Uncovering the saliency of local topological features for Alzheimer's disease characterisation

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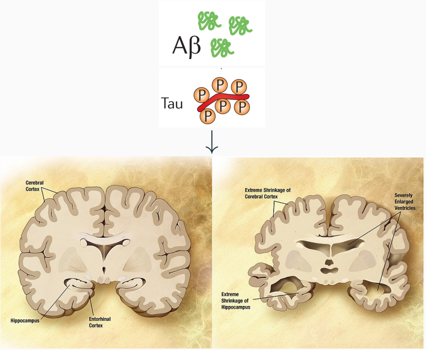
Alzheimer's disease

Alzheimer's disease: 🧠

- Nearly 40 million people live with AD
- Cost in US alone $ 2 trillion by 2030
- Among leading causes of death in EU



Images adapted from Ittner et al and Wikipedia

Topology: 🍩 ☕

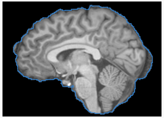
- Concerned with "properties of a geometric object that are preserved under **continuous deformations**, such as [...] crumpling."
- Recently, *persistent homology* has emerged to quantify (differences in) the shape of data.
- **How can we apply persistent homology to quantify changes in shape due to Alzheimer's disease?**

Topology in AD - Research Avenues

1. **Classification**
2. Subtype identification
3. Progression & forecasting

Analysis setting

Unprocessed



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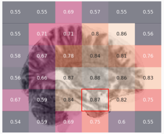
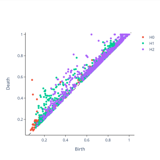
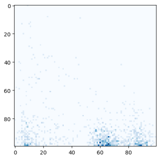


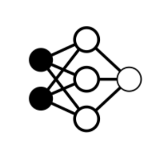
Patch selection



Persistence homology



Persistence Image



Classification

Images adapted from Wikimedia, slicer.org, and Sachin Modgekar

Analysis setting

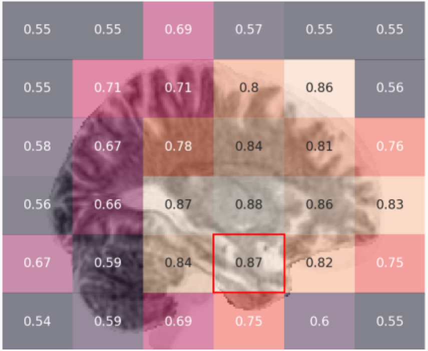
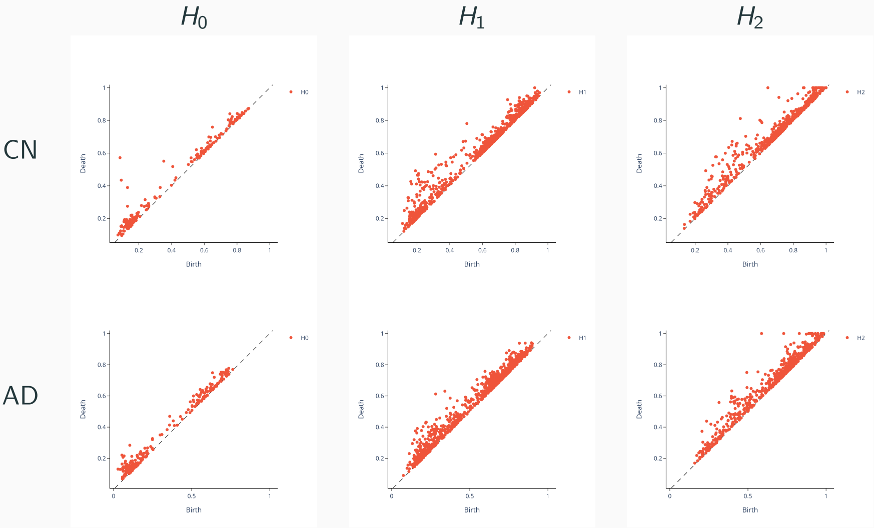
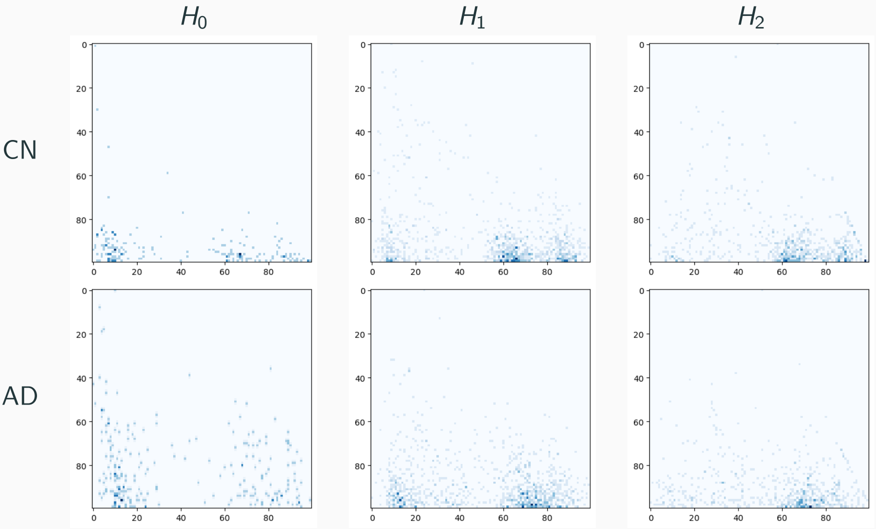


Figure 2: AUPRC on each patch, achieved using a model described in earlier work. Chosen patch for analyses is boxed in red (patch with highest accuracy).

