Prediction of new outlinks for focused Web crawling

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ABSTRACT

Discovering new hyperlinks enables Web crawlers to find new pages that have not yet been indexed. This is especially important for focused crawlers because they strive to provide a comprehensive analysis of specific parts of the Web, thus prioritizing discovery of new pages over discovery of changes in content. In the literature, changes in hyperlinks and content have been usually considered simultaneously. However, there is also evidence suggesting that these two types of changes are not necessarily related. Moreover, many studies about predicting changes assume that long history of a page is available, which is unattainable in practice. The aim of this work is to provide a methodology for detecting new hyperlinks effectively using a short history. To this end, we use a dataset of ten crawls at intervals of one week. Our study consists of three parts. First, we obtain insight in the data by analyzing empirical properties of the number of new outlinks. We observe that these properties are, on average, stable over time, but there is a large difference between emergence of hyperlinks towards pages within and outside the domain of a target page (internal and external outlinks, respectively). Next, we provide statistical models for three targets: the link change rate, the presence of new links, and the number of new links. These models include the features used earlier in the literature, as well as new features introduced in this work. We analyze correlation between the features, and investigate their informativeness. A notable finding is that, if the history of the target page is not available, then our new features, that represent the history of related pages, are most predictive for new hyperlinks in the target page. Finally, we propose ranking methods as guidelines for focused crawlers to efficiently discover new pages, and demonstrate that they achieve excellent performance with respect to the corresponding targets.

Keywords Prediction of changes in the Web, focused crawling, Web mining, statistical models, probabilistic regression

1 Introduction

Web search engines greatly depend on their ability to keep their local collection of indexed Web pages up-to-date with the quickly growing and changing Web. To achieve this, crawlers regularly revisit and download Web pages. Since this process is expensive in terms of time and traffic, there is a vast body of research on efficient crawling policies, starting with seminal work by Cho and Garcia-Molina [13, 14]. For more recent reviews we refer the reader to [5, 29, 45, 6, 34, 42, 19].

A key input for designing a crawling strategy is the change rate of Web pages. On a more detailed level, changes of a Web page can be categorized as changes in content (i.e. changes occurring in the text, images, etc.), and changes in structure (i.e. addition or deletion of hyperlinks between indexed Web pages, or addition of hyperlinks to unindexed Web pages [39]). In this work, we focus on one specific type of change: the addition of new outlinks, that is, the new hyperlinks that point from an indexed page to other pages. This choice is motivated by applications in focused crawling. The aim of a focused crawler is to provide their clients, usually businesses, with detailed content analysis of
specific parts of the Web, close to the client’s interests. In this context, new outlinks are especially important because a new Web page can be found only through an outlink from a page that has already been indexed. Finding new Web pages has high priority for a focused crawler because completeness of its collection is crucial for the thorough Web analytics they wish to provide to their clients. To this end, the research reported here is answering a relevant request from practice, and is performed in collaboration with two French companies specialized, respectively, in focused crawling and business Web analytics.

We emphasize that the problem addressed here differs from the well studied problem of link prediction. Specifically, a link predictor outputs a list of pairs of nodes in a network that are likely to have future interactions \[32\]. This pairwise interaction is in the core of the link prediction problem (see e.g. recent survey \[40\]). In our case, however, we aim to predict the number of new directed edges emanating from a Web page, regardless the destination. Therefore, this work contributes into the literature of predicting changes in the Web rather than link prediction.

Already early work by Koehler et al. \[28\] showed that changes in content and changes in structure in the Web behave differently. For instance, in this four-year study of page change, content change dominates in the first 3 years while addition of hyperlinks dominates in the last year. Nevertheless, structural changes have been rarely addressed in the literature. Edwards et al. \[19\] constructed an adaptive model which derived the change rates and new page creation rates from actual cycles of the crawler (a cycle consists of fetcher, extractor, uniqueness verifier and scheduler). More recently, Radinsky et al. \[39\] provided a classification model for prediction of significant changes in content and mentioned that their prediction model is applicable for predicting new hyperlinks. In particular, they showed that information from related pages, especially related pages of similar temporal change patterns, remarkably improves page change detection. We note that both \[19\] and \[39\] require long history of page changes that is often unavailable in the context of focused crawlers, especially for newly discovered pages.

In this paper, we thoroughly address the problem of predicting new outgoing hyperlinks on a Web page. We start with a detailed statistical analysis of the number of new outlinks, and its dynamics. Next, we train statistical models for predicting three targets: the link change rate, the presence of new outlinks on a page, and the number of new outlinks on a page. One of our trained statistical models employs the recent NGB\textsc{OOST} method \[18\] to predict the average number of new outlinks based on the common assumption that the number of changes on a Web page follows a Poisson distribution \[4\]. We chose this method because it gives us the opportunity to treat the number of new outlinks as a random variable that follows a specific probability distribution.

For feature selection, we build on the existing literature for Web change prediction. We classify the selected features in four categories: the static page (SP) features, such as the content of a page \[21, 44, 22, 17, 40, 41\]; the dynamic page (DP) features that represent the (short) history of SP \[44, 12, 8, 15, 33, 43, 29, 4, 37, 21\]; and the number of new hyperlinks in the past crawls; the static network (SN) features that include incoming hyperlinks, TrustRank, and the SP features of content-related pages \[39, 44, 21, 16\]; the dynamic network (DN) features, which are the (short) history of SN (excluding related page features) and the weighted average link change rate of related pages.

Our conclusion, based on the results obtained from our dataset, is that both DP and DN features are highly informative. In fact, the number of new outlinks in the previous time period (a DP feature) turns out to be a strong baseline for predicting new outlinks. For a full history size (e.g. eight weeks in our experiment), the weighted average link change rate of related pages (a DN feature) is most informative. Interestingly, for the classification model we attain prediction accuracy 84% and higher with a history of only one past time period. SP and SN features are informative to some extent, and many of them are highly correlated.

Finally, from the results of our prediction models, we derive scoring metrics for ranking and prioritizing Web pages. The rankings learned by our models prove effective for quickly discovering new links, and thus they are useful for finding new Web pages by a focused crawler.

Our main contributions are summarised as follows:

- We conduct a literature review on Web page change prediction and summarise the features that have been found informative in previous research. Furthermore, we carry out a thorough analysis of correlations between the features and obtain insight about their informativeness in predicting new outlinks.
- We give insight in Web dynamics by providing detailed statistical summaries for the number of new outlinks.
- We provide several effective methods for predicting three targets for new outlinks: the link change rate, the presence of new outlinks (binary prediction and probability estimation), and the number of new outlinks on a page.
- We implicitly test the assumption of the Poisson distribution of the number of new outlinks by applying the NG-B\textsc{OOST} algorithms to learn its parameters. This approach provides opportunities for learning probability models from data.
We propose ranking methods for pages that enable a focused crawler to efficiently discover new pages in the Web.

This paper is organized as follows. The problem description is presented in Section 2. Section 3 explains how the dataset is obtained. Section 4 covers statistical properties of the number of new outlinks. In Section 5 we present our prediction methods including three prediction targets, the sets of features, and learning methods. Section 6 presents the results on predictive power of static features and dynamic features. In Section 7 we propose ranking metrics based on predicted emergence of new outlinks, and evaluate their performance against baselines and ground truth targets. In Section 8 we summarize the main conclusions and suggest future research directions. Lastly, an overview of related works is given in Section 9.

2 Problem statement

The Web data considered in this work consists of periodic crawls (as in Figure 1) with completion times $t_1, t_2, \ldots, t_n$. For each crawl, the crawling process proceeds from the same set of “seed” pages and follows outgoing links according to a modified breadth-first-search crawling strategy. From the resulting crawls, we study the set of pages which were reached in (almost) all crawls, so for which we have the entire timeline. Due to seed selection and crawling strategies employed by the focused crawler, our collection contains mostly authentic, not spam, Web pages.

