Relatedness of Given Names

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ABSTRACT

As a result of the author's need for help in finding a given name for the unborn baby, the Nameling[1], a search engine for given names, based on data from the "Social Web" was born. Within less than six months, more than 35,000 users accessed Nameling with more than 300,000 search requests, underpinning the relevance of the underlying research questions.

The present work proposes a new approach for discovering relations among given names, based on co-occurrences within Wikipedia. In particular, the task of finding relevant names for a given search query is considered as a ranking task and the performance of different measures of relatedness among given names are evaluated with respect to Nameling's actual usage data. We will show that a modification for the PageRank algorithm overcomes limitations imposed by global network characteristics to preferential PageRank computations.

By publishing the considered usage data, the research community is stipulated for developing advanced recommendation systems and analyzing influencing factors for the choice of a given name.

I INTRODUCTION

Whoever was in the need for a given name knows how difficult it is to choose a suitable name which meets (in the best case) all constraints. The choice of a given name is not only influenced by personal taste. Many influencing factors have to be considered, such as cultural background, language dependent pronunciation, current trends and, last but not least, public perception or even prejudices towards given names.

Though there is a constant demand for finding a suitable name, little aid exists, beside alphabetically ordered lists of names and simple filtering techniques. From a scientist's perspective, the task of ranking and recommending given names is challenging and can be tackled from many different disciplines.

In the present work, we consider the task, where a user searches for suitable names based on a given set of query names. The user thus can, e. g., search for names which are related to his own name, the names of all family members together or just for names which are similar to a name he or she likes.

The proposed approach for discovering relations among given names is based on co-occurrences within Wikipedia,[2] but can as well be applied to other data sources, such as micro blogging systems, news paper archives or collections of eBooks. Manual inspection of a first implementation of cosine similarity (cf. Section III) already showed promising results, but as there is a variety of metrics for calculating similarity in such co-occurrence graphs, the question arises, which one gives raise to the most "meaningful" notion of relatedness.

For assessing the performance of the different similarity metrics, we firstly compare the obtained rankings with an external reference ranking. Secondly, we evaluate the ranking performance with respect to actual usage data from Nameling, which comprises more than 35,000 users with more than 300,000 search queries during the time period of evaluation. We will show that a modification of the PageRank algorithm which we adopted from our previous work on folksonomies [11] overcomes limitations imposed by global network characteristics to preferential PageRank computations. To promote other researchers' efforts in developing new ranking and recommendation systems, all considered data is made publicly available.[3]

The rest of the work is structured as follows: Section II presents related work. Section III summarizes basic notions and concepts. Section IV briefly describes Nameling and Section V presents results on the semantics of the similarity metrics under consideration. In Section VI, the actual usage data of Nameling is introduced and analyzed, which is then used for comparing the performance of different similarity metrics in Section VII as well as comparing approaches for combining multiple query names in Section VIII. Finally, in Section IX, the present work's contributions are summarized and forthcoming work is

[1] http://nameling.net
[2] http://www.wikipedia.org
[3] http://www.kde.cs.uni-kassel.de/nameling/dumps

presented.

II RELATED WORK

The present work tackles the new problem of discovering and assessing relatedness of given names based on data from the social web for building search and recommendation systems which aid (not only) future parents in finding and choosing a suitable name.

Major parts of the underlying research questions are closely related to work on *link prediction* in the context of social networks as well as *distributional similarity*, where, more generally, semantic relations among named entities are investigated. However, this work focuses on the evaluation of similarity metrics relative to actual user preferences as expressed by interactions with names within a live system. This is related to the evaluation of *recommender systems* which exist for many application contexts, such as movies [9], tags [12] and products [19].

Distributional Similarity & Semantic Relatedness The field of distributional similarity and semantic relatedness has attracted a lot of attention in literature during the past decades (see [6] for a review). Several statistical measures for assessing the similarity of words are proposed, as for example in [15, 17, 22, 27]. Notably, first approaches for using Wikipedia as a source for discovering relatedness of concepts can be found in [3, 8, 25].

Vertex Similarity & Link Prediction In the context of social networks, the task of predicting (future) links is especially relevant for online social networks, where social interaction is significantly stimulated by suggesting people as contacts which the user might know. From a methodological point of view, most approaches build on different similarity metrics on pairs of nodes within weighted or unweighted graphs [13, 16, 20, 21]. A good comparative evaluation of different similarity metrics is presented in [18].

Nevertheless, usage data of systems such as Nameling is, to the best of our knowledge, new and was not available before. The present work combines approaches from the link prediction and recommendation tasks with a focus on the performance of structural similarity metrics based on co-occurrence networks obtained from Wikipedia.

III PRELIMINARIES

In this chapter, we want to familiarize the reader with the basic concepts and notations used throughout this paper.

1 GRAPH & NETWORK BASICS

A *graph* $G = (V, E)$ is an ordered pair, consisting of a finite set V of *vertices* or *nodes*, and a set E of *edges*, which are two-element subsets of V. A *directed graph* is defined accordingly: E denotes a subset of $V \times V$. For simplicity, we write $(u, v) \in E$ in both cases for an edge belonging to E and freely use the term *network* as synonym for a graph. In a *weighted graph*, each edge $l \in E$ is given an edge weight $w(l)$ by some weighting function $w\colon E \to \mathbb{R}$. For a subset $U \subseteq V$ we write $G_{|U}$ to denote the subgraph *induced by* U. The *density* of a graph denotes the fraction of realized links, i. e., $\frac{2m}{n(n-1)}$ for undirected graphs and $\frac{m}{n(n-1)}$ for directed graphs (excluding self loops). The *neighborhood* Γ of a node $u \in V$ is the set $\{v \in V \mid (u, v) \in E\}$ of *adjacent* nodes. The *degree* of a node in a network measures the number of connections it has to other nodes. For the *adjacency matrix* $A \in \mathbb{R}^{n\times n}$ with $n = |V|$ holds $A_{ij} = 1$ ($A_{ij} = w(i, j)$) iff $(i, j) \in E$ for any nodes i, j in V (assuming some bijective mapping from $1, \ldots, n$ to V). We represent a graph by its according adjacency matrix where appropriate.

A *path* $v_0 \to_G v_n$ of *length* n in a graph G is a sequence $v_0, \ldots, v_n$ of nodes with $n \geq 0$ and $(v_i, v_{i+1}) \in E$ for $i = 0, \ldots, n-1$. A *shortest path* between nodes u and v is a path $u \to_G v$ of minimal length. The *transitive closure* of a graph $G = (V, E)$ is given by $G^* = (V, E^*)$ with $(u, v) \in E^*$ iff there exists a path $u \to_G v$. A *strongly connected component (scc)* of G is a subset $U \subseteq V$, such that $u \to_{G^*} v$ exists for every $u, v \in U$. A *(weakly) connected component (wcc)* is defined accordingly, ignoring the direction of edges $(u, v) \in E$.

2 VERTEX SIMILARITIES

Similarity scores for pairs of vertices based only on the surrounding network structure have a broad range of applications, especially for the link prediction task [18]. In the following we present all considered similarity functions, following the presentation given in [7] which builds on the extensions of standard similarity functions for weighted networks from [23].

