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Technology Developed in GICE

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Intelligent medicine - Predicting cancer prognosis with deep bimodal networks, ensemble learning, and adversarial networks

Graduate Institute of Communication Engineering, National Taiwan University

from Communication and Signal Processing Group

Introduction

Cancer contributes to one of the top causes for human mortality, and precise and personalized patient prognosis cancer stratification is essential for making therapeutic strategy decisions and reducing patients' suffering under adjuvant treatments. Non-small cell lung cancer (NSCLC) accounts for 85% of lung cancer patients, and its subtype, adenocarcinoma (ADC), draws about 35% of patients with poor prognosis after surgery. Breast cancer is the most diagnosed cancer among females, and it is challenging to predict prognostic consequence outcomes for treatment due to its heterogeneity. Nevertheless, biological in applications, we are often faced with censored records and small patient cohorts, many of which contain multiple heterogeneous data types. To overcome these

issues, we design a bioinformatic pipeline with designated deep learning models and feature selection algorithms to predict cancer patient prognostic conditions (Figure 1).

Bimodal neural network for integrating heterogeneous data sources

From 7 well-known NSCLC biomarkers in the literature, we applied our systems biology workflow (see figure below) and selected a set of 15 novel prognostic biomarkers to NSCLC predict ADC patients' prognosis. We collected patients with these prognostic biomarker expressions and their corresponding clinical information to predict their 5year overall survival with integrative bimodal DNN to combine information shared in the heterogeneous data sources (Figure 2A).

GICE Honors



Prof. Soo-Chang Pei IEEE Life Fellow

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Prof. Ai-Chun Pang IEEE Vehicular Technology Society 2020 Women's Distinguished Career Award



Message from the Director

Hsuan-Jung Su

Professor & GICE Director

Congratulations to Prof. Soo-Chang Pei for becoming an IEEE Life Fellow! On behalf of NTU GICE, we would like to thank him for his contribution and inspiration to members of GICE. We would also like to congratulate Prof. Ai-Chun Pang for receiving the IEEE Vehicular Technology Society 2020 Women's Distinguished Career Award. This is a wonderful news. We are glad to see our colleagues' efforts recognized.

In this issue, we have Prof. Che Lin sharing his interdisciplinary results on using microarray and clinical data to predict cancer patient prognostic conditions with deep learning classifiers. Prof. Shau-Gang Mao shares his research results on high-accuracy UWB indoor positioning system. This issue also includes an article by Mr. Yu-Jhe Li, a GICE student, who shares his experience of visiting the Robotics Institute at Carnegie Mellon University for one year. Students seeking opportunities to visit foreign universities or exchange programs should find this article interesting. We hope that you enjoy reading this issue.

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Fig. 1. Bioinformatic pipeline for cancer patient prognostic conditions prediction.

systems biology feature selector NSCLC cohort StepMiner 7 pairs of biomarker+/-7 PRV (n = 614)algorithm gene interaction networks lists remove patients with overlapping topincomplete clinical data scoring genes well-known NSCLC biomarkers 8 prognostic biomarkers (CUL1, (EPCAM, HIF1A, PKM, PTK7, CUL3, EGFR, ELAVL1, GRB2, ALCAM, CADMI, SLC2AI) NRF1, RNF2, RPA2) total of 15 prognostic biomarkers for NSCLC patients with complete clinical data (n = 512)validation set (n = 85) test set (n = 171) E-MTAB-923 (n = 90)training set (n = 256) train tune hypervalidation independent model parameters validation survival analysis bimodal DNN classifier

Fig. 2A. Our systems biology workflow.

The integrative (bimodal) DNN consists of two subnetworks followed by a merged network. Each subnetwork is pre-trained with microarray and clinical data, respectively, and the output from the merged network is trained with both types of data. Experiment results show that the integrative DNN achieves better prediction results (AUC: 0.8163; Accuracy: 0.7544) compared to the random forest classifier (AUC: 0.7926; Accuracy: 0.7661) and composite risk model (CRM) (AUC: 0.7223; Accuracy: 0.6491) which was proposed in previous research.

