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Authors

Miller, Harvey J
Dodge, Somayeh
Miller, Jennifer
et al.

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Towards an Integrated Science of Movement: Converging Research on Animal Movement Ecology and Human Mobility Science

Harvey J. Miller,
Department of Geography and Center for Urban and Regional Analysis (CURA), The Ohio State University

Somayeh Dodge,
Department of Geography, Environment and Society, University of Minnesota

Jennifer Miller,
Department of Geography and the Environment, The University of Texas at Austin

Gil Bohrer
Department of Civil, Environmental and Geodetic Engineering, The Ohio State University

Abstract

There is long-standing scientific interest in understanding purposeful movement by animals and humans. Traditionally, collecting data on individual moving entities was difficult and time-consuming, limiting scientific progress. The growth of location-aware and other geospatial technologies for capturing, managing and analyzing moving objects data are shattering these limitations, leading to revolutions in animal movement ecology and human mobility science. Despite parallel transitions towards massive individual-level data collected automatically via sensors, there is little scientific cross-fertilization across the animal and human divide. There are potential synergies from converging these separate domains towards an integrated science of movement. This paper discusses the data-driven revolutions in the animal movement ecology and human mobility science, their contrasting worldviews and, as examples of complementarity, transdisciplinary questions that span both fields. We also identify research challenges that should be met to develop an integrated science of movement trajectories.

Introduction

Among the traits shared by animals and humans is intentional movement through space to perform activities. These purposeful movements are fundamental to the dynamics of ecosystems, cities and environments. Consequently, there is a long-standing scientific concern with analyzing and interpreting intentional movement in both basic and applied research. Ecologists and biologists study animal movement patterns to understand behaviors such as habitat selection, migration, territoriality, foraging and mating, and also to understand responses to environmental changes. Human mobility researchers, spanning disciplines such as geography, anthropology, transportation, urban planning and public health, are concerned with how humans move through natural and built environments to conduct required and desired activities such as working, shopping, recreation and socializing, how to plan transportation and cities to facilitate mobility and accessibility, and the impacts of mobility on the environment, health, social capital and well-being.

For years, animal movement and human mobility researchers struggled with scarce data on movement behavior, relying on painstaking data collection (e.g., observational studies, mark-recapture, travel diaries) and/or aggregate data (e.g., seasonal distribution maps, origin-destination flows, intercept counting). This is changing due to stunning advances in location-aware technologies (LATs) for moving objects data (MOD) collection, such as global positioning system (GPS) data recorders, mobile phones, radiofrequency identification (RFID) chips, geotags, radiolocation devices, and georeferenced social media (Kays et al., 2015; Batty, 2012; Giannotti et al., 2011; González et al., 2008). These technologies facilitate the collection of massive individual-level mobility databases on animal and human movement patterns. For example, Figure 1 shows 546,502 GPS points for 55 individual turkey vultures (*Cathartes aura*). Individual tracks cover observation periods of 1 month to 11 years, ~2 years per bird on average, during Nov 2003–Dec 2016. The image includes individuals from both South and North American populations conducting seasonal migrations to and from Venezuela and the Northern Amazon Region (data can be accessed through Bildstein et al. 2016; more details about the dataset in Dodge et al. 2014). Figure 2 shows 2,678,893 GPS points for 536 humans (*Homo sapiens*) over individual one-week time periods in 2013, around Salt Lake City, Utah, USA (data provided by the authors). Complementing the growth of individual movement data is the increasing availability of contextual data about the movement environment via embedded and remote sensors, crowd-sourced observational networks and global reanalysis data (Heipke 2010; Stefanidis and Nittel 2004; Trenberth, Koike and Onogi 2008). A third converging and complementary trend is the rise of geosimulation techniques that can model large systems such as cities, ecosystems and societies at the level of the individual entities that comprise these systems (Benenson and Torrens, 2004).

Collecting and analyzing individual-level animal and human movement data has challenges. LATs have technical issues such as limited battery life, blocked signals and a need to operate continuously in sometimes harsh conditions, sometimes leading to data gaps. Data derived from georeferenced social media and location-based services (LBS) are unlikely to be representative of the larger population or the general behaviors of individuals (Miller and Goodchild 2015). Collecting animal movement data can involve trapping with potential risks to the individual. Both human and animals face locational privacy concerns. Movement data, combined with land use and other data, can reveal intimate details of human lives (Gkoulalas-Divanis and Bettini 2018). Animal location data create risks to species that have economic value to humans (Cooke et al. 2017). Data sharing can be blocked by these privacy concerns, but also the monetary and strategic value of these data (Lazer et al 2009). Despite these persistent challenges, it is not an exaggeration to declare that a data-driven scientific revolution is occurring animal and human movement behaviors and their relationships to other ecological and human dynamics.

The emergence of interdisciplinary scientific communities focusing on *moving objects data analytics* reflects the data-driven revolution in movement and mobility research (Demšar et al., 2015). However, while connections and collaborations are growing among researchers in the respective domains of animal movement and human mobility, linkages across the animal-human divide are not growing as strongly. This is understandable given the different nature of the moving entities in the two domains, and the different scientific and policy questions surrounding their movement at the individual and aggregate levels. However, we believe there is potential for a fundamental science of movement that spans this intentional behavior in both domains. There are potential commonalities in methods used by researchers in both domains for describing movement, and collecting, managing, analyzing, and visualizing moving objects data (see for example, Figure 1 and Figure 2, visualized using similar approaches). There are lessons to be learned by exchanging worldviews, theories and methods across the animal and human divide. The synergy that will be gained by converging animal and human movement science may advance research in both fields, and perhaps support a more holistic approach to understanding movement and other spatial dynamics that will erase the artificial boundary between animal and human worlds.

