



Cornell University



# Prediction-Guided Performance-Energy Trade-off for Interactive Applications

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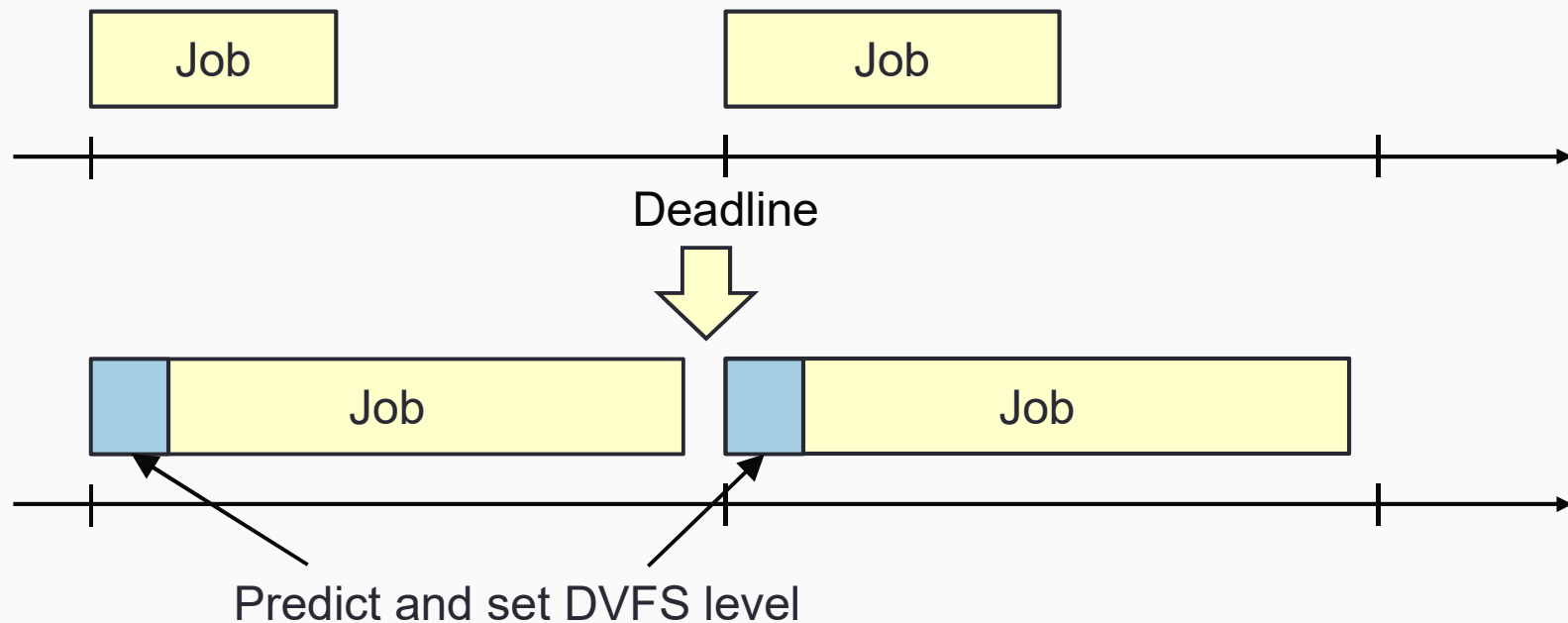
# Interactive Applications

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- Many modern applications are highly interactive
  - Web browsing
  - Games
  - User interfaces
- These interactions have response-time requirements
- Finishing faster does not improve user experience

