Efficient Web Spidering with Reinforcement Learning

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Outline

- Web Spidering Overview
- Web Spidering as Reinforcement Learning
- Experiemental Setup
- Future Work and Related Work

Web Spidering Overview

- Agents that explore the hyperlink graph of the web
- Key to high coverage by search engines
  - Alta Vista, Hotbot
- Aim to find more distinct web pages
- Avoid off-topic area
  - To find pages of particular kind on a particular topic

Web Spidering Overview

- Cora - domain specific search engine for CS research papers
  - Finds title, authors, abstract, references
  - Resolves forward/backward references
  - www.cora.justresearch.com :(not working

Web Spidering as Reinforcement Learning

- Reinforcement Learning
  - State set: $s \in \mathcal{S}$.
  - Action set: $a \in \mathcal{A}$
  - Transition Function $T : \mathcal{S} \times \mathcal{A} \to \mathcal{S}$
  - Reward Function: $R : \mathcal{S} \times \mathcal{A} \to \Re$
  - Goal: to learn a policy, a mapping from states to actions: $\pi : \mathcal{S} \to \mathcal{A}$

Web Spidering as Reinforcement Learning

- More …
  - Discount factor: $0 \leq \gamma < 1$
    - Sooner reward is better than later reward
  - Value of each state: $V^\pi(s) = \sum_{t=0}^{\infty} \gamma^t r_t$
    - For policy: π
  - Optimal policy: π^*
    - Value function of Optimal policy: V^*
  - Value of selecting action a from state s

$$Q^*(s,a) = R(s,a) + p\gamma V^*(T(s,a))$$

Web Spidering as Reinforcement Learning

- More …
  - Optimal Policy: $\pi^*(s) = \arg\max_a Q^*(s,a)$

Cheese-finding v.s. Spidering

- Maze, mouse, cheese
  - Receives a reward for finding a piece
  - Only immediate reward
  - To act optimally, must count future rewards
- Spidering
  - On-topic documents are immediate reward
  - Action: follow a link
  - State: locations to be consumed
  - Number of actions is large and dynamic

Web Spidering as Reinforcement Learning

- Why Reinforcement Learning is the proper frame work
  - Performance is measured in terms of reward over time
  - The environment presents situations with delayed reward

Practical Approximation

- Goal: practically solved
- Problems
  - State space is huge: 2^(# of on-topic doc)
  - Action space is large: # of URLs
- Assumptions for simplification
  - State is independent of the documents consumed, collapse all states into one
  - Actions are distinguished by the the words in the neighborhood of the hyperlink

Practical Approximation

- With these assumptions
  - Q function becomes a mapping:
    - bag-of-words -> scalar (sum of future reward)
  - Two sub-problems
    - Assigning Q values to hyperlinks in training set
    - Learning a mapping from text to Q values

Value Criterion

- Assigning Q values to hyperlinks
  - Simplest mapping
    - 1 to those points to a research paper
    - 0 to others
    - Equivalent to RL framework with $\gamma = 0$
  - Move involved criteria
    - Calculate discounted sum over rewards of the hyperlinks from the web page $\gamma > 0$

