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Inferring Voting Networks in Online Elections

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Contents

Chapter 1

Introduction

In recent years, researchers have become increasingly interested in understanding the behaviour of voters in social networks. Knowledge of the factors that motivate voters, for example, voting for bills in the United States Congress [29] or electing administrators in Wikipedia [10, 28, 35], is of great importance in selecting successful policies or candidates. Voting is a classic problem and has been studied in the fields of game theory and political science [31, 49, 69]. More recently, there is a focus on using information from the interaction network of voters to model their behaviour. This provides an insight into these interactions and effect of influence of other individuals on voters within a community.

Votes can be represented as a *signed* network with positive or negative links. Finding groups using clustering techniques [7, 13, 39] and predicting signed links [14, 36, 37] in these networks is well researched. These approaches provide understanding of the group dynamics at play and predict votes and in such a network. However, they do not consider the iterative and chronological nature of the voting that takes place in these networks. Moreover, in cases where research does focus on voter models, they rely on external features to build machine learning models that are task-specific and static [28, 29].

In this thesis, we propose a model that creates a local signed network consisting of the neighbours of the current voter and the votes already cast in the election in question. It will then predict the vote that when added to the network will comply the most with concepts of balance and status in signed networks. After all the votes are cast in a session, the model can be easily updated to improve quality and is, therefore, iterative and dynamic. The model is also flexible and can incorporate external features to build the local signed network of a voter. The results for Wikipedia administrator elections shows that our model outperforms machine learning based models

and traditional signed link prediction solutions.

1.1 Thesis Outline

The rest of the thesis is organized in the following manner. Firstly, we discuss the background relating to signed graphs and hierarchy in directed networks in Chapter 2. Nexit, in Chapter 3 we describe the vote prediction problem and approaches to solving it. Chapter 4 provides a comprehensive view of Wikipedia and the election process for administrators. In Chapter 5 we explain the datasets used, construction of the model and evaluation criteria. After that, we report our findings in Chapter 6 and discuss their implications. Finally, we conclude the thesis and present future work in Chapter 7.

Chapter 2

Graph Theory

Change Chapter to Background and include signed link prediction theory here as well

In this chapter, we will provide the fundamentals of the graph theory concepts required to understand the rest of the thesis. In Section 2.1 we cover the basic definitions and terminologies used to describe different types of graphs. Then we define a signed graph and discuss its unique properties in Section 2.2. We outline the social theories of balance and status in signed networks in Sections 2.2.1 and 2.2.2. Lastly, we explain techniques of finding hierarchies in directed networks and the concept of agony in Section 2.3.

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2.1 Preliminaries

In this section, we define the various types of graphs and their basic properties. The notation and terminologies used closely follow those used in Diestel [18]. Graphs are structures that describe relationships between entities. These entities are called *vertices* and entities related to one another are joined by edges. The terms graph, vertices and edges can be used interchangeably with *network*, *nodes* and *links* respectively.

Graphs can be classified broadly into two types based on whether the edges posses a direction. We now go on to define them in detail.

2.1.1 Undirected Graphs

An undirected graph is pair $G = (V, E)$, where V is the set of vertices and E is the set $E \subseteq \{(u, v) \mid u, v \in V\}$ of unordered pairs of vertices called edges. In this thesis we will deal only with *simple graphs*, i.e. no self loops,

$(u, v) \in V \times V$, $u \neq v$ and there is at most one edge between vertices u and v.

The number of the vertices in a graph is called the *order* of the graph and is denoted by $n = |G|$. In turn, the *size* of a graph is the number of edges denoted by $m = \|G\|$ or $m = |E|$. A vertex u is *adjacent* to v if they are the end points of an edge, $(u, v) \in E$. All the vertices adjacent to a vertex v is called the *neighbourhood* of v and is denoted by $N(v)$. The *degree* of a vertex v is the number of nodes adjacent to that vertex and is denoted by $d(v) = |N(v)|$.

The edges of an undirected graph can also have an associated value. This value can indicate the distance or similarity between a pair of vertices. These values are called *weights* and the corresponding graph is called a *weighted undirected graph*. Therefore, a weighted graph is defined as a triple $G = (V, E, w)$, where $w : E \to \mathbb{R}^+$ is a function that maps an edge e to a positive real weight $w(e)$. Now an *unweighted graph* is simply a weighted graph where the function w is defined as: if $e \in E$ then $w(e) = 1$ else $w(e) = 0$. The degree of a vertex v in a weighted graph is the sum of the weights to all the neighbours of v and is defined as $d(v) = \sum_{u \in N(v)} w((u, v))$. An example of a weighted undirected graph is shown in Figure 2.1.

Figure 2.1: An example of a weighted undirected graph

2.1.2 Directed Graphs

The main distinction regarding a *directed graph* (or *digraph*) is that the edges are ordered pairs, i.e. $(u, v) \neq (v, u)$. Therefore, a directed graph has a similar definition: a pair $G = (V, E)$, where V is the set of vertices and E is the set of *ordered* pairs of vertices. Now given an edge $e = (u, v)$ we can define a source function src : $E \to V$ such that src$(e) = u$ and a destination function $d : E \to V$ where dest$(e) = v$. These functions classify the vertices in an edge e as either the source or the destination. In this thesis, we deal only

with *simple directed graphs*, i.e. no self-loops, and there can be at most one edge from u to v.

As the edges now have an inherent direction, we can define the *successors* and *predecessors* of a node v. A vertex u is called the *successor* of a node v if there exists a directed edge from v to u, therefore the set of successors for a vertex v can be defined as $S(v) = \{u \mid (v, u) \in E\}$. A *predecessor* of a node v is a vertex u such that there exists a directed edge from u to v, the set of predecessors for a vertex v can de defined as $P(v) = \{u \mid (u, v) \in E\}$. Now, a vertex u that is either a successor or a predecessor of a vertex v can be called a neighbour of the vertex v. Therefore, we define the *neighbourhood* of a vertex v as the set of vertices in the union of successors and predecessor, i.e. $N(v) = S(u) \cup P(v)$. This definition is also compatible with undirected graphs because if $(u, v) \in E$ then $(v, u) \in E$.

Directed graphs can also have values associated with each directed edge called a *weight*. A *weighted directed graph* can be defined as a triple $G = (V, E, w)$, where the weight function $w : E \to \mathbb{R}^+$ maps each edge e to a weight $w(e)$. The indegree of a vertex v is defined as the sum of the edge weights from the predecessors of v and is denoted as $d_{\text{in}}(v) = \sum_{u \in P(v)} w((u, v))$. Similarly, the outdegree of a vertex v is defined as the sum of the edge weights to the successors of v and is denoted by $d_{\text{out}}(v) = \sum_{u \in S(v)} w((v, u))$. Figure 2.2 shows an example of a weighted directed graph.

Figure 2.2: An example of a weighted directed graph
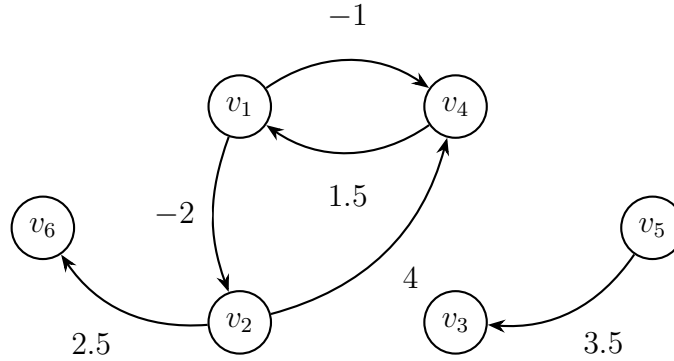
2.2 Signed Graphs

The simple weighted graphs we have defined so far only have non-negative edge weights that can represent similarity or closeness. In the 1950s, social psychologists found it desirable to express liking, disliking or indifference in

social interactions. This was formalized by Harary [24] using graphs with weights $(-1, 0, 1)$. These graphs are therefore called *signed graphs*, where a negative edge weight can denote dissimilarity between a pair of vertices. In this thesis we will use notations and terms similar to Gallier [19], Kunegis et al. [34], Hou [26] and Zaslavsky [68].

A signed graph is a triple $G = (V, E, w)$, where V is the set of vertices, E is the set of pairs of vertices and the weight function $w : E \to \mathbb{R}$. The weight function now takes an edge e and maps it to a signed weight $w(e)$. We can partition the edges into positive and negative edges, $E = E^+ \cup E^-$, where $E^+ = \{e \mid w(e) > 0\}$ and $E^- = \{e \mid w(e) < 0\}$. Similar to Zaslavsky [68], we consider undirected signed graphs and directed signed graphs as distinct and separate entities. We can see some examples of signed graphs in Figure 2.3.

(a) A undirected signed graph

(b) A directed signed graph

Figure 2.3: Examples of Signed Graphs

We can now proceed to define a few more terms. The degree of a vertex v is now the sum of the absolute edge weight of its neighbours, called the

signed degree and is defined as

$$\overline{d}(v) = \sum_{u \in N(v)} |w((u,v))|$$

This can also be extended to *signed indegree* and *signed outdegree* denoted by $\overline{d_{\text{in}}}(v)$ and $\overline{d_{\text{out}}}(v)$ and defined as

$$\overline{d_{\text{in}}}(v) = \sum_{u \in P(v)} |w((u,v))|$$

$$\overline{d_{\text{out}}}(v) = \sum_{u \in S(v)} |w((v,u))|$$

We can create a $n \times n$ square weight matrix W, where each entry w_{ij} is defined as

$$w_{ij} = \begin{cases} w((v_i, v_j)) & \text{if } (v_i, v_j) \in E \\ 0 & \text{if } (v_i, v_j) \notin E \end{cases}$$

The signed degree matrix $\overline{D}$ is a diagonal matrix consisting of the signed verted degrees, $\overline{D} = \text{diag}(\overline{d}(v_1), \ldots, d(v_n))$. We can now define the *signed Laplacian*, $\overline{L}$ as

$$\overline{L} = \overline{D} - W$$

The signed Laplacian along with results from spectral analysis of signed graphs [26, 34], will be useful for balance theory of signed graphs.

2.2.1 Balance Theory

In the 1940s, Heider [25] proposed that when there are either *positive relations* (friendship, love, support) and *negative relations* (enmity, hate, oppose) in a group, the group tends towards *balance*. Balance is the concept that all members aim to maintain consistency in the relations they share with other members of the group. In a group of three members this can be seen as having three positive relations or one positive and two negative relations. In Figure 2.4 the triads B_1 and B_2 are *balanced* and mirror aphorisms such as "the friend of my friend is also a friend" and "the enemy of my enemy is a friend" respectively. Therefore, triads B_3 and B_4 can be called *unbalanced* or *imbalanced* that denotes the cognitive dissonance between the members of the triad. The dissonance can be understood by the counterintuitive nature of the phrase "the friend of my friend is my enemy" described by triad B_3.

