

# Learning How to Convert Pandas Floats to Integers

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When performing data preparation and analysis in [Pandas](#), a frequent requirement is the conversion of numerical data from [float](#) (floating-point) types to [integer](#) types. This seemingly simple operation is crucial for several reasons, including improving data storage efficiency, ensuring compatibility with specific database schemas that require whole numbers, and, most importantly, accurately reflecting the true nature of discrete data (e.g., counts, identifiers, or ages in whole years).

While the [float](#) type offers flexibility by accommodating decimal values and missing data, the [integer](#) type is optimized specifically for whole numbers. Moving from a [float](#) to an [integer](#) minimizes memory overhead and prevents misleading precision in datasets where decimal points are irrelevant.

This comprehensive guide details the precise methodologies for transforming columns within a [Pandas DataFrame](#) from a [float](#) representation to an [integer](#). We will cover the standard conversion using the powerful [.astype\(\)](#) function, explore techniques for bulk column conversion, and address the common challenge of handling missing values (NaNs), which requires special consideration in [Pandas](#).

The fundamental syntax for converting a column named `float_column` is straightforward and relies on direct type casting:

```
df = df.astype(int)
```

The following sections will explore practical scenarios to illustrate how this core syntax is applied effectively in real-world data manipulation tasks.

## Understanding Data Types and the Implications of Conversion

Before initiating any type conversions, it is essential to have a solid grasp of [data types](#) within [Pandas](#). Every column in a [DataFrame](#) is assigned a specific [data type](#) (or `dtype`), which dictates how values are stored in memory and which operations can be executed. Common numerical [data types](#) include [float64](#) for decimal numbers and various integer sizes (e.g., [int32](#), [int64](#)).

[Pandas](#) frequently defaults to [float64](#) for numerical columns. This occurs either because the input data explicitly contained decimal values, or, more commonly, because the column included missing values (NaNs), which standard NumPy [integer](#) arrays cannot represent. The need to convert arises when data, such as a count or ID, is inherently discrete, and storing it as a [float](#) wastes memory and implies unnecessary precision. Converting to an [integer](#) simplifies the data model and ensures alignment with the intended analysis.

The mechanism for conversion is the highly versatile [.astype\(\)](#) method. It casts a Series or a

[DataFrame](#) to a specified [data type](#). Crucially, when converting a [float](#) to an [integer](#) using `.astype(int)`, [Pandas](#) employs [truncation](#). This means the decimal part is discarded without any rounding. For instance, both `10.99` and `10.01` will become `10`. This behavior is fundamental and must be understood, as it results in a loss of data precision. If rounding is required (e.g., using `.round().astype(int)`), it must be performed explicitly before the final type casting.

## Converting a Single Float Column to Integer

We begin with the most common scenario: modifying the [data type](#) of a single column within a [DataFrame](#). We will use a sample dataset representing player statistics where points and assists are initially stored as [float](#) values, even though they might need to be treated as whole numbers for certain analyses.

The first step involves creating the sample [DataFrame](#) and inspecting its current [data types](#) using the `.dtypes` attribute. This initial inspection confirms which columns are currently floats and provides a baseline for verification.

### import pandas as pd

```
#create DataFrame
df = pd.DataFrame({'player': ,
'points': ,
'assists': })

#view data types for each column
df.dtypes

player object
points float64
assists float64
dtype: object
```

The output confirms that `points` and `assists` are both of type [float64](#). We will now proceed to convert only the `points` column to an [integer](#). This is achieved by selecting the column, applying `.astype(int)`, and overwriting the original column data.

### #convert 'points' column to integer

```
df = df.astype(int)
```

```
#view data types of each column
df.dtypes
```

```
player object  
points int32  
assists float64  
dtype: object
```

After executing the conversion, the `df.dtypes` output clearly shows that `points` has been successfully cast to `int32`, indicating the decimal values have been [truncated](#). The `assists` column remains `float64`, confirming the targeted nature of the operation.

## Handling Missing Values (NaN) During Type Casting

A significant challenge in converting [float](#) columns to [integer](#) types is the presence of missing data, typically represented by [NaN](#) (Not a Number). Standard [integer](#) arrays, derived from NumPy, cannot represent [NaN](#), which is inherently a floating-point concept. Consequently, attempting a direct conversion using `.astype(int)` on a column containing a single [NaN](#) will typically result in a `TypeError` or an unexpected conversion failure, forcing the data back to a [float](#) type to accommodate the missing value.

