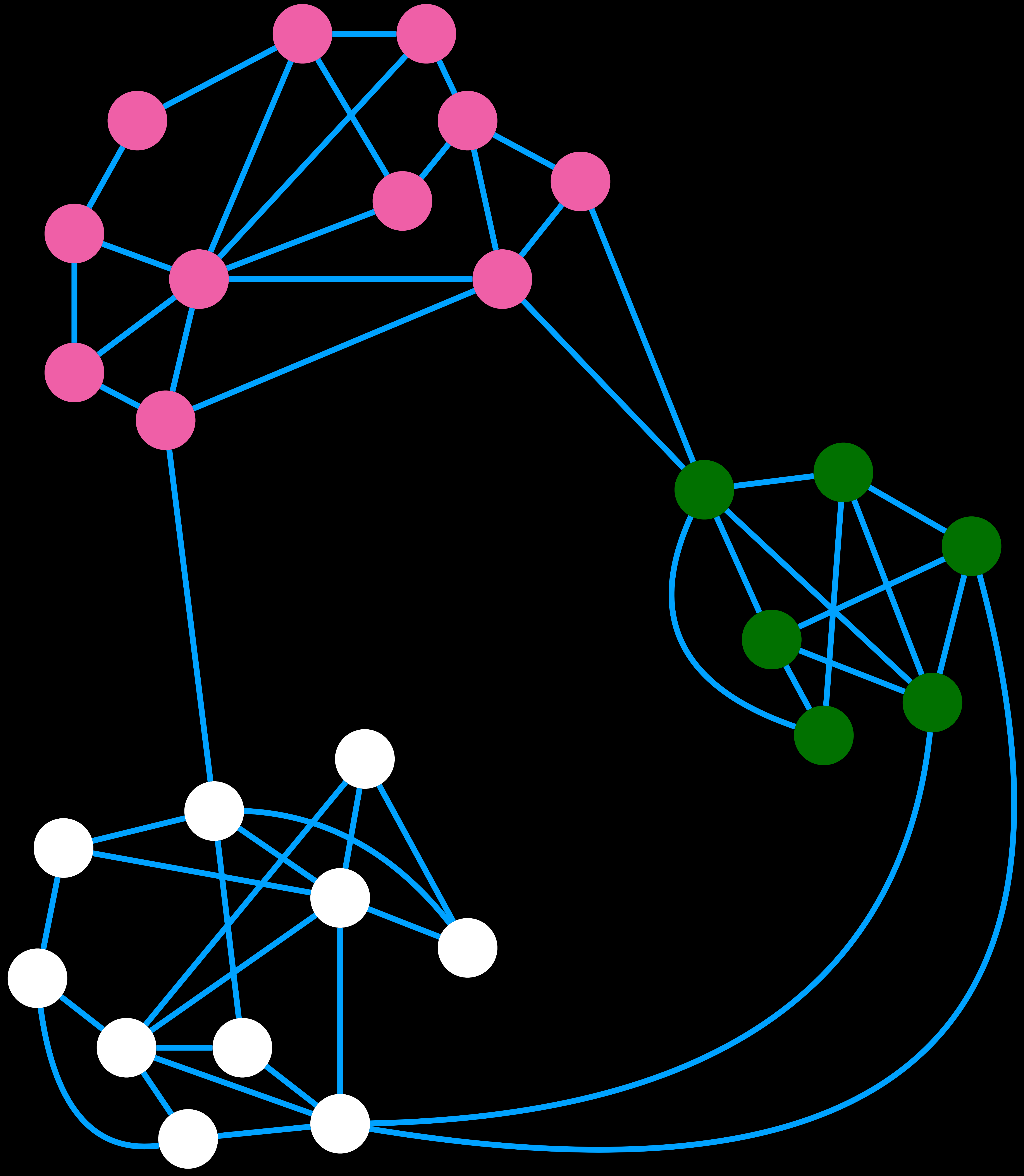
Sublinear-Time Clustering Oracle for Signed Graphs

Stefan Neumann (KTH) and Pan Peng (USTC)
@StefanResearch

ICML'22

Graph Clustering

- Ubiquitous task in machine learning and data science



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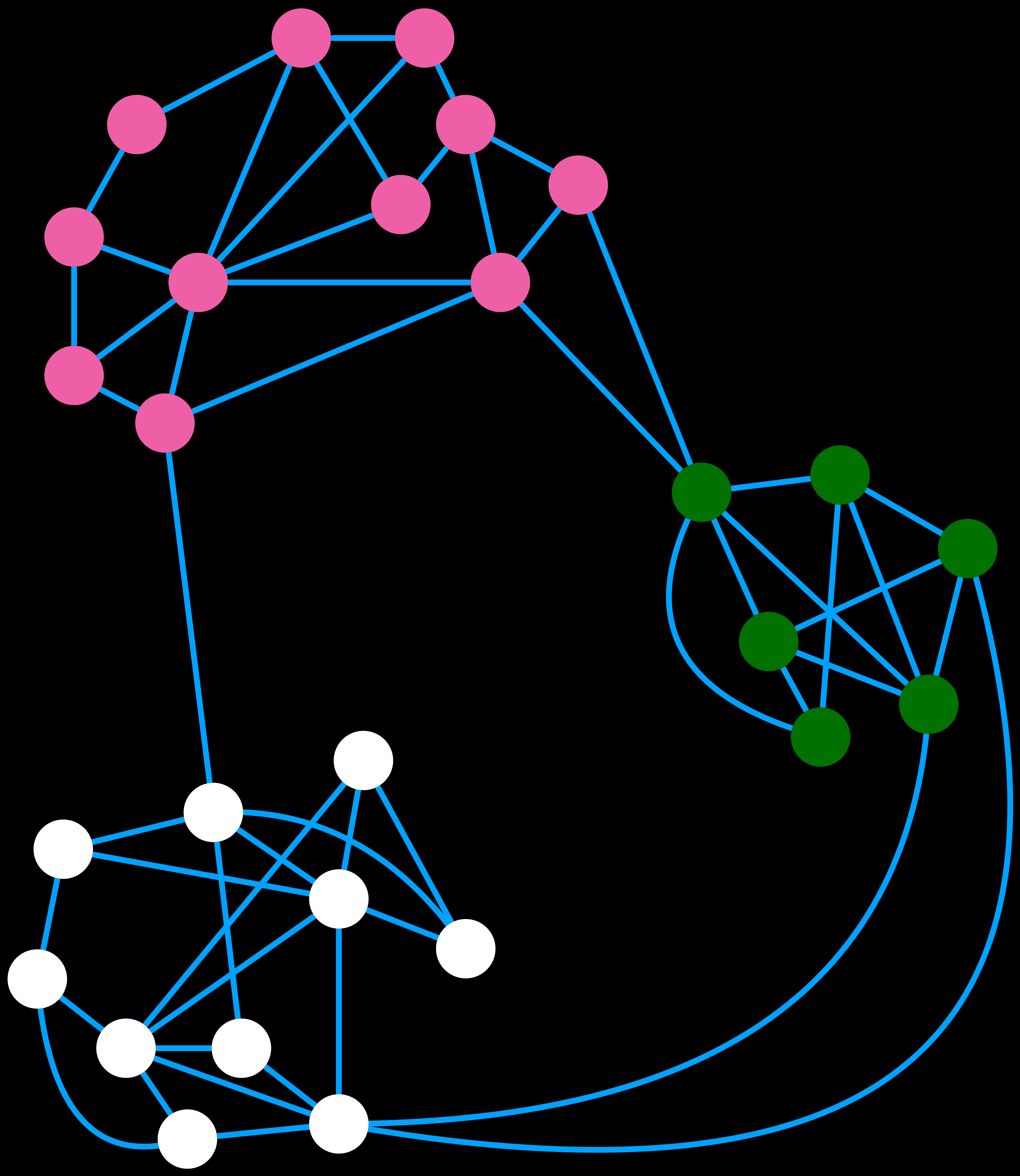
  Find communities in (social) networks



Graph Clustering

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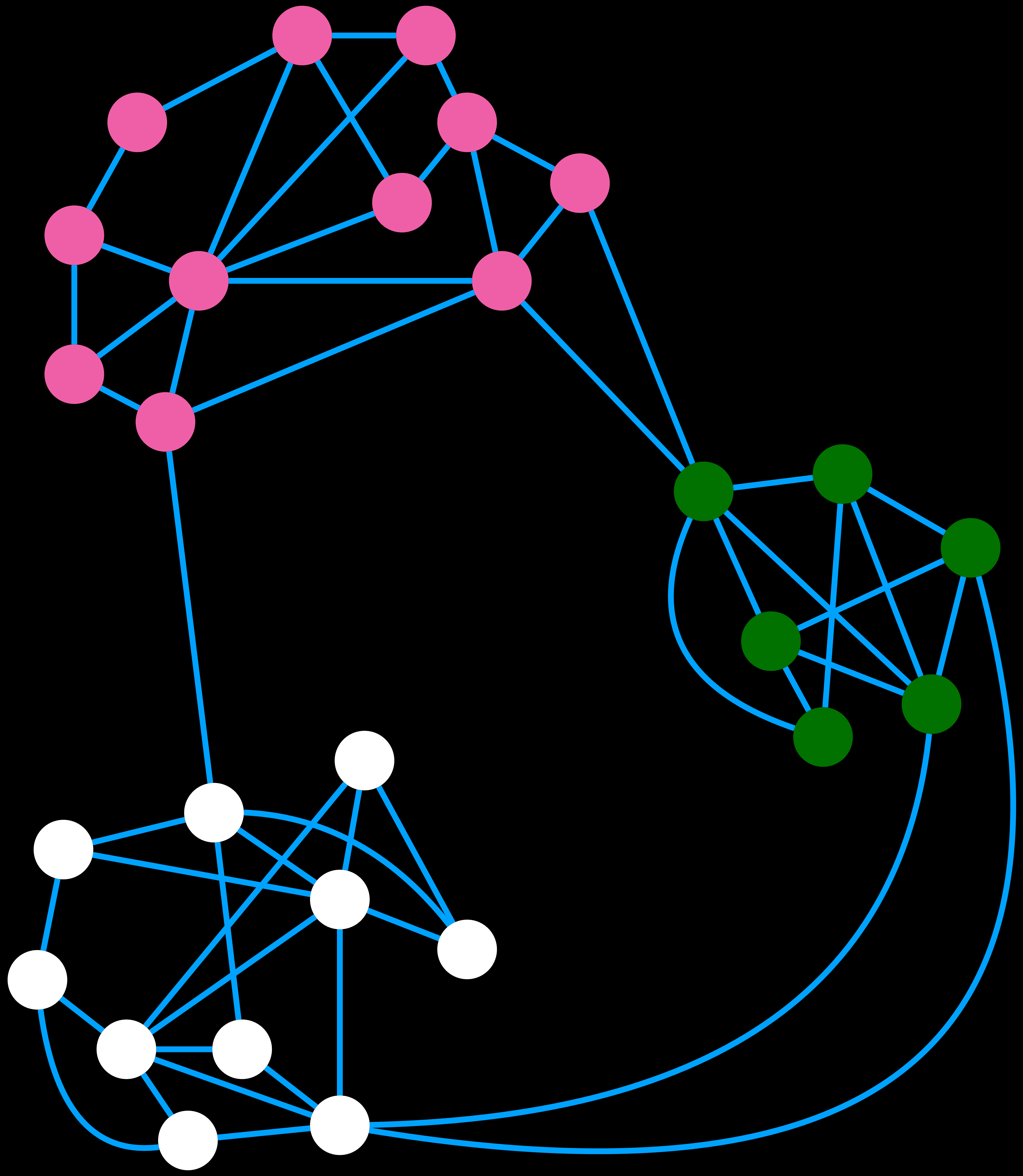
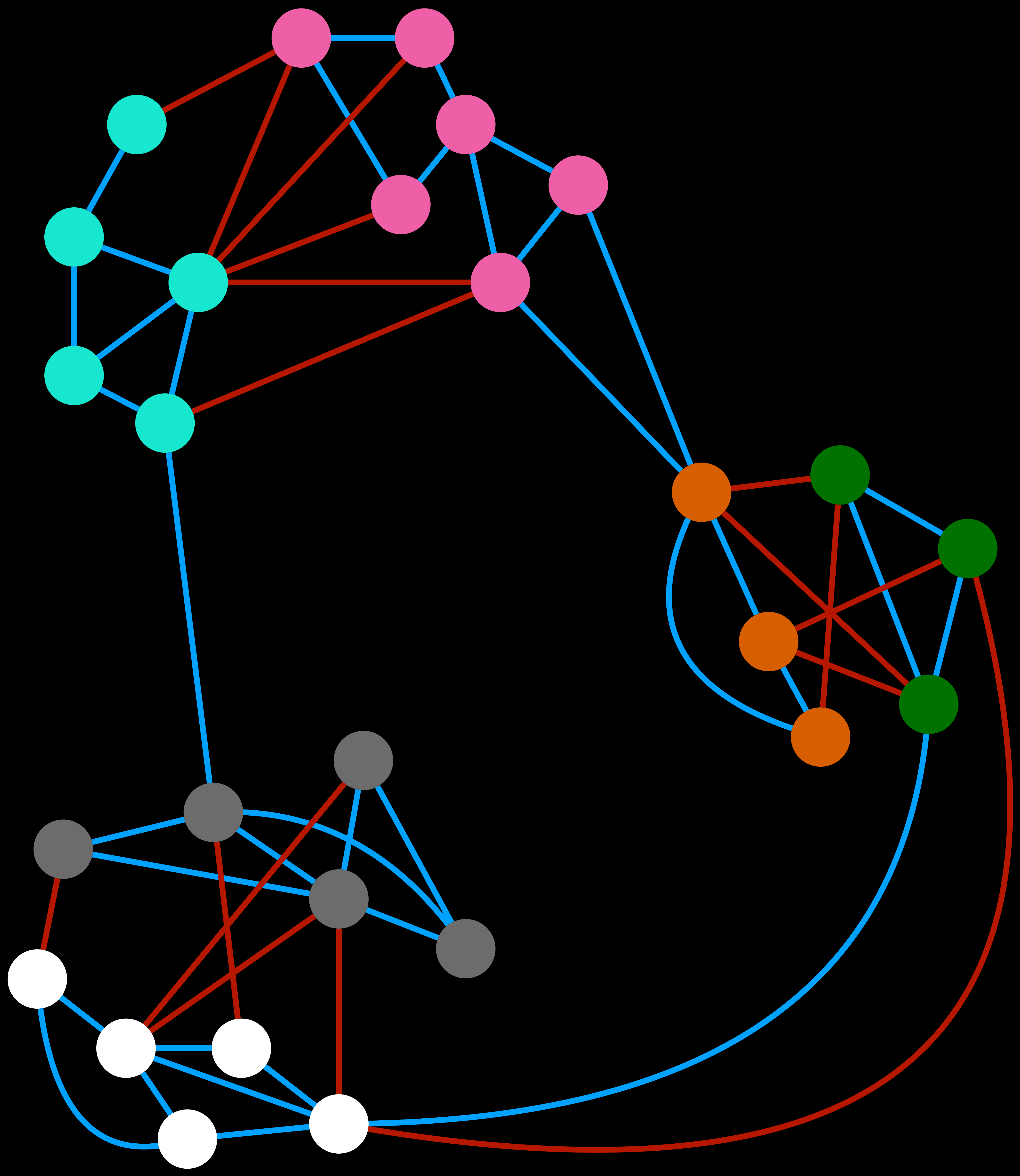
- *Application:*
  Find communities in (social) networks
- Typically studied for *unsigned* graphs



Signed Graphs

- Social networks can be seen as *signed* networks



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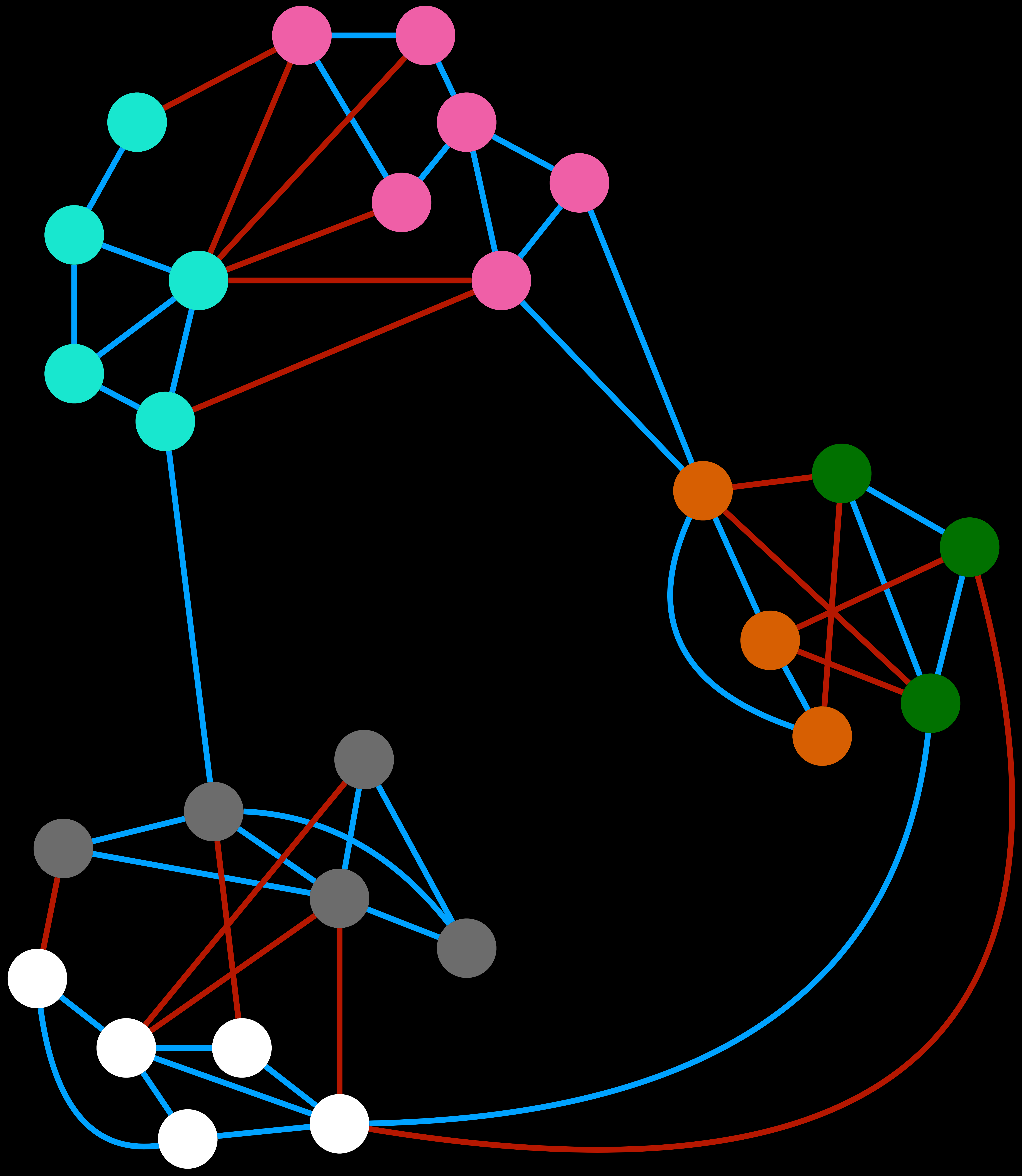

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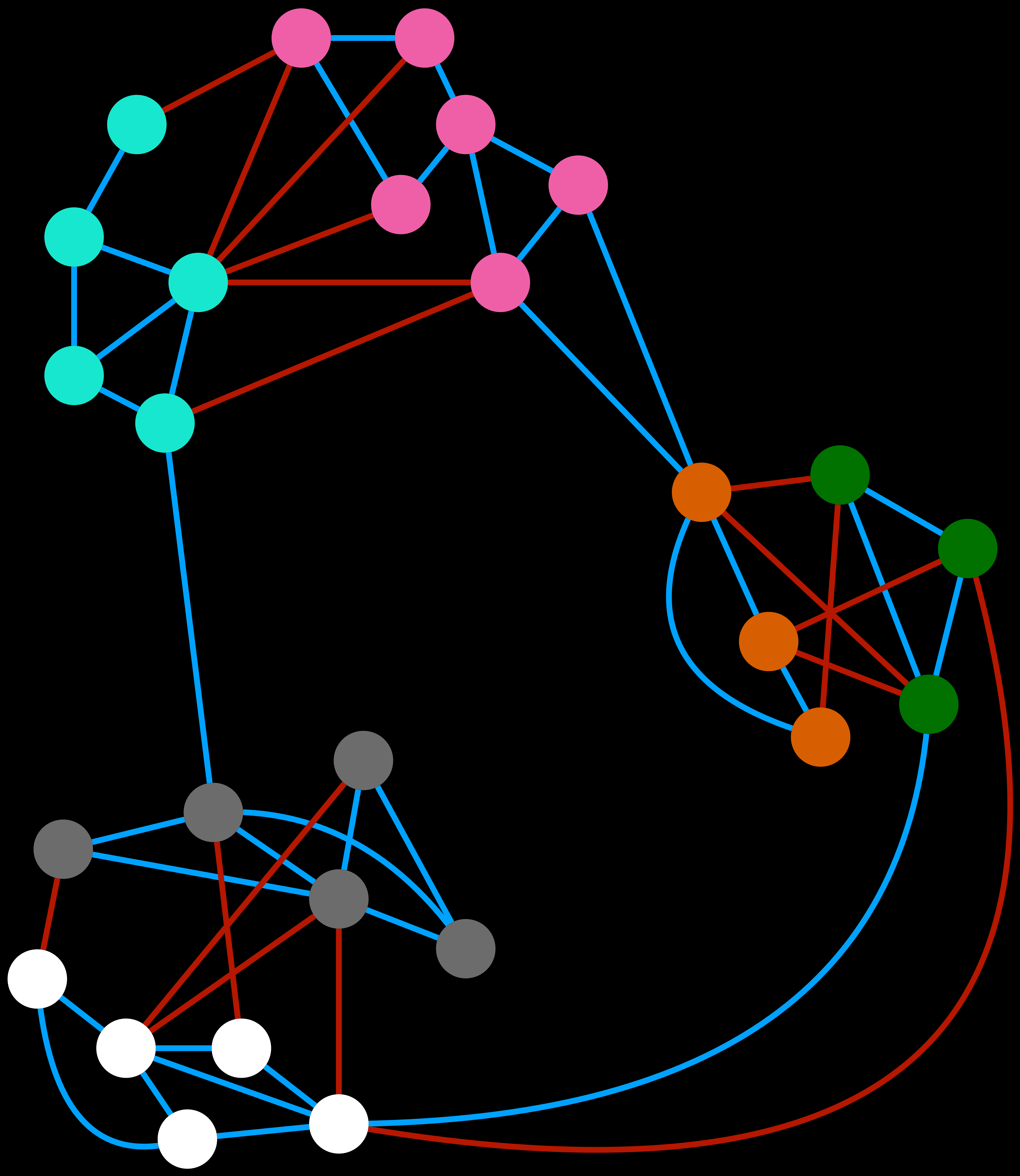

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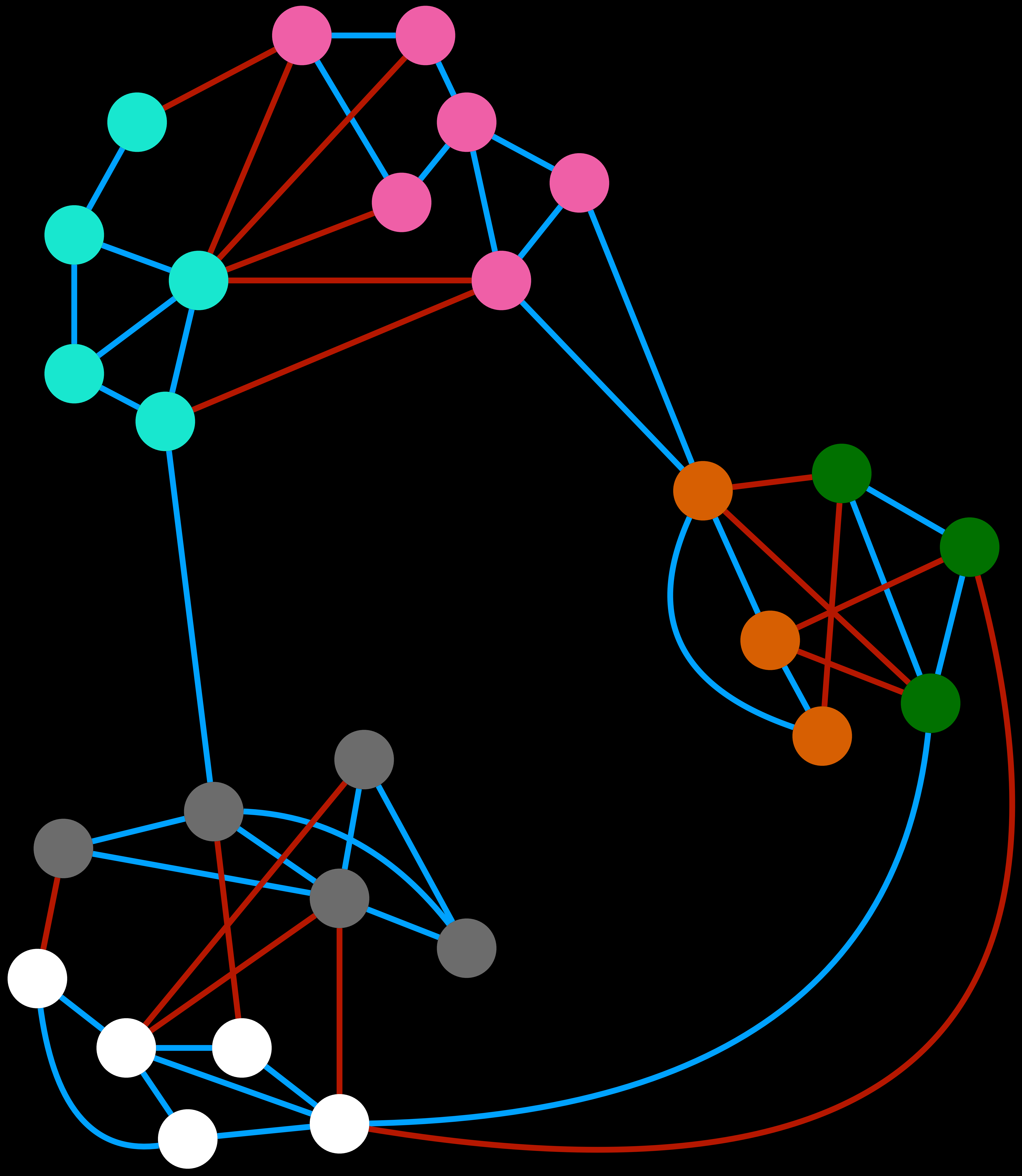

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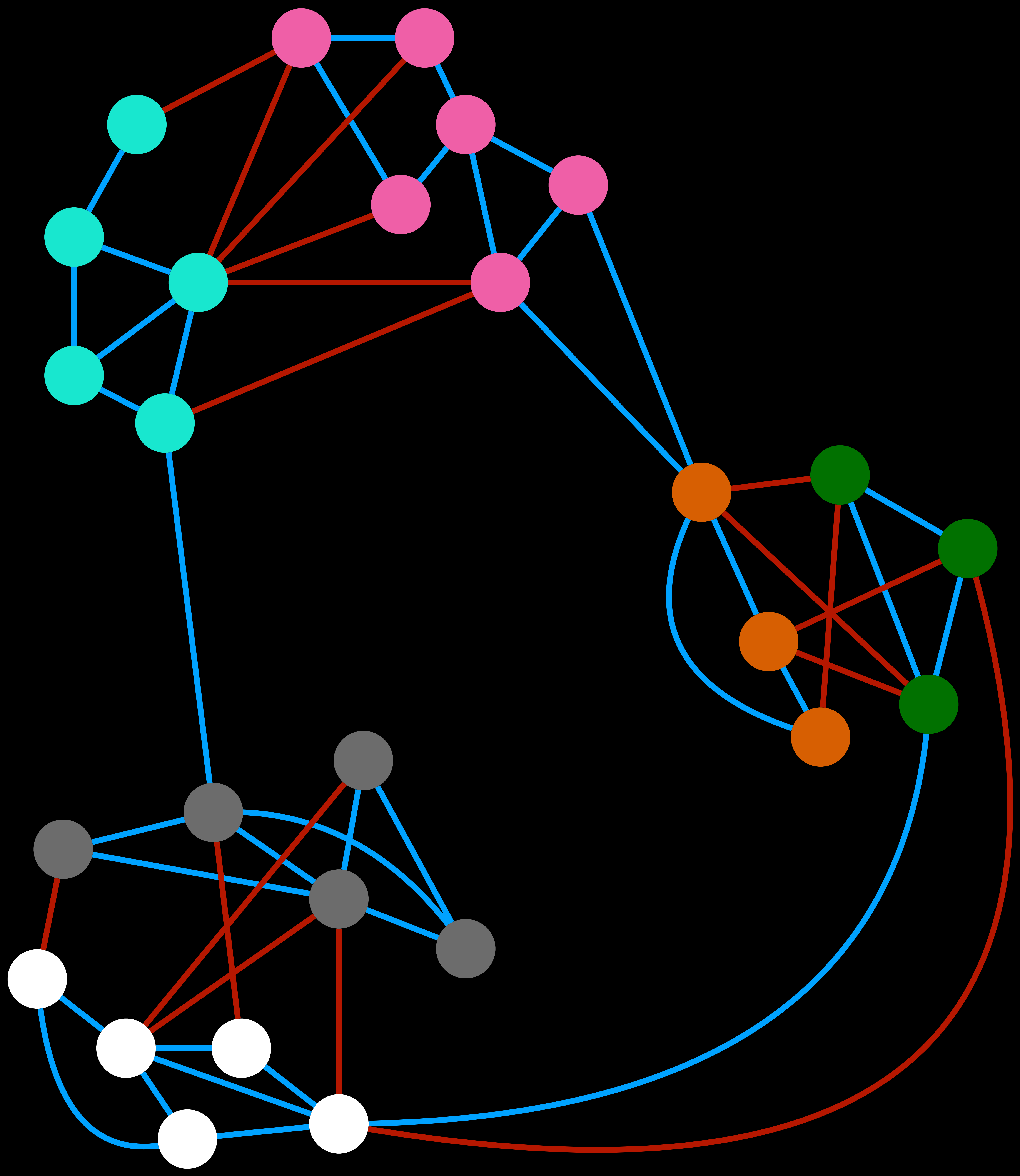

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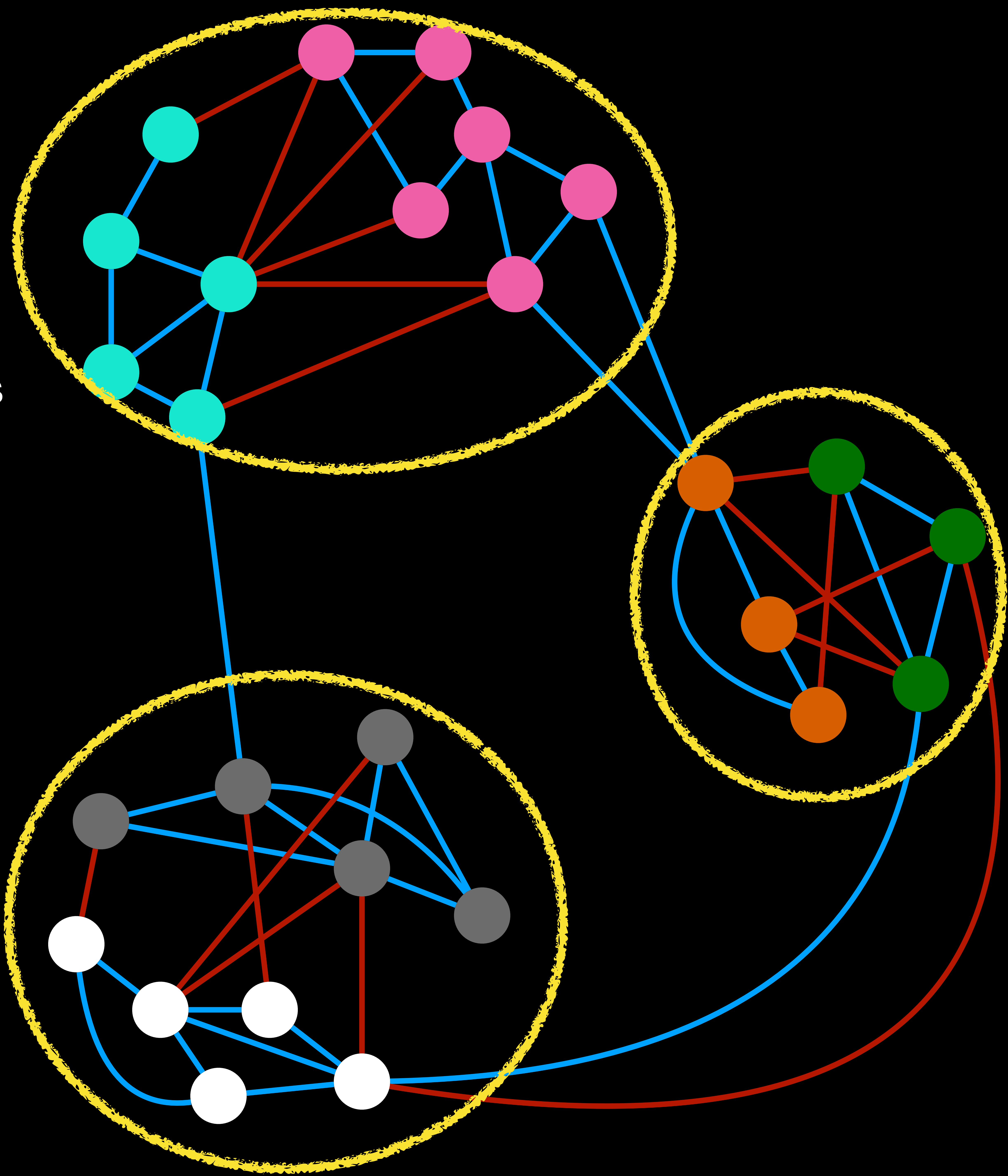

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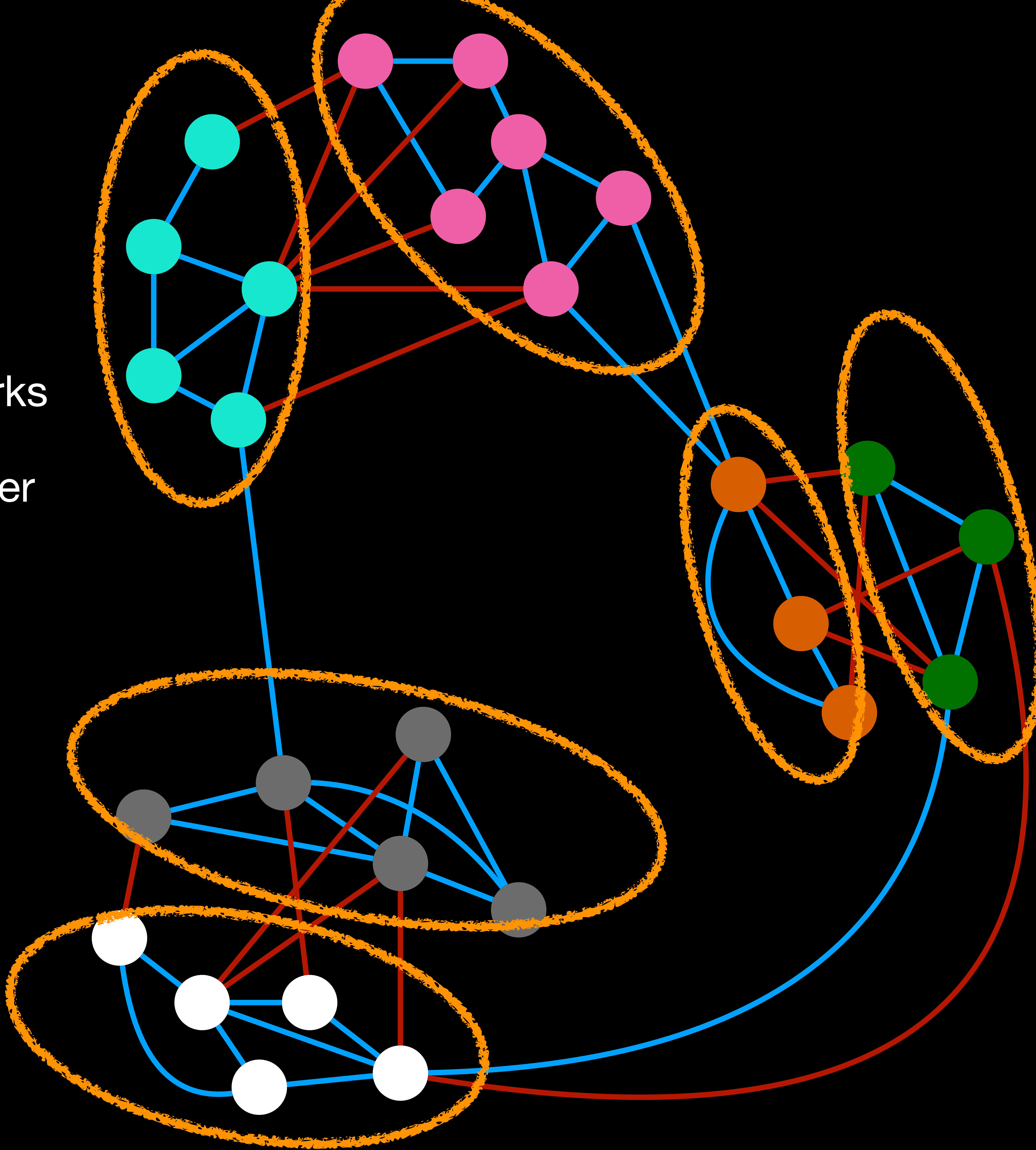

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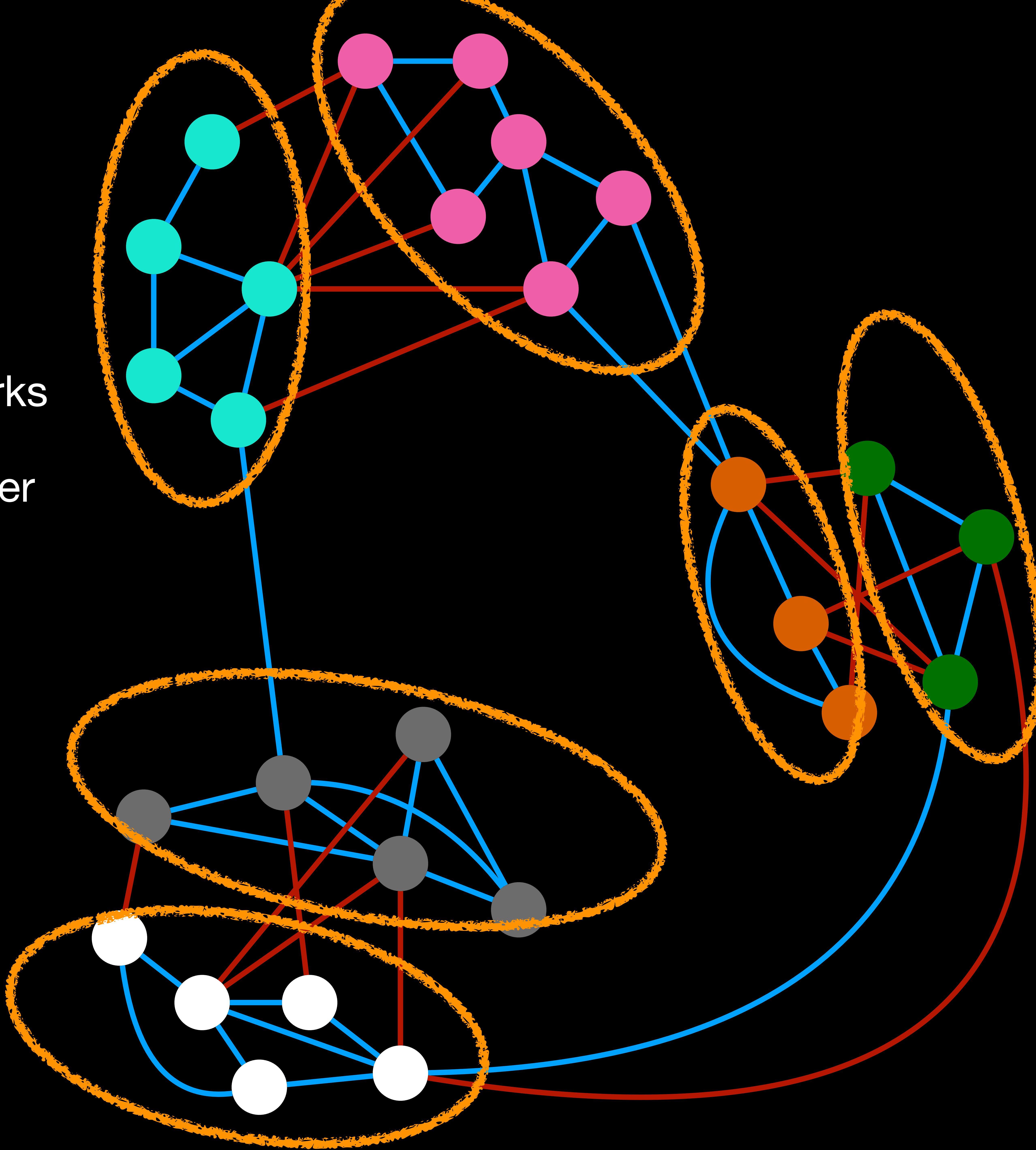

