

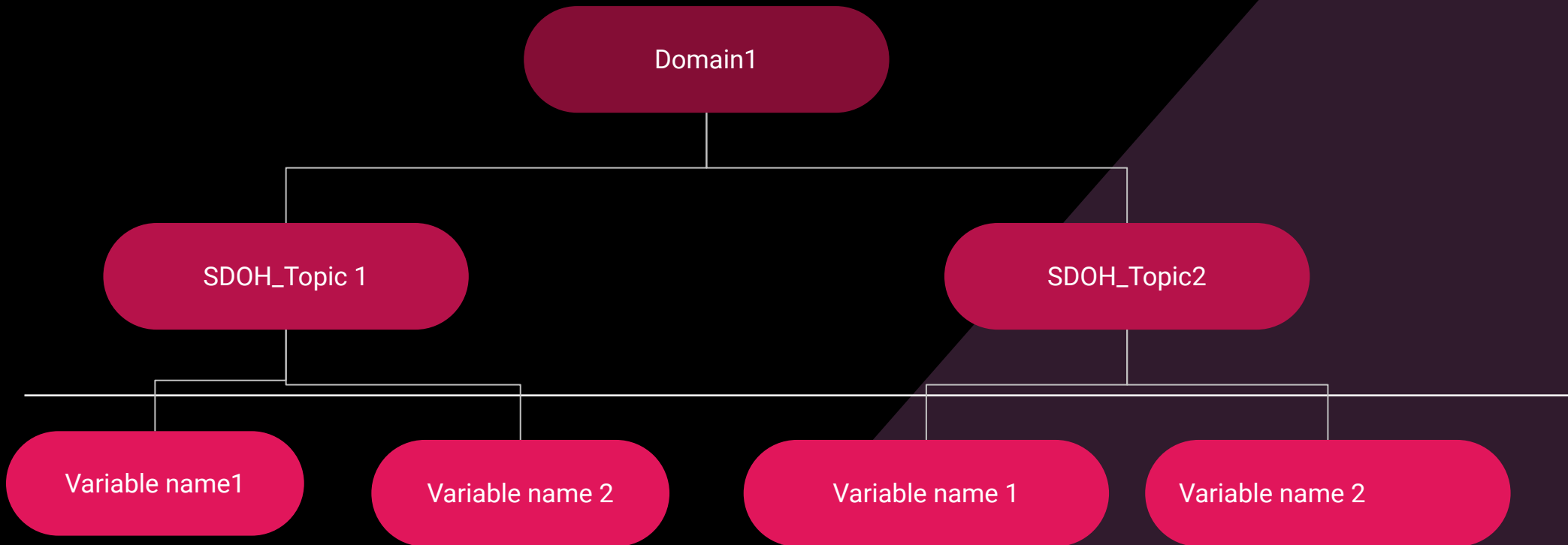
EDA AND PATTERNS OF MISSINGNESS IN SDOH for the EMORY CXR

Team 5 - CXR Dataset

Ali Aslam
Anudeep Errabelly
Enamul Hoq
Zeph Kaffey
David Nyarko
Chiratidzo Sanyika
Veera Venkata Satyavathi
Enzo Ferrante

SOCIAL DETERMINANTS OF HEALTH (SDOH)

- Social factors allocated according to zip code
- 44 sources
- 8 categories (domains)



SO MANY IDEAS

Merge SDOH, metadata, findings



Emeddings



But....



- We discovered there are a lot of missing data in the SDOH dataset



We decided to redirect our plan and
focused on

Characterizing the fingerprint of “missingness”
in the SDOH Dataset

+

Creating embeddings to allow for easier analysis

Why focus on EDA?

- You cannot start running analysis on a dataset that is not well understood
- Patterns of missingness could lead to underrepresenting some groups and therefore sample bias
- Embeddings allow for easier analysis such as model training, and clustering identifies potential shortcuts for classification models



