Diploma thesis

LINKING CONNECTIVITIES AND GENE EXPRESSION PATTERNS IN MICE BRAINS

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proper title?

Abstract

Contents

1 Introduction

General thread for introduction and motivation:

- Gene expression patterns are difficult to analyze in humans → take mouse as model organisms
- The brain is a multi-level system in which the high-level functions are generated by low-level genetic mechanisms. Thus, elucidating the relationship among multiple brain levels via correlative and predictive analytics is an important area in brain research. Currently, studies in multiple species have indicated that the spatiotemporal gene expression patterns are predictive of brain wiring. Specifically, results on the worm Caenorhabditis elegans have shown that the prediction of neuronal connectivity using gene expression signatures yielded statistically significant results.
- no in-depth analysis of mouse brain genetic patterns and their relation to different connectivity patterns has been made yet
- we analyze
- studies have shown circadian patterns of gene expression in human brain and the disruption of those in depressive disorder [Li et al., 2013]
- [Twine et al., 2011] show the importance of gene expression patterns, by linking gene expression abberation with increase in Alzheimer's disease

General Introduction of the Research Study

Research problem or Questions with Sub-Questions

Reasons or Needs for the Research Study/Motivation for my research

Definition and explanation of Key Terminology

Context of Research Study within th Greater Discipline

- Introduction to mouse brains as model organisms for insights into human brain
- Works on mouse brain in general and potential tasks
- works on gene expression in mouse brains
  - traditional approaches
  - importance of gene expression patterns in mouse brains
- neural networks for this purpose
  - how were
- gene expression for general tissue

2 Literature overview

2.1 Gene expression prediction

- [Lee and Lee, 2020] train classifiers using blood gene expression data in order to predict Alheimer's disease in Humans

2.2 Finding spatial patterns in gene expression in mice brains

- Sparked by the Lein et al. [2006]
- [Zapala et al., 2005] is among the earliest works, showing that local structures beared "transcriptional imprint" that coincide with the embryological origin of the examined regions. However, they only were able to identify up to 24 neural tissues. They further conclude that this may be important for functional collaboration within the adult mouse brain.
- Have GCNs be applied before here?
- usage of ontologies?
  - functional graph [Valk et al., 2020]
  - structural ontology?
  - developmental ontology

How to deviate from [Partel et al., 2020]

2.3 Approaches to dimensionality reduction and their application

- Brief Overview of theoretical Foundations Utilized in the study

2.4 Structural and functional connectivity prediction

Structural/Axonal connectivity

- [Fakhry and Ji, 2015] predict axonal connectivity from gene expression patterns in mice brain with an accuracy of 93%
- [Roberti et al., 2019] use transcriptomic information to anatomical connectivity patterns and gene expression of neurons using (shallow) neural networks. Yield a 85% accuracy in prediction of unconnected and connected regions.
- experimental setup from Allen Institute for axonal projection data
- paraphrase description of „Technical tour: Explore the Allen Mouse Brain Connectivity Atlas"

Functional connectivity

- [Whitfield et al., 2003] were one of the first to link transcriptomic data with behavior and hence functional patterns in individual honey bees back in 2003. The authors show that changes in the messenger RNA were connected to behavior.
- [Rankin, 2002] first developed the idea of combining behavioral analyses of *Caenorhabditis elegans* with their genetics. Further, [Sun and Hobert, 2021] only recently described the distinct functional states and the corresponding distinct molecular states within the transcriptome. While honey bees and nematodes are rather simple model organisms, enabling both full transcriptomic analyses

of the organisms, and their bearing and actions. However, "behavior" may be ambiguous and vague for such taxonomically distant animals, from the viewpoint of humans, and may only be linked to very basic meta-tasks such as basic routing, orientation and basic social interaction.

