COMP 551 Project 4: Osprey Migration Tracking

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***Abstract*— Ospreys are severely affected by pollutants in their environment because they are at the top of their food chain. The population of ospreys in the eastern USA significantly decreased due to DDT use in the middle of the twentieth century. It has since recovered. This paper presents the basic methodology and results obtained for an osprey data set chosen from Movebank for predicting the migration periodicity and directionality exhibited by these birds as a group and individually. K-means clustering and the Discrete Fourier Transform were used to predict the migration patterns. Long Short-Term Memory was used to predict the future movement of the birds. This analysis can help identify unusual patterns in bird migration trajectories in the future. If unusual patterns present themselves among many birds, the possible pollutant needs to be identified and eliminated from the region.**

I. Introduction

Ospreys (Pandion haliaetus) are large hawks that eat fish (see Figure 1). They circle over shallow water before diving and grabbing fish [2]. Due to their diet of fish, they live near bodies of water: rivers, ponds, estuaries, etc. They have a lifetime of 15 to 20 years. Ospreys are migratory birds and migrate individually. They typically breed in the northern hemisphere and winter in Central America, South America and Africa [3]. Ospreys are tracked by scientists by strapping lightweight satellite transmitters to the birds' backs [2].

Fig. 1: An osprey in action [1]

Ospreys are very sensitive to environmental changes. They are at the top of a long food chain. This means that they ingest all the contaminants ingested by the creatures below them in the food chain [1]. In fact, the insecticide dichlorodiphenyltrichloroethane (DDT) had nearly wiped out the osprey population in the early 1970s [4]. The osprey helped prove that damage was being done by the use of DDTs in the 1950s. Their eggshells were thinned, killing their embryos [1]. The ban on DDTs allowed the osprey population to recover. For example, on Martha's Vineyard, the population increased from two pairs of ospreys in 1971 to over 70 pairs in 1992 [4]. Many chemicals are released to pollute the natural world. Since ospreys are affected by pollutants they can be indicators of danger. If ospreys have high concentrations of chemicals in their systems, it is important to reduce the release of that chemical. Chemicals may impair the ability of the birds to reproduce. They may also alter their ability to migrate or the time that they begin migration. Therefore, tracking ospreys gives information about the cleanliness of the environment in which they live.

This project analyzes a data set from the Movebank website [5]. The data set is named "Osprey Bierregaard North and South America". This data was collected by Rob Bierregaard (Academy of Natural Sciences of Drexel University). One of the goals of Bierregaard's study was to analyze juvenile osprey dispersal, mortality and migration for the species [4]. Many of the birds in the data set are young birds. The ospreys in Bierregaard's study were tagged in the eastern USA from Chesapeake Bay to northern New Hampshire. Their journey to Central and South America is observed using GPS and Argos Doppler data.

II. Problem Definition and Description of Data

The goal of this project is to analyze the migration pattern of ospreys. The directionality and periodicity of the trajectory of the birds is analyzed and their future positions are predicted.

The "Osprey Bierregaard North and South America" data set consisted of 99 birds with 85 tags at the time we retrieved the data (November 25, 2016). These values may change since this data set is being continuously updated. The data is represented as a set of values collected at time intervals, for a collection of birds. Each record consists of a bird ID number, a time stamp, latitude, longitude, height, and ground speed. In total there are approximately 3.5 million records. The trajectory of one bird is shown in Figure 2.

III. Methodology

A. Data Pre-processing

To pre-process the data, the data set was imported into SQL Server. All records with missing latitude and longitude values were deleted. Records with improper time stamps were also removed. Only the GPS data was used since it is

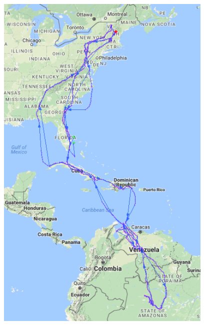

Fig. 2: The trajectory of one osprey [5]

more accurate and there was a significant amount of missing Argos Doppler data [6].

Three types of data were extracted from the data set:

- Data A: All osprey data sorted in ascending order of time stamp, grouped by bird ID
- Data B: The average latitude and longitude of all birds for each day during the study (2007-2016)
- Data C: The top 10 birds with the most time records

Note that Data A and Data C have hourly records, while Data B has daily records (3384 days). With pre-processing, Data A went from 3.5 million records to 2.5 million.

B. Feature Extraction

Once the different data sets were pre-processed, the required features were extracted using the capabilities of SQL Server into a CSV format. Despite having a large data set, SQL Server helped in the seamless extraction of these features.

