course:

Searching the Web (NDBI038)

Searching the Web and Multimedia Databases (BI-VWM)

lecture 7:

Personalized search and social context

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Today's lecture outline

- recommender systems
  - collaborative filtering
  - content recommendation
  - knowledge-based recommendation
  - social recommender systems
- social information retrieval
  - social network = graph
  - social pagerank

Web 2.0

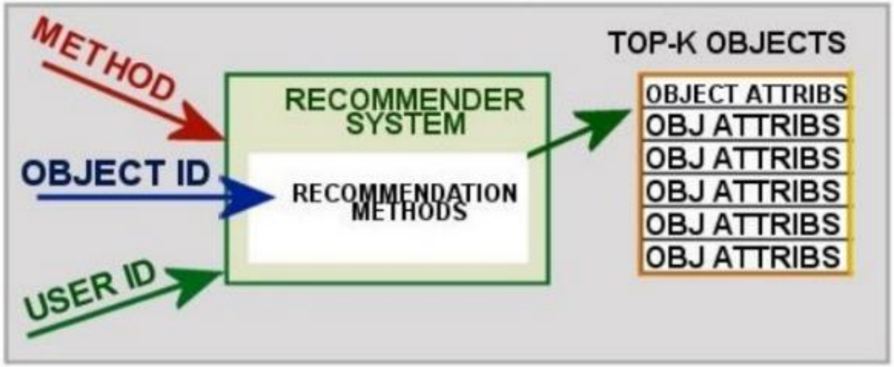
- basic web infrastructure is application-agnostic
- personalization in (web) applications
  - blogs, forums, e-commerce, social media, hosting services, e-banking, e-gov
  - cloud services (office, collaboration, video, etc)
- people part of web creation
  - user-generated content
  - user profiles
  - online communities

Social media

- social media
  - allow people to share content and interact
  - social networks (explicit or inferred)
- information overload
  - blogs, youtube, news, forums, wiki, social networks
- interaction overload
  - friends, followers, comments, sharing, „likers"
- content-based search not sufficient

