## BIBM'22 Submission: B451

bibm-inform <bibm-inform@wi-lab.com>
Wed 10/19/2022 3:30 PM
To: Yu, Yue <yueyu@gatech.edu>;xuan.kan@emory.edu <xuan.kan@emory.edu>;hejie.cui@emory.edu <hejie.cui@emory.edu>;ran.xu@emory.edu <ran.xu@emory.edu>;yujiazh@cmu.edu <yujiazh@cmu.edu>;xiangchensong@cmu.edu <xiangchensong@cmu.edu>;kunz1@cmu.edu <kunz1@cmu.edu>;razieh.nabi@emory.edu <razieh.nabi@emory.edu>;yguo2@emory.edu <yguo2@emory.edu>;Zhang, Chao <chaozhang@gatech.edu>;j.carlyang@emory.edu <j.carlyang@emory.edu>

Dear Yue Yu, Xuan Kan, Hejie Cui, Ran Xu, Yujia Zheng, Xiangchen Song, Kun Zhang, Razieh Nabi, Ying Guo, Chao Zhang, and Carl Yang,

Thanks a lot for your support to the IEEE BIBM 2022 conference. We are sorry to inform you that your paper

B451: Learning Task-aware Effective Brain Connectivity for fMRI Analysis with Graph Neural Networks

was not accepted by the IEEE BIBM 2022 conference.

This year we have received 842 full paper submissions, and each paper was assigned to 4 Program Committee members for review. After the rigorous review process, 97% papers have received at least 3 reviews, and the conference has accepted 167 regular papers (acceptance rate: 19.8%) and 171 short papers (acceptance rate: 20%). Many good papers like yours have to be declined due to schedule constraints. We believe your work and participation is very important to the BIBM community and really hope you are still considering to attend BIBM 2022.

Enclosed at the bottom of this message, please find the review report for your paper. Please carefully take into account of the enclosed comments by the reviewers.

Below is the important message related to the online registration, hotel booking and how to transfer your paper to workshop for further consideration

(1) The IEEE BIBM 2022 is organized as an in-person conference in two sites: Caesars Palace, Las Vegas, USA and WorldHotel Grand Jiaxing Hunan, Changsha, Hunan, China. The participants could choose one of the sites to attend the conference. The participants could access all the sessions in one site in person and also access all the video recordings of the papers presented in the other site. The Las Vegas site program runs from Dec 6-7 and the Changsha site program runs from Dec 7-8, 2022. To book the hotel rooms using the conference discount rate, please follow the link from https://ieeebibm.org/BIBM2022/ to register the conference.

(2) The conference schedule will be announced around mid November. Anyone wants to attend the conference must register the conference. WE will email you the login in instruction to the virtual platform a few days before the event so you could attend all the sessions in person in one site and watch the video recordings of the papers presented in the other site.

(3) We also want to bring your attention that BIBM 2022 also have associated with 27 workshops. If you have selected one of the workshops for further consideration during the paper submission, then your paper is already transferred automatically to the workshop and the workshop organizers will send out the workshop paper notification out in the due date. If you didn't select one of the workshops for further consideration during the paper submission, you have another chance to select one of the workshops now for further consideration. Please follow the link below
https://wi-lab.com/cyberchair/2022/bibm22/scripts/submit.php?subarea=B

Revise an Existing Submission / Select a Workshop to Transfer

with your paper id: B451

and password: p4512866

then select the workshop you would like for further consideration.

If your paper is accepted by a workshop, it will be published in the same conference proceedings as the main conference papers and indexed in IEEE eXplore.

Thanks for your support again. We are going to have a great conference in Las Vegas, USA/Changsha, China.

Program Chairs

Donald Adjeroh West Virginia University, USA
Qi Long, Univ. of Penn, USA
Xinghua (Mindy) Shi, Temple University, USA
Fei Guo, Central South University, China

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--========= Review Reports =========--

The review report from reviewer #1:

*1: Is the paper relevant to BIBM?
[_] No
[X] Yes

*2: How innovative is the paper?
[_] 5 (Very innovative)
[X] 4 (Innovative)
[_] 3 (Marginally)
[_] 2 (Not very much)
[_] 1 (Not)
[_] 0 (Not at all)

*3: How would you rate the technical quality of the paper?
[_] 5 (Very high)
[X] 4 (High)
[_] 3 (Good)
[_] 2 (Needs improvement)
[_] 1 (Low)
[_] 0 (Very low)