We further conducted survival analysis such as Kaplan-Meier (KM) analysis and proportionalhazards model to verify the effectiveness of the proposed model after reclassification where certain thresholds were chosen with the Youden index to stratify patients into good and bad prognosis groups. We observed that the integrative DNN achieves the highest hazard ratio (6.642 (3.313 - 12.601)) compared to the integrative RF (4.598 (2.649 - 7.982)), which indicates that the integrative DNN is capable of utilizing useful information shared among both types of data (Figure 2B). Interested readers are invited to read our paper, "Overall survival prediction of non-small cell lung cancer by integrating microarray and clinical data with deep learning," published in Scientific Reports for more details.



Figure 2B. Performance comparison of the integrative DNN with the random forest classifier.

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Hybrid ensemble prognostic biomarker selection

Gene feature selection is an essential step in our bioinformatic pipeline that can discover potential prognostic biomarkers via a systems biology approach. However, due to the hiah dimensionality but small sample size for microarray data, it is challenging to select robust biomarkers such that the resulting biomarkers are less sensitive to the given data and easier to generalize to unseen data. We designed an ensemble feature selection workflow (Figure 3A) with a hybrid ensemble approach to systematically evaluate the robustness of the selected biomarkers, where hybrid ensemble combines both function and data perturbation approaches found in the literature.



Figure 3A. Ensemble feature selection workflow.

Based on our numerical experiments, we found that rank-mean strategy leads to the best result on random validation sets in each ensemble, where the resulting rank is obtained by averaging the score of the candidate biomarker lists among a set of 7 ensemble feature selectors built with various splitting criteria (Figure 3B). We also utilized bimodal DNN to combine microarray and clinical data for patients in the METABRIC dataset, and we found that the bimodal DNN achieves the highest AUC trained on the selected biomarkers (AUC: 0.7836; Accuracy: 0.7179) compared to other benchmark machine learning classifiers, such as random forest (AUC: 0.7815; Accuracy: 0.7265) and support vector machine (AUC: 0.7677; Accuracy: 0.6752). We have published this work on bioRxiv, "Integrating ensemble systems biology feature selection and bimodal deep neural network for breast cancer prognosis prediction," in which the experimental details can be found.



Figure 3B. Aggregating a different number of functions in function perturbation.

A generative adversarial network approach for limited patient data

In practical biological applications, labeled data are hard to acquire and patient records often consist of lots of missing values resulting from censored patients and different data structures hospitals collected among and research institutes. Advanced data augmentation techniques are therefore of essential importance to assist in training deep classifier training by generating synthetic data via generative models such as generative adversarial networks (GAN) variational autoencoders and (VAE). We extended the previously proposed model, deep augmentation (DADA), adversarial data for cancer patient prognosis prediction by introducing Wasserstein GAN (wGAN) into the model, and proposed WGAN-based deep adversarial data augmentation (wDADA).

To evaluate the robustness of the proposed model, we initialized the network with 30 different seeds and recorded the means and standard deviations for each model. wDADA is trained from scratch without any pre-trained networks, and its performance was compared with benchmark models such as logistic regression (LR) and DADA, and we also compared it with our previously proposed bimodal neural network (Bimodal) which needs calibrated pre-training steps. Experiment results show that wDADA can provide superior averaged results compared to LR and DADA, and achieves relatively small standard deviation when compared to Bimodal in terms of AUC and concordance index (CI). We also conducted KM analysis on each model, results show that the stratification power of wDADA is comparable to Bimodal without any pre-trained networks (Figure 4). This interesting result shed light on the fact that it is possible to train deep classifiers with limited data from scratch with the help of generative models. As such, it is

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straightforward to further introduce semi-supervised learning techniques into the current model so that a large portion of data with missing values can be utilized in training deep classifiers efficiently. This work was recently accepted to the 42nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC 2020), "Generative Adversarial Networks for Robust Breast Cancer Prognosis Prediction with Limited Data Size."

