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Online learning of caching policies

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Abstract

Since the inception of computer science, data retrieval speed has been a major bottleneck for numerous applications. The problem has become only worse following the introduction of the Internet with data potentially retrieved from remote locations. To overcome this limitation caching was introduced. The solution is to store the data closer to the location where it is used or store it in a storage device with higher access speed. A large number of caching policies have been proposed but most of them require ad-hoc tuning of different parameters and none emerges as a clear winner across different applications. For this reason, most of the practical caching systems adopt LRU (Least Recently Used) policy because of its simplicity and relatively good performance.

In this report, we explore the possibility of the application of machine learning algorithms to solve the caching problem. We propose a caching policy which utilizes a feedforward neural network and overperforms state of the art policies on both synthetic and real-world request traces. We also examine other approaches using machine learning techniques to handle the problem and compare their performance with our solution.

Contents

1 Introduction

1.1 Caching problem

The invention of the computer allowed scientists to process vast amounts of data faster than ever before. However, soon a significant bottleneck was discovered - data retrieval speed. The introduction of the Internet only increased the relevance of this problem. According to Cisco, annual global IP traffic is predicted to reach 3.3 zettabytes by 2021 [1]. A massive increase in traffic volume naturally increases the load on the infrastructure. In order to improve performance in various applications and to reduce the impact of traffic growth the concept of caching was introduced. The idea behind this concept is to put the actively used data into storage from which it can be retrieved quicker. The goal is to reduce latency, shorten data access times and improve input/output. Since the workload of most of the applications is highly dependent upon I/O operations, caching positively influences applications performance. Previously described goals can be achieved by using a storage device which is physically closer to the data consumer or which has a higher data access speed. To maximize the utility of the storage devices various caching policies have been introduced. It is impossible to store every object in the cache since the storage capacity is limited. Ideally, we would like to guarantee that the next requested object is stored in the cache. Caching algorithms try to predict this in a variety of ways.

1.2 Caching policies

To compare the performance of caching policies we are going to use cache hit ratio [2] metric which is the most commonly used and effective metric for cache performance evaluation.

Belady's min algorithm is proven to minimize the number of cache misses which is the optimal behavior when the size of all objects is the same [3]. The general idea behind this algorithm is to evict from the cache objects which are requested furthest in the future compared to other objects in the cache. However, this information is not available in most settings thus this algorithm cannot be deployed in a practical system.

First In First Out (FIFO) is one of the first proposed caching policies. Simple to implement and deploy but eventually has been replaced by more sophisticated algorithms with better performance in terms of hit rate. The unbeaten advantage of FIFO is a low computational complexity of $O(1)$.

Least Recently Used (LRU) is the natural evolution of FIFO and the most commonly used caching replacement policy. It offers comparably good performance and does not require a lot of extra storage or CPU time. The policy requires maintenance of a priority queue what leads, in general, to a time complexity of $O(\log C)$ where C is the size of the cache.

Least Frequently Used (LFU) in some cases overperforms LRU, it is optimal in long-term if the objects have static popularity in particular. But requires to track the number of requests for all of the objects observed. This disadvantage limits the number of applications of LFU.

Adaptive Replacement Cache (ARC) [4] is a caching policy introduced by IBM [5] in 2004. It offers better performance than LRU while keeping low computational resources requirements. Roughly, the algorithm requires maintenance of 2 priority queues with some additional constant time operations. Thus, the time complexity is also $O(\log C)$ but the constant is larger. It is considered to be state of the art.

While a large number of caching policies has been introduced, there is still room for improvement in comparison to the optimal algorithm. Moreover, since, as said before, the amount of web traffic is expected to rise, even a small improvement in caching policy performance could lead to significant cost savings in long-term.

1.3 Neural networks

Following recent successful attempts of application of neural networks [6] for complex task solving [7, 8, 9] a question arises - is it possible to apply Neural Networks to learn online a close to optimal caching policy? To tackle this problem, we will try to apply simple feedforward fully connected neural network with a goal to construct a new caching policy which would overperform existing methods. The primary challenge is to construct a policy which would utilize a neural network efficiently. For example, we will try to apply a neural network to predict the future popularity of objects.

1.4 Report organization

In the Chapter 2, we will discuss related work in the area.

In the Chapter 3, we continue by discussing what data is required to develop and test the proposed caching policy. For ease of development, a controlled and customizable environment is required. Thus we will discuss techniques to generate synthetic data which is good at representing the real world. We will continue by discussing what real-world data is used to test the performance of the proposed policy.

After that, in the Chapter 4, we will discuss in more detail the concept of neural networks, how we use neural networks for caching and the iterative process of tuning the architecture of the network.

In the last part, Chapter 5, we will propose an architecture of a caching policy which exploits a neural network to make caching decisions. We will compare the performance of the proposed policy with other approaches including the state of the art approaches.

2 Related work

During the last few years, a number of articles describing the usage of machine learning algorithms for caching purposes appeared. In this chapter, we will give a quick review of them and justify the uniqueness of our proposed approach.

The first reviewed article is [10]. This article has mostly a theoretical flavour of sharing how a machine learning oracle can be used to design online caching algorithms with strong worst case guarantees. In their study, the authors assume the machine learning component to be a complete black box with unknown inner workings and exact distribution of generalization errors. Then the authors expand by providing a modification of Marker algorithm with the application of a machine learning oracle. They prove that as the error of the oracle decreases the performance, in terms of competitive ratios, of the proposed algorithm increases and the performance is always capped by a lower bound which can be achieved even without oracle's predictions. The authors complement their findings with an empirical evaluation of the proposed algorithm on real-world data. The results of the work done by the authors suggest that it is possible to construct a caching policy based on predictions made by a machine learning algorithm and achieve good performance.

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While in most scenarios caching is performed reactively: i.e. the algorithm decides if caching a given object when this is requested, the alternative is to proactively fetch the object if there are reasons to assume that the object is going to be requested in the future. The [11, 12] propose a solution to handle the caching problem by using this approach. The authors of [11] are trying to estimate the gains of proactive fetching in the context of 5G cellular network base stations, which in part overlaps with multi-node caching since every wireless base station can be considered as a caching node of a larger network. The authors of [12] propose a particular approach for proactive caching which relies on reinforcement learning technique. Reinforcement learning is known to produce unstable results so we will avoid it during our research. Moreover, our approach is dealing with classical reactive caching so it can be considered original in relation to these articles.

The final batch of articles is the closest by nature to our approach. The authors of [13] also utilize deep reinforcement learning framework which, as said before, not always produces stable results. Also, the authors do not test their approach on real-world data. The tests on synthetic data are also not convincing since the data is generated with a small number of unique objects and a small number of requests. The authors in [14] apply a different model for predictions - recurrent neural networks, deep long short-term memory network in particular. In both [13] and [14], the authors do not justify why they are using such complex machine learning techniques while bypassing more simple models as in our approach. Another issue with the approach proposed in [14] is the usage of one-hot encoding in the cache eviction decision process which does not scale well with a large number of the unique object usually encountered in caching. We have implemented the approach proposed in [14] and compare it with our approach. The results are discussed in Section 5.7.