The *Jaccard coefficient* measures the fraction of common neighbors:

$$JAC(x, y) := \frac{|\Gamma(x) \cap \Gamma(y)|}{|\Gamma(x) \cup \Gamma(y)|}$$

The Jaccard coefficient is broadly applicable and commonly used for various data mining tasks. For weighted networks the Jaccard coefficient becomes:

$$\widetilde{JAC}(x,y) := \frac{\sum_{z\in\Gamma(x)\cap\Gamma(y)} w(x,z)+w(y,z)}{\sum\limits_{a\in\Gamma(x)} w(a,x)+\sum\limits_{b\in\Gamma(y)} w(b,y)}$$

The *cosine similarity* measures the cosine of the angle between the corresponding rows of the adjacency matrix, which for a unweighted graph can be expressed as

$$COS(x,y) := \frac{|\Gamma(x)\cap\Gamma(y)|}{\sqrt{|\Gamma(x)|}\cdot\sqrt{|\Gamma(y)|}},$$

and for a weighted graph is given by

$$\widetilde{COS}(x,y) := \frac{\sum_{z\in\Gamma(x)\cap\Gamma(y)} w(x,z)w(y,z)}{\sqrt{\sum\limits_{a\in\Gamma(x)} w(x,a)^2}\cdot\sqrt{\sum\limits_{b\in\Gamma(y)} w(y,b)^2}}.$$

The *preferential PageRank* similarity is based on the well known PageRank$^{\text{TM}}$ [2] algorithm. For a column stochastic adjacency matrix A and damping factor α, the *global* PageRank vector $\vec{w}$ with uniform *preference vector* $\vec{p}$ is given as the fixpoint of the following equation:

$$\vec{w} = \alpha A\vec{w} + (1-\alpha)\vec{p}$$

In case of the *preferential PageRank* for a given node i, only the corresponding component of the preference vector is set. For vertices x, y we set accordingly

$$PPR(x,y) := \vec{w}_{(x)}[y],$$

that is, we compute the preferential PageRank vector $\vec{w}_{(x)}$ for node x and take its y'th component. We also calculate an adapted preferential PageRank score by adopting the idea presented in [11], where the global PageRank score PR is subtracted from the preferential PageRank score in order to reduce frequency effects and set

$$PPR{+}(x,y) := PPR(x,y) - PR(x,y).$$

3 EVALUATION METRICS

Several metrics for assessing the perfomance of recommendation systems exists. We apply the *mean average precision* for obtaining a single value performance score for a set Q of ranked predicted recommendations P_i with relevant documents R_i:

$$\text{MAP}(Q) := \frac{1}{|Q|}\sum_{i=1}^{|Q|}\text{AveP}(P_i,R_i)$$

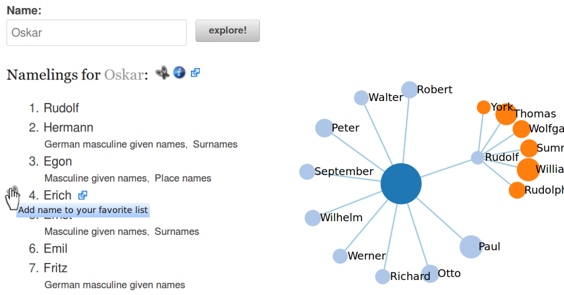
where the *average precision* is given by

$$\text{AveP}(P_i,R_i) := \frac{1}{|R_i|}\sum_{k=1}^{|R_i|}[\text{Prec}(P_i,k)\cdot\delta(P_i(k),R_i)]$$

and $\text{Prec}(P_i,k)$ is the *precision* for all predicted elements up to rank k and $\delta(P_i(k),R_i)=1$, iff the predicted element at rank k is a relevant document ($P_i(k)\in R_i$). Refer to [28] for more details.

IV A SEARCH ENGINE FOR GIVEN NAMES

Nameling is designed as a search engine and recommendation system for given names. The basic principle is simple: The user enters a given name and gets a browsable list of "relevant" names, called "*namelings*". Figure 1(a) exemplarily shows namelings for the classical masculine German given name "Oskar".



Name:

Oskar

explore!

Namelings for Oskar:

1. Rudolf
2. Hermann
   German masculine given names, Surnames
3. Egon
   Masculine given names, Place names
4. Erich
   Add name to your favorite list
   Masculine given names, Surnames
6. Emil
7. Fritz
   German masculine given names

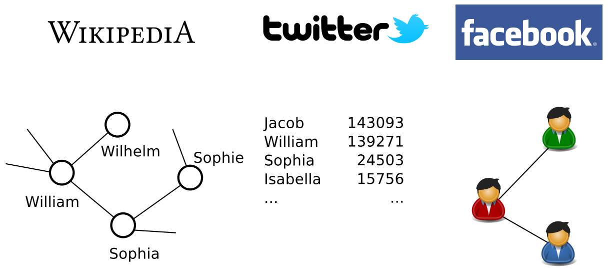
(a) Namelings (b) Co-occurring names

Figure 1: The user queries for the classical German given name "Oskar".

The list of namelings in this example ("Rudolf", "Hermann", "Egon", ...) exclusively contains classical German masculine given names as well. Whenever an according article in Wikipedia exists, categories for the respective given name are displayed, as, e. g., "*Masculine given names*" and "*Place names*" for the given name "Egon". Via hyperlinks, the user can browse for namelings of each listed name or get a list of all names linked to a certain category in Wikipedia. Further background information for the query name is summarized in a corresponding details view, where, among others, popularity of the name in different language editions of Wikipedia as well as in Twitter is shown. As depicted in Fig. 1(b), the user may also explore the "neighborhood" of a given name, i. e., names which co-occur often with the query name.

From a user's perspective, the Nameling is a tool for finding a suitable given name. Accordingly, names can easily be added to a personal list of favorite names. The list of favorite names is shown on every page in the Nameling and can be shared with a friend, for collaboratively finding a given name.

The Nameling is based on a comprehensive list of given names, which was initially manually collected, but then populated by user suggestions. It currently covers more then 35,000 names from a broad range of cultural contexts. For different use cases, three different data sources are respectively used, as depicted in Fig. 2.



(a) Co-Occurrence (b) Popularity (c) Social Context

Figure 2: Nameling determines similarities among given names based on co-occurrence networks from Wikipedia, popularity of given names via Twitter and social context of the querying user via facebook.

Wikipedia As basis for discovering relations among given names, a co-occurrence graph is generated for each language edition of Wikipedia separately. That is, for each language, a corresponding data set is downloaded from the Wikimedia Foundation. Afterwards, for any pair of given names, the number of sentences where they jointly occur is determined. Thus, for every language, an undirected graph is obtained, where two names are adjacent, if they occur together in at least one sentence within any of the articles and the edge's weight is given by the number of such sentences.

Relations among given names are established by calculating a vertex similarity score between the corresponding nodes in the co-occurrence graph. Currently, namelings are calculated based on cosine similarity (cf. Section III).

