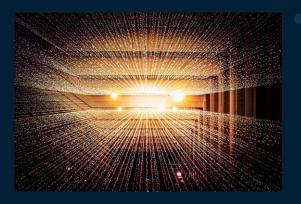
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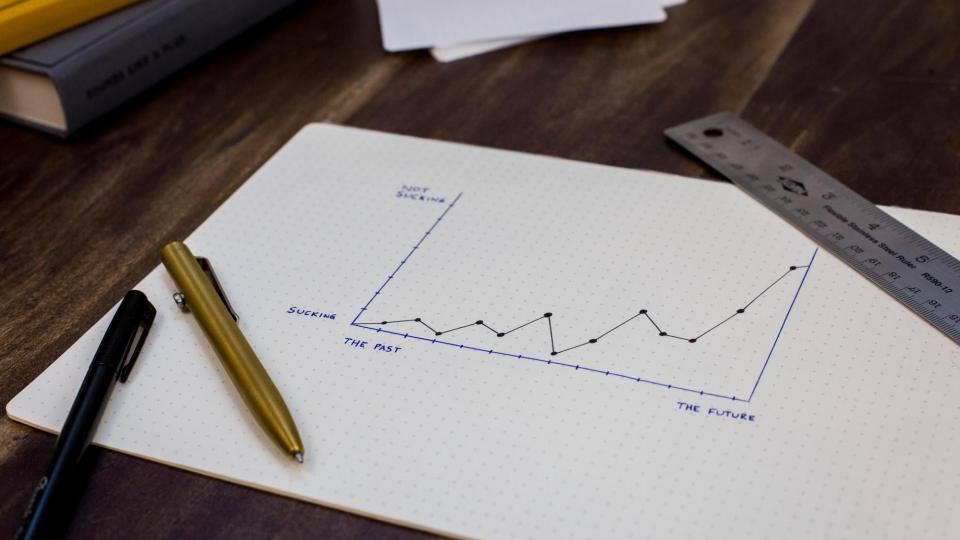






A data scientist's job according to unsplash







Rune Nielsen, PhD Data scientist & Al specialist at SAS Institute

• What is data ethics?

- What should we be aware of?
- Why does it raise problems?
 - How do we handle it?
- Which opportunities does it create?

Agenda





Data pitfalls

How many pitfalls are directly related to the data selection?

DATA FALLACIES TO AVOID

DATA DREDGING

Repeatedly testing new hypotheses against the same

set of data, failing to acknowledge that most

correlations will be the result of chance.

FALSE CAUSALITY

that one must have caused the other.

GAMBLER'S FALLACY

Mistakenly believing that because something has

happened more frequently than usual, it's now less

likely to happen in future (and vice versa).

PALE STIMAL 8

SIMPSON'S PARADOX

When a trend appears in different subsets of data but

disappears or reverses when the groups are combined.



CHERRY PICKING Selecting results that fit your claim and excluding those that don't.



COBRA EFFECT Setting an incentive that accidentally produces the opposite result to the one intended. Also known as a



Drawing conclusions from a set of data that isn't representative of the population you're trying to understand.



REGRESSION TOWARDS THE MEAN When something happens that's unusually good or bad, it will revert back towards the average over time.



OVERFITTING Creating a model that's overly tailored to the data you



GECKOBOARD.COM







Interesting research findings are more likely to be published, distorting our impression of reality.



SURVIVORSHIP BIAS

Drawing conclusions from an incomplete set of data, because that data has 'survived' some selection criteria.



GERRYMANDERING Manipulating the geographical boundaries used to group data in order to change the result.



HAWTHORNE EFFECT The act of monitoring someone can affect their behaviour, leading to spurious findings. Also known as the Observer Effect.



MCNAMARA FALLACY Relying solely on metrics in complex situations and losing sight of the bigger picture.



DANGER OF SUMMARY METRICS Only looking at summary metrics and missing big differences in the raw data.





