Animal Social Network Visualization: ASNViz

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Abstract—We present ASNViz, a multimedia analytics solution that facilitates the visualization and analysis of animal social networks (ASNs). By modeling ASNs as networks of nodes and edges, ASNViz provides valuable insights into the dynamics and evolution of animal communities. The tool quantifies and visualizes the social structure at node and network levels, predicts future interactions when new individuals are added using deep-learning, and allows for manual updates based on empirical observations. The predictions of future interactions are made using Variational Graph Auto-Encoder models [27], which can be retrained and stored by the user while updating the network. A separate view gives insights to the evolution of networks based on the nodes and interactions observed and predicted between versions. ASNViz aims to bridge the gap between biology and complex network sciences, providing accessible network visualizations, interactions, and analytics for researchers interested in studying ASNs.

Index Terms—Animal social networks, edge prediction, network analytics, network visualization

1 Introduction

The social dynamics of animal communities have been of large interest to the biological and sociological scientific communities at least since Darwin's publication of *On the Origin of Species* [14] (for an in-depth overview of the history of the field, refer to Rubenstein & Abbot [42]). In recent decades, the most prominent and standardized tool for research into animal social communities has been network analysis [48]. By modelling a community of individual animals and their interactions as nodes and edges of a network, valuable insights have been gathered in topics such as evolution, animal behaviour, animal communication, and the spread of diseases [49].

While previous research was largely limited to static network data, improvements in methodology now allow us to research the dynamics of social networks through changes in the network over time [4]. With the higher complexity of both networks and analysis methods, appropriate visualizations and measures become crucial to summarise and correctly interpret the structure of a network. Along with technological developments, the topic of edge prediction has also gained more interest and applications over the past years [31]. Predicting how a social network will develop in response to the addition of new individuals can provide valuable insight into animal behavior, the spread of diseases, optimal resource allocation for wildlife conservation, and more. The development of deep-learning models for edge prediction provides a lot of interesting new opportunities in the field [27, 31].

In this paper we present ASNViz: a novel interactive animal social network visualization tool that provides clear and informative insights into the structure, dynamics, and evolution of animal social network data. Firstly, the ASNViz dashboard quantifies and visualizes the social structure in detail by measuring various metrics at node and network levels. Secondly, the tool models how future interactions might happen in an animal social network when we introduce one or more new node(s). The tool provides users with a form interface to add new nodes, after which the edges of the augmented network are predicted using a pre-trained Variational Graph Auto-Encoder (VGAE) model. The tool also allows the user to manually update edges to include their own observations in the network. Thirdly, ASNViz can detect and visualize communities in a social network structure, giving a deeper understanding of an animal social network and the way it will respond to scenarios such as the spread of diseases, limited resources, and the addition of new animals to the network. Additionally, ASNViz contains informative graphs describing the node attributes and their relation to the likelihood of two animals interacting, which may provide insights into the reason animals do or do not interact. Finally, ASNViz provides visualizations to show the user how the animal social network is evolving with the addition of new nodes and edges over time. Currently, ASNViz includes 11 unique datasets from the Animal Social Network Repository [43].

The targeted user base of ASNViz consists of researchers in the area of biology, ecology, and sociology. While many advances are made in both biological and complex network sciences, there remains a gap between the two fields when it comes to analyzing Animal Social Network (ASN) data [10]. ASNViz aims to take a step in bridging this gap by facilitating accessible network analytics to researchers interested in animal social networks.

To summarise, our contributions are as follows:

- Visualization and quantification of the network at node and graph levels.
- Prediction of interactions when adding a new (group of) animal(s) to an existing ASN.
- Provision for users to manually add new interactions.
- Visualization of the evolution of an ASN as it changes over time.

Section 2 introduces us to preliminary concepts of networks, previous work, and existing tools used in social network analysis. Section 3 describes the Animal Social Network Repository Data used. Section 4 provides the requirement analysis for our solution. It also explains an important user-system interaction workflow necessary to track and visualize the evolution of the network. Section 5 delves deeper into the visualization features of the solution, section 6 briefly discusses the software implementation of the application and finally, Sections 7 and 8 discuss the implications and future directions of the development of ASNViz.

2 Domain Background And Relevant Work

2.1 Network Theory

A network (or graph) $G = (V, E)$ is a structure consisting of a set of vertices (or nodes) V and a set of edges (or links) E. An edge $e \in E$ represents a connection from one vertex $v_i \in V$ to another $v_j \in V$. The mathematics of networks has been extensively described in previous literature (e.g. by Newman [36]), so we only give a conceptual summary of animal social networks here. Animal Social Networks (ASN) represent social interactions among animals within a group or population as a graph in which individuals are represented as nodes or vertices, and the connections between them indicate social interactions, forming links or edges (Figure 2) [29]. In recent years, many different network representations of varying complexity have been developed and applied to animal social networks. Some of the more popular

