MATCHING FOR MOBILE USERS IN THE PUBLISH/SUBSCRIBE PARADIGM

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Keywords: Mobile publish/subscribe, nearest neighbor problem, high-dimensional search, singular value decomposition.

Abstract: In a mobile publish/subscribe paradigm, user service discovery and recommendation requires matching user preferences with properties of published services. For example, a user may want to find if there is a moderately priced Chinese restaurant that does not require reservations close by. To generate accurate recommendations, the properties of each user subscription must be matched with those of existing services as accurately as possible. This is a difficult problem when users are mobile, wirelessly connected to a network, and dynamically roaming to different locations. The available data is very large, and the matching must be computed in real time. Existing heuristics are quite ineffective.
We propose novel algorithms that use singular value decomposition as a dimension-reduction technique. We introduce "positive" nearest-neighbor matching to find services whose attribute values *exceed* those of a new user subscription. Making this idea effective requires careful attention to details such as normalization. Performance and quality of matches are reported for datasets representing applications in the mobile publish/subscribe paradigm. For n services and m preference attributes, reasonable matches can be found in time $O(m \log n)$, using $O(nm)$ storage.

1 INTRODUCTION

Publish/subscribe is an asynchronous messaging paradigm for connecting information providers (publishers) with interested information consumers (subscribers) in a distributed environment, providing a dynamic network topology and scalability. The pub/sub paradigm extends, in a natural way, to other kinds of service discovery, where service providers play the role of publishers, and users with preferences are subscribers. In a mobile setting, services are provided in a geographical region, perhaps one cell of a mobile phone system. Hence there are multiple pub/sub systems. Users' service requests are contextualized by and satisfied within the current region. User mobility implies that new service requests can appear at any time, and that they must be satisfied quickly before the user moves on. Either a push model or a pull model of service is possible. In the pull model, a user requests a matching service; in the push model, a service finds a matching user preference and provides a service, perhaps a discount coupon contextualized for the particular location of the user.

The central component of pub/sub systems is the broker (event dispatcher), which facilitates the message staging and routing in the system. Publishers send information to the broker in the form of publications (events). Subscribers indicate interests in events by maintaining a set of subscriptions at the broker. They also indicate situations in which they would like to be notified. The broker acts as a mediator between publishers and subscribers, deciding when to send notifications and who should receive them.

In a pub/sub paradigm, user service discovery requires matching user preferences to available published services in a timely fashion. Hence, the system must find an efficient solution to the problem of matching each subscription against a large number of publications, or matching a publication (event) against a large number of subscriptions. Take, for example, a user with a handheld mobile device that uploads his preference vector to an advertising server. The server will match the preference vector with companies' advertisements, and offers the user a coupon that is valid for X time. Although there have been studies on matching algorithms in these systems, the problem of finding accurate matchings in a timely manner amongst multiple possible publications is new.

This paper presents two efficient matching algorithms for mobile user services in pub/sub systems, using Singular Value Decomposition (SVD) (Golub and Loan, 1989) as a dimension reduction technique. Known service (publication) data is transformed, in a preprocessing stage, so that the high-dimensional space of preferences for many possible services is projected into a low-dimensional space. When a match is to be found, the user's preferences are mapped into the same low-dimensional space, producing values that can be rapidly compared to available service profiles. The first algorithm implements this idea using a single singular value decomposition, while the second uses projections from randomly weighted versions of the global preference data. We evaluate the performance and quality of our algorithms using two datasets representing applications in the mobile publish/subscribe paradigm. In practice, reasonable matches can be found in time $O(m \log n)$, using $O(nm)$ storage space, where n is the number of services (publications) and m the number of attributes or preference possibilities. This is in contrast to "approximate" nearest-neighbor techniques, which require either time or storage exponential in m.

