Solving SCS for bounded length strings in fewer than 2^n steps

Alexander Golovnev * Alexander S. Kulikov [†] Ivan Mihajlin [‡]

Abstract

It is still not known whether a shortest common superstring (SCS) of n input strings can be found faster than in $O^*(2^n)$ time $(O^*(\cdot)$ suppresses polynomial factors of the input length). In this short note, we show that for any constant r, SCS for strings of length at most r can be solved in time $O^*(2^{(1-c(r))n})$ where $c(r) = (1 + 2r^2)^{-1}$. For this, we introduce so-called hierarchical graphs that allow us to reduce SCS on strings of length at most r to the directed rural postman problem on a graph with at most k = (1 - c(r))n weakly connected components. One can then use a recent $O^*(2^k)$ time algorithm by Gutin, Wahlström, and Yeo.

1 Introduction

The shortest common superstring problem (SCS) asks for a shortest string which contains each of the given strings s_1, \ldots, s_n as a substring. The problem has many practical applications including genome assembly and sparse matrix compression. By the *r*-superstring problem (*r*-SCS) we denote the SCS problem for the special case where all input strings have length at most *r*. Both SCS over the binary alphabet and *r*-SCS (for $r \ge 3$) are known to be NP-hard optimization problems [11]. Although approximation algorithms for SCS are widely studied (currently, the best known approximation ratio is $2\frac{11}{23}$ due to Mucha [21]), it is still not known whether SCS can be solved exactly in fewer than $O^*(2^n)$ steps¹. At the same time an easy reduction of SCS to the traveling salesman problem (TSP) gives an algorithm solving SCS in $O^*(2^n)$ time and polynomial space [17, 16, 1]. In this note, we show that for any constant *r*, *r*-SCS can be solved in time $O^*\left(2^{(1-\frac{1}{2r^2+1})n}\right)$. The result is achieved by combining a new combinatorial structure called hierarchical graphs (inspired by de Bruijn graphs) with a recent algorithm solving the directed rural postman problem in $O^*(2^k)$ time where *k* is the number of weakly connected components by Gutin, Wahlström, and Yeo [13].

Thus, the main result shows that SCS can be solved faster than $O^*(2^n)$ when input strings are short. At the same time the other natural special case of SCS when the alphabet size is small is as hard as the general case: Vassilevska [23] proved that an $O^*(c^n)$ -algorithm for SCS over the binary alphabet implies an $O^*(c^n)$ -algorithm for the general case.

Our initial motivation for studying this problem was the existence of similar algorithms for other very well-known NP-hard problems — say, the satisfiability problem (SAT), the maximum satisfiability problem (MAX-SAT), the coloring problem, and the traveling salesman problem. Despite many efforts the best known algorithms for the general versions of these problems have running time $O^*(2^n)$ (*n* being the number of variables/vertices). For SAT and MAX-SAT, $O^*(2^n)$ is the running time of an exhaustive search. For TSP, $O^*(2^n)$ bound is proved using the dynamic programming method by Bellman [3] and Held and Karp [14]. For coloring, $O^*(2^n)$ bound was proved only recently using the inclusion-exclusion principle by Björklund, Husfeldt and Koivisto [6]. At the same time better upper bounds are known for various special cases of these problems:

^{*}New York University

[†]St. Petersburg Department of Steklov Institute of Mathematics. Research is partially supported by the Program for development of Centers of Advanced Studies of Ministry of Tele- and Mass Communications of the Russian Federation.

[‡]St. Petersburg Academic University. Supported by the Government of the Russian Federation (Resolution No. 220).

 $^{{}^{1}}O^{*}(c^{n})$ suppresses polynomial factors of the input length. We omit the star if we round up c.

- SAT: $O(1.308^n)$ for 3-SAT [15]; $O^*((2-2/k)^n)$ for k-SAT [22, 20];
- MAX-SAT: $O(1.731^n)$ for MAX-2-SAT [24, 18], $O(1.109^n)$ for (n, 3)-MAX-2-SAT [19]; $O((2 \varepsilon)^n)$ for formulas with constant clause density [10, 19];
- TSP: $O(1.2186^n)$ for cubic graphs [7]; $O((2-\varepsilon)^n)$ for graphs of bounded maximum/average degree [4, 9];
- Coloring: $O(1.3289^n)$ for 3-coloring [2]; $O((2-\varepsilon)^n)$ for graphs of bounded maximum degree [5];
- SCS: $O(1.443^n)$ for strings of length 3 [12].

