NICE: Network-oriented Information-centric Centrality for Efficiency in Cache Management

Junaid Ahmed Khan
University of Memphis
Memphis, TN, USA
junaid.khan@memphis.edu

Cedric Westphal
Huawei Technology
Santa Clara, CA, USA
cwestphal@gmail.com

J.J. Garcia-Luna-Aceves
University of California, Santa Cruz, CA, USA
jj@soe.ucsc.edu

Yacine Ghamri-Doudane
L3i Lab, University of La Rochelle, France
yacine-ghamri@univ-lr.fr

ABSTRACT

All Information-Centric Networking (ICN) architectures proposed to date aim at connecting *users* to *content* directly, rather than connecting clients to servers. Surprisingly, however, although content caching is an integral of any information-Centric Network, limited work has been reported on information-centric management of caches in the context of an ICN. Indeed, approaches to cache management in networks of caches have focused on network connectivity rather than proximity to content.

We introduce the *Network-oriented Information-centric Centrality for Efficiency* (NICE) as a new metric for cache management in information-centric networks. We propose a method to compute information-centric centrality that scales with the number of caches in a network rather than the number of content objects, which is many orders of magnitude larger. Furthermore, it can be pre-processed offline and ahead of time. We apply the NICE metric to a content replacement policy in caches, and show that a content replacement based on NICE exhibits better performances than LRU and other policies based on topology-oriented definitions of centrality.

KEYWORDS

ICN, Cache Management, Graph Centrality, Content Offloading

ICN '18, September 21–23, 2018, Boston, MA, USA

ACM ISBN 978-1-4503-5959-7/18/09…$15.00
https://doi.org/10.1145/3267955.3267965

ACM Reference Format:
Junaid Ahmed Khan, Cedric Westphal, J.J. Garcia-Luna-Aceves, and Yacine Ghamri-Doudane. 2018. NICE: Network-oriented Information-centric Centrality for Efficiency in Cache Management. In *5th ACM Conference on Information-Centric Networking (ICN '18), September 21–23, 2018, Boston, MA, USA.* ACM, New York, NY, USA, 12 pages. https://doi.org/10.1145/3267955.3267965

1 INTRODUCTION

Under the pressure of rapidly increasing bandwidth demands, Internet Service Providers (ISP) have been trying to offload traffic away from their networks onto local caches, either co-located with access points of WiFi networks, base stations of small cells, or provided by end users in an ad-hoc fashion [1]. The nodes around the end-user form a network from which the consumer can retrieve the content opportunistically. However, selecting what content to cache at these nodes is a complex problem: while the most popular content should be available to most users, it is expected that there will be some redundancy in the caches that are reachable by a given user. Indeed, putting the most popular content in all caches (as a cache replacement policy such as LFU or LRU attempts to emulate) would result in excessive redundancy and a waste of caching capacity.

It has been known [2, 3] since the days of web caching that the coordination of the caches yields better performance. However, as Section 2 elaborates, prior work on networks of caches has focused primarily on caching policies in which each cache makes decisions independently of others or its network placement, or policies that take into account the network connectivity of caches. Centrality [4] is a concept from graph theory typically applied to social networks. It is used to find important nodes in a graph. A high centrality score reflects a high topological connectivity for a node in the network. Typical centrality measures are: degree (the number of directly connected nodes), closeness (the average length of the shortest paths between the node and all other nodes in the graph); betweenness (the number of shortest

paths between all pairs of nodes in the graph going through a specific node), and eigenvector centrality (a measure of node influence in the network). Recent work on networks of caches has used the centrality of caches for content placement [5] [6]. However, using centrality solely based on a graph representing the topology of a network fails to address the fact that the primary role of caches in an information centric network (ICN) is to bring users and content closer to each other, rather than ensuring that a user is close to a specific node or type of node.

The main contribution of this paper is the introduction of an information-centric approach to cache management that scales with the number of caching sites rather than the number of content objects, which would not be feasible.

Section 3 introduces **NICE**, the *Network-oriented Information-centric Centrality for Efficiency* as a metric of centrality for caches that focuses on the main objective of an ICN, which is to bring users closer to content, while taking into account the location of caches and content in a network. Equally important, we introduce a scalable method to calculate NICE without a priori knowledge of the content placement, based only upon pre-computed combinations of caches holding a specific content object. Expanding on the definition of betweenness centrality, for a cache c, its *NICE betweeness* is calculated as a function of the number of shortest paths that include c for content x, the popularity of content x, and the number of shortest paths from the users to content x. We also consider a *NICE closeness*. These are defined more formally in Section 3.

Section 4 demonstrates the utility of the NICE metric by presenting a cache replacement policy and algorithm that take into account the NICE value of a node to update its cache. Namely, we suggest to replace content only if it increases the NICE value of the cache.

Section 5 presents the results of our evaluation of the proposed NICE-based cache replacement policy by simulations using a large number of scenarios. The results show that the proposed NICE-based cache replacement algorithm outperforms typical centrality schemes, or schemes without coordination. Section 6 concludes the paper along insights into future directions.

2 RELATED WORK

Content caching has been studied for some time by the research community, spanning a wide spectrum, including small cell networks (SCNs) [7, 8], content distribution networks (CDNs) [9] and information-centric networks (ICN) [10]. For example, Sourlas et al. [11] study making distributed cache management decisions in order to efficiently place replicas of information in dedicated storage devices attached to nodes in an ICN. Similarly, Wang et al. [12] address the distribution of the cache capacity across routers under a constrained total storage budget for the network. The authors found that network topology and content popularity are two important factors that affect where exactly cache capacity should be placed. Dabirmoghaddam et al. [13] [14] and Fayazbakhsh et al. [15] argue through analytical models and experiments that caching content should be done at caches near consumers; however, these works assume that caching decisions are made by each cache independently of others.

