



Graph Theoretic Approaches to Evaluating Counter Drone Systems

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BACKGROUND

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CASE STUDY

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METHODOLOGY/RESULTS

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FUTURE DIRECTIONS

DRONE USAGE

Civilian Sector



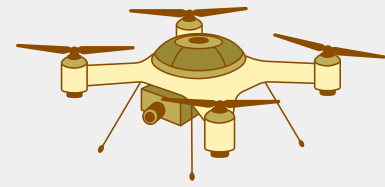
- Humanitarian Aid
- Environmental Monitoring
- Entertainment and Media
- Delivery Services
- Research and Development

- Reconnaissance and Surveillance
- Targeted Strikes
- Logistics and Supply
- Electronic Warfare
- Training

Military Sector



MILITARY APPLICATIONS



Reconnaissance and Surveillance

- Area Monitoring
- Force Protection
- Intelligence Gathering



Targeted Strikes

- Direct Combat
- Designation

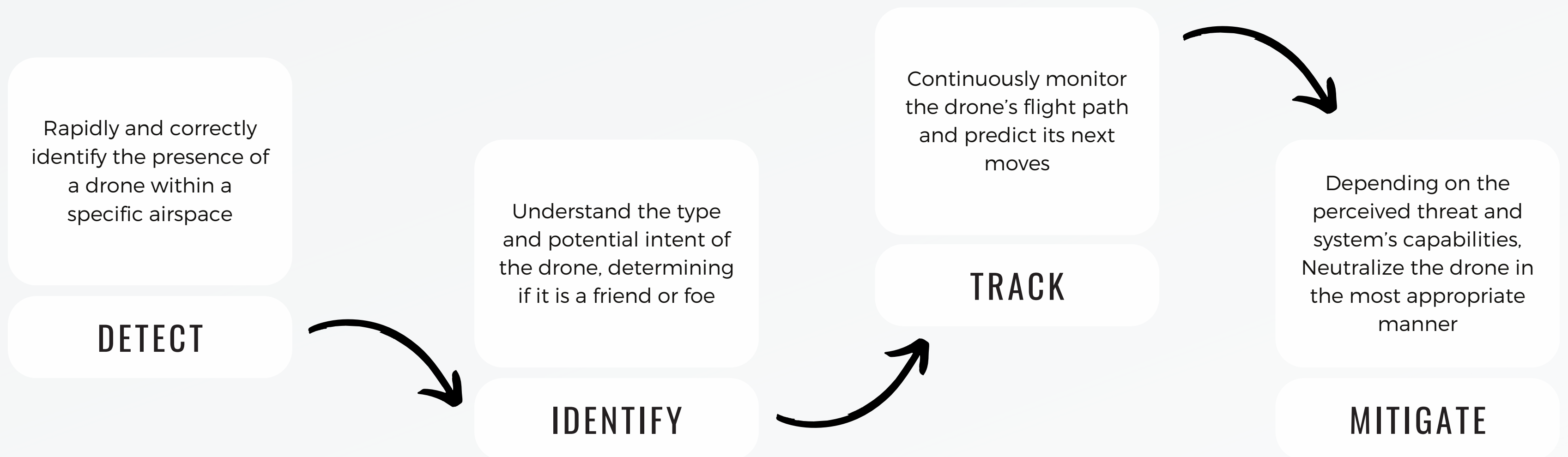


Electronic Warfare

- Jamming
- Radar Decoys
- Signal Interception

OVERVIEW OF COUNTER DRONE SYSTEMS

Counter Drone Systems utilize components such as radar, RF detectors, acoustic sensors, and cameras to detect/identify/track drones. Response mechanisms such as electronic jamming, kinetic weapons, or directed energy weapons are used to neutralize threats.



OVERVIEW OF GRAPH THEORY



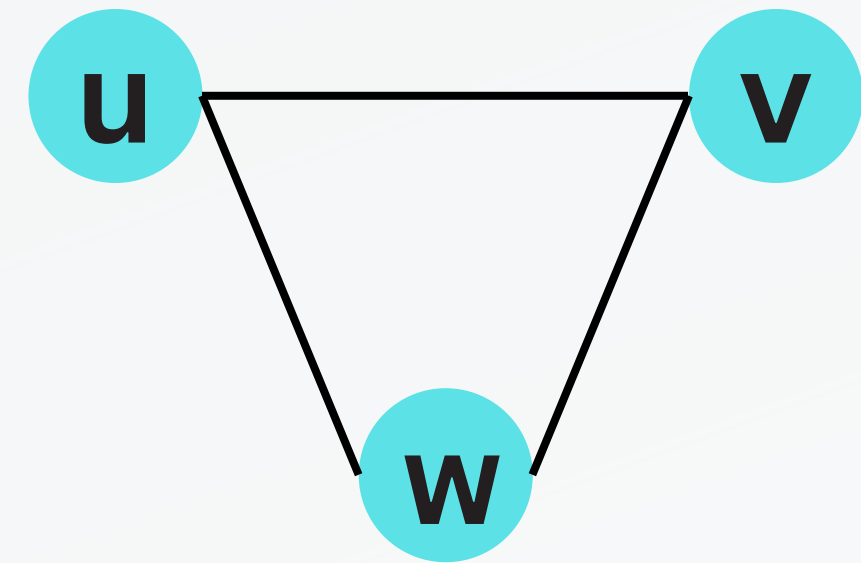
Graph $G = (V, E)$ consists of a set of vertices, denoted by V and a set of edges denoted by E .

Example: $G(V, E)$, $V = \{u, v, w\}$, $E = \{\{u, v\}, \{v, w\}, \{u, w\}\}$



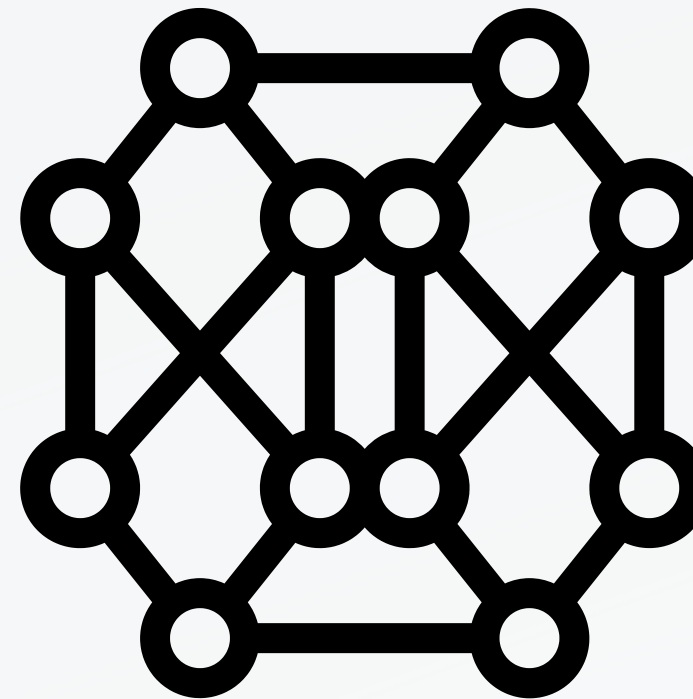
Vertices: The individual points or entities

Edges: The connections between vertices



EXAMPLES OF GRAPH THEORY

- Computer Networks
- Social Networks
- Biological Networks
- Designing Road Networks
- Counter Drone Systems
- etc.