Harary and Cartwright [11] generalized this notion of balance by using signed graphs. As these relations are typically symmetric, balance is usually defined for undirected signed graphs. This can been seen in Figure 2.4 where solid edges are positive and dashed edges are negative. Davies [15] also offers an alternate definition of *weak balance* where triads of type B_2 are considered to have lesser predictive utility as relationships of these type are less common in real-life social networks.

Figure 2.4: Triads in undirected signed graphs. B_1 and B_2 are *balanced* triads as they have even number of negative edges. B_3 and B_4 are *unbalanced* as they have odd number of negative edges.

The concept of balance can be generalized for an undirected signed graph $G = (V, E, w)$. The sign of a cycle C in the signed graph G is defined as the product of the edge weights $sgn(C) = \prod_{e \in C} w(e)$. A signed network G is then said to be balanced if and only if all the sign of all cycles in network are positive. Therefore, every cycle in G must have an even number of negative edges. This leads to result from Harary [24] that states that if a graph G is balanced, then there is a partition of the vertices $V = V_1 \cup V_2$ such that edges within the vertices of each set is positive and edges between the sets are negative. This means that we can have a bipartite graph when we delete the positive edges and negative edges span between the two sets of vertices. An example of a balanced signed graph is shown in Figure 2.5. Here the partition of the vertex set is $V_1 = \{v_1, v_3, v_4, v_7, v_8\}$ and $V_2 = \{v_2, v_5, v_6, v_9\}$.

The signed Laplacian matrix $\overline{L}$ of a signed graph G is always positive-semidefinite and $\overline{L}$ is positive-definite iff G is *unbalanced* [26, 34, 68]. If the smallest eigenvalue of a graph G is denoted by $\lambda_1(G)$, then G is balanced iff $\lambda_1(G) = 0$. Hou [26] provides bounds on the value of $\lambda_1(G)$ and Li et al. [40] show that $\lambda_1(G)$ can be used as a measure of how far the signed graph G is from being balanced.

Figure 2.5: A balanced signed graph. Solid blue edges are positive and dashed red edges are negative. Every cycle in this graph contains an even number of negative edges.

2.2.2   Status Theory

Guha et al. [22] mention implicitly that a signed edge from u to v can be interpreted in a asymmetric manner different from "friend" or "enemy". Leskovec et al. [36, 37] introduce the concept of *status* to contextualize directed singed edges. A positive edge $u \xrightarrow{+} v$ indicates that v has a higher status than u and a negative edge $u \xrightarrow{-} v$ means that v has a lower status than u. This concept of relative status can be propagated transitively along multiple steps which might lead to contradictions with balance theory [37].

Given three vertices v_1, v_2 and v_3, the presence of an edge $v_1 \xrightarrow{+} v_2$ indicates that v_1 thinks v_2 has higher status, the edge $v_2 \xrightarrow{+} v_3$ indicates that v_2 thinks v_3 has higher status. Now we wish to to close this triad with an edge from v_3 to v_1. Status theory would say that through transitivity v_1 has lower status than v_3, therefore the prediction is $v_3 \xrightarrow{-} v_1$. Whereas, in balance theory we would predict a positive edge $v_3 \xrightarrow{+} v_1$ to make the cycle have even number of negative edges. This example can be seen in triads S_1 and S_2 shown in Figure 2.6.

There are also cases when status theory is ambivalent to the edge that closes a triad. Consider the example when we have the edges $v_1 \xrightarrow{+} v_2$ and $v_2 \xrightarrow{-} v_3$. If we were to indicate the status of a vertex v using the function

$\sigma(v)$, then the edges describe the following : $\sigma(v_2) > s(v_1)$ and $\sigma(v_2) > \sigma(v_3)$. Therefore, we have no knowledge of the relative difference in status between the vertices v_1 and v_3. Hence, both edges $v_3 \xrightarrow{+} v_1$ ($\sigma(v_3) > \sigma(v_1)$) and $v_3 \xrightarrow{-} v_1$ ($\sigma(v_1) > \sigma(v_3)$) are equally valid for status theory. Balance theory on the other hand can only predict $v_3 \xrightarrow{-} v_1$ to keep the triad balanced. This case is shown in Figure 2.6 as triads S_3 and S_4.

$$S_1 \qquad\qquad S_2 \qquad\qquad S_3 \qquad\qquad S_4$$

Figure 2.6: Triads in directed signed graphs. Triads S_2, S_3 and S_4 are compliant with status theory. Only triads S_1 and S_3 are compliant with balance theory.

Each positive link inwards ($d_{in}^{+}(v)$) and negative link outwards ($d_{out}^{-}(v)$) increases status. Each positive link outwards ($d_{out}^{+}(v)$) and negative link inwards ($d_{in}^{-}(v)$) decreases status. Therefore, $\sigma(v) = d_{in}^{+}(v) + d_{out}^{-}(v) - d_{out}^{+}(v) - d_{in}^{-}(v)$ is a heuristic for the status of a node [36]. An interesting fact is that the edge $u \xrightarrow{-} v$ can be converted into positive edge in the opposite direction $u \xleftarrow{+} v$. This fact reduces the number of unique triads that can be formed using status theory and will be used in edge prediction tasks that will be discussed in coming chapters.

2.3   Hierarchy in directed networks

Hierarchies exist in all social structures, from the explicit levels found in nature such as the food chain or organizational structures in businesses to more implicit stratification that occurs on social media or online networks. A common method to represent such hierarchies is through a tree, for example, the chain of command in the military or within governments. Trees have well defined levels and a single person at the top. If we generalize this structural concept then we get a *Directed Acyclic Graph* (DAG) which represents a partial ordering set. DAGs have perfect hierarchy while structures such as cycles tend to have no hierarchy. Other directed graphs occur somewhere between these two extremes.

Gupte et al. [23] provide a method to discern the levels of stratification present in a given directed network when no prior information of the hierarchy exists. They define a measure of the hierarchy of a given directed network G as $h(G)$ along with a polynomial algorithm to find the largest hierarchy in that network. They define a concept of *social agony* which posits that agony is present when a person having a higher rank in network interacts with a person who has a lower rank. Therefore, if we define the rank of a node in graph G as the function $r : V \rightarrow \mathbb{N}$, then a directed edge $u \rightarrow v$ causes agony when $r(u) \geq r(v)$. The agony for the edge can be quantified as $\max(r(u) - r(v) + 1, 0)$. The agony of the graph G wrt to rank function r is defined as

$$A(G, r) = \sum_{(u,v) \in E} \max(r(u) - r(v) + 1, 0)$$

As nodes in a graph tend to minimize the overall agony, the agony of a network G is the smallest possible agony over all possible ranking for r, $A(G) = \min_{r \in \text{Rankings}} A(G, r)$. The hierarchy of a given network G, denoted by $h(G)$ can now be expressed in terms of the agony of the network, $h(G) = 1 - \frac{1}{m} A(G)$, where m is the number of edges. We can see examples of hierarchy in unweighted directed graph in Figure 2.7.

Therefore, finding a ranking of the nodes that minimizes the agony of the network gives us the optimal hierarchy present in that network. Gupte et al. [23] and Tatti [51] present a polynomial algorithm that can solve the dual of the agony minimization problem to obtain the optimal ranking r for unweighted graphs. Tatti [52] provides an alternate approach using a capacitated circulation solver that can handle weighted digraphs as well as additional cardinality constraints. These algorithms allows us to find the levels of hierarchy present in any given directed social network and analyse the interaction between members belonging to different strata in that community.

We will explain in future chapters how hierarchies in social network is intrinsically linked to the theory of status in directed signed networks. We show one can use the concept of agony of a directed signed graph G to quantify the violation to status theory and use it as a metric to predict an unknown signed edge.

2.4   Link and Sign Prediction

The *link prediction problem* is defined by Liben-Nowell and Kleinberg [41] as inferring possible future edges between vertices in a social network. The datasets used was split into training edges and testing edges which had a
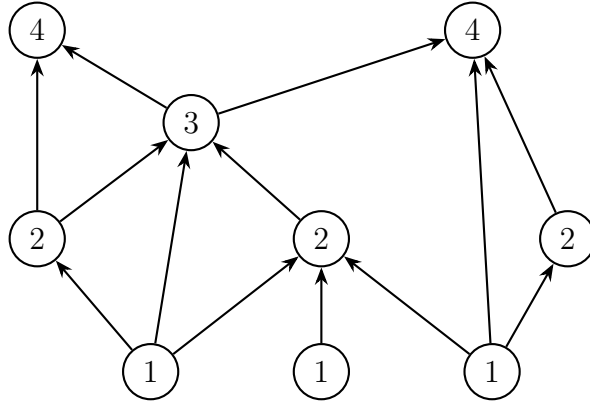
(a) DAG has perfect hierarchy, $h(G) = 1$
and agony of each edge is 0
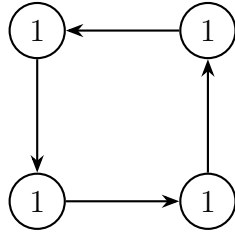
(b) Cycle has no hierarchy, $h(G) = 0$ (c) Graph with some hierarchy $h(G) =$
and each edge has agony of 1 $\frac{2}{5}$. Red dashed edge has agony of 3 and
                                        solid black edges have 0 agony.

Figure 2.7: Examples of hierarchy in unweighted directed graphs. Numbers
inside nodes indicate the rank of vertex.

common core set of vertices. They showed that topological features such as
number of common neighbours and Katz's centrality index can be used in a
unsupervised setting to accurately predict edges.

Leskovec et al. [36] extended the link prediction problem to signed net-
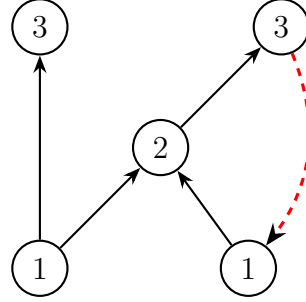works. They also introduced the problem of *edge sign prediction*: predict
the sign of a given edge (u, v) using the existing signed network G. A su-
pervised model for the task is proposed that uses network features such as
indegree and outdegree of a node along with *triad* features. The edge nodes
u and v and a common neighbour w form a triad. The directed edge between
(u, w) and (w, u) can be either forward or backwards and each edge is either
positive or negative. Therefore there are 16 possible triad types for a given
neighbour w. They analyse these triadic features from the trained model and
show how they relate to balance and status theory. For the link prediction

problem, the information from the negative edges in the signed network offers improvement in the overall accuracy of the model. This seminal paper inspired many more approaches to solving these problems for signed graphs.