Several works [16–18] consider the joint routing and caching problem. The goal is to place the content in the cache on the path, so that the cache is reachable by users for a wider range of content. Rossini and Rossi [19] consider the intersection of caching policy within a node, of meta-caching between nodes, and the joint impact of routing, to demonstrate a significant improvement when meta-caching (whether or not to consider an object for caching based upon the other caches) and routing decisions are tightly coupled.

Yu et al. [20] considered on-path caching as a method to increase path capacity, while Ramakrishnan et al. [21] devised a content placement mechanism which improves on the joint utilization of a set of caches.

Pantazopoulos et al. [22] define a "conditional betweenness centrality" and uses this metric to chooses which nodes will cache the content. The Socially-Aware Caching Strategy (SACS) [23] for content-centric networks (CCN) uses social information in order to privilege Influential users in the network by pro-actively caching the content they produce. The authors detect the influence of users within a social network by using the Eigenvector and PageRank centrality measures.

Rossi et al. [24] present a caching approach for ICNs in which the sizing of the content store is based upon centrality. The authors exploit different centralities (betweenness, closeness, stress, graph, eccentricity and degree) to allocate content storage to nodes. It is proposed that a simple degree centrality-based allocation is sufficient to allocate content storage capacity. Similarly, Chai et al. [25] show that a higher cache-hit rate can be achieved if content is cached at high betweenness centrality nodes.

A few efforts [2, 3] study the coordination of caching policies in networks of caches and show the benefit of collaboration in terms of offloading the wide area network. However, this prior work assumes that all caches are accessible by all users, whereas we focus on a scenario in which caches are locally accessed by consumers and distributed throughout the network. MuNCC [26] is a collaborative caching scheme for low cache population networks and uses degree, closeness and betweenness centrality for content placement. However, such node-centric centrality does not address the needs of an Information centric network where the users reachability

to content is of importance rather than to the high centrality nodes.

Cache replacement policies have been studied for a long time. For instance, Fagin [27] and Che [28, 29] have considered the LRU replacement policy which evicts the Least Recently Used. Others [30] have studied FIFO replacement policy, the performance of interconnected caches [31], or TTL policies [32], or other multi-level cache replacement policies [33].

Ren et al. [34] took a step in the direction of this paper by considering the topological relationship between the content, the cache and the user. The proposed MAGIC algorithm replaces content in the cache if the next content offers a larger gain. However, this attempt considers only the latest request from a single user, whereas our use of centrality attempts to capture the relationship between a set of users, a set of content and a set of caches.

We argue that the network connectivity of caches relates to the content only partially, and there is a clear need to consider the content reachability by consumers in the network. Our review of prior work reveals that this has not been addressed by the vast majority of previous work. The work by Khan et al. [35] is the one exception. They considered content centrality in the context of fog networking, but without taking into account content popularity, and without considering the application to cache management and replacement policy. A well connected node in the network is not necessarily closer to end-users requesting the content. To the best of our knowledge, this paper provides the first proposal to compute an information-centric centrality metric that considers the network structure for cache management.

3 NETWORK-ORIENTED INFORMATION-CENTRIC CENTRALITY FOR EFFICIENCY

3.1 Connectivity and Caching Model

We consider an edge network with n nodes where both wired/wireless communication links exist between nodes. The connectivity between nodes is modeled by a graph $G(V, E^v)$ where $V = \{v_1, \ldots, v_n\}$ is the set of nodes and $E^v = \{e_{jk} \mid v_j, v_k \in V, j \neq k\}$ is the set of edges e_{jk} modeling the existence of a communication link between nodes j and k.

We assume that during a particular time period the connecting graph topology is relatively stable and the nodes will stay connected for a while. We consider a network where consumer interests are forwarded along the shortest path (number of hops) towards the content providers. However, it is possible that due to mobility or frequent topology changes, a shortest path between two nodes is not guaranteed and the consumer interest may not be forwarded on the shortest path to the content provider.

Table 1: List of Notations

Notation	Description
$V = \{v\}$	Set of n nodes
E^v	Set of edges between nodes
$X = \{x\}$	Set of N content objects
$C_c(v)$	Cache at node v
c_w/c_l	Cost of content access from server/local link
p_m	Miss probability
C/S	Common/different content in cache
p_x	Popularity of content object x
cp	Cache permutations
$d(u, x)$	Distance from user u to content x
$\sigma(u, x)$	no. of shortest paths b/w user u and content x
$\sigma_v(u, x)$	no. of shortest paths b/w user u and content x passing through node v

The nodes in the graph may cache content by providing a capacity $C_c(v)$ of cache storage at node $v \in V$. This cache capacity could be equal to 0 for nodes who cannot or do not wish to provide storage.

We assume an ICN in which nodes forward requests (or interests) for specific content objects along the shortest paths to the content objects. If there are several shortest paths, then the network splits the flows equally among the shortest paths.

We define the set of known content objects as $X = \{x_1, \ldots, x_N\}$ for a catalog of N pieces of content, where x_j is an indivisible content object or chunk in the network. Without loss of generality, we consider individual content chunks $x \in X$. In practice, larger size content can be composed of several such content chunks.

We assume that at least one node contains a content object at all time, and we denote it as the origin server node. This is a practical requirement to ensure the content is served, but this requirement has no impact on the content-based centrality we describe subsequently.

Each content object has a popularity. More specifically, we define by p_x the probability that a node requests content object x, where $\Sigma_x p_x = 1$. We assume that this probability distribution is constant over the considered time period. The content popularity estimation is done offline by the content provider and is not affected by errors since it is aware of the overall user interests for the content and uses this knowledge to compute the content popularity.

