A Gentle Introduction to Machine Learning in Natural Language Processing using R

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http://ufal.mff.cuni.cz/mlnlpr13

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Day 2

- 2.1 A few necessary R functions
- 2.2 Mathematics
- 2.3 Decision tree learning – Theory
- 2.4 Decision tree learning – Practice
- Summary

Block 2.1
A few necessary R functions

We already know from yesterday

- `<-` ... assignment operator
- `+ - * / ()` ... basic arithmetics
  is applicable also to vectors, BUT works with vector elemets!
- `c()` ... combines its arguments to form a vector
- `str()` ... structure of an object
- `length()` ... length of a vector
- `1:15` ... vector containing the given sequence of integers
- `x[5:7]; y[c(1,2,10)]` ... selecting elements from a vector
- `sample(x)` ... random permutation of a vector
- `help(), ?` ... built-in help

Working with external files

- `getwd()` ... to print the working directory
- `setwd()` ... to set your working directory
- `list.files()` ... to list existing files in your working directory

- `read.table()` ... to load data from a .csv file
  - This function is the principal means of reading tabular data into R.

Your objects in the R environment

- `ls()` ... to get the list of your existing objects
- `rm()` ... to delete an object
- `rm(list=ls())` ... to delete all your existing objects

```
> ls()
 [1] "c"          "data"       "g"          "i"          "index"
 [6] "k"          "m"          "n"          "nn"         "prediction"

> rm(list=ls())
> ls()
character(0)
>
```

Exiting R

```
> q()
```

Vector types

Vector elements can be numerical, logical, or string values

You cannot combine different types within a vector

```
> x <- c(3,6,5,3,2,7,5)
> x
[1] 3 6 5 3 2 7 5
> y <- 3:9
> y
[1] 3 4 5 6 7 8 9

> x == y
[1]  TRUE FALSE  TRUE FALSE FALSE FALSE FALSE

> x < y
[1] FALSE FALSE FALSE  TRUE  TRUE  TRUE  TRUE
>
```

Logical vectors

```
> z <- as.logical(c(T,T,F))
> z
[1]  TRUE  TRUE FALSE

> str(z)
 logi [1:3] TRUE TRUE FALSE

> sum(z)
[1] 2
>
```

Note: When you calculate the sum of a logical vector, logical true values are regarded as one, false values as zero.

```
# Does y have any elements bigger than x?
> sum(y > x)
[1] 4
>
```

Factors

In R, "vectors" of categorical values are called factors.

```
examples <- read.table("wsd.development.csv", header=T)
> str(examples$SENSE)
 Factor w/ 6 levels "cord","division",..: 1 1 1 1 1 1 1 1 ...

> levels(examples$SENSE)
[1] "cord"      "division"  "formation" "phone"     "product"
    "text"
>
```

A factor stores both values and possible levels of a categorial variable. Levels are "names" of categorial values.

Examples: creating factors

```
> word.forms <-
 as.factor(c("lines", "line", "line", "line", "lines", "lines"))

> str(word.forms)
 Factor w/ 2 levels "line","lines": 2 1 1 1 2 2

> table(word.forms)
word.forms
 line lines
    3     3
>


> people <- factor( c(1,1,1,0,1,0,0,0,1,0,1,1,1,1),
                    labels=c("male", "female"))
> table(people)
people
  male female
     5      9
>
```

Looking at data in a data frame – `head()`

```
> examples <- read.table("wsd.development.csv", header=T)

> head(examples)
  SENSE A1 A2 A3 A4 A5 A6 A7 A8 A9 A10 A11     A12     A13     A14    A15 A
1  cord  1  0  0  0  0  0  0  0  0   0   0 safety special install inside
2  cord  0  0  0  0  0  0  0  0  0   0   0   wash       a     and
3  cord  0  0  0  0  0  0  0  0  0   0   0   moor   steel      by        V
4  cord  0  0  0  0  0  0  0  0  0   0   0 frozen     the    thaw      a
5  cord  0  0  0  0  0  0  0  0  0   0   0   dock       a   throw      t
6  cord  0  0  0  0  0  0  0  0  0   0   0  green     the    come      a
  A17 A18   A19      A20
1  IN  DT lines     dobj
2   .   X  line conj_and
3   ,  DT lines    agent
4  IN  DT lines     dobj
5  TO  DT  line     dobj
6  IN  DT  line    nsubj
>
```

Looking at data in a data frame – `table()`

```
> str(examples$SENSE)
 Factor w/ 6 levels "cord","division",..: 1 1 1 1 1 1 1 1 ...
> table(examples$SENSE)
     cord    division   formation      phone    product       text
      336         322         296        380       1838        352
```

Looking at data in a data frame – `table()`

```
> str(examples$SENSE)
 Factor w/ 6 levels "cord","division",..: 1 1 1 1 1 1 1 1 ...
> table(examples$SENSE)
     cord    division   formation      phone    product       text
      336         322         296        380       1838        352
```

2-dimensional `table()`

```
> table(examples$SENSE, examples$A19)

            line lined lines
  cord       226     0   110
  division   250     0    72
  formation  189     2   105
  phone      201     0   179
  product   1319     0   519
  text       207     0   145
```

Mathematicians call it **contingency table** (first used by K. Pearson, 1904).

