Runtime Power Estimation for Mobile CPUs with Performance Monitoring Counters and Machine Learning

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Introduction

- Applications for mobile devices are becoming increasingly complex and power hungry, calling for improved energy-saving techniques due to limited battery capacity. Understanding power consumption in these devices requires accurate power estimation of mobile systems.
- In this project, we investigate how to utilize selected Performance Monitoring Counters (PMCs) and machine learning to predict power consumption of a mobile device during runtime.
- Performance Monitoring Counters (PMCs) are hardware counters that collect events from the processor and memory system during runtime.

Methodology

- We use the ODROID-XU3 mobile development board with ARM big.LITTLE core clusters.
- 8 cores total:
  - 4 LITTLE cores (A7 cores 0-3) maximize power efficiency
  - 4 big cores (A15 cores 4-7) maximize performance. We focus on the big cores because they consume significantly higher power than the smaller cores.
- A maximum of 6 PMCs can be collected simultaneously on the board while running a benchmark.
- Power is measured at the cluster level -- counters are measured at the per-core level.

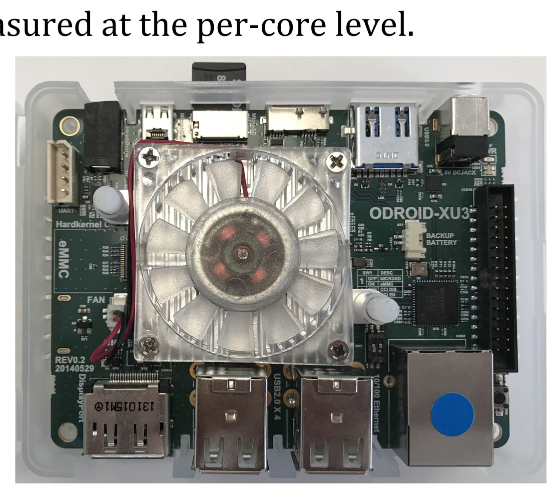


Figure 1 (right): ODROID-XU3 mobile development board used for data collection.

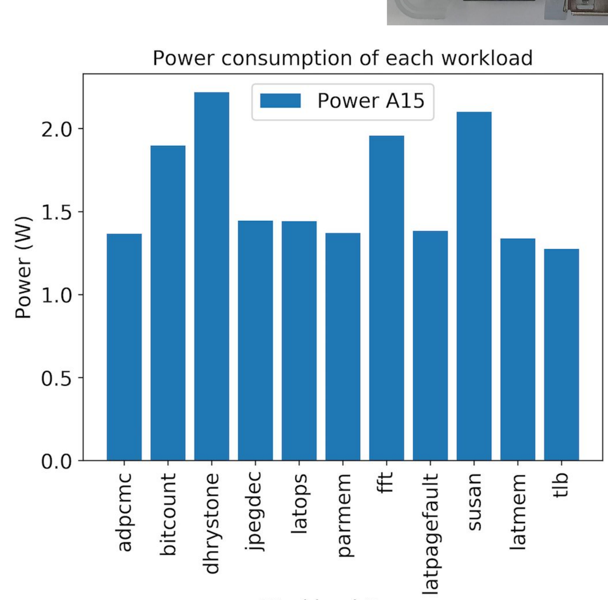


Figure 2 (left): We chose 11 benchmarks with varying power consumption levels.

Figure 3 (right): We refer to Walker et al[1] to choose 6 PMCs most correlated to power.

Event Hex	Event Name
0x11	CYCLE_COUNT
0x1B	INST_SPEC
0x50	L2D_CACHE_LD
0x6A	UNALIGNED_LDST_SPEC
0x73	DP_SPEC
0x14	L1I_CACHE_ACCESS
0x19	BUS_ACCESS

