On list update with locality of reference () Susanne Albers and Sonja Lauer, 2015

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Introduction •000

Introduction

Introduction

- List Update Problem
- A fundamental online algorithmic problem.
- Early approaches based on stochastic analysis.
- Last 30 years of research focused on competitive analysis.

$$A(\sigma) \le c \cdot OPT(\sigma) + \alpha$$

- Arbitrary request sequences (σ) .
- (Usually) Oblivious adversary model generates sequence.
- Empirical performance is better than suggested by competitive analysis.
- Reason: In practice sequences exhibit locality of reference
 - A small subset of items is referenced at any point in time.

Introduction

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List Update Problem

- Maintain a set of items L as linear list.
- ullet Serve a sequence of item requests σ
 - Online: No knowledge of future requests.
 - $\sigma(t) \in L$

Standard Cost Model:

- Accessing the *i*-th item has cost *i*.
- Free exchanges: The accessed item can be moved to another position at no cost.
- Paid exchanges: All other exchanges of consecutive items has cost 1.
- $A(\sigma)$: Total cost incurred by algorithm A in serving σ .

Important Algorithms

Introduction

- OPT: The ideal offline optimum algorithm to compare against.
- Move-To-Front(MTF): c = 2: Move the requested item to the front of the list.
- TimeStamp(TS): c = 1.62: Place requested item x in front of the first item
 preceding x that was requested at most once since the last request to x. On error
 don't move.
- BIT(BIT): c = 1.75: Initialize randomly a bit b(x) for each $x \in L$. On access, complement the item's bit. If value changes to 1, move item to front.
- **COMB(COMB)**: c = 1.6: With probability 4/5 use BIT, else TS.

Model of Locality of Reference

Model of Locality of Reference

Concept

- Intuition: A sequence that references a small subset of items exhibits high locality.
- **Intuition**: If σ requests the same item many times in a row (high locality) then moving the item to the front becomes a very good strategy.
 - How many times is not relevant for the cost.
- When a different item is requested (a **change**), all algorithms should rearrange their lists to be competent.
- This paper proposes a formalization of the locality concept addressing the intuitive elements.

Definitions

- Run: Subsequence of requests to the same item.
 - Short: A single request.
 - Long: More than two requests.
 - Prefixed: Preceded by one or more short runs.
 - Independent: Not prefixed.
 - Change: If the previous log run reference a different item. The first long run is (usually) also a change.
- Intuition: High degree of locality if there are relatively many long runs!

Parameters

For any subsequence $\sigma' \subseteq \sigma$ let:

Parameter	Count
$r(\sigma')$	Runs
$s(\sigma')$	Short runs
$I(\sigma')$	Long runs
$I_p(\sigma')$	Prefixed long runs
$I_i(\sigma')$	Independent long runs
$I_c(\sigma')$	Long run changes
$f_b(\sigma')$	1 if item requested first is in front.
$f_e(\sigma')$	1 if σ' ends with short run and item
	is not in front.

Properties

- $r(\sigma') = s(\sigma') + l(\sigma')$
- $I(\sigma') = I_i(\sigma') + I_p(\sigma')$
- $I_i(\sigma') \leq I_c(\sigma') \leq I(\sigma')$

Introduction

$$\sigma_{xy} = xxyyxxyxyxyxxxxyxxx$$
 $f_{bong run} change$
 $f_{bong run$

Analysis

λ -locality

Introduction

• A class Σ of requests sequences has $\lambda - locality$ if $\forall \sigma \in \Sigma$,

$$\frac{l_c(\sigma)}{r(\sigma)} \ge \lambda$$

- ullet The number of long run changes represent at least a fraction λ of all runs.
- $0 < \lambda < 1$
 - If a sequence consists of long runs only, $\lambda = 1$
 - $\lambda = 0$ if there are no long runs.