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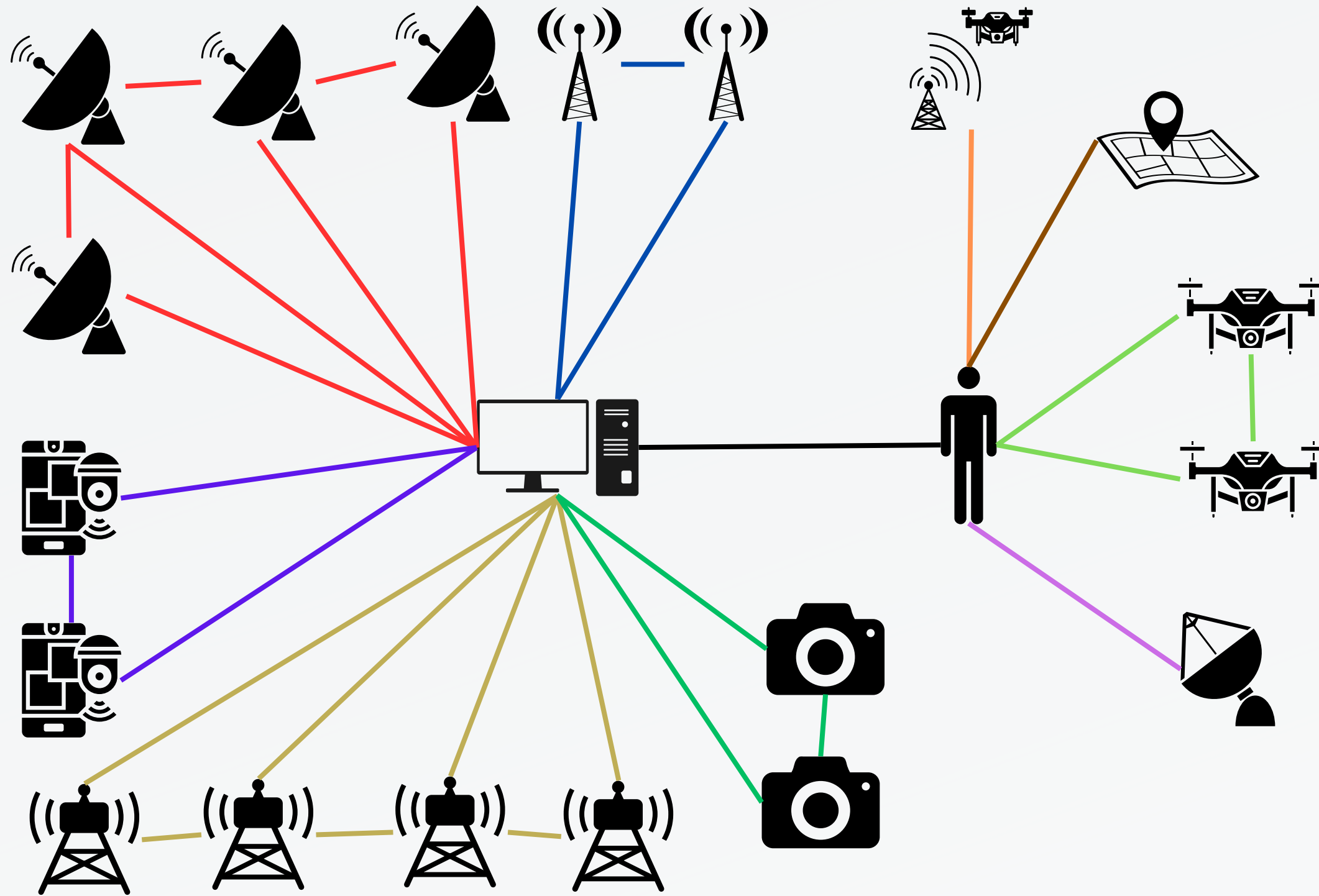
FUTURE DIRECTIONS












GRAPH REPRESENTATION



-  Command and Control Unit
-  Human/Operator
-  RF System
-  Radar System
-  Infrared Camera
-  Acoustic Sensor
-  Electro-Optical Camera
-  RF Jammer
-  GPS Spoofer
-  Interceptor
-  Microwave

GRAPH REPRESENTATION



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FUTURE DIRECTIONS

METRICS

Degree Centrality

- Measure of the number of direct connections a node has.
- A node with high degree centrality is directly connected to many other nodes.
- Computed by dividing the number of nodes that a given node is connected to by the maximum possible degree in the graph.

Degree Centrality

| | |
|-----------|------|
| C2 | 0.75 |
| Human | 0.30 |
| Acoustic | 0.15 |
| EO | 0.10 |
| RF Jammer | 0.05 |

Closeness Centrality

- Measure of how close a node is to all other nodes in the network.
- A node with high closeness centrality can reach other nodes in the network quickly.
- Computed by finding the shortest path distance between a node and all other nodes in the network. Then, compute the reciprocal of the sum of these distances

Closeness Centrality

| | |
|-----------|------|
| C2 | 0.80 |
| Human | 0.58 |
| Acoustic | 0.47 |
| EO | 0.46 |
| RF Jammer | 0.37 |

METRICS

Betweenness Centrality

- The number of times a node acts as a bridge along the shortest path between two other nodes.
- High betweenness centrality often control the flow of information within the network.
- Computed by counting how many shortest paths between pairs of other nodes pass through it.

