RESEARCH STATEMENT

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When Deep Learning Meets Broad Learning

The essence of **Deep Learning** is to compute hierarchical features or representations of the observational data. With the surge of deep learning research and applications in recent years, lots of research works have appeared to apply the deep learning methods, like deep belief network, deep Boltzmann machine, Deep neural network and Deep autoencoder model, in various applications, like speech and audio processing, language modeling and processing, information retrieval, objective recognition and computer vision, as well as multimodal and multi-task learning. **Deep Learning** can serve as the foundation model for representation learning and information fusion with multiple data sources.

Meanwhile, in the real world, about the same information entity, e.g., social media users, patients and communities, a large amount of information can be collected from various sources. These sources are usually of different varieties, like Facebook and Twitter, various medical tests, local weather and nearby POIs. Each information source provides a specific signature of the same entity from a unique underlying aspect. Effective fusion of these different information sources provides an opportunity to understand the entities more comprehensively, which is also the main task covered in **Broad Learning**.

My research interests span across **Deep Learning** and **Broad Learning**, which mainly focus on fusing multiple **large-scale** information sources of **diverse varieties** together, and conducting synergistic knowledge representation learning and discovery tasks across these fused sources in one unified analytic. In my current research, I investigate the principles, methodologies and algorithms for synergistic knowledge representation learning and discovery, and evaluate the corresponding benefits. I need to address the challenges in the effective information representation, fusion and transfer across different aligned information sources, which depends upon not only the relatedness of these information sources, but also the target application problems. I aim at developing a general methodology, which will be shown to work for a diverse set of applications, while the specific parameter settings can be learned for each application from the training data at the same time.

Current Research

My current research works involve two main parts: *deep learning* and *broad learning*. The *deep learning* research works cover both fundamental theoretic research problems together with real-world applications problems, like *deep ensemble learning* [10], *deep model optimization* [9], *intelligent code synthesis with deep models* [8], *network representation learning* [11] and *deep fake news detection* [7]. The *broad learning* research works are mainly based on online social media data, bio-medical data and smart city data, which include *network alignment* [22, 23, 2, 17, 20, 6], heterogeneous links transfer [28, 12, 13, 20, 6], mutual community detection [19, 1, 21, 5], bio-medical patient classification and clustering [4] and spatial-temporal representation learning for smart city studies [31, 3, 30, 24, 15, 16].

A. Deep Learning: General Representation and Optimization

By this context so far, there exists very limited progress in the theoretic studies as well as optimization methods for *deep learning* models. Existing *deep learning* models are mostly trained with the *gradient descent* based optimization methods, and the model learning performance is usually subject to the tuning experiences of domain experts. To understand the representation of deep models, we demonstrate that, by projecting both the input data and the model variables to a high-dimensional space, there exist one unified representation of both deep and shallow learning models [11]. Meanwhile, to effectively train the deep models, by integrating the *gradient descent* with *genetic algorithm*, a new deep model learning method, i.e., GADAM, has been introduced in [9], which can learn the models more effectively.

A.1 Deep Learning with a General Representation: Generally, the conventional machine learning problems aim at recovering a mathematical mapping from the feature space to the label space. Depending on the application settings, such a mapping can be either a simple or a quite complicated equation involving both the variables and extracted features. In [11], we introduce a new machine learning model, namely *reconciled polynomial machine*, which can provide a unified representation of existing shallow and deep machine learning models. *Reconciled polynomial machine* predicts the output by computing the inner product of the feature *kernel function* and variable *reconciling function*. Analysis of several concrete models, including Linear Models, FM, MVM, Perceptron, MLP and Deep Neural Networks, has been provided in [11], which can all be reduced to the reconciled polynomial machine representations.

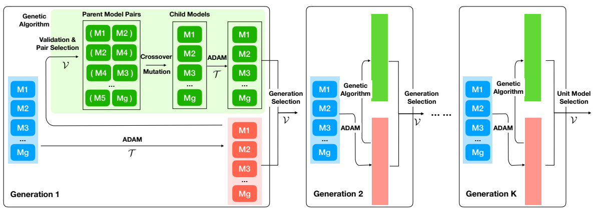

Figure 1: The GADAM Framework.