We denote by $N^+(p(t))$ the set of pages to which page $p$ points at time $t$. These are referred to as outlinks, and our main goal is to predict new outlinks on a page. Furthermore, we denote by $N^-(p(t))$ the set of pages having hyperlinks to $p$ at time $t$. These are referred to as inlinks. Links (both out- and inlinks) fall into two categories:

- **internal links** from page $p$ lead to pages from the same domain and HTTP communication protocol as $p$;
- **external links** lead to pages from different domains or protocols.

For example, for the source page https://www.gender-nrw.de/haeusliche-gewalt/, the outlink https://www.gender-nrw.de/contact/ is categorised as internal, while the outlinks https://www.mkffi.nrw/ and http://gender-nrw.de/newsletter are external: the former because of the domain name, and the latter because of the unencrypted HTTP protocol. Only a small minority of the links are categorised as external when the communication protocol differs, even though the domains match; this is an arbitrary separation, based on the assumption that HTTP and HTTPS are served by different hosts.

Given two consecutive crawls at times $t_i$ and $t_{i+1}$, the set of new outlinks on page $p$ is $N^+(p(t_{i+1})) \setminus N^+(p(t_i))$. These are either internal or external new outlinks; we study the two sets independently. The goal of this work is to provide a thorough analysis and prediction methodology for new outlinks.

3 Dataset

For this research, we perform ten crawls at intervals of one week, starting 13-07-2020 till 14-09-2020. These choices were based on the practical experience and application in focused crawling, where weekly recrawls proved to strike a good balance between the freshness of the index and available resources, while long history requires infeasible storage capacity, and is simply unavailable for newly found pages. Formally, in our data we have $n = 10$, and we consider 9 one-week intervals $[t_i, t_{i+1})$, $i = 1, 2, \ldots, 9$. The predictions are made for week 9, and the DP and DN features are computed based on the history of at most 8 weeks.
For each page $p$ at time $t$ we obtain data that include the URLs on the page, the fetching date, URLs that link to $p$, the PageRank, TrustRank, and the semantic vector $\text{sem}(p(t))$ that describes the content of the page. In Section 5 we will explain in more detail how PageRank, TrustRank and the semantic vector are obtained.

For collecting our dataset, the seeds are 93,684 unique URLs selected as follows: from more than a billion URLs of a previous large crawl, 100,000 URLs have been randomly selected, then truncated to the home page. The crawl is guided by $\text{PageRank} \times \text{TrustRank}$ in which TrustRank is biased toward renowned websites that are historically more Euro- and US-centric. At each crawl, we stopped the crawling process when one million pages have been collected. Many pages have been discarded, for example, pages that did not contain the entire timeline of 10 crawls, or missed some data, for instance, the semantic vector. This resulted in the dataset that contains 384,323 pages with complete information included. The amount of data is sufficient for our purposes and is greater than many comparably detailed data used in the literature. Importantly, in this dataset, for each page, we could compute its most related pages. As we will see, in line with [39], features of related pages greatly improve the quality of predictions. On larger datasets, exact computations of most related pages are infeasible, and we will discuss in Section 8 how this can be overcome in future research.

Since pages from the same top-level domain (TLD) may show a similar behaviour, we have analyzed the distribution of pages over TLD’s in our dataset, see Figure 2. In our crawls, 46.8% of the pages are from .com TLD; the other top TLDs are .org, .net, .edu, and .gov, with also a good representation of European country codes (.de, .uk, .fr).

4 Statistical summaries for the number of new outlinks

In this section we will get initial insights into the emergence of new outlinks, via basic statistical analysis.

The Sankey diagram in Figure 3 shows how the number of internal and external outlinks change over weeks 1, 2, ..., 9. We divide the number of new in/external outlinks into groups such that groups other than 0 have similar sizes. For the number of new internal outlinks, we distinguish four groups of pages, with: 0, 1 or 2, 3 to 10, and > 10 new outlinks. For the number of new external outlinks, we distinguish three groups of pages, with: 0, 1, and > 1 new outlinks. We see that, first, there is a considerable stability over time: from one week to another, the size of each group does not change much, and most pages do not change the group. Second, 68% - 75% of pages have no new internal outlinks, and 91% - 94% of pages have no new external outlinks in one week, so a crawler can find all new outlinks by crawling only a relatively small fraction of indexed pages.

Figure 4a shows the distribution of the change rate of internal outlinks. Just under half the pages are never seen to change their set of internal links; however, a significant fraction do show a change every time they are crawled. The distribution of the change rate of external links (Figure 4b) paints a different picture: only very few pages have a rate of change for external links not zero.

Next, we look at how the number of new outlinks is distributed over pages. Table 1 shows the empirical mean and the standard deviation of the number of new outlinks, and Figure 5 shows the empirical complementary cumulative distribution function (CCDF) for each week in log-log scale. We highlight that the number of new internal outlinks
Figure 3: Changes in the number of new internal outlinks and external outlinks over 9 weeks. a) The pages are divided into four groups by the number of new internal outlinks: 0, 1 or 2, 3 to 10, and > 10. b) The pages are divided into three groups by the number of new external outlinks: 0, 1, and > 1.

Figure 4: Histograms of the change rate of internal outlinks and external outlinks.

Figure 5: Complementary cumulative distribution function (CCDF) of the number of new internal (in.) outlinks, and external (ex.) outlinks in log-log scale for each week (w#).

Table 1: Empirical mean and standard deviation of the number of new outlinks.

| week   | total new outlinks | in. outlinks | ex. outlinks |
|--------|-------------------|--------------|--------------|
|        | µ                  | σ             | µ             | σ             |
| week 1 | 3.1                | 14.4          | 2.7           | 13.5          |
| week 2 | 3.2                | 14.5          | 2.8           | 13.7          |
| week 3 | 3.4                | 15.2          | 3.0           | 14.1          |
| week 4 | 2.6                | 13.3          | 2.2           | 12.6          |
| week 5 | 2.9                | 15.3          | 2.5           | 14.5          |
| week 6 | 3.5                | 15.3          | 3.0           | 14.2          |
| week 7 | 2.6                | 13.0          | 2.3           | 12.4          |
| week 8 | 3.0                | 16.8          | 2.6           | 16.0          |
| week 9 | 3.1                | 15.2          | 2.7           | 14.6          |

is typically much larger than the number of new external outlinks. This is expected because a typical page contains more internal links than external ones. Specifically, the fraction of external outlinks in the last crawl is 14.7%. Also, the empirical distributions in different weeks are very similar. This indicates that the number of new outlinks can be predicted successfully for most pages.
The low mean and the very high standard deviation, especially for the number of new internal outlinks, clearly signal a highly skewed distribution. This is further confirmed by the shape of the empirical CCDF in log-log scale presented in Figure 5, that is clearly heavy-tailed and resembles a power law.

In order to better understand and describe the distribution of the number of new outlinks, we next fit the empirical number of new outlinks to known skewed, or, heavy-tailed, probability distributions (see the definitions in Appendix A1, Table 5): power law (PL), truncated power law (TPL), stretched exponential (SE) and log-normal (LN). We have also included the exponential (EXP) distribution, which is light-tailed. The goodness-of-fit is measured using the Kolmogorov-Smirnov statistic \( D \)

\[
D = \max_{x \geq x_{\min}} |S(x) - P(x)|,
\]

where \( S(x) \) and \( P(x) \) are the cumulative distribution functions of the empirical data and the model, respectively. Because the distribution of the empirical number of new outlinks every week is similar, we use the data from week 9, and we discard the pages that have no new outlinks.

Figure 6 shows the CCDF of the empirical data for the number of new in/external outlinks and their fits, produced using the power-law package [25].

We see that in general, SE always gives the best fit (smallest distance \( D \)) when fitting the entire data or its tail. Note that SE fits very well the tail of the distribution, however, the tail occupies a very small portion of the data (herein 3.3%).
Most of the 10% error comes from the body of the distributions (the number of new outlinks between $1$ and $x_{min}$), which probably does not follow any standard probability model, see Appendix A1, Figure 20 for fitting the body of the empirical data. In particular, fitting separately the body (with EXP) and the tail (with SE) does not significantly improve the result compared to fitting SE to the entire data.