Value Criterion

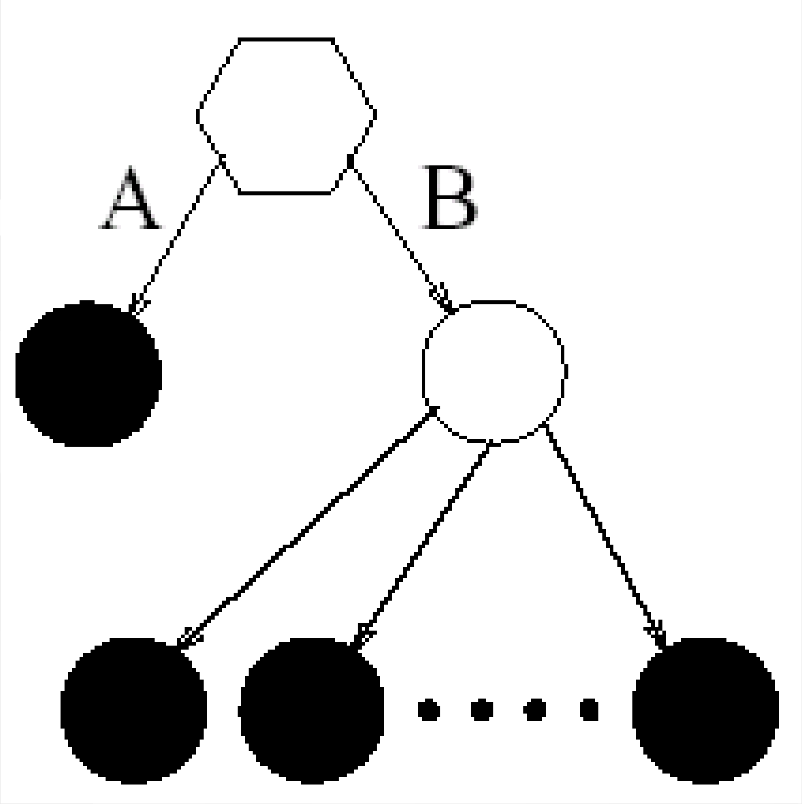
A, B – hyperlinks

Circles – documents

Hexagon – spider

Filled-in circles – reward

Immediate reward always better than future reward



Value Criterion

- Why immediate reward > future reward?
  - Action A: retrieves a paper, reward 1
  - Action B: a web page links to 1000 papers
  - If use A, then B, reward is “1,0,1,1,…”
  - If use B, then A, reward is “0,1,1,1,…”
- Conclusion:
  - Achieve reward as early as possible

Neighborhood Text

- To compare know hyperlinks to unknown hyperlinks, use neighborhood text of the hyperlinks.
  - E.g. anchor text of a hyperlink

"Using the Future to Sort Out the Present: Rankprop and Multitask Learning for Medical Risk Analysis," (postscript) R. Caruana, S. Baluja, and T. Mitchell, Neural Information Processing 7, December 1995.

Neighborhood Text

- Association each hyperlink with two sets of words
  - The anchor text and tokens from the URL
  - The full text of the web page where the hyperlink is located
  - Each hyperlink is identified by the two sets

Naive Bayes

- Terms
  - A document class: c_j
  - Document frequency: $\mathrm{P}(c_j)$
  - A word: w_t Vocabulary: V
  - The frequency that the classifier expects the word to occur in documents of the class: $\mathrm{P}(w_t|c_j)$
  - A document: d_i

Naive Bayes

- Naïve Bayes assumptions to classify documents:
  - Word occur independently
- Calculate probability of each class with given evidence of the document: $P(c_j|d_i)$
- The kth word in document: $w_{d_{ik}}$

$$\begin{aligned} P(c_j|d_i) &\propto P(c_j)P(d_i|c_j) \\ &\propto P(c_j)\prod_{k=1}^{|d_i|} P(w_{d_{ik}}|c_j) \end{aligned}$$

Naive Bayes

- Goal: To learn the parameters:

  $\mathrm{P}(c_j)$ $\mathrm{P}(w_t|c_j))$

- Method: Using a set of labeled training documents

(See paper for detailed formulas)

Regression as Classification

- To construct the model
  - Discretize Q values: the discounted sum of future reward values of training data
  - Place the hyperlinks into bins according to Q values
  - Run Naïve Bayes text classifier

Regression as Classification

- To determine the Q value of an unknown hyperlink
  - Compute the probability of the class membership for each bin
  - Compute a weighted average of the bins' average Q value

Experiment Setup

- Data
  - CS department of Brown, Cornel, U of Pittsburgh, U of Texas Austin
  - 53,012 web pages and ps files, 592,216 hyperlinks
  - Target: computer science research paper
  - Criteria for research paper:
    - Abstract, Introduction, references, bibiography
    - 200 ps files, 95% precision, 2,263 papers identified

Experiments

- Baseline: FIFO action queue
  - Follow hyperlinks in order, breath-first spider
- 3 spiders
  - Immediate spider: γ =0, two classes (0,1)
  - Future spider: γ >0
  - Distance spider: combining two spiders

