Missing Data Imputation: Do Advanced ML/DL Techniques Outperform Traditional Approaches?

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Agenda

1. Introduction
2. Challenges
3. Research Focus
4. Experiments Setting
5. Results and Discussion
6. Conclusion

Introduction:
Definition and Impact of Missing Data

What is Missing data?

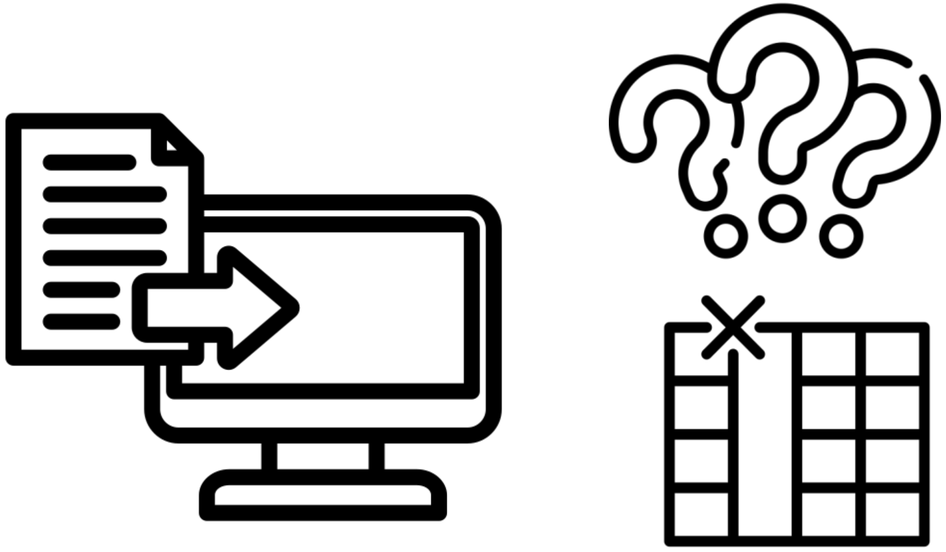
- Absence of values within a dataset
- Occurs in any types of data

How does Missing Data Occur?

- Data Entry, Transformation & storage Error
- Privacy Concern, Non-Response

Impact of Missing Data

- Preserve Data Quality
- Ensure Reliability of Analyses
- Avoid Biases in Results



Introduction:
Factors Influencing the Missing Data

Missing Rate:

- Proportion of data that is missing from a dataset

Missing Mechanism :

- Salary values are randomly missing due to impute error (MCAR)
- Salary values are missing for female employees (MAR)
- Salary values are missing for high-earning employees (MNAR)

Gender	Salary			
	Full	MCAR	MAR	MNAR
F	High	High	High	?
F	High	?	?	?
M	High	?	High	?
F	High	High	?	?
M	High	High	High	?
M	Low	Low	Low	Low
F	Low	?	?	Low
M	Low	Low	Low	Low
M	Low	?	Low	Low
F	Low	Low	?	Low

Introduction:
Solutions to dealing with Missing Data

Imputation Methods

- Statistical-based Methods
- Machine Learning-based (ML) Methods
- Deep Learning-based (DL) Methods

Evaluation Method

- Distance Similarity
  - Root Mean Square Error (RMSE)
  - Mean Absolute Error (MAE)
  - Mean Squared Error (MSE)
- Distributional Similarity
  - Kullback-Leibler (KL) Divergence
  - Wasserstein Distance
- Impact on Downstream Tasks

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Challenges

- **Overlooked Mechanisms in Existing Methods**
  - Limited focus on MAR and MNAR data imputation in current approaches.
- **Inadequate Evaluation Metrics**
  - Existing metrics like RMSE and MAE fail to capture the real-world utility, particularly in downstream tasks.
- **Experimental Limitations**
  - Inconsistent settings and lack of a comprehensive approach in comparing imputation methods across various missing data scenarios.