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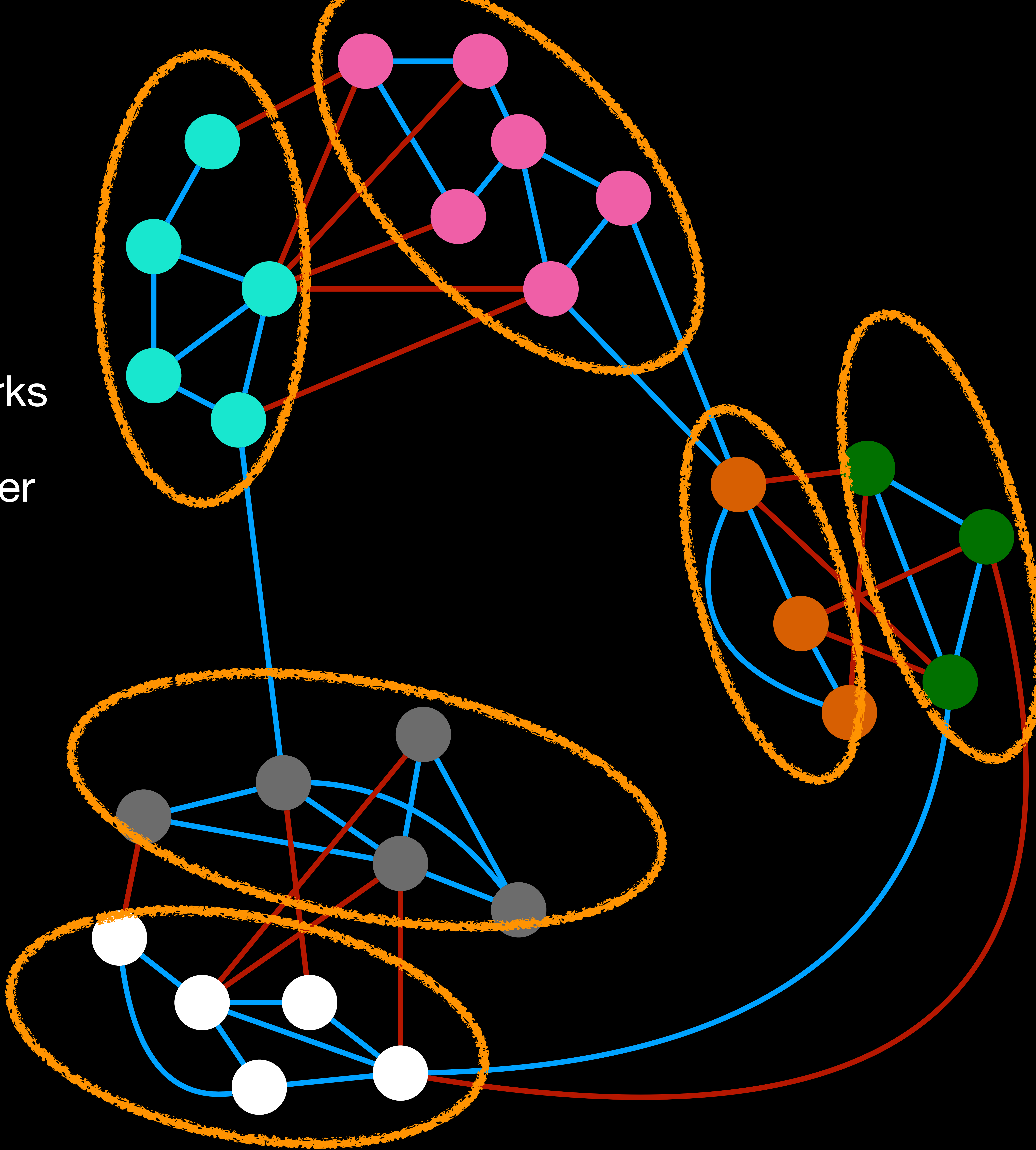
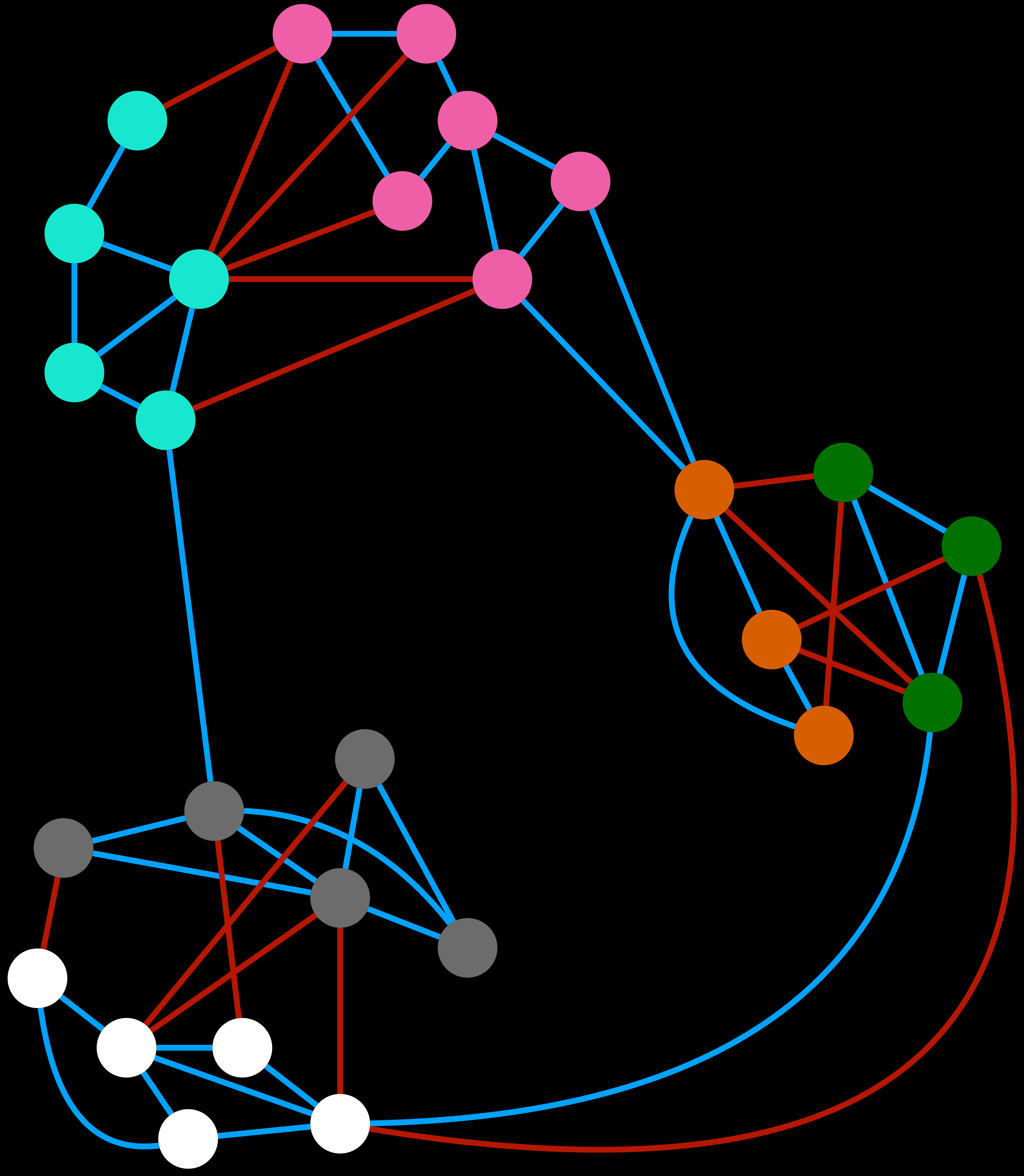
  - ➡ analyze trust in Bitcoin networks



Sublinear-Time Algorithms

- Real-world graphs are huge and clustering the entire graph is often infeasible



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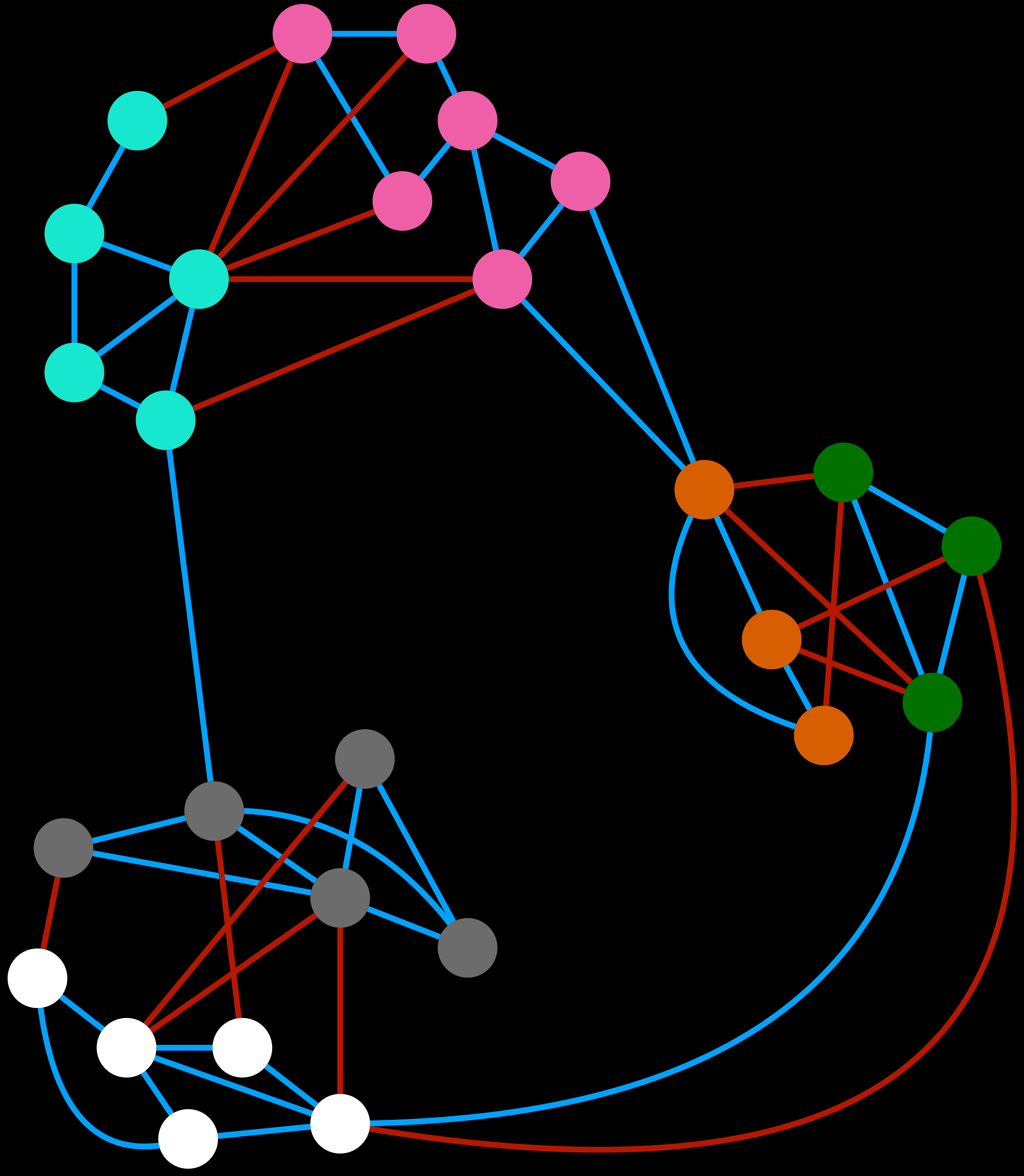

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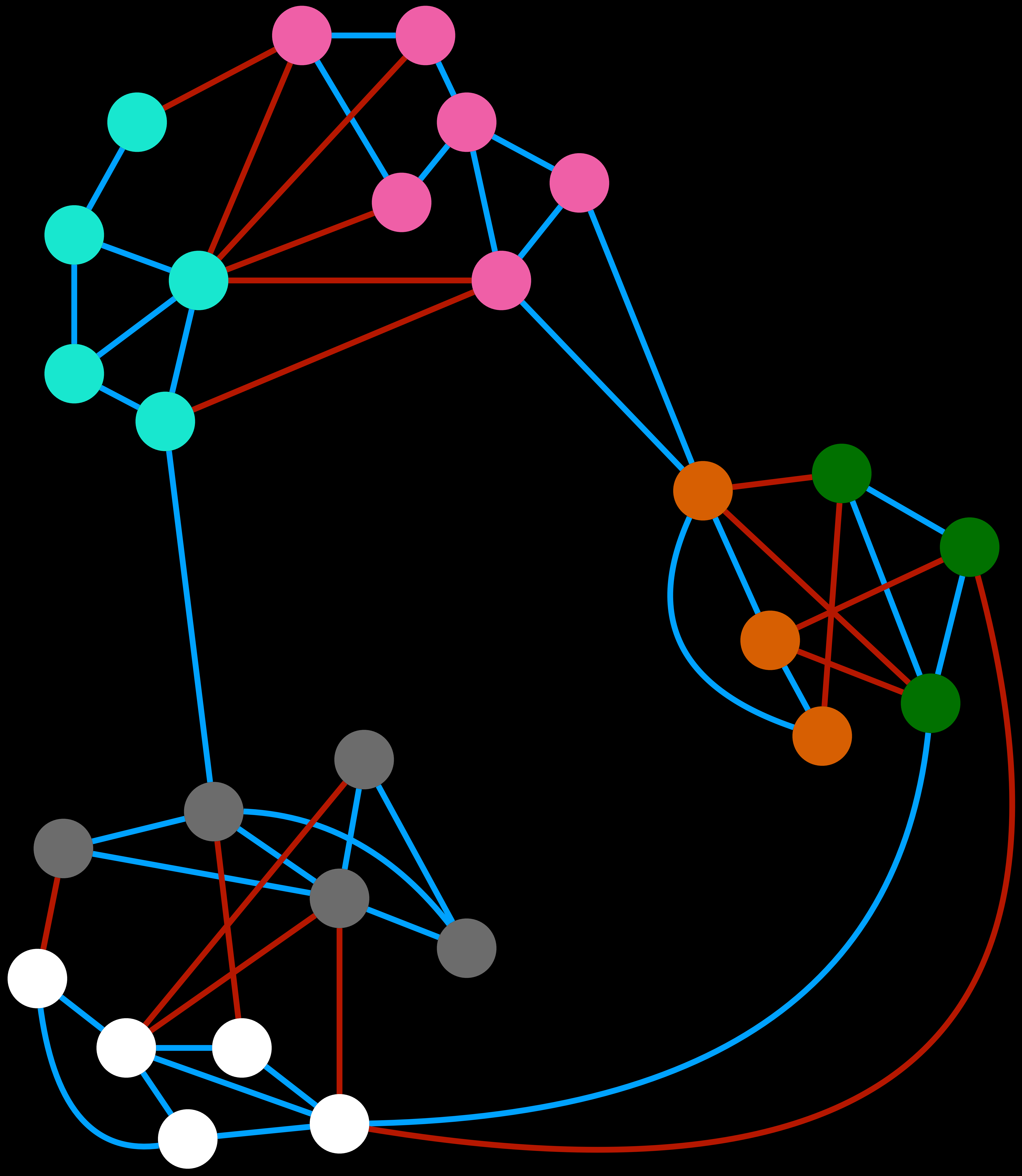

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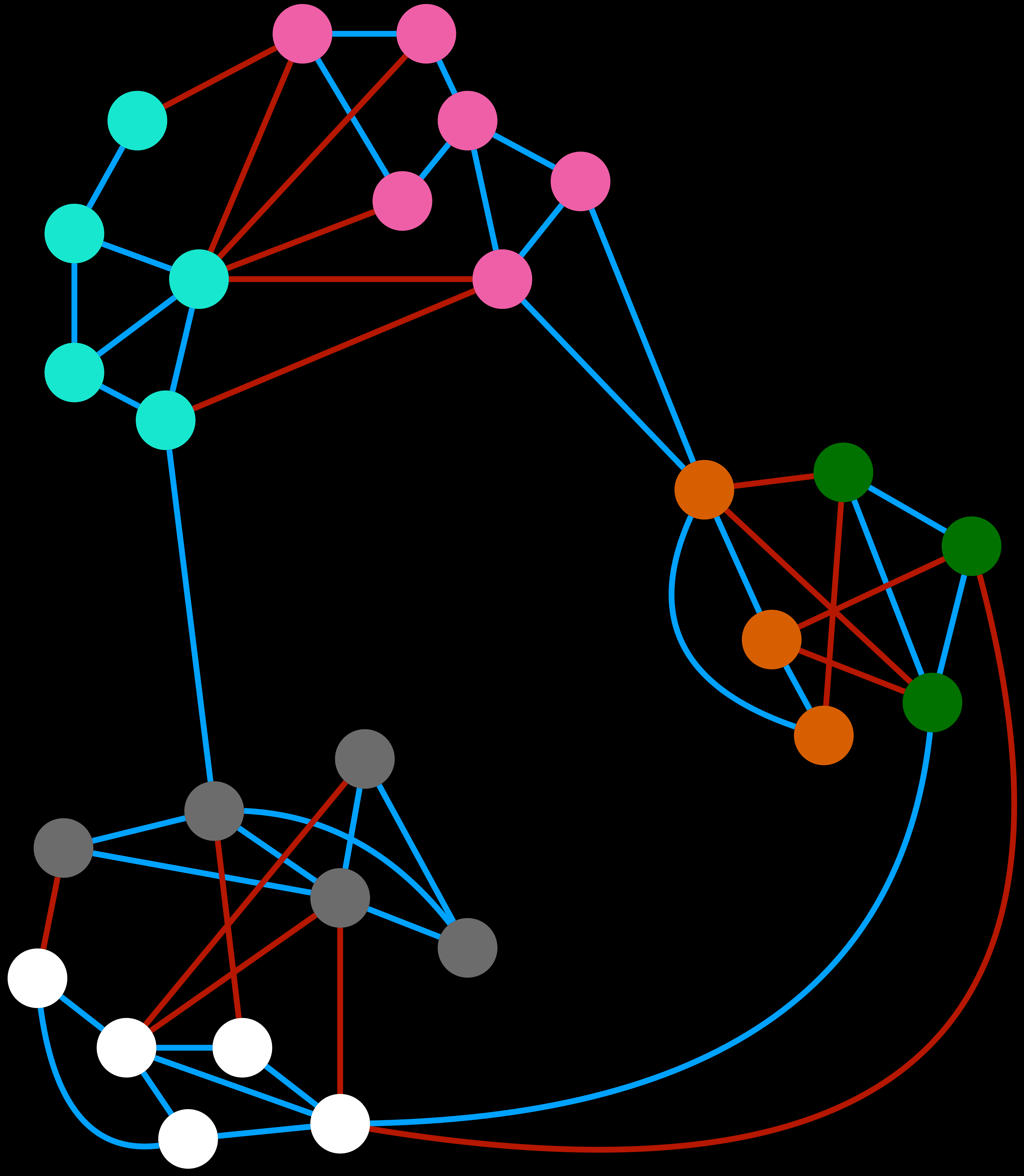

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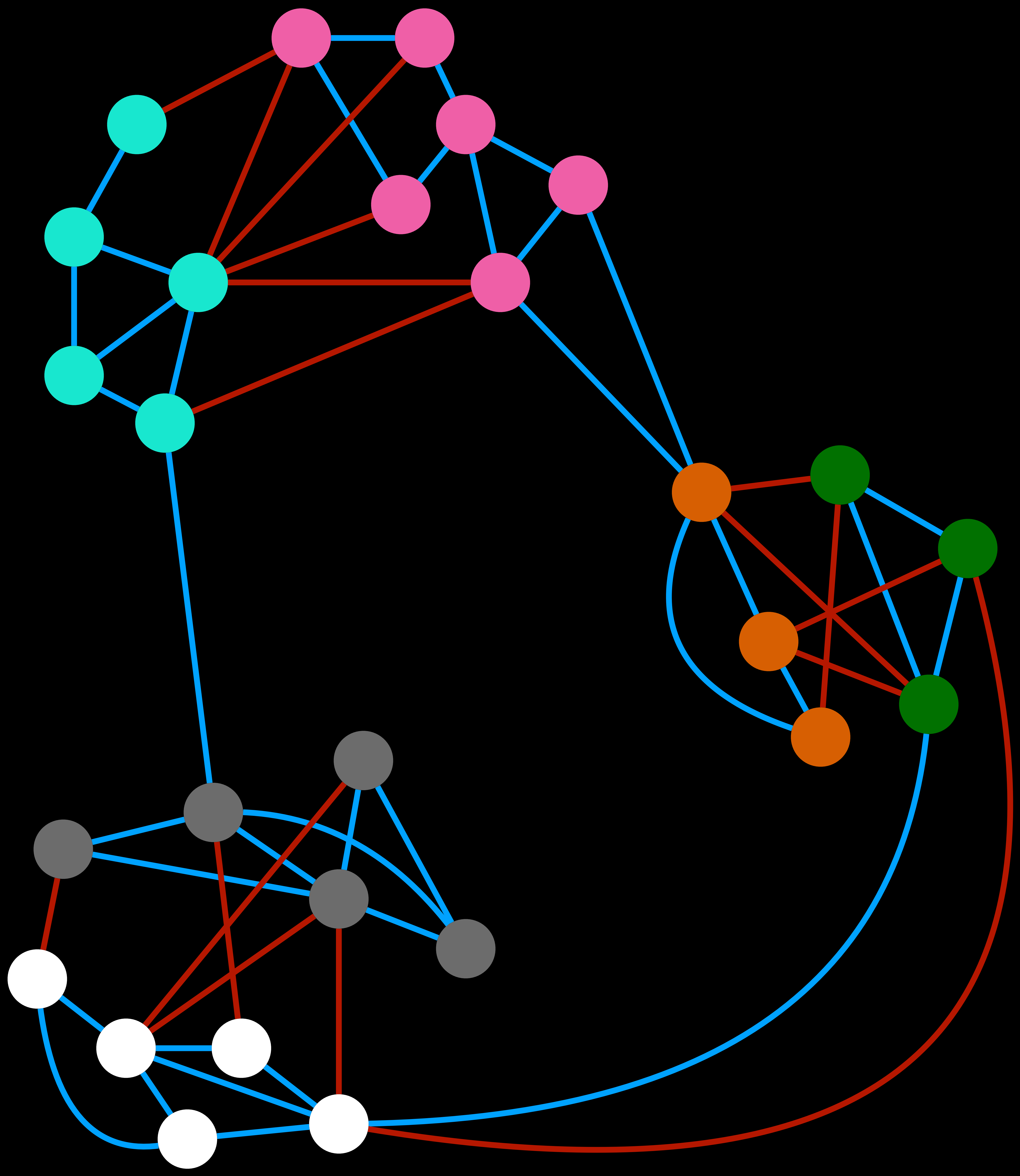

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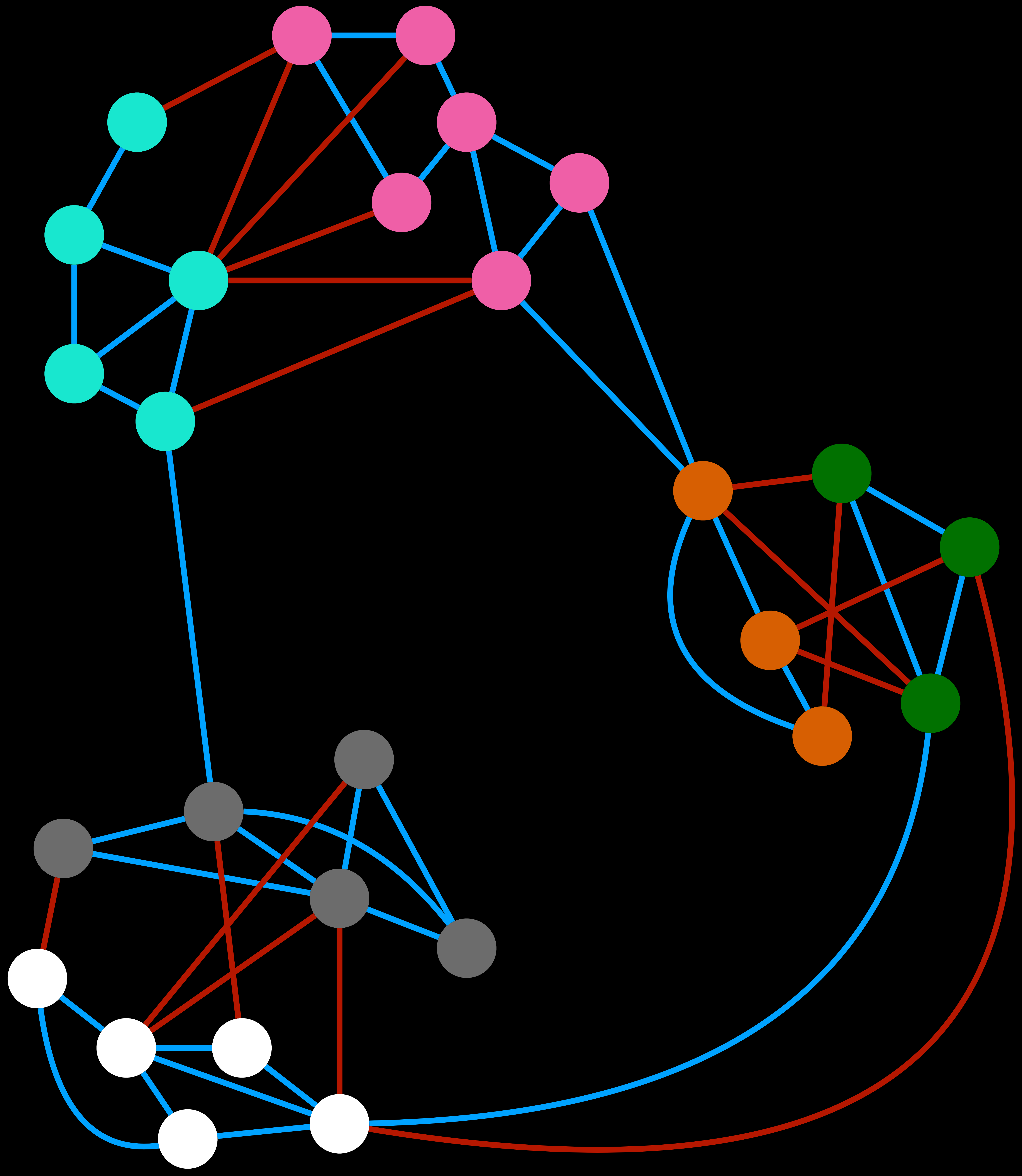
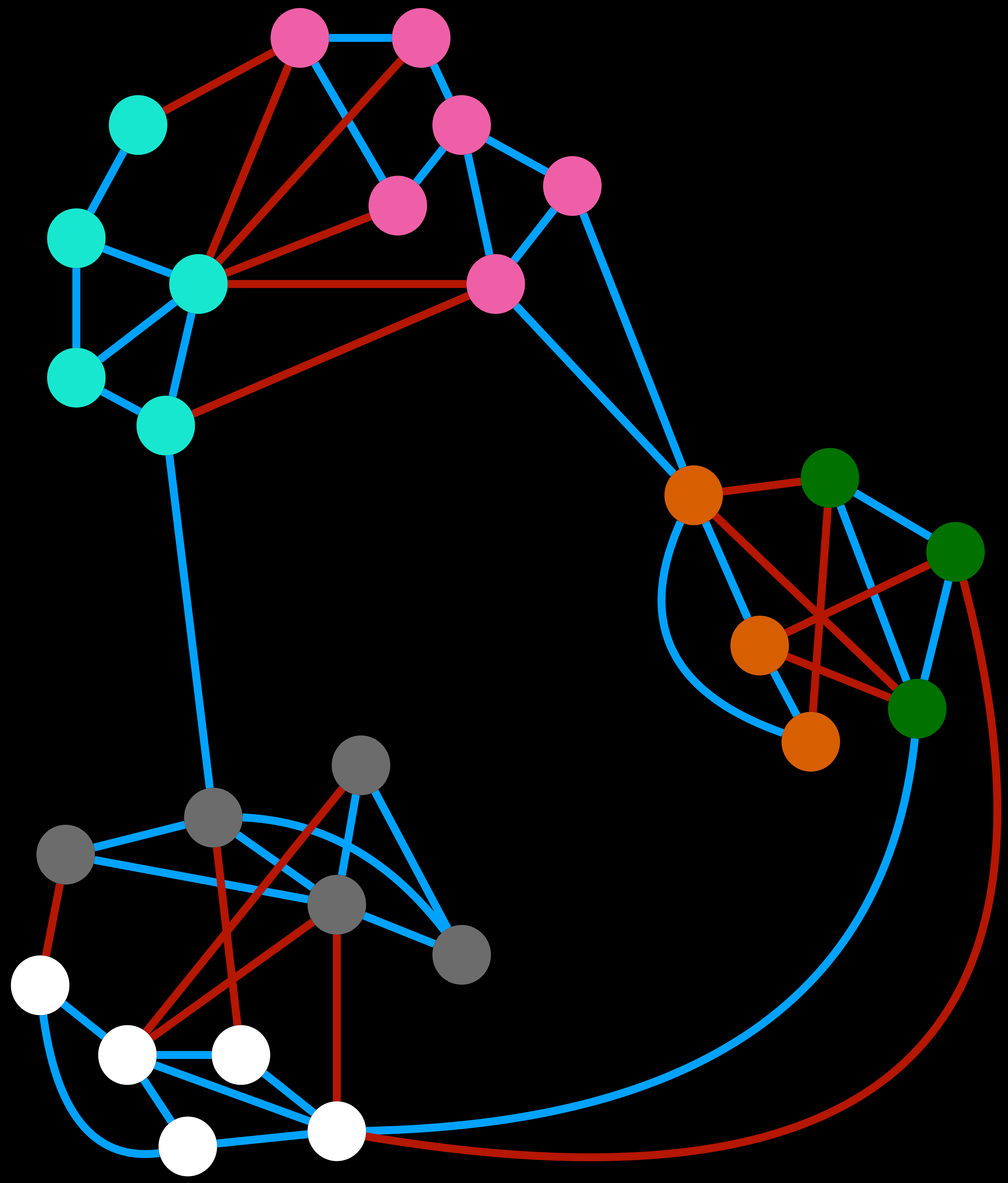
- Must be very fast and space efficient



Our Signed Oracle



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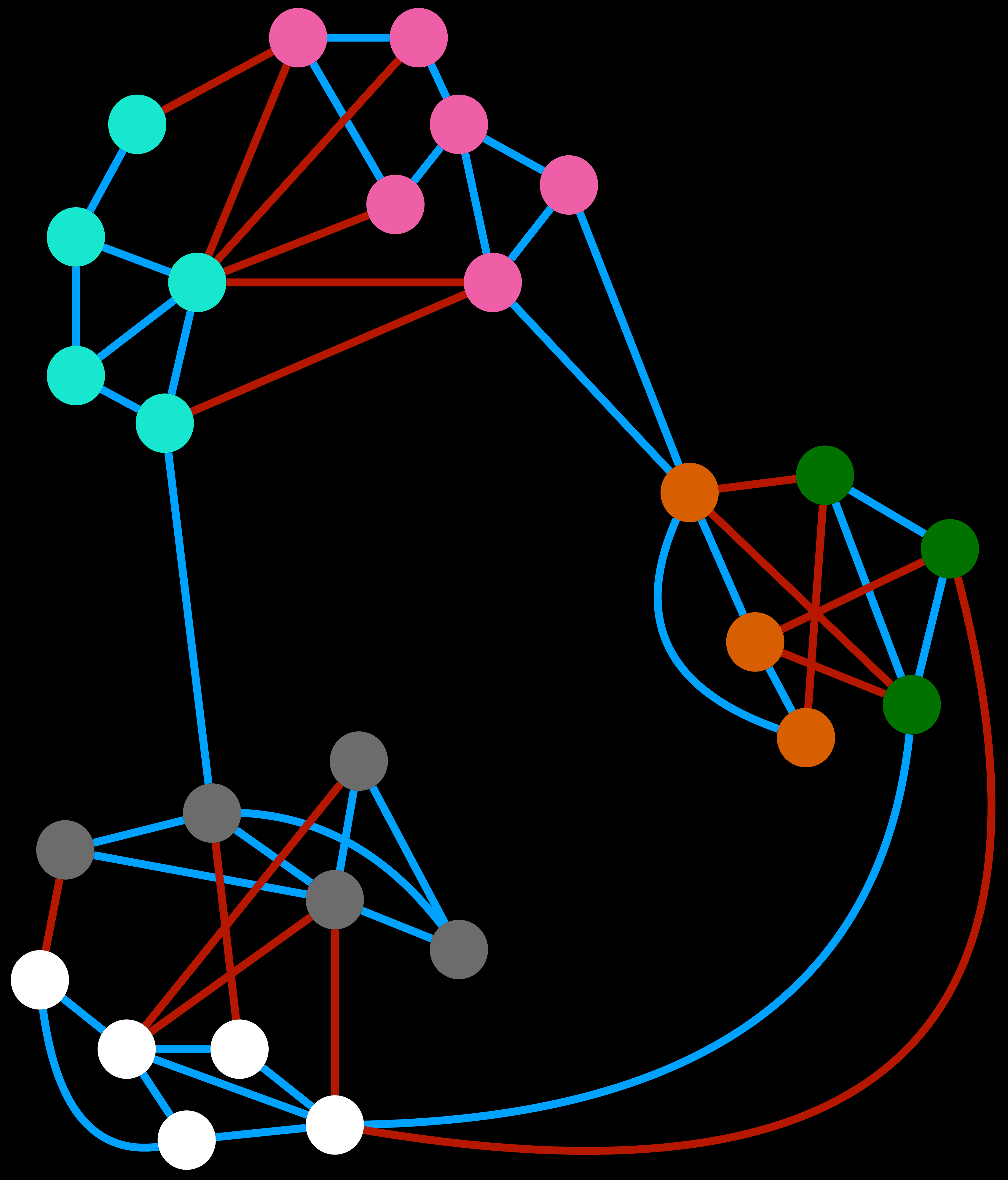

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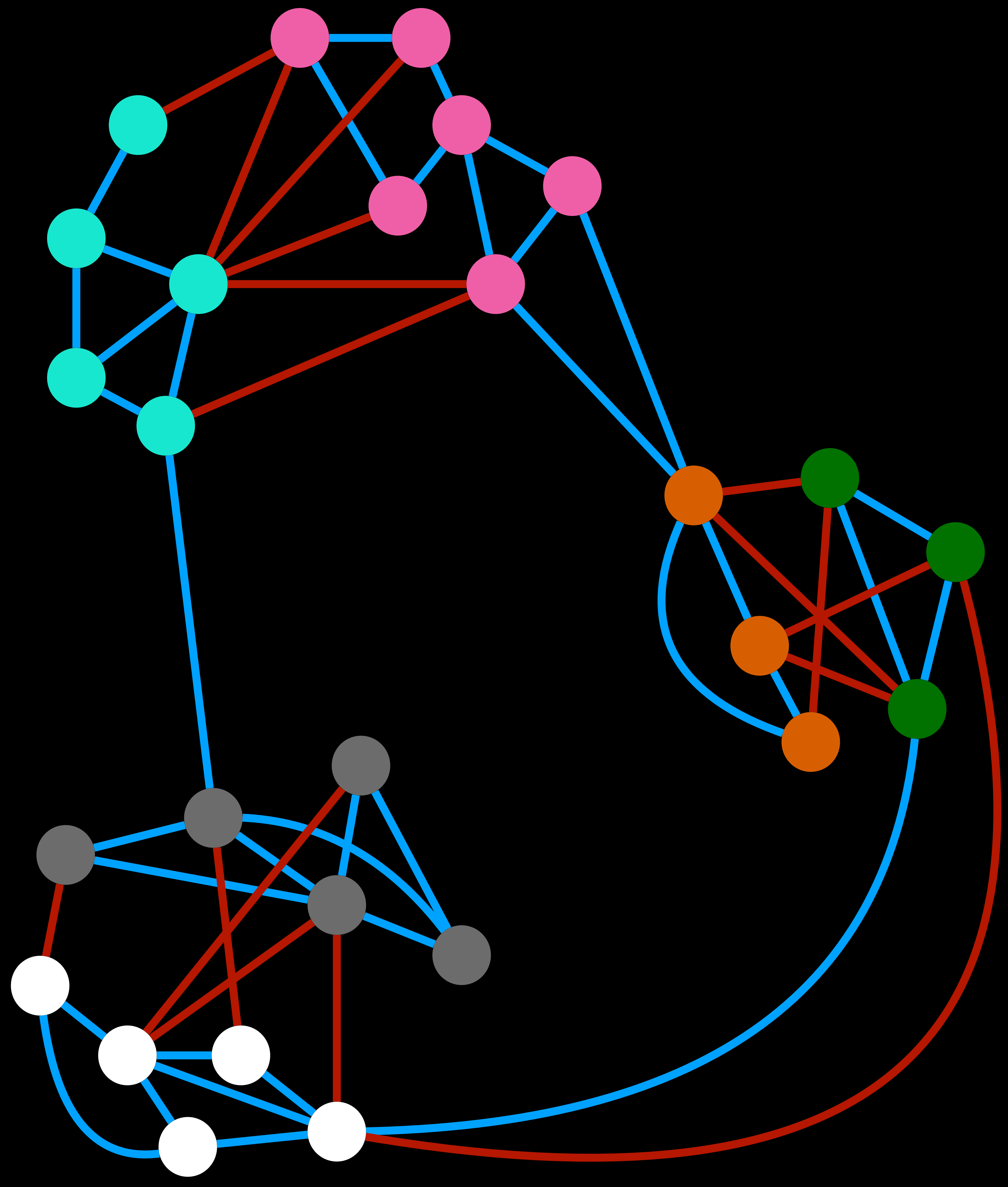

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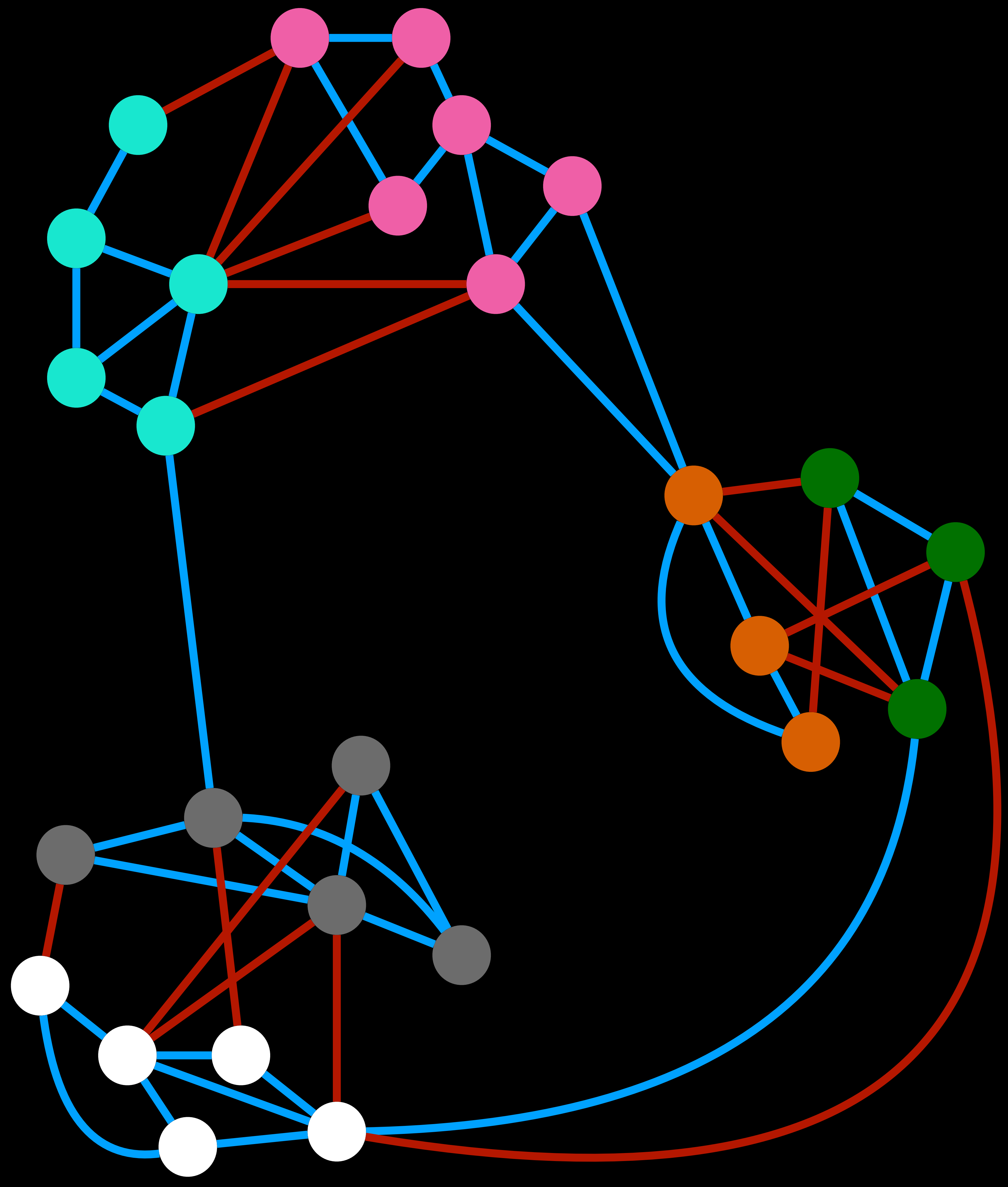

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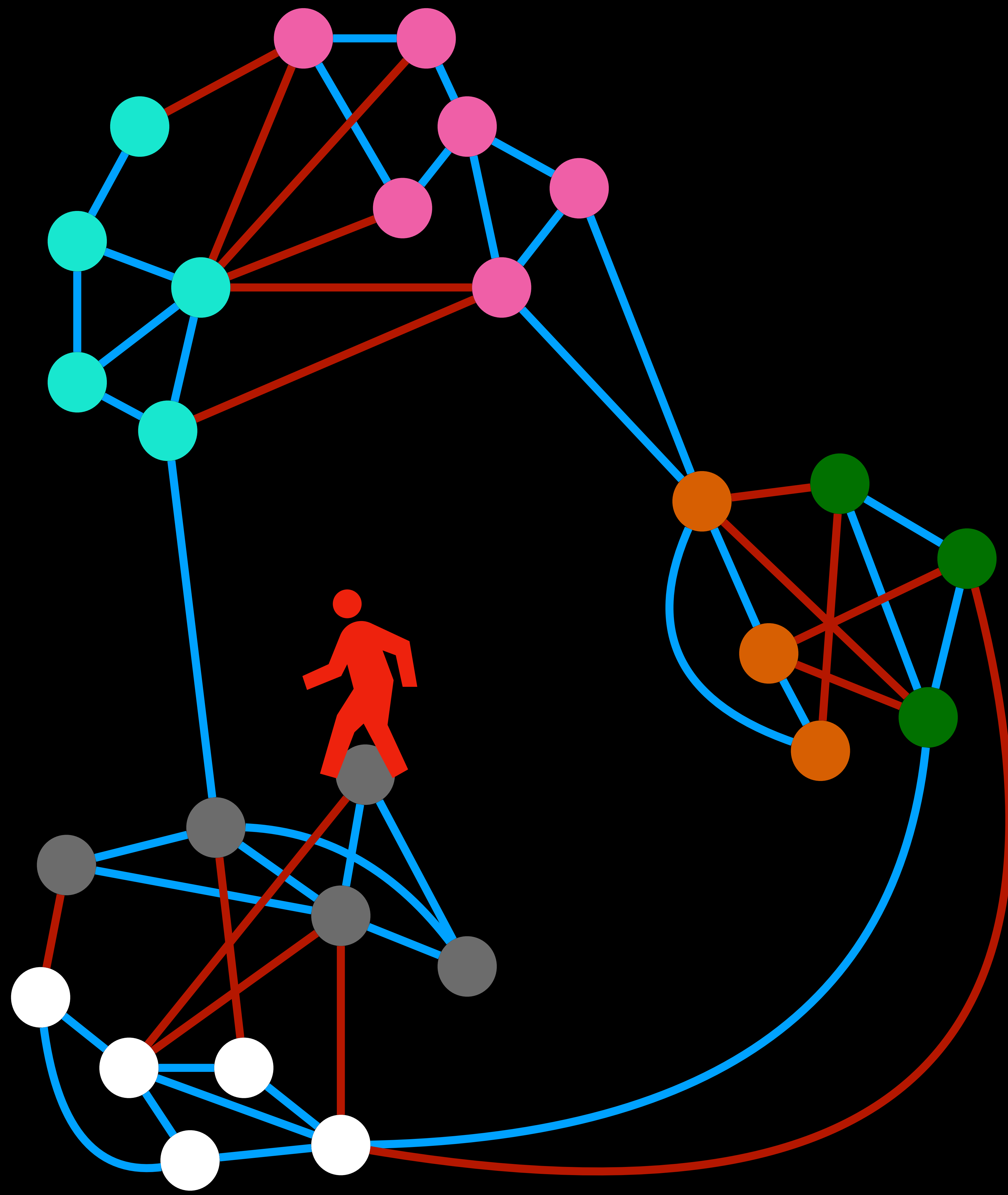

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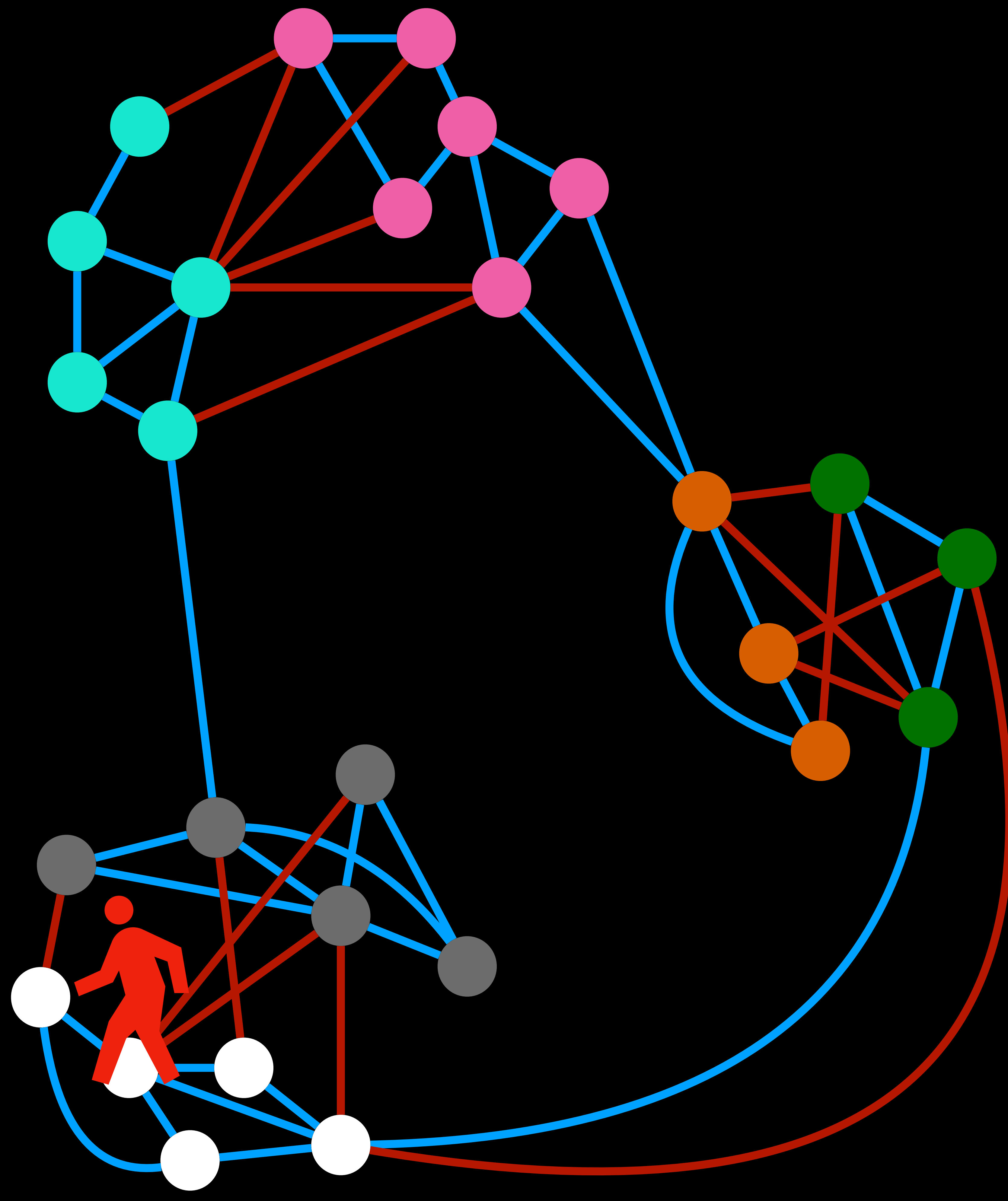