This paper discusses the background, opportunities and challenges underlying a convergent science of movement trajectory data. Although we do not intend to draw sharp boundaries around this field, we focus on entities such as animals and humans that move with intent across geographic space to perform activities. Movement by unintentional entities propelled by purely physical processes such as hurricanes or pollen is relevant; however, this is a subset of broader and more difficult problem of understanding entities that move with an internal drive to conduct activities. Similarly, although movement and kinetics in situations such as sports and dance are intentional, these are special activities that take us beyond the focus of movement as a part of daily life and as a means to arrive at geographic locations to perform activities.

Background

This section discusses the technological advances that are creating a revolution in animal movement ecology and human mobility science. It also describes the interdisciplinary research communities that have evolved separately within each domain. To illustrate the potential synergy from converging animal and human movement research, this section concludes by illustrating several transdisciplinary research questions that span both domains.

Advances in mobile objects data collection and management

A *mobile entity* is an individually identifiable thing in the real world that can change its geometry and/or location frequently with respect to time. In animal movement ecology and in human mobility science, changes in the location of mobile entities are often more important than changes in their geometry, therefore a mobile entity is often conceptualized as a point, although polygons can also be used if the entity has crucial space-occupying properties (e.g., cars on a highway). A *mobile object* is the representation of this entity using mathematical or computational means. A *trajectory* is a mathematical representation of the path of mobile object and is quantified as a time-ordered sequence of locations. *Mobile objects databases* are computerized record-keeping systems that allow integrated storage, updating and querying of mobile objects (Miller, 2008).

Location-aware technologies (LATs) are technologies that can frequently report their location in geographic space. LATs are generally associated with mobile entities: they include the global positioning system (GPS), radiolocation, telemetry, and dead-reckoning techniques coupled with computers and tablets on the desks and laps of humans, sensors transported by vehicles or attached to animals. New generation of multimodal sensors (e.g. smart watches, fitness trackers, GPS collars) equipped with accelerometers and gyroscopes provide auxiliary activity data of moving objects (Long et al., 2018). Geosensor networks are wirelessly communicating, sensor-enabled, small computing devices distributed in geography and connected as a network to enable in-situ monitoring of dynamic properties such as location change and movement (Duckham, 2012). Remote sensing devices include passive and active sensors carried on aircraft and satellites for environmental monitoring over local (urban/ecosystem patch), regional, and global scales using both passive (reflected light) and active (laser) methods (Pettorelli, Safi and Turner 2014). These sensors provide contextual information about the environment of mobile entities. Helping to manage all these data are geographic information systems (GIS), and mobile objects database systems (Miller, 2008): all have seen remarkable growth in their capabilities to handle MOD and data describing dynamic geographic phenomena. We can fuse these locational and environmental data with behavioral and physiological data from animal 'biologgers' (Rutz and Hays, 2009; Kays et al., 2015) and human 'lifeloggers' (Swan, 2012). The result is an explosion of data on moving entities that is outpacing the development of appropriate analytical methods.

Another source of MOD is simulation methods such as agent-based models (ABMs). ABMs can be used to generate trajectories of moving objects over space with respect to time by integrating known aggregate information (such as origin-destination flow totals, population counts, or coarse movement data) with assumed or empirically-derived goals and intentions for individual entities, and parameters for individual movement steps and interactions between objects. Simulated trajectory data is important for cases where tracking is limited or may be impossible (e.g. small or endangered species, large population flows, remote areas, and for data with gaps and signal loss). Application domains include crowd behavior (Torrens, 2014), travel demand (Zhong et al., 2015), habitat analysis (McLane et al., 2011), animal migration (Bennett and Tang, 2006, Bohrer et al., 2014) and foraging and other movement behaviors (Vincenot et al., 2015; Ahearn et al., 2017). These simulation methods can scale to large urban populations and beyond; an example is the TRANSIMS activity and travel simulation system that can model individual movements for the entire population of a large city such as Sydney, Australia (Huynh et al., 2015).

Emergence of interdisciplinary research communities

Human mobility—Scientific study of human mobility emerged in the 1950s with the application of computers and mathematical modeling to analyze traffic patterns in support of urban planning. Most of the early techniques involved undifferentiated flows among aggregated spatial zones using techniques such as regression analysis, spatial interaction modeling and network flow equilibrium. In the mid-twentieth century, time geography emerged as a conceptual framework and notation system for representing individual activities in space and time within human geography – well in advance of the existence of mobility data (Ellegård and Svedin 2012; Hägerstrand 1970). A behavioral turn in the 1970s used consumer choice models based on microeconomic theory and activity-based analysis based on time-use studies; these approaches require survey and diary data that was burdensome, expensive and time-consuming to collect (Lay 2005). The rise of LATs is revolutionizing the scientific study of human mobility by facilitating the acquisition and analysis of detailed movement data.

