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



US Census Income Data

Explorative Datenanalyse

Daten



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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
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- Erste 12 Instanzen mit
- 15 Variablen

Daten

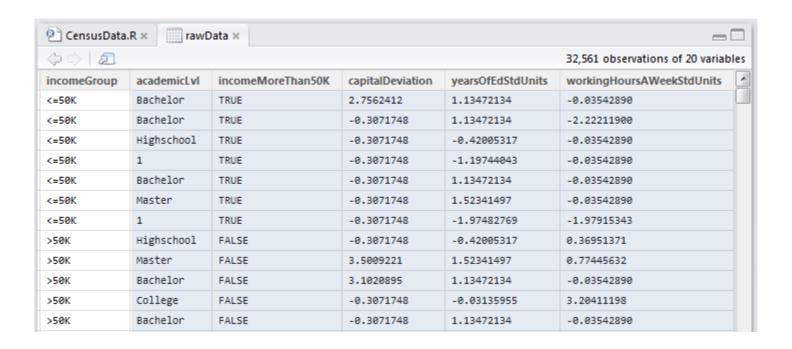


② Ce	nsusD	ata.R × rawDat	a ×						
$\Leftrightarrow \triangleleft$	2	3.					32,561 obse	ervations of 15 variabl	les
	id	employerKind	fnlwgt	degree	yearsOfEd	maritalStatus	occupation	relationshipRole	A
1	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	
2	50	Self-emp-not-inc	83311	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

