2883. Drop Missing Data

Easy

Leetcode Link

Problem Description

In this task, you are given a DataFrame `students` that consists of three columns: `student_id`, `name`, and `age`. The `student_id` column holds integer values representing the unique ID of each student, `name` holds object values representing the names of the students which can be strings, and `age` contains integer values representing the students' ages. It has been noted that some entries in the `name` column are missing. The goal is to write a Python function that will process this DataFrame and remove any rows where the `name` is missing.

A missing value in a DataFrame can cause issues in data analysis and may not be suitable for some types of computations or algorithms that expect non-null values. Handling missing data is therefore a common preprocessing step. The result after processing should only include rows where the `name` has a valid non-null value.

The expected output is a DataFrame that no longer contains the rows with the missing `name` values, preserving all the other rows.

Intuition

To solve this problem, we need to consider an operation that can filter out rows based on the presence of missing values.

Pandas (the library being used) provides several methods for handling missing data. One of those methods is `notnull()`, which returns a Boolean series indicating whether each value in a DataFrame is not null. By applying `notnull()` to the `name` column, we get a series where each row has either `True` if the name is present or `False` if the name is missing.

We then use this series to filter the original DataFrame by passing it inside the square brackets `[ ]`. This is known as boolean indexing and it will only select the rows from `students` where the corresponding value in the boolean series is `True`. As a result, all rows with `True` will be kept and those with `False` will be removed.

The provided function `dropMissingData` simply performs this operation. It returns a new DataFrame without those rows that had missing `name` values, thus achieving the desired preprocessing step needed to clean the data.

Solution Approach

The implementation of the solution utilizes the capabilities of the Pandas library, which is specifically designed for data manipulation and analysis in Python. The solution approach is straightforward and involves the following steps:

1. Use the `notnull()` method provided by Pandas to check which rows in the `name` column have non-missing data. This method is applied column-wise and generates a boolean mask where each value corresponds to a row in the DataFrame.
2. This boolean mask has `True` values for rows where `name` is not null (i.e., not missing) and `False` for rows where `name` is null.
3. Apply the boolean mask to the DataFrame using the square bracket notation `[]`. This is a form of boolean indexing, a powerful feature provided by Pandas that allows for selecting data based on actual values rather than relying on traditional index locations.
4. The DataFrame gets filtered: only rows with `True` in the boolean mask will be kept, effectively dropping the rows where `name` is missing.

The key data structure used in this solution is the DataFrame, which can be imagined as a table or a spreadsheet-like structure where data is organized into rows and columns. Each column can be of a different type and can be accessed or modified easily using Pandas' methods.

The algorithm pattern utilized is known as filtering. The `notnull()` method is crucial in this pattern as it provides the essential step of distinguishing the data to keep from the data to discard.

In summary, here's the pseudocode for the implemented solution, translating the steps into code operations:

```
def dropMissingData(students):
    # Step 1: Generate a boolean mask for non-missing 'name' values
    valid_names_mask = students['name'].notnull()

    # Step 2: Apply the mask to the DataFrame, keeping only valid rows
    clean_students = students[valid_names_mask]

    return clean_students
```

This function `dropMissingData()` when called with a DataFrame as an argument, returns a new DataFrame devoid of any rows with missing `name` values. The returned DataFrame is suitable for further data processing steps where complete information is required.

Example Walkthrough

Let's walk through a small example to illustrate the solution approach described above.

Suppose we have the following `students` DataFrame:

student_id	name	age
1	Alice	20
2	Null	22
3	Charlie	21
4	Null	23
5	Eve	20

In this DataFrame, we can see that the `name` field is missing for `student_id` 2 and 4 (represented by Null for visualization purposes).

Following the steps of the solution:

1. We apply the `notnull()` method to the `name` column to create a boolean mask. This gives us:

student_id	name	age	name.notnull()
1	Alice	20	True
2	Null	22	False
3	Charlie	21	True
4	Null	23	False
5	Eve	20	True

2. Now we have a boolean mask that indicates `True` for rows with a valid name and `False` for rows with a missing name.
3. Next, we filter the original DataFrame by applying this boolean mask with square bracket notation. This leaves us with only the rows that have `True` in the mask:

student_id	name	age
1	Alice	20
3	Charlie	21
5	Eve	20

4. The resultant filtered DataFrame `clean_students` contains only the rows where `name` is not null.

And here is the actual code that would perform this filtering:

```
import pandas as pd

# Assume students is a DataFrame initialized with the provided data
valid_names_mask = students['name'].notnull()
clean_students = students[valid_names_mask]

print(clean_students)
```

The expected output after running the code would be the `clean_students` DataFrame, which no longer contains the rows where the `name` was missing:

```
   student_id     name  age
0           1    Alice   20
2           3  Charlie   21
4           5      Eve   20
```

This cleaned DataFrame is now ready for further analysis or processing without the problem of handling missing name values.

