life	900	8		11		1/04/2021			from Enc, o from N/A, 4
		Life	4177	8		12		1/12/1995			from Physical and 3 from
	Breast Cancer Wisconsir		699		1992			15/07/1992			Social areas. The datasets in
73 1	Mushroom	Life	8124	22	1987	21	5	27/04/1987			Social areas. The datasets in
34 1	Diabetes	Life		20		26		N/A	741148	Z	red, that had to be discarded
14 (Breast Cancer	Life	286	9	1988	29	6	11/07/1988	705622	data	were due to: being in a Z
236 9	seeds	Life	210	7	2012	37	7	29/09/2012	465163	txt	were due to. being in a Z
111 7	Zoo	Life	101	17	1990	40	8	15/05/1990	448279	data	compacted file that the code
31 (Covertype	Life	581012	54	1998	41	9	1/08/1998	444144	data	cannot access the contents
19 (Car Evaluation	N/A	1728	6	1997	10	1	1/06/1997	1748706	data	cannot access the contents
10 /	Automobile	N/A	205	26	1987	18	2	19/05/1987	873273	data	(ID 34); a dataset with
9 /	Auto MPG	N/A	398	8	1993	19	3	7/07/1993	856989	data	100000 attributes (ID 164); a
40 1	Flags	N/A	194	30	1990	49	4	15/05/1990	395601	data	100000 auributes (ID 104), a
164	Bag of Words	N/A	8000000	100000	2008	55		12/03/2008	363665	txt	dataset that is not text (ID
104	University LISP-readabl e	N/A	285	17	1988	70		1/07/1988	292193	data	104); a dataset in HTML (ID
132	Movie	N/A	10000		1999	80		7/07/1999	269872	data	104), a dataset ili HTML (ID
336 (Chronic_Kidney_Disease	N/A	400	25	2015	81	5	3/07/2015	268517	rar	132); a dataset in two
331 9	Sentiment Labelled Sen	N/A	3000		2015	84		30/05/2015	255655	zip	columns (ID 331); a dataset
50 1	mage Segmentation	N/A	2310	19	1990	89	6	1/11/1990	250837	data	columns (ID 331), a dataset
162	Forest Fires	Physical	517	13	2008	15	1	29/02/2008	1184000	csv	where the data are not in one
235	ndividual household el	Physical	2075259	9	2012	32	2	30/08/2012	538670	zip	line, making it impossible to
165 (Concrete Compressive S	Physical	1030	9	2007	59	3	3/08/2007	328451	xls	, & 1
138	Robot Execution Failure	Physical	463	90	1999	60		23/04/1999	324835	data	read it automatically (ID 138
52 1	onosphere	Physical	351	34	1989	62		1/01/1989	311140	data	and a dataset which does not
381 I	Beijing PM2.5 Data	Physical	43824	13	2017	78	4	19/01/2017	270894	csv	
	, ,	Social	649				5	27/11/2014		zip	exhibit names/labels of
		Social	17389	16				20/12/2013			columns/attributes (ID 52).
	ŭ	Social	16	4		51		N/A	392085		cordinis, autionics (ID 32).

rom Physical and 3 from Social areas. The datasets in ed, that had to be discarded vere due to: being in a Z ompacted file that the code annot access the contents ID 34); a dataset with 00000 attributes (ID 164); a lataset that is not text (ID 104); a dataset in HTML (ID 32); a dataset in two olumns (ID 331); a dataset where the data are not in one ine, making it impossible to ead it automatically (ID 138) and a dataset which does not xhibit names/labels of olumns/attributes (ID 52).

Figure 3 – Definition of forty datasets from UCI for second iteration.

1.4 Appendix 4 – Algorithm and Results of Attribute-Based Semantic Type Detection

Here is the Algorithm for this section:

Attribute-Based Semantic Type Detection.

 Read Dataset Information: Load dataset information, such as dataset names and column descriptions, from an external source (e.g., an Excel file).

Clean Columns:

- a. Extract ID, column names, and descriptions from the 'Original Column' data.
- Standardize column names by converting them to lowercase, removing special characters, and separating descriptive information.
- c. Split descriptive information into multiple parts for further analysis.

3. Preprocess Columns:

- a. Further preprocess the standardized column names to replace abbreviations with their full forms using an abbreviations dictionary.
- b. Clean and prepare the column names for semantic analysis.
- 4. Open Formats and Abbreviations Dictionaries: Load dictionaries that contain mappings between abbreviations and their full forms, as well as mappings between column name keywords and their associated data formats.
- 5. Replace Abbreviations in Column Names: For each column name, replace any abbreviations found with their full forms based on the abbreviations dictionary.
- 6. Apply Semantic Analysis:
 - For each column, identify the target word (keyword) from the column name that matches an entry in the formats dictionary.
 - b. Assign the associated data format to the column based on the identified target word.
 - For descriptions associated with each column, perform a similar analysis to identify additional keywords and associated data formats.
 - Special handling for identifying 'ID' columns and handling cases where the column name matches specific
 patterns or criteria.
- 7. Analysis of Column: Determine the final format for each column by comparing the findings from the column name and description analyses. Resolve any discrepancies or special cases according to predefined rules.
- 8. Identify Origin: For each column, identify whether the final format determination came from the analysis of the column name or the description.
- 9. Save Results: Output the analysis results to an external file (e.g., Excel) for further use or review.

This algorithm provides a structured approach to analyzing dataset attributes/columns based on their labels/names and descriptions, utilizing predefined dictionaries for semantic analysis and format identification. The goal is to standardize column names and identify potential data formats for further investigation.

To illustrate the practical application of this algorithm, let us consider its execution on the 'Heart Disease' dataset. Initially, the notebook reads the information from the 'AllColumnsFromTenDatasets.xlsx' file for a specific dataset (Table 3 from section 4.2.1 above) and initially breaks down each column's 'Original Column' data into its constituent parts: ID, Column, and Description. The description is formed from parts of text after the symbols '(' or ':' or '/'. There can be many Descriptions for a single column being analysed. See Table 7 for the result:

Table 2 - Breaking columns and descriptions for the 'Heart Disease' dataset

lex	name	area	Original Column	ID	Column	Description 1	Description 2
45	Heart Disease	Life	. age	1	age		
45	Heart Disease	Life	. sex	2	sex		
45	Heart Disease	Life	. cp (chest pain type)	3	ср	chest pain type	
45	Heart Disease	Life	. trestbps (resting blood pressure Integer)	4	trestbps	resting blood pressure Integer	
45	Heart Disease	Life	. chol (serum cholestoral in mg/dl Integer)	5	chol	serum cholestoral in mg	dl Integer
45	Heart Disease	Life	. fbs (fasting blood sugar > 120 mg/dl Categor	rical) (1 = true; 0 = false) 6	fbs	fasting blood sugar > 120 mg	dl Categorical
45	Heart Disease	Life	. restecg (resting electrocardiographic results	Categorical) 7	restecg	resting electrocardiographic results Categorical	
45	Heart Disease	Life	. thalach (maximum heart rate achieved Integ	ger) 8	thalach	maximum heart rate achieved Integer	
45	Heart Disease	Life	. exang (exercise induced angina (1 = yes; 0 =	no) Categorical) 9	exang	exercise induced angina	1 = yes; 0 = no
45	Heart Disease	Life	0. oldpeak (ST depression induced by exercise r	elative to rest Integer) 10	oldpeak	ST depression induced by exercise relative to rest	Integer
45	Heart Disease	Life	1. slope (the slope of the peak exercise ST segm	ent Categorical) 11	slope	the slope of the peak exercise ST segment Categori	cal
45	Heart Disease	Life	2. ca (number of major vessels (Categorical 0-3)	colored by flourosopy) 12	ca	number of major vessels	Categorical 0-3
45	Heart Disease	Life	3. thal (3 = normal; 6 = fixed defect; 7 = reversal	ble defect Categorical) 13	thal	3 = normal; 6 = fixed defect; 7 = reversable defect (Categorical
45	Heart Disease	Life	4. num (the predicted attribute)	14	num	the predicted attribute	

Notice above that the first two columns don't contain any words besides their own. All the other columns contain a first word and separate words after symbols '(' or '/'. So, description(s) were created.

After the Description is separated there are pre-processing activities that turn all words to lowercase and delete some symbols such as '-' and '_'. The 'CleanedColumn' is then created. In this field the code searches for words that exist in the Formats dictionary, or maybe in the Abbreviations dictionary. The first one found goes to the 'ColumnKeyword'. The format associated with this target word goes to the column 'ColumnFormat'. See below in Table 8.

Observe below that the word 'age' brings the format 'age' which is numerical bounded and the word 'sex' brings the format 'categorical'. Then, all columns until 'slope' (format numerical), do not show any target word found, because the words that exist in the name of the columns do not exist in the formats nor in the abbreviations dictionary. But there are words in the Description parts that exist in the Formats Dictionary, and they are brought together with the format associated:

Table 3 – Obtaining words and formats for the 'Heart Disease' dataset.

ID	Column	Description 1	Description 2	CleanedColumn	ColumnKeyword	ColumnFormat	DescriptionKeyword	DescriptionFormat
1	age			age	age	age		
2	sex			sex	sex	categorical		
3	ср	chest pain type		ср			type	categorical
4	trestbps	resting blood pressure Integer		trestbps			integer	numerical
5	chol	serum cholestoral in mg	dl Integer	chol			integer	numerical
6	fbs	fasting blood sugar > 120 mg	dl Categorical	fbs			categorical	categorical
7	restecg	resting electrocardiographic results Categorical		restecg			categorical	categorical
8	thalach	maximum heart rate achieved Integer		thalach			rate	numerical
9	exang	exercise induced angina	1 = yes; 0 = no	exang			yes	categorical
10	oldpeak	ST depression induced by exercise relative to rest	Integer	oldpeak			integer	numerical
11	slope	the slope of the peak exercise ST segment Categor	ical	slope	slope	numerical	categorical	categorical
12	ca	number of major vessels	Categorical 0-3	ca			categorical	categorical
13	thal	3 = normal; 6 = fixed defect; 7 = reversable defect	Categorical	thal			categorical	categorical
14	num	the predicted attribute		num	num	numerical	predicted	categorical

In the end, the column 'FinalFormat' receives the final data type detection either from the Column Format or from the Description Format. And the word associated with the final format goes to the last column, 'SourceKeyword'. See Table9:

 $Table\ 4-Final\ results\ for\ data\ type\ detection\ for\ the\ 'Heart\ Disease'\ dataset$

ID	CleanedColumn	ColumnKeyword	ColumnFormat	DescriptionKeyword	DescriptionFormat	FinalFormat	SourceKeyword
1	age	age	age			age	age
	sex	sex	categorical			categorical	sex
3	ср			type	categorical	categorical	type
4	trestbps			integer	numerical	numerical	integer
5	chol			integer	numerical	numerical	integer
6	fbs			categorical	categorical	categorical	categorical
7	restecg			categorical	categorical	categorical	categorical
8	thalach			rate	numerical	numerical	rate
9	exang			yes	categorical	categorical	yes
10	oldpeak			integer	numerical	numerical	integer
11	slope	slope	numerical	categorical	categorical	categorical	categorical
12	ca			categorical	categorical	categorical	categorical
13	thal			categorical	categorical	categorical	categorical
14	num	num	numerical	predicted	categorical	categorical	predicted

Above, only the first two 'FinalFormat' results were the same as 'ColumnFormat', and all the others were obtained from 'DescriptionFormat'.

The results of applying this code to all fifty datasets, covering 922 columns/attributes, are compiled in 'AnalysedColumns.xlsx' [Silva, 2024]. It's important to note that during the analysis of each dataset, the dictionaries were iteratively refined to enhance their effectiveness in generating the desired outputs.

Observation: The Python version adopted was 3.9.12.

1.5 Appendix 5 - Algorithm and Results of Attribute-Based Data Quality Assessment

Here is the Algorithm for this section:

Attribute-Based Data Quality Assessment

- 1. Read Ten/Forty Datasets file (depending if first or second set of datasets)
 - a. Import necessary libraries.
 - b. Define the path to the Excel file containing ten/forty datasets' details.
 - c. Load the Excel file into a pandas DataFrame and display its first few rows for verification.
- 2. Read AnalysedColumns file from previous code and Define Dataset Index
 - a. Load the Excel sheet that lists AnalysedColumns for 50 datasets.
 - b. Define the dataset index for which the user wants to find the dataset file URL and name.
 - c. Print the selected dataset index and the current date-time.
- 3. Step 3: Get Dataset File URL
 - a. Define a function get_dataset_file_url that loads dataset details from the first Excel file above and returns the dataset file URL and name for a specific dataset index.
 - b. Call the function with the previously defined Excel file path and dataset index.
 - c. Print the obtained dataset file URL and name of file, or an error message if not found.

