

New Data Science – research methods studying innovation and development

AFRICALICS PhD Supervision and Research Methods Seminar

September 23, 2018

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Assistant Professor
Department of Business and Management



AALBORG UNIVERSITY
DENMARK

About me

New Data Science
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- ▶ Assistant Professor at the IKE group
- ▶ Main fields of interest:
 - ▶ Economic Complexity, Network Theory
 - ▶ Applied Econometric, Datascience, ML&AI



A brief CV

- ▶ Diploma in “Industrial Engineering” (University of Stuttgart)
- ▶ Followed by some experience in consulting (Mercedes Benz) in process and supply chain optimization, supplier auditing
- ▶ Ad-Hoc joint Master IBE (Hohenheim) + MIKE (Aalborg) → Afterwards PhD. at the IKE group
- ▶ Visiting Research Scholar at Stanford → Obsession with Complex System & Networks research.
- ▶ Awarded PhD. in late 2015. Thesis: “The Network Dynamics of Financing Technological (R-) Evolution: The Case of Technological Change in the Renewable Energy Area”
- ▶ Since: Various research projects and publications around the development and application of novel methods in Innovation Studies.
- ▶ Recently: On the advisory board of the European Commission: Promoting Digital Entrepreneurship in Developing Countries
- ▶ Recently: Co-founder and coordinator of the “Social Data Science” program at AAU



Agenda

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SSA's emerging entrepreneurial ecosystems in the digital economy

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OKHi: App that overcomes
lack of physical address



BRCK: “backup generator”
for the internet



Sentry: Uber-like on
demand delivery

Zipline: Drone-delivery of
medicine



Ushahidi: Open source software for information
collection, visualisation, and interactive mapping



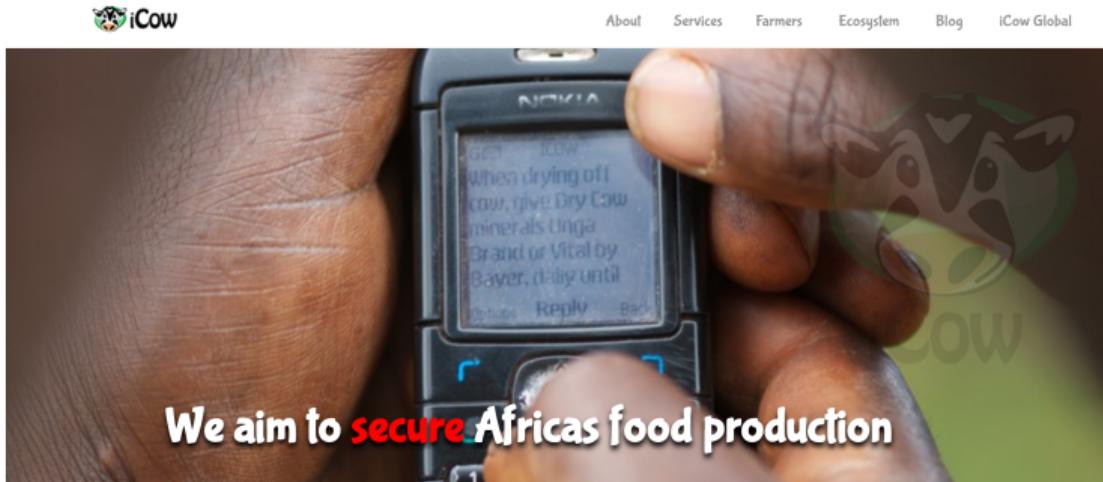
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SSA's inclusive innovation start-ups

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How we do it



[site/about](#)

iCow Global



Our Impact



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Crowdfunding & Social Lending

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kiva Lend ▾

About ▾ Sign in

97% funded
29 days left \$50 to go

Total loan: \$2,000
Powered by 30 lenders

Armenuhi
Verishen village, Armenia / Cattle

\$25 ▾ **Lend now**

A loan of \$2,000 helps to purchase three oxen and high-quality fodder for the cattle, to earn extra income for the education of her two children, whom she is now raising all alone.

Armenuhi's story Loan details

Mark Armenuhi is 97% funded. This loan will disburse on December 12, 2015.

WORLD MAP WITH AMOUNT DISBURSEMENT

I have added red plots to specify the amount of loans that is being distributed by KIVA

Hide

```
leaflet(loan_themes_region) %>% addTiles() %>%  
  addCircles(lng = ~lon, lat = ~lat, radius = ~amount/10, popup = ~country,  
            color = "DarkRed") %>%  
  
# controls  
setView(lng=center_lon, lat=center_lat, zoom=3)
```





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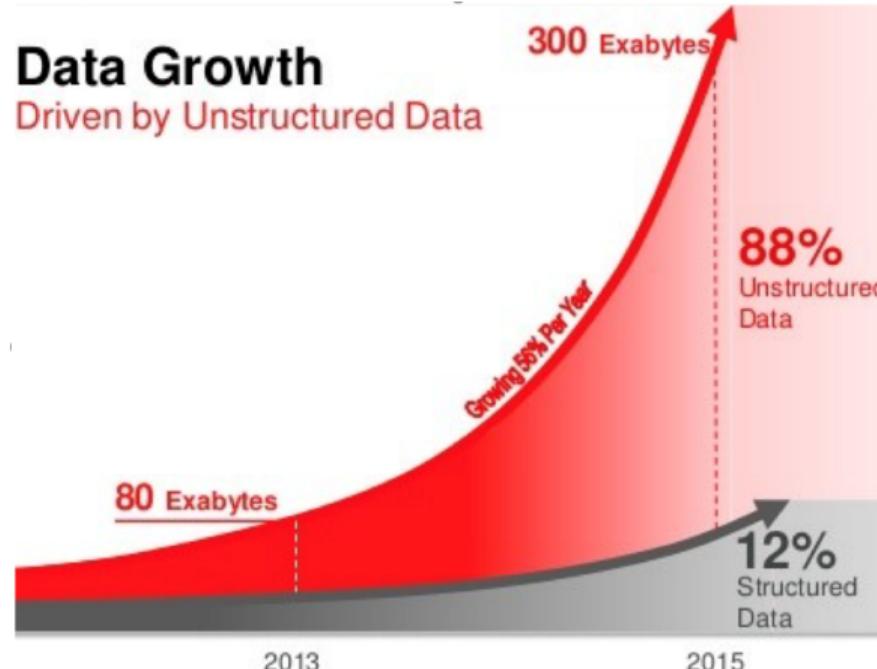
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Data Growth

