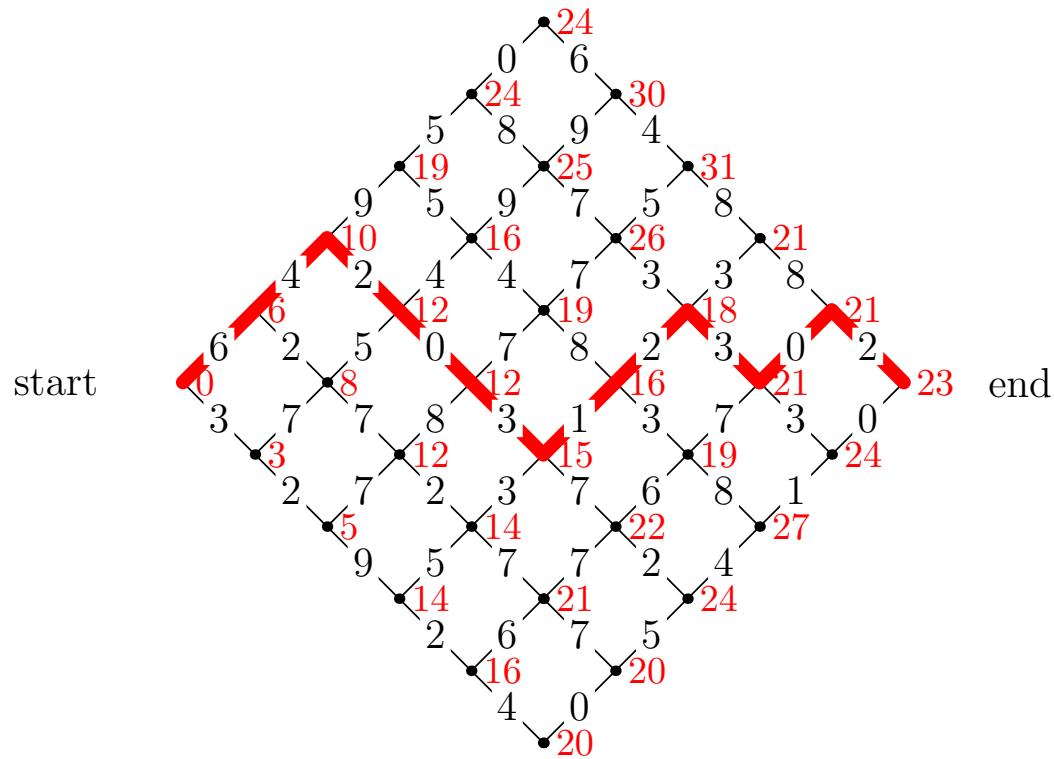


# Algorithms and Analysis

## Lesson 23: *Dynamic Programming*



*Dynamic programming, line breaking, edit distance, Dijkstra, TSP*

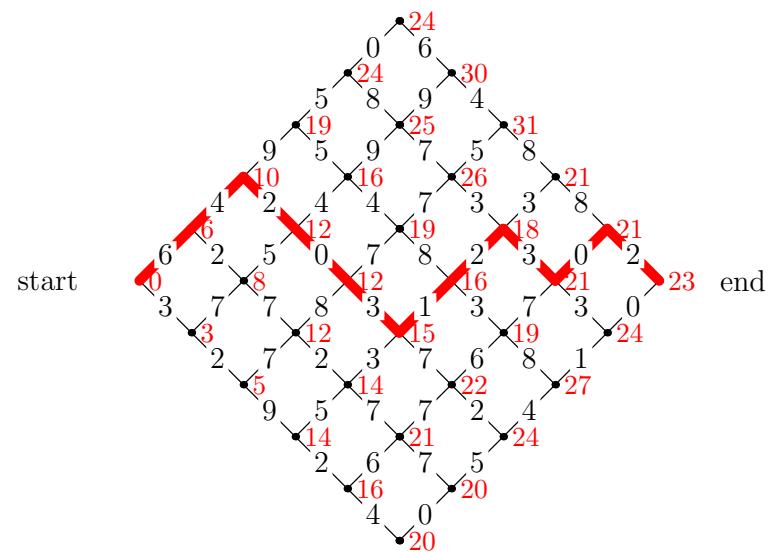
# Outline

## 1. Dynamic Programming

## 2. Applications

- Line Breaks
- Edit Distance
- Dijkstra's Algorithm

## 3. Limitation



# Dynamic Programming

- One of the most powerful strategies for solving optimisation problems is **dynamic programming**
  - ★ Build a set of optimal partial solutions
  - ★ Increase the size of the partial solutions until you have a full solution
  - ★ Each step uses the set of optimal partial solutions found in the previous step
- Developed by Richard Bellman in the early 1950's
- The name is unfortunate as it doesn't have much to do with programming

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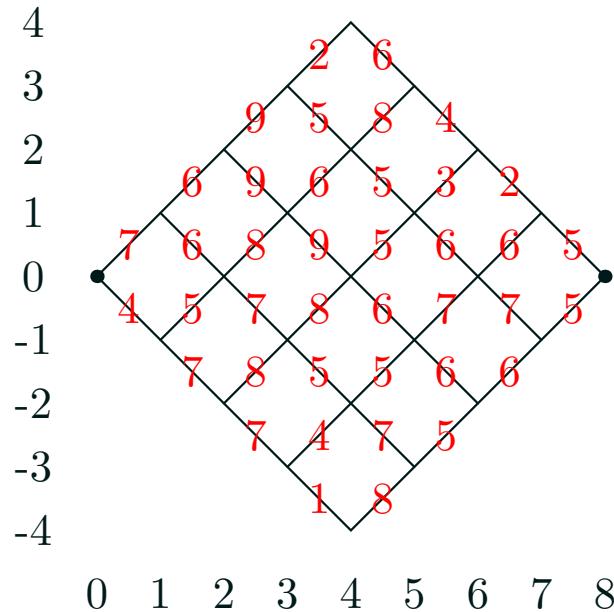
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# A Toy Problem

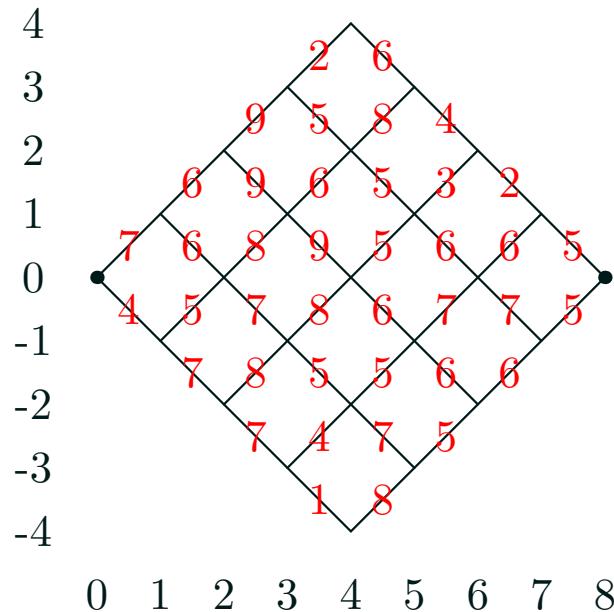
- Consider the problem of find a minimum cost path from point  $(0,0)$  to  $(8,0)$  on the lattice



- The costs of traversing each link is shown in red
- The cost of a path is the sum of weights on each link

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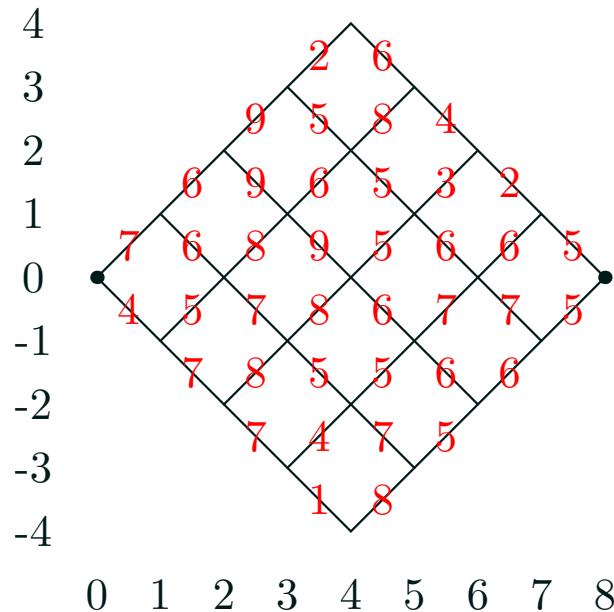
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# Brute Force

- The obvious brute force strategy is to try every path
- For a problem with  $n$  steps we require  $n/2$  to be diagonally up and  $n/2$  to be diagonally down
- The total number of paths is

$$\binom{n}{n/2} \approx \sqrt{\frac{2}{\pi n}} 2^n$$

- For the problem shown above with  $n = 8$  there are 70 paths
- For a problem with  $n = 100$  there are  $1.01 \times 10^{29}$  paths

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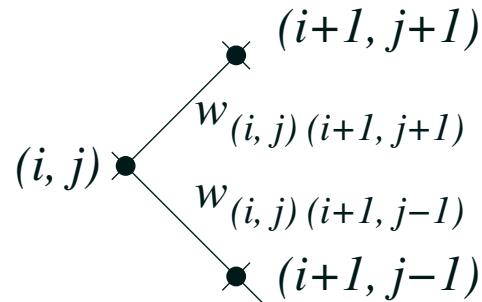
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# Building a Solution

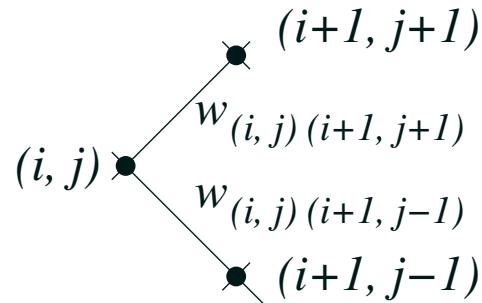
- We can solve this problem efficiently using dynamic programming by considering optimal paths of shorter length
- Let  $c_{(i,j)}$  denote the cost of the optimal path to node  $(i,j)$
- We denote the weights between two points on the lattice by  $w_{(i,j)(i+1,j \pm 1)}$



- Clearly  $c_{(0,0)} = 0$

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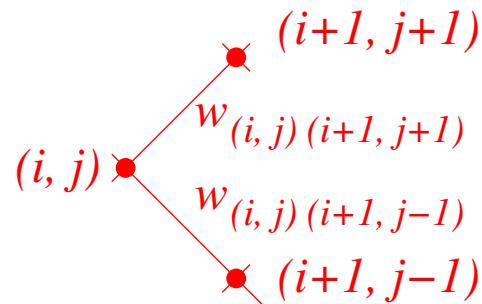
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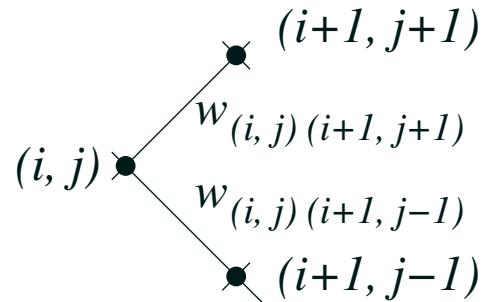
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# Forward Algorithm

- Suppose we know the optimal costs for all the edge in column  $i$
- Our task is to find the optimal cost at column  $i + 1$
- If we consider the sites in the lattice then the optimal cost will be

$$c_{(i+1,j)} = \min(c_{(i,j+1)} + w_{(i,j+1)(i+1,j)}, c_{(i,j-1)} + w_{(i,j-1)(i+1,j)})$$

- This is the defining equation in dynamic programming
- We have to treat the boundary sites specially, but this is just book-keeping

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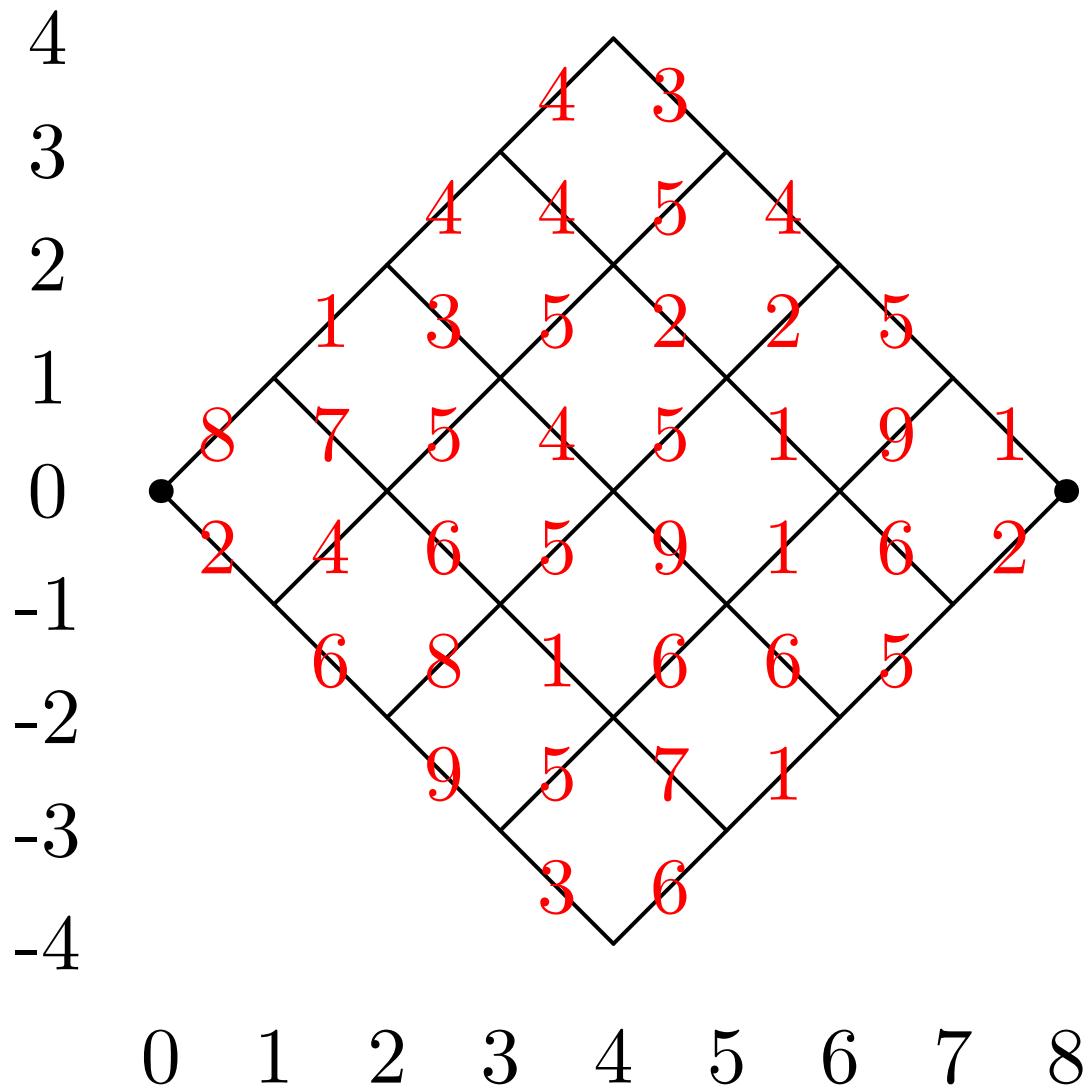
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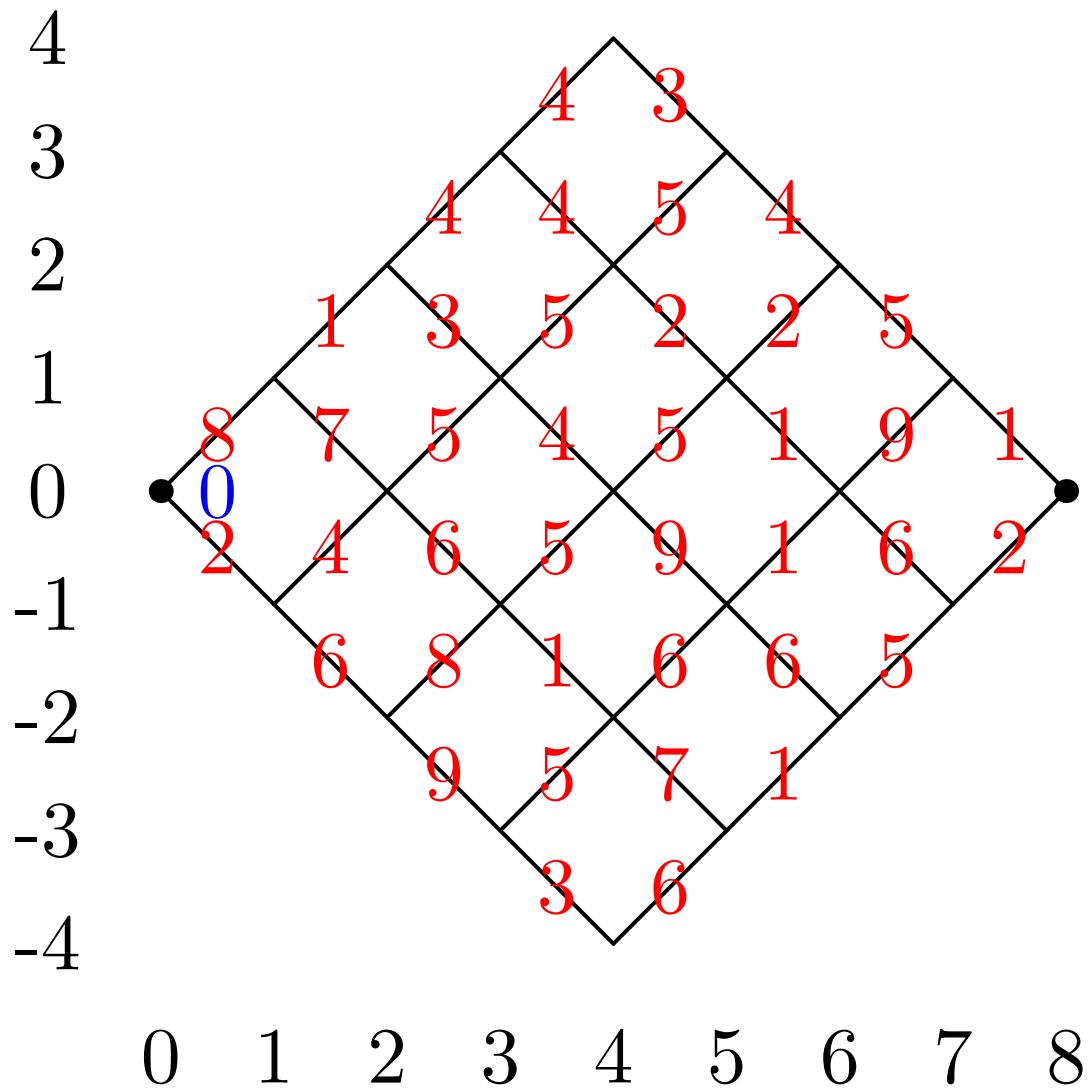
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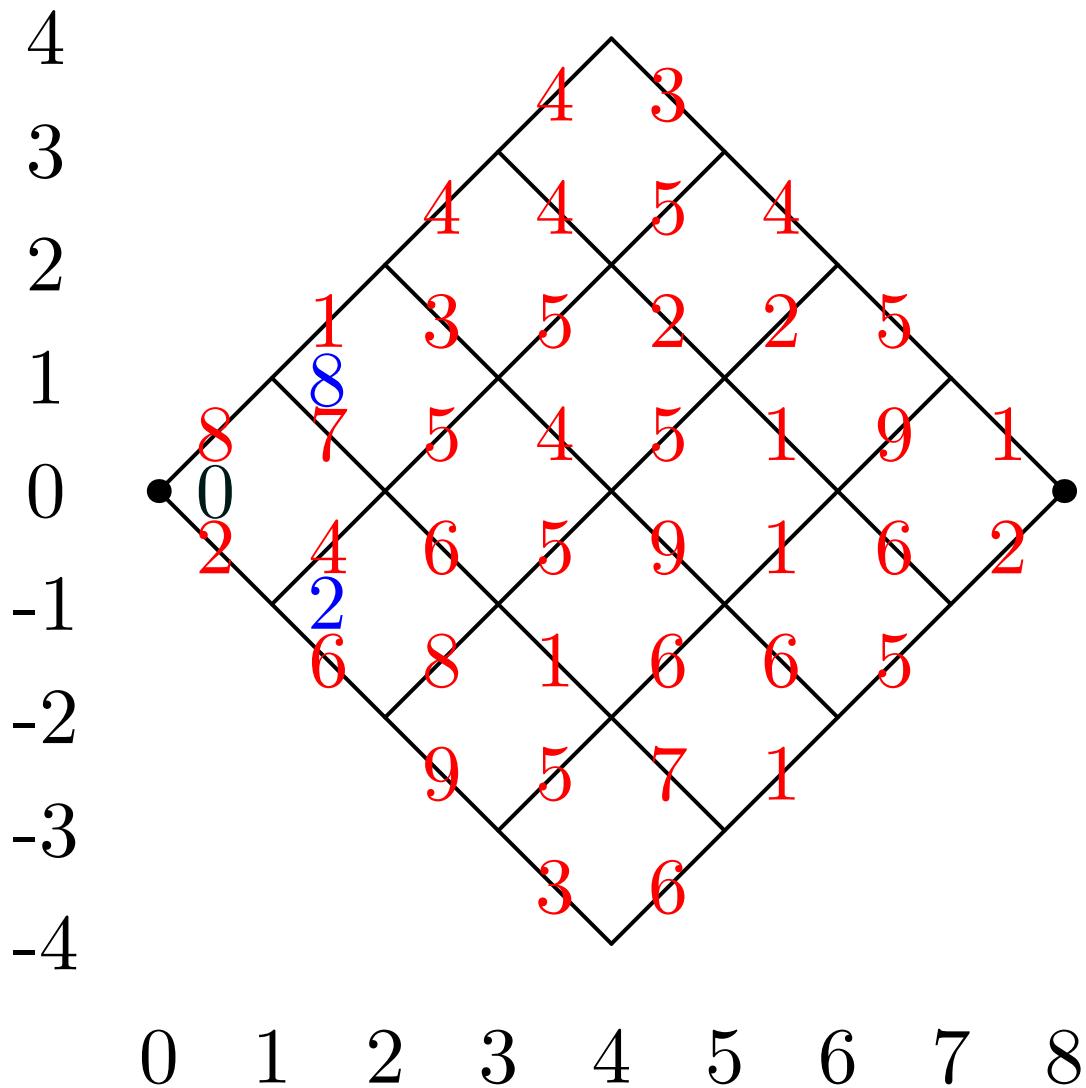
# Example



