Combining Data in Pandas With merge(), .join(), and concat()

Pandas' `Series` and `DataFrame` objects are powerful tools for exploring and analyzing data. Part of their power comes from a multifaceted approach to combining separate datasets. With Pandas, you can **merge**, **join**, and **concatenate** your datasets, allowing you to unify and better understand your data as you analyze it.

In this tutorial, you'll learn how and when to combine your data in Pandas with:

- **`merge()`** for combining data on common columns or indices
- **`.join()`** for combining data on a key column or an index
- **`concat()`** for combining DataFrames across rows or columns

Note: The techniques you'll learn about below will generally work for both `DataFrame` and `Series` objects. But for simplicity and conciseness, the examples will use the term **dataset** to refer to objects that can be either DataFrames or Series.

Pandas `merge()`: Combining Data on Common Columns or Indices

The first technique you'll learn is `merge()`. You can use `merge()` any time you want to do database-like join operations. It's the most flexible of the three operations you'll learn.

When you want to combine data objects based on one or more keys in a similar way to a relational database, `merge()` is the tool you need. More specifically, `merge()` is most useful when you want to combine rows that share data.

You can achieve both **many-to-one** and **many-to-many** joins with `merge()`. In a many-to-one join, one of your datasets will have many rows in the merge column that repeat the same values (such as 1, 1, 3, 5, 5), while the merge column in the other dataset will not have repeat values (such as 1, 3, 5).

As you might have guessed, in a many-to-many join, both of your merge columns will have repeat values. These merges are more complex and result in the Cartesian product of the joined rows.

This means that, after the merge, you'll have every combination of rows that share the same value in the key column. You'll see this in action in the examples below.

What makes `merge()` so flexible is the sheer number of options for defining the behavior of your merge. While the list can seem daunting, with practice you'll be able to expertly merge datasets of all kinds.

When you use `merge()`, you'll provide two required arguments:

1. The `left` DataFrame

2. The `right` DataFrame

After that, you can provide a number of optional arguments to define how your datasets are merged:

- **`how`**: This defines what kind of merge to make. It defaults to `'inner'`, but other possible options include `'outer'`, `'left'`, and `'right'`.
- **`on`**: Use this to tell `merge()` which columns or indices (also called **key columns** or **key indices**) you want to join on. This is optional. If it isn't specified, and `left_index` and `right_index` (covered below) are `False`, then columns from the two DataFrames that share names will be used as join keys. If you use `on`, then the column or index you specify must be present in both objects.
- **`left_on` and `right_on`**: Use either of these to specify a column or index that is present only in the `left` or `right` objects that you are merging. Both default to `None`.
- **`left_index` and `right_index`**: Set these to `True` to use the index of the left or right objects to be merged. Both default to `False`.
- **`suffixes`**: This is a tuple of strings to append to identical column names that are not merge keys. This allows you to keep track of the origins of columns with the same name.

Note: In this tutorial, you'll see that examples always specify which column(s) to join on with `on`. This is the safest way to merge your data because you and anyone reading your code will know exactly what to expect when `merge()` is called. If you do not specify the merge column(s) with `on`, then Pandas will use any columns with the same name as the merge keys.