Weather data was extracted from forecastio using the Dark Sky API [7]. This was done for Data B. The daily weather values that were extracted are the maximum temperature and the minimum temperature. These two values are used to calculate a pseudo-average daily temperature: the average between the maximum and minimum temperature during a day. This weather data was be used in conjunction with location data to better predict future migration patterns.

A summary of the features used is given in Figure 3.

C. K-Means Clustering

To find the migration pattern of the ensemble of the birds, Data A was fed into the k-means classifier of sci-kit learn [8]. Ten random restarts were done for the initial cluster points. The initial cluster points were chosen in such a way that the second cluster point is farthest from the first and the third is farthest from the first and the second. The ospreys in the data set migrate from North America to South America through Cuba and the Caribbean Sea. The number of clusters was set to three to capture the three stages in a migration cycle: the time in North America, the flying time, and the time in South America. This was also done for individual birds from Data C. The result of the clustering was then compared to the true location of the birds to observe the k-means clustering classification accuracy.

Feature Name	Description of the feature	Feature Type
Timestamp	Time of observation	Time stamp
Latitude	The latitude of osprey at the given timestamp	Float
Longitude	The longitude of osprey at the given timestamp	Float
Bird ID	Unique identifier for each bird	Integer
Temperature	Average between the maximum and the minimum temperatures of each day during the study at the latitude and longitude corresponding to Data B	Float

Fig. 3: The features used in the algorithms

D. LSTM

To predict future behaviour of the ensemble of birds (Data A) as well as individual birds (Data C), the Long Short-Term Memory (LSTM) algorithm was used. LSTM is a Recurrent Neural Network (RNN) architecture proposed in 1997 by Sepp Hochreiter and Jurgen Schmidhuber [12]. It is universal in the sense that given enough network units it can compute anything a conventional computer can compute. LSTM is specifically well-suited to learn from experience to classify, process and predict time series when there are long time lags between events. For this reason, LSTM was chosen ahead of alternate RNNs for this project. The LSTM network is trained using backpropagation through time and overcomes the vanishing gradient problem [12]. Instead of neurons, LSTM networks have memory cells that are connected through layers. One such memory cell is shown in Figure 4.

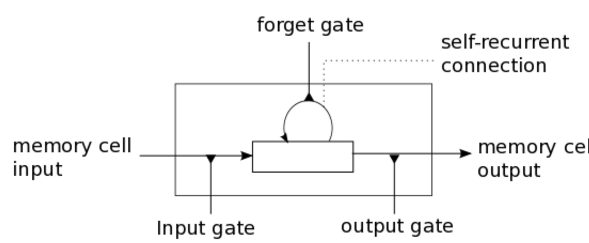

Fig. 4: An iIllustration of an LSTM memory cell

A memory cell is composed of four main elements: an input gate, a neuron with a self-recurrent connection (a connection to itself), a forget gate and an output gate. The self-recurrent connection has a weight of 1.0 and ensures that, barring any outside interference, the state of a memory cell can remain constant from one time step to another. The gates serve to modulate the interactions between the memory cell and its environment. The input gate can allow an incoming signal to alter the state of the memory cell or block it. On the other hand, the output gate can allow the state of the memory cell to have an effect on other neurons or prevent it from doing so. Finally, the forget gate can modulate the memory cell's self-recurrent connection, allowing the cell to remember or forget its previous state, as needed.

The following equations describe how a layer of memory cells is updated at every time step t. In these equations,

- x_t is the input to the memory cell layer at time t
- W_i, W_f, W_c, W_o, U_i, U_f, U_c, U_o and V_o are weight matrices
- b_i, b_f, b_c and b_o are bias vectors

First, we compute the values for i_t, the input gate, and C_t the candidate value for the states of the memory cells at time t:

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \tag{1}$$

$$\widetilde{C_t} = \tanh(W_c x_t + U_c h_{t-1} + b_c) \tag{2}$$

Second, we compute the value for f_t, the activation of the memory cells' forget gates at time t:

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f) \tag{3}$$

Given the value of the input gate activation i_t, the forget gate activation f_t and the candidate state value $\widetilde{C_t}$, we can compute C_t the memory cells' new state at time t:

$$C_t = i_t * \widetilde{C_t} + f_t * C_{t-1} \tag{4}$$

With the new state of the memory cells, we can compute the value of their output gates and, subsequently, their outputs:

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + V_o C_t + b_o) \tag{5}$$

$$h_t = o_t * \tanh C_t \tag{6}$$

We used the Keras library to implement the LSTM architecture [9]. It is a high level neural networks library to be used on top of Tensor-flow [10]. We opted for a standard sequential model in Keras, which is essentially a linear stack of layers.