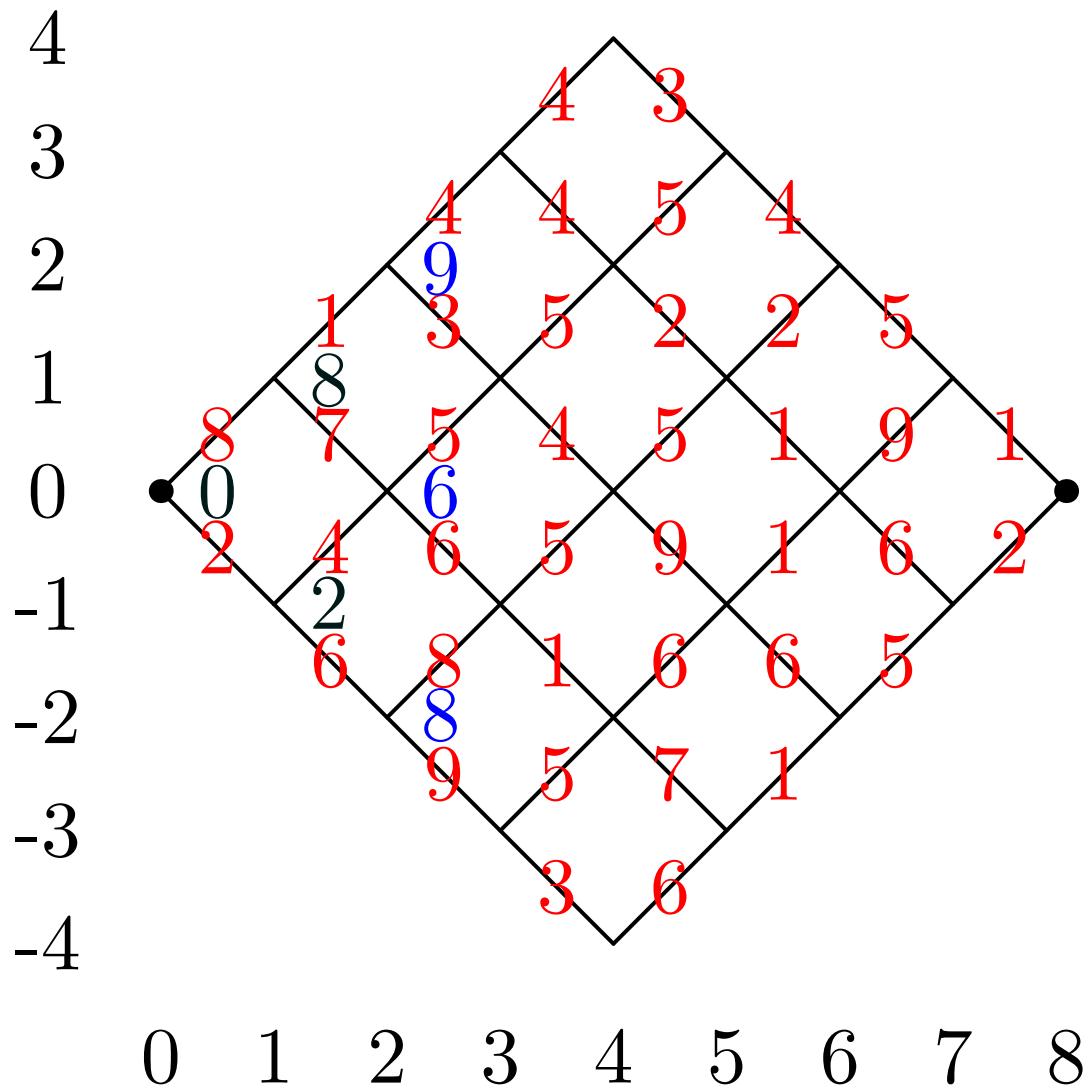
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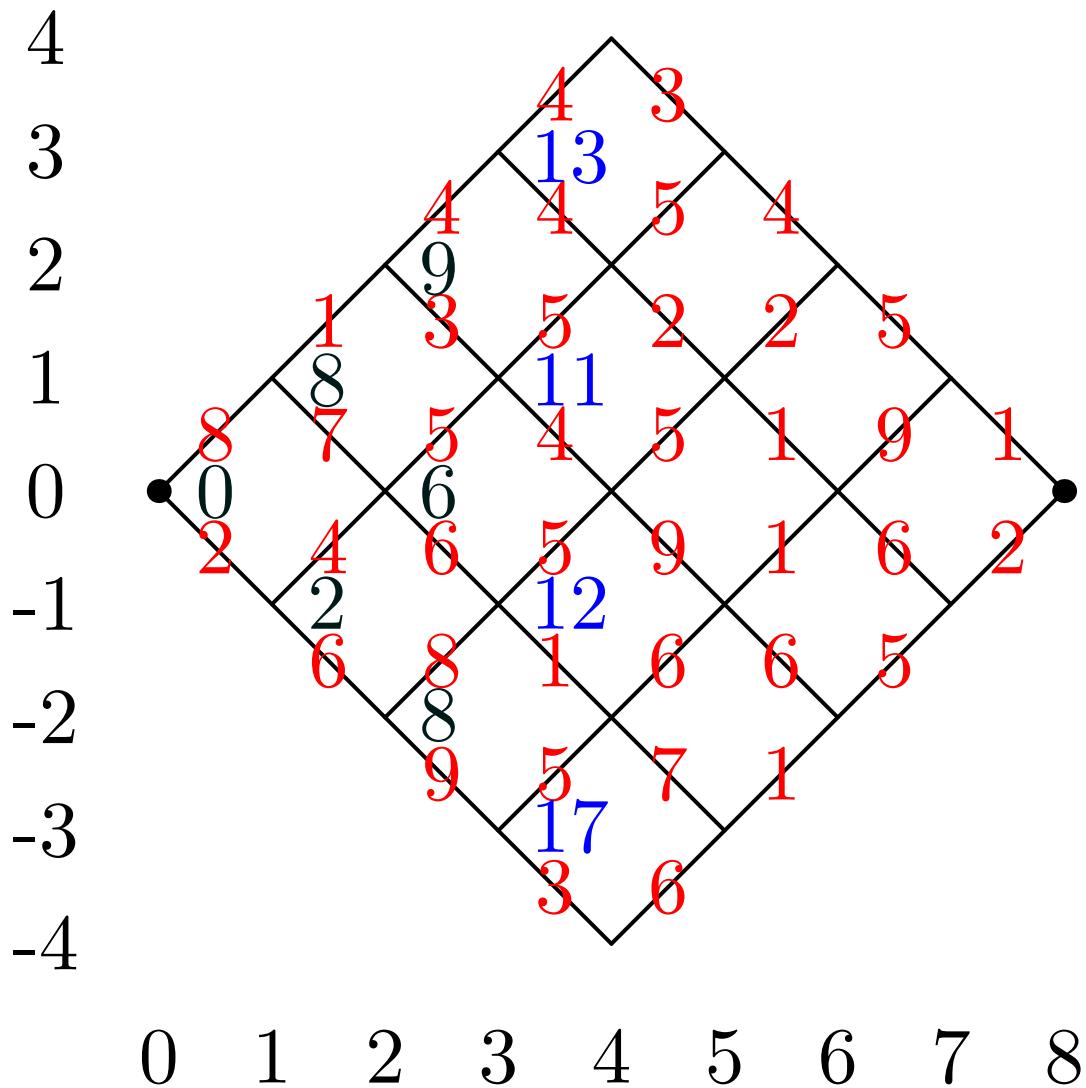
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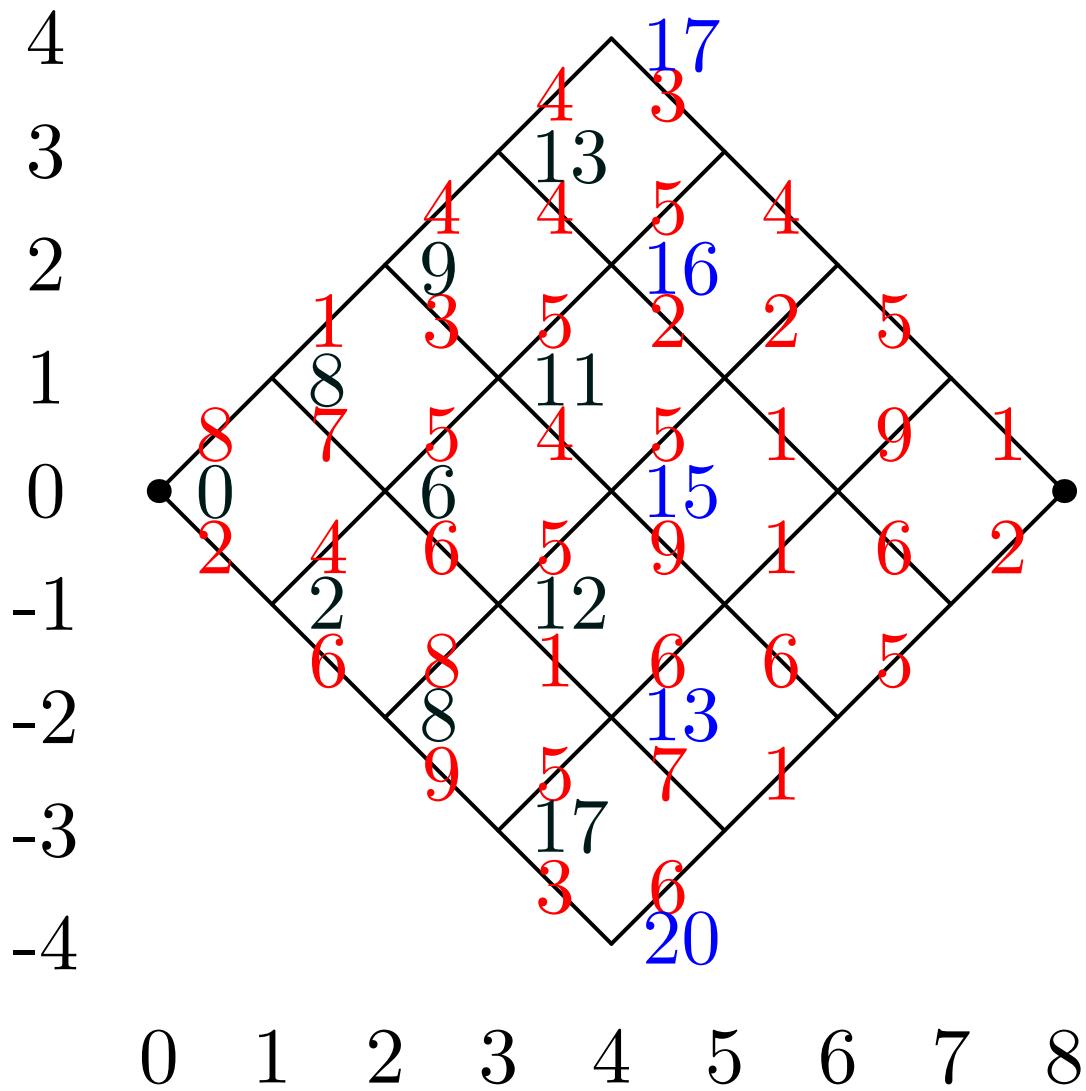
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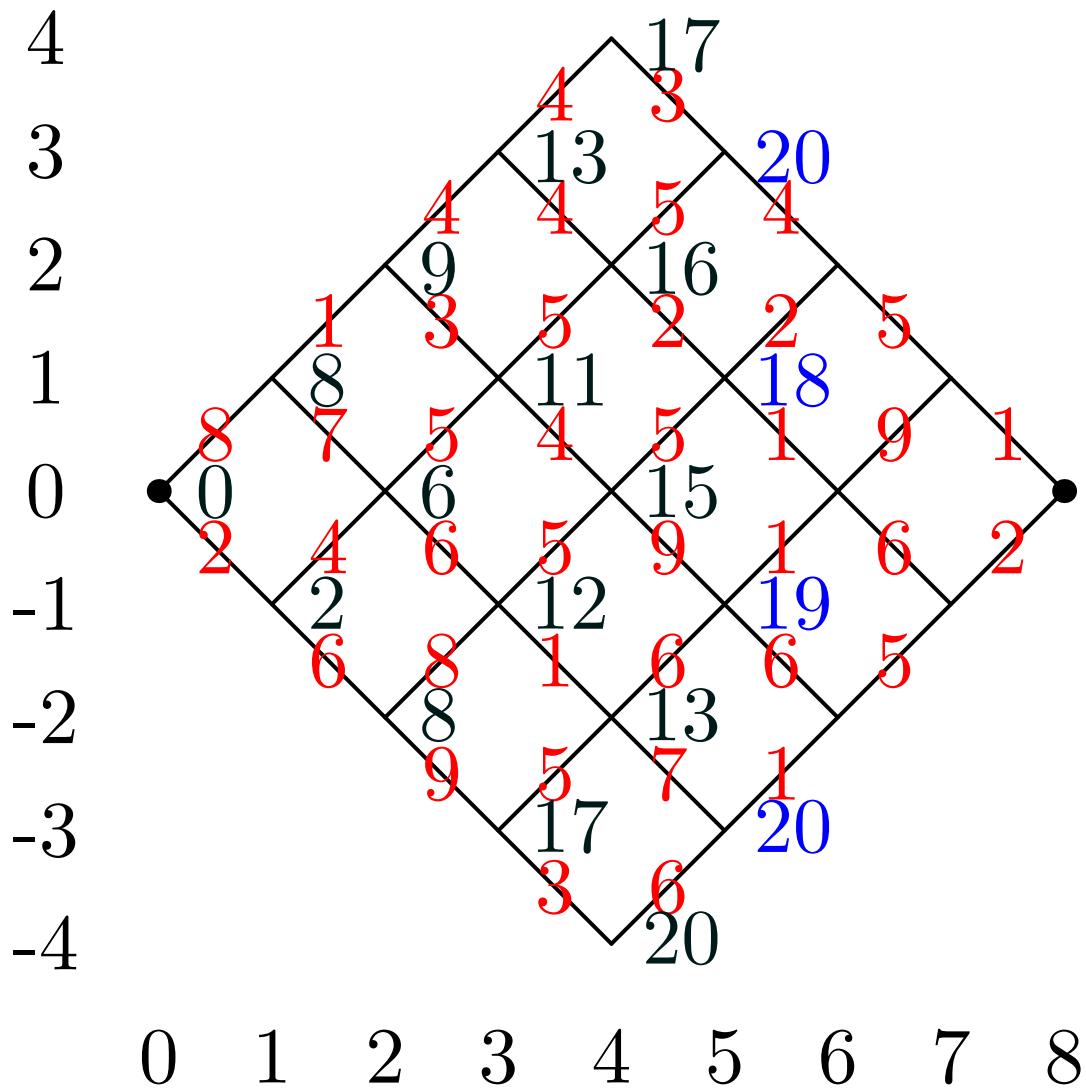
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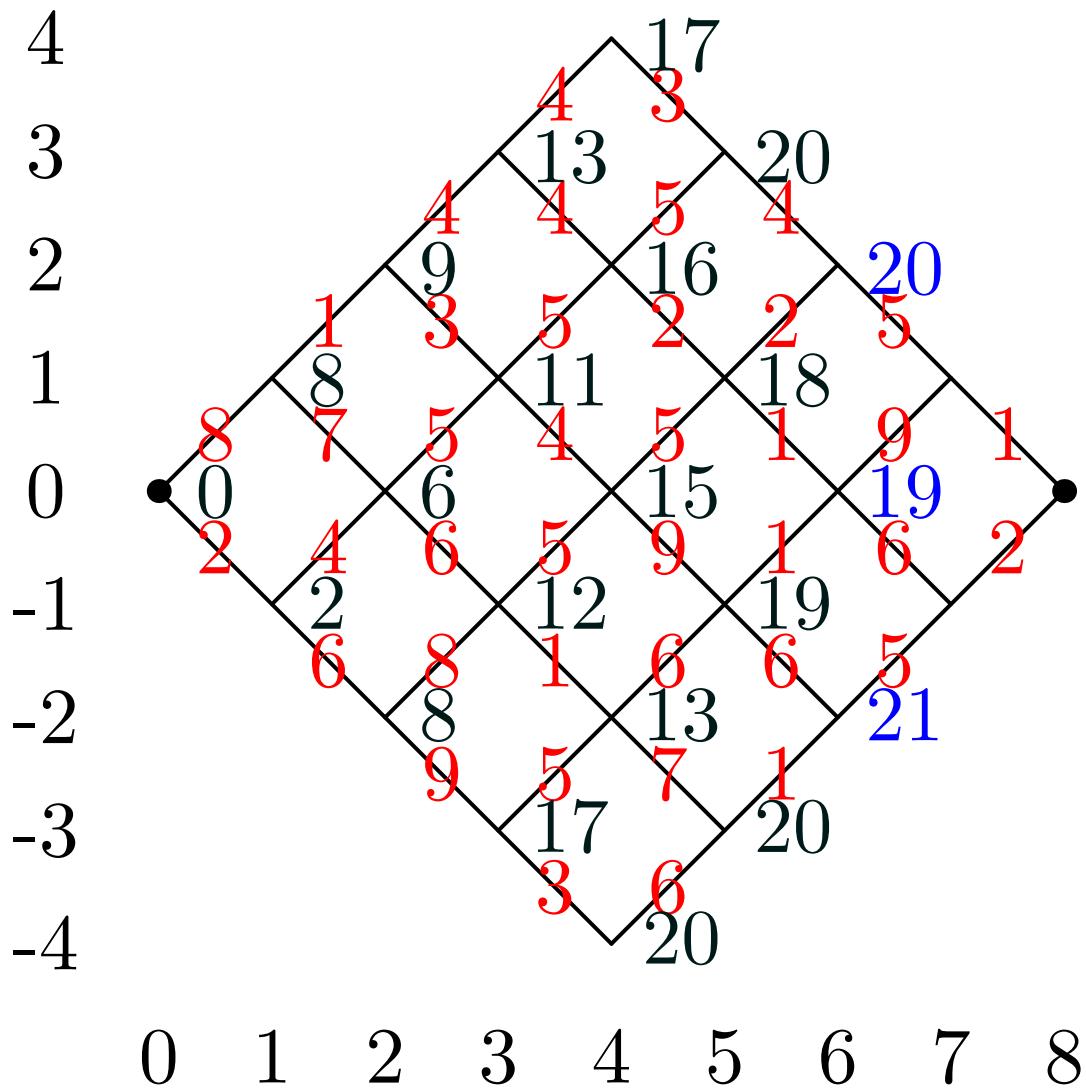
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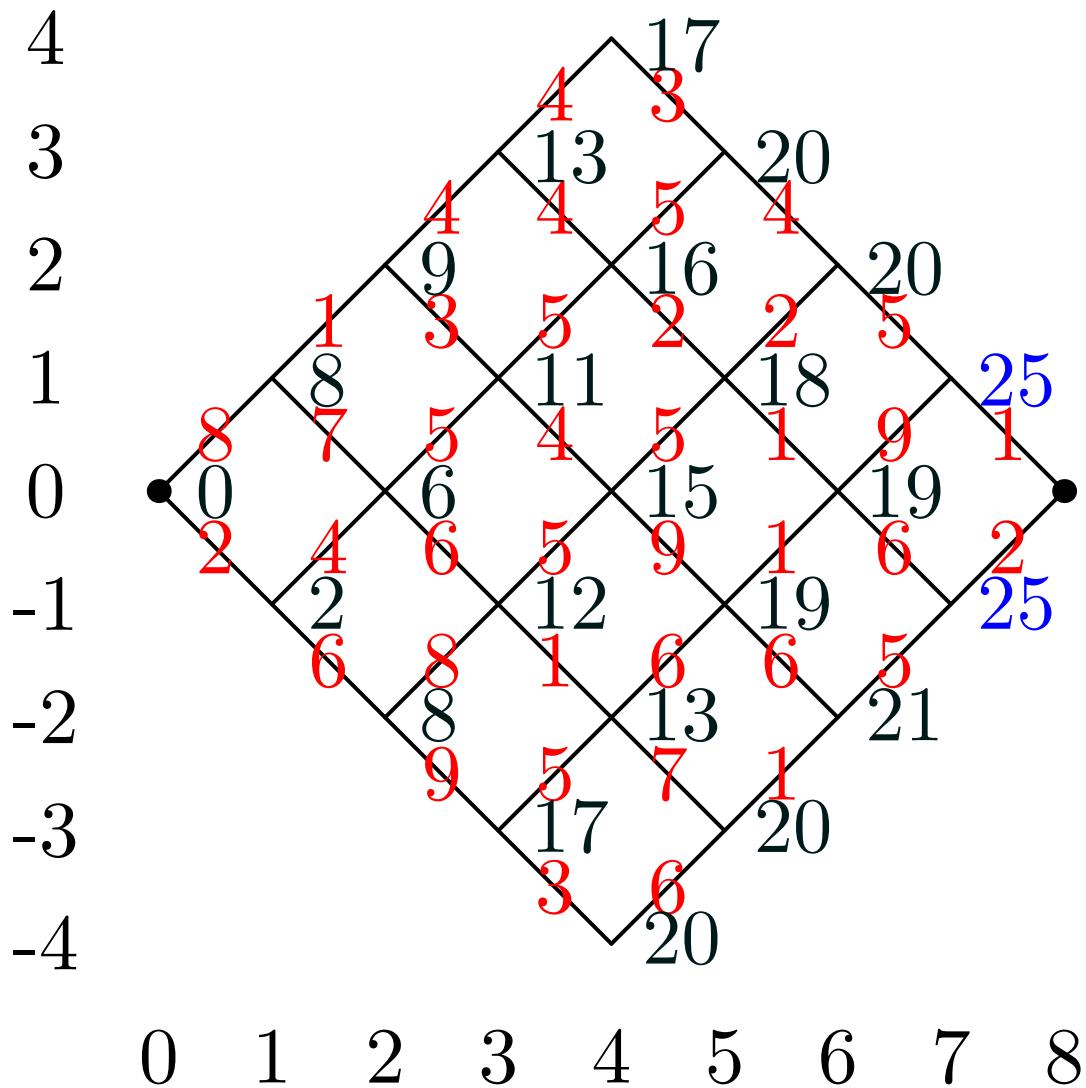
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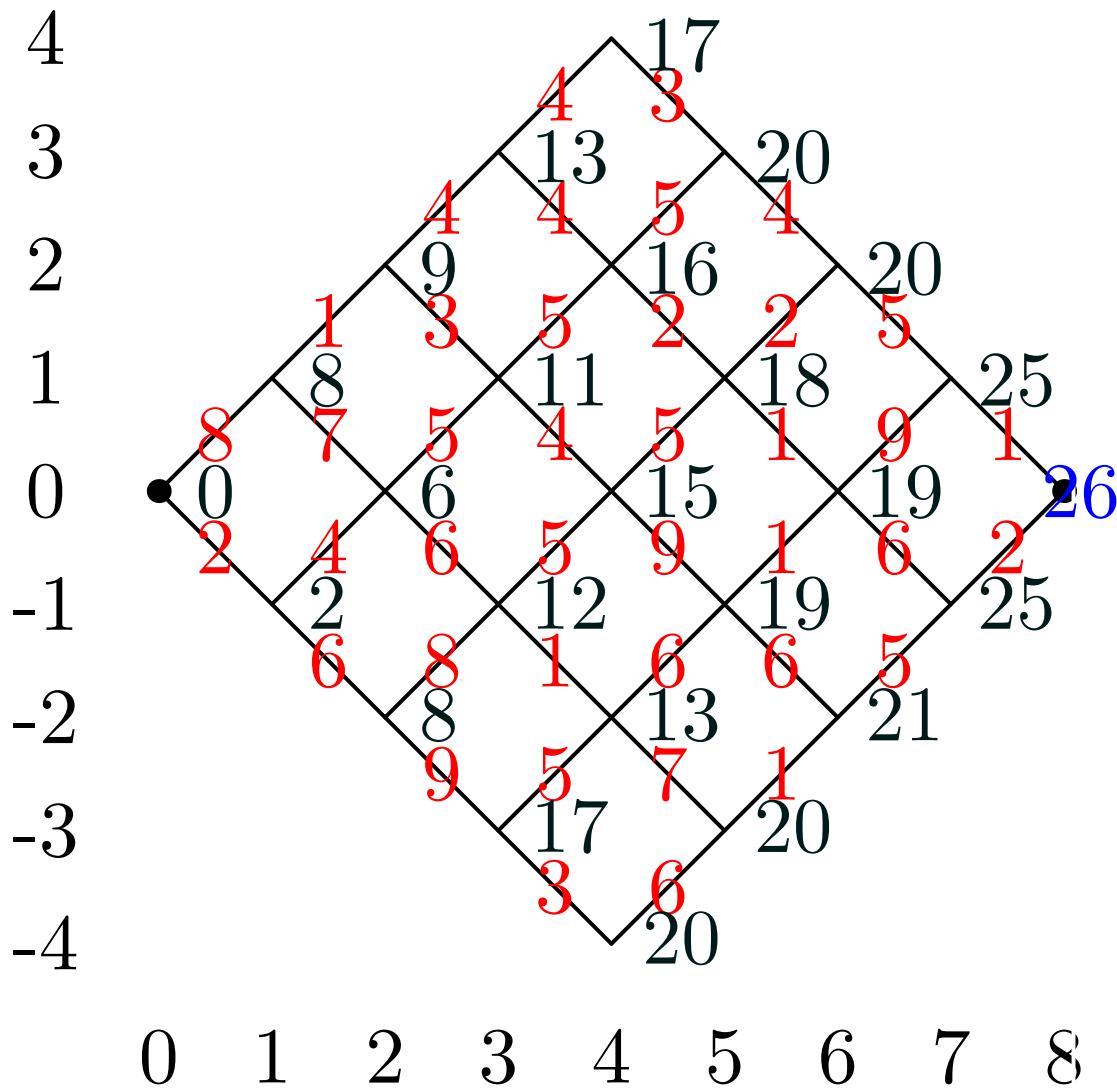
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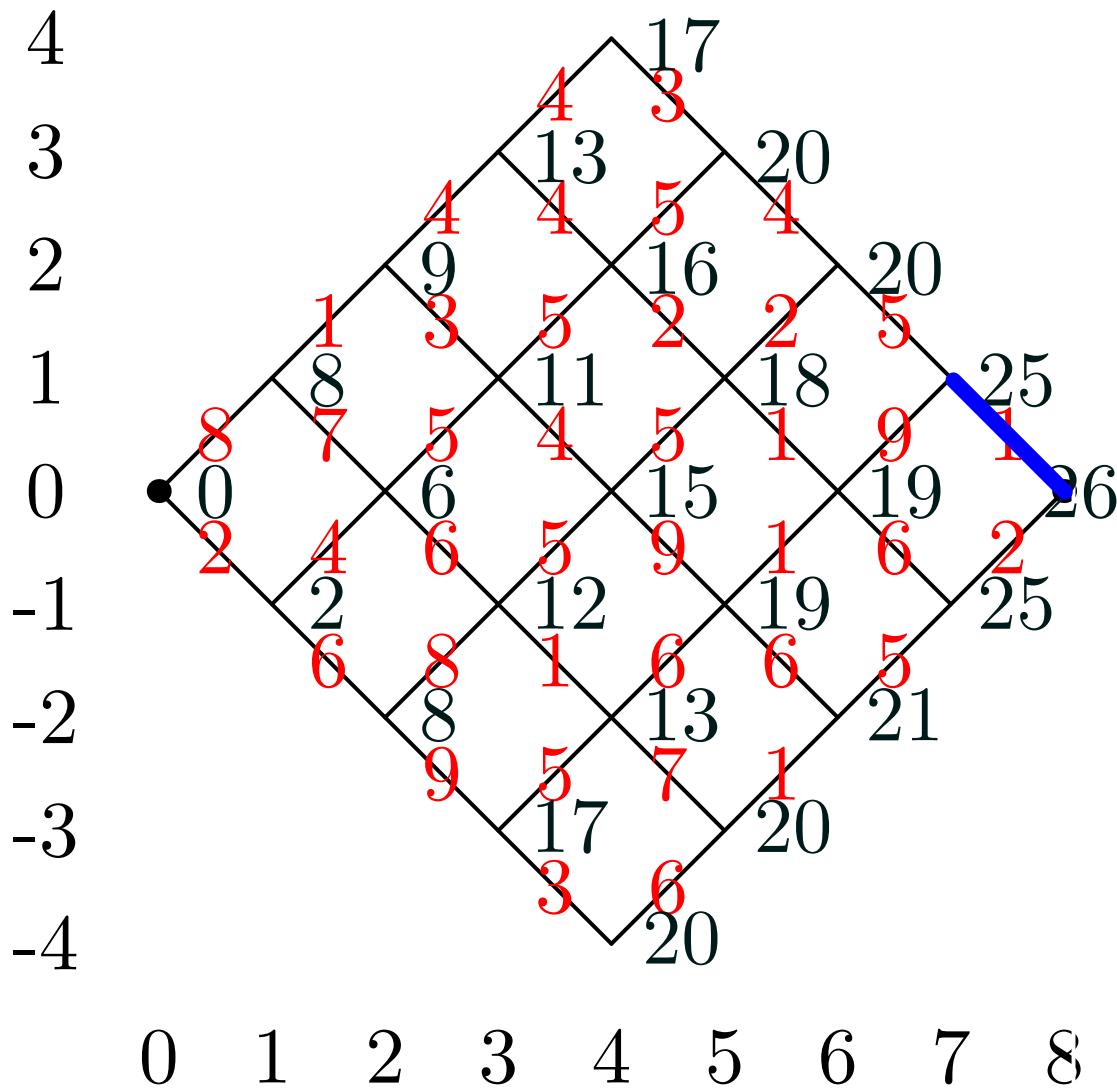
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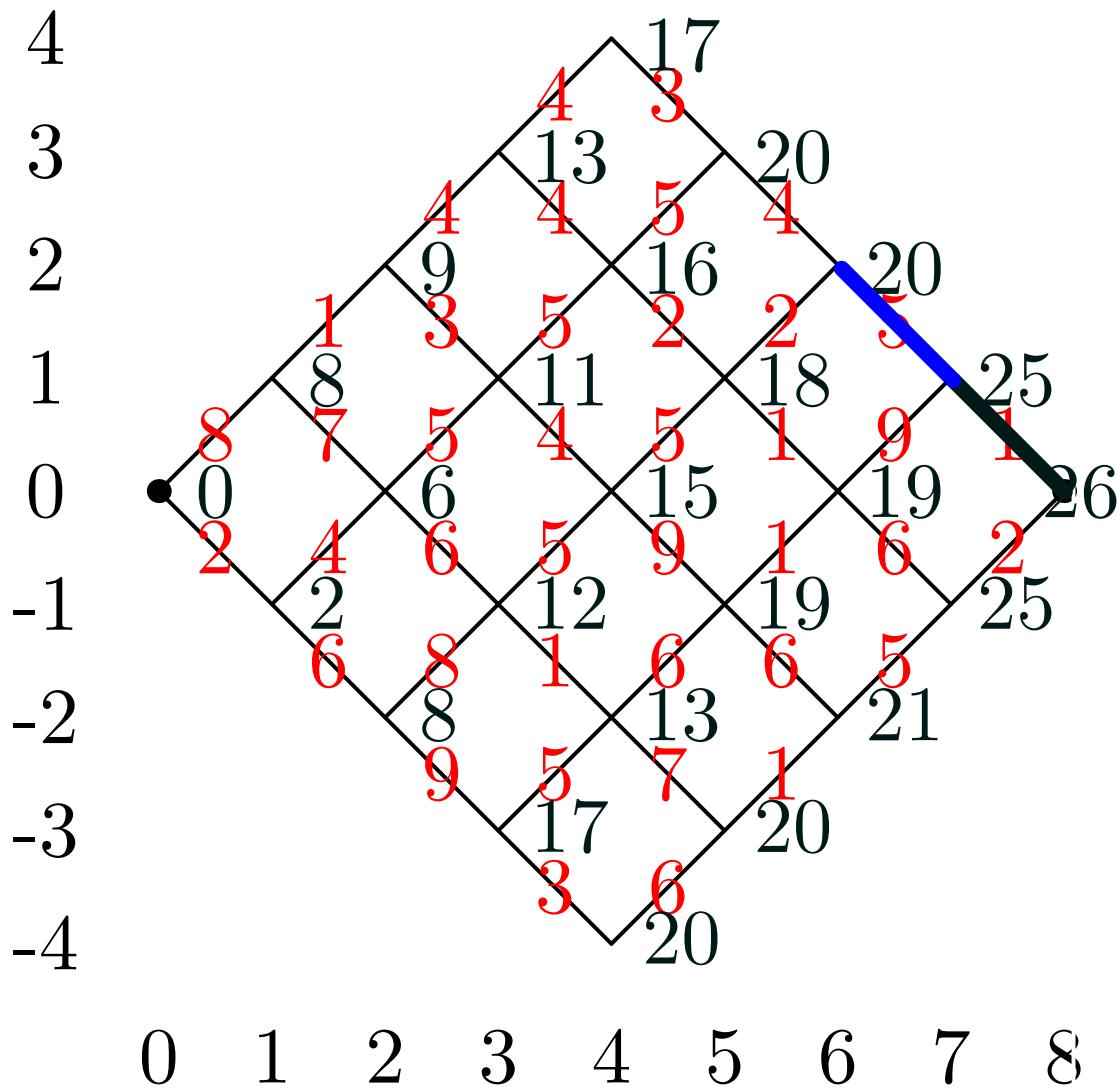
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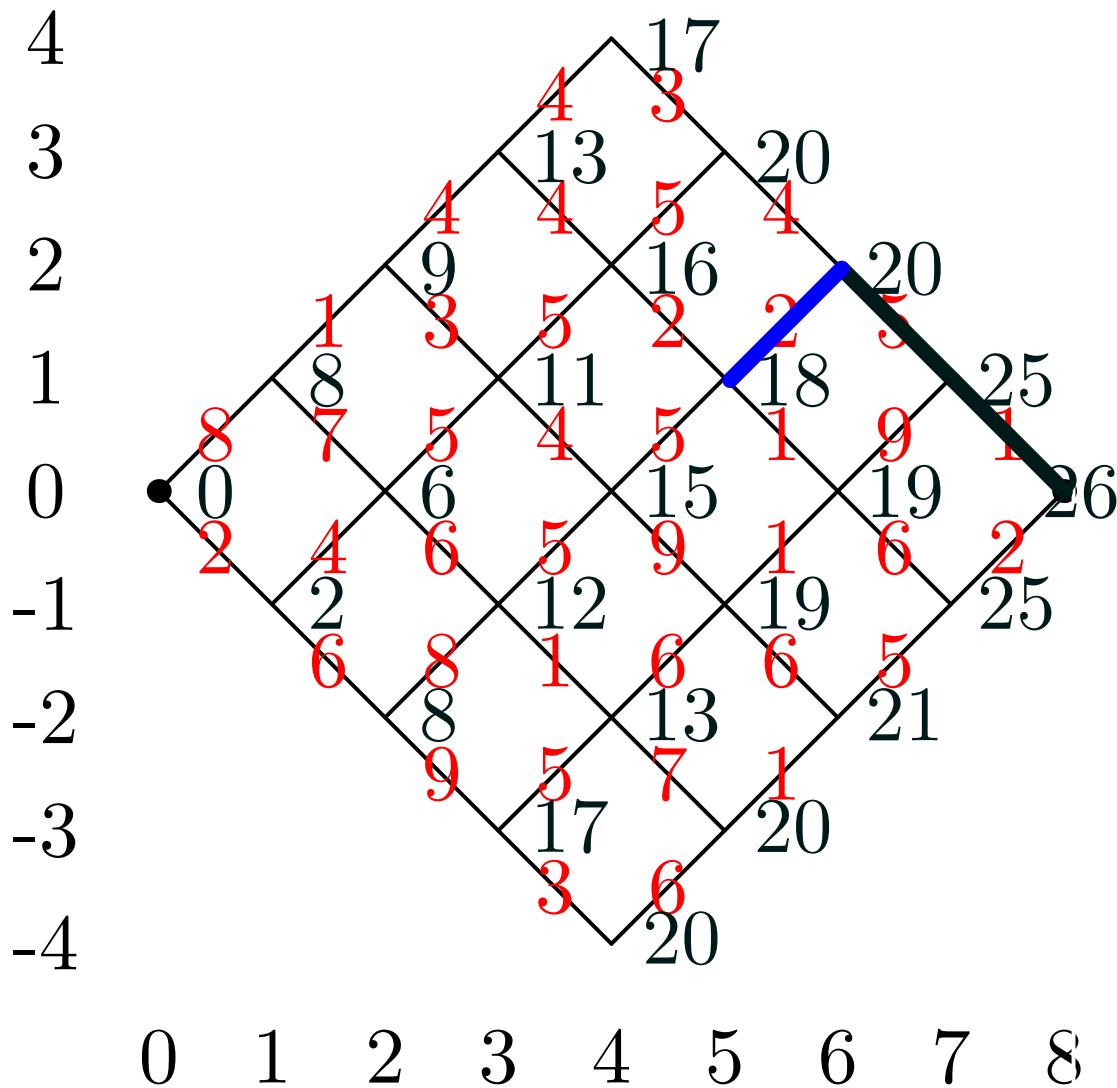
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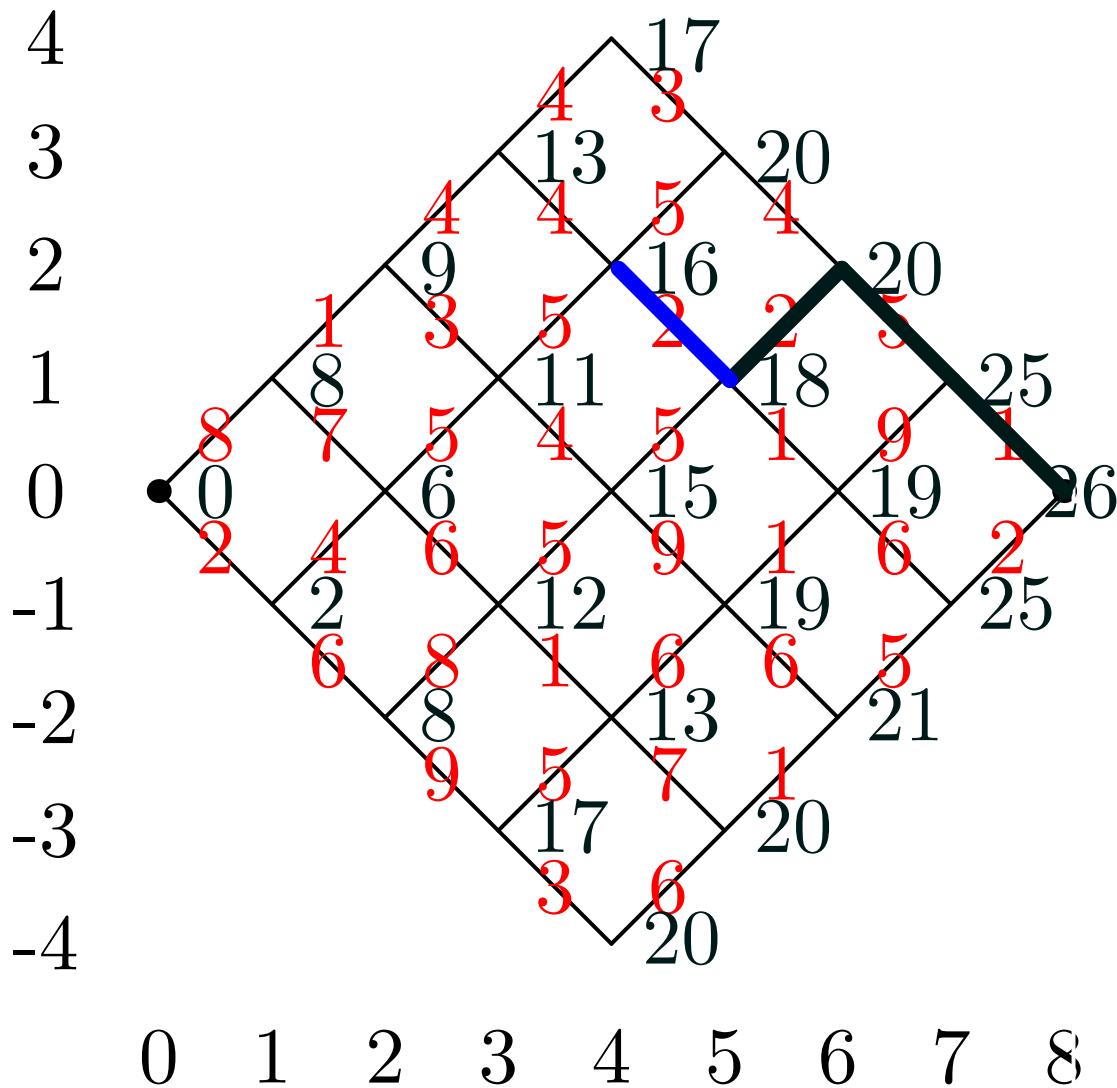
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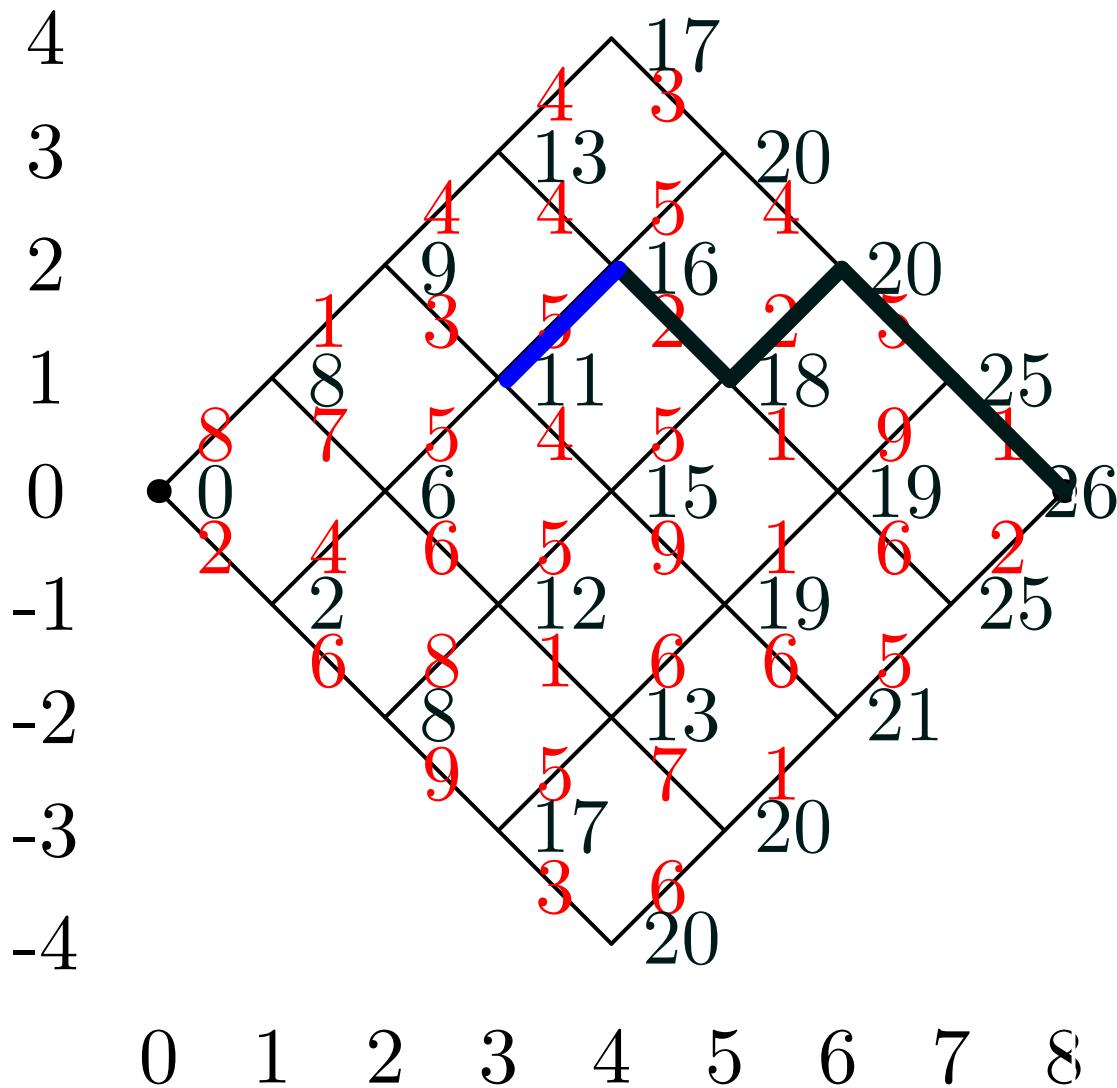
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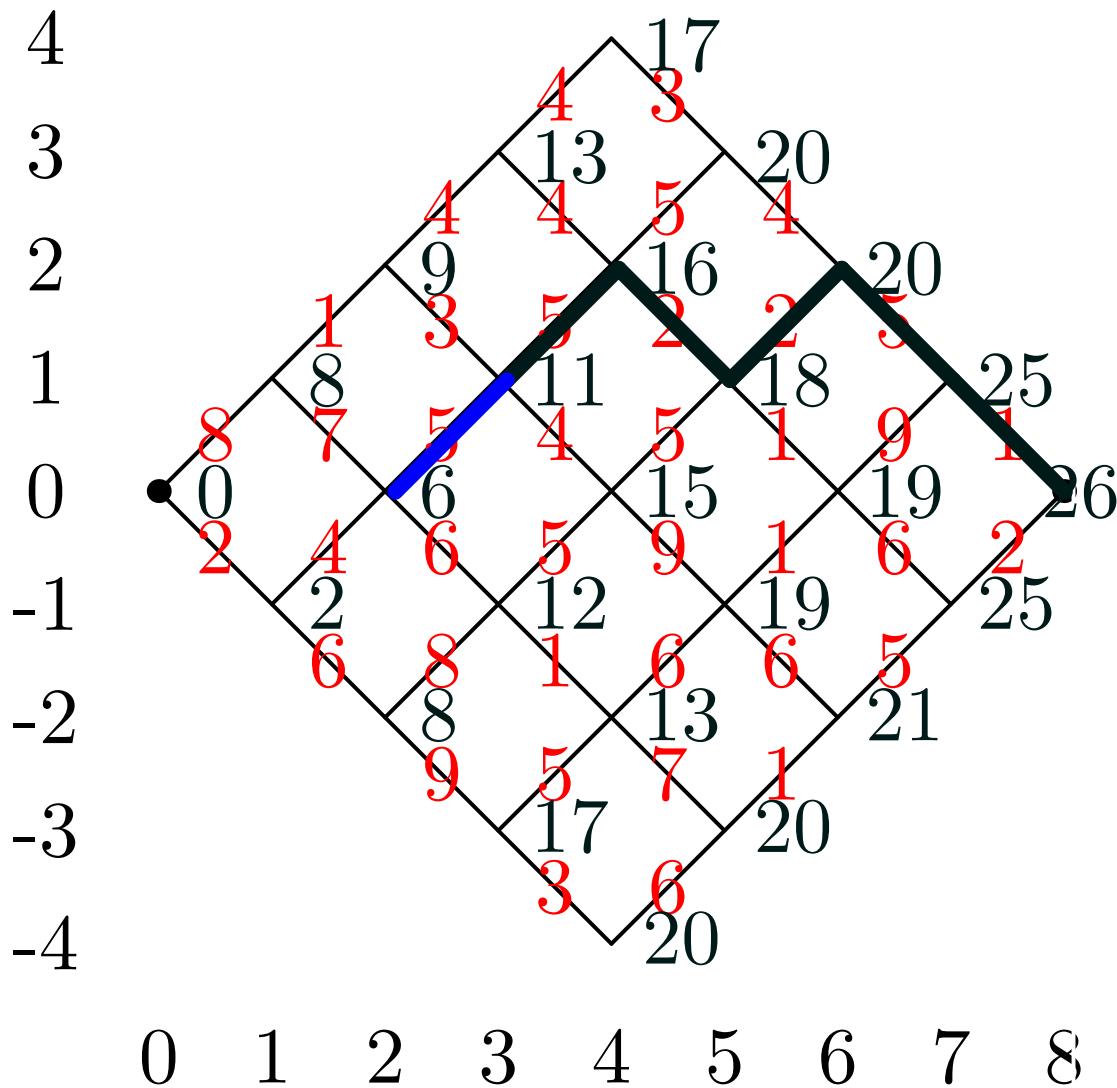
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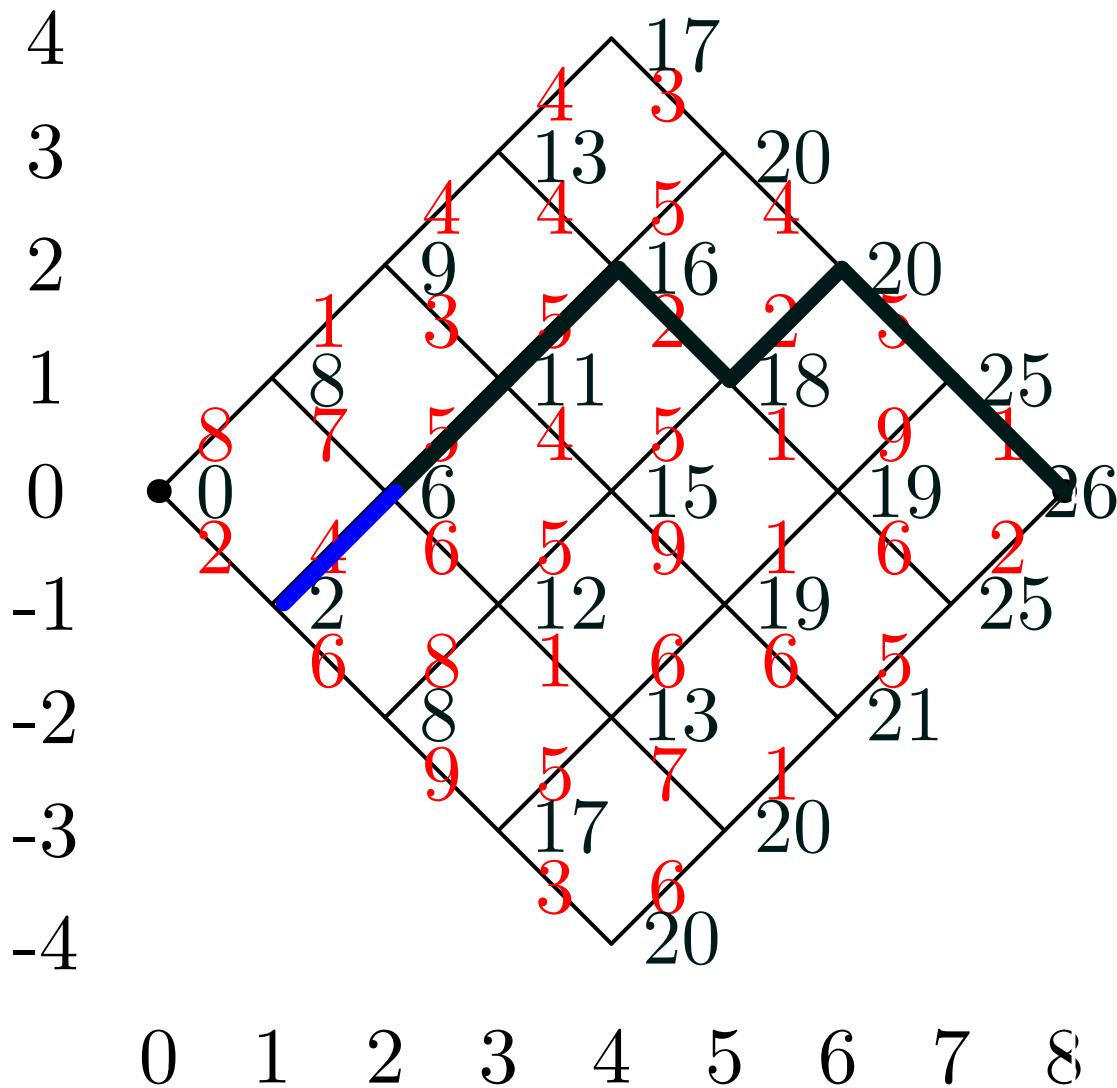
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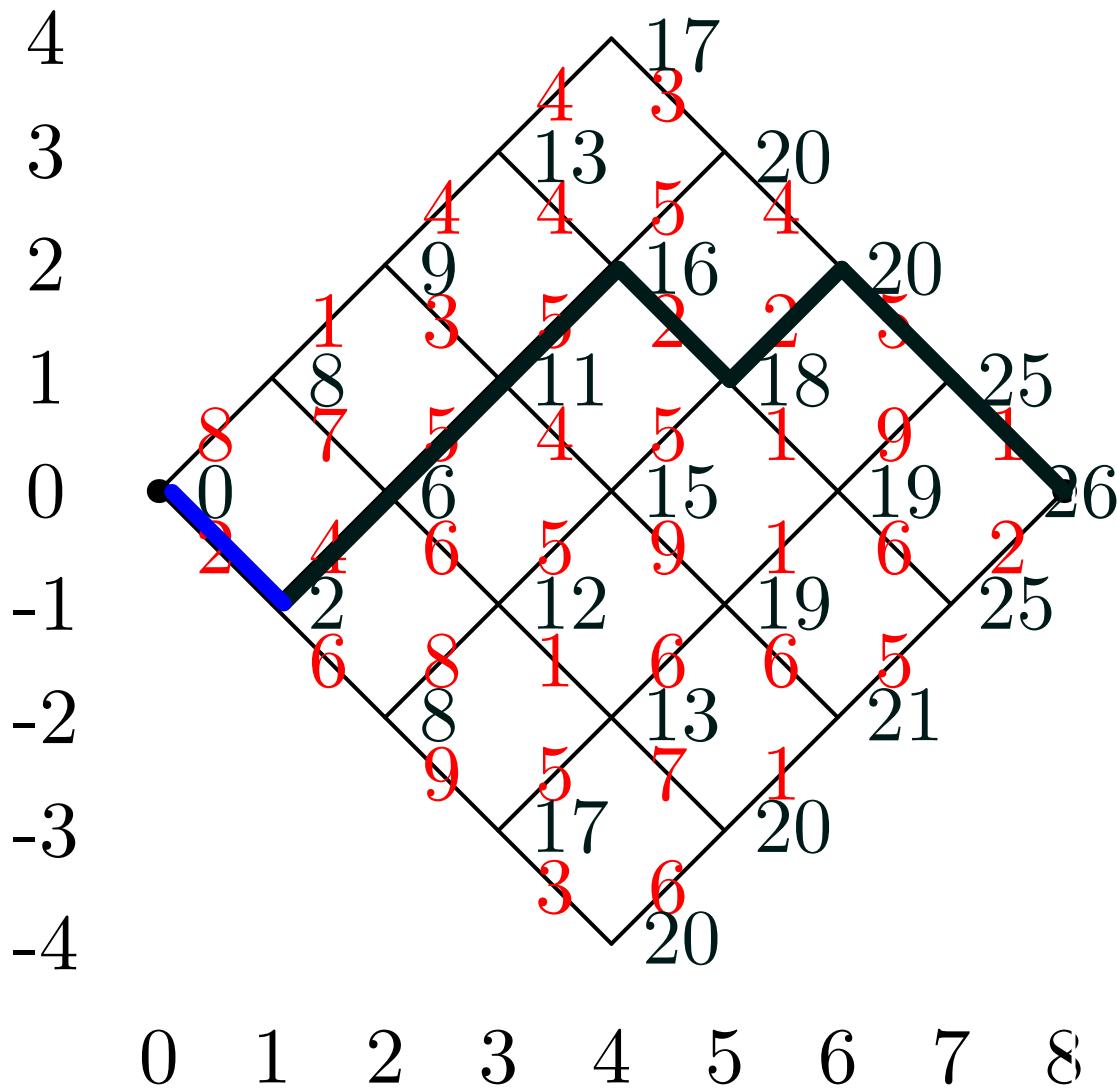
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# Backward Algorithm