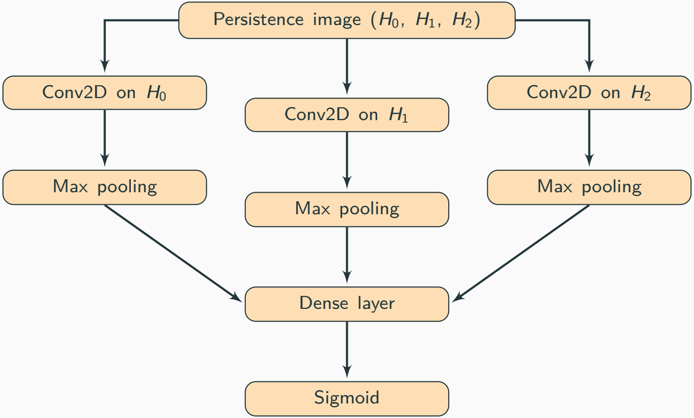
I - Persistent homology



I - Classification - Persistence Images



I - Classification - Network architecture



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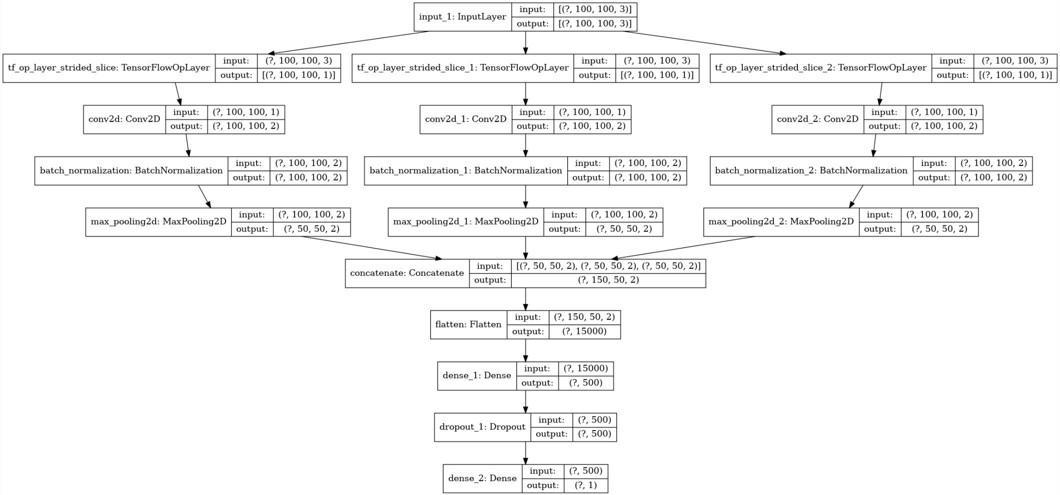


Methodological considerations

- 4 fold CV, 3 inits. Stratified for age, diagnoses and no patients are spread over folds.
- Same experimental settings as from Brüningk, Sarah C *et al* `https://arxiv.org/abs/2011.06531`

I - Classification - Performance

Local	**PI**	3D Conv	
Global			PI
Validation accuracy	0.79 ± 0.02	0.85 ± 0.06	0.76 ± 0.02
Precision	0.81 ± 0.04	0.87 ± 0.04	0.74 ± 0.02
Recall	0.81 ± 0.02	0.87 ± 0.08	0.88 ± 0.08
AUC	0.85 ± 0.03	0.89 ± 0.05	0.78 ± 0.02

Table 1: Performance metrics of the different models trained on the same data.
Metrics from Brüningk, Sarah C *et al* `https://arxiv.org/abs/2011.06531`.

→ Local PI training time is 2 minutes on a **laptop CPU**. Very efficient compression of features!
→ Local 3D Conv training takes 15 minutes on a **server GPU**.
Persistent homology produces **highly salient compressed** features for AD characterization.

Limitations & Outlook 🗺️

Limitations:

- Using **raw** images is **better**, but more **expensive**.
- Does not take atrophy from **other regions** into account

directions:

- Can persistent homology be used to diagnose **prodromal** forms of AD?
- Use a similar approach for **subtype identification**.

Thanks!

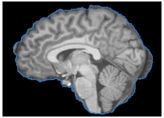
GitHub repository of the project (currently available upon request)

`github.com/pjhartout/TDA_ADNI_MLCB`

With thanks to Bastian Rieck for the supervision and Sarah Brueningk, Felix Hensel, Catherine Jutzeler, Merel Kuijs and Louis Lukas for insightful discussions, code, and data.

Questions?

Unprocessed



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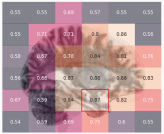

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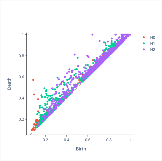
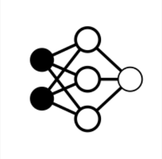
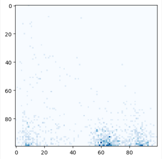


Persistence homology



Classification



Persistence Image

Images adapted from Wikimedia, slicer.org, and Sachin Modgekar