

# A Framework for Longitudinal Data Analysis via Shape Regression

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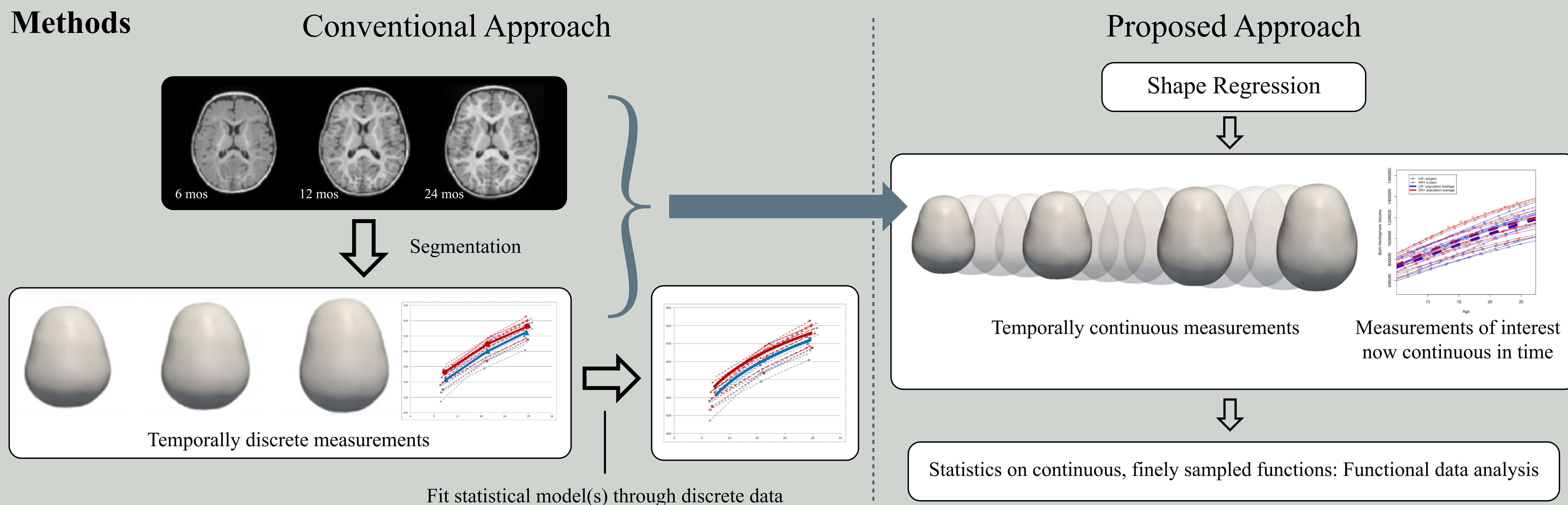
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## Introduction

During the last several years, there has been an increased emphasis on longitudinal analysis in clinical studies. Traditional longitudinal analysis begins by extracting desired clinical measurements, such as volume or head circumference, from discrete imaging data. Typically, the continuous evolution of a scalar measurement is estimated by choosing a 1D regression model, such as kernel regression or fitting a polynomial of fixed degree. In this work, we present a framework for longitudinal analysis centered around the estimation of *shape* evolution.

