J. SAFRA SARASIN
Sustainable Swiss Private Banking since 1841

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Affinity is in the AIRS

Personalized Investment Recommendations Delivered to Clients' E-Services

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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

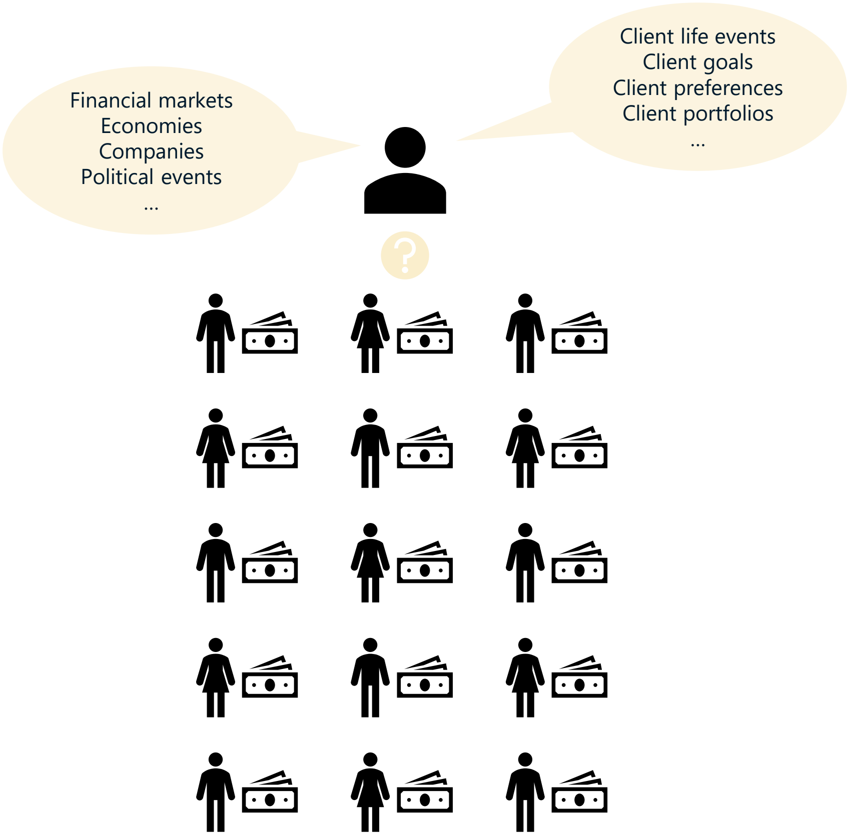
Outline

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

Business Case

Recommender Systems for Financial Advice

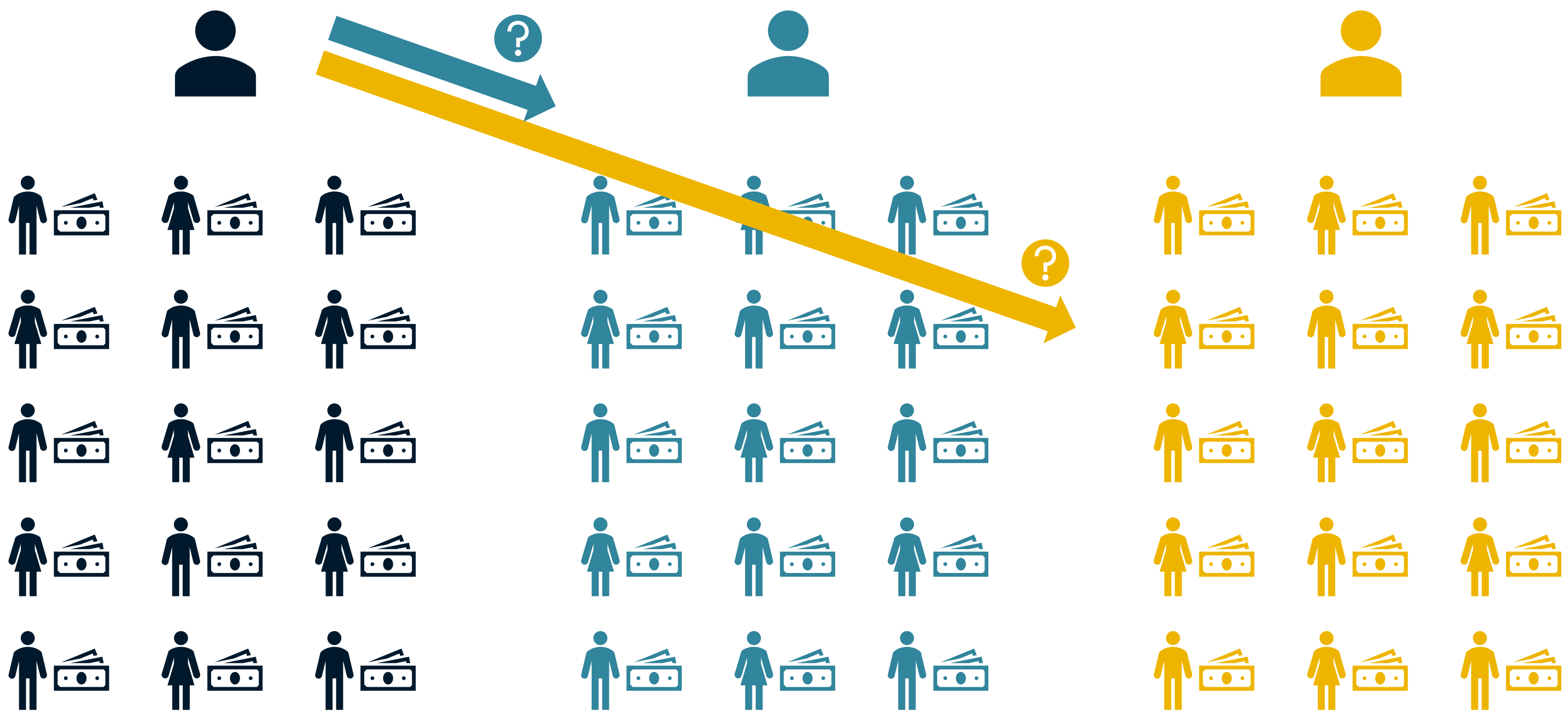


Client Relationship Manager:

- 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

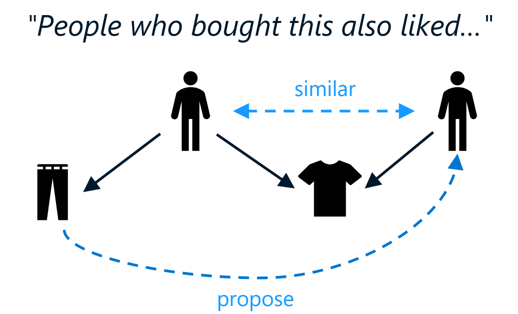
Business Case

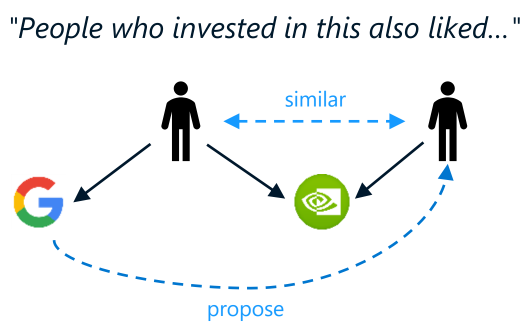
Recommender Systems for Financial Advice

