Network Scalability under Quality of Information Requirements

Abstract—**Practical network scalability, known as *symptotics*, and Quality of Information (QoI) aware network control protocols are both relatively new fields of research for wireless networks, but no work to date has focused on characterizing the relationship between the two. In any practical implementation, knowing the limitations on scalability, the capabilities of deliverable QoI, and the impact of QoI requirements are crucial to designing an operational, effective network. To obtain upper limits on network scalability and, more importantly, to understand how these limits are impacted by QoI functions and requirements, we apply QoI awareness to the symptotics framework. We use two similarity-based image retrieval algorithms to motivate and exemplify the relationship between timely QoI requirements and network scalability. Results show that high QoI and strict timeliness requirements can have a large impact on scalability, which gives a much clearer understanding of the tradeoffs present in network design. We also introduce and show examples of *scalably feasible QoI regions* for special cases, showing clear limitations on QoI requirements that are able to be satisfied by these networks.**

I. Introduction

Symptotic analysis is an emerging field of characterizing practical network scalability instead of the common asymptotic analysis. Introduced in [1], symptotics is extremely useful for applications and network designers that are interested in determining the limits of a specific network implementation as well as how various factors affect these limits in terms of scalability. For example, if one is designing an emergency mesh network to quickly install to replace destroyed infrastructure after a natural disaster, understanding the traffic limitations, what topology allows for the largest feasible network size, or how load balancing will impact capacity are all crucial to successful designing the most effective network.

While including the consideration of Quality of Information (QoI) into network control protocols or analysis is not novel, its limitations and effects on network scalability have not been considered before. This consideration is extremely important, though, because in many recent fields of study, QoI is being used as the primary metric of a network's capabilities. Increasingly, network nodes are becoming more capable of affecting QoI through data fusion, compression, selection, etc. This work aims to begin understanding the connections between these actions and practical network scalability.

Specifically, we consider the practical effects of real networks, including protocol overhead, contention, and traffic loads, in conjunction with QoI to build a framework that provides upper limits on network sizes for defined QoI requirements. Utilizing QoI in this framework is important because the relationship between throughput and QoI is often non-linear, a notion that will be supported in Section **??**. We use timely, similarity-based image collection to provide motivation and concrete applications with which we test our methodology and provide results. The model, though, is designed to be general so that any relationship between data rates and QoI can be inserted for scalability analysis.

The results in Section V show several key insights. First we show the maximum sizes to which the networks can scale for different requested levels of QoI. The QoI depends on timeliness and one of two metrics considered: completeness or diversity. These attributes are defined by the sum similarity of collected images resulting from Top-K queries for completeness, and sum dissimilarity of images collected using the greedy spanner algorithm. These definitions will be explained in more detail in Section III. With these results, we show that the network scalability considerably reduces with higher completeness and diversity requests, as well as with stringent timeliness requirements.

Finally, we identify the trade-off of a given QoI requirement resulting in both a minimum required network size to provide a required number of images and the maximum feasible network size able to support that amount of necessary traffic. We identify the region of QoI requests where the former does not exceed the latter, and, hence, the QoI request can be satisfied.

II. Related Work

We adopt the symptotic scalability framework [1], which has been previously applied to content-agnostic static networks [2] and mobile networks [3]. Other works that characterize capacity of wireless networks, like [4]–[6], do so different by considering how networks scale asymptotically or analyzing only one specific network setup instead of developing a general model for scalability.

A large number of works provide definitions for and frameworks that utilize Quality of Information. We will address only the most relevant ones here. [9] [10] specify a framework called Operational Information Content Capacity, which describes a framework of the obtainable region of QoI, a notion similar to the *scalably feasible QoI region* in Section IV. These approaches use a more general network model, though, and do not provide any method for determining the possible size of the network or impact of various network design choices like medium access protocols.

