A Non-Parametric Analysis of Inter-Individual Relations Using an Attention-Based Neural Network

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Abstract

In the past decade, social network analysis was widely adopted in animal studies and enabled us to reveal global characteristic patterns of animal social systems from pairwise inter-individual relations. While animal social networks are typicaly drawn based on geological proximity and/or frequency of social behaviors (e.g. grooming), the appropriate choice of the distance/closeness metric is not necessarily clear especially when prior knowledge about the spices/data is limited. In this study, we explore a non-parametric analysis of inter-individual relations using a neural network with the attention mechanism that plays a central role in natural language processing today. The high interpretability of the attention mechanism and the flexibility of the entire neural network allow automatic detection of inter-individual relations included in raw data. As case studies, we analyze three-dimensional location data collected from simulated agents and real Japanese macaques.

1 Introduction

Understanding characteristics of animal social groups is a major objective of animal ecology. Complex social systems of eusocial insects and non-human primates are often viewed as biological models of human societies or their precursors, and thus, have also attracted the interest of social scientists. In the past decade, social network analysis was widely adopted in animal studies and enabled us to reveal global characteristic patterns of animal social systems from pairwise inter-individual relations (Krause et al., 2015).

Applications of social network analysis to animal studies prerequisite an appropriate metric for the relational distance/closeness between individual agents. Popular options of the metric include geological proximity (often thresholded and converted to counts of co-appearance within the threshold; Silk et al., 2006b,a; Croft et al., 2008; Clark, 2011; Boyland et al., 2013; Castles et al., 2014; Krause et al., 2015; Schofield et al., 2019) and frequency of social behaviors (e.g., grooming of non-human primates; Chepko-Sade et al., 1989; Silk et al., 2006b,a; Croft et al., 2008; Clark, 2011; King et al., 2011b,a; Castles et al., 2014; Krause et al., 2015). However, the appropriate choice of the metric is not necessarily clear especially when prior knowledge about the spices/data is limited (cf. Castles et al., 2014; Farine and Whitehead, 2015). For example, location information for measuring proximity is available from a wide variety of animals—including ones whose social activities are not yet well-known—and also became more reliable and scalable thanks to the recent developments in bio-logging technology (Heupel et al., 2006; Rutz and Hays, 2009; Rutz et al., 2012; Fehlmann and King, 2016; King et al., 2018; Dore et al., 2020). However, naively measuring the Euclidean

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distance between individuals is not necessarily reasonable because many animals do not fly or dive and thus the vertical and horizontal divergences would not have the same importance in social network analysis. Even horizontal distance could have different social meanings if animal agents are intervened by trees and other objects. Hence, it is ideal to have a non-parametric, end-to-end analyzer of inter-individual relations that runs on raw data.

The present study explores a non-parametric analysis of inter-individual relations using a neural network. Specifically, we exploit an interpretable module called *attention mechanism* as well as the flexibility of the entire neural network that fits to various types of data. The attention mechanism was originally invented for machine translation to represent relations between words in the source and target languages (Figure 1a Bahdanau et al., 2015). More recently, the attention mechanism began to be used to represent word relations within input sentences (self-attention, Figure 1b) and is considered central technology in today's natural language processing (NLP) in general (Vaswani et al., 2017; Devlin et al., 2018). Our study applies this technology to three-dimensional (3D) location data collected from Japanese macaques (*Macaca fuscata*) to reveal their latent relations reflected in the data (Figure 1c) without prior assumptions about possible types of relation structures or noise distributions. We also validate our approach by analyzing simulated data and recovering the latent relations among the virtual agents generating the data. It is to be noted that possible applications of our relation analysis are not limited to location data thanks to the flexibility of the neural network.

Our model organism, Japanese macaques, exhibits rich affiliative and aggressive social behaviors and has been studied extensively over more than fifty years for better understanding of the evolution of social systems in primate lineages including human (Nakagawa et al., 2010). This accumulated knowledge of the species is helpful to interpret/evaluate the results of our novel analysis while the method is not limited to the species or other primates and could even be more valuable for animals that do not show intrepretable social activities.

