ÉCOLE POLYTECHNIQUE
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GENDER RECOGNITION BY VOICE

Project for the course

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1 Introduction

In the last decades, automatic gender recognition (AGD) from speech has grown many interest thanks to the digitization of an extensive number of applications and the development of mobile platforms [1]–[8].

The applications of AGR have increased consequently. Indeed, in general, the accuracy of gender-dependent systems is higher than the one of gender-independent systems [4]. Thus, AGR improves the prediction of other speaker traits such as age [9] and emotional state [10], [11]. It can also facilitate speech recognition by gender-based normalization [12] and is a key feature for more natural and personalized dialog systems such as Siri.

The AGR techniques are based on statistical features extracted from the speech signals such as maximum, minimum and average frequency measured in a time span. These features translate physiological differences between males and females like the length of the vocal chords or the glottal shape [13]. Among all the features, it appears that the fundamental frequency plays a crucial role in gender classification as described in many studies [1], [14], [15]. In recent works, the use of the fundamental frequency coupled with spectral components such as Mel-frequency spectral components [16] or relative spectral perceptual linear predictive coefficients [5] have demonstrated best AGR performances even in noisy environments.

In this project, we study different state-of-the-art classification methods applied to the task of gender recognition by voice. The study is based on a dataset of features extracted from 3168 subjects available on Kaggle[1] and described in details in Chapter 2. A preliminary exploratory data analysis is performed in Chapter 3 which leads us to a first intuitive classification technique described in Chapter **??**. Starting from the conclusions of this intuitive approach, the exhaustive comparison of the methods is achieved in Chapter 4 and the best model is selected. Eventually, the best model is tested on 4 voices recorded by the authors in Chapter 5.

[1] `https://www.kaggle.com/primaryobjects/voicegender`

2 The dataset

2.1 General considerations

The voice gender dataset[1] consists of features extracted from 3168 recorded voice samples, collected from male and female speakers. The features have been computed using tuneR[2] and seewave[3], two acoustic analysis packages of R.

The dataset takes the form of a csv files where each row is composed of the following acoustical features of each voice:

- **meanfreq:** mean frequency (in kHz)
- **sd:** standard deviation of frequency
- **median:** median frequency (in kHz)
- **Q25:** first quantile (in kHz)
- **Q75:** third quantile (in kHz)
- **IQR:** interquantile range (in kHz)
- **skew:** skewness of the spectrum
- **kurt:** kurtosis
- **sp.ent:** spectral entropy
- **sfm:** spectral flatness
- **mode:** mode frequency
- **centroid:** frequency centroid
- **peakf:** peak frequency (frequency with highest energy)
- **meanfun:** average of fundamental frequency measured across acoustic signal
- **minfun:** minimum fundamental frequency measured across acoustic signal
- **maxfun:** maximum fundamental frequency measured across acoustic signal
- **meandom:** average of dominant frequency measured across acoustic signal
- **mindom:** minimum of dominant frequency measured across acoustic signal
- **maxdom:** maximum of dominant frequency measured across acoustic signal
- **dfrange:** range of dominant frequency measured across acoustic signal
- **modindx:** modulation index. Calculated as the accumulated absolute difference between adjacent measurements of fundamental frequencies divided by the frequency range
- **label:** male or female

The features are all quantitative and represents frequency characteristics of the voices.

[1] `https://www.kaggle.com/primaryobjects/voicegender`
[2] `https://cran.r-project.org/web/packages/tuneR/tuneR.pdf`
[3] `https://cran.r-project.org/web/packages/seewave/seewave.pdf`

2.2 Description of the features

Before starting the data analysis, it is important to perfectly understand the features involved in the exercise. This will be very useful in a preprocessing step, since it will allow us to remove collinear features. It will also be a great asset when it will come to the analysis of the most important features in the gender recognition.

As already pointed out in Section 2.1, the extracted features are all related to the spectrum.

Frequency-related features The mean frequency corresponds to a weighted average of the frequency by the amplitude of the spectral components:

$$\mu_f = \sum_{i=1}^{N} f_i y_i, \tag{2.1}$$

where N is the number of frequency components of the spectrum, f_i is the i-th frequency and y_i is the relative amplitude of the i-th component of the spectrum. As described in p.163 of the seewave documentation, it is equal to the feature 'centroid'. The standard deviation is calculated as:

$$\sigma_f = \sqrt{\sum_{i=1}^{N} y_i \left(f_i - \mu_f\right)^2} \tag{2.2}$$

The median frequency is calculated as the frequency where the spectrum is divided into frequency intervals of same energy. The calculation of the quartiles are based on the same criterion. The interquartile range is calculated as the difference between the third and the first quartile.

