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Abstract
One common trend in image tagging research is to focus on visually relevant tags, and this tends to ignore the personal and social aspect of tags, especially on photoblogging websites such as Flickr. Previous work has correctly identified that many of the tags that users provide on images are not visually relevant (i.e. representative of the salient content in the image) and they go on to treat such tags as noise, ignoring that the users chose to provide those tags over others that could have been more visually relevant. Another common assumption about user generated tags for images is that the order of these tags provides no useful information for the prediction of tags on future images. This assumption also tends to define usefulness in terms of what is visually relevant to the image. For general tagging or labeling applications that focus on providing visual information about image content, these assumptions are reasonable, but when considering personalized image tagging applications, these assumptions are at best too rigid, ignoring user choice and preferences.

We challenge the aforementioned assumptions, and provide a machine learning approach to the problem of personalized image tagging with the following contributions: 1.) We reformulate the personalized image tagging problem as a search/retrieval ranking problem, 2.) We leverage the order of tags, which does not always reflect visual relevance, provided by the user in the past as a cue to their tag preferences, similar to click data, 3.) We propose a technique to augment sparse user tag data (semi-supervision), and 4.) We demonstrate the efficacy of our method on a subset of Flickr images, showing improvement over previous state-of-art methods.

1 Introduction
The current dominant notion of tag usefulness is that tags should be useful as search query terms to the images that they accompany, and thereby for the most part, only tags that have an unambiguous visual interpretation in an image are generally considered useful in tagging systems. Resulting from this dominant notion of tag usefulness, a trend in many papers on image tagging is that image tagging is treated as essentially a multi-class labeling problem, where the classes are typically restricted to objects that are salient and visually recognizable in the image (Gong et al. 2013; Li et al. 2011; Lin et al. 2013; Rubinstein, Liu, and Freeman 2012; Tomask, Thiha, and Turnbull 2009; Wang and Mori 2011; Wray and Eklund 2010). Another trend instead focuses on occurrence and co-occurrence statistics of the tags, focusing on either frequency or distinctiveness of the tags (Li, Snoek, and Worring 2008; Zhu, Yan, and Ma 2010), but even research under this trend operates under the same notion of tag usefulness, propagating for the most part only tags that have precise and unambiguous visual interpretations.

We aim to challenge this dominant notion of tag usefulness, especially under the premise of personalized image tagging. It has been shown that the tags that users provide for their images are categorically different from web search query terms (Chung and Yoon 2009). Hence, we believe that when designing user-centric tagging and indexing systems, we need to modify the current notion of tag usefulness (which hinges on their appropriateness as web search query terms) to notions that capture user preferences and behavior. To do this we have to learn what these user preferences are, and it is our assumption, as demonstrated by Nwana and Chen (2015), that these preferences can be inferred from the tag lists users have provided on other images in two ways: 1.) the tags that appear on the list are preferred to those that do not, and 2.) the order that the tags are listed implies a preference on the listed tags such that those listed earlier are preferred to those listed later.

The findings of Nwana and Chen (2015) along with a case of a Flickr design change and subsequent reversal mentioned in their paper, demonstrate our second aforemen-
tioned assumption, leading us to believe user tag preferences can be exploited via tag order.

We propose a new method of image tag prediction using learning to rank framework (Hang 2011; Joachims 2002) that attempts to learn the tag ranking functions which we assume as inherent to each user, so that given a set of good candidate tags for an image, we can rank them in a manner that best mimics what the user would have done if limited to that vocabulary. In addition we propose a semi-supervised framework to generate more seed tags since user generated tags are typically sparse (Ma et al. 2010) which makes it hard for learning to rank algorithms such as RankSVM (Joachims 2002) to learn suitable ranking functions. This new prediction paradigm treats the order that users presented tags in the past as clickthrough data which in the search engine domain is used as useful implicit user feedback. In this sense the user ordered tag lists are treated as (noisy and incomplete) oracles.