2 EXISTING APPROACHES

There have been many designs proposed in the literature to model a pub/sub system. The earliest systems were channel-based, with the broker component acting as a broadcast channel (Babu and Widom, 2001). The most significant limitation of these systems is the lack of flexibility and expressiveness, leading to high network traffic, and necessitating additional subscriber-side filtering. A refinement over the channel-based approach is the topic-based pub/sub model that categorizes events into hierarchical subjects (topics), providing a finer granularity of events (TIBCO, 2006). This model uses a tree-like structure to categorize events, and the matching process is basically a tree traversal. The drawback of this model is the limited selectivity of subscriptions. Today, companies like Netscape, Radio Userland, and Moreover use RSS (RSS, 2006) to distribute and syndicate article summaries and headlines to web users who wish to subscribe to them.

The latest pub/sub systems have the ability to filter information using the contents of a published event. In this model subscriptions are specified as expressions evaluated over the published event contents. This approach provides greater expressiveness to filter publications and is more easily customized for individual subscribers. The information filtering process requires an efficient matching algorithm with high throughput and scalability. Many algorithms proposed for content-based matching (Fabret et al., 2001; Fabret et al., 2000) attempt to optimize algorithms by limiting the expressiveness of subscriptions.

There is also a proposed state-persistent model for pub/sub systems (Leung, 2002) that stores the states of both publications and subscriptions in the system and notifies subscribers only when the states of their subscriptions change. An example of a content-based matching algorithm for state-persistent pub/sub systems was proposed in (Leung and Jacobsen, 2003).

The matching problem in a state-persistent pub/sub system requires storing information about publications and subscriptions, indexing the relationships between them, and detecting state transitions.

In this paper we are targeting users (subscribers) who are mobile, with handheld devices, wirelessly connected to a network, and dynamically roaming to different environments. For mobile users, service discovery requires matching user preferences to available services as accurately as possible (For work on mobile pub/sub see (Burcea et al., 2004)). This is a difficult problem since users are mobile and matches must be done in real-time. The magnitude of the problem increases with respect to the number of attributes in the preference criteria for each user. Take, for example, a user with a handheld mobile device who is in Montreal and would like to eat Chinese food. Such a user might submit a service request (subscription) with the attributes: Chinese restaurant, Montreal, non-smoking, within 15 minutes walking, under 10 minutes seating time, with buffet option, and below a certain price. In addition, there could be several possible restaurants that match the user's criteria, and we might require the system to send one, some, or all of such matches. The selection process in this environment has to find the best matching service(s) (a restaurant in our example) that match the user's request from among many possible matches.

The values used for attributes can be classified into two types as follows. **Binary values** (0 and 1), describing the presence or absence of particular properties of services that a user may require. For example, a user may submit a subscription query for weather reports consisting of the attributes (earthquakes, tsunamis, tornadoes, local weather, etc.). The second type is **ternary values** (1, -1, and 0), describing a preference for *or against* a particular attribute, as well as a neutral value. This could be, for example, the restaurant property for "non-smoking". There is little point in trying for an absolute best fit because the information available to the system can become stale, or the user might change location. Such a dynamic environment benefits more from finding approximate best matches instead.

3 THE NEAREST-NEIGHBOR PROBLEM

Let the number of services be n and the number of attributes be m. n could be in the thousands and m in the tens to hundreds. There is an obvious geometric interpretation of the problem in which each service description tuple and each query (request) tuple are points in an m-dimensional space.

When finding a match in the case of binary-valued attributes, the goal is to find the nearest neighbor of the query tuple – but with the extra difficulty that the value of each of the service-tuple attributes must be no smaller than the value of the corresponding attribute for the query. We refer to such a service tuple as feasible. We are only interested in points that are further away from the origin than the point corresponding to the query, but we want to find, among them, the point that is nearest to the query. Call this the "positive nearest-neighbor". This guarantees that a service tuple contains all the required preferences in the query tuple (represented by '1'). In the case of ternary-valued attributes, the goal is to find the ordinary nearest-neighbor of the query tuple, where the match can be near to the query point in any direction.

