

CSCD01 Group Project

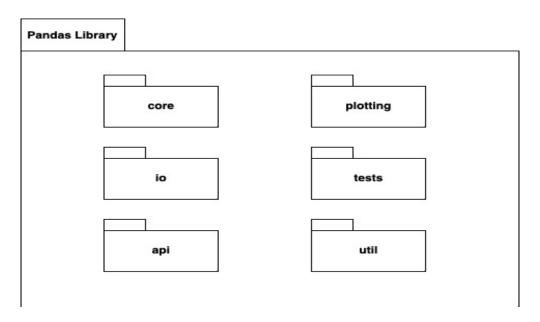
Deliverable 2

Zhiqi Chen Anika Sultana Christina Ma Gabriela Esquivel Gaghi Hyun Woo (Eddie) Shin Arthur Lu Man Hei Ho

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Pandas Library Architecture Overview



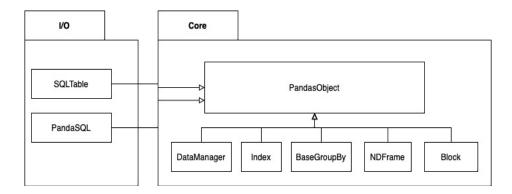
The above diagram roughly describes the high-level architecture of Pandas library. Pandas library contains Core, I/O, API, Plotting, tests and util packages which are essential packages to perform heavy computations, data processing and data visualizations.

- **Core**: The core package provides basics files for various operations in the library and implements key data structures, Series and DataFrames.
- I/O: The I/O package provides the basic functionalities of reading and writing data from external sources.
- API: The API package handles external API imports which are necessary for the library to be functional.
- **Plotting**: The Plotting package works with matplotlib, data visualization package in Python, to plot the data processed in the library.
- Tests: The Tests package contains a suite of test cases which are used to test
 the code changes made by contributors since the library is maintained by the
 open-source community.
- **Utils**: The Utils package contains various helper functions and development tools used in various purposes such as testing and debugging.

Pandas Core

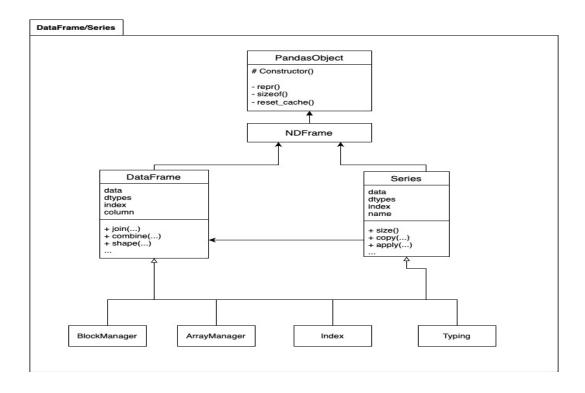
In Pandas, the core module defines the fundamental data structures and their operations, and algorithms for working with the data. In our high-level UML diagram, we chose to dive deeper into the Series, DataFrame, Index, Internals, Groupby, and Dtypes modules.

PandasObject



The PandasObject is the base class for many data structures within Pandas like Series, DataFrame, and Index.

Series and DataFrame



Series and DataFrame are the core Data Structure for storing data within pandas. Series is a one-dimensional data structure, while DataFrame is 2D. Notably, it is mutable, and can have multiple different data types including time series. DataFrames have attributes like data (block manager), dtypes (for type of data that is in the object), index (names of the rows), columns (names of the columns). le.

Would have indexes: 0, 1, 2 and columns: 'c', 'a'.

Series have similar attributes except columns and includes name for the name of the object.

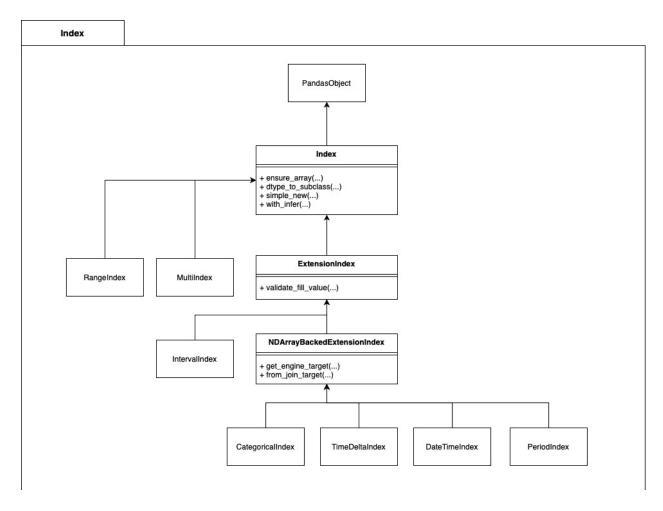
They both have a host of dependencies.

