PREDICTING THE EFFECTIVENESS OF BIDIRECTIONAL HEURISTIC SEARCH

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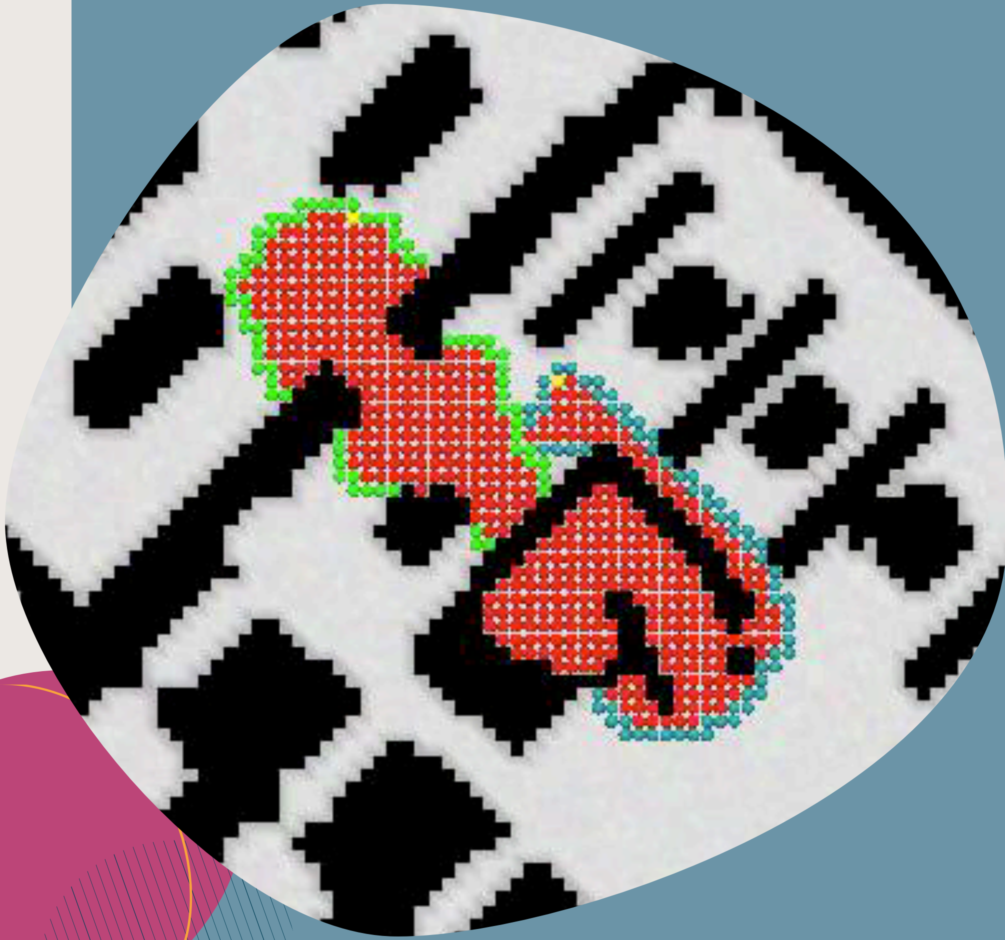
BIDIRECTIONAL SEARCH

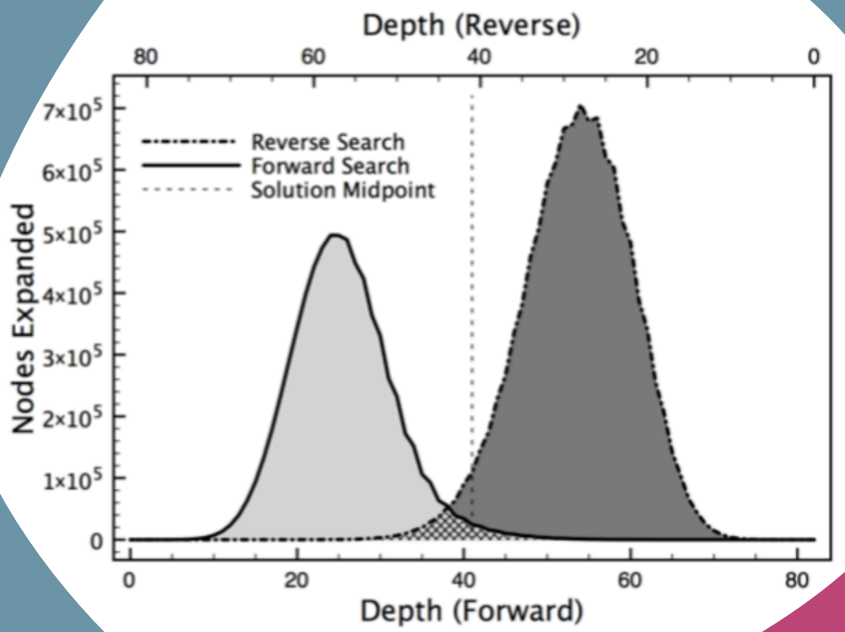
Q: When does bidirectional (heuristic) search perform well?

A: Performance of bidirectional search is positively correlated with the number of states that have heuristics that are both low and inaccurate.



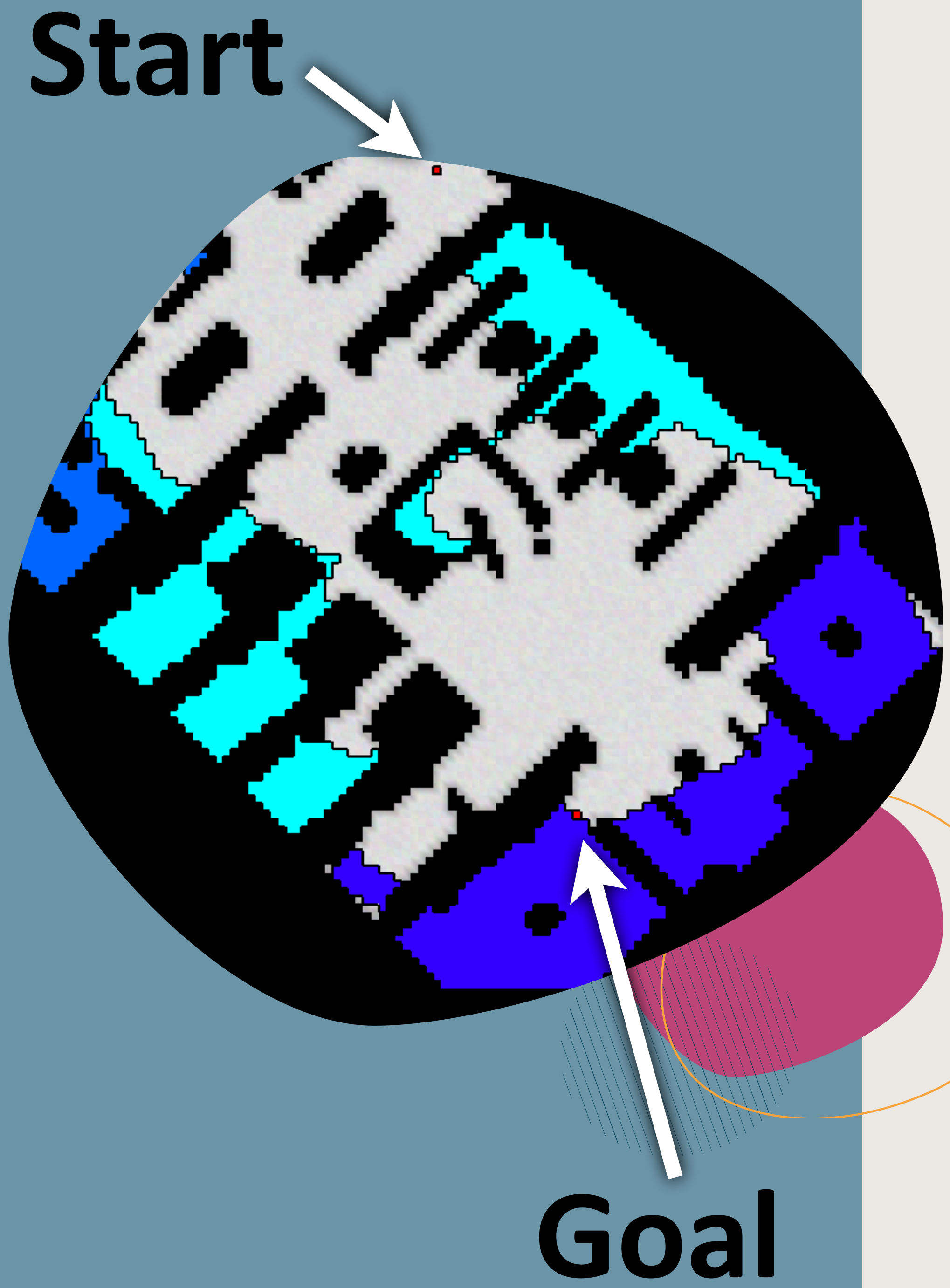
Caveat: Not enough time in talk to be completely precise.

BARKER AND KORF (2015)



A strong heuristic expands a majority of the states in the first half of the search.

BK2: Unidirectional search outperforms bidirectional search with a strong heuristic.



HOLTE ET AL (2017)

MM is guaranteed to meet in the middle.

If |FF| > |RN|, A* will expand more states than MM if the heuristic is weak, fewer if the heuristic is accurate.

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ECKERLE ET AL (2017)

Theorem 6. *Let $I = (G, h_F, h_B) \in I_{CON}$ have an optimal solution cost of C^*. If U is an optimal forward path and V is an optimal backward path such that $U_0 = start$, $V_0 = goal$, and:*

(1) $f_F(U) < C^*$
(2) $f_B(V) < C^*$
(3) $c(U) + c(V) < C^*$

then, in solving problem instance I, any admissible DXBB bidirectional front-to-end search algorithm must expand $(end(U), end(V))$.

Front-to-end bidirectional search

- admissible heuristic

- not necessarily consistent

Corresponds to finding a minimum vertex cover on a bipartite graph

ECKERLE ET AL (2017)

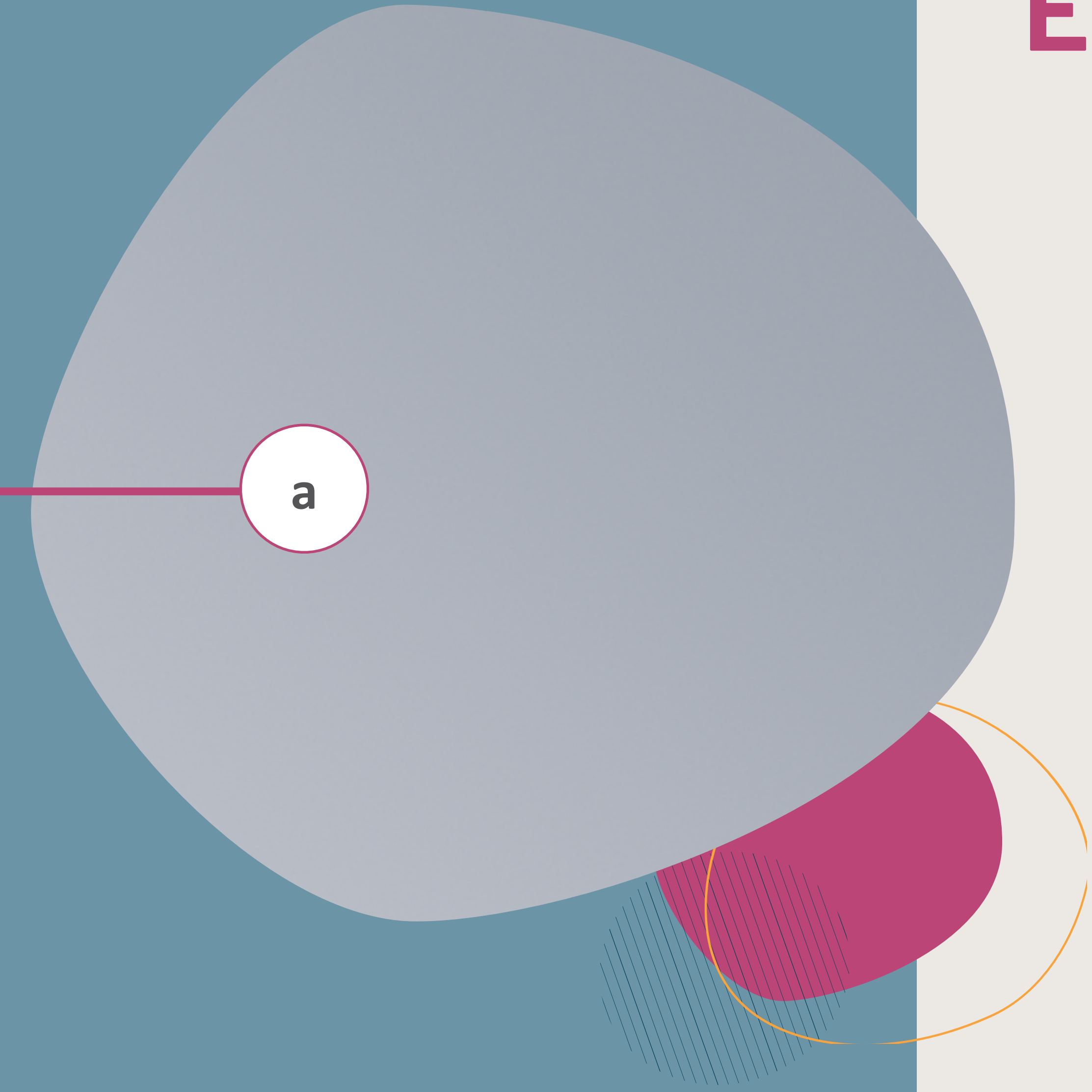
Necessary expansions for a pair of states:

$f_f(a) < C^*$

$f_b(b) < C^*$

$g_f(a) + g_b(b) < C^*$

ECKERLE ET AL (2017)



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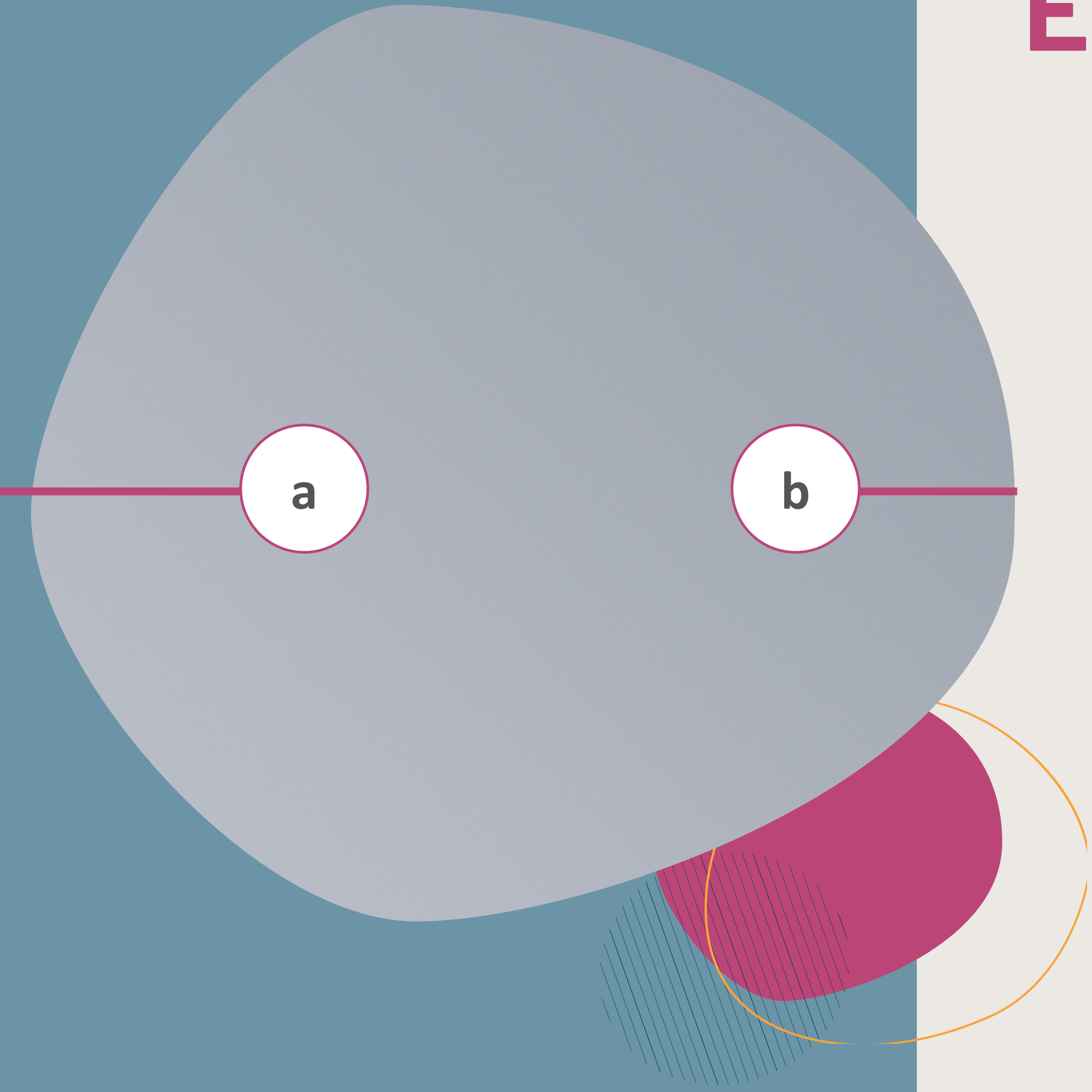