The feature "mode" characterizes the dominant frequency of the spectrum, *i.e.*the one with the highest amplitude. It is very similar to the peak frequency which corresponds to the frequency with the highest energy. The fundamental frequency is the lowest frequency of the spectrum.

The features "meanfun", "minfun", "maxfun", "meandom", "maxdom", "mindom", "dfrange" and "modindx" are based on short-time Fourier transform applied on segments of fixed durations, small compared to the duration of the whole signal. This permits to have features more localized in time.

In addition to the frequency-related features, we can find measures on the shape of the spectrum which may give very interesting additional information.

Skewness of the spectrum The skewness of the spectrum is a measure of its asymmetry around the mean frequency. It is calculated as follows:

$$S = \frac{1}{\sigma_f^3} \frac{\sum_{i=1}^{N} \left(f_i - \mu_f\right)^3}{N-1}. \tag{2.3}$$

From (2.3), it is clear that the sign of S gives information of the left or right asymmetry of the spectrum while the absolute value of S gives the strength of the asymmetry.

Kurtosis The Kurtosis is a measure of the "tailedness" of a probability distribution. It is calculated as the fourth order moment of the frequency distribution, described below:

$$K = \frac{1}{\sigma_f^4} \frac{\sum_{i=1}^{N} \left(f_i - \mu_f\right)^4}{N-1}. \tag{2.4}$$

When $K = 3$, the frequency distribution is normal. When $K < 3$, the frequency distribution is said to be *platikurtic*, it has fewer items around the means than in the tails, compared to a normal distribution. When $K > 3$, the distribution is said to be *leptokurtic* and has more frequency around the mean than in the tails, compared to a normal distribution.

Shannon spectral entropy The Shannon entropy is used to discriminate whether the voice signal is noisy or pure [17]. it is calculated as follows:

$$H = \frac{-\sum_{i=1}^{N} y_i \log_2 (y_i)}{\log_2 (N)} \tag{2.5}$$

If the signal is pure, then all the energy is concentrated in one frequency component, let us say the j-th component for which $y_j = 1$. In this case, $H = 0$. If the signal is a white noise, then $y_i = 1/N$, $\forall i \in \{1, ..., N\}$ and $H = 1$.

Spectral flatness The spectral flatness is rather similar to the spectral entropy. It is measured as the ratio between the geometric mean and the arithmetic mean:

$$F = N \frac{\sqrt[N]{\prod_{i=1}^{N} y_i}}{\sum_{i=1}^{N} y_i}. \tag{2.6}$$

In case of a white noise, the spectrum is flat and $H = 1$. In case of a pure tone, the geometrical mean is equal to zero and $H = 0$.

2.3 Cleaning the dataset

From the description of the features given in Section 2.2, a first cleaning of the dataset may be achieved before starting the analysis. Indeed, several features are exactly the same of collinear:

- The features “meanfreq” and “centroid” are exactly similar. So “centroid” has been removed;
- The following relationship holds: “IQR” = “Q75” − “Q25”. “IQR” has been removed.
- The following relationship holds: “dfrange” = “maxdom” − “mindom”. “dfrange” has been removed.

3 Exploratory Data Analysis

As a preliminary step, we propose to perform an exploratory data analysis. This will give us some hints about the dataset, *e.g.*the most important features, their correlation etc.

In order to have a first overview of the features, a short description is summarized in Table 3.1. It can be noticed the frequencies have low values, which makes sense since they are expressed in kHz. The mean fundamental frequency is about 143 Hz which is coherent with the male and female fundamental frequencies [18].

Regarding the shape of the spectrum, the mean skewness indicates an average right-asymmetry of the spectrum. The mean kurtosis shows that the frequency distribution is leptokurtic. About the flatness of the spectrum, the features “sfm” and “sp.ent” seem to have inconsistent behaviour with respect to the their average value since one is above 0.5 and the other is below. However, the high standard deviation of “sfm” makes an analysis rather difficult.