Individual nodes do not need to have global knowledge about the content popularity in the network, rather the content provider should have this knowledge. The content provider can even compute a dynamic content popularity

where the server can provide the nodes with real-time content popularity at different times and locations either periodically or upon the nodes request. We assume the server has sufficient computational capabilities to do so. The frequency of re-doing such computation depends on how frequently new content are updated by the provider and how the content popularity varies with respect to different locations and times. We simply assume that the caching nodes are aware of the distribution p_x, either because it is periodically provided by the server or by using some empirical estimate from the interests that the caching node observes.

3.2 A Network-oriented Information-centric Centrality Metric

In graph theory, centrality values indicate the importance that nodes hold in a graph. They are typically used for identifying critical nodes in networks. There are several typical centrality metrics, including the node degree, the closeness centrality (namely, the average length of the shortest path between the node and all other nodes in the graph), the betweenness centrality (the number of times a node acts as a bridge along the shortest path between two other nodes), eccentricity (the inverse of the distance to the furthest node), and many others.

However, the ubiquitous use of caches in an ICN shifts the importance of the nodes. A cache at the edge of the network has low centrality by most common centrality measures, but is actually critical in reaching and storing the content that is requested by consumers. If the probability of a hit in the cache is, say 60%, then even if an upstream node fails in the network, the network will still satisfy 60% of the consumers' requests. It is clear that new centrality metrics are needed for ICNs.

We propose the Network-oriented Information-centric Centrality for Efficiency (NICE) metric. For closeness, NICE is defined as the inverse of the sum of the distance from the user to the content, that is:

$$NICE_c = \left(\Sigma_{u,x} d(u,x)\right)^{-1} \quad (1)$$

where u is the set of users, x is the set of content, and $d(u,x)$ is the distance on the shortest path from u to x. Figure 1 shows an example, which we detail in the next section.

For betweenness centrality, NICE is defined as the sum of the ratio of the number of shortest paths from all users to all content objects that passes through the node to the total number of shortest paths between all the (user,content) pairs weighted by the popularity of each content object.

Formally, for probability distribution p_x for content x and if $\sigma_v(u,x)$ is the number of shortest paths from user u to content x going through node v and $\sigma(u,x)$ the total number of shortest paths between u and x, then:

$$NICE_b(v) = \Sigma_{u,x} p_x \frac{\sigma_v(u,x)}{\sigma(u,x)} \quad (2)$$

We can normalize this to a measure between 0 and 1 if needed. Figure 2 shows an example, which we detail in the next section.

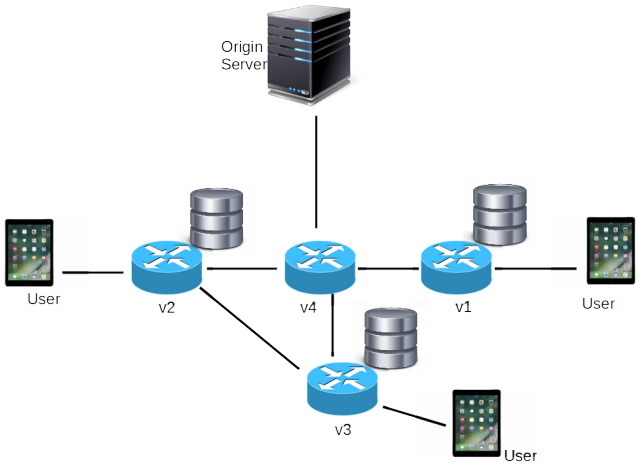


Figure 1: An example of Content-based Centrality (Closeness)

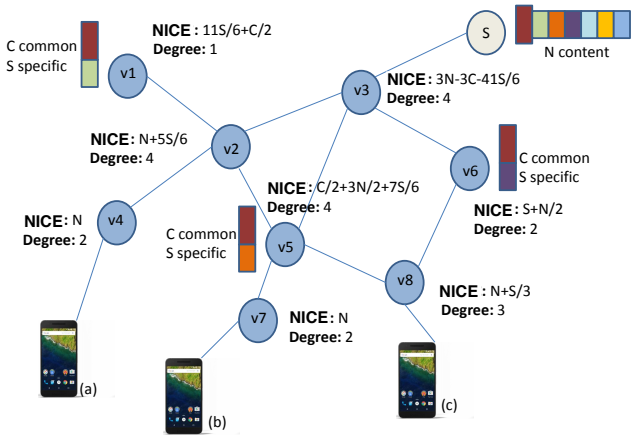


Figure 2: An example of Content-based Centrality (Betweeness)

3.3 Example of NICE

3.3.1 Closeness. Figure 1 shows a simple network where users connect through nodes v_1, v_2 and v_3 to access the content. Assume that each cache can hold one piece of content, and that we have pieces of content $x_1, x_2, x_3, \ldots$ with probability $p_1 > p_2 > p_3 > \ldots$. Further, assume that the distance of a link between the v_i's is c_l (for some local link cost) and the distance between v_4 and the server is c_w (for some wide area link cost). In practice, $c_w >> c_l$.

If we assume each cache works independently, v_1, v_2 and v_3 all cache x_1. The Least Frequently Used (LFU) cache eviction policy would keep the content most frequently requested. Least Recently Used (LRU) evict content that has not been recently requested, and typically keeps the most frequently requested content. Obviously both are poor content placement strategies as a significant fraction $(1 - p_1)$ of the traffic travels the greater distance c_w.

A much better content placement approach is to cache all three for x_1, x_2 and x_3 in the local network. Define by p_m the miss probability $1 - (p_1 + p_2 + p_3)$.

If the content is placed as x_1 in v_1, x_2 in v_2 and x_3 in v_3, then we can compute the distance from v_1 to the content, namely $p_m(c_l + c_w) + 2(p_2 + p_3)c_l$. The distance from v_2 to the content is $p_m(c_l + c_w) + (2p_1 + p_3)c_l$; and the distance from v_3 to the content is $p_m(c_l + c_w) + (2p_1 + p_2)c_l$. The total distance is $3p_m(c_l + c_w) + (4p_1 + 3p_2 + 3p_3)c_l$.