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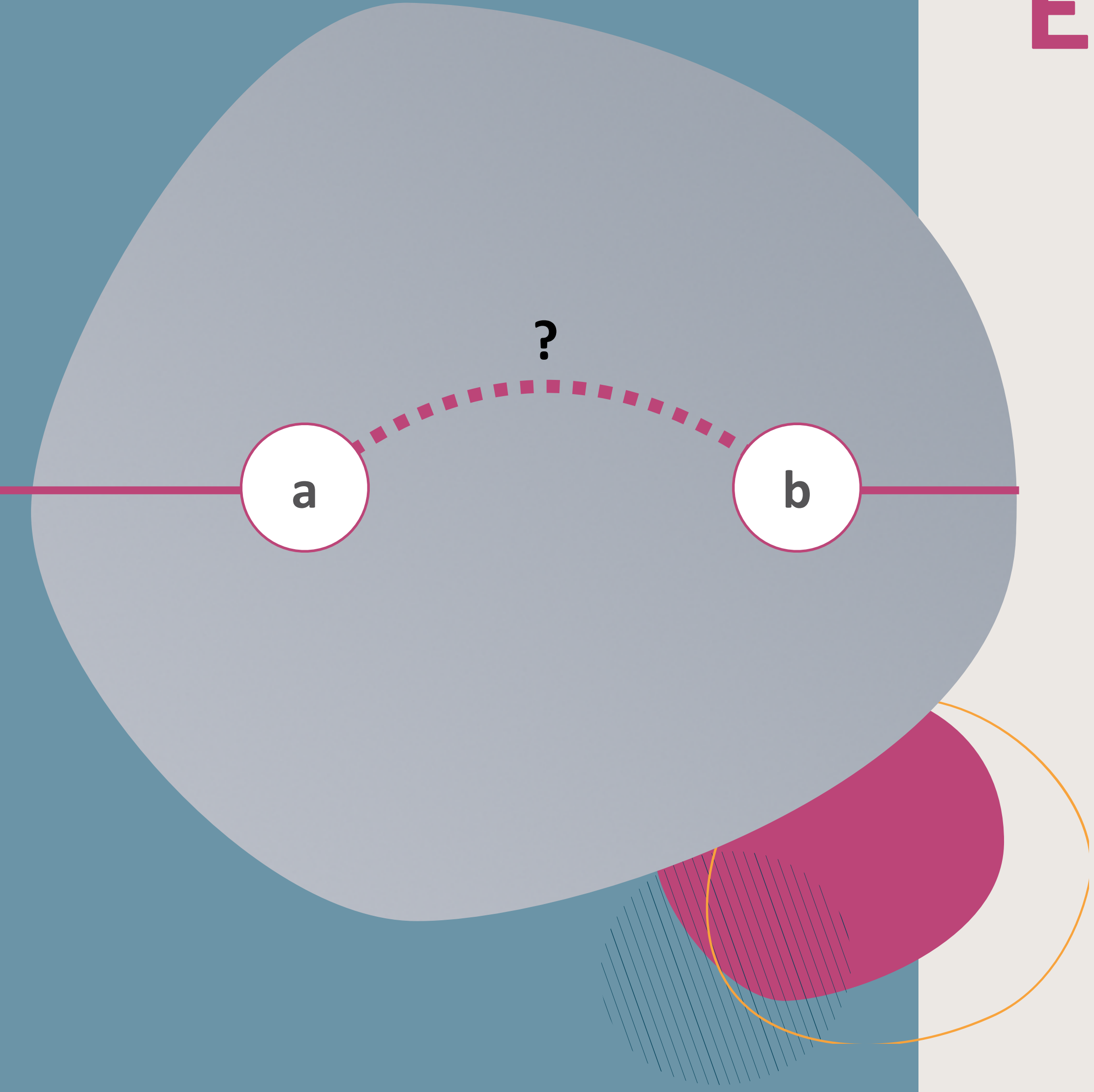
ECKERLE ET AL (2017)



Necessary expansions for a pair of states:

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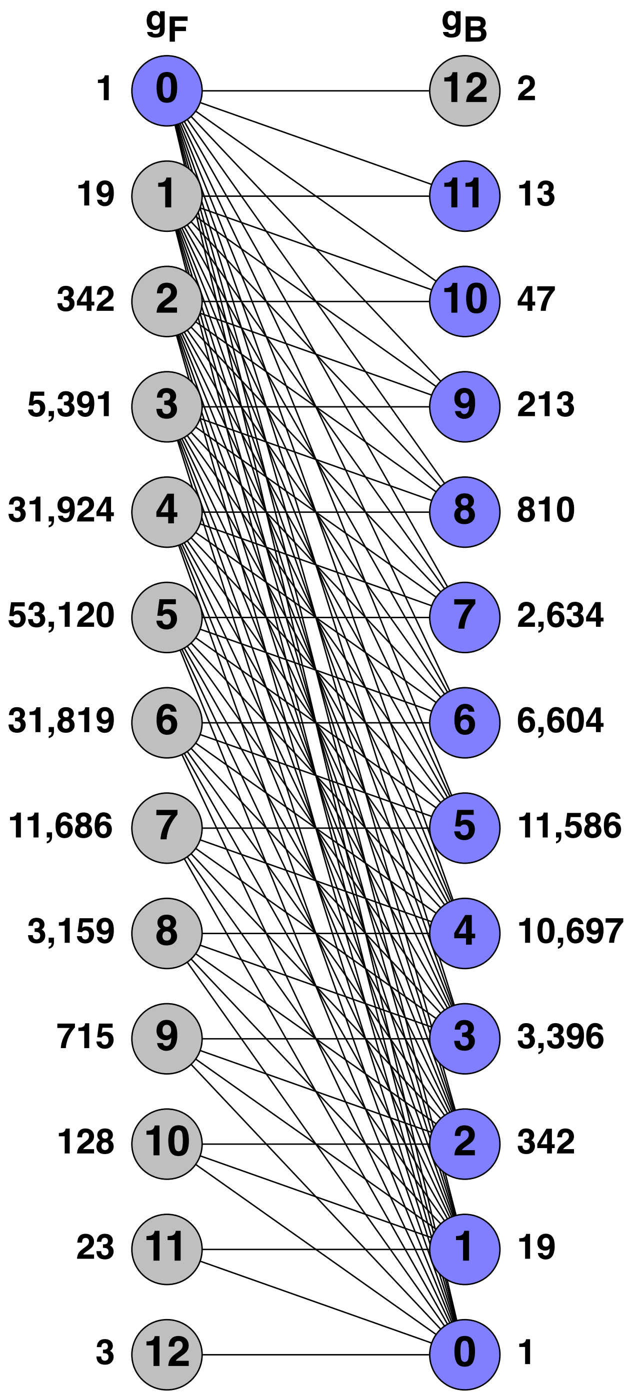
$g_f(a) + g_b(b) < C^*$

C* = 13

EXPLANATION



$C^* = 13$

EXPLANATION

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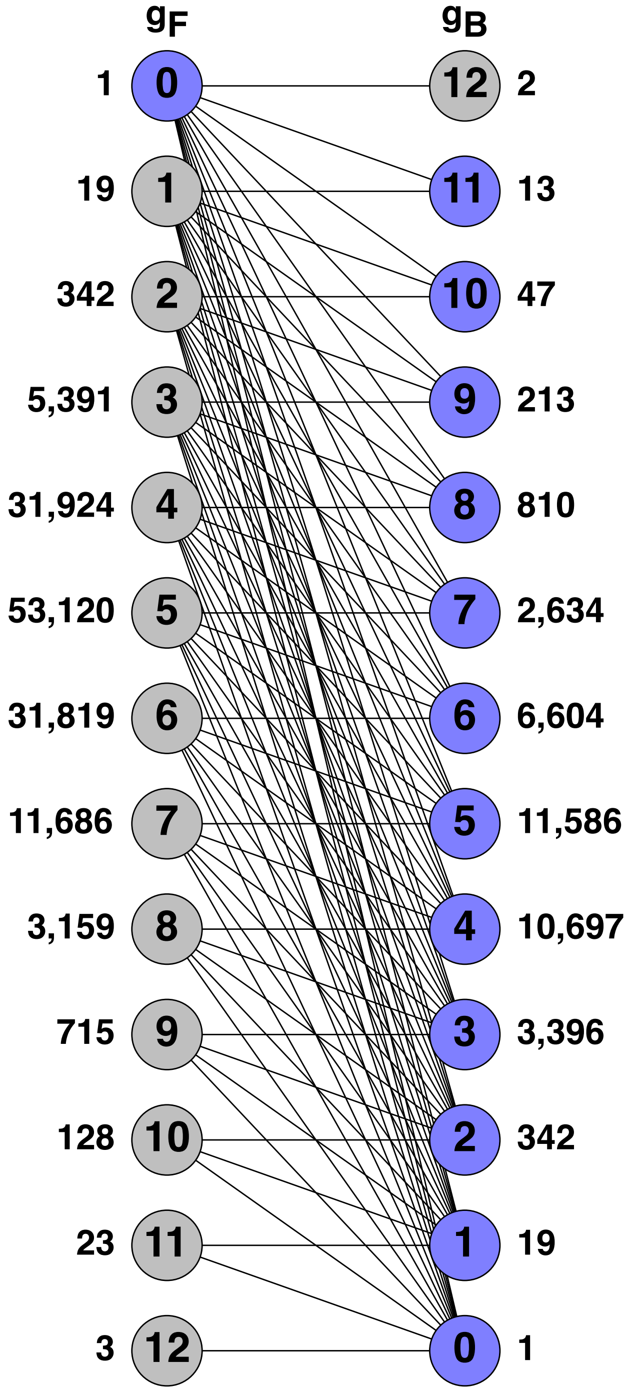

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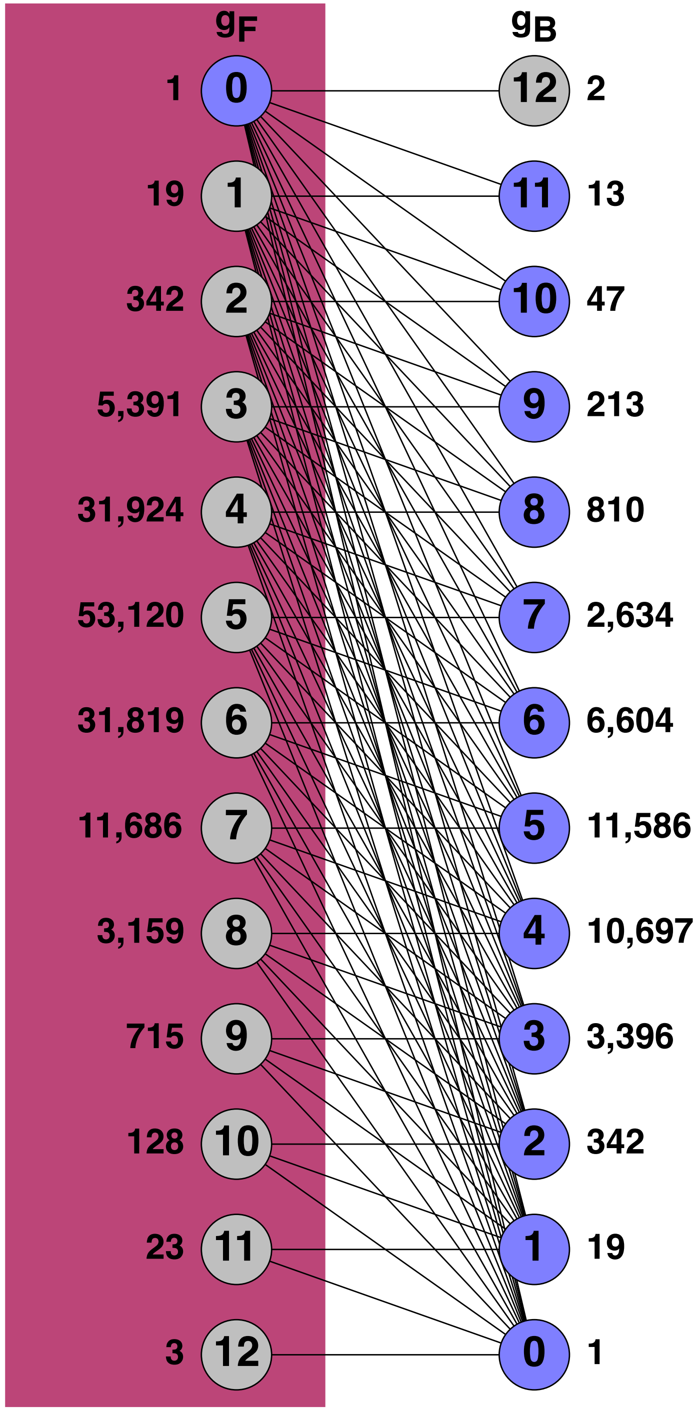

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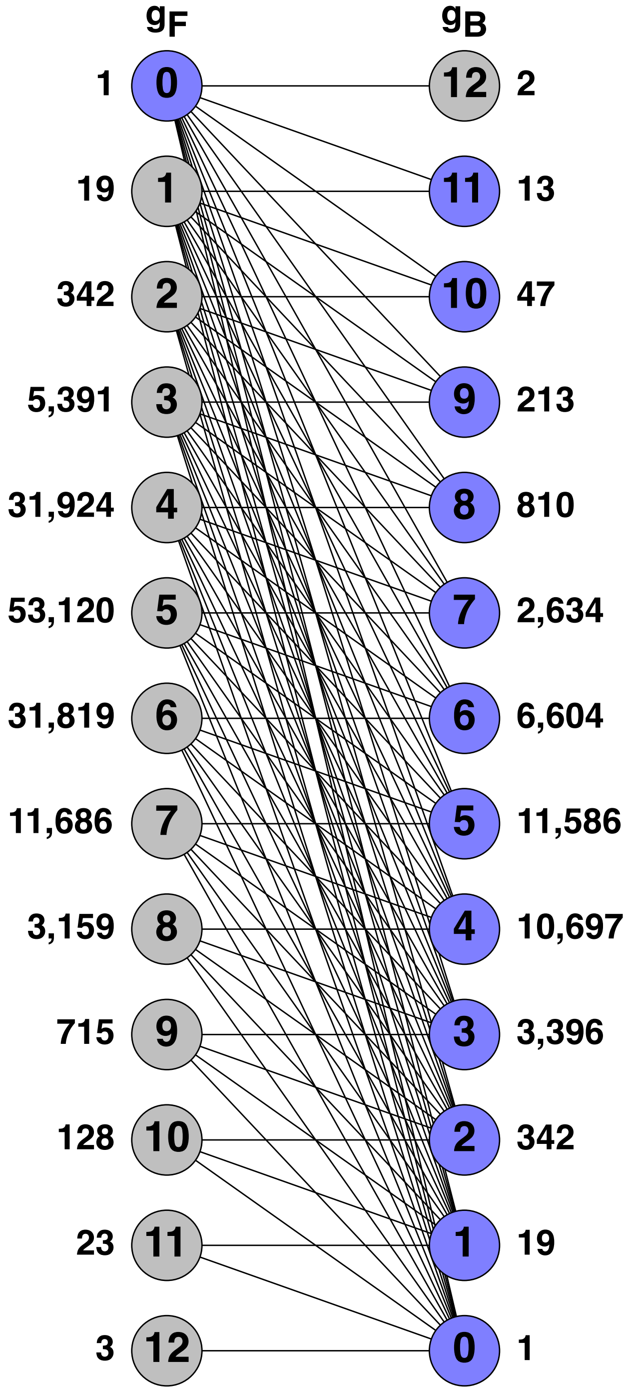

