Module #2 Needs-based recommendation systems, collaborative filtering, Next Best Actions (NBA)

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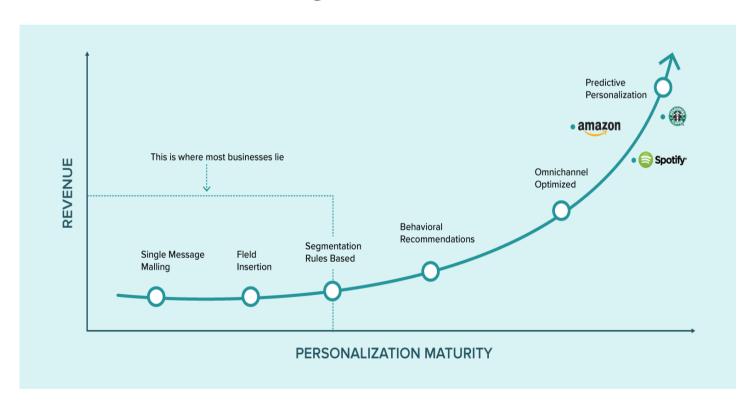




The key to financial personalization

Hyper-personalization

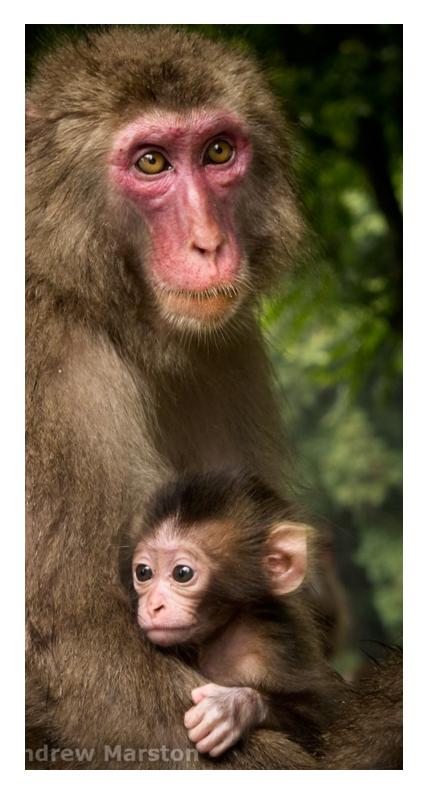
Netflixing" of financial services



«In 2030, up to 80 percent of new wealth-management clients will want to access advice in a

Netflix-style model—that is, data-driven, hyper-personalized, continuous, and potentially, by subscription.»

Source: McKinsey & C



Needs/goals are key to targeting clients

- After all, we are still monkeys: most of us don't really understand financial and insurance products (so we don't buy...)
- But we all have real needs and we understand them, e.g.:
 - protect ourself, our family, our things → insurance
 - buy things → payment tools & services
 - save for future consumption → <u>savings & investments</u>
 - anticipate future consumption, or investments → borrowing

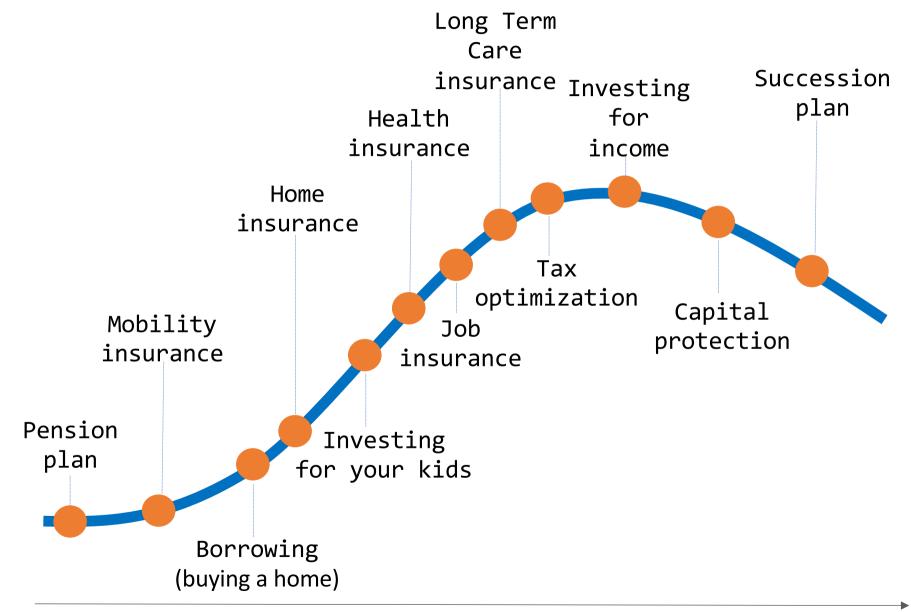
We tend buy what we need: thus, needs are a good starting point for recommending financial products and services in a personalized way

Another good reason to estimate client's needs: the law

- MIFID/IDD: coherence between needs/goals and financial/insurance products sold to clients
- Key information about clients must be collected by the use of a MIFID/IDD questionnaire → Data → a lot of detailed information collected through MIFID/IDD questionnaires can be crunched by algorithms
- Basically, you get <u>a broad survey for free</u> that's the reason why MIFID/IDD questionnaires should be properly prepared

"Make a virtue
out of necessity"

Financial needs: "the theory"



The reality of financial & insurance needs

- Not everybody will start a family at 30...
- Maybe at 72 not everybody is willing to plan her inheritance process, maybe is getting ready for a marathon or sailing around the world
- What about if at 50 you have 2 divorces and 2 maintenance allowances?
- Maybe at 35 someone faces a big recession, is fired, and cannot buy a home

• ...