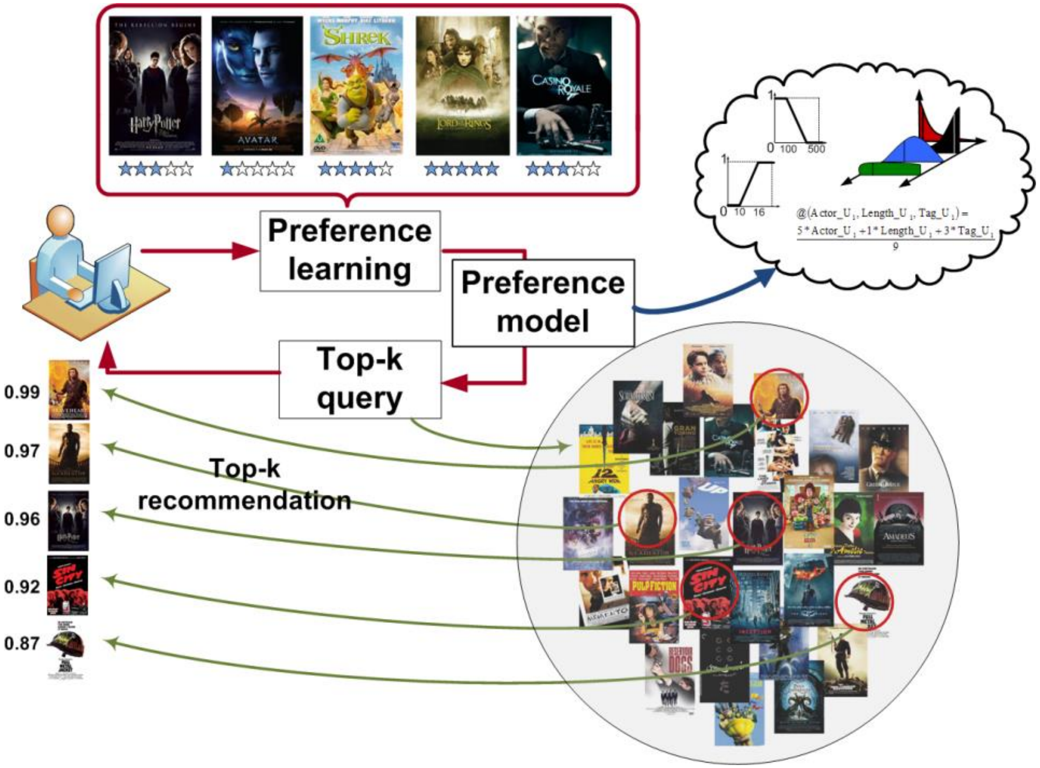
Recommender systems

- subsystems within applications registering users (and items)
- input
  - user + history
  - actual context
    - web page
    - locality
    - time, season
    - actual item displayed
  - item/user attributes (profiles)
- output
  - top-k list of items
  - item ratings
  - presentation and recommendation of top-ranked items



Recommender systems

1. collect user feedback
2. learn preferences
3. recommend top-k items



Moment of recommendation
- front page, sidebar
- follow-up
- on demand

Recommender systems

- user feedback
  - explicit (e.g., ratings) 
    - like annotation
      - \+ precisely stated preference
      - \- not guaranteed, not complete, subjective, inconsistent, etc.,
    - problem in e-commerce – need to buy/try item before
  - implicit (tracking user behavior)
    - noisy, hard to interpret
    - problem – what to track?
      - time on page/object, number of visits, display zoom, mouse clicks/hovers, etc.
    - for free and objective (user cannot fake like by the explicit)

Recommender approaches

- **collaborative filtering** (CF)
  - recommendation based on inter-user similarity
- **content-based recommendation**
  - based on matching features of items to user ratings
- **knowledge-based recommendation**
  - based on matching items to user needs
- **demographic recommendation**
  - based on demographic classes (age, gender, ...)
- hybrid
  - combinations of the above

Recommender approaches

Technique	Model	Source	Method
Collaborative filtering	user-item matrix	rating users x items	identify similar users, extrapolate from their ratings
Content-based	item features	rating users x items	generate a classifier based on user ratings
Knowledge-based	item features	user needs	infer a match between items and user’s needs
Demographic	demographic attributes	demographic attributes	identify similar users, extrapolate from their ratings

Collaborative filtering

- implements recommendation using advice from trusted people (friends, colleagues, etc.)
  - similarities of all users to the active user are computed
  - a subset of most similar users is selected
  - prediction of active user's rating of specific items is computed based on users' rankings
  - recommendation of items with maximum prediction