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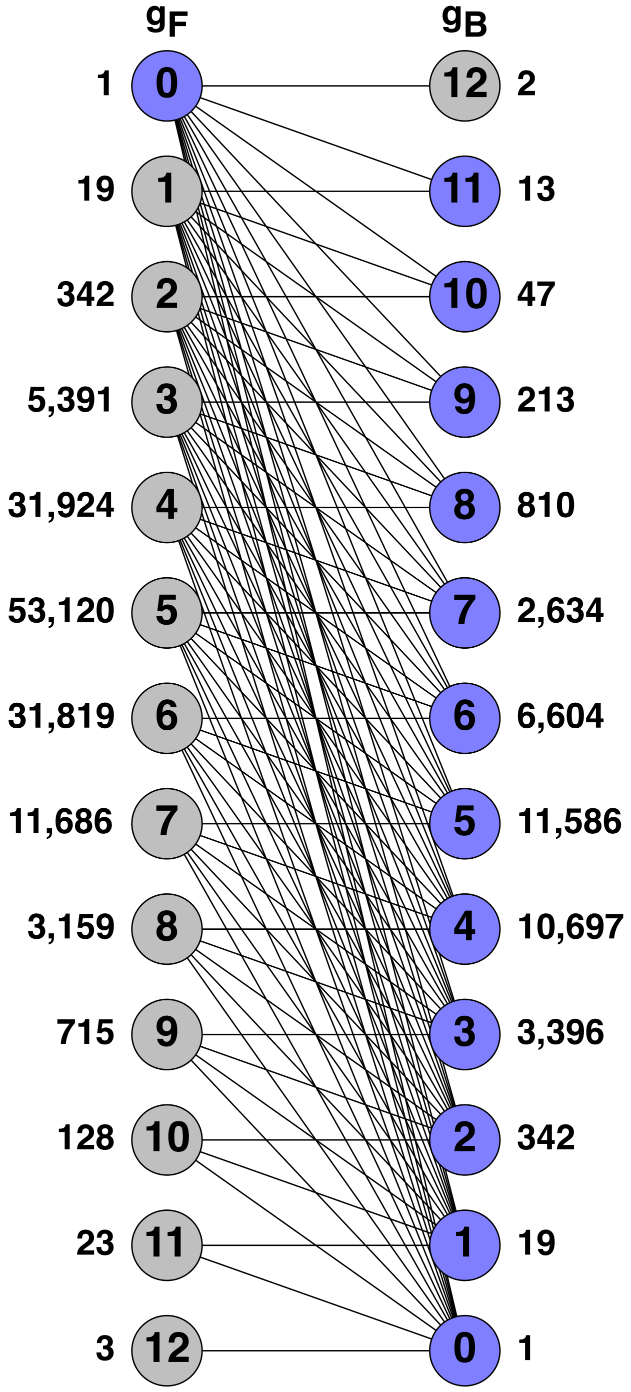
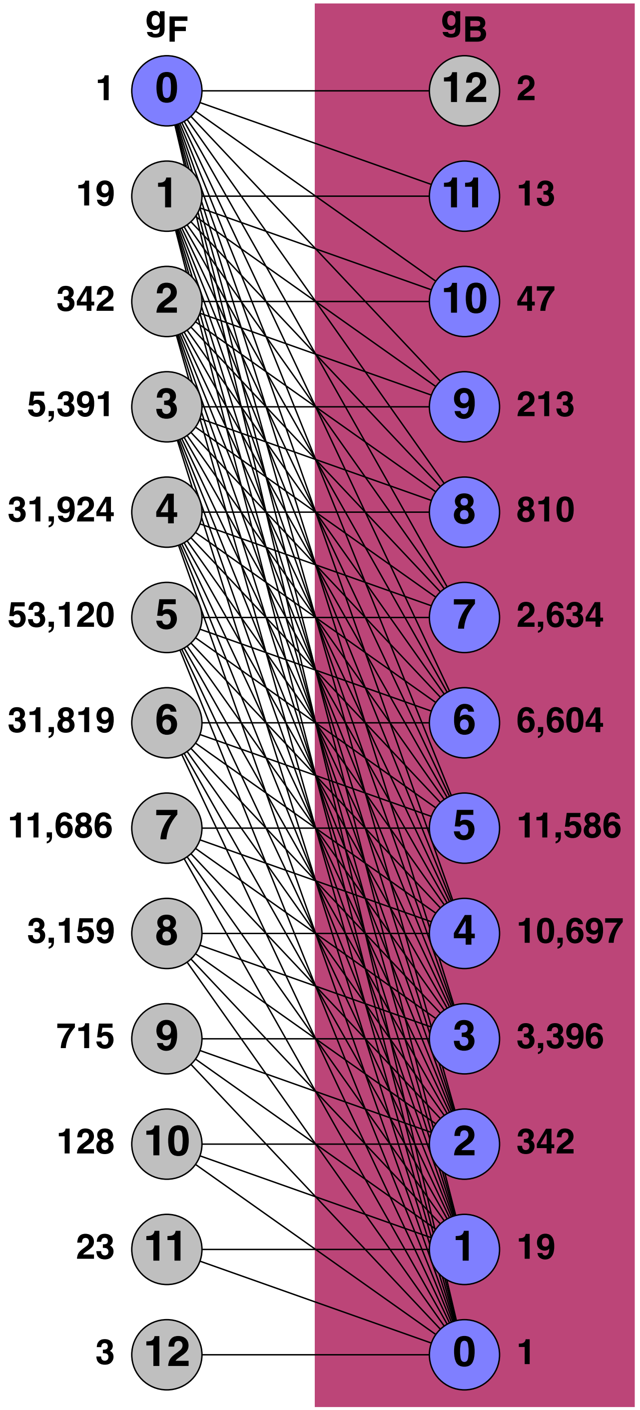


$f_b < C^*$

$C^* = 13$

EXPLANATION

$f_f < C^*$



$f_b < C^*$

EXPLANATION

$C^* = 13$

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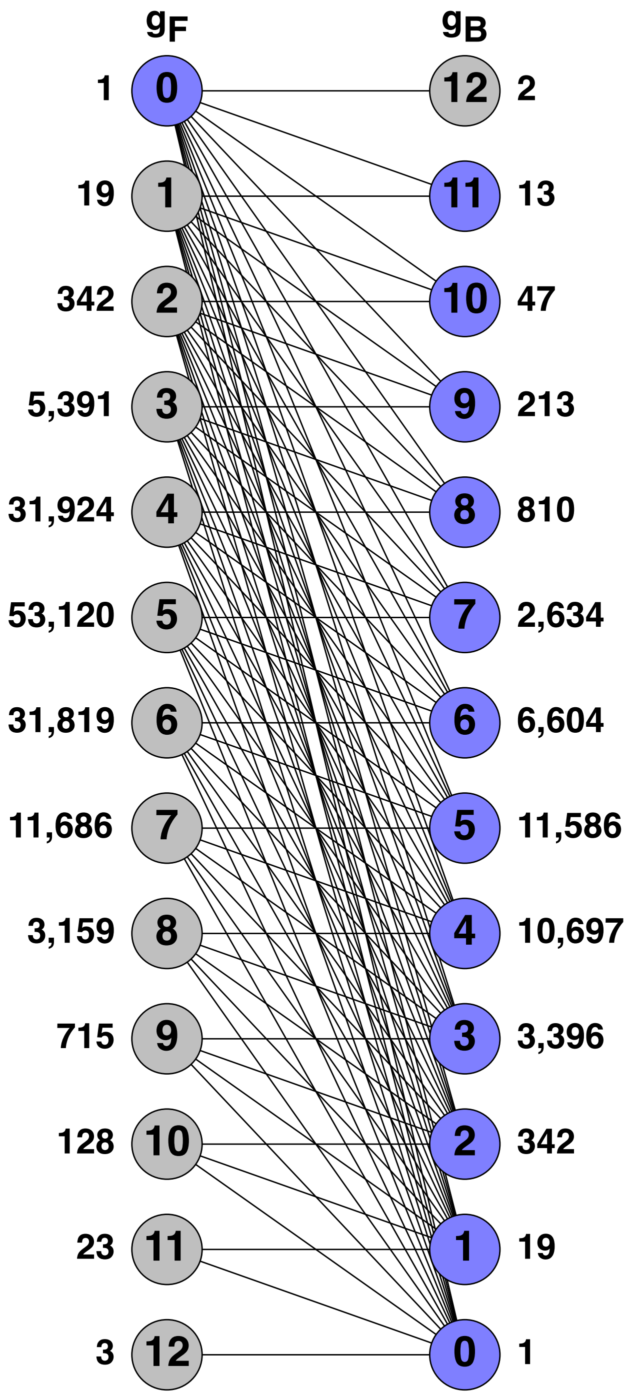

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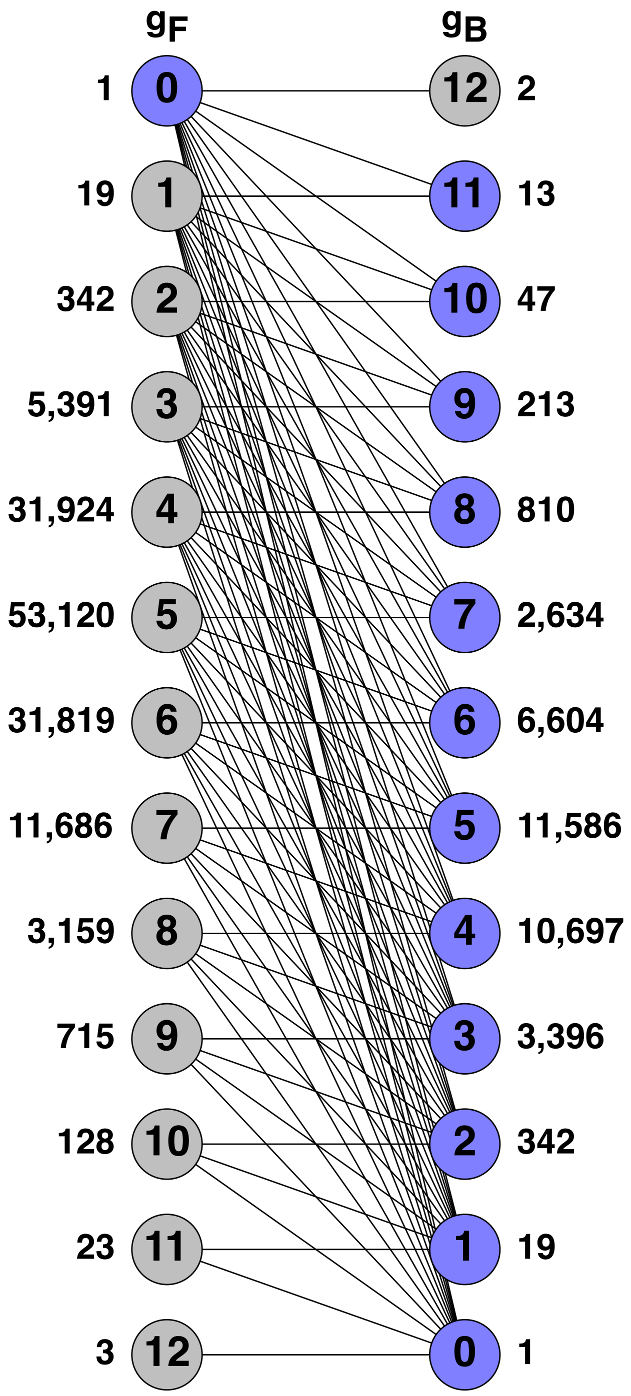
$C^* = 13$