Since $p_1 > p_2 > p_3$, we see it is beneficial to put the content x_1 in v_2, x_2 in v_3 and x_3 in v_1. In this configuration, the distance to the content becomes $p_m(c_l + c_w) + 2(p_1 + p_2)c_l$ for v_1, $p_m(c_l + c_w) + (p_1 + 2p_3)c_l$ for v_2 and $p_m(c_l + c_w) + (p_1 + 2p_2)c_l$ for v_3 for a total of $3p_m(c_l + c_w) + (3p_1 + 3p_2 + 4p_3)c_l$.

Since $p_1 > p_2 > p_3$, the latter placement puts the content closer to the users. The distance to the content is the measure of centrality. Nodes v_2 and v_3 are better connected to the content than v_1 due to the extra link joining them. They have higher content centrality. Therefore it makes sense to place content such that the *content-based* centrality is increased.

On this simple topology, the expression of the distance to the content requires computing paths from all users to all content objects.

3.3.2 Betweenness. We now consider betweenness NICE. Figure 2 shows a graph, where node S is the server, and holds a copy of all the content, nodes v_1, v_5 and v_6 are cache nodes, the users are nodes (a), (b) and (c) and the other nodes v_2, v_3, v_4, v_7 and v_8 act as relays.

Rather than identifying exactly which content is in the cache, for simplicity we have assumed on this figure that the content is distributed in blocks, where the capacity C_c is divided into C content objects that are the same at all caching nodes, and S content objects that are unique to this cache. We assume, for ease of explanation only, that all content is equally likely.

Figure 2 also indicates the NICE value of each node, and the degree centrality as well. The (non-content-based) Betweenness centrality of this graph has little meaning, underlying the need for ICN-specific centrality measure. Computing the betweenness centrality between all the nodes does not capture that only (a), (b) or (c) issue requests, nor that only v_1, v_5, v_6 and S can respond to these interests. For this reason, we do not include this metric on this figure.

To compute the NICE value, let us consider node v_6 in this figure. The user (a) will send traffic to v_6 only for the content that is specific to v_6. The common content C will be served by v_1 for user (a). For this v_6-specific content, half of the requests from (a) will go to v_6, and half will go to S, as both are four hops away from (a) and therefore both are on the shortest path to this content. Therefore the contribution from (a) is S/2, as all S content are equally likely.

For user (b), there are three paths to the content that is v_6-specific: $v_7 - v_5 - v_3 - S$, or $v_7 - v_5 - v_3 - v_6$ or $v_7 - v_5 - v_8 - v_6$. Two out of these three paths end at v_6 therefore (b)'s contribution is $2S/3$. Finally, user (c) sends requests for the content that is v_1-specific through either the 3-hop path to v_1 or the two 3-hop paths to S, including one through v_6 for a total of $S/3$. All the v_6-specific requests from (c) end up at v_6 for a total of S. Half of the common content C from (c) ends up at v_6, the other half goes to v_5, adding $C/2$. Finally, the rest of the content requests go to the server S and half of these follow a path through v_6 (the other half goes through v_5), adding $(N - C - 3S)/2$. Summing all these contributions yield $S + N/2$.

The other nodes' content-based centrality can be computed in an identical manner, by identifying the contribution to each of the other contents from each user. It should be obvious from this simplified example that computing content-based centrality may become complicated, especially once we take into account the content popularity and an increasing number of users. In the previous example, it was straightforward to take into account the popularity, by identifying the aggregated probability that a piece of content was in C or was specific to one of the v_j. However, in practical systems, this gets unwieldy.

We address next how to efficiently compute the NICE value at a node. While we have presented of NICE for two centrality metrics, we now focus exclusively on betweenness centrality as it is a linear expression and therefore easier to work with in practice.

3.4 Scalable Computation of Content-based Centrality

Computing the content-based centrality from Equation 2 may get extremely difficult, since the catalog X may be very large, and it requires knowing the content placement as well as the probability distribution p_x as well.

For this, we propose performing an offline computation for a combination of caches first. Note that this scales with the number of caches, and not with the number of content, dramatically reducing the complexity.

More formally, denote by $\{c_1, \dots c_m\}$ the set of m nodes $v_i \in V$ such that $C_c(v_i) > 0$. These are the caching nodes in the network.

A piece of content can be in any $0 \leq k \leq m$ of these nodes. There are $2^{\{c_1,\dots,c_m\}}$ potential combinations of caches a content can belong to. Denote by cp (for *cache permutation*) an element of $2^{\{c_1,\dots,c_m\}}$, that is a set of anywhere between 0 and m caches.

For each of these combinations, we compute *once* the NICE value of a single item of popularity 1 located at the caches in this combination cp, and no other item anywhere else. That is we consider that content x is the only content that is requested and is placed at the caches $c_i \in cp$. We can compute the NICE value for x and cp at node v.

We do this for all the combinations and store the value for each $cp \in 2^{\{c_1,\dots,c_m\}}$. Namely, we compute $NICE_{cp}(v)$ for all such cp cache combination and store the outcome in a table at each cache.

In practice, adding more copies of the same item in more caches has a decreasing marginal utility, and the network operator may set a limit on the number of copies for any piece of content. Therefore we do not have to compute the NICE value for every $cp \in 2^{\{c_1,\dots,c_m\}}$: we can start by computing $NICE(v)$ for node v with cp of cardinality 1, 2, and keep increasing until we reach the limit set by the operator. We can then stop the process and start with another node w.

While this process is still relatively complex, it scales with the number of cache combinations, and has to be done *offline and only once*.