Getting probability of factor levels using `table()`

```
> table(examples$SENSE)/sum(table(examples$SENSE))

      cord   division  formation      phone    product       text
0.09534620 0.09137344 0.08399546 0.10783201 0.52156640 0.09988649
```

Getting probability of factor levels using `table()`

```
> table(examples$SENSE)/sum(table(examples$SENSE))

      cord   division  formation      phone    product       text 
0.09534620 0.09137344 0.08399546 0.10783201 0.52156640 0.09988649 
```

The same using `nrow()`, and with rounded numbers

```
> round(table(examples$SENSE)/nrow(examples), 3)

     cord  division formation     phone   product      text 
    0.095     0.091     0.084     0.108     0.522     0.100 
>
```

Getting subsets from data frames

Getting a subset of observations

```
> examples.only_lines <- subset(examples, A19=='lines')

> str(examples.only_lines)
'data.frame': 1130 obs. of  21 variables:
 $ SENSE: Factor w/ 6 levels "cord","division",..: 1 1 1 1 1 1 1 ...
 $ A1   : int  1 0 0 0 1 1 0 0 0 0 ...
 $ A2   : int  0 0 0 0 0 0 0 0 0 0 ...
 $ A3   : int  0 0 0 0 0 0 0 0 0 0 ...
>
```

Getting subsets from data frames

Getting a subset of observations

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> examples.only_lines <- subset(examples, A19=='lines')

> str(examples.only_lines)
'data.frame': 1130 obs. of  21 variables:
 $ SENSE: Factor w/ 6 levels "cord","division",..: 1 1 1 1 1 1 1 ...
 $ A1   : int  1 0 0 0 1 1 0 0 0 0 ...
 $ A2   : int  0 0 0 0 0 0 0 0 0 0 ...
 $ A3   : int  0 0 0 0 0 0 0 0 0 0 ...
>
```

Getting selected variables only

