WODwell Workout Analysis Final Report

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For lots of people, getting excited to go into the gym is hard. With every other drain life has on your time and energy, carving out an hour to workout can be really challenging. As a gym owner or workout programmer, how do you keep your members excited to come in and engaged and interested in the workouts you write? There are tons of resources for writing workouts and planning programming but oftentimes you don't know how a workout will be received until after it's been the workout of the day at your gym. Our goal is to identify what aspects of a workout make it popular and what causes people to skip that day, or in other words, cherry pick that workout. Our focus will be on CrossFit, more specifically on workouts logged on WODWELL.com.

Data:

Our data is scraped from wodwell.com using selenium. We have just over 2000 entries, each representing an unique workout with its own format and volume of movements. We have a few general information columns, including workout name and workout href, followed by some more usable statistics. The columns are as listed below:

- **Name:** The name of the workout.
- **HREF:** The link to that workout's specific wodwell page.
- **Views:** The number of views the workout's page has.
- **Likes:** The number of likes the workout's page has.
- **ForTime:** True if the workout is for time, false otherwise.
- **EMOM:** True if the workout is in the format of "every some number of minutes on the minute for some number of minutes, do something," false otherwise.
- **AMRAP:** True if the workout is in the format of "as many rounds and reps as possible in some amount of time", false otherwise.
- **Names of various movements:** The number of a given movement in all rounds of the workout. There are 79 different movements.

- **LikesPerView:** This is a calculated column, it's equal to the number of likes divided by the number of views.

Exploratory Data Analysis:

Initially, our target for analysis was likes. We plotted our different columns against likes.

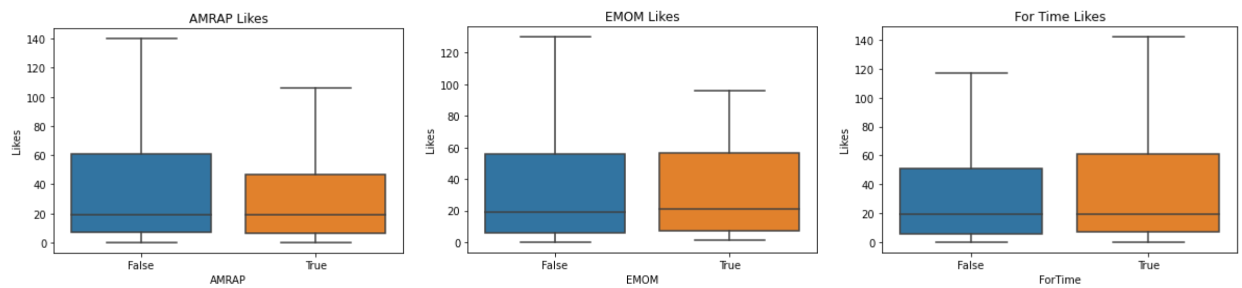

Figure 1: Plots of AMRAP, EMOM, and For Time vs number of likes.

Figure 1 shows our plots of workout formats against likes. We can see a slight preference for workouts of the EMOM and For Time formats but we relatively quickly into our analysis found an issue.

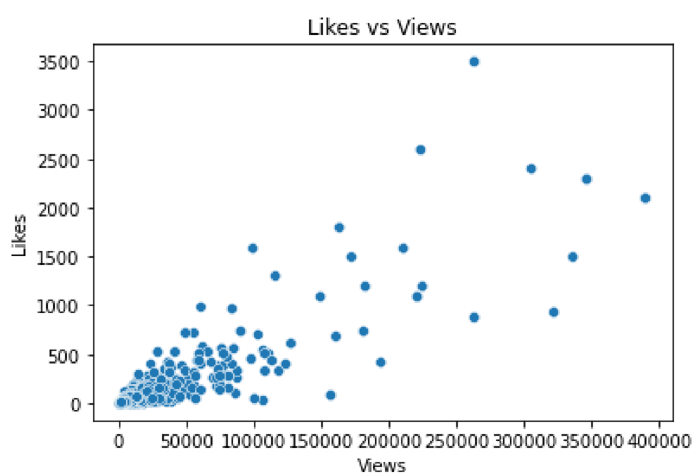

Figure 2: Likes vs Views for all workouts

Figure 2 reveals a problematic fact. When we work with a sheer number of likes, workouts with higher numbers of views have higher numbers of likes. While the relationship isn't completely linear, it's clear that views have such a high impact on number of likes that they would overshadow any other predictor of likes. To address this challenge, we calculated our

LikesPerView column, a calculated column equal to the number of likes a workout received divided by the number of views. This metric gives us a more reliable view of trends.

