Introduction and overview

Machine Learning – Tools and applications for policy – Lecture 1

Iman van Lelyveld – Michiel Nijhuis

DNB Data Science Hub

Introduction and overview

1. Why is this course relevant?
2. What is the structure of the course — what can you expect?
3. How is the tooling, infrastructure and the Fintech landscape developing?

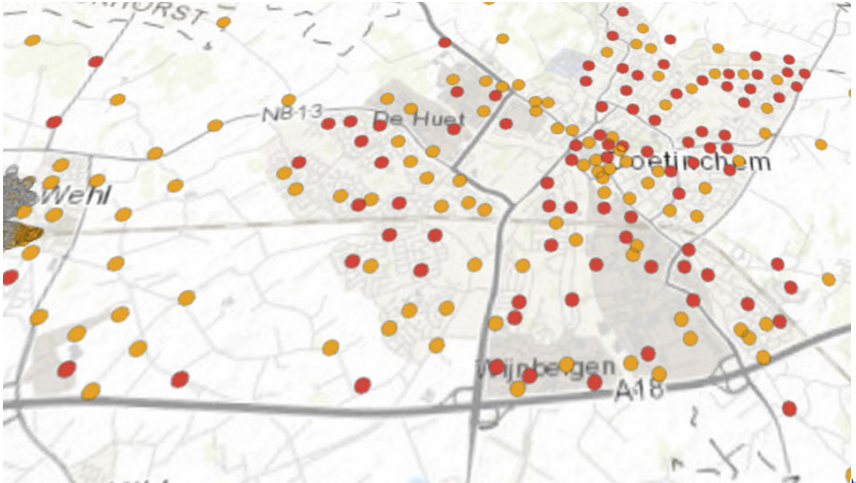
Introducing the instructors - contact details

This course will be taught by Iman van Lelyveld – Michiel Nijhuis

Course coordinator: Iman van Lelyveld
Email: iman.van.lelyveld@vu.nl
Office hours: by appointment
Website: Personal page

Instructor: Michiel Nijhuis
Email: michiel.nijhuis@dnb.nl
Office hours: by appointment

Michiel Nijhuis: Researching Algorithms for the Planning of Electrical Networks



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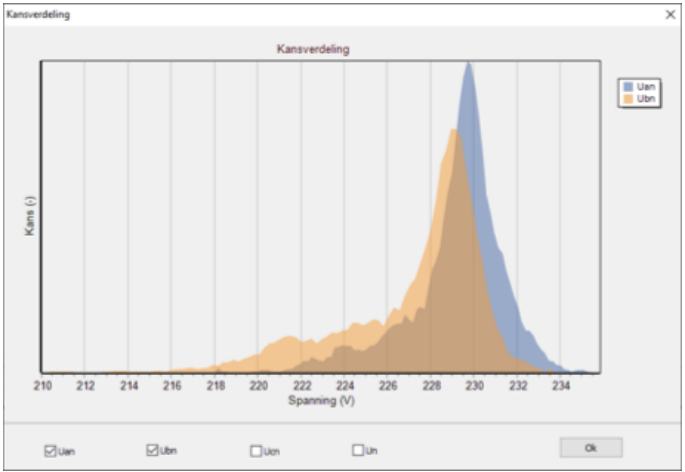
Bringing Machine Learning Algorithms in Production



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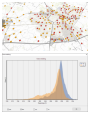
Working with all the money in the world ...

well, the Netherlands, actually



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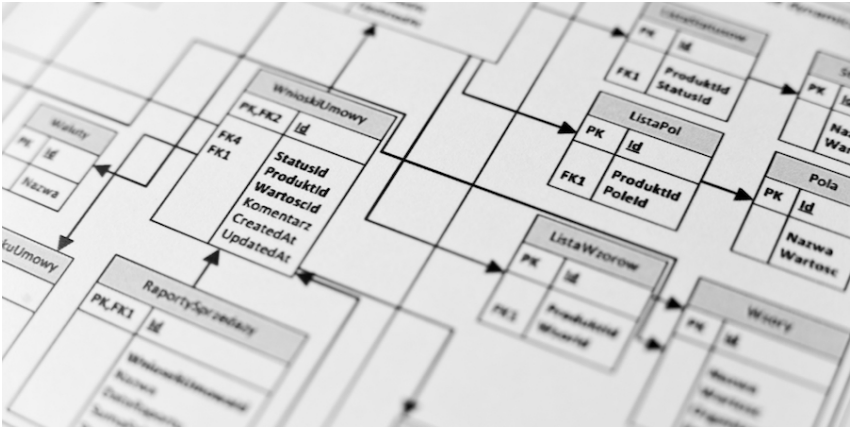
... and interconnectedness of granular data



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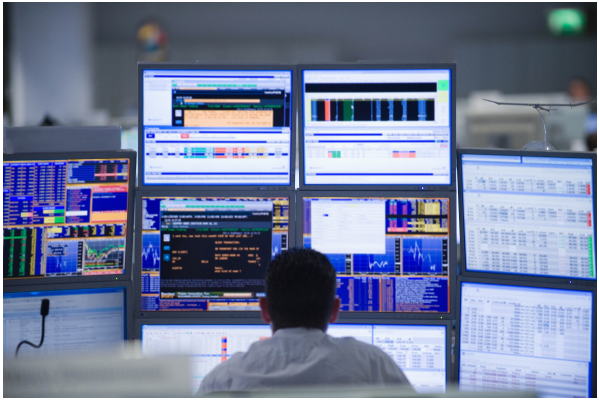
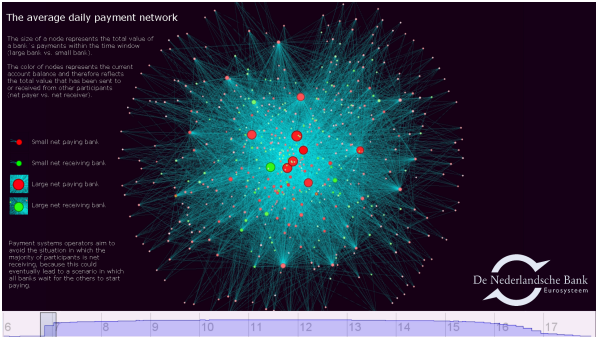
Iman van Lelyveld: Forex trading at Deutsche Bank



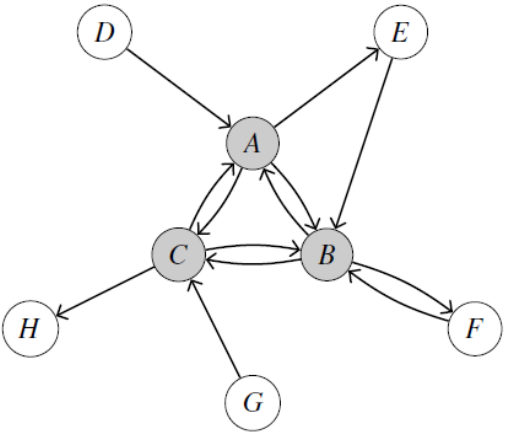
Bank of England in the 2008 crisis

From seeing financial network structure ...