Given a query tuple, there is an obvious brute-force algorithm for finding the nearest neighbor with time complexity $O(nm)$. For a small number of dimensions m, simple solutions suffice, but for larger m, say $m > 10$, the complexity of most methods grows exponentially as a function of m. Dobkin and Lipton (Dobkin and Lipton, 1976) give an upper bound for the time required to search for a nearest neighbor, $O(2^m \log n)$ query time, and $O(n^{2^{m+1}})$ preprocessing time and storage space. Most of the subsequent improvements and extensions require a query time of $\Omega(f(m)\log n)$, where $f(m)$ (sometimes hidden) denotes an exponential function of m. One of the most widely used algorithms relies on the *k-d tree* (Samet, 1990). The average case analysis of heuristics using *k-d trees* for fixed dimension m requires $O(n \log n)$ for preprocessing and $O(\log n)$ query time. Although *k-d trees* are efficient in low dimensions, their query time increases exponentially with increasing dimensionality. The constant factors hidden in the asymptotic running time grow at least as fast as 2^m, depending on the distance metric used.

The complexity of exact nearest neighbor search led to the "approximate" nearest-neighbor problem: finding a point that may not be the nearest-neighbor to the query point, but is not significantly further away from it than the true nearest neighbor. Several approximate nearest-neighbor algorithms have been developed (Kleinberg, 1997)but they either use substantial storage space, or have poor performance when the number of dimensions is greater than $\log n$. The positive-nearest-neighbor requirement means that the performance of such algorithms becomes even worse. For example, the positive nearest neighbor may be quite far from the query point, with many closer but infeasible objects (service tuples). This suggests using a technique that can transform the high-dimensional space of the data into lower-dimensional subspaces. One obvious technique is Singular Value Decomposition (SVD). We have already noted the natural geometric interpretation of a list of tuples describing services. If we regard such a list as an $n \times m$ matrix, then a singular value decomposition can be regarded as transforming the original geometric space into a new one with the following useful property: the first axis of the new space points along the direction of maximal variation in the original data; the second axis along the direction of maximal variation remaining, and so on. Let A be the $n \times m$ matrix representing the services. Then the singular value decomposition of matrix A is given by $A = USV^T$ where ^{T} indicates matrix transpose. If matrix A has r linearly-independent columns (r is the rank of A), then U is an $n \times r$ orthogonal matrix (i.e., $U^T\ U = I$), S is an $r \times r$ non-negative diagonal matrix whose elements (called singular values) are non-increasing, $s_1 \geq s_2 \geq s_r > 0$, and V^T is an orthogonal $r \times m$ matrix. Each row of U gives the coordinates of the corresponding row of A in the coordinate system of the new axes (defined by V). The complexity of computing the SVD of a matrix is $O(n^2 m)$ and the space required to store the data structure is $O(mr + r^2 + rn)$.

One of the most useful properties of an SVD is that the matrices on the right-hand side can be truncated by choosing the k largest singular values and the corresponding k columns of U and k rows of V^T. We show that a tuple of m properties can be encoded by coordinates in a *single* dimension using SVD, given suitable normalization of the data. Matching a query tuple to appropriate service tuples requires encoding the query attributes, and then searching a ranked list of projected service values. We also propose a technique that produces highly accurate matches by using a *collection* of SVD decompositions, in which each decomposition uses data independently weighted by random scalars. This provides several different projections of the data, which tends to reveal the most important latent structure. Hereafter we will refer to nearest-neighbor as n-n.

4 ALGORITHMS

We propose two SVD-based Search (SVDS) techniques for solving the positive and the ordinary n-n matching problem: basic SVDS (*bSVDS*) and random-weighted SVDS (*rwSVDS*). The *bSVDS* algorithm works in two stages: a preprocessing stage and a run-time stage. The natural similarity (proximity) metric is Euclidean distance – a service tuple is a good match for a request tuple if the Euclidean distance between them is small (and the service-tuple attributes meet or exceed the request requirements in the original space for the positive n-n case). We first preprocess the set of service tuples by computing the SVD of the original matrix A after normalization, then truncate the result to one dimension. The resulting list is sorted by increasing values of u_1, the first column of U. When a new query arrives, it must be mapped into the corresponding space of U, and a value created that can be compared to the encoded values. By re-arranging the SVD decomposition equation we get $U = AVS^{-1}$. This multiplication can be applied to new queries with the shape of rows of A to compute their coordinates in the transformed space. Since we have truncated the SVD, this mapping requires only the first column of V and the first singular value, and therefore takes time $O(m)$. After the transformation maps the query tuple to a single value, the value is compared to service' values using binary search to find the service with the closest value. This service tuple may not be feasible (it is similar to the query tuple in the original A matrix but one or more of its attributes is smaller than the corresponding value of the query). In this case, the ranked list is searched by choosing the next closest value on either side of the original entry, until a feasible tuple is found.

