A Scalable Interest-oriented Peer-to-Peer Pub/Sub Network

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***Abstract*—There has been a big challenge in structured peer-to-peer overlay network research area. Generally, a structured overlay network involves nodes evenly or based on their resource availabilities, and gathers nodes' resources to achieve some bigger tasks. The challenge here is to gather resources based on nodes' interests, and only interested nodes are involved in a certain task.**

Toward this challenge, we propose a new scheme to a peer-to-peer publish/subscribe network. Publish/subscribe represents a new paradigm for distributed content delivery. It provides an alternative to address-based communication due to its ability to decouple communication between the source and the destination. We propose a Bloom filter based mapping scheme to map IDs to nodes' interests in addition to new interest proximity metric to forward events and to build nodes' routing tables. We also propose a new approach called "shared interest approach" for network discovery.

To evaluate the algorithms proposed in this work, we conducted simulations in both static and dynamic settings, and found a low false positive rate. We also discuss about a well-known application called Twitter, and show how our scheme would work in a real environment.

I. Introduction

Publish/subscribe systems have received a lot of attention in the last years as they allow efficient, distributed and selective content delivery to a potentially large set of users. In such systems, users register subscriptions representing their interests in content while publishers inject events which are delivered to the matching subscribers.

There are two common types of publish/subscribe systems:

- *Topic-based*, which rely on a set of predefined topics to which subscribers register their interests: all messages related to a particular topic are broadcast to all registered users;
- *Content-based*, which allow subscribers to specify any filter over the entire content. A data event specifies values for a set of attributes associated with the event. Subscribers thus, register their interests in form of filters that are used by the system to deliver relevant events to the subscribers.

In this paper, we focus on content-based publish/subscribe systems. Many applications require content-based publish/subscribe systems with fine grained expressiveness: for example, real-time stock quotes notification, Internet games and sensor network applications, to name a few. However, the implementation of such systems has remained a challenging issue.

Most content-based systems employ an overlay network of event brokers, which support rich subscription languages (e.g. SIENA [1], [2]). However, they commonly have two drawbacks. Firstly, a broker should maintain large routing tables. Indeed, every broker can be an intermediate relay on the paths of an event dissemination tree and should match each incoming event against every known subscription. Secondly, these systems require static overlay networks where the brokers are highly reliable and under administrative control, or assume the entire broker set to be known beforehand [3]. Scalability and reliability issues affecting content-based schemes have been addressed in the literature using system design inspired from the peer-to-peer (P2P) paradigm. Several implementations of content-based systems have been investigated in the literature, for instance Meghdoot[4], Mirinae [5], or HOMED [6]. Although these proposals address scalability and reliability issues, they whether have low overhead but involve not interested nodes in event dissemination [5], [6], [4], or they engage only interested nodes but generate a large amount of overhead (e.g. [7] where nodes use gossiping for membership management and routing table construction).

In this paper, we propose a new peer-to-peer content-based publish/subscribe scheme based on structured overlays. Our system aims at involving only interested nodes in event dissemination while ensuring a low overhead. In order to do so, we map nodes' interests to their identities (IDs) using Bloom filters, and we use a novel proximity metric. This metric is used to cluster nodes according to their subscriptions' similarity. Therefore, events will be directly posted to the proper cluster where they are going to be disseminated efficiently. Indeed, our scheme ensures an upper bound of routing table size that only depends on the size of a node's ID. Furthermore, application overhead is reduced thanks to a new approach to network discovery.

The remainder of the paper is structured as follows: we present related works in Section II. Section III describes the design and the algorithms used by our system. We present a simulation-based evaluation of our system in Section IV and an analytical approach to evaluate application overhead in Section V. We then discuss a use case in Section VI. We conclude in Section VII.

II. Related work

The first implementations of content-based publish/subscribe systems used a network of event brokers to implement distributed content based routing: SIENA[2] and KYRA [8]. Although these approaches can support rich subscription languages, they have two main limitations. Firstly, they require static networks which lead to un-optimized network topology. In other words, the network topology should cope with the changing nodes' interests in order to reduce network congestion and minimize routing depth. This means that for an optimized design, the network of the brokers should be dynamic. Secondly, in these approaches, a broker keeps a large amount of routing information and generates a considerable amount of overhead in order to perform routing and to minimize notifications relaying. A broker needs to keep track of the changing state of its clients as they issue new or cancel subscriptions so that it reflects perfectly its clients' interests. Although summarization using Bloom filter and aggregation using *covering* relation and *merger* are currently used to reduce notification overhead, a leaving node could generate a lot of overhead since it has to forward all the subscriptions it covers.

Other implementations rely on a peer-to-peer architecture in order to achieve self organization and robustness. In a peer-to-peer system, all participants act as subscribers and publishers but, in addition, they also route notification among themselves. Some approaches implement content-based routing on top of DHTs. Terpstra et al. [9] used Chord [10] combined with filter-based routing algorithms (merging and covering) in order to attenuate the overhead generated by event broadcast. A variant based on CAN [11] was implemented in [4]. The nodes build a multidimensional DHT and maintain information about the coordinates of their zones and store coordinate information of their neighboring zones. The idea behind these schemes is to have a rendezvous node for each event. Rendezvous nodes act as an entry point to a distinct overlay network composed by the group of interested nodes. Other approaches aim at clustering nodes semantically using an interest proximity distance to route the events introduced into the overlay and to build routing tables. Some implementations intend to have a mesh-like structure for event dissemination [5], [6] and use the hamming distance combined with a hypercube overlay to route and to disseminate events published by different nodes. In [7], nodes maintain semantic links to nodes with which they share some interests. Moreover, [7] uses gossip algorithms for membership management and provides nodes with random links that represent a partial view of the overlay to ensure connectivity.