Twitter For assessing up-to-date popularity of given names, a random sample of tweets in Twitter is constantly processed via the Twitter streaming api[4]. For each name, the number of tweets mentioning it is counted.

facebook Optionally a user may connect the Nameling with facebook[5]. If the user allows the Nameling to access his or her profile information, the given names of all contacts in facebook are collected anonymously. Thus, a "social context" for the user's given name is recorded. Currently, the social context graph is too small for implementing features based on it, but it will be a valuable source for discovering and evaluating relations among given names.

V SEMANTICS OF SOCIAL CO-OCCURRENCES

The basic idea behind the Nameling was to find relations among given names based on user-generated content in the social web. The most basic relation among such entities can be observed when they occur together within a given atomic context. In case of Wikipedia, such *co-occurrences* were counted based on sentences.

Considering the German and English Wikipedia separately, undirected weighted graphs Wiki^{DE} and Wiki^{EN} are obtained, where name nodes u and v are connected and labeled with weight c, if u and v co-occurred in exactly c sentences. For example, the given names "*Peter*" and "*Paul*" co-occurred in 30,565 sentences within the English Wikipedia. Accordingly, there is an edge $(\text{Peter}, \text{Paul})$ in Wiki^{EN} with a corresponding edge weight. For the present analysis, the co-occurrence networks are derived from the official Wikipedia data dumps, which are freely available for download,[6] whereby the English dump was dated *2012-01-05* and the German dump *2011-12-12*. The following experiments focus on the English Wikipedia unless explicitly stated otherwise.

When Nameling was implemented, the choice of the applied similarity metric on those co-occurrence networks was inspired by previous work on emergent semantics of social tagging systems [22], but only based on manual inspection of a (non representative) sample. This section aims at grounding the obtained notions of relatedness among given names by comparing the different similarity metrics with an external reference similarity.

We built such a reference relation on the set of given names from the on-line dictionary Wiktionary[7] by extracting all category assignments from pages corresponding to given names. Thus, for each of 10,938 given names a respective binary vector was built, where each component indicates whether the corresponding category was assigned to it (in total 7,923 different categories and 80,726 non-zero entries). These vectors were then used for assessing relatedness among given names, based on a categorization which was explicitly established by the authors of the corresponding entries in Wiktionary.

In detail: For any pair (u, v) of names in the co-

[4] https://dev.twitter.com/docs/api/1/get/statuses/sample
[5] http://www.facebook.com
[6] http://dumps.wikimedia.org/backup-index.html
[7] http://www.wiktionary.org

occurrence network which have a category assignment, we calculated the cosine similarity $\mathit{COS}(u,v)$ based on the respective category assignment vectors as well as any of the similarity metrics $s(u,v)$ on the co-occurrence graph as described in Section III. As the number of data points $(\mathit{COS}(u,v), s(u,v))$ grows quadratically with the number of names, we grouped the co-occurrence based similarity scores in 1,000 equidistant bins (in case of COS and JC) or logarithmic bins (in case of PPR and $\mathit{PPR+}$). For each bin, the average cosine similarity based on category assignments was calculated, as shown in Figure 3.

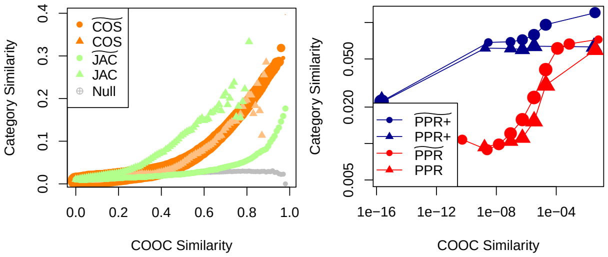


Figure 3: Similarity based on name categories in Wiktionary vs. vertex similarity in the co-occurrence-networks (weighted and unweighted) whereby the null model was obtained by shuffling the mapping of names to categories.

Notably, all considered similarity metrics capture a positive correlation between similarity in the co-occurrence network and similarity between category assignments to names. But significant differences between the applied similarity functions can be observed. The weighted cosine similarity performs very well, firstly in showing a steep slope and secondly in exhibiting a stable monotonous curve progression. The unweighted Jaccard coefficient shows an even more pronounced linear progression, but is less stable for higher similarity scores whereas the weighted Jaccard coefficient shows a higher correlation with the reference similarity for high similarity scores. It is worth noting, that the cosine similarity is only marginally effected by the edge weights of the co-occurrence graph, whereas the weighted Jaccard coefficient significantly differs from its unweighted variant. In case of the PageRank based similarity metrics, the weighted variants consistently outperform the corresponding unweighted variants and the adapted preference PageRank function $\mathit{PPR+}$ outperforms the plain preference PageRank.

For further investigating the interplay of structural similarity in the co-occurrence graph and categories of names, we look in detail at the most prominent attribute of a given name which can be obtained from Wiktionary's categorization; namely its gender. We ask, which fraction of the top similar names are of the same gender as the query name. For this purpose, we selected for each gender the set of names with a corresponding distinct gender categorization in Wiktionary (in particular ignoring gender-neutral names) which resulted in sets of $2,725$ male and $2,361$ female names. For each of this names and every considered similarity metric, we calculated the 100 most similar names based on Wikipedia's co-occurrence graph Wiki^{EN}. For each name u and each $k = 1,\ldots,100$ we then calculated the fraction of names up to position k which have the same gender as u. Figure 4 shows the obtained results, averaged over all names of the same gender. Most notably, both the weighted and unweighted variants of the cosine similarity as well as the unweighted Jaccard similarity show a precision score of around 80% both for male and female names. For all other considered similarity metrics the obtained precision score largely varies depending on the variant and gender.

As for the weighted Jaccard similarity $\widetilde{\mathit{JAC}}$ and the preference PageRank similarity its corresponding weighted and unweighted variants PPR and $\widetilde{\mathit{PPR}}$, a strong bias towards male names can be observed. This bias is due to the skewed distribution of male an female names within Wikipedia, where the considered male names occurred in $67,076,455$ sentences, in contrast to $29,711,215$ occurrences of the female names. This bias is even more pronounced in the co-occurrence graphs, as shown in Figure 5, where the distribution of node strengths (i. e., the sum of all adjacent edge weights) in Wiki^{EN} for male and female names are depicted separately.

Concerning the adapted preference PageRank, the unweighted variant $\mathit{PPR+}$ performs well for female names, but only slighter better then random for male names, conversely to the weighted variant $\widetilde{\mathit{PPR+}}$. Nevertheless, the effect of considering the preference PageRank relative to the global PageRank (cf. Section III) can clearly be observed.

We conclude that all considered similarity metrics on the co-occurrence networks obtained from Wikipedia capture a notion of relatedness which correlates to an external semantically motivated notion of relatedness among given names.

