Report from Dagstuhl Seminar 17282

From Observations to Prediction of Movement

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Abstract

This report documents the program and the outcomes of Dagstuhl Seminar 17282 "From Observations to Prediction of Movement". This seminar brought together researchers from Animal Behaviour, GIS, Computational Geometry, Data Science and other fields to exchange insights from these diverse fields. Presentations focused both on outstanding practical questions, as well as on fundamental mathematical and computational tools.

Seminar July 9–14, 2017 – http://www.dagstuhl.de/17282

1998 ACM Subject Classification I. Computing Methodologies, I.3 Computer Graphics, I.3.5 Computational Geometry and Object Modeling, I.5 Pattern Recognition, I.6 Simulation & Modelling, J.3 Life Sciences, and J.4 Social & Behavioral Sciences with one of the following sub-categories: Boundary representations Geometric algorithms, languages, and systems Physically based modeling

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1 Executive Summary

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Dagstuhl Seminar 17282 took place at Schloss Dagstuhl from 9 to 14 July 2017. We had 29 participants and nine invited talks. The main theme of this seminar was the analysis and prediction of movement trajectories. In particular, we focused on the study of movement patterns of individuals, and the interactions of moving agents with each other and with the environment.

Themes

Movement analysis is key to understanding the underlying mechanisms of dynamic processes. Movement occurs in *space* and *time* across *multiple scales* and through an embedding *context* that influence how entities move. The importance of spatiotemporal aspect of movement

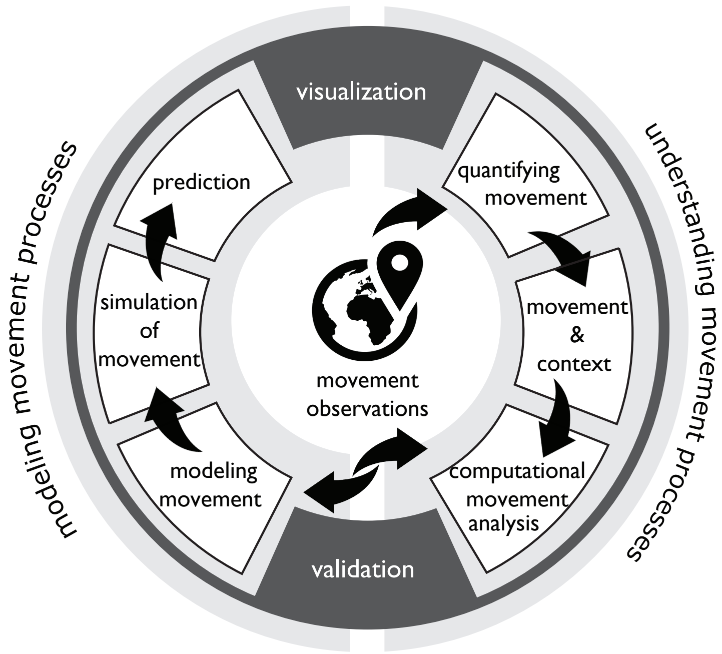

Figure 1 Movement research continuum.

has attracted a wide range of studies. Analysis of movement trajectories is a core element of Movement Ecology in Biology, as well as being important across disciplines as diverse as Geographic Information Sciences (GIS), Transportation, Criminology, Epidemiology, Computer Gaming, and Phylogenetics. Development of efficient algorithms for analyzing and predicting will be vital to realizing the hopes for new generation smart transport systems and smart cities. Furthermore, naturally generated trajectories provide a fascinating context for mathematical and computational study of Geometry and Stochastic Processes.

A trajectory is a time-stamped sequence of locations, representing the movement of entities in space and time. Trajectories are often created by sampling GPS locations, but they can also originate from RFID tags, video, or radar analysis. Time-series of locations can also be associated with other co-temporal data, such as pressure recordings for avian or aquatic animals, activity sensors and accelerometers to measure energy expenditure, or the myriad time-stamped data recorded by modern smartphones alongside GPS locations.