Matrix factorization and latent space approaches facilitate link prediction and sign prediction tasks for multiple edges simultaneously in a signed network [1, 21, 27]. Supervised algorithms for both tasks can be improved using additional node features such as inverse square metric [2] or node rankings [48]. Models that use graph motifs [32, 42] generalize the concept of triadic feature for link and sign prediction. Chiang et al. generalize balance theory for longer cycles and use it as features to improve link prediction [14]. Tang et al. [50] discuss the importance of predicting negative links and highlight methods to overcome the inherent imbalance present in signed network datasets. Cesa et al. [12] and Chiang et al. [13] utilize clustering techniques to solve sign prediction and link prediction respectively. Shuang et al. [65] and Karimi et al. [29] create bespoke models incorporating user behaviour and political party affiliation respectively to predict the sign of edges present in the signed networks.

Chapter 3

Vote Prediction

In this chapter, we cover the main motivation behind predicting the vote of an individual voter and present the methods that can be used to solve this task. We discuss the contrast in perspectives that is present when predicting the result compared to predicting a vote in Section 3.1. Next, we explain how the problem of vote prediction is intrinsically linked to the tasks of edge and sign prediction in signed network in Section 3.2. In Section 3.3, we describe a supervised machine learning framework that can use graphs features from voting and non-voting data. Lastly, we present our novel approach of constructing a local signed graph of the current voter and using balance and status theory to predict the vote in Section 3.4.

3.1 Result versus Vote Prediction

In this thesis, we are interested in the voting behaviour for a collective action. In such cases, members of a community come together as *voters* to decide on a particular *candidate* item during a *session*. In a government parliament the voters are the elected members of the parliament and the candidate is usually a bill or policy matter. When it is promotion within a political party or an online community such as Wikipedia, the members vote on a candidate who has been nominated for the position. In all these cases we have two levels of decisions being made. The first the individual decisions that a voter makes with regard to the candidate. The second is the final decision that the group arrives to after everyone has voted. We refer to task of predicting the former as *vote prediction* and the latter as *result prediction*.

Result prediction provides a macro level perspective of the incentives of a community. We can create models based on the characteristics of a candidate to predict the result of a collective action. This will lead to understanding on

a communal level of what features are preferred and if there are voting blocks formed within the members based on the type of candidate. This translates to practical examples such as party level dynamics in a parliament, the topic of a bill or the credentials of a nominee [9, 66, 67].

On the other hand, when we focus on the vote prediction problem, we get a deeper understanding of the dynamics between voters and the candidate. In fields such as game theory, this is well studied using frameworks such as *strategic voting models* and *momentum* [3, 6, 44, 49, 69]. These models are more theoretical and are studied under synthetic conditions. Nevertheless, they still provide a foundation on which we can construct practical models that can utilize additional external features. One such popular approach is using textual information from bills, speeches and legislature to predict votes of politicians in parliament [8, 20]. The next important step is to represent the voting data as networks and leveraging network features to understand and predict voter behaviour.

3.2 Voting and Signed networks

Votes by nature express a positive or negative relationship between a *voter* and a *candidate*. Therefore, *signed graphs* provide an intuitive way to structurally represent the voting pattern of members in a community. These signed voting networks can be used to develop models to solve the task of vote prediction and analyse voter behaviour.

Correlation clustering and community detection of signed voting graphs can discover trends and vote blocks in communities [4, 7]. Analysing the networks using social theories of balance and status provides knowledge of voter behaviour and features for prediction methods [16, 39]. The vote prediction task can be broken down into two subtasks which are analogous to link and sign prediction in signed networks.

The first subtask is to predict who will vote next given a candidate c and a set of previous votes. This subtask is similar to link prediction in a signed network where we aim to predict possible future edges of the type (v, c). The complexity subtask depends on the format of voting that takes place. If there is a known voting order, such as in roll call in parliamentary proceedings or explicit timestamps then it is essentially solved. If the voting occurs simultaneously, the subtask can be reduced to predicting the possible subset of members who will vote in a given session. When the voting is iterative and there is no known underlying process of who votes next, then a separate model might be required to infer the voting sequence. This case can be combinatorially hard as we would need to find the correct ordering of

votes in a session.

The second subtask is to predict how a voter v will vote for a candidate c given the previous votes in the session. This task translates into predicting the sign of an edge (v, c) in the current session. We call this subtask the *independent vote prediction* problem. It is independent in nature are we are only interested in the decision of the voter v assuming that we have complete prior knowledge of how the previous votes have been cast. This problem can be framed as a supervised learning task, using features of the interaction between the current voter v, previous voters U and the candidate c to predict the sign of the edge (v, c). We can utilize theories of balance and status in signed networks to create models similar to those by Karimi et al. [29] and Jankowski-Lorek et al. [28] to predict voter behaviour.

3.3 Linear Combination of Graphs

In this section we explain how the approaches outlined in Section 2.4 can be applied to solve the *independent vote prediction* problem. As discussed previously, the *edge sign prediction* task in signed network is analogous to vote prediction. The models proposed by Leskovec et al. [36] can be used to predict the sign of the edge (v, c). Voting in a community takes place across many sessions in a chronological manner. Therefore, we must partition the training and testing datasets to avoid data leakage. We propose the following framework to gather features using a linear combination of the voting history and several auxiliary graphs.

We denote the directed signed graph for the current voting session as $S = (V_S, E_S, w_S)$. The current voter in consideration is denoted by v and the candidate of the session is c. In this thesis, for all the models we assume that each session has a unique candidate. The votes that have been cast prior to the current voter exists as edges (u, c) in the session S and the set of prior voters is denoted as $U = \{u \mid (u, c) \in E_S\}$. The history $H = (V_H, E_H, w_H)$ is defined as the directed signed graph containing the votes from sessions chronologically prior to S. We also define a set of auxiliary graphs $A = \{G_1, G_2, \ldots, G_l\}$ based on external non-voting data. These auxiliary graphs can be either directed or undirected, weighted or unweighted, signed or unsigned. This is similar to the relational layer in *Multidimensional Social Networks* (MSN) described by Kazienko et al. [30] and Jankowski-Lorek et al. [28]. However, the auxiliary graphs capture different relations between a subset of the voting members which will be used to generate additional features for the vote prediction task.

Algorithm 1 describes how to generate a feature vector **a** from the auxil-

iary graphs A. The algorithm finds the intersection of the prior voters U and the neighbourhood of the current voter v in the graph G_i which we call the *voting neighbourhood*. Then the feature $\mathbf{a}_i$ is computed as the weighted sum of the voting neighbourhood plus the edge weight to the candidate (v, c). Figure 3.1 provides an example with three auxiliary graphs and two prior voters u_1 and u_2. The dashed red edges are the votes cast in the current session S by the prior voters. We see that in the example G_1 is a directed graph, G_2 is an undirected graph and G_3 is a signed directed graph. The current voter v has different relations to his voting neighbourhood in each auxiliary graph and therefore each feature is a different combination of edge weights.

In addition to the auxiliary feature vector $\mathbf{a}$, we can also create triad features based on the historical voting graph H. Similar to Leskovec et. al. [36] amd Karimi et al. [29] we can form a set of unique triads T. Then, for each node u in the common neighbourhood of N_{vc} we can count the triad formed from the three vertices. Algorithm 2 describes this procedure.

We can now create a feature matrix $\mathbf{X}$ for all the sessions in a given dataset. Each row is the concatenation of the auxiliary feature vector and the triadic feature vector $\mathbf{x} = [\mathbf{a}, \mathbf{t}]$. The target vector $\mathbf{y}$ is the vector of true votes. Now we train a linear machine learning model and use it to predict the votes in a test dataset.

Algorithm 1: Auxiliary feature vector for voter v

Input: Voter v, Candidate c, Set of auxiliary graphs A, Current voting session S and Prior voters U

Result: Auxiliary Feature vector $\mathbf{a}$

1 Initialize $\mathbf{a}$ of length $|A|$
2 **foreach** G_i *in* A **do**
3 $\quad$ $Z = N_i(v) \cap U$ $\qquad$ // neighbours in G_i who have voted
4 $\quad$ $\mathbf{a}_i \leftarrow 0$
5 $\quad$ **foreach** z *in* Z **do**
$\qquad\quad$ /* vote in current session multiplied by the edge
$\qquad\qquad$ weight in G_i $\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad$ */
6 $\quad\quad$ $\mathbf{a}_i \mathrel{+}= w_S((z, c)) \cdot w_i((v, z))$
7 $\quad$ **end**
8 $\quad$ $\mathbf{a}_i \mathrel{+}= w_i((v, c))$ $\qquad$ // Add edge weight to candidate
9 **end**
10 **return** $\mathbf{a}$

$$G_1 \qquad\qquad G_2 \qquad\qquad G_3$$
$$\mathbf{a}_1 = w_a + w_b \qquad \mathbf{a}_2 = w_c - w_b \qquad \mathbf{a}_3 = -(w_e + w_f + w_g)$$
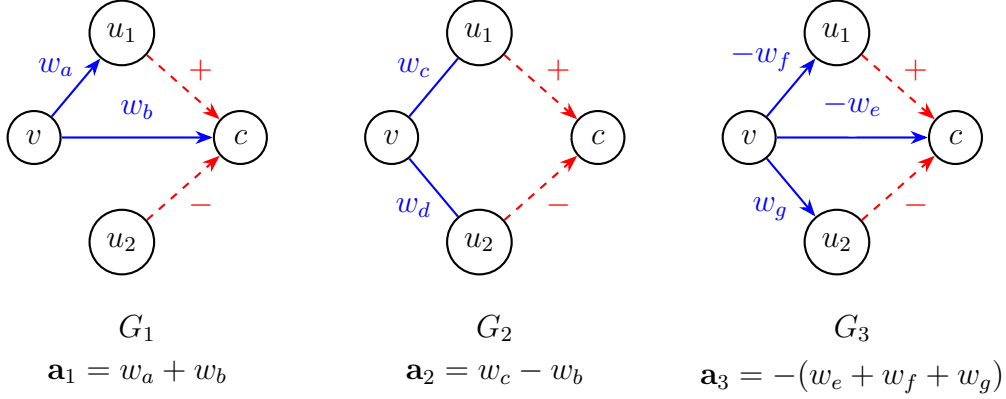
Figure 3.1: Example auxiliary features for v from combination of three graphs and two prior voters u_1 and u_2. Dashed red lines are prior votes in the session. Solid blue lines are edge weights in auxiliary graph. $\mathbf{a}_i$ is feature for voter v from auxiliary graph G_i

---

Algorithm 2: Triad feature vector for voter v

Input: Voter v, Candidate c, Set of unique triads T, Voting history graph H

Result: Triad Feature vector $\mathbf{t}$

1   $k \leftarrow |T|$
2   Initialize counters $cnt_1, \ldots, cnt_k$ to 0
3   $N_{vc} = N_H(v) \cap N_H(c)$ `// common neighbours in H`
4   **foreach** u *in* N_{vc} **do**
5   Let $\triangle$ be the triad formed by vertices $\{v, u, c\}$
6   Classify $\triangle$ as the jth triad in T
7   Increment counter cnt_j
8   **end**
9   $\mathbf{t} \leftarrow [cnt_1, \ldots, cnt_k]$
10 **return** $\mathbf{t}$

3.4 Local Signed Network

In this section, we present an unsupervised method that can be used iteratively in predicting the votes in a session. This method builds on top the concept of a *voting neighbourhood* introduced in the previous section and relies solely on the social theories of balance and status in signed networks to predict a vote. However, unlike the triads features used in the supervised method, we will utilize generic measures of the balance or status of a network

and predict the vote that preserves these measures the best.

