Tailored for Diversity: Adapting Garment Patterns to Fit Diverse Body Shapes

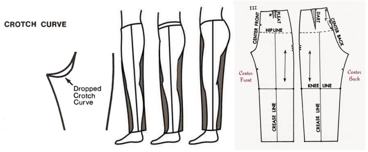
Team 10 : Lily B. Sharma | Xinru Zheng | Xuran Zhang | Yanan Zhang | Yuze Gu

Guide: Sreyoshi Das | Sponsor: Fatima Baytar

Cornell University

Introduction

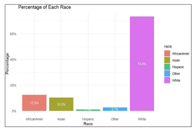
The diversity of human body shapes and sizes across different ethnic backgrounds provides a rich foundation for enhancing the inclusivity and fit of garments. This project focuses on the precise prediction and analysis of crotch curves in relation to race, leveraging detailed anthropometric data and then using it as input in our machine learning model for predicting race. By understanding the unique body measurement dynamics of various ethnicities, particularly in the lower torso, we aim to revolutionize the way pants are designed to offer better comfort and style.



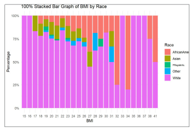
Project Objectives

- To determine if incorporating crotch curve features and female body characteristics can enhance the accuracy of race prediction in garment design.
- To examine variations in lower torso shapes across different races, providing insights into body shape classifications.
- To enhance the fit and inclusivity of pants across all races by integrating precise measurement and prediction models into garment design processes.

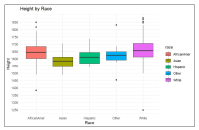
Data Pre-processing& Visualization



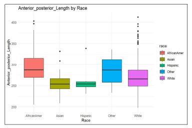
- 73.5% of data composed by white race
- 26.5% of data composed by other race



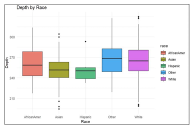
- White and African American group dominate the higher BMI ranges (above 30),



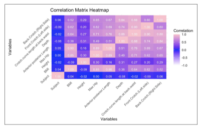
- Asian group displays the smallest median height.
- White and African Americans have a similar distribution.



- Hispanic has the narrowest IQR range.
- Other has the widest IQR range.



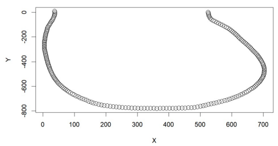
- African American group shows the widest IQR range, indicating more variability within this group.
- Asian have the median depth value lower than the other groups, suggesting racial differences in body depth measurements.



- "BMI" shows a strong positive correlation with "Anterior-posterior.Length" (about 0.9).
- A strong positive correlation between"Crotch.curve.length.at.back.waist"and " Front.Crotch.(Left.side)" (approximately 0.9).

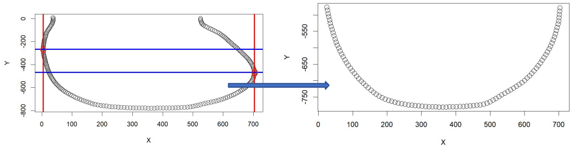
Curve Fitting – Extracting features of the curve

- Crotch curve of one data point, e.g. , Subject 321 (provided in data along with its coordinates.

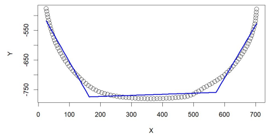


Curve Fitting – Extracting features of the curve

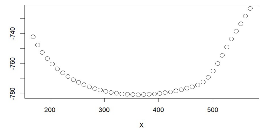
Separated the lower part of the graph. Selected the left most and right most points of the curve. Select the point where the y-values are relatively low. Then, draw a horizontal line through this point to obtain the lower part.