The study of movement involves development of concepts and methods to transform movement observations (trajectory data) to knowledge of the behavior of moving phenomena under known conditions. This knowledge is then used to calibrate simulation models to predict movement and behavioral responses in varying environmental conditions. Figure 1 illustrates a continuum encapsulating fundamental areas of movement research for (1) understanding movement processes through trajectory representation and computational movement analysis (the right side of Figure 1); and (2) modeling behavior of moving phenomena and prediction of their responses to environmental changes though modeling and simulation approaches (the left side of Figure 1). These two processes are tightly connected and feed into each other, often through a validation procedure on the basis of real trajectory observations.

During recent years computational movement analysis tools for trajectory data have been developed within the areas of GIScience and algorithms. Analysis objectives include clustering, similarity analysis, trajectory segmentation into characteristic sub-trajectories, finding movement patterns like flocking, and relating patterns to context, and several others. Since these computations are mostly spatial, algorithmic solutions have been developed in the areas of computational geometry and GIScience. The basic analysis tasks for trajectory data are by now comparatively well understood and efficient algorithms have been developed to perform computational movement analysis. However, to be truly effective and to have real-world impact, trajectory analysis has to move beyond ‘understanding movement’ and tackle substantially more involved questions in ‘modeling, simulation, and prediction’ of movement responses to a changing environment or as results of (social) interactions.

Simultaneously, in the area of ecology the study of motion of animals has also become a topic of increasing interest. Many animal species move in groups, with or without a specific leader. The motivation for motion can be foraging, escape from predators, changing climate, or it can be unknown. The mode of movement can be determined by social interactions, energy efficiency, possibility of discovery of resources, and of course the natural environment. The more fascinating aspects of ecology include interaction between entities and collective motion. These are harder to grasp in a formal manner, needed for modelling and automated analysis. The basic analysis tasks for trajectory data are by now comparatively well understood and efficient algorithms have been developed to perform them. However, to be truly effective and have real-world impact, trajectory analysis has to move beyond these basic tasks and tackle substantially more involved questions, prime examples being (social) interaction and collective motion.

Research Approach and Questions Addressed

Trajectories are mathematical objects with geostatistical properties. Movement is a process that occurs as a response to the state of a moving entity across multiple spatial and temporal scales. The state and resulting behavior of moving entities determine the characteristics and capacities of movement (e.g., speeds, directions, accelerations, path sinuosity), which are highly influenced by interaction with environment, geographic context, and other moving entities. Internal properties of the moving agent such as its propensity to explore, or its power and size, typically distinguish the trajectory from that of other agents. As such no element of a trajectory can truly be independent of its other parts. Therefore, we take a view of trajectory analysis that emphasizes the treatment of the whole trajectory as a unit, rather than a series of moment-by-moment steps.

Trajectories are generated by some underlying process, which is typically assumed to integrate both stochastic elements (such as Brownian motion) and more deterministic interactions between the moving agent and the external world. Many research questions can be posed about such processes, but in this seminar we will focused primarily on identifying the forms of interaction, both with other moving agents and with environmental stimuli, and on predicting the characteristics of future trajectories.

In the seminar, we explored the following questions:

- To what extent movement observations convey information on the underlying *behavior* of moving phenomena?
- How susceptible are behaviors of moving agents to environmental changes?
- To what extent changes in the behavior of moving phenomena indicate changes in the environment?
- What does it mean to *predict* a trajectory? Should we focus on predicting the spatial locations or the geometric properties?
- How can we assess a predictive model?
- How can computational geometry help movement prediction?

- What characteristics of motion are indicative of specific trajectory generating processes, and how can we compute these efficiently?
- What is the role of time in trajectory analysis? Where can we analyze the shapes of paths independently of the time stamps and where are these vital to understanding the underlying mechanisms?
- Can we build a classification of trajectory generating mechanisms and associated trajectory properties, such as navigation by waypoints, explorative foraging
- What is the *home range*? Can we have a concrete definition for home range or activity space?
- What is a *collective*?
- Can we make algorithms that work across scales?
- To what extent *goal oriented movement* can be inferred from *local movement patterns*?

