

# Data Science (CDA)

## Knowledge exploitation

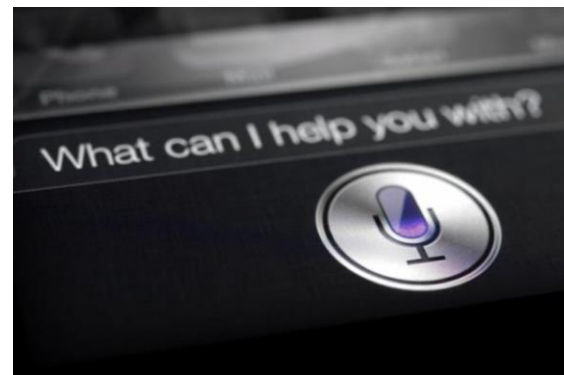
- José Hernández Orallo, DSIC, UPV, [jorallo@upv.es](mailto:jorallo@upv.es)
- Fernando Martínez Plumed
  - Using material from Cèsar Ferri and Toby Segaran's book "Programming Collective Intelligence" (<https://www.safaribooksonline.com/library/view/programming-collective-intelligence/9780596529321/cho2.html> )
  - <http://grouplens.org/datasets/movielens/>



- **Unit 4:** Knowledge exploitation
  - Assistants, prescriptors and recommenders
  - Integration into decision making, dashboards and monitoring.



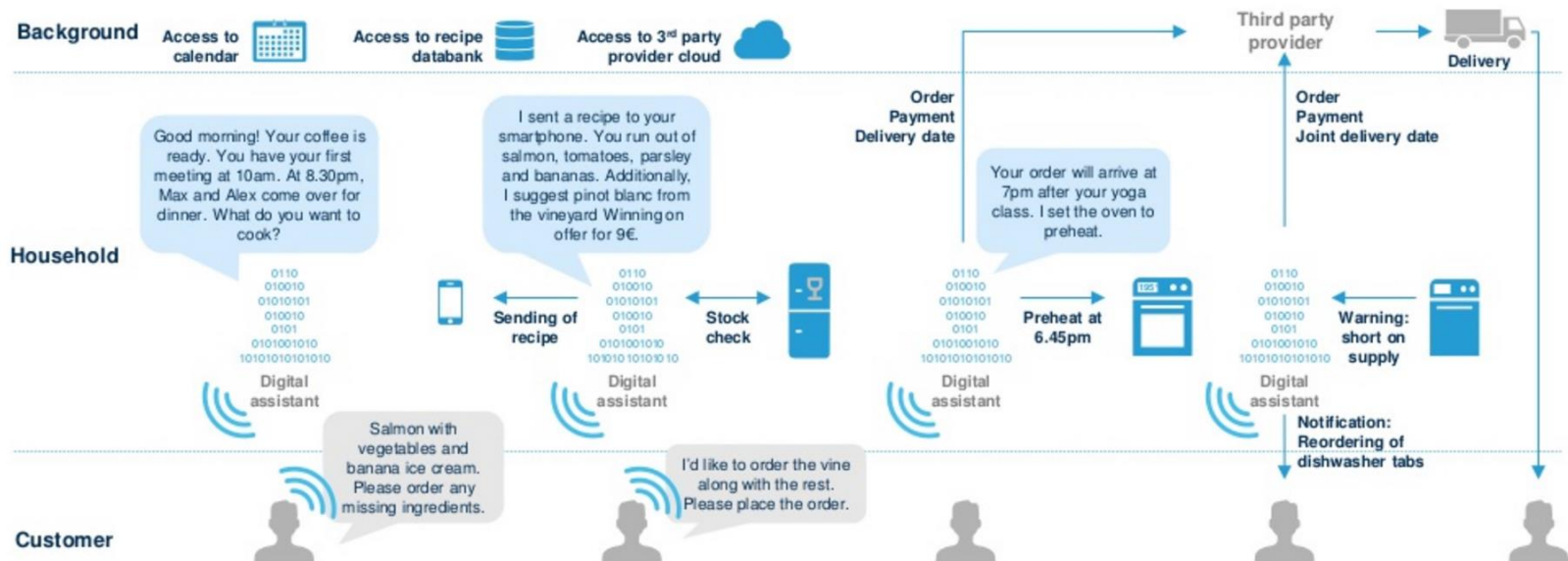
- **Assistants** and **prescriptors** don't give predictions, but must give advice or prescriptions to let the user take the decision:
  - This goes beyond the idea of having soft classifiers, and minimise cost or risk functions.
    - An **assistant** can suggest to take an action and not only be asked about which action to take.
    - A **prescriptor** suggests decisions that are usually accompanied by the implications of those decisions (risks, costs, etc.), and alternative choices.
    - One may (or may not) have a decision made between several courses of action, but never take it!



## ■ Digital assistants (Siri, Google Now, Cortana, ...):

Based on contextual information, digital assistants are able to influence and manage customers' purchase decisions.

