

INFO 251 UC BERKELEY, USA – DECEMBER 2017

"Customer attrition prediction model: A bank in Chile, South America"

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Agenda



- Problem Description
- Main Objectives
- Methodology
- Results and Discussion
- Conclusions

The **Problem**: customer attrition

- ABC, a real bank located in Chile, has a problem related to customers retention.
- ▶ 10% of the total portfolio finish its contract with the bank annually.
- Estimations: around 30% of their total portfolio may potentially finish their contract.
- Resources: to contact and persuade about
 5% of its total portfolio.



Objectives: keep my clients!

"Develop an efficient and effective customer attrition prediction model for a real bank in South America, helping the bank to focus its resources for its retention actions/policies".







The Instance: **ABC** bank dataset

Two Data sets

- DS1: 1248 observations
- DS2: 2807 Observations
- 17 Features (1 ID)
- 1 Binary Label

Bank variables

- Wide ranges
- Different scale
- No missing values
- Numerical

Table 1: Attributes in Data Base

Cod_cliente Client Identification

COD_OFI Office code
COM Province
ED Age in years

SX Sex/Genre (M: men; F: women)

NIV_EDUC Educational level

RENTA Rent in thousand of pesos by month

E_CIVIL Civil state

VIG Validity (in month)

TRX T Number of transactions in month T TRX_T-1 Number of transactions in month T-1 TRX_T-2 Number of transactions in month T-2 $SALDO_T$ Average balance in CL pesos in month T SALDO_T-1 Average balance in CL pesos in month T-1 SALDO_T-2 Average balance in CL pesos month T-2 SALDO T-3 Average balance in CL pesos month T-3 SALDO_T-4 Average balance in CL pesos month T-4

CERRO Indicator if the person closed (1)

or not (0) his account

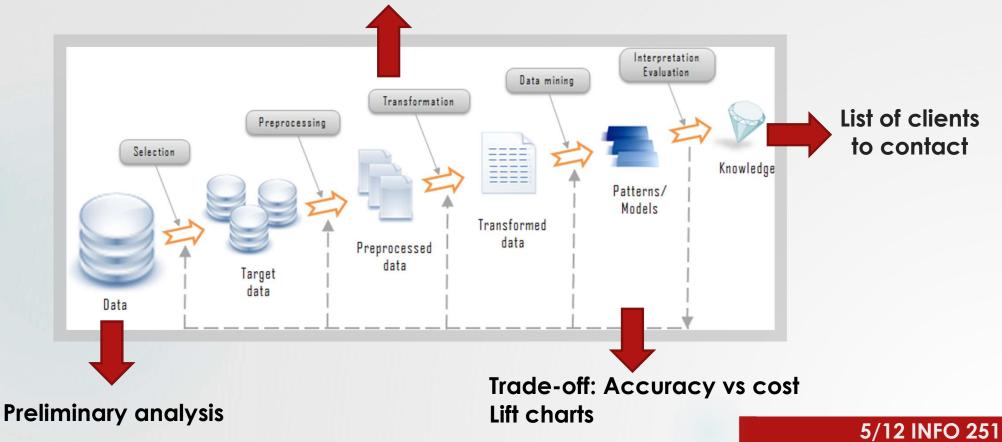
Demographic variables

- Numerical & categorical
- variables (strings)
 9 missina values:
- 8 NIV EDUC & 1 SX

Binary Label

Methodology: when the accuracy is not everything...

String to numerical, missing values, standardization



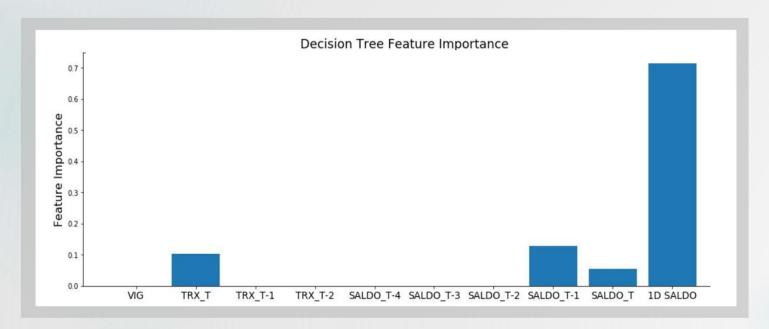
The Instance: Preliminary analysis

- Correlation with label (strongest)

▶ TRX_T
$$\rho = -0.39$$

- ► SALDOT -1 $\rho = -0.32$
- TRX T -1 $\rho = -0.26$

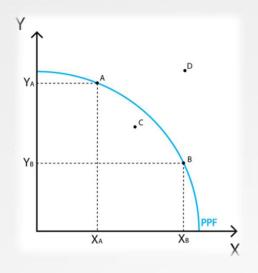
- Feature Engineering
- ► 1D SALDO
- **MEAN SALDO**
- ▶ 1D TRX
- PCA analysis (3 components)

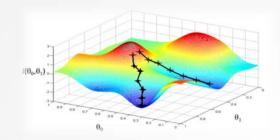


Methodology: when the accuracy is not everything...

