Selection in Scale-Free Small World

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Abstract

In this paper we compare the performance characteristics of our selection based learning algorithm for Web crawlers with the characteristics of the reinforcement learning algorithm. The task of the crawlers is to find new information on the Web. The selection algorithm, called weblog update, modifies the starting URL lists of our crawlers based on the found URLs containing new information. The reinforcement learning algorithm modifies the URL orderings of the crawlers based on the received reinforcements for submitted documents. We performed simulations based on data collected from the Web. The collected portion of the Web is typical and exhibits scale-free small world (SFSW) structure. We have found that on this SFSW, the weblog update algorithm performs better than the reinforcement learning algorithm. It finds the new information faster than the reinforcement learning algorithm and has better new information/all submitted documents ratio. We believe that the advantages of the selection algorithm over reinforcement learning algorithm is due to the small world property of the Web.

1 Introduction

The largest source of information today is the World Wide Web. The estimated number of documents nears 10 billion. Similarly, the number of documents changing on a daily basis is also enormous. The ever-increasing growth of the Web presents a considerable challenge in finding novel information on the Web.

In addition, properties of the Web, like scale-free small world (SFSW) structure \cite{1,12} may create additional challenges. For example the direct consequence of the scale-free small world property is that there are numerous URLs or sets of interlinked URLs, which have a large number of incoming links. Intelligent web crawlers can be easily trapped at the neighborhood of such junctions as it has been shown previously \cite{13,15}.

We have developed a novel artificial life (A-life) method with intelligent individuals, crawlers, to detect new information on a news Web site. We define A-life as

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a population of individuals having both static structural properties, and structural
properties which may undergo continuous changes, i.e., adaptation. Our algorithms
are based on methods developed for different areas of artificial intelligence, such as
evolutionary computing, artificial neural networks and reinforcement learning. All ef-
forts were made to keep the applied algorithms as simple as possible subject to the
constraints of the internet search.

Evolutionary computing deals with properties that may be modified during the cre-
atation of new individuals, called ‘multiplication’. Descendants may exhibit variations
of population, and differ in performance from the others. Individuals may also termi-
nate. Multiplication and selection is subject to the fitness of individuals, where fitness
is typically defined by the modeler. For a recent review on evolutionary computing, see
[7]. For reviews on related evolutionary theories and the dynamics of self-modifying
systems see [8, 11] and [11, 13], respectively. Similar concepts have been studied in other
evolutionary systems where organisms compete for space and resources and cooperate
through direct interaction (see, e.g., [19] and references therein.)

Selection, however, is a very slow process and individual adaptation may be neces-
sary in environments subject to quick changes. The typical form of adaptive learning
is the connectionist architecture, such as artificial neural networks. Multilayer percep-
trons (MLPs), which are universal function approximators have been used widely in
diverse applications. Evolutionary selection of adapting MLPs has been in the focus
of extensive research [32, 33].

In a typical reinforcement learning (RL) problem the learning process [27] is mo-
tivated by the expected value of long-term cumulated profit. A well-known example
of reinforcement learning is the TD-Gammon program of Tesaurio [29]. The author
applied MLP function approximators for value estimation. Reinforcement learning has
also been used in concurrent multi-robot learning, where robots had to learn to forage
together via direct interaction [16]. Evolutionary learning has been used within the
framework of reinforcement learning to improve decision making, i.e., the state-action
mapping called policy [25, 18, 30, 14].

In this paper we present a selection based algorithm and compare it to the well-
known reinforcement learning algorithm in terms of their efficiency and behavior. In
our problem, fitness is not determined by us, but fitness is implicit. Fitness is jointly
determined by the ever changing external world and by the competing individuals
together. Selection and multiplication of individuals are based on their fitness value.
Communication and competition among our crawlers are indirect. Only the first sub-
mitter of a document may receive positive reinforcement. Our work is different from
other studies using combinations of genetic, evolutionary, function approximation, and
reinforcement learning algorithms, in that i) it does not require explicit fitness func-
tion, ii) we do not have control over the environment, iii) collaborating individuals
use value estimation under ‘evolutionary pressure’, and iv) individuals work without
direct interaction with each other.

We performed realistic simulations based on data collected during an 18 days long
crawl on the Web. We have found that our selection based weblog update algorithm
performs better in scale-free small world environment than the RL algorithm, even-
though the reinforcement learning algorithm has been shown to be efficient in finding
relevant information [19, 21]. We explain our results based on the different behaviors of
the algorithms. That is, the weblog update algorithm finds the good relevant document
sources and remains at these regions until better places are found by chance. Individu-
als using this selection algorithm are able to quickly collect the new relevant documents
from the already known places because they monitor these places continuously. The
reinforcement learning algorithm explores new territories for relevant documents and if it finds a good place then it collects the existing relevant documents from there. The continuous exploration of RL causes that it finds relevant documents slower than the weblog update algorithm. Also, crawlers using weblog update algorithm submit more different documents than crawlers using the RL algorithm. Therefore there are more relevant new information among documents submitted by former than latter crawlers.

The paper is organized as follows. In Section 2 we review recent works in the field of Web crawling. Then we describe our algorithms and the forager architecture in Section 3. After that in Section 4 we present our experiment on the Web and the conducted simulations with the results. In Section 5 we discuss our results on the found different behaviors of the selection and reinforcement learning algorithms. Section 6 concludes our paper.