Our proposal is also based on the semantic approach. We aim at clustering nodes based on their interests: in our system events are forwarded using new interest proximity metric while application overhead is reduced through a new mechanism for network discovery.

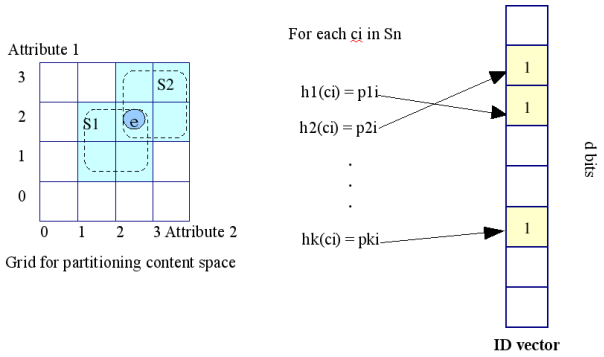


Fig. 1. Process to compute the semantic identifier of a node.

III. Overlay design and event dissemination

This section outlines our content-based publish/subscribe system. Our goal is to organize nodes semantically in a manner that only interested nodes in event e will forward it while minimizing the overhead due to membership management and network discovery.

In the remainder of this section we will make extensive use of the following definitions:

Definition 1. ***Filters:*** *a filter denotes the set of subscriptions issued by a given subscriber.*

Definition 2. ***Coverage:*** *a filter F_1 covers F_2, iff $N(F_1) \subset N(F_2)$ where $N(F)$ is the set of notifications that match the filter F.*

Definition 3. ***Mergers:*** *merger operation consists of deriving new filters from existing ones such that each new filter covers the set of filters it was generated from.*

We now describe the method to assign a "semantic" ID to a node, which is inspired by [5]. In our system, we partition the event space Ω into cells c_i of a regular grid. The process of partitioning the event space depends on the publish/subscribe application. For instance, in a stock quote application, the partitioning could correspond to a price/company's name partitioning.

Specifically, consider a set $S_n = \{c_i, c_i \cap S \neq \emptyset\}$. We use k independent hash functions h_1, ..., h_k, each with range 1 to d. The bits at position $h_1(c_i)$, ..., $h_k(c_i)$ in ID_n are set to 1 for each cell $c_i \in S_n$. As an event has a single cell c_e, its ID is set to 1 at positions $h_1(c_e)$, ..., $h_k(c_e)$. Figure 1 illustrates the process of generating a semantic ID for a node.

Assigning IDs using this approach renders the semantic clustering easier, as the similarity between two nodes can be estimated using the distance between two IDs. Moreover, this ID fulfills a very important property: if a node N is covered by another node M, its ID_M subsumes all 1s of ID_N.

Since node IDs obtained with this method might not be unique, we could concatenate an additional vector to distinguish nodes whose original ID collide. Instead, we organize nodes with the same ID in a cluster that will be transparent to other nodes that have a different ID. Hereafter,

we refer to this ID by $ID_{semantic}$.

Moreover, we assign to each node a *random ID* uniformly drawn from a large identifier space: this ID comes in addition to its $ID_{semantic}$.

A. Building the routing tables

The main challenge in peer-to-peer publish/subscribe systems is how to build a routing table that would ensure no false negatives and at the same time involve only interested nodes in event dissemination. To do so, we use an interest proximity metric which is the product of the inverse of an affinity and the hamming distance normalized by the size of the $ID_{semantic}$ digest d. The distance between two nodes N and M in the network graph G is:

$$d(N,M) = \frac{d_{hamming}(N,M)}{d \times A(N,M)} \quad (1)$$

$A(N,M)$ represents the *affinity* between nodes N and M and is computed according to the following expression:

$$A(N,M) = \frac{|S_n \cap S_m|}{min(|S_n|,|S_m|)} \quad (2)$$

where S_n refers to $\{c_i, c_i \cap S \neq \emptyset\}$ and c_i is the i^{th} cell of the grid obtained by partitioning the event space S and the subscriptions issued by N. Furthermore, $|S_n|$ refers to cardinality of the set S_n.

The distance defined in Equation 1 allows a given node N to connect to the nodes that cover its interests with the smallest hamming distance. Formally, given two nodes N and M, N connects to M when:

$M \in G$, M covers N and $\rightarrow$

$$d_{hamming}(N,M) = min\{d_{hamming}(N,K), K \in G\}$$

We note that when two nodes N and M do not share any interests, the distance $d(N,M)$ will be infinite:

$$if S_n \cap S_m = \emptyset \Rightarrow d(N,M) = \infty$$

In our system, nodes are organized in a containment hierarchy based on covering relationship. Hence, every node N in the network has three types of bidirectional links: *covering links*, which correspond to links to nodes that cover N, *covered links* which refers to links N keeps to nodes it covers, and *neighbor links* that correspond to links N keeps to nodes with which it shares part of its interests. In the following, we present how a node in the overlay picks its neighboring nodes:

- ***Covering links:*** A node N connects first to the closest node in term of hamming distance which covers its interests, this latter is the parent of N.
- ***Covered links:*** N goes through the nodes it knows in increasing order of the random ID (looping when it reaches the maximal sequence ID) and selects a node only if it intersects N's interests at some region not yet covered by the already selected covered nodes. This process is then repeated in decreasing order.
- ***Neighbor links:*** N keeps links to nodes with which it shares a part of its interests. The process of picking these links is identical to the covered links.

