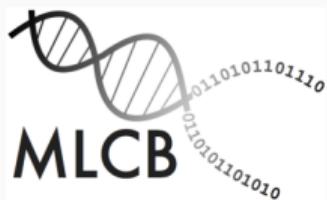


# Uncovering the saliency of local topological features for Alzheimer's disease characterisation

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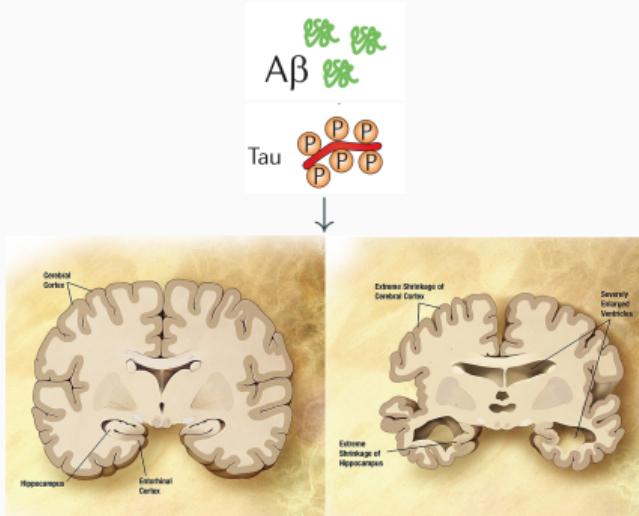


DBSSE

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## 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

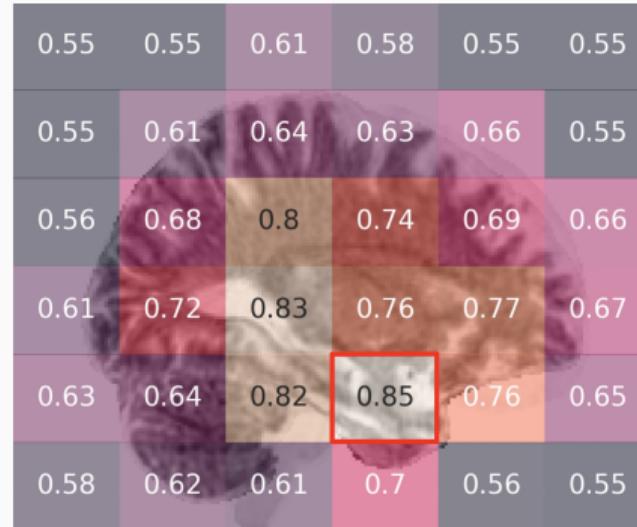
## Topology:

- Concerned with “properties of a geometric object that are preserved under **continuous deformations**, such as [...] crumpling.”
- Recently, *persistent homology* has emerged as a way to quantify 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

## Determining the patch of interest



**Figure 2:** The patch with the highest accuracy was selected. Results from Brüningk, Sarah C et al  
<https://arxiv.org/abs/2011.06531>

## Obtaining topological features from sMRI data

- We use the T1-weighting value (fat  $\approx 1$ ; water  $\approx 0$ ) to compute topological features
- Filtration of point clouds:

**Figure 3:** Point cloud filtration. Adapted from [giotto-ai.github.io/gtda-docs/](https://giotto-ai.github.io/gtda-docs/)

