# Contents

# Abstract

It is known that….

This work addressed the problem from the perspective of…

It could be shown that…

Henceforth, it should be considered that…

# 1 Introduction

A U.S. American veterans organization regularly conducts direct marketing campaigns, asking their members for donations (gifts) for the treatment of veterans with spinal injuries. The goal for the organisation is to maximize the net profit from their campaigns.

Only a small proportion of the members give a gift in reply to a campaign, while each letter sent out has a unit cost of 0.68 $US. In order to maximize profit, it is therefore desirable to only mail members who are likely to donate.

The members are grouped, among other criteria, by the recency of their last gift. Of these groups, the so-called *lapsed* donors are of particular interest. These are members who made their last gift to the organisation 13 to 24 months prior to a given campaign. This group is important for two reasons: Firstly, the likelihood of a member donating decreases with the time the member has not donated. Enticing these lapsed donors to give again therefore maintains an active member base. Secondly, the organisation has found that there is a negative correlation between the dollar amount donated and the likelihood to respond to a campaign. This means it is important to include the most unlikely donors in future mailings because if they donate, the net revenue is particularly large. If these unlikely donors would be suppressed from future campaigns, the gains from additional *small dollar* lapsed donors would not offset the losses from the potential *high dollar* donors.

The data at hand was distributed for the purpose of the KDD-CUP of the year 1998[1]. The cup was until recently held yearly under the aegis of the special interest group on Knowledge Discovery and Data Mining (SIGKDD), which itself is part of the Association for Computing Machinery[2] (ACM).

At the time of the competition, 20 years ago, machine learning was in it's second boom phase. Since then, there was one more period of slump before the current boom that started in the mid-2000's (see Goodfellow, Bengio, and Courville (2016)). Both computing power and tools available have undergone a substantial transformation since 1998, when the frontrunners in the KDD-CUP competition were all big players in the field, showcasing their proprietary software. This thesis thus also demonstrates the possibilities that are currently at hand, from powerful open-source toolkits like scikit-learn to cloud computing.

## 1.1 Task

The task for this thesis was to perform a complete data analysis (data preprocessing, model evaluation, model selction, prediction).

A requirement set by the supervisor of this thesis was that the solution be demonstrated using Python (see Rossum (1995)) as a programming environment.

[1] For an archive of past cups, see SIGKDD - KDD Cup

[2] https://acm.org

## 1.2 Goal

The ultimate goal was to beat the winner of the original cup in terms of the predicted net revenue for the campaign.

Furthermore, the thesis should support future work on the data set by providing a solid basis especially on the preprocessing of the data.

For reference, the exact problem description from the cup announcement is given in verbatim:

> […], the objective of the analysis will be to maximize the net revenue generated from this mailing – a censored regression or estimation problem. The response variable is, thus, continuous (for the lack of a better common term.) Although we are releasing both the binary and the continuous versions of the target variable (TARGET_B and TARGET_D respectively), the program committee will use the predicted value of the donation (dollar) amount (for the target variable TARGET_D) in evaluating the results. So, returning the predicted value of the binary target variable TARGET_B and its associated probability/strength will not be sufficient. The typical outcome of predictive modeling in database marketing is an estimate of the expected response/return per customer in the database. A marketer will mail to a customer so long as the expected return from an order exceeds the cost invested in generating the order, i.e., the cost of promotion. For our purpose, the package cost (including the mail cost) is $0.68 per piece mailed. KDD-CUP committee will evaluate the results based solely on the net revenue generated on the hold-out or validation sample. The measure we will use is: Sum (the actual donation amount - $0.68) over all records for which the expected revenue (or predicted value of the donation) is over $0.68. This is a direct measure of profit. The winner will be the participant with the highest actual sum. The results will be rounded to the nearest 10 dollars.

## 1.3 Glossary

In the scope of this thesis, the following naming conventions are used.

Table 1.1: Naming conventions.

| | |
|---|---|
| **Example** | One observation of the data, a row in the matrix. |
| **Feature** | One variable like *address*, *age* or *time since failure*, a column in the matrix |
| **Generalization Error** | Also called out-of-sample error. The error rate on new observations. |
| **Gift** | A donation made by a member to the veterans organisation |
| **Hyperparameter** | A parameter controlling the learning algorithm. Generally, large (regularization) hyperparameters almost guarantee not overfitting the model at the cost of good performance. |
| **Promotion** | A solicitation to a member of the veterans organisation asking for a donation |
| **Regularization** | Constraints on the learning algorithm defined by *hyperparameters*. These parameters are of the learning algorithm, not the resulting model. |
| **Target** | The solution, or target variable, in the learning dataset. Used in supervised learning to train the algorithm. |

# 2 Experimental Setup and Methods

The general workflow with which the problem was solved is shown in Figure 2.1.

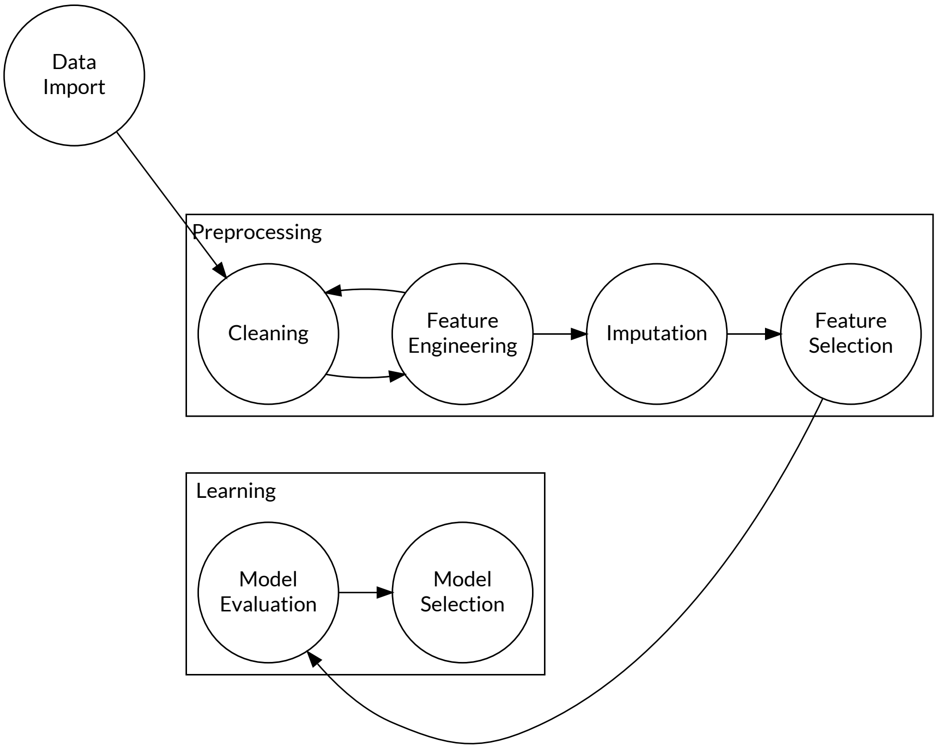


Figure 2.1: Implemented workflow. During import, data was type-cast to usable types. During preprocessing, input errors were corrected, binary features recoded, missing values correclty coded for each feature and categorical data processed manually where necessary. During feature engineering, redundant features were dropped, date features converted to time differences and geographical information acquired to visualize locations of examples.

## 2.1 Tools Used

The problem itself was solved using the python language with several established data-science packages. Except for the development of a helper packge, most programming was performed in interactive notebooks. The report was written in rmarkdown (see Allaire et al. (2016)) and rendered into several different output formats. All work was tracked in version control.

Some key tools are given below.

### 2.1.1 Jupyter Notebook

Following the principle of literate programming first proposed by Knuth (1984), Jupyter by Kluyver et al. (2016) provides a client-server solution that enables interactive programming sessions in the browser. Blocks of code producing output including interactive plots can be mixed with formatted text. These notebooks can easily be shared with others or exported in various formats. The individual steps in the machine learning process outlined in Figure 2.1 were developed in several notebooks which are available online[1], enabling the reproduction of the process.

For this thesis, jupyter notebooks were run in the cloud. The results were then exported and integrated in the report.

### 2.1.2 Pandas

The python package pandas by McKinney (2010) facilitates data loading, inspection and -manipulation. The package is very fast at transforming, filtering and selecting in big data sets.

### 2.1.3 Scikit-learn

The package scikit-learn by Pedregosa et al. (2011) is a self-contained toolset for machine learning purposes in python. Individual tasks in preprocessing, feature engineering and model training can be combined in pipelines. The pipelines ensure that the same transformation steps are applied to all data sets. The pipelines are first trained (fit) on the learning data and then applied (transform / predict) to the test data. A wide range of contribution and 3rd party packages also implement scikit-learn's API so that they can be integrated.

### 2.1.4 Rmarkdown

The report was written in Rmarkdown. Analogous to a jupyter notebook, formatted text and code *junks* can be integrated into one document. The R packages `knitr`, Xie (2015) and `bookdown`, Xie (2016) combined with a latex installation can then be employed to generate high-quality pdf documents and/or html versions.

## 2.2 Data Handling

The complete data is distributed pre-split into a learning and validation data set.

Preprocessing was performed on the learning data set. After preprocessing, the learning data set was split 80/20 into training and validation sets (see Figure 2.2). The training set was used to train different models while the validation set served to tune hyperparameters. The split was performed using a stratified sampling algorithm to preserve the target class frequencies.

[1] see

The validation set was kept back until after model selection. The same preprocessing steps that were applied to the learning data set were then applied to the validation data set and the final prediction performed.

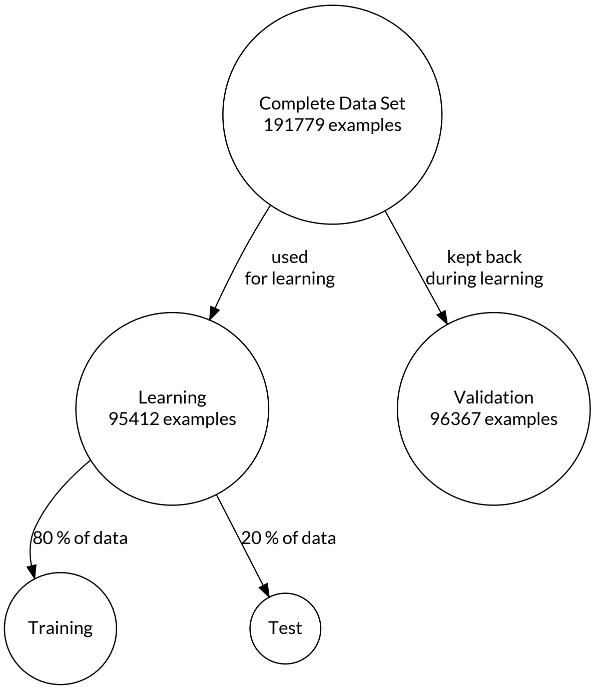


Figure 2.2: Data set use for training and predictions.

## 2.3 Data Preprocessing

To make data usable for learning algorithms, it generally has to be preprocessed. Preprocessing may encompass fixing input errors, coercing data to correct types, encoding categorical (string) data and dealing with missing values through imputation or removal. The result of this process is an all-numeric data set.

The necessary transformations were determined interactively in jupyter notebooks. Once finalized, the tranformations were implemented in the python package `kdd98`[2]. The package can be used to download and read in raw data and apply all transformations. Each transformation is enclosed in a class that implements scikit-learn's API for `BaseEstimator` and `TransformerMixin`, which allows for the transformations to be applied within a pipeline. Furthermore, the transformers can be trained and then persisted on disk for later application on other data.

The data set can be obtained at the following intermediate steps from `kdd98.data_handler.KDD98DataProvider`:

- **raw**, as imported from csv using `pandas.read_csv()`
- **preprocessed**, input errors removed, correct data types for all features, missing at random (MAR) imputations applied

[2] see

- **numeric**, after feature engineering (encoded categories, date and zip code transformations)
- **imputed**, with NaN-values replaced by modelled values
- **all-relevant**, filtered down to a set of relevant features

### 2.3.1 Cleaning

The cleaning stage of preprocessing encompassed the following transformations:

- Removing ‘noise’: Input errors, inconsistent encoding of binary / categorical features
- Dropping constant and sparse (i.e. those where only few examples have a value set) features
- Imputation of values missing at random (MAR)

MAR values in the sense of Rubin (1976) are missing conditionally on other features in the data. For example, there are three related features from the promotion and giving history: *ADATE*, the date of mailing a promotion, *RDATE*, the date of receiving a donation in response to the promotion and *RAMOUNT*, the amount received. For missing *RAMOUNT* values, we can check if *RDATE* is non-missing. If *RDATE* is missing, then the example most likely has not donated and we can set *RAMOUNT* to zero. If, on the other hand, both date features have a value, *RAMOUNT* is truly missing.

