Chase Slater (301230135) Ben Low (301290919)
Eugene Choi (301355965) Jakob Mogg (301317992)

Question 1.

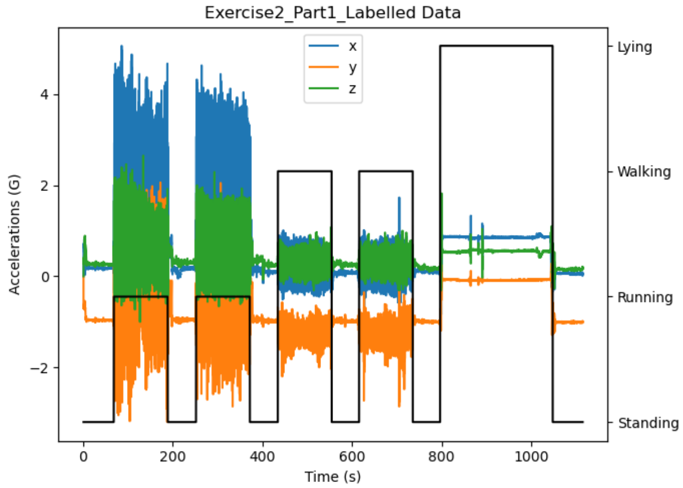

Figure 1. Accelerometer data labelled with respective activities: Running, Walking, Lying, or Standing

Based on the experimental setup (x-axis toward the thumb and y-axis to the fingers), in the standing phase (Figure 1), the x-axis and z-axis are perpendicular to the direction of the gravity, so their values are near zero and the y-axis is parallel toward the floor, so its value is near -1. In the walking phase (Figure 1), the range of measurement increases positively and negatively for all axes due to swinging the arm back and forward. Swinging movement creates dynamic acceleration to the wrist/device in the direction of swinging. When swinging the arm forward, the x-axis changes its angle from perpendicular to toward the upright direction, which is the opposite direction of gravity, so its value increases to near 1. An increase in z-value shows the arm was rotated medially during swinging forward. The y-axis turns from parallel to gravity to more perpendicular, so its value increases from -1 to near 0. When returning from the forward swing, the arm is dropping toward the direction of the gravity, so there is an acceleration downward that makes the y-value more negative than its initial value. By the same acceleration, x-values and z-values also show more negative values, but their value does not reach -1 because, even though there is downward acceleration, these axes are at a perpendicular position than y-axis. The running phase is similar to the walking phase (Figure 1), but overall values are exaggerated and the range is wider than the walking because we swing our arms faster and more vigorously to create higher accelerations. Also, when we run, we bend our elbow and swing the arm in a wider range, so together with the greater acceleration, it results in the larger amplitudes of the overall values. Lastly, in the lying phase (Figure 1), gravity is the only acceleration applied to the wrist/device as the standing phase. Fingers are positioned perpendicular, and the thumb is upright to the floor. In other words, the y-axis is perpendicular to the direction of gravity, so its value is 0, and the x-axis is opposite to gravity, so it results in the value of near 1. The z-value shows between 0 to 1, so I assume the arm was inward rotated to some degree compared to its position during the standing.

Question 2.

It is important to stand between the activities: running, walking, and lying to better distinguish the activities later when analyzing through python. Standing becomes a default no movement activity that allows the frequencies from the accelerometer to stand out better for quick labelling with Lab4Function's code. Another important reason is that Lab4Function will also allow you to choose the beginning and end of each activity and make standing the default activity in between, so one must stand in between activities.

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Question 3.

