Artificial Intelligence Tools & principles

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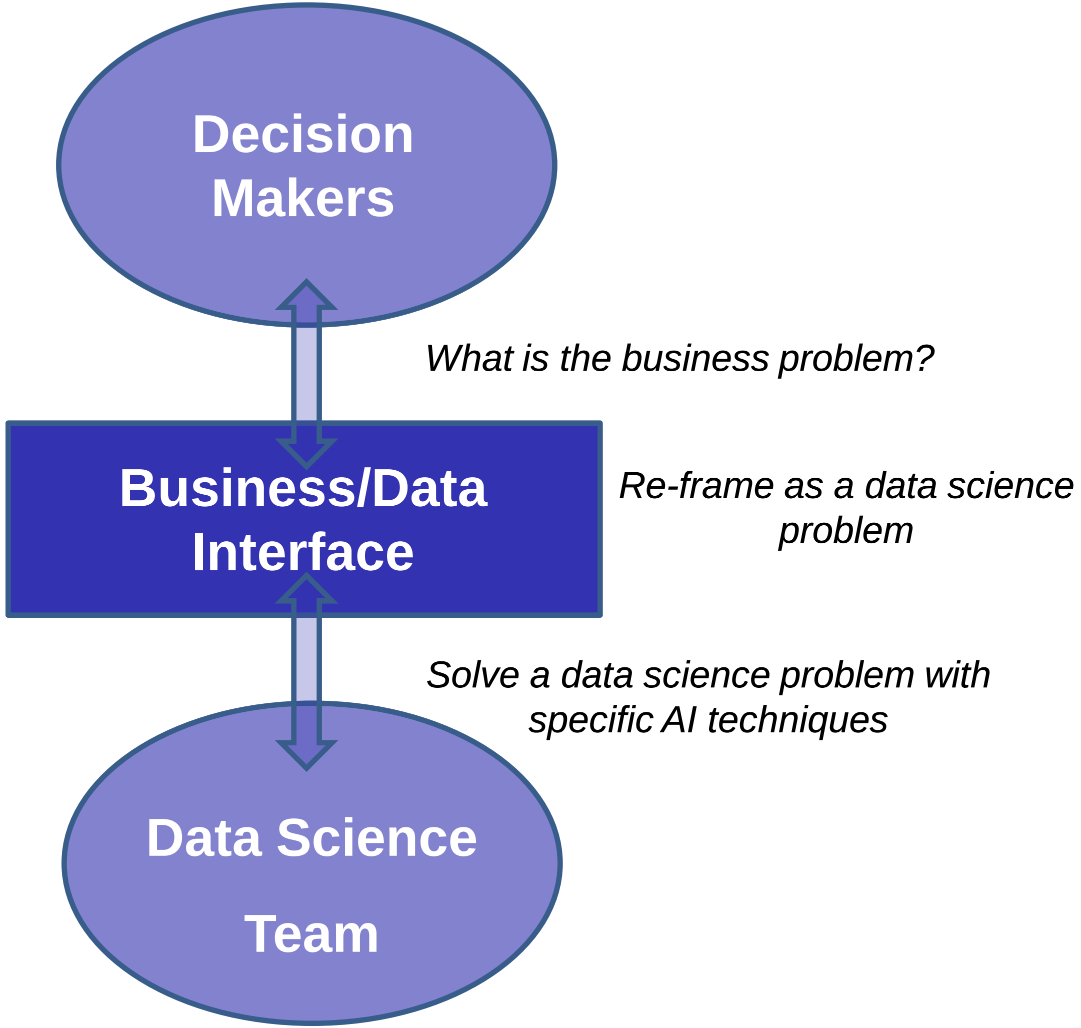
The goal for this lecture is to introduce how to solve real-world problems with AI


Decision Makers
What is the business problem?
Business/Data Interface
Re-frame as a data science problem
Solve a data science problem with specific AI techniques
Data Science Team

To solve real-world problem with AI you don’t need the most advanced AI tools – you need creative problem-solving skills

