Transfer Learning for Improving Model Predictions in Highly Configurable Software

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Performance Influence of Configuration Parameters



102 103 drpc.port: 3772 drpc.worker.threads: 64 104 drpc.max_buffer_size: 1048576 105 drpc.queue.size: 128 106 drpc.invocations.port: 3773 107 drpc.invocations.threads: 64 108 drpc.request.timeout.secs: 600 109 drpc.childopts: "-Xmx768m" 110 drpc.http.port: 3774 111 112 drpc.https.port: -1 drpc.https.keystore.password: "" 113 114 drpc.https.keystore.type: "JKS" drpc.http.creds.plugin: org.apache.storm.security.auth.DefaultHttpCredentialsPlugi 115 drpc.authorizer.acl.filename: "drpc-auth-acl.yaml" 116 drpc.authorizer.acl.strict: false 117 118 transactional.zookeeper.root: "/transactional" 119 transactional.zookeeper.servers: null 120 transactional.zookeeper.port: null 121 122 123 ## blobstore configs supervisor.blobstore.class: "org.apache.storm.blobstore.NimbusBlobStore" 124 supervisor.blobstore.download.thread.count: 5 125 126

- 127 supervisor.localizer.cache.target.size.mb: 10240
- 128 supervisor.localizer.cleanup.interval.ms: 600000







Reasoning + Adaptation + Debugging + Optimization



Idea: Transfer Learning



Exploiting Similarity



Exploiting Similarity



GP for modeling black box response function

 $y = f(\boldsymbol{x}) \sim \mathcal{GP}(\mu(\boldsymbol{x}), k(\boldsymbol{x}, \boldsymbol{x}')),$

 $\mu_t(\boldsymbol{x}) = \mu(\boldsymbol{x}) + \boldsymbol{k}(\boldsymbol{x})^{\mathsf{T}}(\boldsymbol{K} + \sigma^2 \boldsymbol{I})^{-1}(\boldsymbol{y} - \boldsymbol{\mu})$ $\sigma_t^2(\boldsymbol{x}) = k(\boldsymbol{x}, \boldsymbol{x}) + \sigma^2 \boldsymbol{I} - \boldsymbol{k}(\boldsymbol{x})^{\mathsf{T}}(\boldsymbol{K} + \sigma^2 \boldsymbol{I})^{-1} \boldsymbol{k}(\boldsymbol{x})$

Motivations:

1 - mean estimates + variance
2 - all computations are linear algebra
3 - good estimations when few data

$$\boldsymbol{K} := \begin{bmatrix} k(\boldsymbol{x}_1, \boldsymbol{x}_1) & \dots & k(\boldsymbol{x}_1, \boldsymbol{x}_t) \\ \vdots & \ddots & \vdots \\ k(\boldsymbol{x}_t, \boldsymbol{x}_1) & \dots & k(\boldsymbol{x}_t, \boldsymbol{x}_t) \end{bmatrix}$$

 $k(f, g, \boldsymbol{x}, \boldsymbol{x}') = k_t(f, g) \times k_{xx}(\boldsymbol{x}, \boldsymbol{x}'),$



Scenarios and Assumptions

Environment change (configuration option vs. environment change) Different benchmark/workload Different program version Different hardware

Shape of old and new model similar



Some Results ("it works")

First Feasibility Demonstration

Case study & controlled experiments Can we improve prediction accuracy? Tradeoffs among #source and #target samples? Fast enough?

Subject sys.: Cobot, Apache Storm, Cassandra

Example: Performance prediction for CoBot



Example: Performance prediction for CoBot



Example: Performance prediction for CoBot



Accuracy and Costs



Accuracy and Costs





Future work, insights and ideas

Selecting from Multiple Sources (Cost Model)



Checking Assumptions

How similar are source and target models for real environment changes (workload/infrastructure/code changes)?

Expected similarities:

- Constant
- Constant / proportional shift
- More noise but similar trends
- Many features and interactions with similar impact
- Many important features and interactions remain important

Active learning + transfer learning



Goal: find best sample points iteratively by gaining knowledge from source and target domain

Transfer Learning for Improving Model Predictions in Highly Configurable Software

Improves the model accuracy up to several orders of magnitude

Is able to trade-off between different number of samples from source and target enabling a cost-aware model

Exploring similarity across environment changes and active learning