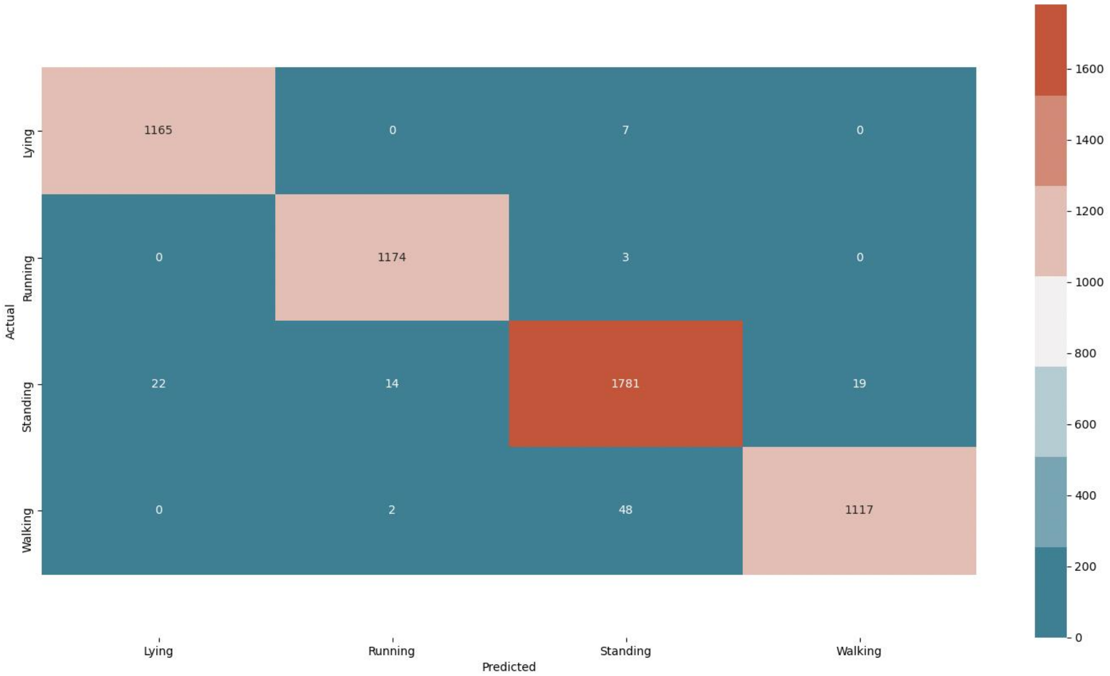

Figure 2. Confusion matrix showing the results of the trained model on predicting the activities: Running, Walking, Lying, or Standing

When lying, the model is very accurate. It only had very minimal (0.6% or 22 cases) error when the algorithm predicted standing when the participant was lying. This small error could be a result of the lack of motion, and potential orientation for the sensor axis of the standing person unintentionally mimicking the wrist position of someone lying down. This may be a result of no strict protocol for the lying down phase as far as wrist placement goes. When running, the model is very accurate with very minimal (0.3% or 3 cases) error where the algorithm predicted standing when the participant was actually running. This could be due to variation in stride (potentially adjusting loose clothing) that allowed for the accelerometer to remain fixed in space, mimicking standing. When standing, the model is still accurate, although slightly less, with minimal (3.0%) error where the algorithm predicted lying(1.2% or 22 cases), running (0.8% or 14 cases) or walking (1.0% or 19 cases) instead of standing. Errors in predicting standing as other activities may be related to other activities having points of zero motion and thus mimicking standing, or moments during standing where fidgeting, or other movement occurred, causing it to resemble other activities. When walking, the model remains accurate, although less accurate than with other predictions, with minimal (4.3%) error where the algorithm predicted standing (4.1% or 48 cases) or running (0.2% or 2 cases) when the participant was actually walking. This could be explained by a lack of arm movement mimicking a standing condition's axis of orientation, and lack of horizontal acceleration.