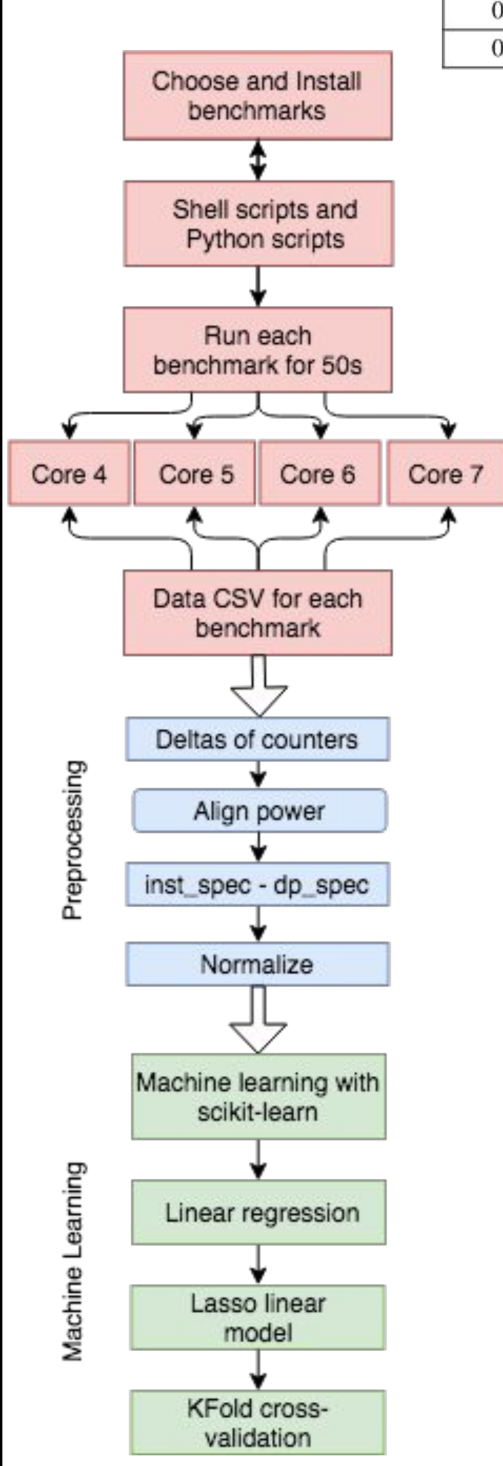
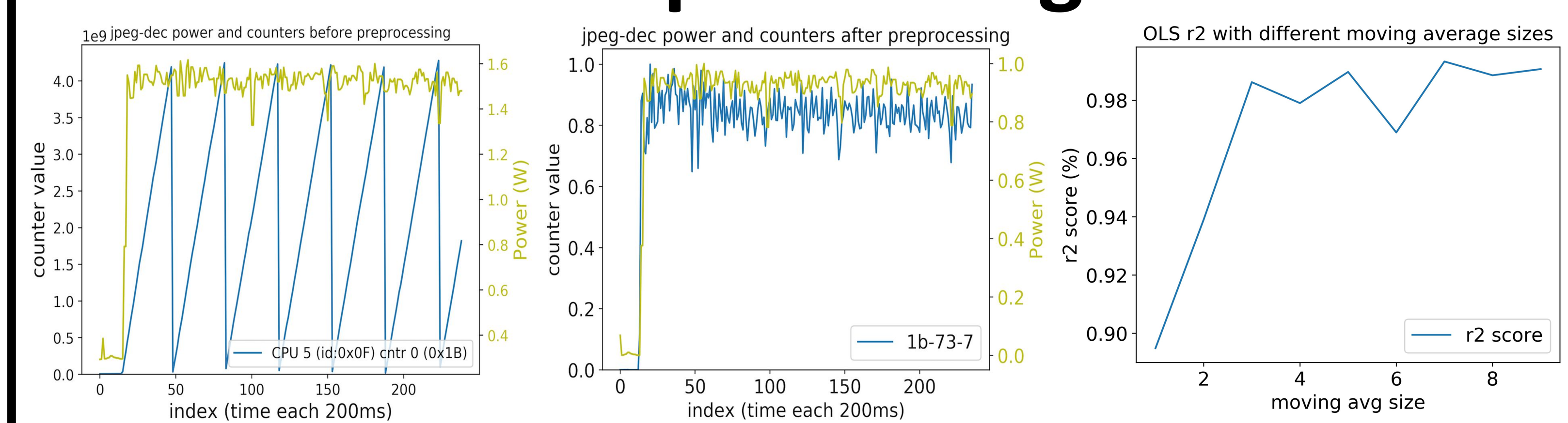


Figure 4 (above): Workflow for the project.