The most similar approach in comparison to our we found in [15], but the difference between this article and all previously reviewed is that the proposed policy in [15] does not utilize a machine learning algorithm. The similarities include:

- Caching decisions are based on the prediction of the popularity of the objects estimated by some criteria.
- Maintenance of priority queue to decide which items to remove from the cache. The priority key is the predicted popularity.

Nevertheless, there are some key differences. First of all, to determine the popularity of the content the authors of [15] apply a technique named “Adaptive Context Space Partitioning”, which they describe in Section V.C., while we apply a neural network for this task. This approach implies the mapping of each request with its metadata to a point in k-dimensional space. When a hypercube accumulates a large number of requests it is split. The popularity of the object is determined by its hypercube, or by two variables - the number of received requests in the hypercube and the sum of the revealed future request rate for those requests, both of which are maintained for each hypercube. Second of all, the mechanism of the update of the priority queue is different. Our approach is based on the update of the priority of random individual objects in the queue at every cache hit and the approach proposed in [15] updates the whole queue every K requests.

Further examination of the topic revealed some attempts of application of learning algorithms trying to improve the performance in multi-node cooperative caching networks [16], explore the advantages, drawbacks and scalability possibilities of such an approach. While this caching method is also a perspective field, we are going to stick to a classical setting with a single caching node. Article [17] is a continuation of work done in [14] with an attempt to extend the application of the policy to multi-node cooperative caching. This may also be a good continuation of development of our approach but it is not explored in the report.

Overall, no substantial work has been done in the application of machine learning techniques for caching. The reviewed approaches claim to overperform established policies, but, as stated previously, have some disadvantages or have not been thoroughly validated. Our proposed policy will bring some light to the research on the topic.

3 Datasets

Caching is intended to help with file retrieval from a distant server. A sequence of requests is called a request trace. Each entry in a request trace contains the time of the request, file ID, and optionally some metadata (size, type, etc.). To develop and test our algorithm we relied both on real-world data and on synthetic data. Real-world data is suitable for final algorithm evaluation since it represents real end-user request pattern. However, during the development process, it is better to use synthetic data, since it provides a controlled environment, e.g. with a fixed number of unique items, having constant popularity, in which the behavior of the system is easier to understand.

3.1 Synthetic data

The primary challenge in the task of creation of the synthetic traces is to create them in such a way that they represent close to real-world data. We define the popularity of the object as the number of times an object is requested divided by overall number of requests. A number of studies have been conducted to show that the popularity of files requested from web servers is distributed by Zipf's law[18]. At the same time, the requests arrival times can be modeled as a Poisson process[19]. These two facts will form the basis of synthetic trace generation.

At the same time, in the real world objects popularity is not constant over time since new contents appear all the time and old contents become less popular. That is why we have decided to prepare two different types of synthetic traces. The first exhibits static popularity. The second type exhibits nonstatic popularity. In this case, the content catalogue is splitted in two equal-sized parts. The first half of the catalogue has static Zipf distributed popularity. The popularity of the second half of the population is also distributed by Zipf's law but the popularity is randomly shuffled every predefined time frame t_0.

	5-day trace	30-day trace
Total requests	$417 * 10^6$	$2.22 * 10^9$
Time span	5 days	30 days
Unique items	$13.27 * 10^6$	$113.15 * 10^6$
Request rate	966.97 requests/s	856.48 requests/s
Min object size	3400 bytes	1 bytes
Max object size	1.15 gigabytes	10.73 gigabytes
Mean object size	$4.85 * 10^5$ bytes	$3.63 * 10^5$ bytes

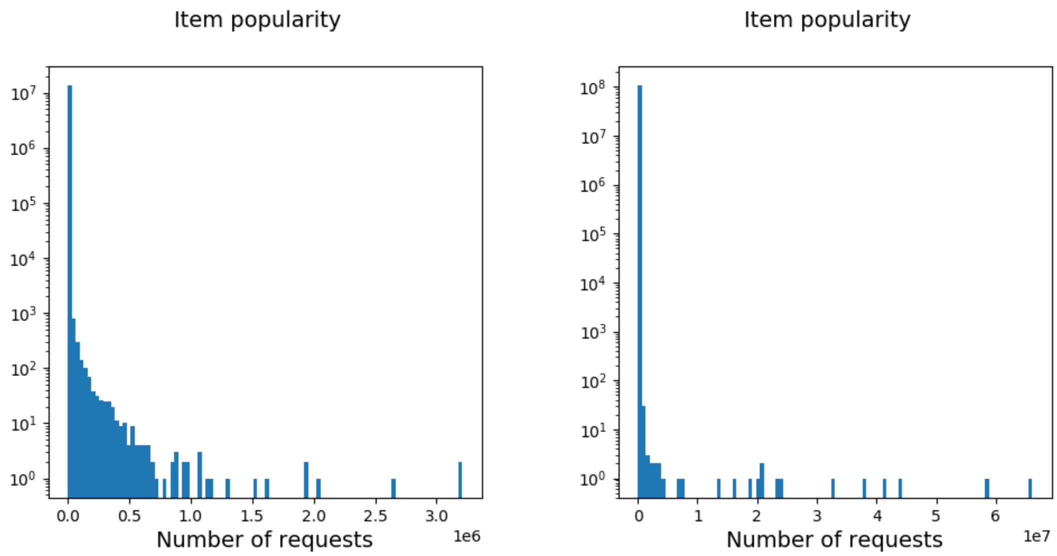
Table 1: Akamai request traces information.

3.2 Real-world data

The real world data has been obtained from Akamai content delivery network[20]. In particular. we were able to get access to two request traces collected from two different vantage points of the Akamai network. The first one spans over 5 days and further will be referred to as the 5-day trace. The second one spans over 30 days and will be referred to as the 30-day trace. The detailed information about the traces can be found in the Table 1 above.

As you can see in the Table 1, request traces contain not only the ID and the time of request arrival but also the size of the object. For now, we will consider that the size of all of the objects is equal and caching one object consumes one discrete place in the cache. The size of the object may later prove itself useful as a metadata feature for the neural network to process. This request traces are going to be used to evaluate the performance of the proposed algorithm and to compare it with other reviewed approaches.

Figure 2 shows the distribution of popularity of objects in the traces. A large number of the objects are requested only once (notice the logarithmic scale of the y axis of the figure). Pure LRU policy is always putting such objects in the cache potentially removing a more popular object from the cache. Such behavior leads to a reduced cache hit ratio and should be avoided by the proposed caching policy.



