A Caching Strategy Based on User Interest in Content-Centric Network

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Abstract. In Content-Centric Networking, content caching is a critical issue. At present, most researches on content network caching mainly focus on network resource utilization, while user interest is neglected. In this paper, we propose a caching strategy based on user interest in the Content-Centric Networking. Firstly, it divides the users into several interest groups. Then get the appropriate caching probability for each node by using grey relational analysis method. Simulation results show that the caching strategy proposed in this paper can achieve higher cache hit ratio and less average hop count than Leave copy everywhere (LCE) and ProbCache.

Keywords: Content-Centric Networking · Caching strategy · User interest
Grey relational analysis

1 Introduction

Content-Centric Networking (CCN) is an innovative network model, and it can achieve the content dissemination effectively. Reference [1] pointed out that CCN content retrieval depends on content rather than IP address. In the research field of CCN, network caching is a very important issue. In [2], the author proposes a strategy for allocating more cache space to important nodes. This strategy needs to measure the importance of each node in the network. Caching metrics such as content popularity, different application classes, and content type were considered in [3, 4]. Reference [3] explored that caching only most popular contents could reduce content copies and cache load at each node. Content types can be used to decide which content files will be cached first [4].

Leave copy everywhere (LCE) and ProbCache are two simple and common strategies. LCE strategy means all nodes along he delivery path cache contents. Reference [5] presented a ProbCache strategy that designed a caching probability with a function of the remained cache capability and the hop reduction from the router to the

content store. The above two strategies mainly considered single layer caching metrics. It is not efficient and cannot improve cache performance very well.

5G (5th-generation) is the fifth generation of mobile communication technology short [6], the existing wireless access technology (including 2G, 3G, 4G and WiFi) technology evolution, 5G system development will be for the 2020 mobile communications needs, Including key technologies such as architecture, wireless networking, wireless transmission, new antenna and radio frequency, and new spectrum development and utilization. In this paper, we design a caching strategy based on user interests (CSUI) in CCN. This strategy is implemented by dividing the interest groups and computing the probability of each node in the return path using the grey relational analysis method. Simulation results show that the strategy improves the cache hit ratio and reduces the average number of hops.

2　Related Works

2.1　Introduction of CCN

The traditional IP network has a long exploratory stage. At the beginning, it was designed for less users, easy application, small flow rate and other characteristics. In this way, it establish a simple and clear network architecture. It is very suitable for the requirement of using Internet at that time. However, with the rapid growth in network size and offered application type, the simple and clear network architecture has become more and more complicated. Figure 1 shows the difference between the traditional IP network and Content-Centric Networking.
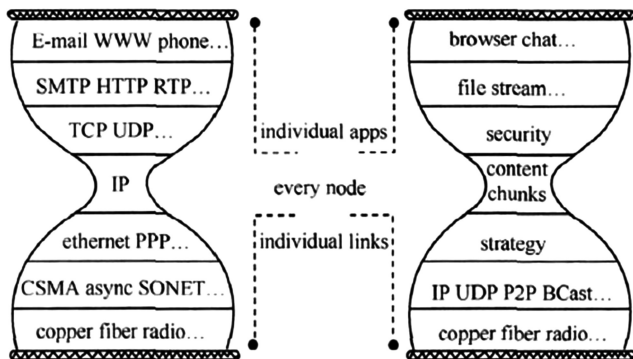

Fig. 1. The difference between the traditional IP network and Content-Centric Networking

From the Fig. 1, we can see the CCN replaced the original IP layer with content identify layer. The middle of the CCN network architecture becomes a simple structure again. Therefore, this new network architecture works more efficiently than the current complicated network architecture.

The mechanism of CCN is on the base of content which is named [7]. CCN takes full advantage of the network equipment's characteristics of big capacity memory and low storage cost. Applying the caching mechanism appropriately can further promote the network performance. Comparing with traditional IP network, in which requirements can be satisfied by the producer, requirements in CCN can also be responded by the intermediate nodes as long as this intermediate node has cached the required content before [8].

If this intermediate node does not have cached this content, it will forward the interest packet to neighbor nodes. This process will continue until the content is satisfied by the provider or the hit node. Then, the hit node or the provider will respond with a data packet [9]. When the data packet is transmitted along the reverse path, the intermediate node which is on the reverse path can cache the content into its content store.

When the content store becomes full, it will adopt the replacement policy in order to make a decision on removing one content from the store for the new content.