4. Step 4: Load Dataset

- a. Implement several functions to load datasets:
 - i. is_header_for_csv: Determines if a line is likely a header based on the presence of numeric values.
 - load_csv: Loads a CSV file into a pandas DataFrame, with adjustments for delimiter detection and header presence.
 - iii. is_header_for_excel: Determines if the first row in an Excel file is likely a header.
 - iv. load_excel: Loads an Excel file into a pandas DataFrame, with adjustments for header presence.
 - v. download_and_extract: Downloads and extracts an archive file from a URL.
 - vi. select_file_from_extracted: Allows the user to select a file from an extracted directory.
 - vii. fetch_file_content: Fetches the content of a file from a URL.
 - viii. load_dataset: Determines the file type and loads it accordingly, supporting local and remote files and handling archives.

5. Assign Column Names

- a. Import necessary libraries.
- b. Define a function assign_column_names that assigns column names to a DataFrame based on a given dataset index from an "AnalysedColumns" DataFrame. It checks if required columns exist in the DataFrame and assigns extracted column names to the target DataFrame.
- Call the function with the analysed columns DataFrame, desired dataset index, and the previously loaded DataFrame to assign column names.

6. Data Quality Issues

- a. Define a class "DataQualityIssues" containing static methods to handle various data quality issues. These methods cover a wide range of issues, including missing data, ambiguous data, extraneous data, outdated temporal data, duplicates, structural conflicts, domain violations, wrong data type, uniqueness violation, and the use of special characters.
- Each method is designed to handle a specific type of data quality issue identified by DQI (Data Quality Issue) numbers or not directly associated with a DQI number.
- c. The methods perform checks and return information about the presence of data quality issues, including the indices of problematic data points, error messages, and the specific data quality issue addressed.

d. This step involves identifying and addressing various data quality issues using the DataQualityIssues class's methods. The specific implementation details of handling each data quality issue are encapsulated within the class's methods.

Below are functions created to evaluate specific formats defined in the previous code.

- a. Each task involves:
 - i. Handling missing or invalid entries (blank, empty, null, NaN)
 - ii. Applying specific validations relevant to the data type or format being checked.
 - iii. Using predefined lists of exceptions where applicable (e.g., linking words for names, acceptable abbreviations for states).
 - iv. Reporting errors and summarizing the results, including value distributions and ranges where applicable.
 - v. Generate and report frequency distributions in some cases to provide insights into the data's distribution.
 - vi. For tasks involving dates, times, or specific formats, the algorithm may deduce the most likely format based on sample values before applying validations.

7. Check Numerical Greater or Equal to Zero

- a. Handle missing or blank values in the specified column.
- b. Validate that all numerical values are greater than or equal to zero.
- c. Report on non-numeric values.
- d. Summarize the findings, including any errors and the range of numeric values.

8. Check Numerical

a. Similar to item 07 but focused on ensuring all values are numerical without the greater than zero condition.

9. Check Numerical Between

- a. Ensure all numerical values fall within a specified range.
- b. Similar error checking as previous tasks, with the addition of validating the numeric range.

10. Check if ID

a. Determine if column values are suitable for use as a Primary Key by checking for uniqueness, non-negative values, and other ID-specific criteria.

11. Check String Content

a. Ensure all values are non-empty strings and report on any values that do not meet this criterion.

12. Check if Categorical

 a. Validate if a column can be considered categorical based on the number of unique values and the presence of predefined unacceptable values.

13. Check Month

a. Verify that all column values are valid representations of months.

14. Check Weekday

a. Ensure all values correctly represent weekdays.

15. Check Date

a. Validate date values, ensuring they adhere to a consistent format and fall within a reasonable range.

16. Check DateTime

a. Similar to the date check but for datetime values, ensuring both the date and time components are valid.

17. Check Time

a. Validate time values, focusing on the format and range of the time component.

18. Check Model Name

 Ensure model names meet certain criteria, such as being non-empty and potentially following a specific format.

Check Name (Task 18.5)

 Validate names, ensuring they do not contain numbers or special characters and adhere to capitalization norms.

19. Check Street

- a. Validate street names for standard conventions (e.g., capitalization, avoiding special characters).
- Find the range of street names.
- c. Return any identified errors along with the range of street names.

20. Check City

- a. Validate city names for proper capitalization and format.
- b. Generate a frequency distribution of city names.
- c. Report on non-standard city names and provide a frequency distribution.

21. Check State

- a. Validate state names or abbreviations for capitalization and correct format.
- b. Create a frequency distribution of state names.
- c. Highlight and report non-standard state names along with the frequency distribution.

22. Check Country

- a. Ensure country names meet expected standards of capitalization and correctness.
- b. Generate and report a frequency distribution for country names.

23. Check Postal Code

- a. Validate postal codes for standard formats (length, numeric/alphanumeric values).
- $b. \quad \text{Report on non-standard postal codes and provide the range of valid postal codes.} \\$

24. Check Phone Numbers

- $a. \quad \ \ Validate\ phone\ numbers\ for\ standard\ formats\ (including\ international\ formats).$
- b. Identify and report non-standard phone numbers and provide the range of valid phone numbers.

25. Check IP Format

- a. Ensure IP addresses are in valid formats (IPv4, IPv6).
- b. Report on any non-standard IP address formats.

26. Check URL Format

- a. Validate URLs for standard formats.
- b. Identify and report non-standard URLs.

27. Check Email Format

- a. Ensure email addresses meet standard email format criteria.
- b. Report on any non-standard email formats.

28. Check Binary Values

- a. Validate if values in a column conform to binary values (e.g., '0', '1', 'true', 'false', and variations thereof).
- b. Provide a frequency distribution of binary values.
- c. Highlight and report non-standard binary values along with their frequency distribution.

29. Analyse Data Quality

This function comprehensively evaluates the quality of data across various columns specified in a DataFrame that specifies the expected data format for each column. The process involves several key steps:

- Initialization and Setup: Define any global parameters or thresholds needed for analysis, such as valid year ranges or thresholds for categorical uniqueness.
- b. Preparation: Determine the set of columns to be analyzed based on a provided desired_dataset_index, which helps to filter analysed_columns_df for relevant columns.
- c. Iteration over Columns: Loop through each column specified for the analysis, ensuring that each column exists in the primary DataFrame.
- d. Determination of Column Format: For each column, identify the desired data format based on the information in analysed_columns_df. This step involves mapping textual descriptions of formats to specific validation functions.
- e. Validation: Apply the appropriate validation function based on the determined format. This might include:
 - Checking for numerical ranges or specific conditions (e.g., greater than zero, within a specific range).
 - ii. Verifying categorical data against a uniqueness threshold.
 - iii. Validating string formats for names, addresses, etc.
 - iv. Confirming the format of dates, times, URLs, email addresses, etc.
- f. Frequency Distribution: For categorical data, generate and display a frequency distribution to provide insights into data diversity and potential anomalies.
- g. Result Compilation and Reporting: Aggregate the results of each column's analysis into a structured format, typically as a dictionary or a text summary, indicating any detected issues or confirming adherence to expected formats.
- Output Presentation: Print or return a comprehensive summary of the data quality analysis, highlighting any columns with issues and providing insights into the distribution of valid data.
- i. Handling Special Cases: Depending on the column's intended format, perform specialized checks (e.g., for IP addresses, geographical coordinates, or binary values) using tailored validation functions.

