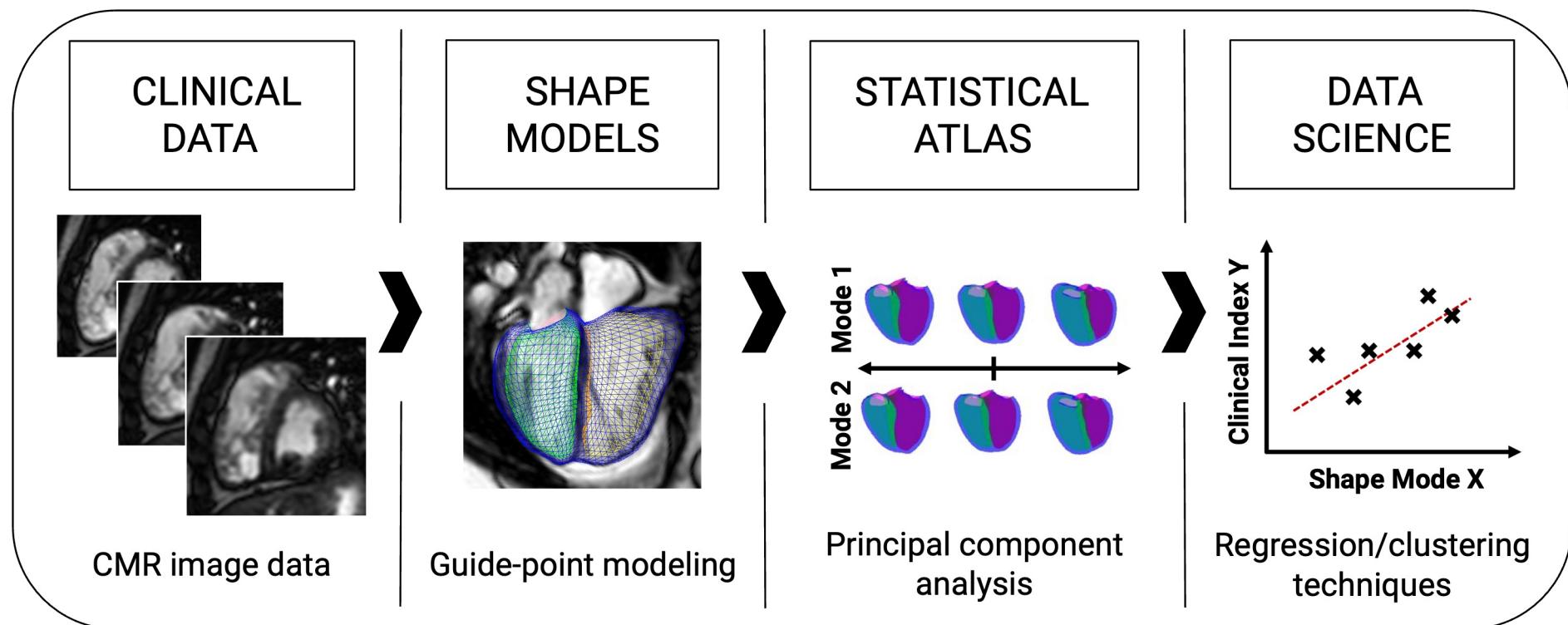
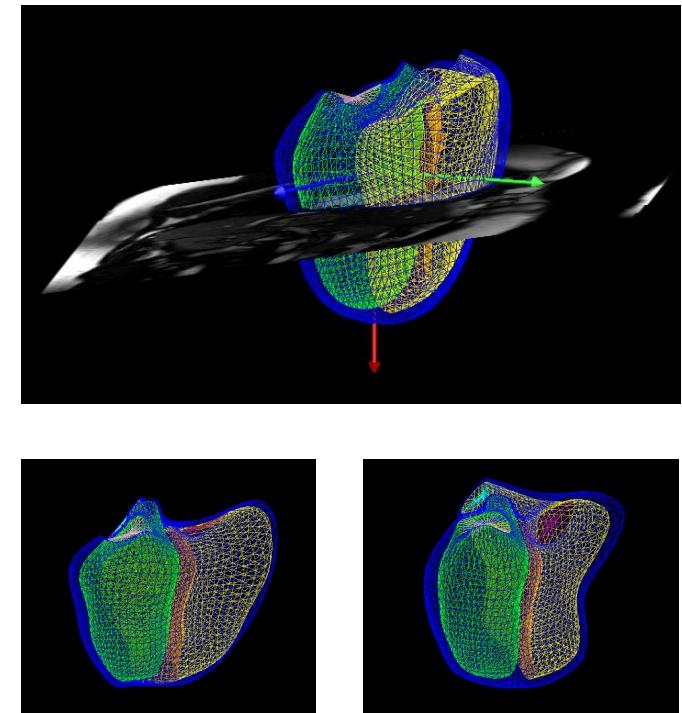