```
> examples[1:20, c('SENSE', 'A4', 'A19')]
>
```

– Will retrieve first 20 observations and select only the 3 given variables.

Block 2.2
Mathematics for machine learning

Machine learning requires some mathematical knowledge, especially

- statistics
- probability theory
- information theory
- algebra (vector spaces)

Why statistics and probability theory?

Motivation

- In machine learning, models come from data and provide insights for understanding data or making prediction.
- A good model is often a model which not only fits the data but gives good predictions, even if it is not interpretable.

Statistics

- is the science of the collection, organization, and interpretation of data
- uses the probability theory

Two purposes of statistical analysis

Statistics is the study of the collection, organization, analysis, and interpretation of data. It deals with all aspects of this, including the planning of data collection in terms of the design of surveys and experiments.

Description

- describing what was observed in sample data numerically or graphically

Inference

- drawing inferences about the **population represented by the sample data**

Random variables

A **random variable** (or sometimes stochastic variable) is, roughly speaking, a variable whose value results from a measurement/observation on some type of random process. Intuitively, a random variable is a numerical or categorical description of the outcome of a random experiment (or a random event).

Random variables can be classified as either

- **discrete**
  = a random variable that may assume either a finite number of values or an infinite sequence of values (countably infinite)
- **continuous**
  = a variable that may assume any numerical value in an interval or collection of intervals.

Features as random variables

In machine learning theory we take features as random variables.

Target class is a random variable as well.

Data instance is considered as a vector of random values.

Probability theory – basic terms

Formal definitions

- random experiment
- elementary outcomes ω_i
- sample space $\Omega = \bigcup \{\omega_i\}$
- event $A \subseteq \Omega$
- complement of an event $A^c = \Omega \setminus A$
- probability of any event is a non-negative value $\mathrm{P}(A) \geq 0$
- total probability of all elementary outcomes is one

$$\sum_{\omega \in \Omega} \mathrm{P}(\omega) = 1$$

- if two events A, B are *mutually exclusive* (i.e. $A \cap B = \emptyset$), then $\mathrm{P}(A \cup B) = \mathrm{P}(A) + \mathrm{P}(B)$

Basic formulas to calculate probabilities

Generally, probability of an event A is

$$\boxed{\mathrm{P}(A) = \sum_{\omega \in A} \mathrm{P}(\omega)}$$

Probability of a complement event is

$$\boxed{\mathrm{P}(A^c) = 1 - \mathrm{P}(A)}$$

Calculating probability by relative frequency

IF all elementary outcomes have the same probability,
THEN probability of an event is given by the proportion of

$$\boxed{\frac{\text{number of desired outcomes}}{\text{total number of outcomes possible}}}$$

What is $\mathrm{P}(A \text{ or } B)$?

$$\boxed{\mathrm{P}(A \text{ or } B) = \mathrm{P}(A \cup B)}$$

For *mutually exclusive* events:

$$\mathrm{P}(A \text{ or } B) = \mathrm{P}(A) + \mathrm{P}(B)$$

otherwise (generally):

$$\boxed{\mathrm{P}(A \text{ or } B) = \mathrm{P}(A) + \mathrm{P}(B) - \mathrm{P}(A \cap B)}$$

What is $\mathsf{P}(A \text{ and } B)$?

$$\boxed{\mathsf{P}(A,\, B) = \mathsf{P}(A \text{ and } B) = \mathsf{P}(A \cap B)}$$

If events A and B come from two different random processes, $\mathsf{P}(A,\, B)$ is called joint probability.

Two events A and B are independent of each other if the occurrence of one has no influence on the probability of the other.

For independent events: $\mathsf{P}(A \text{ and } B) = \mathsf{P}(A) \cdot \mathsf{P}(B)$.

otherwise (generally):

$$\boxed{\mathsf{P}(A \text{ and } B) = \mathsf{P}(A \,|\, B) \cdot \mathsf{P}(B) = \mathsf{P}(B \,|\, A) \cdot \mathsf{P}(A)}$$

Warming exercises

If you want to make sure that you understand well basic probability computing

Rolling two dice, observing the sum. What is likelier?

a) the sum is even

b) the sum is greater than 8

c) the sum is 5 or 7

What is likelier:

a) rolling at least one six in four throws of a single die, OR

b) rolling at least one double six in 24 throws of a pair of dice?

Definition of conditional probability

Conditional probability of the event A given the event B is

$$\boxed{\mathrm{P}(A \mid B) = \frac{\mathrm{P}(A \cap B)}{\mathrm{P}(B)} = \frac{\mathrm{P}(A, B)}{\mathrm{P}(B)}}$$

Or, in other words,