The transformations applied can be studied in the jupyter notebook *1_Preprocessing.ipynb*[3].

### 2.3.2 Feature Engineering

During feature engineering, all non-numeric (i.e. categorical) features were encoded into numeric values. Also, several features were transformed to better usable representations. Care was taken to keep the dimensionality of the data set as low as possible.

The result of this transformation step was an all-numeric data set usable for downstream learning. The transformations applied in feature engineering are described in detail in the jupyter notebook *2_Feature Engineering.ipynb*[4].

#### 2.3.2.1 Dates

All date features were transformed into time differences against a reference date according to Table 2.1.

[3] see

[4] see

Table 2.1: Transformation of dates to time differences

| | Feature Explanation | Reference date | Unit |
|---|---|---|---|
| **DOB** | Date of birth | 1997-06-01 (date of most recent campaign) | Years |
| **RDATE** | Month when donation was received | ADATE (sending date of the corresponding campaign) | Months |
| **LASTDATE** | Most recent donation prior to last campaign | 1997-06-01 | Months |
| **MINRDATE** | Date of smallest donation | 1997-06-01 | Months |
| **MAXRDATE** | Date of highest donation | 1997-06-01 | Months |
| **MAXADATE** | Date of the most recent promotion received | 1997-06-01 | Months |

#### 2.3.2.2 Zip Codes

U.S. zip codes were transformed into coordinates (latitude, longitude of the centroid for a given zip) using zip code tabulation data from United States Census Bureau (2018). Several of the examples are army members, identifiable through their values in feature 'STATE'. For these zip codes, no geographical data is available. These example's latitude and longitude were set to the coordinates of the pentagon, the U.S. department of defense. The 2018 zip code tabulation data was missing several zip codes that existed in 1997, at the time of the campaign. These missing zip codes were looked up on the fly using a web service[5]

#### 2.3.2.3 Categorical Encoding

Categorical data was encoded using three different methods. For nominal features, the encoding method was chosen with respect to the number of levels in the categories. Nominal features with less than 10 levels were one-hot encoded. Those with more levels were binary-encoded. Ordinal features were consistently encoded to integer values.

A one-hot encoded feature with $n$ levels is transformed into $n$ new binary features, each feature representing one of the original levels. For each example, there can be at most one `true` value in these new features (denoting which category the example had in the original feature). If the original value was missing, all new features are set to missing.

Binary encoding first assigns an ordinal value to each category. These integer values are then binary encoded. For each binary digit, one new feature is created. Compared to one-hot encoding, the dimensionality increases less with this method.

As an example, the US states are represented by a categorical variable with 52 levels. While one-hot encoding would result in 52 new features, we can encode 52 values with only 5 binary digits, thus adding 5 instead of 52 new features.

[5] HERE geocoding

### 2.3.3 Imputation

As required by the cup documentation, missing values were imputed. Instead of choosing a simple approach like replacing with the feature's mean or median, a modelling approach was chosen. Package `fancyimpute` provides an iterative imputation algorithm for this purpose. Features are ordered by the fraction of missing values [FINISH EXPLANATION]

### 2.3.4 Feature Selection

One of the biggest caveats in machine learning is the infamous "Curse of Dimensionality" coined by Bellman, Corporation, and Collection (1957). The curse comes from the fact that with an increasing number of dimensions, the required number of examples grows exponentially. In the area of machine learning, high dimensionality frequently leads to an overfitting of the training data, meaning that the generalisation error is unacceptably big (see Goodfellow, Bengio, and Courville (2016)).

It is therefore beneficial to reducde the data set dimensionality while preserving as much relevant information as possible. A method to deal with the problem is called boruta, introduced by Kursa, Rudnicki, and others (2010). The algorithm was found to perform very well regarding selection of relevant features in B. Kursa and Rudnicki (2011). It works sequentially and removes features found to be less relevant at each iteration. By doing so, it solves the so-called all-relevant feature problem. The algorithm is actually a wrapper function around a random forest classifier. A random forest classifier is fast, can usually be run without parameters and returns an importance measure for each feature.

In short, the alogrithm works as follows:

1. The input matrix $\mathbf{X}$ of dimension $n$ x $p$ is extended with $p$ so-called *shadow features*. The shadow features are permuted copies of the features in $\mathbf{X}$. They are therefore decorrelated with the target.
2. On the resulting matrix $\mathbf{X}^*$, a random forest classifier is trained and the Z-scores ($\frac{\bar{loss}}{sd}$) for each of the $2p$ features calculated.
3. The highest Z-score among the shadow features $MZSA$ is determined.
4. All original features are compared against $MZSA$ and those features with a higher score selected as important.
5. With the remaining features, a two-sided test for equality of the Z-scores with $MZSA$ is performed and all features with significantly lower score are deemed unimportant.
6. All shadow copies are removed, go to step 1.

The algorithm terminates when all attributes are marked as either important or not important or when the maximum number of iterations is reached.

For this thesis, a python implementation[6] was used. In effect, it is a port of the original R package by Kursa, Rudnicki, and others (2010) which plugs into scikit-learn.

[6] see scikit-learn-contrib/boruta_py

## 2.4 Model Evaluation

During model evaluation, several algorithms were trained and their performance compared.

Randomized grid search with 10-fold cross validation was used to optimize hyperparameters for the algorithms.

The best parameter combination was determined using *recall* as the performance metric (see 2.4.2).

### 2.4.1 Considered Algorithms

The algorithms were chosen so as to cover a wide range of approaches to learning. A short introduction of each algorithm, along with the hyperparameters used for regularization is given below.

#### 2.4.1.1 Random Forest

#### 2.4.1.2 Gradient Boosting Machine

Boosting is a method that can be applied to any learning algorithm. It was introduced by Freund and Schapire (1997) in the form of the algorithm AdaBoost.M1, intended for classification problems. The main idea behind boosting is to train a set of weak classifiers which are only slightly better than a random decision. The predictions of the individual weak classifiers are then combined into a majority vote.

Gradient boosting extends on this idea. New trees are added in the direction of the gradient of the loss function.

For this thesis, the package `XGBoost` by Chen and Guestrin (2016) was used. The general principle of gradient descent is given below.

Assume we have a data set with $n$ examples and $m$ features: $D = \{\{\mathbf{x_i}, y_i\}\}(|D| = n, \mathbf{x_i} \in \mathbb{R}^m, y_i \in \mathbb{R})$. The implementation uses a tree ensemble using $K$ additive functions (regression trees) to predict the outcome for an example in the data.

$$\hat{y}_i = \phi(\mathbf{x_i}) = \sum_{k=1}^{K} f_k(\mathbf{x_i}), f_k \in F \tag{2.1}$$

where $F = \{f(\mathbf{x}) = w_{q(x)}\}(q : \mathbb{R}^m \to T, w \in \mathbb{R}^T)$ is the space of regression trees. $T$ is the number of leaves in a tree, $q$ is the structure of each tree, mapping an example to the corresponding leaf index. Each tree $f_k$ has an independent structure $q$ and weights $w$ at the terminal leafs. An example is classified on each tree in $F$ and the weights of the corresponding leafs are summed up to calculate the final prediciton.

For learning the functions in $F$, the following loss function is minimized:

$$L(\phi) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k}^{K} \Omega(f_k) \tag{2.2}$$

Here, $l$ is a differentiable, convex loss function that measures the difference between predictions and true values. Since $l$ is convex, we are guaranteed to find a global minimum. $\Omega(f) = \gamma T + \frac{1}{2}\lambda||w||^2$ is a penalty on the complexity of the trees to counter over-fitting.

For learning the model, an additive approach is used. At each iteration $t$, the tree $f_t$ that improves the model most is added. For this, we add $f_t(\mathbf{x_i})$ to the predictions at $t-1$.

$$L^{(t)} = \sum_{i=1}^{n} l(y_i, \hat{y_i}^{t-1} + f_t(\mathbf{x_i})) + \Omega(f_t) \tag{2.3}$$

To find the best $f_t$ to add, the gradients finally come into play. With $g_i$ and $h_i$ the first- and second-order gradient statistics of $l$, the loss function becomes:

$$\tilde{L}^{(t)} = \sum_{i=1}^{n} l(y_i, \hat{y_i}^{t-1} + g_i f_t(\mathbf{x_i}) + h_i f_t^2(\mathbf{x_i})) + \Omega(f_t) \tag{2.4}$$

**Regularization**

Apart from the penalization of complicated trees that is implicitly applied in Eq. (2.2), regularization was controlled with the following hyperparameters:

- Shrinkage: A learning rate < 1.0 decreases step size for the gradient descent, helping convergence. The number of estimators $f_k$ has to be increased for small learning rates in order for the algorithm to converge.
- Early stopping: Based on an evaluation set, learning stops when no improvement on the performance metric is made for a fixed number of steps.
- Column Subsampling: A random sample from the $m$ features of size $s$, $s < m$ is drawn for each $f_k$, countering overfitting and speeding up learning.

#### 2.4.1.3 GLMnet

The GLMnet is an implementation of a generalized linear model (GLM) with penalized maximum likelihood by Hastie and Qian (2014). For the binary target in the data, a logistic regression was chosen. Regularization is achieved through $L^2$ and $L^1$ penalties (i.e. ridge and the lasso or their combination known as elastic net).

The logistic regression model for a two-class response $G = \{0, 1\}$ with target $y_i = I(g_i = 1)$:

$P(G = 1|X = x) = \frac{e^{\beta_0 + \beta^T x}}{1 + e^{\beta_0 + \beta^T x}}$ or, in the log-odds transformation: $log\frac{P(G=1|X=x)}{P(G=0|X=x)} = \beta_0 + \beta^T x$.

The loss function is:

$$\min_{(\beta_0, \beta) \in \mathbb{R}^{m+1}} - \left[\frac{1}{n}\sum_{i=1}^{n} y_i(\beta_0 + x_i^T\beta) - log(1 + e^{\beta_0 + x_i^T\beta})\right] + \lambda\left[\frac{(1-\alpha)}{2}||\beta||_2^2 + \alpha||\beta||_1\right] \tag{2.5}$$

It's first term is the negative log-likelihood for the examples in the data. The second term is the elastic-net penalty. $\lambda$ controls the amount of penalization. Parameter $\alpha, 0 < \alpha < 1$ controls the elastic-net penalty. For $\alpha = 0$, it is pure ridge, for $\alpha = 1$ pure lasso.

For learning, glmnet tries many different $\lambda$ values for a given $\alpha$. Each $\lambda$ is then evaluated through cross validation.

** Regularization **

- The parameter $\alpha$ parametrizes the elastic net.
- The scoring method for cross validation can be chosen (log-loss, classification error, accuracy, precision, recall, average precision, roc-auc)

#### 2.4.1.4 Multi Layer Perceptron (Neural Network)

#### 2.4.1.5 Support Vector Machine

### 2.4.2 Performance Metrics

For classification problems, the confusion matrix (see Table 2.2) helps in constructing several performance measures. If we predict an event correctly, it is a *true positive* (TP), predicting an event if there is none, it is a *false positive* (FP). A *false negative* (FN) occures when predicting no event when there was one and a *true negative* (TN) occurs when no event was predicted correctly.

Table 2.2: Definition of the confusion matrix

| | | True value | |
|---|---|---|---|
| | | Event | No Event |
| **Predicted** | **Event** | TP | FP |
| | **No Event** | FN | TN |

From the confusion matrix, several metrics can be deduced. The definitions of some often-used metrics are given below:

$$\begin{aligned}
\text{Accuracy} &= \frac{TP + TN}{TP + FP + FN + TN} \\
\text{Sensitivity} &= \frac{TP}{TP + FN} \\
\text{Specificity} &= \frac{TN}{TN + FP} \\
\text{Precision} &= \frac{TP}{TP + FP} \\
\text{F1 score} &= \frac{2TP}{2TP + FP + FN}
\end{aligned}$$

In literature the following synonyms are found:

- Precision: Positive predictive value (PPV)
- Sensitivity: Recall, True positive rate (TPR), hit rate
- Specificity: Selectivity, True negative rate (TNR)

It is evident that sensitivity measures the proportion of the predicted events from all events present.