Heijmans et al. (2016)

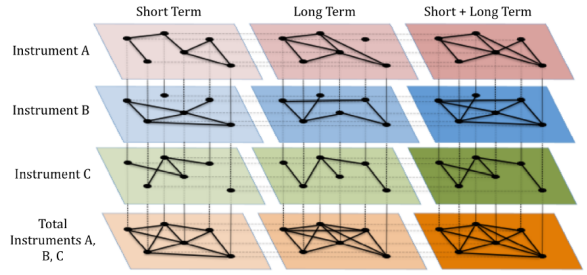
... to more rigorous tests of structure



in 't Veld and van Lelyveld (2014)

BIS – setting up an International Data Hub

DNB Statistics Division – connecting the dots



Aldasoro and Faia (2015)





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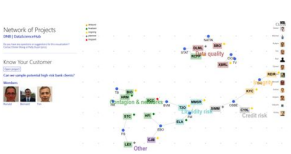
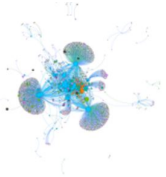
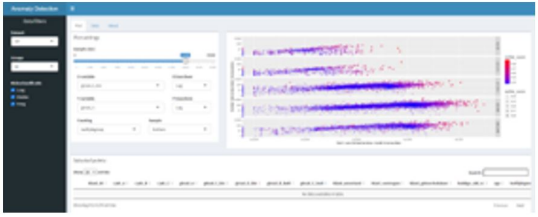
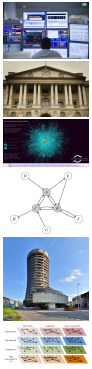
The DNB Data Science Hub

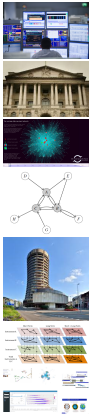








And here we are ...



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HOW
ABOUT
YOU

The intro survey and check-in

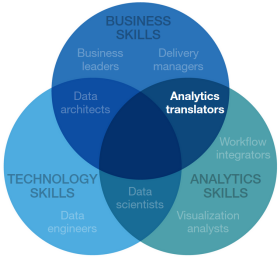
- What are you expecting?
  - How are machine learning models used in practice?
  - What jobs fit Machine Learning?
  - How to apply machine learning to trading?
  - How can we use machine learning for financial research
  - Further improve code complexity
- ... but maybe something entirely different:

What is the objective of the course?

The course goal is not to become experts in the business, technology or analytics 'circle'.

The objective is to:

- Theory
  - provide an overview and understanding of popular Machine Learning (ML) and Artificial Intelligence (AI) techniques
  - understand the opportunities and limitations of these techniques
  - be able to interact with the experts
- Practice
  - work hands-on with ML/AI methods in Python
  - "demystify" the black box of ML/AI
  - prime you so that you can continue to learn by yourself



Source: McKinsey

Outline

Introduction and overview
- Introducing the instructors
- Housekeeping

Course outline
- Opportunities are expanding
- Should we intervene?
- What is so special about Machine Learning?
- The changing landscape

Course Material

- The slides will be provided
- Jupyter Notebooks and other relevant material will be posted to Github
- A good all-round book is Géron (2019)
  - Other good references are Hilpisch (2018), Raschka (2016), and van der Plas (2016)
  - Most of these authors have put their supporting material on-line: see for instance Jake van der Plas's book
- Where relevant, we cite papers and resources in the slides

Course schedule I

L1 – Introduction and overview

1. Why is this course relevant?
2. What is the structure of the course — what can you expect?
3. How is the tooling, infrastructure and the Fintech landscape developing?

L2 – ML1 – introduction

1. What is ML? Can we see OLS as a ML problem?
2. What is ML applied to?
3. The outlines of the ML approach
   - supervised vs. unsupervised learning
   - (hyper)parameters and models
   - gradient descent and grid search
   - pre-processing features

Course schedule II

Tutorial 1 – How to read data and use sklearn

1. Getting started with Python and data manipulation.
2. How is this different from Excel?
3. Read the data and get to know it.
4. Introduction to sklearn: where to find the buttons

L3 – ML2 – the basics

1. How do I assess success?
   - Confusion matrix, Receiver Operator Characteristic (ROC)
2. What are overfitting, bias and variance?
   - L2-regularisation
3. Support Vector Machines (SVM) and k nearest neighbours (KNN)

Course schedule III

Tutorial 2 – Regressions versus Classifiers

1. Logit as a statistical model vs ML model
2. How to find the optimal (hyper)parameters
3. A different classifier: Support vector machines
   - Different types of kernels
   - First glimpse: Dangers of overfitting
   - Evaluating performance

L4 – ML3 – dimensionality and assessment

1. How to reduce dimensionality?
   - Principal Components Analysis (PCA)
2. Feature selection and regularization
   - How to tune model input by selecting features and beat overfitting?
   - How to select the most important features?
   - Examples RIDGE, LASSO, Elastic net

Course schedule IV

3. Is a "good" model always good? What is external validity?
   - Holdout, K-fold cross validation, Stratified K-fold. Leave-one-out (LOO)
4. What if we apply this to asset pricing?