EXPLANATION



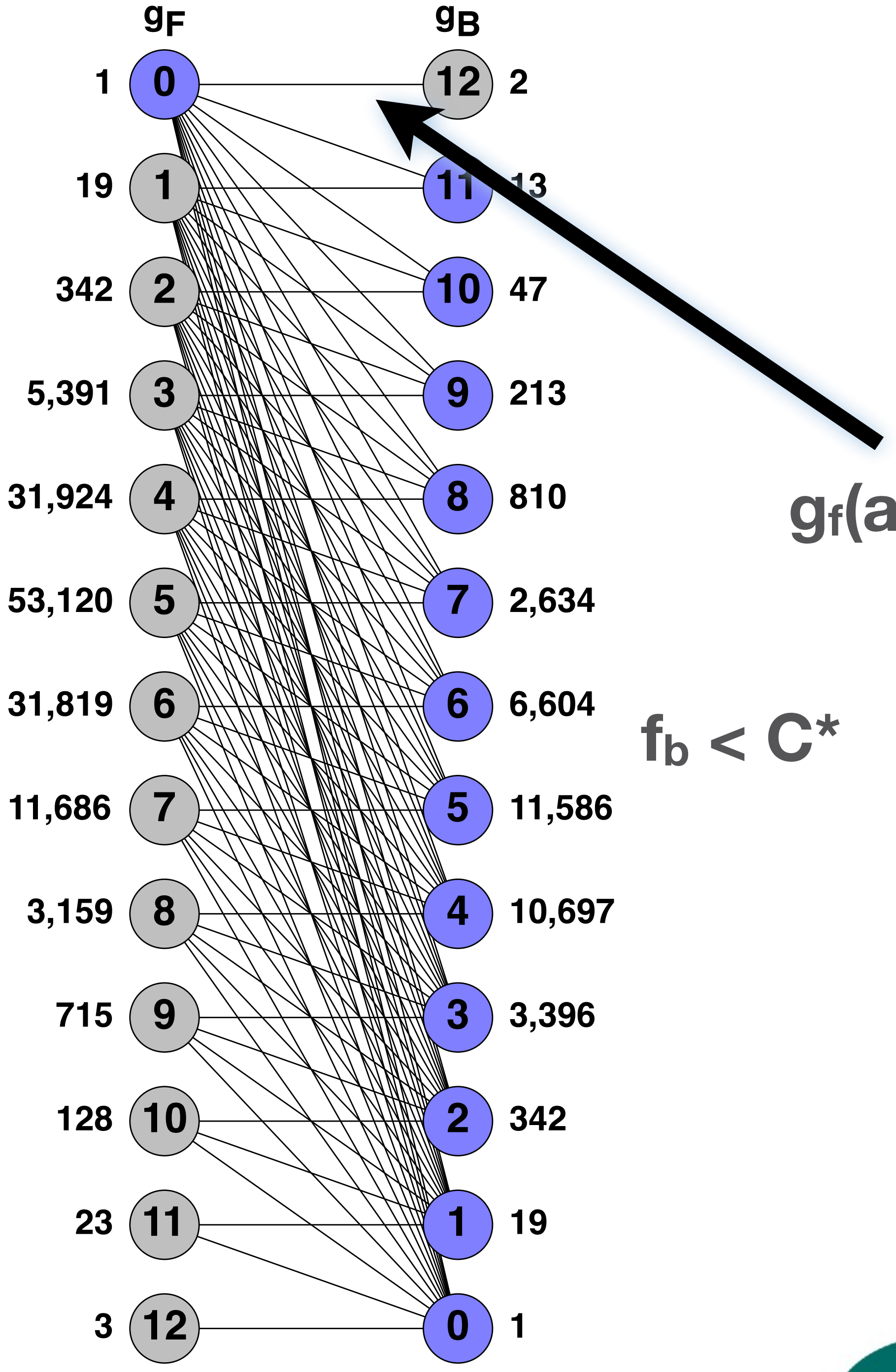
$f_f < C^*$

$g_f(a) + g_b(b) < C^*$

$f_b < C^*$

EXPLANATION

$C^* = 13$



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$f_f < C^*$

$f_b < C^*$

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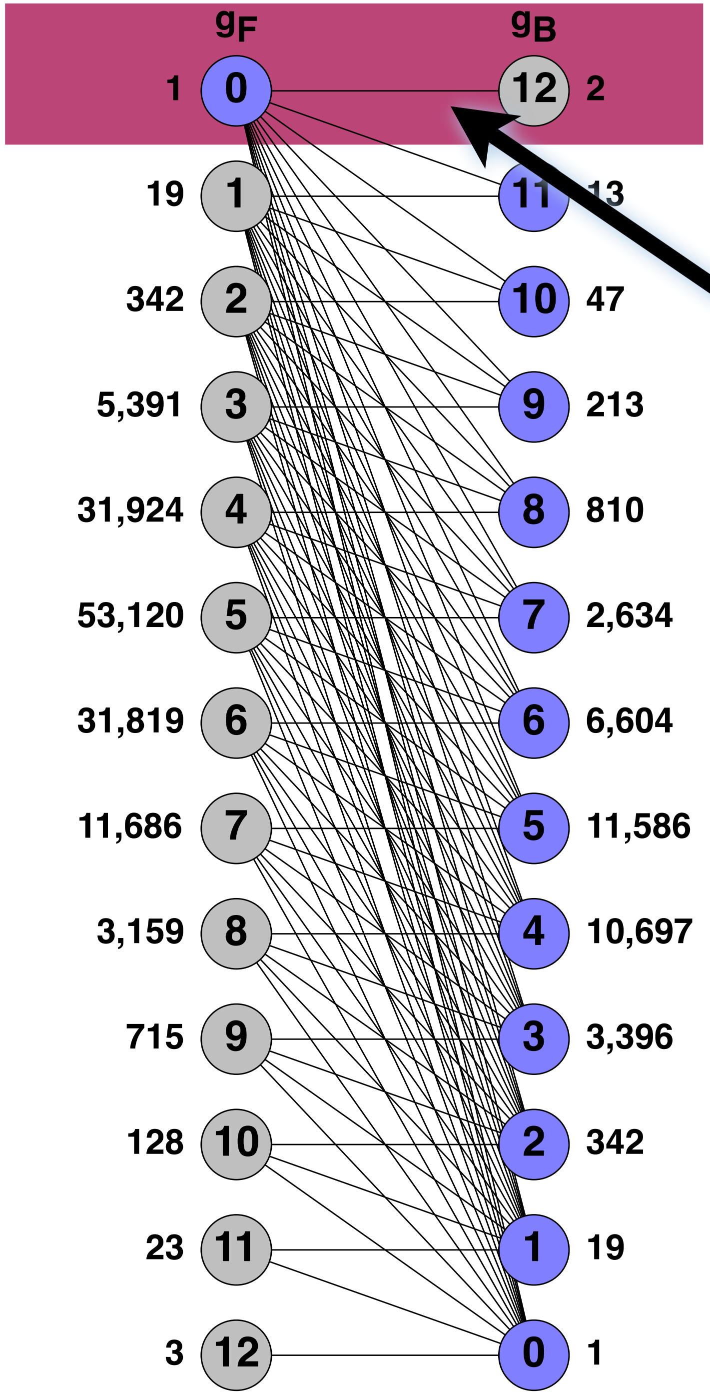

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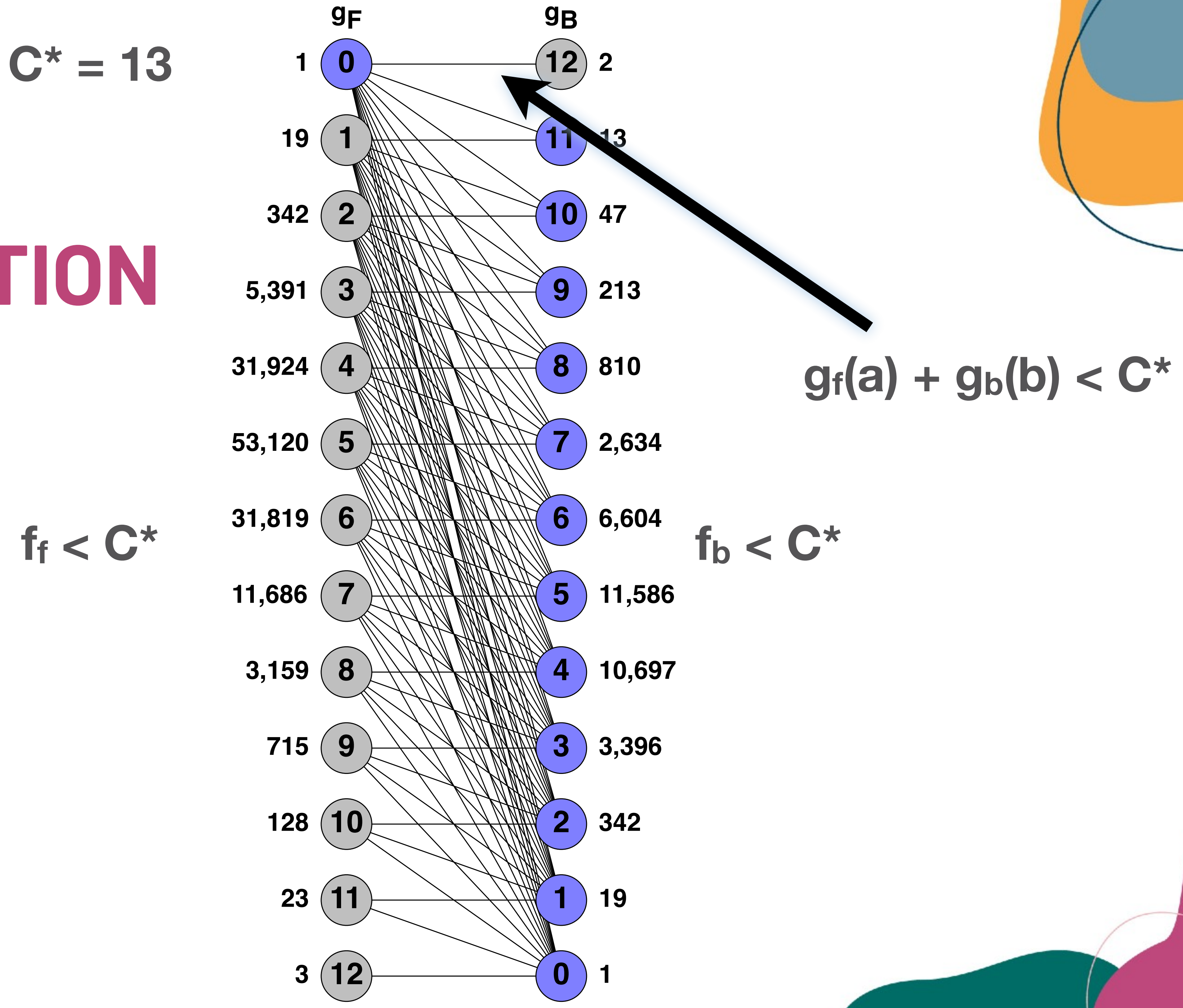

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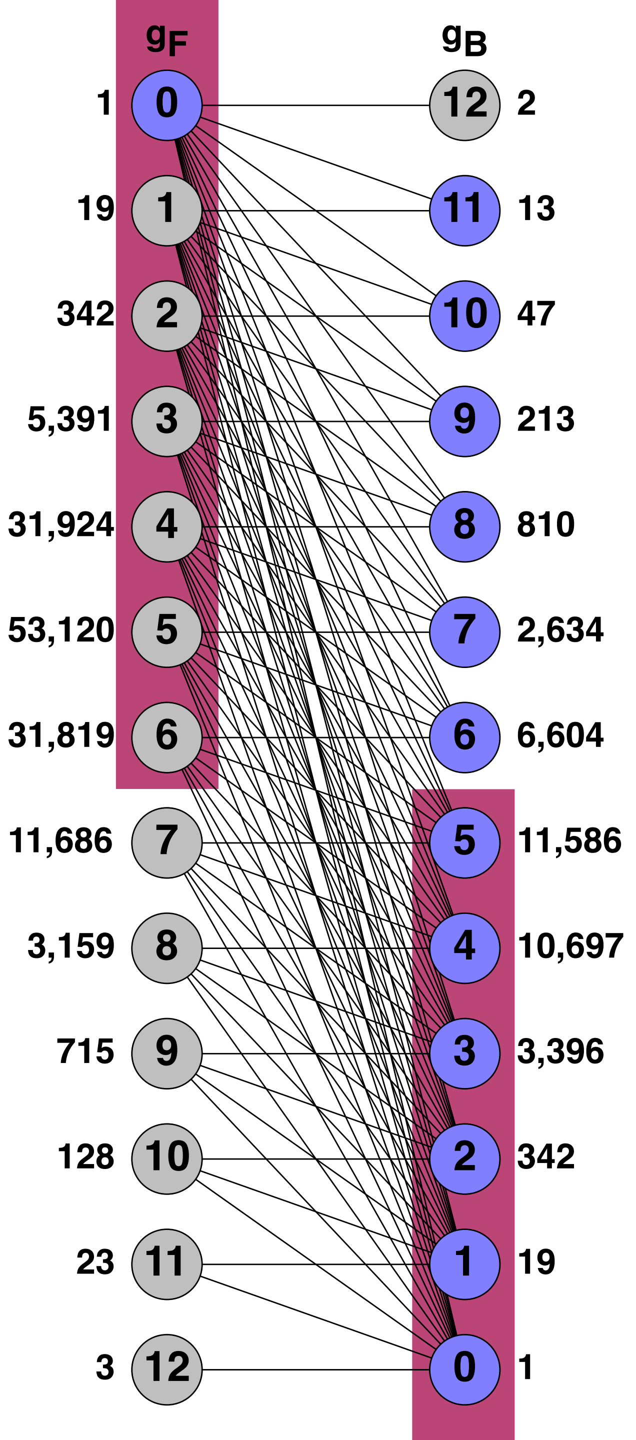

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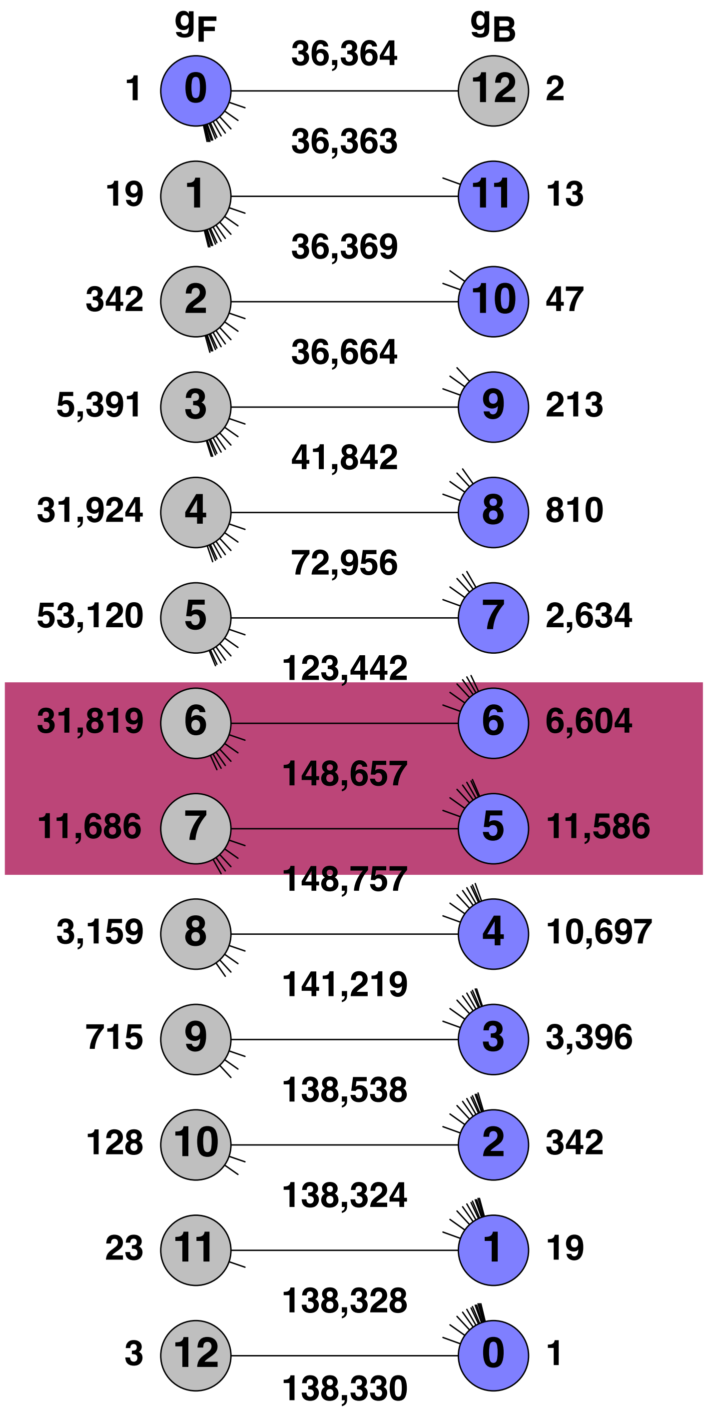
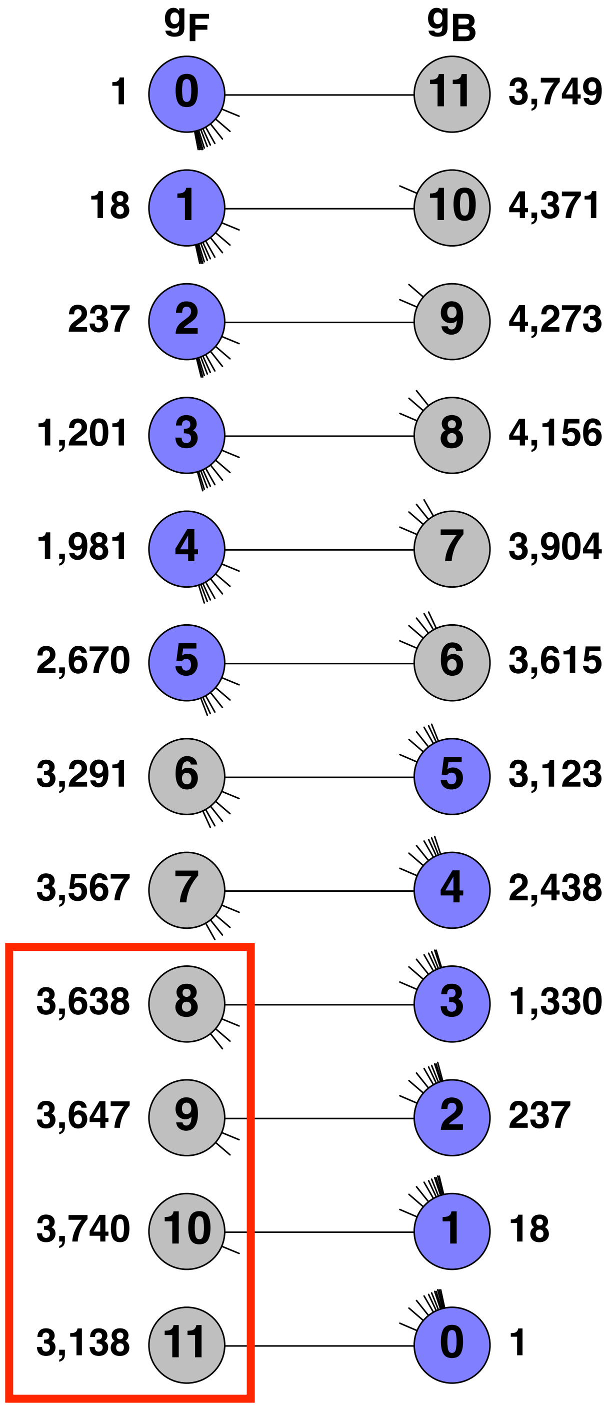


