# Fundamentals of Machine Learning for Predictive Data Analytics

## Chapter 9: Case Study - Customer Churn

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- Acme Telephonica (AT) is a mobile phone operator that has customers across every state of the U.S.A.
- AT struggles with customer **churn prediction**—customers leaving AT for other mobile phone operators.
- In 2010 AT hired Ross, a predictive data analytics specialist, to take a new approach to reducing customer churn.
- This case study describes the work carried out by Ross when he took AT through the CRISP-DM process to develop a predictive data analytics solution to this business problem.

# Business Understanding

- AT did not approach Ross with a well-specified predictive analytics solution. Instead, the company approached him with a business problem—reducing customer churn.
- Ross's first goal was to convert this business problem into a concrete analytics solution.
- Before attempting this conversion, Ross had to fully understand the business objectives of AT.

# Data Understanding

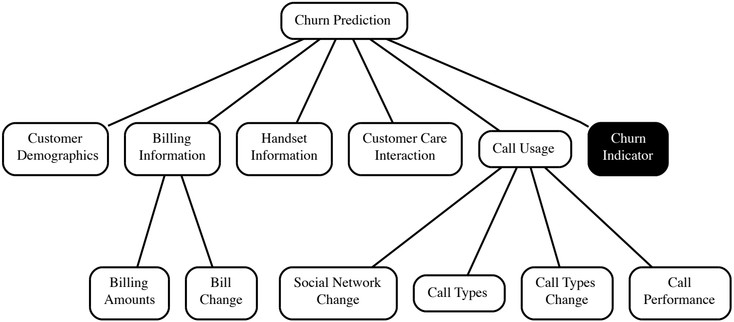



**Figure:** The set of domain concepts for the Acme Telephonica customer churn prediction problem.

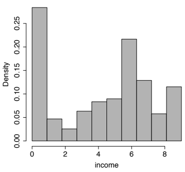
| Feature | Description |
|---|---|
| BILLAMOUNTCHANGEPCT | The percent by which the customer's bill has changed from last month to this month |
| CALLMINUTESCHANGEPCT | The percent by which the call minutes used by the customer has changed from last month to this month |
| AVGBILL | The average monthly bill amount |
| AVGRECURRINGCHARGE | The average monthly recurring charge paid by the customer |
| AVGDROPPEDCALLS | The average number of customer calls dropped each month |
| PEAKRATIOCHANGEPCT | The percent by which the customer's peak calls to off-peak calls ratio has changed from last month to this month |
| AVGRECEIVEDMINS | The average number of calls received each month by the customer |
| AVGMINS | The average number of call minutes used by the customer each month |
| AVGOVERBUNDLEMINS | The average number of out-of-bundle minutes used by the customer each month |
| AVGROAMCALLS | The average number of roaming calls made by the customer each month |
| PEAKOFFPEAKRATIO | The ratio between peak and off peak calls made by the customer this month |
| NEWFREQUENTNUMBERS | How many new numbers the customer is frequently calling this month? |

| Feature | Description |
|---|---|
| CUSTOMERCARECALLS | The number of customer care calls made by the customer last month |
| NUMRETENTIONCALLS | The number of times the customer has been called by the retention team |
| NUMRETENTIONOFFERS | The number of retention offers the customer has accepted |
| AGE | The customer's age |
| CREDITRATING | The customer's credit rating |
| INCOME | The customer's income level |
| LIFETIME | The number of months the customer has been with AT |
| OCCUPATION | The customer's occupation |
| REGIONTYPE | The type of region the customer lives in |
| HANDSETPRICE | The price of the customer's current handset |
| HANDSETAGE | The age of the customer's current handset |
| NUMHANDSETS | The number of handsets the customer has had in the past 3 years |
| SMARTPHONE | Is the customer's current handset a smart phone? |
| CHURN | The target feature |

