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#### February, 2006

Adaptive Sampling for Selection



### 2 Small Samples



Adaptive Sampling for Selection

Problem: Given an array A of n items and a rank m,  $1 \le m \le n$ , find the mth smallest element in A. The algorithm should work in (expected) linear time  $\Theta(n)$ , irrespective of m. Hoare (1962) invents quickselect: pick some element p from the array, called the pivot, rearrange the contents of A so that all elements in A smaller that p are to its left, and all elements larger than p are to its right; if p is at position j = m it is the sought element; if j > m proceed recursively in A[1..j-1], otherwise in A[j+1..n].

```
Elem quickselect(vector<Elem>& A, int m) {
    int l = 0; int u = A.size() - 1;
    int k, p;
    while (l \le u) {
       p = select_pivot(A, l, u, m);
       swap(A[p], A[1]);
       partition(A, l, u, j);
       if (m < j) u = j-1;
       else if (m > j) l = j+1;
       else return A[j];
}
   }
```

• The expectation characteristic function:

$$f(lpha) = \lim_{\substack{n o \infty \ m/n o lpha}} rac{\mathbb{E}[C_{n,m}]}{n}$$

• The second factorial moment characteristic function:

$$g(lpha) = \lim_{\substack{n o \infty \ m/n o lpha}} rac{\mathbb{E} \left[ {C_{n,m}}^2 
ight]}{n^2}$$

· For the variance we have

$$v(lpha) = \lim_{\substack{n o \infty \ m/n o lpha}} rac{\mathbb{V}[C_{n,m}]}{n^2} = g(lpha) - f^2(lpha)$$

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#### Adaptive Sampling for Selection

• Standard quickselect (Knuth, 1971):

$$f(lpha)=m_0(lpha)=2\!-\!2(lpha\lnlpha\!+\!(1\!-\!lpha)\ln(1\!-\!lpha))=2\!+\!2\!\cdot\!\mathcal{H}(lpha)$$

• Median-of-three (Kirschenhofer, Martínez & Prodinger, 1997):

$$f(lpha)=m_1(lpha)=2+3lpha(1-lpha)$$

Adaptive Sampling for Selection









- Adaptive sampling uses a sample of s elements to choose a pivot for each recursive stage of quickselect.
- If the current relative rank is  $\alpha = m/n$ , we select the element of rank  $r(\alpha)$  from the sample

- Standard quickselect:  $s = 1, r(\alpha) = 1$
- Median-of-(2t + 1):  $s = 2t + 1, r(\alpha) = t + 1$
- Proportion-from- $s:\;r(lpha)pprox lpha\cdot s$

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- $\nu$ -find is like proportion-from-3, but cut points located at  $\nu$  and  $1 \nu$ , instead of 1/3 and 2/3
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  ightarrow m_1$  (median-of-three)
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A plot of  $\nu$ -find's characteristic function for various values of  $\nu$ 



Adaptive Sampling for Selection

#### A 3D plot of $\nu$ -find's characteristic function



Adaptive Sampling for Selection

There exists a value  $\nu^*$ , namely,  $\nu^* = 0.182...$ , such that for any  $\nu$ ,  $0 < \nu < 1/2$ , and any  $\alpha$ ,

 $f_{
u^*}(lpha) \leq f_
u(lpha)$ 

Furthermore,  $\nu^*$  is the unique value of  $\nu$  such that  $f_{\nu}$  is continuous, i.e.,

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If we consider average total cost then  $u^* \approx 0.25$ 

Adaptive Sampling for Selection

The expectation characteristic function  $f(\alpha)$  of any adaptive sampling strategy satisfies

$$egin{aligned} f(lpha) &= 1 + rac{s!}{(r(lpha)-1)!(s-r(lpha))!} imes \ & \left[ \int_lpha^1 f\left(rac{lpha}{x}
ight) x^{r(lpha)} (1-x)^{s-r(lpha)} \, dx \ & + \int_0^lpha f\left(rac{lpha-x}{1-x}
ight) x^{r(lpha)-1} (1-x)^{s+1-r(lpha)} \, dx 
ight] \end{aligned}$$

