When to Trust and When Not to Trust Data Science

Saghir Bashir



Definition: "Data Science"

Generally accepted definition does not exist!

Presentation definition:

"Using data, statistics and programming, in a given context, to support decision making."

"Applied Statistics"

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Machine Learning is <u>NOT</u> Data Science!

Machine Learning is type of analysis that you might perform as part of doing Data Science

Outline

Data Data Everywhere
News Headlines & Data Science
Trust & Trustworthy
Trustworthy Data Science
Summary

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Objectives

My objectives are to encourage you to:

- > Challenge your own thinking
- > Be objective & critical about Data Science
 - → "Trustworthy Data Science"

Data Data Everywhere

News Headlines & Data Science
Trust & Trustworthy
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Summary

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We Are Data We Are Data We Are Data

Data Data Everywhere

> Governmental

- → Unemployment, crime, literacy, economic, census, demographic, ...
- > Non-governmental
 - → Homelessness, social inequality, poverty, opinion polls and surveys, ...
- > Business
 - → Stock price, sales data, profits, business confidence, ...

> Internet

- → Social media, search history, web browsing, surveys, ...
- > Health
 - → Disease monitoring, pharmaceutical, live births, ...
- > Environmental
 - → Climate, marine, animal, plants, pollution, ...
- > And so on...

Data Science Everywhere

If we have *DATA* everywhere then we have *DATA SCIENCE* everywhere

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Data Data Everywhere

News Headlines & Data Science

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MailOnline

Lethal legacy of dash for diesel: Air pollution is 'killing 40,000 a year in the UK'

- Diesel cars fuel a health crisis that kills 40,000 people a year in the UK
- · Emissions linked to asthma, heart disease, cancer, diabetes and dementia
- . Ownership of diesel cars has more than trebled in the past 15 years

23 February 2016 https://1n.pm/gTkcE

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theguardian



Air pollution crisis 'plagues' UK, finds UN human rights expert

'Silent pandemic' of air pollution affects UK children and there is no indication protection against toxic waste will be retained after Brexit

theguardian

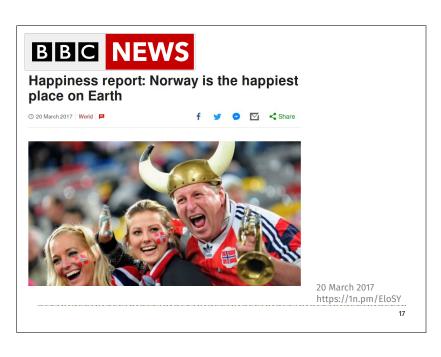
"...between 30,000 and 40,000 early deaths every year are caused by toxic air across the country"

> 31 January 2017 https://1n.pm/0Bkqq













Some Comments

News headlines

- > Catch your attention and give you a flavour of the story
- > The news story may or may not represent the source
- > People will have different views and interpretations
 - → This is not of interest in this presentation
 - → The interest is in the "validity and quality" of the source Data Science

It's Not About Headlines

One day it could be your Data Science 🚱

- > Perhaps not as a news story with a creative headline
- > Perhaps as a summary to your bosses or clients
- > Could you defend your work?

Can we "trust" the source Data Science?

> If not, outcomes could be harmful

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Data Science & Trust

"Air pollution causes 6630 premature deaths in Portugal"

> What would make you "trust" this headline?

Think about:

- > Bias prevention & reduction measures
- > Characterisation of uncertainty
- > Validity and quality

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Data Data Everywhere News Headlines & Data Science

Trust & Trustworthy

Trustworthy Data Science
Summary

Trust

Some thoughts...

- > Earning trust is hard but it is very easy to lose
- > It is not binary
 - → Could trust data but not the analysis
- > Data Science has many potential points of "trust failures" and "trust leaks"

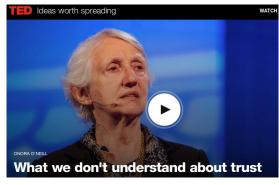
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Trust & Trustworthy

- > It is not about "trust" or "building trust"
 - → Con artists and fraudsters use "trust" to cheat you
 - → "Building trust" or "increasing trust" is their art
- > It is about being "trustworthy"
 - → Competent
 - → Reliable
 - → Honest
- > You must EARN trust to be trustworthy
 - → You should not just expect to receive it

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Must Watch! (10 mins)



https://www.ted.com/talks/onora o neill what we don t understand about trust

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Data Data Everywhere
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Trustworthy Data Science

Summary

Open & Transparent

"Trustworthy Data Science" includes being:

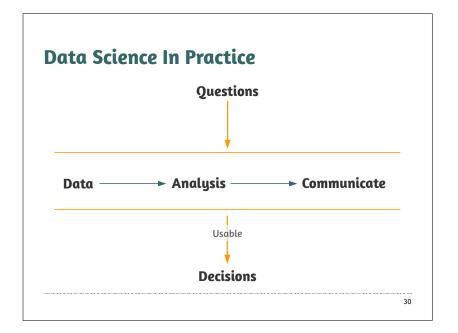
- > Open and Transparent
- > Honest especially about strengths AND weaknesses!
- > Willing to do the same as what you expect of others
 - → You cannot set higher standards for others compared to yourself

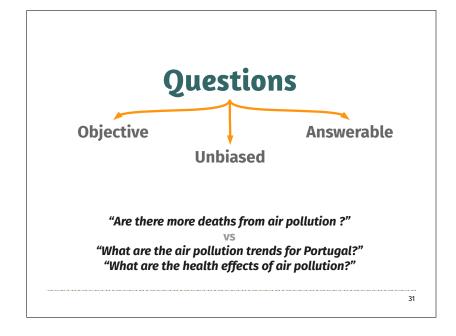
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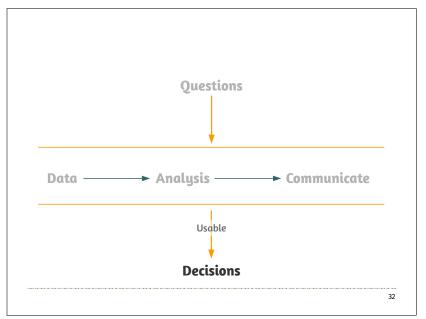
Trustworthy Data Science?