Research Focus

- **Comprehensive Evaluation**
  - Systematically evaluate statistical-based, ML-based, and DL-based imputation methods on tabular data, considering different missing mechanisms (MCAR, MAR, MNAR) and varying levels of missing data.
- **Practical Application**
  - Focus on assessing how these methods perform in real-world scenarios, particularly in downstream tasks like regression, classification, and clustering.
- **Refined Metrics Future Directions**
  - Offer insights into future directions for refining the evaluation metrics of the data imputation problem, aiming to improve the practical application of imputed data.

Experiments Setting: Dataset Selection

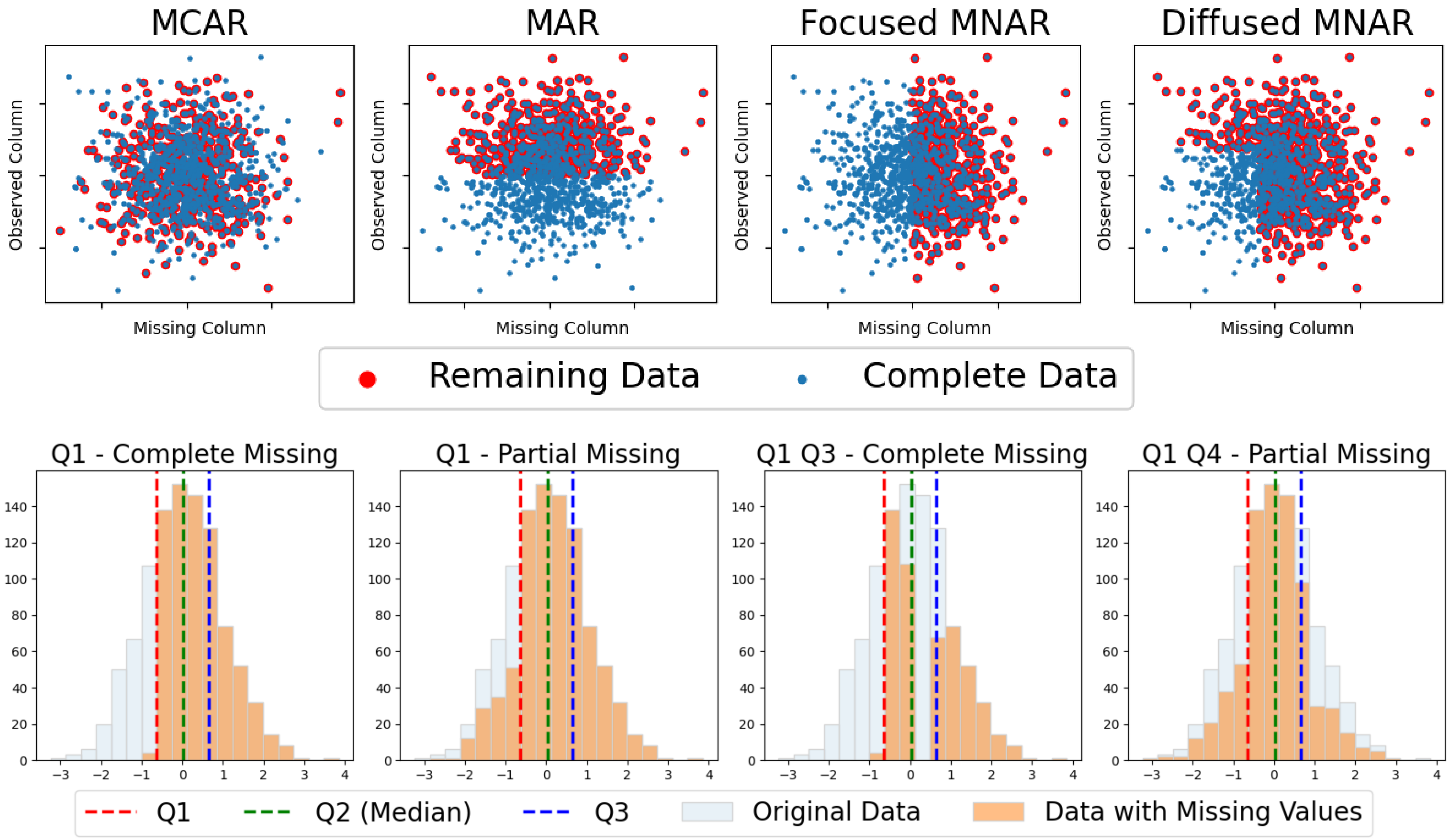
- **Dataset**
  - 10 from the UCI Machine Learning Repository
  - Features are all numerical fields
  - Applied MinMaxScaler to scale features within the range [0, 1]
  - Various tasks including Regression, Classification, and Clustering
  - Clustering methods also applied to datasets typically used for classification