Tutorial 3 – Data pre-processing and assessing model performance

1. How to pre-process: standardize your data
2. Pros and cons of standardization
3. Working with the confusion matrix
   - What if costs are not symmetric?
   - The trade-off between precision and recall

L5 – ML4 – improving weak learners

1. How to grow a decision tree? How to split?
   - Decision trees, purity measures
2. Can Ensemble Classifiers improve weak learners?
   - Bagging, boosting, AdaBoost, XGBoost

Course schedule V

3. Can we use forests in other ways?
    - Isolation forests

Tutorial 4 – Cross-validation applied to LASSO variable selection

1. Looking closer at cross-validation (CV) and holdouts
2. K-fold, Leave-one-out
3. Splitting your data into training and testing samples
4. How to use CV to tune a LASSO model

L6 – ML5 – unsupervised learning and explainability

1. Supervised versus unsupervised learning
2. What can we do with unsupervised learners?
    - K-means, t-SNE, DBSCAN, Gaussian mixtures
3. Can we transfer knowledge?
4. How to open the black box and explain results?

Course schedule VI

Tutorial 6 – Finding clusters and neighbors

1. Implementing K-means and DBSCAN
2. Hierarchical clustering: Bottom-up or Top-down?
3. Visual inspection of results

L7 – ML6 – Neural Nets

1. How to go from Perceptron to Neural Nets and beyond?
   - Multilayer Perceptrons (MLP), ADALine, backpropagation
2. What are common Neural Net architectures?
   - Convolutional NN, Recurrent NN, Long Short Term Memory (LSTM)
3. Other considerations
   - Fairness, adverserial attacks
4. Practical tips for implementation

Course schedule VII

L8 –ML7 – Natural Language Processing

1. What are the main approaches in textual analysis?
2. Going beyond simple word counts
3. The arrival of Large Language Models (LLM)

Tutorial 7 – NLTK and sentiment analysis

1. Constructing a bag of words
2. Classifying sentiments (positive/negative)
3. Example with financial news data

L9 – ML8 – generative models

1. With the release of ChatGPT, generative models have gained center stage
2. What makes them tick?
3. What are the possibilities? What the dangers?

Course schedule VIII

Tutorial 8 – Explainable AI

1. Permutation importance with ELI5
2. Partial dependency plots
3. Shapley values

L10 – Summary

1. Discuss some things that can go wrong
   - survivorship bias, input errors and deceit
   - fairness and discrimination
2. What is the reaction of authorities?

What Math/Stats background do you need?

- For a refresher see a textbook like Greene (2013)
- Partial derivatives, e.g.

$$\frac{\partial(x^3 + y^2 + 1)}{\partial x}$$

- Matrix and vector operations

$$\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} \times \begin{bmatrix} 7 \\ 8 \\ 9 \end{bmatrix} = \begin{bmatrix} 1 \times 7 + 2 \times 8 + 3 \times 9 \\ 4 \times 7 + 5 \times 8 + 6 \times 9 \end{bmatrix} = \begin{bmatrix} 50 \\ 122 \end{bmatrix}$$

- Vector dot product

$$z = \mathbf{w}^{\mathbf{T}}\mathbf{x} = \sum_{j=0}^{m} \mathbf{w_j x_j}$$

$$\begin{bmatrix} 1 & 2 & 3 \end{bmatrix} \times \begin{bmatrix} 4 \\ 5 \\ 6 \end{bmatrix} = 1 \times 4 + 2 \times 5 + 3 \times 6 = 32.$$

Outline

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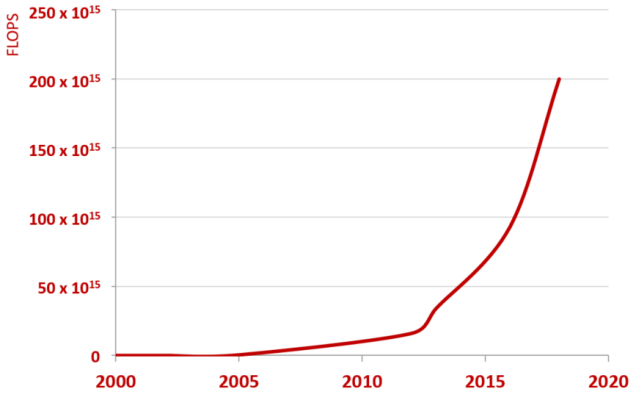
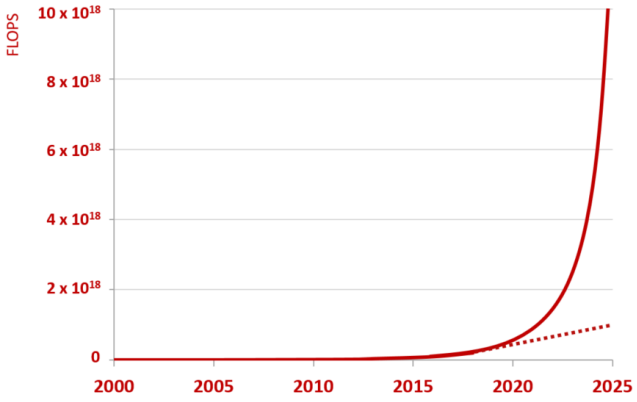
Computing power increases continuously



200,000,000,000,000,000
floating point operations per second
(or: 20,000 high-end PCs)

Computing power increases continuously



10,000,000,000,000,000,000
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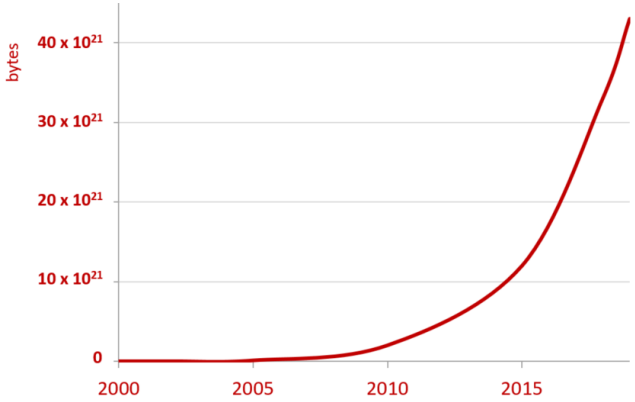
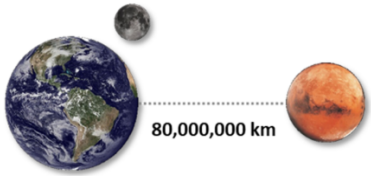
We collect ever more data