To compute the NICE value of a specific content placement, we only need to look up the cache permutation $cp(x)$ of content x. A content object x will belong at any point of time to one cache set $cp(x)$ and the $NICE(v)$ can therefore be computed by:

$$NICE(v) = \Sigma_{x \in X} p_x NICE_{cp(x)}(v) \tag{3}$$

where $NICE_{cp(x)}(v)$ was pre-computed ahead of time.

Algorithm 1: Content Replacement Policy

INPUT: $NICE_{cp}, C_c(v), p_x \forall x \in C_c(v), cp(x)$
OUTPUT: $cp(x) \subseteq 2^{\{c_1,..c_m\}} \forall x \in X$
Initialize $C_c(v) = \phi$ for all $v \in V$
for each new arrival $y, p_y \in X$ at cache c_i **do**
  if $y \notin c_i$ **then**
    $z = \arg\min_{x \in C_c(c_i)}(NICE_x(c_i))$,
    $cp = cp(y) \cup c_i$
    if $NICE_z(v) \leq p_y NICE_{cp}(c_i)$ **then**
      $cp(y) = cp(y) \cup c_i$,
      $cp(z) = cp(z) \setminus c_i$,
    else
      nothing, y is not cached
    end if
  end if
  return $cp(y), cp(z)$
end for

4 CONTENT REPLACEMENT ALGORITHM IN THE CACHE

4.1 Algorithm

Equipped with the tool of content-based centrality and a method to compute it efficiently, we now use it to optimize the cache replacement policy in ICN and network of caches.

Algorithm 1 depicts our proposed cache replacement policy. The intuition of the algorithm is simple. If adding a new content into the cache c_j increases $NICE(c_j)$, then the operation is carried on. Otherwise, the content is not added.

The system is initially empty of any content. Then, when content arrives at the cache and the cache is not full, it is added. When the cache is full, the distributed content placement is optimized at each caching node using Algorithm 1.

We denote by $NICE_x(v)$ the contribution of x to $NICE(v)$, namely $NICE_x(v) = p_x NICE_{cp(x)}(v)$.

The algorithm generates the replacement policy in the cache, while attempting to always increase the content centrality of the cache. Because content centrality increases, the content always gets more reachable.

In this algorithm, at node v, the only computation that is required is the difference between $p_y NICE_{cp(y)}(v)$ where the content placement $cp(y)$ assumes y is cached at c_i, and $p_z NICE_{cp(z)}(v)$. Since $NICE_{cp}$ is computed ahead of time, the only operation is to know $cp(y)$ and $cp(z)$ as well as p_y and p_z.

The values $cp(y)$ and $cp(z)$ should be provided by the protocol to update the routing tables, especially since this update is required to take advantage of the new objects in the cache. p_y and p_z need to be either periodically provided by the

server, or estimated by empirically monitoring the rate of interests for y and z.

4.2 Convergence

Theorem: Algorithm 1 converges to a stable content placement policy

The content placement algorithm only increases the NICE value at each cache for each content inclusion/eviction decision. Hence, it suffices to show that a finite number of increases to NICE values occur at any node.

We have a finite number of pieces of content, and a finite number of permutations; therefore, the increment to a NICE value is bounded below by the smallest change in NICE by which it may occur by either : (a) moving one piece of content from one cache to another, (b) adding a piece of content to a cache, or (c) removing a piece of content from a cache. Since the increment is bounded below, Algorithm 1 will converge in a finite number of decisions.

5 NUMERICAL EVALUATION

We evaluate NICE using the named-data networking module of the NS-3 simulation platform (ndnSIM [36]). The topologies we considered in our analysis are obtained from a publicly available [37] dataset of a large scale realistic mobility trace of Köln, Germany where a large number of nodes, vehicle in this case lie on top of the street network. The Köln 6×6 km^2 city center is divided into 36 neighborhoods comprising 25 nodes. This reflects a city-wide network of edge nodes in an urban environment. The data contains the position of each node in x-y co-ordinates in meters for a duration of 24 hours where we extracted the topology (connectivity) of the 2, 986 nodes at three distinct time snapshots. Three different large scale topologies are used in order to validate the efficiency and scalability of NICE in a real edge caching environment. The topologies are snapshots of the network connectivity at time $t = 0$, $t = 30$ and $t = 60$ minutes, respectively.

Each unique content chunk is of 1KB size and for the 10^5 contents, we can have up to 1000,10, 000, or 100, 000 content chunks in the cache size of 1MB, 10MB and 100MB respectively. Thus, the content catalog of 10^5 chunks completely fits into the $100MB$ cache size.

In our simulations, we consider an edge network with routers and small cell devices cache near the end users where we do not assume that all nodes in the ICN network are caching nodes due to their resource limitations. Therefore, 30% of nodes are caching enabled corresponding to 900 out of the 2, 986 nodes. The total network-wide cache size is 900MB, 9GB and 90GB for individual node cache sizes of 1MB, 10MB and 100MB respectively. While further extending the storage capacity is indeed beneficial to study, however, due to the storage constraints at our computing server, the total cache could not exceed 1TB of storage.