A.2 Deep Learning Optimization with GADAM: Deep neural network learning can be formulated as a non-convex optimization problem. Existing optimization algorithms, e.g., Adam, can learn the models fast, but may get stuck in local optima easily. To resolve such a challenging problem, we introduce a novel optimization algorithm, namely GADAM (Genetic-Evolutionary Adam) in [9], whose architecture is shown in Figure 1. GADAM learns deep neural network models based on a number of unit models generations by generations: it trains the unit models with Adam, and evolves them to the new generations with genetic algorithm. We show that GADAM can effectively jump out of the local optima in the learning process to obtain better solutions, and prove that GADAM can also achieve a very fast convergence.

A.3 Academic Impact Summary:

- *Reconciled polynomial machine* is the first model that can unify the representations of deep and shallow learning models.
- The GADAM learning algorithm can effectively integrate the advantages of both Adam and genetic algorithm.

B. Deep Learning: Representation Fusion across Information Sources

Via multiple layers, the *deep learning* models are capable to learn effective latent representations of various input data, including *social networks* and *program source code*. Subject to the input data properties, different *deep learning* models can be adopted, e.g., *aligned autoencoder* [18] for graph data and *hierarchical sequential network* [8] for the textual data.

B.1 Aligned Heterogeneous Social Network Embedding: Network embedding aims at projecting the network data into a low-dimensional feature space, where the nodes are represented as a unique feature vector and network structure can be effectively preserved. However, the network embedding performance will degrade greatly if the networks are of a sparse structure, like the emerging networks with few connections. In [18], we propose to learn the embedding representation for a target emerging network based on the broad learning setting, where the emerging network is aligned with other external mature networks at the same time. To solve the problem, as shown in Figure 2, a new embedding framework, namely "Deep alIgned autoencoder based eMbEdding" (DIME), is introduced in [18]. DIME handles the diverse link and attribute in a unified analytic based on broad learning, and introduces the multiple aligned attributed heterogeneous social network concept to model the network structure.

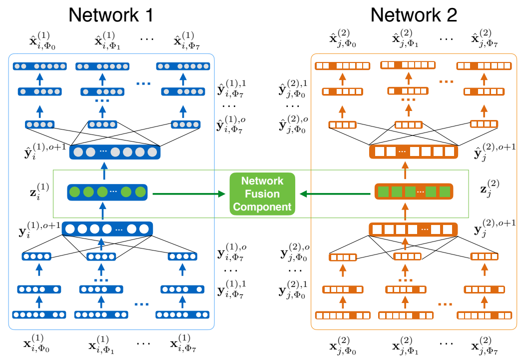

Figure 2: The Aligned Autoencoder Model.

B.2 Intelligent Program Synthesis: We propose to study the intelligent program synthesis problem in [8], and propose a novel deep learning model, named EgoCoder, to address the problem. EgoCoder effectively parses program code into abstract syntax trees (ASTs), where the tree nodes will contain the program code/comment content and the tree structure can capture the program logic flows. Based on a new unit model called HSU (hierarchical sequential unit), EgoCoder can effectively capture both the hierarchical and sequential patterns in the program ASTs. Extensive experimental results on the real-world program dataset demonstrate that EgoCoder can resolve the intelligent program synthesis problem very well, which covers three sub-problems, including *program generation*, *program interpretation* and *program completion*.

B.3 Academic Impact Summary:

- DIME is the first model which integrates *broad learning* and *deep learning*.
- EgoCoder is the first work which unifies and addresses the *intelligent program synthesis* problem.

C. Broad Learning: Heterogeneous Information Network Alignment

In online social networks, the social information generated by users' online social activities can indicate users' personal characteristics. Users' social information is usually of heterogeneous categories, involving both network structure information (like friendship and group membership) and attribute information (like user profile, location checkins and published posts). Formally, we represent this kind of networks as **heterogeneous information networks** [28]. Across social networks, the correspondence relationships between the common users' accounts are defined as the **anchor links** [2]. In network alignment problems, we aim at inferring the potential anchor links between different social networks. I have done significant works on defining, formulating and solving the social network alignment problem based on different learning settings [22, 23, 2, 17, 20, 6].