- Typing that includes various types of data that pandas accept and basic data like Scalor that these data structure use.
- Block and Array Manager for various methods for manipulation of data are found within them.
- Index for indexing and searching data.
- And many more that provide functionalities to these data structures.

Finally, NDFrame facilitates numerous backend and basic functionalities like setting label (names) of index and columns, comparing 2 objects for the same elements, returning an absolute value of the DataFrame/Series, etc.

It's worth noting that they are well decoupled. DataFrame and Series facilitates but the core implementation of functionalities are divided and handled by the Manager, Indexes, or NDFrame.

Index



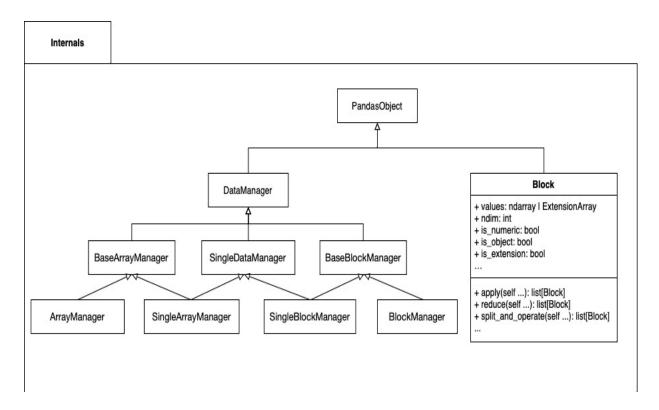
Index is an immutable sequence that is used to index DataFrame and Series. This object stores all axis labels for all pandas objects. An index can be thought of as a label or identifier for each row or column in a pandas DataFrame or Series.

There are 8 distinct instances of Index:

- RangeIndex: the default instance that represents a range of integers
- CategoricalIndex: represents categorical data
- MultiIndex: represents multi-levels, or hierarchy
- IntervalIndex: represents one-dimensional intervals or ranges
- DatetimeIndex: represents n-dimensional arrays of datetime64 data
- TimedeltaIndex: represents n-dimensional arrays of timedelta64 data
- PeriodIndex: represents n-dimensional arrays holding sequences of time periods

All of these instances inherit from the Index class.

Internals

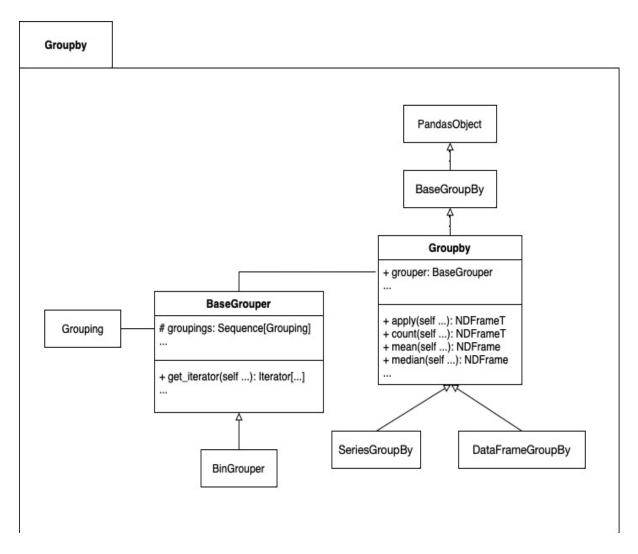


The internals module implements the internal data structures and functions underlying the Pandas objects.

The DataManager class implements the low-level architecture for storing and managing data. The BaseBlockManager extends DataManager and is the core internal data structure that implements DataFrame and Series. Its two children, BlockManager and SingleBlockManager, hold 2-dimensional and 1-dimensional blocks of data respectively; they are typically used to hold rows or columns of DataFrame and Series. The BaseArrayManager along with its children, ArrayManager and SingleArrayManager, is also the core internal data structure to implement DataFrame and Series. It is an alternative to the BaseBlockManager, storing a list of arrays instead of blocks.