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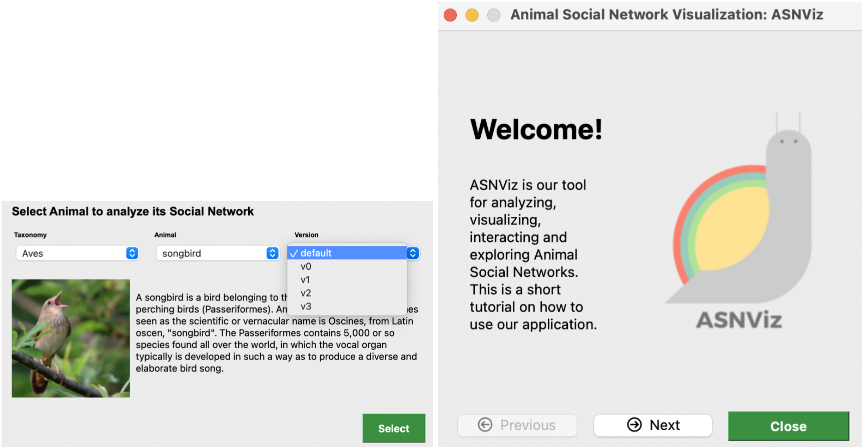


(a) Tree Structured Dropdown Menu

(b) Info Window's Starting Page

Fig. 1: Interfaces of ASNViz

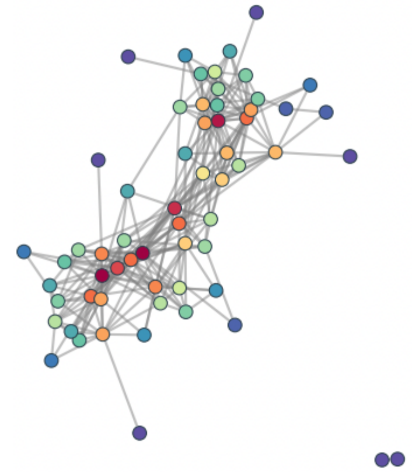


Fig. 2: ASN for Ground Squirrels with 61 nodes and 265 edges. An edge between 2 nodes is an interaction by spatial proximity.

adaptations and expansions of the basic network structure are described below:

1. *Weighted networks:* In weighted networks, edges contain an extra variable representing weight. In the context of animal social networks, this weight can for example represent amount or duration of interactions between a pair of individuals. A special case of weighted networks is *signed networks*, where both positive and negative weights are used. The sign of the weight typically refers to whether the interaction was amicable or hostile.

2. *Multigraphs:* In multigraphs, multiple edges can connect any two nodes. This could be used as an arguably more intuitive way of modeling the amount of interactions between individuals, an additional variable in combination with weights such as the duration of an interaction, or a more useful way of modelling certain variables for later rewiring purposes [24].

3. *Directed networks:* Directed networks allow one-way edges, which can be useful in modeling two different roles in a social interaction. For example, if animal A grooms animal B, one might want to model this by only adding an edge from A to B but not vice versa. Undirected networks are in fact a special case of directed networks, where every edge $(v_i, v_j) \in E$ implies $(v_j, v_i) \in E$.

4. *Bipartite networks:* In bipartite networks, each node is assigned one of two categories. Nodes from the same category cannot have edges between them. This can for example be used to link animals (category 1) to certain locations (category 2) they gravitate to. Manlove et al. [33] constructed a tripartite animal network to model individuals, locations, and time in one network.

5. *Multilayer networks:* Multilayer networks [16] can be seen as a stack of multiple networks with inter- and intra-layer edges. If the nodes in all individual networks refer to exactly the same data-points, the network is called a *multiplex* network. Such a network allows for different types of edges between the same nodes, giving the possibility of linking the same community of animals with different edge types within one structure. Every multilayer network can also be modelled as a larger single-layer network, where edge types are stored using an additional variable (such as a weight) [3].

ASNViz currently supports relatively simple undirected networks, without support for weights. Furthermore, nodes are expected to refer to individual animals, and not to anything else like time or place. However, since we add a temporal dimension to analyze network evolution (see Section 5.3, we do effectively model a bipartite network. Furthermore, since multi-layer networks can be represented as single-layer networks, support for multi-layer networks would only need a few additional steps in the pre-processing of the data. For a more detailed explanation of the different types of network structures and examples of how they are applied to animal social networks, refer to [48].

2.2 Social Network Analysis

Social network analysis (SNA) offers tools and techniques to discover and analyze patterns within a social network [2]. Applying these techniques, researchers can gain insights into the social structure of a population as a whole or study the interactions of specific individuals. Traditionally, SNA relied on static metrics that provide insights into the network characteristics at a given time. However, with the advancements in technology and data collection methods, researchers are now developing methods to study the dynamic nature of social networks and their evolution over time [38]. We can examine temporal patterns, such as the formation and dissolution of social links and the role or influence of each individual within the network, to understand the mechanisms by which they evolve.

ASNs are analyzed to gain insights into the social structure and behavior of animal populations [30]. By studying the interactions and relationships between individuals within a population, researchers can gain a deeper understanding of a wide range of topics in animal behavior and ecology, including mating behavior, dominance hierarchies, anti-predator behavior, and how animals adapt to their changing environment. They can determine how individual characteristics such as age, sex, or social status, and changes in the environment such as climate, the presence of predators, or the availability of food, impact the formation and maintenance of social relationships [38, 47]. Animal SNA can be divided into five main research themes [10].

