

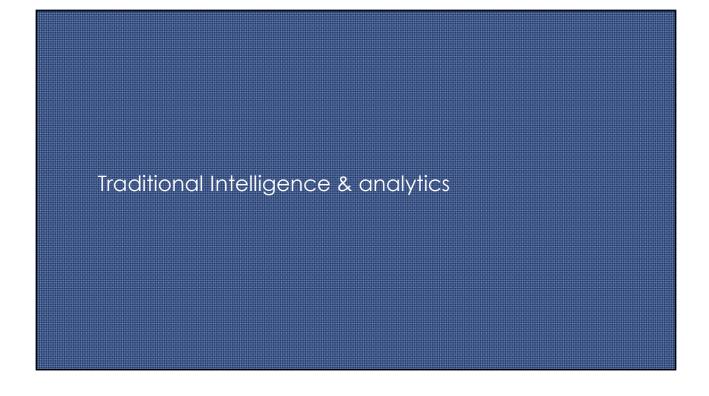
Course Program

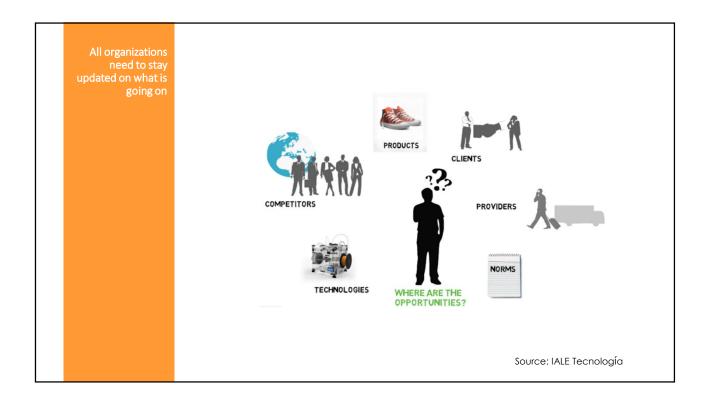
Part 1. ANALYSING AND ANTICIPATING TODAY

- 1.1. Traditional Intelligence & Foresight Tasks
- 1.2. Search, analysis (data & text mining), visualization...

Part 2. CURRENT CHALLENGES

- 2.1. A changing environment
- 2.2. The era of automatization: Al and Machine Learning
- 2.3. The changing role of the analyst-data scientist-futurist?



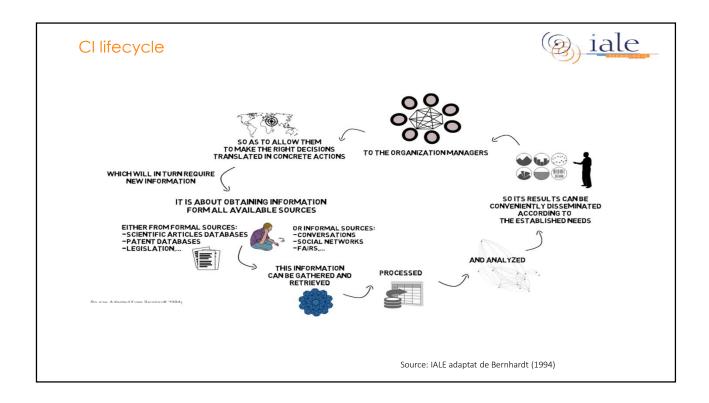


"Competitive Intelligence is the process of obtaining, analyzing, interpreting and diffusing the strategic value information on the industry and competitors, that is transferred to the decision makers at the right moment."

(Gibbons & Prescott, 1996)

"The Information Watch consists in observing and analyzing the scientific, technical, technological, and economical environment of a company to counteract potential threats and seize growth opportunities."

(Jakobiak, 1992)



Added value of Intelligence analytics

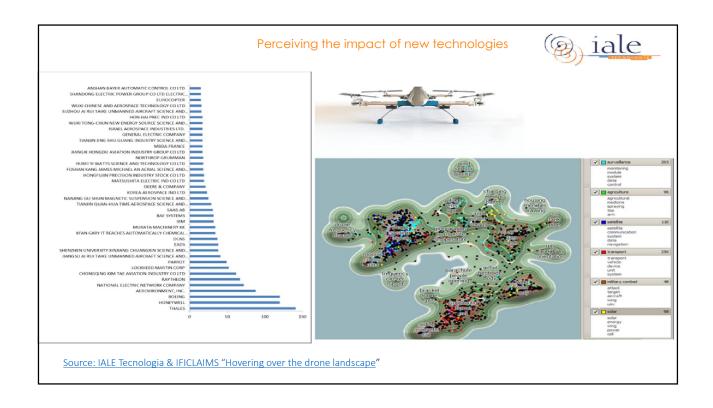


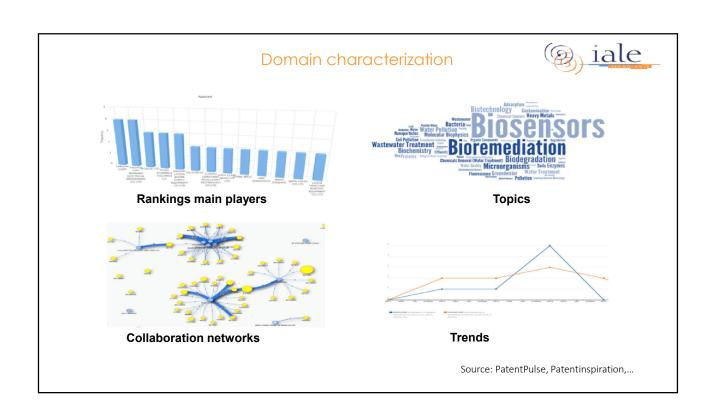
Keeping us up-to-date

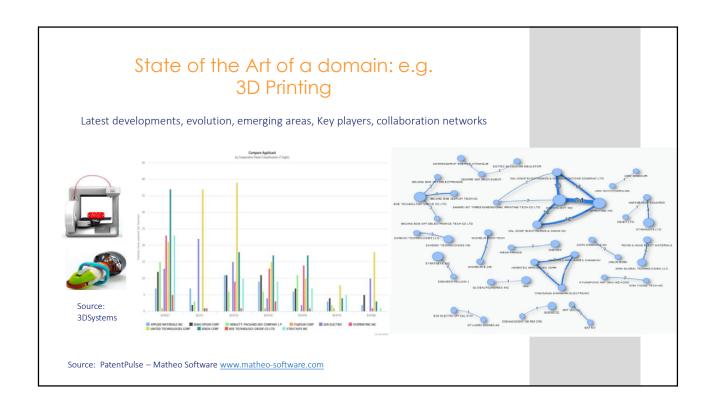
- What are the main research lines in an area or domain?
- What technologies are emerging?
- What are the <u>main players</u> to be aware of?
 (Countries, reference centers, teams, people...)
- What is the market/impact/social context...
- ✓ Avoid carrying out R&D on what is already invented!
- ✓ Profiting from what already exists!
 - Realise of current opportunities for innovation/diversification
 - Buying/licensing an interesting patent,
 - Go for an strategic alliance / Joint venture
 - Hire talent,....

