

Formal Verification of the RANKING algorithm for Online Bipartite Matching

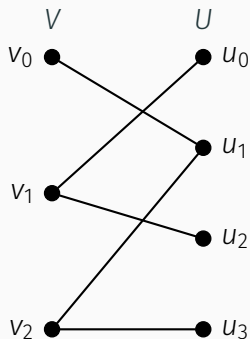
Christoph Madlener

22.06.2022

Online Bipartite Matching (OBM)

Input

- bipartite graph $G = (U, V, E)$



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- *bipartite* graph $G = (U, V, E)$
- *offline* vertices V are known

V
 v_0 ●

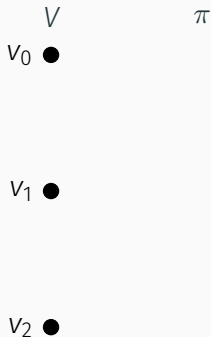
v_1 ●

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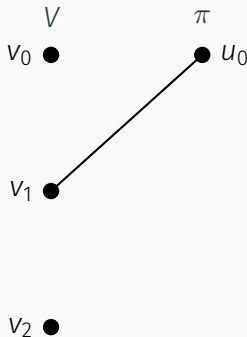
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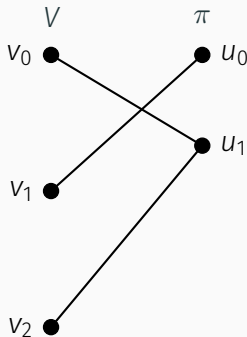
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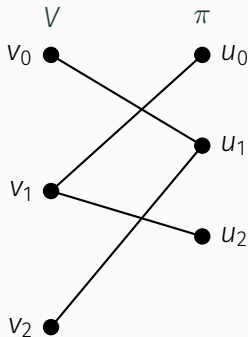
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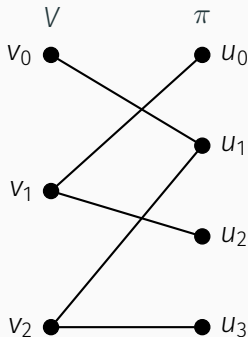
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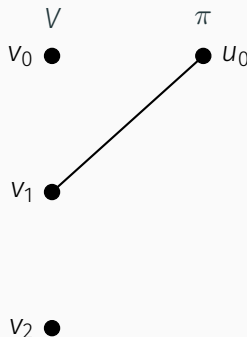
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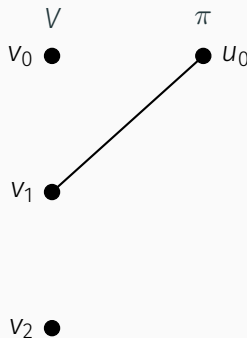
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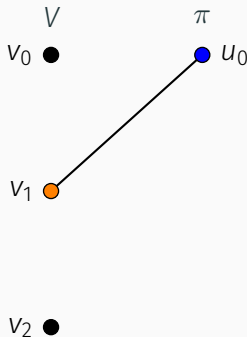
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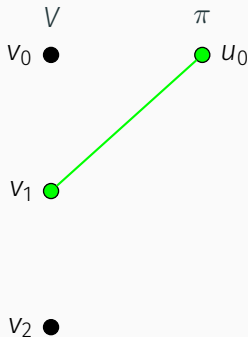
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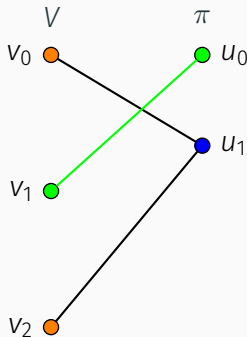
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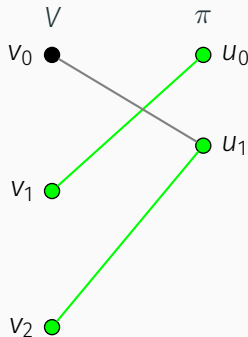
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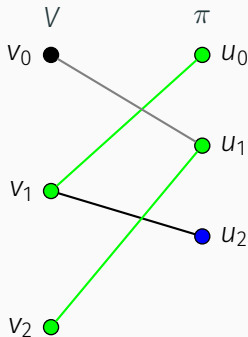
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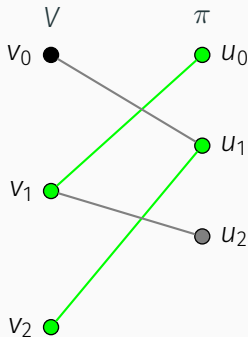
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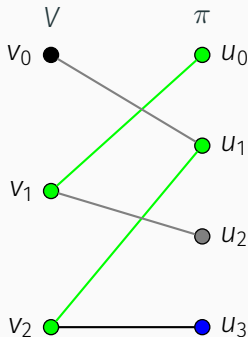
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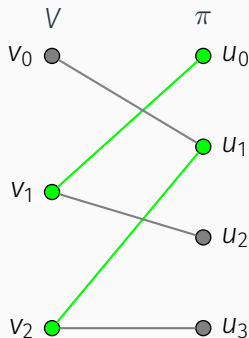
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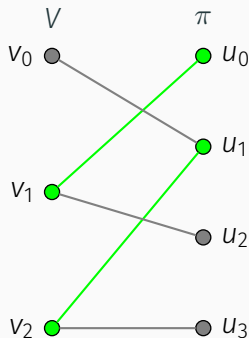
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Competitive Ratio