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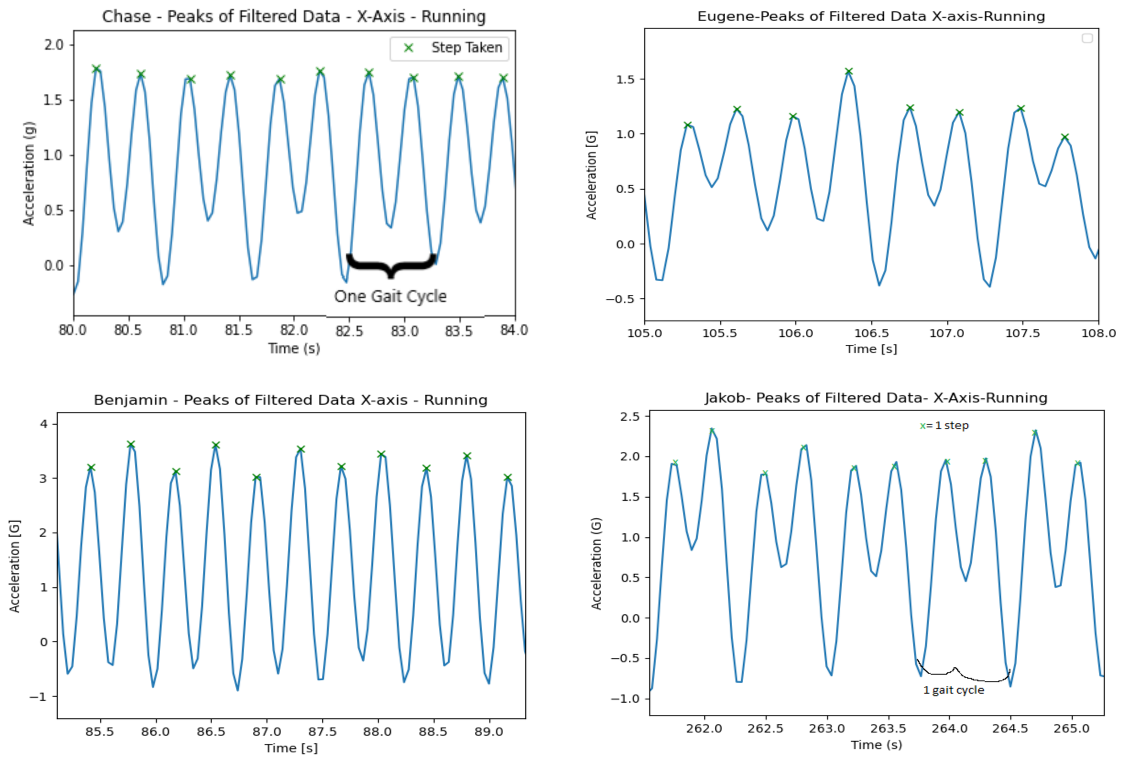
Question 4.



Figures 3. Plots from each group member showing accelerometer force in the x-axis vs. time for running. Chase's plot shows when each step was taken and what one gait cycle looks like.

Question 5.

Changing 'Wn' changes the cutoff-frequency in various filters. In the case of doing a low-pass filter, like this lab, this means that any frequencies above 'Wn' will not pass through and all frequencies below 'Wn' will pass through. Comparing a 'Wn' of 0.05 vs. 0.5, the 0.05 data would be stretched out compared to 0.5 because the cycles per second (Hz) are lower with Wn=0.05 as frequencies higher are not let through (in terms of a low-pass filter). The amplitude may also be lower with Wn=0.05 because the higher frequencies have been filtered out compared to Wn=0.5.

Question 6.

The step-counting algorithm performed quite accurately. For running, it overestimated the first period (308 steps) by 4 steps and underestimated the second period (302 steps) by 2 steps. Walking on the other hand performed worse as it overestimated 18 and 6 steps for first (212s steps) and second (242 steps) periods, respectively. The algorithm calculated how many peaks were in the x-axis accelerometer data and used this to represent steps because they occur in synchrony. When a subject is in a running position, sticking out their thumbs in a "thumbs up" matter represents the x-axis of the accelerometer. As they run, they exert positive acceleration in this direction whenever they take a step with either foot because their whole body is being lifted. This is why we use the x-axis acceleration peaks as a reference for each step. When you are running, you usually keep your hands in front of you and the x-axis maintains a fairly vertical plane, but this is not the case when you are walking. Walking consists of slower movements with the arms swinging in a smaller range of motion down by the hips. If they were to stick out their thumb while walking, the x-axis can be seen to be largely horizontal, resulting in less G force as it is perpendicular to gravity. These are all reasons why the walking data is lower in frequency, amplitude and force. The peaks of this data can still be used to calculate step count during walking as the peaks of acceleration represent when the hand is swinging forward, which happens every two steps. Therefore, the number of peaks for walking activity must be multiplied by two. Two different algorithms with different filters were used to improve accuracy, one for each activity. This is practical because the two activities, distinguished from each other and, therefore, could have unique analytics. The reason that running is more accurate than walking is because of the magnitude of the acceleration recorded. The running data had a range of 5 g's, whereas walking was mostly within a 0g to 0.8g making it much more sensitive. A force of 0.5g's seems negligible in the running range, but could influence a peak during the walking phase. This small force could be caused by extra movements of the arm when encountering differences in terrain, stepping over objects, checking a watch or scratching a nose. Any fidgety movements could be picked up and read as a peak, hence why there is a tendency to overestimate step count while walking. Other problems could occur from incorrect placement of the sensor so the axes are not aligned or a loose fit, where the sensor can wiggle around.

