Focused Retrieval of University Course Descriptions from Highly Variable Sources

Thomas Effland - SUNY University at Buffalo

Acknowledgements: This work is partially supported by **NSF DUE-CCLI-0920335**.
We would like to thank the **UB Honors College** for travel support.
We would like to thank **Dr. Bina Ramamurthy** from **UB CSE** for advising this work.

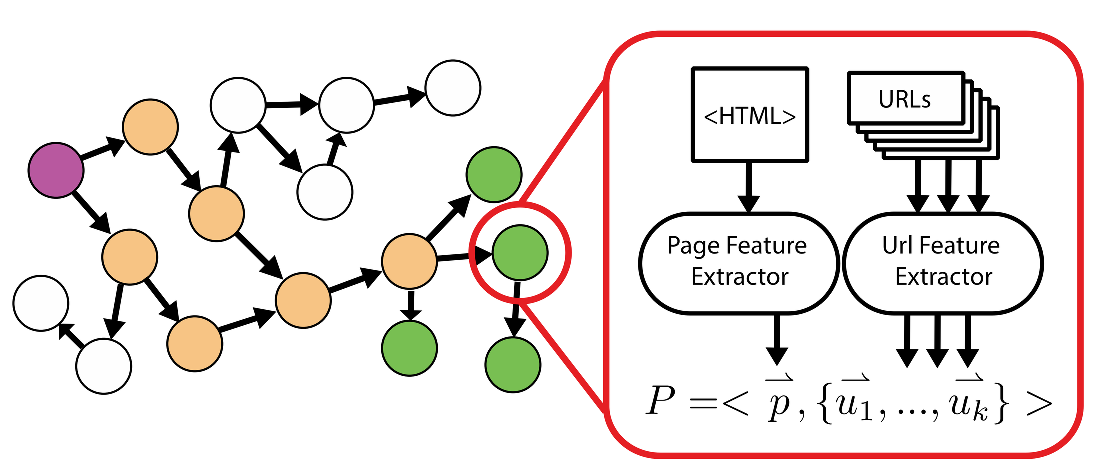
Motivating Question

How can we automatically retrieve semantically similar content (such as university course descriptions) from many disparate sources on the Web that do not reference each other when we only know the domain names and have limited computational and training resources?

Challenges

- Target content is typically very sparse on large sites, so brute force crawling is unreasonable.
- Organizational structure and content location vary highly for each site, thus canonical rule-based approaches are ineffective.
- Typical topical-locality [1] assumptions made in focused web crawling do not hold when sites do not reference each other.
- Retrieving relevant content requires identifying and tunneling through irrelevant pages [2] that lead to target content.
- Gathering hand-labeled data is costly.

Webpage Representation



Each page is represented by a feature vector of the page content and a set of feature vectors for each link on the page.

Page Features

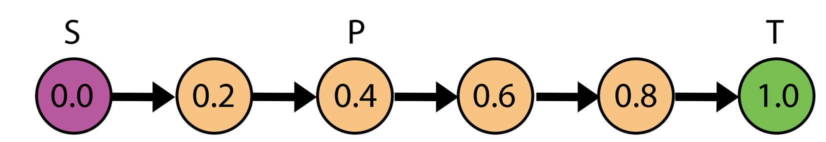
- TF-IDF [3] of words and bigrams of segmented url
- TF-IDF of words and bigrams of the title
- Latent Semantic Analysis (LSA) [4] of TF-IDF of words and bigrams of page body words

Url Features

- TF-IDF of words and bigrams of segmented url
- TF-IDF of words and bigrams of the link anchor text

