European Commission

EaSI Technical Assistance

The Economics of AI for Financial Inclusion

Webinar

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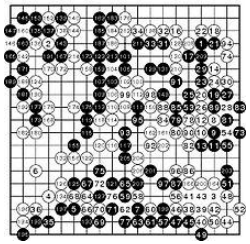
Darthmouth Workshop

"..that 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."



Alpha Go defeats Lee Sedol

Also known as the Google DeepMind Challenge Match, a five-game Go match between 18-time world champion Lee Sedol and AlphaGo, a computer Go program developed by Google DeepMind

1956 **1997** **2016** **2030**

Deep Blue vs. Kasparov

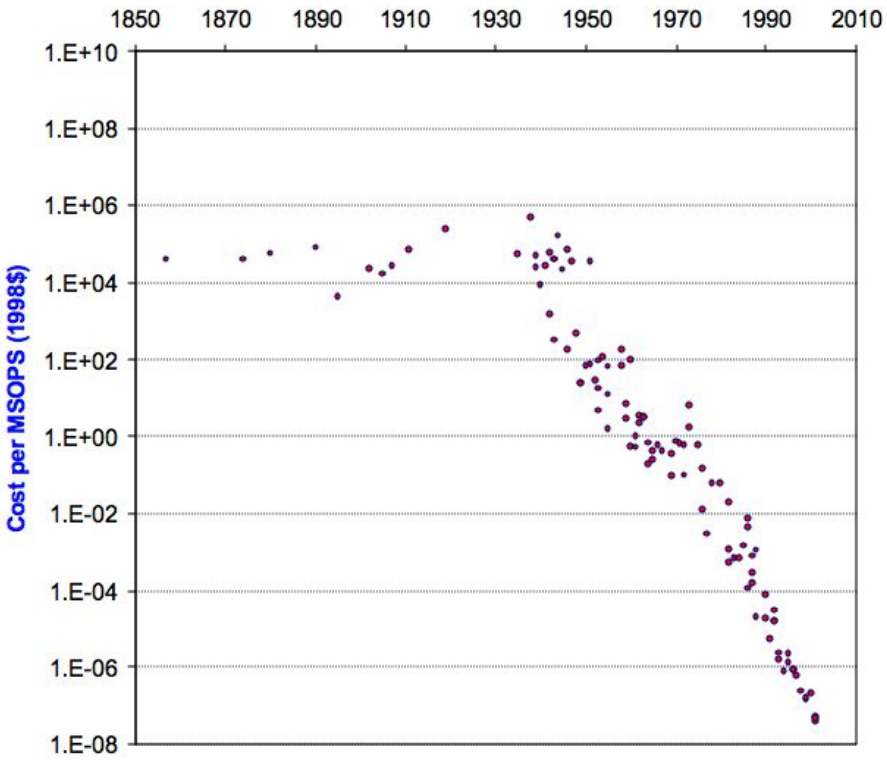
Deep Blue versus Garry Kasparov was a pair of six-game chess matches between world chess champion Garry Kasparov and an IBM supercomputer called Deep Blue. Deep Blue won the second pair played in New York City in 1997.

Self driving cars

According to PwC predictions, 40% of mileage in Europe could be covered by autonomous vehicles by 2030