Predicting future latitudes and longitudes is a regression problem. Latitude and longitude are assumed to be independent of each other in each bird's trajectory. Therefore, they were predicted separately. The latitude varies more throughout the year than the longitude, since birds are migrating form the North to the South. Therefore, the latitude was primarily used for prediction.

Our problem was to predict the next latitude position of a bird, given past latitude positions. A function was used to convert the single-column data of latitude into a two-column data set: the first column containing the latitude of time stamp t and the second column containing the latitude at time stamp $t+1$, to be predicted. Since LSTMs are sensitive to the scale of input, we normalized the data to a range of 0 to 1. LSTM was applied to all data sets (A, B and C).

The network had one input layer, a hidden layer with four LSTM cells, and an output layer that makes a single value prediction. The default sigmoid activation function was used for the LSTM cells. A batch size of 1 is used. Three-fold cross-validation was used to achieve the best epoch value. A dropout layer was also added, with its value chosen with three-fold cross-validation.

E. DFT

The migration of birds is a periodic event. Each bird migrates south exactly once a year. In order to find the average period of migration, we applied the Discrete Fourier Transform (DFT) to Data B as well as several birds in Data C. It was found using the Fast Fourier Transform (FFT) algorithm. This was done in a paper analyzing the movement of geese [11]. The period of migration was found by dividing the number of time records by the frequency at which the FFT achieves maximum amplitude. It was expected that the period for the latitude and longitude is identical and is close to 365 days.

In order to apply the FFT to a signal, the samples of the input signal must be sampled uniformly. This was not the case for both Data B and Data C. In the case of Data B, several days were missing in the time period from 2007 to 2016. These were filled in by doing linear regression between the neighbouring points. Several birds in Data C were not sampled hourly. Several hours had more than one record, while other hours were absent. The first record for each hour was chosen, and the absent hours were added with linear regression.

Since the trajectory data is quite noisy, first a smoothing method and then the more sophisticated moving average filter were applied to the data. The smoothing method replaced the location at each time step by the average of the locations at the previous time step and the next time step. To improve the smoothing, this replacement was done several times. The moving average filter changes the locations in a similar way, but more neighbours are considered instead of only the adjacent ones.

IV. Empirical Results

A. K-Means Clustering

The migration pattern was well represented with three clusters as illustrated in Figure 5. The cluster centroids are marked with a white X.

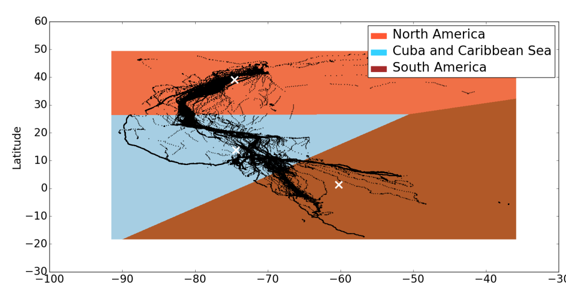

Fig. 5: K-Means Clustering of Data A

The migration pattern for one bird (Bird 120) in Data C was also analyzed using k-means clustering. Bird 120 is the bird with the most time records out of the entire data set. Figure 6 shows four migration cycles for one bird over a period of three years. The winter and summer migration trajectories are represented in magenta and green respectively. The cluster centroids in North America and South America suggest that the cluster points are more dense at the end of the migration path as the bird stays for a longer period of time at these points before migrating again. The cluster centroid for the brown region is almost at the center because during migration the points are equally distributed as the birds were flying.

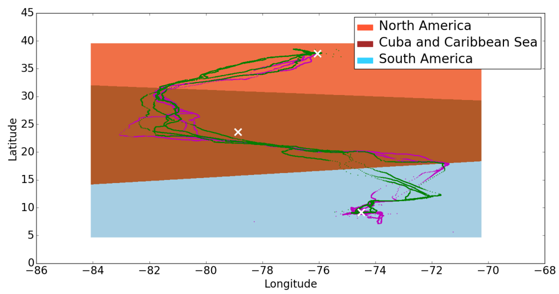

Fig. 6: K-Means Clustering for Bird 120

To test the k-means clustering algorithm, we observed how many true points in each region (South America, North America and Cuba) were actually predicted by the cluster. To observe this we assigned a true y value to each cluster point: 0 for North America, 1 for Cuba and Caribbean Sea and 2 for South America. It was simple to distinguish the three geographical locations based on latitude. All points above latitude 25 were considered to be in North America, points having latitude between 9 and 25 were considered to be in Cuba or the Caribbean Sea, while the others were marked as being in South America. For each latitude, longitude pair, the true y class was compared to the corresponding label predicted by k-means. This is shown in Figure 7.