As defined in the previous section, the directed signed graph of the current session is $S = (V_S, E_S, w_S)$ and v is the voter, c is the candidate and U is the set of prior voters in the session. $H = (V_H, E_H, w_H)$ is the directed signed graph that contains the historical voting records prior to the current session. The first step is to construct a signed *relationship graph* $R = (V_R, E_R, w_R)$ from the history voting graph H. The edges of this graph capture simple signed relationship between the voters such as *agreement* or *concurrence* and can be constructed uniquely based on the given problem. Based on whether we use balance or status theory to predict the vote, the relationship graph is either unweighted or weighted respectively.

We now define the *Local Signed Network* (LSN) of a voter v as the intersection of the session and the relationship graph $LSN = S \cap R$. We assume that candidate c is present in the relationship graph so that we get all the prior vote edges (u_j, c) in the LSN. The *voting neighbourhood* that we described in the previous section is the set of vertices for the LSN i.e., $V_{LSN} = V_S \cap V_R$. There are three main types of edges present in the LSN. The first are the prior vote edges (u_j, c), from the prior voters to the candidate. The second are the relationship edges (v, u_j), from the voter to the prior voters. The third is the relationships between the prior voters (u_j, u_k). All these three types of edges can be seen in the undirected LSN shown in Figure 3.2c. We will now cover how to predict the edge (v, c) in the LSN using balance and status theory.

3.4.1 Prediction Based on Balance Theory

As described in Section 2.2.1, balance theory is applied to undirected signed graphs. Therefore, we construct a undirected signed relationship graph R using voting history. The signed relations the edges E_R in this graph describe should be symmetric in nature for e.g., the probability of agreements or disagreement between a pair of nodes u and v. Now, we create the LSN from the intersection of the session graph S and relationship graph R and keep the LSN an undirected graph by ignoring the direction of the voting edges (u_j, c).

Now, we turn to the task of predicting the sign of the edge (v, c) in the LSN. The voter v can cast either a positive or negative vote for the candidate c. This gives us two possibilities $w_{LSN}((v, c)) = +1$ or $w_{LSN}((v, c)) = -1$. We state that the voter aims to maintain the balance in the LSN. Therefore, we can predict the vote that when added as the edge (v, c) to the LSN results in a more balanced network. This indicates that we require a measure of the *imbalance* of a network. If $\overline{L}_{LSN}$ is the signed Laplacian of the LSN with

eigenvalues $\lambda_1 \leq \lambda_2 \leq \ldots \lambda_n$, then Li et al. [40] show that the smallest eigenvalue λ_1 is a measure of the imbalance of the LSN. Therefore, the larger λ_1 is, the more imbalanced the network is and if $\lambda_1 = 0$, then the network is perfectly balanced.

Combining these concepts we have Algorithm 3. When given a LSN and an edge (v, c) to predict, we first assume the vote is positive, add it to the LSN and compute the smallest eigenvalue denoted by λ_1^+. Next, we assume the vote is negative and add the edge to the LSN and the corresponding smallest eigenvalue is λ_1^-. Now, if $\lambda_1^+ < \lambda_1^-$, then we can predict that the vote is positive as the resulting LSN is more balanced. Similarly, if $\lambda_1^- < \lambda_1^+$, we predict a negative vote as it results in a more balanced network. This deterministic rule does not capture the gap between λ_1^+ and λ_1^-. Therefore, the ratio $r = \frac{\lambda_1^-}{\lambda_1^+}$ can be used to express the confidence in predicting the vote is positive. As λ_1^+ approaches 0 (or λ_1^- increases), r approaches ∞ and when λ_1^- approaches 0 (or λ_1^+ increases), r approaches 0. Also, when $\lambda_1^+ = \lambda_1^-$, $r = 1$ which indicates that we are equivocal between the vote being positive and negative. We can convert the ratio r into a measure of the probability that the given edge (v, c) is positive by defining $p = 1/(1 + e^{(1-r)})$. Therefore, the output of the model is a probability measure that can be compared similar to the output of a logistic regression model.

Figure 3.2 shows an example of how the we can iteratively predict votes using balance theory. The current voter at every iteration i is $v = u_{i+1}$. We start in the first iteration $i = 1$ with one prior voter u_1 who has voted negatively for the candidate c seen by the dotted red line in Figure 3.2a. The current voter v has a negative relation towards u_1 indicated by the solid blue line. Now, in this triad we know "v disagrees with u_1" and "u_1 disapproves of c". Using the intuition provided by balance theory, we can predict that the edge (v, c) is positive as it results in the triad being balanced. This result can be verified empirically by observing the values of smallest eigenvalue. We see that $\lambda_1^+ = 0$ and $\lambda_1^- = 1$ and therefore, the positive vote probability is $p = 1$. Now, in the next iteration, v becomes the prior voter u_2 and we add the edge (u_2, c) with the true vote (in this example we assume it was the same as the prediction made) and we get the next voter as the new v.

In the second iteration $i = 2$, the new voter v has a positive relation with the prior voter u_1 as seen in Figure 3.2b. By preserving the relation between u_1 and u_2 from the previous iteration there are larger cycles in the LSN. Similar to the previous iteration, we can observe the smallest eigenvalues and conclude that a negative vote leads to more balanced network and positive vote probability is now $p = 0$. Now, in the third iteration $i = 3$, the smallest eigenvalues in both cases are equal. Therefore, we are equivocal in the vote

being positive or negative and the positive vote probability is $p = 0.5$.

$\lambda_1^+ = 0, \lambda_1^- = 1$

$(a)\ i = 1$

$\lambda_1^+ = 0.58, \lambda_1^- = 0$

$(b)\ i = 2$

$\lambda_1^+ = 0.55, \lambda_1^- = 0.55$

$(c)\ i = 3$

Figure 3.2: Local Singed Network prediction based on balance theory. At every iteration i the dotted red lines are prior votes, solid blue lines are relationships based on voting records and the dashed black edge (v, c) is the edge whose sign is being predicted. λ_1^+ and λ_1^- correspond to the smallest eigenvalue of the signed Laplacian $\overline{L}_i$ based on whether $w((v, c)) = +1$ or $w((v, c)) = -1$.

3.4.2 Prediction Based on Status Theory

We mentioned in Section 2.2.2 that status theory is described for directed signed networks. The relationship graph R should, therefore, be be constructed from the history H as a directed signed network. The directed edges (u, v) should denote asymmetric relation between the nodes for e.g., the ratio of concurrence: a measure of times that u has voted after v in a session and agreed. The LSN created from the intersection of the session S and the relation is also a directed signed graph.

Algorithm 3: Predict positive vote probability using balance theory

Input: Voter v, Candidate c, Local Signed Network LSN

Result: Probablity of edge (v, c) being positive

1 $w_{LSN}((v, c)) \leftarrow +1$ // Assume positive vote
2 Compute signed Laplacian $\overline{L}_+$
3 $\lambda_1^+ \leftarrow$ smallest eigenvalue of $\overline{L}_+$
4 $w_{LSN}((v, c)) \leftarrow -1$ // Assume negative vote
5 Compute signed Laplacian $\overline{L}_-$
6 $\lambda_1^- \leftarrow$ smallest eigenvalue of $\overline{L}_-$
7 $w_{LSN}((v, c)) \leftarrow 0$ // Reset edge weight
8 $r \leftarrow \lambda_1^- / \lambda_1^+$
9 $p \leftarrow 1/(1 + e^{(1-r)})$
10 **return** p

Similar to predicting the vote using balance theory, the vote is either positive or negative. Now, we state that the voter aims to maintain the status in the resulting LSN. Therefore, we predict the vote (v, c) that when added to the LSN best preserves status in the network. Therefore, we need a measure of how much a given network conforms to the theory of status. However, to the best of our knowledge, there are no existing methods to quantify and measure the extent that a network conforms to status theory. In this thesis, we present a quantitative definition of status theory in a network and also present a novel method of using the agony of a directed network to measure the compliance with status theory.

As we discussed in Section 2.2.2, signed edges can be interpreted as recognition of relative status. This means that a positive edge $u \xrightarrow{+} v$ indicates that v has a higher status than u, and a negative edge $u \xrightarrow{-} v$ indicates that v has lower status than u. Let us assume that there is an implicit status function $\sigma : V \to \mathbb{N}$ that maps each node in the network to a quantity that correlates with status. Therefore, the edges $u \xrightarrow{+} v$ and $u \xrightarrow{-} v$ indicate $\sigma(u) < \sigma(v)$ and $\sigma(u) > \sigma(v)$ respectively. This is how we predict the missing sign of an edge in a triad. Leskovec et al. [37] provide a way to compute this status function σ from the node degrees as seen in Section 2.2.2. However, this measure is still defined locally and can be used only to predict the sign of an edge. We still require a framework to quantify violations and measure how much the network complies with status theory. We define that an edge $e = (u, v)$ *violates* status theory if $w(e)\sigma(u) \not\leq w(e)\sigma(v)$. Now, we can define when a network is perfectly complaint with status.