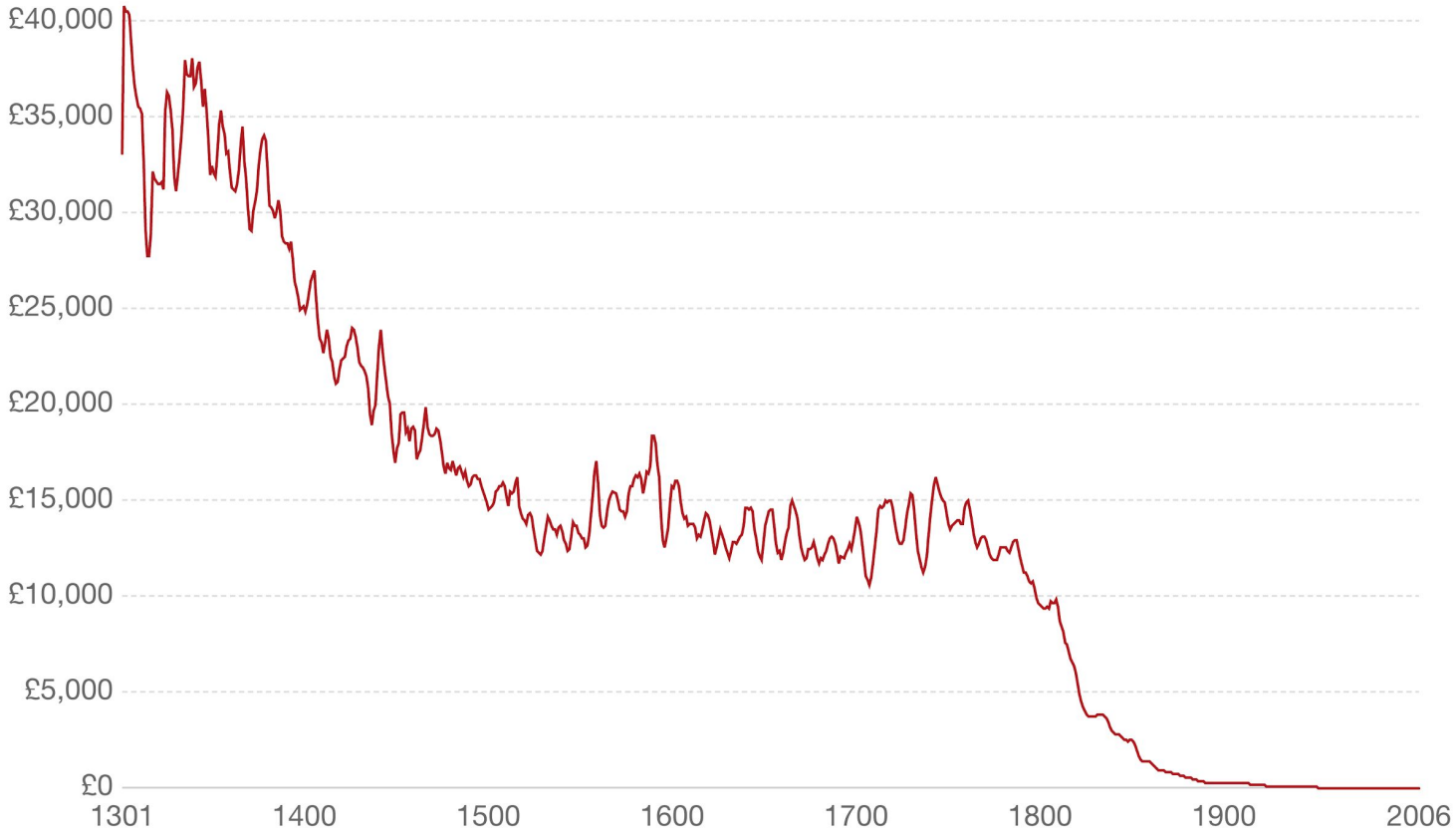
What changed since Dartmouth Workshop in 1956?

