

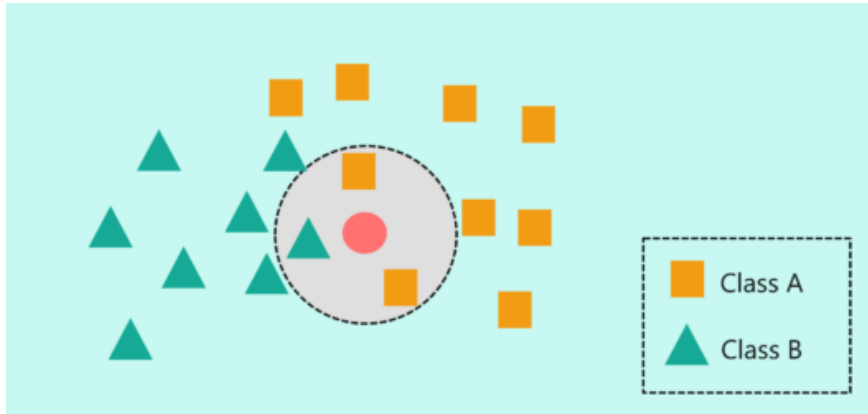
LOENG 8. Klassifitseerimise mudelid

8.1. Lähima naabri meetod (*Nearest Neighbor Classification*)

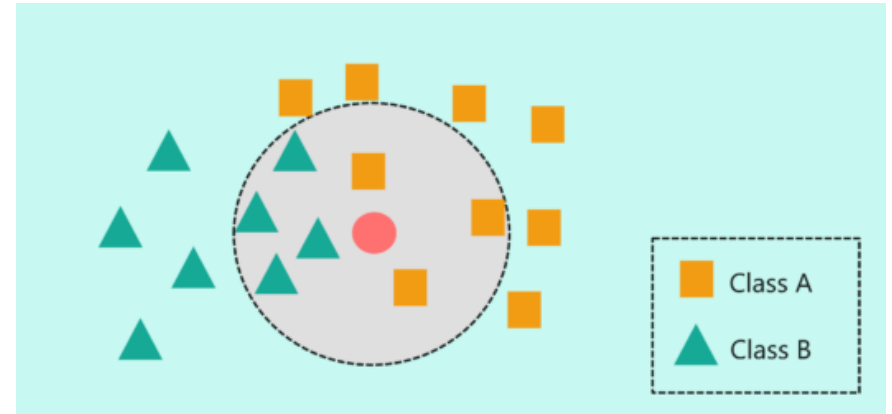
- ❑ Klassifitseerimisprobleemide korral **prognoositav tunnus Y on kategooriaalne** (nominaal- või järjestustunnus), kuid see võib olla arvudega kodeeritud (nt 1 = “jah”, 0 = “ei”).
- ❑ **Ülesanne:** „mudeli“ või „reegli“ väljatöötamine andmestiku objektide Y -i kategooriatele klassifitseerimiseks sõltuvalt argumentide $X_1, X_2, \dots, X_p$ väärtustest.
- ❑ **Argumentide $X_1, X_2, \dots, X_p$ tüüp:** arvuline, mittearvulistest moodustatakse *dummy variables*.
- ❑ **Klassifitseerimisreegel:** moodustada klasterid *k -lähima naabri meetodil* valitud kauguse alusel ning klassifitseerida objekte vastavalt suurema sagedusega klassi väärtusele klasteris ehk kui prognoositav Y võiks olla klassist C_j ja k_j on klassist C_j objektide arv klasteri k objektide seas,
 $j=1, \dots, m$, siis $\sum_{j=1}^m k_j = k$ ja Y -i prognoos klasteris on $k_l = \max_j k_j$
- ❑ Lähima naabri meetod on rakendatav ka regressiooni probleemide korral, Y -i prognoos klasteris määratakse sel juhul klasteri keskmisena

$$\hat{y} = \frac{1}{k} \sum_{i \in N} y_i$$

k-lähima naabri meetod



$k = 3$



$k = 7$

KNN Algorithm Pseudocode:

- Calculate $D(x, x_i)$, where ' i ' = 1, 2,, n and ' D ' is the distance (Euclidean measure) between the data points.
- The calculated (Euclidean) distances must be arranged in ascending order.
- Initialize k and take the first k distances from the sorted list.
- Figure out the k points for the respective k distances.
- Calculate k_i , which indicates the number of data points belonging to the i th class among k points i.e. $k \geq 0$ If $k_i > k_j \forall i \neq j$; put x in class i .

- ❑ ***k-lähima naabri meetodil*** klassifitseerimisel probleemiks võib olla võrdsed klasside väärtuste sagedused klasteris, nt binaarse klassifikatsiooni korral $Y = 1$ ja $Y = 0$ naabrite arvud on võrdsed.
- ❑ Sel põhjusel kasutatakse ***kaalutud lähima naabri klassifikaatorit***, mille korral lähimatele objektidele antakse klassifitseerimisel suurem kaal.
- ❑ ***Kaalutud k-NN klassifitseerimise algoritm:***
 1. Olgu treenimisandmed $T = \{(x_i, y_i), i = 1, \dots, n_T\}$
 2. Leida objekti x ($k + 1$) lähima naabrit kauguste $d(x, x_i)$ alusel.
 3. Kaugus $k + 1$ naabrist kasutatakse k teiste kauguste standardiseerimiseks

$$D_{(i)} = D(x, x_{(i)}) = \frac{d(x, x_{(i)})}{d(x, x_{(k+1)})}$$

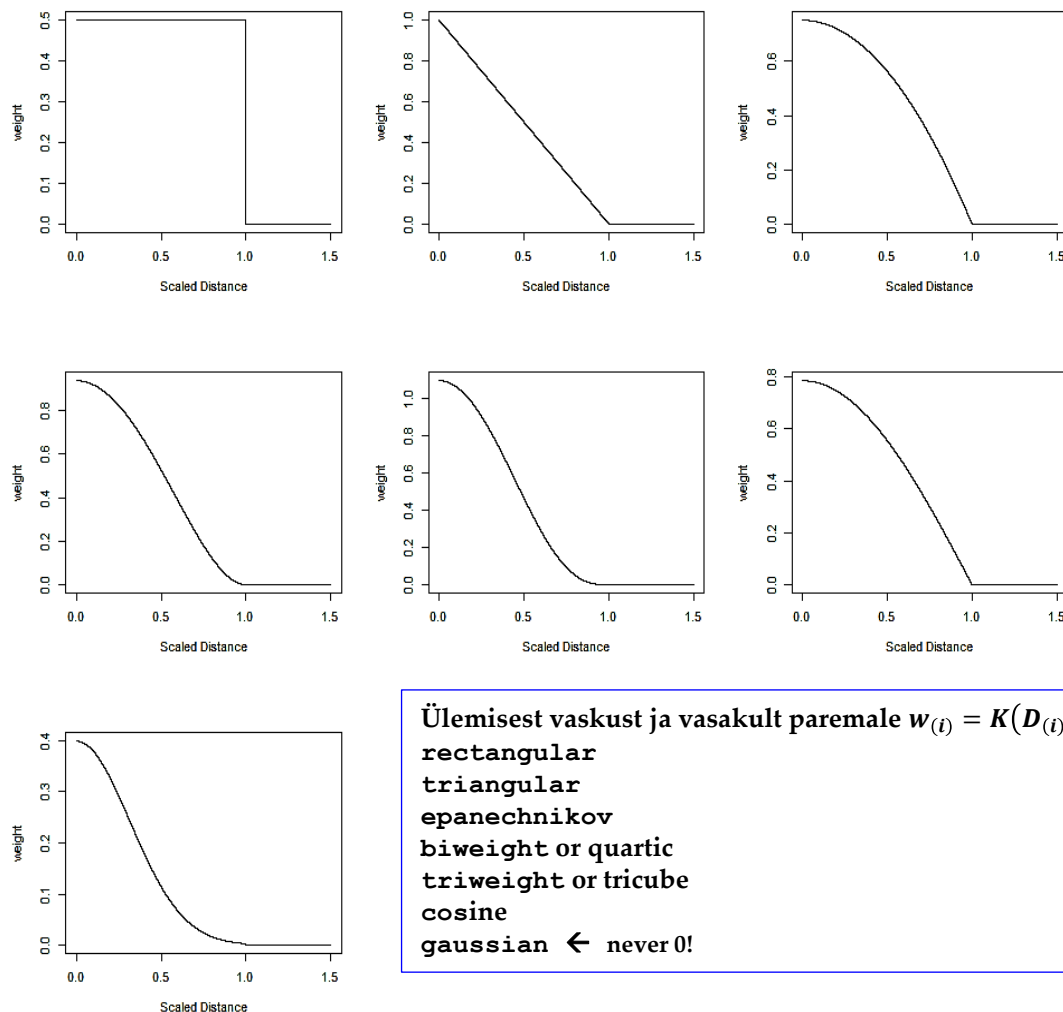
4. Kaalude arvutamiseks kasutatakse sobivat kauguste tuuma (***kernel***) funktsiooni $w_{(i)} = K(D_{(i)})$
5. Prognoositav klass arvutatakse valemiga

$$\hat{y} = \max_j \sum_{i=1}^k w_{(i)} I(y_{(i)} = C_j), \text{ kus } I(y_{(i)} = C_j) = \begin{cases} 1 & \text{if } y_{(i)} \text{ is class } C_j \\ 0 & \text{if } y_{(i)} \text{ is NOT class } C_j \end{cases}$$

6. Klassi kuulumise tõenäosus edasiseks prognoosimiseks hinnatakse valemiga

$$\hat{P}(y = C_j | x) = \frac{\sum_{i=1}^k w_{(i)} I(y_{(i)} = C_j)}{\sum_{i=1}^k w_{(i)}}, \quad j = 1, \dots, m$$

❑ *Kernelid*

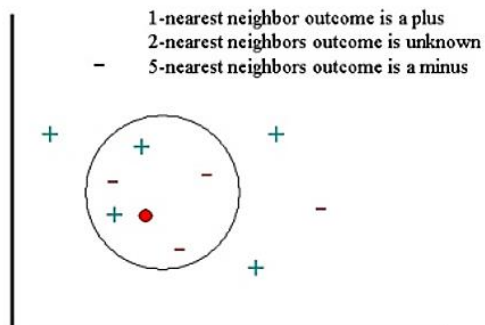


Ülemisest vaskust ja vasakult paremale $w_{(i)} = K(D_{(i)})$:

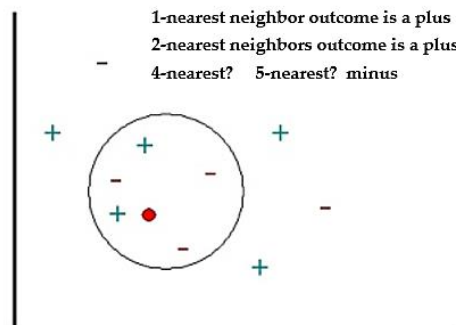
rectangular
 triangular
 epanechnikov
 biweight or quartic
 triweight or tricube
 cosine
 gaussian ← never 0!