Two interrelated fields have emerged at the interface of Geographic Information Science (GIScience) and transportation science. *Computational movement analysis* (CMA) focuses on the development and application of techniques for collecting, managing, and analyzing MOD to better understand moving entities and related spatial dynamics (Gudmundssen et al., 2012). *Mobility science* also focuses on computational techniques for MOD, but with a stronger focus on transportation and cities. Mobility science leverages MOD to move beyond the aggregate and static transportation and urban models of the 20th century to individual-level models that recognize social differences in accessibility and the potential for human systems to exhibit emergent behavior. Applications include human activity and travel demand (Alexander et al., 2015; Toole et al., 2015), urban dynamics (Batty, 2012), potential exposures to environmental hazards (Su et al., 2015), formation and maintenance of social networks (Wang and Song, 2015) and other phenomena associated with humans' use of time, space and technologies associated with movement.

Animal movement—A rapidly growing subfield of ecology, *animal movement ecology* focuses on understanding the "causes, mechanisms, and spatiotemporal patterns of (organismal) movement and their role in various ecological and evolutionary processes" (Nathan et al. 2008: 19052). Ecology is fundamentally spatial, and movement connects these processes operating across heterogeneous landscapes and from the scale of an individual to population (Cagnacci et. al. 2010).

Traditional animal-movement studies dating back to the 1950s were focused on better understanding where animals go and how they use resources in order to improve management strategies. This was typically done by estimating an animal's 'home range', defined by Burt (1943: 351) as "that area traversed by the individual in its normal activities of food gathering, mating, and caring for young". The home range methods are continuously evolving and have been superseded by statistical modelling of space use, geostatistics, and spatially explicit mechanistic models (e.g., Kie et al. 2010, Börger et al. 2008). Nonetheless, the home range concept and methods used to estimate one are still controversial 75 years later, and this disconnect between a better conceptual understanding of what a home range is and the rapid technological advancements in data and algorithms used to measure it provides a good example of putting the "technological cart before the conceptual horse" (Powell and Mitchell 2012: 948).

More contemporary animal movement studies quantify movement patterns (see Turchin, 1998) to make inferences about likely behaviors. The movement ecology paradigm views animal movement phenomena as interactions between internal (e.g. intention, readiness to move, motivation) and external factors (e.g. environment, other individuals), movement and navigation capacities (e.g. speed, modality), generating the observed movement path (Nathan et al 2008). Movement parameters describing these interactions can be compared to determine whether statistically different characteristics are suggestive of different behaviors or processes (e.g., foraging, navigation, environmental preferences). Movement models such as random walks are used as null models to compare real movement parameters (e.g. step length, turn angle, net displacement) for animals as diverse as bottlenose dolphins (Bailey & Thompson, 2006), caribou (Bergman et al., 2000), geckos (Gruber and Henle, 2004), caterpillars (Wallin, 1991), cows (Laube & Purves, 2011), tigers (Ahearn et al., 2017), and butterflies (Root and Kareiva, 1984). Any discrepancies between the null and real movement parameters can help infer the interactions between an organism and its environment that influence the movement process (Miller, 2012; Schick et al., 2008).

Trans-disciplinary questions

While there has been limited collaboration between animal movement ecologists and human mobility researchers, there is evidence of parallel play: researchers in these disparate fields addressing similar research questions in their respective domains. To illustrate the potential synergy from converging animal movement and human mobility research, this section discusses four research questions that have received attention in both fields. These are: i) measuring and interpreting interactions among mobile entities; ii) analyzing movement in geographic context; iii) integrating mobility and sensor data; and, iv) visualizing movement. These questions are not exhaustive; rather, they are illustrative of the difficult but common questions facing both domains.

Measuring and interpreting interactions among mobile entities—The most basic unit for studying interactions is a pair of locations for two individuals (a dyad), but more complex units such as networks can be used as well. While interactions can be considered an extension of movement, the social and psychological explanations and implications of interactions are not as easily discerned or generalized as first order movement properties. For example, what kind of interactions exist among the multiple vultures following similar migration track from North to South America (Figure 1) or among commuters moving toward downtown Salt Lake City (Figure 2)? Do interactions facilitate a more efficient movement: with vulture – help find thermals that other bird detected; for humans – help avoid traffic congestion using crowd-sourced traffic information? Do moving individuals prefer to swarm to the same movement paths or prefer larger space between individuals? Is the timing of the movement (time in the morning for Figure 2, or a particular day in Spring in Figure 1 that an individual starts its movement trajectory) affected by the timing and density of the movements of other individuals?

Movement ecology defines interactions as “actions directed towards, or affecting, the behavior of another animal” (Whitehead, 2009:765). However, measuring interactions between animals is not straightforward, and depending on the objective of the study, what is considered an “interaction” can range from physical contact to sharing common resources, to proximity, or simply being aware of each other. In human mobility science, interactions among moving humans are crucial for understanding a diverse range of phenomena beyond transportation and traffic; these include the dynamic nature of spatial segregation (Palmer et al., 2013), spatial interaction through social media networks (Sui and Goodchild, 2011; Liu et al., 2014), and the spread of infectious disease (Bian et al., 2012; Jacquez et al., 2005).