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**

Challenges in the area of Financial Advice





Typical applications

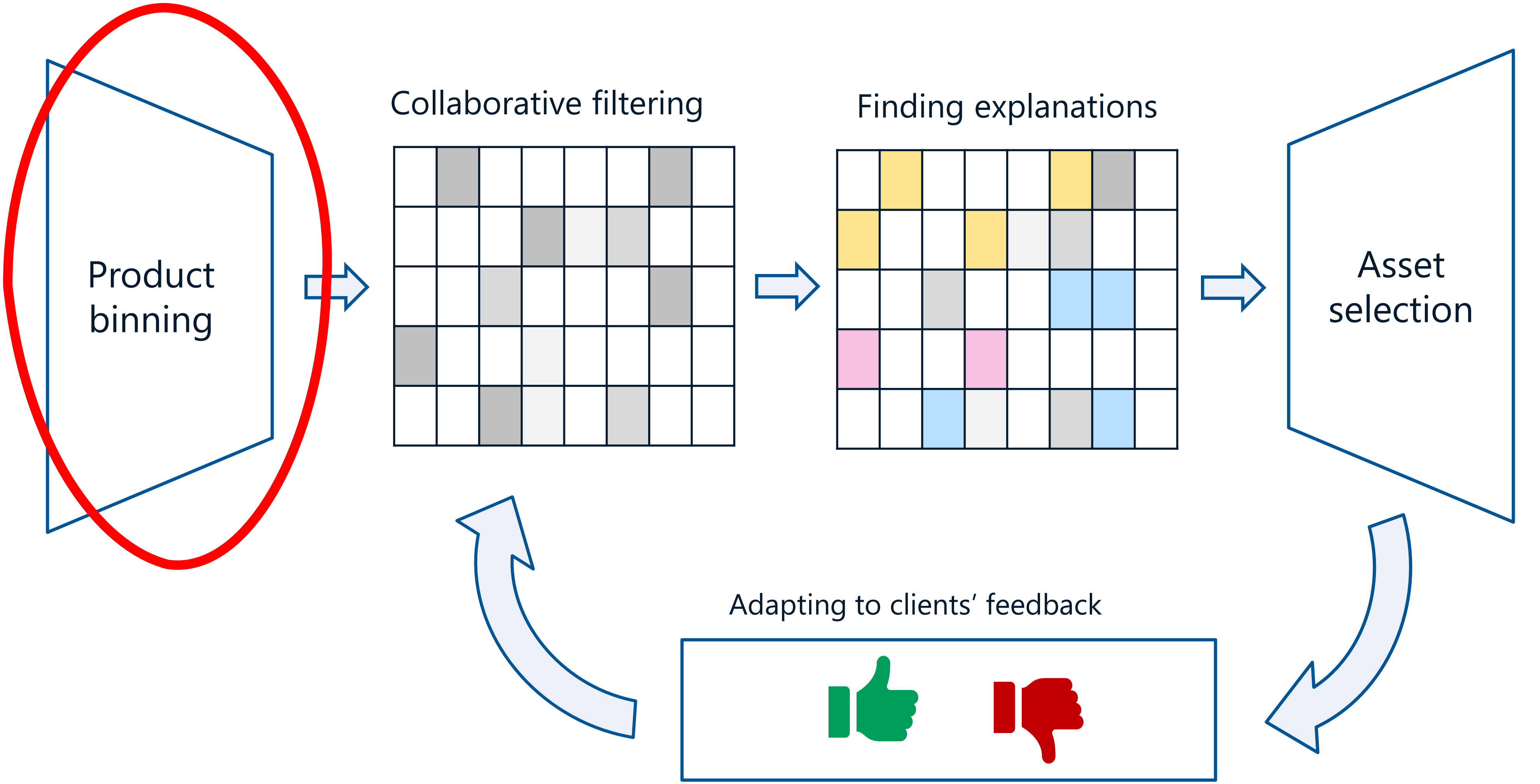
- **Movies** (Netflix)
- **Songs** (Spotify)
- **Books** (Goodreads)
- **E-commerce products** (Amazon)

Challenges in the area of Financial Advice

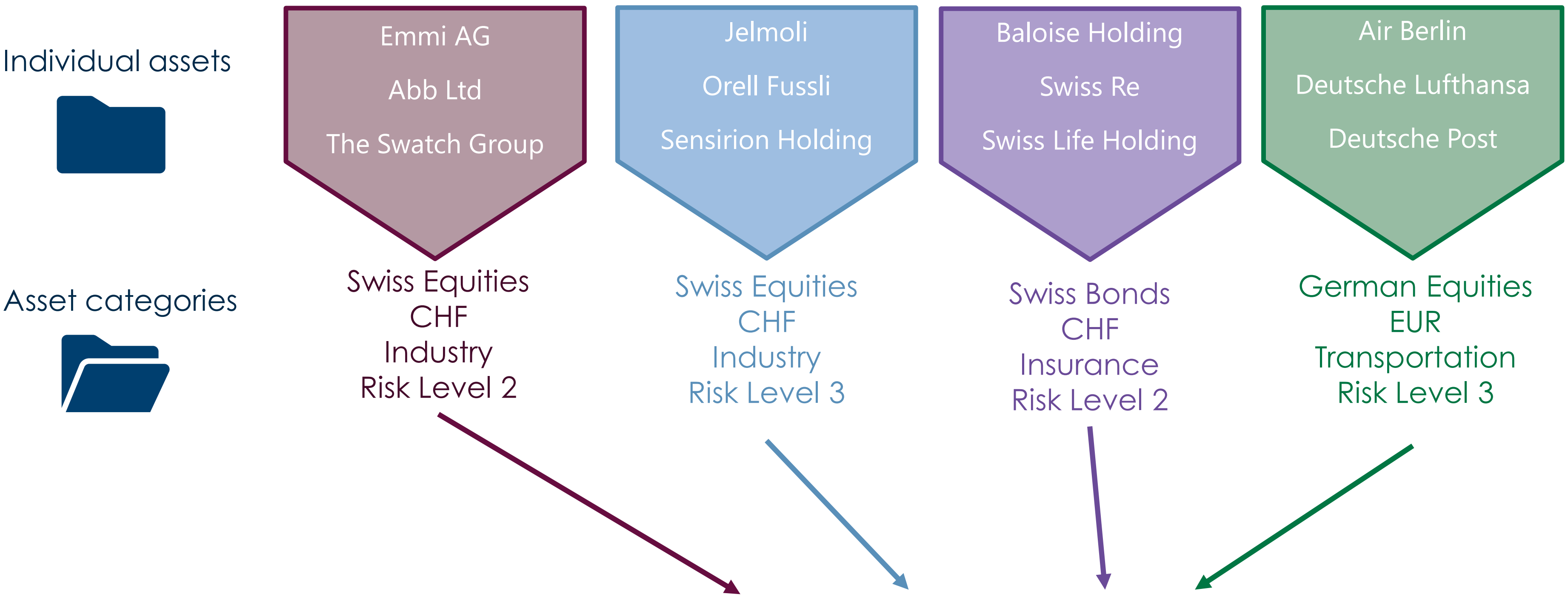
- Regulatory compliance
- Explanations are essential
- No explicit feedback initially
- Need to react to explicit feedback given at later stages
- Product nature might change over time