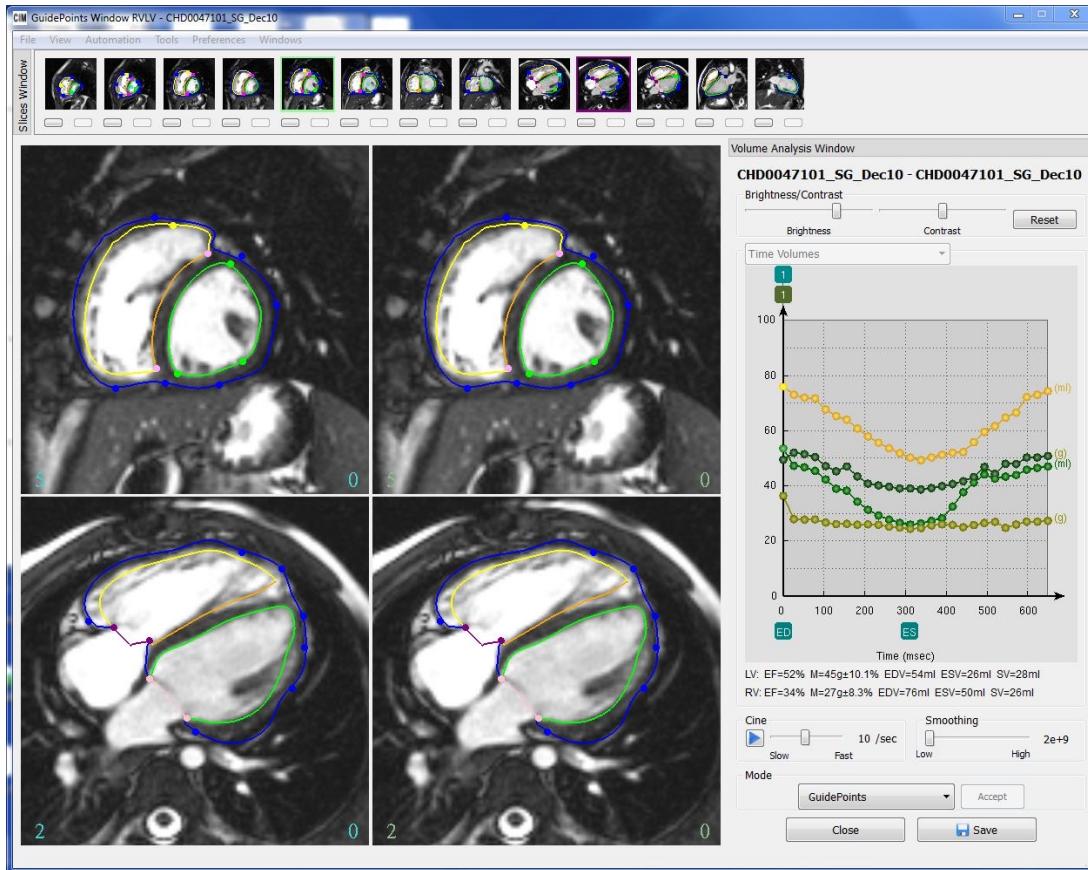