Measuring interactions among moving entities is difficult in both animal and human domains. A common approach is demarcating locations in space and time where interactions could potentially occur. It is straightforward to calculate intersections among individual activity spaces from MOD, indicating where and when social interaction and joint activity participation could have occurred (Farber et al., 2013; Fieberg and Kochenny 2005; Miller 2005; Neutens et al., 2008, 2013). Interactions can also be inferred by measuring the frequency at which multiple individuals are spatially and temporally proximal to each other (i.e. co-location of moving points); these are often termed encounter rates, contact rates (in context of disease spread) and associations in animal movement ecology (Cooper et al., 2008; Ramos-Fernández et al., 2009; Haddadi et al., 2011; Strandburg-Peshkin et al., 2015, Crofoot et al 2008). This quantification is dependent upon subjective decisions with respect to appropriate spatial and temporal thresholds as well as technical limitations of available resolutions and is especially challenging when fine-resolution tracking data are not available due to the uncertainty of observed trajectories.

Recent contributions to study movement interactions have focused primarily on technological advancements related to measuring interactions. One of the most basic methods to measure interaction empirically involves counting paired observations that occurred within a pre-defined spatial and temporal threshold, and comparing this to a null expectation. A recent technological advancement employs proximity loggers that are attached to animals to automate this process. A fix is recorded when a similarly outfitted animal comes within the specified spatial and temporal distances, however, proximity loggers are limited to relatively short distances and do not automatically include location information (see Drewe et al., 2010; Cross et al., 2012 for overview). Bluetooth sensors embedded in mobile phones have potential for inferring human proximity and interaction (Do and Gatica-Perez, 2011; 2013; Matic et al., 2012), although WiFi-based methods have better scalability (Sapiezynsk et al. 2017). However, while these new technologies enable collection of more and higher quality data, there has not been concurrent methodological advancements for improving the ability to characterize, detect, visualize, analyze and understand interactions. Many interaction metrics were developed when MOD had coarser spatial and temporal resolution; the assumptions underlying these metrics are inadequate for the new types of multidimensional MOD now available. In addition, few studies have tested a range of interaction metrics using the same data; when they have been compared, the results are inconsistent (Long et al., 2014; Miller, 2012; 2015). Conclusions about interactions among moving entities are problematic without a better understanding of what interaction metrics are measuring and how they should be interpreted.

Analyzing movement in geographic context—Traditionally, animal movement ecologists place a greater emphasis on geographic context such as habitats and land cover, but these data are typically coarse-scale and static (see Figure 1). Human mobility researchers tend to represent geography using abstract space (focusing on trajectory geometry) or networks (focusing on network routes and flows (see Figure 2), with the latter traditionally involving more detailed representation of transportation infrastructure than the movement within the infrastructure. These differences result from the respective intellectual histories of the two fields. This is changing as high-resolution, detailed geographic data are increasingly available for natural and built environments (Dodge et al., 2016)

Seidel et al. (2018) review recent contributions to path and space-use metrics, including those that incorporate environmental context explicitly (e.g., step selection function). Movement models that include environmental context are effective in determining the drivers of movement behavior and the parameters that describe it, and in shaping path choices (Dodge et al., 2014; Ahearn et al., 2017, Bartlam-Brooks et al 2013, Bohrer et al 2014). For example using a subset of the vultures in Figure 1, Bohrer et al (2012) showed that the vultures prefer to move in locations where thermal uplift is strong. And, with the same dataset, Dodge et al (2014) showed that the extent of movement within the nesting home range (northern edges of the migration tracks) is affected by vegetation greenness and seasonal temperature. In human mobility studies, geographic context has traditionally received less attention than behavioral states or social, and/or demographic factors, although this is changing with newly available data (see, e.g., Brum-Bastos, Long and Demšar 2018; Horanont et al. 2013; Siła-Nowicka et al. 2016). Despite this increasing interest in understanding the geographic context of movement, there has been surprisingly little cross-over between animal movement ecology and human mobility science.

The wealth of MOD provided by LATs comes with a significant cost, namely, the lack of *path semantics* or the motivations and activities associated with the mobility behavior. Consequently, most methods for analyzing MOD focus on the morphology of an entity's trajectory in space with respect to time. For example, a major focus of attention in MOD analytics is *path similarity* or the degree of correspondence between two space-time paths. These methods include *shape-based similarity measures* (such as Euclidean and Hausdorff distances) that focus only on the geometry and *sequence-based methods*, such as sequence alignment (Kwan, Xiao, and Ding 2014; Shoval and Issacson 2007), Fréchet distances and edit-distance functions (Yuan and Raubal, 2014) that exploit sequence and time in the trajectory. Other methods for analyzing collections of space-time paths include *path clustering methods* and *spatial field methods* (Long and Nelson, 2013). Time-geographic approaches have also been used to compare activity spaces of different groups of people and study social context in human mobility (Kwan and Lee, 2004; Kwan et al. 2019; Tribby et al. 2017). Geographic context is frequently ignored, but this can help researchers infer among different behaviors that are consistent with the same mobility behavior, such as whether apparently coordinated movement is coincidental or indicative of a shared activity. For example, most vultures take very similar paths through eastern Central America (Figure 1), but that is probably an outcome of the narrow geography of the region, as vultures cannot fly effectively over water. Similarly, many of the identical paths taken by humans in Salt Lake City (Figure 2) are driven by the structure of the road network and not by social interactions.

Merging movement data with geographic context is often referred to as *track annotation*, (Mandel et al 2011) a term that originates in web-browsing, where environmental variables are used to add attributes to the path. Tools that can handle such merging of movement and geographical context are emerging. Recently, Google announced the development of Earth Engine (https://earthengine.google.org/#intro), "a planetary-scale platform for environmental data and analysis", which could become a common platform for contextual movement analysis. Other, domain-specific tools have also recently become available, for example the Environmental-Data Track Annotation (Env-DATA) system in the on-line animal-movement database "movebank" (www.movebank.org), dedicated to geographic annotation of animal movement data (Dodge et al., 2013, and see a recent example for application of the system: Halworth & Marra, 2015).

