Бібліотека pandas для аналізу даних

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Зміст:

- Вступ та інсталяція бібліотеки
- Базові структури даних: ряд та фрейм
- Базові операції читання та запис
- Об’єднання, групування та зміна форми фреймів
- Практика

Introduction to Python Pandas

- **Core Library Importance:** pandas is a fast, powerful, flexible and easy to use open source data analysis and manipulation tool, built on top of the Python programming language. Pandas is essential for efficient data manipulation and analysis in Python.

- **Wide Adoption:** Its popularity stems from community support, extensive documentation, and suitability for diverse data science tasks.

- **Versatile Functionality:** Pandas offers tools for data cleaning, transformation, and exploration.

Installation of Pandas

- **Installing Pandas:** Install Pandas via pip using

```
pip install pandas
```

- **Specifying Versions:** To install a specific version, use

```
pip install pandas==2.2.1
```

Pandas Data Structures: Series

- **Pandas Series:** A Pandas Series is a one-dimensional labeled array, facilitating index-based data access and manipulation.

- **Key Features:** Series include automatic alignment of data by labels and support for various data types efficiently.

- **Use Cases:** Commonly used for time series data, Series manage chronological values seamlessly for analysis purposes.

Pandas Data Structures: DataFrame

- **DataFrame Structure:** A DataFrame is a two-dimensional labeled array that accommodates heterogeneous data types.
- **Data Handling Abilities:** It allows for complex data operations like filtering, aggregation, and reshaping.
- **Typical Use Cases:** Commonly utilized for storing and manipulating datasets in data analysis.

Creating a Pandas DataFrame

- **Creating DataFrames from Lists:** Utilize pd.DataFrame(list) for seamless conversion of Python lists into Pandas DataFrames, enhancing data structure.

- **Building DataFrames from Dictionaries:** Employ pd.DataFrame(dict) to convert dictionaries into DataFrames, permitting labeled columns based on dictionary keys.

- **Forming DataFrames with NumPy Arrays:** Integrate np.array with pd.DataFrame for generating DataFrames from NumPy arrays.

pandas_constuctor.py

Reading Data with Pandas

- **Reading CSV Files:** Use pd.read_csv('file_path.csv') to load data from CSV files, ensuring proper delimiter configuration.

- **Reading hd5 data:** Utilize pd.read_hdf('file_name.h5’) for import of data from HDF5 (Hierarchical Data Format) files.

Writing Data with Pandas

- **Writing CSV Files:** Utilize df.to_csv('output.csv') for exporting DataFrames as CSV files, ensuring data integrity and structure.

Data Inspection and Exploration

- **Data Inspection Methods:** Utilize head(), tail(), describe(), and info() for insight into dataset structure and statistics.

- **Understanding Head and Tail:** head() previews initial entries, while tail() displays final entries.

- **Descriptive Statistics:** describe() generates summary statistics like mean, std, min, and max, to describe data distribution.

Data Selection, Filtering, Indexing and Slicing

- **Selecting Columns and Rows:** Utilize bracket notation or dot notation for precise column and row selection within DataFrames.

- **Boolean Indexing:** Apply boolean conditions to filter DataFrames, allowing targeted data analysis based on specific criteria.

- **Chaining Selection Techniques:** Combine methods seamlessly by chaining selection techniques, enhancing flexibility and efficiency in data retrieval.

- **Indexing Techniques Overview:** Secondary indexing capabilities are essential for efficient data access and organization in Pandas DataFrames.

- **Using loc Function:** loc allows label-based indexing, enabling users to retrieve rows and columns using index labels effectively.

- **Using iloc Function:** iloc provides position-based indexing, facilitating precise access to data based on integer-location references.

pandas_selection_and_filtering.py

Handling Time Series Data

- **Datetime Indexing:** Utilize Pandas' datetime capabilities for indexing data, enhancing time series analysis through organized temporal data.

- **Resampling Techniques:** Pandas supports resampling methods, allowing users to manipulate time series frequencies efficiently and accurately.

