Dynamic Social Networks In Dairy Cows

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Agenda

- Problem
- Aim
- Method
  - data, adjacency matrices, community detection, etc.
- Result
  - monadic, dyadic, polyadic
- Conclusion

Problem

Three problems:

- How to decrease disease transmission.
- How can we separate cows with minimal impact.
- How to increase milk production.

Aim

Three aims:

- What do social structures look like?
- How consistent are they?
- How do they develop over time?

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Method

Data

- Form of data:
  - Id number of cow
  - Time of data logging
  - Positional data

- 14 days of data in Netherlands

- ~12 million data points per day

id *t* *x* *y*

```
FA,2421879,0024F477,1602806400003,2785,666,183
FA,2225664,0021F600,1602806400052,2277,5280,183
FA,2421800,0024F428,1602806400008,377,6190,183
FA,2421914,0024F49A,1602806400023,2539,10876,183
FA,2360495,002404AF,1602806400080,1583,12907,183
FA,2421191,0024F1C7,1602806400025,266,3984,183
FA,2422632,0024F768,1602806400052,2911,4694,183
```

Conversion to Time Adjacency Matrix

- Look at last known position every 10s
- Compute distance between all cows
- If distance < 150cm : add 10s to matrix
- 150 cm is the size of a cow

	cow1	cow2	...	...	cowN
cow1	0				
cow2		0			
...			0		
...				0	
cowN					0

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Binary and Weighted Adjacency Matrix

Social interaction if more than 1800s in a day is spent in proximity (30 minutes)

	cow1	cow2	...	...	cowN
cow1	0	1	0	0	1
cow2	1	0	0	1	0
...	0	0	0	0	0
...	0	1	0	0	1
cowN	1	0	0	1	0

	cow1	cow2	...	...	cowN
cow1	0	0.5	0	0	1
cow2	0.5	0	0	0.2	0
...	0	0	0	0	0
...	0	0.2	0	0	0.7
cowN	1	0	0	0.7	0

Degree and laplacian matrix

How many connections:

	cow1	cow2	…	…	cowN
cow1	9				
cow2		7			
…			5		
…				9	
cowN					4

Laplacian:

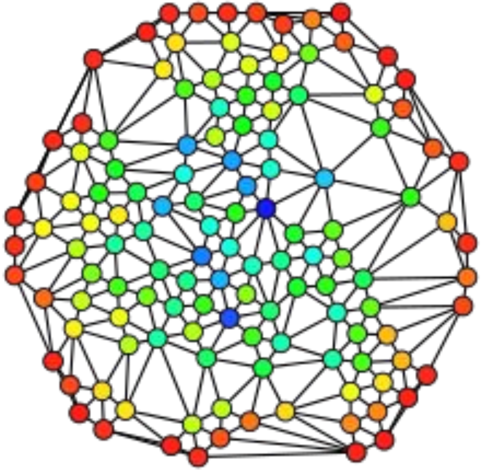
	cow1	cow2	…	…	cowN
cow1	9	-1		-1	
cow2	-1	7			
…			5		-1
…	-1			9	
cowN			-1		4

Social Network

- Consists of:
  - Nodes = Cows
  - Edges = connections

- Very powerful tools in Python to compute metrics

- Allows for visualisation



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Community Detection

- Tools (networkX & sklearn) in Python to detect and analyze communities

- Unweighted graphs
  - Generated from binary adjacency matrices
  - Non-overlapping community detection
    - Girvan-Newman (GN)
    - Louvain
  - Overlapping community detection
    - Clique Percolation Method (CPM)

Community Detection

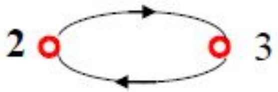
- Weighted graphs
  - Generated from weighted adjacency matrices
  - Use Louvain algorithm and detect non-overlapping communities
  - Apply Louvain on different areas of the barn
    - Whole barn area
    - Specific barn area
      - feeding, bed, general, robot area
- Measures
  - Modularity, Normalized Mutual Information (NMI), etc.