$$\boxed{\mathrm{P}(A, B) = \mathrm{P}(A \mid B)\mathrm{P}(B)}$$

Statistically independent events

Definition: The random event B is *independent* of the random event A, if the following holds true at the same time:

$$\mathrm{P}(B) = \mathrm{P}(B \mid A), \quad \mathrm{P}(B) = \mathrm{P}(B \mid A^c).$$

An equivalent definition is that B is independent of A if

$$\mathrm{P}(A) \cdot \mathrm{P}(B) = \mathrm{P}(A \cap B).$$

Computing conditional probability

Exercise

The probability that it is Friday and that a student is absent is 3 %. Since there are 5 school days in a week, the probability that it is Friday is 20 %.

What is the probability that a student is absent given that today is Friday?

Solution

Random experiment:

At a random moment we observe the day in working week and the fact if a student is absent.

Events:

- A ... it is Friday
- B ... a student is absent

Probabilities:

- $\mathrm{P}(A, B) = 0.03$
- $\mathrm{P}(A) = 0.2$
- $\mathrm{P}(B \mid A) = \mathrm{P}(A, B)/\mathrm{P}(A) = 0.15$

Correct answer: The probability that a student is absent given that today is Friday is 15 %.

Example – probability of target class

Look at the `wsd.development` data. There are 3524 examples in total. **Each example can be considered as a random observation**, i.e. as an outcome of a random experiment.

Occurrence of a particular value of the target class can be taken as an **event**, similarly for other attributes.

Assume that

- event A stands for `SENSE = 'PRODUCT'`
- event B stands for `A19 = 'lines'`

Then **unconditioned probabilities** $\Pr(A)$ and $\Pr(B)$ are

$$\Pr(A) = \frac{\text{number of observations with } \texttt{SENSE='PRODUCT'}}{\text{number of all observations}} = \frac{1838}{3524} = 52.16\,\%$$

$$\Pr(B) = \frac{\text{number of observations with } \texttt{A19='lines'}}{\text{number of all observations}} = \frac{1130}{3524} = 32.07\,\%$$

Example – conditional probability of target class

To compute conditional probability $\Pr(A \mid B)$ **you need to know joint probability** $\Pr(A, B)$

$$\Pr(A, B) = \frac{\text{number of observations with } \texttt{SENSE='PRODUCT'} \text{ and } \texttt{A19='lines'}}{\text{number of all observations}}$$

$$\Pr(A, B) = \frac{519}{3524} = 14.73\,\%$$

$$\Pr(A \mid B) = \frac{\Pr(A, B)}{\Pr(B)} = \frac{14.73\,\%}{32.07\,\%} = 45.93\,\%$$

Or, equivalently

$$\Pr(A \mid B) = \frac{\text{number of observations with } \texttt{SENSE='PRODUCT'} \text{ and } \texttt{A19='lines'}}{\text{number of observations with } \texttt{A19='lines'}}$$

$$\Pr(A \mid B) = \frac{519}{1130} = 45.93\,\%$$

Bayes rule

Because of the symmetry $\mathrm{P}(A, B) = \mathrm{P}(B, A)$, we have

$$\mathrm{P}(A, B) = \mathrm{P}(A \mid B)\mathrm{P}(B) = \mathrm{P}(B \mid A)\mathrm{P}(A) = \mathrm{P}(B, A)$$

And thus

$$\boxed{\mathrm{P}(B \mid A) = \frac{\mathrm{P}(A \mid B)\mathrm{P}(B)}{\mathrm{P}(A)}}$$

Using Bayes rule

Exercise

One coin in a collection of 65 has two heads. The rest are fair.

If a coin, chosen at random from the lot and then tossed, turns up heads 6 times in a row, what is the probability that it is the two-headed coin?

Solution

Random experiment and considered events

We observe if a chosen coin is two-headed (event A), and if all 6 random tosses result in heads (event B). So, we want to know $\mathrm{P}(A \mid B)$.

Probabilities

- $\mathrm{P}(A \mid B)$ is the probability that we are looking for $= \mathrm{P}(B \mid A)\mathrm{P}(A)/\mathrm{P}(B)$ (application of Bayes rule)
- $\mathrm{P}(B \mid A) = 1$ (two-headed coin cannot give any other result)
- $\mathrm{P}(A) = 1/65$; $\mathrm{P}(A^c) = 64/65$
- $\mathrm{P}(B) = \mathrm{P}(B, A) + \mathrm{P}(B, A^c)$ (two mutually exclusive events) $= \mathrm{P}(A)\mathrm{P}(B \mid A) + \mathrm{P}(A^c)\mathrm{P}(B \mid A^c)$ (by definition)
- $\mathrm{P}(B \mid A^c) = 1/2^6 = 1/64$ (six independent events)
- $\mathrm{P}(B) = 1/65 + (64/65)(1/64) = 2/65$
- $\mathrm{P}(A \mid B) = (1/65)/(2/65) = 50\,\%$ (= the correct answer)

Homework 2.1

1. **Practise using R!**
   Go thoroughly through all examples in our presentation and try it on your own
   – using your computer, your hands, and your brain :–)

2. **Study the Homework 1.1 Solution.**
   Understand it. Especially the conditional probability computing.

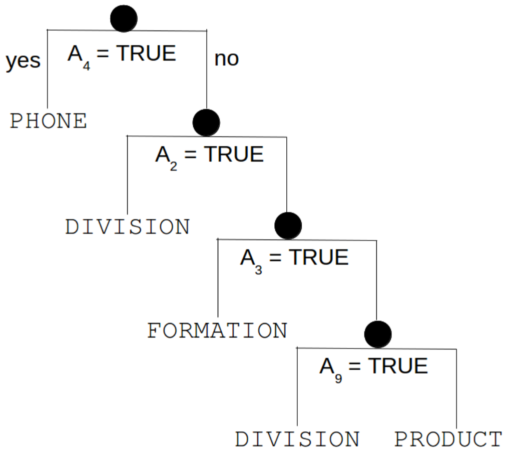
Block 2.3
Decision tree learning – Theory

Machine learning process - five basic steps

1. Formulating the task
2. Getting classified data, i.e. training and test data
3. Learning from training data: **Decision tree learning**
4. Testing the learned knowledge on test data
