How to use a product recommender to make our customers even more happy

la Mobilière | Eva Morstein, Michael Gross

Business Context

Challenge

- Insurance advisors must handle a broad portfolio
- SMEs often have unique requirements
- Impossible to talk to every customer about every coverage regularly

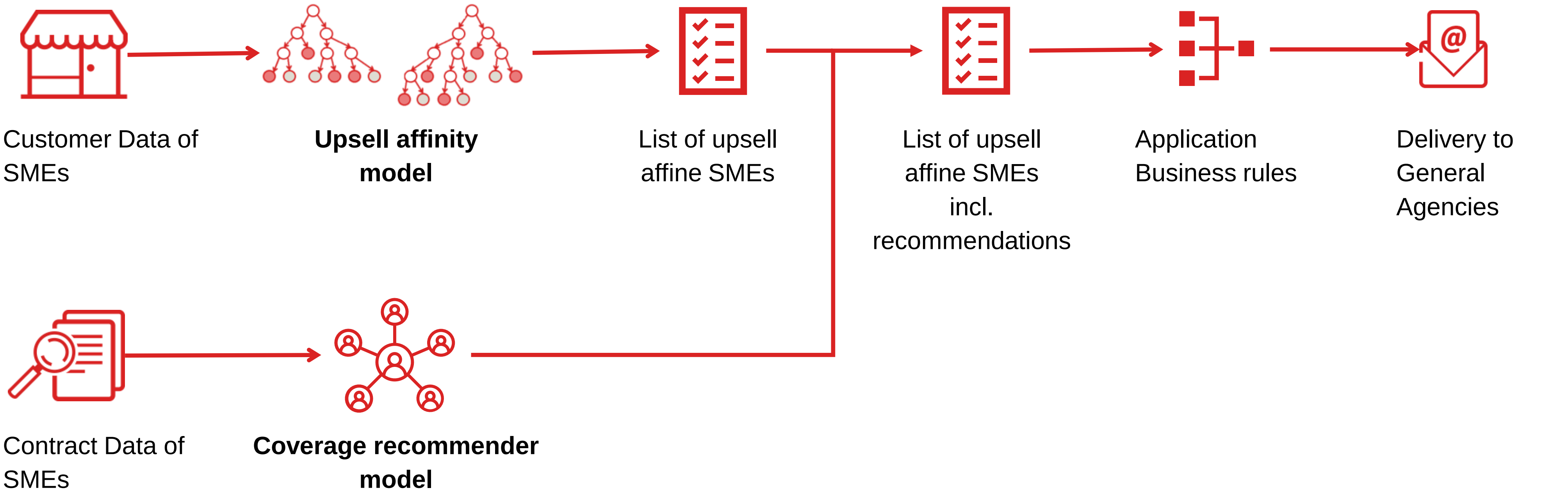
Goal

- Increase time efficiency in the advisory process
- Customers really get what they need
- Diversify overall product portfolio in the SME field

Proof of Concept

- Explore emerging field of graph-based recommender systems

Process Flow



Customer Data of SMEs

Upsell affinity model

List of upsell affine SMEs

List of upsell affine SMEs incl. recommendations

Application Business rules

Delivery to General Agencies

Contract Data of SMEs

Coverage recommender model

Recommender Systems

Neighbor – based collaborative filtering with implicit feedback

- Bases recommendations on user similarity to the target user based on past preferences
- Assumption: similar people prefer similar things
- Feedback: Conclusion of a coverage

items

user	🧩1	🧩2	🧩3	🧩4	🧩5	🧩6
👤	1	1	1	?	0	0
👤	1	1	1	1	0	0
👤	0	0	0	1	0	1
👤	0	0	1	0	1	0

Training

- Different months as train & test data
- Customers need to exist in both data sets
- Ca. 120'000 customers x 1'000 items
- Sparse data

February

userID	itemID	target
👤1	🧩1	1
👤1	🧩2	1
👤1	🧩3	1
👤1	🧩4	0
👤1	🧩5	0
👤1	🧩6	0
👤2	🧩1	1
👤2	🧩2	1
👤2	🧩3	1