- Having found the optimal costs  $c_{(i,j)}$  we can find the optimal path starting from  $(n, 0)$
- At each step we have a choice of going up or down
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- If both directions satisfy the constraint we have more than one optimal path

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# Time Complexity

- In our dynamic programming solution we had to compute the cost  $c_{(i,j)}$  at each lattice point
- There were  $(\frac{n+1}{2})^2$  lattice point
- It took constant time to compute each cost so the total time to perform the forward algorithm was  $\Theta(n^2)$
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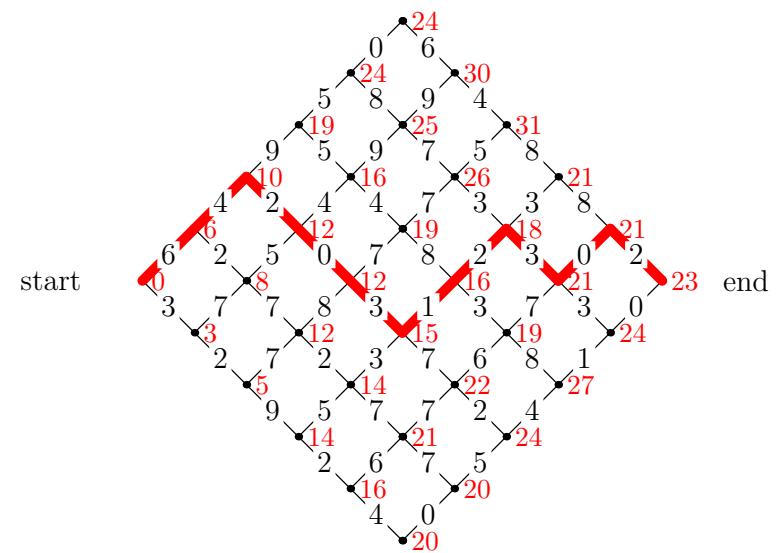
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# Applications of Dynamic Programming

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- Learn this from examples
- Consider writing a word processor that splits paragraphs up into lines
- You want to choose the line breaks so that the lines are all roughly the same length
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paragraph  
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A blue horizontal bar with vertical tick marks above the text "I have a dream that one day this nation will rise up and live out the . . .". The first character 'a' is highlighted in red.