## 2 Related work

Our work concerns a realistic Web environment and search algorithms over this environment. We compare selective/evolutionary and reinforcement learning methods. It seems to us that such studies should be conducted in ever changing, buzzing, wabbling environments, which justifies our choice of the environment. We shall review several of the known search tools including those [13, 15] that our work is based upon. Readers familiar with search tools utilized on the Web may wish to skip this section.

There are three main problems that have been studied in the context of crawlers. Rungswang et al. [23] and references therein and Menczer [17] studied the topic specific crawlers. Risvik et al. [22] and references therein address research issues related to the exponential growth of the Web. Cho and Gracia-Molina [3], Menczer [17] and Edwards et. al [6] and references therein studies the problem of different refresh rates of URLs (possibly as high as hourly or as low as yearly).

Rungswang and Angkawattanawit [23] provide an introduction to and a broad overview of topic specific crawlers (see citations in the paper). They propose to learn starting URLs, topic keywords and URL ordering through consecutive crawling attempts. They show that the learning of starting URLs and the use of consecutive crawling attempts can increase the efficiency of the crawlers. The used heuristic is similar to the weblog algorithm [9], which also finds good starting URLs and periodically restarts the crawling from the newly learned ones. The main limitation of this work is that it is incapable of addressing the freshness (i.e., modification) of already visited Web pages.

Menczer [17] describes some disadvantages of current Web search engines on the dynamic Web, e.g., the low ratio of fresh or relevant documents. He proposes to complement the search engines with intelligent crawlers, or web mining agents to overcome those disadvantages. Search engines take static snapshots of the Web with relatively large time intervals between two snapshots. Intelligent web mining agents are different: they can find online the required recent information and may evolve intelligent behavior by exploiting the Web linkage and textual information.

He introduces the InfoSpider architecture that uses genetic algorithm and reinforcement learning, also describes the MySpider implementation of it. Menczer discusses the difficulties of evaluating online query driven crawler agents. The main problem is that the whole set of relevant documents for any given query are unknown, only a subset of the relevant documents may be known. To solve this problem he introduces two new metrics that estimate the real recall and precision based on an available sub-
set of the relevant documents. With these metrics search engine and online crawler performances can be compared. Starting the MySpider agent from the 100 top pages of AltaVista the agent’s precision is better than AltaVista’s precision even during the first few steps of the agent.

The fact that the MySpider agent finds relevant pages in the first few steps may make it deployable on users’ computers. Some problems may arise from this kind of agent usage. First of all there are security issues, like which files or information sources are allowed to read and write for the agent. The run time of the agents should be controlled carefully because there can be many users (Google answered more than 100 million searches per day in January-February 2001) using these agents, thus creating huge traffic overhead on the Internet.

Our weblog algorithm uses local selection for finding good starting URLs for searches, thus not depending on any search engines. Dependence on a search engine can be a suffer limitation of most existing search agents, like MySpiders. Note however, that it is an easy matter to combine the present algorithm with URLs offered by search engines. Also our algorithm should not run on individual user’s computers. Rather it should run for different topics near to the source of the documents in the given topic – e.g., may run at the actual site where relevant information is stored.

Risvik and Michelsen [22] mention that because of the exponential growth of the Web there is an ever increasing need for more intelligent, (topic-)specific algorithms for crawling, like focused crawling and document classification. With these algorithms crawlers and search engines can operate more efficiently in a topically limited document space. The authors also state that in such vertical regions the dynamics of the Web pages is more homogenous.

They overview different dimensions of web dynamics and show the arising problems in a search engine model. They show that the problem of rapid growth of Web and frequent document updates creates new challenges for developing more and more efficient Web search engines. The authors define a reference search engine model having three main components: (1) crawler, (2) indexer, (3) searcher. The main part of the paper focuses on the problems that crawlers need to overcome on the dynamic Web. As a possible solution the authors propose a heterogenous crawling architecture. They also present an extensible indexer and searcher architecture. The crawling architecture has a central distributor that knows which crawler has to crawl which part of the web. Special crawlers with low storage and high processing capacity are dedicated to web regions where content changes rapidly (like news sites). These crawlers maintain up-to-date information on these rapidly changing Web pages.

The main limitation of their crawling architecture is that they must divide the web to be crawled into distinct portions manually before the crawling starts. A weblog like distributed algorithm – as suggested here – may be used in that architecture to overcome this limitation.

Cho and Garcia-Molina [3] define mathematically the freshness and age of documents of search engines. They propose the Poisson process as a model for page refreshment. The authors also propose various refresh policies and study their effectiveness both theoretically and on real data. They present the optimal refresh policies for their freshness and age metrics under the Poisson page refresh model. The authors show that these policies are superior to others on real data, too.

They collected about 720000 documents from 270 sites. Although they show that in their database more than 20 percent of the documents are changed each day, they disclosed these documents from their studies. Their crawler visited the documents once each day for 5 months, thus can not measure the exact change rate of those
documents. While in our work we definitely concentrate on these frequently changing documents.

The proposed refresh policies require good estimation of the refresh rate for each document. The estimation influences the revisit frequency while the revisit frequency influences the estimation. Our algorithm does not need explicit frequency estimations. The more valuable URLs (e.g., more frequently changing) will be visited more often and if a crawler does not find valuable information around an URL being in it's weblog then that URL finally will fall out from the weblog of the crawler. However frequency estimations and refresh policies can be easily integrated into the weblog algorithm selecting the starting URL from the weblog according to the refresh policy and weighting each URL in the weblog according to their change frequency estimations.