Algorithms 1 and 2 illustrate how covering and covered links are created, where we introduce the following notation:

- nodes_to_add(N) denotes all nodes that N has discovered and used to build its routing table.
- $N \supset M$ denotes that N covers M interests. $N \subset M$ denotes that N's interests are covered by M. Similarly $N \not\supseteq M$ means that N does not cover M's interests.
- $\sqcup\{N_1, ..., N_k\}$ denotes the mergers of N_1 ... N_k

Algorithm 1 Building the overlay -Covering Nodes-

```
for all N ∈ G do
  for i ∈ nodes_to_add(N) do
    if i ⊃ N then
      if
        d_hamming(i, N) <
                    d_hamming(covering_node(N), N)
       then
        covering_node(N) ← i
      end if
    end if
  end for
end for
```

Algorithm 2 Building the overlay -Covered Nodes-

```
for all node N ∈ G do
  Initialize covered_nodes(N)
  Sort nodes_to_add(N) in increasing order of random ID
  for node i ∈ nodes_to_add(N) do
    if n ⊃ i ∧ ⊔(covered_nodes(N)) ⊉ (N) then
      if i ⊃ some of N's interests not covered yet by
      covered_nodes(N) then
        covered_nodes(n).add(i)
      end if
    end if
  end for
  sort nodes_to_add(N) in decreasing order of random ID
  for node i ∈ nodes_to_add(N) do
    if n ⊃ i ∧ ⊔(covered_nodes(N)) ⊉ (N) then
      if i ⊃ some of N's interests not covered yet by
      covered_nodes(N) then
        covered_nodes(n).add(i)
      end if
    end if
  end for
end for
```

Our overlay construction mechanism ensures a published event to be delivered to all interested nodes with high probability. Furthermore, the routing table size is upper-bounded, as derived in the following proposition:

Proposition 1. *The routing table size in the overlay has an upper bound of* $2 \times d + c$*, where* c *is a constant parameter referring to the number of covering links a node* N *can have and* d *is the size of the* $ID_{semantic}$ *digest.*

Proof: If node N has n bits set to 1 then it will have $d - n$ neighbors when Algorithm 1 loops over ID_{random} in increasing sequence order and another $d - n$ neighbor links when Algorithm 1 loops over ID_{random} in decreasing sequence order, at most.

Moreover, N will have n covered links when Algorithm 2 loops over ID_{random} in increasing sequence order and another n covered links when Algorithm 2 loops over ID_{random} in decreasing sequence order, at most.

It is also clear that N has c covering links.

Therefore, N will have $2d + c$ entries in its routing table, at most. ■

B. Event dissemination

In this work, we cluster the overlay network semantically: hence, every node connects to neighbors with shared interests. When an event reaches a matching node N, N relays the message to its neighbors that match the event. Our system differentiates between two types of messages:

- ***Multicast***: When a node N receives a *Multicast* message, it sends a *Multicast* message to its covered nodes and neighbor nodes that match the event.
- ***Forward***: Upon the receipt of a *Forward* message, a node N sends a *Forward* message to its covering and covered nodes, as well as to its neighbor nodes that match the event.

Unlike the works in [5], [6] that rely on a technique to make node IDs unique (as the uniqueness of the semantic IDs cannot be guaranteed), we cluster nodes with the same semantic ID and to organize them into a logical ring[1]. Each ring will have the $ID_{semantic}$ identifier of the member nodes. A leader labeled *primary node* is assigned to each ring: the primary node acts as a relay point between the nodes on the ring and the outer nodes. Therefore, the cluster is transparent to the outer neighbors that will only point to the leader. When the primary node receives an event which it is interested in, it forwards the event on the ring. Leader election is based on joining time: the first node joining a cluster is automatically elected as a primary node. If a primary node fails or leaves, the node that joined the cluster after the failing or leaving leader is elected as the next cluster leader.

C. Membership management

In current peer-to-peer publish/subscribe systems, network connectivity and network discovery is achieved by space splitting and gossip-based membership management. The use of the former approach leads to engaging nodes in disseminating events they are not interested in with high probability. The latter approach allows nodes to maintain random views for membership management but generates a large amount of overhead due to the periodic exchange of views between different nodes.

Our system relies on a new approach we called *shared interest approach*. In this approach, all nodes have a common subscription. This common subscription renders possible to find a route between any two nodes in the network which allows nodes joining the network to find their closest neighbors semantically. This common subscription can just be presented as a fixed bit that is set to 1 in $ID_{semantic}$ of all nodes.

Join: When a node N joins the network, it contacts a bootstrap node that is already a member of the system. In this work we gloss over the details of how system bootstrap is achieved: for example, a list of well-known bootstrap nodes could be published on a separate communication channel. The bootstrap node routes the join query using the distance we defined earlier. The join mechanism takes several steps until the routing table of N converges. The number of these steps depends on the number of bits that are set to 1 in the $ID_{semantic}$. If we assume that subscriptions are uniformly random, the number of these steps will be on average $\frac{d}{2}$ where d is the size of $ID_{semantic}$.