QoI-based scheduling has been considered from a number of various angles, including control choices of data selection [11], [12], routing [13], and scheduling/rate control [14], [15]. It is also the focus of a credibility-aware optimization technique in

[16]. Work in [17] is related in that it evaluates the impact of varying QoI requirements on usage of network resources. These works all provide insights into QoI that we use, but our focus is on understanding the impact of QoI requirements on network size, not on designing network protocols as these works do.

Similarity-based image collection has previously been considered [7] and [8]. In [7], authors consider a DTN network where the objective is to collect the most diverse set of pictures at every node. Authors consider a picture prioritization and dropping mechanism in order to maximize the diversity, defined by dissimilarities of the collection of pictures. However, it does not consider attributes of timeliness, nor the consideration of transmission rates and network topology. [8] considers a smartphone application where different queries called Top-K, spanner, and K-means clustering are defined. Each of these queries are based on image similarity metrics, and we use Top-K and spanner here. While timeliness is considered as an objective in this work, the effects of rates and network topologies are overlooked.

III. QoI Model

The utility of data that is extracted from a sensor or military tactical network is often highly dependent on the context of the data with respect to aspects like the network's goals and the other data being collected from the network. While this effect is often very qualitative by nature, we introduce metrics here that provide real examples of how QoI can be measured quantitatively. These measures are based on the similarity or dissimilarity between images and will be used as examples in the QoI-aware network scalability in Section IV.

A. Image Similarity

First, we must establish a practical method of measuring the similarity of two images. To do so, we can use qualities inherent to a photograph like lightness, contrast, and color. Many techniques have been studied to compare photographs with these qualities. We choose to use one such technique called Color and Edge Directivity Descriptor (CEDD) [18]. With CEDD, each image is described by a vector of 144 different features describing color and spatial color distribution.

Using this CEDD feature vector of each image, we can compare any two images. To achieve a scalar representation of similarity, from comparing two vectors, we use *Tanimoto similarity*, which is commonly considered in the image processing community [19], T_s. The Taminoto similarity metric is defined as follows. Given two images with feature vectors $\mathbf{a}$ and $\mathbf{b}$,

$$T_s(\mathbf{a}, \mathbf{b}) = \frac{\mathbf{a}.\mathbf{b}}{\mathbf{a}.\mathbf{a} + \mathbf{b}.\mathbf{b} - \mathbf{a}.\mathbf{b}}, \tag{1}$$

where $\mathbf{a}.\mathbf{b}$ is the inner product of two vectors. Proper normalization keeps this metric in the $[0, 1]$ range. Naturally, to describe the dissimilarity, or distance, of two photographs, then, we simply use $T_d = 1 - T_s$.

B. Image Selection Algorithms

As a motivating example, we choose a mobile network in which nodes generate photographs that are to exchanged or collected at one or more data sinks. This example covers surveillance missions of military tactical networks or civilian/social scenarios, one example of which could be smartphone users contributing to an image-sharing application. We will provide two example scenarios of using content-based image selection that will motivate the algorithms used and results generated in this work.

The first application occurs when a user would like to find more images that are similar to one already obtained. For example, if a user observes a picture of an unknown suspicious person entering a building, but the person is not identifiable from that image, it would be useful to collect more images that are similar to that one with the possibility that another picture of the building from another user may have a better view of the person in question that can be used for identification or more context. In a social situation, a user may want more views of a particular event of interest like a parade or a concert. Called *Top-K*, the algorithm used for this application will choose the k images with the smallest distance from the given image.

The second application we introduce is called a *spanner*, and it is based on an opposing scenario. Instead of choosing matching images, the goal of a spanner is to select the k images that exhibit the most joint dissimilarity. This algorithm would be useful in a surveillance mission or other setting in which a user would like to get a snapshot of all areas of which photographs were taken that is as complete as possible.

C. Measuring QoI

As already discussed, *Quality of Information* is a very contextual term, so defining metrics to provide objective measurements of it is a challenge within itself. Here, we provide two different methods of calculating scores for completeness or diversity being achieved.