Annual in 2005 ≡ daily in 2020
Or, on CD-rom



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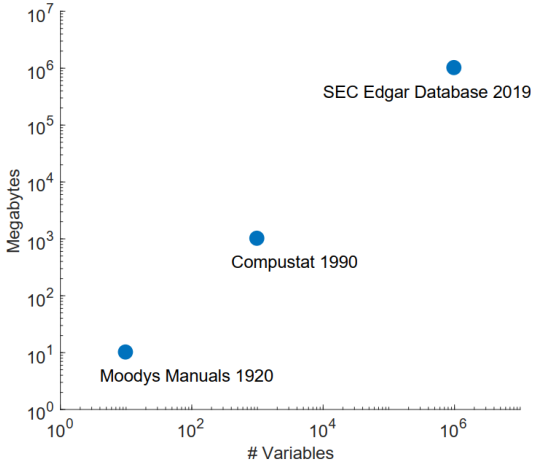
More data available to extend the set of x_t in asset pricing



Source: Nagel (2019)

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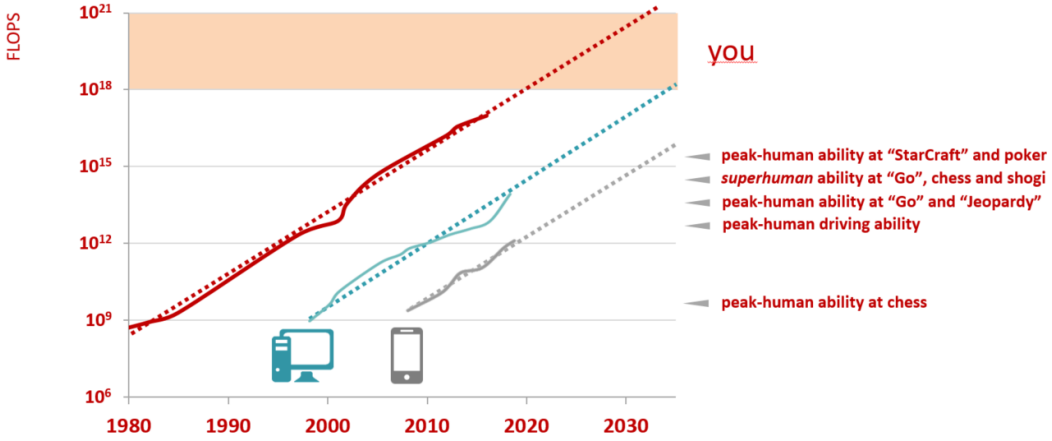
CPU power + algos + data has resulted in astounding progress



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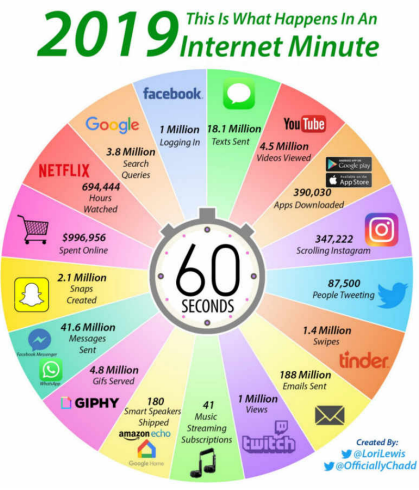
Human activity becomes more digitised



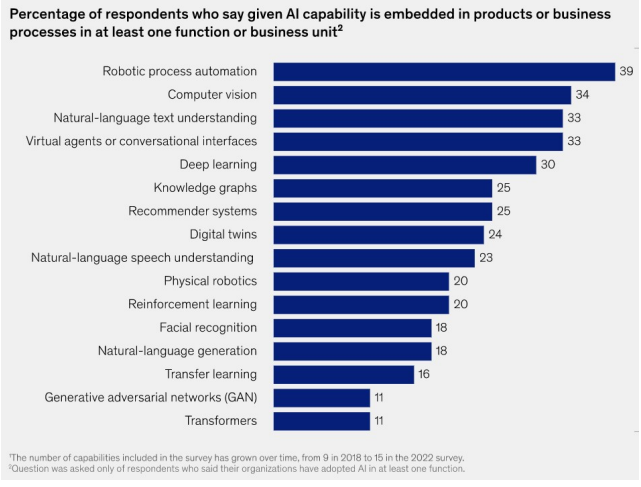
ML is everywhere ...

Changes in personal interests or in population characteristics (adaptive news access)

Adversary activities (avoiding spam filters; credit card fraud)

Changes in population characteristics (credit scoring)

... is used in many ways ...



Source: **StateAI2022**

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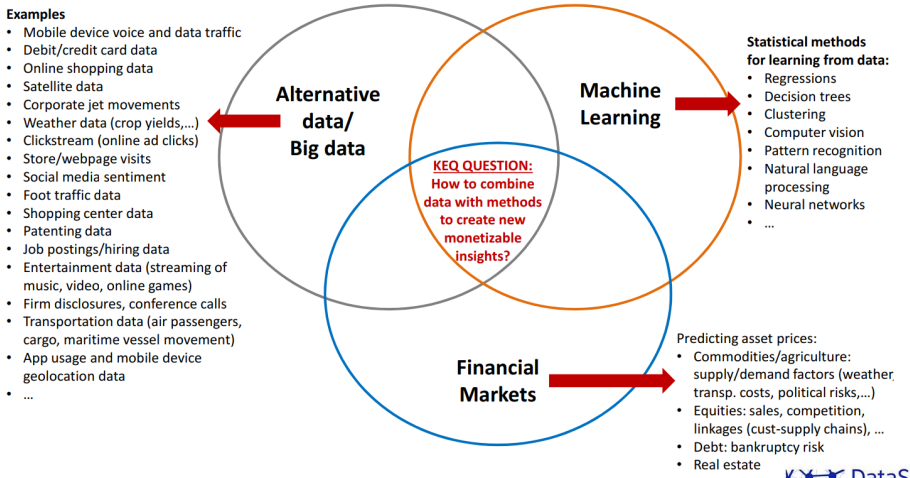
... and has many applications in finance



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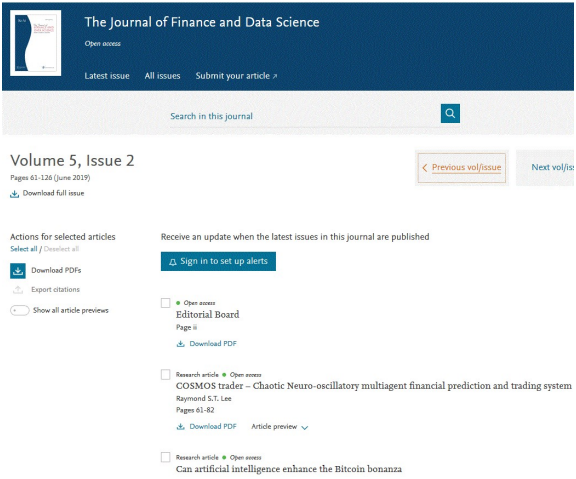
Even has its own journal!



