# Interweaving Public User Profiles on the Web

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**Abstract.** While browsing the Web, providing profile information in social networking services, or tagging pictures, users leave a plethora of traces. In this paper, we analyze the nature of these traces. We investigate how user data is distributed across different Web systems, and examine ways to aggregate user profile information. Our analyses focus on both explicitly provided profile information (name, homepage, etc.) and activity data (tags assigned to bookmarks or images). The experiments reveal significant benefits of interweaving profile information: more complete profiles, advanced FOAF/vCard profile generation, disclosure of new facets about users, higher level of self-information induced by the profiles, and higher precision for predicting tag-based profiles to solve the cold start problem.

## 1 Introduction

In order to adapt functionality to the individual users, systems need information about their users [1]. The Web provides opportunities to gather such information: users leave a plethora of traces on the Web, varying from profile data to tags. In this paper we analyze the nature of these distributed user data traces and investigate the advantages of interweaving publicly available profile data originating from different sources: social networking services (Facebook, LinkedIn), social media services (Flickr, Delicious, StumbleUpon, Twitter) and others (Google). The main research question that we will answer in this paper is the following: what are the benefits of aggregating these public user profile traces?

In our experiments we analyze the characteristics of both traditional profiles – which are explicitly filled by the end-users with information about their names, skills or homepages (see Section 3) – as well as rather implicitly generated tag-based profiles (see Section 4). We show that the aggregation of profile data reveals new facets about the users and present approaches to leverage such additional information gained by profile aggregation. We made all approaches and findings presented in this paper available for the public via the *Mypes*[1] service: it enables users to inspect their distributed profiles and provides access to the aggregated and semantically enriched profiles via a RESTful API.

[1] http://mypes.groupme.org/

## 2 Related Work

Connecting data from different sources and services is in line with today's Web 2.0 trend of creating *mashups* of various applications [2]. Support for the development of interoperable services is provided by initiatives such as the dataportability project[2], standardization of APIs (e.g. OpenSocial) and authentication and authorization protocols (e.g. OpenID, OAuth), as well as by (Semantic) Web standards such as RDF, RSS and specific Microformats. Further, it becomes easier to connect distributed user profiles—including social connections—due to the increasing take-up of standards like FOAF [3], SIOC[3], or GUMO [4]. Conversion approaches allow for flexible user modeling [5]. Solutions for user identification form the basis for personalization across application boundaries [6]. Google's Social Graph API[4] enables application developers to obtain the social connections of an individual user across different services. Generic user modeling servers such as CUMULATE [7] or PersonIs [8] as well as frameworks for mashing up profile information [9] appear that facilitate handling of aggregated user data. Given these developments, it becomes more and more important to investigate the benefits of user profile aggregation in context of today's Web scenery.

In [10], Szomszor et al. present an approach to combine profiles generated in two different tagging platforms to obtain richer interest profiles; Stewart et al. demonstrate the benefits of combining blogging data and tag assignments from Last.fm to improve the quality of music recommendations [11]. In this paper we do not only analyze the benefits of aggregating tag-based user profiles [12, 13], which we enrich with Wordnet[5] facets, but also consider explicitly provided profiles coming from five different social networking and social media services.

## 3 Traditional Profile Data on the Web

Currently, users need to manually enter their profile attributes in each separate Web system. These attributes—such as the user's *full name*, current *affiliations*, or the *location* they are living at—are particularly important for social networking services such as LinkedIn or Facebook, but may be considered as less important in services such as Twitter. In our analysis, we measure to which degree users fill in their profile attributes in different services. To investigate the benefits of profile aggregation we address the following questions.

1. How detailed do users fill in their public profiles at social networking and social media services?
2. Does the aggregated user profile reveal more information about a particular user than the profile created in some specific service?

[2] http://www.dataportability.org/
[3] http://rdfs.org/sioc/spec/
[4] http://socialgraph.apis.google.com
[5] http://wordnet.princeton.edu/

3. Can the aggregated profile data be used to enrich an incomplete profile in an individual service?
4. To which extent can the service-specific profiles and the aggregated profile be applied to fill up standardized profiles such as FOAF [3] and vCard [14]?