With both the Top-K and Spanner algorithms, initial choices exhibit higher degrees of similarity and dissimilarity, respectively, that naturally decrease. Therefore, if we establish a measure of overall QoI being obtained as k is increased, we witness an effect of diminishing returns. For the Top-K algorithm, we define *Sum Similarity*, which is the cumulative sum of the similarity score of each image being selected.

For the spanner algorithm, we employ a greedy algorithm similar to that in [8] to simplify implementation and to define a *Sum Dissimilarity* metric. Here, the algorithm first chooses the two images with the greatest distance between them from all available images. Then, each successive image is chosen to be the one with the greatest minimum distance between it and all images already chosen, until k images are selected. This minimum distance between the image being selected and the images in the collected set is the value added to the running QoI metric of *Sum Dissimilarity*.

Figures 1 and 2 shows the diminishing returns of using similarity and dissimilarity metrics. This effect is important also because it visually shows how Quality of Information

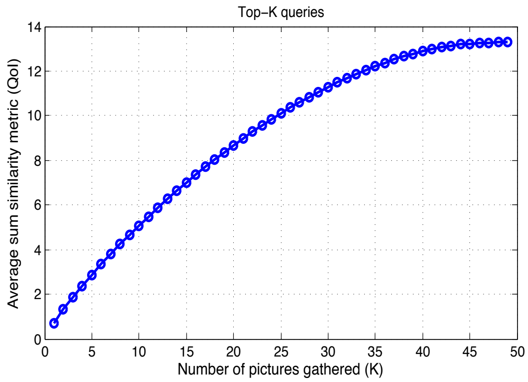


Fig. 1. Sum Similartiy for Top-K Results of Varying k

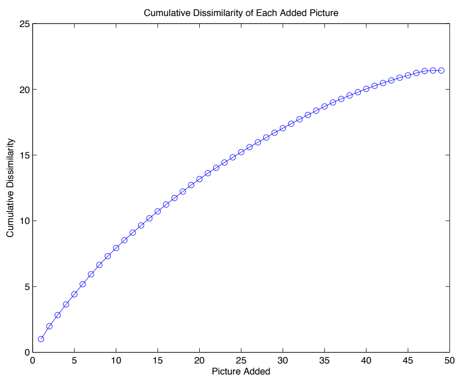


Fig. 2. Sum Dissimilarity for Spanners of Varying k

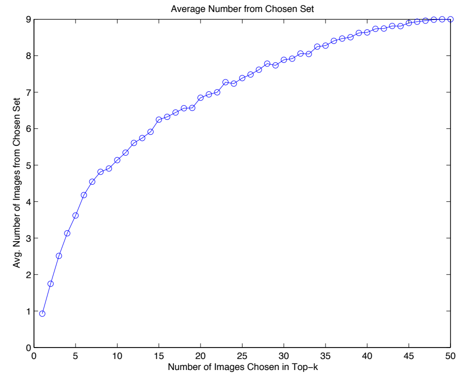


Fig. 3. Average Number of Images Selected from Same Set as Target Image

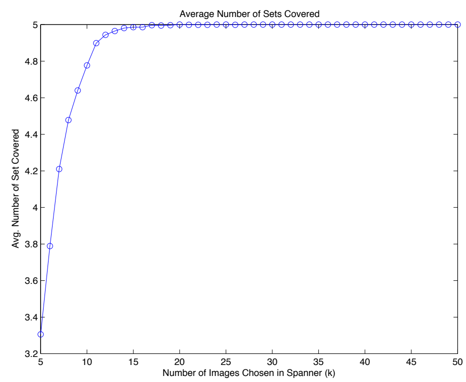


Fig. 4. Average Number of Sets Covered by Returned Images

differs from throughput. As these graphs clearly show, transmission of successive images is not linear in terms of gained completeness. Inversely, this relationship shows that obtaining a certain value of QoI or completeness may require a different number of images depending on the set available and their similarities. Specifically, we can denote the number of images required to achieve a level of completeness, S, as $N(S)$. This relationship will be useful later in determining feasible scalability.

