

Approximation Algorithms III

Lecture 10

September 24, 2015

Subset Sum

Subset Sum

Instance: $X = \{x_1, \dots, x_n\}$ - n integer positive numbers, t - target number

Question: \exists subset of X s.t. sum of its elements is t ?

Assume x_1, \dots, x_n are all $\leq n$. Then this problem can be solved in

- (A) The problem is still **NP-Hard**, so probably exponential time.
- (B) $O(n^3)$.
- (C) $2^{O(\log^2 n)}$.
- (D) $O(n \log n)$.
- (E) None of the above.

Subset Sum

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Instance: $X = \{x_1, \dots, x_n\}$ - n integer positive numbers, t - target number

Question: \exists subset of X s.t. sum of its elements is t ?

M : Max value input numbers.

R.T. $O(Mn^2)$.

```

SolveSubsetSum ( $X, t, M$ )
   $b[0 \dots Mn] \leftarrow \text{false}$ 
  //  $b[x]$  is true if  $x$  can be
  // realized by subset of  $X$ .
   $b[0] \leftarrow \text{true}$ .
  for  $i = 1, \dots, n$  do
    for  $j = Mn$  down to  $x_i$  do
       $b[j] \leftarrow B[j - x_i] \vee B[j]$ 
  return  $B[t]$ 
    
```

Subset Sum

Efficient algorithm???

1. Algorithm solving **Subset Sum** in $O(Mn^2)$.
2. M might be prohibitly large...
3. if $M = 2^n \implies$ algorithm is not polynomial time.
4. **Subset Sum** is **NPC**.
5. Still want to solve quickly even if M huge.
6. Optimization version:

Subset Sum Optimization

Instance: (X, t) : A set X of n positive integers, and a target number t .

Question: The largest number γ_{opt} one can represent as a subset sum of X which is smaller or equal to t .

Subset Sum

2-approximation

Lemma

1. (X, t) ; Given instance of **Subset Sum**. $\gamma_{\text{opt}} \leq t$: Opt.
2. \implies Compute legal subset with sum $\geq \gamma_{\text{opt}}/2$.
3. Running time $O(n \log n)$.

Proof.

1. Sort numbers in X in decreasing order.
2. Greedily - add numbers from largest to smallest (if possible).
3. s : Generates sum.
4. u : First rejected number. s' : sum before rejection.
5. $s' > u > 0$, $s' < t$, and $s' + u > t \implies t < s' + u < s' + s' = 2s' \implies s' \geq t/2$.

5/41



Polynomial Time Approximation Schemes

Definition ()

PROB: Maximization problem.

$\epsilon > 0$: approximation parameter.

$\mathcal{A}(I, \epsilon)$ is a **polynomial time approximation scheme (PTAS)** for **PROB**:

1. $\forall I: (1 - \epsilon) |\text{opt}(I)| \leq |\mathcal{A}(I, \epsilon)| \leq |\text{opt}(I)|$,
2. $|\text{opt}(I)|$: opt price,
3. $|\mathcal{A}(I, \epsilon)|$: price of solution of \mathcal{A} .
4. \mathcal{A} running time polynomial in n for fixed ϵ .

For minimization problem:

$$|\text{opt}(I)| \leq |\mathcal{A}(I, \epsilon)| \leq (1 + \epsilon) |\text{opt}(I)|.$$

6/41

Polynomial Time Approximation Schemes

1. Example: Approximation algorithm with running time $O(n^{1/\epsilon})$ is a **PTAS**.
Algorithm with running time $O(1/\epsilon^n)$ is not.
2. Fully polynomial...

Definition ()

An approximation algorithm is **fully polynomial time approximation scheme (FPTAS)** if it is a **PTAS**, and its running time is polynomial both in n and $1/\epsilon$.

3. Example: **PTAS** with running time $O(n^{1/\epsilon})$ is not a **FPTAS**.
4. Example: **PTAS** with running time $O(n^2/\epsilon^3)$ is a **FPTAS**.