Outline

Overview of the system



Product Binning
Approach



Ratings matrix

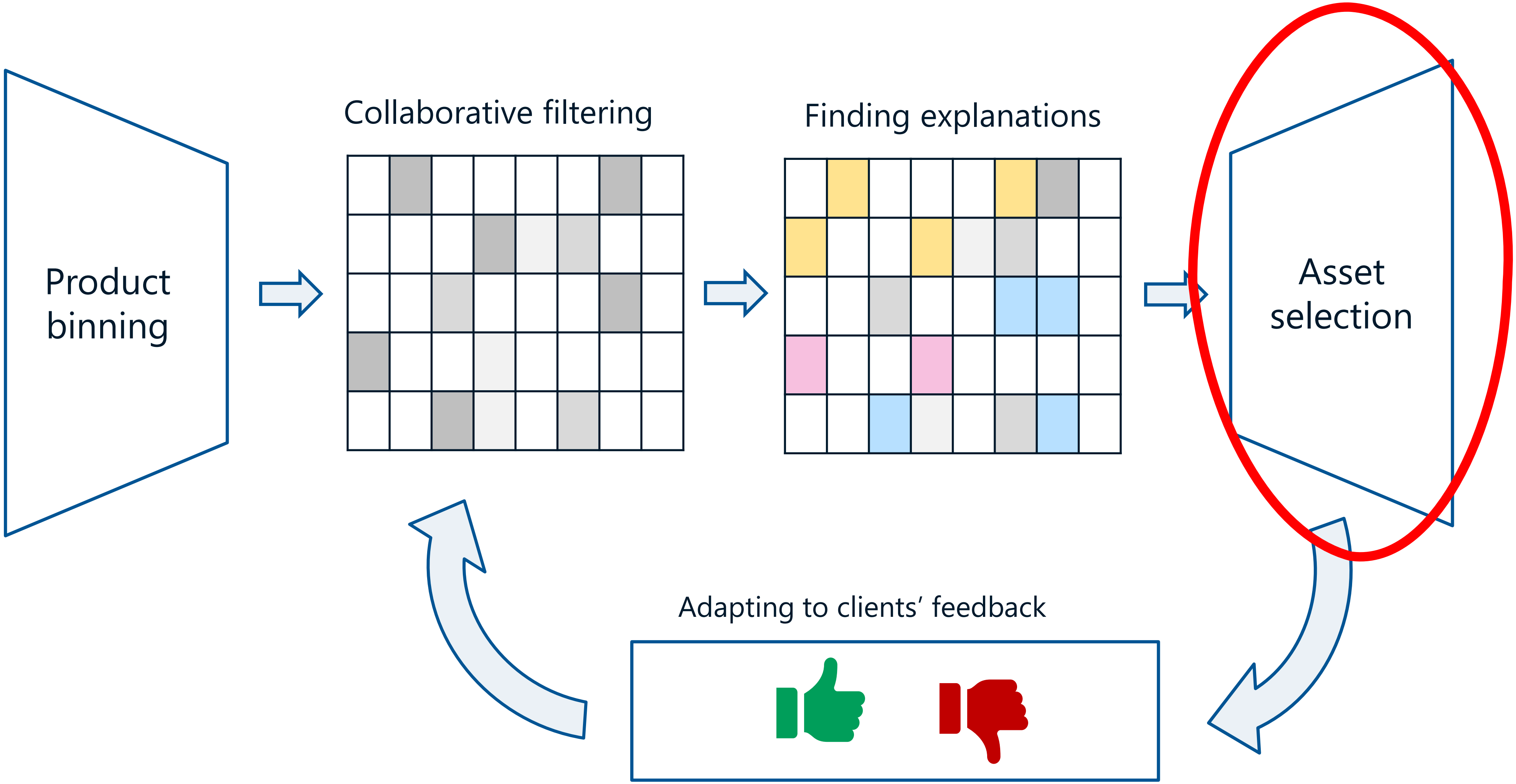
client1	1	0	0	1	1	0
client2	0	1	0	0	0	1
client3	1	1	0	0	0	0
client4	0	0	1	0	0	0
...	0	0	0	1	1	0

Product Binning
Which Issues it Solves

- Cold-start for products
- Time-varying product features
- Too many dimensions
- Too much sparsity

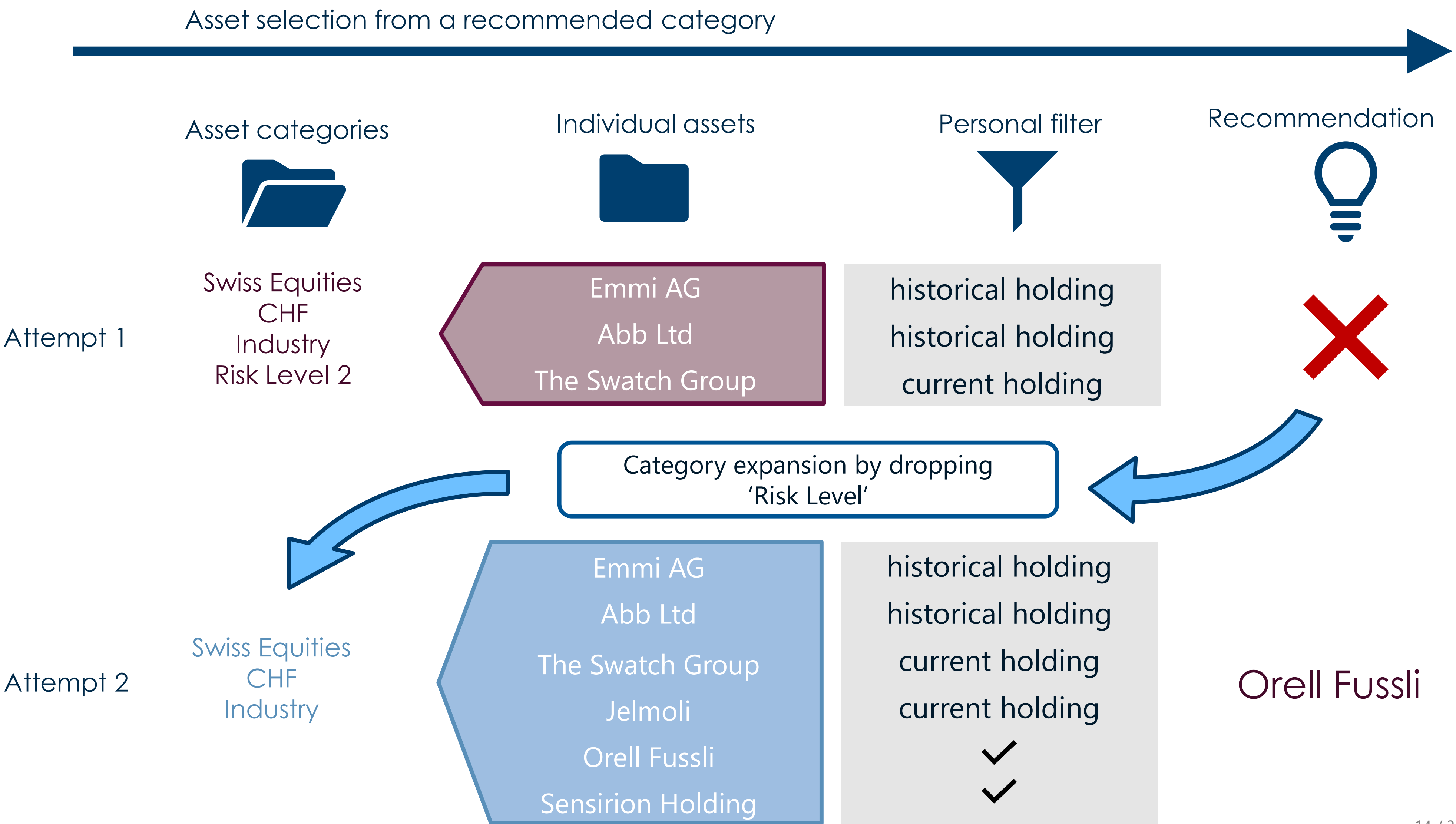
- Allows coupling with business logic
- Can help with extension of bank's recommendation lists