Distance Spider

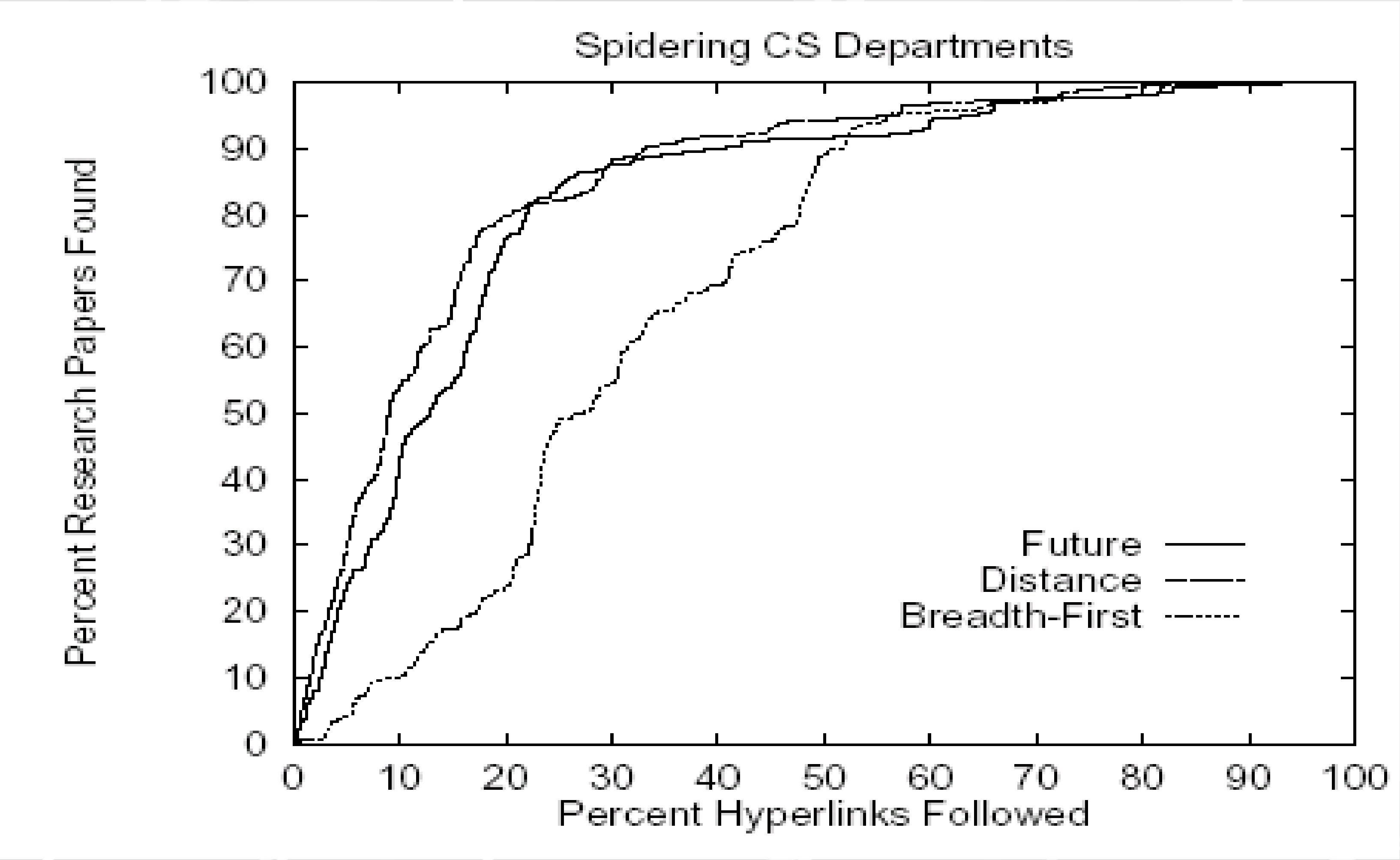
- Properties of distance spider
  - Rank research papers above all others
  - Prioritize others by their future rewards
  - No discounted sum for keeping Q<=1

Max Reward	Distance to nearest reward				
	0	1–2	3–4	5+	∞
0					0.000
1–100	1.000	0.250	0.063	0.016	
101+		0.500	0.125	0.031	

Evaluation Metrics

- Number of pages retrieved before half of the papers retrieved
  - Simple, intuitive, but not may have incredible difficulty for more
- Sum of reward
  - Each reward is discounted by one minus the percent of web pages to be retrieved
  - Calculating area under curve, Integral scores