Driven by Unstructured Data



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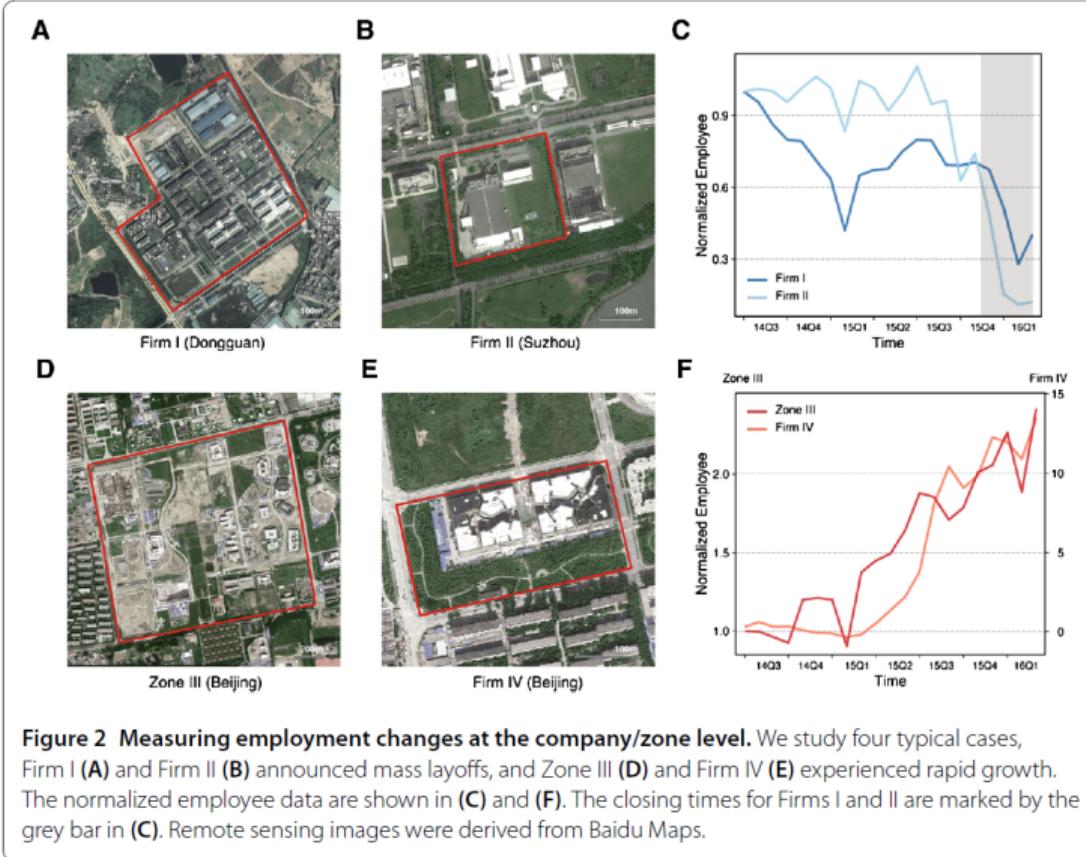


Figure 2 Measuring employment changes at the company/zone level. We study four typical cases, Firm I (A) and Firm II (B) announced mass layoffs, and Zone III (D) and Firm IV (E) experienced rapid growth. The normalized employee data are shown in (C) and (F). The closing times for Firms I and II are marked by the grey bar in (C). Remote sensing images were derived from Baidu Maps.



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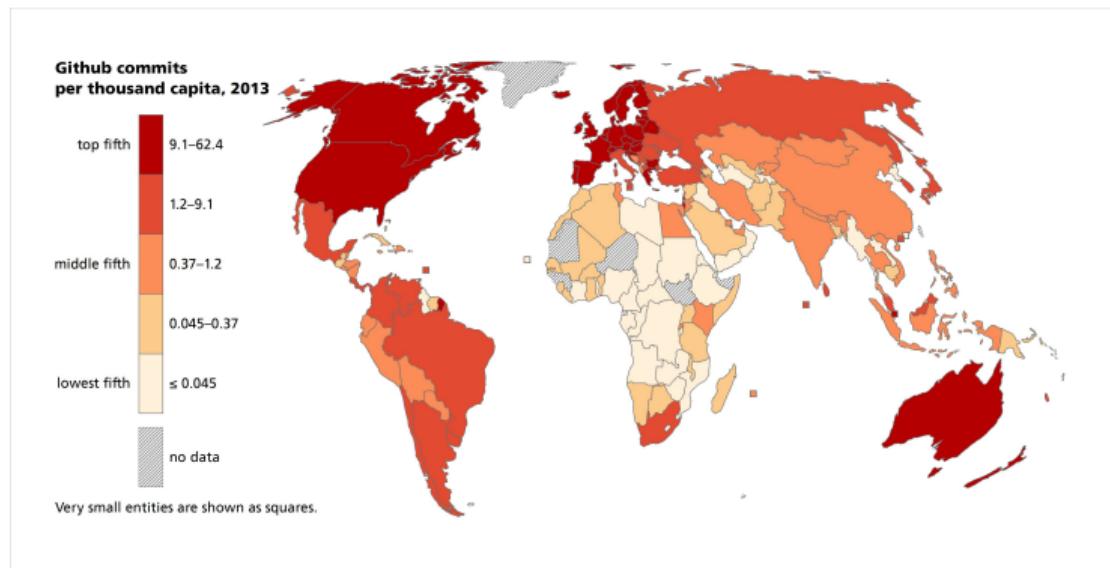
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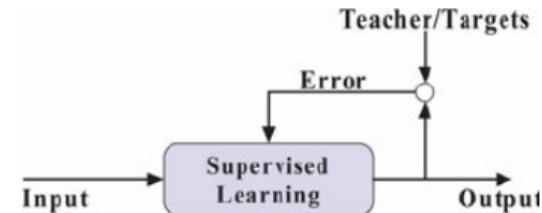
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Supervised ML

