Balancing Thread-level and Task-level Parallelism for Data-Intensive Workloads on Clusters and Clouds

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Fig. 1: Application-level model for execution time: Runtimes predicted by application-level model for varying sizes of reference (R), query (Q), and number of threads (N) in BWA, Bowtie2, and BLASR. Figures in the first row depict behavior of the applications (BWA, Bowtie2, and BLASR, respectively) with respect to reference input. Figures in the second row show the dependence of the applications on query input. Figures in the third row confirm that although runtime reduces with more cores or threads, the corresponding speedup is not proportional, as supported by Amdahl’s law.
Fig. 2: Application-level model for memory: Memory usage predicted by application-level model for varying reference size (R) and number of threads (N) in BWA, Bowtie2, and BLASR. The memory consumed by the applications is directly proportional to the reference size and number of threads used.

Fig. 3: System-level model for execution time: Runtimes predicted by system-level model for varying number of tasks (K) and threads (N) used by each task. As the number of tasks increases, the runtime gradually decreases unless it reaches an optimal $K$ and $N$, beyond which the performance is again degraded. The overhead is caused by the additional cost of splitting, starting up, and joining a given workload.

Fig. 4: System-level model for memory: Memory usage at the master predicted by system-level model. The memory footprint of the master server depends on the data to be split and the data to be joined (R and Q).
Fig. 5: Distribution of values of regression coefficients: Distribution of values of the coefficients $(\beta_1, \beta_2, \gamma_1, \gamma_2, \eta_1, \eta_2, \eta_3, \eta_4, \phi_1, \phi_2)$ in the regression models (equations (1), (2), (3), and (4)). Each histogram contains 10000 values of a coefficient obtained while training each model 10000 times. As the distributions follow the gaussian curve, the mean and variance completely characterize the distributions. The calculated SD is low, showing our model is robust for these training data.