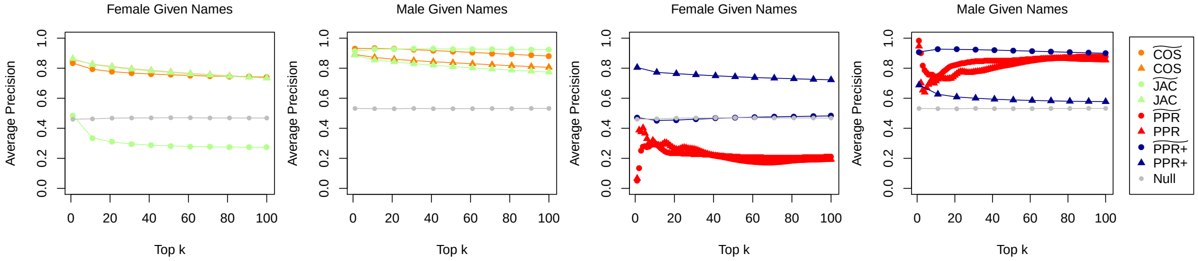


Figure 4: Average fraction of names having the same gender as the query name among the top k similar names.

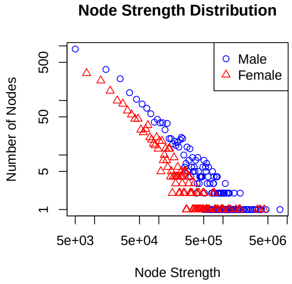


Figure 5: Distribution of node strengths in the co-occurrence graph Wiki$^{\text{EN}}$ for male and female names separately.

VI USAGE DATA

The results presented in the previous section indicate correlations between semantic relatedness among given names and structural similarity within co-occurrence networks obtained from Wikipedia.

This section aims at assessing the performance of the different structural similarity metrics with respect to actual interactions of users within Nameling. For this purpose, we considered the Nameling's activity log entries within the time range *2012-03-06* until *2012-08-10*. In the following, we firstly describe the collected usage data, analyze properties of emerging network structures among names and users and finally compare interrelations between the different networks.

In total, 38,404 users issued 342,979 search requests. Subsequently, we differentiate between the following activities:

- *"Enter":* A user manually entered a given name into search mask.
- *"Click":* A user followed a link to a name within a result list.
- *"Favorite":* A user added a given name to his/her list of. favorite names
- *"Nameling":* All search requests together

Table 1 summarizes high level statistics for these activity classes, showing, e. g., that $35,684$ users entered $16,498$ different given names.

Table 1: Basic statistics for the different activities within the Nameling.

	#Users	#Names
Enter	$35,684$	$16,498$
Click	$22,339$	$10,028$
Favorite	$1,396$	$1,558$

For analyzing how different users contribute to the Nameling's activities, Figure 6 shows the distribution of activities over the set of users, separately for *Enter*, *Click* and *Favorite* requests. Clearly, all activities' distributions exhibit long tailed distributions, that is, most users entered less than 20 names but there are also users with more than 200 requests.

To get a glimpse at the actual usage patterns within the Nameling and the distribution of names within Wikipedia, Table VI exemplarily shows most popular names for the different activity classes as well as the considered data sets derived from Wikipedia. Thereby we assess a name's "popularity" by its frequency within the corresponding Wikipedia dump or the number of search queries for the name within Nameling. Firstly, it is worth noting that indeed in the German Wikipedia German given names are dominant, whereas in the English Wikipedia, accordingly, English given names are the most popular. Secondly, both language editions of Wikipedia are dominated by male given names. As for the Nameling, users (still) mostly originate in Germany and accordingly the corresponding query logs are dominated by search requests for German given names, both male and female.

For a more formal analysis of the relationship between the popularity induced by search queries in the Nameling and corresponding frequencies within a Wikipedia corpus, we calculated Kendall's τ rank correlation coefficient [14] pairwise on the common set of names for all considered

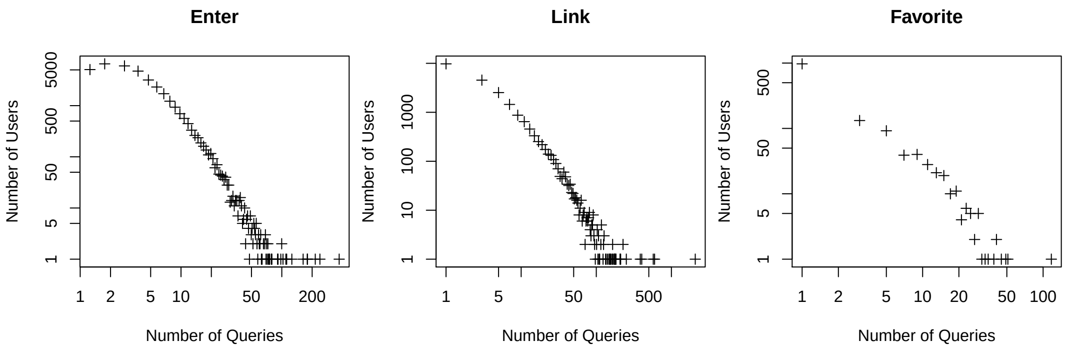


Figure 6: Number of users per query count for *Enter*, *Click* and *Favorite* activities.

Table 2: Most popular names separately for *Enter*,*Click* and *Favorite* activities, as well as global popularity in Nameling and popularity in Wikipedia.

Enter		*Click*		*Favorite*		Nameling (global)		Wikipedia (EN)		Wikipedia (DE)	
Emma	1,433	Emma	1,461	Emma	62	Emma	3,073	John	2,474,408	Friedrich	356,636
Anna	1,125	Jonas	1,010	Lina	49	Anna	2,178	David	1,130,766	Karl	348,879
Paul	1,073	Emil	965	Ida	40	Paul	1,918	William	1,100,253	Hans	309,734
Julia	942	Anna	947	Jakob	39	Jonas	1,856	James	1,051,219	Peter	304,516
Greta	895	Alexander	851	Felix	37	Emil	1,816	George	973,210	Johann	298,575
Michael	878	Daniel	819	Oskar	36	Michael	1,771	Robert	871,368	John	295,563

activity classes and both language editions of Wikipedia, as shown in Table VI.

Table 3: Kendall's τ rank correlation coefficient, pairwise for the popularity induced rankings in the different systems.

	Enter	*Click*	*Favorite*	Nameling	Wiki$^{\text{DE}}$	Wiki$^{\text{EN}}$
Enter	–					
Click	0.62	–				
Favorite	0.54	0.60	–			
Nameling	0.86	0.79	0.59	–		
Wikipedia (DE)	0.35	0.35	0.33	0.40	–	
Wikipedia (EN)	0.28	0.26	0.25	0.33	0.69	–

Firstly, we note that the most pronounced correlation is indicated for pairs of popularity rankings within a system. Nevertheless, rankings induced by search queries in the Nameling and those induced by frequency within Wikipedia are also assessed, which is slightly more pronounced for the German Wikipedia (e. g., $\tau = 0.40$ for the global ranking over all activity classes in the Nameling and the German Wikipedia versus $\tau = 0.33$ for the English Wikipedia).