Analogous, specificity measures the proportion of correctly predicted no events from all no events present.

# 3 Data

The data at hand is a subset of the roughly 3.5 million members of the organization who were targeted by a campaign in 1997. All donors who were contacted in this campaign have donated at least once to the organisation in the past.

The dataset, which is freely available online[1] contains information on a subset of the turnout of a direct mailing addressed to 3.5 million members in the scope of a fundraising campaign that was conducted in 1997. The dataset contains all donors with a *lapsed* donation status, meaning their last donation was made between 13 and 24 months prior to the 1997 campaign.

The data is provided in two sets, of which one is intended for learning, the other for validation.

In the following section, the learning data set will be characterized. All preprocessing and feature engineering steps were also applied identically to the validation data set.

## 3.1 Raw data import

The import through `pandas.read_csv()` was facilitated by providing per-feature specifications for missing values and explicit type casting for nominal categories. Ordinal categories, dates and features with binary values were cast to the type string (Object).

The dimension of the input data is 95412 examples by 481 features. Of the features, two are the targets and one was used as the index, leaving 478 explanatory features.

The dataset structure after import into a `pandas.DataFrame` object is presented in Table 3.1. This corresponds to the *raw* stage in preprocessing.

Table 3.1: Data types after import of raw csv data

| | Data content | Number of features |
|---|---|---|
| Integer | Discrete features, no missing values | 297 |
| Float | Continuous features and discrete features with missing values | 49 |
| Categorical | Nominal and ordinal features | 24 |
| Object | Features with alphanumeric values | 110 |
| Total | | 480 |

[1] See UCI Machine Learning Repository: KDD Cup 1998 Data

## 3.2 Cleaning & Preprocessing

### 3.2.1 Date features

There were 53 date features specified in the documentation. The specified format for these features is ‘yymm’, the two-digit year followed by the two-digit month.

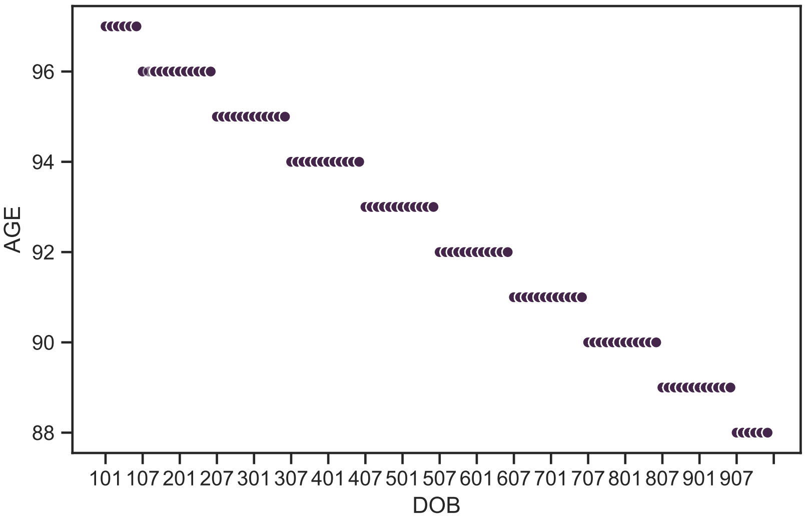


Figure 3.1: Values for date of birth (DOB) with one missing digit versus age. We observe jumps in July of each year, this is because the reference date for age is 1997-06-01. By looking at the ages, it is evident that these values indeed lack a leading zero to put them in the correct decade.

Several values in the feature DOB (date of birth) are only three digits long. Comparing these values with the corresponding example’s values for feature AGE shows that, considering the reference date of June 1997, it is very likely that the 3-digit DOB’s are lacking a leading zero (see Figure 3.1).

All these values were therefore prepended by a zero.

### 3.2.2 Further sanitizations

Several features needed recoding and sanitizing. Information in the data set documentation was used to determine necessary transformations. The transformations are shown in 3.2.

### 3.2.3 Binary Features

There are several codings for the different binary features present in the data set. All were recoded to *1* / *0* with missing data coded as not a number (NaN). The recoding was done through a custom `Transformer` class (see Appendix 6.2.2) derived from scikit-learn’s `TransformerMixin`.

Table (3.3) shows the original coding of the 29 binary features in the raw data set. There are two classes of binary features that have blanks as the *False* value. Even though the data set documentation states

Table 3.2: Overview of trivial data transformations applied.

| | Feature explanation | Operation | Reason |
|---|---|---|---|
| ZIP | U.S. zip code | Remove trailing hyphen | A hyphen after a 5-digit zip most likely stems from incomplete ’ZIP+4’ codes^[see (USPS: ZIP+4 Code)[https://about.usps.com/publications/p |
| MDMAUD_* | Major donor matrix features | Replace X with NaN | Encode NaN as specified by the data set documentation. |
| TARGET_B | Binary target indicating whether an example has donated or not. | Set to 1 when TARGET_D is $ ew$ 0 | When a dollar amount (TARGET_D) was donated, the binary indicator target has to be 1. |
| RFA_* | Multi-byte categorical. Recency, Frequency, Amount. | Set to NaN if length is $ eq$ 3 | The values in these features have to be of length 3, each byte is one categorical. |
| NOEXCH | NOEXCH: Do not exchange address flag | Recode X to 1 | Both X and 1 mean ‘True‘ |
| RAMNT_* | RAMNT_*: Amount donated for a certain campaign. | Set to NaN if corresponding RDATE_* (date of donation reception) is not missing, else set to zero. | Avoid NaN values if possible. |

that blanks should be treated as missing values, in these two classes blanks were interpreted as *False*. For the remaining binary features, blanks were interpreted as missing and coded as `NaN`.

The feature *NOEXCH* had both `X` and `1` for True in the data. This was fixed by replacing all occurrences of `X` by `1`.

### 3.2.4 Multi-byte Categorical Features

Several features combine related information into bytewise codes. These codes were split into individual features. A custom child class of `scikit-learn.TransformerMixin` was written for this purpose (see Appendix 6.2.2).

The donation history contains recency / frequency / amount (RFA) features for each previous mailing. The dataset already contained one mailing (number 2) where this code was split into individual features. The remaining RFA codes were split also.

Table 3.3: Original coding of binary features.

| True | False | Features |
|---|---|---|
| X | blank | PEPSTRFL, MAJOR, RECINHSE, RECP3, RECPGVG, RECSWEEP |
| Y | N | COLLECT1, VETERANS, BIBLE, CATLG, HOMEE, PETS, CDPLAY, STEREO, PCOWNERS, PHOTO, CRAFTS, FISHER, GARDENIN, BOATS, WALKER, KIDSTUFF, CARDS, PLATES |
| 1 | 0 | NOEXCH, HPHONE_D, TARGET_B |
| E | I | AGEFLAG |
| H | U | HOMEOWNR |
| B | blank | MAILCODE |

#### 3.2.4.1 Ordinal Features

Ordinal features were recoded using a custom child classes of `scikit-learn.TransformerMixin` (see Appendix 6.2.2).

### 3.2.5 Missing Values

Missing values were imputed using a k-Neaerest Neighbors (kNN) algorithm provided in the python package `missing_py` Troyanskaya et al. (2001). For each example with a missing value in a specific feature, $k = 3$ nearest neighbors that have a value for the feature are searched for and the missing value imputed with the metric *distance*.

## 3.3 Exploratory Data Analysis

The detailed analysis can be studied online in the corresponding jupyter notebook[2]. The findings are shown here.

### 3.3.1 General structure

The data set is provided pre-cut into a learning and validation set with 95412 and 96367 examples. The features are identical between the two except for the target that has been stripped from the validation set.

There are four main sources of information that make up the data:

- Internal member database (index, personal particulars, several member status features): 85 features
- US census 1990: 286 features

[2] KDD-CUP98: EDA notebook

- Promotion history file: 97 features on promotions received up until the current mailing and response patterns to these promotions
- Giving history file: 13 features, summary statistics giving maximum and minimum amount donated and dates of donations

In total, there are 479 features plus two targets.

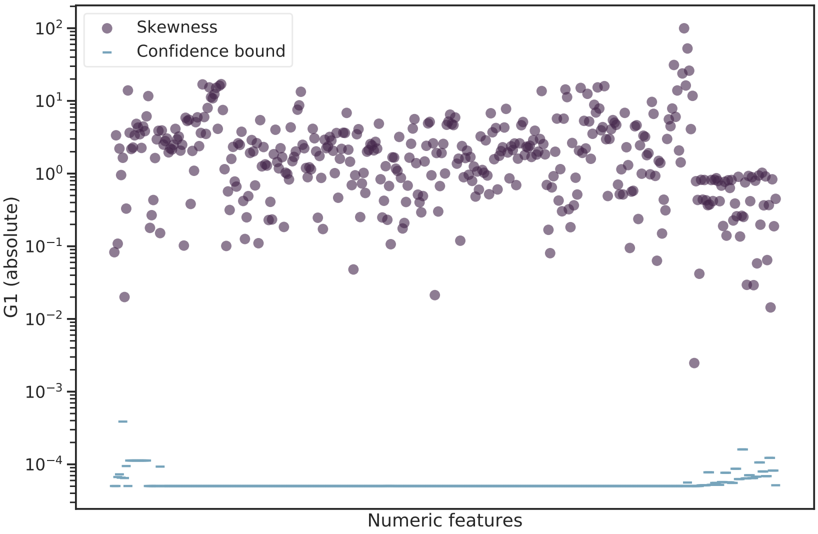
### 3.3.2 Correlations

### 3.3.3 Skewness

Most of the data is skewed. This is an important finding as the data will have to be transformed for learning algorithms that do not perform well for this kind of data.

Figure 3.3.3 gives an abstract idea of the skewness of (numerical) features. It was measured with `pandas.skew()`, which uses the Fisher-Pearson standardized moment coefficient $G_1 = \frac{\sqrt{n(n-1)}}{n-2} \frac{1}{n} \frac{\sum_{i=1}^{n}(x_i - \bar{x})^3}{s^3}$. Here, the term in the denominator is the sample standard deviation.

\begin{figure}



{

}

\caption{Absolute values of the Fisher-Pearson standardized moment coefficient (G1) for all numeric features contained in the dataset. The confidence bound indicates the $\alpha$ = 5 % bound for the skewness of a symmetric distribution for any given feature. It is evident that no feature passes.} \end{figure}

The confidence bound in Figure 3.3.3 gives the $\alpha = 5\%$ bound for a normal distribution. Evidently, no feature was found to be strictly normally distributed, although several features show quite symmetric distributions (see Figure 3.2). These symmetric distributions resemble normal or uniform distributions.

Looking at the most skewed features (see Figure 3.3), we see heavily right-skewed distributions.

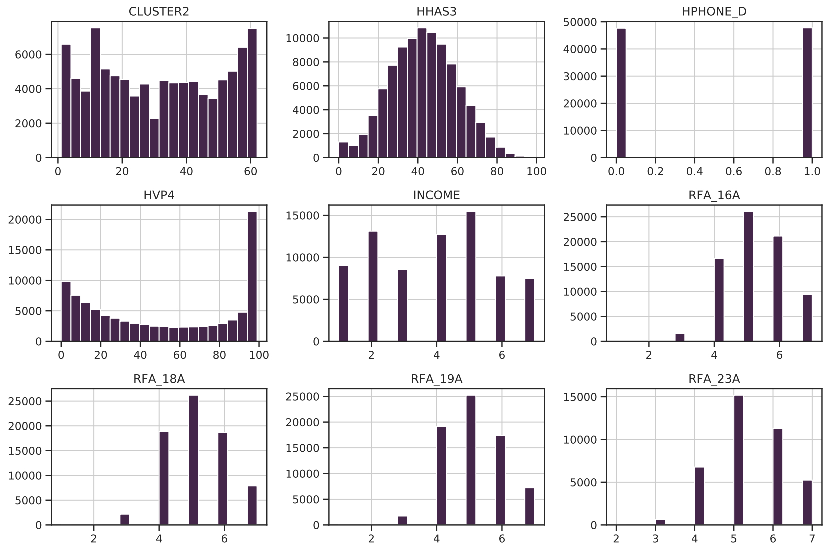


Figure 3.2: The 9 least skewed features. Skewness metric: adjusted Fisher-Pearson standardized moment coefficient.

