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Digitization - Data - Intelligence

# Recommender Systems for Mass Customization of Financial Advice

**Artificial Intelligence in Industry and Finance**
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# Talk Outline

1. Recommender Systems for Financial Advice
2. Retail Banking Use Case
3. Private Banking Use Case
4. Summary and Outlook for the Future

1 **Recommender Systems for Financial Advice**

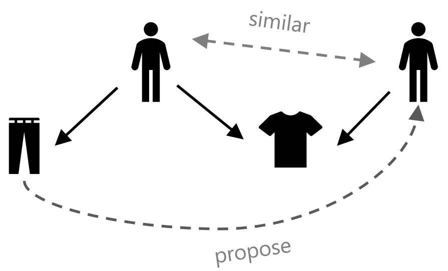
2 Retail Banking Use Case

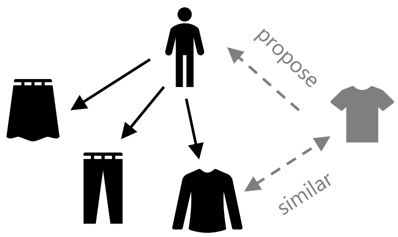
3 Private Banking Use Case

4 Summary and Outlook for the Future

# Typical Applications of Recommender Systems

*"People who bought this also liked…"*




*"If you bought this, you might also like…"*

## Typical applications

- **Movies** (Netflix)
- **Songs** (Spotify)
- **Books** (Goodreads)
- **E-commerce products** (Amazon)

## Typical methods

- Collaborative filtering (CF)
- Content-based filtering (CB)

## Challenges in the area of Financial Advice

- No explicit feedback
- Product nature might change over time
- A recommendation has a financial impact on the client

# Business Case

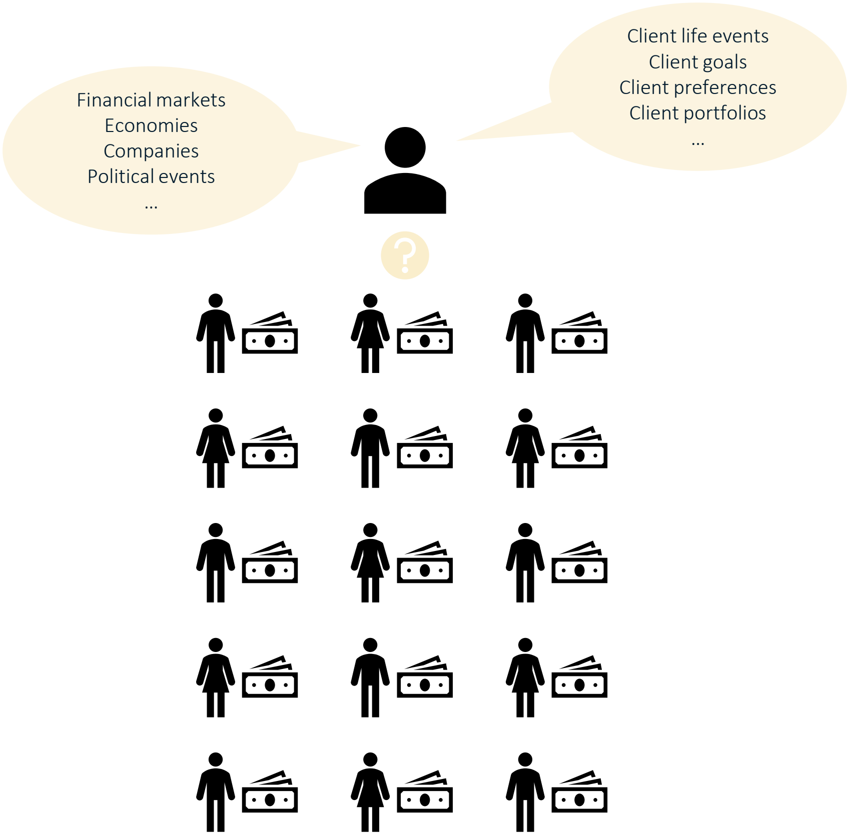
## Recommender Systems for Financial Advice