The Cardiac Atlas Project Derives Statistical Shape Atlases from Cardiac MR Exams



Forsch N, Govil S, Perry JC, Hegde S, Young AA, Omens JH, McCulloch AD (2020)
Computational analysis of cardiac structure and function in congenital heart disease:
Translating discoveries to clinical strategies. *J Comp Sci*

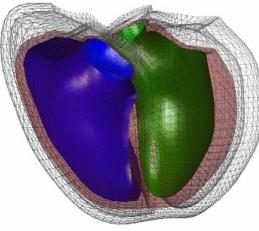
Guide-point modeling for biventricular shape model generation



Cardiac Image Modeller (CIM); Auckland, New Zealand

Biventricular Shape Modes in Tetralogy of Fallot

Overall size

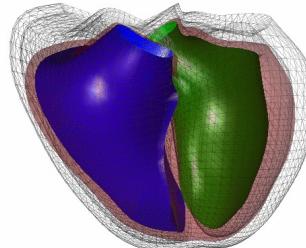


Mode 1

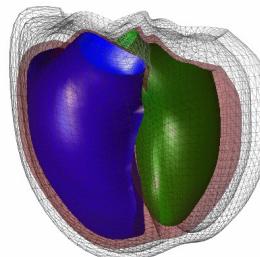
Mode 2

Septal-freewall dimension

Basal vs apical RV bulging



Mode 3

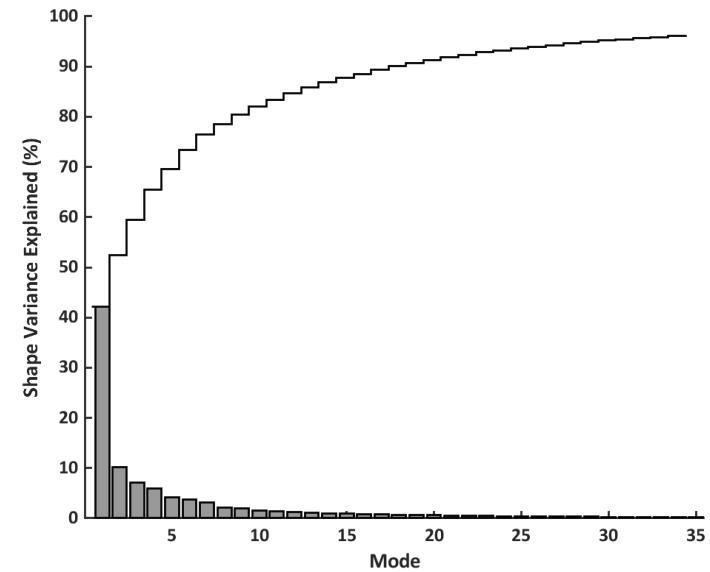


Mode 4

Wireframe shows model at ED and shaded surfaces show the model at ES

First 30 ED Shape Modes

Explain >95% of the shape variation in the population



Dilation of RV outflow tract & RV apex

Govil S, Mauger CA, Hegde S, Occleshaw CJ, Yu X, Perry JC, Young AA, Omens JH, McCulloch AD (2023) Biventricular Shape Modes Discriminate Pulmonary Valve Replacement in Tetralogy of Fallot Better Than Imaging Indices. *Scientific Reports*