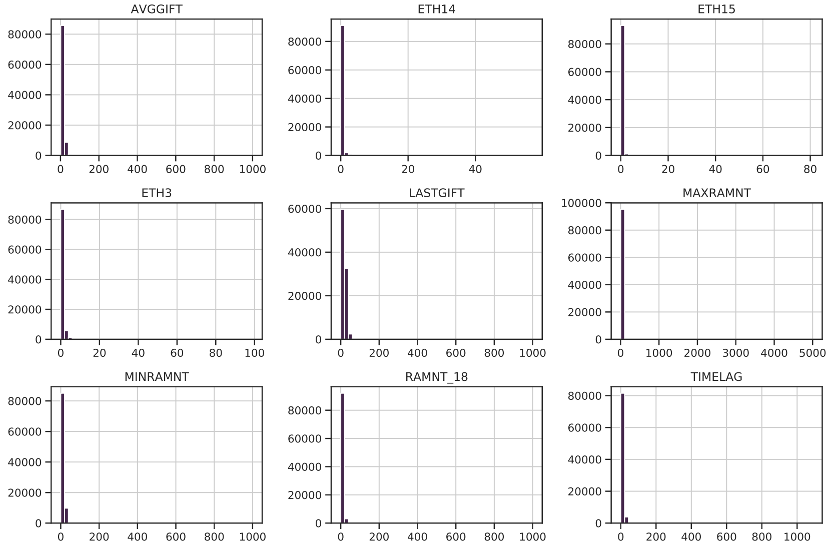


Figure 3.3: The 9 most skewed features. Skewness metric: adjusted Fisher-Pearson standardized moment coefficient.

### 3.3.4 Targets

Of the two targets, one is binary (TARGET_B), the other discrete (TARGET_D). The former indicates whether an example has donated in response to the current promotion. The latter represents the dollar amount donated in response to the current promotion.

The distribution of *TARGET_D*, excluding non-donors, is shown in Figure 3.4. Evidently, most donations are small. The range of donations is between 1 and 200 $ with the 50-percentile at 13 $. The most frequent donation amount is 10 $. There are a few outliers for donations above 100 $.

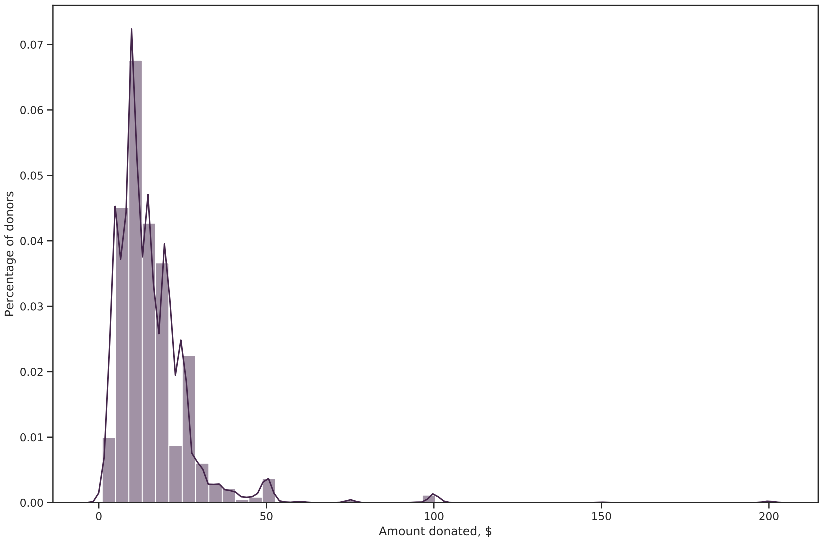


Figure 3.4: Distribution of TARGETD. The donation amount in US dollar has a discrete distribution. Most donations are below 20 dollar, peaks are visible at 50, 75 and 100 dollar, while the maximum donation amount is 200 dollar.

As can be seen in Figure 3.5, the target is imbalanced. Only about 5 % of examples have donated. This poses a challenge in model training because there is a high risk of overfitting.

**Datatypes** An analysis of the dataset dictionary (see 6.4) reveals the following datatypes for features:

- Index: CONTROLN, unique record identifier
- Dates: 48 features in yymm format.
- Binary: 30 features
- Categorical: 90 features
- Numeric: 286

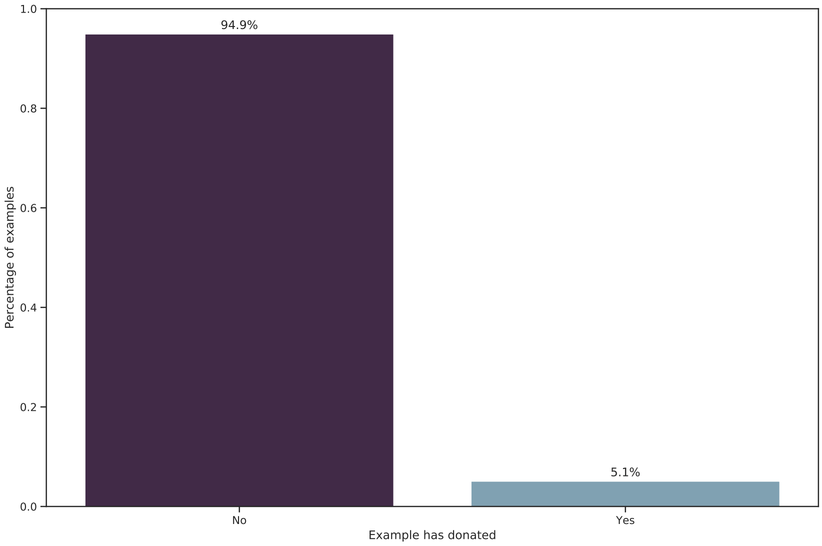


Figure 3.5: Ratio of donating examples. Less than 6 percent have made a donation.

## 3.4 Preprocessing

The dataset contains input errors (noisyness), features with datatypes that are impractical to work with (dates, categorical features) and redundant information. Furhtermore, many features contain missing values.

Noisy and categorical features were processed by the author manually before furhter evaluation of the data. Handling of missing values, zero variance and sparse features was carried out through scikit-learn preprocessors.

### 3.4.1 Noisy data

There were two types of noisyness that were treated manually:

- Binary features with a mixture of 0, 1 and other codes Binary features were all recoded to $\{\text{True}, \text{False}\}$, preserving missing values. 1 was always set to True and 0 was coded False. Specific mappings for True/False values given in the data dictionary per binary field were respected accordingly. As per the data dictionary, ' ' was interpreted as False for some features. For all other features, ' ' was interpreted as missing.
- Dates are expected in *mmyy* as per the dataset dictionary. For several date features, one digit was missing [EXPLAIN HOW FIXED].
- Zip codes: Input errors, inconsistent data (alphanumeric values)

### 3.4.2 Constant features

- Per the cup's documentation, features with zero variance have to be excluded.

### 3.4.3 Missing values / sparse features

- Character features: ' ‘,”
- Numeric features: ' ‘,’‘,’.’
- Missing values are to be kept in the dataset for learning. Approriate methods for imputation are to be employed (median, mean, mode, modeled, …)
- Exception: Features with more than 99.5 % missing values are to be dropped
- Features with a sparse distribution are to be dropped [DEFINITION???]

### 3.4.4 Categorical features

Several variables are aggregated into byte-wise codes (referred to as *symbolic* fields in the data dictionary) that need to be spread out across separate variables.

Most machine-learning methods require strictly numerical data [REFERENCE]. Several methods exist to transform categorical (string-) values into a usable format. These include:

- One-hot tranformation: Creating dummy variables for each category level. This approach greatly increases dimensionality, which is both more resource-intensive and prone to overfitting.
- Ordinal encoding: The categorical targets are transformed to ordinal values (integer numbers). This preserves dimensionality, but the algorithm chosen to assign the ordinal levels can introduce unwanted effects (an implied similarity based on closeness of the ordinal variables) Feature hashing: The individual values are hashed into a value of fixed length.
- Hashing: [DEFINITION]

### 3.4.5 Feature Engineering

### 3.4.6 Feature Selection

-> Selecting the most useful features

### 3.4.7 Feature Extraction

-> Trying to group correlated features into one (dimensionality reduction). Unsupervised learning.

# 4 Model evaluation

Workflow:

Split training dataset 80/20 into training* and test

1. Train on training* dataset
2. Adjust hyperparameters on validation set
3. Run on test dataset to get generalisation error estimate

# 5 Results and Discussion

# 6 Conclusions

## 6.1 Comparison with Cup winners

The KDD-CUP committee evaluated the results based on the net revenue generated on the validation sample. The measure used was the sum (the actual donation amount - \$0.68) over all records for which the expected revenue (or predicted value of the donation) is over \$0.68. This measure is simple, objective and a direct measure of profit. Table 2 depicts the results. The participants are listed based on the last column.

Table 6.1: Top five of the KDD-CUP participants. N* denotes the number for which the predicted donation amount is > $0.68. Sum is the total profit, meaning the donation minus 0.68$ for each example.

| | | Amount, \$ | | | | |
|---|---|---|---|---|---|---|
| | N* | Min | Mean | Std | Max | Sum |
| GainSmarts | 56330 | -0.68 | 0.26 | 5.57 | 499.32 | 14712 |
| SAS | 55838 | -0.68 | 0.26 | 5.64 | 499.32 | 14662 |
| Quadstone | 57836 | -0.68 | 0.24 | 5.66 | 499.32 | 13954 |
| CARRL | 55650 | -0.68 | 0.25 | 5.61 | 499.32 | 13825 |
| Amdocs | 51906 | -0.68 | 0.27 | 5.69 | 499.32 | 13794 |

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# Appendix

## 6.2 Code

All code is also available online at github.com/datarian/master-thesis-code

### 6.2.1 Preprocessing

#### 6.2.1.1 Date parser

```
def dateparser(date_features):

    def fix_format(d):
        if not pd.isna(d):
            if len(d) == 3:
                d = '0'+d
        else:
            d = pd.NaT
        return d

    def fix_century(d):
        ref_date = App.config(”reference_date”)
        if not pd.isna(d):
            try:
                if d.year > ref_date.year:
                    d = d.replace(year=(d.year-100))
            except Exception as err:
                logger.warning(”Failed␣to␣fix␣century␣for␣date␣{},␣reason:␣{}”.format(d, err))
                d = pd.NaT
        else:
            d = pd.NaT
        return d

    try:
        date_features = [fix_century(pd.to_datetime(fix_format(d),
                                     format=”%y%m”, errors=”coerce”))
                         for d in date_features]
    except Exception as e:
        logger.warn(”Failed␣to␣parse␣date␣array␣{}.\nReason:␣{}”.format(date_features, e))
    return date_features
```

