14: 'Big data' og maskinlæring

Videregående kvantitative metoder i studiet af politisk adfærd

Frederik Hjorth
fh@ifs.ku.dk
fghjorth.github.io
@fghjorth

Institut for Statskundskab
Københavns Universitet

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Fagets opbygning
Blok 1

Gang	Tema	Litteratur	Case
1	Introduktion til R	Leeper (2016)	
2	R workshop + tidy data	Wickham (2014), Zhang (2017)	
3	Regression I: OLS brush-up	AP kap 3	Newman et al. (2015), Solt et al. (2017)
4	Regression II: Paneldata	AGS kap 4	Larsen et al. (2017)

Fagets opbygning
Blok 2

5	Introduktion til kausal inferens	Hariri (2012), Samii (2016)	Eckles & Bakshy (2017)
6	Matching	Justesen & Klemmensen (2014)	Nall (2015)
Efterårsferie			
7	Eksperimenter I	AP kap 1+2, GG kap 1+2	Gerber, Green & Larimer (2008)
8	Eksperimenter II	GG kap 3+4+5	Gerber & Green (2000)
9	Instrumentvariable	AP kap 4	Lundborg et al. (2017)
10	Difference-in-differences	AP kap 5	
11	Regressionsdiskontinuitetsdesigns	AP kap 6	Eggers & Hainmueller (2009)

Fagets opbygning

Blok 3

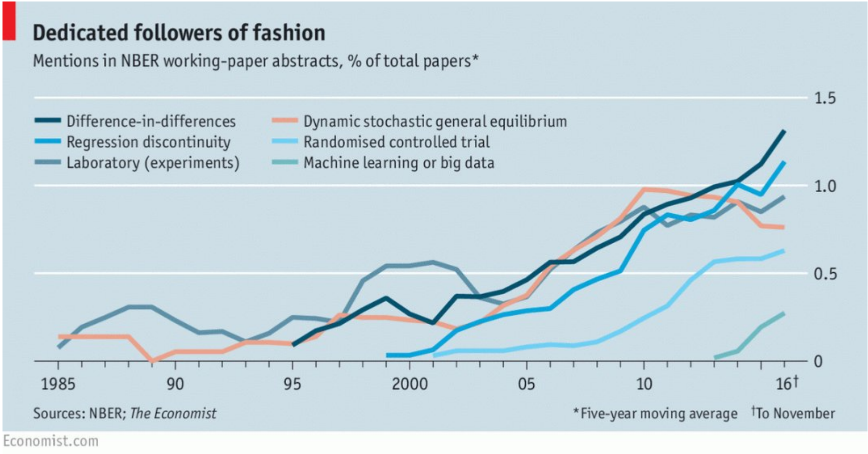
12	Tekst som data	Grimmer & Stewart (2013), Benoit & Nulty (2016)	Baturo & Mikhaylov (2013)
13	Scraping af data fra online-kilder	MRMN kap 9+14	Hjorth (2016)
14	'Big data' og maskinlæring	Varian (2014), Montgomery & Olivella (2017)	Theocharis et al. (2016)

http://bit.ly/vkme17evaluering

Opsamling fra sidst

- screen scraping
- case I: Hjorth (2016)
- etik i scraping
- API'er
- case II: skalering af twitter-brugere

Er big data/ML 'the next big thing'?



Hvad er big data/ML?

»Big Data is the Information asset characterized by such a High Volume, Velocity and Variety to require specific Technology and Analytical Methods for its transformation into Value« (De Mauro et al., 2016)

→ defineres ofte med afsæt i ‘de 3 V’er’

- Volume: doesn’t sample; it just observes and tracks what happens
- Velocity: often available in real-time
- Variety: draws from text, images, audio, video

Hvad er big data/ML?

the subfield of computer science that »gives computers the ability to learn without being explicitly programmed« (Samuel, 1959)

- machine learning + statistik kaldes nogle gange *data science*
- centralt: fokus på *klassifikation/prædiktion* ctr. kausalitet
- m.a.o.: $\hat{y}$ ctr. $\hat{\beta}$
- kanoniske eksempler: Google Self-Driving Car Project, Netflix Prize

vigtig, hyppig sondring inden for ML:

- superviserede metoder
  - out-of-sample klassifikationer bygger på kendte værdier i et 'training set'
  - eks.: logit-model
- usuperviserede metoder
  - klassifikationer bygger på in-sample-fit
  - eks.: cluster- eller faktoranalyse

Typisk samfundsvidenskabeligt datagrundlag de sidste ∼50 år:

- Survey research
- Aggregate government statistics
- One off studies of individual places, people, or events

h/t: Gary King

1. Unstructured text: emails, speeches, reports, social media updates, web pages, newspapers, scholarly literature, product reviews
2. Commerce: credit cards, sales, real estate transactions, RFIDs
3. Geographic location: cell phones, Fastlane, garage cameras
4. Health information: digital medical records, hospital admittances, accelerometers & other devices in cell phones
5. Biological sciences: genomics, proteomics, metabolomics, imaging producing numerous person-level variables
6. Satellite imagery: increasing in scope & resolution
7. Electoral activity: ballot images, precinct-level results, individual-level registration, primary participation, campaign contributions
8. Web surfing artifacts: clicks, searches, and advertising clickthroughs, multiplayer games, virtual worlds

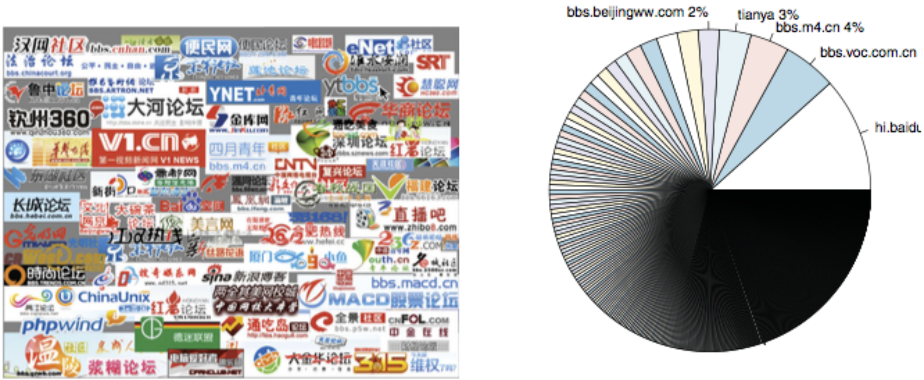
h/t: Gary King

- Opinions of activists: A few thousand interviews → billions of political opinions in social media posts (1B every 2 Days)
- Exercise: A survey: "How many times did you exercise last week? → 500K people carrying cell phones with accelerometers
- Social contacts: A survey: "Please tell me your 5 best friends" → continuous record of phone calls, emails, text messages, bluetooth, social media connections, address books
- Economic development in developing countries: Dubious or nonexistent governmental statistics → satellite images of human-generated light at night, road networks, other infrastructure

h/t: Gary King

King et al. (2013): indsamling af 3.7M posts, analyse af 127k

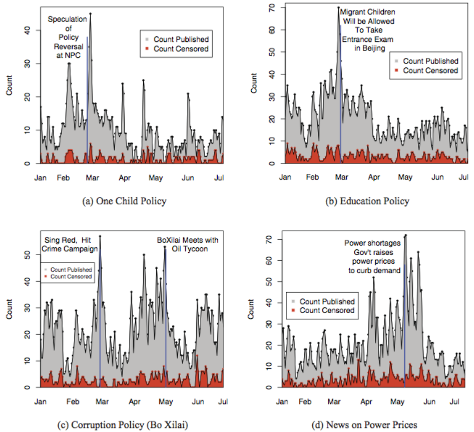
Figure 1. The Fractured Structure of the Chinese Social Media Landscape



(a) Sample of Sites

(b) All Sites excluding Sina

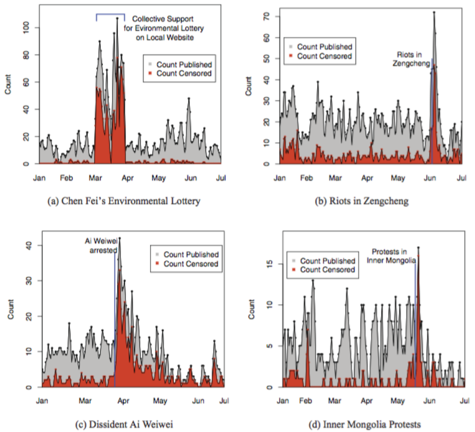
Figure 6. Low Censorship on News and Policy Events (in 2011)