- *Social centrality, evolution, and fitness*: the social environment has to be taken into account to understand the evolution of animal traits. SNA enables comprehensive studies of the impact of the social environment across different species. Research in this area has for example provided evidence that an animal's social network position can be linked to its survival and reproduction chances [18].

- *Spread of disease and information in networks*: ASNs can be used to detect spreading processes such as diseases and information. For example, Silk et al. [49] determined to what extent different types of information spread through the network and examined the relationships between individual positions in the network and disease status to determine the population vulnerability to epidemics.

- *Stability, flexibility, and robustness of social systems*: to understand the resilience and adaptability of social systems, studies have examined the stability of animal social network structures over time, correlations between network structures and environmental factors such as food availability and seasonal changes, and the response of networks to node loss [39].
- *Cooperation in structured populations*: cooperative behavior consists of acting to benefit others even if it comes at a cost to oneself. While experiments have proved that social structure can influence cooperative behavior in humans, the extent to which this holds true for animals is still uncertain [9].
- *Wildlife conservation and animal welfare*: ASN analysis has an important role in wildlife conservation and animal welfare for captive animals. Studies estimate disease control strategies, social behavior during relocation or reintroduction into the wild [51], and management of captive populations [41].

2.3 Edge prediction

Social networks are highly dynamic structures that grow and change rapidly over time. Understanding by which mechanisms animal social networks evolve is one of the fundamental questions for ecologists [4]. Mathematically, this question can be formulated as an edge prediction problem [32]. Edge prediction models can be split up into three categories. Firstly, similarity and proximity-based models, predicting edges based on deterministic measures of similarity between nodes [31]. Secondly, probability-based models, usually incorporating maximum-likelihood estimation of a network's structure [31]. The third and most recent category of deep-learning based models include models such as the Variational Graph Auto-Encoder (VGAE) [27] and the Graph Transformer (GT) [17, 54]. Deep-learning based models can effectively capture rich information about the network structure, and have been shown to outperform previous baselines [27]. ASNViz utilizes the VGAE architecture to predict edges in the evolving network structures. While the more recent GT models could be even more accurate [53], more research into the application of these models to edge prediction needs to be done before we sacrifice the higher speed of the VGAE model.

2.4 Related Work and Tools

Many visualization techniques have been devised for analyzing social networks. Gephi [5] is an interactive 3D visualization tool for the exploration and interpretation of network data. Its visualization techniques include spatializing, filtering, navigating, manipulating, and clustering network data. [1] provides an in-depth analysis of social networks with graph layout visualizations (based on centrality measures or force-directed placements). ORA-LITE [11] provides visualizations across temporal dimensions to highlight structural changes in the networks. UCINET [7], NodeXL [50], igraph [12], Pajek [6], Statnet [23], Netminer [13], and JGraphT [35] are some more tools whose visualizations are based on node-level and network-level metrics. We take inspiration from the existing social network tools to devise useful and insightful visualizations for our project. The novel feature of our application is that we allow our visualizations to be interactive and adaptive based on the user's needs and the deep learning model's feedback. To the best of our knowledge, no network visualization software allows the user to interactively predict edges in a network.

3 Data

ASNViz displays social networks sourced from the Animal Social Network Repository (ASNR) [43]. ASNR is a collection of 790 social networks from more than 45 species across multiple taxonomies [45]. Network datasets have been gathered from published literature and other data repositories of social networks like the Harvard Dataverse [46]. All network datasets of ASNR pass through some validity checks and are transformed into the GraphML format. Networks can be defined as directed, undirected, weighted, unweighted, and finally allow attributes to be assigned to both nodes and edges [8]. ASNR only contains static networks, where data is typically aggregated over a set period of time. The frequency or intensity of interactions is then represented as edge weights. Edge weights carry no significance in ASNViz as in its current version the focus lies on node features and interactions. The meaning of edges, and therefore interactions, varies on a network-per-network basis and can be defined as one of the following types: dominance, foraging, grooming, group membership, non-physical social interaction, physical contact, social projection bipartite, proximity, trophallaxis, or mixed.

For this version of ASNViz, 11 unique animal networks from three taxonomies from ASNR are included. They vary in size from a few to up to hundreds of individuals with up to thousands of connections, demonstrating the features of the platform on different graph scales. Selected networks have at least five node features, either categorical or continuous, to ensure the VGAE model can learn reasonable patterns from the data. We do a few data preprocessing steps which involve cleaning where we get rid of uninformative nodes and transforming where we encode categorical attributes.

4 Functional Requirements And Solution Design

The functional requirements of ASNViz are motivated by two major challenges in the field of Animal Social Network analytics; firstly the system should bridge the gap between network science and biologists [10], and secondly, the system should improve functionality for dynamic networks compared to and inspired by various ASN tools introduced in Section 2.4.

One of the basic-most requirements of our targeted user-biologist is to be able to select a particular animal species whose social network they want to investigate. Next, the user might be interested in investigating more about a particular node. Along with that, they should be able to simulate the evolution of the network by making iterative changes to the existing network. Finally, the user is likely interested in exploratory analyses and visualizations of the current version network.

