Analysis of Animal Movement Strategies in Corroboration with Marie Auger-Methe(2016)

FINAL PROJECT PAPER

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ABSTRACT

This project deals with analyzing varied animal movement data to corroborate with the results of Marie Auger-Methe (2016). The primary research here deals with analyzing and proving how a CCRW based paradigm for animal movement processes, especially with respect to foraging, is a much better predictive tool algorithm when compared with The Levy Walk. This project expands on the base paper's research by testing the hypothesis on a wider variety of animal movement data expanded over widely different foraging environments and distinct ecological cycles. This project also aims to establish better methods to work with movement data and elaborate on statistical variances in such data in order to provide better scope for further mathematical modeling down the line.

1. INTRODUCTION

Animal behavior has been studied in a vast majority of categories, with many models being developed to best represent their strategies. In this research project, we will delve further into the movement of animals and their search strategies. Studies have been conducted by GPS tracking various animals during specific times in the season to match their real-world movements to predicted animal search behavior models previously published. One predictive model, CCRW, found had best represented the behavior of most animals, where another strategy, Truncated Levy was used to predict the outliers. These models, along with others used will be discussed further in the description of background. The current conclusion is that either multiple strategies are needed to predict the movements of animal species or it may be possible for a single strategy may be used to predict a majority of animal movements if it included more variables to target the outliers. Our research will look at more species of animals to see if these results are still consistent.

2. RELATED WORK

This project was based on the research of Auger-Methe *et al.* in the paper, *"Evaluating random search strategies in three mammals from distinct feeding guilds"* (2016), which applied the four accepted animal search behavior models to 3 species of animals in the North American Region. The models are: Brownian Motion, Truncated Levy Walk, Correlated Random Walk and two modifications to the Composite Correlated Random Walk. The models and their properties are further described in the Methods and Models section of this paper. Study species explored in this paper were the caribou, grizzly bear and polar bear. These methods are further expanded in this research paper on new species of animals in different regions of the world to attempt to match new species of animals paths to one of these four strategies, or if different stages of the search can be described with multiple models.

3. MODELS AND METHODS

There are four models used to classify the behaviour of animals during their random walks based on their environment. Brownian motion is represented as a Brownian walk (BW), known to be used in productive environments. Pure Brownian motion is movements classified as being independent, that represents uncorrelated random walks. Whereas, the Levy strategy, represented as the truncated Levy walk (TLW), is classified with longer steps. TLW is a better model representing random search strategies in sparse environments.

Correlated random walk (CRW), which is characterized by long straight movements in sparse environments. Then there are the heterogeneous environments, where the environment is less predictable. There is a two-phase behavior strategy for heterogeneous environments: the Composite correlated random walk. The version presented by the Marie Auger-Methe *et al.* (2015), $CCRW_A$, is quoted as being a "generalized and statistically rigorous version of earlier methods". The earlier method is from Langrock *et al.* (2012), $CCRW_L$. The $CCRW_L$ uses a poisson-distributed transition, whereas in $CCRW_A$ a fixed transition probabilities is utilized.

These are characterized with having both a "long, nearly straight, movement for the extensive phase of the animal's search", but food discovery puts the animals into an "intensive" phase, with slower moves and turns. The CCRW models were what Marie Auger-Methe *et al.* (2016) found to be the best match for the majority of the individual animals used in the study. It is expected that the animals in this study will have a better fit in CCRW than the other random walks described in this paper. This is because the two-phase behavior strategy is very important in the classification in animals foraging in their random search.

Data was loaded from the MoveBank website, with access to thousands of animal tracks used in various research studies. Because research on some animals tracks had yet to be published, many datasets could not be obtained without the owner's consent. Data for the South American jaguar, African baboons, Mongolian wolves and African Kruger buffalo were selected to be used in this study. Animals selected for this study were based on availability of data, timestamp intervals, number of data points throughout the animal's day, number of animals collared, availability of gps tracking, relevance of the original study and differences in species and regions. The initial data received had movement data in latitude and longitudes along with timestamp, species type, taxonomy, and individual animal ID's. The analytics for the study required the data to be in a format of computed step lengths and turning angles. To obtain this, a python script was written and executed, with a considered degree of latitude being 111.3

For computing the "dx" value, the degree of latitude was utilized with shifting latitude sums and along with pi/180. For the "dy" value, the degree of latitude and cumulative latitude difference was used. From that the Pythagorean theorem was used for calculating step length.

