Automatic decoding of White Matter Lesion spatial distribution patterns

Tatiana Miller[1,2], Nora Bittner[1,2], Paulo Dellani [2], Julian Quabs[1,2], Svenja Caspers[1,2]

[1] Institute for Anatomy I, Medical Faculty & University Hospital Düsseldorf, Heinrich Heine University, Düsseldorf, Germany
[2] Institute of Neuroscience and Medicine (INM-1), Research Centre Jülich, 42425 Jülich, Germany

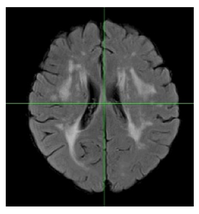
millerfl@hhu.de

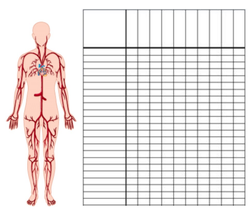
INTRODUCTION

We **aim to automatically decode distinctive White Matter Lesions (WML) spatial distributions** and characterize typical distribution patterns in subjects of large population-based cohorts.

METHODS

Data:
- *MR Imaging*
- *Age*
- *Sex*
- *Blood Pressure*
- *Diabetes diagnosis*
- *Smoking*
- *Cholesterol*

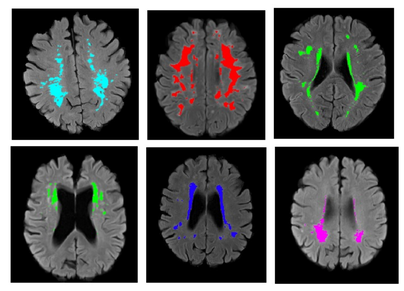




n = 1,052 (age range 18-87)

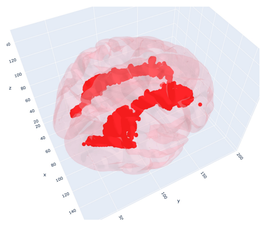
n = 27,769 (age range 19-74)

Data Processing:
- WML segmentation (BIANCA)
- Total amount of WML
- Cardiovascular Age Score



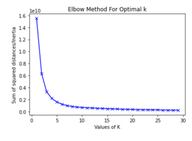
Algorithm:

1- Extraction of **3D lesion matrix**

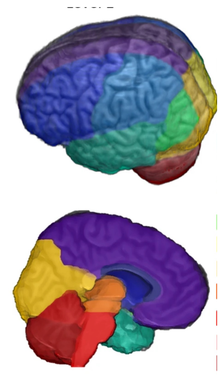


2- **Feature extraction:**
- Center of lesion mass
- Total amount of WML
- Cardiovascular Age Score

3- **Clustering analysis:**
- K-means (scikit-learn library)
- Elbow method



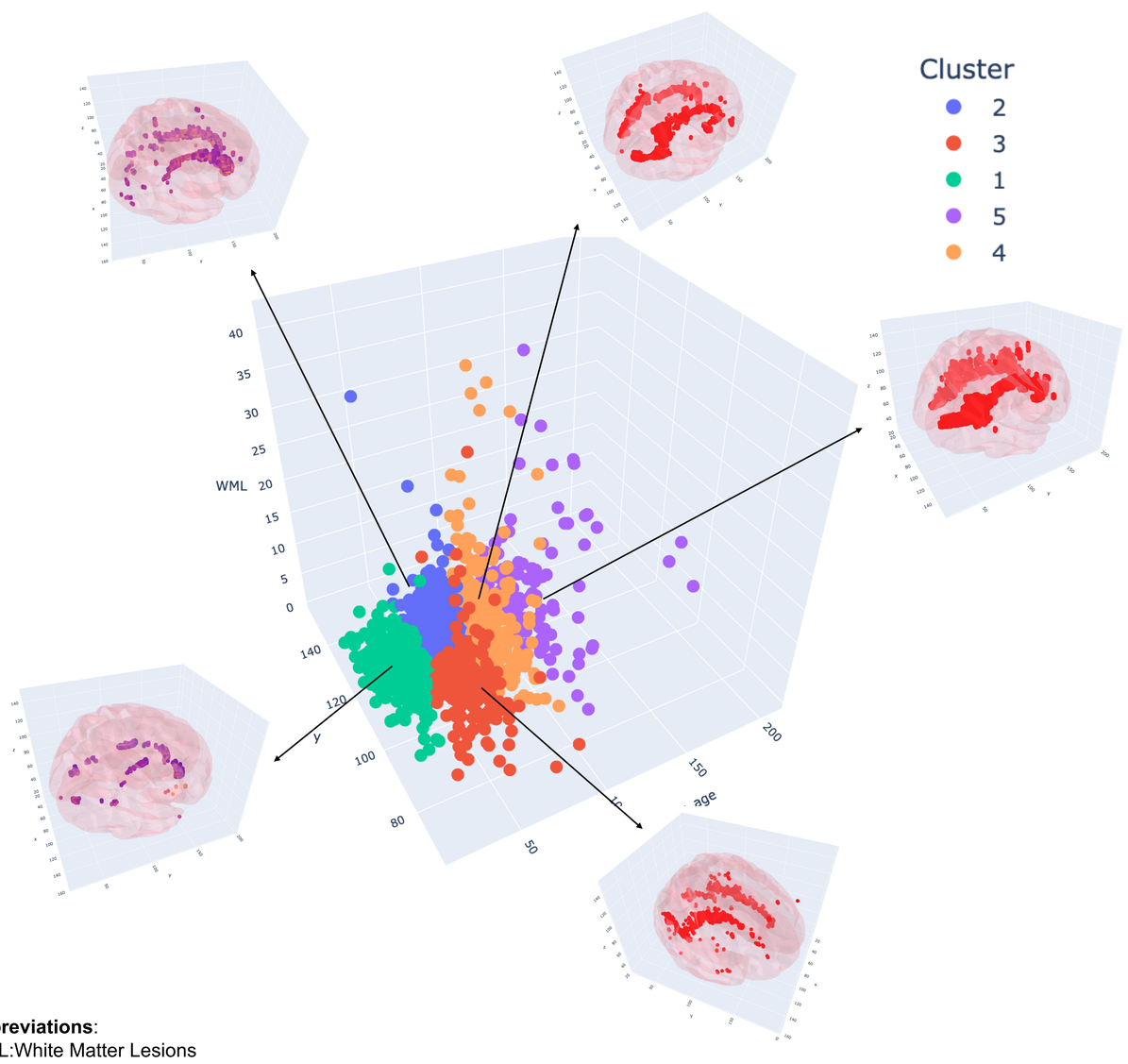
4- **Clustering characterization:**
- Tested the mean WML distribution surpassing 95% bootstrap confidence in 30 arterial territories of the Digital 3D Brain MRI Arterial Territories Atlas



