ARCHITECTURE DESIGN DOCUMENT

(BANK MARKETING ANALYTICS - BI PROJECT)

TANUJ SHARMA

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Document Version Control:

Bank Marketing Analytics - Business Intelligence Project

Version	Date	Author	Change
1.0	09/01/2022	Tanuj Sharma	First version of complete Architecture Design Document

Abstract:

The data is related to direct marketing campaigns (phone calls) of a Portuguese banking institution. The classification goal is to predict if the client will subscribe to a term deposit. The data is related to direct marketing campaigns of a Portuguese banking institution. The marketing campaigns were based on phone calls. Often, more than one contact to the same client was required, in order to access if the product (bank term deposit) would be subscribed or not.

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1. Introduction:

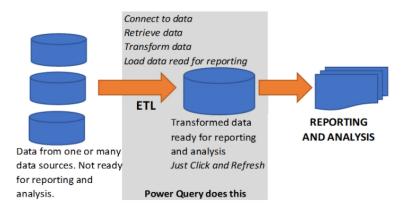
1.1. Why this Low-Level Design Document?

The goal of the LDD or Low-level design document (LLDD) is to give the internal logic design of the actual program code for the Bank Marketing Campaign Analysis. LDD describes the class diagrams with the methods and relations between classes and programs specs. It describes the modules so that the programmer can directly code the program from the document.

1.2. Scope

Low-level design (LLD) is a component-level design process that follows a step-by-step refinement process. The process can be used for designing data structures, required software architecture, source code and ultimately, performance algorithms. Overall, the data organization may be defined during requirement analysis and then refined during data design work.

2. Architecture:



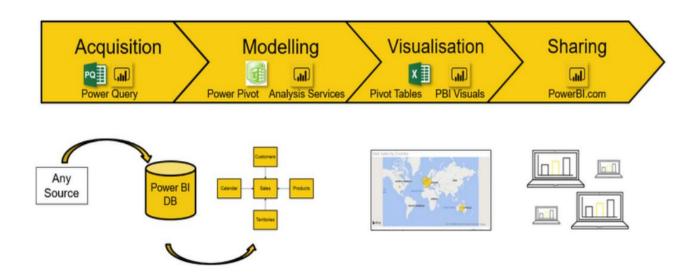
ETL (extract, transform and load) in Power BI uses preparation of data sets for analysis by removing irregularities in the data. It also involves data visualization to draw meaningful patterns and insights.

Based on the results of ETL, companies also make business decisions, which can have repercussions later.

- If ETL is not done properly then it can damage the business a lot in many ways such as loss of client which we are working for, the decision making will go completely wrong and many more issues.
- If done well, it may improve the efficacy of everything we do next.

Below are following steps to follow for ETL:

- 1. Data Sourcing
- 2. Data Cleaning
- 3. Data Modelling
- 4. Data Visualization



3. Architecture Description:

3.1 Data Sourcing:

The dataset is in csv (comma separated values) format. MS Excel is used to load the data.

Citation Request:

This dataset is publicly available for research. The details are described in [Moro et al., 2014].

Please include this citation if you plan to use this database:

[Moro et al., 2014] S. Moro, P. Cortez and P. Rita. A Data-Driven Approach to Predict the Success of Bank Telemarketing. Decision Support Systems, In press, http://dx.doi.org/10.1016/j.dss.2014.03.001

Available at: [pdf] http://dx.doi.org/10.1016/j.dss.2014.03.001 [bib] http://www3.dsi.uminho.pt/pcortez/bib/2014-dss.txt

- 1. Title: Bank Marketing (with social/economic context)
- 2. Sources:

Created by: Sérgio Moro (ISCTE-IUL), Paulo Cortez (Univ. Minho) and Paulo Rita (ISCTE-IUL) @ 2014