- ▶ Input-Output ($A \rightarrow B$) mapping
- ▶ Input and output are known.
- ▶ Computer task: Learn how A causes B



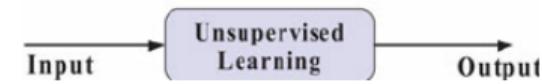
Semi-Supervised ML

- ▶ Actions A cause feedback B (reward)
- ▶ Computer task: Try different A, learn which brings highest reward



Unsupervised ML

- ▶ A is known, B not (maybe there doesn't exist right/wrong B)
- ▶ Computer task: Find meaningful pattern in A





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The Econometric Approach

- ▶ Mostly interested in producing good *parameter estimates*: Construct models with unbiased estimates of β , capturing the relationship x and y .
- ▶ Supposedly “structural” models: Causal effect of directionality $x \rightarrow y$, robust across a variety of observed as well as up to now unobserved settings.
- ▶ How: Carefully draw from theories and empirical findings, apply logical reasoning to formulate hypotheses.
- ▶ Typically, multivariate testing, *ceteris paribus*.
- ▶ Main concern: Minimize standard errors ϵ of β estimates.
- ▶ Not overly concerned with overall predictive power (eg. R^2) of those models, but about various type of endogeneity issues, leading us to develop sophisticated *identification strategies*

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The ML&AI Approach

- ▶ To large extend driven by the needs of the private sector → data analysis is gear towards producing good *predictions* of outcomes.
 - ▶ Recommender systems: Amazon, Netflix, Spotify etc.
 - ▶ “Risk scores”: Eg.g likelihood that a particular person has an accident, turns sick, or defaults on their credit.
 - ▶ Image classification: Finding Cats & Dogs online
- ▶ Often rely on big data (N, x_i)
- ▶ Not overly concerned with the properties of parameter estimates, but very rigorous in optimizing the overall prediction accuracy.
- ▶ Often more flexibility wrt. the functional form, and non-parametric approaches.
- ▶ Yet: No “build in” causality guarantee → verification techniques.

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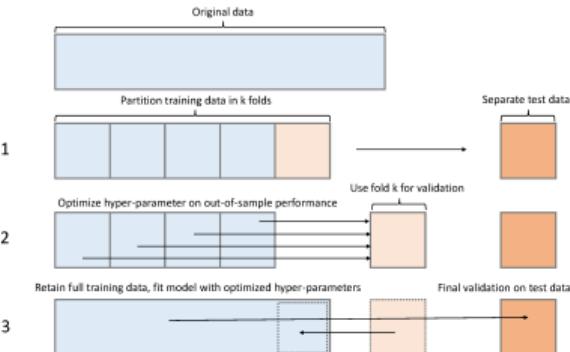
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Partial Solution: Out-Of-Sample Validation

1. Split the dataset in a training and a test sample.
2. Fit you regression (train your model) on one dataset
3. Optimal: Tune hyperparameters by minimizing loss in a validation set.
4. Optimal: Retrain final model configuration on whole training set
5. Finally, evaluate predictive power on test sample, on which model is not fitted.



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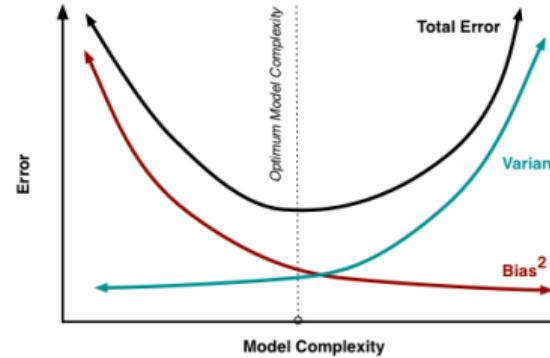
Unsupervised ML

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Overfitting: The main challenge



$$\begin{aligned}
 & \text{minimize} \underbrace{\sum_{i=1}^n L(f(x_i), y_i)}_{\text{in-sample loss}}, \text{ over } \overbrace{f \in F}^{\text{function class}} \text{ subject to} \\
 & \underbrace{R(f) \leq c}_{\text{complexity restriction}}
 \end{aligned} \tag{1}$$

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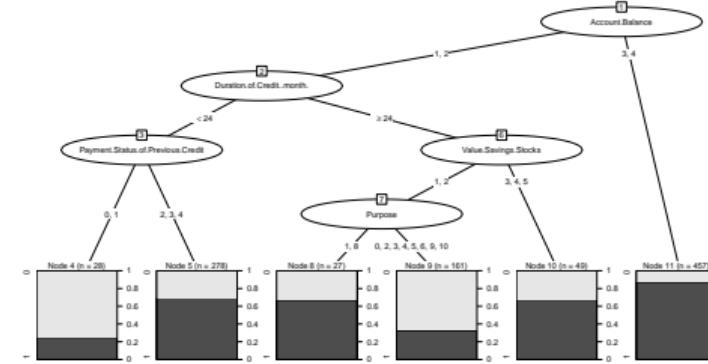
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Regression & Classification Trees

- ▶ Mostly used in classification problems on continuous or categorical variables.
- ▶ Idea: split the population or sample into two or more homogeneous sets (or sub-populations) based on most significant splitter / differentiator in input variables.
- ▶ Repeat till stop criterium reached. Leads to a tree-like structure.