2 Materials & Methods

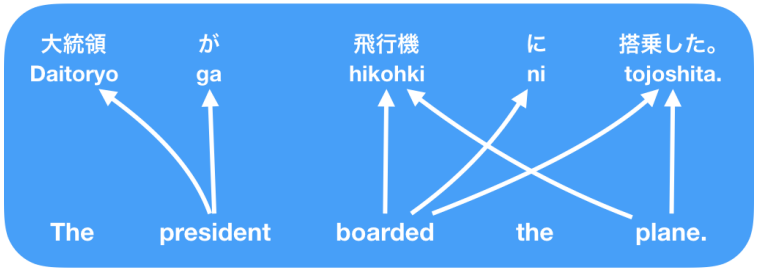
2.1 Overview of the Neural Network

The framework of our relation analysis is to (i) train a neural network that predicts the 3D location of each individual macaque—simulated or real—from that of the other individuals, and then (ii) check how much attention the network pays to each of the referent individuals when it makes the predictions. For simplicity, the network only receives the location data at a single time point and does not analyze temporal changes in the location data, although the temporal information could include important traits of individuals and groups (cf. Morita et al., 2020) and thus should be discussed in future studies.

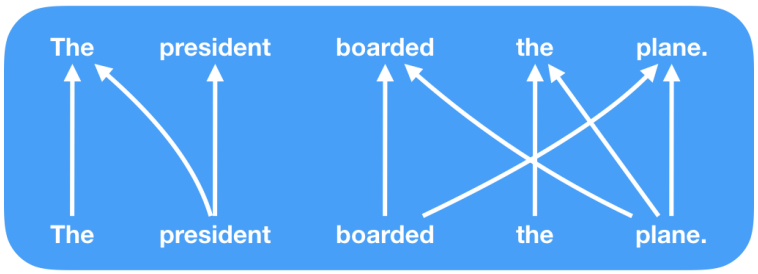
Figure 2 sketches the network structure, abstracting away from fine details (see the supporting information S1 for the full structure of the network). The location of an individual named A is predicted from that of four other individuals, B, C, D, and E. The prediction is made from the weighted sum of (transformed) location information of the four referents, where the weight of each referent—called *attention weight*—is also derived from the location information of the referents. The attention weights govern the information flow from the referents, and thus, intuitively represent *who is contributing how much to the prediction*. Our analysis of relations, between the target and the referents, is performed on these attention weights.

The attention weights are normalized and always sum to 1. This formalization has one disadvantage that the model never detects independence of the target individual, as at least one referent always has a non-zero weight. Accordingly, we compared the predictive performance of the attention model with a baseline model that predicts the target without reference to the other individuals; If the attention weights are redundant, the attention model will have the same level of predictive performance as the no-referent baseline. The baseline model was trained to maximize the likelihood.[1]

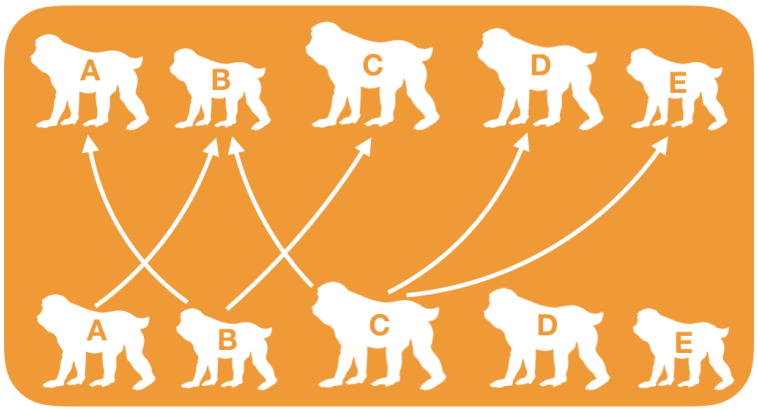
[1] As reported in §2.2, the location of the target individual was discretized, which often improves the performance of neural networks (van den Oord et al., 2016a,b). Hence, the maximum likelihood training of the baseline model was simple: We just counted the occurrences of each discretized location value, and normalized the counts.