*4: How is the presentation?
[_] 5 (Excellent)
[X] 4 (Good)
[_] 3 (Above average)
[_] 2 (Below average)
[_] 1 (Fair)
[_] 0 (Poor)

*5: Is the paper of interest to BIBM users and practitioners?
[X] 3 (Yes)
[_] 2 (May be)
[_] 1 (No)
[_] 0 (Not applicable)

*6: What is your confidence in your review of this paper?
[_] 2 (High)
[X] 1 (Medium)
[_] 0 (Low)

*7: Overall recommendation
[_] 5 (Strong Accept: top quality)
[X] 4 (Accept: a regular paper)

[_] 3 (Weak Accept: could be a poster or a short paper)
[_] 2 (Weak Reject: don't like it, but won't argue to reject it)
[_] 1 (Reject: will argue to reject it)
[_] 0 (Strong Reject: hopeless)

*8: Detailed comments for the authors
In this work, the auhtors proposeTBDS, an end-to-end framework based on Task-aware Brain connectivity DAG Structure generation for fMRIanalysis.

Positive:
1) The key component ofTBDSis the brain networkgenerator which adopts a DAG learning approach to transformthe raw time-series into task-aware brain connectivities.

2) They design an additional contrastive regularization to inject task-specific knowledge during the brain network generation process.Comprehensive experiments on two fMRI datasets, namely Ado-lescent Brain Cognitive Development (ABCD) and PhiladelphiaNeuroimaging Cohort (PNC) datasets demonstrate the efficacy ofTBDS.

3. The paper is well written and easy to follow.

Negative:
1. The code is not published and some baselines are not included

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The review report from reviewer #2:

*1: Is the paper relevant to BIBM?
[_] No
[X] Yes

*2: How innovative is the paper?
[_] 5 (Very innovative)
[_] 4 (Innovative)
[_] 3 (Marginally)
[X] 2 (Not very much)
[_] 1 (Not)
[_] 0 (Not at all)

*3: How would you rate the technical quality of the paper?
[_] 5 (Very high)
[_] 4 (High)
[_] 3 (Good)
[X] 2 (Needs improvement)
[_] 1 (Low)
[_] 0 (Very low)

*4: How is the presentation?
[_] 5 (Excellent)
[_] 4 (Good)
[_] 3 (Above average)
[X] 2 (Below average)
[_] 1 (Fair)
[_] 0 (Poor)

*5: Is the paper of interest to BIBM users and practitioners?
[_] 3 (Yes)
[X] 2 (May be)
[_] 1 (No)
[_] 0 (Not applicable)

*6: What is your confidence in your review of this paper?
[_] 2 (High)
[X] 1 (Medium)
[_] 0 (Low)

*7: Overall recommendation
[_] 5 (Strong Accept: top quality)
[_] 4 (Accept: a regular paper)
[_] 3 (Weak Accept: could be a poster or a short paper)
[X] 2 (Weak Reject: don't like it, but won't argue to reject it)
[_] 1 (Reject: will argue to reject it)
[_] 0 (Strong Reject: hopeless)

*8: Detailed comments for the authors
The paper presents an end-to-end framework based on task-aware brain connectivity DAG structure generation for fMRI analysis. The authors build task-specific DAG networks based on BOLD signals, thus adapt to different prediction tasks. The authors also use the predicted pseudo labels as the truth labels and introduce an additional weighting term to suppress the label noise caused by the pseudolabel.
There are some issues with the paper:
1. The authors mention adjusting the additional term weights to avoid overfitting the noise, but do not describe the specific adjustment method.
2. The authors mention that the more confident the prediction is the lower the entropy of y. However, they do not elaborate on how this conclusion is reached and whether this conclusion also holds using different data for prediction.
3. The authors conducted experiments with too few datasets and suggest adding more datasets to the experiments.
4. The authors mention in their analysis that TBDS has an advantage in runtime, but no experiments were performed to prove this.
5. It is difficult for the authors to confirm the advantage of TBDS on the low-labeled dataset by using only a low-labeled subset of the same dataset for prediction, please add different datasets for supporting evidence.

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The review report from reviewer #3:

*1: Is the paper relevant to BIBM?
[_] No
[X] Yes

*2: How innovative is the paper?
[_] 5 (Very innovative)
[X] 4 (Innovative)
[_] 3 (Marginally)
[_] 2 (Not very much)
[_] 1 (Not)
[_] 0 (Not at all)

*3: How would you rate the technical quality of the paper?
[_] 5 (Very high)
[X] 4 (High)
[_] 3 (Good)
[_] 2 (Needs improvement)
[_] 1 (Low)
[_] 0 (Very low)

*4: How is the presentation?
[_] 5 (Excellent)
[X] 4 (Good)
[_] 3 (Above average)
[_] 2 (Below average)
[_] 1 (Fair)
[_] 0 (Poor)

*5: Is the paper of interest to BIBM users and practitioners?
[X] 3 (Yes)
[_] 2 (May be)
[_] 1 (No)
[_] 0 (Not applicable)

*6: What is your confidence in your review of this paper?

