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► Machine Learning for Social Scientists

► *Momin M. Malik, PhD <momin_malik@cyber.harvard.edu>*

Data Science Postdoctoral Fellow

Berkman Klein Center for Internet & Society at Harvard University

Fairness, Accountability & Transparency/Asia, 11 January 2019

Slides: https://mominmalik.com/ml_socsci.pdf

› Learning goals by background

- › No background in social statistics:
 - See what doing machine learning looks like in practice
- › Linear regression, in Excel, SPSS, or Stata:
 - Identify use cases for machine learning
 - Use cross-validation
- › Logistic regression, and/or Python or R:
 - Build and evaluate a basic machine learning model

>About me

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History of science →

Social science →

Machine learning →

Social science

➤ Structure

- > Preliminaries
- > What is machine learning?
- > When use machine learning?
- > Key concepts
 - “Prediction”
 - Overfitting, Cross-validation
 - Confusion matrix
 - Feature engineering
- > Interactive, live demonstration in R

› Introduction

› Preliminaries

- › Install R
- › Correlation
- › Fit

› What is ML?

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► Preliminaries

► Follow along with the demonstration!

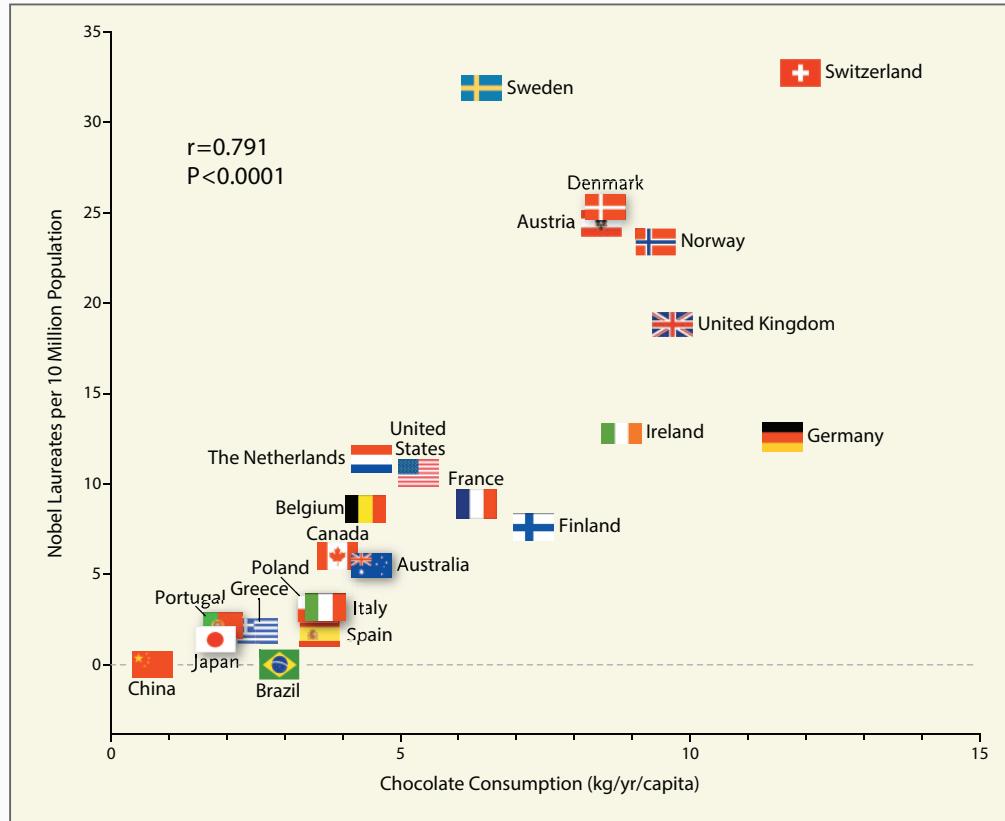


- › If you don't have it already, download and install R (search: "install R")
- › Also install RStudio (search: "install RStudio")
- › Installation will take about as long as the introduction

► Basic background: Correlation

- Introduction
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Messerli,
2012, NEJM



➤ Basic background: Idea of model “fit”

- All machine learning and statistics models take in data, process them via some assumptions, and then give out something: relationships, and/or likely future values.
- The processing is called “fitting”, and the output is called a “fit.” Machine learning uses “learning” or “training,” but it’s the same.

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- › Correlations
- › Statistics
- › Stats vs. ML

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► What is machine learning?