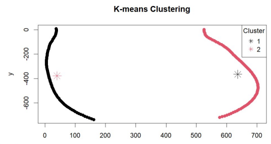
- Get 2 knots- Use the ***Segmented*** package in R to automatically find the 2 knots

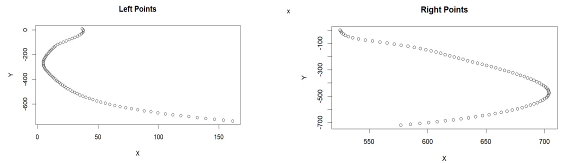


- The middle part of the curve was separated from the lower graph to estimate it separately

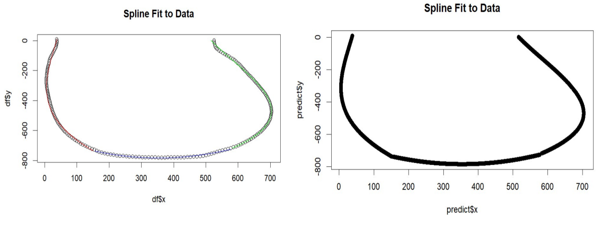


- Used K-means to separate the left and right data points from the above graph





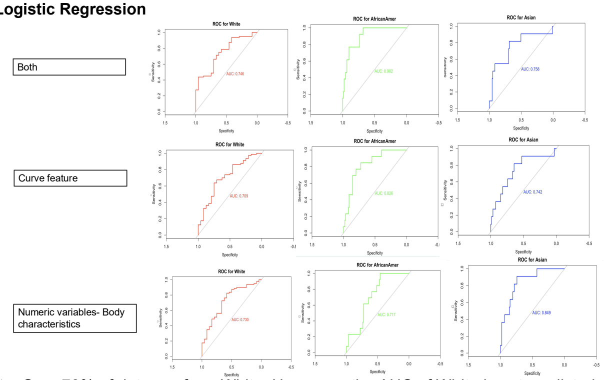
- Fit the left part of the data with a **3rd-order** polynomial model
- Fit the right part of the data with a **3rd-order** polynomial model
- Fit the middle part of the data with a **2nd-order** polynomial model
- Plot the fitted graph



Machine learning models to predict Race

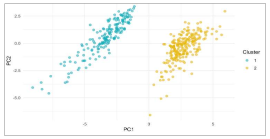
- If curve feature along with characteristic information improves the prediction

Logistic Regression



- Over 70% of data are from White. However, the AUC of White is not predicted as accurate as expected.
- Two cases could cause a low AUC value within White -Imbalance Data & Variation within the White data
- Significant variation observed within the White race.
- Some of our machine learning models failed to capture its pattern and did not predict as expected for this particular race.
- Conducted cluster analysis on White race data only
- Selected 100 samples from one cluster to match other race data counts
- Machine learning algorithm showed improved predictions for White race data after this adjustment

Cluster Analysis on White data



Model Performance(sample data –White)

	Cluster	Accuracy	AUC for White	AUC for AfricanAmer	AUC for Asian
Both	Before	77.9	74.6	90.2	75.8
	After	84.1	**89.8**	**84.4**	**96.1**
Spline	Before	76.9	70.9	82.6	74.2
	After	63.6	71	81.4	86.8
Numeric	Before	75.9	73	71.7	83.4
	After	58.1	72.8	68.5	91.2

- Highest AUC scores: Logistic Regression, Random Forest, and XGBoost models

Machine Model Name	Method	Accuracy	AUC for AfricanAmeri	AUC for Asian	AUC for White
Logistic	Both	**77.88**	**90.2**	**75.8**	**74.6**
	Numeric	75.96	71.7	84.9	73
	Spline Coefficient	76.92	82.6	74.2	70.9
Random Forest	Both	**81.95**	**73.9**	**73.1**	**74.5**
	Numeric	71.43	57.3	52.6	53.5
	Spline Coefficient	75.47	53.0	56.2	54.3
SVM	Both	71.43	60.9	52.6	54.4
	Numeric	72.64	53	53.1	52.7
	Spline Coefficient	69.52	49.5	50	49.3
XGBoost	Both	**80.95**	**77**	**74**	**76.6**
	Numeric	76.19	72.8	62.9	70.1
	Spline Coefficient	77.36	63.2	58.8	64.3
Gradient Boosting	Both	73.1	80.1	77	69.8
	numeric	72.1	70.2	71.9	64.8
	Spline Coefficient	76.9	85.7	77.6	71.4

Conclusion

- Features from spline regression and high-degree polynomial curve fitting improved ethnicity prediction accuracy.
- Despite significant variation within the White group, models like Random Forest and XGBoost effectively captured essential patterns.
- These models outperformed those using only individual characteristics as input.

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