[X] 2 (High)
[_] 1 (Medium)
[_] 0 (Low)

*7: Overall recommendation
[_] 5 (Strong Accept: top quality)
[X] 4 (Accept: a regular paper)
[_] 3 (Weak Accept: could be a poster or a short paper)
[_] 2 (Weak Reject: don't like it, but won't argue to reject it)
[_] 1 (Reject: will argue to reject it)
[_] 0 (Strong Reject: hopeless)

*8: Detailed comments for the authors
Proposes a model that uses a graph neural network to model task-aware brain connectivity network. TBDS uses a DAG to represent fMRI image analysis.
The presentation of the paper is good, it easy to read and the model is well explained, with some observations.
How the model handles negative weights is not quite clear but resorts to ref 22. The problem appears to be simpler than it seems; unless I am missing something in the paper.
Pearson correlation is used to account for relationships between time series. Linear correlation has been used for a while, although other models can be used. It appears that simplicity is the main reason. The work of https://academic.oup.com/bioinformatics/article/26/18/2281/208752 is an example that discusses several models (including nonlinear like Spearman) and presents a model based on universal alignment for 1D signals.
The argument of tr(.) of Eq 13 should be explained. Is tr(.) defined as a function of a matrix f(A), where A is a matrix with (or without) some constraints? The operator of the exponent should be explained too. Is it positive (semi) definite?; otherwise the diag elements may telescope.
In the next paragraph, not clear what F is. But it is set to A in the subsequent paragraph – not quite clear why.
Experiments and results seem well planned and robust. However, it is not clear how the testing/validation sets were selected.
A weakness: not clear why 1D-CNN is used as a baseline model for the time series comparison, as opposed to the RNN/LSTM, which have been shown to be more successful in time series. Or the models as mentioned above.
Overall performance is well justified; accuracy is a bit low, though this might have to do with the problem itself – a few words about this or supporting references could have helped.
Visualization and discussion is good too.
Overall, a good paper and work.

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The review report from reviewer #4:

*1: Is the paper relevant to BIBM?
[_] No
[X] Yes

*2: How innovative is the paper?
[_] 5 (Very innovative)
[X] 4 (Innovative)
[_] 3 (Marginally)
[_] 2 (Not very much)
[_] 1 (Not)
[_] 0 (Not at all)

*3: How would you rate the technical quality of the paper?
[_] 5 (Very high)
[X] 4 (High)
[_] 3 (Good)
[_] 2 (Needs improvement)
[_] 1 (Low)
[_] 0 (Very low)

*4: How is the presentation?
[_] 5 (Excellent)
[X] 4 (Good)
[_] 3 (Above average)
[_] 2 (Below average)

[_] 1 (Fair)
[_] 0 (Poor)

*5: Is the paper of interest to BIBM users and practitioners?
[X] 3 (Yes)
[_] 2 (May be)
[_] 1 (No)
[_] 0 (Not applicable)

*6: What is your confidence in your review of this paper?
[_] 2 (High)
[X] 1 (Medium)
[_] 0 (Low)

*7: Overall recommendation
[_] 5 (Strong Accept: top quality)
[_] 4 (Accept: a regular paper)
[X] 3 (Weak Accept: could be a poster or a short paper)
[_] 2 (Weak Reject: don't like it, but won't argue to reject it)
[_] 1 (Reject: will argue to reject it)
[_] 0 (Strong Reject: hopeless)

*8: Detailed comments for the authors
This paper proposes TBDS, an end-to-end framework based on Task-aware Brain connectivity DAG (short for Directed Acyclic Graph) Structure generation for fMRI analysis. The key component of TBDS is the brain network generator which adopts a DAG learning approach to transform the raw time-series into task-aware brain connectivities. Besides, this work designs an additional contrastive regularization to inject task-specific knowledge during the brain network generation process. Comprehensive experiments on two fMRI datasets, namely Ado- lescent Brain Cognitive Development (ABCD) and Philadelphia Neuroimaging Cohort (PNC) datasets demonstrate the efficacy of TBDS.

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