5.1 Simulation Scenario

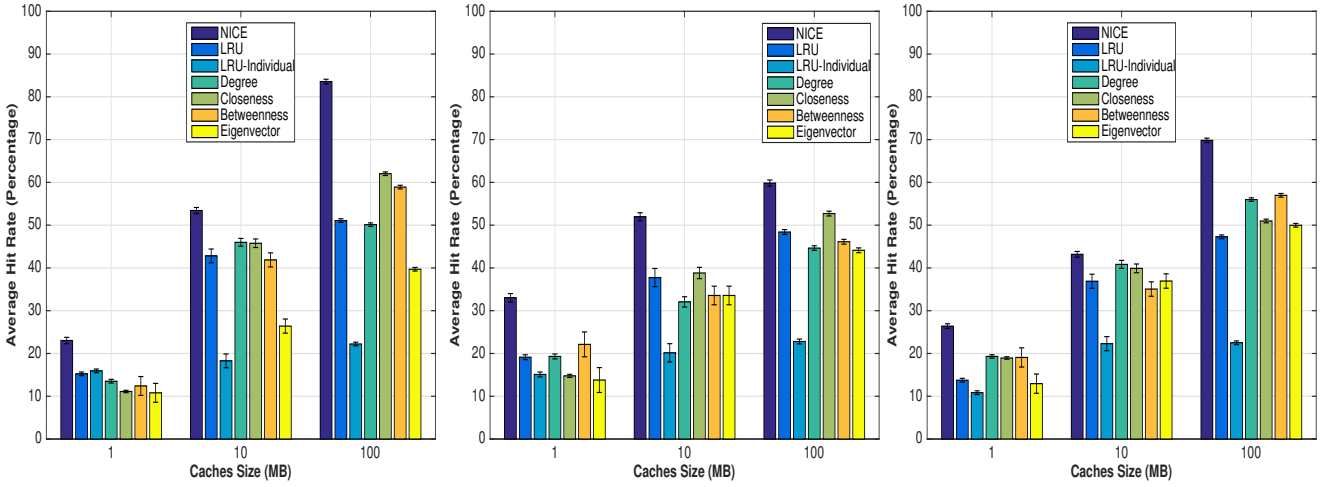
The consumers are located at the leaf nodes in each topology representing the edge of the network while the producers are non-leaf nodes in the topology capable of receiving interest messages. In each simulation, the consumers and producers are randomly chosen resulting in different nodes as consumers and producers from the previous simulation run. Each consumer randomly generates interests following a Zipf distribution (with varying Zipf parameter 0.5, 0.75, 1, 1.5) where the interests are forwarded using the ndnSIM default NFD forwarding strategy "best-route" without modification. We generate the workload of typical web traffic with minimum content size of 1KB and a catalog of 10^5 contents.

The simulation scenario implements consumer nodes which generate up to 10^5 unique content requests varying the cache size from 1, to 10 and to 100 MB. We run each set of parameters for a total of 100 times, each with a new random seed to generate consumer interests.

Any provider node already caching the content responds to the consumers' interests. 30% of the nodes are consumers, 30% are providers/caching nodes with homogeneous storage sizes and the remaining nodes act only as relay nodes in the Information-centric Network.

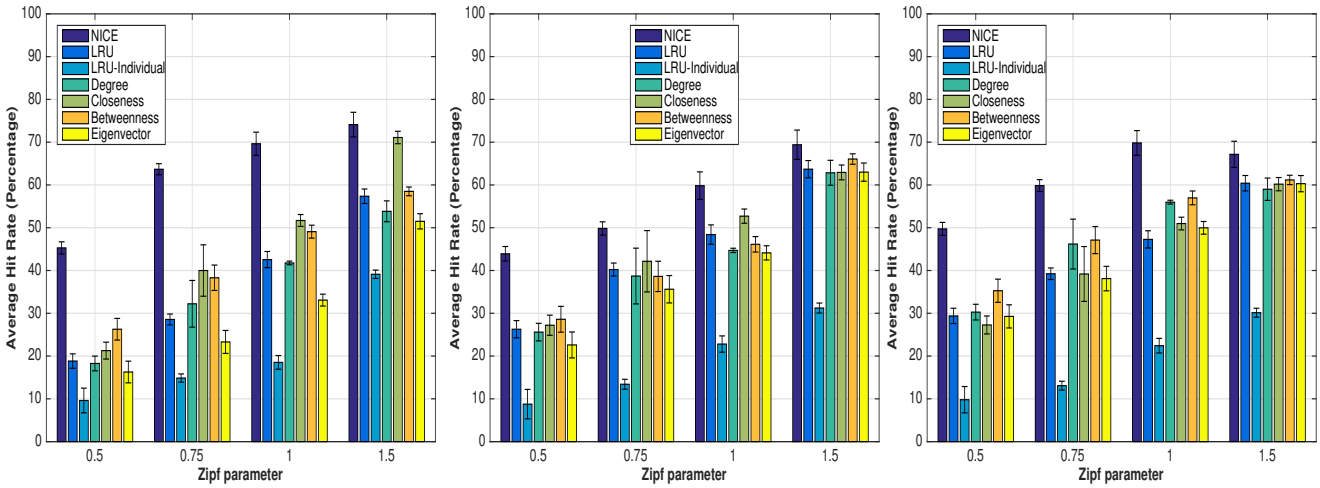
We implement the cache replacement policy where the node caches the content that maximizes its respective NICE (considered here only to be *betweenness* NICE). Besides NICE, we implement three different cache replacement approaches for comparison:

- **Centrality-based:** We cache popular content at high *Degree, Closeness, Betweenness* and *Eigenvector* centrality nodes. For each of these centrality metrics, we rank the nodes by centrality, and populate the cache by placing the most popular content at the highest centrality node, the next most popular content at the next highest centrality node, and so on until all caches are full.
- **Non-centrality based:** We implement a collaborative approach where all the nodes in the network pool their cache space to form one large LRU buffer. This caches the most popular content in the network, but without topological considerations.
- **Non-collaborative based approach:** (LRU-Individual) Each node implements an LRU policy independently of the other nodes. This is a myopic greedy local policy, however it is commonly considered in Information-centric Networks.



(a) Topology 1 (b) Topology 2 (c) Topology 3

Figure 3: Hit rate comparison by varying cache size (Zipf parameter=1) for centrality-based NICE, Degree, Closeness, Betweenness, Eigenvector, non-centrality based or social-unaware (LRU) and non-collaborative (LRU-Individual) caching.

