# Task 1

## (1)

### (a)

Two new data quality problems that have emerged since the publication of the paper are:

1. Handling Unstructured and Semi-Structured Data: With the rise of big data, unstructured (e.g., text, images, videos) and semi-structured data (e.g., JSON, XML) have become more popular. Cleaning and standardizing these data types pose significant challenges, as traditional methods designed for structured data often fail to address issues like inconsistent formatting, embedded metadata, and contextual relevance.

2. Data Privacy and Compliance: As regulations like GDPR(General Data Protection Regulation) have been published, ensuring data quality now includes maintaining privacy and compliance. This introduces challenges in anonymizing personal data while preserving its utility. Inaccuracies or over-cleaning could lead to the loss of critical information, making it harder to ensure compliance without compromising data quality.

### (b)

Yes, many problems raised in the paper are still relevant today.

Those issues stems from the enduring nature of data quality challenges. Despite technological advancements, the **core problems** of data inconsistencies, duplicates, missing values, and integration across heterogeneous sources remain fundamental to ensuring data integrity. These issues are intrinsic to any data management process, whether dealing with traditional databases or modern big data environments.

The **ETL process**, central to the paper, is still crucial for transforming and loading data into warehouses or other storage systems. Even with the advent of real-time processing and advanced tools, ETL remains a vital step where data quality issues must be addressed.

Moreover, the **limitations of tools** and the need for **manual intervention**, as highlighted in the paper, continue to be a challenge. While automation has improved, complex data scenarios often require human expertise, especially when dealing with domain-specific data or ambiguous cases.

Additionally, the expansion of **data types** (e.g., unstructured and semi-structured data) and the growth in **data volume** have magnified these problems, making the paper’s insights even more pertinent today. Thus, the foundational issues and solutions discussed remain relevant as they underpin the challenges faced in modern data environments.

## (2)

When cleaning and integrating the latest Australian census data with previous years’ datasets for decision-making about Aboriginal and Torres Strait Islanders' access to health care, three key data wrangling aspects to consider are:

1. Data Quality and Consistency: Ensuring high data quality across all datasets is critical. This involves identifying and correcting errors like duplicate records, missing values, and inconsistencies that may arise due to variations in data collection methods or human error. For example, changes in the way health conditions or ethnic identities are recorded over different census years could lead to discrepancies. Ensuring consistency in data definitions, formats, and units of measurement across different years is essential for meaningful analysis and decision-making.

2. Data Integration and Schema Matching: Integrating datasets from multiple census years requires careful schema matching. This involves aligning different data structures, such as column names, data types, and categories, to create a unified dataset. For instance, if the way Aboriginal and Torres Strait Islander status is coded has changed over the years, these differences must be reconciled. Effective schema matching helps in combining data without losing context or meaning, ensuring that trends over time are accurately captured.

3. Ethical Considerations and Sensitivity: Handling sensitive data about Aboriginal and Torres Strait Islander communities requires strict attention to ethical considerations. It is vital to ensure that the data is anonymized where necessary and that privacy is protected throughout the data wrangling process. Additionally, care must be taken to avoid introducing bias or misrepresenting these communities. The data should be processed and presented in a way that supports equitable access to healthcare and respects the cultural significance of the information.

# Task 2

L= [25, 11, 40, 17, 17, 41, 21, 31, 46, 26, 86, 74, 100, 28, 15, 97];

L final=[25, 11, 40, 17, 17, 41, 21, 31, 46, 26, 86, 74, 100, 28, 15, 97, 75, 68, 82, 3]

## （1）

Mean=45.15;

Standard deviation =30.25;

## (2)

Median = 35.5;

median absolute deviation=19.5;

## (3)

Mode=17；

## （4）

The dataset is likely positively skewed (right-skewed) because the mode (17) is less than the median (35.5), which is generally less than the mean (which would likely be higher given the presence of large values like 86, 97, and 100). This pattern typically indicates a distribution with a long tail on the right side.

# Task 3

## （1）

Bin 1: [ 19.00 , 19.00, 19.00 , 19.00, 19.00 , 19.00, 19.00 , 19.00 , 19.00 , 19.00 ];

Bin 2: [74.50, 74.50, 74.50, 74.50, 74.50, 74.50, 74.50, 74.50, 74.50, 74.50];

## （2）

Bin 1: [19.40, 19.40, 19.40, 19.40, 19.40, 19.40, 19.40, 19.40, 19.40, 19.40]

Bin 2: [42.33, 42.33, 42.33]

Bin 3: [83.14, 83.14, 83.14, 83.14, 83.14, 83.14, 83.14]

## (3)

Bin 1: [3.00,3.00,3.00,27.25, 27.25, 27.25, 27.25 ,27.25]

Bin 2: [27.25 ,27.25 ,51.5, 51.5, 51.5]

Bin 3: [75.75 ,75.75, 75.75]

Bin 4: [75.75, 75.75 ,100.00,100.00]

## (4)

Bin 1: [3.00 ,17.00 ,17.00,17.00,17.00]

Bin 2: [21.00 ,21.00 ,21.00 ,31.00 ,31.00 ]

Bin 3: [40.00 ,40.00 ,40.00 ,74.00 ,74.00 ]

Bin 4: [75.00 ,75.00 ,75.00 ,100.00 ,100.00 ]