**Typically:**

- high net worth clients receive **tailored** investment advice
- less affluent clients get **standardized** offerings

# Business Case

## Recommender Systems for Financial Advice

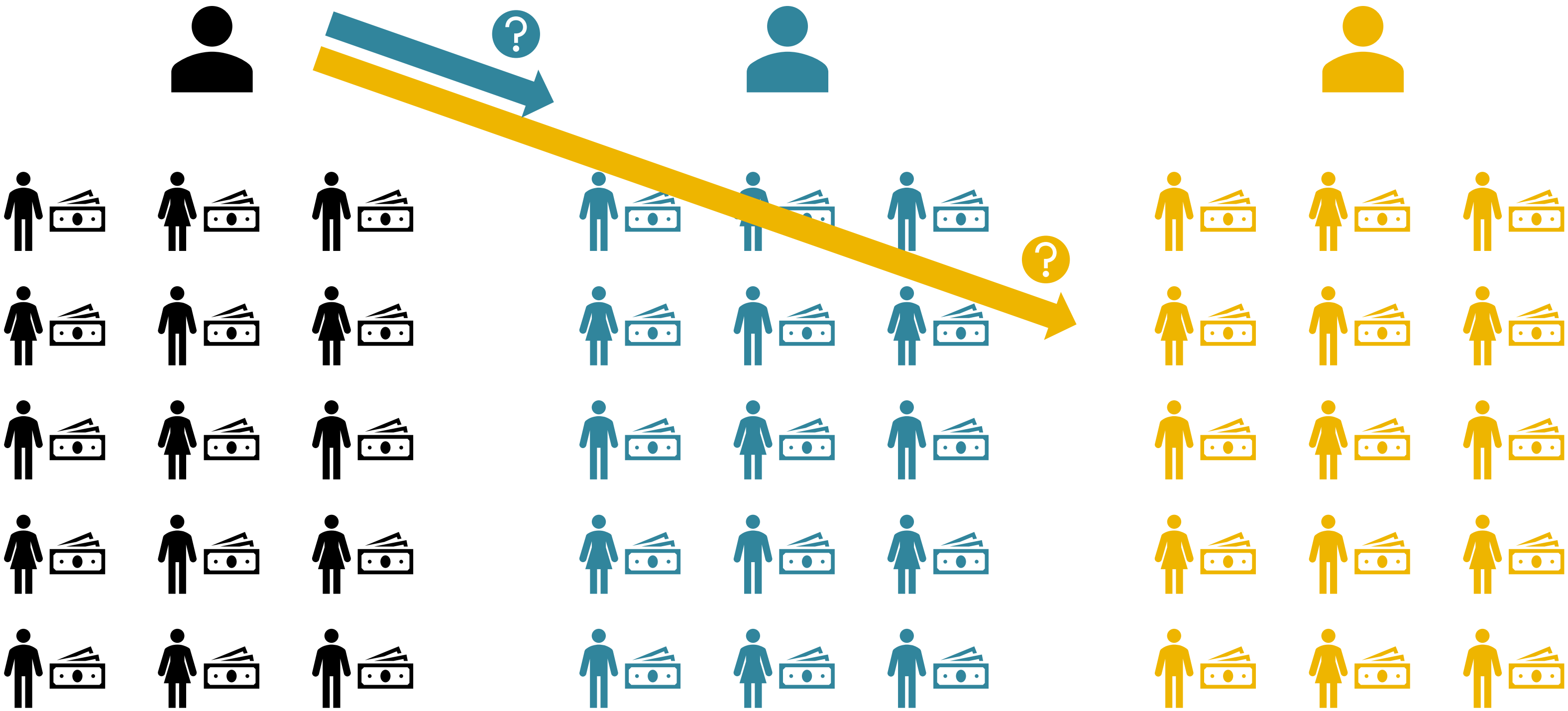



**Client Relationship Manager:**

- manages between 50 and 200 clients
- manually processes information to provide customized advice

