Generating ocean glider trajectories with variational recurrent autoencoders

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1. Problem statement and motivation

Variational autoencoders (VAEs) enable unsupervised representation learning as well as generation by mapping a complex, high-dimensional data to a lower-dimensional latent representation. Our work in class has focused on generating static data such as images. In this project, I propose to explore the use of VAEs on sequential data by the use of variational recurrent autoencoders (VRAEs).

My proposed domain is oceanography. Specifically, I plan to train a VRAE on data from ocean gliders, which are unmanned vehicles that travel around the ocean, collecting information such as pressure, salinity, and conductivity over a long period of time. The trajectory of one glider is naturally sequential, as the current position, depth, and observations of a glider influence the glider's state at the next timestep. By applying VRAEs, I hope to learn a compact representation of a trajectory, generate natural-appearing samples, as well as interpret said representations as possibly reflecting underlying structure in the data. This model could help analyze the ocean conditions in a particular region as well as augment datasets by generating plausible samples.

2. Previous and related works

VRAEs were introduced in 2015 and combine the ELBO objective and reparameterization trick of VAEs with the structure of recurrent neural networks (RNNs) (Fabius & van Amersfoort, 2015). The authors introduce recurrence in the encoder, so that the encoding of point x_t depends both on the features of x_t and the hidden state h_{t-1} that was calculated in the previous timestep. Thus, the relationship between elements of the sequence is captured in the latent space. A similar exposition of variational RNNs appeared the same year in which the authors apply their model to speech data (Chung et al., 2015).

VRAEs have also been applied outside speech and audio. For example, researchers have used ship tracking data for a region of Sweden to cluster and predict ship behavior (Murray & Perera, 2021). This paper, by focusing on trajectories in a defined geographical region, is naturally related to my proposed project. In the specific field of ocean gliders, I was unable to find any papers applying deep generative modelling to the field. Ocean gliders are an area of research in control systems, as the utilization of existing ocean dynamics can enable the glider to move from one location to another (Inanc et al., 2005).

3. Dataset

The trajectories I plan to use to train my generative model come from the Coastal Pioneer Array of the Ocean Observatories Institute off the coast of Martha's Vineyard. 183 trajectories are available through the Integrated Ocean Observing System[1]. A representative trajectory is about 1,200 observations long, with each observation including time, position, depth, and other data.

4. Methodology, experiments, and evaluation

I intend to implement the VRAE as described in Fabius and van Amersfoot, with guidance for non-audio data from Murray and Perera. This may involve breaking up the trajectories into non-overlapping subsequences and additional methods to increase the dataset size.

After running inference, I plan to evaluate my loss on a held-out test set. In addition, I plan to generate samples. I will evaluate these qualitatively by comparing the trajectories to those in my dataset. I will also quantitatively check for consistency and reasonability, e.g. the smoothness of a trajectory.

Finally, I will use my encoder to create low-dimensional representations of the trajectories. I will explore the structure of these embeddings by, for example, running clustering algorithms. Hopefully, the representations will somehow capture underlying sources of variation in the data such as seasonality or weather.

[1] https://data.ioos.us/organization/glider-dac?q=cp_&sort=score+desc

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