

# Encoding Hard String Problems with Answer Set Programming

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warning:

Although I mostly work on algorithms and data structures, we here use artificial intelligence tools for problem solving

## problem setting

- ▶ only a tiny fraction of problems are efficiently solvable
- ▶ infinitely many problems are NP-hard (NP-hard is closed under union/intersection/concatenation)
- ▶ but sometimes we need really to solve a problem, for which no efficient solution exists

What can we do?

- ▶ use heuristics: approximation algorithms, probabilistic tree search, evolutionary algorithm, etc.
- ▶ but may not work if we want the exact solution!

On what problems we want to look at?

# exemplary: CLOSEST STRING

Problem CLOSEST STRING

Input

- ▀ set of  $m$  strings  $\mathcal{S} = \{S_1, \dots, S_m\}$  on an alphabet  $\Sigma$  of size  $\sigma$
- ▀  $|S_j| = n \quad \forall j \in [1..m]$

Task: find string  $T$  with

- ▀  $|T| = n$
- ▀  $\max_{x \in [1..m]} \text{dist}_{\text{ham}}(S_x, T)$  is minimal

where  $\text{dist}_{\text{ham}}(S_x, T) := |\{i \in [1..n] : S_x[i] \neq T[i]\}|$  is Hamming distance between  $T$  and  $S_x$ .

- ▀ problem is NP-hard for  $\sigma \geq 2$  in  $n$  and  $m!$  Frances, Litman'97
- ▀ fortunately: already exist efficient solutions for this problem (ILP solver, etc.)

## example

	1	2	3	4	5	6	7	8	9	10	11	12	13
$S_1 =$	l	n	e	e	p	l	e	s	s	n	e	l	s
$S_2 =$	s	l	e	e	p	s	l	s	s	n	e	s	n
$S_3 =$	n	l	e	l	p	l	e	s	s	n	s	s	s
$S_4 =$	s	n	e	e	p	l	e	l	s	n	s	s	s
$S_5 =$	s	l	l	e	e	l	e	s	s	n	s	s	s

## example

	1	2	3	4	5	6	7	8	9	10	11	12	13
$S_1 =$	l	n	e	e	p	l	e	s	s	n	e	l	s
$S_2 =$	s	l	e	e	p	s	l	s	s	n	e	s	n
$S_3 =$	n	l	e	l	p	l	e	s	s	n	s	s	s
$S_4 =$	s	n	e	e	p	l	e	l	s	n	s	s	s
$S_5 =$	s	l	l	e	e	l	e	s	s	n	s	s	s
$T =$	s	l	e	e	p	l	e	s	s	n	e	s	s

why this problem?

- well-studied:
  - 31 conference papers
  - 22 journal papers
- it is a string problem, and we love strings!

yet. . .

do we have any implementation of a solution available so far?

*“We do not compare with the algorithm in [6], because its code is not available.”*

Shota Yuasa, Zhi-Zhong Chen, Bin Ma, Lusheng Wang:  
*Designing and Implementing Algorithms for the Closest String Problem.*  
Proc. FAW 2017, LNCS 10336, pages 79-90

Of course, the authors also did not publish their code. . .

# So is there any implementation available at all?

The algorithm is explained in detail in the following article:

<https://example.com>

<https://github.com/kirilenkobm/BDCSP> (accessed: 30th of April 2023)

## Other Half-Baked Code Repositories

- ▣ “A challenge to make this basic closest-strings program more efficient. ”  
last update: 3 years ago (2020)  
`https://github.com/robertvunabandi/closest-strings-challenge`
- ▣ “Swarm Intelligence project: Closest string problem”  
last update: 6 years ago (2017)  
`https://github.com/arnomoonens/closest-string-problem`
- ▣ :

Looks like some unfinished student projects. So:

- ▣ will the code run? maybe
- ▣ will it produce correct results? unknown: there are (mostly) no tests



## our aim

exact search:

- ▀ brute-force, exhaustive search : easy to program, but combinatorial explosion prevents from working even on small input sizes
- ▀ Integer linear programming (ILP) or MAX-SAT formulation: burden on the implementation!

want to have: tool for fast prototyping

- ▀ easy implementation
- ▀ speed should be reasonable
- ▀ goals:
  - ◇ fast problem solving
  - ◇ usable for testing coding-intensive implementations at an early stage