(a) 5-day trace.

(b) 30-day trace.

Figure 2: Trace item popularity.

4 A neural network for content popularity prediction

4.1 Fully connected feedforward neural networks

The simplest example of a neural network is a fully connected feedforward neural network. The smallest block of a neural network is a neuron. A neuron sums all of its inputs and produces one output. Neurons are stacked into layers. The output of the layer is a column vector consisting of the outputs of all of the layer's neurons. Let's denote the output of the layer L as o_L. In a fully connected feedforward neural network all of the neurons in a layer are connected with all of the neurons in the next layer. Each connection has a weight. Weights between layers $L-1$ and L form a matrix P^L, where $p^L_{i,j}$ is the weight of connection between i-th neuron of layer $L-1$ and j-th neuron of layer L. Following this notation, we can define the output o_L of the layer L as $o_L = o^{\intercal}_{(L-1)} P^L$.

Each layer can also have an activation function $f(x)$. Activation of the layer L is the $a_L = f(o_L)$. Typical activation functions used are:

Sigmoid: $f(x) = \frac{1}{(1+e^{-x})}$.

Rectified Linear Unit: $f(x) = max(0, x)$.

Hyperbolic Tangent: $f(x) = \frac{sinh(x)}{cosh(x)} = \frac{e^x - e^{-x}}{e^x + e^{-x}}$.

The introduction of the activation functions ads nonlinearity to the input propagation through the neural network which should positively influence the accuracy of predictions.

It is a common practice to add a bias neuron to layers of a neural network. A bias neuron always outputs 1 and is intended to improve the accuracy by allowing to shift the output of any layer in any dimension.

To train the neural network a dataset is required. Each row of the dataset contains the input of the neural network and true output. Forwarding the input through the network provides the output which then can be used to calculate the error, or loss, using the true output from the dataset and the provided loss function, but only for the output layer. The error on the output layer can be used to calculate the error

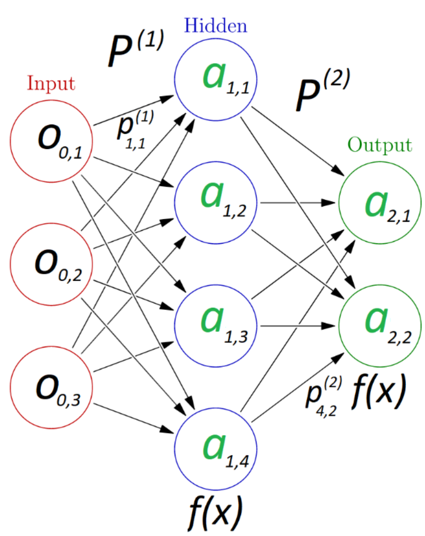


Figure 3: Fully connected feedforward network.

on previous layers in a process called error backpropagation [21]. The error on each layer is used to update the weights through gradient descent. Even though many loss functions to calculate the error have been proposed, we are going to apply classical loss function - Mean Squared Error (MSE):

$$g(x) = \frac{\sum_{i=1}^{N}(y_{true} - y_{pred})^2}{N}$$

4.2 Chosen architecture

There are a few degrees of freedom in neural network usage. The first one is the number of layers. Adding more layers allows learning more complex relations but decreases the performance and requires more learning iterations. The second degree of freedom is the number of neurons in each layer, but usually is limited only to internal layers since the number of neurons in input and output layers is determined by the dimension of input and output data. The tradeoffs are the same as with the number of layers. There are no clear rules or recommendations on the topic of selection of activation functions, we will stick to established well-performing options.

We aim to use a neural network to predict the future popularity of objects based on, mainly, the in past popularity. To extract the data from the request traces and form a dataset for neural network consumption, it is possible to split the request trace in time frames (or time windows) and calculate the popularity of each item in each time frame. Let us denote this popularity as $X_{i,j}$. Each row would consist of $K + 1$ popularities values, K values are input, and 1 is the output. To keep popularity independent of the number of requests in the time frame, the popularity of content is represented as the fraction of requests for that content. Using unchanged popularity values as the input of the neural network led to poor performance since the large difference of popularity values, spanning many orders of magnitude, caused the neural network to learn to make good predictions for the most popular objects sacrificing the prediction accuracy for less popular objects. To fix this issue, we decided to apply a transformation for both input and output popularity values. All of the values are transformed by the next formula: $f(p) = -\log(p + const)$. This transformation reduces the difference between the smallest and the largest values processed by the neural network and improved the accuracy of predictions greatly.

After some consideration, the next neural network architecture has been chosen. We use 4 neurons in the input layer, i.e. we are going to predict the popularity in the future based on popularity in 4 previous time frames with the size of 10^7 seconds. We will further experiment with both these values discussing the performance of the proposed caching policy. Then the input is feedforwarded through 2 hidden layers with 128 neurons in each. We want to predict the popularity in the next time frame, thus the network has only one neuron in the output layer. To every layer except the output, a bias neuron is added. As for the activation, we concluded that rectified linear unit performs the best. To overcome the "dying ReLU"[22] problem, a variation of ReLU is applied i.e. Leaky ReLU:

$$f(x) = \begin{cases} x, & \text{if } x \geq 0; \\ a * x,\ 0 < a \ll 1 & \text{otherwise.} \end{cases}$$