Dataset	Bank	Cali	Climate	Concre	Qsar	Red	Sonar	White	Yachts	Yeast
#Inst	1372	20640	540	1030	1055	1500	208	4898	308	1484
#Dim	5	9	20	8	41	11	60	11	6	8
Task	C	R	C	C	C	R	C	R	R	C

Experiments Setting: Missing Data Generation

- **MCAR**
  - Random
- **MAR**
  - Logistic
- **Focused MNAR**
  - Percentile Rule
  - Logistic
- **Diffused MNAR**
  - Diffused

- **Missing Rate**
  - Ψ: 0.3, 0.5, 0.7



Experiments Setting:
Imputation Models (14 Methods)

Model Name	Type	Subtype
Random Imputer **(RD)**	**Statistical Based**	**Baseline**
Zero Imputer **(ZR)**		
Mean Imputer **(MEAN)**		
K-NN Imputer (2001) **(KNN)**	**Machine Learning Based**	**-**
Matrix Factorization (2001) **(MF)**		**-**
MICE (2011) **(MICE)**		**Regression Based**
XGBImputer (2014) **(XGB)**		**Tree Based**
MissForest (2012) **(MisF)**		**Tree Based**
Optimal Transport (2020) **(OT)**		**Enhanced Machine Learning**
Hyper Imputer (2022) **(HI)**		**Enhanced Machine Learning**
GAIN (2018) **(GAIN)**	**Deep Learning Based**	**GAN Based**
MiWAE (2018) **(Mi)**		**VAE Based**
Not-MiWAE (2020) **(NMi)**		**VAE Based**
Tab-CSDI (2022) **(CSDI)**		**Diffusion Based**

Experiments Setting: Evaluation Process

- **Quantitative Metrics**
  - RMSE/MAE
  - Pearson Correlation (between imputed value and ground truth)
- **Downstream Task**
  - Regression - RMSE
  - Classification – F1
  - Clustering - Adjusted Mutual Information (AMI)