No AI without data

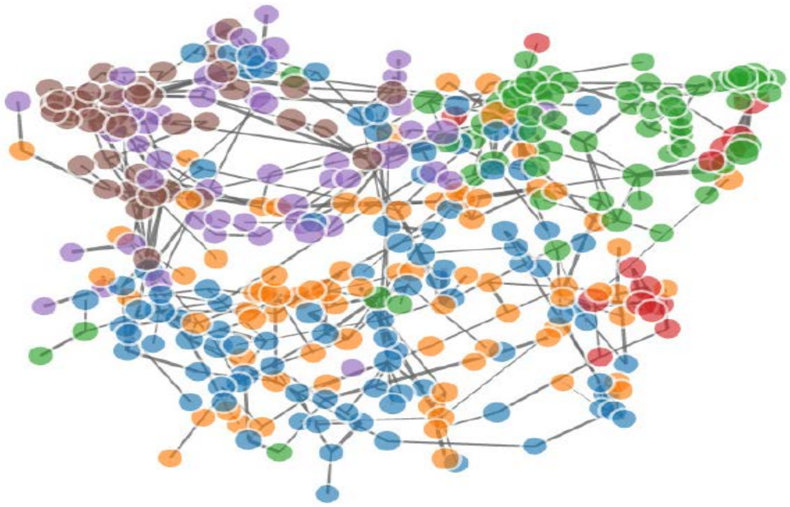
- A lot of discussion around AI algorithms but **data** is what makes **AI** truly possible
- AI problem-solving requires to:
  - know the kind of data AI needs
  - mentally map the problem into a data problem
  - know how to access or collect data
  - perform data transformation (i.e matrix format, rescaling)
  - data cleansing (missing, extreme, wrong...)
  - inspection & validation
  - simple data science models