Financial needs change over time following our random life And our random lifes are not all equal

Financial needs change overtime

How? Ask data!

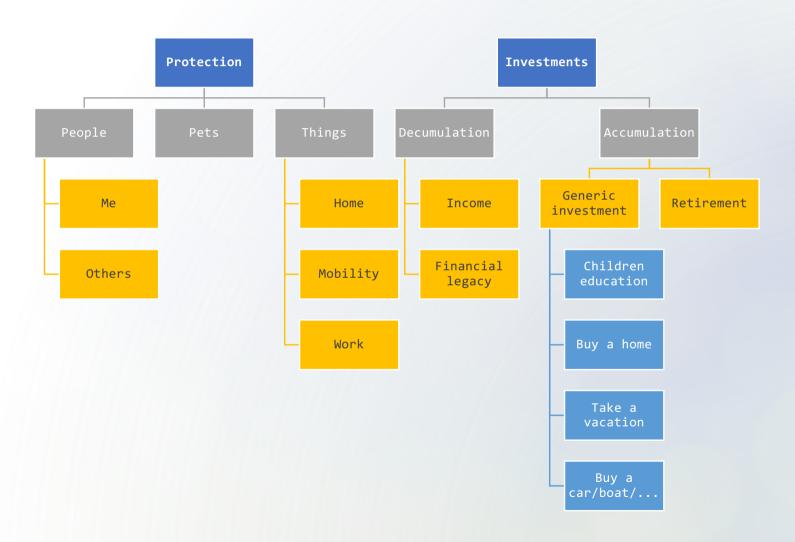
That is (...smell of ML):

$$Y = f(x_1, x_2, x_3, ...)$$

Y = responses = Need

 $x_1, x_2, x_3, \dots = X$ = features = client situation, context

Needs & goals, an example for an insurance company with a wealth management business



Let's look at the data



Estimating needs: a Supervised ML problem

- A client might have/not have a given financial need (or goal)
- Each client might have more needs
- Needs can be satisfied by financial products

I could teach a ML algorithm to recognize presence/absence of needs

It's a typical <u>classification</u> problem (it might be a regression, too)

And what about the Ys? Welcome to the real world!

- In a classification problem we teach an algorithm to put labels
- But... Where are the labels?
- Who is able to say: «Client A has need Z»?
- Needs are not observable!
- Hence, we have our Xs but we are not sure about the Ys → We have a problem...



«I'm Mr Wolf, I Solve Problems»

• Basically, two ways:

1. Straight - explicit labels

«Client A has/has not need Z»

2. Less straight - implicit labels

Case 1: explicit labels = = a human being creates the Ys

• She puts:

```
Y = 1 if client(i) has need(j)
Y = 0 otherwise
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- Quite common in image recognition
- If the human-labeler is reliable → very good
- But: financial needs are not easy to spot they are not cats/dogs/pedestrians/etc
- So: you need investment/insurance/banking experts → expensive

Case 2: Implicit labels = = Ys inferred from expert behaviour

- Learn from those who should know if a given client has a given need: financial advisors
- If an advisor sells a financial product that satisfies a given need, then probably it was in order to satisfy a need
- Thus:

Y = 1 if client(i) owns a product that satisfies need(j)

Y = 0 otherwise

- If the human sells products that maximize <u>HER OWN profits</u> → the algorithm will learn exactly that process (do you remember all these fancy talks about AI and ethics?) → Solutions:
 - filtering experts and their behaviors, doing «expert-picking»
 - using a priori information (Bayesian models)/combine different models (see Bayesian Model Averaging)

One-vs-All models Vs Multiclass models

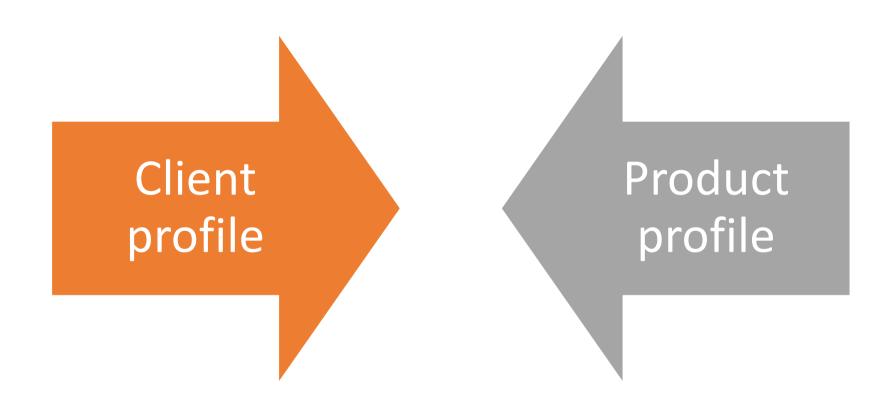
- One-vs-All (Binary classification, Binomial):
- 1 need \leftrightarrow 1 model
- As many models as there are needs (10 needs ↔ 10 models, 30 ↔ needs, etc)



- N needs ↔ 1 model
- One single big model (10 needs ↔ 1 model, 100 needs ↔ 1 model, etc)
 - → often more complex = might be less robust (see Occam's Razor)



From needs to recommendation (NBA): finding the best matching



- Content-based filtering knowledge-based methods that rely mostly on the domainknowledge
- Case-based recommender systems apply case-based reasoning (CBR) that solves the recommendation problem based on similar cases

Other approaches - Collaborative filtering: learning from similar situations/guys

Using Singular Value Decomposition or an Autoencoder to Build a Recommender System

Method based on latent variables

Often it does not go to the heart of the matter: it is unable to manage complex situations (for example, in recommending financial products, it is necessary to take into account many factors, primarily regulatory constraints).



Coding session starts