Multiple-Graph Recurrent Graph Convolutional Neural Network Architectures for Predicting Disease Outcomes

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Introduction & Objective

Variables :

1. $M \in \mathbb{R}^{m \times n}$: features derived from medical examinations. Some values can be missing
2. $Y \in \mathbb{R}^{m \times 1}$: classification labels
3. $\mathcal{G}_i$ $(i = 1, \ldots, P)$: graphs on subjects with edges derived by a similarity metric from subject attributes

Goal : Taking into account the features in M and $\mathcal{G}_i$ $(i = 1, \ldots, P)$, predict the unknown disease outcomes in Y.

Application to Alzheimer's Disease:

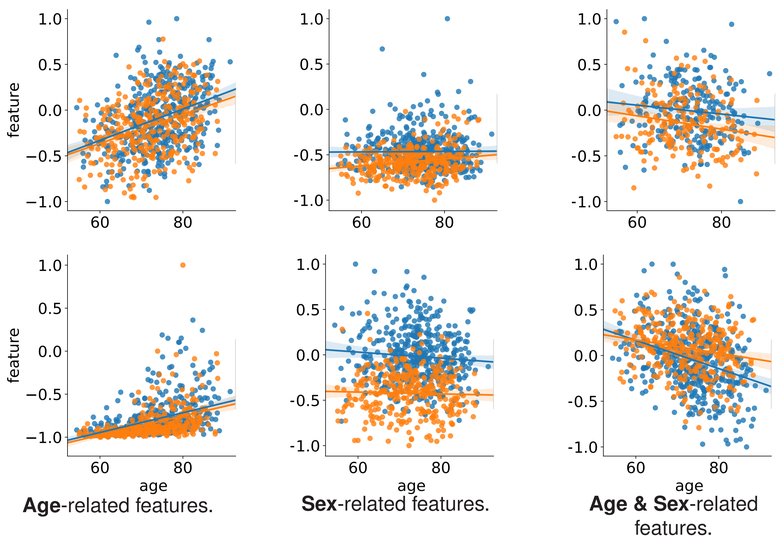
Mild Cognitive Impairment (MCI): Clinical diagnosis

- **Possible Alzheimer's Disease** (AD): irreversible disease, destroys brain cells
- **Dementia**: 46.8 million in 2015
- **Stable**

Feature Dependencies

- In general, many medically-derived features are **not dependent** on **all** of the attributes used to construct the graph.
- Only building one graph based on subject attributes [2, 3] results in **incorrect information diffusion throughout the graph**.

Application to AD: **age and sex** taken as subject attributes.
For each feature in M, plot **available feature values** as a function of **age and sex** (Men, Women).



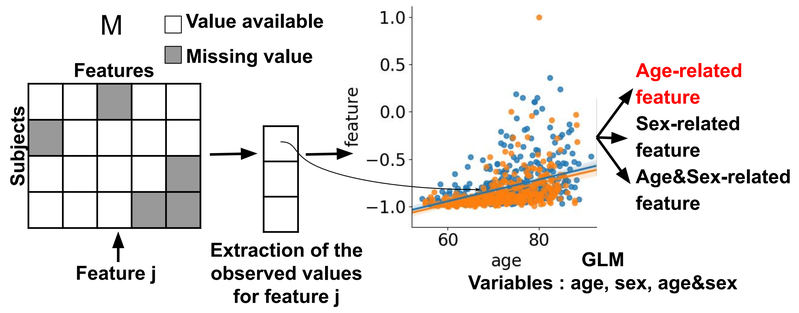
Age-related features. **Sex**-related features. **Age & Sex**-related features.

Different features have **different relationships with age and sex**.

Method

- Use a **linear model** to determine the dependence of each feature and **group the features** by dependence.

  Application to AD: creation of Z_{age}, Z_{sex}, $Z_{age\&sex}$ and Z_{ns} from $Z = [M, Y]$.