The Block class is the base class of classes used internally by Pandas' data structure to store and manage a canonical n-dimensional unit of homogeneous data. The subclasses include ExtensionBlock, NumpyBlock, NumericBlock, etc. Note that Block is index-ignorant, meaning that the container (like DataFrame) should take care of indexing information itself.

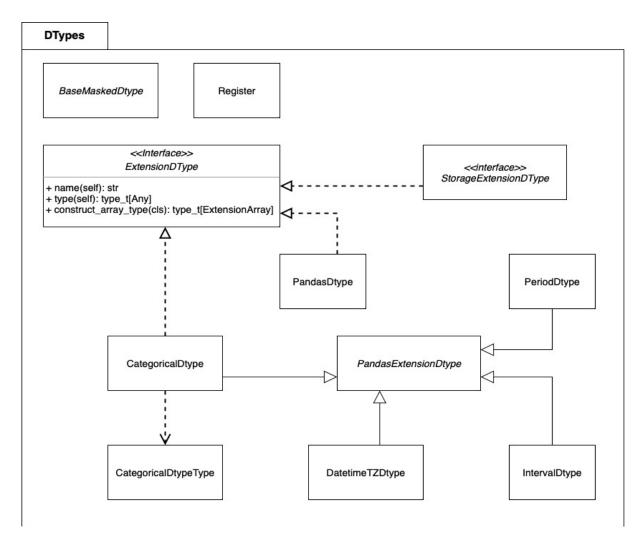
Groupby



The groupby module implements grouping and aggregating functionalities for DataFrame and Series. The groupby() function returns a Groupby object (DataFrameGroupBy or SeriesGroupBy, subclasses of Groupby) which allows users to work with grouped data like aggregating, transforming or applying operations on the grouped data.

Internally, the <code>Groupby</code> class is implemented using the <code>BaseGrouper</code> class which actually holds the generated groups. The <code>BaseGrouper</code> class uses the <code>Grouping</code> class to hold the grouping information for each key.

DTypes



In the dtypes/base.py file, with the purpose of extending Pandas with custom array types, three classes are defined. The first one, <code>ExtensionDType</code>, is an interface which represents a custom data type to be paired with an <code>ExtensionArray</code> (which is an abstract base class for custom 1-D array types). It includes the following abstract methods that must be implemented by its subclasses:

- type(self): type t[Any]
- name(self): str
- construct array type(cls): type t[ExtensionArray]

Secondly, StorageExtensionDtype extends ExtensionDType to allow for an ExtensionDType that is backed by multiple implementations. Lastly, Registry is a class responsible for dtype inference. According to the Pandas Documentation, it allows one to map a string representation of an ExtensionDType to an ExtensionDType.

Furthermore, the dtypes/dtypes.py file defines extension dtypes using the <code>ExtensionDType</code> interface described above. Initially, the class

PandasExtensionDtype (which inherits from *ExtensionDType*) is defined for holding a custom dtype. Then, CategoricalDtypeType is a metaclass to represent the type of the CategoricalDtype class. Afterwards, the file defines the following classes for different dtypes using PandasExtensionDtype:

- CategoricalDtype (which inherits from PandasExtensionDtype and ExtensionDtype) is used as a type for categorical data, and defines two attributes:
 - categories (an Index containing the categories allowed)
 - ordered (a boolean indicating whether it is an ordered Categorical).
- DatetimeTZDtype (which inherits from PandasExtensionDtype) is an ExtensionDtype for timezone-aware datetime data. This class defines two attributes:
 - unit (a str representing the precision of the datetime data)
 - tz (the timezone, represented as a str, int, or datetime.tzinfo)
- PeriodDtype (which inherits from PeriodDtypeBase and PandasExtensionDtype) is an ExtensionDtype for Period data. It defines one attribute:
 - freq, (which is a str or DateOffset indicating the frequency of the PeriodDType).
- IntervalDtype (which inherits from PandasExtensionDtype) is an ExtensionDtype for Interval data. This class has one attribute:
 - subtype (which can be a str or a np.dtype representing the dtype of the Interval bounds)

Next, the class PandasDtype (which implements the <code>ExtensionDtype</code> interface) is a Pandas <code>ExtensionDtype</code> for NumPy dtypes, used mostly for internal compatibility. This class provides implementations for the abstract methods <code>type(self)</code>, <code>name(self)</code>, and <code>construct_array_type(cls)</code>, as required by the interface it implements. Lastly, <code>BaseMaskedDtype</code> (which inherits from <code>ExtensionDtype</code>) is defined as a base class for the dtypes for <code>BaseMaskedArray</code> subclasses.