While trajectory annotation techniques are valuable, there is a paucity of analytical methods that can exploit annotated tracks. A vital research frontier involves developing mobility analytical techniques and movement models that go beyond the movement pattern devoid of geographic context to multi-dimensional models that includes what other things were in the place where the movement occurred. Such context-aware models will enable research on investigating the influence of a changing environment on the behavior of moving individuals (Dodge, 2016).

Integrating mobility and sensor data—LATs can be bundled with other low cost sensors that can concurrently measure physiological states, such as the individual's activity level, heart rate, stress, body temperature, and environmental states, such as ambient temperature, humidity, light, noise and proximity to other individuals with devices. Some devices, such as smartphones and critter-cams, also have cameras and activity logs. These data can be fused with mobility data to better understand the physiological and environmental context of movement.

In movement ecology, researchers combine accelerometer and tracking data to infer the behavioral modes of animals, such as foraging, feeding, aggression and active versus passive flight, and to calculate energy expenditures by animals (Nathan et al. 2012; Shamoun-Baranes et al. 2012; Shepard et al. 2008). In human mobility analysis, fused GPS and accelerometer data can help to infer the transportation modes used by individuals (e.g., walk, bike, drive, bus, light rail) and estimate energy expenditures from active transportation, such as walking and biking (Brown et al. 2016; Brown et al. 2015; Duncan et al. 2016; Lee and Kwan 2018; Miller et al. 2015). Body temperature data can help explain diurnal activity patterns in animals, such as sharks (Papastamatiou et al. 2015), and physiological indicators of stress can help identify 'landscapes of fear' experienced by animals from interactions with predators or proximity to humans (Støen et al. 2015). The diverse set of sensors and activity loggers available in smartphones can capture behavioral features describing movement and physical activity, face-to-face and mediated social interactions, and daily activities such as vacuuming and taking out the trash, health-related symptoms, such as coughing and sleeping patterns (Harari et al. 2016; Harari et al. 2017).

While fused location and sensor data are promising, there are challenges that cross-cut animal and human research. Major research challenges include determining the psychometric and behavioral validity and reliability of sensor data, inferring more complex behaviors (e.g., grooming among animals; business meetings among humans) and understanding the relationships between sensed behaviors and consequential life outcomes such as survival, health and social status (Harari et al. 2016). Another challenge is that some sensors, especially those bundled with smartphones, are consumer-grade rather than carefully calibrated scientific instruments, leading to potential data quality issues (Ganti, Ye and Lei 2011). Finally, the integration of mobility data with seemingly innocuous sensor data can lead to ethical challenges since biometric, environmental and other contextual data can reveal personal information beyond only location and time (Christin et al. 2011). Although privacy concerns may seem more apparent for humans than animals, as noted above these data can expose animals to adverse interactions with humans. Also, attaching the devices is invasive and stressful to animals, and their presence may affect the behavior being monitored and perhaps the survival of the animal (Cooke et al. 2017; Wilson et al. 2015).

Visualizing movement—Visualization can support all stages of movement trajectory data management and analysis, including data exploration, data cleaning and preprocessing, querying, analysis and communication of results. Visualization is especially important in a transdisciplinary science of movement as it provides a common visual language to facilitate data exploration, uncover hidden patterns in data, disseminate knowledge, and even formulate hypothesis through visual exploration of movement patterns (Dodge, 2016). Common visualization approaches for representing trajectory data include point and line density maps (Willems et al., 2009), aggregated maps (Andrienko and Andrienko, 2008), flow maps (Wood, Slingsby, and Dykes, 2011; Guo and Zhu, 2014), and 3D space-time representations (Demšar et al, 2014; Kveladze, Kraak and Van Elzakker 2015).

Movement data is inherently complex due to the intricacies and multidimensionality of movement in time and space, the heterogeneity and diversity of moving objects, events, processes and contexts associated with movement, and the wide variety of spatial, temporal and spatio-temporal properties and relations inherent in these data. Consequently, transforming movement trajectory data into a small set of effective visual channels is challenging. *Visual analytics of movement* refer to technologies, processes and knowledge that allow humans and computers to cooperate in analysis, problem-solving and decision-making with complex movement trajectory data (Andrienko et al. 2013). There are a large number of movement data visual analytical techniques emerging; these can be conceptualized and organized in different ways. For example, Andrienko et al. (2013) arrange their discussion into techniques that focus on the moving objects and their context, spatial events associated with movement, the places visited by the objects, and the times when movement occurred. In contrast, Andrienko and Andrienko (2013) categorize techniques based on whether they examine movement trajectories as a whole, look within the trajectories for variations in movement properties, summarize multiple trajectories, or visualize trajectories within context. Chen, Guo and Wang (2015) organize their discussion based the movement data properties being visualized, namely, spatial, temporal, spatio-temporal, and whether these properties are combined with other object attributes.