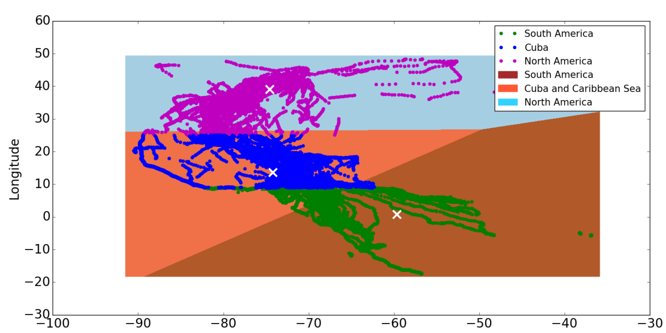

Fig. 7: Validating the k-means algorithm

The dot points indicate the true labels and the shaded area represents the clusters predicted by k-means. The performance metrics for each class is shown in Figure 8.

Class	Precision	Recall	F1-Score
North America	1.00	0.99	1.00
Cuba	0.87	1.00	0.93
South America	0.99	0.74	0.85
Average	0.96	0.96	0.96

Fig. 8: Validating k-means: Performance Metrics

The results show that the k-means algorithm predict the regions with substantial accuracy. It is trickier to predict the points at the border between two of the three main regions, since ospreys feed primarily on fish and so they regularly fly over the water bodies for food, even when they are not migrating.

B. *LSTM*

Phase 1: $t+1$ **LSTM**

The LSTM results are given in two phases. In phase 1, LSTM is used in its usual function to retrieve the pattern of the birds over time. However, it will only indicate how well the LSTM predicts the next time $(t+1)$ data given the previous t. The input data was split into 70% training and 30% testing data.

LSTM was applied to Data A, Data B and Bird 120. The latitude and longitude plots of Data B are shown in Figures 9 and 10. The latitude and longitude plots of Bird 120 are shown in Figures 11 and 12. The full data set is shown in blue, the data used for training and validation is shown in green and the data used as a test set is shown in red (the $t+1$ prediction). LSTM was separately applied to latitude and longitude to observe the migration pattern over the years. The latitude variation is much more prominent.

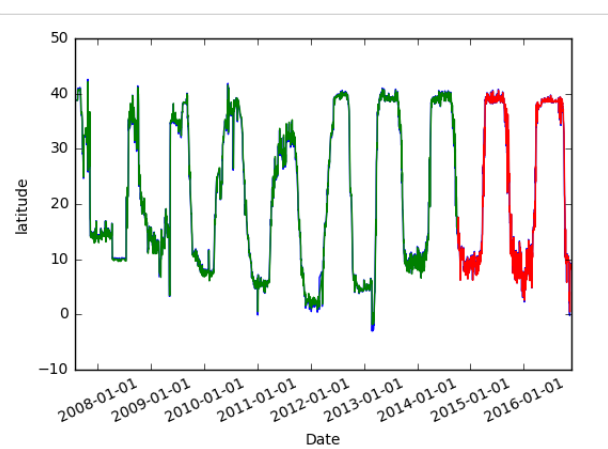

Fig. 9: Phase 1 LSTM results for Data B latitude

The prediction appears to be perfect since only one additional time is being predicted at each step. For each of the data sets used, the training and testing root mean squared error (RMSE) are obtained as shown in Figure 13.