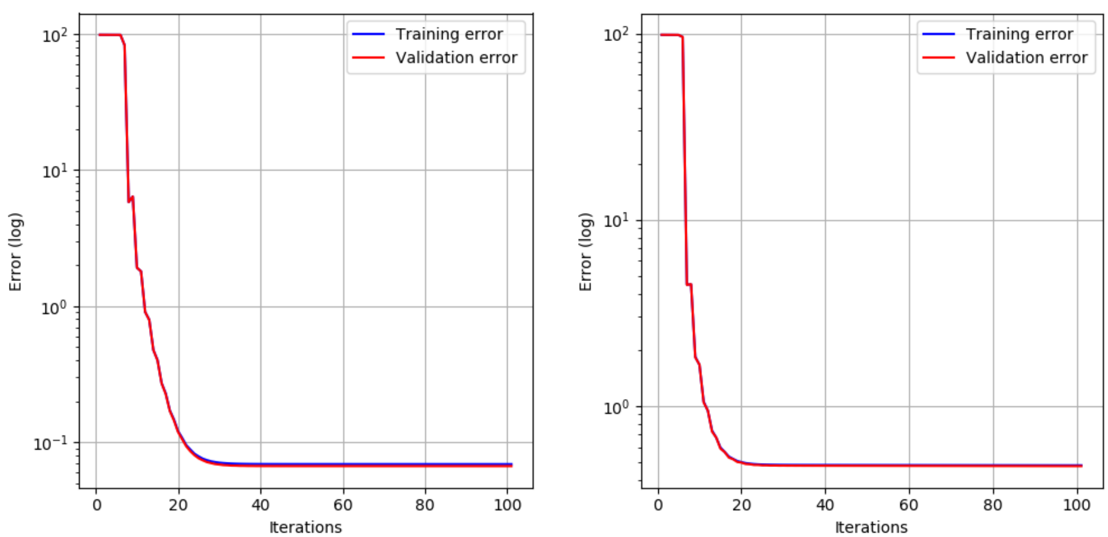
4.3 Performance evaluation

Continuing with neural networks, we need to determine 1) a way to evaluate the state of neural networks, i.e. to check that network has finished training, and 2) to verify that the predictions made by the network are close to desirable. To deal with the first issue, we can observe the behavior of the value of the loss function through iterations. If the value of the loss function is decreasing with each iteration, then the neural network still hasn't finished training. Otherwise, if the loss is stable through iterations, the training is completed. The second issue can also be addressed by observing the value of the loss function. The loss should converge to a small value. But also we can directly check the predictions made by the neural network by plotting the predictions and true output and visually evaluating the quality of predictions.

Finally, to verify that the neural network is good at generalizing the underlying dependency between the input and the output and not just learned to map input-output pairs for the training dataset, what is called overfitting [23], we use a separate dataset to evaluate the prediction quality, called the "validation dataset". If the loss on the training data is low but high on the validation data, it means that the neural network is overfitted and some actions are required to overcome this issue.

4.4 Experimental results

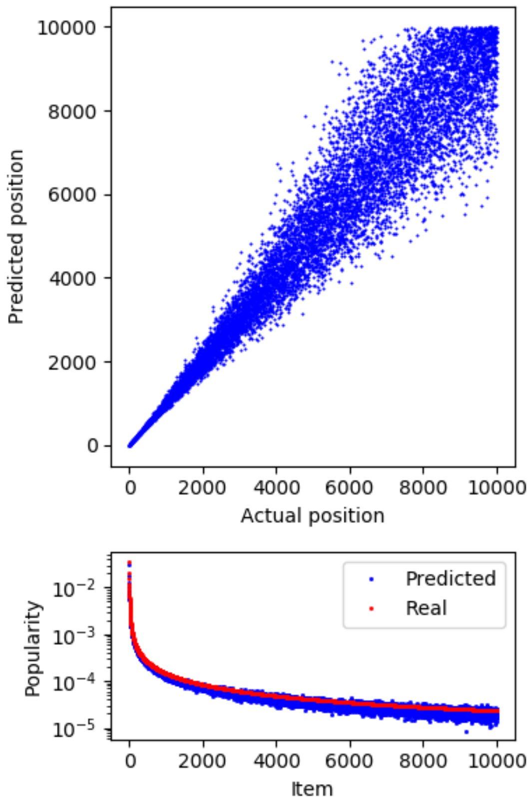
After generating the two synthetic traces with 10000 unique items in both types, with static and nonstatic popularity as described in Section 3.1, 0.8 Zipf's distribution parameter, 20 milliseconds mean time between requests, and 10^7 total requests, we evaluated the performance of the proposed architecture of the neural network. To prepare the data from traces for neural network consumption after the generation of the traces was finished, we generated datasets using a size of the window 10^7 milliseconds. After splitting the datasets into training and validation sets both training and validation loss values converged to small numbers, as you can observe in the Figure 4, which meant that the training is over. In Figure 5 you can see what



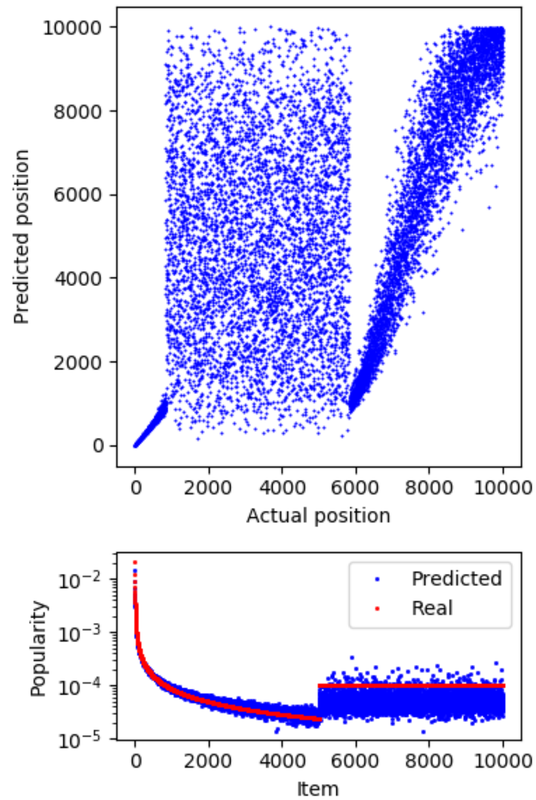
(a) Synthetic trace. Case 1.

(b) Synthetic trace. Case 2.

Figure 4: Evolution of mean squared error through training iterations.



(a) Synthetic trace. Case 1.



(b) Synthetic trace. Case 2.

Figure 5: Evaluation of neural network prediction quality.

prediction neural networks learned to make in both cases of the synthetic traces. Top plots show how the actual ranking of the items according to their popularity compares with the predicted ranking. In the ideal case, values on the x-axis should be equal to values on the y-axis. Bottom plots show how the actual predicted popularity values compare to real popularity values. Blue dots, which represent predicted values, closely follow red dots, which are real popularity values. From this, we can conclude that this architecture of the neural network is suitable for object popularity prediction.

4.5 Adaptation for online scenario

Following the success in the application of a neural network for object popularity predictions, we need to adapt the architecture of the network so it is usable in the online setting, thus the architecture of the neural network is slightly different from the one described in the previous section. In the Figure 6 you can see the proposed usage of the neural network by the policy.

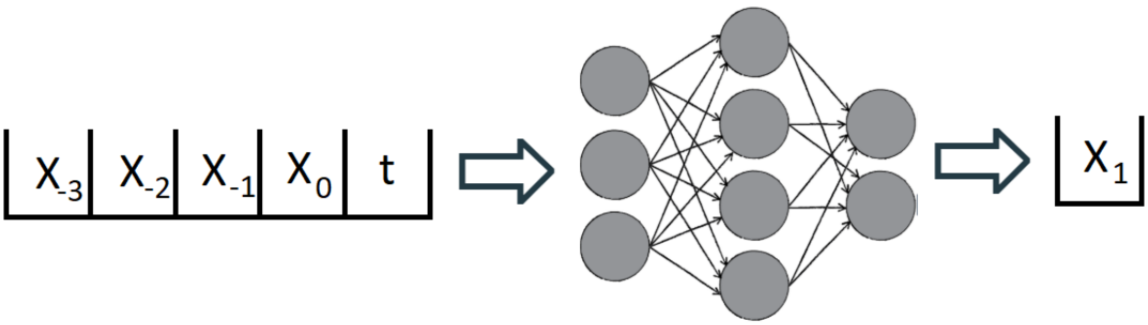


Figure 6: Neural network architecture for caching policy.