Below we can see some of the output of the Data Quality Assessment of Dataset 45 – Heart Disease, that explains the results in easy-to-read descriptions. Observe that it shows the name of the column being analysed, followed by the ('SourceKeyword', when different) found from the previous code, then it exhibits the format being analysed and the respective output, confirming data integrity, with the number of items and the range for numerical values, and possible Data Quality Issues and their associated data quality dimensions, as defined in Appendix 1:

45 Heart Disease

```
Age format: All 303 values are numerical and valid in the range [0, 130].
Actual range of values: (29.0: 77.0)
All 303 values are correctly categorical.
Categorical format with 2 unique values:
Category Frequency
          206
   1.0
trestbps (integer):
Numerical format: All 303 values are numerical in the range (94.0:200.0).
DOI #4 (Ambiguous Data - Accuracy, Consistency):
Unacceptable value(s) at index(es): 166, '?'), (192, '?'), (287, '?'), (302, '?')])
Categorical format with 5 unique values:
Category Frequency
        176
         65
  1.0
         38
          20
```

As seen above the 'age' column has been analysed as a numerical valid in the range [0,130], and the number of values and actual range were provided. The column sex was evaluated as categorical and as such its data integrity show that it had only two values, with the associated frequency. The column 'trestbps' had the word 'integer' in the description, so it is analysed as numerical. The last case provided regards the column 'ca', which due to having the word 'categorical' in the description was evaluated this way. Notice that our code found 4 cases of the content '?', which is an 'Unacceptable value' for categorical data. It was considered Data Quality Issue #4, related to 'Ambiguous Data' and the Data Quality Dimensions of 'Accuracy and Consistency'. Other Data Quality Assessment tools do not find this error.

The complete output from the latest analysis of 50 datasets and 922 columns/attributes is available on GitHub ('Discoveries on the 10 datasets.pdf' and 'Discoveries on the forty datasets.pdf' [Silva, 2024]).

1.6 Appendix 6 – Summary of Discoveries with created bad data

DQI# DQ Issue Description	Data Quality Dimension	Function Name	Cnecka	Format Being Analyz		Tested examples
1 Missing Data	Completeness	check_numerical_ge_zero	1	Numerical >= 0	Blank/Empty/Null/NaN values	None, ", ' ', 'null', nan, ' ', """
1 Missing Data	Completeness	check_numerical	2	Numerical	Blank/Empty/Null/NaN values	None, ", '', 'null', ''
1 Missing Data	Completeness	check_numerical_between	3	Numerical between	Blank/Empty/Null/NaN values	None, ", ", 'NULL', ' '
1 Missing Data	Completeness	check_id_attributes	4	ID	Blank/Empty/Null/NaN values	None, ", '', 'null'
1 Missing Data	Completeness	check_string	5	String	Blank/Empty/Null/NaN values	None, nan, ", ' '
1 Missing Data	Completeness	check if categorical	6	Categorical	Blank/Empty/Null/NaN values	", 'Null', None, ' " ", ' null'
1 Missing Data	Completeness	check_month	7	Month	Blank/Empty/Null/NaN values	None
1 Missing Data	Completeness	check_weekday	8	Weekday	Blank/Empty/Null/NaN values	None
1 Missing Data	Completeness	check_date	9	Date	Blank/Empty/Null/NaN values	", '', nan, None, 'Null'
1 Missing Data	Completeness	check_datetime	10	DateTime	Blank/Empty/Null/NaN values	nan, None, 'Null', ", ' '
1 Missing Data	Completeness	check_time	11	Time	Blank/Empty/Null/NaN values	", None
1 Missing Data	Completeness	check_name	12.5	Name	Blank/Empty/Null/NaN values	1,11
1 Missing Data	Completeness	check_street	13	Street	Blank/Empty/Null/NaN values	None, ", ', 'Null'
1 Missing Data	Completeness	check_city	14	City	Blank/Empty/Null/NaN values	None, ", ' '
1 Missing Data	Completeness	check_state	15	State	Blank/Empty/Null/NaN values	None, ", ' '
1 Missing Data	Completeness	check_country	16	Country	Blank/Empty/Null/NaN values	None, ", ' ', 'Null'
1 Missing Data	Completeness	check postal code	17	Postal Code	Blank/Empty/Null/NaN values	None, ", ' '
1 Missing Data	Completeness	check phone numbers	18	Phone	Blank/Empty/Null/NaN values	None, ", ' '
1 Missing Data	Completeness	check_ip_format	19	IP	Blank/Empty/Null/NaN values	None, ", ' '
1 Missing Data	Completeness	check_url_format	20	URL	Blank/Empty/Null/NaN values	", ' ', None, 'null'
1 Missing Data	Completeness	check_email_format	21	Email	Blank/Empty/Null/NaN values	", ' ', None, 'null'
1 Missing Data	Completeness	check_binary_values	22	Binary	Blank/Empty/Null/NaN values	None, ", ' '
4 Ambiguous Data	Accuracy, Consistency	check_if_categorical	6	Categorical	Unacceptable content	'?'
5 Extraneous Data	Consistency, Uniqueness	check_name	12.5	Name	Extraneous data	'?', 'John3 Doe', 'Emily!', '11'
5 Extraneous Data	Consistency, Uniqueness	check_street	13	Street	Extraneous data	'?', 'Emily!', '11'
5 Extraneous Data	Consistency, Uniqueness	check_city	14	City	Extraneous data	'?', 'Dubail', '11'
5 Extraneous Data	Consistency, Uniqueness	check_state	15	State	Extraneous data	'CA2', '?', 'Californial', '11'
5 Extraneous Data	Consistency, Uniqueness	check_country	16	Country	Extraneous data	'?', 'Canada!', '11'
6 Outdated Temporal Data	Timeliness	check_date	5	Date	Dates not in [1800-2100] period	'3/4/2121', '13101720', '14/5/2222', '01/01/1500', '31/12/2321', '2121/12/25'
6 Outdated Temporal Data	Timeliness	check_datetime	10	DateTime	Datetimes not in [1800-2100] period	'3/4/2121 13:00', '14/5/2222 13:05', '01/01/1500 13:00:10', '31/12/2321 13:20', '2121/12/25 13:00:12'
9 Duplicates	Uniqueness	check_id_attributes	4	ID	Duplicate values	'AB123CD456', 'Duplicate', 1
13 Temporal mismatch	Accuracy, Timeliness	check_date	5	Date	Invalid date values	'32/01/2021', '29/02/2021', '31/11/2021', '00/01/2021', '01/00/2021', '2021/13/01', 'not a date', '2021-0 30', '29022002'
13 Temporal mismatch	Accuracy, Timeliness	check datetime	10	DateTime	Invalid datetime values	13/01/2021 12:60', '2021/16/01 14:00', '18/01/2021 25:00', '2021-01-19T15:30', '21/01/2021 16:00:60', 'not a datetime', '24/01/2021 26:30', '29/02/2021 15:20', '2021-02-30 15:20:05'
13 Temporal mismatch	Accuracy, Timeliness	check time		Time	Invalid time values	'13:61', 'invalid', '02:30 PN', '25:03'
14 Different units/representations	Consistency	check date		Date	Dates without format DDMMYYYY in [1800-2100] period	12/31/2021', '2021/12/25', '2021/04/7', '2021/08/15', '2021/11/03', '12/30/2021', '02282002', '2012021'
14 Different units/representations	Consistency	check datetime	10	DateTime	Datetimes without format DDMMYYYY in [1800-2100] period	'2021-01-11 23:45', '2021/01/12 23:00', 'January 14, 2021 12:00', '2021/01/23'