Improving the $O^*(2^n)$ bound for all these problems (as well as for SCS) remains a challengeable open problem.

2 General Setting

2.1 Strings and Superstrings

By $u \supseteq v$ ($u \sqsubset v$) we denote that u is a suffix (prefix) of v. For strings s and t, by overlap(s,t) we denote the longest suffix of s that is also a prefix of t. By prefix(s,t) we denote the first |s| - |overlap(s,t)| symbols of s. Similarly, suffix(s,t) is the last |t| - |overlap(s,t)| symbols of t. By pref(s) and suf(s) we denote, respectively, the first and the last |s| - 1 symbols of s. The empty string is denoted by ε .

Throughout the paper by $S = \{s_1, \ldots, s_n\}$ we denote a set of *n* input strings, each of length at most r = O(1). We assume that no input string is a substring of another (such a substring can be removed from S while solving SCS for S on the preprocessing stage). Note that SCS is a permutation problem: to find a shortest string containing all s_i 's in a given order one just overlaps the strings in this order. This simple observation makes many connections to other permutation problems, including different versions of TSP.

2.2 Graphs and Walks

By a *path* in a directed graph we mean a path with no repeated vertices. We use the term *walk* for a path in which vertices may be repeated. A *closed walk* is a walk whose first vertex is the same as the last.

In the main result of this note we reduce SCS to the directed rural postman problem (DRPP). In this problem one is given a weighted directed multigraph G = (V, A) together with a set of arcs $R \subseteq A$ and the goal is to find a shortest closed walk going through all the arcs from R. The arcs R are called *required* while all the remaining arcs are called *optional*. Although DRPP is NP-hard in general case, it can be solved in polynomial time if the arcs from R form a single weakly connected component [8] (weakly connected components of a directed graph are connected components in this graph with all directed arcs replaced by undirected edges). We use also the following recent result by Gutin, Wahlström and Yeo [13].

Theorem 1. Let G = (V, A) be a weighted directed multigraph, $R \subseteq A$ be a subset of arcs, l = poly(|V|), then there exists a randomized algorithm with false negatives checking whether the length of a shortest closed walk going through all the arcs from R is at most l in time $O^*(2^k)$, where k is the number of weakly connected components in the subgraph of G induced by R.

3 Hierarchical Graphs

Definition 1 (hierarchical graph). A hierarchical graph $HG_{\mathcal{S}} = (V, A)$ of \mathcal{S} is a weighted directed graph defined as follows:

- The set of vertices V consists of all prefixes and suffixes (including the empty string ε) of the strings from S.
- For two such strings $u, v \in V$, $(u, v) \in A$ when either

- -u is a prefix of v of length |v| 1 (i.e., u = pref(v)); in this case the weight w(u, v) = 1 and (u, v) is called an up-arc, or
- -v is a suffix of u of length |u| 1 (i.e., v = suf(u)); in this case the weight w(u, v) = 0 and (u, v) is called a down-arc.

Figure 1 gives an example of the hierarchical graph as well as shows that the terminology of up- and down-arcs comes from placing all the strings of the same length at the same layer where the *i*-th layer contains strings of length *i*. For an *i*-th layer the (i - 1)-th layer is called *previous* while the (i + 1)-th layer is called *next*. By an *up-path* (resp., *down-path*) we denote a path containing up-arcs (down-arcs) only. A path $d \rightarrow db \rightarrow dbb$ on Fig. 1 is an example of an up-path, a path $abb \rightarrow bb \rightarrow b$ is a down-path.



Figure 1: The hierarchical graph for $S = \{abba, abca, dbb, bab, cab, aac\}$. The strings from S are given in rectangles.

Note that each string from S has exactly one incoming and one outgoing arc in HG_S . Denote the set of all these arcs by R. Any optimal walk must go through all the arcs of R so we call these arcs required (see Fig. 2(a)). Formally, $R = \{(\operatorname{pref}(s), s) : s \in S\} \cup \{(s, \operatorname{suf}(s)) : s \in S\}$. The resulting problem is an instance of the directed rural postman problem with the only exception: optimal walk must go through ε . To guarantee that a rural walk starts in ε and ends in ε we add a self-loop on ε of weight 0 to the set of required arcs.