RUBIK'S CUBE 7-TILE PDB

C* = 12



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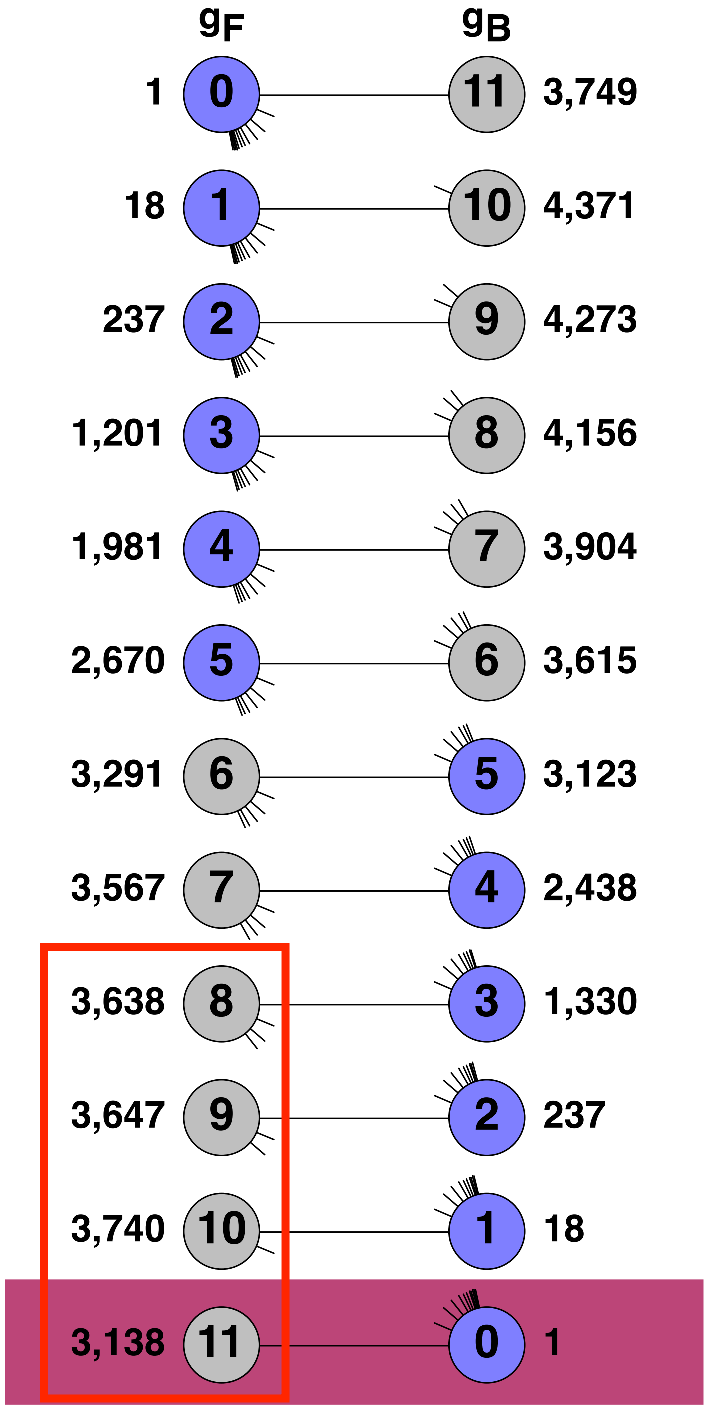

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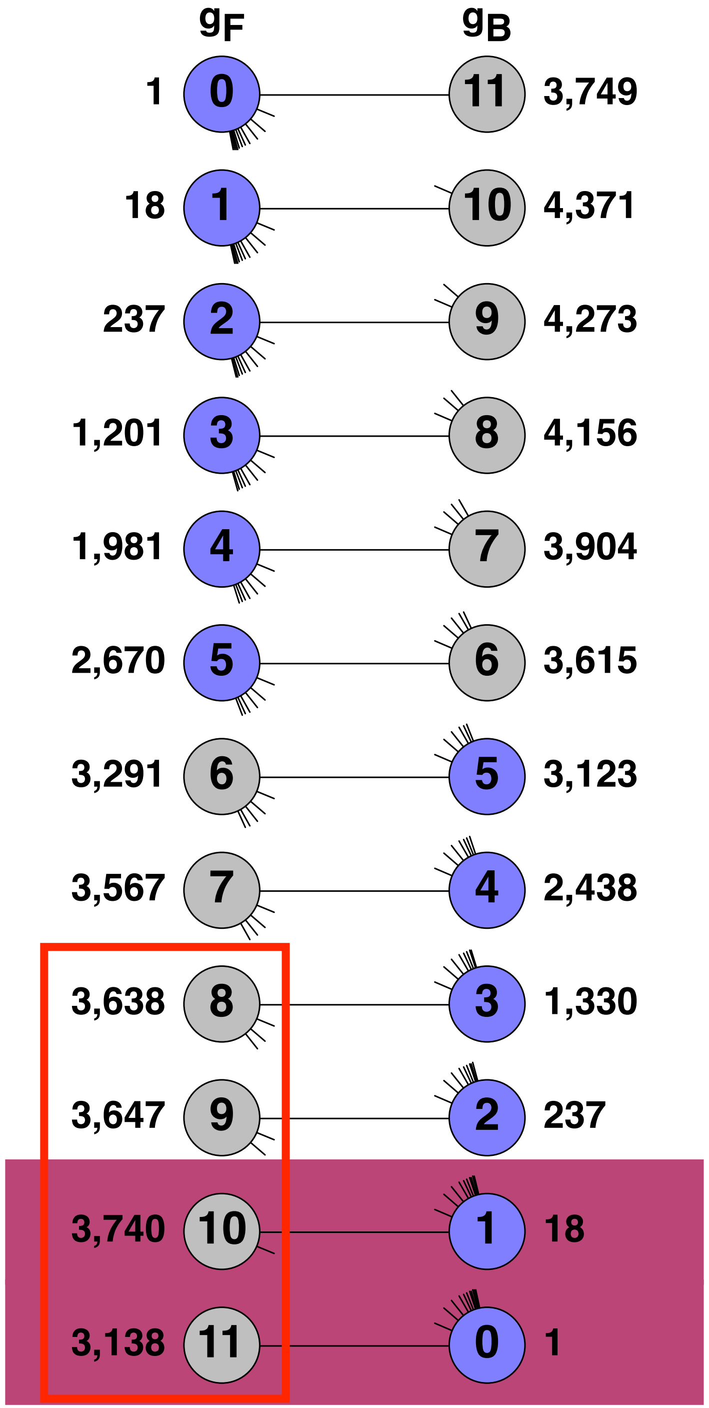

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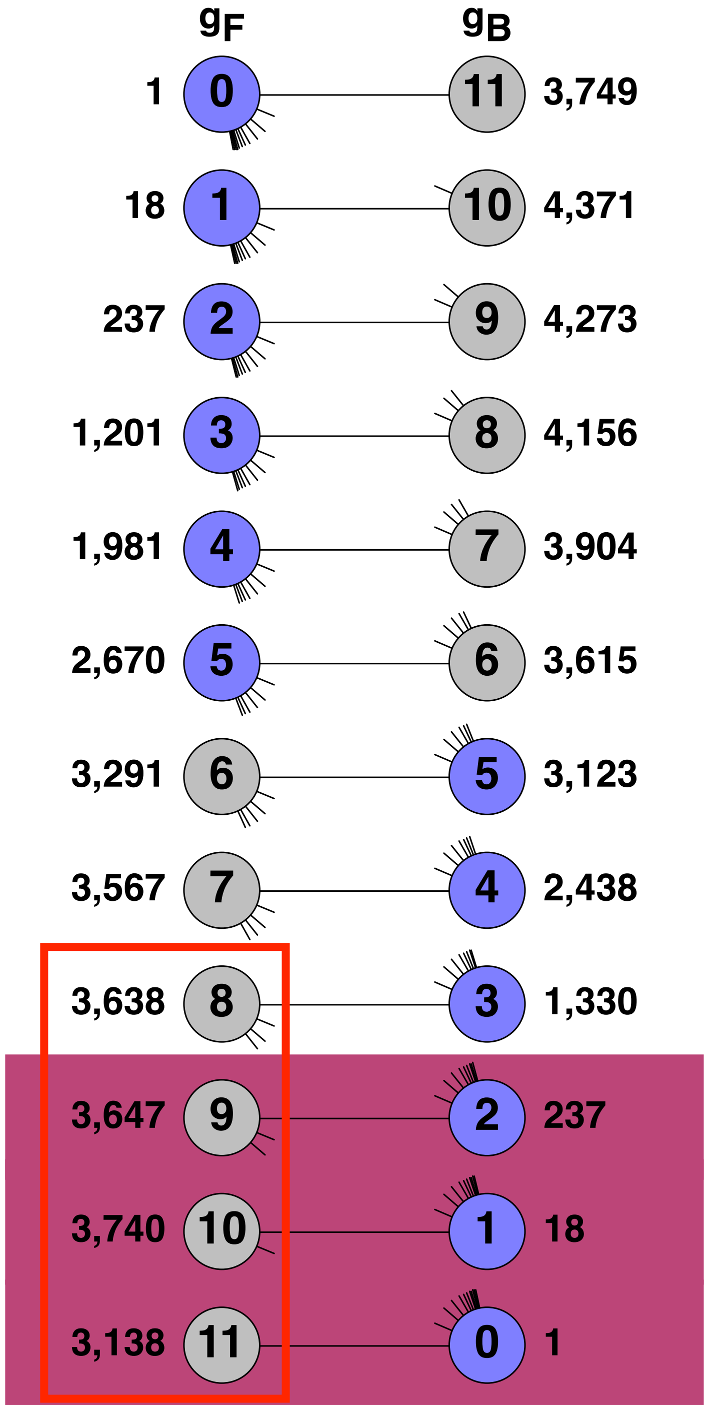

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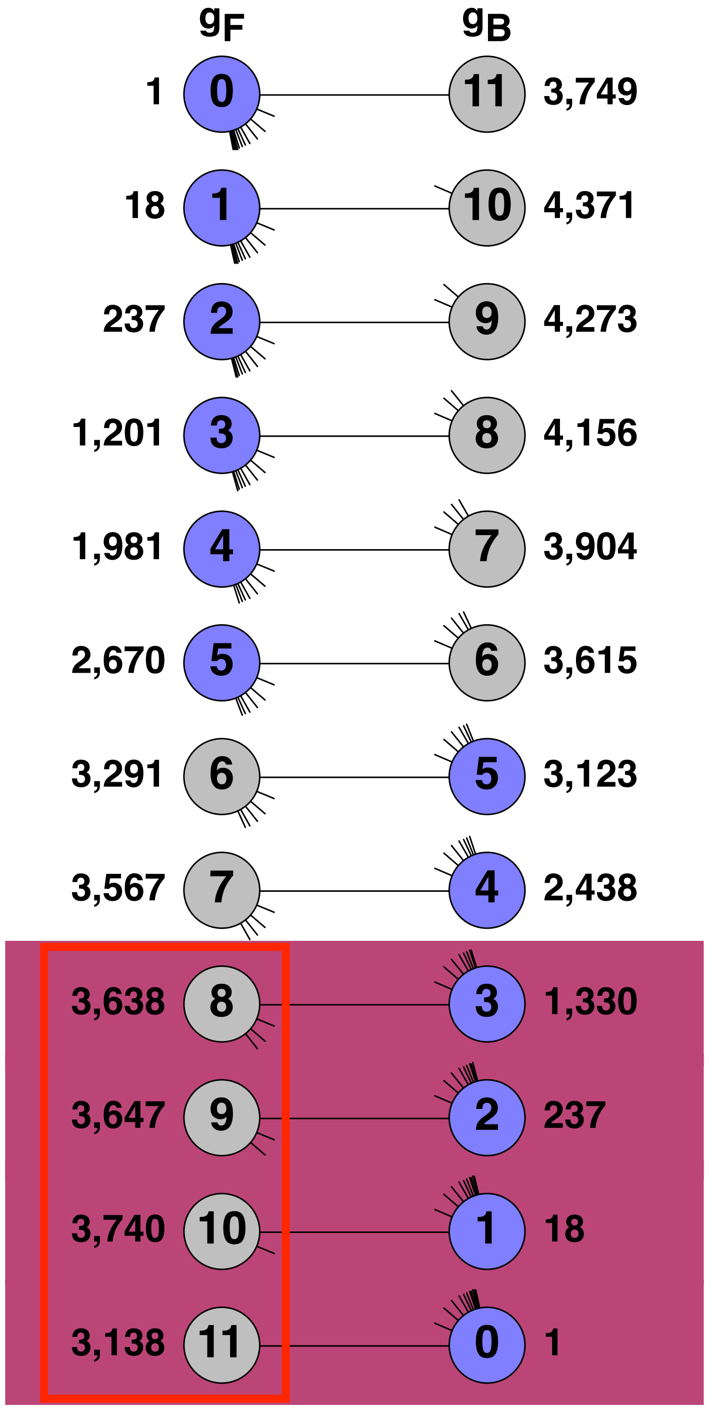

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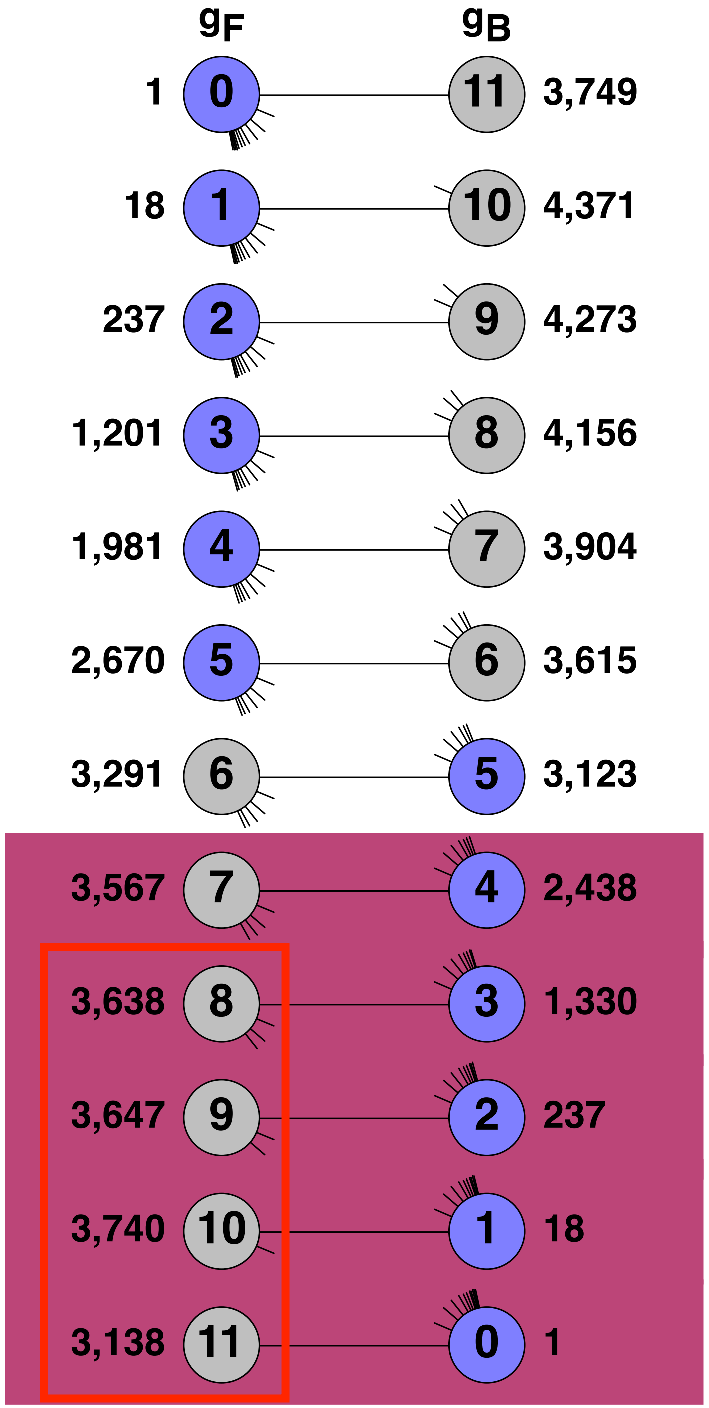