## Prediction-based DVFS Control

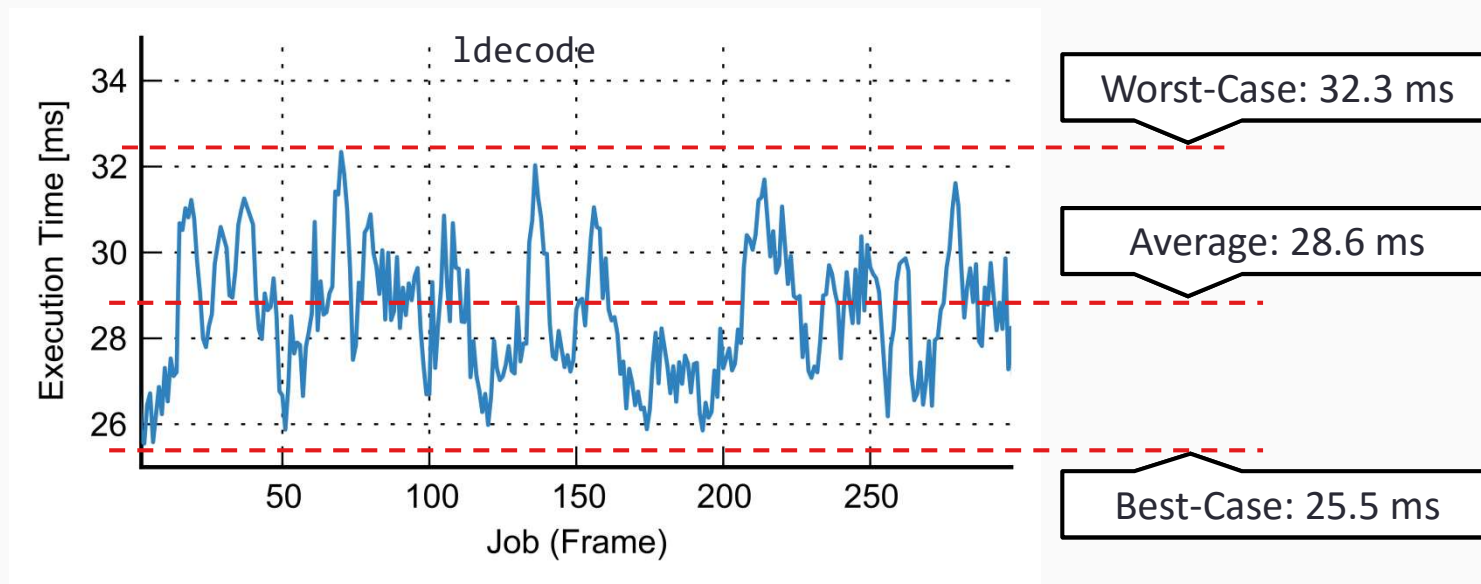
- Run jobs slower in order to save energy while preserving user experience



- Goal:** Pick DVFS level for each job to minimize energy and meet response-time requirement

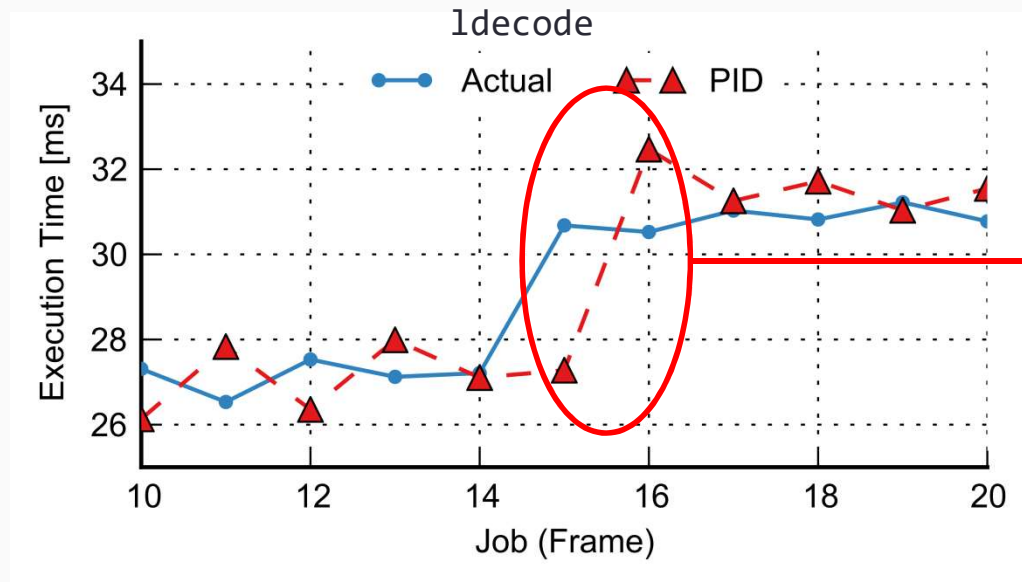
# Execution Time Variation

- **Challenge:** Execution times for an application vary from job to job
  - Optimizing for the worst-case wastes energy
  - Optimizing for the average-case misses deadlines