Overview of the system



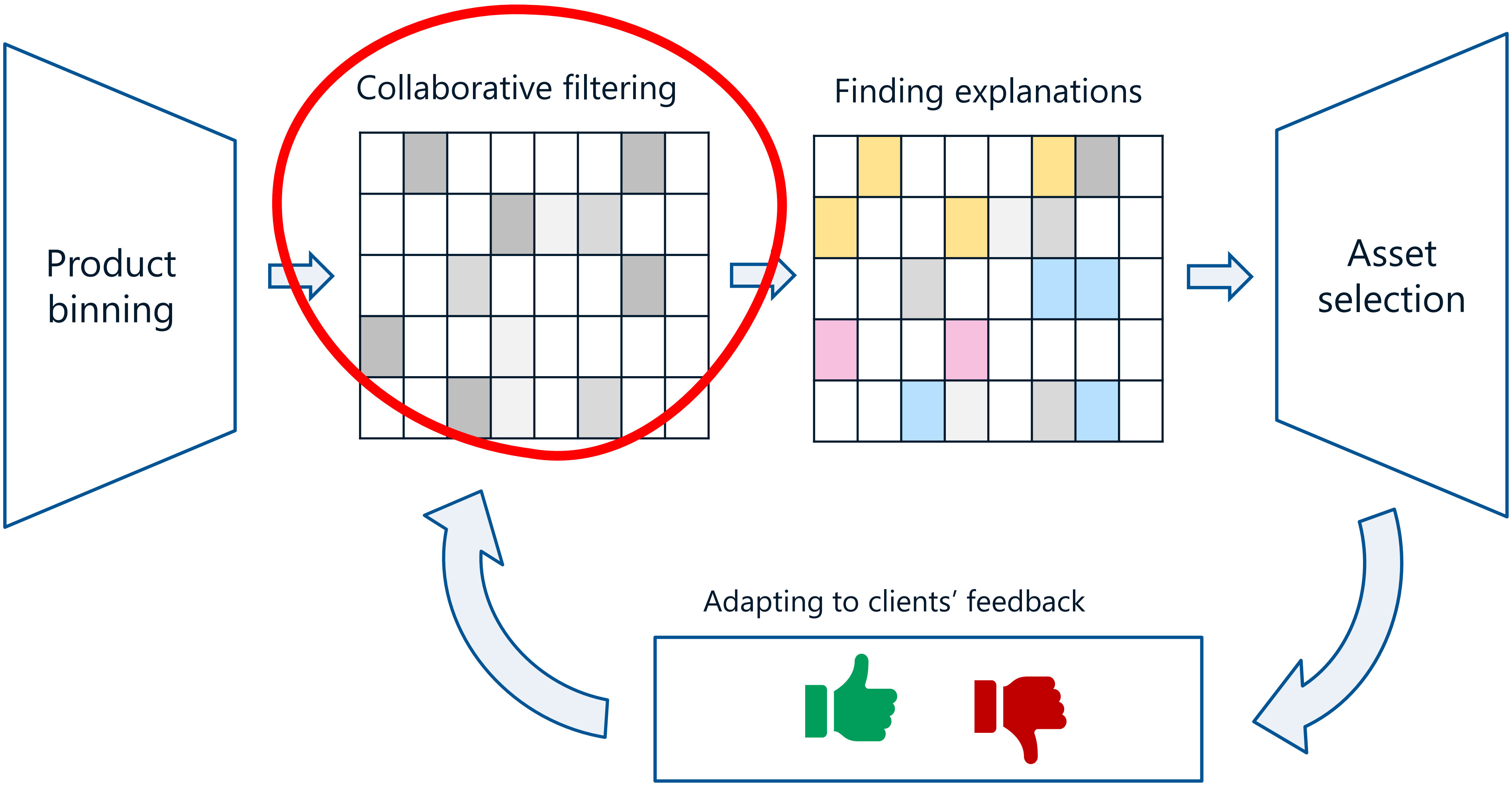
Product Binning

Compliant Selection from the Bin



Outline

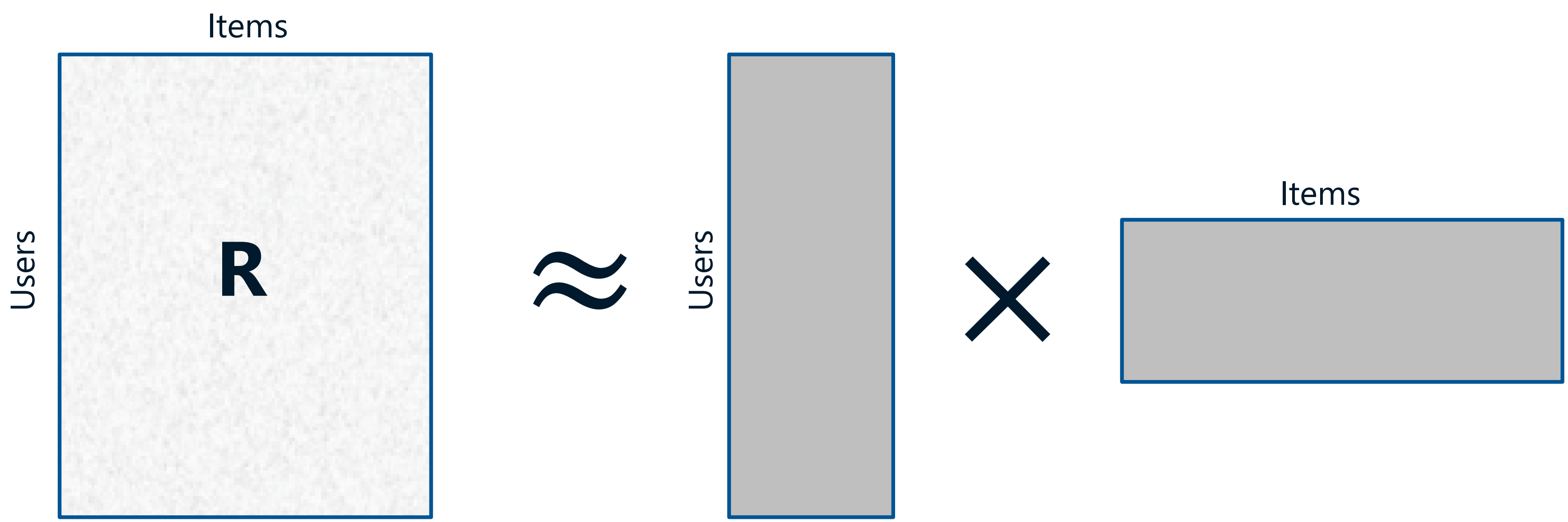
Overview of the system



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:

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

Preference matrix:

$$\boldsymbol{P} = \{p_{ij}\} = \mathbb{I}\{r_{ij} > 0\}$$

Confidence weights

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

$$\widehat{\boldsymbol{P}} = \widehat{\boldsymbol{X}}_{[|U| \text{ x } k]} \cdot \widehat{\boldsymbol{Y}}^{\boldsymbol{T}}_{[|I| \text{ x } k]}$$

