18-755: Networks in the Real World
Fall 2022

Deciding on a Project

The project is a large part of this course and gives you the opportunity to explore a topic or issue that relates to networks and is meaningful to you. We highly encourage you to find a partner in this course to collaborate with on the project. This will allow you to share ideas and benefit from working with someone with a potentially different background than you. We will help facilitate the partner search process. That being said, if you would like to pursue a project individually, please discuss this with the course staff to get approval.

In general, your project must involve networks. You will need to construct and perform analysis on networks that you build from your selected dataset(s). A useful approach for deciding on a project could be to think of a topic that interests you (pandemics, supply chains, misinformation spread, diversity of collaboration in academic networks, drug mapping and interactions, etc.), then find datasets that relate to your topic and evaluate how you could work with them and brainstorm analysis you could perform. For milestone 0, we just want to get an idea of what you want to work on and make sure that your dataset is appropriate and sufficient. Note, you may involve machine learning in your project but it should not be the focus of your work – *it must center around network analysis*.

Below are examples of previous projects that students worked on for this course. You are encouraged to pursue whatever topic you are passionate about but if you encounter difficulty with selecting a topic, feel free to contact the TA or draw inspiration from the previous projects and project ideas.

Prior Projects:

- Airline Transportation Network and COVID-19
- What Are People Talking About During The COVID-19 Pandemic
- Misinformation Spread on a Social Media
- Limiting the spread of misinformation in online social networks
- Social Network Influence Maximization
- Drug-Drug Interactions Prediction
- Discovering Critical Electric Grid Components in Poland
- CANnot: Establishing Covert Channels for Unaltered Automotive Bus Networks
- Analysis of the California Road Network During Wildfire Evacuations
- Networks of High-speed rail in China
- Protest Networks
- Citibike Usage Balancing
- The Vanity Fair - A Deep Insight on Hollywood Based on Network Analysis
- Social Network Analysis on Yelp dataset – Finding Friends Influence on Users

- Hardware prototyping for Distributed Learning Algorithm
- Determining Success on Yelp
- Citibike: Usage balancing through congestion pricing
- Networks of Drugs Interactions
- Satellite Data for Poverty Prediction
- Networks and Dynamics in Political Discussion
- Identifying and Manipulating the Aging of Social Networks
- Risk in Road Networks

Project Suggestions:

Social Factors, Symptoms, and Mental Health	
Overview	Are you interested in exploring potential causalities of mental health problems? Do you know social factors can either improve or deteriorate mental disorders? Relationships with significant others, stigma from the society, social media usage, interactions with people are some common examples of social factors. Can we use network analysis to find correlations between those social factors and mental disorder symptoms? Or can we find overlap symptoms which predict different mental disorders so that it can provide valuable insight for clinicians and researchers to understand complex relationships between mental disorders such as obsessive-compulsive disorder (OCD) and depression.
Tasks	● Use references [1] and [2] as inspirations to find a topic you are interested in, read related papers and download useful dataset. ● Try to create a multilevel network for your problem and analyze the properties. For example, can you find the similarities of symptoms caused by different social factors or can you find several strongest symptoms which cause the mental disorder(s)? ● You can use other statistical methods to visualize and analyze your dataset at the same time to give you more obvious insights of the trends.
References	[1] An example of analyzing network of symptoms of obsessive-compulsive disorder (OCD) and depression: https://www.frontiersin.org/articles/10.3389/fpsyg.2018.01742/full [2] Possible dataset and topics to be used: https://eiko-fried.com/data/

Phone Call Record Data and Link Prediction	
Overview	Given the CDR (cell data records) from the Trentino region of Italy, can we predict the next phone call from thousands of miles away? Furthermore, can we use this data to generate a spatial map of this region? Can we uncover physical or even social stratospheres? In this project, we will explore the following:
Tasks	● Gather call data records from telecommunications datasets for Italy. For instance, certain regions in Italy (e.g., province of Trentino) have datasets ranging from social networks, news data, to weather and energy data, all the way to telecommunications data. ● Construct phone call networks from the available telecommunications data. Analyze the properties of these networks (e.g., degree, communities, centrality, etc.) ● If only a portion of phone call network is available at a given time, can we infer the rest of the network using past phone call networks and the partial phone call network at the given time step? Moreover, can we do calls volume prediction using phone call data? ● Can you characterize people mobility from the phone call networks? Moreover, can we use phone call networks to identify key hotspots in a region and identify city/municipality boundaries?
References	[1] Barlacchi, Gianni, et al. "A multi-source dataset of urban life in the city of Milan and