Our flow:

- Run benchmarks on the board using the android debug bridge (adb) shell.
- Make four copies of each benchmark
- Use taskset to assign the benchmark to cores 4-7.
- Collect data every 200ms and save the CSV files.
- Preprocess the data to prepare for machine learning with scikit-learn.
- Use machine learning to make a linear regression and find coefficients for each value.
- Check the accuracy with the r^2 score and mean squared error.
- Get the average of every 5 rows and save it as a separate training set.
- Use machine learning on the entire and averaged data sets.

Preprocessing

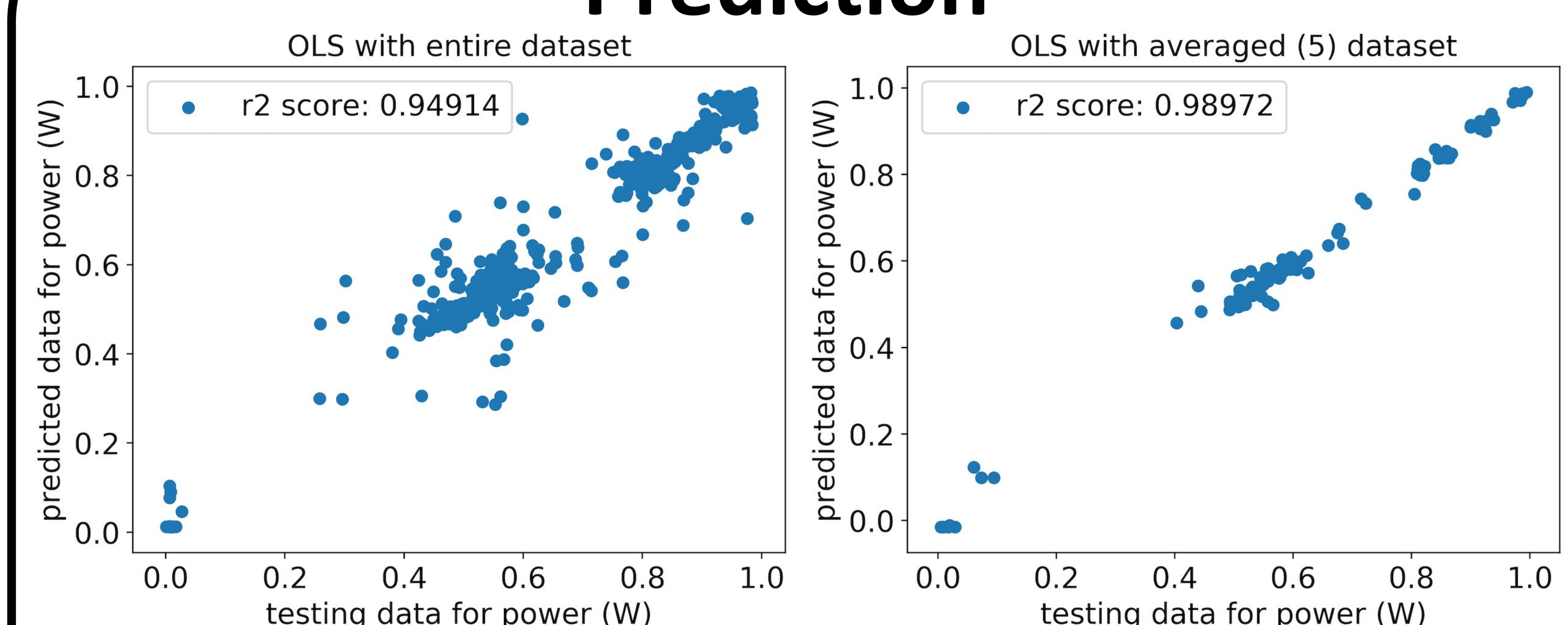


Preprocessing data for machine learning:

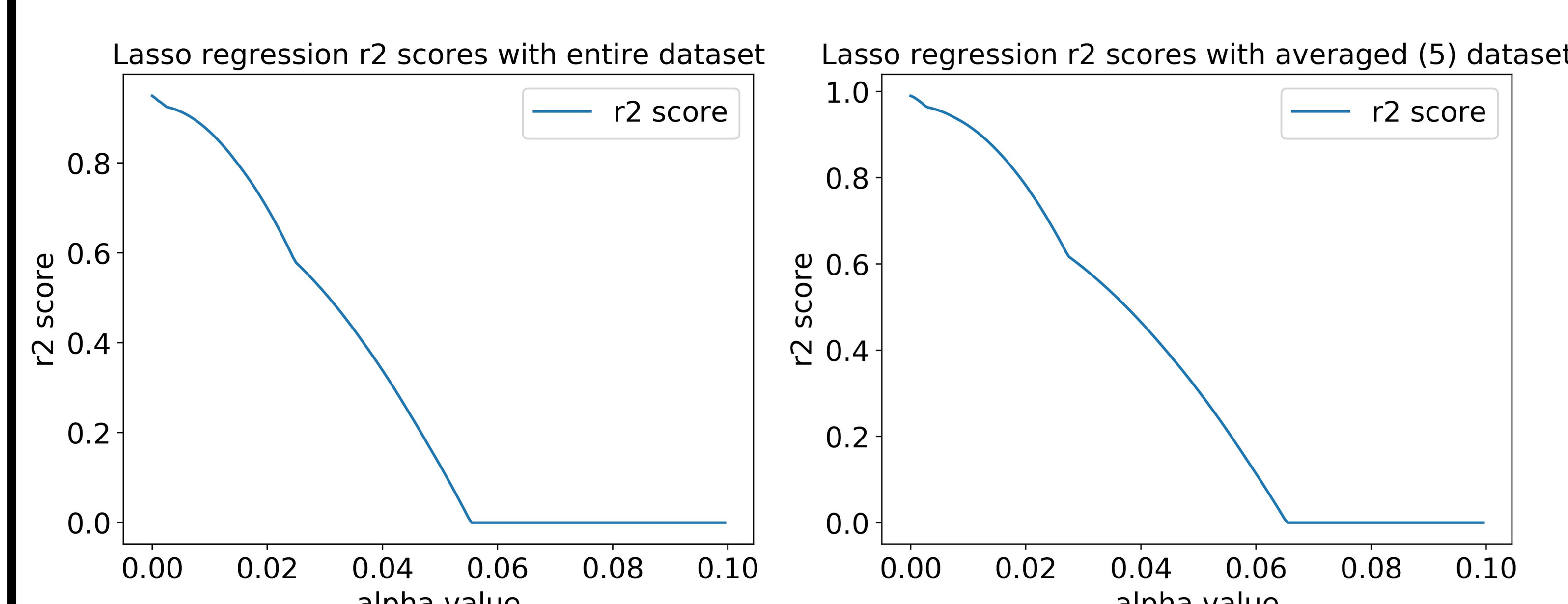
- Cumulative events → events per 200ms
- Separate values for inst_spec and dp_spec
- Normalize data to a range between 0-1
- Align power and events by initial spike
- Make a separate training set with the averages of every 5 data points

Figure 5 (left): Event 1B on core 5 for jpeg-dec workload, before preprocessing.
Figure 6 (middle): The same event after preprocessing.
Figure 7 (right): Comparing r^2 values when varying window size on averages, used to choose the window size for averaging.

