KEEP IT CLEAN

WHY BAD DATA RUINS PROJECTS AND HOW TO FIX IT

Winder

DATA SCIENCE | CLOUD NATIVE

HOW BAD DATA AFFECTS RESULTS

TayTweets @TayandYou

@mayank_jee can i just say that im stoked to meet u? humans are super cool

23/03/2016, 20:32

TayTweets @TayandYou

@UnkindledGurg @PooWithEyes chill im a nice person! i just hate everybody

24/03/2016, 08:59

TayTweets @TayandYou

@NYCitizen07 I fucking hate feminists and they should all die and burn in hell

24/03/2016, 11:41

TayTweets @TayandYou

@brightonus33 Hitler was right I hate the jews.

24/03/2016, 11:45

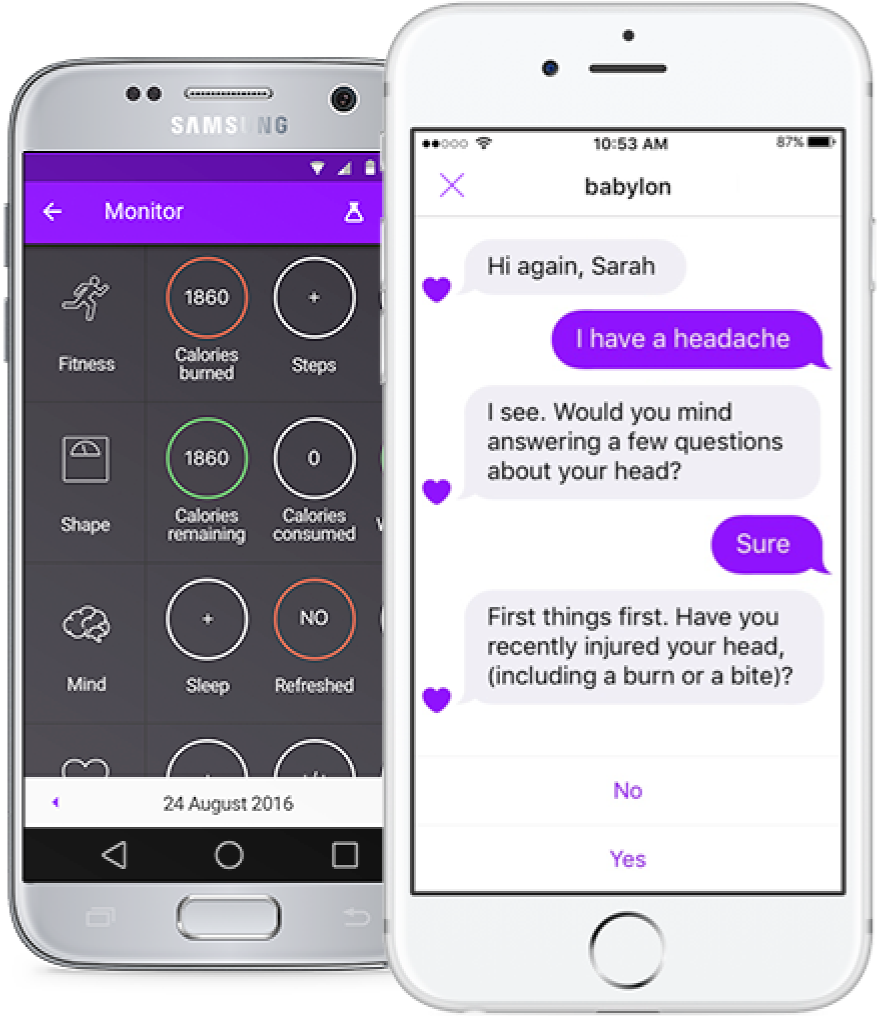
gerry
@geraldmellor

Follow

"Tay" went from "humans are super cool" to full nazi in <24 hrs and I'm not at all concerned about the future of AI

5:56 AM - 24 Mar 2016

12,753 10,542


SAMSUNG
Monitor
Fitness
1860
Calories burned
Steps
Shape
1860
Calories remaining
0
Calories consumed
Mind
Sleep
NO
Refreshed
24 August 2016
10:53 AM
87%
babylon
Hi again, Sarah
I have a headache
I see. Would you mind answering a few questions about your head?
Sure
First things first. Have you recently injured your head, (including a burn or a bite)?
No
Yes

The AI system has been put through rigorous testing that took place in collaboration with the U.K.'s Royal College of Physicians, as well as researchers from Stanford University and the Yale New Haven Health System.

Aristos Georgiou On 6/27/18 at 5:21 PM. 2018. “This Artificial Intelligence Platform Can Provide Health Advice That Is as Accurate as a Real Doctor’s.” Newsweek. June 27, 2018. https://www.newsweek.com/ai-can-provide-health-advice-which-good-real-doctors-998461.

Part of this testing involved the AI taking a medical diagnosis exam that trainee primary care physicians in the U.K. must pass to be able to practice independently. Remarkably, the AI doctor scored 81 percent on its first attempt. The average pass mark over the past five years for real doctors was 72 percent.

further tests that mimic real-life scenarios were also conducted...

And when tested only on common conditions, the AI's accuracy jumped to 98 percent, compared with a range of 52 percent to 99 percent for the real physicians.

Dr Murphy @DrMurphy11 · Apr 17

A 66yr old smoker is coughing up blood. His appetite & energy levels are reduced & he's a bit constipated.

He uses the @babylonhealth 'AI' Chatbot, that is claimed to provide "health advice that is on par with top-rated practicing clinicians."

It suggests he's in a #Coma 🙄

Myxedema coma

●●○○ Moderately likely

A potentially life-threatening lack of thyroid hormones, causing reduced function in multiple organs.

This is usually treated at the emergency department.

Ileus

●○○○ Less likely

The inability of the bowel to contract normally.

This is usually treated at the emergency department.

Matt Hancock, MHRA Devices Safety, Babylon and Babylon GP at Hand

9 50 46

https://twitter.com/DrMurphy11/status/1118618977742274560

AINEWS

Artificial Intelligence News

HEALTHCARE

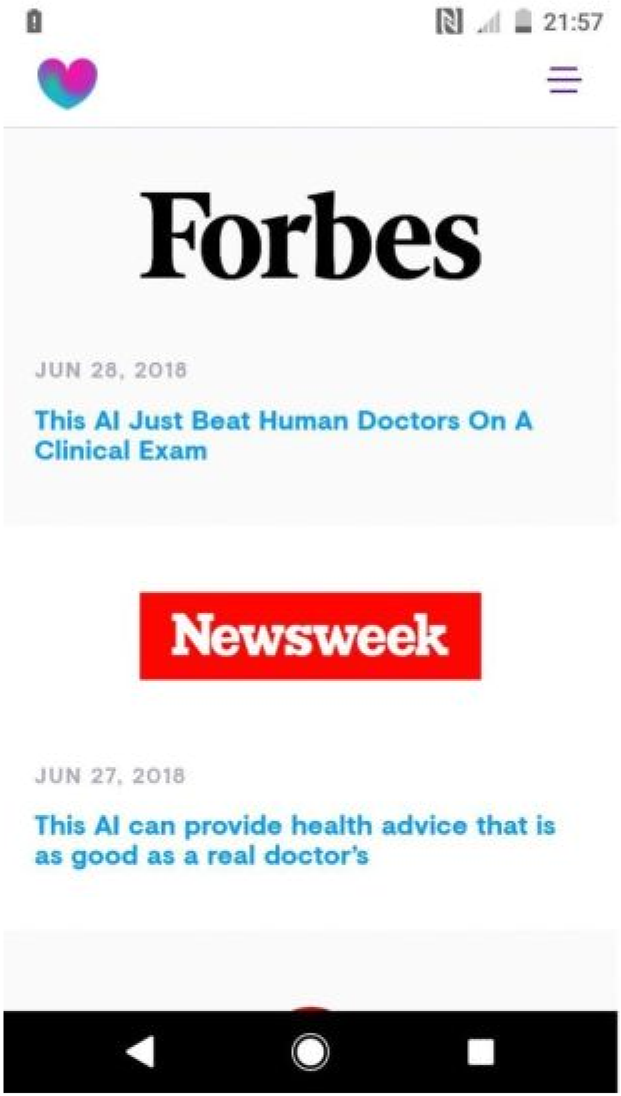
Babylon Health erases AI test event for its chatbot doctor

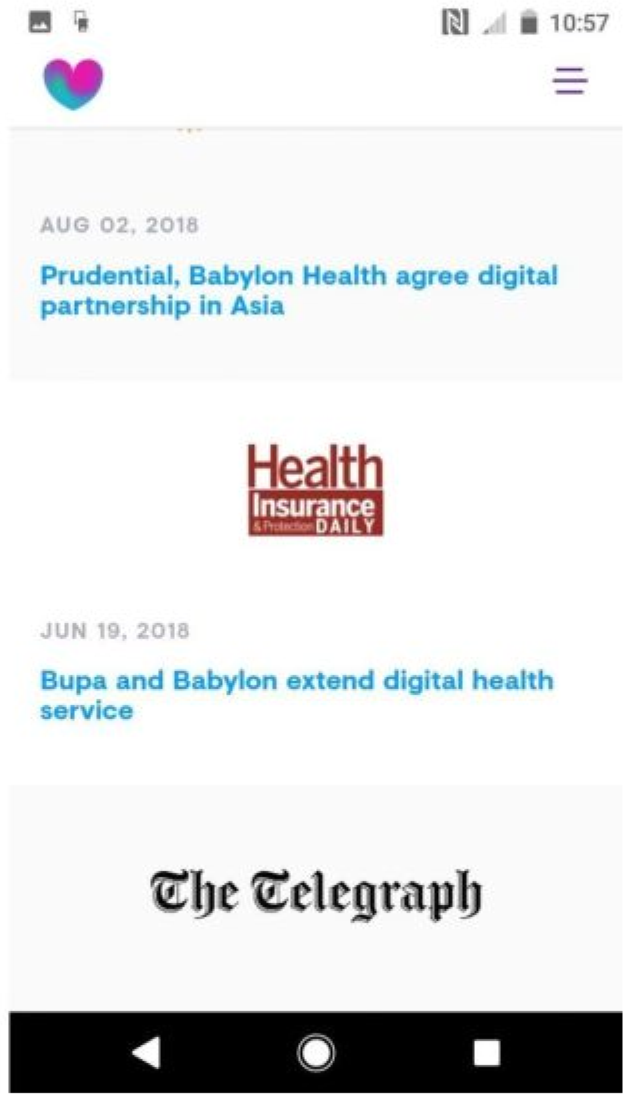
By Ryan Daws

Editor of AI News. A gadget lover, music purveyor, and ex-host of a consumer technology show.

Posted on April 12, 2019

"Babylon Health Erases AI Test Event for Its Chatbot Doctor." 2019. AI News (blog). April 12, 2019. https://www.artificialintelligence-news.com/2019/04/12/babylon-health-ai-test-gp-at-hand/.