Finally, it is interesting to take a closer look at pages that created exceptionally many new outlinks at some point during our crawls. Figure 7 shows the time series for eight selected URLs (URLs with the most number of new outlinks in at least one of the weeks). Herein, we observe notable differences between pages. For instance, the first page, page I, gets about the same number of new internal outlinks every week, and no external ones. This behavior can be observed on spam pages, but page I is not a spam page, in fact, it reports abusive IPs, and its new internal links lead to pages with more information on each abusive IP. The next two pages, II and III, have many new outlinks in the first week while there is no new outlink in the following weeks. Other pages have few new outlinks in some weeks and suddenly have many new outlinks in other weeks. Clearly, such inconsistent behaviour is difficult to predict.

We conclude that in one week, most pages have no new outlinks. Moreover, the distribution of new outlinks over pages is highly skewed. The number of new outlinks is stable over time in the sense that its empirical distributions over all pages in different weeks, are very close. Nonetheless, some individual pages exhibit a large variability in the number of new outlinks in different weeks.

5 Prediction methods

5.1 Prediction targets

We consider three prediction targets, separately for internal and external outlinks. The method readily extends to inlinks or the total number of outlinks. The three targets are defined as follows.

Link change rate in the interval $[0, 1]$ is the fraction of time intervals $[t_i, t_{i+1}]$ out of $n - 1$ time intervals when a page acquired new outlinks. In our case, an interval equals to one week, and we have $n - 1 = 9$ weeks. Although link change rates in our case can take only several discrete values because the number of weeks is not large, we use regression to predict link change rate so that the method extends to an arbitrary number $n$ of crawls.

The presence of new links in the $n - 1$-th time interval (in our case, the 9th week) is predicted as a simple binary label: 0 if the set of new outlinks is empty, and 1+ otherwise. We will use both binary prediction and a probabilistic estimation of the likelihood of a page falling into either of these categories in the next crawl.
The number of new links is predicted for the \( n - 1 \)-th time interval (in our case, the 9\textsuperscript{th} week). This can be viewed as a regression task to predict an unknown fixed (integer) number. Alternatively, as commonly accepted in the literature, we model the number of new outlinks as a Poisson random variable parameter \( \lambda(p) \), and apply probabilistic regression \cite{18} to learn \( \lambda(p) \), which serves as prediction for the number of new outlinks on page \( p \).

5.2 Page features

Based on the literature, we have extracted all features that can be used as predictors. In our work, as a result of extensive experimentation, the feature sets will vary with the prediction target. Figure 8 summarises the feature sets, organised across the following two dimensions.

1. Page (P) features versus Network (N) features, depending on whether the computation of the features requires only the data of an individual page (P), or it requires the data of all pages in a region of the Web graph network (N).

2. Static (S) features versus Dynamic (D) features depending on whether the computation of the features can be done over one crawl (S), or it requires historical data from previous crawls of the same pages (D).

**Static page (SP) features** measure the state of a page \( p \) at a given time \( t \). These features are listed below.

- The **page content size** is the byte size of the page content; we keep only non-empty pages. The **page text size** limits this to the text of the page, excluding the HTML content; the values for this feature may be zero.

- The **text quality** feature has been developed by the crawling company based on the literature and practical experience. We take this value as feature, but its analysis and improvement are outside the scope of this paper. The feature is a non-linear function applied on a ratio of the vocabulary size to the document size.

- Each page \( p(t) \) may contain outlinks \( N^+(p(t)) \), split in two non-overlapping subsets: internal and external. Their counts are used as two separate SP features.

- The **URL path depth** is the directory depth: the page at the URL domain.com/en/news/article123456/ has path depth 3. The **URL domain depth** is the depth within the domain: the page at sub.domain.com has domain depth 3.

- The **semantic vector** \( \text{sem}(p(t)) \) is an embedding of the page text (only if text exists on the page) into a vector space with 192 dimensions, such that the Euclidean norm (or \( L^2 \) norm) equals 1. In this work we used the embedding provided by the crawling company, but any other approach could be used as well. In Appendix A2 we briefly describe how our embedding was obtained.

Both URL path and domain depth remain constant per page, while the remaining SP features may change in time.

**Static network (SN) features** measure the state of the Web graph at a given time \( t \). Although they describe individual pages, they require an entire crawl to be computed. In this work we consider the following SN features.
• Each page may be pointed to by other pages \( N^−(p(t)) \), and these inlinks fall into the same two categories as the outlinks: internal and external. The counts of internal and external links per page give two SN features. The features are computed on the effective crawl (i.e. the obtained dataset and not from outside the crawl). Due to potential delays between updates and synchronisation of computation, the stored inlink information and the actual inlinks can be slightly different.

• PageRank is defined as in the original work \([11]\), it is a stationary distribution of a random walk that restarts from a random page. In our dataset, PageRank is updated dynamically during the crawl. More precisely, when page \( p \) is crawled, its PageRank is re-evaluated by substituting the current PageRank scores of pages that have a hyperlink to \( p \). The current PageRank scores of pages were included in the dataset.

• TrustRank is defined as in the original work \([24]\), it is a stationary distribution of a random walk that restarts from trusted pages. In our dataset, TrustRank is updated dynamically similarly to PageRank. The current TrustRank scores of pages were included in the dataset.

• Each page may be related to other pages in terms of its text content. These pages represent the part of the Web graph that is most relevant for the target page. Therefore, the SN features include the weighted averages of the static features of related pages, with weights proportional to the cosine similarity score between the semantic vectors. In order to compute these features, we use the nearest-neighbor algorithm to find the 30 closest pages to our target page. Then we compute the weighted average of SP features of the found pages. The obtained values are then included in the SN features.

**Dynamic page (DP) features** Some of the SP features may change between crawls: the page content and text size, page text quality, the semantic vector, and the set of outlinks. Dynamic page features are historical values of these static features; DP features with a history size of 1 include, for example, the page content size from the last crawl before the present crawl. The DP features regarding page outlinks are the number of new outlinks between consecutive past crawls, similar to the prediction target measuring the number of new outlinks.

**Dynamic network (DN) features** include the historical values of the external and internal inlink counts, PageRank and TrustRank of a page. Besides, the dynamics of related pages are accounted for by adding weighted average link change rate of related pages as a feature, with weights as described in the SN features of related pages. This feature is dynamic because it is computed using complete historical data. In practice, this translates to a realistic assumption that we know the link change rate of related pages over \( n − 1 \) time periods. The internal and external outlinks give two DN features. These features are part of the DN features for any history size.

### 5.3 Learning methods

**Statistical models** The problems require a learning method able to do at least point regression or classification. For classification tasks, we use classifiers able to provide not only this point prediction, but also the predicted class probabilities of a test page. The statistical models are all nonlinear ensemble learners with decision or regression trees as base learners. For point classification or regression, we train two learners; for each task, we will present the results of the best learner:

**HGBoost or LightGBM** The Histogram-based Gradient Boosting (HGBoost) tree is a scikit-learn \([38]\) implementation inspired by the Light Gradient Boosting Machine (LightGBM) \([27]\). We use HGBoost for regression, but LightGBM for classification, since the classes in our data are unbalanced, and LightGBM has support for training with balancing class weights. Both algorithms scale better to large datasets than the standard gradient-boosting method, but are still significantly more expensive in training time than ensembles of trees.

**ExtraT** is an ensemble of Extremely Randomized Trees (also implemented in scikit-learn \([38]\)), which randomises the splitting rule at each internal node: splitting thresholds are drawn at random for each candidate feature and the best of these is selected. This lowers the variance of the model, and thus its likelihood of overfitting. Since it is an ensemble, rather than sequentially gradient-boosted learners, training ExtraT learners parallels well, so is always the most scalable model to train on large data.