Models	AUC	СІ	ACC
DADA	0.6707 ± 0.0542	0.6058 ± 0.0542	0.6182 ± 0.0774
LR	0.7281 ± 0.0463	0.6318 ± 0.0269	0.6379 ± 0.0339
wDADA	0.7538 ± 0.0328	0.6507 ± 0.0248	0.6726 ± 0.0278
Bimodal	0.7546 ± 0.0183	0.6542 ± 0.0120	0.6889 ± 0.0159
0.8 -		0.8 -	
0.6 -		0.6-	
0.6 - mean surv	val rate (good) val rate (good)	0.6 - mean survival rate	(gosd)
0.6 - 0.4 - mean surv mean surv ± 1 std. de ± 2 std. de	val rate (good) val rate (good) val rate (good) v. (good)	0.6 - 0.4 - mean survival rate ± 1 std. dev. (good ± 2 std. dev. (good	good posy
0.6 - 0.4 - mean surv 1 1 std. de 1 2 std. de 1 2 std. de 1 2 std. de	val rate (good) val rate (good) v. (good) v. (good) v. (good)	0.6 0.4 1 Mid dev. (pod 0.2 0.2 0.2 0.4 0.4 0.4 0.4 0.4 0.4 0.4 0.4	(beop)





Figure 4. Model prediction performance and survival analyses.

(b) LR (bad = 16)

Conclusion

We have proposed a bioinformatic pipeline for using microarray and clinical data to predict cancer patient prognostic conditions with deep learning classifiers. We demonstrate that the proposed pipeline can accurately predict survival status for patients with NSCLC and breast cancer. We believe this can have a significant contribution to applying deep learning models in biological applications even with challenges posed by the scarcity and heterogeneity of patient data.

For more information please contact: Professor Che Lin Email: chelin@ntu.edu.tw

UWB Positioning System with Arbitrary Target Orientation, Optimal Anchor Location, and Adaptive NLOS Mitigation

A. Introduction

Wireless positioning systems have received increasing attention for scenarios with accurate locations of people, objects, and vehicles. Global Navigation Satellite System (GNSS) has been practically used for wide variety of applications. However, indoor location-based service cannot be carried out by GNSS because of signal attenuation and multipath effect in the complicated indoor environment. Ultrawideband (UWB) with high temporal resolution to detect the first path in multipath propagation is attractive to the indoor positioning applications. The UWB positioning system with the characteristics of arbitrary target orientation, optimal anchor location, and adaptive non-line-of-sight (NLOS) mitigation characteristics is proposed and implemented by using the circularly polarized antenna, the genetic algorithm (GA), and the machine learning methods.

B. Arbitrary Target Orientation

To verify the arbitrary target orientation of the UWB system using the proposed circularly polarized antenna, a one-to-one ranging system is established as depicted in Fig. 1(a). The tag antenna is linearly

from Electromagnetics Group

polarized, and its orientation is vertical or horizontal corresponding to the ground plane. The anchor antenna is linearly polarized or circularly polarized, and its orientation is vertical with rotating angle φ from -2250 to 900. Fig. 1(b) displays the range errors of a one-to-one UWB system by using the symmetric double-sided twoway ranging technique. The range errors of a circularly polarized antenna with a vertical tag and a horizontal tag are smaller than 10 cm, which is suitable for an accurate UWB positioning system.

C. Optimal Anchor Location

Fig. 2 displays the experimental setup that is performed in a practical environment, including one room, three pillars, four concrete walls, and two corridors. The proposed GA is applied to determine the anchor locations, and the number of anchors is three, which is the minimal number for positioning the tag in a 2D plane. The optimal anchor locations can be obtained from 226 candidate anchor locations by using the

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proposed GA with gradient descent method. The error of each anchor placement is the average rootmean-square error (RMSE) of all tag locations. The final simulation error using the proposed GA with 100 iterations is 36.72 cm, which is 8.48 cm less than the initial error 45.20 cm. After 100 iterations, the optimal anchor locations with the minimal average RMSE of tag locations are obtained and shown as the red rectangles in Fig. 2.



Fig. 1. (a) Measurement setup of one-to-one ranging system. (b) Range errors measured by one-to-one system with the linearly polarized antenna and the proposed circularly polarized antenna.

D. Adaptive NLOS Mitigation

By using the channel impulse response (CIR) as inputs and mitigating ranges as outputs, the machine learning models can fit even in complicated environment. Fig. 3 presents the measurements of UWB positioning system in 6 different locations with NLOS mitigation. The result demonstrates that RMSE using the optimized LSTM model is less than those using the other models under severe NLOS conditions. To verify the effect of antennas on UWB positioning system, the RMSEs of location 1 to 6 using various optimized models with the linearly polarized and the proposed circularly polarized antennas are shown in Fig. 4. With and without NLOS mitigation, the error of tag position by using the proposed circularly polarized antenna is much less than that by using the linearly polarized antenna.