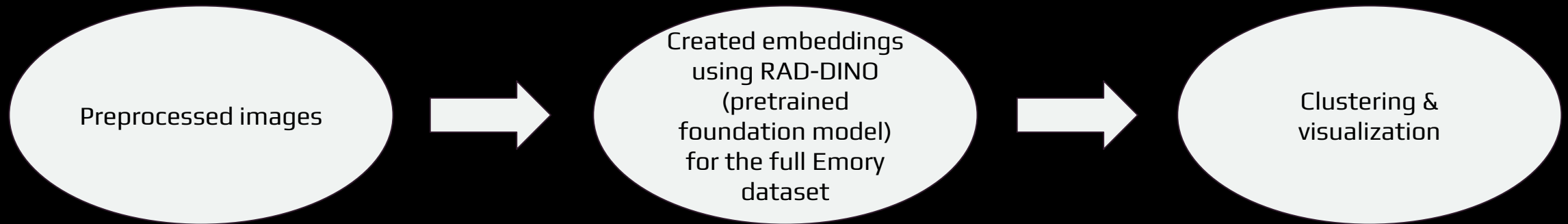
Hypothesis

- Observe patterns of missingness in the SDOH table for different demographic group (sex and race)
 - SDOH (like Gini index) vary strongly for different diseases, races, and sexes
 - The embeddings will clusterize by demographics (sex and race) and SDOH
-