Based on these core requirements, we come up with the following main user and system tasks:

- **T1 User interacts with social network** The user wants to interact with the animal nodes of the social network to know their particular features. The user should be able to manually add nodes and edges to the network.
- **T2 System provides feedback to user interactions** The system should be able to actively monitor user actions, and provide feedback in the form of real-time updates to the network.
- **T3 Analyze the social network** The user should be presented with insightful visualizations summarising information of various aspects - nodes, interactions, and the full network structure. These analytics should adapt to possible changes to the network.
- **T4 Visualizing the iterative evolution of network** The user should be able to see a timeline of how the network has changed from the base snapshot to any updated snapshot.
- **T5 System is adaptable to other networks** The system should be dynamic, and should be able to adapt to any other animal social network.

We design the workflow of our solution following these five tasks as shown in Figure 3. Task **T1** shows the options for additions of nodes and edges. Task **T2** shows the system feedback in response to the user's actions in the form of animal network updates, edge predictions, and retraining of the model. The application design to carry out Task **T3** is described in detail in Section 5.2. While the visualizations pertaining to Task **T4** are discussed in Section 5.3, we discuss its back-end solution design in Sections 4.1 and 4.2.

4.1 Versioning of the Animal Social Networks

To carry out Task **T1** the user makes changes to an existing social network. Task **T2** requires the system to provide feedback to these user interactions, giving us an updated social network. This process can go in iterations giving rise to different snapshots of the social network, which from now on we will refer to as **"versions"**. Figure 8a shows the workflow of this versioning system. The dynamics and structure of the social network will change with two user actions: the addition of nodes and the addition of edges. The addition of nodes by the user further leads to the prediction of new edges by the VGAE model. The user can then prompt the application to save this updated network which leads us to retrain the model on this updated version. We save these versions of the animal network and the trained models so that users can select any version they see fit and work with it. Through the user-guided retraining process, the application can obtain models with better and more accurate edge predictions.

4.2 Edge prediction by Variational Graph Auto-Encoders

The initial VGAE models of all networks included in ASNViz are trained in advance, in order to have fast user interactions while predicting edges. The models are trained using incomplete versions of the animal social networks, where parts of the interactions (edges) have been removed while all node features are kept. The decoder then learns to reconstruct the correct missing edges based on the latent representation of the partial graph and node attributes.

5 Application Design

We divide our solution into three main features:

- Visualization and Interaction With Social Graphs
- Exploration of Social Graphs
- Evolution And Changing Trends Of Social Graphs

5.1 Visualization and Interaction of Social Graphs

To not over-burden the user with a lot of choices at once, we present hierarchically-structured dropdowns where the user first selects the taxonomical category, and then the species of the animal they want to analyze (Figure 1a). Upon selection, the user is presented with the image as well as the relevant biological information about that animal. After the user selects the animal along with the version of the social network, they are redirected to an interactive graph visualization dashboard as shown in Figure 4. The nodes of the ASN are color-coded based on their degree. The system actively monitors two user mouse events: hovering and clicking. When the user hovers or clicks on a node, its attributes are displayed on the left or right side of the graph respectively. Besides node features, a few common centrality measures are also displayed in this view (Table 2). The left-most part of the dashboard is presented with a toolbar, from where the user can make various choices. The various options presented to the user are mentioned in Table 1. Network attributes such as the interaction type (what does the edge between two animals represents), taxonomical category of animal, and data-collection setup are also mentioned.

Button	Usage
	Opens a pop-box for the addition of node.
	Predicts edges for the newly added node
	Creates an edge between two nodes clicked consecutively
	Undo or Redo of any action prior to retraining.
	Saves the modified network and retrains the VGAE model
	Opens a pop-box about navigating through the app as in Figure 1b

Table 1: Functionalities of buttons in the toolbar

5.2 Exploration of Social Graphs

5.2.1 Descriptives

The goal of Task **T3** is to provide the user with interesting exploratory insights into the network data. Firstly, since the edge prediction task is based on the node attributes, we visualize the distribution of these attributes across the network (Figure 5). For categorical variables, we designed horizontal bar plots visualizing the frequency of each possible attribute value. To not clutter the interface with one large legend and to keep the color scheme consistent and clear, the legend for an attribute is presented when that specific bar is clicked (Figure 5a).

For continuous node attributes, ASNViz shows bar plots with nodes on the x-axis and attribute values on the y-axis. By sorting the nodes by their value, the user can get insights into the distribution of any attribute in a single look. Since the goal is to provide visualizations for the complete network structure, the interface is not cluttered with node labels on the x-axis. In the example of Figure 5b, the user can see the songbirds' social network contains a largely equal level of relative dominance, and one clear "pack leader", with a relative dominance much higher than any of the other birds.

5.2.2 Attributes and Edge Correlations

Researchers may be interested in which attributes function as good predictors of whether two animals interact. For this reason, we compute the correlation between attribute similarity and edge existence for all attributes, using all possible node pairs as data points.