	the Province of Trentino." Scientific data 2 (2015): 150055. [2] Link prediction problems have been addressed in a KDD 2016 paper: node2vec. https://cs.stanford.edu/people/jure/pubs/node2vec-kdd16.pdf [3] https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4405276/pdf/pone.0124160.pdf [4] Phone call networks and spatial structure of cities: https://www.nature.com/articles/srep05276.pdf

Criminality Networks	
Overview	How does criminality in Shadyside and Squirrel Hill affect criminality in Oakland? Can Network Science help the Pittsburgh Bureau of Police to better understand the networks of crime? Is the spatial and temporal propagation of crime the same for all types of crimes? This project explores the network nature of crime in urban scenarios (e.g., Pittsburgh, Chicago, New York, etc.) and its characteristics and dynamics across different types of crime, in space and time.
Tasks	● Create a dynamic multi-layer (i.e., involving multiple types of crime) network from borough crime activity. ● Create dynamic a geo-spatial multi-layer (i.e., multiple types of crime) network from crime report data. ● Analyze dynamic network properties to identify types of crime, locations, and times that are central on the spread of criminality. ● Identify key strategies based on dynamic network properties for deterrence, detection, and mitigation of crime in cities.
References	[1] http://csce.ucmss.com/books/LFS/CSREA2017/IKE3704.pdf [2] https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4361400/pdf/pone.0119309.pdf [3] Sample data: https://opendata.cityofnewyork.us/

Satellite Data for Poverty Prediction	
Overview	Do you know that poverty can be estimated with high accuracy using nightlight satellite data? Rather than relying on (paper or phone) surveys which are tedious, time consuming and inaccurate, advanced data mining techniques like Deep Learning (with Convolutional Neural Networks) can be used to transfer knowledge from image processing to economic predictions. Explore more on poverty estimation in this project!
Tasks	● Collect all the necessary data listed in references (code and data collection instructions are very well documented for this project). This would include the survey data, as well as the nightlight satellite data. Learn to use the publicly available code for poverty prediction. ● Try to introduce a network science angle to the problem. For instance, can we discover some similarities between the poverty in different regions using satellite data (e.g., discover similarities between the features learned by the deep learning algorithm)? If so, then we will construct a network of poverty across the globe. ● Analyze the properties of this network (e.g., degree, communities, centrality, etc.). Predict poverty for regions not considered in the original study. Can we use deep learning trained on certain regions to reliably predict poverty in completely different test regions? ● Can we also use the trained deep learning model to predict something else other than poverty (e.g., health, happiness, social participation, etc.)?
References	[1] Jean, Neal, et al. "Combining satellite imagery and machine learning to predict poverty." Science 353.6301 (2016): 790-794. [2] Xie, Michael, et al. "Transfer learning from deep features for remote sensing and poverty mapping." arXiv preprint arXiv:1510.00098 (2015).

	[3] http://sustain.stanford.edu/predicting-poverty [4] NOAA. Monthly Nightlight Satellite Imagery Dataset. https://ngdc.noaa.gov/eog/viirs/download_dnb_composites.html, 2013. [Online; accessed 7-Sept-2018]. [5] The World Bank. Living Standards Measurement Study (LSMS) Dataset. http://microdata.worldbank.org/index.php/catalog/lsms, 2013. [Online; accessed 7-Sept-2018].