5. Evaluation

Decision tree for the task of WDS of *line*

Example



Using the decision tree for classification

Example

Assign the correct sense of *line* in the sentence "Draw a line between the points P and Q."

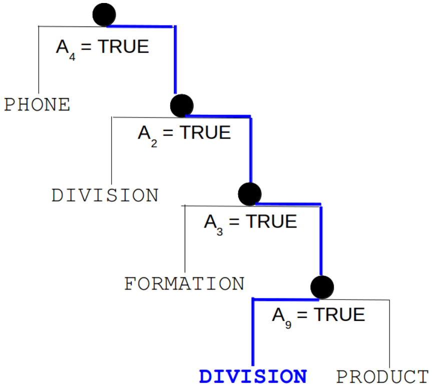
First, get twenty feature values from the sentence

A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}
0	0	0	0	0	0	0	0	1	0	0

A_{12}	A_{13}	A_{14}	A_{15}	A_{16}	A_{17}	A_{18}	A_{19}	A_{20}
a	draw	X	between	DT	IN	DT	line	dobj

Using the decision tree for classification

Second, get the classification of the instance using the decision tree



Using the decision tree for classification

Example

Assign the correct sense of *line* in the sentence "Draw a line that passes through the points P and Q."

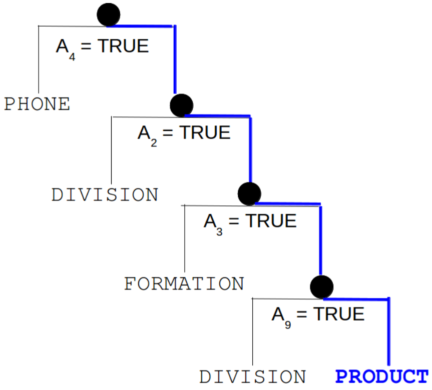
First, get twenty feature values from the sentence

A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}
0	0	0	0	0	0	0	0	0	0	0

A_{12}	A_{13}	A_{14}	A_{15}	A_{16}	A_{17}	A_{18}	A_{19}	A_{20}
a	draw	X	that	DT	WDT	VB	line	dobj

Using the decision tree for classification

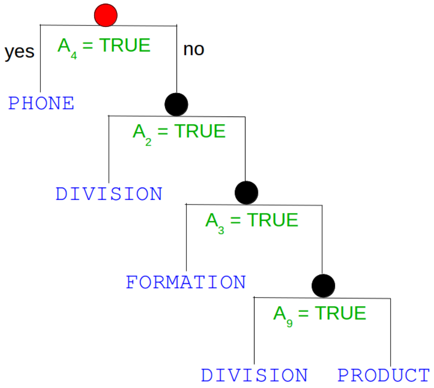
Second, get the classification of the instance using the decision tree



Building a decision tree from training data

Tree structure description

- Nodes
    - Root node
    - Internal nodes
    - Leaf nodes with TARGET CLASS VALUES
- Decisions
    - Binary questions on a single feature, i.e. each internal node has two child nodes

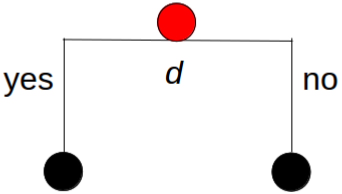


Building a decision tree from training data

Start building a decision tree

- **Step 1** Create a root node.

- **Step 2** Select decision *d* and add two child nodes to an existing node.



Building a decision tree from training data

How to select decision *d*?

Associate the root node with the training set *t*.

Example

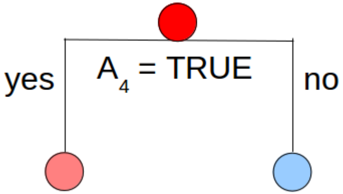
1. Assume decision `if` $\mathrm{A}_4 = \mathit{TRUE}$.
2. Split the training set *t* according to this decision into two subsets – "pink" and "blue".

t

SENSE	...	A4	...
`FORMATION`		TRUE	
`FORMATION`		FALSE	
`PHONE`		TRUE	
`CORD`		TRUE	
`DIVISION`		FALSE	
...	...	...	

Building a decision tree from training data

3. Add two child nodes, "pink" and "blue", to the root. Associate each of them with the corresponding subset t_L, t_R, resp.



t_L

SENSE	...	A4	...
FORMATION		TRUE	
CORD		TRUE	
PHONE		TRUE	
...	...	...	

t_R

SENSE	...	A4	...
FORMATION		FALSE	
DIVISION		FALSE	
...	...	...	

Building a decision tree from training data

How to select decision d?

Working with more than one feature, more than one decision can be formulated.

Which decision is the best?

Focus on a distribution of target class values in associated subsets of training examples.

Building a decision tree from training data

Example

- Assume a set of 120 training examples from the task of WSD.
- Some decision splits them into two sets (1) and (2) with the following target class value distribution:

	CORD	DIVISION	FORMATION	PHONE	PRODUCT	TEXT	
(1)	0	0	0	120	0	0	"pure"
(2)	20	20	20	20	20	20	"impure"

A "pure" training subset contains mostly examples of a single target class value.

Building a decision tree from training data

Which decision is the best?

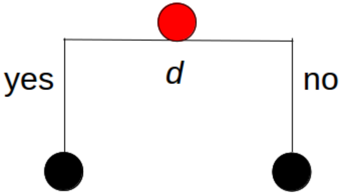
Decision that splits training data into subsets as pure as possible.

Building a decision tree from training data

Decision tree learning algorithm – a very basic formulation

- **Step 1** Create a root node.

- **Step 2** Select decision d and add two child nodes to an existing node.



- **Step 3** Split the training examples associated with the parent node t according to d into t_L and t_R.
- **Step 4** Repeat recursively steps (2) and (3) for both child nodes and their associated training subsets.
- **Step 5** Stop recursion for a node if all associated training examples have the same target class value. Create a leaf node with this value.

Block 2.4
Decision tree learning – Practice

- **Task**
  Assign the correct sense to the target word "line" ("lines", "lined")
- **Objects**
  Sentences containing the target word ("line", "lines", "lined")
- **Target class**
  $\texttt{SENSE} = \{\texttt{CORD}, \texttt{DIVISION}, \texttt{FORMATION}, \texttt{PHONE}, \texttt{PRODUCT}, \texttt{TEXT}\}$
- **Features**
  Binary features $A_1, A_2, ..., A_{11}$

Block 2.4
Decision tree learning – Practice

Subtasks

1. Build a classifier trained on binary feature A4.
2. Build a classifier trained on eleven binary features A1, A2, ..., A11.

Getting classified data

First, get examples into R