### 3.1 Dataset

To answer the questions above, we crawled the public profiles of 116032 distinct users via the Social Graph API. People who have a Google account can explicitly link their different accounts and Web sites; the Social Graph API allows developers to look up the different accounts of a particular user. On average, the 116032 users linked 1.26 accounts while 70963 did not link any account.

For our analysis on traditional profiles we were interested in popular services where users can have public profiles. We therefore focused on the social networking services Facebook and LinkedIn, as well as on Twitter, Flickr, and Google. Figure 1(a) lists the number of public profiles and the concrete profile attributes we obtained from each service. We did not consider private information, but only crawled attributes that were publicly available. Among the users for whom we crawled the Facebook, LinkedIn, Twitter, Flickr, and Google profiles were 338 users who had an account at all five different services.

### 3.2 Individual Profiles and Profile Aggregation

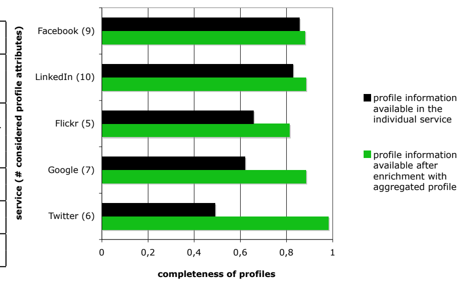
The completeness of the profiles varies from service to service. The public profiles available in the social networking sites Facebook and LinkedIn are filled more accurately than the Twitter, Flickr, or Google profiles—see Figure 1(b). Although Twitter does not ask many attributes for its user profile, users completed their profile up to just 48.9% on average. In particular the *location* and *homepage*—which can also be a URL to another profile page, such as MySpace—are omitted most often. By contrast, the average Facebook and LinkedIn profile is filled up to 85.4% and 82.6% respectively. Obviously, some user data is replicated at multiple services: name and profile picture are specified at nearly all services, location was provided at 2,9 out of five services. However, inconsistencies can be found in the data: for example, 37.3% of the users' *full names* in Facebook are not exactly the same as the ones specified at Twitter.

For each user we aggregated the public profile information from Facebook, LinkedIn, Twitter, Flickr, and Google, i.e. for each user we gathered attribute-value pairs and mapped them to a uniform user model. Aggregated profiles reveal more facets (17 distinct attributes) about the users than the public profiles available in each separate service. On average, the completeness of the aggregated profile is 83.3%: more than 14 attributes are filled with meaningful values. As a comparison, this is 7.6 for Facebook, 8.2 for LinkedIn and 3.3 for Flickr. Aggregated profiles therewith reveal significantly more information about the users than the public profiles of the single services.

Further, profile aggregation enables completion of the profiles available at the specific services. For example, by enriching the incomplete Twitter profiles with

| Service | # crawled profiles | crawled profile attributes |
|---|---|---|
| Facebook | 3080 | nickname, first/last/full name, photo, email (hash), homepage, locale settings, affiliations |
| LinkedIn | 3606 | nickname, first/last/full name, about, homepage, location, interests, education, affiliations, industry |
| Twitter | 1538 | nickname, full name, photo, homepage, blog, location |
| Flickr | 2490 | nickname, full name, photo, email, location |
| Google | 15947 | nickname, full name, photo, about, homepage, blog, location |

(a) Profile attributes




(b) Completing service profiles

**Fig. 1.** Service profiles: (a) number of public profiles as well as the profile attributes that were crawled from the different services and (b) completing service profiles with aggregated profile data. Only the 338 users who have an account at each of the listed services are considered.

information gathered from the other services, the completeness increases to more than 98% (see Figure 1(b)): profile fields that are often left blank, such as location and homepage, can be obtained from the social networking sites. Moreover, even the rather complete Facebook and LinkedIn profiles can benefit from profile aggregation: LinkedIn profiles can, on average, be improved by 7%, even though LinkedIn provides three attributes—*interests*, *education* and *industry*—that are not in the public profiles of the other services (cf. Figure 2(a)).

In summary, profile aggregation results in an extensive user profile that reveals more information than the profiles at the individual services. Moreover, aggregation can be used to fill in missing attributes at the individual services.