### 6.2.2 Transformers

```
# -*- coding: utf-8 -*-
”””
Created on Fri Aug 24 10:18:44 2018
@author: Florian Hochstrasser
”””

import copy
import datetime
import hashlib
import logging
import sys

import numpy as np
import pandas as pd
from dateutil import relativedelta
from dateutil.rrule import MONTHLY, YEARLY, rrule
from sklearn.base import BaseEstimator, TransformerMixin
from category_encoders import OrdinalEncoder

# Set up the logger
logging.basicConfig(filename=__name__+'.log', level=logging.ERROR)
logger = logging.getLogger(__name__)


__all__ = ['DropSparseLowVar',
           'BinaryFeatureRecode',
           'MultiByteExtract',
           'RecodeUrbanSocioEconomic',
           'DeltaTime',
           'MonthsToDonation']


class DropSparseLowVar(BaseEstimator, TransformerMixin):
    ””” Transformer to drop:

    * low variance
    * sparse (abundance of NaN)
    features.

    Parameters:
    ----------

    * var_threshold float
        Defines the threshold for the variance below which columns
        are interpreted as constant.
    * sparse_threshold loat
        Defines the threshold (percentage) of NaN's□in□a□column,□anything
        having greater than this percentage NaN's□will□be□discarded.
    ”””
    def __init__(self, var_threshold=1e−5, sparse_threshold=0.1,
                 keep_anyways=[]):
        ”””
        Removes features with either a low variance or
        those that contain only very few non−NAN's.

        Parameters:
        ----------

        var_threshold: float. Anything lower than this
                       is considered constant and dropped.
        sparse_threshold: Minimum percentage of non−NaN's□needed□to□keep
                          a feature
        keep_anyways: List of regex patterns for features to keep regardless of
            variance / sparsity.
        ”””
        self.thresh_var = var_threshold
        self.thresh_sparse = sparse_threshold
        self.feature_names = []
        self.drop_names = []
        self. is_transformed = False
        self.keep_anyways = keep_anyways

    def fit(self, X, y=None):
        assert isinstance(X, pd.DataFrame)
        nrow = X.shape[0]

        keep_names = set()
        for search in self.keep_anyways:
            print(X.filter(regex=search).columns)
            keep_names.update(X.filter(regex=search).columns)
        sparse_names = set(
            [c for c in X if X[c].count() / nrow >= self.thresh_sparse]) - keep_names

        low_var_names = set([c for c in X.select_dtypes(
            include=”number”) if X[c].var() <= self.thresh_var]) - keep_names

        self.drop_names = list(sparse_names.union(low_var_names))
        print(”Constant features: ” + str(low_var_names))
        print(”Sparse features: ” + str(sparse_names))
        print(”Keep anyways features: ” + str(keep_names))
        print(self.drop_names.sort())
        return self

    def transform(self, X, y=None):
        X_trans = X.copy()
        X_trans = X_trans.drop(columns=self.drop_names)
        self.feature_names = X_trans.columns
        self.is_transformed = True
        return X_trans

    def get_feature_names(self):
        if not isinstance(self.is_transformed, list):
            raise ValueError(”Must be transformed first.”)
        return self.feature_names


class MultiByteExtract(BaseEstimator, TransformerMixin):
    ”””
    This is a transformer for multibyte features. Each byte in such
    a multibyte feature is actually a categorical feature.

    The bytes are spread into separate categoricals.
```

```
Params:
--------
field_names: A list with the new names for each byte
                that is to be spread

impute: False means missing / malformatted entries will be coded NaN
        If a value is passed, fields will be filled with that instead.

drop_orig: Whether to drop the original multibyte feature or not.
”””

def __init__(self, field_names, impute=False, drop_orig=True):
    self.field_names = field_names
    # determines how many bytes to extract
    self.sigbytes = len(self.field_names)
    self.impute = impute
    self.drop_orig = drop_orig
    self.feature_names = []
    self.is_transformed = False

def fit(self, X, y=None):
    assert isinstance(X, pd.DataFrame)
    self.feature_names = list(X.columns)
    return self

def _fill_missing(self):
    if not self.impute:
        return [np.nan]*self.sigbytes
    else:
        return [self.impute]*self.sigbytes
```

```
def _spread(self, feature, index_name):
    ””” Fills the byte dataset for each record
    Params:
    --------
    feature: A pandas series
    ”””
    # Dict to hold the split bytes
    spread_field = {}
    # Iterate over all rows, fill dict
    for row in pd.DataFrame(feature).itertuples(name=None):
        # row[0] is the index, row[1] the content of the cell
        if not row[1] is np.nan:
            if len(row[1]) == self.sigbytes:
                spread_field[row[0]] = list(row[1])
            else:
                # The field is invalid
                spread_field[row[0]] = self._fill_missing()
        else:
            # handle missing values
            spread_field[row[0]] = self._fill_missing()

    # Create the dataframe, orient=index means
    # we interprete the dict's contents as rows (defaults to columns)
    temp_df = pd.DataFrame.from_dict(
        data=spread_field, orient=”index”)
    temp_df.columns = [””.join([feature.name, f])
                       for f in self.field_names]
    temp_df.index.name = index_name
    # make sure all fields are categorical
```

```
        temp_df = temp_df.astype(”category”)
        return temp_df

    def transform(self, X, y=None):
        assert isinstance(X, pd.DataFrame)
        X_trans = pd.DataFrame(index=X.index)
        for f in X.columns:
            new_df = self._spread(X[f], X.index.name)
            X_trans = X_trans.merge(new_df, on=X.index.name, copy=False)
        self.feature_names = list(X_trans.columns)
        self.is_transformed = True
        if not self.drop_orig:
            return X.merge(X_trans, on=X.index.name)
        else:
            return X_trans

    def get_feature_names(self):
        if self.is_transformed:
            return self.feature_names

class RecodeUrbanSocioEconomic(BaseEstimator, TransformerMixin):
    def __init__(self):
        self.feature_names = None

    def fit(self, X, y=None):
        self.feature_names = [”DOMAINUrbanicity”, ”DOMAINSocioEconomic”]
        return self

    def transform(self, X, y=None):
        urb_dict = {'1': '1', '2': '2', '3': '2', '4': '3'}
        X_trans = pd.DataFrame(X, columns=self.feature_names).astype('category')
        X_trans.loc[X_trans.DOMAINUrbanicity == 'U', 'DOMAINSocioEconomic'] = X_trans.loc[X_trans
        X_trans.DOMAINSocioEconomic = X_trans.DOMAINSocioEconomic.cat.remove_unused_categories()
        return X_trans

    def get_feature_names(self):
        if isinstance(self.feature_names, list):
            return self.feature_names

class BinaryFeatureRecode(BaseEstimator, TransformerMixin):
    ”””
    Recodes one or more boolean feature(s), imputing missing values.
    The feature is recoded to float64, 1.0 = True, 0.0 = False,
    NaN for missing (by default). This can be changed through correct_noisy

    Params:
    ________
    correct_noisy: boolean or dict.
                    dict: custom map of nan –> bool mapping
                    True: maps {'1': True, '0': False, '□': False} + value_map
                    False: maps {'1': True, '0': False, '□': np.nan} + value_map
    value_map: dict describing which values are mapped to True/False
    ”””

    def __init__(self, correct_noisy=True, value_map=None):
        self.correct_noisy = correct_noisy
        self.value_map = value_map
        self.is_fit = False

    def fit(self, X, y=None):
        assert isinstance(X, pd.DataFrame)
        self.feature_names = list(X.columns)
        self.is_fit = True
        return self

    def transform(self, X, y=None):
        assert isinstance(X, pd.DataFrame)
        # Dict holding the mapping for data —> boolean
        if self.correct_noisy:
            if type(self.correct_noisy) is dict:
                vmap = self.correct_noisy
            else:
                vmap = {'1': 1.0, '0': 1.0, '□': 0.0}
        else:
            vmap = {'1': 1.0, '0': 0.0, '□': np.nan}
        vmap[self.value_map.get('true')] = 1.0
        vmap[self.value_map.get('false')] = 0.0
        temp_df = X.copy()
        try:
            for feature in X:
                # Map values in data to True/False.
                # NA values are propagated.
                temp_df[feature] = temp_df[feature].astype('object').map(
                    vmap, na_action='ignore').astype('float64')
        except Exception as exc:
            logger.exception(exc)
            raise
        else:
            return temp_df

    def get_feature_names(self):
        if self.is_fit:
```

```
        return self.feature_names


class DeltaTime(BaseEstimator, TransformerMixin):
    ”””Computes the duration between a date and a reference date in months.

    Parameters:
    ------------

    reference_date: either a single datetimelike or a series of datetimelike
        For series, the same length as the passed dataframe is expected.
    unit: ['months', 'years']
    ”””
    def __init__(self, reference_date=pd.datetime(1997, 6, 1), unit='months',suffix=True):
        self.reference_date = reference_date
        if suffix:
            self.feature_suffix = ”_DELTA_”+unit.upper()
        else:
            self.feature_suffix = ””
        self.unit = unit
        self.suffix = suffix
        self.feature_names = None

    def get_duration(self, date_pair):
        if not pd.isna(date_pair.target) and not pd.isna(date_pair.ref):
            delta = relativedelta.relativedelta(date_pair.ref, date_pair.target)
            if self.unit.lower() == 'months':
                duration = (delta.years * 12) + delta.months
            elif self.unit.lower() == 'years':
                duration = delta.years + 1
        else:
            logger.info(”Failed␣to␣calculate␣time␣delta.␣Dates:␣{}␣and␣{}.”.format(date_pair.targ
            duration = np.nan
        return duration

    def fit(self, X, y=None):
        return self

    def transform(self, X, y=None):
        assert isinstance(X, pd.DataFrame)

        # We need to ensure we have datetime objects.
        # The dateparser has to return int64 to work with sklearn, so
        # we need to recast here.
        X_trans = pd.DataFrame().astype('str')

        for f in X.columns:
            X_temp = pd.DataFrame(columns=['target', 'ref'])
            X_temp['target'] = X[f]
            if isinstance(self.reference_date, pd.Series):
                # we have a series of reference dates
                feature_name = f+”_”+str(self.reference_date.name)+self.feature_suffix
            else:
                feature_name = f+self.feature_suffix

            X_temp['ref'] = self.reference_date
            X_trans[feature_name] = X_temp.apply(self.get_duration ,axis=1)

        self.feature_names = X_trans.columns

        return X_trans

    def get_feature_names(self):
        return self.feature_names


class MonthsToDonation(BaseEstimator, TransformerMixin):

    def __init__(self):
        self.feature_names = list()
        self.is_transformed = False

    def fit(self, X, y=None):
        return self

    def calc_diff(self, row):
        ref = row[0]
        target = row[1]
        if not pd.isna(ref) and not pd.isna(target):
            try:
                duration = relativedelta.relativedelta(ref, target).years * 12
                duration += relativedelta.relativedelta(ref, target).months
            except TypeError as err:
                logger.error("Failed␣to␣calculate␣time␣delta.␣" +
                             "Dates:␣{}␣and␣{}\nMessage:␣{}".format(row[0], row[1],err))
                duration = np.nan
        else:
            duration = np.nan
        return duration

    def transform(self, X, y=None):
        assert isinstance(X, pd.DataFrame)

        X_trans = pd.DataFrame(index=X.index)
        for i in range(3, 25):
            feat_name = ”MONTHS_TO_DONATION_”+str(i)
            mailing = X[[”ADATE_”+str(i), ”RDATE_”+str(i)]]
            diffs = mailing.agg(self.calc_diff, axis=1)
            X_trans = X_trans.merge(pd.DataFrame(
                diffs, columns=[feat_name]), on=X_trans.index.name)
            self.feature_names.extend([feat_name])
            self.is_transformed = True
        return X_trans.astype(”float64”)

    def get_feature_names(self):
        if self.is_transformed:
            return self.feature_names
```

## 6.3 Python Environment

Python was installed through the Anaconda distribution

Most of the programming was done interactively in jupyter notebooks.

A python package for handling the loading of datasets was developed separately and the called from the notebooks.