Menczer [17] also introduces a recency metric which is 1 if all of the documents are recent (i.e., not changed after the last download) and goes to 0 as downloaded documents are getting more and more obsolete. Trivially immediately after a few minutes run of an online crawler the value of this metric will be 1, while the value for the search engine will be lower.

Edwards et al. [6] present a mathematical crawler model in which the number of obsolete pages can be minimized with a nonlinear equation system. They solved the nonlinear equations with different parameter settings on realistic model data. Their model uses different buckets for documents having different change rates therefore does not need any theoretical model about the change rate of pages. The main limitations of this work are the following:

• by solving the nonlinear equations the content of web pages can not be taken into consideration. The model can not be extended easily to (topic-)specific crawlers, which would be highly advantageous on the exponentially growing web [23], [22].

• the rapidly changing documents (like on news sites) are not considered to be in any bucket, therefore increasingly important parts of the web are disclosed from the searches.

However the main conclusion of the paper is that there may exist some efficient strategy for incremental crawlers for reducing the number of obsolete pages without the need for any theoretical model about the change rate of pages.

3 Forager architecture

There are two different kinds of agents: the foragers and the reinforcing agent (RA). The fleet of foragers crawl the web and send the URLs of the selected documents to the reinforcing agent. The RA determines which forager should work for the RA and how long a forager should work. The RA sends reinforcements to the foragers based on the received URLs.

We employ a fleet of foragers to study the competition among individual foragers. The fleet of foragers allows to distribute the load of the searching task among different computers. A forager has simple, limited capabilities, like limited number of starting URLs and a simple, content based URL ordering. The foragers compete with each other for finding the most relevant documents. In this way they efficiently and quickly collect new relevant documents without direct interaction.

At first the basic algorithms are presented. After that the reinforcing agent and the foragers are detailed.
3.1 Algorithms

3.1.1 Weblog algorithm and starting URL selection

A forager periodically restarts from a URL randomly selected from the list of starting URLs. The sequence of visited URLs between two restarts forms a path. The starting URL list is formed from the $\text{START\_SIZE} = 10$ first URLs of the weblog. In the weblog there are $\text{WEBLOG\_SIZE} = 100$ URLs with their associated weblog values in descending order. The weblog value of a URL estimates the expected sum of rewards during a path after visiting that URL. The weblog update algorithm modifies the weblog before a new path is started (Algorithm 1). The weblog value of a URL already in the weblog is modified toward the sum of rewards in the remaining part of the path after that URL. A new URL has the value of actual sum of rewards in the remaining part of the path. If a URL has a high weblog value it means that around that URL there are many relevant documents. Therefore it may worth it to start a search from that URL.

Algorithm 1 Weblog Update. $\beta$ was set to 0.3

input
visitedURLs ← the steps of the given path
values ← the sum of rewards for each step in the given path
output
starting URL list
method
cumValues ← cumulated sum of values in reverse order
newURLs ← visitedURLs not having value in weblog
revisitedURLs ← visitedURLs having value in weblog
for each URL ∈ newURLs
    weblog(URL) ← cumValues(URL)
endfor
for each URL ∈ revisitedURLs
    weblog(URL) ← $(1 - \beta) \text{weblog}(URL) + \beta \text{cumValues}(URL)$
endfor
weblog ← descending order of values in weblog
weblog ← truncate weblog after the $\text{WEBLOG\_SIZE}^{\text{th}}$ element
starting URL list ← first $\text{START\_SIZE}$ elements of weblog

Without the weblog algorithm the weblog and thus the starting URL list remains the same throughout the searches. The weblog algorithm is a very simple version of evolutionary algorithms. Here, evolution may occur at two different levels: the list of URLs of the forager is evolving by the reordering of the weblog. Also, a forager may multiply, and its weblog, or part of it may spread through inheritance. This way, the weblog algorithm incorporates most basic features of evolutionary algorithms. This
simple form shall be satisfactory to demonstrate our statements.

### 3.1.2 Reinforcement Learning and URL ordering

A forager can modify its URL ordering based on the received reinforcements of the sent URLs. The (immediate) profit is the difference of received rewards and penalties at any given step. Immediate profit is a myopic characterization of a step to a URL. Foragers have an adaptive continuous value estimator and follow the *policy* that maximizes the expected long term cumulated profit (LTP) instead of the immediate profit. Such estimators can be easily realized in neural systems \[24, 28, 24\]. Policy and profit estimation are interlinked concepts: profit estimation determines the policy, whereas policy influences choices and, in turn, the expected LTP. (For a review, see \[27\].) Here, choices are based on the greedy LTP policy: The forager visits the URL, which belongs to the frontier (the list of linked but not yet visited URLs, see later) and has the highest estimated LTP.

In the particular simulation each forager has a \(k (= 50)\) dimensional probabilistic term-frequency inverse document-frequency (PrTFIDF) text classifier \[10\], generated on a previously downloaded portion of the Geocities database. Fifty clusters were created by Boley’s clustering algorithm \[2\] from the downloaded documents. The PrTFIDF classifiers were trained on these clusters plus an additional one, the \((k+1)_{th}\) representing general texts from the internet. The PrTFIDF outputs were non-linearly mapped to the interval \([-1,+1]\) by a hyperbolic-tangent function. The classifier was applied to reduce the texts to a small dimensional representation. The output vector of the classifier for the page of URL \(A\) is \(\text{state}(A) = (\text{state}(A)_1, \ldots, \text{state}(A)_k)\). (The \((k+1)_{th}\) output was dismissed.) This output vector is stored for each URL (Algorithm 2).

