Digital Media and Social Networks

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Lecture 4: Network Analysis

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In this Lecture

- In this lecture we introduce the concept of network analysis for different social networks.
  - We will look at more natural social networks.
  - But we will still use standard measures and methods.

OSNs in early days (Mislove et al IMC'07 paper)

- Presents large-scale measurement study and analysis of the structure of multiple online social networks
  - 11 M users, 328 M links

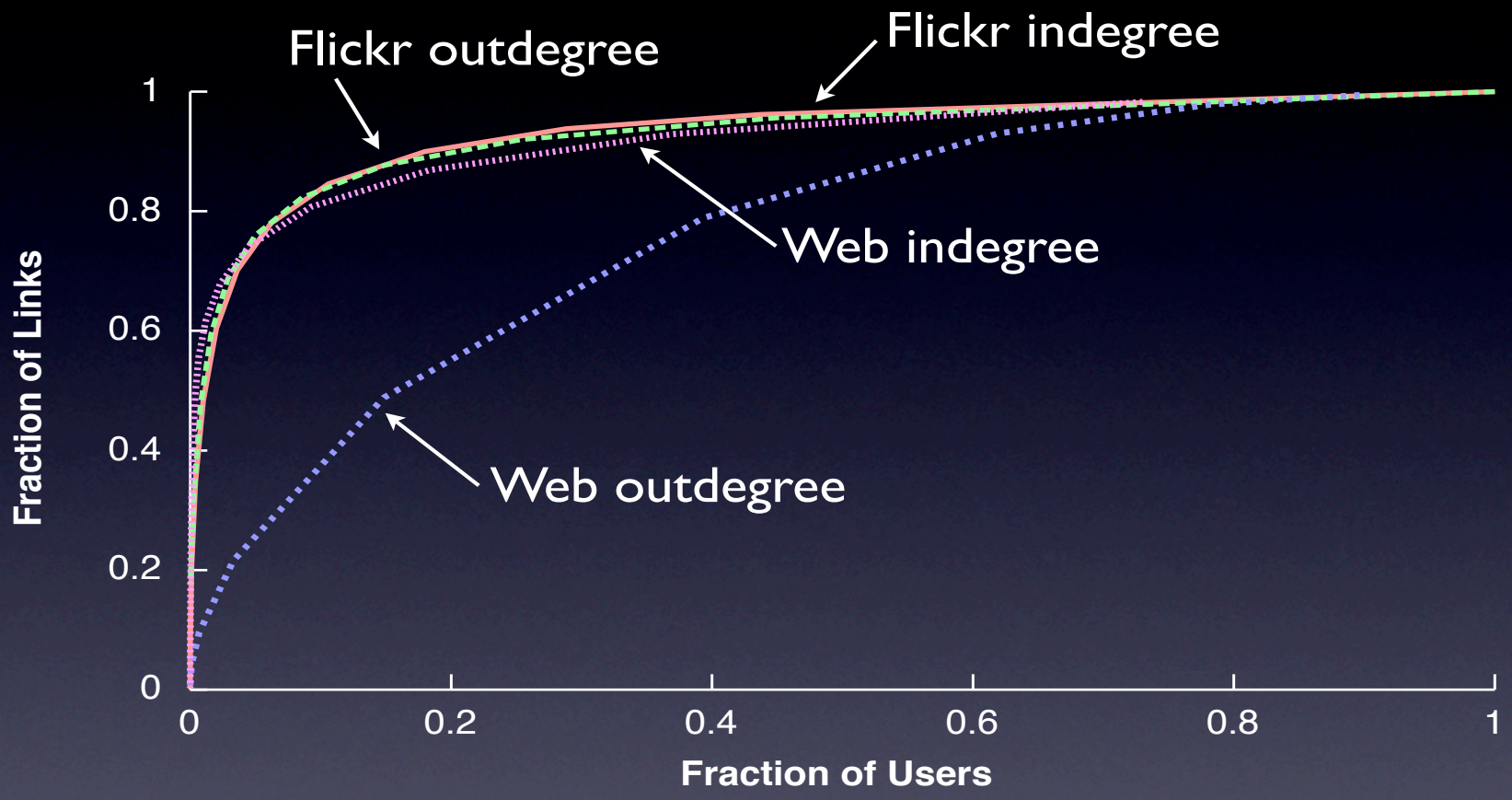
- Data from four diverse online social networks
  - Flickr: photo sharing
  - LiveJournal: blogging site
  - Orkut: social networking site
  - YouTube: video sharing

- Our goals are two-fold:
  - Measure online social networks at scale
  - Understand static structural properties

High-level data characteristics

	Flickr	LiveJournal	Orkut	YouTube
Number of Users	1.8 M	5.2 M	3.0 M	1.1 M
Avg. Friends per User	12.2	16.9	106.1	4.2

How are the links distributed?



- Distribution of indegree and outdegree is similar
  - Underlying cause is *link symmetry*