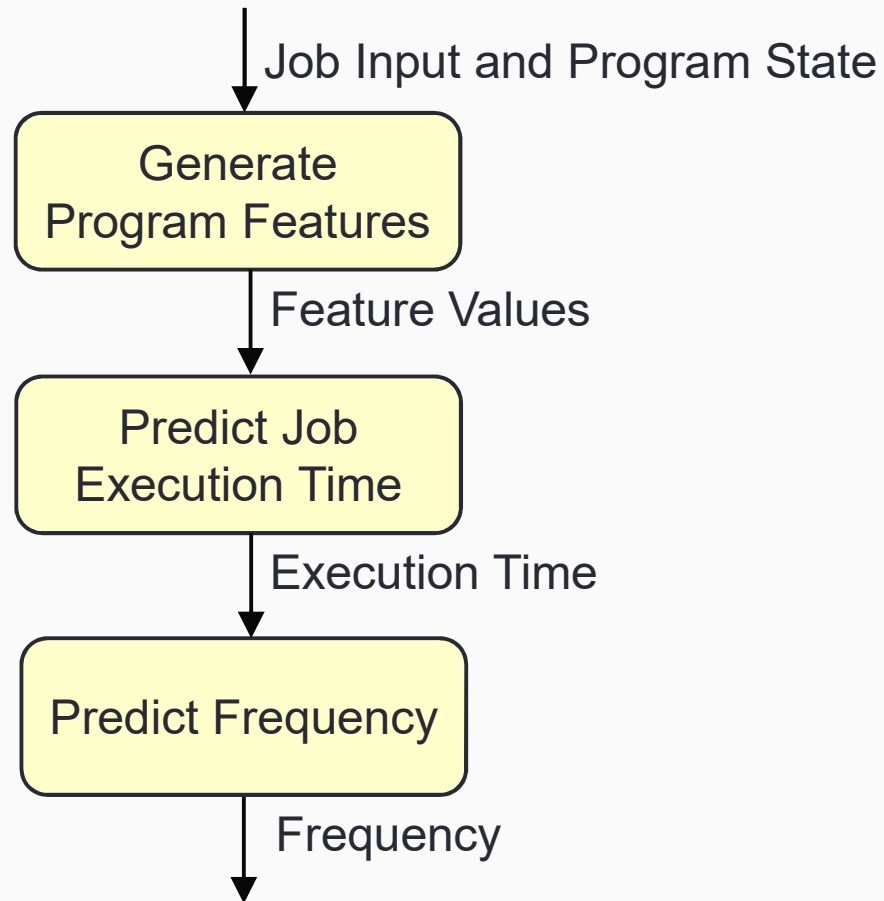
# Design Objectives

- **Proactive control** – History-based DVFS control is too slow to account for variations
  - Predict DVFS level based on job inputs and program state



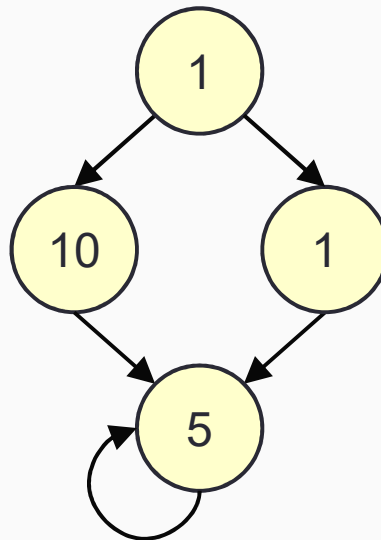
- **General** – applicable to a wide range of applications
- **Automated** – minimal programmer effort

# Prediction Approach



# Feature Selection

- To first order, execution time correlates with number of instructions executed
- Number of instructions depends on control flow
  - Conditionals taken/not taken
  - Loop counts
  - Function calls



