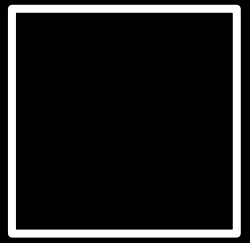
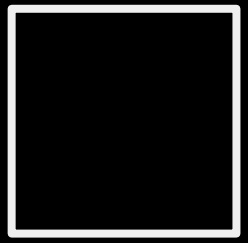
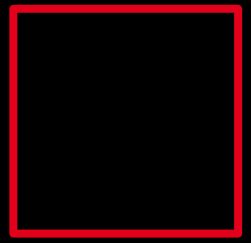
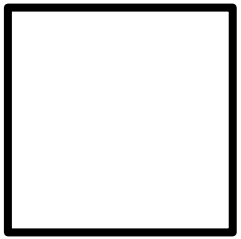
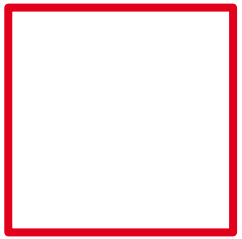




White Text in Red Box





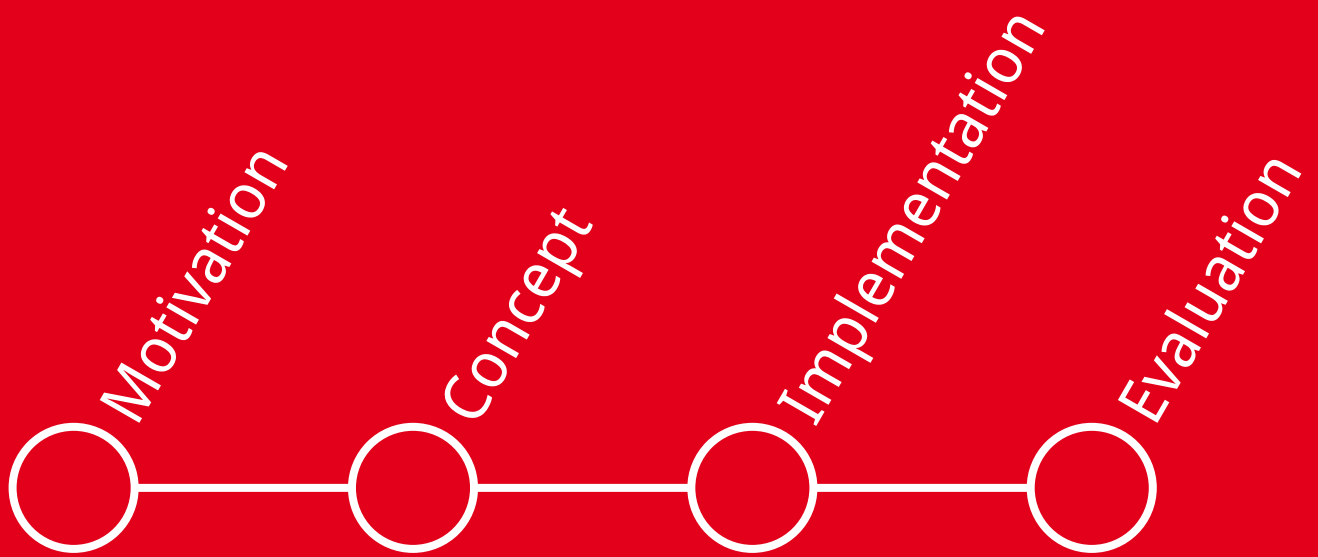
Hello

Torben Reetz
7th Semester SSD

A Recommender Framework for Skills Management

@SinnerSchrader

Agenda



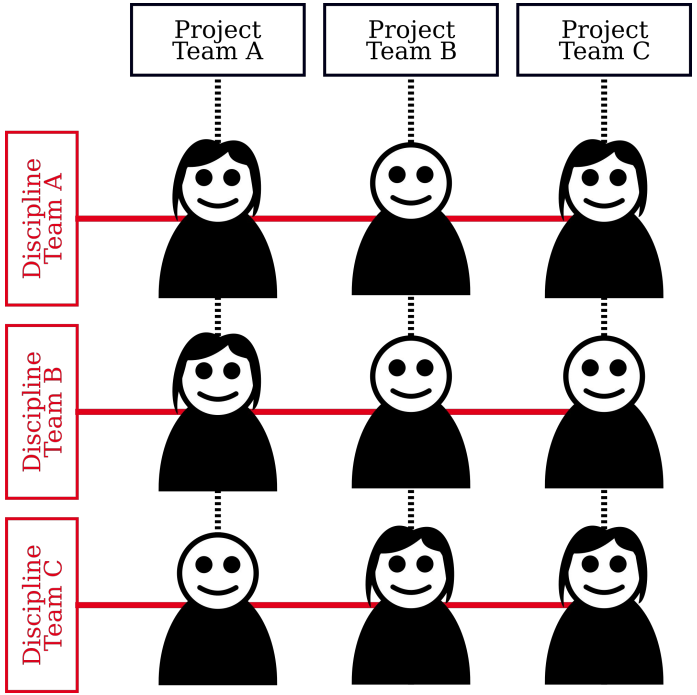
Motivation

Context SinnerSchrader

- Hamburg based
- Full service web agency
- 459 full-time employees
- Revenue > 51M Euro (15/16)

Matrix Organization

- Domain specific teams
- Project teams
- Definitions:
  - Project Manager → Project team
  - Supervisor → Domain specific team



Struggles (Project Manager)

- Employees leave their teams
- Workload changes
- Shift in disciplines

Project managers frequently look for new team members.

Struggles (Looking for Help)

- Different experience and knowledge
- Different disciplines
- Different project setups

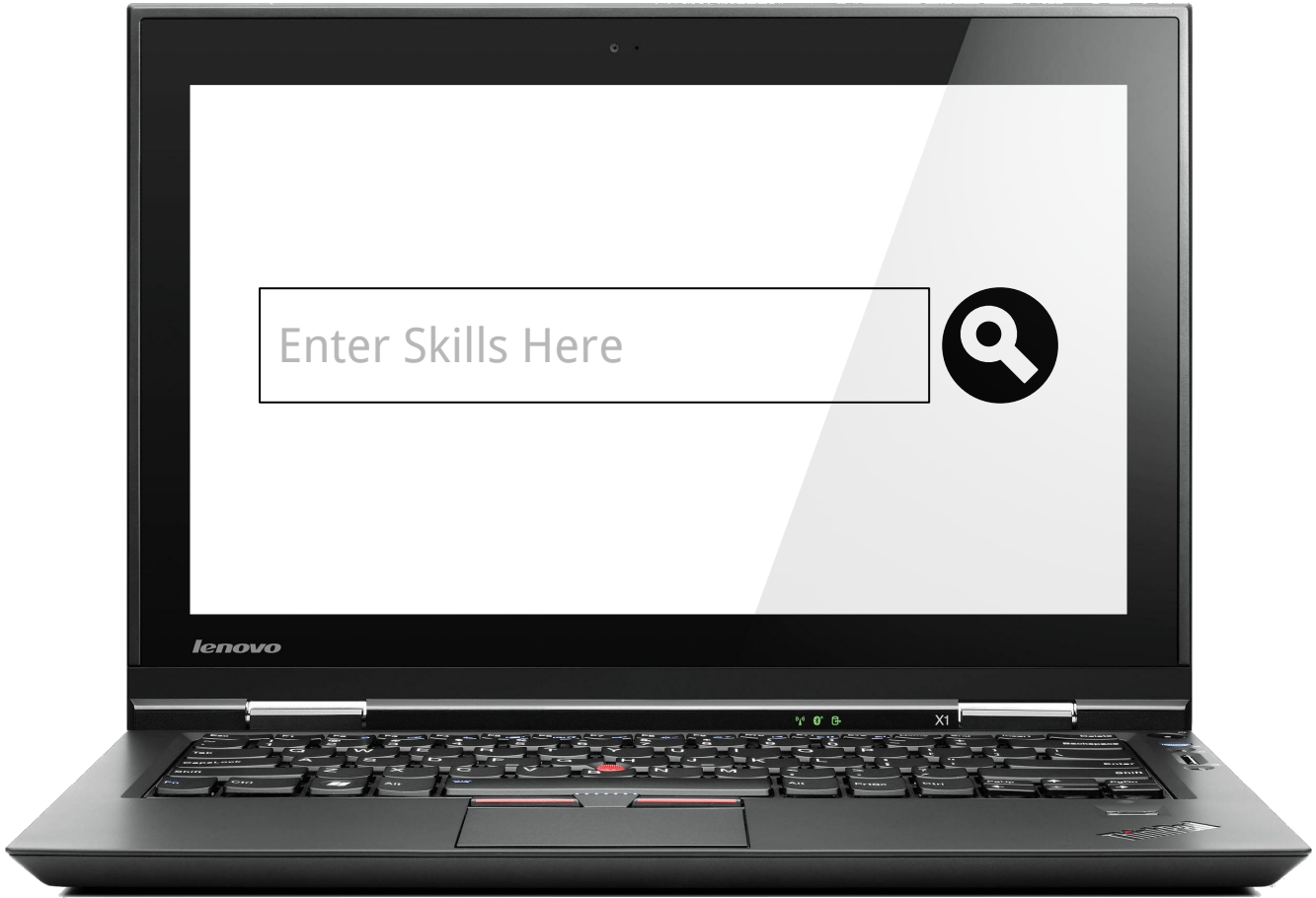
Employees search for people that can help to solve a specific problem.

Challenges to Tackle

- People search for other people that have specific skills
- Create a central source of information
- Focus: Motivation and Cooperation
- This thesis: Backend only
  - Visual concept / Frontend: Strecker

Concept

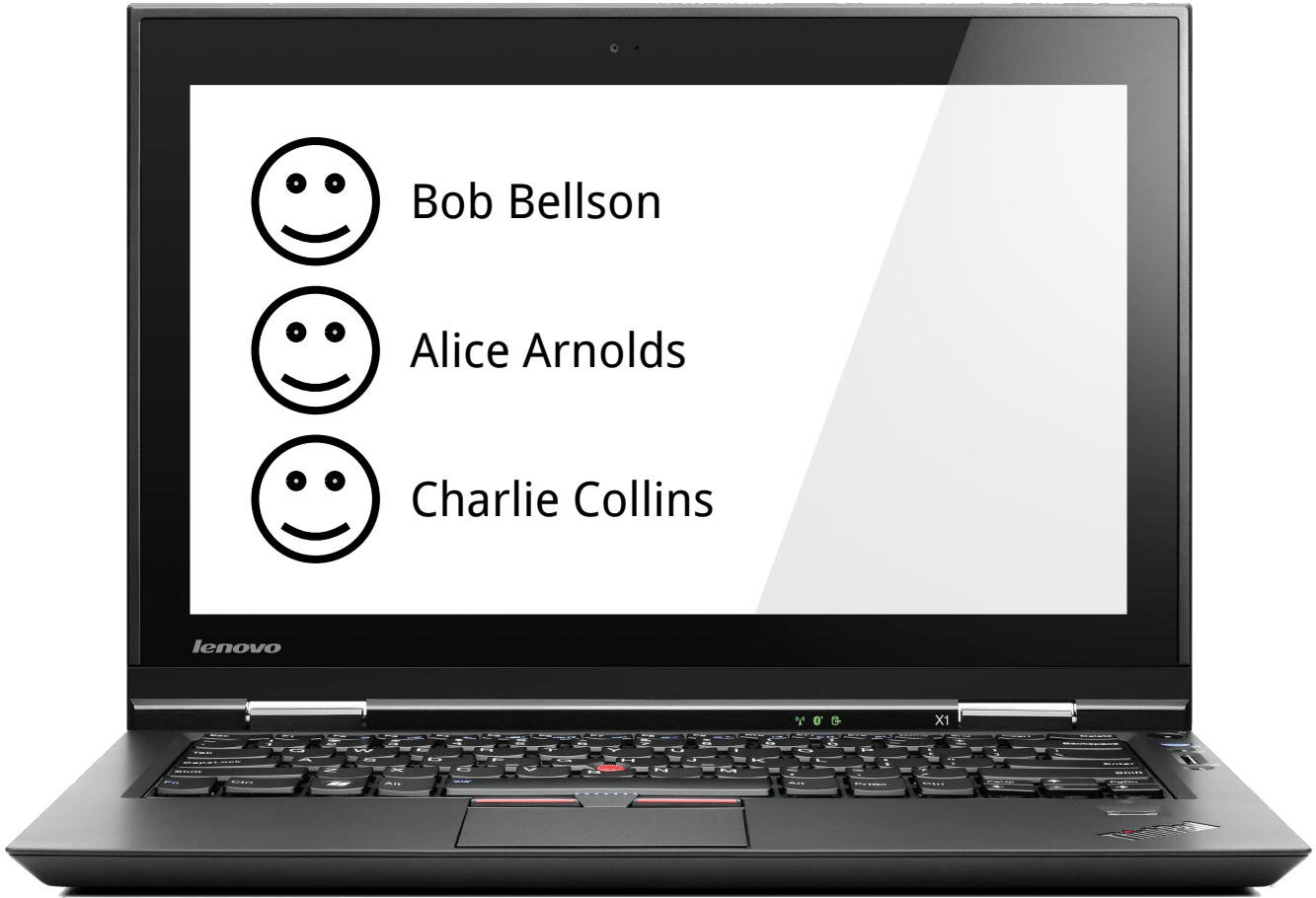
Walkthrough



Walkthrough

Walkthrough

Walkthrough



Walkthrough

Main Features

- Person Search
- Recommending skills to search
- Recommending similar profiles

Person Search

Definitions

- Skill: ability of a specific person
- Levels
  - Skill level: knowledge
  - Will level: motivation
  - Four Step Scale (0-3)
- Fitness: Measurement of how well a person fits into a searched skill set