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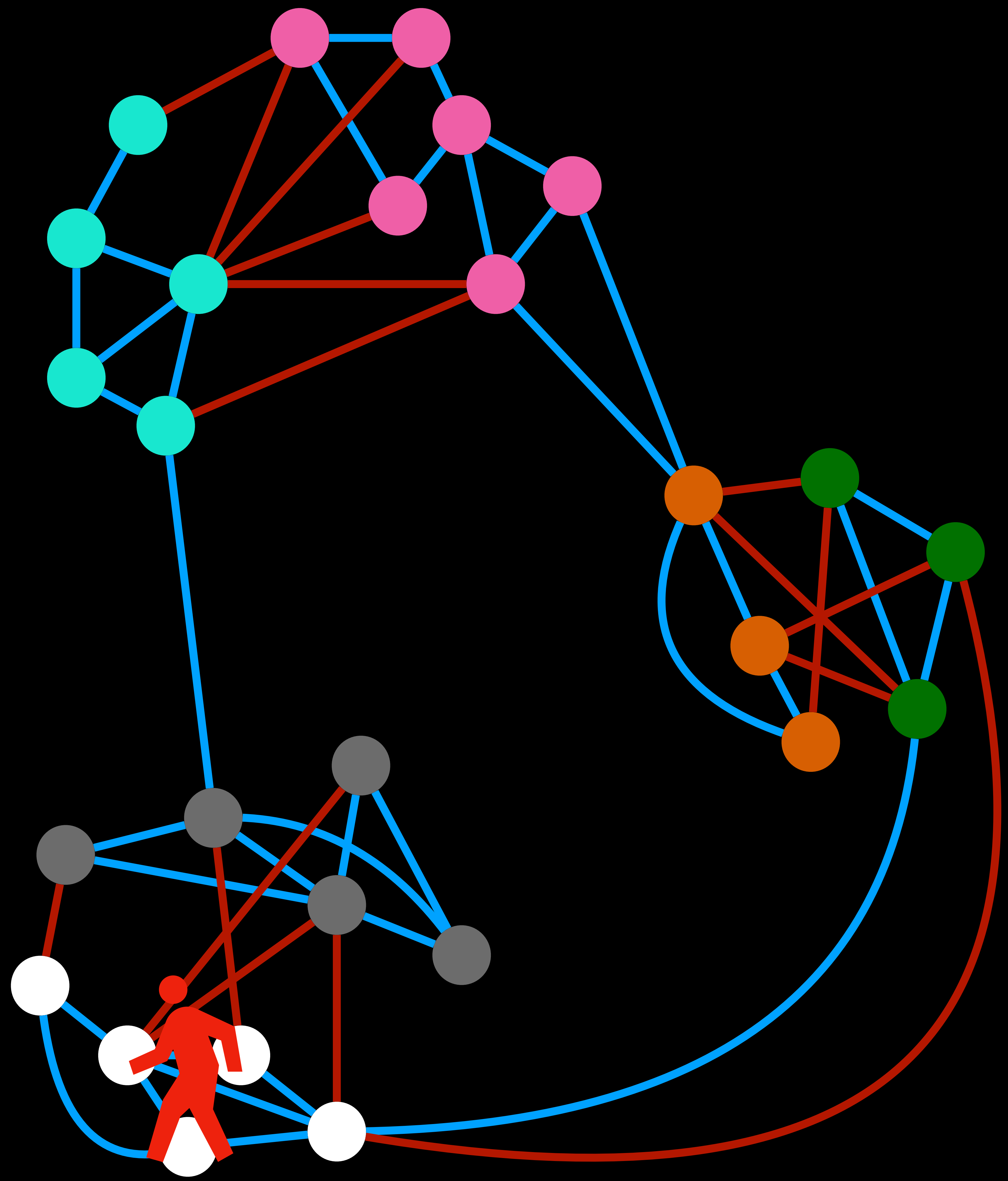

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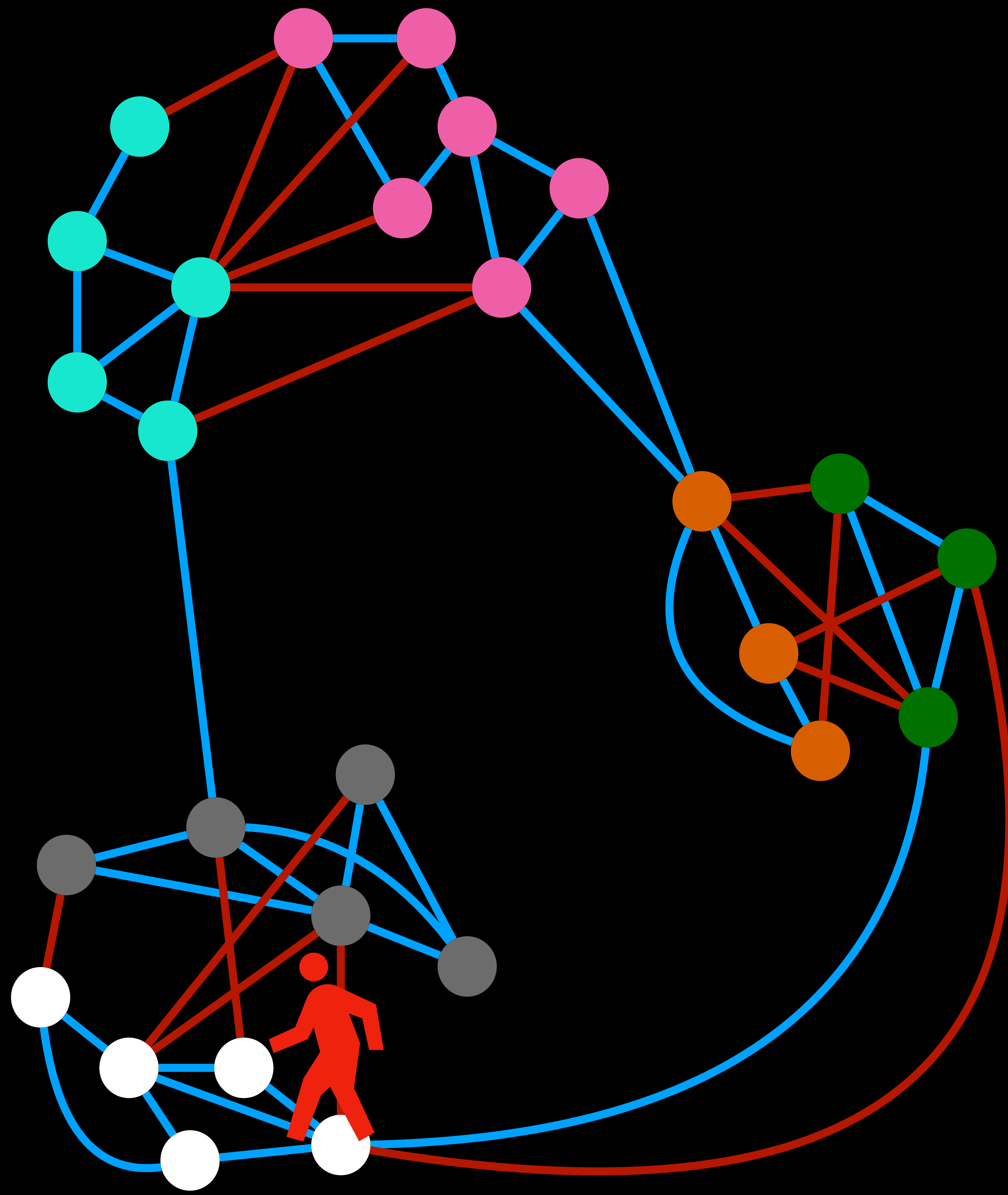

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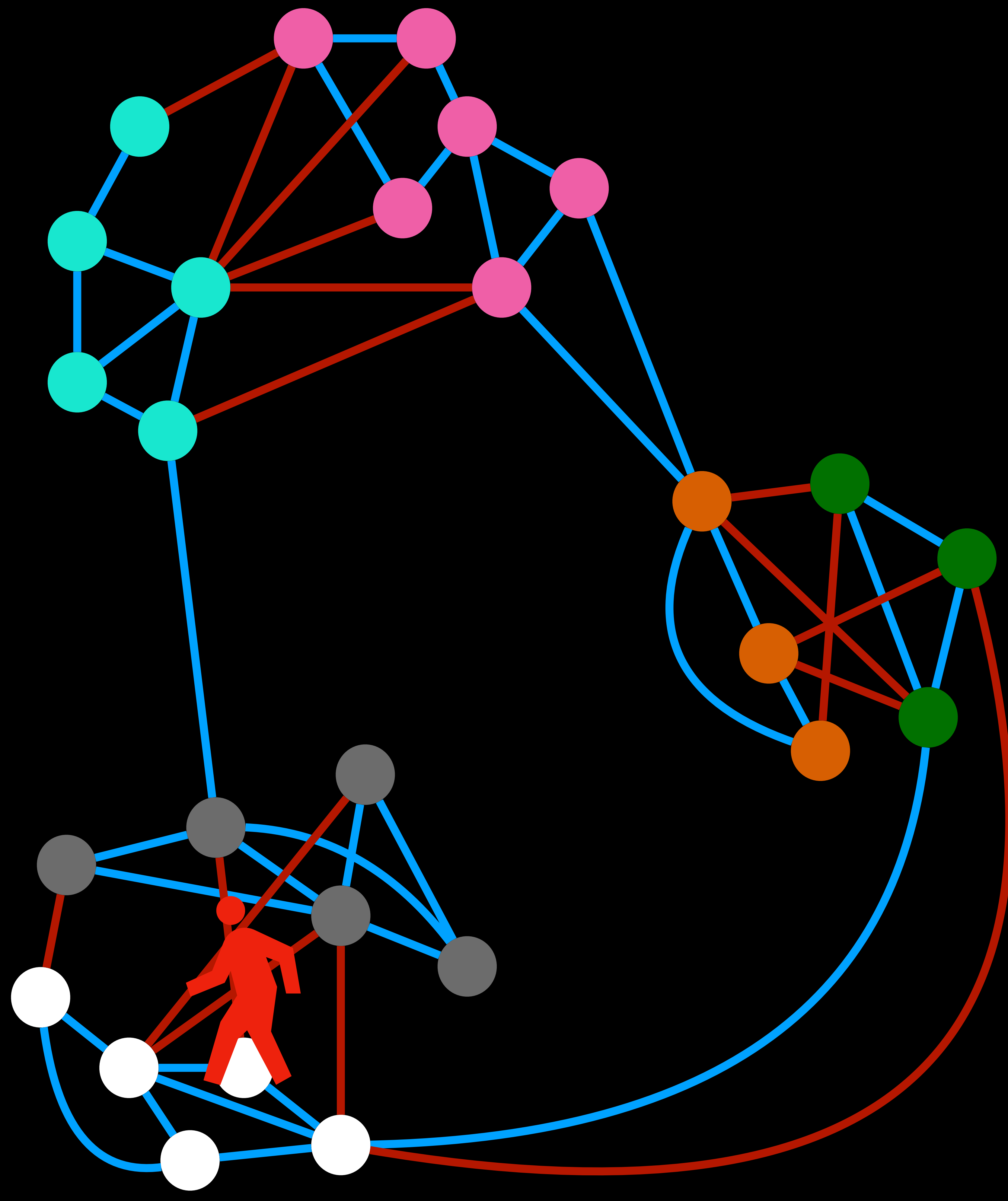

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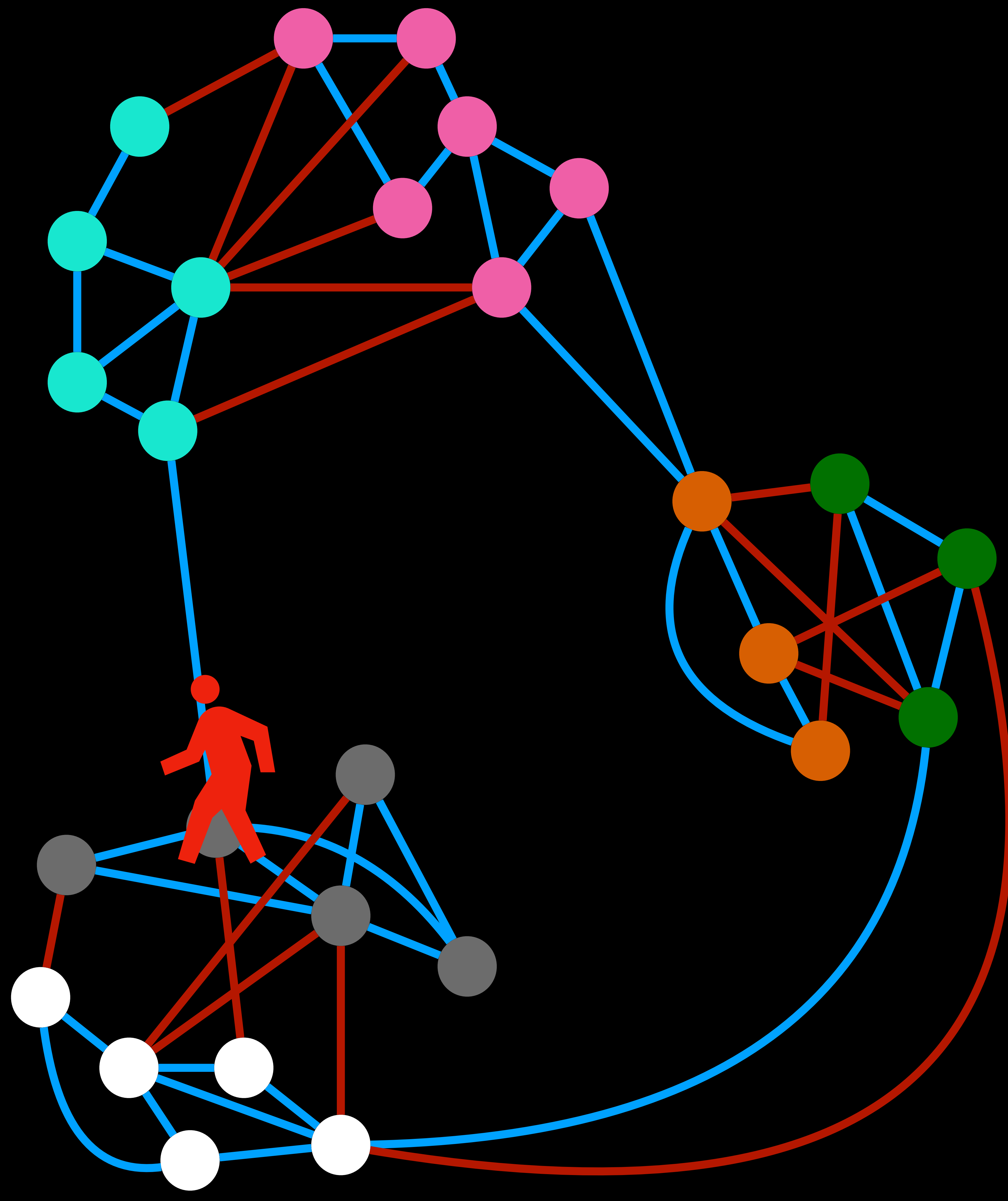

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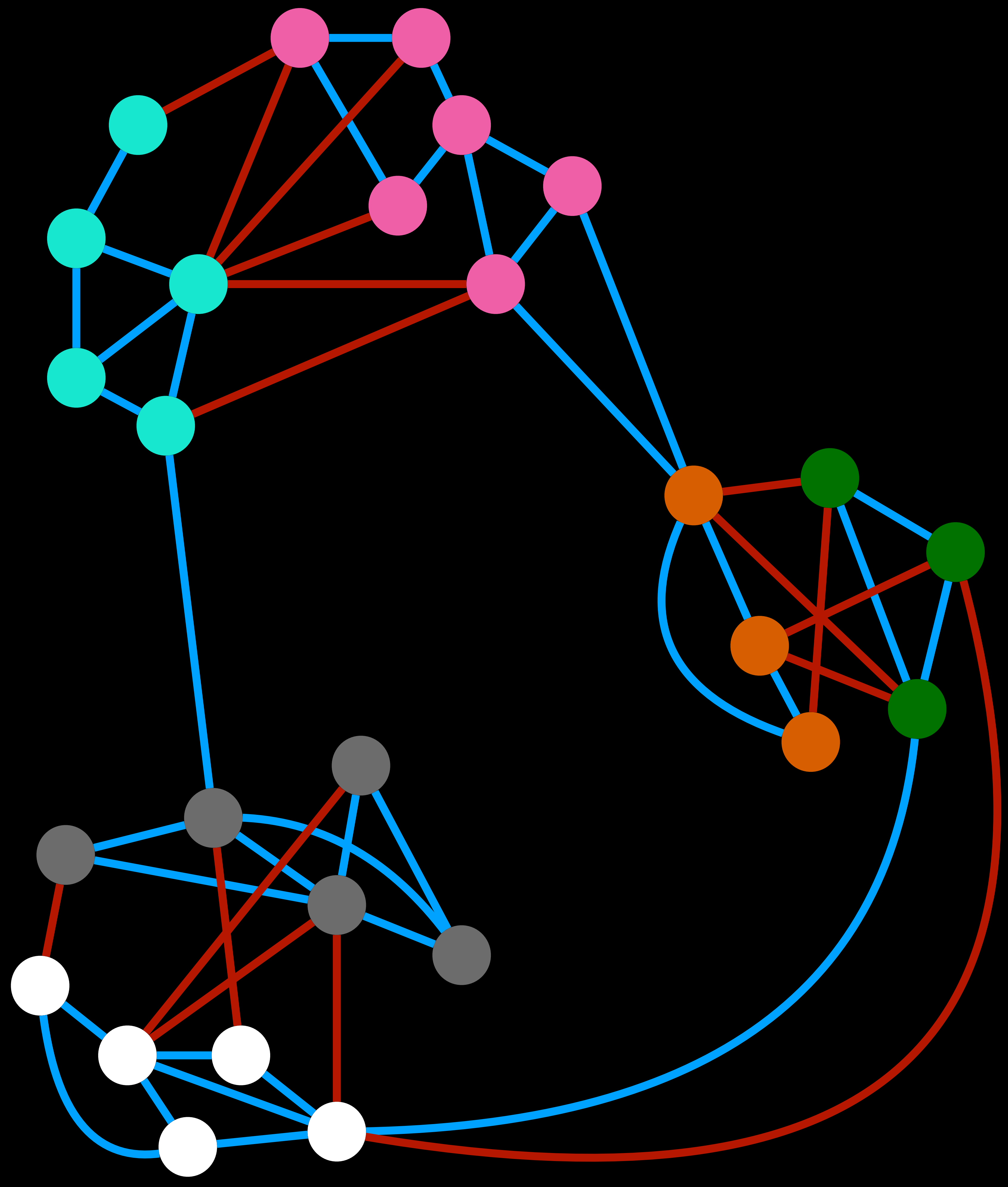

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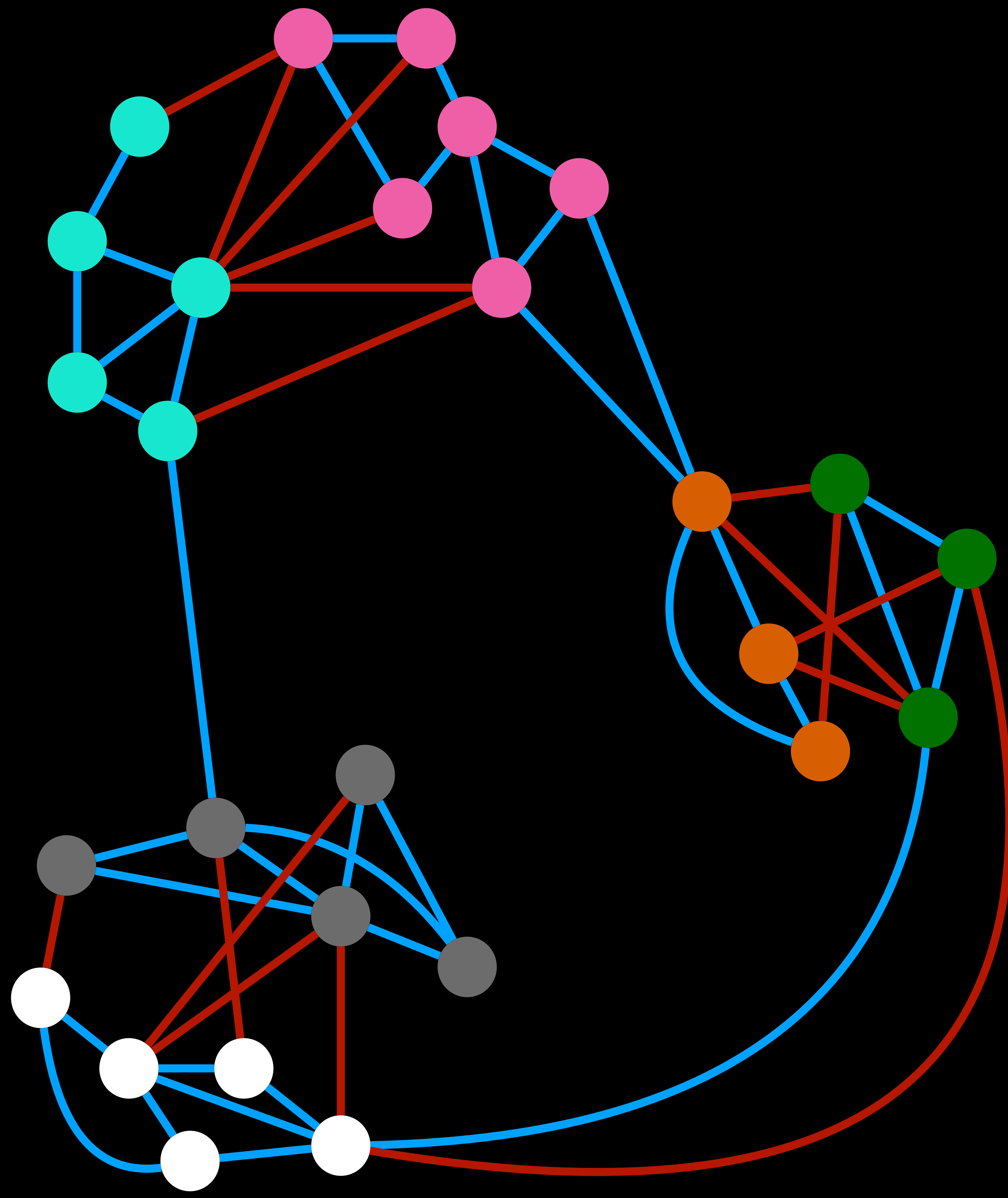

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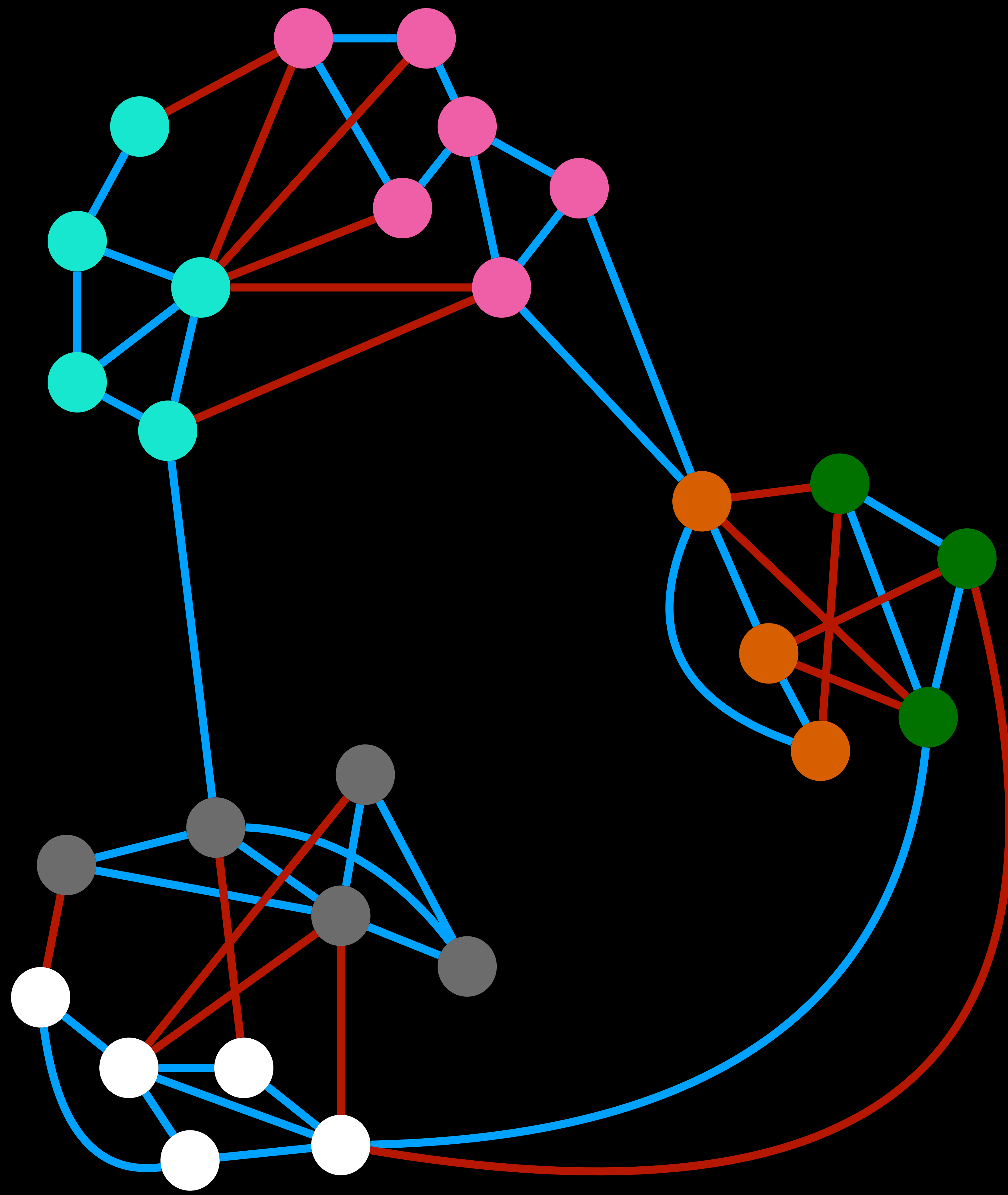
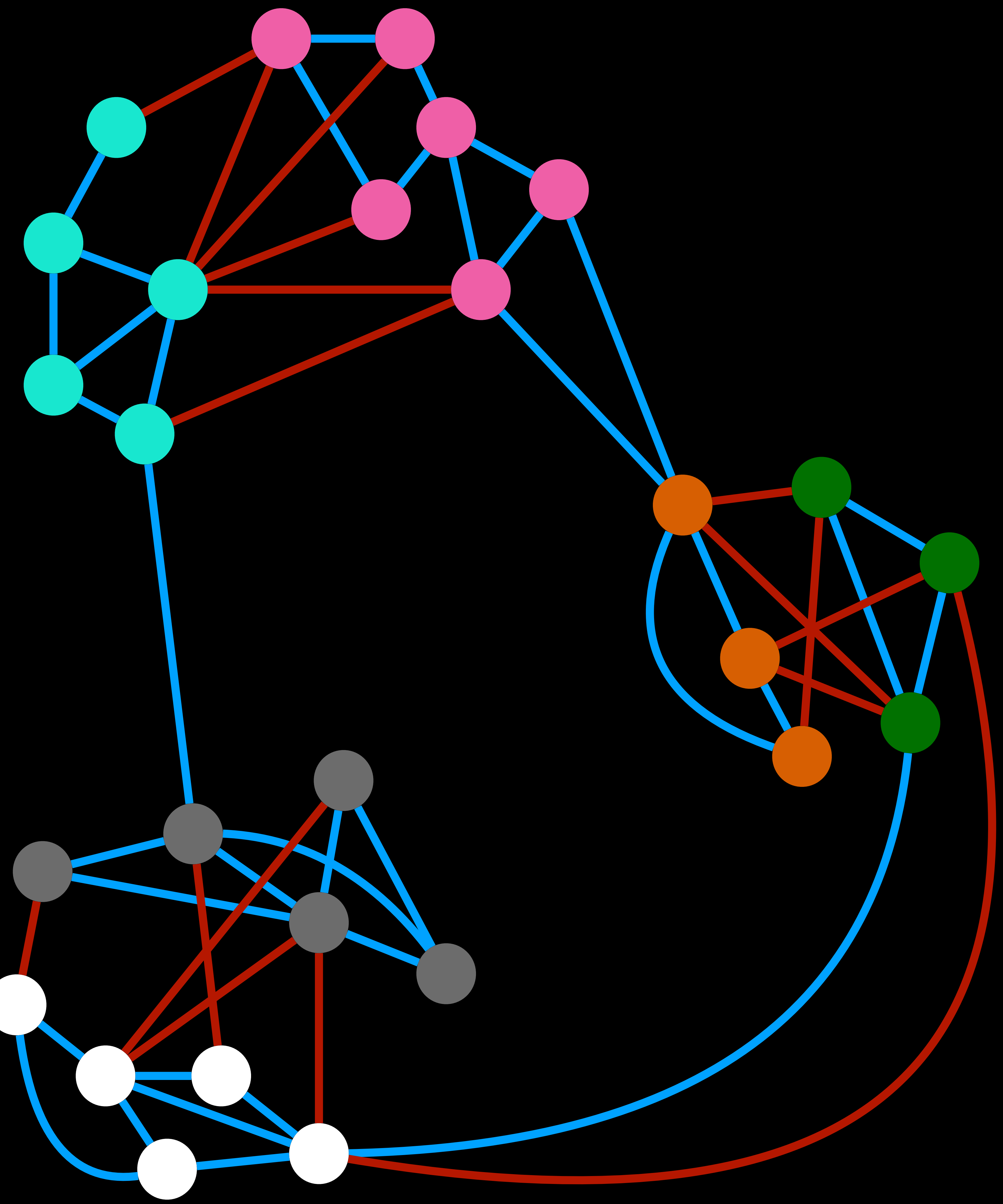
  ➡ Very efficient when only a few vertices need to be classified



We Can Provably Recover Planted Clusters



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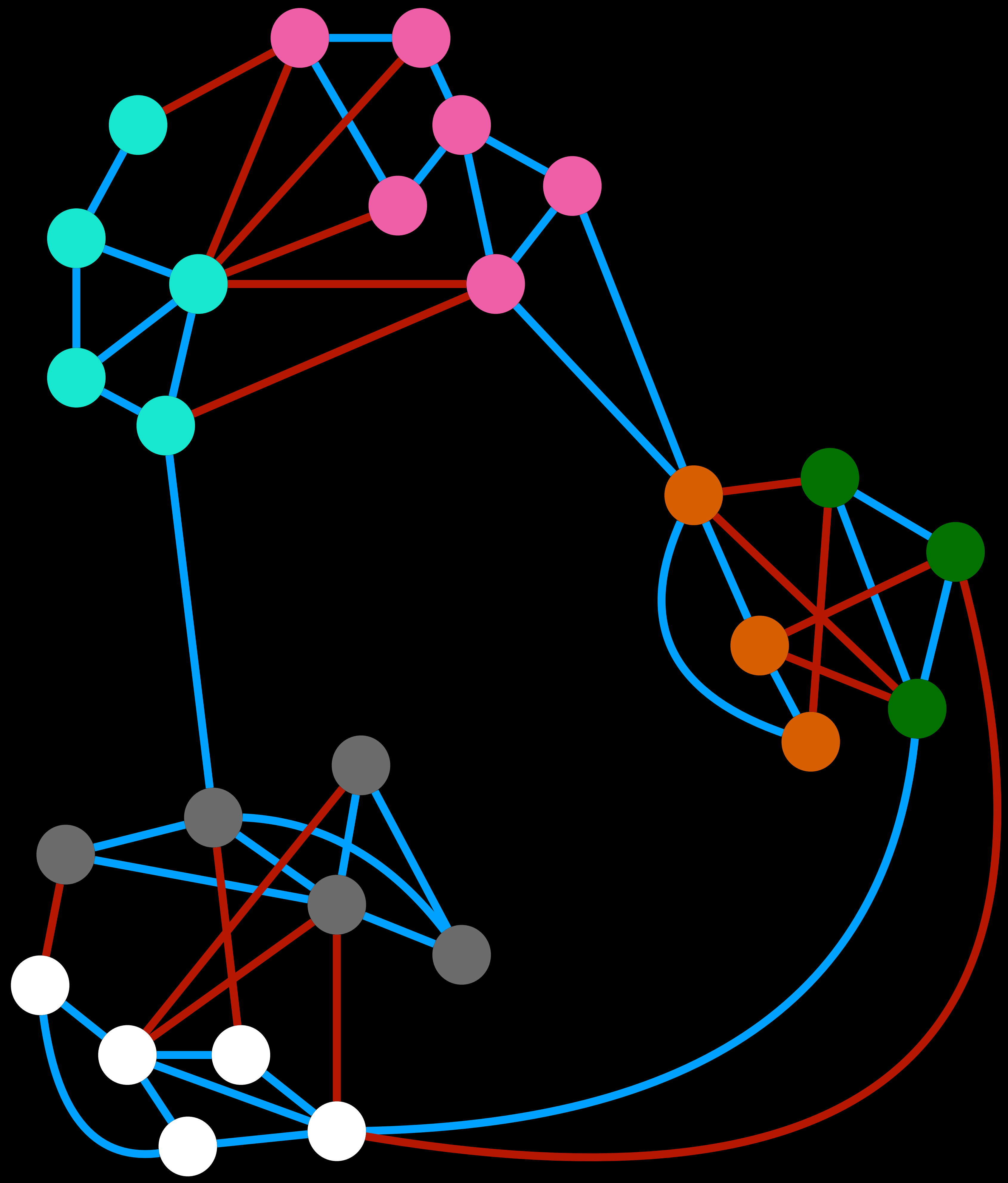

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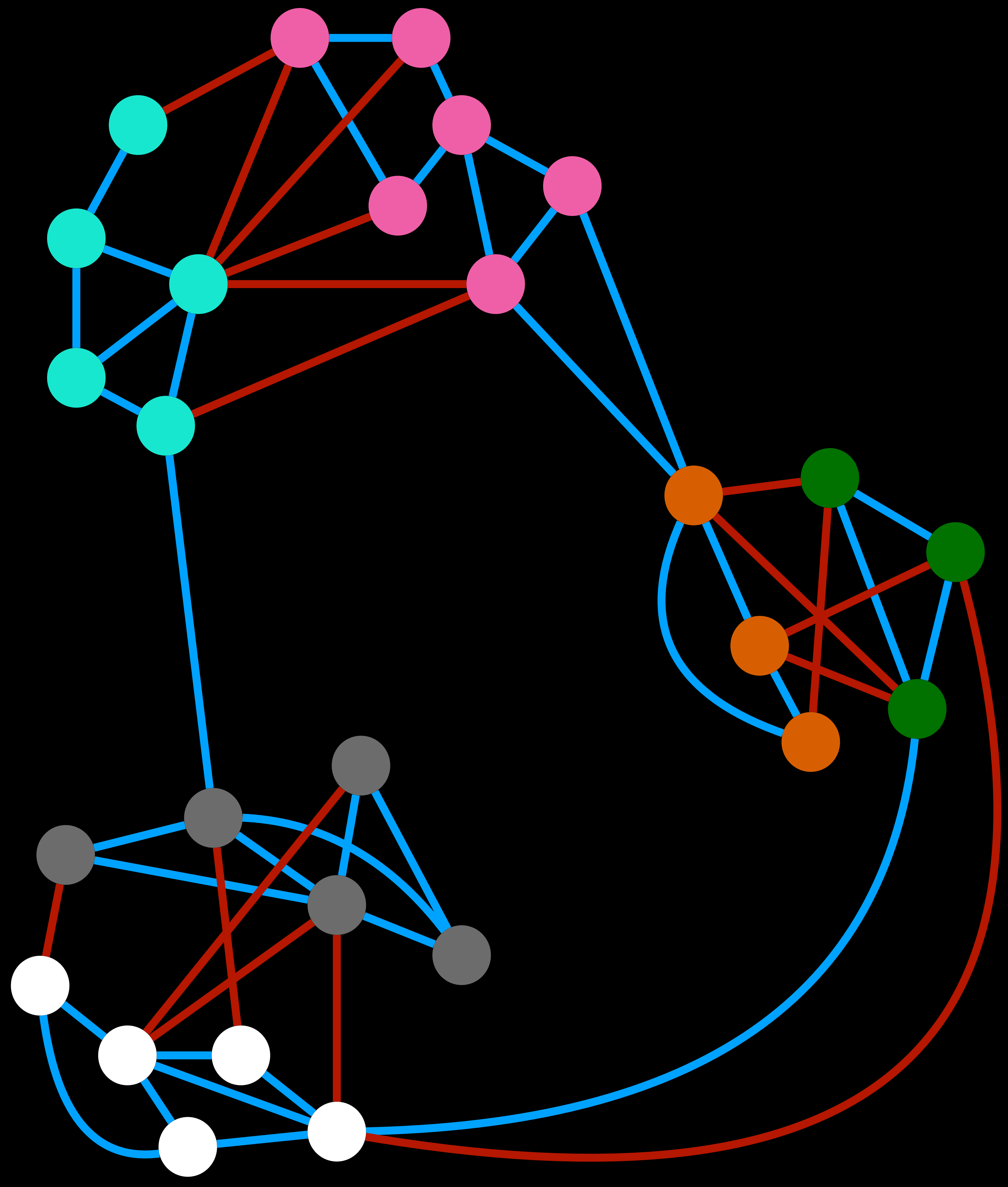

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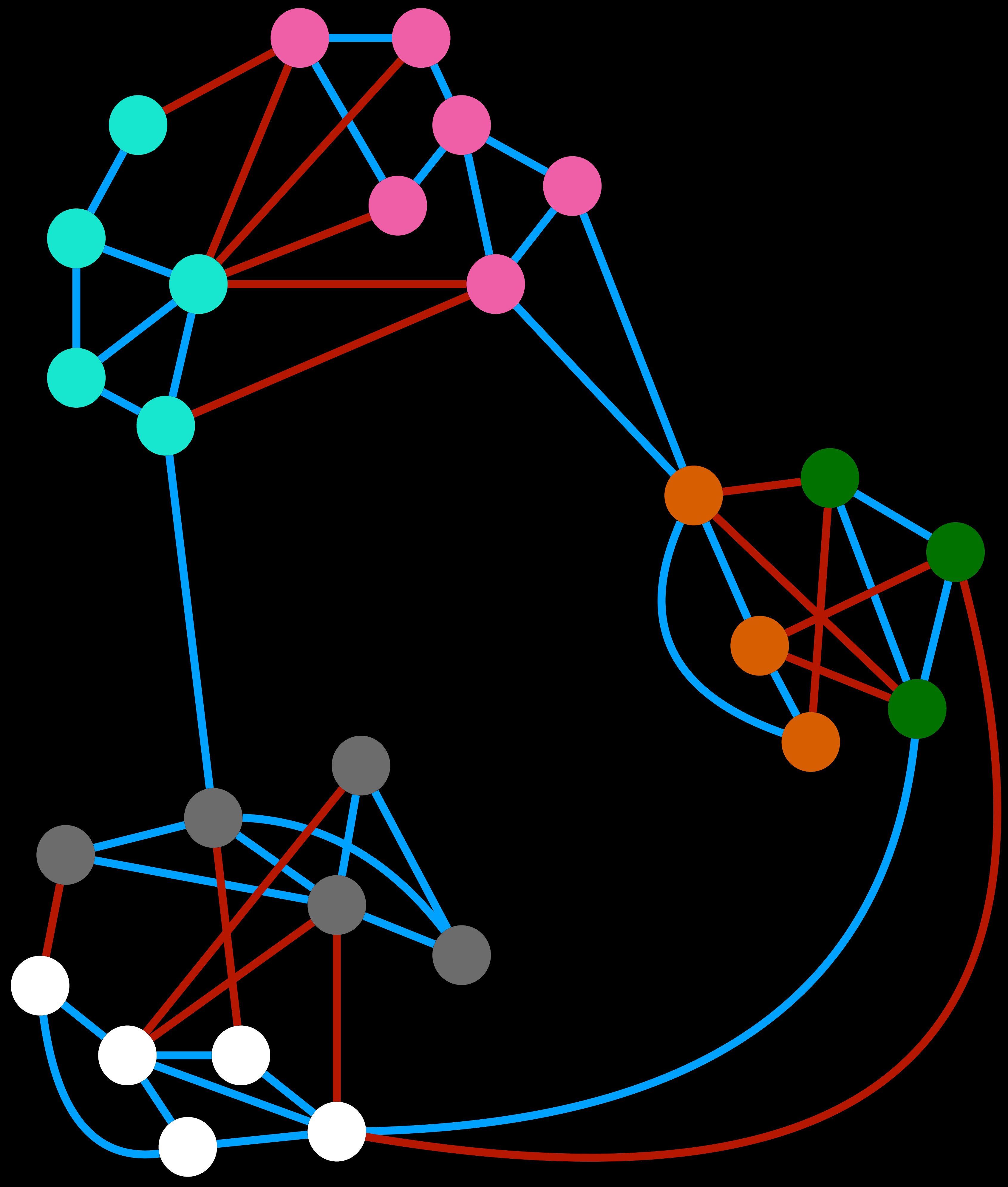