Furthermore, the numpy arctan2 function was used to further calculate the turning angle.

Latitude and Longitude data was converted to Easting and Northing.

Final implementation of the PDFs for each model as well as the subsequent AIC_c values were coded in python and VBA. The Marie Auger-Methe (2016) and (2015) code is available online through an R package in github, however many bugs were encountered through the R studio and so we proceeded to remake the model in VBA and Python based off of the existing mathematical research and data intuition we gained from the animals to factor in the individual changing values for each animal.

Table 1: Formulas for the probability density functions (PDFs) from the different models and the variable restrictions. These formulas were found in the Appendix of Marie Auger-Methe (2016).

Distribution	Symbol	PDF	Restrictions
Exponential	$\phi(l\|\lambda, a)$	$\lambda\, e^{-\lambda(l-a)}$	$a \leq l, \quad \lambda > 0$
Weibull	$w(l\|\beta, \eta)$	$\left(\frac{\beta l^{\beta-1}}{\eta^{\beta}}\right) e^{-\left(\frac{l}{\eta}\right)^{\beta}}$	$\beta > 0, \eta > 0$
Truncated Pareto	$\psi_{\mathrm{T}}(l\|\mu_{\mathrm{T}}, a, b)$	$\frac{(\mu_{\mathrm{T}}-1)\, l^{-\mu_{\mathrm{T}}}}{a^{1-\mu_{\mathrm{T}}} - b^{1-\mu_{\mathrm{T}}}}$	$a \leq l \leq b$ †
Von Mises	$v(\theta\|\kappa)$	$\frac{1}{\int_{-\pi}^{\pi} e^{\kappa\cos(\theta)} d\theta} e^{\kappa\cos(\theta)}$ ‡,§	$\kappa > 0$
Uniform	$v_0(\theta)$	$\frac{1}{2\pi}$	
Wrapped Cauchy	$c(\theta\|\rho)$	$\frac{1}{2\pi}\left(\frac{1-\rho^2}{1+\rho^2-2\rho\cos(\theta)}\right)$ §	$0 < \rho < 1$
Poisson	$p(r\|\alpha)$	$\frac{\alpha^r}{r!} e^{-\alpha}$	$\alpha > 0$

† Unlike in Auger-Méthé *et al.* (2015), we are not placing restrictions on the estimated μ_{T} values.
‡ This is a simplified and expanded equation of the von Mises PDF. The same equation is often written with a modified Bessel function of the first kind and of order 0.
§ These simplified versions assume that the distribution is centred at 0, for full version see Codling, Plank & Benhamou (2008).

