CREATIVITY THROUGH EFFICIENCY

Data Preparation for Churn v1.09

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Modeler
automated modeling

1. Data preparation - Introduction

If you are using "***The Intelligent Mining Machine***" **(TIMi)** inside your datamining projects, the data preparation step is the most time-consuming step in the whole project.

In opposition to other classical datamining softwares, **TIMi** has practically no limitations to the number of columns or rows inside the learning/creation dataset that it can process:

- **TIMi** is able to process dataset containing millions of rows in a few minutes. Sampling (and thus losing information) is (nearly) no longer required with **TIMi**.
- **TIMi** is able to easily process datasets with more than fifty thousands columns. Classical datamining softwares reach their limits around 300 columns (even if they don't "crash" when reaching this limit, the accuracy of the predictive models produced by other softwares is degrading when you increase the number of columns above 300 inside your dataset). This also means that you **do not have** to eliminate arbitrarily (based on some "heuristic") some variables of your dataset in order to stay below the column limitation of the other datamining softwares.

When using **TIMi**, it is strongly suggested to accumulate the highest number of information (rows and columns) about the process to predict: don't reduce arbitraly the number of rows or columns: always keep the "full datatset" (even if the target size is less than one percent). **TIMi** will use this extra information (that is not available to other "limited" datamining softwares) to produce great predictive models that outperform any predictive model constructed with any other datamining software.

Of course, to be completely rigorous, you should also not forget to "let aside" a TEST dataset that will be used to really assert the quality of the delivered predictive models (to be able to compare in an objective way the models constructed with different predictive datamining tools). See this web page that explains the importance of the TEST set:
http://www.business-insight.com/html/intelligence/bi_test_dataset.html

This document describes very briefly the data preparation steps required for a preliminary analysis of your data. This preliminary analysis is just to assess if your databases contains enough useful, exploitable, information about your customers that are actionable from a business perspective.

This document is also useful when you want to setup very rapidly a benchmark to compare the performances of different datamining tools. In this case, the dataset given to **TIMi** should follow the recommendation and guidelines contained within the section 4 ("Creation dataset file format").

2. Set up model design

To build a predictive model you need a database. This database must be presented to TIMi as a large table (the optimal format is as a compressed .csv flat file). The objective of this document is to describe how to build this table.

The table must contain:

- On each row: information related to one customer.

- A special column named the "Target" that contains, basically, two values (no missing values are allowed for the ***target*** column):
  - value '0': the customer did stay (it's still there).
  - value '1': the customer just churned (it left the Telco. operator).

  The exact procedure to create the "Target" column is described in the next section (3.2).

- Many different columns that will be used by the predictive model to predict the target (i.e. to predict if an individual will churn). These columns contain all the "profiling information" of each of your customers.

  The higher the number of columns in the dataset the higher will be the accuracy of the predictive model. The columns must be somewhat related to the target to predict (for example, the name of the individual has no influence at all on the churn, so it's not an useful column).

  To create interesting and useful columns, we will, most of the time, follow the RFM approach. The RFM approach is the following: We will create columns (also named "variables" in technical terms) that are related to:

  - R ("R" means "Recency"):
    - How recent is the last purchase of the individual?
    - How recent is the last contact with the "hot-line"?

  - F ("F" means "Frequency"):
    - How many purchases on the last time period?
    - How many transactions on the last time period?
    - How many calls to the "hot-line"?
    - How many MOU (minute-of-usage) on the last time period?
    - How many MOU (minute-of-usage) on peak, off-peak, on weekend, on evenings on the last time period?
    - How many SMS on the last time period?
    - How many data on the last time period?
    - How many calls towards "outside the network"? By "outside", we mean, either:
      - call from our network to another specific competitor
      - call from our network to national number
      - call from our network to international number
    - How many international calls ?
    - How many MOU on the last time period towards "outside the network"?
    - How many MOU on the last time period towards "inside the network"?
  - M ("M" means "Monetary"):
    - For how much money was the last purchase on the last time period?
    - For how much time is the current subscription still active?
    - For how much time is the current subscription still binding?
    - How many subscriptions are currently active or binding? What's the ratio between active and binding?
    - Which payment method (direct debit, bank transfer, …)?

- What are the capabilities of the GSM? Is it internet enabled? Has the individual a good internet subscription with an internet enabled mobile phone?
- Is the roaming option active and/or used?
- Mean Recurring re-charge per month.
- How much discount on the current subscription(s)? (Has the individual some promo code?)
- Which promotion type? (voice, SMS, data, roaming,etc.)
- Did the customer buy some specific options on his products?

