Classical and quantum algorithms for variants of Subset-Sum via dynamic programming

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joint work with

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PIGEONHOLE EQUAL-SUMS Assumption: s = 0 and $\sum_{i=1}^{n} a_i < 2^n - 1$

Results

Prior work	Classical	Quantum
SUBSET-SUM [HS'74,BJLM'13]	$\widetilde{O}(2^{n/2})$	$\widetilde{O}(2^{n/3})$
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Representation technique approach:

- Standard in average-case analysis of **SUBSET-SUM** [HJ'10]
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Good choice for *p* and *k*:

- the bins are small to keep the cost of search low.
- the bins contain a solution with large probability.

Number of collision values

Collision values:

$$V = \left\{ v \in \mathbb{N} : \exists S_1 \neq S_2, v = \sum_{i \in S_1} a_i = \sum_{i \in S_2} a_i + s \right\}$$

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Lemma: At least $|V| \ge 2^{n-\gamma}$ distinct collision values.

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Difficulty: each step requires one (quantum) query to $T_{p,k}$

 \Rightarrow for some indexing of $T_{\rho,k} = \{S_1, \dots, S_{|T_{\rho,k}|}\}$ we need to implement the oracle

$$O_{T_{p,k}}: \ell \mapsto S_{\ell}, \quad \text{for} \ 1 \le \ell \le |T_{p,k}|$$

Dynamic programming data structure

Compute the cardinality table

$$t_p[i,j] = |\{S \subseteq \{1,\ldots,i\} : \sum_{i \in S} a_i \equiv j \pmod{p}\}|$$

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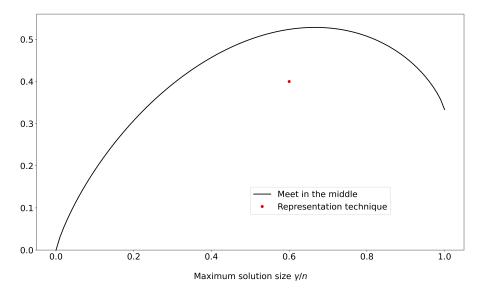
Theorem: Given $1 \le \ell \le t_{p,k}$ and random access to the elements of the table t_p , the ℓ -th set in $T_{p,k}$ can be computed in time O(n).

Computing the oracle

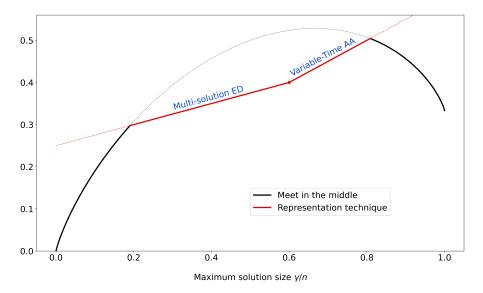
Input: Table t_p , integers $0 \le k \le p-1$ and $1 \le \ell \le t_{p,k}$ Output: ℓ -th set $S \in T_{p,k}$ for \prec . 1) $j = k, S = \emptyset$ 2) for i = n, ..., 1 do 3) if $\ell \le t_p[i-1,j]$ then Do nothing 4) else 5) $S = S \cup \{i\}, \quad \ell = \ell - t_p[i-1,j], \quad j = j - a_j \mod p$

6 Return S

Running time exponent



Running time exponent



Open problem

PIGEONHOLE MODULAR EQUAL-SUMS Input: Set $\{a_1, ..., a_n\}$ and a modulus q s.t. $q \le 2^n - 1$ Output: Subsets $S_1 \ne S_2 \subseteq [n]$ s.t. $\sum_{i \in S_1} a_i \equiv_q \sum_{i \in S_2} a_i$

Generalizes PIGEONHOLE EQUAL-SUMS

Theorem: Can be solved deterministically in time $\tilde{O}(2^{n/2})$

Question: Can be solved quantumly in time $\tilde{O}(2^{2n/5})$?