SOCIAL NETWORK ANALYSIS TO STUDY NETWORK CONNECTEDNESS PRINCIPLES IN MULTI-DOMAIN APPLICATIONS

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by

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to the

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Dedicated to ...

My beloved Father, *who would have been so proud*

Quotes that inspire me

Success is a perception.
There is no living being that has never failed.
Consistent effort has the power to turn failure into success.

Sangita Garg

The moment you make up your mind and realize your potential you start feeling self-empowered.

Sangita Garg

Invest in building your own Social Capital. This is the most valuable and long-lasting asset.

Sangita Garg

The moment we are on this planet as human beings we have the opportunity to serve it with humanity.

Sangita Garg

बढ़ चला था, हर सशक्त कदम, था उसे अपना कर्तव्य निभाना।
पथ है, जटिल एवं पथरीला, ठोकरों ने गिराकर, है सम्भाला।

संगीता गर्ग

गुमशुदा थी नन्ही सी जिन्दगी, दुआओं के काफिले ढूंढ़ लाए ।।

संगीता गर्ग

Certificate

This is to certify that the thesis entitled **"Social Network Analysis To Study Network Connectedness Principles In Multi-Domain Applications"**, being submitted by **Ms. Sangita Garg** to the Department of Electrical Engineering, Indian Institute of Technology-Delhi, for the award of the degree of **Doctor of Philosophy** in **Electrical Engineering**, is the record of the original, bonafide research work carried out by her under our supervision and guidance. In our opinion, the thesis has reached the standards fulfilling the requirements of the regulations related to the award of the degree.

The results contained in this thesis have not been submitted either in part or in full to any other University or Institute for the award of any degree or diploma to the best of our knowledge.

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Date (Sangita Garg)

Abstract

The philosophy of group behaviours, mass movements, and perception building that lies in social ties forms the basis for driving individual preferences. The combination of the actors and the relationships between them create a social network graph. This form can be seen in diamond and graphite or such type of materials that are fundamentally made of carbon atoms, yet display altogether different properties based on bonds formed between the carbon atoms of their molecules. An old proverb also emphasizes the impact of companionship in shaping one's personality, recognises the importance of social networks. In the present times, investing in influential relationships helps individuals build their social capital and to be able to get access to relevant individuals and their networks. The advancements in communication technologies has eliminated geographic distance as a limiting factor which has driven the world to be a single connected entity.

Social network analysis (SNA) is based on graph theory principles, which have been applied to solve specific problems related to information flow and exchange, opinion formation, behavioural sciences, research and innovation, organisation network, drug discovery, etc. In this thesis, we propose that SNA can be universally applied to any domain to study network connectedness principles for understanding behaviours and propagation mechanisms in real-world scenarios. To elucidate, we have selected four diverse domains i.e. animal behaviours, student interaction patterns in a school setup, epidemic spread & surveillance, and brain networks.

The first study is about understanding the behaviour patterns of dolphins, which are known to be the most intelligent animal. The objective was to understand and measure their inter-group and intra-group behaviours by applying SNA techniques. A meta-network structure was built and various centrality measures were mapped with the different leadership qualities such as persuasion, listening, resourcefulness, information-passing, and community building abilities. The display of such

behaviours makes dolphins more vulnerable to attacks and threats. The study findings would be an important input to formulate strategies for saving this endangered species.

In the second set of studies, attempt was made to understand the behavioural pattern of students inside the school premises. SNA techniques were applied to study their direct interactions with other students and teachers. One of the findings was that the students exhibited the concept of homophily, wherein their behaviours were indicative of a significant preference to interact with the same gender and grade level. Further, new measures such as dyadic churn rate, persistence rate, retention rate, and new dyads rate were defined for analysing temporal dyadic relationship and future prediction of new dyads formation among students. In this study, a logical method was defined for constructing a centrality pool of central individuals, considering sufficient representation from all diverse groups. This pool would be an important step for any kind of diversity and inclusion initiatives and hence members of the pool can also act as change agents. The logical method was also applied in a scenario which demonstrated the propagation of contagious disease to be 25% faster when a random student from the centrality pool gets infected as compared to a random student who does not belong to the centrality pool. These inferences are key to formulating the vaccination strategy and also to isolate central students from each other and rest of the students in the network in case of epidemic spread. Also, a comparison of various centrality measures was done which is suggestive of an important factor to consider while deciding between computational redundancy and inclusion.

