# A FASTER PSEUDOPOLYNOMIAL TIME ALGORITHM FOR SUBSET SUM

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## INTRODUCTION

**Input:** A set *S* of *n* positive integers  $x_1, x_2, x_3, ..., x_n$  and a positive target integer *t*.

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**Output:** Is there a subset *T* of *S* such that  $\sum_{x_i \in T} x_i = t$ ?

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Textbook DP algorithm due to Bellman that runs in *O(nt)* **pseudopolynomial** time.

[Bellman '56]

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- $\cdot$  scheduling

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- $\cdot\,$  power indices
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- $\cdot$  applications in security

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- First poly space algorithm:  $\tilde{O}(n^3 t) [\text{Lokshtanov et al. '10}]$

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**Main Theorem [Koiliaris & Xu '17].** The subset sum problem can be decided in  $\tilde{O}(\min{\sqrt{nt}, t^{4/3}})$  time.

Concurrent to our work, Bringmann showed that if **randomization** is allowed the subset sum problem can be decided in  $\tilde{O}(t)$ , with one-sided error probability 1/n.

[Bringmann '17]

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Computing all subset sums for some  $u \ge t$  also answers the subset sum problem with target value t.

### ALGORITHM

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- If sets *S*, *T* lie in a short and light interval, then one can combine their subset sums quickly as their total sum will be small.
- If sets *S*, *T* lie in a long and heavy interval, then one can combine their subset sums quickly by ignoring most of the sums as they exceed the upper bound.

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- The set of all subset sums realizable by subsets of S is denoted by

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· If P and Q form a partition of a set S, then  $\sum(P) \oplus \sum(Q) = \sum(S)$ .

#### SHORT AND LIGHT

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- Notice that since the sets  $L', R' \subseteq [[0 : \sigma]]$ , we can compute  $L' \oplus R'$  in  $O(\sigma \log \sigma)$  time via FFT.
- Since the divide-and-conquer recursion has  $\log n$  levels, we get the  $O(\log n(\sigma \log \sigma))$  promised running time.

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$$\stackrel{\forall}{z} = ix + j \quad \xrightarrow{f} \quad (i, j) \in [0:k] \times [0:\ell k]$$



Higher # dimensions but shorter intervals







Step 2  $\sum(L), \sum(R)$   $\xrightarrow{J}$  $\overset{\mathbb{U}}{z} = ix + j \quad \xrightarrow{f} \quad (i,j) \in \llbracket 0 : k \rrbracket \times \llbracket 0 : \ell k \rrbracket$  $\mathsf{FFT} \Downarrow \operatorname{in} \widetilde{O}(\ell k^2)$  $f^{-1}$  $f\left(\sum(L)\right) \oplus f\left(\sum(R)\right)$  $\sum_{\| \| } (L \cup R)$  $\sum(S)$ and if  $k = \left\lfloor \frac{u}{x} \right\rfloor \implies \widetilde{O}\left( \left( \frac{u}{x} \right)^2 \ell \right).$ 

Higher # dimensions but shorter intervals

#### THE ALGORITHM











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## THE OTHER ALGORITHM

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The second algorithm runs in  $O(\sqrt{nm})$  time, where *m* is the order of the group.

Not trivial!

The challenge is that the previous algorithm throws away many sums that fall outside of [1: u] during its execution, but this can no longer be done for finite cyclic groups, since these sums stay in the group and as such must be accounted for.

## **FUTURE WORK**
Can we use these observations on other similar number-based problems?

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Is there a deterministic  $\tilde{O}(t)$  time algorithm for the subset sum problem matching its conditional lower bound?

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