The RFM columns can be computed at a different granularity:

- At the product level
- At the product type level
- For all products indifferently

The following "M"-type variables should not be used "directly" inside the predictive model:

- Which tariff plan?
- What's the LTV (Life-Time-Value) of the individual?

These variables should rather be used to create different customers segments. Thereafter we can create one predictive model for each segment.

Other interesting columns to include are:

- Tenure Variable: Since how much time is this customer using your service?

- Evolution variables: These variables encode the difference in RFM variables (consumption, frequency of usage, etc.) between two time periods:
  - How much increase (or decrease) in terms of MOU (minute-of-usage) between the last time period and the previous one? You can compute this increase in absolute value and in percentage.
  - How much increase (or decrease) in terms of expenses (in euros) between the last time period and the previous one?

  "Evolution" variables are amongst the most powerful and important variables that you can create!

- Ratio variables: These variables encode the difference and ratio between two related RFM variables:
  - What's the ratio of calls "outside the network" compared to calls "inside the network"?
  - What's the ratio of MOU "outside the network" compared to MOU"inside the network"?
  - What's the ratio of "international" MOU compared to MOU "inside the network"?

- Delta on Evolution Variables: These variables encode the difference in Ratio variables between two time periods:
  - How much increase (or decrease) in terms of ratio of MOU "outside the network" compared to MOU"inside the network" between the last time period and the previous one?

- Standard profiling information:
  - ZIP code
  - Language
  - Sex
  - Handset:
    - Brand,
    - Age of Handset,
    - Functionality,
    - Adequacy between Handset functionality and subscription.
  - Adequacy between current consumption habits and current subscription (this can be computed automatically using a predictive model built with TIMi).

- Social Network Analysis:
  - Are there any recent churners in the immediate vicinity of the individual?

    The "immediate vicinity concept" can be computed in many different ways: for example: Two individuals are "*close together*" (i.e. in the "immediate vicinity" of each other) if:
    - Their postal address is the same.
    - There have been several phone calls between the 2 individuals (this can be computed directly from CDR logs using the LinkAlytics tool from Business-Insight).
    - Their most common location during the evenings and/or the day (estimated using cell-id) is close. (This can be computed directly from CDR logs using the LinkAlytics tool from Business-Insight).
    - They are in the same "group of friends" (see next point).

  - Concept related to "group of friends" (the "group-of-friends" can be computed directly from CDR logs using the LinkAlytics tool from Business-Insight): If we look specifically to the "group of friend" of the current individual:
    - How many churners in this "group of friends"?
    - Are the churners "social leaders" (in this "group of friends")?
    - Is the individual strongly integrated into his "group of friends" or is the connection to his friends "loose"?
    - What's the distance (expressed in "number-of-friends") between the current individual and the closest churner in the "group of friends"?
    - We can also compute all the different RFM, Ratio and Delta variables aggregated at the level of the "group of friends" (this adds many, many interesting variables!). For example:
      - How many subscriptions are currently active or binding in the current "group of friends"?
      - How many MOU on the last time period towards "outside the network" in the current "group of friends"?
      - How much increase (or decrease) in terms of MOU (minute-of-usage) towards "outside the network" between the last time period and the previous one in the current "group of friends"?
      - etc.

- GIS data (geographical data)
  - The ZIP code of an individual is very often related to the revenue of the individual. The "revenue information" is very often a good indicator if an individual can still "afford" the service/subscription (especially for expensive services). Thus, it's common to find the ZIP code as a good predictive variable.
  - The most common location during the evening/during the day (estimated using cell-id) (for the same reason as the previous point) (This can be computed directly from CDR logs using the LinkAlytics tool from Business-Insight).
  - Are there many disconnections on this part of the country? (This can be computed directly from CDR logs using the LinkAlytics tool from Business-Insight).

- Socio-demographic data: You can usually buy such data from external data providers. These data are usually extrapolated from the postal address of an individual: Based on the postal address, you will usually obtain the following variables:
  - an estimation of the revenue,
  - an estimation of the age,
  - an estimation of the number of cars of owned by an individual,

  These values are all estimated based on the postal address and are thus not very reliable. Socio-demographic data are thus usually not very useful in terms of prediction.

Usually, the most important variables for churn prediction are (from the most important one to the least important one):

- Tenure
- Recency (and "Normalized" recency, that is the "Recency" divided by the average time between 2 purchases/contacts/operations)
- Number of binding subscriptions.
- For Telecoms:
  - Number of recent churners in the "Group-of-Friend" (and all the related Delta variables)
  - Ratio of calls "outside the network" compared to calls "inside the network"? (with all the variation around the "outside theme") (and with all the related Delta variables)
  - Handset Brand & Age
- Payment method
- Number of calls to the hot-line
- 2-digit ZIP code
- A few "high level" Monetary & Frequency variables.