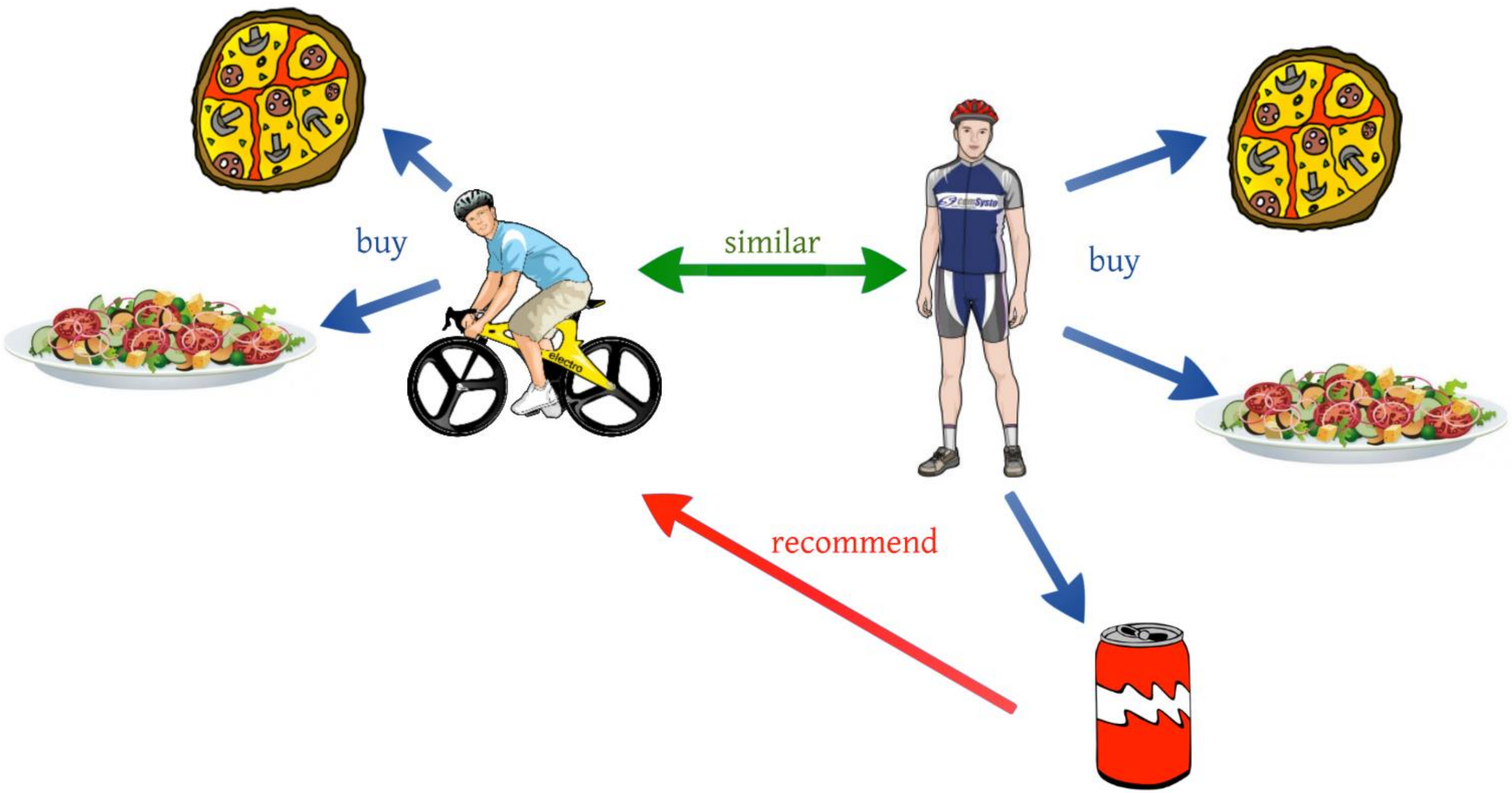
Collaborative filtering

user	Inglourious basterds	Hunger games	Alien
Peter	like	like	dislike
Dana	n/a	dislike	like
Michael	like	like	dislike
Bob	like	like	n/a

Shall we recommend Alien to Bob?

Bob taste is similar to both Peter and Michael, so do **not recommend** Alien to Bob.

Collaborative filtering



Collaborative filtering

- user-based nearest neighbor CF algorithm
  - the mean vote for user i: $$\overline{v}_i = \frac{1}{|I_i|} \sum_{j \in I_i} v_{i,j}$$

    $v_{i,j}$ = vote (ranking) of user i on item j
    I_i = items on which user i has voted (ranked)
  - predicted vote (rank) of active user a:

$$p_{a,j} = \overline{v}_a + \underbrace{\kappa}_{\text{normalizer}} \sum_{i=1}^{n} \underbrace{w(a,i)}_{\text{weights of } n \text{ similar users}} (v_{i,j} - \overline{v}_i)$$

Collaborative filtering

- cosine similarity

$$\text{simil}(x,y) = \cos(\vec{x},\vec{y}) = \frac{\vec{x}\cdot\vec{y}}{||\vec{x}|| \times ||\vec{y}||} = \frac{\sum\limits_{i\in I_{xy}} r_{x,i} r_{y,i}}{\sqrt{\sum\limits_{i\in I_x} r_{x,i}^2}\sqrt{\sum\limits_{i\in I_y} r_{y,i}^2}}$$

