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# Churn analysis

Introduction

#### Context

- Activities and services characterized by:
  - Continuous relationships between consumer/customer and provider
  - Possibility to trace user behavior
  - Competitors

#### Business context

- Telco
- Supermarkets retail

# **Problem Definition**

- Several synonyms
  - Churn
  - Abandon
  - Desertion
- Typically not announced
  - Explicit (Es.: contract termination)
  - Hidden (Es.: change of supermarket)

# **General goals**

#### Customer retention

- Retain old client is less expensive than looking for new ones
- Provide resilience to the service
- Goal:
  - identify the abandoner
  - Implement retention strategies; special offers, new services, special discounts

# **Challenge: FAST identification**

- Often, when churn occurs it is too late
  - Recovering the churner is not possible any more, or
  - Recovering him is not convenient any more
- Foundamental: detect churning immediately or even in advance
- New problem fomulation:
  - Churn Analysis = churn prediction

# **Modalities of Churn**

#### Explicit

Typical of customer relationships that involve a contract with costs or other involvement

> E.g.: Telecom, when a rent is required E.g.: non-free cards

#### Implicit

Typical of customer relationships without contracts and/or free of charge

E.g.: Most loyalty cards

# **Implicit churn**

- Most common situation in retail selling
  - Free loyalty cards
  - The churner simply stops using them
- Q.: how to understand whether a customer is actually a churner?
  - Stops purchasing for 1 month?
  - Stops purchasing for 1 year?
  - Visits the shops less than twice a month?
  - Spends less than 50% of what he used to?

# "Soft" churn

#### Alternative notion of churn

- Switch from a kind of relation with the bussiness to another one
- Extreme case: from "loyal" to "complete churn"

#### In retail selling

- Loyal customers provide (some) guarantees about future income of the seller
- Downgrading from "loyal" to "occasional" has large effects on the company
  - As important as the "hard" churn

# **Predicting churn**

Customer traces allow to reconstruct his history for a given period in the past
 today

Monitored period (in the DW)

The status of the customer can only be evaluated on the information we have "today"

Evaluation of churn -

today

time

# **Predicting churn**

Objective: predicting the *future* status of the customer, based on his recent history

today +1 month

time

Monitored period (in the DW)

Recent history provides clues about the behaviour he is going to follow

Some clues help recognizing the future churners, other do not

Some clues are explicitly available in the dataset, others need to be inferred from it

# **Predicting churn**

- How to learn today the correlations between present situation and future status?
  - Try to learn them looking at the past correlations
  - The correlations "past → today" learnt will be



# Schema of Churn prediction applications

- Define/extract working variables
  - Predictive: the clues available today/past
  - Traget variable: future/today status
- Build the predictive model
  - Look for correlations between predictive and target variables, to be exploited in the prediction phase
- Apply predictive model
  - The correlations are applied to the present situation (i.e. predictive variables) to estimate the target variable

# **BICOOP – Churn Analisys**

# **Problem Definition:**

# Estimate the probability of churn on the base of DW evidences:

- Detailed buying records
- Demographic data

#### Churn risk definition

- For a client the churn risk appears when a dramatic decrease of her/his expenditure measures:
  - Number of visits
  - Total amount of expenditure value
  - Number of items bought

# Predictive analysis

- Collect historical data to build:
  - Demographic and purchase variables, to be used as predictors (green bar)
  - Target variabls (red bar)
- Build a predictive model
  - Learned on historical data
  - To be apply for predictions

|          | today           |      |
|----------|-----------------|------|
| 9 months | 3 m. prediction | Time |
| history  |                 |      |

#### Data preparation – predictive variables (red bar)

Si sono estratte dal data warehouse, per il periodo di 9 mesi (Dicembre 2006 – Agosto 2007) le seguenti informazioni:

- •Dati anagrafici (sesso, età, professione etc.)
- •Dati di spesa
  - Globale
  - Settori specifici: fresco, carni, pesce, ortofrutta
  - Pesata (abbattimento no-food)
- •Trend di spesa:
  - Tipologia cliente (per ogni mese)
  - Regressione spese
  - Regressione spesa
  - Regressione battute

# Il coefficiente di regressione rappresenta l'inclinazione della retta che approssima i punti

(Extract from

**COOP** report)

#### Data preparation – target variables (red bar)

- Over the last 3 months, the following information were extracted from the data warehouse:
  - Number of purchases
  - Purchases variation w.r.t. "green bar"
    - Total amount spent
    - Number of articles bought
    - Number of visits