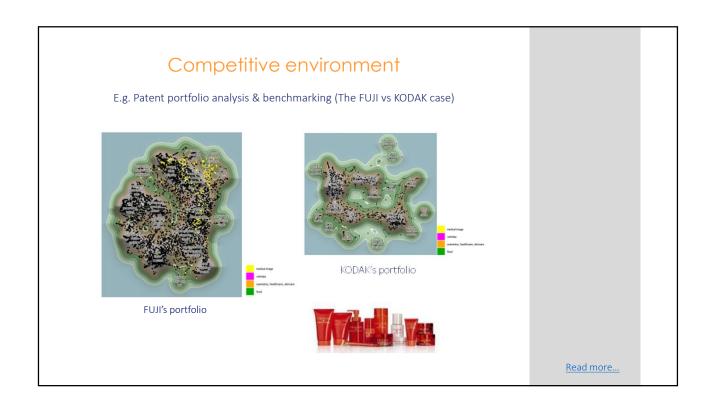


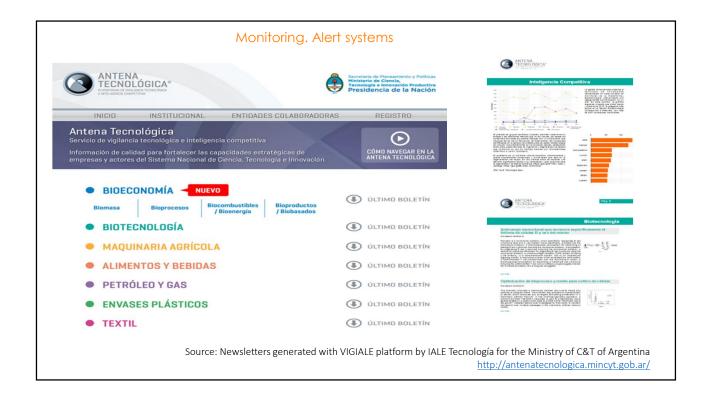
Source: Scott Simmerman

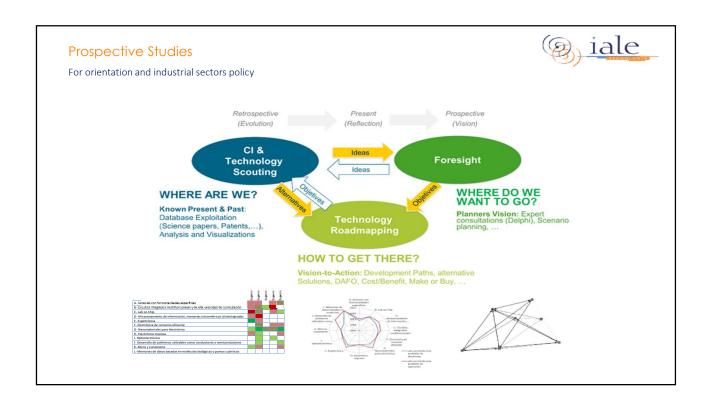


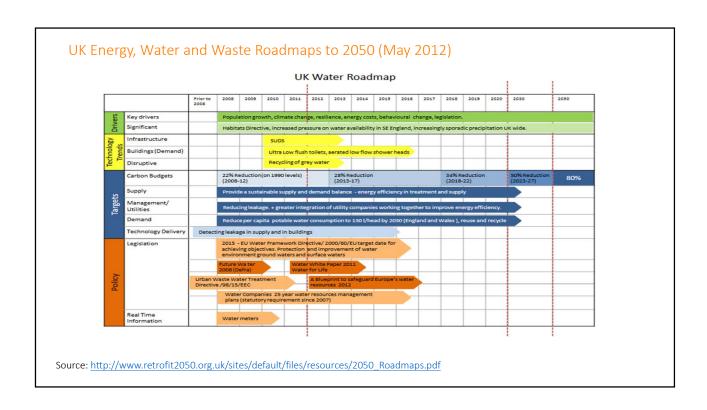


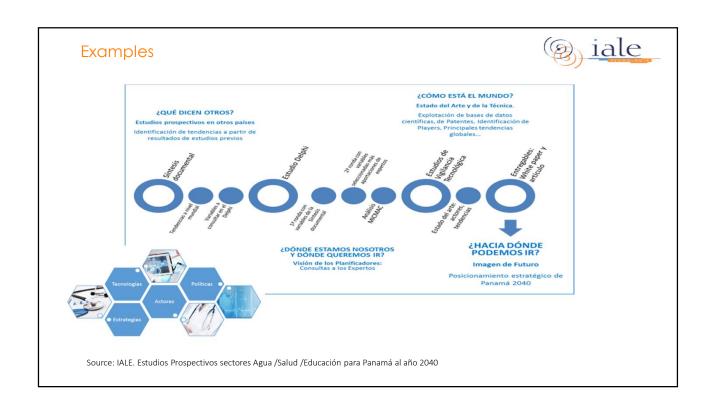


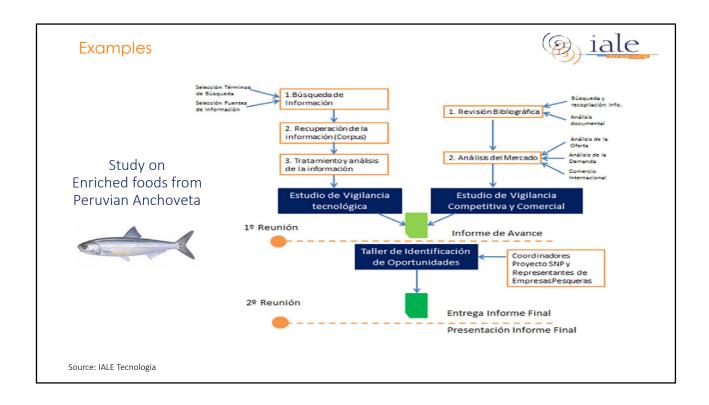


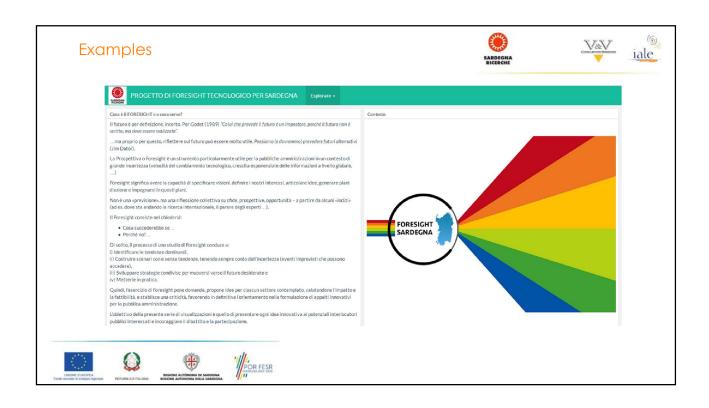


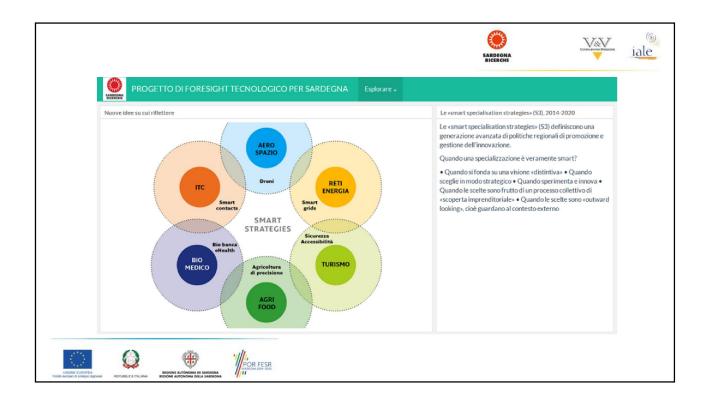


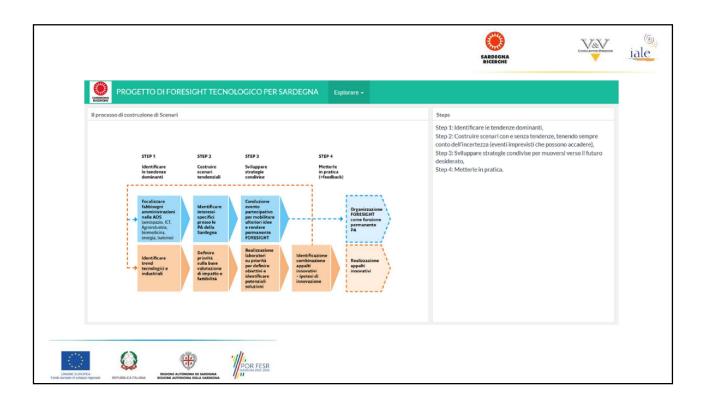


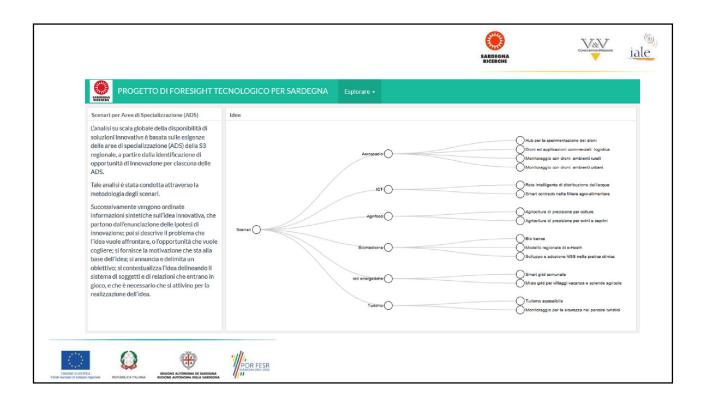




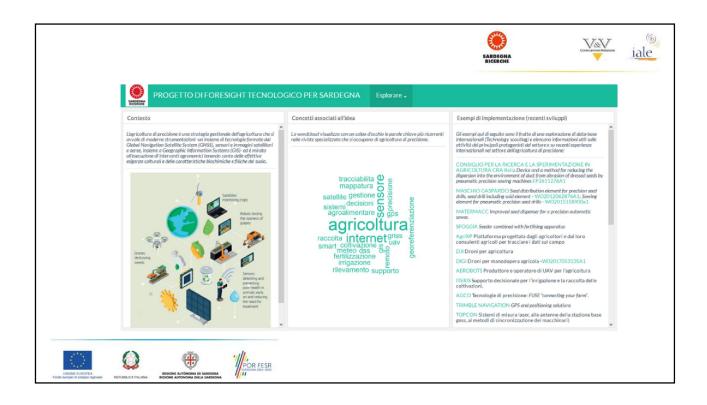