From Fig. 2, we can see when a user R1 requests a content, it first sends the interest packet to node P1. However, P1 does not have this requested content. So, P1 forwards the interest packet hop by hop until it finds the node P which can satisfy the requested content. Then P sends data packet along the reverse path and nodes which are on the reverse path cache the requested content in their content stores. Next time, when user R2 requests the same content, the node P1 can satisfy the request. Therefore, P1 responds the request and send the content back to R2.
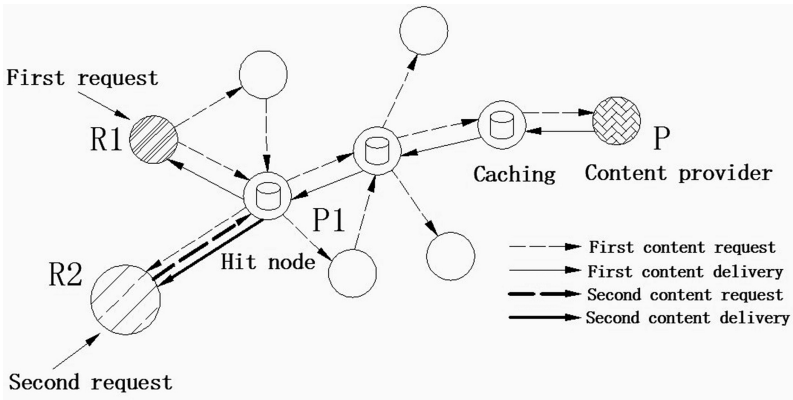

Fig. 2. An example of CCN caching mechanism

2.2   Grey Relational Analysis

The grey relational analysis method is used to compute the two parameters of each node's cache probability: the betweenness B [10, 11] and the cache replacement rate R. In the topology, betweenness is a useful way to judge the importance of nodes in the network. The higher the betweenness is, the more important the node is. The betweenness of user u_j is shown as:

$$B(u_j) = \sum_{s \neq u \neq t \in U} \frac{N_{s,t}(u_j)}{N_{s,t}} \tag{1}$$

Where $N_{s,t}$ is the number of the shortest paths from node s to node t. $N_{s,t}(u_j)$ represents the number of the shortest paths from node s to node t through node u_j.

The caching replacement rate $R(u_j)$ is denoted as:

$$R(u_j) = \frac{\sum_{i=1}^{M} S_j(c_i)}{C(u_j)} \tag{2}$$

Where $C(u_j)$ is the cache size of u_j and $S_j(c_i)$ represents the total number of replaced content for T_1 seconds in the content store of u_j.

Along the delivery path, interest packet is transmitted. During the transmission, interest packet records two caching parameters vectors of each node in the path. We define two parameters vector as a binary group, which is represented as $(B(u_j), R(u_j))^T$. The providers or the hit nodes receive the interest packet and extract the set of the binary groups regarding as comparative sequences. Based on Grey Relational Analysis, the providers or the hit nodes compute the caching probability and response a data packet with computed caching probability. The data packet is forwarded along the reverse path [12].

3 Caching Strategy Based on User Interests (CSUI)

3.1 Resource Matrix Construction Based on Dichotomy Network

A system that has a large number of individuals and interpersonal interactions can be abstracted as a complex network. According to the quantity of node types in the network, the complex network can be classified as single peak network, bipartite network and other forms. Bipartite network has been a research focus.

Bipartite network is made up of two types of nodes and links between two types of nodes. There is no link between the same types of node [13].

Different users may have the same interest, the same user may have multiple interests, so the users and the interests generate relations. The existence of interests depends on the users, because there is no users to have interests, interests do not exist. The interaction between users and interests can be considered a resource allocation process. We think nodes in the same group have similar resource vectors. Therefore, dividing groups toward nodes can be transformed into clustering row vectors of the resource distribution matrix.

Users-interests presents a characteristic of bipartite [14]. We assume the top nodes in bipartite network as users and bottom nodes as interests (see Fig. 3). The initial distribution of resources on the top nodes are x, y and z (see Fig. 3).
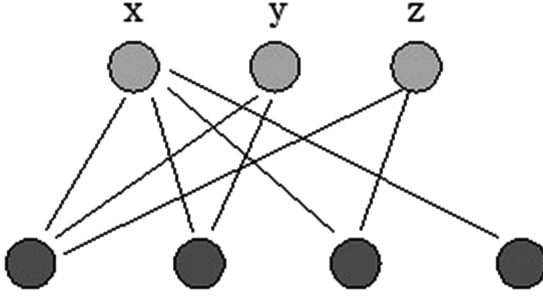
Fig. 3. The initial distribution of resources

All the nodes' resource in the network can be expressed as three-dimensional vectors:

$$
\begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ y_1 \\ y_2 \\ y_3 \\ y_4 \end{pmatrix} = \begin{pmatrix} 7/12 & 5/12 & 5/12 \\ 5/24 & 5/12 & 1/6 \\ 5/24 & 1/6 & 5/12 \\ 1/4 & 1/2 & 1/2 \\ 1/4 & 1/2 & 0 \\ 1/4 & 0 & 1/2 \\ 1/4 & 0 & 0 \end{pmatrix} \begin{pmatrix} x \\ y \\ z \end{pmatrix} \tag{3}
$$

Where x_1, x_2, x_3 represents the resource of the top nodes, y_1, y_2, y_3, y_4 represents the resource of bottom nodes. The matrix that on the right side of the equation is resource distribution matrix.