Once N receives the first join reply, it will build its routing table based on the one it receives from the replying node, and then it will send another join query but this time it will advertise a new ID which represents the interests that are not covered yet by its current neighbor links.

When a node M replies to the join query issued by N it proceeds as following:

- if N covers M, M checks if N is closer than some of its covering links.
- if M covers N, M checks if N covers part of its interests not covered yet by its covered links.
- if N shares just a part of M's interests, M checks if N covers part of its interests not covered yet by its neighbor links.

In each of these cases, M updates its routing table.

If there are nodes in the network which have the same $ID_{semantic}$ as the joining node N, N will join the cluster defined by its $ID_{semantic}$ and copy the routing table from one of the nodes that has the same $ID_{semantic}$.

Leave: When a node N leaves the network or fails, the nodes that point to N will update their routing table based on the routing table of N. These nodes will use merger and covering relationships to update their routing table.

We implement a heart beat mechanism in order to detect failed nodes. When a node N fails, the first node detecting the failure notifies all the nodes pointing to N which we call *incoming links*. These incoming links are piggybacked in the heart beat messages.

IV. Evaluation

We built a discrete event-based simulator, which does not model packet loss and assumes unlimited bandwidth along all the links. In the following, for ease of presentation, we make the case for a stock quote application. In Section VI,

[1]Note that the logical ring is not a DHT.

we will focus on a different and popular Internet application, Twitter.

The events in a stock quote application are generated by various stock exchanges where trading occurs and the subscribers are clients interested in the price of the stocks they trade. Without loss of generality, events in our simulation are mapped to a 2-dimensional event space. In fact, there are well-known methods to map a multidimensional space to one dimensional space using a space filling curve [5].

In our simulations, an event corresponds to the value of these attributes (stock-name, price) and a subscription corresponds to (stock-name, low price, high price).

Metrics: In our evaluation, we will focus on the following metrics:

- *Delivery depth:* this metric account for the number of hops required by a node to receive events it is interested in. We evaluate this metric as it mirrors the delay that an event takes to be disseminated;
- *Routing table size:* this metric measures the size of routing tables stored at each node. Small routing table sizes are preferred as they indicate the ability of a publish/subscribe network to scale with system size;
- *False positives ratio:* A false positive is defined as an event received by a node not interested in it. As we partition the event space and we use Bloom filters, this metric allows us to evaluate the amount of overhead our approach generates.

Parameter space: With the goal of collecting statistics on the average delivery depth and on the routing table sizes, we ran simulations while varying the network size. We assume a uniform, random distribution of users' subscriptions. In all the experiments we conducted the $ID_{semantic}$ size is 1024 bits.

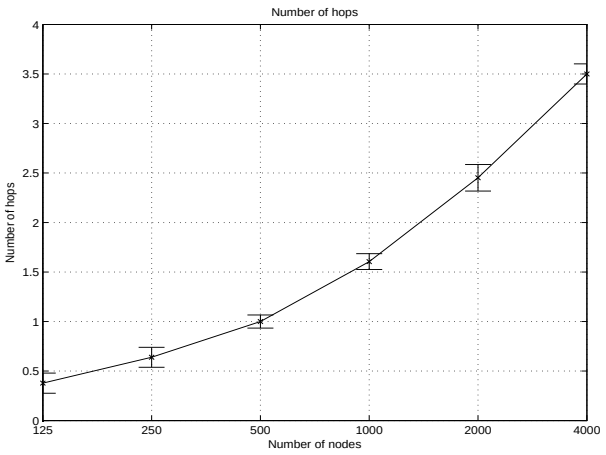
Furthermore, we evaluate the impact of the distribution of users' subscriptions on false positives and routing table sizes by varying its skewness. We first simulate uniformly random subscriptions. Then we focus on subscriptions distributed according to a Pareto law x^{-a}: we vary the distribution skewness by varying the coefficient $a \in [1, 4]$. For these experiments we ran simulations in an overlay of up to 4000 nodes in which every node publishes at most 10 events

In order to gain statistical confidence in our results, we conducted 10 simulation runs for each experiment.

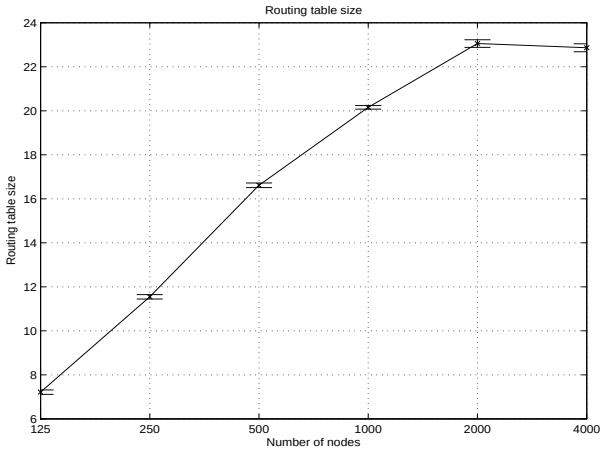
A. Static settings

We ran simulations while varying the network size. We assume a uniformly random distribution of subscriptions.