Betweenness Centrality

| | |
|-----------|------|
| C2 | 0.86 |
| Human | 0.44 |
| Acoustic | 0.00 |
| EO | 0.00 |
| RF Jammer | 0.00 |

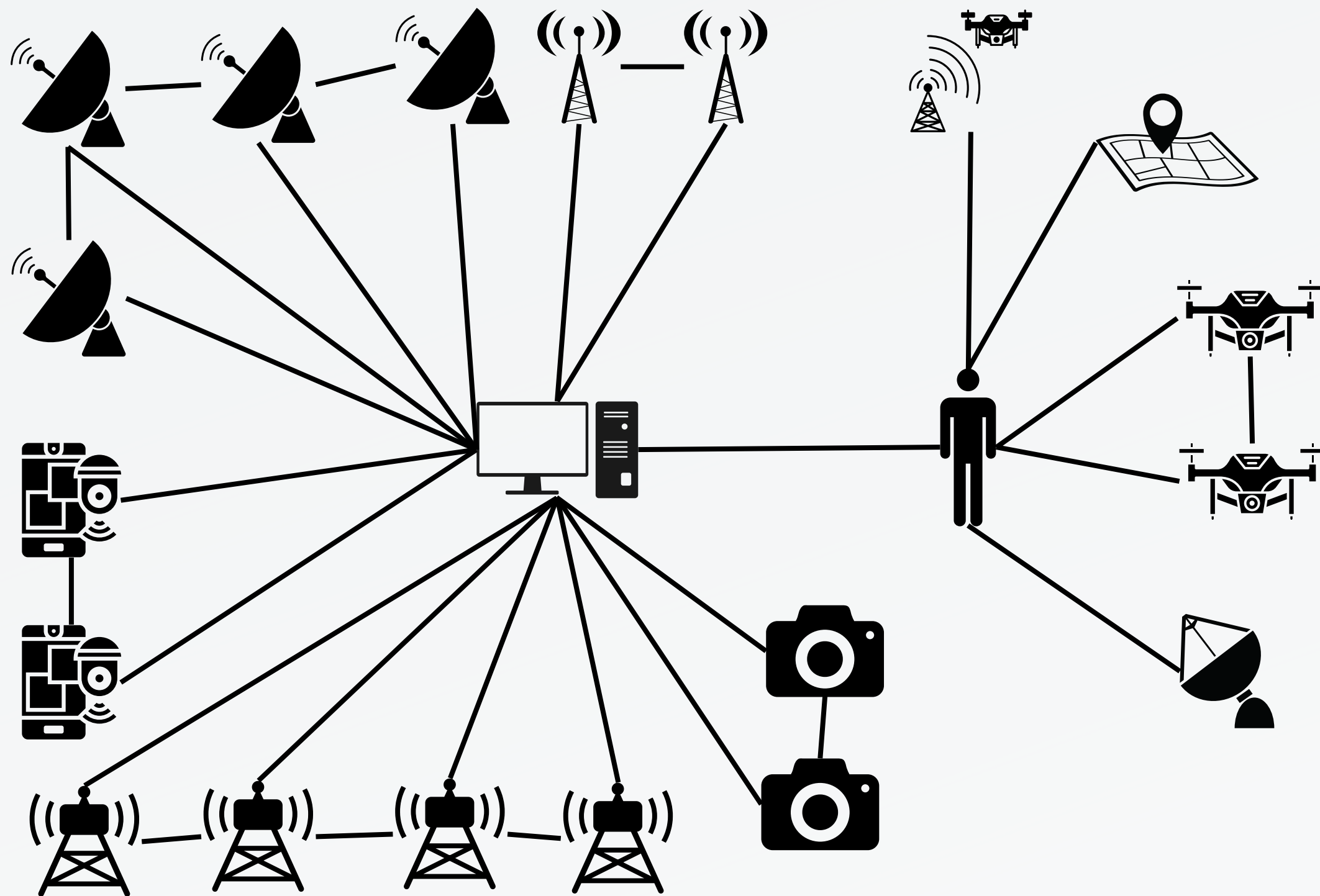
Eigenvector Centrality

- Takes into account the degree of the neighbors of a node.
- Nodes with high eigenvector centrality could be interpreted as a highly influential or important component
- Computed by finding the eigenvector of the graphs adjacency matrix.

Eigenvector Centrality

| | |
|-----------|------|
| C2 | 0.64 |
| Human | 0.18 |
| Acoustic | 0.19 |
| EO | 0.17 |
| RF Jammer | 0.04 |

