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

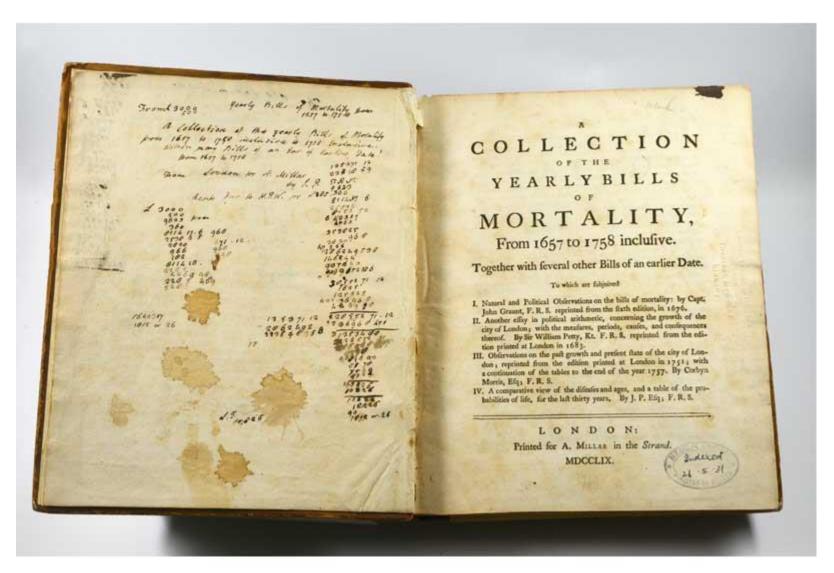


- Google´s Chef-Ökonom Hal Varian
 - "The next sexy job"
 - "The ability to take data to be able to understand it, to process it, to extract value from it, to communicate it that's going to be a hugely important skill."
 - New York Times, 2009
- "Hot new gig in tech" Fortune



Bills of Mortality





Bills of Mortality



the Years of our Lord	rofam)	6451	i i i i	ident	1551					100				A 1				1632	1633	1634	161	11634	1630	1634	164	165	1655	619	Year
er and Still-born	335	129	317 889	351 898	389 780	381 834	384 864 282	433 974 1171	483 743 689	419 892 875	463 869 999	467 1176 1800	411 909	54+ 1095	499 579 856	439 712	410 661	445 671 1108	500 704 953	475	50	323	1793 2475 4418	2005 2814 5235	1341 3136 3865	1587	4812 1 3680 8 4363 4 445	77	85 157 237