❑ Kaalutud ja kaalumata klassifikaatorite võrdlus

Unweighted kNN Classification



Weighted kNN Classification



❑ k-lähima naabri meetod R-is

NÄIDE: kasutame andmestiku olive paketist dslabs

```
library(dslabs)
data(olive)
olive <- olive[,-1] # jätame regiooni välja
levels(olive$area) <- make.names(levels(olive$area))
str(olive)
```

```
'data.frame': 572 obs. of 10 variables:
 $ region      : Factor w/ 3 levels "Northern Italy",...: 3 3 3 3 3 3 3 3
 ...
 $ area        : Factor w/ 9 levels "Calabria","Coast-Sardinia",...: 5 5 5
 $ palmitic    : num 10.75 10.88 9.11 9.66 10.51 ...
 $ palmitoleic : num 0.75 0.73 0.54 0.57 0.67 0.49 0.66 0.61 0.6 0.55 ...
 $ stearic     : num 2.26 2.24 2.46 2.4 2.59 2.68 2.64 2.35 2.39 2.13 ...
 $ oleic       : num 78.2 77.1 81.1 79.5 77.7 ...
 $ linoleic    : num 6.72 7.81 5.49 6.19 6.72 6.78 6.18 7.34 7.09 6.33 ...
 $ linolenic   : num 0.36 0.31 0.31 0.5 0.5 0.51 0.49 0.39 0.46 0.26 ...
 $ arachidic   : num 0.6 0.61 0.63 0.78 0.8 0.7 0.56 0.64 0.83 0.52 ...
 $ eicosenoic  : num 0.29 0.29 0.29 0.35 0.46 0.44 0.29 0.35 0.33 0.3 ...
```

❑ Kuna meetod põhineb kaugustel, arvulised tunnused nõuavad skaleerimist, mitteamvulistest → *dummy variables*

```
olive[,2:9] = scale(olive[,2:9])
RNGkind(sample.kind = "Rounding")
set.seed(123)
sam <- sample(1:nrow(olive),
             floor(nrow(olive)*0.2))
olive.train <- olive[-sam,]
olive.test <- olive[sam,]
```

❑ Kasutame R-i funktsiooni train.kknn paketist kknn

```
library(kknn)
```

Usage

```
train.kknn(formula, data, kmax = 11, ks = NULL, distance = 2, kernel = "optimal",
            ykernel = NULL, scale = TRUE, contrasts = c('unordered' = "contr.dummy",
            ordered = "contr.ordinal"), ...)
cv.kknn(formula, data, kcv = 10, ...)
```

Arguments

formula	A formula object.
data	Matrix or data frame.
kmax	Maximum number of k, if ks is not specified.
ks	A vector specifying values of k. If not null, this takes precedence over kmax.
distance	Parameter of Minkowski distance. https://en.wikipedia.org/wiki/Minkowski_distance
kernel	Kernel to use. Possible choices are "rectangular" (which is standard unweighted knn), "triangular", "epanechnikov" (or beta(2,2)), "biweight" (or beta(3,3)), "triweight" (or beta(4,4)), "cos", "inv", "gaussian" and "optimal".
ykernel	Window width of an y-kernel, especially for prediction of ordinal classes.
scale	logical, scale variable to have equal sd.
contrasts	A vector containing the 'unordered' and 'ordered' contrasts to use.
...	Further arguments passed to or from other methods.
kcv	Number of partitions for k-fold cross validation.

Details

train.kknn performs leave-one-out crossvalidation and is computationally very efficient. cv.kknn performs k-fold crossvalidation and is generally slower and does not yet contain the test of different models yet.

❑ **k-lähima naabri meetod R-is**

Kasutame R-i funktsiooni `train.kknn` paketist `kknn`

```
library(kknn)
RNGkind(sample.kind = "Rounding")
set.seed(123)
olive.knn <- train.kknn(area~., data=olive.train, kmax=10, kernel=c("triangular",
"rectangular", "epanechnikov", "optimal"))
olive.knn
```

Call:
train.kknn(formula = area ~ ., data = olive.train, kmax = 10, kernel = c("triangular", "rectangular",
"epanechnikov", "optimal"))

Type of response variable: nominal
Minimal misclassification: 0.03056769
Best kernel: triangular
Best k: 6

❑ **Segadusmaatriks testandmetel**

```
library(caret)
confusionMatrix(predict(olive.knn, olive.test), olive.test$area, mode = "everything")
```

Confusion Matrix and Statistics

Prediction \ Reference	Calabria	Coast.Sardinia	East.Liguria	Inland.Sardinia	North.Apulia	Sicily	South.Apulia	Umbria	West.Liguria
Calabria	15	0	0	0	0	1	0	0	0
Coast.Sardinia	0	7	0	0	0	0	0	0	0
East.Liguria	0	0	8	0	0	0	0	0	0
Inland.Sardinia	0	1	0	10	0	0	0	0	0
North.Apulia	0	0	0	0	3	0	0	0	0
Sicily	0	0	0	0	0	2	3	0	0
South.Apulia	0	0	0	0	0	0	41	0	0
Umbria	0	0	0	0	0	0	0	11	0
West.Liguria	0	0	1	0	0	0	0	0	11

Overall Statistics

Accuracy : 0.9474
95% CI : (0.889, 0.9804)
No Information Rate : 0.386
P-Value [Acc > NIR] : < 2.2e-16

Kappa : 0.9345

❑ **k-lähima naabri meetodi parameetrite tuunimine paketiga caret**

```
library(caret)
train.control <- trainControl(method = "cv", number = 5 , search = "random", classProbs =
TRUE, summaryFunction = multiClassSummary)
tuneGrid <- expand.grid(kmax = 3:10, distance = 1:4, kernel =
c('gaussian', 'triangular', 'rectangular', 'epanechnikov', 'optimal'))
RNGkind(sample.kind = "Rounding")
set.seed(123)
kknn_fit <- train(area~., olive.train, method = 'kknn', trControl = train.control, tuneGrid =
tuneGrid, metric = "Kappa")
kknn_fit
head(kknn_fit$results[order(-kknn_fit$results$Kappa),], 20)

Kappa was used to select the optimal model using the largest value.
The final values used for the model were kmax = 7, distance = 3 and kernel = epanechnikov.
> head(kknn_fit$results[order(-kknn_fit$results$Kappa) 1 7])
```

❑ **Segadusmaatriks testandmetel**

```
library(caret)
confusionMatrix(predict(kknn_fit, olive.test), olive.test$area, mode = "everything")
```

Confusion Matrix and Statistics

Prediction	Reference									
	Calabria	Coast.Sardinia	East.Liguria	Inland.Sardinia	North.Apulia	Sicily	South.Apulia	Umbria	West.Liguria	
Calabria	15	0	0	0	0	1	1	0	0	
Coast.Sardinia	0	6	0	0	0	0	0	0	0	
East.Liguria	0	0	7	0	0	0	0	0	1	
Inland.Sardinia	0	2	0	10	0	0	0	0	0	
North.Apulia	0	0	0	0	3	0	0	0	0	
Sicily	0	0	0	0	0	2	2	0	0	
South.Apulia	0	0	0	0	0	0	41	0	0	
Umbria	0	0	0	0	0	0	0	11	0	
West.Liguria	0	0	2	0	0	0	0	0	10	

Overall Statistics

```
Accuracy : 0.9211
 95% CI : (0.8554, 0.9633)
No Information Rate : 0.386
P-Value [Acc > NIR] : < 2.2e-16

Kappa : 0.9016
```

8.2. Naïve Bayes Classification

- ❑ NB klassifitseerimine põhineb *Bayesi reeglil*
- ❑ Klass määratakse **suurima klassi kuulumise tõenäosusega**

$$P(C_k|\mathbf{x}) = \max_{1 \leq j \leq m} P(C_j|\mathbf{x})$$

- ❑ Kus klassi tinglik tõenäosus määratakse Bayesi valemiga

$$P(C_j|\mathbf{x}) = \frac{P(\mathbf{x}|C_j)P(C_j)}{P(\mathbf{X} = \mathbf{x})} = \frac{P(X_1 = x_1, X_2 = x_2, \dots, X_p = x_p | C_j)P(C_j)}{P(X_1 = x_1, X_2 = x_2, \dots, X_p = x_p)}$$