# Using Dynamic Programming

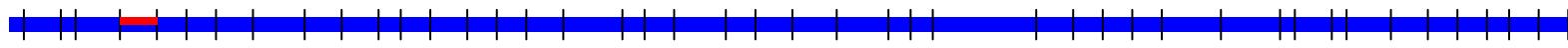
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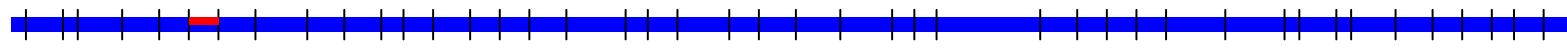
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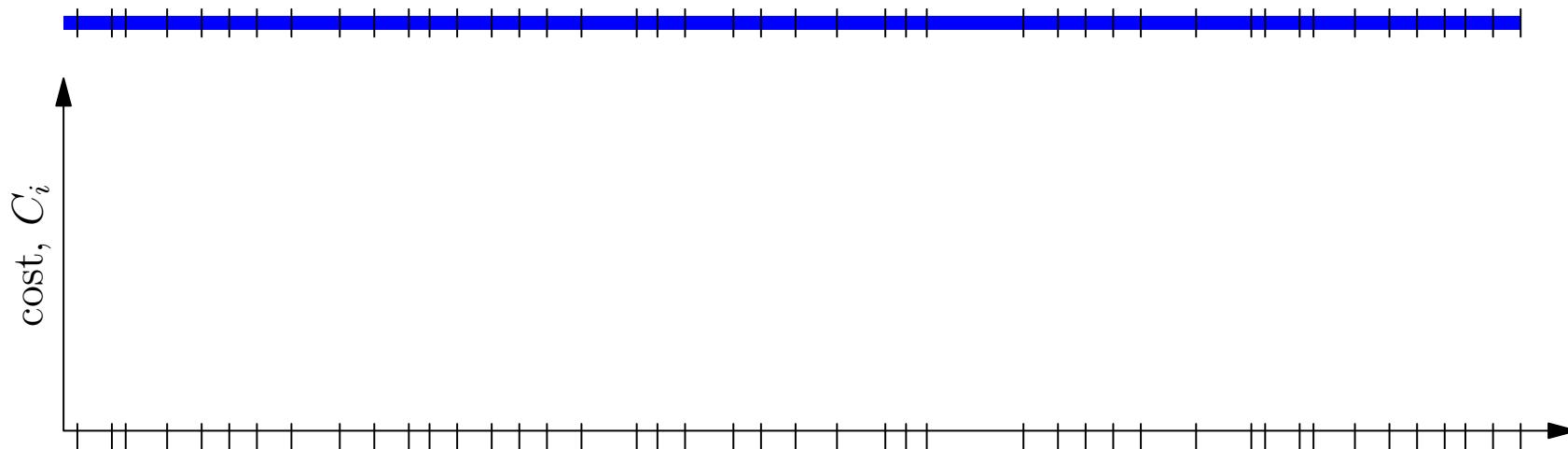
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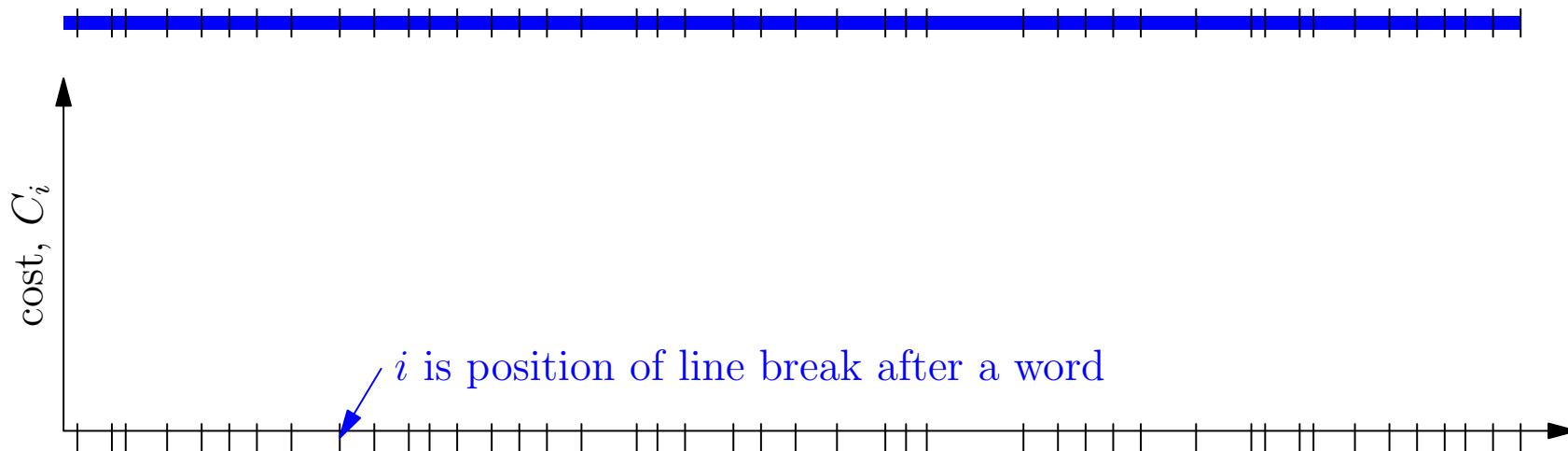
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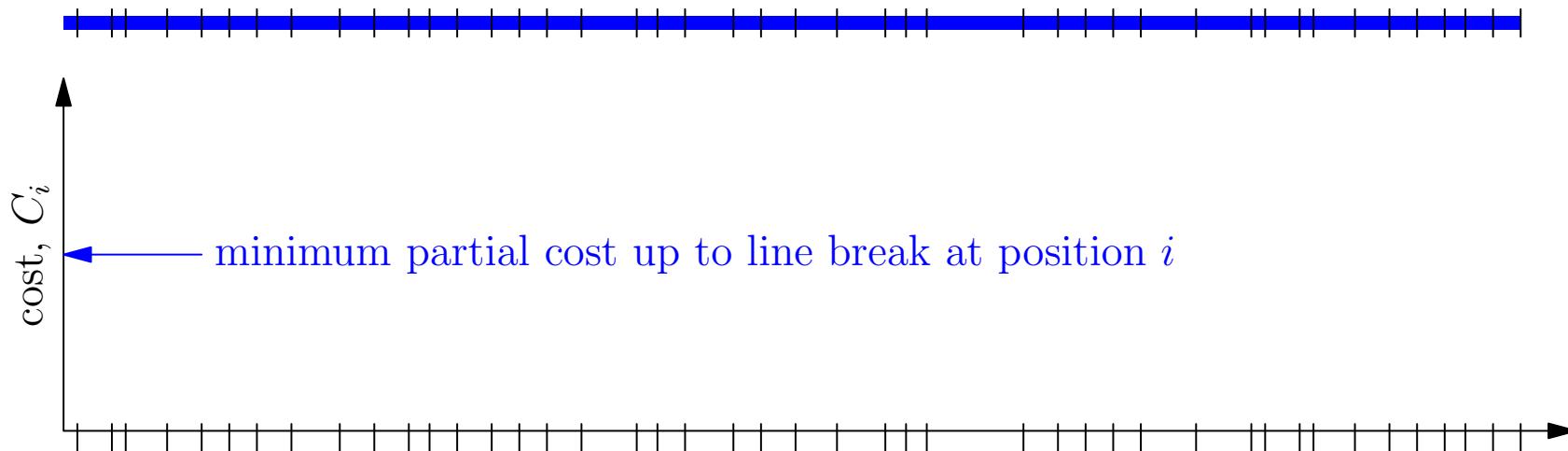
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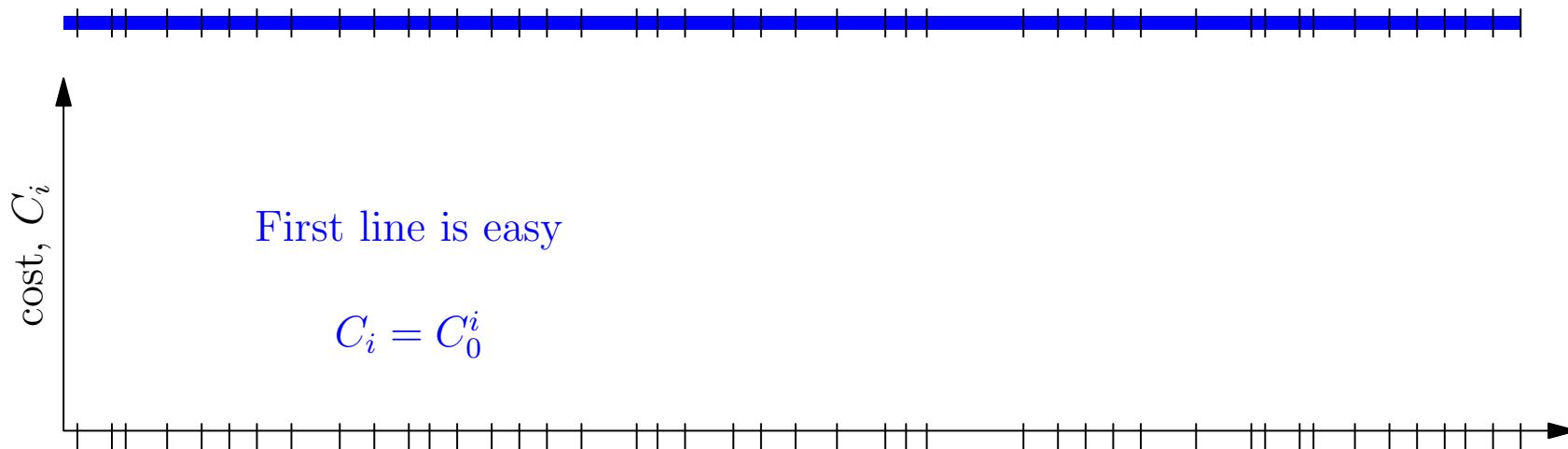
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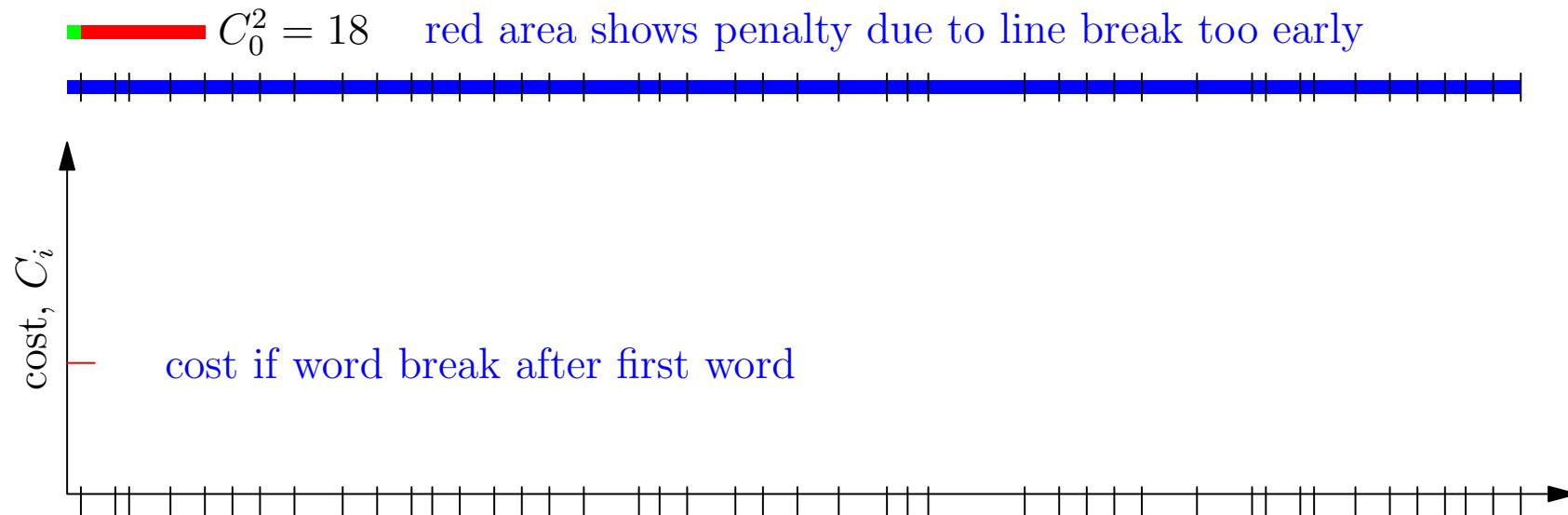
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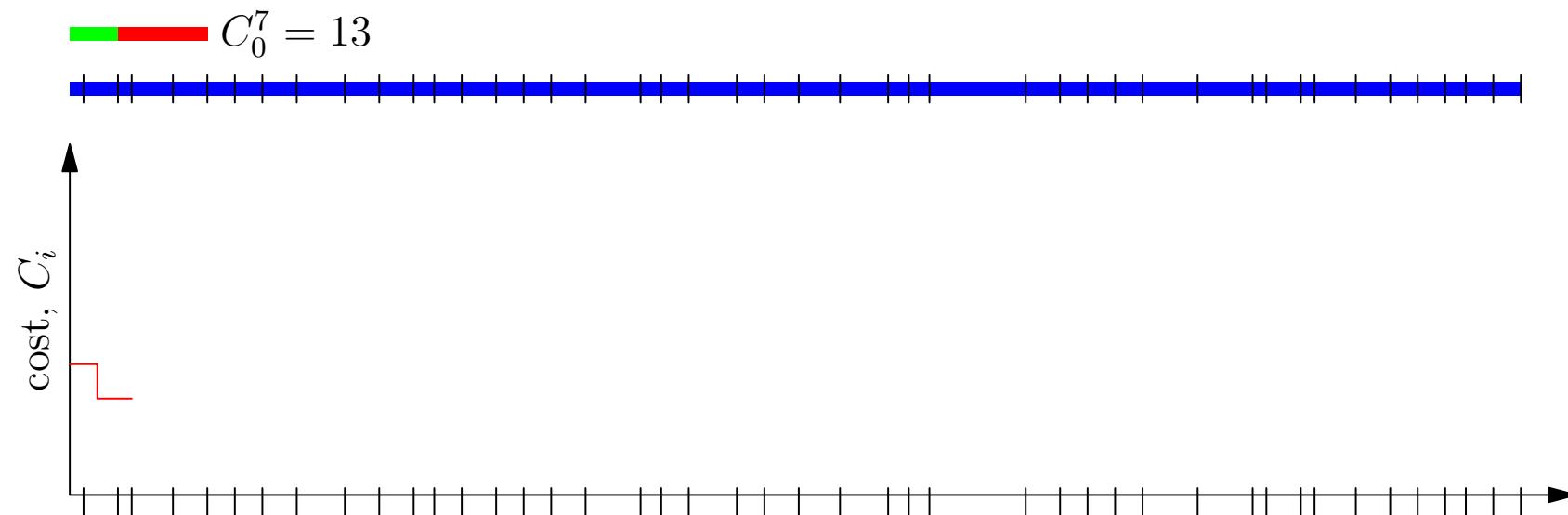
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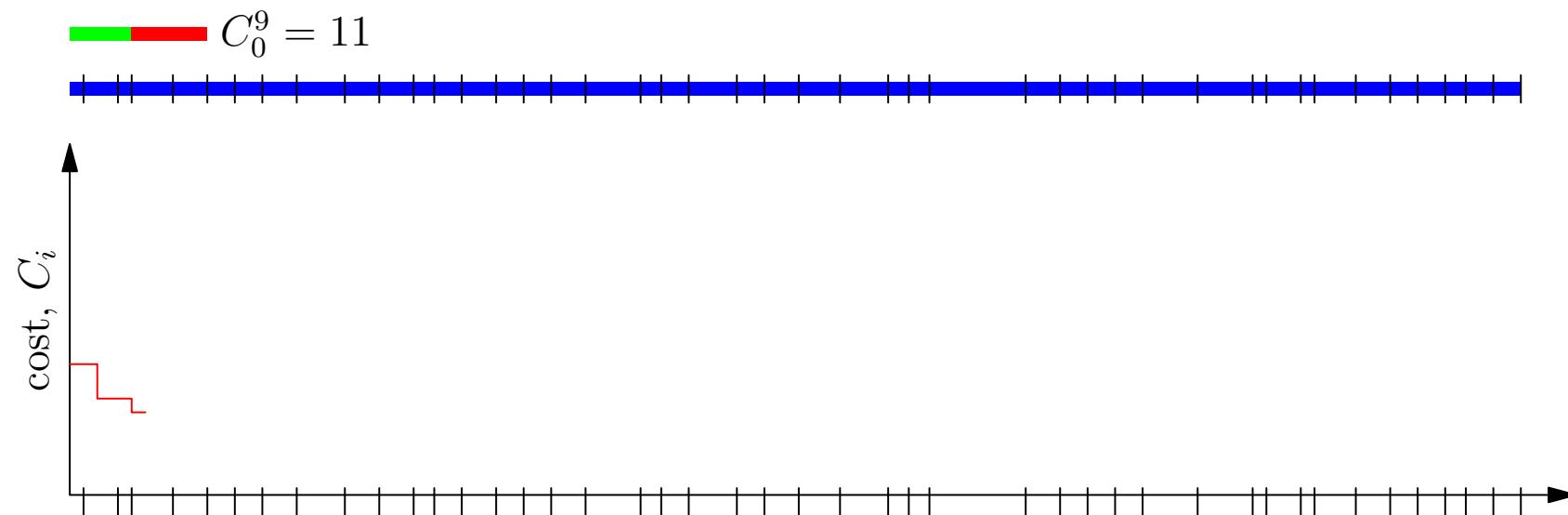
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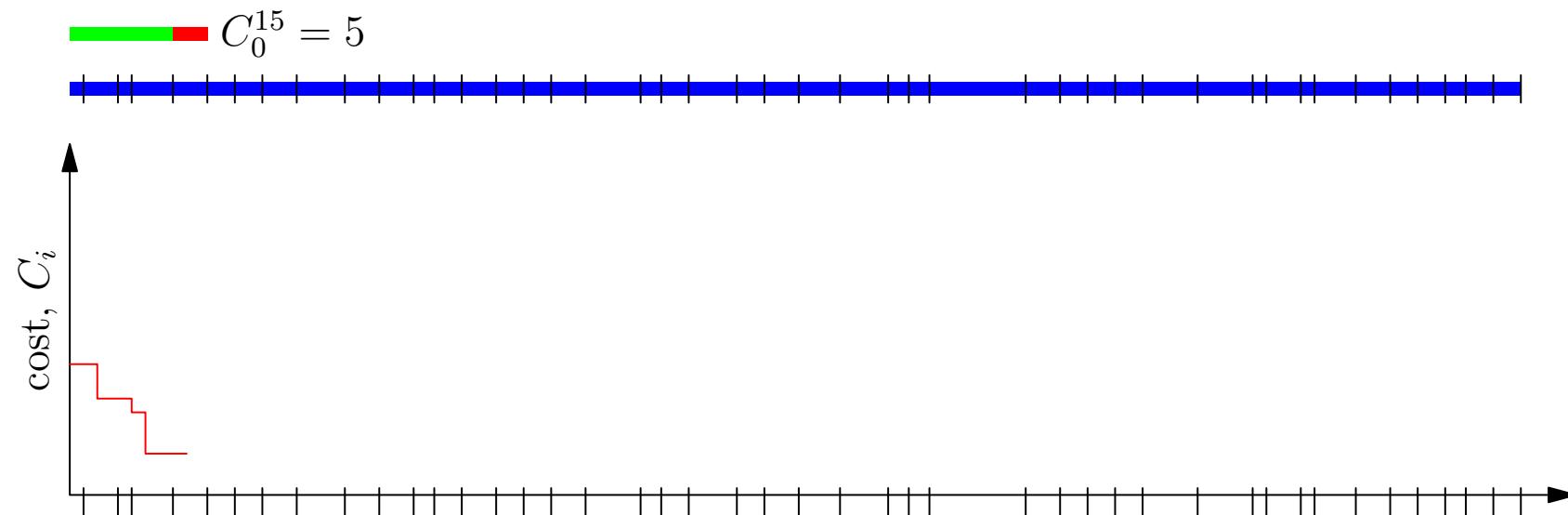
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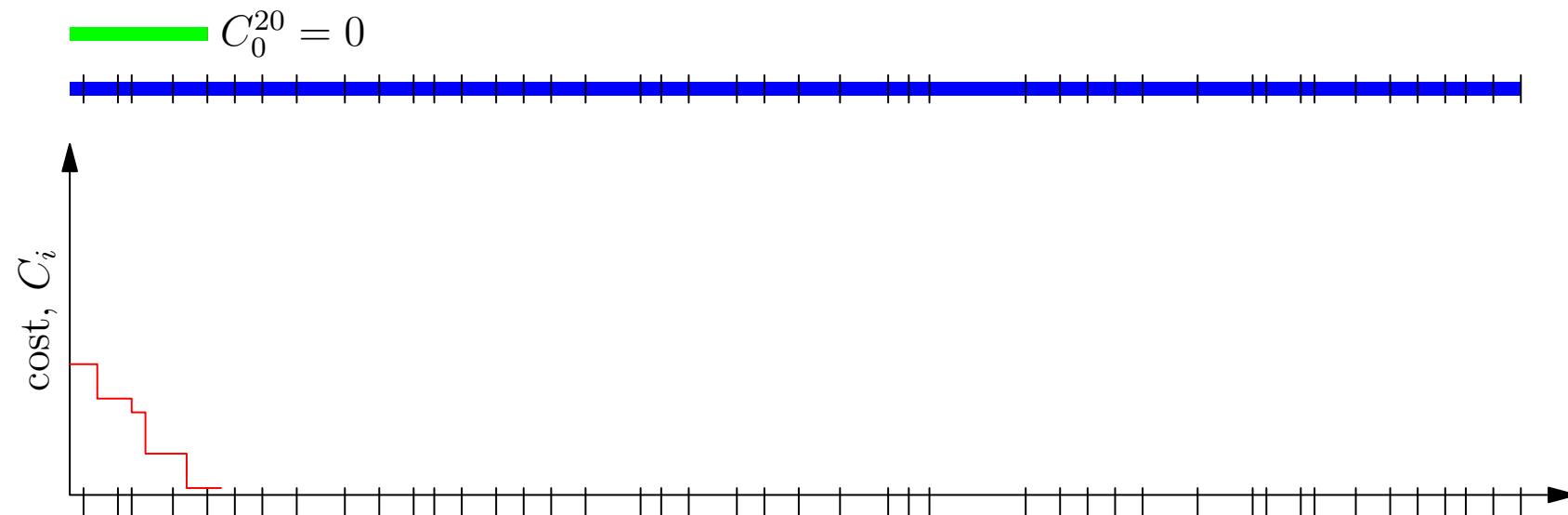
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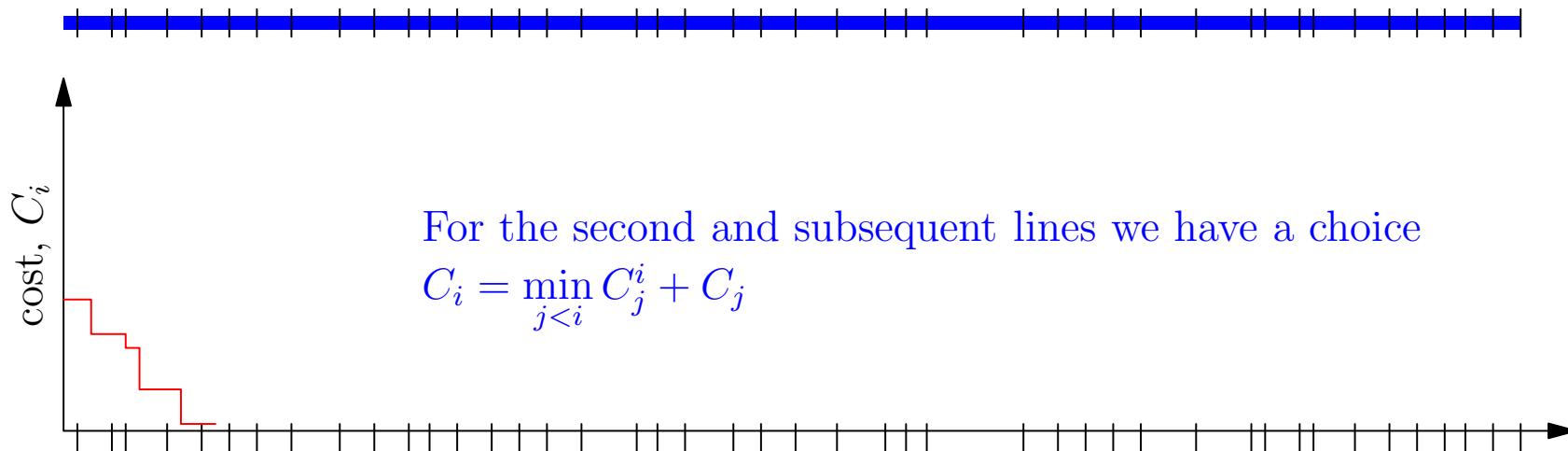
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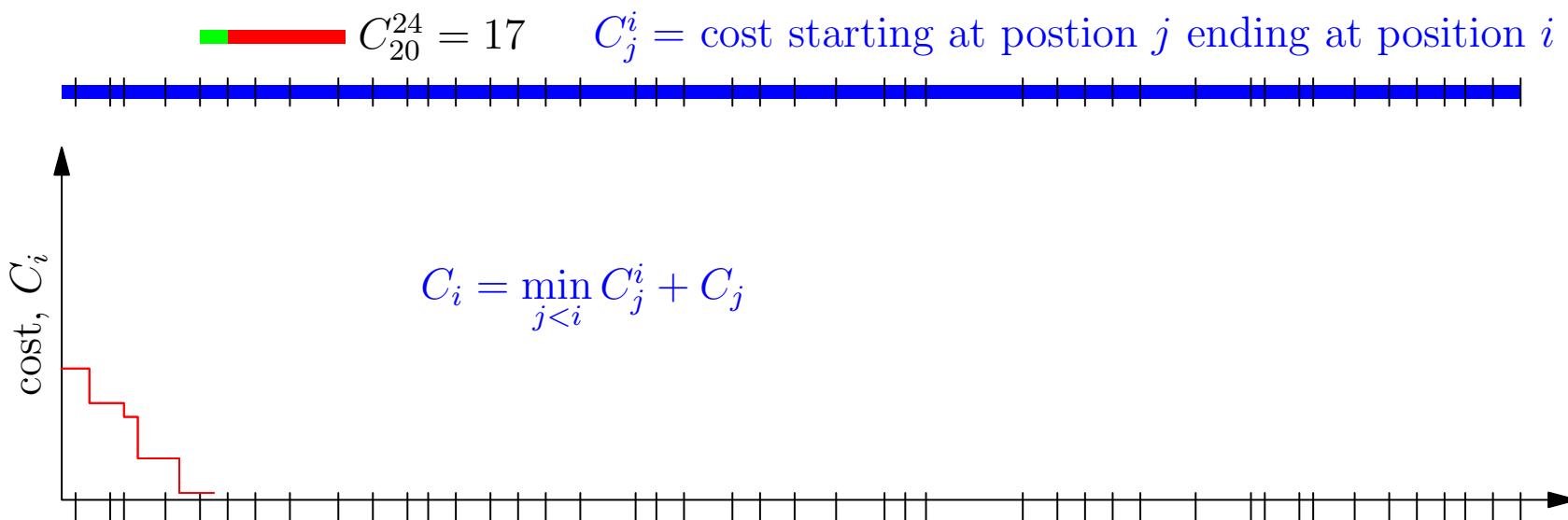
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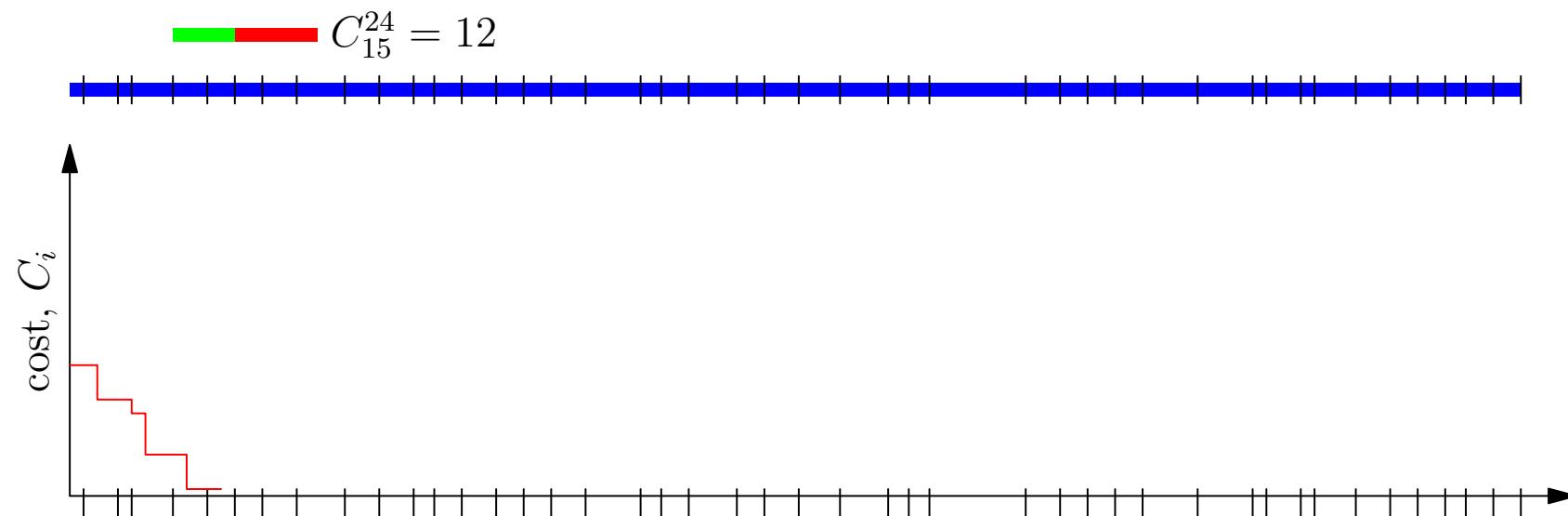
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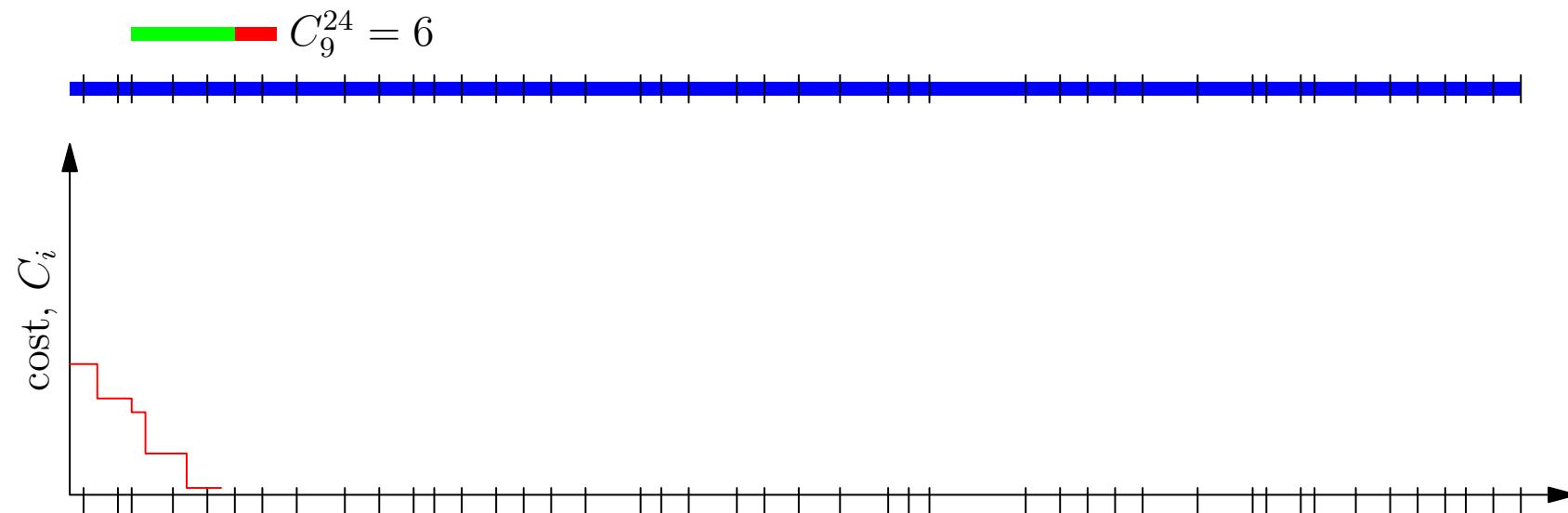
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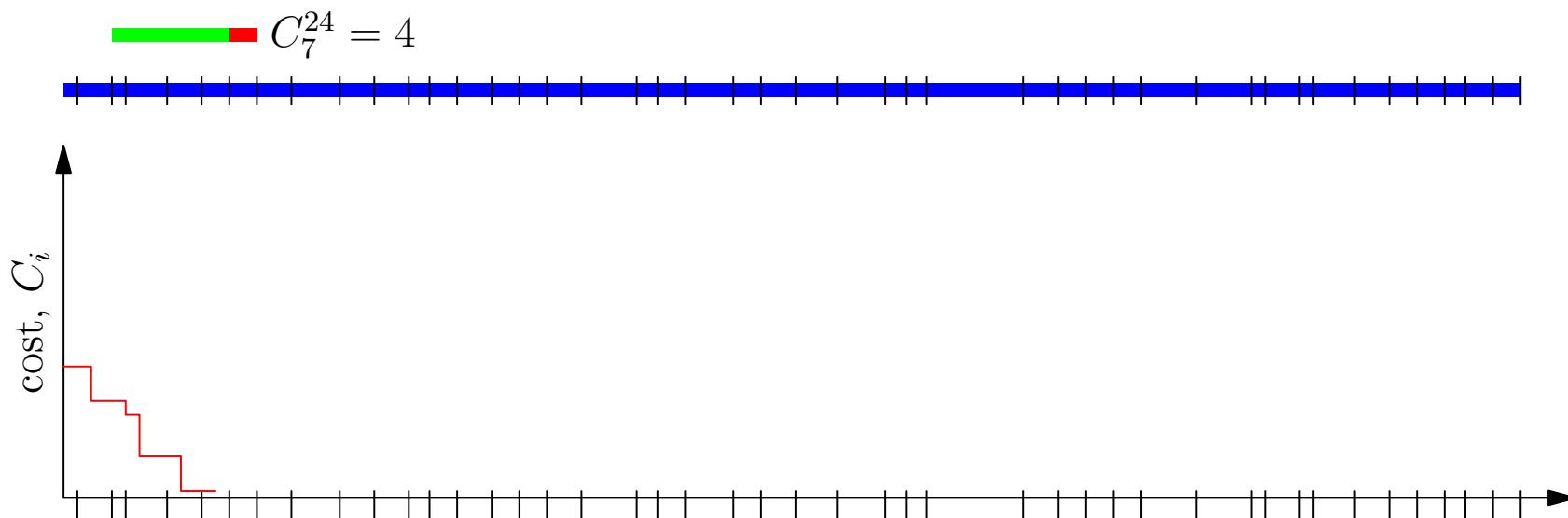
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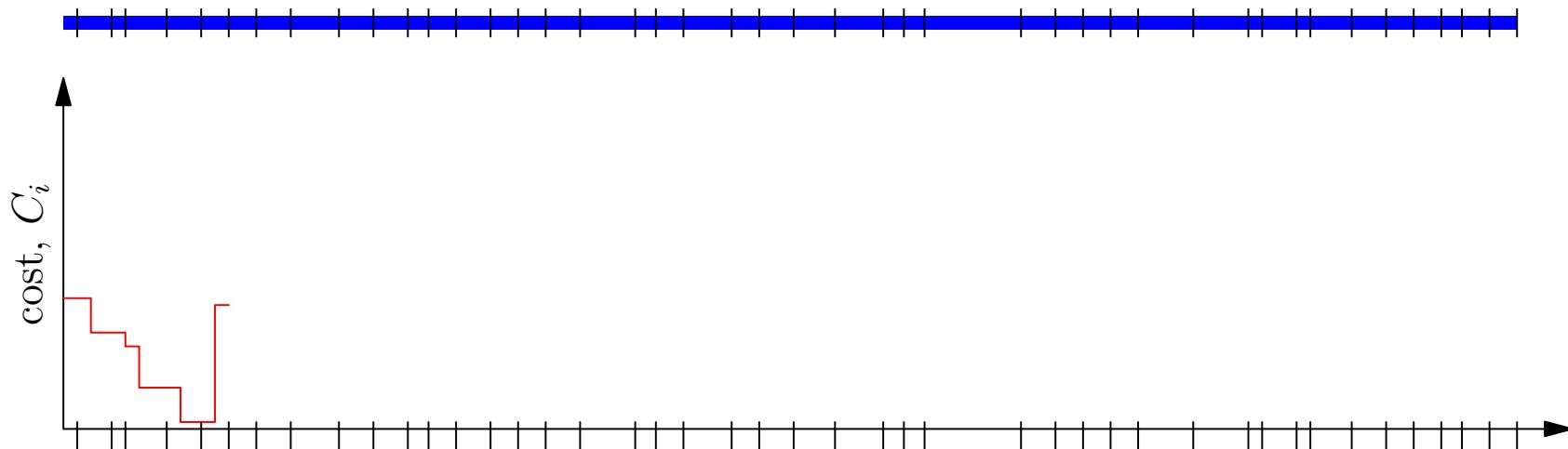
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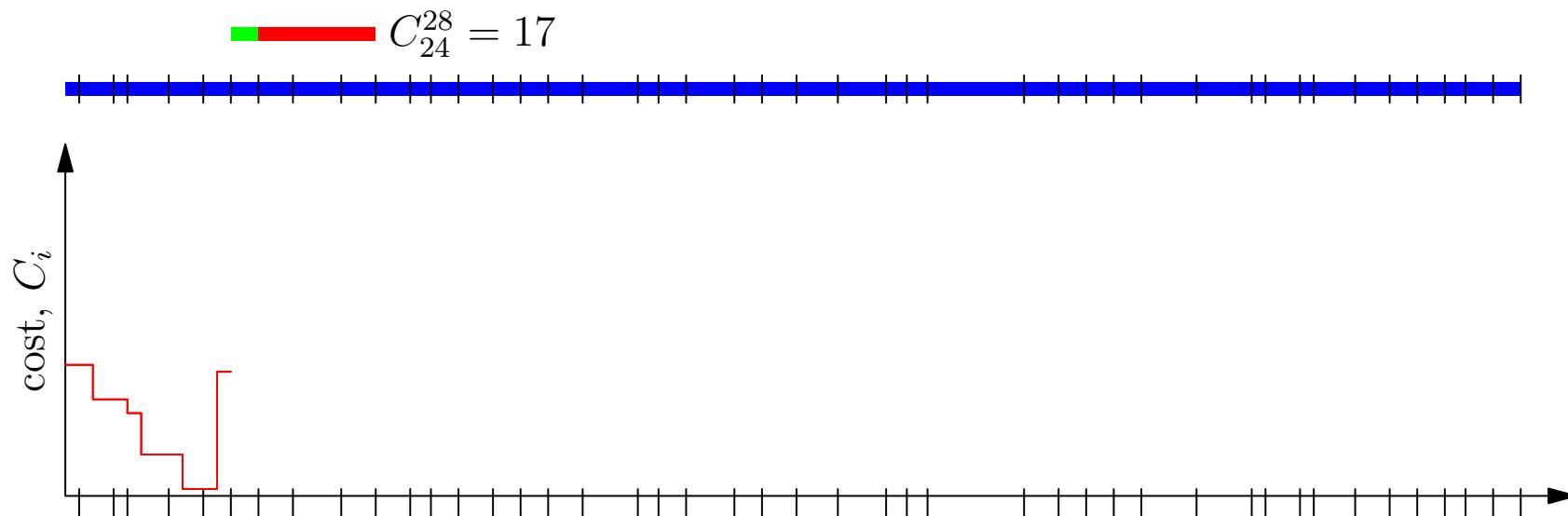
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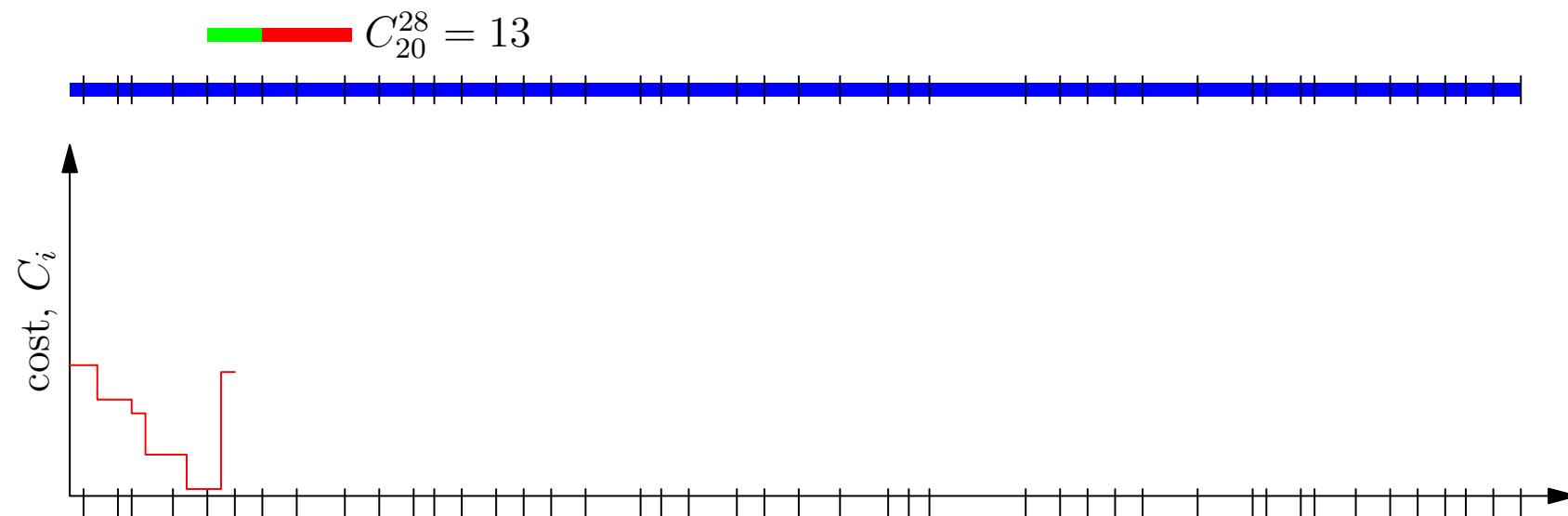
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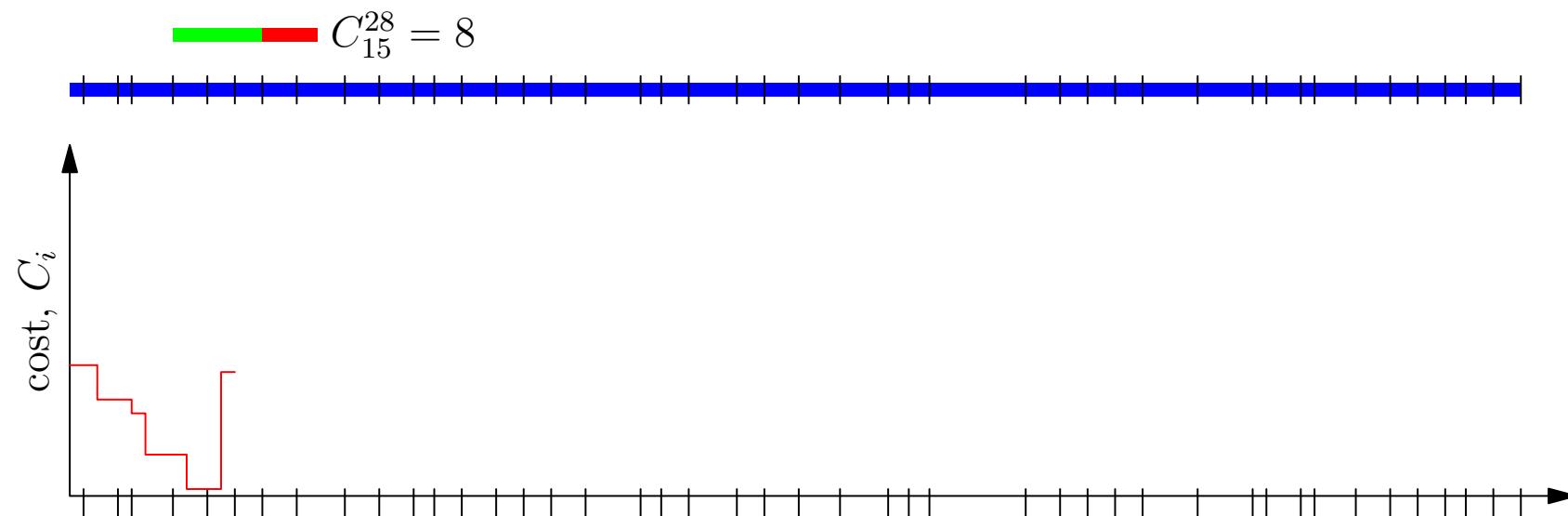
