Affinity is in the AIRS

Personalized Investment Recommendations Delivered to Clients’ E-Services

Aleksandra Chirkina
Data Scientist @ InCube

Richard Jeroense
Head Digitalization and Process Excellence @ Bank J Safra Sarasin
Why recommender for financial advice?

Why not?

Relevant investment ideas with high acceptance probability

Quality control is present

Saves time and effort of CRMs

Increases usage of online banking system

Stimulates client engagement

Trendy
Outline

1. Business Case and Challenges
2. Product Binning
3. Collaborative Filtering and Implicit Ratings
4. Challenge: Explainability
5. Challenge: Reaction to Clients’ Feedback
6. Integration into Core Services
Outline

1. Business Case and Challenges
2. Product Binning
3. Collaborative Filtering and Implicit Ratings
4. Challenge: Explainability
5. Challenge: Reaction to Clients’ Feedback
6. Integration into Core Services
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
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
Challenges in the area of Financial Advice

Typical applications

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

Challenges in the area of Financial Advice

- Regulatory compliance
- Explanations are essential
- No explicit feedback initially
- Need to react to explicit feedback given at later stages
- Product nature might change over time
Outline

1. Business Case and Challenges
2. Product Binning
3. Collaborative Filtering and Implicit Ratings
4. Challenge: Explainability
5. Challenge: Reaction to Clients’ Feedback
6. Integration into Core Services
Overview of the system

Product binning

Collaborative filtering

Finding explanations

Asset selection

Adapting to clients’ feedback
Product Binning

Approach

Individual assets

- Emmi AG
- Abb Ltd
- The Swatch Group

- Jelmoli
- Orell Fussli
- Sensirion Holding

- Baloise Holding
- Swiss Re
- Swiss Life Holding

- Air Berlin
- Deutsche Lufthansa
- Deutsche Post

Asset categories

- Swiss Equities
  - CHF
  - Industry Risk Level 2

- Swiss Equities
  - CHF
  - Industry Risk Level 3

- Swiss Bonds
  - CHF
  - Insurance Risk Level 2

- German Equities
  - EUR
  - Transportation Risk Level 3

Ratings matrix

|     | client1 | client2 | client3 | client4 | ...
|-----|---------|---------|---------|---------|------
| row1| 1       | 0       | 0       | 1       | 1    |
| row2| 0       | 1       | 0       | 0       | 0    |
| row3| 0       | 0       | 1       | 0       | 0    |
| row4| 0       | 0       | 0       | 1       | 1    |
| row5| 0       | 0       | 0       | 1       | 1    |
Product Binning
Which Issues it Solves

⚠️ Cold-start for products

📈 Time-varying product features

🧩 Too many dimensions

_atom_ Too much sparsity

💼 Allows coupling with business logic

ardless Can help with extension of bank’s recommendation lists
Overview of the system

Product binning ➔ Collaborative filtering ➔ Finding explanations ➔ Asset selection

Adapting to clients’ feedback

As shown in the diagrams, the system starts with product binning, followed by collaborative filtering, and then finding explanations. The final step is asset selection. Feedback from clients is incorporated to adapt the system continuously.

The diagrams illustrate the process with color-coded matrices and icons to represent positive and negative feedback.
Product Binning
Compliant Selection from the Bin

Asset selection from a recommended category

Asset categories
- Swiss Equities
  - CHF
  - Industry
  - Risk Level 2

Individual assets
- Emmi AG
- Abb Ltd
- The Swatch Group

Personal filter
- historical holding
- current holding

Category expansion by dropping ‘Risk Level’

Attempt 1
- Swiss Equities
  - CHF
  - Industry
- Risk Level 2

Attempt 2
- Swiss Equities
  - CHF
  - Industry

Recommendation
- Emmi AG
- Abb Ltd
- The Swatch Group
- Jelmoli
- Orell Fussli
- Sensirion Holding

historical holding
current holding

Orell Fussli
Outline

1. Business Case and Challenges
2. Product Binning
3. **Collaborative Filtering and Implicit Ratings**
4. Challenge: Explainability
5. Challenge: Reaction to Clients’ Feedback
6. Integration into Core Services
Overview of the system

<table>
<thead>
<tr>
<th>Product binning</th>
<th>Collaborative filtering</th>
<th>Finding explanations</th>
<th>Asset selection</th>
</tr>
</thead>
</table>