Results

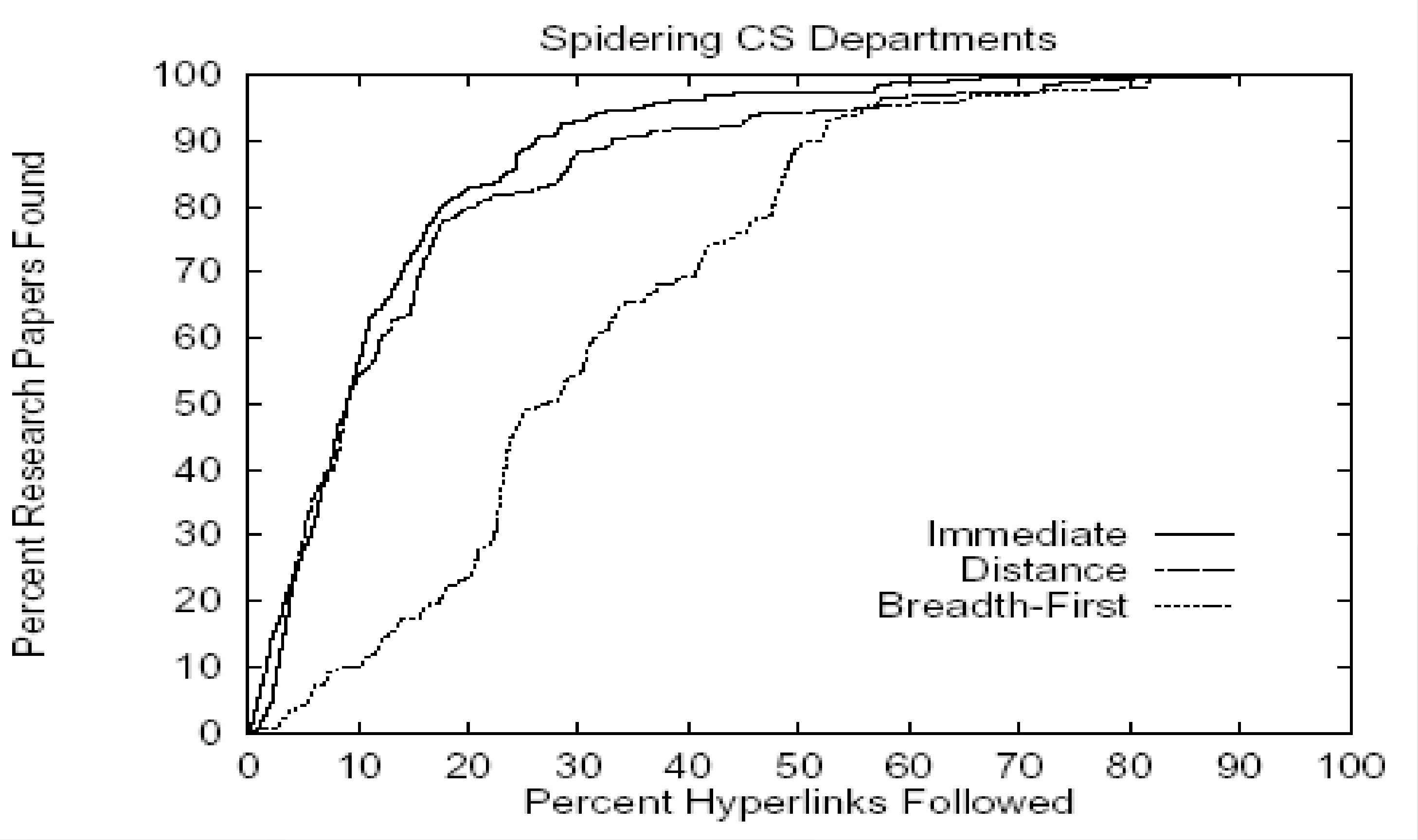


Spidering CS Departments
Percent Research Papers Found
Percent Hyperlinks Followed
0
10
20
30
40
50
60
70
80
90
100
Future
Distance
Breadth-First