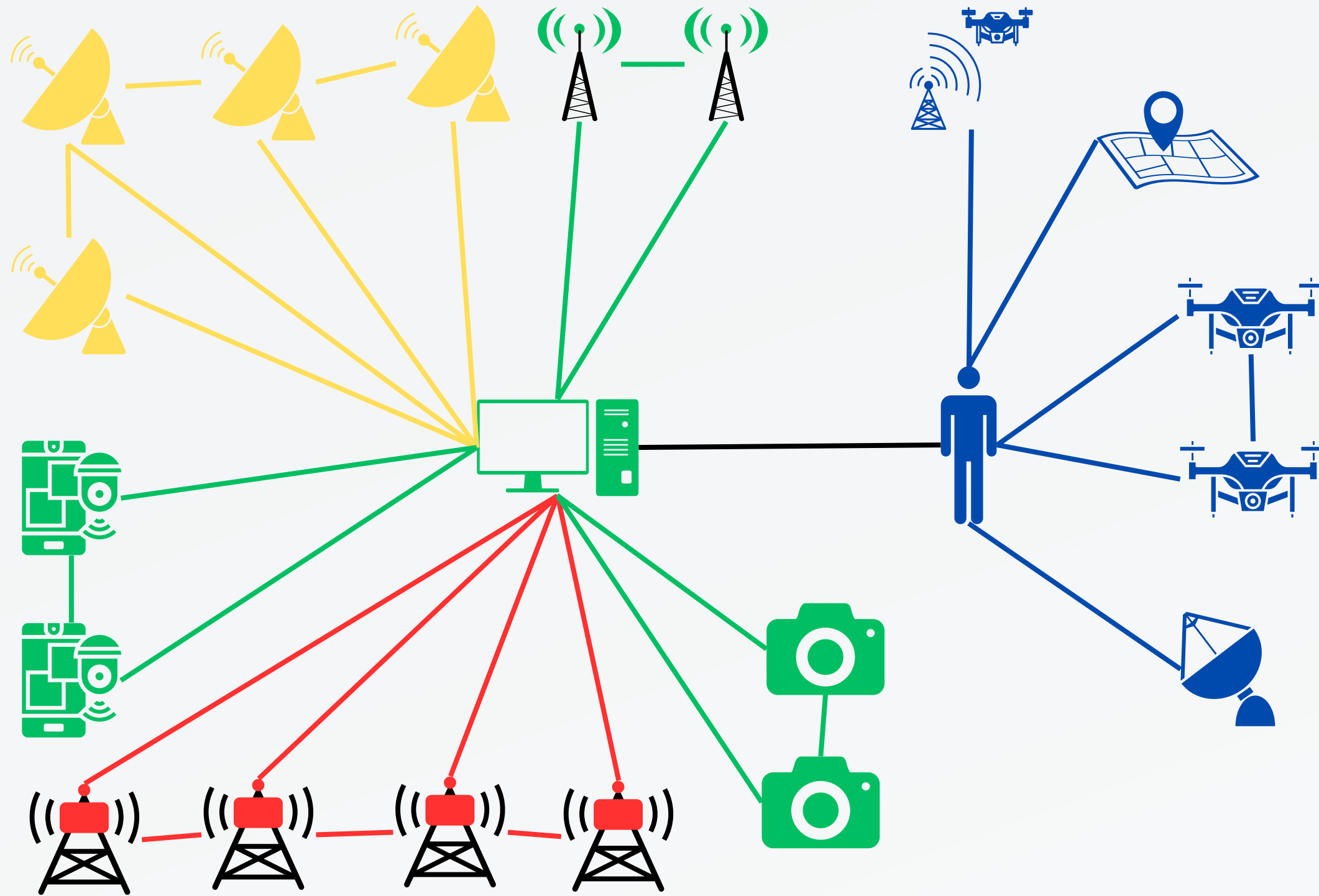
COMMUNITY DETECTION





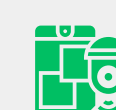








- Command and Control Unit
- Human/Operator
- RF System
- Radar System
- Infrared Camera
- Acoustic Sensor
- Electro-Optical Camera
- RF Jammer
- GPS Spoofer
- Interceptor
- Microwave

INPUT

COMMUNITY DETECTION



-  Radar System
-  Acoustic Sensor
-  RF System
-  Command and Control Unit
-  Infrared Camera
-  Electro-Optical Camera
-  Human/Operator
-  RF Jammer
-  GPS Spoofer
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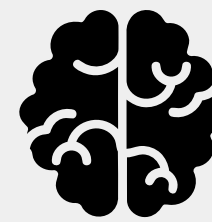
OUTPUT

KEY TAKEAWAYS



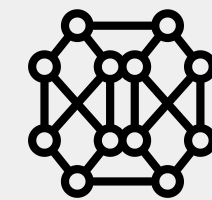
Standardized Approaches for Evaluation

- Graph based approaches enable systematic evaluation and comparison of systems capabilities



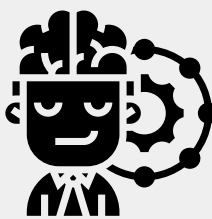
Approach is Scalable

- Graph theory provides a flexible and scalable way to model complex counter drone systems.



Provides New Analytical Methods for Evaluation

- Provides a new framework/tool for evaluating complex systems.



Broad Applications

- Graph theory-based modeling approach has broad applicability beyond counter drone systems.

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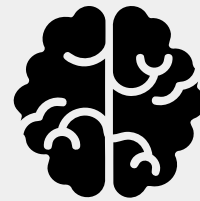
FUTURE DIRECTIONS

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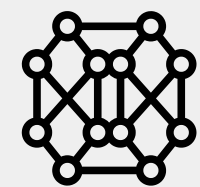
Enhanced Analysis Metrics

- Expanding these analysis metrics to simulate component failures, targeted attacks, bottlenecks, etc.



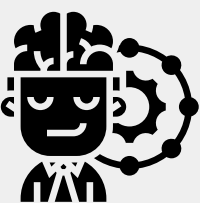
Knowledge Graph Integration

- Can capture a wide range of information about the system, the relationships between them, and the rules or constraints governing their interactions



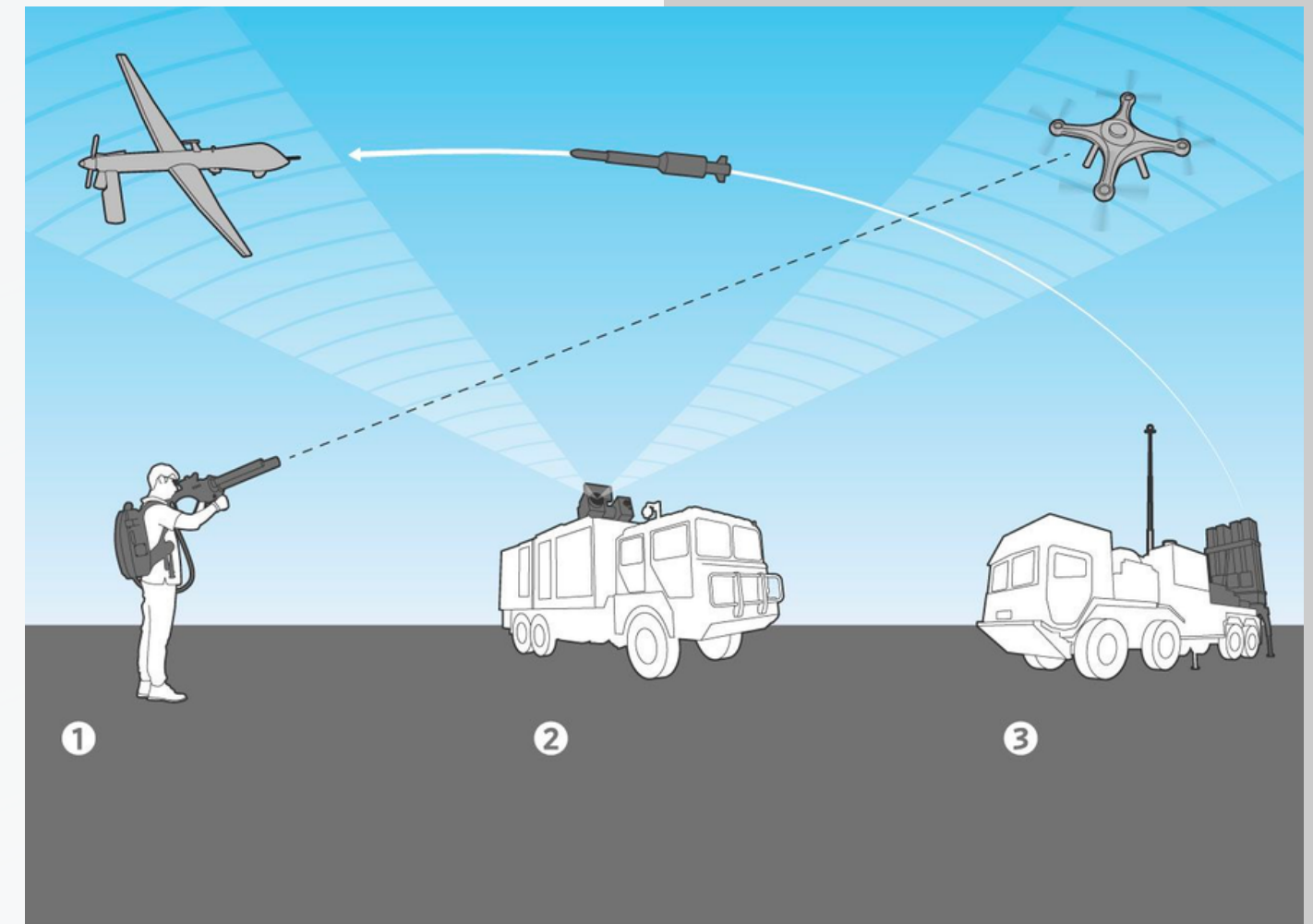
Use of Graph Neural Networks

- Work with graph data, and they have been shown to be effective for tasks such as node classification, link prediction, and graph classification.