Results

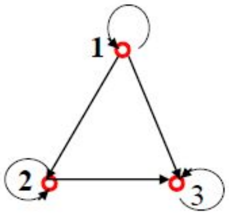
Different “Dimensions”:

- Monadic
  - a relation having an arity of one in logic

- Dyadic
  - a relation having arities of two in logic



- Polyadic
  - a relation having arities of three or more in logic



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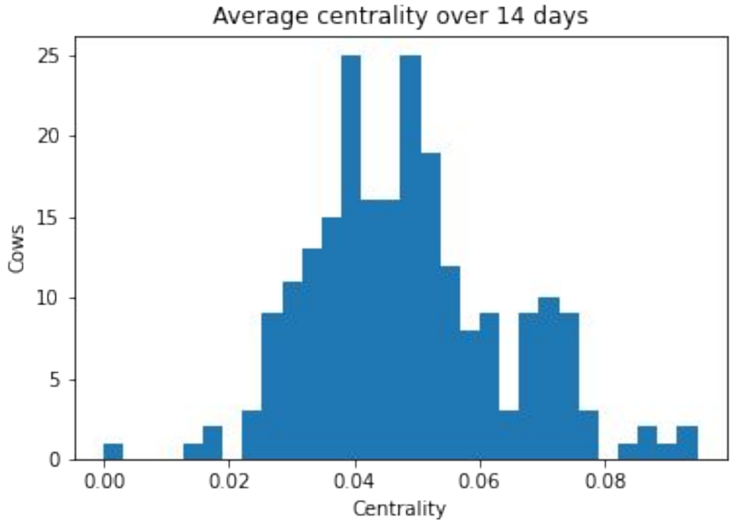
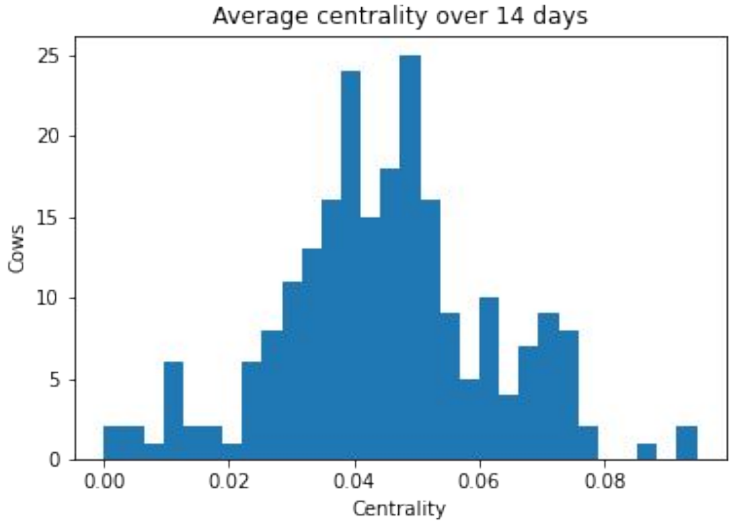
Monadic - Centrality

Distribution of how “Central” or important cows are.



Average over days present



Average over 14 days

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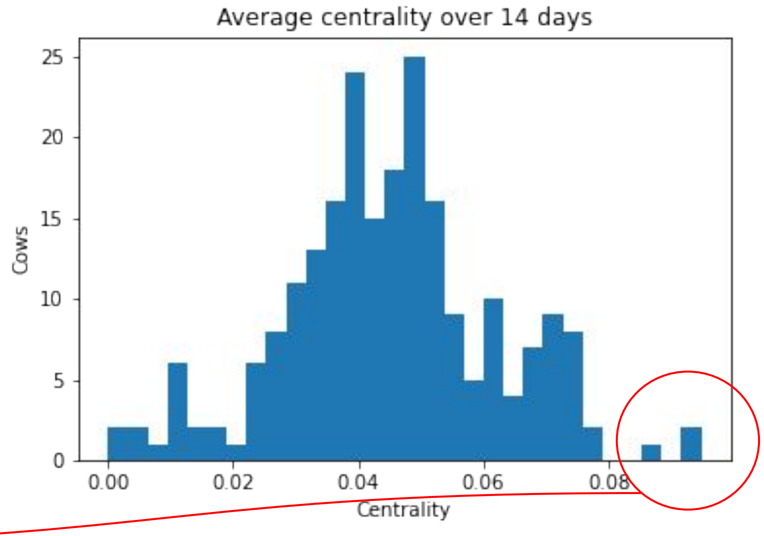
Monadic - Most central cows

- When looking at the top 10% of cows by number of interaction per day:
  - 3 cows in the top for 10 or 11 days
  - No cows between 7 and 10 days
  - Many cows at 7 or less days

- Indicates consistency and a form of hierarchy.