# Business Case

## Recommender Systems for Financial Advice




**Client Relationship Manager:**

- focuses on his own clients
- has little knowledge of other relationship managers' clients

# Business Case

## Recommender Systems for Financial Advice

**Recommender System leverages crowd intelligence:**

- finds **similar** clients across **entire** customer base
- cross-recommends products that are the **most likely to be accepted**
- supports relationship managers: **improved quality of advice and saved time**

# Business Case

## Recommender Systems for Financial Advice

**Recommender System:**

- includes the **less affluent client segments**
- delivers recommendations to clients directly: **access to personalized advice**

# Need for Explanations

## Recommender Systems for Financial Advice

### Why the need for explanations?

**GDPR:** right to explanations

**Clients:** explanations → more trust

**CRMs:** arguments to convince clients

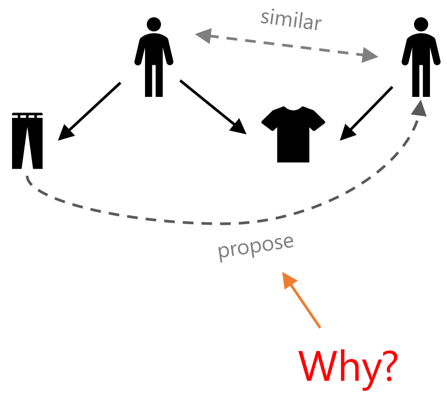
### How to get explanations?

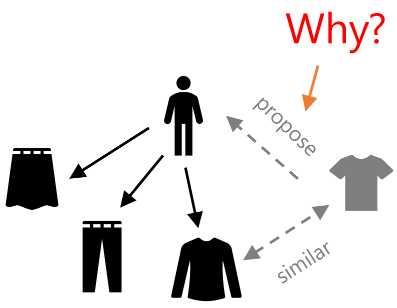
Recommenders are built on similarities

Why are these clients similar?