HGBoost for regression and LightGBM for classification are configured with no maximum depth or maximum number of leaf nodes for the boosted trees, but instead the maximum number of samples on a leaf is tuned with cross-validation between 10 and 25 (with higher values tending to better performance). The maximum number of iterations of the boosting process (or trees) is tuned between 200 and 500 (higher tends better). The learning rate for both is tuned between 0.02 and 0.1 (lower tends better). The loss function used in the boosting process is the default least squares. ExtraT for regression is also configured without a maximum depth or maximum number of leaf nodes for the trees in
the ensemble, but the maximum number of samples on a leaf is tuned with cross-validation between 2 and 25 (with lower values tending to better performance). The number of trees in the ExtraT ensemble is tuned between 200 and 500 (higher tends better). For classification problems, the classes are balanced with adding balancing weights (inversely proportional to class frequencies in the data) to the training process, so the majority class need not be undersampled: all the data is kept. The splitting criterion is the default mean squared error. All other parameters are left on their default scikit-learn values [38].

For the most general task of predicting the number of new links, we also fit probability distributions using a recent method of probabilistic regression. For the probabilistic regression, we train one more learner:

**NGBoost** [18] Natural Gradient Boosting is a recent algorithm for probabilistic estimation based also on gradient boosting. The model estimates the parameters of a conditional probability distribution where condition can be a fixed variance, a set of parameters, etc. and returns a full probability distribution instead of a point estimate. For our prediction, we specify the distribution to be Poisson, conditional on our features as covariates, and leave other parameters as default.

**Training and test datasets** For each prediction problem, we form a dataset out of the predictor and target values, with one data point per Web page. The dimensionality of the semantic vector is reduced to 20 by agglomerative clustering [38], which groups together similar features.

For each dataset, we hold out a random 25% of the Web pages as a test set. From the remaining 75% of example pages (the training set), we initially hold out one third (or 25% of the original dataset size) as a development set for tuning with cross-validation; this optimises the configuration parameters of the machine-learning models. Then, we retrain the tuned statistical model over the entire training set, and this retrained model is tested on the held-out test set. We then repeat the entire process three times. The datasets are large, so for most prediction tasks there is little variation observed in the results of these repetitions. An exception is classification tasks with very imbalanced classes, where the repetitions help to estimate the performance metrics better.

**Performance metrics** As performance metrics for point classification tasks, the most practically important scores are the recall (the fraction of changed pages which are predicted correctly), and the F1-score (a mean between recall and precision: the fraction of pages predicted to change which actually do). We also report precision, and the balanced accuracy score (the average of the recall scores per class). For point regression tasks, we show the coefficient of determination $R^2$, the mean absolute error (MAE), and the median absolute error (MedAE). MedAE is provided because it is more robust to outliers than MAE. The $R^2$ score is the proportion of variance of the target variable that is explained by the independent predictors in the model, with the best possible score 1, and a score of 0 for a constant model that always predicts the expected value of the target, disregarding the input features; negative scores are possible for arbitrarily worse models. Note that since the variance of the target is dataset dependent, $R^2$ is not comparable across datasets, so across prediction tasks for different target variables.

For estimating the importance of individual features for the model learnt, we use permutation importance [10], a model-agnostic metric based on comparing the performance of the model trained with all features with that of the model trained with the feature of interest shuffled among the samples in the dataset, and all other features intact. This is a relative metric (if two or more very strongly correlated features exist, their importance will be low relative to each other), so mainly informative on feature sets without highly redundant features.

### 6 Predictive value of the features

In this section we report the results on how features of the four categories described in Section 5.2 contribute to the prediction. First, we focus on the static page (SP) and static network (SN) features. Next, we study the contribution of the dynamic features DP and DN. We performed experiments for all three targets. In terms of feature importance, the main conclusions are very similar for each target. Therefore, for brevity, here we will illustrate each result using only one of the targets.

#### 6.1 Static features

The static features are important because they can be computed from a single crawl. In figures, by **SP** we denote the feature set without the semantic vector, and by **SPsem** that with the semantic vector. We study these feature sets separately because in many practical or research settings the semantic vector may be computationally expensive to obtain.
In order to better understand the set of static features, we first compute the Spearman correlations between features in SP (excluding the semantic vector) and SN. The results are given in Figure 9. As we see, among the SP features, the page text size and page content size are positively correlated (Spearman rho 0.67), and so are the page content size and the number of internal outlinks (0.63); this means that these SP features may be partially interchangeable in a statistical model. Among the SN features, PageRank strongly correlates with TrustRank (0.79) and positively correlates with the number of internal inlinks (0.64), as expected. TrustRank is moderately positively correlates with the number of internal inlinks (0.57). Since PageRank and TrustRank are very similar in definition, and strongly positively correlated, but TrustRank has smaller correlations with the number of internal inlinks, we further report results including only TrustRank. Most other correlations are modest. Interestingly, we see a green diagonal in the middle of this figure which shows the correlation of each static page feature with the weighted average of the same feature in its similar pages. For example, the text quality feature of each page is correlated with the text quality of its similar pages (Spearman rho 0.79). Consequently, we can say that static features of the related pages are not so informative.

We will next explain how static features influence the prediction performance. To this end, we present the results for predicting the internal and external link change rate (recall that the histograms for the internal and external link change rate are given in Figures 4a and 4b, respectively). The results for the other two targets are similar. HGBoost regressors are tuned to the hyperparameter values: learning rate 0.04, maximum iterations 500, and minimum samples per leaf 25. Figure 10 shows the regression scores across feature sets when predicting the link change rate for internal outlinks. Half of the variance in the target values is explained by learning from only static page features, and this increases to 0.65 by adding the semantic vector. The absolute errors are also low (MAE of 0.14). Interestingly, similar increase in performance is achieved when instead of the semantic vector we add the SN features. Furthermore, adding semantic vector together with the SN features yields further improvement. We conclude that semantic vector as well as SN features are informative, and can improve prediction performance.

Proceeding to the external link change rate, we recall from Figure 4b that there are very few pages with non-zero external link change rate. For such unbalanced data, we design a simple baseline, which predicts a change rate of zero for any page (the most likely change rate). This baseline has a MedAE of zero (due to the majority of the pages being static). Figure 9 shows the Spearman correlations between features, across the feature sets SP (excluding the semantic vector) and SN.
predicted correctly). The same baseline has a negative $R^2 = -0.14$, and a MAE of 0.08. Trained regressors (shown in Figure 11) are beneficial in comparison to the baseline: $R^2 = 0.45$ of the variance of the target is now explained. The performance improves similarly as before when either the semantic vector or SN features are included.

In terms of feature importance, the feature rankings for the internal and external link change rates are similar. Figure 12 shows results for the internal link change rate. The page content and text size, as well as the number of internal and external links and the text quality metric are discriminative features. Both SP and SN features appear in the top 10 list. For regressing the change rate of external links (not shown here), the top nine features are the same, but the number of external outlinks on the page outranks all other features. The results including semantic vector are similar; only the last feature differs. For external outlinks, 4 out of 10 top features are from the semantic vector. It should be also taken into account that although the list contains related pages features, they are highly correlated with SP as shown in Figure 9.

To better understand how the regressors learn from the data, scatterplots for the top features (Figure 13, in each left panel) show that there is a pattern of increasing internal link change rate with a joint increase in page content and text size, as well as an increase in the number of internal outlinks. The pattern of link change rate across different values for the page text quality is instead more fragmented, with some separation between clusters of pages with heavy change. All of these top features add information that is important for the prediction. In each right panel of Figure 13, regression maps show how the learner picks up this pattern from various pairs of features. (Note that the regressor can predict for all possible points in the feature space, so also in regions where no Web pages exist in the data, which explains why the regression map is completely filled.) Since it is retrained with only two features at a time, to be able to show a two-dimensional map, this performance metric is partial, and lower than that of regressors trained with all input features (the 0.18 MAE for feature set SP, from Figure 10).