Algorithm *rwSVDS* is an extension of *bSVDS*; instead of using a single search list to predict the positive n-n point, it uses multiple search lists. *rwSVDS* uses a set of three decision lists to predict the nearest-neighbor point. To create each list, the attributes of the original dataset are weighted with different (randomly chosen) scalars in the range (0,1] to create a new weighted matrix (note that the original input data is not changed, since is later used for feasibility check). This process is repeated three times to generate three differently weighted matrices. SVD is then applied to each matrix independently, to generate three one-dimensional spaces, which are then each sorted. The selection process transforms each query tuple (after scaling it with the corresponding weight vector) into the space of each SVD, then searches all three ranked lists in a concurrent fashion to find a common match. The first feasible service-tuple to have been found on all three lists is reported as the best match. The use of three lists is based on extensive experiments that show that more lists adds cost without improving matches.

5 EXPERIMENTAL SETTING

We generate artificial datasets to represent properties of services in the pub/sub paradigm, with binary-valued attributes (selected randomly with 20% density of 1's) and ternary-valued attributes (selected uniformly randomly). We normalize the data by zero-centering each column. Each experiment result is the average of 70 runs. For comparison purposes, we also consider a ranking algorithm that uses the sum of the attributes. We call it the SUM-based Search algorithm (*SUMS*). The advantage of the sum is that any service tuple whose sum is smaller than the sum of the requirements of a query tuple cannot possibly be feasible. We compute the sum of attributes for each service tuple and sort the list based on the sum of ratings. The sum is then computed for each query tuple, and binary search is used to find the feasible service closest in sum to it. When applying the *SUMS* algorithm to the ternary-valued data, there is a special handling to accommodate for the negative values (-1's); the sum is computed by first incrementing the attributes' values. The same handling is done for the queries before the search starts.

Both our *SVDS* algorithms and *SUMS* algorithm have similar properties: both require $O(nm)$ storage for the ranking information (since the full set of attributes must be checked for feasibility); for both, the cost of binary search is $O(\log n)$; and for both the cost of computing the fit between a query tuple and a service tuple is $O(m)$. The preprocessing required for *SVDS* is more expensive. However, this cost is amortized over all the matches of queries to services. The performance difference between the two rankings depends on how many list elements must be examined to find a feasible match, and on the quality of such a match. We also compare our algorithms' effectiveness with that of randomly selecting services until a feasible one is found (call this simple algorithm *RAND*), and with exhaustive search. *RAND* provides a baseline for the number of probes required to find a good solution, while exhaustive search provides a baseline for how good a solution is possible.

The main performance measures of interest are: **cost** – measured in number of probes needed to find a match, including the cost of binary search (where applicable); **sub-quality** – the Euclidean distance from the match point found by the algorithm to the query point (A higher value represents a lower-quality match; and **sub-optimality ratio** – the ratio of the solution found by an algorithm to the optimal solution. The lower the value the better the quality of the match found.

In our experiments, we search for the positive n-n in binary-valued datasets, and for the ordinary n-n in ternary-valued datasets. For each combination of experiments, the fraction of objects that are feasible for each query are held to approximately 5%. If feasible objects are extremely scarce, then exhaustive search is probably the best matching technique; if the fraction of feasible objects is large, then the system does not provide much discrimination in services which is also an unlikely scenario.

6 RESULTS AND DISCUSSION

We study the effect of varying the number of objects (services) and attributes on the search cost and quality of the solutions.