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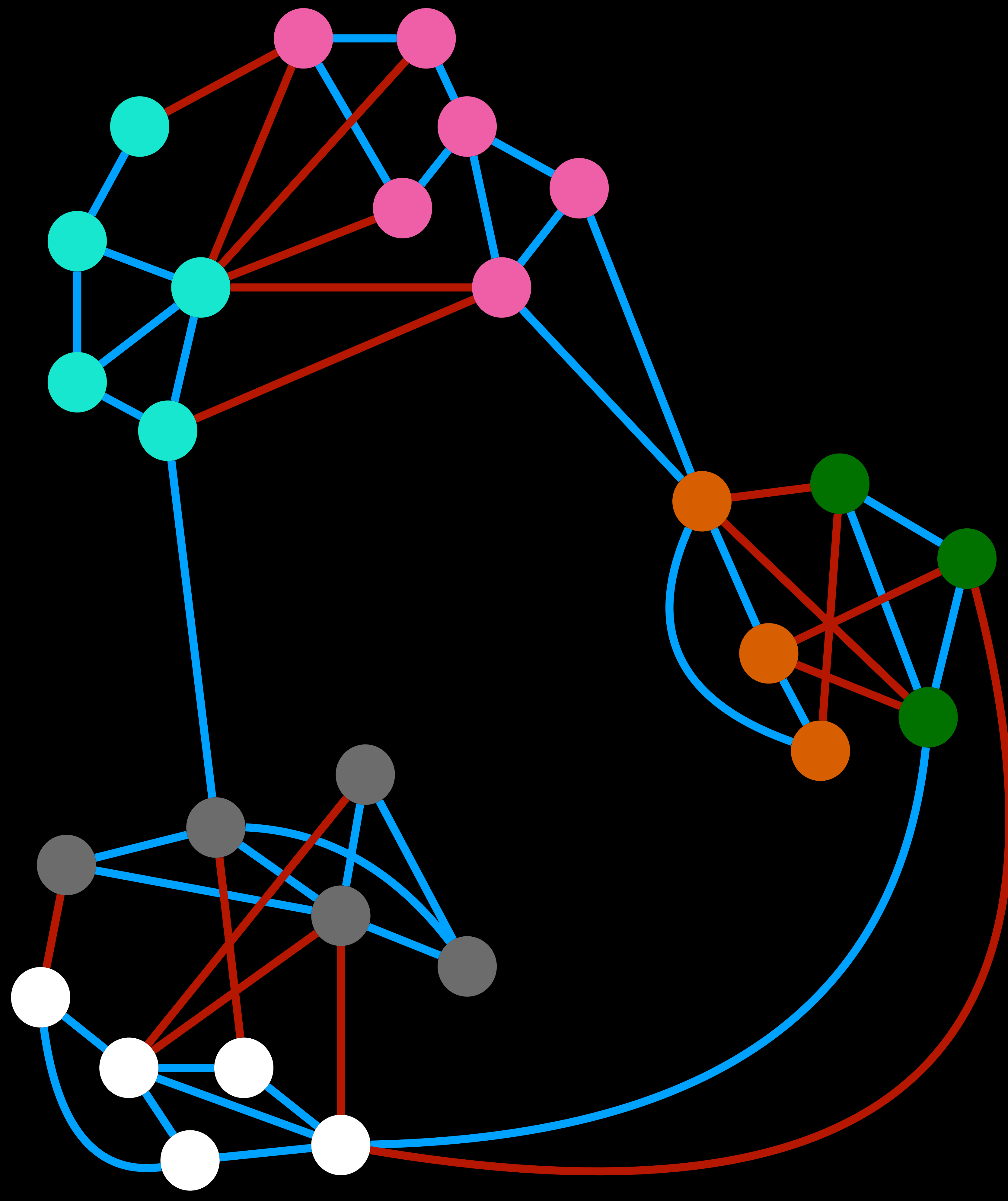

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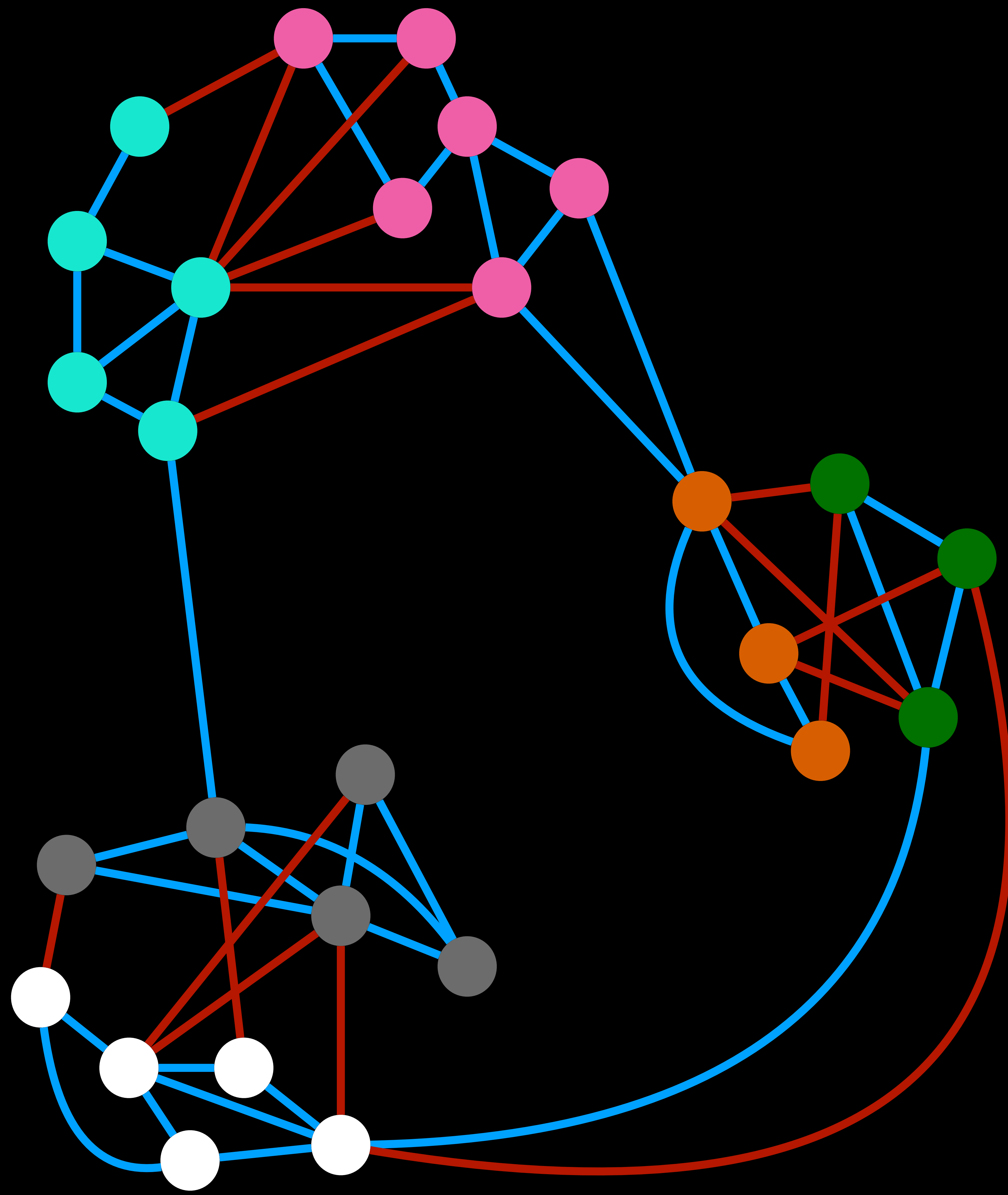

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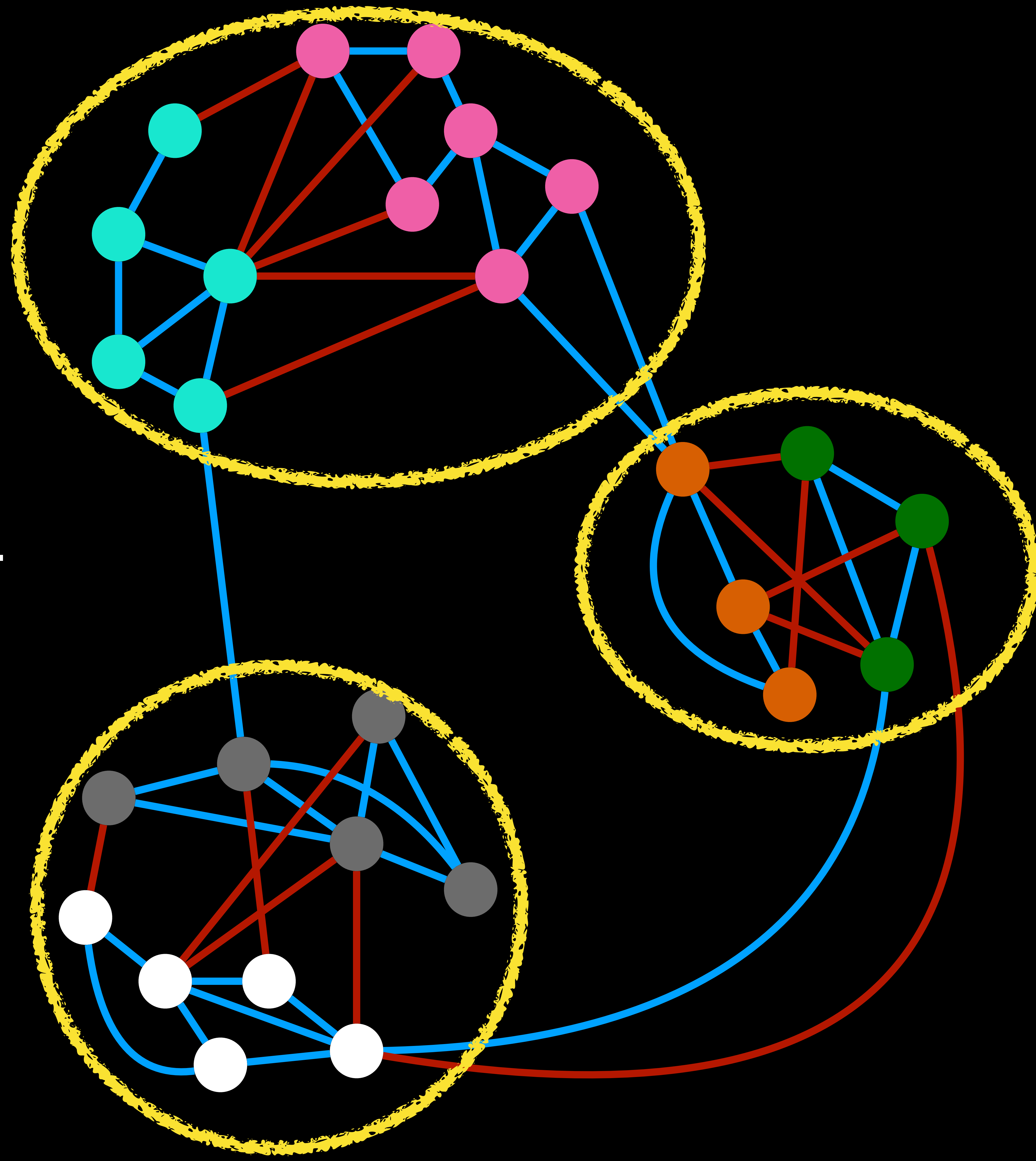

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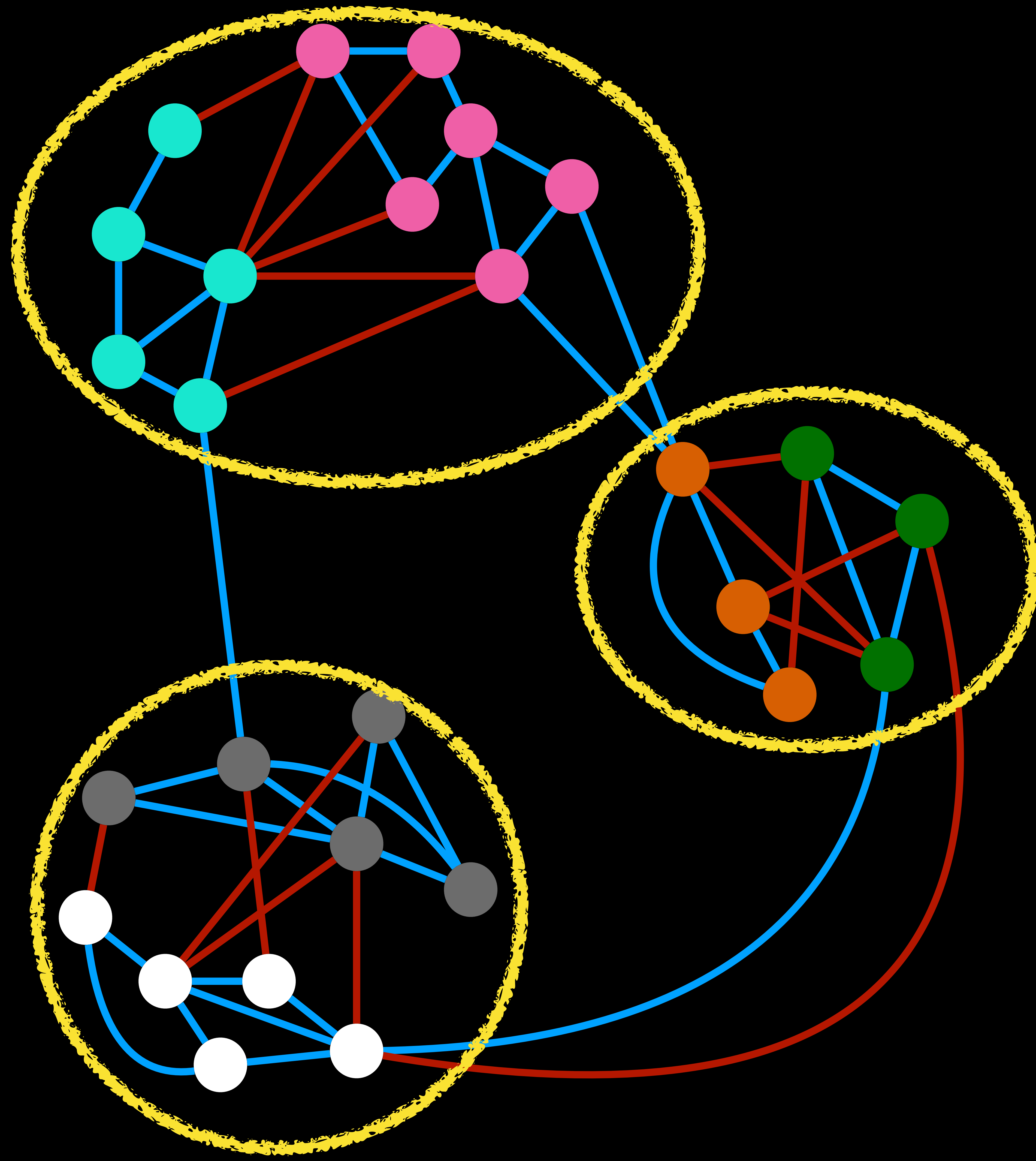

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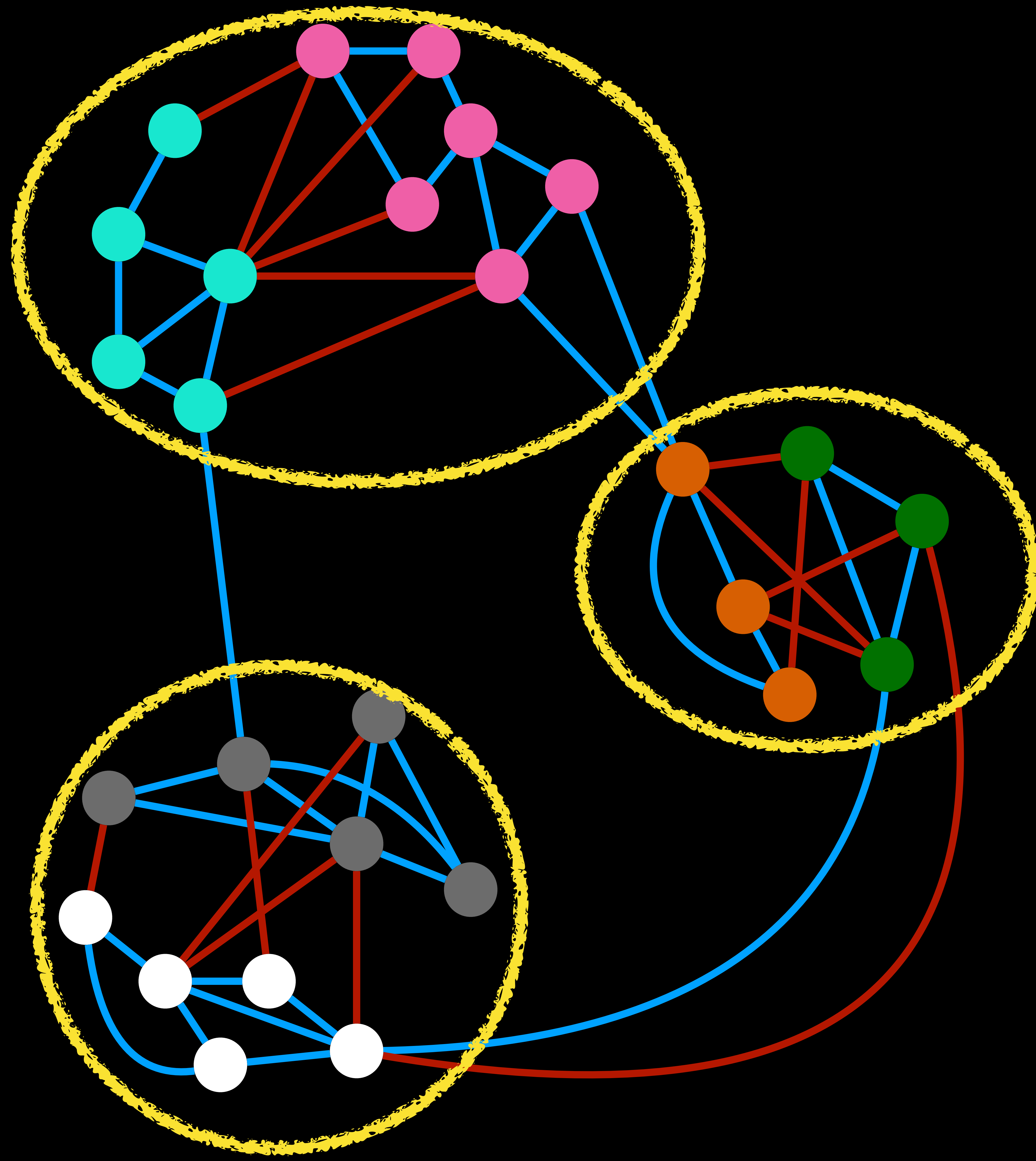

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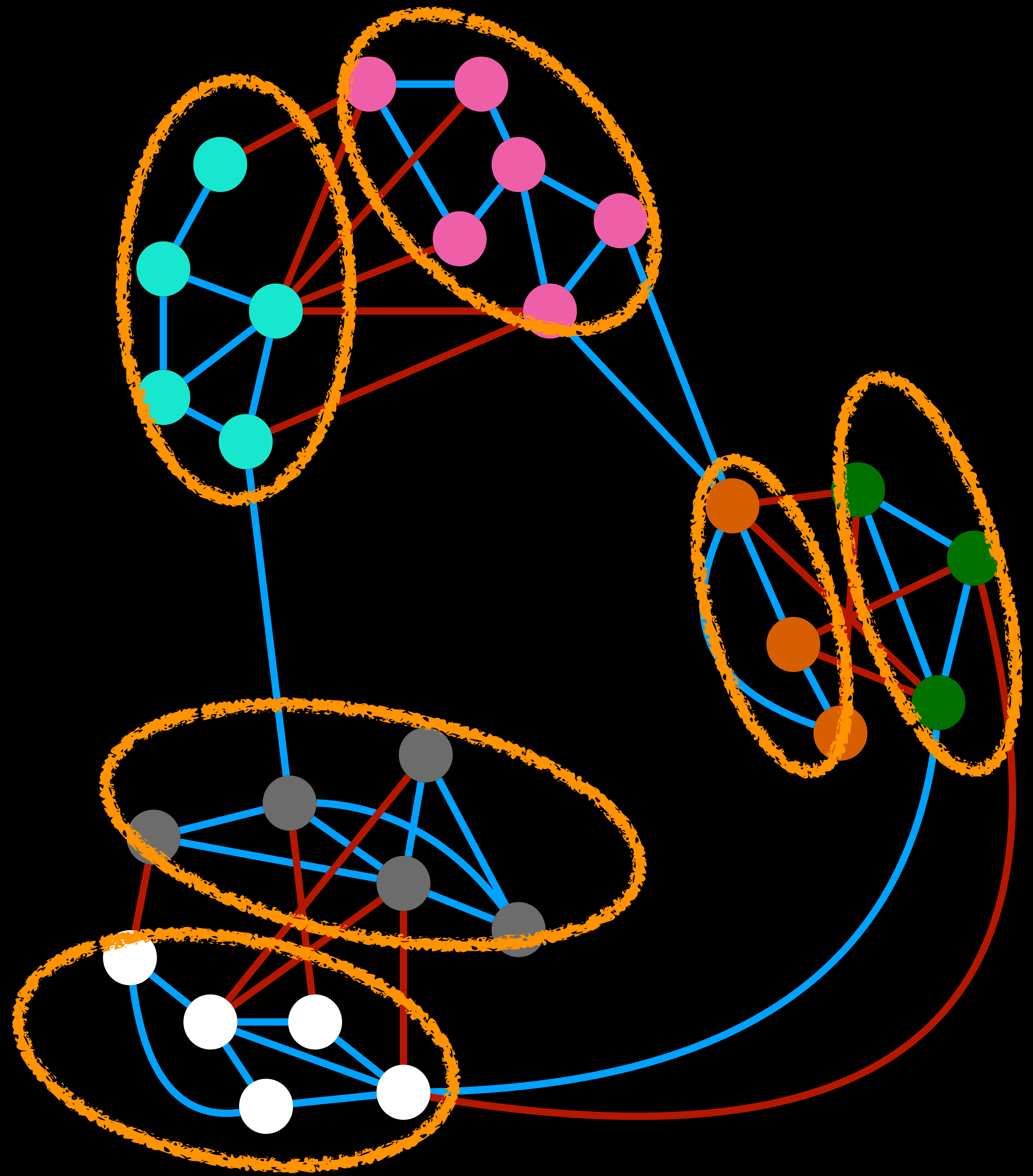

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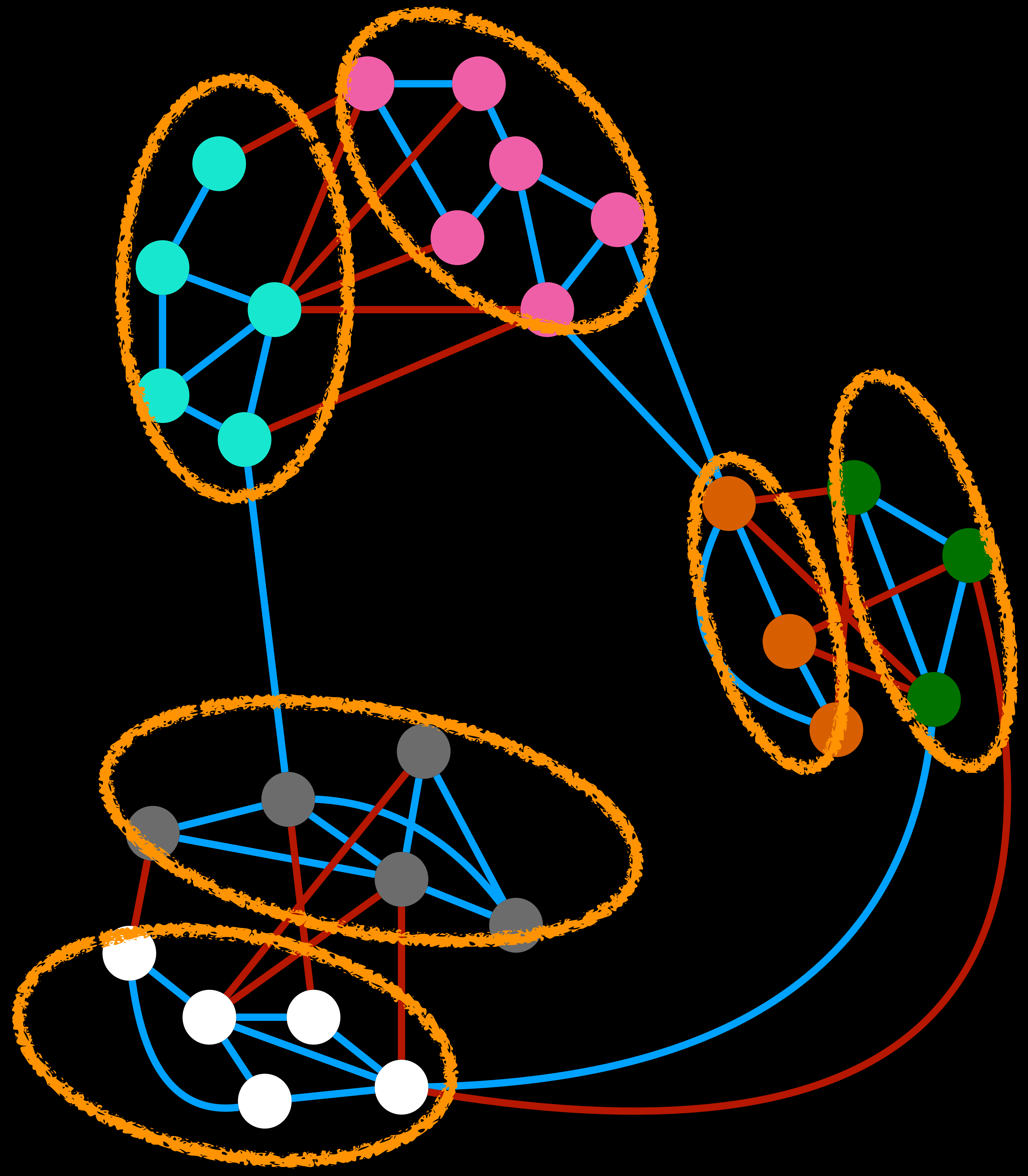

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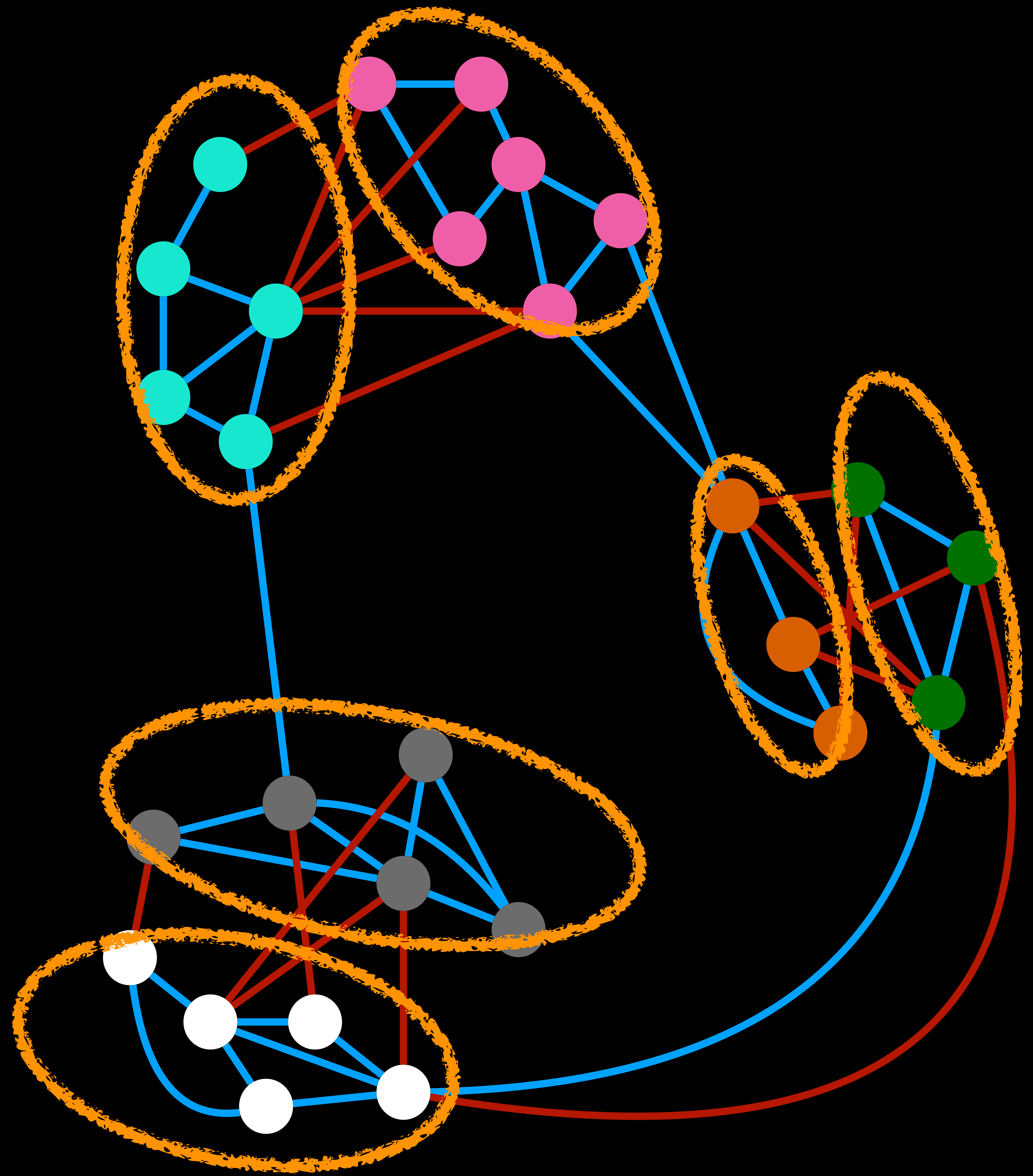

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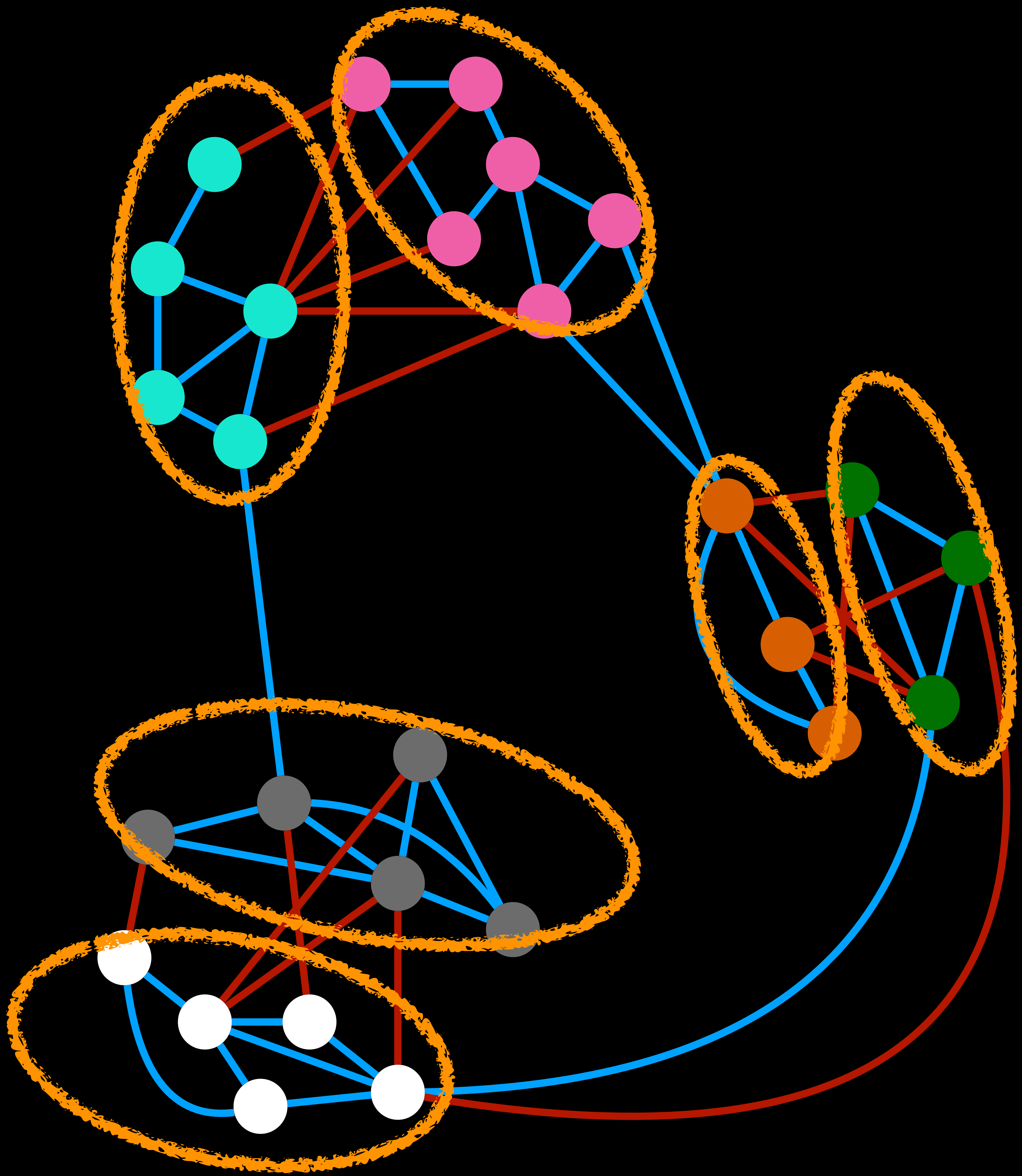

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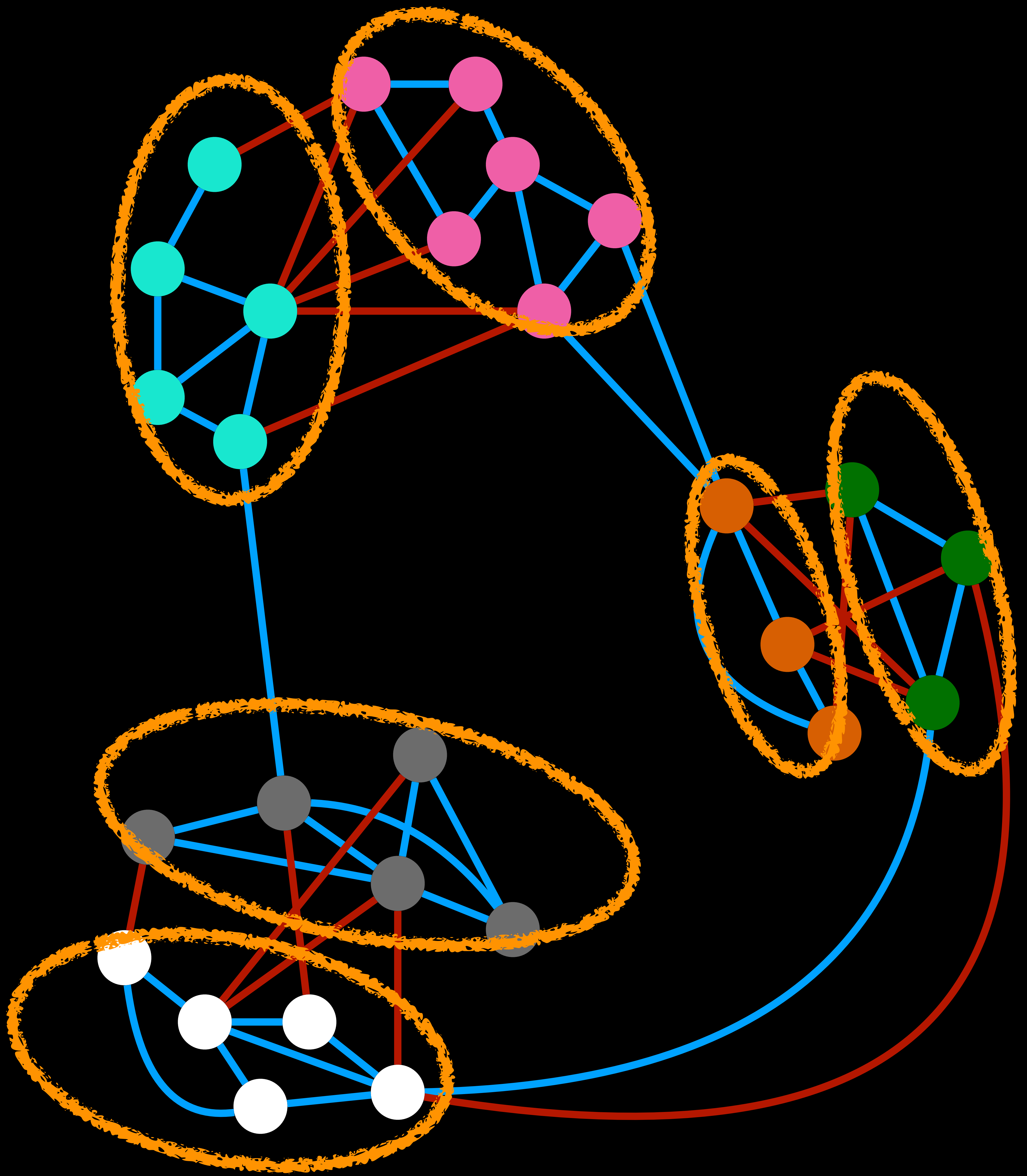

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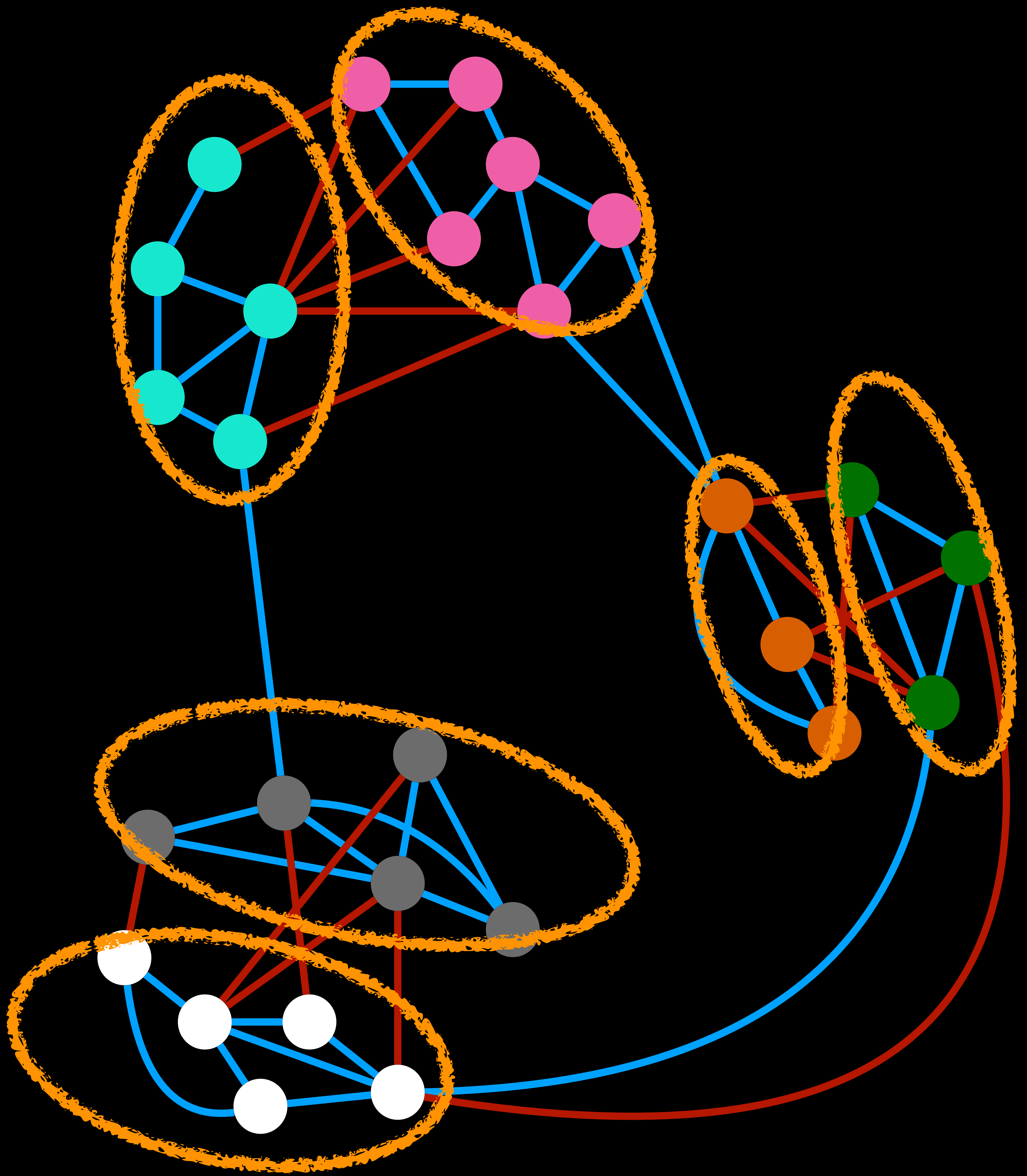
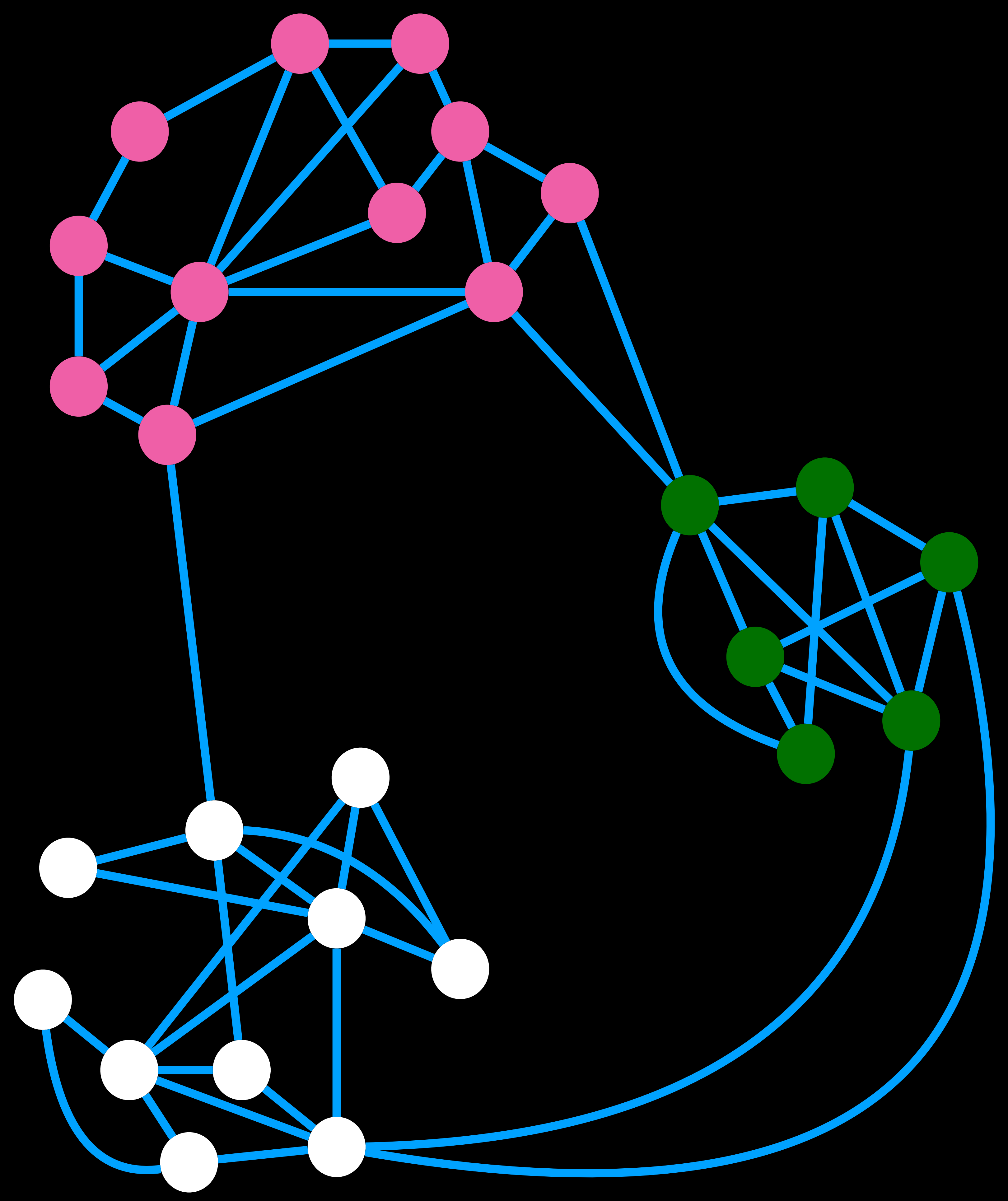
  ➡ Easy to parallelize
- We provide a new signed graph dataset with large ground-truth communities



How Does the Oracle Work?