- Pearson similarity

$$\text{simil}(x,y) = \frac{\sum\limits_{i\in I_{xy}} (r_{x,i} - \bar{r_x})(r_{y,i} - \bar{r_y})}{\sqrt{\sum\limits_{i\in I_{xy}} (r_{x,i} - \bar{r_x})^2 \sum\limits_{i\in I_{xy}} (r_{y,i} - \bar{r_y})^2}}$$

Collaborative filtering

- item-based nearest neighbor CF algorithm
  - similarity of items
  - prediction for an item based on the user's ratings for similar items

user	Inglourious basterds	Hunger games	Alien
Peter	like	like	dislike
Dana	n/a	dislike	like
Michael	like	like	dislike
Bob	like	like	n/a

Dana dislikes Hunger games (similar to Ingl.bast.) $\rightarrow$ do not recommend Hunger games to Dana

Collaborative filtering

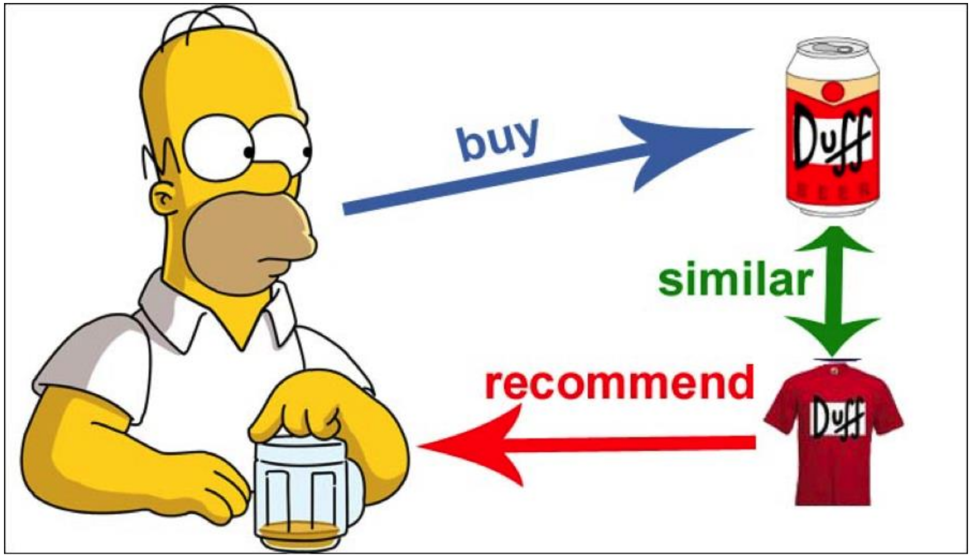
- problems
  - ratings data sparse – prone to skewed correlations
    - nearest neighbor actually not near at all
      - random recommending
  - some users have only single session
    - need to learn fast
  - fails to incorporate agreement about an item in the population
    - controversial vs. loved item
  - expensive calculation of similar users
    - sampling
    - clustering/indexing

Collaborative filtering

- reduce the domain complexity by dimensionality reduction
  - latent topics/tastes/categories in items
  - improve accuracy in predicting
  - reduction of runtime
- SVD and PCA
- recently machine learning
  - e.g., simulated users/ratings to cope with the data sparsity problem

Content-based recommendation

- instead of user-item ratings, we need content information
  - about items (annotation, content-based descriptor)
  - about user profiles (preferences, content-based descriptor)



Content-based recommendation

- CB nearest neighbor recommendation
  - k-nearest neighbors
  - predicting rating for not-yet-seen item
    - find k most similar items (based on features), already rated
    - predict rating based on these
- content-based similarity
  - vector model (bag of words)
    - full-text content
  - other similarity models (also see next lectures)
    - multimedia content
      - metric distances
    - keyword sets A, B
      - Dice coefficient $2*|A \cap B|/(|A|+|B|)$ Jaccard coefficient $|A \cap B|/|A \cup B|$

Content-based recommendation

- classification
  - features $\rightarrow$ rating (like/dislike)
  - machine learning techniques
    - Naive Bayes
    - linear classifiers
    - decision trees
    - neural networks
    - SVM
    - ...

