A Minimal Book Example

Yihui Xie

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Contents

Chapter 1

Introduction

1.1 Abstract

In data-minig, a frequent and major issue for handling with two-class classification is to make reliable predictions with strongly imbalanced distribution of the target variable. Most of the machine learning algorithms assumes by default that all data are balanced. Empirically, a lot of dataset faces this distorsion (fraud detection, anticipation of catastrophes, donators in case of funding campain, unusual returns on stock markets, …). The majority class represents "normal cases", while the minority class represents "abnormal" cases. Because The least common values of the target variable are linked with events which are very relevant for users, we considered the minority class as positive and the majority class as negative.

The commun issue with classifiers is that they are unable to learn from the positive class. It results that the predictions are almost only negative class. Algorithms failed to predict the positive class which is properly what the users need.

Nowadays, the imbalanced data sets problem plays a key role in machine learning. During the last decades, literature was very prolific on this subject. Many tools were developped to solve this problem. This paper has neither ambition to give an exhaustive review of the existing solutions nor exploring new solutions. Moreover, we won't go to far in the explanation of the mathematical principle handling the algorithms. Our purpose is to propose some elements of solution to counteract the effect of imbalanced datatset which can be used an uderstanded by people who like data-minig without having a large scale of knowledge in this domain.

1.2 Document format

On chapter 1, we introduce some tools which allows to measure the effiency of a model.

Chapter 2 briefly presents the differents models we used. We will touch upon the math behind the classifier and the way the algorithm works.

Chapter 3 introduce some remedies to make our classifiers better predictors.

Chapter 4 is an application on three dataset with wich we can evaluate the submitted remedies.

Chapter 5 stands as a conclusion.

Chapter 2

Metrics for classification tasks

Understanding if a model is a good classifier or not require a good comprehension of the predictions he made. We want to know the global effiency but some specific element too. Is he better in predicting one or the other class? What are the strenght and weaknees of the model? Can we be confident towards the results, haw can we know they are not due to chance?

In order to compare the performance's models, we use differents "metrics". The reliability of our tools is higlhy dependant on the structure of our datas. In our case, the imbalanced sample of datas classes has to be take into account in order to find the metrics which allows to give a good evaluation of our models.

2.1 The foundation of the metrics: The Confusion Matrix

The confusion matrix presents the results obtained by a given classifier. This table provides the instances that were correctly classified (True Positive and True negative), and the instances that were wrongly classified (False Positive and False negative). From this table, we can calculate all the metrics described below

	Predicted	
	Positive	Negative
True		
Positive	TP	FN
Negative	FP	TN

2.2 Accuracy and error rate

$$error = \frac{FP + FN}{TN + TP + FP + FN}$$

$$accuracy = 1 - error$$

The first metrics is obviously the global accuracy and its complement the error rate. It is the most frequently used to estimate the performance of a model. If accuracy is too low, we deduce that our learning algolritm is globally inneficient. However In the context of imbalanced dataset, accuracy is not suitable. Indeed, because of the massive representation of the negative class, and as the classifiers failed to identify the positive class, we reach a high value of accuracy. For instance, if only 10% of the cases belong to the positive class and the classifiers predicts all cases as negative, accuracy will be at 90%. This is worthless when users objectives is to predict the rare cases.

To reflect more closely the users needs and priorities, several performance measure exist.

2.3 True Positive rate :

$$TP_{rate} = \frac{TP}{TP + FN} = \frac{TP}{P_{real}}$$

Also called sensitivity, recall or detection power. I personnaly prefer the term detection power because it is more explicit. It is the ratio of the value predicted as positive and which are actually positive among all the real positive. This is the ability of our classifier to detect the positive cases.