## Methods



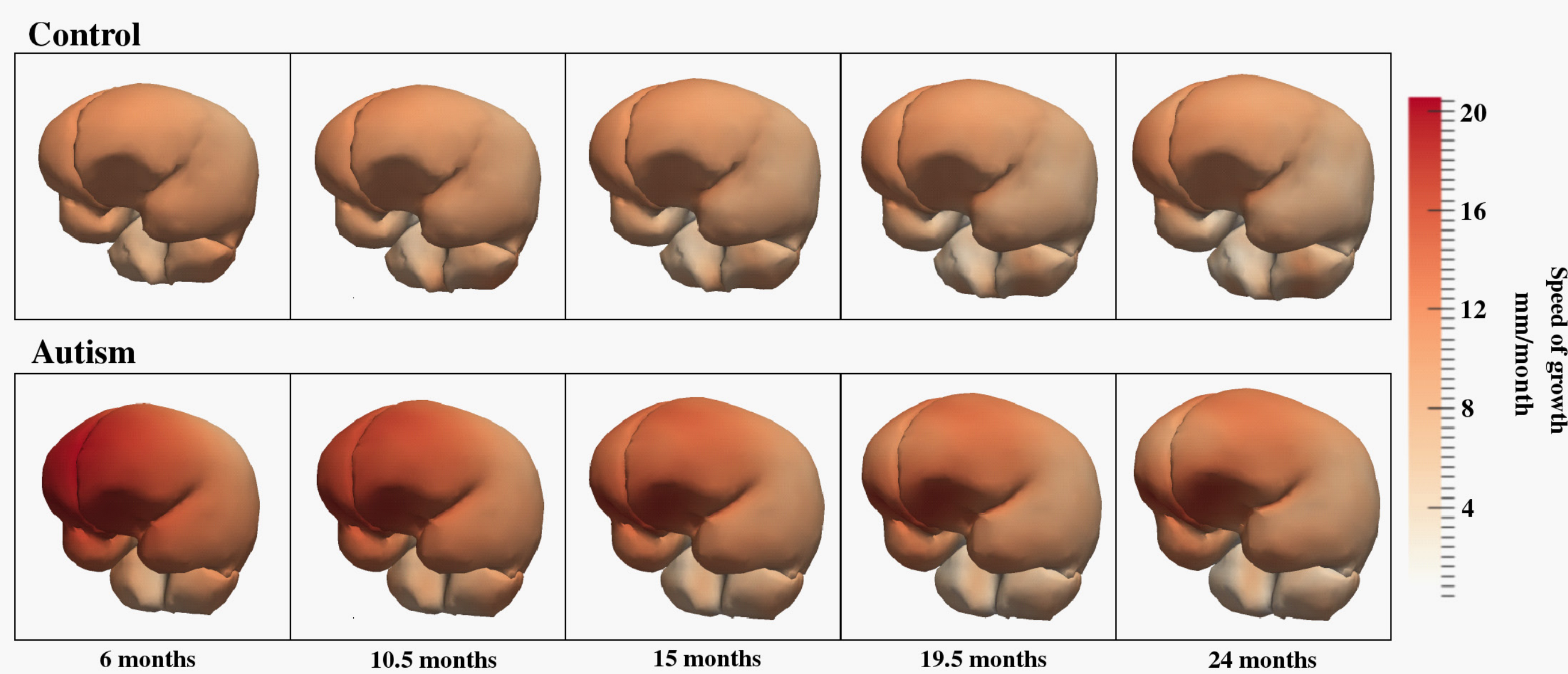
## Experiments

We evaluate the application of our framework with a longitudinal database of 14 controls and 12 children with positive ADOS score (likely to be diagnosed with autism spectrum disorder or autism), from here on referred to as the autism group. Each child has been scanned three times, at approximately 6, 12, and 24 months of age.

### Individual Analysis

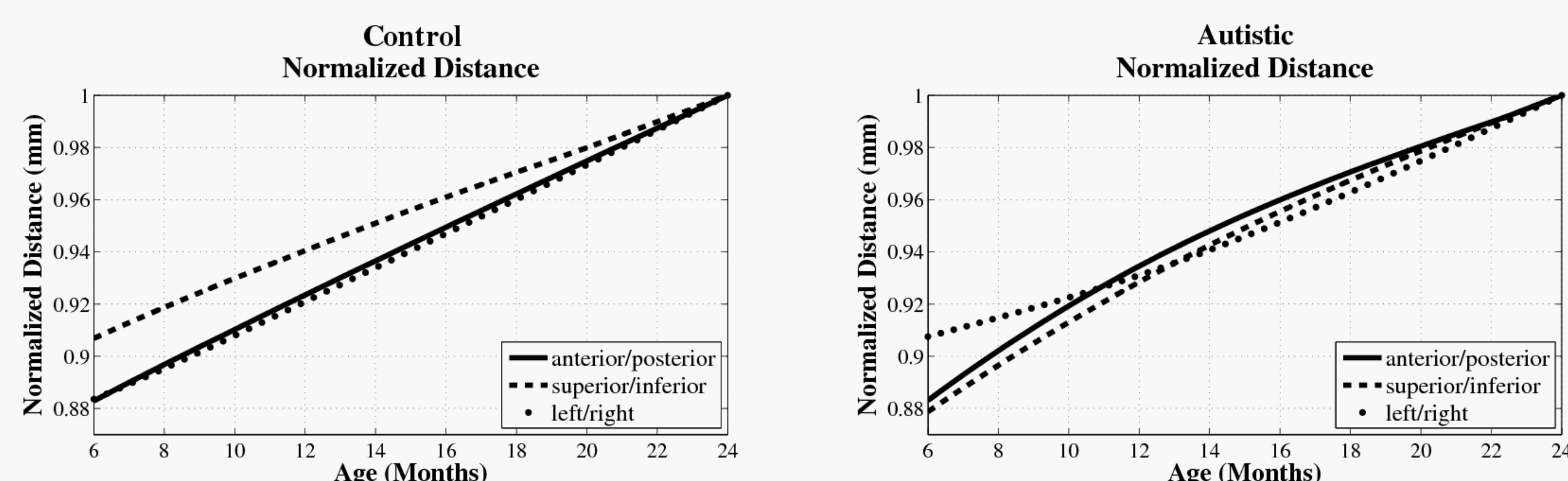
#### Visualization of Shape Evolution

The visualization of shape evolution is a powerful exploratory tool which allows for a researcher to quickly and intuitively explore potentially significant measurements. Here, we show snapshots from the evolution for one particular child from the control and autism group, with color denoting speed of growth.



