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Evaluation of machine learning-readiness in Alzheimer's disease data cohorts

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Introduction

- Build assistive tools for neurology clinics
  - Team: Shangran Qiu, Prajakta Joshi, Xiao Zhou, Matthew Miller, Chonghua Xue, Michael Romano, Cody Karjadi, Joyce Lee, Akshara Balachandra, Diala Lteif, Sandeep Sreerama, Caitlin Newman, Yi Zheng, Lindsey Claus, Yichi Zhang, Olivia Zhou, Rushin Gindra, Anika Walia, Aakash Bhatnagar, Meagan Lauber, Meysam Ahagaran

- PhD students and postdocs in computer science
- MD students, residents and clinical fellows at BUSM
- Trainees with background in neuroscience
- Background in more than a single discipline

Introduction

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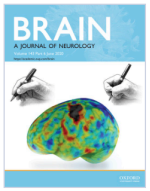

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Abstract

JOURNAL ARTICLE

Development and validation of an interpretable deep learning framework for Alzheimer's disease classification

Shangran Qiu, Prajakta S Joshi, Matthew I Miller, Chonghua Xue, Xiao Zhou, Cody Karjadi, Gary H Chang, Anant S Joshi, Brigid Dwyer, Shuhan Zhu, Michelle Kaku, Yan Zhou, Yazan J Alderazi, Arun Swaminathan, Sachin Kedar, Marie-Helene Saint-Hilaire, Sanford H Auerbach, Jing Yuan, E Alton Sartor, Rhoda Au, Vijaya B Kolachalama

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Interpretable machine learning

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Multimodal deep learning for Alzheimer's disease dementia assessment

Shangran Qiu, Matthew I. Miller, Prajakta S. Joshi, Joyce C. Lee, Chonghua Xue, Yunruo Ni, Yuwei Wang, Ileana De Anda-Duran, Phillip H. Hwang, Justin A. Cramer, Brigid C. Dwyer, Honglin Hao, Michelle C. Kaku, Sachin Kedar, Peter H. Lee, Asim Z. Mian, Daniel L. Murman, Sarah O'Shea, Aaron B. Paul, Marie-Helene Saint-Hilaire, E. Alton Sartor, Aneeta R. Saxena, Ludy C. Shih, Juan E. Small, ... Vijaya B. Kolachalama | + Show authors

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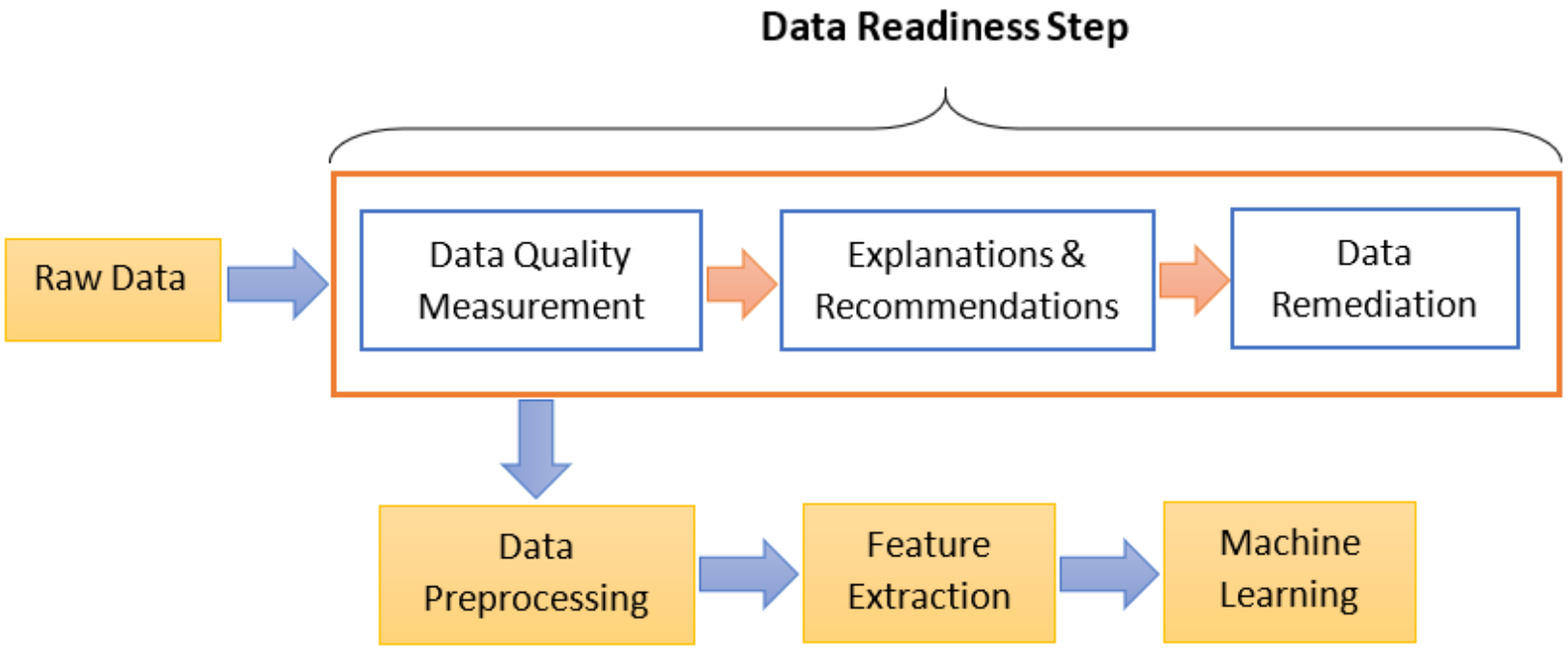
Introduction

