# Graph Analytics for Avian Science Data

Ami Pandat[1][a], Minal Bhise[1][b] and Sanjay Srivastava[2][c]
[1]*Distributed Databases Group, DAIICT, Gandhinagar, India*
[2]*DAIICT, Gandhinagar, India*

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Abstract: Data management solutions are becoming increasingly necessary as more Big Data applications are developed. One such area that deals with Big Data is Big Graphs. Complex relationships exist in graph-based applications. Analytics and data extraction are better solutions for understanding such complex applications. Data from Avian Science has shown significant growth in recent years. Graph analytics can be used to interpret complex scientific data and their relationships. This paper uses graph analytics to discuss the application of graph analytics in avian science. For the eBird Dataset, four Graph Analytics techniques were identified and implemented. These methods extract information about path patterns, node popularity, connections to other nodes, and clustering. The Dataset includes real-time data on bird observation and distribution. Each analytics technique extracts data from the birds' observations. The findings show that graph analytics for avian science data can aid in predicting a wide range of crowd-sourced information. Additionally, the work can be expanded using machine learning methods.

## 1 INTRODUCTION

Popular modern-day applications, Social Networking, Transportation Network, Payment-Purchase History, Crowd-Science, Biodiversity, etc... reports massive growth in data. To manage this increased data, efficient data management techniques are needed. To address the same, there are two approaches: Relational and Graph-based.

The relational approach for data management handles data in a tabular structure with rows and columns. Relationships can be formulated through primary and foreign keys. Complex join operations are required to retrieve the data through queries from multiple tables. Several techniques have been identified for efficient Query Execution in a relational database for large datasets: Data Partitioning and allocation (Pandat et al., 2021),(Padiya and Bhise, 2017), data skipping, and Summarization and Distributed Query Processing are some of the most popular techniques. The graph-based approach manages data in the form of vertex and edge. The Graph is a data structure, visualized through a triple $< vertices,\ edges\ ,and\ relationships\ between\ them >$. Relationships take priority in the Graph-based approach. Edges connecting vertices represent the relationship between two endpoints. The graph-based process eliminates join operation but suffers scalability and security issues (Vicknair et al., 2010). Graph partitioning, Graph summarization (Liu et al., 2016), and Distributed Graph storage are some solutions for efficient RDF Data management and query processing.

The systematic computational analysis of data or statistics, commonly known as analytics, is another question that data management raises. Analytics detects, evaluates, and conveys essential patterns in data. Making smarter decisions also involves utilizing data trends. The structure of the interpretation also varies amongst analytics. Analytics based on graphs or tabular/relational data are also possibilities. The edges connecting the entities are used to carry out the queries in Graph Analytics(Singh et al., 2018). Compared to a relational database, a graph database executes queries more quickly (Vicknair et al., 2010).

The implementation of four types of Graph Analytics algorithms using Avian scientific data is shown in this research. The rest of the article is structured as follows: The next Section contrasts the standard Relational and Graph database approaches for avian research using graph analytics. Section 3 describes the work connected to graph analytics, and Section

[a] https://orcid.org/0000-0002-6882-9881
[b] https://orcid.org/0000-0003-4364-3930
[c] https://orcid.org/0009-0003-8253-067X



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4 discusses the Biodiversity domain. Section 5 discusses the experimental details. Section 6 goes over how to use the four graph analytics techniques. Section 7 is expanded with Hybrid graph analytics techniques, followed by a discussion of the results and future directions.

# 2 RELATIONAL AND GRAPH DATABASES: AVIAN SCIENCE

Comparing both databases concludes that Relational and Graph-based databases have advantages for different use cases (Vicknair et al., 2010)(Patras et al., 2021)(Cheng et al., 2019a). A detailed comparison of the Relational and Graph databases has been presented in (Cheng et al., 2019b) (Pandat and Bhise, 2022). The primary focus of these analyses is the Query execution time for four types of queries. The research states that the Graph database works faster for Projection and join questions than linear and aggregation queries; relational database performs well. Let's compare how relational and Graph databases handle this specific use case:

**1. Data Model:**

- Relational Database: Relational databases are based on tables with rows and columns. In Avian Science data, this would mean representing entities like birds, habitats, and researchers in separate tables with relationships established through foreign keys.
- Graph Database: Graph databases use a graph data model with nodes (representing entities) and edges (representing relationships). Each bird, habitat, researcher, and their connection can be represented as nodes and edges in a graph.