Conversational Commerce – Future Use Case



Note: Future use case as expected by industry experts  
Flash Insight Conversational Commerce at Home | August 2016

Mücke Sturm Company, <http://www.slideshare.net/muecke-sturm/conversational-commerce-65314019>



## ■ Prescriptions (risk or utility management)

Probability

0.9	Very High 71-90%	0.045	0.09	0.18	0.36	0.72
0.7	High 51-70%	0.035	0.07	0.14	0.28	0.56
0.5	Medium 31-50%	0.025	0.05	0.10	0.20	0.40
0.3	Low 11-30%	0.015	0.03	0.06	0.12	0.24
0.1	Very Low up to 10%	0.005	0.01	0.02	0.04	0.08
		0.05	0.1	0.2	0.4	0.8

0.1: Minor  
0.3: Moderate  
0.5: Major  
0.7: Critical  
0.9: Catastrophic

0.05: Very Unlikely  
0.1: Possible  
0.2: Likely  
0.4: Very Likely  
0.8: Almost Certain

Impact

- Risk evaluation is concerned with assessing probability and impact of individual risks.
  - Some risks, such as financial risk, can be evaluated in numerical terms.
  - Others, such as adverse publicity, can only be evaluated in subjective ways.

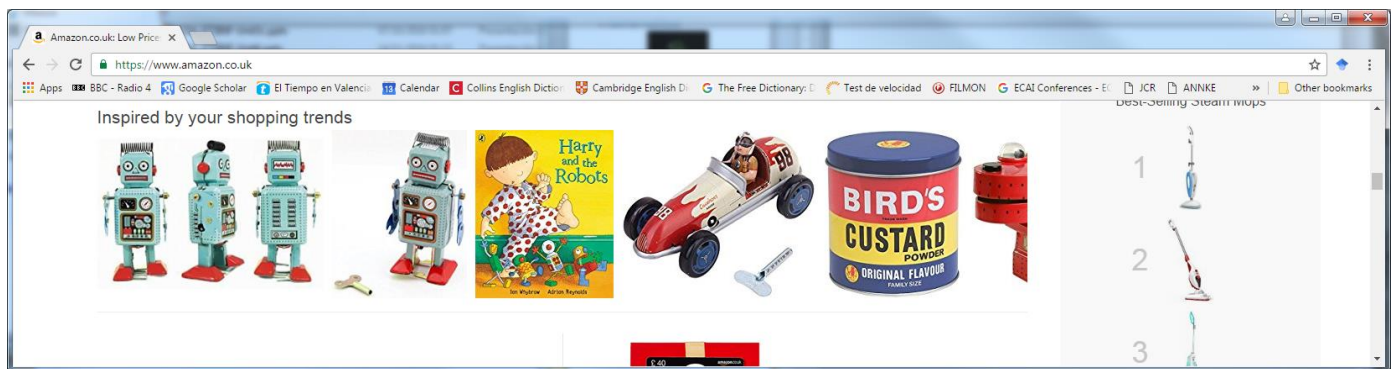
Risk Log - Example of Security Hazards			Tolerability Level = 0.20
Hazard	Impact	Probability	Risk Rating
Computer system failure	0.05	0.9	0.045
Building damage	0.8	0.1	0.08

<http://www.ruleworks.co.uk/riskguide/images/risk-tolerance-en.gif>





- **Recommenders** are the prototypical case of a prescriptor → **Predict the subjective evaluation a user will give to an item.**
- How things are chosen now?
  - New products are recommended exploiting the evaluations or ratings provided by user(s) for previously viewed or purchased items.
    - E.g., Amazon, netflix, Ciao, Booking, Trip advisor, Be2, Delicious, Youtube