3 ‘socialites’ :
2202988
2203574
2202720

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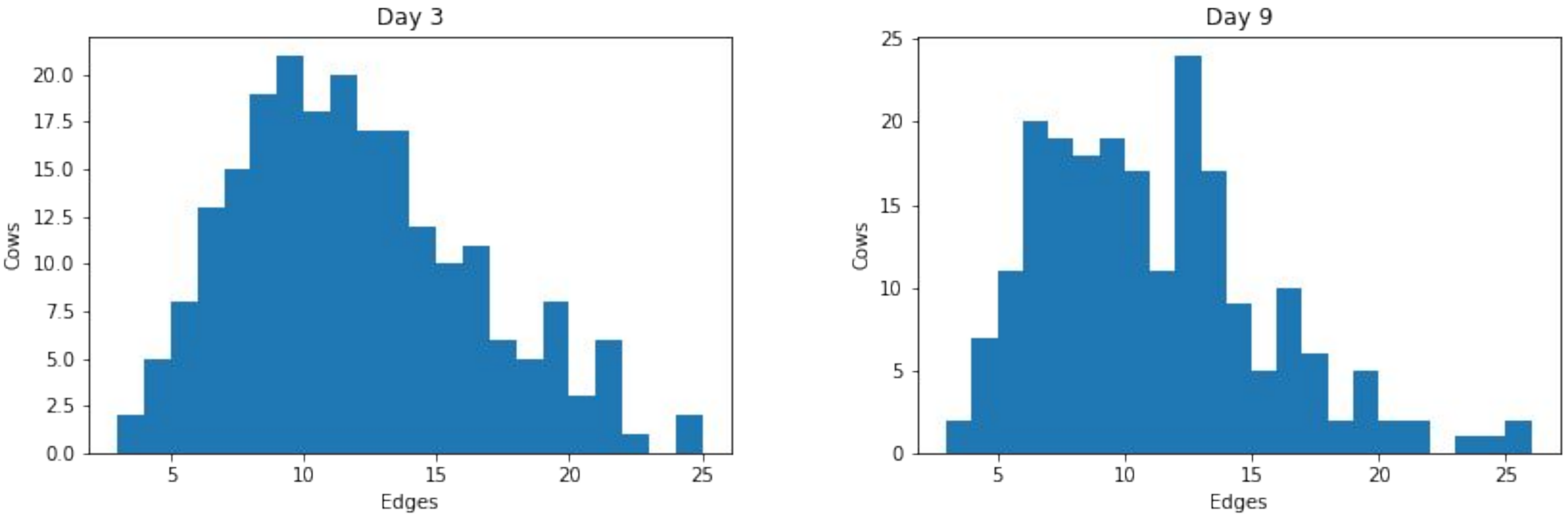
Monadic - Dynamics of edge distribution

Two sample Kolmogorov-Smirnov test: 95% that the days are correlated.



Dyadic - Average shortest path

- Average distance between cows
- No data means not fully connected

Days	Avg shortest path	diameter
1	2.605	5
2	2.544	5
3	2.498	4
4	-	-
5	2.623	5
6	-	-
7	-	-
8	-	-
9	2.465	4
10	2.588	5
11	2.557	4
12	-	-
13	2.546	5
14	2.519	4
mean	2.549	
Std	0.051	

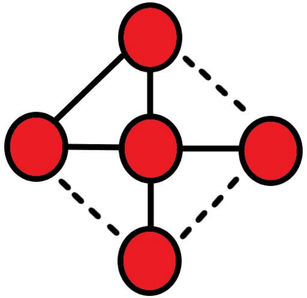
Polyadic - Transitivity

Real data:

Also called the Clustering coefficient

Connected communities

Days	Transitivity
mean	0.0547
Std	0.0075

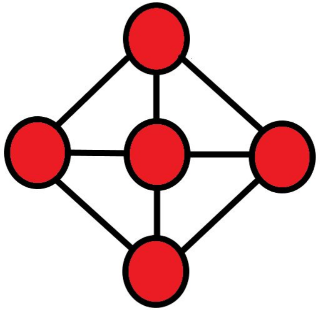


0.25

Simulation:

Degree sequence

Transitivity	Real	Simulated
mean	0.0547	0.1090
Std	0.0075	0.0026



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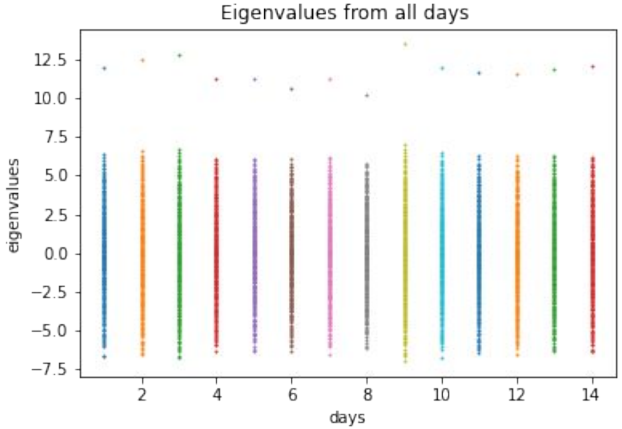
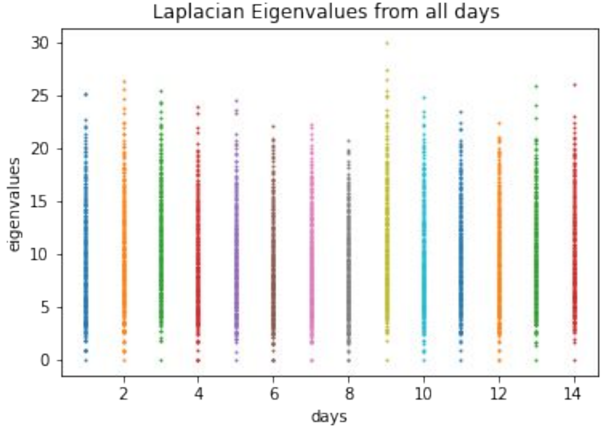
Polyadic - Eigenvalues

- approximates values:
- edge distribution
- connectivity

Day	Fiedler value
1	0.887
2	0.781
3	1.786
4	0.0
5	0.795
6	0.0
7	0.0
8	0.0
9	1.883
10	0.845
11	0.914
12	0.0
13	1.425
14	1.697





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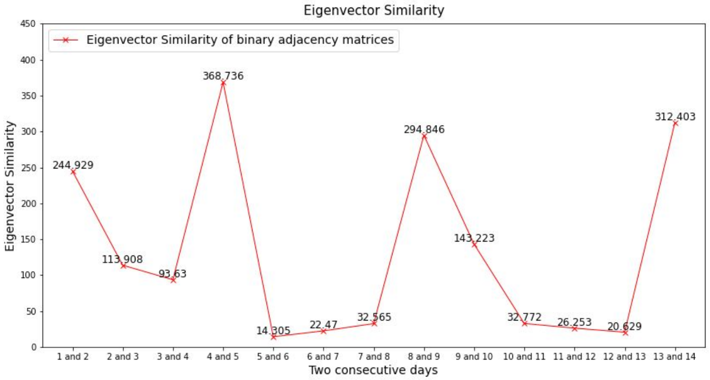
Polyadic - Characteristics of social network

- Number of nodes
  - around 210 nodes
- Number of edges
  - around 1000 edges
- Density
  - around 0.05
- Eigenvector Similarity
  - a similarity metric in the range [0, ∞), where values closer to zero represent more similarity.

Day	Number of nodes	Number of edges	Density
1	213	1009	0.045
2	212	1099	0.049
3	219	1249	0.052
4	208	1108	0.051
5	209	992	0.046
6	208	975	0.045
7	210	1004	0.046
8	210	976	0.044
9	210	1106	0.050
10	209	1006	0.046
11	205	980	0.047
12	210	1045	0.048
13	209	1046	0.048
14	205	1095	0.052