1.1 Related Work

Most works in image tagging exploit “tag-tag” co-occurrence or correlations to make predictions based either on an initial seed of tags (Menezes et al. 2010; Belém et al. 2011) or on “tag-image content” correlations and statistics (Rendle and Schmidt-Thieme 2010; Lipczak and Milios 2011; Wu et al. 2009). Some work has tried to embed both visual features and tags into a shared multidimensional space to try to capture the semantic similarity between tags and images via their distance from one another in the space (Adomavicius et al. 2005; Sen, Vig, and Riedl 2009; Song et al. 2008; Weston, Bengio, and Usunier 2011). These efforts are agnostic to user preferences among tags, but rather emphasize the image’s “preferences” among tags or better yet, a tag’s appropriateness to a given image.

Along the lines of orderings and importance of objects in images, Spain and Perona (2011) define the importance of an object as the probability that the object is mentioned first in the tag list for the image given multiple instances of the tag lists from different users. They assume that each instance of the tag lists are independently and identically distributed, and hence they learn a global notion of importance, while ignoring notions of user importance and preference. Berg et al. (2012) include the notion of object ontologies to their definition of object importance, with a focus on attribute detection and scene understanding to determine the importance of objects and appropriateness of tags in images. But they too focus on global notions of importance, not being able to capture personal preferences of individual users under their framework. Closer to our approach, Hwang and Grauman (2012) consider an object’s importance in the scene as directly proportional to its likelihood of being mentioned early by a human describing the image. They assume that users mention objects of prominence in the image early on their tag list, but their application is limited to using object names as cues for image retrieval applications.

Considering personalization, Rendle and Schmidt-Thieme (2010) represent the tag recommendation problem under the framework of tensor factorization with the constraints on their learning objective being for a given <user,item/image> pair in the training data, the tags mentioned for that pair must be preferred to those that were not, similar to our first assumption, but they do not try to learn or enforce a relation between tags that do appear together, thereby ignoring the structure inherent to the user provided tag lists, which is our other assumption. Lipczak et al. (2011) also treat tags as essentially structureless entities (bag of words) and learn for each user, how to merge tag statistics for each tag from various modalities. Also, Li et al. (2011) in a similar spirit to Lipczak (2011), propose a method for learning how to weight tag scores from multiple tagging functions in order to maximize some desired metric (e.g., mean average precision) on training data per user. To our knowledge, no other work on personalization treats the user provided tag lists as anything more than an orderless, structureless set, and this we believe is one of the novelties of this work with respect to others on personalization. And as mentioned earlier, the work by Nwana and Chen (2015) provides evidence to support that the user tag lists are more than just a bag-of-words. Our proposed method is different from all the prior in that we learn each user’s inherent tagging functions in a semi-supervised manner based on previously observed rankings by the user.

There have been few other works on learning to rank methods for tagging (Belém et al. 2011; Canuto et al. 2013; Wu et al. 2009). Belem et al. (2011) use learning to rank methods, Genetic Programming, and RankSVM to learn functions that capture how well a candidate tag describes the content of the object being tagged. There again, we see that tag relevance is treated in terms of descriptive power of the tag, and its discriminative power among other descriptive tags. In the work by Lan and Mori (2013), they come up with a new framework for modeling structured preferences among tags. In their work, their goal is to rank tags according to their relevance to the image content, and the structure among tags is related to the object ontologies which the tags describe, rather than the user’s inherent preferences. They operate under the global notion of tag relevance, and their ground-truth ranking of tags for an image is given by the number of times that the tag is mentioned as visually present in the image by human annotators on Amazon Mechanical Turk (AMT). Wang et al. (2010) present a semi-supervised approach that treats tag lists as inherently unstructured while occasionally querying expert annotators to rank the tag list according to visual relevance. Liu et al. (2009) also treat the tag lists that accompany images as inherently structureless, and their method for tagging images is purely content based, ignoring higher level semantics and user preferences, and their ground-truth is the “majority vote” of 5 users on each tag into 5 relevance levels (strongly relevant-strongly irrelevant). They propose a random walk over a tag graph (generated using concurrence similarity between tags) to refine tag relevance. Our method is different from these in that we are concerned with personalized notions of
relevance/preference, and we use the user provided tag lists as ground-truth to the correct ranking of tags for that user, thereby implicitly “querying” the user.

2 Problem Formulation

We model the problem of personalized automatic image tagging as an instance of search/retrieval ranking problem, and we employ the learning to rank solution, RankSVM, by Joachims (2002) to learn our user models (i.e., ranking functions).

