Your Next Personal Trainer: Instant Evaluation of Exercise Form

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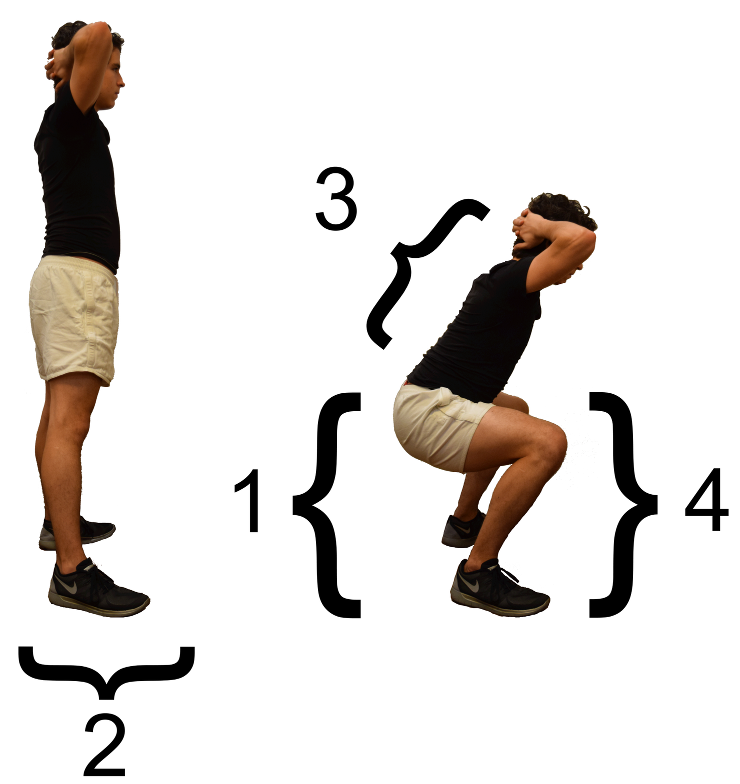
Problem

Millions of people exercise without proper form, which reduces the effectiveness of their workouts and leads to increased injury risk. We aim to **help exercisers improve their form** by giving fitness advice with machine learning. We explore the free standing squat specifically, a fundamental, full-body exercise where proper form is crucial.

What Makes a Squat?



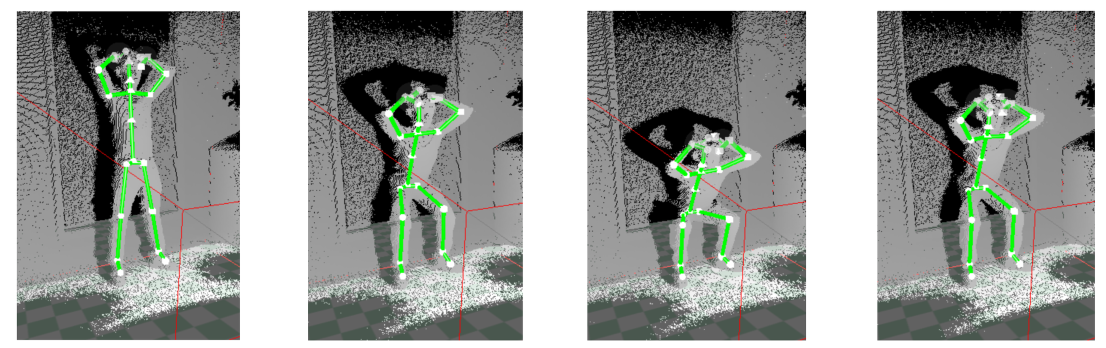
Squat components:

1. Depth: Angle formed between the ankle knee and hip while squatting
2. Stance: distance between feet and center of mass over your ankles
3. Back-Hip Angle: Angle formed between the knees hips and back throughout the squat
4. Knee-Toe Alignment: Location and movement of knees throughout the squat

We consulted with industry experts to analyze the most crucial components of the squat. We built a total of **55 features** corresponding to one or more of each of the components; these included angles and translations over time from the **x, y, z coordinates of 25 joints.**