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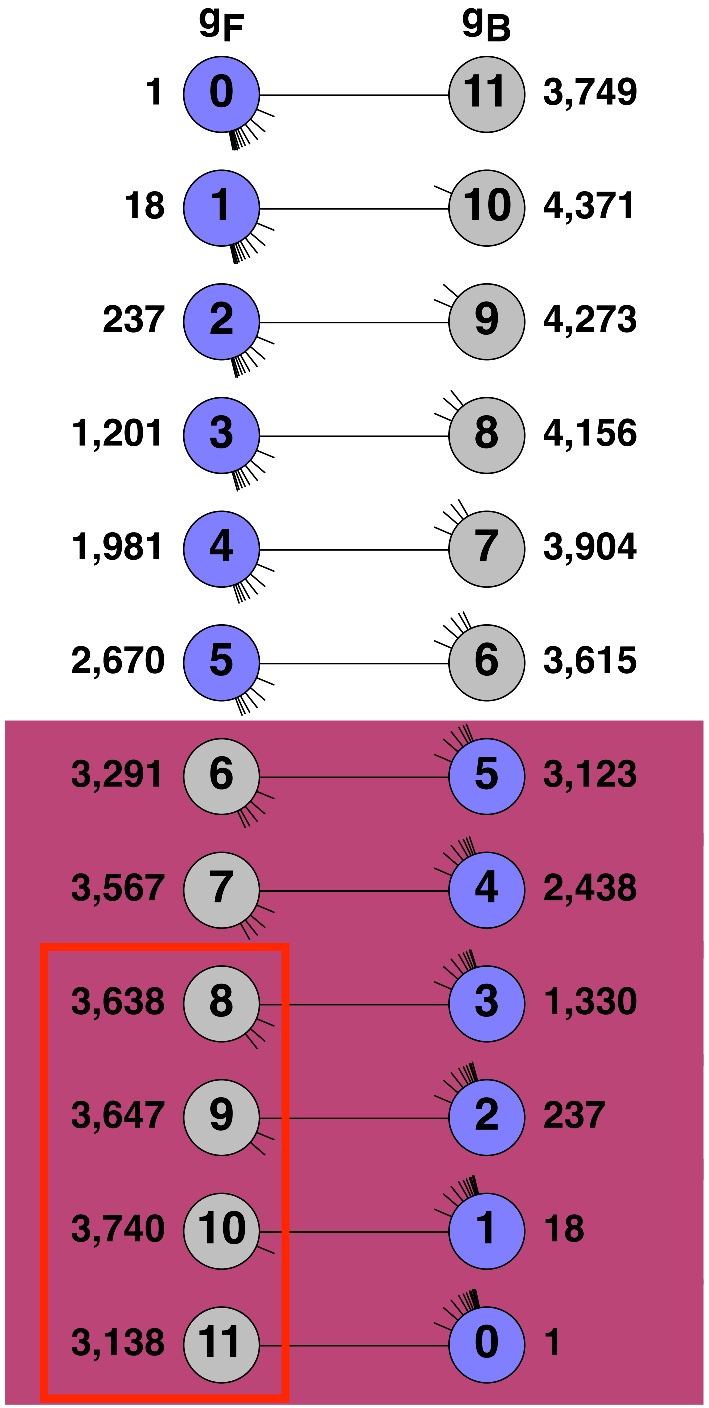

PANCAKE GAP HEURISTIC

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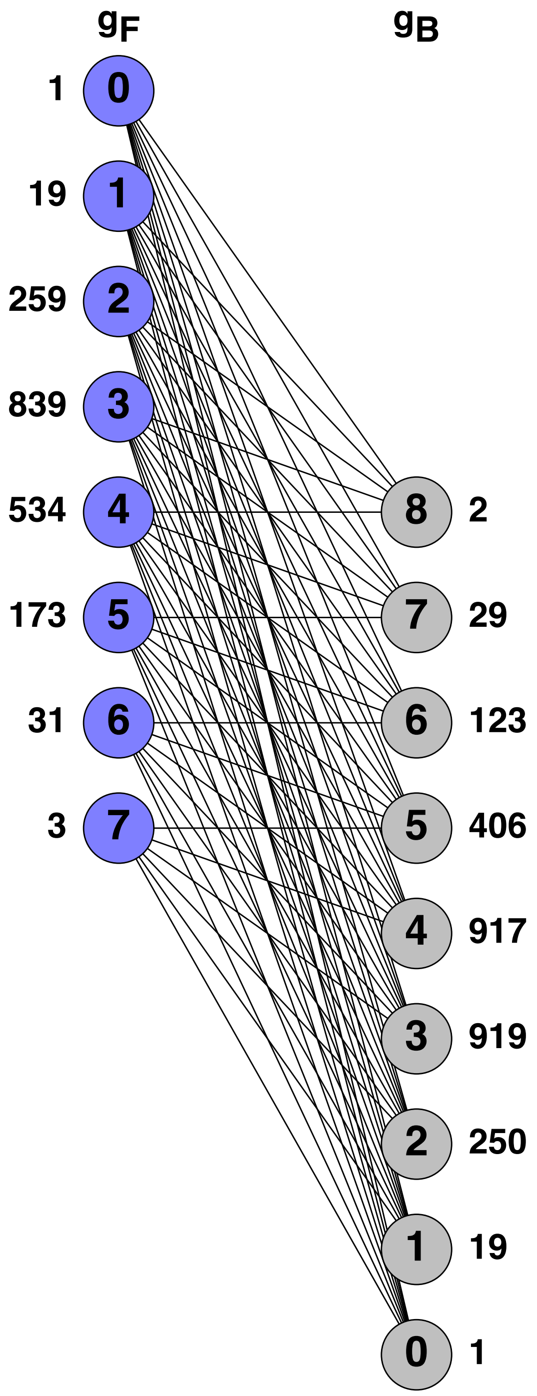

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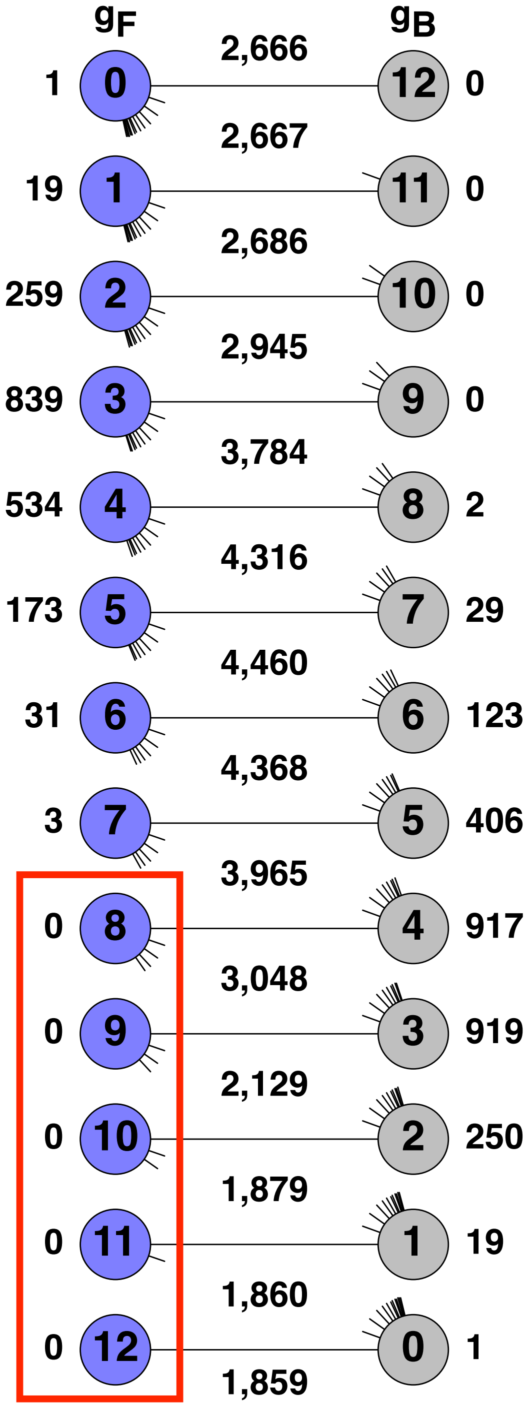

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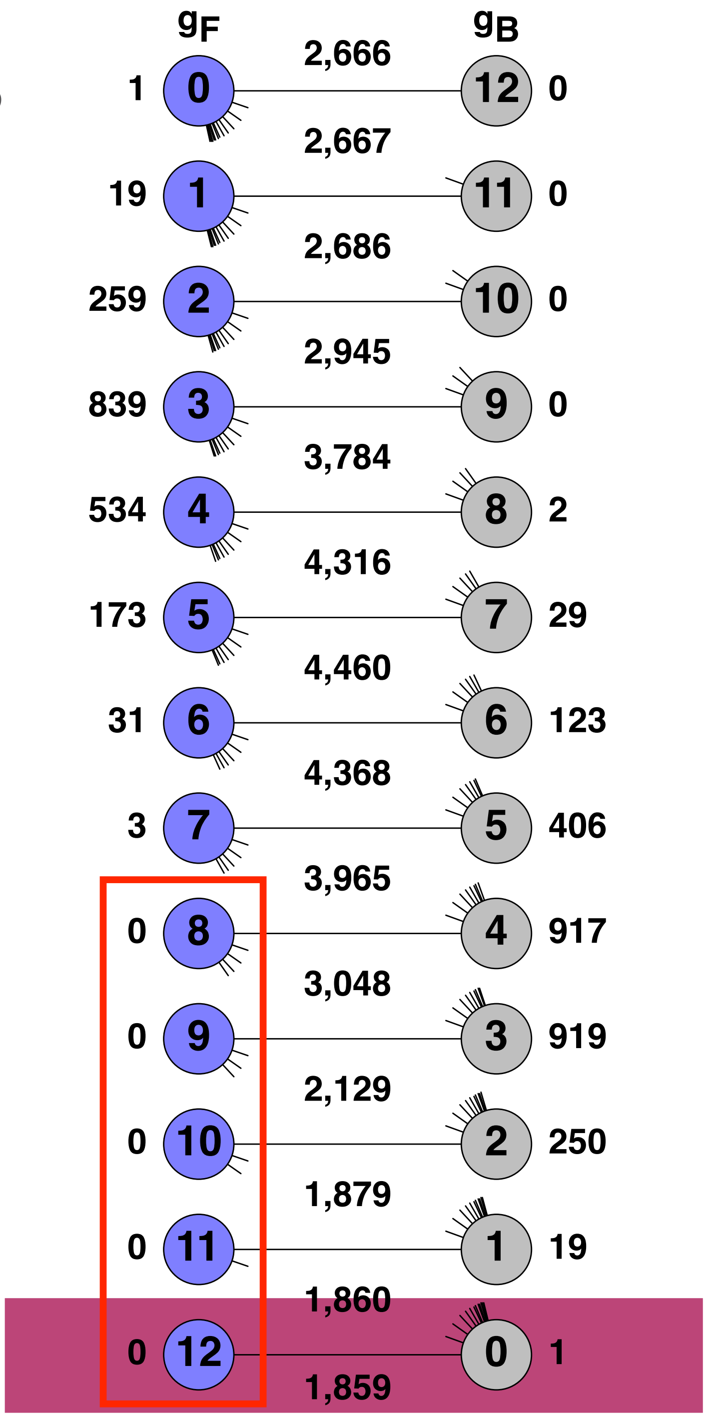

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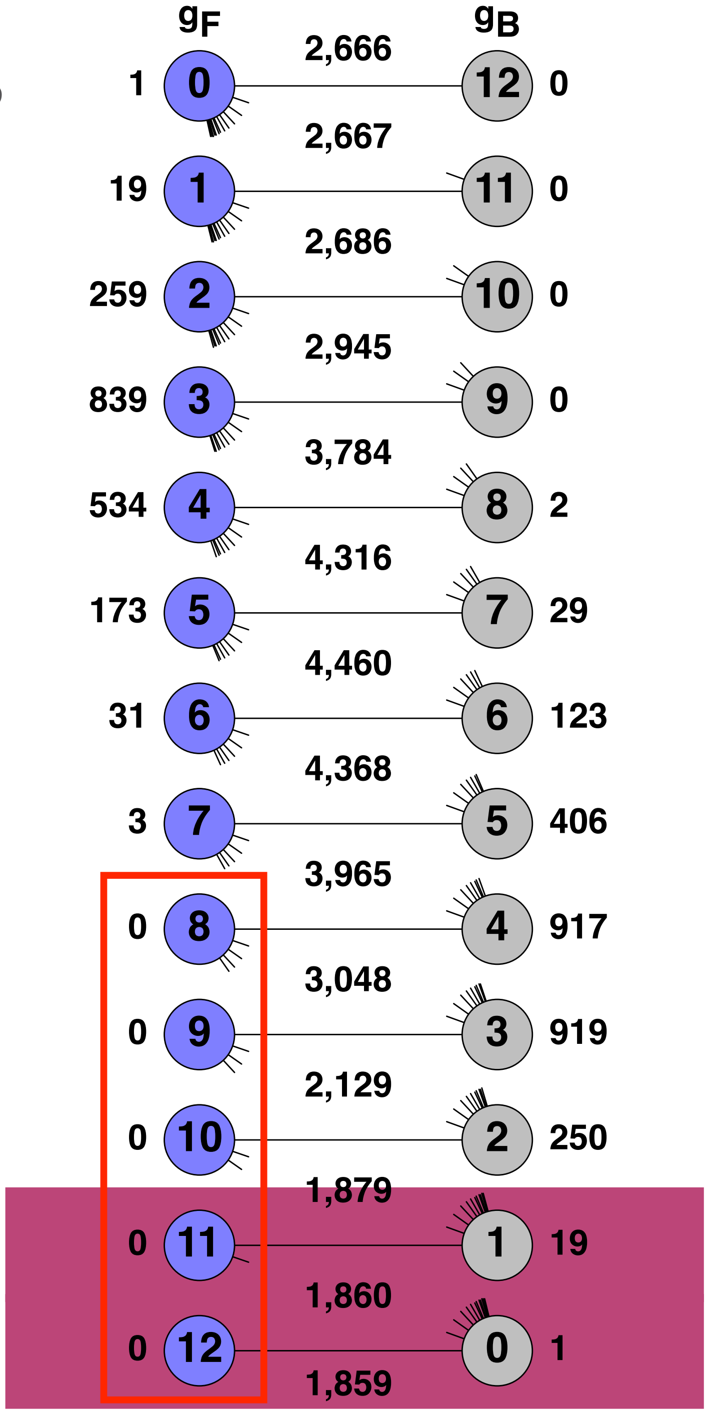