3.2   Divide Users into Interest Group

Divide users into interest group by K-means clustering and F-statistics [15], select K objects as initial cluster center. Then by using the method of iteration, we can divide objects into different groups. Our purpose is to make objects that in the same group have a big similarity and objects that in the different group have a small similarity.

Assume the resource distribution matrix is $U = (u_1, u_2, \ldots, u_{m+n})^T$, $u_j = (x_{j1}, x_{j2}, \ldots, x_{jm})$ (the number of users is m; the number of interests is n). K is the group number. n_i is the number of nodes in ith group. These nodes are: u_1^i, u_2^i to $u_{n_i}^i$. $u^i = (x_1^i, x_2^i, \ldots, x_m^i)$ is the ith group's cluster center.

$$
x_k^i = \frac{1}{n_i} \sum_{j=1}^{n_i} x_{jk} \tag{4}
$$

The definition of F-statistics is

$$F = \frac{\sum\limits_{i=1}^{K} \frac{n_i \|u^i - u\|^2}{K-1}}{\sum\limits_{i=1}^{K} \sum\limits_{j=1}^{n_i} \frac{n_i \|u_j^i - u^i\|^2}{n-K}} \tag{5}$$

The longer the distance between external groups, the shorter the distance in internal groups, the bigger value of the F-statistics. Therefore, when the value of F-statistics reaches its maximum, the effect of dividing groups is the best.

3.3 Calculate the Caching Probability Based on Grey Relational Analysis

When a user requests content c_i, the interest packet adds the binary group information of the requester

$$X_j = (B(u_j), R(u_j))^T \tag{6}$$

The node receives interest packet from the previous neighbor node, if the content store has not the requested content, interest packet is added into binary group information of the node, then it is forwarded to the next hop along the path. If the content store has the requested content [16], they extract the binary groups of the interest packet as the comparative sequences.

The distance from requester to the providers or hit nodes is n hops. The information matrix A′ is denoted as:

$$A' = \left(X_1', X_2', \ldots, X_n' \right)$$
$$= \begin{pmatrix} x_1'(1) & x_2'(1) & \ldots & x_n'(1) \\ x_1'(2) & x_2'(2) & \ldots & x_n'(2) \end{pmatrix} \tag{7}$$

Since each attribute has different ranges, we need to normalize attributes before we calculate the grey grade. The $x_i(k)$ is normalized as:

$$x_i(k) = \frac{x_i'(k) - \min\limits_{1 \le i \le n} \left\{ x_i'(k) \right\}}{\max\limits_{1 \le i \le n} \left\{ x_i'(k) \right\} - \min\limits_{1 \le i \le n} \left\{ x_i'(k) \right\}} \tag{8}$$

$$x_i(k) = \frac{\max\limits_{1 \le i \le n} \left\{ x_i'(k) \right\} - x_i'(k)}{\max\limits_{1 \le i \le n} \left\{ x_i'(k) \right\} - \min\limits_{1 \le i \le n} \left\{ x_i'(k) \right\}} \tag{9}$$

Where k = 1, 2. Pay attention to (8) is used for the-larger-the-better attributes while (9) is used for the-smaller-the-better attributes. Based on this, we can get

$$A = (X_1, X_2, \ldots, X_n)$$
$$= \begin{pmatrix} x_1(1) & x_2(1) & \ldots & x_n(1) \\ x_1(2) & x_2(2) & \ldots & x_n(2) \end{pmatrix} \tag{10}$$

Define reference sequence

$$X_0 = (x_0(1), x_0(2), \ldots, x_0(m))^T = (1, 1, \ldots 1)^T \tag{11}$$

Calculate grey relational coefficient

$$\rho(x_0(j), x_i(j)) = \frac{\Delta_{\min} + \tau \Delta_{\max}}{|x_0(j) - x_i(j) + \mu \Delta_{\max}|} \tag{12}$$

$$\Delta_{\min} = \min_{1 \le i \le n, 1 \le j \le m} |x_0(j) - x_i(j)| \tag{13}$$

$$\Delta_{\max} = \max_{1 \le i \le n, 1 \le j \le m} |x_0(j) - x_i(j)| \tag{14}$$

Where u is distinguishing coefficient, and $\tau \in [0, 1]$. The larger grey relation coefficient is, the closer $x_i(j)$ is to $x_0(j)$.

