# **BDE** Assignment

# Contents

1	Int	troduction	1
2	Ab	oout the datasets	2
		ata Cleaning and Preparation	
		Parsing the data	
		Understanding the datasets	
		Cleaning the datasets	
4	Me	erging the datasets	5
		esults	

## 1 Introduction

This documentation outlines a data engineering project aimed at creating a joined dataset from three distinct sources: Google, Facebook, and Website data.

The report was created by Sándor Kolumbán.

A summary presentation of the results is available here: <a href="https://app.pitch.com/app/public/player/41f05329-b0c7-4cb9-98d9-44566e87fdb4">https://app.pitch.com/app/public/player/41f05329-b0c7-4cb9-98d9-44566e87fdb4</a>

The code belonging to the assignment is available here: <a href="https://github.com/Explorer-Consulting/Test-Assignment-Exadel-BDE">https://github.com/Explorer-Consulting/Test-Assignment-Exadel-BDE</a>

#### 2 About the datasets

We have three different files for the datasets:

- Facebook dataset.csv
- Google dataset.csv
- Website dataset.csv

These datasets contain some basic information about companies (e.g. Company name, address, categories, phone number, etc.) from different sources.

## 3 Data Cleaning and Preparation

#### 3.1 Parsing the data

Reading the datasets was not so straightforward. For the Facebook and Google dataset there were columns which data also contained commas escaped by \ characters, so we had to specify escape character parsing the data. These two datasets also contained some strange values in the 'phone' column, so we had to also tell the pandas to parse the 'phone' column as string. For the website dataset, the data was separated by semicolons.

```
dtype_dict = {
    'phone': str
}

df_facebook = pd.read_csv(path, escapechar='\\', dtype=dtype_dict)
```

Figure 1 Phone numbers must be understood as strings and \ character should be understood as escape character.

#### 3.2 Understanding the datasets

After parsing the datasets, deeper understanding of the data structure was obtained by utilizing the <a href="mailto:pandas.DataFrame.describe()">pandas.DataFrame.describe()</a> method for each dataset, allowing us to examine the fundamental characteristics of the datasets and better comprehend the nature of the data we are working with.

```
| Second Contract | Co
```

Figure 2 Results of describe() for the Facebook data

In the Facebook dataset, we observed a total of 72,010 records (see Figure 2). It's noteworthy that the 'domain' column was unique across all records, with each row featuring a distinct domain entry. This unique characteristic sets the 'domain' column apart from the others in the dataset and made it a good candidate for joining.

```
>> 9000EE DATMORT
Length of the google dataset: 355529

Sample from the google dataset
```

Figure 3 Results of describe() for the Google data

Within the Google dataset (see Figure 3), we encountered a total of 356,520 records. None of the columns exhibited the characteristics of being both unique and set in every row of the dataset, setting it apart from the Facebook dataset. However, an observation was made regarding the 'domain' column, where the unique count equaled 72,010, precisely matching the number of records in the Facebook dataset. This observation suggests a potential correspondence between the domains in the two datasets, indicating that multiple rows within the Google dataset may share the same domain.

	CTTC DATACET														
	SITE DATASET	70040													
Length	of the website dataset:	/2018													
Sample from the website dataset:															
Sample	root domain		suffiv 1s	nguaga		legal nam		main cit	, main	country	main region	phone	site name	+14	s category
12959	unitedexpress.in		in	en		Na Tegat_Hall		kurnoo.			andhra pradesh		United Express		
65329	communitas.ca		ca	en		Na Na		edmonto		canada	allulli a prauesii alberta		The Communitas Group		Housing Programs
17283	mayersanitation.ca		ca		Mayon Gill	es R Sanita		lachut		canada	quebec				Garbage Collection &
48079	stlawrencemarket.com		com	en	ridyer dilli	Na		toront		canada		14163927219			Fruit & Vegetable - M
42150	greenwichbraces.com		com	NaN		Na		greenwic		states		12038692044			Orthodontists
39537	neweracombatsports.com		com		New Era Cor	mbat Sports		kanat		canada		16135924216			Martial Arts Gyms
11408	torontopilatesstudio.com		com	NaN	NEW EI & CO	Na Na		toront		canada		16475190395	Pilates		
6971	kringvrienden.nl		nl	de		Na		winke			north holland				Museums
13565	londonbuildingsolutio		com		London Bui			on upon thame:			england				Home Builders & Renov
	dorland-haightgallery		com			ight Galler		wasaga beacl		canada	ontario		Dorland-Haight Galleries		
33001	dor zana mazginegazzer y		Com	-	DOI TUING THE	-Birc durrer in		masaga ocac		Cariada	orical 10	13030/31/31	bor tana matgire datter tes	Com	70 0 001101103
Descri	Description of the website dataset:														
	root domain domain		language		legal name i	main city mai	n country	main region	phone	site name	tld	s cat	tegory		
count	72017	71900	66826		31989	60966	64869		65640	68714	71757		70634		
unique	72017	667	71		30619	9598	294	1114	60053	67541	293		562		
top	converterman.com	com	en	Blackb	oard, Inc.	toronto	canada	ontario	4.42E+11	Mysite	com Execu	tive, Legislat	iv		
freq	1	33534	56177		211	3293	37618	20027	651	40	33513	- 0	1506		