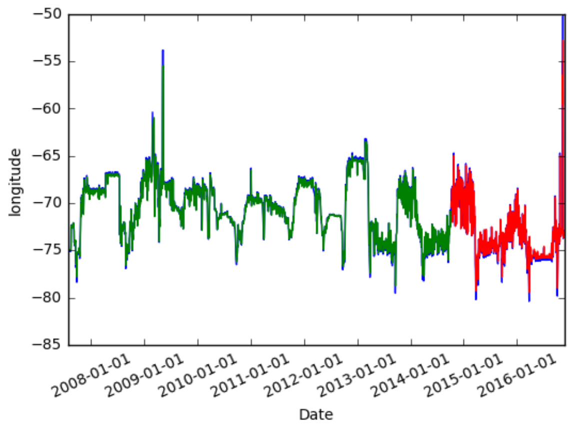

Fig. 10: Phase 1 LSTM results for Data B longitude

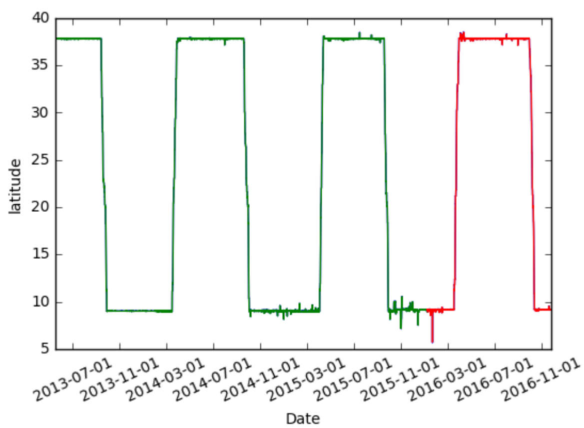

Fig. 11: Phase 1 LSTM results for Bird 120 latitude data

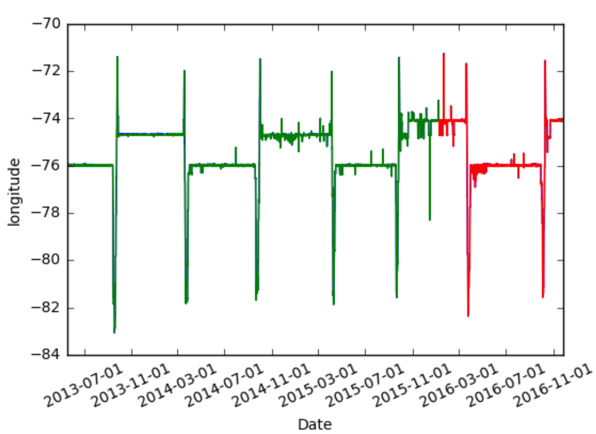

Fig. 12: Phase 1 LSTM results for Bird 120 longitude data

Data set	Training RMSE	Testing RMSE
Data B	1.39	1.76
Data A	0.05	0.13
Bird 120 (Data C)	0.01	0.02
Bird 389 (Data C)	0.03	0.05

Fig. 13: RMSE for training and testing data for LSTM predicting latitude values each with number of epoch at 5 for phase 1 of the results. This is the accuracy of LSTM of predicting $t+1$ data given t.

When LSTM is applied to Data B, the highest RMSE is obtained. The RMSE was calculated by testing the $t+1$ data for each bird against the prediction for Data B. The error is expected to be high since the average in Data B does not take into account specific trajectories for each bird. This is seen in Figure 9. Although the red pattern follows the blue pattern overall, they do not overlap perfectly.

When LSTM is applied to Data A, the error is much smaller than for Data B. Data A includes all birds and all their trajectories, therefore each bird is able to identify its past pattern and give a relatively good prediction of future locations.

Taking specific birds from Data C and training with them gives near perfect accuracy. This indicates that each bird follows a specific pattern every year. This is well represented by the Figure 11.

The same tests were done for the longitude of these data sets. Since the direction followed by the birds vary more in latitude than in longitude, the patterns shown only refer to latitude data.

The default settings were primarily used for LSTM. Three-fold cross-validation over the number of epochs was done. The results are shown in figure 14. The optimum number of epochs is 5. Three-fold cross-validation also yielded a dropout value of 0.2 to help avoid overfitting.

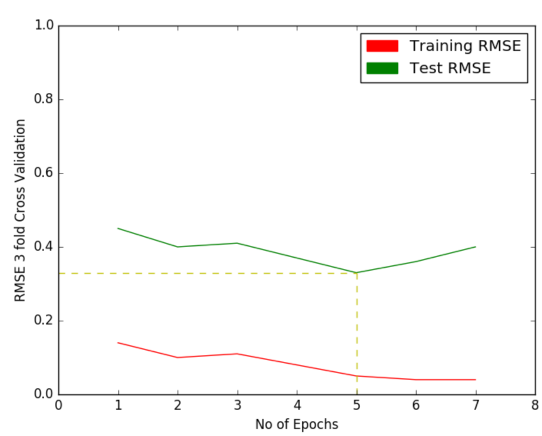

Fig. 14: Three-fold cross-validation results for phase 1

Phase 2: Pattern LSTM

Although the results from phase 1 were encouraging, there were still some problems to be addressed. Phase 1 predicted the next location given the previous location correctly. However, using the output of the LSTM as the input for the next round of predictions caused certain problems. Training with latitude or longitude data alone is not sufficient. More features are required to predict the exact pattern and periodicity of the migration data.