Four Step Scale

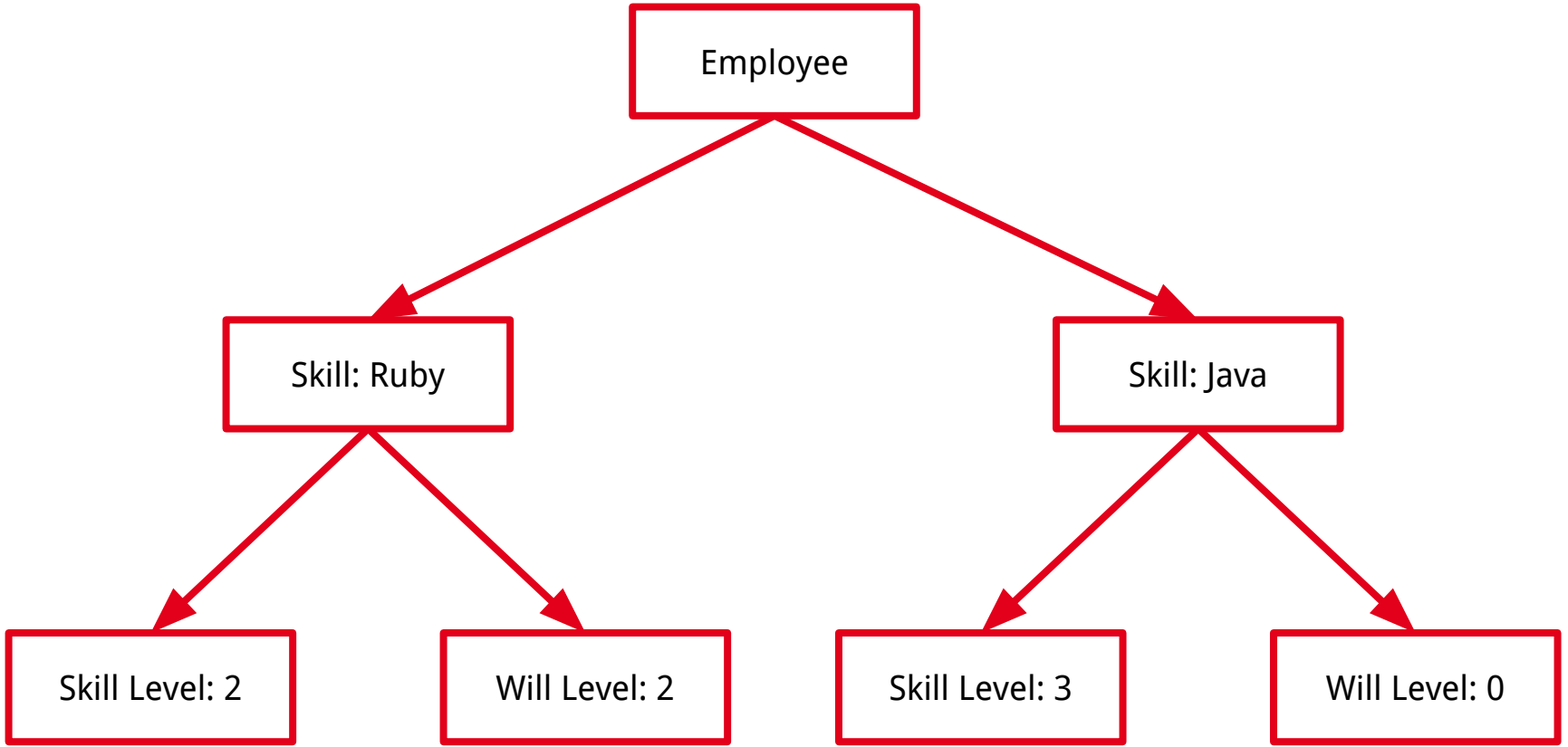
	Skill Level	Will Level
0	Novice	Uninterested
1	Basic Knowledge	Indifferent
2	Advanced Knowledge	Somewhat Interested
3	Expert	Highly Interested

Four Step Scale

	Skill Level	Will Level
0	Novice	Uninterested
1	Basic Knowledge	Indifferent
2	Advanced Knowledge	Somewhat Interested
3	Expert	Highly Interested

- Skill Level = 0 → Person has little knowledge
- No knowledge → Skill not present

Definitions

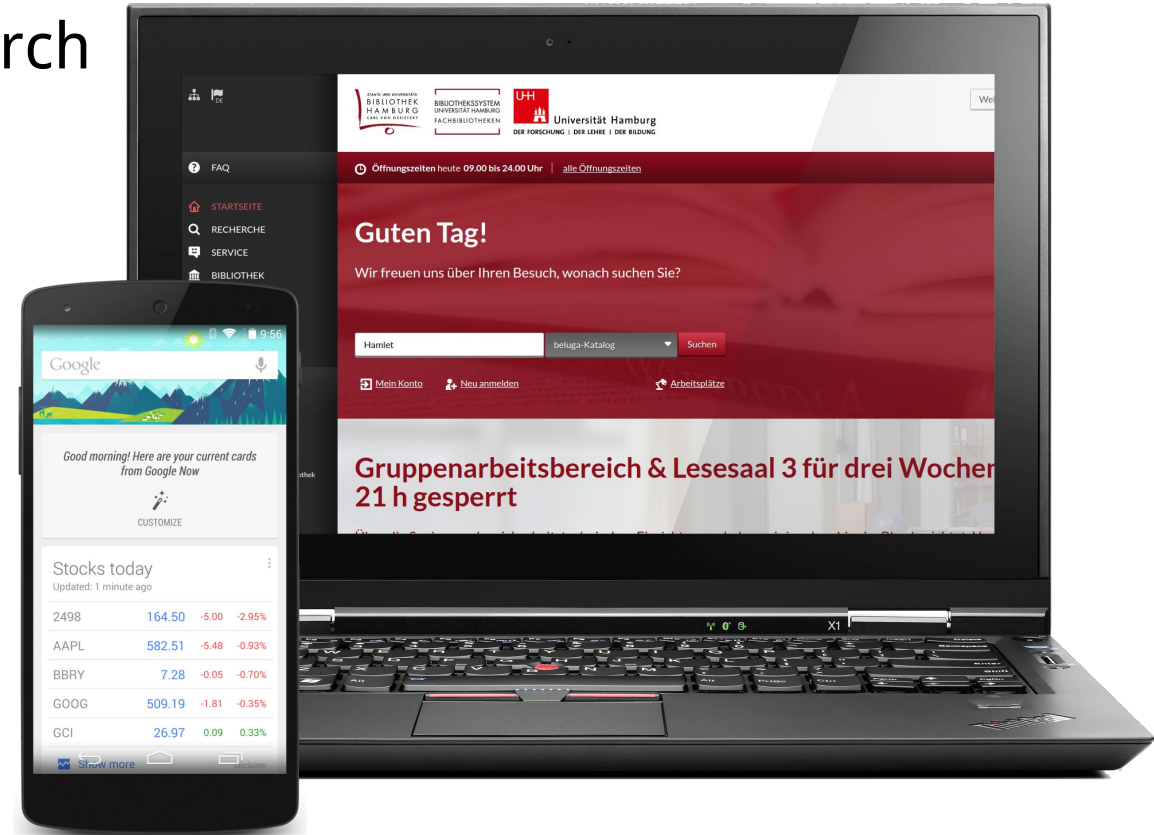


Person Search

- User enters skills to look for
- Systems presents list of results
  - People that have all skills
  - Best match on first Position
- IR System

IR Systems (examples)

- Google
- Facebook Graph Search
- Siri/Alexa
- grep
- …



Information Retrieval (IR) Systems

"Information retrieval (IR) is finding material [...] that satisfies an information need from within large collections."

Christopher D. Manning, Prabhakar Raghavan and Hinrich Schütze, *Introduction to Information Retrieval*, Cambridge University Press. 2008.

Information Retrieval (IR) Systems

Employees

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Search Query

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Information Retrieval (IR) Systems

Employees

"Information retrieval (IR) is finding material [...] that satisfies an information need from within large collections."

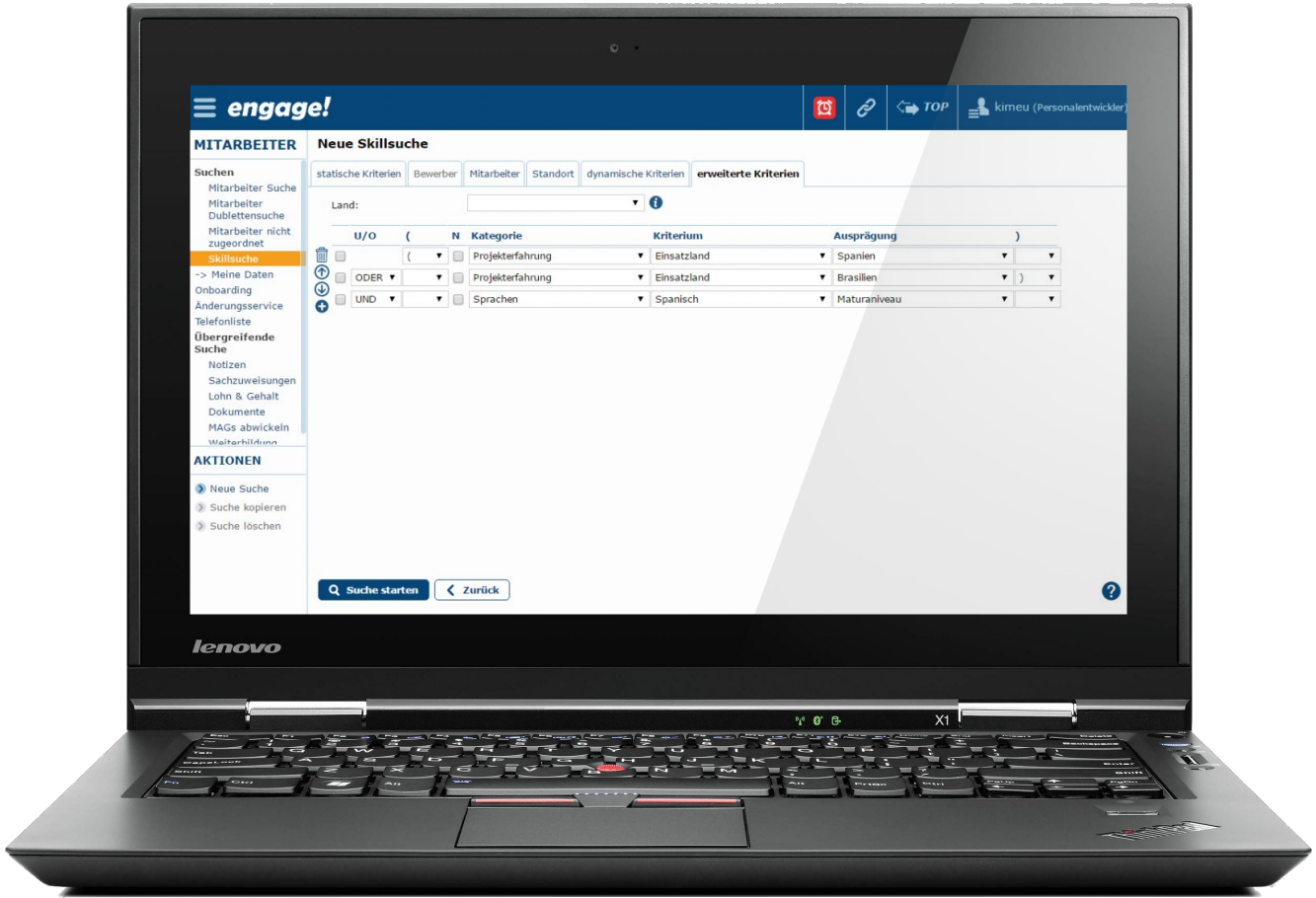
Search Query **Staff**

Christopher D. Manning, Prabhakar Raghavan and Hinrich Schütze, *Introduction to Information Retrieval*, Cambridge University Press. 2008.

Boolean and Ranked IR

- Boolean IR systems
  - Boolean operators
  - Example: Jira Query Language
    - “priority in (Blocker, Critical) AND project in (ProjA, ProjB, ProjC)”
- Ranked IR systems
  - Items ranked→ Best match first
  - Example: Google

Person Search in Talent Management (engage!)



Person Search in Talent Management (engage!)

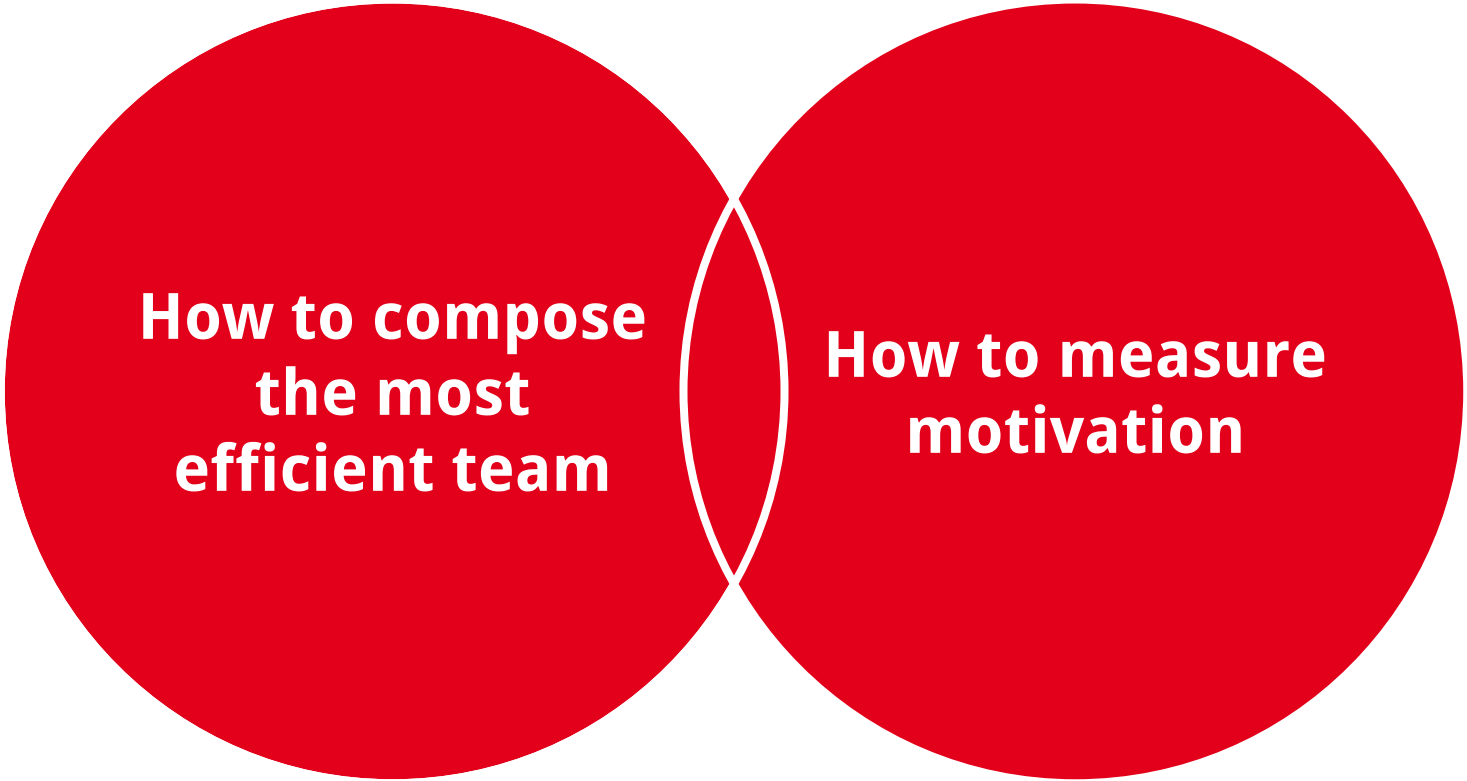
Person Search (Commercial Solution)

- Boolean Systems
- Complex queries
- Bloated interfaces
- No ranking

Person Search (Chosen Approach)

- Ranked IR system
- No complex queries
- Best match first
  - Fitness Score

Fitness Score (Research)



Fitness Score (Basic Principle)

- Adaption of Spoonamore et al.
- Weighted mean of factors
  - Average skill level in searched skills
  - Average will level in searched skills
  - Specialization (skill levels)
  - Specialization (will levels)
- Weighting parameters configurable

Example (Java and Ruby in HH)

- $w_{as} = w_{aw} = w_{ss} = w_{sw} = 0.25$
- Notation: skill level|will level
- Java and Ruby
- In Hamburg

Example (Java and Ruby in HH)

Person	Location	Java	Ruby	C++
Alice	Hamburg	2|1	2|2	3|3
Bob	Hamburg	2|3	0|3	0|1
Charlie	Hamburg	3|3	2|1	1|2
Donald	Hamburg	3|3	-	2|2
Erika	Frankfurt	1|1	2|3	3|1

Example (Java and Ruby in HH)

Person	Location	Java	Ruby	C++
Alice	Hamburg	2|1	2|2	3|3
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Erika	Frankfurt	1|1	2|3	3|1

Example (Java and Ruby in HH)

Person	Location	Java	Ruby	C++	f
Alice	Hamburg	2|1	2|2	3|3	0.44
Bob	Hamburg	2|3	0|3	0|1	0.71
Charlie	Hamburg	3|3	2|1	1|2	0.69
Donald	Hamburg	3|3	-	2|2	
Erika	Frankfurt	1|1	2|3	3|1	

