# Development of Recommender Systems with a Focus on Improving User Satisfaction

## Entwicklung von Empfehlungssystemen mit dem Schwerpunkt auf der Verbesserung der Benutzerzufriedenheit

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# What are Recommender Systems?

**Recommender Systems(RS)**

Software tools and techniques that provide suggestions for items that are most likely to interest a particular user

- History goes back to mid 1990's
- Became mainstream with e-commerce
- Problem: Users overloaded with information
- Solution: RS as a way to filter information for users

# Problem

Aim of developers and researchers:

- Increase interaction
- Increase coverage
- Increase user satisfaction

Evaluation metrics and properties used:

- Accuracy

**Problem**

User satisfaction may also depend on other properties such as privacy, data security, diversity, serendipity, labeling and presentation.

# Motivation

Find answers to these questions:

- Does high accuracy guarantee high user satisfaction?
- Does diversity affect user satisfaction positively?
- Would a feedback loop enhance user satisfaction?

**Use-case**

Individual and group recommendation of talents to roles or projects.

# Types of Recommender Systems

Two main categories:

- Personalized
- Non-personalized

Among personalized approaches are:

- Content-based filtering
- Collaborative filtering
- Knowledge-based filtering
- Hybrid methods

**Solution**

Only used content-based filtering in this thesis.

# Overview of Content-Based Recommender Systems

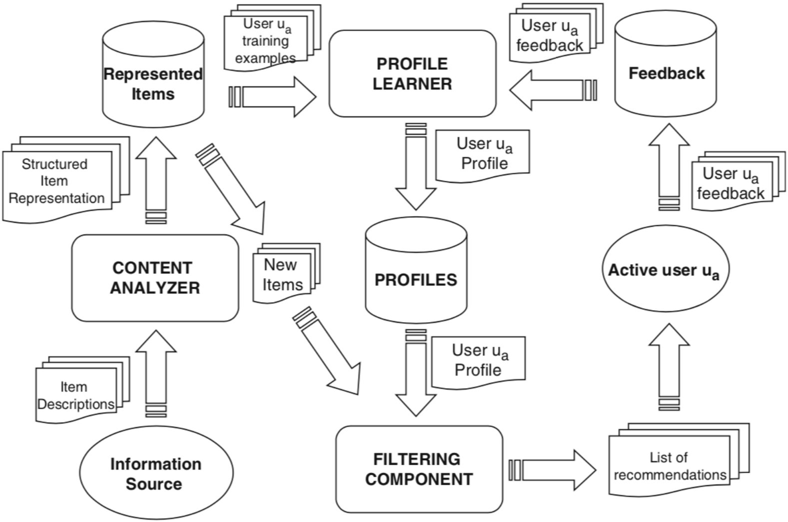



Figure: High level architecture of a content-based recommender

# Advantages and Drawbacks of Content-Based Filtering

Advantages:

- User Independence
- Transparency
- New Item

Drawbacks:

- Limited Content Analysis
- Over-specialization
- New User

# Recommender System Evaluation Properties

- Accuracy
- Coverage
- Confidence
- Trust
- Novelty
- Serendipity
- Diversity
- Utility
- Risk
- Robustness
- Privacy
- Adaptivity
- Scalability

# Accuracy and Diversity

Accuracy:

$$\mathrm{RMSE}(f) = \sqrt{\frac{1}{|\mathcal{R}_{test}|} \sum_{r_{iu}} (f(u,i) - r_{ui})^2} \tag{1}$$

Diversity:

$$\mathrm{ILD} = \frac{1}{|R|(|R|-1)} \sum_{i \in R} \sum_{j \in R} d(i,j). \tag{2}$$

## Others

We also used other methods such as aggregate diversity, shannon entropy and gini index.

# Datasets

Freelancer.com Dataset:

- 30.606 unique roles
- 32.922 unique talents
- 463.536 bids
- 941 unique skills

Motius Dataset:

- 375 unique roles
- 795 unique talents
- 1768 unique skills

## Combination

We combine datasets, remove skillss less than 5 and we have 923 total skills.