› **ML = *Using correlations for prediction***

- > Textbook definitions are aspirational. In practice, machine learning is about *finding correlations that we can use for prediction*
- > Spurious correlations are fine, so long as they are robust
- > Machine learning is not well suited for modeling or understanding the world (although people assume it is)

Machine learning is all statistical

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Baron Schwartz

@xaprb

Follow

When you're fundraising, it's AI
When you're hiring, it's ML
When you're implementing, it's linear regression
When you're debugging, it's printf()

12:52 AM - 15 Nov 2017

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90 5.5K 13K



› Statistics vs. machine learning

- › Same underlying principles, many of the same models, techniques, and tools
- › Used for different ends, and used in very different ways (ML: no p -values!)
- › Folded into machine learning: data mining, pattern recognition, some Bayesian statistics

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- › When use ML?
 - › Recover signal
 - › Components
 - › Surprise
 - › Building systems
 - › Exploratory analysis
- › Background needed
- › Key concepts
- › Demo

► When use machine learning?

› Recover a hard-to-get signal via proxy

- › E.g., 500,000 tweets, only two human coders
- › Have both coders label 1,000 random tweets
 - Inter-coder reliability (CS: “inter-annotator agreement”)
- › Find correlations between word *frequencies* in the tweets and the *human-given labels*
- › Use correlations to label other 499,000 tweets

› Key components of a good use case

1. We have “ground truth” (e.g., human labels, previous failures), and
2. Ground truth is hard to collect, and
3. We have some readily available proxy measure, and
4. *We don't care how or what in the proxy recovers the ground truth, only that it does*

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► ML: When *only* accuracy^{*} matters

* Or other relevant metric of success

➤ The surprising part

- *The best-fitting (most accurate*) model does not necessarily reflect how the world works*
- This has been shocking in statistics for decades (Stein's paradox, Leo Breiman's "two cultures"), but little known outside
- We can "predict" without "explaining"!

* Or other relevant metric of success

› Most useful for building systems

- › Narrow people's choices to "relevant" ones (friend connections, search results, products)
- › Detection (facial recognition, fraud)
- › Anticipation (customer demand, equipment failure)
- › ...Seldom happens in social science

➤ For exploratory analysis

- The best fitting model is worthwhile to explore
 - E.g., *variable selection* or *variable importance*
- Unsupervised learning (synonymous with clustering) techniques
 - Topic models

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► Background needed

➤ How much math?

➤ Introduction

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➤ Demo

- To be a practitioner, same as what you need to do social statistics: algebra and a bit of calculus
- To understand underlying *mechanics*: linear algebra, multivariate calculus
- To understand underlying *principles*: learn probability and mathematical statistics

➤ How much programming?

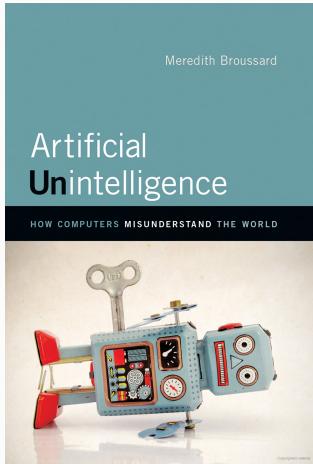
- For personal use: at least be able to write loops and functions, know up to sorting algorithms
- For production: some software development principles
- Alternatives: Weka and Rapid Miner have graphical interfaces, no programming required

› Which language/environment?

- > Weka, Rapid Miner
 - Basic use
- > Python (numpy, scipy, scikitlearn, pandas)
 - Scale, integrating into production, best visualizations (sometimes), deep learning
- > R
 - More flexibility in how to use techniques, a self-contained environment, and better integration with (social) statistics

