Datenanalyse

Automotive Communications Financial Services Government Insurance Life Science & Healthcare Travel & Logistics Utilities Automotive Communications Financial Services Government Insurance Life Science & Healthcare Travel & Logistics Utilities Automotive Communications Financial Services Government Insurance Life Science & Healthcare Travel & Logistics Utilities Automotive Communications Financial Services Government Insurance Life Science & Healthcare Travel & Logistics Utilities Automotive Communications Financial Services Government Insurance Life Science & Healthcare Travel & Logistics Utilities Automotive Communications Financial Services Government Insurance Life Science & Healthcare Travel & Logistics Utilities Automotive Communications Financial Services Government Insurance Life Science & Healthcare Travel & Logistics Utilities Automotive Communications Financial Services Government Insurance Life Science & Healthcare Travel & Logistics Utilities Automotive Communications Financial Services Government Insurance Life Science & Healthcare Travel & Logistics Utilities Automotive Communications Financial Services Government Insurance Life Science & Healthcare Travel & Logistics Utilities Automotive Communications Financial Services Government Insurance Life Science & Healthcare Travel & Logistics Utilities Automotive Communications Financial Services Government Insurance Life Science & Healthcare Travel & Logistics Utilities Automotive Communications Financial Services Insurance Life Science & Healthcare Travel & Logistics Utilities Automotive Communications Financial Services Government Insurance Life Science & Healthcare Travel & Logistics Utilities Automotive Communications Financial Services Government Insurance Life Science & Healthcare Travel & Logistics Utilities Automotive Communications Financial Services Government Insurance Life Science & Healthcare Travel & Logistics Utilities Automotive Communications Financial Services Government Insurance Life Science & Healthcare Travel & Logistics Utilities Automotive Communications Financial Services Government Insurance Life Science & Healthcare Travel & Logistics Utilities Automotive Communications Financial Services Government Insurance Life Science & Healthcare Travel & Logistics Utilities Automotive Communications Financial Services Government Insurance Life Science & Healthcare Travel & Logistics Utilities Automotive Communications Financial Services Government Insurance Life Science & Healthcare Travel & Logistics Utilities Automotive Communications Financial Services Government Insurance Life Science & Healthcare Travel & Logistics Utilities Automotive Communications Financial Services Government Insurance Life Science & Healthcare Travel & Logistics Utilities Automotive Communications Financial Services Government Insurance Life Science & Healthcare Travel & Logistics Automotive Utilities

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Datenanalyse nach Drew Conway



ML / AI

Informatik

Statistik / Mathematik

Datenanalyse

IT-Beratung

Wissenschaft

Fachwissen



Explorative Datenanalyse

Daten



```
adult.data

1 39, State-gov, 77516, Bachelors, 13, Never-married, Adm-clerical, Not-in-family, White, Male, 2 50, Self-emp-not-inc, 83311, Bachelors, 13, Married-civ-spouse, Exec-managerial, Husband, White 3 38, Private, 215646, HS-grad, 9, Divorced, Handlers-cleaners, Not-in-family, White, Male, 0, 0, 4 53, Private, 234721, 11th, 7, Married-civ-spouse, Handlers-cleaners, Husband, Black, Male, 0, 0 28, Private, 338409, Bachelors, 13, Married-civ-spouse, Prof-specialty, Wife, Black, Female, 0, 6 37, Private, 284582, Masters, 14, Married-civ-spouse, Exec-managerial, Wife, White, Female, 0, 7 49, Private, 160187, 9th, 5, Married-spouse-absent, Other-service, Not-in-family, Black, Female, 8 52, Self-emp-not-inc, 209642, HS-grad, 9, Married-civ-spouse, Exec-managerial, Husband, White, 9 31, Private, 45781, Masters, 14, Never-married, Prof-specialty, Not-in-family, White, Female, 1 42, Private, 159449, Bachelors, 13, Married-civ-spouse, Exec-managerial, Husband, White, Male, 37, Private, 280464, Some-college, 10, Married-civ-spouse, Exec-managerial, Husband, Black, Mal 30, State-gov, 141297, Bachelors, 13, Married-civ-spouse, Prof-specialty, Husband, Asian-Pac-Is
```