Algorithm & System Design

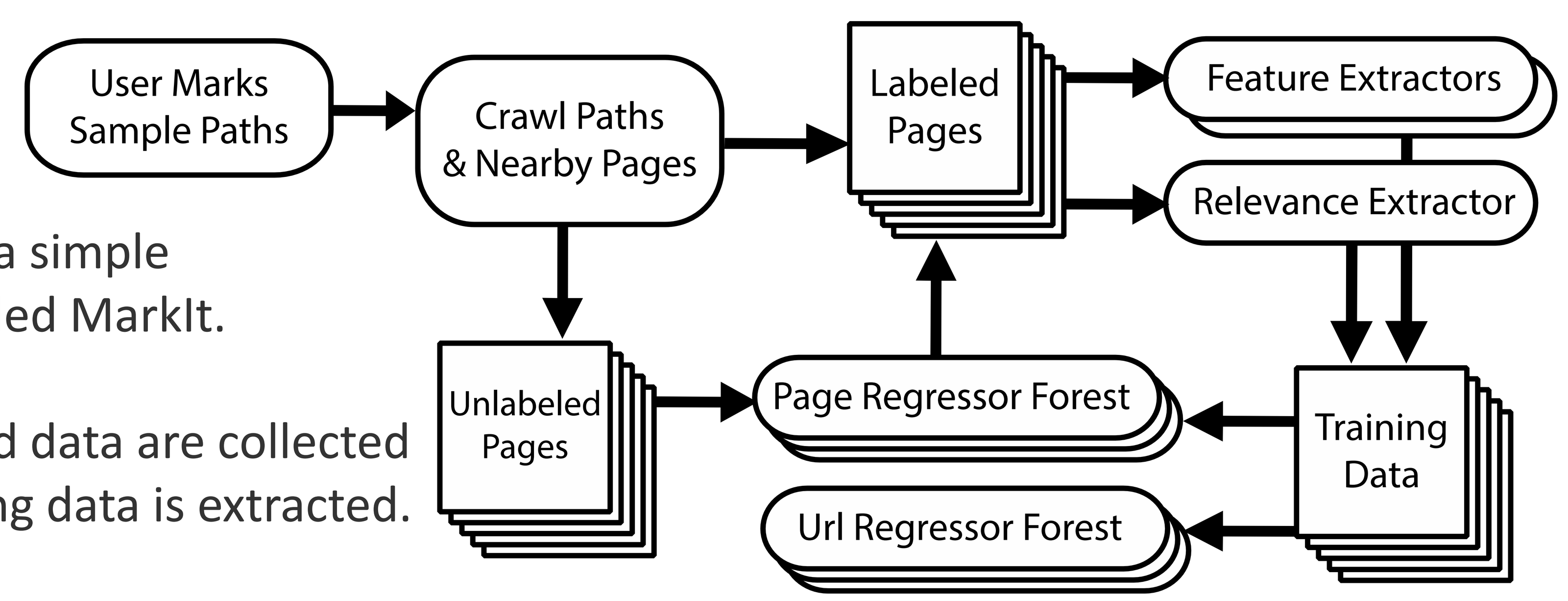
Defining a Relevance Metric



To obtain a measure of how close an irrelevant page is to a target content page, we define the label **R** of a page as the normalized link distance from the page to the target.
This relevance metric helps address variable structure of sites.

$$R(P) = 1 - \frac{LinkDist(P,T)}{LinkDist(S,T)}$$

Training Stage



1) **User marks sample traversal paths** using a simple Chrome extension called MarkIt.

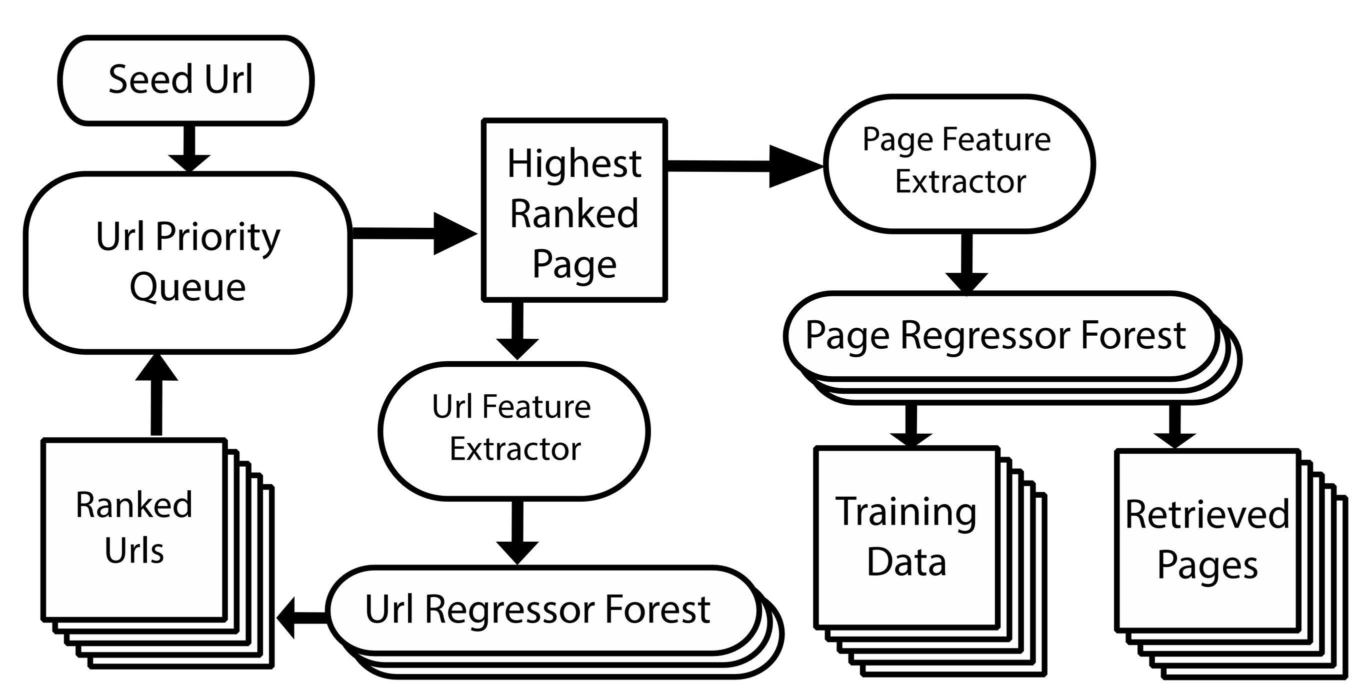
2) Labeled and unlabeled data are collected from paths and training data is extracted.