Let $G = (V, E)$ be a network, where each node v_i has one or more attributes given by $v_i(a_k)$. For a given node pair (v_1, v_2), the dependent variable *edge existence* is equal to 1 if $(v_1, v_2) \in E$, and equal to 0 otherwise. For any continuous attribute a_k and node pair (v_i, v_j), we define similarity as:

$$\text{sim}(k)_{ij} = \frac{1}{|v_i(a_k) - v_j(a_k)| + 1}.$$

For a discrete attribute a_l the similarity score is given by:

$$\text{sim}(l)_{ij} = \begin{cases} 1, & \text{if } v_i(a_l) = v_j(a_l) \\ -1, & \text{otherwise.} \end{cases}$$

These similarity scores are entered as independent variables, together with the dependent variable, into a standard two-tailed correlation test. The Pearson correlation coefficient of each attribute is visualized on the dashboard, as shown in Figure 5c. Furthermore, attributes for which the correlation might be significant are automatically marked with an asterisk.

5.2.3 Attribute Interactions

ASNViz uses a chord diagram (Figure 7) as a visualization tool to represent animal interactions based on their attributes. A chord diagram consists of a circular layout, where the sections along the circumference symbolize different attribute values. The thickness of the links between these sections indicates the existence and frequency of connections between animals possessing those attribute values [28]. To optimize readability, for diagrams containing a high number of links, by default we only show the 20 most occurring edges to ensure users can interpret the diagram more easily. However, we give the user the option to adjust the number of links displayed to personalize the diagram to their specific needs.

This diagram allows users to visually explore and analyze the influence that specific attribute values may have on animal interactions. Attribute pairs with a high number of links suggest that animal pairs with those specific attributes may interact more than average. In other words, the graph enables the exploration of patterns and relations between animal connections and their corresponding attribute values, assessing if certain attribute value combinations lead to more frequent connections. This can be helpful to determine the factors that affect interactions within the network and help gain deeper insights into its underlying dynamics.

5.2.4 Community Detection

Community detection analysis is one of the most common and insightful types of analyses applied to (social) network data [19]. Identifying communities can help in understanding and identifying the structure,

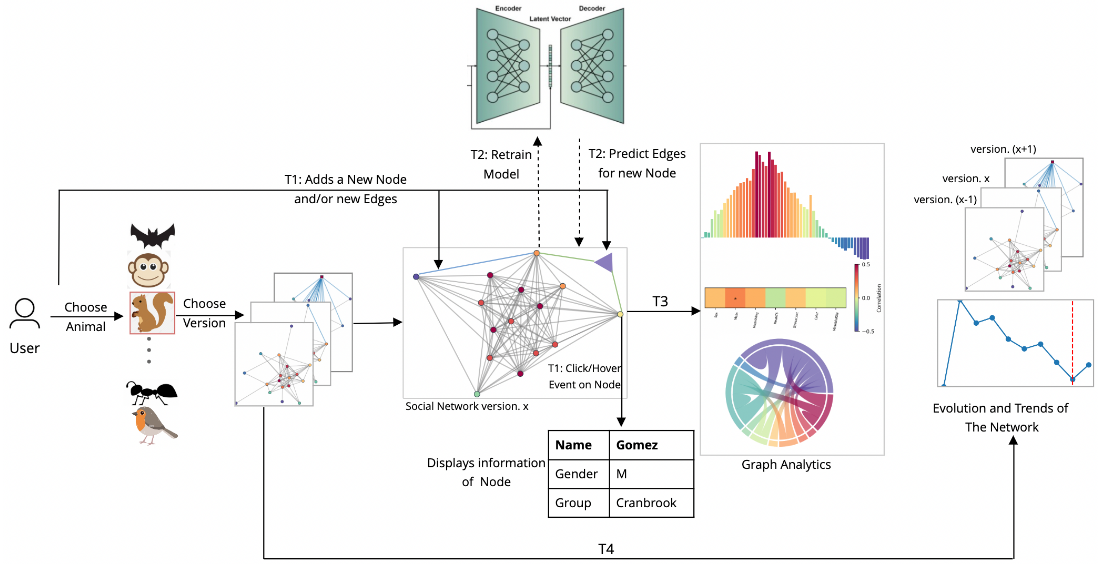


Fig. 3: Workflow Diagram for ASNViz. Some arrows are labeled with tasks (Section 4) to highlight which feature delivers which task.