Results and Discussion Baseline Methods

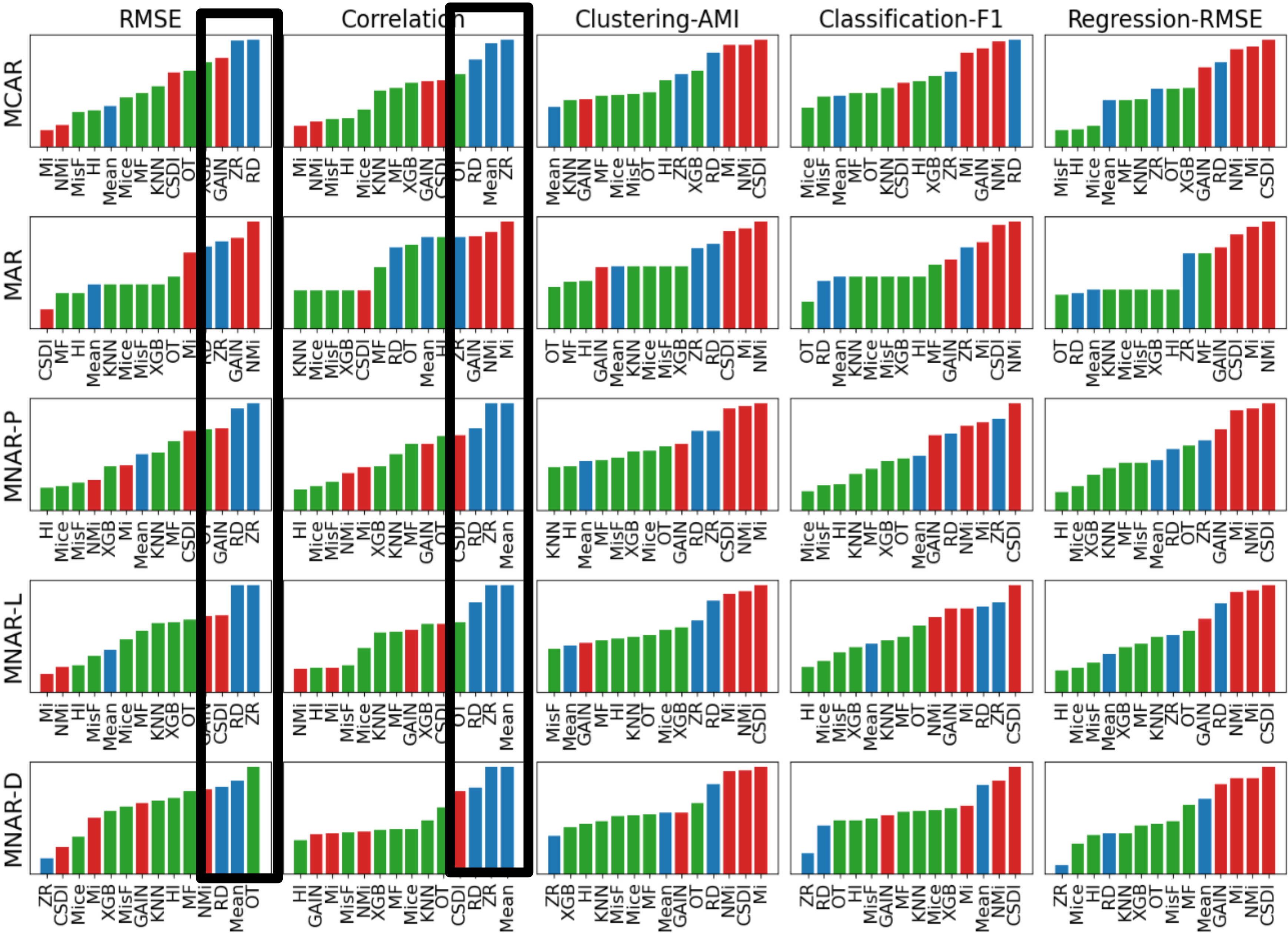
Baseline Methods

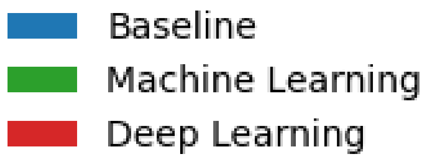
Quantitative Results:

- Not performing well.

MNAR-D Performance:

- Shows promising (Mean Imputer)