**2. Schema Flexibility:**

- Relational Database: Changing the schema to accommodate new relationships or properties can be challenging and require altering tables, which can be complex and time-consuming.
- Graph Database: Graph databases are inherently flexible for handling relationships. You can easily add new connections or properties to nodes without changing the overall schema.

**3. Querying:**

- Relational Database: Queries in relational databases may require complex JOIN operations to traverse relationships, which can be slower for deep or complex queries.
- Graph Database: Graph databases excel at traversing relationships, making them well-suited for graph analytics tasks. Querying for patterns and relationships is more intuitive and efficient.

**4. Performance:**

- Relational Database: Relational databases are generally optimized for structured data with simple relationships. Complex graph analytics queries can be slower in relational databases.
- Graph Database: Graph databases are designed specifically for graph-related tasks, offering superior performance for graph analytics.

**5. Scalability:**

- Relational Database: Scaling a relational database to handle large-scale graph data can be challenging and often requires horizontal partitioning or sharding.
- Graph Database: Graph databases are inherently scalable for graph-related tasks as they are designed to handle graph data efficiently.

**6. Use Cases:**

- Relational Database: Relational databases are suitable for data with well-defined, structured relationships and when graph analytics is not the primary focus.
- Graph Database: Graph databases are ideal when the relationships within the data are the primary focus, such as in Avian Science data, where bird behaviors, interactions, and habitat dependencies are crucial.

Research states that graph database management systems still require more security-related features, and relational databases need more flexibility to adapt to data changes.

## 2.1 Database and Ecology

Technically, environmental and ecological data frequently take the form of matrices that may be effectively stored and analyzed using a relational database management system (RDBMS) or another tabular data structure.

$$\begin{aligned} \text{table\_join\_cost}(R,S) &= \text{table\_scan\_cost}(R) \\ +\text{record}(R) \times \text{selectivity} &\times \text{records\_per\_key}(S) \\ &\times (CPIO + CPR) \end{aligned} \quad (1)$$

(Tanaka and Ishikawa, 2019)

When integrating big datasets, the result is frequently kept in volatile memory, a constraint. Table indices in a standard database design take O(log(n)) time, where n is the size of the input dataset. Reverse and recursive lookups may be required in a query with many joins (from various data tables), which might increase the load from O(n) to $O(n^k)$, where k is the number of data tables to join. Figure 1 explains the cost of join operation (Tanaka and Ishikawa, 2019) where CPIO is the I/O cost per page stored record for DBMS access, and CPR is the CPU cost per record.

## 3 RELATED WORK

Various algorithms have been devised to discover the analytical observations from the available data using the Graph-based approach. These algorithms help real-life applications efficiently analyze the data. This section summarizes the application of graph analytics and technical advances observed in Graph Analytics. Several tools implement the extraction of data using graph analytics. Many applications, such as perturbation analysis and power failure analysis from graphs constructed by the power grid, create multiple views by removing or updating a set of nodes and edges and then performing computations like path analysis and so on from scratch inefficient. The motivation behind the Graphsurge (Sahu and Salihoglu, 2021) system is a technique that can organize views in a specific order and carry out the analysis in a manner that can optimize the time and impair performance.

TurboGraph++ (Ko and Han, 2018) is a scalable and fast graph analytics system. It uses the layered windowed streaming paradigm to conduct neighborhood-centric analytics quickly and efficiently with a limited memory budget. The relational database also implements some of the analytics based on graph algorithms. Vertexica (Jindal et al., 2014) is an Analytical tool that performs query execution in SQL engine for graph queries. It leverages relational features and uses much more graph analysis. The popular graph algorithms Page Rank and Shortest Paths show Vertexica outperforms (Apache, 2011) and regular Graph Database.The recent tutorial presented in (Wang et al., 2020) discusses the application of Graph Analytics in healthcare, specifically for COVID-19. To deal with large datasets for Graph Analytics using multi-distributed GPUs has been presented in (Jatala et al., 2020). It finds the evaluation based on four points. (1) The Cartesian vertex-cut partitioning policy, (2) static load imbalance, (3) device-host communication, and (4) asynchronous execution.

Above all, the framework and operations for Big data sought a general framework. Recently, in (Bellandi et al., 0), a multi-modal Big data analytics framework has been proposed. The proposed work helps to optimize the cost and helps to improve the performance of analytical operations. One of the analytical-based works for the avian science domain is BioSpytial (Escamilla Molgora et al., 2020). It is a hybrid analytical tool for crowd science data. It supports both Relational and Graph-based query processing. The work presented in this paper uses the general framework to implement graph analytics operations. It uses one of the crowd science data eBird (eBird Database available at:, 2014).