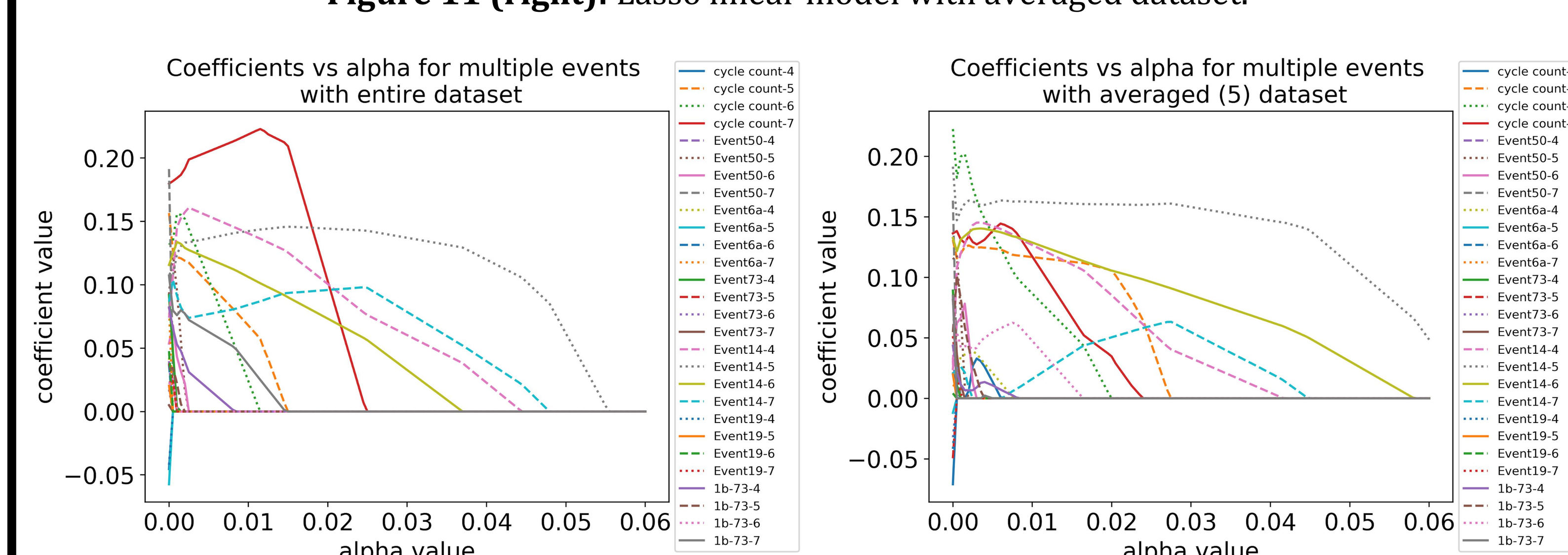
Prediction



Comparison of the linear regression, actual power vs. predicted power
Figure 8 (left): Prediction when using individual data points as training values.
Figure 9 (right): Prediction when using a moving average with window size 5.