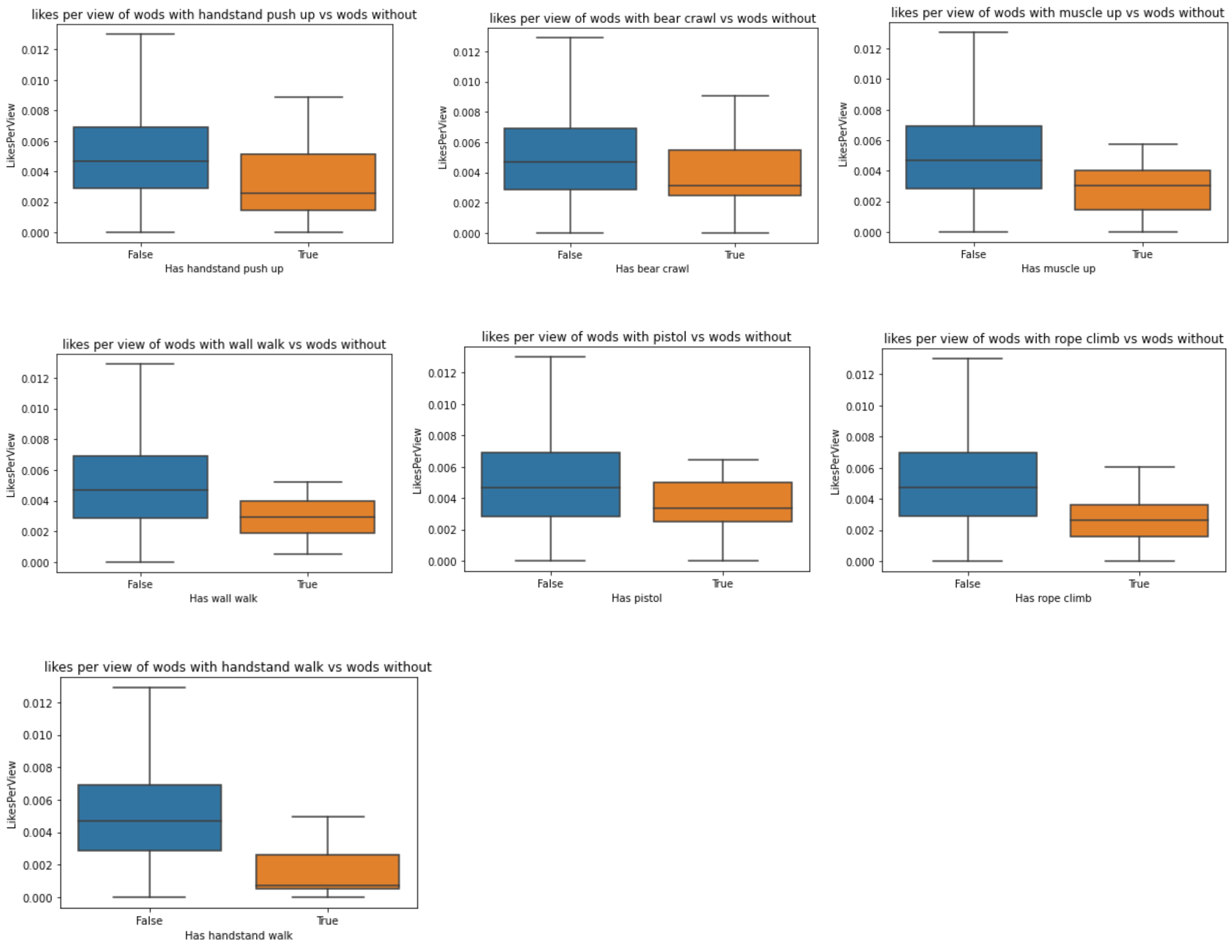

Figure 3: High skill gymnastics movements vs likes per view

As shown in Figure 3, movements that fall into the category of high skill gymnastics movements are less popular than workouts without those movements. This isn't terribly surprising as it stands to reason that the higher the skill barrier, the less likely any given person is to be able to do the workout as written and it's a safe assumption that, generally, people are more likely to like a workout if they can do it as written.