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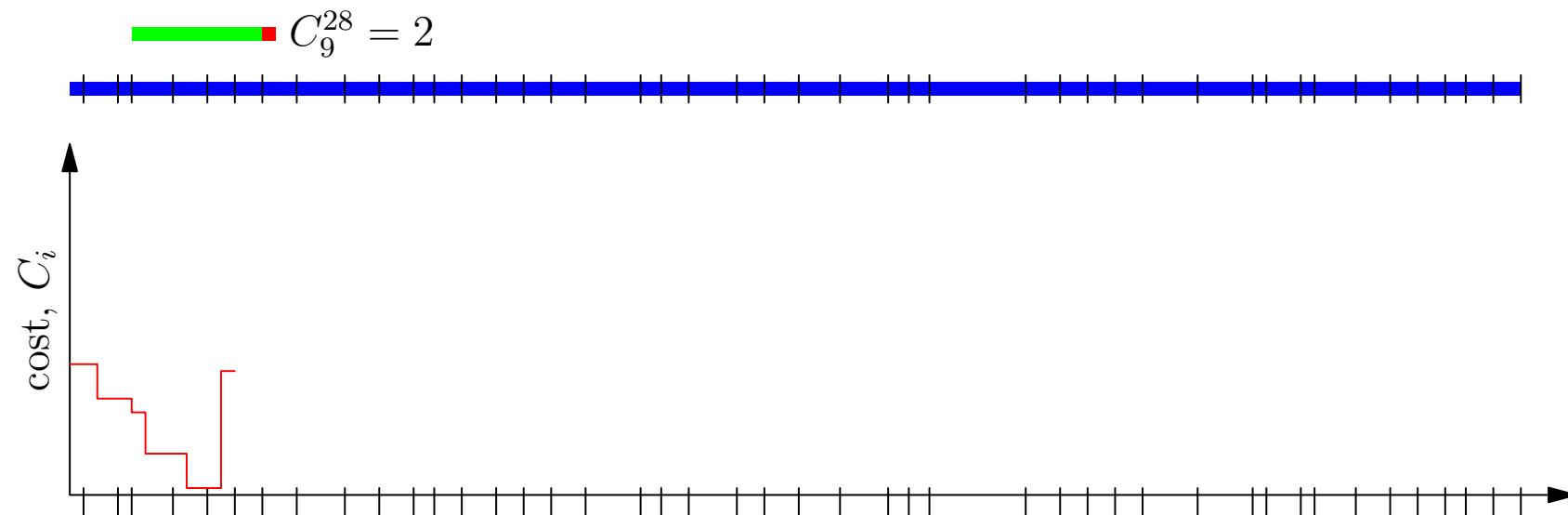
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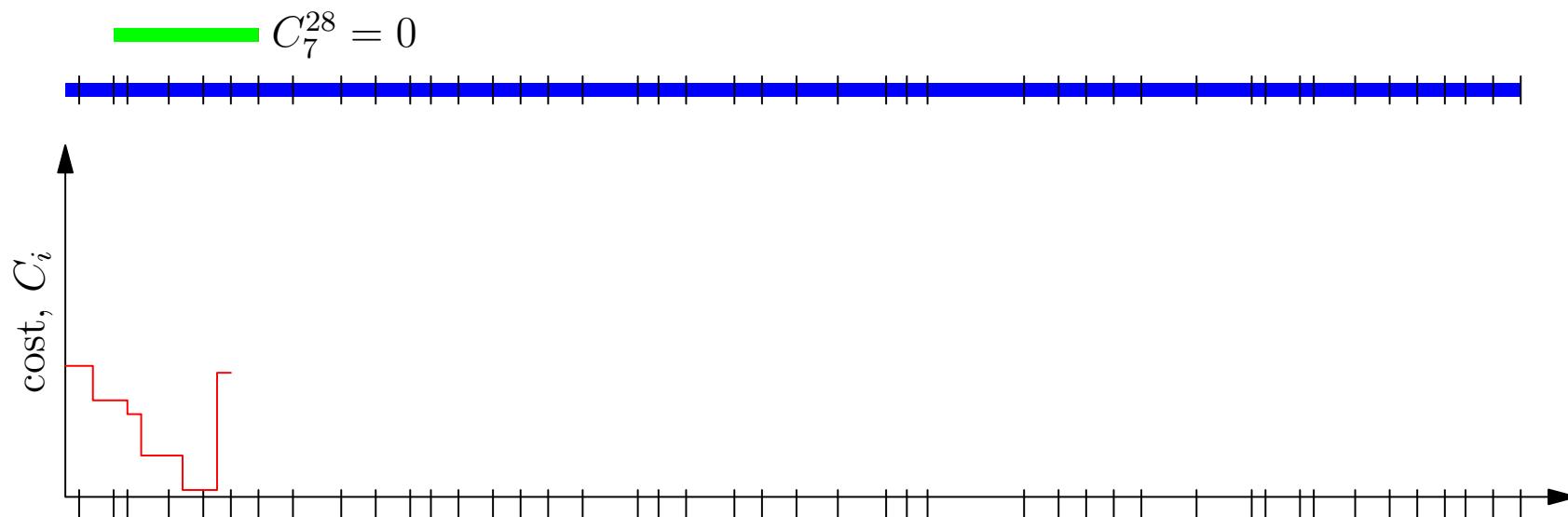
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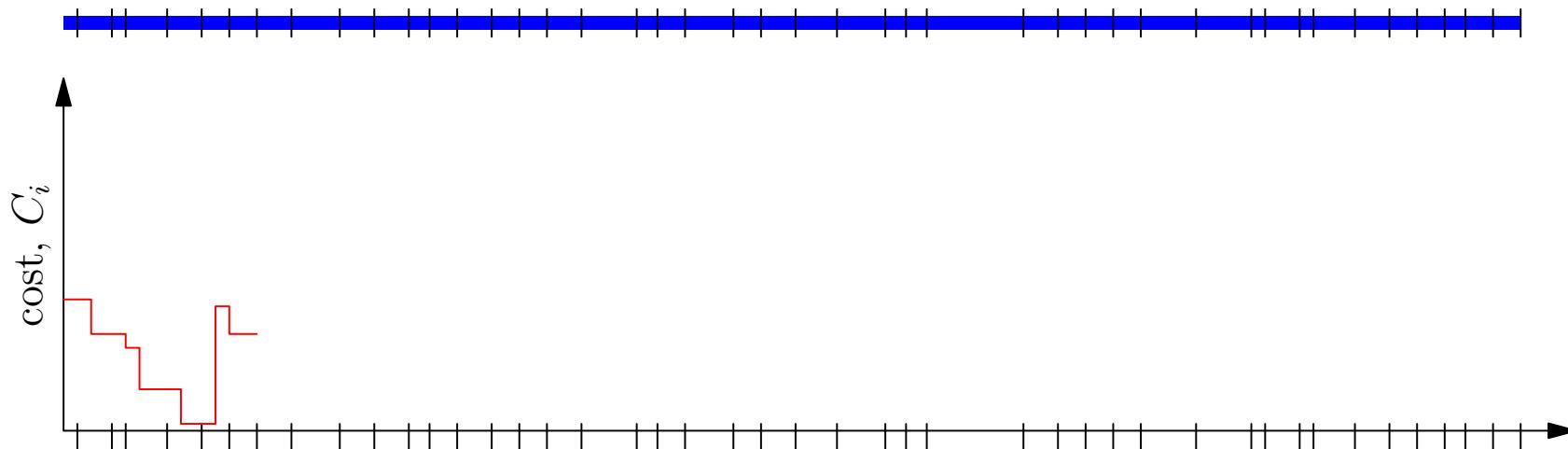
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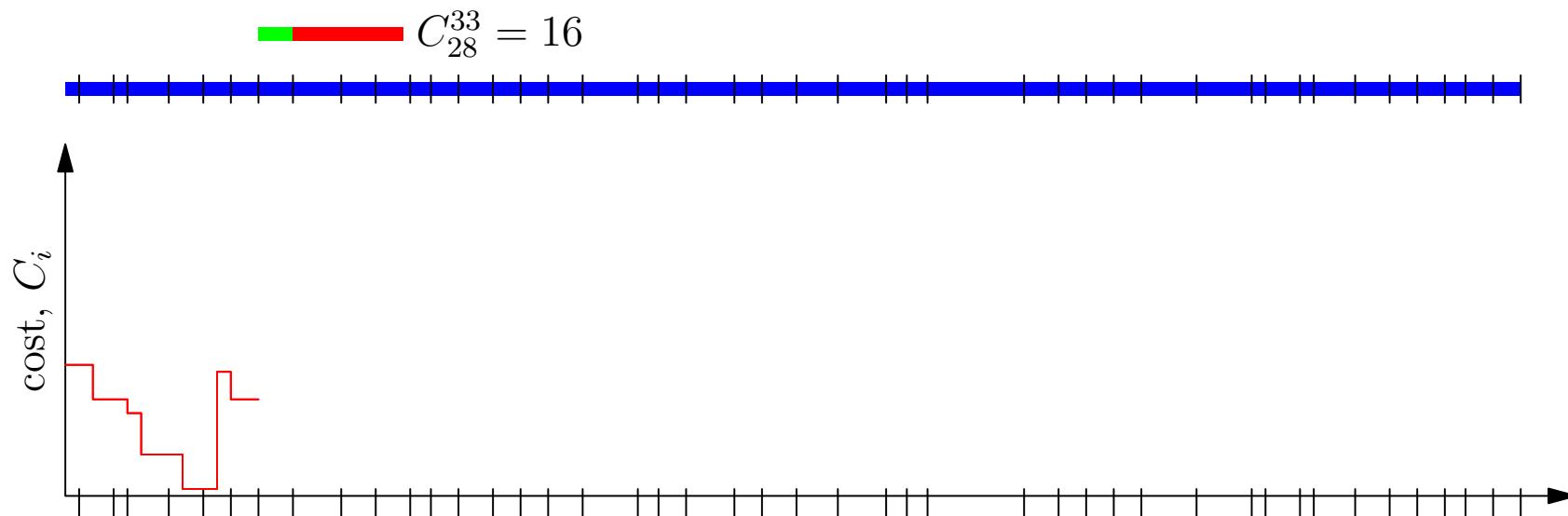
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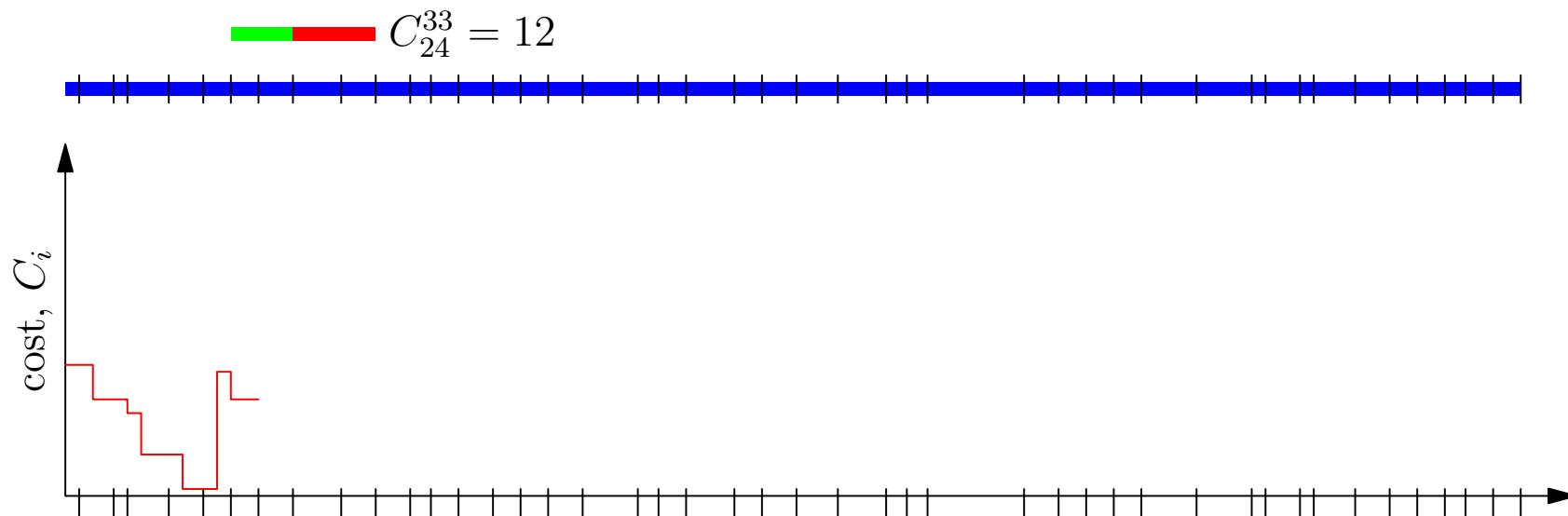
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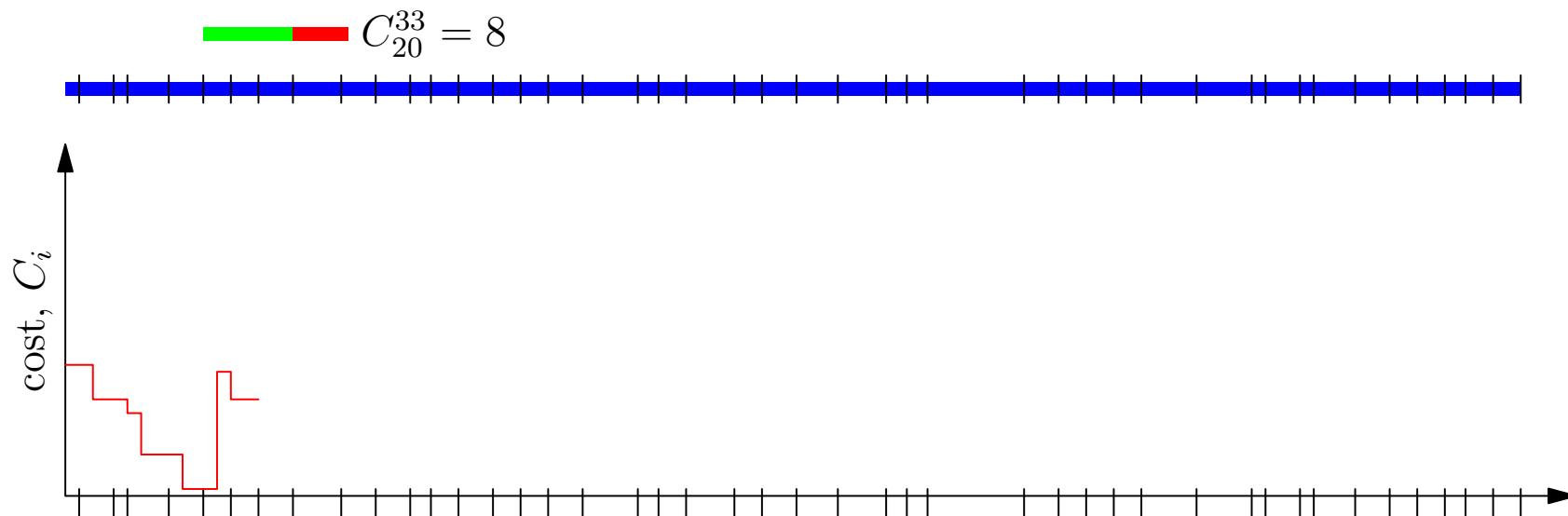
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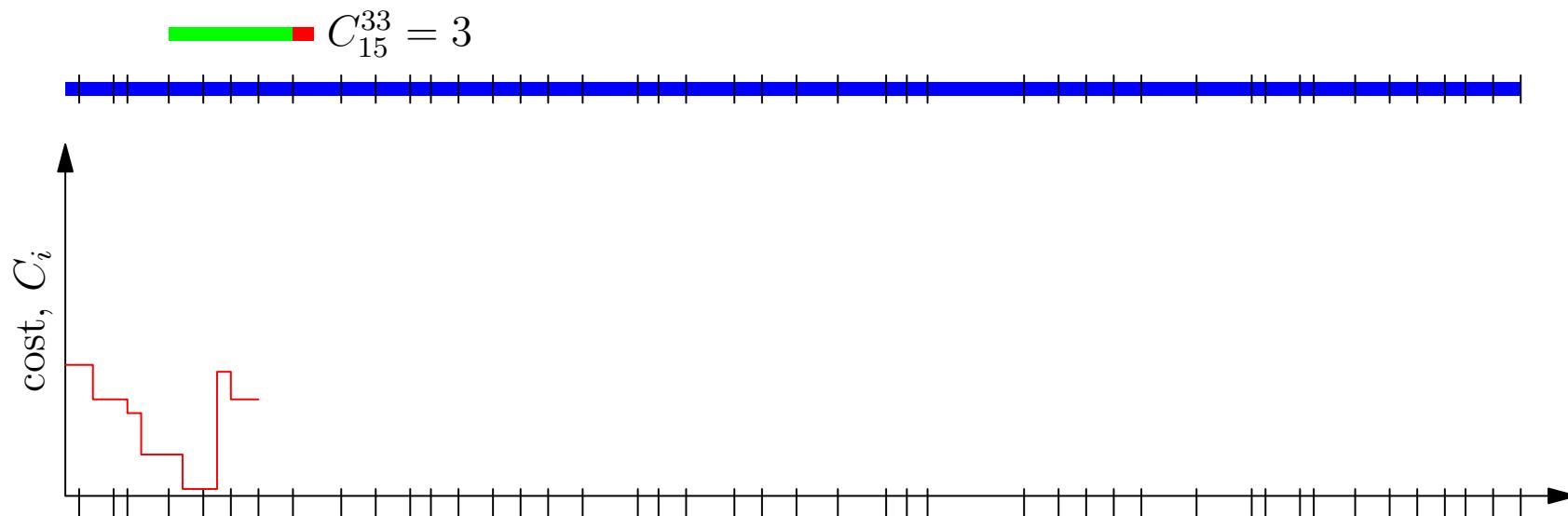
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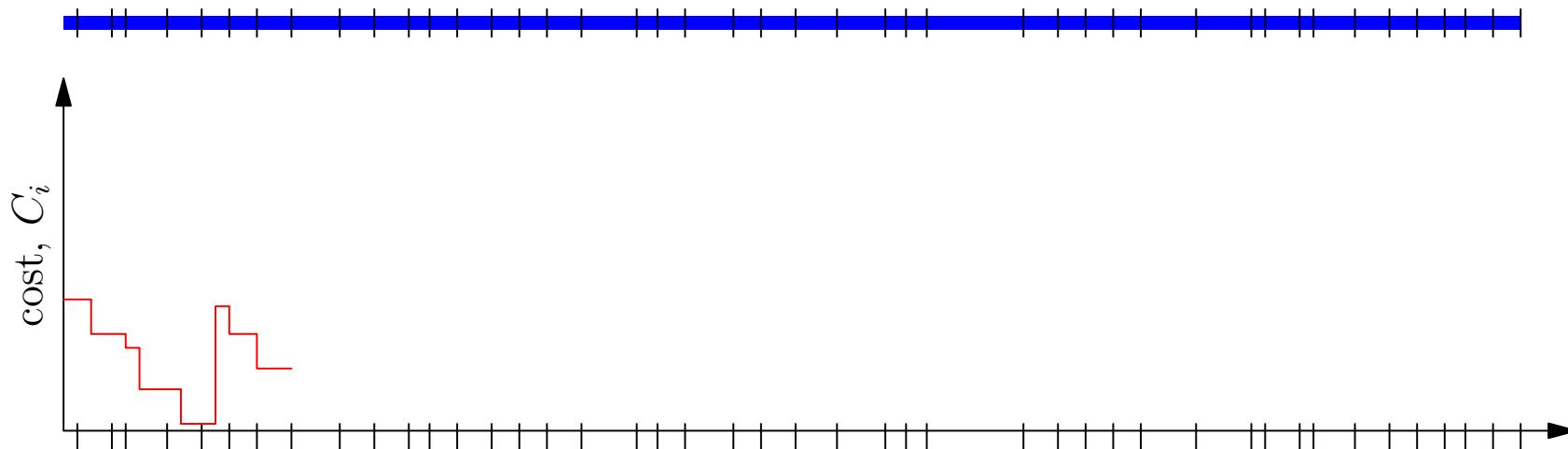
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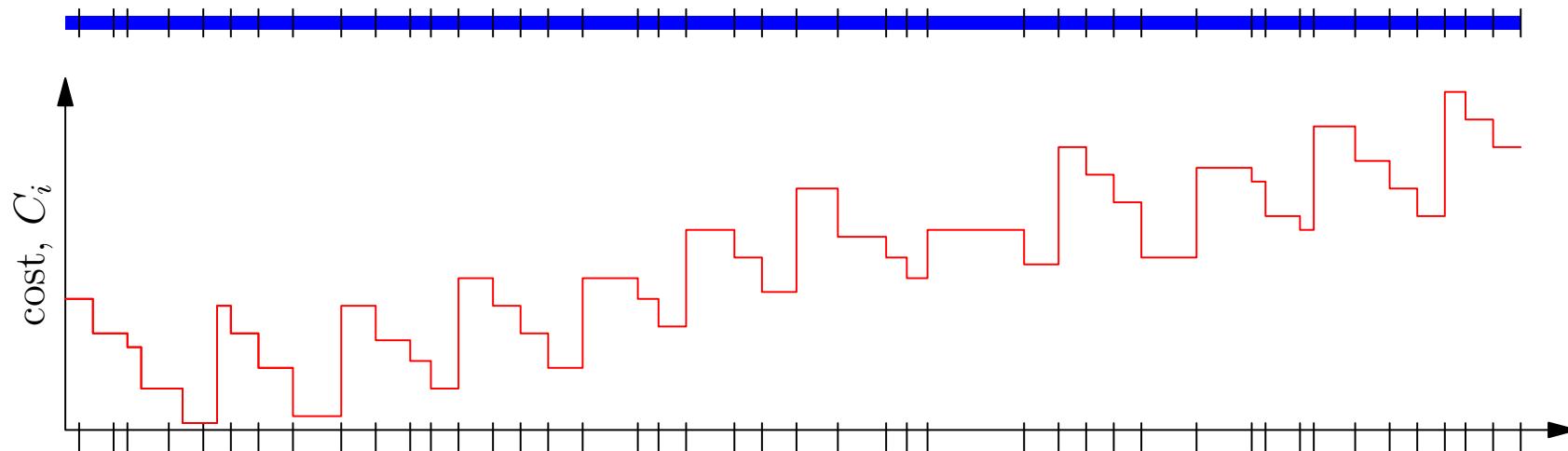
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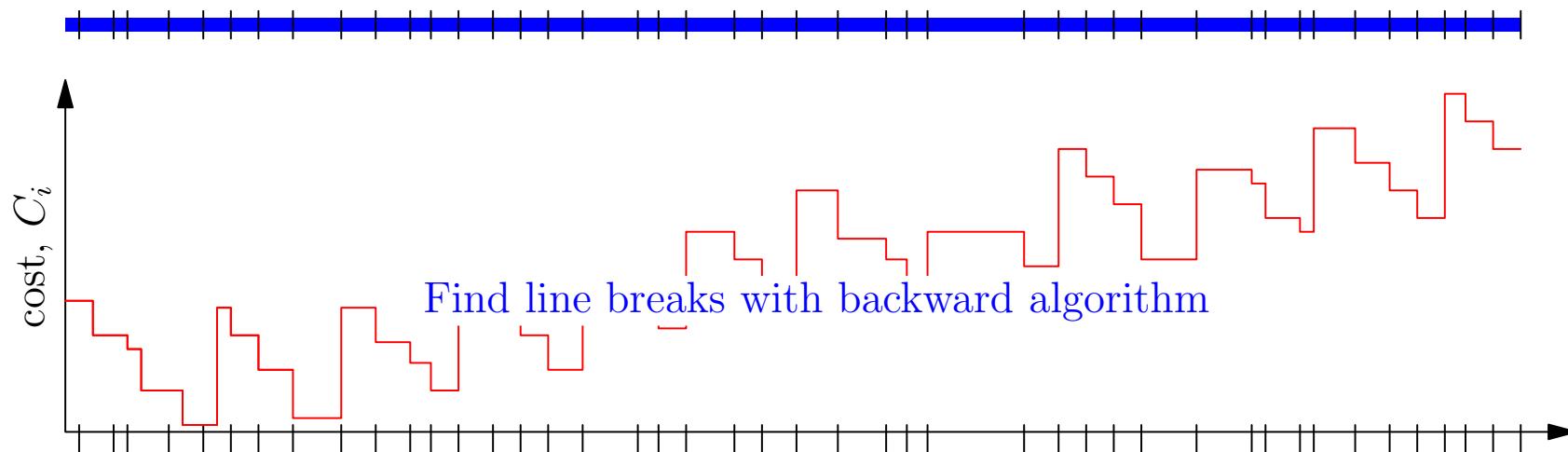
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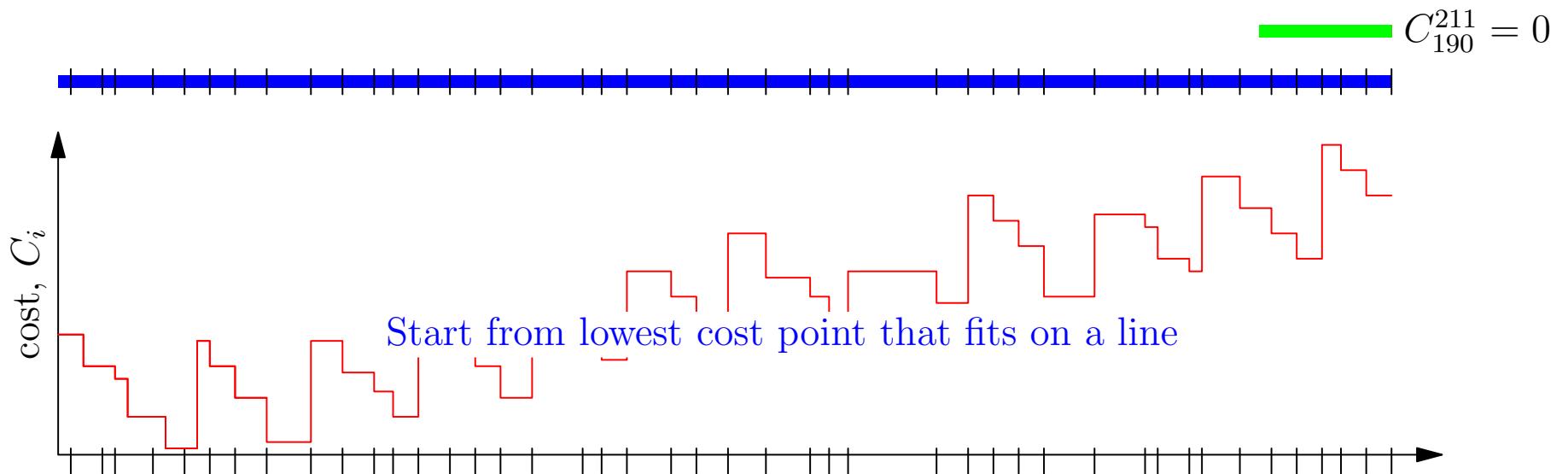
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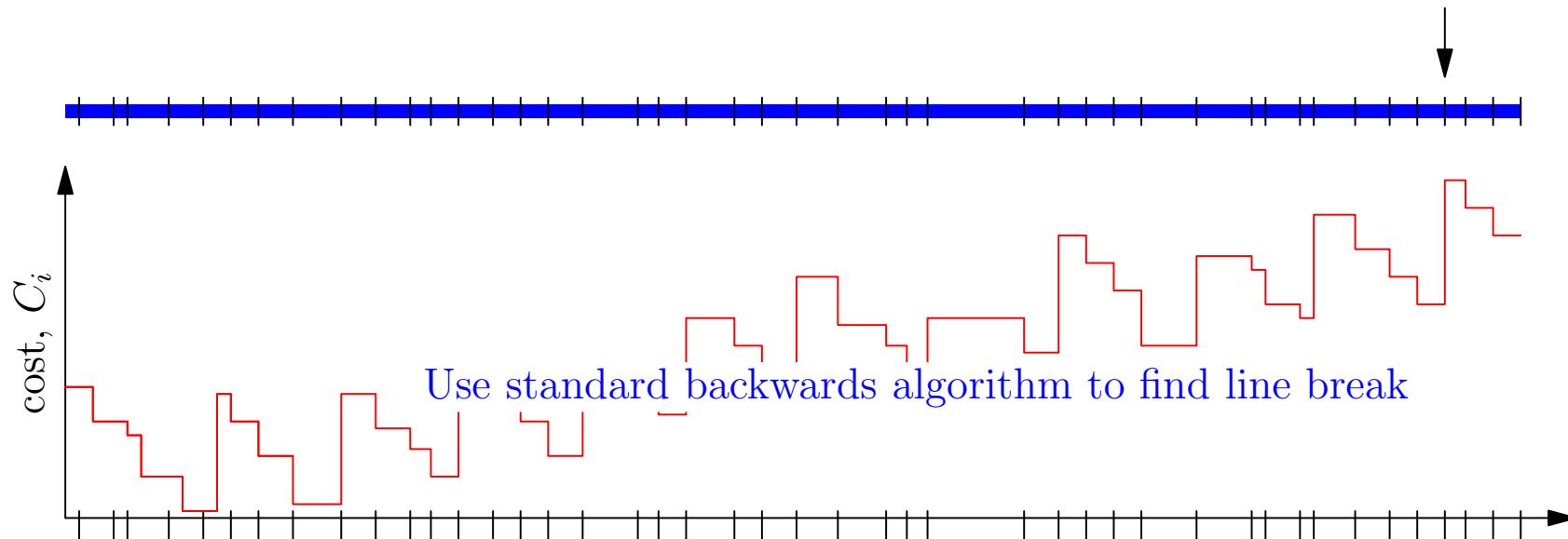
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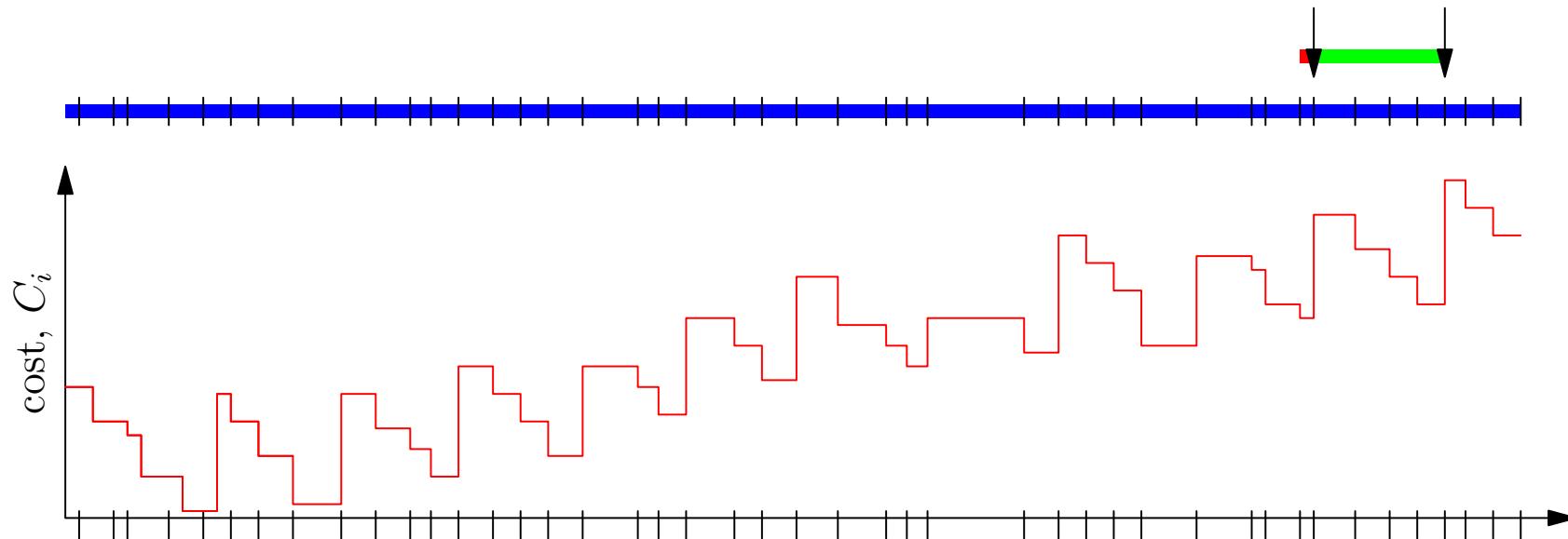
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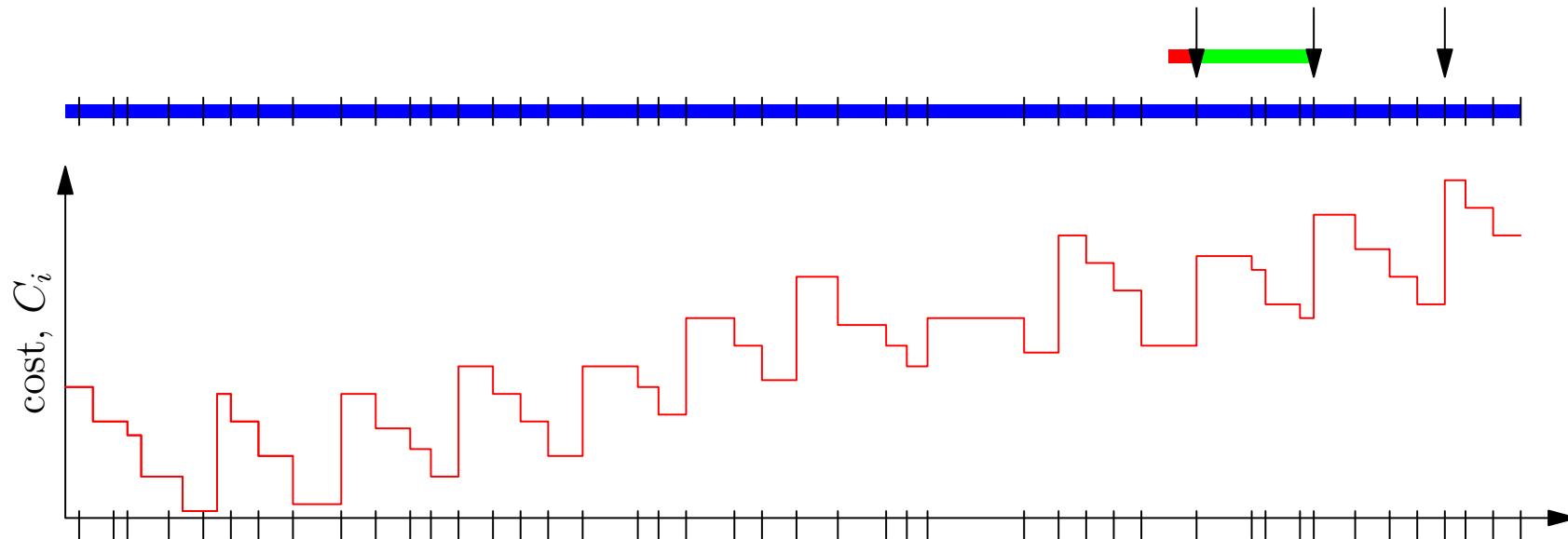
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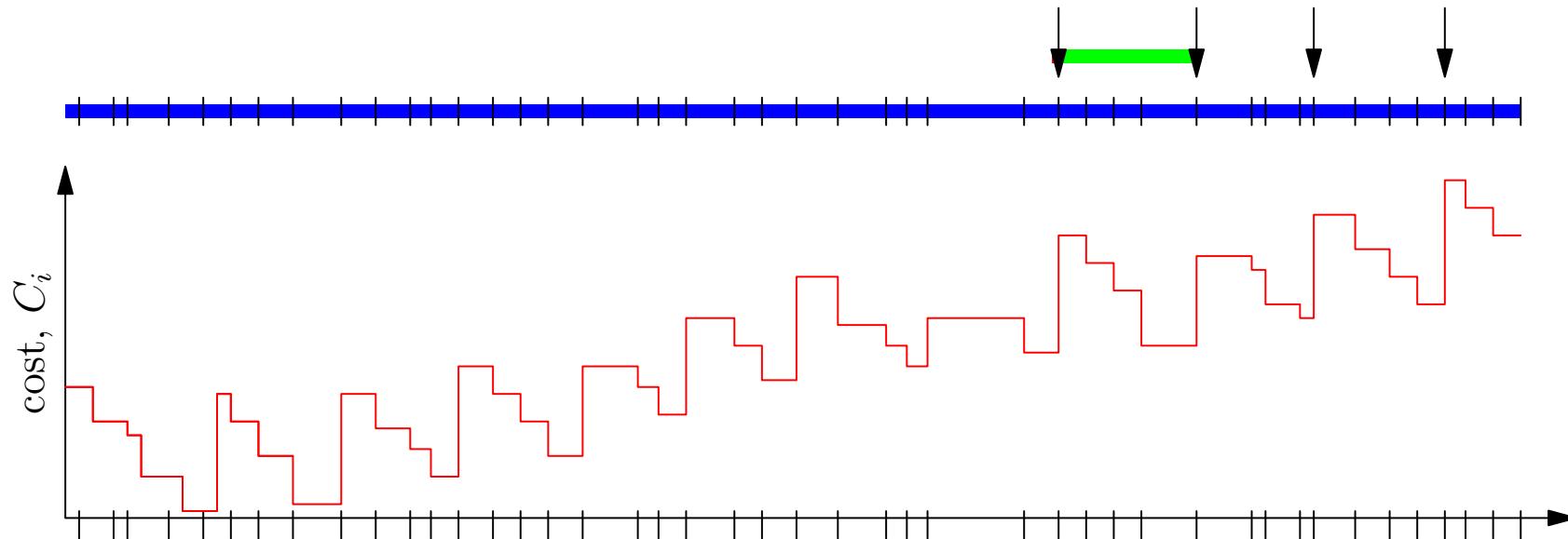
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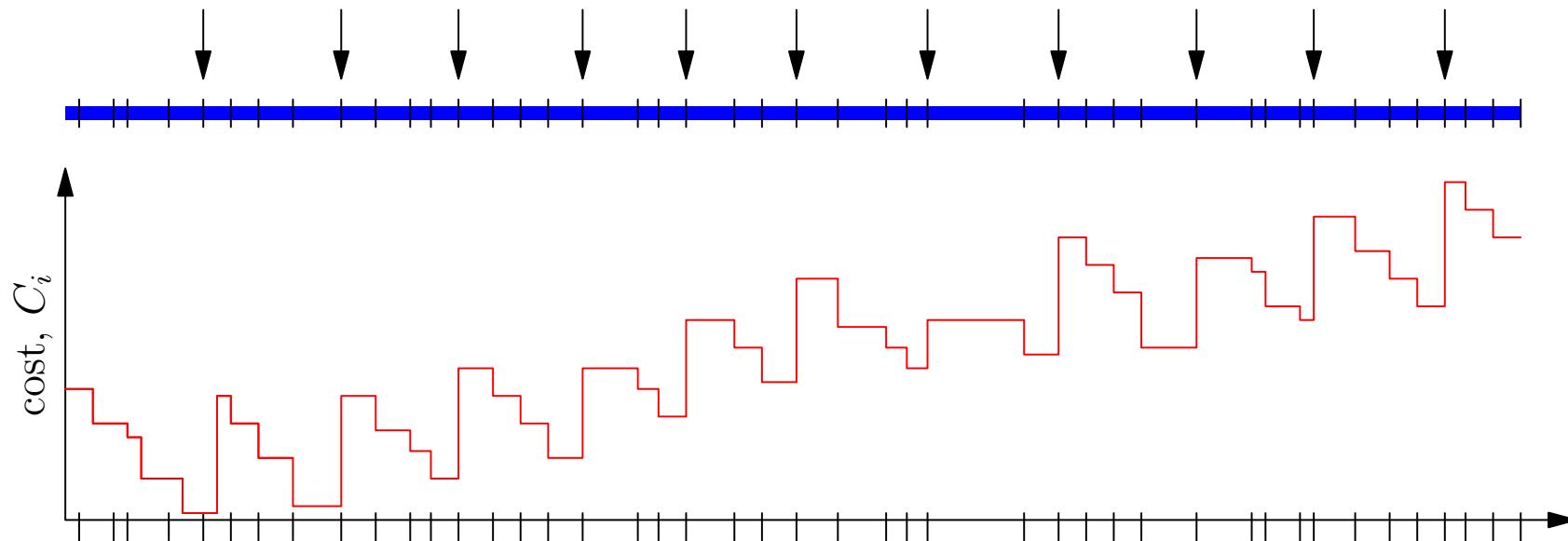
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- In advanced word processing you care about hyphenation, large gaps at the end of lines, etc.
- These all affect the way you would assign costs
- Dynamic programming is used in  $\text{\LaTeX}$  to produce nice line breaks
- A similar algorithm is used to produce nice page breaks