UK Biobank Imaging Cohort

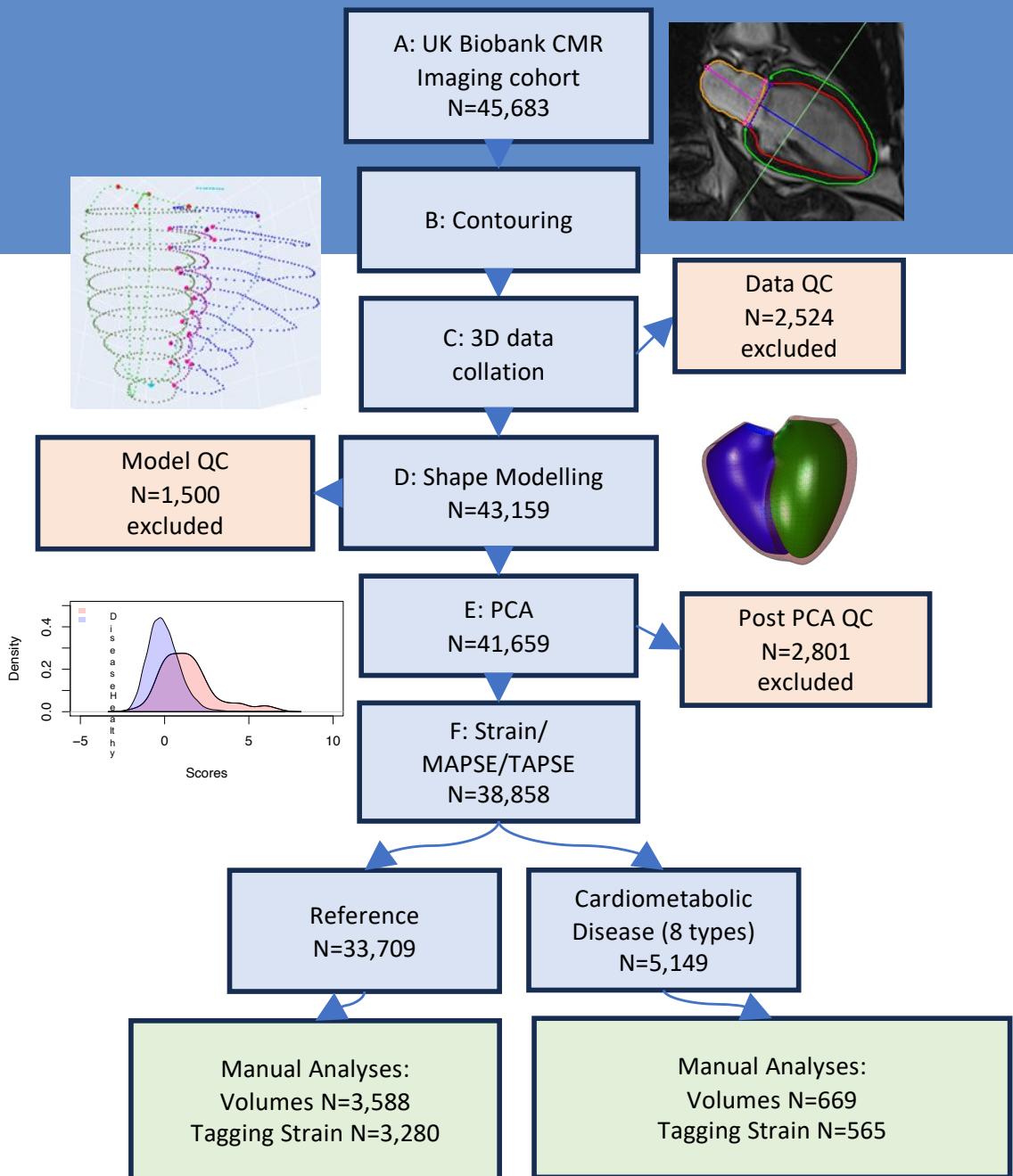