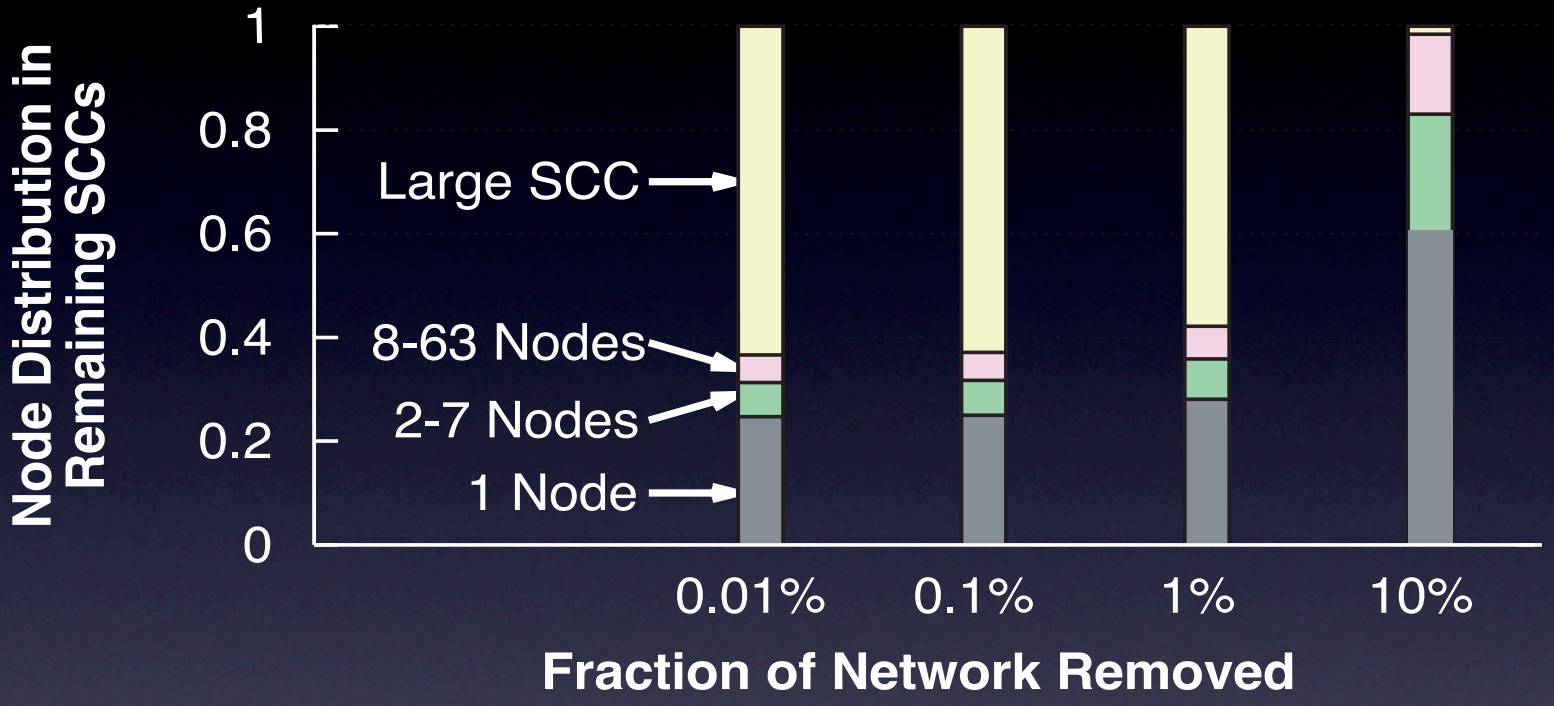
Link symmetry

- Social networks show high level of link symmetry
  - Links in most networks are directed

	Flickr	LiveJournal	Orkut	YouTube
Symmetric Links	62%	73%	100%	79%

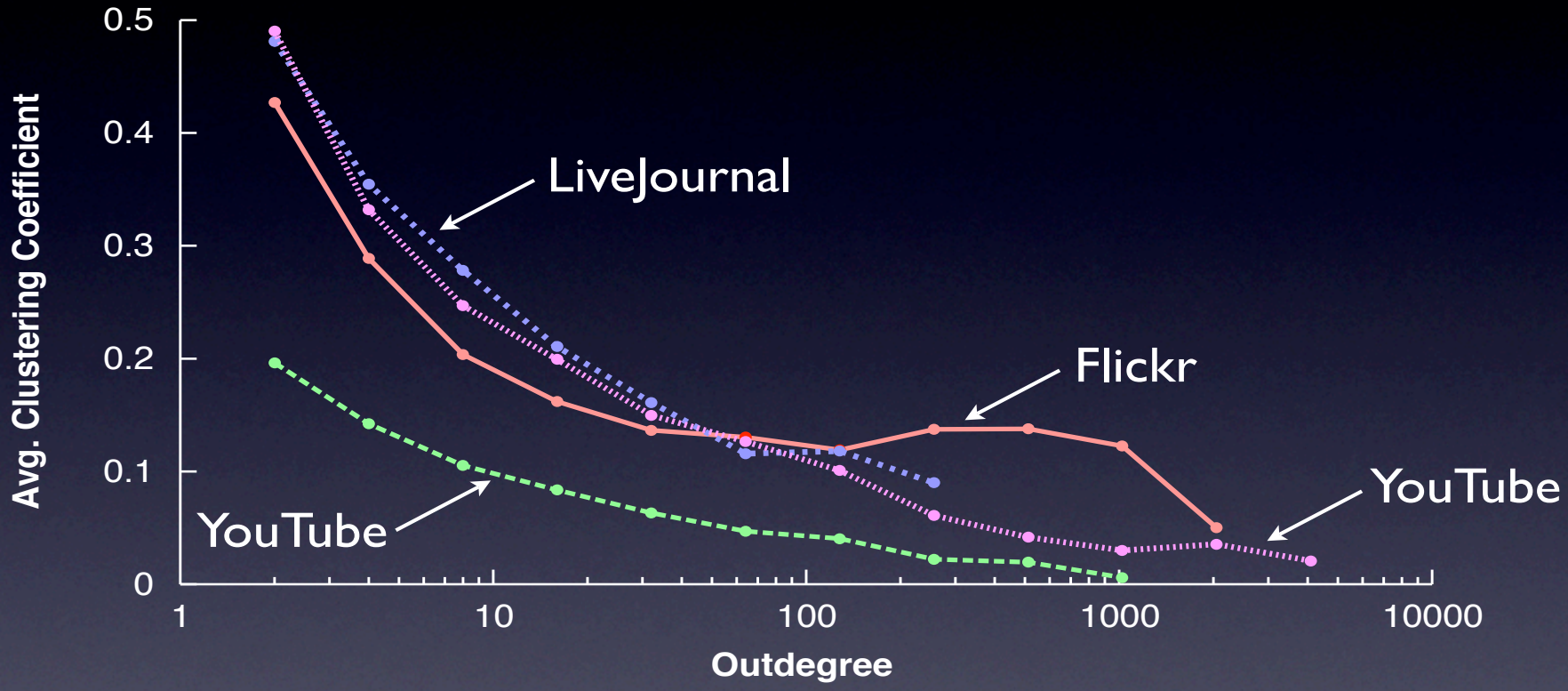
- High symmetry increases network connectivity
  - Reduces network diameter

Does a core exist?



- Yes, networks contain core consisting of 1-10% of nodes
  - Removing core disconnects other nodes

Are the fringes more clustered?



- Low-degree users show high degree of clustering
  - Networks are small-world, may be scale-free

Implications of network structure

- Network contains dense core of users
  - Core necessary for connectivity of 90% of users
  - Most short paths pass through core
  - Could be used for quickly disseminating information

- Fringe is highly clustered
  - Users with few friends form mini-cliques
  - Similar to previously observed offline behavior
  - Could be leveraged for sharing information of local interest

User Generated Content on YouTube

Name	Category	# Videos	Tot. views	Tot. length	Data collection period
YouTube	Ent	1,687,506	3,708,600,000	15.2 years	Dec 28, 2006 (crawled once)
YouTube	Sci	252,255	539,868,316	1.8 years	Jan 14 - 19, '07 (daily), Feb 14, '07, Mar 15, '07 (once)
Daum	All	196,037	207,555,622	1.0 year	Mar 1, 2007 (crawled once)

The graph shows that 10% of the top popular videos account for nearly 80% of views, while the rest 90% of the videos account for very requests.

Pareto Principle (or 80-20 rule) ?