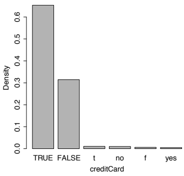
# Data Preparation

| Feature | Count | % Miss. | Card. | Min. | $1^{st}$ Qrt. | Mean | Median | $3^{rd}$ Qrt. | Max. | Std. Dev. |
|---|---|---|---|---|---|---|---|---|---|---|
| age | 10,000 | 11.47 | 40 | 0.00 | 0.00 | 30.32 | 34.00 | 48.00 | 98.00 | 22.16 |
| income | 10,000 | 0.00 | 10 | 0.00 | 0.00 | 4.30 | 5.00 | 7.00 | 9.00 | 3.14 |
| numHandsets | 10,000 | 0.00 | 19 | 1.00 | 1.00 | 1.81 | 1.00 | 2.00 | 21.00 | 1.35 |
| handsetAge | 10,000 | 0.00 | 1,923 | 52.00 | 590.00 | 905.52 | 887.50 | 1,198.00 | 2,679.00 | 453.75 |
| handsetPrice | 10,000 | 0.00 | 16 | 0.00 | 0.00 | 35.73 | 0.00 | 59.99 | 499.99 | 57.07 |
| avgBill | 10,000 | 0.00 | 5,588 | 0.00 | 33.33 | 58.93 | 49.21 | 71.76 | 584.23 | 43.89 |
| avgMins | 10,000 | 0.00 | 4,461 | 0.00 | 150.63 | 521.17 | 359.63 | 709.19 | 6,336.25 | 540.44 |
| avgrecurringCharge | 10,000 | 0.00 | 1,380 | 0.00 | 30.00 | 46.24 | 44.99 | 59.99 | 337.98 | 23.97 |
| avgOverBundleMins | 10,000 | 0.00 | 2,808 | 0.00 | 0.00 | 40.65 | 0.00 | 37.73 | 513.84 | 81.12 |
| avgRoamCalls | 10,000 | 0.00 | 850 | 0.00 | 0.00 | 1.19 | 0.00 | 0.26 | 177.99 | 6.05 |
| callMinutesChangePct | 10,000 | 0.00 | 10,000 | -16.422 | -1.49 | 0.76 | 0.50 | 2.74 | 19.28 | 3.86 |
| billAmountChangePct | 10,000 | 0.00 | 10,000 | -31.67 | -2.63 | 2.96 | 1.96 | 7.56 | 42.89 | 8.51 |
| avgReceivedMins | 10,000 | 0.00 | 7,103 | 0.00 | 7.69 | 115.27 | 52.54 | 154.38 | 2,006.29 | 169.98 |
| avgOutCalls | 10,000 | 0.00 | 524 | 0.00 | 3.00 | 25.29 | 13.33 | 33.33 | 610.33 | 35.66 |
| avgInCalls | 10,000 | 0.00 | 310 | 0.00 | 0.00 | 8.37 | 2.00 | 9.00 | 304.00 | 17.68 |
| peakOffPeakRatio | 10,000 | 0.00 | 8,307 | 0.00 | 0.78 | 2.22 | 1.40 | 2.50 | 160.00 | 3.88 |
| peakOffPeakRatioChangePct | 10,000 | 0.00 | 10,000 | -41.32 | -6.79 | -0.05 | 0.01 | 6.50 | 37.78 | 9.97 |
| avgDroppedCalls | 10,000 | 0.00 | 1,479 | 0.00 | 0.00 | 0.50 | 0.00 | 0.00 | 9.89 | 1.41 |
| lifeTime | 10,000 | 0.00 | 56 | 6.00 | 11.00 | 18.84 | 17.00 | 24.00 | 61.00 | 9.61 |
| lastMonthCustomerCareCalls | 10,000 | 0.00 | 109 | 0.00 | 0.00 | 1.74 | 0.00 | 1.33 | 365.67 | 5.76 |
| numRetentionCalls | 10,000 | 0.00 | 5 | 0.00 | 0.00 | 0.05 | 0.00 | 0.00 | 4.00 | 0.23 |
| numRetentionOffersAccepted | 10,000 | 0.00 | 5 | 0.00 | 0.00 | 0.02 | 0.00 | 0.00 | 4.00 | 0.155 |
| newFrequentNumbers | 10,000 | 0.00 | 4 | 0.00 | 0.00 | 0.20 | 0.00 | 0.00 | 3.00 | 0.64 |