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# Inexact Matching

- A second example of dynamic programming is to find inexact matches
- The edit distance between two strings is the number of changes needed to move from one string to another
- The exact metric depends on the application, but might include number of substitutions, insertions and deletions
- This has many applications, e.g. in genomics to see what DNA strings (or proteins) are related

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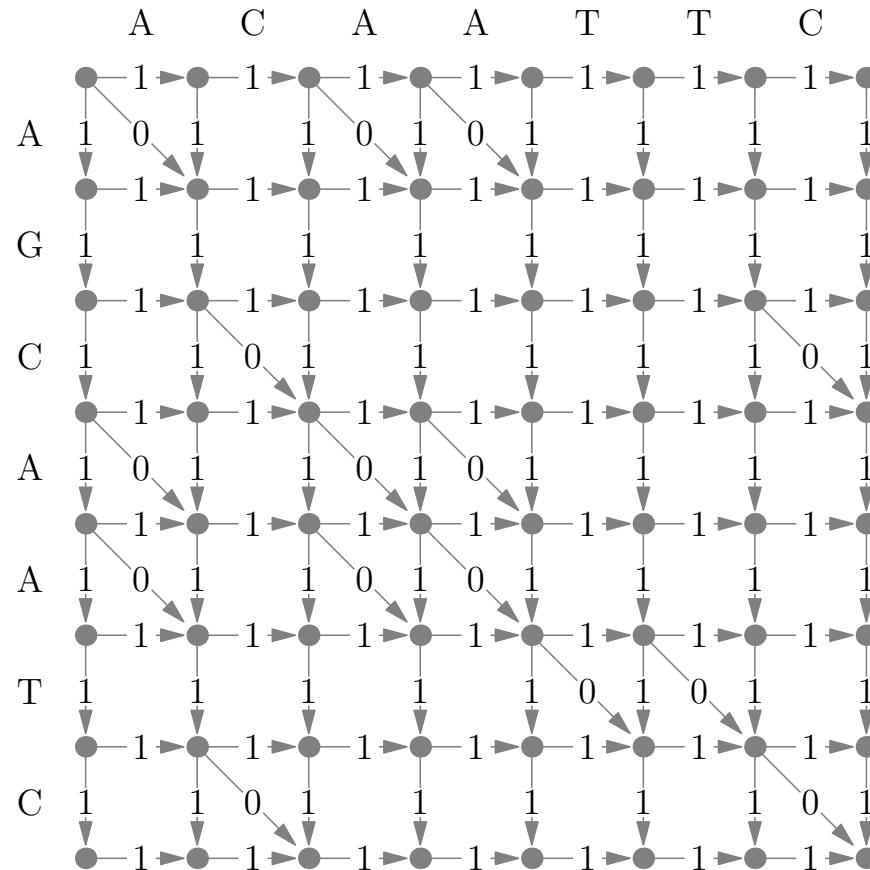
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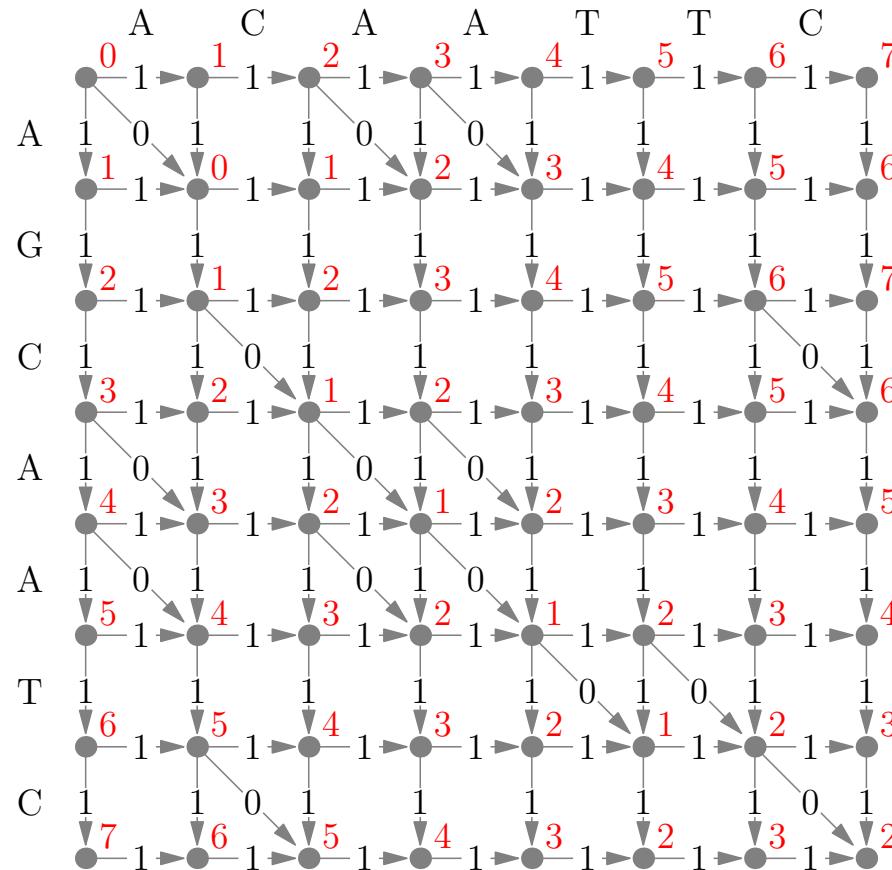
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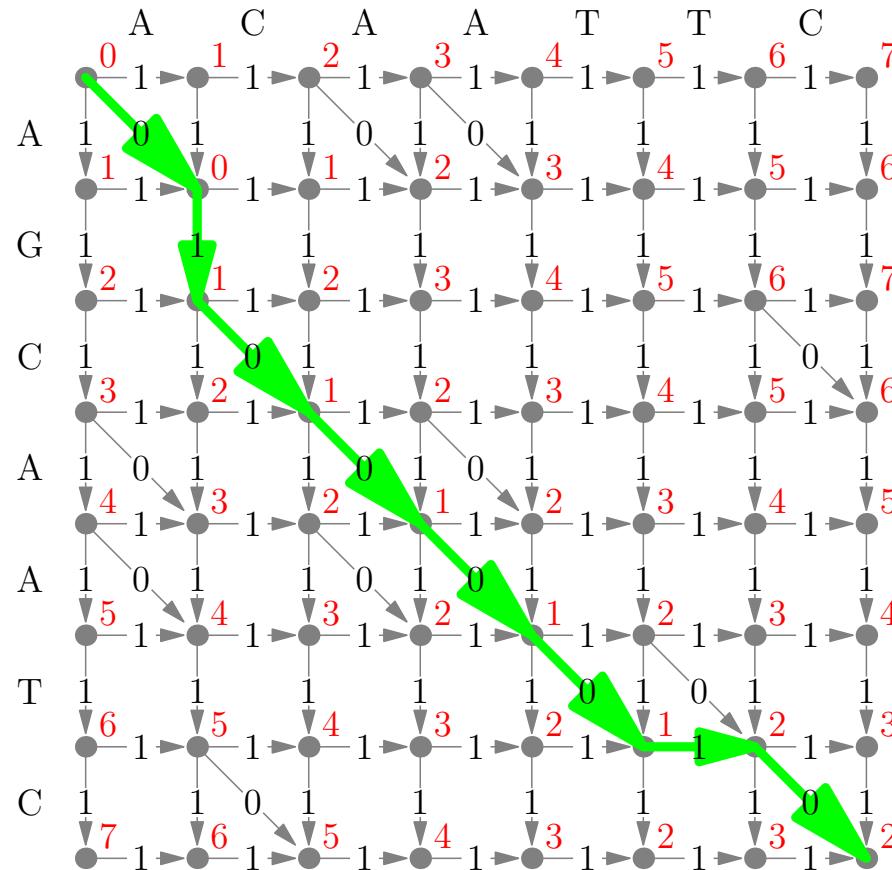
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# Dijkstra's Algorithm