- Erste 12 Instanzen mit
- 15 Variablen

Daten

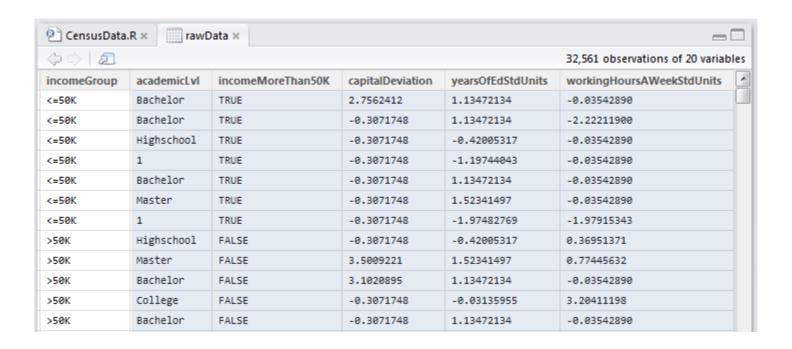


② Ce	nsusD	ata.R × rawDat	a ×						
$\Leftrightarrow \triangleleft$	2	3.					32,561 obse	ervations of 15 variabl	les
	id	employerKind	fnlwgt	degree	yearsOfEd	maritalStatus	occupation	relationshipRole	A
1	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	
2	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	
3	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	
4	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	
5	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	
6	37	Private	284582	Masters	14	Married-civ-spouse	Exec-managerial	Wife	
7	49	Private	160187	9th	5	Married-spouse-absent	Other-service	Not-in-family	
8	52	Self-emp-not-inc	209642	HS-grad	9	Married-civ-spouse	Exec-managerial	Husband	
9	31	Private	45781	Masters	14	Never-married	Prof-specialty	Not-in-family	
10	42	Private	159449	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	
11	37	Private	280464	Some-college	10	Married-civ-spouse	Exec-managerial	Husband	
12	30	State-gov	141297	Bachelors	13	Married-civ-spouse	Prof-specialty	Husband	