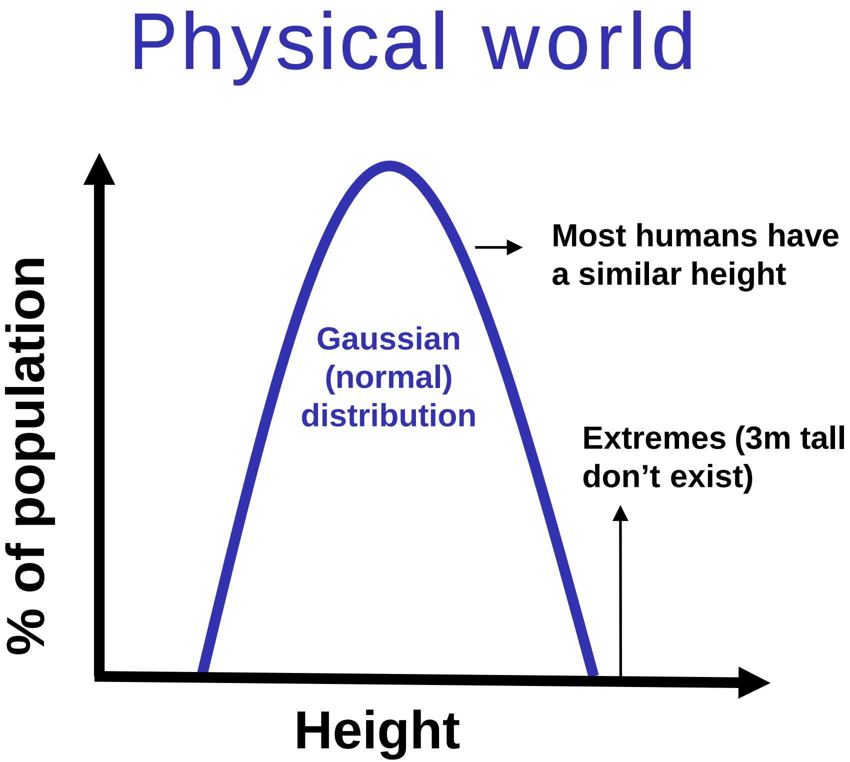
Two types of data

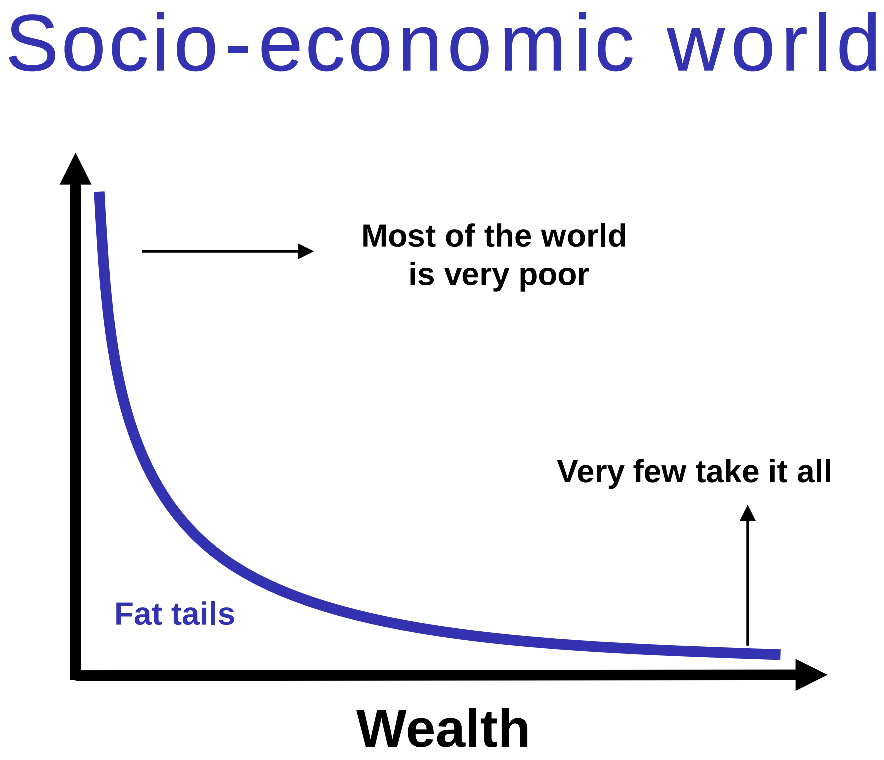
Individual characteristics

	Model 1	
Variables	*b*	SE
Control variables		
Male	0.42***	0.04
White	−0.06	0.05
Age (≤19)	−0.05	0.04
Major	0.16**	0.05
Unemployed	−0.04	0.04
Internet proficiency	0.17***	0.02
Internet variety	0.10***	0.03
Internet speed	0.33***	0.06
Intercept	−2.75***	0.14

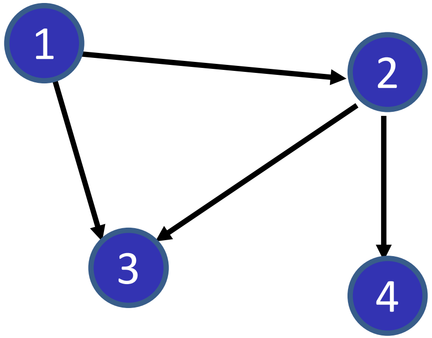
Interconnection data




Physical world
% of population
Gaussian
(normal)
distribution
Most humans have
a similar height
Extremes (3m tall
don’t exist)
Height


Socio-economic world
Most of the world
is very poor
Very few take it all
Fat tails
Wealth

Directed graph (digraph)