Another type of interdependence among the different activity classes can be revealed by applying association rule mining [1] which is commonly used, e. g., for market basket analysis. Table VI exemplarily shows a few association rules obtained from all favorite name activities within the Nameling, whereby all requests of a user a aggregated to a single transaction. Much more rules with various support and confidence levels can be found and directly be used for implementing a recommendation system, based on other users search patterns.

Table 4: Examples for association rules obtained from the Nameling's activity log. The second example reads as follows: 85.71% of 7 users which have added "Charlotte" and "Johanna" as a favorite name, also added "Emma" to the favorite name list.

Rule	Support	Confidence
Emma ← Teresa	6	83.33%
Emma ← Charlotte Johanna	7	85.71%
Ida ← Frieda Lina	8	87.50%

For assessing the interdependence of name contexts established by search queries within the Nameling and cooccurrences within Wikipedia, we further constructed for each activity class $C \in \{\textit{Enter}, \textit{Click}, \textit{Favorite}\}$ and each node type $T \in \{\text{User}, \text{Name}\}$ a corresponding weighted projection graph G_C^T, where an edge (u, v) exists with weight k, if users u and v have searched for k common names (or, respectively, names a and b are connected by an edge with label k, if k users searched for both names a and b). Table VI summarizes various high level network statistics for all considered projection graphs. It is worth noting that $G^{\text{User}}_{\textit{Enter}}$ is the largest graph, indicating that most users directly entered names whereof 62% actively followed proposed names by clicking on corresponding links. All projection graphs encompass a giant connected component [24], giving raise to a notion of relatedness among users and names, respectively, based on the implicitly expressed interest in names.

Table 5: High level statistics for all considered projection graphs with the number of weakly connected components #wcc and largest weakly connected components lwcc.

	$\lvert V\rvert$	$\lvert E\rvert$	#wcc	lwcc	D
$G^{\text{User}}_{\textit{Enter}}$	$35,113$	$31,118,016$	18	$35,078$	7
$G^{\text{Name}}_{\textit{Enter}}$	$15,992$	$996,930$	72	$15,834$	7
$G^{\text{User}}_{\textit{Click}}$	$21,925$	$6,371,132$	28	$21,865$	9
$G^{\text{Name}}_{\textit{Click}}$	$9,665$	$2,633,220$	79	$9,465$	10
$G^{\text{User}}_{\textit{Favorite}}$	$1,205$	$42,770$	25	$1,155$	7
$G^{\text{Name}}_{\textit{Favorite}}$	$1,365$	$60,124$	23	$1,306$	7

For analyzing the strength of interdependence among users and names induced by the set of searched names, Figure 7 shows the distribution of the number of common names among pairs of users and the number of common users among pairs of names, respectively. All distributions exhibit long tailed characteristics. For example, there are around ten million pairs of users which have clicked on a single common node and only around 100,000 users clicked on two common names. But there are also pairs of users, which have clicked on more than 200 common names.

Please note that these usage graphs themselves can be used for calculating similarity among given names, e. g., by applying the same similarity metrics as discussed for the co-occurrence graphs. Table VI exemplarily shows similar names for the given name "Kevin" as calculated with the adapted preferential PageRank on the co-occurrence graph Wiki$^{\text{EN}}$ and the shared search graph $G^{\text{Name}}_{\textit{Enter}}$. While the former gives raise to a list of American male given names (as expected), the latter yields a list of American and French male as well as female given names. It is therefore natural to ask, whether and to which extend the network structures obtained from Wikipedia and Nameling's usage date interrelate.

Table 6: Similar names for the given name "Kevin", calculated with the weighted adapted preferential PageRank on Wikipedia's co-occurrence graph (left) and on the shared search graph (right).

Kevin	*Kevin*
Tim	Chantal
Danny	Justin
Jason	Jaqueline
Jeremy	Sky
Nick	Chantalle
Wiki$^{\text{EN}}$	$G^{\text{Name}}_{\textit{Enter}}$

The quadradic assignment procedure (QAP) test is an approach for inter-network comparison, common in literature. It is based on the correlation of the adjacency matrices of the considered graphs [4, 5].

For given graphs $G_1 = (V_1, E_1)$ and $G_2 = (V_2, E_2)$ with $U := V_1 \cap V_2 \neq \emptyset$ and adjacency matrices A_i corresponding to $G_{i|U}$ (G_i reduced to the common vertex set U, cf. Section III), the graph *covariance* is given by

$$cov(G_1, G_2) := \frac{1}{n^2 - 1} \sum_{i=1}^{n} \sum_{j=1}^{n} (A_1[i,j] - \mu_1)(A_2[i,j] - \mu_2)$$

where μ_i denotes A_i's mean ($i = 1, 2$). Then $var(G_i) := cov(G_i, G_i)$ leading to the graph correlation

$$\rho(G_1, G_2) := \frac{cov(G_1, G_2)}{\sqrt{var(G_1)\, var(G_2)}}.$$

The QAP test compares the observed graph correlation to the distribution of resulting correlation scores obtained on repeated random row/column permutations of A_2. The fractions of permutations π with correlation $\rho^\pi \geq \rho_o$ is used for assessing the significance of an observed correlation score ρ_o. Intuitively, the test determines (asymptotically) the fraction of all graphs with the same structure as $G_{2|U}$ having at least the same level of correlation with $G_{1|U}$.

Table VI shows the pairwise correlation scores for all considered name-based networks.

Table 7: Graph level correlations for all pairs of considered networks. All observed correlations are significant according to the quadradic assignments procedure (QAP).

	$G^{\text{Name}}_{\textit{Enter}}$	$G^{\text{Name}}_{\textit{Click}}$	$G^{\text{Name}}_{\textit{Favorite}}$	Wiki^{DE}	Wiki^{EN}
$G^{\text{Name}}_{\textit{Enter}}$	–				
$G^{\text{Name}}_{\textit{Click}}$	0.466	–			
$G^{\text{Name}}_{\textit{Favorite}}$	0.370	0.364	–		
Wiki^{DE}	0.138	0.110	0.040	–	
Wiki^{EN}	0.054	0.056	0.032	0.406	–