Content-based recommendation

- advantages
  - user independence – does not depend on other users (and so possible sparsity)
  - transparency – explanations, understandable
  - new items can be easily included – no cold start like in CF
- limitations
  - limited content analysis
    - some content not easily extractable (multimedia)
    - domain dependent
    - annotation insufficient/missing
  - overspecialization – too similar items
  - new user – user features missing at the beginning, must be collected

Knowledge-based recommendation

- some application domains
  - not frequently purchased items, few ratings
    - expensive items (supersport car, house, yacht)
    - professional items (surgeon instruments, tools)
  - time span important (tech products)
  - explicit requirements of user (vacation)
- collaborative filtering not applicable
- content-based filtering – insufficient similarity

→ knowledge-based recommendations

Knowledge-based recommendation

- constraint-based
  - explicitly defined conditions
  - constraint satisfaction problem
- case-based
  - similarity to specified requirements

Knowledge-based recommendation

- knowledge base
  - customer (user) properties V_C
  - product (item) features V_{PROD}
  - constraints (on customer properties) C_R
  - filter conditions C_F – relationship between customer and product
  - products C_{PROD} – possible instantiation

$V_C = \{kl_c$: [expert, average, beginner] .... /* level of expertise */
wr_c: [low, medium, high] .... /* willingness to take risks */
id_c: [shortterm, mediumterm, longterm] .... /* duration of investment */
aw_c: [yes, no] .... /* advisory wanted ? */
ds_c: [savings, bonds, stockfunds, singleshares] ...... /* direct product search */
sl_c: [savings, bonds] .... /* type of low-risk investment */
av_c: [yes, no] .... /* availability of funds */
sh_c: [stockfunds, singlshares] .... /* type of high-risk investment */ }

$V_{PROD} = \{name_p$: [text] .... /* name of the product */
er_p: [1..40] .... /* expected return rate */
ri_p: [low, medium, high] .... /* risk level */
$mniv_p$: [1..14] .... /* minimum investment period of product in years */
$inst_p$: [text] .... /* financial institute */ }

$$C_R = \{CR_1: wr_c = high \rightarrow id_c \neq shortterm,$$
$$CR_2: kl_c = beginner \rightarrow wr_c \neq high\}$$

$$C_F = \{CF_1: id_c = shortterm \rightarrow mniv_p < 3,$$
$$CF_2: id_c = mediumterm \rightarrow mniv_p \geq 3 \wedge mniv_p < 6,$$
$$CF_3: id_c = longterm \rightarrow mniv_p \geq 6,$$
$$CF_4: wr_c = low \rightarrow ri_p = low,$$
$$CF_5: wr_c = medium \rightarrow ri_p = low \vee ri_p = medium,$$
$$CF_6: wr_c = high \rightarrow ri_p = low \vee ri_p = medium \vee ri_p = high,$$
$$CF_7: kl_c = beginner \rightarrow ri_p \neq high,$$
$$CF_8: sl_c = savings \rightarrow name_p = savings,$$
$$CF_9: sl_c = bonds \rightarrow name_p = bonds\ \}$$

$$C_{PROD} = \{CPROD_1: name_p = savings \wedge er_p = 3 \wedge ri_p = low \wedge mniv_p = 1 \wedge inst_p = A;$$
$$CPROD_2: name_p = bonds \wedge er_p = 5 \wedge ri_p = medium \wedge mniv_p = 5 \wedge inst_p = B;$$
$$CPROD_3: name_p = equity \wedge er_p = 9 \wedge ri_p = high \wedge mniv_p = 10 \wedge inst_p = B\}$$

