Transfer Learning for Performance Analysis of Highly-Configurable Software Systems

Abstract

Modern software systems (e.g., autonomous systems, big data analytics, robotics, deep neural architectures) are built configurable. We are often interested in reasoning about the performance of such systems under different configurations to tune the system or detect performance bugs.

Usually, users know little about the influence of configurations, recent research has done black-box learning to predict the performance of the system given a configuration. However, as modern systems become more complex, there are many configuration options that may interact, leading to a highly-dimensional space. Naturally, this does not scale when relying on real measurements. For example, it will take over 60 years to explore the whole configuration space of a system with 25 binary options. In this talk, I will present our solution to tackle the scalability challenge: Instead of taking the measurements from the real system, we learn the model using samples from other sources, such as simulators that approximate performance of the real system at a low cost. My core insight is that, despite the high cost of measurement, learning performance models can become surprisingly cheaper, as long as we can reuse information across environments.

In the second half of the talk, I will present some empirical evidence why and when transfer learning works by showing the similarities of performance behavior across environments. I will present the details of our explorations going into some environmental changes (such as hardware, workload, and software versions) for a selected set of configurable systems to identify the key knowledge pieces that can be exploited for transfer learning. Our results show that in small environmental changes (e.g., homogeneous workload change), a linear transformation will provide accurate predictions for the performance behavior of the systems, while for severe environmental changes (e.g., drastic workload change), we require a more sophisticated learning strategy that can capture non-linear relationships across environments. The empirical results open the door to more efficient sampling, more accurate learning, and more effective performance testing and debugging. I will also share a few thoughts where my research is going and what is my vision for future directions of my work.

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Biography

Pooyan Jamshidi is a postdoctoral researcher at Carnegie Mellon University (advised by Christian Kaestner). Prior to his current position, he was a research associate at Imperial College London. He holds a PhD from Dublin City University. His general research interests are in the intersection of software engineering and machine learning, and his focus lies predominantly in the areas of highly-configurable and self-adaptive systems (more details: https://pooyanjamshidi.github.io/research/ https://pooyanjamshidi.github.io/research/).