#### Algorithm 2 Page Information Storage

| input  | \(pageURLs\) ← URLs of pages to be stored |
| output | \(state\) ← the classifier output vectors for pages of \(pageURLs\) |
| method | for each \(URL \in pageURLs\)  
|        | \(page \leftarrow\) text of page of \(URL\)  
|        | \(state(URL) \leftarrow\) classifier output vector for \(page\)  
| endfor |

A linear function approximator is used for LTP estimation. It encompasses \(k\) parameters, the *weight vector* \(\text{weight} = (\text{weight}_1, \ldots, \text{weight}_k)\). The LTP of document of URL \(A\) is estimated as the scalar product of \(\text{state}(A)\) and \(\text{weight}: \text{value}(A) = \sum_{i=1}^{k} \text{weight}_i \text{state}(A)_i\). During URL ordering the URL with highest LTP estimation is selected. The URL ordering algorithm is shown in Algorithm 3.

The weight vector of each forager is tuned by Temporal Difference Learning \[26, 28, 24\]. Let us denote the current URL by \(URL_n\), the next URL to be visited by
Algorithm 3 URL Ordering

input
  \[\text{frontier} \leftarrow \text{the set of available URLs}\]
  \[\text{state} \leftarrow \text{the stored vector representation of the URLs}\]
output
  \[\text{bestURL} \leftarrow \text{URL with maximum LTP value}\]
method
  for each \(\text{URL} \in \text{frontier}\)
    \[\text{value}(\text{URL}) \leftarrow \sum_{i=1}^{k} \text{weight}_i \text{state}(\text{URL})_i\]
endfor
  \[\text{bestURL} \leftarrow \text{URL with maximal LTP value}\]

\(URL_{n+1}\), the output of the classifier for \(URL_j\) by \(\text{state}(URL_j)\) and the estimated LTP of a URL \(URL_j\) by \(\text{value}(URL_j) = \sum_{i=1}^{k} \text{weight}_i \text{state}(URL_j)_i\). Assume that leaving \(URL_n\) to \(URL_{n+1}\) the immediate profit is \(r_{n+1}\). Our estimation is perfect if \(\text{value}(URL_n) = \text{value}(URL_{n+1}) + r_{n+1}\). Future profits are typically discounted in such estimations as \(\text{value}(URL_n) = \gamma \text{value}(URL_{n+1}) + r_{n+1}\), where \(0 < \gamma < 1\). The error of value estimation is

\[\delta(n, n + 1) = r_{n+1} + \gamma \text{value}(URL_{n+1}) - \text{value}(URL_n).\]

We used throughout the simulations \(\gamma = 0.9\). For each step \(URL_n \rightarrow URL_{n+1}\) the weights of the value function were tuned to decrease the error of value estimation based on the received immediate profit \(r_{n+1}\). The \(\delta(n, n + 1)\) estimation error was used to correct the parameters. The \(i^{th}\) component of the weight vector, \(\text{weight}_i\), was corrected by

\[\Delta \text{weight}_i = \alpha \delta(n, n + 1) \text{state}(URL_n)_i\]

with \(\alpha = 0.1\) and \(i = 1, \ldots, k\). These modified weights in a stationary environment would improve value estimation (see, e.g., [27] and references therein). The URL ordering update is given in Algorithm 4.

Without the update algorithm the weight vector remains the same throughout the search.

3.1.3 Document relevancy

A document or page is possibly relevant for a forager if it is not older than 24 hours and the forager has not marked it previously. Algorithm 5 shows the procedure of selecting such documents. The selected documents are sent to the RA for further evaluation.

3.1.4 Multiplication of a forager

During multiplication the weblog is randomly divided into two equal sized parts (one for the original and one for the new forager). The parameters of the URL ordering
Algorithm 4 URL Ordering Update

input
  $URL_{n+1}$ ← the step for which the reinforcement is received
  $URL_n$ ← the previous step before $URL_{n+1}$
  $r_{n+1}$ ← reinforcement for visiting $URL_{n+1}$
output
  weight ← the updated weight vector
method
  $\delta(n, n+1) ← r_{n+1} + \gamma\text{value}(URL_{n+1}) - \text{value}(URL_n)$
  weight ← weight $+ \alpha \delta(n, n+1) \text{state}(URL_n)$

Algorithm 5 Document Relevancy at a forager

input
  pages ← the pages to be examined
output
  relevantPages ← the selected pages
method
  previousPages ← previously selected relevant pages
  relevantPages ← all pages from pages which are
  not older than 24 hours and
  not contained in previousPages
  previousPages ← add relevantPages to previousPages

algorithm (the weight vector of the value estimation) are either copied or new random parameters are generated. If the forager has a URL ordering update algorithm then the parameters are copied. If the forager does not have any URL ordering update algorithm then new random parameters are generated, as shown in Algorithm 6.