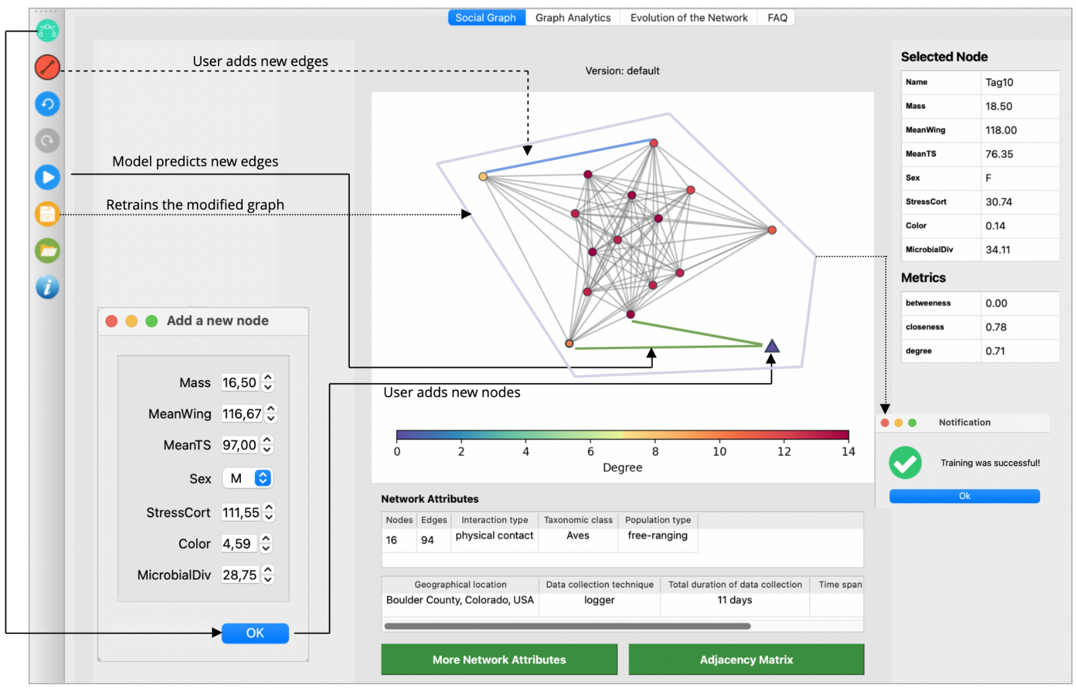


Fig. 4: Interface for Visualization and Interaction with the ASN

robustness, and important nodes of a social network. The extent to which a network can be split up into a fixed number of communities N is quantified using a modularity score, reflecting the ratio of the amount of intra-community edges to the amount of inter-community edges. Utilizing the Girvan-Newman algorithm [20], ASNViz presents the modularity score for all possible N (Figure 6a). Furthermore, ASNViz shows the graph color-coded for the optimal community structure (Figure 6b).

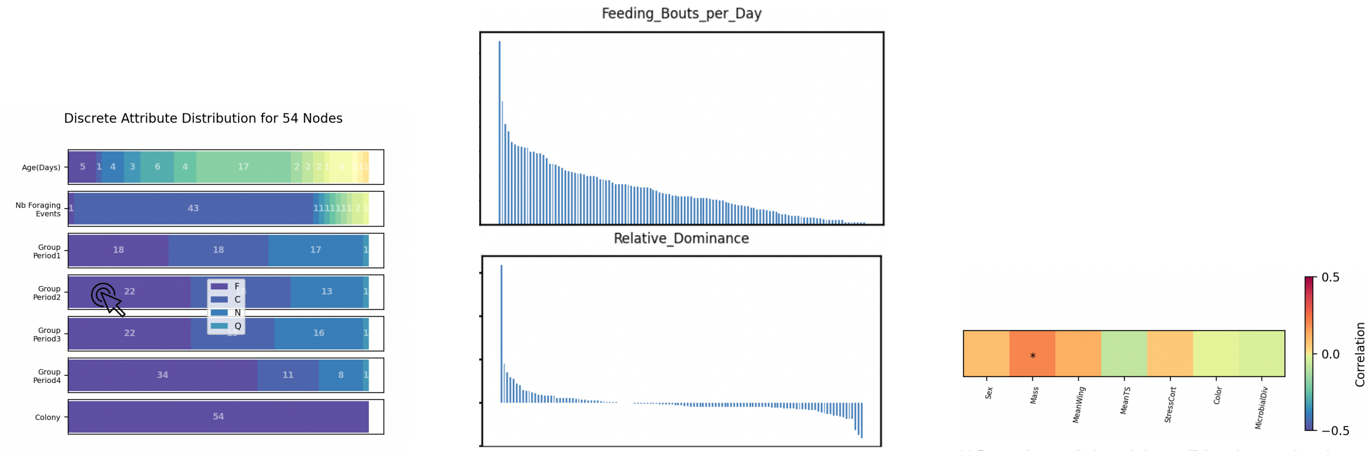
Next to the visual plots, a table with network-wide metrics is given, listing some common metrics of interest to researchers such as the network's density, diameter, average degree, etc. These metrics are listed in Tables 2 and 3.

Measure	Definition
Degree-based	
Degree	For a node v, fraction of nodes connected to it.
Eigenvector	Measure of the degree of node v and the degree of its neighbors.
Shortest-path based	
Betweenness	Measure of the number of shortest paths a node v is part of
Closeness	Measure of how close a node v is to the other nodes

Table 2: Centrality Measures

5.3 Evolution and Changing Trends of Social Graphs

We saw in Section 4.1 how multiple versions of the network can exist. To let the user sequentially get insightful views of the changing dynam-