Adding the day of the year as a feature was expected to help the LSTM to predict the periodicity of the bird and would be able to generate the time series on its own. This algorithm with this added feature was trained for 40 epochs as it had higher errors at the beginning. Three-fold cross-validation justified the use of 40 as epoch number.

The results for this new algorithm applied to Data B are shown in Figure 15. The green lines represent the original data set and the red line is the LSTM prediction after training. The prediction follows the periodicity of the original data very well. However, there is still significant error in the amplitude of the prediction.

The same algorithm was used for Bird 120 to predict its complete pattern. the results are shown in Figure 16. Again, the LSTM was able to predict the periodicity well albeit with some error at the southward migrations. The amplitude of the prediction is well represented.

The weather data which was scraped from the Dark Sky API was then combined to Data B. It was expected that the LSTM would better be able to predict the pattern with the use of average temperature data. The addition of the temperature data appears to have improved the pattern recognition, as seen in Figure 17.

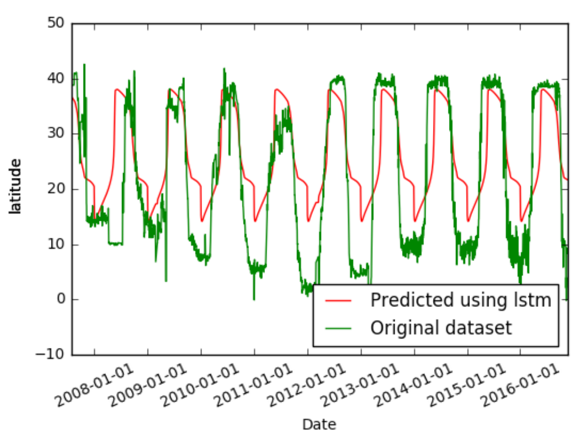

Fig. 15: Phase 2 LSTM results for Data B latitude

As can be seen from the figure 18, the RMSE rate is much higher when the LSTM has to predict the complete data set. Nevertheless, it is still able to predict a reasonable pattern of osprey migration. The number of epochs in this case for the optimal solution is much higher because of the increased error rate. This is captured by a three-fold cross-validation and the optimal solution is at epoch 40. The epoch number was calculated using Data B with weather data. This epoch number was used for all other tests with weather data.