Adapting to clients’ feedback
Model Based Collaborative Filtering

Overview

- Trains on historical portfolio holdings
- Deals with **missing** datapoints: **no purchase** doesn’t imply **no affinity**
- Deals with **implicit** ratings: **purchase** doesn’t imply **affinity**
Model Based Collaborative Filtering
Matrix Factorization with Confidence Weights

Implicit ratings matrix:
$$R = \{r_{ij}\} = \begin{cases} 0, & \text{if user } i \text{ did not consume item } j \\ a_{ij} > 0, & \text{if user } i \text{ consumed item } j \end{cases}$$

Preference matrix:
$$P = \{p_{ij}\} = \mathbb{I}\{r_{ij} > 0\}$$

Confidence weights
$$c_{ij} = 1 + \beta \log \left(1 + \frac{r_{ij}}{\varepsilon}\right)$$

Preference matrix:
$$\hat{P} = \hat{X}_{[|U| \times k]} \cdot \hat{Y}^T_{[|I| \times k]}$$

such that
$$\sum_{i,j} c_{ij} (p_{ij} - \hat{p}_{ij})^2 + \lambda \left(\|\hat{X}\|_2^2 + \|\hat{Y}\|_2^2\right) \rightarrow \min$$

$$\hat{X}_{[|U| \times k]}, \hat{Y}_{[|I| \times k]}$$ - ‘latent features’ matrices
$$\hat{P}$$ - imputed ratings matrix
Implicit ratings handling matters

There are plenty approaches to handling of implicit ratings

- Indicator: \{0, 1\}
- Holding period in months: \{0, 1, 2, ...\}
- Trading activity pattern: low ~ high \(\rightarrow [0, 1]\)

Model Based Collaborative Filtering
Approach to Modeling of Implicit Ratings
Outline

1. Business Case and Challenges
2. Product Binning
3. Collaborative Filtering and Implicit Ratings
4. Challenge: Explainability
5. Challenge: Reaction to Clients’ Feedback
6. Integration into Core Services
Overview of the system

Product binning → Collaborative filtering → Finding explanations

Adapting to clients’ feedback → Asset selection
### Explainability

**Find Co-clusters in the Matrix**

<table>
<thead>
<tr>
<th></th>
<th>📸</th>
<th>🎬</th>
<th>🎧</th>
<th>📱</th>
<th>🎮</th>
<th>🌐</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

**Goal:** produce recommendation for client 4

Reinhard Heckel, Michail Vlachos, Thomas Parnell, Celestine Duenner, *Scalable and interpretable product recommendations via overlapping co-clustering*, In IEEE International Conference on Data Engineering (ICDE) 2017
### Explainability

Find Co-clusters in the Matrix

<table>
<thead>
<tr>
<th></th>
<th>Camera</th>
<th>Device</th>
<th>Music</th>
<th>Headset</th>
<th>Phone</th>
<th>Gamepad</th>
<th>Camera</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>6</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>7</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

**Observation:** blocks in the matrix (co-clusters) combine similar users and items
**Recommendation**: uncovering co-cluster membership, we can recommend other items from these co-clusters
**Recommendation**: Item 4 is recommended to Client 4 because:

<table>
<thead>
<tr>
<th></th>
<th>Camera</th>
<th>Music</th>
<th>Movies</th>
<th>Music</th>
<th>Phone</th>
<th>Games</th>
<th>Camera</th>
</tr>
</thead>
<tbody>
<tr>
<td>Client 1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Client 2</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Client 3</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Client 4</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Client 5</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Client 6</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Client 7</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>
**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
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**
Explainability
Find Co-clusters in the Matrix

<table>
<thead>
<tr>
<th></th>
<th>📸</th>
<th>🎬</th>
<th>🎧</th>
<th>📱</th>
<th>🎮</th>
<th>📺</th>
</tr>
</thead>
<tbody>
<tr>
<td>Client 1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Client 2</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Client 3</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Client 4</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Client 5</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Client 6</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Client 7</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

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**
Outline

1. Business Case and Challenges
2. Product Binning
3. Collaborative Filtering and Implicit Ratings
4. Challenge: Explainability
5. Challenge: Reaction to Clients’ Feedback
6. Integration into Core Services
Overview of the system

Product binning → Collaborative filtering → Finding explanations → Asset selection

Adapting to clients’ feedback

Aset selection
Explicit Feedback

Approach

Clients can rate the ideas: binary feedback

Feedback enters the prediction loop for the next batch of recommendations

Experiments showed this approach to be legit

\[ L = \sum_{i,j} c_{ij} (p_{ij} - \hat{p}_{ij})^2 \]

- \( p_{ij} = 0 \)
- \( c_{ij} = c_{max} \)
- \( \hat{p}_{ij} \) is forced to be 0

- \( p_{ij} = p_{max} \)
- \( c_{ij} = c_{max} \)
- \( \hat{p}_{ij} \) must be high
Explicit Feedback
Experiments

“How my feedback affects my recommendations?”