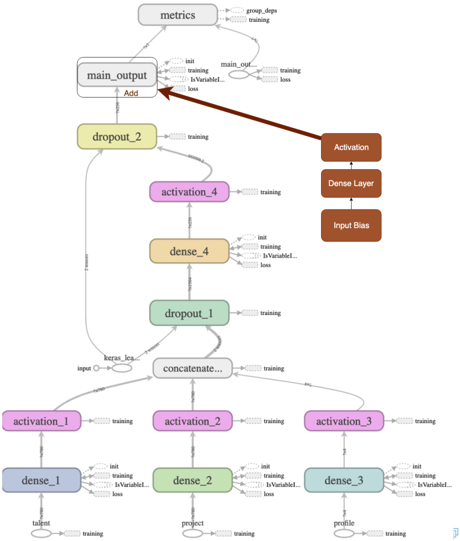
# Unsupervised Individual Recommender

- Recomendation by Similarity

$$\cos(x, y) = \frac{(x \bullet y)}{\|x\|\|y\|} \tag{3}$$

- Recomendation by Popularity
- Hybrid Recommendation

# Supervised Individual Recommender with Feedback Learning



# Group Recommenders

- Group Recommendation using Clustering

| | .NET | 2D Animation | 360-degree video | 3D Animation | 3D Design | 3D Model Maker | 3D Modelling | 3D Printing | 3D Rendering | 3ds Max | ... | iPhone | jQuery / Prototype | node.js | phpMyAdmin |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Segment 0 | -0.212465 | -0.004102 | -0.019304 | -0.095342 | 0.063749 | -0.031560 | -0.123809 | -0.053663 | -0.089939 | -0.127223 | ... | -0.225476 | -0.279852 | -0.131371 | -0.027035 |
| Segment 1 | -0.081847 | -0.055546 | -0.015600 | -0.196805 | -0.166759 | -0.046560 | -0.244780 | -0.051745 | -0.240299 | -0.162773 | ... | -0.077620 | 0.500239 | 0.035455 | 0.019867 |
| Segment 2 | 2.467993 | -0.061241 | -0.038406 | -0.222762 | -0.197445 | -0.049275 | -0.256107 | -0.066796 | -0.251231 | -0.177760 | ... | -0.119369 | 0.142341 | -0.028433 | 0.005529 |

Figure: Examples of some centers of clusters that are projected on a 2D space

- Unsupervised Group Recommender
- Supervised Group Recommender

# Unsupervised and Supervised Group Recommender

- Baseline Recommender
- Diverse Recommender

$$g(R, \lambda) = (1 - \lambda) \frac{1}{|R|} \sum_{i \in R} f_{rel}(i) + \lambda div(R). \tag{4}$$

**Diversity Enhancement Algorithm**

Find the best talent for every role of the project with the equation.

# Dashboard Main

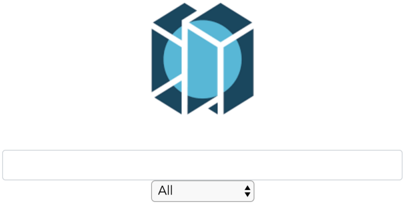



Figure: Main screen of the dashboard

# Dashboard Projects


Figure: A snippet from the list of all projects that start with the letter *a*

# Dashboard Individual

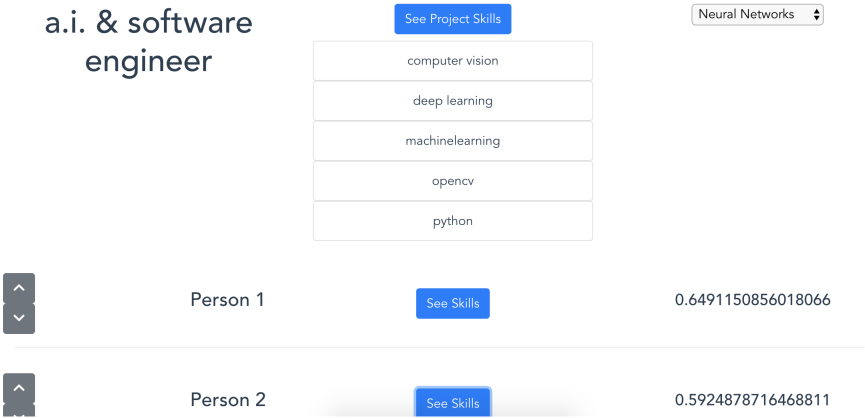



Figure: A screenshot from the list of all recommendations from neural networks for the project *a.i. & software engineer*