C.1 Supervised Network Full and Partial Alignment: By treating the known anchor links as the training set, the network alignment problem can be formulated as a constrained supervised anchor link prediction problem. To solve the problem, I proposed a novel two-phase approach MNA: anchor link prediction + network matching [2] (see Figure 3). In inferring potential anchor links, a classifier is built with a set of structural and attribute information based features extracted from the heterogeneous information across different networks. Based on the preliminary link inference results, the MNA approach identifies the final alignment results by applying constrained stable matching to prune the redundant anchor links. MNA [2] performs very well for fully aligned social networks, in which all the users are anchor users. To resolve the alignment problem for partially aligned networks, we propose another novel supervised network alignment algorithm named PNA in [17]. In PNA, we extend the conventional intra-network meta path concept to the inter-network scenario by introducing the *anchor meta path* concept. A set of explicit and implicit features are extracted for anchor links based on the inter-network meta paths. To handle the users who are not connected by anchor links, we allow users to stay isolated in the generic stable matching across the networks.

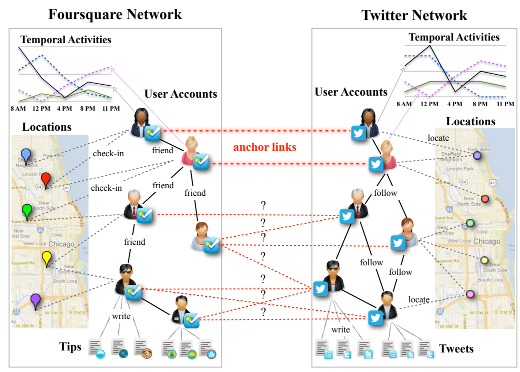

Figure 3: An example of social network alignment based on heterogeneous information.

C.2 Semi-supervised and Unsupervised Network Alignment: Anchor link training data is very expensive to obtain, since manual identification of common users' accounts across social networks is very challenging. To resolve such a challenge, I propose to study the network alignment problem based on *semi-supervised* and *unsupervised* learning settings respectively. I have introduced a PU (Positive and Unlabeled) learning based network alignment framework, named CLF [20], to utilize the unlabeled user pairs in model building. In CLF, several new concepts, like *existence probability*, *formation probability* and the *bridging probability*, about anchor links are introduced. By inferring anchor links' *bridging probability* from the training and validation sets, we can build models with a small number of partially observed anchor links together with the unlabeled anchor links to infer the network alignment results. Furthermore, in the case that no known anchor links can be identified, I develop two other novel unsupervised frameworks for aligning multiple heterogeneous social networks, which are called M-NASA[22] and PCT [23] respectively. By studying the social network data, we observe that the shared users tend to have very similar social structure and attribute information in different social networks (especially for those of similar categories). By minimizing the structure loss and maximizing the attribute closeness of the inferred mappings, M-NASA and PCT formulate the network alignment problem as a constrained optimization problem.

C.3 Academic Impact Summary:

- MNA [2] is the first paper proposing the concepts of *multiple aligned social networks*, *anchor user* and *anchor link*. It is also one of the mostly cited paper in the proceedings of CIKM' 13, and it has received 149 citations already.
- PNA [17] is the first work introducing the partial network alignment problem. CLF [20] is the first paper on PU network alignment, and it has received 51 citations. PCT [23] is the first work on social network co-alignment via different categories of shared information entities with 22 citations.
- M-NASA [22] is the first work introducing the *transitivity law* when aligning multiple networks, which has been cited by 49 papers already in two years. An extension work of M-NASA [22] has been accepted the AISC journal [29].

D. Broad Learning: Synergistic Knowledge Discovery across Multiple Information Sources

Generally, with the data across multiple information sources, we can acquire a more comprehensive knowledge about the information entities, e.g., social media users, patients and offline POIs/communities/routes. Based on such abundant prior knowledge, we can provide much better recommendation services [12, 13, 28, 20, 6], detect more accurate community structures [21, 1, 5], achieve broader impacts in information diffusion [33, 32], identify more correct patient brain network clusters [4], and learn more useful representations for POIs or traffic routes [31, 3, 30, 24, 15, 16].

D.1 Broad Learning based Social Knowledge Discovery: A common problem encountered in recommendation services is the *information sparsity/cold start* problem when providing services for users with limited prior knowledge about their preferences. To resolve such a severe problem, I propose to study the POI recommendation across multiple aligned social networks [13]. Instead of targeting at regular users or networks, I study the friend recommendation problem for new users [12] and new networks [13, 28, 20] specifically. Besides link transfer, I have also studied the synergistic mutual community detection problem across aligned networks to identify the community structure in each network respectively [19, 21, 1, 5]. Furthermore, via the shared users, information can be effectively propagated across social networks with social activities like tweet/tip repost. To model such an important observation, we propose a Multi-source Multi-channel information diffusion model to depict how information propagates across aligned networks in [33].