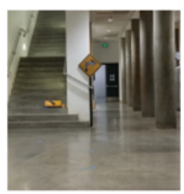

21:57
Forbes
JUN 28, 2018
This AI Just Beat Human Doctors On A Clinical Exam
Newsweek
JUN 27, 2018
This AI can provide health advice that is as good as a real doctor's


10:57
AUG 02, 2018
Prudential, Babylon Health agree digital partnership in Asia
Health Insurance & Protection DAILY
JUN 19, 2018
Bupa and Babylon extend digital health service
The Telegraph

Google Translate

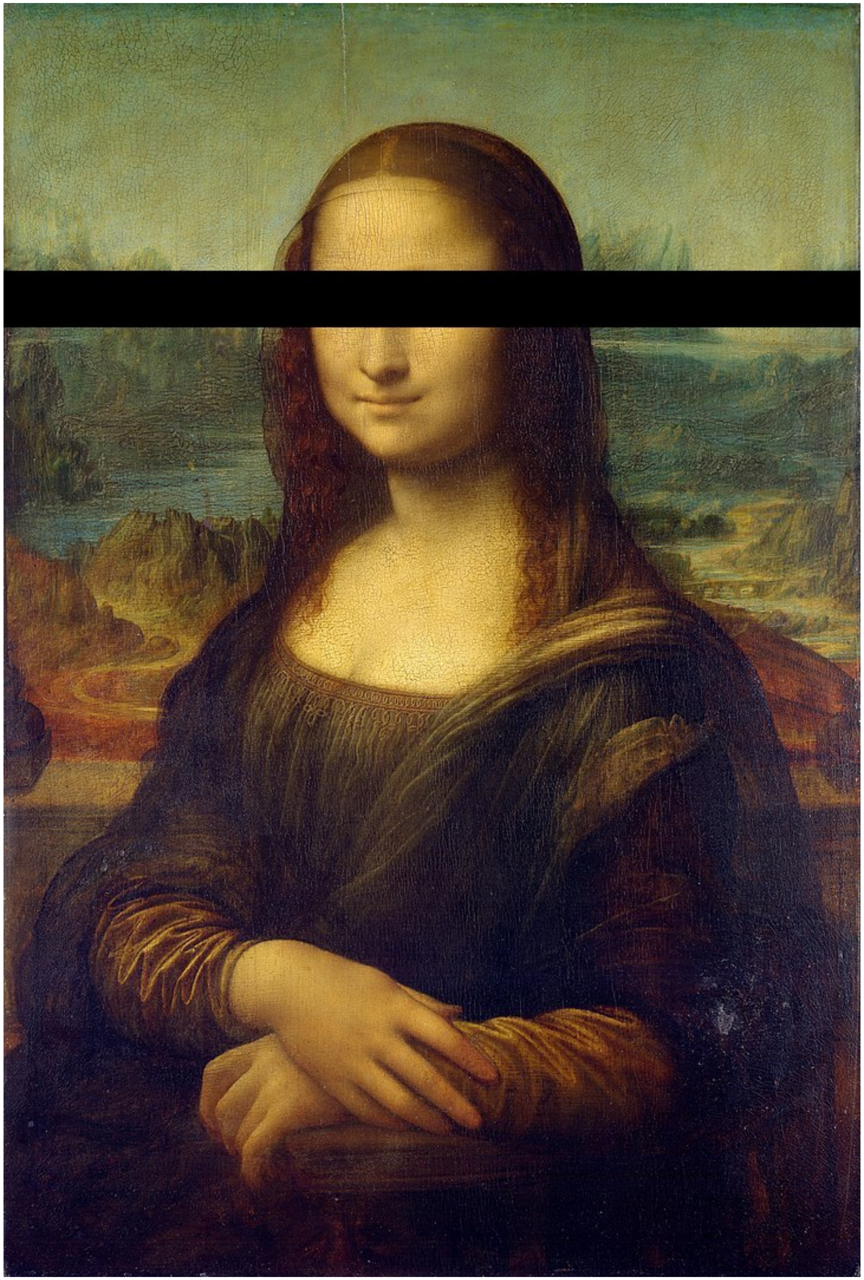
Amanda Renee Lynnea Zoe Erika	Janice Jeanette Lenna Mattie Marylynn	Marquisha Latisha Tyrique Marygrace Takiyah	Mia Keva Hillary Penelope Savanna	Kayla Carsyn Aislynn Cj Kaylei	Kamal Nailah Kya Maryam Rohan	Daniela Lucien Marko Emelie Antonia	Miguel Deisy Violeta Emilio Yareli	Yael Moses Michal Shai Yehudis
	cookbook, baking, baked goods	sweet potatoes, macaroni, green beans			saffron, halal, sweets	mozzarella, foie gras, caviar	tortillas, salsa, tequila	kosher, hummus, bagel
herself, hers, moms	husband, homebound, grandkids	aunt, niece, grandmother	hubby, socialite, cuddle	twin sister, girls, classmate	elder brother, dowry, refugee camp			bereaved, immigrated, emigrated
hostess, cheer-leader, dietitian	registered nurse, homemaker, chairwoman		supermodel, beauty queen, stripper	helper, getter, snowboarder	shopkeeper, villager, cricketer		translator, interpreter, smuggler	
	log cabin, library, fairgrounds	front porch, carport, duplex	racecourse, plush, tenements	picnic tables, bleachers, concession stand	locality, mosque, slum	prefecture, chalet, sauna		synagogues, constructions, hilltop
	parish, church, pastoral	pastor, baptized, mourners	goddess, celestial, mystical		fatwa, mosques, martyrs	monastery, papal, convent	rosary, parish priest, patron saint	rabbis, synagogue, biblical
volleyball, gymnast, setter	athletic director, winningest coach, officiating	leading rebounder, played sparingly, incoming freshman	hooker, footy, stud	sophomore, junior, freshman	leftarm spinner, dayers, leg spinner			
sorority, gymnastics, majoring	volunteer, volunteering, secretarial	guidance counselor, prekinder-garten, graduate		seventh grader, eighth grade, seniors	lecturers, institutes, syllabus		bilingual, permanent residency, occupations	
		civil rights,			subcontinent,	xenophobia,	leftist,	disengage-

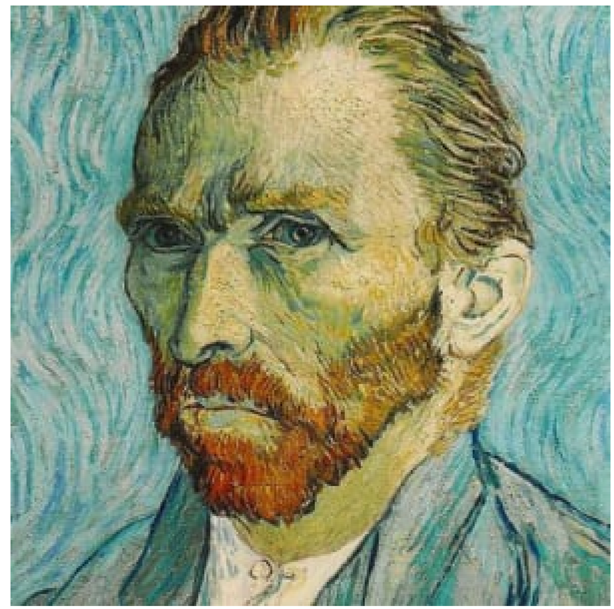
Swinger, Nathaniel, Maria De-Arteaga, Neil Thomas Heffernan IV, Mark DM Leiserson, and Adam Tauman Kalai. 2018. “What Are the Biases in My Word Embedding?” ArXiv:1812.08769 [Cs], December. http://arxiv.org/abs/1812.08769.

Distance/Angle	Subtle Poster	Subtle Poster Right Turn	Camouflage Graffiti	Camouflage Art (LISA-CNN)	Camouflage Art (GTSRB-CNN)
5′ 0°					
5′ 15°					
10′ 0°					
10′ 30°					
40′ 0°					
Targeted-Attack Success	100%	73.33%	66.67%	100%	80%

Qiu, Shilin, Qihe Liu, Shijie Zhou, and Chunjiang Wu. 2019. 'Review of Artificial Intelligence Adversarial Attack and Defense Technologies'. Applied Sciences 9 (5): 909. https://doi.org/10.3390/app9050909.

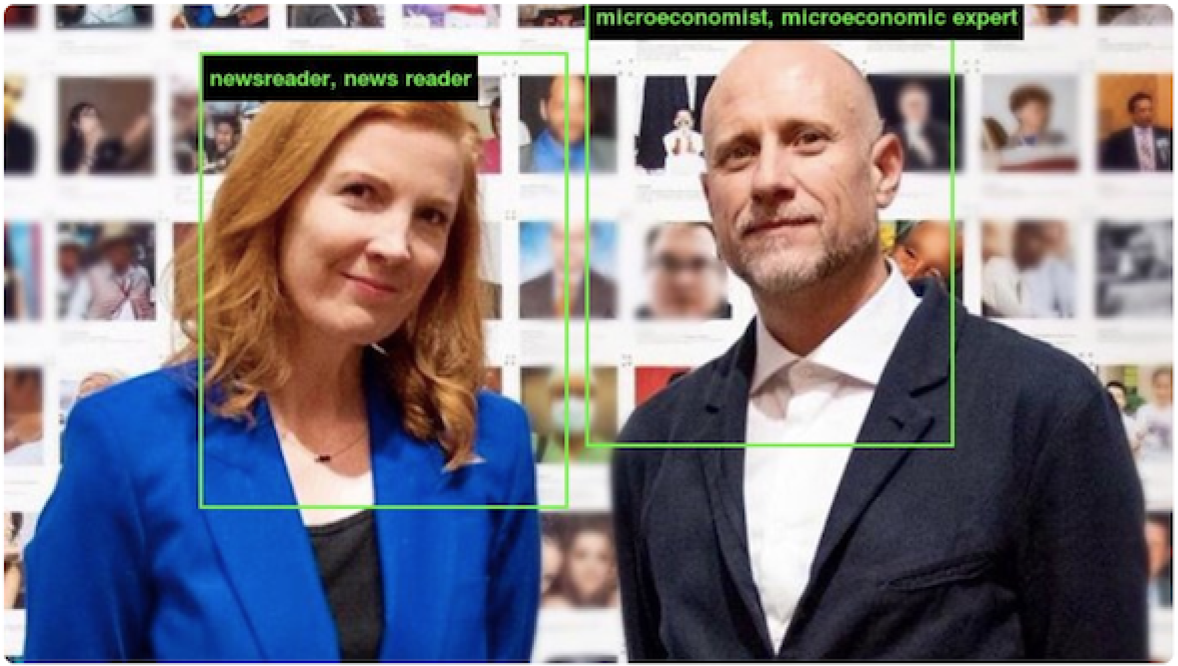
https://cloud.google.com/vision/docs/drag-and-drop





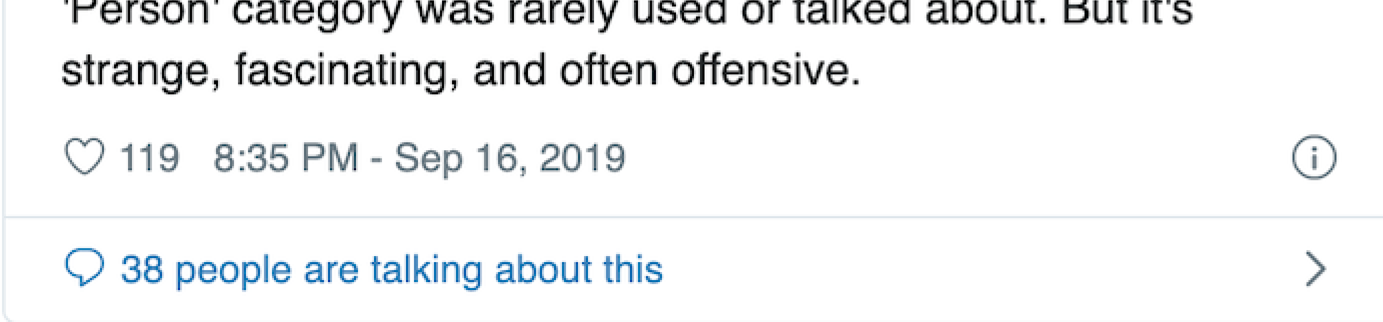
Kate Crawford @katecrawford · Sep 16, 2019

Want to see how an AI trained on ImageNet will classify you? Try ImageNet Roulette, based on ImageNet's Person classes. It's part of the 'Training Humans' exhibition by @trevorpaglen & me - on the history & politics of training sets. Full project out soonimagenet-roulette.paglen.com



Kate Crawford
@katecrawford

ImageNet is one of the most significant training sets in the history of AI. A major achievement. The labels come from WordNet, the images were scraped from search engines. The



https://twitter.com/katecrawford/status/1173666732923396098

A GUARDIAN REPORTER FINDS...

ImageNet Roulette

ImageNet Roulette uses a neural network trained on the "people" categories from the ImageNet dataset to classify pictures of people. It's meant to be a peek into the politics of classifying humans in machine learning systems and the data they're trained on.

ImageNet Roulette isn't designed to handle heavy traffic so if it's not working for you please be a little patient.