### 3.3 FOAF and vCard Generation

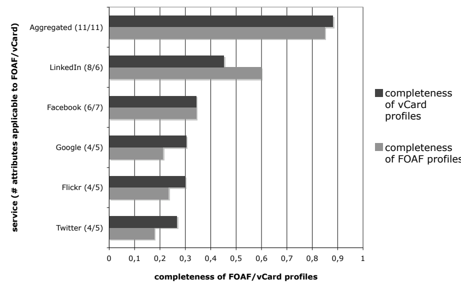
In most Web 2.0 services, user profiles are primarily intended to be presented to other end-users. However, it is also possible to use the profile data to generate FOAF [3] profiles or vCard [14] entries that can be fed into applications such as Outlook, Thunderbird or FOAF Explorer.

Figure 2(a) lists the attributes each service can contribute to fill in a FOAF or vCard profile, if the corresponding fields are filled out by the user. Figure 2(b) shows to which degree the real service profiles of the 338 considered users can actually be applied to fill in the corresponding attributes with adequate values.

Using the aggregated profile data of the users, it is possible to generate FOAF profiles and vCard entries to an average degree of more than 84% and 88% respectively—the corresponding attributes are listed in Figure 2(a). Google, Flickr and Twitter profiles provide much less information applicable to fill the FOAF and vCard details. Although Facebook and LinkedIn both provide seven attributes that can potentially be applied to generate the vCard profile, it is interesting to see that the actual LinkedIn user profiles are more valuable and produce vCard entries with average completeness of 45%; using Facebook as a data source this is only 34%. In summary, the aggregated profiles are thus

| Attribute | vCard | FOAF | Fa | L | T | Fl | G |
|---|---|---|---|---|---|---|---|
| nickname | x | x | x | x | x | x | x |
| first name | | x | x | x | | | |
| last name | | x | x | x | | | |
| full name | x | x | x | x | x | x | x |
| profile photo | x | x | x | | x | x | x |
| about | x | | | x | | | x |
| email | x | x | x | | | x | |
| homepage | x | x | x | x | x | | x |
| blog | x | x | | | x | | x |
| location | x | x | | x | x | x | x |
| locale settings | x | | x | | | | |
| interests | | x | | x | | | |
| education | | x | | x | | | |
| affiliations | x | x | x | x | | | |
| industry | x | | | x | | | |

(a) Services and available attributes




(b) Completing FOAF/vCard profiles

**Fig. 2.** FOAF/vCard profile generation: (a) services and attributes available in the the public profiles of Facebook (Fa), LinkedIn (L), Twitter (T), Flickr (Fl), and Google (G) that can be applied to fill in a FOAF profile or a vCard entry and (b) completing FOAF and vCard profiles with the actual user profiles.

a far better source of information to generate FOAF/vCard entries than the service-specific profiles.

### 3.4 Synopsis

Our analysis of the user profiles distributed across the different services point out several advantages of profile aggregation and motivate the intertwining of profiles on the Web. With respect to the key questions raised at the beginning of the section, the main outcomes can be summarized as follows.

1. Users fill in their public profiles at social networking services (Facebook, LinkedIn) more extensively than profiles at social media services (Flickr, Twitter) which can possibly be explained by differences in purpose of the different systems.
2. Profile aggregation provides multi-faceted profiles that reveal significantly more information about the users than individual service profiles can provide.
3. The aggregated user profile can be used to enrich incomplete profiles in individual services, to make them more complete.
4. Service-specific profiles as well as the aggregated profiles can be applied to generate FOAF profiles and vCard entries. The aggregated profile represents the most useful profile, as it completes the FOAF profiles and vCard entries to 84% and 88% respectively.

