Data science is a culture not a science

Matthew Brett

Handout

https://github.com/matthew-brett/data-science-discussions/blob/master/berkeley-talk/data_science_as_culture_handout.pdf

An orientation

An answer to “What is data science?” through “How would we recognize data science?”

A definition and a warning

> *The now-contemplated field of Data Science amounts to a superset of the fields of statistics and machine learning which adds some technology for ‘scaling up’ to ‘big data’. This chosen superset is motivated by commercial rather than intellectual developments. Choosing in this way is likely to miss out on the really important intellectual event of the next fifty years.*

(Donoho 2015)

A mystery for machine-learning + big data

"Data scientists mostly do arithmetic and that's a good thing"

https://m.signalvnoise.com/data-scientists-mostly-just-do-arithmetic-and-that-s-a-good-thing-c6371885f7f6

Recommended reading for "What the *&!% is data science?" from Hadley Wickham's "STATS 337: Readings in Applied Data Science" https://github.com/hadley/stats337

Another mystery for machine-learning + big data

- Careers
- Education and Training
- Tools and Software
- Reproducibility and Open Science
- Physical and Intellectual Space
- Data Science Studies

Moore-Sloan Data Science Environments: Themes.
http://msdse.org/themes

Back to history

See “A very short history of data science”

(Press 2013)

But in modern use

DATA

Data Scientist: The Sexiest Job of the 21st Century

by Thomas H. Davenport and D.J. Patil

FROM THE OCTOBER 2012 ISSUE

(Davenport and Patil 2012)

The data scientist in industry

> *When Jeff Hammerbacher and I talked about our data science teams, we realized that as our organizations grew, we both had to figure out what to call the people on our teams. "Business analyst" seemed too limiting. "Data analyst" was a contender, but we felt that title might limit what people could do. After all, many of the people on our teams had deep engineering expertise. "Research scientist" was a reasonable job title used by companies like Sun, HP, Xerox, Yahoo, and IBM.*

(Patil 2011)

Koan 1

What would a degree programme, division or institute of “research science” look like?

How would it differ from a programme in “data science”?

The data scientist in industry

> *. . . what data scientists do is make discoveries while swimming in data . . . At ease in the digital realm, they are able to bring structure to large quantities of formless data and make analysis possible. . . . Data scientists' most basic, universal skill is the ability to write code.*

(Davenport and Patil 2012) - "Who Are These People?"

The data scientist in industry

> *Some of the best and brightest data scientists are PhDs in esoteric fields like ecology and systems biology. George Roumeliotis, the head of a data science team at Intuit in Silicon Valley, holds a doctorate in astrophysics.*

(Davenport and Patil 2012) - "Who Are These People?"

The data scientist in industry

> *The best data scientists tend to be "hard scientists," particularly physicists, rather than computer science majors.*

Attributed to DJ Patil in (Loukides 2010)

The data scientist in industry

> *Roumeliotis was clear with us that he doesn't hire on the basis of statistical or analytical capabilities. He begins his search for data scientists by asking candidates if they can develop prototypes in a mainstream programming language . . .*

(Davenport and Patil 2012) - "Who Are These People?"

The data scientist in industry

> *... on any given day, a team member could author a multistage processing pipeline in Python, design a hypothesis test, perform a regression analysis over data samples with R, design and implement an algorithm for some data-intensive product or service in Hadoop, or communicate the results of our analyses to other members of the organization.*

Jeff Hammerbacher quoted in (Loukides 2010)

Koan 2

Data scientist is an industry term, but data scientists largely came from the empirical sciences.

How did that happen?

What should we teach?

The origins of data science

> *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.*

(Tukey 1962)

Tools

If we are to make progress in data analysis .. we need to pay attention to our tools and our attitudes. If these are adequate, our goals will take care of themselves.

We dare not neglect any of the tools that have proved useful in the past. But equally we dare not find ourselves confined to their use. If algebra and analysis cannot help us, we must press on just the same, making as good use of intuition and originality as we know how.

(Tukey 1962)

Attitudes

> *Almost all the most vital attitudes can be described in a type form: willingness to face up to X.*

where X includes:

- more realistic problems,
- the necessarily approximate nature of useful results in data analysis,
- the need for collecting the results of actual experience with specific data-analytic techniques,
- the need for iterative procedures,
- free use of ad hoc and informal procedures, and
- the fact that data analysis is intrinsically an empirical science.

(Tukey 1962)

Tukey and data science

- Fire Control Research Office
- Bell Labs
- The Kinsey Report (Cochran, Mosteller and Tukey, 1953, 1954);
- Panel on Seismic Improvement (Tukey, 1959);
- Environmental pollution (Tukey et al., 1965; Tukey, 1966);
- The National Halothane Study (Subcommittee on the National Halothane Study, 1966; Gentleman, Gilbert and Tukey, 1969);
- National Assessment of Educational Progress (Tukey, 1970);
- Impacts of Stratospheric Change (Tukey, 1976);
- Adjustment of the U.S. Census (Ericksen et al, 1989; Tukey, 1990).