Techniques for visual analytics of movement data can crossover between the human and animal domains since tasks, such as pattern discovery, clustering, summarization and generalization, are required in both. Major differences between techniques in the domains concern the types of decisions supported and the role of context in the visualization process. Visual analytics for human mobility data go beyond exploration and analysis to also support modeling forecasting, planning and situational awareness for operational management of transportation, cities and other socio-technical systems (Andrienko et al. 2017; Chen, Guo and Wang 2015). Visualizing movement within its geographic context is important in both human and animal domains, although human movement is typically more constrained by infrastructure than animal movement, meaning that the infrastructure itself can serve as a basis for visualization (Andrienko et al. 2017; Xavier and Dodge 2014). A challenge facing researchers in both human and animal domains is balancing the need for sophisticated and powerful techniques for analyzing complex movement trajectory data with user-friendliness for domain scientists and decision-makers (Pack 2010; Slingsby and van Loon 2016).

Towards an integrated science of movement: Research challenges

The wealth of movement data generated by LATs, managed by MODs and leveraged with ancillary georeferenced data is not only revolutionizing animal movement ecology and human mobility science but also creating potential synergies between these communities. As noted above, both communities are undergoing a similar transition from a data-poor to a data-rich research environment. At the same time, this also involves a transition from thick data (i.e., highly attributed via painstaking but rich observational or survey methods) to thin data (i.e., sparingly attributed, often containing only the entity type and its movement trace). This convergence on similar opportunities and challenges creates the possibility for cross-fertilization and integration of concepts and methods.

New insights derived from the unprecedented analysis of large collections of human trajectories have revealed mobility features that have parallels in animal movement. The central paradigm of animal movement ecology - how resource variability across landscapes interact with internal drivers and movement and navigation capacities to affect the performance of individuals and population-level demography – is equally applicable to the study of humans (Meekan et al. 2017). For example, the density of places of employment is likely an important factor in the daily movement from the outskirts to the center of Salt Lake City (Figure 2), or seasonal changes in prey density that drive large-distance migrations (Figure 1). At the same time, data-driven approaches that have “fast-tracked” human mobility science, such as the identification of emergent movement properties, activity space analysis, analysis of networks of movement and behavior, and the development and application of machine learning, advanced visualization and other exploratory techniques, can inform animal movement ecology (Thums et al. 2018).

This section explores the possibility of a transdisciplinary science of movement that encompasses both humans and animals. We identify several cross-cutting research challenges that should be resolved to advance scientific understanding in both domains and the integration of these fields into a unified research community.

Different approaches to the same problem

Animal movement ecologists tend to follow a bottom-up approach known as *step selection functions* (SSFs): they analyze the animal’s selection of step length and direction at the microscale, inferring the animal’s activities from the movement Thurfjell, Ciuti and Boyce 2014). Conversely, human mobility researchers tend to follow a top-down approach that starts with the activities that a human needs or wants to conduct, and models the mobility needed to fulfill the activity schedule (Miller 2014). The source of this schism is likely the different approaches used to understand movement in the two domains. With animal movement, a bottom-up, inductive approach evolved because it is difficult to know why an animal took a particular step. Consequently, SSFs associate movement with habitat and environmental factors. With people, a top-down, deductive approach evolved since investigators could ask why movement occurred. However, this is not as feasible with big data. We believe there is value in both approaches; a key research frontier is integrating these approaches into a common conceptual framework.

The challenge of big but thin data

Both animal movement and human mobility researchers are facing the same challenge regarding data. In both domains, data was historically scarce but richly attributed. New location-aware technologies are generating data that is plentiful but thinly attributed. In both domains, these new data sources favor phenomenological (observed pattern summary and reproduction) descriptions over mechanistic (process models rooted in first principles) descriptions. How do we derive explanatory models from data that favors correlation over causality?

The role of quasi and natural experiments

In both animal and human domains, location-aware technologies, sensors and other technologies increasingly allow ongoing, persistent observation of movement patterns. Persistent observation allows the possibilities of natural and quasi experimental designs in anticipation (prospective) or response (retrospective) to real-world changes or events. These approaches can reconcile some of the issues with big but thin data since experimental designs allow stronger causality claims.

Focus: Individual or collective?

For both human and animal movement, there are questions surrounding the research focus. Do we care more about characterizing individual movement to a high degree, or collective patterns? To what extent are movement patterns of individuals representative of collective patterns and vice versa? Theoretically, both fields are concerned with individuals as a basic unit. However, from a pragmatic perspective, understanding collective movement patterns is often easier since it is simpler to separate general trends and tendencies from idiosyncratic or episodic behaviors. Furthermore, collective movement has bigger impacts on broader systems, such as ecosystems, populations, and cities.

Different scales of movement

Animal-movement ecologists and human-mobility analysts focus on different scales of both collective and individual movement and tend to use different point of view for the analysis. Animal movement ecologists tend to focus on collective behaviors, such as flocking and schooling using a Lagrangian point of view, focusing on the movement of the dynamic collective object (e.g., Couzin et al 2002), while human mobility analysts tend to treat collective movement at broader scales, such as traffic patterns and origin-destination flows, and represent these using an Eulerian, fixed-frame point of view that focus on locations of interest, where collective movement may occur. In movement ecology, movement is typically modeled through step-selection functions or random walks with an emphasis on local movement choices of individuals and the characteristic of proximate space. In human mobility, movement is often modeled as global patterns and origin-destination flow. New multi-scale approaches emerging from the intersection of these models may benefit both areas to study movement across scales. Can we make movement analytics techniques that work across scales? Can we combine Eulerian and Lagrangian frameworks? To what extent goal-oriented movement can be inferred from local movement patterns?

