Analyzing Lower Torso Curves for Computational Apparel Design and Modeling

Team Curve: Wenxuan Hong (wh459), Aristotle Kolefas (aak99), Diane Xu (sx265), Zongjie Yin (zy347), Fanjun Zeng (fz224) .

Advisor: Dr. Sreyoshi Das

Clients: Dr. Sumanta Basu, Dr. Fatma Baytar

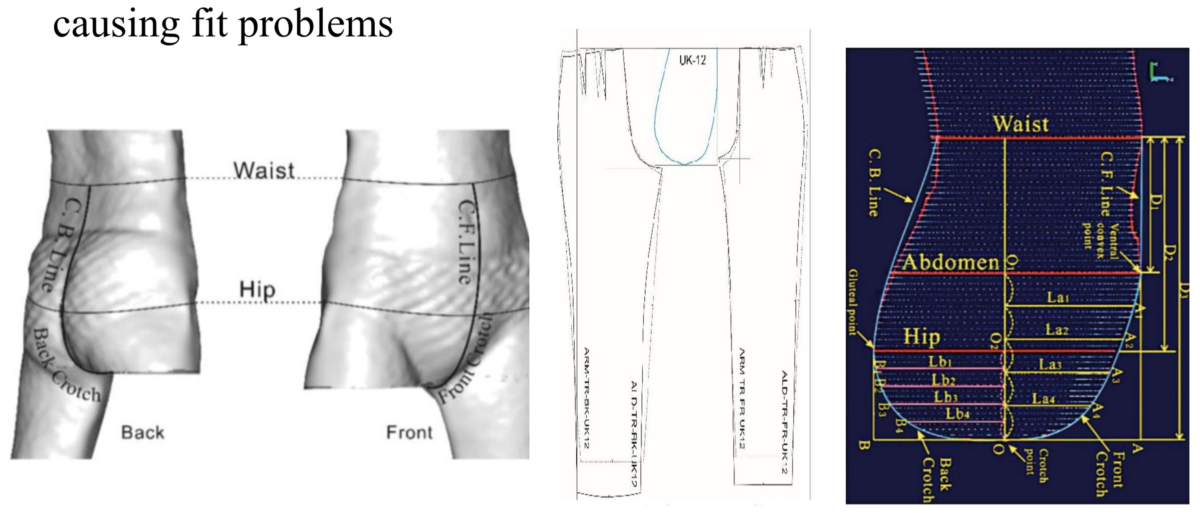
Background

Fashion system is flawed in terms of ready-to-wear clothing fit for women

- Approximately 50% of women struggle to find well-fitting clothes
- Dr. Baytar's friend in the apparel industry reports challenges with rise shapes, especially for non-flat/curvy body types

Why?

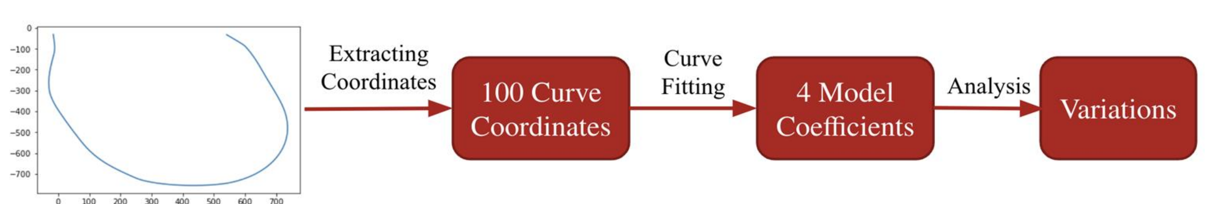
- Crotch curve is often drawn haphazardly in pants pattern creation, causing fit problems



Q1: Do body shapes vary based on factors such as ethnicity, height, or BMI?