Figure: A regression-tree example on credit defaults



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- Backfed Input Cell
- Input Cell
- △ Noisy Input Cell
- Hidden Cell
- Probabilistic Hidden Cell
- △ Spiking Hidden Cell
- Output Cell
- Match Input Output Cell
- Recurrent Cell
- Memory Cell
- △ Different Memory Cell
- Kernel
- Convolution or Pool

Neural Networks

© 2016 Fjodor van Veen - asimovinstitute.org

Perceptron (P)



Feed Forward (FF)



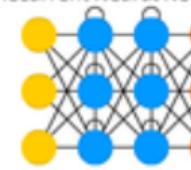
Radial Basis Network (RBF)



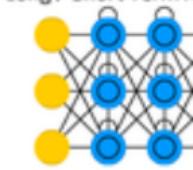
Deep Feed Forward (DFF)



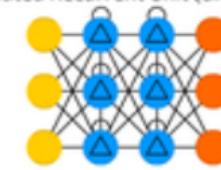
Recurrent Neural Network (RNN)



Long / Short Term Memory (LSTM)



Gated Recurrent Unit (GRU)



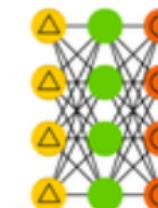
Auto Encoder (AE)



Variational AE (VAE)



Denoising AE (DAE)



Sparse AE (SAE)





Supervised Machine Learning 101

On model complexity

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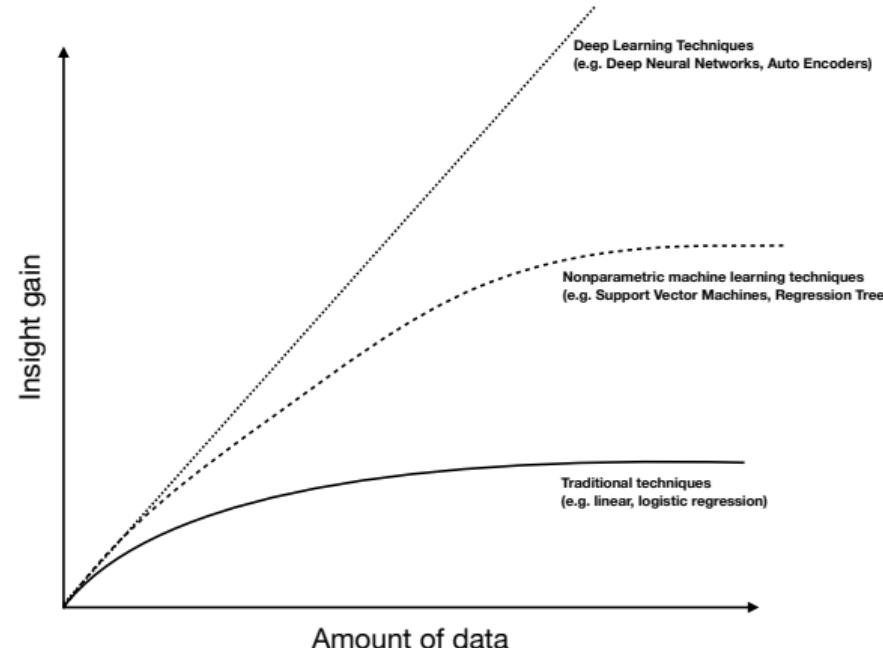
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On model explainability

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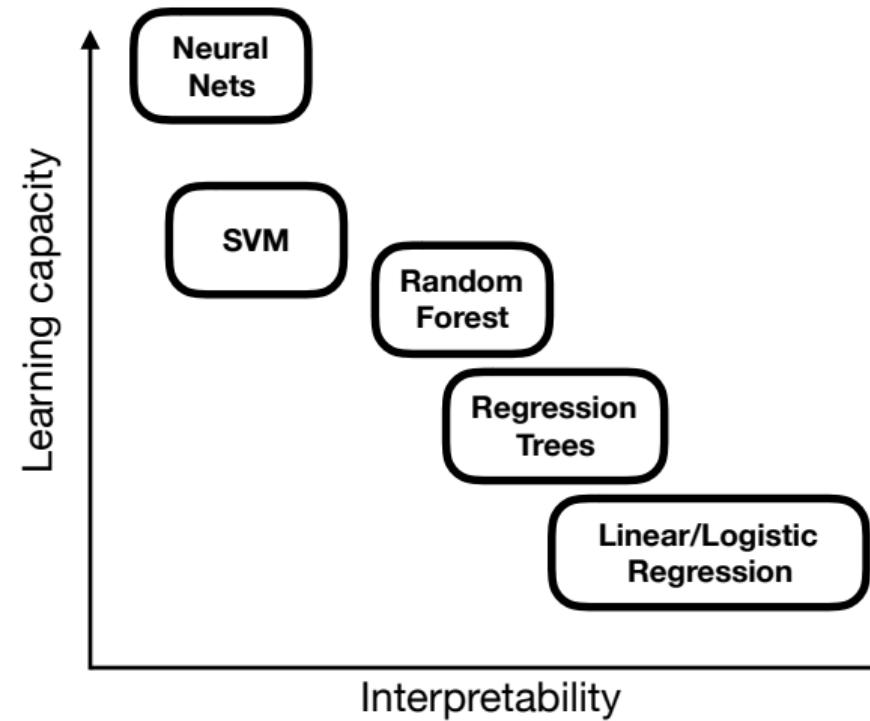
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Unsupervised Machine Learning