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3 Overview of Talks

3.1 Calibrating Agent Based Models as Multiple Scales

Sean Ahearn (City University of New York, US)

The availability of GPS enabled devices has enhanced our ability to quantitatively analyze the movement and interaction of animals and people. In this analysis, we show how these data can be used to uncover behaviors at multiple spatial and temporal scales through segmentation and through the analysis of spatial-temporal usage of a tiger's home range. We use a time-geography approach to quantifying interaction between female tigers and analyze their boundary as a function of terrain characteristics (i.e. slope). It is suggested how these data are input into an agent-based model for calibration.

3.2 Analysing and Predicting Movement – A Computational Geometry Perspective

Maike Buchin (Ruhr-Universität Bochum, DE)

Analysing movement data leads to geometric problems and hence is interesting from a computational geometry perspective. In the past 10 years much research has been done in this direction. I discuss results on two topics related to prediction of movement: analysing delays and segmenting and classifying trajectories. Segmentation and classification ask to split respectively group trajectories by their movement behaviour. Two different approaches have been followed for characterizing similar movement: by spatio-temporal criteria and by the parameter of a random movement model. I give an overview of algorithms and their application for these two settings.

3.3 Using Time Geography to Model Movement in Three Physical Dimensions

Urska Demšar (University of St Andrews, GB)

Joint work of Demšar, Urska; Long, Jed
Main reference Demšar U, Long JA, "Time-Geography in Four Dimensions: Potential Path Volumes around 3D Trajectories", Short Paper Proceedings of GIScience 2016, Montreal, Canada, 27-30 Sept 2016.
URL https://doi.org/10.21433/B3117gc866qs

An increase in availability and accuracy of 3D positioning requires development of new analytical approaches that will incorporate the third positional dimension, the elevation and model space and time as a 4D concept. To address this we propose the extension of time geography into four dimensions. We generalise the time geography concept of a Potential Path Area into a Potential Path Volume around a 3D trajectory, present its mathematical definition and an algorithm for calculating these volumes around a set of given 3D trajectories. The algorithm was tested on simulated data and real 3D data from movement ecology.

3.4 Using Prediction to Explore the Mechanisms and Consequences of Social Life

Damien Farine (MPI für Ornithologie – Radolfzell, DE)

Maintaining cohesion during movement is fundamental for animals to gain the benefits of living in groups. Yet studying the mechanisms underlying collective movement is challenging using traditional measurement frameworks. I demonstrate how movement prediction can inform the mechanisms that underpin movement, using case studies from baboons and predator-prey interactions.

3.5 From Fish to Worms: Spatial Cognition, Movement and Postures in Three-Dimensions

Robert Holbrook (University of Leeds, GB)

Joint work of Victoria Davis, Theresa Burt de Perera, Richard Mann, Mate Nagy, Dora Biro, Sarah Schumacher, Thomas Ranner, Felix Schafer, David Pertab, Ian Hope, Netta Cohen

The real world is spatially three-dimensional. Animals, including humans, live in and move through three-dimensions every day. However, the majority of the research on animal movement has focused on only two-dimensions. For some animals with only two translational degrees of freedom of movement, the complexity of the navigation task may not change between two- and three-dimensions significantly, but for those animals with an extra degree of freedom of movement such as those that fly or swim, accurate navigation becomes a much more difficult task. Here I show examples of how a fish, *Astyanax fasciatus*, navigate through three-dimensional mazes by separating out the vertical and horizontal components of space and then integrating these when they need to navigate. The separation of the vertical component is likely aided by the use of an additional cue – hydrostatic pressure. This cue can be used alone for successful navigation in the vertical dimension, with the rate in change of swim-bladder volume a likely candidate sensory system. Despite the importance of the vertical component during navigation, it appears that it is not so important when deciding whom to pay attention to while shoaling in three-dimensions, with at least one two-dimensional implementation of a model accurately predicting the behaviour of 3D fish shoals.