The cost of computing power per million standard operations per sec



The analogy of artificial lightning

The cost for lighting per million lumen hours in the UK in british pound

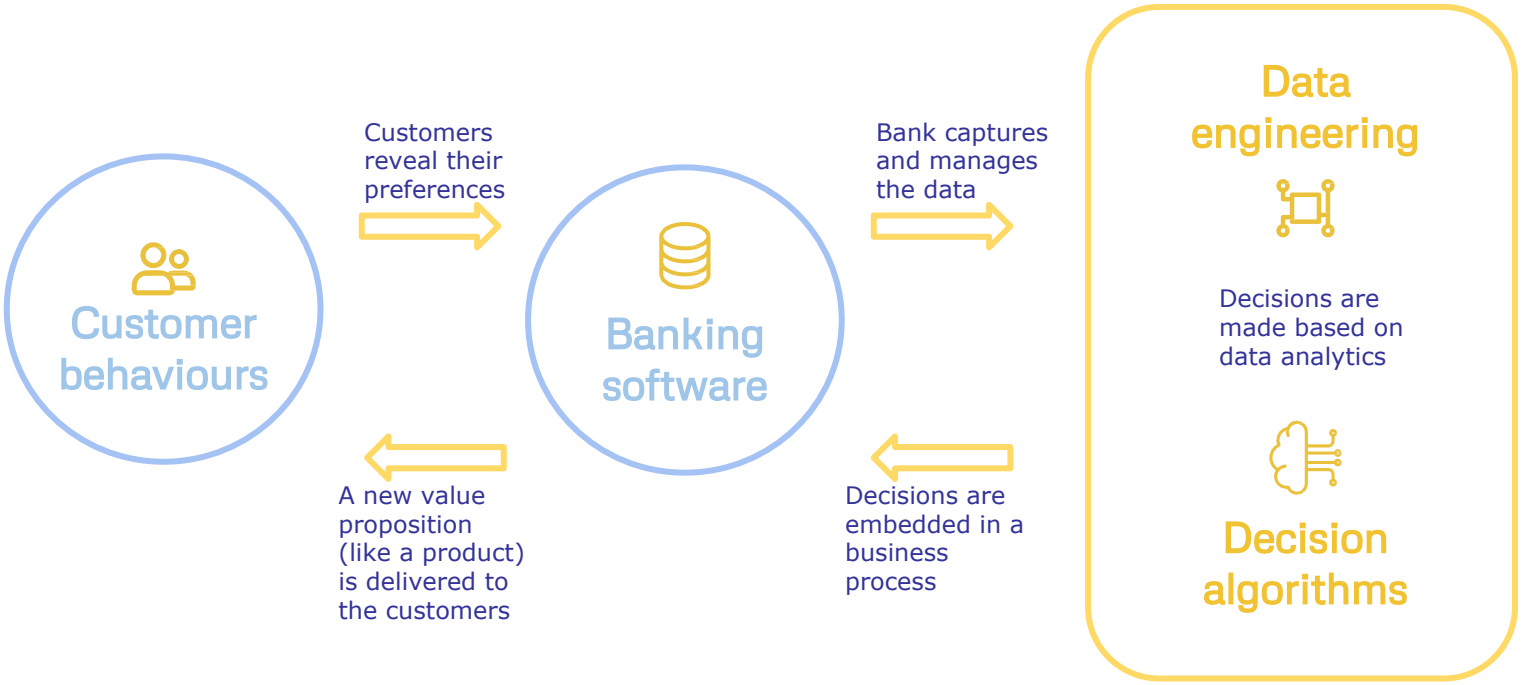


A paradigm shift

A paradigm shift

A paradigm shift

How does AI work in Financial Services?



AI is a decision making machine

AI in Credit Committee

What could happen if we would hold a credit committee everyday for all clients?

i.e. with the available data, how much would we lend the customer?

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For the bank

- **reduce the turnaround time by anticipating client request;**
- **increase by 58% the number of good clients returning;**
- **re-focus officers time to more complex tasks than the repetitive loan application assessment;**
- **Reduced churn by proactively send offers to clients to inform them about their eligibility**

AI in Credit Committee

What could happen if we could hold a credit committee everyday for all clients?

i.e. with the available data, how much would we lend the customer?

For the client

- **It helps clients to have a more reliable and predictive source of financing;**
- **It allows to build short term small amount loan product that would not be economically viable before, but that are better at managing long term risks both for the client and the bank;**
- **automated 30% of the loan renewal requests.**

3 types of decision making algorithms

SCORECARDS

The expert knowledge translated in an algorithm
- Does not rely in any specific data
- Simple vector operations provide eligibility (amount?);
- Easy to implement;
- ½ data based evidence;
- Explainable (conditional to complexity);
- Usually poor results.

COMPUTATIONAL INTELLIGENCE

A method that accommodates all complexity
- Requires loan repayment history;
- Requires huge datasets and processing power;
- Optimises any decision;
- Always good results;
- Over-fitting;
- Blackbox;
- Attention to selection bias

BAYESIAN DECISION THEORY

Models that are empirically calibrated
- Allow using of loan repayment history and other available data;
- Requires medium sized datasets;
- Estimates the properties of modeled phenomena;
- "What are the pertinent ways to model the repayment behaviour?";
- Possible to empirically model the business question, like max profit generation, min risk, min cost;
- Usually good results.