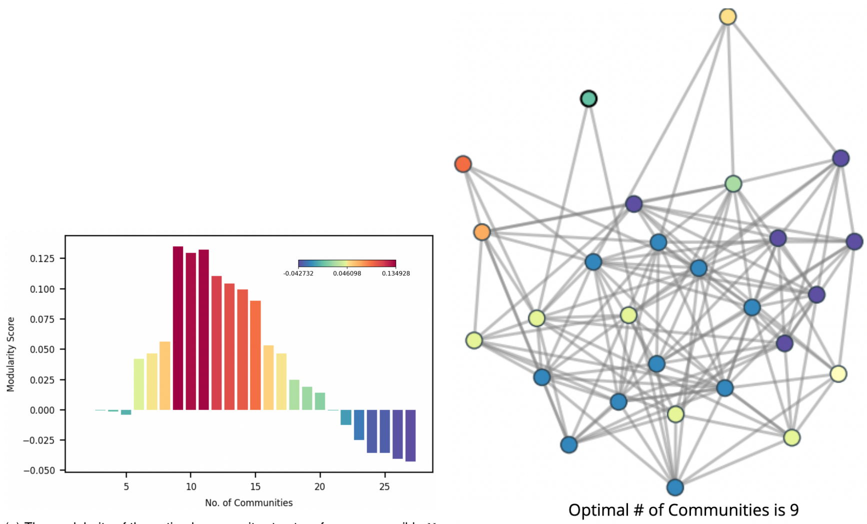


(a) Visualisation of the distribution of discrete node attributes of songbirds.

(b) Continuous distribution for attributes: Feeding Bouts per Day and Relative dominance of Songbirds plotted for each node, sorted by value.

(c) Pearson's two-tailed correlation coefficients between the existence of an edge between nodes, and similarity between the two nodes for songbird's node attributes

Fig. 5: Visualizations related to Social Network Analysis



(a) The modularity of the optimal community structure for every possible N of communities for beetles network.

(b) Visualization of the optimal community structure for beetles

Fig. 6: Community Detection

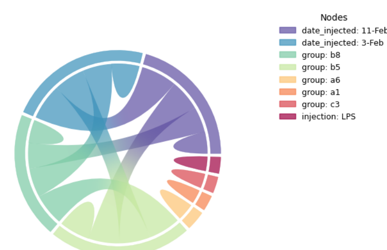


Fig. 7: Chord diagram of most occurring connections between attribute values for mice.

Measure	Definition
Density	Ratio between the edges present in a graph and the maximum number of edges that the graph can contain.
Diameter	Length of the shortest path between the most distanced nodes
Clustering Coefficient	Measure of the degree to which nodes in a graph tend to cluster together
PageRank	Measures the importance of each node within the graph, based on the number of incoming relationships

Table 3: Graph-based Measures

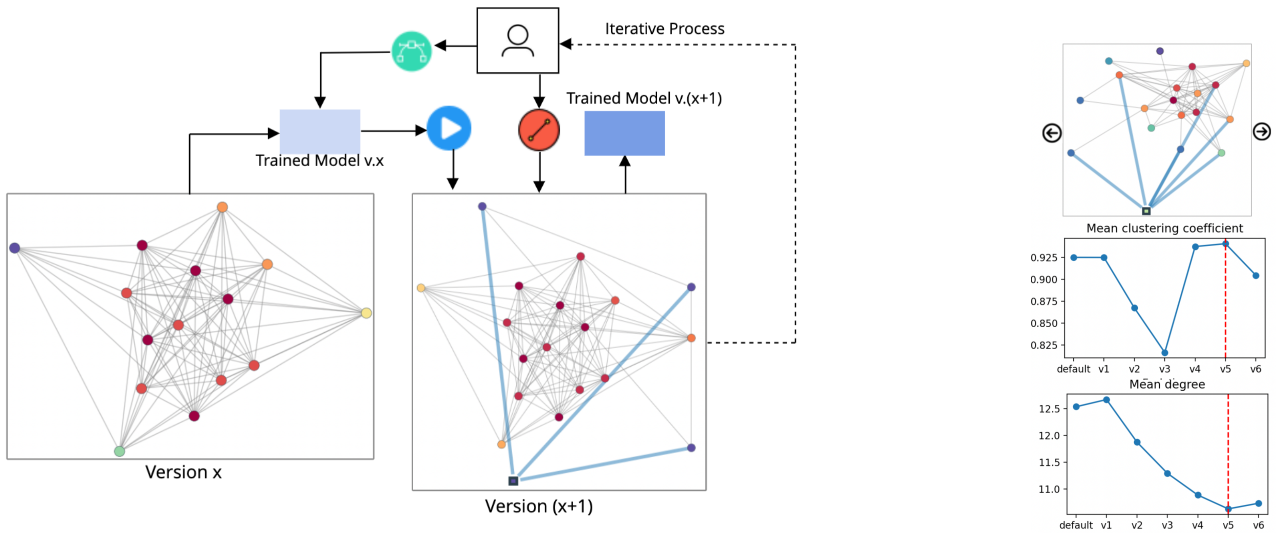
ics of the network, we provide an event-timeline visualization. Here, the user can navigate to the previous and next versions with respect to the current version. The changes made during the last time-step are highlighted with different colors and shapes for nodes and edges respectively. Alongside this, the changes in specific metrics of interest are tracked; we provide line plots to visualize the trends in the mean degree and clustering coefficient of the network over versions as seen in Figure 8b.

6 Implementation

Our application is based on PyQt framework [40]. We use PyQt6 libraries for developing our components. The software infrastructure for ASNViz consists of four key modules:

- Data-loader module: This module is responsible for processing the animal social network (ASN) data provided in the form of .graphml files to graph objects while cleaning and transforming the data. We use the networkx library [22] to transform the .graphml files into graph objects.
- Interaction module: This module provides scripts for users to interact with the graph by the addition of new edges and nodes. Firstly, to make the graph interactive we use the netgraph library[1]. Then, using the signals and slots mechanism from PyQT, we let different components communicate with each other so that the graph updates in real-time in response to user actions.
- VGAE Module: We use PyTorch library [37] for training and prediction tasks of model. We use a 32-dim hidden layer and 16-dim latent variables for our 2-layer GCN of the VGAE's encoder.