- **Machine learning:** data + model → prediction
- Quality of prediction depends on both good models and high-quality data
- Scientists spend about **3/4th** of their time in iterative pre-processing of data
- Pre-processing: **cleansing**, **validation** and **transformation**



Data quality measures

- **Class Overlap:** Overlapping regions among different classes
- **Label Purity:** Noise ratio and the number of noisy samples in the data
- **Class Parity:** Class imbalance ratio
- **Feature Relevance:** Importance of each feature with respect to the target variable (class) and other features
- **Data Homogeneity:** Transformation of data into the user's intended format
- **Data Fairness:** Identifies the bias in the dataset and returns the disparate impact score
- **Correlation Detection:** Detect correlated features
- **Data Completeness:** Detects missing values
- **Outlier Detection:** Detect and remove outliers (deviates so much from other observations) in the dataset
- **Data Duplicates:** Remove duplicate records to clean the data

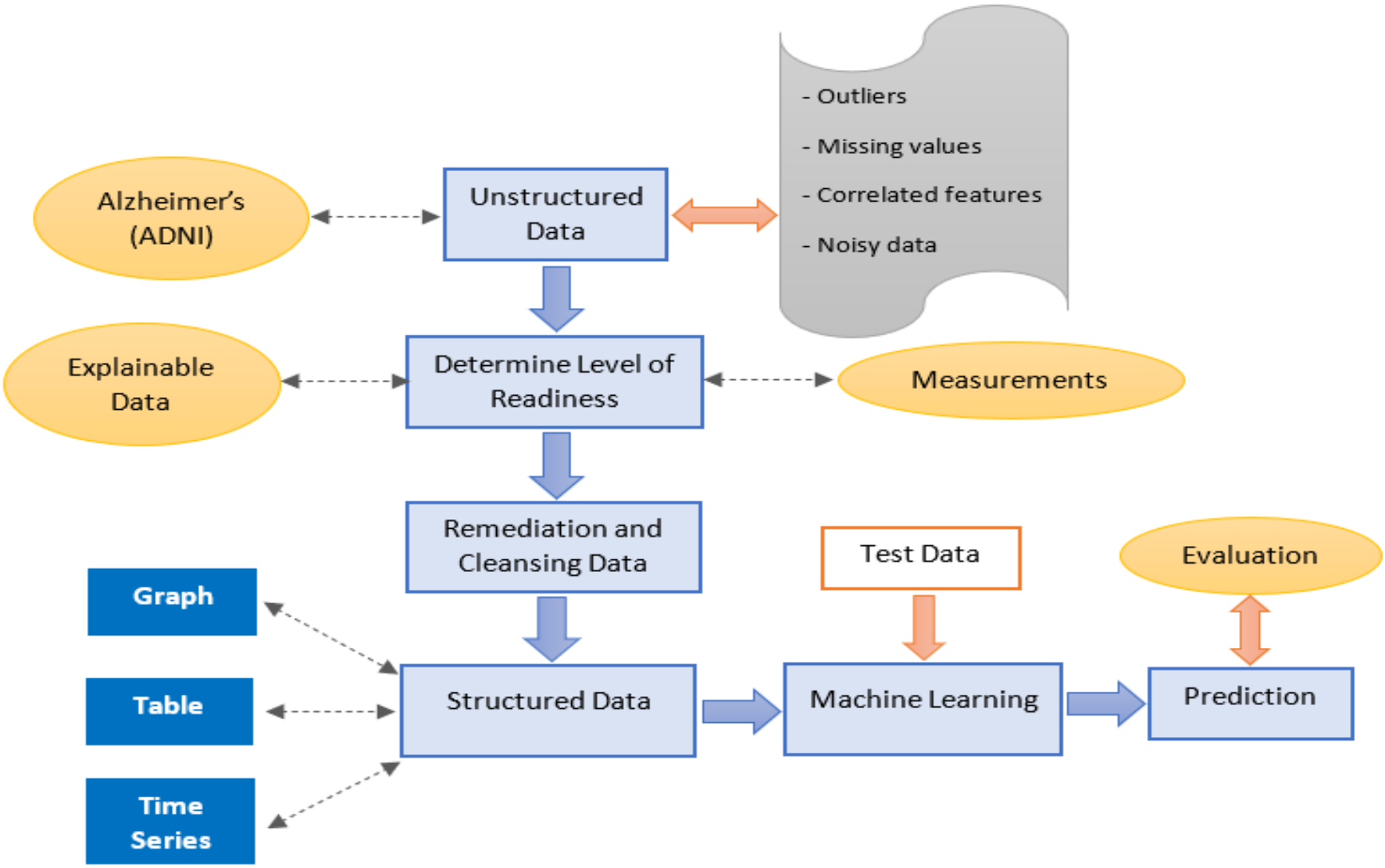
Assumptions

- **Class Overlap:**
- **Label Purity:**
- **Class Parity:**
- **Feature Relevance:**
- **Data Homogeneity:**
- **Data Fairness:**
- **Correlation Detection:**
- **Data Completeness:**
- **Outlier Detection:**
- **Data Duplicates:**

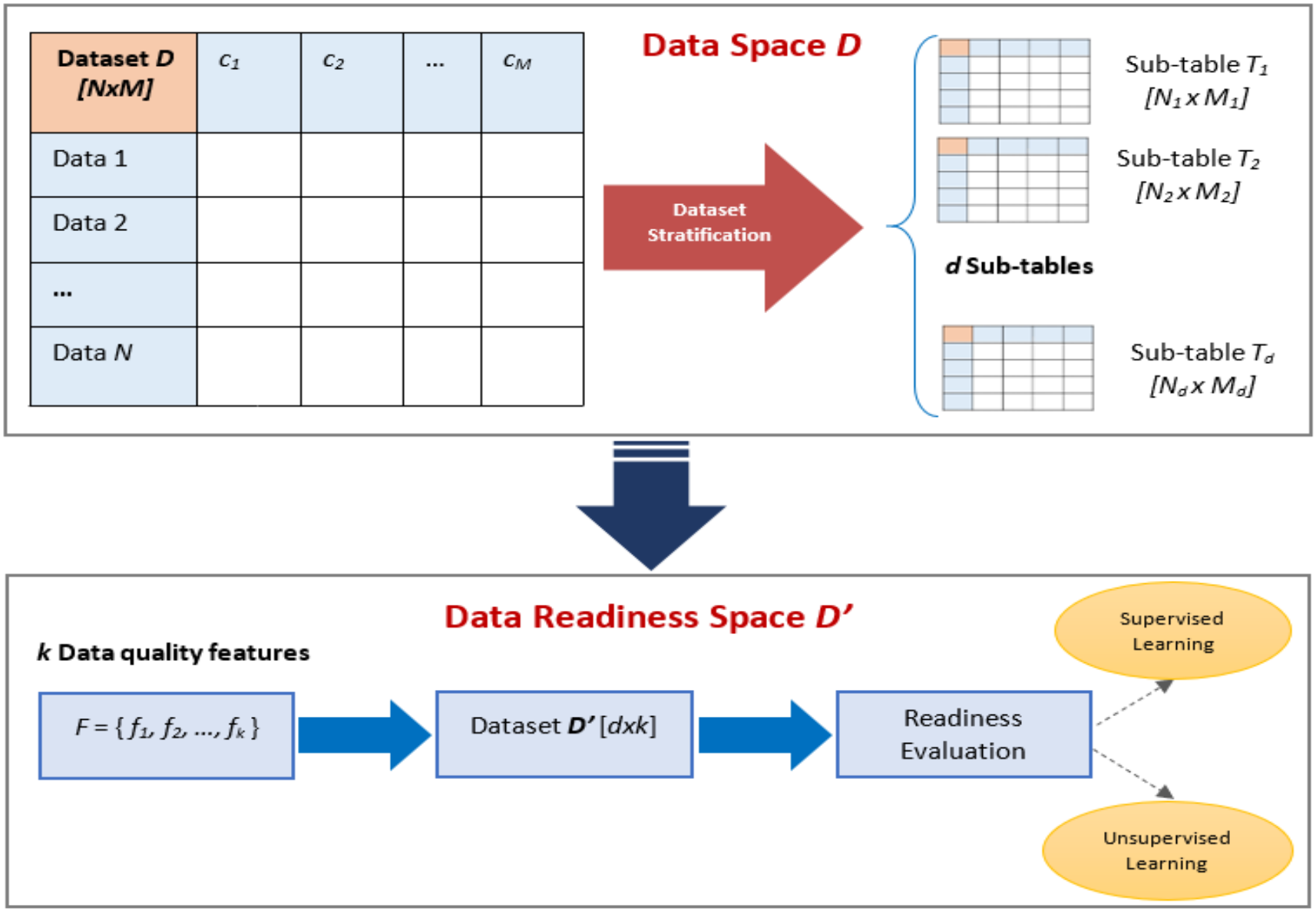
Most people evaluate these quality metrics independently and assume that poor quality affects outcomes