Strategy

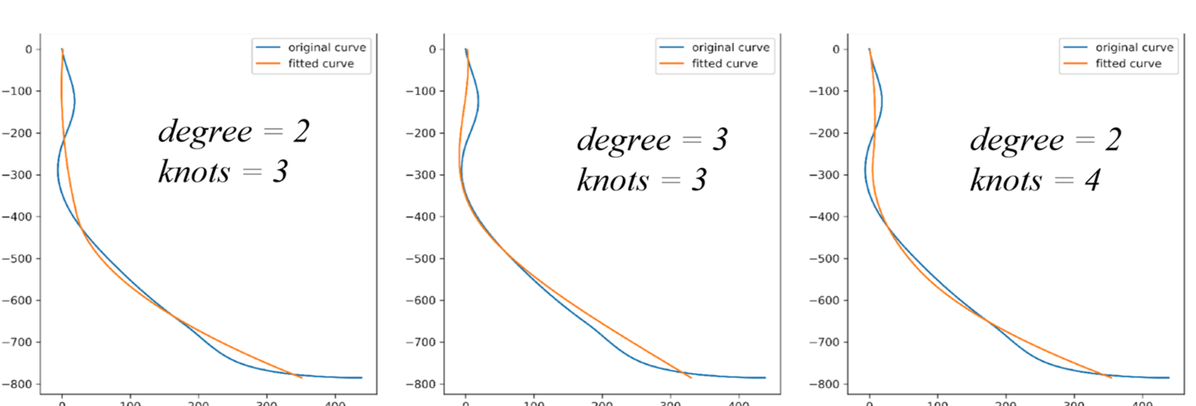
- Fit the curve with a model and extract model coefficients
- Use model coefficients to characterize the corresponding curve
- Analyze the variations of model coefficients based factors



Curve Fitting – Model Selection

- Spline models can generate a fixed number of coefficients
- Fit curves by spline models with different hyperparameters
- Compared the fit of the curves to find the best model hyperparameters
- Spline model with degree = 2 and knots = 3 is optimal (a high accuracy and a low model complexity)
- 4 coefficients for each curve

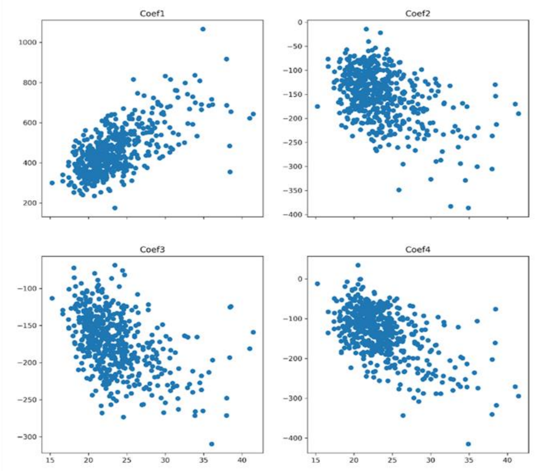
Fitted Curve vs. Original Curve with different hyperparameters



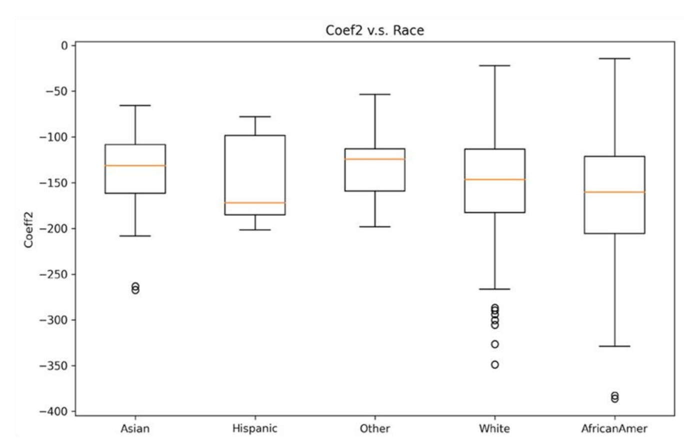
Median R-Squared Values of Fitted and Original Curves

Race	White	African American	Asian	Hispanic	Other
Median R-Squared	0.992	0.991	0.992	0.991	0.992

Variations – Coefficients vs. BMI and Race



Coefficients vs. BMI



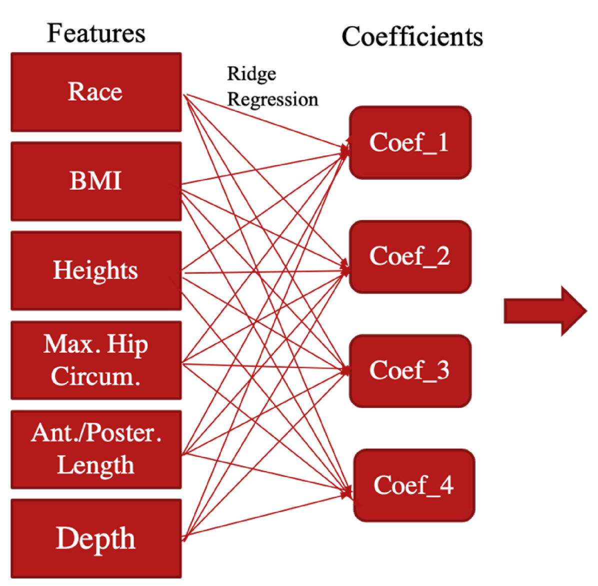
Coefficient2 vs. Race

Q2: Is it possible to predict curve shapes based on measurements such as max hip and crotch depth?