### Dynamic features

As defined in Section 5.2, the dynamic features DP and DN are in fact the historical data of the static features from previous crawls. However, it should be noted that link change rate itself is obtained from the historical data and if we have such data, we can obtain the link change rate directly. Therefore, in this section we will demonstrate the results using another target, the presence of new links. Recall that this is as a binary classification task: predicting whether pages will get 1+ new outlinks (class 1+) or not (class 0) in the next week.

As shown in Figure 3, most of the pages have zero new outlinks in the target week. The imbalance ratios for internal and external outlinks are 2.57 and 12.15, respectively. Therefore, with respect to whether pages will get 1+ new outlinks or not, the external outlink is much more imbalanced. Both LightGBM and ExtraT classifiers are able to handle the imbalance datasets, and scaled well. However, ExtraT shows better prediction performance than LightGBM, thus we only report the results of the ExtraT classifier. The models are trained with increasingly complex feature sets and increasing history size. In other words, for the history size of one, just one week of dynamic features has been included and for the history size of eight, the feature set contains all dynamic features. The target score for tuning the
hyperparameters of ExtraT classifier has been set to balanced accuracy. Table 2 shows the tuned hyperparameters of ExtraT classifier for different history sizes.

| History size | Internal outlinks | External outlinks |
|--------------|-------------------|-------------------|
|              | Number of estimators | Minimum samples per leaf |
| 0            | 300 500 400 500 500 400 500 400 | 2 2 2 2 2 2 2 2 |
| 1            | 300 300 400 200 300 400 500 400 500 | 10 10 10 10 10 10 10 10 10 |
| 2            | 300 300 400 500 300 400 500 400 500 | 2 2 2 2 2 2 2 2 2 |
| 3            | 300 300 400 400 300 400 500 400 500 | 10 10 10 10 10 10 10 10 10 |

Table 2: Hyperparameters used for training the ExtraT classifier with different history size of feature set.

As can be seen from our initial statistical analysis (see Figure 3) most pages retain their class in subsequent weeks. This motivates us to compare the results to a very simple baseline that predicts the same number of new outlinks as in the previous week (NNL-Pr). Thus, in week 9 NNL-Pr predicts the same class as in week 8. Note that the class in week 8 is a DP feature.

The results are depicted in Figures 14a and 14b for internal and external outlinks, respectively. As it can be seen, using more historical features improves the performance of the models for all used metrics. The high value of the balanced accuracy metric, Accuracy (b), indicates that the models classify both Class 0 and Class 1+ accurately. For internal outlinks, all of the metric values are close together. This means that the strength of the model for both classes is roughly the same. However, for external outlinks, Class 0 is better classified than Class 1+. This is visible from the lower value of the recall metric than that of the balanced accuracy. It means that Class 1+ exhibits many types of behaviour, but there is little data to learn from, for each type.

In Figures 14a and 14b we can see that increasing the history size has more influence on the prediction of external outlinks than internal outlinks. Notably, there is a very prominent improvement in the classification performance when we go from history size of zero to one. As we add more history, we see less improvement in the classification performance, especially for internal outlinks. We note also that the NNL-Pr baseline performs well, but a statistical model that includes all features with a history of size one, clearly outperforms this baseline.

The feature permutation importance for the best result is shown in Figure 15. For internal outlinks, the weighted average internal link change rate of the related pages (a DN feature introduced in this work) is significantly more informative than the other features. Recall that related pages are most similar in content to the target page. Hence, historical data of related pages are strong predictors for the change in the target page. This is an important finding, especially if historical information for the target page is not available. Interestingly, all historical values of the number of new internal outlinks (DP features) are among the top 10 features.
Figure 14: Classification scores when predicting (a) the presence of new internal outlinks and (b) the presence of new external outlinks in the next crawl, with increasingly complex feature sets and increasing history size. The NNL-Pr predicts the same class as in the previous time period; this class is a part of the DP features.

Figure 15: Permutation-based feature importance when predicting the presence of new outlinks.

For external outlinks, the weighted average external link change rate of the related pages is also the most informative feature. Like in the case of internal outlinks, historical features including the number of new external outlinks in previous weeks are the next important features. It is worthwhile to note that except page text quality, all of the most important features are dynamic features (DP or DN).

We conclude that dynamic features improve prediction performance. Specifically, the historical data of related pages is very informative for predicting the change in the target page.
7 Ranking methods for discovering new outlinks

Our predictions for each target can be used as scores for ranking Web pages, from the highest value of the target to the lowest (the pages with the highest values are so-called hot pages). These rankings can be then employed by a focused crawler to quickly discover new outlinks. In this section, we propose ranking methods based on the predictions, and compare their performance against baselines and ground truth targets.

7.1 Ranking methods

As a ground truth, we take our three targets from Section 5.1: the link change rate over 9 weeks (LCR), the presence of new outlinks in week 9 (NL), and the number of new outlinks in week 9 (NNL). These results in target-based rankings, listed in Table 3 at the top.

Table 3 further shows the rankings obtained from the prediction of a specific target using our proposed learning methods. For example, LCR-ET means ranking by the predicted link change rate obtained by applying the ExtraT regressor. When training NL-ET, NNL-ET, and NNL-NGB we use all features with full history size 8. When training LCR-ET, we exclude the DP features because, as mentioned before, the LCR itself is computed based on historical data.

Finally, we include three baseline rankings derived from only one feature. These include: the average number of new outlinks in previous weeks (NNL-Av), the number of new outlinks in the previous week (NNL-Pr), and the content change rate (CCR), see Table 3 at the bottom. The advantage of using one-feature baselines is that they can be computed directly from the historical data without a machine learning algorithm. The NNL-Av and NNL-Pr baselines are motivated by the stability of the distribution of new outlinks over pages, demonstrated in Section 4, see Figures 3, 5. In addition, NNL-Av is interesting because change statistics are often used for predicting change in crawling strategies [15, 4]. It shows to what extend the change statistics are predictive.

The reason to consider the CCR baseline is that the content and network changes are often considered together in the literature [42, 39], and therefore we want to know whether CCR provides a meaningful ranking metric for the link change targets. For calculating CCR, we require a timeline of \( n \) crawls. A page is marked as having its content changed between two crawls if its content digest (computed over the page content, excluding any outlinks) is different. Given \( n \) crawls and a page \( p \), the value of the content change rate for \( p \) is the fraction of intervals in which a content change was observed in \( p \); in other words, this is the content change count divided by the number of recrawls. The change rates are thus in the interval \([0, 1]\). A value of 1 means that \( p \) was observed to change in every recrawl, or \( n - 1 \) times.

7.2 Performance measures

We will compare the predicted rankings to the ground truth using two performance metrics: the Spearman rank correlation coefficient, \( \text{Spearman rho} \), and \( \text{Precision}@k\% \). The latter is a version of the standard \( \text{Precision}@k \), and is visualized in a line chart. On the horizontal axis we plot the value \( k \) from 0\% to 100\%, and on the vertical axis we plot the percentage of the top \( k\% \) pages of the ground truth that appear in the top \( k\% \) of the predicted ranking. The higher value on the vertical axis, the better. For easier comparison, we have also calculated the area under each curve. Clearly, the higher area means the greater similarity between the obtained ranking and the target ranking. The maximal area of one is achieved when the obtained ranking is identical to the ground truth.

| Rank by:                        | Abbreviation |
|--------------------------------|--------------|
| target                         | LCR          |
| presence of 1+ new outlinks in | NL           |
| the target week                | NNL          |
| number of new outlinks in the  |              |
| target week                    |              |
| prediction                     | LCR-ET       |
| estimated value for LCR using  |              |
| ExtraT regressor               |              |
| estimated value for NL using   | NL-ET        |
| ExtraT classifier (a binary    |              |
| classification task)          |              |
| probability of the presence of | PNL-ET       |
| 1+ new outlinks in the target  |              |
| week using ExtraT classifier   |              |
| estimated value for NNL using  | NNL-ET       |
| ExtraT regressor               |              |
| estimated value for NNL using  | NNL-NGB      |
| NGBoost algorithm              |              |
| one-feature baseline           | NNL-Av       |
| estimated value for NNL using  |              |
| the average number of new      |              |
| outlinks from previous weeks   |              |
| estimated value for NNL using  | NNL-Pr       |
| the value from the previous    |              |
| week                          | CCR          |
| content change rate calculated |              |
| over weeks                     |              |

Table 3: Approaches used for obtaining the rankings.
Figure 16: Spearman’s rho of different rankings with respect to the targets. In each row, the lightest and the darkest colors correspond to, respectively, the smallest and the largest numbers in this row.