Figure 1: Migration.

## 4 AVIAN SCIENCE

Biodiversity data is increasing daily as researchers and ecologists digitize ecology data. Avian science is a subset of the vast domain of ecology. Birds and their observation data help ornithologists and computer scientists analyze their effect on the real world. Through migration, population, and other factors, analytics of avian science data help researchers in many ways. Birds are affected majorly by environmental changes. One such case is Migration. Figure 1 is designed to represent the typical bird migration season. We can analyze the increasing and decreasing number of birds in one area over time. The migration of birds depends not only on time but also on the area they live in and the availability of resources.

BioSpytial (Biodiversity + Spatial + Python) (Escamilla Molgora et al., 2020) aims to discover the co-occurrence of jaguars with other threatened species in the borderline of Mexico area. It uses both Raster and Vector data formats to analyze the Spatial data. The Graph traversals for 4-neighborhood have been used to analyze the occurrence of Jaguars in Mexico. It has been found that 29% Rodents, 23% bats, 15% deers, and 2% parrots were there in neighboring cells. There is a clear relation between graph data and ecological/biodiversity data to find a network of the same species in the neighborhood.

This research aims to apply Big Graph Analytics

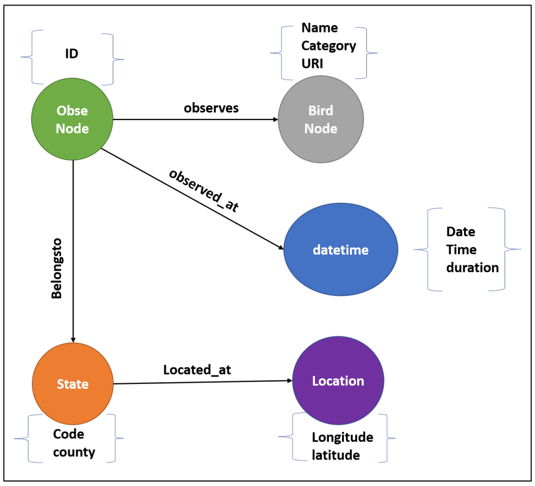



Figure 2: eBird Graph.

capabilities to determine the statistical impact of the aforementioned environmental changes on Avian Science.

# 5 EXPERIMENTAL SETUP

This section discusses the experimental setup used for the evaluation of this work. The Graph Analytics techniques have been implemented for the following Dataset utilizing the hardware and software below.

## 5.1 eBird

eBird (eBird Database available at:, 2014) is a platform Cornell Lab of Ornithology managed to keep updated data about birds worldwide. eBird is a website collecting bird occurrence and relative abundance data at specified English, Spanish, and French places. Users can choose a place from a drop-down menu of birding ”hotspots” (shared locations) or utilize eBird's online mapping tools to select from or build new reporting locations when reporting bird sightings. Many participants, for example, designate their home as a private site and record birds daily, but others bird a nearby park every day.

Participants can make repeated observations from the same area because the chosen locations are saved in the database. For experiments, two years [2010-2012] of data for India have been used. The data size is 80MB, containing 2.3 lacs tuples and 41 attributes. We have prepared a brief structure that explains the details included in the development of the Neo4j graph shown in Figure 2. Five entities are created for Observers, Birds, Location, State, and Date-Time details. The Graph shown in Figure 2 is a Property graph. Each node contains properties about that entity. There are four relationships identified between available entities. The generated Graph is a directed graph.

## 5.2 Hardware and Software

Implementation is done on the system, Intel® Core (TM) i3-2100 CPU@ 3.10GHz 3.10 GHz 24GB. For Query execution, Neo4j Desktop 1.1.10 is used, and Neo4j (Desktop:, 2012) browser version 3.2.19 is used for visualization. For Analytics purposes, the Graph data science (GDS) library has been installed and used for the evaluation. GDS enables hybrid data analytics. It also needs to be interfaced with Python language.