# Instrumentation

- Instrument program source to count these features

|             | Original Code                                                                                                     | Instrumented Code                                                                                                                                                          |
|-------------|-------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Conditional | <pre>if (condition) {<br/>    ...<br/>}</pre>                                                                     | <pre>if (condition) {<br/>    <b>feature[0]++;</b><br/>    ...<br/>}</pre>                                                                                                 |
| Loop        | <pre>for (i=0; i&lt;n; i++)<br/>{<br/>    ...<br/>}<br/><br/>while (n = n-&gt;next)<br/>{<br/>    ...<br/>}</pre> | <pre><b>feature[1] += n;</b><br/>for (i=0; i&lt;n; i++)<br/>{<br/>    ...<br/>}<br/><br/>while (n = n-&gt;next)<br/>{<br/>    <b>feature[2]++;</b><br/>    ...<br/>}</pre> |



# Prediction Slice

- **Problem:** Instrumented job will take as long as original job to run
- **Solution:** Use program slicing to create minimal job to calculate features

Instrument Code

```
if (x)
{
    feature[0]++;
    compute();
}

feature[1] += n;
for (i=0; i<n; i++)
{
    compute2();
}
```

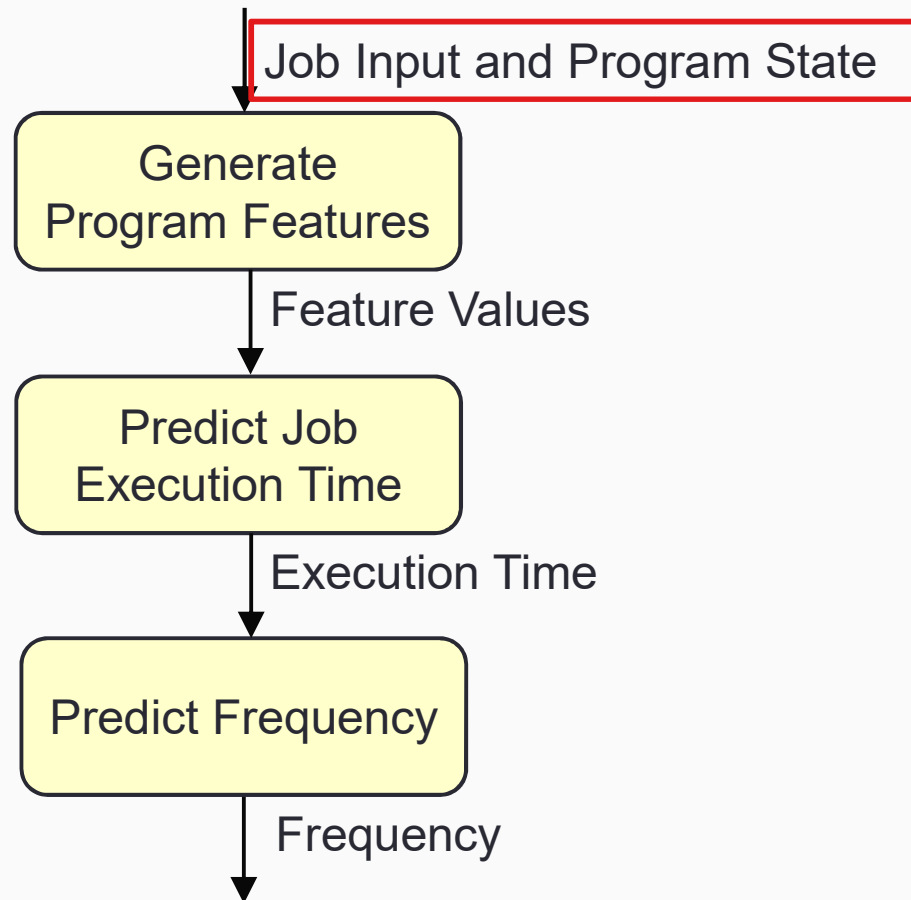


Program Slice

```
if (x)
{
    feature[0]++;
}

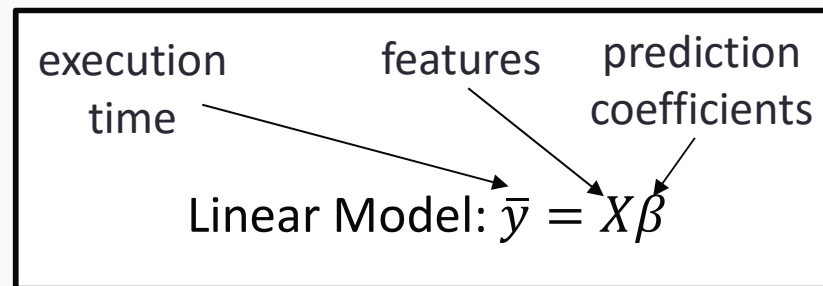
feature[1] += n;
```