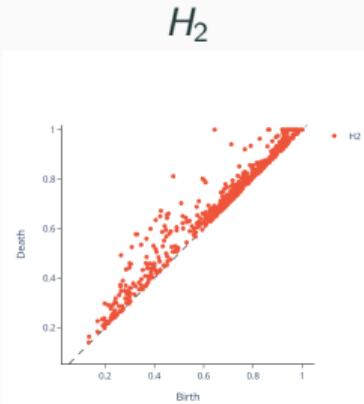
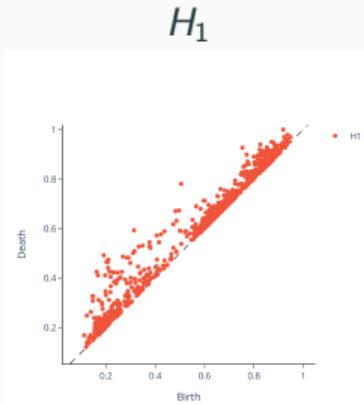
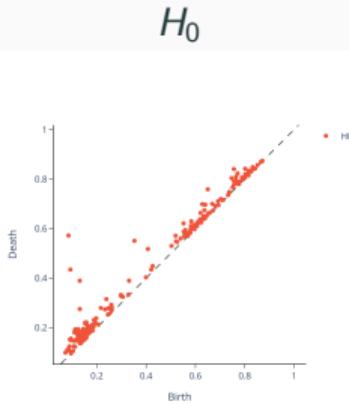
## Obtaining topological features from sMRI data

- We use the T1-weighting value (fat  $\approx 1$ ; water  $\approx 0$ ) to compute topological features
- Filtration of cubical complexes to examine the connected components, cycles, and voids.

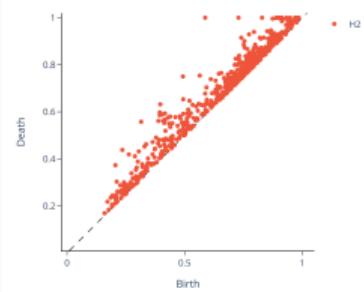
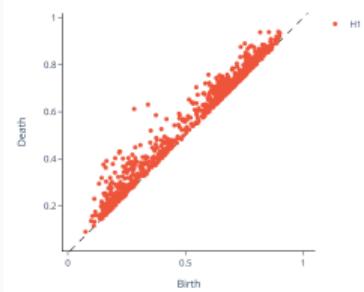
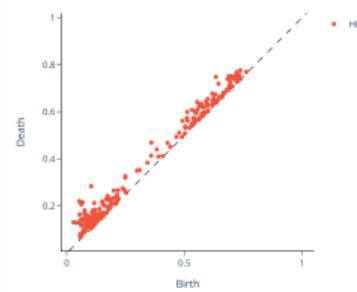
**Figure 4:** Cubical complex filtration. Adapted from Bastian Rieck <https://youtu.be/4mBcwy1t0J4>