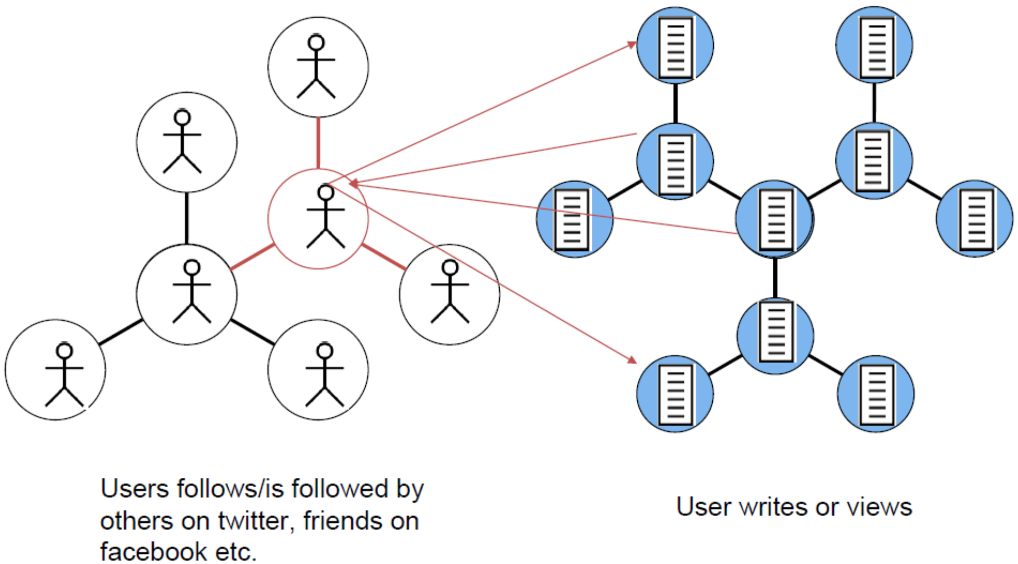
Recommender Systems Handbook; Developing Constraint-based Recommenders

Knowledge-based recommendation

- development of knowledge bases
  - difficult, expensive
  - specialized tools
  - methodology
    - rapid prototyping, detection of invalid constraints
  - unsatisfied constraints
    - problem of empty result – similar to restrictive Boolean query
    - constraint relaxation, hints to the relaxation
  - user guidance
    - elicitation process – conversational dialogs, user profile