2.4 True Negative and Flase positive rate

Also called specificity. It is the ratio of the value predicted as negative and which are actually negative among all the real negative case.

$$TN_{rate} = \frac{TN}{TN + FP}$$

I prefer its complement, the False positive rate, also called False alarm. Indeed, the terme “False alarm” is more relevant than specificity.

$$FP_{rate} = \frac{FP}{TN + FP} = 1 - TN_{rate}$$

TPrate (detection power) and FP rate (False alarm) are often quote in the litterature as benefits and costs, respectively. These terms refers to a central

point of our problematic. Indeed, a key point to find good remedies is to make a trade-off between what it cost in terms of False alarm and the benefits gained in terms of detection power.

2.5 Positive prediction value : Precision

$$PP_{value} = \frac{TP}{TP + FP} = \frac{TP}{P_{pred}}$$

The precision measures the rate of True positive among all cases predicted as positive.

2.6 F-measure

The F-measure is a combiination of both precision and recall. This metric value is high when both recall (a measure of completness) and precision (a measure of exactness) are high (citation). Hence, this metrics is particuilary suitable on predicting the case that matter to the user.

$$F_\beta = \frac{(1 + \beta^2) \times recall \times precision}{\beta^2 \times recall + precision}$$

Beta is a coefficient to adjust the weight of recall against precision. In this paper, we choose a value of 1 which give the same weights to recall and precision.

2.7 Kappa

$$K = \frac{P_{agree} - P_{chance}}{1 - P_{chance}}$$

$$P_{agree} = \frac{TP + FN}{number\ of\ cases}$$

$$P_{chance} = \frac{P_{pre} \times P_{act}}{number\ of\ cases^2} + \frac{N_{pre} \times N_{act}}{number\ of\ cases^2}$$

Kappa is a very interesting metrics in context of imbalanced datas. The calculation is based on the difference between how much agreement(positive) is actually present ("observed") compared to how much positive would be expected to be present by chance alone ("expected"). We want to know how different the observed positive are from the expected. Kappa is a measure of this difference (citation).

Kappa Agreement < 0 Less than chance agreement 0.01–0.20 Slight agreement 0.21– 0.40 Fair agreement 0.41–0.60 Moderate agreement 0.61–0.80 Substantial agreement 0.81–0.99 Almost perfect agreement

2.8 ROC Curve

A receiver operating characteristic curve, or ROC curve, is a graphical plot that illustrates the diagnostic ability of a binary classifier system as its discrimination threshold is varied.

The ROC curve is created by plotting the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings.

Chapter 3

Classifiers

3.1 LDA

Linear discriminant analysis (LDA), normal discriminant analysis (NDA), or discriminant function analysis is a generalization of Fisher's linear discriminant, a method used in statistics and other fields, to find a linear combination of features that characterizes or separates two or more classes of objects or events.

In this approach, Fishers sought to find the linear combination of the predictors such that the between-group variance was maximized relative to the within-group variance. In other words, he wanted to find the combination of the predictors that gave maximum separation between the centers of the data while at the same time minimizing the variation within each group of data.

3.2 logistic regression

In statistics, the logistic model (or logit model) is used to model the probability of a certain class or event existing such as pass/fail, win/lose, alive/dead or healthy/sick. This can be extended to model several classes of events such as determining whether an image contains a cat, dog, lion, etc. Each object being detected in the image would be assigned a probability between 0 and 1, with a sum of one. Logistic regression is a statistical model that in its basic form uses a logistic function to model a binary dependent variable, although many more complex extensions exist. In regression analysis, logistic regression (or logit regression) is estimating the parameters of a logistic model (a form of binary regression)

3.3 SVM

definition: There are many hyperplanes that might classify the data. One reasonable choice as the best hyperplane is the one that represents the largest separation, or margin, between the two classes. So we choose the hyperplane so that the distance from it to the nearest data point on each side is maximized. If such a hyperplane exists, it is known as the maximum-margin hyperplane and the linear classifier it defines is known as a maximum-margin classifier; or equivalently, the perceptron of optimal stability. More formally, a support-vector machine constructs a hyperplane or set of hyperplanes in a high- or infinite-dimensional space, which can be used for classification, regression, or other tasks like outliers detection. Intuitively, a good separation is achieved by the hyperplane that has the largest distance to the nearest training-data point of any class (so-called functional margin), since in general the larger the margin, the lower the generalization error of the classifier.