As user profiles distributed on the Web describe different facets of the user, profile aggregation brings some advantages: users do not have to fill their profiles over and over again; applications can make use of more and richer facets/attributes of the user (e.g. for personalization purposes). However, our analysis shows also the risk of intertwining user profiles. For example, users who deliberately leave out some fields when filling their Twitter profile might not be aware that the corresponding information can be gathered from other sources.

| | Flickr | StumbleUpon | Delicious | Overall |
|---|---|---|---|---|
| **tag assignments** | 3781 | 12747 | 61884 | 78412 |
| **distinct tags** | 691 | 2345 | 11760 | 13212 |
| **tag assignments per user** | 27.2 | 91.71 | 445.21 | 564.12 |
| **distinct tags per user** | 5.22 | 44.42 | 165.83 | 71.82 |

**Table 1.** Tagging statistics of the 139 users who have an account at Flickr, StumbleUpon, and Delicious.

## 4 User Activity Data on the Web

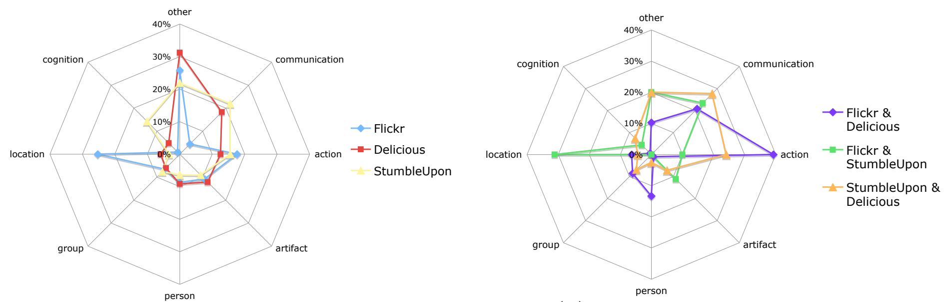
Most social media systems enable users to organize content with tags (freely chosen keywords). The tagging activities of a user form a valuable source of information for determining the interests of a user [12, 13]. In our analysis we examine the nature of the tag-based profiles in different systems. Again, we investigate the the benefits of aggregating profile data and answer the following questions.

1. What kind of tag-based profiles do individual users have in the different systems?
2. Does the aggregation of tag-based user profiles reveal more information about the users than the profiles available in some specific service?
3. Is it possible to predict tag-based profiles in a system, based on profile data gathered from another system?

### 4.1 Individual Tagging Behavior across different Systems

From the 116032 users , 139 users were randomly selected who linked their Flickr, StumbleUpon, and Delicious accounts. Table 1 lists the corresponding tagging statistics. For these users, we crawled 78412 tag assignments that were performed on the 200 latest images (Flickr) or bookmarks (Delicious and StumbleUpon). Overall, users tagged more actively in Delicious than in the other systems: more than 75% of the tagging activities originate from Delicious, 16.3% from StumbleUpon and 5% from Flickr. The usage frequency of the distinct tags shows a typical power-law distribution in all three systems, as well as in the aggregated set of tag assignments: while some tags are used very often, the majority of tags is used rarely or even just once.

On average, each user provided 564.12 tag assignments across the different systems. The user activity distribution corresponds to a gaussian distribution: 26.6% of the users have less than 200 tag assignments, 10.1% have more than 1000 and 63.3% have between 200 and 1000 tag assignments. Interestingly, people who actively tagged in one system do not necessarily perform many tag assignments in another system. For example, none of the top 5% taggers in Flickr or StumbleUpon is also among the top 10% taggers in Delicious. This observation of unbalanced tagging behavior across different systems again reveals possible




(a) Type of tags in the systems

(b) Type of overlapping tags

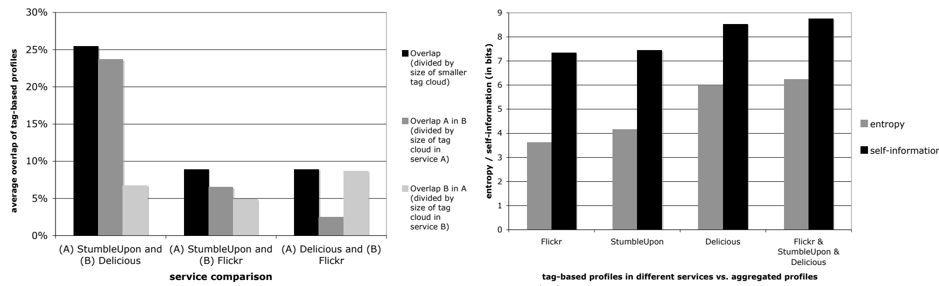
**Fig. 3.** Tag usage characterized with Wordnet categories: (a) Type of tags users apply in the different systems and (b) type of tags individual users apply in two different systems.

advantages of profile aggregation for current tagging systems: given a sparse tag-based user profile, the consideration of profiles produced in other systems might be used to tackle sparsity problems.