2.1 General Search/Retrieval Ranking Problem

For a typical search engine, the search/retrieval ranking problem is as follows: Given a text query, \( q \), the system should retrieve a set of related documents, \( D_q = \{d_1, d_2, \ldots \} \), and return, as a result of this query, the documents in \( D_q \), in order of decreasing relevance. In the context of personalization, relevance has to be considered as user-specific rather than global. In most search engine systems, there is no direct way of learning the user preferences so implicit cues like clickthrough data on the ranked documents are used as signals of user preferences. The idea being that returned documents that are clicked are preferred to those that are not, so future query results are biased towards these implicit signals. Although clickthrough data may be noisy, and are not perfect relevance judgments, it has been shown to convey useful information that has been used to improve and optimize search engines (Joachims 2002). Learning to Rank using RankSVM We briefly discuss how RankSVM (Joachims 2002) learns ranking functions from preference judgments. We define for simplicity a search session, \( S \), as the tuple of \((q, D_q, C)\), where \( q \) is the query, \( D_q \), the set of retrieved documents, and \( C \subset D_q \), the set of clicked documents. From each session, \( S \), we derive pairwise preference judgments, \( P_S \), of the form \( P_S = \{d_i \succ d_j : d_i \in C, d_j \in D_q \setminus C\} \). We use \((d_i, d_j)\) as shorthand for \(d_i \succ d_j \) in the rest of the paper. Let \( S \) be the training set of all observed sessions. The objective of RankSVM simply stated is, given \( S \), learn a ranking function \( \tilde{w} \) that minimizes the number of reversed preference judgments over all observed sessions. More concretely:

\[
\text{minimize : } V(\tilde{w}, \xi) = \frac{1}{2} \tilde{w} \cdot \tilde{w} + C \sum \xi_{i,j,k} \tag{1}
\]

subject to:

\[
\forall (d_i, d_j) \in P_S : \tilde{w} \Phi(q_1, d_i) > \tilde{w} \Phi(q_1, d_j) + 1 - \xi_{i,j,1}
\]

\[
\cdots
\]

\[
\forall (d_i, d_j) \in P_S : \tilde{w} \Phi(q_n, d_i) > \tilde{w} \Phi(q_n, d_j) + 1 - \xi_{i,j,n}
\]

\[
\forall i,j,k : \xi_{i,j,k} \geq 0
\]

Where \( \tilde{w} \) is the (linear) ranking function, \( \Phi(q, d) \) is a mapping onto features describing the query and document, \( \xi_{i,j,k} \) a slack variable that allows some degree of error in the learned preference judgment between documents \( i \) and \( j \) for session \( k \), and \( C \) the parameter that controls the trade-off between minimizing training error, and generalization (i.e. reducing over-fitting).

Given a new query, \( q' \), to rank the set of retrieved documents, \( D_{q'} \), one only has to compute \( \tilde{w} \cdot \Phi(q', d), \forall d \in D_{q'} \) and sort in descending order.

2.2 Tag Ranking Formulation

We adapt the framework of RankSVM to our problem of personalized automatic image tagging in the following way: a session \( S \) is represented by tuple, \((I, V, T)\) where \( I \) is the image being tagged and is analogous to the text query, \( q \), in section 2.1. \( V \) the set of available tags (or vocabulary), analogous to the documents, and \( T \) the tags that were given by the user, analogous to the clicked pages.

We make the following assumptions on \( V \) and \( T \):

1.) \( T \) has inherent structure in that the tags which are mentioned earlier are implicitly preferred to those mentioned later. Note that this assumption in section 2.1 would have been analogous to saying that the pages which were clicked first are preferred to the later pages, but this assumption would likely not be a good one in that setting since the user is usually estimating based on limited information (title and excerpt) that they will find the page relevant, or get some utility from it. In fact it is probably the case that the fact they keep clicking implies they haven’t found something satisfactory, and they will stop either when they find a more satisfactory page or after some upper bound on time spent searching. But in our setting the users have potentially full information, that is knowledge of the content of the image (this makes sense since they observe the image before tagging), and knowledge of the vocabulary (again another sensible assumption, especially in light of personalization).

2.) The elements in \( T \) are also implicitly preferred to the elements in \( V \setminus T \). This is similar to the assumption in section 2.1 in that given a vocabulary of tags (or set of “documents”), the subset of tags the user mentioned for the image are analogous to the subset of “documents” the user would have clicked on.