Table 3.1 Description of the features of the dataset

	meanfreq	sd	median	Q25	Q75	skew	kurt	sp.ent	sfm
mean	0.181	0.0571	0.186	0.140	0.225	3.14	36.6	0.895	0.408
std	0.0299	0.0167	0.0364	0.0487	0.0236	4.24	134	0.0450	0.178
min	0.0394	0.0184	0.0110	0.000229	0.0429	0.142	2.07	0.739	0.0369
25 %	0.164	0.0420	0.170	0.111	0.209	1.65	5.67	0.863	0.258
50 %	0.185	0.0592	0.190	0.140	0.226	2.20	8.32	0.902	0.396
75 %	0.199	0.0670	0.211	0.176	0.244	2.93	13.7	0.929	0.534
max	0.251	0.115	0.261	0.247	0.273	34.7	1310	0.982	0.843

	mode	meanfun	minfun	maxfun	meandom	mindom	maxdom	modindx
mean	0.165	0.143	0.0368	0.259	0.829	0.0526	5.05	0.174
std	0.0772	0.0323	0.0192	0.0301	0.525	0.0633	3.52	0.119
min	0.00	0.0556	0.00977	0.103	0.00781	0.00488	0.00781	0.00
25 %	0.118	0.117	0.0182	0.254	0.420	0.00781	2.07	0.0998
50 %	0.187	0.140	0.0461	0.271	0.766	0.0234	4.99	0.139
75 %	0.221	0.170	0.0479	0.277	1.18	0.0703	7.01	0.210
max	0.280	0.238	0.204	0.279	2.96	0.459	21.87	0.932

Regarding the distribution of the samples, there are 1584 recording of male voices and 1584 recording of female voices. So the classes are perfectly balanced.

Let us have a look to the correlation between the features. The correlation matrix, displayed in Figure 3.1, exhibits high correlations between “skew” and “kurt” and between “sp.ent” and “sfm”, which make sense since they quantify similar quantities. It can also be noticed that “meanfreq” and “median”, “Q25”, “Q75” are highly correlated which is self-evident given their definition. Thus, feature selection methods should be efficient in removing such redundancies in the dataset.

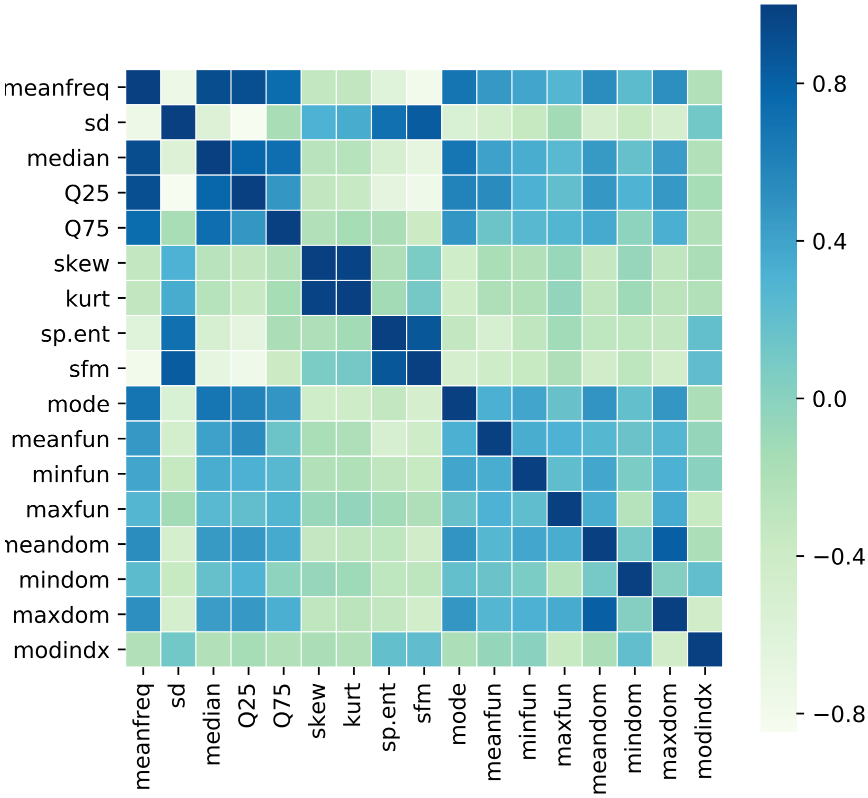
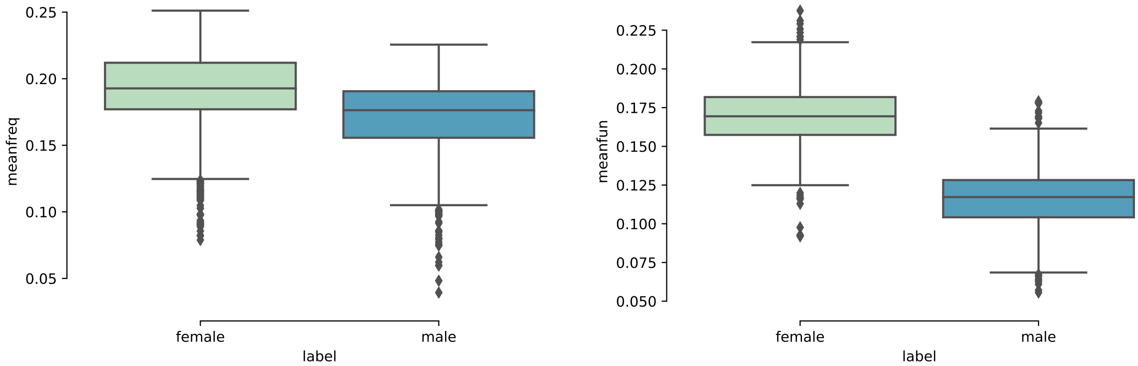