# Dashboard Individual Hybrid

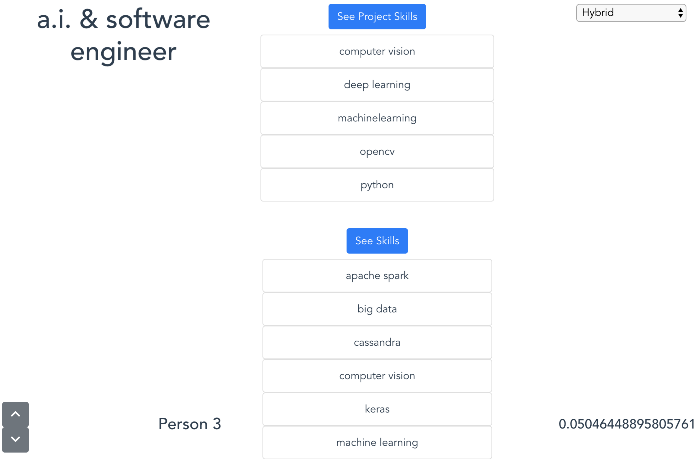



Figure: A screenshot from the list of all recommendations from neural networks for the project *a.i. & software engineer*

# Dashboard Group

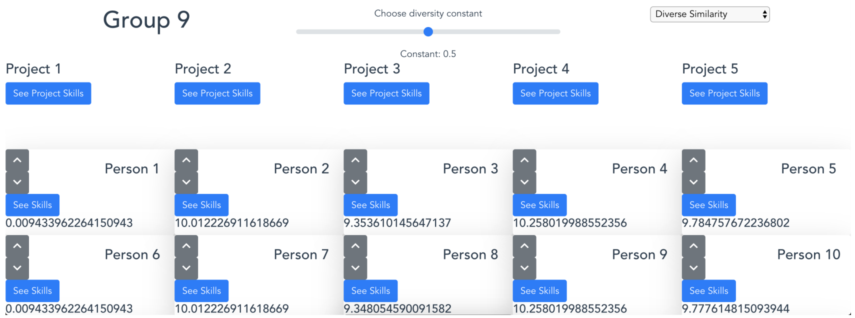



Figure: A screenshot from the list of all recommendations from diverse cosine similarity for the group 9

# Evaluation Methods

- Offline evaluation: evaluation using algorithms
- Online evaluation: letting users interact with system and analyzing results
- User studies: asking users questions without giving them information about your aim etc.

# Offline Accuracy of Individual Recommenders

Table: Offline evaluation results for different recommenders are shown.

| Type | Name | Top 1 | Top 5 |
|---|---|---|---|
| Unsupervised | Motius | 0.07 | 0.21 |
| Unsupervised | Similarity | 0.28 | 0.36 |
| Unsupervised | Popularity | 0.07 | 0.45 |
| Unsupervised | Similarity&Popularity | 0.12 | 0.29 |
| Supervised | Neural Network | 0.19 | 0.56 |
| Supervised | Neural Network & Similarity | 0.1 | 0.49 |

# User Study Result of Individual Recommenders

Table: Offline evaluation results for different recommenders are shown.

| Type | Name | First Item Value | Satisfaction |
|---|---|---|---|
| Unsupervised | Similarity | 4.375 | 3.8125 |
| Supervised | Neural Network | 2.5625 | 2.8125 |
| Supervised | Hybrid | 4.5 | 4.0625 |