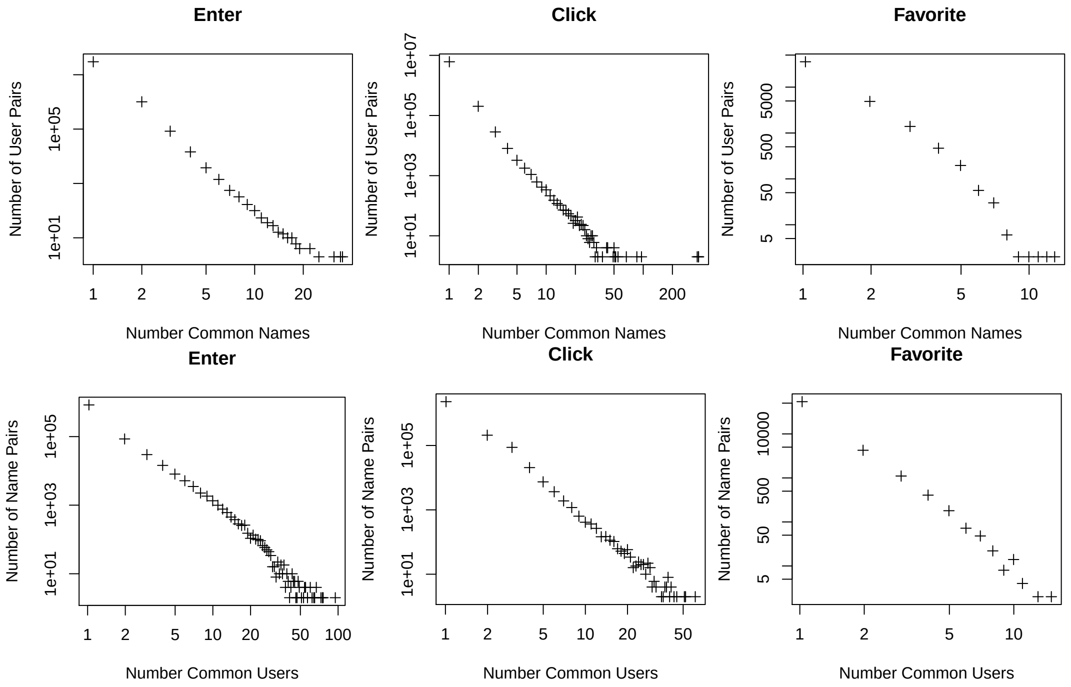


Figure 7: Distribution of the number of common names between pairs of users and the number of common users between pairs of names in the different projection graphs corresponding to *Enter*, *Click* and *Favorite* activities.

Again, correlations are more pronounced within a system (e. g., 0.406 for the co-occurrence networks of the English and German Wikipedia). But the graph level correlations for networks obtained from the Nameling exhibit significantly higher correlation scores for the co-occurrence network obtained from the German Wikipedia, indicating that the dominance of German users has an impact on the emerging name contexts within the search based networks which are more related to the accordingly language dependent network structure within the co-occurrence network from Wikipedia.

VII PERFORMANCE OF STRUCTURAL SIMILARITY METRICS

Up to now, the performance of the various structural similarity metrics presented in III are evaluated with respect to an external notion of semantic relatedness, as summarized in Section V. This section presents a comparative evaluation of the considered similarity metrics' performance with respect to actual name preferences of users as indicated by the usage data presented in Section VI.

For this purpose, an according ranking scenario is formulated, where for a given (set of) name(s), a ranking on all names is obtained by calculating pairwise similarity with all other names based on the considered similarity metrics with respect to the co-occurrence networks obtained from Wikipedia. Then, an established evaluation metric is applied for assessing the relative quality of the different similarity functions.

Firstly, we need a "ground truth" as a reference for evaluating the performance of a given ranking on the set of given names. Considering the usage data presented in Section VI, a first natural choice would be to predict for each search request of a user the names which will be added as favorites. But thereby, the evaluation would be biased towards the similarity metric which was implemented in Nameling during the period of evaluation. Thus, these evaluation target is only valid in a live setting, where different ranking systems are comparatively presented to a user.

We therefore consider for each user u the corresponding

- set of names which were directly entered ($\textit{Enter}_u$),
- the set of names the user clicked on ($\textit{Click}_u$) and
- the set of u's favorite names ($\textit{Favorite}_u$).

We argue, that by directly entering a name into the search mask, a user already expresses interest in the corresponding name. Furthermore, a name which a user entered into the search mask is not directly influenced by the names which were presented based on the similarity function implemented in Nameling during the period of evaluation.

We evaluate the performance of a structural similarity metric SIM, by randomly selecting just one name $i \in \mathit{Enter}_u$ and calculating the *average precision* score $\mathrm{AveP}(\mathit{SIM}(i, *), \mathit{Enter}_u)$ for every user u and then calculating the *mean average precision* MAP (cf. Section III). For reference, we also computed as a baseline the MAP score for randomly ordered given names (labeled with "RND" in the corresponding figures). All results in this section are averaged over five repetitions of the corresponding random experiments.

Figure 8 shows the obtained results for each considered similarity metric in its weighted and unweighted variant, separately evaluated on the *Enter*, *Click* and *Favorite* sets. First of all we have to note that all MAP scores are very low. Partly, this is due to the uncleaned evaluation data set which also contains search queries for names, which are not contained in the list of known names and therefore could not be listed by the considered similarity metrics. Also we retained from requiring a minimum number of search queries per user (despite that there must be at least one to predict). This renders the task of predicting "missing" names even more hard, as the profile of a user who searched for more than 20 names is expected to be more consistent than the profile of a user who just entered two search queries (depending on the similarity metric, the results are improved by 40% to 150% if only users with more than 10 search queries are considered). We argue that the usage data which is taken as a reference should be applied without further adjustments, as other ranking algorithms may overcome some of the mentioned factors. Such improvements can then be assessed by applying the same evaluation on the new system and comparing the gain in MAP over the present approaches.

In any case, all considered similarity metrics show significant better performance than the random baseline. We firstly consider the *Enter* sets. Notably, all but $\mathit{PPR}+$ are negatively effected by the weights in the co-occurrence graph. On the other hand, the performance of $\mathit{PPR}+$ drops to the level of the considered baseline for the unweighted case. The dependence of $\mathit{PPR}+$ on the edge weights is in line with the motivation of its design, as the global PageRank score is subtracted to reduce the impact of global frequencies, which are absent in the unweighted case. Please note that the influence of weights is discussed in the related field of link prediction in social networks (cf. [7, 21]). Altogether, the PageRank based similarity metrics outperform the other metrics.

As for the *Click* set, the weighted cosine similarity COS significantly outperforms all other metrics. This is in line with the bias towards the implemented similarity metric within Nameling, as all result lists were ordered according to the weighted cosine similarity during the time period of evaluation. Considering the *Favorite* set, the unweighted Jaccard coefficient JAC performs surprisingly well, outperforming even the weighted cosine similarity.

Summing up, the results of the experiment described above indicate that the weighted variant of the adjusted PageRank similarity should be considered for ranking result lists within Nameling as an alternative to the weighted cosine similarity, as it consistently performs well on all considered test sets.

VIII RANKINGS FOR MULTI TERM QUERIES

A user might be interested in names, which are most suitable for a given set of names (consider, e. g., the given names of both parents or possible siblings) rather than for just a single name. Therefore, we also applied a "*take-k-in*" evaluation paradigm, where, for each user u, we randomly selected k names from his search profile Enter_u. These names are then used for predicting the remaining names. The prediction accuracy is evaluated by calculating mean average precision with respect to the user's remaining search profile. As with varying k the size of the corresponding evaluation data also varies and induces a bias towards lower k, we additionally select $n - k$ names from Enter_u with $n := |\mathit{Enter}_u|$. These names are then ignored while calculating the corresponding average precision score.

For similarity metrics based on the preference PageRank, the combination of multiple query names is straightforward by giving equally preference to each of the queried names. At least for the basic preference PageRank, linearity of the preference PageRank [10] allows to calculate rankings each query name separately in advance. These pre-calculated rankings can then be combined by means of the applied database management system.