The nematode worm, *Caenorhabditis elegans*, also moves through three-dimensional environments, yet all the kinematic and biomechanical research to date has been done on two-dimensional flat plates. We may therefore be missing some important behavioural repertoire from the worm in its natural habitat. Here I attempt to rectify this by analysing worm trajectories and postures while it moves though a three-dimensional gelatin cube. The worm exhibits three-dimensional behaviour more often than planar behaviour, both in trajectories and postures. Importantly, there appears to be a helical gait motion that seems to be present for much of the time the worm is moving through higher viscosities of gelatin, a behaviour which has not yet been documented.

3.6 Scalable Methods for Modelling Movement Patterns: from Areal to Road Segment Levels

Robin Lovelace (University of Leeds, GB)

Joint work of Alan Wilson
Main reference Robin Lovelace, Anna Goodman, Rachel Aldred, Nikolai Berkoff, Ali Abbas, James Woodcock, "The Propensity to Cycle Tool: An open source online system for sustainable transport planning", Journal of Transport and Land Use, 10(1), 2017.
URL http://dx.doi.org/10.5198/jtlu.2016.862

From: http://rpubs.com/RobinLovelace/290584

It is important to know where people travel for a number of reasons. Most important among these is the urgent need to transition away from fossil fuels: models of travel patterns can help identify the most effective interventions to make this happen.

This paper explores globally scalable methods for generating estimates of travel patterns that build on areal and point-based data to estimate movements down to the road network level currently, and under scenarios of the change. The presentation is based on my experience developing the Propensity to Cycle Tool (PCT) and scaling it across all areas and major cyclable roads in England (see pct.bike) and recent experiments extending it internationally with a case study in Seville, Spain.

Methodologically I will explore the possibility of extending the methods to be dynamic and multi-modal, themes that will be prominent during the summer school.

3.7 The Moving Across Places Study (MAPS): Public Transit, Physical Activity and Walking Route Choice

Harvey J. Miller (Ohio State University, US)

The Moving Across Places Study (MAPS) is a quasi-experimental study of the impacts of light rail transit and street rehabilitation on physical activity and walking route choice. Participants (n=536) wore GPS recorders and accelerometers for one week before and after the construction of a light rail transit (LRT) line and walkability enhancements in a neighborhood of Salt Lake City, Utah, USA. We are able to demonstrate that these design interventions resulted in more physical activity and new physical activity time that did not draw from recreational physical activity time or cannibalize existing us ridership. We compare theory-driven and data-driven approaches to understanding walking route choice through this built environment. The theory-driven approach is easier to explain, but the data-driven approach fits the data better and also points more directly to actionable knowledge.

3.8 Random Trajectories in Movement Ecology: A Path to Crossing Scales in Movement Ecology?

Kamran Safi (MPI für Ornithologie – Radolfzell, DE)

With the advances of technological developments the granularity and volume of movement data is ever increasing raising the need for new analytic tools. Partially the problem lies buried in the way movement data is collected by discretising a continuous process, where with increasing resolution in time and space the discretisation suffers from increasing autocorrelation. The discretisation affects, in interaction with the underlying continuous movement process, almost all quantities usually derived from trajectories, such as speed or turning angle and the amount of autocorrelation detectable. The definition of Null models in movement ecology being inherently difficult task has become more challenging mainly as the assumption of independence in the data becomes more evidently violated. Different methods have been suggested to incorporate some formal continuous time movement model to integrate the autocorrelation structure. With the increasing volume and accessibility of movement data, however, another alternate path might open: the use of empirical distributions to create conditional random trajectories. In this talk I present the eRTG, the empirical random trajectory generator, which is based on using empirical joint distributions of speed and turning angle derived from discretised movement data to create random trajectories connecting a given start and end point maintaining the original geometry of the template. Finally, I use two case examples to highlight the potential of the eRTG to explore hypothesis and formulate hypothesis. First, the eRTG is used to show the difference in orientation task in the white stork when migrating along the Western or Easter migratory flyways based on the fusion of movement data with banding recoveries. Based on the eRTG, the Eastern migratory flyway should pose higher orientation demands on the white storks than the western route population. I conclude with a study using eRTG to investigate the potential of wild waterfowl tranporting avian influenza.

