The study of animal movement has broad applications across various disciplines, including the planning of anthropogenic projects such as dams (Weber, 2006) and roads (Colchero, 2011), the design of marine protected areas (Fulton, 2015), the study of environmental ecology (Johnson, 2008), population dynamics (Morales, 2010), and the modeling of disease spread (Wilber, 2022), among others. This wide range of applications is matched by an equally diverse set of movement models. Generally, these models fall into one of three categories: Eulerian, which treats movement at the population level similarly to fluid dynamics; Lagrangian, which models individual movement as a parametric function of time; and agent-based models, which simulate individual movement as interactions between agents and their environment (Weber, 2006). Agent-based models are particularly useful as they explicitly capture the ways individuals respond to their surroundings and to one another.

A variety of approaches exist for developing agent-based models, ranging from stochastic difference equations (Preisler, 2004) to state-space models (Newman, 1998) and weighted distribution models (Johnson, 2008). Each of these approaches requires explicit assumptions about underlying processes. More recently, machine learning models have gained attention for their ability to relax these assumptions (Wijeyakulasuriya, 2020). However, most machine learning models, including those developed by (Wijeyakulasuriya, 2020), frame movement prediction as a problem of forecasting specific displacements at each time step. This approach makes them unsuitable for multi-step simulations, as prediction errors compound over time. Effective long-term simulations require models that either achieve extreme accuracy—an impractical demand—or generate distributions over possible future movements. The continuous nature of typical machine learning predictions makes integrating over all possible movement paths computationally prohibitive.

A promising alternative is to discretize the space into a grid of possible “choices” and then frame movement modeling as a probabilistic deep learning classification problem where each class represents an option available to the animal. In this formulation, at each time step, the animal's movement can be represented as a decision, , among a set of possible choices, where each choice corresponds to a grid cell the animal might reasonably move to given its current location. Then, with information about these choices, , the model would predict the conditional probability of the animal moving to a specific grid cell in the next time step. The advantage of this alternative is that by limiting movement to a finite set of choices at each time step, this approach allows for the efficient computation of full probability distributions over multiple time steps, making it far more suitable for multi-step simulations.

In this paper we provide a guide on how to overcome some of the practical challenges that arise when applying probabilistic deep learning to movement data and then illustrate the technique with an example involving Chinook salmon movement data.

Weber, L. J., R. A. Goodwin, S. Li, J. M. Nestler, and J. J. Anderson. 2006. “Application of an Eulerian–Lagrangian–Agent Method (ELAM) to Rank Alternative Designs of a Juvenile Fish Passage Facility.” *Journal of Hydroinformatics* 8(4):271–95. doi: [10.2166/hydro.2006.006](https://doi.org/10.2166/hydro.2006.006).

Fulton, Elizabeth A., Nicholas J. Bax, Rodrigo H. Bustamante, Jeffrey M. Dambacher, Catherine Dichmont, Piers K. Dunstan, Keith R. Hayes, Alistair J. Hobday, Roland Pitcher, Éva E. Plagányi, André E. Punt, Marie Savina-Rolland, Anthony D. M. Smith, and David C. Smith. 2015. “Modelling Marine Protected Areas: Insights and Hurdles.” *Philosophical Transactions of the Royal Society B: Biological Sciences* 370(1681):20140278. doi: [10.1098/rstb.2014.0278](https://doi.org/10.1098/rstb.2014.0278).

Johnson, Devin S., Dana L. Thomas, Jay M. Ver Hoef, and Aaron Christ. 2008. “A General Framework for the Analysis of Animal Resource Selection from Telemetry Data.” *Biometrics* 64(3):968–76. doi: [10.1111/j.1541-0420.2007.00943.x](https://doi.org/10.1111/j.1541-0420.2007.00943.x).

Wilber, Mark Q., Anni Yang, Raoul Boughton, Kezia R. Manlove, Ryan S. Miller, Kim M. Pepin, and George Wittemyer. 2022. “A Model for Leveraging Animal Movement to Understand Spatio‐temporal Disease Dynamics” edited by P. Rohani. *Ecology Letters* 25(5):1290–1304. doi: [10.1111/ele.13986](https://doi.org/10.1111/ele.13986).

Morales, Juan M., Paul R. Moorcroft, Jason Matthiopoulos, Jacqueline L. Frair, John G. Kie, Roger A. Powell, Evelyn H. Merrill, and Daniel T. Haydon. 2010. “Building the Bridge between Animal Movement and Population Dynamics.” *Philosophical Transactions of the Royal Society B: Biological Sciences* 365(1550):2289–2301. doi: [10.1098/rstb.2010.0082](https://doi.org/10.1098/rstb.2010.0082).

Colchero, F., D. A. Conde, C. Manterola, C. Chávez, A. Rivera, and G. Ceballos. 2011. “Jaguars on the Move: Modeling Movement to Mitigate Fragmentation from Road Expansion in the Mayan Forest: Modeling Jaguar Movement to Locate Wildlife Passes.” *Animal Conservation* 14(2):158–66. doi: [10.1111/j.1469-1795.2010.00406.x](https://doi.org/10.1111/j.1469-1795.2010.00406.x).

Wijeyakulasuriya, Dhanushi A., Elizabeth W. Eisenhauer, Benjamin A. Shaby, and Ephraim M. Hanks. 2020. “Machine Learning for Modeling Animal Movement” edited by J. Zhang. *PLOS ONE* 15(7):e0235750. doi: [10.1371/journal.pone.0235750](https://doi.org/10.1371/journal.pone.0235750).

Newman, Ken B. 1998. “State-Space Modeling of Animal Movement and Mortality with Application to Salmon.” *Biometrics* 54(4):1290. doi: [10.2307/2533659](https://doi.org/10.2307/2533659).

Preisler, Haiganoush K., Alan A. Ager, Bruce K. Johnson, and John G. Kie. 2004. “Modeling Animal Movements Using Stochastic Differential Equations.” *Environmetrics* 15(7):643–57. doi: [10.1002/env.636](https://doi.org/10.1002/env.636).