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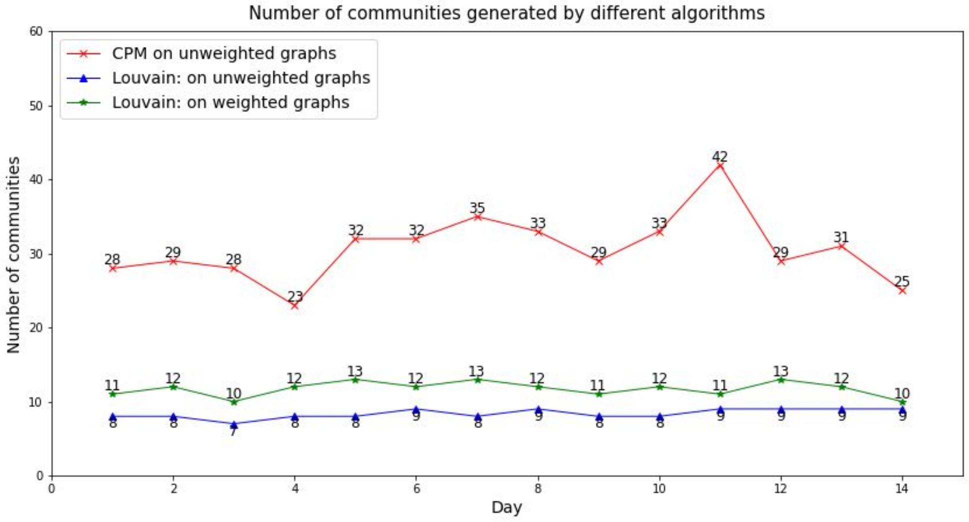
Polyadic - Characteristics of communities

Number of generated communities

expected to be stable

- Girvan-Newman
  - on unweighted graphs
  - based on betweenness
  - requires prior knowledge to pre-specify
  - test and set to be 20
- CPM
  - on unweighted graphs
  - not stable
- Louvain
  - on weighted and unweighted graphs
  - stable



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Polyadic - Characteristics of communities

Modularity

scale the results between 0 (no partition) and 1 (perfect partition), expected to be larger than 0.3

- Girvan-Newman
  - on unweighted graphs
  - poor
  - not suitable for cow communities
- CPM
  - on unweighted graphs
  - does not work with overlapping communities
- Louvain
  - on weighted and unweighted graphs
  - weighted version better

Day	Girvan-Newman	Louvain(unweighted)	Louvain(weighted)
1	0.030	0.327	0.488
2	0.014	0.296	0.446
3	0.031	0.302	0.470
4	0.013	0.287	0.457
5	0.054	0.329	0.486
6	0.050	0.317	0.493
7	0.059	0.322	0.488
8	0.034	0.330	0.490
9	0.056	0.316	0.492
10	0.026	0.321	0.478
11	0.011	0.324	0.489
12	0.027	0.300	0.483
13	0.044	0.320	0.476
14	0.015	0.302	0.451

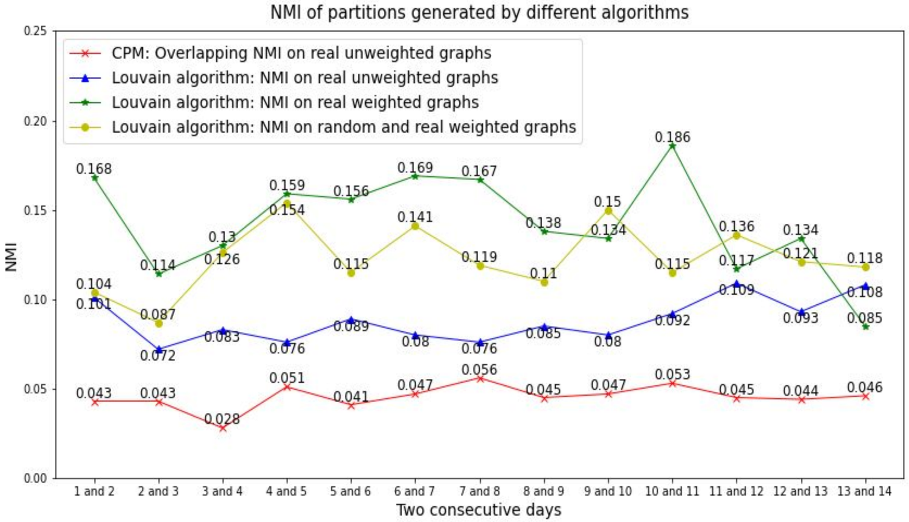
Modularity of different algorithms

Polyadic - Characteristics of communities

Normalized Mutual Information (NMI)

scale the results between 0 (no mutual information, unstable communities) and 1 (perfect correlation, stable communities)