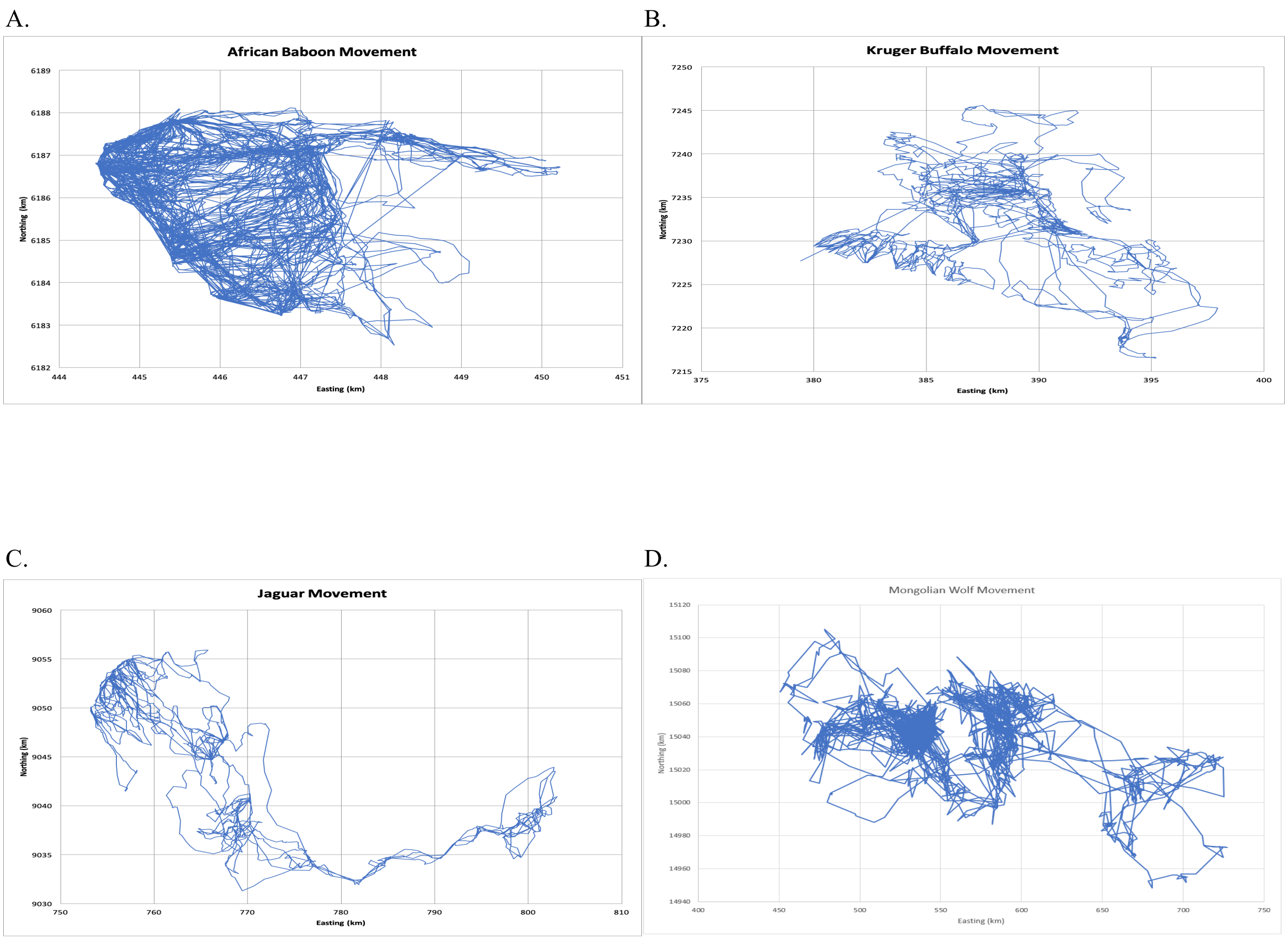


Figure 1: Movement path; Easting and Northing plots of every species of animal

4. RESULTS

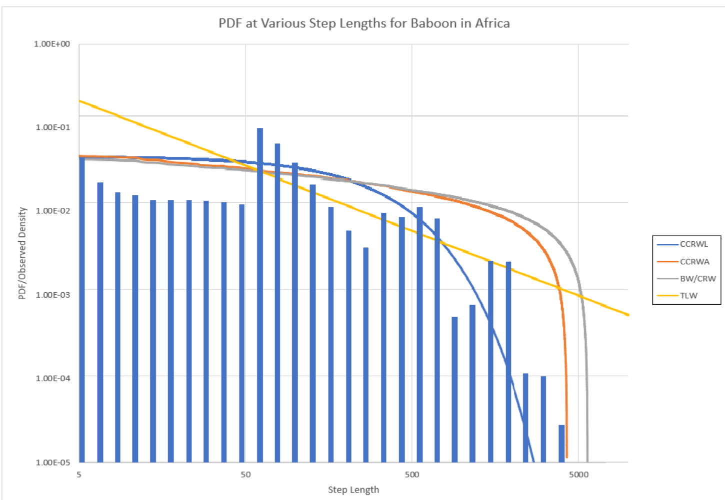
Based on the graphs in Figure 2 for the Probability Distribution function, we realized how CCRW algorithms were generally a better fit for movement pattern evaluation in comparison to alternatives like a Brownian Walk or a Levy Walk, even though both of these have their own set of advantages to provide from a mathematical standpoint. Our results also helped solidify the hypothesis presented in the base paper over evaluation against a wider set of animals.