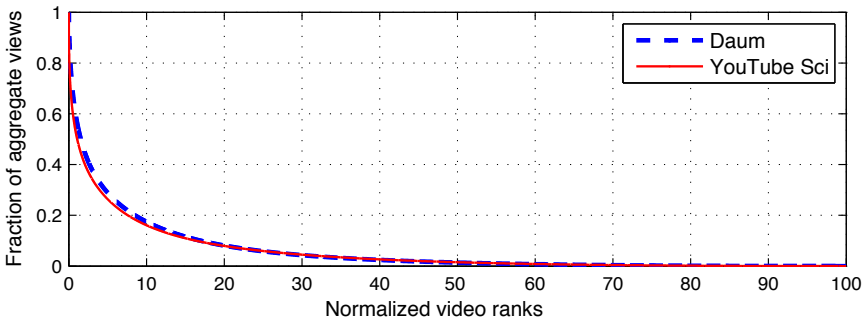
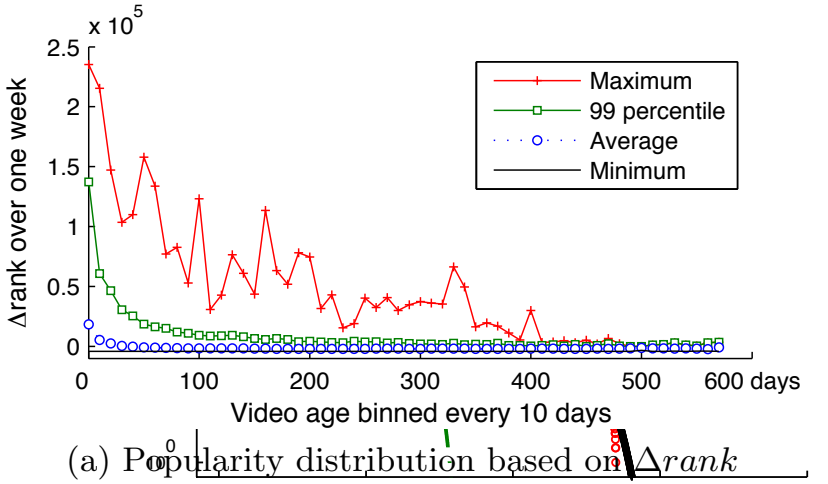
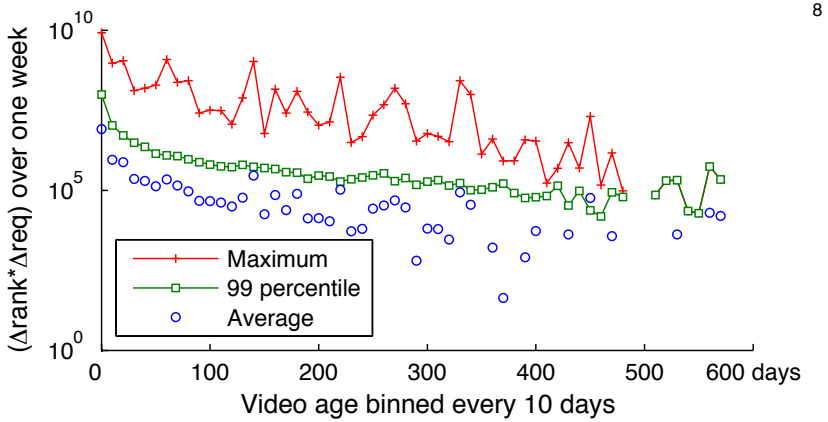


Figure 2: Skewness of user interests across videos

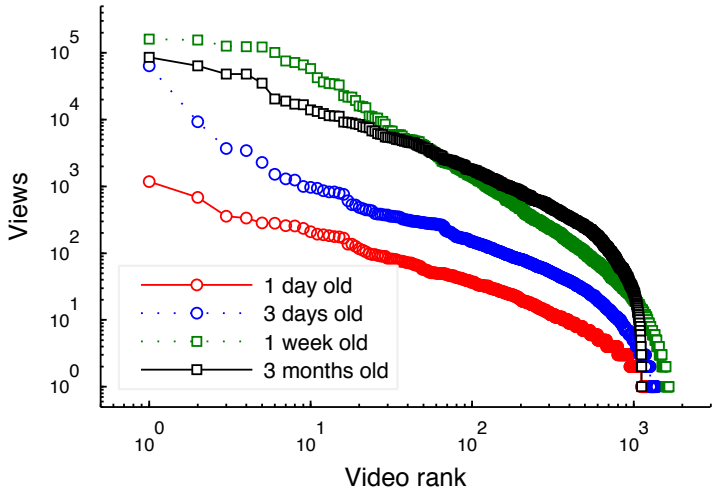
More video: age!



(a) Popularity distribution based on $\Delta rank$



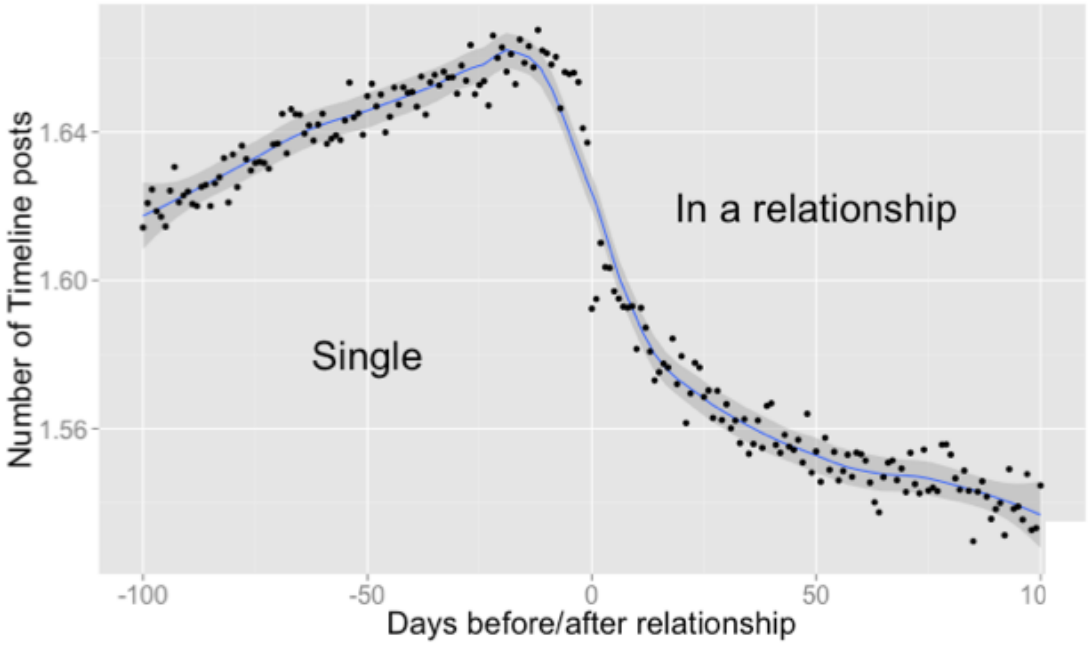
(b) Popularity distribution based on $\Delta rank \cdot \Delta views$



