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Lecture 6:

Applications; Implementation

SI583: Recommender Systems

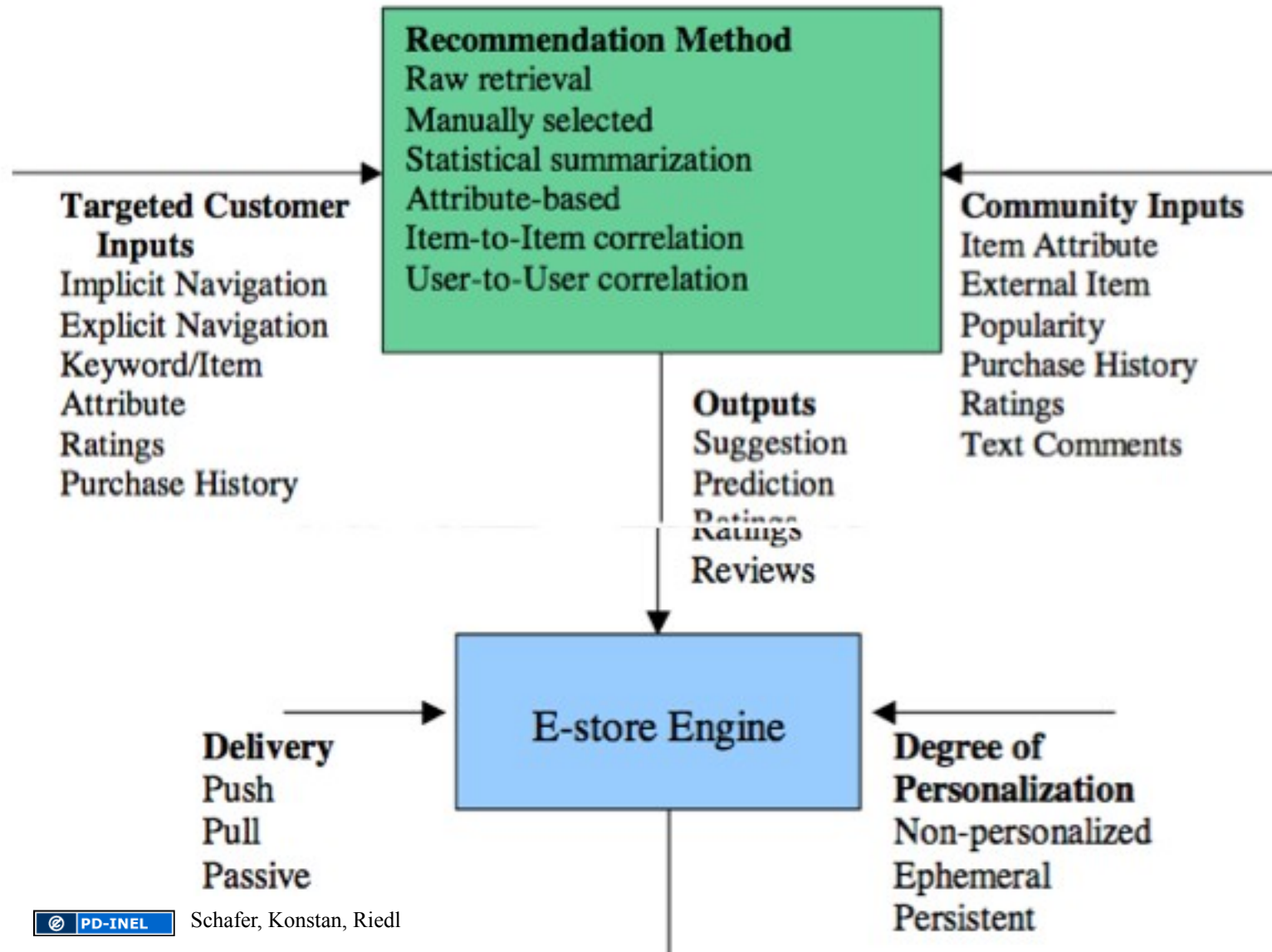


Taxonomy of E-Commerce Applications [Schafer, Konstan, Riedl]

- Characterize systems based on
 - Functional Inputs & Outputs
 - note: navigational inputs
 - Recommendation Method
 - user-user, item-item, PageRank, etc.
 - Other design issues (esp., personalization)