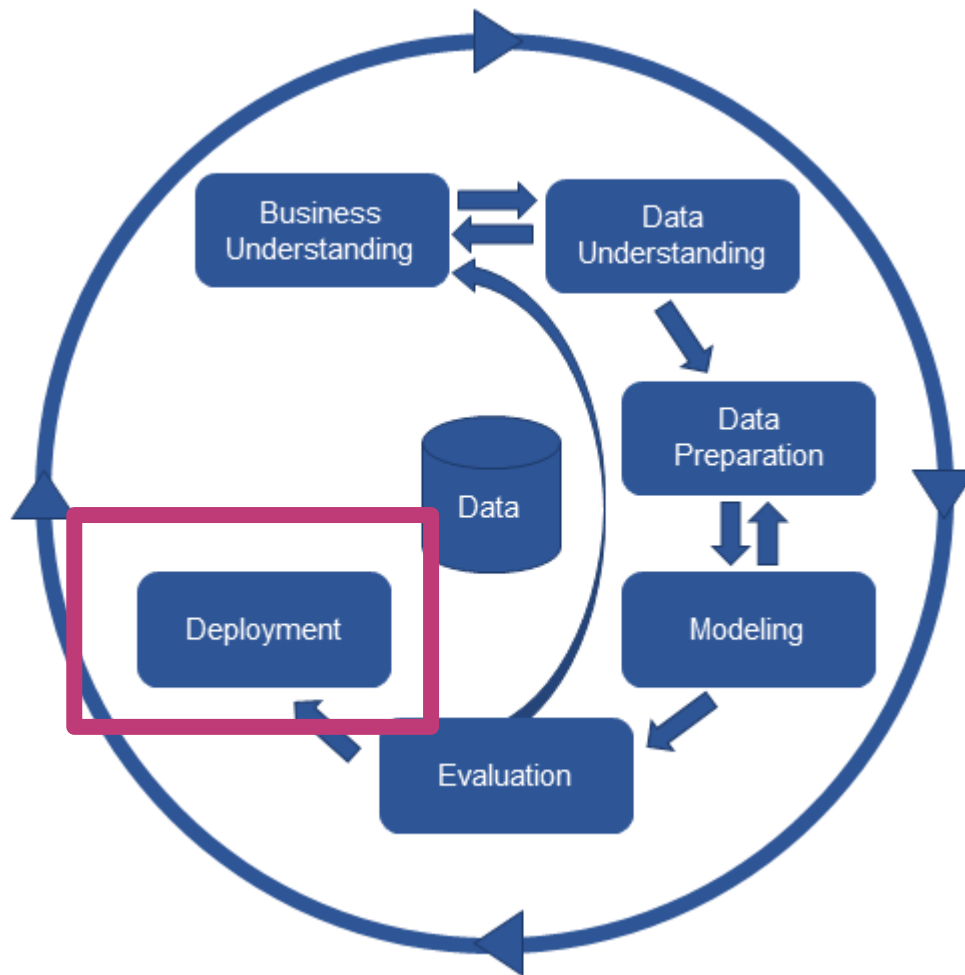
- Approaches:
  - **Collaborative filtering:** They collect and analyse data about the preferences of the users. They recommend new items by observing preferences of similar users
    - Facebook, Linkedin, Last.Fm...
  - **Content-based filtering:** They collect information about items and then similarities are computed among them. When a user expresses preference about an item, the system recommends the most similar items
    - Imdb, Rotten tomatoes, Pandora,...
  - **Hybrid systems:** Combine both techniques
    - Netflix, seethisnext...



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- The idea is to **exploit** the potential of the extracted models, **integrate** them into the decision-making processes of the organisation, **spread** reports about the extracted knowledge, etc.

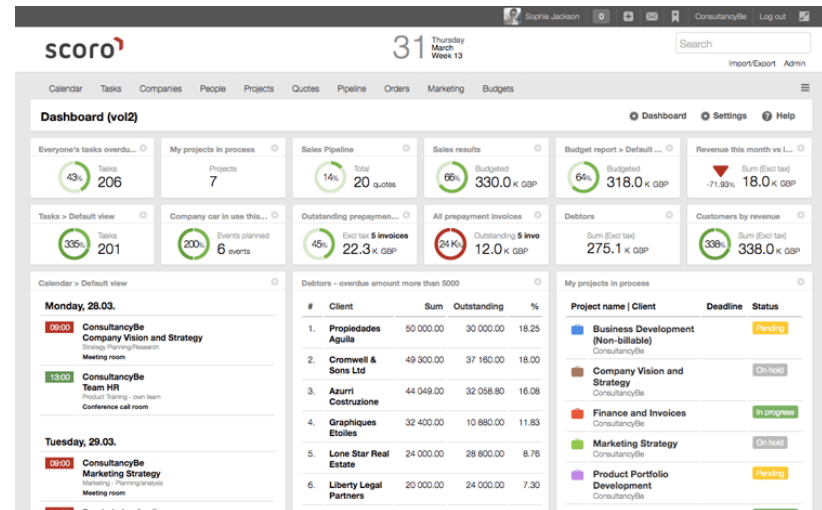


- In order to **apply a model** we need to:
  - Interpret and understand it.
    - Contrast it with the previous knowledge.
  - Combine it with other models of the same problem or combine them globally (simulation).
  - Exchange and spread it.
    - Integrate it, if necessary, in software applications, DSS and the organisation structure.
  - Adapt it to new application context.



## ■ Understand the knowledge:

- Black-box models can be made more understandable:
  - Converted into rules by rule extraction or distillation.
  - Represented graphically.
- Models in general can be presented as (interactive) reports on the web.
  - Dashboards may include model prescriptions and simulation.



## ■ Combining models and simulation

- (Not talking about boosting, bagging or random forest)
- We're talking about using several models (of different characteristics, including manual models).
  - Through weighting majority, stacking or cascade
- Outputs of a model can be input of another
  - (predictions of the customer affluence model are used as input for sales model).

## ■ Exchange and Integration.

- How to insert models into our applications?
- How to export models to other platforms?
  - Need for standards:
    - PMML: predictive model markup language
    - <http://dmg.org/pmml/products.html>



## ■ Monitoring

- Detects if the model doesn't work as well as it usually did (or as it should).
- Periodic evaluation using fresh data
  - Alarms
- Open to comments from the users.
- Detect context changes.

## ■ Revision

- If the model cannot be adapted to the new context or change of data, revision is needed:
  - Partial: part of the model is changed (e.g., obsolete rules) and part is preserved.
  - Total: the new model changes drastically.
- If revision is not possible:
  - The model is retrained completely.

