Explaining Predictive Scheduling in Cloud

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Problem Definition and Motivation

Machine learning-based techniques require complete data to produce better prediction results. However, in practice, it may happen that the data is incomplete and the data with more missing attribute values can negatively affect the outcome of the predictions [1]. Therefore, interpolation of missing attribute values is crucial for better predictions. Interpolating missing attribute values with existing methods results in extensive computational time [2]. Therefore, reducing the computational time and achieving acceptable accuracy is one of the major issues.

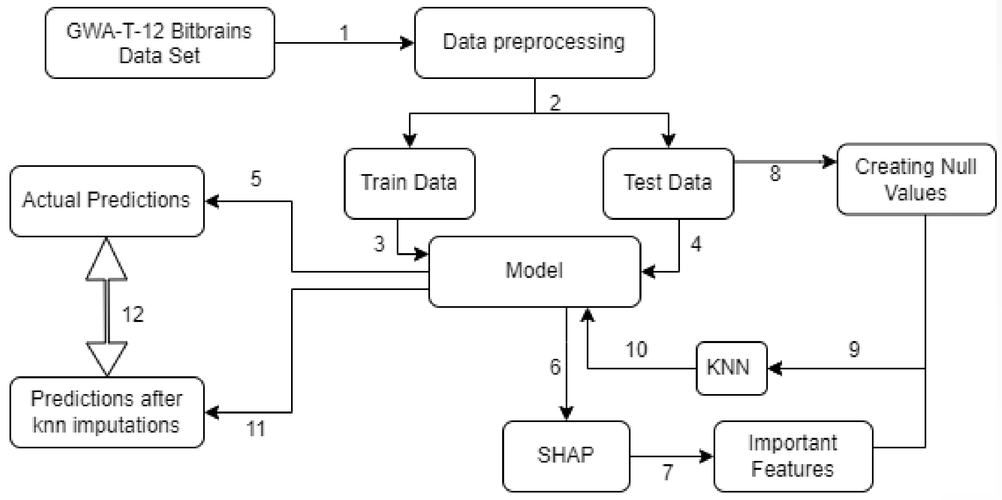
Dataset

- We used a publicly available dataset from Delft University of technology GWA-T-12 Bitbrains (tudelft.nl) that provides the performance matrices of VM such as CPU cores, CPU capacity provisioned, CPU usage, memory provisioned (memory requested), memory usage, disk read throughput, disk write throughput, network received throughput and network transmitted throughput [3].
- We considered only the Rnd traces of the dataset which is 500 VMs

Contribution

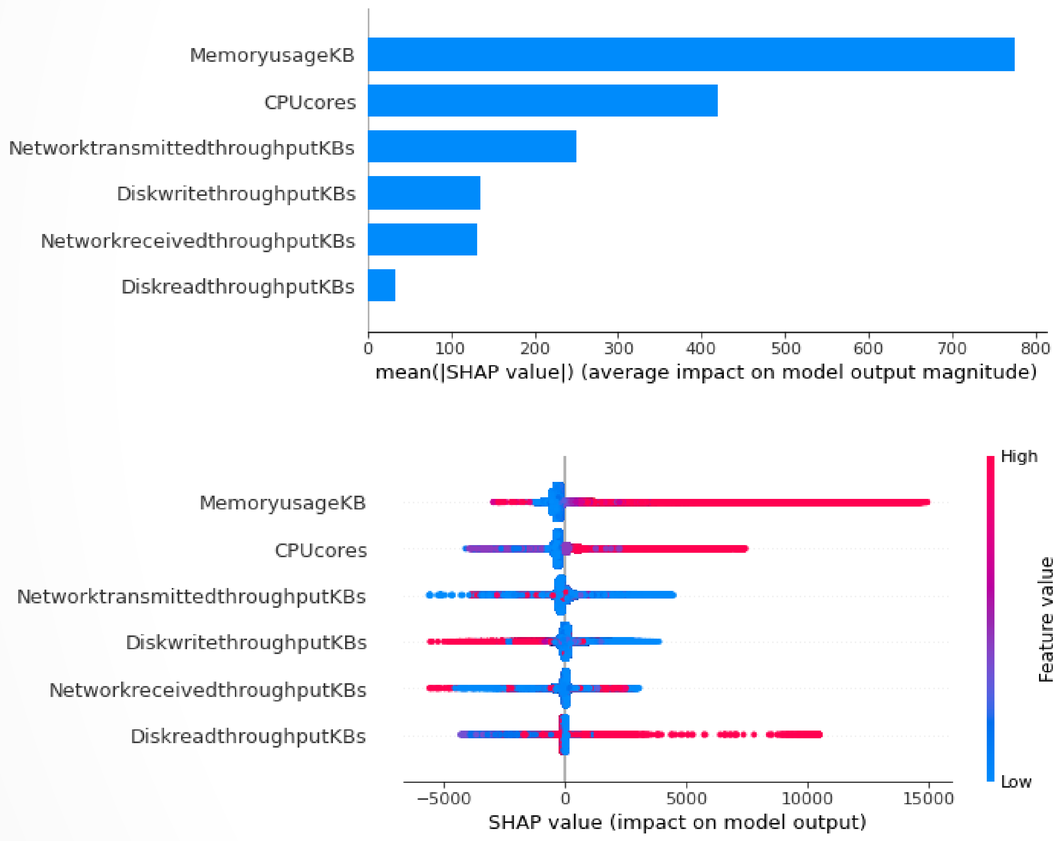
- Using SHapley Additive exPlanations (SHAP) for model explanation and extracting important features [4]. Furthermore, using K-Nearest Neighbor (KNN) and SHAP explanations for interpolation of missing values to reduce computational time. Finally, using Light Gradient Boosting Machine (LightGBM) model for predicting CPU resources with the interpolated dataset to achieve acceptable accuracy.

