Learning to Schedule Webpage Updates Using Genetic Programming

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Where we are in Brazil

The Problem

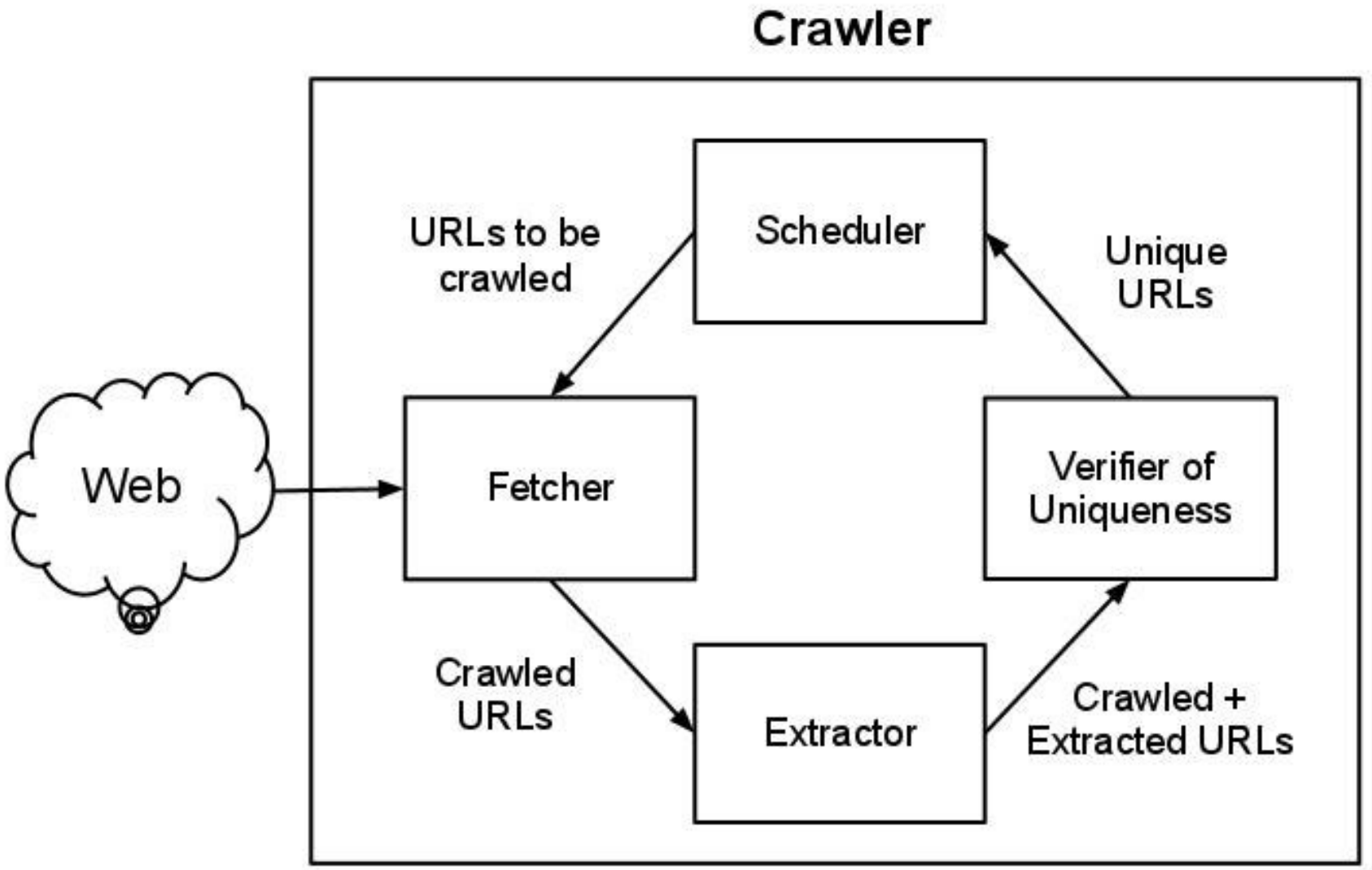
Estimate the likelihood that a webpage has been modified