3.9 On Language for Observation & Prediction

Jack Snoeyink (University of North Carolina at Chapel Hill, US)

"Language shapes the way we think, and determines what we can think about." I present four vignettes on how to think about the languages used in collaboration between movement science(s) and computational geometry:

1. Computer Scientists create languages – e.g., object programming creates nouns and attaches their verbs.
2. Languages that can aid ones thinking can still hinder communication if not shared.
3. Boundary objects, which can be described by each collaborator in their own way, facilitate collaboration.
4. When creating computational models, create scientific "unit tests" that use a language of features and their distributions to circumscribe desired behavior.

3.10 Collective Motion: More than the Sum of its Parts

Zena Wood (University of Greenwich, GB)

To sufficiently analyse collective motion, and predict or simulate future motion, we need to look at more than just the level of the individual members. The level of the collective, and the environment where the motion takes place, must also be considered. This talk will illustrate how concepts from formal ontology and other disciplines, such as group organisation theory, can influence the analytical methods that we develop to analyse collective motion. The challenges and opportunities relating to the analysis of collective motion will also be discussed.

References

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2 Wood, Zena. (2013). Profiling Spatial Collectives. In Max Bramer and Miltos Petridis, editors, Incorporating Applications and Innovations in Intelligent Systems XXI Proceedings of AI-2013, The Thirty-third SGAI International Conference on Innovative Techniques and Applications of Artificial Intelligence: 95–108. Springer.
3 Wood, Zena., (2014). What can Spatial Collectives tell use about their environment? IEEE Symposium Series on Computational Intelligence (IEEE SSCI 2014), 329–336.
4 Galton, Antony, and Zena Wood. (2016) "Extensional and intensional collectives and the de re/de dicto distinction." Applied Ontology 11.3: 205–226.

4 Working groups

4.1 Computational Topology and Movement Data

Kevin Buchin (TU Eindhoven, NL), Maike Buchin (Ruhr-Universität Bochum, DE), Brittany Terese Fasy (Montana State University – Bozeman, US), Kristine Pelatt (St. Catherine University – St. Paul, US), and Carola Wenk (Tulane University, US)

Main reference Gurjeet Singh, Facundo Mémoli, Gunnar E. Carlsson: "Topological Methods for the Analysis of High Dimensional Data Sets and 3D Object Recognition", in Proc. of the Symposium on Point Based Graphics, Prague, Czech Republic, 2007. Proceedings, pp. 91–100, Eurographics Association, 2007.
URL http://dx.doi.org/10.2312/SPBG/SPBG07/091-100

Computational Topology has proved effective in a wide range of applications, but has so far only found few applications in movement analysis. The aim of this working group was to explore how existing software for topological data analysis can be used to analyze movement.

The working group focused on TDAmapper, an R package for using discrete Morse theory to analyze a data set using the Mapper algorithm (Singh et al., 2007), and demonstrated it on Galapagos Albatross tracks; see Figure 2.

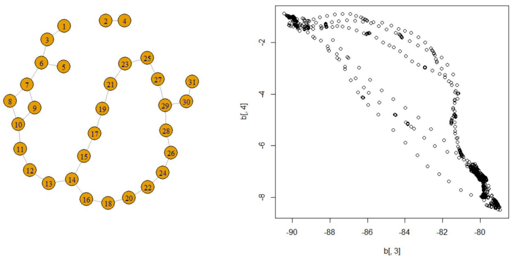

Figure 2 Output of the mapper algorithm (left) for Albatross trajectory data (right).