Average ranking of different imputation methods

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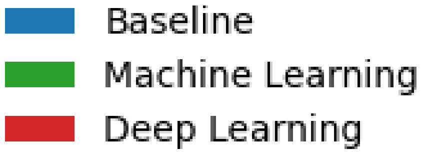
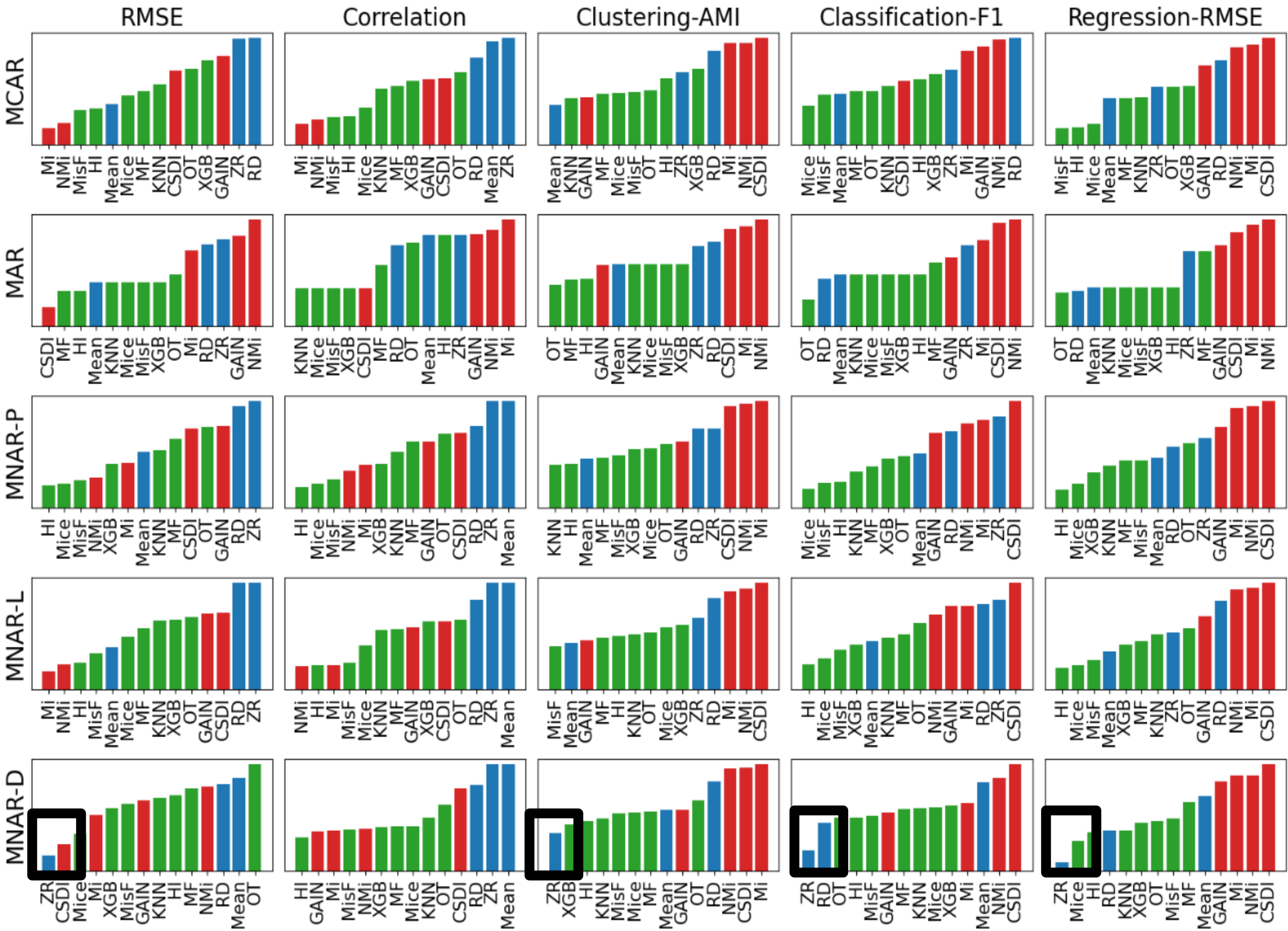