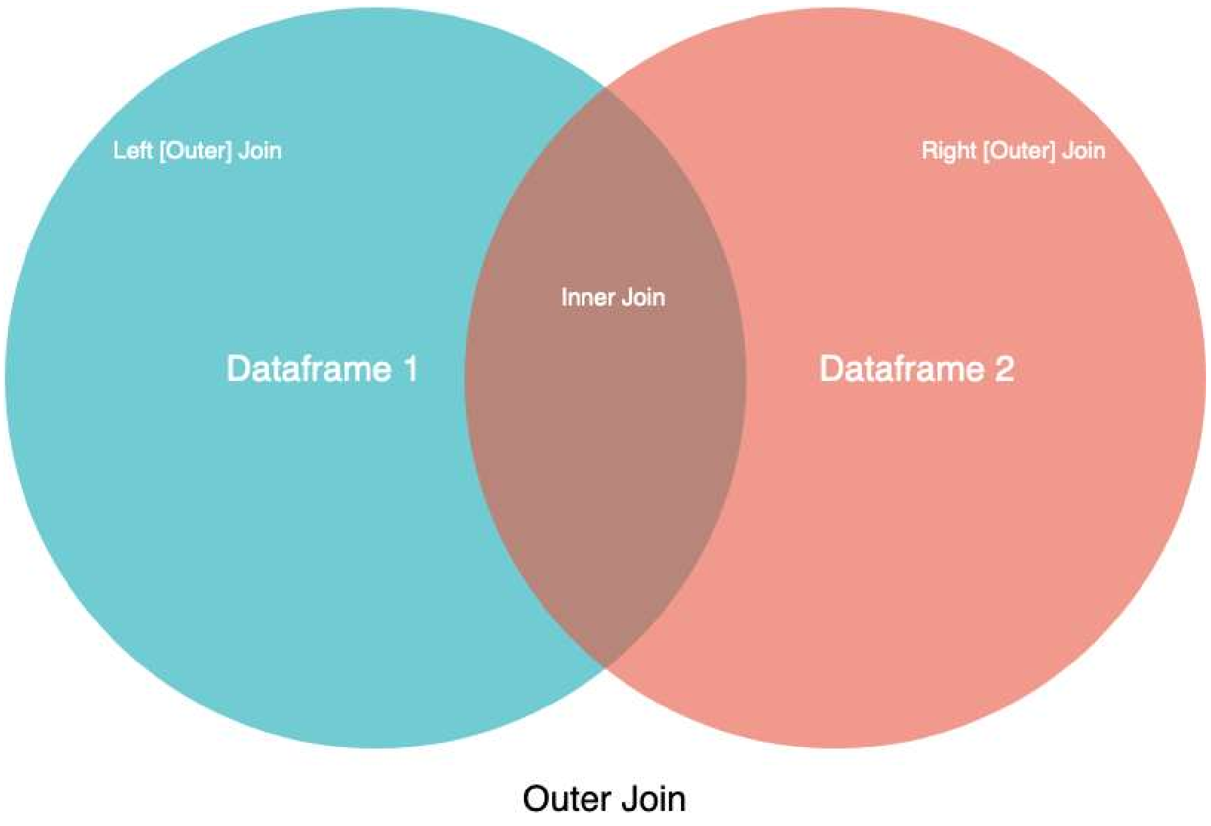
How to `merge()`

Before getting into the details of how to use `merge()`, you should first understand the various forms of joins:

- `inner`
- `outer`
- `left`
- `right`

Note: Even though you're learning about merging, you'll see `inner`, `outer`, `left`, and `right` also referred to as join operations. For this tutorial, you can consider these terms equivalent.

You'll learn about these in detail below, but first take a look at this visual representation of the different joins:



Visual Representation of Join Types

In this image, the two circles are your two datasets, and the labels point to which part or parts of the datasets you can expect to see. While this diagram doesn't cover all the nuance, it can be a handy guide for visual learners.

If you have an SQL background, then you may recognize the merge operation names from the `JOIN` syntax. Except for `inner`, all of these techniques are types of **outer joins**. With outer joins, you'll merge your data based on all the keys in the left object, the right object, or both. For keys that only exist in one object, unmatched columns in the other object will be filled in with `NaN` (Not a Number).