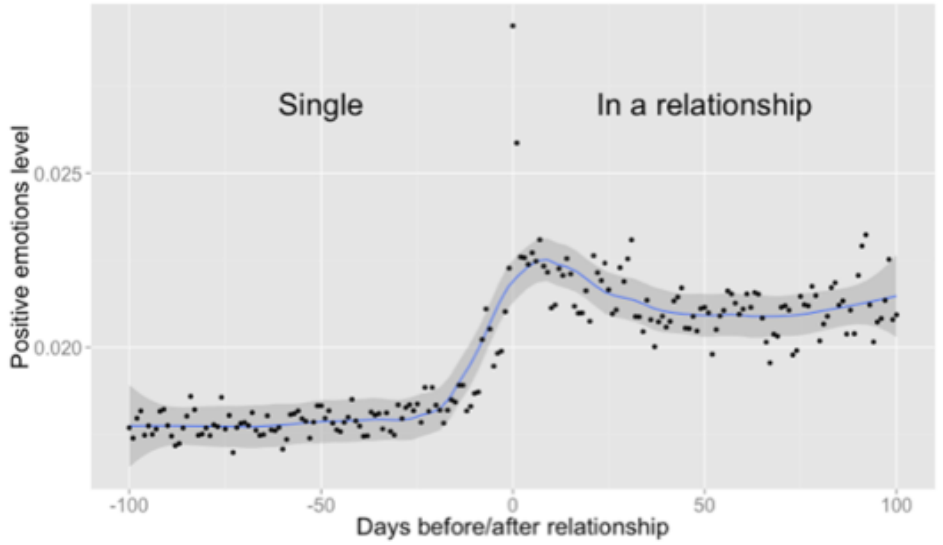
(b) Popularity distribution of videos with varying ages

Figure 9: Changes in ranking and popularity

The Formation of Love



https://www.facebook.com/notes/facebook-data-science/the-formation-of-love/10152064609253859



Growing Closer on Facebook

- Receiving written content—things that take some effort—like comments, posts on a friend's Timeline, and messages are linked to improvements in relationships.

- Likes, on the other hand, have little to no effect on relationships, possibly because Likes "cost less" socially.

- Reading about a friend through feed stories and their Timeline is also associated with growing closer (regardless of whether you talk to that friend online).

- These effects happen *even after you take into account* how often two people talk on the phone, see each other in person, and email. Facebook adds something over these other channels.

- Family relationships aren't affected by Facebook use as much as non-family relationships are. But family members say Facebook helps them see a different side of their relative; Dad becomes a “social person.”


Hamed Haddadi
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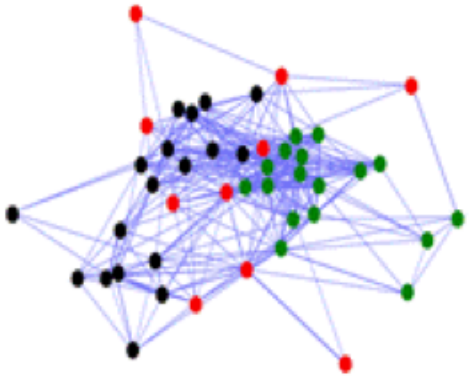

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Experiment

- Study subjects (n = 46) were taken from a flock of n = 300 merino sheep (Ovis aries) grazed at SARDI, and split into three groups: group A (n=10), group B (n=18) and group C (n=18).
- Sheep were kept in these three groups for 2 weeks in identical sized 0.9-km^2 rectangular fields, and given ad libitum access to hay and water. The three groups were then mixed together.

Location tracking

- All day
- GPS module capable of recording single frequency L1 raw range data at 10 Hz (uBlox LEA-4T GPS module), an IMU comprising a three axis MEMS accelerometer, three axis of MEMS gyroscope and three axis of magnetometer and a GPS patch antenna, MSP430 microcontroller and a rechargeable 2,200 mAh lithium polymer battery.
- Batteries charged overnight

Question: Who's my buddy?

- Using our GPS data, we created spatial matrices detailing the straight line distance between all dyads in the flock
- These data provided us with the total number of seconds sheep i spent at a certain distance from sheep j.
- Preliminary observations of sheep flocking at the site and previous research on Merino sheep suggested that individuals tend to be spaced 1–3 m during normal activity
- calculated adjacency matrices for 30 different spatial–temporal scales that ranged from two individuals spending 1 min at 1 m from one another, to five consecutive minutes at 3.5 m.
- Dyads were therefore defined as 'associating' every time that criterion was met.

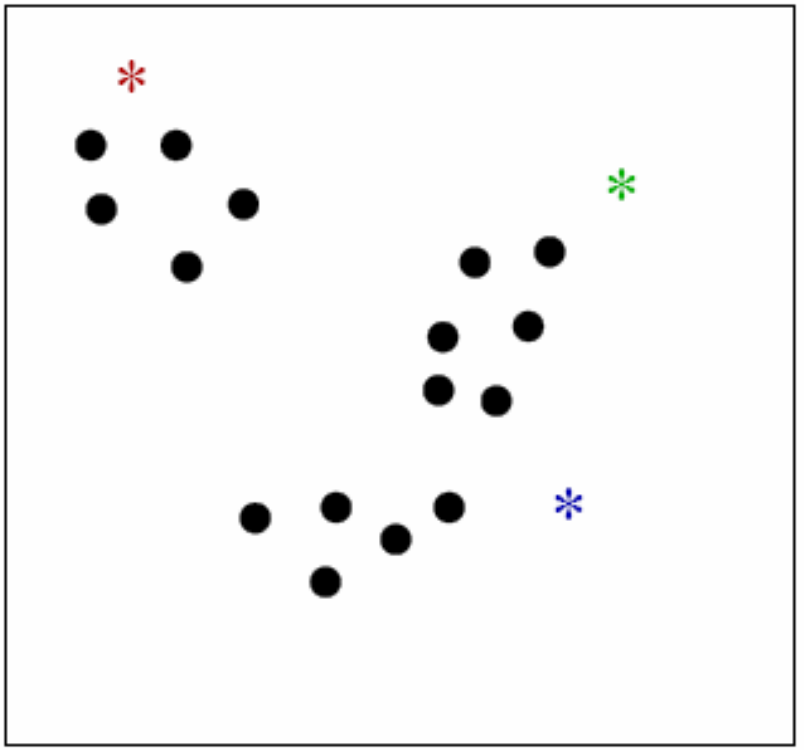
K-Means clustering

- K = # of clusters (given); one "mean" per cluster
- Interval data

- Initialize means (e.g. by picking k samples at random)
- Iterate:

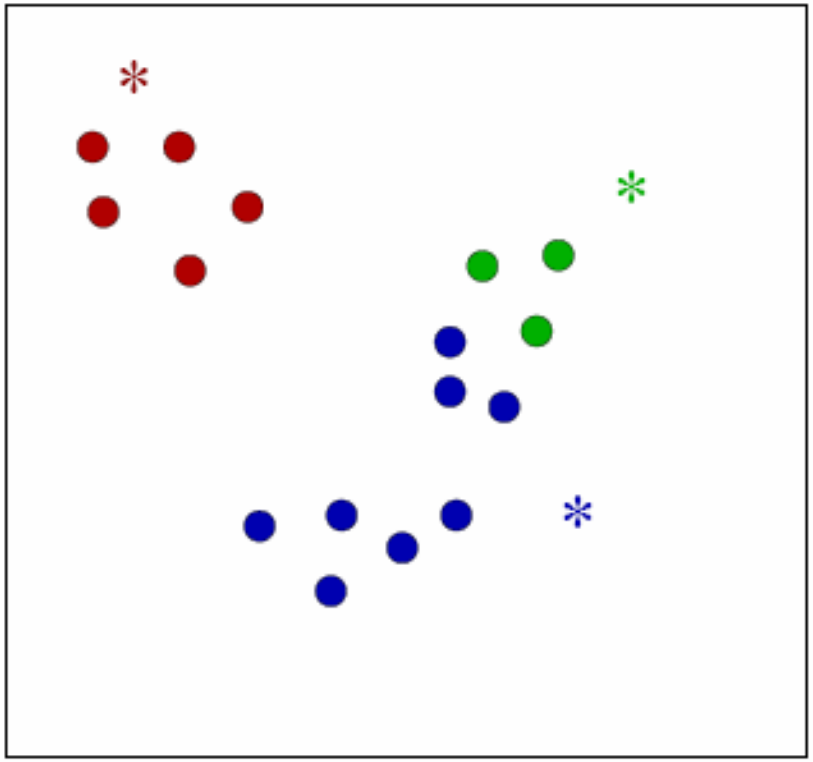
(1) assign each point to nearest mean

(2) move "mean" to center of its cluster.

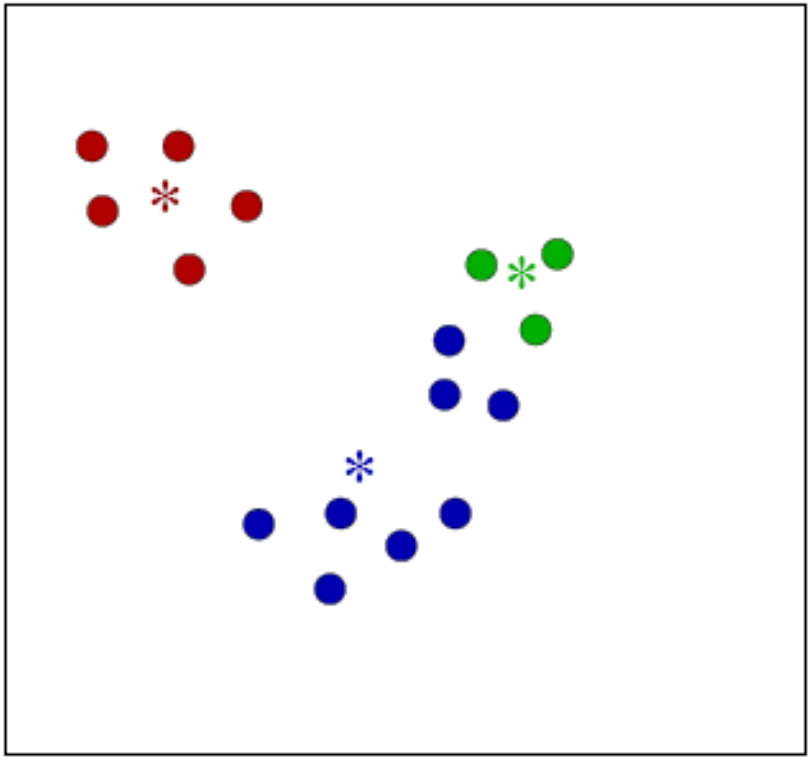


Initialize representatives ("means")

Assignment Step; Means Update



Assign to nearest representative

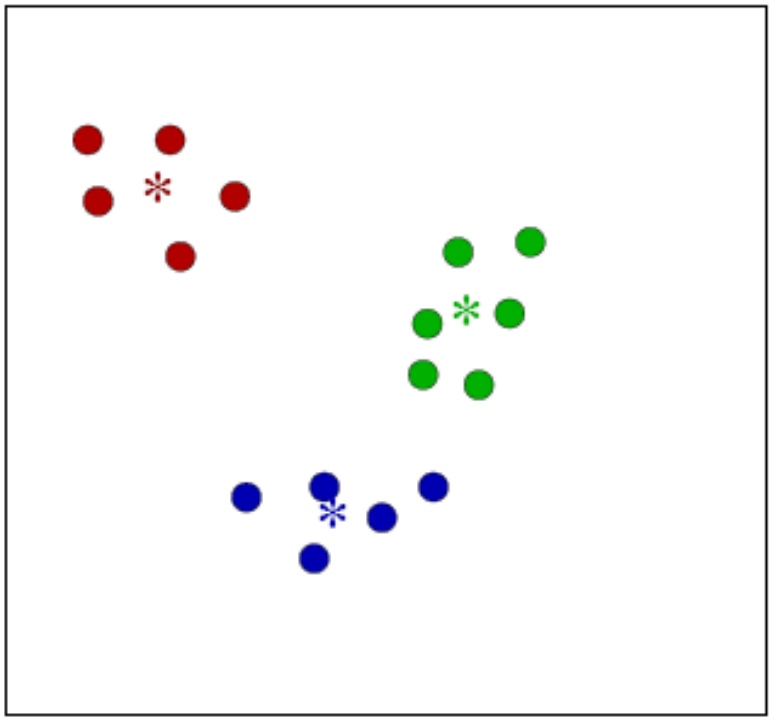


Re-estimate means

Convergence after another iteration

Complexity:

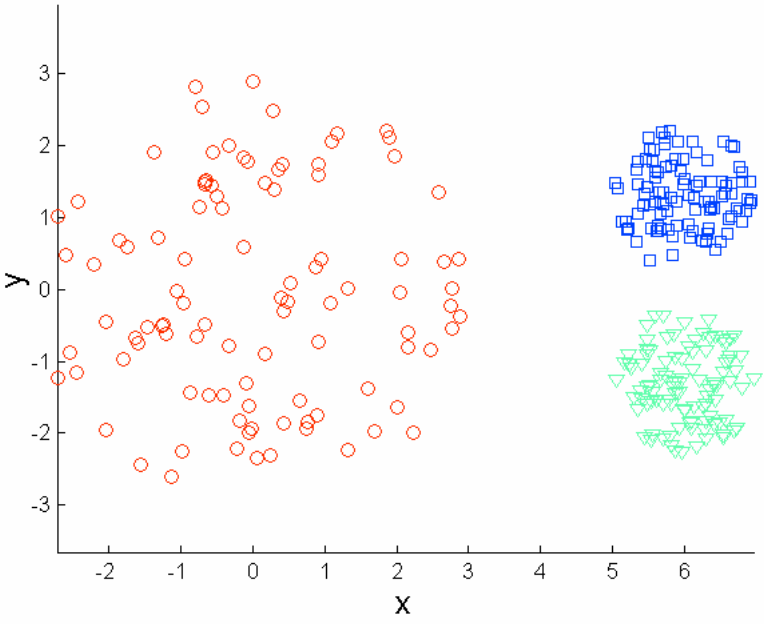
O(k . n . # of iterations



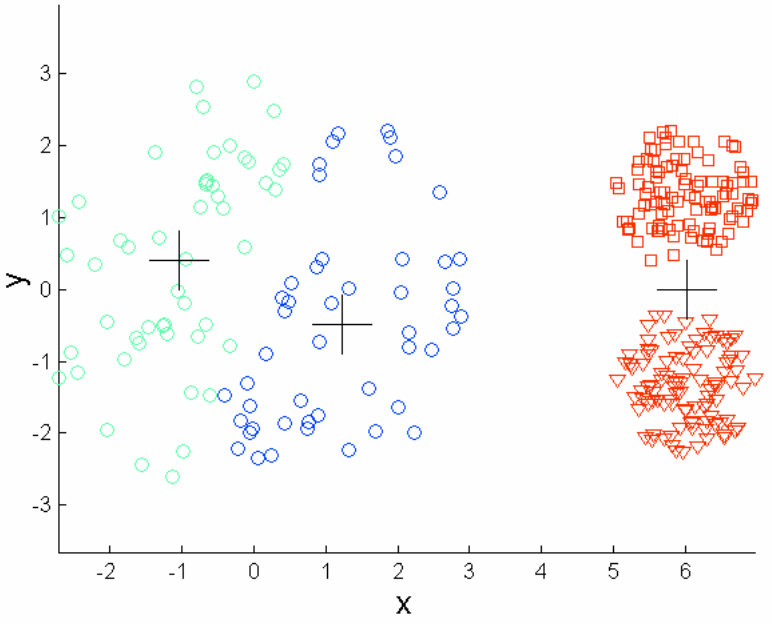
The objective function is

$$\min_{\{\boldsymbol{\mu}_1,\cdots,\boldsymbol{\mu}_k\}} \sum_{h=1} \sum_{\mathbf{x}\in\mathcal{X}_h} \|\mathbf{x}-\boldsymbol{\mu}_h\|^2$$

Limitations of K-means: Differing Density

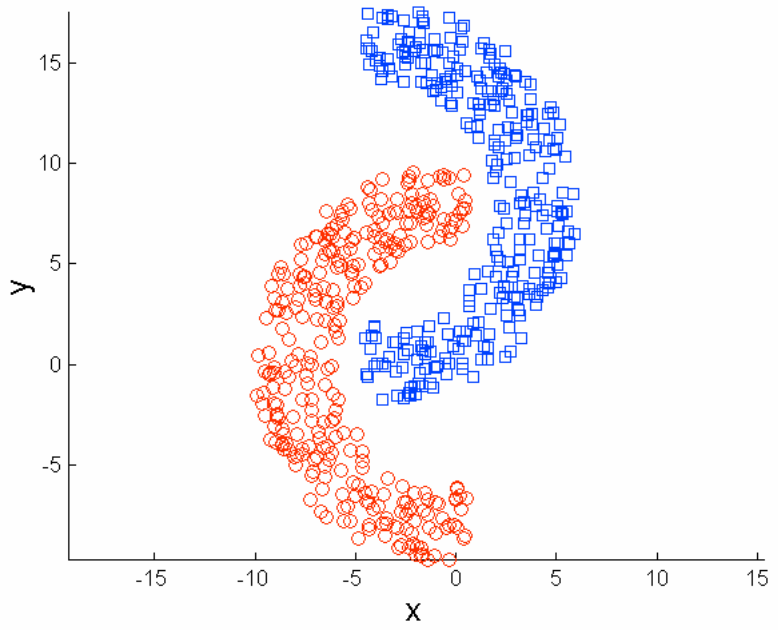


Original Points

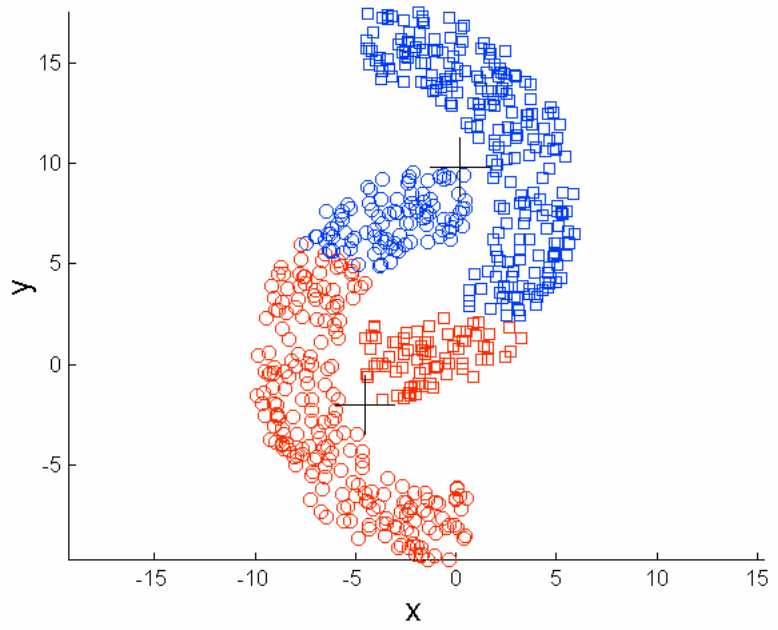


K-means (3 Clusters)