- This estimation is used to define the order in which those pages should be visited
- Reduce the cost of monitoring crawled webpages for keeping updated versions

Dificulty of the Problem

- Web: over 60 trillion individual webpages
- Scheduler define the order in which URLs should be visited
- Crawlers use a score function to assign a weight to each known URL
- Only the top k pages are taken to be visited
- Full scan of prior crawled webpages to assure freshness is unfeasible

Crawler Architecture: Complete Cycle



The Scheduler

Driven by two main goals:

- *Coverage*: fraction of desired pages downloaded successfully
- *Freshness*: degree to which downloaded pages remain up-to-date
- This work is focused on freshness

Related Work

- Estimator for change frequency of pages: visit pages proportionally more often
  - Estimator is used as baseline
  - [Cho and Garcia-Molina, ACM TOIT, 2003]
- Group pages into k clusters with similar change behavior and sort them based on the mean change frequency of a sample of each cluster
  - They proposed four strategies to compute weights associated with a change, all used as baseline
  - [Tan and Mitra, ACM TOIS, 2010]

GP for Incremental Crawling (GP4C)

Iterative process with two phases:

- Train with an initial set of pages
  - Training set is crawled first
- Validate results with a distinct set of pages
  - A set of validation pages is crawled
  - Fitness function is used in this phase
- Experimental tests apply the resulting function in a third set of pages
- Best individuals are selected as scheduling solutions

Best Individuals in the Validation Step

- Run GP process *N* times with distinct seeds
- Pick best individual: $GP4C_{Best}$
- Average performance: $GP4C_{Avg}$
- Sum of each individual: $GP4C_{Sum}$
- For $GP4C_{Avg}$ and $GP4C_{Sum}$
  - Considered performances of each individual in both training and validation sets minus SD of such performance when selecting best individuals

Experimental Evaluation

- Crawl simulation to ensure that all policies are compared under same conditions
- Built a dataset collected from the Brazilian Web
  - Repository of around 200 million pages
  - We selected 3,059,698 pages, daily monitored

Monitoring period	Number of webpages	Number of websites	Number of webpages/site		
			Min	Max	Average
57 days	417,048	7,171	1	2,336	58.15

Baselines [Cho and Garcia-Molina, 2003]

$$\mathrm{CG} = -\log\left(\frac{n - X + 0.5}{n + 0.5}\right)$$

- CG: estimates the change frequency of *p* pages
- *n*: number of times page *p* was visited
- *X*: # of times a page *p* changed in *n* visits

Baselines [Tan and Mitra, 2010]

$$\lambda_p = \sum_{i=1}^{n} w_i \cdot \mathrm{I}_i(p)$$

- λ_p : parameter of a Poisson process
  - assuming each page *p* follows a Poisson process
- *n* : number of visits
- w_i : weight of change in the i^{th} download
  - NAD, SAD, AAD, GAD
- $\mathrm{I}_i(p)$: 1 if page *p* changed; 0 otherwise

Baselines [Tan and Mitra, 2010]

$$\lambda_p = \sum_{i=1}^{n} w_i \cdot \mathrm{I}_i(p)$$

- w_i : weight of change in the *i*th download
  - NAD (Nonadaptive): all change events have equal weight
  - SAD (Shortsighted adaptive): considers the current change status of the page
  - AAD (Arithmetically adaptive)
  - GAD (Geometrically adaptive)

Evaluation Metric

- ChangeRate at cycle *i* is the fraction of pages downloaded that were changed

$$C_i = \frac{D_i^c}{D_i}$$

  - ChangeRate used as fitness function
  - [Douglis et al., Rate of change and other metrics: a live study of the world wide web, USENIX 1997]

Experimental Methodology

- 5-fold cross validation
  - 4 folds equally divided into training set and validation set and 5th fold as test set
- Simulate a crawl using dataset to evaluate score functions and compute fitness values