The third domain of study is regarding epidemic spread and its surveillance. The objective was to formulate a single strategy at the national level and thereby to consolidate the efforts of individual states and union territories (States/UTs). SNA approach is proposed to constitute four regional hubs in India. The regional hub control centres (RHCC) were also identified for each regional hub as the location for governance based on the regional hub control scores (RHCS). Using Regional Hub Network Score (RHNS, few States/UTs were found to be the most vulnerable to any epidemic spread. Hence it was recommended to keep a close watch on these states and to formulate strategies to curtail the epidemic spread from the onset itself. This will further reduce the wastage of time, effort, and money of individual States/UTs.

The fourth domain of study was that of brain connectivity. The objective was to develop brain topology template for 128-channel geodesic sensors used to capture signals using Electroencephalography (EEG). Using SNA, the network graph was generated and was overlayed on the brain topology template for all four different image stimuli i.e., positive, chimeric, eyes only, and negative. Brain network analysis was performed to analyse brain functional connectivity. Also, a comparative analysis was done to identify the similarity between two categories of stimuli. The visual representation of the brain networks overlayed on the template will help medical practitioners detect the existence or absence of pseudo-structural and functional channels in brain circuitry to diagnose various neurological disorders.

The application of network connectedness principles using SNA led to an important area of research as elucidated in four diverse domains in this presented thesis. The applications of SNA are domain agonistics and its principles are universally applicable in any field.

KEYWORDS: *Social Network Analysis, Centrality measures, Epidemic Surveillance model, Dolphin database, Contact database, Brain networks*.

सार

समूह व्यवहार, जन आंदोलन और सामाजिक संबंधों में निहित धारणा निर्माण का दर्शन व्यक्तिगत प्राथमिकताओं को संचालित करने का आधार बनता है। अभिनेताओं का संयोजन और उनके बीच संबंध एक सामाजिक नेटवर्क ग्राफ बनाते हैं। यह रूप हीरे और ग्रेफाइट या इस तरह की सामग्रियों में देखा जा सकता है जो मूल रूप से कार्बन परमाणुओं से बने होते हैं, फिर भी उनके अणुओं के कार्बन परमाणुओं के बीच बने बंधनों के आधार पर पूरी तरह से अलग गुण प्रदर्शित करते हैं। एक पुरानी कहावत भी किसी के व्यक्तित्व को आकार देने में संगति के प्रभाव पर जोर देती है, सामाजिक नेटवर्क के महत्व को पहचानती है। वर्तमान समय में, प्रभावशाली संबंधों में निवेश करने से व्यक्तियों को अपनी सामाजिक पूंजी बनाने और संबंधित व्यक्तियों और उनके नेटवर्क तक पहुँच प्राप्त करने में मदद मिलती है। संचार प्रौद्योगिकियों में प्रगति ने भौगोलिक दूरी को एक सीमित कारक के रूप में समाप्त कर दिया है जिसने दुनिया को एक एकल जुड़ी हुई इकाई बना दिया है।

सामाजिक नेटवर्क विश्लेषण (एसएनए) ग्राफ सिद्धांत सिद्धांतों पर आधारित है, जिसका उपयोग सूचना प्रवाह और विनिमय, राय निर्माण, व्यवहार विज्ञान, अनुसंधान और नवाचार, संगठन नेटवर्क, दवा खोज आदि से संबंधित विशिष्ट समस्याओं को हल करने के लिए किया गया है। इस थीसिस में, हम प्रस्ताव करते हैं कि वास्तविक दुनिया के परिदृश्यों में व्यवहार और प्रसार तंत्र को समझने के लिए नेटवर्क कनेक्टिविटी सिद्धांतों का अध्ययन करने के लिए एसएनए को सार्वभौमिक रूप से किसी भी डोमेन पर लागू किया जा सकता है। स्पष्ट करने के लिए, हमने चार विविध डोमेन चुने हैं, जैसे कि पशु व्यवहार, स्कूल सेटअप में छात्र बातचीत पैटर्न, महामारी का प्रसार और निगरानी, और मस्तिष्क नेटवर्क।