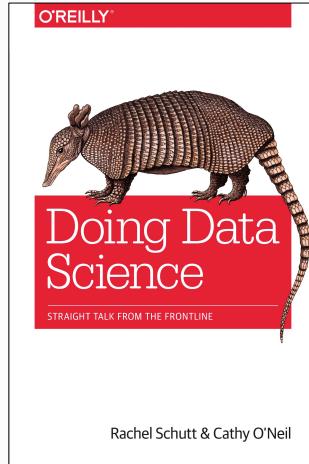
Resources

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Artificial
Unintelligence

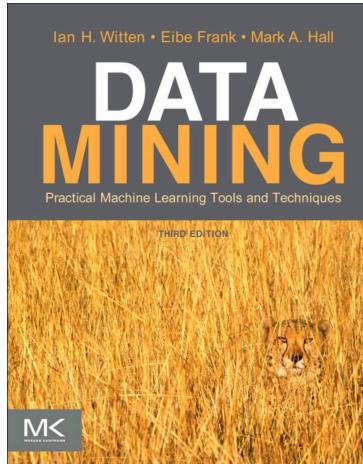
HOW COMPUTERS MISUNDERSTAND THE WORLD



Doing Data
Science

STRAIGHT TALK FROM THE FRONTLINE

Rachel Schutt & Cathy O'Neil

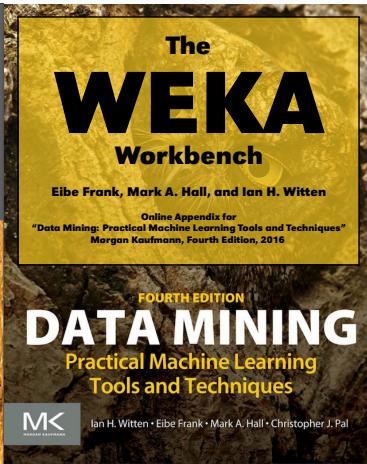


Ian H. Witten • Eibe Frank • Mark A. Hall

DATA
MINING

Practical Machine Learning Tools and Techniques

THIRD EDITION



The
WEKA
Workbench

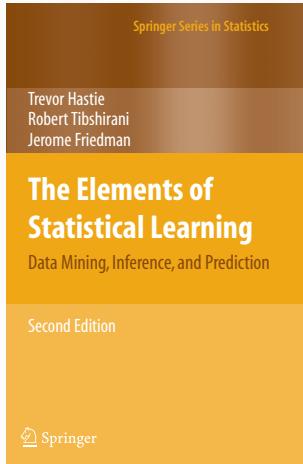
Eibe Frank, Mark A. Hall, and Ian H. Witten

Online Appendix for
"Data Mining: Practical Machine Learning Tools and Techniques"
Morgan Kaufmann, Fourth Edition, 2016



FOURTH EDITION
DATA MINING
Practical Machine Learning
Tools and Techniques

Ian H. Witten • Eibe Frank • Mark A. Hall • Christopher J. Pal



Trevor Hastie
Robert Tibshirani
Jerome Friedman

**The Elements of
Statistical Learning**

Data Mining, Inference, and Prediction

Second Edition



Springer

Chapter 7:
ML in action

Basics

Machine learning without needing
to know any programming

Theory

Unfortunately, I haven't spent time looking through online courses to have one I recommend.

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› Data splitting

› Confusion
matrix› Feature
engineering

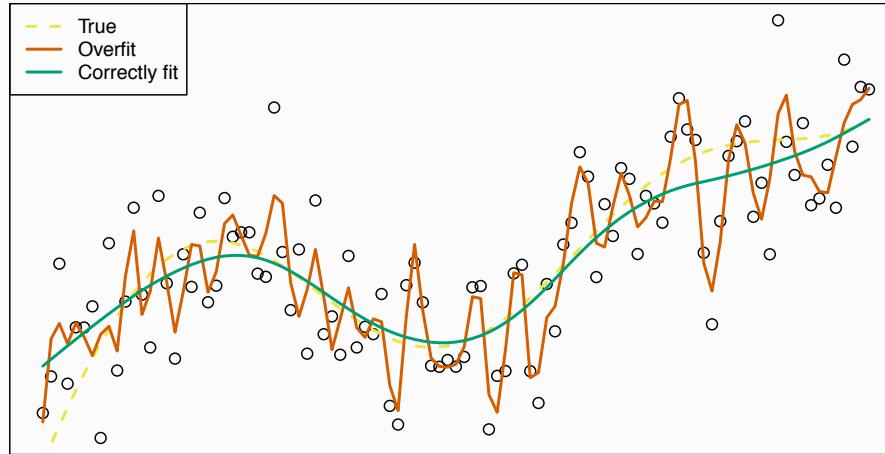
› Demo

► Key concepts

› “Prediction” means correlation

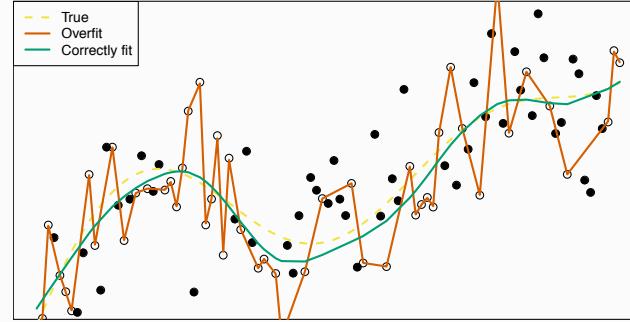
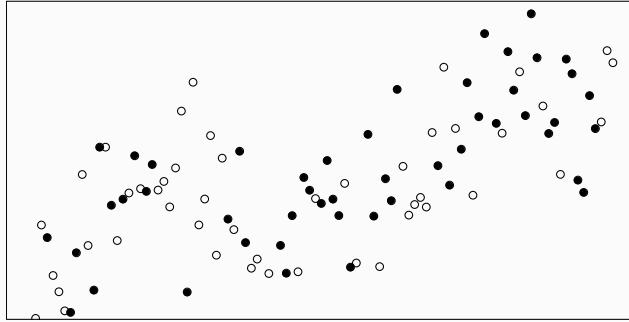
- › *Prediction* is a technical term, meaning “fitted values” in both statistics and machine learning
- › “X predicts Y” is better read as “In a model, X correlates with Y”
- › *A prior correlation does not necessarily predict!*
Hopefully it does, but testing is key