Source: Journal of Finance and Data Science

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Outline

Opinion **Artificial intelligence**

Why Google thinks we need to regulate AI

Companies cannot just build new technology and let market forces decide how it will be used

SUNDAR PICHAI + Add to myFT

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Intelligent computers have held promise for a long time ...

In 1958 the New York Times reported that the Perceptron, an early AI machine developed at Cornell University with military money, was "the embryo of an electronic computer that [the American Navy] expects will be able to walk, talk, see, write, reproduce itself and be conscious of its existence".

(Economist, May 14th 2015)

More on Artificial Intelligence (AI)

> *"Every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it."*
>
> *(Dartmouth Artificial Intelligence Conference (1956))*

AI can refer to anything from a computer program playing a game of chess, to a voice-recognition system like Amazon's Alexa interpreting and responding to speech.

The technology can broadly be categorized into three groups:

- narrow AI: skilled at one specific task, e.g. IBM's Deep Blue (beat chess grand master Garry Kasparov – 1996), or Google DeepMind's AlphaGo (Go master Lee Sedol – 2016).
- artificial general intelligence (AGI) ≡ human-level
- superintelligent AI

  > *"an intellect that is much smarter than the best human brains in practically every field, including scientific creativity, general wisdom and social skills"*

  In other words, it's when machines have outsmarted us.

More Machine Learning (ML) definitions ...

- "Machine learning research is part of research on artificial intelligence, seeking to provide knowledge to computers through data, observations and interacting with the world. That acquired knowledge allows computers to correctly generalize to new settings."
- "A well-posed learning problem: A computer program is said to learn from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E."
- "Machine learning is the science of getting computers to act without being explicitly programmed."
- "Machine learning algorithms can figure out how to perform important tasks by generalizing from examples."

Machine learning = Statistics + Programming!

What is the difference, really ...

Whatever your definitions, environment used is largely irrelevant

Fitting Elastic Net regression in:

R

```r
eNet <- glmnet(X, Y, alpha = 0.5, lambda = myLambdas)
```

MATLAB

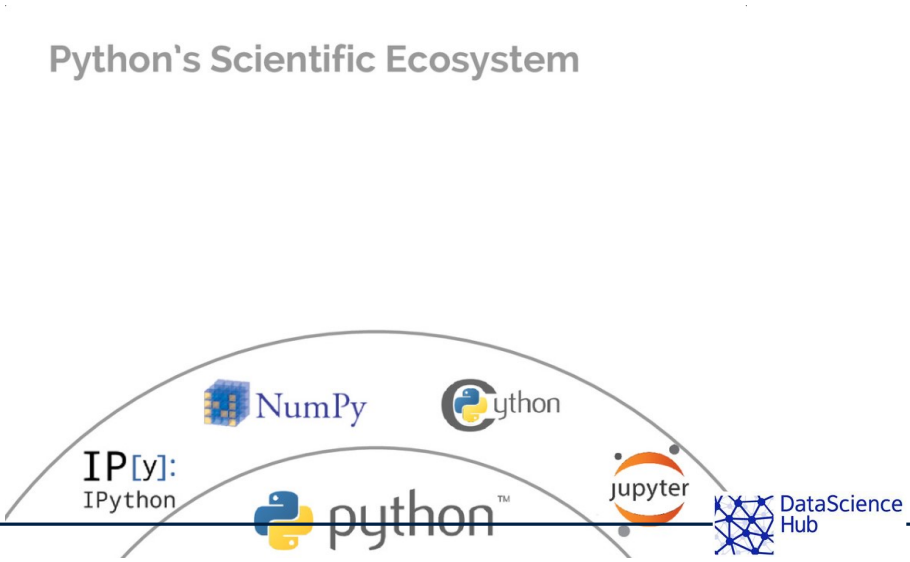
```matlab
eNet = lasso(X, Y, 'Alpha', 0.5, 'Lambda', myLambdas)
```

PYTHON/scikitLearn:

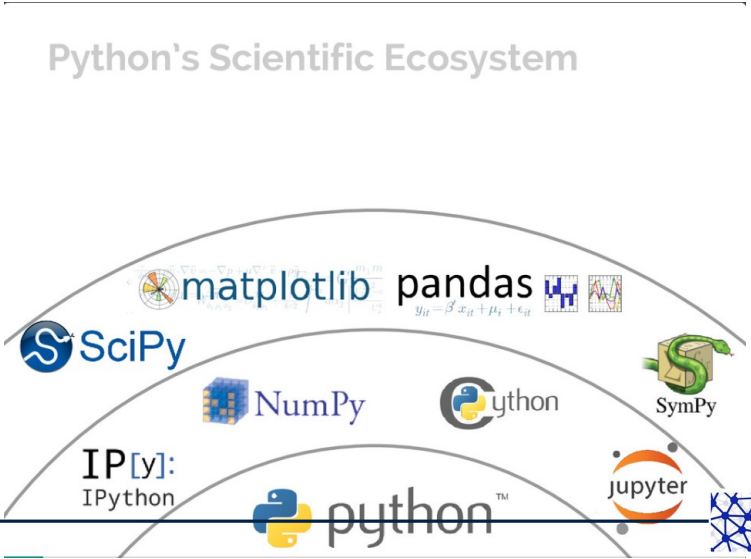
```python
eNet = ElasticNet(alpha = myLambda, l1_ratio= 0.5)
eNet.fit(X, Y)
```

The crucial thing is to know what elastic net, alpha and lambda mean!