- ❑ Maksimeerimist nõuab ainult lugeja, kus $P(C_j)$ määratakse klasside osakaaludega treenimisandmestikus
- ❑ $P(\mathbf{x}|C_j)$ hinnangu saamiseks eeldatakse litsustamise mõttes, et $X_1, X_2, \dots, X_p$ on sõltumatud, mis praktiliselt kunagi ei ole täidetud, siit pärinebki nimetus „naïivne“

$$\begin{aligned} P(\mathbf{x}|C_j) &= P(\mathbf{X} = \mathbf{x}|C_j) = P(X_1 = x_1, X_2 = x_2, \dots, X_p = x_p | C_j) \\ &= P(X_1 = x_1 | C_j)P(X_2 = x_2 | C_j) \dots P(X_p = x_p | C_j) = \prod_{i=1}^p P(X_i = x_i | C_j) \end{aligned}$$

$P(X_i = x_i | C_j)$ hindamine

❑ **Kategoriaalne X_i on tasemel $l \rightarrow$ kasutame treenimisandmed**

$$\hat{P}(X_i = x_i | C_j) = \frac{\hat{P}(X_i = x_i \cap Y = C_j)}{\hat{P}(Y = C_j)} = \frac{\#(X_i = x_i \cap Y = C_j)}{\#(Y = C_j)}$$

- Kuna lugeja võiks olla 0, ehk võivad puududa paarid $X_i = x_i \cap Y = C_j$, siis lisatakse virtuaalsed paarid ehk rakendatakse *Laplace Smoothing*

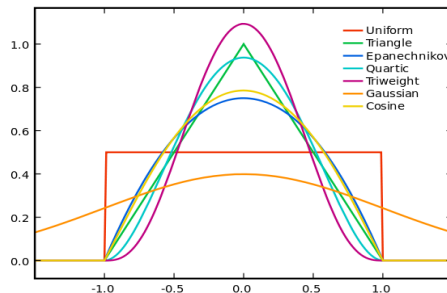
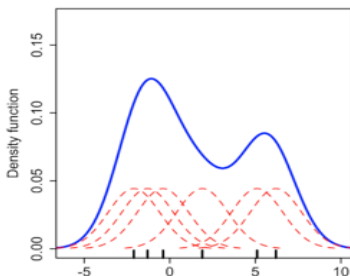
$$\hat{P}(X_i = x_i \cap Y = C_j) = \frac{\#(X_i = x_i \cap Y = C_j) + 1}{\#(Y = C_j) + \#(\text{levels for } X_i)} \quad \text{or} \quad \frac{\#(X_i = x_i \cap Y = C_j) + k}{\#(Y = C_j) + k \cdot \#(\text{levels for } X_i)}$$

❑ **Pidev $X_i \rightarrow$ kasutame normaalsuse eeldust või, kui eeldus ei ole täidetud rakendame Box-Cox/Yeo-Johnson teisendusi ja lähendame tõenäosust normaaljaotuse tihedusega**

$$\hat{P}(X_i = x_i | C_j) = \hat{f}(x | C_j) = \frac{1}{\sqrt{2\pi\hat{\sigma}_{ij}^2}} \exp\left(-\frac{(x_i - \hat{\mu}_{ij})^2}{2\hat{\sigma}_{ij}^2}\right)$$

❑ **Praktikal tiheduse asemel rakendatakse *kernel smoother***

$$\hat{f}(x | C_j) = \frac{1}{nh} \sum_{i=1}^{n_j} K\left(\frac{x - x_i}{h}\right) \quad \text{where } n_j = \# \text{ of obs. with } Y = \text{level } j \text{ \& } h > 0$$



Kernel Functions, $K(\cdot)$

bandwidth $h > 0$ (adjust) kontrollib kerneli laiust.
Suuremad h annavad siledama tiheduse hinnangu,
väikesed h annavad rohkem müra hinnangule.

Naïve Bayesi klassifitseerimise näide:

Lähtume valemist

$$\hat{P}(\mathbf{x}|C_k) = \max_{1 \leq j \leq m} \hat{P}(\mathbf{x}|C_j) \propto \max_{1 \leq j \leq m} \prod_{i=1}^p \hat{P}(X_i = x_i | C_j) = \max_{1 \leq j \leq m} \hat{P}(X_1 = x_1 | C_j) \hat{P}(X_2 = x_2 | C_j) \cdots \hat{P}(X_p = x_p | C_j)$$

Fruit	Long?	Sweet?	Green?	Total
Banana	400	350	50	500
Apple	0	200	150	300
Other	100	150	50	200

□ Eeldusel $P(C_j) = 1/3$ klassifitseeri

$\mathbf{x}_1 = (Long? = Yes, Sweet? = No, Green? = No)$

$\hat{P}(\mathbf{x}_1|Banana) \approx$

$0.8 \times 0.3 \times 0.9 = .216$ (not Laplace corrected)

$0.786 \times 0.311 \times 0.893 = 0.218$ (Laplace corrected)

$\hat{P}(\mathbf{x}_1|Apple) \approx$

$0 \times 0.333 \times 0.5 = 0$ (not Laplace corrected)

$0.016 \times 0.349 \times 0.508 = 0.003$ (Laplace corrected)

$\hat{P}(\mathbf{x}_1|Other) \approx$

$0.5 \times 0.25 \times 0.75 = .094$ (not Laplace corrected)

$0.488 \times 0.279 \times 0.744 = 0.101$ (Laplace corrected)

Thus $\mathbf{x}_1$ is classified as a Banana

$\hat{P}(Yes Class)$	$\hat{P}(Yes Class)$ Laplace ($k = 5$)
$\hat{P}(Long Banana) = \frac{400}{500} = 0.8$	$\frac{400 + 5}{500 + 5 * 3} = 0.786$
$\hat{P}(Sweet Banana) = \frac{350}{500} = 0.7$	$\frac{350 + 5}{500 + 5 * 3} = 0.689$
$\hat{P}(Green Banana) = \frac{50}{500} = 0.1$	$\frac{50 + 5}{500 + 5 * 3} = .107$
$\hat{P}(Long Apple) = \frac{0}{300} = 0$	$\frac{0 + 5}{300 + 5 * 3} = 0.016$
$\hat{P}(Sweet Apple) = \frac{200}{300} = 0.667$	$\frac{200 + 5}{300 + 5 * 3} = 0.651$
$\hat{P}(Green Apple) = \frac{150}{300} = 0.5$	$\frac{150 + 5}{300 + 5 * 3} = 0.492$
$\hat{P}(Long Other) = \frac{100}{200} = 0.5$	$\frac{100 + 5}{200 + 5 * 3} = 0.488$
$\hat{P}(Sweet Other) = \frac{150}{200} = 0.75$	$\frac{150 + 5}{200 + 5 * 3} = 0.721$
$\hat{P}(Green Other) = \frac{50}{200} = 0.25$	$\frac{50 + 5}{200 + 5 * 3} = 0.256$

❑ Naïve Bayesi klassifitseerimine R-is

Kasutame R-i funktsiooni `NaiveBayes` paketest `klaR`

Description

Computes the conditional a-posterior probabilities of a categorical class variable given independent predictor variables using the Bayes rule.

Usage

```
## S3 method for class 'formula'
NaiveBayes(formula, data, ..., subset, na.action = na.pass)
## Default S3 method:
NaiveBayes(x, grouping, prior, usekernel = FALSE, fL = 0, ...)
```

Arguments

x a numeric matrix, or a data frame of categorical and/or numeric variables.
grouping class vector (a factor).
formula a formula of the form `class ~ x1 + x2 + ...`. Interactions are not allowed.
data a data frame of predictors (categorical and/or numeric).
prior the prior probabilities of class membership. If unspecified, the class proportions for the training set are used. If present, the probabilities should be specified in the order of the factor levels.
usekernel if TRUE a kernel density estimate ([density](#)) is used for density estimation. If FALSE a normal density is estimated.
fL Factor for Laplace correction, default factor is 0, i.e. no correction.
... arguments passed to [density](#).
subset for data given in a data frame, an index vector specifying the cases to be used in the training sample. (NOTE: If given, this argument must be named.)
na.action a function to specify the action to be taken if NAs are found. The default action is not to count them for the computation of the probability factors. An alternative is `na.omit`, which leads to rejection of cases with missing values on any required variable. (NOTE: If given, this argument must be named.)

Kernels	Bandwidth selectors
Gaussian	nrd0 (Silverman's rule-of-thumb)
Epanechnikov	nrd (variation of the rule-of-thumb)
Rectangular	ucv (unbiased cross-validation)
Triangular	bcv (biased cross-validation)
Biweight	SJ (Sheather & Jones method)
Cosine	
Optcosine	

`library(klaR)`

❑ Arvulised tunnused nõuvad **skaleerimist**,
mittearvulistest → **dummy variables**