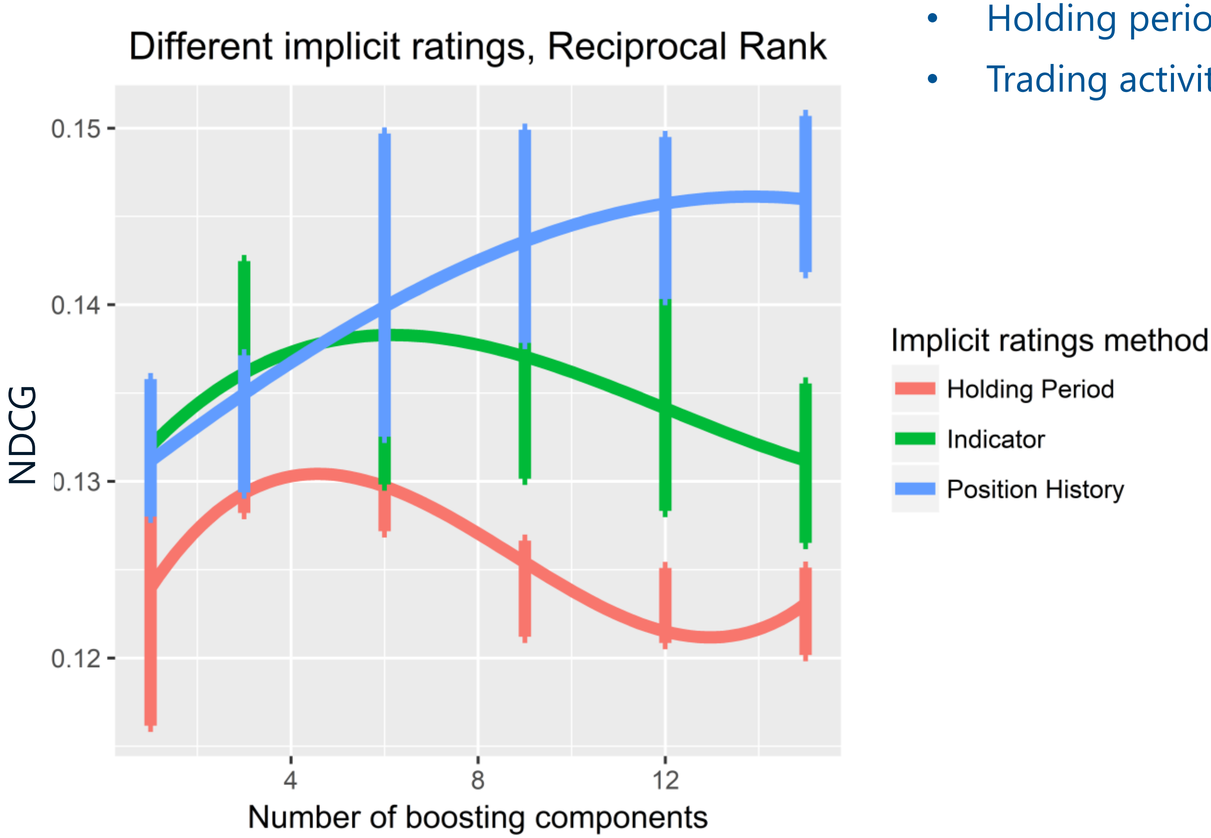
$$\text{such that} \sum_{i,j} {\color{red}c_{ij}} \left(p_{ij} - \hat{p}_{ij}\right)^2 + \lambda\left(\|\widehat{\boldsymbol{X}}\|_2^2 + \|\widehat{\boldsymbol{Y}}\|_2^2\right) \longrightarrow \ min$$

$\widehat{\boldsymbol{X}}_{[|U| \text{ x } k]}, \widehat{\boldsymbol{Y}}_{[|I| \text{ x } k]}$ - ‘latent features’ matrices

$\widehat{\boldsymbol{P}}$ - imputed ratings matrix

Model Based Collaborative Filtering

Approach to Modeling of Implicit Ratings



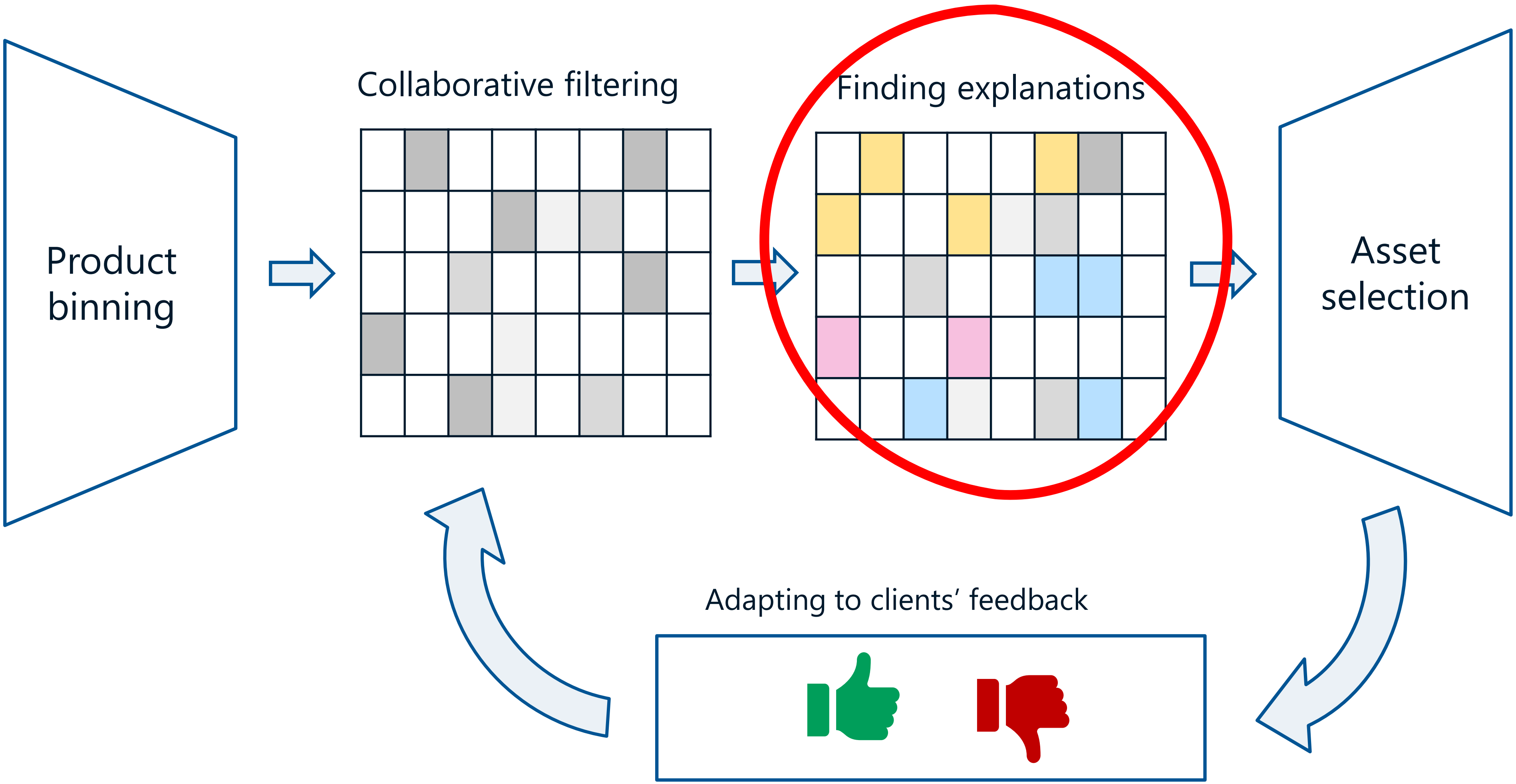
Implicit ratings handling matters

There are plenty approaches to handling of implicit ratings

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

Outline

Overview of the system



Explainability

Find Co-clusters in the Matrix

	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

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

	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

Explainability

Find Co-clusters in the Matrix

	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

Explainability

Find Co-clusters in the Matrix

	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:

Explainability

Find Co-clusters in the Matrix

	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**

Explainability

Find Co-clusters in the Matrix

	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**

Explainability

Find Co-clusters in the Matrix

	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

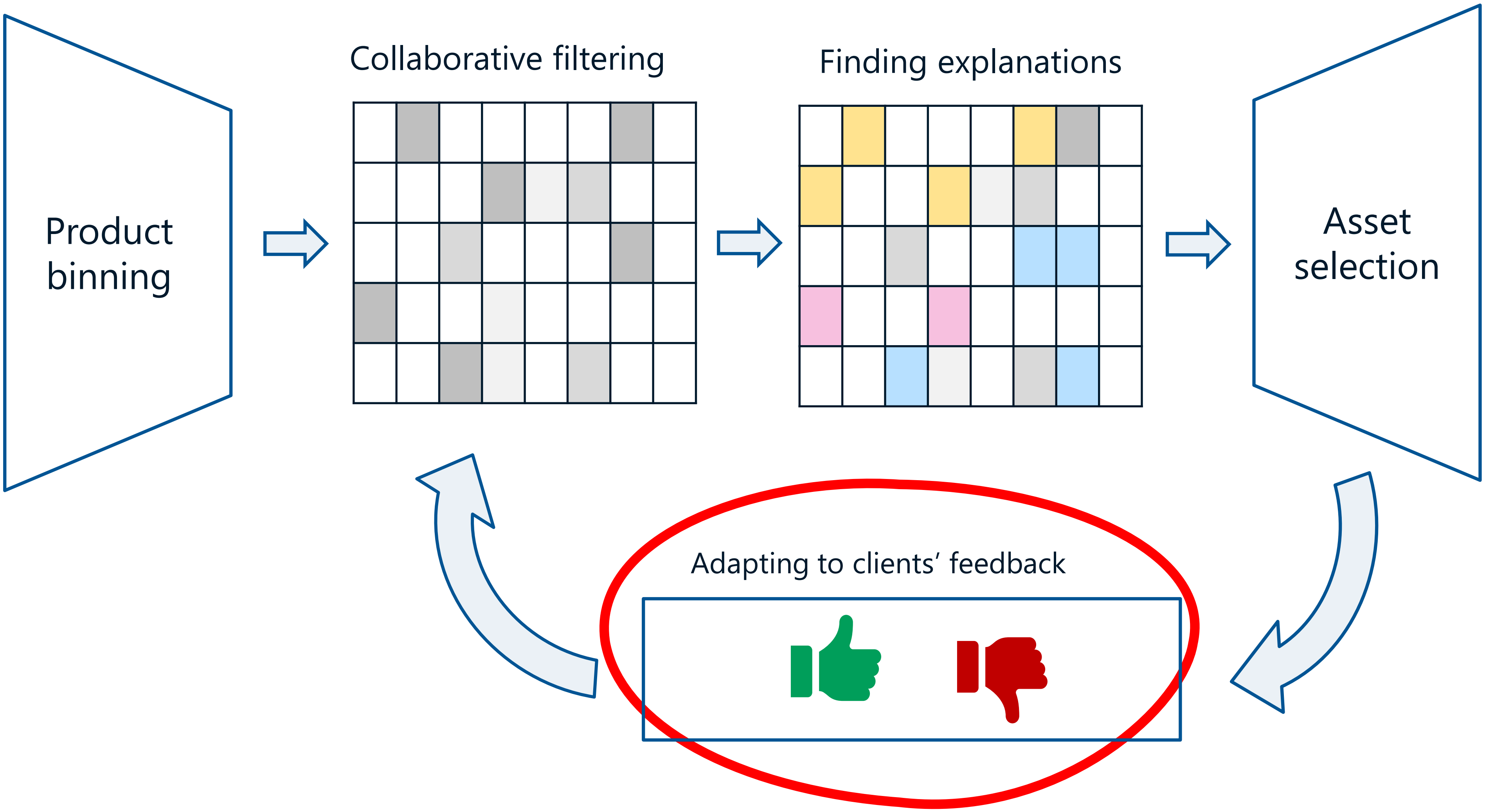
Recommendation: **Item 4** is recommended to **Client 4** because:

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**

Outline

Overview of the system



Explicit Feedback

Approach

Clients can rate the ideas: binary feedback

Feedback enters the prediction loop for the next batch of recommendations

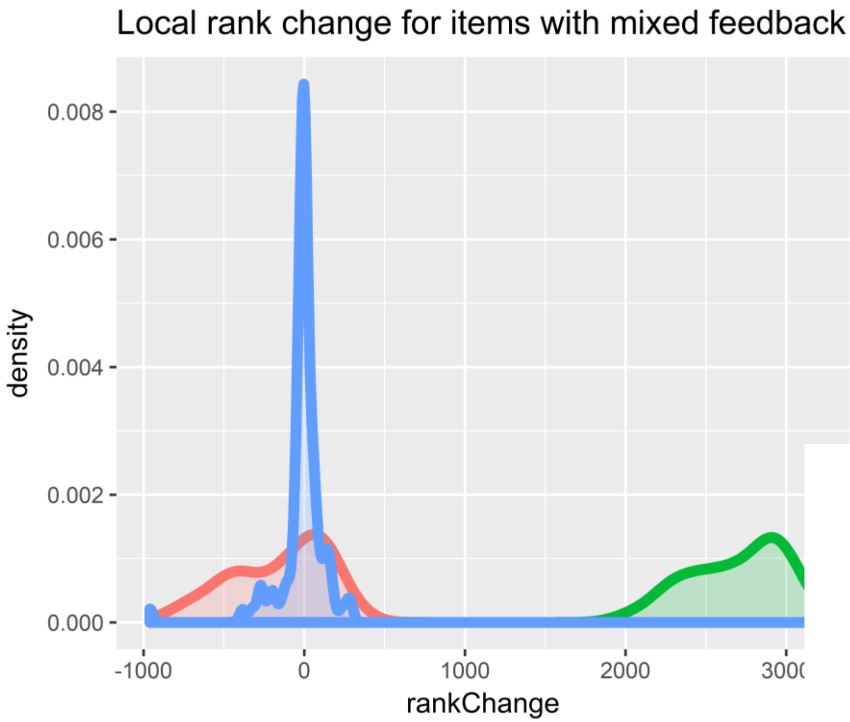
Experiments showed this approach to be legit

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

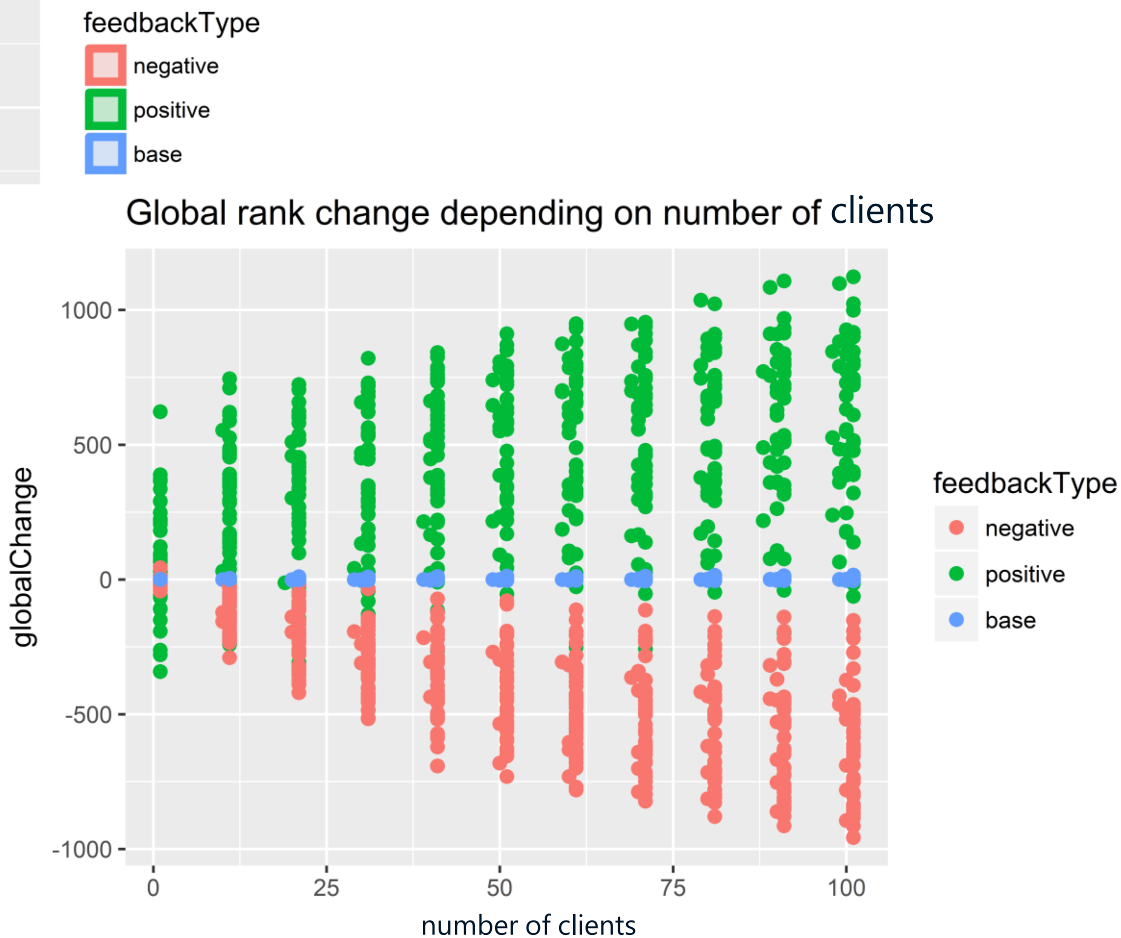
- $p_{ij} = 0$
- $c_{ij} = c_{max}$
- $\hat{p}_{ij}$ is forced to be 0