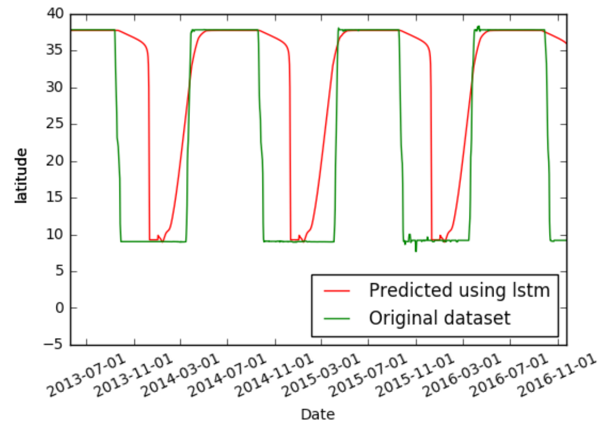

Fig. 16: Phase 2 LSTM results for Bird 120 latitude data

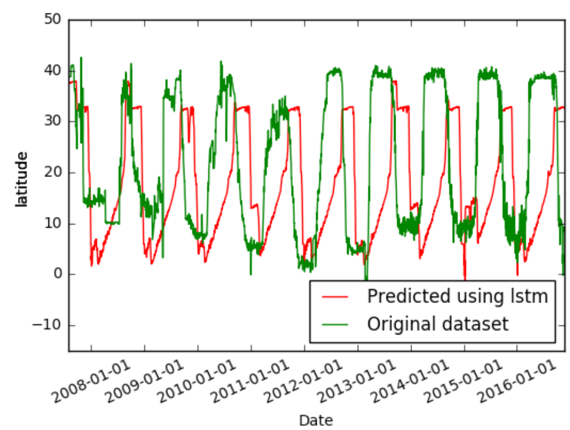

Fig. 17: Phase 2 with temperature LSTM results for Data B latitude

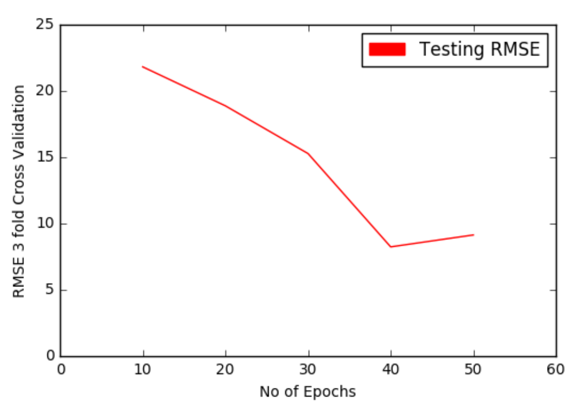

Fig. 18: Three-fold cross-validation results for phase 2

A summary of the RMSE is shown in Figure 19. Adding temperature as a feature decreases the error by 4.19. The error for Bird 120 is much lower. LSTM with weather data was not applied to Bird 120 due to the computational constraints of running 40 epochs for ten times as many records as Data B does.

Data set	Complete Testing RMSE
Data B	12.39
Data B with temperature	8.20
Bird ID 120	2.75

Fig. 19: RMSE for the complete data set. This is the phase 2 results with LSTM predicting the complete migration pattern on its own. The RMSE rates are much higher compared to phase 1 but it gives a reasonable estimate on the next location of an osprey albeit with some error.

C. Discrete Fourier Transform

It is obvious from the latitude plot of Data B that the data is periodic (Figure 9). When the FFT algorithm was applied to Data B, the frequency with maximum amplitude was 10 and the period of migration was found to be 341.2 days. The period for the longitude was exactly the same as the period of the latitude.

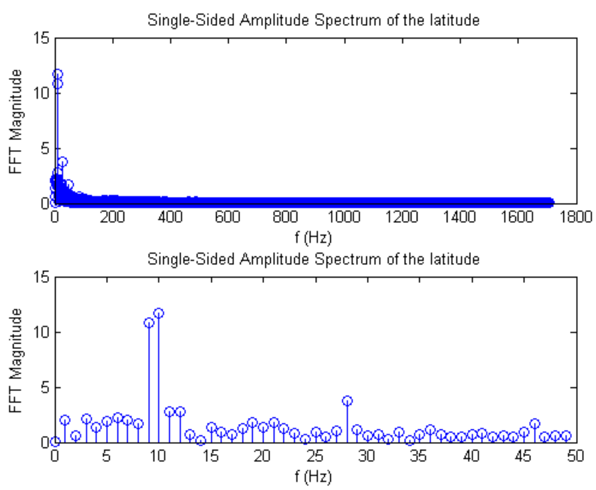

Fig. 20: The DFT of Data B latitude

The DFT was also computed for individual birds. Figure 11 shows the latitude of Bird 120 in blue. The result of applying the FFT is shown in Figure 21. The frequency at which the FFT achieves maximum frequency is 4. The period of migration was found to be 321.9896 days. Again, the period for the longitude was exactly the same as the period of the latitude.

Several birds do not have many records and therefore no periodicity is observed in their trajectories. Figure 22 shows the results obtained for several birds in Data C. As

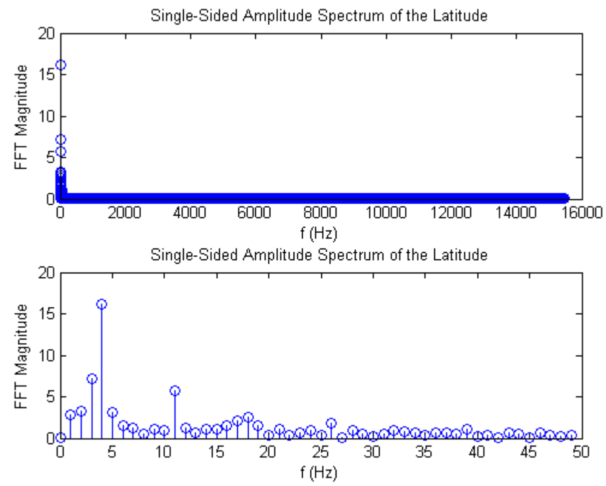

Fig. 21: The DFT of Bird 120's latitude

the number of records increases, the period is closer to 365 days. Birds 118 and 119 in fact have records for less than a year. Therefore, it is not expected that the FFT algorithm will yield a good period.