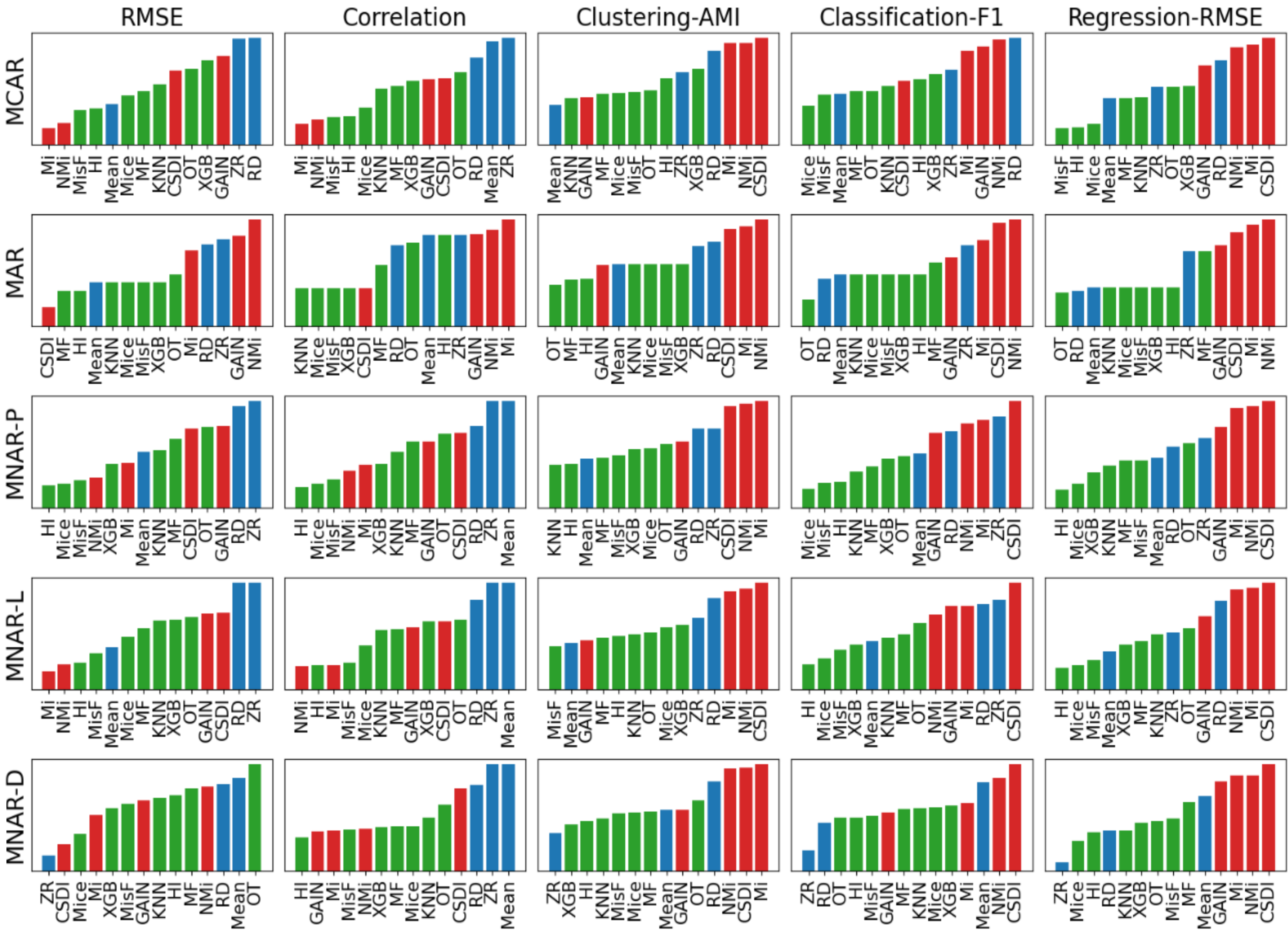
Average ranking of different imputation methods

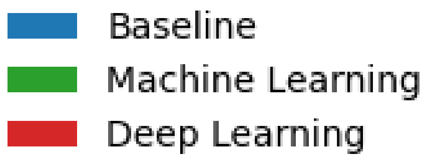
Results and Discussion
Baseline Methods

ML-Based Methods:

Quantitative & Downstream:

- Generally performs well in both, showing balanced effectiveness.