(a) One Child Policy (b) Education Policy

(c) Corruption Policy (Bo Xilai) (d) News on Power Prices

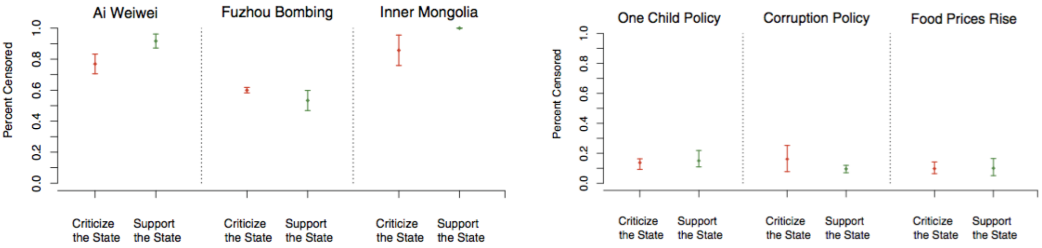
Figure 5. High Censorship During Collective Action Events (in 2011)



(a) Chen Fei's Environmental Lottery (b) Riots in Zengcheng

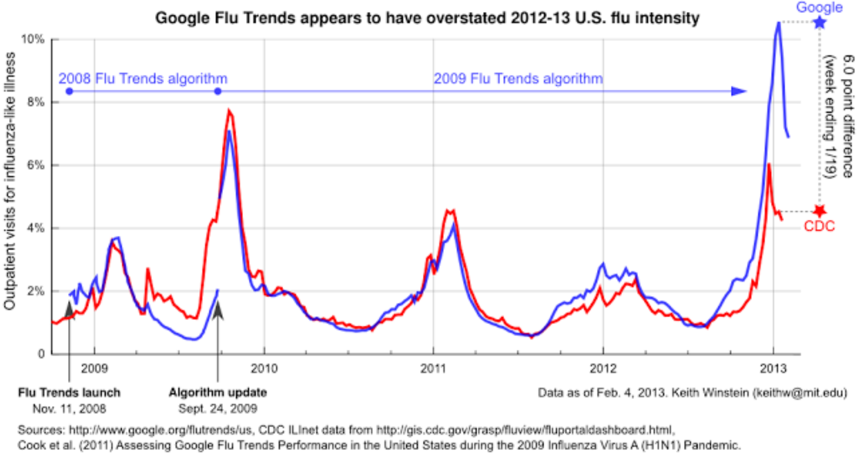
(c) Dissident Ai Weiwei (d) Inner Mongolia Protests

Figure 8. Content of Censored Posts by Topic Area

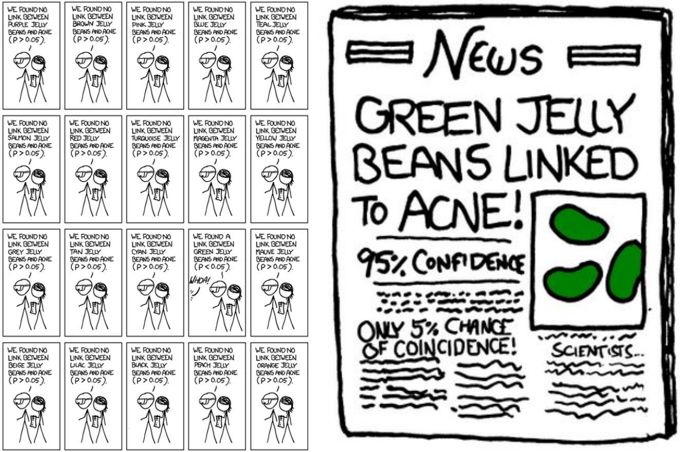


Big data $\approx$ The Literary Digest Poll

Paradigmatisk anekdote: Google Flu Trends



Multiple hypothesis testing



Maskinlæring kan reproducere sociale patologier:

- billedsøgning på 'CEO' returnerer kun hvide mænd
- Google Photo identificerer sorte mænd som 'gorillaer'
- YouTubes text-to-speech modul kan ikke genkende kvindestemmer
- HP Cameras' ansigtsgenkendelsesmodul kan ikke genkende asiatiske ansigter
- Amazon klassificerer LGBT-litteratur som porno
- søgninger efter afroamerikanske navne giver annoncer for baggrundstjeks for kriminalitet

Kilde: Kate Crawford, https://twitter.com/math_rachel/status/938170475594649600

Centralt analytisk mål i ML: prediktion uden *overfitting*

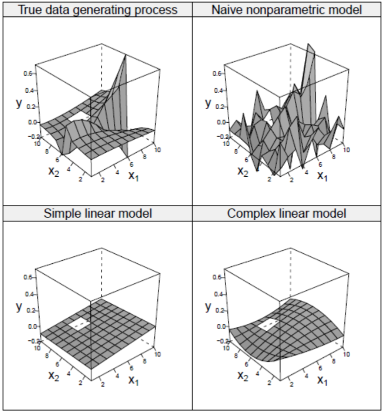


Figure 2. True and recovered relationship in simulated data. The true DGP is $y_i = \frac{1}{100} \times \sqrt{x_{i1}x_{i2}}\frac{(5.5-x_{i1})^2}{(5.5-x_{i1})(5.5-x_{i2})} + \epsilon_i$ where $\epsilon_i \sim N(0, 0.35)$. The simple linear model is $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2$, while the complicated model is $y = \beta_0 + \text{poly}(x_1, 2) \times \text{poly}(x_1, 2)$ (where $\text{poly}(x, d)$ is the sequential polynomial generating function, d is the highest degree generated, and the $\times$ operator generates all main effects and interactions).