Bird ID	Number of records	Period (days)
120	30911	321.9896
122	25161	349.4583
121	22502	312.5278
117	19260	401.2500
337	14279	297.4792
118	13419	559.1250
119	6718	139.9583

Fig. 22: FFT results for several birds in Data C

Although the smoothing method and the moving average filter considerably reduce the noise in the data, the resulting period did not change after the FFT was applied to the cleaned data.

V. Discussion

Many improvements can be made to these methods. First, the addition of features could improve the results obtained in the k-means clustering and LSTM methods. The weather data extraction process through Dark Sky API was a tedious task. Only 1000 records could be accessed per day. Therefore only the temperature for 3384 days of the study was collected, at the average location of the birds. Capturing the minute variations in temperatures throughout each day would pay greater dividends in the final prediction. Only the maximum and minimum temperatures of each day were extracted. Other weather data such as pressure, precipitation, humidity, wind speed and wind bearing could be added to improve accuracy of the predictions. Furthermore, this project had problems with missing data. Many of the birds had hourly GPS data from 10am to 10pm only. We believe having this intermediate data would have further improved the accuracy with the clustering and periodicity predictions. In addition, there was data from Movebank that was not used in this project: ground speed and height. Both of these would help determine if a bird is migrating or not at any given time. However, these two features had a lot of missing data.

To improve the clustering method, it would have been ideal to use DBSCAN [13] to get a density-based clustering, in addition to k-means clustering. This would provide a better estimate on the time the ospreys stay at a specific place. This was not done because it was demanding high memory and it was not feasible due to the limitations of the systems used. Using density-based clustering is expected to provide a better picture on the exact migration patterns.

LSTM was implemented using the Keras library. The code was run on a GPU - NVIDIA 940M. Although the package by itself was highly optimized and running on the GPU cores, it was not feasible to test the algorithms on all possible permutations of the hyperparameters. The LSTM model chosen was a simple model with a single hidden layer. This could further have been improved and tested on a higher number of layers and LSTM cells which in turn would have provided better results. The RMSE obtained was not low and for a larger data set it was difficult to train for a larger number of epochs. Being able to use cross-validation to extract all the optimal hyperparameters would have been ideal. Unfortunately due to a lack of high performance systems, it was not possible and had to be approximated to a certain extent.

The DFT method is only logical to use with periodic data. Some of the birds had less than one year of data. In such cases the FFT found an incorrect period. In order to obtain more accurate data, there need to be records for each bird for a longer period of time. Since ospreys usually live from 15 to 20 years, this should be possible to obtain. The DFT applied to Data B yielded a period of 341.2 days. The fact that this is not closer to 365 can be attributed to the fact that all the birds do not migrate from the same location, or to the same location. They also do not migrate exactly at the same time. To improve the period obtained from Data B, Data B should be taken from a set of birds traveling close to each other both in time and in space. However, such data may not exist since each osprey makes its own decisions.

This periodicity analysis can be useful to ornithologists who study migration patterns. If additional data is obtained for this bird, a change in migration period can be detected.

Despite the limitations of the LSTM model, the sheer quantity of data extracted from Movebank has considerably helped in identifying the migration patterns with some confidence. The addition of weather information has helped in training of the model for better predictions. The model could be tested for future dates as well with the inclusion of future temperature data from the Meteorological department. Thus this model would assist ornithologists to predict the prospective location of these osprey with a moderate to high level of confidence. This model could also be used to track certain ospreys if their GPS malfunctions.

If an unusual migration period, migration trajectory, or migration start time is detected, this may indicate a change in the osprey's natural surroundings. It can then be determined if the osprey has unusual amounts of certain chemicals in its body, and appropriate actions can be taken by the surrounding regions to reduce their emissions of those chemicals in order to save the ospreys' lives. We believe these predictions can help save ospreys from future threats of extinction due to new chemicals introduced in their environment.

The methodology used in this report could also be applied to any other migratory bird in their own environment.

VI. Statement of Contributions

Rebecca Carrington retrieved osprey background information, gathered weather data, pre-processed the data for the DFT, implemented the DFT method, wrote the corresponding sections of the report and edited the report.

Ramchalam Kinattinkara Ramakrishnan implemented the LSTM section of the project, did the pre-processing of the data in SQL Server. He is responsible for the completion of the corresponding sections in the report.

Jaspal Singh helped in data extraction and implemented k-means clustering. He is responsible for the corresponding parts of the report.

We hereby state that all the work presented in this report is that of the authors.

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