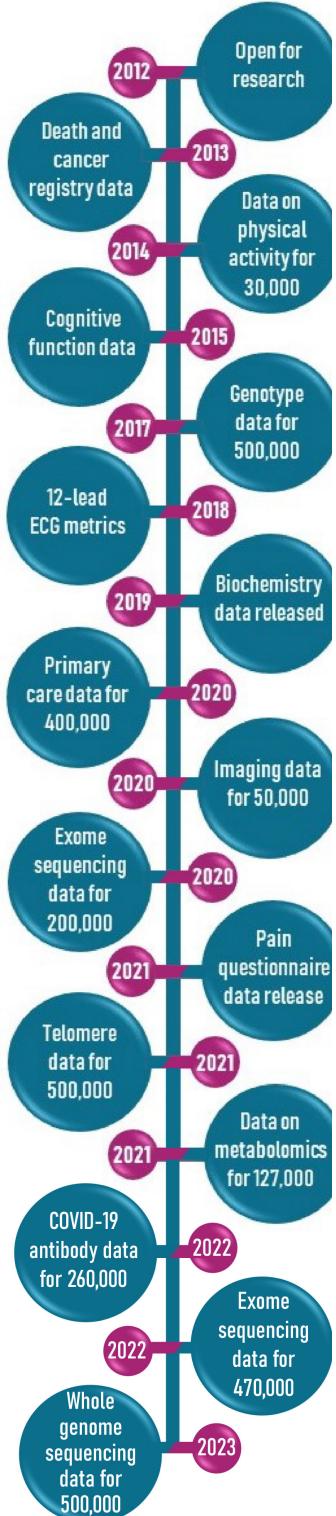
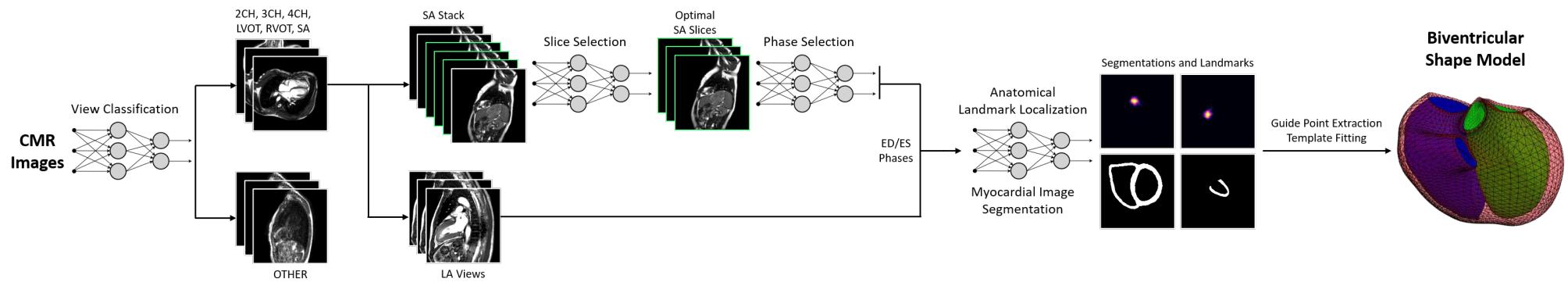