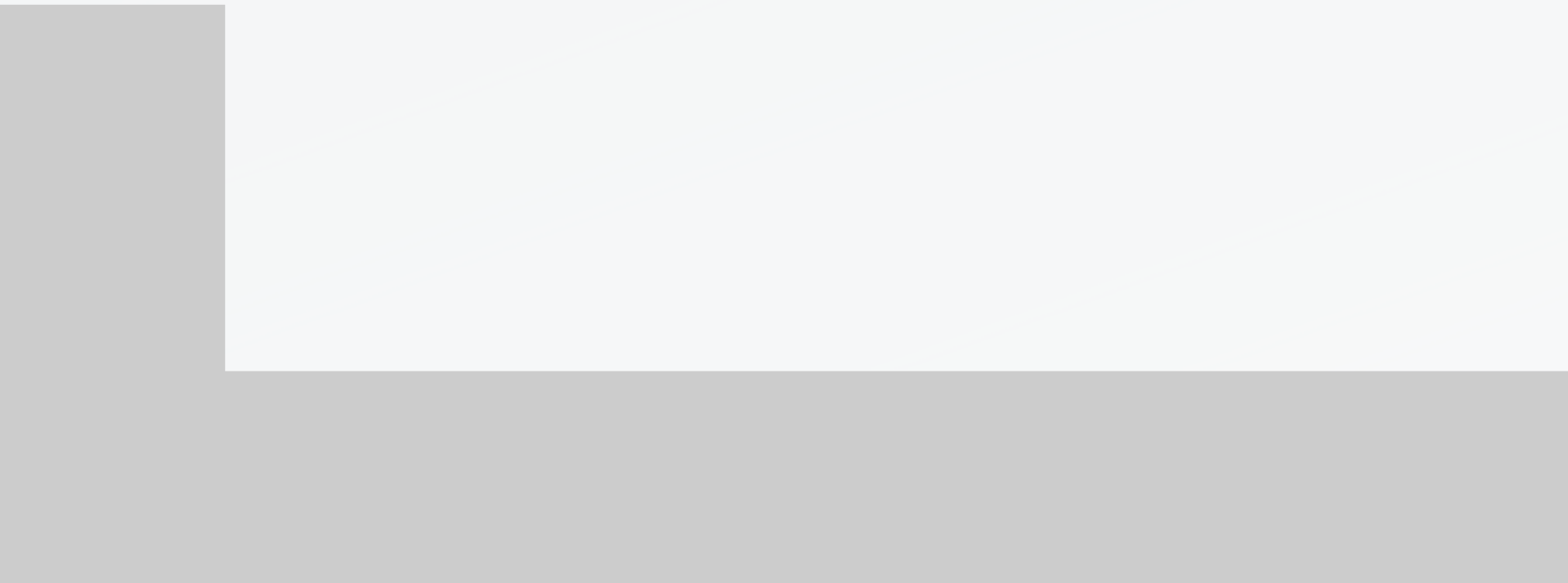
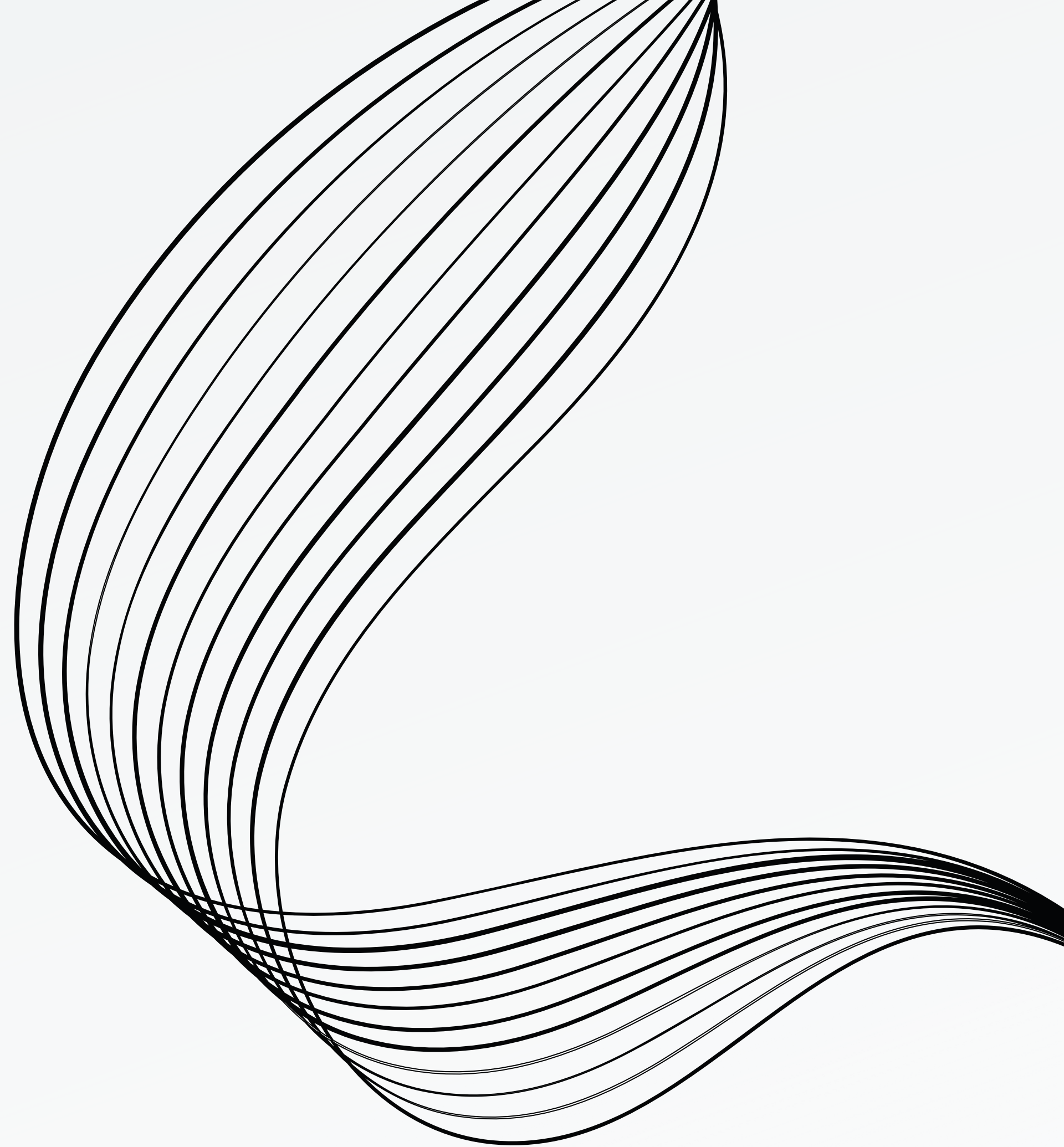
Multi-modal Machine Learning for Modeling Capabilities

