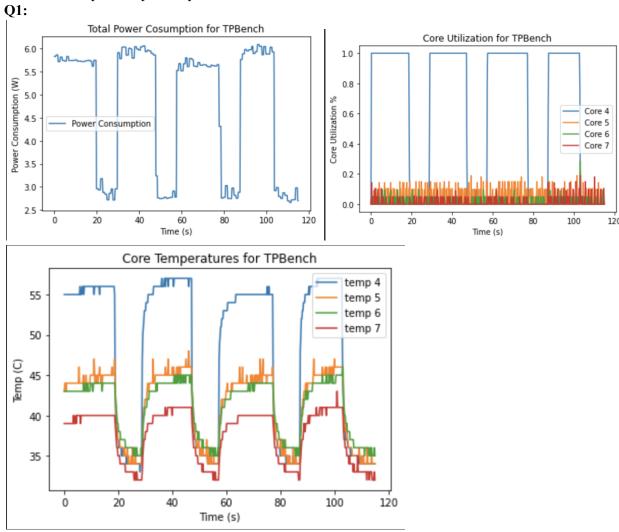
Homework #2

Problem #1:Cyber-Physical Systems and Benchmarks



Q2: There were 4 phases for the benchmark

Q3:

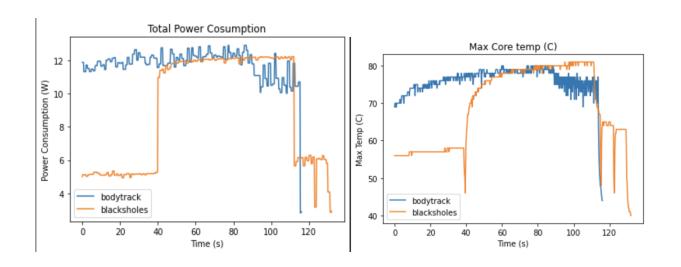


Table 1

Benchmark	Run time [s]	Avg. power [W]	Avg. max temp [°C]	Max temp [°C]	Energy [J]
blacksholes	132.26	8.96	69.03	81.0	1184.23
bodytrack	116.29	11.80	75.86	80.0	1367.19

Problem #2: System Power Prediction Q1:

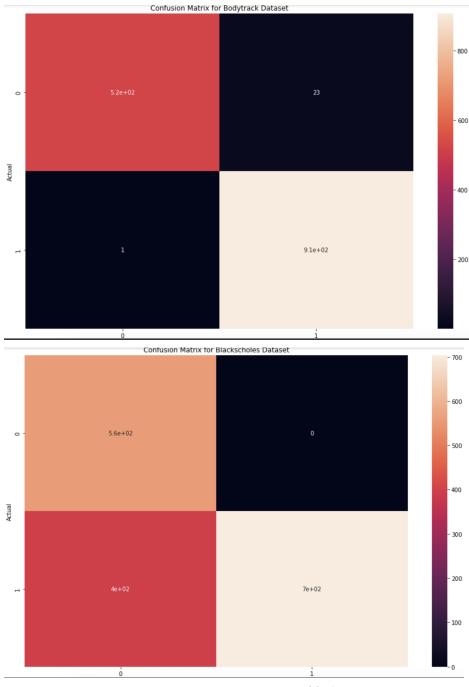


Table 2

Benchmarks	Accuracy	Precision	Recall	F1-Score
blackscholes	0.8173	0.9962	0.7276	0.8410
bodytrack	0.9834	0.9878	0.9856	0.9867

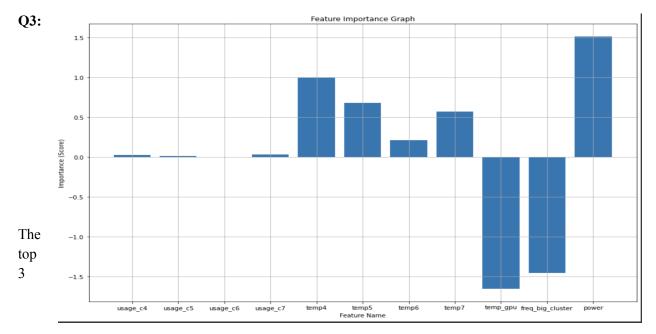
Our accuracys are high for body track, with almost the precision, recall, and F1-score all being high as well. This indicates that our model is well rounded and making predictions with minimal error. The

accuracy for the blacksholes data set wasn't as high but was solid. The precision was high and didn't make a single false positive. While the recall was low due to the model having high false negatives which led to a decrease in accuracy as well.

Q2:

Table 3

Dataset	training	blacksholes	bodytrack
\mathbb{R}^2	0.9869	0.9566	0.9224
MSE	0.0101	0.0594	0.1215



features are dynamic power, temp4, and temp5 - this means these are the features that have the highest coefficients and subsequently the highest feature importances for the system power. We don't use any of the power features (the ones that directly impact system power) to notice which features that don't directly correspond to the power function can have the most influence over the system power.

Problem #3: System Temperature Prediction Q1:

Table 5

Dataset	Test MSE (Core 4)	Test MSE (core 5)	Test MSE (Core 6)	Test MSE (Core 7)
blacksholes	773.2488	1670.77	1837.0898	1512.3059
bodytrack	1260.3250	969.9160	1137.8717	942.0565

Q2:

1. We can tune the hyperparameters - especially the 'hidden_layer_sizes' - by utilizing *grid search* which basically evaluates the performance of the model for different combinations of the number

- of hidden layers and the number of neurons in each hidden layer. A grid search could be performed over combinations such as (2,64), (2,128), (3,64), (3,128)...until we find the most optimized combination. We can test this on the validation set and see which one performs best
- 2. We can also use regularization techniques such as L1, L2, and dropout functions to prevent overfitting and control the complexity of the model, reducing the risk of overfitting. Our model does not specifically target any of these techniques for this section, but we could just implement an alpha value or a dropout parameter to optimize the model.

Bonus:

What are the possible "cyber-physical" trade-offs when having such a governor running? Discuss such trade-offs by comparing the runtime, average power consumption, thermal limits and energy consumption of each benchmark.

In terms of runtime, both benchmarks show similar performance with blacksholes taking 140.60 seconds and bodytrack taking 138.66 seconds. This suggests that the on-demand governor does not have a significant impact on runtime. However, there is a difference in average power consumption, with blacksholes having an average power consumption of 6.40W and bodytrack having an average power consumption of 7.85W. This suggests that the bodytrack benchmark is more power-hungry than the blacksholes benchmark. In terms of thermal limits, both benchmarks have an average maximum temperature of around 55-60°C and a maximum temperature of 64°C. This suggests that the on-demand governor is effectively managing the system's temperature, keeping it within a safe range. For energy consumption, blacksholes has an energy consumption of 923 J and bodytrack has an energy consumption of 1111 J. This difference in energy consumption can be attributed to the higher power consumption of the bodytrack benchmark compared to the blacksholes benchmark.

The on-demand governor has the potential to trade off runtime for power consumption and thermal management. The governor's effectiveness in managing the temperature of the system can result in reduced energy consumption. Still, it may also result in increased power consumption compared to a system without thermal management.

Both partners were present at solving all three problems while Ethan headed question 1 and Harshika headed 2 and 3. We learned how to use mc1 to separate our workload and observe how the cores utilized the workload, sometimes with multiple threads. We also learned how to use and improve various models to predict outcomes via a binary classifier and a linear regression.