Figure 4 Results of describe() for the Website data

We identified 72,018 records within the Website dataset (see Figure 4), which is slightly surpassing the number of records in the Facebook dataset. Similarly to the Facebook dataset, the **domain** column in the Website dataset was unique, and the count of unique domains closely matched those in the other datasets. This consistent pattern of unique domains across the dataset indicates that the **domain** column held distinct values in each dataset and was pivotal in our data analysis.

With the understanding that the **domain** column could serve as the key for joining the dataset, we sought to determine the presence of domains in each of the datasets. Our objective was to assess whether all domains were represented in every dataset and how many times each domain appeared in which dataset.

To achieve this, we counted the occurrence of every domain within each dataset. A portion of the results is given in Figure 5.

Domain T	Nr_in_google ▼	Nr_in_facebook	Nr_in_website
facebook.com	71983	1	1
postoffice.co.uk	6010	1	1
instagram.com	5647	1	1
ihg.com	4356	1	1
marriott.com	3979	1	1
hilton.com	3477	1	1
doctolib.fr	3105	1	1
ameripriseadvisors.com	2378	1	1
choicehotels.com	1625	1	1
uhaul.com	1518	1	1
gov.uk	1511	1	1
bit.ly	1486	1	1
spar.co.uk	1428	1	1
411habitation.com	1097	1	1
bestwestern.com	1093	1	1
etsy.com	1054	1	1
dignitymemorial.com	1050	1	1
uchealth.org	1032	1	1
anchorhanover.org.uk	1012	1	1
vagaro.com	992	1	1

Figure 5 Occurrence nr. of domains in various datasets (the list continues).

Our analysis now provides a clear overview of the frequency with which domains are represented in the datasets. It's clear now that only the Google dataset contains domains appearing multiple times.

The multiple occurrences of domains in the Google dataset may have different underlying reasons. So, the next step was to see what is the relationship between entries in the Google dataset sharing the same domain.

Our investigation also extended to examining the differences between the sets of domains in the three datasets, which resulted in the following observations:

- Unique to Google: An empty set, indicating no domain is unique to the Google dataset.
- Unique to Facebook: An empty set, implying no domain is exclusively found in the Facebook dataset.
- Unique to Website: Several unique entries were identified, and all of them were non-domain entries like 'Fitzwilliam NH 03447', 'Avenida Food Hall & Fresh market', 'Paint &', 'MARTIN-LAFLAMME' and others.

These distinctive entries are specific to the Website dataset and are not shared with the other datasets.

## 3.3 Cleaning the datasets

Prior to commencing the dataset integration process, we recognized the need to standardize and prepare the data. To begin this data preparation, we applied the **\_(dataset\_name)** suffix to every column in each of the datasets. The first step involved working with the Google dataset.

In the Google dataset, we encountered non-conforming values within the **address** and **raw\_address** columns. These values included unnecessary information, which we successfully removed using regular expressions (regex), see Figure 6.

```
# Remove the unnecessary part from the address and raw address columns
regex = r'(\d+)\+ years in business · '
df_google['address'] = df_google['address'].str.replace(regex, '', regex=True)
df_google['raw_address'] = df_google['raw_address'].str.replace(regex, '', regex=True)

# Remove quotes from the address columns
regex = r'\".*\"'
df_google['address'] = df_google['address'].str.replace(regex, '', regex=True)
df_google['raw_address'] = df_google['raw_address'].str.replace(regex, '', regex=True)
Figure 6 Remove years in business and quotation marks from address fields in Google data
```

Next, we turned our attention to the **categories** column, where we observed variations in how categories were presented. In order to standardize this data and improve its consistency, we made the decision to separate the category values and transform them into a list of categories within a dedicated column.

Figure 7 Splitting category information into a list format

We also performed column renaming to establish a more standardized and consistent naming

convention, to ensure that the column names across the datasets followed a uniform pattern, making it easier to work with and integrate the data seamlessly.