- X_{-3} through X_{-1} are popularities of the object in the previous 3 time frames;
- X_0 is the popularity of the object in the current time frame;
- t is the fraction of the current time window that has already passed;
- X_1 is the popularity of the object in the future;

The difference is caused by the nature of the application of caching policies. The policy is working in the real-time thus we cannot operate in the framework of only previous and next time frames. X_0 represents the popularity in the current time frame. But at the beginning of the time frame, the quality of the value X_0 may be low since there will not be enough requests in the time window to estimate the popularity with reasonable accuracy. To help with this issue, we decided to add the parameter t. Using this parameter, the neural network will be able to learn to judge the quality of the parameter X_0 and make better predictions. Further, we will also experiment with different number of prediction windows and trying to add other metadata to improve the accuracy of predictions.

Next, we are going to introduce a caching policy which relies on neural network presented here to make caching decisions.

5 Neural network based caching policy

5.1 Architecture

After we have established the suitable neural network architecture for predicting content popularity, it is time to present a caching policy which is utilizing such network. After each object request, it is possible to construct an input to the neural network, i.e. values X_{-3}, ... , X_0 and t, and obtain the predicted popularity X_1. After the prediction is made, the value X_1 is used to decide if the object should be put in the cache. The policy maintains a priority queue in which the key of each entry is the predicted popularity, and the values are IDs of the objects currently stored in the cache. When a new object is requested, and it has not been stored in the cache, the neural network predicts the popularity of the object in the future - X_1. Then, an object with the smallest predicted popularity is fetched from the priority queue, and its popularity is denoted as X_{old}. If the value X_1 is greater than X_{old}, then the old object is removed from the cache, and the new one is put in its place and into the priority queue. Otherwise, no change occurs.

With this design, a problem may arise - if the prediction of popularity for some object has been calculated to be very high, it may never be removed from the cache since it will never be fetched for replacement. A solution to this problem is to update the priority for a few random objects stored in the cache at each cache hit.

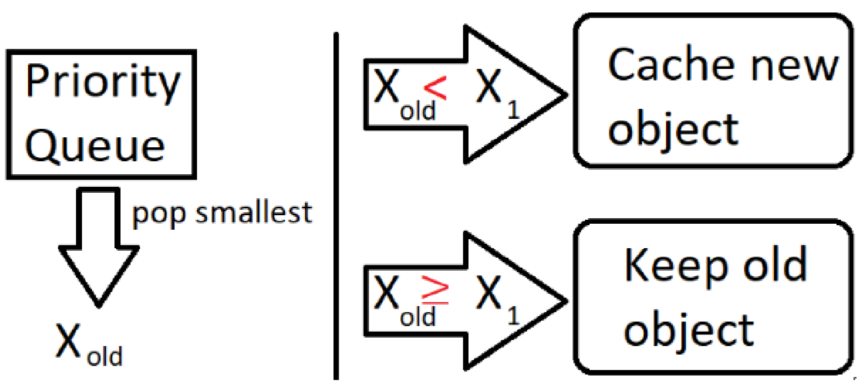


Figure 7: Usage of prediction by the policy.

5.2 Online learning

One of the most important parts of a caching policy is to be able to perform well in different environments with different traffic patterns. That is why it is important to make the policy adaptable. In our case, such adaptability is provided by the ability of the neural network to continuously evolve by training on the newly arrived data. After the end of each time frame, it is possible to generate a new training dataset and use it to train the neural network, possibly asynchronously. But by training only on the latest data, we may encounter the problem of catastrophic forgetting [24, 25]. In short, the issue is that by training only on the latest data the neural network will forget the information about the old underlying relations between input and output even though they still may be relevant for predictions.

To overcome this issue, we incorporate a technique of keeping the training datasets of previous time frames and training the neural network also on them. But since they represent less relevant data, the error, which is backpropagated during the training of the neural network, is scaled down with a parameter α^M, where $0 < \alpha < 1$ and M is the distance from current time frame to previous time frames. In this way, the error on the most recent data will stay unchanged since the value of M is 0. Moving further in the past α^M becomes smaller and the influence of the old data is reduced. When α^M reaches a specific small value called forget threshold, the old training data becomes too irrelevant and can be removed from the memory. Using this approach with the value of $\alpha = 0.5$ and a forget threshold of 0.001 it is required to store training datasets generated only for 10 latest time frames while keeping the predictions made by the neural network accurate and relevant.

5.3 Popularity prediction explained

In the Section 5.1 we were referring to the output of the neural network as predicted popularity and denoted it as X_1. There is a need for a more specific explanation. Using X_1 as the popularity of the object in the next time frame, as in the previous offline case, did not show good performance when evaluating the hit rate on real-world data described in Section 3.2. Figure 8 demonstrates the performance.

The identified problem was that the prediction was made too far in the future. This lead to poor performance in the following two cases:

1. If the object is popular in the current time window but then gets unpopular in the next, it would not be put into the cache, assuming the neural network correctly predicted low popularity in the next time frame. But since the current time window is not finished, and the object is still popular, a lot of cache misses will occur.

2. Conversely, when the object is not popular but then gets popular. This object will take place in the cache even though it is not popular yet.

To resolve this issue, we changed the scope of the value X_1. The desirable performance has been achieved when X_1 represents the popularity in the current time frame but evaluated when the time frame is finished. We would like to emphasize that the value X_0, which is passed as part of the input of the neural network, is not the same as X_1 since X_0 is the immediate evaluated popularity in the current