(a) Machine Translation



(b) Self-Attention



(c) Inter-Individual Relations

Figure 1: History of the use of the attention mechanism. (a) The original use in machine translation, relating words in the source language (English) to ones in the target language (Japanese). (b) More recent application in NLP that represent relations between words within the input sentences. (c) Application to inter-individual relations investigated in this study.

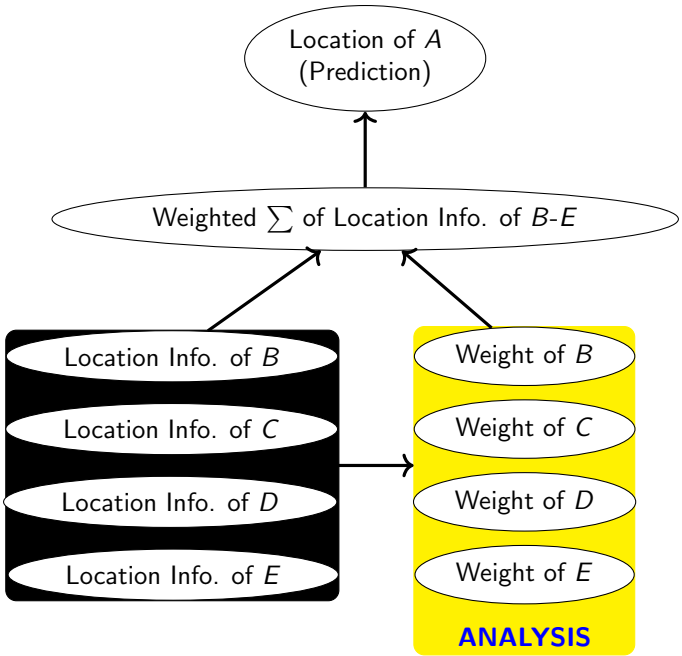


Figure 2: Schematic of the attention-based analysis.

2.2 Data

We performed the attention-based relation analysis on two simulated data (§2.2.1) and one real data (§2.2.2).

2.2.1 Simulated Data

We tested the reliability of our attention-based relation analysis on two types of simulated data. Following the real data collected from Japanese macaques (see §2.2.2), both the simulations had five individuals located in a bounded 3D space ($[0.0, 5.0] \times [0.0, 4.0] \times [0.0, 2.5]$), resembling the group cage where the macaques were kept.

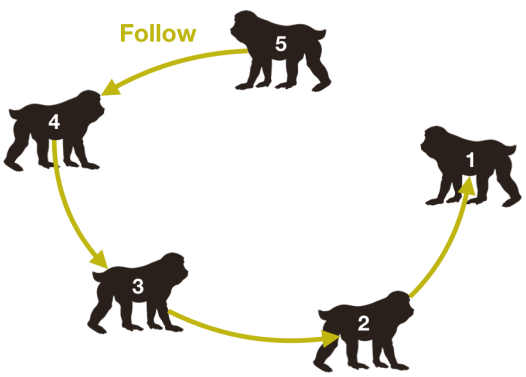
The first simulation modeled the situation where the five agents moved in a sequence, each following another (Figure 3a). We simulated this by sampling the 3D location of each individual from the neighborhood of its predecessor: (i) the first individual was located uniformly randomly in the domain, and (ii) the $i+1$-th individual was located uniformly randomly in the intersection of the domain and the sphere with 1.5 radius centered at the i-th individual's location, which was implemented by the rejection sampling (Figure 3c).

