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A PROBABILISTIC ANALYSIS OF THE NEXT FIT DECREASING BIN PACKING HEURISTIC

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A probabilistic analysis is presented of the Next Fit Decreasing bin packing heuristic, in which bins are opened to accommodate the items in order of decreasing size.

bin packing • probabilistic analysis • Next Fit Decreasing heuristic

1. Introduction

Given a list of n items of size $a_1, \ldots, a_n$ ($0 < a_i < 1$), the famous bin packing problem is to find the smallest number of bins in which these items can be packed, subject to the constraint that the total size of the items assigned to any bin cannot exceed 1. This problem is well known to be NP-hard, and the analysis of simple approximation methods for its solution represents a permanent challenge (see, e.g., Coffman et al. [2]).

The Next Fit Decreasing (NFD) heuristic is a good example of such a method. The items on the list are first reindexed so that

$$a_1 \geq a_2 \geq \ldots \geq a_n.$$  \hspace{1cm} (1)

They are then assigned to bins in this order; a new bin is opened whenever there is not enough room left in the one most recently opened to accommodate the current item. The number of bins opened according to this rule can be shown to exceed the minimum number possible by slightly less than 70 percent in the worst case (Baker and Coffman [1]).

We are interested, however, in a probabilistic analysis of this heuristic, carried out under the assumption that $a_1, \ldots, a_n$ are drawn independently from a uniform distribution on $[0, 1]$. It is well known that the optimal solution value $\text{OPT}(n)$ satisfies

$$\lim_{n \to \infty} \frac{\text{E(\text{OPT}(n))}}{n/2} = 1. \hspace{1cm} (2)$$

For the NFD heuristic, it will be shown below that

$$\lim_{n \to \infty} \frac{\text{E(\text{NFD}(n))}}{n/2} = 2\left(\frac{\pi^2}{6} - 1\right) = 1.289\ldots, \hspace{1cm} (3)$$

so that the expected deviation from optimality is slightly less than 30 percent. This result and some powerful generalizations turn out to have been...
2. The expected solution value

To analyse the expected solution value $E(\text{NFD}(n))$, we approximate the performance of the NFD heuristic by that of the Sliced NFD heuristic with parameter $r$ (SNFD$_r$), in which first items larger than $1/r$ are packed according to the NFD heuristic, the last opened bin is completed to contain at most $r-1$ items and any remaining items are packed in groups of size $r$. Obviously, for any realization of the item sizes, SNFD$_r(n) \geq \text{NFD}(n)$ and $\lim_{n \to \infty} \text{SNFD}_r(n) = \text{NFD}(n)$.

Let $k_i$ be the number of items whose size falls in the interval $(1/(i+1), 1/i]$ ($i = 1, 2, \ldots$), and let $K_i = k_i + k_{i+1} + \cdots + k_r$. Then, clearly,

$$\text{SNFD}_r(n) \leq k_1 + \frac{k_2}{2} + \cdots + \frac{k_{r-1}}{r-1} + \frac{K_r}{r} + r, \quad (4)$$

where the last term is induced to allow for rounding errors. Since $E(k_i) = n/(i(i+1))$ and $E(K_r) = n/r$, the expected value of the right hand side of (4) is equal to

$$n \sum_{i=1}^{r-1} \frac{1}{i^2(i+1)} + n \frac{n^2}{r^2} + r \quad (5)$$

and hence, from choosing $r$ appropriately as a function of $n$,

$$\limsup_{n \to \infty} \frac{E(\text{NFD}(n))}{n/2} \leq 2 \left( \frac{n^2}{6} - 1 \right). \quad (6)$$

On the other hand, if the items are packed by the NFD rule and bins containing items from more than one interval $(1/(i+1), 1/i]$ as well as bins containing items smaller than $1/r$ are ignored, then we have that

$$\text{NFD}(n) \geq (k_1 - 1) + \left( \frac{k_2}{2} - 1 \right) + \cdots + \left( \frac{k_{r-1}}{r-1} - 1 \right). \quad (7)$$

so that, for any fixed $r$,

$$\liminf_{n \to \infty} \frac{E(\text{NFD}(n))}{n/2} \geq 2 \sum_{i=1}^{r-1} \frac{1}{i^2} - 2 + \frac{1}{r}. \quad (8)$$