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Falsely assuming when two events appear related Perverse Incentive,



SAMPLING BIAS



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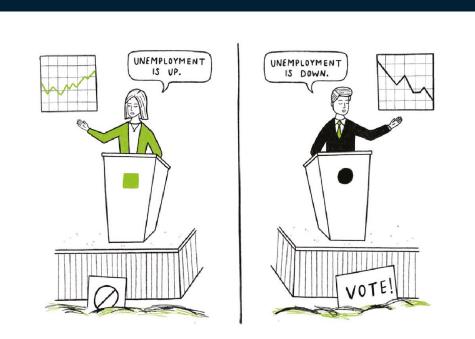
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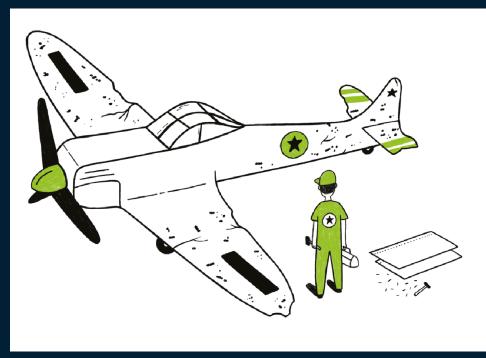
Cherry Picking





Survivorship bias





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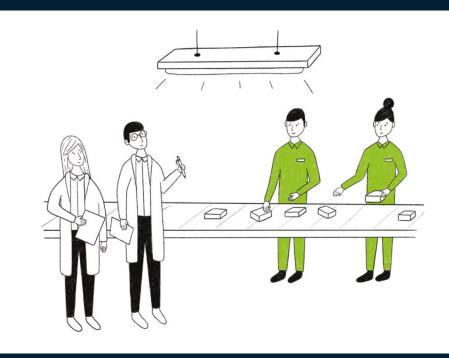
Sampling bias





Hawthorne's effect







Data pitfalls

How many pitfalls are directly related to how we treat data under the model development?

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data fallacies to avoid

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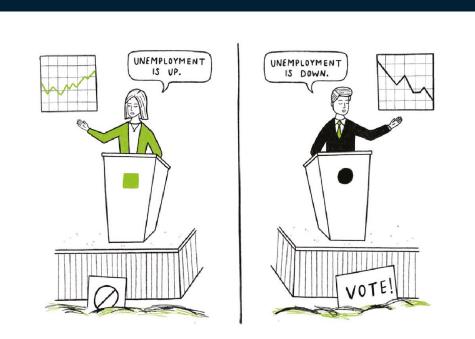
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Read more at data-likeracy.geokoboard.com



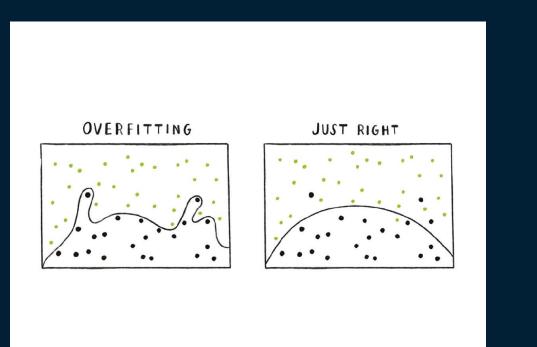


Cherry Picking





Overfitting





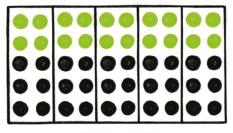
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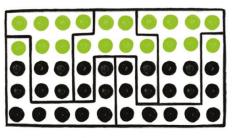


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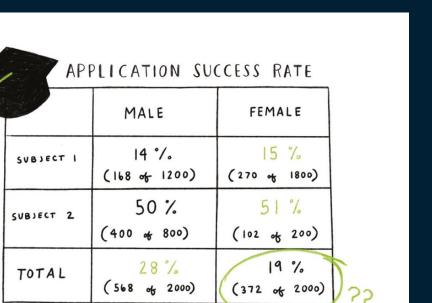
BLACK WINS



GREEN WINS



Simpson's Paradox





Data pitfalls in relation to data treatment.