# Dataset

- The final dataset contains a row for each customer, excluding those without any purchse in the period
  - 517.000 rows
  - 47 attributes

| Predittori Anagrafici | Predittori di spesa | Predittori di trend | Variabili target |
|-----------------------|---------------------|---------------------|------------------|
| CLIENTE_ID            | data_ultima_spesa   | TIPOLOGIA_01        | T_NUM_SPESE      |
| SESSO                 | NUM_SPESE           | TIPOLOGIA_02        | T_RAPP_SPESE     |
| STATO_CIVILE          | SPESA_TOT           | TIPOLOGIA_03        | T_RAPP_SPESA     |
| PROFESSIONE           | SPESA_TOT_PESATA    | TIPOLOGIA_04        | T_RAPP_BATTUTE   |
| TITOLO_STUDIO         | spesa_media         | TIPOLOGIA_05        |                  |
| PROVINCIA             | SPESA_MEDIA_PESATA  | TIPOLOGIA_06        |                  |
| REGIONE               | BATTUTE             | TIPOLOGIA_07        |                  |
| ANNO_SOCIO            | FRESCHI_TOT         | TIPOLOGIA_08        |                  |
| FASCIA_ANNO_SOCIO     | FRESCHI_SPESE       | TIPOLOGIA_09        |                  |
| FL_INVIO_RIVISTA      | CARNI_TOT           | TIPOLOGIA_MEDIA     |                  |
| COD_NEGOZIO           | CARNI_SPESE         | TIPOLOGIA_ZERI      |                  |
| ETA                   | PESCE_TOT           | REGR_NUM_SPESE      |                  |
| ETA_FASCIA            | PESCE_SPESE         | REGR_SPESA          |                  |
|                       | ORTOFRUTTA_TOT      | REGR_SPESA_PESATA   |                  |
|                       | ORTOFRUTTA_SPESE    | REGR_BATTUTE        |                  |

# **Data Exploration**

# Distribution of expenditure trends



Customers with total purchases > 400€

# **Target variables**



# Funzioni Obiettivo (Extract from COOP report)

NUM\_SPESE: spese del cliente nel periodo target

RAPP\_SPESE: rapporto tra il numero delle spese del periodo target e quello del periodo d'osservazione

RAPP\_SPESA: rapporto tra la spesa del periodo target e quella del periodo d'osservazione

RAPP\_BATTUTE: rapporto fra le battute di cassa del periodo target e quelle del periodo d'osservazione

# Normalized measures







# Discretizing target vars.

- Choose an alarm threshold
- Result: three churn binary variables
- Chosen threshold: 0.5 i.e. 50% decay
- Distributions obtained
  - (F= low risk, V = high risk)



F-0 100.000 Conteggio F-0 300.000 400.000



**OB3: RAPP BATTUTE** 

OB1: RAPP\_SPESE



# Discretizing target vars.

Combined variable:

• Alarm = alarm in all 3 variables seen before

#### OB\_AND: OB1 and OB2 and OB3



# Results

#### Churn distribution w.r.t. expenditure & weighted expenditure



# Sample classification rules

if REGIONE = TOSCANA & NUM\_SPESE <= 128 & TIPOLOGIA\_01 = 7 & TIPOLOGIA\_09 = 0 & TIPOLOGIA\_ZERI > 2 & REGR\_BATTUTE <= -0,98 then V (conf. 82,8%)

if DATA\_ULTIMA\_SPESA > 183 & NUM\_SPESE <= 21 & TIPOLOGIA\_ZERI > 1 & REGR\_NUM\_SPESE <= -0,02 & REGR\_BATTUTE <= -0,98 then V (conf. 92%)

# Performances of classifier

#### • Accuracy:

- 81.06% on training set (70% of the dataset, 360.000 rows)
- 80.94% on test set (30% of the dataset, 155.000 rows)

# Confusion matrices Predictions

|      | Training Set | F V     | V      | Test Set | F       | V      |       |
|------|--------------|---------|--------|----------|---------|--------|-------|
| lues | F            | 256.608 | 17.920 | F        | 110.029 | 7.767  | 66.9% |
|      | V            | 50.540  | 36.466 | v        | 21.855  | 15.734 | B     |

# Performances of classifier

# • Lift chart