# Prediction Approach



# Execution Time Model

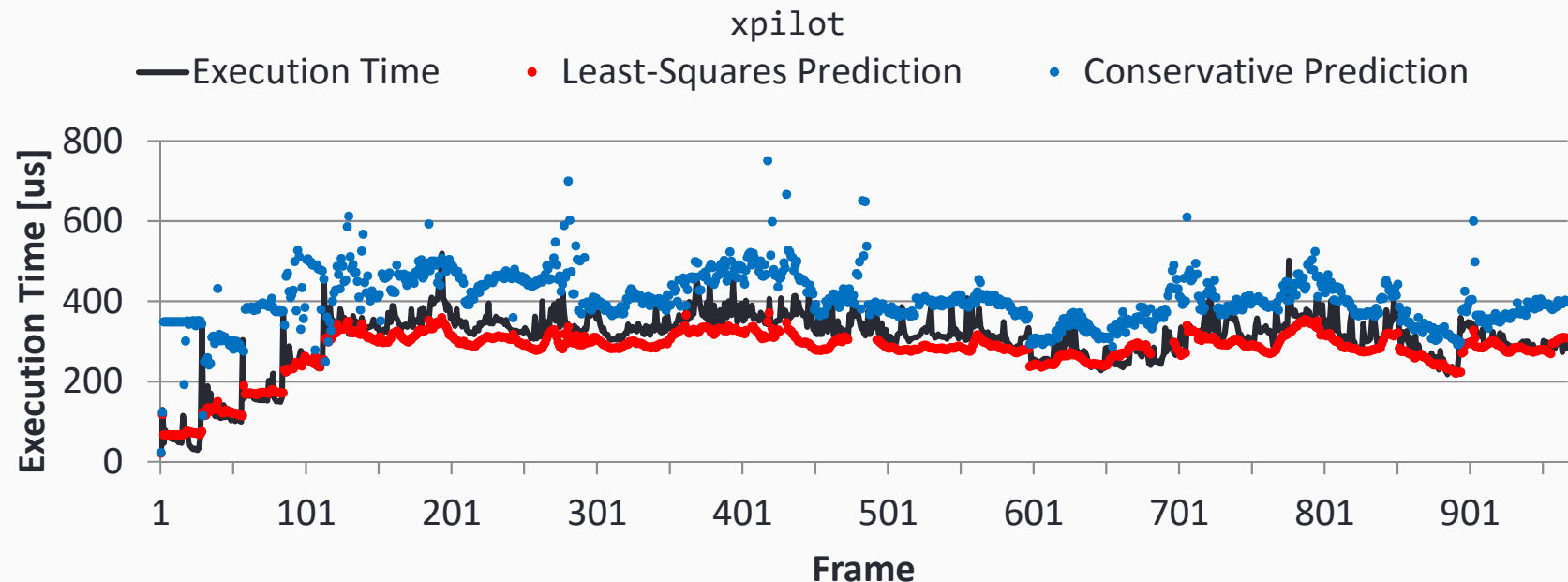
- Linear model to map features to execution time
  - Captures first-order effect of control flow on execution time
  - Fast to evaluate



- Use profiling data to fit model coefficients
  - Multiple possible ways to calculate coefficients

# Conservative Prediction

- Least-squares prediction leads to both under-prediction and over-prediction
  - Under-prediction results in deadline misses
- Want to skew prediction towards over-prediction



# Prediction Model

- Use convex optimization with custom objective
  - Avoid under-prediction – leads to missed deadline
  - Minimize features needed

The diagram illustrates the Linear Model and its objective function. At the top, three labels with arrows point to the components of the equation  $\bar{y} = X\beta$ : "execution time" points to  $\bar{y}$ , "features" points to  $X$ , and "prediction coefficients" points to  $\beta$ . Below this, the equation "Linear Model:  $\bar{y} = X\beta$ " is shown. Underneath the equation is the objective function to minimize:  $\|pos(X\beta - y)\|^2 + \alpha\|neg(X\beta - y)\|^2 + \gamma\|\beta\|_1$ . Three labels with arrows point to parts of this function: "overpredict" points to the  $pos(X\beta - y)$  term, "underpredict" points to the  $neg(X\beta - y)$  term, and "number of features" points to the  $\|\beta\|_1$  term.