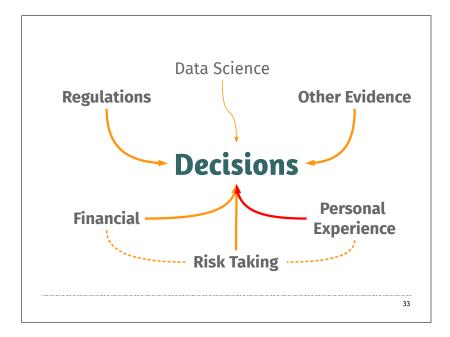
The following slides give some ideas on how to achieve or assess trustworthiness

- > They are not a comprehensive list and they are not intended to be
- > "It's a little bit more complicated than that!"

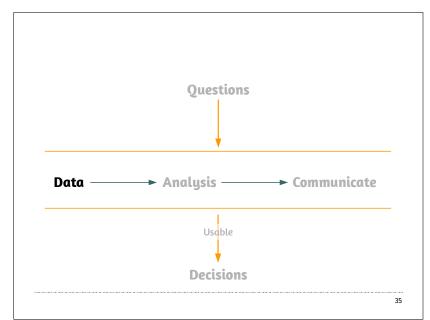


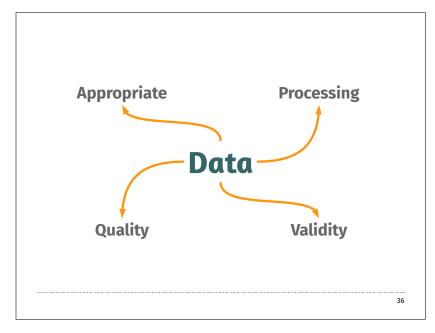


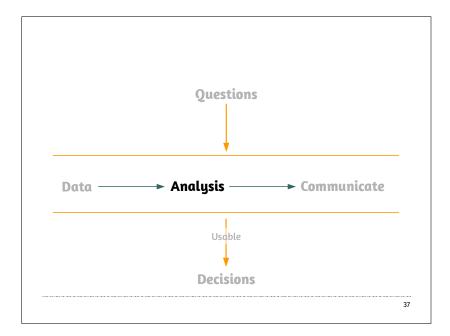


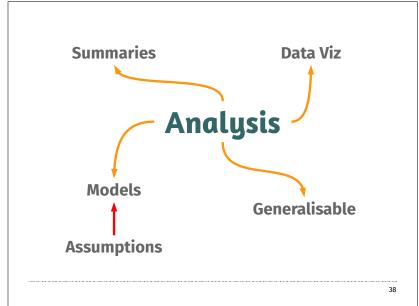












Quotes

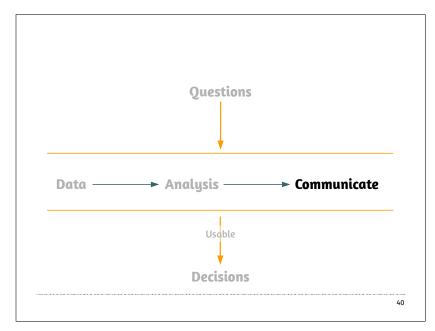
"Remember that all models are wrong; the practical question is how wrong do they have to be to not be useful."

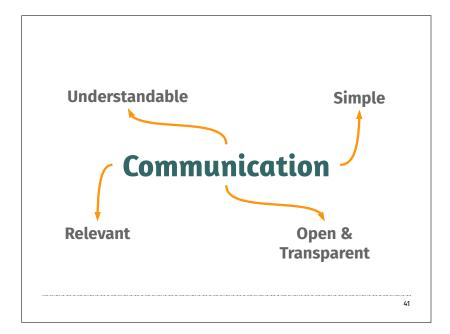
George E.P. Box (1987)

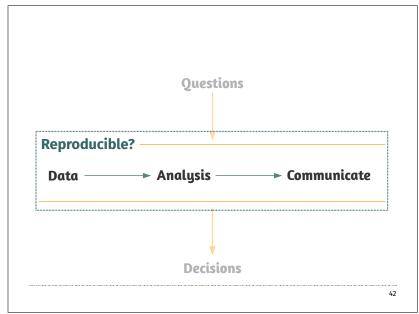
"Far better an approximate answer to the right question, which is often vague, than an exact answer to the wrong question, which can always be made precise."

John W. Tukey (1962)

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When to Trust and When Not to Trust Data Science? It is about "trustworthiness" Competent, Reliable & Honest Trust must be EARNED to be trustworthy Bias prevention & reduction measures, state uncertainties, ... Openness & transparency about strengths and weaknesses "Trustworthy Data Science" Objective and critical evaluation of your work and that of others Reproducibility is an important part but it is not the whole



References

- > "What we don't understand about trust", Onora O'Neill
- > https://www.ted.com/talks/onora_o_neill_what_we_don_t_understand_about_trust
- > Short link: https://1n.pm/PhP7
- > Box, George E. P. & Norman R. Draper (1987). "Empirical Model-Building and Response Surfaces", Wiley.
- > John W. Tukey (1962). "The future of data analysis", Annals of Mathematical Statistics 33: 1-67

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