the original problem may be stated in a finite-dimensional space, it often happens that the sets to discriminate are not linearly separable in that space. For this reason, it was proposed[5] that the original finite-dimensional space be mapped into a much higher-dimensional space, presumably making the separation easier in that space

The support vector machines create an optimum hyperplane that separates the training data by the maximum margin. However, sometimes we would like to allow some misclassifications while separating categories. The SVM model has a cost function, which controls training errors and margins. For example, a small cost creates a large margin (a soft margin) and allows more misclassifications. On the other hand, a large cost creates a narrow margin (a hard margin) and permits fewer misclassifications. In this recipe, we will illustrate how the large and small cost will affect the SVM classifier.

Concerning the gamma value in the SVM, gamma says how far the 'reach' of each training example is (http://scikit-learn.org/stable/auto_examples/svm/plot_rbf_parameters.html), but can be just thought of as a regularization parameter. The higher the gamma, the more local the reach, and you have to watch out that your model keeps a general behavior since it is prone to adjust too much to the training examples.

3.4 classification tree

Tree-based models consist of one or more nested if-then statements for the predictors that partition the data. Within these partitions, a model is used to predict the outcome.

if Predictor A >= 1.7 then

```
| if Predictor B >= 202.1 then Outcome = 1.3
```

```
| else Outcome = 5.6
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else Outcome = 2.5 In this case, two-dimensional predictor space is cut into three regions (or terminal nodes) and, within each region, the outcome categorized into either "Class 1" or "Class 2." Figure 14.1 presents the tree in the predictor space. Just like in the regression setting, the nested if-then statements could be collapsed into rules such as

if Predictor A >= 0.13 and Predictor B >= 0.197 then Class = 1 if Predictor A >= 0.13 and Predictor B < 0.197 then Class = 2 if Predictor A < 0.13 then Class = 2

3.5 random forest

parameters :

mtry : number of variables randomy sampled at each split ntree : number of tree to grow nodesize : minimum number of observation in a terminal node. setting it lower heads to trees with a larger depth which means that more splits are performed until the terminal nodes. (default value is 1 for classification and 5 for regression -diaz urirarte and de andres 2006).

3.6 Naives bayes

basics of formula :

$$P(A \cap B) = P(A)P(B|A) \iff P(B|A) = \frac{P(A \cap B)}{P(A)}$$

def wiki: In statistics, naive Bayes classifiers are a family of simple "probabilistic classifiers" based on applying Bayes' theorem with strong (naïve) independence assumptions between the features

Naives : The joint probability calculation is simpler for independent events. so we consider events are independent. (it will be too complexe for more than two events)

Laplace correction will allow a small chance for these types of unforeseen circumstances (if joint event probabilty equals to 0.)

numeric data use bins to regroup them (hour cans be group by morning/afternoon/evening, temperature can be group by hot/warm/cold)

3.7 plan pr chaque sous partie ci dessus

- présentation
- concept mathématique
- paramètres du classifier

Chapter 4

Remedies

A lot of research have been made concerning this problem. Our goal is not to make an exhaustive review of all the technics to remedies this issue. In this study, we will focus on methods than we can repoduce with our level of competence. It appears to us that it is interesting to separate the choosen methods in three levels :

- First, some remedies we can use before launching the machine learning algorithm (Preprocessing).
- Secundly, some remedies we can use during the computation of a fitted models by the machine (learning method tuning).
- At last, som remedies that can be used after the machine learning algorithm (postprocessing).

4.1 different strategies :

- Special-purpose learning method : Modifications of the learning algorithm
  - advantages :
    - users goals are incorporated directly into the models
    - model obtained more comprehensive for the users
  - disadvantages :
    - user is restricted in his algorithmm choices or have to developp new algorithm
    - if the target of the loss function changes, model must be relearned
    - requires deep knowlegde of the learning algorithm implementation
- Data Pre-processing : changes on the data before the learning process takes place