Merging and Joining DataFrames

- **Merging DataFrames:** Merge combines two DataFrames based on common fields.
  - merge(): Combine two Series or DataFrame objects with SQL-style joining
- **Joining Techniques:** Join methods facilitate relational merges similar to SQL operations.
  - DataFrame.join(): Merge multiple DataFrame objects along the columns
- **Concatenation Methods:** Concat stacks DataFrames vertically or horizontally.
  - Merge multiple Series or DataFrame objects along a shared index or column
  - concat() makes a full copy of the data, and iteratively reusing concat() can create unnecessary copies

pandas_merging.py

Data Cleaning in Pandas

- **Handling Missing Values:** Employ fillna() to substitute missing data, ensuring continuity and quality in datasets through imputation.

- **Removing Duplicates:** Utilize drop_duplicates() for elimination of duplicate records.

pandas_na_duplicates.py

Data Transformation

- **Applying Functions:** Utilize apply() to execute functions across DataFrame rows or columns, enhancing data transformation flexibility.
- **Mapping Values:** Map() allows element-wise transformations within a Series, crucial for straightforward value conversions and replacements.
- **Lambda Functions:** Leverage lambda functions in conjunction with apply() for concise, custom transformations on DataFrame elements.

pandas_transformation.py

GroupBy Functionality

- **GroupBy (split-apply-combine) Overview:** The GroupBy operation allows data aggregation through specification of key columns for analysis of subsets of data.This refers to a chain of three steps:
  - **Split** a frame into groups.
  - **Apply** some operations to each of those smaller tables.
  - **Combine** the results.

- **Aggregation Functions:** Utilize functions like sum() and mean() to compute aggregated statistics applicable across grouped data subsets.

- **Flexible Grouping:** GroupBy supports flexible operations, accommodating different aggregation strategies based on dataset characteristics.

pandas_groupby.py

Electroweak symmetry breaking mechanism

Higgs mechanism. Electroweak sector.

- Higgs doublet (four real components)

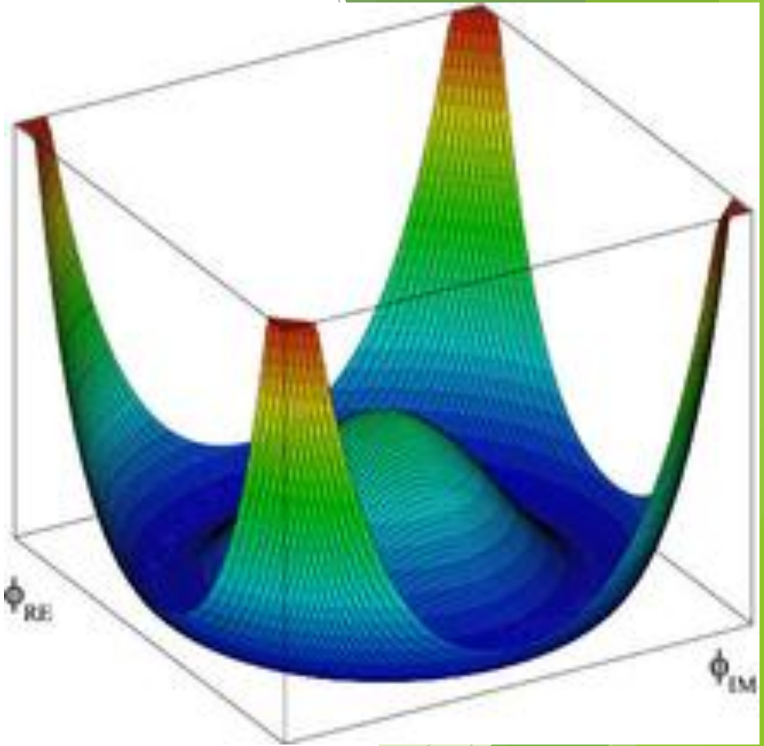
$$\phi = \frac{1}{\sqrt{2}} \begin{pmatrix} \phi^1 + i\phi^2 \\ \phi^0 + i\phi^3 \end{pmatrix} ,$$

