

A Data Mining Approach for Determining Gait Abnormalities in Runners with Patellofemoral Pain Syndrome

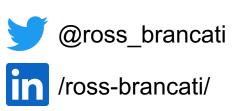
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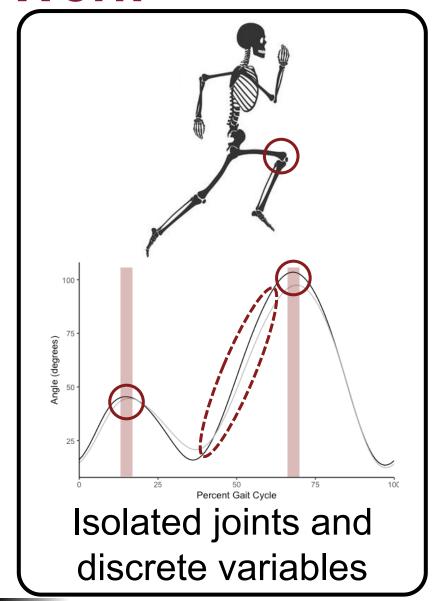
Patellofemoral Pain Syndrome

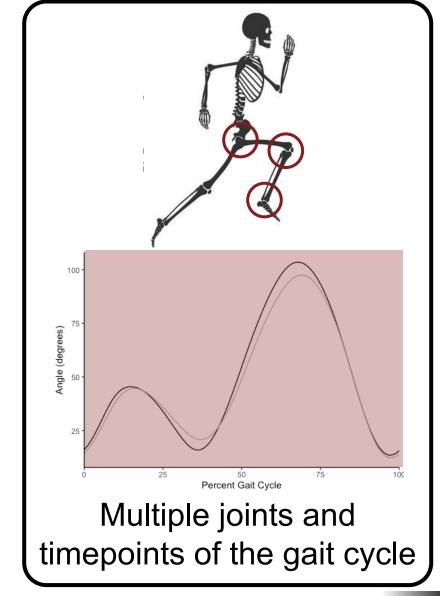
- Patellofemoral pain (PFP) is a common musculoskeletal pain disorder, often presenting as anterior knee pain
- Although PFP occurs at the knee, distal and proximal joints should be considered as well
- Data mining approaches may offer better insight into the complex etiology of PFP





Prior Work

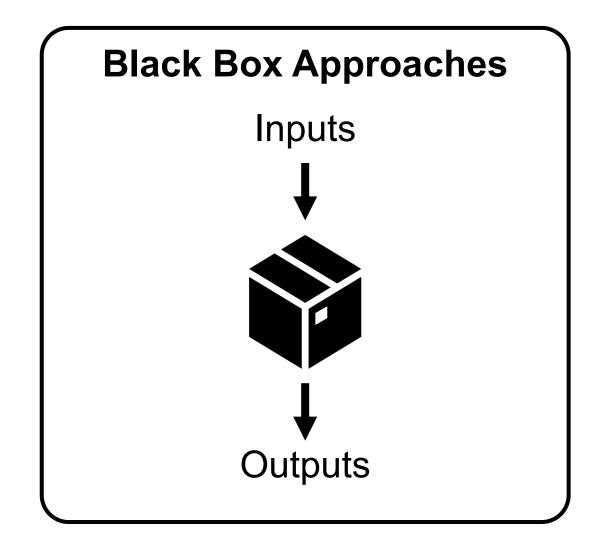


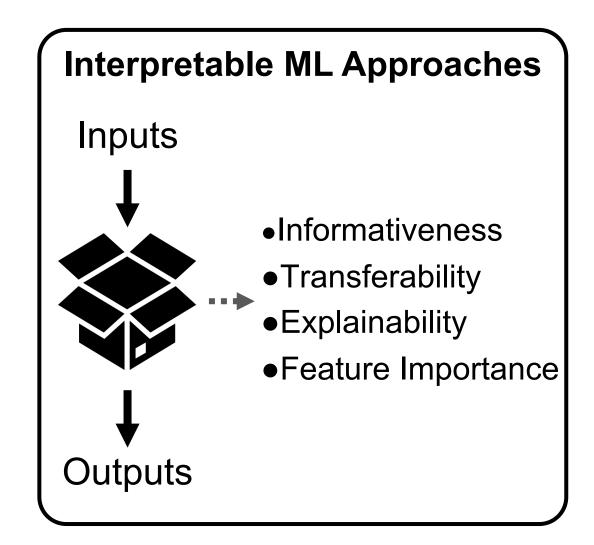






Interpretable Machine Learning (ML)









Methods – Data Collection

41 recreational runners

- 15 healthy (H)
- 14 symptomatic PFP (S)



Runners completed a 21-minute treadmill run at self-selected speed







M21

Kinetic, kinematic, electromyography, RPE, and subjective pain scores collected at 1st (M1) and 21st (M21) minutes





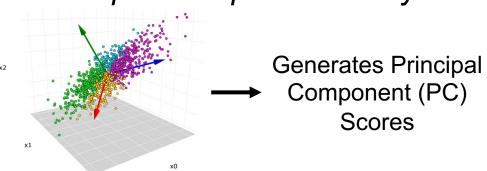
Methods - Data Processing

1. Generate variable matrices

Subject ID	Group	t1	t2	 t101
Subject 1 M1	Н	Datapoint	Datapoint	 Datapoint
Subject 1 M21	Н	Datapoint	Datapoint	 Datapoint
Subject 2 M1	S	Datapoint	Datapoint	 Datapoint
		Datapoint	Datapoint	 Datapoint
Subject 29 M21	R	Datapoint	Datapoint	 Datapoint