Citibike Usage Balancing through Congestion Pricing	
Overview	Citibike is the New York City bicycle sharing scheme, and is the largest such system in the USA. Bicycles are locked in stations distributed all throughout the city. Users make one-way trips by unlocking a bike from one of the departure station docks, riding to a station close to their destination, and locking the bike into a dock at that station. The current pricing is based on long- and short-term subscriptions, typically linked to a credit card. Short trips (e.g., under 35 min) are included in the price of the subscription, while longer rentals are progressively penalized by additional cost, in an attempt to prevent users from monopolizing bikes. The system suffers from one major drawback: users tend to follow unidirectional flows at various times of the day. For example, in the morning everyone tends to ride away from the train station to their workplace. As a consequence, it is often the case that there are no bikes in the morning near the train stations. The opposite situation also occurs quite often. The user may find all docks occupied at the destination and cannot return the bicycle. Instead, they must find another station with empty docks, often quite far away, at the cost of extra time and frustration. The existence of an app that accurately indicates the location and state of every station in the city, offers only meager redemption. Currently, Citibike attempts to rebalance the system by moving bikes in bulk by truck or van from full stations to empty ones, but the results are less than spectacular. This project is about improving this situation via network modeling and optimization.
Tasks	● Introduce a congestion-based pricing scheme. For instance, an user should pay more for unlocking a bike from a nearly empty station and for locking a bike at an almost full station. Conversely, a user should be paid to unlock a bike from an almost full station and for leaving it at a nearly empty one. Ideally the scheme should be cost neutral, simple to deploy, and easy to explain to the general public. ● Make use of the enormous amount of Open Data available from nyc.gov. This includes data from bicycles, pedestrians, bike stations, citibike station status feeds, traffic, etc. Construct various kinds of networks – Citibike network, pedestrian mobility networks, traffic networks, etc. using the NYC open data. Do you notice any similarities between these networks? ● Build weighted networks of trips for each month and o Perform community analyses at multiple scales (e.g., neighbourhood, borough, city) o Compare network structure and dynamics across weeks, months, etc. Are there any seasonality effects? ● Feel free to formulate other/additional analyses; interpret and visualize your findings
References	[1] http://citibikenyc.com/system-data [2] Agent-based simulation' environment: https://en.wikipedia.org/wiki/NetLogo [3] http://www.treehugger.com/bikes/citi-bike-reveals-how-new-yorkers-ride-their-bikes.html Citibike mobile app for iOS and Android gives a good idea about the system

Determining Success on Yelp	
Overview	Can you use machine learning to determine the success of a business on Yelp? Using data provided by Yelp [1], analyze the relationship between users and restaurants to identify features which may predict the success of a business on Yelp. Can you build a network of users based on their comments and predict the success of a video or a business? Can you identify users, which act as trend setters and visit places before they become popular?
Tasks	● Download the Yelp dataset, which includes information about local businesses in 10 metropolitan areas across 2 countries. ● Try creating a network of similarity between different users' comments and also connect these comments to business descriptions (e.g., by determining similarity between the comments and descriptions). NLP can be used for determining similarities. Look into the words that make a review positive or negative and uncover the reasoning using [3] ● Mine the networks via node2vec [2] (or some new modified approach similar to node2vec) to determine the success-related features from the network. Use these to predict success of the videos or businesses.
References	[1] Yelp has json, as well as other datasets available: https://www.yelp.com/dataset/download [2] A. Grover, J. Leskovec, Node2vec: Scalable Feature Learning for Networks, KDD 2016. [3] https://arxiv.org/abs/1802.07814

Smart Campus: Learning Student Mobility Patterns	
Overview	Besides class periods, are there other significant patterns of student movement on campus? If so, why do they happen? Can we use machine learning to predict where students will be concentrated throughout the day? Can we allocate resources (e.g. furniture in a cafeteria, food in vending machines, etc.) better by observing the student mobility patterns? How do campus events or weather changes influence these behaviors? Students can belong to many communities (e.g., department, clubs, extra-curricular activities, etc.). Can we detect these communities and then discern interesting behaviors (e.g., ECE students spend much less time at the UC than the normal student)? This project will characterize and visualize how students move throughout the CMU Pittsburgh campus. In particular, this project will focus on the detection of rare and unique behaviors, and the relationship between events and behaviors.
Tasks	• Use pre-existing data, collected anonymously from Bluetooth signals across the CMU Pittsburgh campus. Collect a list of events that may have influenced student behavior on campus during the observation period (say, for a couple of weeks). • Preprocess and visualize collected data. This step may provide great insights into interesting patterns hidden within the data. Investigate the effect of noise removal by using various types of data visualization before training an applicable model of mobility pattern. Define a few interesting research questions. Some possible ideas are: 1. Nearly everyone on campus has a department affiliation. Using the collected datasets, can we detect and classify the Bluetooth devices belonging to these departments? Is there interesting information about a certain department community? 2. How do various campus events influence students' behavior? How does advertising (social media, email, posters, fliers) influence students' behavior? What types of events are the most likely to create significant changes in behavior? 3. How can the efficiency of resource allocation be improved given observed mobility patterns? How can better paths be designed such that students can easily move across the Pittsburgh campus?
References	[1] https://arxiv.org/ftp/arxiv/papers/1702/1702.00546.pdf [2] M.C. Gonzalez, C.A. Hidalgo, and A.-L. Barabasi, "Understanding individual human