  - advantages:
    - can be applied to any existing tools

        * choosen models are biased to the goals of the users
    - inconevnient:
        * difficult to relate modification of the data wit the loss function
    - methods :
        * weighting data spaces
        * re sampling
        * active learning
- Prediction Post-processing : transformations applied to the predictions of the learned model
    - advantages :
        * not necessary to know user preference biases at learning time
        * any standard learning tool can be used
    - drawbavks :
        * models do not reflect user preferences
        * models interpretability is meaningless because loss function was not optimized following user preference bias
    - methods :
        * threeshold methods
        * cost sensitive
- Hybrid solutions

4.2 Pre processing resampling

resampling dataset method:

from smote pdf (chawla)

about over and down sampling

Japkowicz (2000)discussed the effect of imbalance in a dataset. She evaluated threestrategies: under-sampling, resampling and a recognition-based induction scheme. We focuson her sampling approaches. She experimented on artificial 1D data in order to easilymeasure and construct concept complexity. Two resampling methods were considered.Random resampling consisted of resampling the smaller class at random until it consistedof as many samples as the majority class and "focused resampling" consisted of resamplingonly those minority examples that occurred on the boundary between the minority andmajority classes. Random under-sampling was considered, which involved under-samplingthe majority class samples at random until their numbers matched the number of minorityclass samples; focused under-sampling involved under-sampling the majority class sampleslying further away. She noted that both the sampling approaches were effective, and she alsoobserved that using the sophisticated sampling techniques did not give any clear advantagein the domain considered (Japkowicz, 2000)

One approach that is particularly relevant to our work is that of Ling and Li (1998).They combined over-sampling of the minority class with under-sampling

of the majorityclass

4.2.1 CARET up and down sample :

"downSample will randomly sample a data set so that all classes have the same frequency as the minority class. upSample samples with replacement to make the class distributions equal"

4.2.2 ROSE

Creates a sample of synthetic data by enlarging the features space of minority and majority class examples. Operationally, the new examples are down from a conditionnal kernel density estimate of the two classes as describe in Menardi and torelli (2013)

The ROSE strategy to deal with class imbalance ROSE (Menardi and Torelli, 2014) provides a unified framework to deal simultaneously with the two above-mentioned problems of model estimation and accuracy evaluation in imbalanced learning. It builds on the generation of new artificial examples from the classes, according to a smoothed bootstrap approach (see, e.g., Efron and Tibshirani, 1993). Consider a training set Tn, of size n, whose generic row is the pair (xi, yi), i = 1, . . . , n. The class labels yi belong to the set fY0, Y1g, and xi are some related attributes supposed to be realizations of a random vector x defined on Rd, with an unknown probability density function f (x). Let the number of units in class Yj, j = 0, 1, be denoted by nj < n. The ROSE procedure for generating one new artificial example consists of the following steps: 1. Select y = Yj with probability pj. 2. Select (xi, yi) 2 Tn, such that yi = y, with probability 1 nj . 3. Sample x from KHj (, xi), with KHj a probability distribution centered at xi and covariance matrix Hj. Essentially, we draw from the training set an observation belonging to one of the two classes, and generate a new example (x, y) in its neighborhood, where the shape of the neighborhood is determined by the shape of the contour sets of K and its width is governed by Hj. It can be easily shown that, given selection of the class label Yj, the generation of new examples from Yj, according to ROSE, corresponds to the generation of data from the kernel density estimate of f (xjYj), with kernel K and smoothing matrix Hj (Menardi and Torelli, 2014). The choices of K and Hj may be then addressed by the large specialized literature on kernel density estimation (see, e.g. Bowman and Azzalini, 1997). It is worthwhile to note that, for Hj ! 0, ROSE collapses to a standard combination of over- and under-sampling. Repeating steps 1 to 3 m times produces a new synthetic training set T m, of size m, where the imbalance level is defined by the probabilities pj (if pj = 1/2, then approximately the same number of examples belong to the two classes). The size m may be set to the original training set size n or chosen in any way