3.) \( V \) also has structure, in that we can define functions over \( V \) that measure the relevance of the tags in \( V \) to the image \( I \), so that we can order the set \( V \) for image \( I \).

3 Model

3.1 Image Representation

In this work, we follow an implicit (feature similarity based) approach to mining tags through visually similar images (Li et al. 2011; Li, Snoek, and Worring 2008; Rendle and Schmidt-Thieme 2010; Zhu, Yan, and Ma 2010), in contrast to explicit (classifier and rule based) approaches. To that end, every image in our dataset is represented by a 500-D bag of visual-words based on SIFT (Lowe 2004) descriptors extracted in training. This allows us to use the euclidean distance between image descriptors as a measure of their visual similarity. The implicit approach is preferred because it is more scalable since one doesn’t have to learn a classifier for each new tag word, and also some tag concepts may not be visually representable which is typically problematic for explicit rule based approaches.
Figure 2: Figure shows how the average DCG changes as a function of the number of tags used per training image. The average is taken over all the images in the test set. We can see that increasing the number of tags increases the perform up to a point where it then saturates.

Figure 3: Figure shows how the average DCG@10 changes as a function of the number of tags used per training image. The average is taken over all the images in the test set. We can see that increasing the number of tags increases the perform up to a point where it then saturates.

3.2 Personalization Model

We approach personalization in two ways. First, for each user, $u$, we learn a ranking function $\hat{w}_u$ using their observed “sessions”, that is, the set of tuples, $S = (I, V, T)$, $S \in S_u$ induced by that user. Secondly, for each user session we generate an ordered set of relevant tags, $\hat{V}(I,u)$, based on the global vocabulary, $V$ as follows: Let $T_u(I)$ be the set of ground-truth tags the user provided for image $I$, and let $I_u$ be the set of images tagged by the user, we define

\[
pb_u(t) = \frac{|\{I : t \in T_u(I), I \in I_u\}|}{|I_u|}
\]

as the probability the user, $u$, mentions that tag on any image. Let $I_0$ be the set of all images from all users, we define

\[
rb(t) = \frac{|\{I : t \in T(I), I \in I_0\}|}{|I_0|}
\]

as the probability that any user mentions that tag on any image. Let $NN(I,m)$ be the set of the $m$ most visually similar images to $I$, we define,

\[
sb_{NN(I,m)}(t) = \frac{|\{I' : t \in T(I'), I' \in NN(I,m)\}|}{m}
\]

as the probability that $t$ is mentioned among the $m$ most similar images to $I$. Finally we give a score of

\[
v_u(t,I,m) = pb_u(t) + sb_{NN(I,m)}(t) - rb(t)
\]

to the tag $t$, for image $I$. For session $S = (I, V, T)$ in $S_u$, we define,

\[
\hat{V}(I,u) = \langle t_1, t_2, \ldots \rangle \ s.t. \ t_i, t_j \in V \setminus T,
\]

$s_i, s_j \geq 0$ (4)

Intuitively, the function $v_u(t,I,m)$ measures the uniqueness of the tag $t$ as is suggested by its visually similar neigh-
Figure 4: Figure shows how the average DCG changes as a function of the number of tags used per training image. The average is taken over the average of the mean performance within each users’ images in the test set. We also observe that increasing the number of tags increases the performs up to a point where it then saturates.

Figure 5: Figure shows how the average DCG@10 changes as a function of the number of tags used per training image. The average is taken over the average of the mean performance within each users’ images in the test set. We also observe that increasing the number of tags increases the performs up to a point where it then saturates.

So given a user “session”, $S = (I, V, T)$, let $T$ be represented as an ordered set $< t_1, t_2, \ldots, t_{|T|} >$, under the assumptions from section 2.2, our implied preference judgments, $P_S$, becomes:

$$P_S = O_S(T) \cup O_S(T, V) \cup O_S(\hat{V})$$

(5)

where $O_S(T)$, $O_S(T, V)$, $O_S(\hat{V})$ are the preference judgments derived from the first, second, and third assumptions from section 2.2 respectively,

$$O_S(T) = \{(t_i, t_j) : t_i, t_j \in T, i < j\}$$

$$O_S(T, V) = \{(t_i, t_j) : t_i \in T, t_j \in V \setminus T\}$$

(6)

$$O_S(\hat{V}) = \{(t_i, t_j) : t_i, t_j \in \hat{V}, v_u(t_i, I, m) > v_u(t_j, I, m)\}$$

With this definition of $P_S$, we are able to learn the personalized ranking functions in a semi-supervised way by augmenting the observed order preferences in the set $T$ with other relevant unobserved order preferences from $\hat{V}$.