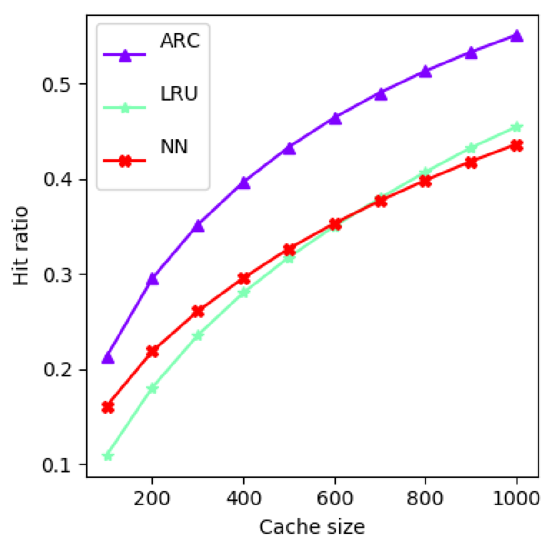
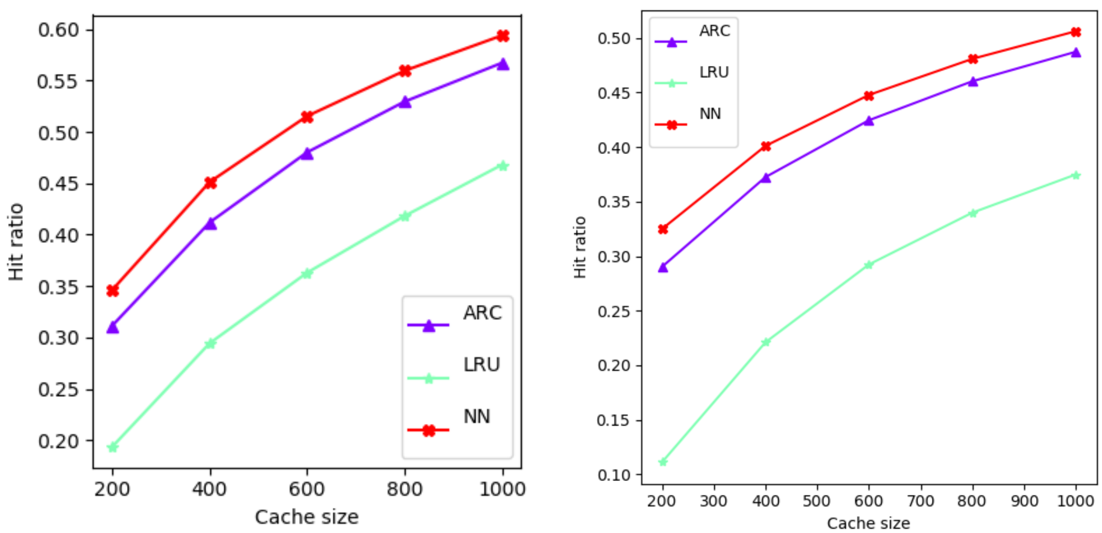


Figure 8: Hit rate evaluation on real-world data for different cache sizes.

time frame while X_1 is evaluated when the current time frame is finished, i.e. in the future. The improved performance is displayed in the Figure 9. Probably it is still possible to improve the performance by fine tuning the parameters.



(a) 5-day trace.

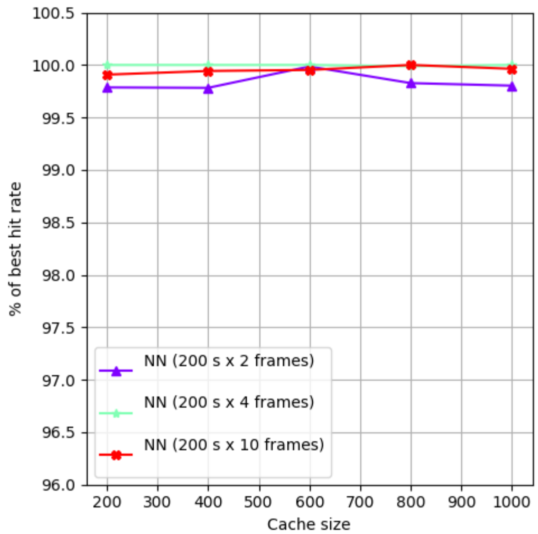
(b) 30-day trace.

Figure 9: Hit rate evaluation on real-world data for different cache sizes after improvements.

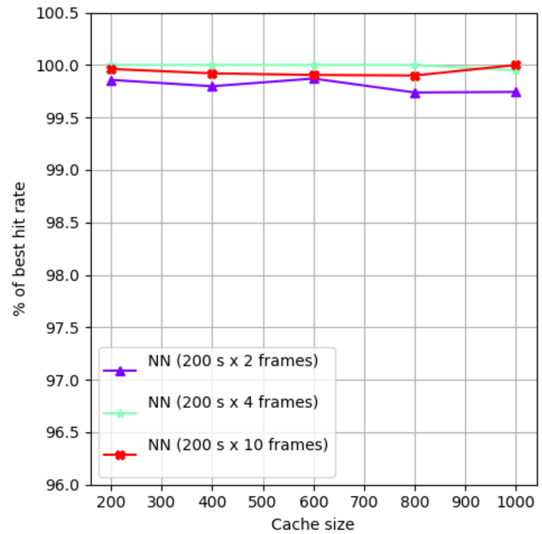
5.4 Parameter selection

In Section 5.3 we have shown that our NN-based caching policy achieves good performance on both of the real traces and overperforms state-of-the-art policy ARC for all cache sizes, as seen in the Figure 9. Parameters there have not been selected carefully. In this section we will explore the optimal way to select the parameters.

The first step we decided to check is the required number of time windows. To establish this experiment, we have fixed the length of the time frame at the value of 200 seconds and tested three configurations: 1) 2 time frames (previous + current), 2) 4 time frames (3 previous + current) and 2) 10 time frames (9 previous + current).



(a) 5-day trace.



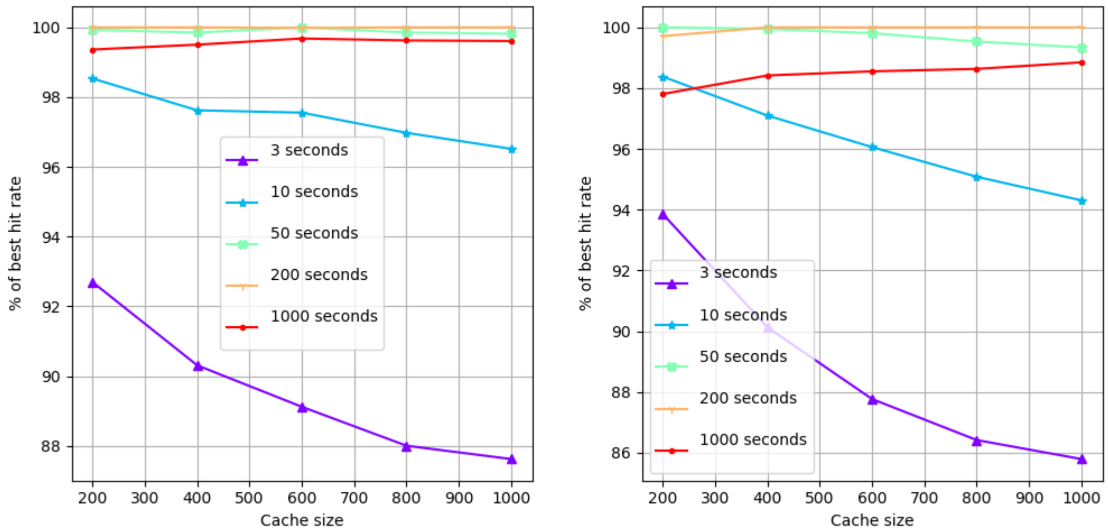
(b) 30-day trace.