3.2 Reinforcing agent

A reinforcing agent controls the "life" of foragers. It can start, stop, multiply or delete foragers. RA receives the URLs of documents selected by the forager, and responds with reinforcements for the received URLs. The response is $REWARD = 100$ (a.u.) for a relevant document and $PENALTY = -1$ (a.u.) for a not relevant document. A document is relevant if it is not yet seen by the reinforcing agent and it is not older than 24 hours. The reinforcing agent maintains the score of each forager working for it. Initially each forager has $INIT\_SCORE = 100$ score. When a forager sends a URL to the RA, the forager’s score is decreased by $SCORE^- = 0.05$. After each relevant page sent by the forager, the forager’s score is increased by $SCORE^+ = 1$ (Algorithm 6).
Algorithm 6 Multiplication

input
   weblog
   weight vector of URL ordering
output
   newWeblog
   newWeight
method
   newWeblog ← WEBLOG_SIZE/2 randomly selected URLs and values from weblog
   weblog ← delete newWeblog from weblog
   if forager has URL ordering update algorithm
      newWeight ← copy the weight vector of URL ordering
   else
      newWeight ← generate a new random weight vector
   endif

When the forager’s score reaches MAX_SCORE = 200 and the number of foragers is smaller than MAX_FORAGER = 16 then the forager is multiplied. That is a new forager is created with the same algorithms as the original one has, but with slightly different parameters. When the forager’s score goes below MIN_SCORE = 0 and the number of foragers is larger than MIN_FORAGER = 2 then the forager is deleted (Algorithm 8). Note that a forager can be multiplied or deleted immediately after it has been stopped by the RA and before the next forager is activated.

Foragers on the same computer are working in time slices one after each other. Each forager works for some amount of time determined by the RA. Then the RA stops that forager and starts the next one selected by the RA. The pseudo-code of the reinforcing agent is given in Algorithm 9.

3.3 Foragers

A forager is initialized with parameters defining the URL ordering, and either with a weblog or with a seed of URLs (Algorithm 10). After its initialization a forager crawls in search paths, that is after a given number of steps the search restarts and the steps between two restarts form a path. During each path the forager takes MAX_STEP = 100 number of steps, i.e., selects the next URL to be visited with a URL ordering algorithm. At the beginning of a path a URL is selected randomly from the starting URL list. This list is formed from the 10 first URLs of the weblog. The weblog contains the possibly good starting URLs with their associated weblog values in descending order. The weblog algorithm modifies the weblog and so thus the starting URL list before a new path is started. When a forager is restarted by the RA, after the RA has stopped it, the forager continues from the internal state in which it was stopped. The pseudo code of step selection is given in Algorithm 11.

The URL ordering algorithm selects a URL to be the next step from the frontier
Algorithm 7 Manage Received URL

input
URL, forager ← received URL from forager
output
reinforcement to forager
updated forager score
method
relevants ← relevant pages seen by the RA
page ← get page of URL
decrease forager’s score with SCORE−
if page ∈ relevants or page date is older than 24 hours
   send PENALTY to forager
else
   relevants ← add page to relevants
   send REWARD to forager
   increase forager’s score with SCORE+
endif

URL set. The selected URL is removed from the frontier and added to the visited URL set to avoid loops. After downloading the pages, only those URLs (linked from the visited URL) are added to the frontier which are not in the visited set.

In each step the forager downloads the page of the selected URL and all of the pages linked from the page of selected URL. It sends the URLs of the possibly relevant pages to the reinforcing agent. The forager receives reinforcements on any previously sent but not yet reinforced URLs and calls the URL ordering update algorithm with the received reinforcements. The pseudo code of a forager is shown in Algorithm 7.
Algorithm 8 : Manage Forager

\textbf{input}
\begin{itemize}
\item \textit{forager} ← the forager to be multiplied or deleted
\end{itemize}

\textbf{output}
\begin{itemize}
\item possibly modified list of foragers
\end{itemize}

\textbf{method}
\begin{itemize}
\item \textbf{if} \ (\textit{forager}'s score} \ \geq \ \textit{MAX\_SCORE} \ \text{and} \ \ \text{number of foragers} \ \lt \ \textit{MAX\_FORAGER})
\item \hspace{1em} \textit{weblog}, \textit{URLordering} ← call \textit{forager}'s 
\hspace{1em} \textbf{Multiplication, Alg. 6}
\item \hspace{1em} \textit{forager} may modify it’s own \textit{weblog}
\item \hspace{1em} \textit{newForager} ← create a new forager with the received
\item \hspace{1em} \hspace{1em} \textit{weblog} and \textit{URLordering}
\item \hspace{1em} set the two foragers' score to \textit{INIT\_SCORE}
\item \textbf{else if} \ (\textit{forager}'s score} \ \leq \ \textit{MIN\_SCORE} \ \text{and} \ \ \text{number of foragers} \ \gt \ \textit{MIN\_FORAGER})
\item \hspace{1em} delete \textit{forager}
\item \textbf{endif}
\end{itemize}

Algorithm 9 : Reinforcing Agent

\textbf{input}
\begin{itemize}
\item seed URLs
\end{itemize}

\textbf{output}
\begin{itemize}
\item \textit{relevants} ← found relevant documents
\end{itemize}

\textbf{method}
\begin{itemize}
\item \textit{relevants} ← empty set /*set of all observed relevant pages
\item initialize \textit{MIN\_FORAGER} foragers with the seed URLs
\item set one of them to be the next
\item \textbf{repeat}
\item \hspace{1em} start next forager
\item \hspace{1em} receive possibly relevant URL
\item \hspace{1em} call \textbf{Manage Received URL, Alg. 7} with URL
\item \hspace{1em} stop forager if its time period is over
\item \hspace{1em} call \textbf{Manage Forager, Alg. 8} with this forager
\item \hspace{1em} choose next forager
\item \textbf{until} time is over
\end{itemize}
Algorithm 10 Initialization of the forager

input
   weblog or seed URLs
   URL ordering parameters
output
   initialized forager
method
   set path step number to MAX_STEP + 1 /*start new path
   set the weblog
      either with the input weblog
      or put the seed URLs into the weblog with 0 weblog value
   set the URL ordering parameters in URL ordering algorithm