Examples

Many Pandas online tutorials provide very simple DataFrames to illustrate the concepts they are trying to explain. This approach can be confusing since you can't relate the data to anything concrete. So, for this tutorial, you'll use two real-world datasets as the DataFrames to be merged:

1. Climate normals for California (temperatures)
2. Climate normals for California (precipitation)

You can explore these datasets and follow along with the examples below using the interactive Jupyter Notebook and climate data CSVs:

These two datasets are from the National Oceanic and Atmospheric Administration (NOAA) and were derived from the NOAA public data repository. First, load the datasets into separate DataFrames:

```
>>> import pandas as pd
>>> climate_temp = pd.read_csv("climate_temp.csv")
>>> climate_precip = pd.read_csv("climate_precip.csv")
```

In the code above, you used Pandas' `read_csv()` to conveniently load your source CSV files into `DataFrame` objects. You can then look at the headers and first few rows of the loaded DataFrames with `.head()`:

```
>>> climate_temp.head()
             STATION            STATION_NAME  ... DLY-HTDD-BASE60 DLY-HTDD-
NORMAL
0  GHCND:USC00049099  TWENTYNINE PALMS CA US  ...              10
15
1  GHCND:USC00049099  TWENTYNINE PALMS CA US  ...              10
15
2  GHCND:USC00049099  TWENTYNINE PALMS CA US  ...              10
15
3  GHCND:USC00049099  TWENTYNINE PALMS CA US  ...              10
15
4  GHCND:USC00049099  TWENTYNINE PALMS CA US  ...              10
15

>>> climate_precip.head()
             STATION  ... DLY-SNOW-PCTALL-GE050TI
0  GHCND:USC00049099  ...                   -9999
1  GHCND:USC00049099  ...                   -9999
2  GHCND:USC00049099  ...                   -9999
3  GHCND:USC00049099  ...                       0
4  GHCND:USC00049099  ...                       0
```

Here, you used `.head()` to get the first five rows of each DataFrame. Make sure to try this on your own, either with the interactive Jupyter Notebook or in your console, so that you can explore the data in greater depth.

Next, take a quick look at the dimensions of the two DataFrames:

```
>>> climate_temp.shape
(127020, 21)
>>> climate_precip.shape
(151110, 29)
```

Note that `.shape` is a property of `DataFrame` objects that tells you the dimensions of the DataFrame. For `climate_temp`, the output of `.shape` says that the DataFrame has 127,020 rows and 21 columns.

Inner Join

In this example, you'll use `merge()` with its default arguments, which will result in an inner join. Remember that in an inner join, you will lose rows that don't have a match in the other DataFrame's **key column**.

With the two datasets loaded into `DataFrame` objects, you'll select a small slice of the precipitation dataset, and then use a plain `merge()` call to do an inner join. This will result in a smaller, more focused dataset:

```
>>> precip_one_station = climate_precip[climate_precip["STATION"] ==
"GHCND:USC00045721"]
>>> precip_one_station.head()
                STATION  ... DLY-SNOW-PCTALL-GE050TI
1460  GHCND:USC00045721  ...                   -9999
1461  GHCND:USC00045721  ...                   -9999
1462  GHCND:USC00045721  ...                   -9999
1463  GHCND:USC00045721  ...                   -9999
1464  GHCND:USC00045721  ...                   -9999
```

Here you have created a new DataFrame called `precip_one_station` from the `climate_precip` DataFrame, selecting only rows in which the `STATION` field is `"GHCND:USC00045721"`.

If you check the `shape` attribute, then you'll see that it has 365 rows. When you do the merge, how many rows do you think you'll get in the merged DataFrame? Remember that you'll be doing an inner join:

```
>>> inner_merged = pd.merge(precip_one_station, climate_temp)
>>> inner_merged.head()
             STATION            STATION_NAME  ...  DLY-HTDD-BASE60  DLY-
HTDD-NORMAL
0  GHCND:USC00045721  MITCHELL CAVERNS CA US  ...               14
19
1  GHCND:USC00045721  MITCHELL CAVERNS CA US  ...               14
19
2  GHCND:USC00045721  MITCHELL CAVERNS CA US  ...               14
19
3  GHCND:USC00045721  MITCHELL CAVERNS CA US  ...               14
19
4  GHCND:USC00045721  MITCHELL CAVERNS CA US  ...               14
19

>>> inner_merged.shape
(365, 47)
```

If you guessed 365 rows, then you were correct! This is because `merge()` defaults to an inner join, and an inner join will discard only those rows that do not match. Since all of your rows had a match, none were lost. You should also notice that there are many more columns now: 47 to be exact.