#### Evolution of Scalar Measurements: Brain-box Analysis

Based on our observations of shape evolution, we investigate the evolution in the direction of the three major axis of the brain. A 'brain-box' analysis is conducted on the same two subjects as before, by measuring the length, width, and height of the bounding box for each shape complex over time.

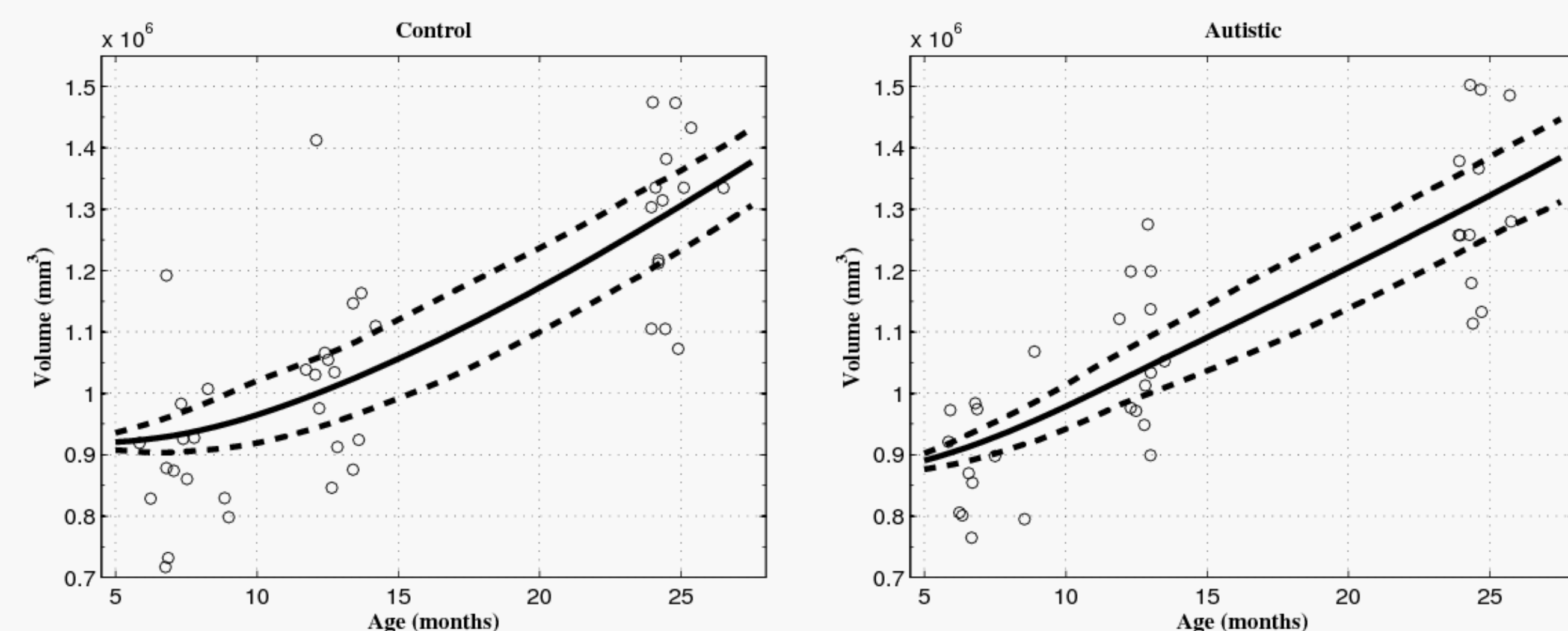


### Population Analysis

#### Bootstrapping

The bootstrapping procedure involves sampling each group, with replacement, creating a new data set with the same number of samples as the original. A mean scenario is then estimated for each group based on the new samples, and the process is repeated 100 times to simulate the variability within each group. In the end, we have 100 average growth scenarios for each population.

From the mean growth scenarios, we extract 90% confidence intervals of volume for each group, by discarding the largest and smallest 5%.



## Conclusion

We have introduced a framework for the analysis of longitudinal data based on the continuous evolution of shape. After shape regression, any number of measurements can simply be extracted from the shapes continuously. We have shown that

- One growth model realistically captures the evolution of multiple anatomical shapes
- Visualization of shape evolution can improve data exploration, highlighting significant measurements that might have otherwise been overlooked
- Analysis is done individually (personalized profiles), or population wide (group statistics)

## Acknowledgments

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