# Accuracy of Unsupervised Group Recommender

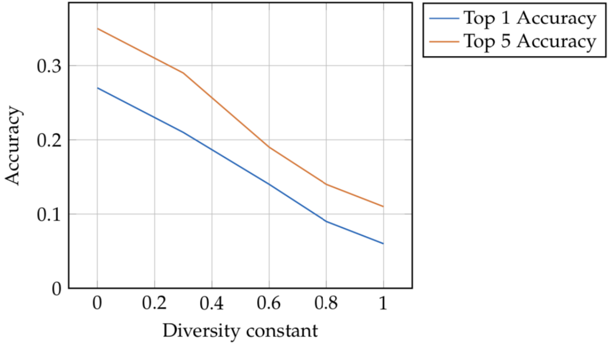



Figure: Effect of diversity constant on unsupervised group recommender to the accuracy

# Accuracy of Unsupervised Group Recommender

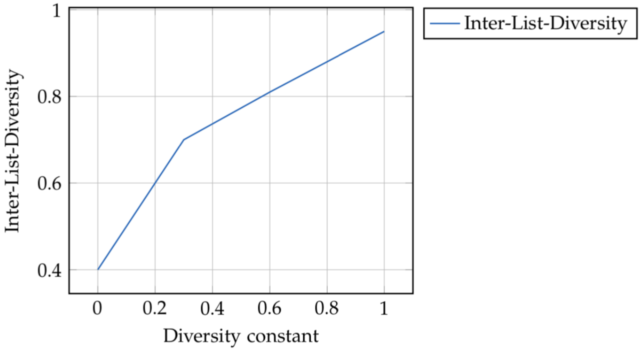



Figure: Effect of diversity constant on unsupervised group recommender to the diversity

# User Study about Unsupervised Group Recommender

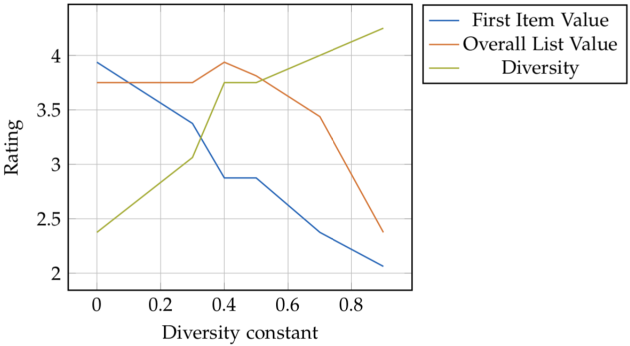



Figure: Effect of diversity constant on unsupervised group recommender to the average user opinion

# Accuracy of Supervised Group Recommender

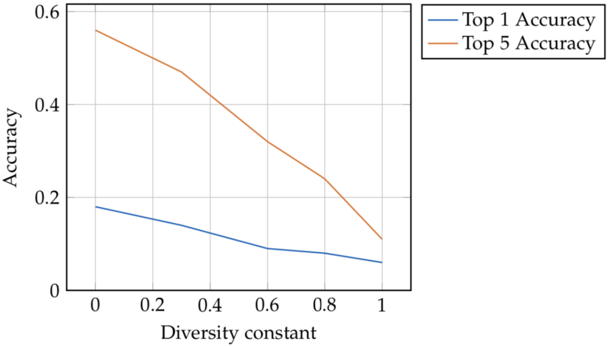



Figure: Effect of diversity constant on supervised group recommender to the accuracy

# Accuracy of Supervised Group Recommender

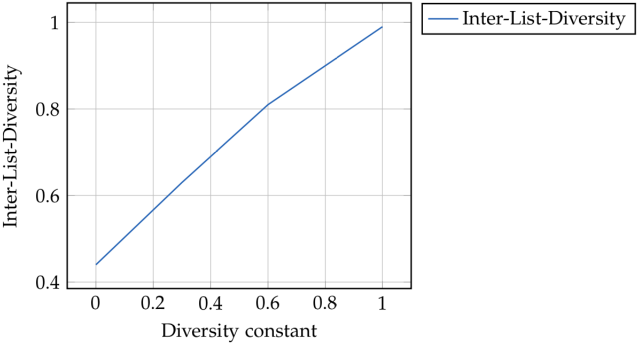



Figure: Effect of diversity constant on supervised group recommender to the diversity