2. Principal Component Analysis



$$h_{\theta}(x_i) = g(\theta_0 + \sum_{i=1}^{m} \boldsymbol{\theta_i} x_i)$$

$$\rightarrow \theta_1, \theta_2, \dots, \theta_n$$

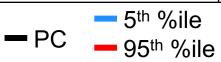
Extract Feature Coefficients





Feature	PC Plot	Waveforms	Logistic Regression Coefficient	PC Interpretation
Knee Flexion Angle PC3	0.2 0.1 0.0 -0.1 -0.2 0 25 50 75 Percent Gait Cycle	100- 75- 50- 25	3.617	Related to peak stance angle, toe-off angle, and peak swing angle
Hip Adduction Moment PC3	1.0 0.5 0.0 -0.5 -1.0 0 25 50 75 Percent Stance	0.3 Adduction (+) 0.2 0.1	1.301	Related to peak hip abduction moment in early and late stance
Glute Max Activation PC2	1.0 0.5 0.0 -0.5 -1.0 0 25 50 75 Percent Pre Activation plus Stance	0.15 0.10 0.05 0.00 25 50 75 Percent Pre Activation plus Stance	0.929	Related to magnitude of activation in prestance and late stance
Hip Adduction Moment PC1	1.0 0.5 0.0 0.0 0.0 0.0 1.0 0.0 1.0 0.0 1.0 0.0 1.0 0.0 0	0.3 Adduction (+) 0.2 0.1	0.801	Related to overall magnitude of moment in mid-stance





Healthy

Injured



Results – Minute 21

Feature	PC Plot	Waveforms	Logistic Regression Coefficient	PC Interpretation
Knee Flexion Moment PC2	0.2 0.1 0.0 -0.1 -0.2 -0.3 0 25 50 75 Percent Stance	Extension (+) Flexion (-) Percent Stance	2.341	Related to loading rates in early and late stance
Hip Adduction Moment PC3	1.0 0.5 0.0 -0.5 -1.0 0 25 50 75 Percent Stance	0.3 Adduction (+) 0.2 0.1	1.608	Related to peak hip abduction moment in early and late stance
Knee Flexion Angle PC3	0.2 0.1 0.0 -0.1 -0.2 0 25 50 75 Percent Gait Cycle	100 75 50 25 0 25 50 75 Percent Gait Cycle	1.515	Related to peak stance angle, toe-off angle, and peak swing angle
Knee Adduction Moment PC3	0.25 0.00 -0.25 -0.50 0.00 -0.25 Percent Stance	Abduction (+) -0.25 Adduction (-) 0 25 50 75 Percent Stance	1.479	Related to 1st and 2nd peak moments, or magnitude of moment in stance





Healthy

Injured



Results - Summary

Group	Pain Level Change (M1 > M21)	BORG RPE Change (M1 > M21)	
Healthy	0	5	
Symptomatic	3	3	

At M1, Healthy group demonstrated

- Greater range of knee flexion
- Larger magnitude of hip abduction loading
- More glute max activation

At M21, Healthy group demonstrated

- Greater loading in knee flexion
- Larger magnitude of knee adduction loading





Conclusions

Dimensionality reduction and interpretable machine learning approaches capture important biomechanical adaptations.

Sagittal plane knee angles and frontal plane hip angles are pertinent features in runners with PFP.

With the onset of pain, runners with PFP avoid knee flexion and adduction loading patterns.

Future research should consider systematic approaches to optimize interventions in clinical populations.





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Questions?





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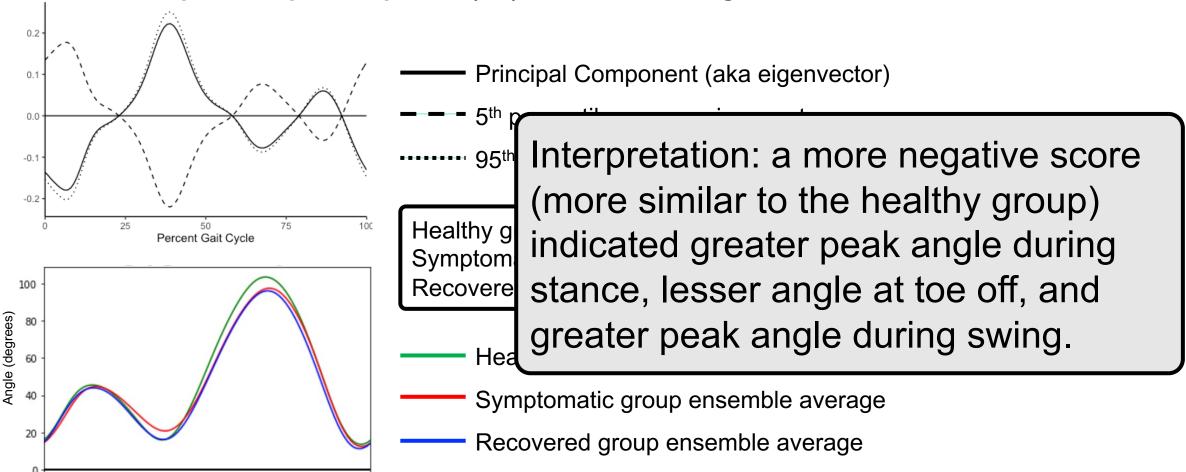
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Interpreting Principal Components

Example Principal Component (PC): Knee Flexion Angle PC 3





25

75

Percent Gait Cycle

100