Figure 2.(a) shows the average delivery depth we measured as the system scale increases: we observe that the average delivery depth growth can be roughly approximated to a logarithmic growth. Figure 2.(b) illustrates that the average routing table size stabilizes with system scale. Indeed, when the size of the network is small, nodes are not able to build complete routing tables whose mergers cover their interests. Hence, when the size of the network grows the size of the routing tables do so. When the size of the network becomes large, the nodes are able to build routing tables that cover their interests and thus, the size of the routing table will not vary drastically.



(a) Average delivery depth in static settings.



(b) Routing table size in static settings.

Fig. 2. Evaluation of our system in a static setting with uniformly distributed subscriptions and with a size of $ID_{semantic}$ of 1024 bits

Figure 3 shows that the percentage of false positives decreases with subscriptions popularity. Figure 4 shows that the process of building routing tables depends on the distribution of interests when the size of the network is large and the routing table size decreases with subscriptions popularity. These observations indicate that our system would prove effective when considering realistic system sizes, which can be safely assumed to be large.

B. Dynamic settings

We now study the impact on delivery depth and routing table size of dynamic settings. We assume nodes join the network at random point of time.

In this work, we do not simulate node departures since our main focus is on the scalability of the overlay network, presented by the average delivery depth and the size of routing table. Moreover, as the incoming links of a node are piggybacked in the heartbeat messages as discussed in

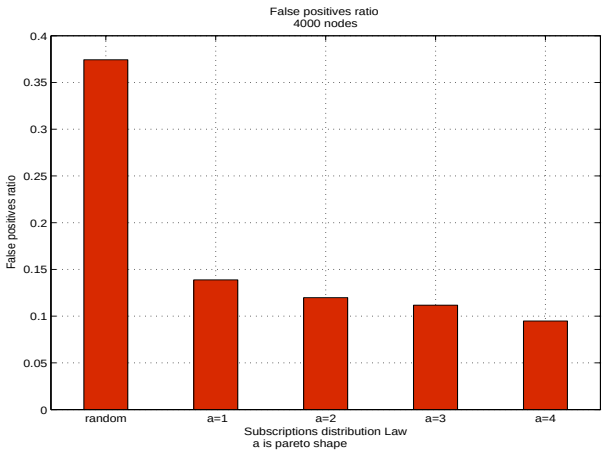


Fig. 3. False positives ratio as a function of the subscriptions law.

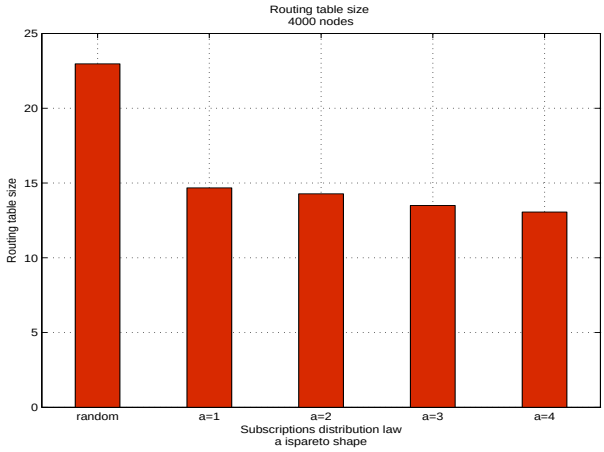
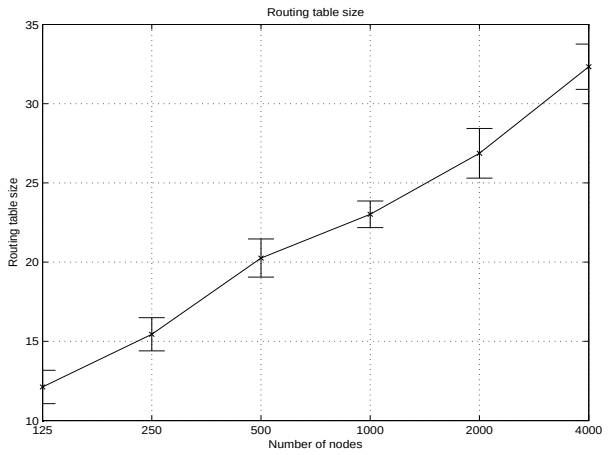
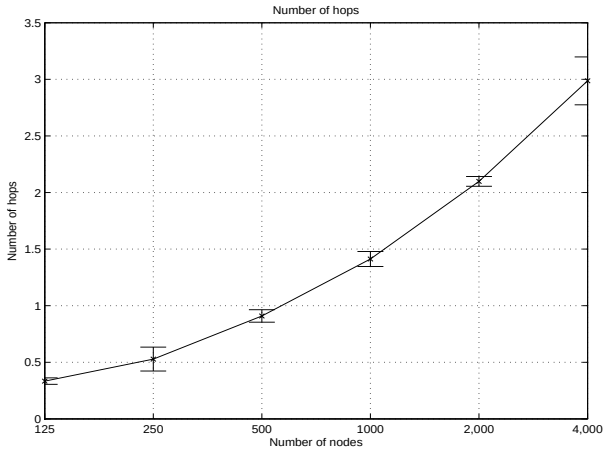


Fig. 4. Routing table size as a function of the subscriptions law.



(a) Routing table size in dynamic settings.



(b) Average delivery depth in dynamic settings.

Fig. 5. Evaluation of our system in a dynamic setting with uniformly distributed subscriptions and with a size of $ID_{semantic}$ of 1024 bits

Section III, the nodes in the network will be able to update their routing table whenever one of their neighbors leaves or fails.