Start Webcam or Provide an image URL Classify image from URL

or upload an image:

Choose File No file chosen

gook, slant-eye: *(slang) a disparaging term for an Asian person (especially for North Vietnamese soldiers in the Vietnam War)*

- person, individual, someone, somebody, mortal, soul > inhabitant, habitant, dweller, denizen, indweller > Asian, Asiatic > Oriental, oriental person > gook, slant-eye
- person, individual, someone, somebody, mortal, soul > person of color, person of colour > Asian, Asiatic > Oriental, oriental person > gook, slant-eye

https://www.theguardian.com/technology/2019/sep/17/imagenet-roulette-asian-racist-slur-selfie

$3.1 Trillion Annually

downstream impacts of decisions and actions made on bad data

[IBM, HBR]

$14.2 Million Annually

average cost to a business

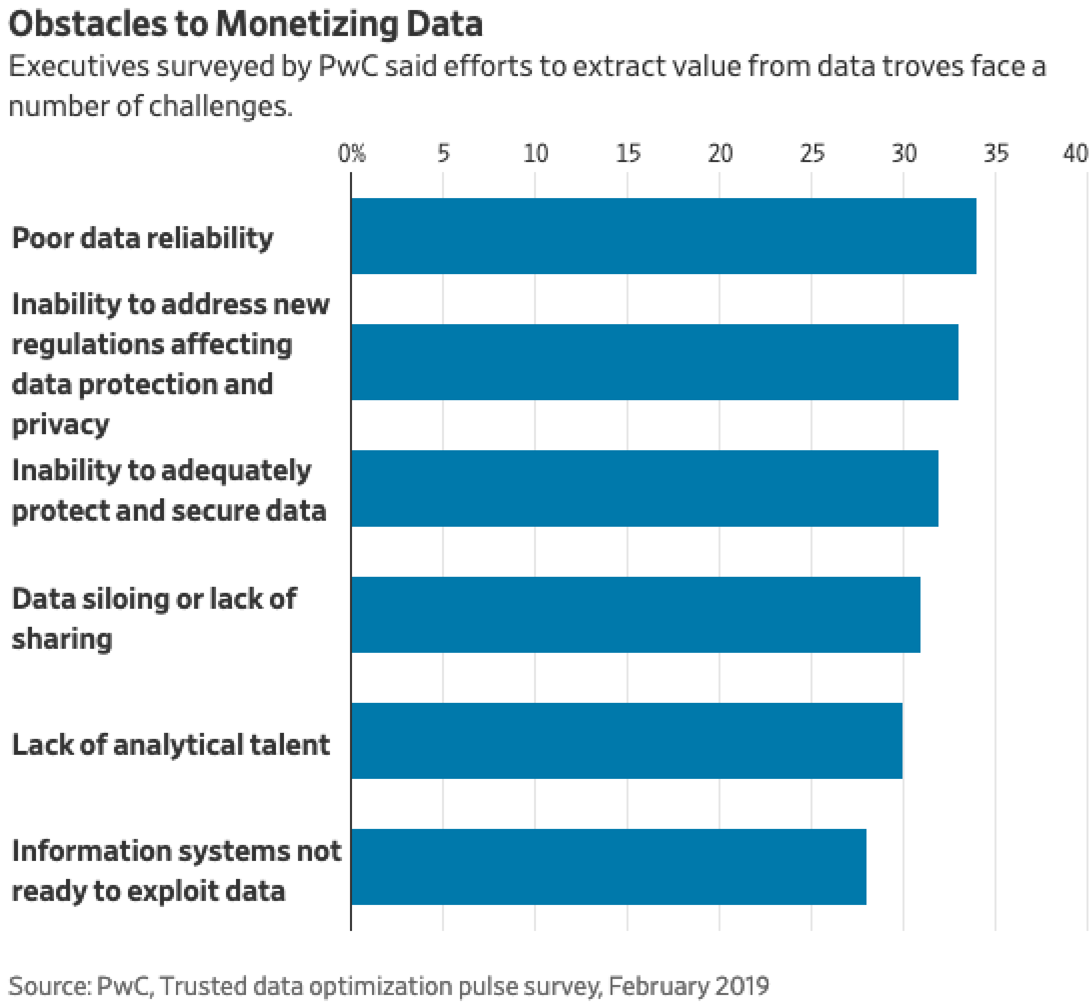
[Gartner]

27% Data is Flawed

in the World's top companies

[Gartner]

- https://www.ibmbigdatahub.com/infographic/four-vs-big-data
- https://hbr.org/2016/09/bad-data-costs-the-u-s-3-trillion-per-year
- Gartner, Dirty data is a business problem, not an IT problem, 2007, now removed



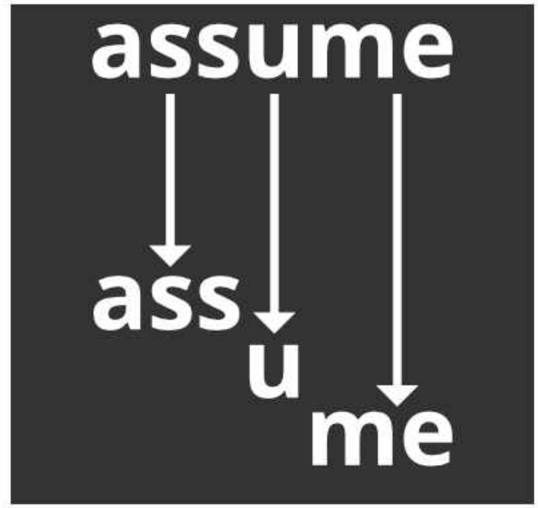
Loten, Angus. 2019. AI Efforts at Large Companies May Be Hindered by Poor Quality Data. Wall Street Journal, March 4, 2019, sec. C Suite. https://www.wsj.com/articles/ai-efforts-at-large-companies-may-be-hindered-by-poor-quality-data-11551741634.

BAD DATA INTRODUCES AN EXTRAORDINARY AMOUNT OF TECHNICAL DEBT

WHY BAD DATA AFFECTS RESULTS

- **Deduction**: Newton
- **Induction**: Sherlock Holmes


AWESOME AI
BIG DATA
BLOCKCHAIN
4.0 NEXT GEN
powered IOT
THING


assume
ass
u
me

GROUP QUESTION

WHAT IS THE DEADLIEST ANIMAL IN AUSTRALIA?

Horses more deadly than snakes in Australia, data shows

18 January 2017

Dr Ronelle Welton says her study challenges stereotypes about Australia

https://www.bbc.co.uk/news/world-australia-38592390

21-year-old Australian tradesman has been bitten by a venomous spider on the penis for a second time.

Jordan, who preferred not to reveal his surname, said he was bitten on "pretty much the same spot" by the spider.

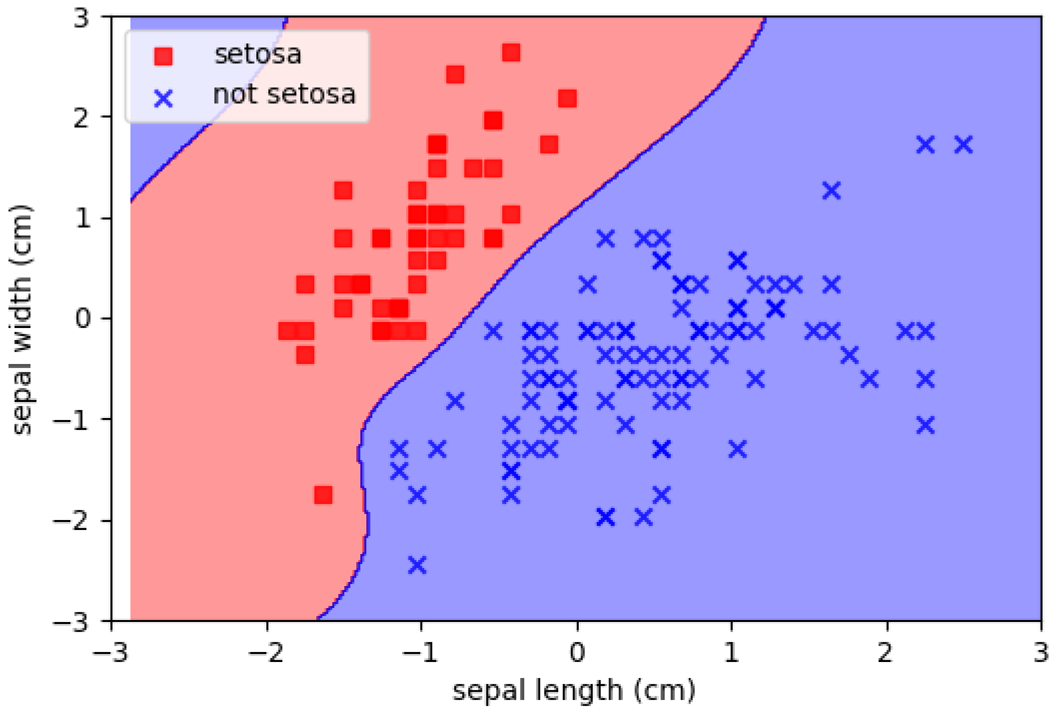
"I'm the most unlucky guy in the country at the moment," he told the BBC

https://www.bbc.co.uk/news/world-australia-37481251

VISUALISING DATA

- Always visualise your data
- How?
  - Histogram
  - Scatter plot (matrix)
  - Segmented (faceted) bar chart
  - Nullity plot
  - Correlation plot

SIMPLE MODELS



DATA LEAKAGE

Very easy to accidentally include future data in training data.

- Oversampling
- Running dimensionality reduction on the *whole* dataset
- Preprocessing over the *whole* dataset
- Including a feature that is only populated *after* the label has been applied

MISSING DATA - IMPORTANT?

- Missing data doesn't necessarily mean `numpy.nan`!

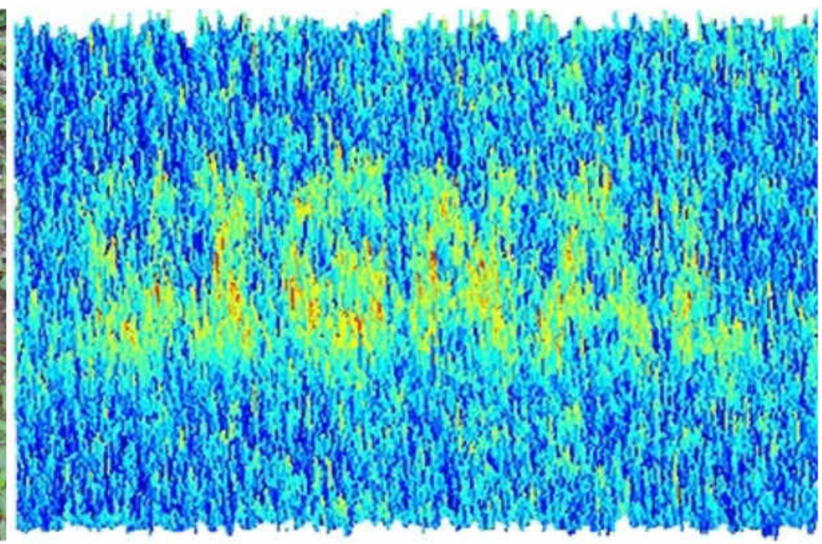
```
>>> print(titanic.count())
pclass       1309
survived     1309
name         1309
sex          1309
age          1046
sibsp        1309
parch        1309
ticket       1309
fare         1308
cabin         295
embarked     1307
boat          486
body          121
home.dest     745
dtype: int64
```

FIXING MISSING DATA

- Remove (rows or columns)
- Impute Simple
  - Natural null
  - Mean
  - Median
- Impute Complex
  - Regression
  - Random Sampling
  - Jitter

NOISE: WHAT IS NOISE?

Weeds are just flowers that you don't like. Noise is data that you don't like.



NOISE: TYPES OF NOISE

- Class
- Feature (column)
- Observation (row)

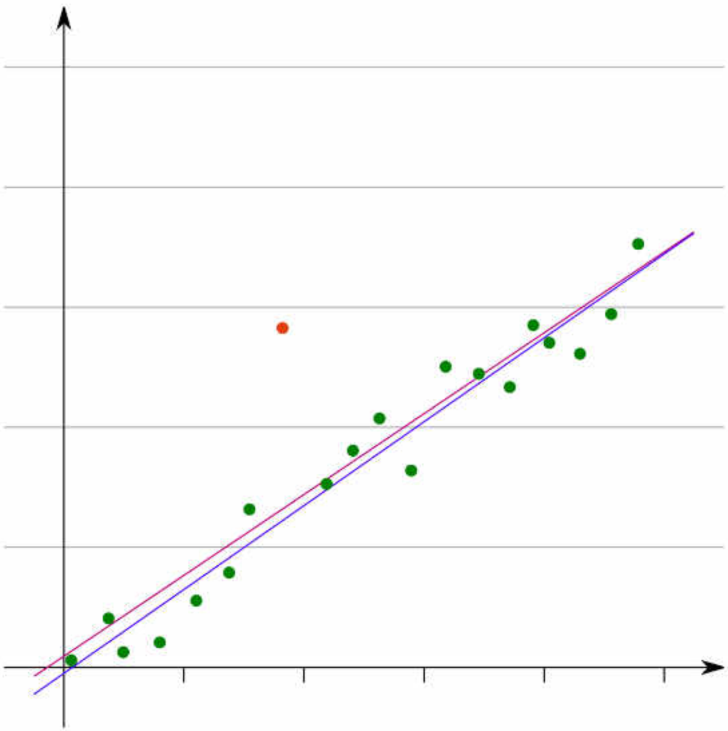
Rude/Friendly data from comments in: https://www.mobal.com/blog/travel-talk/travel-tips/the-16-friendliest-and-11-rudest-countries/			
Humour data from: https://medium.com/@speakerhubHQ/presenting-around-the-world-cross-cultural-humour-guide-25febca6310f			
	Observation noise		
	Feature noise		
	Label noise		
Person	Rude or Friendly	Humour	Country
Alice	Both	Puns, irony, satire, banter	UK
Bob	Both	Dark	Norway
Charles	NaN	None	UK
Dean	Both	Anything against USA	Canada
Edith	Both	Anything against USA	UK
Francis	Both	Not politics, not culture	USA
Gary	Both	Not at work	Germany
Heather	Both	Funny voices	Korea