3. Past Usage:

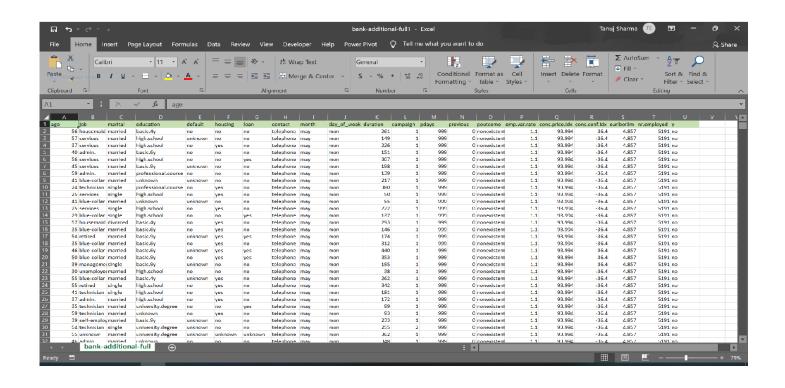
The full dataset (bank-additional-full.csv) was described and analyzed in: S. Moro, P. Cortez and P. Rita. A Data-Driven Approach to Predict the Success of Bank Telemarketing. Decision Support Systems (2014), doi:10.1016/j.dss.2014.03.001.

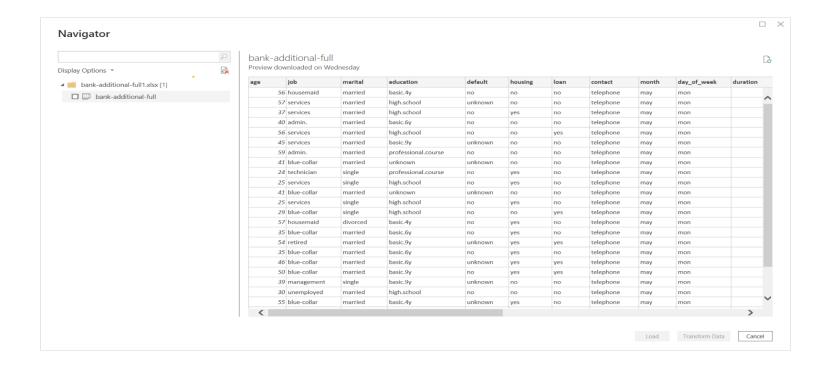
3.2 Data Overview:

- This dataset is based on "Bank Marketing" UCI dataset (please check the description at: http://archive.ics.uci.edu/ml/datasets/Bank+Marketing).
- The data is enriched by the addition of five new social and economic features/attributes (national wide indicators from a ~10M population country), published by the Banco de Portugal and publicly available at: https://www.bportugal.pt/estatisticasweb.
- This dataset is almost identical to the one used in [Moro et al., 2014] (it does not include all attributes due to privacy concerns).
- Using the rminer package and R tool (http://cran.r-project.org/web/packages/rminer/), we found that the addition of the five new social and economic attributes (made available here) lead to substantial improvement in the prediction of a success, even when the duration of the call is not included. Note: the file can be read in R using: d=read.table("bank-additional-full.csv",header=TRUE,sep=";")

The zip file includes two datasets:

- bank-additional-full.csv with all examples, ordered by date (from May 2008 to November 2010).
- 2) bank-additional.csv with 10% of the examples (4119), randomly selected from bank-additional-full.csv.
- 3) The smallest dataset is provided to test more computationally demanding machine learning algorithms (e.g., SVM).
- 4) The binary classification goal is to predict if the client will subscribe a bank term deposit (variable y).
- 5) Number of Instances: 41188 for bank-additional-full.csv
- 6) Number of Attributes: 20 + output attribute.