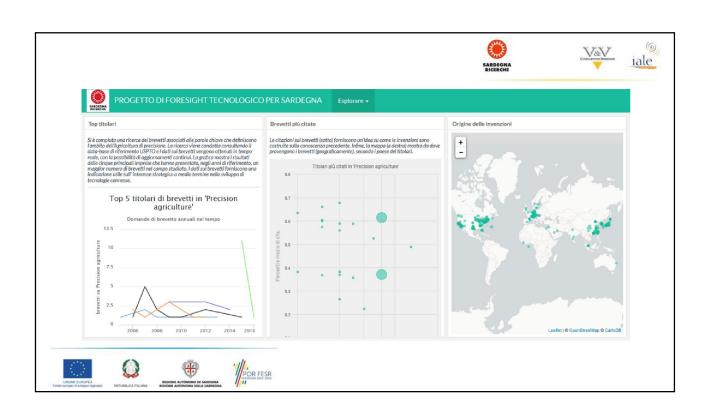


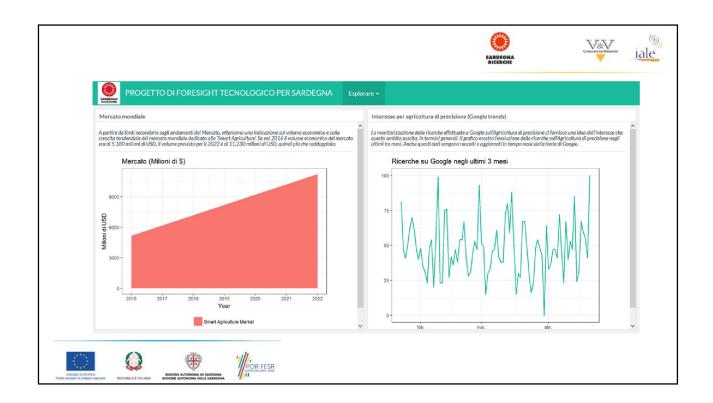


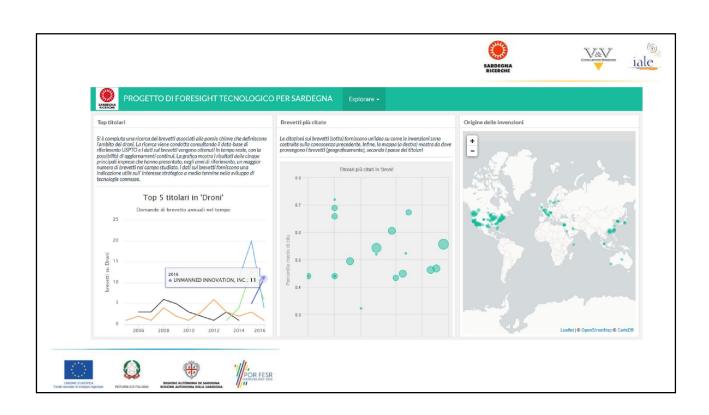




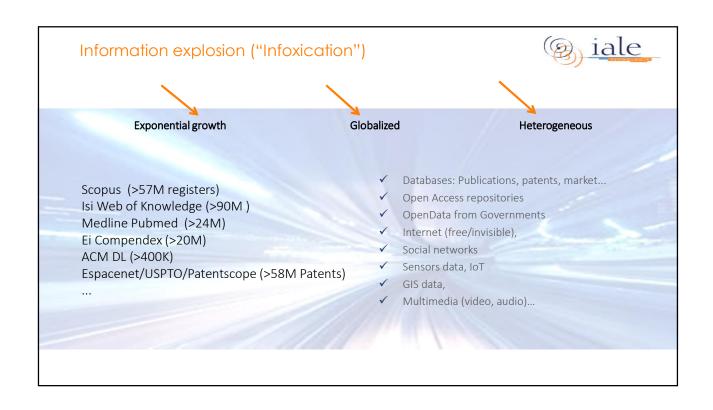


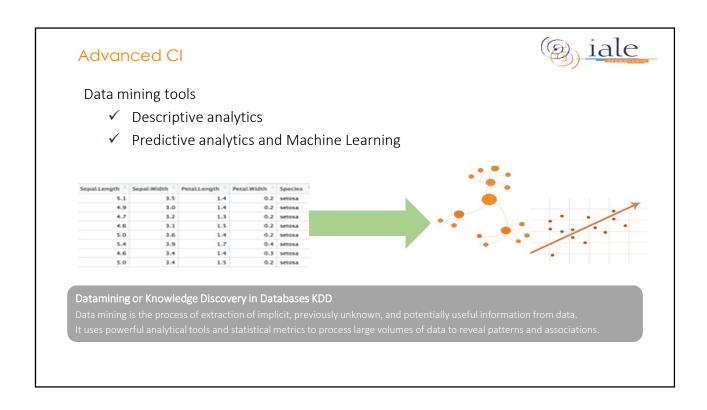


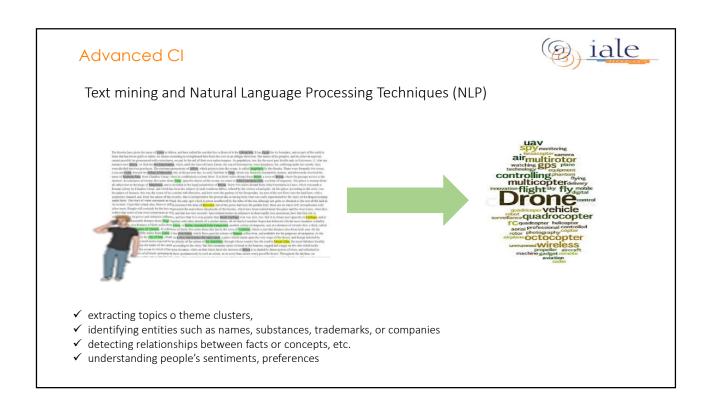


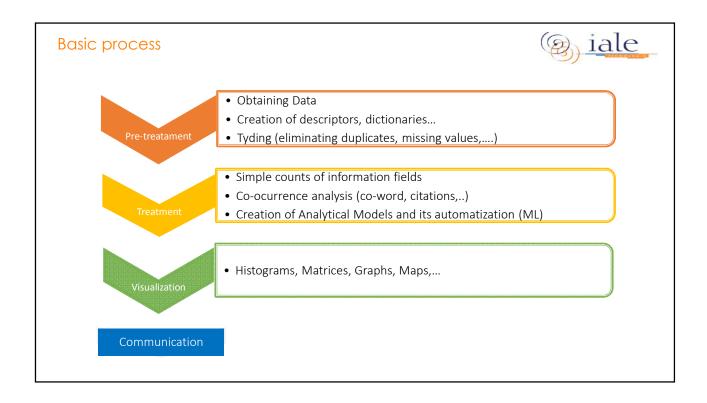


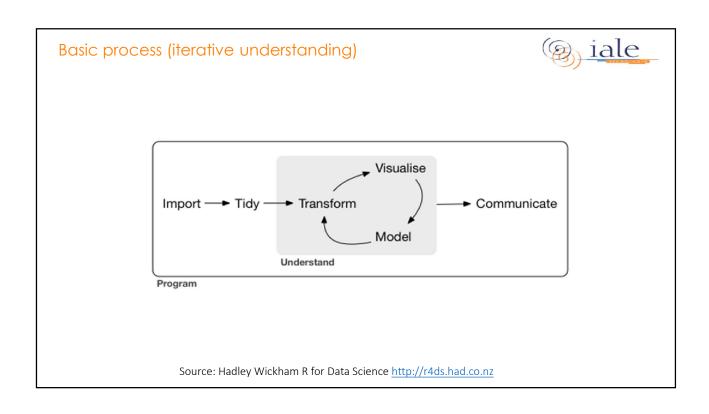












Reproducible research

In the current context of global science trends (open access, open data, and open source tools), **Reproducibility** becomes crucial.

Writing code for our analysis allows:

- 1. Transparency throughout all the analytical process (not only in the results)
- 2. Sharing and collaboration
- 3. Re-executing this analysis either with same data or with new data (Reproducibility)

```
mydata <- 15 #I define a variable, my data
sum(mydata, 10) #I apply operations and functions,...
## 25 #I obtain results</pre>
```

...then I can save all that in a file: "myanalisis" and share it!