Performance of online algorithm \mathcal{A}

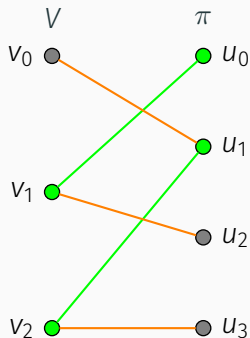
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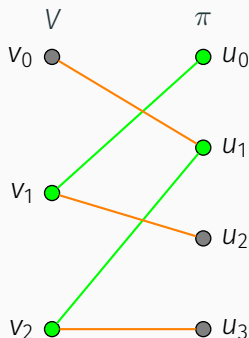
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Competitive ratio for OBM

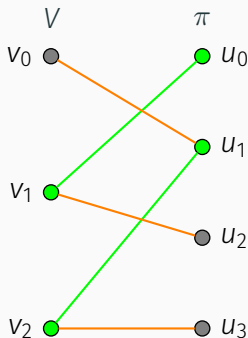
$$\min_G \min_{\pi} \frac{|\mathcal{A}(G, \pi)|}{|M|}$$

where M is a maximum cardinality matching in G .

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Competitive ratio for OBM

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V π
 v_0 ●

Initialization: Choose a random permutation
(ranking) σ of V

v_1 ●

Online Matching:

On arrival of $u \in U$

v_2 ●

$N(u) \leftarrow$ set of unmatched neighbors of u

if $N(u) \neq \emptyset$

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v_3 ●

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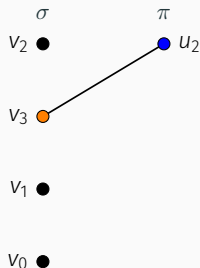
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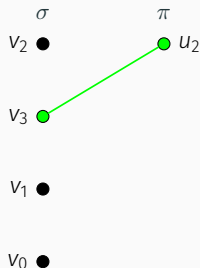
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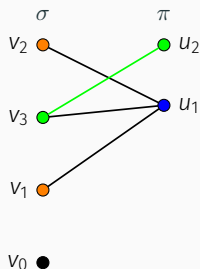
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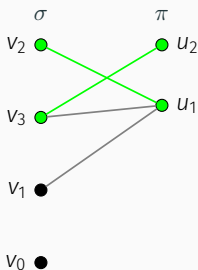
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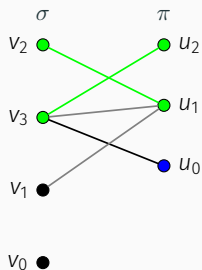
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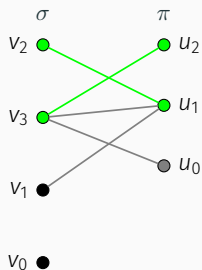
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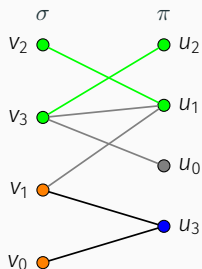
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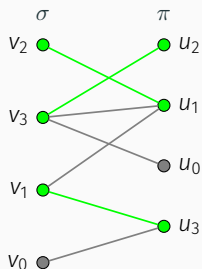
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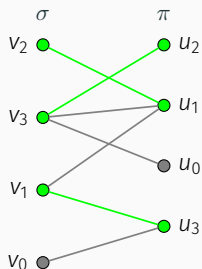
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- competitive ratio of $1 - \frac{1}{e}$ (best possible)