	mobility patterns," Nature, vol. 453, pp. 479-482, 2008. doi: 10.1038/nature06958 [3] A. Noulas, S. Scellato, R. Lambiotte, M. Pontil, and C. Mascolo, "A Tale of Many Cities: Universal Patterns in Human Urban Mobility," PLoS ONE, vol. 7, no. 5, 2012. doi:10.1371/journal.pone.0037027

Mitigating Risk in Road Networks	
Overview	Road traffic is a complex system with many agents (e.g., vehicles, pedestrians) interacting at micro-scale using a given infrastructure (road network). Thus, the emerging traffic behavior is non-linear in nature and hard to predict. However, it is widely acknowledged that the road infrastructure, namely the topology of the road network largely influences the macro-scale behavior. In this project, we connect topological features of road networks to the dynamic patterns of traffic, in order to identify the specific topological features of risky intersections (nodes) and paths (smaller sub-graphs). Such an insight can help answering a very important question: If we are to "engineer" the road system (e.g., add a new network link) in the vicinity of a problematic intersection or path, which intersections do we need to connect differently?
Tasks	● Build, visualize, and analyze road network with real data taken from [1]. ● Use the methodology in [2] (based on static analysis of network centralities) or the formal method in [3] (which connects the topology to its dynamics) to identify the key nodes and key paths for the network's information flow. ● Find a link between the network properties of the key nodes/paths and the location of fatal accidents taken from [4]. To this end, we suggest to avoid using the Pearson correlation because it can be misleading particularly in non-linear systems. Instead, we suggest to use the mutual information entropy [5] to explore the links between key paths/nodes and crash locations. ● Find the placement of a new link, in the vicinity of a risky node/path such that the specific network property of the node/path is altered towards a non-risky value. Other variations on this idea are encouraged.
References	[1] https://snap.stanford.edu/data/#road [2] Stephen P. Borgatti. Centrality and network flow. Social Networks 27(1): Pages 55-71 (2005) [3] Uzi Harush, Baruch Barzel. Dynamic patterns of information flow in complex networks. Nature Communications, Vol 8, Article number: 2181 (2017) [4] http://metrocosm.com/10-years-of-traffic-accidents-mapped.html [5] https://people.cs.umass.edu/~elm/Teaching/Docs/mutInf.pdf

Networks and Dynamics of Political Discussion	
Overview	Are the patterns of online discussion and communication independent of their contents? How do social interactions differ across the political spectrum? Can political bias be inferred from the users patterns of communication? Can we assign users to a spatial region based on their collective commenting patterns? Furthermore, can we study the commenting behavior of identified suspicious accounts and use them to uncover other suspicious accounts? Can we determine if they worked to target other users or target the content? This project allows you to explore the dynamics of social networks of discussion in Reddit, quantify and characterize the patterns of communication in different (political and apolitical) subreddits.
Tasks	● Construct dynamic networks from Reddit data for different subreddits representing different politically affiliated groups.

	● Identify different network characteristics and patterns of interaction among users affiliated with different subreddits. ● Analyze the possibility of political bias inference from the patterns of communication among users and groups of users. ● Infer the spatial region of users based on the time of day they comment on posts. ● Utilize the published list of suspicious accounts linked to the Russian Influence Campaign of 2016 and study their reach on subreddits and work to quantify their 'influence'.
References	[1] http://people.cs.vt.edu/~badityap/papers/composite-ccr12.pdf [2] http://www.cs.cmu.edu/~deswaran/papers/pakdd17-prone.pdf Sample data: https://www.reddit.com/r/datasets/comments/3mg812/full_reddit_submission_corpus_now_available_2006/ https://files.pushshift.io/reddit/ https://www.reddit.com/wiki/suspiciousaccounts https://www.reddit.com/r/announcements/comments/8bb85p/reddits_2017_transparency_report_and_suspect/