For vector based similarity metrics such as COS and JAC (cf. Section III), it is straightforward to combine multiple query vectors just by calculating the corresponding centroid. But it is not obvious whether the centroid vector is still semantically grounded, that is, for example, whether the combination of two male given names is again most similar to other male given names. Alternatively, each name could be queried separately and the respective result sets combined afterwards. The latter would be of practical use, as it is computationally not feasible to calculate all pairs of cosine similarity online in the running system and, again, similarity scores are pre-calculated for each possible query term and combined by means of the database management system.

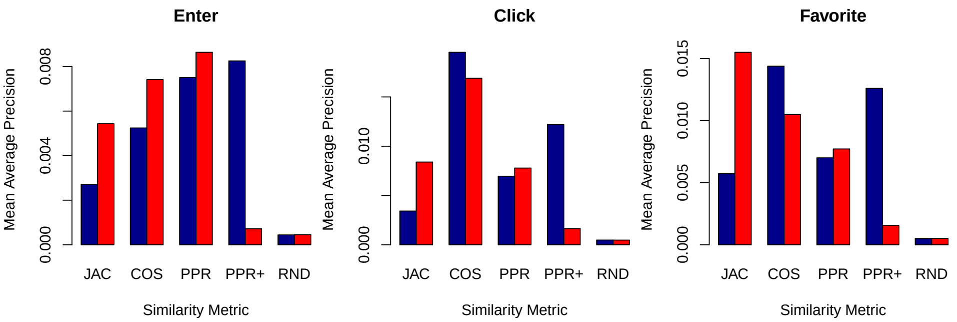


Figure 8: Mean average precision for all considered structural similarity metrics and activity classes in the weighted (blue) and unweighted (red) case.

Therefore, the following four types of combining multiple query vectors $\vec{u}_1, \ldots, \vec{u}_n$ or respective result list corresponding to query names $u_1, \ldots, u_n$ were evaluated:

- Query relative to the *centroid vector* $\vec{u}$:

$$u_i := \frac{1}{n} \sum_{j=1}^{n} \vec{u}_j(i) \qquad (\mathit{COMB})$$

- Average the resulting similarity scores:

$$\mathit{SIM}(\{u_1, \ldots, u_n\}, i) := \frac{1}{n} \sum_{j=1}^{n} \mathit{SIM}(u_j, i) \qquad (\mathit{AVG})$$

- Take the minimum similarity score:

$$\mathit{SIM}(\{u_1, \ldots, u_n\}, i) := \min_{j=1}^{n}(\mathit{SIM}(u_j, i)) \qquad (\mathit{MIN})$$

- Take the maximum similarity score:

$$\mathit{SIM}(\{u_1, \ldots, u_n\}, i) := \min_{j=1}^{n}(\mathit{SIM}(u_j, i)) \qquad (\mathit{MAX})$$

Figure 9 shows the results obtained on the *Enter* set for the different similarity metrics in all considered variants.

As for the adapted preferential PageRank based similarity metrics we note a constant improvement in terms of MAP with increasing number of queried names, although its weighted significantly outperforms the unweighted variant. The plain preferential PageRank's MAP scores are not affected by the varying number of “known” names. This is probably caused by the dominance of the global network structure which is explicitly reduced by construction in case of the adapted preferential PageRank.

The results obtained for the unweighted and weighted Jaccard coefficient *JAC* shows a progression in terms of MAP score with increasing number of names for *AVG*, *COMB* and *MAX*. In its weighted variant, only *MAX* and *COMB* yield better results with increasing k. In both variants, the *MIN* result aggregation decreases MAP performance.

As for the cosine similarity, we first note that for the weighted cosine similarity $\widetilde{COS}$ on the *Enter* set, the average query combination scheme yields the best results, even outperforming the computationally more involved centroid approach. Concerning the relative ranking of the different combination approaches, the unweighted and weighted cosine similarity show no consistent behavior.

Summing up, the results presented in this chapter indicate that the cosine similarity and the adjusted preference PageRank are candidates for recommending similar names, based on co-occurrences of given names within Wikipedia. Altogether, the latter showed more stable and consistent results in the different settings. For recommendations based on a single query term it yielded better results than the weighted cosine similarity, though slightly worse then the plain preference PageRank on the unweighted co-occurrence graphs. But it showed consistent well performance scores even in the evaluation sets *Click* and *Favorite* which are strongly biased towards the weighted cosine similarity. Also the combination of multiple query terms is straightforward and showed stable and consistent improvements with an increasing number of query terms. Nevertheless, the much simpler weighted cosine similarity showed comparable results, or even better performance scores, in case of the combination of multiple query terms.

Of course, the usage data can be used for personalizing search results or implementing recommendation systems based on the own name preferences and those of similar users. Even the very simple baseline recommender which just recommends the most popular names yields results which significantly outperform all statical name rankings considered in this paper. Building recommendation sys-

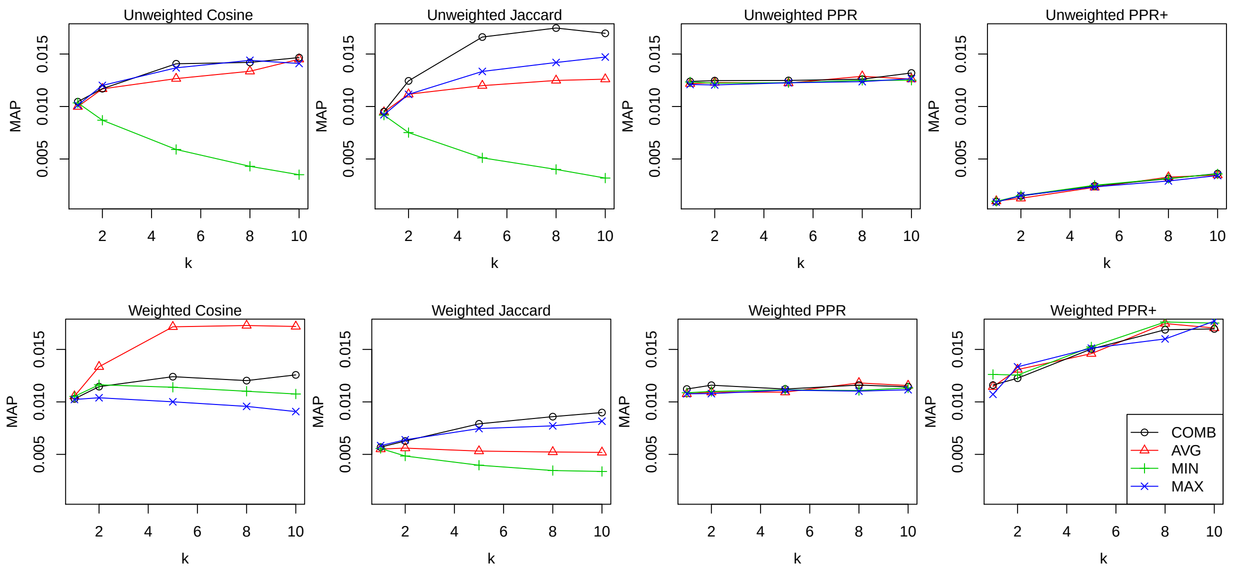


Figure 9: Mean average precision for all considered structural similarity metrics (weighted and unweighted) for varying number of known entered names k and different combination of query vectors (COMB, AVG, MIN, MAX).

tems which apply collaborative filtering techniques [26] are expected to yield results which outperform those presented above by magnitude. A thorough discussion and evaluation of according recommendation systems is out of the scope of the present work and are subject to future research.