Experimental Methodology

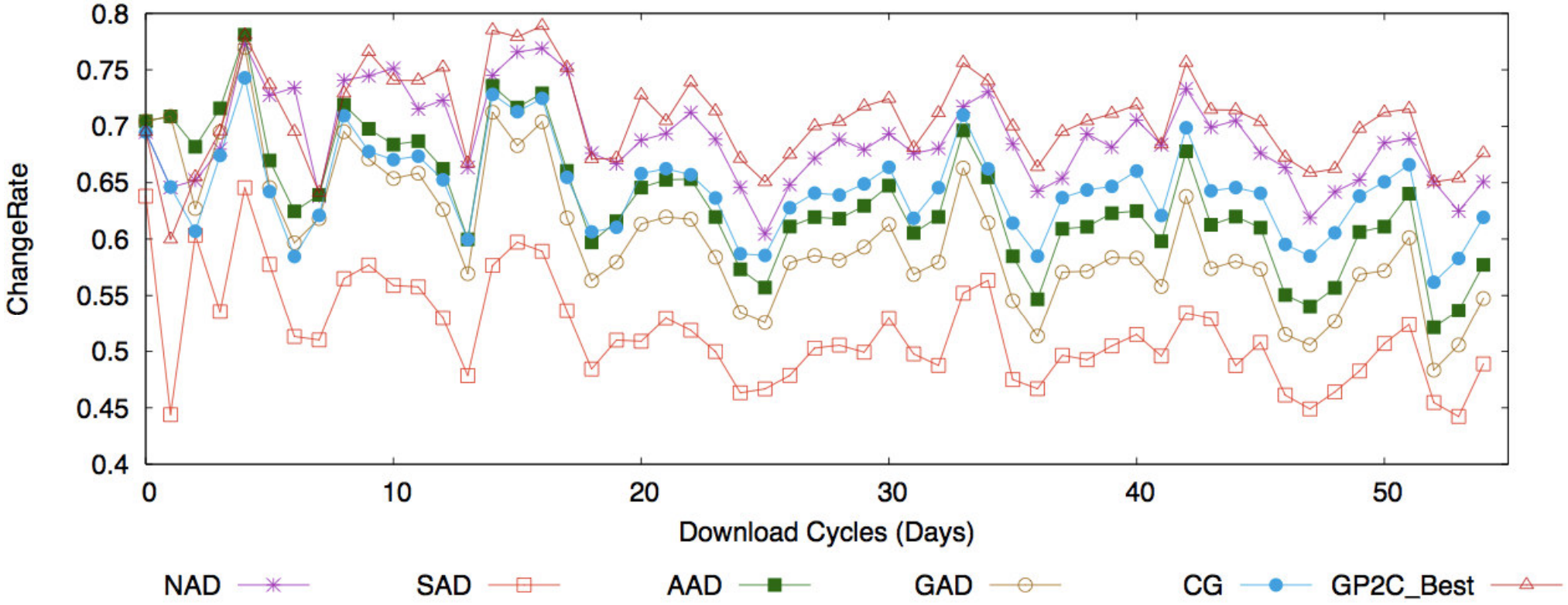
- GP framework:
  - $N_p = 300$ individuals
  - $N_g = 50$ generations as termination criterion
  - Maximum tree depth = 10
  - Terminals:

    n : # of times page p was visited

    X : # of times page p changed in n visits

    t : # of cycles since page p was last visited

Average ChangeRate on Each Cycle



Average ChangeRate for All Days

Rand	Age	NAD	SAD	AAD	GAD	CG	$GP4C_{Best}$	$GP4C_{Sum}$	$GP4C_{Avg}$
0.1857	0.2130	0.6892	0.5166	0.6344	0.6016	0.6439	0.7058	0.7008	0.7034
$\pm$	$\pm$	$\pm$	$\pm$	$\pm$	$\pm$	$\pm$	$\pm$	$\pm$	$\pm$
0.0007	0.0009	0.0056	0.0066	0.0095	0.0059	0.0067	0.0096	0.0176	0.0107

Conclusions

- GP framework to automatically generate score functions for schedulers
- Rank webpages according to their likelihood of being modified since last crawled
- Compared three variations of GP4C against seven state-of-the-art baselines
- $GP4C_{Best}$ is statistically superior to all baselines
- Framework quite flexible to (as future work)
  - derive new score functions (e.g., Pagerank of pages)
  - alternative fitness functions to balance coverage and freshness

Thanks

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