Methods - SDOH

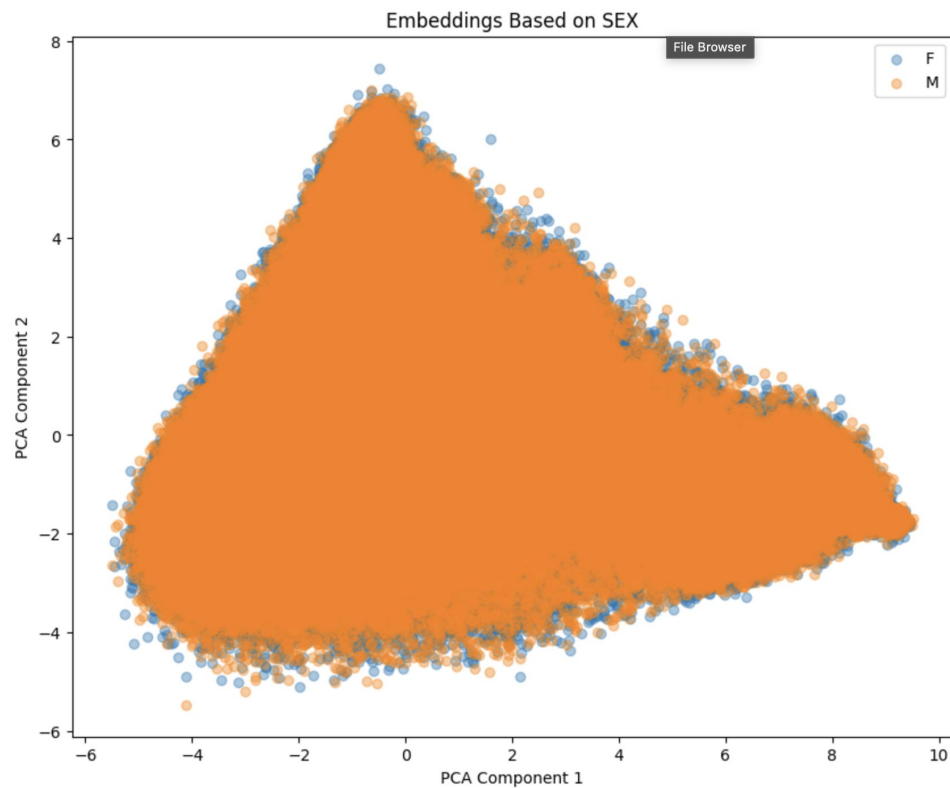


Methods - Embeddings

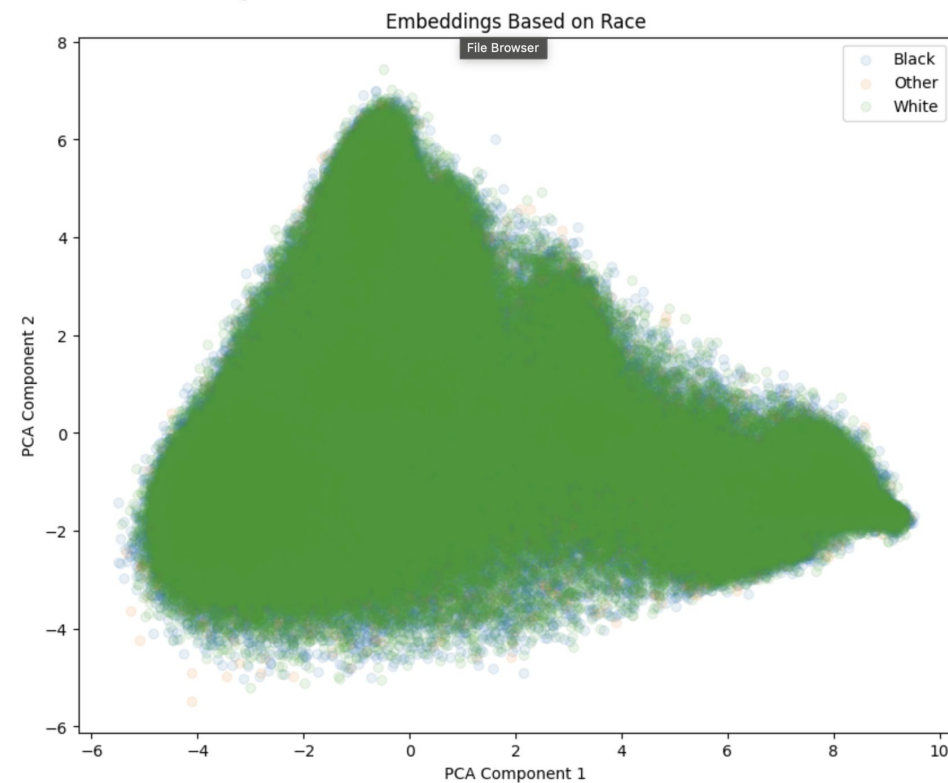