Adaptive Sampling for Selection

The second factorial moment characteristic function  $g(\alpha)$  of any adaptive sampling strategy satisfies

$$g(lpha)=2f(lpha)-1+rac{s!}{(r(lpha)-1)!(s-r(lpha))!} imes \ \left[\int_{lpha}^{1}g\left(rac{lpha}{x}
ight)x^{r(lpha)+1}(1-x)^{s-r(lpha)}\,dx 
ight. \ \left.+\int_{0}^{lpha}g\left(rac{lpha-x}{1-x}
ight)x^{r(lpha)-1}(1-x)^{s+2-r(lpha)}\,dx
ight]$$

Adaptive Sampling for Selection



Introduction

### 2 Small Samples



Adaptive Sampling for Selection

- Intuition: Using very large sample and proportion-from-s helps, because we get a very good pivot, very close to the sought element
- We should make sure that our pivot is very close BUT at the right side of the sought element! (i.e., slightly to the right if  $\alpha < 1/2$ , slightly to the left if  $\alpha > 1/2$ )

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# Definition A family of sampling strategies is Biased if, for lpha < 1/2, $r(lpha) > s \cdot lpha + 1 - lpha$

Adaptive Sampling for Selection

Biased proportion-from-s sampling with  $s \rightarrow \infty$  achieves optimal expected performance:

$$f(lpha) = 1 + \min(lpha, 1 - lpha)$$

Adaptive Sampling for Selection

The proof of Martínez, Panario, Viola (2004) for fixed-size sampling with  $s \to \infty$  works also for variable-size samples, i.e., s = s(n), as long as  $s(n) \to \infty$  and  $s(n)/n \to 0$  when  $n \to \infty$ .

#### Theorem

For Biased proportion-from-s sampling with increasing variable-size samples (i.e.,  $s = s(n) \rightarrow \infty, s/n \rightarrow 0$ ),

$$\mathbb{E}[C_{n,m}] = n + \min(m,n-m) + \Theta\left(\max\left(s,rac{n}{s}
ight)
ight)$$

Adaptive Sampling for Selection

Biased proportion-from-s sampling with  $s \to \infty$  has subquadratic variance:

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$$v(lpha) = \lim_{\substack{n o \infty \ m/n o lpha}} rac{\mathbb{V}[C_{n,m}]}{n^2} = 0.$$

The same holds true for median-of-(2t+1), when  $t 
ightarrow \infty$ 

Adaptive Sampling for Selection

For Biased proportion-from-s sampling with increasing variable-size samples (i.e.,  $s = s(n) \rightarrow \infty, s/n \rightarrow 0$ ),

$$\mathbb{V}[C_{n,m}] = \Theta\left(\max\left(rac{n^2}{s}, n\cdot s
ight)
ight)$$

Adaptive Sampling for Selection

The optimal sample size to minimize both the variance and the expected value of proportion-from-s is

$$s^* = \Theta(\sqrt{n})$$

Adaptive Sampling for Selection

# Open Problems

- Obtain explicit solutions for interesting particular cases
- Show that for any fixed sample size s, the optimal strategy is proportion-from-s at appropriate cut points (like v-find)
- Find a simple (exact or approximate) formula for the location of optimal cut points
- Why the coefficient of n<sup>2</sup> in the variance of median-of-3 is Bimodal? Any intuitive explanation?
- Better asymptotic estimates for the optimal sample size  $s^*$  (namely, the coefficient of  $\sqrt{n}$ ). How does it depend on  $\alpha$ ?

# Sources

- J. Daligault and C. Martínez. On the variance of quickselect. In Proc. of the 3rd ACM-SIAM Workshop on Analytic Algorithmics and Combinatorics (ANALCO'06), 2006.
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