- Erste 12 Instanzen als Data-Frame mit
- 8 von 15 Variablen

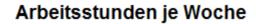
Daten

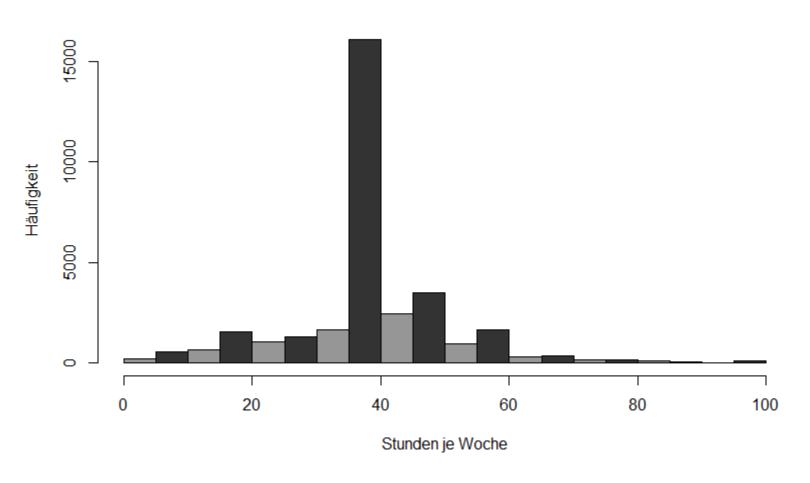




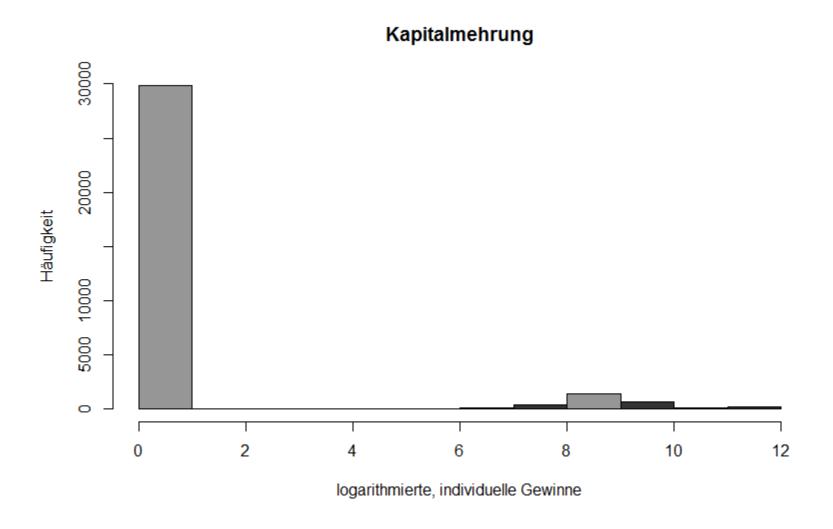
5 Sekundärvariablen



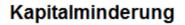


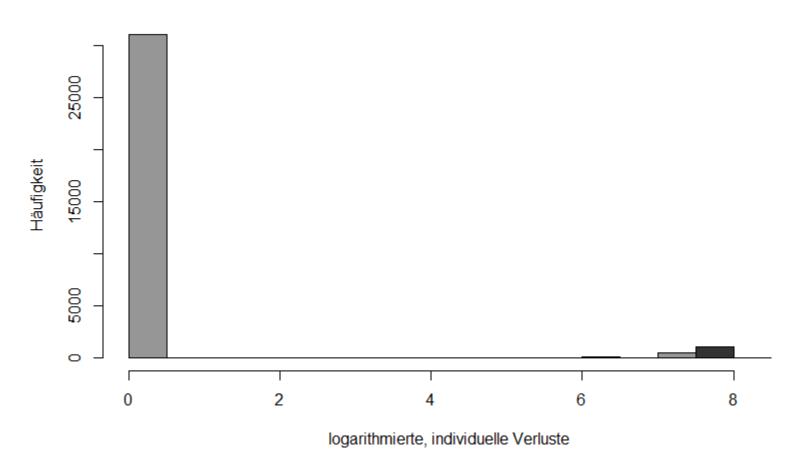




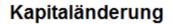


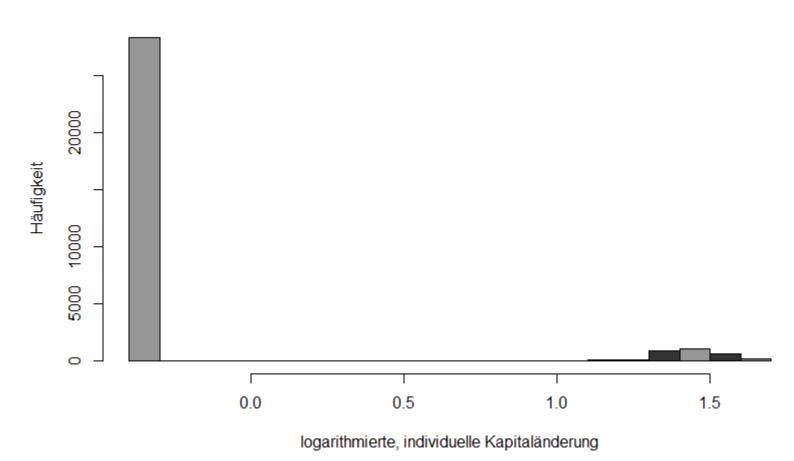