- CPM
  - on unweighted graphs
  - overlapping NMI (modified NMI version)
  - poor
- Louvain
  - on unweighted graphs
    - poor
  - on weighted graphs
    - random simulation to compare
    - better but not enough



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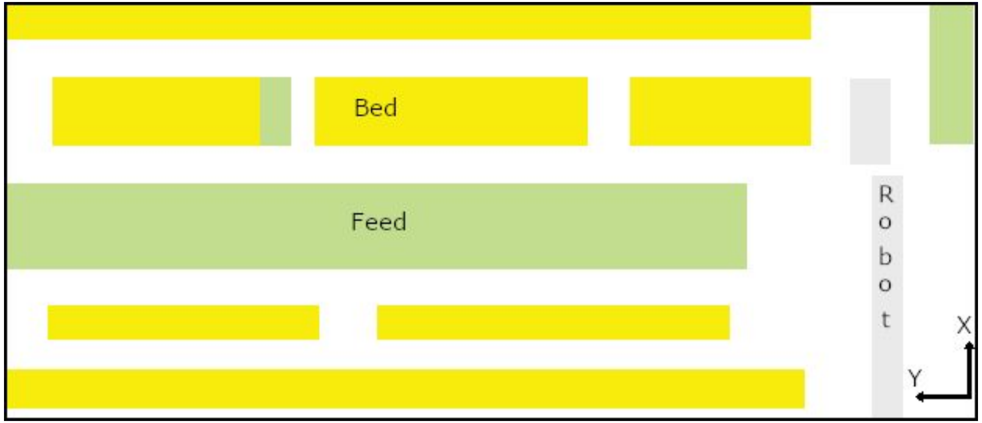
Unstable communities need more investigation!



the layout of the barn

Apply Louvain on the whole barn area

The whole barn area could be divided into specific areas:
Green: Feed area
Yellow: Bed area
Grey: Robot area
White: General area

Apply Louvain on the specific areas

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Polyadic - Characteristics of communities

Modularity

scale the results between 0 (no partition) and 1 (perfect partition), expected to be larger than 0.3

- Apply Louvain and weighted graphs
- Four specific areas
  - Feeding area
  - General area
  - Bed area
  - Robot area
    - where cows are milked
    - no community
    - need new threshold
- Combination of different areas
  - fail to result in better results

Day	Feeding area	Bed area	General area	Feeding&general area
1	0.775	0.597	0.726	0.687
2	0.831	0.519	0.776	0.737
3	0.765	0.577	0.776	0.709
4	0.887	0.538	0.794	0.757
5	0.800	0.555	0.794	0.753
6	0.879	0.561	0.819	0.769
7	0.798	0.569	0.847	0.799
8	0.867	0.554	0.807	0.777
9	0.719	0.584	0.785	0.723
10	0.879	0.553	0.759	0.744
11	0.888	0.590	0.812	0.763
12	0.751	0.559	0.768	0.713
13	0.863	0.559	0.771	0.744
14	0.804	0.514	0.730	0.706