Strategy

- Use supervised learning to predict the 4 spline model coefficients based on features (i.e. max hip, depth, height) for each curve
- Plot the predicted crotch curves based on the predicted coefficients

Predicting Coefficients

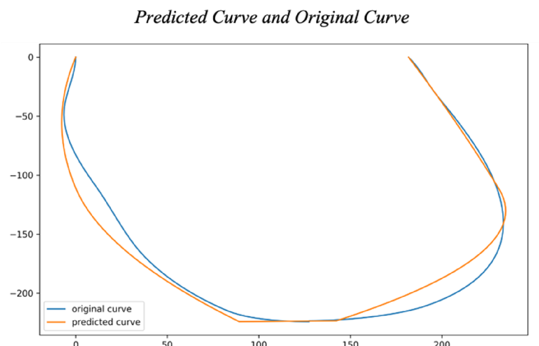


R-Squared Values of Predicted Coefficients

Coefficient	Training Set for Back Curves	Testing Set for Back Curves	Training Set for Front Curves	Testing Set for Front Curves
coef1	0.24	0.05	0.58	0.38
coef2	0.41	0.17	0.4	0.22
coef3	0.52	0.31	0.63	0.33
coef4	0.43	0.34	0.41	0.33

Plotting Predicted and Original Curves

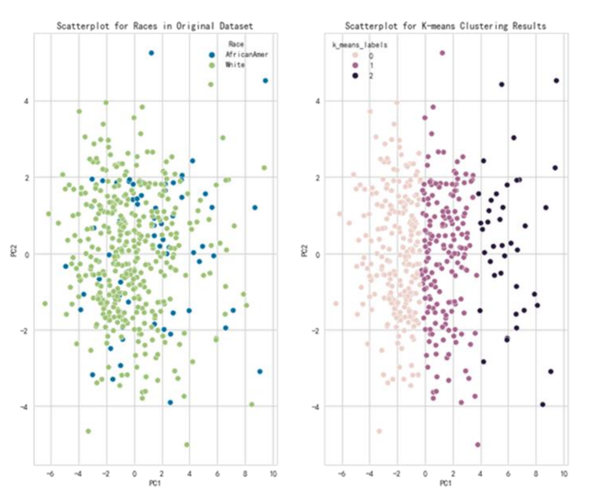
- Plotted the front and back curves separately using predicted coefficients
- Concatenated the front and back curves using the anterior and posterior length
- Compared the predicted and original curves



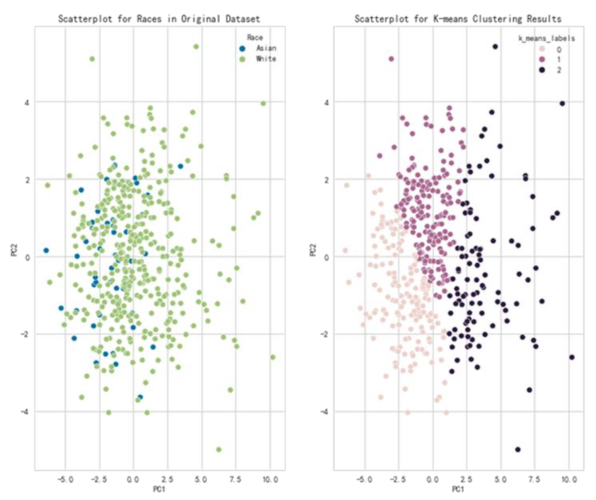
Median R-Squared Values of Predicted and Original Curves

Race	White	African American	Asian	Hispanic	Other
Median R-Squared	0.985	0.974	0.958	0.292	0.795
Sample Size	396	66	55	6	14

Q3: Is there any distinct pattern that differentiates the races?