Platforms for collaboration & version control

A form of resistance!:

- ✓ Know the data sources
- ✓ Create your own tools
- ✓ Be accountable, be transparent
- ✓ Keep reproducibility
- ✓ Collaborate / Share / Learn...

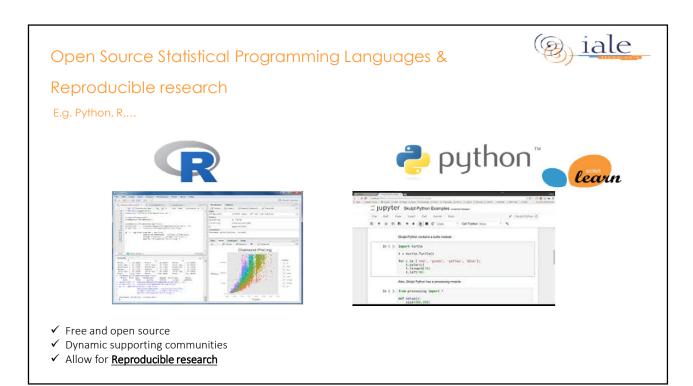
Program or be programmed

Microsoft is acquiring GitHub for \$7.5

As of June 2018, there were 28 million developers in the GitHub community, as well as 85 million code repositories, making it the world's largest host of source code.











Tidyverse, ensemble of packages including:

- **Dplyr** (for data manipulation)
- Tidyr (for data tidying)



https://www.tidyverse.org/



- Pandas (working with tables)
- Scipy (numerical computation),...







http://pandas.pydata.org/

Packages/libraries for Text Mining





Many packages:

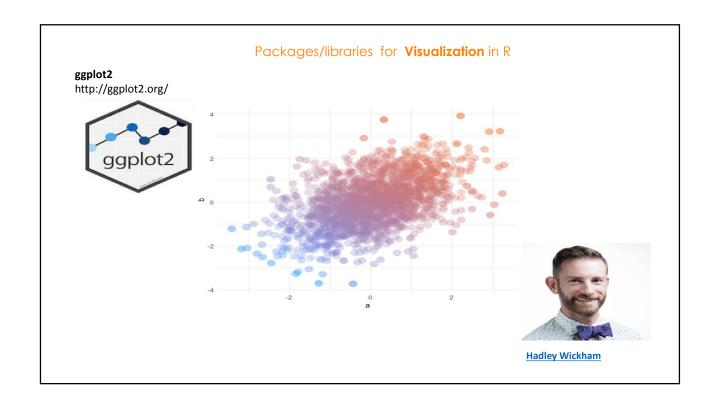
- tm
- OpenNLP
- Tidytext
- quanteda
- stringr...

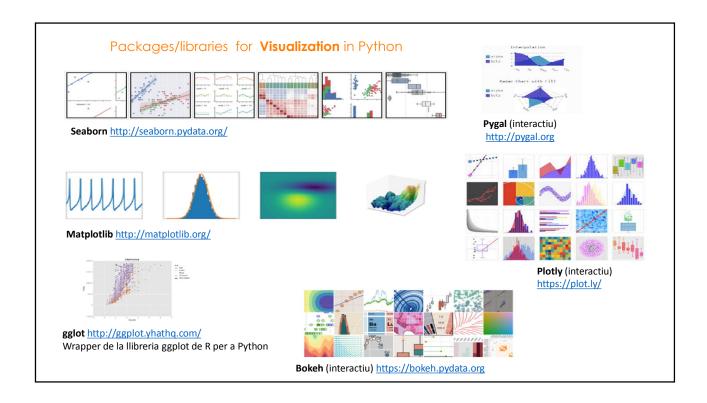


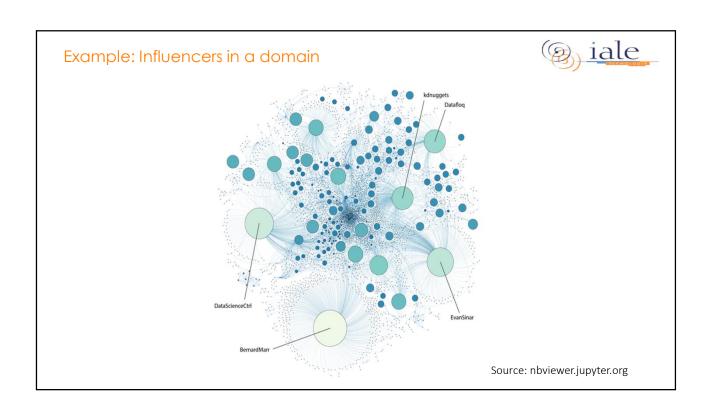


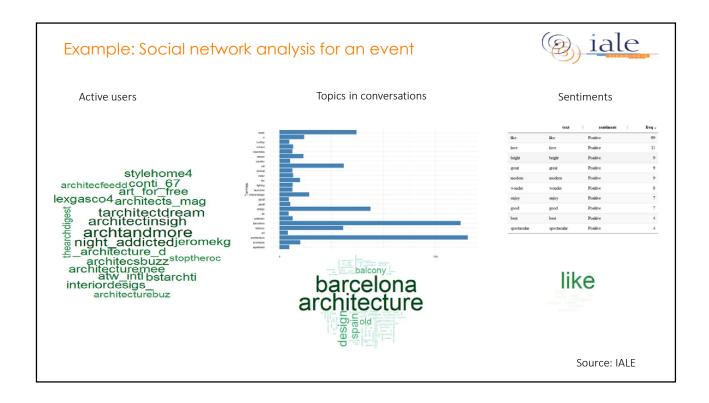
https://radimrehurek.com/gensim/

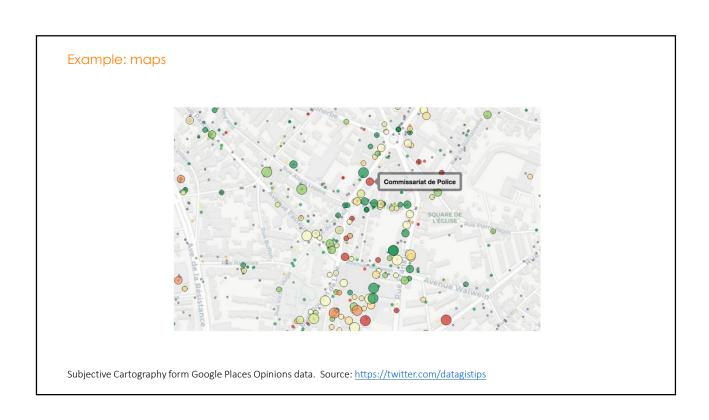
https://cran.rproject.org/web/views/NaturalLanguageProc essing.html