# introduction to answer set programming (ASP)

- ▶ Prolog-like declarative language
- ▶ most classic problems like traveling salesman problem can be expressed in a few lines of code, but still performant on small instance sizes
- ▶ current standard: ASP-Core-2 Calimeri+'19
- ▶ standard reference implementation: `clingo`
  - in active development at <https://potassco.org/clingo/> (University of Potsdam) by Torsten Schaub
  - shipped with common Linux distributions such as Ubuntu/Debian:  
`adb install gringo`

# how to solve CLOSEST STRING with ASP?

with seven lines of code:

```
1 mat(X,I) :- s(X,I,_).
2 1 {t(I,C) : s(_,I,C)} 1 :- mat(_,I).
3 c(X,I) :- t(I,C), s(X,I,A), C != A.
4 cost(X,C) :- C = #sum {1,I : c(X,I)}, mat(X,_).
5 mcost(M) :- M = #max {C : cost(_,C)}.
6 #minimize {M : mcost(M)}.
7 #show t/2. #show mcost/1. #show cost/2.
```

## how does the input look like?

transform texts

▀  $S_1 = \text{lneeplessnls}$

▀  $\vdots$

▀  $S_5 = \text{slleelessnsss}$

write  $S_j[i]$  as  $s(j, i, \text{rank}(S_j[i]))$ , where  $\text{rank}$  is the ASCII rank of the symbol

▀  $l \mapsto 108$

▀  $n \mapsto 110$

▀  $e \mapsto 101$

▀  $s \mapsto 115$

ASP input

1  $s(0, 0, 108).$

2  $s(0, 1, 110).$

3  $s(0, 2, 101).$

4  $\dots$

5  $s(4, 10, 115).$

6  $s(4, 11, 115).$

7  $s(4, 12, 115).$

# modelling the input

- so we have at startup tuples  $s(i, j, S_i[j])$
- next we create a boolean matrix `mat` that specifies whether  $S_i[j]$  exists

```
1 mat(X,I) :- s(X,I,_).
2 1 {t(I,C) : s(_,I,C)} 1 :- mat(_,I).
3 c(X,I) :- t(I,C), s(X,I,A), C != A.
4 cost(X,C) :- C = #sum {1,I : c(X,I)}, mat(X,
    _).
5 mcost(M) :- M = #max {C : cost(_,C)}.
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7 #show t/2. #show mcost/1. #show cost/2.
```

but how do we get to the closest substring of that?

# Restriction of Optimal Solution

Lemma (Kelsey, Kotthoff'11)

*There exists an optimal solution  $T$  with  $T[i] \in \{S_1[i], \dots, S_m[i]\}$ .*

Proof.

- ▮ if  $T[i] \notin \{S_1[i], \dots, S_m[i]\}$ , then  $T$  mismatches with all input strings at position  $i$
- ▮ if  $T[i] = S_j[i]$ , then the distance to at least  $S_j$  is better, so it does not worsen the distance

□

Definition

define  $\Sigma_i := \{S_1[i], \dots, S_m[i]\}$  effective alphabet for position  $i \in [1..n]$

# modelling $T$

- model  $T[i]$  as a boolean matrix  $T_{i,c} = 1 \Leftrightarrow T[i] = c$
- state that  $T[i] = S_x[i]$ , i.e., only one  $T_{i,c}$  is set:

$$\forall i \in [1..n] : \sum_{c \in \Sigma_i} T_{i,c} = 1$$

$$[\mathcal{O}(n), \mathcal{O}(\min(m, \sigma))]$$

complexity  $(x,y)$ :

- $x$  : # clauses
- $y$  : # variables per clause

```
1 mat(X,I) :- s(X,I,_).
2 1 {t(I,C) : s(_,I,C)} 1 :- mat(_,I).
3 c(X,I) :- t(I,C), s(X,I,A), C != A.
4 cost(X,C) :- C = #sum {1,I : c(X,I)}, mat(X,
    _).
5 mcost(M) :- M = #max {C : cost(_,C)}.
6 #minimize {M : mcost(M)}.
7 #show t/2. #show mcost/1. #show cost/2.
```

# modelling costs

- define  $C_{i,x} \in \{0, 1\}$ :  
 $\forall i \in [1..n], x \in [1..m]$  with  
 $C_{i,x} = 1$  if  $T[i] \neq S_x[i]$ .