With `merge()`, you also have control over which column(s) to join on. Let's say you want to merge both entire datasets, but only on `Station` and `Date` since the combination of the two will yield a unique value for each row. To do so, you can use the `on` parameter:

```
inner_merged_total = pd.merge(climate_temp, climate_precip, on=["STATION",
"DATE"])
inner_merged_total.head()
inner_merged_total.shape
```

You can specify a single key column with a string or multiple key columns with a list. This results in a DataFrame with 123,005 rows and 48 columns.

Why 48 columns instead of 47? Because you specified the key columns to join on, Pandas doesn't try to merge all mergeable columns. This can result in "duplicate" column names, which may or may not have different values.

"Duplicate" is in quotes because the column names will not be an exact match. By default they are appended with `_x` and `_y`. You can also use the `suffixes` parameter to control what is appended to the column names.

To prevent surprises, all following examples will use the `on` parameter to specify the column or columns on which to join.

Outer Join

Here, you'll specify an outer join with the `how` parameter. Remember from the diagrams above that in an outer join (also known as a **full outer join**), all rows from both DataFrames will be present in the new DataFrame.

If a row doesn't have a match in the other DataFrame (based on the key column[s]), then you won't lose the row like you would with an inner join. Instead, the row will be in the merged DataFrame with `NaN` values filled in where appropriate.

This is best illustrated in an example:

```
outer_merged = pd.merge(precip_one_station, climate_temp, how="outer",
on=["STATION", "DATE"])
outer_merged.head()
outer_merged.shape
```

If you remember from when you checked the `.shape` attribute of `climate_temp`, then you'll see that the number of rows in `outer_merged` is the same. With an outer join, you can expect to have the same number of rows as the larger DataFrame. That's because no rows are lost in an outer join, even when they don't have a match in the other DataFrame.

Left Join

In this example, you'll specify a left join—also known as a **left outer join**—with the `how` parameter. Using a left outer join will leave your new merged DataFrame with all rows from the left DataFrame, while discarding rows from the right DataFrame that don't have a match in the key column of the left DataFrame.

You can think of this as a half-outer, half-inner merge. The example below shows you this in action:

```
left_merged = pd.merge(climate_temp, precip_one_station,
                       how="left", on=["STATION", "DATE"])
left_merged.head()
left_merged.shape
```

`left_merged` has 127,020 rows, matching the number of rows in the left DataFrame, `climate_temp`. To prove that this only holds for the left DataFrame, run the same code, but change the position of `precip_one_station` and `climate_temp`:

```
left_merged_reversed = pd.merge(precip_one_station, climate_temp,
how="left", on=["STATION", "DATE"])
left_merged_reversed.head()
left_merged_reversed.shape
```

This results in a DataFrame with 365 rows, matching the number of rows in `precip_one_station`.

Right Join

The right join (or **right outer join**) is the mirror-image version of the left join. With this join, all rows from the right DataFrame will be retained, while rows in the left DataFrame without a match in the key column of the right DataFrame will be discarded.

To demonstrate how right and left joins are mirror images of each other, in the example below you'll recreate the `left_merged` DataFrame from above, only this time using a right join:

```
right_merged = pd.merge(precip_one_station, climate_temp, how="right",
on=["STATION", "DATE"])
right_merged.head()
right_merged.shape
```

Here, you simply flipped the positions of the input DataFrames and specified a right join. When you inspect `right_merged`, you might notice that it's not exactly the same as `left_merged`. The only difference between the two is the order of the columns: the first input's columns will always be the first in the newly formed DataFrame.

`merge()` is the most complex of the Pandas data combination tools. It's also the foundation on which the other tools are built. Its complexity is its greatest strength, allowing you to combine datasets in every which way and to generate new insights into your data.