Algorithm 11 URL Selection

input
   frontier ← set of URLs available in this step
   visited ← set of visited URLs in this path
output
   step ← selected URL to be visited next
method
   if path step number ≤ MAX_STEP
      step ← selected URL by URL Ordering, Alg. 8
      increase path step number
   else
      call the Weblog Update, Alg. 1 to update the weblog
      step ← select a random URL from the starting URL list
      set path step number to 1
      frontier ← empty set
      visited ← empty set
   endif
Algorithm 12 Forager

input
frontier ← set of URLs available in the next step
visited ← set of visited URLs in the current path

output
sent documents to the RA
modified frontier and visited
modified weblog and URL ordering weight vector

method
repeat
    step ← call URL Selection, Alg. [11]
    frontier ← remove step from frontier
    visited ← add step to visited
    page ← download the page of step
    linkedURLs ← links of page
    newURLs ← linkedURLs which are not visited
    frontier ← add newURLs to frontier
    download pages of linkedURLs
    call Page Information Storage, Alg. [2] with newURLs
    relevantPages ← call Document Relevancy, Alg. [5] for all pages
    send relevantPages to reinforcing agent
    receive reinforcements for sent but not yet reinforced pages
    call URL Ordering Update, Alg. [4] with the received reinforcements
until time is over
4 Experiments

We conducted an 18 day long experiment on the Web to gather realistic data. We used the gathered data in simulations to compare the weblog update (Section 3.1.1) and reinforcement learning algorithms (Section 3.1.2). In Web experiment we used a fleet of foragers using combination of reinforcement learning and weblog update algorithms to eliminate any biases on the gathered data. First we describe the experiment on the Web then the simulations. We analyze our results at the end of this section.

4.1 Web

We ran the experiment on the Web on a single personal computer with Celeron 1000 MHz processor and 512 MB RAM. We implemented the forager architecture (described in Section 3) in Java programming language.

In this experiment a fixed number of foragers were competing with each other to collect news at the CNN web site. The foragers were running in equal time intervals in a predefined order. Each forager had a 3 minute time interval and after that interval the forager was allowed to finish the step started before the end of the time interval. We deployed 8 foragers using the weblog update and the reinforcement learning based URL ordering update algorithms (8 WLRL foragers). We also deployed 8 other foragers using the weblog update algorithm but without reinforcement learning (8 WL foragers). The predefined order of foragers was the following: 8 WLRL foragers were followed by the 8 WL foragers.

We investigated the link structure of the gathered Web pages. As it is shown in Fig. 1 the links have a power-law distribution \( P(k) = k^{-\gamma} \) with \( \gamma = -1.3 \) for outgoing links and \( \gamma = -2.57 \) for incoming links. That is the link structure has the scale-free property. The clustering coefficient \( C \) of the link structure is 0.02 and the diameter of the graph is 7.2893. We applied two different random permutations to the origin and to the endpoint of the links, keeping the edge distribution unchanged but randomly rewiring the links. The new graph has 0.003 clustering coefficient and 8.2163 diameter. That is the clustering coefficient is smaller than the original value by an order of magnitude, but the diameter is almost the same. Therefore we can conclude that the links of gathered pages form small world structure.

The data storage for simulation is a centralized component. The pages are stored with 2 indices (and time stamps). One index is the URL index, the other is the page index. Multiple pages can have the same URL index if they were downloaded from the same URL. The page index uniquely identifies a page content and the URL from where the page was download. At each page download of any foragers we stored the followings (with a time stamp containing the time of page download):

1. if the page is relevant according to the RA then store “relevant”
2. if the page is from a new URL then store the new URL with a new URL index and the page’s state vector with a new page index
3. if the content of the page is changed since the last download then store the page’s state vector with a new page index but keep the URL index
4. in both previous cases store the links of the page as links to page indices of the linked pages
   (a) if a linked page is from a new URL then store the new URL with a new URL index and the linked page’s state vector with a new page index
Figure 1: **Scale-free property of the Internet domain.** Log-log scale distribution of the number of (incoming and outgoing) links of all URLs found during the time course of investigation. Horizontal axis: number of edges (log \(k\)). Vertical axis: relative frequency of number of edges at different URLs (log \(P(k)\)). Dots and dark line correspond to outgoing links, crosses and gray line correspond to incoming links.

(b) if the content of the linked page is changed since the last check then store the page’s state vector with a new page index but same URL index

### 4.2 Simulation

For the simulations we implemented the forager architecture in Matlab. The foragers were simulated as if they were running on one computer as described in the previous section.

#### 4.2.1 Simulation specification

During simulations we used the Web pages that we gathered previously to generate a realistic environment (note that the links of pages point to local pages (not to pages on the Web) since a link was stored as a link to a local page index):

- Simulated documents had the same state vector representation for URL ordering as the real pages had
- Simulated relevant documents were the same as the relevant documents on the Web
- Pages and links appeared at the same (relative) time when they were found in the Web experiment - using the new URL indices and their time stamps
- Pages and links are refreshed or changed at the same relative time as the changes were detected in the Web experiment – using the new page indices for existing URL indices and their time stamps
- Simulated time of a page download was the average download time of a real page during the Web experiment.