Example (Java and Ruby in HH)

#	Person	Location	Java	Ruby	C++	f
3	Alice	Hamburg	2|1	2|2	3|3	0.44
1	Bob	Hamburg	2|3	0|3	0|1	0.71
2	Charlie	Hamburg	3|3	2|1	1|2	0.69
	Donald	Hamburg	3|3	-	2|2	
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Example (Java and Ruby in HH)

#	Person	Location	Java	Ruby	C++	f
1	Bob	Hamburg	2|3	0|3	0|1	0.71
2	Charlie	Hamburg	3|3	2|1	1|2	0.69
3	Alice	Hamburg	2|1	2|2	3|3	0.44

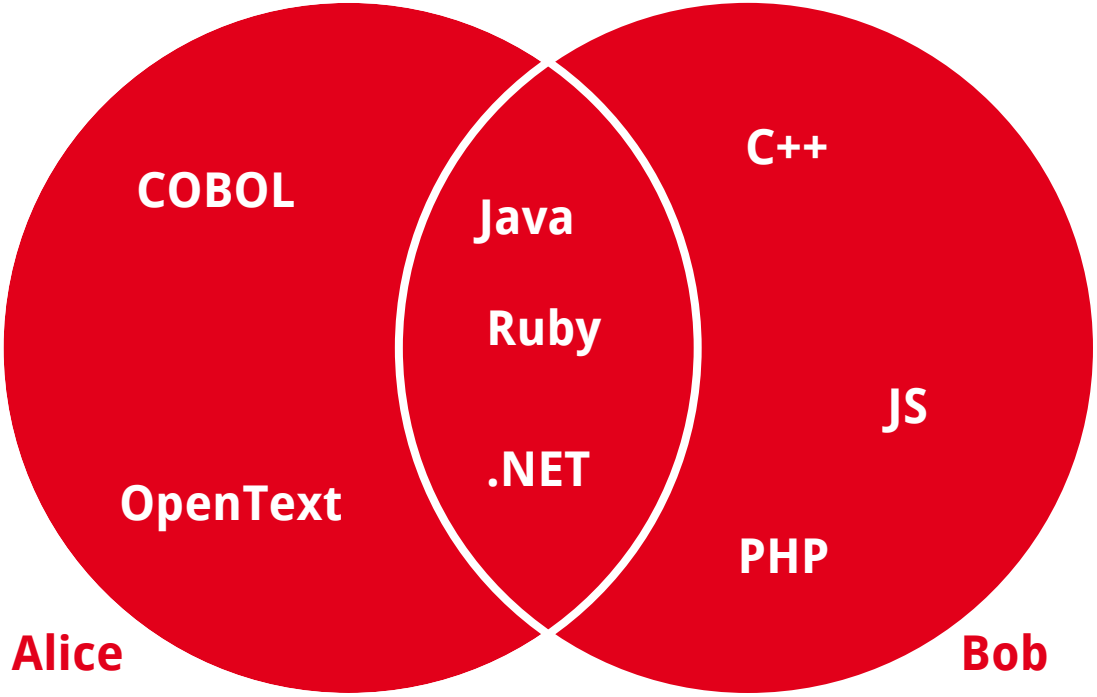
Recommending Similar Users

Recommending Similar Users

- Recommender System
  - Content-based filtering
- User = Set of Skills
- Jaccard Similarity Coefficient (JSC)

Recommending Similar Users (JSC)

- Size of intersection: 3
- Size of union: 8
- JSE: 3 / 8 (37.5%)



Recommending Skills to Search

Recommending Skills to Search

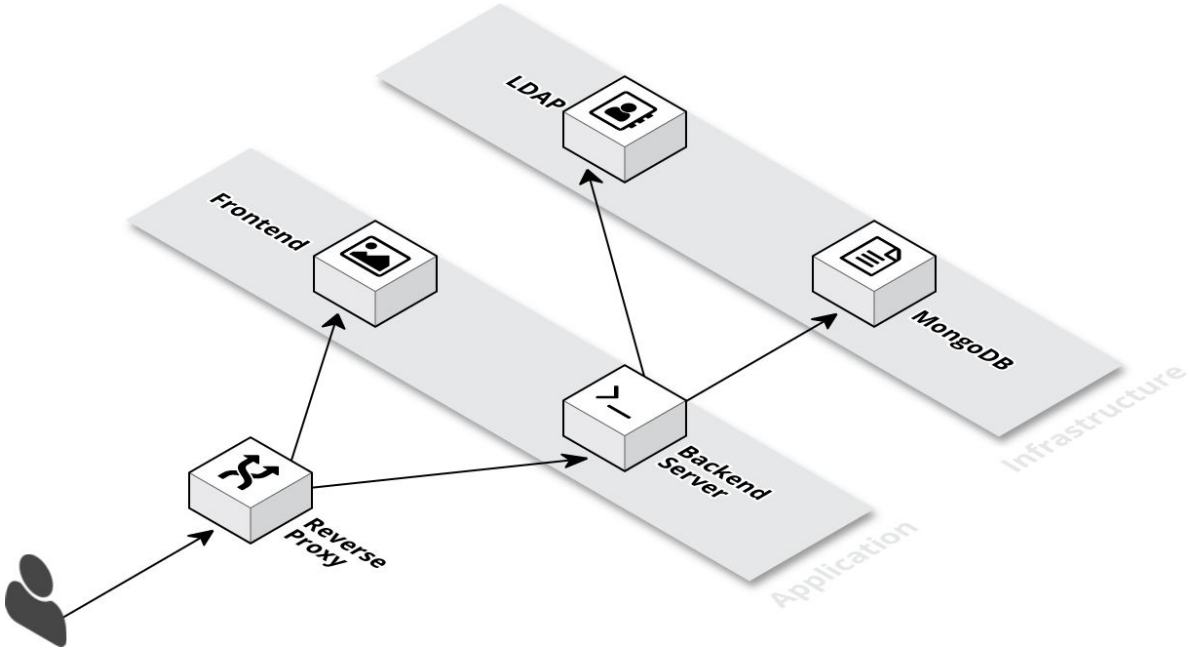
- Skills: name and icon
- No user context
- Item-based (collaborative) filtering
  - Examine what skills other users' searched for
  - Recommend those skills

Recommending Skills to Search (Outline)

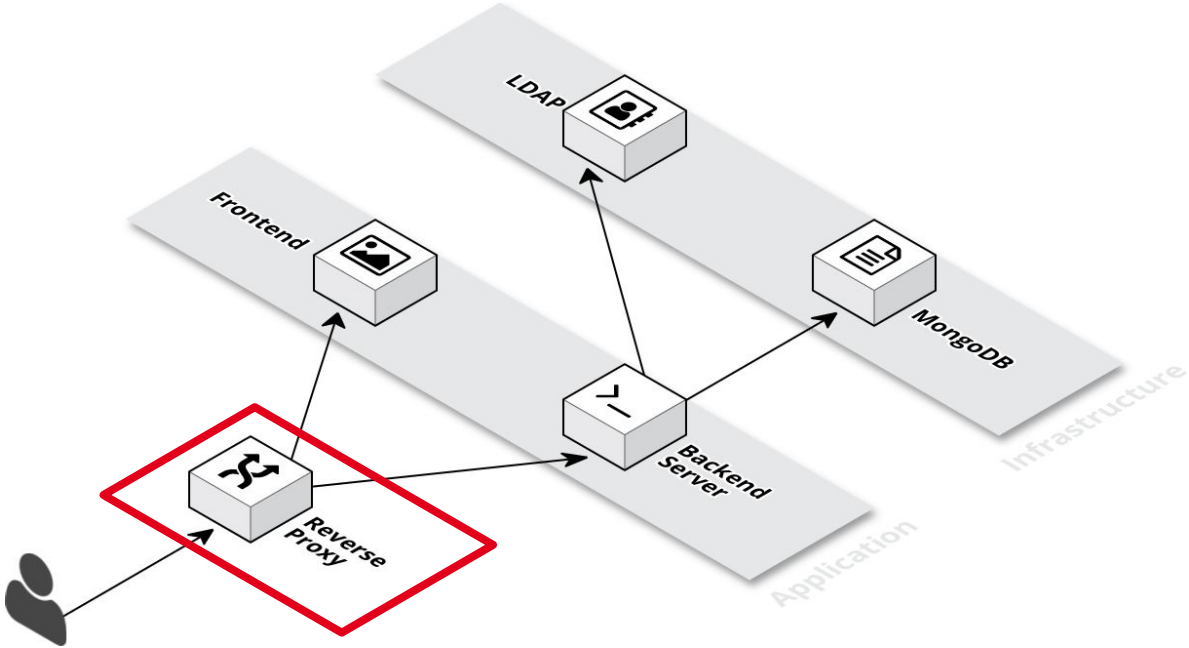
- Markov Chain
- States: Single Skills
- Transitions: Count of joint searches
- Generate Recommendations:
  - Get all suggestions from entered items
  - Aggregate suggestions (add counts)
  - Remove entered items
  - Sort by search count
  - Return first n items

Implementation

Application Structure

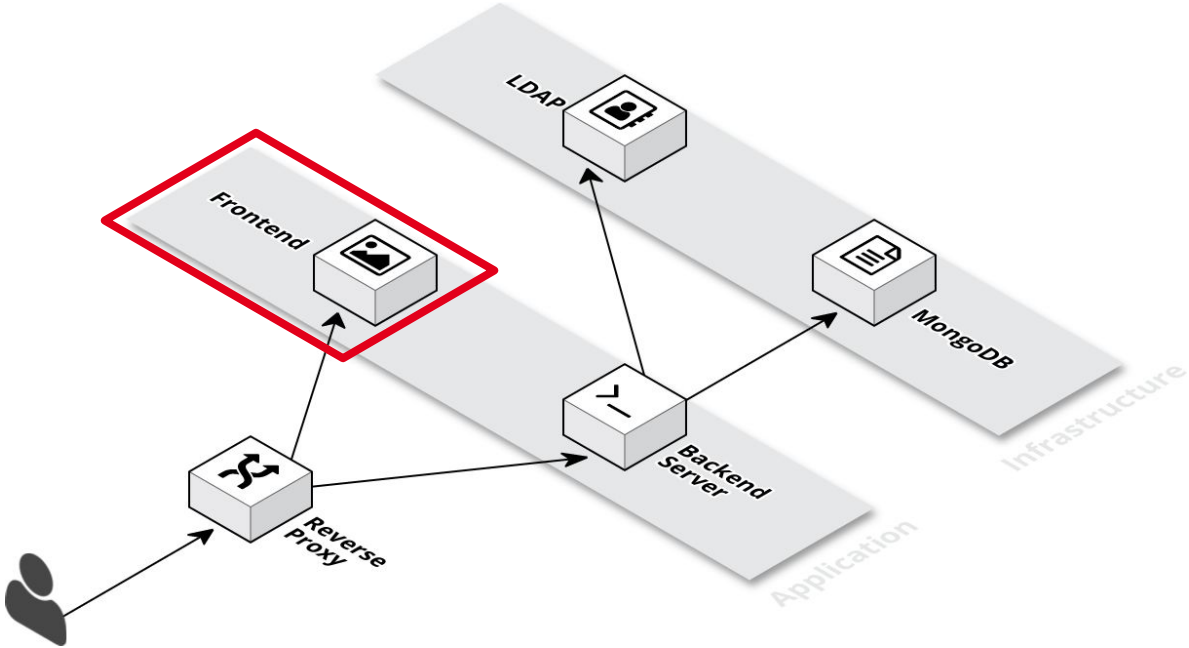


Application Structure



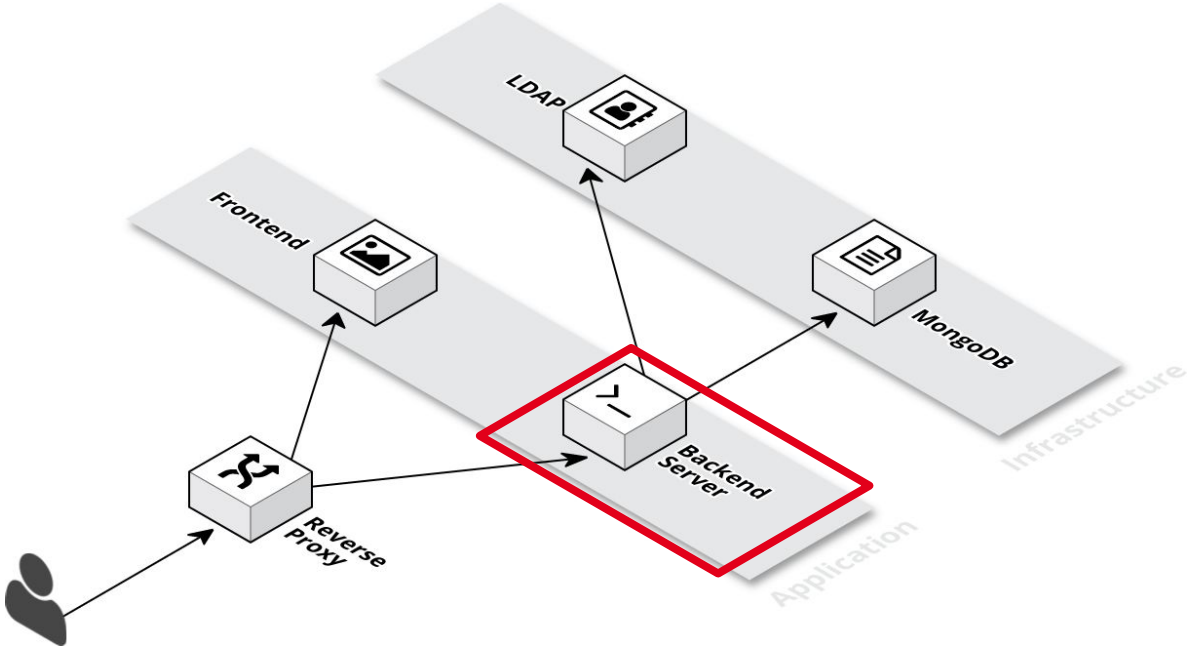
- Serve static files
- Forward API calls
- SSL endpoint

Application Structure



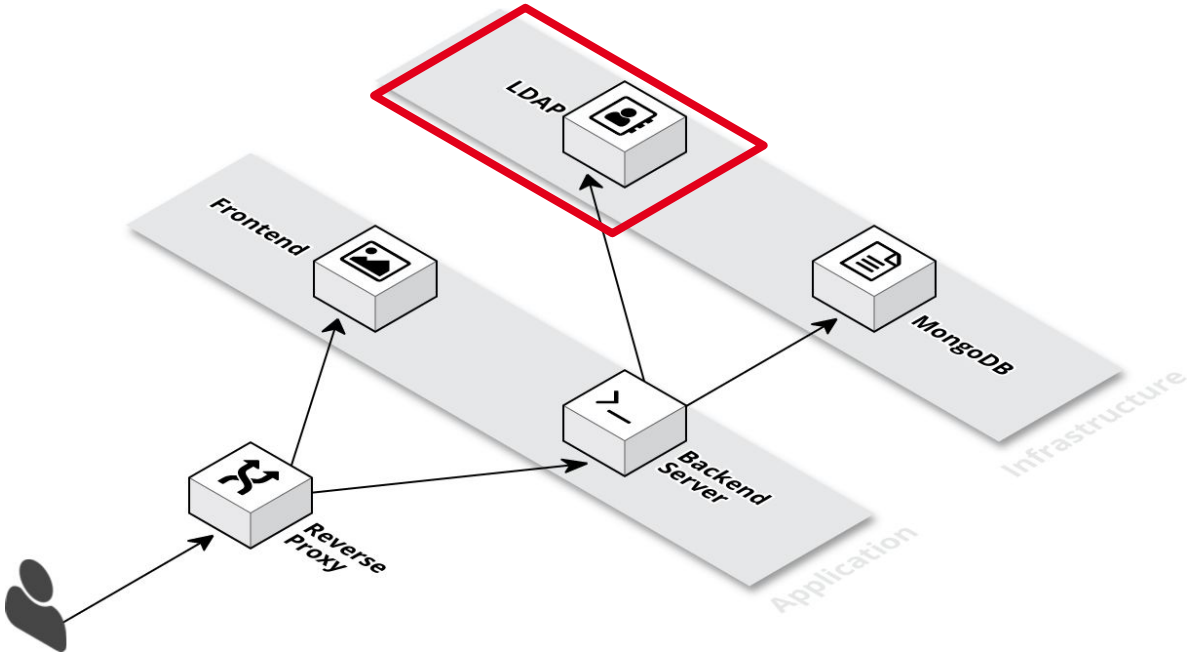
- Graphical Interface
- HTML, CSS, JS, Assets
- Executes API calls (AJAX)