4.2.3 Smote family (smoteNC, BLSMOTE, ADASYN)

smote chawla quote :

We propose an over-sampling approach in which the minority class is over-sampled by cre-ating "synthetic" examples rather than by over-sampling with replacement. This approachis inspired by a technique that proved successful in handwritten character recognition (Ha& Bunke, 1997). They created extra training data by performing certain operations onreal data. In their case, operations like rotation and skew were natural ways to perturbthe training data. We generate synthetic examples in a less application-specific manner, byoperating in "feature space" rather than "data space". The minority class is over-sampledby taking each minority class sample and introducing synthetic examples along the linesegments joining any/all of thekminority class nearest neighbors. Depending upon theamount of over-sampling required, neighbors from theknearest neighbors are randomlychosen. Our implementation currently uses five nearest neighbors. For instance, if theamount of over-sampling needed is 200%, only two neighbors from the five nearest neigh-bors are chosen and one sample is generated in the direction of each. Synthetic samplesare generated in the following way: Take the difference between the feature vector (sample)under consideration and its nearest neighbor. Multiply this difference by a random numberbetween 0 and 1, and add it to the feature vector under consideration. This causes theselection of a random point along the line segment between two specific features. Thisapproach effectively forces the decision region of the minority class to become more general

SMOTE (Chawla et. al. 2002) is a well-known algorithm to fight this problem. The general idea of this method is to artificially generate new examples of the minority class using the nearest neighbors of these cases. Furthermore, the majority class examples are also under-sampled, leading to a more balanced dataset.

The SMOTE function oversamples your rare event by using bootstrapping and k-nearest neighbor to synthetically create additional observations of that event. The definition of rare event is usually attributed to any outcome/dependent/target/response variable that happens less than 15% of the time. For more details about this algorithm, read the original white paper, SMOTE: Synthetic Minority Over-sampling Technique, from its creators.

- references
  - Chawla, N. V., Bowyer, K. W., Hall, L. O., and Kegelmeyer, W. P. (2002). Smote: Synthetic minority over-sampling technique. Journal of Artificial Intelligence Research, 16:321-357.
  - Torgo, L. (2010) Data Mining using R: learning with case studies, CRC Press (ISBN: 9781439810187).

!!!! a lot of new techniques directly derived from this one as ADASYN

4.3 Learning method tuning

4.3.1 Metaparameters tuning

4.3.2 direct sensitive learning with cart classifer

The incorporation of benefits and/or costs (negative benefits) in existing algorithms, as a way to express the utility of different predictions, is one of the known approaches to cope with imbalanced domains.

Instead of optimizing the typical performance measure, such as accuracy or impurity, some models can alternatively optimize a cost or loss function that differentially weights specific types of errors. (no results with weighted data but cart works)

Theory We summarize the theory of cost-sensitive learning, published mostly in (Elkan, 2001; Zadrozny and Elkan, 2001). The theory describes how the misclassification cost plays its essential role in various cost-sensitive learning algorithms. Without loss of generality, we assume binary classification (i.e., positive and negative class) in this paper. In cost-sensitive learning, the costs of false positive (actual negative but predicted as positive; denoted as FP), false negative (FN), true positive (TP) and true negative (TN) can be given in a cost matrix, as shown in Table 1. In the table, we also use the notation C(i, j) to represent the misclassification cost of classifying an instance from its actual class j into the predicted class i. (We use 1 for positive, and 0 for negative). These misclassification cost values can be given by domain experts, or learned via other approaches. In cost-sensitive learning, it is usually assume that such a cost matrix is given and known. For multiple classes, the cost matrix can be easily extended by adding more rows and more columns. Table 1. An example