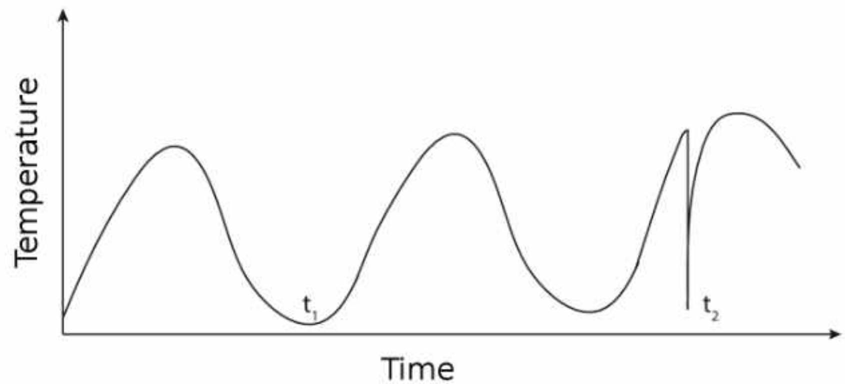
NOISE: IMPROVING NOISE

- Aggregation
  - Average (stacking/beamforming/radon transform
  - Median (popcorn noise)
- Simple modelling
  - Smoothing
  - Normalisation
- Complex modelling
  - Regression or fitting
- Dimensionality Reduction and Restoration
  - Transformations (FFT, Wavelet)
  - Encoding/Embedding (Autoencoder, NLP Embeddings)

ANOMALIES (A.K.A. OUTLIERS)

Data that is not expected (in a statistical sense)




Temperature
Time
t_1
t_2

ANOMALY TYPES

- Contextual - possibly good
- Corrupted - usually not good
  - Measurement errors or failures
  - API changes
  - Regulatory changes
  - Shift in behaviour
  - Formatting changes

DETECTING ANOMALIES

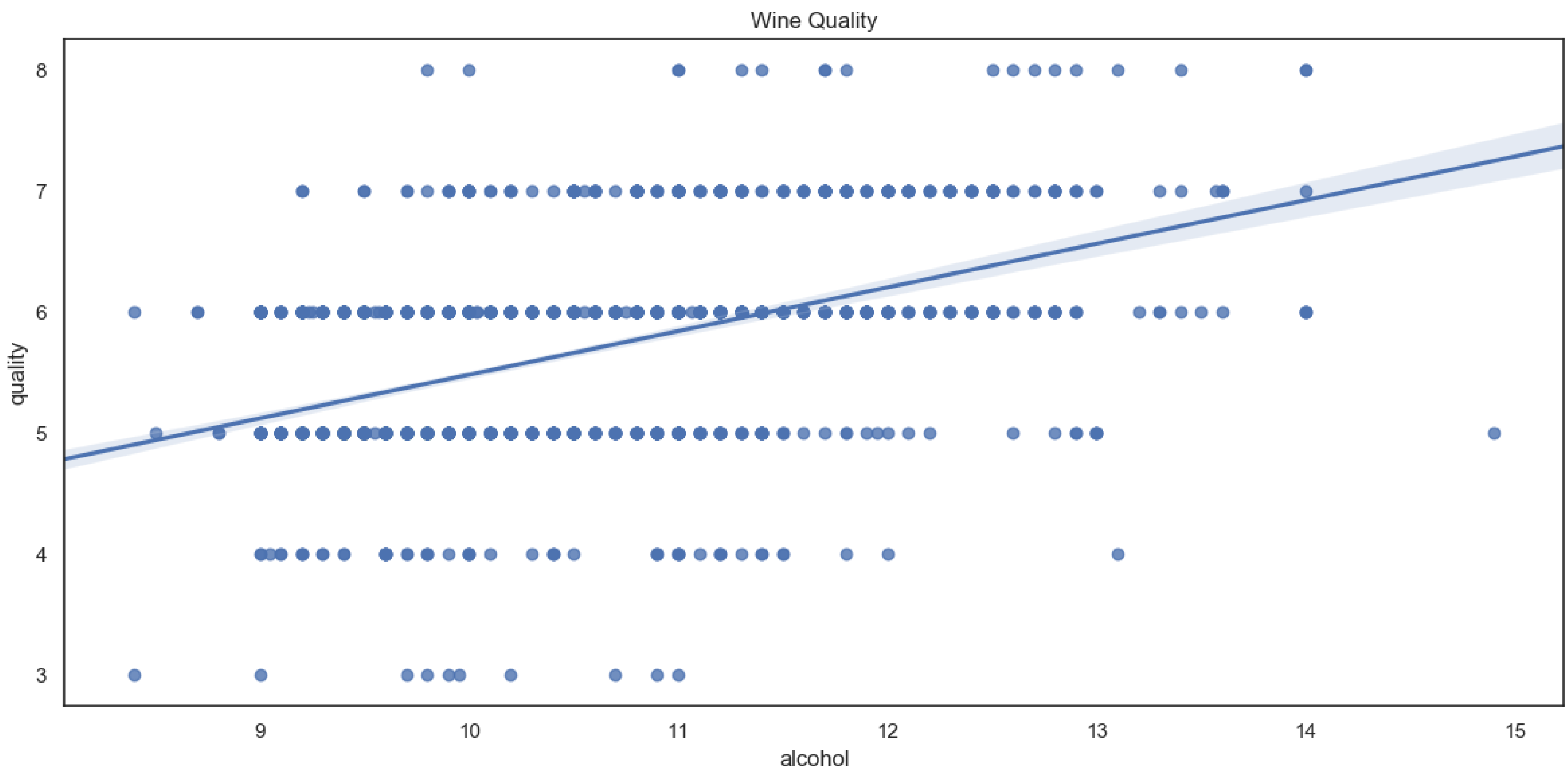
a large field in its own right

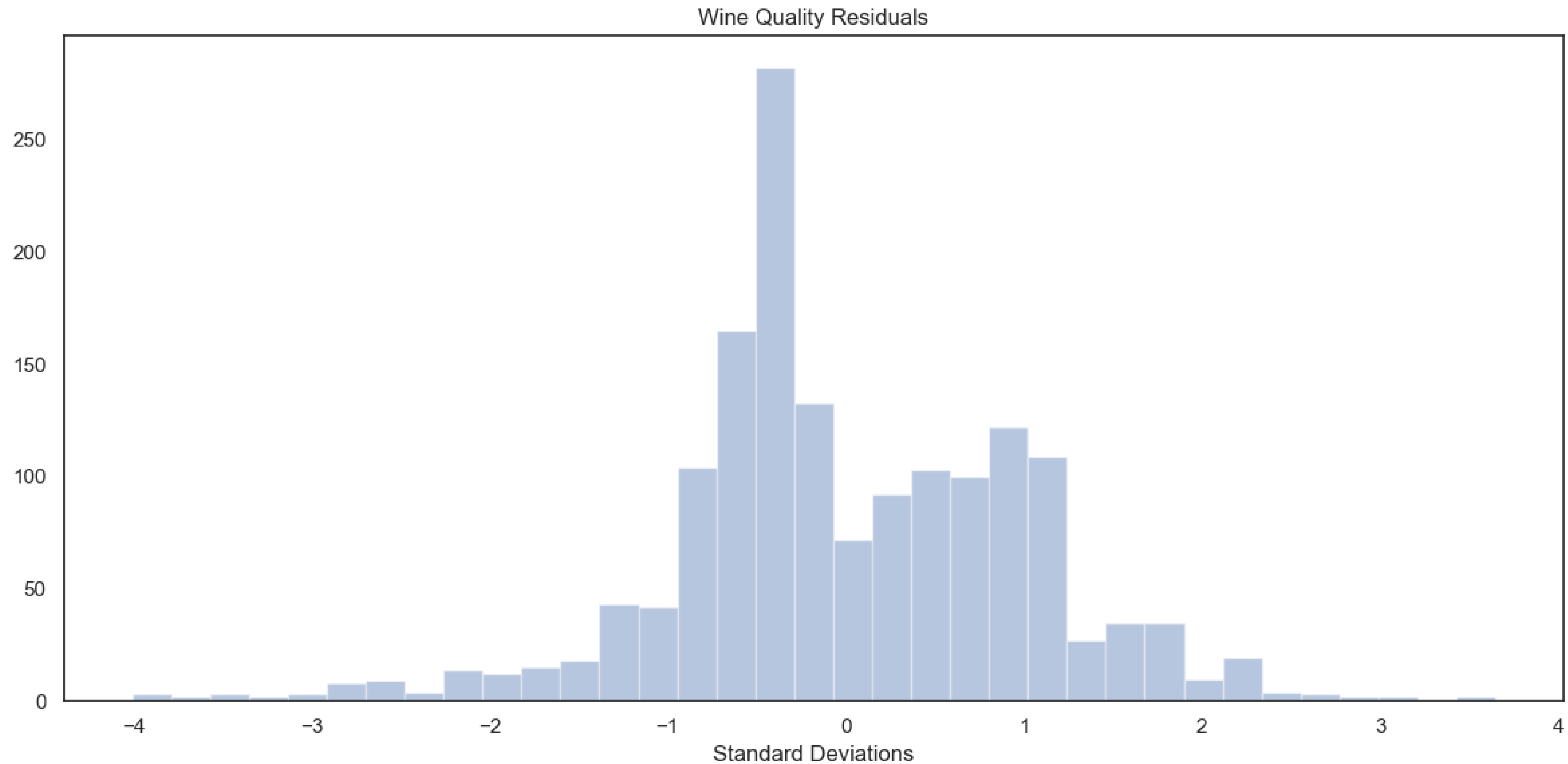
1. Define what is normal (through a model)
2. Set a threshold to define "not normal"

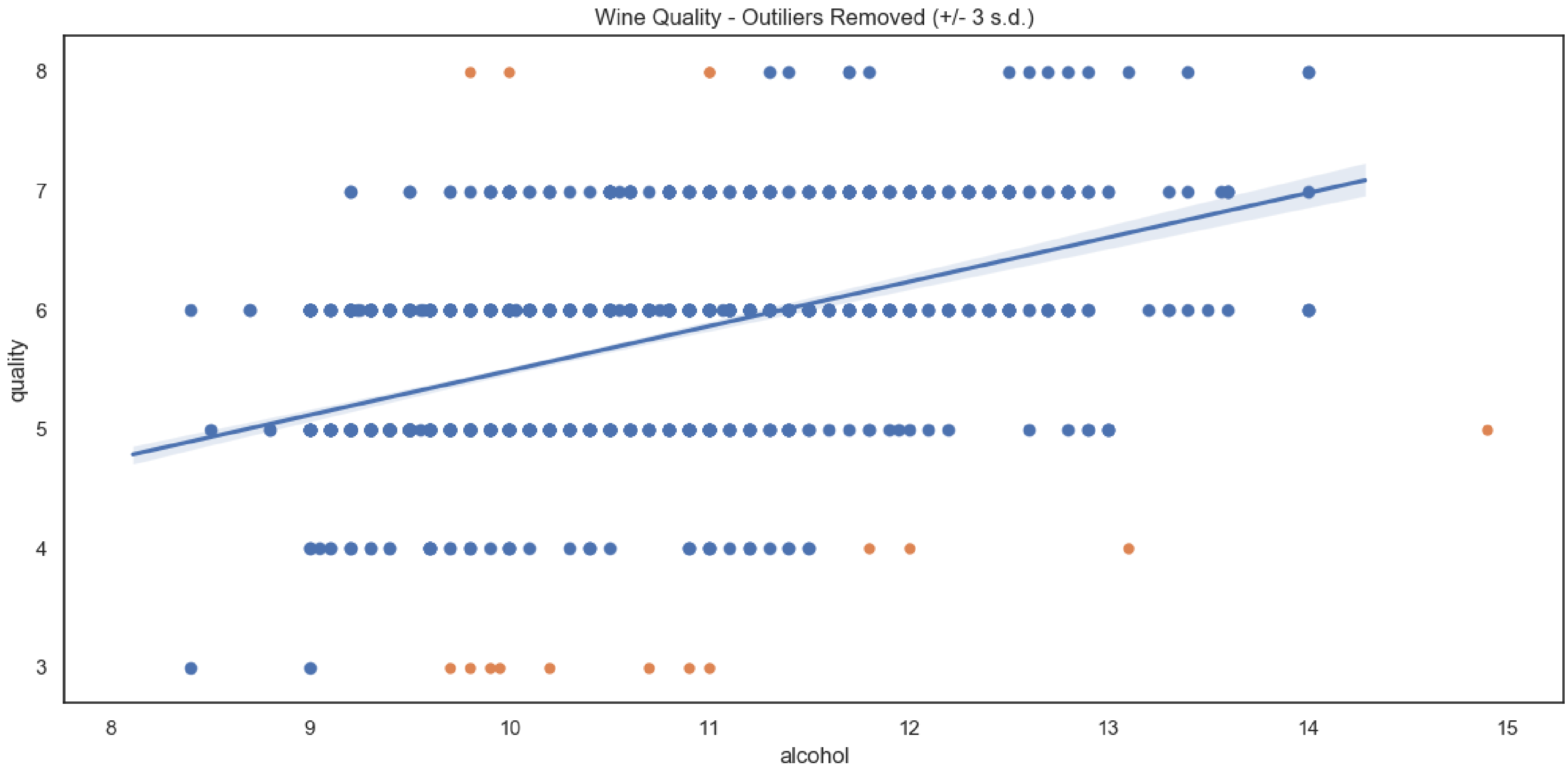
DETECTING ANOMALIES FOR DATA CLEANING

1. Visualise your data!
2. Everything else
    1. Classification task
    2. Clustering
    3. Regression/fitting + thresholds