Limitations of K-means: Non-globular Shapes

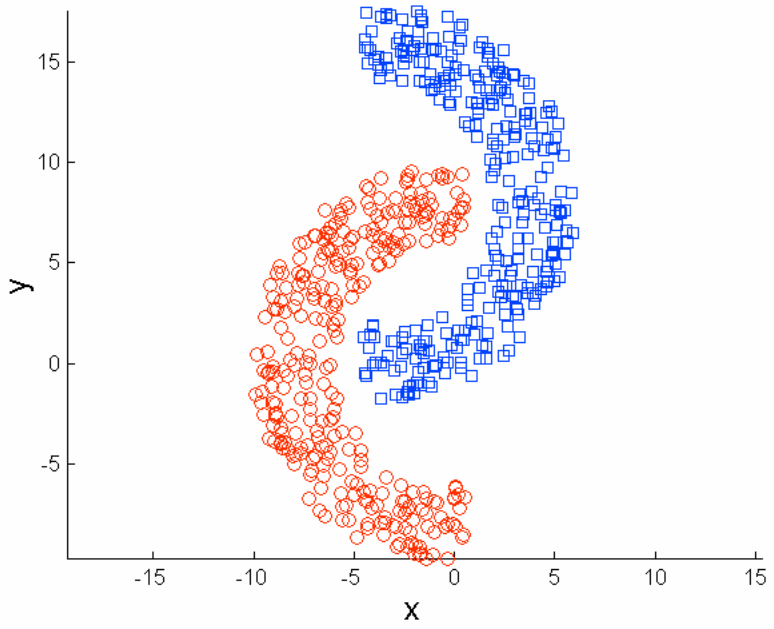


Original Points

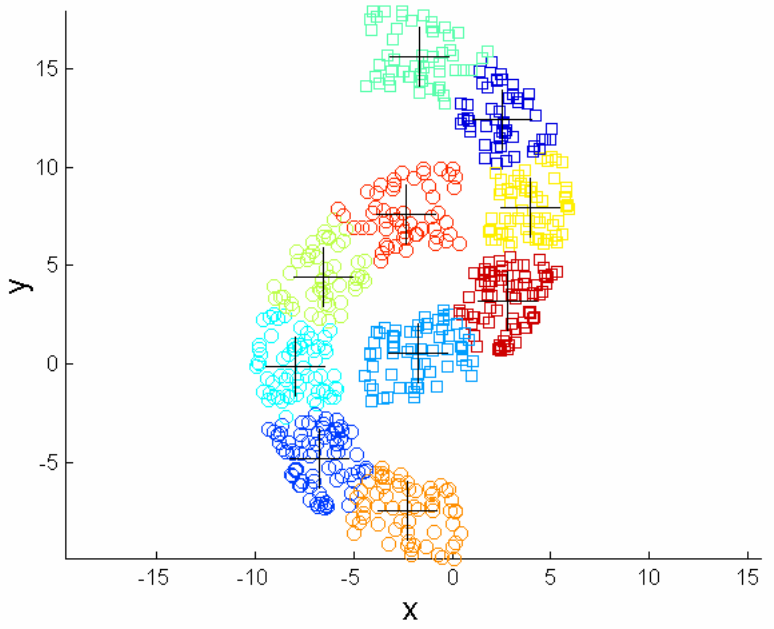


K-means (2 Clusters)

Overcoming K-means Limitations



Original Points



K-means Clusters

Spatial–temporal criterion

Table 1 Performance of k-means in detecting familiar individuals once mixed together into one larger flock at 30 different spatial–temporal scales

		Distance (meters)					
		1	1.5	2	2.5	3	3.5
Time (minutes)	1	0.56	0.58	0.60	0.59	0.85	0.79
	2	0.49	0.57	0.46	0.58	0.64	0.72
	3	0.37	0.55	0.60	0.85	0.69	0.70
	4	0.52	0.58	0.81	0.80	0.70	0.70
	5	0.51	0.56	0.57	0.81	0.80	0.75

Warmer colours in the plot represent higher accuracy

Entropy rate

We calculate the network graph entropy rate—a measure of ease of spreading of information (e.g. a disease) in a network—for every second of our dataset to determine the minimum sampling rate required to capture the variability observed in our sheep networks during distinct activity phases.

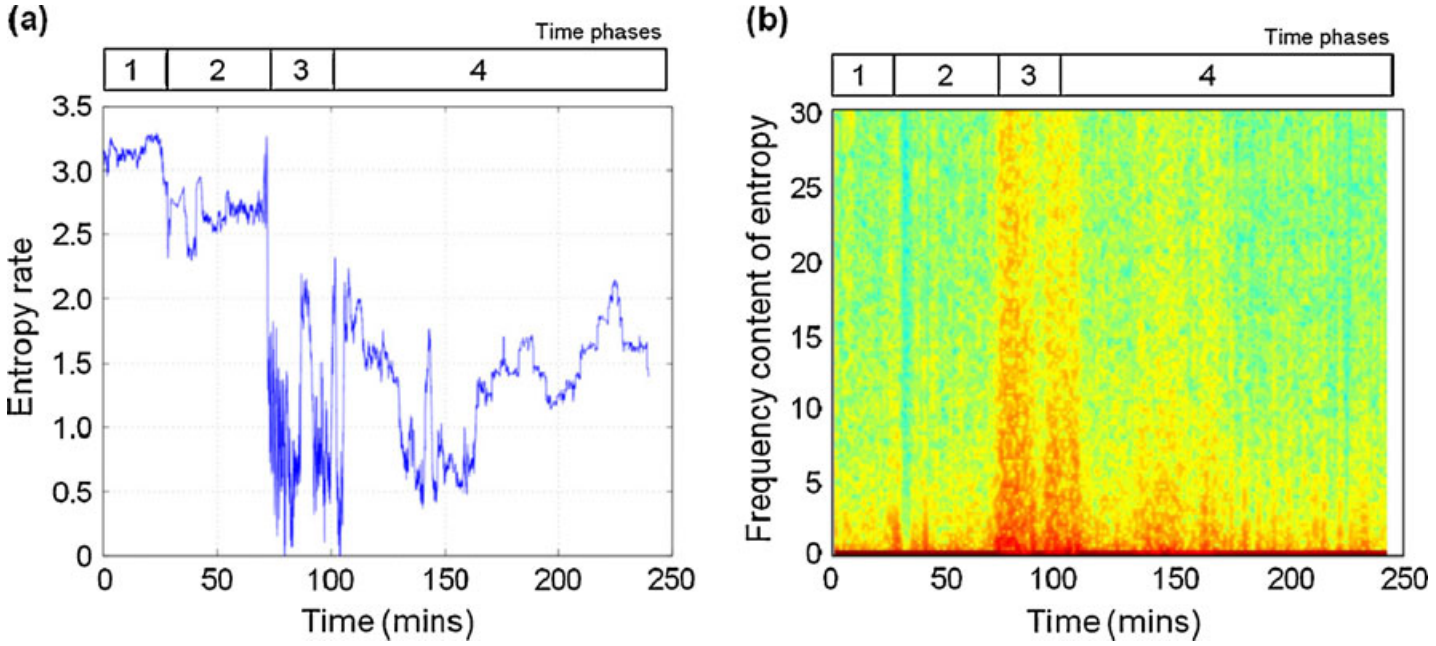
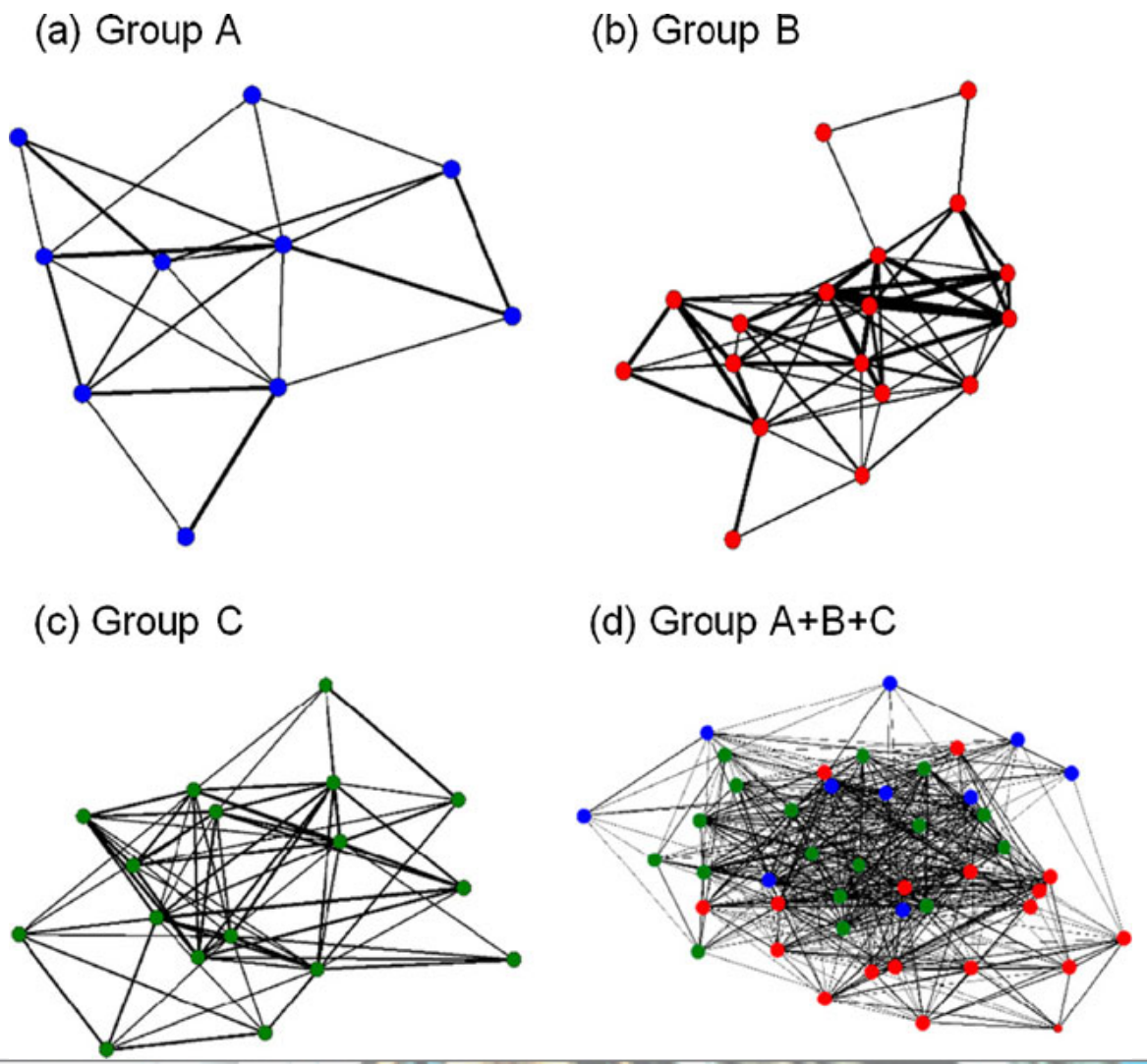