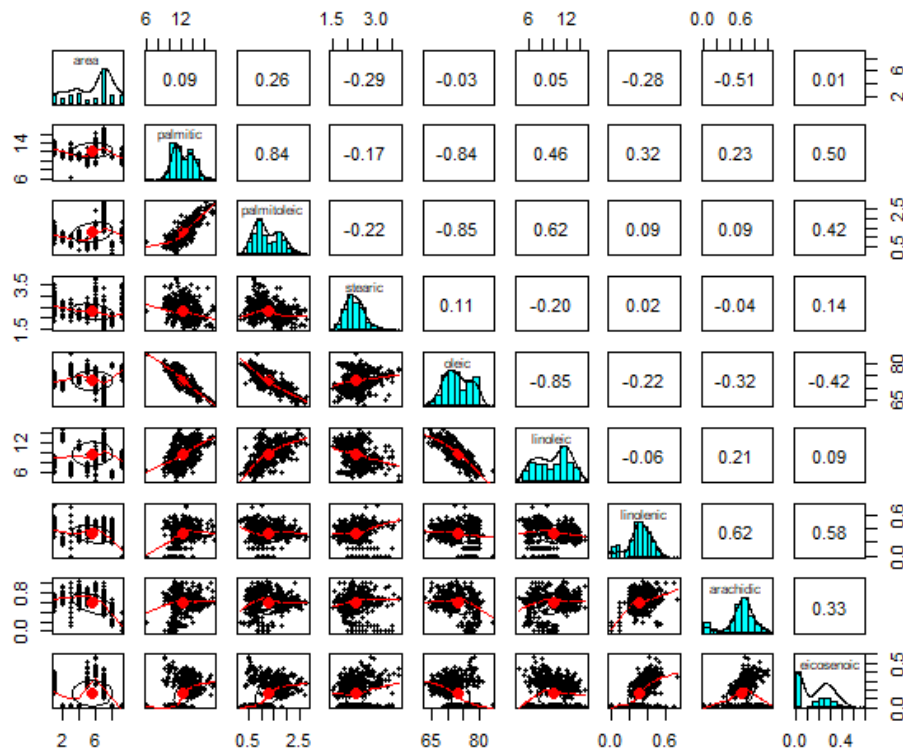
NÄIDE: kasutame andmestiku olive paketist dslabs

```
library(psych)
pairs.panels(olive[, -1])
```

□ Mõned argumendid ei vasta normaalsuse eeldusele

```
olive.NB =
NaiveBayes(area~., data=olive.train)
ypred =
predict(olive.NB, newdata=olive.test)
```

```
Warning messages:
1: In FUN(X[[i]], ...) :
  Numerical 0 probability for all classes with observation 5
2: In FUN(X[[i]], ...) :
  Numerical 0 probability for all classes with observation 31
```



```
confusionMatrix(predict(olive.NB, olive.test)$class, olive.test$area, mode = "everything")
```

Confusion Matrix and Statistics

Prediction \ Reference	Calabria	Coast.Sardinia	East.Liguria	Inland.Sardinia	North.Apulia	Sicily	South.Apulia	Umbria	West.Liguria
Calabria	14	0	0	0	0	1	2	0	0
Coast.Sardinia	0	8	0	0	0	0	0	0	0
East.Liguria	0	0	6	0	0	0	0	0	1
Inland.Sardinia	0	0	0	10	0	0	0	0	0
North.Apulia	0	0	0	0	3	0	0	0	0
Sicily	1	0	0	0	0	2	2	0	0
South.Apulia	0	0	0	0	0	0	40	0	0
Umbria	0	0	1	0	0	0	0	11	0
West.Liguria	0	0	2	0	0	0	0	0	10

Overall Statistics

```
Accuracy : 0.9123
95% CI : (0.8446, 0.9571)
No Information Rate : 0.386
P-Value [Acc > NIR] : < 2.2e-16
```

Kappa : 0.8911

❑ *Naïve Bayesi* parameetrite tuunimine paketiga caret

```
library(caret)
train.control <- trainControl(method = "cv", number = 5 , search = "random", classProbs =
TRUE, summaryFunction = multiClassSummary)
tuneGrid <- expand.grid(usekernel = c(FALSE, TRUE), fL = 0:5, adjust = 0:5)
RNGkind(sample.kind = "Rounding")
set.seed(123)
nb_fit <- train(area~., olive.train, method = 'nb', trControl = train.control, tuneGrid =
tuneGrid, metric = "Kappa")
nb_fit
head(nb_fit$results[order(-nb_fit$results$Kappa), ], 5)
```

Kappa was used to select the optimal model using the largest value.

The final values used for the model were fL = 0, usekernel = FALSE and adjust = 0.

❑ Segadusmaatriks testandmetel

```
library(caret)
confusionMatrix(predict(nb_fit, olive.test), olive.test$area, mode = "everything")
```

Confusion Matrix and Statistics

	Reference									
Prediction	Calabria	Coast.Sardinia	East.Liguria	Inland.Sardinia	North.Apulia	Sicily	South.Apulia	Umbria	West.Liguria	
Calabria	14	0	0	0	0	1	2	0	0	
Coast.Sardinia	0	8	0	0	0	0	0	0	0	
East.Liguria	0	0	6	0	0	0	0	0	1	
Inland.Sardinia	0	0	0	10	0	0	0	0	0	
North.Apulia	0	0	0	0	3	0	0	0	0	
Sicily	1	0	0	0	0	2	2	0	0	
South.Apulia	0	0	0	0	0	0	40	0	0	
Umbria	0	0	1	0	0	0	0	11	0	
West.Liguria	0	0	2	0	0	0	0	0	10	

Overall Statistics

```
Accuracy : 0.9123
 95% CI : (0.8446, 0.9571)
No Information Rate : 0.386
P-Value [Acc > NIR] : < 2.2e-16

Kappa : 0.8911
```

8.3. Närvivõrkude klassifitseerimismudelid

- Ühekihilise närvivõrgu mudeli võrrandi üldkuju klassifitseerimise ülesannete korral on järgmine

$$P(y_i = C_k | X = x_i) = \phi_o(\alpha_k + \sum_h w_{hk} \phi_h(\alpha_h + \sum_{j=1}^p w_{ih} x_{ij}))$$

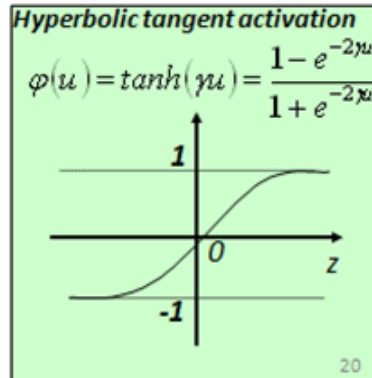
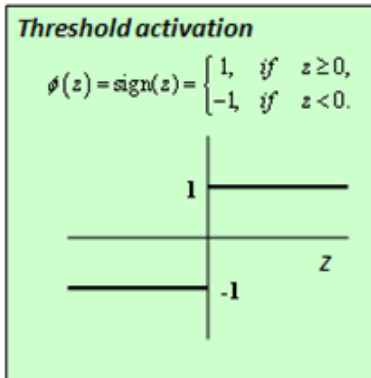
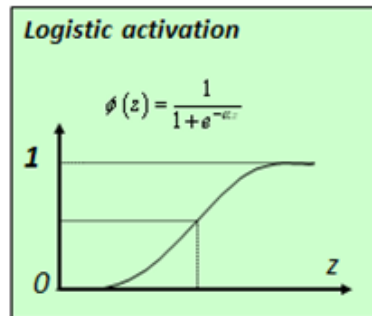
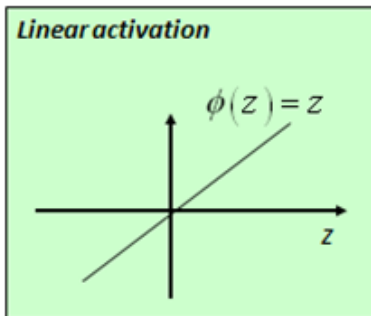
- Mudel prognoosib Y -i klassi C_k kuulumise tõenäosust sõltuvalt argumentide $X_1, X_2, \dots, X_p$ väärtustest
- Aktiveerimisfunktsioonid ϕ_h

$\phi_o(z)$ *logistic* → klassifitseerimine

$$\text{Sigmoid: } f(x) = \frac{1}{1 + e^{-x}}$$

- $\phi_o(z)$ funktsioonina on lubatud ka
- threshold* binaarklassifitseerimisel ja
 - (hyperbolic tangent + 1)/2*, mis annab väärtused vahemikus (0,1)

- Närvivõrkude mudelid on kõrgelt parametrizeeritud, **ristvalideerimine** on vajalik **ülesobituse** (*overfitting*) vältimiseks



❑ Närvivõrgud klassifitseerimiseks R-is

Kasutame R-i funktsiooni `nnet` paketest `nnet` ühe varjutud kihiga mudeli loomiseks, 2- või 3- kihilise närvivõrgu loomiseks kasutame paketti `neuralnet`

```
library(nnet)
```

Fit Neural Networks

Description:

Fit single-hidden-layer neural network, possibly with skip-layer connections.

Usage:

```
nnet(x, ...)
```

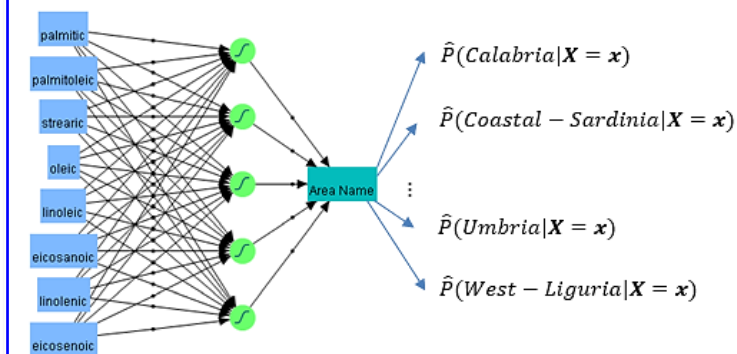
```
## S3 method for class 'formula':
```

```
nnet(formula, data, weights, ...,  
     subset, na.action = na.fail, contrasts = NULL)
```

```
## Default S3 method:
```

```
nnet(x, y, weights, size, Wts, mask,  
     linout = FALSE, entropy = FALSE, softmax = FALSE,  
     censored = FALSE, skip = FALSE, rang = 0.7, decay = 0,  
     maxit = 100, Hess = FALSE, trace = TRUE, MaxNWts = 1000,  
     abstol = 1.0e-4, reltol = 1.0e-8, ...)
```

Närvivõrk olive andmestiku klassifitseerimisel



Märkused:

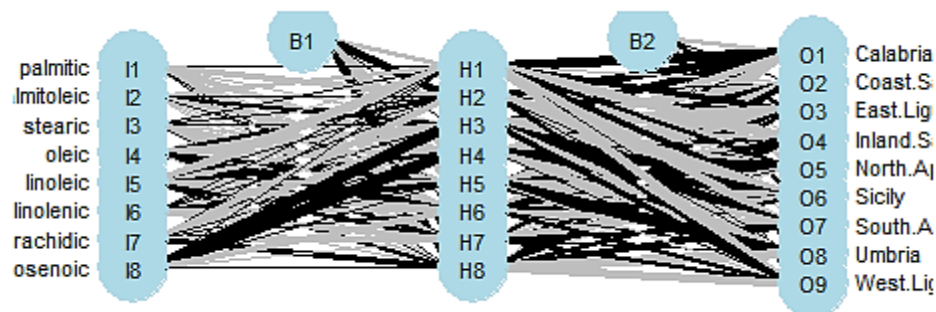
- ❑ Suurem *size* suurendab mudeli täpsust.
- ❑ Suurem *decay* pikendab mudeli otsingut, kuid reeglina leitakse parem, ehkki kerkib ülesobituse probleem.
- ❑ Maksimaalse korduste arvu (*maxit*) suurendamine on vajalik, eriti *size* ja/või *decay* suurenemisel.
- ❑ `linout=FALSE` → klassifitseerimine

- ❑ Arvulised tunnused nõuvad **skaleerimist**, mittearvulistest → **dummy variables**

NÄIDE: kasutame andmestiku olive paketist dslabs

```
library(nnet)
RNGkind(sample.kind = "Rounding")
set.seed(123)
olive.nn<-nnet(area~.,data=olive.train,size=8,decay=.025,maxit=5000,trace=FALSE)
olive.nn
```

a 8-8-9 network with 153 weights
 inputs: palmitic palmitoleic stearic oleic linoleic linolenic arachidic eicosenoic
 output(s): area
 options were - softmax modelling decay=0.025



```
library(NeuralNetTools)
plotnet(olive.nn, cex=0.7)
```

```
library(caret)
confusionMatrix(as.factor(predict(olive.nn,type="class")),olive.train$area,mode =
"everything")
confusionMatrix(as.factor(predict(olive.nn,newdata= olive.test, type="class")),
olive.test$area,mode = "everything")
```

Prediction	Reference	Calabria	Coast.Sardinia	East.Liguria	Inland.Sardinia	North.Apulia	Sicily	South.Apulia	Umbria	West.Liguria
Calabria	40	0	0	0	0	0	0	0	0	0
Coast.Sardinia	0	25	0	0	0	0	0	0	0	0
East.Liguria	0	0	41	0	0	0	0	0	0	0
Inland.Sardinia	0	0	0	55	0	0	0	0	0	0
North.Apulia	0	0	0	0	22	0	0	0	0	0
Sicily	1	0	0	0	0	33	0	0	0	0
South.Apulia	0	0	0	0	0	0	162	0	0	0
Umbria	0	0	0	0	0	0	0	40	0	0
West.Liguria	0	0	0	0	0	0	0	0	0	39

Accuracy	: 0.9978
95% CI	: (0.9879, 0.9999)
No Information Rate	: 0.3537
P-Value [Acc > NIR]	: < 2.2e-16
Kappa	: 0.9973

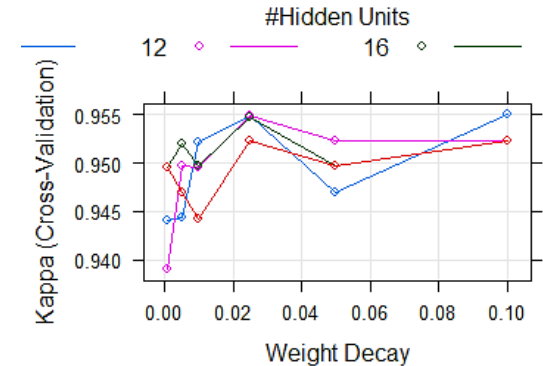
Prediction	Reference	Calabria	Coast.Sardinia	East.Liguria	Inland.Sardinia	North.Apulia	Sicily	South.Apulia	Umbria	West.Liguria
Calabria	14	0	0	0	0	0	0	2	0	0
Coast.Sardinia	0	8	0	0	0	0	0	0	0	0
East.Liguria	0	0	7	0	0	0	0	0	0	0
Inland.Sardinia	0	0	0	10	0	0	0	0	0	0
North.Apulia	0	0	0	0	3	0	0	0	0	0
Sicily	1	0	0	0	0	3	0	2	0	0
South.Apulia	0	0	0	0	0	0	0	40	0	0
Umbria	0	0	0	0	0	0	0	0	11	0
West.Liguria	0	0	2	0	0	0	0	0	0	11

Accuracy	: 0.9386
95% CI	: (0.8776, 0.975)
No Information Rate	: 0.386
P-Value [Acc > NIR]	: < 2.2e-16
Kappa	: 0.9238

❑ Närvivõrgu parameetrite häälestus paketiga caret

```
library(caret)
train.control <- trainControl(method = "cv", number = 5 , search = "random", classProbs =
TRUE, summaryFunction = multiClassSummary)
nnet_grid <- expand.grid(size = c(8,12,16,20),
                        decay = c(0.1,0.05,0.025,0.01,0.005,0.001))
RNGkind(sample.kind = "Rounding")
set.seed(123)
cv_nn <- train(area~., data=olive.train,
               method = "nnet", linout = FALSE, skip=T, trace = F,
               metric = "Kappa",
               trControl = train.control, tuneGrid = nnet_grid)
plot(cv_nn)
head(cv_nn$results[order(-cv_nn$results$Kappa),],1)
```

size	decay	Accuracy	Kappa	AccuracySD	KappaSD
8	0.1	0.9630856	0.9549798	0.01778169	0.02161567



```
confusionMatrix(as.factor(predict(cv_nn$finalModel,type="class")),olive.train$area,mode
= "everything")
confusionMatrix(as.factor(predict(cv_nn$finalModel,newdata= olive.test, type="class")),
olive.test$area,mode = "everything")
```

Confusion Matrix and Statistics										
Prediction	Reference	Coast.Sardinia	East.Liguria	Inland.Sardinia	North.Apulia	Sicily	South.Apulia	Umbria	West.Liguria	
Calabria	Calabria	39	0	0	0	1	0	0	0	0
Coast.Sardinia	0	24	0	0	0	0	0	0	0	0
East.Liguria	0	0	41	0	0	0	0	0	0	0
Inland.Sardinia	0	1	0	55	0	0	0	0	0	0
North.Apulia	0	0	0	0	22	0	0	0	0	0
Sicily	1	0	0	0	0	30	1	0	0	0
South.Apulia	1	0	0	0	0	2	161	0	0	0
Umbria	0	0	0	0	0	0	0	40	0	0
West.Liguria	0	0	0	0	0	0	0	0	39	0
Overall Statistics										
Accuracy : 0.9847										
95% CI : (0.9688, 0.9938)										
No Information Rate : 0.3537										
P-Value [Acc > NIR] : < 2.2e-16										
Kappa : 0.9813										

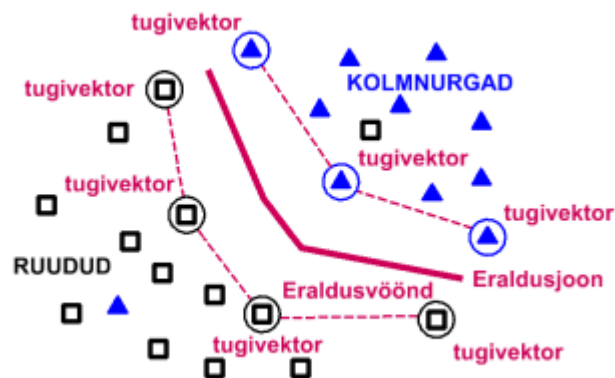
Confusion Matrix and Statistics										
Prediction	Reference	Coast.Sardinia	East.Liguria	Inland.Sardinia	North.Apulia	Sicily	South.Apulia	Umbria	West.Liguria	
Calabria	Calabria	15	0	0	0	0	0	1	0	0
Coast.Sardinia	0	8	0	0	0	0	0	0	0	0
East.Liguria	0	0	6	0	0	0	0	0	0	0
Inland.Sardinia	0	0	0	10	0	0	0	0	0	0
North.Apulia	0	0	0	0	3	0	0	0	0	0
Sicily	0	0	0	0	0	3	3	0	0	0
South.Apulia	0	0	0	0	0	0	40	0	0	0
Umbria	0	0	2	0	0	0	0	11	0	0
West.Liguria	0	0	1	0	0	0	0	0	0	11
Overall Statistics										
Accuracy : 0.9386										
95% CI : (0.8776, 0.975)										
No Information Rate : 0.386										
P-Value [Acc > NIR] : < 2.2e-16										
Kappa : 0.9238										