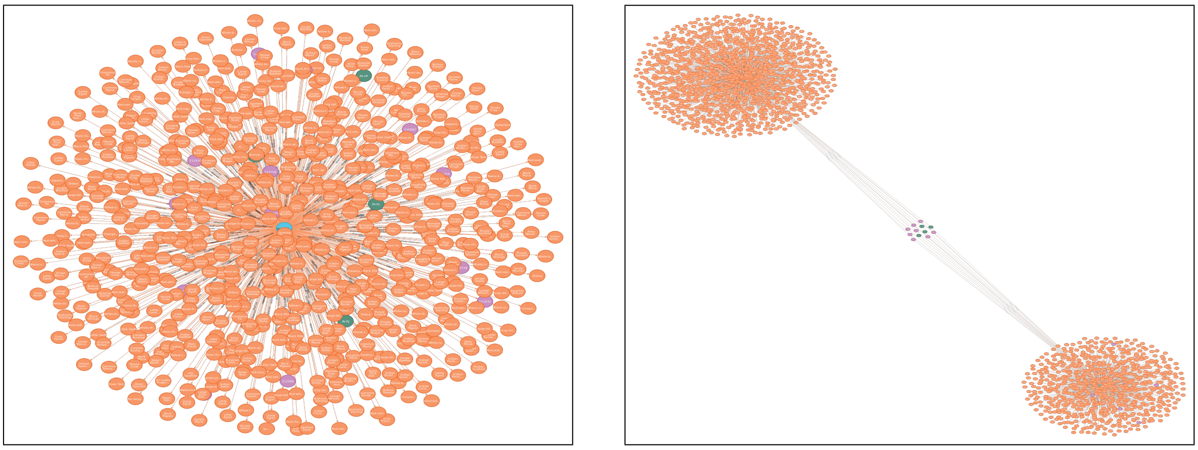
# 6 GRAPH ANALYTICS

Graph analytics include techniques for identifying strategic entities, uncovering structural data, and calculating data flow in a network. Graph Analytics helps to analyze and understand the strength between two nodes using Properties applied to the Graph. For different use cases, specific analytics can be used as an algorithm and gives result relevant to the product/company. Regular analytics explores statistics, computer programming, and operations research to uncover insights. Graph analytics includes graph-specific algorithms to analyze relationships between entities. Clustering, partitioning, PageRank, and shortest path algorithms are unique to graph analytics. One can apply four types of Analytics to the Graph databases. This section describes all four types of graph analytics for the ecological Dataset. We have used the eBird Dataset available at (eBird Database available at:, 2014).

This motivates a knowledge of its utility and adaptability for discovery-style analysis for specific business problems, their prevalence, and why they are prevalent. Graph analytics techniques are built on a model for describing distinct entities and the various types of relationships that connect them. It uses graph abstraction to represent connectedness, consisting of vertices (nodes or points) representing the modeled items, joined by edges (links, connections, or relationships) that capture how two things are associated.

## 6.1 Steps to Set up Analytics Environment

The following steps have been followed to perform the Big graph analytics on Avian science data.



(a) Original Graph. (b) Clustering Analytics.

Figure 3: Analytics Results.

1. Download the eBird dataset by sending an application to eBird developers (it takes around 3-4 working days to get it done)
2. Clean the Dataset based on the attributes you need for your experiment. (For graph analytics, we have chosen the attributes mentioned in Figure 2
3. Setup Neo4j Browser and Desktop/Neo4j Aura based on your system specification.
4. For analytics load the labeled in one graph in Neo4j(for this experiment original generated graph is presented in Figure 3a)
5. To perform all four types of analysis, create separate folders in the Neo4j browser to download the results and queries
6. Connect the Neo4j browser with Graph Data Science(GDS) library
7. Perform your desired analytics experiments as suggested in the GDS library.

The four Graph Analytics techniques used to perform avian science data analytics are explained in the following subsections.

## 6.2 Path Analytics

Path Analytics examines the relationships between nodes. They are primarily used in shortest-distance problems. It analyzes similar shapes and distances from different paths that connect entities within the Graph.

We can find the following details if we map the eBird dataset to path analytics. 1. The nearest neighbor of the same species. 2. Shortest path between two common species found in a particular state 3. n-hop reachability between two vertices.

**Cypher Query:** *MATCH p=shortestPath((a:BirdNode)-[*]-(c:ObseNode)) Return p, length(p) LIMIT 25*

## 6.3 Connectivity Analytics

This type of Analytics determines how strongly or weakly connected two nodes are. Connectivity analysis outlines the number of edges flowing into the node and those flowing out. This analysis provides a method to identify malicious or unexpected patterns within the data. It gives the best solution to finding connectivity between different entities.