Find new bounds as a function of λ for the competitiveness of online algorithms

Analysis

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Analysis

Overview

- Given an algorithm A, decompose its cost over all subsequences comprehended by a pair of items.
- Draw relationships between the projected cost and the cost of subsequences.
- Bound the cost for each phase ended by a long run.
- Add all up to get the resulting cost.
- Compare against OPT to get the competitiveness.

The cost A of an algorithm on σ can be evaluated novelty: incorporate paid exchanges

Analysis

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Basic Cost Analysis

At time t a request i made for item $\sigma(t)$.

Let:

•
$$A_x(t,\sigma) = 1$$
 if $x < \sigma(t)$.

• $A_{p}(t,\sigma)$ the number of paid exchanges performed by A.

$$A(\sigma) = \sum_{t=1}^{|\sigma|} \left(1 + A_p(t, \sigma) + \sum_{x \in L} A_x(t, \sigma) \right)$$

$$= |\sigma| + \sum_{t=1}^{|\sigma|} A_p(t, \sigma) + \sum_{x \in L} \sum_{t=1}^{|\sigma|} A_x(t, \sigma)$$

$$= |\sigma| + \sum_{t=1}^{|\sigma|} A_p(t, \sigma) + \sum_{\substack{\{x, y\} \subseteq L \\ x \neq y}} \sum_{\substack{t: \\ \sigma(t) \in \{x, y\}}} A_x(t, \sigma) + A_y(t, \sigma)$$

On List Update With Locality Of Reference

Analysis

Basic Cost Analysis

Now let:

- $A_{p,xy}(\sigma)$ the number of paid exchanges performed by A to change the relative order between x and y while serving σ .
- $A_{xy}(\sigma) = \sum_{\substack{\{x,y\} \subseteq L \\ x \neq y}} A_{p,xy}(\sigma) + \sum_{\substack{\sigma(t) \in \{x,y\}}} (A_x(t,\sigma) + A_y(t,\sigma))$ is the cost of Aprojected over $\{x, y\}$.

Then,

$$A(\sigma) = |\sigma| + \sum_{\substack{\{x,y\} \subseteq L \\ x \neq y}}^{\text{Partial cost model}} A_{xy}(\sigma)$$
 (1)

Analysis

Basic Cost Analysis - Projection

Let σ_{xy} be the subsequence obtained by projecting σ on $\{x,y\}$.

- Most algorithms satisfy $A_{xy}(\sigma) = A(\sigma_{xy})$
- $OPT_{xy}(\sigma) \geq OPT(\sigma_{xy})$

Decomposes σ_{xy} in ρ_{xy} phases ending with a long run (except perhaps the last phase).

- Let's $\pi(i)$ be the *i*-th phase.
- WLOG $\pi(i)$ starts with x.
- There are only two possible structures:

Introduction

$$(xy)^k x^l \quad k \ge 0, \quad l \ge 1 \tag{2}$$

$$(xy)^k y^l \quad k \ge 1, \quad l \ge 0 \tag{3}$$

On List Update With Locality Of Reference

Analysis

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Basic Cost Analysis - Final observations

- Definitions f_b and f_e apply for any σ_{xy}
- Eventually they values must be added over all item pairs.
- ullet Their added values don't depend on $|\sigma|$
- They will allow finding bounds when considering the first and last phases respectively.
- On σ_{xy} a long run change occurs only if phase structure is $(xy)^k x^l$ with $l \ge 2$.

OPT for two item lists

• Move to front only on the first request of a long run.

Claim

Introduction

$$OPT_{xy}(\sigma) \ge OPT(\sigma_{xy}) \ \forall \ x, y \in L, x \ne y$$

Proof:

- Assume we serve σ_{xy} with algorithm algorithm O' such that:
 - O' changes the relative order of x and y only when OPT does so when servicing σ over L.
- By design O' incurs (partial) cost $OPT_{xy}(\sigma)$
- By definition its cost can't be lower than the optimum for the sequence being served.
- Then $OPT_{xy}(\sigma) \geq OPT(\sigma_{xy})$

Optimal Offline Algorithm

Lemma 1

$$OPT(\sigma) \ge \frac{1}{2} (r(\sigma) + l_c(\sigma) + f_e(\sigma)) - f_b(\sigma) + |\sigma|$$

Proof:

- Using eq.1 and the Claim we can find a lower bound just by adding the item pairs decomposition (σ_{xy}) .
- The idea is to study many cases. There are actually a lot.