Figure 4 - First part of Summary of Discoveries with created bad data.

This sheet shows that, many cases of bad data such as contents: None, ", '', 'null', nan, ' ', """ are related to Data Quality Issue #1, Missing Data, related to Data Quality Dimension 'Completeness', and are found in all different format functions, and their Error Explanation is Blank/Empty/Null/NaN values.

This sheet shows also other Data Quality Issues, such as number 4, Ambiguous Data, related to Data Quality Dimensions 'Accuracy and Consistency', found in the 'Categorical' function when a '?' was considered 'Unacceptable content'.

The same error related to content '?' is considered Data Quality Issue number 5, Extraneous Data, related to Consistency and Uniqueness, when the data is a geographic format. Other examples such as 'CA2', for state or 'Canada!', for country are also shown. These geographic functions do not consider valid characters different than text in their content.

Besides these there are above errors related to Duplicates for ID columns, and Temporal mismatch (such as outdated of future dates), and Different units/representations for Temporal columns, such as impossible dates (e.g. '32/01/2021').

1	DQII	DQ Issue Description	Data Quality Dimension	Function Name	Check# Format Bei	ng Analyz Error Explanation	Tested examples
38			Accuracy	check_numerical_ge_zero	1 Numerical		-1
39			Accuracy	check_numerical_between		between Values outside range [0, 130]	131, -1
40				check_id_attributes	4 ID	Negative values; Floating-point numbers	-1, 5.67
41	1	5 Domain Violation	Accuracy	check_month	7 Month	Invalid month values	'0', '13', 'not a month', 'mn'
42	1	5 Domain Violation	Accuracy	check_weekday	8 Weekday	Invalid weekday values	0, 'not a weekday', -1, 'Mn'
43	1	5 Domain Violation	Accuracy	check_name	12.5 Name	Capitalization/Format issues	jane doe'
44	1	5 Domain Violation	Accuracy	check_street	13 Street	Capitalization/Format issues	'InvalidStreet', 'Sunset boulevard'
45	1	5 Domain Violation	Accuracy	check_city	14 City	Capitalization/Format issues	'los angeles', 'new delhi', 'San francisco'
46	1	5 Domain Violation	Accuracy	check_state	15 State	Capitalization/Format issues	'New york', 'new south wales', 'new Jersey', 'n york'
47	1	5 Domain Violation	Accuracy	check_country	16 Country	Capitalization/Format issues	'puerto rico', 'guatemala', 'papua New Guinea'
48	1	5 Domain Violation	Accuracy	check_postal_code	17 Postal Cod	Short length alphanumeric values	'11'
49	1	5 Domain Violation	Accuracy	check_phone_numbers	18 Phone	Incorrect telephone number format	'InvalidNumber', '?', 'John Doe', '0405 833 952!', '11'
50	1	5 Domain Violation	Accuracy	check_ip_format	19 IP	Invalid IP format	'1.1', '::1', '2001:db8::1234:5678', 'fe80::1ff:fe23:4567:890a', '?', '0.0.0.0.0!', '11', 'incorrect:ipv6:address'
51	1	5 Domain Violation	Accuracy	check_url_format	20 URL	Invalid URL format	'ftp://example.com', 'http://exa_mple.com', 'https://", 'http://exam/ple.com', 'https://www.example.com', 'http:// example.com', 'justsometext', '12345', 'https:-www.uol.com.br', 'https://www.uol.com.br'
						Invalid email format	"example.com", userewample.com", "name.domain.com", user@.com", "name@", "user name@example.com", "namedomain.com", "user@example.com", "namedomain.com", "user@example.com", "namedomain.com", "user@example.com", "pedomain.com", user@example.com", "name@domain.godomain.com", user@example.com", "user@example.com", user@example.com", user@example.com, user@example.com, user@example.com, user@example.com, user@example.com, user@example.com, user.gom,
52		5 Domain Violation		check_email_format	21 Email		'user[name]@example.com', 'name[123]@domain.com', 'extremely long email'
53				check_binary_values	22 Binary	Non-binary values	'Invalid', '2', 3, '?', 0.1, '-2'
54				check_numerical_ge_zero	1 Numerical		'a3', '?'
55				check_numerical	2 Numerical	Non-numeric values	'a3', '?'
56				check_numerical_between		between Non-numeric values	'a3', '?'
57				check_id_attributes	4 ID	Inconsistent length or format in alphanumeric va	
58				check_string	5 String	Non-string values	11, 5.67, True, ('key': 'value')
59				check_postal_code	17 Postal Cod		'?', '10001'
60	1	9 Uniqueness Violation	Uniqueness	check_id_attributes	4 ID	Uniqueness violation	'AB123CD456', 'Duplicate', 1

Figure 5 – Second part of Summary of Discoveries with created bad data.