To provide a second approach to measuring QoI, we can use a model in which each image belongs to one of n sets, Q_n, which can each represent a particular setting of interest. Naturally, then, when executing a Top-K query, the goal is for the algorithm to return images from the same set as the target image. In the case of a spanner query, the goal is to return images from different sets.

Using these two naturally-occuring goals, we can measure the effectiveness of the algorithms, providing QoI values. For Top-K, the QoI value is the number of photographs returned that are in the same set as the target image. For the spanner algorithm, the QoI value can either be the number of sets covered by at least one of the returned images, or it can be the likelihood that all n sets will be covered by the returned images, as long as $k \geq n$.

To provide example values of these QoI metrics, experiments were run on photographs taken at 5 different settings around the Penn State campus. Each of the settings is of a pictorially different setting, e.g. a particular building, a downtown street, or a lawn setting, and over 20 images of each was taken. Then, for individual trials, sets of Q_n with 10 images in each set were randomly selected from this group of photographs and the Top-K and spanner algorithms were run over these 50 images with the target image being randomly selected in the case of Top-K.

Figures 3-4 show the average results of 1000 trials. In Figure 3, it is evident that a value of only $k \approx 10$ is needed to collect 5 images matching the target content, while collecting an additional 2 from the same usually requires collecting over twice the number of pictures.

This diminishing return is also evident in the spanner algorithm results. Figure 4 shows the number of sets represented by the algorithm output for increasing k. Here, if the goal is to achieve at least one image from each of the different settings as might be in a surveillance application, the spanner achieves it on average at $k \approx 17$. The same trend is evident in Figure 5 where the probability of covering all sets is plotted against k. Using this metric, the application can use the probability of achieving full coverage as the QoI metric. From this example application, if collecting at least one image from each set with 90% probability of success is acceptable, then only $k = 13$ images are necessary.

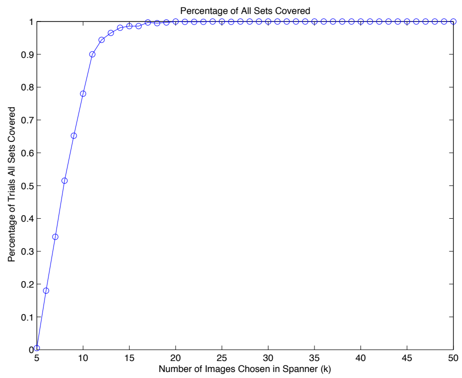


Fig. 5. Average Percentage All Sets Covered by Returned Images

IV. QoI Scalability

As discussed in the previous sections, QoI is typically a highly non-linear function of the number of packets delivered at the destination. Given this behavior, simply delivering the highest possible rate is not necessarily the best option from a user QoI viewpoint. More generally, we would like to know the capacity of a network (and relatedly, the scalability achievable) if we wanted *not* the maximum *throughput* (as traditional asymptotic analyses targets), but the maximum *QoI*. In other words, given a certain QoI (e.g. completeness/diversity-timeliness pair) that is desired by the user of a network, what is the the number of nodes that the network can scale to? *And how sensitive is the scalability to the QoI that is desired?*

We investigate this question in the context of multihop wireless networks (such as mesh and sensor networks). In [1] an approximate upper bound on the scalability of a network was considered in terms of the "residual capacity", that is, the difference between the available and used capacities at a node. Assuming homogeneity, a coarse-grained model was developed based on the simple observation that the network can support the offered flows if and only if the residual capacity at every node in the network is positive. A generic expression was derived there:

$$R(m) = W(m) - \sum_j (1+\gamma_j) D^j(m), \tag{2}$$

where $R(m)$ is the *residual capacity* at a given node m, indicating the capacity remaining at a node after taking into account the load from all traffic sources from all nodes (Fig. 6). This is the difference between the *available capacity* $W(m)$ and the capacity $D^j(m)$ demanded by each source j (control overhead is regarded as one kind of source), where γ_j in the equation is the *contention factor*, which is a rough inverse measure of the spatial reuse, and indicates the number of nodes that have to defer on a transmission. We refer the reader to [1] for details on the contention factor and derivation of Equation (2), and focus here on adapting the formulation to accommodate QoI.