### 4.2 Commonalities and Differences in Tagging Activities

In order to analyze commonalities and differences of the users' tag-based profiles in the different systems, we mapped tags to Wordnet categories and considered only those 65% of the tags for which such a mapping exists. Figure 3(a) shows that the type of tags in StumbleUpon and Delicious are quite similar, except for *cognition* tags (e.g., research, thinking), which are used more often in StumbleUpon than in Delicious. For both systems, most of the tags—21.9% in StumbleUpon and 18.3% in Delicious—belong to the category *communication* (e.g., hypertext, web). By contrast, only 4.4% of the Flickr tags refer to the field of communication; the majority of tags (25.2%) denote locations (e.g., Hamburg, tuscany). *Action* (e.g., walking), *people* (e.g., me), and *group* tags (e.g., community) as well as words referring to some *artifact* (e.g., bike) occur in all three systems with similar frequency. However, the concrete tags seem to be different. For example, while artifacts in Delicious refer to things like "tool" or "mobile device", the artifact tags in Flickr describe things like "church" or "painting". This observation is supported by Figure 3(b), which shows the average overlap of the individual category-specific tag profiles. On average, each user applied only 0.9% of the Flickr artifact tags tags also in Delicious. For Flickr and Delicious, action tags allocate the biggest fraction of overlapping tags. It is interesting to see that the overlap of location tags between Flickr and StumbleUpon is 31.1%, even though location tags are used very seldomly in StumbleUpon (3.3%, as depicted in Figure 3(a)). This means that if someone utilizes a location tag in StumbleUpon, it is likely that she will also use the same tag in Flickr.

Having knowledge on the different (aggregated) tagging facets of a user opens the door for interesting applications. For example, a system could exploit Stum-



(a) Overlap of tag-based profiles (b) Entropy and self-information

**Fig. 4.** Aggregation of tag-based profiles: (a) average overlap and (b) entropy and self-information of service-specific profiles in comparison to the aggregated profiles.

bleUpon tags referring to locations to recommend Flickr pictures even if the user's Flickr profile is empty. In Section 4.4 we will present an approach that takes advantage of the faceted tag-based profiles for predicting tagging behavior.

### 4.3 Aggregation of Tagging Activities

To analyze the benefits of aggregating tag-based profiles in more detail we measure the information gain, entropy and overlap of the individual profiles. Figure 4(a) describes the average overlap with respect to three different metrics: given two tag-based profiles A and B, the overlap is (1) $overlap = \frac{A \cap B}{min(|A|,|B|)}$, (2) $overlap_{AinB} = \frac{A \cap B}{|A|}$, or (3) $overlap_{BinA} = \frac{A \cap B}{|B|}$. For example, $overlap_{AinB}$ denotes the percentage of tags in A that also occur in B.

The overlap of the tag-based profiles produced in Delicious and StumbleUpon is significantly higher than the overlap of service combinations that include Flickr. However, on average, a user still just applies 6.8% of her Delicious tags also in StumbleUpon, which is approximately as high as the percentage of tags a StumbleUpon user also applies in Flickr. Overall, the tag-based user profiles do not overlap strongly. Hence, users reveal different facets of their profiles in the different services.

Figure 4(b) compares the averaged entropy and self-information of the tag-based profiles obtained from the different services with the aggregated profile. The entropy of a tag-based profile T, which contains of a set of tags $t$, is computed as follows.

$$entropy(T) = \sum_{t \in T} p(t) \cdot \mathit{self\text{-}information}(t) \quad (1)$$

In Equation 1, $p(t)$ denotes the probability that the tag $t$ was utilized by the corresponding user and $\mathit{self\text{-}information}(t) = -log(p(t))$. In Figure 4(b), we summarize self-information by building the average of the mean self-information of the users' tag-based profiles. Among the service-specific profiles, the tag-based profiles in Delicious, which also have the largest size, bear the highest entropy and average self-information. By aggregating the tag-based profiles, self-information increases clearly by 19.5% and 17.7% with respect to the Flickr and StumbleUpon profiles respectively. Further, the tag-based profiles in Delicious can benefit from the profile aggregation as the self-information would increase by 2.7% (from 8.53 bit to 8.76 bit) which is also considerably higher, considering that self-information is measured in bits (e.g., with 8.53 bits one could describe 370 states while 8.76 bits allow for decoding of 434 states).