Application Structure



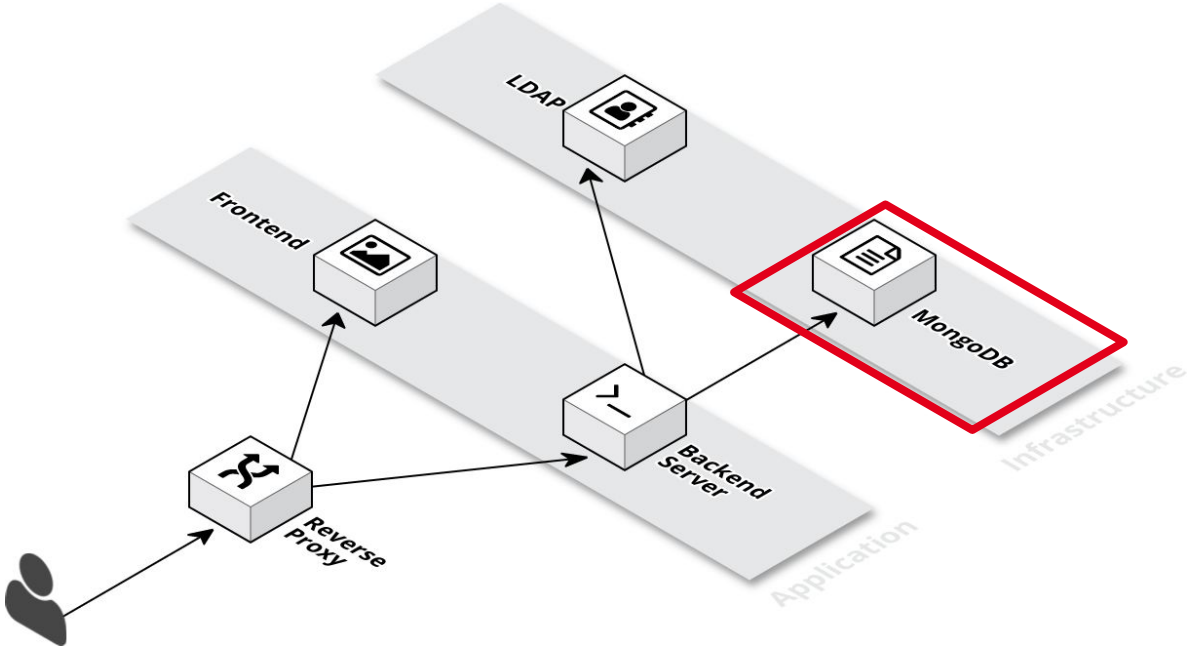
- Main Application
- REST API

Application Structure



- Personal Data
- Authentication
- Used for most internal services

Application Structure



- Application data
- NoSQL

Backend Technologies

Backend Technologies

Backend Technologies

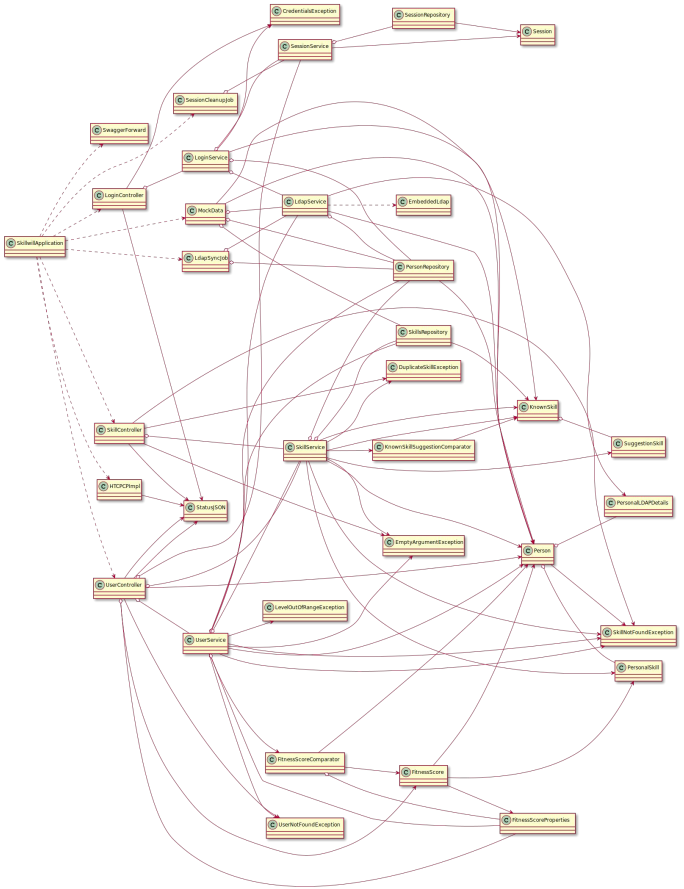
Backend Technologies

Backend Technologies

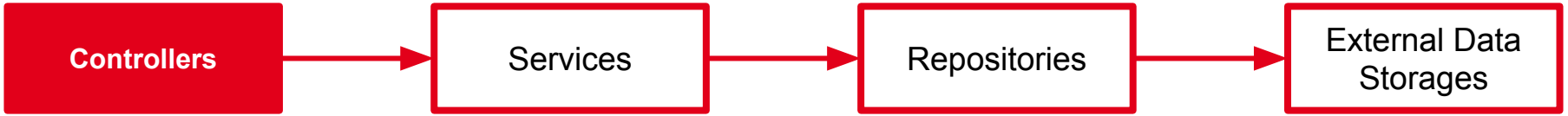
Backend Technologies

Backend Structure

- Controllers
- Services
- Repositories
- Jobs
- Helpers
- Data Types

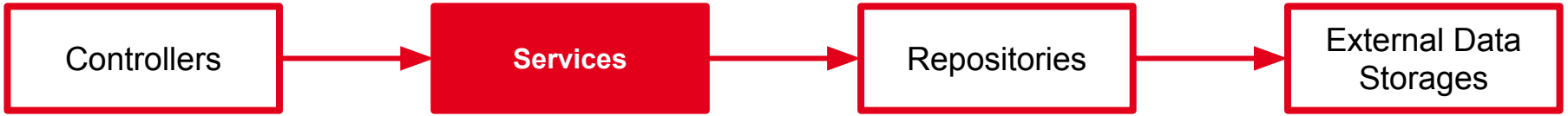


Backend Structure



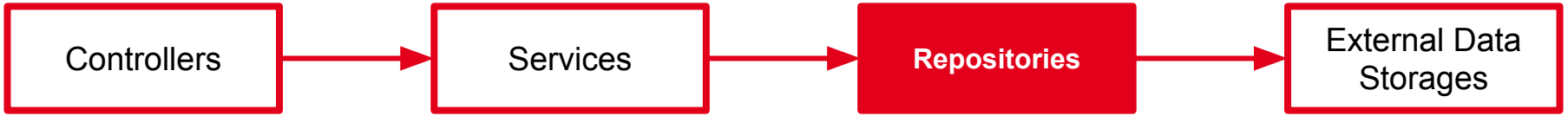
- Listen to API endpoints
- Use services to
  - Get data
  - Send data
  - Send commands
- Convert Objects to JSON

Backend Structure



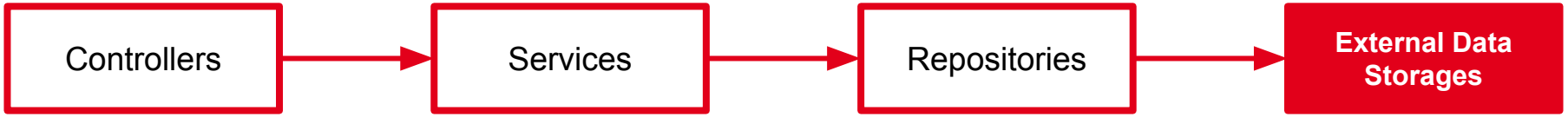
- Get, filter, transform, edit data
- Use repository objects to
  - Retrieve data from external sources
  - Write data to external sources
- Contain business logic

Backend Structure



- Spring Data repository objects
- Provide Methods for CRUD operations
- Wrappers to simplify storage access

Backend Structure



- MongoDB
- Skills
- Persons
- Sessions

Evaluation

Evaluation

- Scalability
- Response times (1s)
- Search algorithm
  - Are results distributed uniformly?
  - Do algorithm’s and managers’ ratings correlate?

Evaluation

- Scalability ✔
- Response times (1s) (✔)
- Search algorithm
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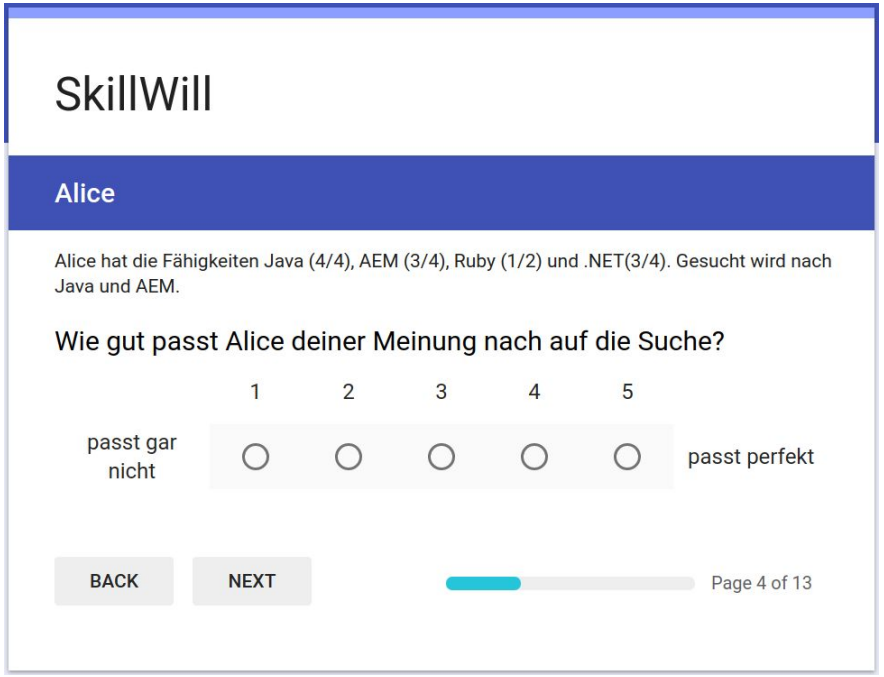
Evaluation

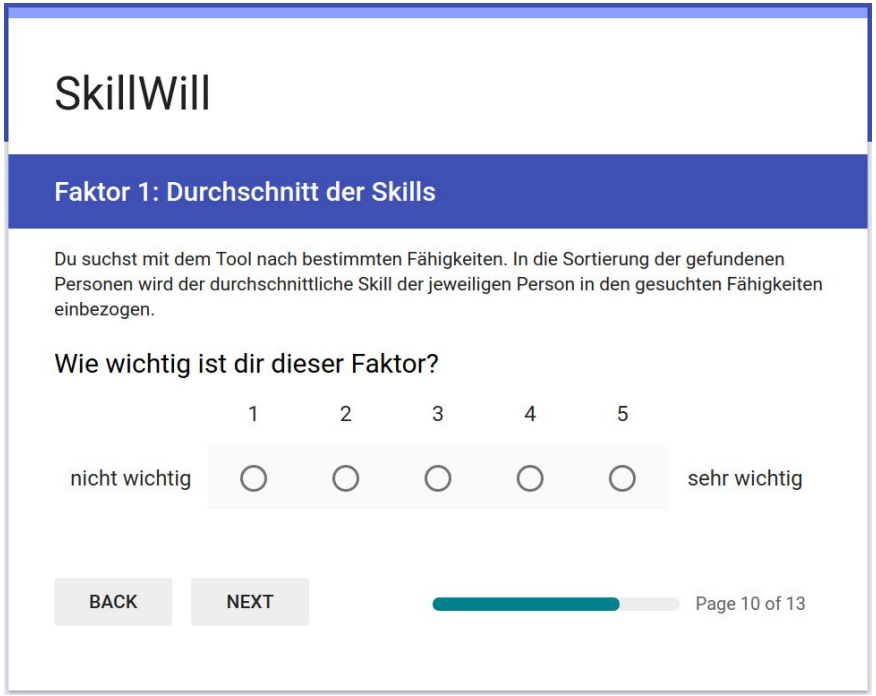
- Scalability ✔
- Response times (1s) (✔)
- Search algorithm
  - Are results distributed uniformly? ✔
  - Do algorithm’s and managers’ ratings correlate?