A Taxonomy for Recommender Applications



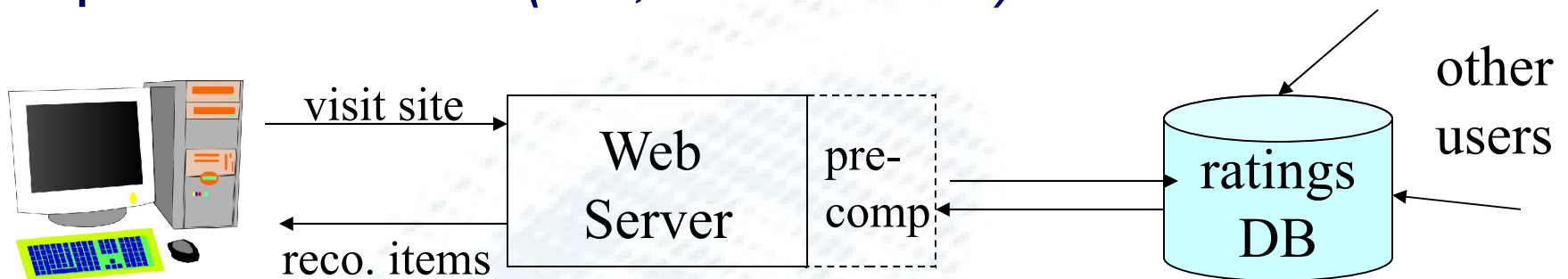
Degrees of Personalization

- Unpersonalized
- Ephemeral personalization
 - e.g., based on shopping cart alone
 - user profile is not long-lived
- Persistent personalization
- What factors would influence your choice?



Software Architecture

- Don't try to do the entire recommendation process *online* (i.e., in real time)

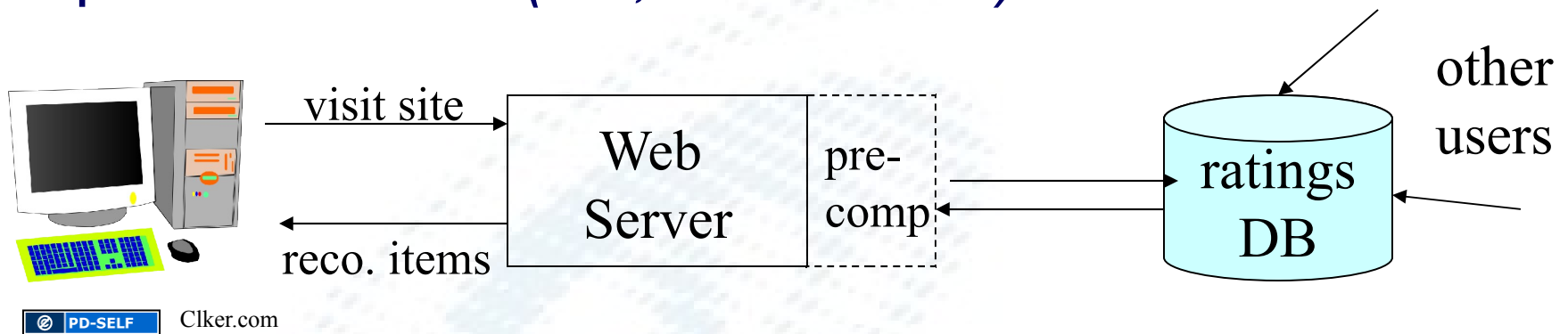


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- Goal: precompute as much as possible, and do as little as necessary when you have to generate a recommendation

Software Architecture

- Don't try to do the entire recommendation process *online* (i.e., in real time)



- Goal: precompute as much as possible, and do as little as necessary when you have to generate a recommendation
 - Tradeoff: precomputed values may be “stale”



User-User algorithm: Precompute what?

To recommend items to Joe:

- Normalize all ratings by user means, standard deviations
- Compute similarity (Pearson correlation coefficient) between Joe and each other user
- Compare a set of nearest neighbors based on similarity scores
- Compute the weighted average of other users' z-scores on each item X
- Either:
 - denormalize and report predicted value
 - or, sort and report ranked list of items



User-User algorithm: Precompute what?