4.2 Defining Axes and Metrics to Characterise Collective Motion

Somayeh Dodge (University of Minnesota – Minneapolis, US), Urska Demšar (University of St Andrews, GB), Jed Long (University of St Andrews, GB), Andrea Perna (University of Roehampton – London, GB), Alexander Szorkovszky (Uppsala University, SE), Johan van de Koppel (Royal Netherlands Inst. for Sea Research – Yerseke, NL), and Zena Wood (University of Greenwich, GB)

In this working group we worked towards the identification of relevant axes along which to characterise, and ideally to quantify, collective motion phenomena.

We started from considering properties that define a group, such as the spatial proximity (or proximity in non-spatial dimensions), the differentiation of roles across group members, the coherence of mutual positions and of collective motion. From this, we moved to analysing the drives that determine group formation in terms of costs and benefits for the individuals that compose the group, and benefits for the entire group. At one extreme, animals can exhibit collective motion, in the form of an aggregation in a single place, without any form of interaction: this is the case of animals that aggregate for instance around a resource such as a source of food or water. In many exampls of naturally occurring animal groups, the individuals form a group because they experience a direct benefit from being with other members of the group in terms of avoiding predation or gaining protection from natural phenomena (waves, low temperature etc.) We proposed that the costs and benefits of group formation could be characterised by using a classification similar to the one traditionally used to characterise ecological interactions such as predation and parasitism (whereby some members of the group benefit from the association, to the detriment of other members of the group), mutualism and symbiosis (in which both units participating in the association gain a benefit) and commensalism (whereby some individuals benefit from the association, with no detriment or benefit for the other individuals).

The natural next step would be defining axes that are more specific to the collective motion of animal groups, and not simply to the aggregation behaviour or to the characterisation of static groups. Both computer scientists working on ontologies and ecologists have been independently working on definition of the properties of (animal) groups and the possibility to exchange ideas between these two disciplines in this working group was particularly insightful.

4.3 Multi-scale Movement Modeling

Somayeh Dodge (University of Minnesota – Minneapolis, US), Kevin Buchin (TU Eindhoven, NL), Urska Demšar (University of St Andrews, GB), Harvey J. Miller (Ohio State University, US), Kristine Pelatt (St. Catherine University – St. Paul, US), Alexander Szorkovszky (Uppsala University, SE), and Johan van de Koppel (Royal Netherlands Inst. for Sea Research – Yerseke, NL)

Movement occurs at multiple spatial and temporal scales, which can result in a range of embedded local to global movement patterns. The way in which context influences patterns of movement differs across scales. Movement ecology models have mainly involved random searches and step selection strategies at local scales. These models incorporate the environmental factors and social interactions that influence local movement choices of individuals. On the other hand, human mobility studies have traditionally focused on modeling macro-level patterns such as origin-destination flows. These models mainly consider global behavioral patterns and goal-oriented movement of humans. While both approaches are essential in the study of moving phenomena, there is a gap in methodology for tackling multiple scales of movement and their associations to the individual's behavior and environment. In a multi-scale movement modeling approach, global models should describe the process and local models should describe the local variabilities of movement. Our group discussed the differences between data-driven and theory-driven modeling approaches and ways in which they could potentially be used to integrate multiple scales of movement. As a data-driven approach, the group discussed the potential usage of topological modeling to filter data to the big trend and then extracting the details of local movement patterns. The theory-driven approach could potentially benefit from applying both local rules and global rules to model movement across multiple scales. The group also came up with the following relevant research questions/challenges:

- how can we generate algorithms that work properly across scales?
- how can we connect different scales of movement, in terms of both geographic scale and time scale?
- to what extends can we infer a goal-oriented movement from local movement patterns?
- do global objectives of movement emerge from local rules or does the global objective of movement influence local movement rules?

The group concluded that 'multi-scale modeling of movement' is a challenging research gap in the field and deserves more attention from the scientific community.