Evaluation (Survey)

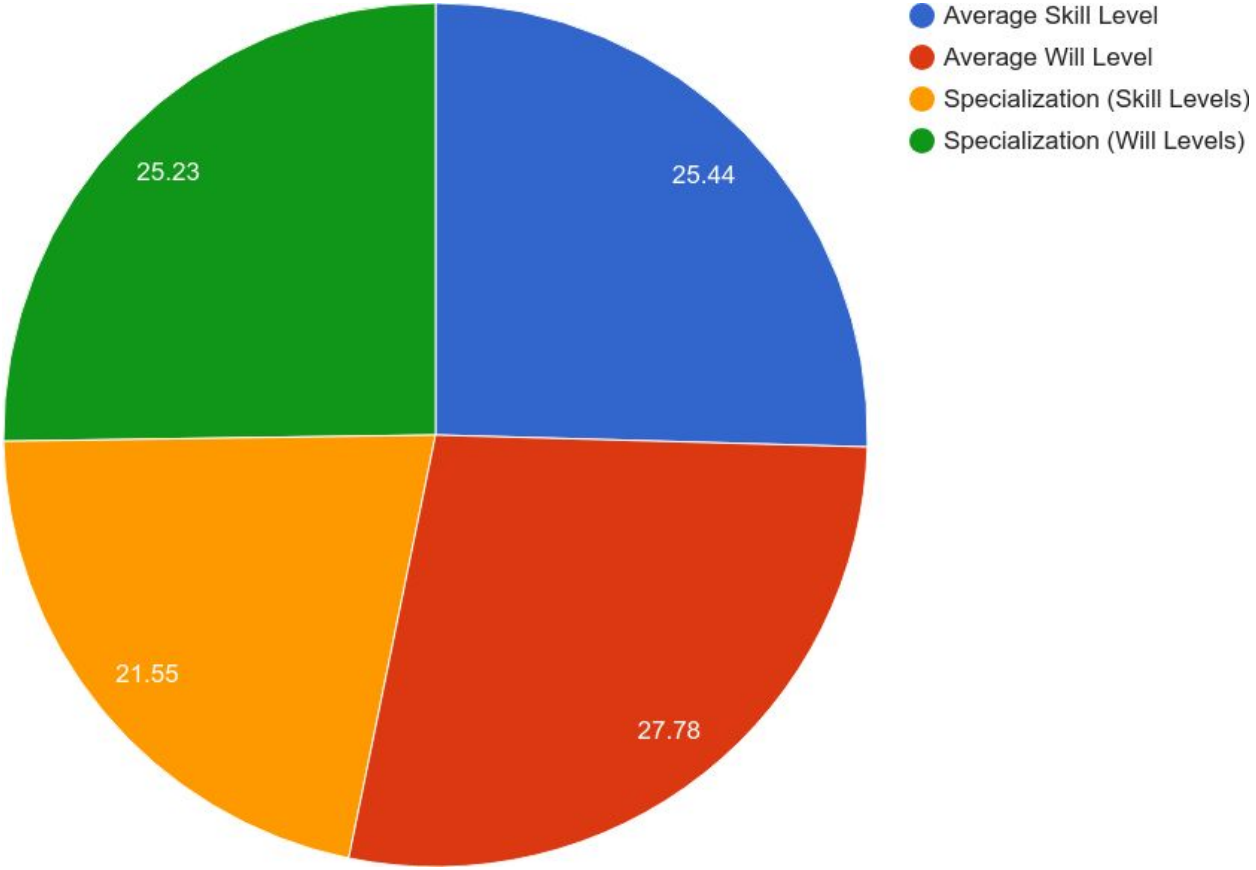
- Online Survey (Google Forms)
- 41 participants (8% of the staff)
- 9 Questions

Evaluation (Survey)

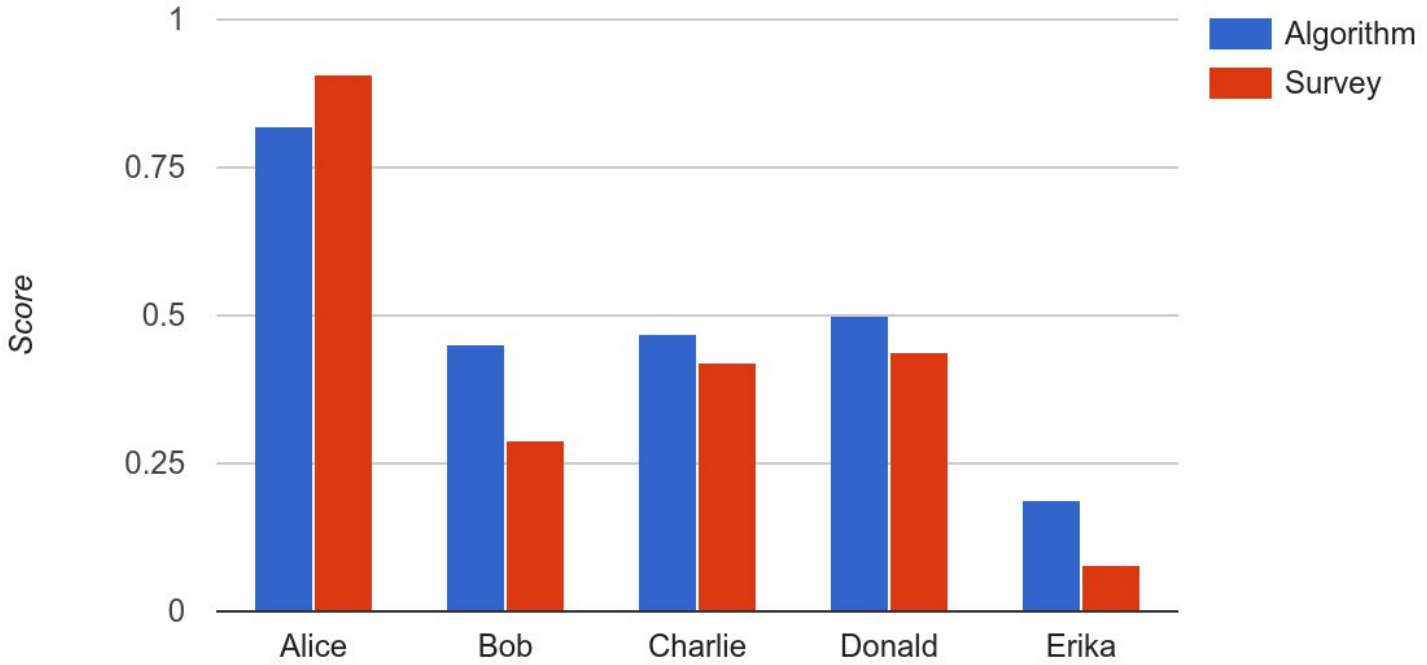




Evaluation (Survey)



Evaluation (Survey)



Evaluation (Survey)

- Two-tailed heteroscedastic T-Test
- $p \geq 0.1 \rightarrow$ No significant deviation
- $p \geq 0.05 \rightarrow$Two data rows deviate significantly

Evaluation

- Scalability ✔
- Response times (1s) (✔)
- Search algorithm
  - Are results distributed uniformly? ✔
  - Do algorithm’s and managers’ ratings correlate?

Evaluation

- Scalability ✔
- Response times (1s) (✔)
- Search algorithm
  - Are results distributed uniformly? ✔
  - Do algorithm’s and managers’ ratings correlate? ✔

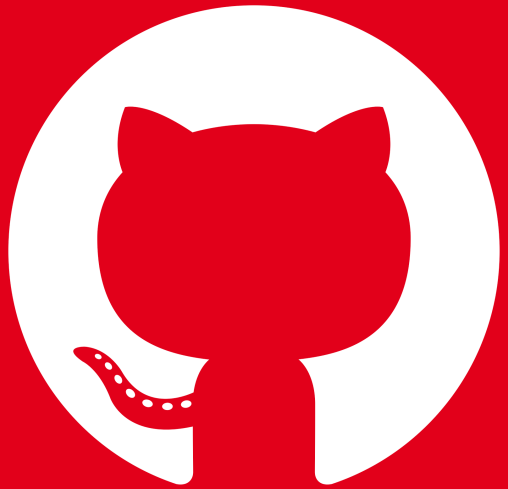
That’s it

Demo

Demo

https://demo.torben.xyz

Thanks



github.com/t0rbn/BSc
github.com/sinnerschrader*

*soon

Contact

Github: @t0rbn
Mail: 3reetz@informatik.uni-hamburg.de
More: http://torben.xyz

Image Sources

Thinkpad X1: https://www.bhphotovideo.com
Google Now on Nexus 5: ttps://www.androidcentral.com/google-now
Screenshot engage!: https://www.infoniqa.com/hr-software/talent-management
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Octocat: https://github.com/logo
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Maven Logo: https://maven.apache.org/images/maven-logo-black-on-white.png
Git Logo: https://git-scm.com/images/logos/logomark-orange@2x.png
Gitlab Logo: https://upload.wikimedia.org/wikipedia/commons/thumb/1/18/GitLab_Logo.svg/2000px-GitLab_Logo.svg.png
Flapdoodle Logo: https://avatars0.githubusercontent.com/u/1661811?v=3&s=280
Unboundid Logo: https://media.licdn.com/mpr/mpr/shrink_200_200/AAEAAQAAAAAAAAUtAAAAJGEyYmI1MDlmLWFkMjktNGU3ZS1hOTk2LWM0MDJjZTQ5MzA2Mw.png
Jacoco Logo: https://cdn.liviutudor.com/wp-content/uploads/2016/02/Jacoco.png
Spring Logo: https://upload.wikimedia.org/wikipedia/en/2/20/Pivotal_Java_Spring_Logo.png

Q&A

Bonus Slides

Requirements

Functional Requirements

- Person search
  - Enter skills → find best matching person
- User profiles
  - Skills, personal data, direct contact
  - Enter own skills (knowledge, motivation)
  - Login
- Management of registered Skills
  - Pool of predefined skills
  - Add new skills
  - Rename skills
  - Delete skills

Non Functional Requirements

- Different devices
  - Primary: Desktops
  - Mobile devices optional
- Browser support
  - Chrome, Firefox, Safari
  - No support for IE/Edge
- Response Times (RAIL)
  - 100ms to acknowledge input
  - 1s to finish rendering results
- Scalability
  - Increased number of users should not be a problem
  - Enlarge storage and computing resources

Related Work

Fitness Score (Research)

- Ivanovska et. al: Algorithms for Effective Team Building
- Canós-Darós: An algorithm to identify the most motivated employees
  - General Motivation ↔ Task specific
  - Asking employees to rate their motivation generates suitable data
- Spoonamore et. al: Matching Sailors to Positions Based on Skill

Matching Sailors to Positions Based on Skill

- Multiple Factors
  - Rating
  - Pay grade
  - NECs
- Basic priciple: weighted mean of factors
  - $S = \alpha$ ratingscore + β paygradescore + γ NECscore

Fitness Score Algorithm

Fitness Score (Definitions and Helpers)

$$V = \{x \in \mathbb{N}_0^+ \mid 0 \leq x \leq 3\}$$

$$S = \{Java, Ruby, C++, ...\}$$

$$E = \{x \in S \mid \text{employee has skill x}\}$$

$$Q = \{x \in S \mid \text{user searches for skill x}\}$$

$$v_s : E \mapsto V$$

$$v_w : E \mapsto V$$

Fitness Score (Factors)

$$a_s = \left(\sum_{x \in E \cap Q} v_s(x) \right) \cdot \frac{1}{|E \cap Q|}$$

$$a_w = \left(\sum_{x \in E \cap Q} v_w(x) \right) \cdot \frac{1}{|E \cap Q|}$$

$$s_s = \frac{max(V) \ + a_s - \left(\left(\sum_{x \in E \setminus Q} v_s(x) \right) \cdot \frac{1}{|E \setminus Q|} \right)}{2max(V)}$$

$$s_w = \frac{max(V) \ + a_w - \left(\left(\sum_{x \in E \setminus Q} v_w(x) \right) \cdot \frac{1}{|E \setminus Q|} \right)}{2max(V)}$$

Fitness Score (Basic Algorithm)

$$f = \frac{w_{as} \cdot a_s}{max(V)} + \frac{w_{aw} \cdot a_w}{max(V)} + w_{ss} \cdot s_s + w_{sw} \cdot s_w$$

Refining the Fitness Score Algorithm

- Estimated Factors ≅ 0.25
- Setting all to 0.25
  - Simplifies algorithm
  - No drastic effect on accuracy

$$f = \frac{w_{as} \cdot a_s}{max(V)} + \frac{w_{aw} \cdot a_w}{max(V)} + w_{ss} \cdot s_s + w_{sw} \cdot s_w$$

$$\Rightarrow f = \frac{a_s + a_w}{4max(V)} + \frac{s_s + s_w}{4}$$

Recommender Systems

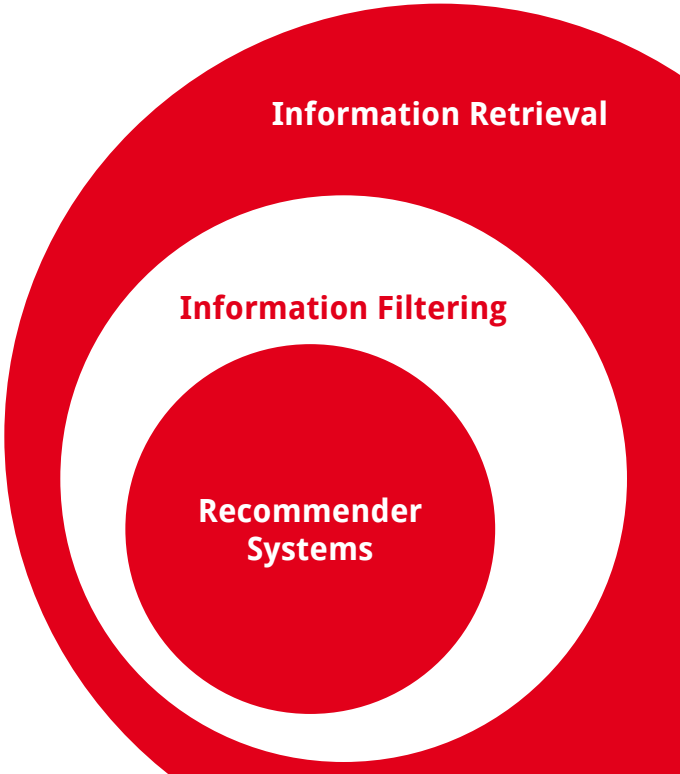
Recommender Systems (Definition)

“information filtering systems that deal with the problem of information overload by filtering vital information fragment out of large amount of [...] information [sic]”

I SINKAYE , F.O. ; F OLAJIMI , Y.O. ; O JOKOH , B.A.: Recommendation systems: Principles, methods and evaluation.

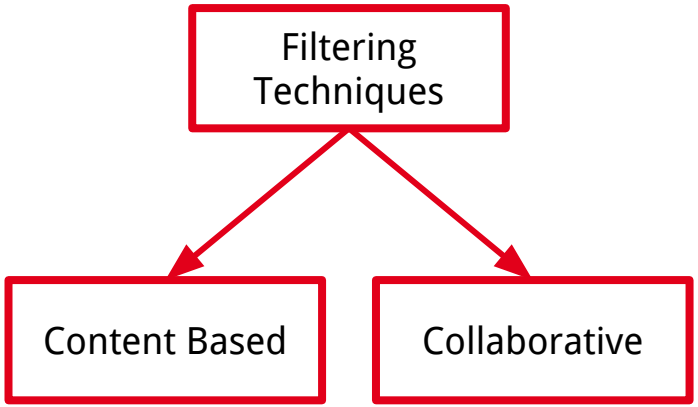
Recommender Systems and IR

- Subset of IR systems
- Both find relevant information
- Recommender Systems → “zero query” IR
  - IR: user actively searches
  - Recommender: system proactively recommends
  - Person search is not a recommender system



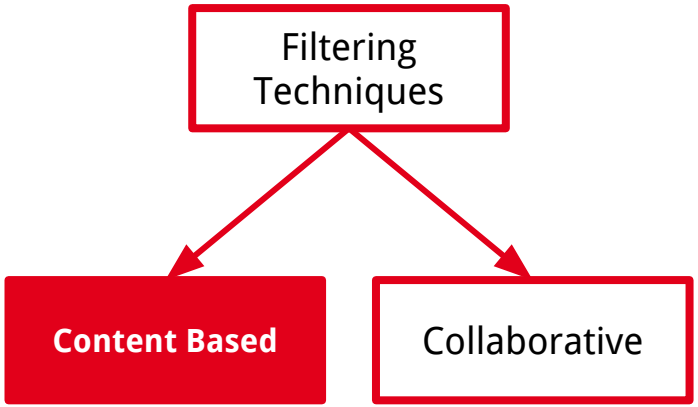
Filtering Techniques

- Isinkaye et al.
- Techniques to find the items to suggest
- Hybrid filtering: combine multiple techniques