❑ treenimisandmetel

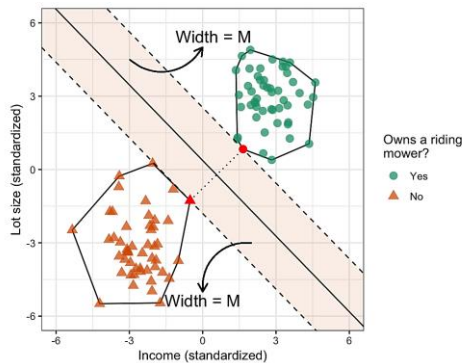
❑ testandmetel

8.4. Tugivektormasinad (*Support Vector Machines, SVM*)

- ❑ Tugivektormasinad kuuluvad suurima eraldusvööga klassifikaatorite (*maximum margin classifiers*) hulka. <https://bookdown.org/mpfoley1973/data-sci/maximal-margin-classifier.html>
- ❑ SVM-meetod otsib tunnuste ruumi jagavat tasapinda, millele lähimate andmepunktide (tugivektorite) omavaheline kaugus on kõige suurem. Klasse eraldava tasapinna asend sõltub vaid tugivektoritest.
- ❑ **Tugivektorid on klasside eralduspinnale kõige lähemal olevad andmepunktid.**
- ❑ Tugivektormasinad on algselt leiutatud nominaalse funktsioontunnuse ja pidevate seletavate tunnuste jaoks. **Nominaalsete argumenttunnuste puhul moodustatakse *dummy variables*. Pidevad argumendid normaliseeritakse.**
- ❑ **Tugivektormasinad on rakendatavad ka pideva muutuja väärtuste prognoosimiseks ehk regressiooniülesandeks.** <https://koalatea.io/r-svm-regression/>

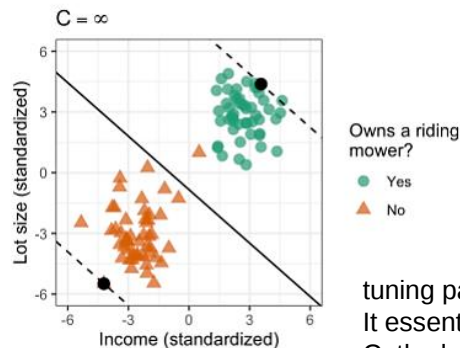
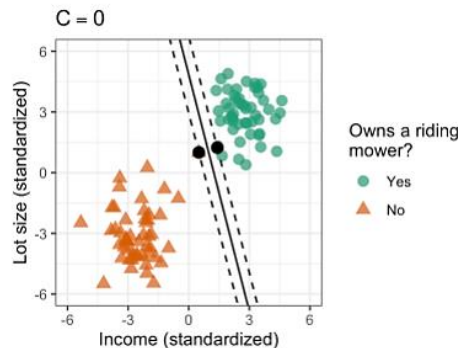


- ❑ **HMC (*hard margin classifiers*):** valida kaks paralleelset hüpertasandit, mis eraldavad kaks andmeklassi, nii et nende vaheline kaugus M oleks võimalikult suur. Nende kahe hüpertasandi piiratud piirkonda nimetatakse „eraldusvööndiks,, (*margin*) ja *maximum-märgin* hüpertasand on nende vahel poolel teel asuv hüpertasapind



$$\begin{aligned} & \text{maximize} && M \\ & \beta_0, \beta_1, \dots, \beta_p \\ & \text{subject to} && \begin{cases} \sum_{j=1}^p \beta_j^2 = 1, \\ y_i (\beta_0 + \beta_1 x_{i1} + \dots + \beta_p x_{ip}) \geq M, \quad i = 1, 2, \dots, n \end{cases} \end{aligned}$$

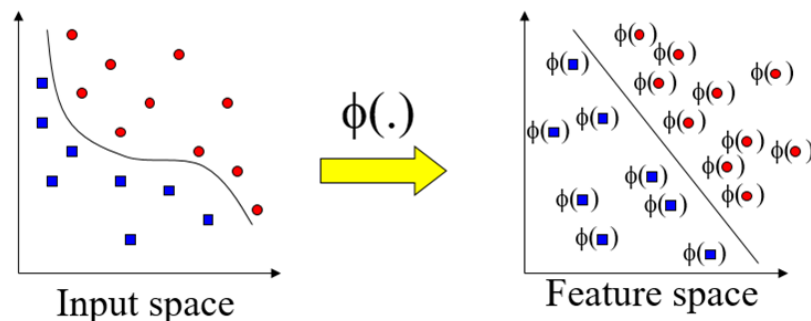
- ❑ **SMC (*soft margin classifiers*):** erineb HMC-st selles, et lubab objekti olemasolu eraldusvööndis, C on SVM meetodi tuunimisparameeter



$$\begin{aligned} & \text{maximize} && M \\ & \beta_0, \beta_1, \dots, \beta_p \\ & \text{subject to} && \begin{cases} \sum_{j=1}^p \beta_j^2 = 1, \\ y_i (\beta_0 + \beta_1 x_{i1} + \dots + \beta_p x_{ip}) \geq M(1 - \xi_i), \quad i = 1, 2, \dots, n \\ \xi_i \geq 0, \\ \sum_{i=1}^n \xi_i \leq C \end{cases} \end{aligned}$$

tuning parameter C , also known as Cost, that determines the possible misclassifications. It essentially imposes a penalty to the model for making an error: the higher the value of C , the less likely it is that the SVM algorithm will misclassify a point

❑ **Kernel trick:** ruumi teisendus ϕ

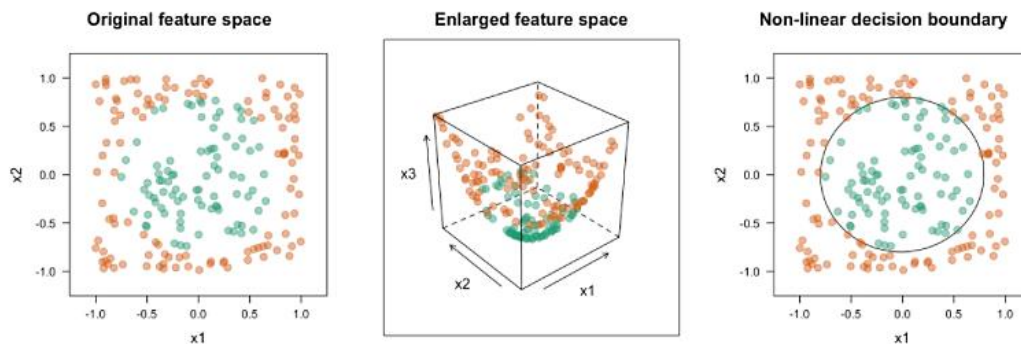


❑ **Kernel function:** $K(x_i, x_j) = \phi(x_i)^T \phi(x_j)$

❑ **Populaarsemad kernel-funktsioonid SVM meetodil**

- d -th degree polynomial: $K(x, x') = \gamma(1 + \langle x, x' \rangle)^d$
- Radial basis function: $K(x, x') = \exp(\gamma \|x - x'\|^2)$
- Hyperbolic tangent: $K(x, x') = \tanh(k_1 \|x - x'\| + k_2)$

❑ **Igale kernel-funktsioonile vastavad oma häälestatavad parameetrid**



**Teisendus $X_3 = X_1^2 + X_2^2$
polünomiaalkerneliga $d=2$**

Kasutame R-i funktsiooni `ksvm` paketist `kernlab`

library(kernlab)

ksvm (kernlab)

R Documentation

Support Vector Machines

Description

Support Vector Machines are an excellent tool for classification, novelty detection, and regression. `ksvm` supports the well known C-svc, nu-svc, (classification) one-class-svc (novelty) eps-svr, nu-svr (regression) formulations along with native multi-class classification formulations and the bound-constraint SVM formulations. `ksvm` also supports class-probabilities output and confidence intervals for regression.

Usage

```
## S4 method for signature 'formula'
ksvm(x, data = NULL, ..., subset, na.action = na.omit, scaled = TRUE)
```

type `ksvm` can be used for classification, for regression, or for novelty detection. Depending on whether `y` is a factor or not, the default setting for `type` is C-svc or eps-svr, respectively, but can be overwritten by setting an explicit value.
Valid options are:

- C-svc C classification
- nu-svc nu classification
- C-bsvc bound-constraint svm classification
- spoc-svc Crammer, Singer native multi-class
- kbb-svc Weston, Watkins native multi-class
- one-svc novelty detection
- eps-svr epsilon regression
- nu-svr nu regression
- eps-bsvr bound-constraint svm regression

kernel the kernel function used in training and predicting. This parameter can be set to any function, of class kernel, which computes the inner product in feature space between two vector arguments (see [kernels](#)). `kernlab` provides the most popular kernel functions which can be used by setting the kernel parameter to the following strings:

- `rbfdot` Radial Basis kernel "Gaussian"
- `polydot` Polynomial kernel
- `vanilladot` Linear kernel
- `tanhdot` Hyperbolic tangent kernel
- `laplacedot` Laplacian kernel
- `besseldot` Bessel kernel
- `anovadot` ANOVA RBF kernel
- `splinedot` Spline kernel
- `stringdot` String kernel

Setting the kernel parameter to "matrix" treats `x` as a kernel matrix calling the `kernelMatrix` interface.

The kernel parameter can also be set to a user defined function of class kernel by passing the function name as an argument.

kpar

the list of hyper-parameters (kernel parameters). This is a list which contains the parameters to be used with the kernel function. For valid parameters for existing kernels are :

- `sigma` inverse kernel width for the Radial Basis kernel function "rbfdot" and the Laplacian kernel "laplacedot".
- `degree`, `scale`, `offset` for the Polynomial kernel "polydot"
- `scale`, `offset` for the Hyperbolic tangent kernel function "tanhdot"
- `sigma`, `order`, `degree` for the Bessel kernel "besseldot".
- `sigma`, `degree` for the ANOVA kernel "anovadot".
- `length`, `lambda`, `normalized` for the "stringdot" kernel where `length` is the length of the strings considered, `lambda` the decay factor and `normalized` a logical parameter determining if the kernel evaluations should be normalized.

Hyper-parameters for user defined kernels can be passed through the `kpar` parameter as well. In the case of a Radial Basis kernel function (Gaussian) `kpar` can also be set to the string "automatic" which uses the heuristics in [sigest](#) to calculate a good `sigma` value for the Gaussian RBF or Laplace kernel, from the data. (default = "automatic").