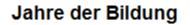


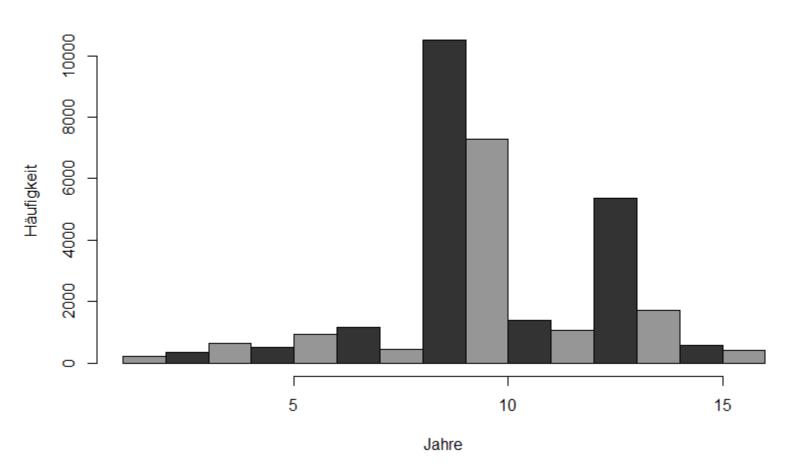






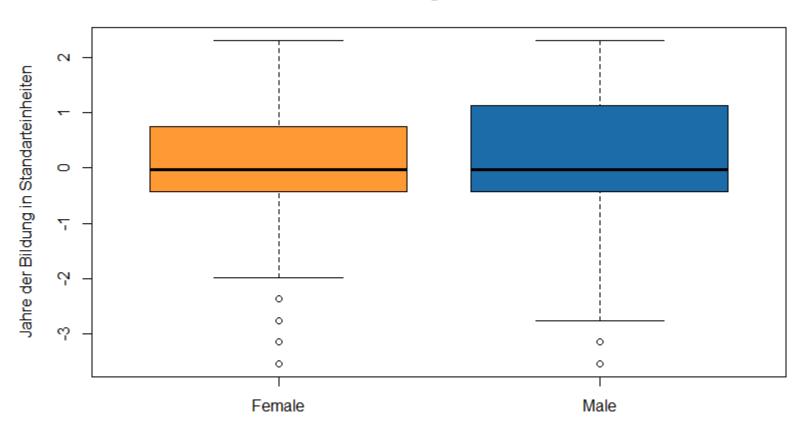






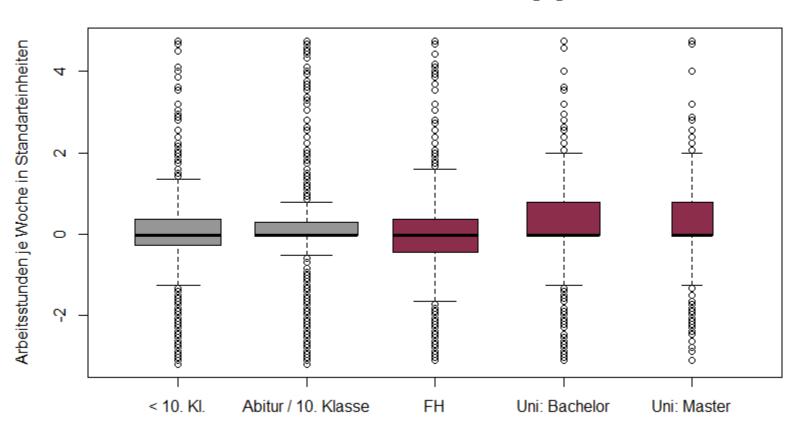


Jahre der Bildung nach Geschlecht



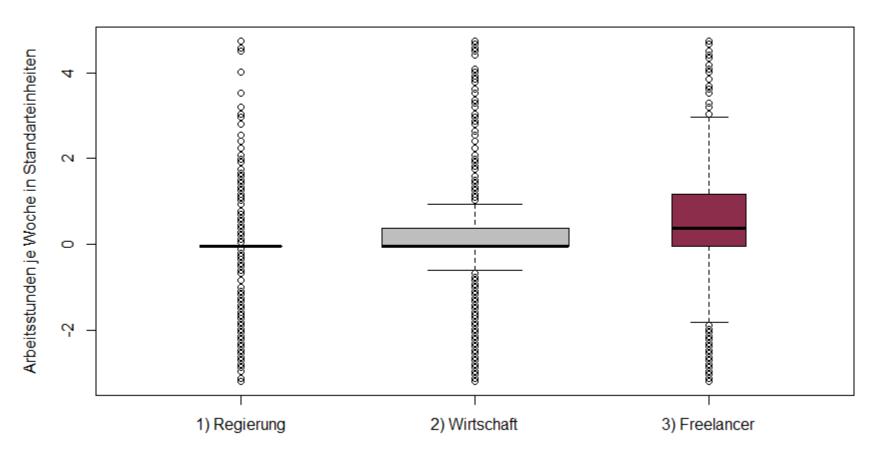


Arbeitsstunden nach Bildungsgrad



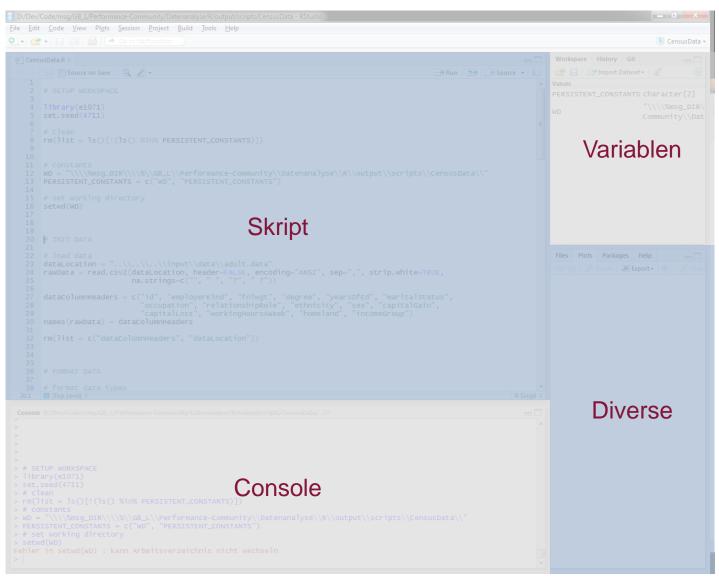