3.3 Query-Document Mapping

In order to learn a ranking function for the tags, according to section 2.1, we need to define a mapping, $\Phi(q, t)$, from the query image, and candidate tag to some feature
space. To that end, we use the word2vec tool\footnote{https://code.google.com/p/word2vec Last Accessed: 03/24/2015} to learn vector representations for the tags. We denote the tag \( t \)’s vector representation from word2vec as \( w2v(t) \). To train our word2vec model, each observed image in our training set represents a document, with the accompanying tags as the words in the document. We train our word2vec model using the skip-gram architecture (Mikolov et al. 2013a; 2013b), and we chose to embed the tags in 100-dimensional space.

We also included the following tag statistics as features: 1.) \( mp(t) \): The tag’s mean position on the tag lists it appears on. 2.) \( vp(t) \): The variance of the tag’s position on the tag lists it appears on. 3.) \( cb(t) \): The probability the tag is mentioned on any tag list.

Finally we have,

\[
\Phi(q,t) = w2v(t) :: mp(t) :: vp(t) :: cb(t)
\]

where the \( :: \) operator is the append operator. You will notice here that the we do not use the query, \( q \), (that is, the image) in our mapping function. We leave the incorporation of the query to the mapping function as future work.

4 Experiments & Results

We discuss how we evaluate our model, from the choice of the dataset, choice of baseline and choice of evaluation metric.

4.1 Dataset

We work with the NUS-WIDE dataset (Chua et al. July 8 10 2009) which is a subset of 269,648 images from Flickr. For each image in the dataset, we know, via the Flickr API, the corresponding user that uploaded that image, and the sequence of tags that user chose to annotate the image with. Since we are particularly concerned about personalization, we only select images from this database which satisfy the following criteria: the users who uploaded the image must have at least 6 images in this dataset, similar to the setting in (Li et al. 2011). This results in about 91,400 images from 5000 users. We split this dataset into a training and test partition, by randomly assigning half of each users’ images to the training, and half to the test set. For each image we only retain the tags that occurred frequently enough across the dataset, in order to make some sort of meaningful inference on the tags. We made the design choice of working with tags that occurred at least 50 times in the dataset. This results in a vocabulary of 5,326 unique tags.

4.2 Baselines

We use two baselines for comparison, both of which are evaluated on the NUS-WIDE dataset:

1.) The first from Li et al. (2011), which was considered the state-of-art in personalized image tagging prior to the second baseline method. Their main idea is that for a given tag, each user has 2 weighting variables, one to weight how much to rank the tag according to its frequency among the user’s past images independent of visual content, and the other how much to weight the uniqueness of the tag according to its frequency among visually similar images, versus its frequency from all previous images (not just the user’s). These weights are user dependent, and the score given to a tag is based on the combination of these two factors. Their main contribution was a method to optimize these weights. We implement their method using the two tagging functions corresponding to the two factors described above, and find the weights for the PersonalPreference (Sawant et al. 2010) factor and Visual(Li, Snoek, and Worring 2010) factor. For the visual factor, we also use the 500-D bag of words based on SIFT descriptors for consistency. They ignore the inherent structure to the tag lists, and treat tag list as essentially a bag-of-words. We denote this method as \( XE \) (for cross-entropy).