RESULTS: Embeddings

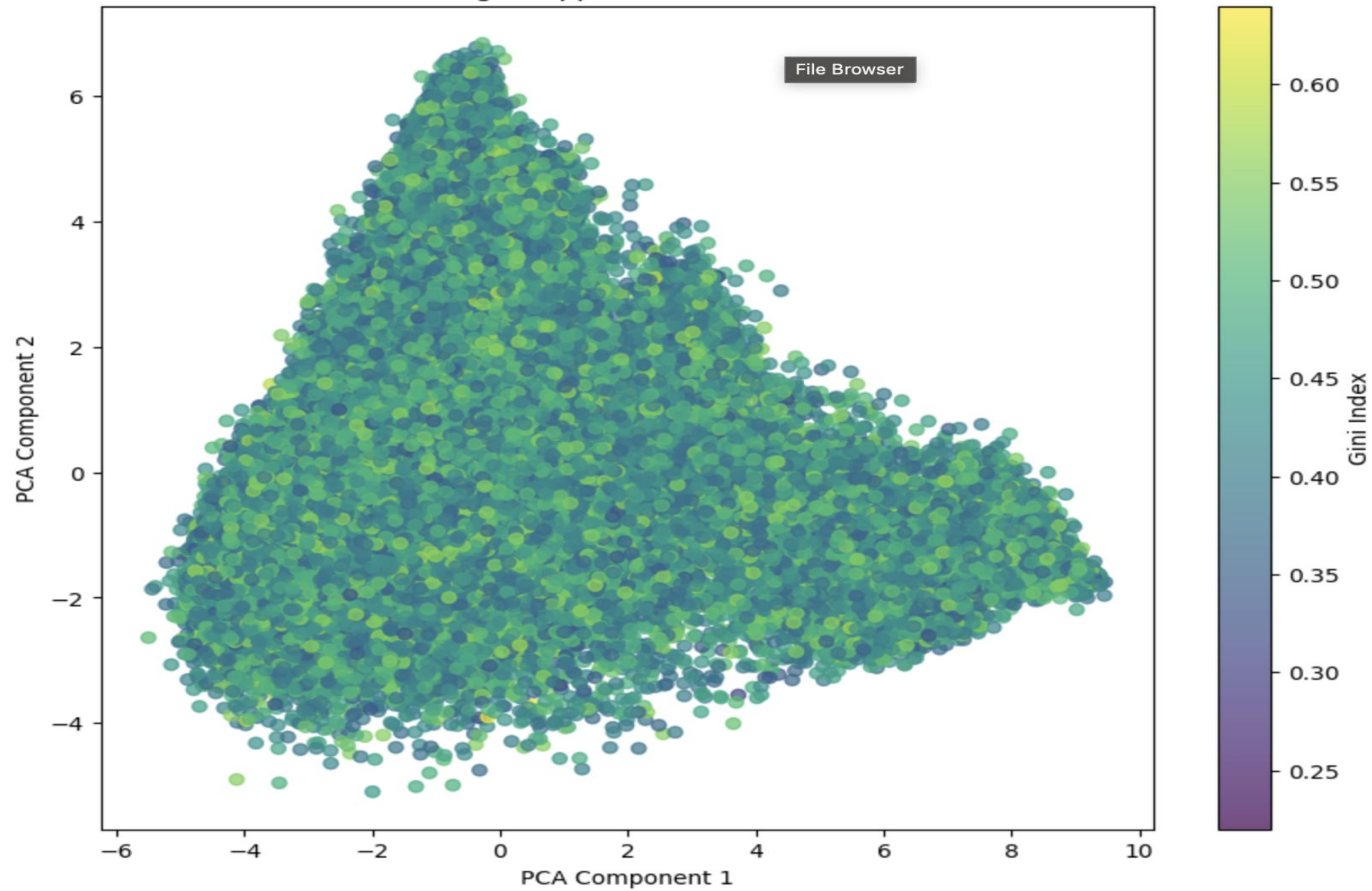
Mismatch: 397509 embeddings vs 572579 sex labels