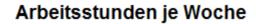


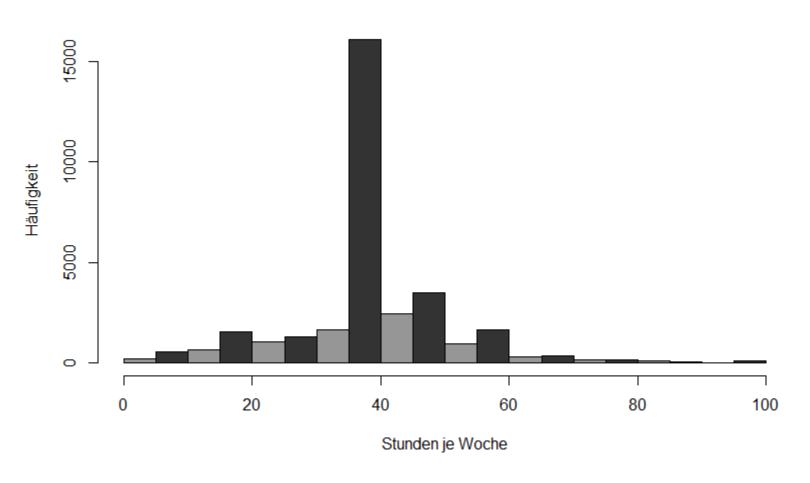


5 Sekundärvariablen

Visualisierungen



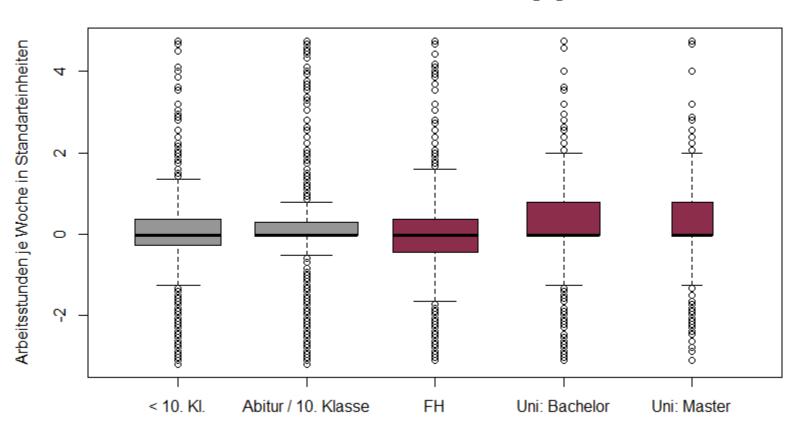




Visualisierungen



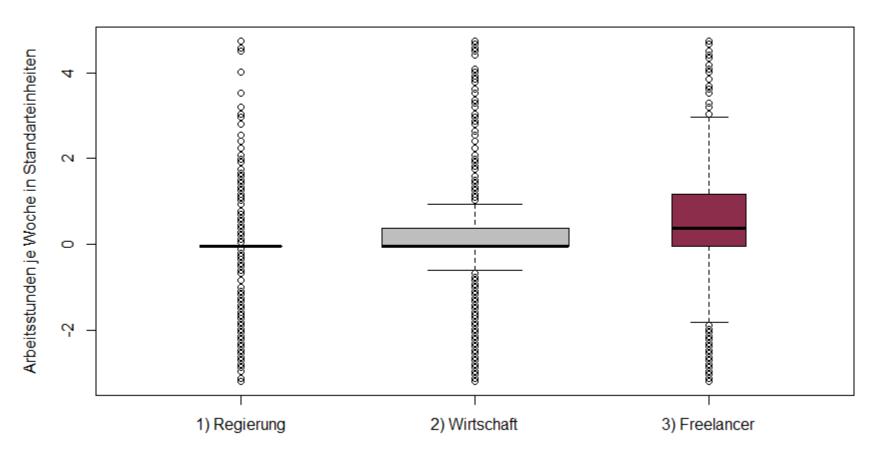
Arbeitsstunden nach Bildungsgrad



Visualisierungen

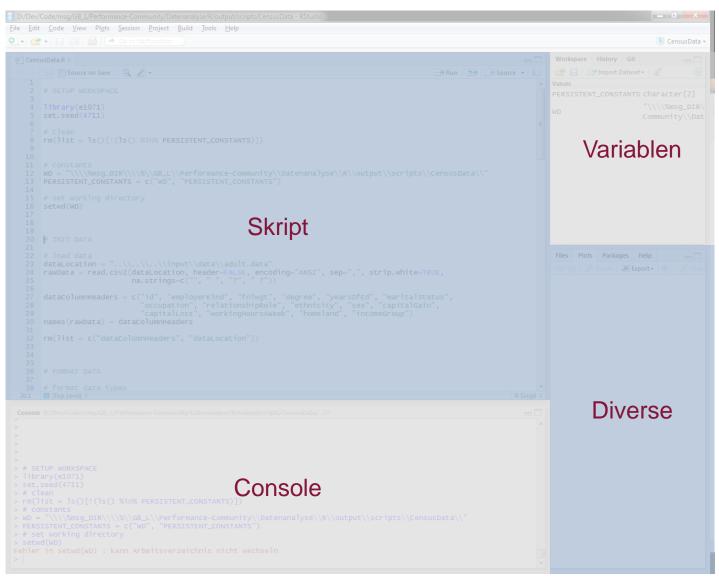


Arbeitsstunden nach Anstellungsart



RStudio





15

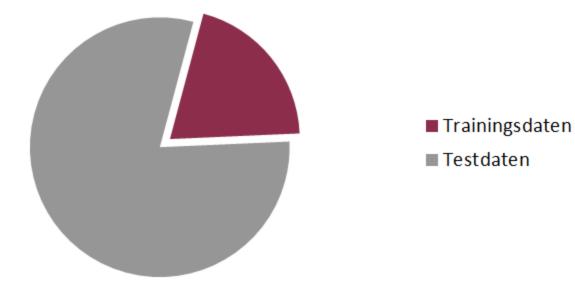


US Census Income Data

Klassifikation

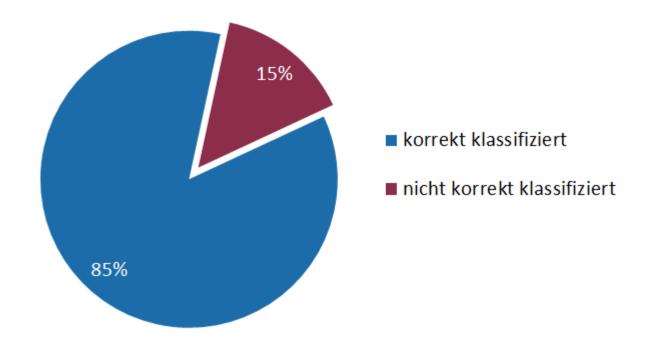
Klassifizierung





Klassifizierung







Anwendungsbeispiele

Anwendungsbeispiele



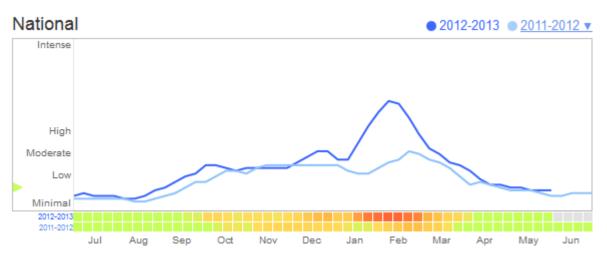




Anwendungsbeispiele







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

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Datenquellen

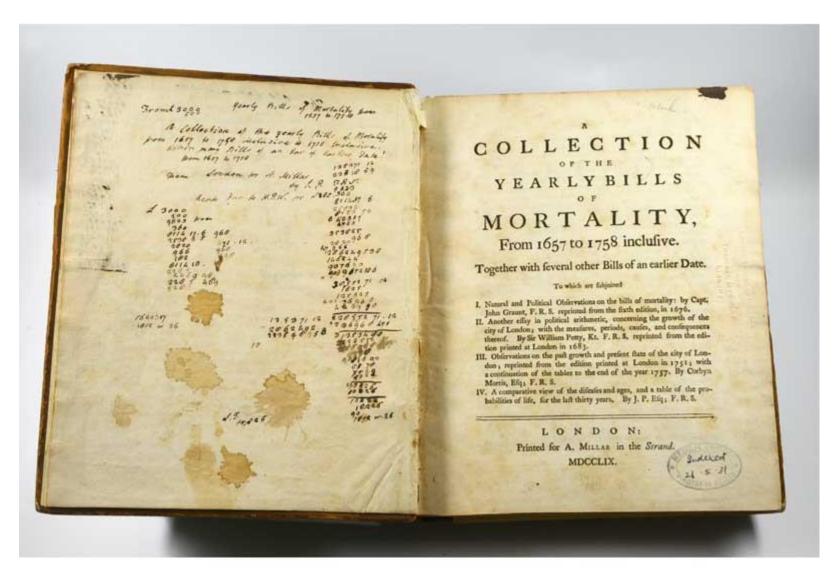




data.gov

Bills of Mortality





Bills of Mortality



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Wöchentliche Todesstatistiken

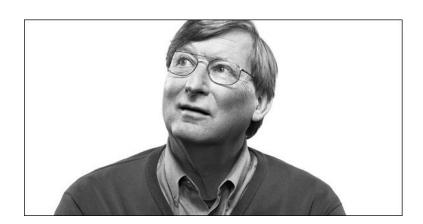


Resumée

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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