Arbeitsstunden nach Anstellungsart



RStudio



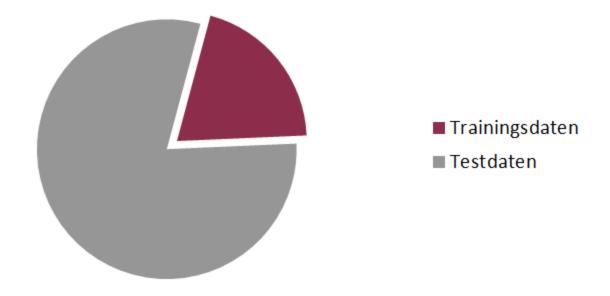


15



Klassifikation



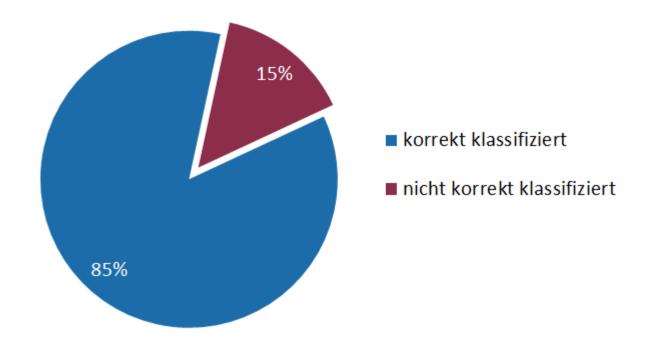




Klassifikation: Sensitivität & Spezifität

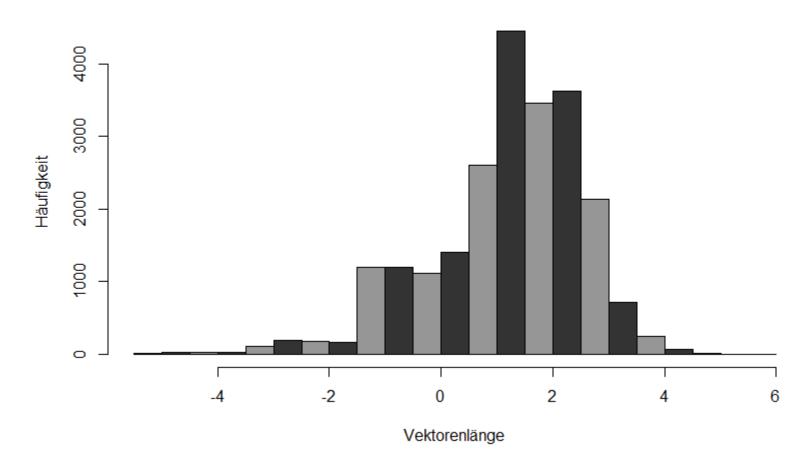
	tatsächlich nicht hohes	tatsächlich hohes
	Einkommen	Einkommen
geschätzt nicht hohes Einkommen	13%	5%
geschätzt hohes Einkommen	10%	72%