6.1 Binary-valued Datasets

First, we test the basic *SVDS* algorithm (*bSVDS*). Figure 1 plots the number of probes (cost) required to find a feasible object for a query (left column), and the sub-quality of this match (right column) when attributes are binary values. Plots (a) and (b) show the number of probes required and the sub-quality for *bSVDS*, plots (c) and (d) show the same for *SUMS*, and plots (e) and (f) show them for *RAND*.

We see in Figure 1 that *bSVDS* requires the lowest number of probes to find a match. Although the cost and sub-quality of the match found by all algorithms increases with increasing numbers of objects and attributes, the number of probes required by *SUMS* increases rapidly. However, this increase comes at a tradeoff with sub-quality. Nevertheless, for what might be considered the most practical cases, i.e., those where the number of attributes is relatively small, *bSVDS* is a clear winner in both cost and quality of matches. *bSVDS* requires, on average, only 11% of the probes of *SUMS*, and finds better-quality matches that are 78% of the sub-quality of *SUMS*.

In comparison to *RAND*, algorithm *bSVDS* requires 77% of the probes that *RAND* requires, especially for small numbers of attributes, and finds better-quality matches that are 38% of the sub-quality of *RAND*, for a moderate number of attributes. On the other hand, *SUMS* requires many more probes than *RAND* in almost all settings, except for small numbers of objects and attributes. This comes at a tradeoff with match quality for all parameter settings. Although the sub-quality of *bSVDS* increases with the number of attributes, it actually gets closer to the optimal solution, as shown in Figure 2.

Figure 3 plots the number of probes (left column) and the sub-quality (right column) for (*rwSVDS*). It achieves better performance and better-quality matches than *bSVDS* for all parameter settings – an average of 19% lower probes and 10% better quality. This improvement affects, in its turn, the cost and quality ratios to *SUMS* and *RAND*. Algorithm *rwSVDS* now requires, on average, only 15% of the probes of *SUMS*, and finds slightly better-quality matches, of 94% the sub-quality of matches found by *SUMS*,

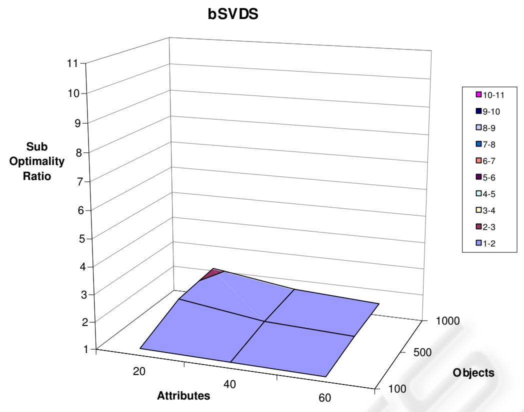


Figure 2: Positive n-n in binary-valued dataset: *bSVDS* sub-optimality ratio.

with the best results observed for small numbers of attributes. As for *RAND*, *rwSVDS* requires only 33% as many probes, and finds better-quality matches of 40% the sub-quality of those found by *RAND*. Figure 3(b) shows that the sub-quality of the match found by *rwSVDS* increases with increasing numbers of attributes, but starts to plateau as these become large.

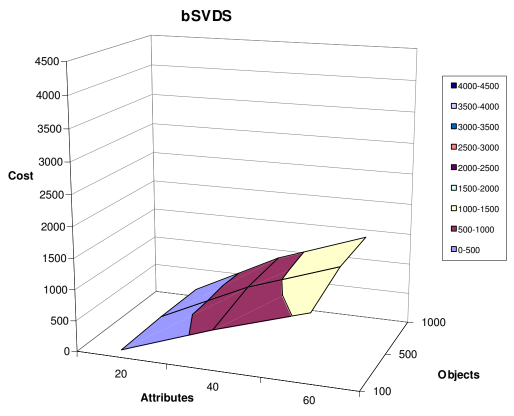
Algorithm *rwSVDS* finds the best-quality matches with better overall performance than *bSVDS*. Compared to *SUMS*, it also achieved, by far, lower search cost and better match quality for small numbers of attributes. For higher numbers of attributes, it still achieved near-optimal results.