3.3 Data Description

Input variables:

Bank client data:

- 1 age (numeric)
- 2 job : type of job (categorical: "admin.","blue-collar","entrepreneur","housemaid","management","retired","self-employed","services","student","technician","unemployed","unknown")
- 3 marital : marital status (categorical: "divorced", "married", "single", "unknown"; note: "divorced" means divorced or widowed)
 - 4 education (categorical:
- "basic.4y","basic.6y","basic.9y","high.school","illiterate","professional.course","uni versity.degree","unknown")
 - 5 default: has credit in default? (categorical: "no", "yes", "unknown")
 - 6 housing: has housing loan? (categorical: "no", "yes", "unknown")
 - 7 loan: has personal loan? (categorical: "no", "yes", "unknown")

related with the last contact of the current campaign:

- 8 contact: contact communication type (categorical: "cellular", "telephone")
- 9 month: last contact month of year (categorical: "jan", "feb", "mar", ..., "nov", "dec")

- 10 day_of_week: last contact day of the week (categorical: "mon", "tue", "wed", "thu", "fri")
- 11 duration: last contact duration, in seconds (numeric). Important note: this attribute highly affects the output target (e.g., if duration=0 then y="no"). Yet, the duration is not known before a call is performed. Also, after the end of the call y is obviously known. Thus, this input should only be included for benchmark purposes and should be discarded if the intention is to have a realistic predictive model.

Other attributes:

- 12 campaign: number of contacts performed during this campaign and for this client (numeric, includes last contact)
- 13 pdays: number of days that passed by after the client was last contacted from a previous campaign (numeric; 999 means client was not previously contacted)
- 14 previous: number of contacts performed before this campaign and for this client (numeric)
- 15 poutcome: outcome of the previous marketing campaign (categorical: "failure", "nonexistent", "success")
 - # Social and economic context attributes
 - 16 emp.var.rate: employment variation rate quarterly indicator (numeric)
- 17 cons.price.idx: consumer price index monthly indicator (numeric)
- 18 cons.conf.idx: consumer confidence index monthly indicator (numeric)
- 19 euribor3m: euribor 3 month rate daily indicator (numeric)
- 20 nr.employed: number of employees quarterly indicator (numeric)

Output variable (desired target):

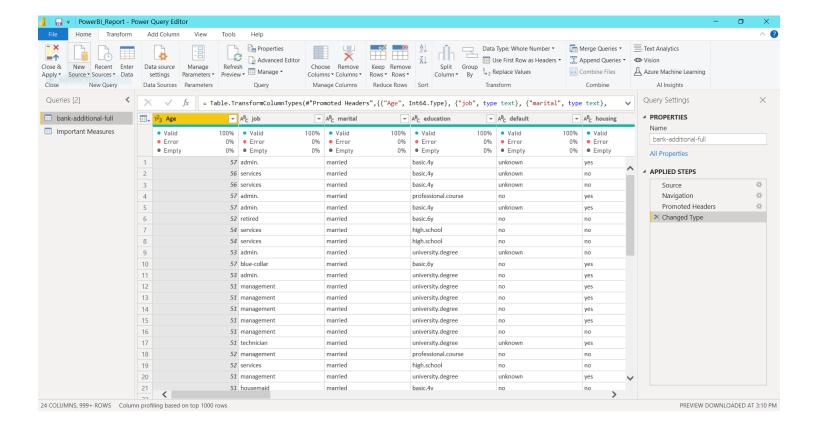
21 - y - has the client subscribed a term deposit? (binary: "yes", "no")

3.4 Data loading in Power BI Query Editor

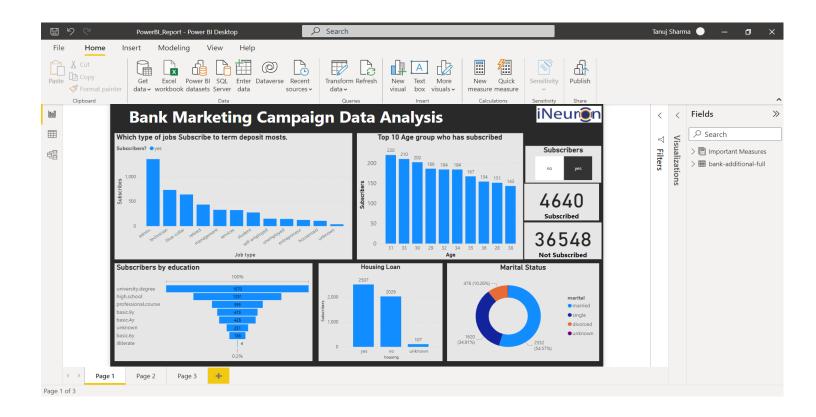
Power Query is the data connectivity and data preparation technology that enables end users to seamlessly import and reshape data from within a wide range of Microsoft products, including Excel, Power BI, Analysis Services, dataverse, and more with the following characteristics:

There can be multiple rows and columns in the data.