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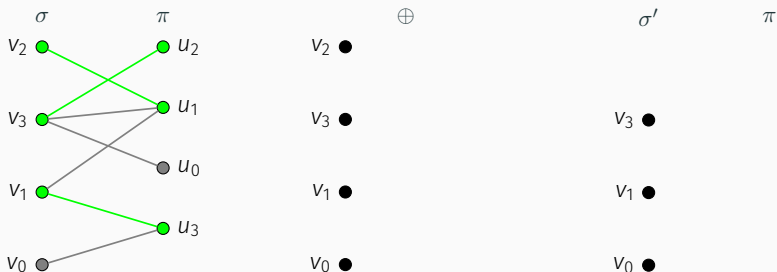
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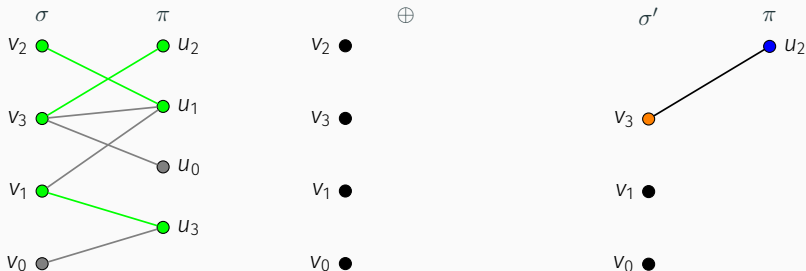
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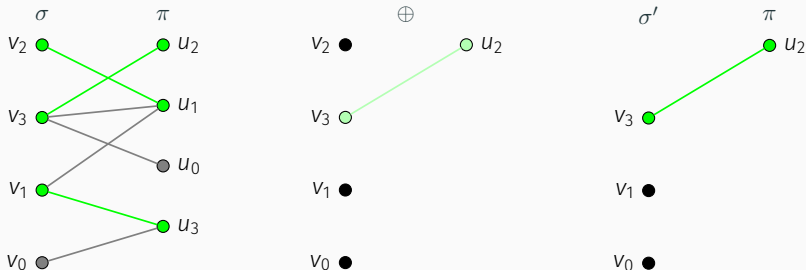
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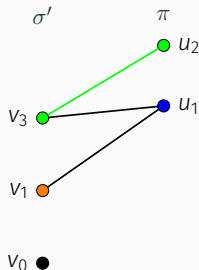
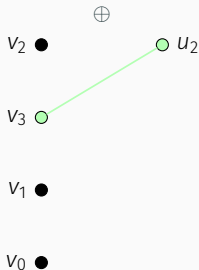
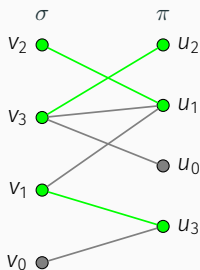
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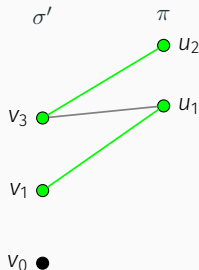
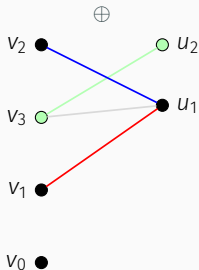
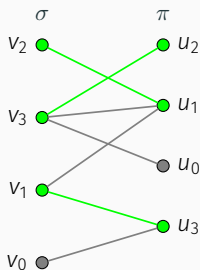
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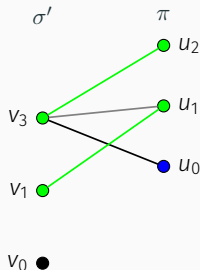
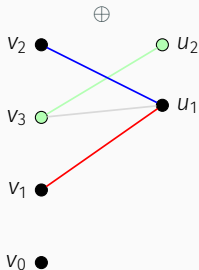
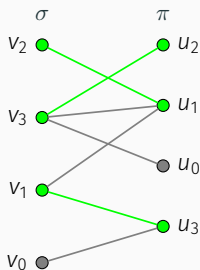
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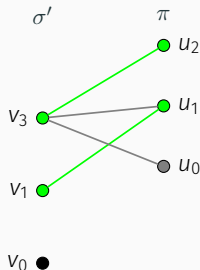
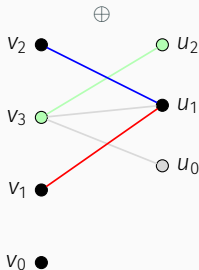
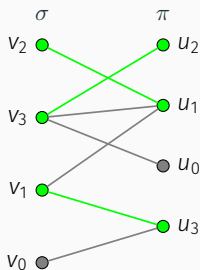
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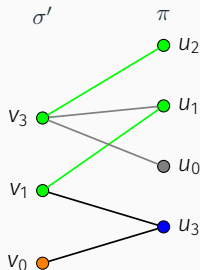
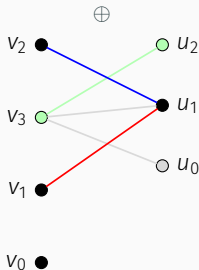
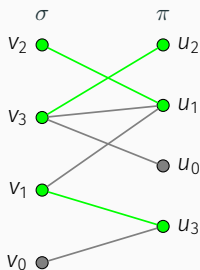
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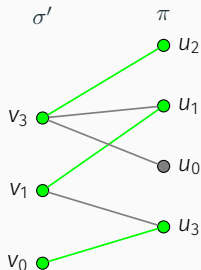
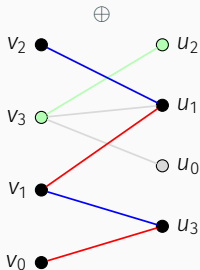
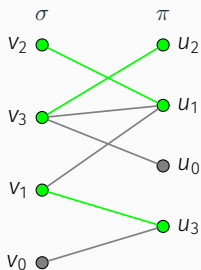
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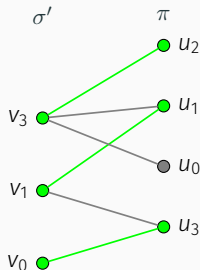
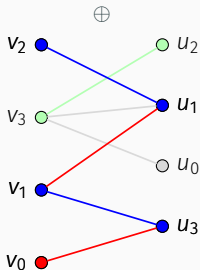
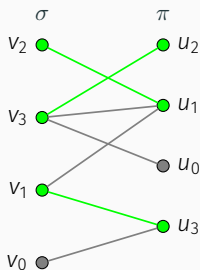
Reducing Analysis to Graphs with Perfect Matching