- $p_{ij} = p_{max}$
- $c_{ij} = c_{max}$
- $\hat{p}_{ij}$ must be high

Explicit Feedback
Experiments



"How my feedback affects my recommendations?"

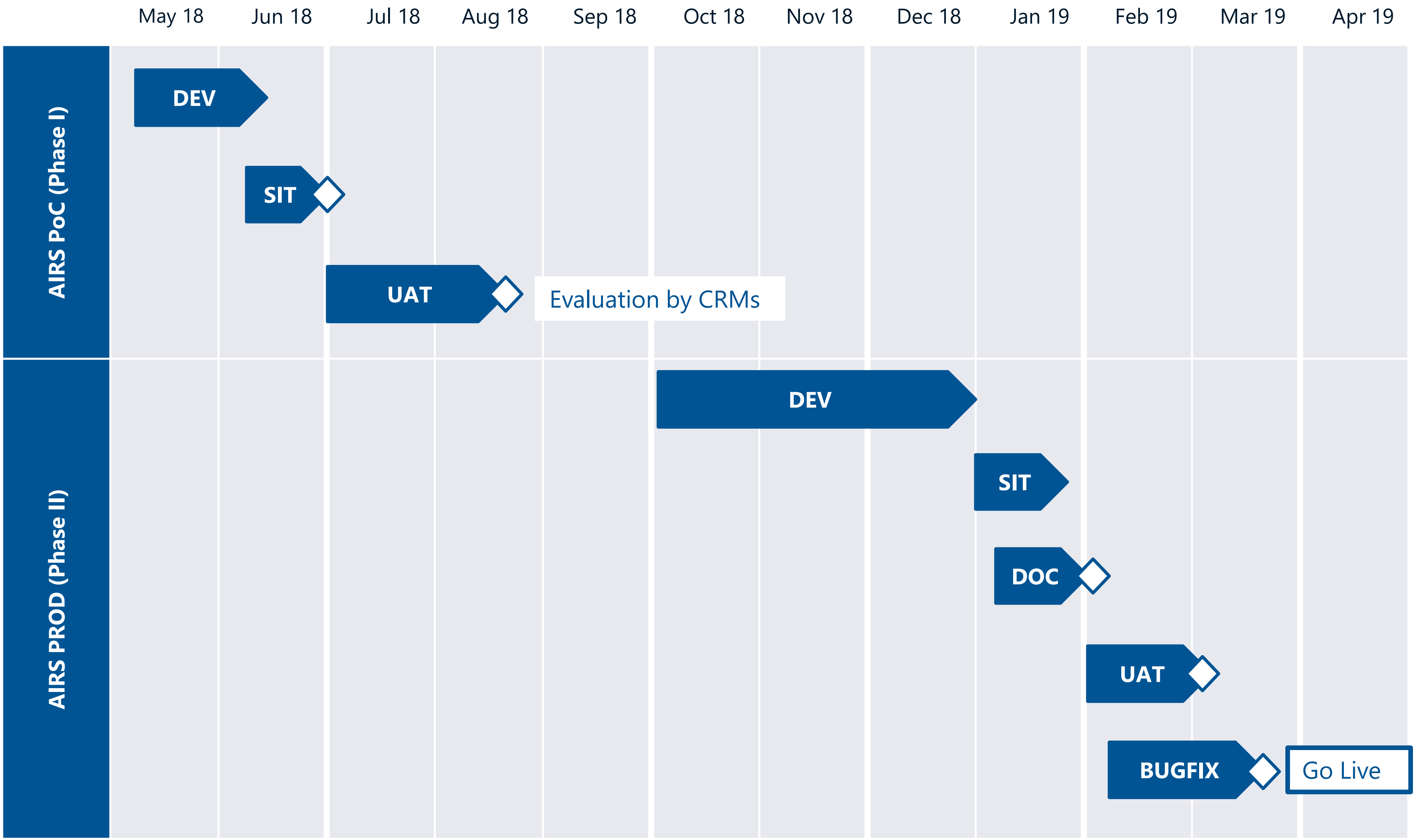


"How feedback of other clients affects my recommendations?"

Outline

Integration into Core Services

Project Timeline



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

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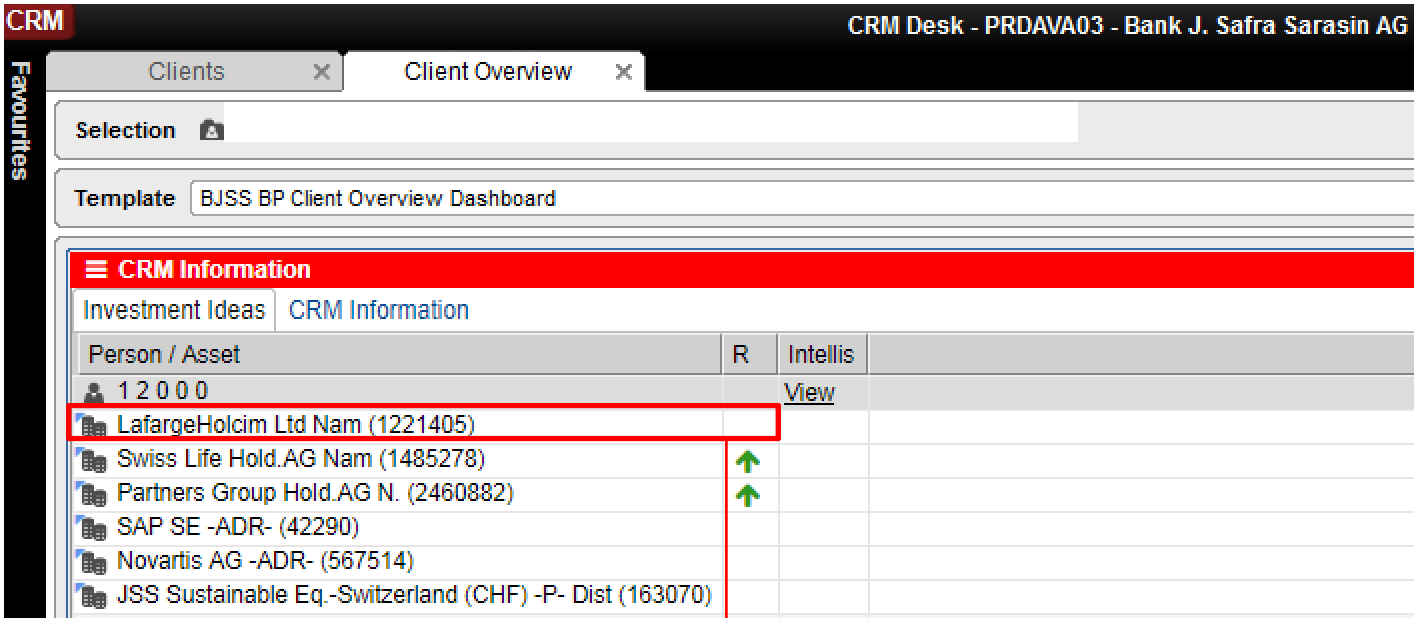