- Each node in the graph could be associated with a neural network that represents its capabilities

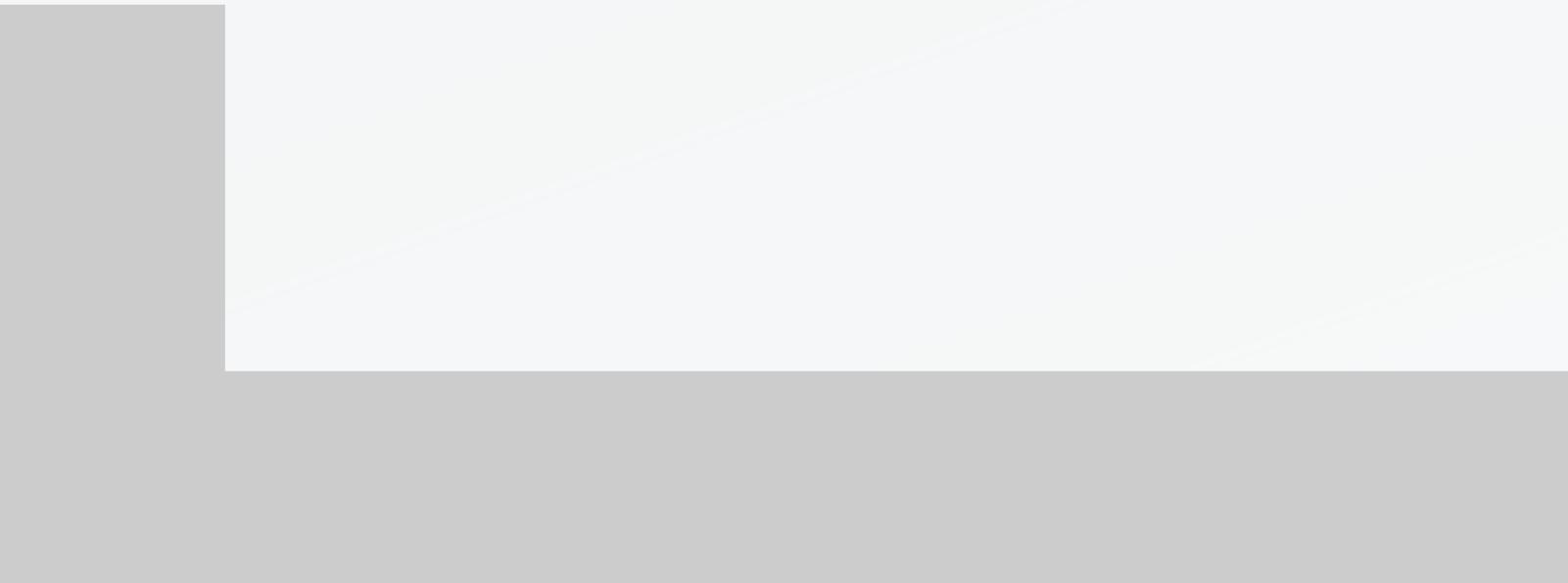
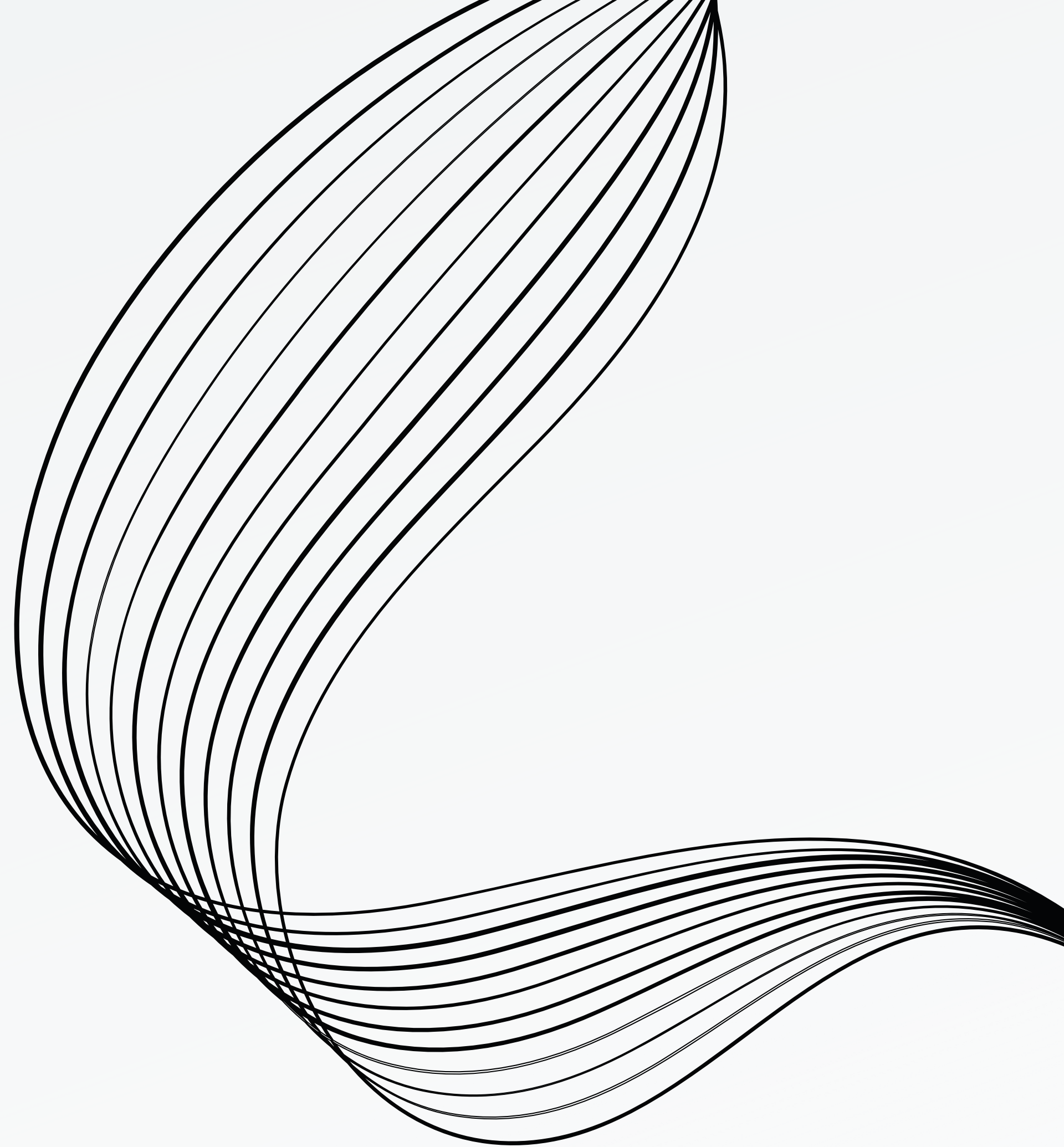


THANK YOU

Questions?



