Pandas
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What is Pandas?

• Opensource data analysis library
• Main objects:
  • 2-dimensional DataFrame
  • 1-dimensional Series
• Built on NumPy
What is Pandas?

• Optimized for wide variety of data analysis
  • I/O to/from formatted files and data bases
  • Missing data handling
  • Slicing, indexing, reshaping, adding columns
  • Powerful grouping for aggregating and transforming data sets
  • Merging and joining data sets
  • Time-series functionality

• Applied in finance, neuroscience, economics, statistics, advertising, web analytics, and more.

• Virtually no modeling capabilities (easy to integrate with scikit-learn)
Series

• One-dimensional array
• Possible heterogeneous type (although usually not)
• Each element has a label referred to as index
• Missing values are represented as NaN
• May be MultiIndexed hierarchically
Series constructors

- \texttt{pd.Series(ndarray, index=None)} — series from array-like in same order
  - \texttt{ndarray} must be 1-dimensional
  - If \texttt{index} is provided, must be same length as \texttt{ndarray}
  - If \texttt{index} is not provided, will be 0, ..., \texttt{len(ndarray)} – 1
  - If \texttt{index} is tuples, MultiIndexed series

- \texttt{pd.Series(dict, index=None)} — series from dictionary
  - If \texttt{index} is provided, it gives the order over \texttt{dict}
  - If \texttt{index} contains keys not in \texttt{dict}, treated as missing value
  - If \texttt{index} does not contain some key in \texttt{dict}, it is discarded
  - If \texttt{index} is not provided, order will be insertion order into \texttt{dict} (for Python >= 3.6)

- \texttt{pd.Series(scalar, index)} — repeated scalar value
  - \texttt{index} is required
Indexing and slicing Series

• Indices must be hashable types
• Index labels may not be unique, although that will raise errors in certain functions that require uniqueness
• Series objects can be indexed by either their index labels or their underlying 0-based index
• Slicing can also be done by either index type
  • Slicing based on index labels is done based on the order of the Series
• MultiIndexed Series are indexed hierarchically
  • Accessing only the outer index returns a sub-Series with all lower indices
  • Can index like ndarrays, with tuple indices
Series miscellaneous

• Series is array-like: valid argument for most NumPy functions
  • Array functions are modified to ignore missing values (NaN)
• Series is dict-like: get and set values by index label
• Series can be treated as arrays for vectorized operations
• Indices are automatically aligned: operating on two Series with different indices gives a Series with the *union* of the indices, where non-common indices are given NaN values
DataFrame

• 2-dimensional labeled structure
• Possibly heterogeneous type (common across columns)
• Intuition: spreadsheet or SQL table
  • Each column is an attribute
  • Each row is a record
• Also: like a dictionary of Series objects
Dataframe constructors

- **pd.DataFrame(dict, index=None, columns=None)** — dict of Series or dicts
  - Keys from outer dict are columns, keys from inner dict are indices
  - If the keys in the outer dict are tuples, columns are MultiIndexed
  - `index` and `columns` treated like `index` for creating a Series from a dict
  - Missing index/column discarded, order from index/columns, additional index/column treated as empty
DataFrame constructors

- `pd.DataFrame(dict, index=None, columns=None)` — dict of array-like
  - All arrays in dict must be the same length
  - If `index` is present, must be the same length as arrays
  - `columns` is treated same as above

- `pd.DataFrame(list, index=None, columns=None)` — list of dicts
  - Each dict is treated as a row
  - Column names are the union of the keys in all the dicts
Accessing DataFrame columns

- DataFrames can be indexed like dicts for accessing, adding, and deleting columns.
- Adding can be done with Series, array-like, or scalar:
  - `df[col] = Series` — Series with indices not in the DataFrame get those indices removed.
  - `df[col] = ndarray` — Array-like must have the same length as the indices in the DataFrame.
  - `df[col] = scalar` — Scalars are propagated to fill all indices.
- Columns are added at the end:
  - Use `insert()` to specify a different location.
Indexing DataFrame