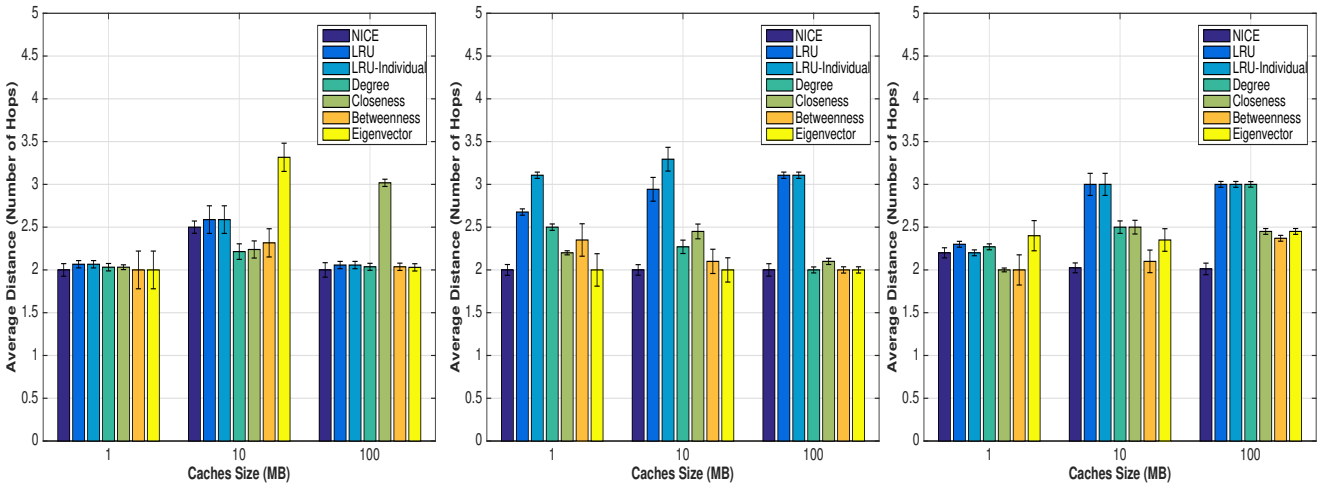


(a) Topology 1 (b) Topology 2 (c) Topology 3

Figure 4: Hit rate comparison by varying Zipf parameter (cache size=100 MB) for centrality-based (NICE, Degree, Closeness, Betweenness, Eigenvector), non-centrality based or social-unaware (LRU) and non-collaborative (LRU-Individual) caching.

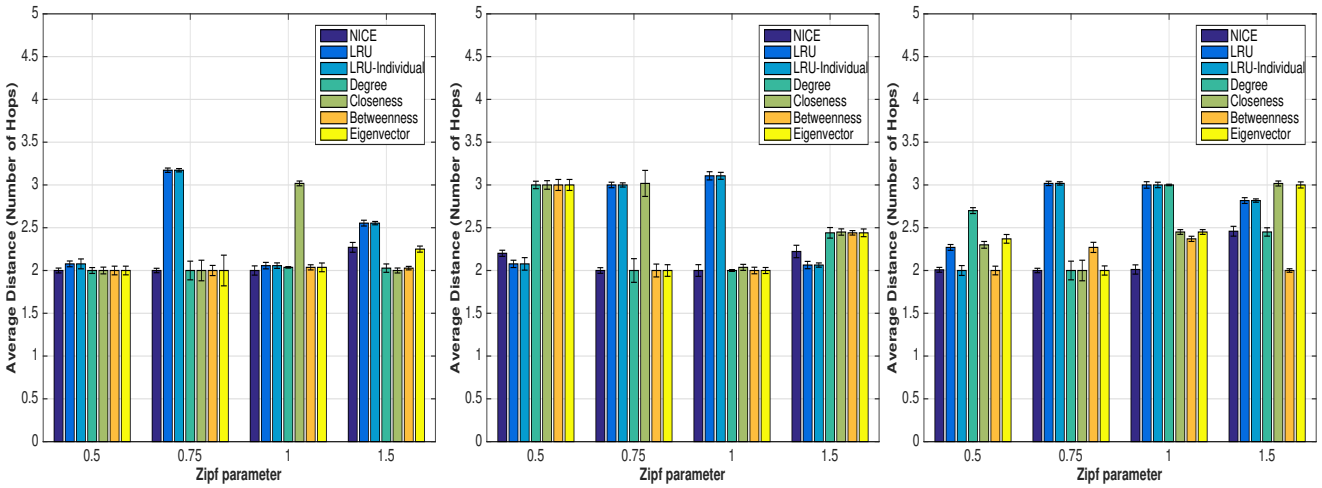
The following performance metrics are used to evaluate NICE along the benchmark cache replacement approaches:

- Cache Hits: This the average number of content responses from the caching nodes, calculated as the ratio of the number of content chunks served by the cache to the number of received interests by the nodes.
- Distance to content (Hop count): This is computed as the distance in terms of average number of hops traversed by the content en route to the consumer. A lower number of hops traversed by the content high reflects better content reachability.
- Delay in content retrieval: This is measured as the overall delay in retrieving all content requests generated by nodes.



(a) Topology 1 (b) Topology 2 (c) Topology 3

Figure 5: Hop count comparison by varying cache size (Zipf parameter=1) for centrality-based (NICE, Degree, Closeness, Betweenness, Eigenvector), non-centrality based or social-unaware (LRU) and non-collaborative (LRU-Individual) caching.



(a) Topology 1 (b) Topology 2 (c) Topology 3

Figure 6: Hop count comparison by varying Zipf parameter (cache=100MB) for centrality-based (NICE, Degree, Closeness, Betweenness, Eigenvector), non-centrality based or social-unaware (LRU) and non-collaborative (LRU-Individual) caching.