On the other hand, this complexity makes `merge()` difficult to use without an intuitive grasp of set theory and database operations. In this section, you've learned about the various data merging techniques, as well as many-to-one and many-to-many merges, which ultimately come from set theory.

Now, you'll look at a simplified version of `merge()`: `.join()`.

Pandas `.join()`: Combining Data on a Column or Index

While `merge()` is a **module function**, `.join()` is an **object function** that lives on your DataFrame. This enables you to specify only one DataFrame, which will join the DataFrame you call `.join()` on.

Under the hood, `.join()` uses `merge()`, but it provides a more efficient way to join DataFrames than a fully specified `merge()` call. Before diving in to the options available to you, take a look at this short example:

```
precip_one_station.join(climate_temp, lsuffix="_left", rsuffix="_right")
```

With the indices visible, you can see a left join happening here, with `precip_one_station` being the left DataFrame. You might notice that this example provides the parameters `lsuffix` and `rsuffix`. Because `.join()` joins on indices and doesn't directly merge DataFrames, all columns, even those with matching names, are retained in the resulting DataFrame.

If you flip the previous example around and instead call `.join()` on the larger DataFrame, then you'll notice that the DataFrame is larger, but data that doesn't exist in the smaller DataFrame (`precip_one_station`) is filled in with `NaN` values:

```
climate_temp.join(precip_one_station, lsuffix="_left", rsuffix="_right")
```

How to `.join()`

By default, `.join()` will attempt to do a left join on indices. If you want to join on columns like you would with `merge()`, then you'll need to set the columns as indices.

Like `merge()`, `.join()` has a few parameters that give you more flexibility in your joins. However, with `.join()`, the list of parameters is relatively short:

- **`other`**: This is the only required parameter. It defines the other DataFrame to join. You can also specify a list of DataFrames here, allowing you to combine a number of datasets in a single `.join()` call.
- **`on`**: This parameter specifies an optional column or index name for the left DataFrame (`climate_temp` in the previous example) to join the `other` DataFrame's index. If it's set to `None`, which is the default, then the join will be index-on-index.
- **`how`**: This has the same options as `how` from `merge()`. The difference is that it is index-based unless you also specify columns with `on`.
- **`lsuffix` and `rsuffix`**: These are similar to `suffixes` in `merge()`. They specify a suffix to add to any overlapping columns but have no effect when passing a list of `other` DataFrames.
- **`sort`**: Enable this to sort the resulting DataFrame by the join key.

Examples

In this section, you'll see examples showing a few different use cases for `.join()`. Some will be simplifications of `merge()` calls. Others will be features that set `.join()` apart from the more verbose `merge()` calls.

Since you already saw a short `.join()` call, in this first example you'll attempt to recreate a `merge()` call with `.join()`. What will this require? Take a second to think about a possible solution, and then look at the proposed solution below:

```
inner_merged_total = pd.merge(climate_temp, climate_precip, on=["STATION",
"DATE"])
inner_merged_total.head()
inner_joined_total = climate_temp.join(
    climate_precip.set_index(["STATION", "DATE"]),
    lsuffix="_x",
    rsuffix="_y",
    on=["STATION", "DATE"],
)
inner_joined_total.head()
```

Because `.join()` works on indices, if we want to recreate `merge()` from before, then we must set indices on the join columns we specify. In this example, you used `.set_index()` to set your indices to the key columns within the join.

With this, the connection between `merge()` and `.join()` should be more clear.