Prediction of movement

Prediction is a common research interest in both movement ecology and human mobility domains. Movement prediction is essential to inform the mechanisms that underpin movement (Dodge 2016; Birkin et al., 2018). In mobility it is important to predict patterns of movement flows at aggregate levels such as migration flows between countries and traffic flows in urban areas. Here the emphasis is less on individual trajectories and rather on aggregate movement patterns. Similarly, animal ecologists are also interested in the prediction of aggregate movement patterns (e.g. predictions of home ranges, migration corridors, and migration times). However, in some ecological applications the fine-detail predictive models at individual levels are also important to generate insight into behavioral differences and responses of individuals to their changing environment. Nevertheless, the general question is how to predict trajectories or collective movement patterns in space and time across spatial and temporal scales.

Validation and calibration of methods

Access to tracking data provide a new opportunity to calibrate and parametrize models using knowledge constructed from actual observations, for example how does scale affect calculation of movement parameters (Laube and Purves 2011)? Future research should leverage data to advance methodologies in movement science through a combination of theory-driven models and data-driven analytics.

Do we need a grand theory of movement?

An encompassing theory is an obvious goal of a scientific field. However, it is unclear whether a grand theory of movement is currently possible. Some animal ecologists contend there are too many species for a grand theory; some human mobility researchers contend there are too many types of travel for an overall theory. A crucial question is the possibility and utility of a grand theory of movement and whether this is necessary for a new interdisciplinary science of movement.

Relationships to grand scientific challenges

To establish the importance of the new interdisciplinary science, we must articulate the contributions to movement science to grand societal challenges such as environmental change, sustainability, resilience and social equity.

Conclusion

Due to its fundamental role in the dynamics of life at scales from the individual to ecosystems, there is long-standing scientific interest in animal and human movement behavior and patterns. In the past, collecting, managing and analysis data on moving objects was onerous, leading to small (but thick) individual-level datasets or aggregate measures. Concepts and methods in the animal movement and human mobility domains developed independently due to the nature of the entities being studied, leading to distinct emphases in both fields. Location-aware and geospatial technologies have shattered these limitations, leading to parallel revolutions in the animal movement ecology and human mobility science, including the development of interdisciplinary research communities. While scientific frontiers are advancing in both domains, there has been minimal cross-fertilization across the animal and human divide. In a classic example of parallel-play, both fields are converging on the use of big but thin data derived from low-cost sensors but maintain distinct worldviews. We argue there are potential synergies to be gained from a transdisciplinary science of intentional movement with respect to geographic space. Breaking down the conceptual walls between animal movement ecology and human mobility science requires deliberate effort: history matters, even in science. This paper is a step in the direction of an integrated science of movement trajectories.

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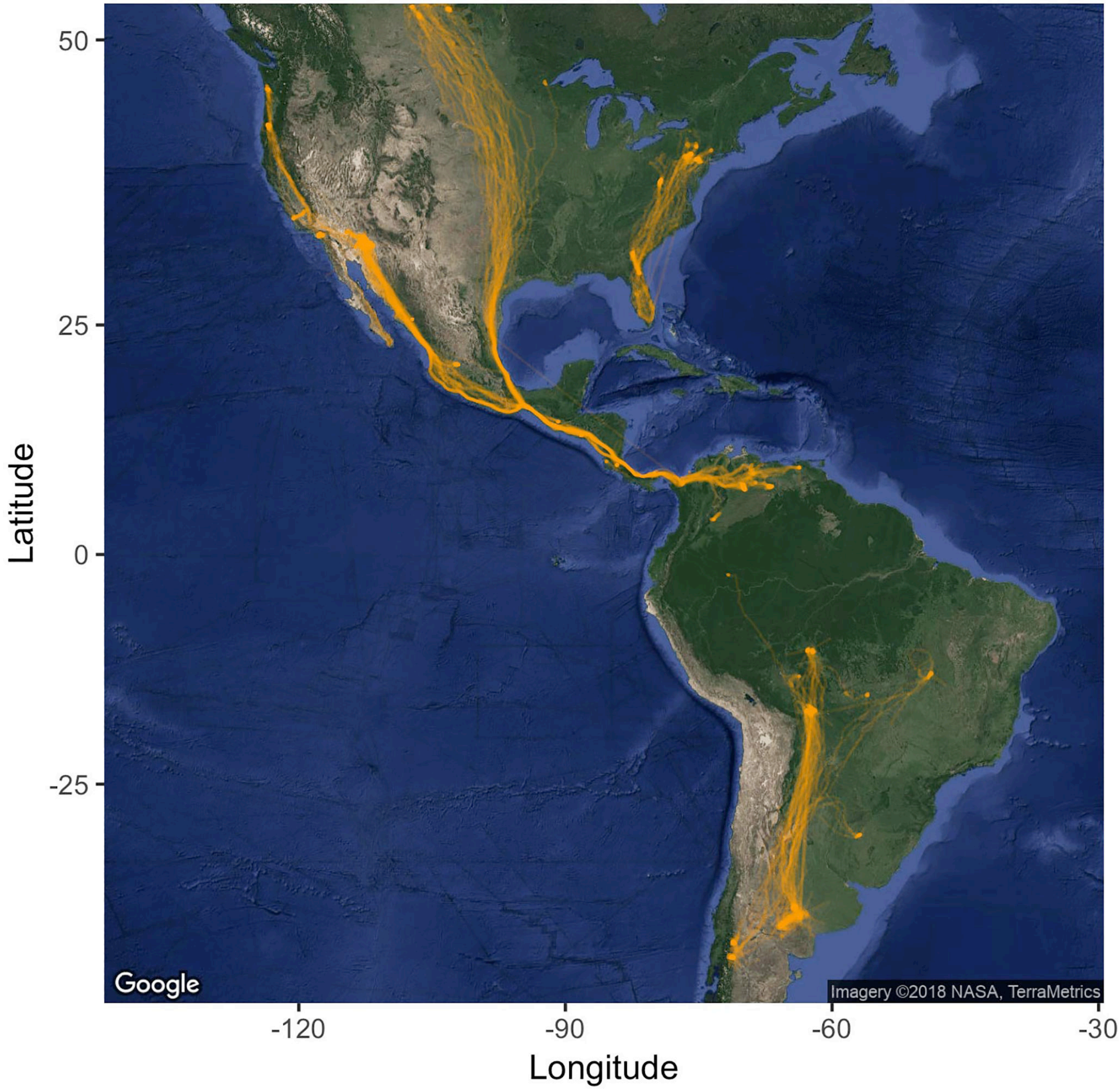