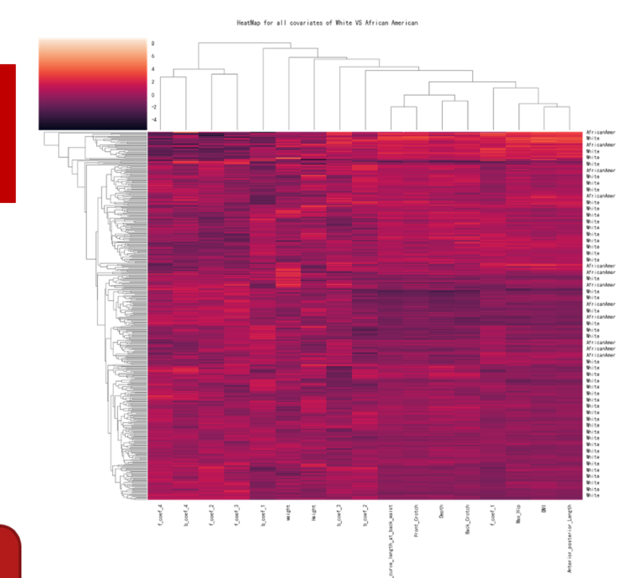


K-mean scatterplot for Whites vs. African Americans

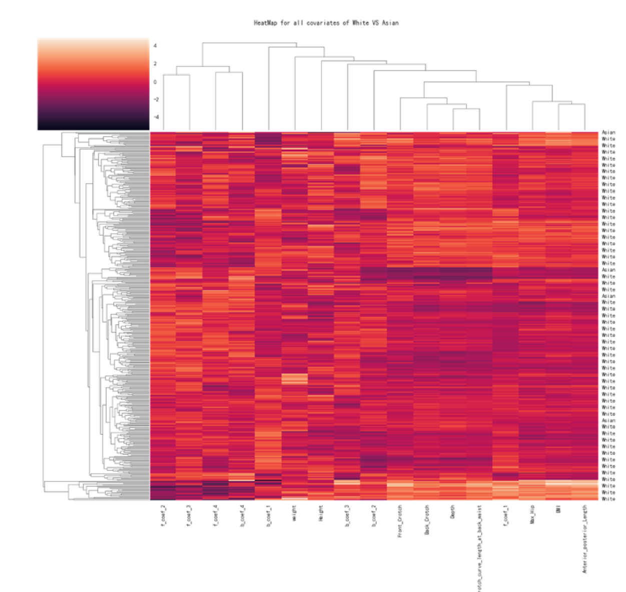


K-mean scatterplot for Whites vs. Asians

- No distinct pattern that differentiates the races



Heatmap for Whites vs. African Americans



Heatmap for Whites vs. Asians

- Four of the front and back curve coefficients shared traits, as did the remaining eight features
- The clustering approach did not provide evidence that the features are strong predictors of race

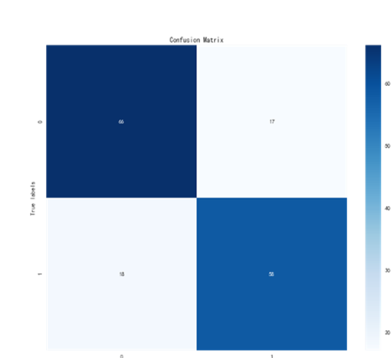
Footnotes: f_coef stands for the front curve coefficient; b_coef stands for the back curve coefficient

Q4: Is it possible to predict the race of the subject based on his/her body measurements and front and back curve coefficients?

Results from Logistic Regression

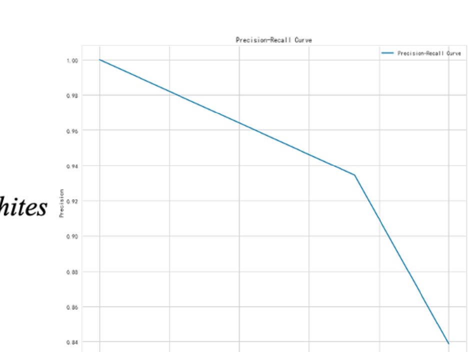
	White vs. African Americans		Whites vs. Asians	
	Balanced training set			
	Balanced test set	Imbalanced test set	Balanced test set	Imbalanced test set
Accuracy	0.78	0.73	0.68	0.62
Precision	0.77	0.93	0.63	0.88
Recall	0.76	0.73	0.80	0.65
AUC	0.83	0.80	0.81	0.52

•Body measurements and both front and back curve coefficients have predictive power for race
•Data imbalance affects the accuracy of logistic regression