As the Figure 5.(a) shows, the size of the routing tables is larger than in the static setting: indeed, a node N does not have global knowledge of the network when it builds its routing table, hence the routing tables are not optimal. As the number of hops is inversely proportional to the size of routing tables, we notice that the delivery depth of events is slightly smaller than the one observed in the static setting, yet the logarithmic growth is preserved, as Figure 5.(b) illustrates.

These results indicate the ability of our system to cope with system dynamics.

V. Analysis

In this section, we are interested in comparing our approach to the work presented in [5]. We present a theoretical approach to estimate the overhead generated by both schemes. We limit the comparison to [5] as we think it is the closest scheme to ours; both schemes rely on Bloom filters for ID assignment but differ in overlay building and event dissemination. As [5] and our system use both Bloom filters we can safely assume they generate the same amount of false positives that depend on the size of Bloom filter used and the event space.

The work described in [5] might involve un-interested nodes in forwarding events while nodes in our system send multiple messages to correctly join the overlay. We thus estimate the overhead generated by both approaches. We will use the following notation:

- d refers to the size of $ID_{semantic}$.
- n denotes the number of nodes in the overlay.
- λ_{join} and $\lambda_{publish}$ denote the join rate and the publication rate respectively.
- k denotes to the number of join messages sent at each round.

Proposition 2. *On average, our scheme generates* $k \times \frac{d}{2} \times \ln n \times \lambda_{join}$ *join messages.*

Proof: We assume that the overlay graph is a random graph. In this case the diameter of the graph will be $O(\ln n)$

where n is the number of nodes. For a node N with m bits in its $ID_{semantic}$ digest set to 1 there will be m join messages generated in the worse case. If the interests are distributed uniformly at random we can safely assume that the probability for a given bit in the $ID_{semantic}$ digest to be set to 1 is 1/2.

Therefore, on average we will have $k \times \frac{d}{2} \times \ln n \times \lambda_{join}$. ■

Proposition 3. *The overhead due to event dissemination in [5] amounts to:*

$$p \times \ln n \times \lambda_{pub}$$

where p is the probability that node N gets an event that it is not interested in.

Proof: A node N will forward an event e that is not interested in if it is in the path of this event. This happens if its ID cover matches the event. This could occur if one of the bits that are set to 0 in its ID digest are set to * in the ID cover.

Let N be a node with m bits set to 1 and p_m the probability that node N gets an event that it is not interested in, given m bits of N's ID are set to 1. Then:

$$p_m = 1 - (1 - \frac{1}{d})^{d-m} \tag{3}$$

where $\frac{1}{d}$ is the probability that one of the d bits is set to *.

Furthermore, let q_m be the probability that m bits of N's ID digest are set to 1. Then:

$$q_m = C_d^m \frac{1}{d}^m (1 - \frac{1}{d})^{d-m} \tag{4}$$

$$event_A = \text{N gets an event that it is not interested in}$$

$$event_B = \text{m bits of N's ID are set to 1}$$

$$Pr(event_A \cap event_B) = p_m \times q_m \tag{5}$$

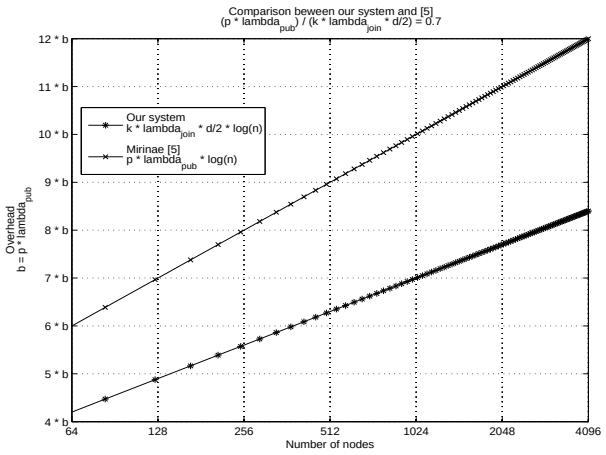
Let p denote the probability that node N gets an event that it is not interested in. Then

$$p = \sum_{m=0}^{d} p_m \times q_m \tag{6}$$

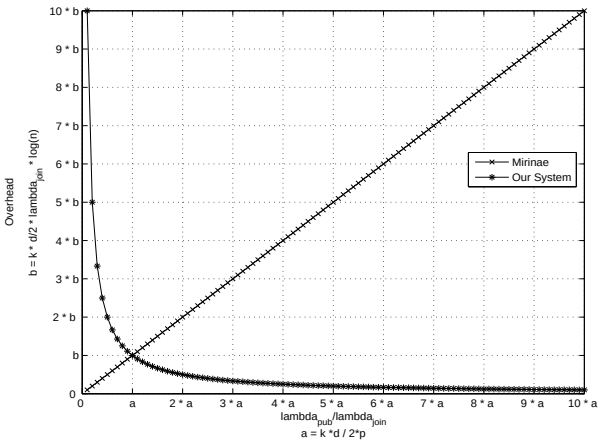
As described in [5], the event dissemination happens in $\ln n$ steps on average therefore: $p \times \ln n \times \lambda_{pub}$ approximates the overhead generated by event dissemination. ■

We now illustrate the impact of system parameters on the overhead generated by our system and the one described in [5]. There two important parameters we focus on are the join rate λ_{join} and the publication rate λ_{pub}. If we assume that λ_{pub} is larger than λ_{join}, our scheme performs better. Such an assumption holds in practice if we rely on a system model where nodes remain on-line for reasonably long periods of time [3].