- We saw early Dijkstra's algorithm for find the minimum distance between a source and destination node
- We grouped this with the greedy algorithms as we choose the next node to add to the minimum-distance spanning tree to be the closest node to the source we could access
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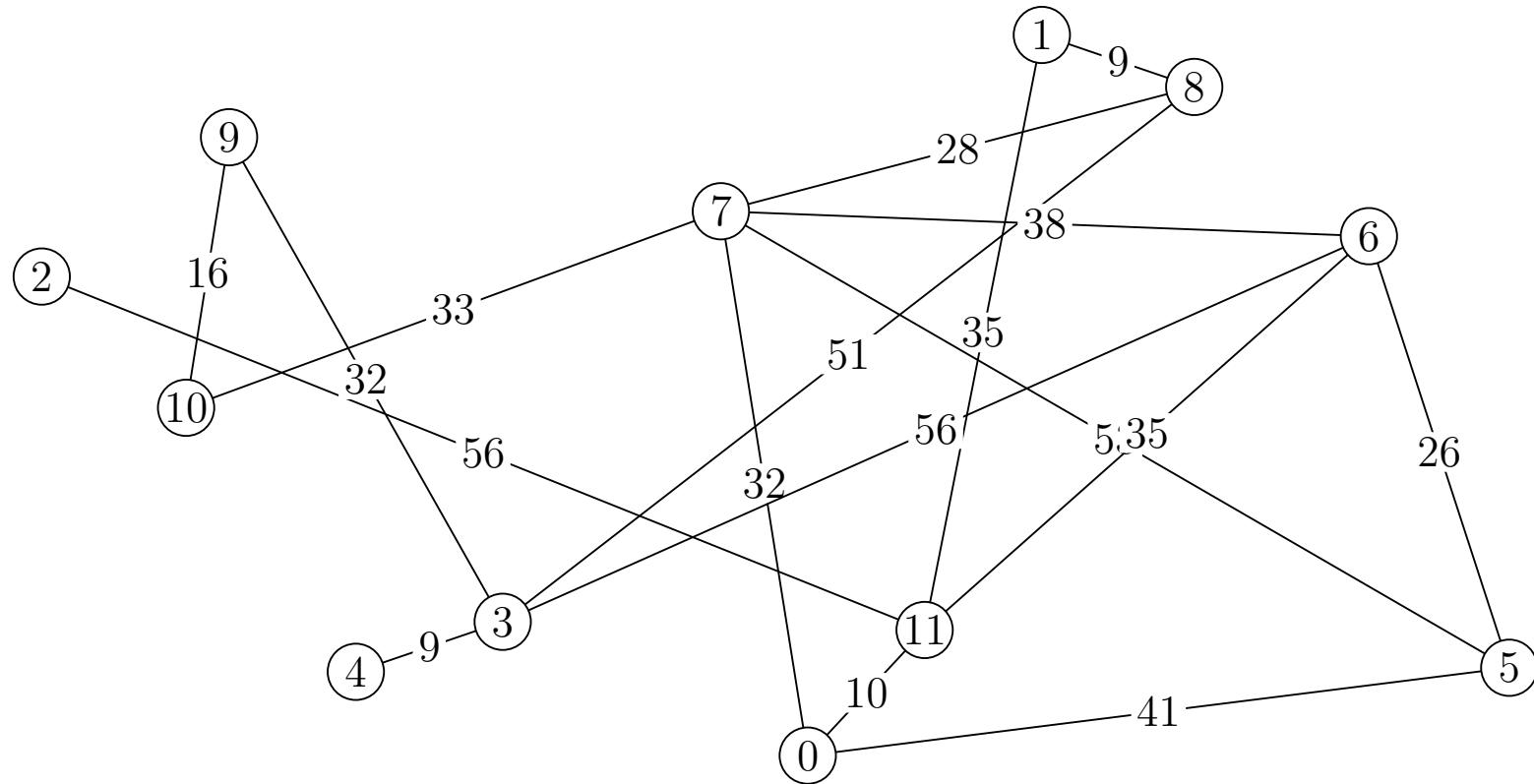
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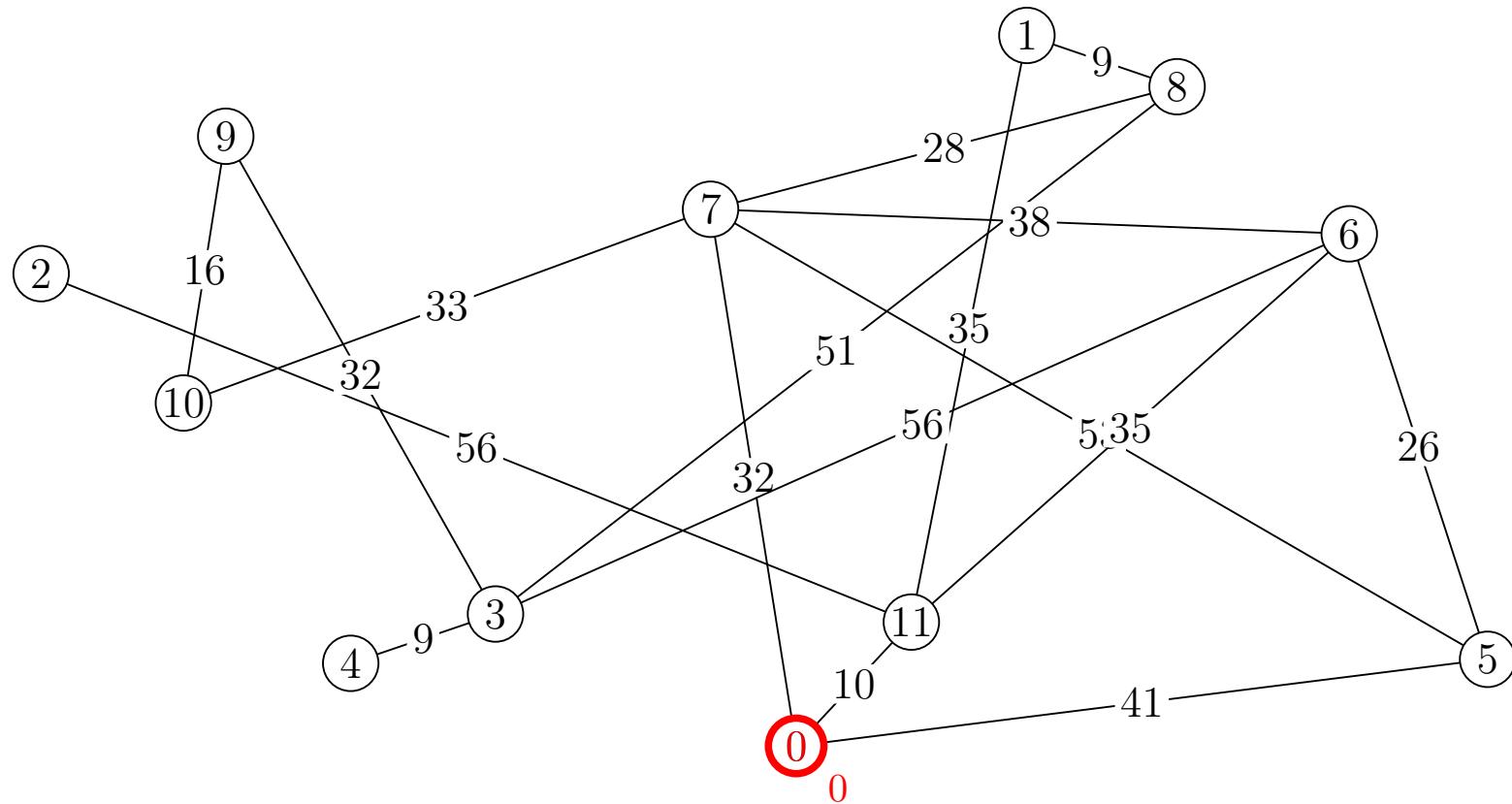
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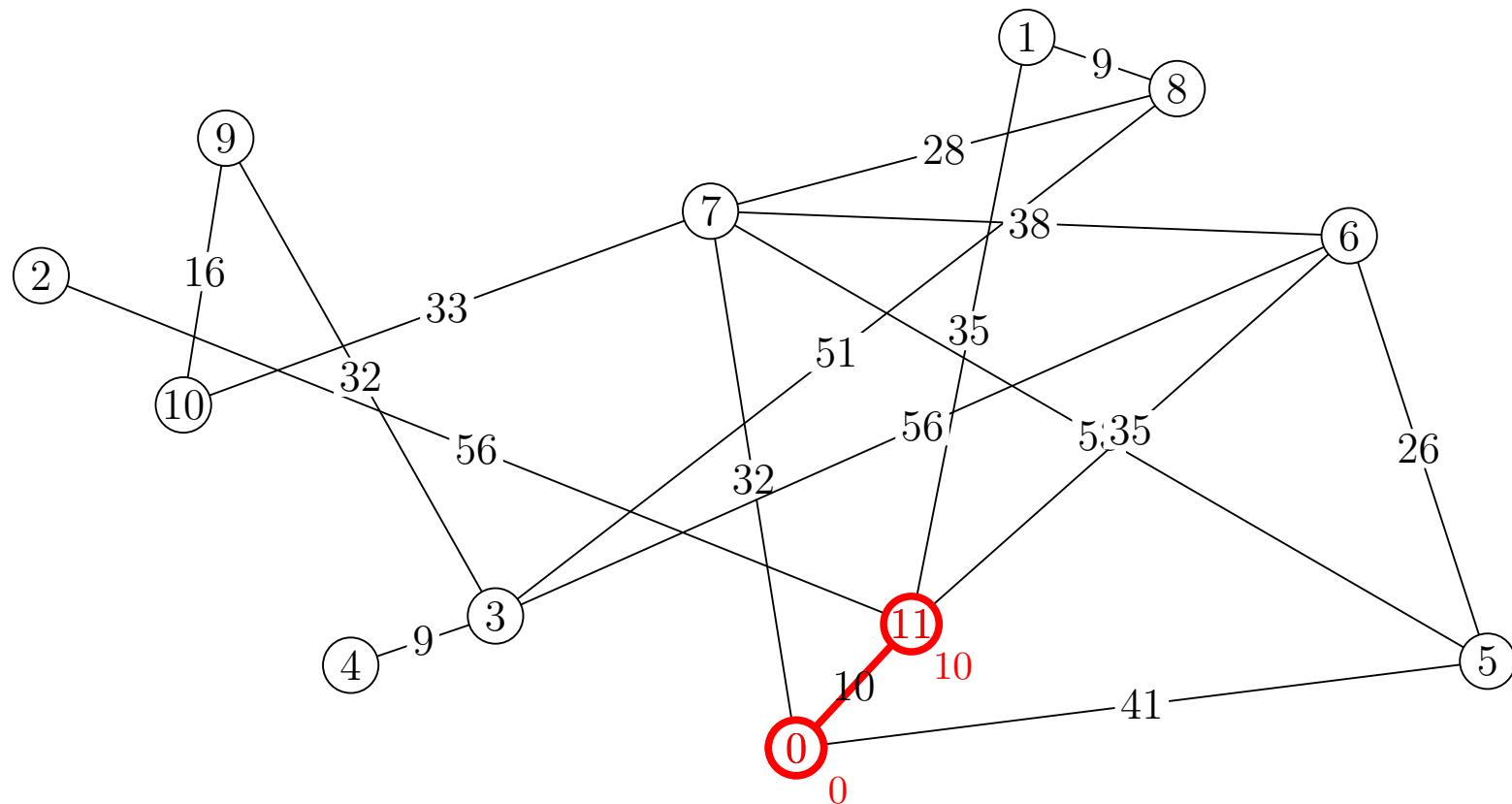
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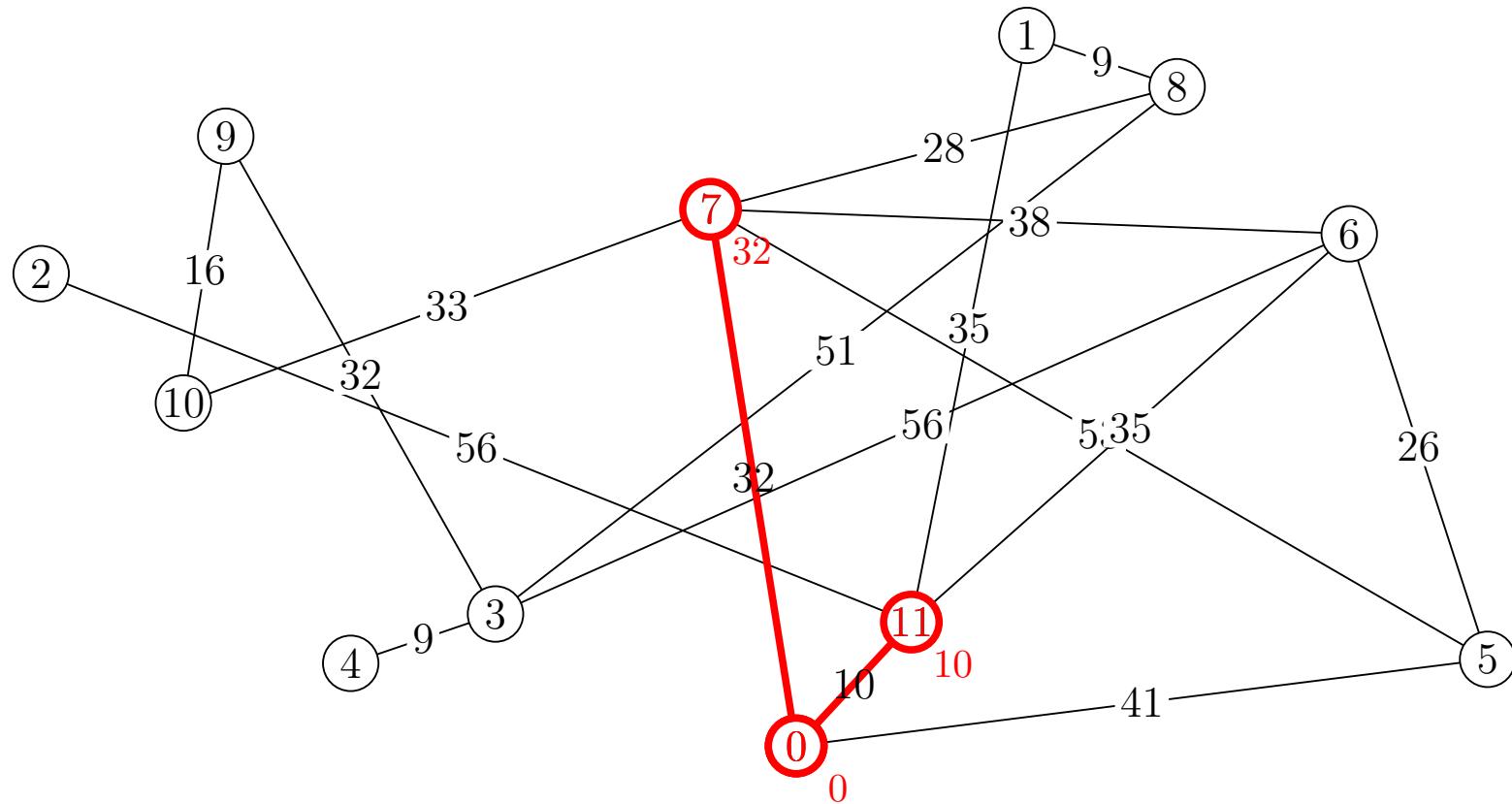
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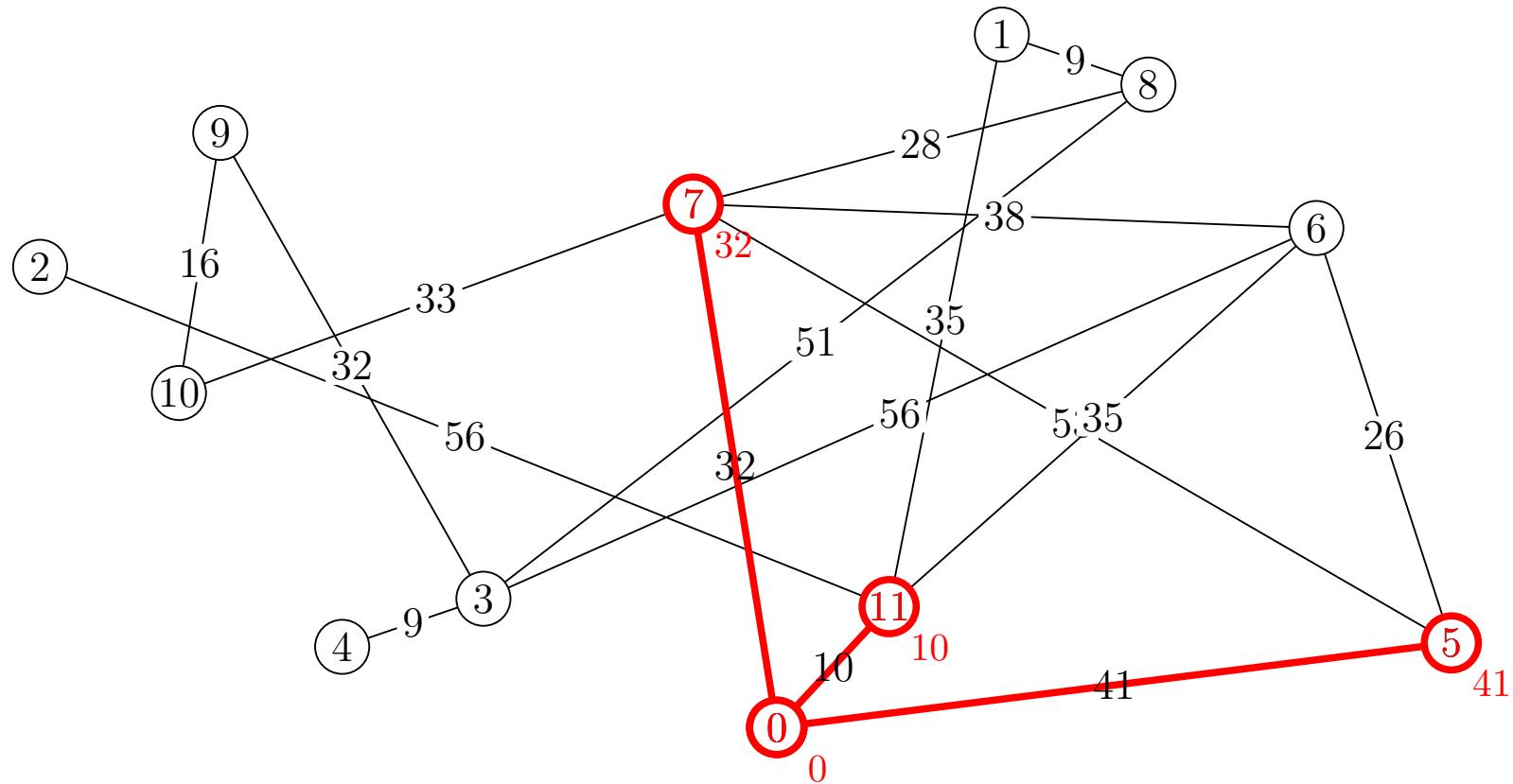
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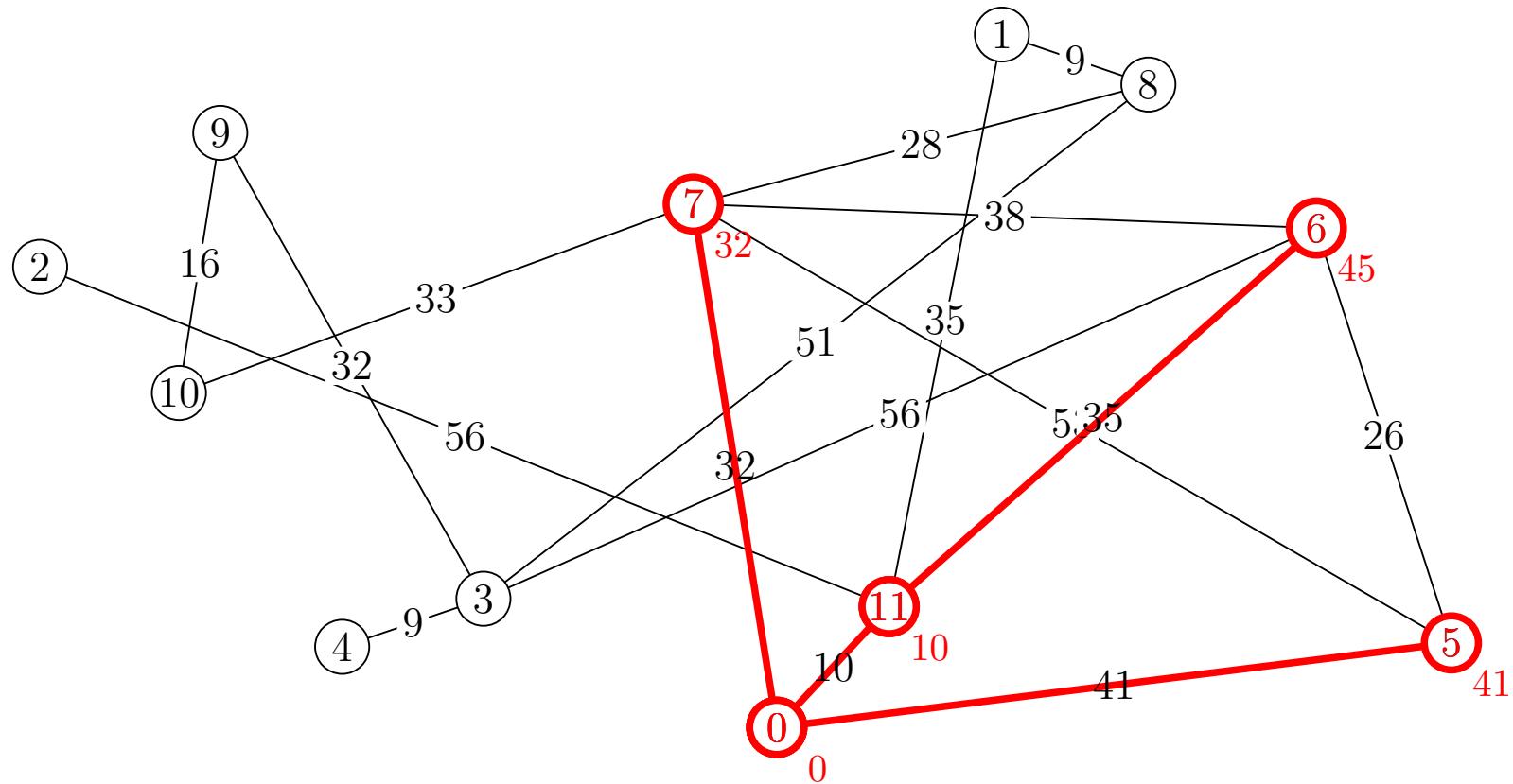
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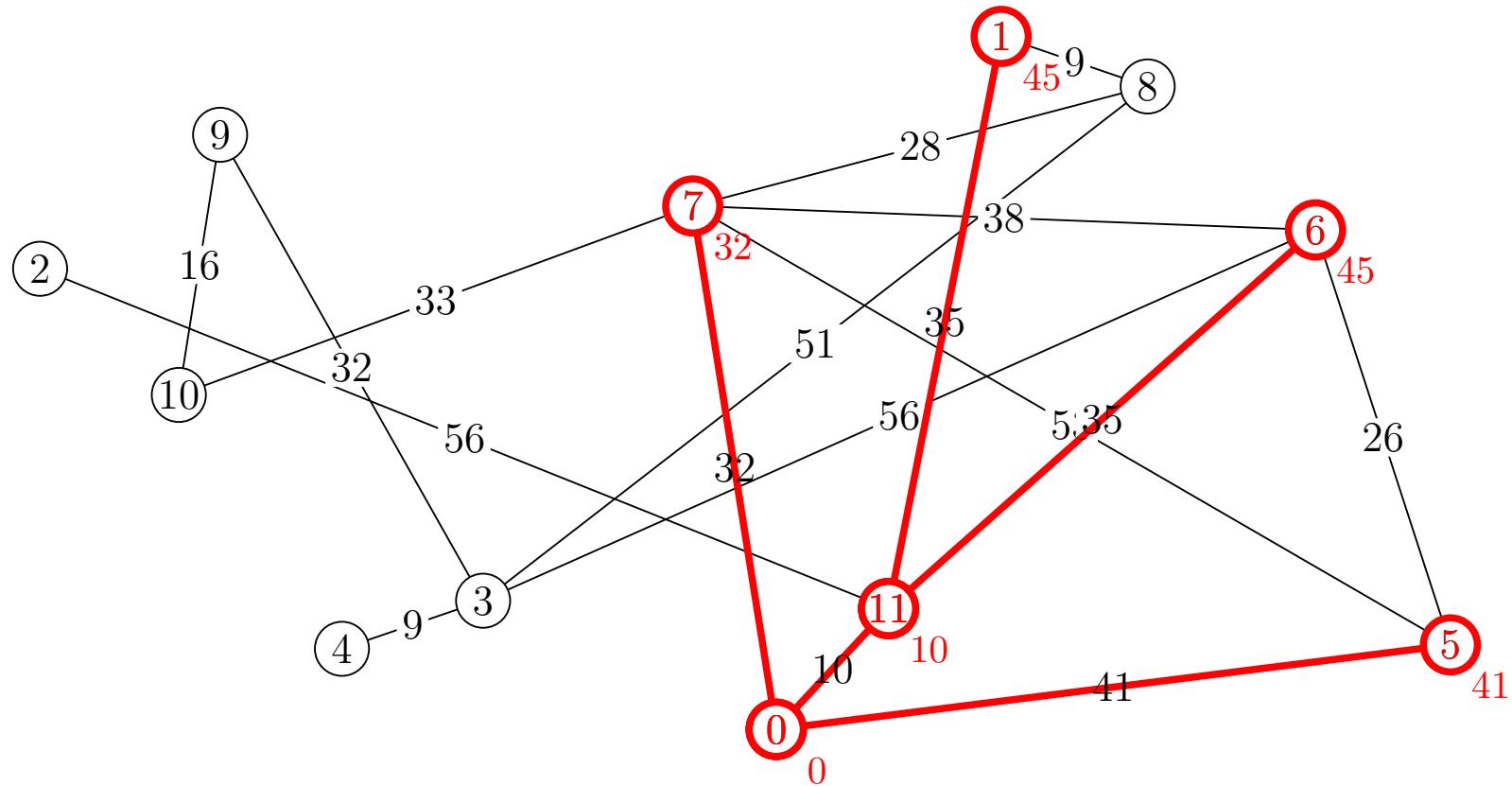
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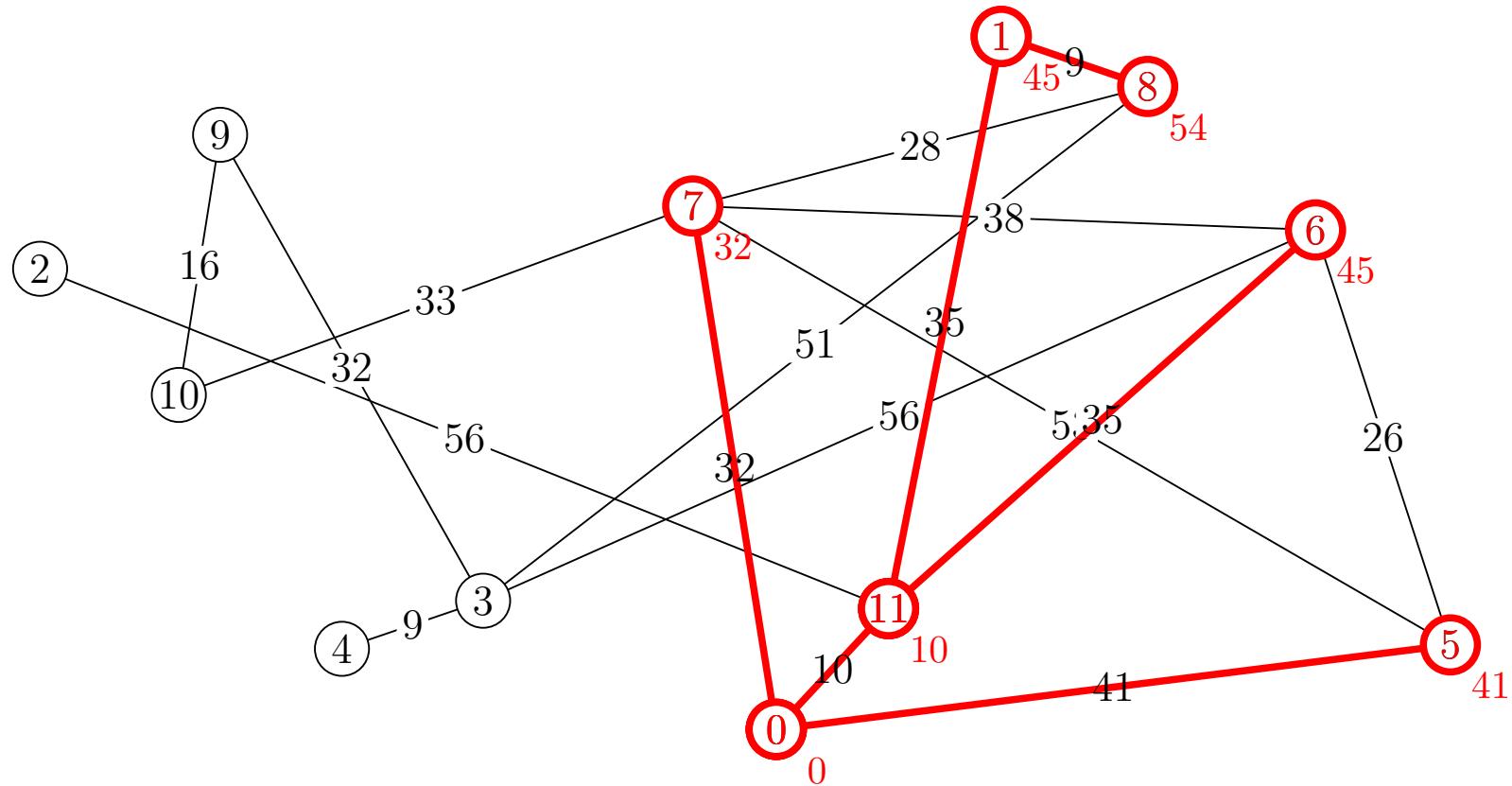
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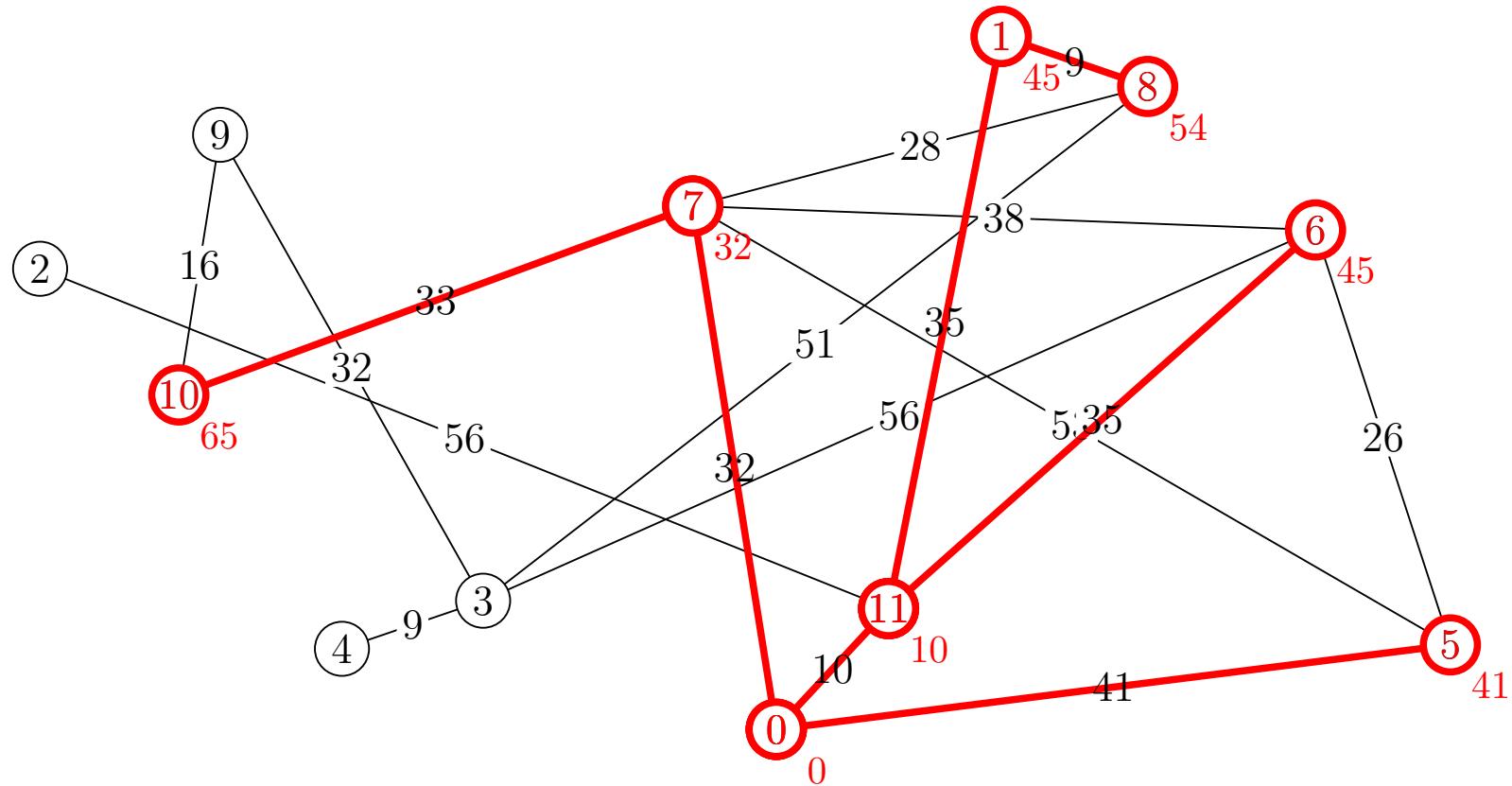
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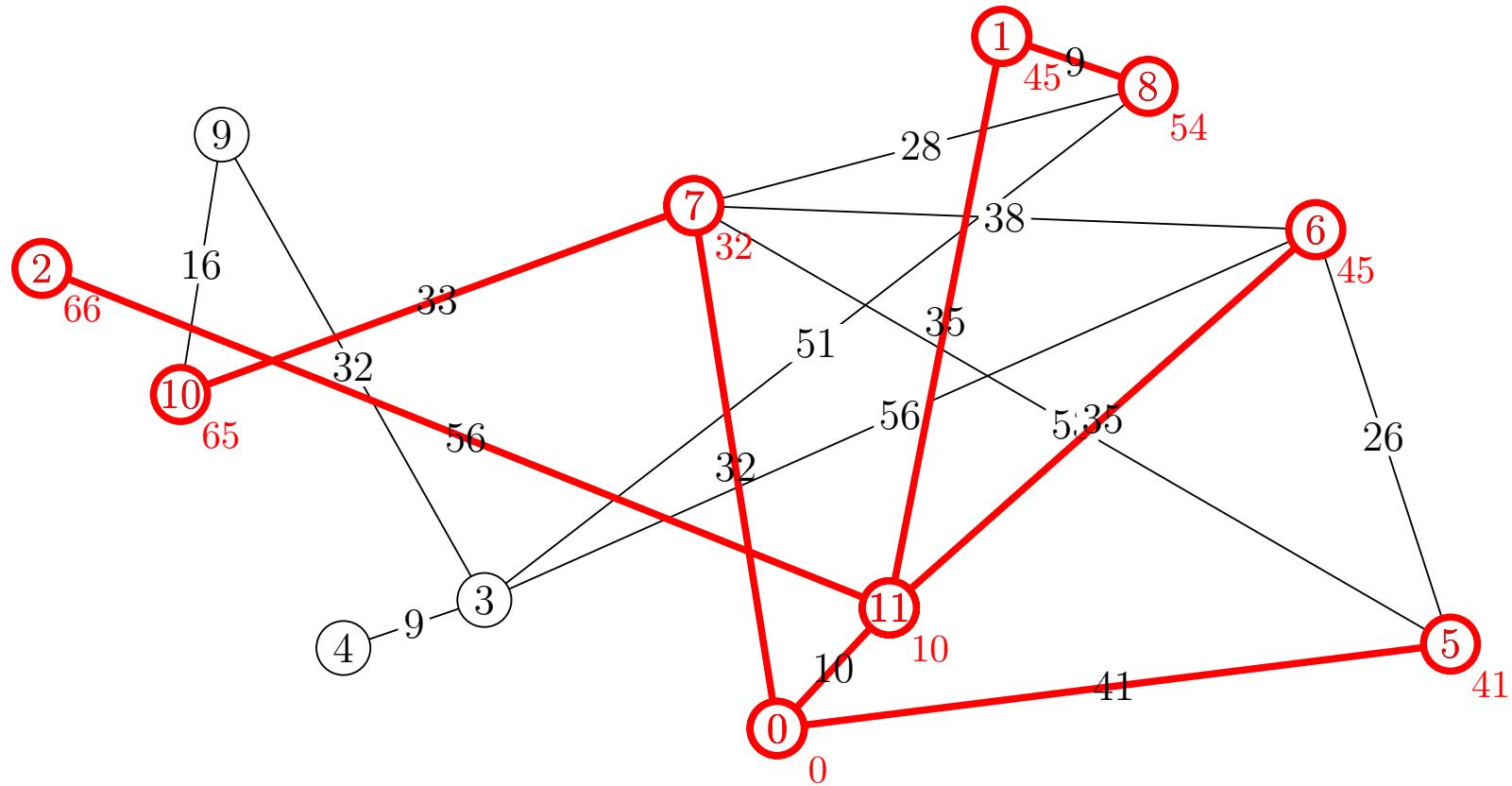
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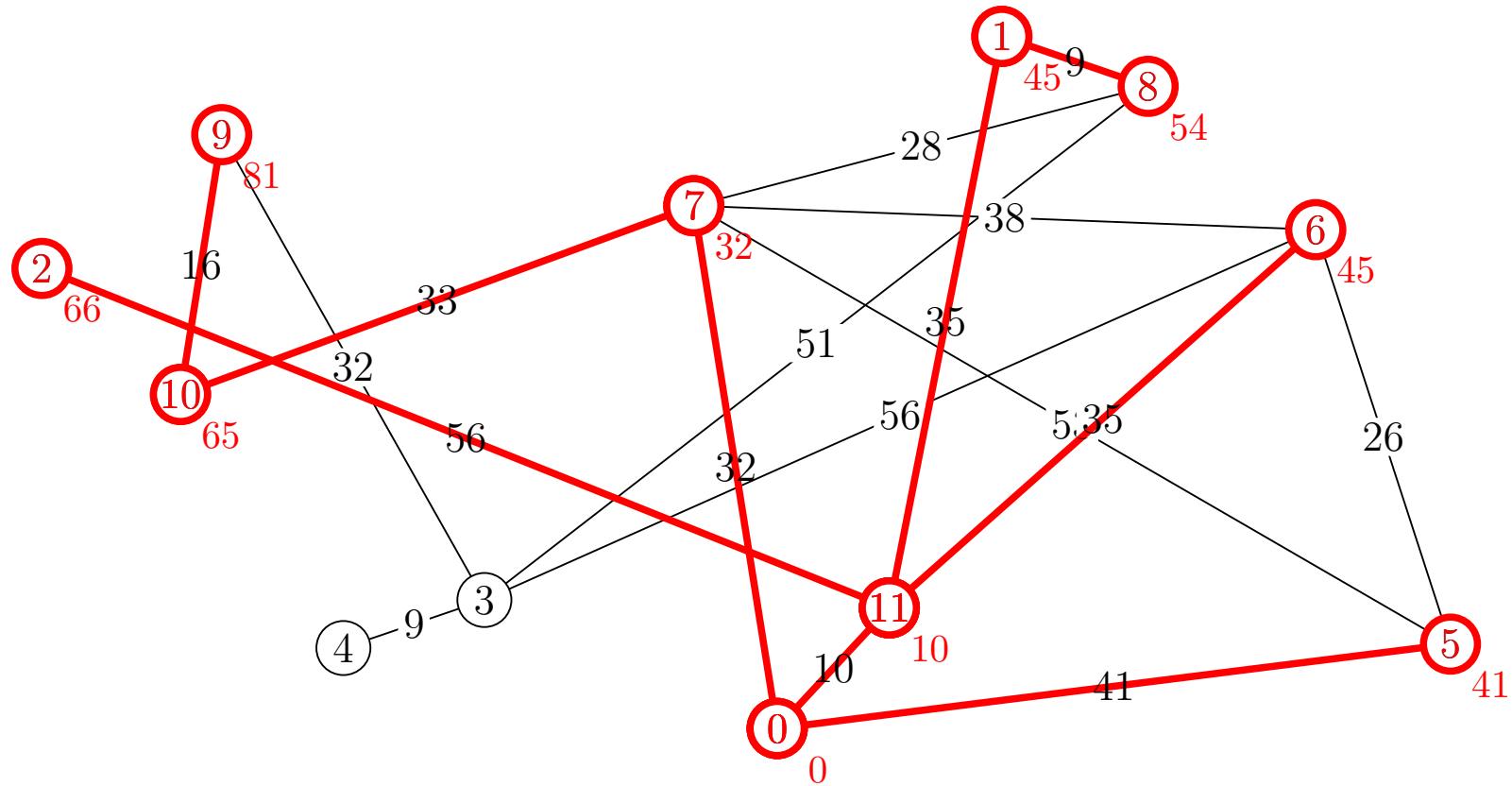
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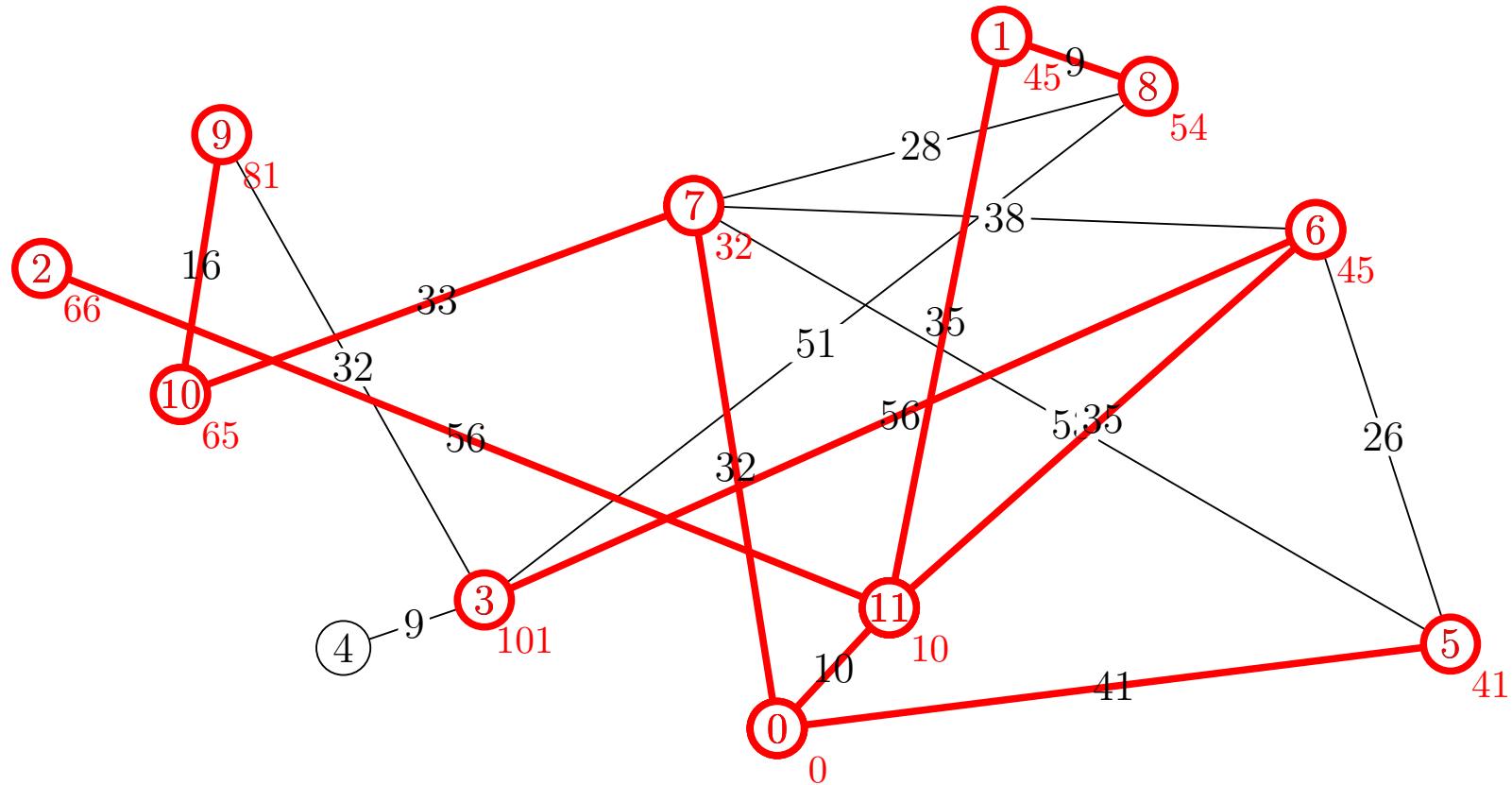
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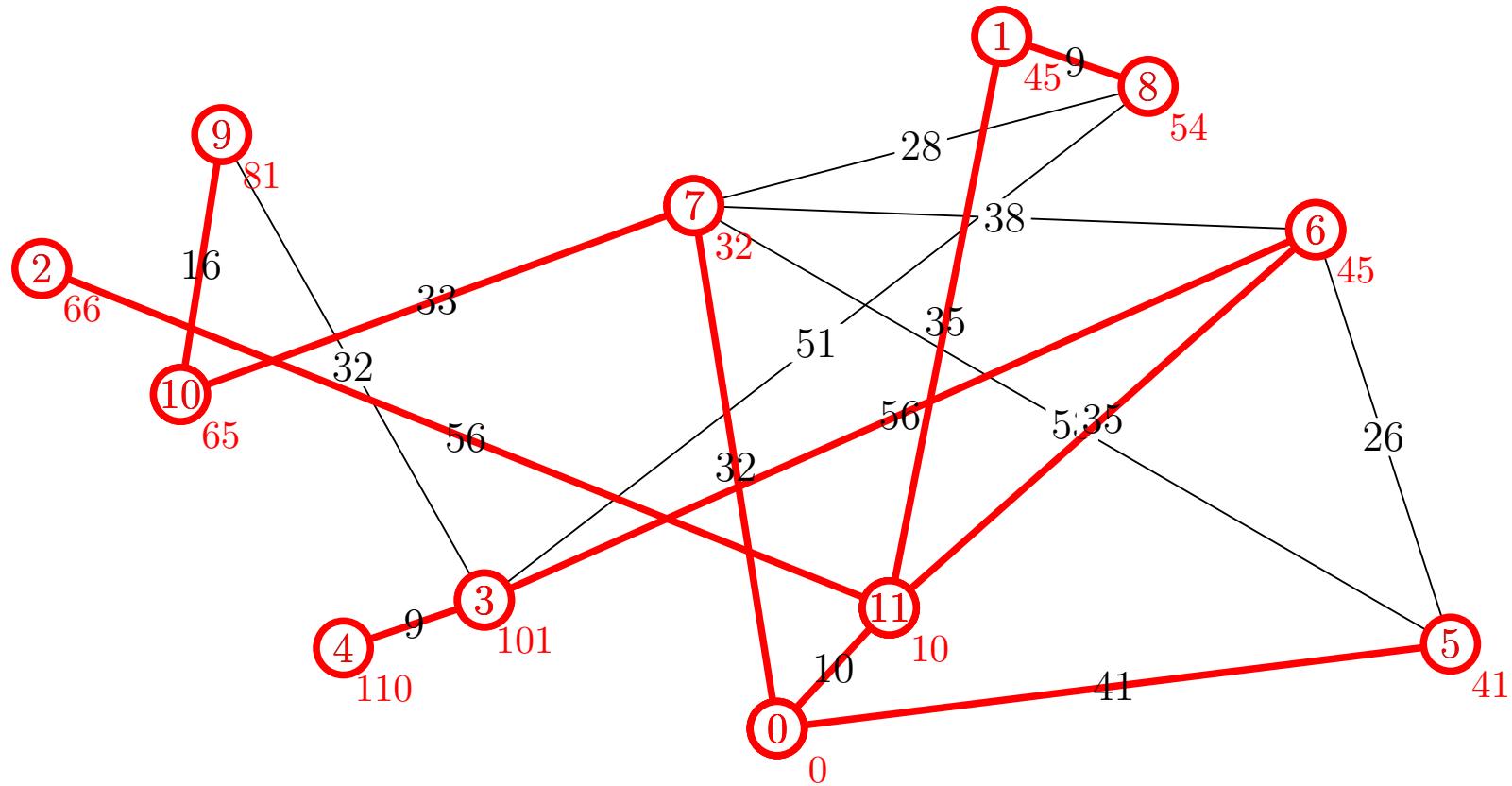
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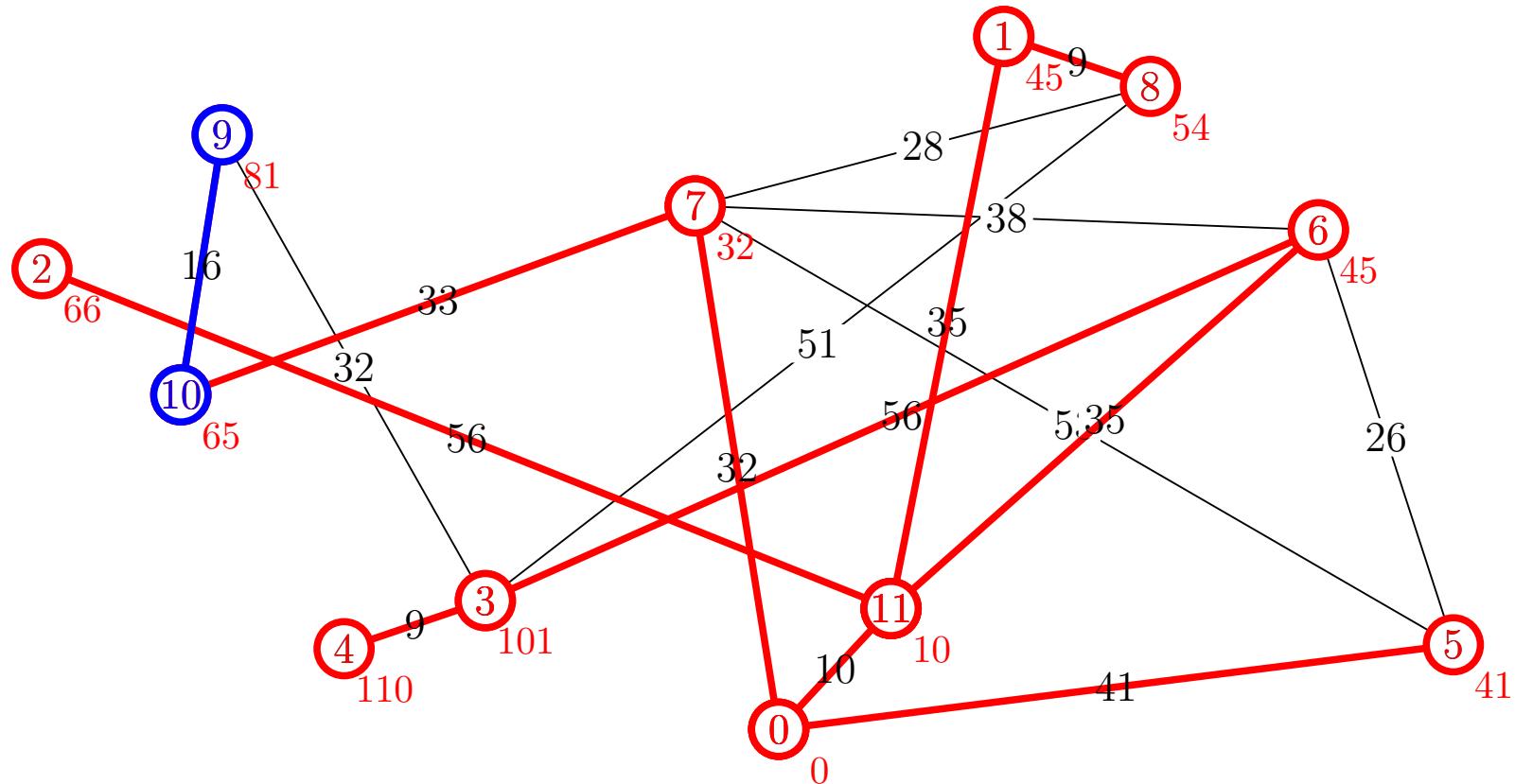
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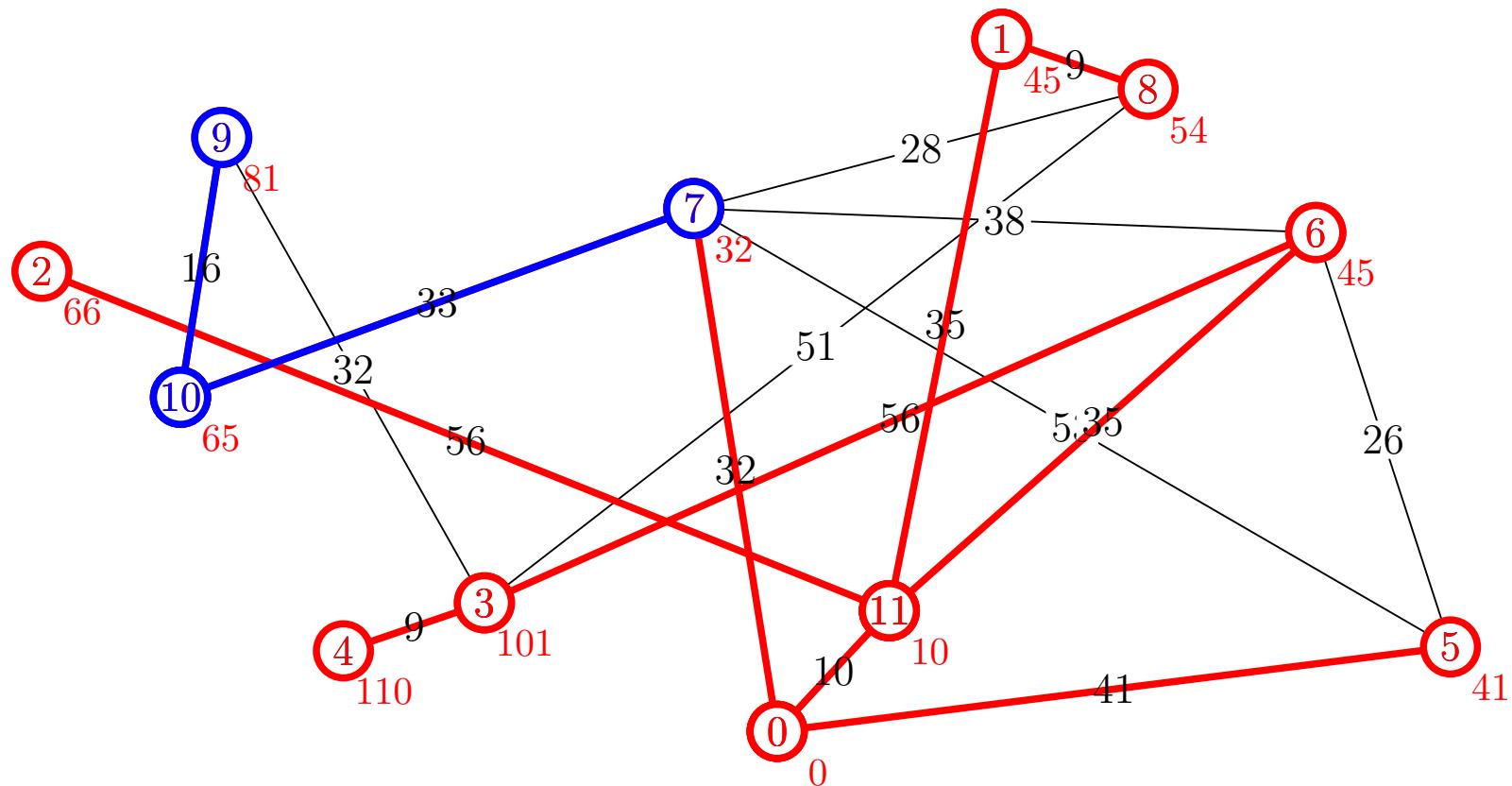
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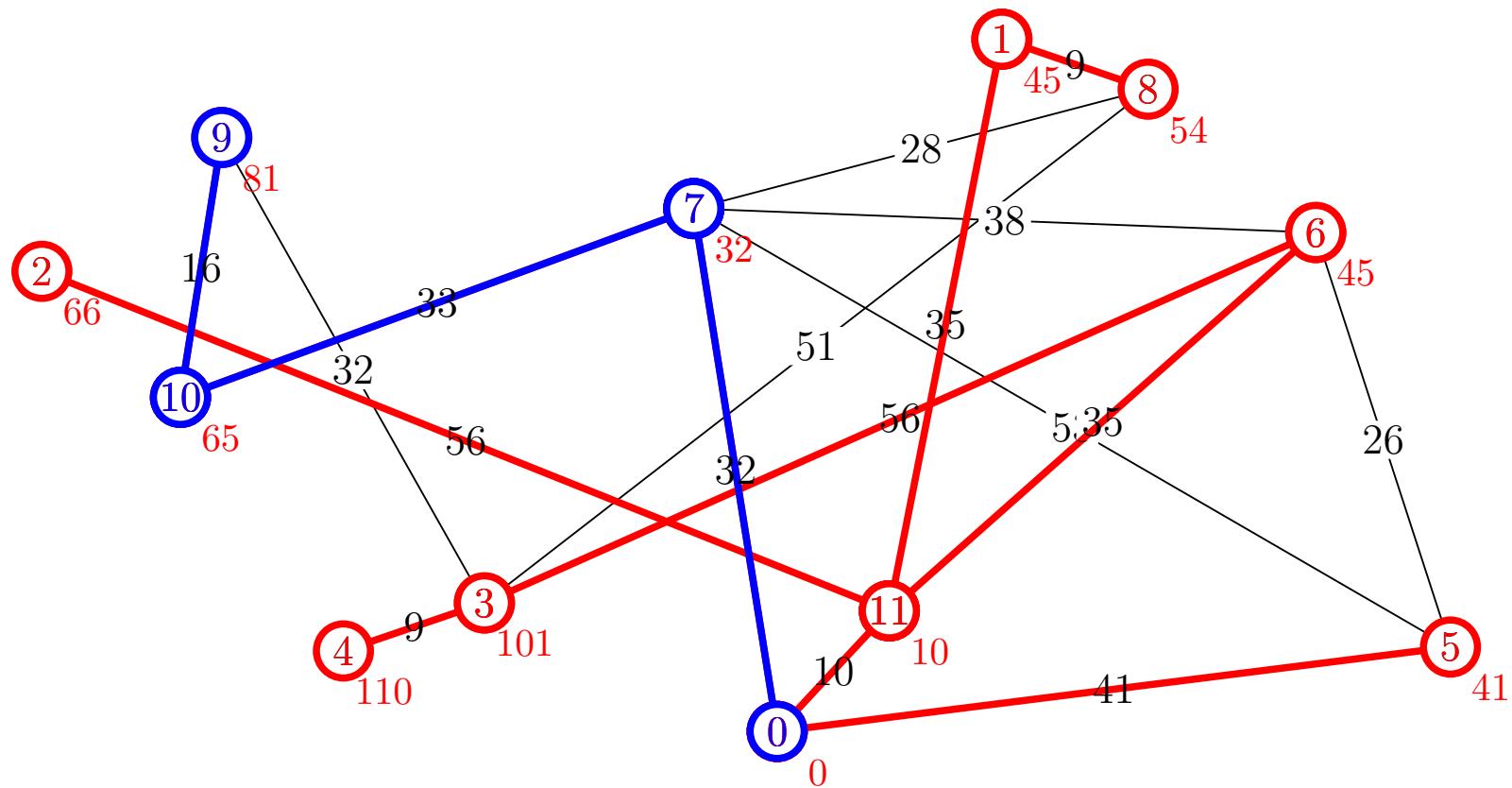
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# Uses of Dynamic Programming