Suppose that a network has M types of flows. Each flow j has its own QoI-rate function $QRF_j(u_j)$ where u_j is one of the possible QoI values[1] for the application corresponding to flow j. Let $\xi(s)$ be a function that maps a source rate s to its average contribution to a node's demanded capacity per Equation (2). ξ depends upon a number of factors such as the average length of the flow, whether it is unicast or multicast etc. and is instantiated in the context of the particular network. With these, the demanded capacity from flow j is

$$D^j = \xi(QRF_j(u_j)), \tag{3}$$

where u_j is the desired QoI of the application using flow j.

Combining with Equation (2), we have:

$$R(m) = W(m) - \sum_j (1+\gamma_j(m))\xi(QRF_j(u_j)(m)). \tag{4}$$

We are given application QoI requirements, and QRF can be obtained by empirical studies or given as part of the application profile. ξ needs to be calculated on a case by case basis given the topology and the traffic profile.

For instance, given a Top-K query with QoI demand $\mathbf{q} = (C, T)$, we first determine the number K_{req} to provide completeness C from *graph sumsim*. This results in a load in bits of $K_{req} * B$ where B is the nominal image size. Next, we obtain the required rate, which is $r_{req} \geq \frac{K_{req}B}{T}$. The QRF function for the spanner is also found similarly, where QoI demand $\mathbf{q} = (D, T)$ relates the requested diversity D to the number of images, again also defining the traffic requirement when timeliness requirements are considered.

We illustrate the relationship between QoI and scalability using a specific example. Consider a regular mesh network (also known as a "Manhattan grid") of N nodes. A continuous stream of traffic sent from each node to another node chosen uniformly at random.[2] Suppose further that we run the queries and request a specific QoI level $\mathbf{q}$. How many nodes can the network support (i.e., what is the upper bound on N) as a function of $\mathbf{q}$?

To determine this, we apply Equation (4) to the scenario, with $QRF(q)$ determined using the number of pictures required for the first QoI attribute, image size and timeliness.

Since the source and destination are chosen randomly, the scope of a flow is the average path length. In [20], the average path length for a regular mesh of N nodes is shown to be

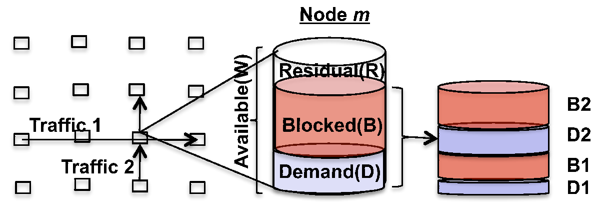


Fig. 6. Residual Capacities, Mesh Scenario

[1] Per flow QoI allows flexibility to have the range of values appropriate for the application for that flow.

[2] This is not intended to model any particular operational scenario, only an example to illustrate our model in a simple manner.

$\frac{2}{3} \cdot \sqrt{N}$. Thus, the used capacity per node in an N node network each node generating x bps is approximately $\xi(x) = \frac{2}{3} \cdot \sqrt{N} \cdot x$.

Finally, the contention factor for unicast traffic in a mesh network is $\gamma_1 = 7$ since the receiver plus three neighbors of each of sender and receiver have to defer on this transmission. Since we consider a stationary network, and are only looking for an approximate upper bound on the scalability, we ignore the routing overhead and assume the overhead due to MAC control messages is negligible.