We conducted simulations with two different kinds of foragers. The first case is when foragers used only the weblog update algorithm without URL ordering update
Table 1: Investigated parameters

| Parameter            | Description                                                                 |
|----------------------|-----------------------------------------------------------------------------|
| downloaded           | is the number of downloaded documents                                        |
| sent                 | is the number of documents sent to the RA                                     |
| relevant             | is the number of found relevant documents                                    |
| found URLs           | is the number of found URLs                                                   |
| download efficiency  | is the ratio of relevant to downloaded documents in 3 hour time window throughout the simulation. |
| sent efficiency      | is the ratio of relevant to sent documents in 3 hour time window throughout the simulation. |
| relative found URL   | ratio of found URLs to downloaded at the end of the simulation               |
| freshness            | is the ratio of the number of current found relevant documents and the number of all found relevant documents. A stored document is current, up-to-date, if its content is exactly the same as the content of the corresponding URL in the environment. |
| age                  | A stored current document has 0 age, the age of an obsolete page is the time since the last refresh of the page on the Web. |

(WL foragers). The second case is when foragers used only the reinforcement learning based URL ordering update algorithm without the weblog update algorithm (RL foragers). Each WL forager had a different weight vector for URL value estimation – during multiplication the new forager got a new random weight vector. RL foragers had the same weblog with the first 10 URLs of the gathered pages – that is the starting URL of the Web experiment and the first 9 visited URLs during that experiment. In both cases initially there were 2 foragers and they were allowed to multiply until reaching the population of 16 foragers. The simulation for each type of foragers were repeated 3 times with different initial weight vectors for each forager. The variance of the results show that there is only a small difference between simulations using the same kind of foragers, even if the foragers were started with different random weight vectors in each simulation.

4.2.2 Simulation measurements

Table 1 shows the investigated parameters during simulations.

Parameter ‘download efficiency’ is relevant for the site where the foragers should be deployed to gather the new information while parameter ‘sent efficiency’ is relevant for the RA. Note that during simulations we are able to immediately and precisely calculate freshness and age values. In a real Web experiment it is impossible to calculate these values precisely, because of the time needed to download and compare the contents of all of the real Web pages to the stored ones.

4.2.3 Simulation analysis

The values in Table 2 are averaged over the 3 runs of each type of foragers.

From Table 2 we can conclude the followings:

- RL and WL foragers have similar download efficiency, i.e., the efficiencies from the point of view of the news site are about the same.
Table 2: Simulation results. The 3rd and 5th columns contain the standard deviation of the individual experiment results from the average values.

| type                  | RL      | std RL | WL      | std WL |
|-----------------------|---------|--------|---------|--------|
| downloaded            | 540636  | 9840   | 669673  | 9580   |
| sent                  | 9747    | 98     | 6345    | 385    |
| relevant              | 2419    | 45     | 3107    | 60     |
| found URLs            | 31092   | 1050   | 33116   | 3370   |
| download efficiency   | 0.0045  | 0.0001 | 0.0046  | 0.0001 |
| sent efficiency       | 0.248   | 0.003  | 0.49    | 0.031  |
| relative found URL    | 0.058   | 0.001  | 0.05    | 0.006  |
| freshness             | 0.7     | 0.006  | 0.74    | 0.011  |
| age (in hours)        | 1.79    | 0.04   | 1.56    | 0.08   |

- WL foragers have higher sent efficiencies than RL foragers, i.e., the efficiency from the point of view of the RA is higher. This shows that WL foragers divide the search area better among each other than RL foragers. Sent efficiency would be 1 if none of two foragers have sent the same document to the RA.
- RL foragers have higher relative found URL value than WL foragers. RL foragers explore more than WL foragers and RL found more URLs than WL foragers did per downloaded page.
- WL foragers find faster the new relevant documents in the already found clusters. That is freshness is higher and age is lower than in the case of RL foragers.

Figure 2: Efficiency. Horizontal axis: time in days. Vertical axis: download efficiency, that is the number of found relevant documents divided by number of downloaded documents in 3 hour time intervals. Upper figure shows RL foragers’ efficiencies, lower figure shows WL foragers’ efficiencies. For all of the 3 simulation experiments there is a separate line.

Fig. 2 shows other aspects of the different behaviors of RL and WL foragers. Download efficiency of RL foragers has more, higher, and sharper peaks than the
download efficiency of WL foragers has. That is WL foragers are more balanced in finding new relevant documents than RL foragers. The reason is that while the WL foragers remain in the found good clusters, the RL foragers continuously explore the new promising territories. The sharp peaks in the efficiency show that RL foragers find and recognize new good territories and then quickly collect the current relevant documents from there. The foragers can recognize these places by receiving more rewards from the RA if they send URLs from these places.

Figure 3: Freshness and Age. Horizontal axis: time in days. Upper vertical axis: freshness of found relevant documents in 3 hour time intervals. Lower vertical axis: age in hours of found relevant documents in 3 hour time intervals. Dotted lines correspond to weblog foragers, continuous lines correspond to RL foragers.

The predefined order did not influence the working of foragers during the Web experiment. From Fig. 2 it can be seen that foragers during the 3 independent experiments did not have very different efficiencies. On Fig. 3 we show that the foragers in each run had a very similar behavior in terms of age and freshness, that is the values remains close to each other throughout the experiments. Also the results for individual runs were close to the average values in Table 2 (see the standard deviations). In each individual run the foragers were started with different weight vectors, but they reached similar efficiencies and behavior. This means that the initial conditions of the foragers did not influence the later behavior of them during the simulations. Furthermore foragers could not change their environment drastically (in terms of the found relevant documents) during a single 3 minute run time because of the short run time intervals and the fast change of environment – large number of new pages and often updated pages in the new site. During the Web experiment foragers were running in 8 WLRL, 8 WL, 8 WLRL, 8 WL, ... temporal order. Because of the fact that initial conditions does not influence the long term performance of foragers and the fact that the foragers can not change their environment fully we can start to examine them after the first run of WLRL foragers. Then we got the other extreme order of foragers, that is the 8 WL, 8 WLRL, 8 WL, 8 WLRL, ... temporal ordering. For the overall efficiency and behavior of foragers it did not really matter if WLRL or WL foragers run first and one could use mixed order in which after a WLRL forager a WL forager runs and after a WL forager a WLRL forager comes. However, for
higher bandwidths and for faster computers, random ordering may be needed for such comparisons.