Average ranking of different imputation methods

Results and Discussion
Baseline Methods

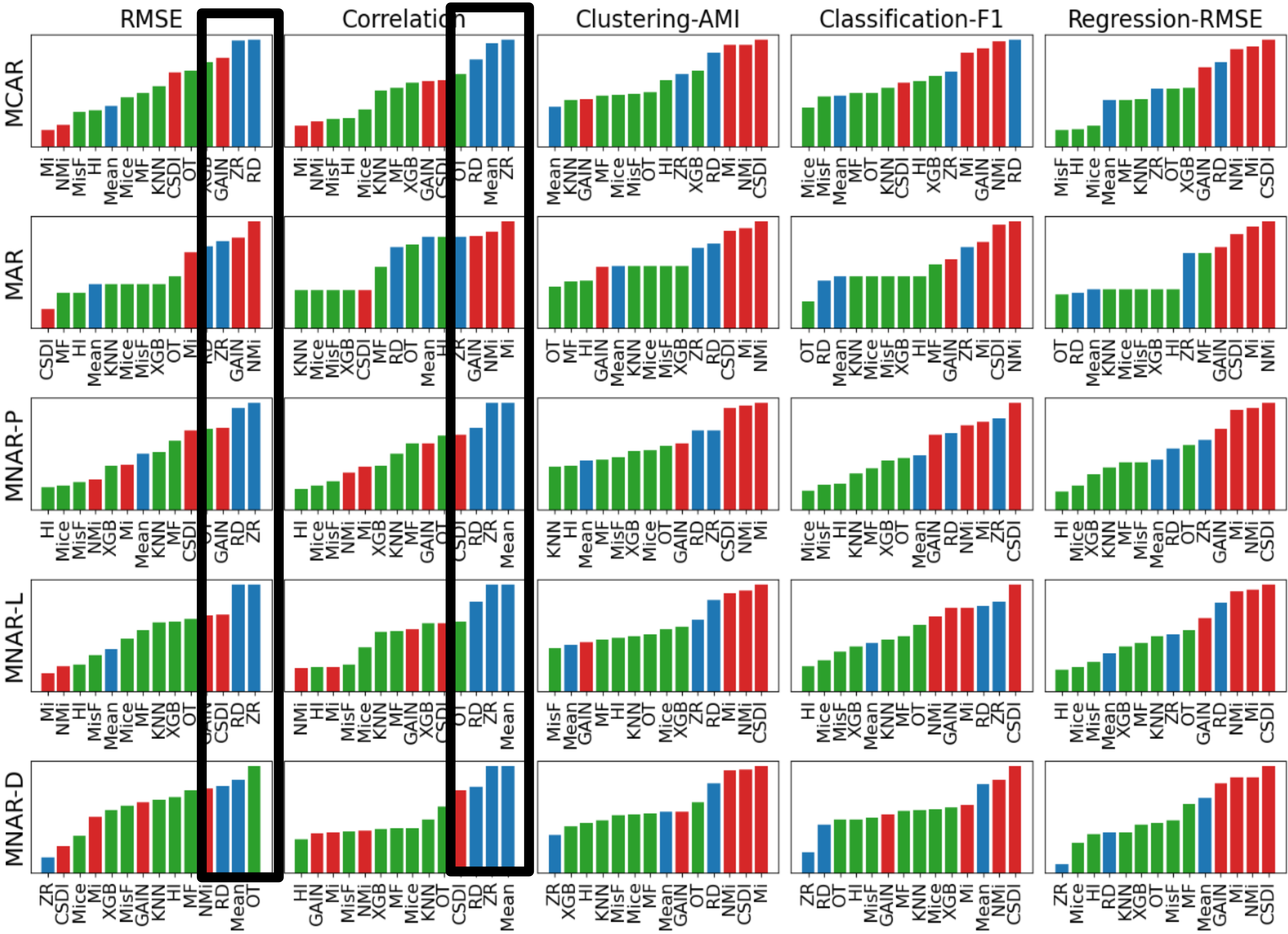
DL-Based Methods:

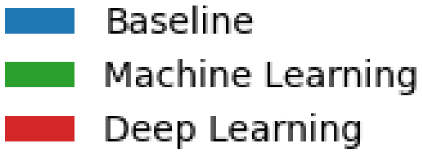
Quantitative Analysis:

- Generally, excels in quantitative analysis, yielding strong RMSE and MAE scores.

Downstream Tasks:

- Fails to perform effectively in downstream tasks.





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Results and Discussion
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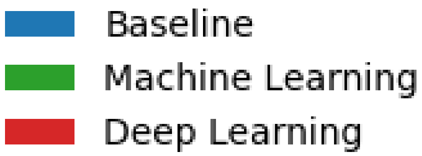