पहला अध्ययन डॉल्फ़िन के व्यवहार पैटर्न को समझने के बारे में है, जिन्हें सबसे बुद्धिमान जानवर माना जाता है। इसका उद्देश्य SNA तकनीकों को लागू करके उनके अंतर-समूह और अंतर-समूह व्यवहार को समझना और मापना था। एक मेटा-नेटवर्क संरचना बनाई गई और विभिन्न केंद्रीयता उपायों को विभिन्न नेतृत्व गुणों जैसे अनुनय, सुनना, संसाधनशीलता, सूचना-संचार और समुदाय निर्माण क्षमताओं के साथ मैप किया गया। इस तरह के व्यवहार का प्रदर्शन डॉल्फ़िन को हमलों और खतरों के प्रति अधिक संवेदनशील बनाता है। अध्ययन के निष्कर्ष इस लुप्तप्राय प्रजाति को बचाने के लिए रणनीति तैयार करने के लिए एक महत्वपूर्ण इनपुट होंगे।

अध्ययनों के दूसरे सेट में, स्कूल परिसर के अंदर छात्रों के व्यवहार पैटर्न को समझने का प्रयास किया गया। अन्य छात्रों और शिक्षकों के साथ उनकी सीधी बातचीत का अध्ययन करने के लिए SNA तकनीकें लागू की गईं। निष्कर्षों में से एक यह था कि छात्रों ने होमोफिली की अवधारणा को प्रदर्शित किया, जिसमें उनके व्यवहार समान लिंग और ग्रेड स्तर के साथ बातचीत करने के लिए एक महत्वपूर्ण प्राथमिकता के संकेत थे। इसके अलावा, छात्रों के बीच अस्थायी द्वैत संबंध और नए द्वैत गठन की भविष्य की भविष्यवाणी का विश्लेषण करने के लिए द्वैत मंथन दर, दृढ़ता दर, अवधारण दर और नए द्वैत दर जैसे नए उपायों को परिभाषित किया गया था। इस अध्ययन में, सभी विविध समूहों से पर्याप्त प्रतिनिधित्व पर विचार करते हुए, केंद्रीय व्यक्तियों के एक केंद्रीयता पूल के निर्माण के लिए एक तार्किक विधि को परिभाषित किया गया था। यह पूल किसी भी तरह की विविधता और समावेशन पहल के लिए एक महत्वपूर्ण कदम होगा और इसलिए पूल के सदस्य परिवर्तन एजेंट के रूप में भी कार्य कर सकते हैं। तार्किक विधि को एक ऐसे परिदृश्य में भी लागू किया गया था, जिसने संक्रामक रोग के प्रसार को 25% तेजी से प्रदर्शित किया जब केंद्रीयता पूल से एक यादृच्छिक छात्र संक्रमित हो जाता है, जो केंद्रीयता पूल से संबंधित नहीं है। ये निष्कर्ष टीकाकरण रणनीति तैयार करने और महामारी फैलने की स्थिति में केंद्रीय छात्रों को एक-दूसरे से और नेटवर्क में बाकी छात्रों से अलग करने के लिए महत्वपूर्ण हैं। साथ ही, विभिन्न केंद्रीयता उपायों की तुलना की गई जो कम्प्यूटेशनल अतिरेक और समावेशन के बीच निर्णय लेते समय विचार करने के लिए एक महत्वपूर्ण कारक का सुझाव देती है।

अध्ययन का तीसरा क्षेत्र महामारी के प्रसार और उसकी निगरानी से संबंधित है। इसका उद्देश्य राष्ट्रीय स्तर पर एक एकल रणनीति तैयार करना और इस प्रकार व्यक्तिगत राज्यों और केंद्र शासित प्रदेशों (राज्यों/केंद्र शासित प्रदेशों) के प्रयासों को समेकित करना था। भारत में चार क्षेत्रीय हब गठित करने के लिए एसएनए दृष्टिकोण प्रस्तावित है। क्षेत्रीय हब नियंत्रण केंद्र (आरएचसीसी) की पहचान प्रत्येक क्षेत्रीय हब के लिए क्षेत्रीय हब नियंत्रण स्कोर (आरएचसीएस) के आधार पर शासन के स्थान के रूप में भी की गई थी। क्षेत्रीय हब नेटवर्क स्कोर (आरएचएनएस) का उपयोग करते हुए, कुछ राज्य/केंद्र शासित प्रदेश किसी भी महामारी के प्रसार के लिए सबसे अधिक संवेदनशील पाए गए। इसलिए इन राज्यों पर कड़ी नजर रखने और शुरुआत से ही महामारी के प्रसार को रोकने के लिए रणनीति तैयार करने की सिफारिश की गई थी। इससे व्यक्तिगत राज्यों/केंद्र शासित प्रदेशों के समय, प्रयास और धन की बर्बादी को और कम किया जा सकेगा।