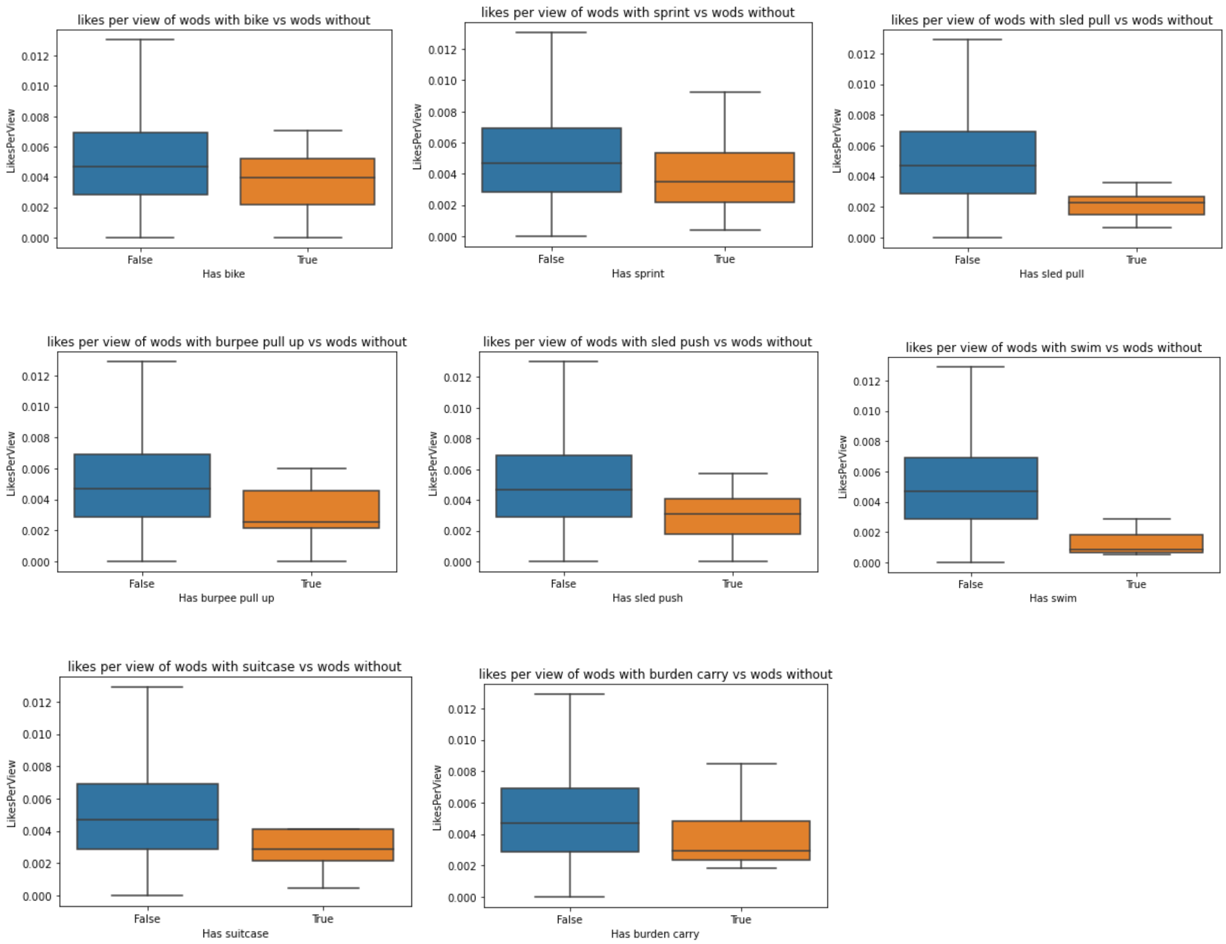

Figure 4: Grunt work movements vs likes per view

While Figure 3 shows us a general dislike for high skill movements, Figure 4 shows a general dislike for low skill movements, movements we classify as “grunt work” movements that are a pure test of grit and power with relatively low skill involved. These movements include things like sled pushes and burden carries. Given that extremely low skill and extremely high skill movements seem to be generally disliked, we next turn to examining the medium skill movements and this is where we find perhaps our most surprising discovery.