5.2 Simulation Results

5.2.1 Cache Hits. We observed the cache hit rate for each scheme: (i) NICE, Degree, Closeness, Betweenness and Eigenvector centrality, (ii) non-centrality based (LRU), and (iii) LRU-Individual where individual nodes cache indifferently, i.e. no collaboration on cache replacement. In Figure 3 we compare the hit rate of our approach for three topologies from the Köln trace and three cache sizes (1MB,10MB and 100MB). Figures 3a, 3b and 3c show results for each topology. The first observation is that the average cache hit rates achieved differ with respect to topology and cache size. Furthermore, we trivially observe that for all topologies there is an increase in the cache hit rate with increasing cache size.

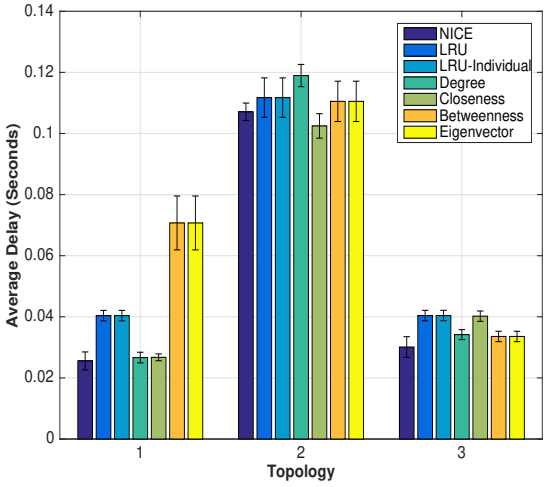


Figure 7: Average delay in content retrieval for all interests (Zipf parameter= 1, Cache size= 100MB)

Further, we see that NICE achieves a high cache hit rate when compared to all other approaches. It resulted in a maximum of 83% hit rate for Topology 1, 60% for Topology 2 and 70% for Topology 3.

Similarly, Figure 4 show the hit rate comparison for each topology by varying the Zipf parameter. Here as well, NICE outperforms the other schemes where there is a substantial difference (up to 2×) for low values of Zipf parameters. This is because other schemes fail to cache the maximum number of popular content objects for low Zipf parameter values. We also observe that all the centrality schemes resulted in substantially higher hit rate than the case LRU-Individual, which achieves the lowest average hit rate (below 50% overall) thus confirming the well-known benefit of collaborative caching. However, the caching decision in our case is fully distributed: each node assesses the benefit on content centrality locally. NICE captures locally the impact on the overall network.

The comparative analysis of cache hit rate on three different topologies, three caches size and four variants of Zipf parameter reveals that NICE achieves a better hit rate and in a scalable manner.

5.2.2 Distance to content (Hop Count). We also compute the average distance to content from the consumers. Figures 5 and 6 show the average number of hops the content traverses from the caching node which responds to the interest, to the consumer.

Figure 5 compares the hop count for each topology by varying the cache size. We first observe that NICE results in the fewest number of hops overall (around 2 hops), where the case of LRU (both with and without collaboration) yields highest distance to content. In terms of distance, there is not much difference between the compared centrality schemes however, we observe that in general, centrality-based cache replacement approaches result in better performance.

Note that other centrality measures, such as closeness or eccentricity, are specifically tuned to use shortest paths and in result minimize the distance to retrieve content. However, the proposed content-based betweenness centrality seems to perform well in this regard without requiring it to consider the nodes in the shortest path for content retrieval.

Similarly, Figure 6 compares the average hop count for each scheme by varying the Zipf parameter. We observe a variation in the hop counts between different centralities, however we observe that most of the schemes are successful in providing content within two hops, though, NICE achieves relatively better results, i.e. within a distance of 2 hops, for all variations of Zipf parameter. However, we see that LRU (both with and without collaboration) fails to provide content within 2 hops for most of the cases.

The hop count analysis overall suggests that centrality based cache replacement, and NICE in particular, provides an efficient and scalable approach to enhance cache performance in Information-Centric Networks.

5.2.3 Delay in content retrieval. To validate the time efficiency of the proposed content replacement approach, NICE, we compute the average delay in seconds for the content retrieval using each scheme. Figure 7 shows the average delay observed using each topology, for a cache size of 100MB and Zipf parameter = 1. We observe that NICE is able to achieve the least delay among the compared schemes. The topology 2 yielded high delay values (around 0.1s to 0.12s) where NICE showed similar results as the compared schemes due to the high delay in retrieving content for all schemes in this particular topolology. However, overall it outperformed the other compared schemes when evaluated on different topologies such as shown in Figure 7 for Topology 1 and 3.

Thus, we can infer that NICE is an efficient content replacement approach in ICN with respect to delay. Overall evaluations on a city-wide network shows that NICE is a scalable solution to cache content at the network edge and closer to large number of consumers in an urban environment.

6 CONCLUSIONS AND FUTURE DIRECTIONS

We observed that Information-Centric networks require a new approach for cache management, as well as new graph theoretical measures. The current definitions of centrality are inadequate when dealing with connecting users to content. These measures are agnostic to the opportunity for the network to keep content in the caches. Therefore well-connected users in the traditional sense of centrality may be poorly connected in the sense of content-based centrality, if what they are looking for is not locally available.

We described NICE, a content-based centrality, and gave examples based both upon closeness and betweenness centrality. We showed a more scalable method to compute such centrality. We applied NICE to a content replacement policies in the caches. Our simple NICE-based cache replacement policy evicts content whenever the insertion of a new content object improves the content-based centrality of the node. This cache replacement policy performs extremely well in a set of simulations against LRU and graph centrality based policies. In our evaluations, we have shown that, while making a local, distributed decision to either keep or evict content in the cache, the NICE-based policy distributes the content in the network so that its average distance and delay to the users is lower and the cache hit rate is higher than the other benchmarks.

Future work is to evaluate other forms of content-based centrality, i.e. based upon closeness centrality and eccentricity along a practical implementation of NICE over NDN.

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