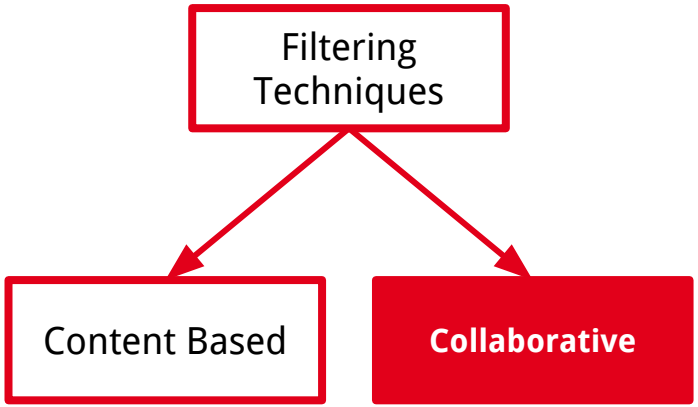
Filtering Techniques (Content Based)

- Examine content
- Find items that are similar to the ones the user interacted with



Filtering Techniques (Collaborative)

- Users behave similarly
- Find “neighbours”
- Recommend items neighbours interacted with
- Subclasses:
  - Model based
  - Memory based
    - Item based
    - User based



Example: Amazon (Collaborative)

Example: Heise (Content Based)

Recommending Skills to Search (Example)

Recommending Skills to Search (Example)

- Entered: Java, PHP
- Number to recommend (n): 1

	Java	PHP	CSS	COBOL
Java	-	7	3	1
PHP	7	-	9	5
CSS	3	9	-	8
COBOL	1	5	8	-

Recommending Skills to Search (Example)

- PHP (7)
- CSS (3)
- COBOL (1)
- Java (7)
- CSS (9)
- COBOL (5)

	Java	PHP	CSS	COBOL
Java	-	7	3	1
PHP	7	-	9	5
CSS	3	9	-	8
COBOL	1	5	8	-

Recommending Skills to Search (Example)

- PHP (7)
- Java (7)
- CSS (12)
- COBOL (6)

	Java	PHP	CSS	COBOL
Java	-	7	3	1
PHP	7	-	9	5
CSS	3	9	-	8
COBOL	1	5	8	-

Recommending Skills to Search (Example)

- CSS (12)
- COBOL (6)

	Java	PHP	CSS	COBOL
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Recommending Skills to Search (Example)

- CSS (12)
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Recommending Skills to Search (Example)

- CSS (12)

	Java	PHP	CSS	COBOL
Java	-	7	3	1
PHP	7	-	9	5
CSS	3	9	-	8
COBOL	1	5	8	-

API Endpoints

REST API Endpoints (Login)

URL	Method	Feature
/login	POST	User Login
/logout	POST	User Logout

- Login to edit user’s skills
- No login needed to search

REST API Endpoints (Users)

URL	Method	Feature
/users	GET	Main person search function
/users/{user}	GET	Get specific user's details
/users/{user}/skills	POST	Add/Update user's skills
/users/{user}/skills	DELETE	Remove skill from user's profile
/users/{user}/similar	GET	Recommend similar users

- New users added on their first login
- No removing of users

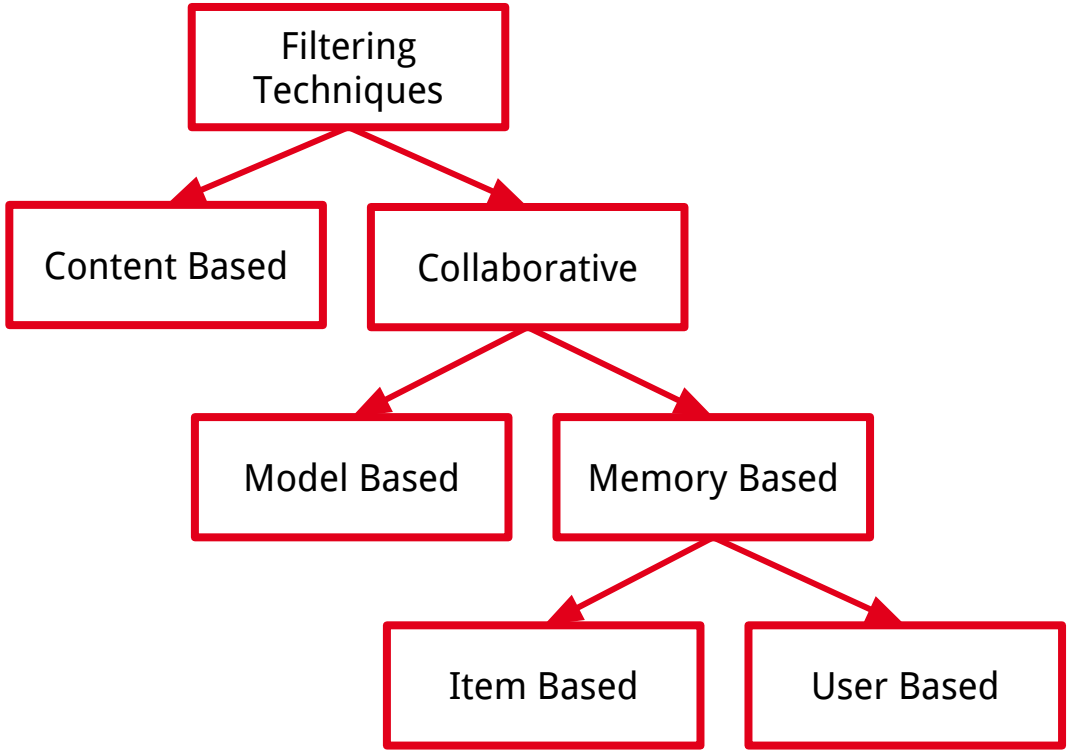
REST API Endpoints (Skills)

URL	Method	Feature
/skills	GET	Get all skills/text autocomplete
/skills	POST	Create new Skill
/skills/next	GET	Recommend next skill to enter
skills/{skill}	PUT	Edit skill (rename)
skills/{skill}	DELETE	Delete skill

Concept: Collaborative Filtering Techniques

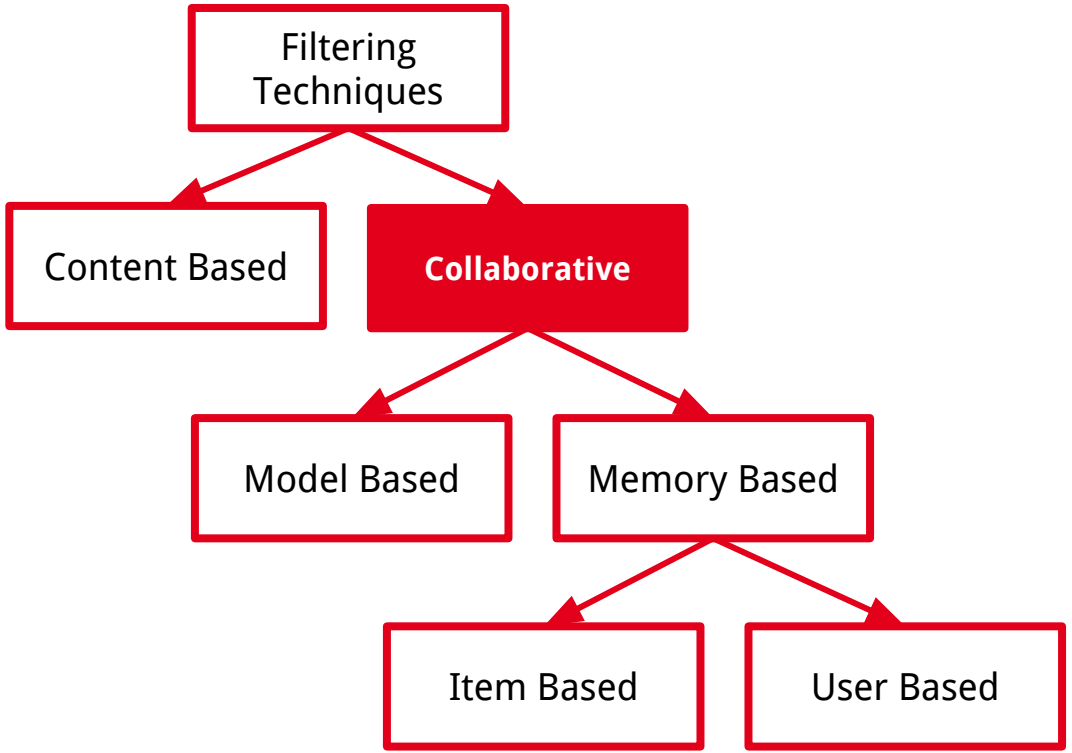
Filtering Techniques

- Isinkaye et al.
- Techniques to find the items to suggest
- Hybrid filtering: combine multiple techniques



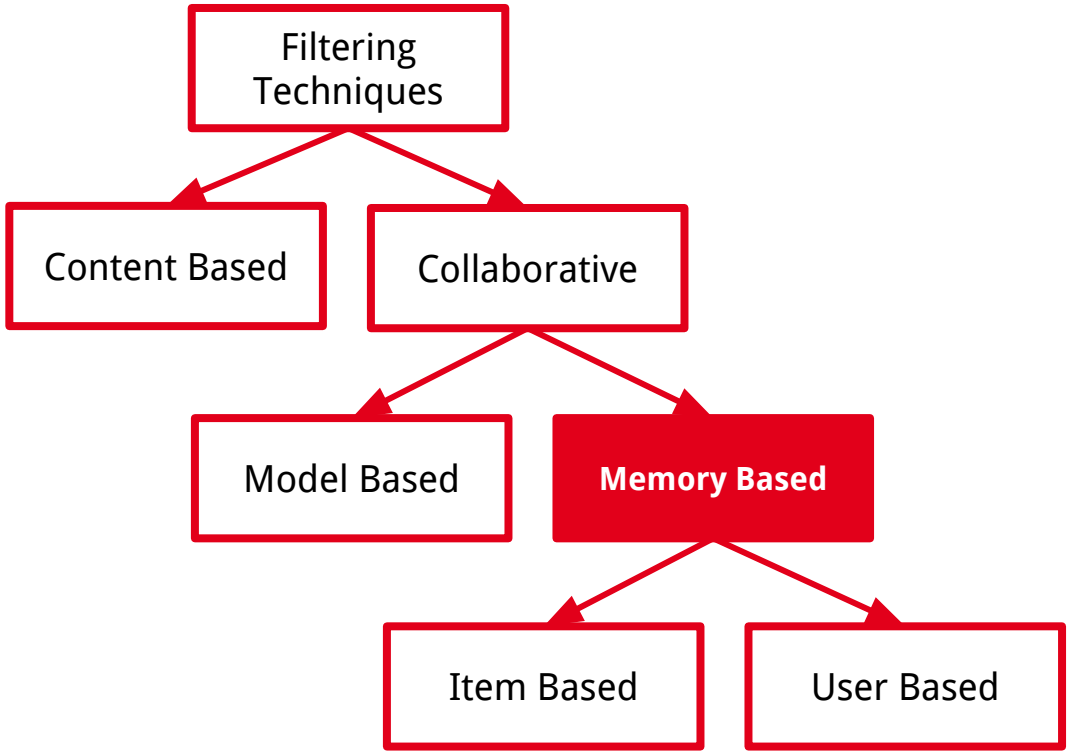
Filtering Techniques (Collaborative)

- People behave similarly
- Find neighbours



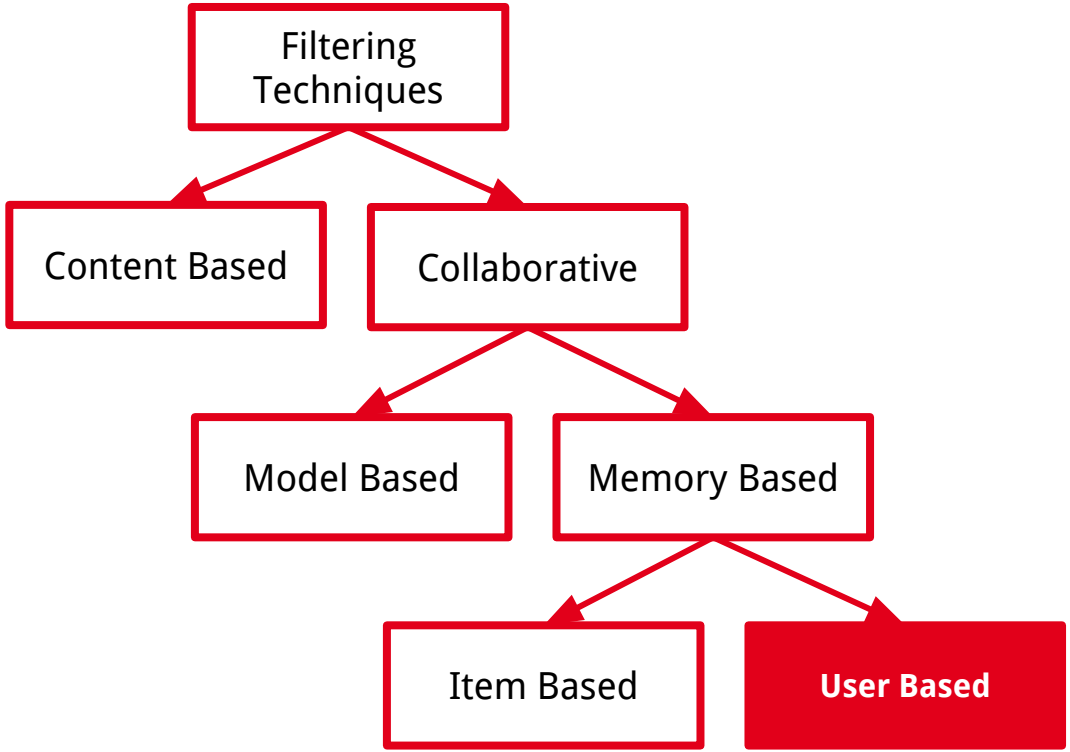
Filtering Techniques (Memory Based)

- Subset of collaborative filtering
- Operates directly on saved interaction history



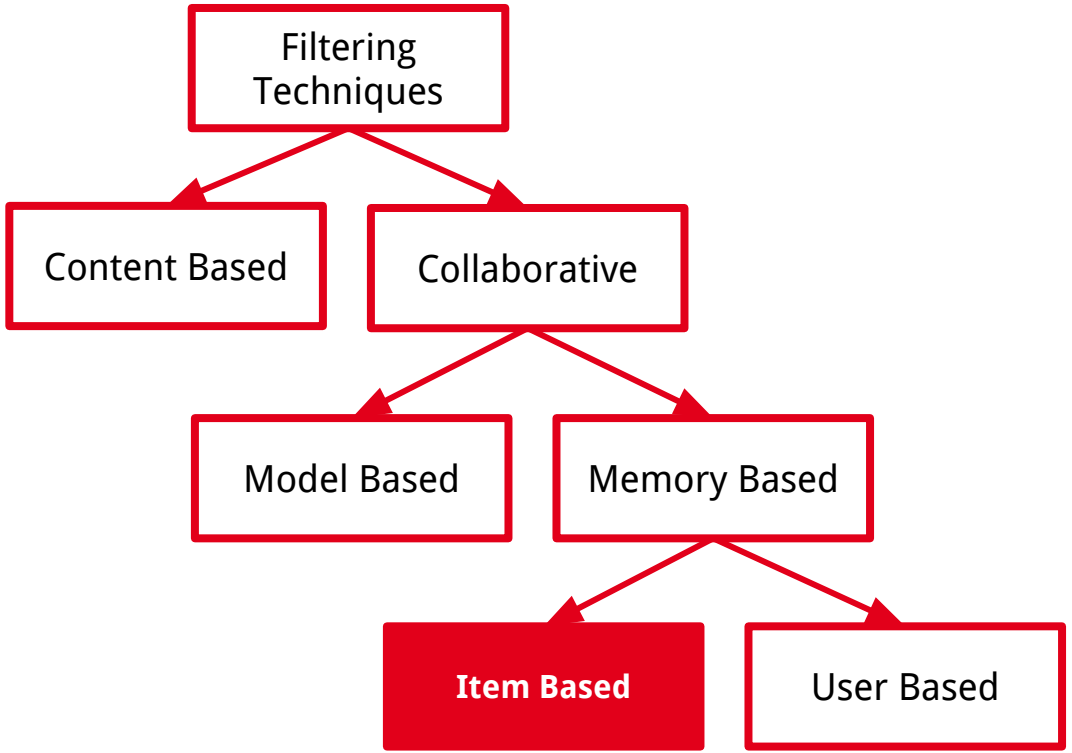
Filtering Techniques (User Based)