The grey relation grade p_i can be calculated as

$$p_i = \sum_{j=1}^{m} a_j \rho(x_0(j), x_i(j)) \tag{15}$$

Where $\sum_{j=1}^{m} a_j = 1$ and a_j represents the weight of j_{th} attribute.

Providers or hit nodes send data packet that the requester is requiring. Data packet carries above calculated grey relation grades along the reverse path [17]. Intermediate node receives data packet and caches content with the corresponding caching probability, which is equal to the node grey relational grade.

4   Simulation Analysis

4.1   Simulation Environment

We use the software ndnSIM [18] to simulate the GRA-based caching strategy. It is a chunk-level simulator developed in the NS-3 framework.

The network topology is a 7 * 7 grid network.

We evaluate our caching strategy by comparing two common caching strategies.

(1) LCE, all nodes along the delivery path cache the content.
(2) ProbCache, by which nodes along the delivery path cache the content with the fixed probability 0.5.

In the evaluation, we consider the independent variable as cache size which is the cache capacity in terms of content units. The cache size ranges from 50 to 200.

4.2 Evaluation Metrics

Caching hit ratio is defined as:

$$\beta = \frac{S}{R} \tag{16}$$

Where S denotes the numbers of requests satisfied by caching node, and R represents the total number of requests in the network.

Caching hit ratio gain β_{gain}

$$\beta_{gain} = \frac{\beta - \beta_{LCE}}{\beta_{LCE}} \tag{17}$$

Where β is the hit ratio of caching strategy, and β_{LCE} is the hit ratio of LCE.

Average hops

Average hops indicates the delay for user to fetch the content and it is a good way to estimate the access delay to the content. The same as the β_{gain}, hop reduction ratio η is represented as:

$$\eta = \frac{H - h}{H} \tag{18}$$

Where H is the average hops from user to the content provider or hid nodes in the LCE strategy, h is the average hops from the user to content provider or hit nodes for CSUI and ProbCache.

4.3 Simulation Diagram

In order to better verify the performance of CSUI strategy, the following experiment was done to draw the relationship between the cache hits and the average hops corresponding to different cache sizes.

From Fig. 4, we can see that the cache hit ratio of all compared caching strategies increases as the cache size increases. When the cache size become larger, the better diversity of cached contents will satisfy more requests. We can calculate that our CSUI strategy can achieve about 13%–27% cache hit ratio gain compared with LCE and ProbCache as the cache size changes.
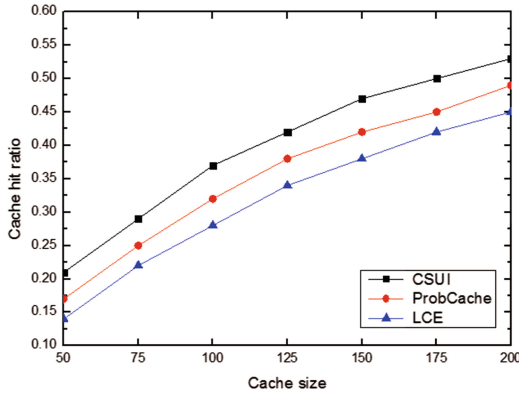
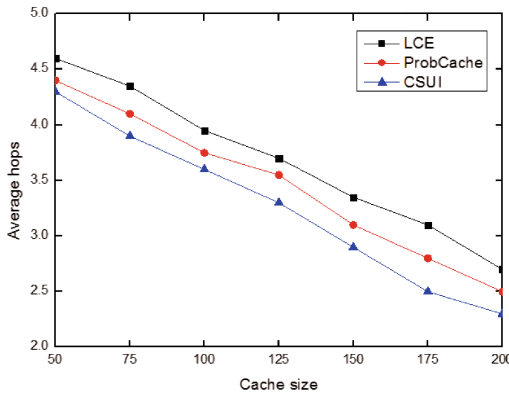**Fig. 4.** Caching hit ratio with different cache sizes

Fig. 5. Average hops with different cache sizes

Figure 5 illustrate the average hops and hop reduction ratio for each strategy with different cache sizes respectively. When the cache size is 50, the average hops reduction is little, about 4%. However, when the cache size is 200, hop reduction can reach 11%.

Therefore, it is obvious that our strategy CSUI performs better than LCE and ProbCache.

5   Conclusion

In this paper, we design a caching strategy that considers the interest of CCN users. On the basis of dichotomous network, we divide the users into appropriate interest groups, and then use the grey correlation analysis method to calculate the cache probabilities of each node in each interest group. This is a CCN caching strategy that takes into account

user interest. Simulation results show that compared with LCE and ProbCache caching strategies, the strategy of this paper (CSUI) achieves higher cache hit ratio and fewer average hops.

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