The recommended solution in modern [Pandas](#) (version 0.24.0 and newer) is the use of [nullable integer data types](#). These types, such as `'Int64'` (note the capital 'I'), are native [Pandas](#) extensions that allow [integer](#) columns to contain missing values without reverting the entire column to a [float](#). If your dataset contains NaNs that you must preserve, using `.astype('Int64')` is the most robust and pythonic approach for converting to an [integer data type](#).

Alternatively, if preserving the [NaN](#) representation is not necessary, you must explicitly handle the missing values before conversion. The most common pre-conversion technique is imputation using the `.fillna()` method. You might replace [NaNs](#) with a meaningful placeholder, such as `0`, the mean, or the median of the column. For example, `df.fillna(0).astype(int)` first replaces all missing entries with zero and then safely converts the column to a standard [integer](#) type. The choice between using a nullable [integer](#) type or imputation depends entirely on the requirements for data integrity in your analytical model.

## Converting Multiple Float Columns to Integer

When working with large [DataFrames](#), manually converting columns one by one is inefficient. [Pandas](#) facilitates simultaneous conversion of multiple columns by allowing users to select a list of column names and apply the `.astype()` method across the entire selection. This technique is highly efficient and streamlines the data preparation workflow significantly.

Using the same player statistics [DataFrame](#), where both `points` and `assists` are currently

`float64`, we will now convert both columns to [integers](#) in a single, atomic operation. The key is to access the [DataFrame](#) using a list of column names (e.g., `df[]`) before applying the type cast.

### import pandas as pd

```
#create DataFrame
df = pd.DataFrame({'player': ,
'points': ,
'assists': })

#convert 'points' and 'assists' columns to integer
df[] = df[].astype(int)

#view data types for each column
df.dtypes

player object
points int32
assists int32
dtype: object
```

The final output confirms that both columns have been successfully cast to the [int32 data type](#). This method is particularly useful when dealing with datasets where dozens of columns need the same type of conversion, providing a clean and declarative way to manage bulk changes while ensuring the consistent [truncation](#) behavior is applied uniformly.

## Advanced Considerations: Optimizing Memory and Alternatives

For data scientists dealing with extremely large [DataFrames](#), merely converting to an [integer](#) is often insufficient; selecting the most appropriate [integer](#) size is critical for minimizing memory footprint and boosting performance. While [int32](#) and `int64` are the default target types, NumPy and [Pandas](#) offer smaller types like `int8` and `int16`. These smaller types consume significantly less memory but can only represent a narrower range of values.

To implement memory optimization, you must assess the range of values in your column. For example, if all your [integer](#) counts are between 0 and 255, using `.astype('uint8')` (unsigned 8-bit [integer](#)) will use four times less memory than a standard [int32](#) column. Always choose the smallest safe [integer](#) type to maximize memory efficiency.

An excellent, automated alternative to manual size selection is the [pd.to\\_numeric\(\)](#) function, particularly when used with the `downcast` argument. This function is typically used to convert

objects or strings to numerical types, but when combined with `downcast='integer'`, it automatically selects the smallest possible [integer data type](#) (e.g., `int8`, `int16`) that can safely contain all the data in the column, providing substantial memory savings without manual range calculation. This function is often preferred when performing large-scale numerical optimization after data ingestion.

## Conclusion

Converting [float](#) columns to [integer](#) types in [Pandas](#) is a non-negotiable step for data integrity and optimization. The primary method, `.astype()`, provides a straightforward way to cast data, but mastery requires understanding its implications, particularly the behavior of [truncation](#).

Furthermore, effective data processing demands careful handling of missing values using the specialized nullable [integer](#) type (`'Int64'`) or implementing robust imputation strategies. By incorporating memory optimization techniques--either by selecting specific small [integer](#) sizes or utilizing the automated capabilities of `pd.to_numeric()`--you ensure your [DataFrames](#) are not only structurally correct but also highly efficient for large-scale analytical tasks.

## Additional Resources

To further enhance your data manipulation skills in [Pandas](#) and [Python](#), consider exploring the following essential documentation and tutorials:

[Pandas User Guide on Data Types](#)

[Pandas Documentation on Missing Data](#)

[Python Official Documentation on Numeric Types](#)

[Pandas Cheat Sheet for Data Scientists](#)