- Subset of memory based filtering
- Save interaction history per user
- Find groups of users that have similar interaction histories



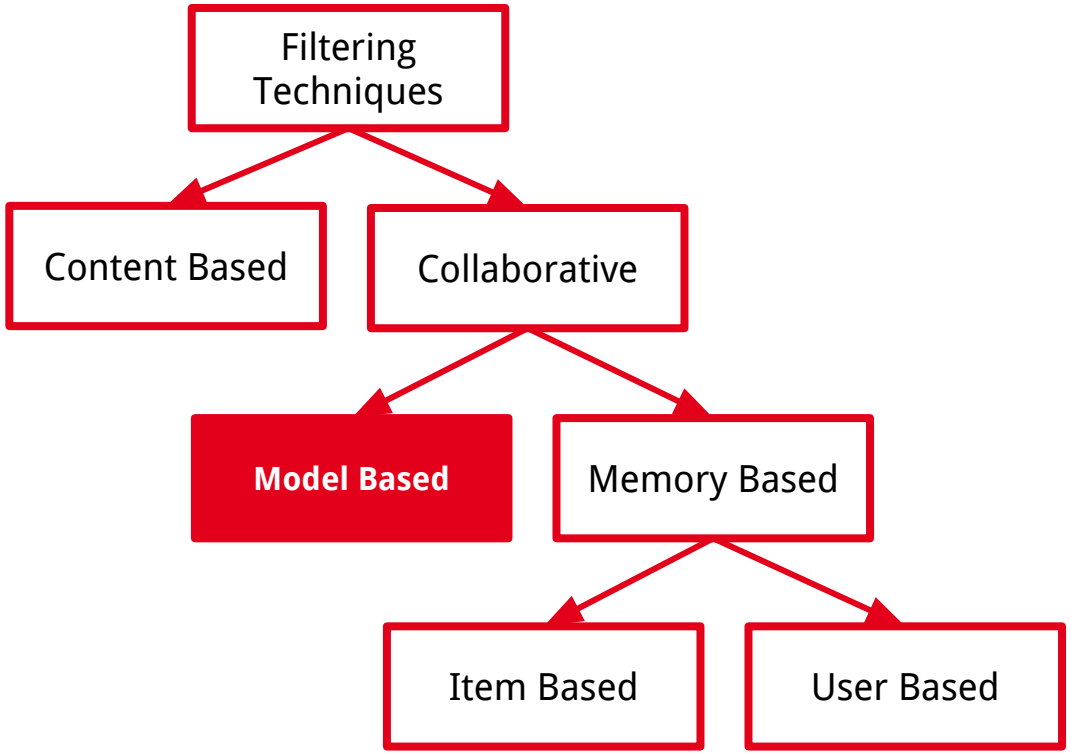
Filtering Techniques (Item Based)

- Subset of memory based filtering
- Save interaction history per item
- Find items that are similar to each other



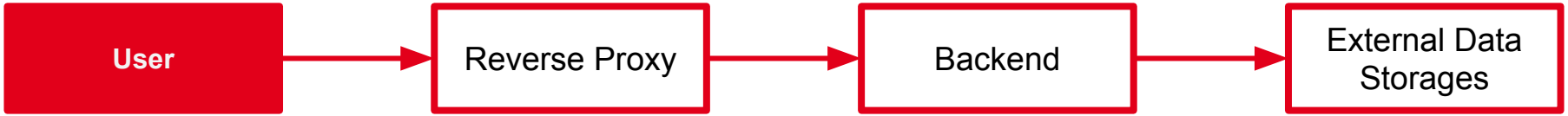
Filtering Techniques (Model Based)

- Subset of collaborative filtering
- Model used to create suggestions
- Interactions to learn the model



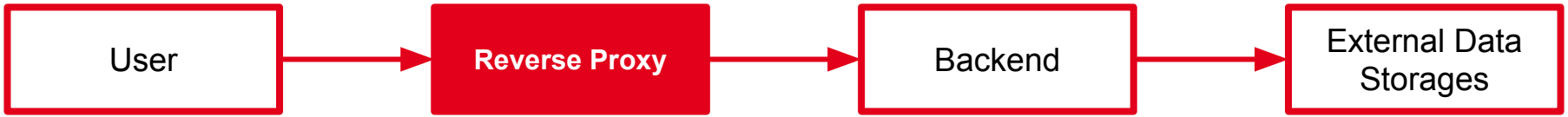
Example: API Call

API Call (Search for Java and Ruby in HH)



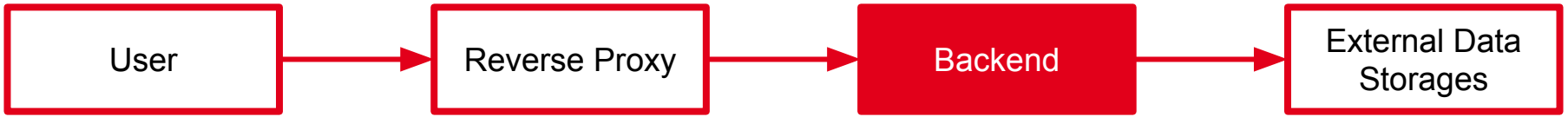
- Search for Java and Ruby in HH
- Browser Calls API
  - *api.some.tld/users?skills=Java,Ruby&location=Hamburg*

API Call (Search for Java and Ruby in HH)



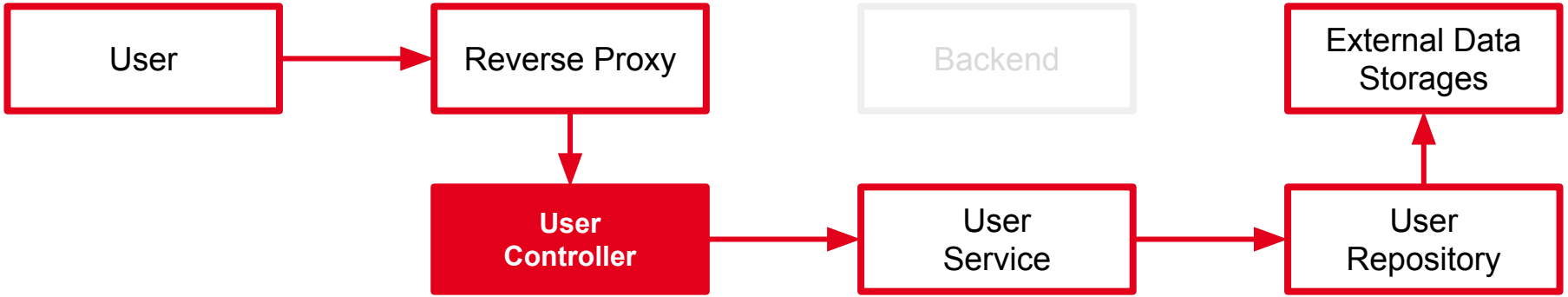
- Recognize API Call (Domain)
- Forward to Backend Server

API Call (Search for Java and Ruby in HH)



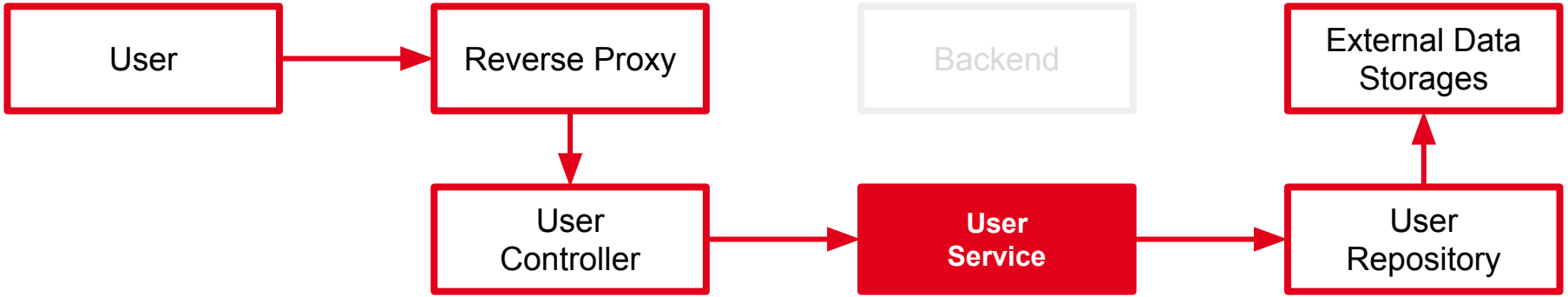
- Waits for HTTP Requests
- Dispatching to Controller

API Call (Search for Java and Ruby in HH)



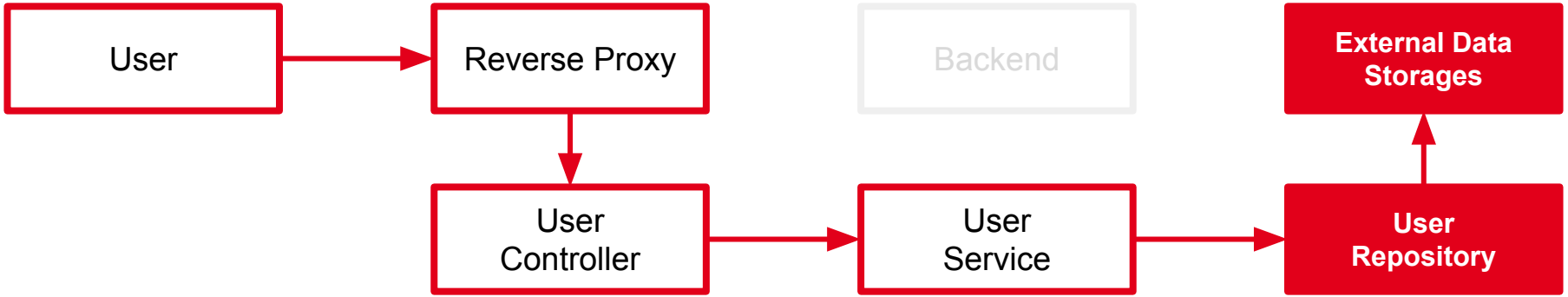
- Call method based on request URL and Parameters
  - /users/
  - ?skills=Java,Ruby&location=Hamburg
- Request matching persons from UserService

API Call (Search for Java and Ruby in HH)



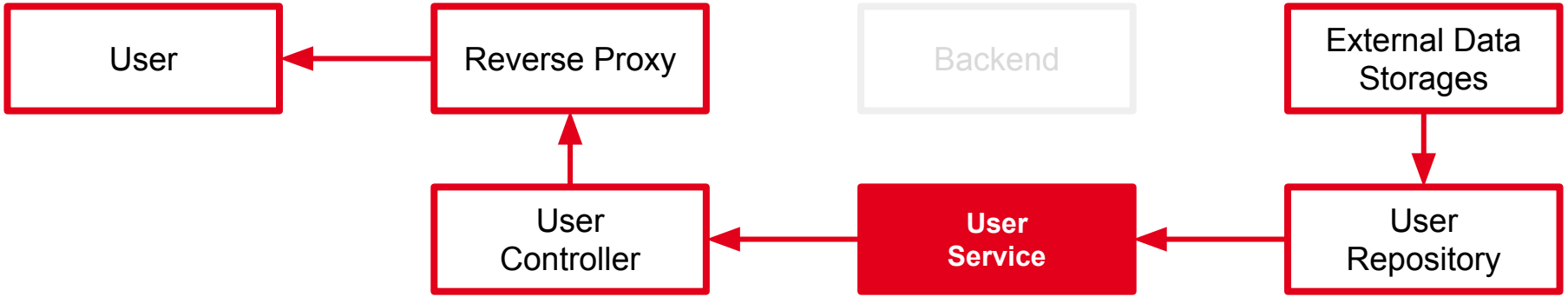
- Request needed users from Repository

API Call (Search for Java and Ruby in HH)



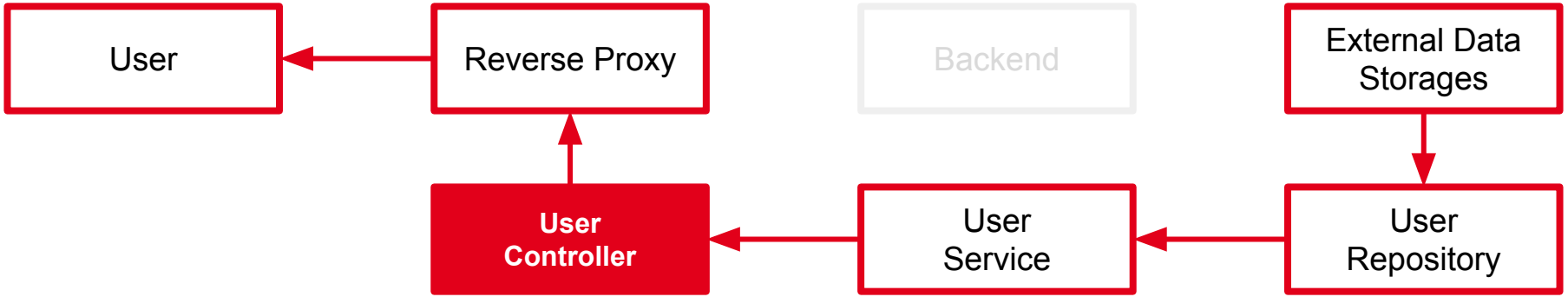
- Get data from MongoDB
- Return user objects to UserService

API Call (Search for Java and Ruby in HH)



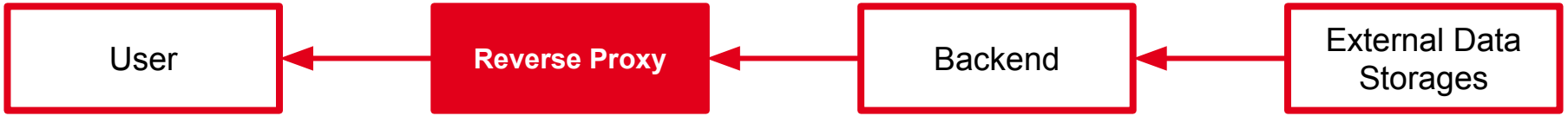
- Process retrieved user objects
- Apply search and fitness score algorithms

API Call Cycle (Search for Java and Ruby in HH)



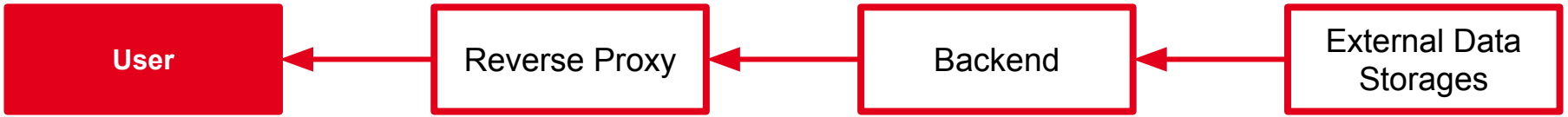
- Convert found user objects to JSON
- Return HTTP Response
  - In case of error, return corresponding HTTP Code