Vector Space Modeling as example

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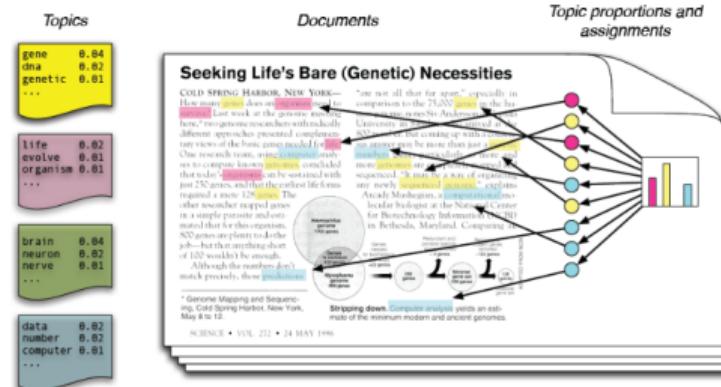
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How would you turn text into numbers, preserving semantic features?

- ▶ One-hot encoding 0, 1, 0, 1, 0, 0
- ▶ Term Frequency-inverse document frequency TF-IDF 0, 0.7, 0, 2, 0, 0
- ▶ Latent semantic indexing (LSA)
- ▶ Sidenote: Recently more focus on word embeddings (e.g. Word2Vec, GloVe, FastText)



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Unstructured Data

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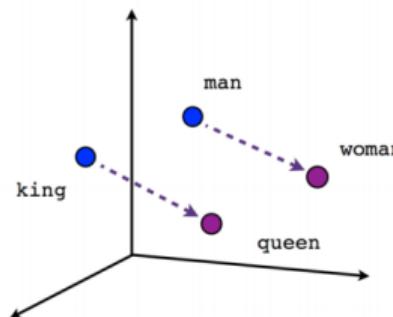
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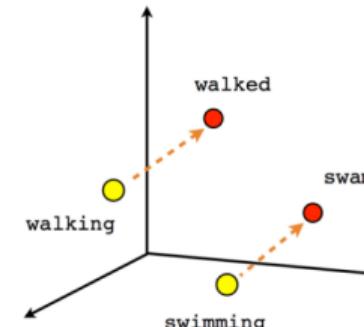
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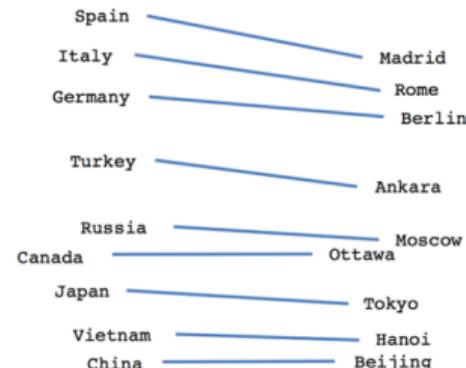
- ▶ Text data
- ▶ Visual Data
- ▶ Everything2Vec: NLP & Computer Vision



Male-Female



Verb tense



Country-Capital



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Opportunities

- ▶ Better Estimates
- ▶ Understanding human behavior
- ▶ Rare event prediction
- ▶ MAPPING and understanding complex & dynamic systems
- ▶ Analysis of traditionally data-sparse environments

Challenges

- ▶ Handling Big Data
- ▶ Prediction vs. Deriving desired statistical properties
- ▶ Approaching new tools
- ▶ Institutional Inertia

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The screenshot shows the LinkedIn profiles of several Ushahidi team members. At the top, it lists Erik Hersman (Co-Founder), Nathaniel Manning (Director of Business Development), Dry Okelloh (Co-Founder), and Baudu Were (Project Director - Africa). Below this, the 'Graph Insights' section shows that investors in Ushahidi have also invested in Act On Software, Add Technologies, and AerisCloud. The 'Ushahidi's Current Team worked at' section lists ThinkFirst, Afribudget, and Google. The 'Ushahidi's Past Team now works at' section lists BRCK, Intel, and WeRobotics. A red arrow points from the LinkedIn profile of David Kobia (Co-Founder) to the 'Graph Insights' section.

Hain, D. S., Christensen, J.L. & Jurowetzki, R.: The Value of Human Capital Signals for Investment Decision Making under Uncertainty, 2017, tbs @ DRUID NYC

Table 3: GLM regression results (link=Logit): Investments (Foreign only, Post-PSM)

	Dependent variable: Investor participates in round					
	EU (1)	KINGS (2)	EU (3)	KINGS (4)	EU (5)	KINGS (6)
<i>Deal characteristics (controls)</i>						
round.seed	-0.349 (0.058)	-0.399 (0.059)	-0.292 (0.056)	-0.327* (0.056)	-0.375 (0.059)	-0.650 (0.444)
round.venture	0.016 (0.722)	-0.563 (0.437)	0.013 (0.727)	-0.637 (0.441)	0.080 (0.725)	-0.561 (0.444)
inv.sum	-0.012 (0.072)	0.039** (0.016)	-0.067 (0.076)	0.041** (0.017)	-0.069 (0.076)	0.043** (0.017)
log(round.usd)	-0.126 (0.002)	0.0002 (0.063)	-0.063 (0.008)	-0.117 (0.017)	-0.001 (0.001)	
<i>VC characteristics</i>						
inv.exp	-0.019*** (0.003)	-0.0005 (0.001)	-0.009*** (0.003)	-0.006 (0.004)	-0.011*** (0.003)	-0.0005 (0.001)
inv.exp.de	0.171*** (0.021)	0.254*** (0.076)	0.182*** (0.023)	0.274*** (0.078)	0.181*** (0.024)	0.210*** (0.080)
<i>PC human capital signals</i>						
comp.press	0.001 (0.104)	-0.0004 (0.059)	0.0004* (0.106)	-0.0006 (0.060)	0.003 (0.105)	0.001 (0.060)
per.entrp	-0.11 (0.208)	0.275 (0.195)	-0.101 (0.247)	0.643** (0.215)	-0.295 (0.303)	0.309** (0.221)
per.edu	0.109 (0.151)	-0.006 (0.085)	0.097 (0.196)	-0.114 (0.093)	0.187 (0.211)	0.110** (0.064)
per.mng	-0.022 (0.090)	-0.001 (0.076)	0.034 (0.132)	-0.071 (0.083)	0.012 (0.134)	-0.025 (0.082)
<i>VC * PC interaction terms</i>						
per.entrp:inv.exp		-0.004 (0.007)	0.015* (0.008)			
comp.press:inv.exp		-0.0001* (0.0001)	0.0001* (0.0001)			
per.edu:inv.exp		-0.001 (0.006)	-0.0004 (0.003)			
per.mng:inv.exp		-0.001 (0.004)	0.0006* (0.003)			
per.entrp:inv.edc					0.023 (0.028)	0.108** (0.047)
comp.press:inv.edc					-0.003 (0.0002)	-0.019 (0.0007)
per.edu:inv.edc					0.012 (0.021)	-0.116** (0.157)
per.mng:inv.edc					-0.002 (0.012)	0.173** (0.081)
comp.country	Yes	Yes	Yes	Yes	F(4, 8)	F(4, 8)
Observations	1,002	894	1,002	894	1,002	894
Log Likelihood	-229.100	-376.900	-224.700	-342.600	-227.900	-314.100