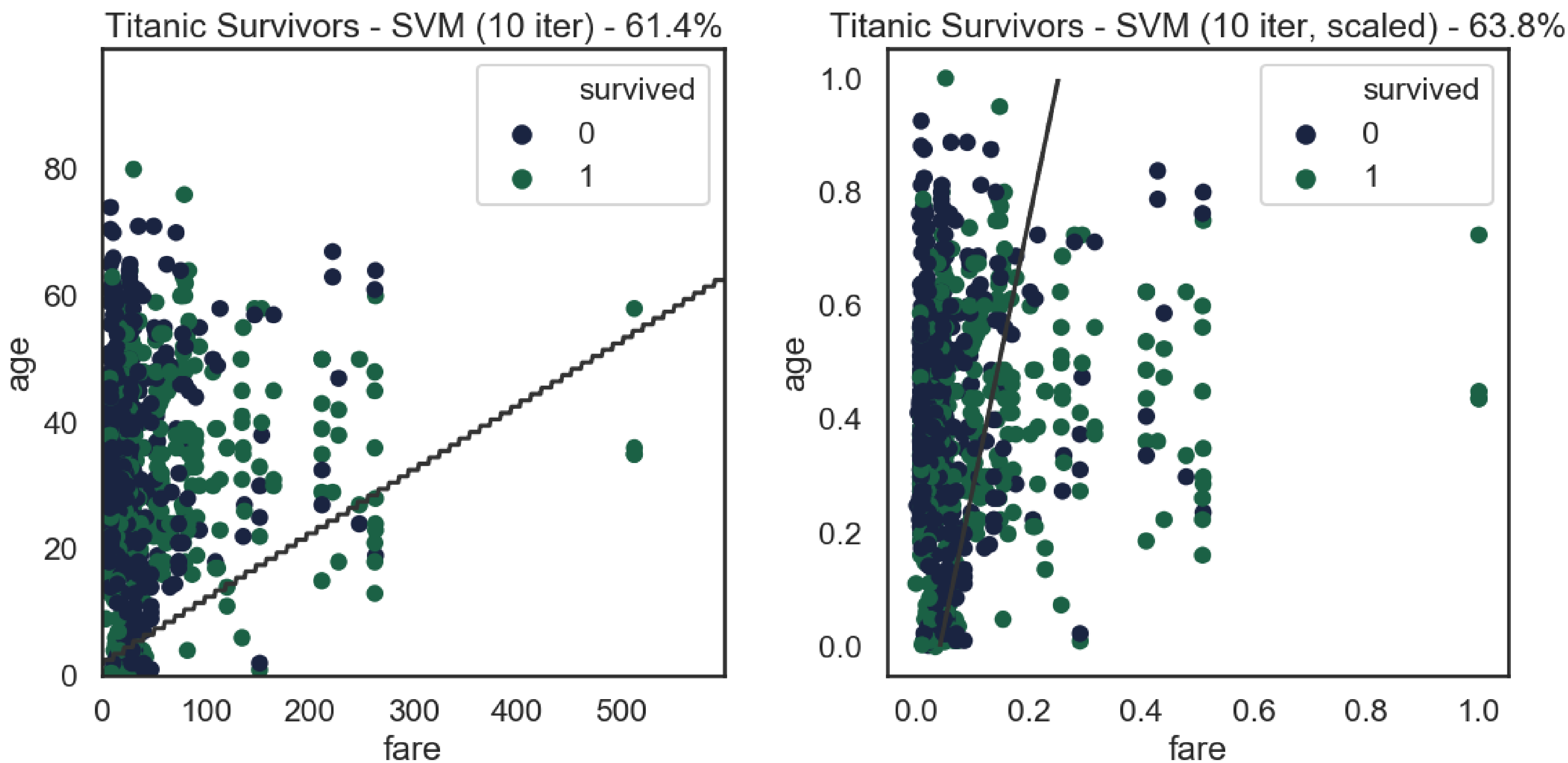
EXAMPLE REGRESSION TASK - WINE QUALITY



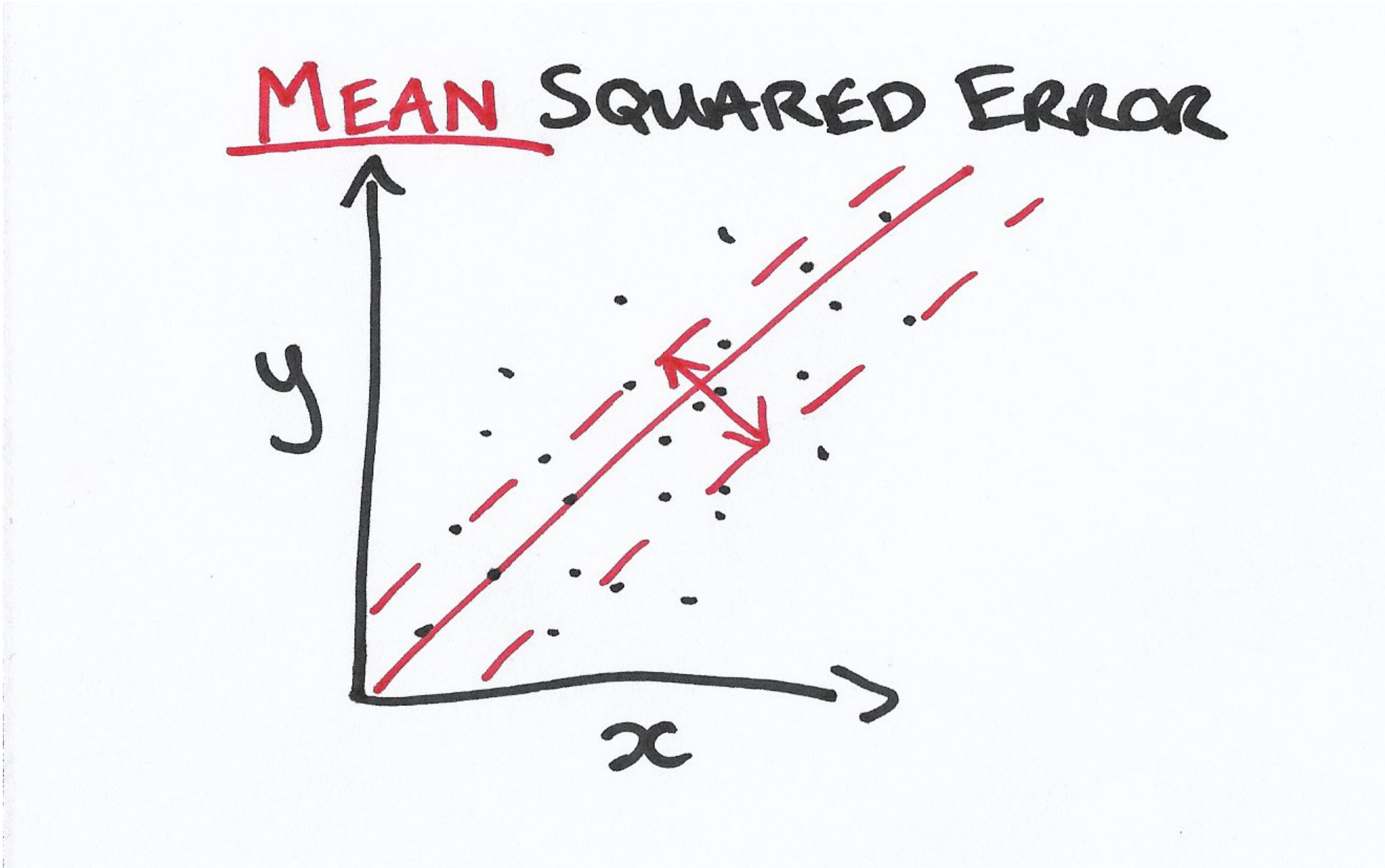

Wine Quality Residuals
250
200
150
100
50
0
−4
−3
−2
−1
0
1
2
3
4
Standard Deviations

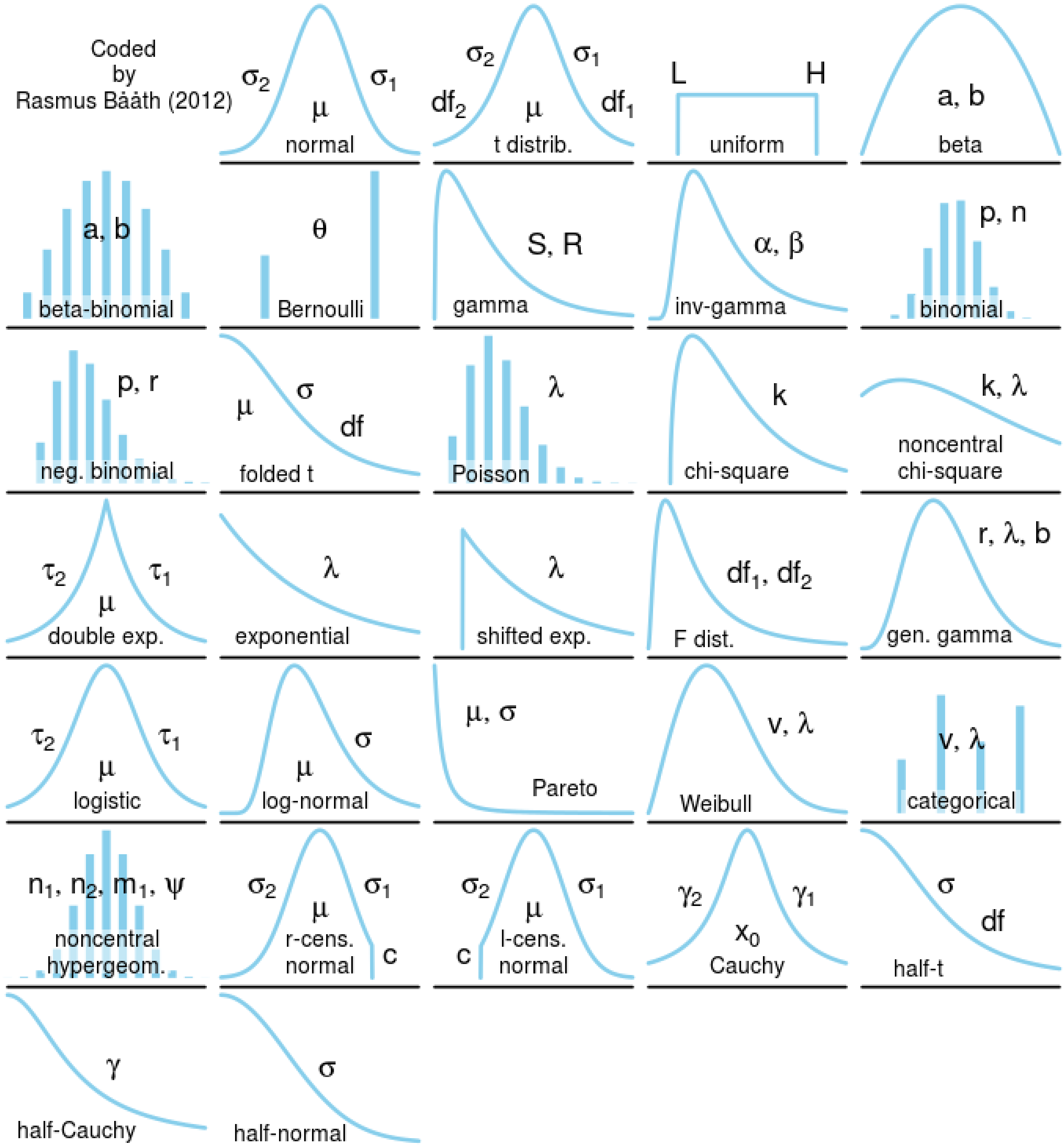

Wine Quality - Outiliers Removed (+/- 3 s.d.)
quality
alcohol
8
7
6
5
4
3
8
9
10
11
12
13
14
15