The data preparation phase before obtaining a first dataset (the table) required to create a predictive model can be quite long (especially if your operational system does not contain the appropriate information).

There is no actual limit to the amount of information that you can extract from your operational system to build your predictive models (**TIMi** is unlimited in the number of columns that it can process). The only limit is your imagination and creativity! The higher the number of variables available to make the prediction, the better will be your predictive models. Thus, the temptation to spend still a little bit more time in data preparation to create still another new variable (that can possibly increase substantially the quality of your models) is big.

Before investing time and resources in a very long and expensive data preparation effort, we suggest you to contact our datamining experts. Our team of dataminers will examine the data already available in your operational system and will propose to you the best alternative possible: A data preparation phase as short as possible (selecting only the data the easiest to obtain) but still delivering the most important variables for modelization. Our consultants can also perform all the data preparation phase for you, if required (and if the data confidentiality protection rules of your particular company allows it). The objective here is to rapidly arrive to a preliminary model to rapidly demonstrates, on your specific case, the large ROI delivered by predictive analytics.

3. Preparing the Dataset: defining a good "Target"

3.1. Targeting Commercial churners

This section is about churners in a specific context: For a PayTV subscription that you must pay every month for 12 consecutive months minimum (i.e. the minimum duration of the subscription contract is 12 months and, if you stop before the end of the 12 months, you have to pay a small "penalty").

All churners are not equal. Some churners are:

- **Commercial churners:** They stopped their subscription willingly because, for example, they don't like the service anymore. Commercial churners are defined as individuals that churn and the end of their subscription (more precisely: when no contracts are binding them anymore).
- **Financial churners:** They stopped their subscription because they don't have any money any more. Financial churners are defined as individuals that churn at any time: i.e. not at the end of their subscription. Financial churners prefer to pay a small "penalty" (because they stopped early their subscription) than continue paying for the whole year.

Based on the analysis presented in this video: https://youtu.be/oQS2kBQbPS8?t=35
… we only want to detect and predict the people that will become "*Commercial Churners*" because, if you contact "Financial churners", the retention rate will actually decrease! (…and that's exactly the opposite of what we want!).

3.2. Taking into account the TIME aspect

Let's assume the following situation: You have a database containing all your recent customers: some of them just churned, most of them are still there. You want to predict, for each customer, the probability that he will churn in the next time period. Classically, in Telecom, the "Time period" for churn analysis is 3 months.

To create the predictive model, you need a table (a flat file). Each line of the table represents one customer. The columns of the table are information about the customer (see section 2 about some good ideas of columns). One column of the table has a special meaning: it's the ***target***: It's the column you want to predict. The ***target*** column contains two values (no missing values are allowed for the ***target*** column):

- value '0': the customer did stay (it's still there).
- value '1': the customer did churn (he left the Telco. operator).

Let's assume that you have:

Database SnapShot at the end of January

id	name	age	revenu	gender	date of churn	target
1	frank	32	4000	M		0
2	sabrina	29	4000	F		0
3	max	20	2000	M		0

Current Database at the end of April

id	name	age	revenu	gender	date of Churn	target
1	frank	32	4000	M		0
2	sabrina	29	4000	F	2-14-07	1
3	max	20	2000	M		0

May

No data Yet

Please note that Sabrina deciced to churn at some point in time after the "End-of-January".

The table that you should provide to TIMi to build a predictive model is the following (this table is called the ***model creation/learning dataset***):

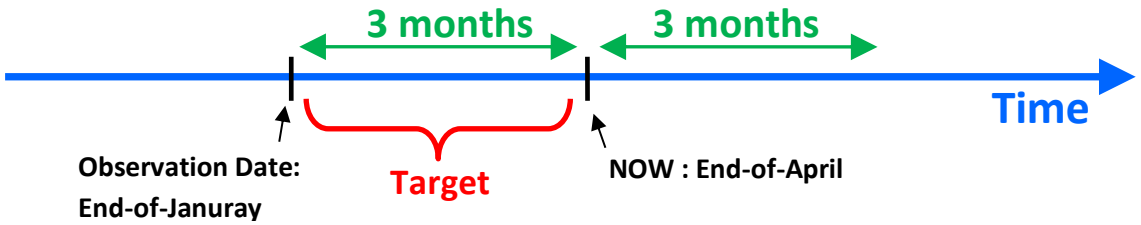
The target is based on what happened **after** Januray: It is simply the target column extracted from the most recent update of your database

Snapshot from end-of-January

id	name	age	income	gender	date of Churn	target
1	frank	32	4500	M		0
2	sabrina	25	4000	F		1
3	max	33	2000	M		0

The table (i.e. the ***creation/learning dataset***) above is the best option: TIMi will construct a new predictive model ***m*** that will use the customer profiles as they appeared at the end-of-January to predict the ***target*** in {February, March, April} (the "Time-Period" is 3 month). The date "*End-of-January*" is called in technical term the "**Observation date**": it's the date where we "*observed*" the profile of the customers to construct the ***learning dataset***.