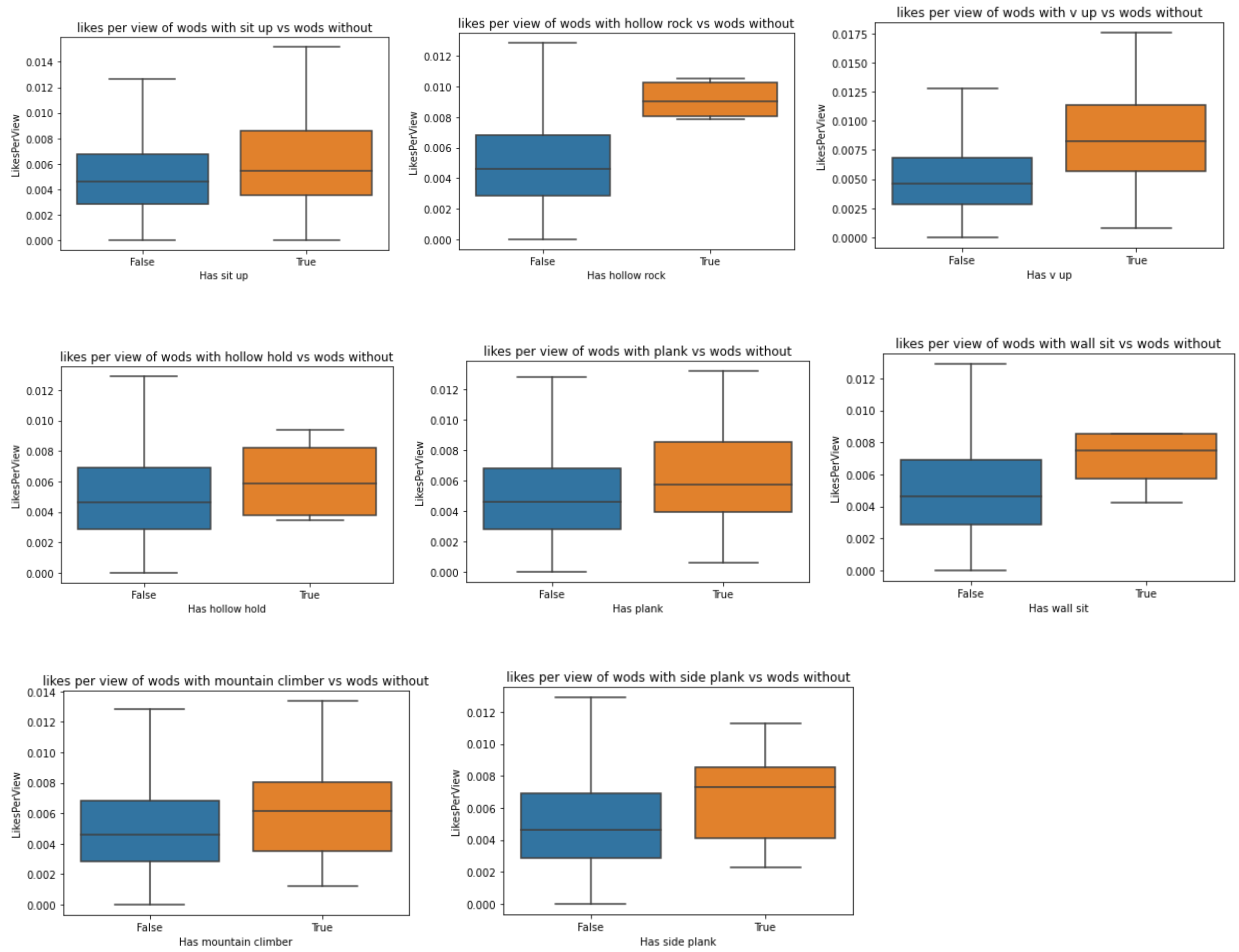

Figure 5: Ab movements vs likes per view

Oftentimes in the gym, anecdotally, you will hear members constantly complain about the ab portion of a workout. They will tell you it's their least favorite part of the day. Yet Figure 5 suggests that across the board, our medium skill ab movements are actually some of the most liked workouts. Even within this subset of movements, we can see in Figure 5 that sit ups, the lowest skill ab movement in our list, has one of the lowest differences between present and not present in the workout, while hollow rocks, a solidly middling skill movement, has the largest difference between present and not present. Supporting this idea that medium skill movements are what attract people are the results shown in Figure 6.