5 Discussion

Our first conjecture is that selection is efficient on scale-free small world structures. Lőrincz and Kókai [15] and Rennie et al. [21] showed that RL is efficient in the task of finding relevant information on the Web. Here we have shown experimentally that the weblog update algorithm, selection among starting URLs, is at least as efficient as the RL algorithm. The weblog update algorithm finds as many relevant documents as RL does if they download the same amount of pages. WL foragers in their fleet select more different URLs to send to the RA than RL foragers do in their fleet, therefore there are more relevant documents among those selected by WL foragers than among those selected by RL foragers. Also the freshness and age of found relevant documents are better for WL foragers than for RL foragers.

For the weblog update algorithm, the selection among starting URLs has no fine tuning mechanism. Throughout its life a forager searches for the same kind of documents – goes into the same ‘direction’ in the state space of document states – determined by its fixed weight vector. The only adaptation allowed for a WL forager is to select starting URLs from the already seen URLs. The WL forager can not modify its (‘directional’) preferences according goes newly found relevant document supply, where relevant documents are abundant. But a WL forager finds good relevant document sources in its own direction and forces its search to stay at those places. By chance the forager can find better sources in its own direction if the search path from a starting URL is long enough. On Fig. it is shown that the download efficiency of the foragers does not decrease with the multiplication of the foragers. Therefore the new foragers must found new and good relevant document sources quickly after their appearances.

The reinforcement learning based URL ordering update algorithm is capable to fine tune the search of a forager by adapting the forager’s weight vector. This feature has been shown to be crucial to adapt crawling in novel environments [13, 15]. An RL forager goes into the direction (in the state space of document states) where the estimated long term cumulated profit is the highest. Because the local environment of the foragers may changes rapidly during crawling, it seems desirable that foragers can quickly adapt to the found new relevant documents. Relevant documents may appear lonely, not creating a good relevant document source, or do not appear at the right URL by a mistake. This noise of the Web can derail the RL foragers from good regions. The forager may “turn” into less valuable directions, because of the fast adaptation capabilities of RL foragers.

Our second conjecture is that selection fits SFSW better than RL. We have shown in our experiments that selection and RL have different behaviors. Selection selects good information sources, which are worth to revisit, and stays at those sources as long as better sources are not found by chance. RL explores new territories, and adapts to those. This adaptation can be a disadvantage when compared with the more rigid selection algorithm, which sticks to good places until ‘provably’ better places are discovered. Therefore WL foragers, which can not be derailed and stay in their found ‘niches’ can find new relevant documents faster in such already known terrains than RL foragers can. That is, freshness is higher and age is lower for relevant documents found by WL foragers than for relevant documents found by RL foragers. Also, by
finding good sources and staying there, WL foragers divide the search task better than RL foragers do, this is the reason for the higher sent efficiency of WL foragers than of RL foragers.

We have rewired the network as it was described in Section 4.1. This way a scale-free (SF) but not so small world was created. Intriguingly, in this SF structure, RL foragers performed better than WL ones. Clearly, further work is needed to compare the behavior of the selective and the reinforcement learning algorithms in other then SFSW environments. Such findings should be of relevance in the deployment of machine learning methods in different problem domains.

From the practical point of view, we note that it is an easy matter to combine the present algorithm with URLs offered by search engines. Also, the values reported by the crawlers about certain environments, e.g., the environment of the URL offered by search engines represent the neighborhood of that URL and can serve adaptive filtering. This procedure is, indeed, promising to guide individual searches as it has been shown elsewhere [20].

6 Conclusion

We presented and compared our selection algorithm to the well-known reinforcement learning algorithm. Our comparison was based on finding new relevant documents on the Web, that is in a dynamic scale-free small world environment. We have found that the weblog update selection algorithm performs better in this environment than the reinforcement learning algorithm, eventhough the reinforcement learning algorithm has been shown to be efficient in finding relevant information [15, 21]. We explain our results based on the different behaviors of the algorithms. That is the weblog update algorithm finds the good relevant document sources and remains at these regions until better places are found by chance. Individuals using this selection algorithm are able to quickly collect the new relevant documents from the already known places because they monitor these places continuously. The reinforcement learning algorithm explores new territories for relevant documents and if it finds a good place then it collects the existing relevant documents from there. The continuous exploration and the fine tuning property of RL causes that RL finds relevant documents slower than the weblog update algorithm.

In our future work we will study the combination of the weblog update and the RL algorithms. This combination uses the WL foragers ability to stay at good regions with the RL foragers fine tuning capability. In this way foragers will be able to go to new sources with the RL algorithm and monitor the already found good regions with the weblog update algorithm.

We will also study the foragers in a simulated environment which is not a small world. The clusters of small world environment makes it easier for WL foragers to stay at good regions. The small diameter due to the long distance links of small world environment makes it easier for RL foragers to explore different regions. This work will measure the extent at which the different foragers rely on the small world property of their environment.
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