Some systems have a ready answer, some don’t

*"People who bought this also liked…"*




*"If you bought this, you might also like…"*

1 Recommender Systems for Financial Advice

2 **Retail Banking Use Case**

3 Private Banking Use Case

4 Summary and Outlook for the Future

# Nature of the Use Case and Data Description

## Retail Banking Use Case

**Goal:** personalized recommendations of **retail banking products**, such as accounts and credit cards

**Relatively few offered products** (tens to hundreds; current or savings accounts, credit cards, etc.)

**Clients typically own few products**

**Clients rarely change** products

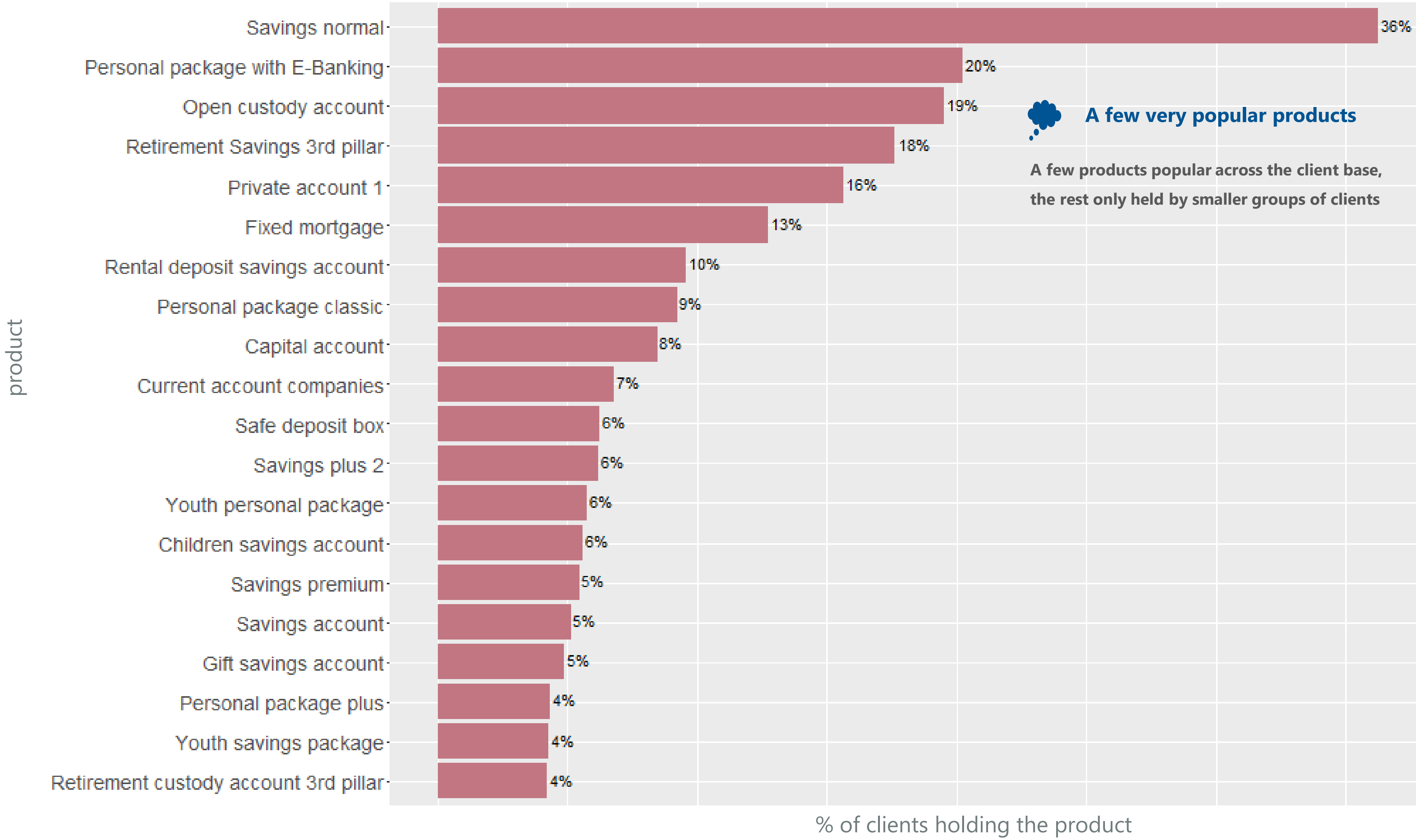
### Data from Nidwaldner Kantonalbank

- ✓ provided by the Nidwaldner Kantonalbank (NKB) and anonymised for the purpose of this presentation
- ✓ **~100 products**
- ✓ **~3 products per client** (on average)
- ✓ Product categories:
  - Current accounts
  - Savings accounts
  - Credit card accounts
  - Investment accounts
  - Mortgages and loans
  - etc.

Nidwaldner Kantonalbank

# Data Overview: Top 20 Most Popular Products

## Retail Banking Use Case




**A few very popular products**

A few products popular across the client base, the rest only held by smaller groups of clients

# Why Model Based CF Fails & Our Model Choice

## Retail Banking Use Case

**RESULTS**

| | **Model-based CF** | **Popular Model** |
|---|---|---|
| **Accuracy** | **8.96** ± 0.18% | **20.43** ± 0.23% |
| **Mean Reciprocal Rank** | **17.72** ± 0.18% | **31.53** ± 0.22% |

### "Popular" (non-personalised) model performs better than model-based CF

- clients consume **too few products** (3 on average)
- **low variety** of the most popular products

### Memory-based demographic collaborative filtering

\+ cold-start solved through user features
\+ easily interpretable: explanations for recommendations
\- requires collection of features
\- need to store full matrix

→ useful for retail banking use case (limited history)

# Memory Based Collaborative Filtering

## Retail Banking Use Case

### Step 1: Demographic segmentation

For each client, find a neighbourhood of k similar clients (**k-NN**) based on the **Gower** distance and features:

- gender
- age group
- wealth group
- e-banking usage
- 3rd pillar payments
- …

### Step 2: Product popularity

Within each client's neighbourhood:

- **determine the popularity of each product** - how many clients in the neighbourhood consumed it
- **identify explanatory features and values** - values of features most common in the neighbourhood (e.g. age 18-24)

### Step 3: Personalized recommendation

For each client:

- sort the products the client has not yet consumed by popularity
- **recommend the top 5 products**
- **bonus: explanations** via shared features in a neighbourhood

# Results

## Retail Banking Use Case

**RESULTS**

| | Model-Based CF | Popular Model | Memory-Based Demographic CF |
|---|---|---|---|
| **Accuracy** | **8.96** ± 0.18% | **20.43** ± 0.23% | **45.11** ± 1.27% |
| **Mean Reciprocal Rank** | **17.72** ± 0.18% | **31.53** ± 0.22% | **58.44** ± 1.01% |

**Memory based demographic CF wins** against popular model and model-based CF

**Explanations** are naturally provided by the algorithm

# Qlik Sense User Interface

## Retail Banking Use Case

Retail Banking: Personal Recommender

**Table of customers and their recommended products, ordered by the number of similar users that have this product**

| Client ID | Rank 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| 34840 | Savings account up to 20 years | Savings plan | Youth personal package | Savings account |

**Products already owned**

| Product |
|---|
| Retirement Savings 3rd pillar |
| Youth personal package premium |
| Youth savings package |

# Qlik Sense User Interface
## Retail Banking Use Case

Retail Banking: Personal Recommender

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**Customer already owns Retirement Savings and Youth Savings accounts**

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Customer already owns Retirement Savings and Youth Savings accounts

**Recommend a savings account up to 20 years**

# Qlik Sense User Interface

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Retail Banking: Personal Recommender

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Customer already owns Retirement Savings and Youth Savings accounts

Recommend a savings account up to 20 years

**Explanation: popular product in a youth neighborhood between 18 and 24 with single civil status**

# Qlik Sense User Interface
## Retail Banking Use Case

Retail Banking: Personal Recommender

**Table of customers and their recommended products, ordered by the number of similar users that have this product**

| Client ID | Rank 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| 12619 | Current account companies | Capital account | Open custody account | Savings plus 2 | Time deposit (long term) |

**Products already owned**

| Product |
|---|
| Private account 1 |
| Savings normal |

# Qlik Sense User Interface
## Retail Banking Use Case

### Retail Banking: Personal Recommender

**Table of customers and their recommended products, ordered by the number of similar users that have this product**

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**Products already owned**

| Product |
|---|
| Private account 1 |
| Savings normal |


**Customer already owns Private and Savings accounts**

# Qlik Sense User Interface
## Retail Banking Use Case

### Retail Banking: Personal Recommender

**Table of customers and their recommended products, ordered by the number of similar users that have this product**

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**Products already owned**

| Product |
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| Private account 1 |
| Savings normal |