2.) The second is a heuristic method we proposed (currently under review at another venue) by demonstrating another use of the pairwise tag biases observed from users’ past tagging histories to re-rank existing tag functions. The main idea is that if the pairwise order \(< A, B >\) is observed significantly more often than \(< B, A >\), for a user \( u \), then strictly enforce \(< A, B >\) in future predictions for that user while preserving pairwise relationships among tag pairs that need no re-ordering (either because there is no strong preference, or they are already in the correct order). This method takes the tags from some default rank, \( D \) and then re-ranks those tags according to strength of pairwise preferences from the training set. The pairwise strength is here defined as:

\[
p_{ab} = \frac{\# \text{ Times tag } a \text{ is mentioned before tag } b}{\# \text{ Times tags } a \text{ and } b \text{ are both mentioned together}}
\]

For the purposes of this experiment, we only consider preference strengths greater than 0.8 (chosen empirically) so as to prevent over-fitting. These strengths among candidate tags can be represented succinctly in a directed constraint graph, and a ranking that respects these constraints can be gotten via a topological sort (using the default ranking \( D \) to resolve ties and cycles). One drawback of this heuristic method is that it is not generalizable to tag pairs that never occurred together in data, while the method we propose in this paper is. We denote this heuristic baseline as \( PT \text{ \_rerank} \).

4.3 Metrics

Since we assume that the order which a user tags an image is of some importance, we would like a metric that takes order into account. And since we are interested in personalization, we treat the user provided tag list order as the ground-truth order and this is supported by the claims by Nwana and Chen (2015). More concretely, if we have an ordered set of tags, \( \{t_1, \cdots , t_k\} \), we define the importance or relevance of each tag as follows: Let \( rank^u(t_i) \) be the rank of \( t_i \) with respect to the ground-truth order (and \( \infty \) if the tag is not among the ground-truth),
Table 1: Average DCG@10 percentage improvement over the PT_rerank baseline. All improvements were calculated to have p-value < .001 using a two-sided student’s t-test.

|             | QUOTE([T]) | QUOTE(∞) | QUOTE(10) | QUOTE(100) | QUOTE(200) |
|-------------|------------|----------|-----------|------------|------------|
| Per Image   | -36.0%     | 5.9%     | -38.1%    | 11.3%      | 7.7%       |
| Per User    | -41.1%     | 0.003%   | -35.7%    | 4.3%       | -0.001%    |

Table 2: Average DCG percentage improvement over the PT_rerank baseline. All improvements were calculated to have p-value < .001 using a two-sided student’s t-test.

|             | QUOTE([T]) | QUOTE(∞) | QUOTE(10) | QUOTE(100) | QUOTE(200) |
|-------------|------------|----------|-----------|------------|------------|
| Per Image   | -22.1%     | 5.0%     | -24.9%    | 7.7%       | 6.1%       |
| Per User    | -23.4%     | 4.6%     | -21.1%    | 7.1%       | 4.7%       |

rel($t_i$) = $\frac{1}{\text{rank}^*(t_i)}$, $\forall t_i$

The above equation is defined as the reciprocal-rank (or zipf-rank), and in simple terms states that the $i$th tag presented by the user (i.e. ground-truth) is only $\frac{1}{\text{rank}^*(t_i)}$ times as relevant as the first presented tag.

More common metrics, such as precision, recall, and average precision, assume that all tags are equally relevant, so we do not utilize those metrics in this paper. Instead we use the more appropriate discounted cumulative gain, DCG. This is a common metric used in evaluating search engine results. For an ordered set $T = \{t_1, \cdots, t_k\}$, such that $i < j \rightarrow t_i \succ t_j$, we define the DCG with respect to the ground-truth as:

$$\text{DCG}(T) = \sum_{i \in T, i \neq 1} \frac{\text{rel}(t_i)}{\log_2(i)}$$

Notice that in Equation 8, $\text{rank}^*(t_i) = i \forall i$, if and only if the ranked list $T$ is exactly the same as the ground-truth. This metric is called discounted because the later we include a tag in our ranking, the less gain we get from it (i.e. its relevance is discounted by the inverse of the log of its position in the ranking, not the ground-truth).

Like the precision, recall, and average precision metrics, we can also parameterize the DCG metric to calculate the DCG@k. That is, calculate the metric using only the first $k$ entries of the ranked lists. Let $T[: k]$ be the first $k$ entries of $T$, then:

$$\text{DCG}@k(T) = \text{DCG}(T[: k])$$

4.4 Experiment Setup

Training Phase: In the training phase of our experiments, for every user, $u$, we produced a ranking example from each image, $i$, that the user tagged in the training set by collecting the “supervised” tag order for that image, $T_i$, as the user provided tag list with order preserved and the “semi-supervised” tag order from tags mined from the image’s most visually similar neighbors and ordered according to Equation 4 to produce the semi-supervised set $V_i$. We then learn the user’s ranking function $\hat{w}_u$ by solving the RankSVM objective using the constraints described in section 3.2, with the svm-lite software package.