Unsigned Graphs



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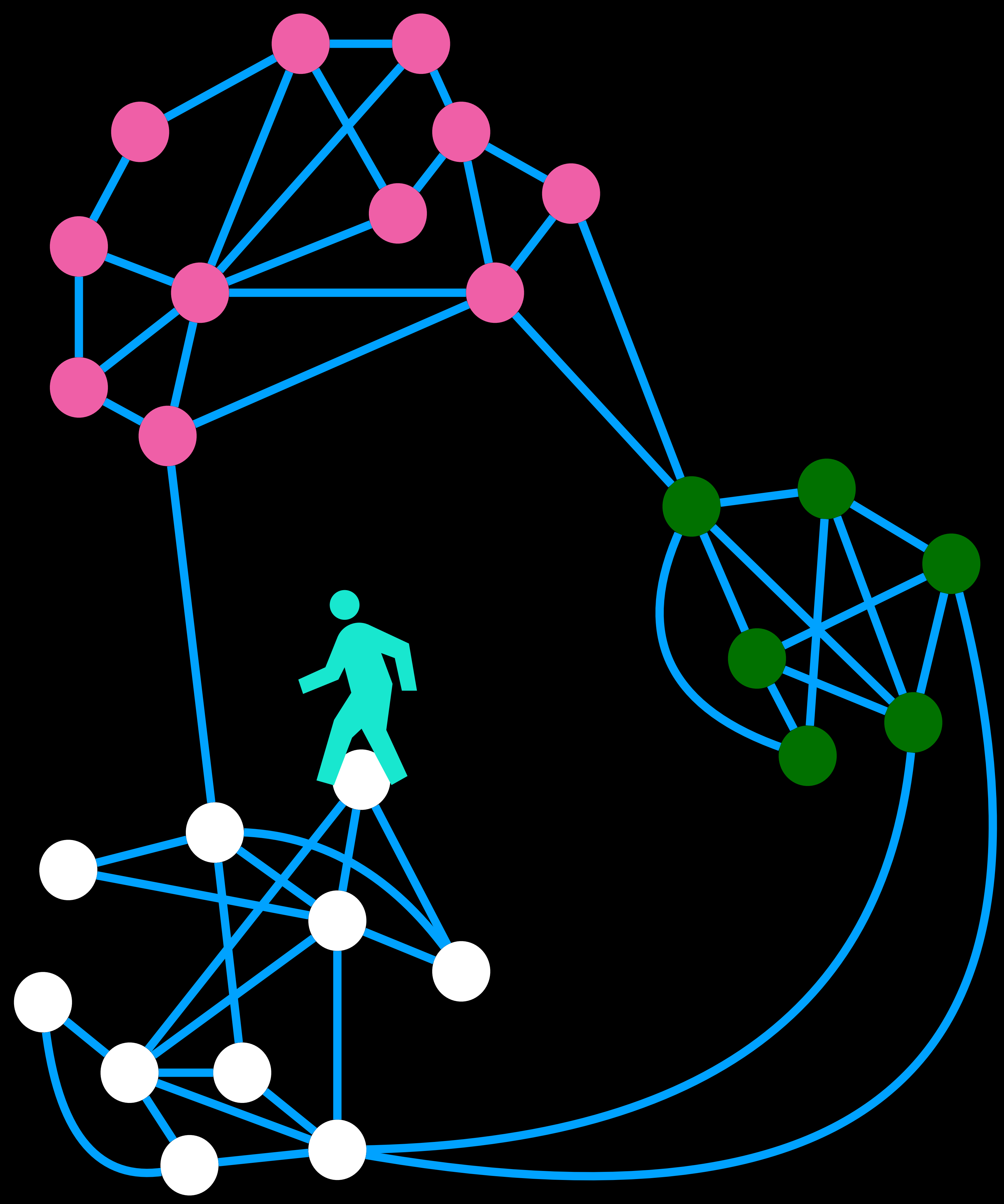

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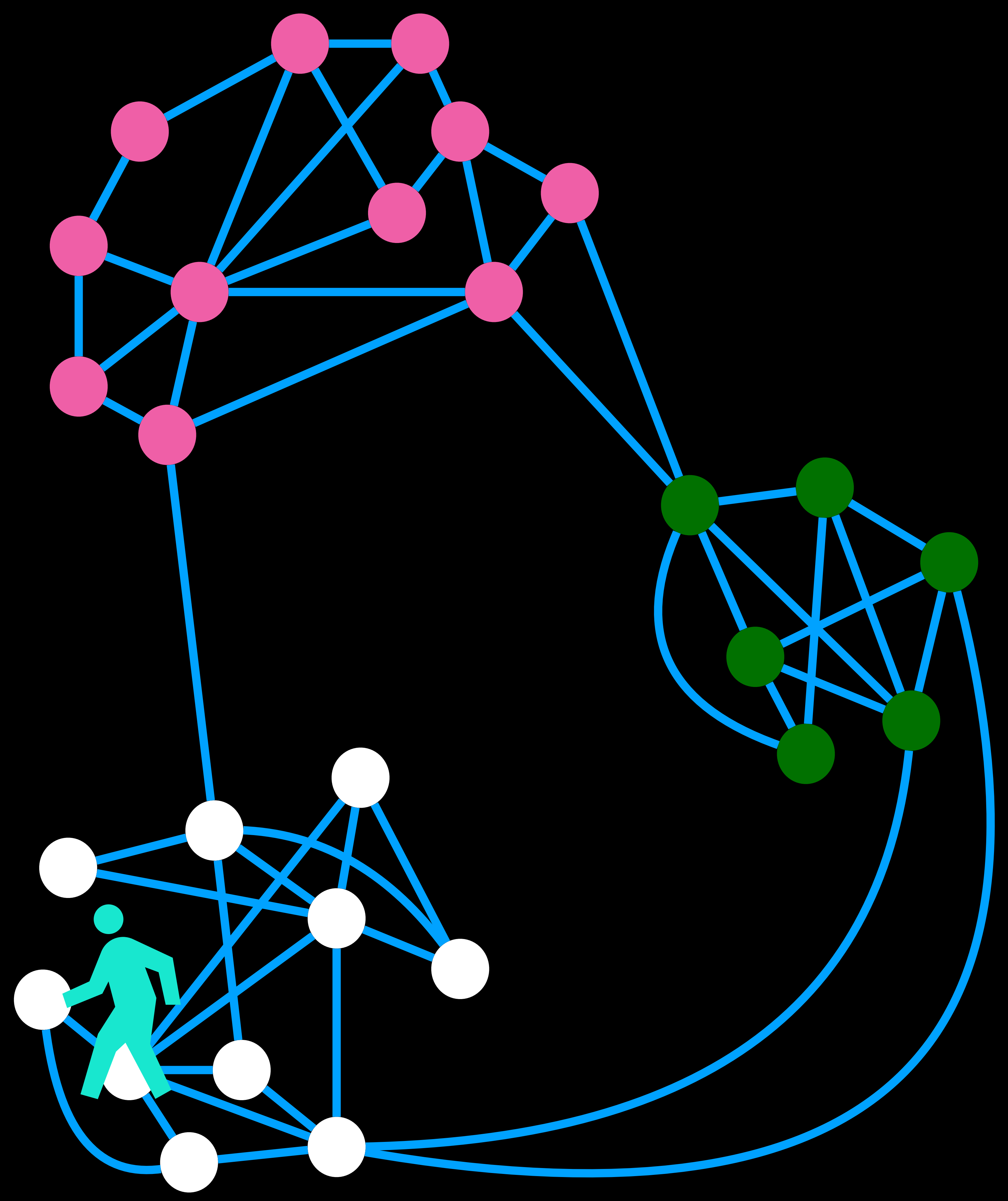

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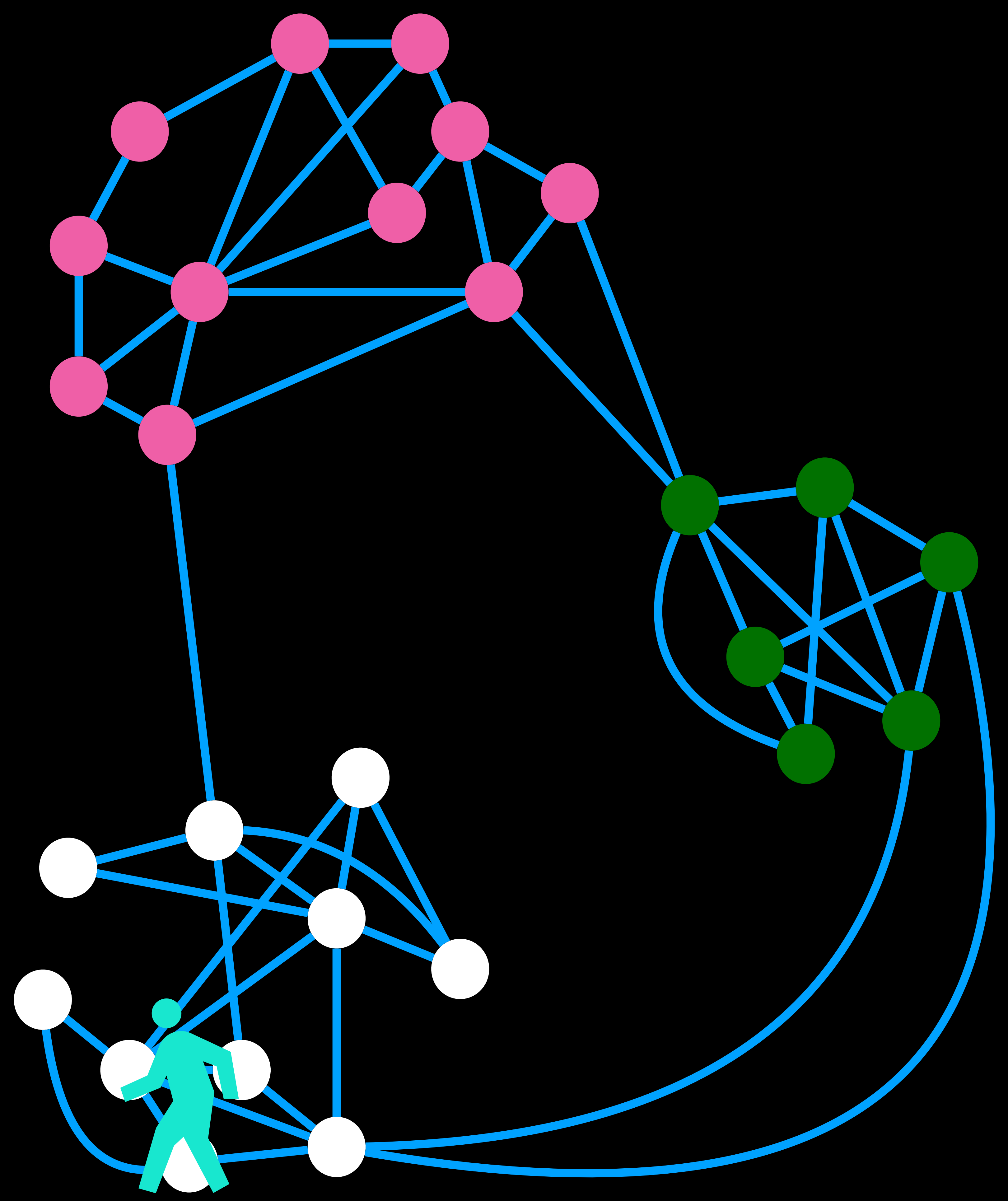

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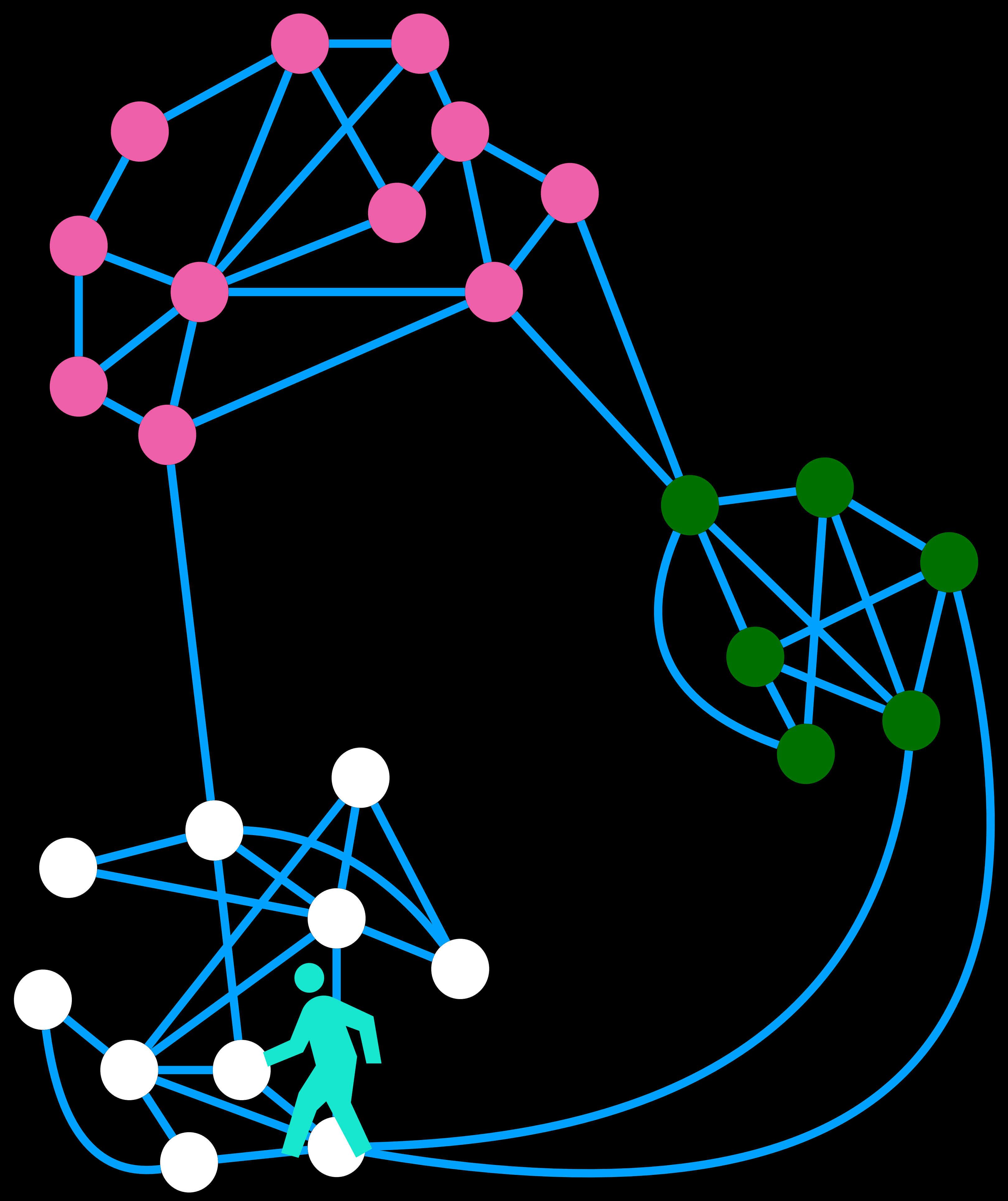

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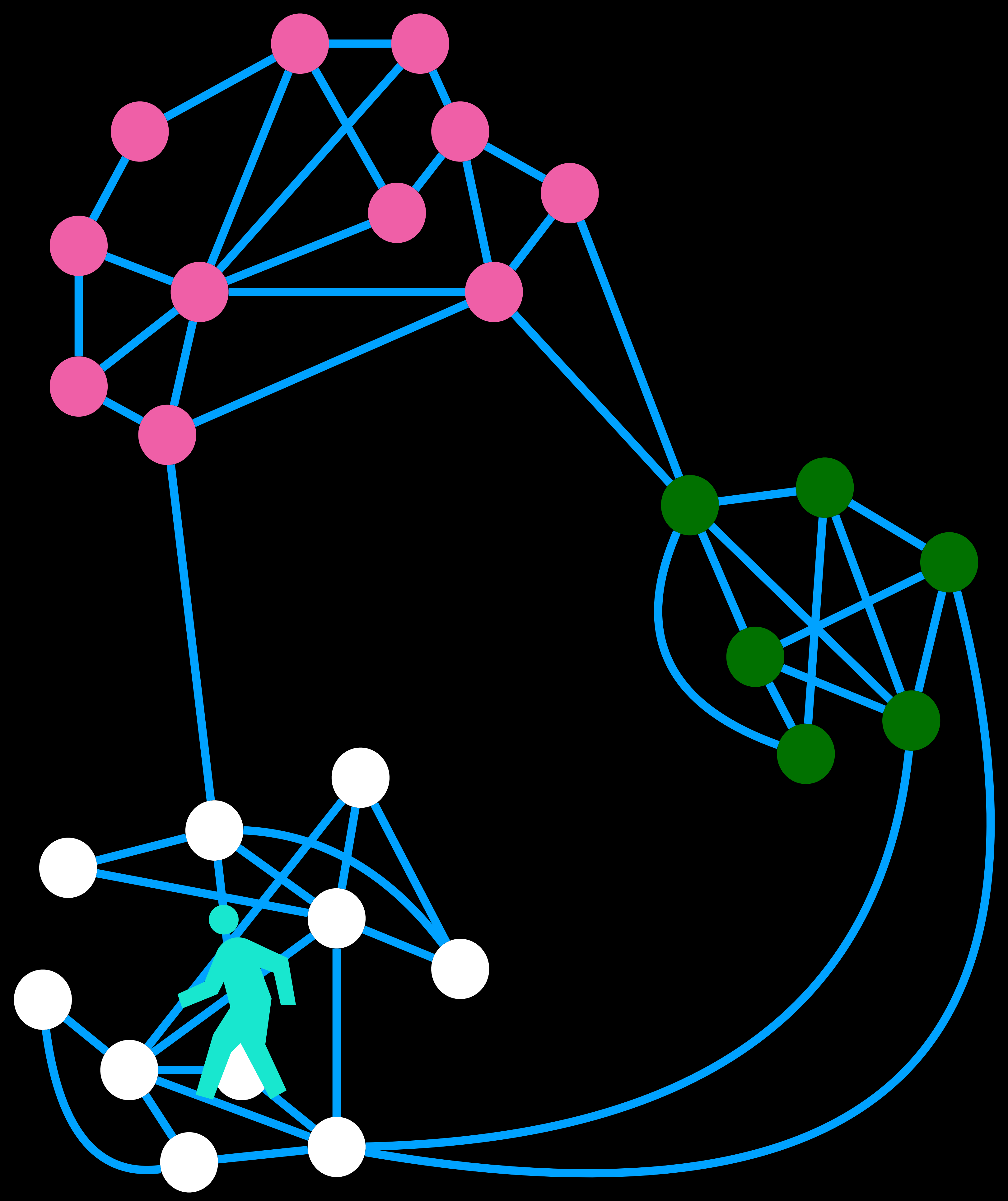

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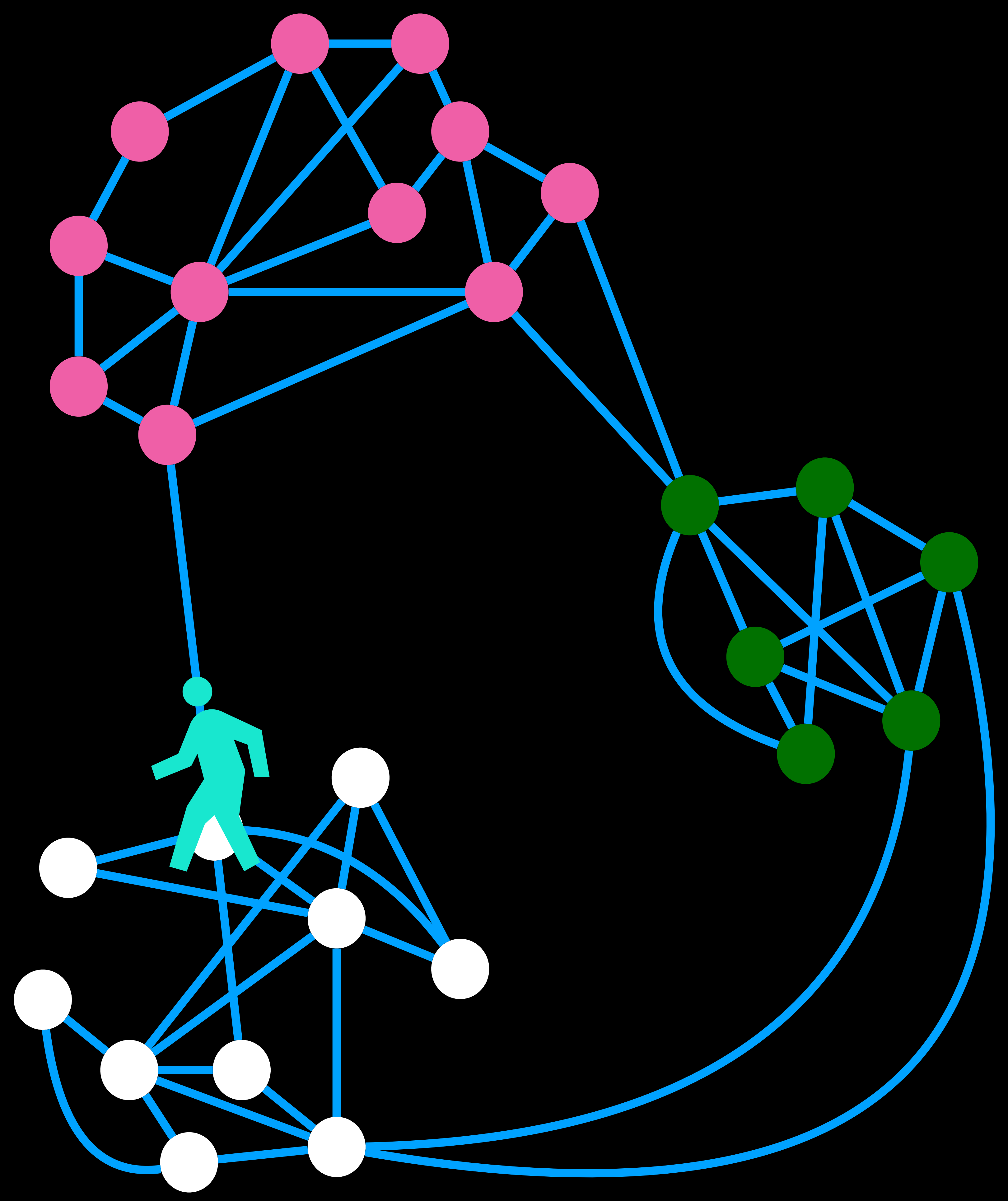
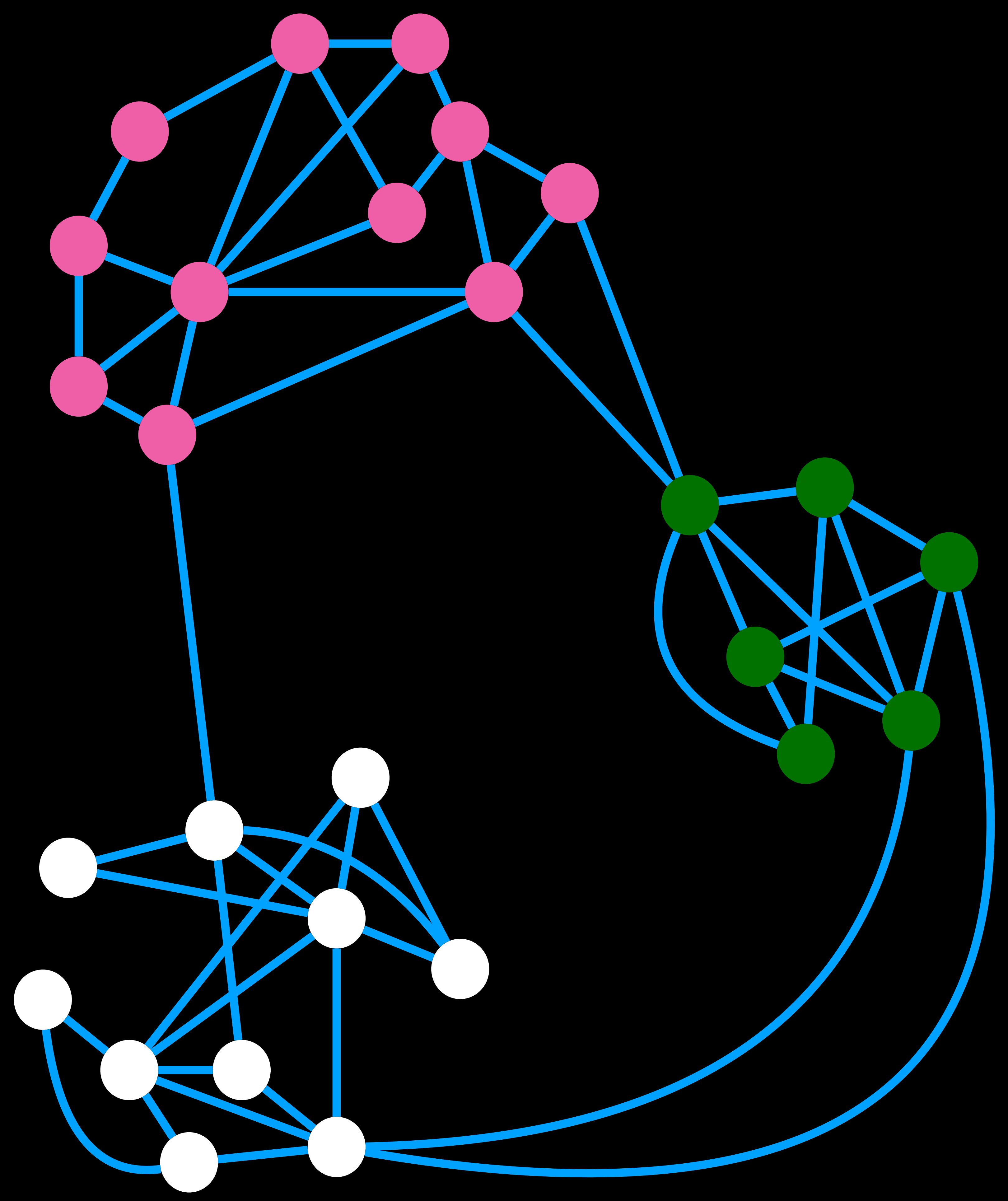
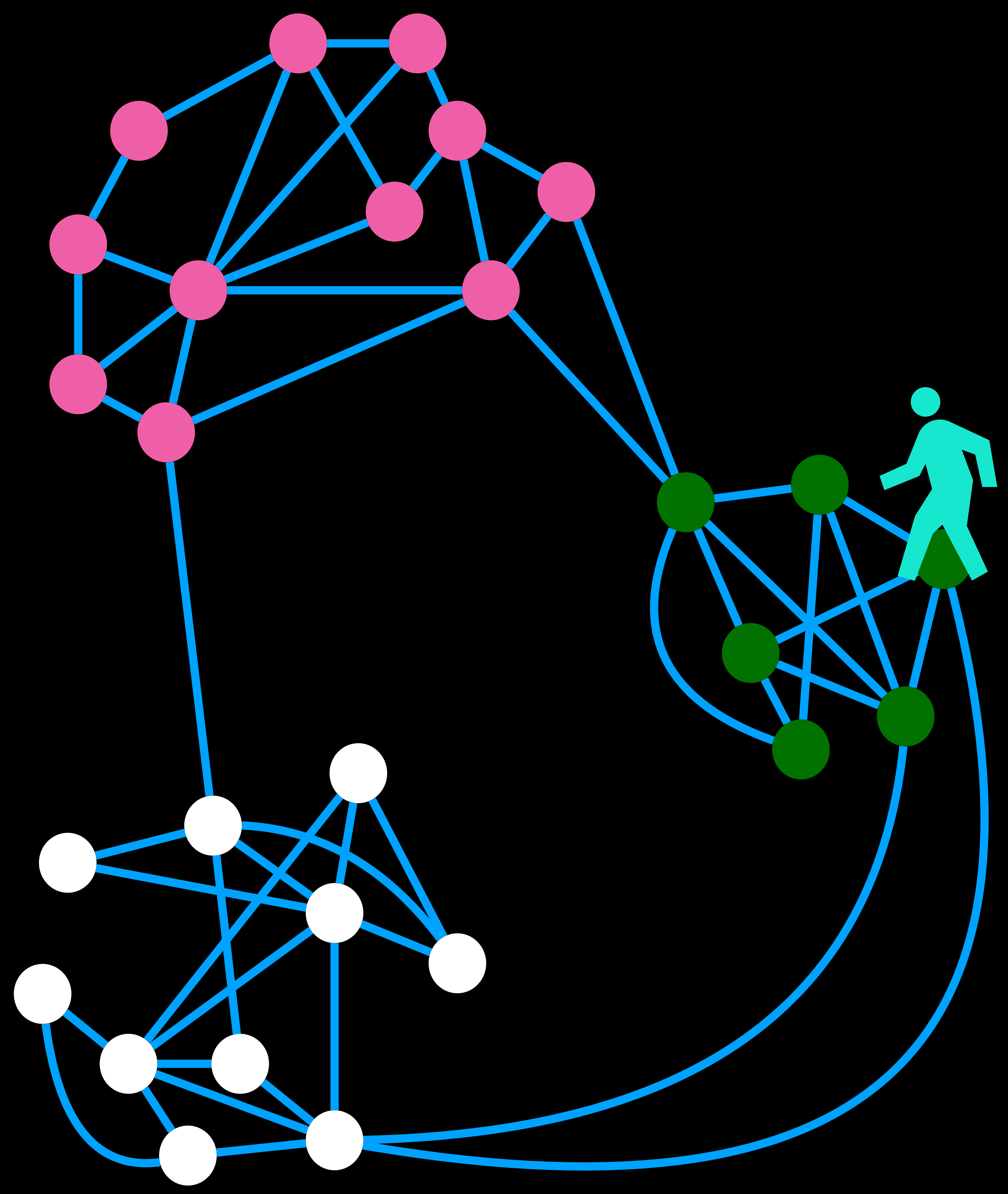


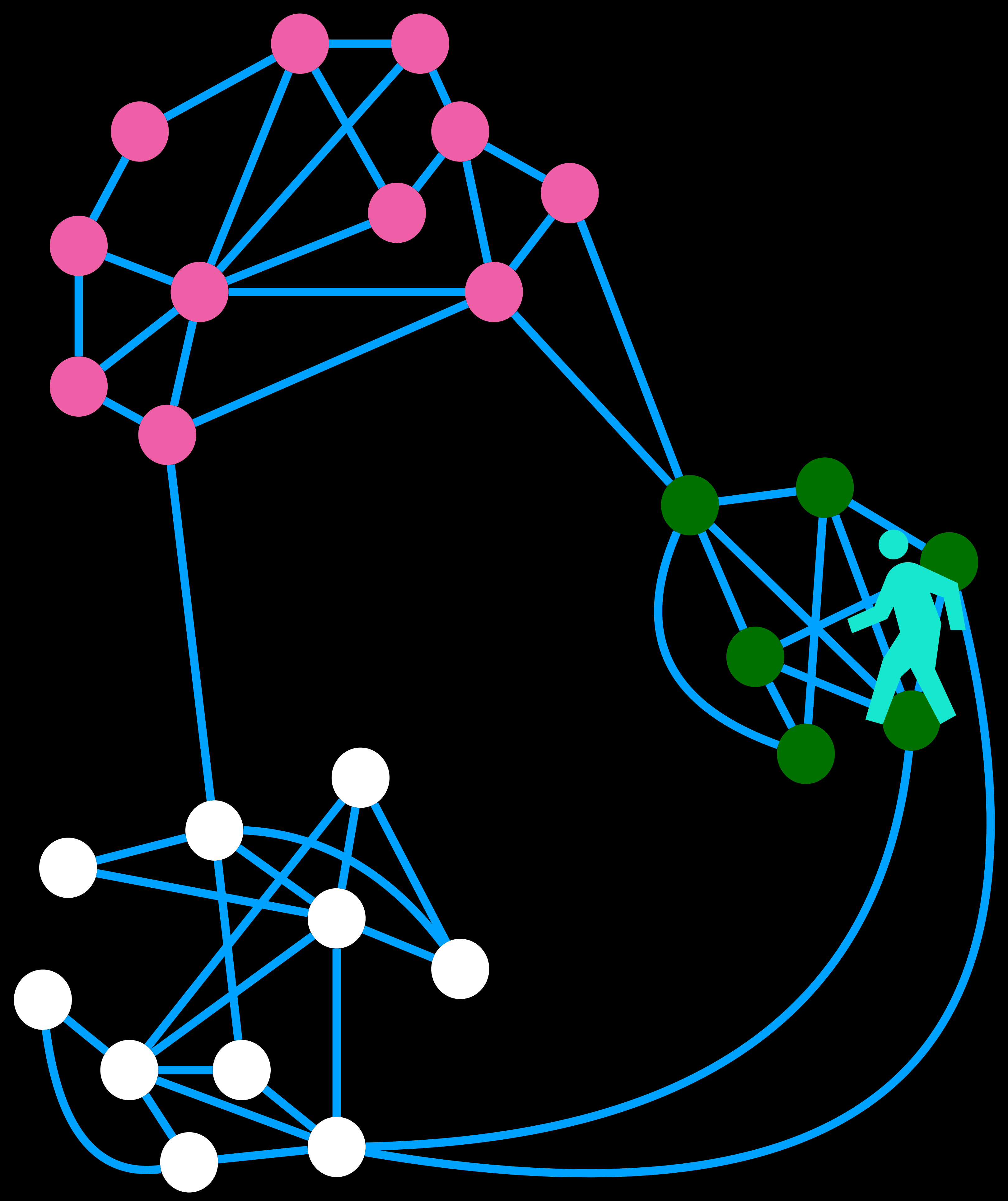
Unsigned Graphs



Unsigned Graphs



Unsigned Graphs



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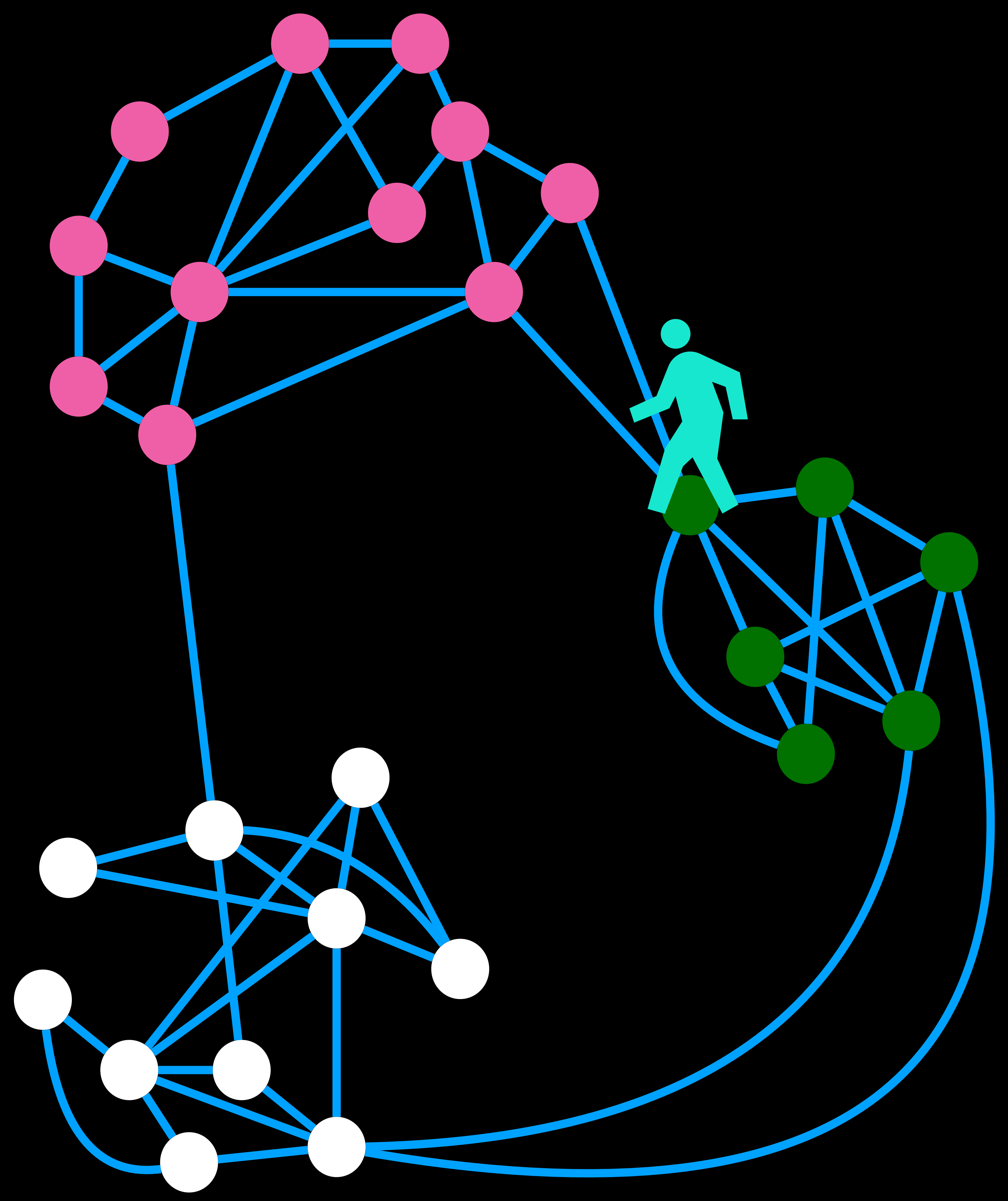

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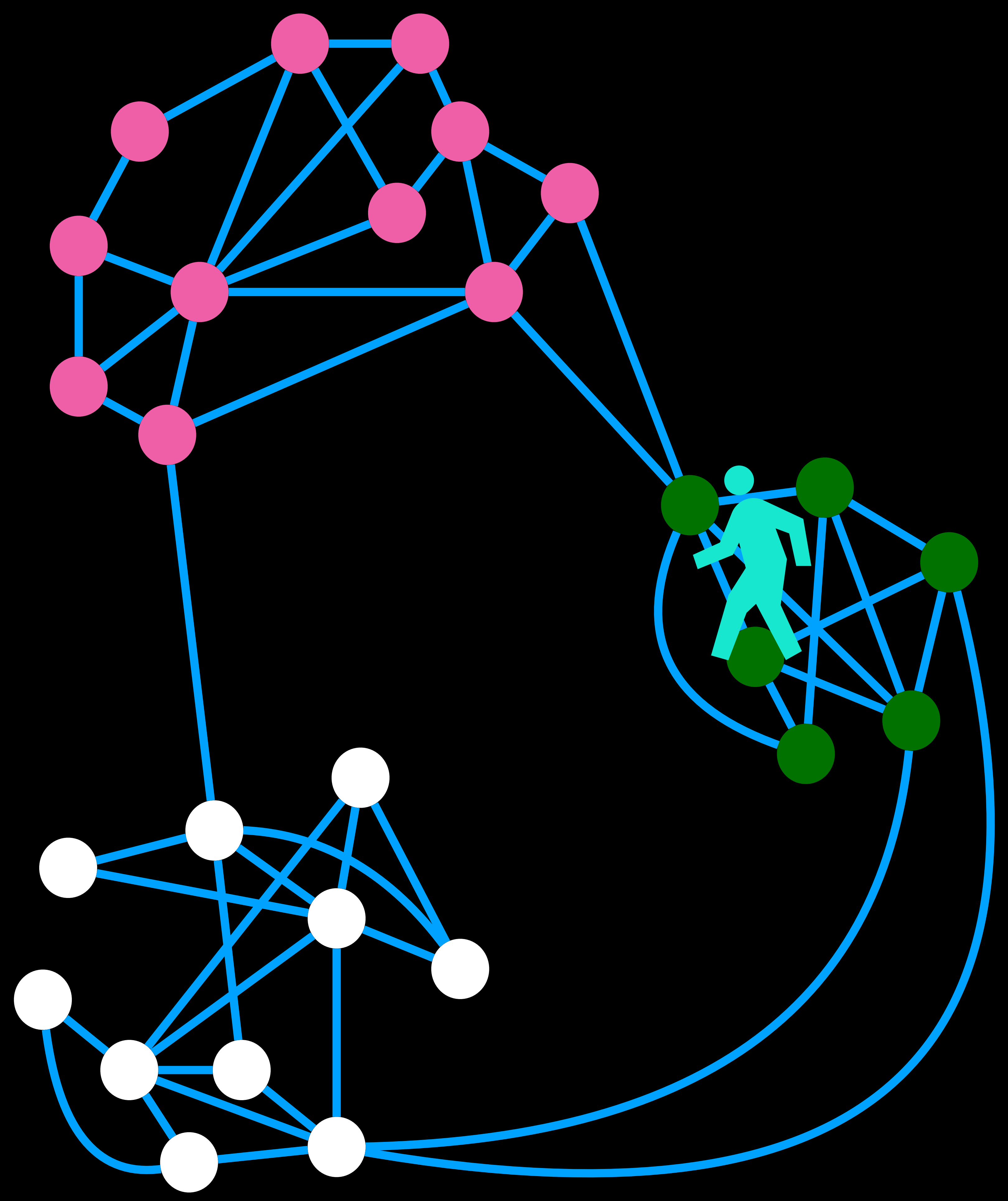

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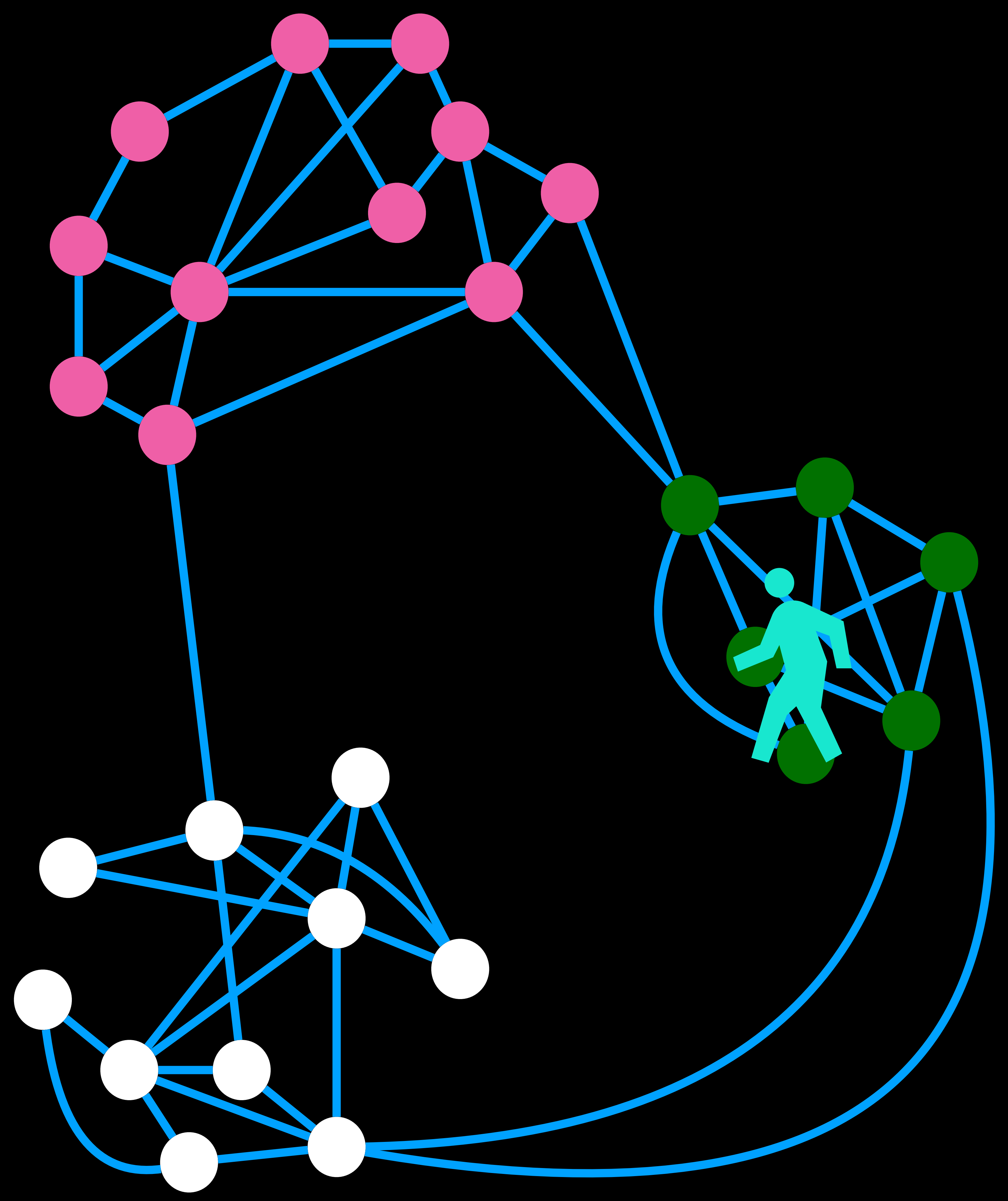