Customer already owns Private and Savings accounts

**Recommend a current account for companies**

# Qlik Sense User Interface

## Retail Banking Use Case

Retail Banking: Personal Recommender

**Table of customers and their recommended products, ordered by the number of similar users that have this product**

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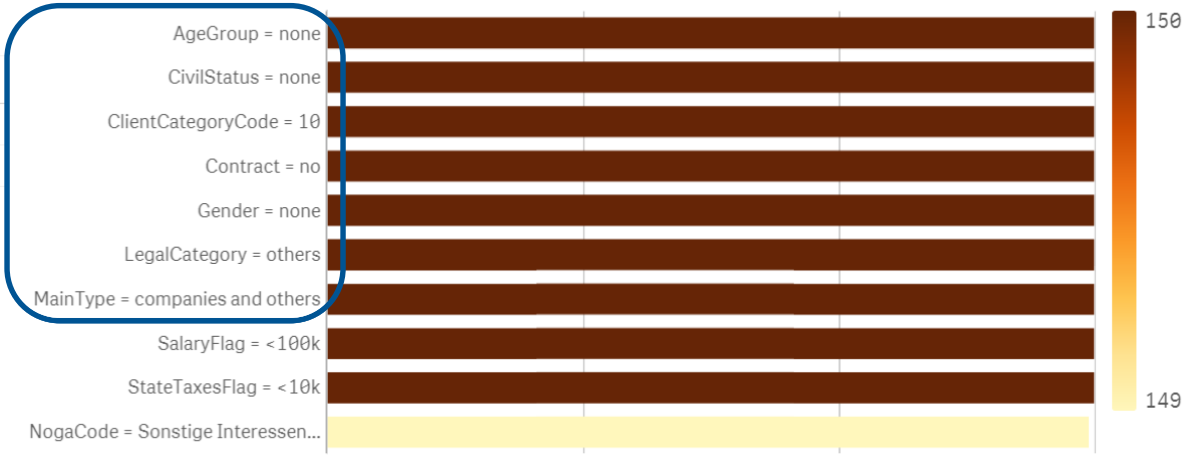


Customer already owns Private and Savings accounts

Recommend a current account for companies

**Explanation: popular product in neighborhood with no age or gender info, and of type “companies”**

1 Recommender Systems for Financial Advice

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3 **Private Banking Use Case**

4 Summary and Outlook for the Future

# Nature of the Use Case and Data Description

## Private Banking Use Case

**Goal:** personalized recommendations of **financial instruments**, such as stocks and bonds

**Many offered products** (thousands; financial instruments such as stocks, bonds, derivative instruments, etc)

**Clients typically own many products**

Clients buy and sell investments - **substantial history** of user-product "ratings"

### Subset of data from Nidwaldner Kantonalbank

- ✓ provided by the Nidwaldner Kantonalbank (NKB) and anonymised for the purpose of this presentation
- ✓ **1117 users**, **1788 items**
- ✓ **~18 products per person** (on average)

Nidwaldner Kantonalbank

# Model Based Collaborative Filtering

## Private Banking Use Case

### Model-based collaborative filtering (CF)

+ no user or item features required
+ typically more accurate than other models
- difficult to interpret

→ useful for private banking use case (abundant history)

### Challenges

**missing data points**
→ client didn't want the product? OR doesn't know about it?

**implicit ratings**
→ how to determine if the clients liked the products they bought?

**explanations must be worked out separately**
→ matrix-based CF is a black box, it doesn't give explanations along the way

### Modeling approach

1. **Ratings matrix factorization** to discover latent features
2. **Confidence weights** – fix confidence weights in one model
3. **Boosting** – confidence weights estimated from the ensemble model

# Results

## Private Banking Use Case

**RESULTS**

| | Model-based CF | Popular Model |
|---|---|---|
| **AUC** | **0.9077** ± 0.0003 | **0.8728** |
| **nDCG** | **0.5737** ± 0.0057 | **0.4287** |
| **aRHR** | **0.4597** ± 0.0072 | **0.2719** |

**Model based CF wins** against the popular model

**But explanations** remain a missing piece

# Explanations for Model Based CF: Best Attempt

## Private Banking Use Case

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 0 | 1 | 0 | 1 | 1 | 0 | 0 |
| | 1 | 0 | 1 | 0 | 0 | 1 | 1 |
| | 0 | 1 | 0 | | 1 | 1 | 0 |
| | 0 | 0 | 0 | 1 | 1 | 1 | 0 |
| | 1 | 0 | 1 | 0 | 1 | 1 | 0 |
| | 1 | 0 | 0 | 1 | 0 | 1 | 0 |
| | 0 | 1 | 0 | 1 | 1 | 0 | 0 |
| $\sum$ | | **2** | | | **3** | **2** | |

The product that appears together with the recommended one for similar users most often is the **explanatory product**