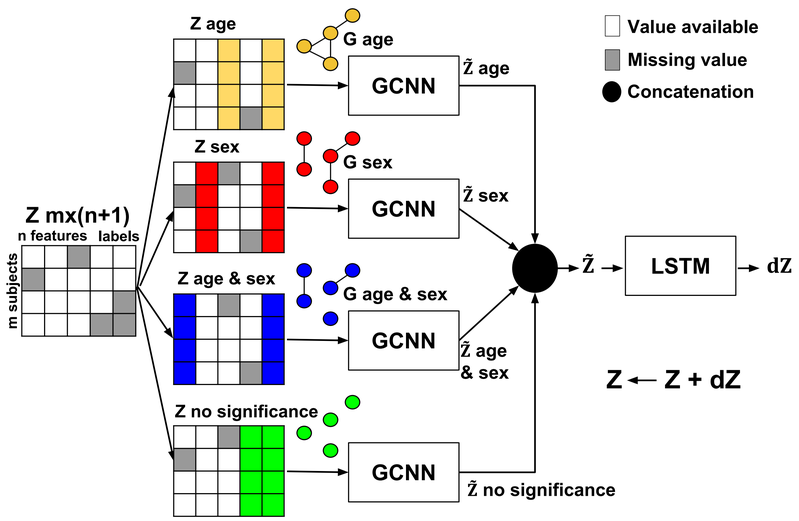


- Build the identified **graphs**.

  Application to AD: creation of $\mathcal{G}_{age}$, $\mathcal{G}_{sex}$ and $\mathcal{G}_{age\&sex}$.

- **Optimization problem**: try to form an estimate Z of $[M, Y]$ that:

1. is **faithful** to the input data;
2. is **smooth** with respect to the identified **graphs**;
3. achieves **good classification** error on a training/validation set.



Graph Convolutional Neural Network [1]: Feature values should be **more closely related to those of people of the same sex/age**. Learn features, do smoothing with respect to the graph.

Long-Short Term Memory: determines a **suitable dZ in the direction of the gradient of the optimization function**.

Results

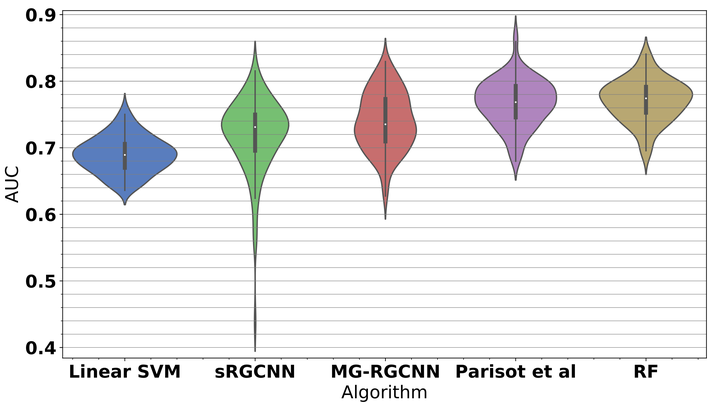
- TADPOLE dataset : Matrix composed of **medical examinations** from several modalities (MRI, PET, CSF and DTI). Missing data: 21%.

Task: Classification of **779 MCI** subjects between:

- **MCI converters**: Patients that have **converted to AD before 48 months from first time diagnosed as MCI**.
- **MCI non converters**: Patients that remained stable and do not **convert to AD in the course of the study**.

Split train/validation/test set: 60%/20%/20%.

- **Performance Metric** : Integral of ROC (Receiver Operating Characteristic) : AUC (Area Under The Curve).
- ROC measures the true positive rate achieved for a specific false positive rate. AUC ranges from 0 to 1, with 1 being the best.



Comparison of the violin plots of the test AUC

Main Outcomes & Future work

- Demonstration that **different features behave differently** and that a change in the graph structure can be useful.
- **Improvement of 2% in the mean AUC** compared to the results of Vivar et al. [3].
- **Outperformed** by Random Forest and Parisot et al. [2]. Performance difference due to the **size of the dataset** and the **number of missing values** that is not enough to interfere with the classification results.
- Applying MG-RGCNN to datasets with more missing values.
- Applying MG-RGCNN to predict other disease outcomes.

References

[1] M. Defferrard, X. Bresson, and P. Vandergheynst, "Convolutional neural networks on graphs with fast localized spectral filtering," in *Proc. Advances Neural Inform. Process. Syst.*, 2016.

[2] S. Parisot et al., "Spectral graph convolutions for population-based disease prediction," in *Proc. Int. Conf. Medical Image Computing and Comput-Assisted Intervention*, 2017, pp. 177–185.

[3] G. Vivar, A. Zwergal, N. Navab, and S.-A. Ahmadi, "Multi-modal disease classification in incomplete datasets using geometric matrix completion," in *Proc. Int. Workshop Graphs Biomedical Image Analysis (GRAIL)*, Granada, Spain, Sept. 2018, pp. 24–31.