- `df[col]` — return a Series/DataFrame corresponding to the column(s) with key `col`
- `df.loc[idx, col]` — return a Series/DataFrame corresponding to the row(s) with index label(s) `idx` and column label(s) `col`
- `df.iloc[n_idx, n_col]` — return a Series/DataFrame corresponding to the row(s) with 0-based index(es) `n_idx` and column 0-based index(es) `n_col`
- `df[slice]` — return a DataFrame with all columns and rows sliced by `slice`
  - Slicing is like with Series, can be 0-indexed or label-indexed
- `df.at[idx, col], df.iat[idx, col]` — optimized versions of `loc, iloc` for accessing a scalar
**Boolean indexing of DataFrames**

- `df[bool_vec]` — return a DataFrame with all columns and rows indexed by a Boolean array
- `df[bool_df]` — return DataFrame with original values where `bool_df` is True and NaN where it is False
- `df.mask(bool_df)` — return DataFrame with original values where `bool_df` is False and NaN where it is True
- `df.duplicated(subset=None)` — return Boolean DataFrame with True where a row is duplicated and False where it is not
- `df.drop_duplicates(subset=None)` — return DataFrame with original values but with duplicated rows removed (optional `inplace` argument)
DataFrames are aligned automatically both on columns and rows
  • Operations on misaligned DataFrames result in the union of columns and rows
• Series are broadcasted row-wise when operating with DataFrames
  • Exception: if the index is a date stamp, broadcasting is column-wise
• Scalar operations are elementwise
• DataFrames can be transposed with `df.T`
• NumPy functions can operate on DataFrames with numeric types
## Pandas I/O

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<th>Data Description</th>
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<th>Writer</th>
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<td>to_clipboard</td>
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<td>read_gbq</td>
<td>to_gbq</td>
</tr>
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</table>
MultiIndexing

• Hierarchical indices for representing higher-dimensional data
  
  • `pd.MultiIndex.from_tuples(list_of_tuples, names=None)` — first index in each tuple is highest level, last index is lowest level
  
  • `pd.MultiIndex.from_product(list_of_lists, names=None)` — cartesian product: all possible combinations from lists
  
  • `pd.MultiIndex.from_frame(DataFrame)` — each row is a multi-index, names from columns

• `index.levels` — unique indices from each level

• `index.get_level_values(level_idx)` — all indices in order at the level_idx level
Combining DataFrames

- **pd.concat(list)** — concatenate list (or iterable) of DataFrames/Series
  - axis=0: 0 concatenate rows, 1 columns
  - join=‘outer’: ‘outer’ union over index, ‘inner’ intersection
  - ignore_index=False: whether to drop the index of concatenation axis. Useful if indices aren’t meaningful but may be repeated
  - keys=None: if present, create MultiIndex with keys at the outermost level (must be the length of list)
Combining DataFrames

- **pd.merge(left, right)** — implement SQL join operations on columns or indices
  - **how=’inner’**
    - ‘inner’: SQL inner join, intersection of keys. Preserve order of left keys
    - ‘outer’: SQL outer join, union of keys. Sort keys lexicographically
    - ‘left’: SQL left outer join, only keys from left. Preserve order of left keys
    - ‘right’: SQL right outer join, only keys from right. Preserve order of right keys

- **on=None**: which key to join on. If None, intersection of columns
- **left_on/right_on=None**: which key from left/right to join on
- **left_index/right_index=False**: use index from left/right as the join key
Visualization

• Pandas integrates Matplotlib plotting functionality
• df/s.plot() — plot DataFrame or Series
  • If DataFrame, plot all rows as a separate Series with appropriate labeling
  • kind
    • ‘bar’ or ‘barh’ for bar plots
    • ‘hist’ for histogram
    • ‘box’ for boxplot
    • ‘kde’ or ‘density’ for density plots
    • ‘area’ for area plots
    • ‘scatter’ for scatter plots
    • ‘hexbin’ for hexagonal bin plots
    • ‘pie’ for pie plots
Takeaways

• Pandas is a powerful tool for data analysis
• Supports 1-D and 2-D data with Series and DataFrames
• Little support for higher dimensional data with MultiIndexing
• I/O to/from virtually any type of data file
• Integrated with Matplotlib for easy visualization
• Can be used as input to scikit-learn for modeling