The second simulation modeled the hub and spoke relation in which a single, hub individual was followed by the other four spoke dependents (Figure 3b). We simulated this situation by (i) first sampling the location of the hub individual uniformly from the domain, and (ii) sampling the location of the spoke individuals uniformly from the intersection of the domain and the sphere with 1.5 radius centered at the hub individual's location.

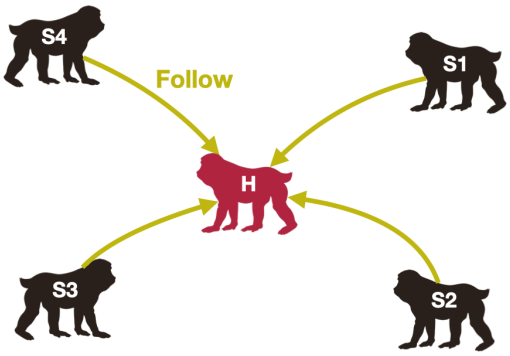
We generated 100,000 samples—each containing 3D coordinates of the five individuals—for each of the two simulations.[2] All the samples were used for the training and the attention analysis after the training; That is, we did not held out a test portion of the data, as our purpose here is not to test the general applicability of the model predictions, but rather to reveal the dependency relations in the data (just as in the linear regression tests).

Note that in both cases, the only information available to the neural network analyzer was those location samples. In other words, the settings of the simulations—including the type of the interindividual relations and the form of the conditional distributions—were not hard-coded in the analyzer, unlike more classical

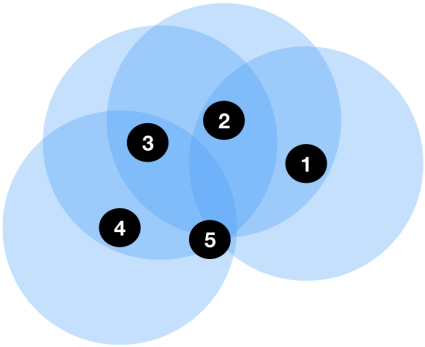
[2]Since we analyzed all the possible partitions of the five individuals into one target and four referents, the number of different target-referents pairs observed by the neural network was $5 \times 100,000 = 500,000$.



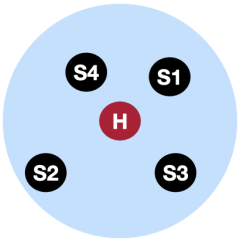
(a) Serial followers



(b) Spoke followers



(c) Serial followers



(d) Spoke followers

Figure 3: Two patterns of simulated data. (a) and (c) model animal agents that move in a sequence. (b) and (d) model the situation where there is a single, hub individual (red) that is followed by the other four spoke dependents (black). (a) and (b) depict the relations among the animal agents modeled in the simulations. (c) and (d) describe the distributions from which the location data are sampled: The blue circles represent the support of the uniform distribution centered at each followee individual.

analyses assuming a limited hypothesis space including the correct generative model (e.g., Bayesian inference). For example, when analyzing the data from the second simulation, the network had to (i) discover the hub structure behind the data, among many other possible relation patterns, and (ii) identify the hub individual, while all the five agents were always close to one another.

While the simulated data took on continuous values (residing in the bounded subspace of the 3D Euclidean), it has been reported that neural networks are often better at predictions of discrete categories (due to the flexibility of categorical distributions; van den Oord et al., 2016a,b, similar discrete predictions of location data were also adopted by Takeda and Komatani, 2016). Accordingly, we split the domain into 400 cubes ($0.5 \times 0.5 \times 0.5$), and the network was trained to make a discrete prediction of the cube containing the target's location.