Troll Farm CMU: Identifying and Manipulating the Aging of Social Networks	
Overview	Did you know that we can observe the life cycle of a social media community through network properties? Researchers tracked the growth, maturity, and death of an online terrorist recruiter network through analyzing the average path length, average node degree, and clustering coefficient. Building on prior research, can you devise social media agents, or trolls, that alter the aging behavior of Reddit political and apolitical discussion? Can you pull inspiration from natural behavior changing agents such as parasites? The goal of this project is two-fold: 1. Study the natural life cycle of Reddit social media networks. 2. Devise and deploy trolls that stunt or prolong the network life span.
Tasks	● Construct dynamic networks from Reddit data for different subreddits. ● Utilize network properties to chart the network life span. ● Devise a method to alter the life span by injecting upvotes, subscribers, posts, comments, or upvotes into a subreddit. ● Study the behavioral changes in surrounding users and social media network as a whole. Other directions can also be explored.
References	[1] https://www.nature.com/articles/s41598-018-22027-z [2] https://jeb.biologists.org/content/jexbio/216/1/3.full.pdf Sample data: https://files.pushshift.io/reddit/ https://www.reddit.com/wiki/suspiciousaccounts

Networks of Drugs Interaction	
Overview	The complex chemical drug structures are interacting with complex biological environments. As such, drugs have multiple properties which cannot be foreseen at the time of market release, although they undergo rigorous clinical trials. For instance, aspirin was originally introduced as an anti-fever drug. After years of practice, it was discovered that aspirin can also be used as a potent anti-inflammatory drug. Then, it was found that aspirin inhibits platelet aggregation. An important aspect related to the complexity of drug activity is polymedication (i.e. what happens in the human body when one patient uses more than one drug at the same

	time). Drug-drug interactions can be responsible for unexpected or even dangerous effects. Therefore, drug-drug interactions are intensively researched, documented, and recorded in specialized databases. Network interactomes (i.e., networks where nodes are drugs and links are interactions between drugs) are used to visualize, explore, and analyze the landscape of drug-drug interactions. Specifically, drug-drug interactomes can be used to discover new drug properties (hence, drug repurposing) and to predict new – previously unaccounted – drug-drug interactions. Explore the fascinating and complex world of drugs in this project!
Tasks	● Collect all the necessary data related to drugs and their interactions from the latest version (5.1.4) of the comprehensive DrugBank database [1], as well as from a much earlier release (e.g., 4.5.0). DrugBank is free but requires registration with a valid e-mail. Learn to use the publicly available drug dataset releases. ● Can we predict previously unaccounted for drug-drug interactions? Deep Learning can be employed for training a neural network to detect drug-drug interactions [2], using the drug-drug interactions dataset in DrugBank 4.5 as Gold Standard, and various drug features listed in DrugBank 4.5 as inputs. For instance, we can use chemical structures as inputs, in the form of chemical structure encodings, such as SMILES or InChI. Another approach is to use the biological targets listed in DrugBank as inputs. For validation, we take new and experimental drugs from the latest DrugBank release (5.1.1) to see if their reported interactions are indeed predicted by our Deep Learning approach. ● We can also uncover previously unknown drug properties, i.e., drug repurposing. To this end, a drug-drug interactome is build, based on drug interaction information from DrugBank 5.4.1, which is then clustered with a force-directed layout method [3][4]. Each resulted topological cluster is assigned a tag according to the dominant property/properties of the drugs within. One method for drug repurposing is to identify drugs which apparently do not belong to their cluster; for instance, drug x is placed within the antibiotic cluster but it is not known to have antibiotic properties – this indicates that x may be repurposed as an antibiotic. Conventionally, assigning tags to interactome topological clusters is made manually, using expert analysis (from pharmacologists). However, by using functional properties of drugs from DrugBank as features, we can apply machine learning (decision trees) to automatically tag clusters.
References	[1] https://www.drugbank.ca/releases [2] J. Y. Ryu, H. U. Kim, and S. Y. Lee. Deep learning improves prediction of drug–drug and drug–food interactions. PNAS 115 (18) E4304-E4311 (2018). [3] M. Jacomy, T. Venturini, S. Heymann, M. Bastian. ForceAtlas2, a Continuous Graph Layout Algorithm for Handy Network Visualization Designed for the Gephi Software. PLoS ONE 9(6): e98679 (2014) [4] L. Udrescu, L. Sbârcea, A. Topîrceanu, A. Iovanovici, L. Kurunczi, P. Bogdan, M. Udrescu. Clustering drug-drug interaction networks with energy model layouts: community analysis and drug repurposing. Scientific Reports 6: 32745 (2016)