Edge list

Vertex	Vertex
1	2
1	3
2	3
2	4

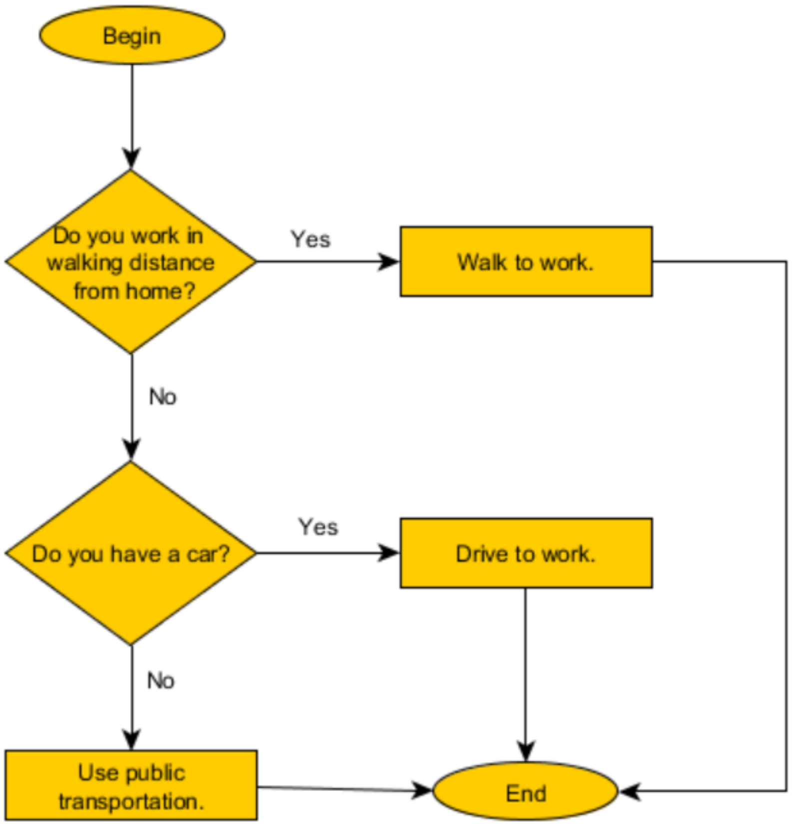
Adjacency matrix

Vertex	1	2	3	4
1	-	1	1	0
2	0	-	1	1
3	0	0	-	0
4	0	0	0	-

AI algorithms have considerably evolved since the 1950s

Simple algorithms

- Humans have solved algorithms before computers
- An algorithm is a sequence of operations (series of steps)
- Complex problems require huge amount of numeric computation (time) – non-human computers are perfect for this task
- AI algorithms deal with problems that usually require human intelligence



AI expert systems

- Improvement compared to hard-coded algorithms
- Introduce **flexibility** in the rule (more adapted to a complex environment)
- Knowledge base and inference engine are constructed from human **experts**
- Still exist today for some very **codified problems** (grammar checkers)
- Also relevant today problems that have **ethical** and **legal** considerations (require transparent rules)

Machine learning

- Solutions capable of learning **directly** from **data**
- **ML** is particularly adapted to problems that humans don't know how to codify in pre-defined steps
- ML creates a mathematical representation of the world that it guesses by seeing (a lot of) data
- ML can be applied **after** careful data analysis (to provide correct **input**)
- Learning = **associating** inputs and outputs – not **understanding** (we talk about training)

What makes ML special

- **Traditional algorithm**: you know the inputs (10 and 2), you know the function (*) but you don't know the results (20)
- **ML algorithm**: you know the inputs (10 and 2), you know the results (20), but you don't know the function (*)
- Replace theory with **data** (deduction VS induction) & hypothesis testing in the scientific method
- You need a **lot of** data!

The limits of ML

- ML can only solve **single** and **specific** problems (representation issue)
- Overfitting = like students studying too much passed exams. Internal functions **memorize** and don’t **learn** from the data
- Bias can be magnified

How do ML learn?

- **Supervised learning**: humans train the ML with good **labeled** data examples and the algorithm derives rules from these specific examples

  → regression & classification problems
- **Unsupervised** learning: no labeled data - the algorithm guesses that some objects or events cluster together (belong to the same class) without being explicitly told (find similar patterns)
- **Reinforcement learning**: lack labels too, but humans provide positive/negative feedback

Deep learning

- **DL** is the latest major advance in AI algorithms (2012) that sparked a renewed major interest in AI
- If you don't have much data: expert systems, a lot: ML, a gigantic amount: DL
- DL is neural networks on steroids
- Major breakthroughs: backpropagation + vanishing gradients (signal fades)