# Explanations for Model Based CF: Best Attempt

## Private Banking Use Case

### Explaining matrix factorization CF

+ gives useful and reasonable explanations
- requires additional computational step
- tries to imitate algorithm logic

### What would be better

A CF matrix-factorisation algorithm that provides explanations on the way

- can also work with missing ratings
- is as accurate as Model Based CF

# OCuLaR: Probabilistic Explainable Recommender
## Private Banking Use Case

**OCuLaR:** Co-Clustering Recommendation Algorithm

**Originally applied on:**

- IBM products
- Scientific articles
- Movielens
- Netflix

We applied it on the NKB **private banking data**

Reinhard Heckel, Michail Vlachos, Thomas Parnell, Celestine Duenner,
“Scalable and interpretable product recommendations via overlapping co-clustering”, 2017

# OCuLaR: Probabilistic Explainable Recommender

## Private Banking Use Case

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 0 | 1 | 1 | 1 | 0 | 0 | 0 |
| | 0 | 1 | 1 | 1 | 0 | 0 | 0 |
| | 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| | 0 | 1 | 1 | 0 | 1 | 1 | 0 |
| | 0 | 0 | 0 | 1 | 1 | 1 | 1 |
| | 0 | 0 | 0 | 1 | 1 | 1 | 0 |
| | 0 | 1 | 0 | 0 | 0 | 1 | 1 |

**Goal**: produce recommendation for client 4

# OCuLaR: Probabilistic Explainable Recommender
## Private Banking Use Case

| | | | | | | |
|---|---|---|---|---|---|---|
| 0 | 1 | 1 | 1 | 0 | 0 | 0 |
| 0 | 1 | 1 | 1 | 0 | 0 | 0 |
| 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| 0 | 1 | 1 | 0 | 1 | 1 | 0 |
| 0 | 0 | 0 | 1 | 1 | 1 | 1 |
| 0 | 0 | 0 | 1 | 1 | 1 | 0 |
| 0 | 1 | 0 | 0 | 0 | 1 | 1 |

**Observation**: blocks in the matrix (**co-clusters**) combine similar users and items

# OCuLaR: Probabilistic Explainable Recommender

## Private Banking Use Case

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 0 | 1 | 1 | 1 | 0 | 0 | 0 |
| | 0 | 1 | 1 | 1 | 0 | 0 | 0 |
| | 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| | 0 | 1 | 1 | | 1 | 1 | 0 |
| | 0 | 0 | 0 | 1 | 1 | 1 | 1 |
| | 0 | 0 | 0 | 1 | 1 | 1 | 0 |
| | 0 | 1 | 0 | 0 | 0 | 1 | 1 |

**Recommendation**: uncovering co-cluster membership, we can recommend other items from these co-clusters

# OCuLaR: Probabilistic Explainable Recommender

## Private Banking Use Case

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 0 | 1 | 1 | 1 | 0 | 0 | 0 |
| | 0 | 1 | 1 | 1 | 0 | 0 | 0 |
| | 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| | 0 | 1 | 1 | | 1 | 1 | 0 |
| | 0 | 0 | 0 | 1 | 1 | 1 | 1 |
| | 0 | 0 | 0 | 1 | 1 | 1 | 0 |
| | 0 | 1 | 0 | 0 | 0 | 1 | 1 |

**Recommendation**: **Item 4** is recommended to **Client 4** because:

# OCuLaR: Probabilistic Explainable Recommender

## Private Banking Use Case

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 0 | 1 | 1 | 1 | 0 | 0 | 0 |
| | 0 | 1 | 1 | 1 | 0 | 0 | 0 |
| | 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| | 0 | 1 | 1 | **0** | 1 | 1 | 0 |
| | 0 | 0 | 0 | 1 | 1 | 1 | 1 |
| | 0 | 0 | 0 | 1 | 1 | 1 | 0 |
| | 0 | 1 | 0 | 0 | 0 | 1 | 1 |