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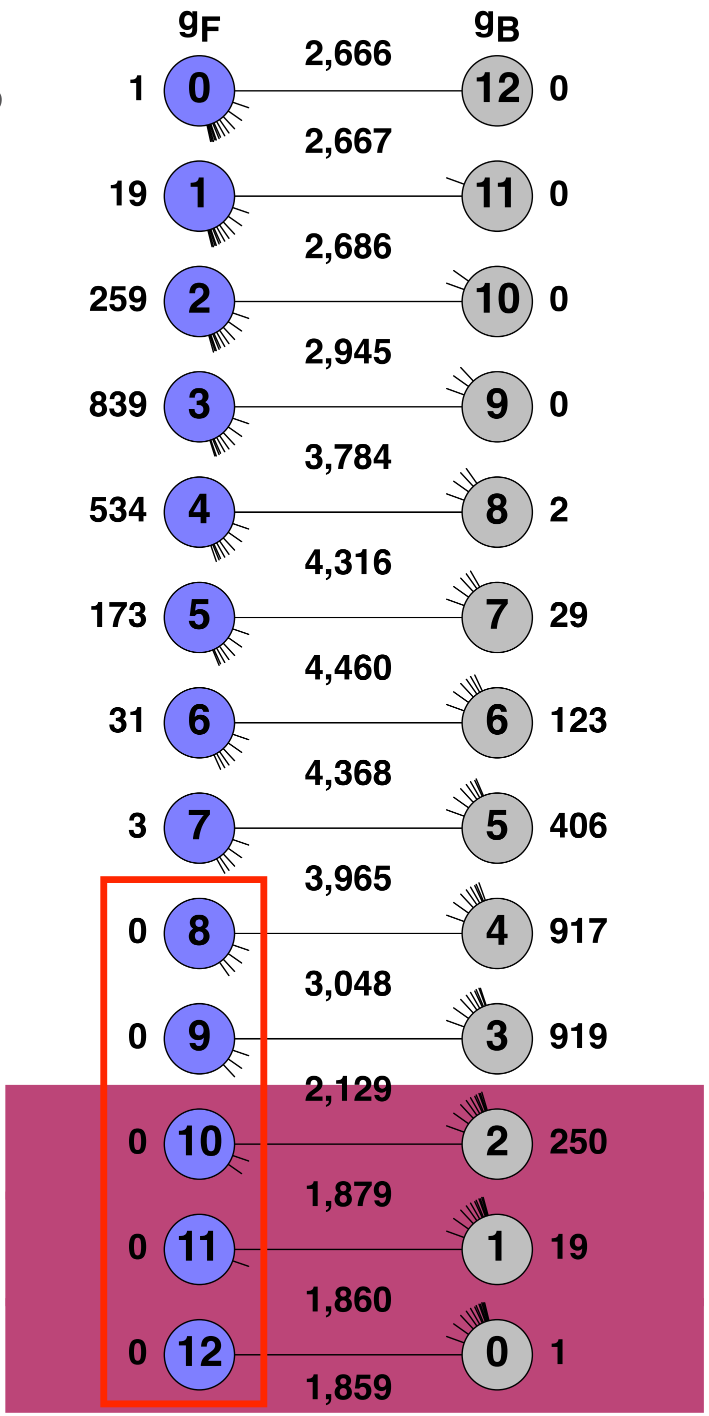

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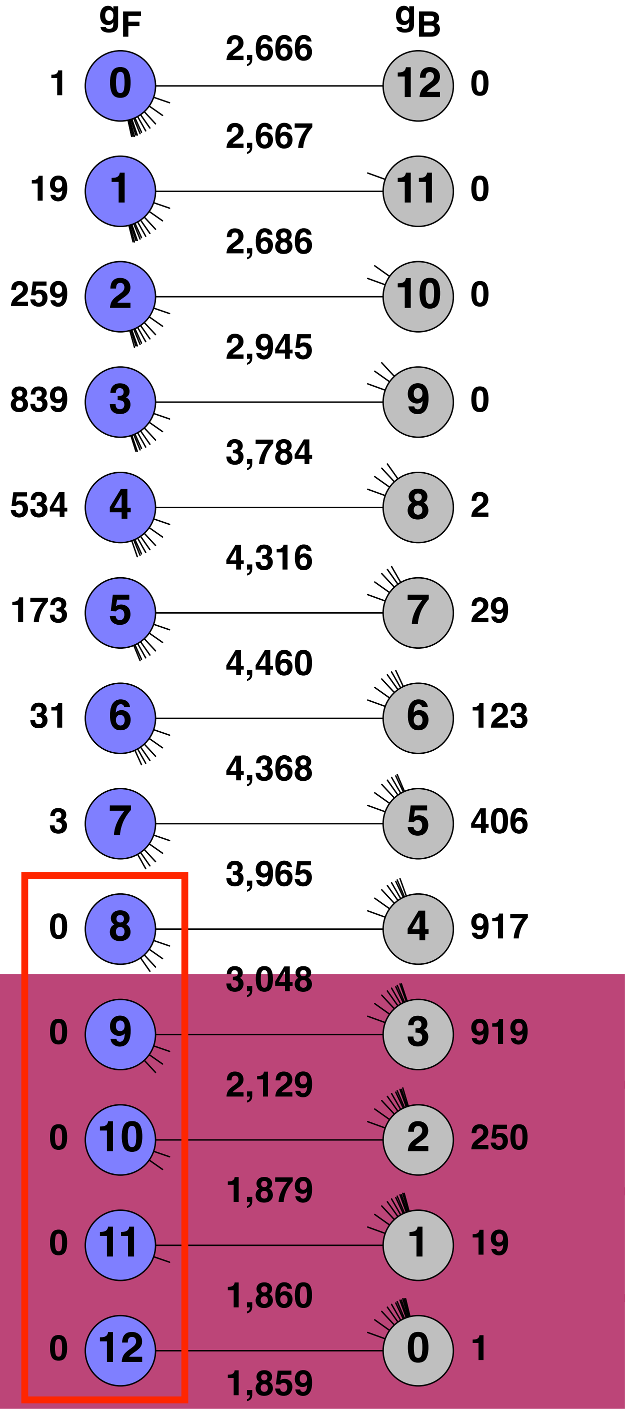

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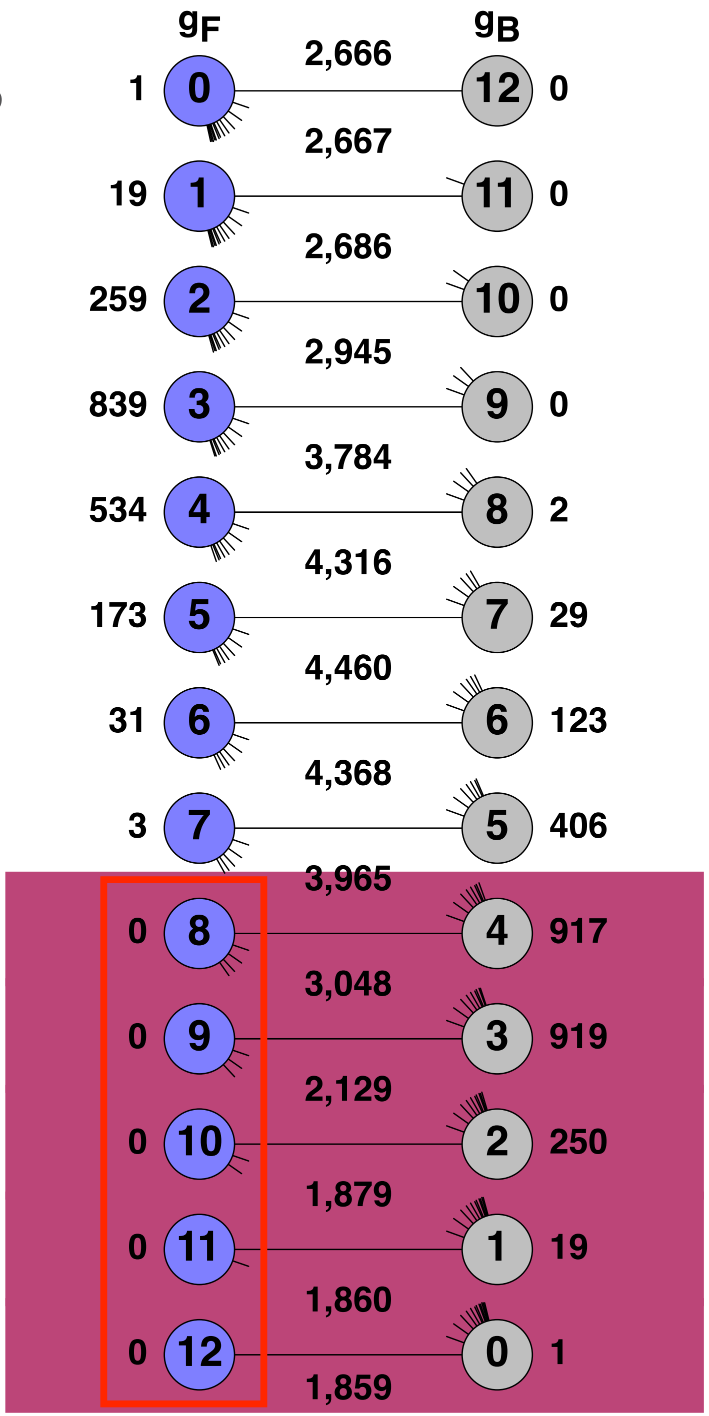

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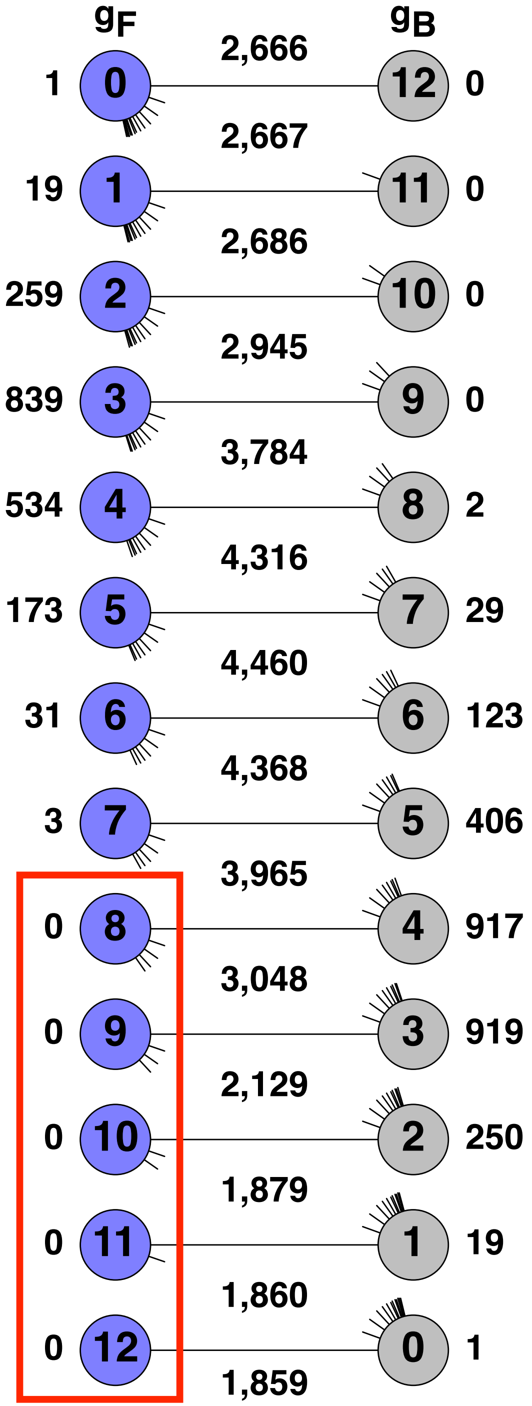

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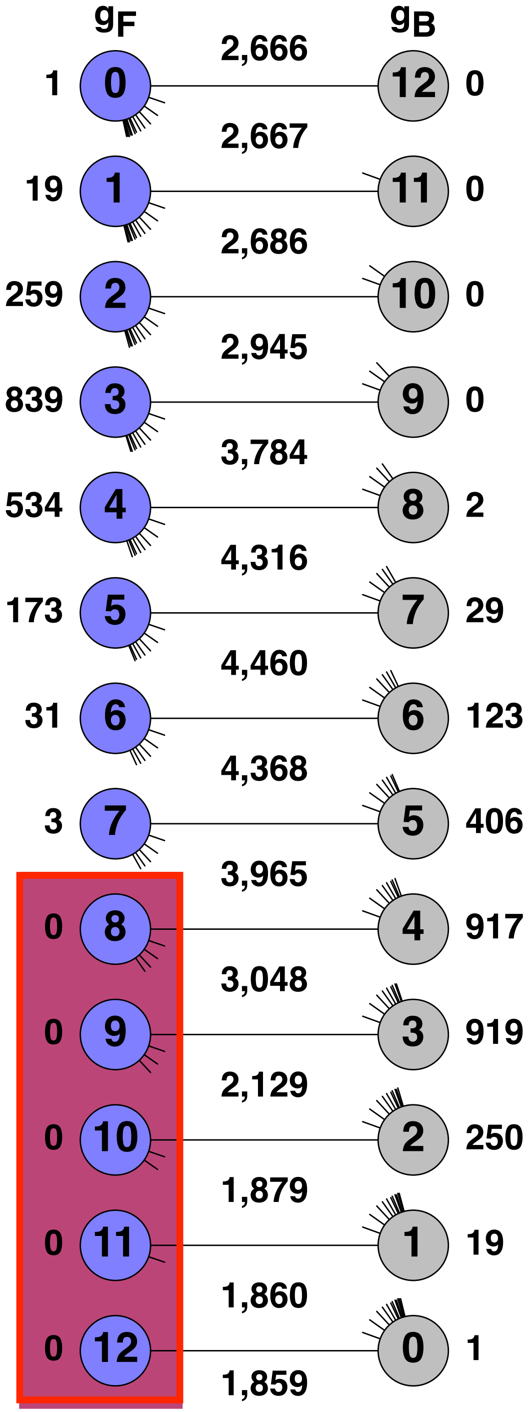
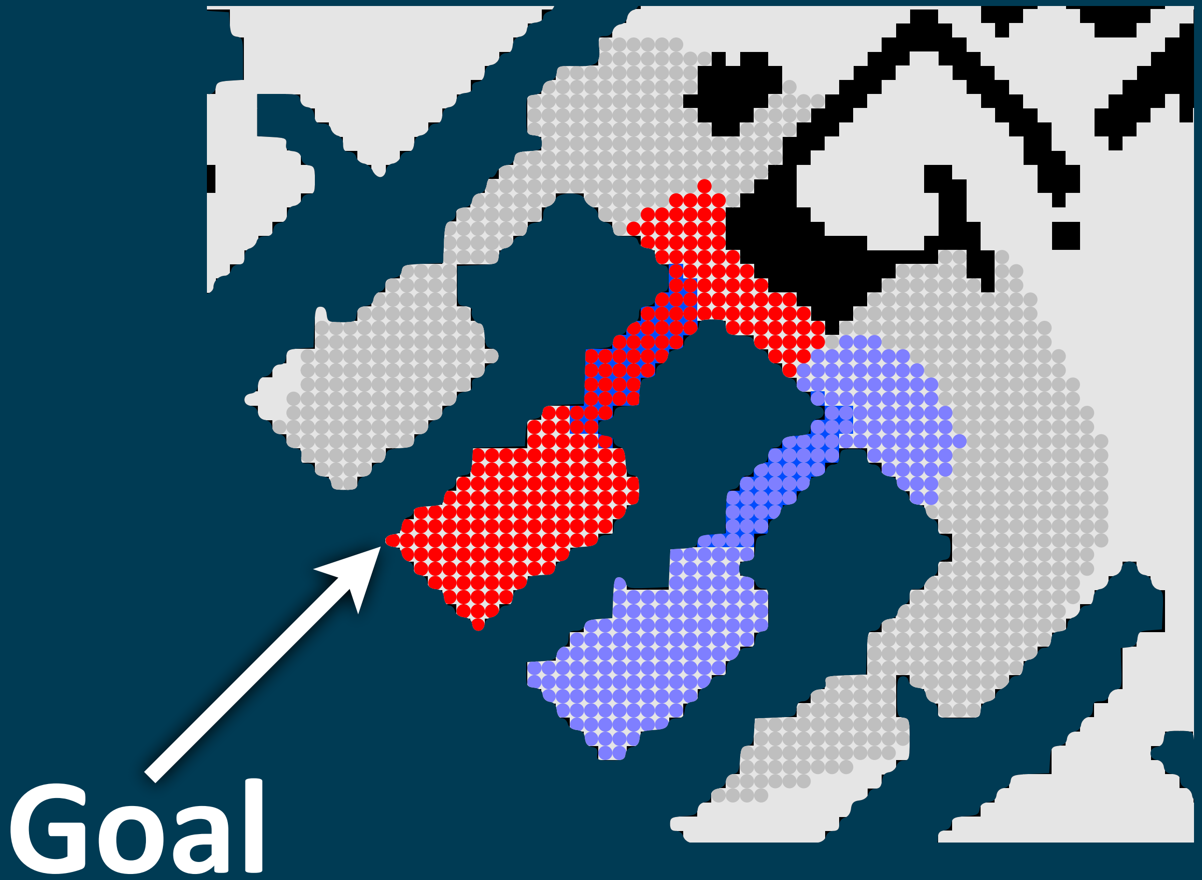