Definition 1. *Perfect Status Compliance A directed signed network $G = (W, E, w)$ with an implicit status function $\sigma : V \to \mathbb{N}$ is said to be perfectly status complaint if $\forall e = (u, v) \in E$, $\mathrm{sgn}(w(e))\sigma(u) \leq \mathrm{sgn}(w(e))\sigma(v)$*

Therefore, the number of edges that are in violation to status theory can be a rudimentary measure of the status compliance of a given network. However, in the case of most signed directed networks, we do not possess the implicit status function σ. Hence, even computing the number of edges that violate status theory is not possible. Therefore, if we can infer the status function σ from the structure of the signed network then we can measure the status compliance of that network.

We can now use the concept of *agony* described in Section 2.3 to find the optimal hierarchy of a given directed network. The notion of hierarchy is strongly related to status theory for signed networks. In a DAG, then there no cycles and we can find a status function σ such that there are no edges that violate status theory. Moreover, agony is a measure of the violation of edges with respect to a ranking function. Nevertheless, agony and hierarchy were primarily defined for unsigned networks. We can easily remedy this by using the fact that a negative edge $u \xrightarrow{-} v$ can be transformed into a positive edge $u \xleftarrow{+} v$. If G is a signed network then we denote the unsigned directed network obtained from the transformation described as G'.

Now, the agony of an edge (u, v) in G' given a status function (called rank function in Gupte et al. [23]) is $\max(\sigma(u) - \sigma(v) + 1, 0)$. Therefore, agony is a quantification of the status violation of an edge. The agony of the network with respect to a status function σ is defined as the sum of the agony of each edge in the network denoted by $A(G', \sigma)$. The agony of the network $A(G') = \min_{\sigma}(A(G', \sigma))$ is the smallest agony over all possible ranking of the nodes. In this way, the agony of the network is a more generalized measure of status compliance than just counting the number of violating edges. Therefore, we can use one of the algorithms mentioned in Section 2.3 to compute agony of G'. We call this value as the agony of the original signed network G and denote $\alpha = \alpha(G) = A(G')$. The complete process is outlined in Algorithm 4. Now, the agony of a signed network G is a measure of how far G is from being perfectly status complaint. Theorem 1 shows that when $\alpha = 0$ the network is perfectly status complaint.

Theorem 1. *Let $G = (V, E, w)$ be a directed signed graph. Then $\alpha(G) = 0$ if and only if G is perfectly status complaint.*

Proof. The transformed unsigned directed network is $G' = (V', E', w')$. The agony of a the directed network G^prime is 0 when the network has perfect hierarchy [23]. Therefore, there exists a status function σ such that the agony

of all edges G' i.e., $\sigma(u) \leq \sigma(v), \forall (u,v) \in E'$. Therefore, there are no edges in G that violate status theory and G is perfectly status complaint. Hence proved. $\qquad\square$

Algorithm 4: Compute Agony for a directed signed network

Input: Directed siged graph $G = (V, E, w)$
Result: Signed Agony α of G

1 Initialize $G' = (V', E', w')$
2 $V' \leftarrow V$
3 **foreach** $e \in E$ **do**
4   **if** $w(e) < 0$ **then**
5 $e' \leftarrow (\text{dest}(e), \text{src}(e))$ `// Change direction of the edge`
6 $E' \leftarrow E' \cup \{e'\}$
7 $w'(e') \leftarrow -w(e)$ `// Make the weight positive`
8   **else**
9 $E' \leftarrow E' \cup \{e\}$
10 $w'(e) \leftarrow w(e)$
11   **end**
12 **end**
13 $\alpha \leftarrow Agony(G')$
14 **return** α

Now, we can compute the agony of the LSN and utilize it to predict the sign of the vote. We follow a process similar to predicting the sign using balance theorem. First, first assume the vote is positive and add the edge (v, c) to the LSN and compute the agony and call it as α^+. Next, we assume the vote is negative and add the edge and compute the agony of the LSN and call it α^-. If $\alpha^+ < \alpha^-$, then it means that the positive vote results in a LSN that has fewer violations of status and therefore, we can predict the vote is positive. Similarly, we predict a negative vote if $\alpha^- < \alpha^+$. Alternatively, we can also compute the probability of a positive vote as $p = 1/(1 + e^{(1-r)})$, where $r = \alpha^-/\alpha^+$. This process is detailed in Algorithm 5.

We see a directed LSN similar to the one in Figure 3.2a in Figure 3.3. The branches indicate the two possibilities for the vote edge (v, c). The left branch assumes that the vote is positive and adds it to the LSN. When we transform the negative edges in the LSN we get a cycle. As a cycle indicates that there is no hierarchy in the LSN the agony $\alpha^+ = 3$ reflects the fact that each edge violates status theory. The right branch assumes that the vote is negative and includes it in the LSN. After transformation, we see that all

the edges comply with status theory and therefore, the agony $\alpha^- = 0$. Now, the corresponding positive vote probability is $p = 0$ indicating that we would predict a negative vote. Note this result is contradictory to balance theory where we predict a positive vote for the same LSN.

Algorithm 5: Predict positive vote probability using status theory

Input: Voter v, Candidate c, Local Signed Network LSN
Result: Probablity of edge (v, c) being positive

1 $w_{LSN}((v, c)) \leftarrow +1$ `// Assume positive vote`
2 $\alpha^+ \leftarrow SignedAgony(LSN)$
3 $w_{LSN}((v, c)) \leftarrow -1$ `// Assume negative vote`
4 $\alpha^- \leftarrow SignedAgony(LSN)$
5 $w_{LSN}((v, c)) \leftarrow 0$ `// Reset edge weight`
6 $r \leftarrow \alpha^- / \alpha^+$
7 $p \leftarrow 1/(1 + e^{(1-r)})$
8 **return** p

3.4.3 Iterative Prediction Model

Now, Algorithm 6 describes a model that can predict the votes in a session iteratively. We have the order of votes in the session denoted by O and the true votes function w^*. We create the session graph and initialize it with the candidate c and the first voter as seen in line 6. This is because we need at least one prior vote information to effectively predict a vote. In most settings, such as bills in a government parliament or promotion of a member in a community, there are always sponsors or nominators who propose the candidate in that session. Therefore, we are justified in starting the session with the candidate and the first vote cast in the session graph S. Next, for each subsequent voter v in the list, we add it the session and create the LSN. The *Predict* function in line 12 can be based on either balance (Algorithm 3) or status theory (Algorithm 5). Then, we add the true vote of voter v to the session G and move on to the next voter in the list. After all the votes are predicted in the session, we can update the relationship graph H with the data from the current session S. This can include operations such as adding nodes that were not present in R and updating the edge weights based on the votes cast in the current session.

In this process we can predict all the votes in all the sessions by starting with an empty relationship graph and updating it after every session. Therefore, the model can be compared to a "*batch*" machine learning model,

Figure 3.3: Example of LSN sign prediction using status theory.

where each batch is a voting session and the model parameter is the relationship graph R. In a batch, the model will predict votes based the paramters which is the information gathered from the previous sessions contained in the relationship graph R. After the batch is complete, the model updates its "parameters" or the graph with data from the current session. We can bootstrap the model from a complete *blank slate* where R is an empty graph and then iteratively predicts sessions and updates R. The model iteratively improves.

Algorithm 6: Iterative Prediction Model

Input: Candidate c, Relation graph $R = (V_R, E_R, w_R)$, Order of
voters in current session O and true votes w^*

Result: Predictions for current session

1 $k \leftarrow |O|$

2 $u \leftarrow O[1]$ `// First voter`

3 $V_S \leftarrow \{c, u\}$ `// candidate and first voter`

4 $E_S \leftarrow \{(u, c)\}$ `// first vote`

5 $w_S((u, c)) \leftarrow w^*((u, c))$ `// Assign true vote`

6 Initialize session graph $S = \{V_S, E_S, w_S\}$

7 $predictions \leftarrow \emptyset$

8 for $i \leftarrow 2$ **to** k **do**

9 $v \leftarrow O[i]$

10 $V_S \leftarrow V_S \cup \{v\}$

11 $LSN \leftarrow S \cap R$

12 $p \leftarrow Predict(v, c, LSN)$

13 $predictions \leftarrow predictions \cup p$

14 $E_S \leftarrow E_S \cup \{(v, c)\}$

15 $w_S((v, c)) \leftarrow w^*((v, c))$ `// Assign true vote`

16 end

17 $Update(R, S)$ `// Update Relations graph`

18 return $predictions$

Chapter 4

Wikipedia

In this chapter, we provide an overview of the inner workings and decision making processes of Wikipedia. Firstly, in Section 4.1 we state the fundamental principles of Wikipedia and how it guides editors on the website. Next, we describe the roles and responsibilities of the different categories of Wikipedia users in Section 4.2. Lastly, we explain the election process for administrators and discuss the voting behaviour in terms of existing research.

4.1 Principles of Wikipedia

Wikipedia is the largest online encyclopedia, with over six million pages of content in the English version. It is maintained by an open collaborative effort of multiple editors from all across the world. All the knowledge and content is free and is supported by the non-profit Wikimedia Foundation. The size and popularity of Wikipedia is attributed to the ability for anyone to edit any content. All editors on Wikipedia follow five fundamental principles, called the "Five Pillars", shown in Figure 4.1. These five pillars provide a foundational framework for collaboration amongst users and contribution towards the betterment of the Wikipedia project.

The first pillar states that Wikipedia is first and foremost an encyclopedia [63]. Therefore, it must not contain any original research, propaganda or advertisements [61]. Materials that do not have reliable references will be removed by other edits.

The second pillar specifies that articles on Wikipedia should strive for a neutral point of view. This might include presenting multiple perspectives on the same subject accurately and not championing any one viewpoint as "correct" or "the truth". If disagreements are present, then discussions must take place for building consensus.
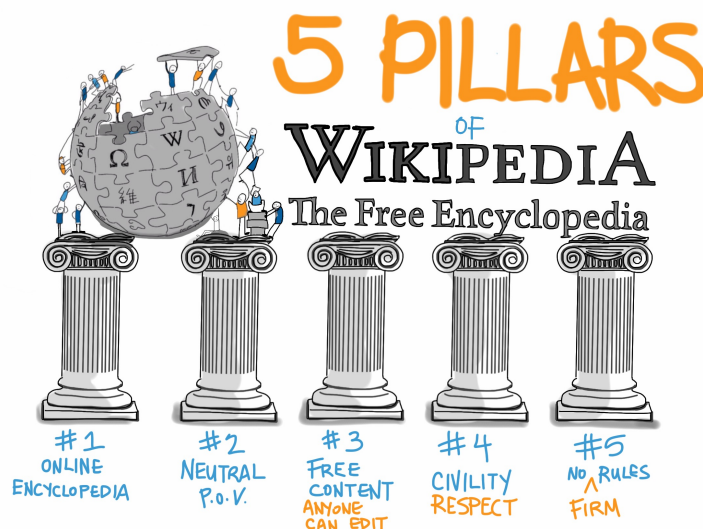
Figure 4.1: Five Pillars of Wikipedia. Image downloaded from `https://www.flickr.com/photos/gforsythe/21684596874`

The third principle enshrines the ideal that all content available on Wikipedia is free to edit and share. However, this does not mean copyright violation and plagiarism is tolerated by the community. There is no ownership of an article by an editor; anyone may freely modify any content.