For any two vertices u and v of this graph such that none of them is a substring of the other one there is a *natural* path from u to v: it first goes down from u to overlap(u, v) and then goes up to v (see Fig. 3). We call a rural walk *normal* if between visiting two consecutive vertices from S it alternates directions only once (i.e., any subpath between two consecutive vertices from S is a natural path). It is easy to see that there always exists a normal optimal walk (recall that any $s \in S$ is not a substring of any other $s' \in S$).

If all overlaps of a particular string $s \in S$ (with other strings from S) are short we know for sure that any optimal rural walk has a long down-path out of s. Returning to the example of Fig. 1, it is easy to see that no string from S starts from bb. This means that any optimal rural walk in HG_S must go down from dbb to at least b. We formalize this intuition in the definition below.

Definition 2 (extended set of required arcs). For a string $s \in S$, denote by maxpref_S(s) (resp., maxsuf_S(s)) the longest prefix (resp., suffix) of s which is also a suffix (prefix) of some other string $s' \in S$. Clearly,

$$\begin{aligned} |\operatorname{maxpref}_{\mathcal{S}}(s)| &= \max\{|\operatorname{overlap}(s',s)| \colon s' \in \mathcal{S} \setminus \{s\}\}, \\ |\operatorname{maxsuf}_{\mathcal{S}}(s)| &= \max\{|\operatorname{overlap}(s,s')| \colon s' \in \mathcal{S} \setminus \{s\}\}. \end{aligned}$$



Figure 2: (a) The set R of required arcs is shown in bold. (b) An optimal superstring dbbabcabbaac defines a walk of length 12 in HG. Note that both the superstring and the optimal walk are defined by a permutation $\sigma = (dbb, bab, abca, cab, abba, aac)$. The extended set of required arcs ER is shown in bold.



Figure 3: A natural path between vertices s_{i_j} and $s_{i_{j+1}}$.

Then an extended set of required arcs $ER \subseteq E(HG_S)$ is the set of required arcs R plus the following set of arcs:

- the up-path from maxpref_S(s) to s: all arcs (u, v) where $u, v \sqsubset s, |u| = |v| 1$ and $|u| \ge |\text{maxpref}_{S}(s)|$;
- the down-path from s to $\max \sup_{\mathcal{S}}(s)$: all $\operatorname{arcs}(u, v)$ where $u, v \sqsupset s, |u| = |v| + 1$ and $|v| \ge |\max \sup_{\mathcal{S}}(s)|$;
- the loop $(\varepsilon, \varepsilon)$ of weight 0.

E.g., for $S = \{abba, abca, dbb, bab, cab, aac\}$, maxpref_S(abca) = ab, maxsuf_S(abca) = ca, maxpref_S(dbb) = ε , maxsuf_S(dbb) = b.

Lemma 1. The length of an optimal superstring of a set of strings S is equal to the length of an optimal rural postman closed walk in HG_S where the required arcs are ER.

Proof. Consider an optimal rural closed walk w and represent it as a sequence of vertices $v_0 = \varepsilon, v_1, \ldots, v_k = \varepsilon$. This walk spells a string s in a natural way: initially, set $s = \varepsilon$ and start traversing the walk; each time when it goes up (i.e., $|v_i| = |v_{i-1}| + 1$) add the corresponding symbol to s. This way we preserve the following two invariants:

- the length of the current string equals the length of the traversed subwalk;
- when at a vertex v_i , the current string s contains v_i as a suffix.

Since w goes through all the strings from S the resulting string s is a superstring of S. Clearly, the length of s equals the length of w. Thus, the length of an optimal superstring does not exceed the length of an optimal rural walk.