D.2 Broad Learning based Patient Disease Detection: In the era of big data, we can easily access information from multiple views which may be obtained from different sources or feature subsets. Besides the social media, as shown in Figure 4, in medical science, measurements from a series of medical examinations are documented for each subject, including clinical, imaging, immunologic, serologic and cognitive measures which are obtained from multiple sources. It is desirable to combine all these features in an effective way for disease diagnosis. In [4], we have studied the human brain networks clustering problem based on the multiple source data. We propose a multi-graph clustering approach (MGCT) based on the interior-node topology of graphs. Specifically, we extract the interior-node topological structure of each graph through a sparsity-inducing interior-node clustering. We merge the interior-node clustering stage and the multi-graph clustering stage into a unified iterative framework, where the multi-graph clustering will influence the interior-node clustering and the updated interior-node clustering results will be further exerted on multi-graph clustering.

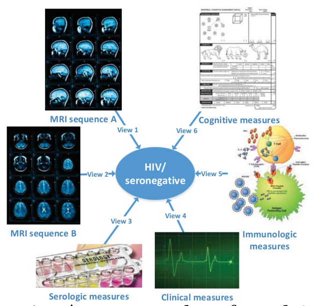

Figure 4: An example of multi-view learning in bio-medical studies.

D.3 Broad Learning based Smart City Analysis: The increasing pervasiveness of GPS-equipped devices and location based smart phone applications has accumulated a variety of spatial, temporal, and textual data, such as Point-of-Interests data (spatial), taxi trajectories (spatiotemporal), bus trips (spatiotemporal), bike GPS traces (spatiotemporal), and geo-tagged posts (spatiotemporal textual) as shown in Figure 5. Such spatial, temporal, and textual data are collected from different locations, times, networks, users, devices, and applications [31, 3, 30]. By fusing such abundant data together, we study the problem of ranking vibrant communities in [31], as developing vibrant communities can help boost commercial activities, enhance public security, foster social interaction, and thus yield livable, sustainable, and viable environments.

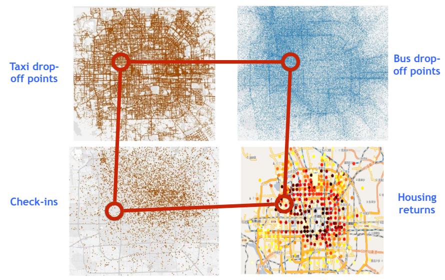

Figure 5: An example of multi-source based in smart city studies.

Assisted with such multi-source data, city traffic can be greatly improved. Problems, like *bicycle sharing system redeployment* [16] and *trip destination prediction* [3, 15], have been studied for the city *bicycle sharing systems* [3, 24, 15, 16]. Furthermore, based on the spatiotemporal traffic data, we have also studied the problem on analyzing human driving behavior [30], which can help us assess driver performances, improve traffic safety, and, ultimately, promote the development of intelligent and resilient transportation systems.

D.4 Academic Impact Summary:

- MLI [28] is the first paper on friend recommendation in multiple networks simultaneously, and it is also the first paper introducing inter-network meta path concept. Currently, MLI [28] has been cited by 98 other research works. SCAN-PS [12] and TRAIL [13] are the first works studying recommendations with the cold start problem. By now, they have received 65 and 76 citations already.
- MGCT [4] is the first research paper on brain network clustering with multiple graphs and the interior-node topology.
- Paper [16] is the first research work on station re-deployment; [30] is the first work on human driving behavior analysis; and [31] is the first paper studying the community vibrancy.

Future Agenda

As more data is being generated in different disciplines, the needs for effective and efficient data fusion and representation learning algorithms will keep increasing steadily.

A. Long-term Goal: Theoretic Foundation for Deep Learning and Broad Learning

Academic Goal: My future research interests are directed towards a long-term goal of making sense of deep and broad learning in a holistic perspective. In the future, I plan to integrate the *deep learning* and *broad learning* works into a unified framework and focus on fusing data from different sources for effective representation learning. To achieve performance guarantees, a complete theoretic framework for deep learning and broad learning is to be introduced. Theoretic performance bounds will be derived for input data following different distributions. Robust information source selection and representation learning methods will also be studied to resolve the domain difference problem. Based on the theoretic foundation, different broad learning and deep learning frameworks will be proposed to deal with various categories of datasets, ranging from traditional feature vector represented data, to graph/network data, text data, time series data and image/video data.