We also accounted for the Akaike Information Criterion (AIC) values in evaluating our results and identify the model with the best fit.

Mongolian Wolf	Kruger Buffalo	African Baboon	African Jaguar
$CCRW_A$ ~ AIC=0.86	$CCRW_L$ ~ AIC=0.89	$CCRW_A$ ~ AIC=0.81	$CCRW_A$ ~ AIC=0.91

Figure 3: The above table displays the AIC values for the model with the best fit for all four respective animal movement data, and it shows how CCRW models are still the best fit for our data.

A.



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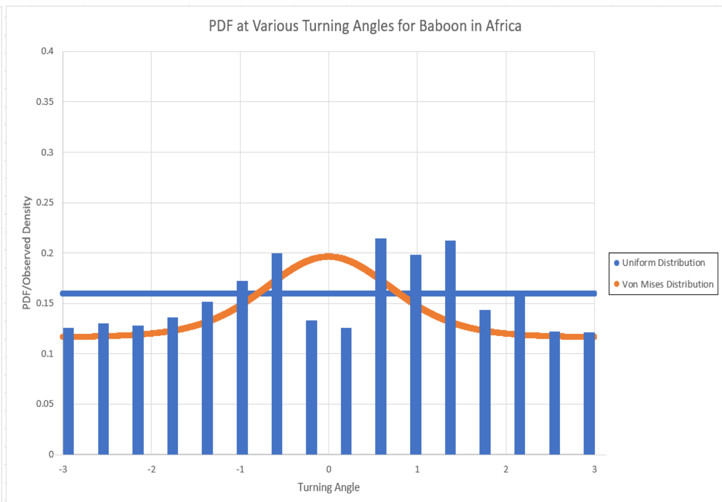

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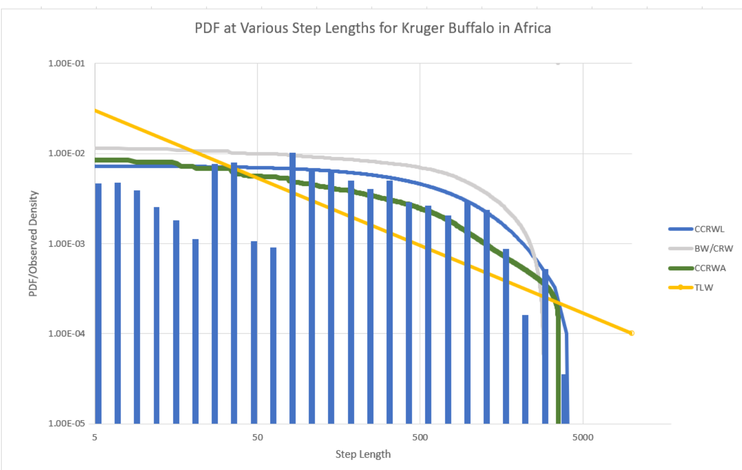