- A straightforward accuracy score does not Paint the whole picture.
- A customer predicted to stay that actually leaves is a more costly error.
- The models allow for class weights.

Cost Matrix	Predicted: Stay	Predicted: Leave
Actual: Stay	TN: 0	FP: 350
Actual: Leave	FN: 1000	TP: 250



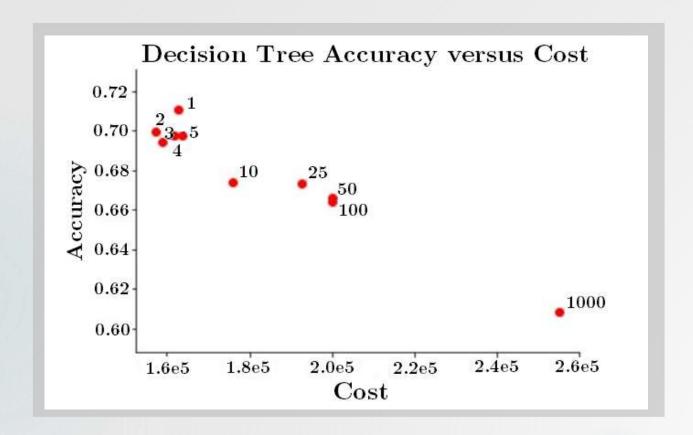


Results and Discussion: Models comparison

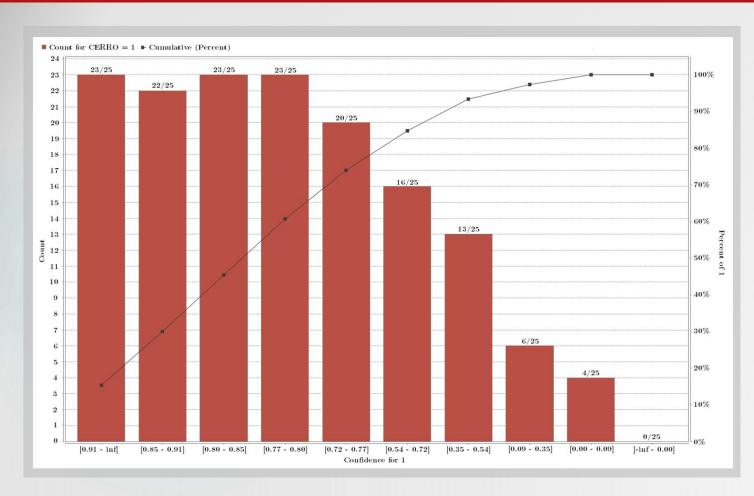


Model	Decision Tree	Random Forest	Logistic Regression	SVM	Neural Network	K-NN
Training Accuracy	84.9%	88.1%	83.4%	85.3%	80.8%	71.2%
Testing Accuracy	77.6%	83.1%	86.1%	76.5%	73.8%	61.2%
TP	109	116	114	118	87	67
TN	82	90	91	73	96	85
FP	45	37	36	27	40	60
FN	12	5	7	32	25	36
Weight	2	5	4	3	-	-
GAP Cost	6.3%	10.5%	17.4%	2.32%	-	-

Results and **Discussion**: Cost vs Accuracy



Results and **Discussion**: Lift charts



- The best performance is obtained by the logistic regression model.
- Only 9 observations are not well classified among the first 100 classified as abandoning clients, in other words, an error of 9.00%
- Customers that are "most likely" to reflect a positive response are identified.

Results and **Discussion**: Error analysis and interpretation

Classification	AVG SALDO_T	AVG SAIDO_T-1	AVG TRX_T	AVG TRX_T-1	AVG Renta	AVG VIG
TP	-0.072	-0.310	20.9	26.9	660.9	43.6
FN	-0.095	-0.160	61.0	42.1	1219.8	76.3
TF	0.261	0.522	62.0	54.9	743.3	73.4
FP	-0.276	-0.318	21.4	22.7	681.2	39.7

- ► FN are misclassified due to differences in the number of transactions: 2 types of customer behaviors when closing the account.
- ► FP observations associated with customers having a loan with the bank.





Conclusions





- ▶ The study was successful: tackle a real-world problem while using different approaches from the ones applied during the course.
- ► Trade-off: complexity of the model vs easy to follow decision rules (Logit vs Decision tree).
- Information about the effectiveness of the offers/MKT campaigns is needed: optimal thresholds of the models.
- Real life implementation: The next challenge of the project consists of implementing it

Thanks for your attention!