Testing Phase: During test time, for a query image, $i$, its nearest neighbors are used to generate candidate the tags that need to be ranked by that user’s learned ranking function $\hat{w}_u$ from the training phase. These candidate tags are the tags from $\hat{V}(I, u)$ according to Equation 4.

Parameter Settings and Design Choices For our RankSVM formulation we need to make a choice for the regularization term $C$ which controls the size of the slack variable and hence the trade-off between training error and generalization. We chose a value of $C = 0.01$ in our experiments. We tried a few choices of $C$ between 0.01 and 10 but the choice did not seem impact the results, so we chose $C = 0.01$ since it was the fastest for training among the values we tried.

Another design decision was how much data to use in creating the preference orders, $P_S$, per training image as described in section 3.2. Given some “session” $(I, V, T)$, users tend to give too few tags, but using the entire set $V \setminus T$ as negative tag examples used in creating $Q_S(T, V)$ in equation 6 might, 1.) slow down the training phase due to too many pairwise constraints, and 2.) create noisy/meaningless constraints since not all the tags in our vocabulary are related to the image in question. So to address these issues we decided to focus not on the whole dictionary but instead on those tags which are related/relevant as denoted by $\hat{V}$ in equation 4. That is we set $V$ to $\hat{V}$.

We also analyzed the effect of the number of tags given per example by defining, $\hat{T} = T :: \hat{V}$, which is the tag order defined by equation 4 (semi-supervised data) appended to the ground-truth user generated tags. To study the effect of number of tags used we parameterize $\hat{T}(n) = \hat{T}[: n]$, as the first $n$ elements of $\hat{T}$. With some abuse of notation, this corresponds to setting $T = T(n)$, and $V = \hat{V} = \emptyset$ in equations 5 and 6.

Since both the training and testing phases of our method require nearest neighbor search, we also have to decide the number of nearest neighbors to consider, and in this work, we chose to use $m = 50$ nearest neighbors.

Another design choice was to group the tags in $\hat{T}$ into
levels of relevance, with tags within the same relevance level having no preference among one-another, but tags in lower levels preferred to tags in higher levels. We assigned the first 5 tags in \( T \) to levels 1-5 respectively, and then group the next set of 5 tags into increasing levels (For example, tags 6-10 are level 6, and tags 11-15, level 7). This helps to prevent overfitting due to potential noise in the data, and also reduces the number of constraints to enforce in training each user, thereby speeding up training.

4.5 Evaluations

We evaluate our method by using the DCG metric both on a per-image and per-user basis. Especially since we are concerned with personalization, we want to know what the average performance of our method is for each user compared to the baselines. We also present the DCG@10 since in our dataset the average number of tags per-user is about 10.

We explore the effect of using only supervised orders, \( QUOTE([T]) \), without supervised orders, \( QUOTE([V]) \) and also the effect of using all the tags generated during the semi-supervised step, \( QUOTE(\infty) \). We also explore the effect of the number of tags, \( n \), per image when training our method, hereafter referred to as \( QUOTE(n) \).

To make sure that our method truly captures personalization, we also compare our method to a modified version which in the testing phase uses some other user's ranking function (randomly) to sort the tags mined from the nearest neighbors. We refer to this setting as \( randQUOTE \).

4.6 Observations & Discussion

We see from figures 2 - 5 that the number of ordered tags (clickthrough data) that are provided per training example profoundly affects the performance of our method as expected. The more ordered tags are provided the better performance we get up to a point (100 tags), when we observe a slight degradation and then saturation. This degradation and saturation is probably due to the fact that our method of adding more tags to the training images in our semi-supervised method start to include some less than relevant tags for the image as we provide more tags according to equation 4. As we increase more tags past 100, our method seems to asymptotically approach the performance of when all the semi-supervised provided tags are included for training. We also notice that at 40 training tags, our method already begins to match and outperform the \( PT_{rerank} \) baseline which itself outperforms the previous state-of-art (Li et al. 2011).Given the size of our vocabulary (over 5000 tags) we do not think that 40-100 tags per image in training is in anyway excessive, especially when generated cheaply without need for expert knowledge.