Work Flow of Experiments



Experimental Results

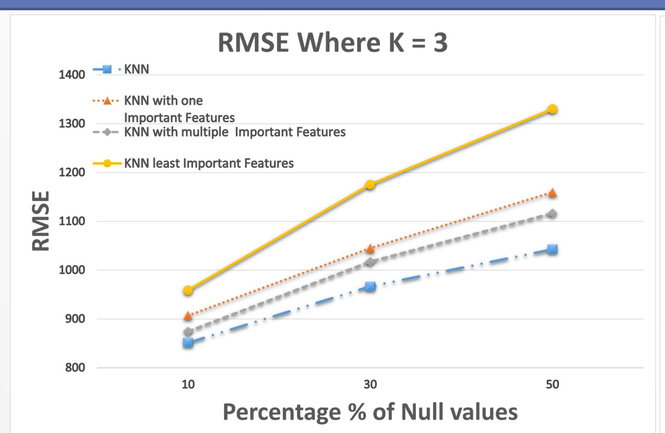
SHAP Explanations

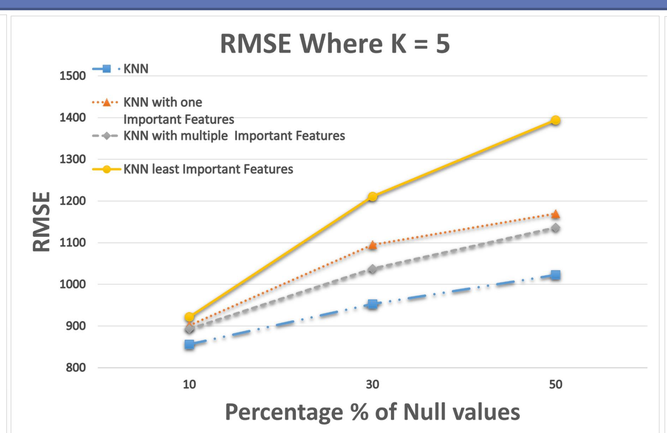


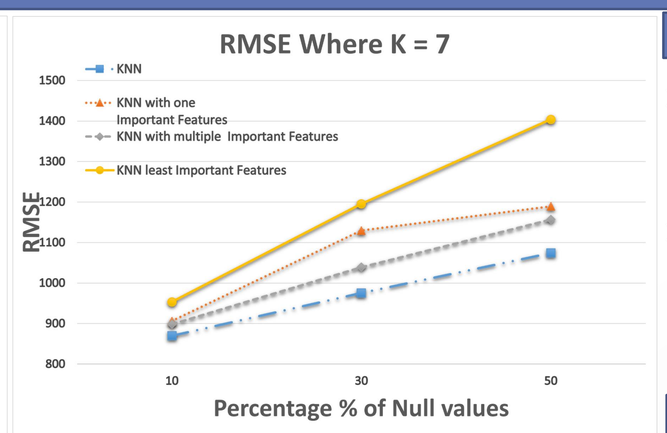
Results

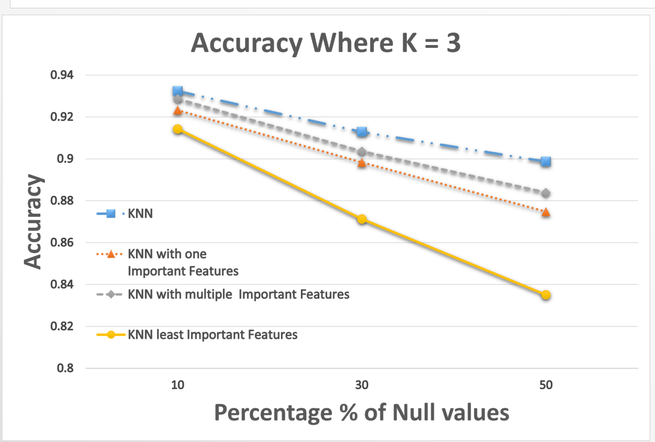
Actual		RMSE: 805.15 Test Data Accuracy: 0.9396								
Percentage of Null values		10 %			30 %			50 %		
K-nearest neighbors		K=3	K=5	K=7	K=3	K=5	K=7	K=3	K=5	K=7
KNN	RMSE:	851.33	856.07	869.78	966.59	952.73	975.49	1042.74	1022.83	1074.18
	Accuracy:	0.9324	0.9317	0.9295	0.9129	0.9154	0.91136	0.8987	0.9025	0.8925
	Computational time:	1h 9min 26s	1h 16min 41s	1h 14min 14s	3h 15min 58s	3h 19min 58s	3h 14min 20s	4h 7min 54s	4h 20min 11s	4h 38min 24s
KNN with Most Important Attribute	RMSE:	907.00	901.40	906.34	1044.82	1095.30	1129.89	1159.38	1169.75	1189.46
	Accuracy:	0.9233	0.9243	0.9234	0.8983	0.8882	0.8810	0.8748	0.8725	0.8682
	Computational time:	1h 5min 1s	1h 11min 59s	1h 17min 52s	2h 46min 8s	3h 1min 14s	3h 3min 6s	4h 39s	4h 13min 21s	4h 15min 57s
KNN with mult-iple attributes	RMSE:	874.38	893.33	898.37	1017.24	1037.77	1039.21	1116.30	1136.53	1156.82
	Accuracy:	0.9287	0.9256	0.9248	0.9036	0.8996	0.8994	0.8839	0.8796	0.8753