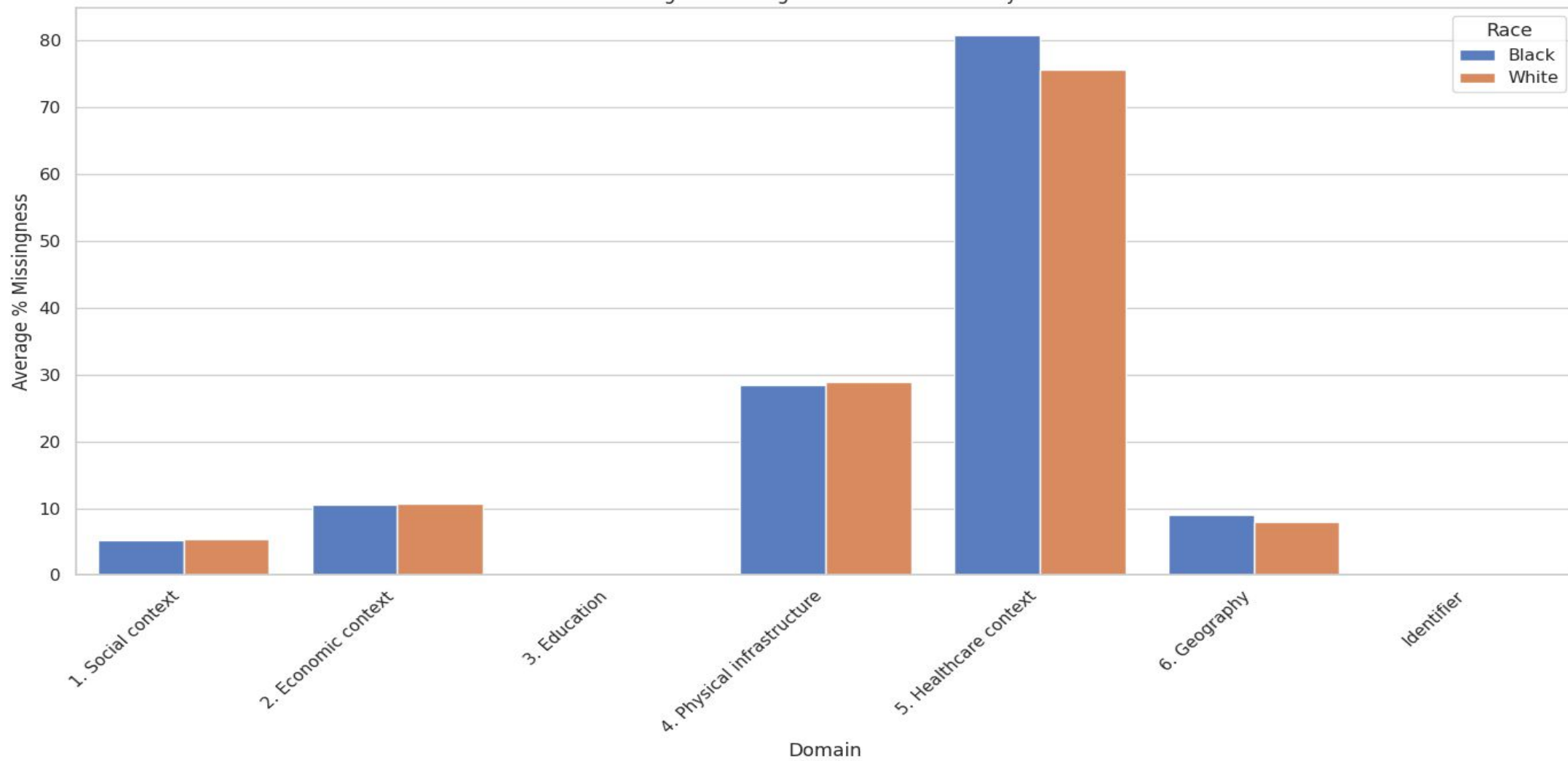
Mismatch: 396605 embeddings vs 572579 race labels