Graphically, this can be illustrated in this way:

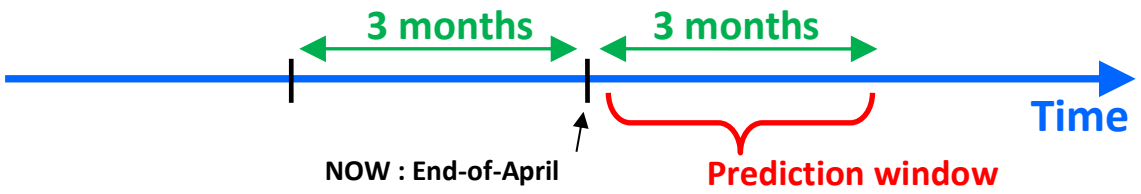


In the above example, the target is defined on a period of 3 months (i.e. it's defined based on the period that extends between "now" and the "observation date"): in technical terms, the "**Prediction Window**" is 3 months.

More formaly, we can also write the predictive model in the following way:

$$\boldsymbol{m}(\text{ CustomerProfile}_{\text{Time}=T_{\text{observation}}}) = \text{TargetPrediction}_{\text{Time} \in [T_{\text{observation}}\ T_{\text{observation+3months}}]}$$

Once you have constructed your predictive model ***m***, you can apply it on the most up-to-date version of your customer database (from End-Of-April) to predict who are the customers that will churn in {March, June, July}. Graphically, this can be illustrated in this way:



To build such a ***creation/learning dataset***, you need a database structure that supports time logging (or you need to create several "snapshots" of your customer database at different point in time) because you are mixing columns from End-Of-January (containing the profile of your customers) with one column from End-Of-March (containing the target column). Such complex database structure is not always available. As an alternative (but less accurate) solution**,** you can also use the following ***creation/learning dataset***:

Most Up-ToDate database from End-of-March

id	name	age	income	gender	date of Churn	target
1	frank	32	2000	M		0
2	sabrina	25	4000	F	2-14-07	1
3	max	33	2000	M		0

You should try to avoid this second approach because it has many flaws. Unfortunately, inside the industry, this approach is used 99% of the time because it does not require time logging (nor snapshots).

The first major drawback of this second approach is: when you use TIMi (or any other predictive analytic tool) to construct a predictive model on this ***creation dataset***: you will obtain the following predictive model:

If ("date of churn" is missing) then target=0 else target=1

The above predictive model has not identified the ***cause*** of the churn but the ***consequence***. The column "*date of churn*" does not contain any information that could be used to predict if a customer will churn (because this column is initialized ***after*** a churn). When you use TIMi to construct a predictive model, you must tell to TIMi to ignore all the "consequences" columns. The visual interface to TIMi allows you to ignore a column very easily with only one mouse-click. 99% of the modelization time is usually spent finding these bad "consequences" columns. Usually, you don't know them "in advance", before starting the modelization process. TIMi allows you to find these "consequences"

columns very easily (because of the very concise and intuitive reports auto-generated by TIMi). At the end, your ***creation dataset*** will be:

Current database from beginning of March
minus all "consequence" columns.

id	name	age	income	gender	target
1	frank	32	2000	M	0
2	sabrina	25	4000	F	1
3	max	33	2000	M	0

To summarize, the ***creation/learning dataset*** to prepare before using TIMi can either be:

- **Approach 1 (this is the best approach):** A mix of different time period:

Snapshot from end of January

the ***target*** column (extracted from the most up-to-date customer database)

Id	name	age	income	gender	date of Churn	target
1	frank	32	4500	M		0
2	sabrina	25	4000	F		1
3	max	33	2000	M		0

- **Approach 2 :** The database in its current state **and** a list of "consequence" columns to ignore

Most Up-To-Date customer database

id	name	Age	income	gender	date of Churn	target
1	frank	32	2000	M		0
2	sabrina	25	4000	F	2-14-07	1
3	max	33	2000	M		0