4.4 Using and Explaining Non-Traditional Metrics in Biology Publications

Damien Farine (MPI für Ornithologie – Radolfzell, DE), Robert Holbrook (University of Leeds, GB), Richard Philip Mann (University of Leeds, GB), Andrea Perna (University of Roehampton – London, GB), and Kamran Safi (MPI für Ornithologie – Radolfzell, DE)

We were concerned with the issue of how to present metrics from movement studies in biology journals. These metrics do not typically come in the form of significance tests and p-values, but might for instance be the likelihood ratio between two models, comparisons of analyses between real and permuted data sets, or effect-sizes (with uncertainties)

Overall we agreed that a crucial aspect was the ability to communicate clearly the value and rigour of the alternative metric. This might be aided by having a shared resource that explains these metrics clearly, perhaps by analogy with more well-known measures. This could be in the form of a paper or web page. However, to create this would require referencing established literature where these metrics are used, and ideally also justified. To this end we should also seek to explain clearly why we use the metrics that we do, and why we do not follow established significance test methods, in our own papers. By doing this we can create cultural change that will make the use of new methods easier in future.

4.5 Learning Connections Between Landscape and Trajectories from Recorded Data

Richard Philip Mann (University of Leeds, GB), Maike Buchin (Ruhr-Universität Bochum, DE), Robert Holbrook (University of Leeds, GB), and Nicholas Ouellette (Stanford University, US)

We discussed how data from navigating pigeons, combined with landscape images, could be used to understand how the landscape drives movement. This followed on from related discussions at the previous Dagstuhl seminar nr. 16022. We assumed that pigeons' trajectories should result from some sort of optimisation process, involving landscape characteristics under the path. We have data from early, learning flights to later consistent flights, which offers the possibility of understanding the dynamics of this optimisation. We initially considered constructing a 'energy'-potential that would define the 'energy' of any route, and combining this with localised improvements to the route to lower potentials, in a framework similar to step-selection. However, it became clear based on earlier trials of this idea and further discussion that this would not work – changes in routes do not appear to be local, but global. We therefore wondered how we could understand the process of exploring different trajectories and settled on ideas similar to markov-chain monte carlo or simulated annealing. However, we concluded that the data we had would probably be insufficient to infer the potential landscape within this regime. As such we determined that a fruitful next step would be to create simulated data from a known ground truth and assess how much/what type of trajectory data we would need to accurately infer the learning process and the potential landscape used.

4.6 Potential Applications of Ecology on Transport and the Implications on Policy

Samuel A. Micka (Montana State University – Bozeman, US), Mark Birkin (University of Leeds, GB), Maarten Löffler (Utrecht University, NL), Robin Lovelace (University of Leeds, GB), Richard Philip Mann (University of Leeds, GB), Kathleen Stewart (University of Maryland – College Park, US), and Carola Wenk (Tulane University, US)

The activity spaces of people provide important information about where they travel on a day-to-day basis. The aim of this working group was to identify similarities between the ecological term "home range", which defines a similar concept for animals, and activity spaces. Drawing similarities between these ideas could help identify more information about the motivations behind human actions within their activity spaces. Ultimately, this information could determine where people are throughout the day, and why they are there. This sort of predictive model could provide input for route planning algorithms and city planners. However, the definitions of activity spaces and home ranges vary drastically in different contexts, making a relationship difficult to define. Despite these difficulties, we explored different types of data sets and how they may fit into a predictive model. These data sets included origin-destination pairings, trajectory data, survey data (where do you work, where do you live, etc.), and census data. We considered different models that would accept the different data types as input, such as dynamic graphs that could store the intent of trips.

4.7 Formalizing the Notions of "Activity Spaces" and "Homeranges": Mathematical Definitions, Similarities, and Differences

Jack Snoeyink (University of North Carolina at Chapel Hill, US), Sean Ahearn (City University of New York, US), Samuel A. Micka (Montana State University – Bozeman, US), Harvey J. Miller (Ohio State University, US), David Millman (Montana State University – Bozeman, US), and Frank Staals (Aarhus University, DK)

Activity spaces and home ranges both generalize the trajectories representative of where humans and animals travel for their daily tasks and activities. These spaces, on the surface, appear as geometric summaries of these trajectories. However, cross-disciplinary understandings of home ranges and activity spaces differ, creating ambiguity in the definitions leading to inconsistent mathematical representations. To create cohesion between these fields we propose a space partitioning data structure which provides tunable rules to create home ranges/activity spaces from trajectory data. By offering a general data structure to geometrically represent these spaces, the definitions and respective representations will become more consistent and easily communicated in cross-disciplinary research.