Note: *p<0.1; **p<0.05; ***p<0.01

, standard errors in parentheses

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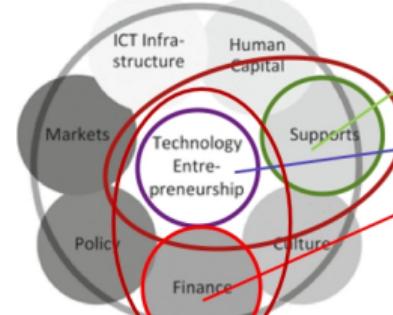
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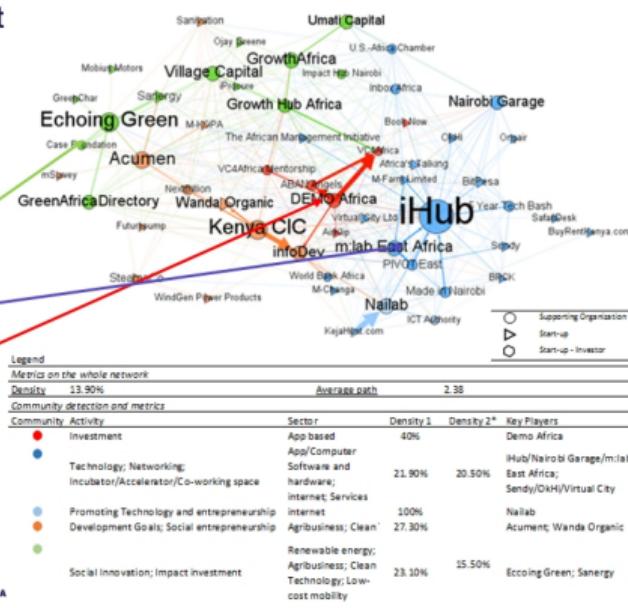
The Emerging Entrepreneurial Ecosystem in SSA, cont'd

- Bottom up emerging ecosystem
- Vivid mix of foreign / local support institutions, investors ect.
- “Link” function of VCs
- But that's another story...



Park, E.; Martins, R.M; Hain, D. S. & Jurowetzki, R. 2017:
Entrepreneurial Ecosystem for Technology Start-ups in Nairobi:
Empirical analysis of Twitter networks of Start-ups and Support
organizations, 2017, IKE Working Paper Series

Figure 3 Direct interactions (mentions) between start-ups and supporting organizations. Colors denote statistical communities detected by the Louvain algorithm.



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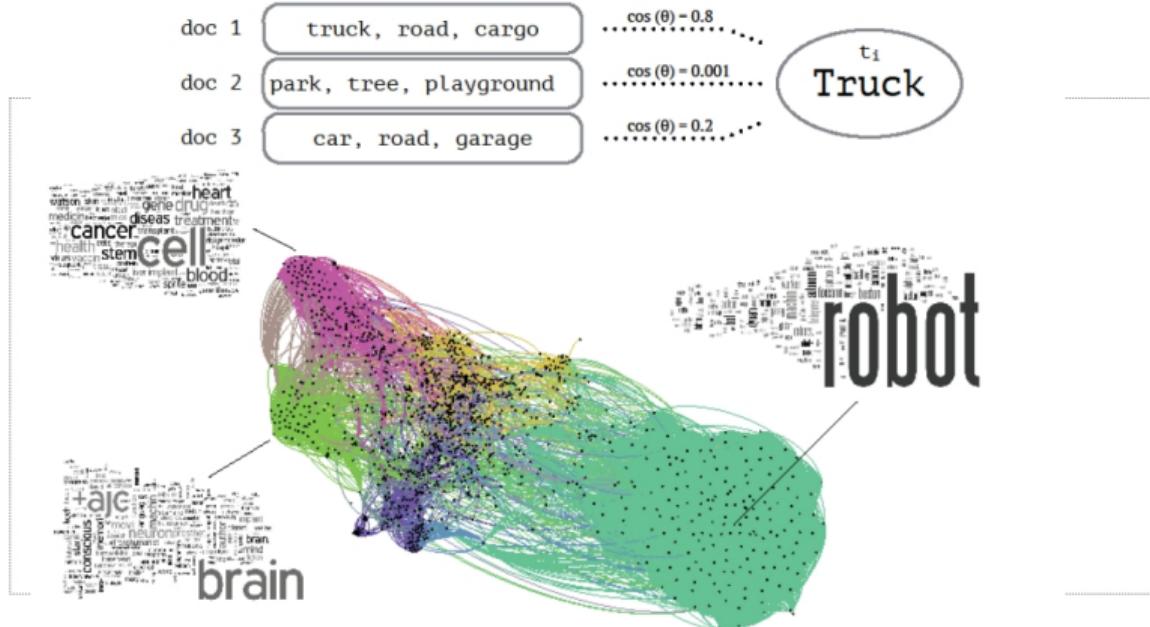
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1st Results: Static technology network (semantic similarity)





