

Scaling out Big Data Missing Value Imputations

(Pythia vs. Godzilla)

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Missing Data



Data quality in Big Data processing: •Missing Values (MV) in multidimensional data.

$$\mathbf{x} = [x_1, x_2, ?, x_4, \dots, ?, x_d]$$

• **Example**: survey databases; industrial databases; medical databases; gene expression microarray datasets.

...bias is introduced into the induced knowledge.





Common solutions to the MV problem:

- Ignore or exclude MV data.
- Fill-in MVs (*imputation*)
 - MV (Substitution) Algorithm replaces MVs with plausible values.
 - **Imputation error:** difference between *actual (unknown)* value and *predicted (imputed)* value.

Motivation



MV Algorithms ensure low imputation errors but are computationally expensive;
 ...performance depends on data size!

• Deal with **large-scale** datasets, which grow significantly with time!

User community can be very large;
MV imputation requests' arrival rate becomes high too!

Motivation



• Not all MV substitution tasks are 'embarrassingly parallelizable'.

• If so,

• not all *regions* of a dataset are **'relevant**' for imputation;

•...some data regions might negatively contribute or even 'hurt' the result of the MV Algorithm.





Observation



• A single machine 'Godzilla' contains a massive dataset.

• Godzilla serves **MV imputation requests** by performing a MV algorithm.

Idea No 1



Replace Godzilla by a fixed number of commodity machines 'Cohorts'.

- **1. Partition** (randomly) the dataset.
- 2. Each Cohort contains a portion of the dataset.
- 3. Cohorts perform locally a MV Algorithm.
- 4. Aggregate all imputations.

Benefit: We obtain **efficiency** and **scalability**





Idea No 2



Pythia predicts the appropriate subset of Cohorts for engaging them in performing MV Algorithm in parallel.

Pythia locally maintains a specific information for each Cohort's dataset: 'Signature'.

Benefit: Comparable / better accuracy instead of • engaging all Cohorts! • using only Godzilla!





- Information used for predicting a subset of Cohorts.
- Each Cohort incrementally clusters its data.
 - Adoption of Adaptive Resonance Theory (ART).

Signature is the set of cluster-heads of a Cohort's dataset.
Pythia collects all Signatures and stored them locally.

Cohort prediction



• Consider an MV imputation request (input):

• Pythia **predicts** a Cohort iff the **input** is classified to at least one cluster-head from the Cohort's Signature.

• An **input** is **classified** to a cluster-head iff the Euclidean distance between **non-MVs** is less than a **threshold** (*vigilance* parameter in ART).

Pythia algorithm







- •...Cohort whose cluster-head is the closest to the input among all **predicted** Cohorts.
- Pythia communicates **only** with this Cohort.







Accuracy-aware Subset Selection algorithm

- Pythia communicates with each predicted Cohort.
- Pythia performs a **weighted aggregator operation** over those Cohorts' results which are not assumed as *outliers**.



**outlier* determined by a statistic using the *median* and the *median absolute deviation about the median* of the set of the predicted estimates.

Performance Metrics

Imputation efficiency

- Latency: the time a system requires to process a MV request.
- **Speedup**: the ratio of Godzilla latency over Pythia latency.
- **Throughput**: the rate of imputations delivered by a system.

• Imputation accuracy, i.e., RMSE

• Imputation algorithms *k*NN (weighted *k*-nearest neighbors)^[15]; REG (sequential multivariate regression) ^[17]

90-dimensional vectors





m : number of Cohorts

imputations of Rate

90-dimensional vectors

384-dimensional vectors





m : number of Cohorts



Thank you!

m : number of Cohorts





Dataset size (90-dimensional vectors)