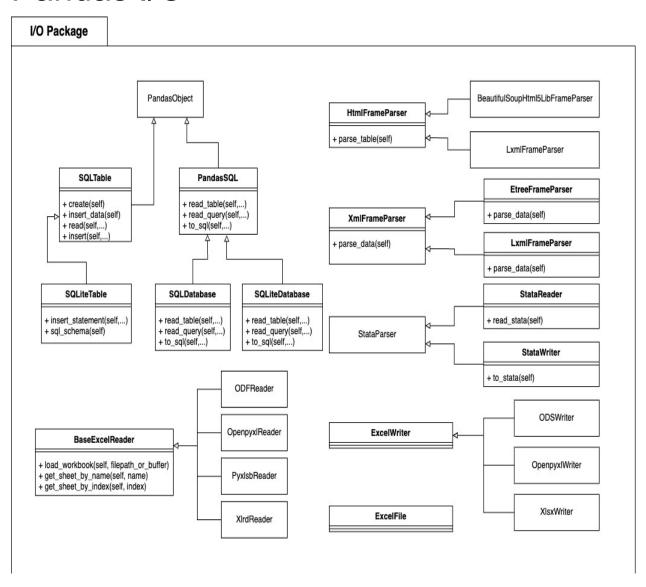
<code>BaseMaskedDtype</code> requires its subclasses to implement the following class methods:

- from numpy dtype(cls, dtype: np.dtype): BaseMaskedDtype
- construct array type(cls): type t[BaseMaskedArray]

Other

Other modules within the Pandas core module define other operations for the Pandas data structures. As examples, the computation module defines the operators and provides a set of functions for performing mathematical and statistical operations on the Pandas data structure like DataFrame and Series. The ops module provides a set of functions for arithmetic and logical operation on Pandas data structure like add, subtract, kleen and, etc. The reshape module provides functions to transform a Pandas data structure including pivoting and merging.

Pandas I/O



One of the key responsibilities of the I/O package in Pandas library is handling different types of input data formats. Some of the main data formats that Pandas can process are Excel, JSON, SQL, HTML and XML. Based on the high level structure of the I/O package, we were able to identify key modules and classes which contain key attributes and methods for the primary I/O operations for each data format. The publicly available methods widely used by Pandas users are read_[data_format] and to_[data_format]. These methods are implemented differently depending on data formats, and Pandas provide an interface for these methods within the I/O package. More detailed information about IO tools in Pandas can be found here. In the following, we explained how I/O functionalities of some of the major data formats are implemented.

XML Format

XML files can be parsed into DataFrames using the internal class called XMLFrameParser. Inside the same module, EtreeFrameParser inherits from XMLFrameParser to override some parent functions for the Python standard XML module library. LxmlFrameParser also inherits from XMLFrameParser to override some parent functions to incorporate the use of a third-party lxml library.

HTML Format

HTML files can be parsed into DataFrames using the internal class called HtmlFrameParser. BeautifulSoupHtml5LibFrameParser inherits from HtmlFrameParser to use BeautifulSoup under the hood and LxmlFrameParser inherits from HtmlFrameParser to use lxml under the hood.

Excel Format

There are three base classes which are <code>BaseExcelReader</code>, <code>ExcelWriter</code> and <code>ExcelFile</code>. <code>BaseExcelReader</code> is an abstract class which provides method signatures which can be implemented when it is inherited. Currently, <code>BaseExcelReader</code> is inherited by four different classes which are <code>ODFReader</code>, <code>OpenpyxlReader</code>, <code>PyxlsbReader</code> and <code>XlrdReader</code>. They handle different file extensions which make them have different method implementations from the parent class. <code>ExcelWriter</code> is responsible for writing <code>DataFrame</code> objects into excel sheets.

Currently, ExcelWriter is inherited by ODSWriter, OpenpyxlWriter and XlsxWriter. Lastly, ExcelFile is a general class which parses tabular excel sheets into DataFrame objects.

Stata Format

There is a base class called <code>StataParser</code> which provides the binary conversion functionality. The base class is inherited by <code>StataReader</code> and <code>StataWriter</code>. <code>StataReader</code> is responsible for reading Stata binary files and <code>StataWriter</code> is responsible for writing Stata binary files.