# I - Persistent homology

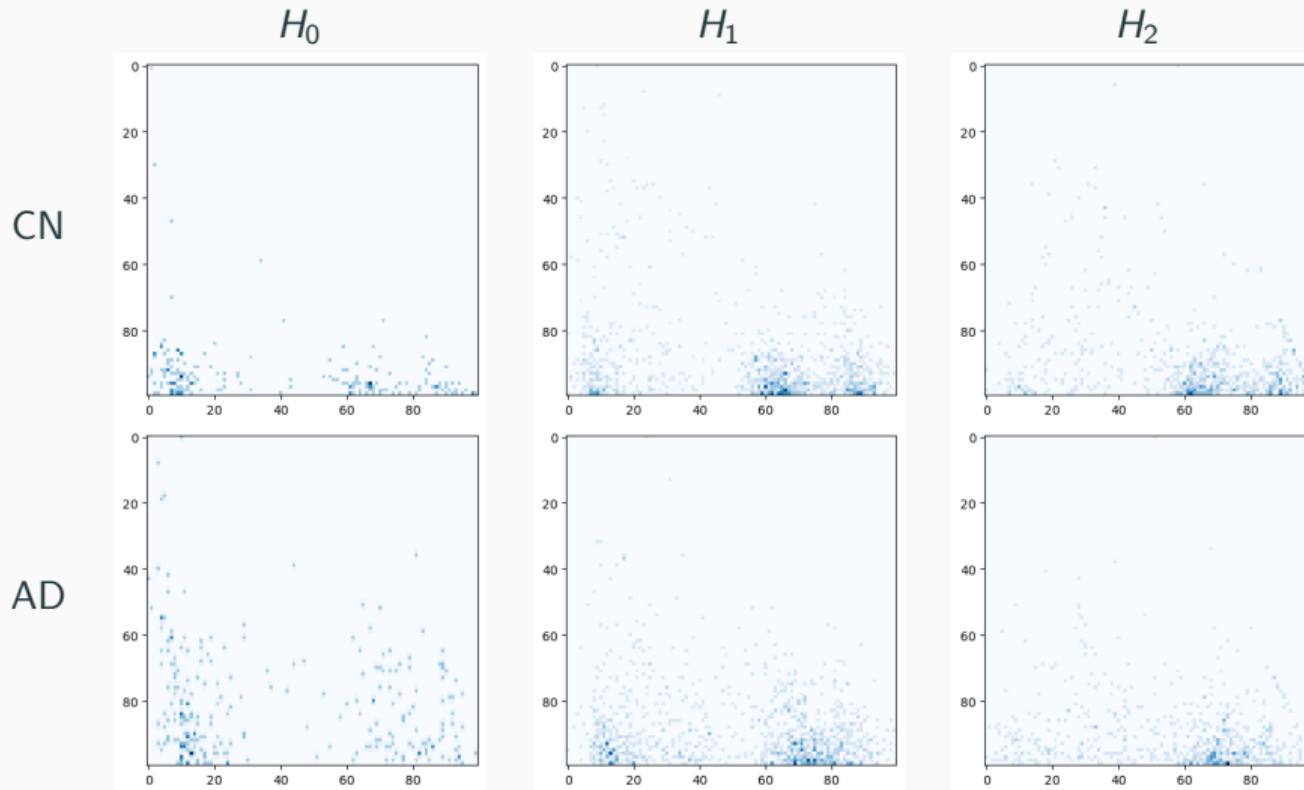
CN



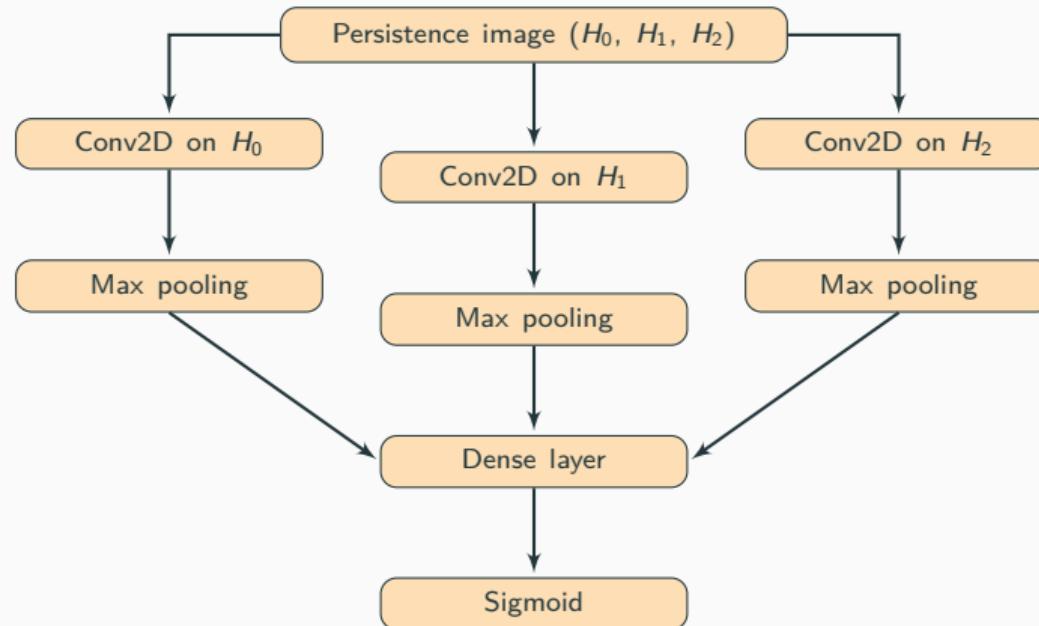
AD



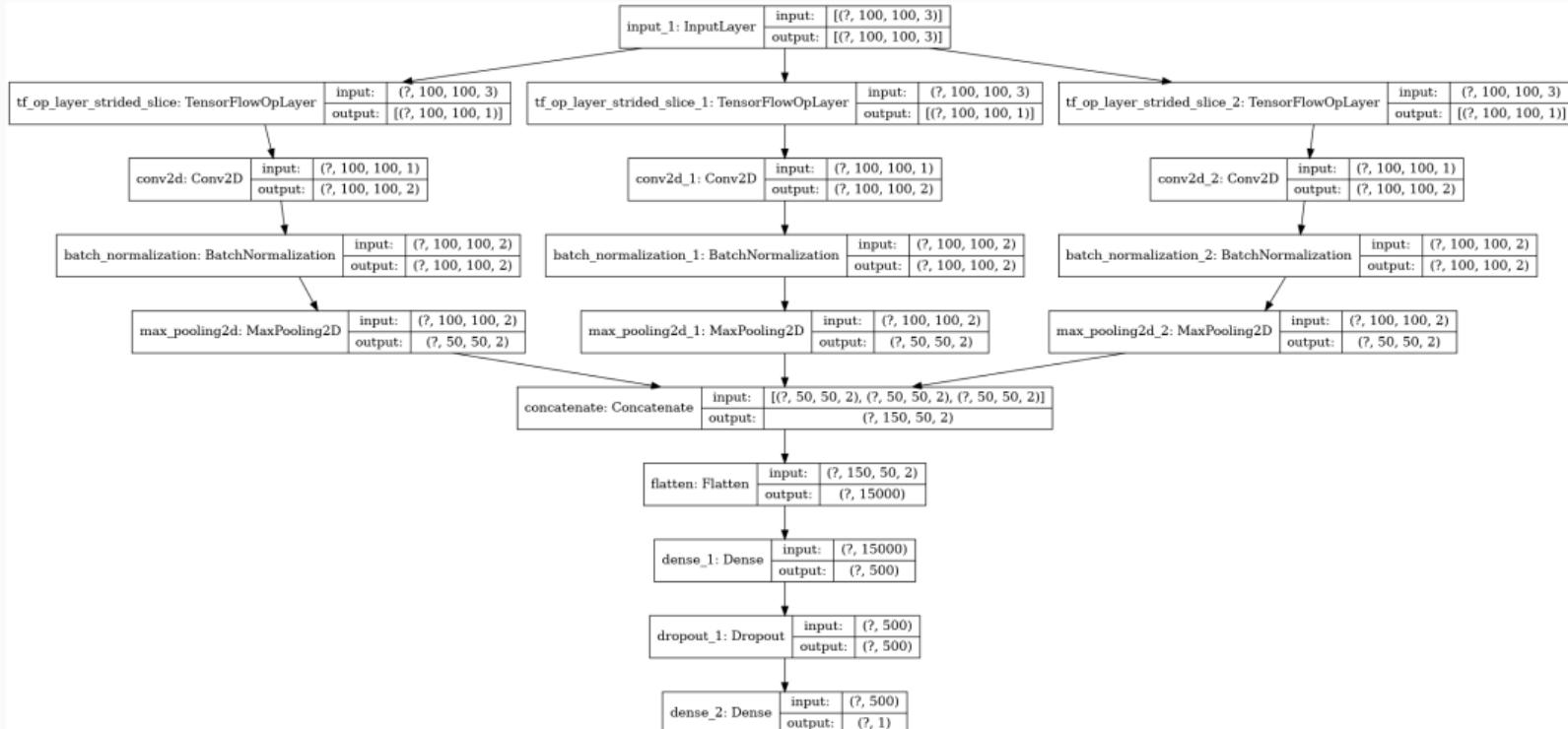
# I - Classification - Persistence Images



# I - Classification - Network architecture



# I - Classification - Network architecture



## Methodological considerations

- 4 fold CV, 3 inits. Stratified for age, diagnoses and patients spread over folds.
- Same settings as in Brüningk, Sarah C *et al* <https://arxiv.org/abs/2011.06531>

## I - Classification - Performance

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

**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 3D Conv training takes 15 minutes on a **server GPU**.

→ Local PI training time is 2 minutes on a **laptop CPU**.