```
## Read the file with examples
> examples <- read.table("wsd.development.csv", header=T)

## Review the data
> str(examples)
'data.frame':   3524 obs. of  21 variables:
 $ SENSE: Factor w/ 6 levels "cord","division",..: 1 1 1 1 ...
 $ A1   : logi  TRUE FALSE FALSE FALSE FALSE FALSE ...
 $ A2   : logi  FALSE FALSE FALSE FALSE FALSE FALSE ...
...
 $ A8   : logi  FALSE FALSE FALSE FALSE FALSE FALSE ...
...
 $ A12  : Factor w/ 920 levels ".",",","``","-",..: 667 862 512
...
 $ A19  : Factor w/ 3 levels "line","lined",..: 3 1 3 3 1 ...
 $ A20  : Factor w/ 80 levels "advcl","agent",..: 12 6 2 12 ...
```

Splitting classified data into training and test data

Second, split them into the training and test sets

```
## Get the number of input examples
> num.examples <- nrow(examples)

## Set the number of training examples = 90% of examples
> num.train <- round(0.9 * num.examples)

## Set the number of test examples = 10% of examples
> num.test <- num.examples - num.train

## Check the numbers
> num.examples
[1] 3524
> num.train
[1] 3172
> num.test
[1] 352
```

Splitting classified data into training and test data

```
## Randomly split examples into training and test data
## Use set.seed() to be able to reconstruct the experiment
## with the SAME training and test sets

> sample(10)
 [1]  8  7 10  3  1  4  2  6  5  9
> sample(10)
 [1]  9  8  5 10  7  6  3  2  4  1
> sample(10)
 [1]  7  4  6 10  1  9  5  2  3  8
> sample(10)
 [1]  9 10  4  5  1  6  8  2  3  7
> set.seed(123)
> sample(10)
 [1]  3  8  4  7  6  1 10  9  2  5
> set.seed(123)
> sample(10)
 [1]  3  8  4  7  6  1 10  9  2  5
```

Splitting classified data into training and test data

```
## Randomly split examples into training and test data

## Use set.seed() to be able to reconstruct the experiment
## with the SAME training and test sets

> set.seed(123)
> s <- sample(num.examples)
```

Splitting classified data into training and test data

s	...	...	...	...	...

```
### Get the training set
## First, generate indices of training examples ("blue" ones)
> indices.train <- s[1:num.train]

## Second, get the training examples
> train <- examples[indices.train,]

### Get the test set (see "pink" indeces)
> indices.test <- s[(num.train+1):num.examples]
> test <- examples[indices.test,]

## Check the results
> str(train); str(test)
```

Learning from training data

Load the package `rpart`

```
## Use the "rpart" package
## ! Run install.packages("rpart"), ***if not installed***.