अध्ययन का चौथा क्षेत्र मस्तिष्क कनेक्टिविटी का था। इसका उद्देश्य इलेक्ट्रोएन्सेफेलोग्राफी (ईईजी) का उपयोग करके संकेतों को पकड़ने के लिए उपयोग किए जाने वाले 128-चैनल जियोडेसिक सेंसर के लिए मस्तिष्क टोपोलॉजी टेम्पलेट विकसित करना था। एसएनए का उपयोग करके, नेटवर्क

ग्राफ तैयार किया गया था और सभी चार अलग-अलग छवि उत्तेजनाओं यानी सकारात्मक, काइमेरिक, केवल आंखें और नकारात्मक के लिए मस्तिष्क टोपोलॉजी टेम्पलेट पर ओवरले किया गया था। मस्तिष्क कार्यात्मक कनेक्टिविटी का विश्लेषण करने के लिए मस्तिष्क नेटवर्क विश्लेषण किया गया था। साथ ही, उत्तेजनाओं की दो श्रेणियों के बीच समानता की पहचान करने के लिए एक तुलनात्मक विश्लेषण किया गया था। टेम्पलेट पर ओवरले किए गए मस्तिष्क नेटवर्क का दृश्य प्रतिनिधित्व चिकित्सा चिकित्सकों को विभिन्न तंत्रिका संबंधी विकारों का निदान करने के लिए मस्तिष्क सर्किटरी में छद्म संरचनात्मक और कार्यात्मक चैनलों की मौजूदगी या अनुपस्थिति का पता लगाने में मदद करेगा।

एसएनए का उपयोग करके नेटवर्क कनेक्टिविटी सिद्धांतों के अनुप्रयोग ने अनुसंधान के एक महत्वपूर्ण क्षेत्र को जन्म दिया, जैसा कि इस प्रस्तुत थीसिस में चार विविध डोमेन में स्पष्ट किया गया है। एसएनए के अनुप्रयोग डोमेन एगोनिस्टिक्स हैं और इसके सिद्धांत किसी भी क्षेत्र में सार्वभौमिक रूप से लागू होते हैं।

कीवर्ड: सामाजिक नेटवर्क विश्लेषण, केंद्रीयता उपाय, महामारी निगरानी मॉडल, डॉल्फिन डेटाबेस, संपर्क डेटाबेस, मस्तिष्क नेटवर्क।

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List of Abbreviations

AI	**A**rtificial **I**ntelligence
BC	**B**etweenness **C**entrality
CC	**C**loseness **C**entrality
DC	**D**egree **C**entrality
DIR	**D**aily **I**nfection **R**ate
EC	**E**igen **V**ector **C**entrality
EE	**E**lectrical **E**ngineering
EEG	**E**lectro**e**ncephalo**g**raphy
FMRI	**F**unctional **M**agnetic **R**esonance **I**maging
GNN	**G**raph **N**eural **N**etwork
GPS	**G**lobal **P**ositioning **S**ystem
IITD	**I**ndian **I**nstitute of **T**echnology-**D**elhi
IN	**In**dia
LS	**L**ok **S**abha
LSTM	**L**ong **S**hort-**T**erm **M**emory
ML	**M**achine **L**earning
MLP	**M**ulti-**L**ayer **P**erceptron
MRI	**M**agnetic **R**esonance **I**maging
PCA	**P**rincipal **C**omponent **A**nalysis
RHCC	**R**egional **H**ub **C**ontrol **C**entre
RHCS	**R**egional **H**ub **C**ontrol **S**core
RHNS	**R**egional **H**ub **N**etwork **S**core
SIR	**S**usceptible-**I**nfected-**R**emoved
SIS	**S**usceptible-**I**nfected- **S**usceptible
SNA	**S**ocial **N**etwork **A**nalysis
UT	**U**nion **T**erritory