4.8 Going Beyond the Level of the Individuals

Zena Wood (University of Greenwich, GB), Maike Buchin (Ruhr-Universität Bochum, DE), Brittany Terese Fasy (Montana State University – Bozeman, US), Jed Long (University of St Andrews, GB), Jennifer Miller (University of Texas – Austin, US), and Nicholas Ouellette (Stanford University, US)

The group discussed the relationship between the individual members and the collective itself. Key questions/topics included whether a hierarchical structure exists; the relationship between roles and members; how roles are defined and identified within a spatiotemporal dataset; how a true collective can be identified; and, the metrics that can be applied to a collective but not the individual members.

To address how a true collective could be identified, and whether it be done independent to an application, the properties of collectives were discussed. Individual members know that they are part of a collective with each collective having an identity. Identifying changes in behaviour of an individual could be used to identify membership. Both collective and individual goals can be considered. Distinct roles can lead to individuals participating in a collective goal in different ways. Properties can be ascribed to the collective that cannot be ascribed to the individuals. It is not clear which properties would be considered meaningful given a dataset. We discussed methods that might prove useful in identifying collectives (e.g., connected components looking for persistent features). Instead of identifying true collectives, you could try to determine if something is not a collective using adversary detection.

Going forward there are lots of questions with no apparent answers. It is clear that we need to develop metrics and identify some examples of collective motion (e.g., examples where the individual goal is fundamentally different to the collective goal).

5 Fishbowl discussion

Over the course of an afternoon, a fishbowl conversation was used to encourage discussion. In this session, three attendees discussed a topic in front of the rest of the seminar. The positions in the center were vacated and refilled by others as people wanted to make contributions to the conversation. One moderator was responsible for asking questions and providing talking points. Here, we outline some of the major contributions and conclusions drawn from this session.

The first part of the session was centered around defining the characteristics of prediction of movement. Differences were highlighted between local and global behaviors, human and animal trajectories, and the purposes of predictions. Many speakers had different interpretations of prediction and what it could be used for. The conversation moved on the role of geometry in prediction of trajectories. Specifically, can deterministic methods be used to help predict real world movement? Despite predictive models being available for cell life and animal populations, the speakers decided that it would not be realistic to predict animal behavior deterministically. This topic led to the discussion of fundamental laws, such as the ones found in physics. The general consensus was that animals have goals, and use movement to achieve these goals. Some goals are predictable, but a universal predictive model is not feasible. Later, the idea of naïve movement was introduced. Naïve movement encapsulates the idea of natural, predictable movement, like water flow in physics. Since each animal has a different interpretation of its surroundings, defining a universal a set of senses is difficult.

For many animals, home ranges encompass a large number of simple, and predictable, behaviors. This led to the discussion of how animals interpret their own homeranges, which again, was decided to be subjective. However, some animals possess a cognitive map of their surroundings, which could help in predictive models for certain behaviors and species. In particular, pigeons have an uncanny ability to navigate.

The role of mathematicians and computer scientists in this field of research also emerged as a topic. The desire for a common language to communicate animal behavior rose. The idea being that, if we can communicate these movements across disciplinaries in a way that everyone understands, we will be able to more easily develop models. One of the major problems with communicating these biological results with mathematicians and computer scientists is that, without a set of fundamental rules, how are methods verified? The speakers agreed that verification should be achieved through observation and professional opinions. However, with a lack of a deterministic model for animal movement, prediction is still a very animal-specific and difficult problem to approach.

Participants

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