7/41

Approximating Subset Sum

Subset Sum Approx

Instance: (X, t, ϵ) : A set X of n positive integers, a target number t , and parameter $\epsilon > 0$.

Question: A number z that one can represent as a subset sum of X , such that $(1 - \epsilon)\gamma_{\text{opt}} \leq z \leq \gamma_{\text{opt}} \leq t$.

8/41

Approximating Subset Sum

Looking again at the exact algorithm

ExactSubsetSum(S, t)

```

 $n \leftarrow |S|$ 
 $P_0 \leftarrow \{0\}$ 
for  $i = 1 \dots n$  do
     $P_i \leftarrow P_{i-1} \cup (P_{i-1} + x_i)$ 
    Remove from  $P_i$  all elements  $> t$ 

return largest element in  $P_n$ 
    
```

- $S = \{a_1, \dots, a_n\}$
 $x + S = \{a_1 + x, a_2 + x, \dots, a_n + x\}$
- Lists might explode in size.

9/41

Trim the lists...

L' : Inc. sorted list of numbers

Trim(L', δ)

```

 $L = \langle y_1 \dots y_m \rangle$ 
 $curr \leftarrow y_1$ 
 $L_{out} \leftarrow \{y_1\}$ 
for  $i = 2 \dots m$  do
    if  $y_i > curr \cdot (1 + \delta)$ 
        Append  $y_i$  to  $L_{out}$ 
     $curr \leftarrow y_i$ 
return  $L_{out}$ 
    
```

Definition

For two positive real numbers $z \leq y$, the number y is a δ -approximation to z if $\frac{y}{1 + \delta} \leq z \leq y$.

Observation

If $x \in L'$ then there exists a number $y \in L_{out}$ such that $y \leq x \leq y(1 + \delta)$, where $L_{out} \leftarrow \text{Trim}(L', \delta)$.

10/41

Trim the lists...

Trim(L', δ)

```

 $L = \langle y_1 \dots y_m \rangle$ 
 $curr \leftarrow y_1$ 
 $L_{out} \leftarrow \{y_1\}$ 
for  $i = 2 \dots m$  do
    if  $y_i > curr \cdot (1 + \delta)$ 
        Append  $y_i$  to  $L_{out}$ 
     $curr \leftarrow y_i$ 
return  $L_{out}$ 
    
```

ApproxSubsetSum(S, t)

```

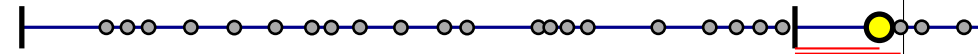
//  $S = \{x_1, \dots, x_n\}$ ,
//  $x_1 \leq x_2 \leq \dots \leq x_n$ 
 $n \leftarrow |S|$ ,  $L_0 \leftarrow \{0\}$ ,
 $\delta = \epsilon/2n$ 
for  $i = 1 \dots n$  do
     $E_i \leftarrow L_{i-1} \cup (L_{i-1} + x_i)$ 
     $L_i \leftarrow \text{Trim}(E_i, \delta)$ 
    Remove from  $L_i$  elems  $> t$ .

return largest element in  $L_n$ 
    
```

E_i : Computed by merging two sorted lists in linear time.

11/41

Understanding trimming



12/41

Remark

1. Can assume that trimmed lists L_i are sorted...
2. Algorithm: $E_i \leftarrow L_{i-1} \cup (L_{i-1} + x_i)$
3. So, this is just copy, shift, and merge of two sorted lists.
4. ... resulting in a sorted list.
5. takes linear time in size of lists.

13/41

Analysis

1. E_i list generated by algorithm in i th iteration.
2. P_i : list of numbers (no trimming).

Claim

For any $x \in P_i$ there exists $y \in L_i$ such that $y \leq x \leq (1 + \delta)^i y$.