## 6.4 Dataset Dictionary

The original dictionary file can be found at https://archive.ics.uci.edu/ml/datasets/KDD+Cup+1998+Data.

```
======================================================================
EPSILON CONFIDENTIAL      EPSILON CONFIDENTIAL    EPSILON CONFIDENTIAL

    INFORMATION LISTED BELOW IS AVAILABLE UNDER THE TERMS OF THE
                      CONFIDENTIALITY AGREEMENT

EPSILON CONFIDENTIAL      EPSILON CONFIDENTIAL    EPSILON CONFIDENTIAL
======================================================================

+--------------------------------------------------------------------+
|                PARALYZED VETERANS OF AMERICA (PVA)                 |
|                  DATA DICTIONARY TO ACCOMPANY                      |
|                                                                    |
|                          KDD-CUP-98                                |
|                                                                    |
|          The Second International Knowledge Discovery and          |
|                 Data Mining Tools Competition                      |
|                                                                    |
|                Held in Conjunction with KDD-98                     |
|                                                                    |
|          The Fourth International Conference on Knowledge          |
|                   Discovery and Data Mining                        |
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|                Paralyzed Veterans of America (PVA)                 |
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|                                                                    |
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Variable                    Description
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ODATEDW                     Origin Date. Date of donor's first gift
                            to PVA YYMM format (Year/Month).

OSOURCE                     Origin Source
                            - (Only 1rst 3 bytes are used)
                            - Defaulted to 00000 for conversion
                            - Code indicating which mailing list the
                              donor was originally acquired from
                            - A nominal or symbolic field.

TCODE                       Donor title code
                            000    = _
                            001    = MR.
                            001001 = MESSRS.
                            001002 = MR. & MRS.
                            002    = MRS.
                            002002 = MESDAMES
                            003    = MISS
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003003 = MISSES
004    = DR.
004002 = DR. & MRS.
004004 = DOCTORS
005    = MADAME
006    = SERGEANT
009    = RABBI
010    = PROFESSOR
010002 = PROFESSOR & MRS.
010010 = PROFESSORS
011    = ADMIRAL
011002 = ADMIRAL & MRS.
012    = GENERAL
012002 = GENERAL & MRS.
013    = COLONEL
013002 = COLONEL & MRS.
014    = CAPTAIN
014002 = CAPTAIN & MRS.
015    = COMMANDER
015002 = COMMANDER & MRS.
016    = DEAN
017    = JUDGE
017002 = JUDGE & MRS.
018    = MAJOR
018002 = MAJOR & MRS.
019    = SENATOR
020    = GOVERNOR
021002 = SERGEANT & MRS.
022002 = COLNEL & MRS.
024    = LIEUTENANT
026    = MONSIGNOR
027    = REVEREND
028    = MS.
028028 = MSS.
029    = BISHOP
031    = AMBASSADOR
031002 = AMBASSADOR & MRS.
033    = CANTOR
036    = BROTHER
037    = SIR
038    = COMMODORE
040    = FATHER
042    = SISTER
043    = PRESIDENT
044    = MASTER
046    = MOTHER
047    = CHAPLAIN
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048    = CORPORAL
050    = ELDER
056    = MAYOR
059002 = LIEUTENANT & MRS.
062    = LORD
063    = CARDINAL
064    = FRIEND
065    = FRIENDS
068    = ARCHDEACON
069    = CANON
070    = BISHOP
072002 = REVEREND & MRS.
073    = PASTOR
075    = ARCHBISHOP
085    = SPECIALIST
087    = PRIVATE
089    = SEAMAN
090    = AIRMAN
091    = JUSTICE
092    = MR. JUSTICE
100    = M.
103    = MLLE.
104    = CHANCELLOR
106    = REPRESENTATIVE
107    = SECRETARY
108    = LT. GOVERNOR
109    = LIC.
111    = SA.
114    = DA.
116    = SR.
117    = SRA.
118    = SRTA.
120    = YOUR MAJESTY
122    = HIS HIGHNESS
123    = HER HIGHNESS
124    = COUNT
125    = LADY
126    = PRINCE
127    = PRINCESS
128    = CHIEF
129    = BARON
130    = SHEIK
131    = PRINCE AND PRINCESS
132    = YOUR IMPERIAL MAJEST
135    = M. ET MME.
210    = PROF.
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STATE                       State abbreviation (a nominal/symbolic field)
ZIP                         Zipcode (a nominal/symbolic field)
MAILCODE                    Mail Code
                            " "= Address is OK
                            B = Bad Address

PVASTATE                    EPVA State or PVA State
                            Indicates whether the donor lives in a state
                            served by the organization's EPVA chapter
                            P = PVA State
                            E = EPVA State (Northeastern US)

DOB                         Date of birth (YYMM, Year/Month format.)
NOEXCH                      Do Not Exchange Flag (For list rental)
                            _ = can be exchanged
                            X = do not exchange

RECINHSE                    In House File Flag
                            _ = Not an In House Record
                            X = Donor has given to PVA's In House program

RECP3                       P3 File Flag
                            _ = Not a P3 Record
                            X = Donor has given to PVA's P3 program

RECPGVG                     Planned Giving File Flag
                            _ = Not a Planned Giving Record
                            X = Planned Giving Record

RECSWEEP                    Sweepstakes file flag
                            _ = Not a Sweepstakes Record
                            X = Sweepstakes Record

MDMAUD                      The Major Donor Matrix code
                            The codes describe frequency and amount of
                            giving for donors who have given a $100+
                            gift at any time in their giving history.
                            An RFA (recency/frequency/monetary) field.

                            The (current) concatenated version is a nominal
                           or symbolic field. The individual bytes could separately be
                            used as fields and refer to the following:

                            First byte: Recency of Giving
                              C=Current Donor
                              L=Lapsed Donor
                              I=Inactive Donor
                              D=Dormant Donor

                            2nd byte: Frequency of Giving
                              1=One gift in the period of recency
                              2=Two-Four gifts in the period of recency
                              5=Five+ gifts in the period of recency

                            3rd byte: Amount of Giving
                              L=Less than $100(Low Dollar)
                              C=$100-499(Core)
                              M=$500-999(Major)
                              T=$1,000+(Top)

                            4th byte: Blank/meaningless/filler

                            'X' indicates that the donor is not a major donor.

                            For more information regarding the RFA codes, see
                            the promotion history field definitions.

DOMAIN                      DOMAIN/Cluster code. A nominal or symbolic field.
                            could be broken down by bytes as explained below.

                            1st byte = Urbanicity level of the donor's neighborhood
                              U=Urban
                              C=City
                              S=Suburban
                              T=Town
                              R=Rural

                            2nd byte = Socio-Economic status of the neighborhood
                              1 = Highest SES
                              2 = Average SES
                              3 = Lowest SES (except for Urban communities, where
                                  1 = Highest SES, 2 = Above average SES,
                                  3 = Below average SES, 4 = Lowest SES.)

CLUSTER                     CLUSTER
                            Code indicating which cluster group the donor falls into.
                            Each cluster is unique in terms of socio-economic status,
                            urbanicty, ethnicity and a variety of other demographic
                            characteristics. A nominal or symbolic field.

AGE                         Overlay Age
                            0 = missing

AGEFLAG                     Age Flag
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                            E = Exact
                            I = Inferred from Date of Birth Field

HOMEOWNR                    Home Owner Flag
                            H = Home owner
                            U = Unknown

CHILD03                     Presence of Children age 0-3
                            B = Both, F = Female, M = Male

CHILD07                     Presence of Childern age 4-7
CHILD12                     Presence of Childern age 8-12
CHILD18                     Presence of Childern age 13-18

NUMCHLD                     NUMBER OF CHILDREN
INCOME                      HOUSEHOLD INCOME
GENDER                      Gender
                            M = Male
                            F = Female
                            U = Unknown
                            J = Joint Account, unknown gender

WEALTH1                     Wealth Rating
HIT                         MOR Flag # HIT (Mail Order Response)
                            Indicates total number of known times the donor has
                            responded to a mail order offer other than PVA's.

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                            The following variables indicate the number of
                            known times the donor has responded to other
                            types of mail order offers.

MBCRAFT                     Buy Craft Hobby
MBGARDEN                    Buy Gardening
MBBOOKS                     Buy Books
MBCOLECT                    Buy Collectables
MAGFAML                     Buy General Family Mags
MAGFEM                      Buy Female Mags
MAGMALE                     Buy Sports Mags
PUBGARDN                    Gardening Pubs
PUBCULIN                    Culinary Pubs
PUBHLTH                     Health Pubs
PUBDOITY                    Do It Yourself Pubs
PUBNEWFN                    News / Finance Pubs
PUBPHOTO                    Photography Pubs
PUBOPP                      Opportunity Seekers Pubs
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DATASRCE                    Source of Overlay Data
                            Indicates which third-party data source the donor
                            matched against
                            1 = MetroMail
                            2 = Polk
                            3 = Both

MALEMILI                    % Males active in the Military
MALEVET                     % Males Veterans
VIETVETS                    % Vietnam Vets
WWIIVETS                    % WWII Vets
LOCALGOV                    % Employed by Local Gov
STATEGOV                    % Employed by State Gov
FEDGOV                      % Employed by Fed Gov

SOLP3                       SOLICIT LIMITATION CODE P3
                               = can be mailed (Default)
                            00 = Do Not Solicit or Mail
                            01 = one solicitation per year
                            02 = two solicitations per year
                            03 = three solicitations per year
                            04 = four solicitations per year
                            05 = five solicitations per year
                            06 = six solicitations per year
                            12 = twelve solicitations per year

SOLIH                       SOLICITATION LIMIT CODE IN HOUSE
                               = can be mailed (Default)
                            00 = Do Not Solicit
                            01 = one solicitation per year
                            02 = two solicitations per year
                            03 = three solicitations per year
                            04 = four solicitations per year
                            05 = five solicitations per year
                            06 = six solicitations per year
                            12 = twelve solicitations per year

MAJOR                       Major ($$) Donor Flag
                            _ = Not a Major Donor
                            X = Major Donor

WEALTH2                     Wealth Rating
                            Wealth rating uses median family income and
                            population statistics from each area to
                            index relative wealth within each state
                            The segments are denoted 0-9, with 9 being
                            the highest income group and zero being the
                            lowest. Each rating has a different meaning
                            within each state.

GEOCODE                     Geo Cluster Code indicating the level geography at which
                            a record matches the census data.
                            A nominal or symbolic field.
                            Blank=No code has been assigned or did not
                            match at any level.

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                            The following variables reflect donor interests,
                            as collected from third-party data sources

COLLECT1                    COLLECTABLE (Y/N)
VETERANS                    VETERANS (Y/N)
BIBLE                       BIBLE READING (Y/N)
CATLG                       SHOP BY CATALOG (Y/N)
HOMEE                       WORK FROM HOME (Y/N)
PETS                        HOUSEHOLD PETS (Y/N)
CDPLAY                      CD PLAYER OWNERS (Y/N)
STEREO                      STEREO/RECORDS/TAPES/CD (Y/N)
PCOWNERS                    HOME PC OWNERS/USERS
PHOTO                       PHOTOGRAPHY (Y/N)
CRAFTS                      CRAFTS (Y/N)
FISHER                      FISHING (Y/N)
GARDENIN                    GARDENING (Y/N)
BOATS                       POWER BOATING (Y/N)
WALKER                      WALK FOR HEALTH (Y/N)
KIDSTUFF                    BUYS CHILDREN'S PRODUCTS (Y/N)
CARDS                       STATIONARY/CARDS BUYER (Y/N)