[1] https://netgraph.readthedocs.io/en/latest/index.html



(a) Workflow for Versioning the ASN and trained models (The icons in the figure have the same functionality as described in Table 1)

(b) Changing trends of Network and Metrics

Fig. 8: Evolution of the Animal Social Network

The model is trained for 100 epochs with Adam optimizer and a learning rate of 0.01 as suggested by Kipf and Welling [27]. As part of training, we have to create validation and test sets by masking edges at random, which requires some preprocessing on the adjacency matrix of our graphs. This is done by the SciPy library [52].

- Visualization modules: These modules facilitate the exploration and analysis of the ASN. The components developed for visualization are PyQT Widgets which comprise graphs developed using networkx and netgraph and charts developed using matplotlib library [25]. We use the networkx library for the computation of the various metrics we present. To display the chord diagram we use mpl_chord_diagram [2], a Python module that offers a convenient way to plot chord diagrams using matplotlib.

The implementation code of our application can be found here [3].

7 Discussion

ASNViz is a helpful tool for interpreting animal social network data. As an example, consider the high-impact study by Godfried et al. [21], in which network analysis was used to deduce and predict transmission opportunities of parasite infections in lizards, based on attributes such as group membership, connectivity, and amount of crevice-sharing. In such a research project, ASNViz could be used in the exploratory stage; identifying patterns, communities, and attributes of interest. Furthermore, the predictive model can add new insights into the evolutionary dynamics of the social network.

We also argue that the features implemented in ASNViz are not only useful for animal social networks but could, in fact, be applied to almost all network data. It could for example be applied to online social network data [15], recommender systems, or biological networks (e.g. protein networks [34]). The only requirement for the network is that nodes come with informative attributes and that an edge prediction task makes sense in the context of the research.

The current version of ASNViz comes with a few limitations. Firstly, the application is best suited for smaller networks of a few hundred nodes or less. For meticulously collected animal social network data, this is typically enough. However, if one attempts to use the application for larger networks, the processing time of the application increases due to the time-consuming community detection algorithm. Options for other community detection algorithms that are more efficient (but possibly less accurate) would improve the performance. Secondly, as of now, ASNViz does not allow the user to remove nodes and edges. The best one can do is go back to a previous version, but it is not possible to remove anything from the base network without manually changing the original data. Such functionality would pave the way for very interesting analyses related to robustness and percolation of the network, and could for example be applied to epidemic models (e.g. [44]). Finally, the current version of ASNViz only supports relatively simple network structures. Most notably, all networks are simplified to unweighted networks. This is a major limitation in the context of animal social networks since binarized interactions tend to leave out a lot of important data from the network [26].

For instance, it might make more sense to employ weighted interactions where the disease spread between two animals, depends not only on the existence of their contact but also on the time period in which they were in contact. Weights are often used to represent the intensity or duration of interactions for such networks. Thus, the lack of support for weights is one of the larger limitations of the current version of ASNViz. We hope to address this limitation in future work where we incorporate the edge weights while training edge-link prediction models.

8 Conclusion and Future Work

In this paper, we have described the functionality of the novel animal social network visualization and analysis tool, ASNViz. ASNViz allows researchers in fields related to biology, sociology, and ecology to easily carry out exploratory analyses of network structures. The interactive capabilities of ASNViz ensure that the user is able to update the network, both manually and through edge prediction models while keeping track of the way the network responds to these changes. The static analyses currently provided in ASNViz include common metrics of interest, plots, and statistical tests that give insights into which attributes facilitate social interaction. The dynamic analyses clearly show which interactions are predicted to happen after one or more nodes are added, and allow for manual addition of edges. Furthermore, by saving versions of the network when new nodes enter, ASNViz is able to visualize changes in the network. These changes are further quantified by specific metrics of interest over a series of versions. While other social network visualization tools exist (Section 2.4), ASNViz stands out by utilizing a deep-learning model to predict future interactions.

While the current version of ASNViz focuses on the application to ASNs from the Animal Social Network Repository [43], the program can function equally well for any other network structure where nodes

[2] https://pypi.org/project/mpl-chord-diagram/
[3] https://github.com/madhurapawaruva/animalsocialnw_team7

come with domain-related attributes. Thus, ASNViz could be applied to other networks that tend to evolve over time, such as information networks and biological networks. Further development should aim to add functionality for removing nodes and edges. This would allow users to study the robustness of a network more directly; something that is especially relevant in animal social networks. Such analyses could for instance help researchers predict what will happen once a specific animal of a community passes which is relevant for behavioral research. Or is quarantined, which is relevant for research into the spread of diseases. In conclusion, ASNViz presents a powerful and accessible tool for analyzing, predicting, and visualizing animal social networks, with potential applications in biology, sociology, and ecology. Future developments should focus on expanding the functionality to allow for versatility in changes of the network, allowing for more advanced analyses.

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