The right hand side of (8) is monotonically increasing in $r$ and converges to $2(\pi^2/6 - 1)$. Hence, in combination with (6), we conclude that

$$\lim_{n \to \infty} \frac{E(\text{NFD}(n))}{n/2} = 2 \left( \frac{\pi^2}{6} - 1 \right). \quad (9)$$

3. Deviations from the expected value

In this section, we study the deviation probability,

$$\Pr \left\{ |\text{NFD}(n) - E(\text{NFD}(n))| \geq nt \right\}. \quad (10)$$

It is, of course, bounded (from above) by

$$\Pr \left\{ \text{NFD}(n) - E(\text{NFD}(n)) \geq nt \right\}$$

and hence,

$$\Pr \left\{ \sum_{i=1}^{r-1} k_i + \frac{K_r}{r} + r - E(\text{NFD}(n)) \geq nt \right\}, \quad (12)$$

the second one is bounded by (cf. (7))

$$\Pr \left\{ \sum_{i=1}^{r-1} k_i - (r-1) - E(\text{NFD}(n)) \leq -nt \right\}. \quad (13)$$

Now, the Laplace-Stieltjes transform

$$\mathbb{E}(\exp(\sum_{i=1}^{r-1} \lambda k_i + \lambda K_r))$$

is well known to equal $\sum_{i=1}^{r-1} \exp(\lambda i)/(i(i+1)) + \exp(\lambda r)/r$. Hence, for every $\lambda > 0$,

$$\mathbb{E}(\exp(\lambda \sum_{i=1}^{r-1} k_i / i + K_r / r)) = \sum_{i=1}^{r-1} \exp(\lambda i)/(i(i+1)) + \exp(\lambda r)/r).$$

Using this Laplace-Stieltjes transform, one now easily verifies that, for every $r$, $\Sigma_{i=1}^{r-1} k_i / i + K_r / r$ is distributed as $\sum_{j=1}^{n} y_j$, where the $y_j$ are i.i.d. random variables with $\Pr(y_j = 1/i) = 1/(i(i+1))$ ($i = 1, \ldots, r-1$) and $\Pr(y_j = r - 1) = 1/r$.

Similarly, one verifies that $\Sigma_{i=1}^{r-1} k_i / i$ is distributed as $\sum_{j=1}^{n} z_j$, with $\Pr(z_j = 1/i) = 1/(i(i+1))$ ($i = 1, \ldots, r-1$) and $\Pr(z_j = 0) = 1/r$.

Hence, (12) can be rewritten as

$$\Pr \left\{ \sum_{j=1}^{n} y_j - E(\text{NFD}(n)) \geq nt \right\}. \quad (14)$$
which, in combination with (7), is easily shown to be bounded by
\[
\Pr\left( \sum_{j=1}^{n} \left( y_{jr} - E(y_{jr}) \right) \geq n \left( t - \frac{1}{r^2} \right) \leq -2r + 1 \right).
\]
\[(15)\]
Similarly, (13) is bounded by
\[
\Pr\left( \sum_{j=1}^{n} (z_{jr} - E(z_{jr})) \leq -n \left( t - \frac{1}{r^2} \right) + 2r - 1 \right).
\]
\[(16)\]
Now, since both \( y_{jr} \) and \( z_{jr} \) are bounded by 1, a famous result from Hoeffding [4] implies that (15) and (16) are bounded by \( \exp(-2n(t - 1/r^2 - 2r/n)^2) \). Taking \( r = \lfloor n^{1/3} \rfloor \), we obtain the strong result that, for all \( t \),
\[
\Pr\left( |NFD(n) - E(NFD(n))| \geq n t \right) \leq 2 \exp\left( -2n \left( t - \frac{3}{n^{2/3}} \right) \right).
\]
\[(17)\]
We refer to Rhee and Talagrand [7] for similar results obtained for other bin packing heuristics by quite different techniques.