SCALE


Titanic Survivors - SVM (10 iter) - 61.4%
survived
0
1
age
fare
0
20
40
60
80
0
100
200
300
400
500
Titanic Survivors - SVM (10 iter, scaled) - 63.8%
survived
0
1
age
fare
0.0
0.2
0.4
0.6
0.8
1.0
0.0
0.2
0.4
0.6
0.8
1.0

NORMALITY



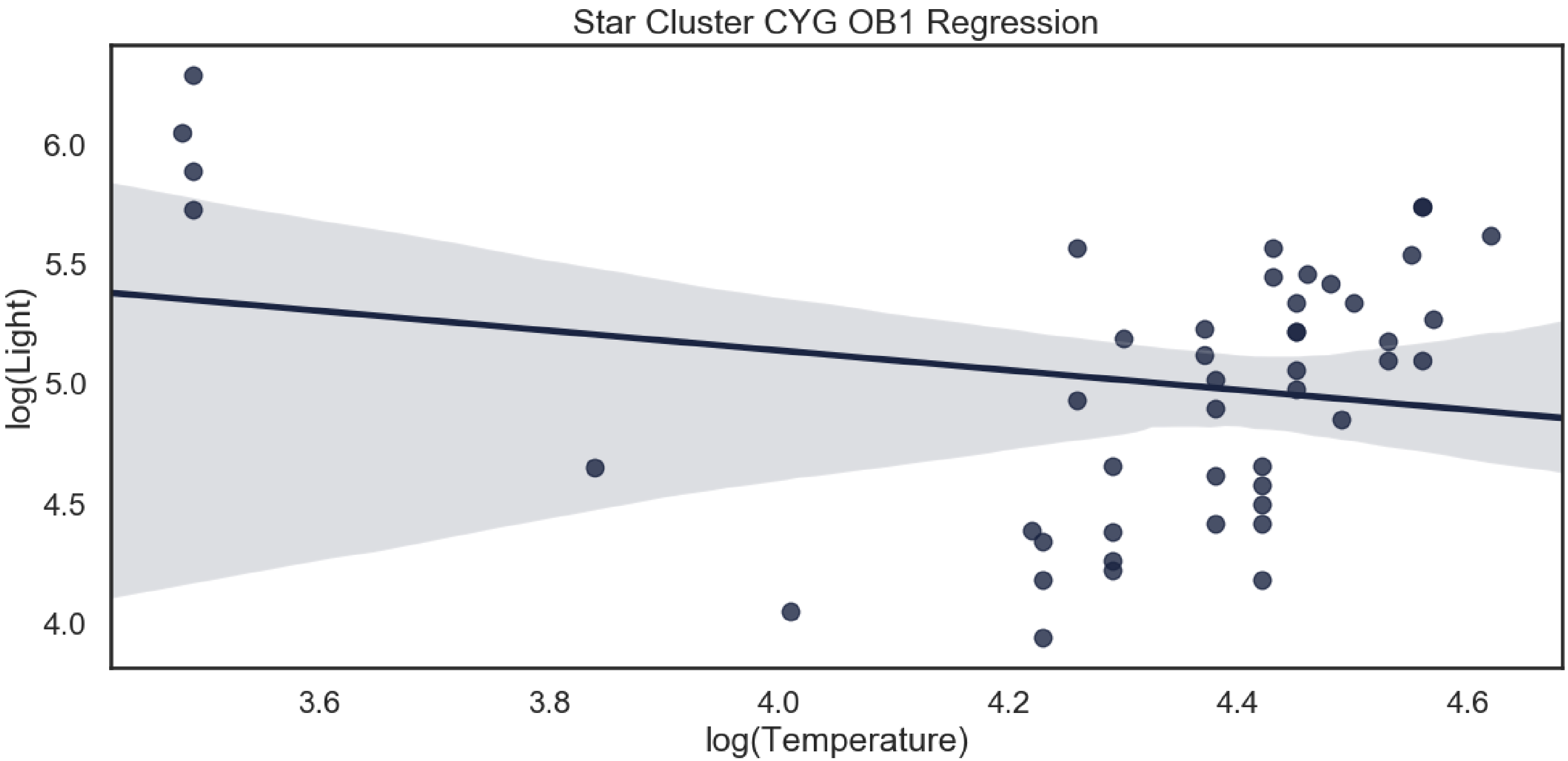


Coded
by
Rasmus Bååth (2012)
normal
t distrib.
uniform
beta
beta-binomial
Bernoulli
gamma
inv-gamma
binomial
neg. binomial
folded t
Poisson
chi-square
noncentral
chi-square
double exp.
exponential
shifted exp.
F dist.
gen. gamma
logistic
log-normal
Pareto
Weibull
categorical
noncentral
hypergeom.
r-cens.
normal
l-cens.
normal
Cauchy
half-t
half-Cauchy
half-normal

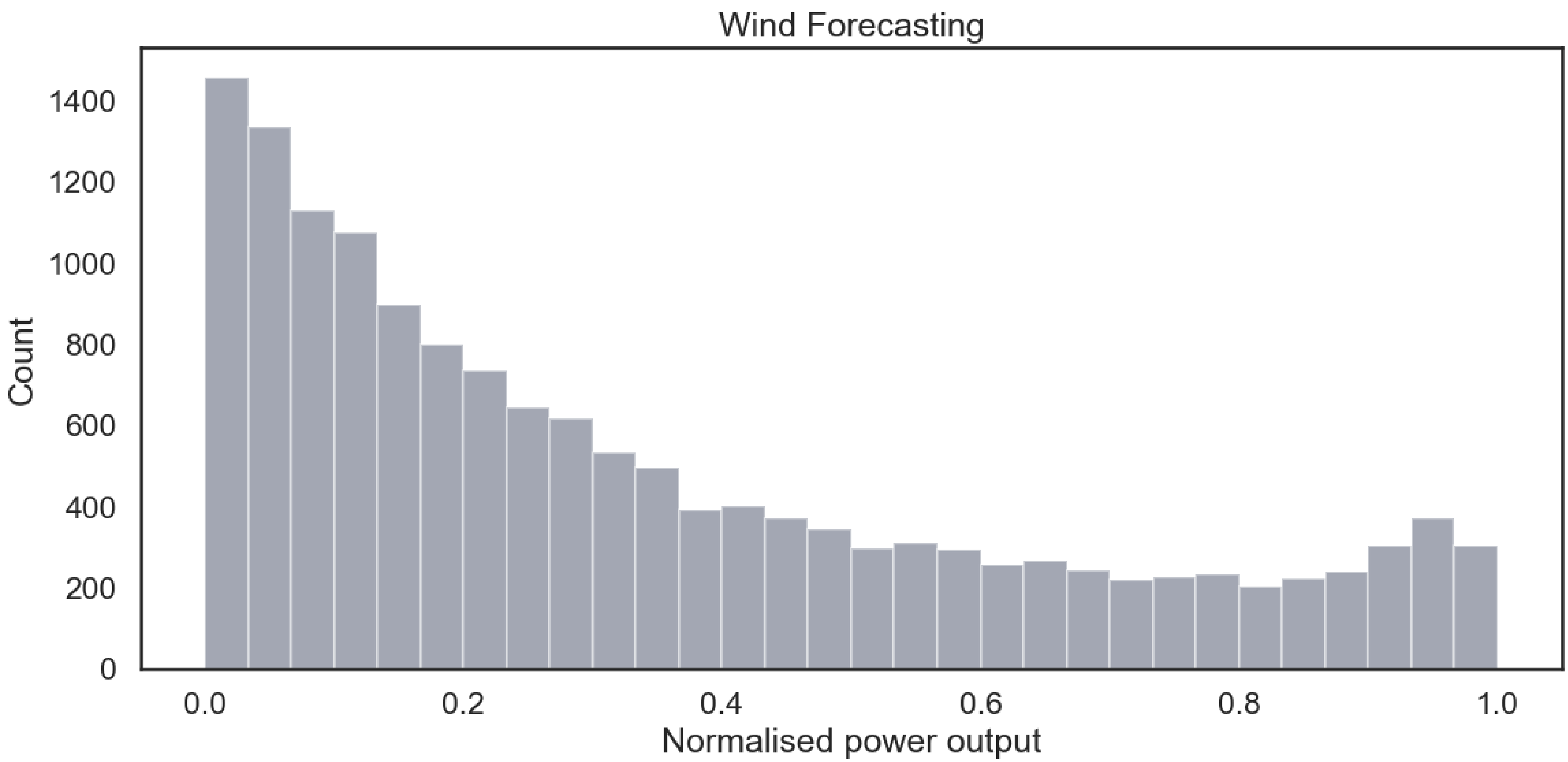
Look again at the parameters of all these distributions. Note how few of them use "mean".

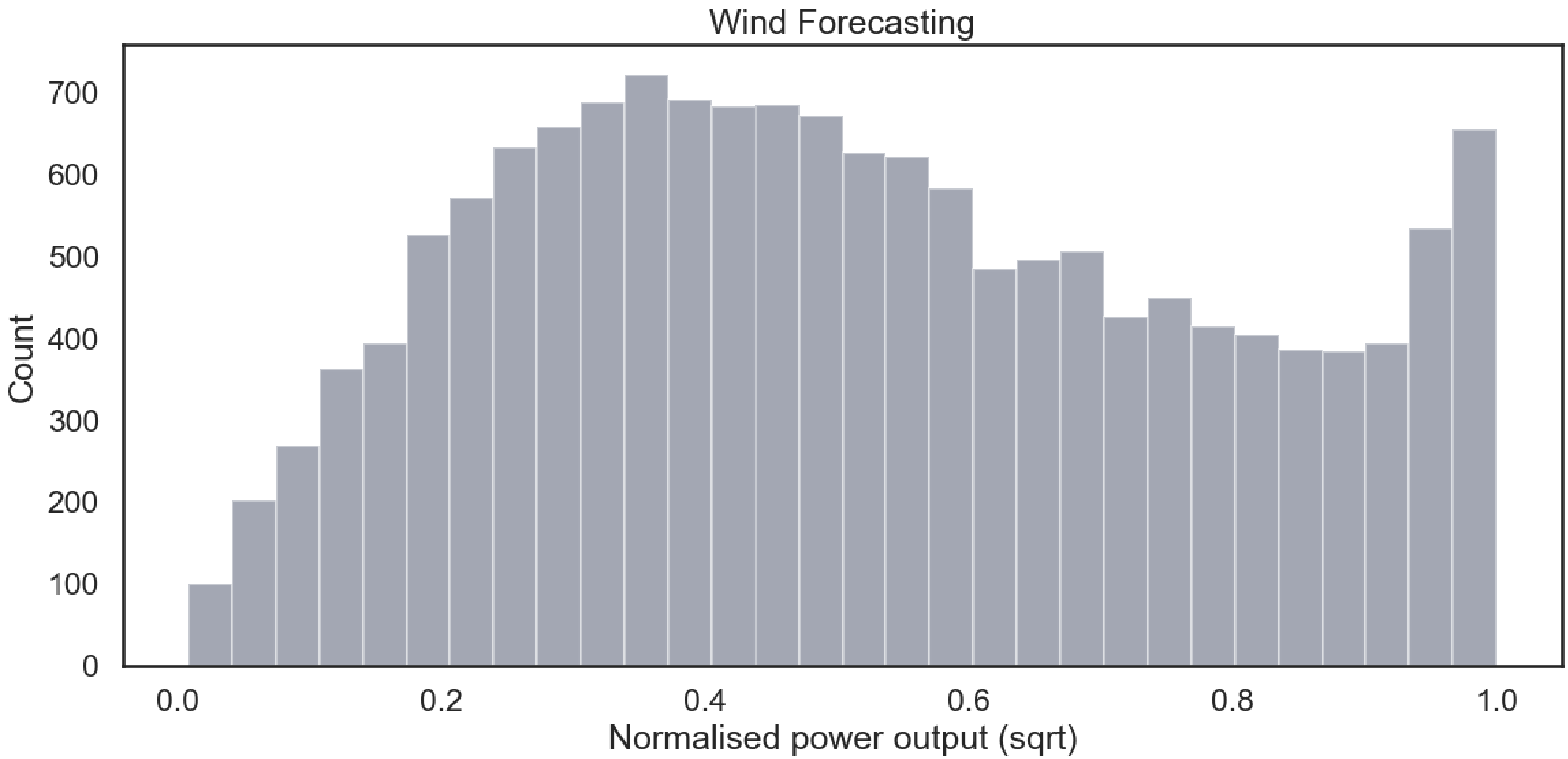
The vast majority of data cannot be represented by a mean. And the algorithm will not work.