The list of "consequence" columns to ignore is: *date of Churn*

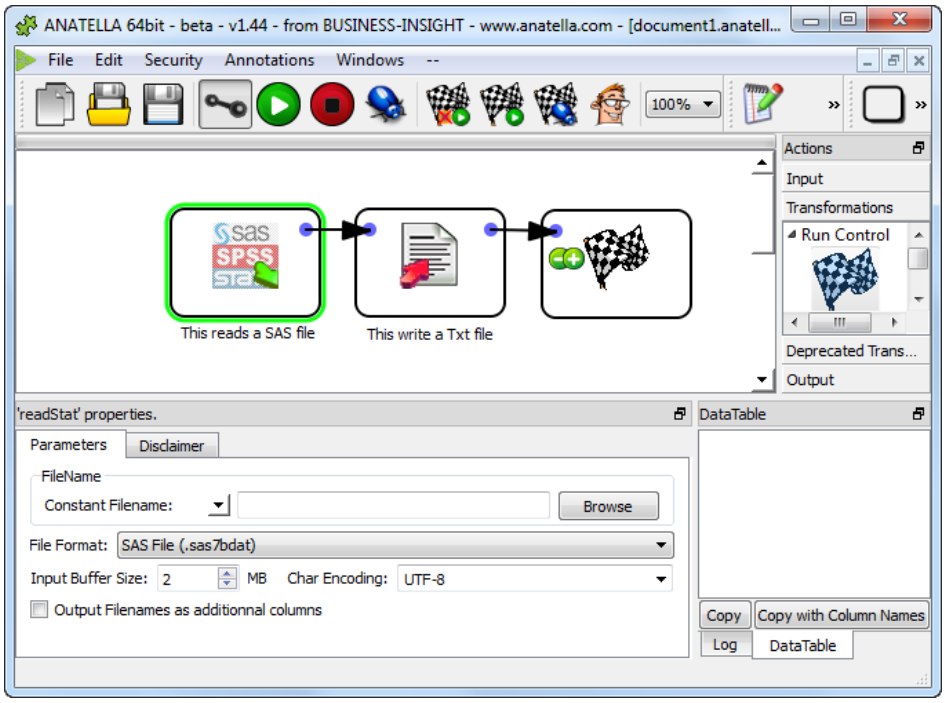
4. Creation/Learning dataset file format

TIMi can read datasets from many data sources: simple "txt" or ".csv" flat files, SAS files, ACCESS files, ODBC & OleDB links to any databases (Teradata, Oracle, SQLServer,etc.). **But** for a first “quick benchmark”, it‘s suggest to store the ***creation dataset*** inside a simple "txt" or ".csv" flat file (in order to prevent any inter-operability errors).

The "txt" or ".csv" flat file should follow the following format:

- The ***creation dataset*** is a "txt" or ".csv" file where the separator is a dot-comma ‘;’. The first line of the file must contain the column names.

  WARNING: "txt" files exported from SAS have a size limitation: one line cannot exceed 65535 characters. If you encounter this bug in SAS, the easiest solution is the following: Convert the .sas7bdat SAS file to a simple "txt" file using Anatella (or even better: convert to a .gel_anatella file!): Use the following Anatella-data-transformation-graph:



- Column names must be unique.

  WARNING: TIMi is case IN-SENSITIVE (as is SQL)
- Column names are NOT within quotes.
- The data in the columns are NOT within quotes (never)
- The field separator character (here ‘ ;’) is not allowed (neither in the data, neither in the column names).
- The ***creation dataset*** contains one unique primary key.
- The decimal character is a dot and not a comma (Standard English notation or Scientific notation for numbers).

- If The ***target*** column (the column to predict) is:
  - Binary: then it must contains only '0' and '1' values (and the "one's" are the value to predict and must be the **minority case**).
  - Continuous: then it should not contain any "missing value".

- Missing values must always be encoded as empty values ("").

- OPTIONAL: The ***creation dataset*** should not contain any "consequence columns". If the dataset nevertheless contains some "consequence columns", it's good to know their name in advance. However, you can always use **TIMi** to find all the "consequence columns" easily.

- OPTIONAL: the flat file can be compressed in RAR (.rar), GZip(.gz), Winzip(.zip)

- OPTIONAL: all the columns that represent a "True/False" information may contain only two different value: '0' (for false) or '1' (for true) or are empty ("") if the value is missing.

- OPTIONAL: all the columns that represent either:
  - a number
  - an information that can be ordered

  … should be encoded as pure number. For example:

number of cats
missing
no cat
one cat
2 cats
3 or more

number of cats
0
1
2
3

Social class
missing
poor
middle
rich

social class
0
1
2