Figure 10: Comparison of hit rates obtained by evaluating proposed policy on real-world traces with fixed time frame size and different number of frames.

The results of the experiment can be seen in the Figure 10. As seen in the figure, the 10-frame curve and 4-frame curve closely follow each other while 2-frame curve trails a little behind. From this, we can conclude that it is enough to use 4 time frames for popularity predictions and there is no point in increasing this number since the improvement in performance not present or negligible. There is also no point in decreasing the number of frames since the performance in terms of hit rate is decreased.

Following this, we have to determine the optimal way to select the length of the time frame. We have established an experiment trying to evaluate this value. We will fix the number of windows to be 4 and test different configurations of time window size with cache sizes:

- Time frame sizes: 3 s, 10 s, 50 s, 200 s, 1000 s.
- Cache sizes: 200, 400, 600, 800, 1000.



(a) 5-day trace.

(b) 30-day trace.

Figure 11: Comparison of hit rates obtained using modifications of the proposed policy with different sizes of time frame.

- Trace length: first 50 000 000 requests from both real traces.

The experiment showed that the size of the window has a stronger influence on the performance than the number of windows. For both traces, the size of 200 s showed the best performance for all cache sizes with the exception of cache size 200 on the 30-day trace, as you can observe on the Figure 11. The figure shows the ratio between the hit ratio of the best performing time frame size and all of the others. From this, we can propose a rule of thumb for selecting the size of the time frame for the policy. It is reasonable to assume that the lower the request rate the higher the size of the time frame should be, since with fixed length of the time frame and decreasing request rate the accuracy of the estimation of the popularity of the objects also decreases. Both traces have approximately 900 requests/s request rate and show the best performance at the size of the window of 200 s. Thus, the rule of thumb is to select the size of the window such that the next equation holds true:

$$frame\_size * request\_rate \approx 180000$$

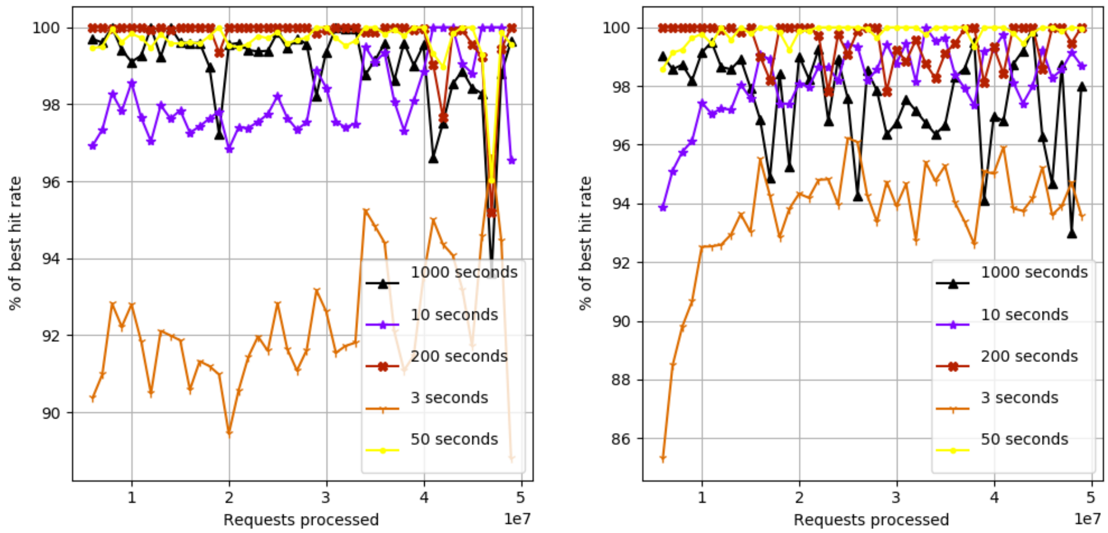
.

Another point to notice can be observed from Figure 11 (b). As the cache size increases, the 50 second time frame policy is on the downward trend while 1000 second time frame is on the upward trend. From this, we can conclude that the available size of the cache also should be accounted for when selecting the time frame size.

We are not claiming that the proposed rule is the best way to select the size of the time frame since in all cases the performance of the 50 second frame size was very close to the best performing size of 200 seconds, even overperforming it in one case but following the provided rule of thumb should give close to optimal results.

5.5 Perspective improvements

Examining the cumulative hit rate revealed that the time frame size of 200 seconds performed the best. But studying closely the immediate hit rate, i. e. evaluating the hit rate after each million of requests rather than the total hit rate, revealed some interesting behavior. Figure 12 shows the ratio between the best-performing policy modification and other modifications evaluating immediate hit rate as described before for both of the real traces and cache size of 200. The figure reveals that the best-performing cumulatively time frame size does not perform the best at each point in time of the traces. At some segments of the traces, the 50 second size performs the best, what could be expected since this size was very close to the best-performing in all tests, but at some segments the size of 10 seconds performed the best. Examining the segments of the traces on which the size of 10 seconds performed the best revealed that the rate of requests was very high which allowed the 10 second modification to estimate the popularity of the objects with high accuracy while being the fastest to adapt to the changes since it naturally follows from the smaller size of the time frame. Such behavior suggests that possibly it is better to



(a) 5-day trace.

(b) 30-day trace.

Figure 12: Comparison of immediate cache hit ratio for different time frame sizes.

reject the concept of time-based time frames and switch to request count-based time frames, i. e. the time frame will not span a fixed amount of time but a fixed number of requests. Such an approach should remove the dependence on the request rate of the request trace and could allow simplifying the parameter selection for the policy. But in the report, we will not touch such a modification and leave it for the future research.

We also tried improving the quality of predictions made by the neural network by passing as input some metadata alongside with the popularity in previous time frames, in our case, they were the size of the object and the time of the day, but they did not improve the performance of the policy. However, the approach of adding metadata to the input of the neural network should not be discarded. It is possible that some other metadata could improve the quality of predictions and the performance of the caching policy as consequence but search for such metadata is left for future research.

5.6 Computational and memory cost

Having figured out the optimal way for parameter selection, we can now evaluate the computational cost and memory footprint introduced by our solution.