Proof

1. If $x \in P_1$ then follows by observation above.
2. If $x \in P_{i-1} \implies$ (induction) $\exists y' \in L_{i-1}$ s.t. $y' \leq x \leq (1 + \delta)^{i-1} y'$.
3. By observation $\exists y \in L_i$ s.t. $y \leq y' \leq (1 + \delta)y$, As such,

$$y \leq y' \leq x \leq (1 + \delta)^{i-1} y' \leq (1 + \delta)^i y.$$

14/41

Proof continued

Proof continued

1. If $x \in P_i \setminus P_{i-1} \implies x = \alpha + x_i$, for some $\alpha \in P_{i-1}$.
2. By induction, $\exists \alpha' \in L_{i-1}$ s.t. $\alpha' \leq \alpha \leq (1 + \delta)^{i-1} \alpha'$.
3. Thus, $\alpha' + x_i \in E_i$.
4. $\exists x' \in L_i$ s.t. $x' \leq \alpha' + x_i \leq (1 + \delta)x'$.
5. Thus,
 $x' \leq \alpha' + x_i \leq \alpha + x_i = x \leq (1 + \delta)^{i-1} \alpha' + x_i \leq (1 + \delta)^{i-1} (\alpha' + x_i) \leq (1 + \delta)^i x'$. ■

15/41

Running time of ApproxSubsetSum

Lemma

For $x \in [0, 1]$, it holds $\exp(x/2) \leq (1 + x)$.

Lemma

For $0 < \delta < 1$, and $x \geq 1$, we have

$$\log_{1+\delta} x \leq \frac{2 \ln x}{\delta} = O\left(\frac{\ln x}{\delta}\right).$$

See notes for a proof of lemmas.

16/41

Running time of ApproxSubsetSum

Observation

In a list generated by **Trim**, for any number x , there are no two numbers in the trimmed list between x and $(1 + \delta)x$.

Lemma

$|L_i| = O\left(\frac{n}{\varepsilon} \log n\right)$, for $i = 1, \dots, n$.

17/41

Running time of ApproxSubsetSum

Proof.

1. $L_{i-1} + x_i \subseteq [x_i, ix_i]$.
2. Trimming $L_{i-1} + x_i$ results in list of size

$$\log_{1+\delta} \frac{ix_i}{x_i} = O\left(\frac{\ln i}{\delta}\right) = O\left(\frac{\ln n}{\delta}\right),$$

3. Now, $\delta = \varepsilon/2n$, and

$$\begin{aligned} |L_i| &\leq |L_{i-1}| + O\left(\frac{\ln n}{\delta}\right) \leq |L_{i-1}| + O\left(\frac{n \ln n}{\varepsilon}\right) \\ &= O\left(\frac{n^2 \log n}{\varepsilon}\right). \end{aligned} \quad \square$$

18/41

Running time of ApproxSubsetSum

Lemma

The running time of **ApproxSubsetSum** is $O\left(\frac{n^3}{\varepsilon} \log n\right)$.

Proof.

1. Running time of **ApproxSubsetSum** dominated by total length of L_1, \dots, L_n .
2. Above lemma implies
$$\sum_i |L_i| = O\left(n \times \frac{n^2}{\varepsilon} \log n\right) = O\left(\frac{n^3}{\varepsilon} \log n\right).$$
3. **Trim** runs in time proportional to size of lists.
4. Overall, R.T. $O\left(\frac{n^3}{\varepsilon} \log n\right)$.

□

19/41

ApproxSubsetSum

Theorem

ApproxSubsetSum returns $u \leq t$, s.t.

$$\frac{\gamma_{\text{opt}}}{1+\varepsilon} \leq u \leq \gamma_{\text{opt}} \leq t,$$

γ_{opt} : opt solution.

Running time is $O\left(\frac{n^3}{\varepsilon} \log n\right)$.

Proof.