C

cost of constraints violation (default: 1) this is the 'C'-constant of the regularization term in the Lagrange formulation.

❑ SVM R-is

NÄIDE: kasutame andmestiku olive paketist dslabs

```
library(kernlab)
olive.ksvm = ksvm(area~.,data=olive.train,cross=5)
```

Support Vector Machine object of class "ksvm"

SV type: C-svc (classification)
parameter : cost C = 1

Gaussian Radial Basis kernel function.
Hyperparameter : sigma = 0.185374140325592

Number of Support Vectors : 193

Objective Function Value : -2.3216 -5.604 -3.1965 -7.0842 -20.1885 -13.9204 -3.4147 -3.1398 -2.5556
-10.2563 -2.1744 -2.5396 -3.6441 -1.919 -2.0458 -4.9526 -4.8609 -5.8839 -4.5266 -9.7304 -8.0733 -3.
0435 -3.4035 -4.4822 -2.5006 -2.6668 -13.4514 -4.6628 -3.8983 -2.7443 -16.2974 -3.6477 -3.5127 -3.17
4 -3.4797 -2.9593
Training error : 0.026201
Cross validation error : 0.030578

❑ Tulemus testandmetel

```
confusionMatrix(predict(olive.ksvm,newdata= olive.test, type="response"), olive.test$area,  
mode = "everything")
```

Confusion Matrix and Statistics

	Reference								
Prediction	Calabria	Coast.Sardinia	East.Liguria	Inland.Sardinia	North.Apulia	Sicily	South.Apulia	Umbria	West.Liguria
Calabria	15	0	0	0	0	1	1	0	0
Coast.Sardinia	0	7	0	0	0	0	0	0	0
East.Liguria	0	0	6	0	0	0	0	0	1
Inland.Sardinia	0	1	0	10	0	0	0	0	0
North.Apulia	0	0	0	0	3	0	0	0	0
Sicily	0	0	1	0	0	2	2	0	0
South.Apulia	0	0	0	0	0	0	41	0	0
Umbria	0	0	1	0	0	0	0	11	0
West.Liguria	0	0	1	0	0	0	0	0	10

Overall Statistics

Accuracy : 0.9211
95% CI : (0.8554, 0.9633)
No Information Rate : 0.386
P-Value [Acc > NIR] : < 2.2e-16

Kappa : 0.9016

❑ Parameetri C häälestus

```
olive.ksvm = ksvm(area~.,data=olive.train,cross=5,C=15)
```

Support Vector Machine object of class "ksvm"

SV type: C-svc (classification)
parameter : cost C = 15

Gaussian Radial Basis kernel function.
Hyperparameter : sigma = 0.180937609718721

Number of Support Vectors : 171

Objective Function Value : -2.3158 -6.0281 -3.1983 -10.7657 -76.2714 -43.4095 -3.4136 -3.1087 -2.5594 -27.8989 -2.1693 -2.5343 -3.8073
-1.9082 -2.0362 -5.0306 -5.0193 -6.2555 -4.475 -14.0068 -10.7377 -3.0489 -3.3977 -4.5753 -2.4959 -2.665 -28.4399 -4.8419 -3.9643 -2.70
81 -65.5709 -3.6427 -3.464 -3.1354 -3.433 -2.9725
Training error : 0.002183
Cross validation error : 0.048017

❑ Tulemus testandmetel

```
confusionMatrix(predict(olive.ksvm,newdata= olive.test, type="response"), olive.test$area,  
mode = "everything")
```

Confusion Matrix and Statistics

Prediction	Reference								
	Calabria	Coast.Sardinia	East.Liguria	Inland.Sardinia	North.Apulia	Sicily	South.Apulia	Umbria	West.Liguria
Calabria	15	0	0	0	0	1	1	0	0
Coast.Sardinia	0	8	0	0	0	0	0	0	0
East.Liguria	0	0	7	0	0	0	0	0	1
Inland.Sardinia	0	0	0	10	0	0	0	0	0
North.Apulia	0	0	0	0	3	0	0	0	0
Sicily	0	0	1	0	0	2	2	0	0
South.Apulia	0	0	0	0	0	0	41	0	0
Umbria	0	0	1	0	0	0	0	11	0
West.Liguria	0	0	0	0	0	0	0	0	10

Overall Statistics

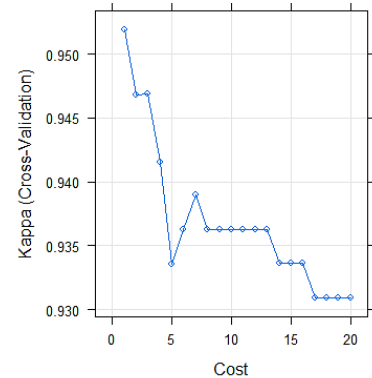
Accuracy : 0.9386
95% CI : (0.8776, 0.975)
No Information Rate : 0.386
P-Value [Acc > NIR] : < 2.2e-16

Kappa : 0.9235

❑ SVM parameetrite tuunimine paketiga caret

```
library(caret)
train.control <- trainControl(method = "cv", number = 5)
RNGkind(sample.kind = "Rounding")
set.seed(123)
svm1 <- train(area~., data=olive.train, method = "svmLinear", trControl =
train.control, tuneGrid = expand.grid(C=0:20), metric = "Kappa")
plot(svm1)
head(svm1$results[order(- svm1$results$Kappa), ], 1)
```

C	Accuracy	Kappa	AccuracySD	KappaSD
1	0.9606987	0.9519006	0.02632914	0.03221578



❑ Tulemus testandmetel

```
confusionMatrix(predict(svm1, newdata= olive.test), olive.test$area, mode = "everything")
```

Confusion Matrix and Statistics

Prediction \ Reference	Calabria	Coast.Sardinia	East.Liguria	Inland.Sardinia	North.Apulia	Sicily	South.Apulia	Umbria	West.Liguria
Calabria	15	0	0	0	0	0	1	0	0
Coast.Sardinia	0	8	0	0	0	0	0	0	0
East.Liguria	0	0	6	0	0	0	0	0	1
Inland.Sardinia	0	0	0	10	0	0	0	0	0
North.Apulia	0	0	0	0	3	0	0	0	0
Sicily	0	0	0	0	0	3	2	0	0
South.Apulia	0	0	0	0	0	0	41	0	0
Umbria	0	0	1	0	0	0	0	11	0
West.Liguria	0	0	2	0	0	0	0	0	10

Overall Statistics

Accuracy : 0.9386
 95% CI : (0.8776, 0.975)
 No Information Rate : 0.386
 P-Value [Acc > NIR] : < 2.2e-16

Kappa : 0.9235

❑ SVM parameetrite häälestus paketiga caret

```
library(caret)
train.control <- trainControl(method = "cv",number = 5 ,search = "random")
RNGkind(sample.kind = "Rounding")
set.seed(123)
svm2 <- train(area~.,data=olive.train, method = "svmRadial", trControl = train.control,
tuneLength = 20,metric = "Kappa")
plot(svm2)
head(svm2$results[order(- svm2$results$Kappa),],1)
```

```
sigma      C  Accuracy   Kappa AccuracySD   KappaSD
0.0980105 11.57506 0.9672698 0.959978 0.01081871 0.01327759
```

❑ Tulemus testandmetel

```
confusionMatrix(predict(svm2,newdata= olive.test), olive.test$area, mode = "everything")
```

Confusion Matrix and Statistics

Prediction	Reference									
	Calabria	Coast.Sardinia	East.Liguria	Inland.Sardinia	North.Apulia	Sicily	South.Apulia	Umbria	West.Liguria	
Calabria	15	0	0	0	0	1	1	0	0	
Coast.Sardinia	0	8	0	0	0	0	0	0	0	
East.Liguria	0	0	8	0	0	0	0	0	1	
Inland.Sardinia	0	0	0	10	0	0	0	0	0	
North.Apulia	0	0	0	0	3	0	0	0	0	
Sicily	0	0	0	0	0	2	2	0	0	
South.Apulia	0	0	0	0	0	0	41	0	0	
Umbria	0	0	1	0	0	0	0	11	0	
West.Liguria	0	0	0	0	0	0	0	0	10	

Overall Statistics

```
Accuracy : 0.9474
 95% CI : (0.889, 0.9804)
No Information Rate : 0.386
P-Value [Acc > NIR] : < 2.2e-16

Kappa : 0.9344
```

❑ SVM parameetrite häälestus paketiiga caret

```
library(caret)
train.control <- trainControl(method = "cv",number = 5 ,search = "random")
RNGkind(sample.kind = "Rounding")
set.seed(123)
svm3 <- train(area~.,data=olive.train, method = "svmPoly", trControl = train.control,
tuneLength = 20,metric = "Kappa")
plot(svm3)
head(svm3$results[order(- svm3$results$Kappa),],1)
```

```
degree      scale      C Accuracy      Kappa AccuracySD      KappaSD
2 0.1930864 0.6236088 0.9650959 0.9572086 0.02374813 0.02925871
```

❑ Tulemus testandmetel

```
confusionMatrix(predict(svm3,newdata= olive.test), olive.test$area, mode = "everything")
```

Confusion Matrix and Statistics

Prediction	Reference									
	Calabria	Coast.Sardinia	East.Liguria	Inland.Sardinia	North.Apulia	Sicily	South.Apulia	Umbria	West.Liguria	
Calabria	15	0	0	0	0	1	1	0	0	
Coast.Sardinia	0	8	0	0	0	0	0	0	0	
East.Liguria	0	0	8	0	0	0	0	0	2	
Inland.Sardinia	0	0	0	10	0	0	0	0	0	
North.Apulia	0	0	0	0	3	0	0	0	0	
Sicily	0	0	0	0	0	2	2	0	0	
South.Apulia	0	0	0	0	0	0	41	0	0	
Umbria	0	0	1	0	0	0	0	11	0	
West.Liguria	0	0	0	0	0	0	0	0	9	

Overall Statistics

```
Accuracy : 0.9386
95% CI : (0.8776, 0.975)
No Information Rate : 0.386
P-Value [Acc > NIR] : < 2.2e-16
```

```
Kappa : 0.9235
```

8.5. Logistiline regressioon

❑ Logistilse regressiooni puhul prognoositakse $\theta(X) = P(Y = 1|X)$.