4. A central limit theorem

In this final section, we shall prove that for every \( x \),
\[
\lim_{n \to \infty} \Pr\left( \frac{NFD(n) - n \left( \frac{n^2}{6} - 1 \right)}{\sqrt{n} \sigma_{\infty}} \leq x \right) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} \exp\left( -y^2/2 \right) dy,
\]
\[(18)\]
where
\[
\sigma_{\infty}^2 = \lim_{r \to \infty} \var\left( z_{jr} \right),
\]
\[
= \lim_{r \to \infty} \sum_{i=1}^{r-1} \frac{1}{i^2(i+1)} - \left( \sum_{i=1}^{r-1} \frac{1}{i^2(i+1)} \right)^2 = \frac{1}{3} - \left( \frac{\pi^2}{6} - 1 \right).
\]
\[
= \zeta(3) - \left( \frac{\pi^2}{6} - 1 \right) = \frac{\pi^2}{6} - \frac{\pi^4}{36} = 0.14118 \ldots,
\]
\[(19)\]
where \( \zeta \) is the Riemann zeta function. One easily verifies that \( \lim_{r \to \infty} \var\left( z_{jr} \right) \) is also equal to (19).

To prove this central limit theorem, we first observe that
\[
\Pr\left( \frac{NFD(n) - n \left( \frac{n^2}{6} - 1 \right)}{\sqrt{n} \sigma_{\infty}} \leq x \right) = \exp\left( -\frac{1}{2} \left( x - n(t - 1/r^2 - 2r/n)^2 \right) \right)
\]
\[
= \Pr\left( \frac{\sum_{i=1}^{n} (z_{jr} - E(z_{jr})) - n(t - 1/r^2 - 2r/n)^2}{\sqrt{n} \sigma_{\infty}} \leq x \right)
\]
\[
= \Pr\left( \frac{\sum_{i=1}^{n} (z_{jr} - E(z_{jr})) - n(t - 1/r^2 - 2r/n)^2}{\sqrt{n} \sigma_{\infty}} \leq x \right)
\]
\[
= \Pr\left( \frac{\sum_{i=1}^{n} (z_{jr} - E(z_{jr})) - n(t - 1/r^2 - 2r/n)^2}{\sqrt{n} \sigma_{\infty}} \leq x \right) + \frac{r - 1}{\sqrt{n} \sigma_{\infty}} \left( x - \frac{\sum_{i=1}^{n} 1/i^2(i+1)}{\sqrt{\var\left( z_{jr} \right)}} \right) \right).
\]
\[(20)\]
Taking \( r = \lfloor n^{1/3} \rfloor \), we find that the right hand side of the final inequality converges to \( x \) as \( n \to \infty \). But then we can apply Theorem 7.1.2 in Chung [3] to conclude that (20) converges to \( \left( 1/\sqrt{2\pi} \right) \int_{-\infty}^{x} \exp\left( -y^2/2 \right) dy \) as \( n \to \infty \).

The random variables \( y_{jr} \) provide a lower bound on \( \Pr((NFD(n) - n \left( \frac{n^2}{6} - 1 \right))/\sqrt{n} \sigma_{\infty} \leq x) \) in an exactly similar fashion. Together, the lower and the upper bound yield the desired result (18).

It turns out that the above result can be used to compute \( \lim_{n \to \infty} \text{E}(NFD(n)) \) for any \( k > 0 \). We also observe that the results in this note can now all be extended to a larger class of distribution functions \( F \) than the uniform one. E.g., the results in the last two sections are essentially also valid if the item sizes are generated from any distribution whose density function \( f \) satisfies \( \lim_{x \to 0} f'(x) = c > 0 \). These details are left to the reader; essentially, one redefines \( y_{jr} \) and \( z_{jr} \) by letting \( \Pr( y_{jr} = 1/i) = \Pr( z_{jr} = 1/i) = F(1/i) - F(1/(i+1)) \) for \( i = 1, \ldots, r - 1 \), \( \Pr( y_{jr} = 1/r) = \Pr( z_{jr} = 0) = F(1/r) \), and uses the information on \( f \) to bound the latter right hand side.

As a final note, we observe that our results are also valid for the Harmonic heuristics introduced in Lee and Lee [6]. They can be easily adapted to
show that the Revised Harmonic (RH) heuristic introduced in the same paper satisfies

$$\lim_{n \to \infty} \frac{E(RH(n))}{n/2} = 1.237 \ldots$$

(21)

i.e., slightly better than NFD, but still surprisingly poor for the heuristic that from a worst case point of view is the best on-line heuristic currently known.

References