Graph Analytics based on connectivity helps to find a connection between observers and bird species. We can apply the same to find the below-mentioned query solution.

1. Number of observers who observed particular species
2. Number of species observed by a particular observer
3. Number of observers at a particular landmark

**Cypher Query:** *Match (n:BirdNode)-[r]-() return n.Name, count(distinct r) as degree Order by degree*

## 6.4 Centrality Analytics

Estimates how important a node is for the connectivity of the network. Using the PageRank algorithm helps to estimate the most influential people in a social network or most frequently accessed web pages.

It helps to evaluate the importance of a present node within the graph network and its connectivity to others. If one would like to find the most influential node, this is the technique. For eBird, we can find the

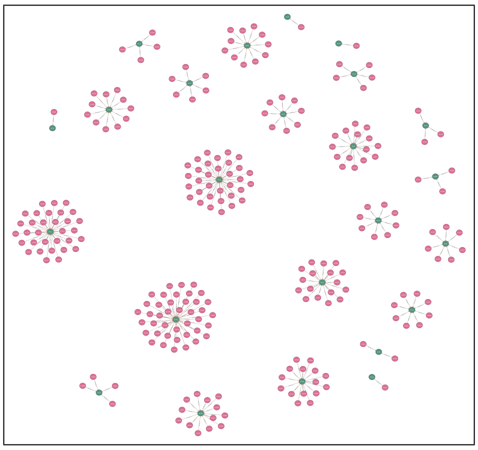


Figure 4: Community Analytics.

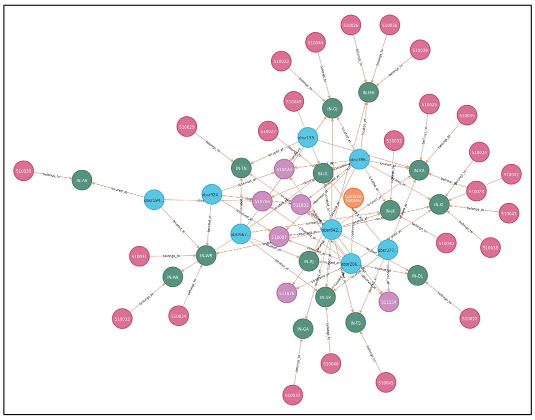


Figure 5: Path Analytics.

most visited place or species by an observer in all the seasons. It will help to put analysis in a time-ordered manner.

### 6.5 Community Analytics

Distance and density of relationships can be used to find groups of people frequently interacting in a social network. Community analytics also deals with the detection and behavior patterns of communities. Using graph analytics saves time. Graph analytics are easier to work with than the traditional techniques being used. Modeling the data and its storage becomes easy. Patterns can aid data-driven decision-making when appropriately understood with the correct meaning derived from the data. Overloaded and strained resources within the organization can be identified and reconfigured using graph analytics. The more it is connected, the most important it is in the network. The community analysis helps to find the most frequently observed bird species from the network.
**Cypher Query:** *MATCH (n:ObseNode)-[r]-¿(m:BirdNode) WHERE n.Name =”obsr360080” RETURN n,r,m*

## 7 HYBRID ANALYTICS

In cases where interpretation must be made from one or more analytics, hybrid analytics can be performed. For the same, we have conducted two hybrid analytics.

### 7.1 Path-Cluster Analytics

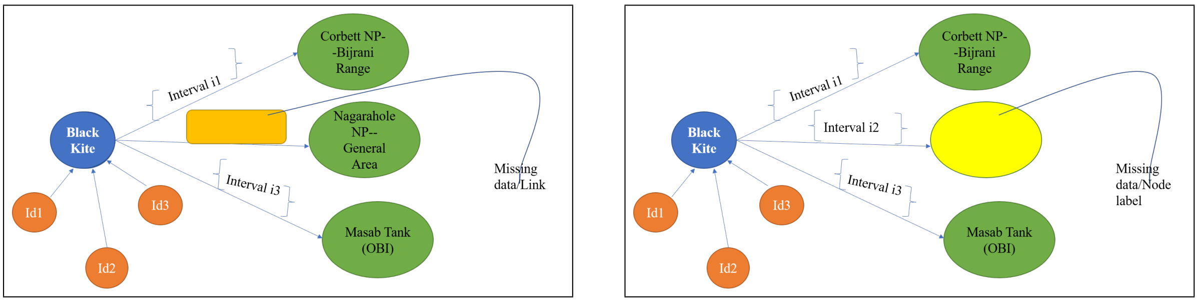
In avian science, we are often required to find a flock of birds moving or migrating in certain paths. Clustering analytics results in clusters of species. To find those clusters' source and target destination, the clusters would be fed to the path analytics query, and the moving path can be analyzed.
**Cypher Query:** *Find a path of clusters of Yellow-browed Bulbul between any two locations.*