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

Future directions:

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

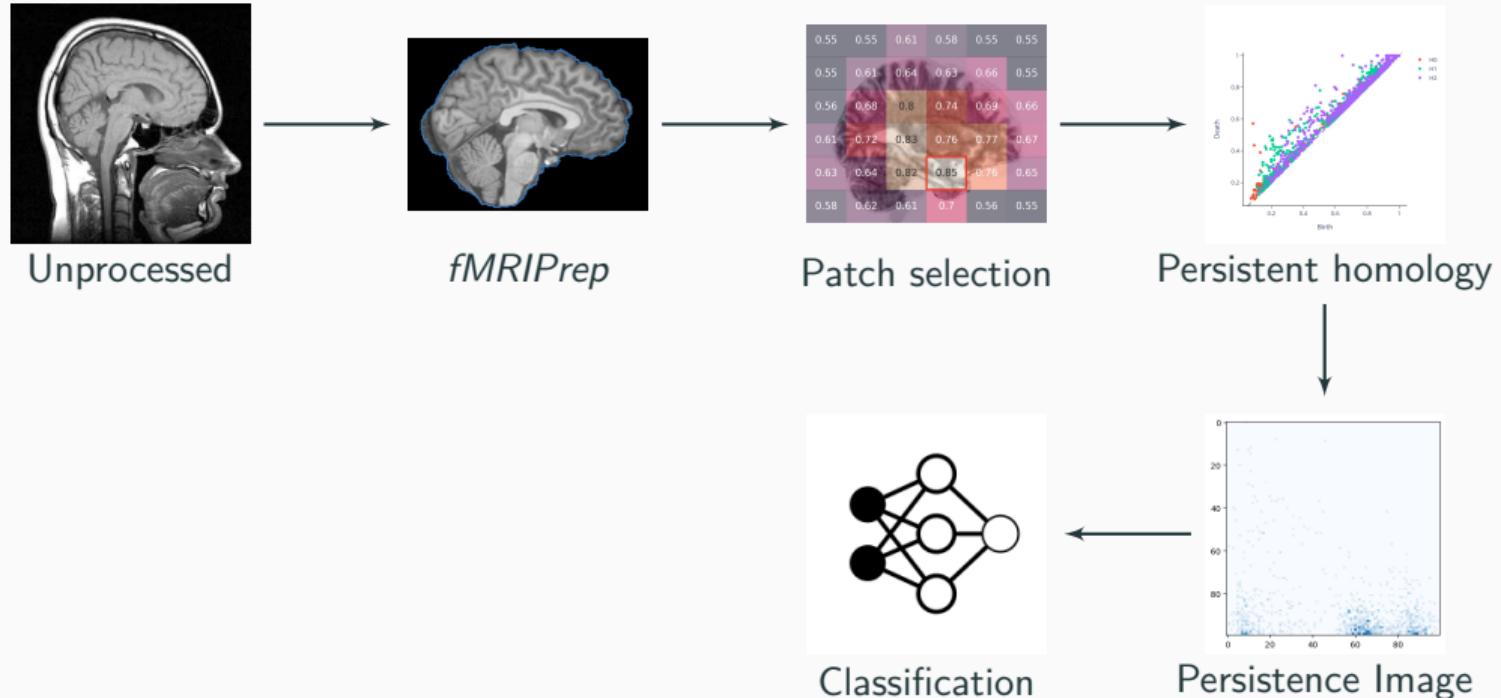
# Thanks!

GitHub repository of the project (currently available upon request)

[github.com/pjhartout/TDA\\_ADNI\\_MLCB](https://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 & Karsten Borgwardt for providing the research setting.

# Questions?



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