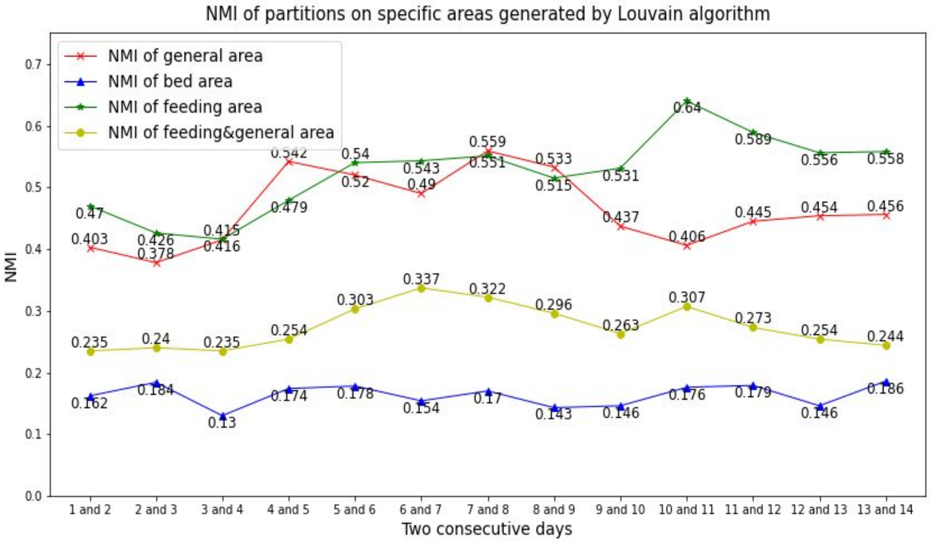
Modularity of different areas

Polyadic - Characteristics of communities

Normalized Mutual Information (NMI)

scale the results between 0 (no mutual information, unstable communities) and 1 (perfect correlation, stable communities)

- Apply Louvain and weighted graphs
- Four specific areas
  - Feeding area
  - General area
  - Bed area
    - exhibits strong randomness
    - not stable
  - Robot area
- Combination of different areas
  - fail to result in more stable communities



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Polyadic - Characteristics of communities

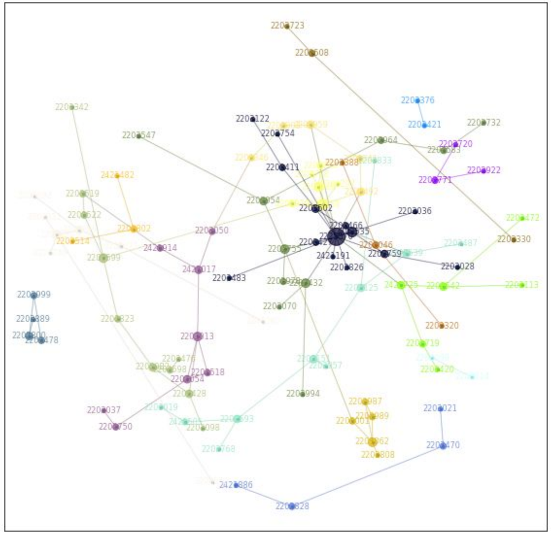
Detailed comparison of communities:

- Day 1 & Day 2 and Day 2 & Day 3
- Feeding area
- High NMI
- At most 4 nodes in the intersection of the 2 days' communities

Current communities are still not stable enough.

Visualization:

- node: cows
- edge: relationship between cows
- color: community
- size of nodes: degree of cows



Day 7: Louvain community detection results on Feeding area

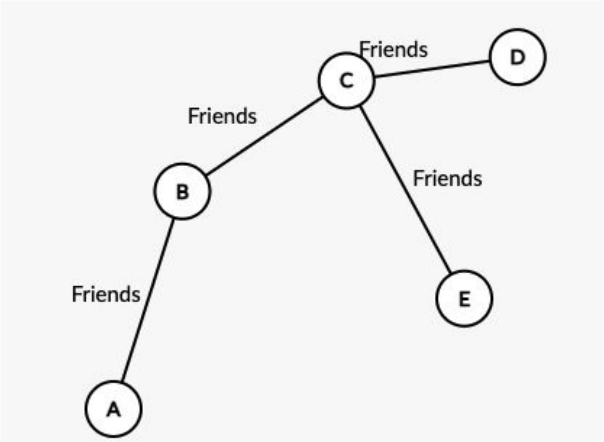
Conclusions

Conclusion: Monadic

- Cows form hierarchies, with some “leaders”
- The distribution of interactions are consistent
- Cows have a consistent social structure at this level

Conclusion: Dyadic

- Cows social connections are more branched instead of clustered



The relationships the cows prefer

Conclusion: Polyadic

- Social network graphs have similar basic statistics such as density, number of nodes, etc.
- There are stable communities, but only when looking at some specific areas.
- The communities depend on in which area interactions happen.
- Sleeping is an activity with less social meaning.

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Aim - Conclusion

- What do social structures look like？
    - Centralised and branched communities that depend on area
    - Highly important central individuals
- How consistent are they？
    - Communities on feeding area and general area are relatively consistent
    - The important individual are relatively consistent
- How do they develop over time？
    - Current communities are still not stable enough to study the development
    - Current methods on specific areas show a possibility to analyze it.
    - Methods need further improvements

Thank you for your attention!

Any questions?