- Why do we not directly investigate gene expression patterns in human brains?
  - only few data points are given for the entirety of the human brain, while spatial decomposition and partitioning is crucially more complex.
- [Wang et al., 2022] recently proposed a novel-network based method integrating molecular-based gene association networks such as protein-protein interaction networks with brain connectome data. They further link these gene expression patterns to four brain diseases, including Alzheimer's disease, Parkinson's disease, major depressive disorder and autism.
- Where is data coming from? [Pallast et al., 2019]
- How to calculate functional connectivity matrix → AIDAconnect (no paper yet? cite dataset?
- How to combine functional connectivity for multiple samples?
- [Zerbi et al., 2021]

Brief Overview of LIterature Reviewed, Discussed and applied

Study Model and Process Aligning with literature reviewed

Hypotheses and justifications tied to prior sections and statements

The Scope of the study with theoretical assumptions and limitations

To be searched

- read across citations of DeepMOCCA/Takata et al. [2021]
- find other papers on
  - gene expression patterns within mouse brain and both possible hypothesis and tasks, and models over this
  - gene knockout models and whether they can learn propagation of those?
  - connection of FC and gene expression patterns and how to prove such interaction/correlation?
  - possible gene knockout targets within mouse brain and possible structural influences

To be sorted somewhere

- Variability and different interpretations of different graph convolutional neural filters [Kipf and Welling, 2016, Li et al., 2020, Hamilton et al., 2017] etc.
- Guilt by association over gene networks [Oliver, 2000, Gillis and Pavlidis, 2012]
- protein function prediction from PPI networks [Vazquez et al., 2003]
- DeepGOPlus for feature generation [Kulmanov and Hoehndorf, 2019]
- discussion of DeepMocca by Sara [Althubaiti et al., 2021]
- discussion of different PPI network databases [Szklarczyk et al., 2014]

- discussion of potential databases associating gene expression data with their spatial distribution [Hawrylycz et al., 2011]
- discussion of best neural learning/graph convolutional methods [Paszke et al., 2019, Fey and Lenssen, 2019]
- how to handle highly imbalanced data, metrics, preprocessing, sampling, modification of loss function [Jeni et al., 2013] and optimization over them (with Adam[Kingma and Ba, 2015])
- maybe introduction of PhenomeNET for MP/GO for more sophisticated protein representation [Hoehndorf et al., 2011, Ashburner et al., 2000, Carbon et al., 2020, Smith and Eppig, 2009] and derive features from DL2vec [Chen et al., 2020, Mikolov et al., 2013]
- evaluation of „Using ontology embeddings for structural inductive bias in gene expression data analysis"[Trebacz et al., 2020]
- take some ideas from Zitnik and Leskovec [2017] with title „Predicting multicellular function through multi-layer tissue networks". (OhmNet)
- potentially group results based on InterPro[Blum et al., 2020] families eventually
- RayTune[Liaw et al., 2018] for automated hyperparameter tuning

Spatial patterns of gene expression

Data discussion, hypotheses and traditional approaches:

- [noa]
- Possible effects of rabies virus on gene expression[Prosniak et al., 2001] for potential knockout targets
- Review paper on regional variation in gene expression in mouse brain [Pavlidis and Noble, 2001]

Modern approaches on learning from gene expression patterns in mouse brain:

- Deep learning methods for capturing spatiality w.r.t. gene expression withing the brain [Zeng et al., 2015]
- R package for simulating gene expression from graph structures over general biological pathways [Kelly and Black, 2020]

  Read this

3 Materials and methods

In this study, we utilized and incorporated various approaches from other works and applied them to diverse datasets. The following section will give a brief overview over all modules of the proposed model, while the combined method will be presented and described in the results section (Section 4).

Introduction and general description, study method and study design

3.1 Problem description

Here we give a brief introduction to each of the three tackled issues and further summarize data properties, challenges and goals of each problem.