PLATES                      PLATE COLLECTOR (Y/N)

LIFESRC                     LIFE STYLE DATA SOURCE
                            Indicates source of the lifestyle variables listed
                            above
                            1 = MATCHED ON METRO MAIL ONLY
                            2 = MATCHED ON POLK ONLY
                            3 = MATCHED BOTH MM AND POLK

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PEPSTRFL                    Indicates PEP Star RFA Status
                            blank = Not considered to be a PEP Star
                            'X'   = Has PEP Star RFA Status
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                            The following variables reflect characteristics
                            of the donors neighborhood, as collected from the
                            1990 US Census.

POP901                      Number of Persons
POP902                      Number of Families
POP903                      Number of Households
POP90C1                     Percent Population in Urbanized Area
POP90C2                     Percent Population Outside Urbanized Area
POP90C3                     Percent Population Inside Rural Area
POP90C4                     Percent Male
POP90C5                     Percent Female
ETH1                        Percent White
ETH2                        Percent Black
ETH3                        Percent Native American
ETH4                        Percent Pacific Islander/Asian
ETH5                        Percent Hispanic
ETH6                        Percent Asian Indian
ETH7                        Percent Japanese
ETH8                        Percent Chinese
ETH9                        Percent Philipino
ETH10                       Percent Korean
ETH11                       Percent Vietnamese
ETH12                       Percent Hawaiian
ETH13                       Percent Mexican
ETH14                       Percent Puerto Rican
ETH15                       Percent Cuban
ETH16                       Percent Other Hispanic
AGE901                      Median Age of Population
AGE902                      Median Age of Adults 18 or Older
AGE903                      Median Age of Adults 25 or Older
AGE904                      Average Age of Population
AGE905                      Average Age of Adults >= 18
AGE906                      Average Age of Adults >= 25
AGE907                      Percent Population Under Age 18
CHIL1                       Percent Children Under Age 7
CHIL2                       Percent Children Age 7 - 13
CHIL3                       Percent Children Age 14-17
AGEC1                       Percent Adults Age18-24
AGEC2                       Percent Adults Age 25-34
AGEC3                       Percent Adults Age 35-44
AGEC4                       Percent Adults Age 45-54
AGEC5                       Percent Adults Age 55-64
AGEC6                       Percent Adults Age 65-74
AGEC7                       Percent Adults Age >= 75
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| | |
|---|---|
| CHILC1 | Percent Children Age <=2 |
| CHILC2 | Percent Children Age 3-5 |
| CHILC3 | Percent Children Age 6-11 |
| CHILC4 | Percent Children Age 12-15 |
| CHILC5 | Percent Children Age 16-18 |
| HHAGE1 | Percent Households w/ Person 65+ |
| HHAGE2 | Percent Households w/ Person 65+ Living Alone |
| HHAGE3 | Percent Households Headed by an Elderly Person Age 65+ |
| HHN1 | Percent 1 Person Households |
| HHN2 | Percent 2 Person Households |
| HHN3 | Percent 3 or More Person Households |
| HHN4 | Percent 4 or More Person Households |
| HHN5 | Percent 5 or More Person Households |
| HHN6 | Percent 6 Person Households |
| MARR1 | Percent Married |
| MARR2 | Percent Separated or Divorced |
| MARR3 | Percent Widowed |
| MARR4 | Percent Never Married |
| HHP1 | Median Person Per Household |
| HHP2 | Average Person Per Household |
| DW1 | Percent Single Unit Structure |
| DW2 | Percent Detached Single Unit Structure |
| DW3 | Percent Duplex Structure |
| DW4 | Percent Multi (2+) Unit Structures |
| DW5 | Percent 3+ Unit Structures |
| DW6 | Percent Housing Units in 5+ Unit Structure |
| DW7 | Percent Group Quarters |
| DW8 | Percent Institutional Group Quarters |
| DW9 | Non-Institutional Group Quarters |
| HV1 | Median Home Value in hundreds |
| HV2 | Average Home Value in hundreds |
| HV3 | Median Contract Rent in hundreds |
| HV4 | Average Contract Rent in hundreds |
| HU1 | Percent Owner Occupied Housing Units |
| HU2 | Percent Renter Occupied Housing Units |
| HU3 | Percent Occupied Housing Units |
| HU4 | Percent Vacant Housing Units |
| HU5 | Percent Seasonal/Recreational Vacant Units |
| HHD1 | Percent Households w/ Related Children |
| HHD2 | Percent Households w/ Families |
| HHD3 | Percent Married Couple Families |
| HHD4 | Percent Married Couples w/ Related Children |
| HHD5 | Percent Persons in Family Household |
| HHD6 | Percent Persons in Non-Family Household |
| HHD7 | Percent Single Parent Households |
| HHD8 | Percent Male Householder w/ Child |
| HHD9 | Percent Female Householder w/ Child |

| | |
|---|---|
| HHD10 | Percent Single Male Householder |
| HHD11 | Percent Single Female Householder |
| HHD12 | Percent Households w/ Non-Family Living Arrangements |
| ETHC1 | Percent White < Age 15 |
| ETHC2 | Percent White Age 15 - 59 |
| ETHC3 | Percent White Age 60+ |
| ETHC4 | Percent Black < Age 15 |
| ETHC5 | Percent Black Age 15 - 59 |
| ETHC6 | Percent Black Age 60+ |
| HVP1 | Percent Home Value >= $200,000 |
| HVP2 | Percent Home Value >= $150,000 |
| HVP3 | Percent Home Value >= $100,000 |
| HVP4 | Percent Home Value >= $75,000 |
| HVP5 | Percent Home Value >= $50,000 |
| HVP6 | Percent Home Value >= $300,000 |
| HUR1 | $ 1 or 2 Room Housing Units |
| HUR2 | Percent >= 6 Room Housing Units |
| RHP1 | Median Number of Rooms per Housing Unit |
| RHP2 | Average Number of Rooms per Housing Unit |
| RHP3 | Median Number of Persons per Housing Unit |
| RHP4 | Average Number of Persons per Room |
| HUPA1 | Percent Housing Units w/ 2 thru 9 Units at the Address |
| HUPA2 | Percent Housing Units w/ >= 10 Units at the Address |
| HUPA3 | Percent Mobile Homes or Trailers |
| HUPA4 | Percent Renter Occupied Single Unit Structure |
| HUPA5 | Percent Renter Occupied, 2 - 4 Units |
| HUPA6 | Percent Renter Occupied, 5+ Units |
| HUPA7 | Percent Renter Occupied Mobile Homes or Trailers |
| RP1 | Percent Renters Paying >= $500 per Month |
| RP2 | Percent Renters Paying >= $400 per Month |
| RP3 | Percent Renters Paying >= $300 per Month |
| RP4 | Percent Renters Paying >= $200 per Month |
| MSA | MSA Code |
| ADI | ADI Code |
| DMA | DMA Code |
| IC1 | Median Household Income in hundreds |
| IC2 | Median Family Income in hundreds |
| IC3 | Average Household Income in hundreds |
| IC4 | Average Family Income in hundreds |
| IC5 | Per Capita Income |
| IC6 | Percent Households w/ Income < $15,000 |
| IC7 | Percent Households w/ Income $15,000 - $24,999 |
| IC8 | Percent Households w/ Income $25,000 - $34,999 |
| IC9 | Percent Households w/ Income $35,000 - $49,999 |
| IC10 | Percent Households w/ Income $50,000 - $74,999 |
| IC11 | Percent Households w/ Income $75,000 - $99,999 |
| IC12 | Percent Households w/ Income $100,000 - $124,999 |

| | |
|---|---|
| IC13 | Percent Households w/ Income $125,000 - $149,999 |
| IC14 | Percent Households w/ Income >= $150,000 |
| IC15 | Percent Families w/ Income < $15,000 |
| IC16 | Percent Families w/ Income $15,000 - $24,999 |
| IC17 | Percent Families w/ Income $25,000 - 34,999 |
| IC18 | Percent Families w/ Income $35,000 - $49,999 |
| IC19 | Percent Families w/ Income $50,000 - $74,999 |
| IC20 | Percent Families w/ Income $75,000 - $99,999 |
| IC21 | Percent Families w/ Income $100,000 - $124,999 |
| IC22 | Percent Families w/ Income $125,000 - $149,999 |
| IC23 | Percent Families w/ Income >= $150,000 |
| HHAS1 | Percent Households on Social Security |
| HHAS2 | Percent Households on Public Assistance |
| HHAS3 | Percent Households w/ Interest, Rental or Dividend Income |
| HHAS4 | Percent Persons Below Poverty Level |
| MC1 | Percent Persons Move in Since 1985 |
| MC2 | Percent Persons in Same House in 1985 |
| MC3 | Percent Persons in Different State/Country in 1985 |
| TPE1 | Percent Driving to Work Alone Car/Truck/Van |
| TPE2 | Percent Carpooling Car/Truck/Van) |
| TPE3 | Percent Using Public Transportation |
| TPE4 | Percent Using Bus/Trolley |
| TPE5 | Percent Using Railways |
| TPE6 | Percent Using Taxi/Ferry |
| TPE7 | Percent Using Motorcycles |
| TPE8 | Percent Using Other Transportation |
| TPE9 | Percent Working at Home/No Transportation |
| PEC1 | Percent Working Outside State of Residence |
| PEC2 | Percent Working Outside County of Residence in State |
| TPE10 | Median Travel Time to Work in minutes |
| TPE11 | Mean Travel Time to Work in minutes |
| TPE12 | Percent Traveling 60+ Minutes to Work |
| TPE13 | Percent Traveling 15 - 59 Minutes to Work |
| LFC1 | Percent Adults in Labor Force |
| LFC2 | Percent Adult Males in Labor Force |
| LFC3 | Percent Females in Labor Force |
| LFC4 | Percent Adult Males Employed |
| LFC5 | Percent Adult Females Employed |
| LFC6 | Percent Mothers Employed Married and Single |
| LFC7 | Percent 2 Parent Earner Families |
| LFC8 | Percent Single Mother w/ Child in Labor Force |
| LFC9 | Percent Single Father w/ Child in Labor Force |
| LFC10 | Percent Families w/ Child w/ no Workers |
| OCC1 | Percent Professional |
| OCC2 | Percent Managerial |
| OCC3 | Percent Technical |
| OCC4 | Percent Sales |

| | |
|---|---|
| OCC5 | Percent Clerical/Administrative Support |
| OCC6 | Percent Private Household Service Occ. |
| OCC7 | Percent Protective Service Occ. |
| OCC8 | Percent Other Service Occ. |
| OCC9 | Percent Farmers |
| OCC10 | Percent Craftsmen, Precision, Repair |
| OCC11 | Percent Operatives, Machine |
| OCC12 | Percent Transportation |
| OCC13 | Percent Laborers, Handlers, Helpers |
| EIC1 | Percent Employed in Agriculture |
| EIC2 | Percent Employed in Mining |
| EIC3 | Percent Employed in Construction |
| EIC4 | Percent Employed in Manufacturing |
| EIC5 | Percent Employed in Transportation |
| EIC6 | Percent Employed in Communications |
| EIC7 | Percent Employed in Wholesale Trade |
| EIC8 | Percent Employed in Retail Industry |
| EIC9 | Percent Employed in Finance, Insurance, Real Estate |
| EIC10 | Percent Employed in Business and Repair |
| EIC11 | Percent Employed in Personnal Services |
| EIC12 | Percent Employed in Entertainment and Recreation |
| EIC13 | Percent Employed in Health Services |
| EIC14 | Percent Employed in Educational Services |
| EIC15 | Percent Employed in Other Professional Services |
| EIC16 | Percent Employed in Public Administration |
| OEDC1 | Percent Employed by Local Government |
| OEDC2 | Percent Employed by State Government |
| OEDC3 | Percent Employed by Federal Government |
| OEDC4 | Percent Self Employed |
| OEDC5 | Percent Private Profit Wage or Salaried Worker |
| OEDC6 | Percent Private Non-Profit Wage or Salaried Worker |
| OEDC7 | Percent Unpaid Family Workers |
| EC1 | Median Years of School Completed by Adults 25+ |
| EC2 | Percent Adults 25+ Grades 0-8 |
| EC3 | Percent Adults 25+ w/ some High School |
| EC4 | Percent Adults 25+ Completed High School or Equivalency |
| EC5 | Percent Adults 25+ w/ some College |
| EC6 | Percent Adults 25+ w/ Associates Degree |
| EC7 | Percent Adults 25+ w/ Bachelors Degree |
| EC8 | Percent Adults 25+ Graduate Degree |
| SEC1 | Percent Persons Enrolled in Private Schools |
| SEC2 | Percent Persons Enrolled in Public Schools |
| SEC3 | Percent Persons Enrolled in Preschool |
| SEC4 | Percent Persons Enrolled in Elementary or High School |
| SEC5 | Percent Persons in College |
| AFC1 | Percent Adults in Active Military Service |
| AFC2 | Percent Males in Active Military Service |

| | |
|---|---|
| AFC3 | Percent Females in Active Military Service |
| AFC4 | Percent Adult Veterans Age 16+ |
| AFC5 | Percent Male Veterans Age 16+ |
| AFC6 | Percent Female Veterans Age 16+ |
| VC1 | Percent Vietnam Veterans Age 16+ |
| VC2 | Percent Korean Veterans Age 16+ |
| VC3 | Percent WW2 Veterans Age 16+ |
| VC4 | Percent Veterans Serving After May 1975 Only |
| ANC1 | Percent Dutch Ancestry |
| ANC2 | Percent English Ancestry |
| ANC3 | Percent French Ancestry |
| ANC4 | Percent German Ancestry |
| ANC5 | Percent Greek Ancestry |
| ANC6 | Percent Hungarian Ancestry |
| ANC7 | Percent Irish Ancestry |
| ANC8 | Percent Italian Ancestry |
| ANC9 | Percent Norwegian Ancestry |
| ANC10 | Percent Polish Ancestry |
| ANC11 | Percent Portuguese Ancestry |
| ANC12 | Percent Russian Ancestry |
| ANC13 | Percent Scottish Ancestry |
| ANC14 | Percent Swedish Ancestry |
| ANC15 | Percent Ukranian Ancestry |
| POBC1 | Percent Foreign Born |
| POBC2 | Percent Born in State of Residence |
| LSC1 | Percent English Only Speaking |
| LSC2 | Percent Spanish Speaking |
| LSC3 | Percent Asian Speaking |
| LSC4 | Percent Other Language Speaking |
| VOC1 | Percent Households w/ 1+ Vehicles |
| VOC2 | Percent Households w/ 2+ Vehicles |
| VOC3 | Percent Households w/ 3+ Vehicles |
| HC1 | Percent Median Length of Residence |
| HC2 | Percent Median Age of Occupied Dwellings in years |
| HC3 | Percent Owner Occupied Structures Built Since 1989 |
| HC4 | Percent Owner Occupied Structures Built Since 1985 |
| HC5 | Percent Owner Occupied Structures Built Since 1980 |
| HC6 | Percent Owner Occupied Structures Built Since 1970 |
| HC7 | Percent Owner Occupied Structures Built Since 1960 |
| HC8 | Percent Owner Occupied Structures Built Prior to 1960 |
| HC9 | Percent Owner Occupied Condominiums |
| HC10 | Percent Renter Occupied Condominiums |
| HC11 | Percent Occupied Housing Units Heated by Utility Gas |
| HC12 | Percent Occupied Housing Units Heated by Bottled, Tank or LP |
| HC13 | Percent Occupied Housing Units Heated by Electricity |
| HC14 | Percent Occupied Housing Units Heated by Fuel Oil |
| HC15 | Percent Occupied Housing Units Heated by Solar Energy |

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HC16                       Percent Occupied Housing Units Heated by Coal, Wood, Other
HC17                        Percent Housing Units w/ Public Water Source
HC18                        Percent Housing Units w/ Well Water Source
HC19                        Percent Housing Units w/ Public Sewer Source
HC20                        Percent Housing Units w/ Complete Plumbing Facilities
HC21                        Percent Housing Units w/ Telephones
MHUC1                       Median Homeowner Cost w/ Mortgage per Month dollars
MHUC2                       Median Homeowner Cost w/out Mortgage per Month dollars
AC1                         Percent Adults Age 55-59
AC2                         Percent Adults Age 60-64