E. Conclusion

This work presented a high-accuracy UWB positioning system in the indoor environment with severe NLOS condition. By using the proposed circularly polarized antenna, the orientation between anchor and tag can be arbitrary. The locations of anchor in the UWB system are effectively optimized by using the proposed GA to minimize the RMSE of each tag location in dense multipath area.

The adaptive NLOS mitigation is investigated by optimizing DNN, CNN and LSTM, and the threeanchor UWB system is presented to demonstrate the positioning in the complicated indoor environment. By using the proposed circularly polarized antenna, the proposed GA algorithm and optimized LSTM model, the proposed UWB positioning system is suitable for practical applications.



Fig. 2. Floor plane for UWB positioning system verification. The 226 candidate anchor locations are shown as the crosses, and the simulated RMSEs of all tag locations with best anchor placement are depicted as the colored squares. The values of RMSEs are shown in log scale on the right-hand side, and the three best anchor locations are depicted as red triangles.



Fig. 3. Measured positioning RMSEs of tag location 1 to 6 with various optimized models. The original measurement result without NLOS mitigation is also depicted for comparison.



Fig. 4. Measured positioning RMSEs of tag locations with various optimized models using the linearly polarized antenna and the proposed circularly polarized antenna. The original measurement result without NLOS mitigation is also depicted for comparison.

For more information please contact: Professor Shau-Gang Mao Email: sgmao@ntu.edu.tw

Invited talk

Topic: Wireless Communications Systems Design with Deep Learning: Advantages and Challenges Lecturer: Professor Chia-Han Lee



Chia-Han Lee received the B.S. degree from National Taiwan University in 1999, the M.S. degree from the University of Michigan, Ann Arbor, in 2003, and the Ph.D. degree from Princeton University in 2008, all in electrical engineering. From 1999 to 2001, he served in the ROC Army as a Missile Operation Officer. From 2008 to 2009, he was a Postdoctoral Research Associate with the University of Notre Dame, USA, From 2010 to 2016, he was with Academia Sinica as an Assistant Research Fellow and then an Associate Research Fellow. In 2016, he joined National Chiao Tung University as an Associate Professor and Hwa Tse Roger Liang Junior Chair Professor (2018-2019), and became a Professor in 2019. He received Intel Labs Distinguished Collaborative Research Awards in 2014 and was named Intel Labs Distinguished Collaborator in 2015 (for years 2010-2015). He serves as Industry Presentations and Demonstrations Co-Chair for IEEE GLOBECOM 2017, Symposium Co-Chair for IEEE GLOBECOM 2019 and Tutorials Co-Chair for IEEE GLOBECOM 2020. His research interest is deep learning-based wireless communications and networks. He is an Editor of IEEE Communications Letters from 2014 to 2018, an Editor of IEEE Transactions on Wireless Communications from 2014 to 2019, and an Editor of IEEE Transactions on Communications since 2019.

Deep learning has recently been applied to many fields, and the society of wireless communications has also begun to embrace this trend. Different from the traditional wav of designing wireless communications systems, the deep learning-based approach impacts design philosophy the and discipline of wireless systems. In this talk, we will discuss why deep learning is interested by the communications society, and how wireless the design of communications systems will benefit from the advance of deep learning. The deep learning-based design, however, requires new design thinking and workflow. Challenges of deep learning-based designs of wireless systems will thus be discussed as well.



Professor Chia-Han Lee National Chiao Tung University

Invited talk

Topic: Multichannel Rendezvous in Cognitive Radio Networks Lecturer: Professor Cheng-Shang Chang