Network Destroy-Repair Game	
Overview	Robustness and reliability are very important properties for complex networks. Biological networks are particularly robust, as they have evolved in adverse environments over long periods of time. For instance, the biological systems have developed mechanisms of network formation and evolution which can efficiently respond to the environment's aggressiveness and volatility. Such response mechanisms have the characteristic of all complex systems: simple micro-scale processes which trigger complex and unexpected behavior at macro-scale. Here, we want to explore the basic principles of countering adversity in networks by building a competition game.
Tasks	● This a two-persons project and each participant (player) will design a network attack and a network repair mechanism. The first game consists of making each player's attack

	mechanism compete with the other player's repair mechanism. The other game scenario consists of making both players' repairs compete against an automated attack agent build with machine learning (e.g., reinforcement learning). ● The starting network structure needs to be a social network from SNAP [1]. The attack and repair mechanisms will remove or add links; this means that nodes cannot be removed by attacks and that new nodes cannot be added. The attack mechanism is a strategy of smartly selecting the links to be removed at any given step. Some nodes will be directly affected, because they will lose some of their links. As such, the repair mechanism needs to be a strategy of smartly selecting which subset of affected nodes need to be helped by adding new links. At each game step, we enforce a fixed number k of removed and added links. ● Each participant will receive a "budget" of p points; this is because, cutting or adding links incurs certain costs (e.g., we can calculate the cost as the sum of degrees of the two nodes incident to the link). At each step, the attack and repair mechanisms cannot use more than f*p points from the budget, where f is the allowed fraction of the budget to be spent. Normally the attack is more effective than any repair (i.e., it's easier to destroy than re-build something), therefore the game consists of running successive steps until the network becomes weak enough or when the one player simply spends all the budget. For instance, the Molloy-Reed criterion as an indicator of network weakness (i.e., there is no giant component anymore) [3]. ● The winner is the player who has least/most steps accumulated up to that point as an network attacker/defender.
References	[1] https://snap.stanford.edu/data/ [2] A.-L. Barabasi. Network Science. Cambridge University Press (2016) http://barabasi.com/f/619.pdf

Learning at the Edge	
Overview	Applications, from social modeling to biological simulations, demand more and more data in order to achieve greater insight into the system they investigate. The simple solution is to distribute these applications across multiple nodes within large computing clusters or data centers. However, for applications operating in an IoT architecture, unreliable or costly network communication makes these types of decisions less obvious. With so many different domains and application requirements a simple "one-shoe-fits-all" mentality does not fit well. How does someone decide the optimal configuration for a distributed application? How much does the communication protocols and network affect the application? In this project, using a simple Raspberry Pi 3 computing cluster to emulate a distributed learning IoT edge environment, you will begin to investigate these questions and more.
Tasks	● Find two-three interesting applications that can be easily distributed across a cluster of computing nodes. Choose one application from each of the following categories: Big-Data, a coordinated application where multiple nodes must cooperate to complete a task, and one of your choice. ● Develop multithreaded C/C++ code for each application. Implement this code across Raspberry Pis using MPI or gRPC. Note that, applications can also belong to a recent edge computing trend where the idea is to distribute a large Deep Neural Network on multiple edge devices (e.g., see reference [4] below). ● Discover the relationship between an application's characteristics, an application's performance, and the choices made for distribution and communication across a network of devices. ● Evaluate and optimize the implementations on the basis of application execution time and power consumption for unconstrained and constrained (e.g., power-limited) environments.

	● Use ML techniques to optimize the system performance (which can be a focus for this project). For example, find some nodes that are very busy at certain times and learn to balance their workload. Or focus on optimizing the system performance while accounting for the networking costs.
References	[1] OpenMPI: https://www.open-mpi.org/ [2] gRPC: http://www.grpc.io/ [3] Raspberry Pi 3: https://www.raspberrypi.org/ [4] MoDNN paper: https://ieeexplore.ieee.org/document/7927211/