Figure 3.1 Correlation matrix of the dataset.

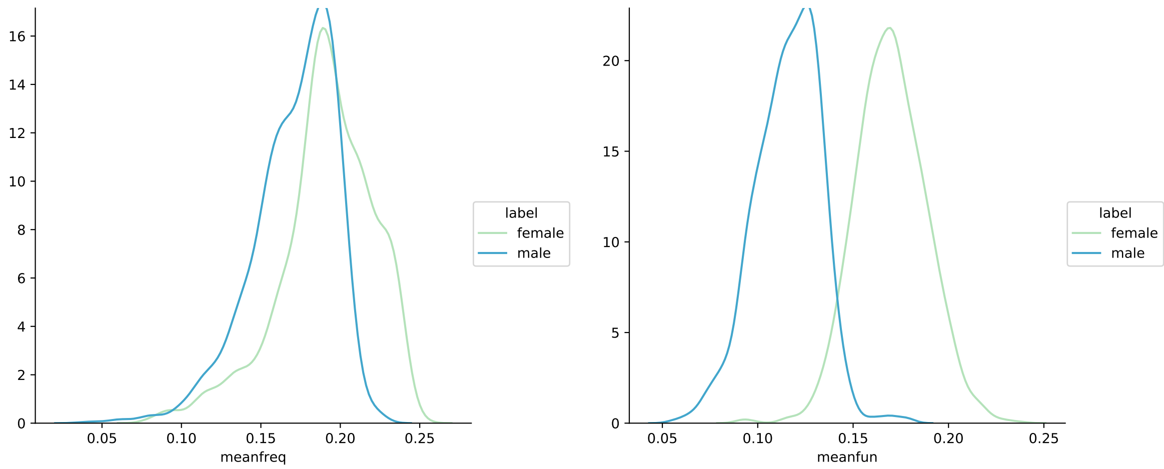
In the state-of-the-art, it appears that the fundamental frequency is a key feature for AGR, as stated in Chapter 1. Intuitively, we also think that the mean frequency should be a good classifier. In order to analyze this, Figs. 3.2a and 3.2b represent the box plots of "meanfreq" and "meanfun" respectively. It can be noticed that "meanfun" is indeed a key feature for classification since the overlap between male and female is very low. Regarding "meanfreq", the overlap is bigger than for "meanfun" but remains rather low.

Figs. 3.3a and 3.3b represent the distribution of male and female with respect to "meanfreq" and "meanfun" respectively. They confirm the analysis made with the box plot, *i.e.* that "meanfun" is a key component in AGR and is a far better classifier than "meanfreq".



(a) (b)

Figure 3.2 Box plots for (a)-“meanfreq” and (b)-“meanfun” features.



(a) (b)

Figure 3.3 Distribution of “male” and “female” for (a)-“meanfreq” and (b)-“meanfun” features.