Deep learning

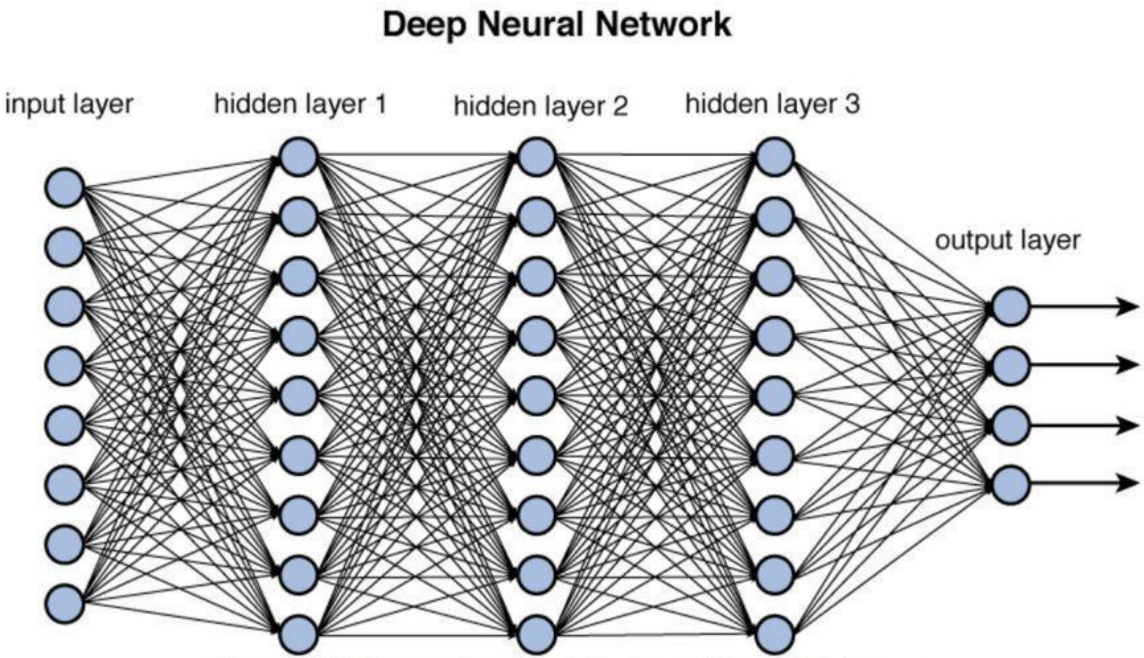
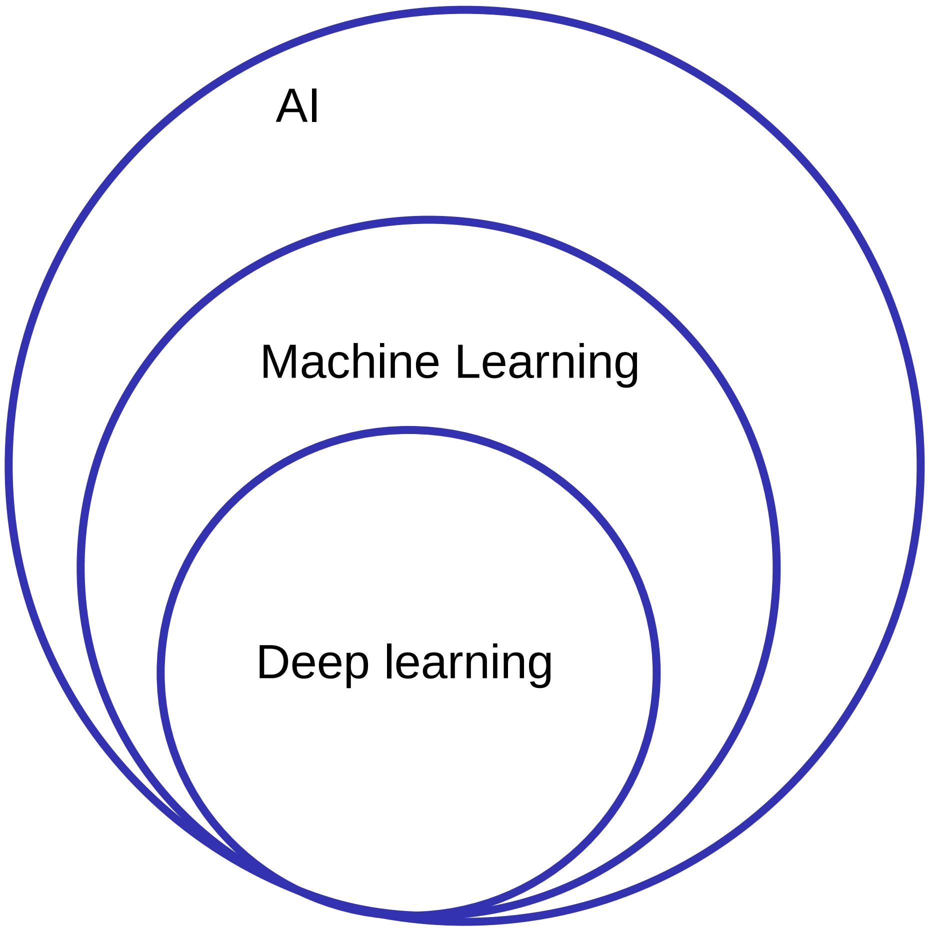


Figure 12.2 Deep network architecture with multiple layers.