Figure 1.
546,502 GPS points for 55 individual turkey vultures (Cathartes aura) from 2003 to 2016. (Source: Bildstein et al. 2016)

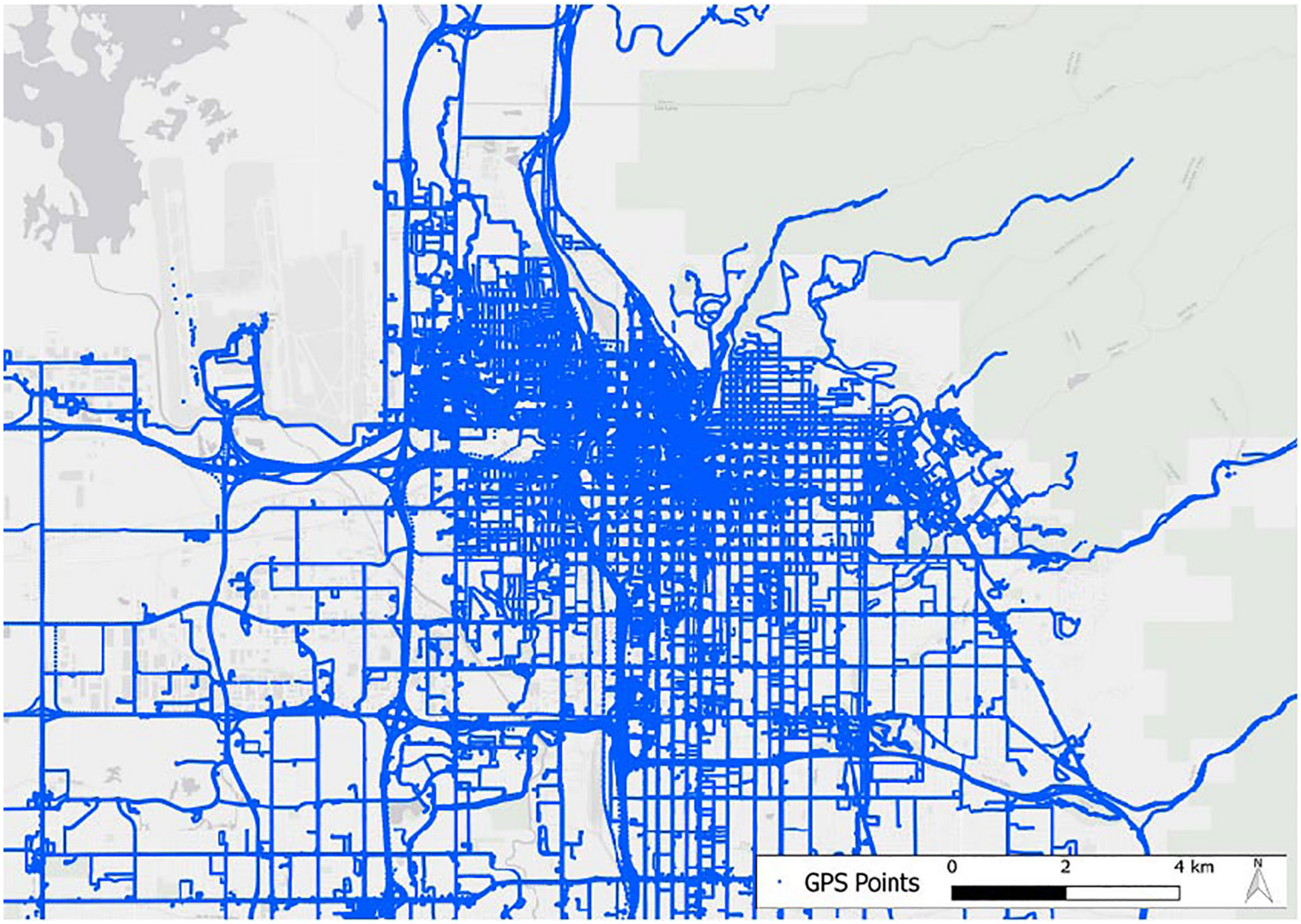

Figure 2.
2,678,893 GPS points for 536 humans (Homo sapiens) over individual one-week time periods in 2013.
(Source: authors)