- original paper (and earlier simplifications) assume G has a perfect matching
- Birnbaum & Mathieu state a *simple structural observation* which allows to generalize to arbitrary graphs:

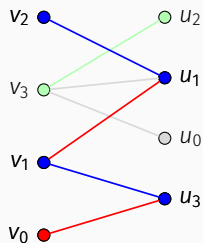


Reducing Analysis to Graphs with Perfect Matching

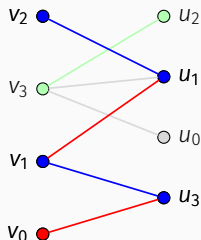
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First proof of a *simple structural observation*



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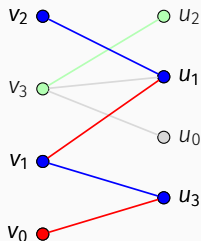
Let $R := \text{Ranking}(G, \pi, \sigma)$ for a fixed graph G , arrival order π , and ranking σ .

Specification of alternating path

$$\text{zig}(x) = \begin{cases} x \# \text{zag}(y) & \{x, y\} \in R \\ [x] & x \text{ unmatched} \end{cases}$$

$$\text{zag}(y) = \begin{cases} y \# \text{zag}(x') & x' \text{ matched instead} \\ [y] & \text{no other match} \end{cases}$$

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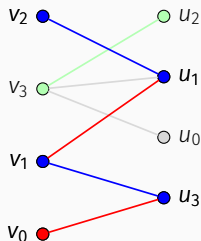
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- Berge's Lemma [AMN19] for repeated application

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- rephrase everything as $_p m f$ (probability mass function)

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For $t = 1$ and $V = \{1, 2, 3\}$:

$$\mathbb{P}_1(\{[3, 2, 1]\}) = \frac{1}{3!}$$

$$\begin{aligned}\mathbb{P}_2(\{[3, 2, 1]\}) &= \mathbb{P}_1(\{[2, 3, 1], [3, 1, 2], [3, 2, 1]\}) \cdot \mathbb{P}_V(\{2\}) \\ &= \frac{3}{3!} \cdot \frac{1}{3} = \frac{1}{3!}\end{aligned}$$

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