# User Study about Supervised Group Recommender

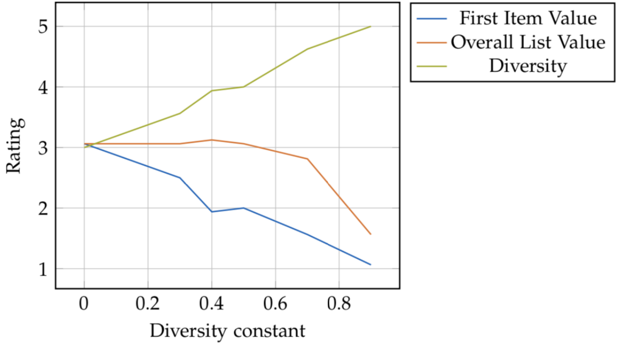



Figure: Effect of diversity constant on supervised group recommender to the average user opinion

# Online Evaluation and User Study about Feedback Learning

Table: A table that shows the user opinions before and after re-training.

| First Item Value | Overall List Value | Diversity |
|---|---|---|
| 3.125 | 3 | 2.375 |
| 3.75 | 3.6875 | 2.5625 |

# Conclusion

Initial questions:

- Does high accuracy guarantee high user satisfaction?
- Does diversity affect user satisfaction positively?
- Would a feedback loop enhance user satisfaction?

Answers:

- No, we proved otherwise.
- Yes from our experiments. However, more experiments with more subjects are needed.
- Yes, if there are enough feedback.

# Artificial Neural Networks

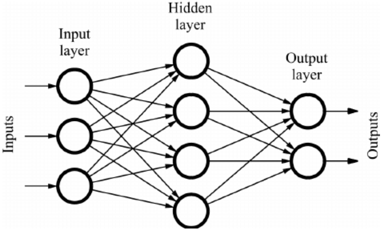



Figure: High level architecture of a feedforward neural network

$$f(\boldsymbol{x}; \boldsymbol{w}, b) = \sigma(\boldsymbol{x}^\top \boldsymbol{w} + b) \tag{5}$$

## Embeddings

Embeddings layers are used to reduce dimensionality.

# Others Evaluation Methods

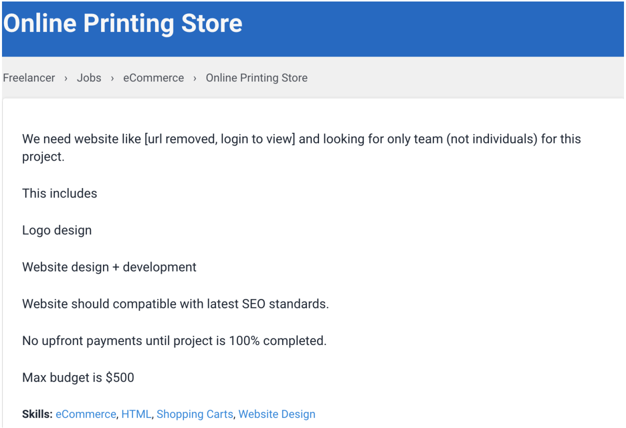
$$\text{ILD} = \frac{1}{|R|(|R|-1)} \sum_{i \in R} \sum_{j \in R} d(i,j). \tag{6}$$

$$\text{Unexp} = \frac{1}{|R|\,|\mathcal{J}_u|} \sum_{i \in R} \sum_{j \in \mathcal{J}_u} d(i,j), \tag{7}$$

where

$$\mathcal{J}_u \stackrel{\text{def}}{=} \{i \in \mathcal{J} | r(u,i) \neq \emptyset\}. \tag{8}$$

# Freelancer.com Dataset(1)



## Online Printing Store

Freelancer › Jobs › eCommerce › Online Printing Store

We need website like [url removed, login to view] and looking for only team (not individuals) for this project.

This includes

Logo design

Website design + development

Website should compatible with latest SEO standards.

No upfront payments until project is 100% completed.