Eksempel i Varian (2016): overlevelse i Titanic-forliset

Figure 1
A Classification Tree for Survivors of the *Titanic*

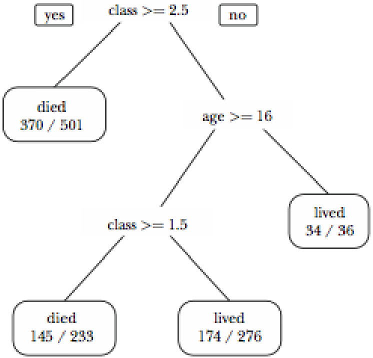


Table 3
Logistic Regression of Survival versus Age

Coefficient	*Estimate*	*Standard error*	*t value*	*p value*
Intercept	0.465	0.0350	13.291	0.000
Age	−0.002	0.001	−1.796	0.072

Note: Logistic regression relating survival (0 or 1) to age in years.

Logikken i regressionstræer:

1. antag fx. to kovariater X_{i1}, X_{i2}
2. SSE uden kovariater: $\sum_{i=1}^{N}(Y_i - \hat{Y})^2$
3. split X_{i1} eller X_{i2} ved c sådan at c minimerer SSE
4. gentag (3) i hvert af de to nye subset ('blade')
5. fortsæt sålænge kriterium for forbedring i fit er opfyldt

Regressionstræ anvendt på Montgomerys simulerede data:

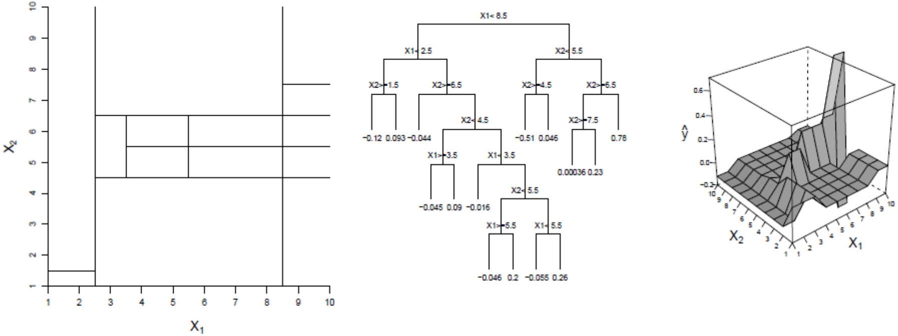


Figure 3. Left: example of a partition of a 2-covariate space into 14 rectangular prediction regions. Center: A binary tree that corresponds to the partition depicted on the left. Right: 3D plot of the prediction surface corresponding to regions defined in the left and center panels.

Udgangspunkt: least squares-estimatoren for n observationer og p variable:

$$\hat{\beta} = \arg\min \|\mathbf{Y} - \mathbf{X}\beta\|_2^2 = \arg\min_{\beta} \sum_{i=1}^{n} (Y_i - X_i^T \beta)^2. \tag{1}$$

i *penalized regression* estimeres i stedet:

$$\hat{\beta} = \arg\min_{\beta} \left(\sum_{i=1}^{n} (Y_i - X_i^T \beta)^2 + \lambda \sum_{j=1}^{p} [(1-\alpha)|\beta_p| + \alpha|\beta_p|^2] \right) \tag{2}$$

$\rightarrow$ den ekstra sum er en *regulariseringsterm*

» The second (and contrary) need is to avoid overfitting the data, a goal sometimes labeled regularization. Overfitting occurs when the model is so complex that it makes predictions based on idiosyncratic features of the data unrelated to the true DGP.« (Montgomery & Olivella, 3)

$$\hat{\beta} = \arg\min_{\beta} \left(\sum_{i=1}^{n} (Y_i - X_i^T \beta)^2 + \lambda \sum_{j=1}^{p} [(1-\alpha)|\beta_p| + \alpha|\beta_p|^2] \right) \quad (3)$$

- denne generelle form: *elastic net regression*
- hvis $\lambda = 0$: reducerer til OLS
- hvis $\alpha = 1$: *ridge regression*
- hvis $\alpha = 0$: *least absolute shrinkage and selection operator* (LASSO)