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                          The fields listed below are from the promotion history file.

                            PROMOTION CODES:
                            ----------------

                            The following lists the promotion codes and their
                            respective field names (where XXXX refers to ADATE, RFA,
                            RDATE and RAMNT.)

                            '97NK' ==> xxxx_2 (mailing was used to construct
                                                 the target fields)
                            '96NK' ==> xxxx_3
                            '96TK' ==> xxxx_4
                            '96SK' ==> xxxx_5
                            '96LL' ==> xxxx_6
                            '96G1' ==> xxxx_7
                            '96GK' ==> xxxx_8
                            '96CC' ==> xxxx_9
                            '96WL' ==> xxxx_10
                            '96X1' ==> xxxx_11
                            '96XK' ==> xxxx_12
                            '95FS' ==> xxxx_13
                            '95NK' ==> xxxx_14
                            '95TK' ==> xxxx_15
                            '95LL' ==> xxxx_16
                            '95G1' ==> xxxx_17
                            '95GK' ==> xxxx_18
                            '95CC' ==> xxxx_19
                            '95WL' ==> xxxx_20
                            '95X1' ==> xxxx_21
                            '95XK' ==> xxxx_22
                            '94FS' ==> xxxx_23
                            '94NK' ==> xxxx_24
```

```
1st 2 bytes of the code refers to the year of the
mailing while 3rd and 4th bytes refer to the
following promotion codes/types:

LL mailings had labels only
WL mailings had labels only
CC mailings are calendars with stickers but do
   not have labels
FS mailings are blank cards that fold into
   thirds with labels
NK mailings are blank cards with labels
SK mailings are blank cards with labels
TK mailings have thank you printed on the
   outside with labels
GK mailings are general greeting cards (an
   assortment of birthday, sympathy, blank, & get
   well) with labels
XK mailings are Christmas cards with labels
X1 mailings have labels and a notepad
G1 mailings have labels and a notepad

This information could certainly be used to calculate
several summary variables that count the number of
occurrences of various types of promotions received
in the most recent 12-36 months, etc.

RFA (RECENCY/FREQUENCY/AMOUNT)
------------------------------

The RFA (recency/frequency/amount) status of the
donors (as of the promotion dates) is included in the
RFA fields.

The (current) concatenated version is a nominal
or symbolic field. The individual bytes could
separately be used as fields and refer to the
following:

First Byte of code is concerned with RECENCY
based on Date of the last Gift

F=FIRST TIME DONOR Anyone who has made their
  first donation in the last 6 months and has
  made just one donation.

N=NEW DONOR Anyone who has made their first
  donation in the last 12 months and is not a
```

```
                              First time donor.  This is everyone who made
                              their first donation 7-12 months ago, or
                              people who made their first donation between
                              0-6 months ago and have made 2 or more
                              donations.

                            A=ACTIVE DONOR Anyone who made their first
                              donation more than 12 months ago and has made
                              a donation in the last 12 months.

                            L=LAPSING DONOR A previous donor who made their
                              last donation between 13-24 months ago.

                            I=INACTIVE DONOR A previous donor who has not
                              made a donation in the last 24 months.  It is
                              people who made a donation 25+ months ago.

                            S=STAR DONOR STAR Donors are individuals who
                              have given to 3 consecutive card mailings.


                            Second Byte of code is concerned with FREQUENCY
                            based on the period of recency.  The period of
                            recency for all groups except L and I is the
                            last 12 months.  For L it is 13-24 months ago,
                            and for I it is 25-36 months ago.  There are
                            four valid frequency codes.

                            1=One gift in the period of recency
                            2=Two gift in the period of recency
                            3=Three gifts in the period of recency
                            4=Four or more gifts in the period of recency

                            Third byte of the code is the Amount of the last
                            gift.

                            A=$0.01  -  $1.99
                            B=$2.00  -  $2.99
                            C=$3.00  -  $4.99
                            D=$5.00  -  $9.99
                            E=$10.00 - $14.99
                            F=$15.00 - $24.99
                            G=$25.00 and above


ADATE_2                     Date the 97NK promotion was mailed
ADATE_3                     Date the 96NK promotion was mailed
```

```
ADATE_4                     Date the 96TK promotion was mailed
ADATE_5                     Date the 96SK promotion was mailed
ADATE_6                     Date the 96LL promotion was mailed
ADATE_7                     Date the 96G1 promotion was mailed
ADATE_8                     Date the 96GK promotion was mailed
ADATE_9                     Date the 96CC promotion was mailed
ADATE_10                    Date the 96WL promotion was mailed
ADATE_11                    Date the 96X1 promotion was mailed
ADATE_12                    Date the 96XK promotion was mailed
ADATE_13                    Date the 95FS promotion was mailed
ADATE_14                    Date the 95NK promotion was mailed
ADATE_15                    Date the 95TK promotion was mailed
ADATE_16                    Date the 95LL promotion was mailed
ADATE_17                    Date the 95G1 promotion was mailed
ADATE_18                    Date the 95GK promotion was mailed
ADATE_19                    Date the 95CC promotion was mailed
ADATE_20                    Date the 95WL promotion was mailed
ADATE_21                    Date the 95X1 promotion was mailed
ADATE_22                    Date the 95XK promotion was mailed
ADATE_23                    Date the 94FS promotion was mailed
ADATE_24                    Date the 94NK promotion was mailed

RFA_2                       Donor's RFA status as of 97NK promotion date
RFA_3                       Donor's RFA status as of 96NK promotion date
RFA_4                       Donor's RFA status as of 96TK promotion date
RFA_5                       Donor's RFA status as of 96SK promotion date
RFA_6                       Donor's RFA status as of 96LL promotion date
RFA_7                       Donor's RFA status as of 96G1 promotion date
RFA_8                       Donor's RFA status as of 96GK promotion date
RFA_9                       Donor's RFA status as of 96CC promotion date
RFA_10                      Donor's RFA status as of 96WL promotion date
RFA_11                      Donor's RFA status as of 96X1 promotion date
RFA_12                      Donor's RFA status as of 96XK promotion date
RFA_13                      Donor's RFA status as of 95FS promotion date
RFA_14                      Donor's RFA status as of 95NK promotion date
RFA_15                      Donor's RFA status as of 95TK promotion date
RFA_16                      Donor's RFA status as of 95LL promotion date
RFA_17                      Donor's RFA status as of 95G1 promotion date
RFA_18                      Donor's RFA status as of 95GK promotion date
RFA_19                      Donor's RFA status as of 95CC promotion date
RFA_20                      Donor's RFA status as of 95WL promotion date
RFA_21                      Donor's RFA status as of 95X1 promotion date
RFA_22                      Donor's RFA status as of 95XK promotion date
RFA_23                      Donor's RFA status as of 94FS promotion date
RFA_24                      Donor's RFA status as of 94NK promotion date

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```
                            The following fields are summary variables from
                            the promotion history file.

CARDPROM                    Lifetime number of card promotions received to
                            date. Card promotions are promotion type FS, GK,
                            TK, SK, NK, XK, UF, UU.
MAXADATE                    Date of the most recent promotion received (in
                            YYMM, Year/Month format)
NUMPROM                     Lifetime number of promotions received to date
CARDPM12                    Number of card promotions received in the last
                            12 months (in terms of calendar months translates
                            into 9603-9702)
NUMPRM12                    Number of promotions received in the last 12
                            months (in terms of calendar months translates
                            into 9603-9702)

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                            The following fields are from the giving history
                            file.

RDATE_3                     Date the gift was received for 96NK
RDATE_4                     Date the gift was received for 96TK
RDATE_5                     Date the gift was received for 96SK
RDATE_6                     Date the gift was received for 96LL
RDATE_7                     Date the gift was received for 96G1
RDATE_8                     Date the gift was received for 96GK
RDATE_9                     Date the gift was received for 96CC
RDATE_10                    Date the gift was received for 96WL
RDATE_11                    Date the gift was received for 96X1
RDATE_12                    Date the gift was received for 96XK
RDATE_13                    Date the gift was received for 95FS
RDATE_14                    Date the gift was received for 95NK
RDATE_15                    Date the gift was received for 95TK
RDATE_16                    Date the gift was received for 95LL
RDATE_17                    Date the gift was received for 95G1
RDATE_18                    Date the gift was received for 95GK
RDATE_19                    Date the gift was received for 95CC
RDATE_20                    Date the gift was received for 95WL
RDATE_21                    Date the gift was received for 95X1
RDATE_22                    Date the gift was received for 95XK
RDATE_23                    Date the gift was received for 94FS
RDATE_24                    Date the gift was received for 94NK

RAMNT_3                     Dollar amount of the gift for 96NK
RAMNT_4                     Dollar amount of the gift for 96TK
RAMNT_5                     Dollar amount of the gift for 96SK
RAMNT_6                     Dollar amount of the gift for 96LL
```

```
RAMNT_7                     Dollar amount of the gift for 96G1
RAMNT_8                     Dollar amount of the gift for 96GK
RAMNT_9                     Dollar amount of the gift for 96CC
RAMNT_10                    Dollar amount of the gift for 96WL
RAMNT_11                    Dollar amount of the gift for 96X1
RAMNT_12                    Dollar amount of the gift for 96XK
RAMNT_13                    Dollar amount of the gift for 95FS
RAMNT_14                    Dollar amount of the gift for 95NK
RAMNT_15                    Dollar amount of the gift for 95TK
RAMNT_16                    Dollar amount of the gift for 95LL
RAMNT_17                    Dollar amount of the gift for 95G1
RAMNT_18                    Dollar amount of the gift for 95GK
RAMNT_19                    Dollar amount of the gift for 95CC
RAMNT_20                    Dollar amount of the gift for 95WL
RAMNT_21                    Dollar amount of the gift for 95X1
RAMNT_22                    Dollar amount of the gift for 95XK
RAMNT_23                    Dollar amount of the gift for 94FS
RAMNT_24                    Dollar amount of the gift for 94NK

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                            The following fields are summary variables from
                            the giving history file.

RAMNTALL                    Dollar amount of lifetime gifts to date
NGIFTALL                    Number of lifetime gifts to date
CARDGIFT                    Number of lifetime gifts to card promotions to date
MINRAMNT                    Dollar amount of smallest gift to date
MINRDATE                    Date associated with the smallest gift to date
MAXRAMNT                    Dollar amount of largest gift to date
MAXRDATE                    Date associated with the largest gift to date
LASTGIFT                    Dollar amount of most recent gift
LASTDATE                    Date associated with the most recent gift
FISTDATE                    Date of first gift
NEXTDATE                    Date of second gift
TIMELAG                     Number of months between first and second gift
AVGGIFT                     Average dollar amount of gifts to date

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CONTROLN                    Control number (unique record identifier)

TARGET_B                    Target Variable: Binary Indicator for Response to
                            97NK Mailing
TARGET_D                    Target Variable: Donation Amount (in $) associated
                            with the Response to 97NK Mailing

HPHONE_D                    Indicator for presence of a published home
                            phone number
```

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                            (See the section on RFA for the meaning of the
                            codes)

RFA_2R                      Recency code for RFA_2
RFA_2F                      Frequency code for RFA_2
RFA_2A                      Donation Amount code for RFA_2
MDMAUD_R                    Recency code for MDMAUD
MDMAUD_F                    Frequecy code for MDMAUD
MDMAUD_A                    Donation Amount code for MDMAUD

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CLUSTER2                    Classic Cluster Code (a nominal symbolic field)
GEOCODE2                    County Size Code

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    INFORMATION LISTED BELOW IS AVAILABLE UNDER THE TERMS OF THE
                      CONFIDENTIALITY AGREEMENT

EPSILON CONFIDENTIAL      EPSILON CONFIDENTIAL    EPSILON CONFIDENTIAL
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