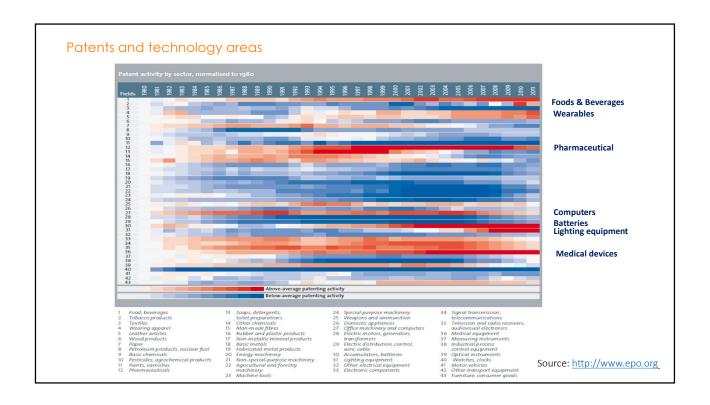


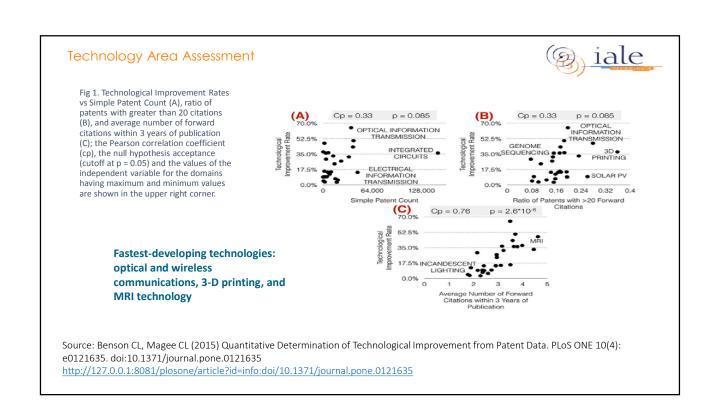


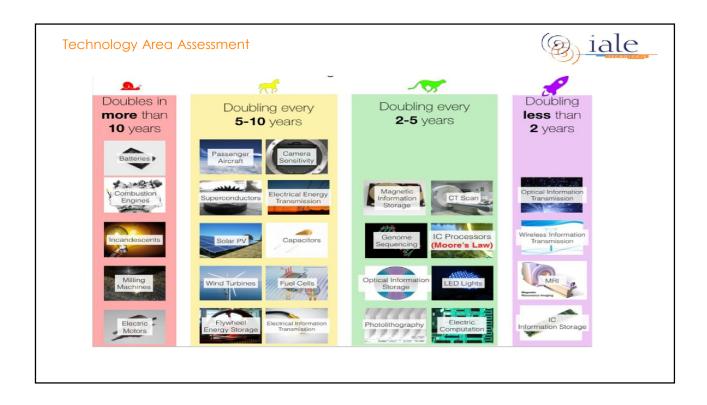


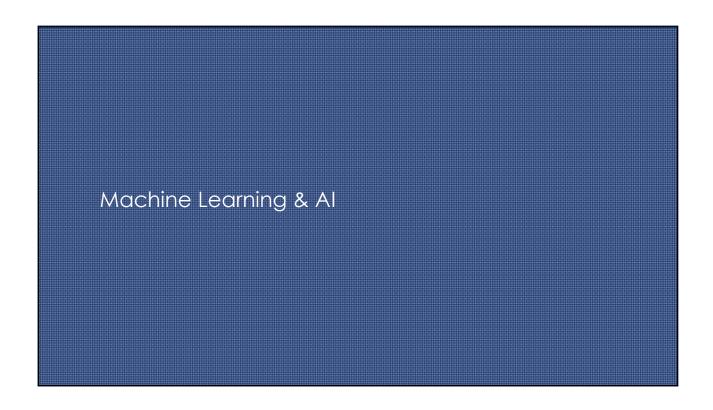












Basic statistical terminology





Observation (Normally Rows in a table)

=Observation = Sample = Example = Instance = Record = Mostra



Feature (Normally Columns in a Table)

=Characteristic = Predictor = Attribute = Input = Regressor

=Independent variable



Response (Each value we want to predict)

= Response = Target = outcome = Output = Label = Dependent variable

	Colour	texture	size	
Sample 1	Golden yellow	Smooth	6,5 cm	→ Golden apple?
Sample 2				

Main machine Learning Methods





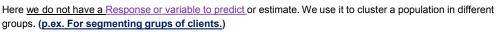
✓ Supervised Learning Classification and Regression



We can predict a response from several atributs (or independent variables). We generate a function to map inputs to desired outputs. (p.ex. Filtering spam mails). We train this model until a desired level of precision over the training data.

Examples of Algorithms) *Regression, Decision trees, Random Forest, kNN, Logístic regression,...*

✓ Unsupervised Learning Clusterizing



Examples of Algorithms) Apriori, K-means, hierarchic clusterization

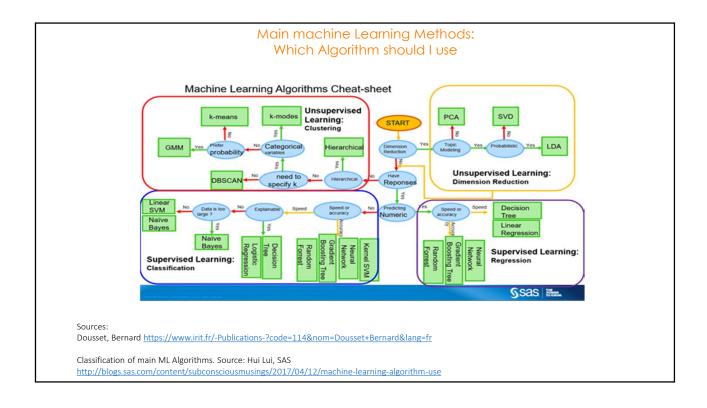


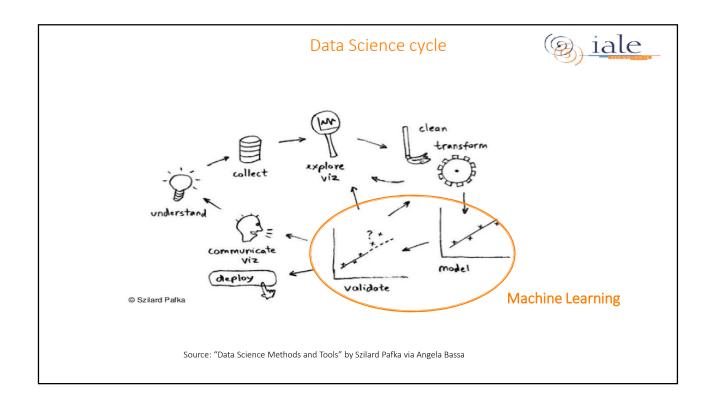
✓ Reinforced Learning

Automatism exposed to an environment where it can continuously self-train through trial and error and reward. It learns from experience trying to capture best knowledge to make precise decisions.