6.2 Ternary-Valued Datasets

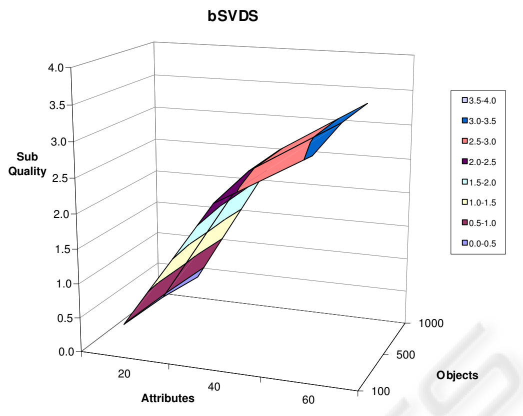
Figure 4 plots the number of probes required by algorithm (*bSVDS*) to find a match (ordinary n-n) for each query, and the sub-quality of this match when attributes are ternary values.

Figure 4 shows that, in comparison to the positive n-n case, algorithms *bSVDS* and *SUMS* require many fewer probes to find a match when the feasibility condition is relaxed, whereas *RAND*, by definition, takes only one probe. *SUMS* requires slightly more probes than random matching (mainly due to the overhead of the initial binary search) but maintains almost constant cost. Algorithm *bSVDS* comes last in terms of performance, with slightly more probes than *SUMS*, but only a constant number of probes are required after the binary search (see Figure 4(a)). As for the quality of the solution, *bSVDS* finds better-quality matches than *SUMS* and *RAND* – an average of 67% of the sub-quality of *SUMS*, and 64% of the sub-quality of *RAND*, with the best quality for small numbers of attributes.

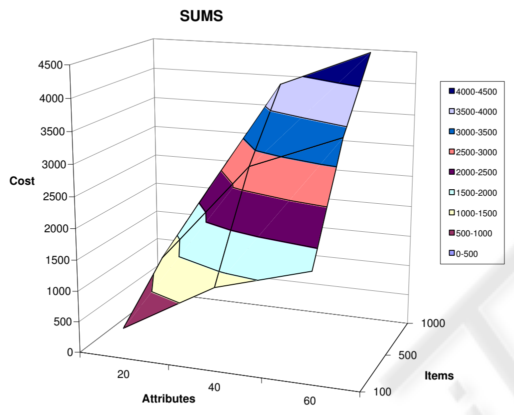
Algorithm *rwSVDS* results are shown in Figure **??**. *rwSVDS* requires more probes than *bSVDS* but, on



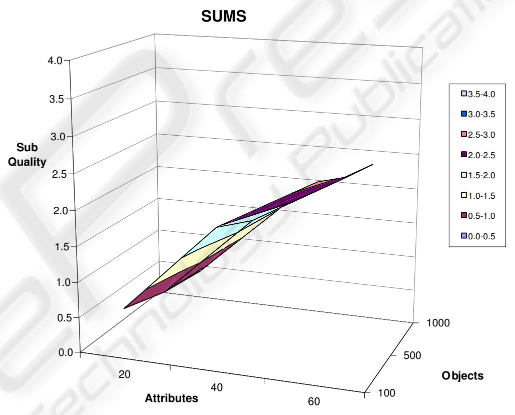
(a)



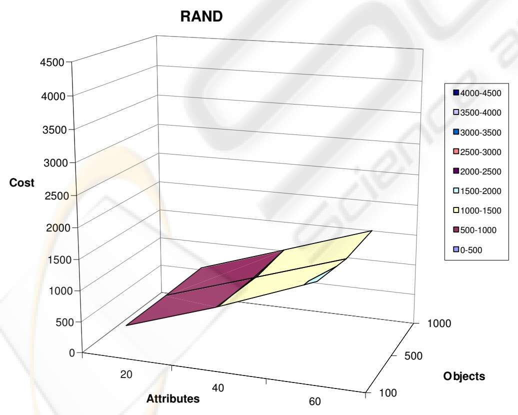
(b)