LafargeHolcim Ltd Nam (1221405)	
Reason	As you bought ABB Ltd Nam. (1222171) you may like LafargeHolcim Ltd Nam (1221405)
Selection Path	CH0012214059 LafargeHolcim Ltd Nam (1221405) chosen at ReducedMarketSetMarket level from ModelPortfolio. Category name : Equities Switzerland Currency : CHF. Filter info: Start with 2 candidates. KnE removed no assets. last 3 months removed no assets. existing recommendations LdsId 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

J. SAFRA SARASIN
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J. SAFRA SARASIN — DASHBOARD | FINANCES | PAYMENTS | TRADING | SERVICES — 277

INDICES (WORLD)

EURO STOXX 50	3'343.22	0.29 % ↗
DAX	12'114.52	0.49 % ↗
NIKKEI 225	23'094.67	1.20 % ↗
DOW JONES SINGAPORE(SGD)	263.92	0.21 % ↗
SMI	8'966.82	0.08 % ↗

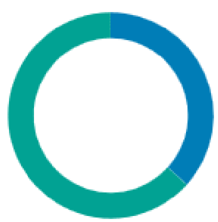
INDICES (EUROPE)

CAC 40	5'354.92	0.50 % ↗
EURO STOXX 50	3'343.22	0.29 % ↗
DAX	12'114.63	0.49 % ↗
AEX	540.63	0.21 % ↗
RTS INDEX	1'094.00	0.87 % ↗

EXCHANGE RATES

USD/CHF	0.9664	0.0083 % ↗
EUR/USD	1.1669	-0.1925 % ↘
USD/JPY	111.9790	-0.0411 % ↘
GBP/USD	1.3099	-0.0824 % ↘
EUR/CHF	1.1275	-0.1956 % ↘
GBP/CHF	1.2659	-0.0703 % ↘

PORTFOLIO GRAPH



PORTFOLIO POSITIONS

Allianz SE Nam. -vink.- (322646) ALV / 196.00	36'365.84 134.06 %
ASML Holding NV (19531091) ASML / 205.00	35'526.50 76.15 %
Atlantia SpA (1683373) AUT / 1'340.00	24'964.20 -0.32 %
Axa (486352) CS / 1'320.00	28'683.60 127.54 %

EQUITY MARKETS (SMALL)

SMI

SMI 0.08 %
8'966.82 CHF 14.09.2018 15:35

1D 1W 1M 3M YTD 1Y 5Y MAX

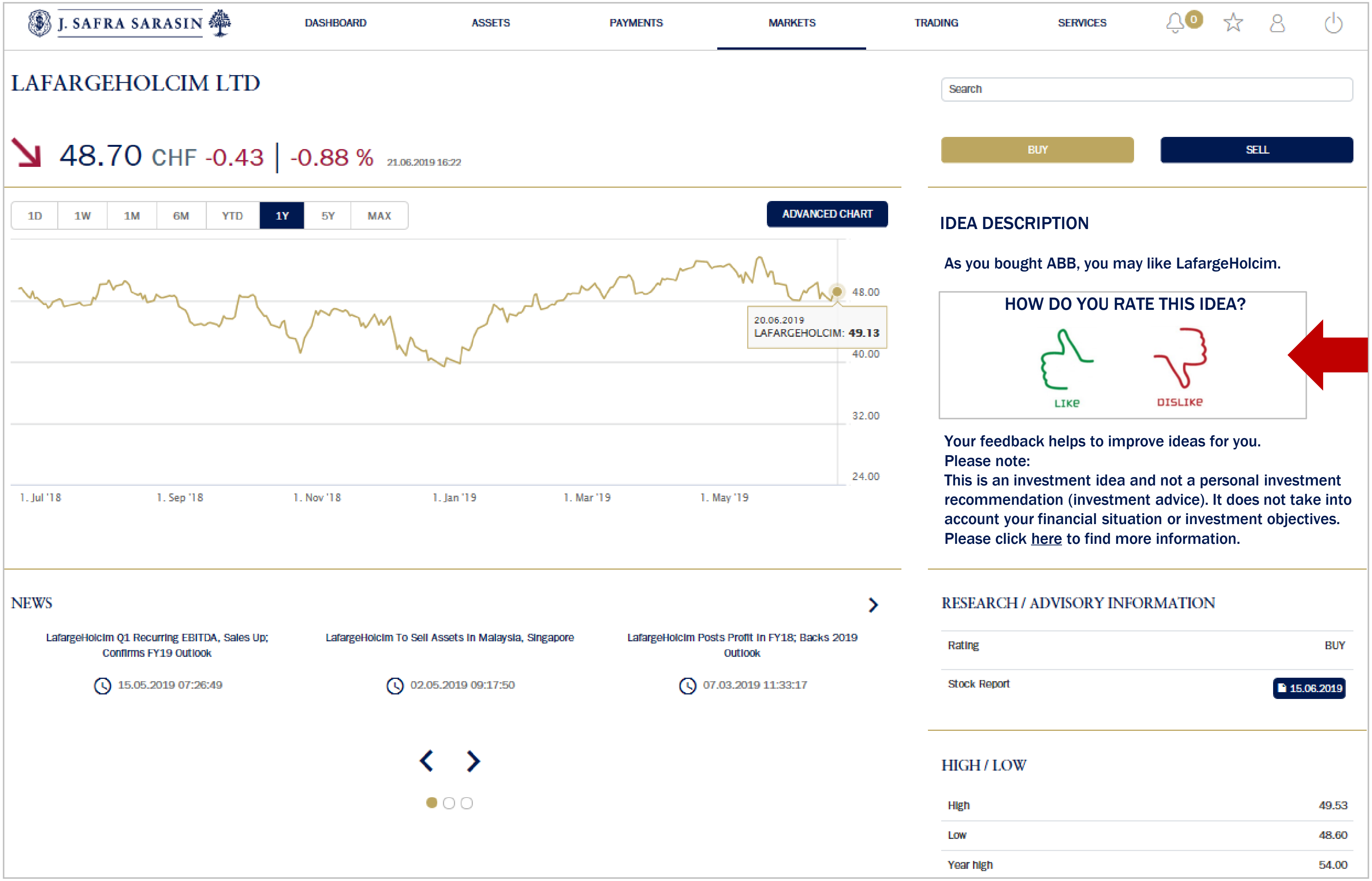
Best

SWISS RE	88.02 CHF	0.76 % ↗
GEBERIT N	448.20 CHF	0.74 % ↗
CIE FIN RICHEMONT	81.60 CHF	0.69 % ↗
SWATCH GROUP	383.70 CHF	0.66 % ↗
ABB LTD	23.28 CHF	0.56 % ↗

INVESTMENT IDEAS

LafargeHolcim	Share
Swiss Life	Share
Partners Group	Share
SAP SE	Share
Novartis	Share
JSS Sustainable Equities Switzerland (CHF)	Equity fund

AIRS Learns Based upon Feedback



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