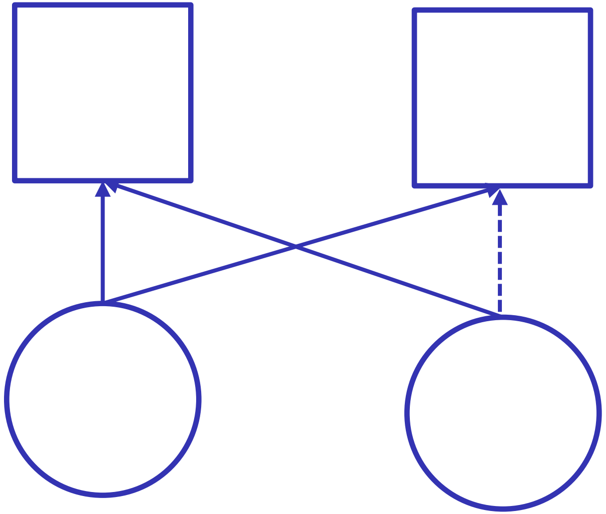
Major limitations with DL

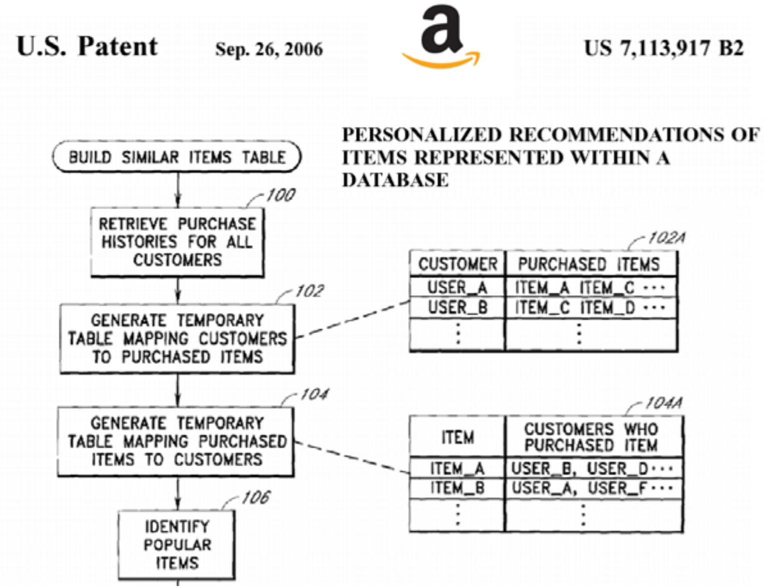
- It is a black box – humans also don’t understand what happens within the neural network
- Requires a huge number of examples/data (impractical in many ways)
- DL can not transfer knowledge to higher level (can’t create hierarchies of knowledge)


AI
Machine Learning
Deep learning

Building your own recommender system with simple unsupervised ML

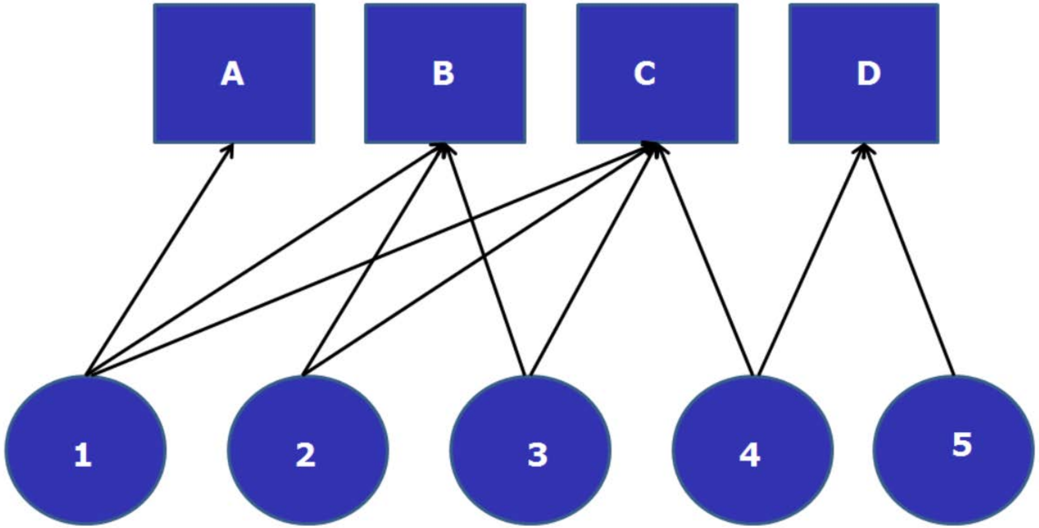
What AI can predict





Modern **AI** techniques are good at predicting the evolution of **simple** network structures