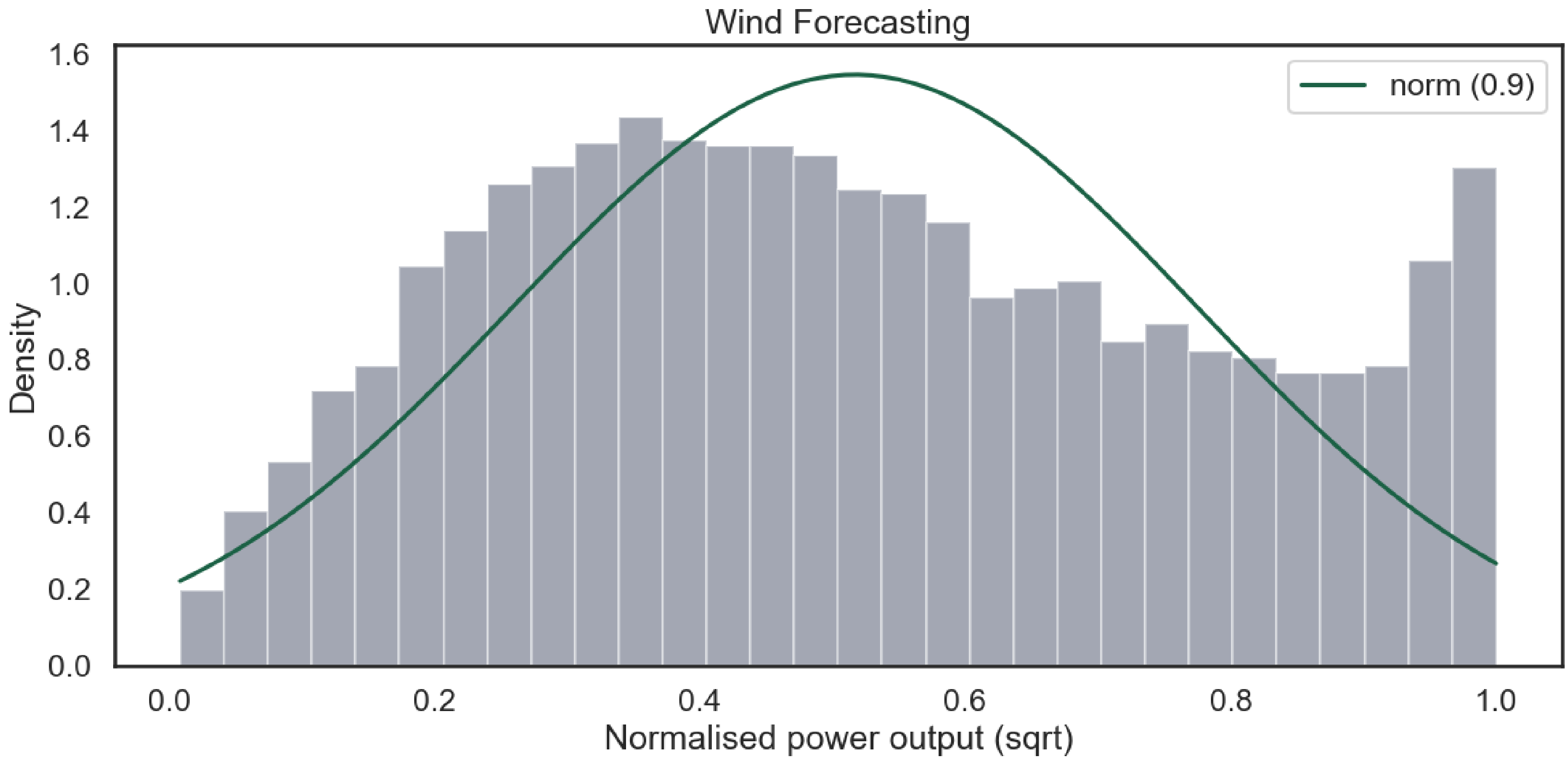
The best case...

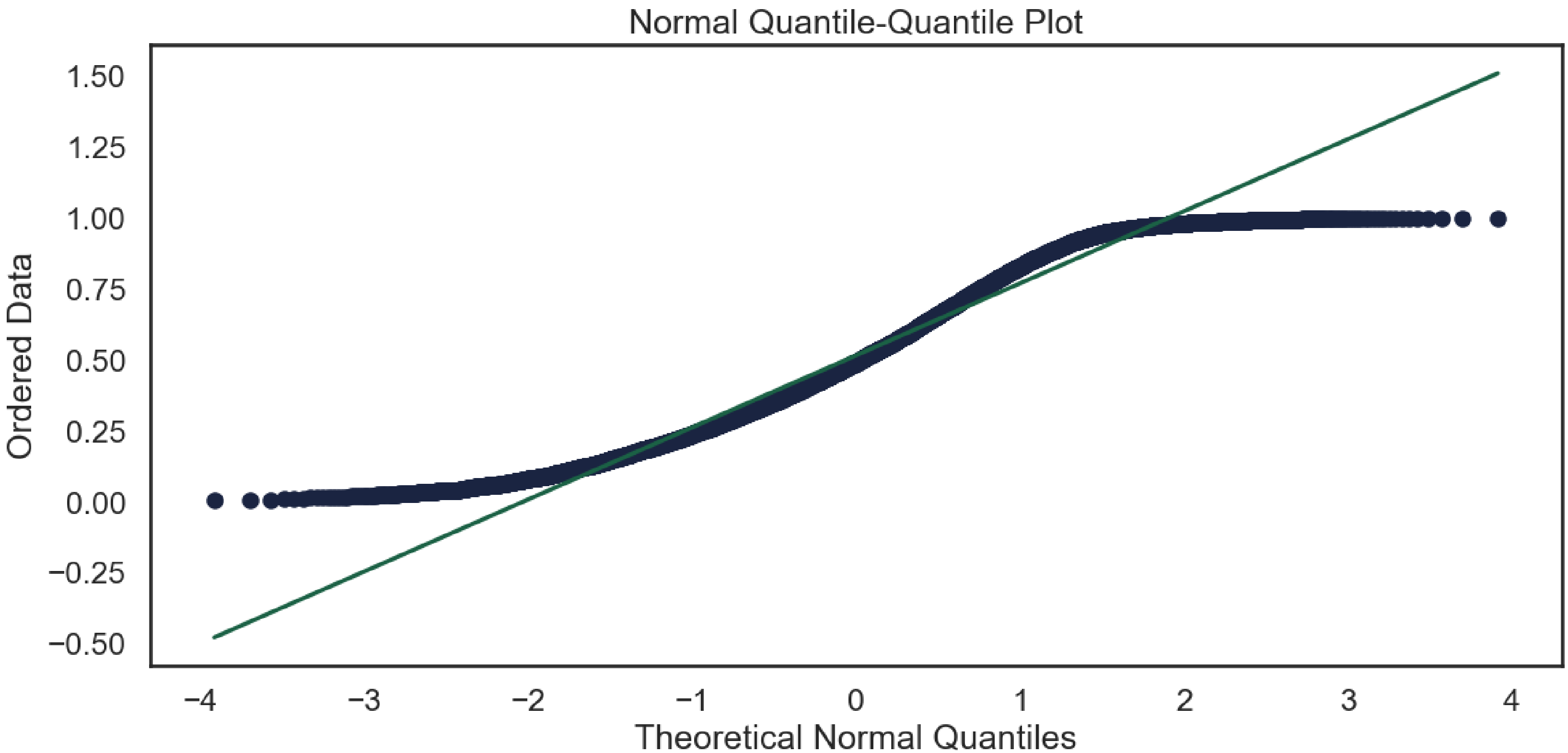

Star Cluster CYG OB1 Regression
log(Light)
6.0
5.5
5.0
4.5
4.0
3.6
3.8
4.0
4.2
4.4
4.6
log(Temperature)

FIXING: DOMAIN KNOWLEDGE




Wind Forecasting
Count
Normalised power output (sqrt)
0
100
200
300
400
500
600
700
0.0
0.2
0.4
0.6
0.8
1.0

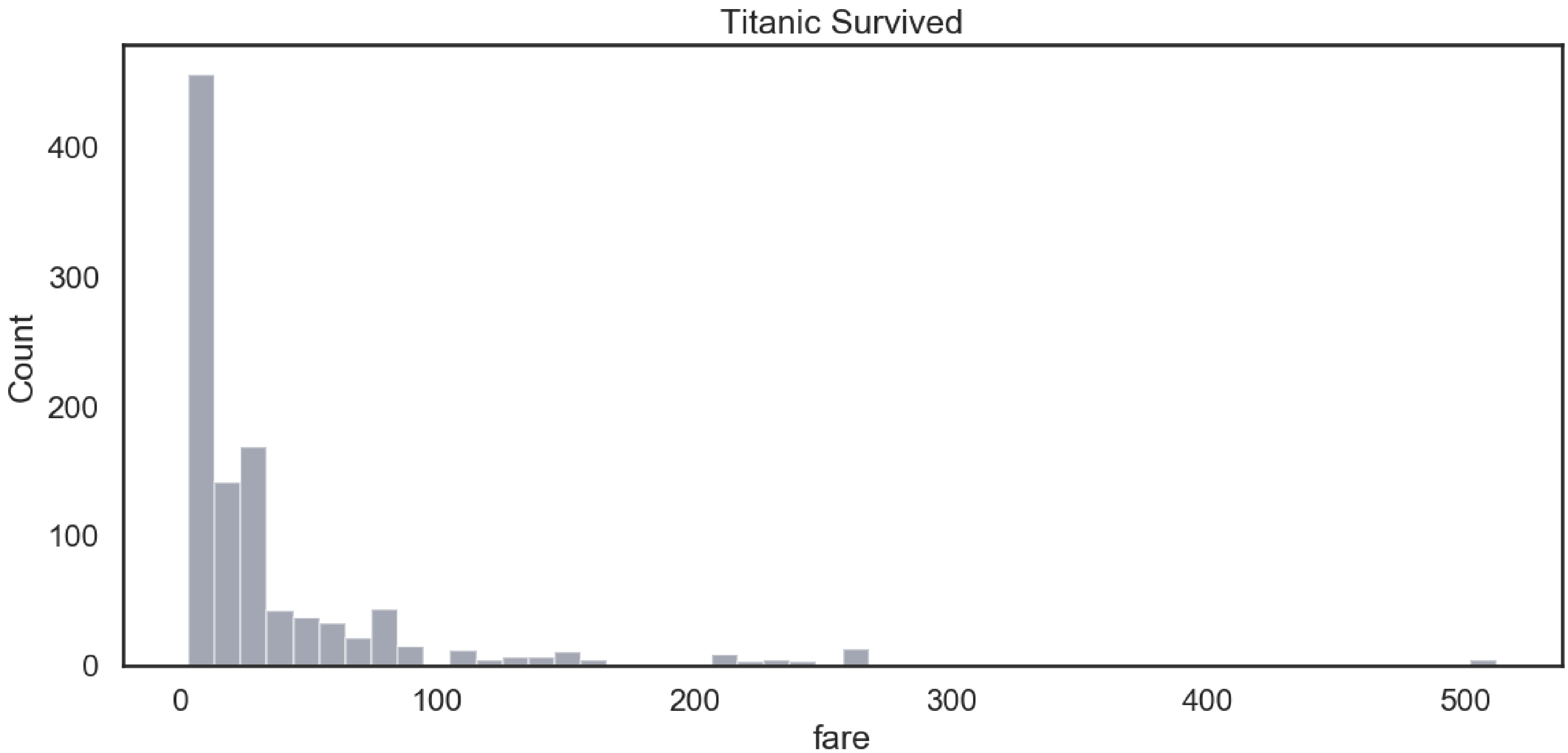

Wind Forecasting
norm (0.9)
Density
Normalised power output (sqrt)
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1.6