2.2.2 Real Data

In addition to the simulated data described in §2.2.1, we analyzed real 3D location data of five captive Japanese macaques in the Primate Research Institute, Kyoto University (KUPRI), Japan. The subjects were two adult males and three adult females. The location recordings of the five macaques were conducted for two weeks in an outdoor group cage ($4 \times 5 \times 2.5$ m), where the subjects were allowed to freely move and interact with one another. Each subject carried two Bluetooth® Low Energy beacons, and their 3D location was estimated from signals from these beacons (Quuppa Intelligent Locating System™). See Morita et al. (2020)—where we analyzed the same data—for more details on the data collection procedure.

Although the system sampling frequency was set at 9 Hz, the actual rate was unstable because of uncontrollable signal interference and reflection perturbation. Sampling from the $2 \times 5 = 10$ beacons did not synchronize in timing, either. Accordingly, we took the median value of the samples from each individual (i.e. from two beacons) for each dimension collected in every 3000 msec interval. The medians over the same interval constituted the input-output pair for the neural network.[3] This sacrifices time resolution of the collected data, but was not fatal to this study as the temporal information was ignored in the analysis. The preprocessing above yielded 327,592 sets of data in total.[4] Just as in the simulations, we used all the data for the model training and attention analysis, without holding out a test portion, and discretized the target locations into 400 cubes ($0.5 \times 0.5 \times 0.5$ m).

3 Results

Figure 4 reports the average attention weights among five individuals in two representations: The heatmaps on the left-hand side represent the attention weight assigned to each referent individual (column) upon the prediction of the target individual (row) by the color density of the corresponding cell; The directed graphs on the right-hand side represent the same information by the color density of the arrows reaching from the referents to the targets.

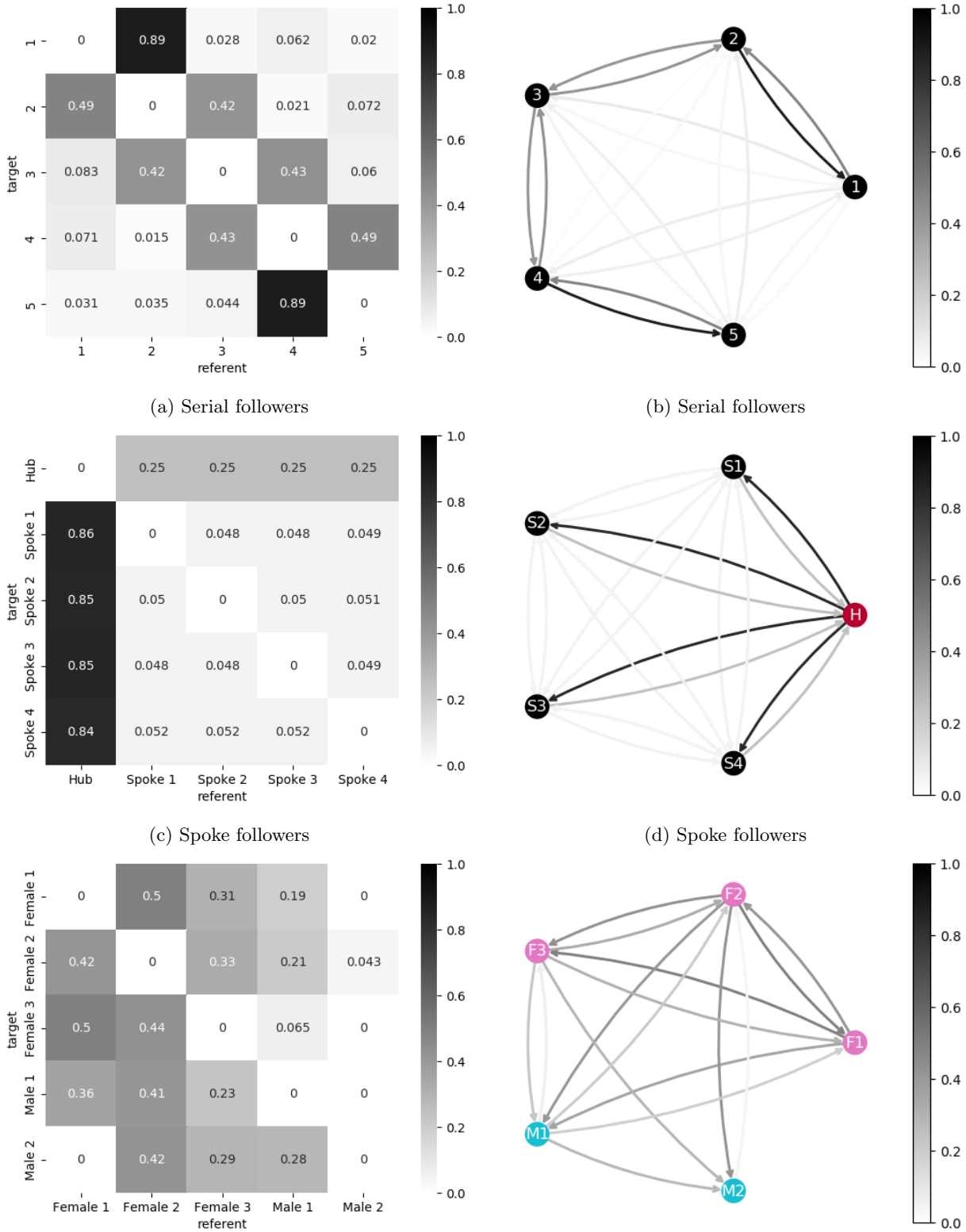
The attention-based analysis correctly distinguished the two simulation patterns. Given the data from the serial follower simulation, the analyzer correctly assigned heavy weights (> 0.1) to the relations between the individuals with successive indices (e.g., "2" and "3"; Figure 4a,b). The hub-spoke simulation, on the other hand, concentrated the attention weights to the hub individual when predicting the spoke dependents, and evenly distributed the weights to the spokes when predicting the hub (Figure 4c,d).