(Hoaglin 2003)

Leo Breiman and culture in statistics

Two cultures - “data modeling” and “algorithmic modeling”

a) Focus on finding a good solution - that’s what consultants get paid for. hfillbreak

(Breiman 2001)

Leo Breiman and culture in statistics

Two cultures - "data modeling" and "algorithmic modeling"

a) Focus on finding a good solution - that's what consultants get paid for. hfillbreak
b) Live with the data before you plunge into modeling. hfillbreak

(Breiman 2001)

Leo Breiman and culture in statistics

Two cultures - “data modeling” and “algorithmic modeling”

a) Focus on finding a good solution - that’s what consultants get paid for. hfillbreak
b) Live with the data before you plunge into modeling. hfillbreak
c) Search for a model that gives a good solution, either algorithmic or data. hfillbreak

(Breiman 2001)

Leo Breiman and culture in statistics

Two cultures - “data modeling” and “algorithmic modeling”

a) Focus on finding a good solution - that’s what consultants get paid for. hfillbreak
b) Live with the data before you plunge into modeling. hfillbreak
c) Search for a model that gives a good solution, either algorithmic or data. hfillbreak
d) Predictive accuracy on test sets is the criterion for how good the model is. hfillbreak

(Breiman 2001)

Leo Breiman and culture in statistics

Two cultures - “data modeling” and “algorithmic modeling”

a) Focus on finding a good solution - that’s what consultants get paid for. hfillbreak
b) Live with the data before you plunge into modeling. hfillbreak
c) Search for a model that gives a good solution, either algorithmic or data. hfillbreak
d) Predictive accuracy on test sets is the criterion for how good the model is. hfillbreak
e) Computers are an indispensable partner hfillbreak

(Breiman 2001)

Breiman on the modeling culture

> *My feeling is, to some extent, that academic statistics may have lost its way. When I came, after consulting, back to the Berkeley Department, I felt like I was almost entering Alice in Wonderland. That is, I knew what was going on out in industry and government in terms of uses of statistics, but what was going on in academic research seemed light years away. It was proceeding as though it were some branch of abstract mathematics.*

(Olshen and Breiman 2001)

Breiman and consulting

> *... trying to figure out what freeway traffic looked like and what its statistical characteristics were.*
>
> *A lot of the problems that we dealt with in those days involved large amounts of data. For instance, in one big project we had seven years of hourly and daily data on over 450 variables relevant to air pollution. We were trying to predict next day ozone levels in the Los Angeles Basin.*
>
> *a study of delay in criminal courts in Colorado.*

(Olshen and Breiman 2001)

John Chambers and data science

> *John McKinley Chambers is the creator of the S programming language, and core member of the R programming language project.*

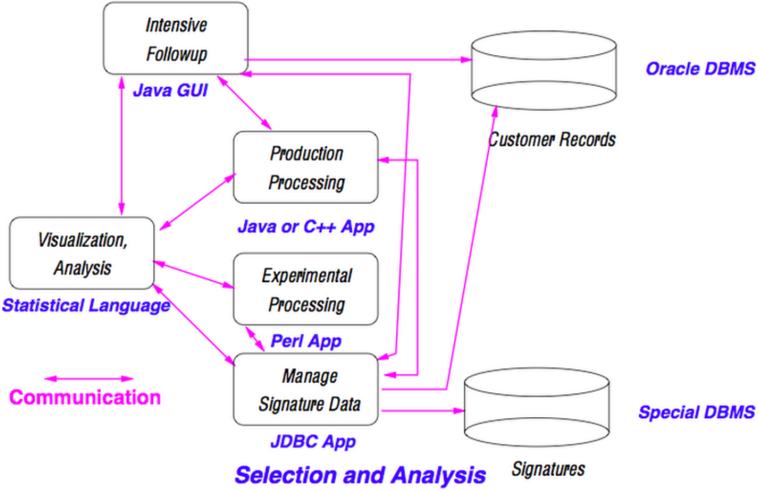
https://en.wikipedia.org/wiki/John_Chambers_(statistician)

Chambers and tools

> *... in modern computing, there should not be a sharp distinction between users and programmers. Most programming with statistical systems is done by users, and should be. As soon as the system doesn't do quite what the user wants, the choice is to give up or to become a programmer, by modifying what the system currently does.*

(Chambers 1999)

Chambers and consulting



(Chambers 1999)

Koan 3

Is Tukey a data scientist?

Is Breiman?

Is Chambers?

Koan 3

Why now?

Why now?

- Rise of computing.
- Programming languages;
- Tools;
- Process.

Returning to the mysteries

- “Data scientists mostly do arithmetic and that’s a good thing”
- Tools and Software, Reproducibility and Open Science.

Data science as analysis culture

What does this mean for the relationship between data science and:

- big data;
- machine learning;
- artificial intelligence;
- statistics;
- computer science;
- open-source computing;
- reproducibility;
- getting a job as a "data scientist"?

What does this mean for

- Undergraduate teaching?
- Graduate teaching?
- Research process?

Teaching and research process

"Teaching computational reproducibility for neuroimaging"

https://arxiv.org/abs/1806.06145

The future of data analysis

> *The future of data analysis can involve great progress, the overcoming of real difficulties, and the provision of a great service to all fields of science and technology. Will it? That reamains to us, our willingness to take up the rocky road of real problems in preference to the smooth road of unreal assumptions, arbitrary criteria, and abstract results without real attachments. Who is for the challenge?*

(Tukey 1962)

Is this the end?

Yes, it's the end of the talk.

All material for this talk at: https://github.com/matthew-brett/data-science-discussions/tree/master/berkeley-talk