1. Running time from above.
2. $\gamma_{\text{opt}} \in P_n$: optimal solution.
3. $\exists z \in L_n$, such that $z \leq \text{opt} \leq (1 + \delta)^n z$
4. $(1 + \delta)^n = (1 + \varepsilon/2n)^n \leq \exp\left(\frac{\varepsilon}{2}\right) \leq 1 + \varepsilon$, since $1 + x \leq e^x$ for $x \geq 0$.
5. $\gamma_{\text{opt}}/(1 + \varepsilon) \leq z \leq \text{opt} \leq t$.

□

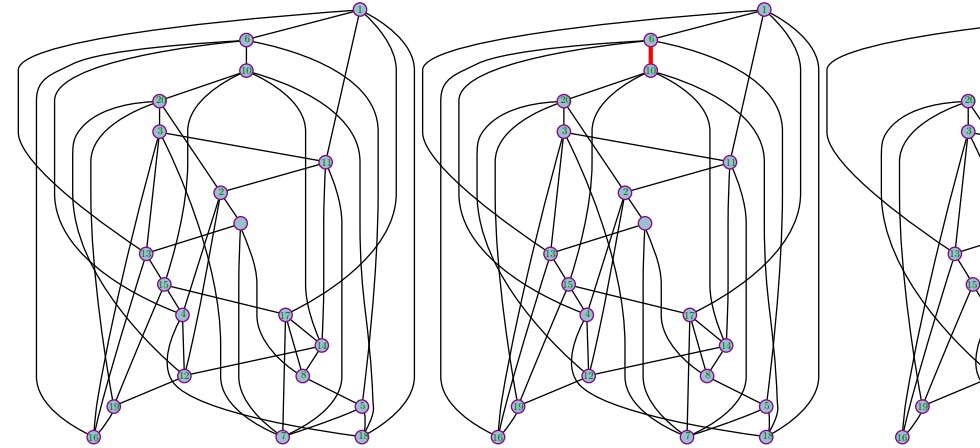
20/41

Maximal matching

1. $G = (V, E)$
2. Compute maximal matching...
3. $X \subseteq E$ which is maximal and independent.
4. Maximal = can not improved by adding an edge.
5. Maximum = largest possible set among all possible sets.
6. Computing the maximum is hard then computing maximal solution.
7. Q: Find maximal matching quickly and of large size...

21/41

An example of the greedy algorithm...



22/41

Maximal matching: Algorithm

1. Algorithm: Repeatedly pick an arbitrary edge and remove it.
2. M : Generated matching. X : Maximal matching.
3. Clearly a maximal matching...
4. This is a **2**-approximation to the maximum matching.
5. Because...
6. Every edge in M “kills” two edges of X in the worst case.

23/41

Maximal matching: Result

Theorem

Given a graph G one can compute in $O(n + m)$ time, a maximal matching with at least $|X|/2$ edges, where X is the size of the maximum (optimal) matching.

24/41

Bin packing

Problem definition

Bin Packing

Instance: v : Bin size. $S = \{\alpha_1, \dots, \alpha_n\}$: n items
 α_i : size of i th item.

Target: Find min # B , and a decomposition S_1, \dots, S_B of S , such that $\forall j \quad \sum_{x \in S_j} \leq v$.

1. $\cup_i S_i = S$ and $\forall i \neq j \quad S_i \cap S_j = \emptyset$.
2. **NP-Hard** from **Partition**.
3. **NP-Hard** to approximate within $3/2$.
4. Natural problem...
5. How to approximate?
6. First fit: Have a row of bins, insert items greedily into the first bin that fits them.
7. First fit decreasing: Sort the elements first...

25/41

Bin packing: First fit

Analysis

Lemma

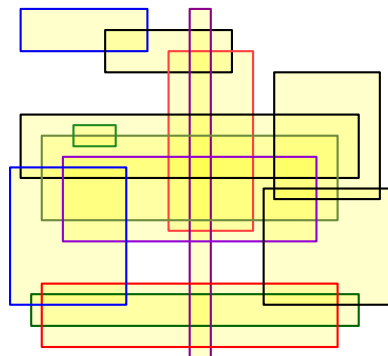
First fit is a 2-approximation.