Below you'll see an almost-bare `.join()` call. Because there are overlapping columns, you'll need to specify a suffix with `lsuffix`, `rsuffix`, or both, but this example will demonstrate the more typical behavior of `.join()`:

```
climate_temp.join(climate_precip, lsuffix="_left")
```

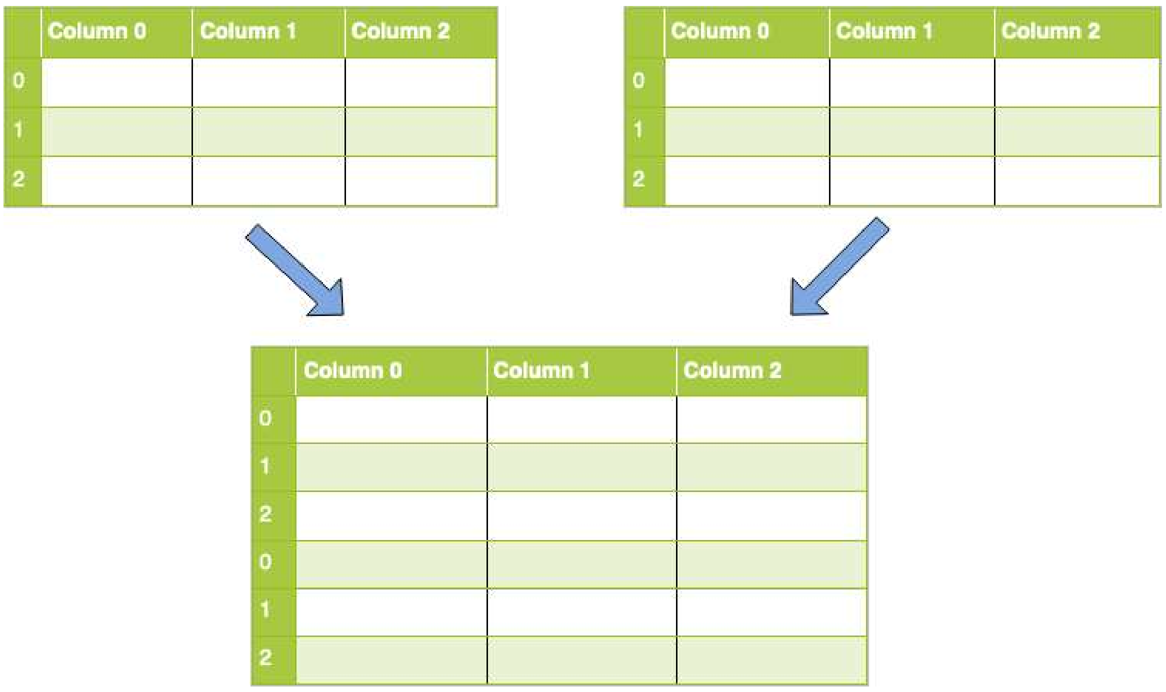
This example should be reminiscent of what you saw in the introduction to `.join()` earlier. The call is the same, resulting in a left join that produces a DataFrame with the same number of rows as `cliamte_temp`.

In this section, you have learned about `.join()` and its parameters and uses. You have also learned about how `.join()` works under the hood and recreated a `merge()` call with `.join()` to better understand the connection between the two techniques.

Pandas `concat()`: Combining Data Across Rows or Columns

Concatenation is a bit different from the merging techniques you saw above. With merging, you can expect the resulting dataset to have rows from the parent datasets mixed in together, often based on some commonality. Depending on the type of merge, you might also lose rows that don't have matches in the other dataset.

With concatenation, your datasets are just stitched together along an **axis** — either the **row axis** or **column axis**. Visually, a concatenation with no parameters along rows would look like this:

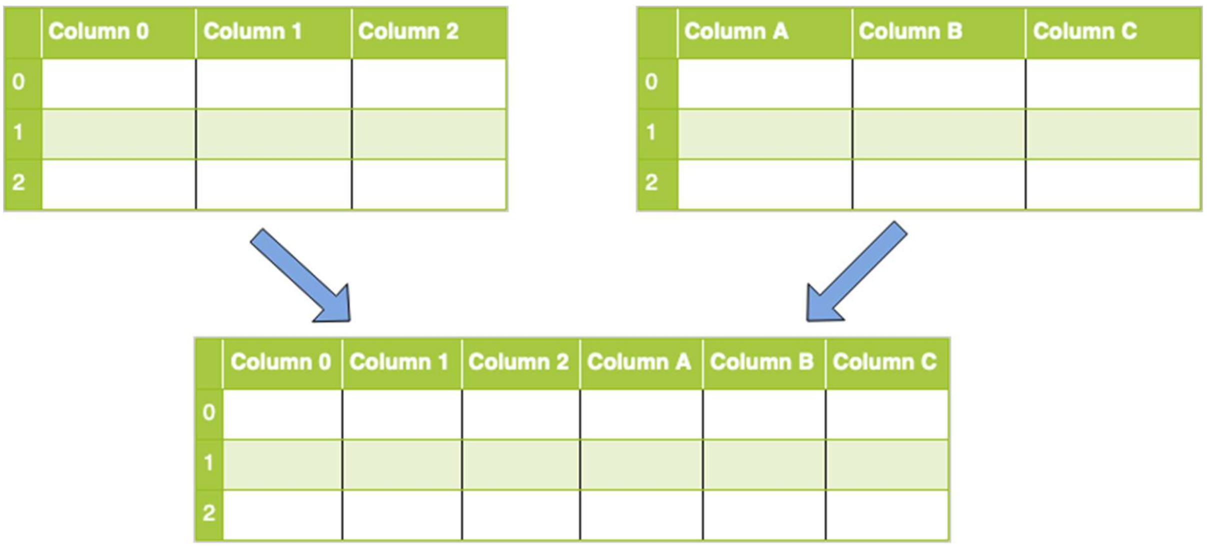


To implement this in code, you'll use `concat()` and pass it a list of DataFrames that you want to concatenate. Code for this task would like like this:

```
concatenated = pandas.concat([df1, df2])
```

Note: This example assumes that your column names are the same. If your column names are different while concatenating along rows (axis 0), then by default the columns will also be added, and `NaN` values will be filled in as applicable.

What if instead you wanted to perform a concatenation along columns? First, take a look at a visual representation of this operation:



To accomplish this, you'll use a `concat()` call like you did above, but you also will need to pass the `axis` parameter with a value of `1`:

```
concatenated = pandas.concat([df1, df2], axis=1)
```

Note: This example assumes that your indices are the same between datasets. If they are different while concatenating along columns (axis 1), then by default the extra indices (rows) will also be added, and `NaN` values will be filled in as applicable.

You'll learn more about the parameters for `concat()` in the section below. As you can see, concatenation is a simpler way to combine datasets. It is often used to form a single, larger set to do additional operations on.

Note: When you call `concat()`, a copy of all the data you are concatenating is made. You should be careful with multiple `concat()` calls, as the many copies that are made may negatively affect performance. Alternatively, you can set the optional `copy` parameter to `False`

When you concatenate datasets, you can specify the axis along which you will concatenate. But what happens with the other axis?

Nothing. By default, a concatenation results in a **set union**, where all data is preserved. You've seen this with `merge()` and `.join()` as an outer join, and you can specify this with the `join` parameter.

If you use this parameter, then your options are `outer` (by default) and `inner`, which will perform an inner join (or **set intersection**).

As with the other inner joins you saw earlier, some data loss can occur when you do an inner join with `concat()`. Only where the axis labels match will you preserve rows or columns.

Note: Remember, the `join` parameter only specifies how to handle the axes that you are *not* concatenating along.

Since you learned about the `join` parameter, here are some of the other parameters that `concat()` takes:

- **`objs`**: This parameter takes any sequence (typically a list) of `Series` or `DataFrame` objects to be concatenated. You can also provide a dictionary. In this case, the keys will be used to construct a hierarchical index.
- **`axis`**: Like in the other techniques, this represents the axis you will concatenate along. The default value is `0`, which concatenates along the index (or row axis), while `1` concatenates along columns (vertically). You can also use the string values `index` or `columns`.
- **`join`**: This is similar to the `how` parameter in the other techniques, but it only accepts the values `inner` or `outer`. The default value is `outer`, which preserves data, while `inner` would eliminate data that does not have a match in the other dataset.
- **`ignore_index`**: This parameter takes a Boolean (`True` or `False`) and defaults to `False`. If `True`, then the new combined dataset will not preserve the original index values in the axis specified in the `axis` parameter. This lets you have entirely new index values.