Continuing the analysis from the previous content, this Figure 5 shows many cases of Data Quality Issue #15, Domain Violation, related to Accuracy. Many different functions related to many formats are exhibited for this DQI.

For format 'Numerical >= 0', 'Negative Values' are shown.

For Format 'Numerical between', Values outside range are shown.

For ID attributes the content cannot be negative or floating-point numbers.

For 'Month' values cases such as numbers 0 or 13 or contents 'not a month' or 'mn' are flagged errors.

For 'Weekday' we don't accept 0, -1, 'Mn'.

But months from 1 to 12 or any variation on names such as 'December', 'FEB', and weekdays from 1 to 7, or 'Mon', 'TUE', and 'FR' are valid.

Geographic formats, such as Street, City, State and Country do not accept words which are not Capitalized or some cases such as 'Short length alphanumeric values' for Postal Code.

Phone, IP, URL and Email values are also quite restricted. See above many cases when the data are considered bad data for Accuracy.

Binary values also just accept the maximum of 2 distinct values, and usually cases such as 0 and 1 or 'Yes' and 'No', are accepted.

Another interesting DQ Issue is #17, 'Wrong Data Type', related to Dimension Consistency, and used in many functions such as numerical functions when non-numerical values are not accepted, or ID attributes when there is an "Inconsistent length or format in alphanumeric values". This has to do with an analysis that is made from the first 10 items and if the format changes due to different length of content this is flagged. It also flags unacceptable formats in ID data, such as '?', '—' or 'aa'.

Besides Wrong Data Type there is another case for DQI 17, Non-String Data Type, when the format being tested is 'String', and the content is 'Non-String'. Values such as 11, 5.67, True, {'key': 'value'} are examples for this.

DQI# DQ Issue Description	Data Quality Dimension	Function Name	Check# Format Being Analyzed	Error Explanation	Data Issues	Dataset	Columns - Attributes
4 Ambiguous Data	Accuracy, Consistency	check_if_categorical	6 Categorical	Unacceptable content	'?'	45 Heart Disease	ca, thal
4 Ambiguous Data	Accuracy, Consistency	check_if_categorical	6 Categorical	Unacceptable content	'?'	2 Adult	workclass, occupation
5 Extraneous Data	Consistency, Uniqueness	check_country	15 Country	Extraneous data	13,	2 Adult	native-country
							handicapped-infants, water- project-cost-haring, adoption of-the-budget-resolution, physician-fee-freeze, el- salvador-aid, religious-group- in-schools, and-saellith-est- ban, aid-to-nicaraguan-contra mc-missile, immigration, synfuels-corporation-cubasic deducation-spending, superfund-right-to-sue, crim- duty-free-exports, export- administration-act-south-in-act-south-
4 Ambiguous Data	Accuracy, Consistency	check_if_categorical	6 Categorical	Unacceptable content	171	103 Congressional Voting Records	africa,
4 Ambiguous Data	Accuracy, Consistency	check_if_categorical	6 Categorical	Unacceptable content	'?'	27 Credit Approval	A1, A4, A5, A6, A7
17 Wrong Data Type	Consistency	check_numerical_ge_zero	1 Numerical >= 0	Non-numeric values	'?'	27 Credit Approval	A2, A14
17 Wrong Data Type	Consistency	check_numerical	2 Numerical	Non-numeric values	'C536379', 'C536383', etc	352 - Online Retail	InvoiceNo
10 Structural Conflicts	Consistency, Uniqueness	check_if_categorical	6 Categorical	Data seems not categorical or has too many ca	4070 categories	352 - Online Retail	StockCode
1 Missing Data	Completeness	check_string	5 String	Blank/Empty/Null/NaN values		352 - Online Retail	Description
17 Non-String Data Type	Consistency	check_string	5 String	Non-string values	1	0713 352 - Online Retail	Description
1 Missing Data	Completeness	check_id_attributes	4 ID	Blank/Empty/Null/NaN values	W.	352 - Online Retail	CustomerID
		where the standards	4 ID	Duplicate values	17850, 13047, etc	352 - Online Retail	CustomerID
9 Duplicates	Uniqueness	check_id_attributes	4 10	Duplicate values		ane - Orinine Herrall	Customento

Figure 6 – First part of Summary of Discoveries with real bad data from UCI datasets.

This sheet shows all bad data from the first 10 datasets analysed and also from one dataset in the second set of datasets. The datasets with real bad data are only four: 45 – Heart Disease, 2 – Adult, 103 – Congressional Voting Records and 27 – Credit Approval. The dataset 352 – Online Retail is the first from the second set of 40 datasets from the UCI Catalogue.

Here we can see many cases where '?' exist in the datasets and are considered Data Issues. In fact, in the first set of 10 datasets, the only problems found were the appearance of '?'. According to the format being analysed, from the words that appeared in the attribute label, an appropriate output was presented. In Datasets 45, 2, 103 and 27 the DQI# was 4, related to Ambiguous Data, according to the table presented in Appendix 1. They were all associated with attributes that the dictionaries considered to be Categorical information. Line 2, presenting the attributes 'ca' and 'thal', were considered categorical because in the descriptions on the 'attributes information' column obtained in the original procedure where the information from all 622 datasets from UCI Catalogue came, there is the word 'Categorical' for these two attributes. Line 3, from Dataset 2, has '?' in attributes 'workclass' and 'occupation'. These are words that are automatically considered Categorical from the formats dictionary. Line 4 has another format being analysed, also from Dataset 2. The attribute is titled 'native-country', so, the format being analysed is Country. Country has some specific rules, not accepting lower-case names, for example, but it also does not accept Extraneous data, and '?' is considered so. Extraneous Data is Data Quality Issue #5, associated to Dimensions 'Consistency and Uniqueness'. Line 5, from dataset 103, contains many attributes that are considered Categorical because in the description the word 'yes' do appear. 'Yes' is automatically considered Categorical. Then, in all the attributes presented there are cases where '?' appear. Line 6 shows 5 attributes that are too generical, titled A1 to A7, but in the description of these attributes there is the word 'Categorical'. Therefore, they follow the same rule as the previous case. Line 7 shows a case where the description has the word 'Continuous'. Then, the attributes A2 and A14 are considered Numerical >= 0. And for this format '?' is considered 'Non-numeric values', leading to the Data Quality Issue (DQI) #17, 'Wrong Data Type', and Data Quality Dimension 'Consistency'.