4 Evaluation of the Best Classification Method

4.1 Considered classification methods

The goal of our analysis is to classify $y \in \{female, male\}$ given the data matrix $\mathbf{X}$ of our 17 predictors. We are interested in determining not only the model with the best predictive performance, but also the most significant features of human voice. We argue that sensitivity and specificity are of equal importance in our setting and, thus, our objective is to minimize total misclassification error. Also we note that our classes our perfectly balanced (50/50), so we use a threshold of 0.5 for our Bayes plug-in estimator. In our analysis we implement the following statistical learning methods to predict the class of $y \in \{female, male\}$.

- **Logistic Regression:** models the posterior probability of response $y \in \{female, male\}$, given the predictors $\mathbf{X}$, using the logistic function;
- **Regularized Logistic Regression:** The ℓ_1-penalty (LASSO) can be used for variable selection and shrinkage with logistic regression. It is a useful approach to examine which features are important in voice analysis;
- **Linear Discriminant Analysis (LDA):** LDA makes the assumption that the conditional densities $f(\mathbf{X}|y = male)$ and $f(\mathbf{X}|y = female)$ are both multivariate Gaussian with a common covariance matrix. It belongs to a family of techniques that use linear boundaries to separate classes in classification problems. If the assumption of normality is realistic, then LDA is expected to provide better results than logistic regression;
- **Quadratic Discriminant Analysis (QDA):** QDA is a similar method to LDA. The multivariate normality assumption remains, but unlike LDA, QDA assumes that each class has its own covariance matrix. If QDA has better predictive performance than LDA, it is an indication that a linear boundary is not the optimal to separate the 2 classes.
- **k-Nearest Neighbors (kNN):** kNN is a non-parametric approach which is highly flexible and uses non-linear decision boundaries. Before the implementation of kNN, it is crucial to scale the data, since this method relies on the euclidean distance between observations;
- **Classifications Trees:** Classification trees stratify the feature space recursively into simple regions and assign the label female or male using the majority vote. Bagging, random forests and gradient tree boosting are also implemented with the aim of improving predictive performance;
- **Support Vector Machines (SVM):** SVM perform well in classification problems where there is a clear margin of separation. We experiment with 2 kernels: the linear and the radial basis function (RBF).

4.2 Classification based on the fundamental frequency

Based on the exploratory data analysis described in Chapter 3, we propose to perform the classification based on the "meanfun" feature alone. This will give a baseline for further analysis described in the remaining of this Chapter.

To perform the analysis, we randomly split the dataset into a training set (80 %) and a test set (20 %). The training set is used to fit the models and for best parameter selection if needed. The test set is used to compute the classification error and to compare the models. The classification error considered in the study is the $0-1$ loss. The experiments have been performed on Python 3[1] with a single seed number for reproducibility of the results.

Table 4.1 Classification Error of the Methods for Classification With "meanfun" Feature

Type	Methods	
Max. Likelihood	Logistic reg.	0.0536
	Logistic reg. - Ridge	0.0505
	LDA	**0.0489**
	QDA	**0.0489**
Trees	Tree	0.0505
	Bagging	0.0505
	XGBoost	0.0505
SVM	Linear	0.0505
	Gaussian	**0.0489**
x	kNN	0.0520

The results, summarized in Table 4.1, show that the classification error is already very low when considering only the "meafun" feature. Indeed the average classsification error of the different classifiers is 0.0509. Thus, "meafun" is a very good feature for classification which is in accordance with the exploratory data analysis described in Chapter 3.

Regarding the classifiers, it can be seen that some of the ones described in Section PUTREF, are not mentioned in Tabel 4.1. Indeed, they do not make sense when considering only one feature for classification. About the relative performance of the different classifiers, the results are homogeneous around the average classification error and all the classifiers perform well. Zero-order methods such as tree-based methods (with one predictor, tree-based methods are nothing else than a threshold) already give a low classification error. More sophisticated methods, such as linear methods or kernel SVM, give results very similar to or slightly better than zero-order methods.

4.3 Classification based on a $80/20$ split of the dataset

4.3.1 Experimental settings

To perform the analysis, we randomly split the dataset into a training set (80 %) and a test set (20 %). The training set is used to fit the models and for best parameter selection if needed. he test set is used to compute the classification error and to compare the models. The classification error considered in the

[1]`https://github.com/AdriBesson/Statistical_learning_course/tree/develop/project`

study is the $0-1$ loss.