Case 1
$$|\sigma| = 1 \Rightarrow r = 1, I_c = 1$$

Case 1.1 x in front of y ("x|y") \Rightarrow OPT = 0, $f_b = 1$, $f_c = 0$. Direct.

Case 1.2 $y|x \Rightarrow OPT = 1$, $f_b = 0$, $f_e = 1$. Direct.

Case 2 $|\sigma| > 1$. Split in phases ending in long runs.

• Note: Long run change occurs only if structure is $(xy)^k x^l$ with $l \ge 2$.

Analysis

Optimal Offline Algorithm

Consider then that there are many phases.

- If $f_e(\sigma_{xy}) = 1$ then $p_{xy} > 1$.
 - \bullet Phase starts with request to x and finishes to request to x.
 - 2 $I_c(\pi(p_{xy})) = I(\pi(p_{xy})) = 0$
 - r = 2k + 1
 - 4

$$OPT = k + 1 = \frac{1}{2} (r + l_c + f_e)$$

- else if $f_e(\sigma_{xy}) = 0$ or just $\pi(i)$ for $1 < i \le p_{xy}$:
 - Initial list: y|x
 - If structure is $(xy)^k x^l \Rightarrow r = 2k + 1 \Rightarrow OPT = k + 1 = \frac{1}{2}(r + l_c)$
 - If structure is $(xy)^k y^l \Rightarrow l_c = 0, r = 2k \Rightarrow OPT = k = \frac{1}{2}(r + l_c)$
- first phase
 - If $y|x \Rightarrow f_b = 0 \Rightarrow$ same as before $\Rightarrow OPT = k \ge \frac{1}{2}(r + l_c f_b)$
 - If $x|y \Rightarrow f_b = 1 \Rightarrow OPT = \lfloor r/2 \rfloor \geq \frac{1}{2} (r + l_c f_b)$
- Add up over all phases and pairs (as per 1).



(4)

Move-to-Front - Claim

Move the requested item to the front of the list.

Claim

Introduction

$$MTF_{xy}(\sigma) = MTF(\sigma_{xy}) \ \forall \ x, y \in L, x \neq y$$

Proof:

- On both the original and the xy-pair lists, x precedes y iif the last request to either of them was to x.
- Say σ has $|\sigma_{xy}|$ requests to $\{x,y\}$
- Any request i s.t $1 \le i \le |\sigma_{xv}|$ contributes 1 to $MTF_{xv}(\sigma)$ iif $MTF(\sigma_{xv}) = 1$
- There are no paid exchanges.
- $MTF_{xy}(\sigma) = MTF(\sigma_{xy})$

Move-to-Front Algorithm - Lemma

Lemma 2

$$MTF(\sigma) \le r(\sigma) - f_b(\sigma) + |\sigma|$$

Proof:

- Using eq.1 and the Claim we can find an upper bound just by adding the item pairs decomposition (σ_{xy}) .
- **1** On σ_{xy} , the first request of each run the referenced item is moved to the front with cost 1.
- 2 Exception is the first run if item was already in front $(f_b = 1)$
- $\bullet \Rightarrow MTF(\sigma_{xv}) = r f_h$
- 4 Add up over all phases and pairs (as per 1).

Analysis

Move-to-Front Algorithm

Theorem 1

$$\frac{MTF(\sigma)}{OPT(\sigma)} \le \frac{2 + 2\alpha(\sigma)}{1 + 2\alpha(\sigma) + \beta(\sigma)}$$

Where:

•
$$\alpha(\sigma) = \frac{|\sigma| - (f_b(\sigma))}{r(\sigma)}$$
 and $\beta(\sigma) = \frac{l_c(\sigma)}{r(\sigma)}$

Corollary 1

If σ has λ -locality, then

$$\frac{\textit{MTF}(\sigma)}{\textit{OPT}(\sigma)} \leq \frac{2}{1+\lambda}$$

This results in a much better performance guarantee under high locality!