APPENDIX



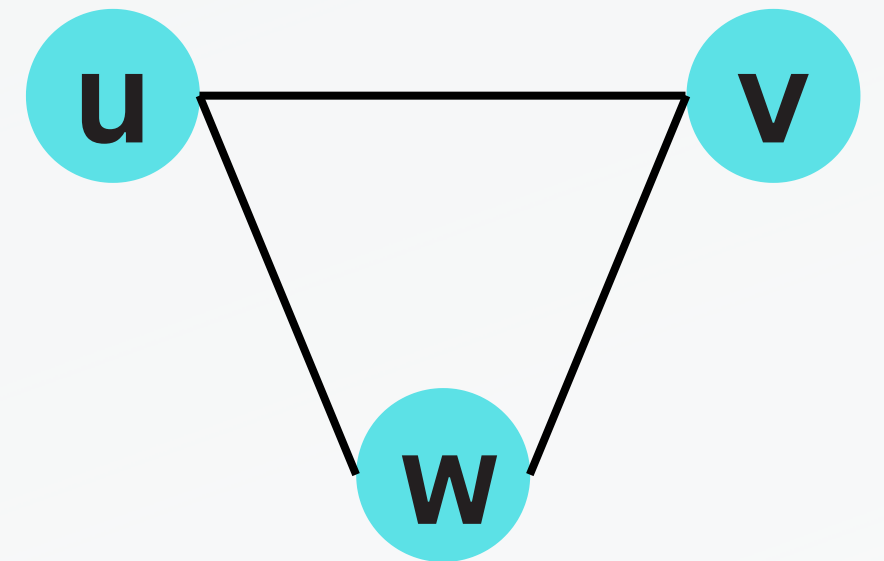
DEGREE CENTRALITY



Degree centrality is a measure of the number of direct connections a node has



The degree centrality metric is computed by dividing the number of nodes that a given node is connected to by the maximum possible degree in the graph. In other words, it calculates the proportion of nodes that a node is connected to.



$C(v)$ = Degree of node

$C(v)$ = 2

Normalized = $C(v) / n-1$, where n is number of nodes

$C(v) = 2 / (3-1) = 1$, connected to all nodes

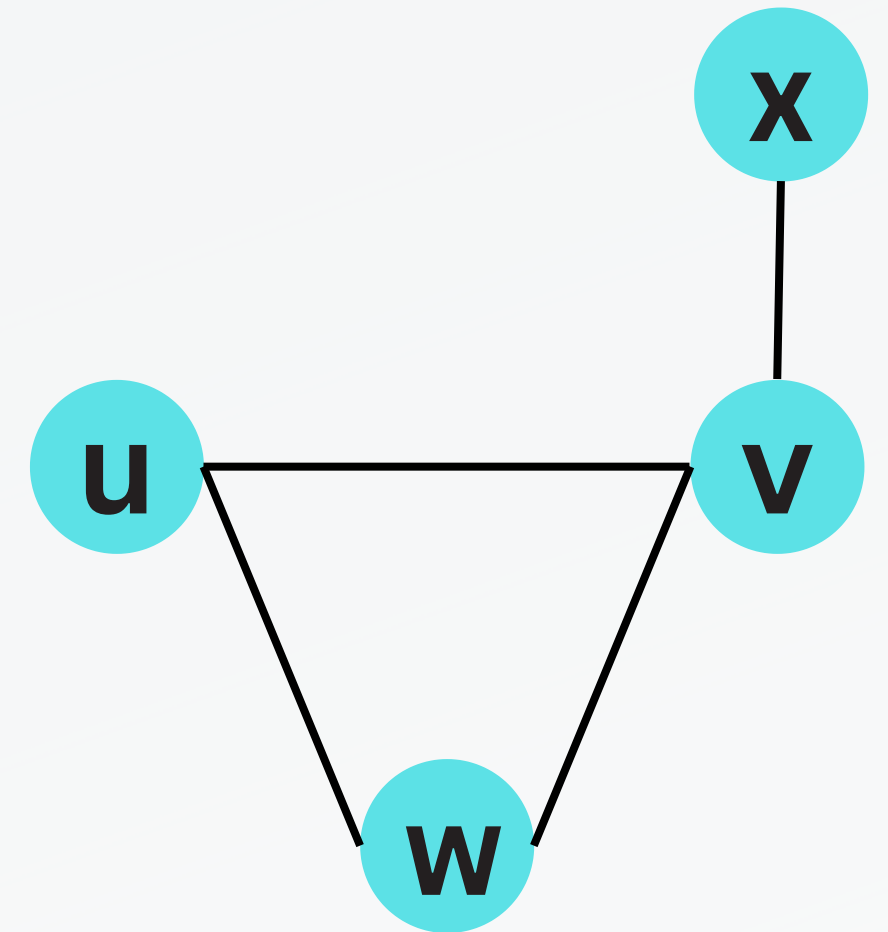
CLOSENESS CENTRALITY



Closeness centrality is a measure of how close a node is to all other nodes in the network



To calculate closeness centrality, you need to find the shortest path distance between a node and all other nodes in the network. Then, compute the reciprocal of the sum of these distances. Repeat this process for each node.



1. Calculate the shortest path distance to all other nodes in the network
2. Sum the shortest path distances
3. Compute closeness
 - a. $C(v) = (N-1) / (\text{Sum of shortest path distances})$