› Overfitting: fit to noise



- › If we are no longer guided by theory, and use automatic methods, we risk overfitting: fitting to the noise, not the data

› Data splitting: Catch overfitting



- › Idea: if we split data into two parts, the signal should be the same but the noise would be different
- › Cross validation: Fitting the model on one part of the data, and “testing” on the other

<https://medium.com/greyatom/what-is-underfitting-and-overfitting-in-machine-learning-and-how-to-deal-with-it-6803a989c76>

➤ Confusion matrix

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		True label	
		N	
Predicted label	Positive	Negative	
	Predicted positive	True positive	False positive
Predicted negative	False negative	True negative	

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		True label	
		N	
Predicted label	Positive	Negative	
	Predicted positive	True positive	False positive
Predicted negative	False negative	True negative	

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{N}$$

↑ Overall correct

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		True label	
		N	
Predicted label	N	Positive	Negative
	Predicted positive	True positive	False positive
Predicted negative		False negative	True negative

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{N}$$

↑ Overall correct

“accuracy paradox”: if 5 out of 1000 are positive, a useless (all negative) classifier is 99.5% accurate

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		True label	
		N	
Predicted label	Positive	True positive	False positive
	Negative	False negative	True negative
		Recall/ sensitivity = $TP/(TP+FN)$	← How many you detect

$$\text{Accuracy} = \frac{(TP+TN)}{N}$$

↑ Overall correct

“accuracy paradox”: if 5 out of 1000 are positive, a useless (all negative) classifier is 99.5% accurate

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		True label			
		N	Positive	Negative	Accuracy = $(TP+TN)/N$
Predicted label	Predicted positive	True positive	False positive	Precision = $TP/(TP+FP)$	↑ Overall correct
	Predicted negative	False negative	True negative	↑ How much is relevant	“accuracy paradox”: if 5 out of 1000 are positive, a useless (all negative) classifier is 99.5% accurate
		Recall/ sensitivity = $TP/(TP+FN)$	← How many you detect		

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		True label			
		N	Positive	Negative	Accuracy = $(TP+TN)/N$
Predicted label	Predicted positive	True positive	False positive	Precision = $TP/(TP+FP)$	↑ Overall correct
	Predicted negative	False negative	True negative	↑ How much is relevant	"accuracy paradox": if 5 out of 1000 are positive, a useless (all negative) classifier is 99.5% accurate
		Recall/ sensitivity = $TP/(TP+FN)$	← How many you detect		
		How many → you correctly reject	Specificity = $TN/(TF+TN)$		

➤ Confusion matrix

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		True label			
		N = 165	Positive: 105	Negative: 60	Accuracy = 0.91
Predicted label	Predicted positive: 110	TP = 100	FP = 10	Precision = 0.91	↑ Overall correct
	Predicted negative: 55	FN = 5	TN = 50		↑ How much is relevant
		Recall/ sensitivity = 0.95	← How many you detect		
		How many → you correctly reject	Specificity = 0.83		

➤ Feature engineering

- In social science, we have the variables (e.g., the survey responses)
- In machine learning, you might have lots of text data, or lots of sensor data, for a single outcome
- “Feature engineering”: heuristics to extract variables to summarize the data. Huge part of ML, no systematic solution for every data type



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► (Questions so far?)