- Recurrent solutions to lattice models for protein-DNA binding
- Backward induction as a solution method for finite-horizon discrete-time dynamic optimization problems
- Method of undetermined coefficients can be used to solve the Bellman equation in infinite-horizon, discrete-time, discounted, time-invariant dynamic optimization problems
- Many string algorithms including longest common subsequence, longest increasing subsequence, longest common substring, Levenshtein distance (edit distance)
- Many algorithmic problems on graphs can be solved efficiently for graphs of bounded treewidth or bounded clique-width by using dynamic programming on a tree decomposition of the graph.
- The Cocke–Younger–Kasami (CYK) algorithm which determines whether and how a given string can be generated by a given context-free grammar
- Knuth's word wrapping algorithm that minimizes raggedness when word wrapping text

- The use of transposition tables and refutation tables in computer chess
- The Viterbi algorithm (used for hidden Markov models)
- The Earley algorithm (a type of chart parser)
- The Needleman–Wunsch and other algorithms used in bioinformatics, including sequence alignment, structural alignment, RNA structure prediction
- Floyd's all-pairs shortest path algorithm
- Optimizing the order for chain matrix multiplication
- Pseudo-polynomial time algorithms for the subset sum and knapsack and partition problems
- The dynamic time warping algorithm for computing the global distance between two time series
- The Selinger (a.k.a. System R) algorithm for relational database query optimization
- De Boor algorithm for evaluating B-spline curves
- Duckworth–Lewis method for resolving the problem when games of cricket are interrupted

- The value iteration method for solving Markov decision processes
- Some graphic image edge following selection methods such as the "magnet" selection tool in Photoshop
- Some methods for solving interval scheduling problems
- Some methods for solving word wrap problems
- Some methods for solving the travelling salesman problem, either exactly (in exponential time) or approximately (e.g. via the bitonic tour)
- Recursive least squares method
- Beat tracking in music information retrieval
- Adaptive-critic training strategy for artificial neural networks
- Stereo algorithms for solving the correspondence problem used in stereo vision
- Seam carving (content aware image resizing)
- The Bellman–Ford algorithm for finding the shortest distance in a graph
- Some approximate solution methods for the linear search problem
- Kadane's algorithm for the maximum subarray problem

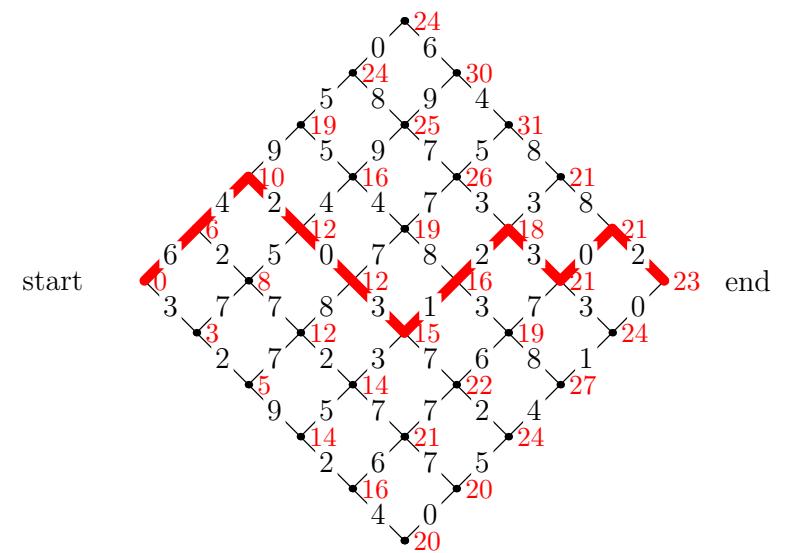
# Outline

## 1. Dynamic Programming

## 2. Applications

- Line Breaks
- Edit Distance
- Dijkstra's Algorithm

## 3. Limitation



# When You Can't Use It

- Not all problems can be split neatly to make dynamic programming possible
- Dynamic programming works on problems with some natural ordering
- We need this to build up a list of optimum cost of partial solutions—these have to depend on the cost of previous partial solutions
- Sometime no natural ordering exists

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# Travelling Salesman Problem

- For TSP we can find a dynamic programming solution by considering optimal sub-tours (paths) involving sets of  $k$  cities
- If we know the optimal sub-tour through all sets of cities of size  $k$  (starting and finishing at each possible pair in the set) then we can quickly compute the optimal sub-tour between set of size  $k + 1$

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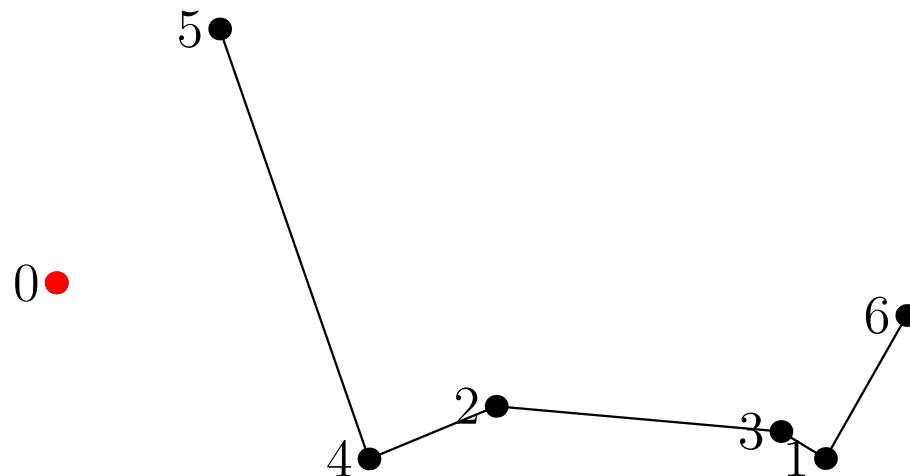
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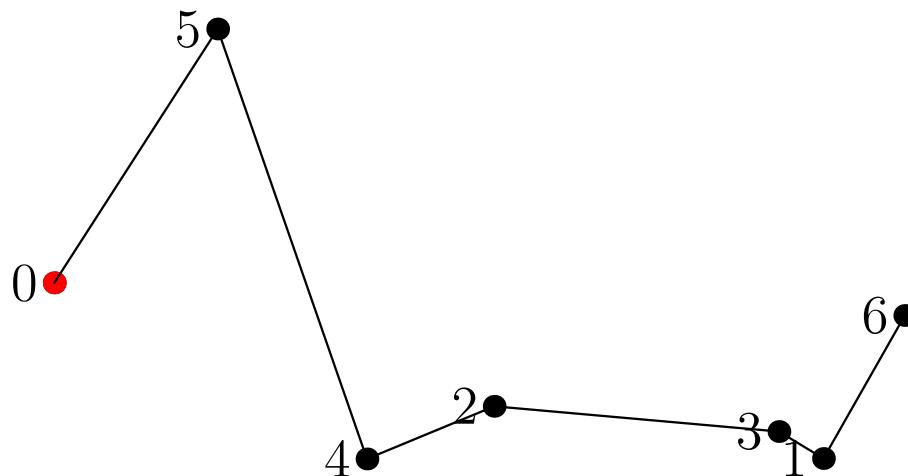
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- If we know the optimal sub-tour through all sets of cities of size  $k$  (starting and finishing at each possible pair in the set) then we can quickly compute the optimal sub-tour between set of size  $k + 1$



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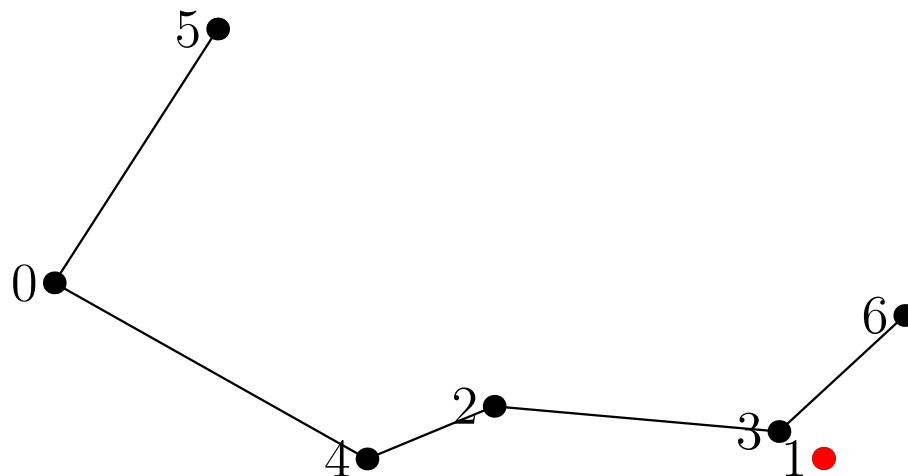
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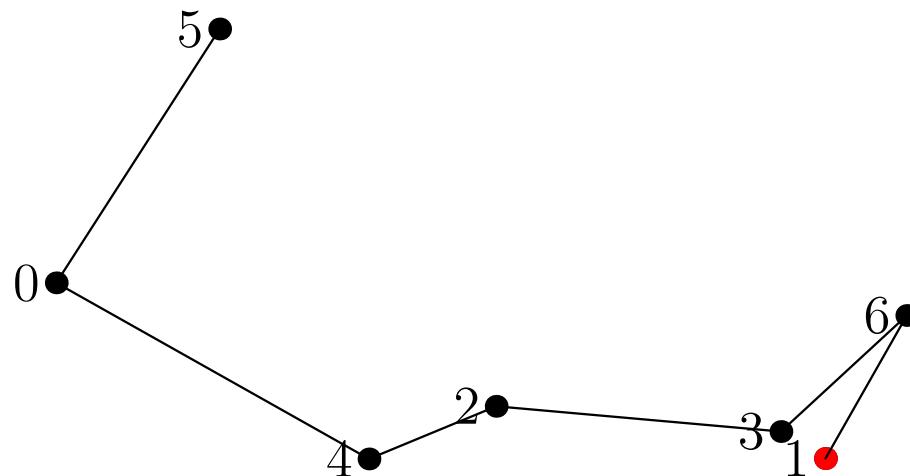
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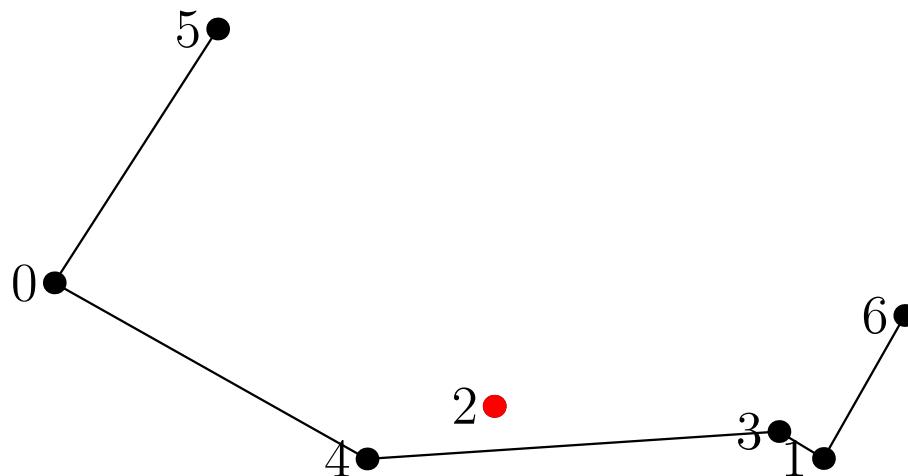
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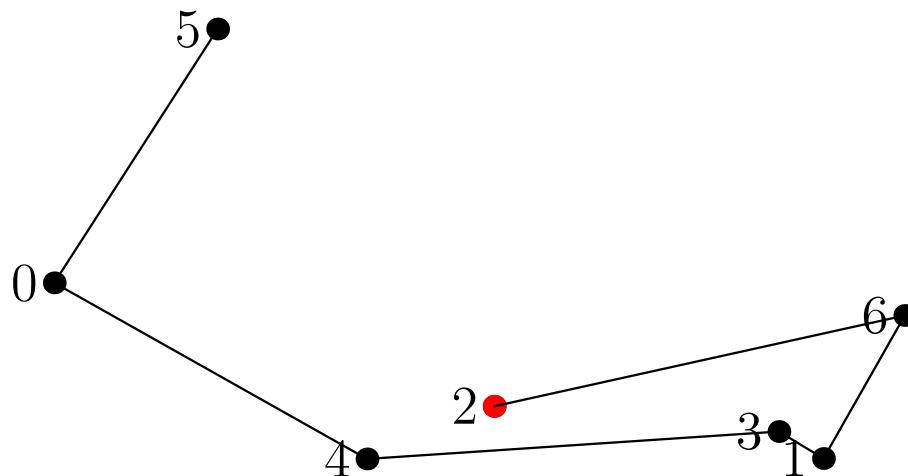
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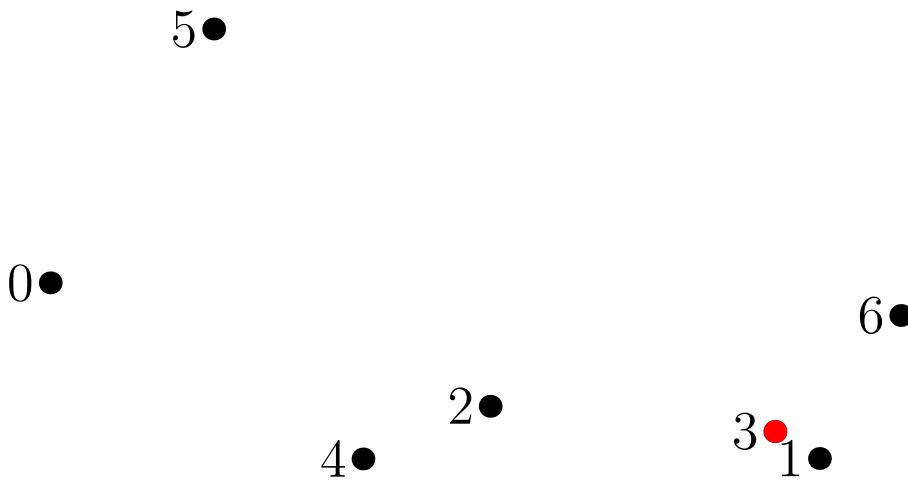
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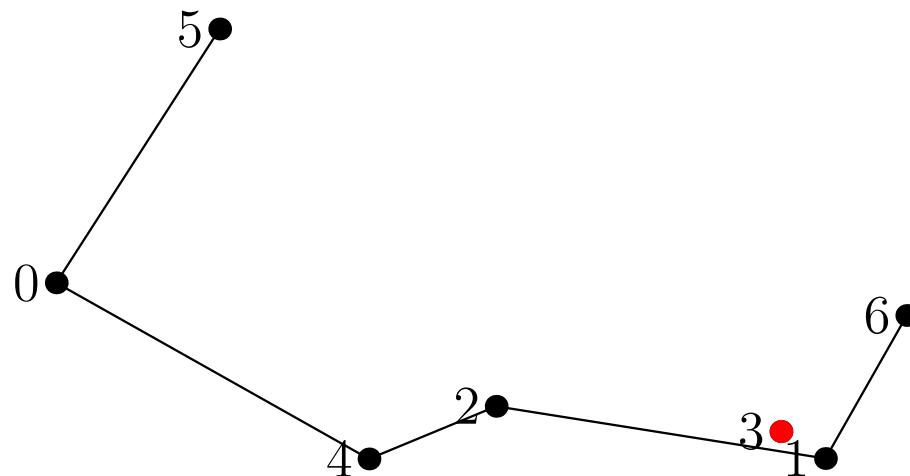
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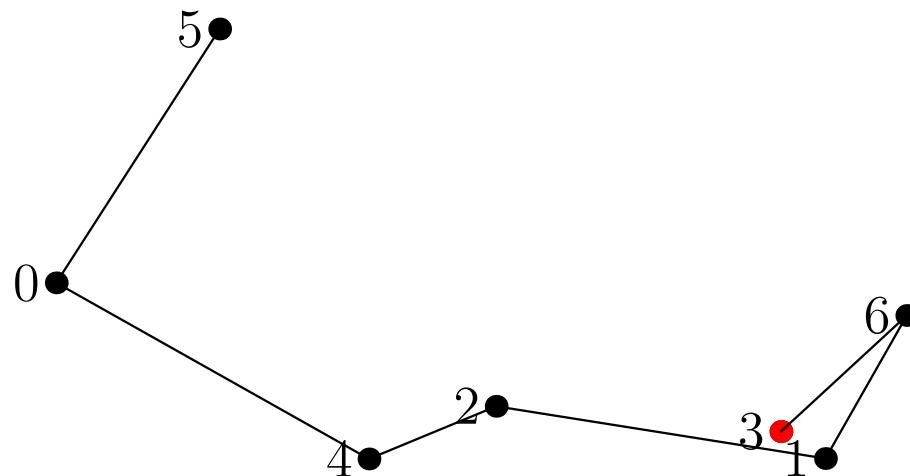
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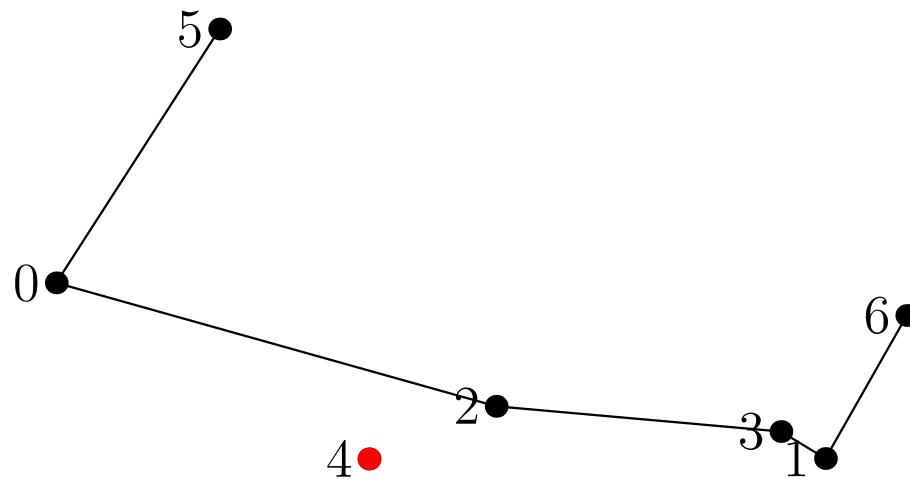
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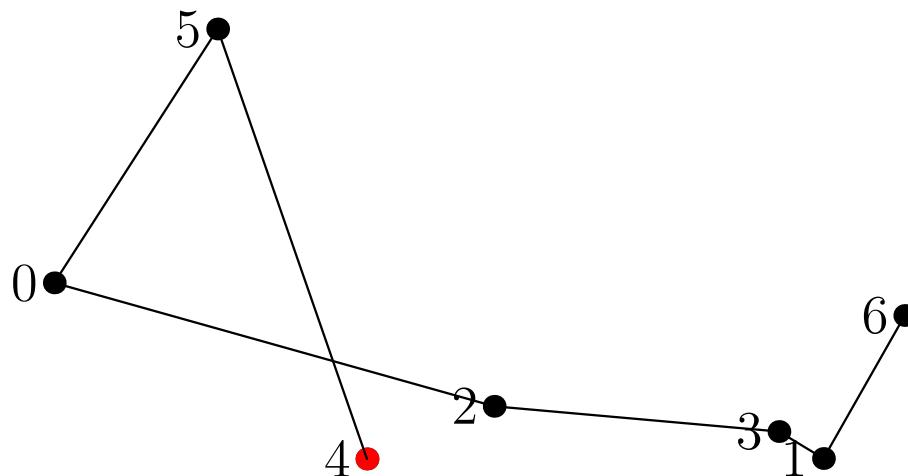
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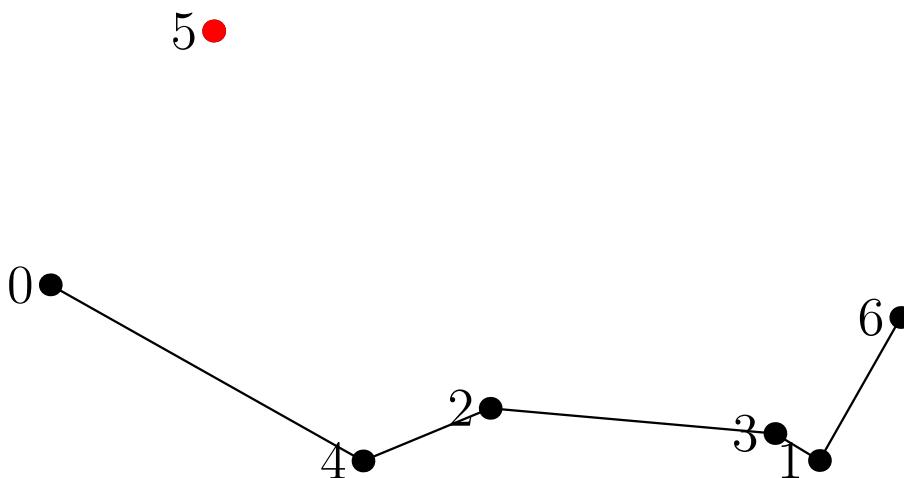
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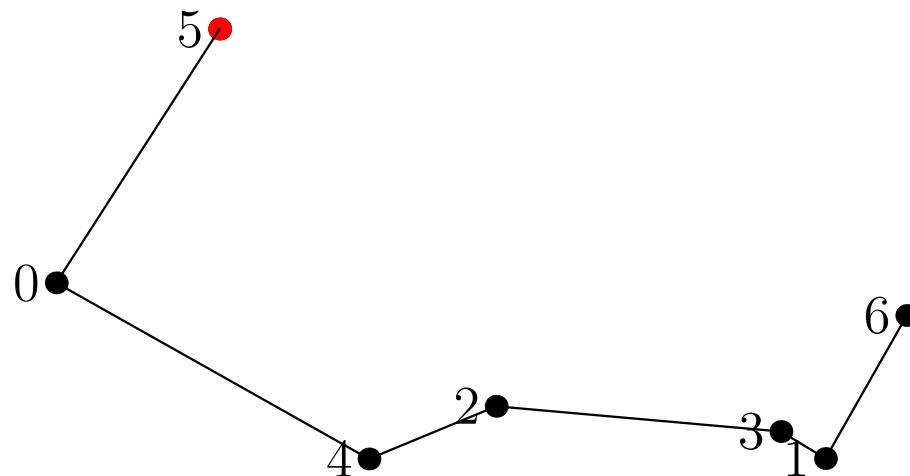
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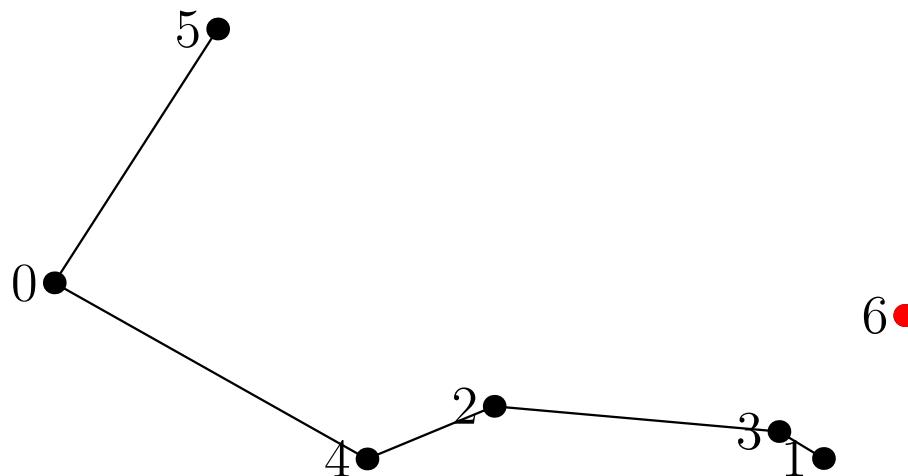
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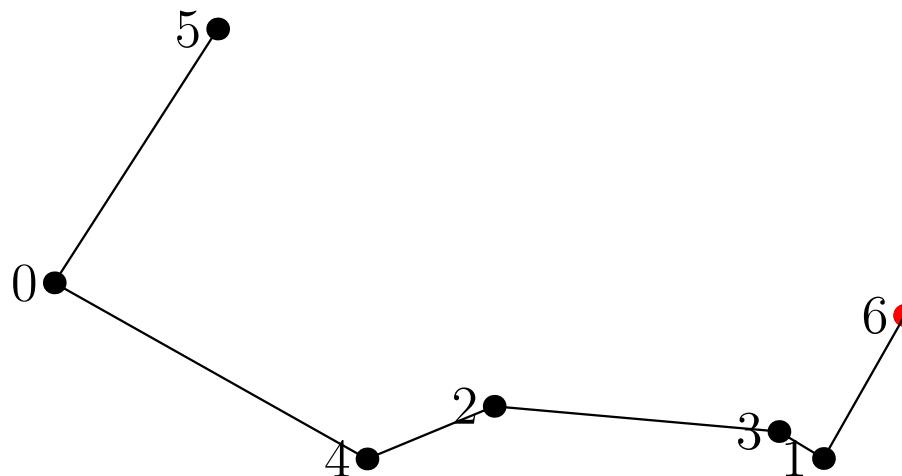
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- The problem is there are  $\binom{n}{k}$  subsets consisting of  $k$  cities out of a possible  $n$
- The total number of subsets that need to be considered is

$$\sum_{k=0}^n \binom{n}{k} = 2^n$$

- The time complexity of the DP solution is  $n^2 2^n$  which is better than  $n!$  and is currently the fastest known exact algorithm for TSP

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# Conclusions

- Dynamic programming is one of the most powerful strategies for solving hard optimisation problems
- It works by iteratively building up costs for partial solutions using the costs of smaller partial solutions
- When it works it is great and there are hosts of practical algorithms which use DP
- However, it doesn't always work

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