Framework: Evaluate the data quality by defining an objective and looking at the overall model performance.

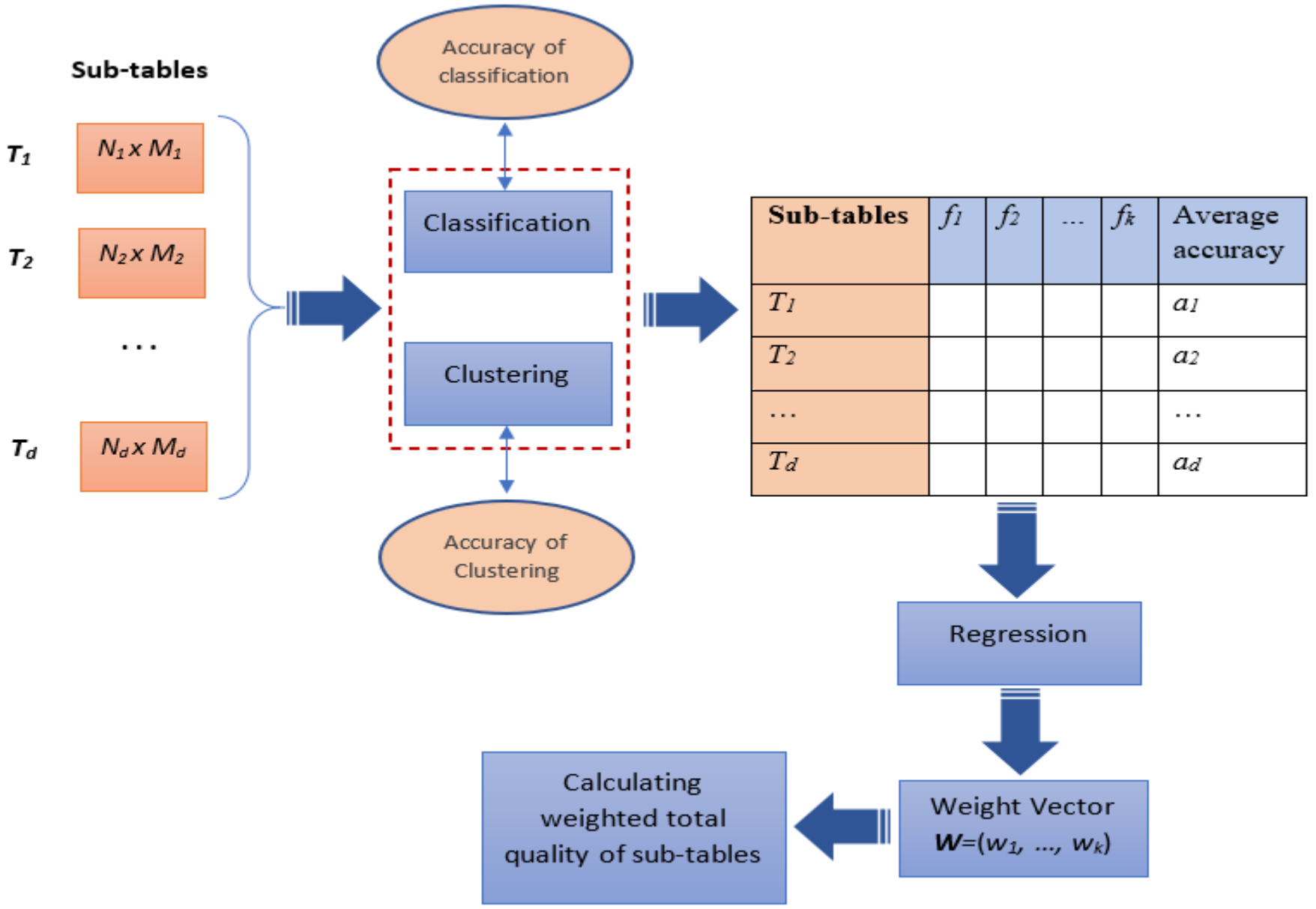