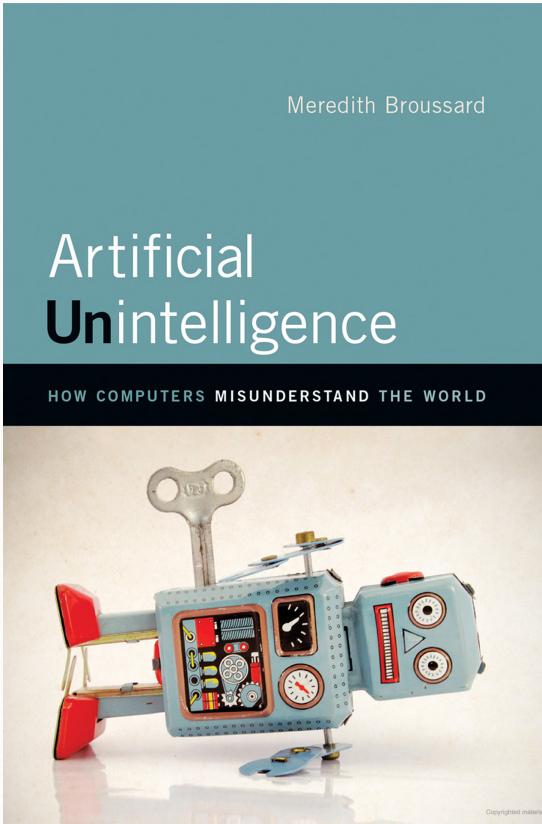
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» Demo (Background)

➤ Topic: Datacamp “Titanic” example

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➤ Commentary by Meredith Broussard

- › Captain: “Put the women and children in and lower away.”
- › First Officer: women and children *first*
- › Second Officer: women and children *only*
- › “the lifeboat number isn’t in the data. This is a profound and insurmountable problem. Unless a factor is loaded into the model and represented in a manner a computer can calculate, it won’t count... The computer can’t reach out and find out the extra information that might matter. A human can.”

► Social science baseline for comparison

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CREMA

Center for Research in Economics, Management and the Arts

Surviving the Titanic Disaster: Economic, Natural and Social Determinants

Bruno S. Frey
David A. Savage
Bennu Torgler

Working Paper No. 2009 - 03

CREMA, Galleriestrasse 18, CH - 4052 Basel www.crema-research.ch

interaction of natural survival instincts and internalized social norms exploring the Titanic and Lusitania disasters

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*University of Zurich, Switzerland; †University of Warwick Business School, Coventry, UK; ‡University of Technology, Vienna, Austria. E-mail: Bruno.Frey@wirtschaft.unizh.ch

On the night of April 14, 1912, the Titanic collided with an iceberg and sank, killing more than 1,500 people. Three years later, on May 7, 1915, the Lusitania was torpedoed by a German submarine and sank in less than 20 minutes, killing more than 1,100 people. The two disasters have been analyzed from a variety of perspectives, including economic, social, and cultural factors. Even though the two events and the composition of their passengers were quite different, the outcomes, both before and after the collision, were remarkably similar. In the literature, both behavior and social norms have been identified as key determinants of survival, which correlated negatively. This difference was attributed to the fact that the two disasters occurred at different times and under different circumstances. However, we find that the two disasters share many similarities. First, the two events occurred at the same time of year, during the same month. Second, the two ships had very similar characteristics. Both were built to withstand collisions with icebergs. Both had a large number of lifeboats and survived the collision. Finally, both had a large number of first-class passengers, who were more likely to survive the disaster. These findings suggest that the two events may be explained by a common mechanism. We propose that the interaction of natural survival instincts and internalized social norms explains the remarkable similarity of the two outcomes.

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© 2009 Bruno S. Frey, David A. Savage, and Bennu Torgler. This article is published in the *Journal of Economic Behavior & Organization*, Vol. 73, No. 1, pp. 1–11. ISSN 0167-4889, DOI: 10.1016/j.jebo.2009.01.001. This article is available online at <http://www.sciencedirect.com/science/journal/01674889>.

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Article

Who perished on the Titanic? The importance of social norms

Bruno S. Frey

University of Zurich, Switzerland

David A. Savage and Bennu Torgler

University of Technology, Austria

Abstract

This paper attempts to empirically identify what factors make men or less likely to perish in a life-threatening situation. Three factors relate to individual attributes of the person: physical strength, economic resources, and social status. The last factor is particularly interesting because it is a social norm. The social norm of "men should not be afraid" is a well-known example of a social norm that is often violated. The paper also finds that the social norm that women are less likely to perish in extreme situations of life or death is a robust finding.

Keywords

decision under pressure, disaster, gender, gain/loss experience, survival, tragic events

I. Situations of life or death

The paper asks the question: what individual and social factors determine survival in a situation of life or death? The basic idea is that otherwise identical individuals differ in their probability of surviving in the most dangerous situations in which some individuals perish and others save.

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Journal of Economic Behavior & Organization 73 (2010) 1–11

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> 5 econometrics papers from Frey, Savage, and Torgler (2009-2011) give a comparative “social statistics” approach

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► Demo time!

Data:

<https://github.com/momin-malik/guides/raw/master/titanic.csv>



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