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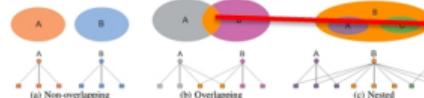
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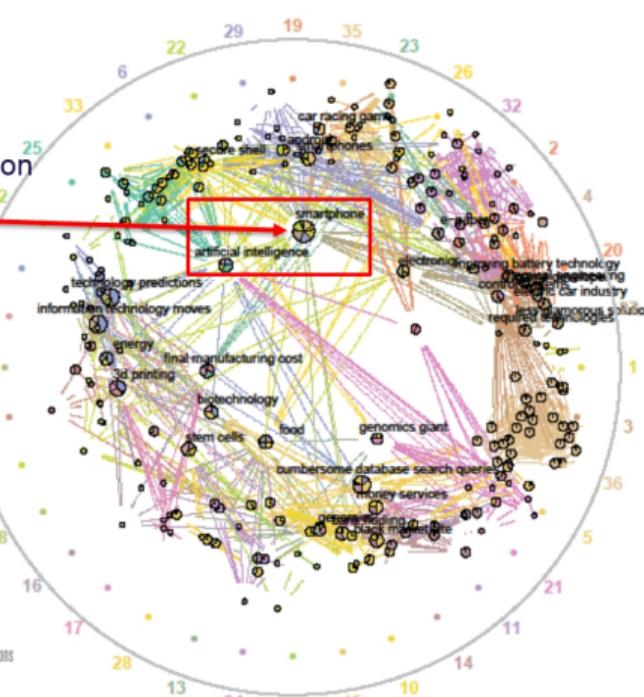
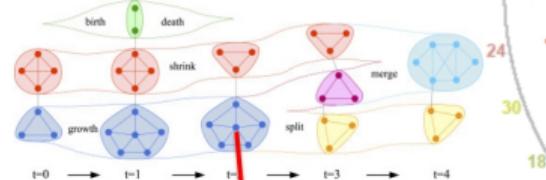
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- Overlapping Community Detection



- Dynamic Community Detection



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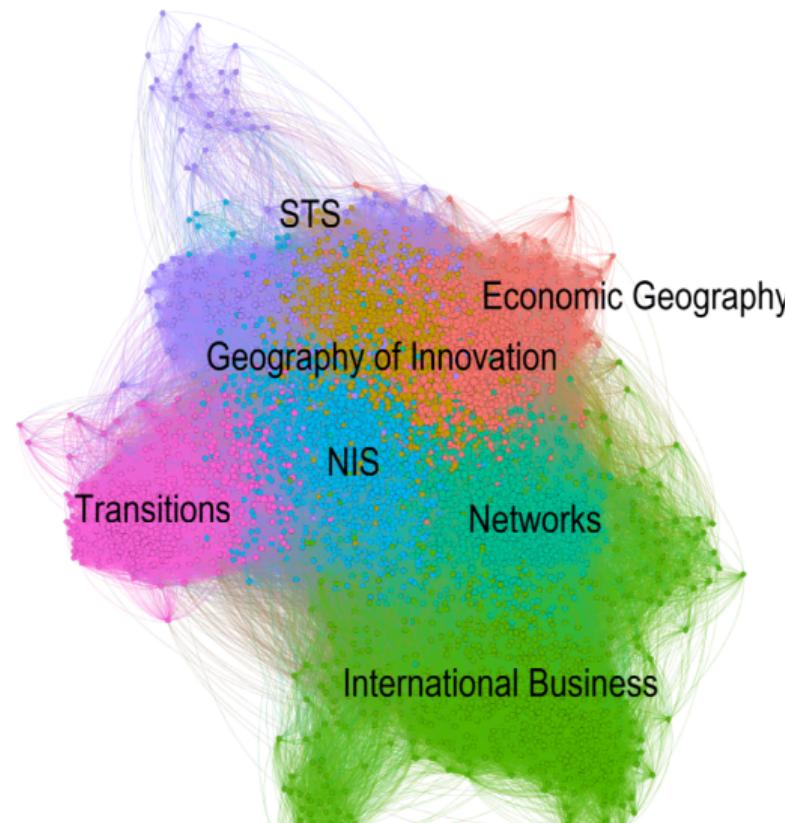
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Figure 4: Bibliographic coupling network of the IS literature





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New Ways of Teaching 30
Data Science

Dept. of Business and
Management

New Ways of Teaching Data Science



New Ways of Teaching Data Science

Point of departure

New Data Science
research methods
studying innovation
and development

New Problems and
Dynamics

New Data Sources
(and Types)

New Methods
ML&AI 101
Supervised ML
Unsupervised ML
Some own examples

New Ways of Teaching
Data Science

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- ▶ **exponential growth** of data in all domains
- ▶ **availability** of data
- ▶ exponential growth of **computer performance**
- ▶ **industry** makes enormous **efforts** to develop analysis techniques and capitalise on data
- ▶ OpenSourcing of easy-to learn, professional tools:
 - ▶ R & Python
 - ▶ NLTK, Spacy, Gensim and other language modelling libraries
 - ▶ recent developments in deep learning: Google's Tensorflow, Theano, Keras (and R alternatives), Open AI Gym
 - ▶ pre-trained deep learning models: Inception, Word2Vec
 - ▶ picking up in research