To recommend items to Joe:

(typically precomputed)

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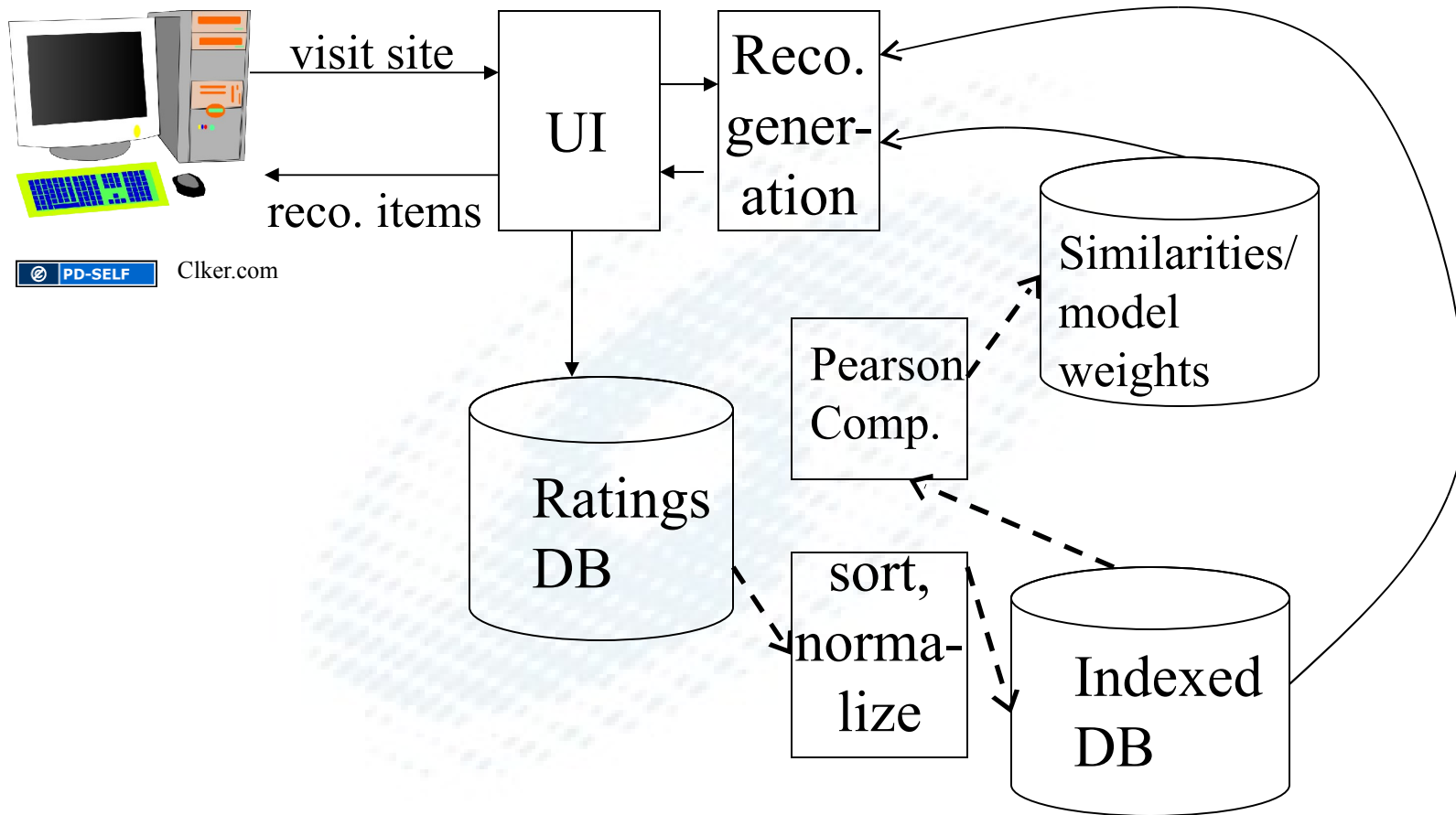


Rationale

- Similarity between users is more likely to be stable over time => it should not matter too much if you use slightly old value
- Neighborhoods decided using only similarity info=> no additional damage if they are also pre-computed
- Recent items may have many new ratings => pre-computing these would lose a lot of information



Software modules



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Recap: Term papers

- A short paper that is a mock “consultant’s report” which
 - identifies a potential application for a recommender system
 - explores the design space of a recommender system for that domain
 - suggests a design
 - points out strengths and weaknesses/pitfalls
- Due by Feb 20th (before winter break)



Case Study: Recommending email messages from a list

- Domain: email list for an online community
- How a recommender might help: guide users to interesting messages