### 7.2 Community-Cluster Analytics

The degree of nodes, i.e., Community analytics, answers the number of nodes connected to several nodes. However, the issue arises when we would like to find only the degree of nodes in clusters. For that, we need first to form a cluster, and then one can count the degree in a cluster of nodes. This hybrid analytics helps to answer some of the following queries of Avian Science data.
**Cypher Query:** *Find a number of locations where Slaty-blue Flycatcher is found in a flock of 100.*

## 8 ANALYTICS RESULTS AND DISCUSSION

This section discusses the results from the experiments performed for all four types of analytics. Figure 3b shows the clusters formed from the original Graph. The clustering analytics help to retrieve the information that can be clustered together. The figure shows the two clusters generated from the original Graph in Figure 3a. The clusters help to identify the connectedness of similar entities. Community analytics is just the extended version of clustering analytics. Clusters formed based on the particular community can be identified, and as shown in Figure 4, a different community of bird species and observers are represented. Numerous species are available in the Dataset; each can be identified as a community. This




(a) Link Prediction.

(b) Node Prediction.

Figure 6: Machine Learning Approaches.

Table 1: Centrality Analytics.

| Species | Centrality |
|---|---|
| **Greenish Warbler** | 0.78 |
| **Slaty-blue Flycatcher** | 0.23 |
| **Yellow-browed Bulbul** | 0.67 |
| **Oriental Honey-buzzard** | 0.37 |
| **Black Kite** | 1 |

type of analytics helps to determine the similar data available in the Dataset.

Path Analytics helps to analyze the path-related properties between two entities. We can determine particular entities' shortest, largest, and nearest neighbors. Figure 5 shows the available path between bird species found in nearby areas. This analytics can be applied to find the n-neighborhood of the entities.

The centrality analytics help to identify the most popular nodes in the network. The value of centrality varies between 0 to 1. The value 1 shows the most central node in the network. The table shows the centrality values for the bird node. Four types can represent centrality analytics. Degree centrality analytics is one of them. The result shown in the table is for degree centrality analytics.

## 8.1 Challenges

Numerous characteristics of graph problems provide severe obstacles to effective parallelism. High-degree vertices in graphs are prevalent. These graphs could be more computationally burdensome to partition. In real-world graphs, most vertices have comparatively few neighbors, while a few have numerous neighbors. More computation, coordination, and communication are needed to partition the sparse graphs.

Natural graphs have colossal sizes that are too large to fit in a single memory. There are communication costs as a result of the high-degree vertices.

# 9 MACHINE LEARNING TECHNIQUES FOR GRAPH ANALYTICS

Graph analytics applications aren't just for interpreting data; they can also predict how data will change shortly. Graph analytics applications can use data from recent years to forecast future changes in the centrality and community of bird data.

As shown in Figure 6a and 6b, we can predict the missing observation data from the eBird dataset. In observation, there may be a case where nodes or links are missing in the data. Machine Learning (ML) algorithms help to find the same. We can identify and categorize the birds based on their characteristics using classification and graph analytics techniques. For example, some birds are autumn birds in one location but spring birds in another. Machine learning solutions can be used to perform these classifications. The rate of change in bird observation data and noise in the data can be analyzed using a regression approach. Various open issues in avian science can be addressed by combining machine learning and graph analytics.

# 10 CONCLUSION

Big Graph Analytics techniques for Avian Science data have been implemented in this paper. Popular bird observation data eBird has been used to perform the experiments. The analytics experiments help identify the dependence between observers and birds, including locality parameters. Community analytics form clusters of identical communities; connectivity shows the strongly connected component with numbers in the form of in-degree and out-degree, whereas centrality analytics help to identify the most popular entity, and path analytics determine the path between the source and target entity. When dealing with

Avian Science data and performing analytics, a graph database is generally a better choice due to its flexibility, performance, and inherent support for handling complex relationships within the data. Relational databases can work for this use case but may be less efficient and more complicated to model and query. Hybrid analytics techniques help determine the significance of multiple analytics on a domain. Further, ML techniques help to predict the relationship/link between different entities.

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