- then  $\text{dist}_{\text{ham}}(T, S_x) = \sum_{i \in [1..n]} C_{i,x}$  is Hamming distance between  $T$  and  $S_x$

$$\forall i \in [1..n], c \in \Sigma, x \in [1..m] : \\ T_{i,c} \wedge S_x[i] \neq c \implies C_{i,x} \\ [\mathcal{O}(nm\sigma), \mathcal{O}(1)]$$

```
1 mat(X,I) :- s(X,I,_).
2 1 {t(I,C) : s(_,I,C)} 1 :- mat(_,I).
3 c(X,I) :- t(I,C), s(X,I,A), C != A.
4 cost(X,C) :- C = #sum {1,I : c(X,I)}, mat(X,
    _).
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```



## maximum of summed costs

- add helper variables

$$\text{cost}_x := \sum_{i \in [1..n]} C_{i,x} = \text{dist}_{\text{ham}}(T, S_x)$$

- and compute the maximum value  $\text{mcost} := \max\{\text{cost}_1, \dots, \text{cost}_m\}$

```
1 mat(X,I) :- s(X,I,_).
2 1 {t(I,C) : s(_,I,C)} 1 :- mat(_,I).
3 c(X,I) :- t(I,C), s(X,I,A), C != A.
4 cost(X,C) :- C = #sum {1,I : c(X,I)}, mat(X,
   _).
5 mcost(M) :- M = #max {C : cost(_,C)}.
6 #minimize {M : mcost(M)}.
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```

## setting the objective

- statement for setting  $C_{i,x}$  to false is not needed: optimizer will do so if it does not violate Line 3
- for that, our objective is:

$$\text{minimize } \max_{x \in [1..m]} \sum_{i \in [1..n]} C_{i,x}$$

$[\mathcal{O}(1), \mathcal{O}(mn)]$

```
1 mat(X,I) :- s(X,I,_).
2 1 {t(I,C) : s(_,I,C)} 1 :- mat(_,I).
3 c(X,I) :- t(I,C), s(X,I,A), C != A.
4 cost(X,C) :- C = #sum {1,I : c(X,I)}, mat(X,
    _).
5 mcost(M) :- M = #max {C : cost(_,C)}.
6 #minimize {M : mcost(M)}.
7 #show t/2. #show mcost/1. #show cost/2.
```

## specifying the output

output  $T$ , mcost, and cost

```
1 mat(X,I) :- s(X,I,_).
2 1 {t(I,C) : s(_,I,C)} 1 :- mat(_,I).
3 c(X,I) :- t(I,C), s(X,I,A), C != A.
4 cost(X,C) :- C = #sum {1,I : c(X,I)}, mat(X,
    _).
5 mcost(M) :- M = #max {C : cost(_,C)}.
6 #minimize {M : mcost(M)}.
7 #show t/2. #show mcost/1. #show cost/2.
```

# complexities

- ▶  $\mathcal{O}(n\sigma)$  selectable variables  
( $T_{i,c}$ )
- ▶  $\mathcal{O}(nm)$  helper variables  
( $C_{i,x}$ ),
- ▶  $\mathcal{O}(nm\sigma)$  clauses (Line 3).

```
1 mat(X,I) :- s(X,I,_).
2 1 {t(I,C) : s(_,I,C)} 1 :- mat(_,I).
3 c(X,I) :- t(I,C), s(X,I,A), C != A.
4 cost(X,C) :- C = #sum {1,I : c(X,I)}, mat(X,
    _).
5 mcost(M) :- M = #max {C : cost(_,C)}.
6 #minimize {M : mcost(M)}.
7 #show t/2. #show mcost/1. #show cost/2.
```

## interpreting output

- since  $mcost = 3$ , we have at most three errors at each text position
- (actually we have exactly three errors at all positions when looking at cost for this solution)
- by remapping ASCII ranks to characters from  $t(i, rank(T[i]))$ , we obtain  $T = \text{sleeplessness}$

```
mcost(3)
cost(0,3) cost(1,3) cost(2,3)
cost(3,3) cost(4,3)
t(0,115) t(1,108) t(2,101) t(3,101)
t(4,112) t(5,108) t(6,101) t(7,115)
t(8,115) t(9,110) t(10,101)
t(11,115) t(12,115)
```

## works in practice

freely available at <https://github.com/koepp1/aspstring>

- ▀ python wrapper around ASP/clingo calls
- ▀ input and output: plain string(s)
- ▀ framework for working with strings: easy to write code for other string-related problems

evaluation with brute-force approach (test every possible value for  $T[1..n]$ )