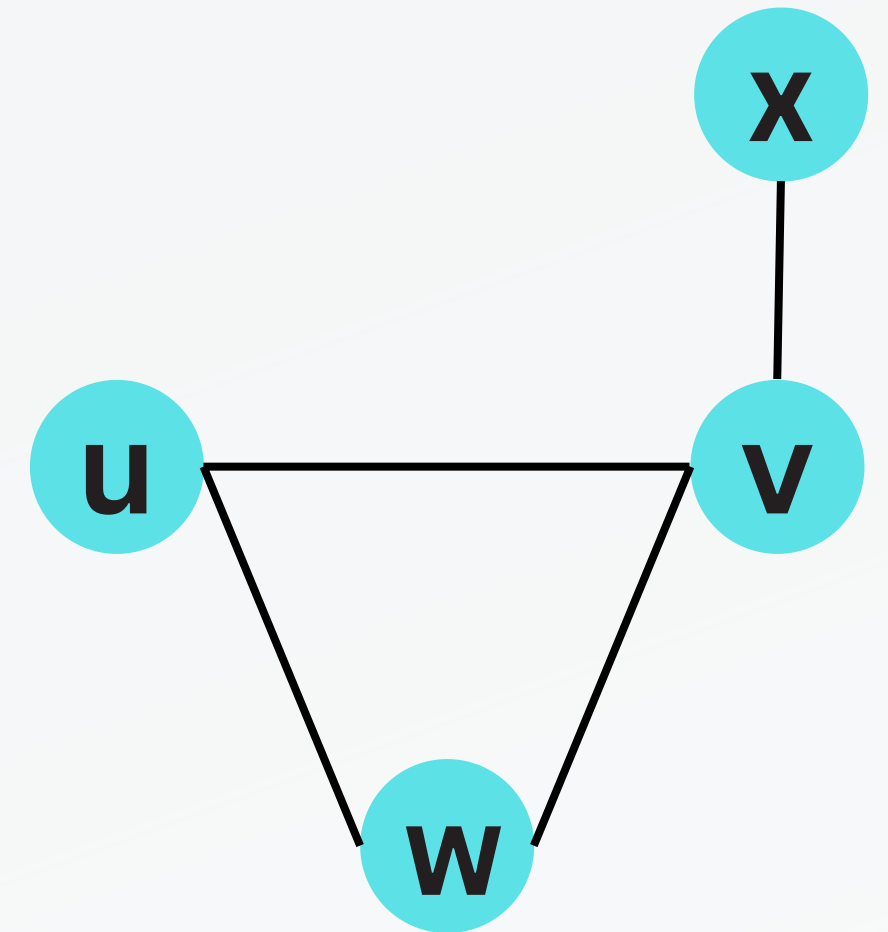
BETWEENNESS CENTRALITY



Betweenness centrality quantifies the number of times a node acts as a bridge along the shortest path between two other nodes.



To compute, find all the shortest paths between pairs of nodes in the network. For each node, determine the fraction of these paths that pass through that node. Sum up these fractions for all pairs of nodes in the network



1. For each pair of nodes, compute shortest path
2. For each node v , count how many of the shortest paths pass through v
3. Count how many of these shortest paths pass through v

EIGENVECTOR CENTRALITY

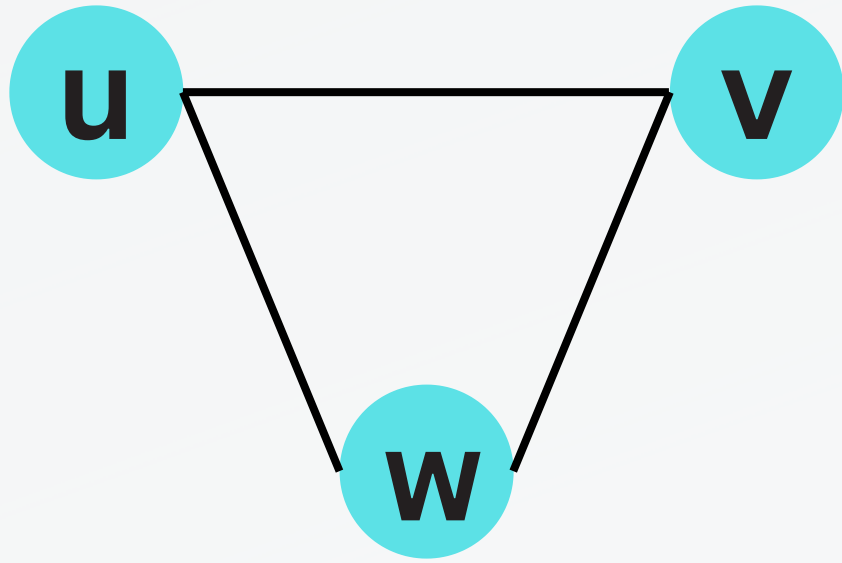


Eigenvector centrality takes into account the degree of the neighbours of a node. A node is considered more central if it is connected to other nodes that are themselves well-connected.



To calculate eigenvector centrality, you need to compute the eigenvector associated with the largest eigenvalue of the adjacency matrix of the graph

1. Let A be the adjacency matrix
2. Let x be the eigenvector of A corresponding to the largest eigenvalue
3. Eigenvector Centrality = corresponding entry in x



To

| | From | | |
|---|------|---|---|
| | u | v | w |
| u | 0 | 1 | 1 |
| v | 1 | 0 | 1 |
| w | 1 | 1 | 0 |

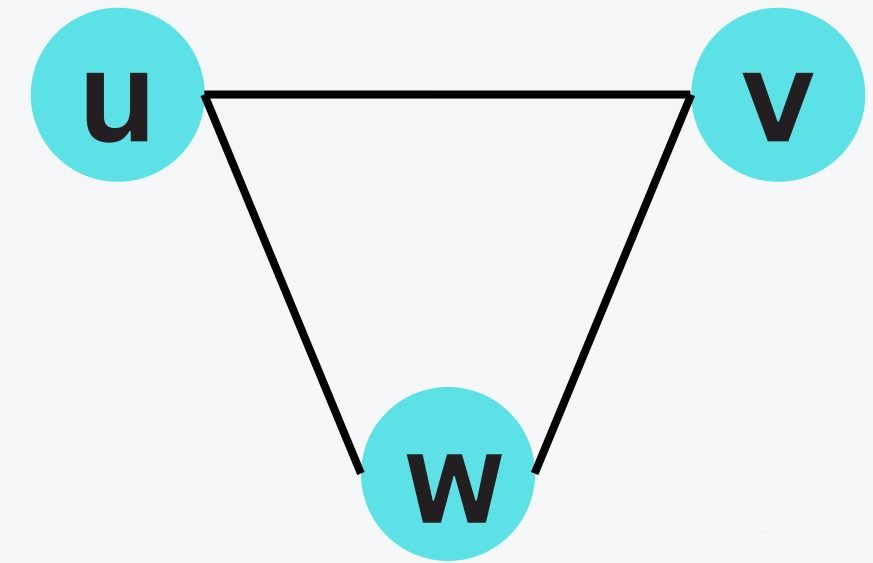
CLAUST-NEWMAN-MOORE ALGORITHM



Imagine you have a big group of friends and you're trying to split them into smaller groups (communities) where everyone knows each other well.



Begin with each node in its own community and repeatedly join the pair of communities that lead to the largest modularity until no further increase in modularity is possible



1. Starting with everyone in their own separate groups
2. Constantly merging the two groups that know each other the best (or have the most connections between them)
3. Continuing this until merging any more groups doesn't make them more interconnected.