The fourth pillar describes Wikipedia's code of conduct. It asks users to act in good faith and assume good faith on the part of other editors. Wikipedia etiquette urges disputes and disagreements, such as edit wars [58], to be resolved with civility while respecting other editors.

The fifth and last pillar reminds users that all rules in Wikipedia are essentially just policies and guidelines meant to help with collaboration. They can evolve and change to reflect the requirement of the community. It assuages the fear of making mistakes and encourages editors to be bold, though not reckless.

4.2 Formal Organization of Wikipedia

In this section, we describe the various categories of users and explain their roles and responsibilities. All the facts and figures we provide in this thesis are from the English version of Wikipedia. We define a "user" of Wikipedia as a person who contributes to the encyclopedia and a "reader" as someone who simply accesses the content.

Wikipedia began as completely open platform with no restrictions on who could edit a page or create a new article. Changes and edits that were made to a page were be published immediately. This led to many pages that contained erroneous text, biased content and gibberish. Therefore, this led to the English version of Wikipedia introducing restrictions and tools to protect the more controversial pages. They also introduced categories of users to help protect and maintain the quality of the content available on Wikipedia. We proceed to explain the four main user types as seen in Figure 4.2.

(a) Editors

(b) Administrators

(c) Bureaucrats

(d) Arbitration Committee

Figure 4.2: Logos for each category of user that signify the role that they play in the Wikipedia community.

4.2.1   Editors

Editors (or Wikipedians) are the primary users who edit and create all the content on Wikipedia [64]. Figuratively, they hold Wikipedia in the palm of their hands, as seen by the logo in Figure 4.2a. There are two main types of editors on Wikipedia, namely *registered* and *unregistered*. A registered user is someone who has a unique username and a permanent *talk page* to communicate with other users. By contrast, unregistered users contribute without a registered username and are usually referred to as *IPs*, as they are only identified by their IP addresses. Unregistered users usually have similar rights as those of regular users to edit, discuss and contribute, but with

certain exceptions [59]. Unregistered users cannot create a new article, edit a protected page, become administrators or vote in elections to promote users within Wikipedia. As the focus of the thesis will be on the elections within Wikipedia, when we refer to editors in the coming chapters and sections, we refer to registered users.

Wikipedia has over 38 million registered users, and this number is constantly rising. However, only roughly 0.37% ($\approx 144\,000$) of registered users are active, i.e., have performed some action in the past 30 days. An even smaller percentage of those active users participate in the community discussion forums on Wikipedia. Now, we will explain what tasks editors perform and how contribution is recorded in Wikipedia.

Each page in Wikimedia is classified into a *namespace* based on the type of information that page contains [60]. Namespaces separate pages into sets to distinguish content pages from administrative or editor related pages. For example, the MAIN (or ARTICLE) namespace contains all the encyclopedic content and the USER namespace contains the user pages and information related to their user accounts. Each page in Wikipedia also has a corresponding *talk page*, which are used by editors to discuss changes to the page in question. For instance, the USER TALK namespace has talk pages corresponding to each user page and acts as a system to message particular users. Figure 4.3 shows a list of the subject namespaces and their corresponding talk namespaces. Now, we define a *user contribution* as any addition, deletion or modification of a page under any namespace in Wikipedia [55]. Wikipedia collects and stores every user contribution so that it can track cases of vandalism and copyright infringement.

The quality and quantity of the contribution of each editor varies significantly. There are many occasional users who merely correct minor spelling and grammar errors in articles. At the same time, there are dedicated editors who constantly create new articles, update large portions of text, and include new references and images.

4.2.2 Administrators

Administrators (or *admins*) are editors who are given access to certain tools and powers to maintain content on Wikipedia. Administrators can delete and restore deleted pages, block and unblock users and IP addresses from editing, and protect and remove protection from sensitive pages [56]. These tools are associated with a mop that is used to clean up Wikipedia and is represented by their logo, seen in Figure 4.2b. There are currently 1 141 administrators, of whom 500 are active. Although admins have access to these tools, they are considered to be no more important than regular editors. Administrators

Wikipedia data structure

Namespaces			
Subject namespaces		**Talk namespaces**	
0	(Main/Article)	Talk	**1**
2	User	User talk	**3**
4	Wikipedia	Wikipedia talk	**5**
6	File	File talk	**7**
8	MediaWiki	MediaWiki talk	**9**
10	Template	Template talk	**11**
12	Help	Help talk	**13**
14	Category	Category talk	**15**

Figure 4.3: A list of the namespaces in Wikipedia [60].

are elected through a week-long process called *Request for Adminship* (RfA), at the end of which successful candidates are instated by a Bureaucrat. We will cover the RfA process in detail in the coming sections.

Along with the tools and power, administrators also have certain responsibilities. They are not to misuse the tools at their disposal in conflicts of interest or disrupt Wikipedia by acting in bad faith. Administrators serve indefinitely, but can be removed by Bureaucrats on the decision of the Arbitration Committee for abuse of powers or inactivity. Admins help with various areas of Wikipedia, such as processing administrative backlogs, helping with ant-vandalism efforts, and managing copyright issues.

4.2.3 Bureaucrats

Bureaucrats (or *Crats*) are users who perform certain actions [57]. They are usually administrators and oversee procedural rules and enforce decisions. There are a total of 19 bureaucrats currently in the English Wikipedia. Bureaucrats are involved in the granting or revoking of administrator status to users and adding and removing bots (software robots that carry out repetitive tasks on Wikipedia). Bureaucrats are bound by the policy and the consensus of the community in granting these roles or permissions and are, therefore, expected to be good arbiters of consensus. Hence, they should be

able to identify criteria for a "consensus" and also explain the reasons behind their actions when requested.

Bureaucrats are also elected through a process similar to RfA, called *Request for Bureaucratship* (RfB), but higher thresholds of acceptance are usually demanded for considered selection. Interestingly, Bureaucrats are also appointed following the final decision of another Bureaucrat, therefore, they have complete control over the whole process. However, a Bureaucrat cannot revoke the bureaucratic position of others. They also carry out the requests from the Arbitration Committee to remove the permissions and privileges of admins or bots. As their name suggests, Crats perform only bureaucratic duties and are therefore represented by the logo seen in Figure 4.2c.

4.2.4 Arbitration Committee

The *Arbitration Committee* (or *ArbCom*) resolves disputes that have not reached a resolution through community discussion or administrator oversight [54]. Their goal is to decisively bring binding solutions to ongoing disputes and is reflected in the fact their logo is a balance scale, as seen in Figure 4.2d. It is formed by a panel of experienced editors, usually administrators, who are elected by the community annually. There are currently 11 active members of the ArbCom.

The ArbCom only deals with disputes related to editor conduct and not content related disputes. It can impose sanctions that would restrict editors from contributing to certain topics and also recommend the revoking of administrative privileges in cases of misuse. Although the ArbCom can take the initiative on matters it deems are important, it usually acts on formal requests made to the committee. As it is the last step in dispute resolution, it only accepts a case when all other methods have failed. This is evident from the fact that only 9 cases were accepted in 2019.

4.3 Request for Adminship

In this section, we will describe the election process to select administrators in the English version of Wikipedia called *Request for Adminship* (RfA). We cover the origin and history of the process, the evolution of the format and the properties that lead to successful candidates. Lastly, we also cover the existing research that has been carried out in understanding and predicting RfAs.

In the early days of Wikipedia, the founder, Jimmy Wales, directly sent emails to the users to appoint them as administrators. Jimmy said that he

felt that getting administrative privileges is "not a big deal". However, as
the Wikipedia community grew, a long and intense process was developed to
select future administrators. A RfA is a week-long period during which all
registered Wikipedia users can vote on a candidate standing for the position
of administrator.

There are four main phases of a RfA: the nomination and beginning the
period, answering questions posed by the community, voting to show support,
opposition or neutrality towards the candidate, and the closing of the RfA
by a Bureaucrat.

The first phase begins with the creation of a RfA page for the nomi-
nee. The candidates are most often nominated by another well-known and
respected editor. However, self-nomination is a possibility. Self-nominated
candidates are usually under more scrutiny to ensure they are not overeager
new users nor editors with prior issues. Nominations are usually accompanied
by an introductory statement from the nominator indicating the qualities the
candidate possesses. Nominees can decline a nomination if they wish to, in
which case the RfA is closed immediately as unsuccessful. Therefore, nom-
inators usually only choose candidates who show good promise and discuss
the potential nomination prior to starting the RfA process.

Once a candidate accepts the RfA nomination, they are required to answer
three standard questions.

1. What admin work do you intend to take part in?

2. What are your best contributions to Wikipedia, and why?

3. Have you been in any conflicts over editing in the past or have other
   users caused you stress? How have you dealt with it and how will you
   deal with it in the future?

The first question aims to discern the value addition that a particular can-
didate will bring to Wikipedia if given admin privileges. The community
tends to look for initiative from nominees in utilizing existing tools to help
with chores such as reverting errors, identifying vandalism or copyright in-
fringements. The answer to the second question provides the community
the candidate's achievements and quality of work. Editors who have several
multiple good contributions tend to be more successful. In answering the
third question candidates demonstrate their conflict management skills. The
community values users who can interact in a civil manner and an admin-
istrator is also involved in resolving disputes and therefore, users who were
involved in heated discussions or edit wars are unfavourable. Apart from

these three fixed questions the candidate may also receive several open questions aimed at testing their knowledge of Wikipedia procedures or opinions on controversial issues.

Once all questions have been answered, the RfA moves to the voting phase. During this phase, any registered user may vote in either Support, Oppose or Neutral sections. Votes are generally followed by a comment providing reasoning that explains their vote. Candidates can reply to opposition commenters to try and resolve any issues and convert their views. However, candidates should refrain from verbose rebuttals as it might invite more opposition. This phase is nerve-racking for the candidate as the tide of the election changes constantly throughout the week and it is not possible to reply to every comment in a civil and respectful manner.

At any point in the RfA, the candidate can withdraw their nomination for any reason. At the end of the week, a Bureaucrat halts the voting and proceeds to read all the comments. The Bureaucrat has to conclude if consensus has been reached or not regarding the nomination. Bureaucrats are highly experienced and will discount votes cast by sockpuppets (users who have multiple accounts) and meatpuppets (new users recruited to influence decisions). Although the decision is not based on majority voting, RfAs with more than 75% support generally pass and by contrast ones with lesser than 65% support are bound to fail.