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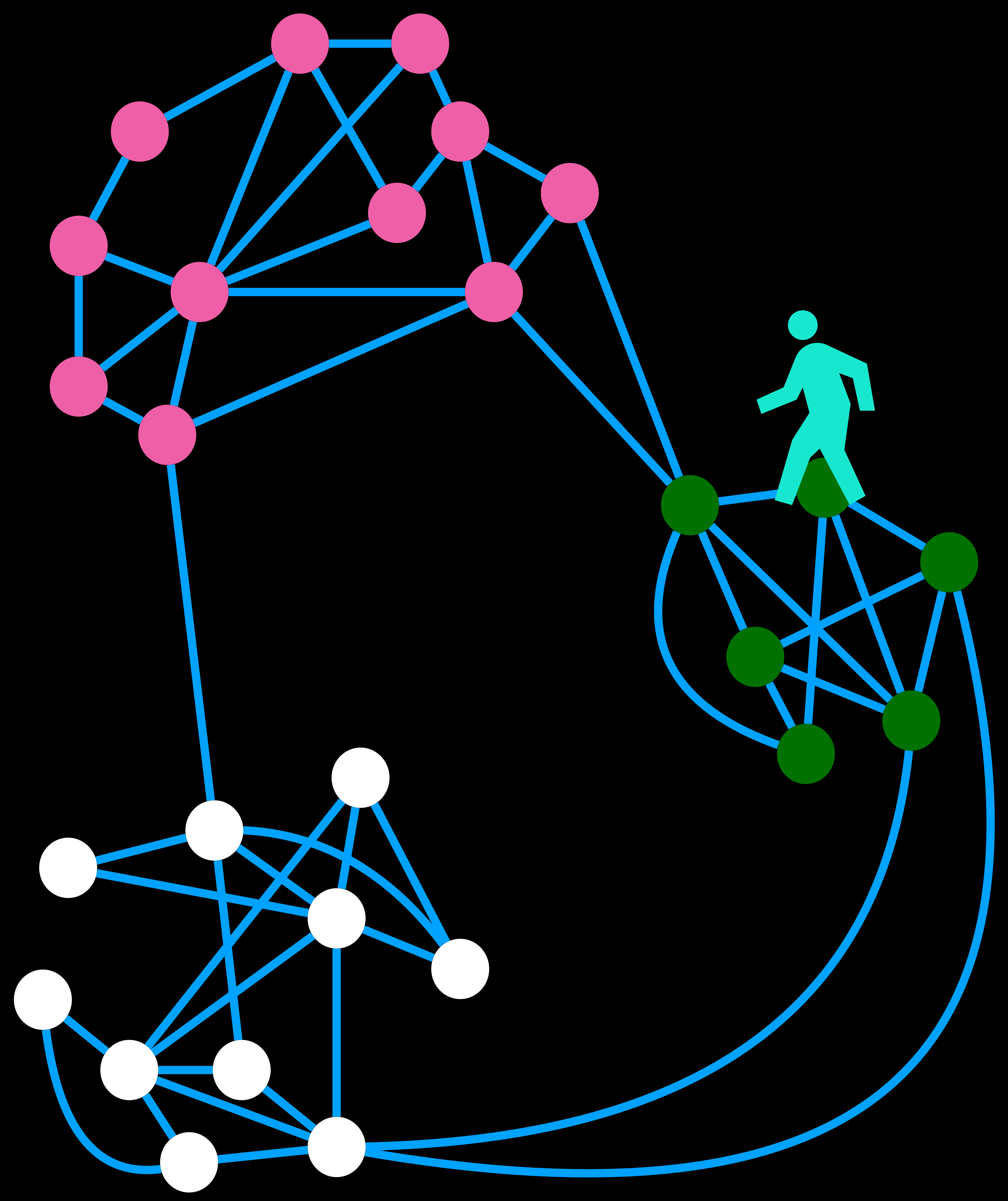

Unsigned Graphs


Computing communities in large networks using random walks
P Pons, M Latapy - International symposium on computer and information …, 2005 - Springer
Dense subgraphs of sparse graphs (communities), which appear in most real-world complex networks, play an important role in many contexts. Computing them however is generally …
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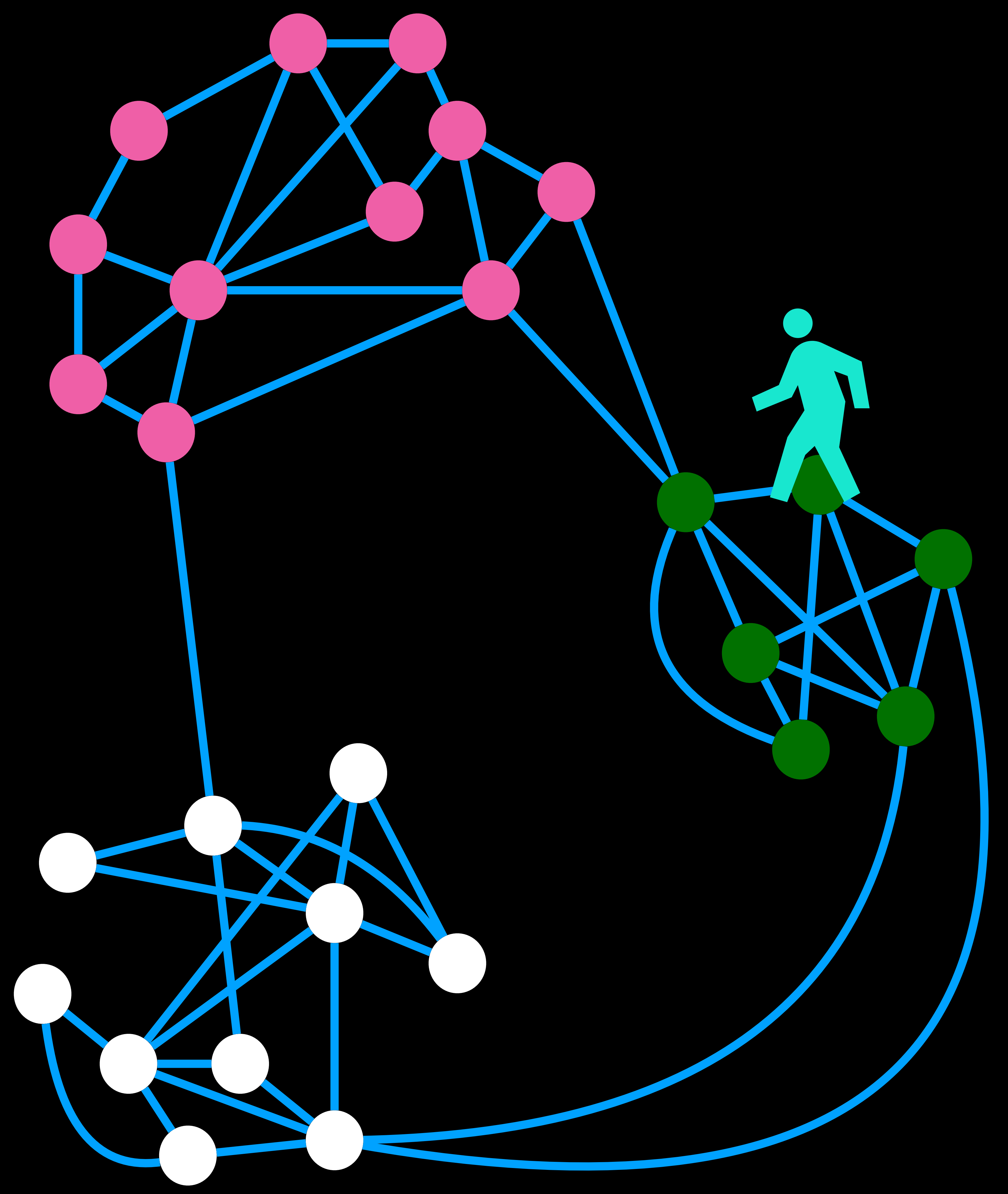

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Testing cluster structure of graphs
A Czumaj, P Peng, C Sohler - Proceedings of the forty-seventh annual …, 2015 - dl.acm.org
We study the problem of recognizing the cluster structure of a graph in the framework of property testing in the bounded degree model. Given a parameter ε, a d-bounded degree graph is defined to be (k, φ)-clusterable, if it can be partitioned into no more than k parts, such that the (inner) conductance of the induced subgraph on each part is at least φ and the (outer) conductance of each part is at most cd, k ε 4 φ 2, where cd, k depends only on d, k. Our main result is a sublinear algorithm with the running time~ O (√ n· poly (φ, k, 1/ε)) that …
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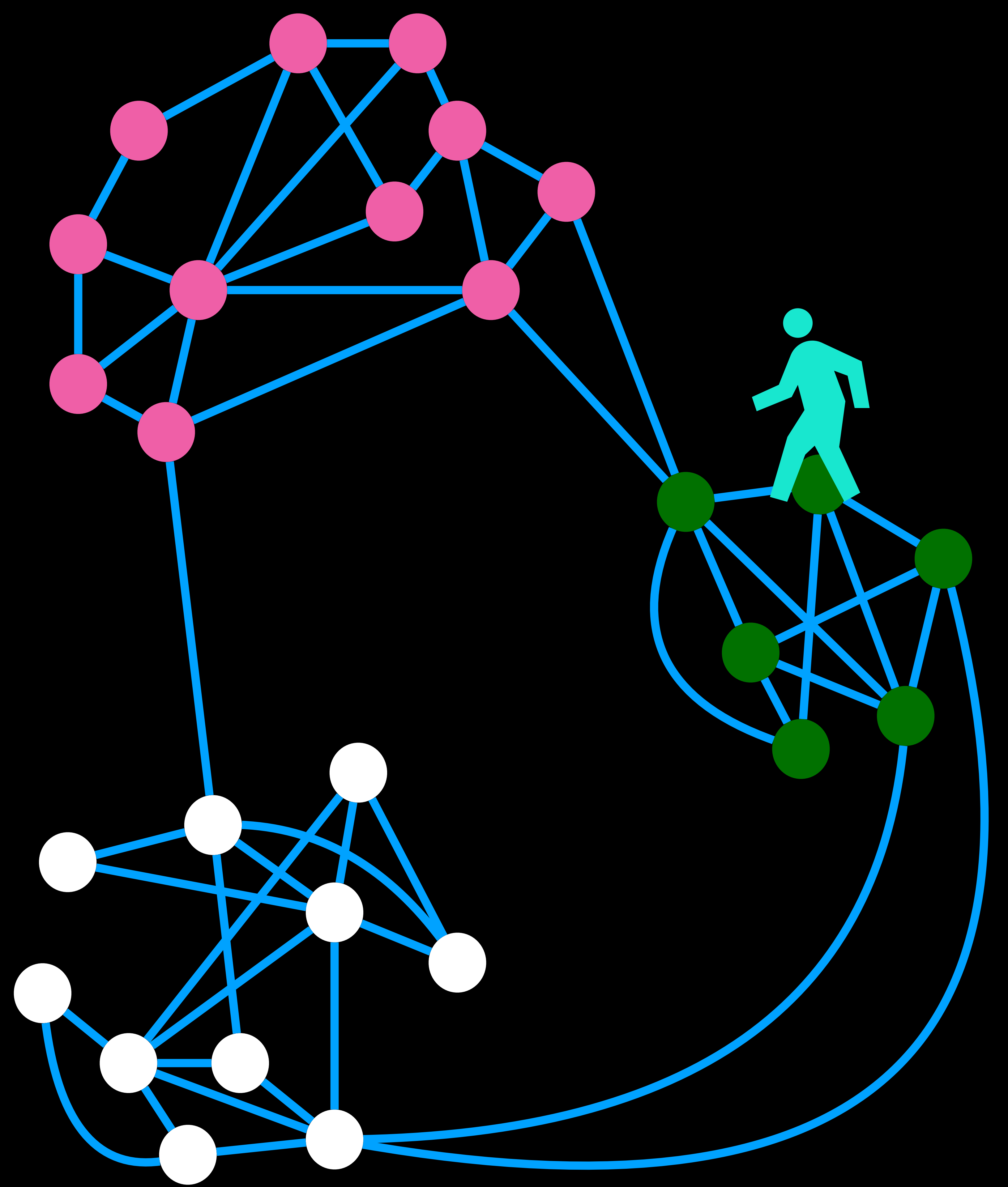
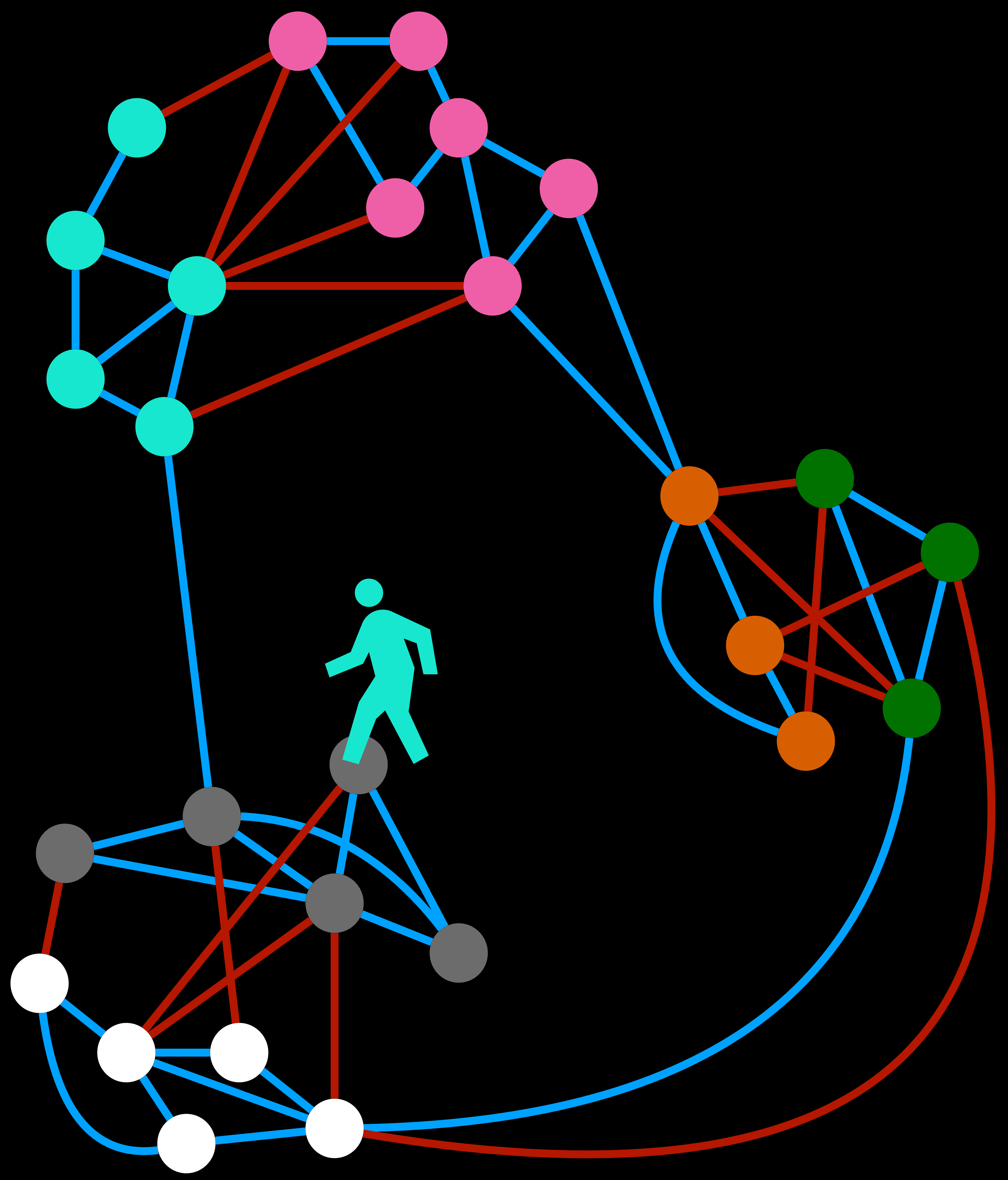
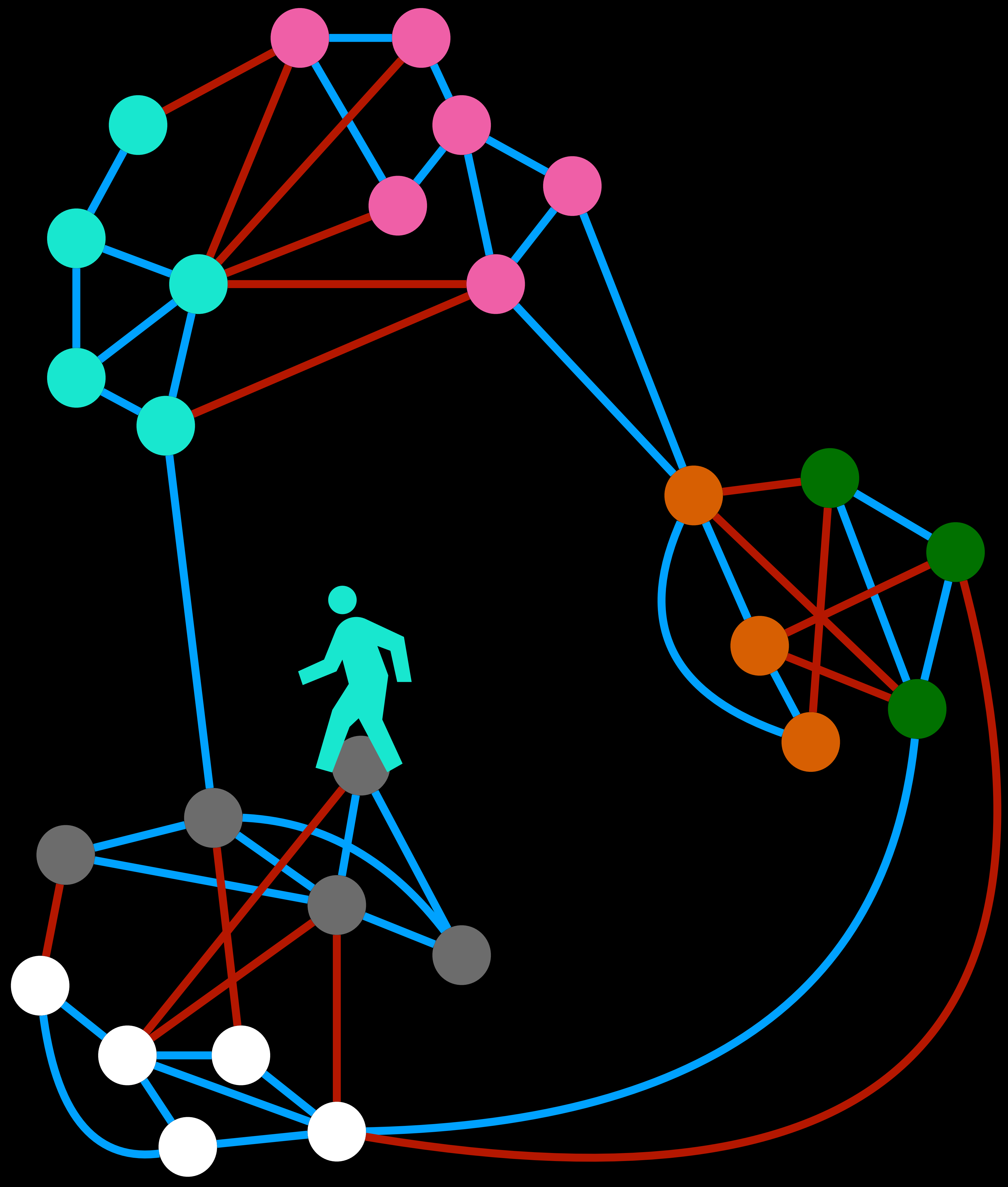


Signed Graphs

What changes when we have signs?

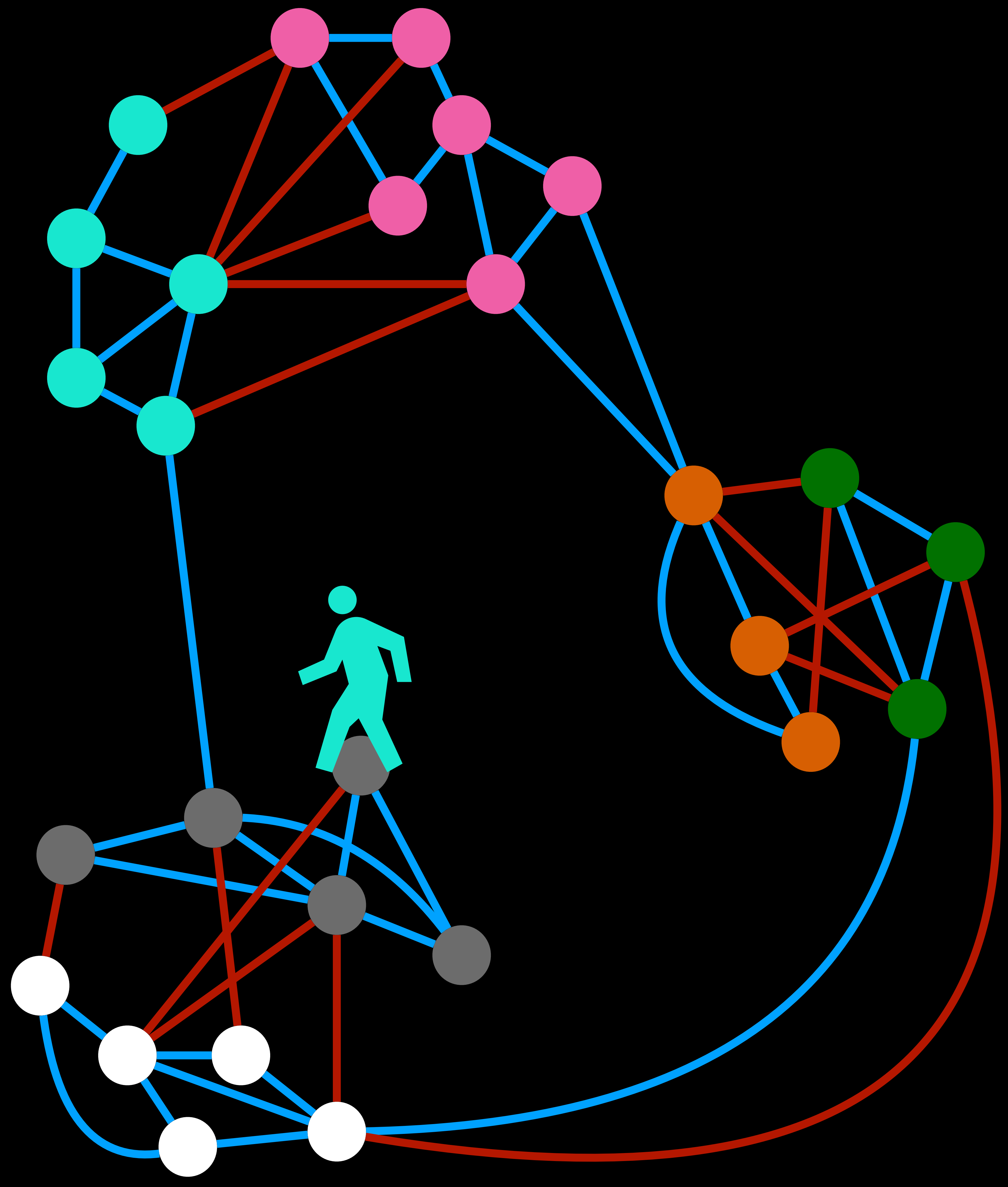


Random Walks With Signs



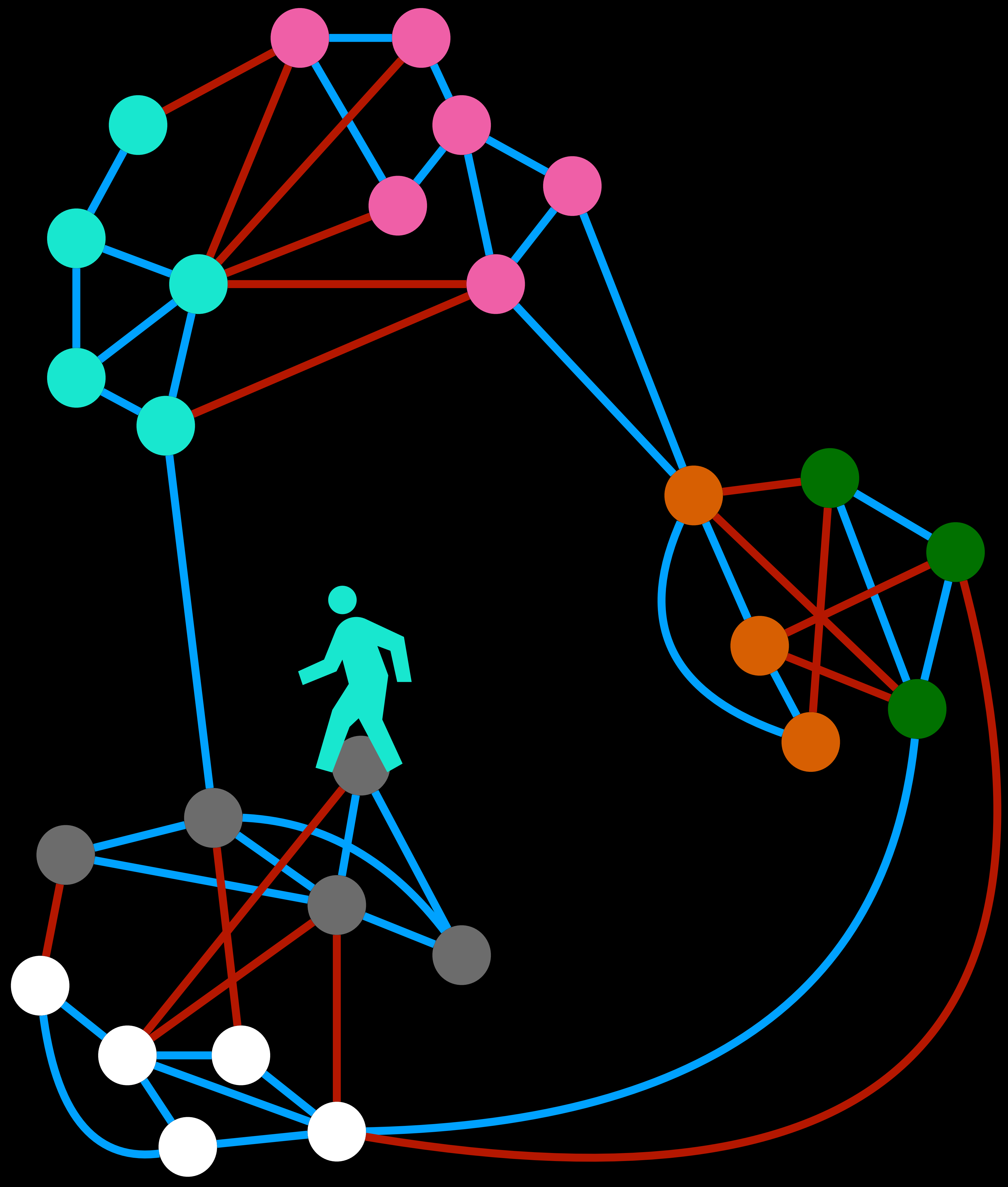
Random Walks With Signs

- Initialize sign $s = +$



Random Walks With Signs

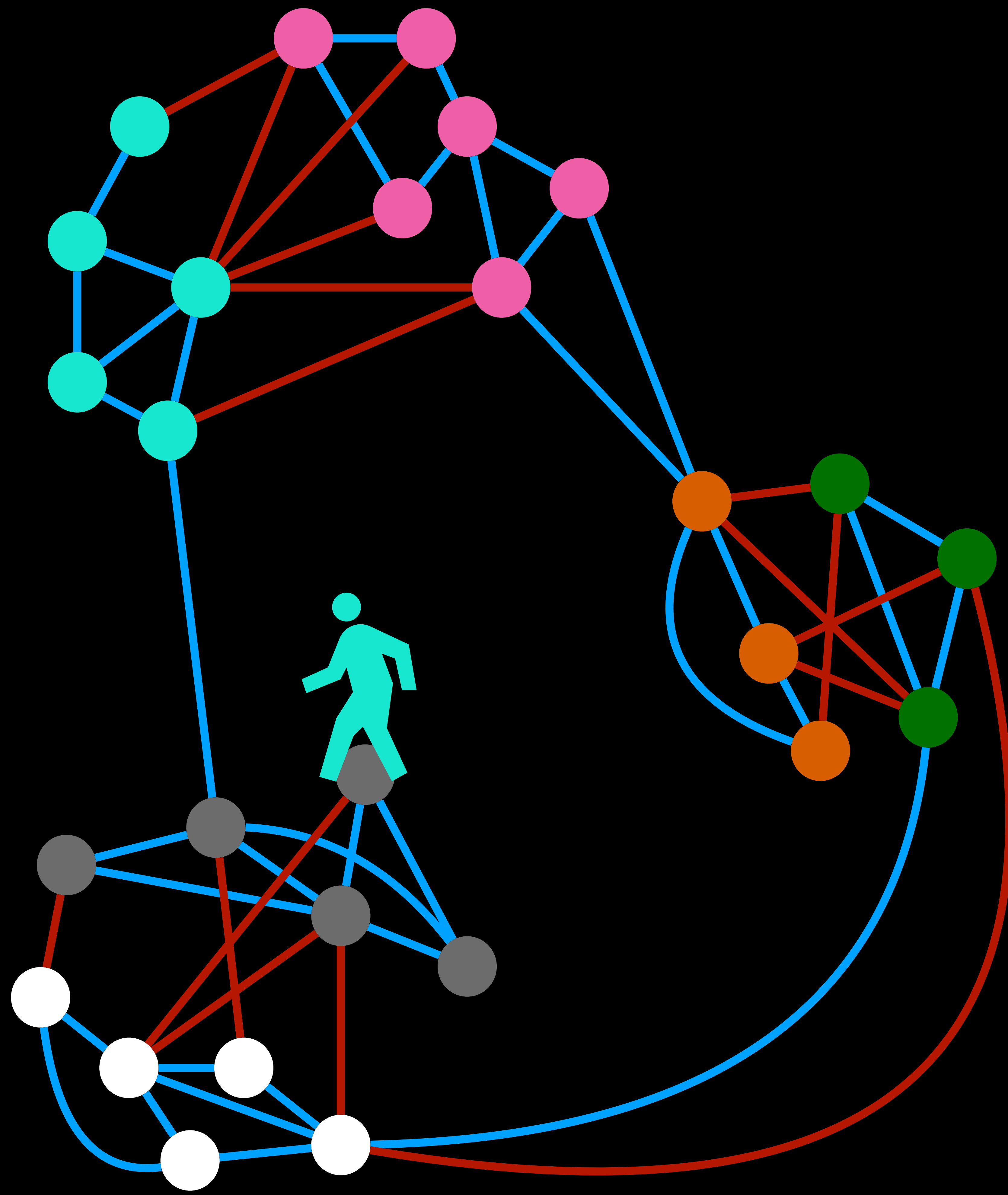
- Initialize sign $s = +$
- When traversing an edge, multiply s with the edge sign



Random Walks With Signs

- Initialize sign $s = +$
- When traversing an edge, multiply s with the edge sign

➡ the friend of my friend is my friend
if $s = +$ and we traverse a positive edge, new sign $s = +$



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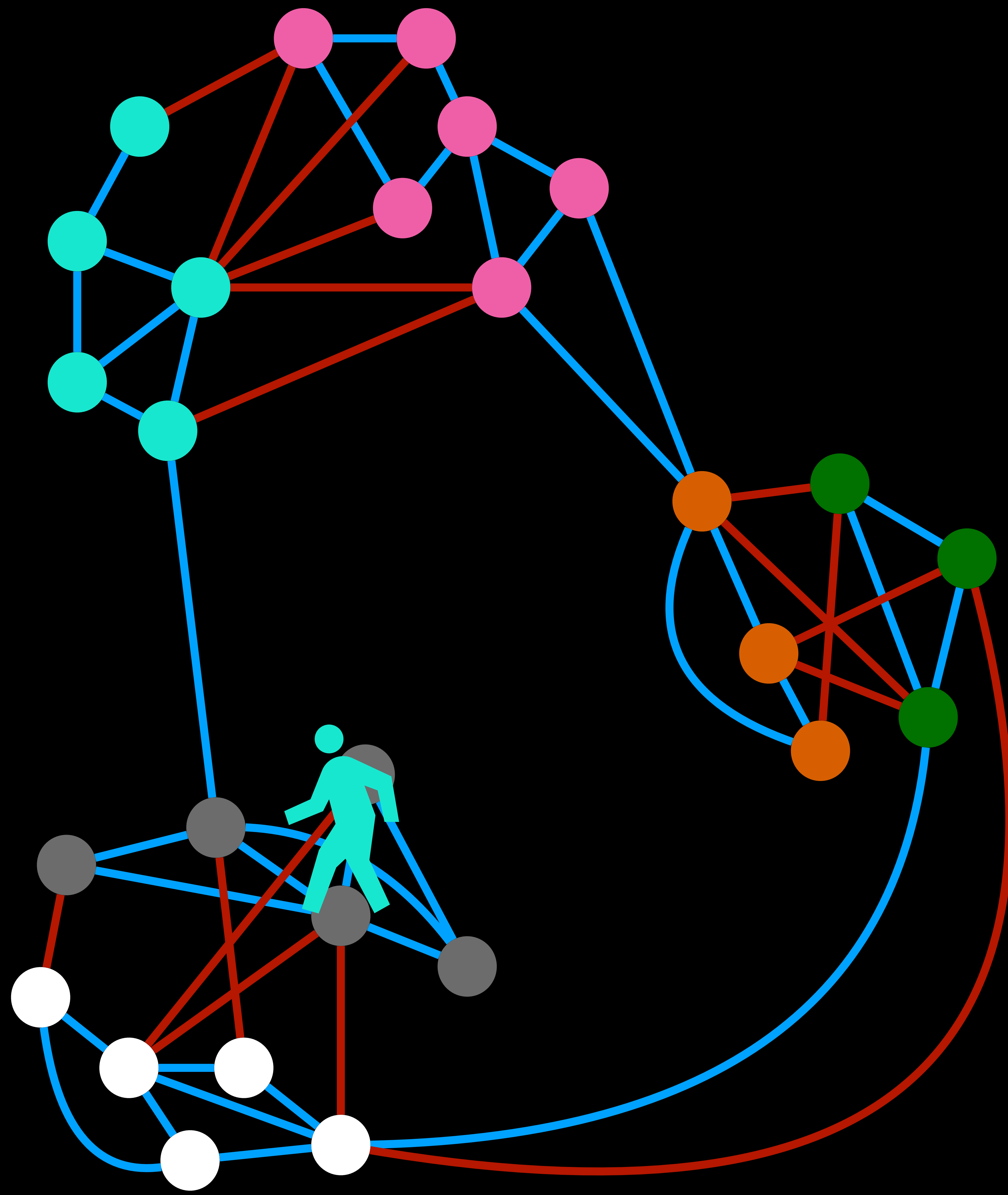

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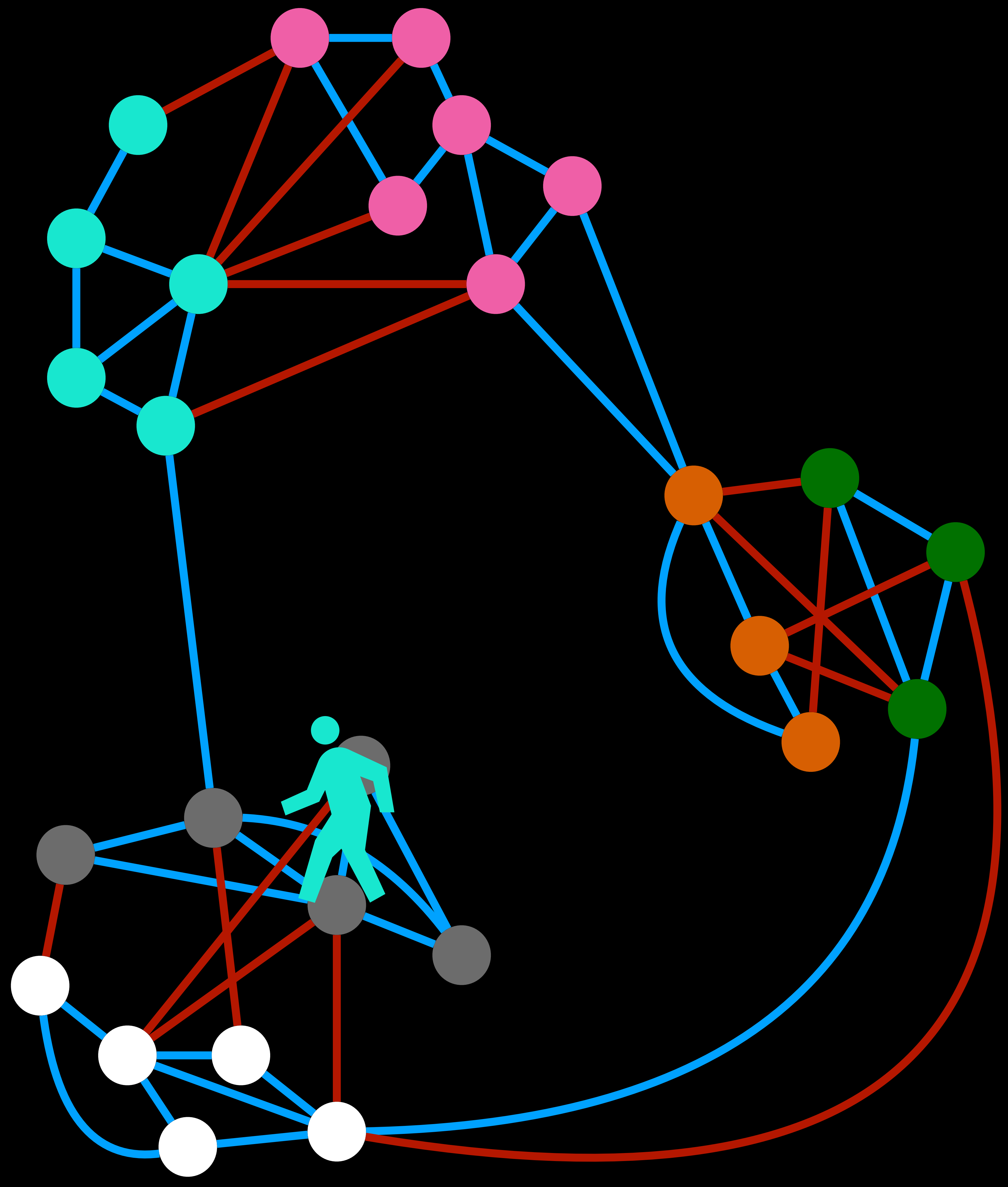
if $s = +$ and we traverse a positive edge, new sign $s = +$

➡ the enemy of my friend is my enemy
if $s = +$ and we traverse a negative edge, new sign $s = -$



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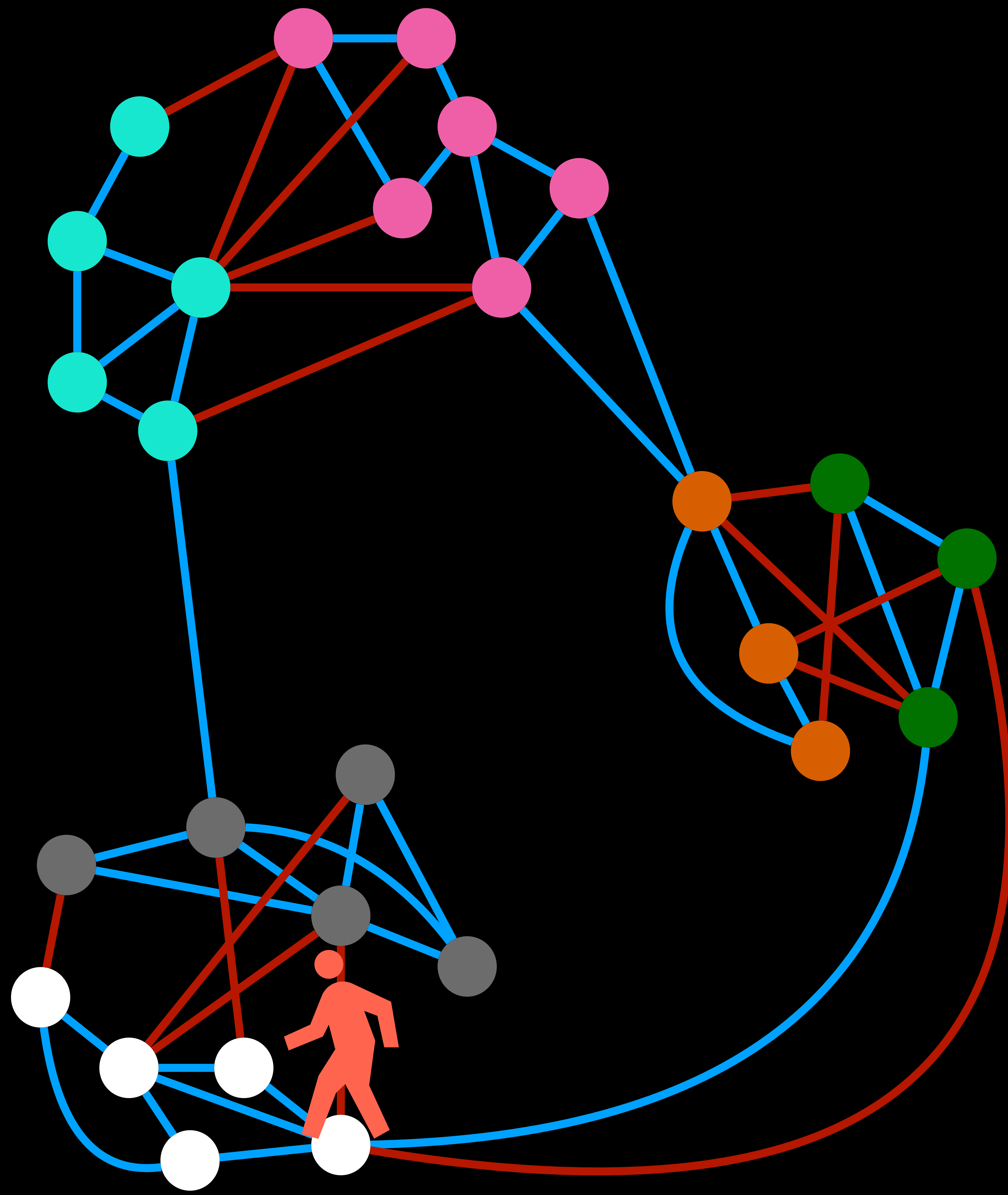


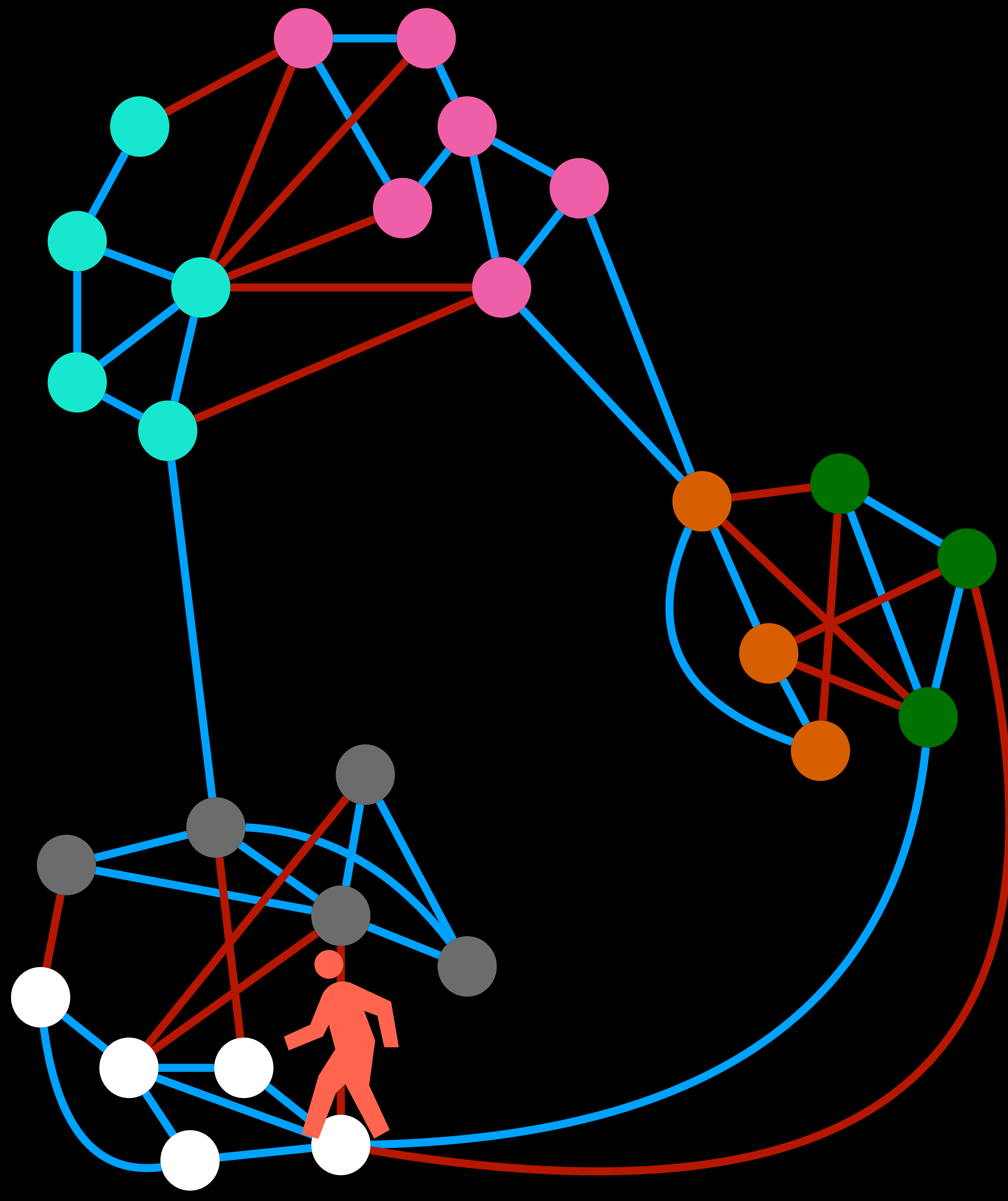
Random Walks With Signs

- Initialize sign $s = +$
- When traversing an edge, multiply s with the edge sign