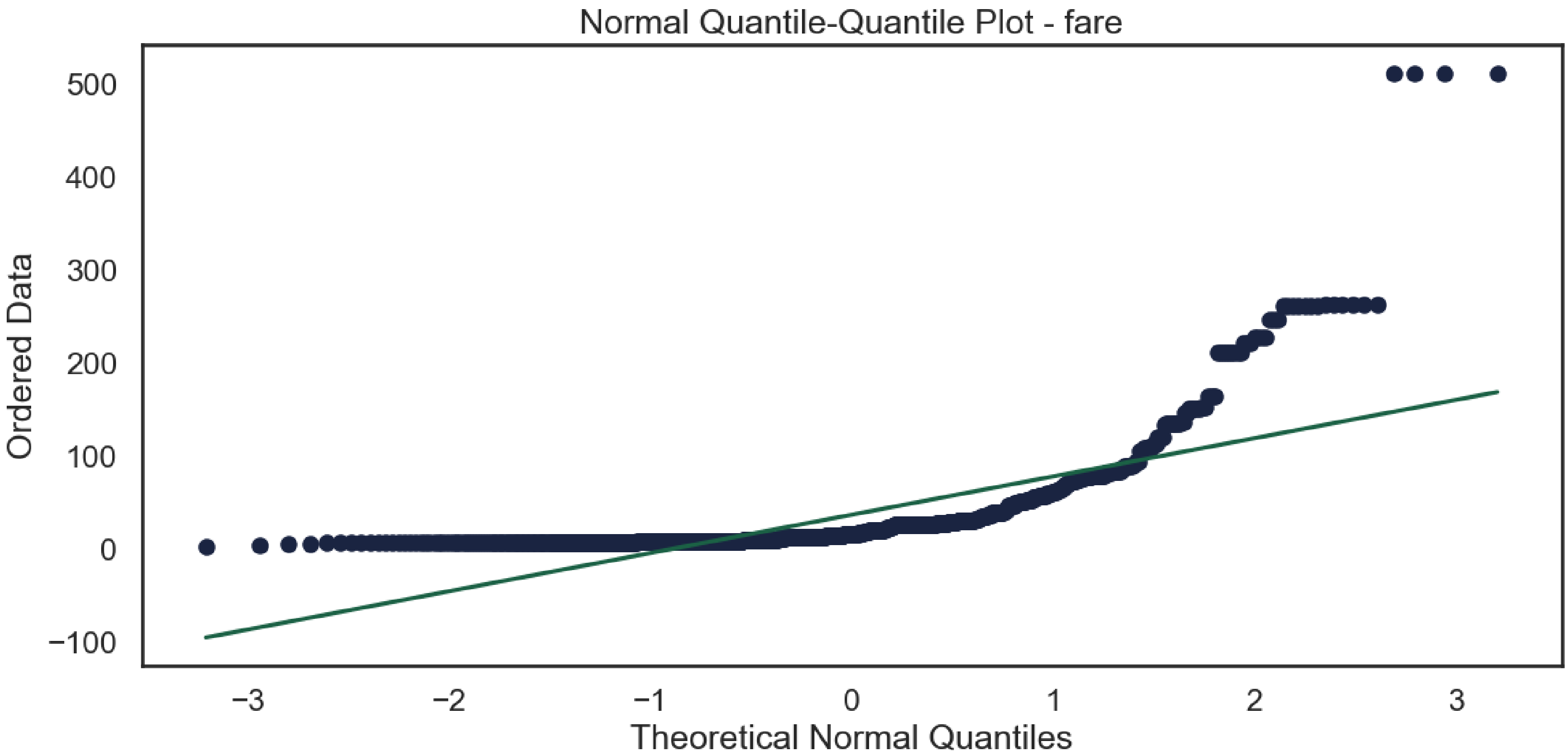

Normal Quantile-Quantile Plot
Ordered Data
Theoretical Normal Quantiles
1.50
1.25
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−4
−3
−2
−1
0
1
2
3
4

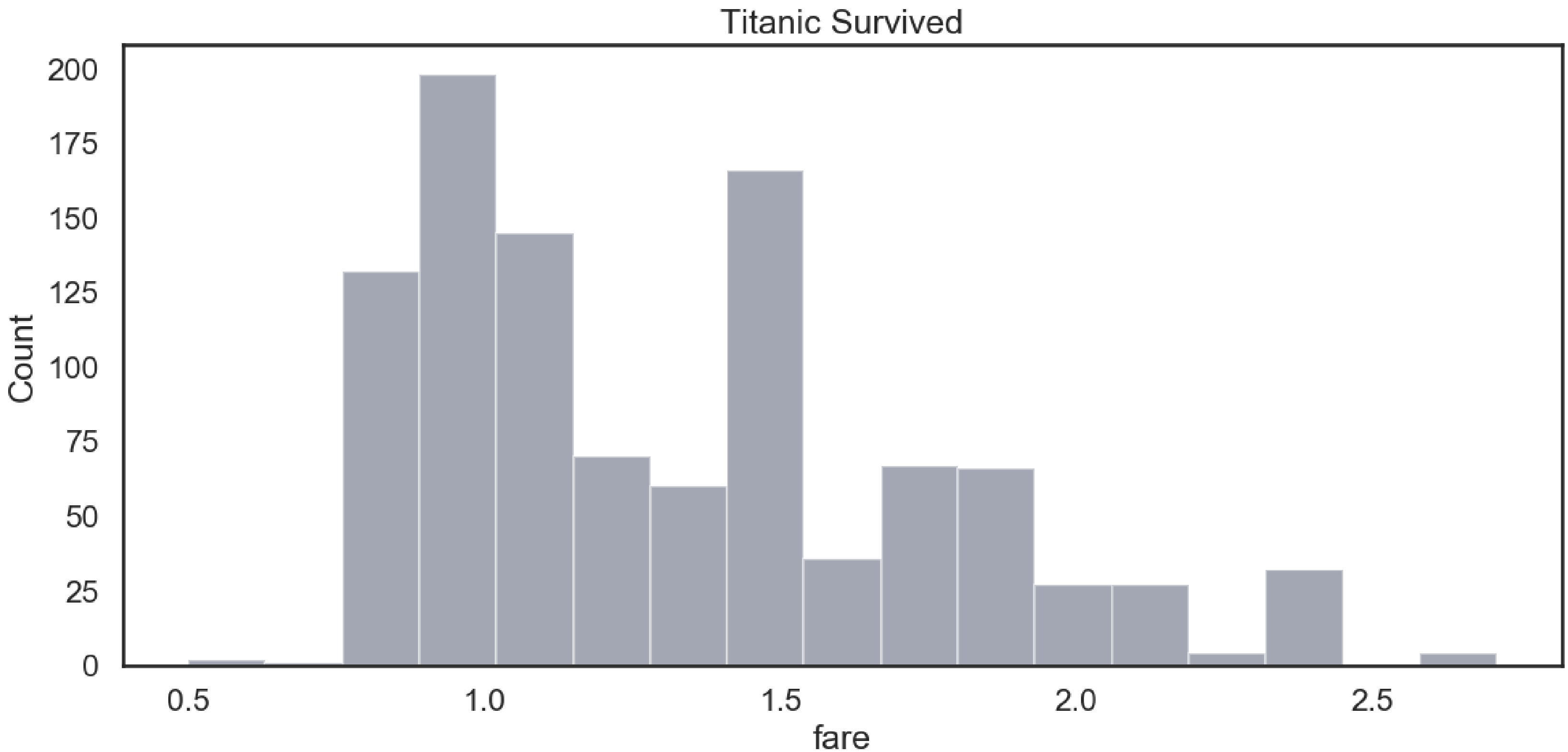
FIXING: ARBITRARY FUNCTIONS

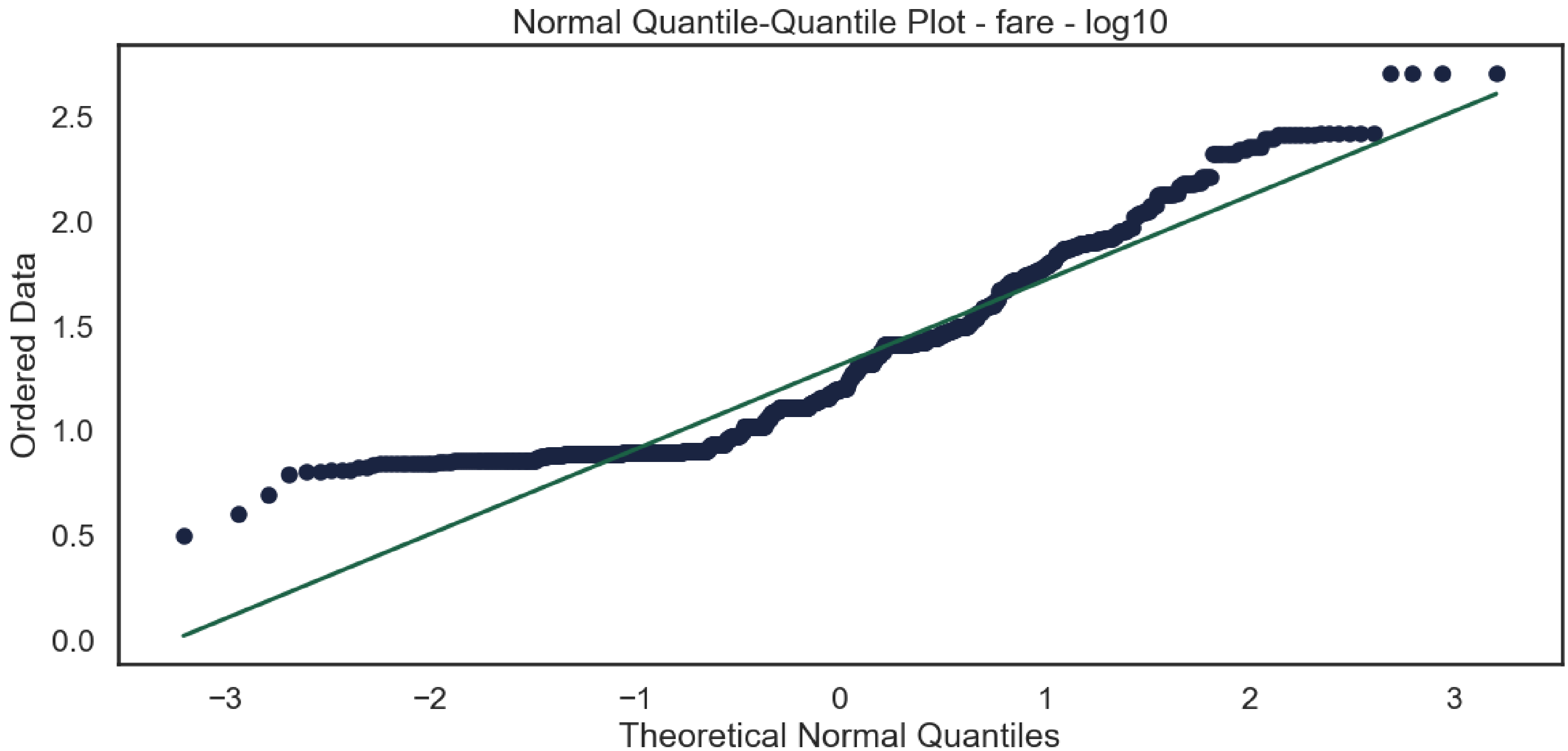
- We can use **any** mathematical function to transform our data*

*so long as it's invertible


Titanic Survived
Count
0
100
200
300
400
fare
0
100
200
300
400
500


Normal Quantile-Quantile Plot - fare
Ordered Data
500
400
300
200
100
0
−100
−3
−2
−1
0
1
2
3
Theoretical Normal Quantiles


Titanic Survived
Count
200
175
150
125
100
75
50
25
0
0.5
1.0
1.5
2.0
2.5
fare


Normal Quantile-Quantile Plot - fare - log10
Ordered Data
0.0
0.5
1.0
1.5
2.0
2.5
−3
−2
−1
0
1
2
3
Theoretical Normal Quantiles

THINGS I'VE SKIPPED OVER

- Practical examples
- Windsorising
- Types of data
- Scaling
- Derived Data
- Box Cox transform
- Time series data
- Feature selection
- Dimensionality reduction
- Data integration
- Probably lots more!

CONCLUDING REMARKS

- Data Cleaning:
  - is important
  - is open to interpretation
  - is (arguably) a manual process
  - takes a lot of time (approx 60% of a Data Scientist time)
  - requires domain knowledge

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DATA SCIENCE | CLOUD NATIVE

Data Science **Training, Consultancy, Development**

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