The Bureaucrat can also invoke clauses such as "Not Now" (WP:NOTNOW [53]) and "Not a snowball's chance in hell" (WP:SNOW [62]) to terminate RfAs that they deem have no chance to pass. These measure exists so that frivolous RfA do not waste the time of the community. If the Bureaucrat decides that the nomination is successful, the candidate is promoted and the RfA is closed as successful. If the nomination fails then the Bureaucrat explains their reasoning and closes the RfA as a failure. Renomination of a failed candidate can occur after waiting for a reasonable period of time from the previous failed RfA.

RfAs have been extensively studied from a sociological and behavioural aspects [17, 33]. Burke et al. [9] proposed a model based on RfA guides to predict the success of a potential nomination. Since then, there have been various models based on social networks [10, 46, 47] or user features and contributions [5, 45] to identify influential voters and overall voting patterns.

Chapter 5

Experiments

In this chapter, we will outline the experiments carried out on the Wikipedia elections of administrators using the vote predicition models that we presented in chapter 3. Firstly, we describe the existing sources of data from Wikipedia and the datasets used in the experiments in Section 5.1. Next, in Section 5.2, we discuss the implementation of the linear combination of graph model described in Section 3.3. Then, we cover the implementation of the vote predicition models based on the theories of balance and status in signed networks in Section 5.3. Furthermore, in Section 5.4, we discuss the experiments conducted on the voting order and its impact on the predictive power of the models proposed. Lastly, we explain the metrics which we can ue to evaluate the performance of the models in Section 5.5.

5.1   Datasets

As we discussed in Section 4.3 and 4.2.1, Wikipedia keeps detailed information on the election proceedings for the RfA process as well as contributions made by every editor on Wikipedia. These act as sources to get data regarding the elections and user contributions. There are existing datasets compiled by the Stanford Network Analysis Project (SNAP) [38] on both Wikipedia RfAs and edit histories. However, the RfA dataset has missing features and timestamps for votes that would restrict the usability in the proposed voting models. Similarly, the *wiki-meta* and *wiki-talk* datasets possess information until 2008 and lack a username mapping to the network nodes. Due to these limitations, we proceeded to scrape Wikipedia dumps and APIs to obtain our own RfA and user contribution datasets, which we will now describe.

5.1.1 Wikipedia RfA Data

To obtain the RfA data, we parsed through the entire XML dump of Wikipedia from January 2019. We filtered the pages related to the RfA process and then extracted each vote and the corresponding comment and timestamp. Each vote extracted has the features show in Table 5.1.

Table 5.1: Features of each vote in the WIKI-RFA dataset

Feature	Data Type	Description
SRC	text	username of the source
TGT	text	username of the target
VOT	$[-1, 0, 1]$	Oppose, Neutral or Support vote
RES	$[-1, 1]$	Failure or Success of RfA
YEA	date	year of the RfA
DAT	date & time	timestamp of the vote
TXT	text	accompanying textual comment
UID	alphanumeric	unique identifier for the RfA

As we can see, the format of the data is very similar to the SNAP dataset. We have an additional unique identifier field, called UID, to aid in distinguishing RfA of users who have had multiple nominations. We collected 226 781 votes from 4 557 elections with over 13 000 unique usernames. There are 166 214 ($\approx 73\%$) support, 46 918 ($\approx 20\%$) oppose and 13 649 ($\approx 6\%$) neutral votes. As the voting format of RfA changes throughout the years, there might be issues in successfully extracting the source username or timestamp information. Regardless, only 1.6% of votes have missing timestamps and 0.4% have a missing source. We will refer to this dataset as WIKI-RFA and it will provide the information regarding the votes cast in a RfA.

5.1.2 User Contribution Data

As we discussed in Section 4.2.1, every edit made by a user is stored as a contribution. Wikipedia provides an API to query all the contributions of a particular user [43]. We utilized this API and collected the contribution data of all the unique users we obtained from the WIKI-RFA dataset. There are 16 features that the API provides for each edit; we describe the most import features in Table 5.2.

As many users change their username, some of the usernames present in the WIKI-RFA dataset might not have any contributions linked to their old usernames. We were able to collect the user contribution details more than

Table 5.2: Important features of each contribution in the USER-CONTRIB dataset

Feature	Data Type	Description
user	text	username of the editor
title	text	title of the page edited
namespace	int	namespace of the page edited
timestamp	date & time	timestamp of the edit
size	int	new size of the edit
sizediff	int	size delta of the edit against its parent
new	boolean	if the editor created a new page
minor	boolean	if it is a minor edit
comment	text	accompanying comment

11000 of the total unique username, amounting to 100GB of data. We call this dataset USER-CONTRIB and it provides a wealth of information on the editing habits of the users who take part in Wikipedia RfAs. For instance, grouping the contributions of a particular user by the namespace, we get the proportion of the edits in different Wikipedia namespaces and the respective sizes and quality of their edits.

5.2 Linear Combination of Graphs Model

In this section, we describe how we implement the model proposed in Section 3.3. The model requires auxiliary graphs derived from other non-election based information as well as triadic features derived from the election data. Therefore, we first discuss the auxiliary graphs that we create from the USER-CONTRIB dataset and then describe the triadic features from the WIKI-RFA data. Then, we describe the process of preparing the data to suit the supervised machine learning task and to also prevent data leaks. Lastly, we discuss the logistic regression model that we use as the linear predictor trained on the features derived from the auxiliary and signed networks.

The terms used in Chapter 3 can now be defined for the problem of predicting votes in a Wikipedia RfA. A candidate c is the nominee who wishes to gain administrators privileges in the Wikipedia RfA. The voters v are the registered users in Wikipedia. A session relates to the proceedings of a particular RfA.

5.2.1   Graphs

First, we discuss the creation of the topic similarity network of users. Then, we describe the process of forming the talk graph between users. Lastly, we define the triadic features we extract from the previous voting data.

5.2.1.1   Topic Similarly Graph

In Table 5.2, we see that every contribution has a title of the page where the edit was made. We can utilize the page titles to understand the topics that the user most edits. For a particular user, we gather all their edits in the MAIN namespace. We choose the MAIN namespace as it contains all the content articles on Wikipedia. By contrast, the edits in other namespaces such as, USER and HELP, are not indicative of the topics that they are most likely to possess information about. Then, we count the number of edits grouped by each page title and choose the top 100 most edited pages in the MAIN namespace. Then we create a set of the words from all the top 100 page titles and remove common stop words using a natural language corpus. This set now indicates the users topics of interest. Once we have collected the topic set for all the unique users in the WIKI-RFA dataset, we can compute the similarity between a pair of users using the Jaccard similarity measure. We can take this similarity measure and construct a undirected weighted graph where a link between nodes indicates the similarity in the topics of the user nodes. However, we threshold the value of similarity so that we can obtain only meaningful edges and not a complete graph.

5.2.1.2   Talk and Interaction Graph

We discussed in the previous chapter on how every registered user has a talk page and how it is used as a medium of communication. Therefore, we can similarly gather the contributions of a certain editor in the USER TALK namespace and use it to measure interactions with other users. We will create two auxiliary graphs in this manner, a *user talk graph*, where each edge also contains the number of times they have written on another users page and a *interaction graph*, which only indicates if two users have interacted via a talk page. We can obtain the number of talk page edits and the target user by grouping by the page titles and extracting the username from the page title respectively. These graphs will be directed in nature and the talk graph is weighted, while the interaction graph is unweighted. In both these graphs, an edge $u \rightarrow v$ indicate that user u has written in the talk page of user v.

In the Line 3 described in Algorithm 1, we can define N_i in directed graphs G_i as successors of a node rather the neighbourhood. This allow us

to understand the influence of edge direction in directed auxiliary graphs. Therefore, we will construct two more additional auxiliary graphs which are reversed, i.e., an edge $u \rightarrow v$ indicates that user v has written on the talk page of user u. Hence, we can compare the contribution each direction brings to the model by analysing the feature importances.

5.2.1.3 Signed Graph and Triadic Features

The WIKI-RFA dataset contains the voting information of users in RfAs. These votes form a signed directed network and we can utilize triadic features as proposed by Leskovec et al. [36]. We utilize a slightly modified naming scheme to identify unique triads in the RfA data. Considering the edge we want to predict between a voter v and a candidate c and the other node u. There are two directions for the edges (v, u) and (u, c) and each edge can have three values, namely -1, 0 or +1 corresponding to oppose, neutral or support respectively. This leads to $2 \times 2 \times 3 \times 3 = 36$ possible triads.

We denote the edge $v \rightarrow u$ as "F" and the edge $v \leftarrow u$ as "B" indicating a forward or a backward edge. Similarly, the edge $u \rightarrow c$ is "F" and $u \leftarrow c$ is "B". The edge labels are "-", "0", and "+" corresponding to oppose, neutral and support. We have a nomenclature where "FB+-", indicates $v \xrightarrow{+} c$ and $u \xleftarrow{-} c$. Figure 5.1 shows more examples of this triad nomenclature.
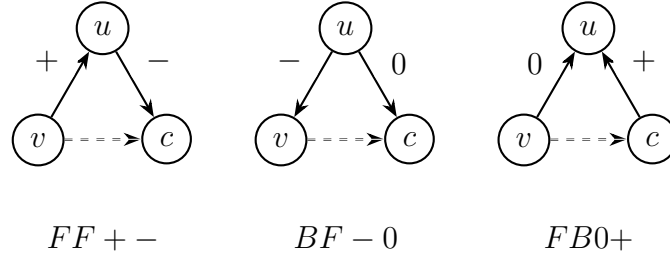

$$FF + - \qquad BF - 0 \qquad FB0+$$

Figure 5.1: Examples of triad nomenclature in Wikipedia RfA elections

We collect all the 36 unique triads in the set T and then utilize it to count the triads for a particular edge, as seen in Algorithm 2. Therefore, for each edge to be predicted (v, c), we have a triadic feature vector of length 36 containing the counts of the triads formed by all the common neighbours u.