Länge der Entscheidungsvektoren





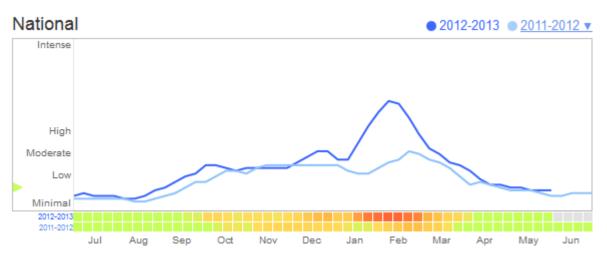
















Stanford University





Prof. Sebastian Thrun mit autonom fahrenden VW Touareg "Stanley"

Resourcen







Training Dataset for R Beginners

Last updated 3 minutes ago



AddHealth-Data-Analysis

The analysis of biases and influencer in attendance of religious services

Last updated a month ago

github.com/danielschulz/LearningR

Datenquellen





UCI Machine Learning Repository archive.ics.uci.edu/ml

Datenquellen



kaggle

kaggle.com

Datenquellen

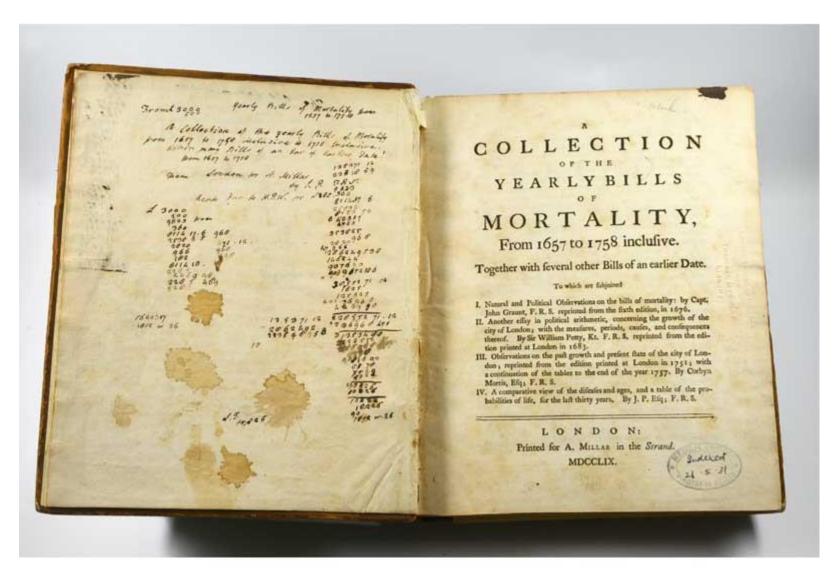




data.gov

Bills of Mortality





Bills of Mortality



The Years of our Level	udati	16481	1610	1640	1851			T 1654										1632	1633	1634	163	1630	1630	1634	1648	1651	1655 1657 16, 1658 165	o Year
cire and Still-born and Fever airs and Suddenly	335 916 1160 68	119	317 889	351 898	389 780	381 834	384 864 282	433 974	483 743 689	419 892 875	463 869 999	467	411 909 303	544 1095 1148	499	439 713 1091	410	445	500	475 623 1279	50 794 1621	323	1793 2475 4418	2005	1341 3116 1865	1587 1452 1903	1812 124 3680 237 4363 401 445 27	7 1575
of district of the state of the	4 3 155 3 1	176 6	10	189	833 ##	6 4 763 5 2	5	386 7 1 37	4 7 168 10	36h	7 33	+	6	251	3	5 435 10	352 7	13 4 345 5	1	512 512 3	341	330	54 16 15 85 85	4	11 412 24 2 105	4	14 1 19 1 16:159 26 1: 3	125
or Sore-mouth and Thruth strd sexant Infants and Wind and Cough	66 161 1369 103	28 106 1254	54 116 1065	117	68	51 113 1280	158	72	177	81 201 393	15 236 162	225	73 215 858	68 104	150	4 157 1378 1378 1378	4	171	132	143	163	80.05	15 590 2778 105 174	608 453 4 87 107	678 4 841 60	769 910 559 77	161 133 859 490 758 4515 497 247 140 43	1389
ny con and Cough neven and Cough notes no and Tympany total	185 47	491	530 1 421	493 508	350 569 444 48	653	606	865 2 828 704 20	702	037	807	841	742 646	4	1827	87	18	5	754 221 0 1 166 37	5	0801 418 0 2 315 31	477 709 0 2 389 41	498 1 648 1 139	734 1	10	6501	9 1 11 47	9073 2 18 9623 827