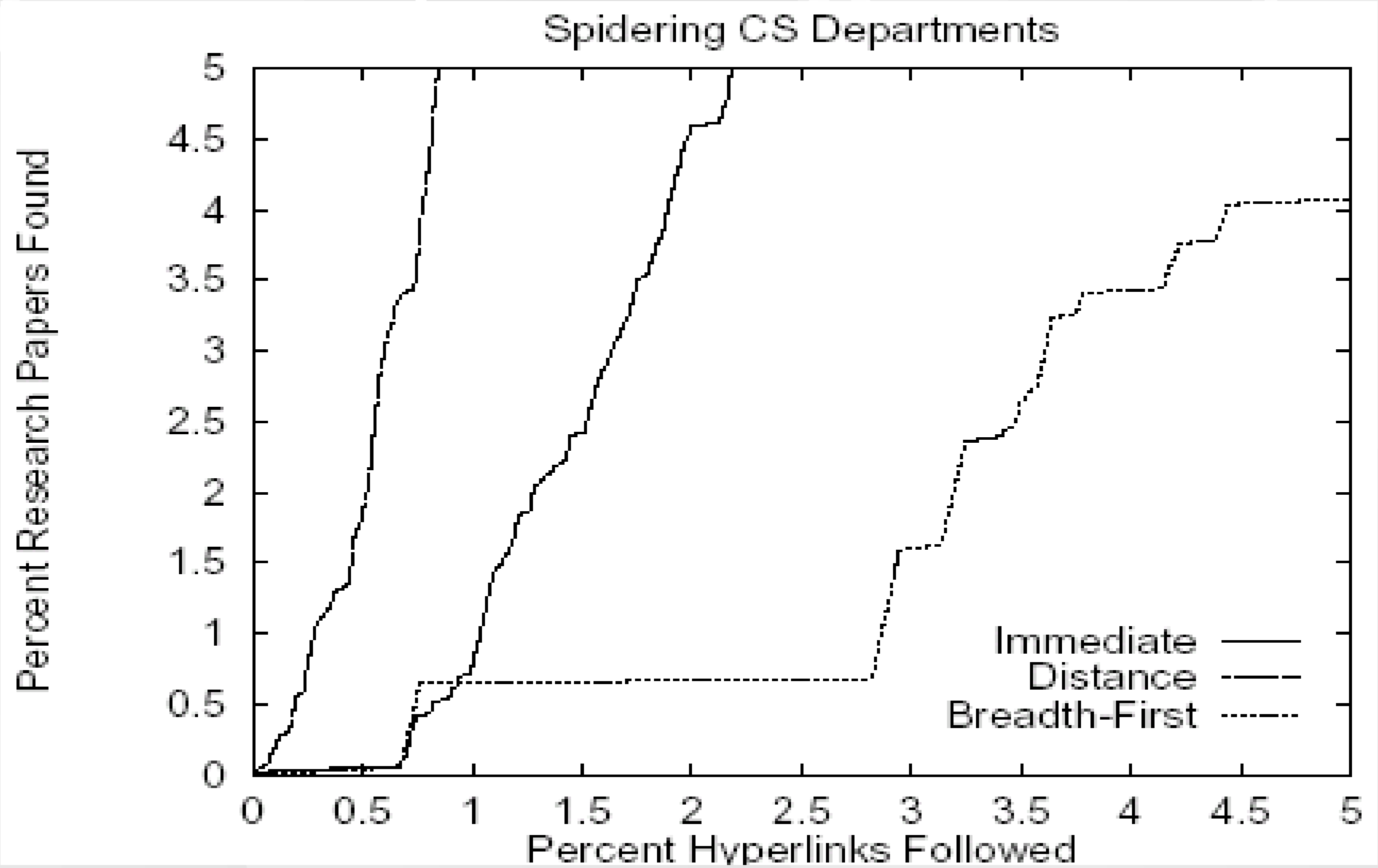
Results

- Distance and Future performs significantly better than breath-first
- Surprising fact:
  - Immediate spider outperforms distance and future
  - However, distance is significantly better than immediate spider at the early stages

Immediate v.s. Distance



Results – early stages



Discussion

- Why immediate spider works so well
  - Some words are commonly used by CS department and professors
  - E.g. “technical”, “report”, and “papers”

0.0238	proceedings	0.0072	report
0.0166	pp	0.0069	science
0.0128	postscript	0.0069	technical
0.0120	computer	0.0068	tr
0.0120	international	0.0065	intelligence
0.0117	conference	0.0063	boyer
0.0115	acm	0.0061	workshop
0.0105	proc	0.0061	springer
0.0104	symposium	0.0061	aaai
0.0098	systems	0.0061	artificial
0.0083	paper	0.0061	algorithms
0.0078	computing	0.0060	reasoning
0.0076	logic	0.0060	lifschitz
0.0072	learning	0.0060	papers
0.0072	ieee	0.0058	vol

Future Work

- Facts
  - Distance spider performs better at early stages
  - Immediate spider performs better in the long run
- Combine the properties of two spiders

Future Work

- Wrong Assumption
  - State of a spider is not important for identifying the value of an action.
- E.g. choosing action A may change the Q value of action B
- Using more features of a link, e.g. HTML, and web around the link