of cost matrix for binary classification. Actual negative Actual positive Predict negative C(0,0), or TN C(0,1), or FN Predict positive C(1,0), or FP C(1,1), or TP Note that C(i, i) (TP and TN) is usually regarded as the "benefit" (i.e., negated cost) when an instance is predicted correctly. In addition, cost-sensitive learning is often used to deal with datasets with very imbalanced class distribution (Japkowicz and Stephen, 2002). Usually (and without loss of generality), the minority or rare class is regarded as the positive class, and it is often more expensive to misclassify an actual positive example into negative, than an actual negative example into positive. That is, the value of FN or C(0,1) is usually larger than that of FP or C(1,0). This is true for the cancer example mentioned earlier (cancer patients are usually rare in the population, but predicting an actual cancer patient as negative is usually very costly) and the bomb example (terrorists are rare). Given the cost matrix, an example should be classified into the class that has the minimum expected cost. This is the minimum expected cost principle. The expected cost R(i|x) of classifying an instance x into class i (by a classifier) can be expressed as: j R(i | x) P(j | x)C(i, j) , (1) where P(j|x) is the probability estimation of classifying an instance into class j. That is, the classifier will classify an instance x into positive

class if and only if: P(0|x)C(1,0) + P(1|x)C(1,1) P(0|x)C(0,0) + P(1|x)C(0,1) This is equivalent to: P(0|x)(C(1,0) – C(0,0)) P(1|x)(C(0,1) – C(1,1)) Thus, the decision (of classifying an example into positive) will not be changed if a constant is added into a column of the original cost matrix. Thus, the original cost matrix can always be converted to a simpler one by subtracting C(0,0) to the first column, and C(1,1) to the second column. After such conversion, the simpler cost matrix is shown in Table 2. Thus, any given cost-matrix can be converted to one with C(0,0) = C(1,1) = 0. 1 In the rest of the paper, we will assume that C(0,0) = C(1,1) = 0. Under this assumption, the classifier will classify an instance x into positive class if and only if: P(0|x)C(1,0) P(1|x)C(0,1) Table 2. A simpler cost matrix with an equivalent optimal classification. True negative True positive Predict negative 0 C(0,1) – C(1,1) Predict positive C(1,0) – C(0,0) 0 As P(0|x)=1 – P(1|x), we can obtain a threshold p* for the classifier to classify an instance x into positive if P(1|x) p, *where . (1,0) (0,1)* (1,0) FP FN FP C C p C (2) Thus, if a cost-insensitive classifier can produce a posterior probability estimation p(1|x) for test examples x, we can make it cost-sensitive by simply choosing the classification threshold according to (2), and classify any example to be positive whenever P(1|x) p*. This is what several cost-sensitive meta-learning algorithms, such as Relabeling, are based on (see later for details). However, some cost-insensitive classifiers, such as C4.5, may not be able to produce accurate probability estimation; they are designed to predict the class correctly. Empirical Thresholding (Sheng and Ling, 2006) does not require accurate estimation of probabilities – an accurate ranking is sufficient. It simply uses cross-validation to search the best probability from the training instances as the threshold.

4.4 post processinf threesholding

Alternate Cutoffs

Not efficient in my spotify works

> When there are two possible outcome categories, another method for increasing the prediction accuracy of the minority class samples is to determine alternative cutoffs for the predicted probabilities

Not a real solution for our issue because it changes our definition classes

> which effectively changes the definition of a predicted event.

Unless we do it with care / i don't think it is a good solution

> There may be situations where the sensitivity/specificity trade-off can be accomplished without severely compromising the accuracy of the majority class (which, of course, depends on the context of the problem)

Interesting if :

- focus on a compromise beetween sensityvioty and specificity. > particular target that must be met for the sensitivity or specificity,
- we want to maximise accuracy. > Find the point on the ROC curve that is closest (i.e., the shortest distance) to the perfect model (with 100 % sensitivity and 100 % specificity)
- use of Youden's J index ??? > (see Sect. 11.2), which measures the proportion of correctly predicted samples

Chapter 5

Applications

5.1 Introduction

In order (Xie, 2015) to illustrate and discuss the different remedies proposed in the previous chapter, we are handling each on different dataset. Hence we can make comparisons and try to measure their efficiency.