3.1.1 Spatial gene expression prediction

Firstly, the issue of gene expression prediction

3.1.2 Dimensionality reduction in mice brains

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3.1.3 Structural and functional connectivity prediction

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Assumptions of study method and study design with implied

3.2 Datasets

in-depth description of the study design/datasets used and motivation why they were used for these experiments

Explanation of Sample used in the study

- show distribution (histo, mean, median, boxplot?) of expression densities see 'get_ge_structure_mat'
- how to normalize expression intensity (see discussion in DeepMOCCA paper, Sara Alghamdi), as there are regions with much more activity than others (e.g. bone narrow vs. bone boarder); thresholds for intensity varies across genes
  - over all intensities →
  - per structure →
  - per gene →
- why were these datasets used and not others?
- How did we achieve the matching?
- what are premises of the dataset?
- transfer learning working for other structure/regions
- dataset: Allen Mouse brain atlas vs.
  - phenoview impc data
  - mousephenotype

  - HPO/MP project expression data

- Allen mouse brain atlas [Lein et al., 2006]
  - discussion on different normalization schemes
- STRING for PPI network and how we chose suitable interactions [Szklarczyk et al., 2014]

Four graphs were used in this study:

- Protein-protein interaction graph from STRING
- structure hierarchy/ontology from [Lein et al., 2006]
- structural connectivity data from (Mouse Projection data)
- functional connectivity data from [Pallast et al., 2019]

3.3 Model

Explanation of Measurement, Definitions, Indexes, Reliabililty and Validity of study method and study design

Description of Analytical Tehcniques to be Applied and justification for them

Reliability and validity of internal/external design and related subtypes

3.3.1 Feature generation

Data preparation for regression task

- unbalanced data for prediction task

3.3.2 Graph convolutional neural layers

We include these molecular and ontology-based sub-models within a graph neural network (GNN) [Kipf and Welling, 2016]. The graph underlying the GNN is based on the protein–protein interaction (PPI) graph. The PPI dataset is represented by a graph $G = (V, E)$, where each protein is represented by a vertex $v \in V$, and each edge $e \in E \subseteq V \times V$ represents an interaction between two proteins. Additionally, we introduce a mapping $x : V \to \mathbb{R}^d$ projecting each vertex v to its node feature $x_v := x(v)$, where d denotes the dimensionality of the node features.

A graph convolutional layer [Kipf and Welling, 2016] consists of a learnable weight matrix followed by an aggregation step, formalized by

$$\mathbf{X}' = \hat{\mathbf{D}}^{-1/2}\hat{\mathbf{A}}\hat{\mathbf{D}}^{-1/2}\mathbf{X}\mathbf{\Theta} \tag{1}$$

where for a given graph $G = (V, E)$, $\hat{A} = A + I$ denotes the adjacency matrix with added self-loops for each vertex, D is described by $\hat{D}_{ii} = \sum_{j=0} \hat{A}_{ij}$, a diagonal matrix displaying the degree of each node, and Θ denotes the learnable weight matrix. Added self-loops enforce that each node representation is directly dependent on its own preceding one. The number of graph convolutional layers stacked equals the radius of relevant nodes for each vertex within the graph.

The update rule for each node is given by a message passing scheme formalized by

$$\mathbf{x}'_i = \mathbf{\Theta} \sum_{j}^{N} \frac{1}{\sqrt{\hat{d}_j \hat{d}_i}} \mathbf{x}_j \tag{2}$$

where both $\hat{d}_i, \hat{d}_j$ are dependent on the edge weights e_{ij} of the graph. With simple, single-valued edge weights such as $e_{ij} = 1 \; \forall (i,j) \in E$, all $\hat{d}_i$ reduce to d_i, i.e., the degree of each vertex i. We denote this type of graph convolutional neural layers with GCNConv.