Question 7.

It is useful to keep track of how many steps you take each day to monitor health. Especially in a pandemic where people are working from home and in lockdown, it becomes very easy to underestimate the amount of movement and physical activity one does each day. Counting the amount of steps, you take each day is a great way to quantify your baseline of activity. 10,000 steps a day has been a trend as the minimum amount to achieve health benefits, such as lower blood pressure, stable glucose levels and better moods (Carter, 2021). A step counter holds people accountable as self-reported daily steps tend to be overestimated and the average middle-aged adult takes around 4000 steps per day (Jahan & Shenoy, 2017). There is a positive correlation between steps per day and physical fitness (Jahan & Shenoy, 2017), but it has its limitations. Pedometers cannot accurately determine physical activity as they do not directly measure the intensity, duration, or frequency (Ainsworth et., 2015). Someone could be doing weighted lunges and it would be calculated to have the same energy expenditure as doing that many steps. Pedometers do not measure non-ambulatory movement, such as activities that use the upper arms, swimming, or biking and often rely on general algorithms to calculate data, which can be inaccurate (Ainsworth et., 2015). Some of the benefits of using step counts to quantify physical activity is that walking is an activity almost everyone can do as it does not need any special equipment. This makes it a great way to motivate sedentary people or those who cannot do vigorous activities. It can be incorporated throughout the day and tracks activities you might not have considered, like walking around the mall or grocery store. It is an inexpensive and accessible device that can also trigger behaviour change techniques, such as self-monitoring and goal setting, for motivation (Foster et al., 2010). This can also be utilized to competitively motivate peers and promote active living.

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Question 8.

a. To quantify a whole day's worth of physical activity on myself, I would need to use the accelerometer from the 409 lab. I would need to set up the microcontroller with the appropriate code, the openlog with a micro-SD card to collect my movement, and a fresh battery to provide the power source. The accelerometer would benefit from being placed at my waist to get my body's total movement instead of on my wrist picking up hand movement, which may not be related to physical activity. If possible, setting up the ECG to record heart rate would also improve quantifying physical activity by helping determine intensity during the day. The system could be set up and plugged in at the beginning of the day and unplugged at the end of the day to analyze the data collected by the openlog.

b. A global positioning system (GPS) would improve the quantification of daily physical activity. In combination with an accelerometer, a GPS can be used to analyze intensity and pattern of activities (Carter, 2021) as well as distance travelled. An altimeter could also improve quantification of physical activity. An altimeter can determine the change in altitude during an activity and this can also aid in determining intensity levels with the rate of change in altitude.

Question 9.

Accelerometer measures both static and dynamic acceleration that is acting on the device and gives information about the orientation of the device (Kok et al., 2017). The accelerometer that we used has three axes and provides the orientation of the device by the relative position of these axes with respect to the gravity force, but it does not give information on how fast it rotated because the accelerometer cannot measure the angular velocity (Sparkfun, n.d.). To measure the accurate orientation, we need a gyroscope that measures the angular velocity. Inertial measurement unit (IMU) is the device that combines both accelerometer and gyroscope, so it provides two to six degrees of freedom and compensates the limitation of each sensor (Sparkfun, n.d.; Wirth et al., 2019). The accelerometer provides the linear acceleration (m/sec^2), the gyroscope provides the angular velocity (degree/sec), and also IMU combines the magnetometer as well and uses its measurement to reduce the accumulating error from the gyroscope (Wirth et al., 2019). Therefore, all the experiments that used an accelerometer also can be done with IMU. For the experiments that rotation is a significant movement, IMU will provide more accurate data than using an accelerometer, but for measuring less rotating movements, IMU may provide too much information than we need.

Question 10.

The purpose of test data is to see if the model is able to generalize with new data. If the data is not actually new to the predictive model, then this has not been achieved (Google Developers, 2020). If the model has not been tested against new data, then it has not been validated. In much the same way that two points on a graph can be predicted by a linear model, but also based on exponential or logarithmic models, the machine-learning prediction based on tested data may not be able to generalize, and only holds true for the tested data. Basically, it would be unclear whether the model was only good at describing the data it was built with, or that it could predict the outcomes based on the various independent factors.

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