Figure 17: Ranking performance with respect to LCR ground truth.

Importantly, most pages have targets equal to zero, but they are included in prediction. We resolve such ties in the rankings as follows. For Spearman rho, we use the average rank of tied values. For Precision@k\% we need to assign different ranks to all pages, so we resolve the ties at random and show the curves that are averaged over five different realizations. Furthermore, due to the large number of zeros, we will see that for large k the Precision@k\% curve tends to behave like a random ranking.

7.3 Performance of ranking methods

Link Change Rate (LCR) The first row of Figure 16 shows the Spearman’s rho between the obtained rankings and the ground truth LCR ranking. As we see, LCR-ET has the highest Spearman’s rho for both internal and external outlinks. The best result is achieved when this regressor is configured with the minimum number of samples per leaf of 2 and the number of trees set to 400. The results for the other targets below will confirm that ExtraT trained for the same target as in the ground truth, consistently results in highest Spearman rho. Notably, the second-best ranking for the LCR target is NNL-NGB, which uses the NGBoost algorithm, and is originally designed for a different target, the number of new outlinks (NNL). We can explain this high correlation by the fact that NGBoost predicts the parameter of Poisson distribution, and, if such model is valid, then the LCR is a monotone function of this parameter. It is interesting that our methods capture this monotonicity even though the Poisson model does not accurately describe the data.

Precision@k\% for the obtained rankings have been depicted in Figure 17. The one-feature predictions are shown in orange. Again, LCR-ET has the largest area, followed by NNL-NGB ranking. This is consistent with the results for Spearman rho.

It is interesting to compare LCR and CCR. We see that CCR has the smallest Spearman’s rho in Figure 16 as well as the smallest area under the curve in Figure 17b. This confirms that the content change rate, although correlated with the link change rate, is not a strong predictor for the latter. Remarkably, Precision@k\% shows that CCR is very uninformative for finding pages with highest LCR for external links.
Figure 18: Ranking performance with respect to NL ground truth.

Taking a closer look at internal versus external outlinks, we notice that the results in Figure 16 are consistent with our observations in Section 6 that external outlinks are harder to predict than internal outlinks. However, surprisingly, Figure 17 shows that the hottest external LCR pages are found sooner by our methods than the hottest internal LCR pages.

Presence of new links (NL) As stated before, for this target we have trained a binary classifier with the ExtraT statistical model. As shown in the second row of Figure 16, NL-ET and NNL-ET have the highest correlation value with NL. Looking at the PNL-ET, recall that the PNL-ET scoring results from the ExtraT binary classifier trained for the same ground truth target (NL), that outputs the probability that new outlinks are present. That Spearman’s rho of PNL-ET is lower than that of NL-ET and NNL-ET is an artifact from the ties resolution for calculating Spearman’s rho. Indeed, the target NL vector and the prediction NL-ET vector are binary, and the NNL-ET vector consists of integers and has many zeros, while PNL-ET consists of real numbers between 0 and 1 and has much less ties. When calculating Spearman’s rho, the ties are resolved using average ranking, and this makes the NL ranking closer to the NL-ET and NNL-ET rankings than to PNL-ET. Precision@k% in Figure 18 confirms that PNL-ET shows the best performance, closely followed by NNL-ET. Further, the LCR-ET ranking performs very well, which is not surprising as LCR is in fact the empirical estimation of PNL over several time periods. Generally, the ranking obtained for internal outlinks have higher correlation value with the target ranking than that of external outlinks. However, Precision@k% for external links again shows that our algorithms find pages with largest number of new external links by crawling only a small fraction of pages. Interestingly, the content change rate for this target performs almost as bad as random.

Number of new links (NNL) The last row of Figure 16 shows Spearman rho for the NNL target. As we see, the NL-ET and NNL-ET are the most correlated rankings with NNL for both internal and external outlinks. Again, the average resolution of ties explains the high Spearman’s rho between NNL and NL-ET. An interesting point in Figure 16 is that the NNL-Av ranking is a good representation of the NNL ranking. It means that if we have the historical data of the pages, we can simply follow the ranking obtained by averaging the number of new outlinks in previous weeks to predict the NNL ranking. Figure 19 depicts Precision@k% performance of different rankings compared to the NNL target ranking for different values of k. NNL-ET again produces the best ranking, we observe that it has the highest values for almost any k. In particular, NNL-ET can detect the hottest pages in the leftmost region of the charts better than other rankings. Again, since random resolution of ties is used to compute Precision@k%, the right region of the former tends to look like the random ranking. This is more visible for external outlinks because this data contains more zeros. It should be taken into account that although training the regressor for NNL-ET might be a time-consuming process, once the model is constructed, it can be used to generate the estimation of NNL in a very short time.

8 Conclusions and further research

In this work, we have extensively analyzed the problem of predicting emergence of new outlinks on a Web page using the data of ten weekly crawls. We have established that there is a significant difference between internal and external outlinks, thus, we have considered them separately.
Statistical analysis reveals that most Web pages have no new outlinks in one week. Among the pages that have new outlinks, there is a high variability in the number new outlinks, both internal and external. Nevertheless, there is a considerable stability in the distribution of the new outlinks over pages from one time period to another. This observation motivates a very simple but informative prediction heuristic, NNL-Pr, that predicts the same number of new outlinks in the next period as in the previous period.

In order to achieve high prediction performance for emergence of new outlinks, as well as to obtain insights into most informative features of the page and the network, we have introduced statistical models for predicting three targets: link change rate, the presence of new outlinks, and the number of new outlinks. The models are built based on a short history, which is important in the context of focused crawling, when long history is often not available (in our case, we used the history of at most 8 previous weeks). Among the proposed models, ExtraT model gives the best prediction results. Generally, prediction accuracies of internal outlinks are higher than those of external outlinks, partially because internal outlinks appear more frequently in a page than external ones. Nevertheless, we could accurately predict the pages with largest number of new external outlinks.

We have noticed that the important features for the three targets are very similar. One of the conclusions is that the content of a page is important, because the semantic vector as well as features of content-related pages greatly enhance prediction performance. Even more remarkably, the dynamic (historical) features proved to be very informative. Significant improvement in prediction is achieved already by adding the history of just one, previous, time period. Moreover, when longer history information is available, the weighted average link change rate of related pages (DN feature) becomes the most important feature. The important conclusion, especially in focused crawling, is that we can predict new links for a page regardless of its historical information, as long as we have the history of related pages. On the other hand, the content change rate is not very informative for emergence of new outlinks. In general, we recommend to design prediction methods separately for the content and the link change rate.

In our work, we used cosine distance as content similarity metric for computing related pages. Although the cosine distance is more efficiently calculated than the temporal content similarity metrics as in [39], the nearest neighbor search is still computationally expensive, and can jeopardize the scalability of our methods. This can be potentially resolved by, for example, using GPU as in recent work [26], or parallel implementation as proposed e.g. in [17]. Both approaches are promising for scaling our methods to larger datasets.