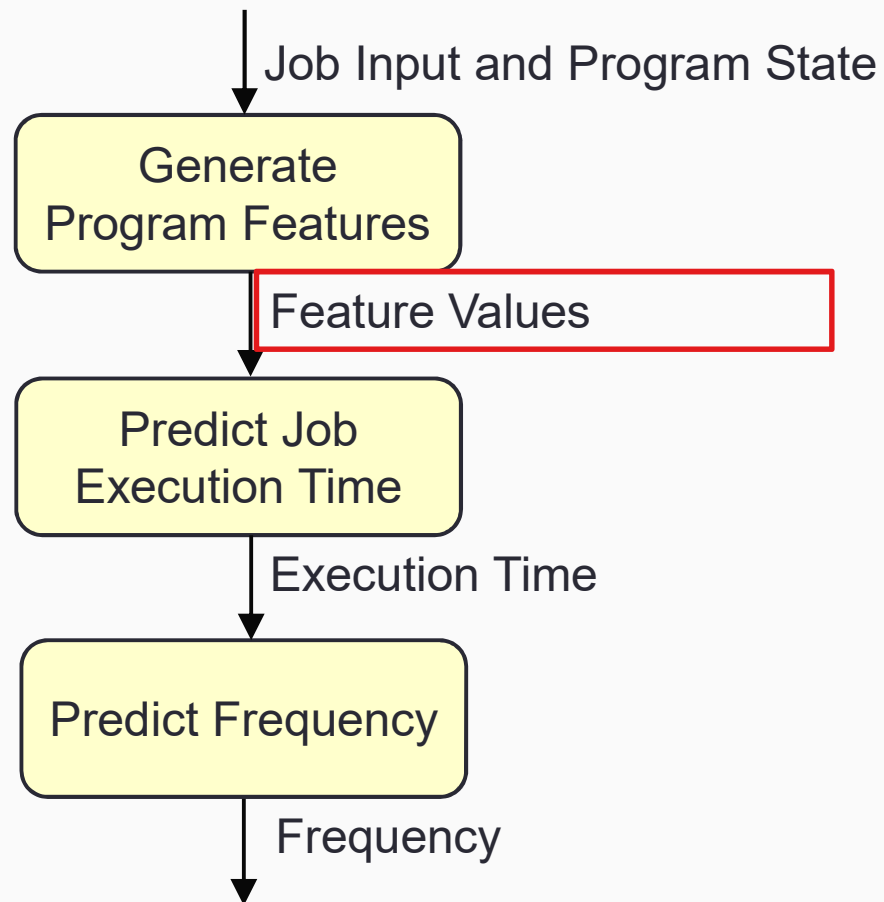
execution time      features      prediction coefficients

Linear Model:  $\bar{y} = X\beta$

Minimize:  $\|pos(X\beta - y)\|^2 + \alpha\|neg(X\beta - y)\|^2 + \gamma\|\beta\|_1$