1. Seeing the data matrix



$$
\begin{array}{c c}
 & A\,B\,C\,D \\
\begin{array}{c}1\\2\\3\\4\\5\end{array} & \begin{pmatrix} 1 & 1 & 1 & 0 \\ 0 & 1 & 1 & 0 \\ 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 \end{pmatrix}
\end{array}
$$

2. Multiply t(M) by M

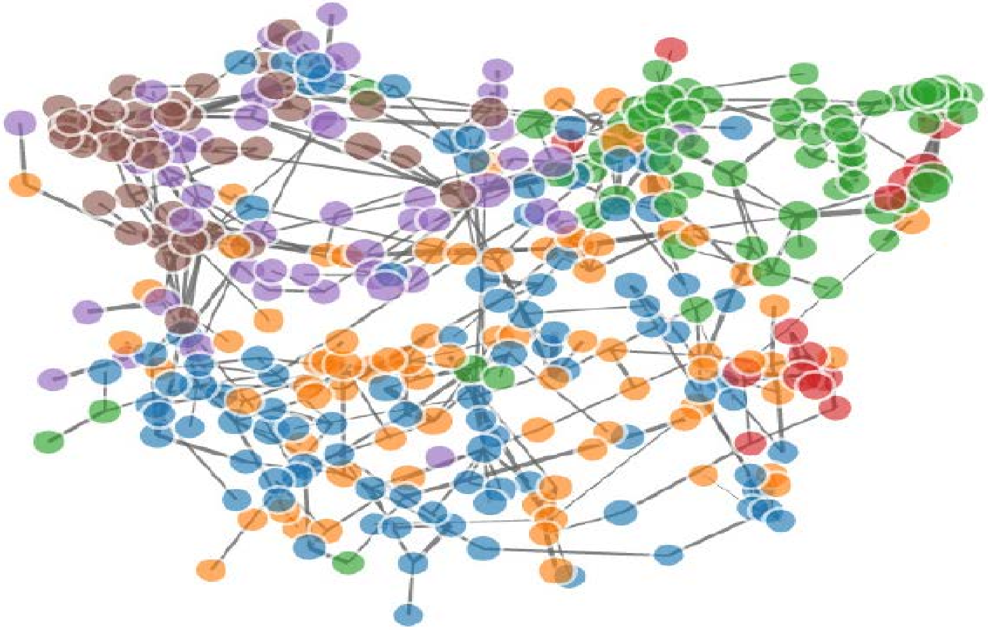
$$
\begin{array}{c c}
 & \begin{array}{ccccc} 1 & 2 & 3 & 4 & 5 \end{array} \\
\begin{array}{c} A \\ B \\ C \\ D \end{array} &
\begin{pmatrix}
1 & 0 & 0 & 0 & 0 \\
1 & 1 & 1 & 0 & 0 \\
1 & 1 & 1 & 1 & 0 \\
0 & 0 & 0 & 1 & 1
\end{pmatrix}
\end{array}
\times
\begin{array}{c}
\begin{array}{cccc} A & B & C & D \end{array} \\
\begin{pmatrix}
1 & 1 & 1 & 0 \\
0 & 1 & 1 & 0 \\
0 & 1 & 1 & 0 \\
0 & 0 & 1 & 1 \\
0 & 0 & 0 & 1
\end{pmatrix}
\end{array}
=
\begin{array}{c c}
\begin{array}{cccc} A & B & C & D \end{array} & \\
\begin{pmatrix}
1 & 1 & 1 & 0 \\
1 & 3 & 3 & 0 \\
1 & 3 & 4 & 1 \\
0 & 0 & 1 & 2
\end{pmatrix}
& \begin{array}{c} A \\ B \\ C \\ D \end{array}
\end{array}
$$

*1*1+1*1+1*1+0*1+0*0 = 3*

3. Normalization

$$\begin{pmatrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 3 & 0 \\ 1 & 3 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{pmatrix} \qquad if \ \ \frac{observed \ \ co\text{-}occurences}{expected \ \ co\text{-}occurences} \ > \ 1 \ \ \text{-->} \ \ related$$