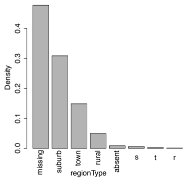
| Feature | Count | % Miss. | Card. | Mode | Mode Freq. | Mode % | $2^{nd}$ Mode | $2^{nd}$ Mode Freq. | $2^{nd}$ Mode % |
|---|---|---|---|---|---|---|---|---|---|
| OCCUPATION | 10,000 | 74.00 | 8 | professional | 1,705 | 65.58 | crafts | 274 | 10.54 |
| REGIONTYPE | 10,000 | 47.80 | 8 | suburb | 3,085 | 59.05 | town | 1,483 | 28.39 |
| MARRIAGESTATUS | 10,000 | 0.00 | 3 | unknown | 3,920 | 39.20 | yes | 3,594 | 35.94 |
| CHILDREN | 10,000 | 0.00 | 2 | FALSE | 7,559 | 75.59 | TRUE | 2,441 | 24.41 |
| SMARTPHONE | 10,000 | 0.00 | 2 | TRUE | 9,015 | 90.15 | FALSE | 985 | 9.85 |
| CREDITRATING | 10,000 | 0.00 | 7 | B | 3,785 | 37.85 | C | 1,713 | 17.13 |
| HOMEOWNER | 10,000 | 0.00 | 2 | FALSE | 6,577 | 65.77 | TRUE | 3,423 | 34.23 |
| CREDITCARD | 10,000 | 0.00 | 6 | TRUE | 6,537 | 65.37 | FALSE | 3,146 | 31.46 |
| CHURN | 10,000 | 0.00 | 2 | FALSE | 5,000 | 50.00 | TRUE | 5,000 | 50.00 |



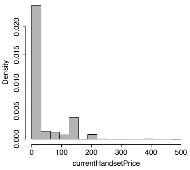

(a) INCOME



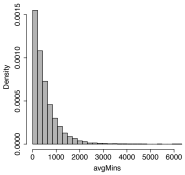

(b) CREDITCARD



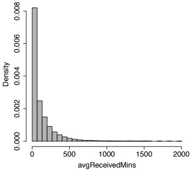

(c) REGIONTYPE



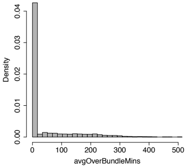

(d) HANDSET-PRICE




(e) AVGMINS

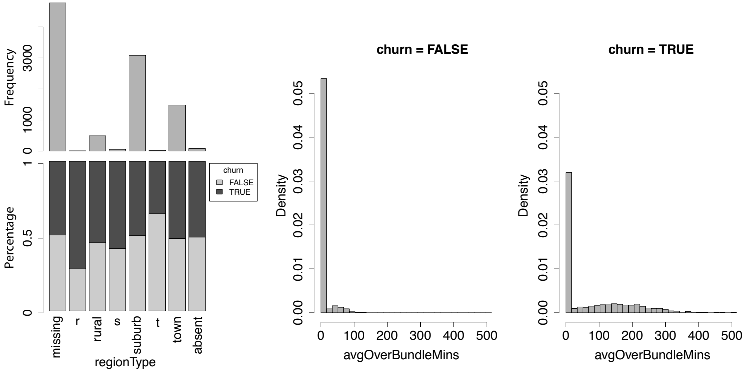



(f) AVGRECEIVED-MINS




(g) AVGOVER-BUNDLEMINS

**Figure:** (a) - (c) Histograms for the features from the AT ABT with irregular cardinality. (d) - (g) Histograms for the features from the AT ABT that are potentially suffering from outliers.




(a) REGIONTYPE (b) AVGOVERBUNDLEMINS

**Figure:** (a) a stacked bar plot for the REGTIONTYPE FEATURE. (b) histograms for the AVGOVERBUNDLEMINS feature by target feature value.

# Modelling

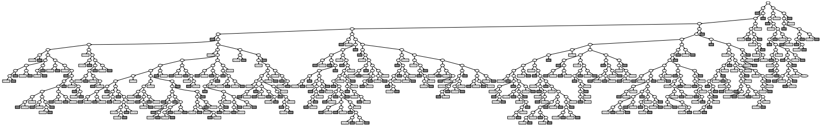


**Figure:** An unpruned decision tree built for the AT churn prediction problem (shown only to indicate its size and complexity). The excessive complexity and depth of the tree are evidence that over-fitting has probably occurred.