The analysis of the real data revealed that the female macaques were more informative referents than the males, especially when predicting the other females: The attention weight to Male 1 as a referent was smaller than all the females except when Male 2 was predicted (where Female 1 collected zero attention);[5] and Male 2 was almost never used as a referent (Figure 4e,f). It should be noted, however, that the males did not move independently of the other individuals. Predictions of the males' location were based on three other individuals (Male 1 was dependent on the females and Male 2 on Female 2, 3, and Male 1). While the

[3] The network simultaneously analyzed all the possible choices of one individual for the prediction target and four for the referents.

[4] Again, we analyzed all the possible partitions of the five individuals into one target and four referents, and thus, the number of different target-referents pairs observed by the neural network was $5 \times 327,592 = 1,637,960$.

[5] The average attention to Male 1 upon the predictions of Male 2 looked similar to the attention to Female 3, but actually was statistically significantly smaller according to 10,000 samples of bootstrapping.



(a) Serial followers

(b) Serial followers

(c) Spoke followers

(d) Spoke followers

(e) Real data

(f) Real data

Figure 4: Attention weights. The same data are reported in heatmaps on the left-hand side and in directed graphs on the right-hand side. Top (a,b): results from the simulation with serial followers (Figure 3a,c). Middle (c,d): results from the simulation with a single hub individual and four spoke dependents (Figure 3b,d). Bottom (e,f): results from the real location data collected from two male and three female Japanese macaques (§2.2.2).

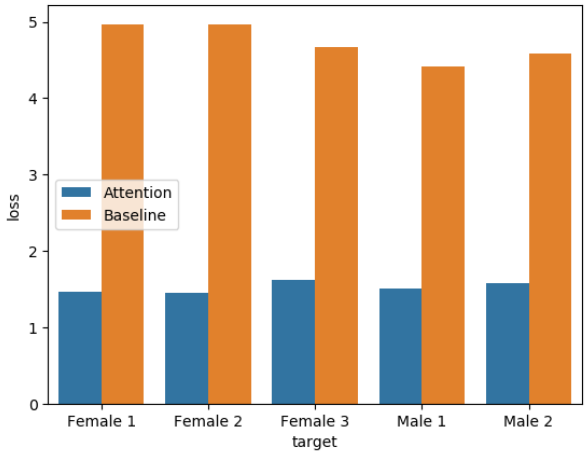


Figure 5: Average prediction loss (negative log probability) of the attention-based neural network and the no-referent baseline.