CRITICAL STATES

- Sample states near goal and find heuristic inaccuracies



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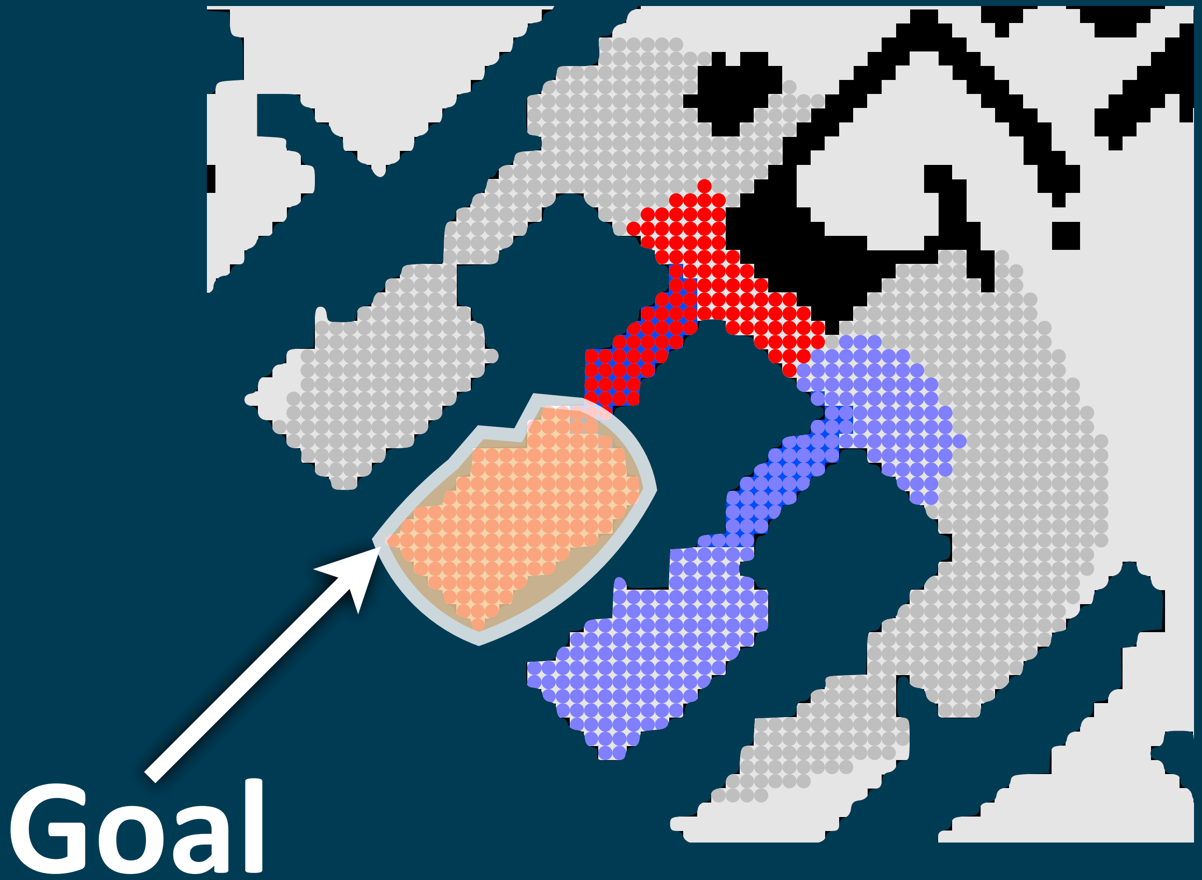

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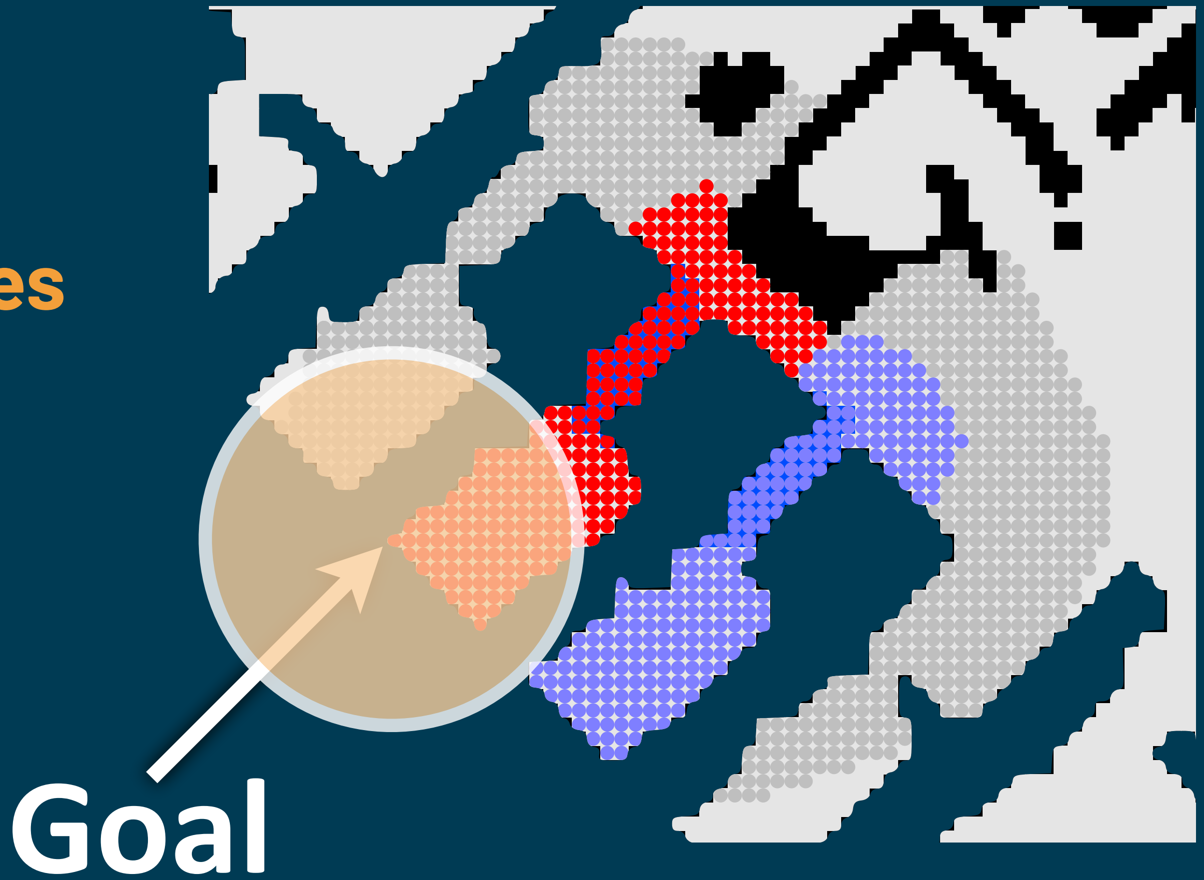
- Sample the heuristic to find how many low heuristic values there are



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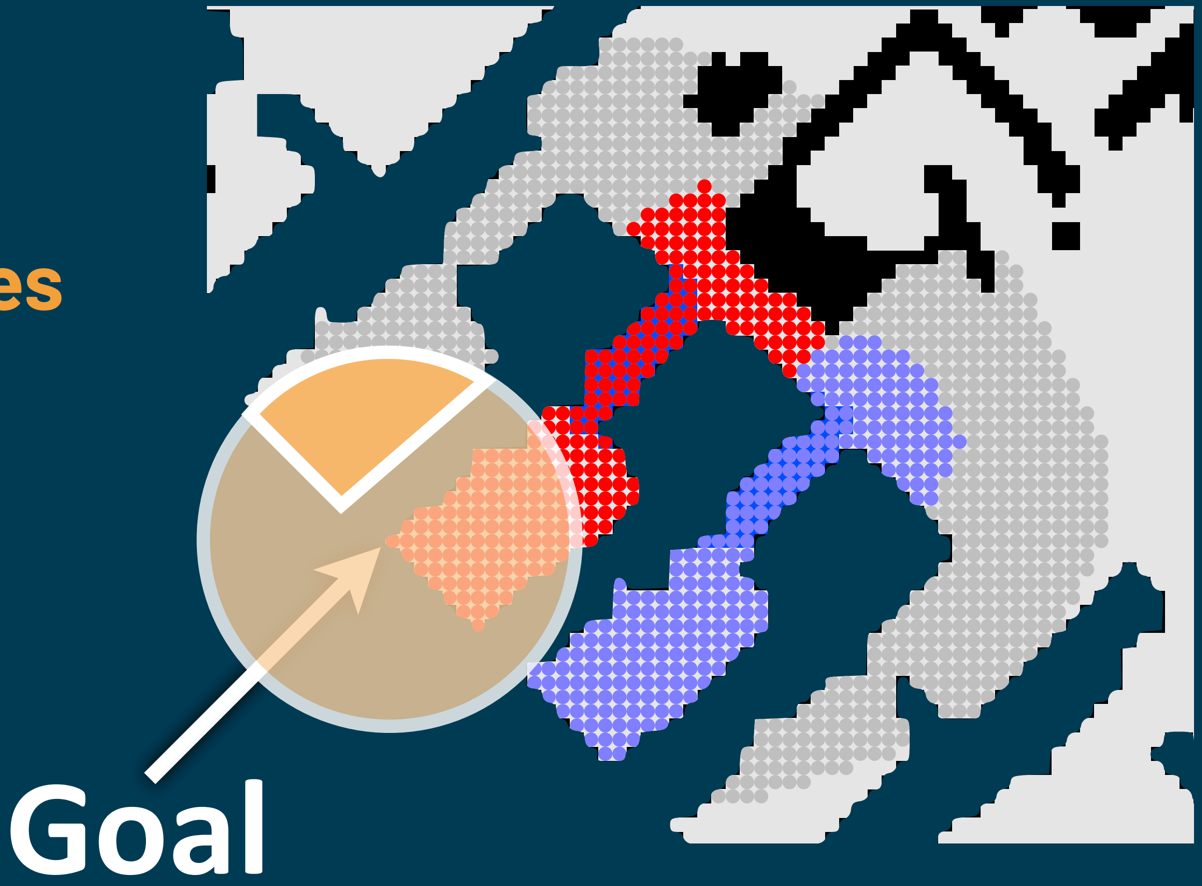


ASYMMETRY

- Sample states near goal and find heuristic inaccuracies
- Sample the heuristic to find how many low heuristic values there are
- Look at the asymmetry of the state space

EXAMPLE: TOH WITH PDB HEURISTIC

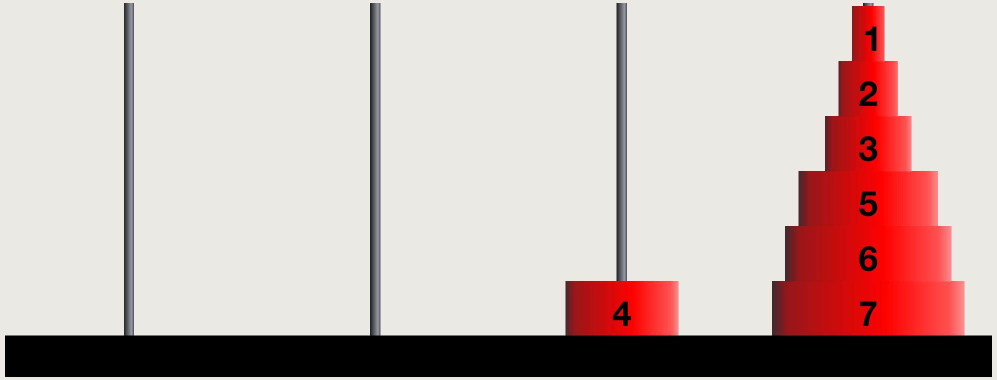
$\phi(s)$ is close to the goal and has a low heuristic value

s is far from the goal

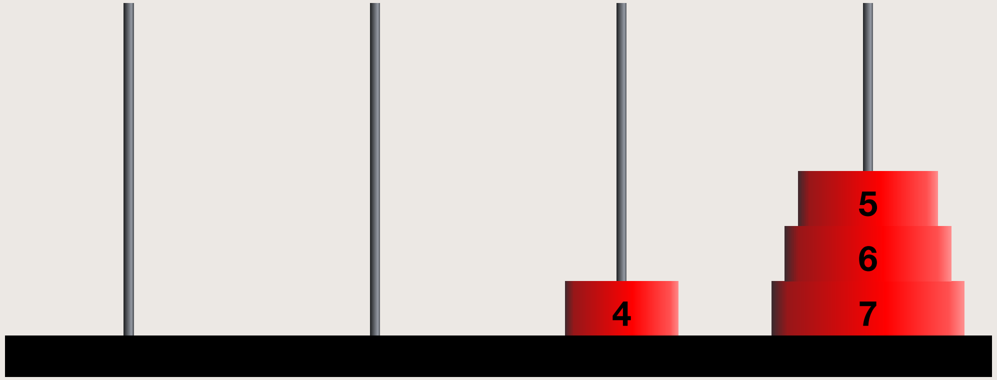
<u>Low heuristics are inaccurate</u>

Bidirectional heuristic search *outperforms* unidirectional search

Problem State s

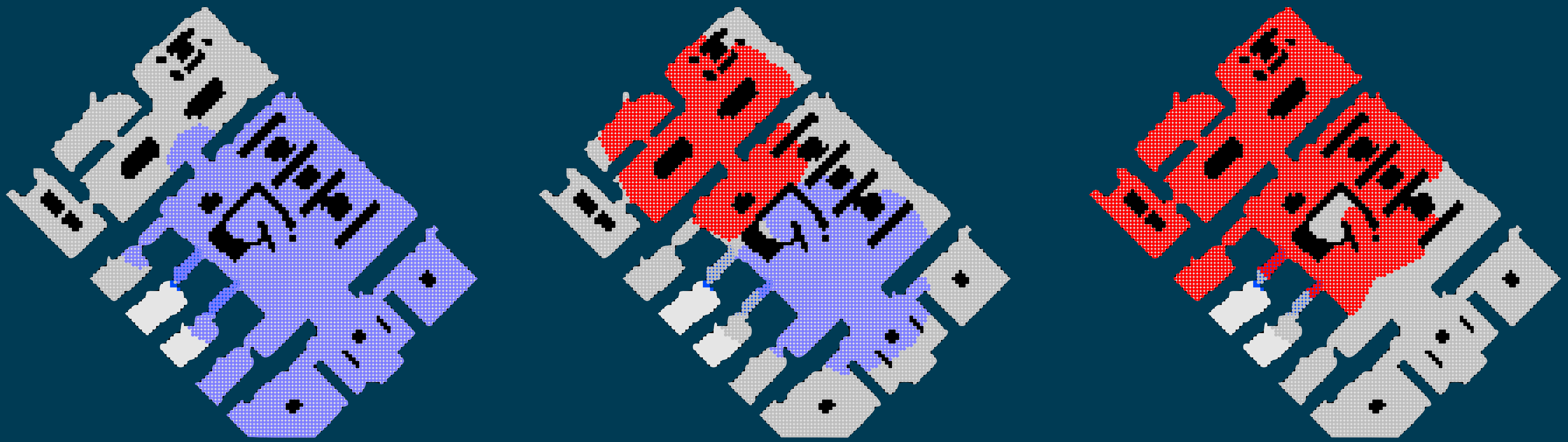


PDB Abstraction $\phi(s)$



EXAMPLE: UNINFORMED SEARCH

Low and inaccurate heuristics for almost all states



CONCLUSION

Critical states have both low and inaccurate heuristics

Need critical states for bidirectional search to perform well

More critical states → bidirectional search will do better

https://webdocs.cs.ualberta.ca/~nathanst/papers/sturtevant2020unibidi.pdf