Our first choice as classifiers was to use LDA, LR, RF and SVM. having ascertained that LDA et LR give very similar results, we decide to substitute LR by naives bayes'classifier in order to proposed a richer experience (show plots). Notice that we firs try to use glmnet instead of glm but it doesn't deliver better results (see spot.rmd). It is not unexpected that LR and LDA give nearly predictions, indeed they both are linear models and litteracy confirms they both give similar results (quote). !! maybe put it in classifiers part !!!!

About the code : We don't introduce here all the manipulations done on the datasets, either the preparation of the dataset. You can find them in this github repositery, wich contains the .rmd for each dataset. In this repositery, you can also find the .R file which contains also the functions we code in order to avoid to many repetition in the code. At last, the alldat.Rdata stocked all objects built in the .rmd, it is used here to call the object we need.

We choose four dataset with different level of imabalanced.

Let's briefly presents those datasets:

- Spotify ...
- Recidivism ...
- Creditcard ...
- Hacked ...

Table of priors ratio between positive and negative class

Table 5.1: Confusion matrix spotify

	0	1	Sum	0	1	Sum
	rf			bayes		
0	4431	975	5406	4373	983	5356
1	147	115	262	205	107	312
Sum	4578	1090	5668	4578	1090	5668
	lda			svm		
0	4559	1078	5637	4566	1075	5641
1	19	12	31	12	15	27
Sum	4578	1090	5668	4578	1090	5668

Table 5.2: Spotify metrics

	accuracy	FNrate	TPrate	kappa	PrecisionPPV	Fscore
rf	0.8020466	0.8944954	0.1055046	0.1032829	0.4389313	0.1701183
Bayes	0.7904023	0.9018349	0.09816514	0.07332293	0.3429487	0.1526391
lda	0.8064573	0.9889908	0.01100917	0.01088917	0.3870968	0.02140946
svm	0.8082216	0.9862385	0.01376147	0.01772557	0.5555556	0.02685765

5.2 First Models

The function models compute our four models. We show the function in order to show the basic parameters. This parameters will be change in a following section. For now, we just want to observe results with basic parameters. This first computation can be used as a start reference to measure the remedies tested later.

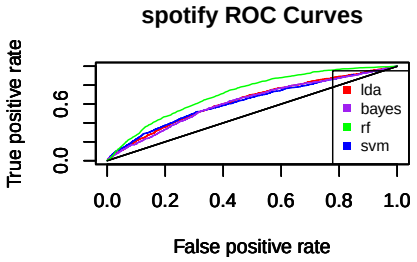
The table … shows the confusion matrix resulting to the four classifiers used on the spotofy dataset. We observe the unabilty to properly predict the unpopular songs. A look on the metrics sharps this observation.

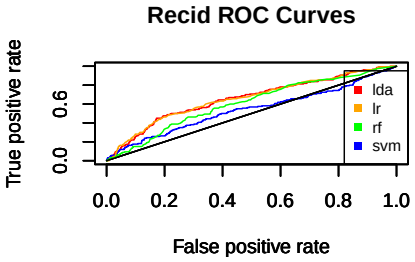
First we note that accuracy is very good, wigch confirms accuracy is not a relaible metrics concerning imbalance dataset. a simple view on Detection power(TPr) shows that we don't achieve to predict what songs are very un popular. FN rate is obviously good because of the imblalanced ratio. Here FN won't be a good metrics.

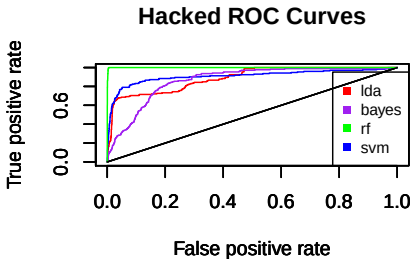
Let see the plot curve for all datasets.

Table 5.3: Hacked metrics

	accuracy	FNrate	TPrate	kappa	PrecisionPPV	Fscore
rf	0.9949815	0.05813953	0.9418605	0.9419781	0.9473684	0.9446064
Bayes	0.9477021	0.872093	0.127907	0.1597342	0.3142857	0.1818182
lda	0.9537771	0.7732558	0.2267442	0.287576	0.4814815	0.3083004
svm	0.9635499	0.7034884	0.2965116	0.4098061	0.75	0.425







!!! discuss the better results for creditcard and hacked !!! - from kaggle (datasets directly from professional use, more relevant, data more reliable) ? preprocessing (pca, onlynumeircal), extreme imbalanced ?

Even if creditcard and hacked seems not to need remedies to counteract imbalanced data, let see the detection power. We can argue that 3/4 of detection power is not enough to reassure users. In a professional use, we can wish at leat 90% of TPr.

At last, it is sure that all explicative variable are dependent to the variable to predict and and non colinear between them. for spotify we can'b sure that these variable can explain popularity, mayb there's no link between them. As the variable for recid, are they really a good choice.

On this one, we can see that only rf has very good results. Detection power and Fscore allows to judge the performance classifiers, contrarly to accuracy or FNr which are not usefull here. Rf has the better results, In second position

comes svm, even if he detects only a third among True positive, its quite a good results for a first try with an imbalanced data set, and Fscore ank kappa are not so bad.

5.3 Preprocessing : Resampling methods

5.4 Direct cost sensisitive learnig

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C5graph(Spot, "popularity", captest = "Kappa depending cost", captest2 = "Sensitivity \n and
```