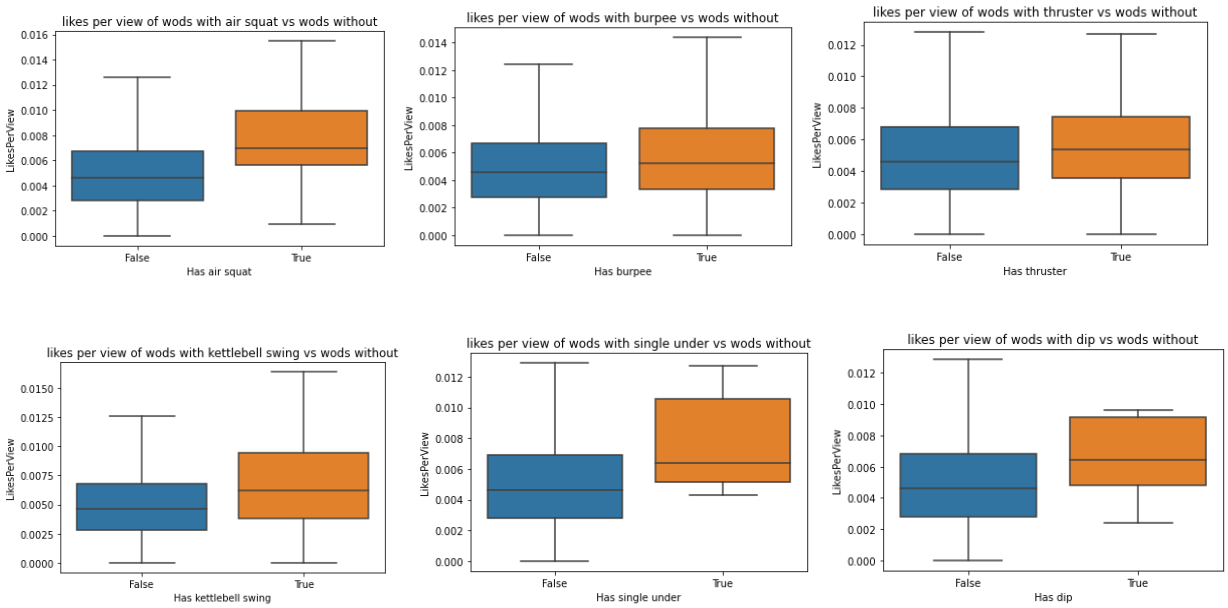

Figure 6: Air squat, burpee, thruster, kettlebell swing, single under, and dip vs likes per view

Figure 6 shows the 6 other movements we found with a higher true than false when compared to likes per view. These movements are also categorized as medium skill movements. Something that any random individual might not be able to execute on their first attempt, or might do horribly inefficiently on their first go at it, but don't have such a high skill bar that it takes months or years to learn. It seems that potentially people like movements that make them feel like they are using a new learned skill, something they didn't use to be able to do, but not something so hard that even the majority of your average CrossFit athlete can't do it.

So how then do we determine if a workout will receive a large number of likes or not? We can try to intuit from our data exploration if a workout will be well liked but we have more accurate tools for such a challenge. In the next section we explore applying machine learning to our data set in order to predict the popularity of a given workout.

Machine Learning:

We began by preprocessing our data. We have already ensured its cleanliness and usability as we were the ones who scraped in from WODwell.com. We first check to see if any of our features are in different units and need to be scaled. We find that as all of our numerical units are measured in number of reps, there is no need to scale our data. There is a difference in the amount of time it takes to complete one rep of a single under versus one rep of a squat clean, but the counting structure doesn't change. Our next step is to split the data into a training set and a testing set, preserving our testing set so we have unseen, labeled data to test on.

We move on to modeling. For this particular problem we are using a continuous variable, the total number of likes, as our target. We hyperparameter tuned multiple models to determine which would be most effective for our purpose. Our two top performing models were XGBoost and Random Forest with XGBoost having an r-squared of .43 and Random Forest at .52. We chose to move forward with Random Forest as it slightly out performed XGBoost, though were this model put into production by a gym owner interested in keeping their model up to date, its possible that XGBoost would be preferable as Random Forest tends to have a long training time on new data. Our mean absolute error for our Random Forest model was 118.35, meaning on average, our model could miss the true number of likes by about 118 likes in either direction. Given that we are dealing with hundreds of thousands of views and tens of thousands of likes on some of our workouts, this error falls within the acceptable range of error for the model to still be useful.

Conclusion:

We scraped thousands of workouts from WODwell.com and broke them down into their component pieces. We analyzed workout popularity based on movement and workout format. We found that low and high skill movements tend to be less popular, while medium skill movements and abdominal work tend to lead to popular workouts. Of particular note, we found that burpees and thrusters were actually quite popular even though you often hear them complained about if you spend time hanging around your local CrossFit gym. We applied machine learning to our dataset and created a model that will predict likes within an accuracy of around 100 likes. This model is a potential tool for gym owners and workout programmers to double check their intuition about what their athletes will enjoy with a data driven analysis based on what has been previously popular.