For the reverse direction, consider a superstring s for S. It defines an order s_{i_1}, \ldots, s_{i_n} of the strings from S. Consider now the following normal rural walk: it starts at ε , goes up to s_{i_1} , then for all $j = 1, \ldots, n-1$ it goes down from s_{i_j} to $\operatorname{overlap}(s_{i_j}, s_{i_{j+1}})$ and then goes up to $s_{i_{j+1}}$, then it goes down from s_{i_n} to ε , and finally it goes through the loop $(\varepsilon, \varepsilon)$. It is easy to see that the length of the resulting closed walk equals the length of s. It is also a valid rural postman walk since for each string s_{i_j}

$$|\operatorname{overlap}(s_{i_{j-1}}, s_{i_j})| \leq |\operatorname{maxpref}_{\mathcal{S}}(s_{i_j})|, |\operatorname{overlap}(s_{i_i}, s_{i_{i+1}})| \leq |\operatorname{maxsuf}_{\mathcal{S}}(s_{i_j})|.$$

Hence the walk necessarily traverses all the arcs from ER. Thus, the length of an optimal rural closed walk is not greater than the length of an optimal superstring.

Definition 3 (bottom vertex). A vertex v in HG_S is called a bottom vertex if

$$\{(u,v) \in ER : |u| = |v| - 1\} = \{(v,u) \in ER : |u| = |v| - 1\} = \emptyset \text{ and}$$
$$|\{(u,v) \in ER : |u| = |v| + 1\}| + |\{(v,u) \in ER : |u| = |v| + 1\}| \ge 1.$$

In other words, v is not connected to the previous (i.e., (|v|-1)-th) layer by the arcs of ER, but is connected to the next (i.e., (|v|+1)-th) layer.

Lemma 2. $V_b = \{ \operatorname{maxpref}_{\mathcal{S}}(s), \operatorname{maxsuf}_{\mathcal{S}}(s) : s \in \mathcal{S} \}.$

Proof. Clearly, any bottom vertex is either $\operatorname{maxpref}_{\mathcal{S}}(s)$ or $\operatorname{maxsuf}_{\mathcal{S}}(s)$ for some $s \in \mathcal{S}$. For the other direction, consider a vertex $v = \operatorname{maxsuf}_{\mathcal{S}}(s)$ and assume that it has an incoming up-arc $(u, v) \in ER$. This arc must lie on an up-path from $\operatorname{maxpref}_{\mathcal{S}}(t)$ to t for some $t \in \mathcal{S}$. But then $v \sqsubset t$ and $v \sqsupset s$ and v is strictly longer than $\operatorname{maxpref}_{\mathcal{S}}(t)$ which contradicts to the definition of $\operatorname{maxpref}_{\mathcal{S}}(t)$. By a similar argument one can show that v does not have outgoing down-arcs. This shows that $\operatorname{maxsuf}_{\mathcal{S}}(s)$ is indeed a bottom vertex. \Box

E.g., for the set S from Fig. 1, {maxpref}_{S}(s): $s \in S$ } = { ε , ba, ab, ca, a} and {maxsuf}_{S}(s): $s \in S$ } = {b, ab, ca, ba, c}.

Definition 4 (good vertex). A bottom vertex is called good if it is not a substring of any other bottom vertex. The set of all good vertices is denoted by V_q .

In Fig. 2(b) the bottom vertices are ε , b, ba, ab, ca, a, c. Among them, ba, ab, and ca are good.

Note that a good vertex t is a meeting point of a down-path from $s \in S$ to $t = \text{maxsuf}_{S}(s)$ and an up-path from $t = \text{maxpref}_{S}(s')$ to $s' \in S$. Indeed, since a good vertex is a bottom vertex, it has either a down-path $s \rightsquigarrow t$ or an up-path $t \rightsquigarrow s'$ in ER. Consider the case that the path $s \rightsquigarrow t$ is in ER (the other case is symmetric). If the entire path $t \rightsquigarrow s' = \{t = v_0 \rightarrow v_1 \rightarrow \ldots \rightarrow v_k = s'\}$ is in ER then we are done. Assume, to the contrary, that there is a vertex v_i in the path such that $(v_{i-1}, v_i) \notin ER$ while the path $v_i \rightsquigarrow s' \in ER$. In order to get a contradiction, we want to show that v_i is a bottom vertex (this cannot be the case since t is a substring of v_i while by definition t is not a substring of any bottom vertex). Indeed, there is an arc from v_i to a vertex v_{i+1} from the next layer, but there are no connections to the previous layer:

- the up-arc $(v_{i-1} = \operatorname{pref}(v_i), v_i) \notin ER$ by the assumption;
- the down-arc $(v_i, \operatorname{suf}(v_i)) \notin ER$ because any down-path from an input string to v_i stops at v_i or earlier (more formally, if $(v_i, \operatorname{suf}(v_i)) \in ER$ then there exists an input string $s_0 \in S$ such that $|\max \operatorname{suf}_S(s_0)| \leq |\operatorname{suf}(v_i)| = |v_i| 1$; at the same time $|\max \operatorname{suf}_S(s_0)| \geq |\operatorname{overlap}(s_0, s')| \geq |v_i|$, a contradiction).