Python's Scientific Ecosystem
python™


Python's Scientific Ecosystem
NumPy
Cython
IP[y]:
IPython
python™
jupyter
DataScience
Hub

We choose Python because of the ecosystem



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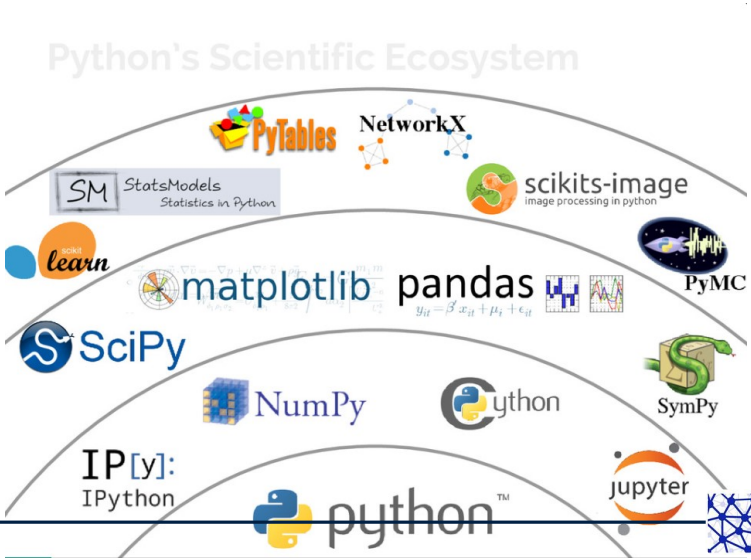
We choose Python because of the ecosystem



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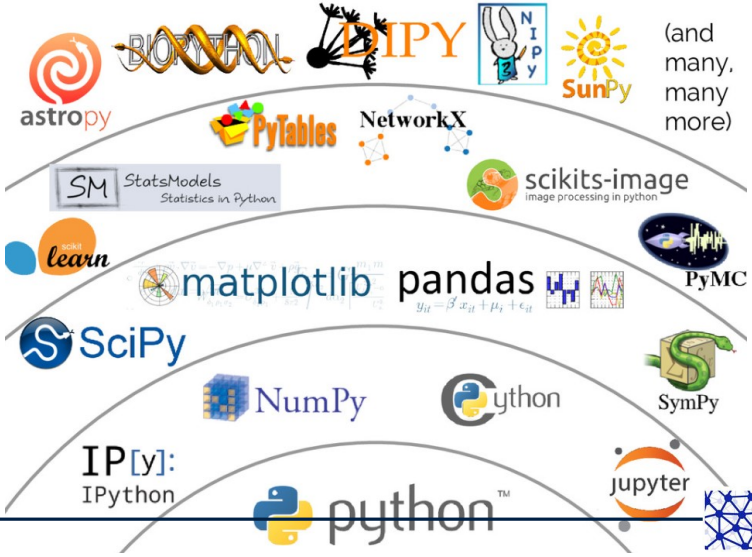
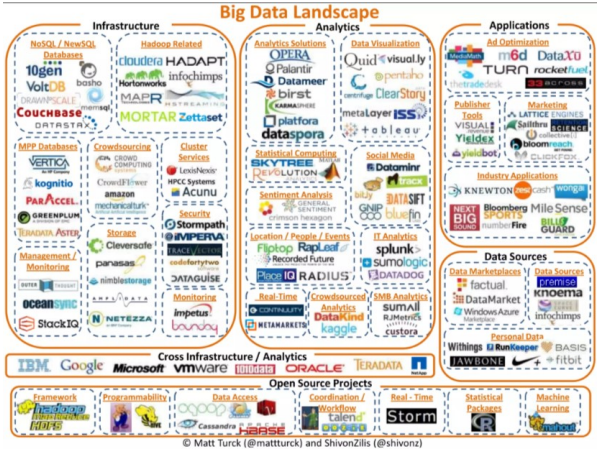
We choose Python because of the ecosystem



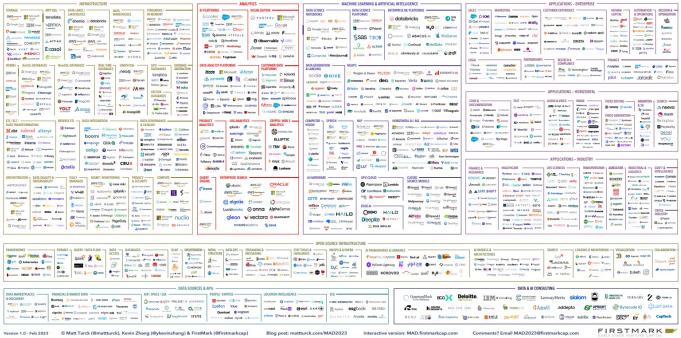
Outline

Tooling is evolving fast ...



2012

Tooling is evolving fast ...



2023

View in full size: click here.

2012

2016

2020

2021

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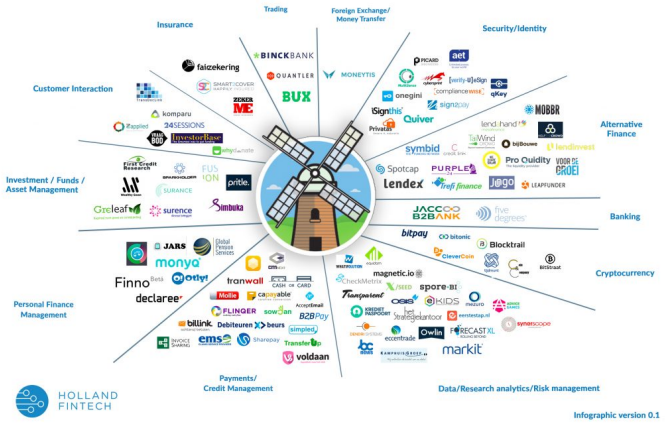
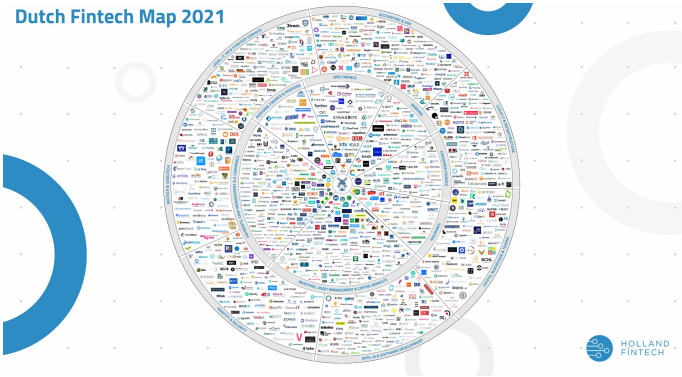
... as well as the Fintech landscape