ex and Suddenly	4 4	74	64	74	106	2 6 4	113	2	47	102	5	138	91	67	13	8 2	10	13	6	4	25	+	75 54 16 15 15 15	14	5	12	14	10 17	78
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n See-mouth and Thruth led	66 161 1369	1254	2000	117	1237	113	1050	1343	177	201	236	229	818	194	2595	157	112	171 2268	132	143	163	100	15 590 92778 105	451	190 498 678	769	161 1 859 4 4788 45 497 2	90	330
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ed fmall Fox Lidead in the States h-Fox	159	400 6 39	1190	. 4	375	1279	119 14 10	4	3	\$13 4 33	31	- 11	1525 2 51	354	18	33	- 30	- 6	13	17	177	22 3	85 51 2	24 17	19 80	34 81 5	116	9 7 9 10	31
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Wöchentliche Todesstatistiken

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,
5 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
10 42, Private, 159449, Bachelors, 13, Married-civ-spouse, Exec-managerial, Husband, White, Male,
11 37, Private, 280464, Some-college, 10, Married-civ-spouse, Exec-managerial, Husband, Black, Mal
12 30, State-gov, 141297, Bachelors, 13, Married-civ-spouse, Prof-specialty, Husband, Asian-Pac-Is
```

- Erste 12 Instanzen mit
- 15 Variablen

msg systems ag, 12. Juni 2013

Daten

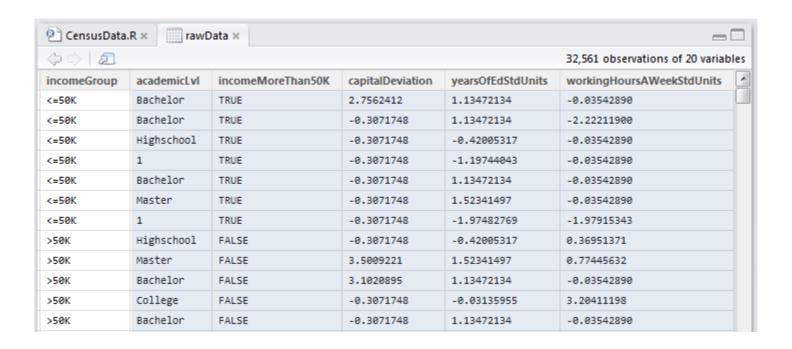


1 0	1 6							
þ þ	2	_					32,561 obse	ervations of 15 variab
	id	employerKind	fnlwgt	degree	yearsOfEd	maritalStatus	occupation	relationshipRole
1	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family
2	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband
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

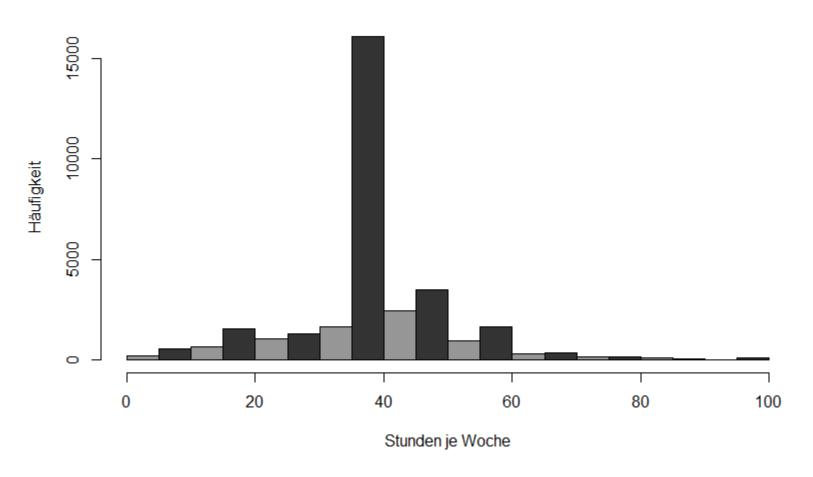




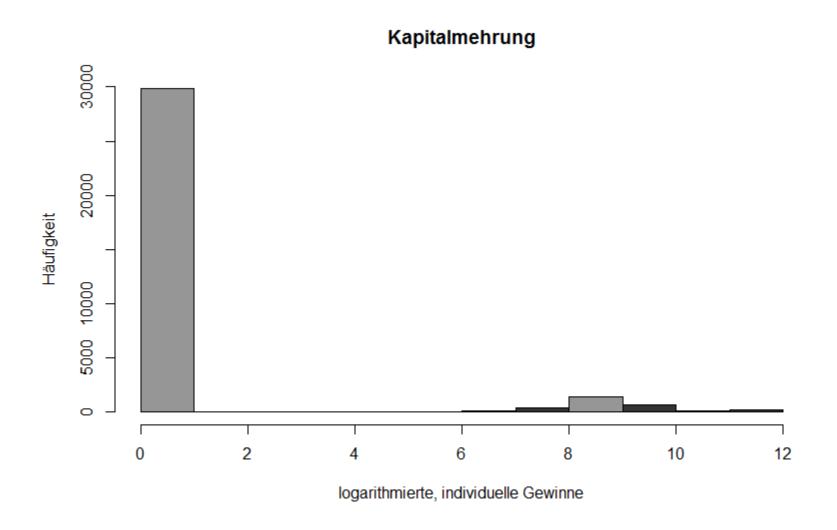