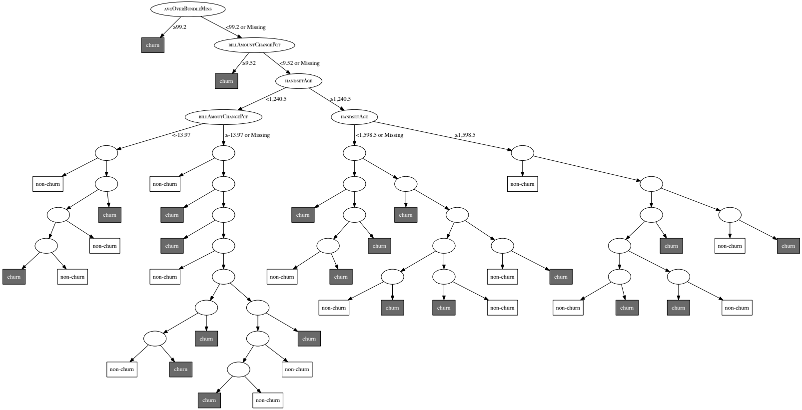



**Figure:** A pruned decision tree built for the AT churn prediction problem. Grey leaf nodes indicate a churn prediction while clear leaf nodes indicate a non-churn prediction. For space reasons we only show the features tested at the top level nodes.

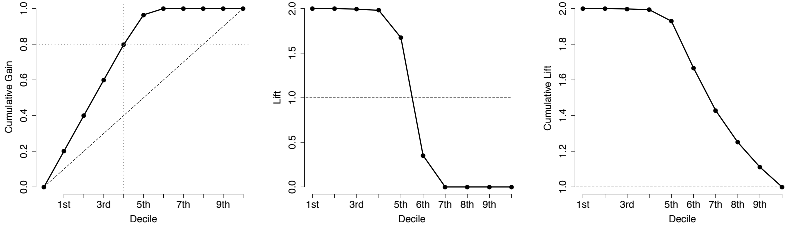
**Table:** The confusion matrix from the test of the AT churn prediction stratified hold-out test set using the pruned decision tree in Figure 5 [17].

| | | Prediction | | |
|---|---|---|---|---|
| | | ***'churn'*** | ***'non-churn'*** | **Recall** |
| **Target** | ***'churn'*** | 1,058 | 442 | 70.53 |
| | ***'non-churn'*** | 152 | 1,348 | 89.86 |

# Evaluation

**Table:** The confusion matrix from the test of the AT churn prediction non-stratified hold-out test set.

| | | Prediction *'churn'* | Prediction *'non-churn'* | **Recall** |
|---|---|---|---|---|
| **Target** | ***'churn'*** | 1,115 | 458 | 70.88 |
| | ***'non-churn'*** | 1,439 | 12,878 | 89.95 |




(a) Cumulative gain (b) Lift (c) Cumulative lift

**Figure:** (a) cumulative gain, (b) lift and (c) cumulative lift charts for the predictions made on the large test data sample.

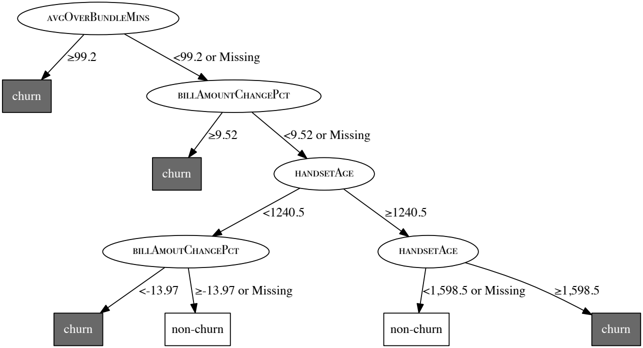



**Figure:** A pruned and stunted decision tree built for the Acme Telephonica churn prediction problem

# Deployment

- Because AT was already using a process in which its retention team generated call lists based on collected data, deployment of the new decision tree model was reasonably straight-forward.
- Ross worked with the AT IT department to develop deployment-ready **extract-transform-load** (ETL) routines to generate queries for the model.
- The last step in deployment was to put in place an **on-going model validation** plan to raise an alarm if evidence arose indicating that the deployed model had gone **stale**.