Python Solution

```
import pandas as pd

def dropMissingData(students: pd.DataFrame) -> pd.DataFrame:
    # Drop rows from the 'students' DataFrame where the 'name' column has missing values.
    # notnull() is used to select the rows where 'name' column is not NA/NaN
    clean_students = students[students['name'].notnull()]
    return clean_students

```

Java Solution

```
import java.util.ArrayList;
import java.util.List;
import java.util.Map;
import java.util.stream.Collectors;

// A class to demonstrate the equivalent operation in Java, albeit with plain data structures
public class DataFrameUtils {

    /**
     * Drops rows from a list of rows where the 'name' column has missing values.
     * @param students List of Map entries representing rows of a student DataFrame.
     * @return List of Map entries after removing rows with missing 'name'.
     */
    public static List<Map<String, String>> dropMissingData(List<Map<String, String>> students) {
        // Use stream to filter out any rows where the 'name' value is null or empty
        List<Map<String, String>> cleanStudents = students.stream()
                .filter(row -> row.get("name") != null && !row.get("name").isEmpty())
                .collect(Collectors.toList());
        return cleanStudents;
    }

    // Usage example
    public static void main(String[] args) {
        List<Map<String, String>> students = new ArrayList<>();
        // Populate the list 'students' with data
        // ...

        List<Map<String, String>> cleanStudents = dropMissingData(students);
        // ...
    }
}

```

C++ Solution

```
#include <iostream>
#include <vector>
#include <optional>
#include <algorithm>

// Define a structure for Student which holds an optional name and other attributes
struct Student {
    std::optional<std::string> name;
    // Add other attributes for Student if needed
};

// Function to drop rows from a vector of Student structs where the 'name' is missing
std::vector<Student> DropMissingData(const std::vector<Student>& students) {
    // Create a new vector to store students with valid names
    std::vector<Student> cleanStudents;

    // Use the copy_if algorithm to copy only those students whose name is present
    std::copy_if(
        students.begin(), students.end(),
        std::back_inserter(cleanStudents),
        [](const Student& s) {
            return s.name.has_value(); // Check if 'name' is not missing
        }
    );

    // Return the new vector with all students that have a name
    return cleanStudents;
}

// Assuming you have some method to populate the students vector
std::vector<Student> populateStudents();

int main() {
    // Populate your students vector (assuming this function is implemented)
    std::vector<Student> students = populateStudents();

    // Use the DropMissingData function to remove students without a name
    std::vector<Student> studentsWithNames = DropMissingData(students);

    // Now studentsWithNames contains only students with non-missing names
    // Process the clean list as required...

    return 0;
}

```

Typescript Solution

```
interface Student {
  name?: string; // The '?' denotes that the 'name' property is optional and can be undefined
  // include other student properties as needed
}

function dropMissingData(students: Student[]): Student[] {
  // Drop objects from the 'students' array where the 'name' property is missing or undefined
  let cleanStudents: Student[] = students.filter(student => student.name != null);
  // The 'filter' method goes through each student and keeps those where 'name' is not 'null' or 'undefined'

  return cleanStudents;
}

```

Time and Space Complexity

The given function `dropMissingData` is intended to remove rows from a pandas DataFrame where the values in the 'name' column are missing. Below is the time and space complexity of the provided function:

Time Complexity: The function uses `notnull()` method combined with the DataFrame indexing to filter out rows with non-null 'name' values. The time complexity of `notnull()` and the boolean indexing in pandas is linear with respect to the number of rows, n, since each element in the 'name' column needs to be checked once for a null condition. Therefore, the time complexity can be expressed as $O(n)$.

Space Complexity: Since pandas often uses views instead of copies, the space complexity for the filtering operation is $O(1)$. However, if a copy is created during the operation due to pandas internal optimizations based on the DataFrame size or data types, the space complexity could be $O(n)$ as a new DataFrame object is created to hold the filtered data. In the worst case, we consider the space complexity to be $O(n)$.