Lemma 3. $r^2 |V_g| \ge |V_b|$.

Proof. Recall that a bottom vertex v is not good iff there is another bottom vertex u such that v is a substring of u. This allows to define recursively the following mapping $f: V_b \to V_g$: if $v \in V_b$ is good then f(v) = v; otherwise take a vertex $u \in V_b$ such that v is a substring of u and set f(v) = f(u) (this is feasible since |u| > |v|). I.e., we go up from v till we reach a good vertex. Now note that for any $v \in V_b$, v is a substring of f(v). Since each vertex has at most r^2 substrings we have $r^2|V_g| \ge |V_b|$.

Theorem 2. The set ER of extended required arcs consists of at most $(1 - \frac{1}{2r^2+1})n$ weakly connected components.

Proof. Let k be the total number of weakly connected components and m_i be the number of weakly connected components that contain exactly i strings from S. Then

$$\sum_{i=1}^{n} m_i = k$$
 and $\sum_{i=1}^{n} i m_i = n$.

Since only bottom vertices have no connections to the previous layer, each weakly connected component contains at least one bottom vertex, hence $k \leq |V_b|$.

Also, each weakly connected component containing i input strings contains at most i good vertices. Indeed, a good vertex t is a meeting point of a down-path from $s \in S$ and an up-path to $s' \in S$. At the same time any $s \in S$ produces no more than two good vertices (one corresponding to maxpref_S(s) and one corresponding to maxsuf_S(s); recall Lemma 2). Hence $\sum_{i=2}^{n} im_i \geq |V_g|$ (clearly a component with only one input string does not contain good vertices at all).

Using these estimates and applying Lemma 3 we get

$$n = \sum_{i=1}^{n} im_i = k + \sum_{i=1}^{n} (i-1)m_i \ge k + \sum_{i=2}^{n} \frac{im_i}{2} \ge k + \frac{|V_g|}{2} \ge k + \frac{|V_b|}{2r^2} \ge k + \frac{k}{2r^2} = k\left(1 + \frac{1}{2r^2}\right).$$

4 Main Result

Theorem 3. There exists a randomized algorithm solving r-SCS on n strings in time $O^*\left(2^{\left(1-\frac{1}{2r^2+1}\right)n}\right)$.

Proof. Lemma 1 tells that to find a shortest superstring for S it is enough to find a shortest rural postman closed walk in HG_S for a set of required arcs ER. Theorem 2 guarantees that the number k of weakly connected components of ER is at most $(1 - \frac{1}{1+2r^2})n$. Finally, Theorem 1 shows that one can check whether such a graph contains a closed walk of total length l = poly(|V|) going through all required arcs in time $O^*(2^k)$. In our case l is indeed poly(|V|) since the optimal length of a superstring of S does not exceed rn. \Box

5 Further Directions

The natural next step is to solve the general version SCS in $O^*((2 - \epsilon)^n)$. It would also be interesting to show hardness of SCS (under Strong Exponential Time Hypothesis or, e.g., by reducing TSP with *n* vertices to SCS with *n* strings).

References

[1] Eric Bax and Joel Franklin. A finite-difference sieve to count paths and cycles by length. *Inf. Process. Lett.*, 60:171–176, November 1996.