$\rightarrow \lambda$ fungerer som *tuning-parameter*

Regularisering reducerer risiko for over-fitting $\rightarrow \uparrow$ out-of-sample fit:

> »one might consider why the penalty term is needed at all outside the case where there are more covariates than observations. (...) Ordinary least squares is unbiased; it also minimizes the sum of squared residuals for a given sample of data. That is, it focuses on in-sample goodness- of-fit. One can think of the term involving the penalty as taking into account the 'over-fitting' error, which corresponds to the expected difference between in-sample goodness of fit and out-of-sample goodness of fit.« (Athey & Imbens 2016, 47)

LASSO illustrerer dermed også spændingen ml. maskinlæring og kausal inferens:

»LASSO penalizes the inclusion of covariates, and some will be omitted in general; LASSO will favor a more parsimonious functional form, where if two covariates are correlated, only one will be included, and its parameter estimate will reflect the effects of both the included and omitted variables. Thus, in general LASSO coefficients should not be given a causal interpretation.« (Athey & Imbens 2016, 53)

- regressionstræer: `rpart()` i `rpart`-pakken + plots med `rpart.plot`
- LASSO: `glmnet()` i `glmnet`-pakken

Fremgangsmåde:

1. hent tweets fra/om kandidater i EP-valget 2014 fra ES, DE, UK, GR ($N \approx 800k$)
2. håndkod stikprøve à 7k tweets fra hvert land
3. saml tweettekst i en document-feature matrice
4. brug regulariseret regression til at klassificere hver enkelt tweet

Mestprædiktive features pr. kategori

Table C3: Top predictive stemmed n-grams for classifiers

	Communication style
Broadcasting	just, hack, #votegreen2014, :, and, @ ', tonight, candid, up, tonbridg, vote @, im @, follow ukip, ukip @, #telleurop, angri, #ep2014, password, stori, #vote2014, team, #labourdoorstep, crimin, bbc news
Engaging	@ thank, @ ye, you'r, @ it', @ mani, @ pleas, u, @ hi, @ congratul, :), index, vote # skip, @ good, fear, cheer, haven't, lol, @ i'v, you'v, @ that', choice, @ wa, @ who, @ hope
	Politeness
Impolite	cunt, fuck, twat, stupid, shit, dick, tit, wanker, scumbag, moron, cock, foot, racist, fascist, sicken, fart, @ fuck, ars, suck, nigga, nigga ?, smug, idiot, @arsehol, arsehol
Polite	@ thank, eu, #ep2014, thank, know, candid, veri, politician, today, way, differ, europ, democraci, interview, time, tonight, @ think, news, european, sorri, con- gratul, good, :, democrat, seat
	Morality and democracy
Others	@ ha, 2, snp, nice, tell, eu, congratul, campaign, leav, alreadi, wonder, vote @, ;), hust, nh, brit, tori, deliv, bad, immigr, #ukip, live, count, got, roma
Moral/Dem.	democraci, polic, freedom, media, racist, gay, peac, fraud, discrimin, homosexu, muslim, equal, right, crime, law, violenc, constitut, faith, bbc, christian, marriag, god, cp, racism, sexist

Nøgleresultat: 'engagerende' tweets får også flere uhøflige svar

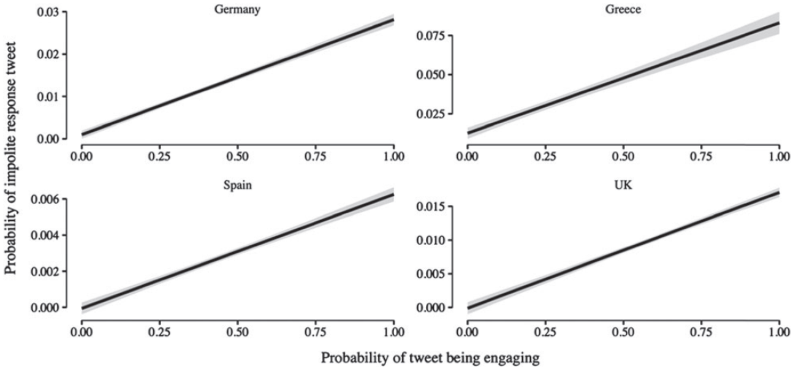


Figure 3 Impoliteness in responses to individual tweets at estimated probabilities of being engaging, by country.


Wear pajamas.
Drink hot chocolate.
Talk about getting health insurance.
#GetTalking
barackobama.com/talk

Tak for nu!