The models compared in the study are the ones described in Section 4.1. The errors are computed for 5 seed numbers in order to study the variability of the models with respect to the training/test sets and their initialization. The results are reported in Table 4.2.

Table 4.2 Classification Error of the Methods for Different Seed Numbers With 80/20 Split

Type	Methods	Seed number					Mean	Std.
		1	2	3	4	5		
Max. Lik.	Log. reg.	0.0158	0.0347	0.0315	0.0237	0.0221	0.0256	0.00760
	Log. reg. - ℓ_2	0.0158	0.0315	0.0315	0.0189	0.0284	0.0252	0.00740
	Log. reg. - ℓ_1	0.0315	0.0363	0.0379	0.0284	0.0300	0.0328	0.00408
	LDA	0.0315	0.0410	0.0379	0.0284	0.0268	0.0331	0.00611
	QDA	0.0347	0.0347	0.0347	0.0268	0.0363	0.0334	0.00377
Trees	Tree	0.0379	0.0426	0.0315	0.0284	0.0300	0.0341	0.00596
	Pruned Tree	0.0394	0.0473	0.0347	0.0363	0.0300	0.0375	0.00645
	Bagging	0.0237	0.0410	0.0142	**0.0174**	0.0284	0.0249	0.0106
	Random Forest	0.0189	0.0347	**0.0126**	0.0205	0.0205	0.0215	0.00809
	XGBoost	0.0189	**0.0268**	**0.0126**	0.0205	**0.0189**	**0.0196**	0.00506
SVM	Linear	**0.0142**	0.0315	0.0284	0.0189	0.0252	0.0237	0.00705
	Gaussian	0.0205	0.0284	0.0126	0.0189	0.0221	0.0199	0.00575
x	kNN	0.0300	0.0347	0.0252	0.0379	0.0300	0.0315	0.00486

4.3.2 Maximum-likelihood methods

Logistic Regression If we run logistic regression on our 17 features, we obtain an error rate of 0.0158. The reported p-values indicate that, at 5 % significance level, the coefficients of the following features are significantly non-zero: “Q25”, “Q75”, “sp.ent”, “sfm”, “meanfun” and “minfun”. We observe that the lowest p-value corresponds to meanfun, which shows the importance of this particular feature in voice analysis.

Regularized Logistic Regression We observe that Ridge regularization gives the same results as logistic regression. However, Lasso regularization performs worse providing a test error of 0.0315. Lasso shrinks the coefficients of 9 predictors to zero, letting only non-zero the following ones: “Q25”, “Q75”, “skew”, “sfm”, “mode”, “minfun”, “maxfun”. The largest coefficient corresponds to “meanfun”, confirming its significance.

Plots of parameter skrinkage

Linear Discriminant Analysis LDA gives a test error of 0.0315. In order to check whether the model assumptions are actually satisfied, we resort to Mardias Test for multivariate normality. Mardias Test is based on the multivariate extensions of skewness and kurtosis measures. Under the null hypothesis, our sample is drawn from a multivariate normal. We run Mardias Test on the two data matrices corresponding to male and female classes and conclude that normality assumption is violated. However, the two covariance matrices are quite similar and one can argue that the assumption of a common covariance matrix is realistic. To sum up, LDA seems to perform well, despite the lack of normality. We suspect that the reason lies in some particularity of our data set.

Quadratic Discriminant Analysis As we have seen above, the two covariance matrices of our two classes (male/female) are indeed close. Hence we expect QDA to perform worse than LDA. Indeed, its performance is slightly worse reporting a test error rate of 0.035.