5 Sekundärvariablen



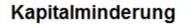


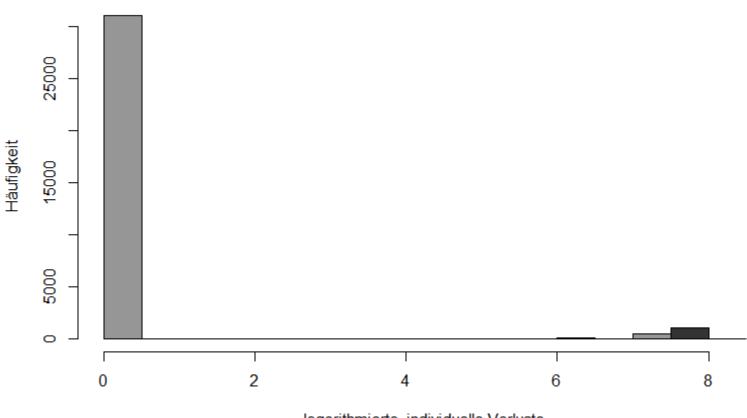




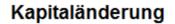


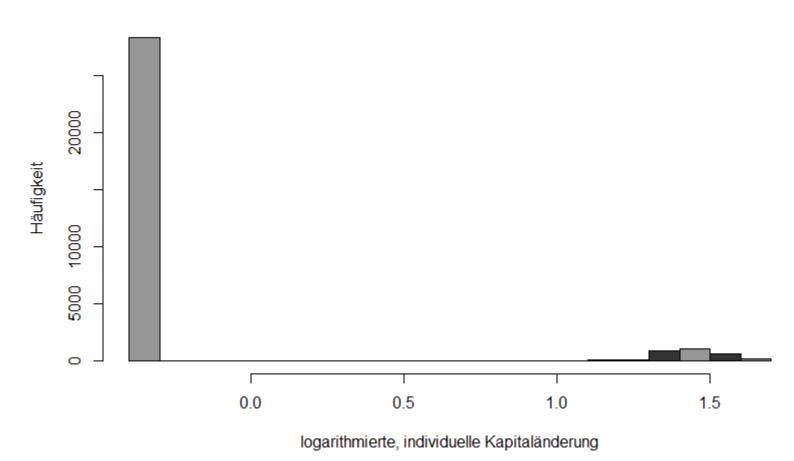




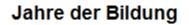


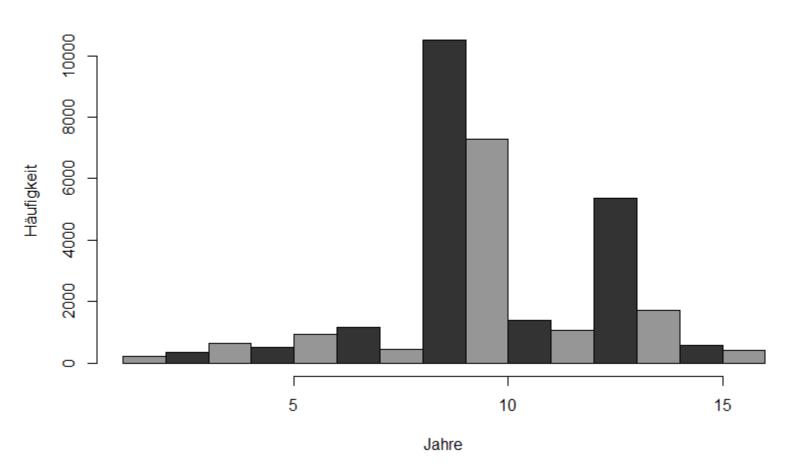






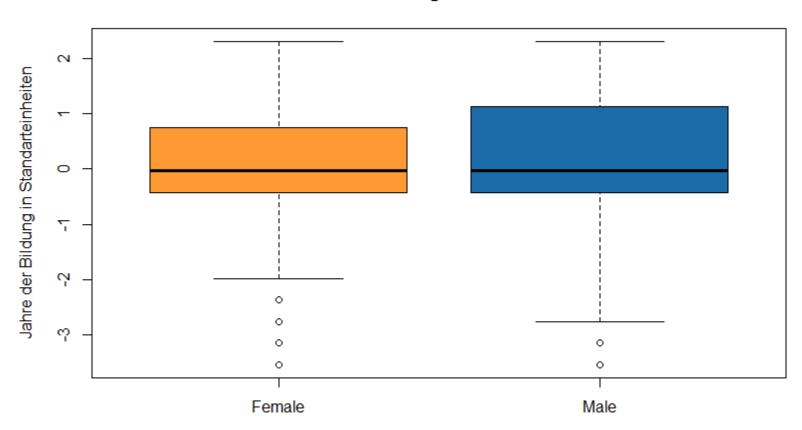






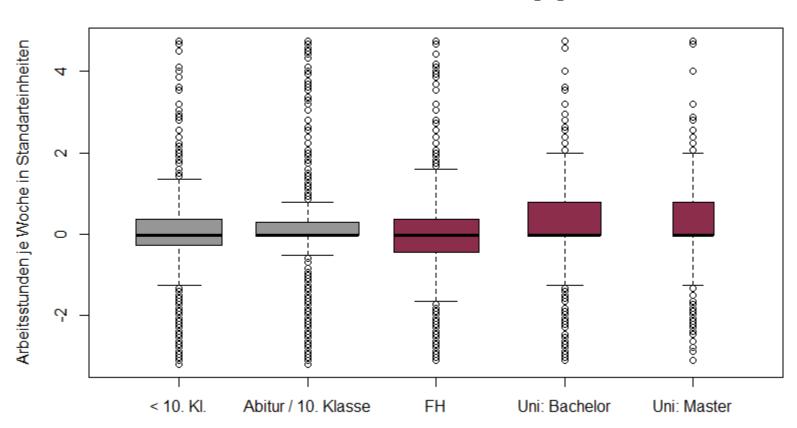


Jahre der Bildung nach Geschlecht



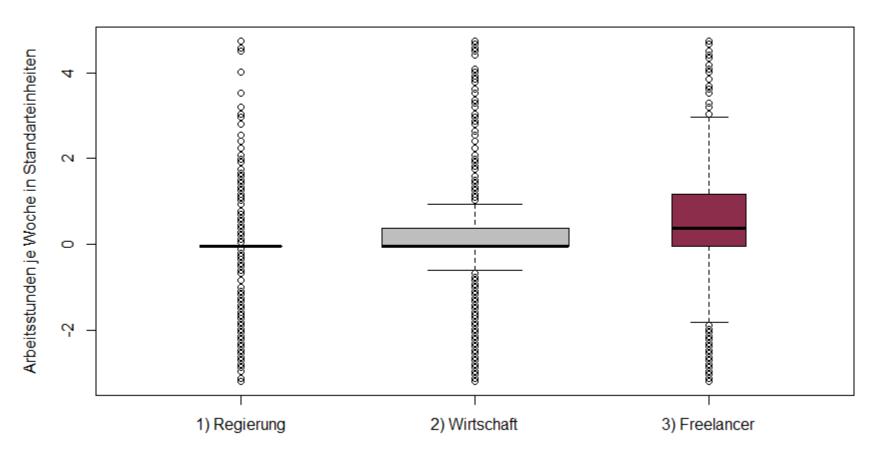


Arbeitsstunden nach Bildungsgrad



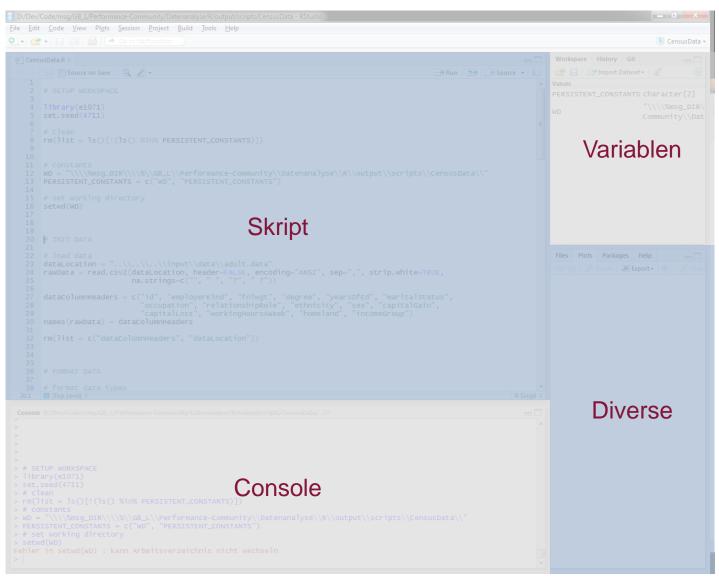


Arbeitsstunden nach Anstellungsart



RStudio



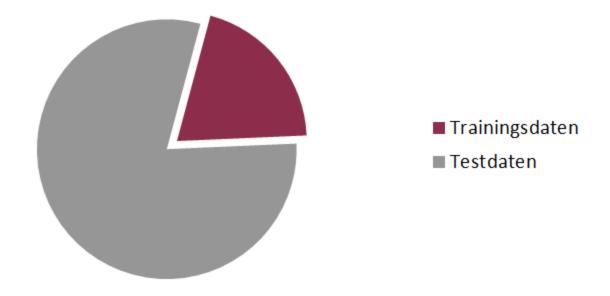


18



Klassifikation



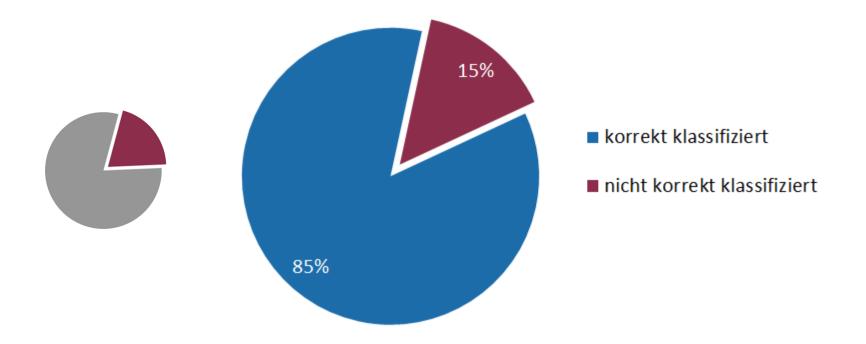




Klassifikation: Sensitivität & Spezifität

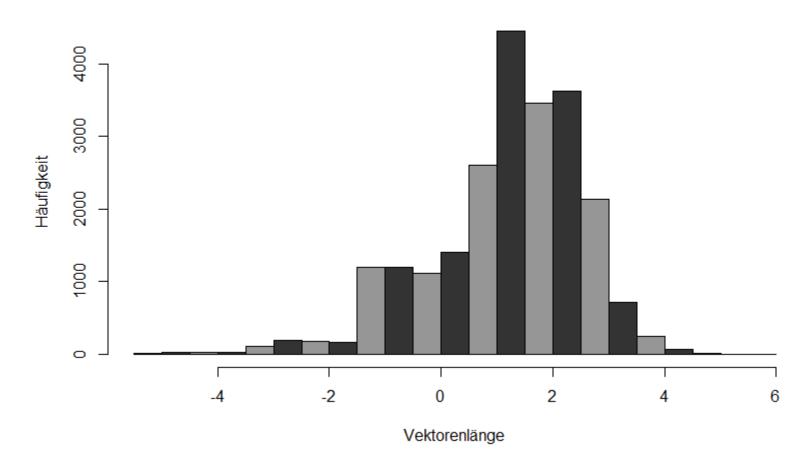
	tatsächlich nicht hohes	tatsächlich hohes