overpredict      underpredict      number of features

# Prediction Approach

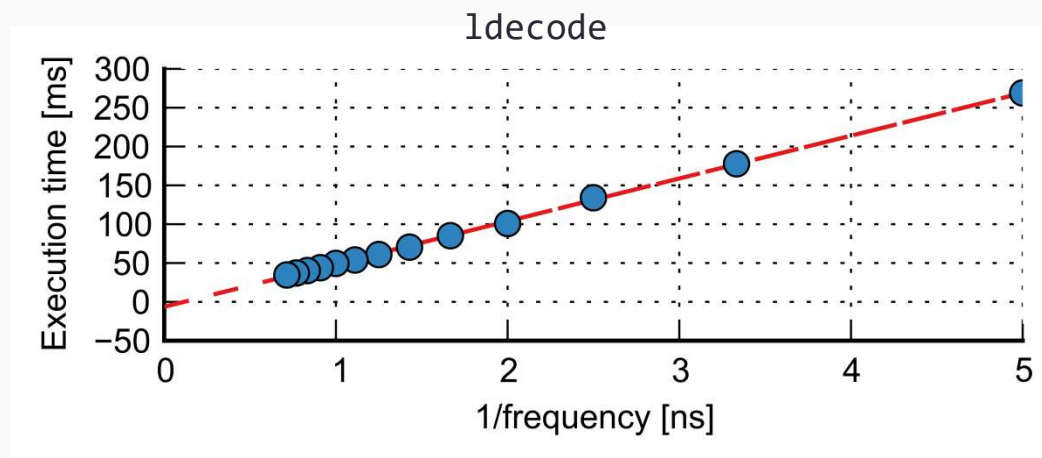


# DVFS Model

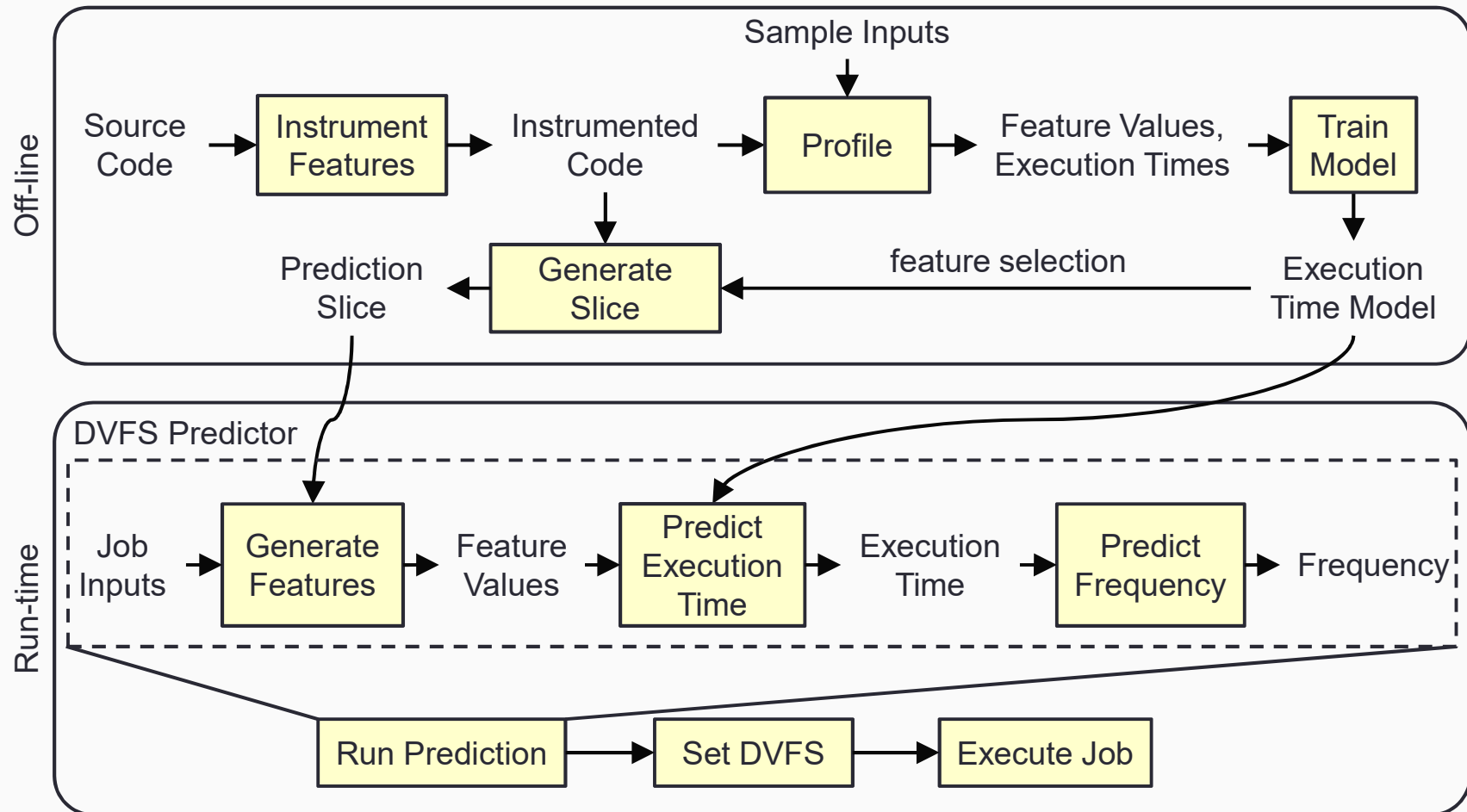
- Need a model of how execution time scales with frequency
  - Simple linear model

$$t = T_{mem} + N_{dependent}/f$$

- Empirical data shows that this is reasonable
  - $r^2 > 0.99$  for all benchmarks