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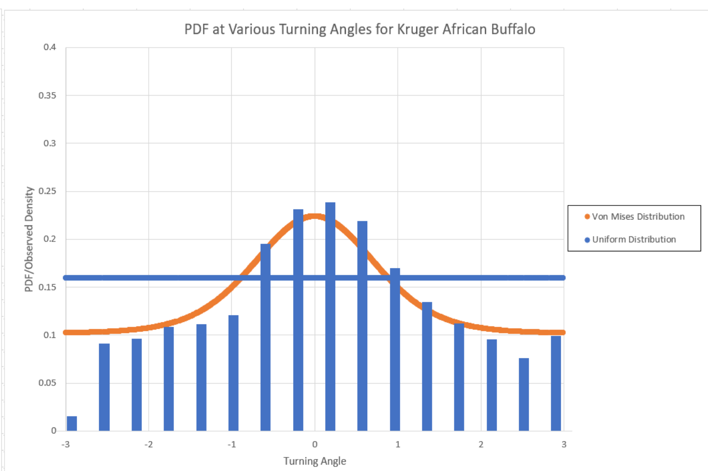

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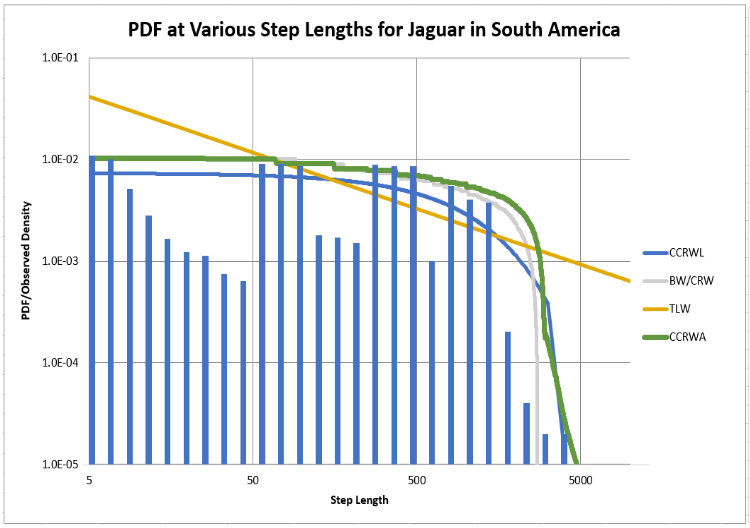

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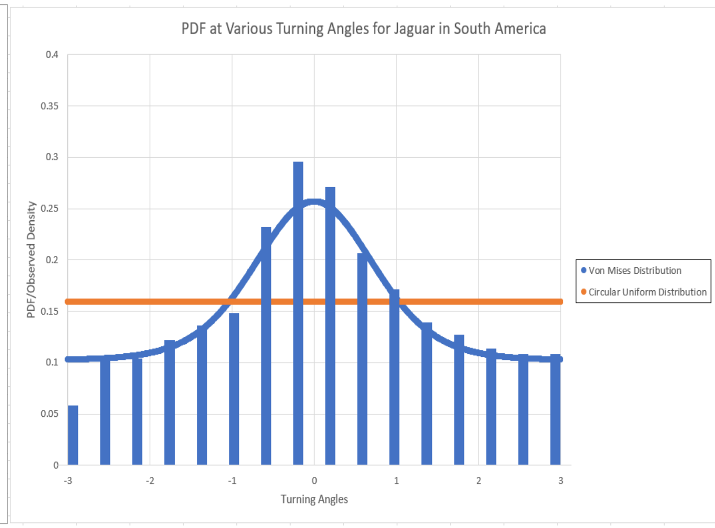

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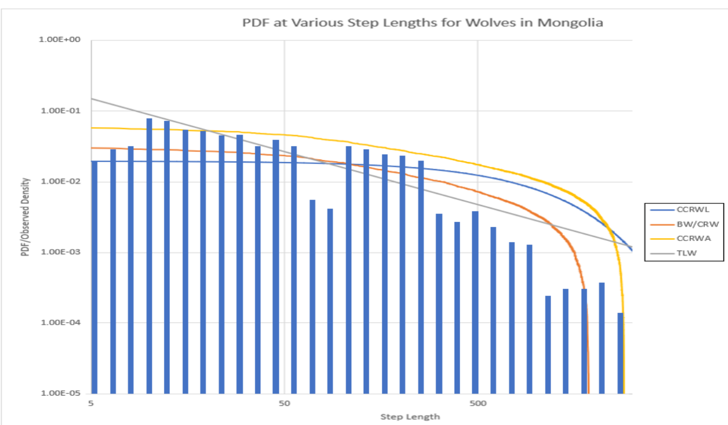

H.