Analysis

BIT - Claims

Introduction

- Initialize randomly a bit b(x) for each $x \in L$. On access, complement the item's bit. If value changes to 1, move item to front.
- Note: Assume y|x while servicing σ_{xy} at time t-1. Then $\mathbb{E}[BIT(\sigma_{xy}(t))]=1/2$
- Note: Assume last requests were xyx. Then $\mathbb{E}[BIT(\sigma_{xy}(t))|\sigma_{xy}(t)=x]=1/4$ and $\mathbb{E}[BIT(\sigma_{xy}(t))|\sigma_{xy}(t)=y]=3/4$.

Claim

$$BIT_{xy}(\sigma) = BIT(\sigma_{xy}) \ \forall \ x, y \in L, x \neq y$$

Proof:

- On the i-th request to x or y, x precedes y in the original list iif it does on the xy-pair list.
- The rest of the argument is analogous to that of MTF.
- $BIT_{xy}(\sigma) = BIT(\sigma_{xy})$



BIT - Lemma

Introduction

Lemma 2

(On expectation)
$$BIT(\sigma) \leq \frac{3}{4}r(\sigma) + \frac{1}{4}I(\sigma) + \frac{1}{2}I_i(\sigma) + \frac{1}{4}f_e(\sigma) + |\sigma|$$

Proof Outline:

- Using eq.1 and the Claim we can find an upper bound just by adding the item pairs decomposition (σ_{xy}) .
- Decompose in phases ending in long runs. Term for f_e is due to last phase only.
- Non-last phases satisfy: $BIT(\sigma) \leq \frac{3}{4}r(\sigma) + \frac{1}{4}I(\sigma) + \frac{1}{2}I_i(\sigma)$
- **4** A generic phase $\pi(i)$ starts with y|x.
- ② Then first request costs 1, and the second has expected cost 1/2 (Claim note 1).
- Any further short runs in the phase have expected value 3/4(Claim note 2).
- The long run (if any) has worst case cost 1 (3/4 + 1/4, Claim note 2).
- **5** Go through the initial and final cases to introduce adjustments.
- 6 Add up over all phases and pairs (as per 1).



Introduction

Theorem 3

$$\frac{BIT(\sigma)}{OPT(\sigma)} \leq \frac{1.5 + 2\alpha(\sigma) + \delta(\sigma)}{1 + 2\alpha(\sigma) + \beta(\sigma)}$$

Where:

•
$$\alpha(\sigma) = \frac{|\sigma| - (f_b(\sigma))}{r(\sigma)}$$
, $\beta(\sigma) = \frac{l_c(\sigma)}{r(\sigma)}$ and $\delta(\sigma) = \frac{l(\sigma)/2 + l_i(\sigma) + 2f_b(\sigma)}{r(\sigma)}$.

Corollary 2

If σ has λ -locality, then

$$\frac{BIT(\sigma)}{OPT(\sigma)} \le \min\left\{1.75, \frac{2}{1+\lambda}\right\}$$

This results in a better performance guarantee for $\lambda > 1/3$

Analysis

- No improvement in the upper bounds for TIMESTAMP or COMB.
- They can't exploit locality.
- Empirical competitiveness against pairwise offline optimum confirmed expected results.
 - Particularly accurate results achieved with MTF.

Analysis

Conclusions

Conclusions

Conclusions

- Useful model of locality.
 - Mainly based in detailed characterization of runs in σ .
 - Captures intuition.
 - Allows new analysis of online algorithms.
- Found new, better bounds for MTF and BIT under locality.
 - Particularily for MTF that approaches OPT for large λ
- The paper also provides an experimental study backing the results.

Thank You

Thank You for listening! Questions?