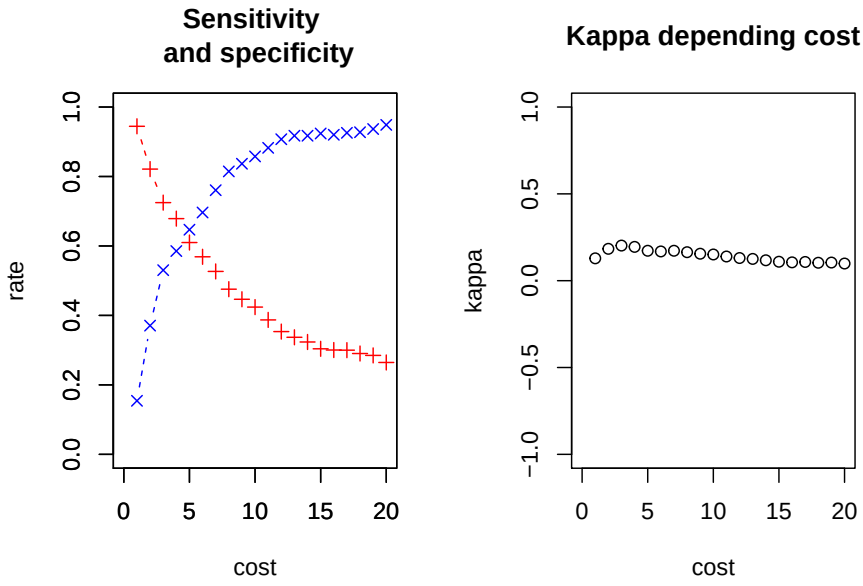

5.5 Post processing Threesholding

Chapter 6

Summary

Bibliography

Xie, Y. (2015). *Dynamic Documents with R and knitr*. Chapman and Hall/CRC, Boca Raton, Florida, 2nd edition. ISBN 978-1498716963.