Ex) Markov Decision Processes

The learning agent can be a neural net that maps states and actions (Deep learning)... (p.e. artificial vision),....

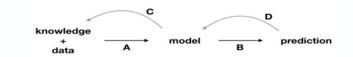




Data Science cycle



Typical workflow in ML



- A.Modelling is a process in which domain knowledge and data are turned into models.
- B. Models are used to generate predictions.
- C. Understanding of model structure may increase our knowledge and in consequence leads to a better model. *DALEX helps here*.

 D. Understanding of drivers behind particular model predictions may help to
- D.Understanding of drivers behind particular model predictions may help to correct wrong decisions and in consequence leads to a better model. DALEX helps here.

Source: https://github.com/pbiecek/DALEX_docs/blob/master/workshops/eRum2018/Workshop_eRum_2018_part1.pdf

Packages/libraries for Machine Learning

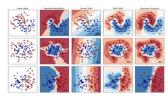


Many packages:

- e1071
- randomForest
- · Caret,
- ...

https://cran.r-project.org/web/packages/caret/caret.pdf





http://scikit-learn.org/stable/

Environments and Packages for Deep Learning (many are Open Source)

- Torch i Pytorch (Facebook)
- TensorFlow (Google)
- CNTK (deep learning) i DMTK (machine learning) from Microsoft
- Deepmask (deep learning per a visió artificial) from Facebook
- Caffe2 (deep learning for Artificial vision) Yangqing Jia, Facebook
- DSSTNE (deep learning) d'Amazon
- Mahout (Machine learning) i BigDL (Deep Learning) from Apache
- **SystemML** from IBM (also Watson & Bluemix)
- PaddlePaddle from Baidu (Andrew Ng)
- MxNet (Pedro Domingos, U.Washington, Amazon)
- **DL4J** (Deeplearning for Java, Open source)

Keras (François Chollet, Google)

Python API for Tensorflow



Associacions Word2Vec Font: Tensorflow



Object detection in Pictures, Source: Google Blog.





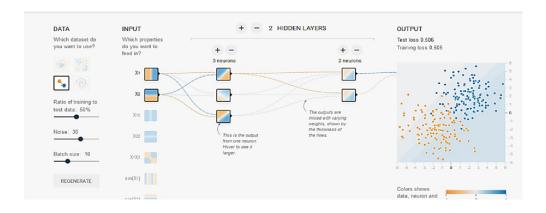


Font: MIT Introduction to Deep Learning 6.S191: Lecture 1 Foundations of Deep Learning Lecturer: Alexander Amini

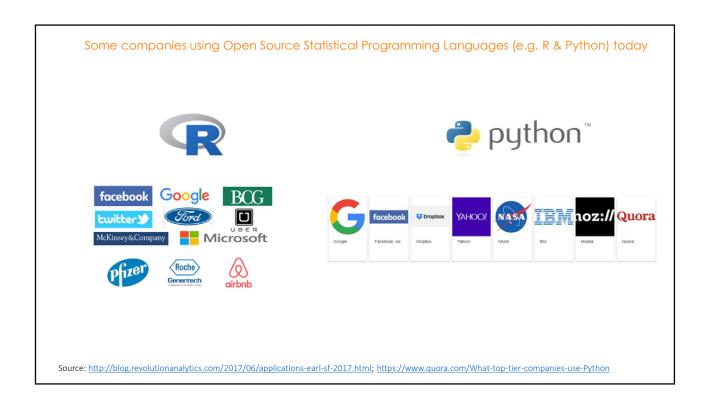
Neural Networks and Deep Learning

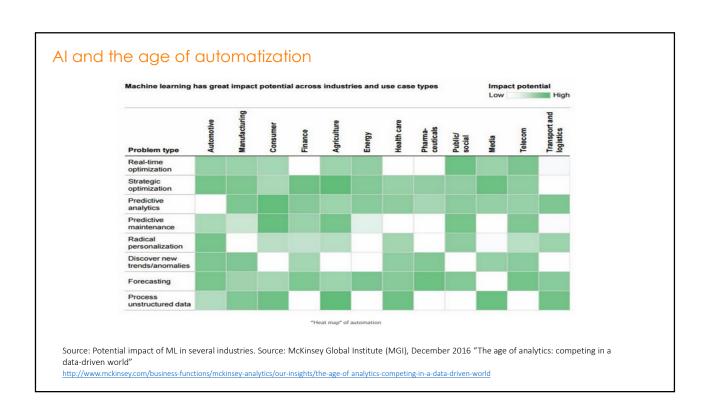


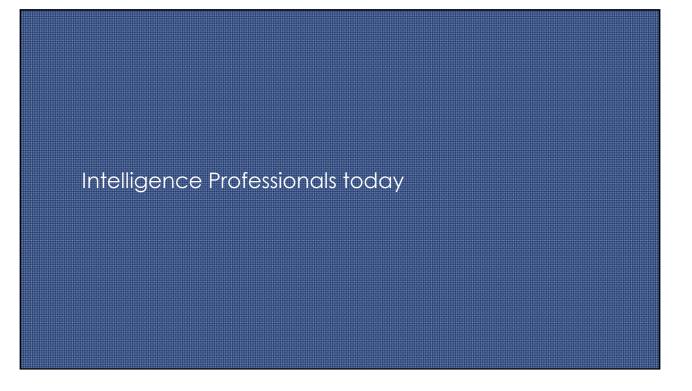
TensorFlow from Google is Opensource and allows you to experiment with Neural Nets (http://playground.tensorflow.org)



Source: Neural Networks and Deep Learning by Michael Nielsen & Deep Learning by Ian Goodfellow, Yoshua Bengio y Aaron Courville.









CI Professionals today

✓ Domain Expertise

✓ Business and industry Knowledge, context, social, cultural, normative, IP, analytical mind, strategic thinking, etc.

✓ Mathematics & Statistics

✓ Some key issues: control overfitting, detect/handle outliers, differenciate correlation/causation, Inference algorithms, etc.