Max budget is $500

**Skills:** eCommerce, HTML, Shopping Carts, Website Design

Figure: An example project from the Freelancer.com Website

# Freelancer.com Dataset(2)

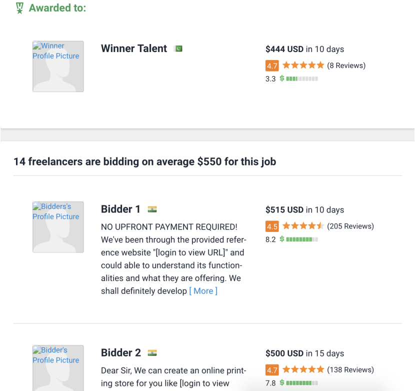



Figure: The winner and other bidders to the same project

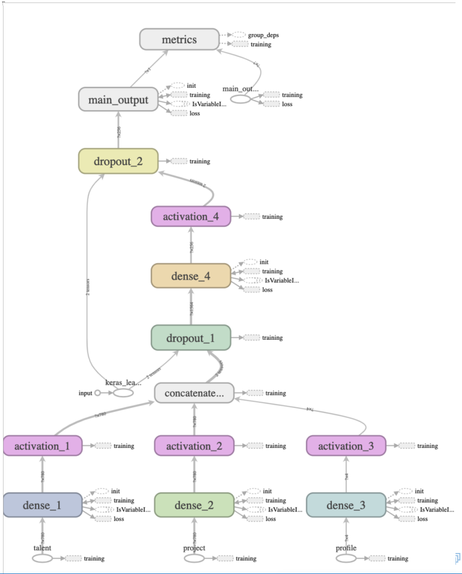
# Freelancer.com Dataset(3)

### My Top Skills

| | |
|---|---|
| PHP | 17 |
| Website Design | 13 |
| HTML | 13 |
| Graphic Design | 11 |
| Javascript | 3 |
| Mobile App Development | 2 |
| WordPress | 2 |
| CSS | 2 |
| Script Install | 1 |
| Web Scraping | 1 |

Figure: The list of tops skills by a talent on Freelancer.com web page

# Model of Sparse Input



# Supervised Individual Recommender

- Using Sparse Input

| user_url | .net | 2d animation | 360-degree video | 3d animation | 3d design | 3d model maker | 3d modelling | 3d printing | 3d rendering | 3ds max | ... | xero | xml | xmpp | xslt | yii | youtube | zbrush | zen cart | zend |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Talent 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Talent 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Talent 3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Talent 4 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Talent 5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Talent 6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Talent 7 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Talent 8 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Talent 9 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 1 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Talent 10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

10 rows × 780 columns

Figure: The talent skill matrix from freelancer.com

- Using Embeddings

| | project_url | bidder_url | outcome | 0 | 1 | 2 | 3 | 4 | 5 | 6 | ... | 32 | 33 | 34 | 35 | 36 | 37 | 38 | 39 | 40 | 41 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | a.i. & software engineer | Talent 1 | 0.0 | 69.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | ... | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| 1 | a.i. & software engineer | Talent 2 | 0.0 | 577.0 | 778.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | ... | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| 2 | a.i. & software engineer | Talent 3 | 0.0 | 350.0 | 396.0 | 487.0 | 0.0 | 0.0 | 0.0 | 0.0 | ... | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| 3 | a.i. & software engineer | Talent 4 | 0.0 | 69.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | ... | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| 4 | a.i. & software engineer | Talent 5 | 0.0 | 222.0 | 460.0 | 776.0 | 0.0 | 0.0 | 0.0 | 0.0 | ... | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |

Figure: Training data that contains padded embedding skill vectors

# Extra Profile Information

| bidder_url | experience_level | star_rating | number_of_reviews | hourly_rate |
|---|---|---|---|---|
| Talent 1 | 5 | 4.8 | 385 | 12 |
| Talent 2 | 17 | 4.9 | 162 | 25 |
| Talent 3 | 17 | 5.0 | 5 | 15 |
| Talent 4 | 6 | 4.9 | 116 | 30 |
| Talent 5 | 6 | 0.0 | 0 | 2 |
| Talent 6 | 6 | 0.0 | 0 | 3 |
| Talent 7 | 6 | 5.0 | 24 | 40 |
| Talent 8 | 6 | 5.0 | 2 | 5 |
| Talent 9 | 6 | 5.0 | 16 | 20 |
| Talent 10 | 3 | 5.0 | 67 | 20 |

Figure: The talent extra information matrix from Freelancer.com