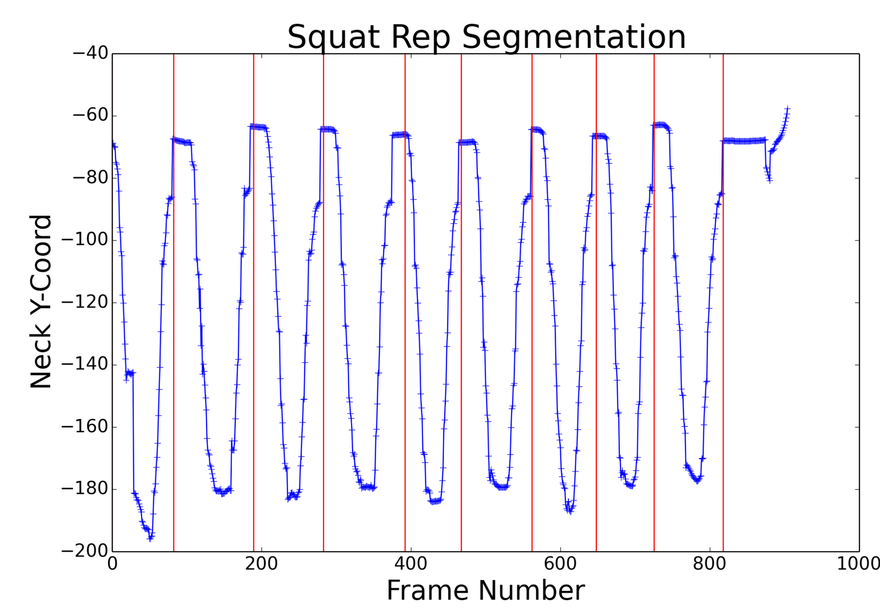
Classification Pipeline

1. Observe data with Kinect (10 reps)

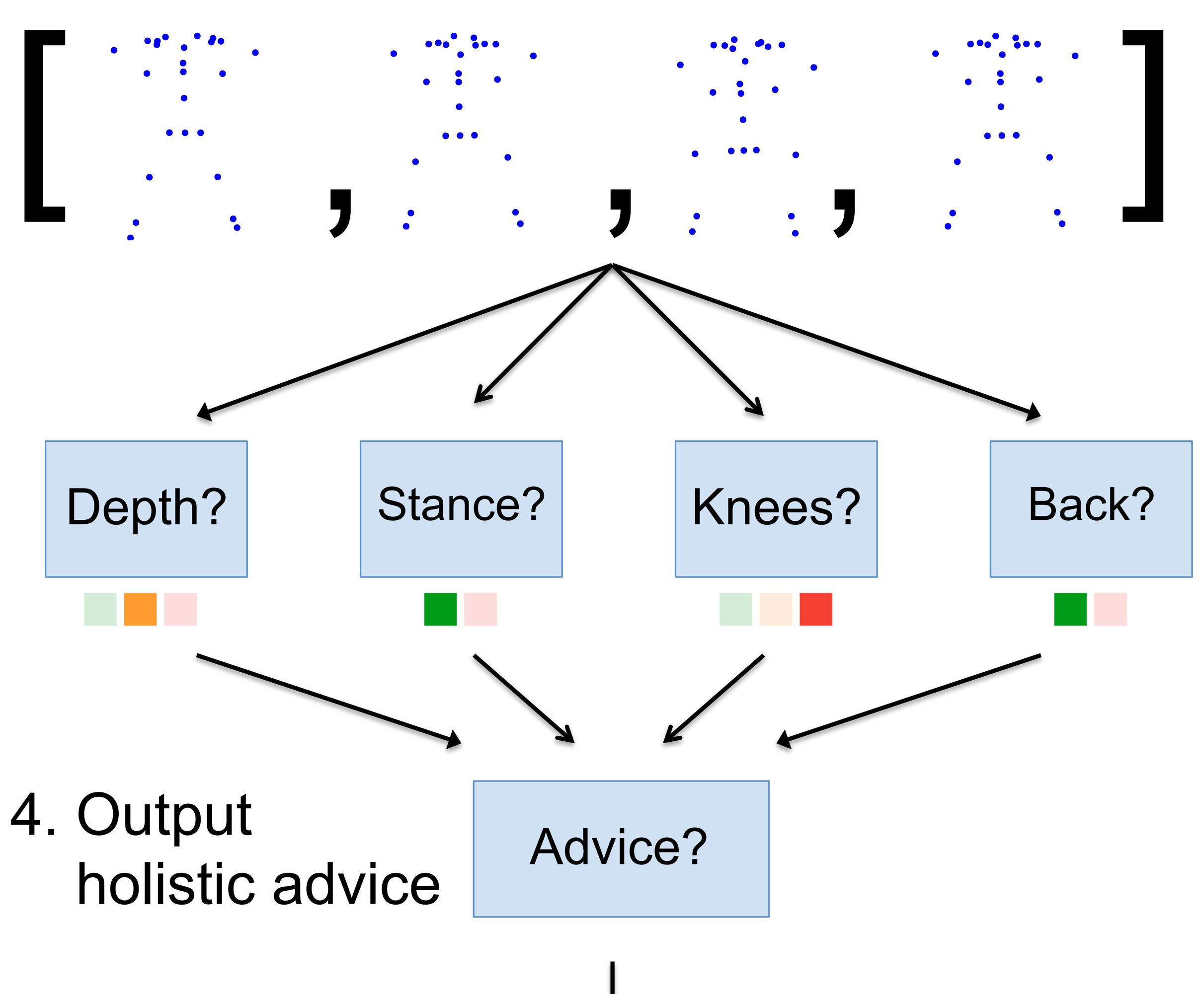


Example squat rep with resolution τ = 4

2. Segment data into discrete reps



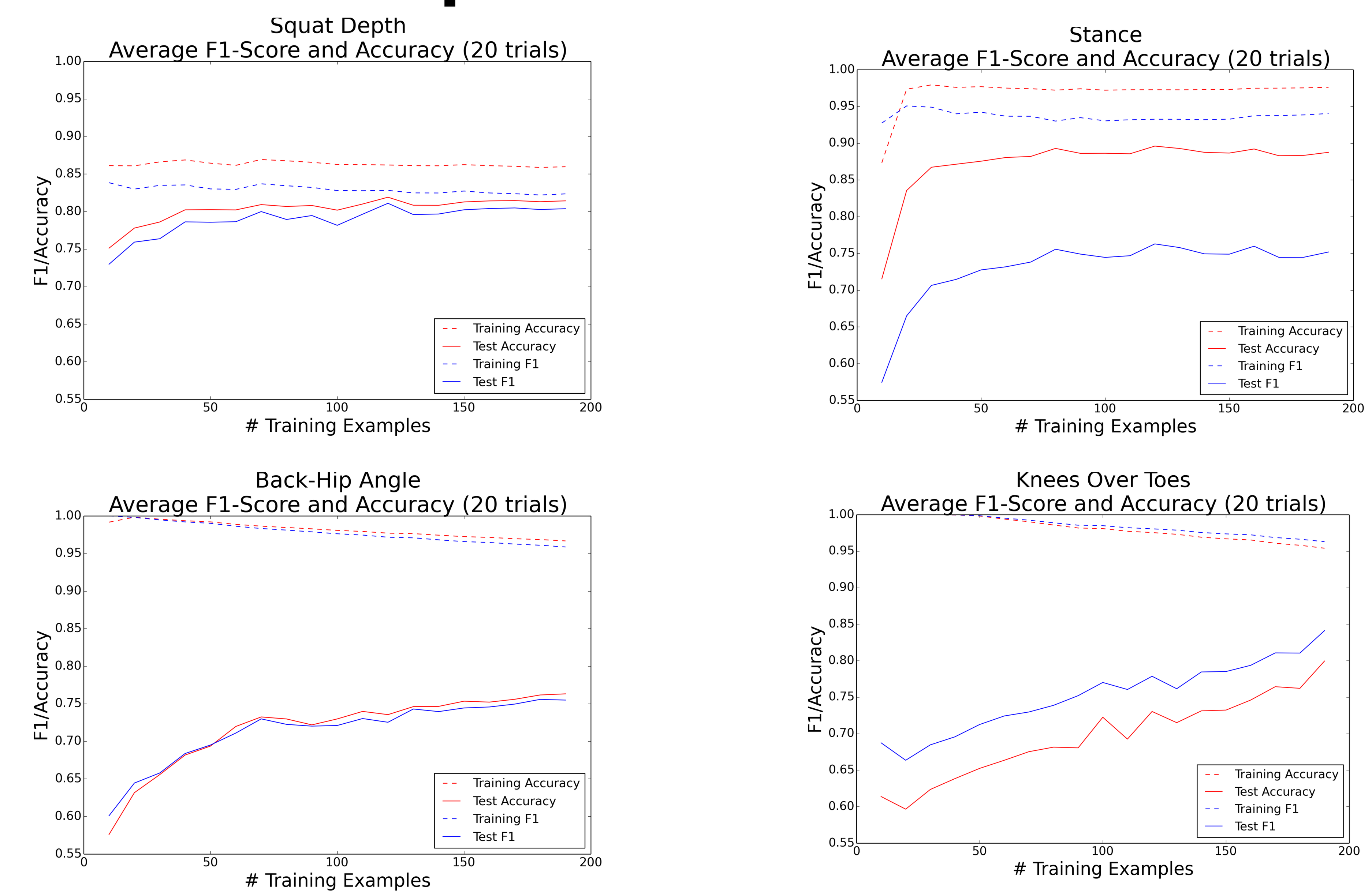
3. Run reps through component classifiers



4. Output holistic advice

"You need to get lower on your squats. Also, keep your knees behind your toes."

Experimental Results



We experimented with several different models and hyperparameters for each component. These results are with the highest performing classifiers: logistic regression with L1 regularization (left), decision tree with a max depth of 3 and maximizing information (right).

Analysis

- Certain components, such as required depth, stance and the angle at the hip, are fairly well-defined problems.
  - **Logistic Regression with L1 regularization** proved effective in reducing overfitting and identifying the well-defined decision boundaries.
  - Stance and squat depth error quickly levels out. We believe we are limited by the fidelity of Kinect's coordinates and the accuracy of our labeling.
- Complex, nuanced components, such as knee-toe alignment and simultaneous bending of the back and hip (not shown), were classified using **decision trees**.
  - **We maximized information gain** instead of accuracy by using **entropy** instead of Gini impurity as our metric for splitting. This helped with a data set with much fewer positive than negative examples
  - We limited our depth to 3 to prevent gross overfitting
  - We used a larger amount of features to learn and, consequently, need more training data to better our numbers