# Task Discussion Carsharing

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This task is based on the paper "Scheduling Transfers of Resources over Time: Towards Car-Sharing with Flexible Drop-Offs" by Kateřina Böhmová, Yann Disser, Matúš Mihalák and Rastislav Šrámek.

#### Problem Statement

#### ■ Given:

- A list of S rental stations with the number of initally available cars.
- A list of *N* car rental requests each with start and end time and location and its profit.
- Wanted: Find a feasible subset of the requests that maximizes the total profit.

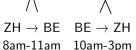
#### Subtasks:

- Only a single car
- 2 At most 20 requests
- 3 At most 10000 requests
- 4 Many different times
- 5 Many rental stations













 $ZH \rightarrow ZH$ 

4pm-9pm

# First Subtask: A Single Car

For a single car and only two stations, we can efficiently solve all the subproblems of the following form using **Dynamic Programming**:

What is the maximum profit if the car ends at stations s at time t?

Such a DP-table DP[s][t] has size  $2 \times \lceil 100'000/30 \rceil$  and can be filled quickly:

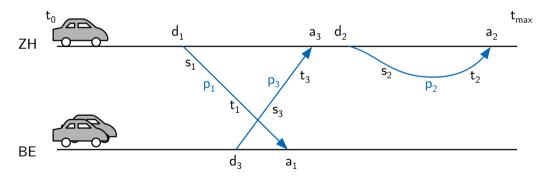
- initialize the cells with DP[s][0] = 0 and DP[s][t] = DP[s][t-1]
- for all requests r that end at time  $30 \cdot t$  at stations s: DP[s][t] = max(DP[s][t], DP[r.s][r.d/30] + r.p);
- final answer is max(DP[0][MAXT-1], DP[1][MAXT-1])

This solution does not easily generalize to multiple vehicles.

### Second Subtask: Min Cost Max Flow

Instead, let us model it as a flow problem:

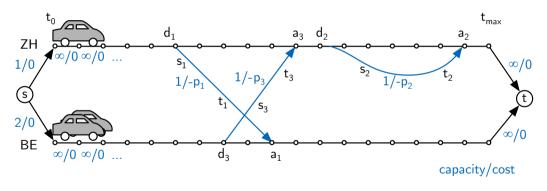
Every car is a unit of flow that flows through time and space.



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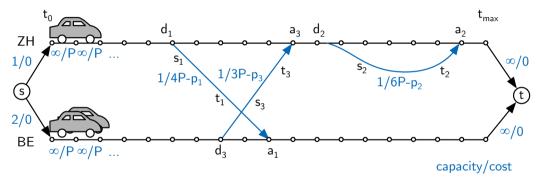
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Use cycle\_canceling to handle the negative weigths.

# Third Subtask: Handle more requests

The usual speedup problem: transform the graph to get non-negative weights so that we can use the faster Min Cost Max Flow algorithm.



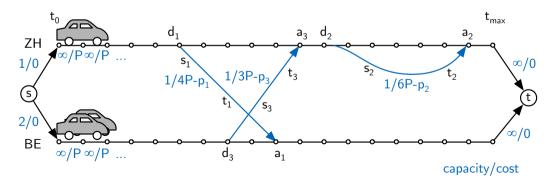
Add offset P (= the maximum profit per request) to every timestep. Note that every s-t-path encounters the same amount of P offsets.

# Fourth Subtask: Fine-grained time resolution

If the time resolution is 1 instead of 30 minutes, the graph gets 30 times bigger.

Note: At most 20'000 out of 200'000 vertices have degree > 2 at all.

We can compress these long paths and only create vertices for timesteps where some request starts or ends. This technique is often called *coordinate compression* and reduces the graph size roughly 10 times.

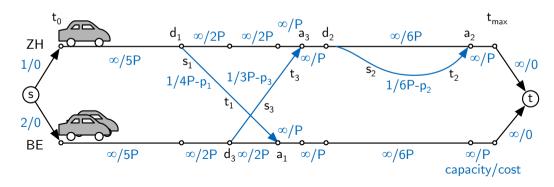


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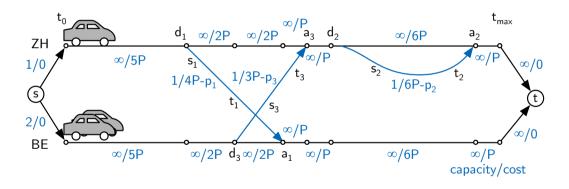
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# Fifth Subtask: Multiple Stations

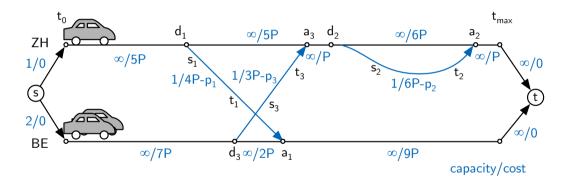
Compressing the coordinates per station reduces the graph size again S times.



Implementation detail: Use a std::map<int,int> per station to easily map the input times to their compressed coordinates and get the neighboring timestamps.

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