SQL Format

In sql.py, there are SQLTable class and PandasSQL class which are the two base classes for handling I/O operations from SQL. Both of the base classes inherit from PandasObject is the base class for various pandas objects. PandasObject class is located in base.py inside the core package, and this is one example of how two different packages are related to each other.

Based on the codebase, PandasSQL is an abstract class providing only the method signatures which must be implemented by child classes. SQLDatabase is a child class of PandasSQL which implements the methods defined in PandasSQL. In the end, SQLDatabase enables conversion between DataFrame and SQL databases. SQLTable is responsible for mapping pandas tables to SQL tables.

Given the fact that SQL has a lighter version called SQLite, SQLiteTable inherits from SQLTable and SQLiteDatabase inherits from PandasSQL. The basic functionalities are basically equivalent to their parent classes but small modifications are made to be used with SQLite.

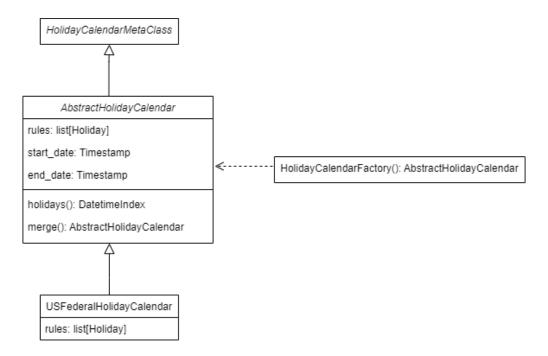
JSON Format

There are three key classes to handle JSON files in Pandas library. Writer class provides a backbone structure of writing in JSON files. SeriesWriter and FrameWriter inherit from the Writer class. The only difference between SeriesWriter and FrameWriter is how they work with axes as Series and DataFrames have different dimensions. JSONTableWriter subsequently inherits from FrameWriter to convert the data into JSONTable format.

JsonReader class handles reading JSON files by providing an interface for read operations in JSON. The JsonReader class contains many overloaded method signatures which can be implemented differently by its subclasses.

Lastly, it's important for Pandas to correctly parse JSON files, and the Parser class provides a backbone structure of parsing operations in JSON. SeriesParser and FrameParser inherit from the Parser class, and the difference in terms of their implementations is subtle due to the difference in dimensionality of Series and DataFrame.

Design Pattern #1 – Factory Method

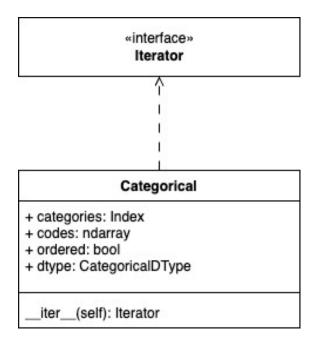


The above UML diagram highlights an implementation of the factory method pattern in the Pandas codebase. AbstractHolidayCalendar (line 389) is an abstract class based on the metaclass HolidayCalendarMetaClass that stores a list of Holidays (line 146) over a period of time defined by start_date and end_date. It is given one concrete implementation in the predefined USFederalHolidayCalendar class (line 556), an example calendar that contains federal holidays as specified by the American government. Pandas uses these calendars to perform data analysis over periods of time while accounting for holidays (i.e; skipping over them when calculating work days).

The factory method <code>HolidayCalendarFactory()</code> (line 583) provides an interface to create new <code>AbstractHolidayCalendar</code> type objects or combine existing calendars. Since this design pattern was used, the client does not have to specify what class of calendar will be created, instead receiving whatever type object (as in <code>PyTypeObject</code>) is returned by the factory method. Though this implementation differs slightly in that the factory method is declared outside of a class, the goal of using this method to generate different subclasses of <code>AbstractHolidayCalendar</code> remains the same.

Code Location: pandas/tseries/holiday.p, line 382–586

Design Pattern #2 – Iterator Pattern



Categorical is a data type in pandas and all values of categorical data are either in categories or np.nan. Categorical is not a numpy array but it is a python object. An iterator design pattern is used to iterate over a collection or group of objects. This helps mask the specific implementations of the object. In pandas, a specific example is inside Categorical.py, where a method is declared in line 1786, which implements an iterator for Categorical (the return type is an iterator). Since Categorical has values, we need to iterate over them and therefore an iterator has been declared. The method makes a call to iter(), which converts an iterable to iterator.

Code Location: pandas/core/arrays/categorical.py lines 1786-1793