# Full Approach



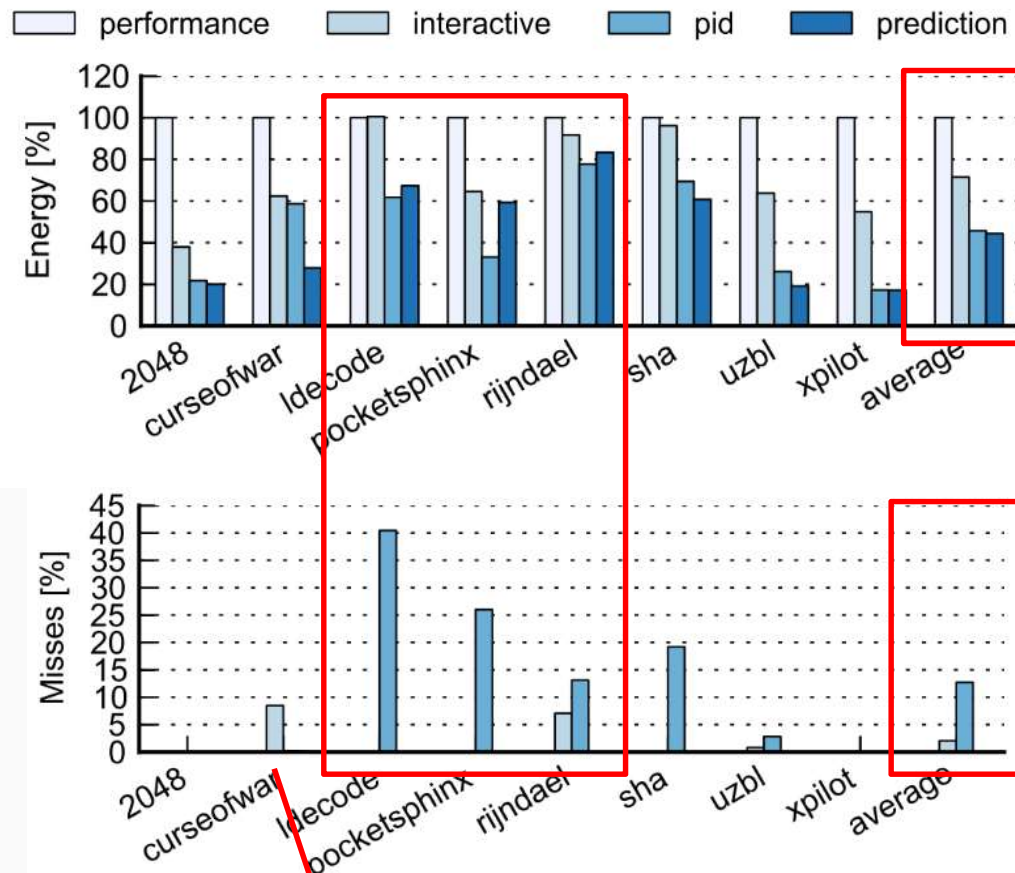


# Evaluation Setup

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- ODRROID-XU3 development board
  - ARM Cortex-A7 core (100 MHz steps from 200 MHz to 1.4 GHz)
  - Ubuntu 14.04
- Baseline controllers
  - performance – always max frequency
  - interactive – Linux governor based on utilization
  - pid – PID-based controller
- Benchmarks
  - web browser (uzbl)
  - speech recognition (pocketsphinx)
  - video decoding (ldecode)
  - games (2048, curseofwar, xpilot)
  - MiBench kernels (rijndael, sha)

# Results



prediction energy savings  
vs. performance: 65%  
vs. interactive: 38%  
vs. PID: 2%

2% deadline misses for interactive  
13% deadline misses for PID

0.1% deadline misses for prediction

# Conclusion

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- Opportunities exist to improve the energy usage of interactive applications
- History-based DVFS controllers are not quick enough to respond to job-to-job variations in execution time
- Prediction-based DVFS control outperforms traditional power governors and PID-based controllers
  - Lower energy usage
  - Almost no deadline misses