# Check if the package is installed
> library()

## Load the package
> library(rpart)

# to get help info
> help(rpart)
```

Learning from training data

Subtask 1 Build a dependency tree classifier using only one feature, namely A4

Train decision tree model M1

```
## Run the learning process using function "rpart"
M1 <- rpart(SENSE ~ A4, data=train, method="class")
>
```

Learning from training data

`rpart` documentation

```
rpart(formula, data= , method= , ...  )
```

- `formula` is `y` $\sim$ `model` where
  - `y` is a target class
  - $\sim$ stands for 'is modeled as'
  - `model` is a combination of features (model by statisticians).
- `data` specifies the training set,
- `method="class"` for classification,

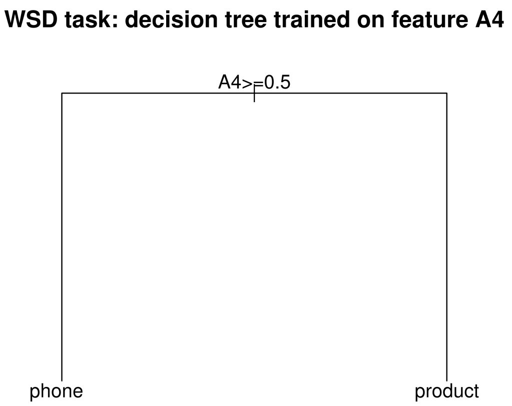
Learning from training data

Display the trained tree

```
## Draw tree on screen
> plot(M1); text(M1)

## Draw tree to a file
> png("../img/dtM1.png", width=4.8, height=4.8,units="in",
                              res=600, bg="transparent")
> plot(M1, margin=0.05)
> text(M1)
> title(main = "Decision tree trained on feature A4")
> dev.off()
```

Trained decision tree



Trained decision tree

### Display the model M1

```
## Display the model
> M1
n= 3172

node), split, n, loss, yval, (yprob)
      * denotes terminal node

1) root 3172 1526 product (0.096 0.093 0.084 0.11 0.52 0.099)
  2) A4>=0.5 150    8 phone (0 0 0 0.95 0 0.053) *
  3) A4< 0.5 3022 1376 product (0.1 0.097 0.089 0.068 0.54 0.1) *
```

Trained decision tree

How to read the model

```
n= 3172

node), split, n, loss, yval, (yprob)
      * denotes terminal node
```

`n=3172`	The number of training examples.
`node)`	A node number.
`split`	Decision.
`n`	The number of training examples associated to the given node.
`loss`	The number of examples incorrectly classified with the majority class value yval.
`yval`	The default classification for the node by the majority class value.
`yprob`	The distribution of class values at the associated training subset.

Testing trained decision tree on test data

Prediction on test data

```
### Test the trained model M1 on test examples
## Use the function predict()

> ?predict()
predict         package:stats      R Documentation

Model Predictions

Description:

     ‘predict’ is a generic function for predictions
     the results of various model  ...

> P11 <- predict(M1, test, type="class")
```

Evaluation

Comparing the predicted values with the true senses

```
> str(P11)
 Factor w/ 6 levels "cord","division",..: 5 5 5 5 5 5 5 5 5 5 ..
> str(test$SENSE)
 Factor w/ 6 levels "cord","division",..: 1 5 5 5 5 6 5 2 6 6 ..
> print(table(test$SENSE, P11))
         P11
          cord division formation phone product text
  cord         0        0         0     0      33    0
  division     0        0         0     0      28    0
  formation    0        0         0     0      28    0
  phone        0        0         0    12      21    0
  product      0        0         0     0     192    0
  text         0        0         0     1      37    0
```

57.95 % of test examples are predicted correctly

```
> round(100*sum(P11 == test$SENSE)/num.test,2)
[1] 57.95
```

Testing trained decision tree on train data

Prediction on training data

```
### Test the trained model M1 on training examples.

> P12 <- predict(M1, train, type="class")
>
```

Evaluation

Comparing the predicted values with the true senses

```
> print(table(train$SENSE, P12))
           P12
            cord division formation phone product text
  cord         0        0         0     0     303    0
  division     0        0         0     0     294    0
  formation    0        0         0     0     268    0
  phone        0        0         0   142     205    0
  product      0        0         0     0    1646    0
  text         0        0         0     8     306    0
```

56.37 % of training examples are predicted correctly

```
> message(round(100*sum(P12 == train$SENSE)/num.train, 2), "%")
[1] 56.37
```

Learning from training data

Subtask 2 Build a dependency tree classifier using all binary features, namely A1, ..., A11

Train decision tree model M2