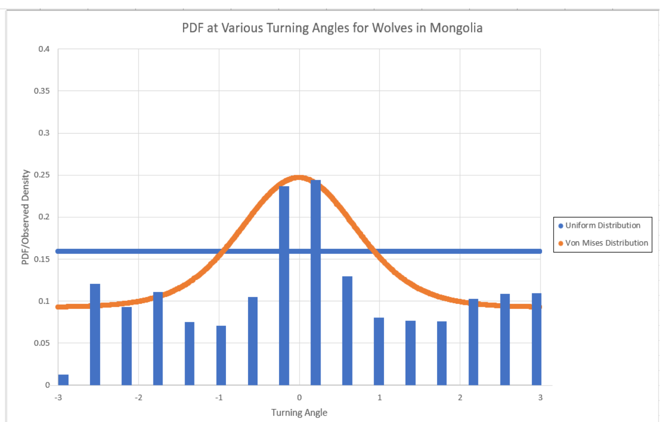

Figure 2: Fit of the models on the movement paths of each species in the study. First column is the northing and easting of each species in the study. Second column is the step length frequency for each bin value (histogram) against the probability density function (PDF) on a log-log axis for each of the 4 models. Third column is the turning angle of the probability density function (PDF) of the various distributions assigned to the 4 models.

5. DISCUSSION

Our models performed in sync with the results from the paper we were corroborating with. However, even though our results did showcase the end results we expected it to, it was not completely full proof. Firstly, our movement data was received without any idea of collaring periods and seasonal movement pattern changes, which led to a few discrepancies in the results from our expectations. Secondly, even though the results were still consistent throughout, the patterns were computed together rather than simulate different algorithms in different experimental circumstances. These two circumstances aside, we did get to achieve the end results we were looking to throughout. We also gained credible insight into how ecological surroundings do affect random walk behavior. For example, african buffaloes in the savannah are generally more docile herbivorous animals in vast stretches of sparse land and hence the random walk patterns and subsequent PDF shows the difference from that of a Baboon or a Mongolian Wolf with very different ecological environments, showcasing how even though our end results were similar, the process associated with them were different and was extremely accountable to the habits and habitats of the animals being considered, only lending more support to the generalization of the hypothesis put forward in the base paper we expanded upon in our project.

6. FUTURE WORK

These figures give us an idea about how the plots allow us to reject the null hypothesis so as to preserve the independent relationship between the step lengths and the turning angle. Also, the pearson correlation factor explains an independent relationship between the two factors, allowing for a statistical plot to derive from for future mathematical correlations to derive a more accurate representation of animal movement using factors like cognitive variance and sensory inputs. This is indeed the focus of current research in the field and the general progress of this project allows for progress along the grounds of it.