The observations under the image level averages (figures 2 and 3), and the user level averages (figures 4 and 5) are similar. This shows that we do not just learn global notions of tag preference, but more importantly personalized tag preferences. So for the “average” user in our dataset, we are able to learn a ranking function that leverages the user’s inherent ranking and preference of tags in order to improve the task of personalized image tagging. Tables 1 and 2 show the average percentage improvement of our method over the \( PT_{rerank} \) baseline, and we again observe that using more tags improves our method.

In Table 3 we observe that using the constraints without the supervised order performs better than when we only use the supervised constraint, and this is not too surprising as we stated earlier, because there are typically much fewer supervised constraints since users tend to only provide a small number of tags (\( \sim 10 \) on average). But as expected the combination of both the supervised and unsupervised constraints leads to an improvement over both. We also see that our method indeed learns personal models, since the \( randQUOTE \) which ranks queries from one user by a random user’s ranking function performs drastically worse.

To verify that the improvements reported in Tables 1, 2 and 3 are statistically significant, we performed two-sided student t-tests, and all of our improvement have p-values of less than 0.001 which implies that our findings are indeed statistically significant. We also provide qualitative examples in Figure 6.

Our method is also more efficient than the previous state of the art. We use \( O(|\text{Users}|) \) parameters, whereas (Li et al. 2011) requires \( O(|\text{Users}| \cdot |\text{Tags}|) \), and \( PT_{rerank} \) requires \( O(|\text{Users}| \cdot |\text{Tags}|^2) \) parameters to train the respective models. For (Li et al. 2011) the training time per user was 1 minute (not including I/O), whereas for ours, it was under 1 second (with I/O time).

5 Conclusion & Future Work

We proposed a novel measurement of tag preferences and a learning to rank framework, which exploits implicit user preference “feedback”, and adds tags in a semi-supervised manner to enrich our data in order to leverage the power of RankSVM. As opposed to prior work we did not make the assumption that tags which are visually relevant or are about objects in the image are more important to be mentioned before and over tags that have more higher-level and abstract meanings. Especially for the purpose of personalization, we believed that prevalent assumption to be too restrictive.

Our experiments demonstrated the efficacy of our approach and contrary to other learning to rank methods does not require expert knowledge to train nor evaluate, as the implicit human signals, used smartly, have been demonstrated to be good enough to produce state-of-art results for tag personalization. Our method is also more efficient than the previous state-of-art in tag personalization.

We think it would be an interesting future direction to jointly embed the image features and tag features to learn a better mapping that leverages both the image content and tag meaning using deep recurrent and convolutional neural networks. We also think that it would be interesting to explore what cognitive processes drive a user’s tagging order. Do they follow an ontology in a top-bottom or bottom-top manner? Is there some latent hierarchy on tags, or maybe parts-of-speech which exists? What role does sentiment play in tagging?

Another interesting question is could the auto-tagging problem be posed as an instance of the machine translation
Table 3: This table shows the comparison of the different components of our proposed method. \( QUOTE(T) \) measures the performance of just the supervised, \( QUOTE(\hat{V}) \) measures the performance of the non-supervised order, and \( QUOTE(\infty) \) the combined performance. \( randQUOTE(T) \) measures the performance not using user-specific models. All improvements were calculated to have \( p \)-value < .001 using a two-sided student’s t-test.

|                | \( QUOTE(T) \) | \( QUOTE(\hat{V}) \) | \( QUOTE(\infty) \) | \( randQUOTE(T) \) |
|----------------|----------------|----------------------|---------------------|---------------------|
| dgc per image  | 0.632          | 0.817                | 0.852               | 0.455               |
| dgc@10 per image | 0.378       | 0.588                | 0.626               | 0.173               |
| dgc per user   | 0.563          | 0.728                | 0.770               | 0.408               |
| dgc@10 per user | 0.348       | 0.544                | 0.593               | 0.168               |

Figure 6: This figure shows example images from our experiment with their groundtruth tags and the output of the different algorithms compared in this paper.

problem: Given an image, output the most likely sequence of words (tags)? We believe that when the restriction to visually relevant tags is lifted, the personalized image tagging problem becomes richer, allowing us to leverage structure and signals in novel ways as we have demonstrated in this paper.

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