We can then substitute these expressions into Equation (4) and note that the maximum scalability occurs when *R(m) = 0* for the node m at which $R(m)$ reaches zero first, also called the *bottleneck node*. Assuming this node m and dropping the per-node notation on R and W, resulting in the maximum node capacity of $W = (1 + 7) \cdot \frac{2}{3} \cdot \sqrt{N} \cdot f^{-1}(q)$, which simplifies to a maximum network size of

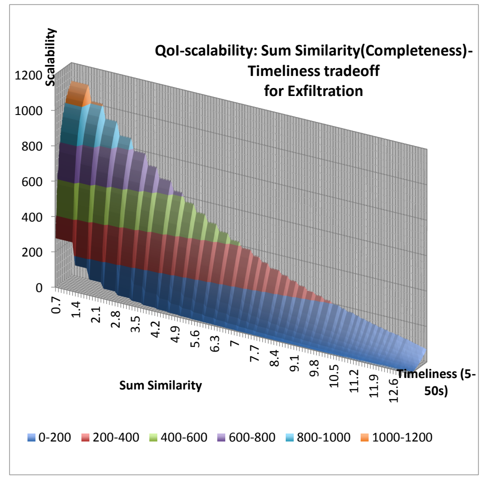
$$N = [\frac{3 \cdot W}{16 \cdot f^{-1}(q)}]^2. \quad (5)$$

We note that given the coarseness of the model and the abstraction of many details, the above is by no means intended to be an accurate predictor of N in a real network. However, since the main intent is to study how the scalability *changes* with respect to QoI (rather than focus on absolute values), such an approximate upper bound suffices.

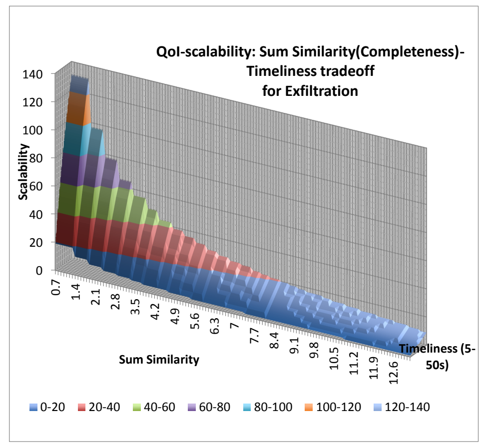
V. Results

In Figures 7 and 8, we demonstrate network scalability as a function of QoI requirements for different traffic properties in a mesh setting.

Clearly, there is a remarkable difference in the scalability depending upon the QoI. The fact that QoI makes a difference is not surprising, but the *magnitude* of the impact is surprising, along with the fact that there are some critical thresholding points. Our preliminary work shows that scalability analysis with QoI awareness has the potential to open up new tradeoff points with significant potential benefits in scalability. For instance, it can potentially indicate when it makes sense to reduce QoI a bit and possibly gain significantly in scalability (e.g. increasing timeliness constraints for small Sum Similarity/Dissimilarity values) and when such reductions will only give a marginal increase in scalability (e.g. increasing timeliness for high values of Sum Similarity/Dissimilarity).



(a) Unicast Traffic



(b) Flooding

Fig. 7. Top-K: Sum Similarity vs. Scalability vs. Timeliness

A. Scalably Feasible QoI Regions

For the special case where each node possesses one image, we have observed the following dilemma. To achieve a certain level of desired QoI q, which can be defined as (C, T) for Top-K queries and (D, T) for spanner queries, the completeness/diversity attribute necessitates a number $K_{req}(q)$ images to be collected. When each node can contribute with at most one picture, this implies a minimum network size of $K_{req}(q)$ that is necessary for the QoI level. On the other hand, the same QoI pair also results in a maximum network size $S(q)$ from the scalability framework. When $S(q) < K_{req}(q)$, it is not possible to provide QoI level q. Hence, we state that the QoI level q is infeasible, or *scalably infeasible*.