Data readiness in AD



Proposed method



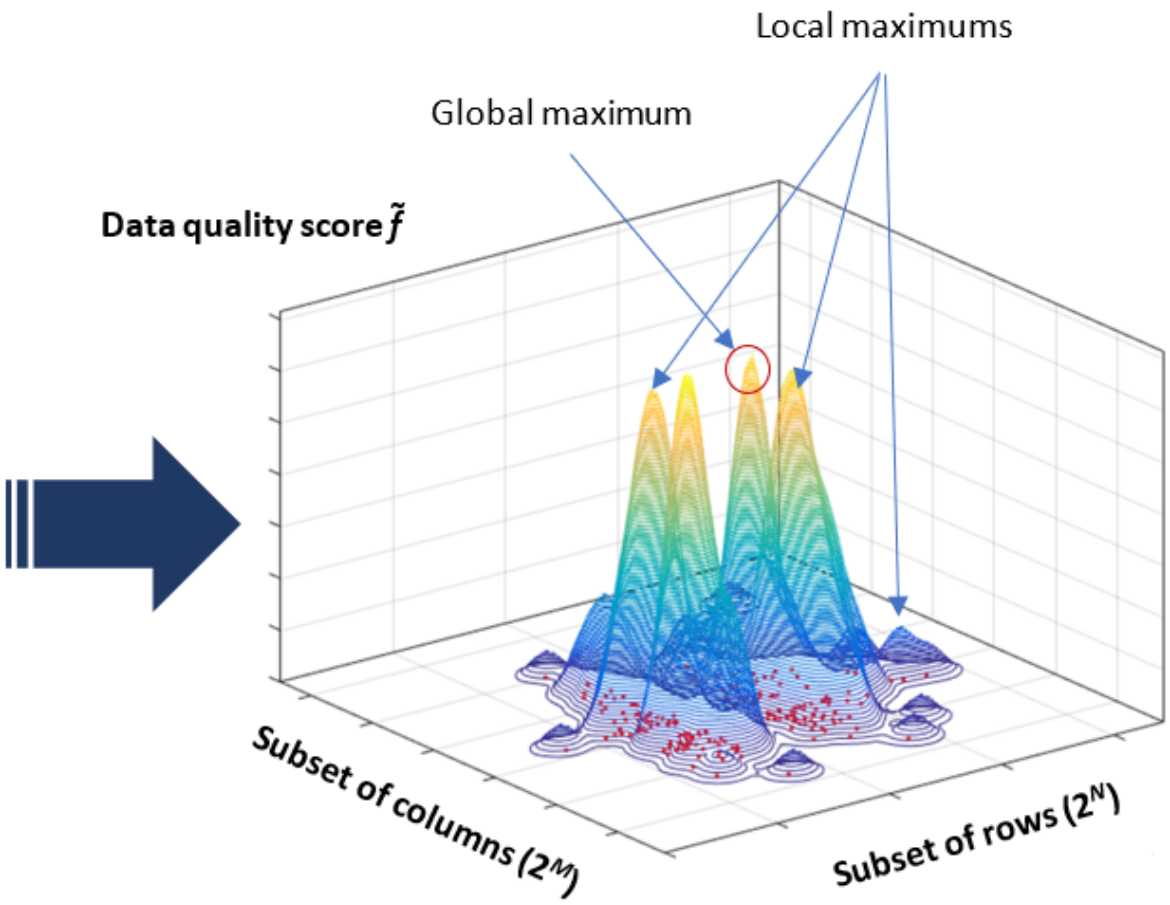
Learning weights of data quality measures