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Appendix: Data Set summary

		Table 2:	ABC Bank data set summary	5	
Attribute	Variable	Type	Mean/Mode	Range and Frequencies	Missing
Id	Cod_Cliente [ID]	integer	avg = 624.500 + /-360.411	[1.000; 1248.000]	0.0
Label	CERRO [LABEL]	binominal	mode = 0.0 (629) least = 1.0 (619)	0.0 (629)- 1.0 (619)	0.0
Regular	COD_OFI	integer	avg = 74.268 + /-49.723	[10.000; 247.000]	0.0
Regular	COM	integer	avg = 122.481 + /-91.050	[1.000; 516.000]	0.0
Regular	ED [years]	integer	avg = 41.319 + /- 12.013	[21.000; 86.000]	0.0
Regular	SX [M male,F women]	binominal	mode = M (839) $least = F (408)$	M (839)- F (408)	1.0
Regular	NIV_EDUC	nominal	mode = UNV (525) least = BAS (5)	UNV (525), MED (298), TEC(400), BAS (5), EUN (12)	8.0
Regular	RENTA [M CLP/month]	integer	avg = 729.071 + /-514.604	[250.000; 5400.000]	0.0
Regular	E_CIVIL	nominal	mode = CAS (822), least = VIU (21)	CAS (822), SOL (348), VIU (21)SEP (57)	0.0
Regular	VIG [months]	integer	avg = 55.654 + / -53.425	[3.000; 366.000]	0.0
Regular	TRX_T [N°/month]	integer	avg = 38.632 + /- 36.569	[0.000; 417.000]	0.0
Regular	TRX_T-1 [N°/month]	integer	avg = 37.557 + /-34.400	[0.000; 390.000]	0.0
Regular	TRX_T-2 [N°/month]	integer	avg = 43.248 + / -38.089	[0.000; 391.000]	0.0
Regular	SALDO_T-4 $[\overline{CLP}/\text{month}]$	numeric	avg = 1174103.212 + /-3481175.370	[-568443.750;60791570.550]	0.0
Regular	SALDO_T-3 $[\overline{CLP}/\text{month}]$	numeric	avg = 1148645.272 + /-3298359.403	[-556992.860; 70450696.350]	0.0
Regular	SALDO_T-2 $[\overline{CLP}/\text{month}]$	numeric	avg = 1235826.283 + /-3016768.011	[-757777.710 ; 35383283.950]	0.0
Regular	SALDO_T-1 $[\overline{CLP}/\text{month}]$	numeric	avg = 3084470.349 + /-8149275.790	[-1359252.860 ; 98154458.100]	0.0
Regular	SALDO_T $[\overline{CLP}/\text{month}]$	numeric	avg = 4327925.344 + /-11252574.346	[-3814728.100; 159122938.570]	0.0

Appendix: Feature importance tests

Variable	\mathbf{cov}
TRX_T	-0.19688583
$SALDO_{-}T$	-0.16113672
TRX_T-1	-0.13091134
SALDO_T-2	-0.10996098
TRX_T-2	-0.10332789
SALDO_T-4	-0.09200732
VIG	-0.09049295
SALDO_T-3	-0.08612740
SALDO_T	-0.06300822
ED	-0.06297507

Variable	Squared-Chi
$TRX_{-}T$	1
SALDO_T-1	0.607376208
TRX_T-1	0.545469436
SALDO_T-2	0.316205238
TRX_T-2	0.256617819
VIG	0.253020294
ED	0.250801476
SALDO_T	0.179847769

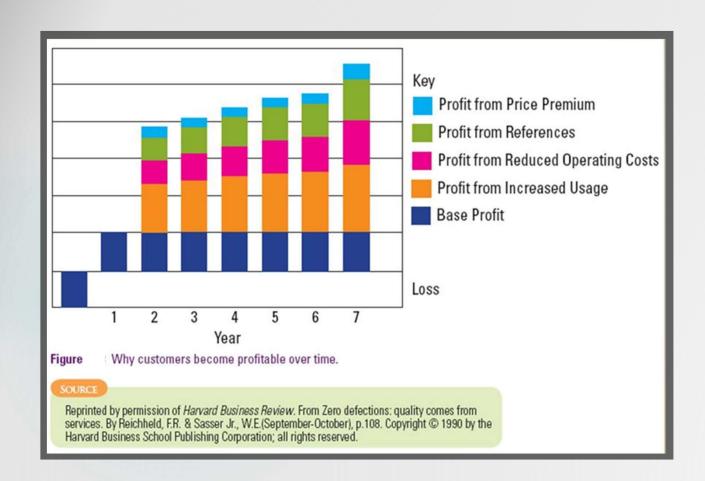
Covariance and Chi-Square tests

Gini index analysis

Variable	Gini index
SALDO_T-1	1
$SALDO_T-2$	0.540096249
$TRX_{-}T$	0.527380709
SALDO_T-3	0.39007159
SALDO_T-4	0.369913197
TRX_T-1	0.273530545
SALDO_T	0.251854852
$TRX_{-}T-2$	0.166606362

Variable	Gini Index		
VIG	0.09999627		
ED	0.06936445		
COM	0.01351656		
COD_OFI	0.01148478		
E_CIVIL	0.00928331		
NIV_EDUC	0.0081042		
RENTA	0.00741076		
SX	0		

Customers lifetime & Profit



- New client is more risky than an "old" client
- 5 6 times more expensive than actually keeping an old client
- Total utility from a client is proportional to his/her lifetime