chive drinking cured ted in a Bath ng-Sicknell and fmall Fox	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	17	3	45	24	12 3 1279	19	21	19 4	22	30	15	7	19	19 3 72 18	13	7 58 20	6	13	13 X 4 8	11 0 151	13 8 117 14 22	02 27 701 1 85	52 24 40 s	19	14	79 51 8 9 161 2781 2, 29	243
od dead in the Streets oft Fox hted of of ged, and coade-away themfolye	18 4 9 11		15 12 16 11	18 97	-3	136	2	20 6 17 9	29 = 8 10 14	13 17 13 16	23 8 10 24	53 13 12 18	51 14 13 11	31 2 4 36	17 18 18 8	12	12	11 4 11 15	7	8 17 5 17 3	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	3 b 20 7 a	14 71 75 0	10 10 0	80 9 15 48 48	5 25 59 47	31 25 40 47 7- 3- 17 46	193 21 114 279 223 011

Wöchentliche Todesstatistiken



Übersicht: Code-Sektionen Schritt für Schritt



```
1
2  # SETUP WORKSPACE
3
4 library(e1071)
5 set.seed(4711)
6
7  # clean
8 rm(list = ls()[!(ls() %in% PERSISTENT_CONSTANTS)])
9
```

Workspace einrichten



```
19
20 # INIT DATA
21
22 # load data
23 dataLocation = "..\\..\\input\\data\\adult.data"
rawData = read.csv2(dataLocation, header=FALSE, encoding="ANSI", sep=",", strip.white=TRUE, na.strings=c("", " ", "?", " ?"))
26
   27
28
                      "capitalLoss", "workingHoursAWeek", "homeland", "incomeGroup")
29
  names(rawData) = dataColumnHeaders
30
31
32 rm(list = c("dataColumnHeaders", "dataLocation"))
33
```

Daten laden, Headernamen zuweisen



```
35
36 # FORMAT DATA
  # format data types
39 rawData$id = as.numeric(rawData$id)
   rawData$employerKind = as.factor(rawData$employerKind)
   rawData$degree = as.factor(rawData$degree)
42
   # assign secondary variable academic level
43
  rawData$academicLvl = "none"
   rawData$academicLvl = as.factor(rawData$academicLvl)
46
   rawData$academicLvl = ifelse ("Doctorate" == rawData$degree || "Prof-school" == rawData$degree,
47
                                  "PhD", rawData$academicLv1)
48
49 rawData$academicLvl = ifelse ("Masters" == rawData$degree, "Master", rawData$academicLvl)
50 rawData$academicLvl = ifelse ("Bachelors" == rawData$degree, "Bachelor", rawData$academicLvl)
51 rawData$academicLvl = ifelse ("Some-college" == rawData$degree, "College", rawData$academicLvl)
52 rawData$academicLvl = ifelse ("HS-grad" == rawData$degree, "Highschool", rawData$academicLvl)
53
```