... as well as the Fintech landscape



2021

Source: Holand Fintech

2015

2016

2017

2018

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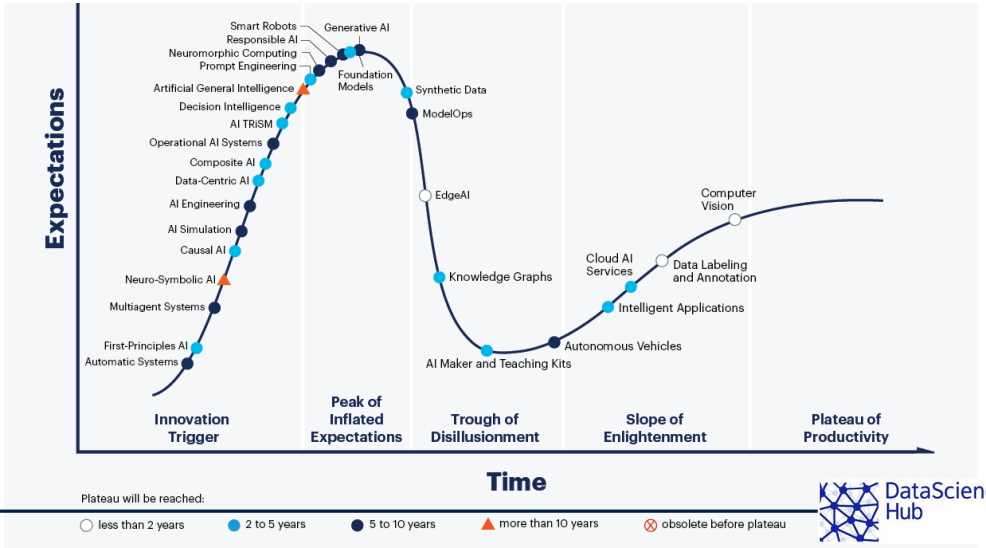
Data Science Hype Cycle – 2023



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Summary

In this lecture we covered:

1. Introductions and housekeeping
2. Why is this course relevant and how does it fit in the Honors programme
3. A first discussion of how ML is different
4. Sketching the landscape

Some definitions

- Artificial intelligence (AI): A broad discipline with the goal of creating intelligent machines, as opposed to humans' and animals' natural intelligence. It is a catch-all term that nonetheless captures the long term ambition of the field to build machines that emulate and then exceed the full range of human cognition.
- Machine learning (ML): A subset of AI that often uses statistical techniques to give machines the ability to "learn" from data without being explicitly given the instructions for how to do so. This process is known as "training" a "model" using a learning "algorithm" that progressively improves model performance on a specific task.
- Deep learning (DL): An area of ML that attempts to mimic the activity in layers of neurons in the brain to learn how to recognize complex patterns in data. The "deep" in deep learning refers to the large number of layers of neurons in contemporary ML models to achieve performance gains.
- Reinforcement learning (RL): An area of ML concerned with developing software agents that learn goal-oriented behavior by trial and error in an environment that provides rewards or penalties in response to the agent's actions (call
towards achieving that goal.

What if you haven't had enough?

- This course is too short to cover everything
- Luckily, there are a number of very good free courses out there
  - Google's crash course on Machine Learning
  - An excellent full length MOOC by Andrew Ng on Coursera
  - Courses from Harvard, IBM and Microsoft at EDX
  - Also see Udemy, although you have to pay a little bit
  - coding for economists
- Check out the use cases at Kaggle
- Or if you are in for a game: Code Combat
- Please let us know if you have come across others!

What about softcopy resources?

- There are an insane amount of blogs, repo's out there. Here is wildly incomplete list
  - Some really good links about ML an Econ on Dario Sansone's webpage
  - Economics and Data Science resources
  - For code, see the website paperswithcode.com
  - A nice book on interpretability as a website or as a Pact book Molnar (2019)
  - Great book (in progress) Coding for economists with great Python examples.
  - Very nice cheatsheets for folks coming from other languages: Stata, R, Matlab, Excel
  - Resources that go with the Python for Finance by Hilpisch
  - More Quant resources at O'Reilly
  - Cheatsheets for folks coming from other languages: Stata. Still looking for R, Matlab, Excel
  - Great newslettern Data Mining Gaps

- Please let us know if you have come across others!

What about hardcopy resources?

- There are also numerous books out there, some of them free and all of them come with a lot of supplementary material
  - McKinney, W. (2022). Python for Data Analysis, 3rd edition. https://wesmckinney.com/book/
  - Géron, A. (2019). Hands-on Machine Learning with Scikit-Learn, Keras, and TensorFlow. O'Reilly. Retrieved April 21, 2019, from https://www.oreilly.com/library/view/hands-on-machine-learning/9781492032632/
  - Wentworth, P., Elkner, J., Downey, A. B., & Meyers, C. (2019). How to think like a computer scientist: Learning with Python [arXiv: 1011.1669v3 ISSN: 1098-6596].
  - Raschka, S., & Mirajalili, V. (2017). Python machine learning: Machine learning and deep learning with Python, scikit-learn, and TensorFlow. Retrieved July 27, 2019, from https://www.packtpub.com/big-data-and-business-intelligence/python-machine-learning-second-edition
  - James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). An Introduction to Statistical Learning: With Applications in R.
  - Hastie, T., Tibshirani, R., & Friedman, J. (2017). The Elements of Statistical Learning: Data Mining, Inference, and Prediction [arXiv: 1011.1669v3 ISSN: 03436993].
  - Efron, B., & Hastie, T. (2017). Computer Age Statistical Inference.
  - Provost, F., & Fawcett, T. (2013). Data Science for Business: What you need to know about data mining and data-analytic thinking (O'Reilly, Ed.).
  - Sweigart, A. (2015). Automating the Boring Stuff with Python. https://automatetheboringstuff.com/

What about your tech stack

This course is not about research methods but if you want to take things serious you should invest in the following technologies

- Organize your thoughts: OneNote, Mindmap, Gingko App
- Organize your references: Zotero, Mendeley, Jabref. You might find this tedious but it will pay off by the time you have to find that one article or get the reference right.
- Use LaTeX. Overleaf makes it really easy to start
- Pick your favourite editor – preferably suitable for multiple languages and LaTeX. VSCode, Sublime Text, PyCharm.
  - Visual Studio Code ()≠ Visual Studio). Has an active marketplace and integrates well with the Microsoft stack
- Check out Open metric for a much more thorough list

Things are moving fast so please let us know if you have come across interesting tools!