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What is the cause of the issue?



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Ordinary least squares (OLS)

OLS assumptions:

- 1. Random sample
- 2. Linear in parameters
- 3. No multi-collinearity
- 4. The independent variables are exogenous
- 5. The error term is homoscedastic
- 6. The error term is normally distributed with mean 0 and constant variance (Hypothesis test)
- Only one point is about data?

Are you allowed to plot your data before an hypothesis test?

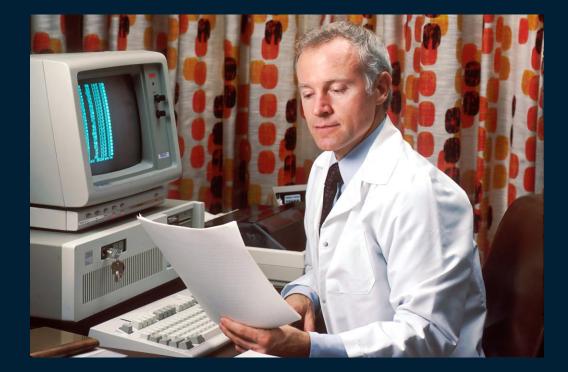
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Culture as a part of the modelling toolbox

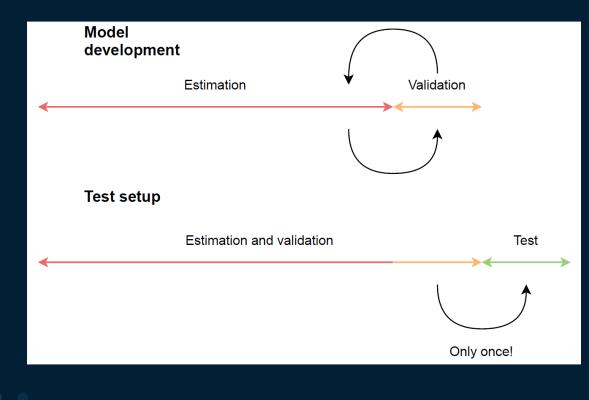




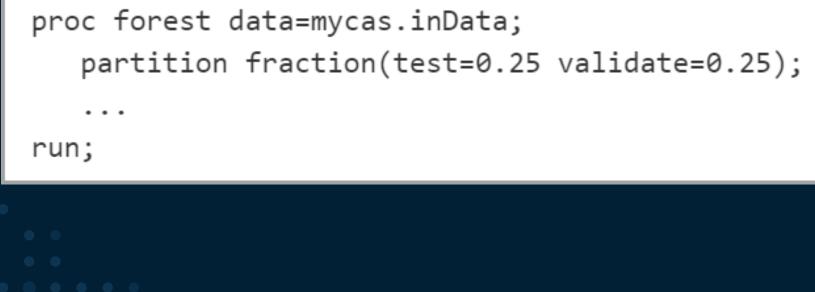
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Which opportunities does it create?

Ordinary least squares (OLS)

- 1. Random sample
- 2. Linear in parameters
- 3. No multi-collinearity
- 4. The independent variables are exogenous
- 5. The error term is homoscedastic
- 6. The error term is normally distributed with mean 0 and constant variance (Hypothesis test)



Which opportunities does it create?

- Flexible model development
 - Enabling iterative model development
- Business focus
 - Focus on the performance of the model (e.g. forecast precision)
 - Less time on assumptions

References

- Data fallacies to avoid: <u>Geckoboard</u>
- Billeder fra Unsplash: Ramón Salinero, Myriam Jessier, Joshua Sortino, David Pupaza, ThisisEngineering RAEng, Firmbee.com, Isaac Smith, C Drying, h heyerlein, Emily Morter, National Cancer Institute, Patrick Weissenberger





Rune Hjorth Nielsen Providing insights within data science and Al for SAS customer advisory