4.3.3 k-Nearest Neighbors

We use 10-fold cross validation with one-standard-error rule to find that the optimal value for parameter k, is $k = 9$. Then we implement 9-NN, which yield a test error of 0.03. We observe a slight improvement compared to LDA and QDA, which can be attributed to the high flexibility of kNN. We reckon that the linear boundary is not the most appropriate to separate the 2 classes.

$$Plot\ for\ determing\ k\ with\ CV\ one - standard - errorrule$$

4.3.4 Tree-based methods

Classification Trees We begin with fitting a large unpruned tree to our data. We use the cross-entropy impurity measure to grow our tree and obtain a test error of 0.038. Although its predictive performance is quite good in our case, its high complexity prevents it from being interpretable.

$$Plot\ of\ the\ ugly\ large\ tree$$

After fitting a large tree, it is sensible to prune it in order to improve its interpret-ability and avoid overfitting. We prune our tree using 10-fold cross validation to determine the cost-complexity parameter, and misclassification error as the loss function. Although the test error has slightly increased, the pruned tree can now be used to convey meaningful results. We also observe that “meanfun” is used in the first node, confirming, for one more time, its integral role.

$$Plot\ of\ the\ pruned\ tree$$

Bagging Unpruned trees have low bias but suffer from high variance. Bagging can substantially reduce the variance of unstable procedures like trees, and improve predictive performance. Bagging indeed improves accuracy of our trees, since we obtain a test error of 0.0237. We also stress the importance of Out-of-Bag error estimate, which, in our case, is quite close to the test error.

$$Plot\ of\ OOB\ error\ estimate$$

Random Forests We proceed our analysis with running a random forest. We are particularly interested in this method, since random forests provide measures of variable importance. Mean decrease accuracy and mean decrease gini metrics indicate that “meanfun” is the most influential feature, followed by “Q25”. The test error is 0.0189, which confirms the superb predictive performance of random forests. Again, Out-of-Bag error estimate gives an accurate estimate of test error.

$$Plot\ of\ OOB\ error\ estimate$$

Partial dependence plots are useful to interpret variable importance in complex “black box” methods, such as random forests. These plots illustrate the marginal effect of the selected feature after integrating out the other features. Below we present the partial dependence plot on “meanfun”. The shape of the curve indicates that the fitted random forest uses a clear threshold that separate the two classes (female/male). Consequently, we can argue that the steepness of the curve in the middle pinpoints the importance of “meanfun”.

Plot of partial dependence

Gradient Tree Boosting In our quest of determining the model with the best accuracy, we then implement gradient tree boosting by using XGBoost R package. We choose stumps, which are simple trees with two leaves, to be the slow learners. We obtain a test error of 0.0189, which confirms the superiority of boosting compared to trees and bagged trees.

4.3.5 Support Vector Machines

SVM with a linear kernel We apply SVM with a simple linear kernel using 10-fold cross validation for parameter selection. We obtain a test error of 0.0142.

maybe ROC curve

SVM with a RBF kernel Finally, we implement SVM with a gaussian radial kernel. 10-fold cross validation is used to determine the best combination of the kernel parameter γ and the margin parameter C.

4.3.6 Conclusion

4.4 Classification based on a 50/50 split of the dataset

4.4.1 Experimental settings

Table 4.3 Classification Error of the Methods for Different Seed Numbers With 50/50 Split

Type	Methods	Seed number 1	2	3	4	5	Mean	Std.
Max. Likelihood	Logistic reg.	0.0221	0.0262	0.0310	0.0261	0.0291	0.0269	0.00339
	Logistic reg. - Ridge	0.0196	0.0214	0.0305	0.0248	0.0278	0.0248	0.00449
	Logistic reg. - Lasso	0.0284	0.0294	0.0368	0.0348	0.0364	0.0332	0.00397
	LDA	0.0291	0.0269	0.0342	0.0309	0.0313	0.0305	0.00274
	QDA	0.0280	0.0257	0.0370	0.0362	0.0365	0.0327	0.00542
Trees	Tree	0.0284	0.0317	0.0387	0.0454	0.0468	0.0382	0.00814
	Pruned Tree	0.0394	0.0473	0.0347	0.0363	0.0300	0.0380	0.01329
	Bagging	0.0209	0.0244	0.0319	0.0253	0.0302	0.0266	0.00445
	Random Forest	0.0191	0.0206	0.0305	0.0248	0.0290	0.0248	0.00500
	XGBoost	**0.0170**	**0.0149**	**0.0259**	**0.0197**	**0.0227**	**0.0201**	0.00439
SVM	Linear	0.0209	0.0149	0.0259	0.0197	0.0227	0.0257	0.00362
	Gaussian	0.0184	0.0188	0.0272	0.0211	0.0234	0.0218	0.00361
x	kNN	0.0273	0.0312	0.0326	0.0410	0.0382	0.0340	0.00551

4.4.2 Results and best classification method

5 Application of the best classifier on an acquired dataset

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