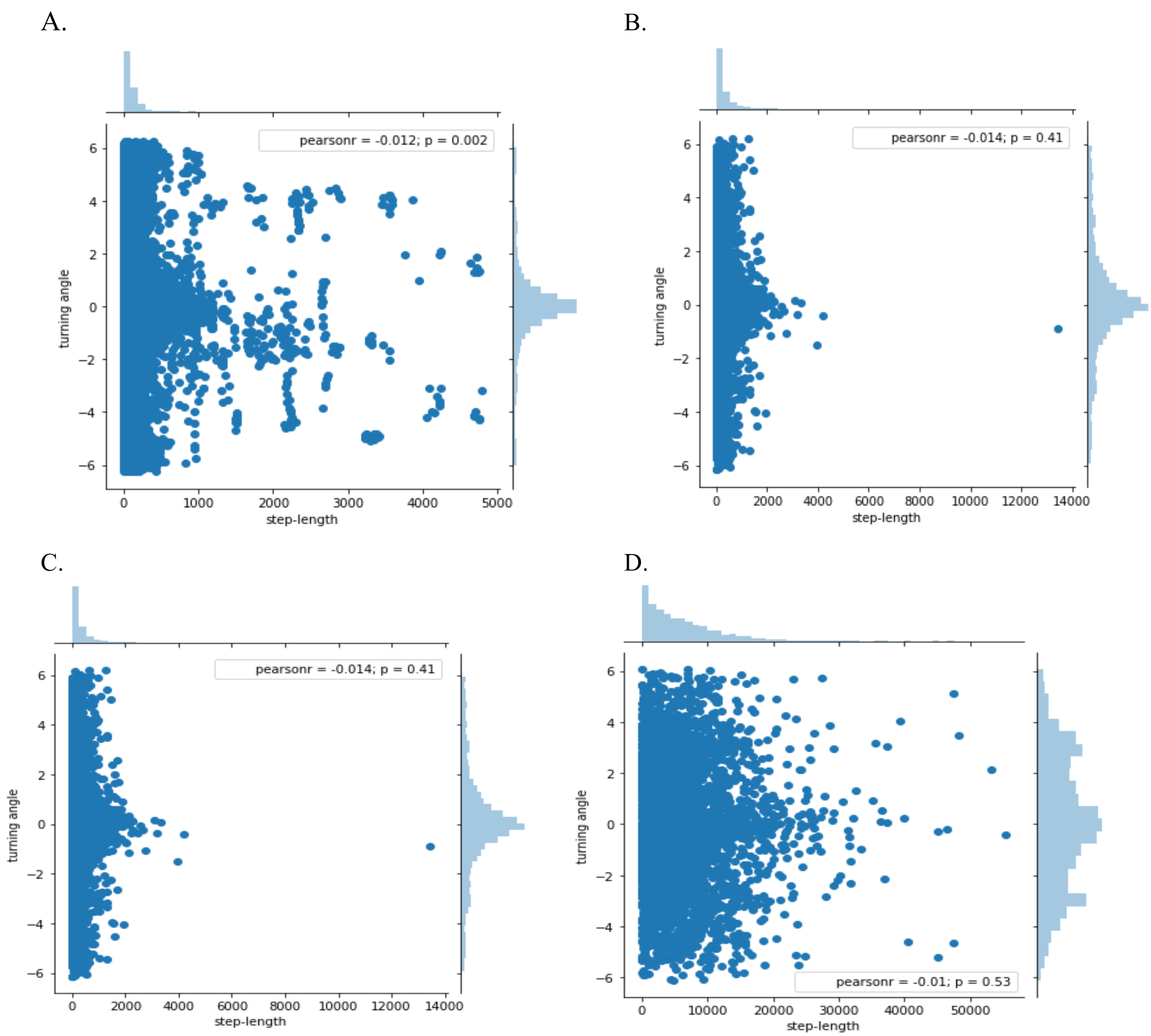

Figure 4: These plots show the general distribution of step lengths and turning angles with a pearson correlation and p-value calculated for A. African Baboon, B. Kruger Buffalo, C. South African Jaguar and D. Mongolian Wolf, respectively.

7. ACKNOWLEDGEMENTS

This project would not have been possible without the research work in the base paper cited here. The work done in that paper is seminal to the progress of foraging algorithms in animal movement and helped us formulate this project as an expansion of existing research. We are also really thankful to the movebank website for providing us with the animal movement data in such a cleaned and succinct manner.
This project would not have been possible without the immense amount of help we received from Prof. Orit Peleg through her lectures, her codes in her assignments and her input on our progress throughout the course of the semester, so we really thank her for this wonderful experience.

8. PROJECT CONTRIBUTIONS

This project involved shared team work on building the python scripts, which will soon be open sourced, for data conversion from the format we received it in, to a format generally used for the mathematical models. We also worked on writing code for the mathematical models in python and VBA to do our analysis and to generate statistical evaluations for important variables utilized in our evaluations. The plots and results, the in-class presentation and this report are all end products of our hard work on this project.

10. REFERENCES

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