  ➡ the friend of my friend is my friend
  if $s = +$ and we traverse a positive edge, new sign $s = +$

  ➡ the enemy of my friend is my enemy
  if $s = +$ and we traverse a negative edge, new sign $s = -$

  ➡ the friend of my enemy is my enemy
  if $s = -$ and we traverse a positive edge, new sign $s = -$



Random Walks With Signs

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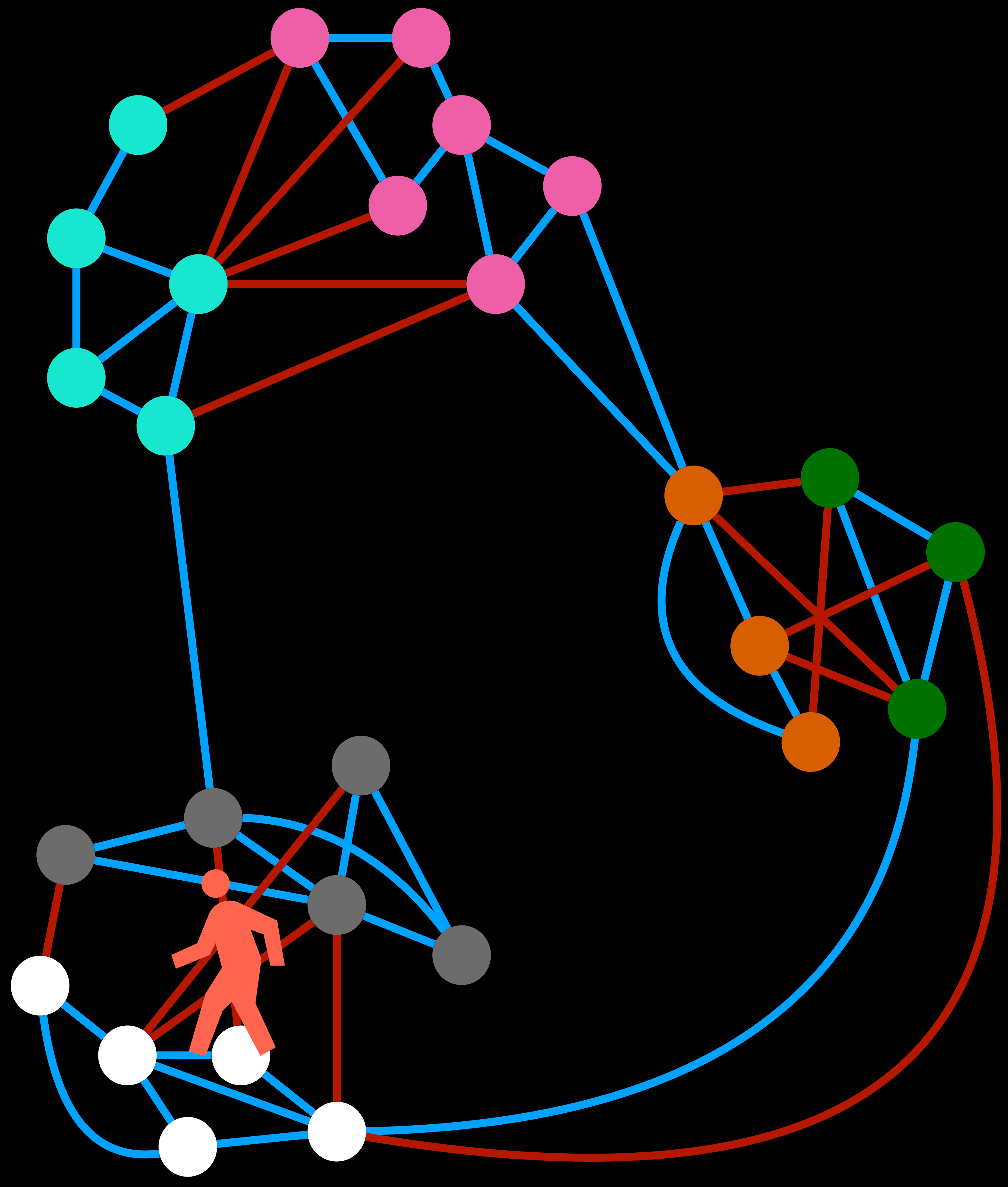
➡ the enemy of my friend is my enemy
if $s = +$ and we traverse a negative edge, new sign $s = -$

➡ the friend of my enemy is my enemy
if $s = -$ and we traverse a positive edge, new sign $s = -$



Random Walks With Signs

- Initialize sign $s = +$
- When traversing an edge, multiply s with the edge sign
  - ➡ the friend of my friend is my friend
    if $s = +$ and we traverse a positive edge, new sign $s = +$
  - ➡ the enemy of my friend is my enemy
    if $s = +$ and we traverse a negative edge, new sign $s = -$
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    if $s = -$ and we traverse a positive edge, new sign $s = -$
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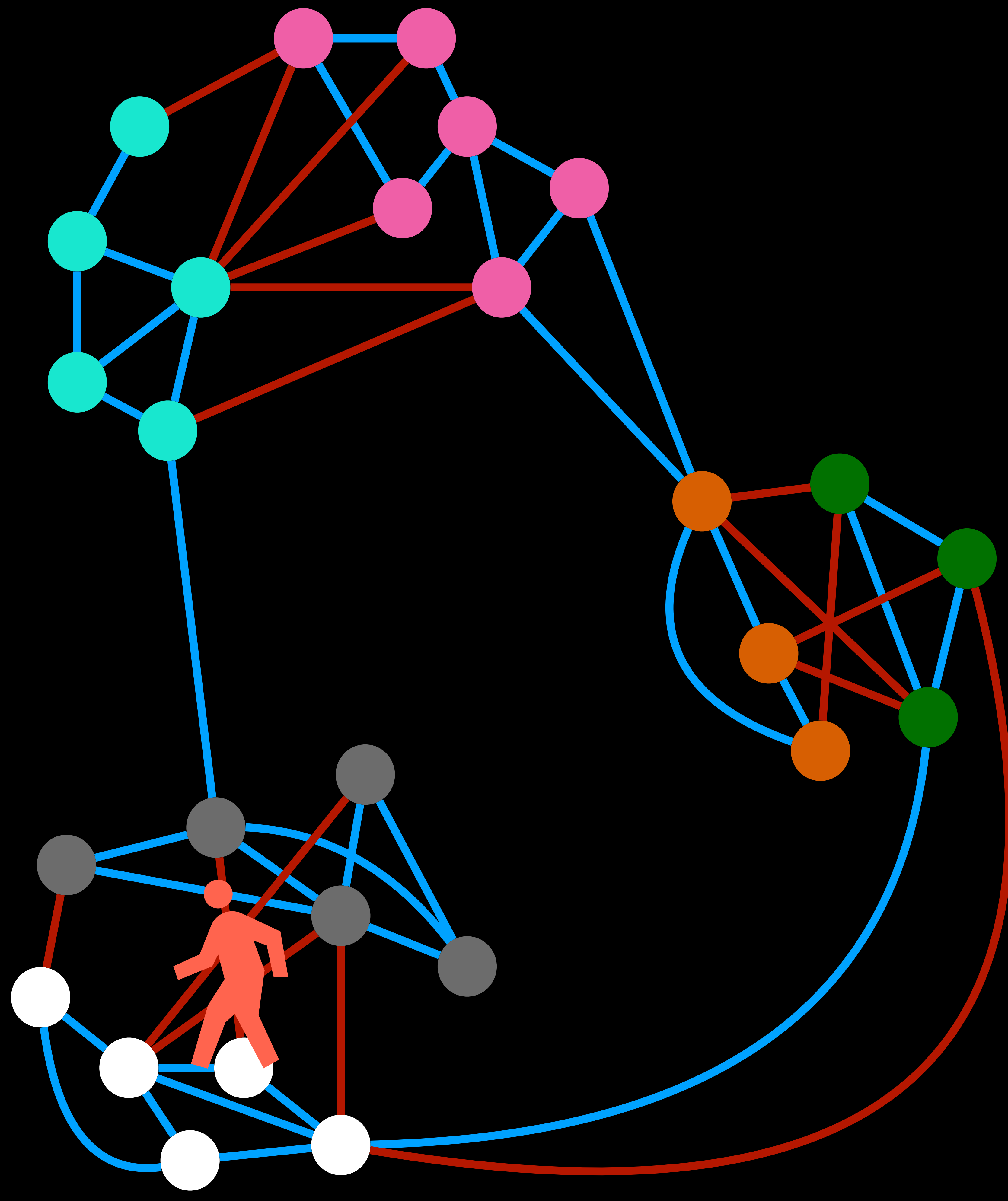

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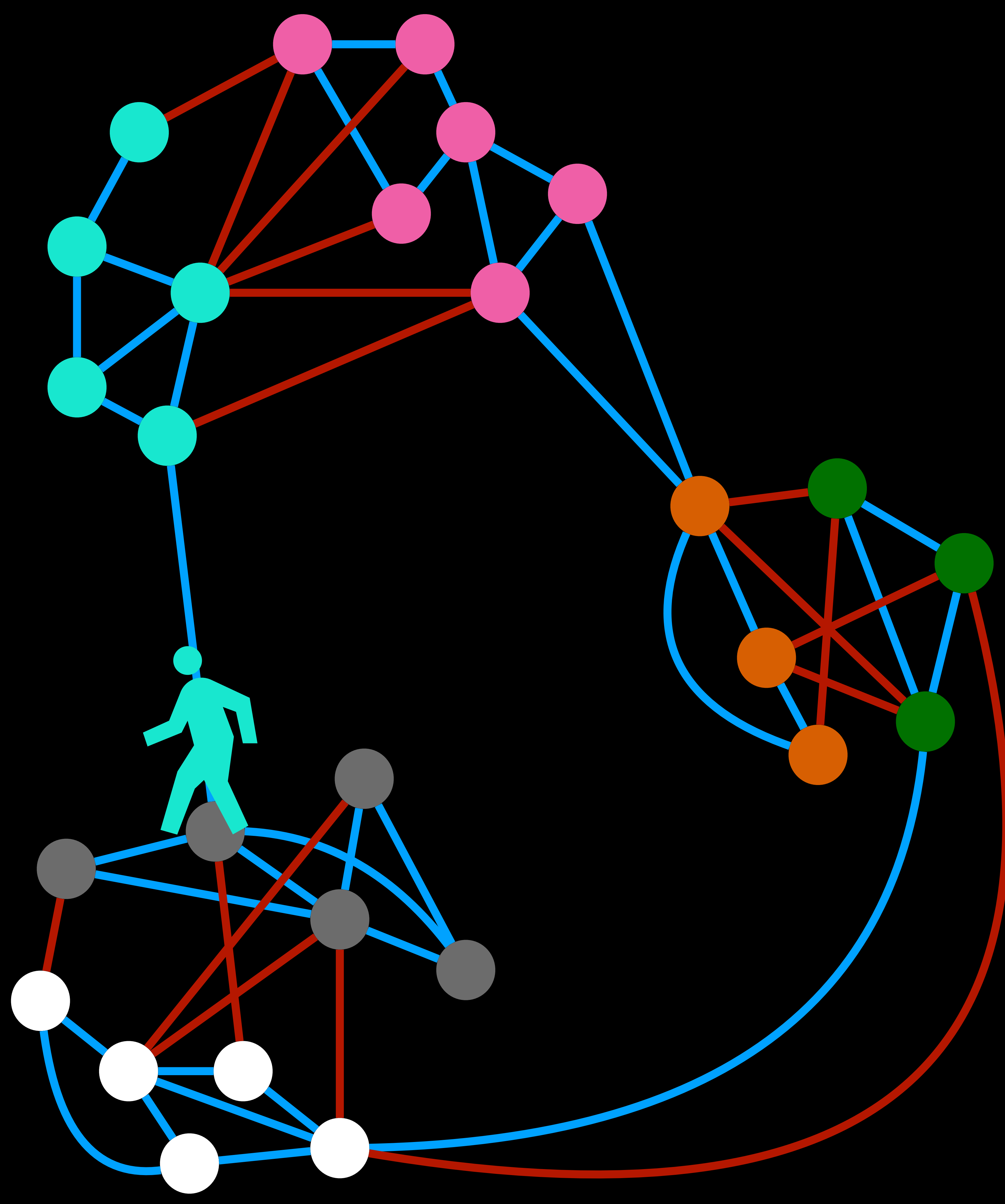

Random Walks With Signs

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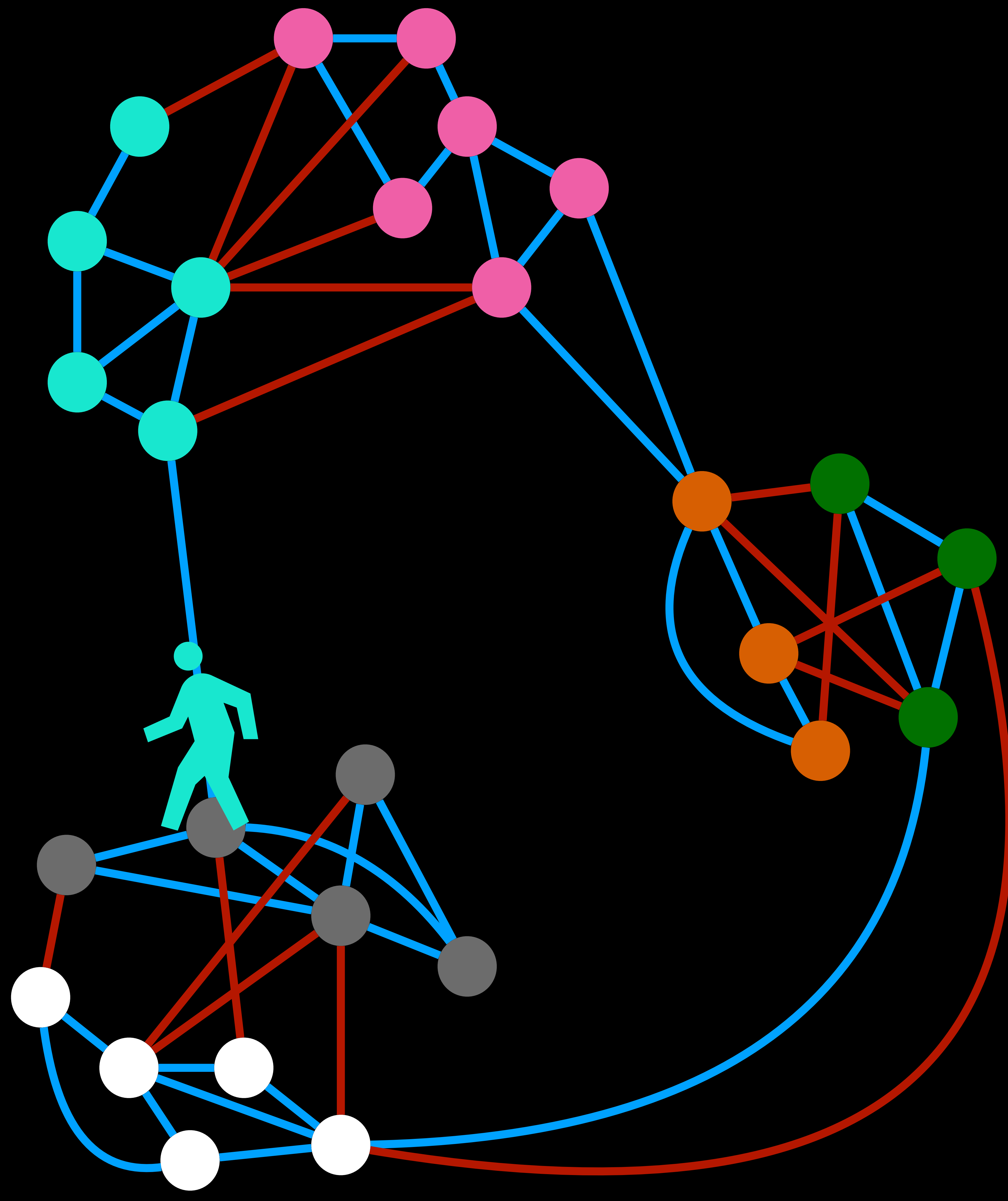
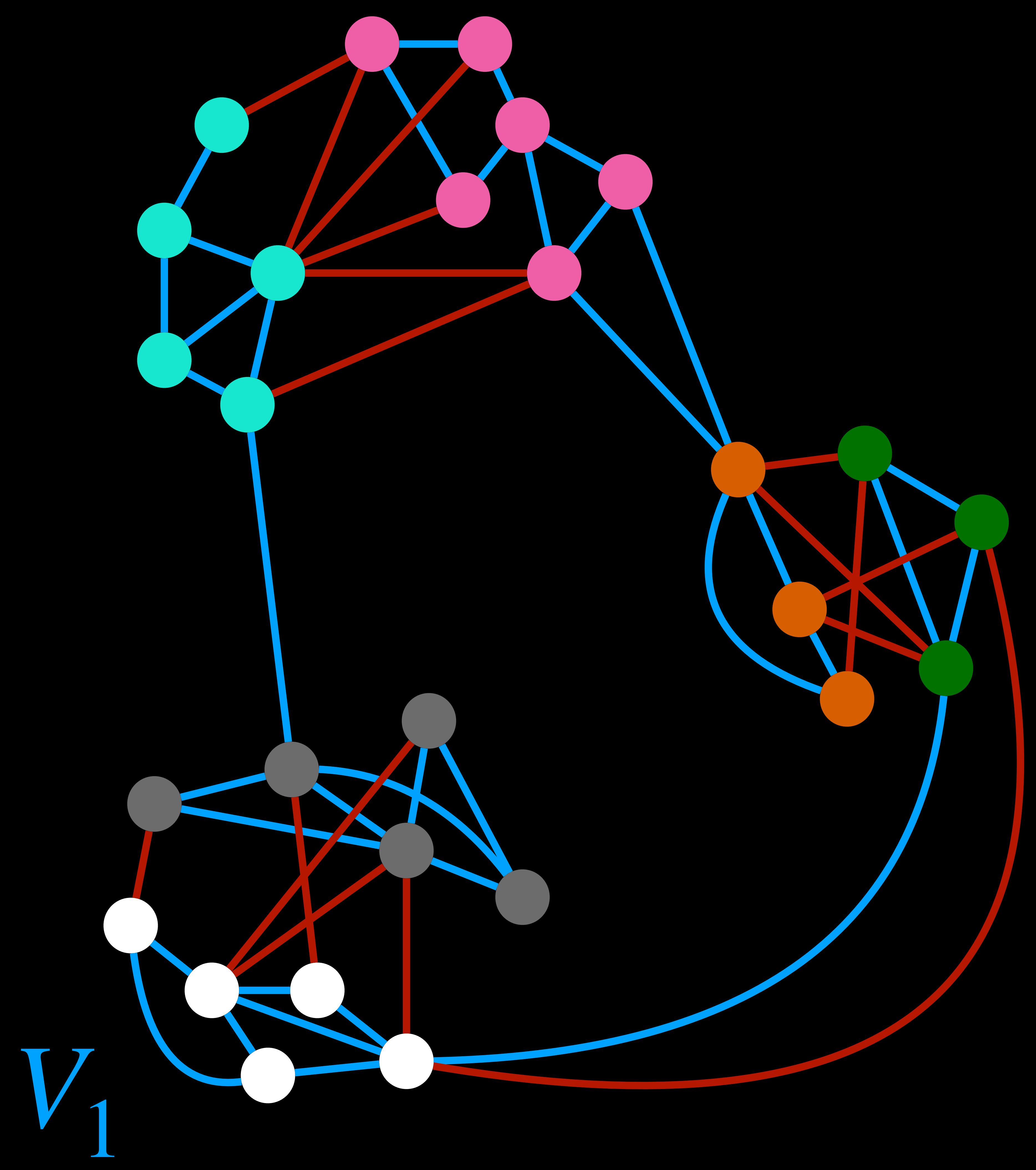
    if $s = -$ and we traverse a positive edge, new sign $s = -$
  - ➡ the enemy of my enemy is my friend
    if $s = -$ and we traverse a negative edge, new sign $s = +$
- We do not make any changes to the randomness of the walk



Some Intuition

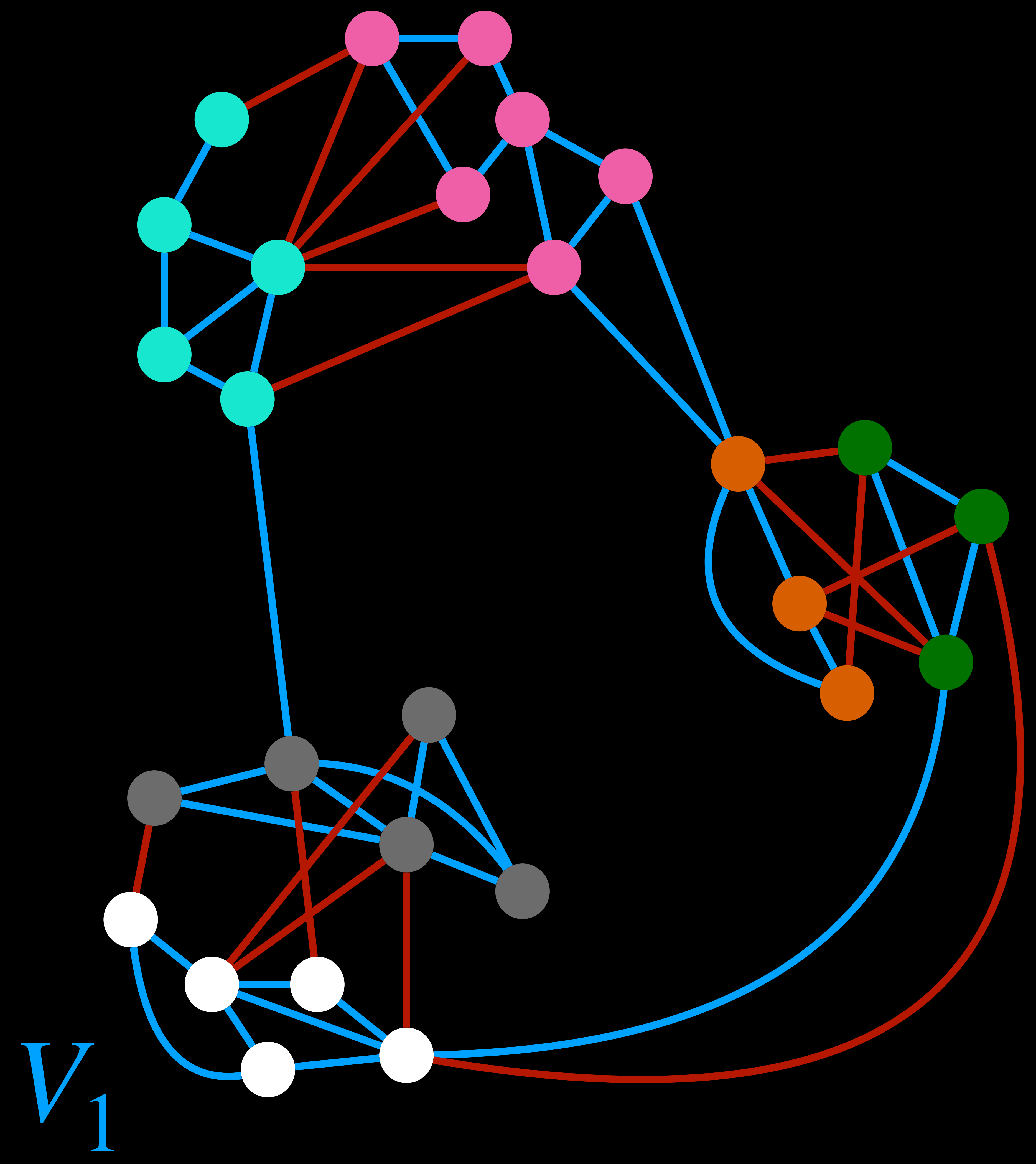
What signs of random walks do we expect?



Some Intuition

What signs of random walks do we expect?

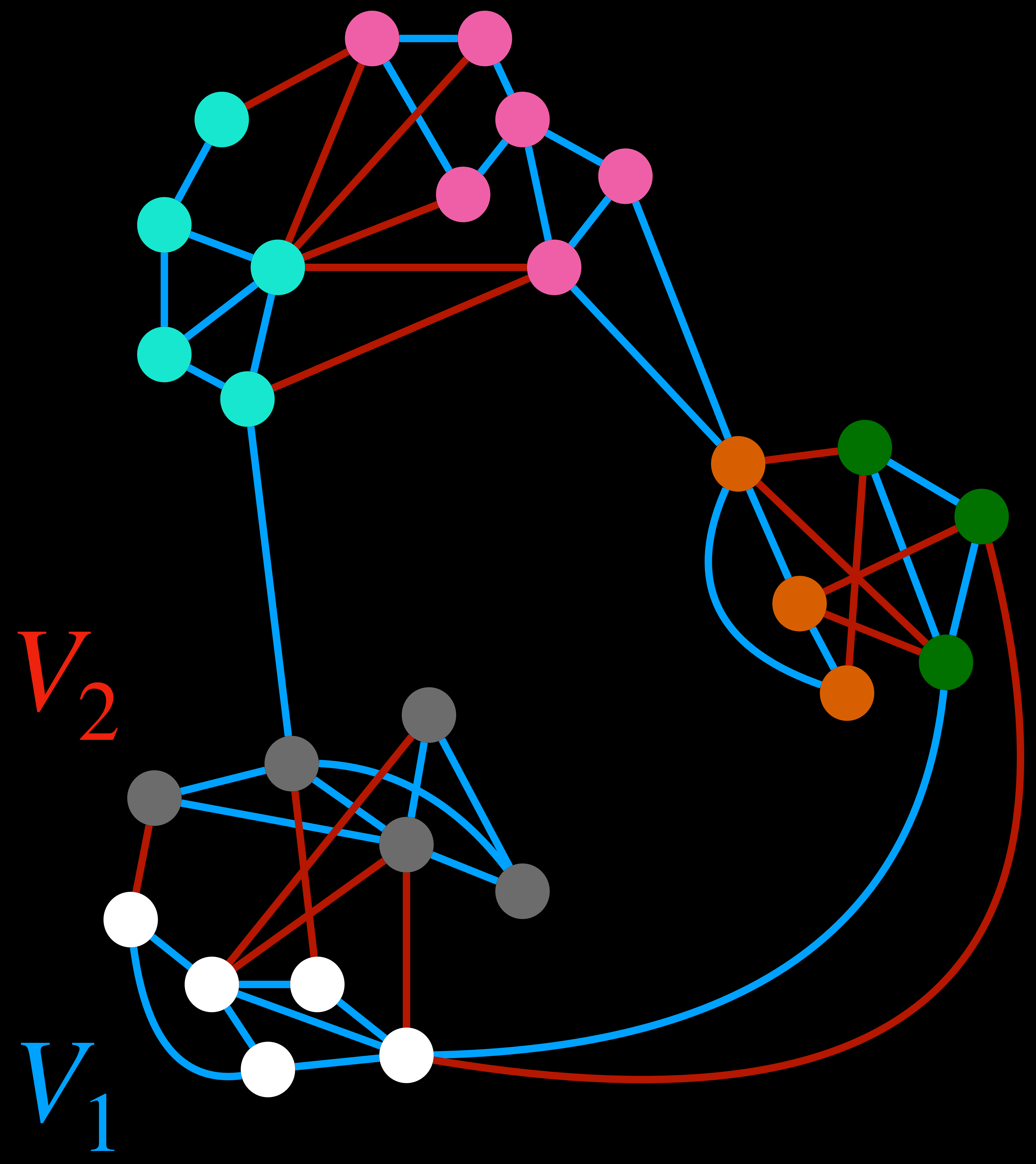
- If we start in V_1 and end in V_1, sign should be $+$



Some Intuition

What signs of random walks do we expect?

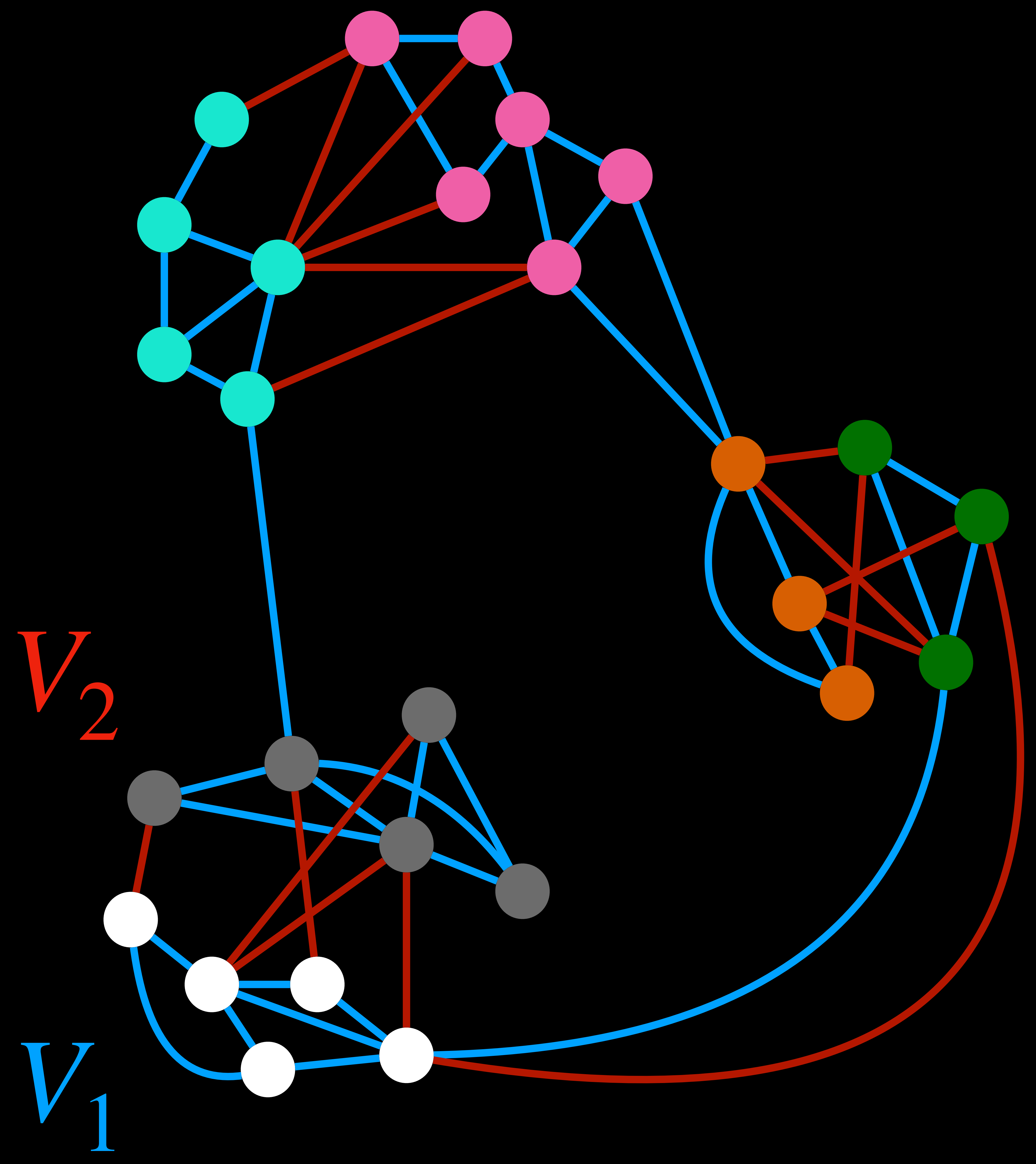
- If we start in V_1 and end in V_1, sign should be $+$
- If we start in V_1 and end in V_2, sign should be $-$



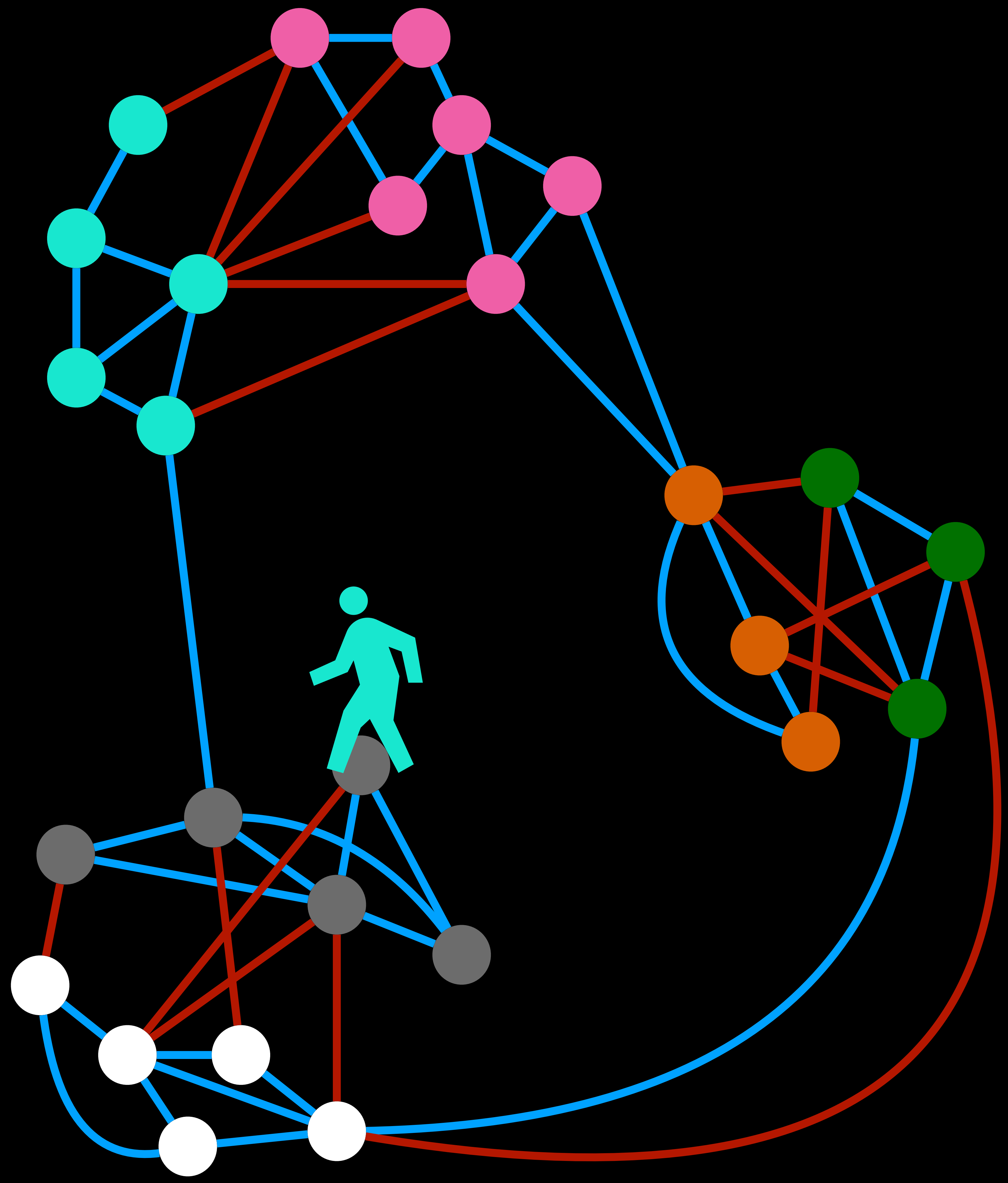
Some Intuition

What signs of random walks do we expect?

- If we start in V_1 and end in V_1, sign should be $+$
- If we start in V_1 and end in V_2, sign should be $-$
- If we start in V_1 then the probability to end in $V\backslash(V_1 \cup V_2)$ should be very small

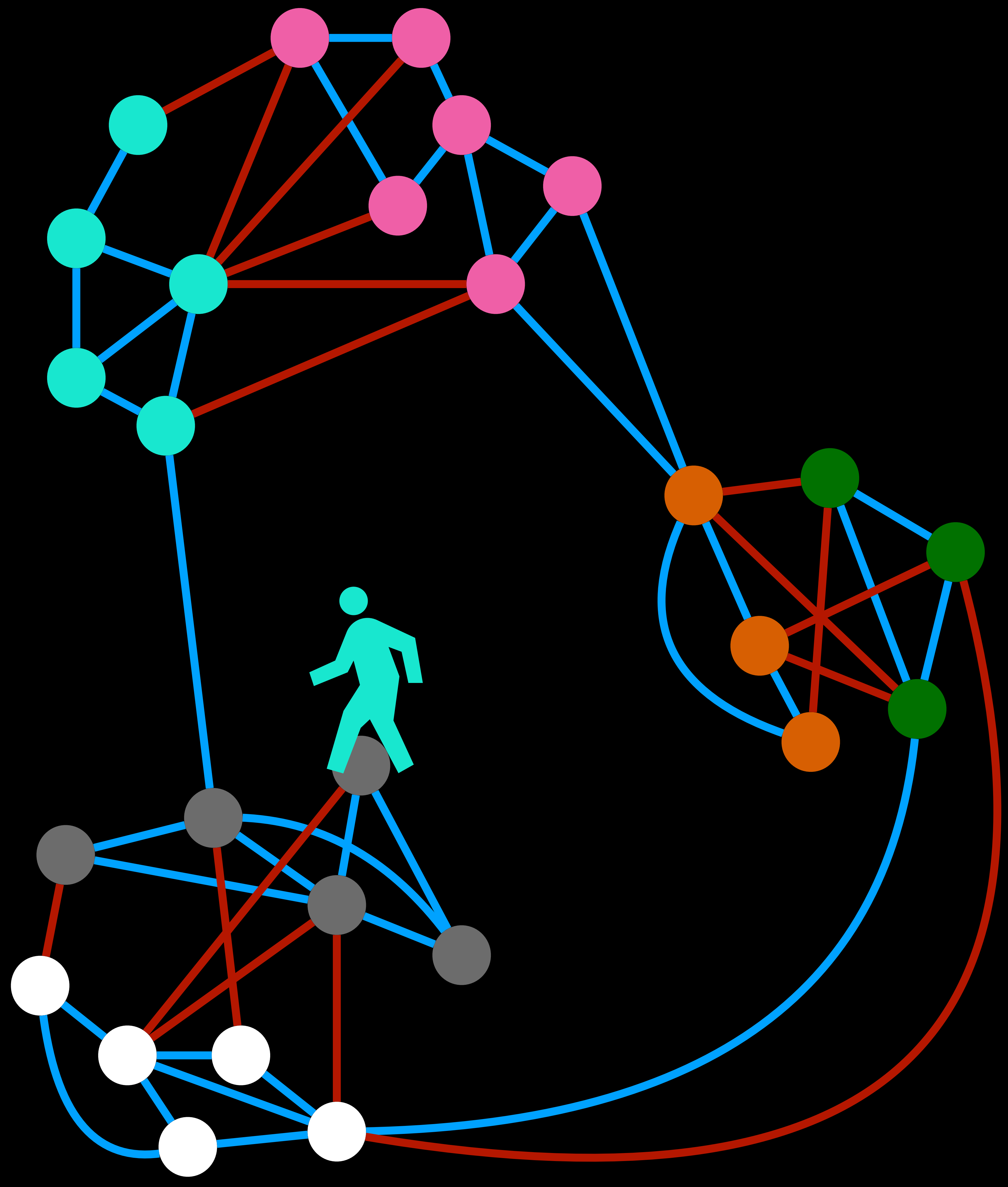


Community Vectors



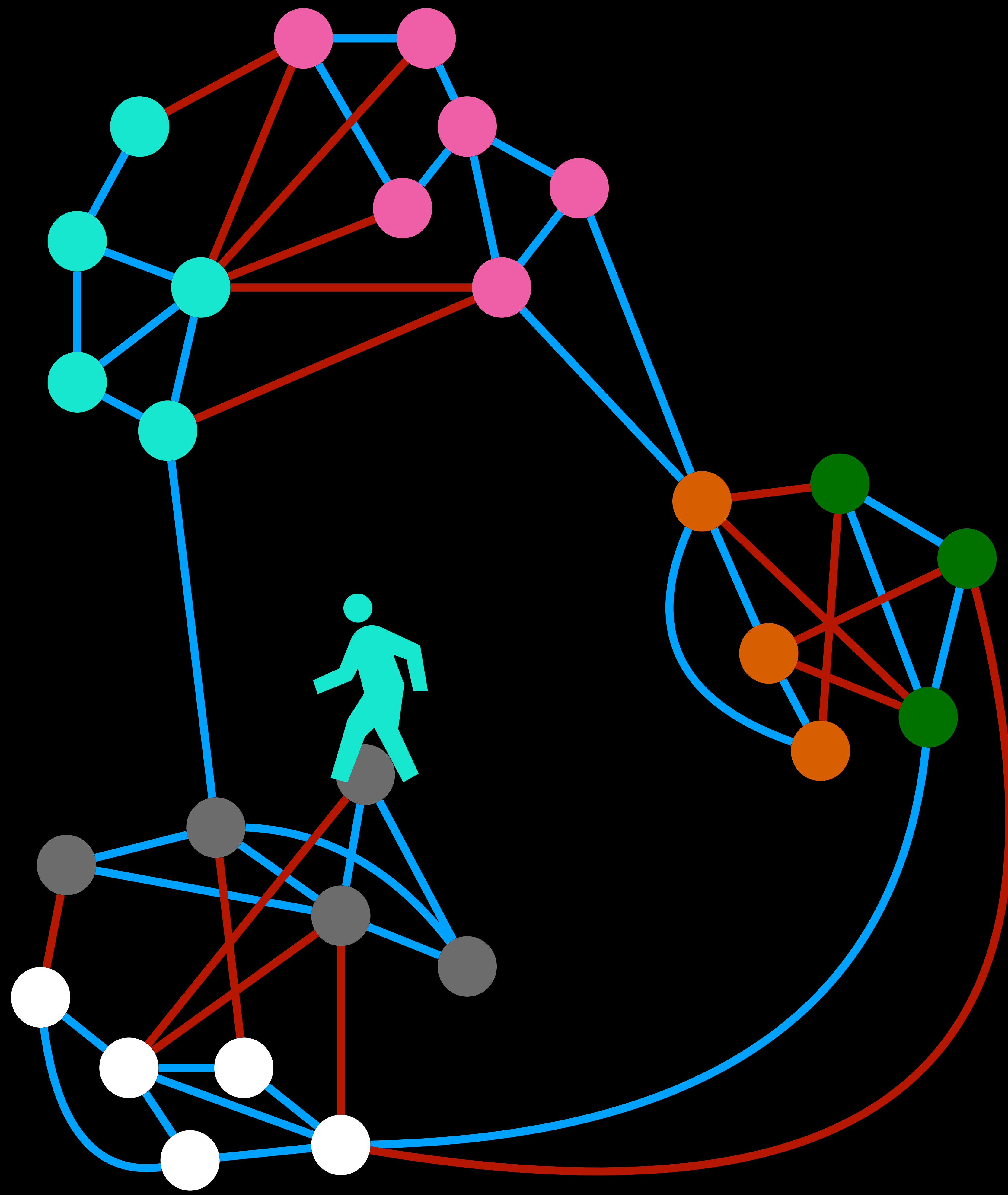
Community Vectors

- SignedCommunityVector(u):