While in this initial formulation of a GCNConv the node-wise update step is defined by the sum over all neighboring node representations, we can alter this formulation to other message passing schemes. We can rearrange the order of activation function σ, aggregation AGG, and linear neural layer MLP with this formulation as proposed by [Li et al., 2020]:

$$\mathbf{x}'_i = \text{MLP}\left(\mathbf{x}_i + \text{AGG}\left(\{\sigma\left(\mathbf{x}_j + \mathbf{e_{ji}}\right) + \epsilon : j \in \mathcal{N}(i)\}\right)\right) \tag{3}$$

where we only consider $\sigma \in \{\text{ReLU}, \text{LeakyReLU}\}$. We denote this generalized layer type as GENConv following the notation of PyTorch Geometric [Fey and Lenssen, 2019]. While the reordering is mainly important for numerical stability, this alteration also addresses the vanishing gradient problem for deeper convolutional networks [Li et al., 2020]. Additionally, we can also generalize the aggregation function to allow different weighting functions such as learnable SoftMax or Power for the incoming signals for each vertex, substituting the averaging step in GCNConv. Hence, while GCNConv suffers from both vanishing gradients and signal fading for large scale and highly connected graphs, each propagation step in GENConv emphasizes signals with values close to 0 and 1. The same convolutional filter and weight matrix are applied to and learned for all nodes simultaneously. We further employ another mechanism to avoid redundancy and fading signals in stacked graph convolutional networks, using residual connections and a normalization scheme [Li et al., 2019] [Li et al., 2020] as shown in Supplementary 3. The residual blocks are reusable and can be stacked multiple times.

- what is GATConv?
- what is KerGNN and what is its idea?
- add some sentences to the section above

3.3.3 Dimensionality reduction techniques

3.3.3.1 Principal component analysis

3.3.3.2 tSNE

3.3.3.3 UMAP

3.3.3.4 Parametric UMAP

3.3.4 Combined prediction model

3.3.5 Hyperparameter tuning

3.4 Evaluation and metrics

- self-build metric for evaluation

4 Results

4.1 Gene expression prediction

- We originally started from the per section prediction in order to paste its performance and results to other "related" structures within in the mouse brain. We propose multiple ideas ….. As mentioned we used three different feature types in this study. …(molecular features, phenotypical features, pure taxonomic features (InterPro embedding))) …Due to the poor performance of the predictor with all three used feature types, we abandoned these plane
  - –
- structure specific features?
  - structural ontology / closeness
  - developmental hierarchy of tissue

Our model also allows us to test different ways of representing omics data. We tested different ways to normalize values assigned to genes as these normalizations convey different biological information; in the matrix of values assigned to genes from cancer samples, we can normalize values across the entire matrix, across each row (cancer sample), or across each column (gene). While a global normalization is more common, row-based normalization allows us to highlight values that are significantly higher or lower within one sample (e.g., which genes are expressed at high or low levels within a single sample), and column-based normalization allows us to highlight values assigned to a particular gene that are significantly higher or lower within one sample (e.g., whether a gene is expressed at higher or lower levels within one sample compared to all others). We find that column-based normalization performs better than row-based normalization, while the global normalization approach performs close to random. The best results are achieved when combining both row- and column-based normalization (Supplementary Table 2).

4.2 Dimensionality reduction and its combination with different graphs structures

- plot for showing validity of embeddings: K-means colour with respect to cluster
- plot colour parent structure all similar

4.3 On the linkage of connectivities and gene expression patterns

Brief Overview of Material

Findings (Results) of the Method of Study and Any Unplanned or Unexpected Situations that Occurred

Brief Descriptive Analysis Reliability and Validity of the Analysis

Explanation of the Hypothesis and Precise and Exact Data (Do Not Give Your Opinion)

5 Discussion

Brief Overview of Material

Full Discussion of Findings (Results) and Implications

Full Discussion of Research Analysis of Findings

Full Discussion of Hypothesis and of Findings

Post Analysis and Implications of Hypothesis and of Findings

6 Conclusion

Summary of Academic Study

Reference to Literature Review

Implications of Academic Study

Limitations of the Theory or Method of Research

Recommendations or Suggestions of Future Academic Study

- gene expression patterns within mouse brain and both possible hypothesis and tasks, and models over this
- gene knockout models and whether they can learn propagation of those?
- connection of FC and gene expression patterns and how to prove such interaction/correlation?
- possible gene knockout targets within mouse brain and possible structural influences

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