Figure 6.(a) shows the overhead as a function of the number of nodes: when $k \times \frac{d}{2} \times \lambda_{join} < p \times \lambda_{pub}$, our scheme generates less overhead than [5]. Moreover, Figure 6.(b) shows the overhead as function of $\frac{\lambda_{pub}}{\lambda_{join}}$: we observe that [5] performs better up to a threshold which corresponds to $\frac{\lambda_{pub}}{\lambda_{join}} = \frac{k \times d}{2 \times p}$ after which our scheme performs better.



(a) Overhead as a function of number of nodes



(b) Overhead as a function of $\frac{\lambda_{pub}}{\lambda_{join}}$

Fig. 6. Comparison between our system and [5]

VI. A USE CASE FOR PUB/SUB SYSTEMS: TWITTER

We now try and address the question of whether our pub/sub system would fit applications in which a very large number of users maintain relationships to a potentially vast set of followers by updating their status. A prominent example of such an application is Twitter [12]. In the following, we extract user data by crawling Twitter and derive realistic publish/subscribe patterns that are then fed to the simulator described in Section IV.

A. Twitter: a microblogging tool

As remarked in previous research [13], [14], Twitter is a new communication tool often called microblogging, in which users post messages of 140 characters without specifying the destinations of the messages and read messages filtered by users' interests. Twitter is designed to relay new messages to users in a near real-time fashion: a user sees

a notification of a new message without any actions (a.k.a. push). The number of active users in Twitter is estimated to be 18 million in the United States[2]. Twitter can be cast as a publish/subscribe application, characterized a variety of users' interest patterns, a near real-time nature, and its very large scale. In this work, we make the case for a peer-to-peer based architecture to implement the same functionality delivered today through a client-server system design.

Before we discuss some properties about Twitter, let us introduce some terminologies in Twitter.

- ***Status:*** a short message posted by a user (a.k.a. Tweet).
- ***Public timeline:*** all the status messages sorted in a timeline.
- ***User timeline:*** all the status messages posted by a certain user sorted in a timeline.
- ***Follow:*** an action that represent a user's interest to another user. If a user A follows a user B, B is called a friend of A, and A is called a follower of B.
- ***Hashtag:*** a keyword in a status starting with "#" for easy search.

B. Twitter subscription traces

A subscription in Twitter is labeled *Follow*, which implies a user is interested in receiving status updates posted by another user. Some users *follow* a handful of their real friends, whereas some *follow* many not-acquainted users. To understand the distribution of *follow* subscriptions, we crawled the Twitter application: we collected a 24-hour trace of the *public timeline* with a 1 minute granularity during Nov. the 1-th 2009. Because the *public timeline* is collected for 24 hours, we expect that the collected data represent a good sample of full *public timeline*, even though each *public timeline* includes only 20 statuses[3]. In our data, we observed 27196 unique users: for each of these users we gathered the number of friends except for 1674 of them who had a protected profile. Figure 7 shows the histogram of the number of friends with the upper bound of 2000 friends which excludes 725 users. We estimated the Pareto distribution of the subscriptions, and found the Pareto shape parameter $a = 0.6719$. We ran a single simulation as described in Section IV-A with this coefficient. The result of this simulation shows that the average routing table size is 15.357 and the average false positives ratio is 0.1454. Those numbers are far smaller than those with the uniform distribution, and realistic. Hence, we conclude that our system is potentially suitable to be used as status notification architecture for Twitter.

C. Twitter event traces

To gain a deeper understanding of the behavior of our peer-to-peer pub/sub system, we conducted trace-driven simulations using real event data as collected from the Twitter application. The data consist of user and friend relations, but they are very sparse. Therefore, we filtered the data by selecting users that have at least one friend in our data. The filtered data include 10927 users, and the Pareto distribution of the number of friends is estimated with $a = 0.3294$, which indicates the distribution is relatively more uniform but the popularity still exists. Figure 8 shows the relationship between the number of friends and the routing table size for each node, out of the simulation result. Each point in the figure represents a node. We found an overall correlation between the number of friends and the routing table size, and some exceptions where a node has a big routing table even with a few friends. A closer look at the exceptions reveals that those nodes have many neighbors in their routing tables and they are likely to be *primary nodes*. Figure 9 shows the relationship between the number of friends and the incoming messages for each node, out of the simulation result. Similar to Figure 8, the correlation can be observed. It is worth to note here that this is one of the major contributions of our system; if users have less friends they get less messages, if they have more they get more. Although there is an open question about reducing exceptions, we conclude our system

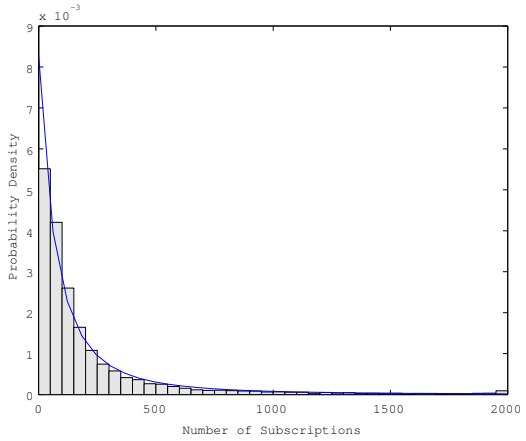


Fig. 7. Histogram of the number of friends and its Pareto distribution estimation