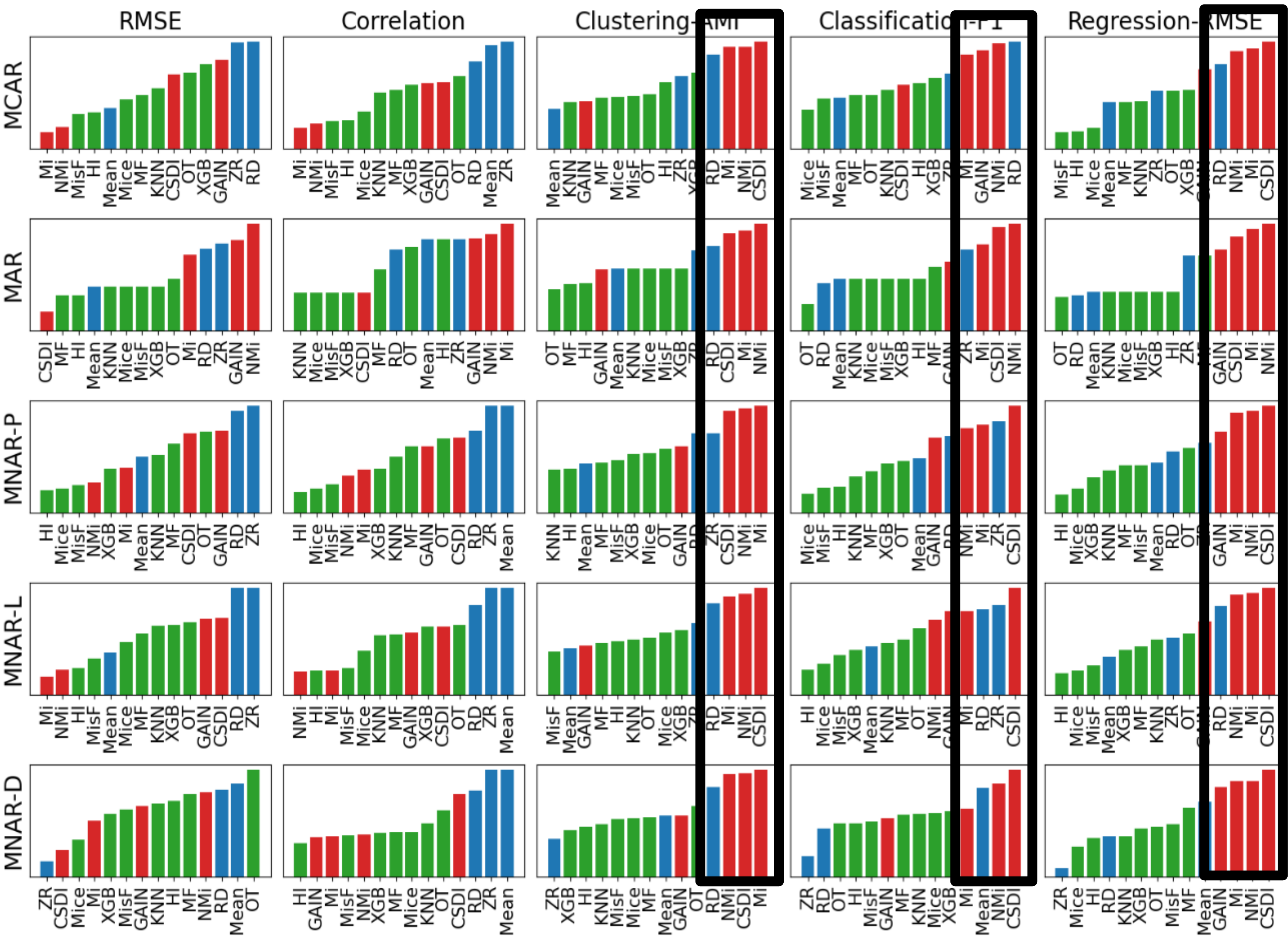

Average ranking of different imputation methods

Conclusion

Key Findings:

- **Performance Across Missing Mechanisms:**
  - Imputation methods show strong performance under MCAR but face challenges with MAR and MNAR due to their complexity.
- **Imputation Model Insights:**
  - Statistical Methods: Effective, especially in complex missing scenarios.
  - ML-Based Methods: Robust across both quantitative metrics and downstream tasks.
  - DL-Based Methods: While promising in qualitative analysis, often fail in downstream tasks, likely due to the limited size of tabular datasets.

Conclusion

Future Directions:

- **Broader Evaluation Metrics:**
  - Beyond RMSE, explore a wider set of metrics to better assess imputation quality across various analytical tasks.
- **Focus on MAR and MNAR:**
  - Develop techniques tailored to handle MAR and MNAR mechanisms, as they are more prevalent in real-world scenarios.
- **Handling Diverse Data Types:**
  - Extend research to address missing data in discrete and categorical forms, beyond the current focus on numeric data.

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