Social information retrieval

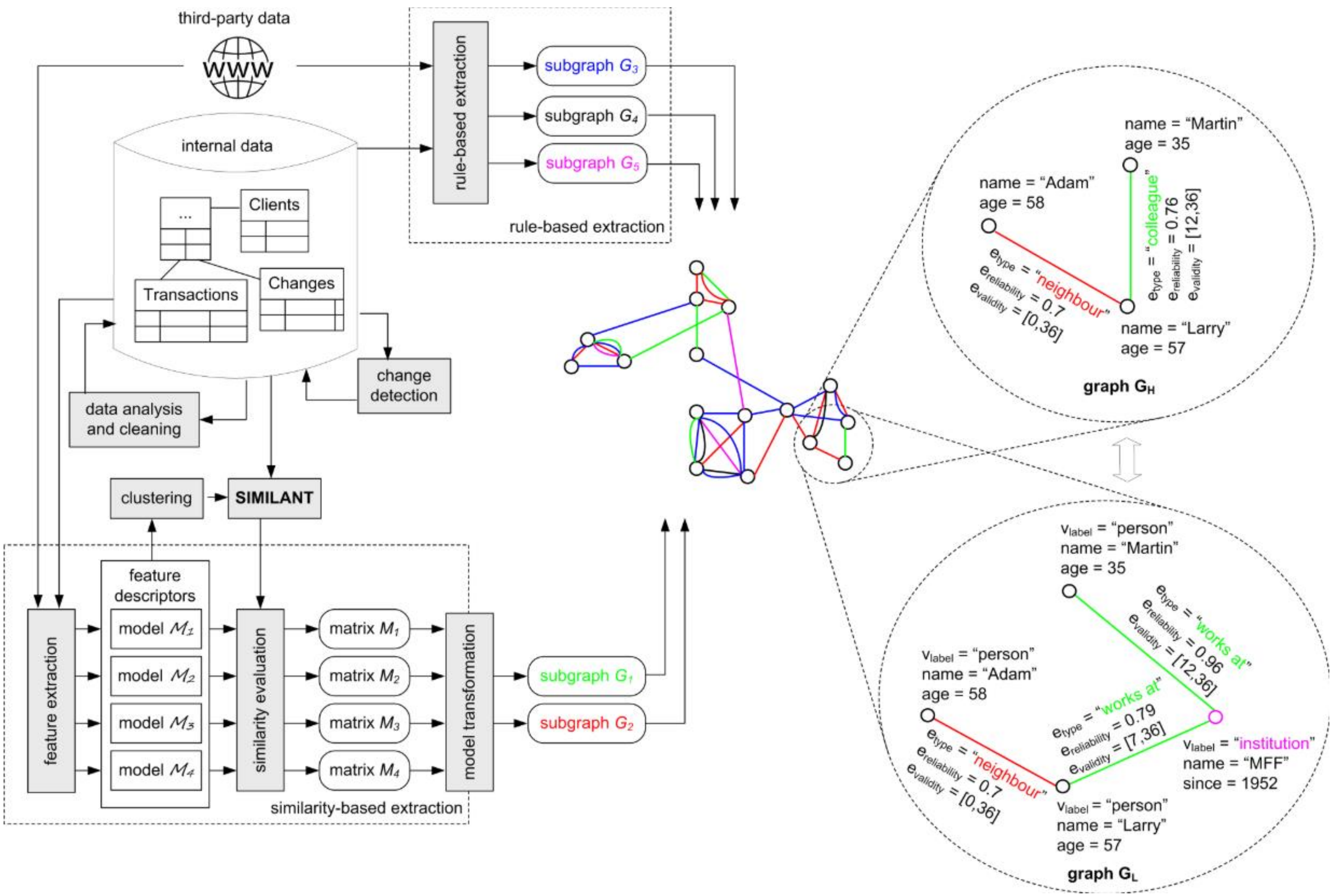
- social network platform
- users and documents (posts)
- multi-graph



Social information retrieval

- inferred social networks
  - constructed from other data by spatial/similarity joins (see later lectures)
  - domain-specific construction, legal issues
- examples
  - network of bank clients
    - similarity join on client profiles
  - COVID-19 suspects
    - spatial join on phone-localized data

Social information retrieval



I. Holubová, M. Svoboda, T. Skopal, D. Bernhauer, L. Peška. **Advanced Behavioral Analyses Using Inferred Social Networks: a Vision**, *TIR 2019*, Springer, 2019

Social information retrieval

- social PageRank
  - different graph, the same purpose as original PageRank
  - a tweeter is reliable/popular if retweeted by other popular tweeters
  - could be fine-grained to some domains (e.g., #hashtags)
    - tweeter reliable in technological topics but not in general topics