We will start with the analysis of the memory footprint. In Section 4.2 we have discussed the architecture of the neural network. We chose the architecture with 4 neurons in the input layer, this choice has been confirmed to be optimal in Section 5.4, 2 hidden layers with 128 neurons in each and 1 neuron in the output layer. Adding to this an extra neuron to the input layer which takes the time fraction of the current time frame, discussed in Section 4.5, and an extra bias neuron for each layer except the output brings the total number of connections between layers to be:

$$6 * 129 + 129 * 129 + 129 * 1 = 17544$$

Assuming the connections are represented as double-precision floating point numbers, brings the total memory footprint of the neural network to be:

$$17544 * 8 = 140352 \text{ bytes } \approx 140 \text{ kB}$$

The policy also requires to keep track of popularity, i.e. number of requests, for each object. Assuming worst case scenario, each request in the time window is a unique object, using recommended parameters brings the total number of requests in a time frame to be around 180000. Counter for each item is assumed to consume 12 bytes, 8 bytes ID and 4 bytes counter itself. This gives a per-window memory footprint of:

$$180000 * 12 = 2160000 \text{ bytes } = 2160 \text{ kB}$$

Accounting for 4 to be recommended number of windows, brings the total memory footprint for keeping track for content popularity to be:

$$2160 * 4 = 8640 \text{ kB}$$

Finally, to train the neural network the policy requires to keep training datasets for last 10 windows, as explained in section 5.2. Each row of the dataset has 6 floating point numbers, amounting to 48 bytes per row. One request adds a row to the dataset, thus the memory footprint of keeping training datasets in memory:

$$10 * 180000 * 48 = 86400000 \text{ bytes } = 86400 \text{ kB}$$

Adding to this the requirement to maintain a priority queue, which consumes $16 * C$ bytes, brings the total memory footprint to be:

$$140 \text{ kB } + 8640 \text{ kB } + 86400 \text{ kB } + 16 * C \text{ B } = 95180 \text{ kB } + 16 * CB$$

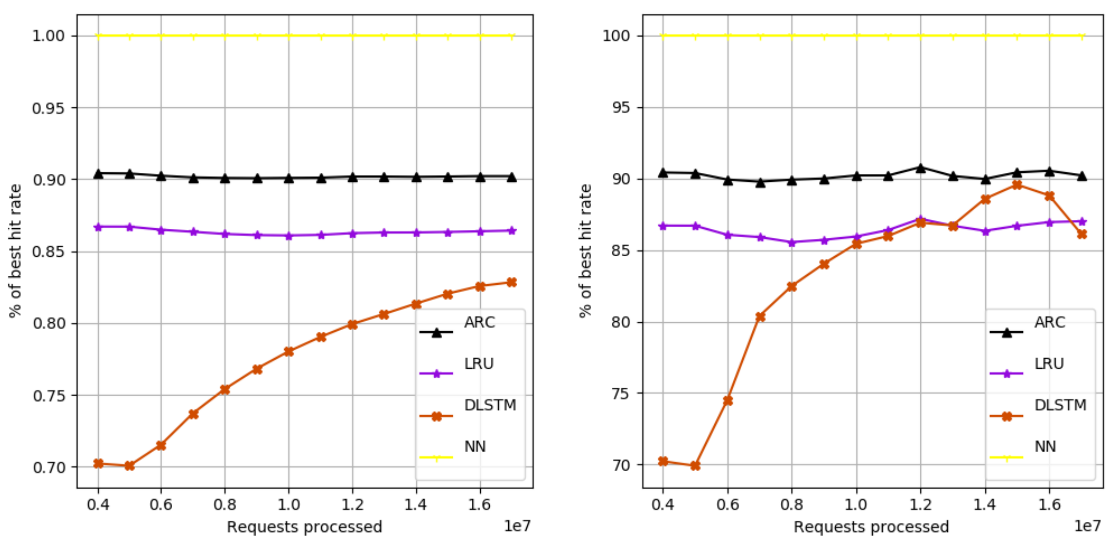
This number can be further decreased by switching to single-precision floating point numbers. In this way, the contribution of the highest contributing member to the total footprint would be halved.

Moving on with the calculation of the computational cost, we have proposed fixed values for each of the performance-influencing variables. Thus, only the size of the cache is the influencing factor to the time complexity. Cache size influences only the performance of the priority queue, thus, the time complexity is $O(\log C)$, but with a much larger constant than in case of ARC or LRU. If we assume that the architecture of the neural network is also variable, we need to account for matrix multiplication involved in input propagation through the neural network. This adds roughly $O(n^3)$ to the time complexity, where n is the number of neurons in the largest layer of the network, bringing the total complexity to be

$$O(\log C + n^3)$$

5.7 Comparison with other proposed solutions

We have shown before that our proposed caching policy overperform well established and frequently used policy LRU and industry leader policy ARC by close to 12% and 3% in absolute cache hit ratio and by 75-25% and 11-5% in relative cache hit ratio (depending on cache size) respectfully. But, as mentioned before, there are some proposed policies which also rely on machine learning algorithms for caching purposes. We have selected the approach proposed in [14] to compare with the method proposed by us. As explained before, the policy proposed in [14] applies deep long short-term memory network to determine the caching priority and decide which objects to store/remove in/from the cache. We have implemented the policy using the PyTorch library, which was also used to implement the neural network in our approach. DLSTM approach deals with a fixed number of items, so we filtered the 5-day trace to contain only 300000 most popular objects. After selecting the parameters of the policy as proposed by the author of [14], we evaluated the hit rate on our filtered trace. The produced hit rate values were less than 1%. Probably, poor performance is caused by the inability of the neural network to tune all of its weights without a substantial number of iterations which is impossible to achieve while keeping performance suitable for the online task. And one-hot encoding utilized by DLSTM policy keeps the number of weights very high ($4.6 * 10^6$ weights between second hidden and output layers) increasing the impact of the problem. We reduced the number of unique items to 1000 and repeated the experiment, now with



(a) % of cumulative hit rate.

(b) % of immediate hit rate.

Figure 13: Comparison of performance of DLSTM policy with other policies on 5-day trace.

a better result shown in the Figure 13. The policy is showing some promise as can be seen by the upward trend in the cumulative cache hit ratio but the slow speed of adaptation at the first half of the trace caused a lower final cache hit ratio than achieved by ARC or our approach. Adding the disadvantage of a limited number of unique items to the slow adaptation speed of DLSTM policy we can claim that our approach is superior to the one proposed in [14].

6 Conclusions

In the report, we have explored the topic of application of machine learning algorithms for caching purposes. We have reviewed the work done in the field, including recently proposed approaches for constructing a caching policy, established solutions and industry-leading policies. We continued by discussing the data which is required to conduct experiments and moved to a discussion of the applicability of feedforward neural networks for object popularity prediction. We proposed an architecture of a neural network which is suitable for this task. Based on the proposed architecture of the neural network we introduced a new caching policy. We evaluated the performance of the proposed caching policy on real-world data using the cache hit rate metric and achieved the performance higher than with any other solution. Then we discussed the optimal ways to configure the proposed policy and designed a rule of thumb for easy policy tuning. We continued by proposing further development of the policy and finished with a comparison of our approach to the one proposed by another research team. Our policy showed better performance in all tests.

Overall, the proposed solution improves over established policies and based on the performance shown can be considered as a future industry standard.

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