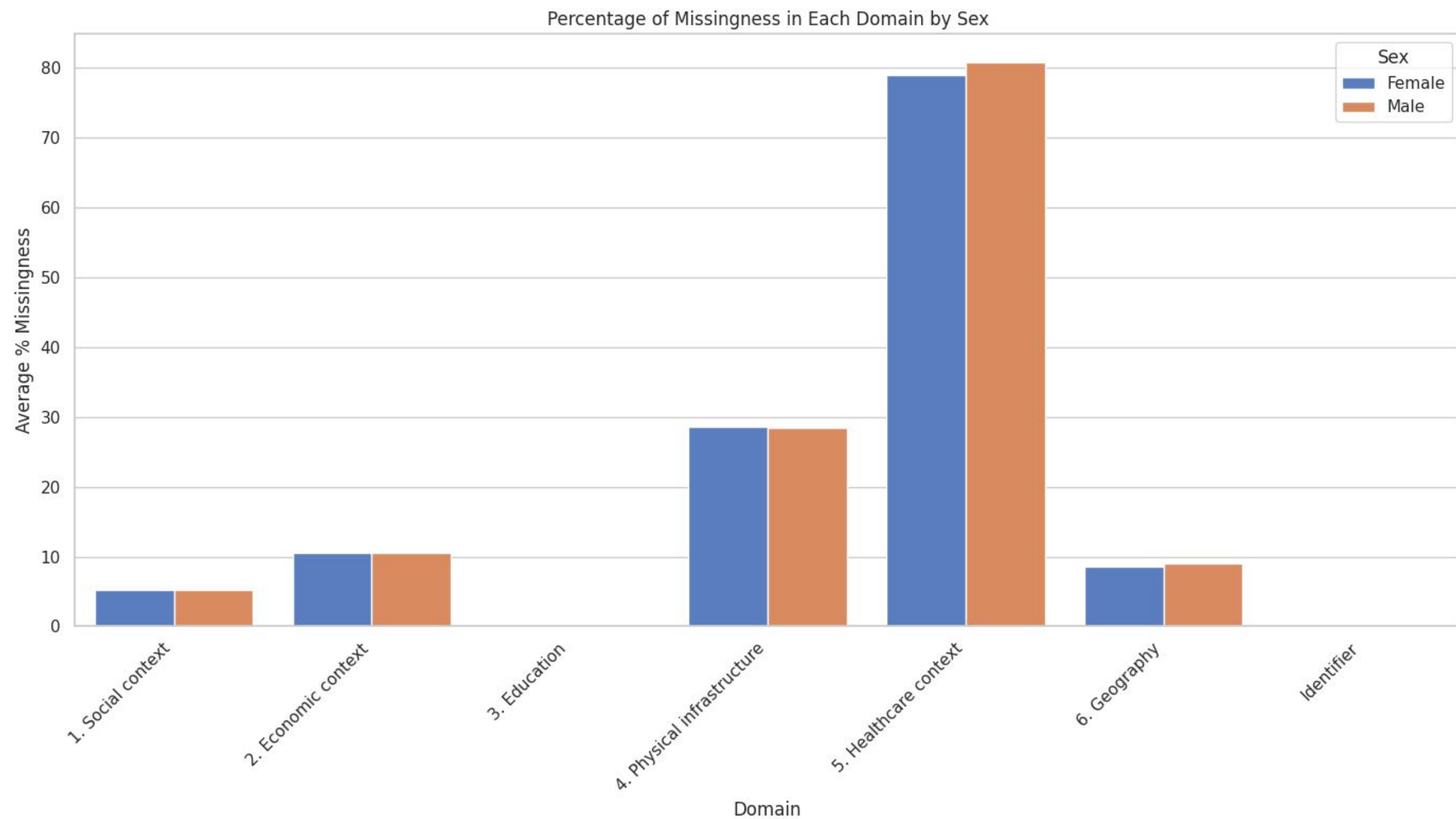


Embeddings Mapped Based on Gini Index

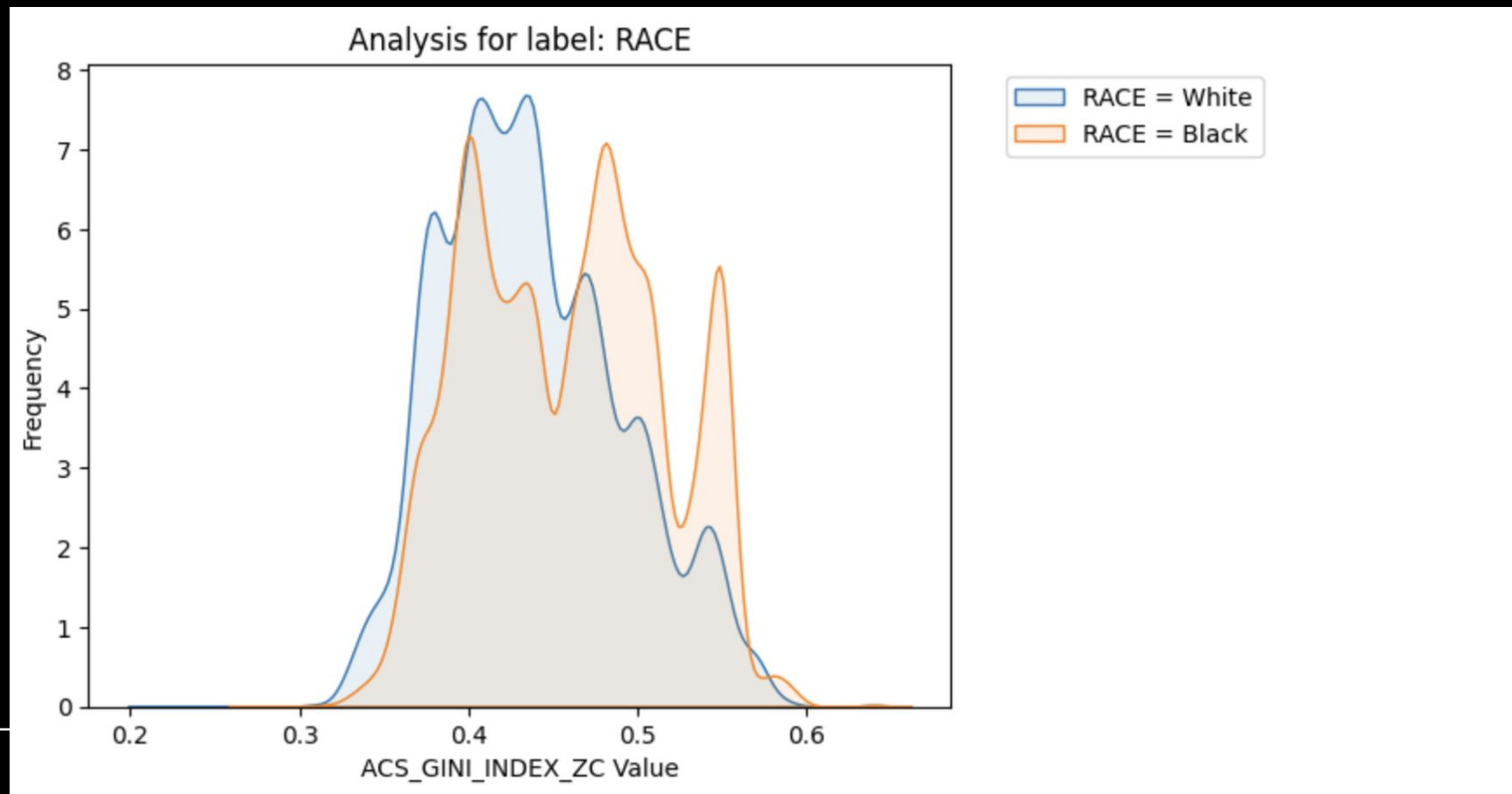


Percentage of Missingness in Each Domain by Race





RESULTS: Example of subpopulation analysis for the SDOH per Race



Conclusion/Relevance

- Lay the framework for preparing & clustering embeddings, and interactive graphs to see who is and is not represented in the SDOH dataset
-