In the future, we would like to experiment with different temporal similarity metrics. For example, Dynamic Time Warping (DTW) [9], a dynamic programming algorithm that finds patterns in time series data, that has been used in [39]. DTW has been shown superior to other similarity measures but it has prohibitive computational complexity on large datasets. A promising recent development is the Scalable Warping Aware Matrix Profile (SWAMP) introduced by Alaee et al. [3], the exact algorithm for DTW motif discovery in massive datasets. Using these new computational algorithms, DTW can be introduced in our methods and potentially improve predictions.
9 Related Work

In this section we provide a literature review for measurements and prediction of changes in Web pages. Table 4 contains the summary of features found to be correlated with or predictive for page changes in previous studies.

| Feature                              | References |
|--------------------------------------|------------|
| page size                            | [21, 8, 44]|
| top-level domain                     | [21, 22, 2, 44]|
| URL depth                            | [2, 37, 44, 40]|
| directory level                      | [8]        |
| page content semantics (topic)       | [2, 37, 41]|
| spam content                         | [21]       |
| page or domain popularity or relevance for users | [2, 20, 37]|
| number of images, tables, words      | [37, 44]   |
| number of links, e-mail addresses    | [8, 37, 44]|
| PageRank                             | [44]       |
| decay (a measure of dead links)      | [7]        |
| existence of HTTP header Last-Modified | [8]      |
| history of change in page size       | [44]       |
| history of change in page checksum, digest | [15, 33, 8, 43, 29, 4]|
| history of change in words on the page | [21, 37, 44]|
| history of change in number of images, tables, words | [44] |
| history of change in number of links, e-mail addresses | [8, 44] |
| history of change in PageRank         | [44]       |
| history of page additions, deletions, text updates on website | [12] |

Table 4: Features either correlated with or predictive of page change in related work.

9.1 Measurements of page change

Many hints for features come from Web measurement studies, which observe correlations between page features and page change. Over a crawl of 150 mil. pages once a week for 11 weeks, with content page similarity measured as the overlap in word n-grams (shingles) between the page variants, good predictors of page change are: the degree of previous content change, the length of the page (longer pages change at a higher rate), and the top-level domain of the page. For example, the rate of page text change for .edu pages was below 10%, but that of .com pages was almost 30% [21]. Additionally, they found that keyword-spam pages have a particularly high rate of change.

Adar et al. [2] analyzed a crawl of 55,000 Web pages. Data was collected from 612,000 English-speaking users of a live search toolbar over a period of 5 weeks (so biased in favor of pages that do change, since they were chosen by humans to visit). They considered 4 types of intervals: those based on the browsing behavior of the toolbar users, hourly crawls over a period of 5 weeks, sub-hour crawls over a period of 4 days for pages that changed a lot in the hourly crawl, and a simultaneous crawl with 2 clock-synchronized crawlers for pages that changed a lot within less than 2 minutes. They show page change frequency and amount is correlated with top level domain, page topic, url depth, and page popularity. Overall, 34% of pages in their crawl did not change in the interval, while the remaining 66% changed on average once every 123 hours.

Elsas et al. [20] crawled a set of 2 mil. Web pages every week for a period of 10 weeks. They report that 62% of the pages did not change significantly in said period. All documents were part of a set of queries and were assigned a relevance score ranging from 0 (bad) to 4 (perfect) by human judges. They find that highly relevant pages are more likely to change than regular pages.

Bar-Yossef et al. [7] study the decay (dead links) of the Web. They find that some pages and large subgraphs of the Web can decay rapidly. They propose a measure of decay and hypothesize that this could be used for more efficient crawling. They mention the issue of Web pages that return a 200 status code containing an error message, which they call soft-404 pages. The decay measure needs to be calculated post-crawl but could then be used as a feature in future crawls. Saad et al. [40] considered 100 pages of a French television archive, which they monitored hourly. They find that page change rate lowers significantly as URL depth increases.

Santos et al. [41] studied the temporal dynamics of the Web with respect to specific topics. They collected data daily for 30 days on pages in two distinct topics (Ebola and movies), for which they considered the same 22,200 and 27,353
pages each day per topic respectively. They find that page topic is an important predictor for change frequency and for the expected number of new links. They also find that revisiting already downloaded pages leads to new pages, but those pages don’t necessarily have the same topic. For both topics almost all pages either have a change frequency in the 0 to 0.1 or 0.9 to 1.0 range, so either very often or not at all. This work is limited in the fact that they only studied two topics, and their definition of page change might be somewhat loose in the sense that it does not account for dynamic html content such as ads.

Ntoulas et al. [35] have crawled weekly snapshots of 154 websites over the course of a whole year, where they downloaded up to 200,000 pages per site each week. They find that there is a high turnover rate for pages (birth and death), and even higher for links. The degree of content shift is likely to remain consistent over time: pages that change in one week are likely to change to a similar degree in the next week, and pages with little change will continue to experience little change; however, this correlation can vary significantly between websites (these observations are in line with ours). Pages were created at a rate of 8% per week, and they estimate that 20% of pages will no longer be accessible after a year. Links proved to be significantly more dynamic than content, they measured 25% new links per week and after a year about 80% of all links were replaced by new ones. Once pages are created they usually go through only minor or no changes. Half of the pages that were still available after a year did not change.

Olston and Pandey [56] study 2 separate sets of 10,000 urls, one with 50 snapshots and the other with 30 snapshots each spaced 2 days apart. They introduced information longevity, that is, ephemeral content such as ads versus lasting content such as blog posts, as an important metric for the effectiveness of crawls. They find that change frequency is not correlated with information longevity. They propose a crawl policy that takes the average staleness of fragments of the page into account instead of the page as a whole, which prioritizes content with high longevity. The rationale behind this policy is that although longevity is not a predictor for page change, it is an important factor for the usefulness of a page change.

Grimes [22] did 500 hourly crawls on 23,200 pages, where the pages with less than 48 hours between changes were downsamples. They found that few cases were consistent with a Poisson model, but only a small portion differed significantly. They aggregated pages by locality, by looking at the top-level domain, and showed that changes occur less frequently during night time and over weekends.

Gupta et al. [23] crawled 87 Indian news sources once every 30 minutes for 20 days. They observed that the rate at which new news articles are added varies per topic, and that fewer new articles are created on weekends compared to week days.

9.2 Predicting page change from the history of change

Assuming the homogeneous Poisson process model of change, the framework in [15] estimates the change rate \( \lambda \) statistically out of an (incomplete and irregularly sampled) history of change for an individual page with an offline maximum likelihood estimator (MLE), whose solution is found numerically. The baseline is the naive estimator: the number of detected changes divided by the sampling period, which is biased towards smaller values when the change history is sampled too infrequently. The evaluation is done with a simulated weekly crawler on the daily Web data from [14]: the page is considered to have changed if its checksum has. Only pages which changed less than once every 3 days were selected, so the correct rate of change could be assumed to equal the baseline. The MLE has a lower bias, and, for 83% of pages, it predicts a value closer to the baseline than the naive estimator. Other, less practical, estimators were also proposed, which assume that last-change dates are provided for the page [14] [33]. Later, [29] integrates the learning of the change rate from [15] with the scheduling of an optimised crawler, using a staleness penalty function and model-based reinforcement learning. A page change is defined as an alteration in the page’s content digest, as computed automatically by any data extractor. The change rates learnt are not shown. In [4], the change rates are instead learnt with two online (or incremental) estimators (the law of large numbers, LLE and stochastic approximation, SA) of comparable performance to MLE on synthetic change data.

A more general non-homogeneous Poisson process is assumed in [43], so that localised rather than global rates of change need to be learnt. This is done in time windows, which are determined such that the update points within a window appear consistent. A Weibull estimator has a lower mean squared error (MSE) than methods which assume a homogeneous Poisson model, over 27,000 frequently accessed Web pages, crawled daily for two months. The type of change measured in a page is not specified; it is likely a change in the checksum, as in the closely related work [18].

Predictions of change have also been done without an underlying mathematical model of change. The count of content changes to pages on three highly dynamic major news websites are forecast via time-series analysis in [12]. In this work, 29,000 pages from these websites are crawled every 15 minutes over 2-3 months. Per website, the number of changes (pages are added, deleted, or updated in textual content, as seen from cosine similarity) forms a time series,
which is then decomposed into a weekly and daily periodic and irregular components, which are then shown to be predictable.