This phenomenon defines the concept of *scalably feasible QoI regions*, which define the set of QoI pairs that can be supported, given a given traffic structure. This region is given by a set of (completeness, timeliness) pairs for Top-K, and (diversity, timeliness) pairs for spanner queries. We demonstrate the scalably-feasible QoI regions in Figures 9-10.

As expected, the feasible QoI region is smaller for flooding compared with unicast. Moreover, these regions clearly demonstrate the tradeoff between the completeness/diversity that can be obtained and the timeliness that can be tolerated.

VI. Conclusion

Wrap it up with the highlights/takeaways. Maybe also include future work.

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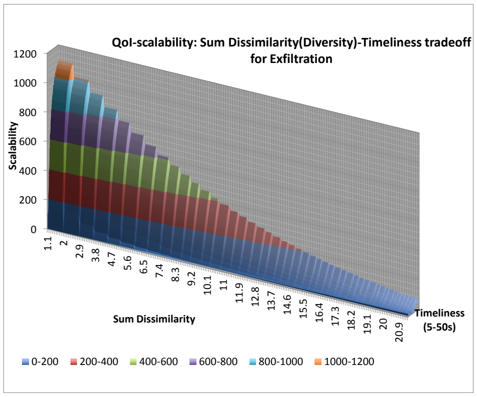
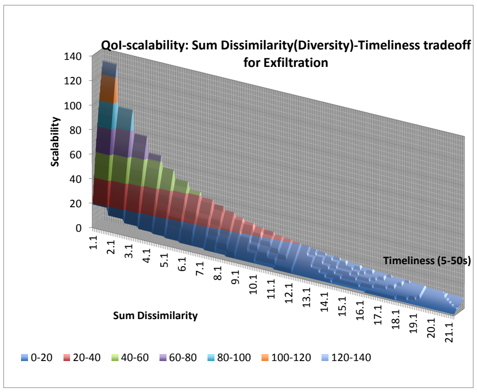


(a) Unicast Traffic



(b) Flooding

Fig. 8. Spanner: Sum Dissimilarity vs. Scalability vs. Timeliness

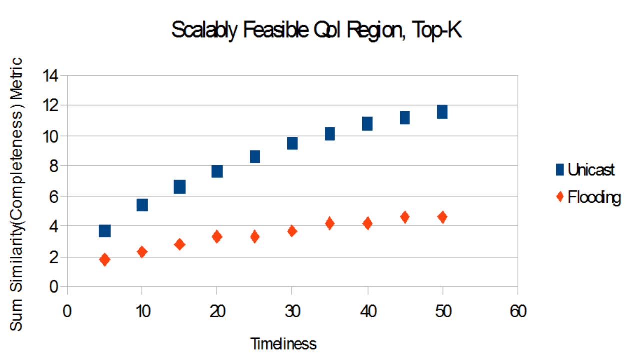


Fig. 9. Feasible Scalability Region of Top-K Algorithm

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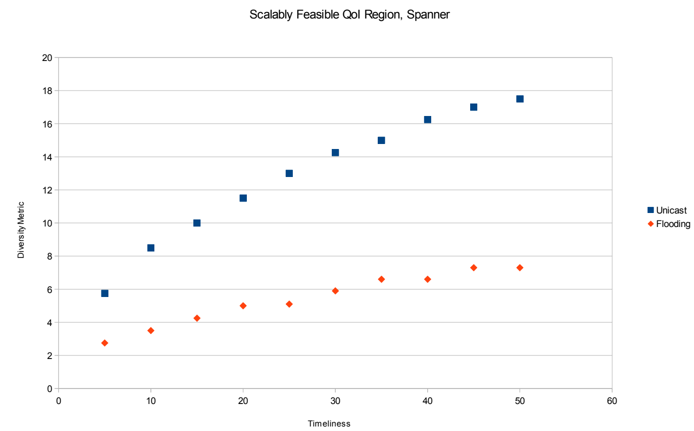

Fig. 10. Feasible Scalability Region of Spanner Algorithm

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