**Recommendation**: **Item 4** is recommended to **Client 4** because:

**Client 4** has purchased **Items 2-3**: clients with similar purchase history (**clients 1-3**) also bought **Item 4**

# OCuLaR: Probabilistic Explainable Recommender

## Private Banking Use Case

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 0 | 1 | 1 | 1 | 0 | 0 | 0 |
| | 0 | 1 | 1 | 1 | 0 | 0 | 0 |
| | 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| | 0 | 1 | 1 | **0** | 1 | 1 | 0 |
| | 0 | 0 | 0 | 1 | 1 | 1 | 1 |
| | 0 | 0 | 0 | 1 | 1 | 1 | 0 |
| | 0 | 1 | 0 | 0 | 0 | 1 | 1 |

**Recommendation**: **Item 4** is recommended to **Client 4** because:

**Client 4** has purchased Items 2-3: clients with similar purchase history (clients 1-3) also bought **Item 4**

**Client 4** has purchased **Items 5-6**: clients with similar purchase history (**clients 5-6**) also bought **Item 4**

# OCuLaR: Probabilistic Explainable Recommender

## Private Banking Use Case

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | 0 | 1 | 1 | 1 | 0 | 0 | 0 |
| | 0 | 1 | 1 | 1 | 0 | 0 | 0 |
| | 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| | 0 | 1 | 1 | | 1 | 1 | 0 |
| | 0 | 0 | 0 | 1 | 1 | 1 | 1 |
| | 0 | 0 | 0 | 1 | 1 | 1 | 0 |
| | 0 | 1 | 0 | 0 | 0 | 1 | 1 |

**Recommendation**: **Item 4** is recommended to **Client 4** because:

**Client 4** has purchased **Items 2-3**: clients with similar purchase history (**clients 1-3**) also bought **Item 4**

**Client 4** has purchased **Items 5-6**: clients with similar purchase history (**clients 5-6**) also bought **Item 4**

# OCuLaR: Probabilistic Explainable Recommender

## Private Banking Use Case

| | OCuLaR | State-of-art Matrix Factorization |
|---|---|---|
| Similarities | Can work with **missing or implicit** ratings | |
| | Decompose the ratings matrix into **compact** representation | |
| | Use the notion of **latent features**, applicable both to users and items | |
| Differences | Predicts **probability** of a purchase | Predicts **ratings** |
| | $P[r_{ui} = 1] = 1 - \exp(-\langle f_u, f_i \rangle)$ | $r_{ui} = \langle f_u, f_i \rangle$ |
| | Latent factors are confined to model **co-clusters** | Provides **no interpretation** of latent features |
| | **Explanatory** products are revealed **automatically** | Provides **no explanation** for recommendations |

# Private Banking Use Case
## Results

**RESULTS**

| | OCuLaR | Model-based CF | Popular Model |
|---|---|---|---|
| **AUC** | **0.9305** ± 0.0022 | **0.9077** ± 0.0003 | **0.8728** |
| **nDCG** | **0.5709** ± 0.0039 | **0.5737** ± 0.0057 | **0.4287** |
| **aRHR** | **0.4932** ± 0.0039 | **0.4597** ± 0.0072 | **0.2719** |

**OCuLaR and Model based CF** both win against the popular model

**OCuLaR** provides explanations automatically

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4 **Summary and Outlook for the Future**

# Summary and Outlook

## Recommender Systems for Mass Customization of Financial Advice

### **Retail Banking:** personalized recommendations of accounts, credit cards, mortgages, etc.

**Few** products per user, **limited** history of ratings

**Memory-based** Demographic Collaborative Filtering

- **explanations** come as a part of algorithm through user features

### **Private Banking:** personalized recommendations of financial instruments

**Many products**, **abundant history** of ratings per user

**Model-based** Collaborative Filtering

- probabilistic co-clustership model provides **explanations** on the way

### Ongoing projects

Working with **two large Swiss banks** on an advisory recommender system in private banking

- A/B testing
- Portfolio context
- Features changing in time
- Hybrid models


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# Thank you!

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