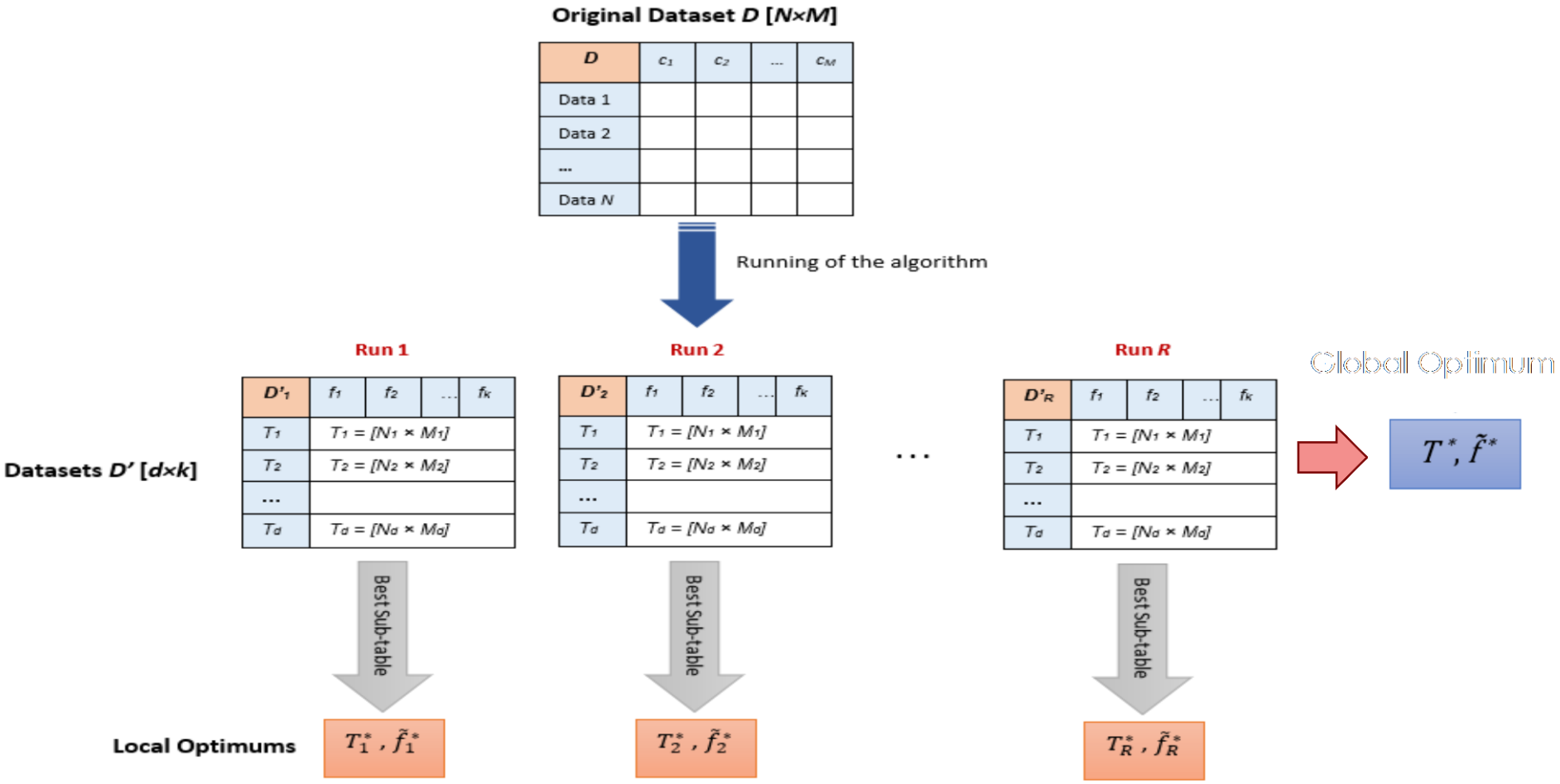
Problem's computational complexity

NP-Complete problem similar with ***Subset-Sum*** Problem

Dataset *D* [NxM]	c_1	c_2	...	c_M
Data 1				
Data 2				
...				
Data *N*				



Running the proposed algorithm



Static features of the ADNI dataset (ADNIMERGE table)

Feature Type	Column Name
Baselines (44 features)	CDRSB_bl, ADAS11_bl, ADAS13_bl, ADASQ4_bl, MMSE_bl, RAVLT_immediate_bl, RAVLT_learning_bl, RAVLT_forgetting_bl, RAVLT_perc_forgetting_bl, LDELTOTAL_BL, DIGITSCOR_bl, TRABSCOR_bl, FAQ_bl, mPACCdigit_bl, mPACCtrailsB_bl, Ventricles_bl, Hippocampus_bl, WholeBrain_bl, Entorhinal_bl, Fusiform_bl, MidTemp_bl, ICV_bl, MOCA_bl, EcogPtMem_bl, EcogPtLang_bl, EcogPtVisspat_bl, EcogPtPlan_bl, EcogPtOrgan_bl, EcogPtDivatt_bl, EcogPtTotal_bl, EcogSPMem_bl, EcogSPLang_bl, EcogSPVisspat_bl, EcogSPPlan_bl, EcogSPOrgan_bl, EcogSPDivatt_bl, EcogSPTotal_bl, ABETA_bl, TAU_bl, PTAU_bl, FDG_bl, PIB_bl, AV45_bl, FBB_bl.
Demographics (6 features)	AGE, PTGENDER, PTEDUCAT, PTETHCAT, PTRACCAT, PTMARRY
Genetics (one feature)	APOE4
Diagnosis class (one feature)	DX_bl

Simulation

- Random sub-tables were generated (R=4, d=500)
- Five diagnosis groups of patients at baseline (**CN, pMCI, sMCI,** and **AD**)
- Data quality features: **Pearson Correlation (PC), Missing Values, Spearman Correlation, Outliers,** and **Class overlap**
- **Classification method: Random Forest (RF) classifier**