New Ways of Teaching Data Science

Potentials to improve data proficiency of students

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Old paradigm in instruction

- ▶ (naïve) Assumption of an **existing, clean dataset** in a world full of unstructured data
- ▶ Data preparation (i.e. collecting, mining, cleaning & organising) makes up **80% of the time use** of professional data scientist (Forbes, 2016).
- ▶ No or very limited training in **relational data** (networks), while these concepts receive enormous attention otherwise
- ▶ Lock-in in (soon to be) **obsolete proprietary software** (e.g. SAS, Stata, SPSS), and Office/Administration software that is not suited for serious data analysis (e.g. Excel)



New Ways of Teaching Data Science

Demand side

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Data Science 33

- ▶ Extreme demand for analytical skills in Finance, Insurance, Consulting, and other sectors
- ▶ growing awareness in the public sector
- ▶ growing demand for “data-driven decision makers”
- ▶ → not only tech-skills but also domain insight



ARTWORK: TAMAR COHEN, ANDREW J BIBOLTZ, 2011, SILK SCREEN
ON A PAGE FROM A HIGH SCHOOL YEARBOOK, 8.5" X 12"

DATA

Data Scientist: The Sexiest Job of the 21st Century

by Thomas H. Davenport and D.J. Patil

FROM THE OCTOBER 2012 ISSUE

SUMMARY SAVE SHARE COMMENT TEXT SIZE PRINT \$8.95 BUY COPIES

When Jonathan Goldman arrived for work in June 2006 at LinkedIn, the business networking site, the place still felt like a start-up. The company had just under 8 million accounts, and the number was growing quickly as existing members invited their friends and colleagues to join. But users weren't seeking out connections with the people who were already on the site at the rate executives had expected. Something was apparently missing in the social experience. As one LinkedIn manager put it, "It was like arriving at a conference reception and realizing you don't know anyone. So you just stand in the corner sipping your drink—and you probably leave early."

Goldman, a PhD in physics from Stanford, was intrigued by the linking he did see going on and by the richness of the user profiles. It all made for messy data and unwieldy analysis, but as he began exploring people's connections, he started to see possibilities. He began forming theories, testing hunches, and

WHAT TO READ NEXT



Big Data: The Management Revolution

VIEW MORE FROM THE
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New Data Science
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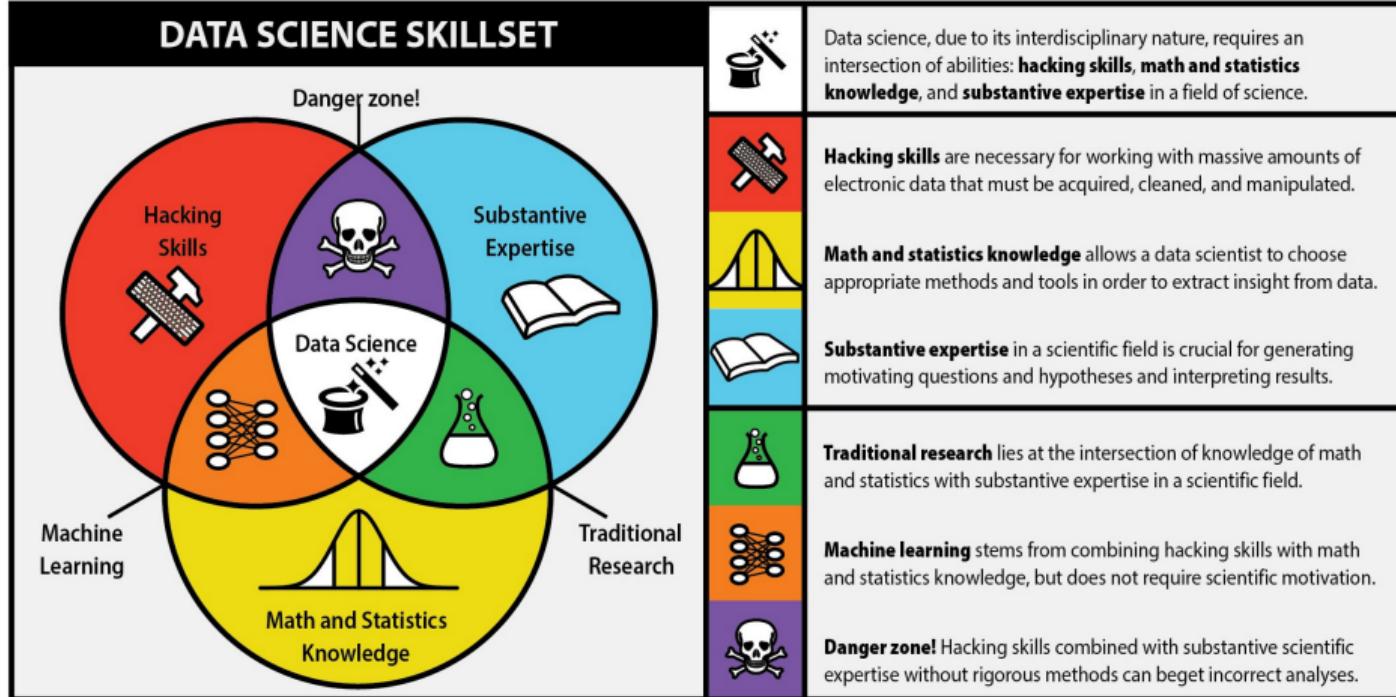
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The Data Science Skillset





Wrapping up

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New Content

- ▶ Dynamics of technological & economic opportunities.

New Data

- ▶ Rise of unstructured data.

New Methods

- ▶ Extremely rapid progress in predictive methods, alignment of opportunities in research, policy, business.

New Ways of Teaching

- ▶ Critical point in time, where new approaches get accessible for non computer-science PhDs
- ▶ Drawing largely from open source and open access.
- ▶ Enormous potential for self study.

Thank you for your attention. Any questions?



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