# Tutorial Problem Real Estate Market

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ETH Zürich

December 6, 2017

#### Input describing a big property sale:

- N bidders for M locations that each belong to one of S states
- $B = (b_{i,i})$ , the bid of bidder i for location j
- $\ell = (\ell_1, \dots, \ell_S)$ : limit on number of locations sold per state
- $s = (s_1, \ldots, s_M)$ : locations to state assignments

Question: How many sites can be sold and what is the maximum profit?

# 

■ 
$$N = 3$$
,  $M = 3$ ,  $S =$ 
■  $\ell = (2)$ ,  $s = (1, 1, 1)$ 
■  $B = \begin{pmatrix} 7 & 7 & 8 \\ 2 & 9 & 3 \\ 5 & 2 & 4 \end{pmatrix}$ 

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#### Example 1:

$$N = 3$$
  $M = 3$   $S = 1$ 

$$\ell = (3), s = (1, 1, 1)$$

#### Example 2:

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#### Example 3:

$$N = 3, M = 3, S = 2$$

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## First Steps

#### Look at the limits!

- *N*, *M* ≤ 100
- Bruteforcing all subsets is too slow.
- Greedy will probably not work.
- Can we formulate it as an LP? Or as a flow problem?

#### We formulate it as an integer linear program:

- $N \cdot M$  variables:  $x_{i,j} \in \{0,1\}$  $x_{i,j} = 1$  if and only if bidder i gets location j.
- Objective function: maximize  $\sum_{i,j} x_{i,j} \cdot b_{i,j}$ .
- Constraints:
  - At most one location per buyer:  $\forall i$ :  $\sum_{i} x_{i,j} \leq 1$ .
  - At most one buyer per location:  $\forall j \colon \sum_i x_{i,j} \leq 1.$ 
    - At most  $l_i$  sales per state:  $\forall k: \sum_{j \in \{j \mid s_i = k\}} \sum_i x_{i,j} \leq \ell_k$

Relax it to a linear program:  $x_{i,j} \in [0,1]$ .

#### Will it work?

It is not obvious why this relaxation works, i.e. why there is always an integer solution that achieves the maximum profit of the LP. (But it does as we will see.)

Will it be fast enough?

- $N \cdot M = 10'000$  variables.
  - $\sim$  1 minute per testcase )

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Will it be fast enough?

- $N \cdot M = 10'000$  variables. ⇒ It will be too slow. (≈ 1 minute per testcase.)
- So let us try something else.

#### Look at the first subtask!

- N = M, S = 1, ℓ₁ = N There is a location for every bidder. No other constraints from the states.
- $1 \le b_{i,j} \le 100$ No negative or zero bids. If we can sell more, we do sell more.
- ⇒ We will sell all *M* locations and "just" need to find the permutation that assigns the bidders to locations in the optimal way

- Very similar to the fruit delivery problem we saw in class.
- Only differences: supplies and demands are all 1 and maximum profit instead of minimum cost
- Formally: maximum weight perfect matching in a bipartite graph
- ⇒ Rephrase it as a MaxCostMaxFlow.

#### Look at the first subtask!

- N = M, S = 1,  $\ell_1 = N$ There is a location for every bidder. No other constraints from the states.
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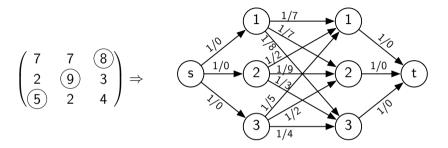
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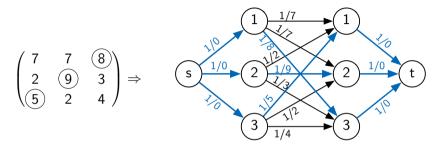
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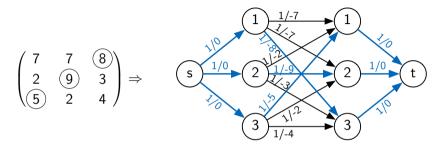
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- Negate all the costs to get a Min Cost Max Flow problem.
- Use cycle\_canceling() and get the 20 points for this subtask.



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How to incorporate the state legislations?

• Add an extra layer of vertices to the graph to limit the flow per state.

$$N = 3, M = 3, S = 2$$

$$\ell = (1, 1), s = (1, 2, 2)$$

$$B = \begin{pmatrix} 7 & 7 & 8 \\ 2 & 9 & 3 \\ 5 & 2 & 4 \end{pmatrix} \Rightarrow$$

$$N \qquad M \qquad S$$

$$1/7 \qquad 1/7 \qquad 1/9 \qquad 2/9 \qquad 1/9 \qquad 2/9 \qquad 1/9 \qquad 2/9 \qquad 1/9 \qquad 1/9$$

If you do this and submit, you will get the verdict CORRECT for the first four test cases and so score at least 80 points.

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#### Are we done?

Will we get 100 points? How can we find out before looking at the verdict of the last subtask?