9.3 Predicting page change using also page content features

The content of a page, when used in addition to the change history, is shown to improve prediction \[8, 37, 21, 39, 34\]. While assuming a fixed change rate for each page, static page features are used as predictors for the first time in [8]. Alongside historical data for the page change, the predicted variable is the change rate, but the task is transformed into a classification task by discretising the change rate into four change-rate classes using k-means clustering; these classes are first balanced to the same size of 5,000 pages. The training and testing set consist of 85,000 well-accessed pages on the Brazilian Web, crawled daily for 100 days. A page is said to have changed if its checksum differs. The static page features which were found to be important are: the number of links, e-mail addresses, and images, the existence of the HTTP header Last-Modified, the file size in bytes (excluding HTML tags), and the directory level of the URL from the URL root. Unlike in later studies [2, 40], the URL depth was not found important. A pruned decision tree was the best classifier using static page features, and when historic change data is also available, it can refine the decision of the classifier by moving the page to another class. The error rate is 15%; the relative feature importance values are not provided.

Specific focus is given to predicting, still using mostly static page features, the number of in-links to pages [37], as a sign of page status on the Web. The ground truth is obtained by a Google Web Search. The features are diverse: the number of words, the URL depth, the scope of the topics covered, the number of out-links, the textual cosine similarity between two snapshots of the page, and the popularity (traffic) on the entire domain; all appear important to the prediction. A nonlinear regression using model trees (algorithm M5') performed best, however, this predicts (across a dataset of 82,068 pages) a number of in-links that has a correlation coefficient with the ground truth below 0.7.

Clustering 300,000 pages (obtained from the WebArchiv\[1\] across 210 websites (collected from the Internet Archive\[2\] over one year) by combining static and dynamic page features leads to clusters with similar page change patterns [44] (the precise type of page change is not specified). Some static page features are content-related: features computed out of the term frequency–inverse document frequency (TF-IDF) statistics of the 1000 most frequently appearing words in both the page and the URL, the number of images, tables, or words, the file size and type (HTML, plain text). Others are URL features: the depth of the page in its domain, and the top-level domain. Four linkage features are also used: PageRank, the number of incoming/outgoing links, and the number of email addresses. Since the URLs don’t change, the dynamic content and linkage features that can be used to measure the change in time in: content (computed by cosine similarity), number of images, tables, words, file size, PageRank, number of links and email addresses. The combination of static and dynamic features leads to better change prediction (of the top changing pages in particular) than either type of feature alone.

The page change frequency estimator in [44] uses as dynamic predictive features the change value of a page (computed at eight rates, from every 4 h to every 72 h). This change value includes page layout (or attribute changes), and three types of content changes for page elements: element additions, deletions, and modifications. The target to be predicted is the categorical frequency of change, with five such categories defined. The dataset consists of only 3,122 pages with different changing rates, crawled over 12 weeks; neither the domains of the pages, nor the class sizes are specified. The prediction is done by a modified Random Forest classifier: 87.98% of the pages in the test set of 624 were classified correctly. This method has a serious shortcoming: acquiring the features of a page via frequent crawling is an extremely expensive process, which explains the limited testing.

9.4 Predicting page change using related page features

Radisky et al. [39] crawled 54,816 pages hourly for a 6 months period. The pages selected to be crawled, were visited by at least 612,000 users during the period of five weeks (i.e. data collected similarly to the work by Adar et al. [2]). Related pages were introduced using three selection methods: graph distance, content similarity and temporal content similarity. Indeed, including related pages of similar temporal change patterns increases prediction accuracy to 72.72% from 62.93% when using only page features. In order to predict changes in each target page, the authors choose to use 50-days history of 20 most related pages; this training size was chosen experimentally. Then, for each of the 20 related pages, a unique classifier was trained to predict whether the target page will change. Then, the 20 classifiers vote whether the target page is predicted to change or not. The final prediction is the sum of weighted votes with weights proportional to the similarity score of the related pages to the target page.

http://webarchive.cs.ucla.edu/
https://archive.org/
9.5 Scoring functions for pages

A scoring function models the likelihood of change, and can be used for ranking pages. Such scoring function is learnt in \[42\] only from the history of the page change; the precise type of change is not specified. The function is learnt as an expression tree whose inner nodes are simple operators (such as addition and the exponential function), and whose terminal nodes contain the time elapsed since the last page visit, the number of visits and changes, other estimators for the change rate from \[15, 44\], and constants. The fitness function is the measured quality of a crawling schedule based on the function learnt; this schedule simply uses the score function to rank the pages, and crawls the top ranked. The evaluation was done on 400,000 pages from the Brazilian Web, which were recrawled daily for 2 months. A variety of score function alternatives were produced (some relatively simple), which were an improvement over existing change-rate estimators. In this work we propose scoring functions based on prediction of new out-links.

Acknowledgements

This work was supported by the project Eurostar E!113204 WebInsight, http://webinsight-project.com/.

Conflict of Interest

The authors declare that they have no conflict of interest.

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Appendix

A1. Heavy-tailed distributions

Table 5 provides the formal definitions of probability distributions, as summarized in [1]. We use these distributions to fit the data in Section 4, see Figure 6.

| Probability Model  | Probability Mass Function |
|--------------------|----------------------------|
| Power law          | \(P(X = k) = (\alpha - 1)k_{\text{min}}^{-\alpha}k^{-\alpha}, \alpha > 1, k_{\text{min}} > 0\) |
| Truncated power law| \(P(X = k) = \frac{\lambda^{1-\alpha}}{1 - \alpha k_{\text{min}}} (-\alpha \lambda k^{\alpha - 1}) k^{-\alpha - 1} e^{-\lambda k}, \alpha > 1, k_{\text{min}} > 0, \lambda > 0\) |
| Exponential        | \(P(X = k) = \lambda e^{-\lambda (k - k_{\text{min}})}, k_{\text{min}} > 0, \lambda > 0\) |
| Stretched exponential | \(P(X = k) = \lambda \beta k^{\beta - 1} e^{-\lambda (k^{\beta} - k_{\text{min}}^{\beta})}, k_{\text{min}} > 0, \lambda > 0, \beta \in [0, 1]\) |
| Lognormal          | \(P(X = k) = \frac{1}{k} \exp\left(-\frac{(\ln k - \mu)^2}{2\sigma^2}\right) \sqrt{\frac{2\pi}{\sigma^2} \text{erfc}\left(\frac{\ln k_{\text{min}} - \mu}{\sqrt{2}\sigma}\right)}^{-1}, k_{\text{min}} > 0\) |

Table 5: Probability models used to fit the empirical distributions for the number of new outlinks.

Figure 20 visualizes the CCDF of the body of the empirical data for the number of new in/external outlinks and their fits.

Figure 20: The body \([x_{\text{min}}, x_{\text{max}}] = [1, 19]\) of the empirical data and of the models fitted to the body.

A2. Approach for obtaining the semantic vector

A common approach for embedding is to create a TF-IDF (Term Frequency-Inverse Document Frequency) matrix which reflects how important a word is to a document (in our case: the page text). The TF measures the number of times a term occurs in a document; and the IDF is a measure of whether a term is common in the Web pages, which is obtained by dividing the total number of Web pages by the number of Web pages containing the term. Each element of the matrix is then calculated by multiplying the TF by the IDF. Due to the large number of the words in the vocabulary, the TF-IDF matrices are mostly very large and sparse.

Latent Semantic Analysis (LSA) [31] is a method that reduces the dimension of such large sparse matrix into a small dense one by applying randomized Singular Value Decomposition technique. In our experiments, the embedding was obtained using our own algorithm based on the principle of LSA, with a set of significant changes that alter both the speed and the quality of the embedding. The key advantages of our technique are related to the computing efficiency.