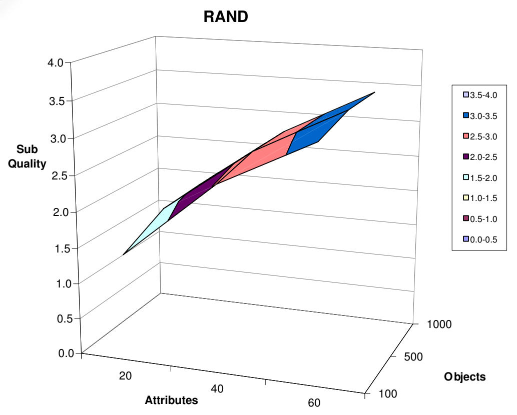
(c)



(d)



(e)

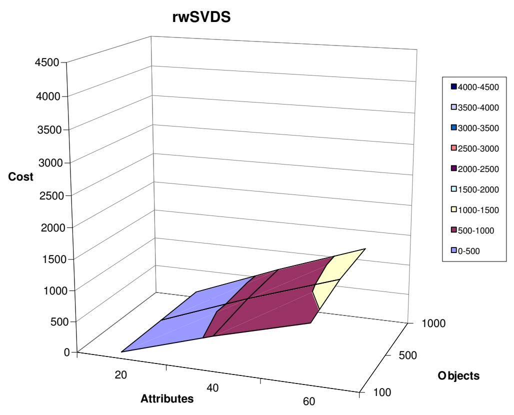


(f)

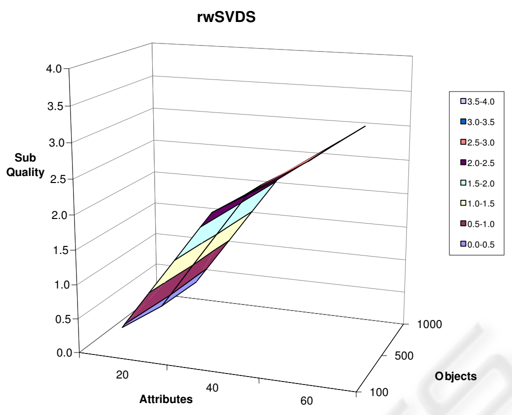
Figure 1: Positive n-n in binary-valued dataset: Search cost and sub-quality for: (a) and (b) *bSVDS*, (c) and (d) *SUMS*, (e) and (f) *RAND*.

the other hand, it finds matches of twice the quality. This improvement in match quality, consequently, affects the quality ratios to matches found by *SUMS* and *RAND*, with more emphasis on the tradeoff between search cost and match quality.

It is not so obvious which algorithm is best in terms of cost and quality; *bSVDS* has slightly worse performance than *SUMS* and *RAND*, but it achieves better



(a) Cost



(b) Sub-quality

Figure 3: Positive n-n in binary-valued dataset: Search cost and sub-quality for *rwSVDS*.

match quality, which would justify some sacrifice in performance. Relative to *rwSVDS*, the tradeoff on performance and quality is much more apparent. Algorithm *bSVDS* has better performance, but lower match quality.

7 CONCLUSIONS

One of the critical research challenges in the development of pub/sub systems that support services for mobile-user interactive applications is the discovery of an efficient matching algorithm that is scalable and reasonably effective, and provides good matches between user requests and available services. As the number of services and their attributes increase, solutions that are cheap to implement are required. We have presented two projection and search techniques based on SVD, using SVD as a preprocessing step to project service properties into low-dimensional spaces. Careful normalization, and the use of multiple projections based on random weighting of attributes result in one-dimensional lists that can be searched, in practice, in only a constant number of probes beyond the basic binary search required to find the right part of the list. The overall complexity of matching is $O(m \log n)$ time and $O(nm)$ storage space.