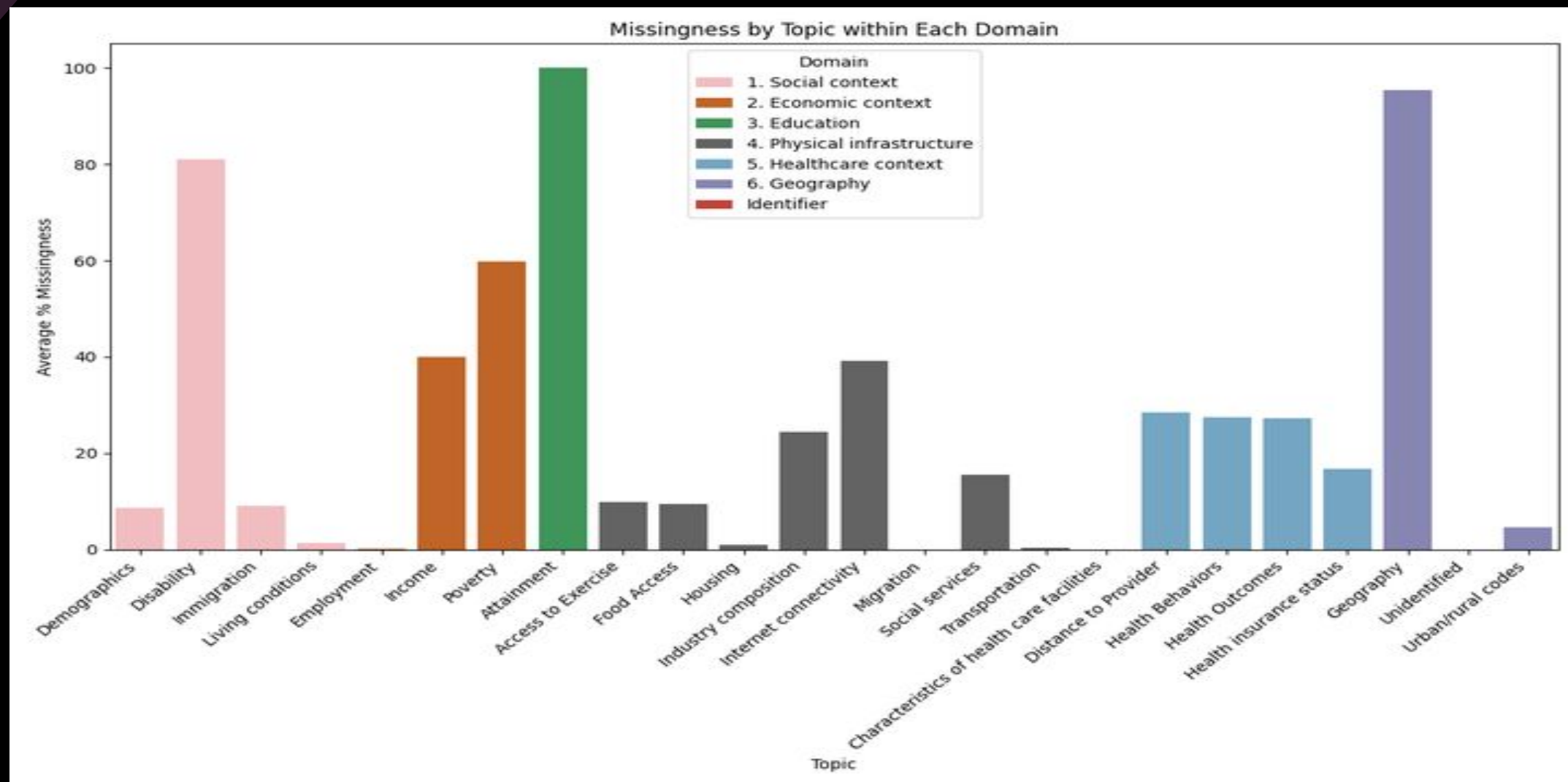


MEET THE TEAM

Extra Slides



RESULTS



RESULTS