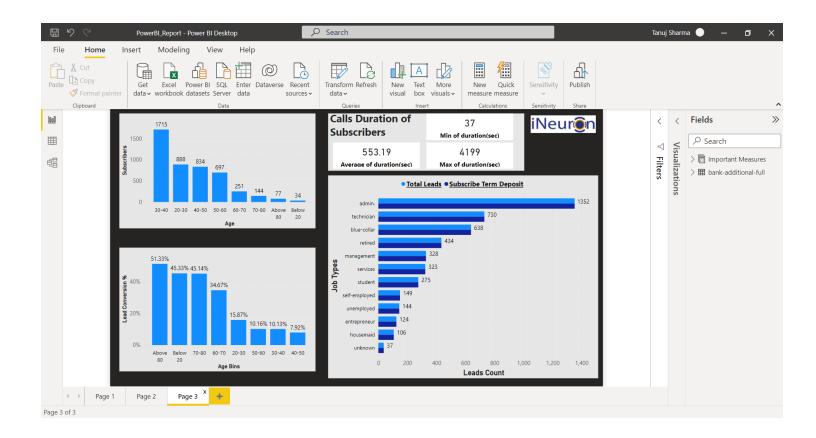
- · Each row represents a sample of data,
- Each column contains a different variable that describes the samples (rows).
- The data in every column can be a differents type of data e.g. numbers, strings, dates, Boolean etc.



3.5 Data to Insights through Visualizations and Excel Data Analysis







euribor3m		
Mean	3.6212908	
Standard Error	0.0085463	
Median	4.857	
Mode	4.857	
Standard Deviation	1.7344474	
Sample Variance	3.0083078	
Kurtosis	-1.4068026	
Skewness	-0.709188	
Range	4.411	
Minimum	0.634	
Maximum	5.045	
Sum	149153.73	
Count	41188	

emp.var.rate		
Mean	0.0818855	
Standard Error	0.0077407	
Median	1.1	
Mode	1.4	
Standard Deviation	1.5709597	
Sample Variance	2.4679145	
Kurtosis	-1.0626315	
Skewness	-0.7240955	
Range	4.8	
Minimum	-3.4	
Maximum	1.4	
Sum	3372.7	
Count	41188	

cons.price.idx		
Mean	93.575664	
Standard Error	0.0028522	
Median	93.749	
Mode	93.994	
Standard Deviation	0.57884	
Sample Variance	0.3350558	
Kurtosis	-0.8298086	
Skewness	-0.2308877	
Range	2.566	
Minimum	92.201	
Maximum	94.767	
Sum	3854194.5	
Count	41188	

cons.conf.idx		
Mean	-40.5026	
Standard Error	0.0228048	
Median	-41.8	
Mode	-36.4	
Standard Deviation	4.6281979	
Sample Variance	21.420215	
Kurtosis	-0.3585583	
Skewness	0.3031799	
Range	23.9	
Minimum	-50.8	
Maximum	-26.9	
Sum	-1668221.1	
Count	41188	

nr.employed		
Mean	5167.0359	
Standard Error	0.3560096	
Median	5191	
Mode	5228.1	
Standard Deviation	72.251528	
Sample Variance	5220.2833	
Kurtosis	-0.0037604	
Skewness	-1.0442624	
Range	264.5	
Minimum	4963.6	
Maximum	5228.1	
Sum	212819875	
Count	41188	

4. Deployment to Power BI Service