Aggregation of tag-based profiles thus reveals more valuable new information about individual users than focusing just on information from single services. However, some fraction of the profiles also overlap between different systems, as depicted in Figure 4(a). In the next section we analyze whether it is possible to predict those overlapping tags.

### 4.4 Prediction of Tagging Behavior

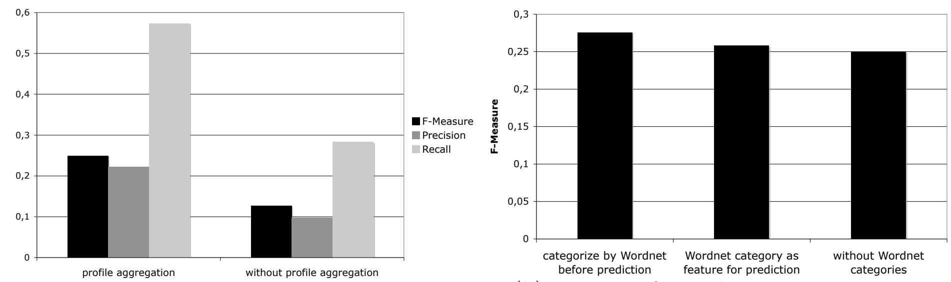
Systems that rely on user data usually have to struggle with the *cold start problem*; especially those systems that are infrequently used or do not have a large base of users require solutions to that problem. In this section we investigate the applicability of profile aggregation. Therefore, we evaluate different approaches with respect to the following task.

**Tag prediction task.** *Given a set of tags that occur in the tag-based profile of user u in system A, the task of the tag prediction strategy is to predict those tags that will also occur in u's profile in system B.*

We measure the performance by means of *precision* (= correctly classified as overlapping tags / classified as overlapping tags), *recall* (= correctly classified as overlapping tags / overlapping tags), and *f-measure* (= harmonic mean of precision and recall). Our intention is not to find the best prediction algorithm, but to examine the impact of features extracted from profile aggregation. Hence, we apply a *Naive Bayes classifier*, which we feed with different features. The benchmark tag prediction strategy (*without profile aggregation*) bases its decision on a single feature: (F1) overall usage frequency of $t$ in system B. In contrast, the strategy that makes use of *profile aggregation* also applies (F2) $u$'s usage frequency of $t$ in system A and (F3) size of $u$'s profile in system A.

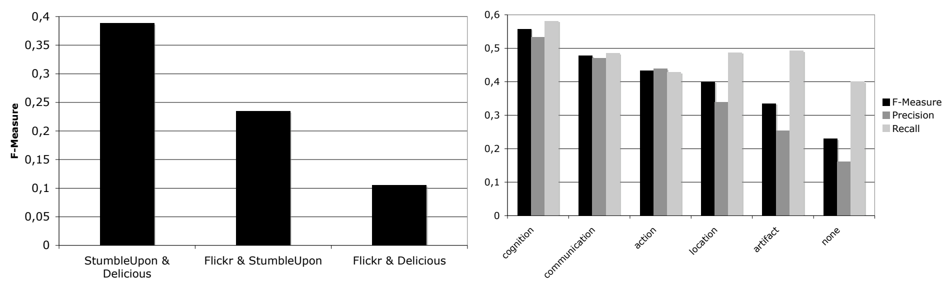
Figure 5(a) compares the average performance of both tag prediction strategies. For each of the 139 users and each service combination (Flickr → Delicious, Delicious → Flickr, StumbleUpon → Delicious, etc.) the strategies had to tackle the prediction task specified above. The benefits of the profile aggregation features are significant. The profile aggregation strategy performs—with respect to the f-measure—96.1% better than the strategy that does not benefit from profile aggregation (correspondingly, the improvement of precision and recall is explicit). Further, it is important to notice that the average percentage of overlapping tags is less than 4%. Thus, a random strategy, which simply guesses whether tag $t$ will overlap or not (probability of 0.5), would fail with a precision lower than 2%.