DO’S and DON’TS

in AI projects for Microfinance

1. Understand what each data point reveals

The example of WAVA™ : a comprehensive theoretical framework developed by Rubyx to categorize raw data for credit scoring

ω	*	α	/	σ	|	δ
Willingness		Ability		Volatility		Awareness

- **a structure for processing heterogeneous data into a single piece of information**
- **information on the reasons underlying the scoring.**
- **better fit to play a role in different business applications,**

2. More data is not always better

The introduction of more data can lead to negative effects on the quality of the models, it should not be an objective

Block	Sub-block	Model 1	Model 2	Model 3
Business Profile	Business Registration	↑	⇆	
	Well Constituted BOD and Management		⇈	
	Business Site and Premises		⇆	
	Business Knowledge and other Risk Indicators		⇆	
	Business Documentation and Financials		⇆	
Credit Indicators	Loan / OD Acquisition	⇊	↓↓	↓↓
	Repayment History		⇊	⇊
	Collateral Issues		↓↓	↓↓
	Loan Utilization and Market potential		⇆	⇆
Deposit Indicators	Account Type and Actual Figures	⇆		
	Account Activity against Loan Request			
	Account Activity against Deposit standard			
Adjusted R^2		18%	25%	24%
Num. observations		54	233	238

Analysis of a scorecard for a Microfinance institution in Ghana

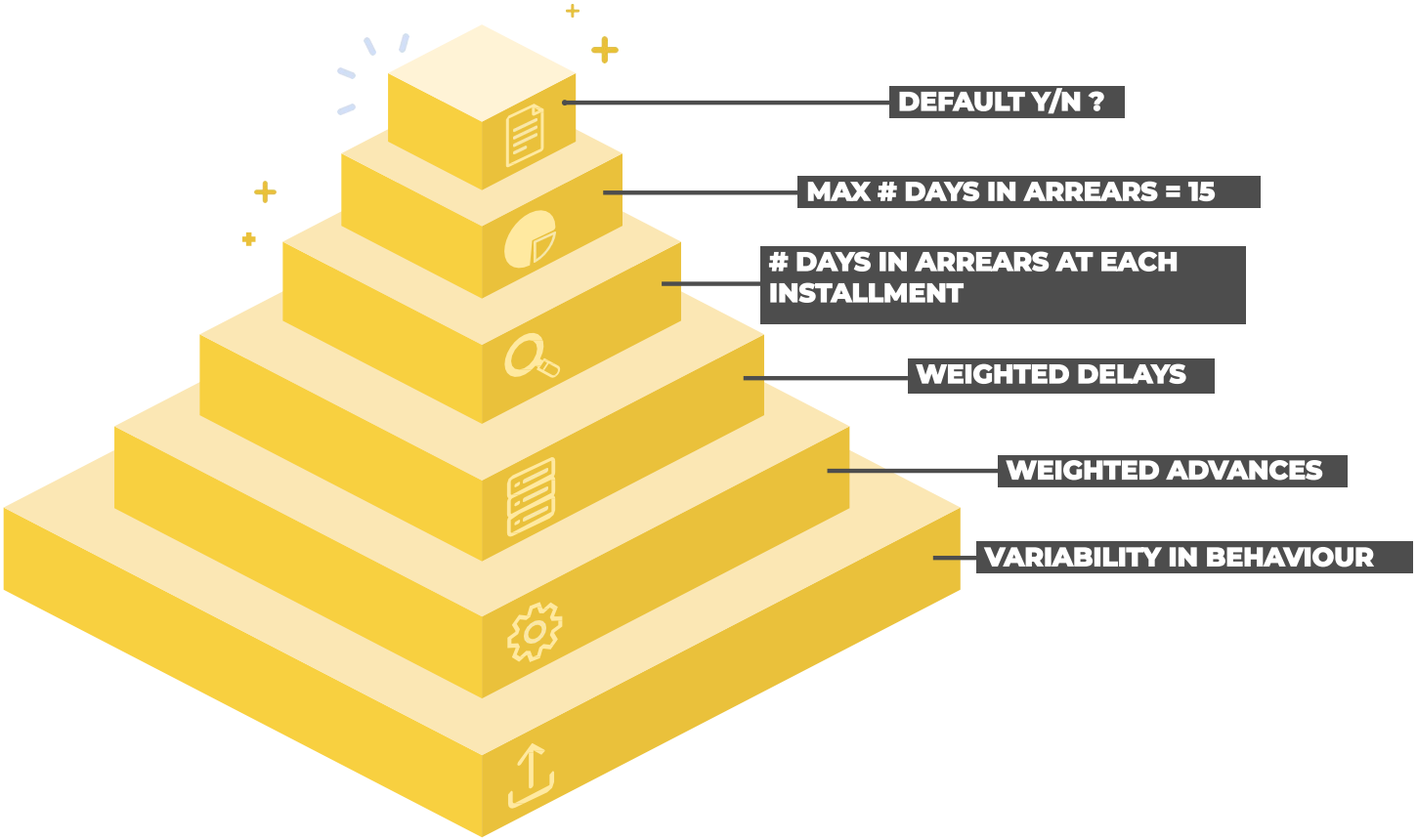
"History of late payment at the MFI was also taken out because the factor was too influential and would greatly diminish the relationship of other factors in the model."