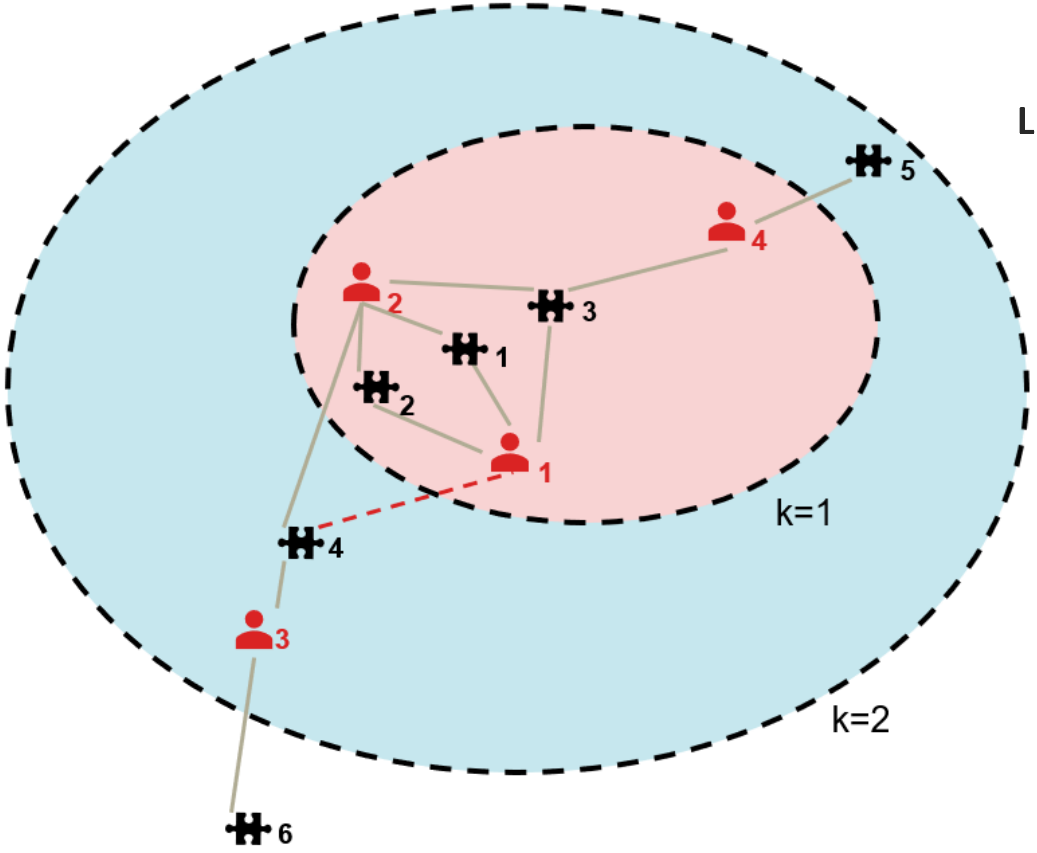
...

March

userID	itemID	target
👤1	🧩1	1
👤1	🧩2	1
👤1	🧩3	1
👤1	🧩4	1
👤1	🧩5	0
👤1	🧩6	0
👤2	🧩1	1
👤2	🧩2	1
👤2	🧩3	1

...

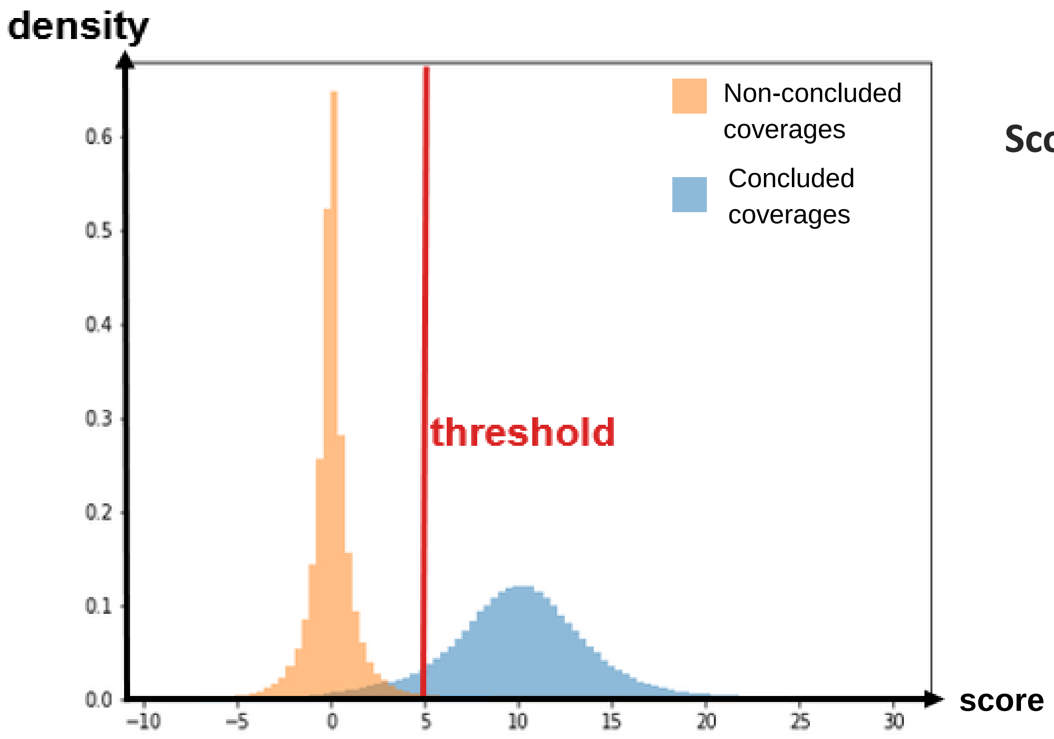
(Light) Graph Convolutional Neural Network



LightGCN

- Models similarity without user or item features
- Instead uses connections between users and items
- Creates user embeddings and item embeddings based on neighbours
- Size of neighbourhood (k) can be varied

(Light) Graph Convolutional Neural Network



Scoring

- Score = product of user & item embeddings
- PoC yielded scores between -10 and 30
- Good distinction between non-concluded and concluded coverages
- Mapping of score to binary recommendation via threshold
- Application via "highly recommended" vs "recommended"

Results & Next Steps

Feedback so far

- General agencies made many appointments with customers
- So far 2-3 successful conclusions
- Lists helps to push more niche products and identify "gaps" in coverages
- New agents and big general agencies profit the most

Outlook

- Final quantitative and qualitative evaluation
- Potential integration into productive systems
- One-time deliveries to interested agencies

Thank you!

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