Social information retrieval

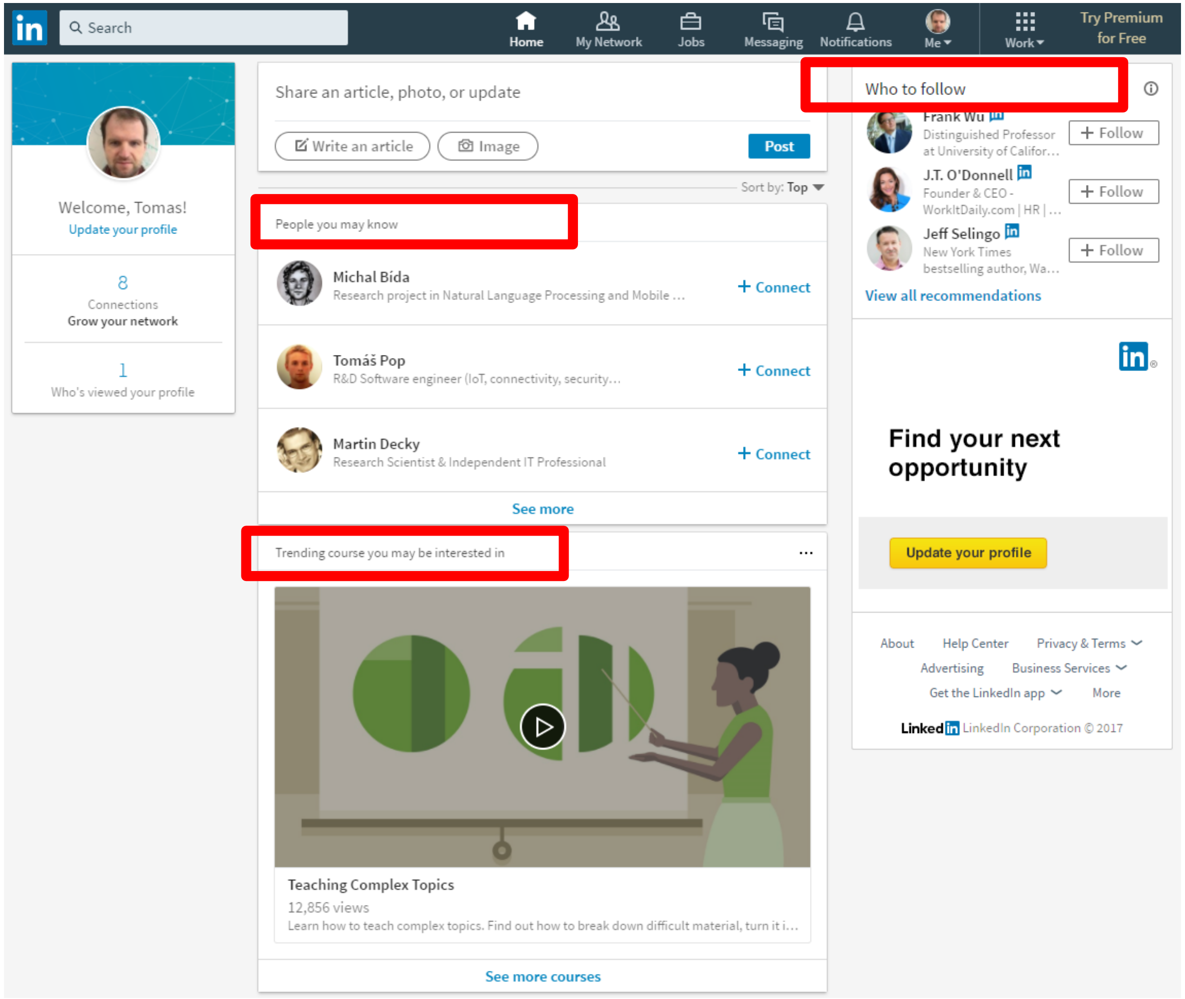
- social recommender systems
  - ratings observes from “likes”, “retweets”, “follows”, etc.
  - set relevant users for recommendation reduced to “friends”
    - collaboration filtering
    - content-based
  - additional ranking of items by “friends”
    - top-k
    - re-ranking
  - global/local trends

Social recommender systems

- recommender systems (RS) for social media domain
- battle the social overload
- offer personalization techniques
  - content
  - ads
- social media and recommender systems benefit from each other

recommender systems	→ RS impact the success of social media as each user is present with most relevant items suiting her needs → ← social media provide new types of data and metadata to be leveraged by RS (tags, comments, likes, relationships) ←	social media

Example (LinkedIn homepage)



Example (YouTube homepage)