Rendezvous search that asks two persons to find each other among a set of possible locations has regained tremendous research interest lately in the research community of cognitive radio networks (CRNs). In a CRN, there are two types of users: primary spectrum users (PUs) and secondary spectrum users (SUs). SUs are only allowed to share spectrum with PUs provided that they do not cause any severe interference to the PUs. To do this, SUs first sense a number of frequency channels. If a channel is not blocked by a PU, then that channel may be used for SUs to establish a communication link. One of the fundamental problems in a CRN is then for two SUs to find a common unblocked channel by hopping over their available channels. Such a rendezvous search problem in a CRN is known as the multichannel rendezvous problem. The objective of this tutorial is to provide a tutorial on the multichannel rendezvous problem under various categories and assumptions, including asymmetric/symmetric roles, synchronous/asynchronous clocks, homogeneous/heterogeneous available channel sets, and oblivious/nonoblivious rendezvous. Instead of giving rigorous mathematical proofs of the results in the multichannel rendezvous problem, we will provide the needed insights/intuitions to understand these results. Though there are many mathematical theories associated with the multichannel rendezvous problem, including Galois fields, finite projective planes, orthogonal Latin squares, quorum systems, and difference sets, in our view the fundamental theorem for the multichannel rendezvous problem is the Chinese Remainder Theorem and the development of this tutorial will be focused on the Chinese Remainder Theorem.



Prof. Cheng-Shang Chang Distinguished Professor IEEE Fellow

Prof. Cheng-Shang Chang received the B.S. degree from National Taiwan University, Taipei, Taiwan, in 1983, and the M.S. and Ph.D. degrees from Columbia University, New York, NY, USA, in 1986 and 1989, respectively, all in Electrical Engineering. From 1989 to 1993, he was employed as a Research Staff Member at the IBM Thomas J. Watson Research Center, Yorktown Heights, N.Y. Since 1993, he has been with the Department of Electrical Engineering at National Tsing Hua University, Taiwan, R.O.C., where he is a Tsing Hua Distinguished Chair Professor. His current research interests are concerned with network science, high speed switching, communication network theory, and mathematical modeling of the Internet. Dr. Chang received an IBM Outstanding Innovation Award in 1992, an IBM Faculty Partnership Award in 2001, and Outstanding Research Awards from the National Science Council, Taiwan, in 1998, 2000 and 2002, respectively. He was elected to an IEEE Fellow in 2004. He received the Merit NSC Research Fellow Award from the National Science Council, R.O.C. in 2011, the Academic Award in 2011, and the National Chair Professorship in 2017 from the Ministry of Education, R.O.C. He also received the IEEE INFOCOM Achievement Award in 2017. He is the author of the book "Performance Guarantees in Communication Networks" and the coauthor of the book "Principles, Architectures and Mathematical Theory of High Performance Packet Switches."

Corner of student news

Experience in the Robotics Institute at Carnegie Mellon University

Starting from September 2019 till June 2020, I was serving as visiting scholar (research assistant) in The Robotics Institute at Carnegie Mellon University. From there, I have learned a whole lot of things including the culture of Pittsburgh in United States and the friendly environment at Carnegie Mellon University (CMU) besides academic research. To talk about the experience completely, I would like to share these memories from academic, social, and entertaining aspects.

Right, so learning from their academic resources is definitely the reason for heading Carnegie Mellon. To begin with, CMU actually has a great deal of academic courses worth auditing. For example, several well-known textbooks such as the Statistics by Larry are from CMU. If you are able to go for the class yourself, you will be granted the chance to see the authors of several textbooks. In addition, since statistics and machine learning are prevalent in CMU, almost every student from different major (Civil engineering, management, or even fined arts) know little bit about machine learning (statistics). That being said, you can often see machine learning in the academic research from each department. That is amazing! CMU is entirely the college of learning algorithms.

Besides the academic resources, you will be getting many opportunities to know many people and several ones can be your partners when you are doing research in CMU. For example, CMU encourages students to discuss or chat with others in open area at each department building. Compared with NTU, each



Article by Yu-Jhe Li

Lab in CMU is actually sharing a big public space with seats randomly arranged. In this way, you will be able to talk with other graduate students sitting next to you. Sometimes if you meet someone that has same research interest, you all can be collaborators in the same research paper. For life and entertaining part, I would say CMU can be quite boring ha-ha comparing with NTU if you think about foods, parties, and stores. Yet, CMU indeed has its pros, which is that CMU has a free sports gym as well as sports court outside. Since it usually snows in Pittsburgh, you can probably go skiing in some facilities nearby. If you never ski in Taiwan, that would be very fun. Moreover, cooking is also the common indoor activities in US since the food sold outside are always expensive. You will be learning how to cook very soon because you want to save your money for sure.

In general, I have made so many friends including Taiwanese, Chinese, Japanese, and locals. They all love to help each other and which made me feel blessed. For academic part, I complete two academic projects there and one of them is submitted to publisher.

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