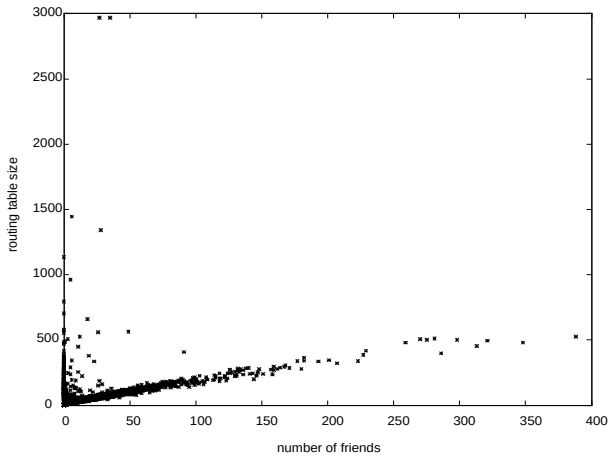


Fig. 8. Friends and routing table size relationship

[2]http://www.emarketer.com/Article.aspx?R=1007271

[3]This 20 limit per minute is because of the Twitter cache for performance reasons.

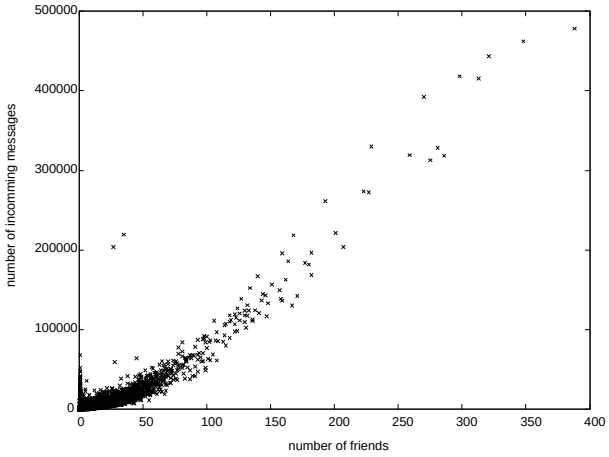


Fig. 9. Friends and messages relationship

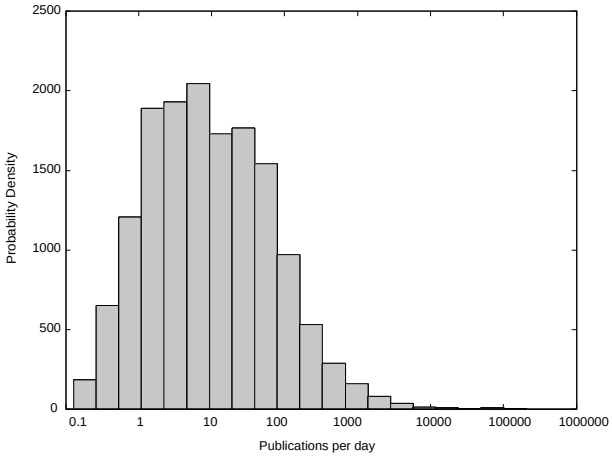


Fig. 10. Histogram of hashtag publication rate

should work well for Twitter-like applications.

D. Twitter interest traces

Twitter has a functionality that allows users to search for status updates in the system based on their interests. Although users can search statuses by arbitrary words or phrases, 1*hashtags* are often used for search keywords for a historical reason[4]. *Hashtags* are embedded in users' statuses, and they essentially explain the users' interests. To understand the distribution of *hashtags*, we collected larger *public timeline* from Oct. 21st 2009 3:56pm until Nov. 16th 2009 9:17pm in Japan Standard Time. Even though the data is not very complete due to the Twitter API limit control and network problems, it is collected uniformly over the period. The number of collected statuses is 690229 and the number of unique hashtags extracted from the statuses is 22344. We extracted only alphabetical and numerical hashtags of 4 characters to 16 characters, and searched latest 15 statuses for each valid hashtag. We then estimated a publication rate for each hashtag by linear least square fit. Figure 10 shows the histogram of the publication rate. Note that the x-axis represents the number of publications per day in logarithmic scale. The result indicates that there are some hashtags that are used very often, but most of hashtags are not likely to be used in common. This means users in Twitter have very diverse interests, and publish/subscribe system are not very good at the diverse interests because of too many subscriptions. Hence, we conclude that our system should be combined with a DHT-based lookup functionality or a centralized indexing-service to support (arbitrary) keyword-based search.

VII. Conclusion

In this paper, we presented a new peer-to-peer approach for publish/subscribe systems. Our scheme can build a semantic overlay based on nodes' interests and disseminate events using new interest proximity metric. The novelty of our approach is that it ensures only interested node to be involved in event dissemination while the overhead is low as we do not use any gossiping protocol. We conducted simulations with synthetic events and showed low false negative and false positive rates. Furthermore, we analyzed data collected from a popular Internet application, Twitter, and showed that our distributed architecture is suitable to a large extent to be used as an update notification substrate. We believe our work to constitute a solid grounding for the development of peer-to-peer based, large-scale update notification systems over the Internet.

[4]Search functionality was not implemented when Twitter was firstly released, and the use of *hashtags* is invented by user community.

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