On average, the profile aggregation strategy can thus detect 57.4% of the tags in system A that will also be part of the tag-based profile in system B. The




(a) Average performance of tag prediction (b) Impact of Wordnet categorization

**Fig. 5.** Performance of tag prediction: (a) with and without aggregation of tag-based profiles and (b) improving prediction performance (with profile aggregation) by means of Wordnet categorization.




(a) Performance for the different services (b) Delicious → StumbleUpon

**Fig. 6.** Tag prediction performance for specific services.

performance can further be improved by clustering the tag-based profiles according to Wordnet categories. Figure 5(b) shows that the consideration of Wordnet features—(F4) Wordnet category of $t$ and (F5) relative size of corresponding Wordnet category cluster in $u$'s profile—leads to a small improvement from 0.25 to 0.26 regarding the f-measure. However, if tag predictions are done for each Wordnet cluster of the profiles separately, the improvement is considerably high as the f-measure increases from 0.25 to 0.28.

Figure 6 shows the tag prediction performance (using features F1-5) focusing on specific service combinations. While tag predictions for Flickr/Delicious based on tag-based profiles from Delicious/Flickr perform quite weak, the predictions between Flickr and StumbleUpon show a much better performance (f-measure: 0.23). For the two bookmarking services, StumbleUpon and Delicious, which also have the highest average overlap (cf. Figure 4(a)), tag prediction works best with f-measure of 0.39 and precision of 0.36. Figure 6(b) illustrates for what kind of tags prediction works best between Delicious and StumbleUpon. For tags that cannot be assigned to a Wordnet category (*none*), the precision is just 16% while recall of 40% might still be acceptable. However, given tags that can be mapped to Wordnet categories, the performance is up to 0.57 regarding f-measures. Given *cognition* tags (e.g., search, ranking) of a particular user $u$, the profile aggregation strategy, which applies the features F1-5, can predict the cognition tags $u$ will use in StumbleUpon with a precision of nearly 60%: even if a user has not performed any tagging activity in StumbleUpon, one could recommend 10 cognition tags out of which 6 are relevant for $u$.

### 4.5 Synopsis

The results of our analyses and experiments indicate several benefits of aggregating and interweaving tag-based user profiles. We showed that users reveal different types of facets (illustrated by means of Wordnet categories) in the different systems. By combining tag-based profiles from Flickr, StumbleUpon, and Delicious, the average self-information of the profiles increases significantly. Although the tag-based service-specific profiles overlap just to a small degree, we proved that the consideration of profile data from other sources can be applied to solve cold start problems. In particular, we showed that the profile aggregation strategy for predicting tag-based profiles significantly outperforms the benchmark that does not incorporate profile features from other sources.

## 5 Conclusions and Future Work

In this paper we analyzed the benefits of interweaving public profile data on the Web. For both explicitly provided profile information (e.g. name, hometown, etc.) and rather implicitly provided tag-based profiles (e.g. tags assigned to bookmarks), the aggregation of profile data from different services (e.g, LinkedIn, Facebook, Flickr, etc.) reveals significantly more facets about the individual users than one can deduce from the separated profiles. Our experiments show the advantages of interweaving distributed user data for various applications, such as completing service-specific profiles, generating FOAF or vCard profiles, producing multi-faceted tag-based profiles, and predicting tag-based profiles to solve cold start problems. End-users and application developers can immediately benefit from our research by using the Mypes service (http://mypes.groupme.org/).

In our future work we will focus on possible correlations between traditional and tag-based profiles. For example, in initial experiments we analyzed whether tag-based profiles conform to the skills users specified at LinkedIn. Given the dataset described in Section 3, 76.2% of the users applied at least one of the, on average, 8.56 LinkedIn skills also as a tag in Delicious. Further, we found first evidence that for users, who belong to the same group based on their social networking profile (in particular location and industry), the similarities between the tag-based profiles is higher than for users belonging to different groups. In the future, we will continue these experiments and investigate how explicitly provided profile data can be exploited in social media systems, and how tag-based profiles can be semantically enhanced to enrich traditional social networking profiles.

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