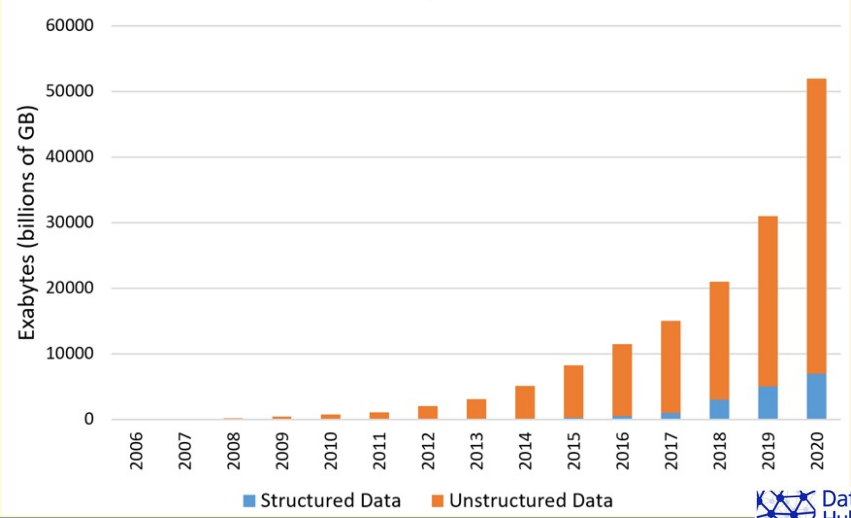
Where to find data?

- Most financial data sets are under lock and key but some of it is free

Araujo 2023	Open source package to access a wide range of public finance related sites
Awesome list	Overview of public data sets, mostly trade. Opencorporates
DB.nomics	Amazing portal with data from BIS, ECB, OECD and many others. It has an API from within Python
WRDS	Wharton Database, See Leonard Wolk's lectures
Yahoo finance	Various APIs available (e.g., Rapidapi)
Mockaroo	If you need to make up a test data set with realistic features
Draw my data	Generate a data set with some properties
Kolanovic and Krishnamachari (2017)	has a great chapter "Handbook of Alternative Data"
COVID travel data	
Synthetic data (JP Morgan)	useful to generate realistic (but fake) data
Google trend and financial time series	
Google Trend and unemployment	Nice example of what to do with Google Trend
re3data	Database of data sets

- See the api-packages-overview.xls with an overview of available APIs on De Nederlandsche Bank GitHub. Let us know if you have comments or data_science@dnb.nl

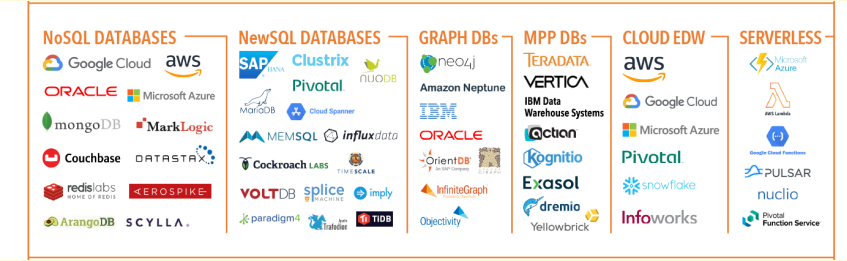
The Cambrian explosion ... of data



DataScience Hub

What types of database are out there

- Relational vs Non-relational databases
  - Relational engines require consistency at the end of each transaction, whereas non-relational engines only require that the database be consistent at some point in time (i.e., eventually)



Relational Database Management Systems (RDMS)

- strictly enforce type (e.g. numeric, string, etc.)
- example: SAS

strong layout data is known in advance but use not yet
weak variable data

Source: Perkins et al. (2018)

Key-value (KV)

- Simple keys to values
- example: key-value stores

strong (horizontally) scalable and fast for unrelated data (e.g. users' session data)
weak no index hence only basic CRUD (**C**reate, **R**ead, **U**pdate, **D**elete)

Source: Perkins et al. (2018)

SWOT of non-relational databases

Key-value (KV)

- Simple keys to values
- example: key-value stores

strong (horizontally) scalable and fast for unrelated data (e.g. users' session data)
weak no index hence only basic CRUD (**C**reate, **R**ead, **U**pdate, **D**elete)

Columnar

- Everything in a column, rows are not kept together, nice versioning
- example: Monet db

strong indexing web pages
weak it would be best if you know query structure in advance

Source: Perkins et al. (2018)

Document

- any number of fields with unlimited nesting, JavaScript Object Notation (JSON)
- example: MongoDB, CouchDB, document stores

strong highly variable data, good match with object-oriented languages
weak verbose

Graph

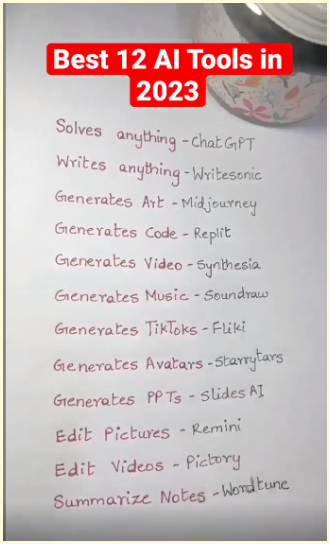
- focus on the relation between nodes than on the actual node information
- example: Neo4J, graph databases

strong social network queries
weak comparing node info between 2 nodes $\rightarrow$ this is then stored elsewhere

Source: Perkins et al. (2018)

Where to find handy tidbits?

- Holidays can be found using the Holidays PyPi package
- ISO codes for countries, currencies etc. can be found with the pycountry PyPi package
- Testing out your regular expression regex101 site
- Papers with code
- Compute the distance between locations (API) at https://developer.here.com
- The list is endless ... please let me know if you find other interesting ones.



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