IX CONCLUSION & FUTURE WORK

The present work introduces the research task of discovering relations among given names. A new approach for ranking names based on co-occurrence graphs is proposed and evaluated. For this, usage data from the running system Nameling is firstly introduced and thoroughly analyzed and then used for setting up an experimental framework for evaluating the performance of name rankings. The results presented in Sections VII,VIII and V form a basis for deciding which similarity metric can be used for ranking names relative to a given set of query terms.

By making all considered usage data publicly available, other researchers are invited to build and evaluate new ranking and recommendation systems. The success of the Nameling indicates that there is a need for such recommendation systems and the inherent interdisciplinary research questions render the task of discovering relations among given names fascinating and challenging to tackle.

For future work we plan to implement personalized recommendation and ranking systems, thereby incorporating further influencing factors, such as, e. g., the geographic distance among users. Additionally we plan to implement an open and flexible recommendation framework which will allow other research to directly integrate and evaluate their approaches within the running system.

We conclude by observing that the field of recommending given names is lacking scientific contributions. Yet many approaches for discovering relations exist, ready to be adapted to this domain. We expect that further research will support future parents in finding and choosing a suitable given name.

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References

[1] R. Agrawal and R. Srikant. Fast algorithms for mining association rules in large databases. In *Proceedings of the 20th international conference on Very Large Data Bases (VLDB'94)*, pages 478–499. Morgan Kaufmann, September 1994.

[2] S. Brin and L. Page. The anatomy of a large-scale hypertextual web search engine. In *Computer Networks and ISDN Systems*, pages 107–117, 1998.

[3] R. Bunescu and M. Pasca. Using encyclopedic knowledge for named entity disambiguation. In *Proc. of EACL*, volume 6, pages 9–16, 2006.

[4] C. Butts. Social network analysis: A methodological introduction. *Asian J. of Soc. Psychology*, 11(1):13–41, 2008.

[5] C. T. Butts and K. M. Carley. Some simple algorithms for structural comparison. *Comput. Math. Organ. Theory*, 11:291–305, December 2005.

[6] T. Cohen and D. Widdows. Empirical distributional semantics: methods and biomedical applications. *J Biomed Inform*, 42(2):390–405, Apr. 2009.

[7] H. de Sá and R. Prudencio. Supervised link prediction in weighted networks. In *Neural Networks (IJCNN), The 2011 Int. Joint Conference on*, pages 2281–2288. IEEE, 2011.

[8] E. Gabrilovich and S. Markovitch. Computing semantic relatedness using wikipedia-based explicit semantic analysis. In *Proc. of the 20th int. joint conference on artificial intelligence*, volume 6, page 12. Morgan Kaufmann Publishers Inc., 2007.

[9] J. Golbeck and J. Hendler. Filmtrust: Movie recommendations using trust in web-based social networks. In *Proceedings of the IEEE Consumer communications and networking conference*, volume 96. Citeseer, 2006.

[10] T. Haveliwala. Topic-sensitive pagerank: A context-sensitive ranking algorithm for web search. *Knowledge and Data Engineering, IEEE Transactions on*, 15(4):784–796, 2003.

[11] A. Hotho, R. Jäschke, C. Schmitz, and G. Stumme. Information retrieval in folksonomies: Search and ranking. In Y. Sure and J. Domingue, editors, *The Semantic Web: Research and Applications*, volume 4011 of *Lecture Notes in Computer Science*, pages 411–426, Heidelberg, June 2006. Springer.

[12] R. Jäschke, L. Marinho, A. Hotho, L. Schmidt-Thieme, and G. Stumme. Tag recommendations in social bookmarking systems. *Ai Communications*, 21(4):231–247, 2008.

[13] G. Jeh and J. Widom. Simrank: a measure of structural-context similarity. In *Proc. of the eighth ACM SIGKDD int. conference on Knowledge discovery and data mining*, KDD '02, pages 538–543, New York, NY, USA, 2002. ACM.

[14] M. G. Kendall. A new measure of rank correlation. *Biometrika*, 30(1/2):81–93, 1938.

[15] T. Landauer and S. Dumais. A solution to plato's problem: The latent semantic analysis theory of acquisition, induction, and representation of knowledge. *Psychological Review*, 104(2):211, 1997.

[16] E. Leicht, P. Holme, and M. Newman. Vertex similarity in networks. *Physical Review E*, 73(2):026120, 2006.

[17] M. Lesk. Word-word associations in document retrieval systems. *American documentation*, 20(1):27–38, 1969.

[18] D. Liben-Nowell and J. Kleinberg. The link-prediction problem for social networks. *J. of the American society for inf. science and technology*, 58(7):1019–1031, 2007.

[19] G. Linden, B. Smith, and J. York. Amazon. com recommendations: Item-to-item collaborative filtering. *Internet Computing, IEEE*, 7(1):76–80, 2003.

[20] L. Lü, C. Jin, and T. Zhou. Similarity index based on local paths for link prediction of complex networks. *Physical Review E*, 80(4):046122, 2009.

[21] L. Lü and T. Zhou. Link prediction in weighted networks: The role of weak ties. *EPL (Europhysics Letters)*, 89:18001, 2010.

[22] B. Markines, C. Cattuto, F. Menczer, D. Benz, A. Hotho, and G. Stumme. Evaluating similarity measures for emergent semantics of social tagging. In *18th Int'l WWW Conference*, pages 641–641, 2009.

[23] T. Murata and S. Moriyasu. Link prediction of social networks based on weighted proximity measures. In *Web Intelligence, IEEE/WIC/ACM Int. Conference on*, pages 85–88. IEEE, 2007.

[24] M. E. J. Newman. The structure and function of complex networks. *SIAM Review*, 45(2):167–256, 2003.

[25] M. Strube and S. P. Ponzetto. WikiRelate! Computing semantic relatedness using Wikipedia. In *proc. of the 21st national conference on Artificial intelligence - Volume 2*, AAAI'06, pages 1419–1424. AAAI Press, 2006.

[26] X. Su and T. Khoshgoftaar. A survey of collaborative filtering techniques. *Advances in Artificial Intelligence*, 2009:4, 2009.

[27] P. Turney. Mining the web for synonyms: Pmi-ir versus lsa on toefl. In *Proc. of the 12th European Conference on Machine Learning*, pages 491–502. Springer-Verlag, 2001.

[28] E. Voorhees, D. Harman, N. I. of Standards, and T. (US). *TREC: Experiment and evaluation in information retrieval*, volume 63. MIT press Cambridge, 2005.