Figure 1: Automated analysis pipeline. CMR, cardiovascular magnetic resonance; PCA, principal component analysis; APSE, annular plane systolic excursion; PC, principal component; IQR, interquartile range.

UK Biobank has collected and continues to collect extensive environmental, lifestyle, and genetic data on half a million participants. New data are uploaded into the database regularly.



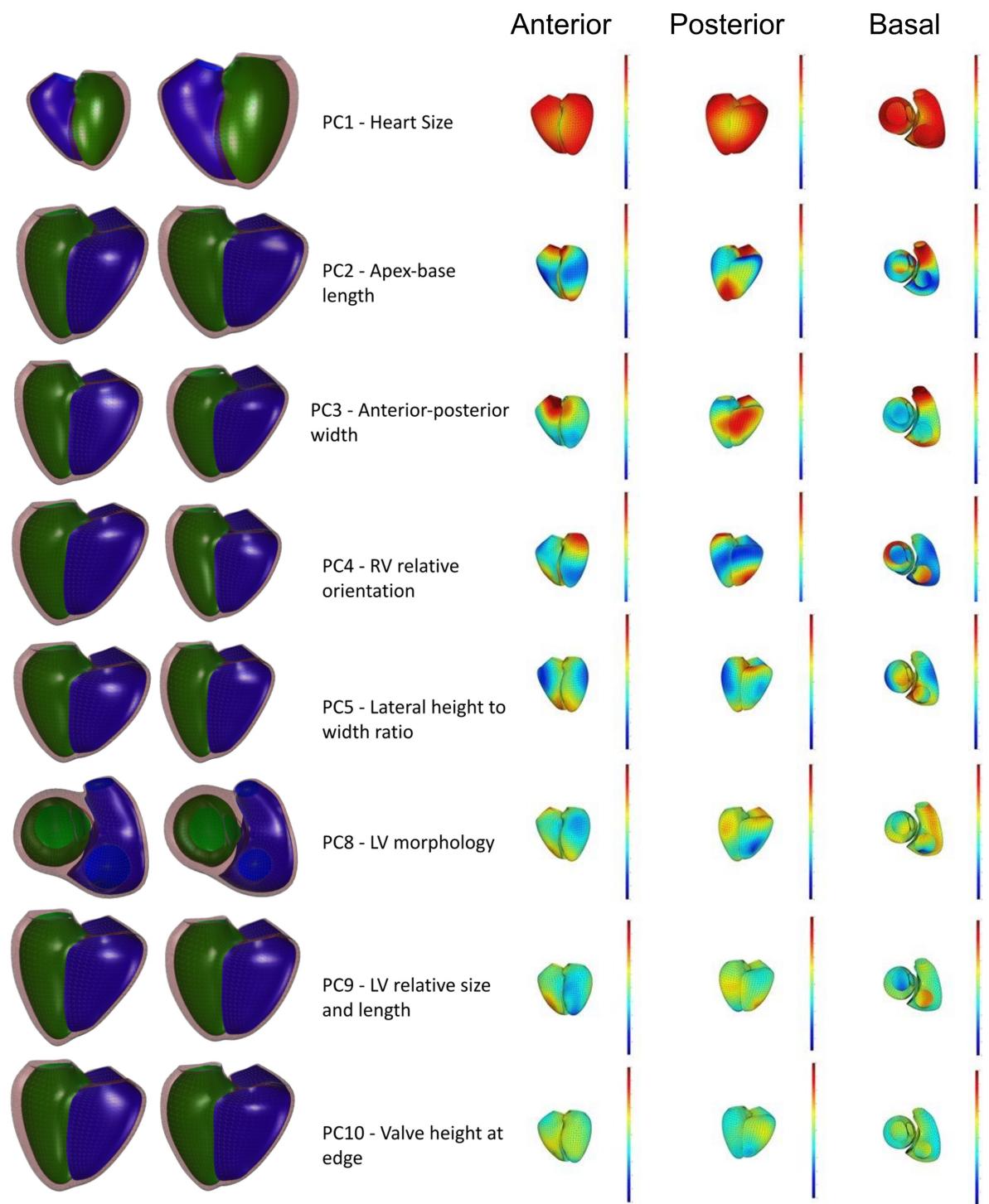
Deep Learning Pipeline



- Designed to be modular so that each of the networks can be improved upon independently of each other
- Designed to have manual confirmation or override at each step for quality control

Govil S, Crabb BT, Deng Y, Toso LD, Puyol-Anton E, Pushparajah K, Hegde S, Perry JC, Omens JH, Hsiao A, Young AA, McCulloch AD (2023) A Deep Learning Approach for Fully Automated Cardiac Shape Modeling in Tetralogy of Fallot. *Journal of Cardiovascular Magnetic Resonance*.

UK Biobank Shape Modes



Principal Component Analysis (PCA)

- ▶ PCA is a dimensionality reduction technique that captures the primary modes of variation in data.
- ▶ PCA finds a set of orthogonal bases or axes (principal components) that are linear combinations of the original features that maximize variance across the observations.
- ▶ Useful for compressing or visualizing high-dimensional data.
- ▶ PCs are ordered by the amount of variance they explain from greatest to least.
- ▶ Given a dataset with n observations (samples) and p features (measurements), put the data in a $n \times p$ matrix $[X]$, where:
 - ▶ Each row is a data sample.
 - ▶ Each column is a feature centered around the mean μ of each column: $\bar{X}_i = X_i - \mu$