Our data cleaning process for the Facebook dataset followed a pattern, like the one for the Google dataset. We maintained consistency in naming conventions by renaming specific columns. The category values were transformed into a list of categories also.

In the Website dataset, we executed transformations akin to those performed in the other datasets. We converted its category column named **s\_category** into a list of categories, and column renaming was applied to standardize the naming conventions as well.

Furthermore, in the Website dataset it was required to determine the most accurate company name, by evaluating and choosing between two of its columns: **legal\_name** and **site\_name**. Following consideration and analysis of the data, we made the decision to prioritize **site\_name** whenever it was available for determining the company name. In most cases it seemed more accurate than the value in the **legal\_name** column, however there may still be room for improvement.

## 4 Joining the datasets

Upon gathering the insights into the data, we quickly determined that joining the datasets based on the **domain** columns was the most logical and effective approach. However, we also recognized the unique challenge posed by the Google dataset, which contained multiple rows for each domain. To successfully address this, we would need to find out a suitable strategy to handle these multiple entries withing the Google dataset while integrating it with the others.

Our approach was to merge the datasets based on the **domain** column, creating rows that included the columns of each dataset for every domain entry. Subsequently, we undertook the task of selecting the most accurate values for the final columns that held significance for us, such as **Company Name**, **Address**, **Category**, and more.

In most cases, the values found in the Google dataset proved to be the most suitable and reliable choice for the final columns, so we chose them when they were available. However, in cases where the Google dataset values were not present, we selected the Facebook dataset as our secondary choice, favoring it over the Website dataset.

Of all the columns, two specific columns that required distinct treatment were the **category\_list** and **company name** columns.

#### 4.1 Category lists

For the **category\_list** column, our approach involved consolidating the content of category lists from all the dataset columns. This method was effective in most cases, allowing us to merge category lists seamlessly.

However, it's important to note that in some instances, we encountered values that did not align with the other category list values (e.g. a business doing car repairs and car part sales was also

marked as yoga studio). As a continuation of the data cleaning process, currently popular LLMs could be asked to determine of there is an outlier in a given category list.

#### 4.2 Company name

Resolving the **company\_name** column presented a more complex challenge, primarily due to the data in the Google dataset. In certain rows, the company names in the Google dataset included human names, which could be interpreted as employees or individuals. However, in other cases, there were sub-company names associated with a single domain. Based on this insight we classified domains in the Google dataset in three categories:

- A domain representing a single company, with proper data.
- A domain appearing multiple times, and the multiple occurrences are due to employees or individuals of the same company being recorded multiple times.
- A domain that can be thought of as an aggregator.

The case of aggregator domains (a large number of entries in the Google dataset sharing the same domain) can occur when smaller businesses don't own their own domain and their most visible online presence is under an aggregator domain (like facebook.com).

To achieve this classification, we needed to determine when to rely exclusively on the data from the Google dataset (in case of aggregator domains, i.e. facebook, there is no point in joining data belonging to facebook.com to every small business only visible there) and when to choose the most appropriate value from the available values in all datasets. For this, we looked at the domain count table (Figure 5) and decided that when a domain is encountered more than a specific number (in our case 500), we prioritize using the **company\_name\_google** value whenever it's available. This approach addresses scenarios where multiple companies are associated with a single website, such as in the case of **facebook.com**.

We also had to address the second situation, where the values in the company\_name column from the Google dataset appeared to be employee names. To tackle this issue, we implemented a relatively straightforward solution involving the use of a regular expression (regex) to identify titles resembling human names, like M.D., Ph.D., and others. While this method may not be entirely foolproof, it effectively resolves the issue in the majority of cases. There are packages that allow recognition of human names as well, utilizing such a package might improve the detection of such cases.

All other cases were thought of as regular companies, represented by proper entries in the Google dataset, having matching data in other datasets. In order to get an improved version of the Company name, we utilized the **Levenshtein** distance metric. The choice for the company name in the joined dataset was the most central one according to this metric. If not all three datasets contained a company name, then the central one is not uniquely defined, in such cases we prioritized Google over Facebook, and the data from Website was used as last resort.

Following the completion of the joining process, we shifted our focus to address the potential issue of duplicated values, which had not been previously handled. To resolve this, we made the decision to eliminate duplicate entries based on the **address** and **phone** columns.

## 5 Results

In the final stages of this process, we generated two datasets. The first dataset containes all the merged columns from the three original datasets, along with our chosen values. The second dataset contains only the selected values. Both datasets were organized and sorted based on the **domain** column.