5.2.2 Data Preparation

As only roughly 6% of all votes are neutral votes, we will not try to predict neutral votes. This is in line with the Wikipedia RfA process where neutral votes are not counted for the support percentage. However, we will use the

neutral votes to gather the triadic features and can utilize the additional information to predict votes. As we discussed in Section 3.2, the graph combination model is an extension of the sign prediction models for the voting setting. A major requirement to predict votes is to ensure that there is no *data leakage* when creating the training features $\mathbf{X}$, similar to the process used by Kairimi et al. [29]. A data leak is when we have information about the future present in the training data. This can cause the model that we train to overfit on the leaked data and not generalize. In our problem setting, we divide the whole WIKI-RFA into three parts, namely *dev*, *train* and *test*. As we are predicting votes, we will split the datasets based on the number of votes chronologically and round up to the closest RfA so that it is contiguous.

The *dev* (or development) dataset will be the set of RfAs which we use to construct the auxiliary and signed graphs. We ensure that the USER-CONTRIB dataset is also restricted to the edits that happened until the date of the last RfA in the dev dataset. Therefore, all the five auxiliary graphs and the signed graphs are created only with information that is present in the time frame of the dev dataset.

Next, the *train* (or training) dataset is what we use to create the feature matrix $\mathbf{X}$ and target matrix $\mathbf{y}$. In this dataset, we only consider the support and oppose votes to be part of the prediction task and hence, filter out all the neutral votes. Now, for each vote, we create the auxiliary feature vector $\mathbf{a}$ using the five auxiliary graphs and the triadic feature vector t from the signed voting graph as described in Algorithms 1 and 2 respectively. These features are concatenated into a feature vector $\mathbf{x}$, which is of length 41 (5 auxiliary and 36 triadic) and is a row in the feature matrix. The corresponding true vote is also collected in the target y_i. The *dev* and *train* splits ensure that the auxiliary and triadic features are strictly not overlapping. This allows the feature matrix $\mathbf{X}$ to be independent of time and therefore, be cross validated.

Lastly, the *test* dataset contains votes that the model trained on the training dataset would not have seen and can be used to evaluate the performance of the model. The feature matrix for the test dataset, $\mathbf{X}_{test}$ and the target, $\mathbf{y}_{test}$ are also constructed in a similar manner. For each vote in the test dataset, we gather the auxiliary and triadic features from the same graphs as we used for the training phase. We create each row of $\mathbf{X}_{test}$ by concatenating these features and gathering the true vote as the target.

5.2.3 Supervised Classification

Once we have created the training and testing feature matrices, $\mathbf{X}$ and $\mathbf{X}_{test}$ and the target vectors, $\mathbf{y}$ and $\mathbf{y}_{test}$, the task is a regular supervised classification problem. We can use any traditional linear classification models such

as support vector classifiers (e.g.,linear SVC), logistic regression models or gradient boosting methods (e.g., XGBoost). We choose a logistic regression (LR) model for its interoperability and robustness to overfitting.

Given a feature vector $\mathbf{x} = (x_1, x_2, \ldots, x_n)$ with n features, a logistic regression model learn to predict the probability of the form

$$P(\text{support} \mid \mathbf{x}) = \frac{1}{1 + e^{-(\beta_0 + \boldsymbol{\beta}\mathbf{x})}} \tag{5.1}$$

Where β_0 and $\boldsymbol{\beta} = (\beta_1, \beta_2, \ldots, \beta_n)$ are the coefficients that the model learns using the training data.

The WIKI-RFA dataset has a class imbalance problem. Support votes are 73% compared to oppose votes at 20%. Therefore, we will utilize class weights inversely proportional to the class frequencies while training so that the model learns to predict negative votes effectively. As the training features $\mathbf{X}$ are independent of time, we acn use k-fold cross validation to tune the regularization parameter for the logistic regression model.

5.3 Local Signed Network Models

We now discuss the implementation and significance of the local signed network models discussed in Section 3.4 to predict votes in Wikipedia RfAs.

These models are iterative models and an important feature is that they are unsupervised. Therefore, they do not require any learning of parameters or preparation of data for training. Consequently, we can bootstrap the models to start from the first available RfA. We achieve this by beginning with an empty relationship graph R. In the first RfA, the LSN network for all the votes contain only the nodes for voter v and candidate c. Therefore, the model will predict all votes with probability 0.5 of being support votes, as there is no information available. After the first RfA is over, the relationship graph R will be updated with the voting details. Now, in the second RfA there is more information present and the model can be predict votes with more certainty. In this manner,the models can iteratively learn and predict all the votes present in the WIKI-RFA dataset.

In a similar fashion, the iterative models elegantly handle new users for whom we have no information . If at any point the current voter v is new and there is no information in the relationship graph , then the model predicts support vote probability of 0.5, because the LSN contains only the nodes v and c . This new voter is then integrated into the relationship graph when it is updated after the RfA session, shown in Line 17. Therefore, this new voter's information is now available for future vote predictions.

In this thesis, we wish to separately study the votes that are predicted with no information. Therefore, in our implementation we specifically mark these votes. Firstly, we can accurately evaluate the models using only on the votes predicted with information. Next, we can analyse the distribution of the informationless votes and devise strategies to effectively guess the vote in the case when it is a new user. Lastly, we can verify if there is some herd mentality when new voters vote for the first time.

We proposed two models, one using balance theory and another using status theory. Both the models make use of only the election data, therefore, we will the WIKI-RFA dataset. First, we describe the iterative balance model and define the relationship graph based on agreement between voters in Wikipedia RfAs. Secondly, we explain the iterative status model and the relationship graph based on follower ratio in RfAs.

5.3.1   Iterative Balance Model

The *Iterative Balance* model uses balance theory of the local signed network to predict the independent vote in a Wikipedia RfA. As discussed in Section 3.4.1, we require a signed symmetric measure between two voters. We now propose a measure based on the *agreement ratio* between two users u and v. The ratio is the number of times u and v have voted the same divided by the number of common RfAs they have participated in. For example, if u and v have participated in 12 common RfAs and have voted the same in 9 RfAs, then the agreement ratio is 0.75, indicating that they agree more than they disagree. Therefore, if they have an agreement ratio of 0.5, then they neither agree or disagree to a significant degree. The agreement ratio is symmetric and we can covert into a signed measure by subtracting 0.5 from the ratio.

Hence, we define a signed undirected *agreement graph* $A = (V_A, E_A, w_A)$, where the weight function is defined as seen in Equation (5.2).

$$w_A((u,v)) = \frac{\text{Number of times } u \text{ and } v \text{ have voted the same}}{\text{Number of common RfAs for } u \text{ and } v} - 0.5 \quad (5.2)$$

This agreement graph A is the relationship graph R for the iterative balance model described in Algorithm 6. In Line 17 there is a a method, $Update(R, S)$ to update the relationship graph after the end of a voting session. Therefore, we require a method to update the signed weights in the agreement graph A given the RfA voting details in a session S.

For notational ease, we assume that each edge $e = (u, v) \in E_A$ contains two attributes, *e.agree* and *e.common*, the agreement ratio and the number of common RfAs between the nodes respectively. Then, once we get the

voting information from the session, we can update the agreement ratio and the number of common RfAs in a straightforward manner. This process is shown in Algorithm 7. We can bootstrap the model by beginning with an empty agreement graph A. Then for votes with no information the predicted support probability is 0.5. After the RfA session is over, these new voters can be incorporated into the agreement graph when it is updated, as seen in Line 17.

Algorithm 7: Update Agree graph after a session

Input: Session graph S, Candidate c, Agree graph A
Result: Updated Agree graph A
// Get all voters
1 $O \leftarrow V_S - \{c\}$
2 Order O by timestamp
3 **for** $v \in O$ **do**
4 $\quad$ $vote_v \leftarrow w_S((v, c))$
5 $\quad$ **foreach** u *who voted after* v **do**
6 $\quad\quad$ $vote_u \leftarrow w_S((u, c))$
7 $\quad\quad$ $e \leftarrow (v, u)$
8 $\quad\quad$ **if** $e \in E_A$ **then**
9 $\quad\quad\quad$ $agree \leftarrow e.agree$
10 $\quad\quad\quad$ $common \leftarrow e.common$
11 $\quad\quad\quad$ **if** $vote_v = vote_u$ **then**
12 $\quad\quad\quad\quad$ $agree \leftarrow ((agree \cdot common) + 1)/(common + 1)$
13 $\quad\quad\quad$ **else**
14 $\quad\quad\quad\quad$ $agree \leftarrow (agree \cdot common)/(common + 1)$
15 $\quad\quad\quad$ **end**
16 $\quad\quad\quad$ $common \leftarrow common + 1$
17 $\quad\quad$ **else if** $vote_u = vote_v$ **then**
$\quad\quad\quad$ // if e is a new edge
18 $\quad\quad\quad$ $common \leftarrow$ number of elections v and u have in common
19 $\quad\quad\quad$ $agree \leftarrow 1/common$
20 $\quad\quad\quad$ $E_A \leftarrow E_A \cup \{e\}$
21 $\quad\quad$ **end**
22 $\quad\quad$ $e.agree \leftarrow agree$
23 $\quad\quad$ $e.common \leftarrow common$
24 $\quad\quad$ $w_A(e) \leftarrow e.agree - 0.5$
25 $\quad$ **end**
26 **end**
27 **return** A

5.3.2 Iterative Status Model

- Describe how status is derived from the Follows graph in a local signed network

- Discuss Agony algorithm used as blackbox

- Discuss how the Follows graph is updated after every election

- Describe the probabilistic results.

5.4 Voting Order Experiments

5.5 Evaluation Metrics

- Discuss the issues with the imbalance in the dataset

- Illustrate the issues with accuracy

- Discuss ROC and Precision Recall curves for probability based predictions

- Discuss AUC ROC and AUC posPR and AUC negPR

Chapter 6

Results and Discussion

In this section we will present the results of the models and discuss their implications.

6.1 Linear Combination of Graphs

- Present results for each linear classifier

- Discuss the different splits of the dataset to check for robustness and chronological consistency

- Show the feature importances and discuss their relevance

- Compare the raw accuracy versus the macro f1 scores

- Highlight the difficulty of predicting negative votes

6.2 Local Signed Network

- Present the Iterative Balance model results

- Discuss quality of predictions using evaluation metrics

- Mention the difference between deterministic and probabilistic prediction accuracies

- Explain the Iterative Status model results

- Discuss the issues with local model of status and the potential reasons for lower score and quality

6.3 Comparison

- Compare results from signed edge prediction and Iterative signed models

- Discuss Static Linear combination predictions versus Iterative signed predictions

- Discuss the assumptions used in the models and limitations

Chapter 7

Conclusions and Future Work

- Explain the quality of results with the election perspective

- Future work is to extend this to other election settings and investigate generality of this approach

- Possible future work in congressional voting data

- Can also tackle the other problem in information cascade theory of how to predict who is most likely to vote next

- This can lead to a complete model of election dynamics and could incorporate elements of game theory and network inference

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