Fig. 4 **a** Entropy rate over time and **b** frequency content of entropy (a spectrogram) depicting the changing structure of the flock over time. In each figure, four distinct activity periods are labelled as time phases: 1='holding pen'; 2='herding'; 3='entry into field'; 4='in field' (see Methods for more details). At low entropy, rates indicate the flock is very dispersed, while a high entropy rate indicates a highly associated flock (also see Fig. 6). The spectogram shows that the frequency content illustrates the highly variable structure of the flock (*warm colours*) during phase 3 when the sheep flock enters the novel new field

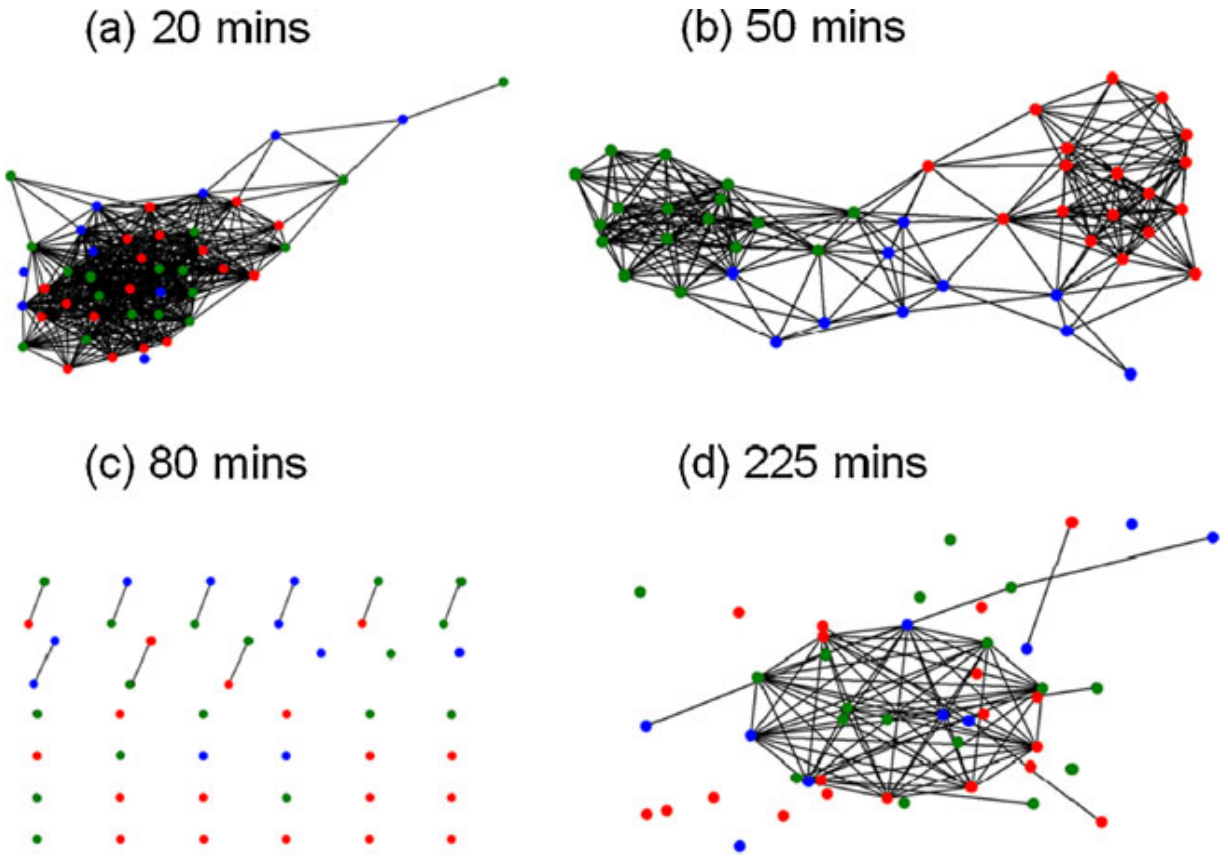
Mixing it up!

Fig. 3 Sociograms depicting spatial associations of the three individual groups before mixing **a**, **b** and **c**, and the mixed group on day of mixing **d**. In **d**, *blue nodes* represent sheep in group A, *green nodes* represent sheep in group C and *red nodes* represent sheep in group B. In all cases, the thickness of the *lines* (edges) indicates the frequency of associations between each dyad, and the network is filtered so that only links above the group mean average are shown for ease of illustration



Bonding

Fig. 5 Sociograms depicting spatial associations of the mixed group taken at four different single second 'snapshots' for a newly formed sheep flock. Nodes represent individual sheep and *lines* (edges) indicate an association between dyads at 2.5 m. Each network's corresponding entropy rate can be seen in Fig. 5a



https://www.youtube.com/watch?v=o54zO30lnas

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