API Call Cycle (Search for Java and Ruby in HH)



- Forward JSON response to client

API Call Cycle (Search for Java and Ruby in HH)

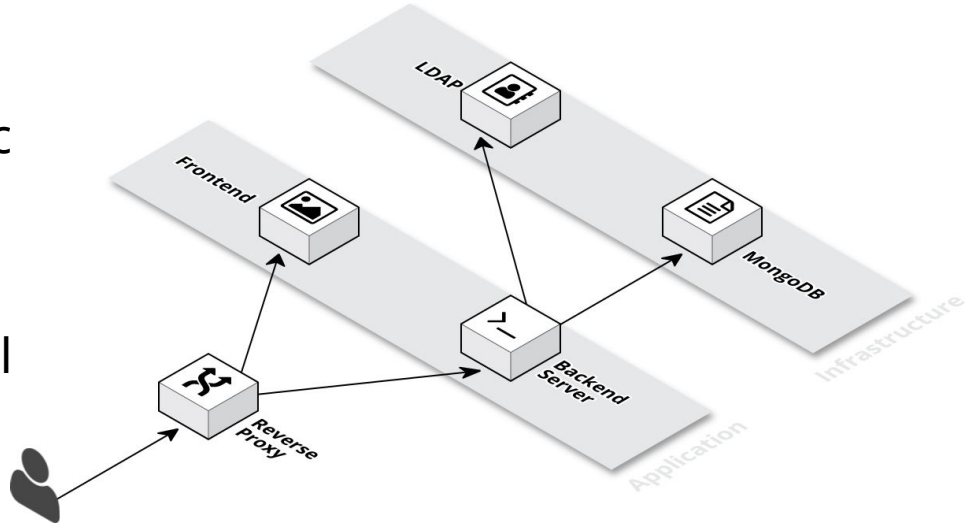


- Parse JSON response
- Render result list

Evaluation: Scalability

Evaluation (Scalability)

- MongoDB
  - Designed and shown to be sc
- LDAP
  - Six servers
  - Cluster is transparent to appl
- Frontend
  - CDN
- Backend
  - Stateless Application
  - Reverse proxy as load balancer
  - Tested



Evaluation (Scalability)

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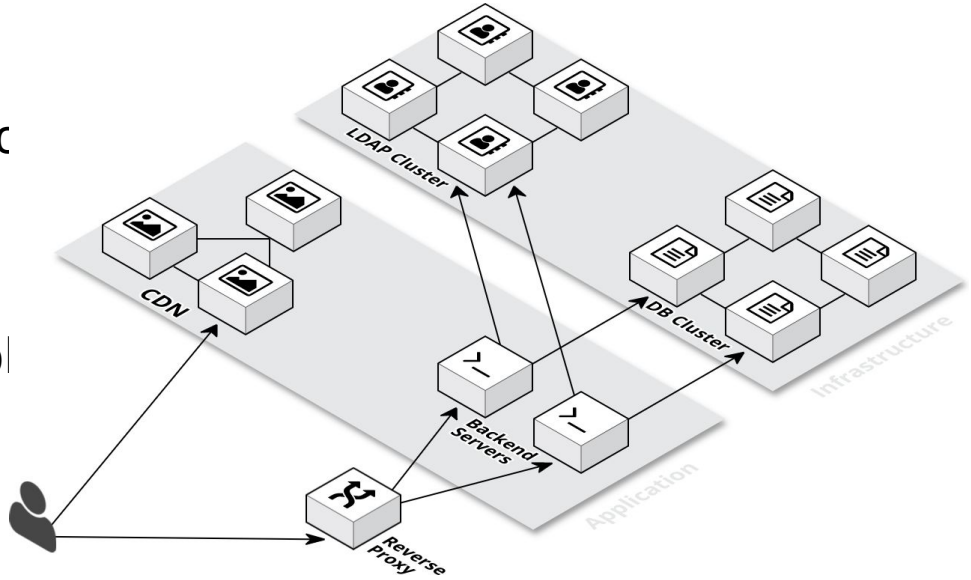


Evaluation (Scalability)

SINNERSCHRADER AG UND ACCENTURE VEREINBAREN ZUSAMMENSCHLUSS; ACCENTURE KÜNDIGT FREIWILLIGES ÖFFENTLICHES ÜBERNAHMEANGEBOT FÜR SÄMTLICHE AKTIEN DER SINNERSCHRADER AG AN

AD-HOC NEWS

20. Februar 2017, 7:21

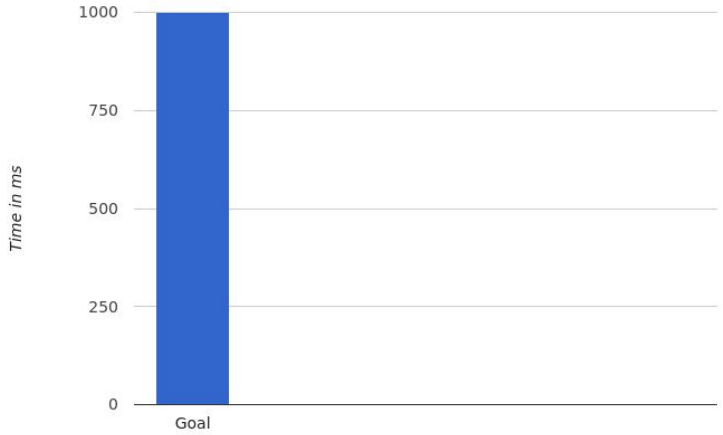
Die SinnerSchrader Aktiengesellschaft („SinnerSchrader") hat heute nach entsprechenden Beschlüssen von Aufsichtsrat und Vorstand mit der Accenture Digital Holdings GmbH, einer 100-prozentigen... **weiter lesen**

Alle Finanznachrichten ›

Evaluation: Response Times

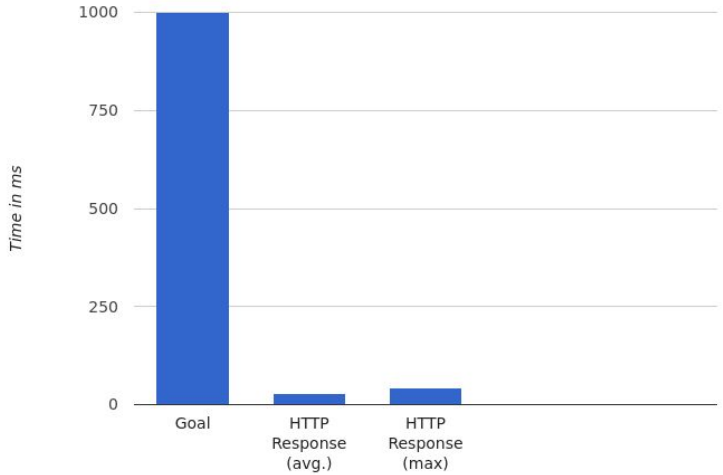
Evaluation (Response Times)

- Goal: 1s max to finish rendering



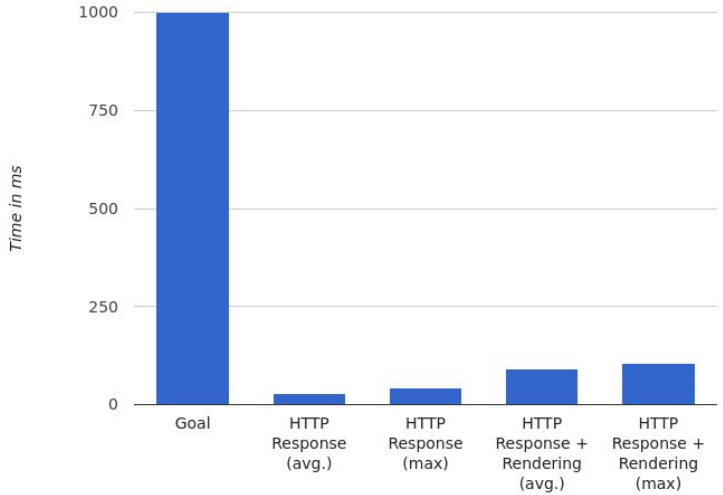
Evaluation (Response Times)

- Goal: 1s max to finish rendering
- HTTP Response: 33ms/44ms (40 samples)



Evaluation (Response Times)

- Goal: 1s max to finish rendering
- HTTP Response: 33ms/44ms (40 samples)
- + Rendering: 90ms/106ms (16 samples)

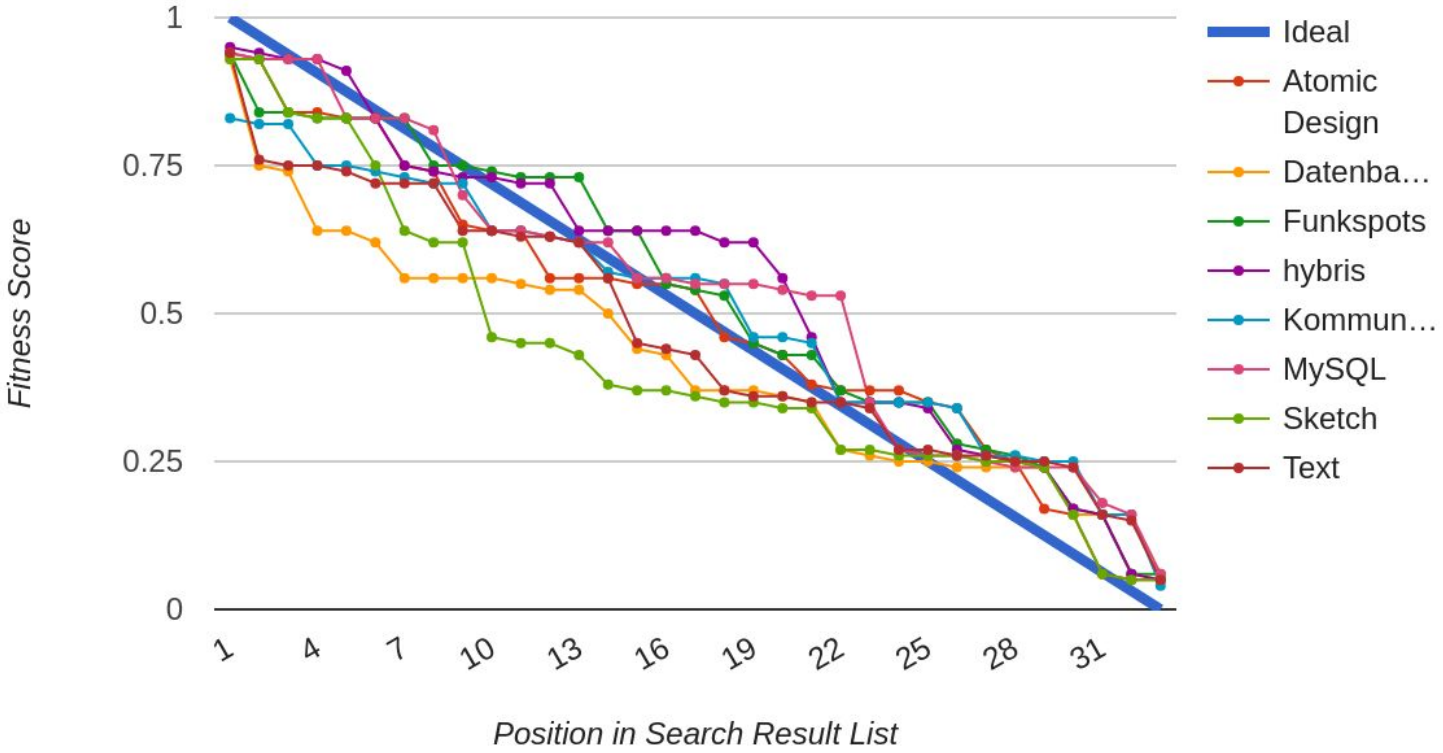


Evaluation: Uniform Distribution of Fitness Scores

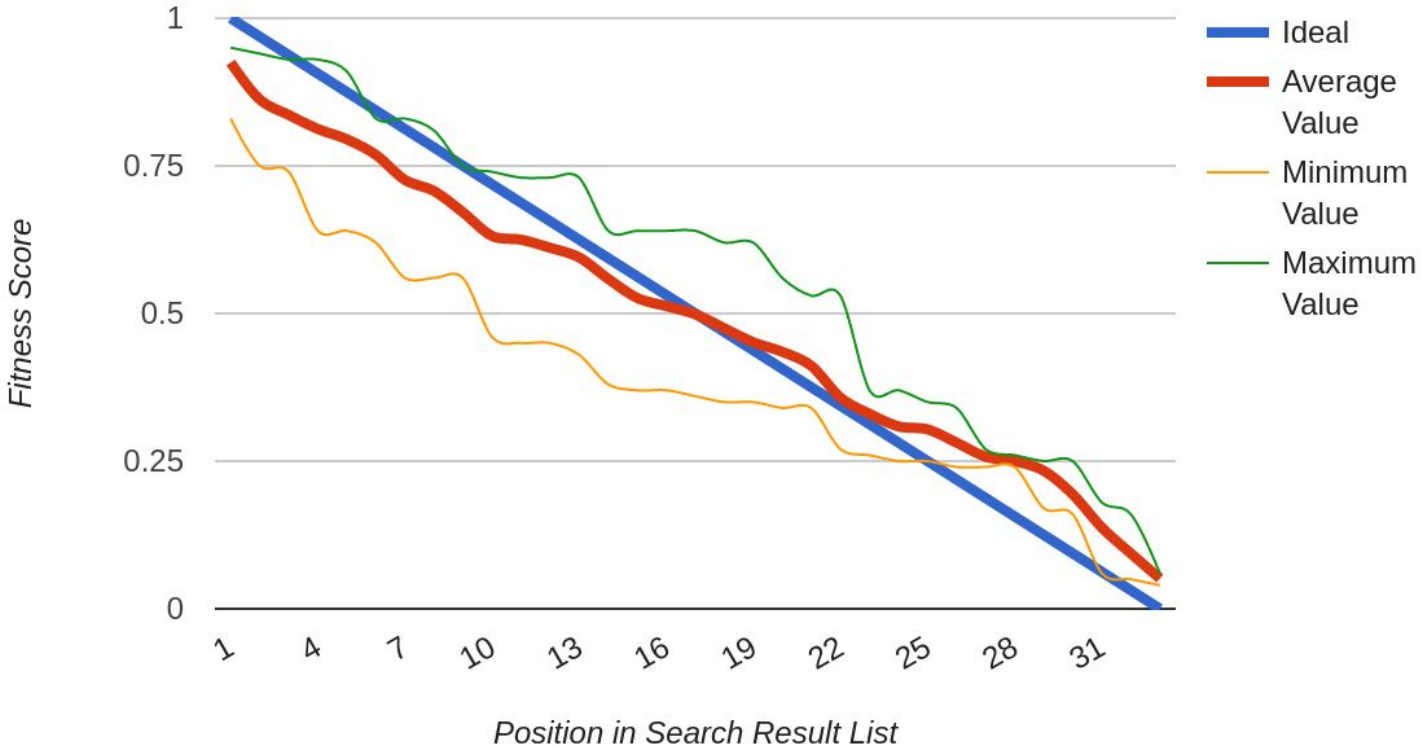
Evaluation (Distribution of Fitness Scores)

- 100 users
- ≤ 17 skills per users
- Random levels
- Fitness of employees distributed uniformly
- Are fitness scores distributed uniformly?

Evaluation (Distribution of Fitness Scores)



Evaluation (Distribution of Fitness Scores)



Evaluation (Distribution of Fitness Scores)

- Average Deviation: 6%
- Maximum Deviation: 27%