```
## Run the learning process using function "rpart"
M2 <- rpart(SENSE ~ A1+A2+A3+A4+A5+A6+A7+A8+A9+A10+A11,
                                  data=train, method="class")
>
```

Learning from training data

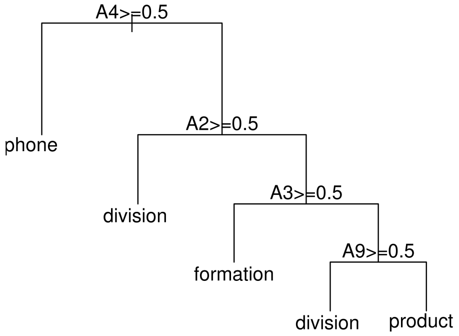
Display the trained tree

```
## Draw tree on screen
> plot(M2); text(M2)

## Draw tree to a file
> png("../img/dtM2.png", width=4.8, height=4.8,units="in",
                              res=600, bg="transparent")
> plot(M2, margin=0.05)
> text(M2)
> title(main = "Decision tree trained on all binary features")
> dev.off()
```

Trained decision tree

WSD task: decision tree trained on A1,...,A11



Trained decision tree

Display the trained model M2

```
> ## Display the model
> M2
n= 3172

node), split, n, loss, yval, (yprob)
      * denotes terminal node

 1) root 3172 1526 product (0.096 0.093 0.084 0.11 0.52 0.099)
   2) A4>=0.5 150    8 phone (0 0 0 0.95 0 0.053) *
   3) A4< 0.5 3022 1376 product (0.1 0.097 0.089 0.068 0.54 0.1)
     6) A2>=0.5 88    0 division (0 1 0 0 0 0) *
     7) A2< 0.5 2934 1288 product (0.1 0.07 0.091 0.07 0.56 0.1)
      14) A3>=0.5 79    5 formation (0.063 0 0.94 0 0 0) *
      15) A3< 0.5 2855 1209 product (0.1 0.072 0.068 ...)
        30) A9>=0.5 66    3 division (0.015 0.95 0 ...) *
        31) A9< 0.5 2789 1144 product (0.11 0.051 0.07 ...) *
```

Testing trained decision tree on test data

Prediction on test data

```
### Test the trained model on test examples.

> P21 <- predict(M2, test, type="class")
```

Evaluation

Comparing the predicted values with the true senses

```
> print(table(test$SENSE, P21))
           P21
              cord division formation phone product text
  cord           0        0         0     0      33    0
  division       0       15         0     0      13    0
  formation      0        0         6     0      22    0
  phone          0        0         0    12      21    0
  product        0        1         0     0     191    0
  text           0        0         1     1      36    0
>
```

63.64 % of test examples are predicted correctly

```
> round(100*sum(P21 == test$SENSE)/num.test,2)
[1] 63.64
```

Testing trained decision tree on trainig data

Prediction on training data

```
### Test the trained model on training examples.

> P22 <- predict(M2, train, type="class")
```

Evaluation

Comparing the predicted values with the true senses

```
> print(table(train$SENSE, P22))
            P22
              cord division formation phone product text
  cord           0        1         5     0     297    0
  division       0      151         0     0     143    0
  formation      0        0        74     0     194    0
  phone          0        1         0   142     204    0
  product        0        1         0     0    1645    0
  text           0        0         0     8     306    0

>
```

63.43 % of training examples are predicted correctly

```
> round(100*sum(P22 == train$SENSE)/num.train,2)
[1] 63.64
```

Run the script in R

The R script `DT-WSD.R`

- builds the classifier M1 using the feature A4, classifies training and test data using M1 and computes the performance of M1.
- builds the classifier M2 using binary features $\mathrm{A}_1, ..., \mathrm{A}_{11}$, classifies training and test data using M2 and computes the performance of M2.

Download the script from the course page and run in R

```
> source("DT-WSD.R")
>
```

Homework 2.2

Generate the same training and test sets as we did in practice above. Assume the following feature groups:

1. $\mathrm{A}_2, \mathrm{A}_3, \mathrm{A}_4, \mathrm{A}_9$
2. $\mathrm{A}_1, \mathrm{A}_6, \mathrm{A}_7$
3. $\mathrm{A}_1, \mathrm{A}_{11}$

For each of them, build a decision tree classifier and list its percentage of correctly classified training and test examples.

Summary of Day 2

Theory

- Decision tree structure: nodes, decisions
- A basic formulation of decision tree learning algorithm

Summary of Day 2

Practice

We built two decision tree classifiers (M1, M2) on two different sets of features and we tested them on both training and test sets.

features used	trained model	data set	performance
A_4	M1		
		train	57.37
		test	57.95
A_1, ..., A_{11}	M2		
		train	63.43
		test	63.64

!!! You know how to build a decision tree classifier from training examples in R. Performance is not important right now. !!!