- Daten-Typen zuweisen
- Sekundärvariablen einfügen



```
54
55 # assign secondary variable income to be more than 50000 USD / yr
56 rawData\incomeMoreThan50K = FALSE
57 rawData$incomeMoreThan50K = as.logical(rawData$incomeMoreThan50K)
  rawData$incomeMoreThan50K = ifelse ("<=50K" == rawData$incomeGroup, TRUE, rawData$incomeMoreThan50K)
59
60
   # assign secondary variable capitial deviation / difference in standard units
61
   rawData$capitalDeviation = rawData$capitalGain - rawData$capitalLoss
   rawData$capitalDeviation = scale(log(rawData$capitalDeviation + 1))
64
65
   # assign secondary variable working hours / wk in standard units
   rawData$yearsOfEdStdUnits = scale(rawData$yearsOfEd)
   rawData$workingHoursAWeekStdUnits = scale(rawData$workingHoursAWeek)
67
68
  # format data types
70 rawData$marita|Status = as.factor(rawData$marita|Status)
71 rawData$occupation = as.factor(rawData$occupation)
72 rawData$relationshipRole = as.factor(rawData$relationshipRole)
73 rawDataSethnicity = as.factor(rawDataSethnicity)
74 rawData$sex = as.factor(rawData$sex)
75  rawData$homeland = as.factor(rawData$homeland)
76 rawData$capitalDeviation = as.numeric(rawData$capitalDeviation)
   rawData$workingHoursAWeekStdUnits = as.numeric(rawData$workingHoursAWeekStdUnits)
78 rawData$yearsOfEdStdUnits = as.numeric(rawData$yearsOfEdStdUnits)
79
```

- Daten-Typen zuweisen
- Sekundärvariablen einfügen



Nicht benötigte Spalten entfernen



```
91
 92 # SAMPLE TRAINING AND TEST DATA
 93 rawData$clazz = sample(1:5, dim(rawData)[1], replace=TRUE)
 94 rawData$clazz = as.factor(rawData$clazz)
 95
 96 data = rawData
 97 data = na.omit(data) # drop missing value instances
 98
 99 train = subset(data, 1 == data$clazz)
100 test = subset(data, 1 != data$clazz)
101
102 dropColumns = c("clazz")
103 train = train[,!(names(train) %in% dropColumns)]
104 test = test[,!(names(test) %in% dropColumns)]
105 data = data[,!(names(data) %in% dropColumns)]
106
107 # remove dropping column from workspace value list
108 rm(list = c("dropColumns", "rawData"))
109
```

Trainings- und Testdaten erzeugen



```
111
112 # TRAIN CLASSIFICATION MODEL SUPPORT VECTOR MACHINES AND EVALUATE ACCURANCY
113
    svm = svm(train$incomeMoreThan50K ~ ., train, type="C-classification", probability=TRUE,
114
               gamma=0.0001, cost=100000)
     pr = predict(svm, test, probability=TRUE)
115
    # plot(formula=train$capitalDeviation ~ train$workingHoursAWeekStdUnits, data=train)
116
     # plot(formula=test$capitalDeviation ~ test$workingHoursAWeekStdUnits, data=test)
117
118
119 table = table(classifications = pr, test$incomeMoreThan50K)
120 table
121
    # chisquare = chisq.test(table)
122
123 # chisquare
     # summary(chisquare)
124
125
126
127
     sumInTable = 0
128
129 - for (i in c(1:4)) {
       sumInTable = sumInTable + table[i]
130
131
132 - for (i in c(1:4)) {
       table[i] = table[i] / sumInTable
134
135
    # prediction accurancy is one the main diagonal table[1] + table[4] or for table t: t_11 + t_22
136
    table
137
138
139 rm(list = c("i", "sumInTable", "chisquare"))
140
```

SVM-Classifizierung trainieren und testen



Resumée

Datenanalyse



- Google´s Chef-Ökonom Hal Varian
 - "The next sexy job"
 - "The ability to take data to be able to understand it, to process it, to extract value from it, to communicate it that's going to be a hugely important skill."
 - New York Times, 2009
- "Hot new gig in tech" Fortune



Vielen Dank für Ihre Aufmerksamkeit



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