✓ Data management

✓ Collect & Wrangling, Data Visualization, Tools, APIs, mashups, dashboards, DDBB querying, programming languages (SQL, Python, R,...)...

✓ Communication

✓ Storytelling, report drafting, configuring tailored alert systems, newsletters, social media, etc

Sources:

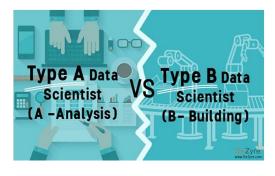
Roger Huang https://www.springboard.com/blog/how-to-become-a-data-scientist/

Thomas C. Redman "Data Scientists get out and talk to people" https://hbr.org/2017/01/the-best-data-scientists-get-out-and-talk-to-people

CI Professionals today

Some distinguish from type "A" data Scientist vs Type "B" data Scientist

Type "A" (Analysis): have strong statistics skill and the ability to work with messy data and communicate results.



Type "B" (build):

have very strong coding skills, maybe have a background in software engineering, and focus on putting machine learning models, such as recommendation systems, into production.

Sources:

Michael Hochser https://www.quora.com/What-is-data-science/answer/Michael-Hochster Emily robinson http://hookedondata.org/Advice-for-Applying-to-Data-Science-Jobs/Dzyre https://www.dezyre.com/article/type-a-data-scientist-vs-type-b-data-scientist/194

Theory driven (deductive) vs Data driven (inductive)

Traditional science (deductive)

Observation-> Hipotesis-> Experiment-> validation

THE TYPES OF REASON.

DEDUCTIVE REASONING:

- Commonly associated with "formal logic."
- Involves reasoning from known premises, or premises presumed to be true, to a certain conclusion.
- The conclusions reached are certain, inevitable, inescapable.

Commonly known as "informal logic," or "everyday argument."

INDUCTIVE REASONING

- Involves drawing uncertain inferences, based on probabilistic reasoning.
- The conclusions reached are probable, reasonable, plausible, believable.

...AND THEIR ROLE IN DATA SCIENCE TRADECRAFT.

The Types of Reason and Their Role in Data Science Tradecraft

DEDUCTIVE REASONING:

- Formulate hypotheses about relationships and underlying models.

INDUCTIVE REASONING

- Exploratory data analysis to discover or refine hypotheses.
- Carry out experiments with the data to test hypotheses and models.

 Discover new relationships, insights and analytic paths from the data.

Machine Learning (inductive)

Data&knowledge-> Ass./patterns (modeling)-> Insights/Predictions

Kuonen, Diego Keynote NTTS 2017, Brussels, Belgium March 14, 2017

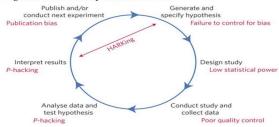
Booz Allen Hamilton. "The Field Guide to Data Science" 2015. Web Accessed 1 February 2017. SSRN

Theory driven (deductive) vs Data driven (inductive)

Dangers of deductive reasoning:

- ✓ P-hacking, HARKing (hypothezing after the results are known)
- ✓ Need for constantly contrasting and leveraging results with the real world

Figure 1: Threats to reproducible science.



An idealized version of the hypothetico-deductive model of the scientific method is shown Various potential threats to this model exist (indicated in red), including lack of replication⁵, hypothesizing after the results are known (HARKing)⁷, poor study design, low statistical power2, analytical flexibility51, P-hacking4, publication bias3 and lack of data sharing6, Together these will serve to undermine the robustness of published research, and may also impact on the ability of science to self-correct.

Source: Mainfesto Reproducibility: http://www.nature.com/articles/s41562-016-0021

Theory driven (deductive) vs Data driven (inductive)

Dangers of inductive reasoning:

- ✓ Today certain automatisms make decisions that affect business and sometimes our culture and our lives (biased decisions based in race, location or gender)
- ✓ Algorithms are Black boxes for the common of mortals. Are algorithms fair?

(at least they need to be more transparent)

"All models are wrong but some of them are useful"

George Box (1919-2013)



Replacing one type of reasoning for the other (<u>both need to go together</u>; <u>we actually need to mix them</u>) We must always go back to the real world and keep humans in the loop

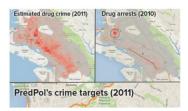
Sources:

Peter Norvig, Director Research Google "the unreasonable effectiveness of data" Stanford https://www.youtube.com/watch?v=yvDCzhbjYWs Katharine Jarmul PyData, Amsterdamm 2017 https://www.youtube.com/watch?v=hDgXIUM3Rmw

Ethical aspects: ALGORITHMIC IMPACT ASSESSMENT (AIA)



Automated crime prediction



Early diagnosis of deseases

nature ARTICLES biomedical engineering ARTICLES was also a construction of the constru

Prediction of cardiovascular risk factors from retinal fundus photographs via deep learning

Garg S. Company U. Spring "and Dall R. Webster" before the company of the compan

- Respect the public's right to know which systems impact their lives and how they do so by publicly listing and describing algorithmic systems used to make significant decisions affecting identifiable individuals or groups, including their purpose, reach, and potential public impact;
- Ensure greater accountability of algorithmic systems by providing a
 meaningful and ongoing opportunity for external researchers to review,
 audit, and assess these systems using methods that allow them to
 identify and detect problems;
- Increase public agencies' internal expertise and capacity to evaluate the systems they procure
- Ensure that the public has a meaningful opportunity to respond to and, if necessary, dispute an agency's approach to algorithmic accountability.

Source: https://medium.com/@AlNowInstitute/algorithmic-impact-assessments-toward-accountable-automation-in-public-agencies-bd9856e6fdde; https://ainowinstitute.org/aiareport2018.pdf

In summary: current roles of the Intelligence analyst

- ✓ Human resource for Intelligence/Data Science/Analytical /Futurist tasks is its main asset. An it is an scarce one.
- ✓ Need for a professional figure dedicated to **understanding data**, its origin and nature, the involved adquisition methods, its quality and context
- ✓ That is able to propose/derive possible uses according to specific motivations or social, organizational or industrial problems, acting as the bridge between human and/or organizational needs and algorithms potentially augmenting our capabilities.
- ✓ That ensures the dialog between deductive and inductive reasoning
- ✓ That is able to work cooperatively in networks
- ✓ That is able to **comunicate** and share analytical processes and results

Supporting strategic decisions, leveraging -based on them- the necessary data, contrasting the value of information and distinguishing from noise, contrasting the veracity and usefulness of models with the real world, and proposing creative ways of identifying problems and deploying meaningful shared narratives.

A brilliant, challenging future, awaits for the intelligence analyst!