Lines 8 to 14 are from Dataset 352, and they contain many different situations. The first one is similar to the previous one. It is also DQI# 17, buy now the attribute is 'InvoiceNo', with the word 'number' in the description, associated with format numerical, and the content has a letter in the beginning. Instead of being a number the bad data are: 'C536379', and 'C536383', etc., so these show a case different than the usual '?' values presented earlier. Line 9 shows the first case of DQI# 10, 'Structural Conflicts', Dimensions 'Consistency and Uniqueness'. The attribute is 'StockCode', associated with the word code, which is considered 'Categorical'. But there are 4070 unique values in this attribute, which is not common to Categorical cases. Lines 10 and 11 are for Attribute 'Description', which is considered format 'string'. But there are many cases of content "and one case of content 20713. The first is a case for Data Quality Issue #1, Missing Data, dimension Completeness. And the second case is again for DQI 17, due to 'Non-String Data Type'.

The next 3 cases are related to the attribute 'CostumerID'. Due to having the letters 'ID' in the name it is considered an 'ID column format'. The first problem is DQI#1 again, 'Missing Data', due to the value ". The second problem is related to the existence of 'Duplicates', associated with 'Dimension Uniqueness'. Some values that appear more than once are 17850 and 13047. This causes DQI#19 'Uniqueness'.

1 D	QI# DQ Issue D	Description	Data Qu	ality Dimension	Functio	n Name	Check# Format	Being Analyze	d E	rror Explana	ition		Data Issues			Datas	et	Columns - Attributes
																		Relative Humidity, AH
5	15 Domain Vi		Accurac			numerical_ge_z				legative val					-2	00 360 -	Air quality	Absolute Humidity
B	elow are 1	ines 524		Observe th	nat many	other valu	es have the c	ontent -20	0, beside	s the tw	o last Humidit	y values:						
4			CO				D700 000 H	110.10	0700 00010	NOO								
В	Date	Time	(GT	PT08.S1(CO)	NMHC(G	C6H6(G	PT08.S2(NMH	NOx(G T)	PT08.S3(NO x)	NO2(GT)	PT08.S4(NO2)	PT08.S5(0	, ,	RH	AH			
	Date	1 ime	7	00)	1)	1)	C)	1)	X)	(1)	F100.54(NO2)	3)		Kn	АП			
	1/04/2004	14:00:00	1.7	-200	222	-200.0	-200	99	-200	72	-200	-200	200	200	200			
	1/04/2004	15:00:00	1.9	-200	197	-200.0	-200	108	-200	81	-200	-200	200	200	200			
	1/04/2004	16:00:00	2.3	-200	319	-200.0	-200	131	-200	93	-200	-200	200	200	200			
ŀ			and the same of					101						and the same of				
	9 Duplicates		Uniquer			d_attributes	4 ID			iuplicate val			144552912,				3D Road Network (North Jutil	
	17 Wrong Dat		Consiste			d_attributes	4 ID				length in alphanume						3D Road Network (North Jutil	
	19 Uniquene		Uniquer			d_attributes	4 ID			Iniqueness v			144552912,		5, etc		3D Road Network (North Jutil	
	10 Structural			ency, Uniquene		f_categorical	6 Catego	rical			ot categorical or has						Buzz in social media	Feature to predict
	5 Extraneou			ency, Uniquene			12.5 Name			xtraneous d			'constrecte				Perfume Data	Perfume_name
	10 Structural			ency, Uniquene			6 Catego	rical			ot categorical or has						Restaurant & consumer data	the_geom_meter
	5 Extraneou	s Data	Consiste	ency, Uniquene	ss check_r	name	12.5 Name		E	xtraneous d	ata		'Restaurant	e 75', 'Ce	enaduria i	El F 225 - I	Restaurant & consumer data	name
	15 Domain Vi	iolation	Accurac	γ	check_r	ame	12.5 Name		c	apitalizatio	n/Format issues		'puesto de	tacos', 'li	ttle pizza		Restaurant & consumer data	name
	5 Extraneou	s Data	Consiste	ency, Uniquene	ss check_s	treet	13 Street		E	xtraneous d	ata		171			225 - 1	Restaurant & consumer data	address
	15 Domain Vi		Accurac		check_s		13 Street				n/Format issues		'esquina sa	ntos deg	ollado y l		Restaurant & consumer data	address
	5 Extraneou		Consiste	ency, Uniquene			14 City			xtraneous d			13,				Restaurant & consumer data	city
	15 Domain Vi		Accurac		check_c		14 City				n/Format issues		's.l.p.', 'vict	oria', et	c		Restaurant & consumer data	city
	5 Extraneou			ency, Uniquene			15 State			xtraneous d			15,				Restaurant & consumer data	state
	15 Domain Vi		Accurac		check_s		15 State				n/Format issues		's.l.p.', 'tam	aulipas',	etc		Restaurant & consumer data	state
	5 Extraneou			ency, Uniquene			16 Countr			xtraneous d			171				Restaurant & consumer data	country
	15 Domain Vi		Accurac		check_c		16 Countr	γ			n/Format issues		'mexico'				Restaurant & consumer data	country
	15 Domain Vi	iolation	Accurac	Y	check_s	phone_numbers					phone number form	at	121				Restaurant & consumer data	fax
	17 Wrong Dat	ta Type	Consiste	ency	check_c	oostal_code	17 Postal	Code	N	ion-alphanu	meric values		171				Restaurant & consumer data	zip
	15 Domain Vi	iolation	Accurac	У	check_u	irl_format	20 URL		Ir	nvalid URL fo	ormat		121			225 - 1	Restaurant & consumer data	url

Figure 7 – Second part of Summary of Discoveries with real bad data.

Continuing the analysis, the next Dataset is 360 - Air Quality. Our code provided the information that there are Negative values in the attributes 'Relative Humidity' and 'AH Absolute Humidity'. Checking the output, it was found the value '-200', which is surely a not expected value for these attributes. Observing the content, it was noticed that many other columns also contain this value '-200'. The other columns did not output the Data Quality Issue because they were considered only numerical, not numerical greater or equal to 0. Humidity is the word that determined that this analysis should be for values >= 0. This is something unique in our research.

In Lines 25 to 27, attribute OSM_ID also contain issues associated with an ID column. Besides Duplicates and Uniqueness as before, now there is the DQI# 17, due to 'Inconsistent length in alphanumeric values'. Notice that the values shown in the Data Issues have a smaller size than the ones shown in the other cases.

Line 28 shows again a case of DQI# 10, where the Attribute 'Feature to predict' is considered a Categorical format, due to the word 'feature' on it, but it contains 8895 different values, which might be a problem.