“How feedback of other clients affects my recommendations?”
Outline

1. Business Case and Challenges
2. Product Binning
3. Collaborative Filtering and Implicit Ratings
4. Challenge: Explainability
5. Challenge: Reaction to Clients’ Feedback
6. Integration into Core Services
Integration into Core Services
Project Timeline

May 18  Jun 18  Jul 18  Aug 18  Sep 18  Oct 18  Nov 18  Dec 18  Jan 19  Feb 19  Mar 19  Apr 19

AIRS PoC (Phase I)

DEV
SIT
UAT
Evaluation by CRMs

AIRS PROD (Phase II)

DEV
SIT
DOC
UAT
BUGFIX
Go Live
Integration into Core Services

CRM Feedback

**Question**: Would the client like this idea?

**Acceptance rate**: 56%

**Question**: Do you think the client would buy the asset?

**Acceptance rate**: 52%
# Investment Ideas in the Core Banking System

## CRM Information

<table>
<thead>
<tr>
<th>Person / Asset</th>
<th>R</th>
<th>Intellis</th>
<th>View</th>
</tr>
</thead>
<tbody>
<tr>
<td>LafargeHolcim Ltd Nam (1221405)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Swiss Life Hold AG Nam (1485278)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Partners Group Hold.AG N. (2460882)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SAP SE -ADR- (42290)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Novartis AG -ADR- (567514)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>JSS Sustainable Eq.-Switzerland (CHF) -P- Dist (163070)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

---

### LafargeHolcim Ltd Nam (1221405)

**Reason:**
As you bought ABB Ltd Nam (1222171) you may like LafargeHolcim Ltd Nam (1221405)

**Selection Path:**
LafargeHolcim Ltd Nam (1221405) chosen at ReducedMarketSetMarket level from ModelPortfolio. Category name: Equities Switzerland Currency: CHF. Filter info: Start with 2 candidates. KnE removed no assets, last 3 months removed no assets, existing recommendations LtdId removed no assets, existing recommendations issuer removed no assets, country removed no assets, historical asset removed 1, historical bonds and equities issuer removed no assets, historical maturity date removed no assets, corporate state removed no assets, similar funds removed no assets, 1 remaining after applying all filters.

**ISIN:** CH0012214059

**Telekurs ID:** 1221405

**Asset type:** Registered share
Publishing Ideas on the E-Banking Platform

INVESTMENT IDEAS
- LafargeHolcim
- Swiss Life
- Partners Group
- SAP SE
- Novartis
- JSS Sustainable Equities Switzerland (CHF)

INDICES (WORLD)
- EURO STOXX 50
- DAX
- NIKKEI 225
- DOW JONES SINGAPORE (SGD)
- SMI

INDICES (EUROPE)
- CAC 40
- EURO STOXX 50
- DAX
- AEX
- RTS INDEX

EXCHANGE RATES
- USDCHF
- EURUSD
- USDJPY
- GBPUSD
- EURCHF
- GBPCHF

PORTFOLIO POSITIONS

EQUITY MARKETS (SMALL)
AIRS Learns Based upon Feedback

How do you rate this idea?

Your feedback helps to improve ideas for you.
Please note:
This is an investment idea and not a personal investment recommendation (investment advice). It does not take into account your financial situation or investment objectives. Please click here to find more information.

IDEA DESCRIPTION

As you bought ABB, you may like LafargeHolcim.

Research/Advisory Information

Rating: Buy
Stock Report: 02.06.2019 08:01:50
Why recommender for financial advice?

- Relevant investment ideas with high acceptance probability
  - ✔ Are achieved by employing the collaborative filtering approach with implicit ratings

- Quality control
  - ✔ Is easily integrated through product binning and smart post-filtering

- Saves time and effort of CRMs
  - ✔ By automatically providing detailed explanations

- Increases usage of online banking system
  - ✔ By presenting the ideas in an appealing way

- Stimulates client engagement
  - ✔ Through collecting the feedback and adapting accordingly