4. Network graph

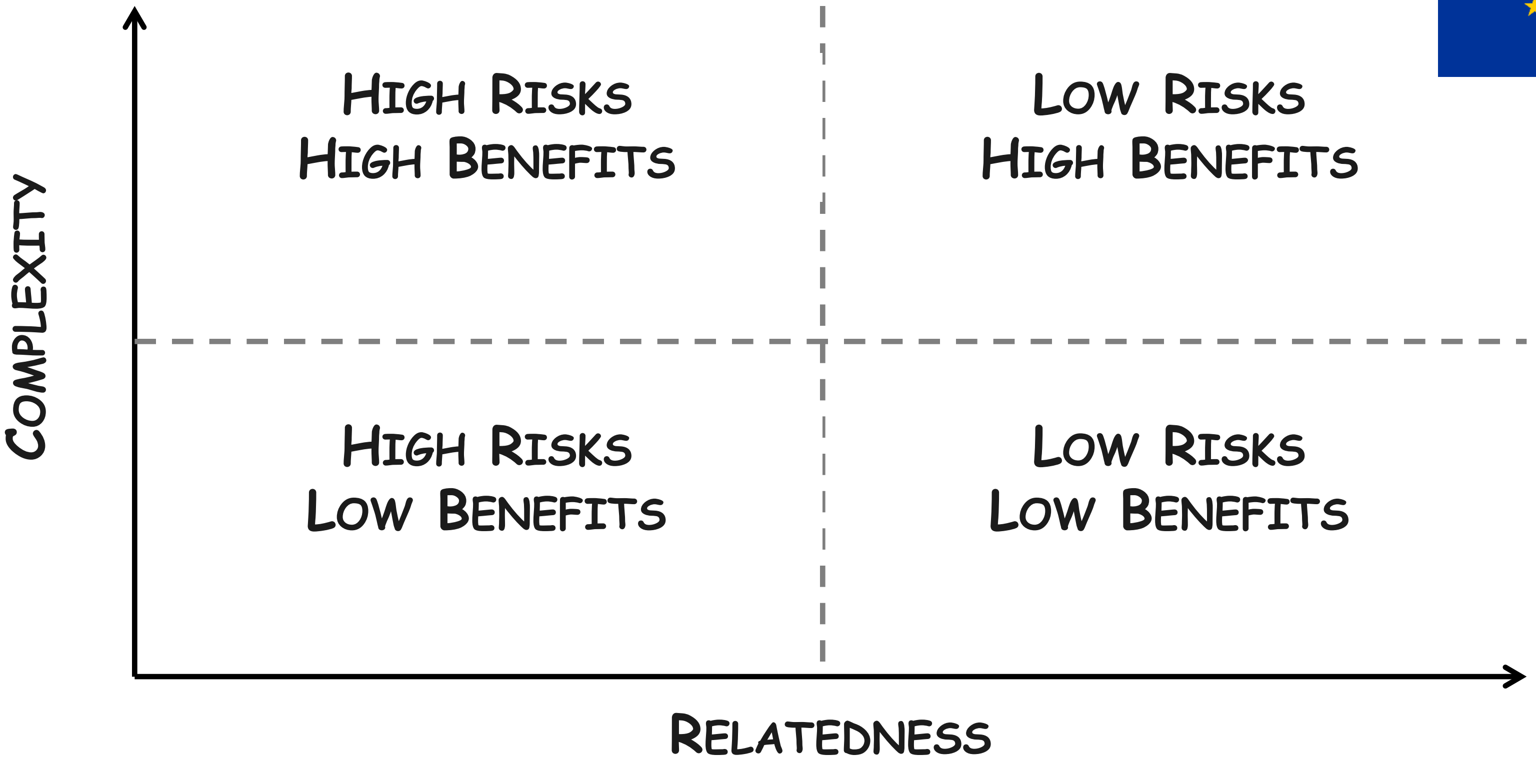


5. Recommendation list

$$D_{i,c,t} = \frac{\sum_{i} x_i \varphi_{ij}}{\sum_{i} \varphi_{ij}} \times 100$$

$$\begin{pmatrix} 100 & 100 & 80 & 100 \\ 100 & 75 & 60 & 100 \\ 100 & 75 & 60 & 100 \\ 50 & 75 & 20 & 100 \\ 0 & 0 & 20 & 0 \end{pmatrix}$$

EU smart specialization ($120 billion)



Balland, P.A., Boschma, R., Crespo, J. and Rigby, D. (2019) Smart Specialization policy in the EU: Relatedness, Knowledge Complexity and Regional Diversification, *Regional Studies*