Industrial Goal: Besides the academic goals, I also plan to introduce the proposed *deep learning* and *broad learning* to the industry. Potential application of these proposed research works include (1) the fusion of different departments in big companies, and (2) the alignment of big companies with small startups. On the premise that privacy concerns are not violated, by connecting various company internal departmental information together, such as Google Search, Gmail, Google Maps and Youtube, big companies like Google can greatly improve the services provided by these departments in the company simultaneously. Furthermore, forming alliance between big companies and emerging startups can lead to a win-win payoff for both of them via information sharing. With the abundant information shared from big companies, startups can survive and become prosperous much easier. Meanwhile, big companies can also utilize their data advantages to tap into novel or disruptive technologies to keep their leadership positions in the future industrial evolutions.

B. Short-term Goal: Scalable Fusion and Representation Learning of Various Multi-Source Data

Scalable Broad Learning Algorithms: Data generated nowadays is usually of very large scale, and fusion of such big data from multiple sources together will render the problem more challenging. For instance, the online social networks (like Facebook) usually involve millions even billions of active users, and the social data generated by these users in each day will consume more than 600 TB storage space (in Facebook). One of the major short-term objective of my research is to develop scalable data fusion and mining algorithms that can handle such a **large volume** (of **big data**) challenge. One tentative approach is to develop information fusion algorithms based on distributed platforms, like Spark and Hadoop [1], and handle the data with a large distributed computing cluster. Another method to resolve the scalability challenge is from the model optimization perspective. Optimizing existing learning models and proposing new approximated learning algorithms with lower time complexity are desirable in the future research projects. In addition, I'm also interested in applying deep learning models to fuse and mine the large-scale datasets.

Broader Deep Learning Applications: Besides the research works on social network datasets, I have also applied the *deep learning* and *broad learning* on other categories of datasets, like enterprise internal data [25, 14, 27, 26], bike-sharing system data [15, 32, 16], knowledge base data, and pure text data. I have some prior research works on representation learning with the geo-spatial data [30, 31, 3]. By analyzing a large-scale urban and mobile data related to residential communities, we find that in order to effectively identify vibrant communities, we should not just consider community "contents" such as buildings, facilities, and transportation, but also take into account the spatial structure. Therefore, we propose to learning the representations of communities by integrating very diverse data categories together, which can be useful for *urban vibrancy ranking* [31], *trip destination prediction* [3], and *human driving behavior analysis* [30]. In the future, I'm interested in further integrating the contextual data into the representation learning model to cover broader smart city information. I'm also interested in fusing multiple knowledge bases, like Douban and IMDB, for representation learning with *deep learning* models.

C. Fundings and Collaborations

I have written and submitted 6 grant proposals as the PI/sole-PI to NSF and other external funding programs, three of which have been funded with a total budget about $1.7M (my current active share is $550K). For the remaining proposals which are currently pending, they have a total budget around $3.5M (my share is $1.7M). As the PI/sole-PI of these proposal, I'm responsible for defining new research problems and designing new algorithms to solve the problems. In the future, to continue my research in *deep* and *broad learning*, I plan to write several grant proposal to apply for more research fundings from NSF and NIH. In addition, in the past years, close collaboration with researchers in both academia and industry have shaped my research style a lot and brought about lots of novel ideas. With Dr. Philip S. Yu (from University of Illinois at Chicago), we have studied the social network fusion and mining problems. With Dr. Charu C. Aggarwal (from IBM T. J. Watson Research), we have studied the signed network mining problems by fusing links belonging to different polarities into an integrated mining framework. With Dr. Xiangnan Kong (from Worcester Polytechnic Institute), we have studied the social media mining and analysis. With Dr. Yanjie Fu (from Missouri S&T University), we have studied the representation learning problems in smart city and urban computing. With Dr. Yuanhua Lv (from Microsoft Research), we have studied the problems to fuse and mine enterprise internal information sources. With Dr. Jianhui Chen (from Yahoo! Research), we have focused on optimizing broad learning models to lower down their time complexities. In the near future, I will continue the close collaboration with more researchers both within and outside my area in carrying out projects about *data fusion and representation learning.*

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