# evaluation on random datasets

file	x	ASP				brute-force	
		rules	vars	choices	[s]	choices	[s]
s05m07n009i0	6	1025	264	673	0.01	327 680	2.19
s05m07n009i1	6	1002	262	608	0.01	172 800	1.15
s05m07n009i2	6	977	253	589	0.01	98 304	0.66
s05m08n009i0	6	1122	290	605	0.01	230 400	1.74
s05m08n009i1	6	1123	290	975	0.01	216 000	1.64
s05m08n009i2	6	1136	291	716	0.01	288 000	2.17
s05m09n009i0	6	1288	321	725	0.01	640 000	5.47
s05m09n009i1	7	1258	319	1723	0.02	409 600	3.48
s05m09n009i2	7	1273	320	1828	0.02	512 000	4.33
s06m07n009i0	6	1039	265	974	0.01	384 000	2.57
s06m07n009i1	7	1078	268	1767	0.02	768 000	5.12
s06m07n009i2	6	1002	262	569	0.01	172 800	1.15
s06m08n009i0	6	1191	295	1074	0.01	750 000	5.67
s06m08n009i1	7	1248	299	2378	0.02	1 800 000	13.63
s06m08n009i2	7	1248	299	2128	0.02	1 800 000	13.61
s06m09n009i0	7	1303	322	1837	0.02	800 000	6.81
s06m09n009i1	7	1396	328	1849	0.02	2 700 000	22.97
s06m09n009i2	6	1336	324	1874	0.02	1 080 000	9.07

s05m07n009i0 denotes

- ▀  $\sigma = 5$
- ▀  $m = 7$
- ▀  $n = 9$
- ▀  $i = 0$ -th sample (iteration)

columns:

- ▀  $x = \text{mcost}$
- ▀  $[s]$ : time in seconds

observation:

- ▀  $\#$  choices  
correlates with time
- ▀ ASP has much fewer to check

but wait. . .

. . . if there are good solutions like with ILP for CLOSEST STRING, why bother?

maybe you work on a variation: CLOSEST STRING  $\Rightarrow$  CLOSEST SUBSTRING

- ▀ fewer references, much fewer implementations
- ▀ hard to adapt ILP/MAX-SAT implementations to this variation
- ▀ but easy with ASP! (see code repository)



## weakness

- ASP is slower than good MAX-SAT implementation, e.g.: string attractor
- Bannai+'22: MAX-SAT for string attractor in pysat, 566 line of code
- but ASP for string attractor in 5 line of code:

```
1 { in(1..n) }.
2 sub_str(S,E) :- cover(S,E,_).
3 :- not 1 { in(P) : cover(S,E,P) }, sub_str(S,E).
4 #minimize { 1,P : in(P) }.
5 #show in/1.
```

adjacent positions,



various constraints on  $ref_{i \rightarrow j}$   
+ auxiliary vars

Total  $O(n^4)$  size

Bannai+'22

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# conclusion

introduction of ASP to hard string problems

- ▀ fast prototyping
- ▀ actual code available for comparison, benchmarks, etc.
- ▀ framework to implement new code easily
- ▀ usually faster than naive implementations but slower than sophisticated ones

<https://github.com/koepp1/aspstring>  
happy coding 🎵

P.S.: Initial code has already been improved by an anonymous CPM reviewer.  
Thanks for that!

# does it work with ChatGPT? (asked by Pierre Peterlongo)

seems (un)fortunately hard:

Can you encode the closest string problem in the answer set programming (ASP) language such that I can run the code with the program clingo? The code should accept a list of input strings  $S_1, \dots, S_5$ . All strings have exactly the same length. The solution is a string that has also the same length. Your encoding must output the solution string. As an example, can you encode the input strings as  $S_1 = \text{"lneeplessnels"}$ ,  $S_2 = \text{"sleepslssnesn"}$ ,  $S_3 = \text{"nlelplessnsss"}$ ,  $S_4 = \text{"sneepelnsnsss"}$ ,  $S_5 = \text{"slleelessnsss"}$ ? The code must not include the solution, and should work without a parameter specifying the maximal allowed distance. Note that neither the syntax `"#int"` nor `"#len"` is valid in ASP.

output of ChatGPT:

```
1 % Define the input strings
2 input_string("lneeplessnels").
3 input_string("sleepslssnesn").
4 input_string("nlelplessnsss").
5 input_string("sneepelnsnsss").
6 input_string("slleelessnsss").
7
8 % Define the length of the input
   strings
9 len(N) :- input_string(S), len(S,
   N).
10 ...
```

Not even the first line, the definition of `len(S,N)` works...