- Our code takes 0.2s for subtask 4 where  $N \cdot M < 10^3$  holds.
- Timelimit is 0.5s and subtask 5 has limits of  $N \cdot M \le 10^4$ .
- Our code will be at least 10x slower on subtask 5, so it will be too slow.

submissions scoreboard problem overview logout

#### Submission details

Problem: Real Estate Market [AL1503]

Time limit: 0.5s Submitted: 16:47

Language: C++ & CGAL & BGL

Result: CORRECT

#### Results for each test-set

	Name	Result	Points	CPU Time
1	subtask1	CORRECT	20	0.142s
2	subtask2	CORRECT	20	0.26s
3	subtask3	CORRECT	20	0.122s
4	subtask4	CORRECT	20	0.207s
5	sample	CORRECT	0	0s

#### **Compilation output**

There were no compiler errors or warnings.

#### Can we use a faster algorithm or do we need a fundamentally different solution?

- successive\_shortest\_path\_nonnegative\_weights() faster but requires non-negative weights
- Next guestions: How can we use it and how much faster will it be?

- Recall the runtime bounds from the documentation:
  - cycle\_canceling():  $\mathcal{O}(C \cdot (nm))$
  - successive\_shortest\_path\_nonnegative\_weights():  $\mathcal{O}(|f| \cdot (m + n \log n))$
- Estimate the variables:
  - $n = N + M + S + 2 \approx 300, m = N \cdot M + N + M + S \approx 10'000.$
  - $C \le \max b_{i,j} \cdot \min(N, M) \le 10'000, |f| \le \min(N, M) \le 100$
- Get the rough estimates:
  - cycle canceling(): Order of  $10^{10} \Rightarrow \text{too slow}$
  - lacksquare successive\_shortest\_path\_nonnegative\_weights(): Order of  $10^6 \Rightarrow$  ok

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  - $n = N + M + S + 2 \approx 300, m = N \cdot M + N + M + S \approx 10'000.$
  - $C \le \max b_{i,j} \cdot \min(N, M) \le 10'000, |f| \le \min(N, M) \le 100$
- Get the rough estimates:
  - cycle\_canceling(): Order of  $10^{10} \Rightarrow too slow$
  - lacksquare successive\_shortest\_path\_nonnegative\_weights(): Order of  $10^6 \Rightarrow$  ok

Can we use a faster algorithm or do we need a fundamentally different solution?

- successive\_shortest\_path\_nonnegative\_weights()
  faster but requires non-negative weights
- Next questions: How can we use it and how much faster will it be?

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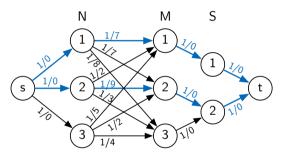
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#### How can we use it? How can we eliminate the negative weights?

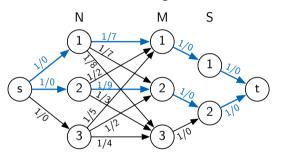
 $\blacksquare$  What if we add a constant  $\triangle$  to all the edges between bidders and locations?



- Every unit of flow uses exactly one edge that got more expensive.
- Total cost increases by  $|f| \cdot \Delta$  and the optimum matching does not change.
- If we set  $\Delta = \max b_{i,i}$  or  $\Delta = 100$ , we get non-negative costs.
- For the final result, we just subtract  $|f| \cdot \Delta$  from the costs that we got.

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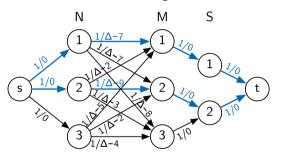
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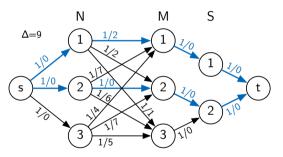
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If we submit again, we see that our program got roughly 10x faster and we have factor 25x left for the last subtask.

submissions scoreboard problem overview logout

#### **Submission details**

Problem: Real Estate Market [AL1503]

Time limit: 0.5s Submitted: 09:31

Language: C++ & CGAL & BGL

Result: CORRECT

#### Results for each test-set

	Name	Result	<b>Points</b>	<b>CPU Time</b>
1	subtask1	CORRECT	20	0.015s
2	subtask2	CORRECT	20	0.023s
3	subtask3	CORRECT	20	0.018s
4	subtask4	CORRECT	20	0.021s
5	sample	CORRECT	0	0s

#### **Compilation output**

There were no compiler errors or warnings.

## General Tips and Tricks

Use the public test sets, run and time your solution on them before you submit.

■ Pipe input/output from the files: (no need for copy/pasting)

```
$ time ./program < input.in > youroutput.out
    real 0m0.349s
    user 0m0.335s
    sys 0m0.009s
```

Use diff to check for mistakes: (no output = no mistake)

• One line to do it all: (quick way of running it on all the samples before submitting)

```
$ for f in *.in; do echo "--_{\sqcup}$f_{\sqcup}--"; time ./program < $f > ${f} \hookrightarrow %.*}.myout; diff ${f%.*}.out ${f%.*}.myout; done
```