RESULTS

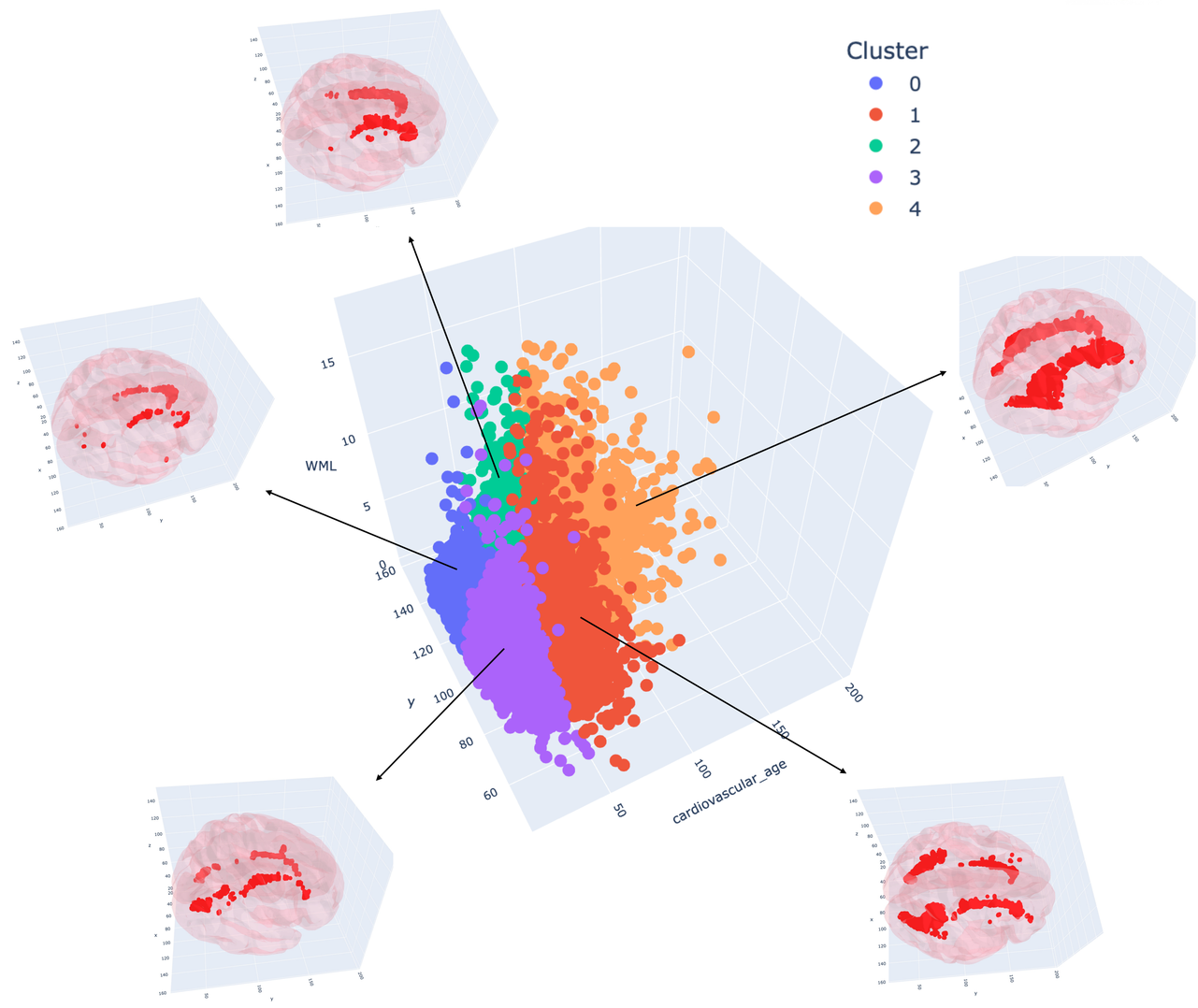
K = 5
n = 1,052

WML spatial distributions: 1000BRAINS



K = 5
n = 27,769

WML spatial distributions: NAKO



Abbreviations:
WML:White Matter Lesions

CONCLUSION

- By combining neuroimaging data, demographics and cardiovascular risk factors we were able to extract 3 features to automatically identify different WML spatial distributions in two independent cohorts.
- We identified spatial patterns that exhibit varying degrees of WML accumulation in specific arterial territories, providing valuable insights of the WML spatial distribution in relation to the subject's cardiovascular health.

Literature
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