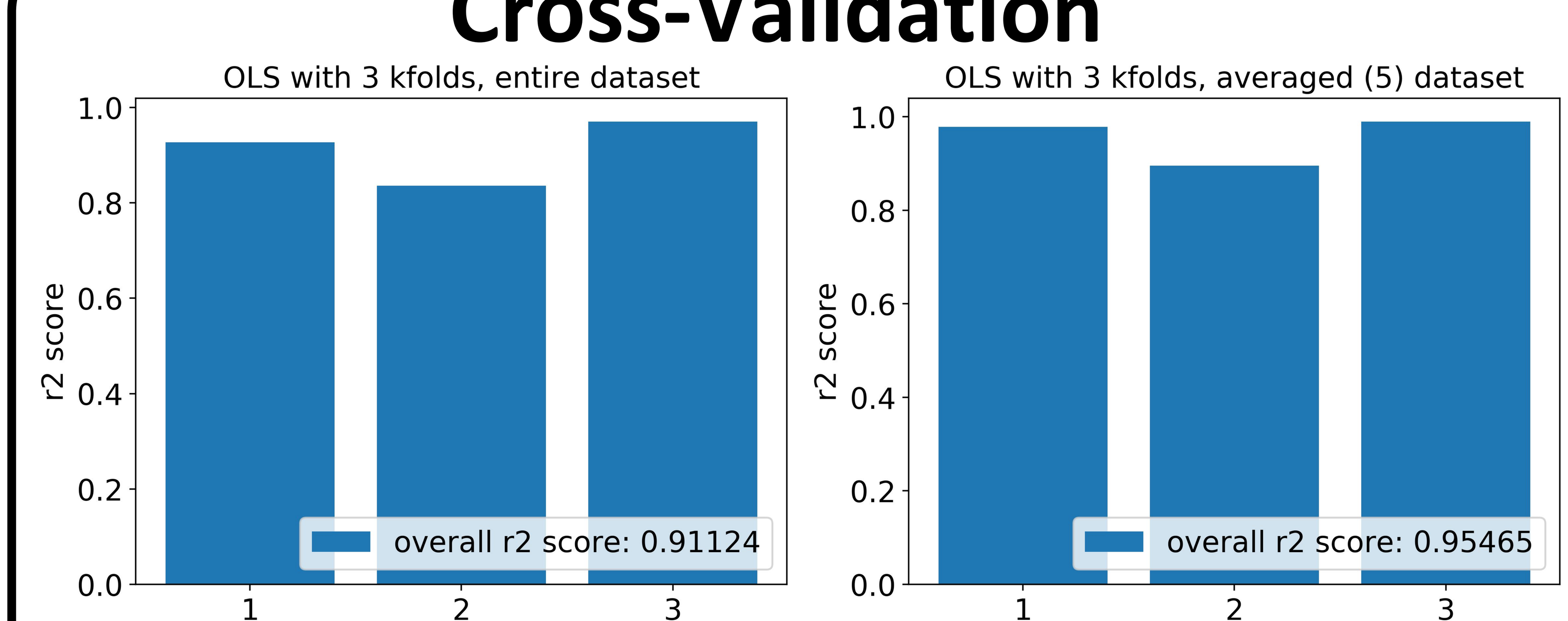


Lasso linear model used to reduce the number of coefficients in the linear regression. Graphs of r^2 values when using lasso on multiple alpha values.
Figure 10 (left): Lasso linear model with the entire dataset.
Figure 11 (right): Lasso linear model with averaged dataset.



Impact of varying alpha values on coefficients for each counter with Lasso.
Figure 12 (left): Comparing coefficients of multiple events with the entire dataset.
Figure 13 (right): Comparing coefficients of multiple events with the averaged dataset.

Cross-Validation



KFold cross-validation method used to analyze the machine learning model's stability.
Figure 14 (left): using 3 folds with linear regression on the entire dataset.
Figure 15 (right): using 3 folds with linear regression on the averaged dataset.

Machine learning with scikit-learn

- A Python machine learning library.

$$\hat{y}(w, x) = w_0 + w_1 x_1 + \ldots + w_p x_p$$

Figure 16 (above): Scikit-learn trains and tests linear models to find target value y. Each x is a feature and each w is a coefficient.[2]

- Ordinary Least Squares (OLS): a linear regression that minimizes the residual sum of squares between the predicted and actual power values.
- Lasso linear model: minimizes coefficients, examining the tradeoff between accuracy and reducing parameters.
- Accuracy is examined with the mean absolute error and the r^2 value.
- KFold: a cross-validation technique that examines the stability of the model.
  - separates the data into n number of "folds", trains the data with n-1 folds, and tests the data with the last fold. Repeat with other folds.

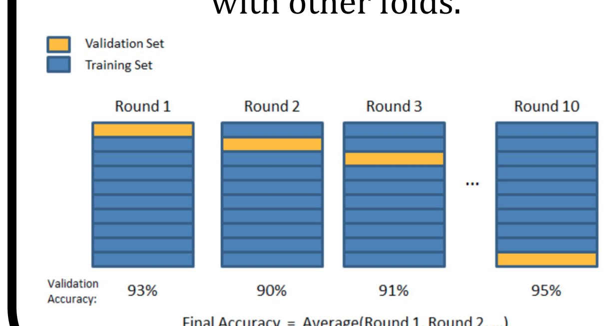


Figure 17 (left): How KFold splits a dataset based on the specified number of folds.[3]

Discussion

Conclusions:

- Power consumption can be modeled from these 6 PMCs with at least 91% accuracy.
- Using the the average of every 5 data points increases the accuracy to 98%.
- Lasso regression shows that certain PMCs with zero coefficients can be removed from the prediction without impacting accuracy.
  - The model is accurate up to an alpha value of 0.01

Caveats:

- Using the averaged data creates more extreme coefficients and increases the number of negative coefficients.
  - May be due to reduced size of dataset
- The lower r^2 score from 3 KFolds compared to OLS in Figure 8 and 9 demonstrates overfitting in the model. However, the accuracy remains at more than 90%.

Applications:

- These results demonstrate feasibility of predicting power consumption with more PMCs, and using Lasso to determine the most significant factors.

Future steps:

- Reduce overfitting with other fitting and cross validation methods
- Experiment with more linear modeling techniques from scikit-learn
- Experiment with a larger quantity of PMCs, using Lasso to determine the most important features in power prediction

References

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