Quote of a data scientist who developed a scorecard for an MFI in Asia

Do you think that microfinance institutions have enough data internally to build predictive AI models?

3. Intensive use of key data

Making intensive use of key data rather extensive use of junk data

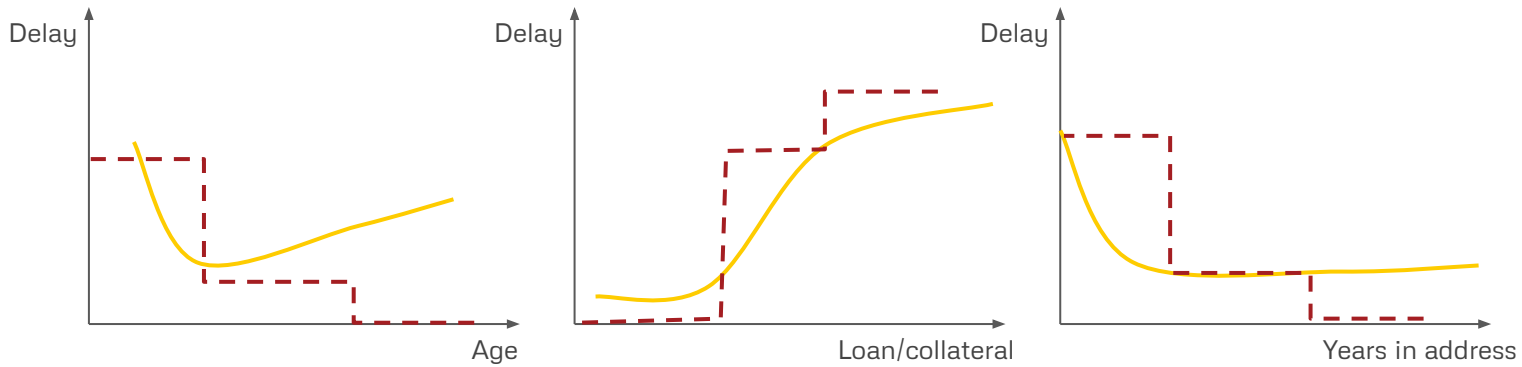


3. Intensive use of key data

Customer	Contract ❷	Seq #	Due Date ❶	Amount
B_51655	B_190-922107	14	Dec 2, 2020	1027090
B_51655	B_190-922107	13	Nov 2, 2020	1001063
B_51655	B_190-922107	12	Oct 2, 2020	975694
B_51655	B_190-922107	11	Sep 2, 2020	950969
B_51655	B_190-922107	10	Aug 3, 2020	926871
B_51655	B_190-922107	6	Apr 2, 2020	836430
B_51655	B_190-922107	5	Mar 2, 2020	815234

4. Keep high resolution

Adapt the analysis to the available data, not the other way around to avoid lowering the resolution. We observe often grouping continuous variables among the explanatory variables (risk factors) instead of using the full information



5. Selection Biases , the selection of past data

When the credit committees tend to be more cautious ("I better be very cautious with this kind of request") models generate a scorecard that rewards risky loans.

"(...) the loan size factor was found to have a negative relationship with risk."

Quote of a data scientist who developed a scorecard for an MFI in Asia

Would you trust AI models to make a credit decision that you are responsible for?

6. Distrust in AI, distrust in humans

Getting the trust from the humans who will be involved is a must.

"25% of consumers would trust a decision made by an AI system over that of a person regarding their qualification for a bank loan," Pega study, 2019

		Staff				Total
		A	B	C	D	
Scorecard	A	0.53%	19.64%	4.40%	0.20%	24.77%
	B	0.41%	25.83%	7.56%	0.42%	34.21%
	C	0.23%	17.70%	6.43%	0.42%	24.78%
	D	0.23%	10.34%	5.14%	0.53%	16.24%
Total		1.39%	73.51%	23.54%	1.56%	100.00%

Confusion matrix between humans and scorecard in an MFI

Cohen's Kappa 2,55% -> Very poor agreement

7. Humans and AI

Rather than AI vs. Humans.
AI should not be thought in terms of replacing and competing with staff in performing any tasks.