- [2] Richard Beigel and David Eppstein. 3-coloring in time O(1.3289ⁿ). Journal of Algorithms, 54(2):168–204, 2005.
- [3] Richard Bellman. Dynamic programming treatment of the travelling salesman problem. J. ACM, 9:61-63, January 1962.
- [4] Andreas Björklund, Thore Husfeldt, Petteri Kaski, and Mikko Koivisto. The travelling salesman problem in bounded degree graphs. In Automata, Languages and Programming, volume 5125 of LNCS, pages 198–209. Springer Berlin / Heidelberg, 2008.
- [5] Andreas Björklund, Thore Husfeldt, Petteri Kaski, and Mikko Koivisto. Trimmed moebius inversion and graphs of bounded degree. *Theory of Computing Systems*, 47(3):637–654, 2010.
- [6] Andreas Björklund, Thore Husfeldt, and Mikko Koivisto. Set partitioning via inclusion-exclusion. SIAM Journal on Computing, 39(2):546–563, 2009.
- [7] Hans L. Bodlaender, Marek Cygan, Stefan Kratsch, and Jesper Nederlof. Deterministic single exponential time algorithms for connectivity problems parameterized by treewidth. In Automata, Languages, and Programming, pages 196–207. Springer, 2013.
- [8] Nicos Christofides, V. Campos, A. Corberan, and E. Mota. An algorithm for the Rural Postman problem on a directed graph. In *Netflow at Pisa*, volume 26 of *Mathematical Programming Studies*, pages 155–166. Springer Berlin Heidelberg, 1986.
- [9] Marek Cygan and Marcin Pilipczuk. Faster exponential-time algorithms in graphs of bounded average degree. In Automata, Languages, and Programming, volume 7965 of Lecture Notes in Computer Science, pages 364–375. Springer Berlin Heidelberg, 2013.
- [10] Evgeny Dantsin and Alexander Wolpert. MAX-SAT for formulas with constant clause density can be solved faster than in $O(2^n)$ time. In Proceedings of the 9th International Conference on Theory and Applications of Satisfiability Testing, volume 4121 of LNCS, pages 266–276, 2006.
- [11] John Gallant, David Maier, and James A. Storer. On finding minimal length superstrings. Journal of Computer and System Sciences, 20(1):50–58, 1980.
- [12] Alexander Golovnev, Alexander S. Kulikov, and Ivan Mihajlin. Solving 3-superstring in 3^{n/3} time. In Mathematical Foundations of Computer Science 2013, volume 8087 of Lecture Notes in Computer Science, pages 480–491. Springer Berlin Heidelberg, 2013.
- [13] Gregory Gutin, Magnus Wahlström, and Anders Yeo. Parameterized rural postman and conjoining bipartite matching problems. arXiv preprint arXiv:1308.2599, 2013.
- [14] Michael Held and Richard M. Karp. A dynamic programming approach to sequencing problems. Journal of the Society for Industrial and Applied Mathematics, 10(1):196–210, 1962.
- [15] Timon Hertli. 3-SAT faster and simpler unique-SAT bounds for PPSZ hold in general. In Foundations of Computer Science (FOCS), pages 277 –284, oct. 2011.
- [16] Richard M. Karp. Dynamic programming meets the principle of inclusion and exclusion. Operations Research Letters, 1(2):49–51, 1982.
- [17] Samuel Kohn, Allan Gottlieb, and Meryle Kohn. A generating function approach to the traveling salesman problem. In ACN'77: Proceedings of the 1977 annual conference, pages 294–300, New York, NY, USA, 1977.
- [18] Mikko Koivisto. Optimal 2-constraint satisfaction via sum-product algorithms. Information processing letters, 98(1):24–28, 2006.

- [19] Alexander S. Kulikov and Konstantin Kutzkov. New upper bounds for the problem of maximal satisfiability. Discrete Mathematics and Applications, 19:155–172, 2009.
- [20] Robin A. Moser and Dominik Scheder. A full derandomization of Schöning's k-SAT algorithm. In Proceedings of the 43rd annual ACM symposium on Theory of computing, STOC '11, pages 245–252. ACM, 2011.
- [21] Marcin Mucha. Lyndon words and short superstrings. In Proceedings of the Twenty-Fourth Annual ACM-SIAM Symposium on Discrete Algorithms, SODA'13, pages 958–972. Society for Industrial and Applied Mathematics, 2013.
- [22] Uwe Schöning. A probabilistic algorithm for k-SAT based on limited local search and restart. Algorithmica, 32(4):615–623, 2002.
- [23] Virginia Vassilevska. Explicit inapproximability bounds for the shortest superstring problem. In Mathematical Foundations of Computer Science 2005, volume 3618 of LNCS, pages 793–800. Springer Berlin / Heidelberg, 2005.
- [24] Ryan Williams. A new algorithm for optimal 2-constraint satisfaction and its implications. Theoretical Computer Science, 348(2-3):357–365, 2005.