	Einkommen	Einkommen
geschätzt nicht hohes Einkommen	13%	5%
geschätzt hohes Einkommen	10%	72%







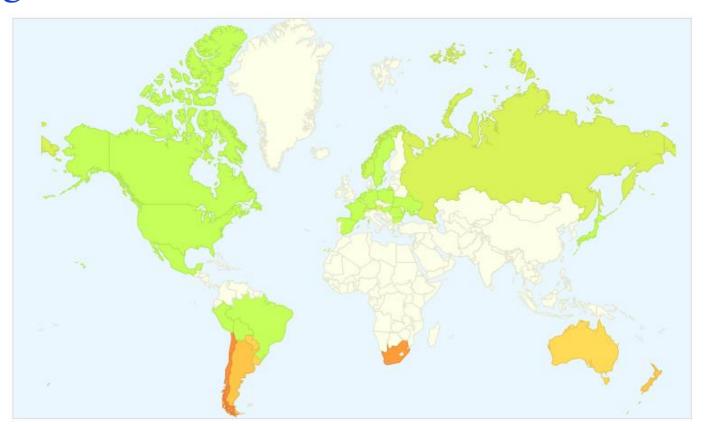
Länge der Entscheidungsvektoren





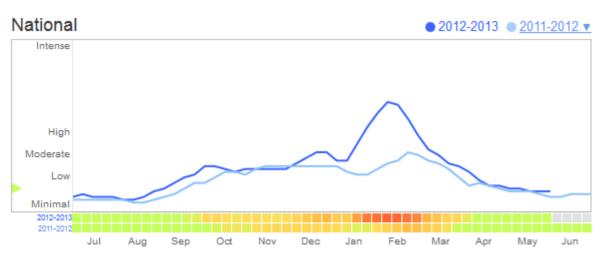


Google













Stanford University





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

Datenquellen





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

Datenquellen



kaggle

kaggle.com

Datenquellen





data.gov

Ressourcen







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



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
```

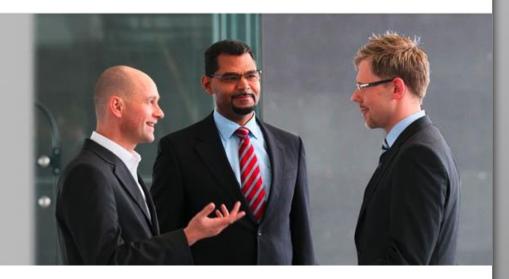
Trainings- und Testdaten erzeugen



```
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

Vielen Dank für Ihre Aufmerksamkeit



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