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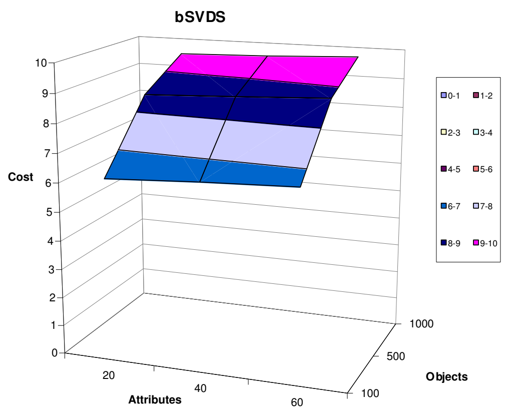
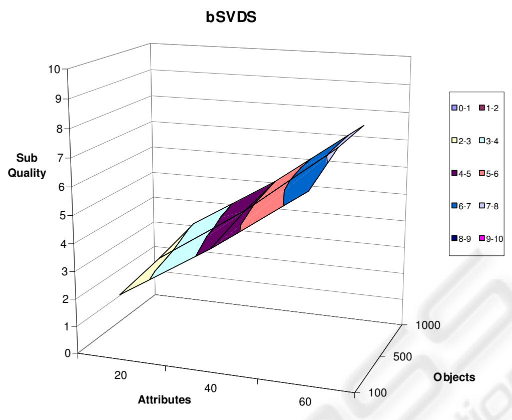


(a)



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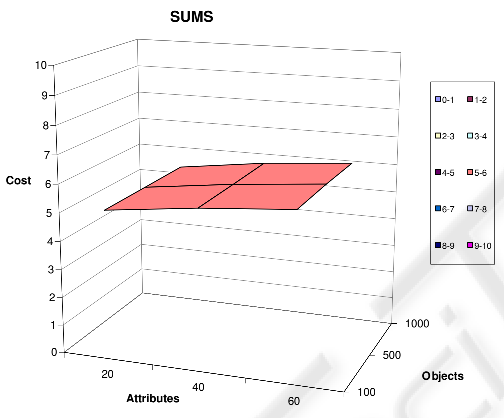

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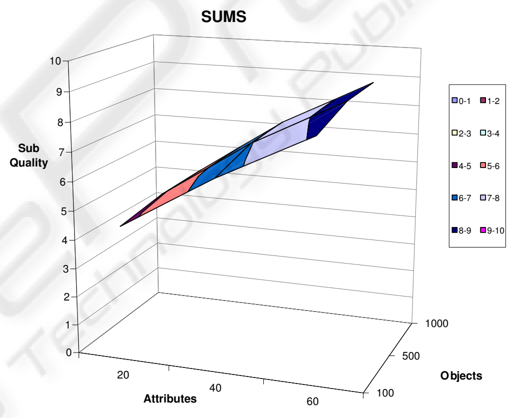

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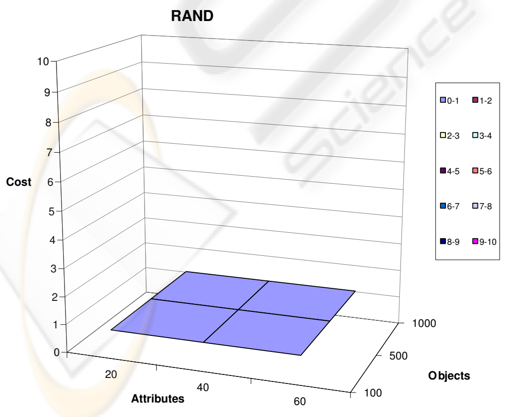

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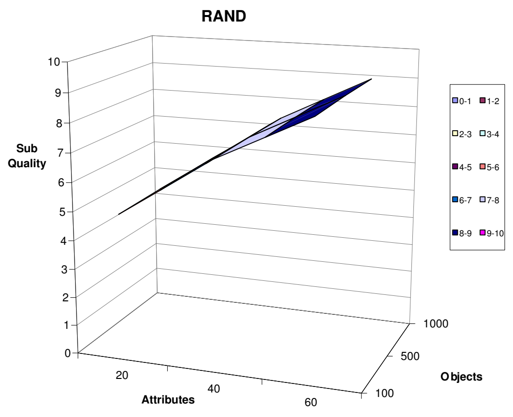

(f)

Figure 4: Ordinary n-n in ternary-valued dataset: Search cost and sub-quality for: (a) and (b) *bSVDS*, (c) and (d) *SUMS*, (e) and (f) *RAND*.