- **Clustering method: Agglomerative** and **k-means clustering** (Silhouette Coefficient for calculating the accuracy of clustering)
- **Random Forest Regression** for learning the weight vector

Results

- **Mean weight vector:** **W* = (0.2005, 0.207, 0.2812, 0.0115, 0.2998)** for PC, Spearman Correlation, Missing Values, Outliers, and Class Overlap, respectively
- Weights of five data quality measures:

Run	PC	Spearman	Missing Values	Outliers	Class Overlap
1	0.1727	0.2331	0.2729	0.0088	0.3125
2	0.2123	0.181	0.3034	0.0042	0.299
3	0.2062	0.2177	0.2733	0.0132	0.2895
4	0.2109	0.1962	0.275	0.0197	0.2982

- Details of the best sub-table:

Run	Rows	Columns	PC	Spearman	Missing values	Outliers	Class Overlap	Classification Accuracy	Total Quality
1	1532	21	0.6708	0.6736	0.7685	1	0.495	0.7383	0.6499
2	1394	18	0.6563	0.6502	0.7277	1	0.4924	0.7188	0.6299
3	1474	16	0.7606	0.7492	0.8023	1	0.3212	0.6459	0.641
4	1994	16	0.7198	0.7163	0.6372	1	0.6433	0.7678	0.6761

Take home messages

- Data readiness is important to evaluate, and it encompasses various aspects related to data quality
- We developed a data readiness framework to evaluate AD cohorts with an objective to improve dementia assessment
- **Limitation:** Building frameworks to evaluate data readiness without considering objectives can reduce their value
- **Limitation:** Over reliance on such measures can lead to good modeling frameworks but can limit progress towards building true AI-based systems

Acknowledgments

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