	Computational time:	1h 10min 12s	1h 14min 41s	1h 38min 32s	2h 52min 55s	3h 16min 33s	3h 26min 33s	4h 5min 9s	4h 19min 16s	4h 30min 12s
KNN with least Important Attribute	RMSE:	958.88	922.17	953.40	1175.37	1211.14	1195.62	1330.29	1394.31	1404.14
	Accuracy:	0.9143	0.9207	0.9153	0.8713	0.8633	0.8668	0.8351	0.8189	0.8115
	Computational time:	1h 5min	1h 7min 21s	1h 9min 54s	3h 23s	3h 4min 58s	3h 10min 5s	3h 58min 33s	4h 10min 20s	4h 12min 50s

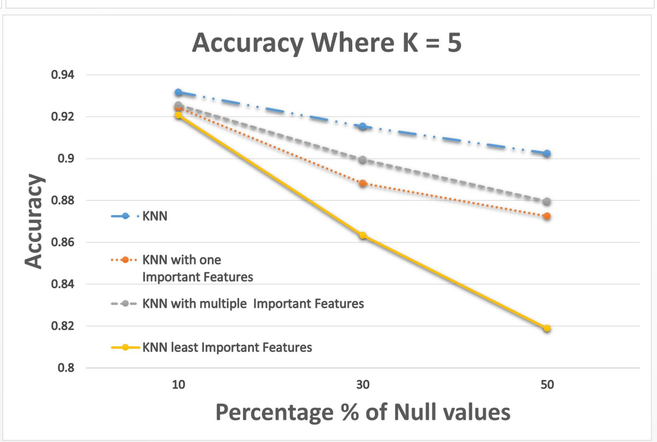
Analysis

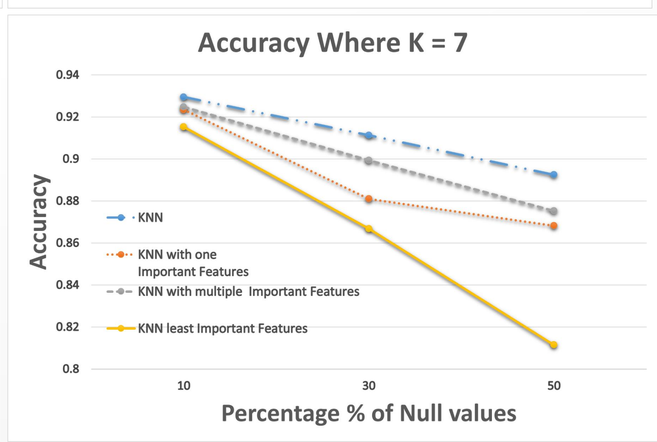












Conclusion

- SHAP explanations can be helpful for cloud providers in the selection of important features for interpolation of missing values.
- SHAP-based interpolation results in lower computational time along with acceptable accuracy in comparison with KNN-based interpolation

Future Work

- Comparisons with other interpolation methods such as Classification and Regression Tree (CART), multilayer perceptron neural network (MLP), naive Bayes, and Support Vector Machine (SVM)

Published In

- This work is published at 14th Asian Conference on Intelligent Information and Database Systems (ACIIDs) [5]

References

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