Line 29 shows a case of DQI# 5 for the format 'Name', in the attribute titled 'Perfume_name' on dataset 303. The Data Issue is in the content 'constructed2'. The check name function considers an error when a number appears on it.

The next lines are all for Dataset 225 – Restaurant & consumer data. It contains many geographical columns that contain data issues. '?' appears in the 'address' attribute (the system uses check street function to analyse address information), in the city attribute, in the state, country, fax, zip, and url attributes. Each one of these attributes is analysed by a specific function.

Besides that, the first line analyses a possible categorical attribute (the geom_meter), because in its description there is the word Nominal, which is classified as Categorical. Unfortunately, there are 130 different values, and it may be an issue for DQI# 10.

The 'name' attribute is associated with two different DQI's. DQI 5 for Extraneous Data, because there are numbers in the name ('Restaurante 75'), and DQI# 15, for Domain Violation, due to the Problem in 'Capitalization/Format Issues' because there are words that are not Capitalized ('puesto de tacos').

The address attribute also contains Capitalization issues ('esquina santos degollado y leon guzman'), as well as the city attribute ('s.l.p.'), the state attribute (also 's.l.p.'), and the country attribute ('mexico').

1 [QI# DQ Issue Description	Data Quality Dimension	Function Name	Check# Format Being Analyzed	Error Explanation	Data Issues	Dataset	Columns - Attributes
44	9 Duplicates	Uniqueness	check_id_attributes	4 ID	Duplicate values	1017023, 1033078, etc	15 - Breast Cancer Wisconsin (Origina	Sample code number
45	17 Wrong Data Type	Consistency	check_id_attributes	4 ID	Inconsistent length in alphanumeric value(s)	128059, 144888, etc	15 - Breast Cancer Wisconsin (Origina	Sample code number
46	19 Uniqueness Violation	Uniqueness	check_id_attributes	4 ID	Uniqueness violation	1033078, 1070935, etc	15 - Breast Cancer Wisconsin (Origina	Sample code number
47	17 Wrong Data Type	Consistency	check_numerical	2 Numerical	Non-numeric values	171	15 - Breast Cancer Wisconsin (Origina	Bare Nuclei
48	4 Ambiguous Data	Accuracy, Consistency	check_if_categorical	6 Categorical	Unacceptable content	191	73 - Mushroom	node-caps, breast-quad
49	17 Non-String Data Type	Consistency	check_string	5 String	Non-string values	3, 1, etc	10 - Automobile	symboling
50	17 Wrong Data Type	Consistency	check_numerical	2 Numerical	Non-numeric values	131	10 - Automobile	normalized-losses, price
51	4 Ambiguous Data	Accuracy, Consistency	check_if_categorical	6 Categorical	Unacceptable content	191	10 - Automobile	num-of-doors
								bore, stroke, horsepower,
52	17 Wrong Data Type	Consistency	check_numerical_ge_zero	1 Numerical >= 0	Non-numeric values	131	10 - Automobile	peak-rpm
53	17 Wrong Data Type	Consistency	check_numerical_between	3 Numerical between [1800, 2100]	Value(s) outside range [1800, 2100]	70, 82, etc	10 - Automobile	model year
54	5 Extraneous Data	Consistency, Uniqueness	check_name	12.5 Name	Extraneous data	buick skylark 320', 'ford galaxie	10 - Automobile	car name
55	17 Wrong Data Type	Consistency	check_numerical_ge_zero	1 Numerical >= 0	Non-numeric values	121	9 - Auto MPG	horsepower
56	17 Wrong Data Type	Consistency	check_numerical_betweer	3 Numerical between[1800, 2100]	Value(s) outside range [1800, 2100]	70, 82, etc	9 - Auto MPG	model year
57	5 Extraneous Data	Consistency, Uniqueness	check_name	12.5 Name	Extraneous data	buick skylark 320', 'ford galaxie	9 - Auto MPG	car name
58	17 Wrong Data Type	Consistency	check_numerical_between	3 Numerical between [0, 130]	Non-numeric values	131	336 - Chronic_Kidney_Disease	Age
								Blood Pressure, Blood Glucose Random, Blood Urea, Serum Creatinine, Sodium,
59	17 Wrong Data Type	Consistency	check_numerical	2 Numerical	Non-numeric values	778		Potassium, Hemoglobin Specific Gravity, Albumin, Sugar, Red Blood Cells, Pus Cell, Pus Cell clumps, Bacteria, Hypertension, Diabetes Mellitus, Coronary Artery Disease, Appetite, Pedal
60	4 Ambiguous Data	Accuracy, Consistency	check_if_categorical	6 Categorical	Unacceptable content	'?'	336 - Chronic_Kidney_Disease	Edema, Anemia Packed Cell Volume, White Blood Cell Count , Red Blood
61	17 Wrong Data Type	Consistency	check_numerical_ge_zero	1 Numerical >= 0	Non-numeric values	131	336 - Chronic_Kidney_Disease	Cell Count
			-					global_active_power, global_reactive_power, voltage, global_intensity, sub_metering_1, sub_metering_2,
62	17 Wrong Data Type	Consistency	check_numerical	2 Numerical	Non-numeric values		235 - Individual household electric po	sub_metering_3
63	17 Wrong Data Type	Consistency	check_numerical_ge_zero	1 Numerical >= 0	Non-numeric values	'NA'	381 - Beijing PM2.5 Data	pm2.5

Figure 8 - Final part of Summary of Discoveries with real bad data.

Finalising this analysis, we observe Dataset 15, with two different Attributes. 'Sample code number' has in its description the information that it is an 'id number'. Therefore, it is being analysed as an ID. Unfortunately, there are Duplicates and Uniqueness violations, and it also has an 'Inconsistent length in alphanumeric values' situation. And the second attribute, 'Bare Nuclei', being considered a Numerical, because in its description there is the text: 1 - 10', contains some '?' data issues.

The next dataset, 73 shows an Ambiguous Data DQI# 4, also due to '?'.

The next two datasets, 10 and 9 are for Automobile related information. They contain many attributes that are the same. '?' appears in some cases for numerical and categorical attributes, but also there are two new cases related to DQI# 17, Wrong Data Type, for Values outside range [1800-2100], for the same attribute 'model year', where there are values 70 and 82 for example. This is surely a case of year with two digits only, but it is an interesting output. Other two cases are related to the 'car name' attribute, where the names of cars are not Capitalized.

The dataset 336 contains only numerical and categorical cases due to '?'.

The same happens with dataset 235.

The final dataset, 381, contains once again DQI# 17, but now the data issue is not '?', but 'NA'.