Community Vectors

- SignedCommunityVector(u):
  - Initialize an empty vector $m \in \mathbb{R}^n$



Community Vectors

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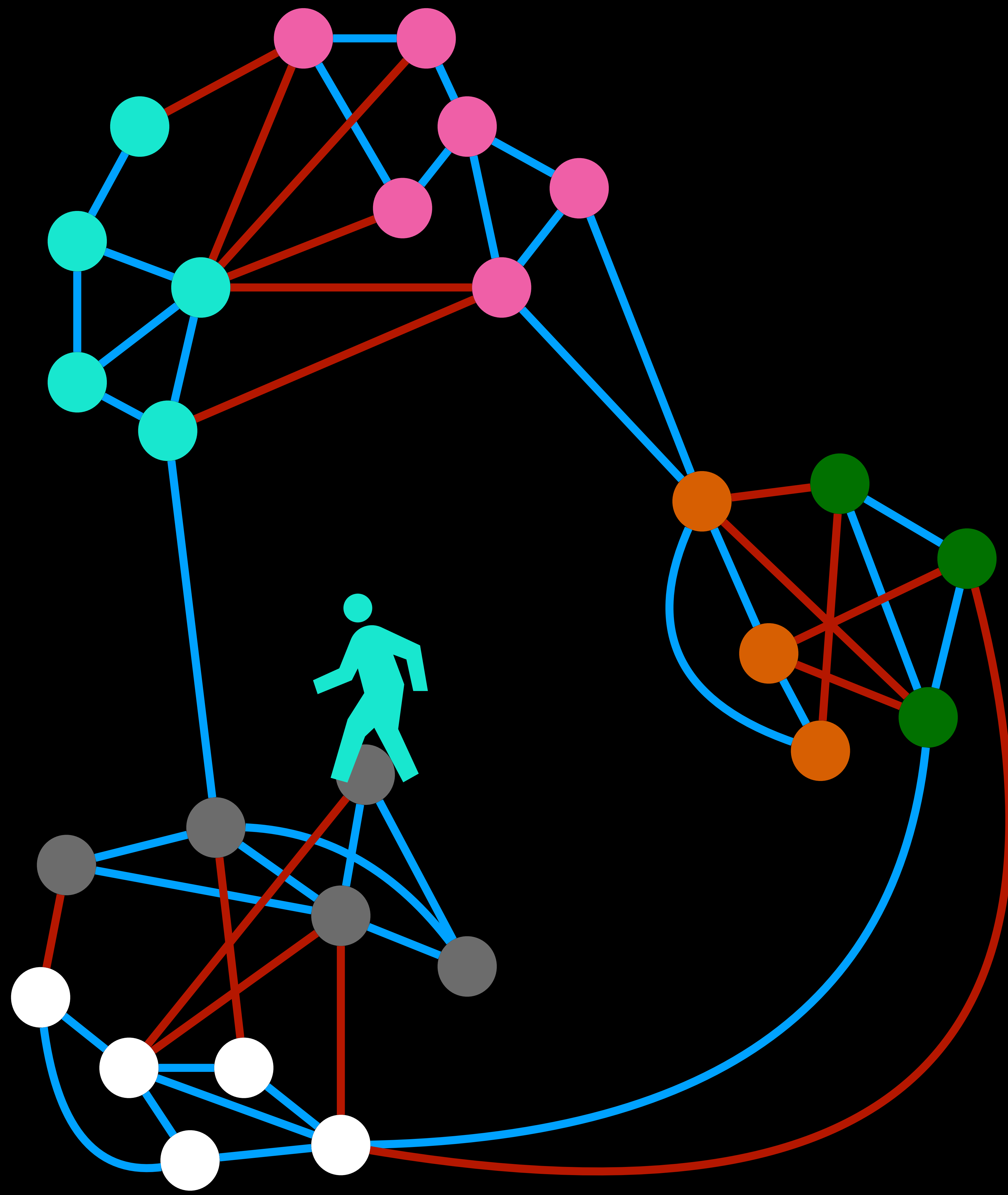
  - Initialize an empty vector $m \in \mathbb{R}^n$
  - Perform $\sqrt{n}$ random walks of length $\log n$ starting at u



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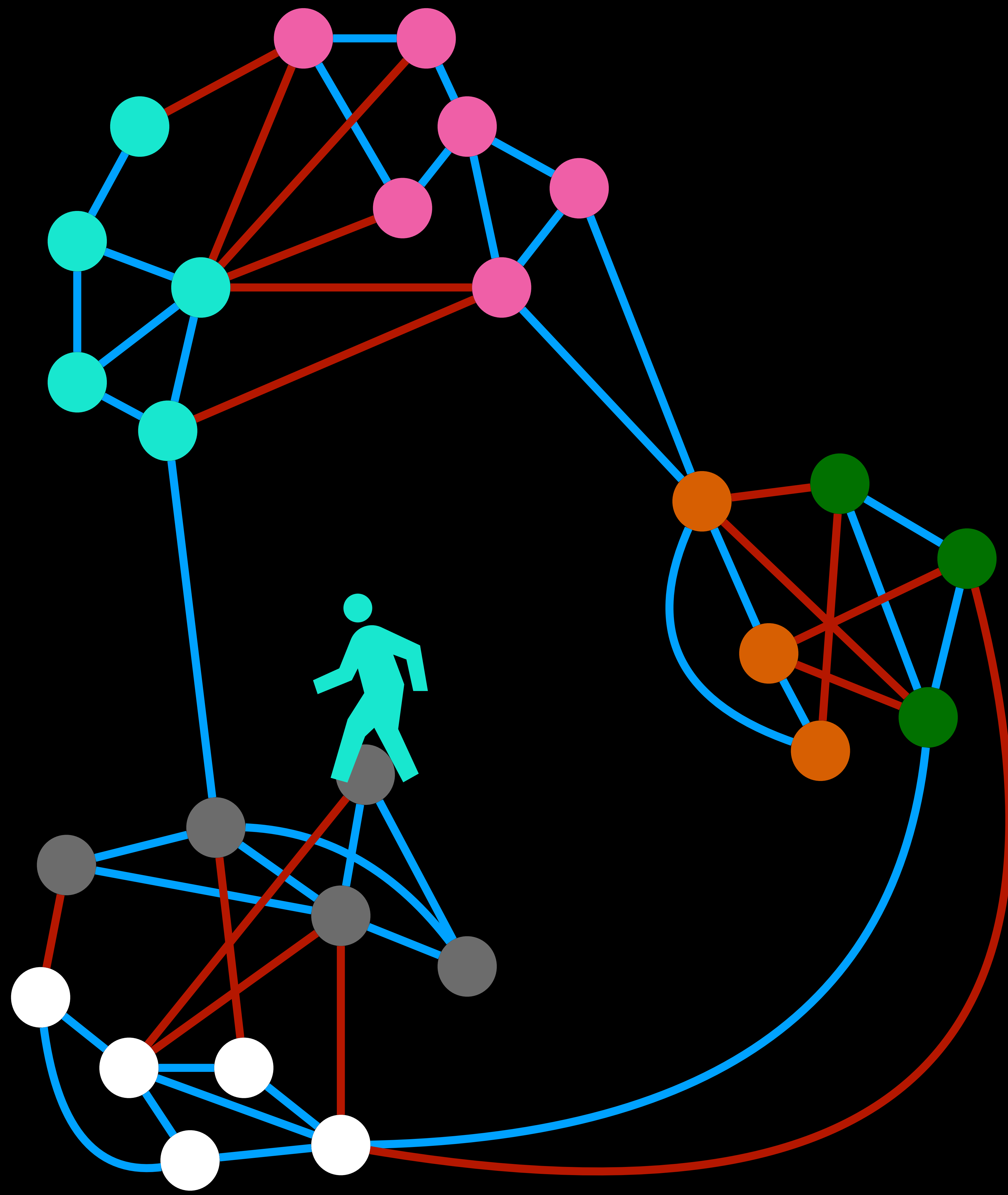

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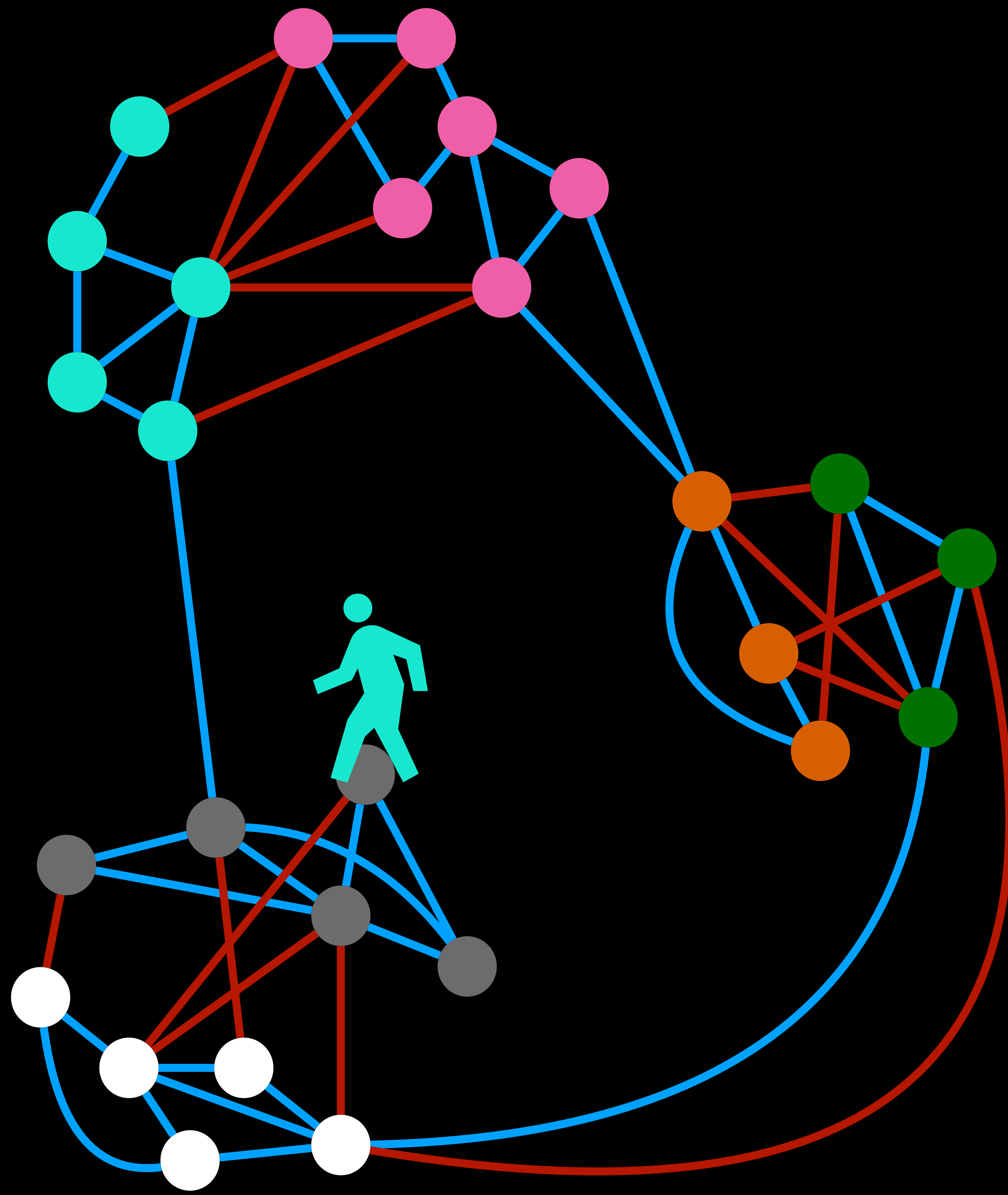

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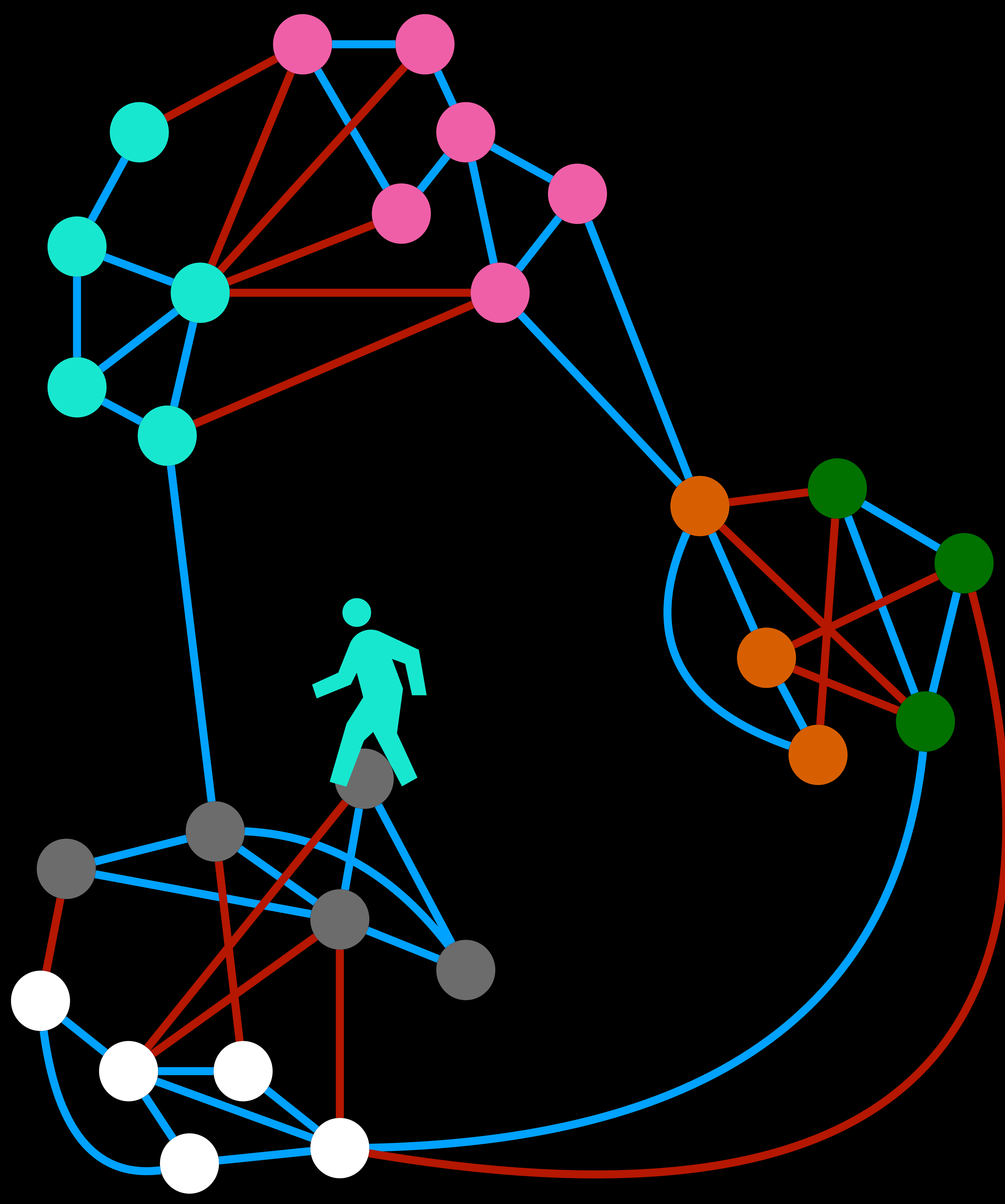

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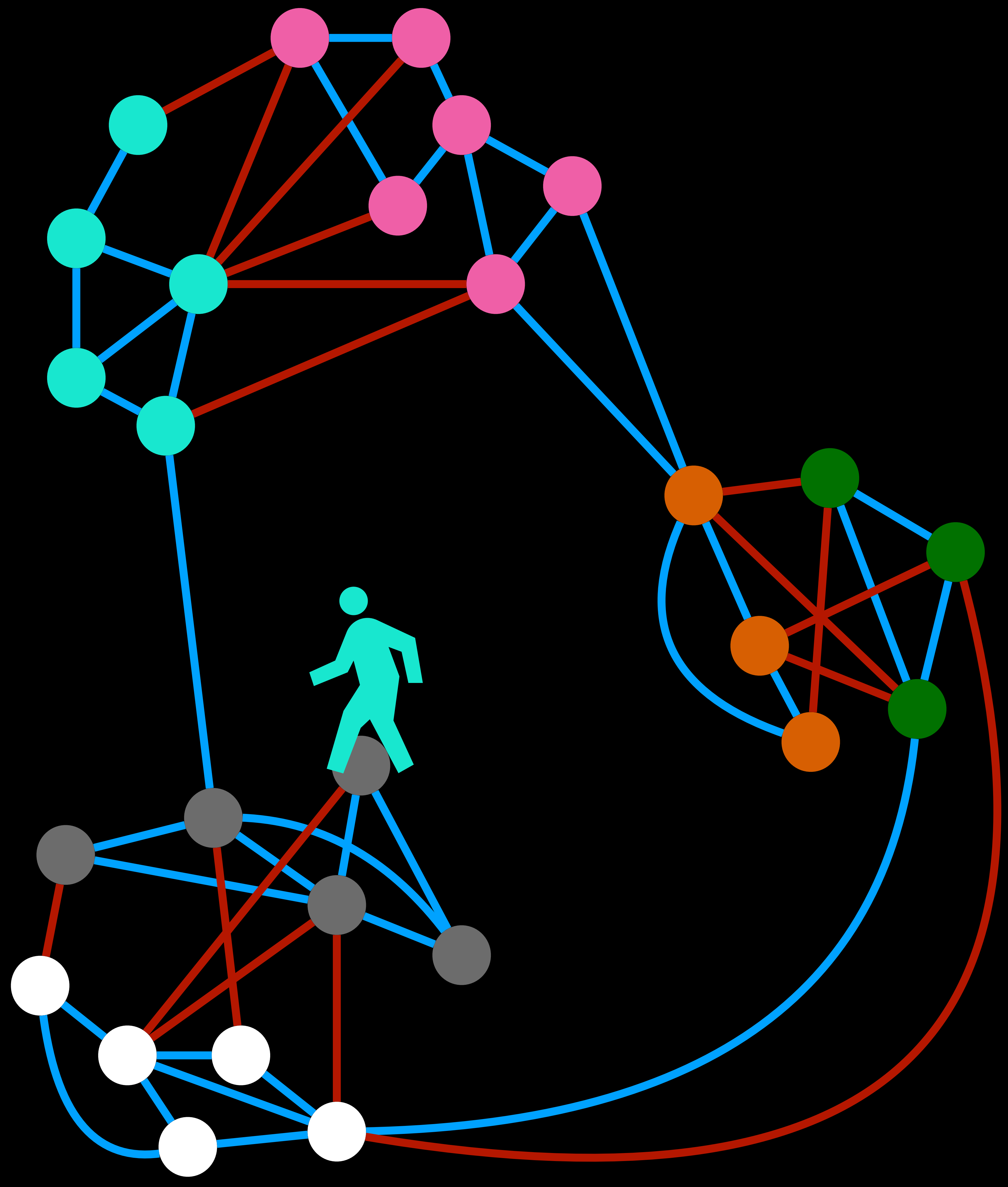
    - $m(w) \leftarrow m_+(w) - m_-(w)$



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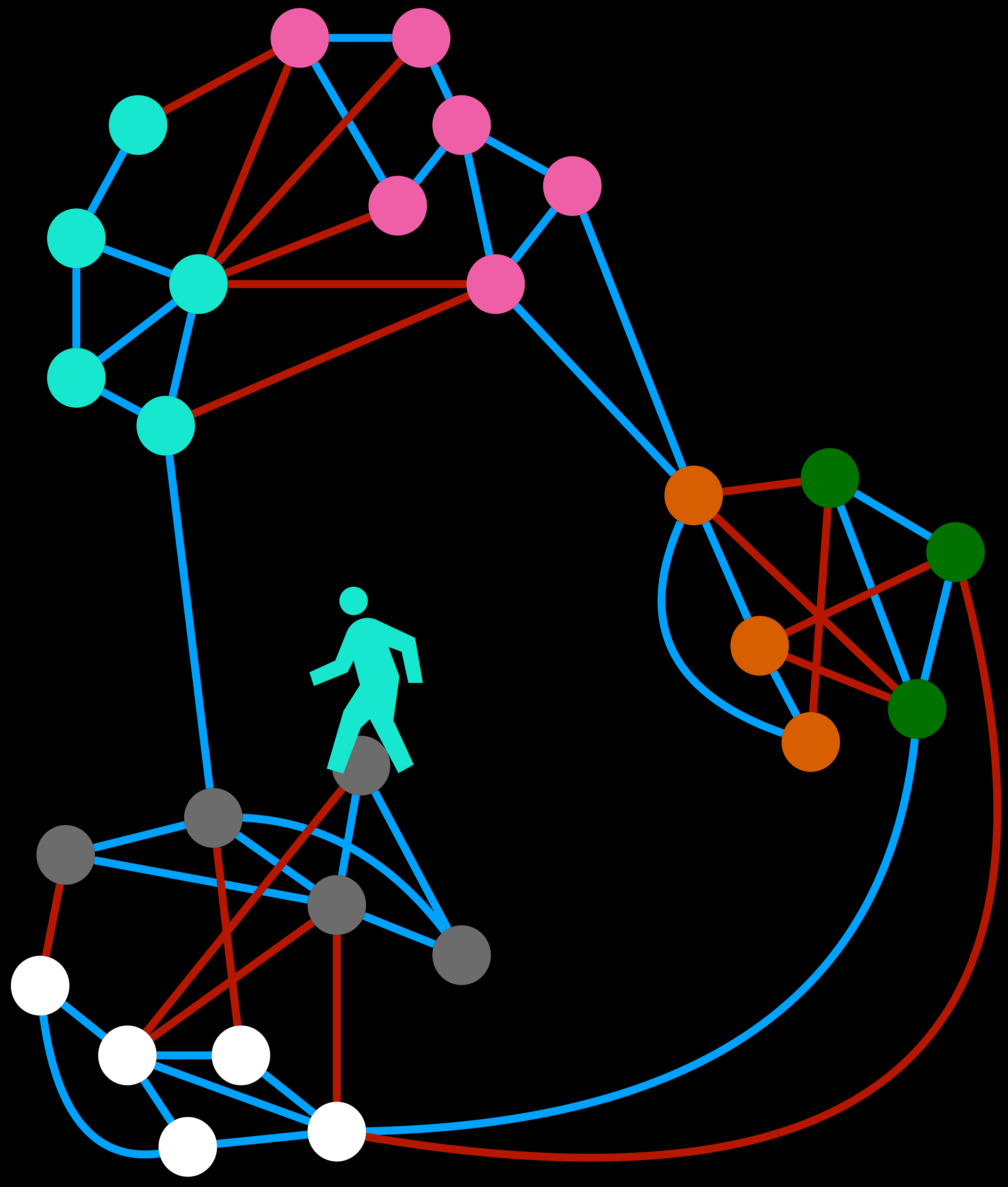
➡ we expect that if w is on the same side as u then $m(w) \gg 0$,
if w is on the other side of u then $m(w) \ll 0$, and
if w is from a different cluster then $m(w) \approx 0$



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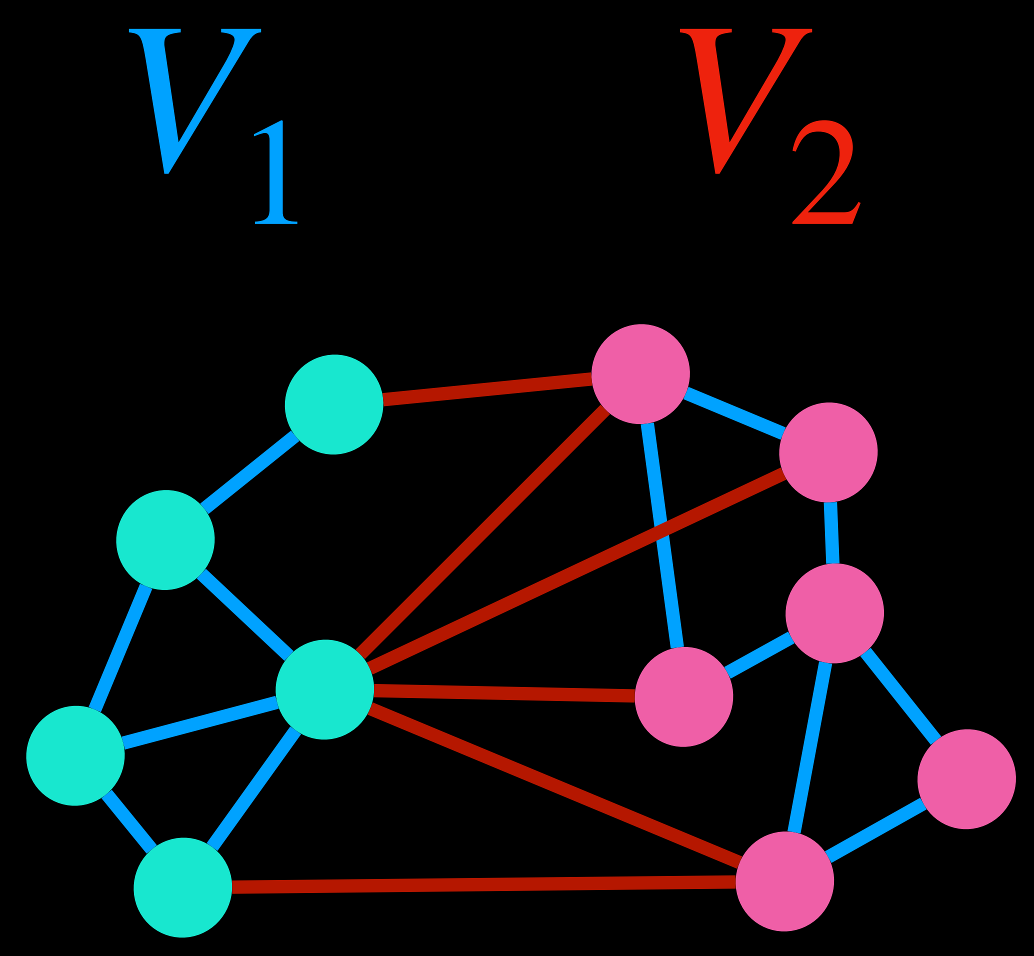
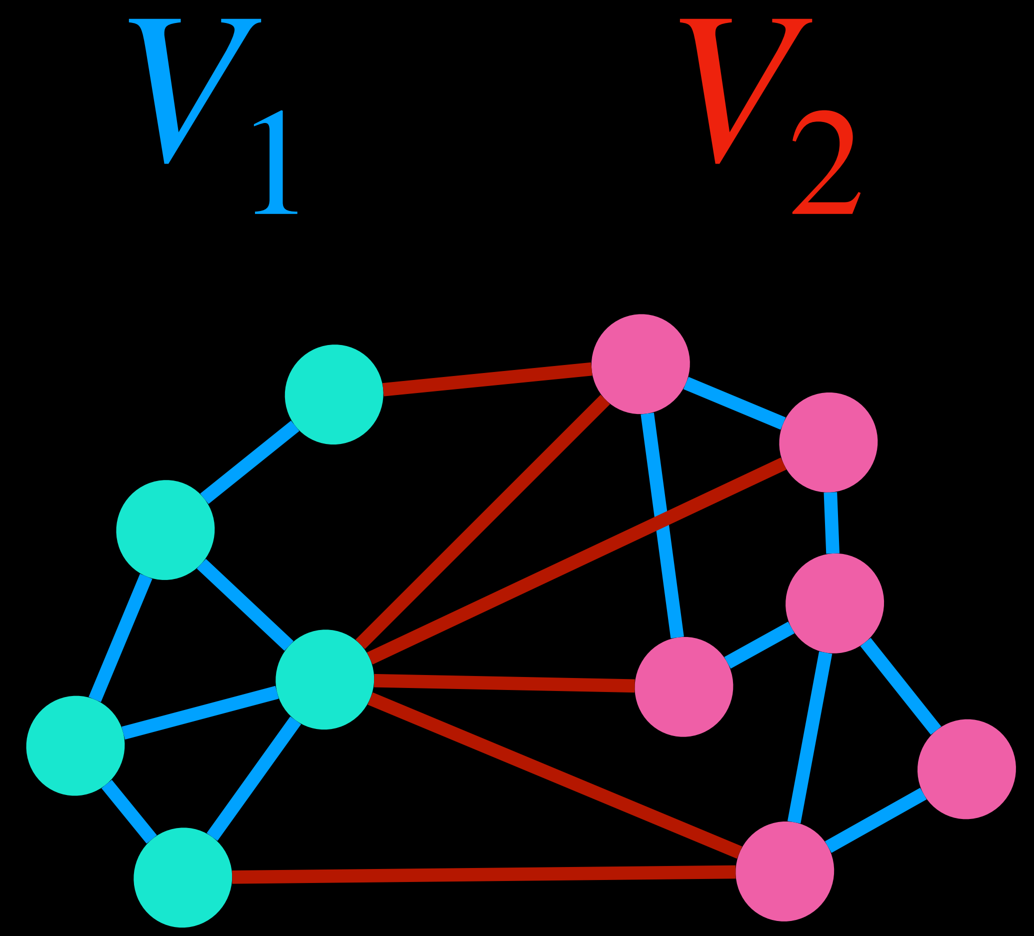
- Suppose that for each cluster $C_1, \ldots, C_k$ we know a seed-vertex $v_i \in C_i$
- **WhichCluster(u):**
  - $m_u \leftarrow$ SignedCommunityVector(u)
  - $m_{v_i} \leftarrow$ SignedCommunityVector(v_i) for all i
  - $i^* = \arg\min_i \min\{\|m_u - m_{v_i}\|_2, \|m_u + m_{v_i}\|_2\}$
  - Return that u is from cluster i^*

➡ **Intuition:** if u is from cluster i^*,
then the community vectors of m_u and $m_{v_{i^*}}$
should be similar

Main Technical Result

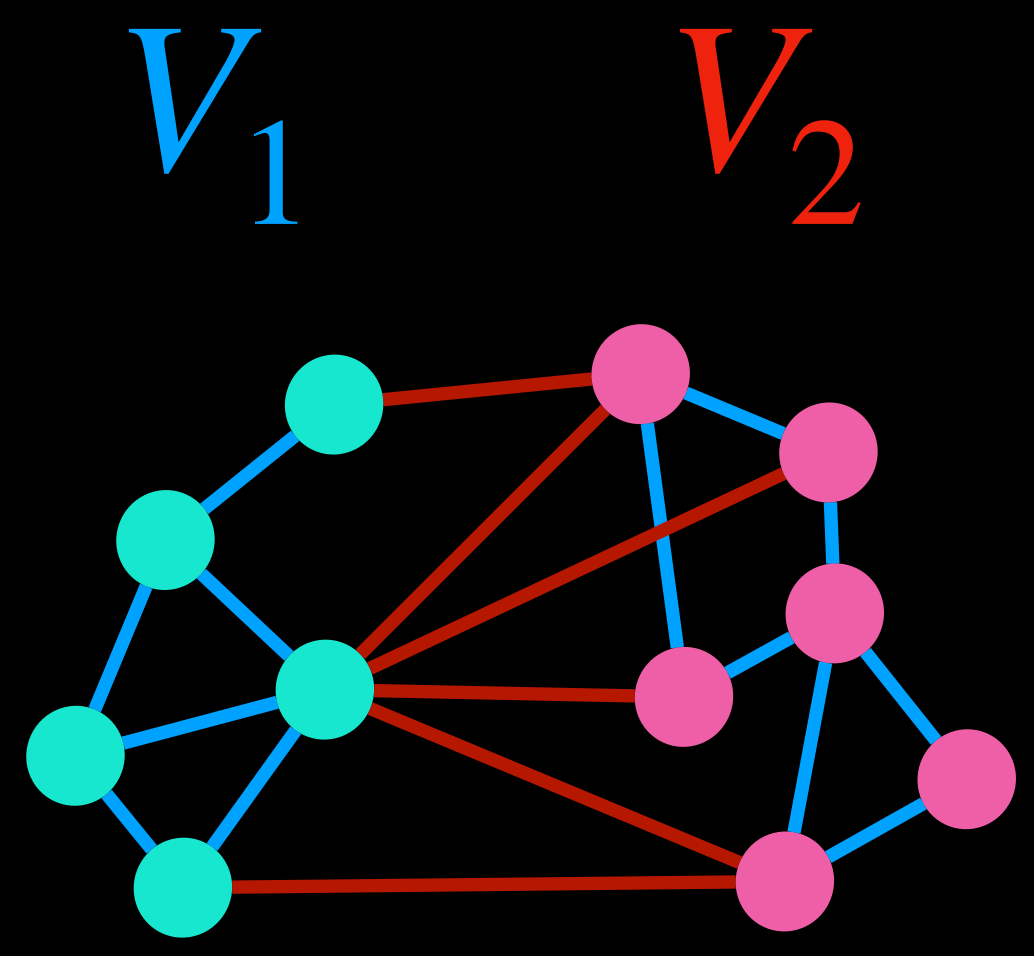


Main Technical Result



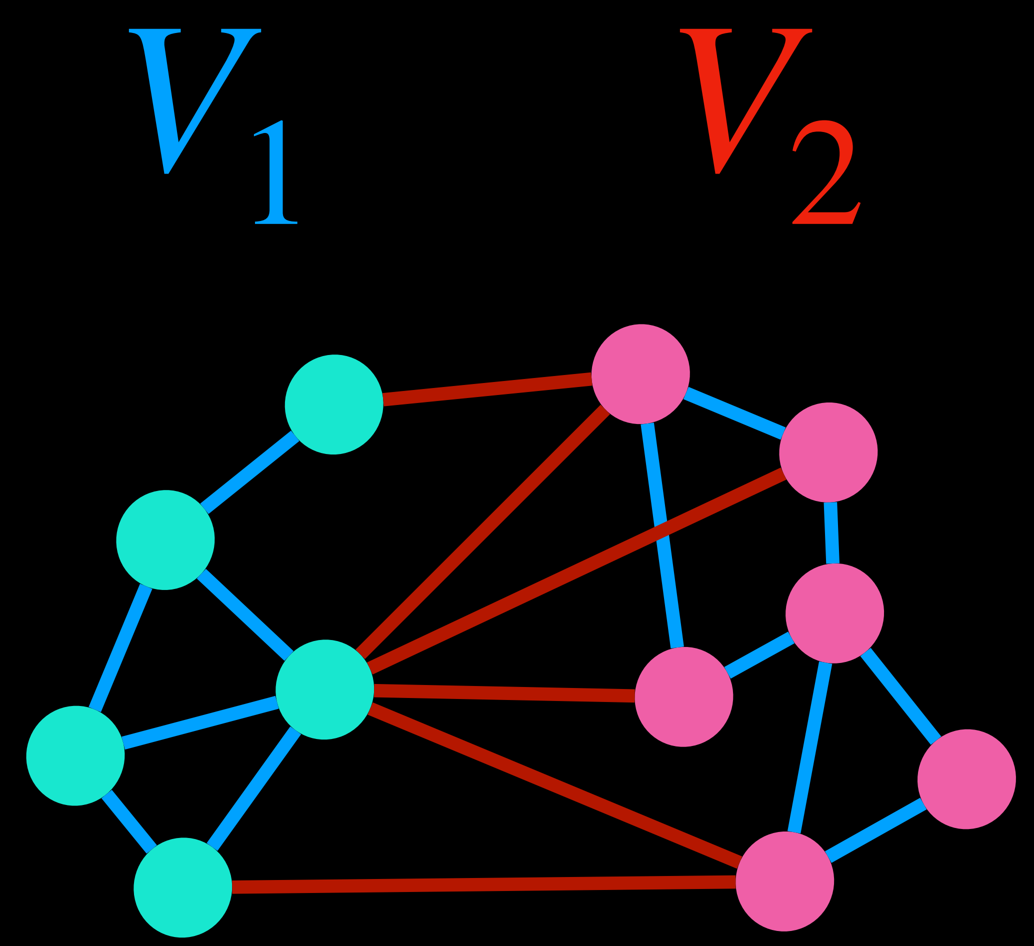
- Let $\mathscr{L} = \mathbf{I} - \mathbf{D}^{-1/2}\mathbf{A}\mathbf{D}^{-1/2}$ be the *signed normalized Laplacian*

Main Technical Result



- Let $\mathscr{L} = \mathbf{I} - \mathbf{D}^{-1/2}\mathbf{A}\mathbf{D}^{-1/2}$ be the *signed normalized Laplacian*
- Let $\mathbf{v}_1, \ldots, \mathbf{v}_n$ be the orthonormal row eigenvectors of $\mathscr{L}$, i.e., $\lambda_i \mathbf{v}_i = \mathbf{v}_i \mathscr{L}$, and assume that $0 \leq \lambda_1 \leq \cdots \leq \lambda_n$

Main Technical Result



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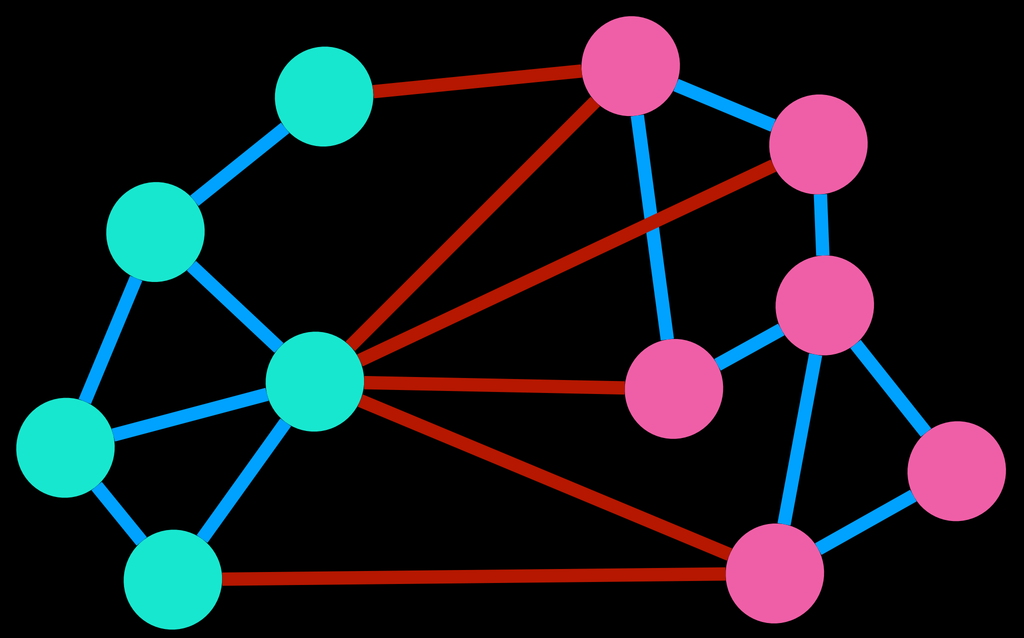
➡ *The vectors $\mathbf{v}_1, \ldots, \mathbf{v}_k$ essentially reveal the polarized communities*

Main Technical Result



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➡ *The vectors $\mathbf{v}_1, \ldots, \mathbf{v}_k$ essentially reveal the polarized communities*

- More formally, consider a polarized cluster $U = (V_1, V_2)$.
  Then (if G is degree-bounded, clusterable, and still simplifying a lot) for all $i \leq 1, \ldots, k$,

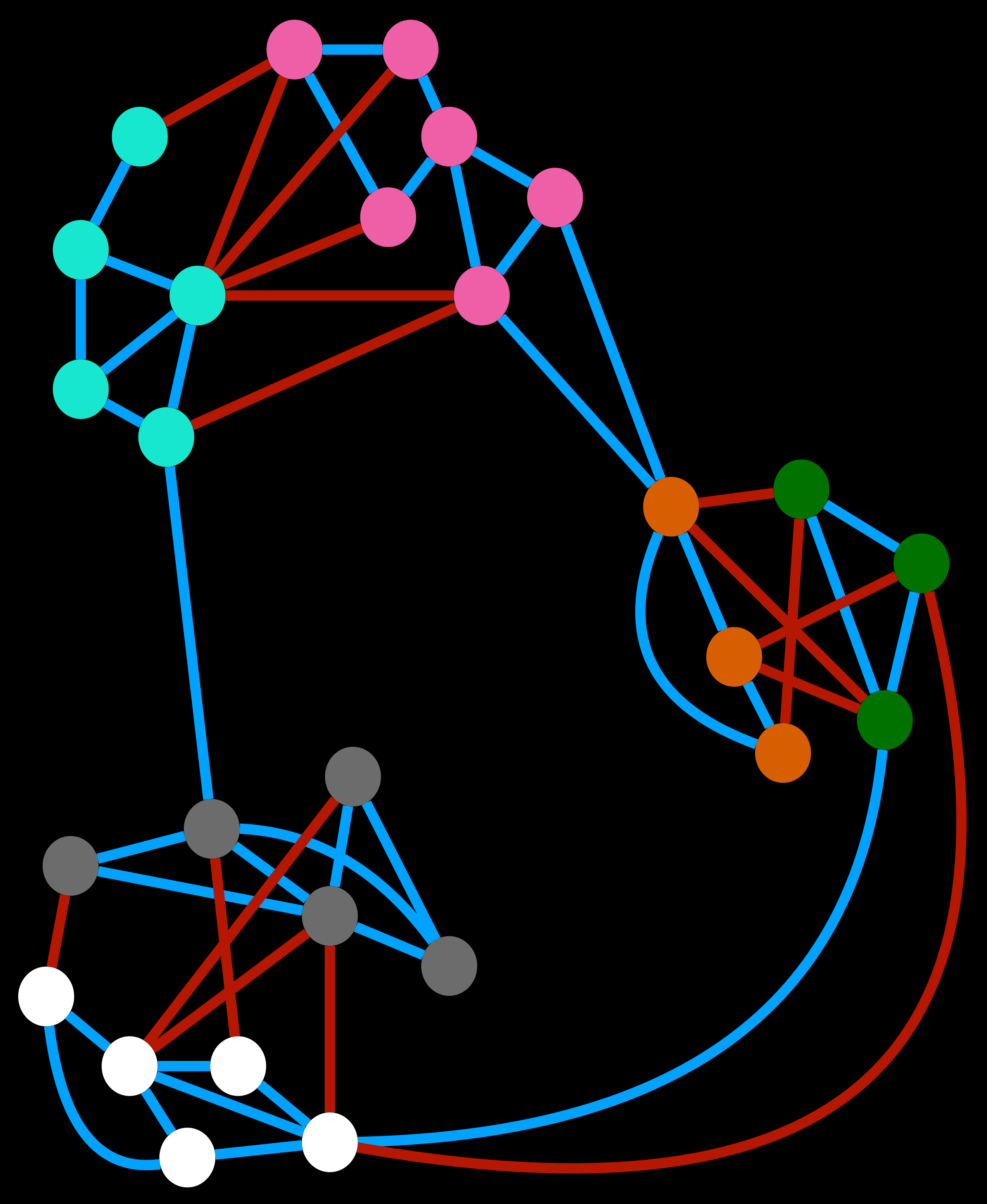
$$\mathbf{v}_i(u) \approx +\frac{1}{|U|} \text{ if } u \in V_1 \quad \text{and} \quad \mathbf{v}_i(u) \approx -\frac{1}{|U|} \text{ if } u \in V_2$$

Sublinear-Time Clustering Oracle for Signed Graphs

***Stefan Neumann* (KTH) and Pan Peng (USTC)**
@StefanResearch

- We provide a sublinear-time clustering oracle that returns the communities of vertices in signed graphs
- We prove that it works and give new insights into spectral graph theory for signed random walks
- Highly scalable and works well in practice for large clusters
- We provide a new signed graph dataset with large ground-truth communities

- Open questions:
    - Give guarantees for our heuristic
    - Use our theoretical insights for better practical algorithms
    - What else can we do with signed random walks?



Sublinear-Time Clustering Oracle for Signed Graphs

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Thank you!

- We provide a sublinear-time clustering oracle that returns the communities of vertices in signed graphs
- We prove that it works and give new insights into spectral graph theory for signed random walks
- Highly scalable and works well in practice for large clusters
- We provide a new signed graph dataset with large ground-truth communities

- Open questions:
    - Give guarantees for our heuristic
    - Use our theoretical insights for better practical algorithms
    - What else can we do with signed random walks?