Proof.

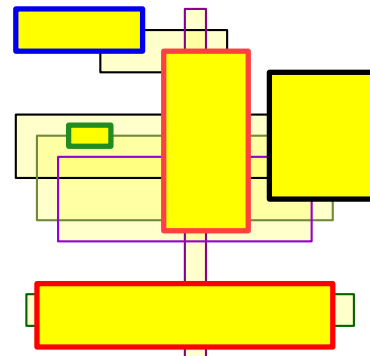
Observe that only one bin can have less than $v/2$ content in it... \square

26/41

An example



Input
Assume: Open rectangles.

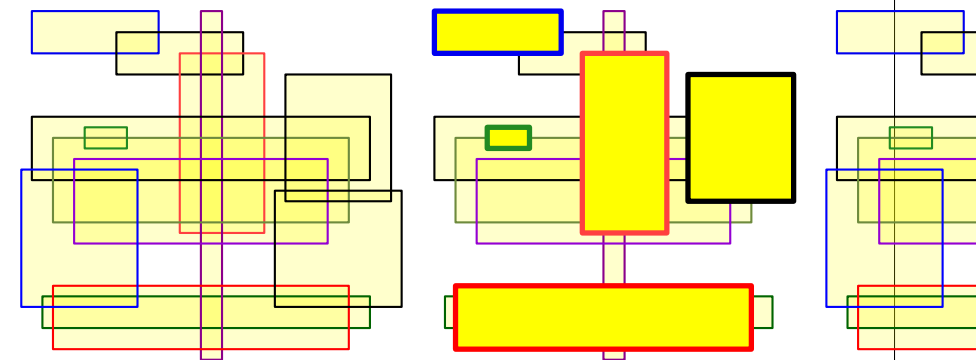


Independent set of rectangles.

27/41

Independent set of rectangles

Algorithm: Divide & Conquer



28/41

Independent set of rectangles

Algorithm: Divide & Conquer

\mathcal{R} : A set of axis parallel rectangles.

RectIndep(\mathcal{R}):

if $|\mathcal{R}| \leq 10$ then

Solve by brute force

return size of solution

x_M : Median of right x -coordinate of rects in \mathcal{R}

ℓ : Vertical line through x_M .

\mathcal{R}_M : Rects of \mathcal{R} intersecting ℓ

$\mathcal{R}_L, \mathcal{R}_R$: Rectangles in \mathcal{R} left/ right of ℓ .

$S_L \leftarrow \text{RectIndep}(\mathcal{R}_L)$

$S_R \leftarrow \text{RectIndep}(\mathcal{R}_R)$

$S_M \leftarrow$ compute opt solution for \mathcal{R}_M (intervals!)

return $\max(S_M, S_L + S_R)$

29/41

Analysis

1. If $S_M \geq \text{Opt}/(2 \lg n)$... done.
2. $\text{Opt}_L + \text{Opt}_R \geq (1 - 1/(2 \lg n))\text{Opt}$.
3. By induction: $S_L \geq \text{Opt}_L/(2 \lg(n/2))$ and $S_R \geq \text{Opt}_R/(2 \lg(n/2))$.
4. $S_L + S_R \geq \frac{(1-1/(2 \lg n))\text{Opt}}{2 \lg(n/2)}$
5.
$$\frac{(1 - 1/(2 \lg n))}{2 \lg(n/2)} = \frac{1}{2 \lg n - 2} - \frac{1}{(2 \lg n)(2 \lg n - 2)}$$
$$\geq \frac{2 \lg n - 1}{(2 \lg n)(2 \lg n - 2)} \geq \frac{2 \lg n - 2}{(2 \lg n)(2 \lg n - 2)} \geq \frac{1}{2 \lg n}$$
6. Conclude: If $S_M \leq \text{Opt}/(2 \lg n)$, then $S_L + S_R \geq \text{Opt}/(2 \lg n)$.
7. Algorithm is $2 \lg n$ approximation.

30/41