❑ Klassifitseerimise reegel:

If $\hat{\theta}(X) = P(Y = 1|X) \geq p$ then classify Y as being from class 1, i.e. “Yes” or “Success”.

If $\hat{\theta}(X) = P(Y = 1|X) < p$ then classify Y as being from class 0, i.e. “No” or “Failure”.

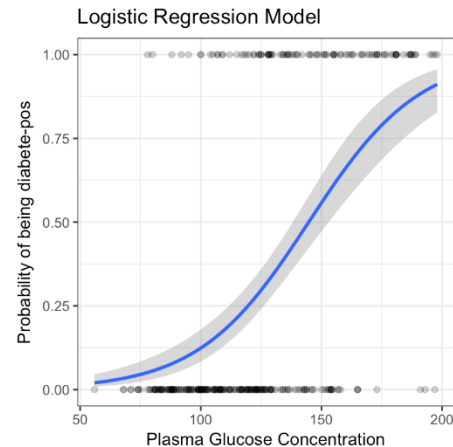
❑ Tõenäosuste prognoosimiseks kasutatakse üldistatud lineaarne mudel (*generalized linear model, GLM*) $\theta(X)$ logit teisendusest

$$L = \ln\left(\frac{\theta(X)}{1 - \theta(X)}\right) = \beta_0 + \beta_1 U_1 + \beta_2 U_2 + \cdots + \beta_{k-1} U_{k-1}$$

❑ Omakorda tõenäosuste prognoosimiseks kasutatakse valemit

$$\hat{\theta}(X) = \frac{e^{\hat{L}}}{1 + e^{\hat{L}}} = \frac{1}{1 + e^{-\hat{L}}}, \quad \text{kus } L = \beta_0 + \beta_1 U_1 + \beta_2 U_2 + \cdots + \beta_{k-1} U_{k-1}$$

❑ Nagu MLR mudeli korral, mudeli argumentide kohal saab proovida polünomiaaltegurid ja tegurite koosmõjusid.



❑ Logistiline regressioon R-is: binaarklassifitseerimine

Binaarklassifitseerimise korral kasutame baaspaketi funktsiooni `glm`

```
glm(mudeli valem, data=andmestik, family="binomial")
```

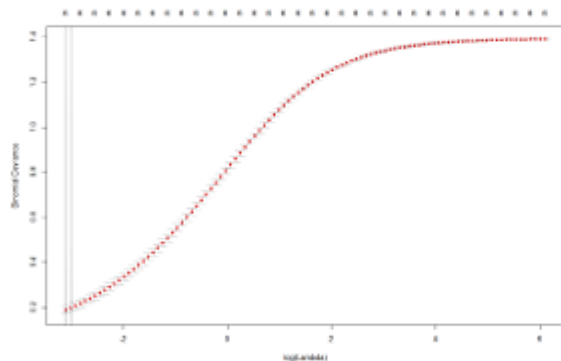
❑ On võimalik rakendada ka regulariseerimist nagu MLR mudeli puhul

Ridge Logistic: $\ln\left(\frac{\theta(x)}{1-\theta(x)}\right) = \beta_o + \sum_{j=1}^k \beta_j u_j + \lambda \sum_{j=1}^k \beta_j^2$

Lasso Logistic: $\ln\left(\frac{\theta(x)}{1-\theta(x)}\right) = \eta_o + \sum_{j=1}^k \beta_j u_j + \lambda \sum_{j=1}^k |\beta_j|$

Elastic Net Logistic: $\ln\left(\frac{\theta(x)}{1-\theta(x)}\right) = \eta_o + \sum_{j=1}^k \beta_j u_j + \lambda_1 \sum_{j=1}^k |\beta_j| + \lambda_2 \sum \beta_j^2$

```
> ridge.cv = cv.glmnet(X, y, alpha=0, family="binomial")
> lasso.cv = cv.glmnet(X, y, alpha=1, family="binomial")
> plot(ridge.cv)
```



```
> ridge.lam = ridge.cv$lambda.min
> ridge.lam
[1] 0.04476108
```

```
> ypred.ridge = predict(forg.ridge, newx=X, s=ridge.lam, type="response")
> ypred.lasso = predict(forg.lasso, newx=X, s=lasso.lam, type="response")
```

```
> table(ypred.ridge>.5, y)
      y
      0  1
FALSE 100  1
TRUE   0  99
```

```
> table(ypred.lasso>.5, y)
      y
      0  1
FALSE 100  0
TRUE   0 100
```

<http://www.sthda.com/english/articles/36-classification-methods-essentials/151-logistic-regression-essentials-in-r/>

https://rpubs.com/jkylearmstrong/logit_w_caret

❑ Logistiline regressioon R-is: mitme klassi probleem

NÄIDE: kasutame andmestiku olive paketist dslabs

Kasutame R-i funktsiooni multinom paketist nnet

```
library(nnet)
olive.logreg = multinom(area ~ ., data = olive.train)
olive.logreg
```

```
Call:
multinom(formula = area ~ ., data = olive.train)
```

Coefficients:

	(Intercept)	palmitic	palmitoleic	stearic	oleic	linoleic	linolenic	arachidic	eicosenoic
Coast.Sardinia	-689.77354	-471.80532	-22.40131	145.09978	335.97442	2559.7291	-261.51813	767.58459	-1031.45350
East.Liguria	-315.74730	-46.22965	134.97086	-50.78624	303.69043	245.6318	-625.36266	697.68685	-2248.84729
Inland.Sardinia	718.42352	-1309.34432	138.87780	-316.05679	-607.34789	496.9249	-647.30516	621.85036	-1200.78590
North.Apulia	-1461.07970	1634.80283	277.16975	-481.87591	4938.86556	1812.4357	249.69744	618.76999	296.83326
Sicily	71.83472	816.20448	304.73555	292.32462	2218.38967	1359.3080	-380.25922	673.05959	228.77351
South.Apulia	1177.60533	1992.33268	1317.94564	631.96835	6083.74275	4853.7885	-698.29453	279.53126	297.71604
Umbria	53.77488	-821.19029	158.27505	-779.75170	25.85475	211.8562	-43.75252	40.14769	-1193.08956
West.Liguria	-212.50558	-878.91881	889.21881	-15.37689	758.98033	1423.1793	-987.83062	-707.77933	66.83135

Residual Deviance: 3.169948

AIC: 147.1699

❑ Tulemus testandmetel

```
confusionMatrix(predict(log.reg,newdata= olive.test), olive.test$area, mode = "everything")
```

Confusion Matrix and Statistics

Prediction \ Reference	Calabria	Coast.Sardinia	East.Liguria	Inland.Sardinia	North.Apulia	Sicily	South.Apulia	Umbria	West.Liguria
Calabria	15	0	0	0	0	0	0	0	0
Coast.Sardinia	0	8	0	0	0	0	0	0	0
East.Liguria	0	0	8	0	0	0	0	0	0
Inland.Sardinia	0	0	0	10	0	0	0	0	1
North.Apulia	0	0	0	0	3	0	0	0	0
Sicily	0	0	0	0	0	3	3	0	0
South.Apulia	0	0	0	0	0	0	41	0	0
Umbria	0	0	0	0	0	0	0	11	0
West.Liguria	0	0	1	0	0	0	0	0	10

Overall Statistics

Accuracy : 0.9561
95% CI : (0.9006, 0.9856)
No Information Rate : 0.386
P-Value [Acc > NIR] : < 2.2e-16

Kappa : 0.9455

❑ Ristvalideerimine paketiiga caret

```
library(caret)
RNGkind(sample.kind = "Rounding")
set.seed(123)
train.control <- trainControl(method = "cv", number = 5)
fit <- train(area~., data=olive.train, method = "multinom", trControl = train.control, trace
= FALSE, tuneLength = 20, metric = "Kappa")
head(fit$results[order(- fit$results$Kappa),], 1)
```

```
      decay Accuracy      Kappa AccuracySD      KappaSD
0.03162278 0.9521194 0.9415574 0.01608578 0.01957019
```

❑ Tulemus testandmetel

```
confusionMatrix(predict(fit, newdata= olive.test), olive.test$area, mode = "everything")
```

Confusion Matrix and Statistics

Prediction \ Reference	Calabria	Coast.Sardinia	East.Liguria	Inland.Sardinia	North.Apulia	Sicily	South.Apulia	Umbria	West.Liguria
Calabria	15	0	0	0	0	0	0	0	0
Coast.Sardinia	0	8	0	0	0	0	0	0	0
East.Liguria	0	0	7	0	0	0	0	0	1
Inland.Sardinia	0	0	0	10	0	0	0	0	0
North.Apulia	0	0	0	0	3	0	0	0	0
Sicily	0	0	0	0	0	3	3	0	0
South.Apulia	0	0	0	0	0	0	41	0	0
Umbria	0	0	2	0	0	0	0	11	0
West.Liguria	0	0	0	0	0	0	0	0	10

Overall Statistics

```
Accuracy : 0.9474
95% CI : (0.889, 0.9804)
No Information Rate : 0.386
P-Value [Acc > NIR] : < 2.2e-16
```

```
Kappa : 0.9346
```