neural network was unable to flag independence as the attention weights were never all zeros, these detected dependencies were not redundant because the network outperformed the no-referent baseline. As shown in Figure 5, the average prediction loss (i.e. negative log probability) of the attention model was smaller than that of the baseline across all the individuals.

4 Discussion

Our attention analysis correctly identified the latent relations behind the two types of simulated data, one having serial followers and the other having the spoke followers. While these simulations were simple, it should be noted that the analyses were performed without prior assumptions about possible types of inter-individual relations or random distributions involved. Thus, the proposed method would be effective to visualize latent dependency patterns especially when little is yet known about the properties of data, compared to the traditional distance/closeness-based analyses (Silk et al., 2006b,a; Croft et al., 2008; Clark, 2011; Boyland et al., 2013; Castles et al., 2014; Krause et al., 2015; Schofield et al., 2019).

We also demonstrated that the attention analysis is applicable to raw real data, reporting a case study of Japanese macaques. We found that the location of females is more informative than that of males in order to locate the other female individuals. This result is consistent with the female-oriented social system of the macaques: Japanese macaques are a female philopatrics species (represented by parturition in the natal group and male emigration) and females usually build firmer and more stable social relationships with one another than males (e.g., matrilineal social rank succession/takeover/inheritance; Yamada, 1963; Furuichi, 1984; Mitani, 1986; Nakagawa et al., 2010). Females of the species are also reported to exhibit more tight and frequent spatial cohesion (Otani et al., 2014). Thus, knowing the location of some females is expected to increase the chance of locating other females in the same group. In addition, our earlier study on the same data showed that males' movements (i.e. trajectories of the 3D location) reflect a greater degree of individuality than that of females (Morita et al., 2020). Because of such idiosyncratic movements, males' location may not be informative predictors of the other individuals' location. The analysis of the real data also revealed that one individual (Male 2) was almost never attended by the others. Discovery of such distinguished individuals is useful to build new hypotheses about the animal society and plan behavioral experiments targeting them.

Since the attention analysis does not exploit any behavioral patterns that are particular to Japanese macaques, we can use it for location data of other animals, including ones that do not exhibit prototypical social behaviors like grooming and the conventional metric of distance/closeness is unavailable. We further emphasize that the attention analysis is not limited to location data; The flexibility of the neural network would allow its applications to a wide variety of data with interacting components. For example, vocal

communication has been of major interest to behavioral biologists as well as evolutionary linguists (Levinson, 2016). Our attention analysis could potentially reveal the latent communication flow when applied to recordings of vocalization of multiple individuals. It is to be noted, however, that we would need to extend and refine the proposed method for such broader applications as well as for more detailed analyses of location/movement. For example, the current version does not process temporal changes in location while implementation of the temporal analysis is crucial when analyzing dynamic behaviors and vocal communication. Since the attention mechanism was developed for NLP, however, processing time series data should not be so hard (see Vaswani et al., 2017; Shaw et al., 2018; Dai et al., 2019, for popular ways to encode time information).

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Ethical Statement

All the procedures were reviewed and approved by the Animal Welfare and Care Committee of KUPRI (Permission # 2018-203) and complied with the institutional guidelines (Primate Research Institute, 2010).

Author contributions

Project organization: IM HK; Animal arrangements: HK SA NSH; Apparatus building: AT IM HK; Data acquisition: AT IM HK; Animal cares: AK AT IM HK; Data management; HK AT TM; Computational modeling: TM; Manuscript writing: IM HK TM.

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