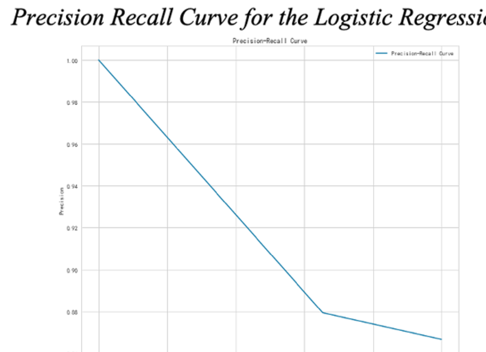


African Americans vs. Whites

Confusion matrix for the Logistic Regression



Asians vs Whites



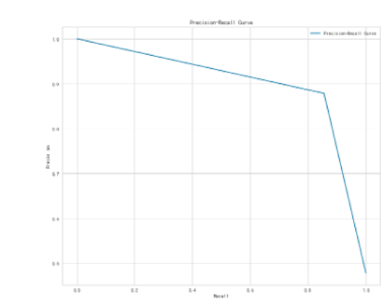
Precision Recall Curve for the Logistic Regression

Results from Random Forest

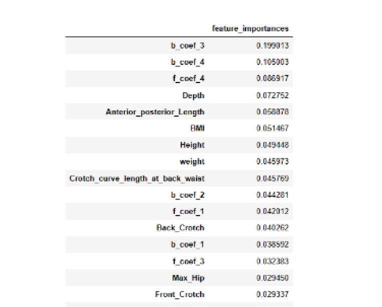
	Whites vs. African Americans		Whites vs. Asians	
	Balanced training set			
	Balanced test set	Imbalanced test set	Balanced test set	Imbalanced test set
n_estimators	100	100	1000	500
max_features	'sqrt'	'sqrt'	'auto'	'sqrt'
max_depth	50	30	50	50
min_samples_split	2	2	2	2
min_samples_leaf	1	2	1	1
Accuracy	0.88	0.81	0.92	0.86

- Body measurements, along with front and back curve coefficients, can predict race reasonably well
- Random forest is less sensitive to data imbalance, leading to a smaller reduction in accuracy
- If accuracy improves, it may suggest the presence of interactions between covariates

Footnotes: n_estimators stands for the total number of trees; max_features stands for the maximum number of features selected at every split; max_depth stands for the maximum depth of each individual tree; min_samples_split stands for the minimum number of samples required to split an internal node; min_samples_leaf stands for the minimum number of samples in each leaf

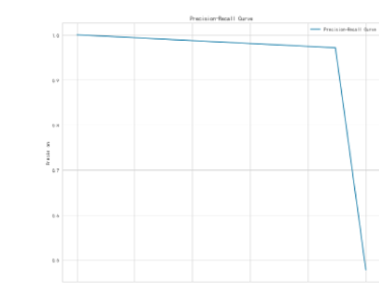


African Americans vs Whites

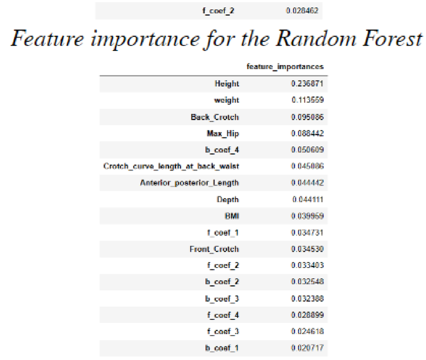


Precision Recall Curve for the Random Forest

Feature importance for the Random Forest



Asians vs Whites



Conclusion and Limitations

Conclusion

- The body shapes vary based on the races and BMI
- There is no distinct pattern that differentiates the races
- Body measurements and both front and back curve coefficients can predict race well
- There are interactions between covariates
- Factors such as max hip, BMI play important roles in predicting the body shapes

Limitations

- Sample size for different racial cohorts are uneven, such that curve predictions for some races are more reliable than others
- Other covariates not present in the data, such as age and body fat ratio, may have a stronger relationship with the shape of the curves

REFERENCES

- Song, H. K., & Ashdown, S. P. (2011). Categorization of lower body shapes for adult females based on multiple view analysis. Textile Research Journal, 81(9), 914–931.
- Su, J., Ke, Y., Kuang, C., Gu, B., & Xu, B. (2019). Converting lower-body features from three-dimensional body images into rules for individualized pant patterns. Textile Research Journal, 89(11), 2199–2208.

Cornell University