- **`keys`**: This parameter allows you to construct a hierarchical index. One common use case is to have a new index while preserving the original indices so that you can tell which rows, for example, come from which original dataset.
- **`copy`**: This parameter specifies whether you want to copy the source data. The default value is `True`. If the value is set to `False`, then Pandas won't make copies of the source data.

How to Add to a DataFrame With `append()`

Before getting into `concat()` examples, you should know about `.append()`. This is a shortcut to `concat()` that provides a simpler, more restrictive interface to concatenation. You can use `.append()` on both `Series` and `DataFrame` objects, and both work the same way.

To use `.append()`, you call it on one of the datasets you have available and pass the other dataset (or a list of datasets) as an argument to the method:

```
concatenated = df1.append(df2)
```

You did the same thing here as you did when you called `pandas.concat([df1, df2])`, except you used the instance method `.append()` instead of the module method `concat()`.

Examples

First, you'll do a basic concatenation along the default axis using the DataFrames you've been playing with throughout this tutorial:

```
double_precip = pd.concat([precip_one_station, precip_one_station])
```

This one is very simple by design. Here, you created a DataFrame that is a double of a small DataFrame that was made earlier. One thing to notice is that the indices repeat. If you want a fresh, 0-based index, then you can use the `ignore_index` parameter:

```
reindexed = pd.concat([precip_one_station, precip_one_station],
ignore_index=True)
```

As noted before, if you concatenate along axis 0 (rows) but have labels in axis 1 (columns) that don't match, then those will be added and filled in with `NaN` values. This results in an outer join:

```
outer_joined = pd.concat([climate_precip, climate_temp])
```

With these two DataFrames, since you're just concatenating along rows, very few columns have the same name. That means you'll see a lot of columns with `NaN` values.

To instead drop columns that have any missing data, use the `join` parameter with the value `"inner"` to do an inner join:

```
inner_joined = pd.concat([climate_temp, climate_precip], join="inner")
```

Using the inner join, you'll be left with only those columns that the original DataFrames have in common: `STATION`, `STATION_NAME`, and `DATE`.

You can also flip this by setting the `axis` parameter:

```
inner_joined_cols = pd.concat([climate_temp, climate_precip], axis=1,
join="inner")
```

Now you have only the rows that have data for all columns in both DataFrames. It's no coincidence that the number of rows corresponds with that of the smaller DataFrame.

Another useful trick for concatenation is using the `keys` parameter to create hierarchical axis labels. This is useful if you want to preserve the indices or column names of the original datasets but also to have new ones one level up:

```
hierarchical_keys = pd.concat([climate_temp, climate_precip], keys=["temp",
"precip"])
```

If you check on the original DataFrames, then you can verify whether the higher-level axis labels `temp` and `precip` were added to the appropriate rows.

Finally, take a look at the first concatenation example rewritten to use `.append()`:

```
appended = precip_one_station.append(precip_one_station)
```

Notice that the result of using `.append()` is the same as when you used `concat()` at the beginning of this section.

Conclusion

You have now learned the three most important techniques for combining data in Pandas:

1. **`merge()`** for combining data on common columns or indices
2. **`.join()`** for combining data on a key column or an index
3. **`concat()`** for combining DataFrames across rows or columns

In addition to learning how to use these techniques, you also learned about set logic by experimenting with the different ways to join your datasets. You also learned about the APIs to the above techniques and some alternative calls like `.append()` that you can use to simplify your code.

You saw these techniques in action on a real dataset obtained from the NOAA, which showed you not only how to combine your data but also the benefits of doing so with Pandas' built-in techniques.