But AI can supercharge credit officer by removing the repetitive tasks and refocusing them on complex tasks requiring social intelligence.

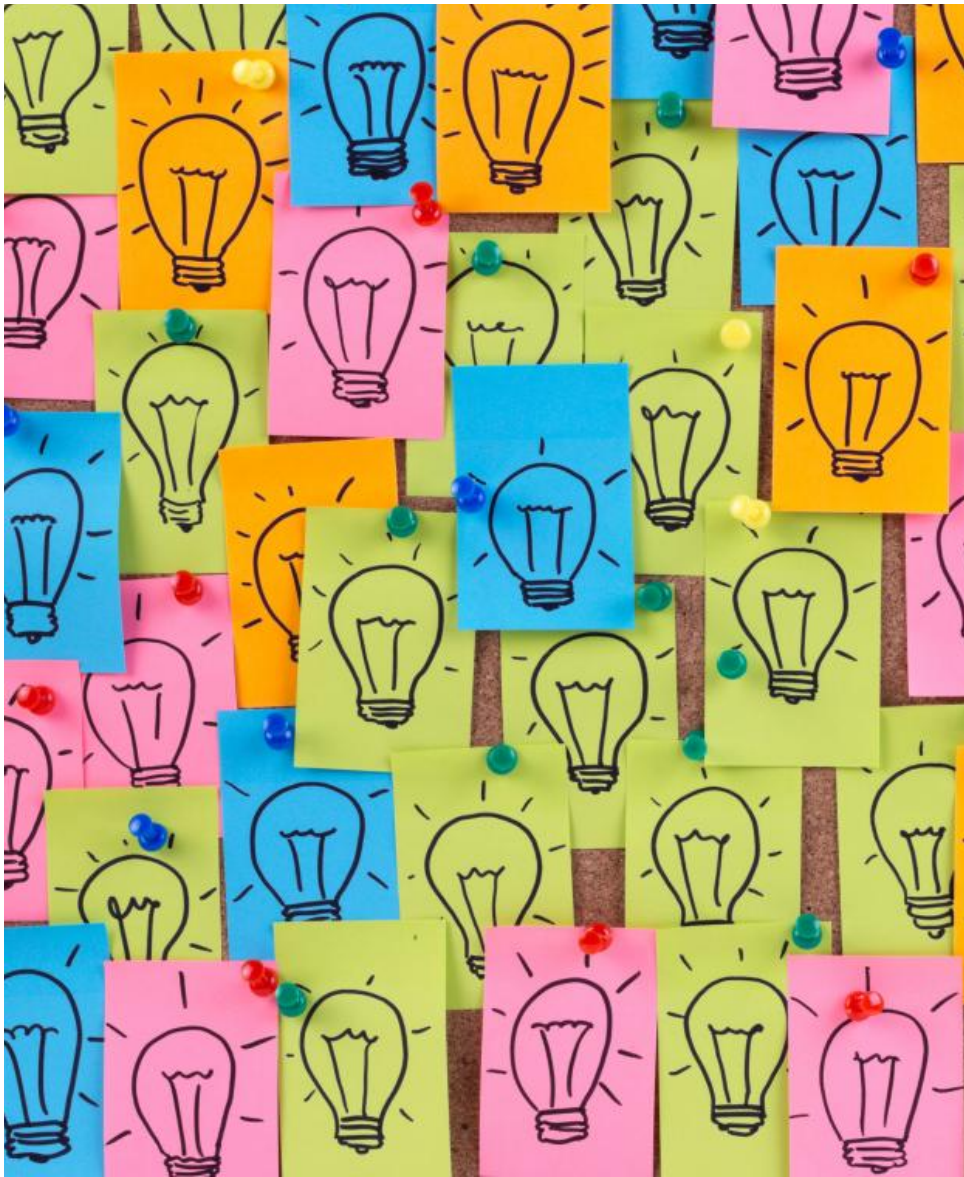
Ex: automate renewal vs. new loans

8. Be useful

Build interesting products, achieve new financial inclusion goals.

It is not about technology.

It is about Service Design to unleash the Economics of Artificial Intelligences



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*EU Programme for Employment and Social Innovation