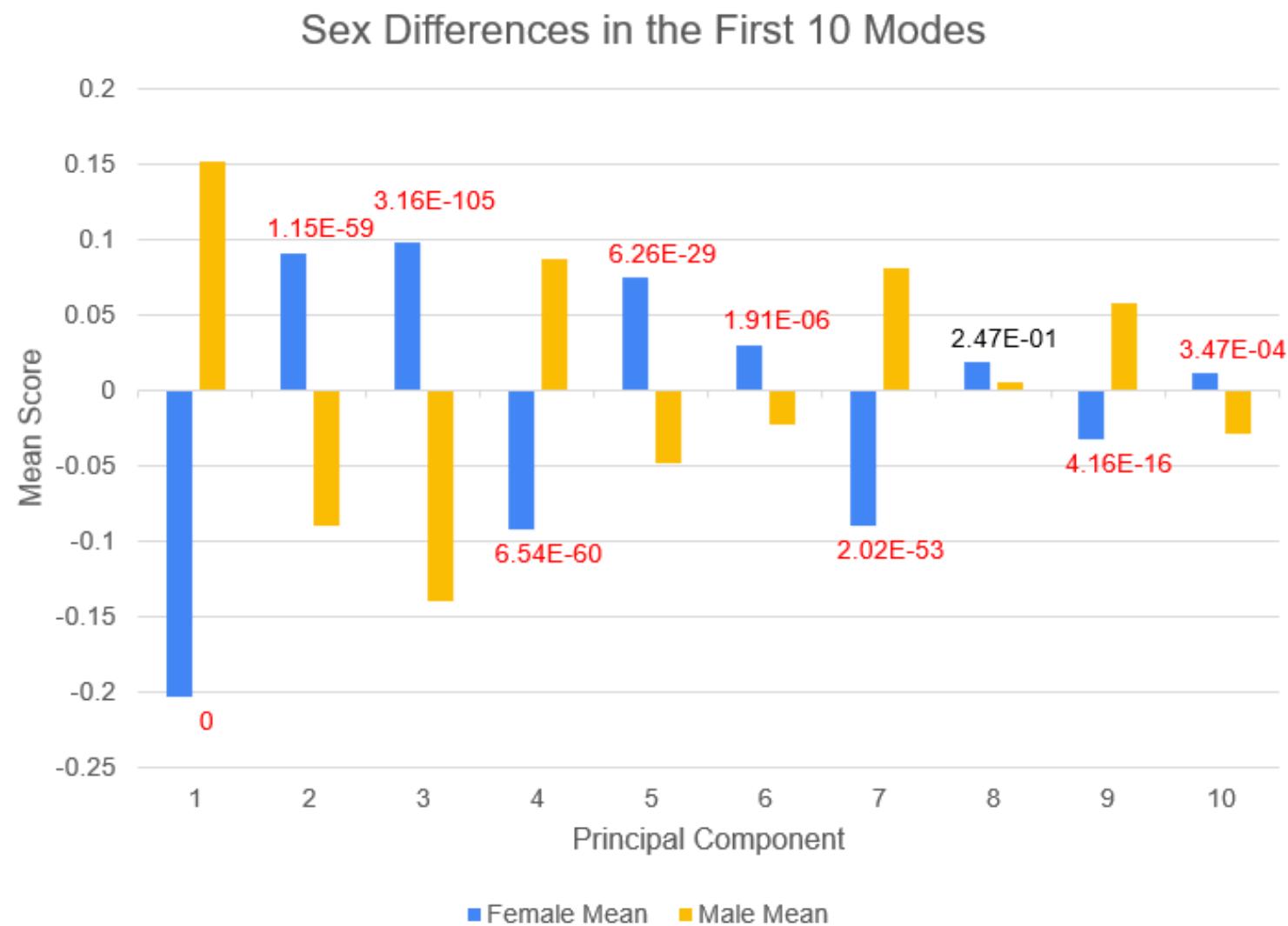
PCA uses the Singular Value Decomposition (SVD)

- ▶ Compute the Singular Value Decomposition (SVD):
 $[X] = [U][\Sigma][V]^T$
- ▶ The covariance matrix is:
 $[C] = \frac{1}{n-1}[\bar{X}]^T[\bar{X}] = [V]\left(\frac{[\Sigma]^2}{n-1}\right)[V]^T$
- ▶ The columns of $[V]$ are the eigenvectors of $[C]$ (principal directions)
- ▶ $[\Sigma]$ is the diagonal matrix of singular values,
 $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_p \geq 0$, where $\sigma_i^2/(n-1)$ is the variance explained by the i -th PC
- ▶ The columns of $[U]$ are the PC scores (how each sample projects onto each PC).
- ▶ Truncating $[\Sigma]$ and $[V]$ and projecting the original data onto the new axes: $[Z] = [X][V]$ gives the coordinates of the data in the reduced PC space.

Jupyter Notebook Example

```
from sklearn.decomposition import PCA
pca = PCA(n_components=10)
pca_data = pca.fit_transform(measurements)
explained_variance = pca.explained_variance_ratio_
```

Sex Differences in Cardiac Shape Modes From UK Biobank



Regression Analysis