3) Two **Random Forest Regressors** [5] are fit to training data.

4) Regressors are used to **generate more training data from unlabeled data by ranking pages** and labeling highly ranked pages or asking user for input on middle ranked pages.
This **semi-supervised** approach combines **self-training** [6] with **active learning** [7] and saves considerable time in generating **large training set from significantly less intervention**.

This yields **flexible regressors** from only a **small number of sample traversals from a few sites.**

Deployment Stage



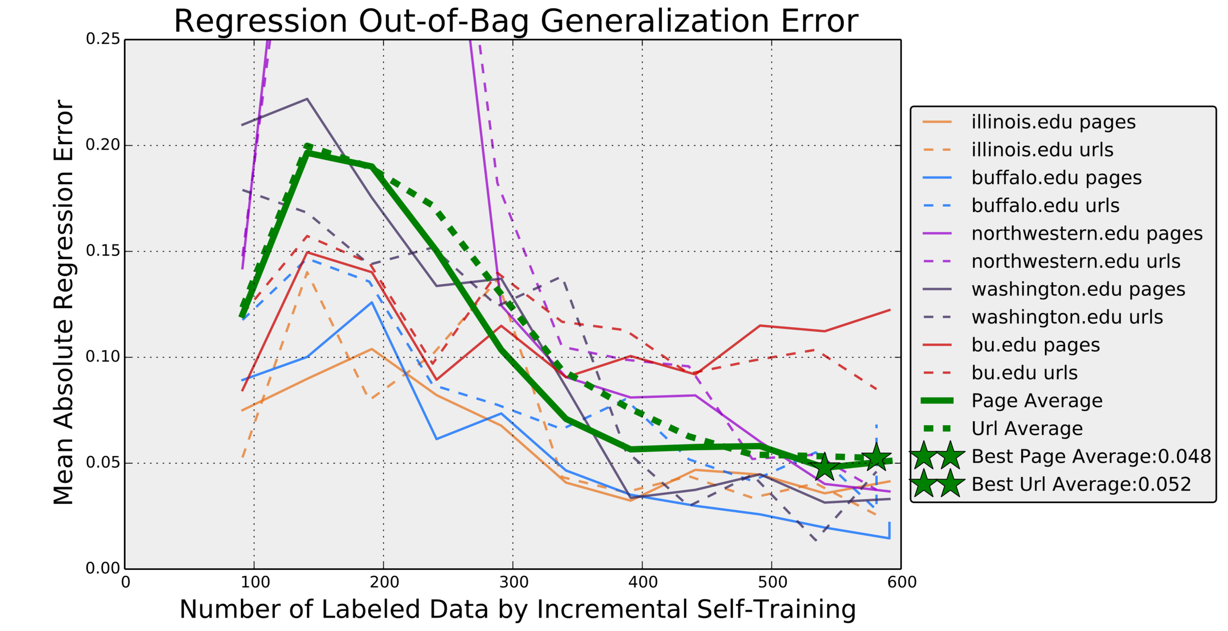
1) Top level url is input in queue. Queue pops top url.

2) Features for each url on page are extracted and **urls are ranked by relevance prediction**, then pushed into priority queue.

3) Features for page content are extracted and relevance is predicted. If **relevance prediction for the page is high** and agrees within threshold amount with initial prediction from its url, the **page is classified as a target page**. The user may review the proposed retrieval and classify the prediction as correct or not and the page is added to the training data.
This is is an example of **active learning.**

4) The next page from the queue is popped and the cycle continues until user-specified endpoint.

Results



Here we show how the **absolute regression error** for the page and url regressors **improves by using self-training**. Regressors for each school were trained on data from the other schools. The **thick green lines show the average among all five schools.**

The **best generalization scores** are labeled with stars and are **0.048** and **0.052** for the page and url regressors respectively.

This graph shows how we are able to automatically train incrementally more accurate general regressors, starting with less than 100 initially labeled pages.

Conclusions & Impact

- **General Information Retrieval framework** in problem domain where seed pages are irrelevant and no topical locality assumption.
- **Novel reformulation of page relevance** as normalized link-distance.
- **Novel combination of self-training and active-learning** for focused crawling on little training data.
- **Novel focused-crawling architecture.**

References

[1] B.Davison, ACM SIGIR. ACM, 2000.
[2] M. Diligenti et al. VLDB, pages 527–534, 2000.
[3] Rajaraman, A. pp. 1–17. ISBN 9781139058452, 2011.
[4] S. Dumais, Annual Review of Information Science and Technology 38: 188. 2005.
[5] L. Breiman (2001).Machine Learning 45 (1): 5–32.
[6] O. Chapelle et al. MIT Press. ISBN 978-0-262-03358-9, 2005.
[7] B. Settles, Computer Sciences Technical Report 1648. 2010