- Physical photon and Z-boson

$$\begin{pmatrix} \gamma \\ Z^0 \end{pmatrix} = \begin{pmatrix} \cos\theta_{\mathrm{W}} & \sin\theta_{\mathrm{W}} \\ -\sin\theta_{\mathrm{W}} & \cos\theta_{\mathrm{W}} \end{pmatrix} \begin{pmatrix} B \\ W_3 \end{pmatrix},$$

- Physical W-bosons

$$W^{\pm} = \frac{1}{\sqrt{2}} \left(W_1 \mp iW_2 \right) .$$

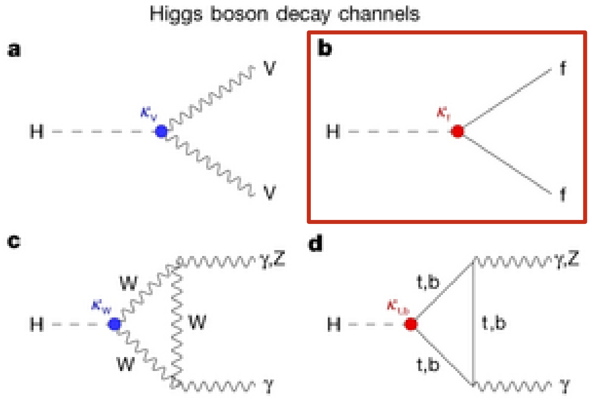


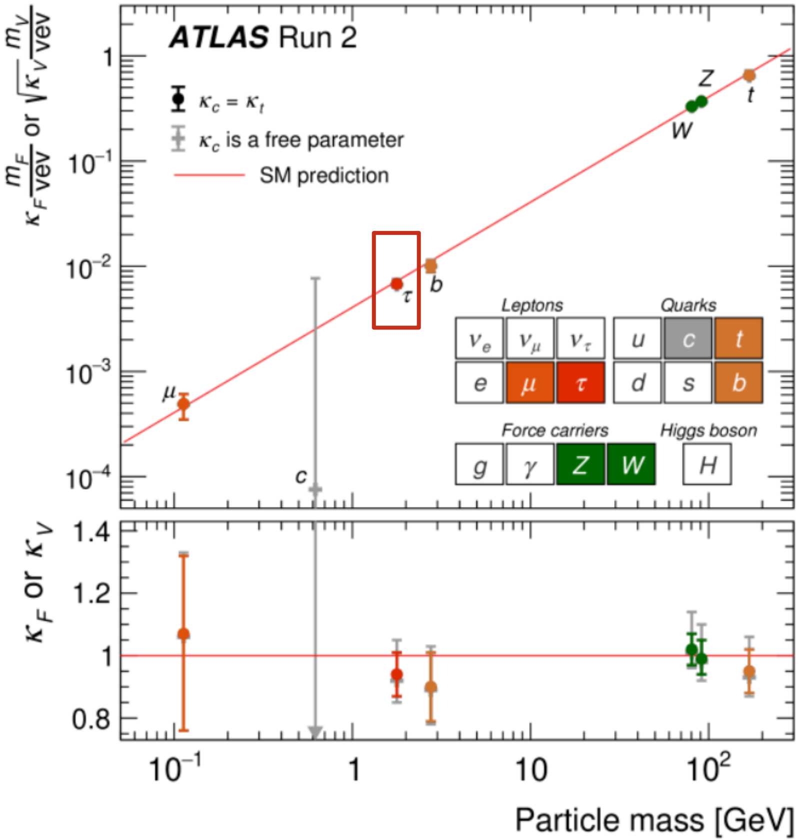
$$\mathcal{L}_{\mathrm{H}} = \left|\left(\partial_\mu - igW_{\mu\,a}\tfrac{1}{2}\sigma^a - i\tfrac{1}{2}g' B_\mu\right)\phi\right|^2 + \mu_{\mathrm{H}}^2 \phi^\dagger\phi - \lambda\left(\phi^\dagger\phi\right)^2 ,$$

Higgs mechanism.
Fermionic sector.

- Yukawa terms

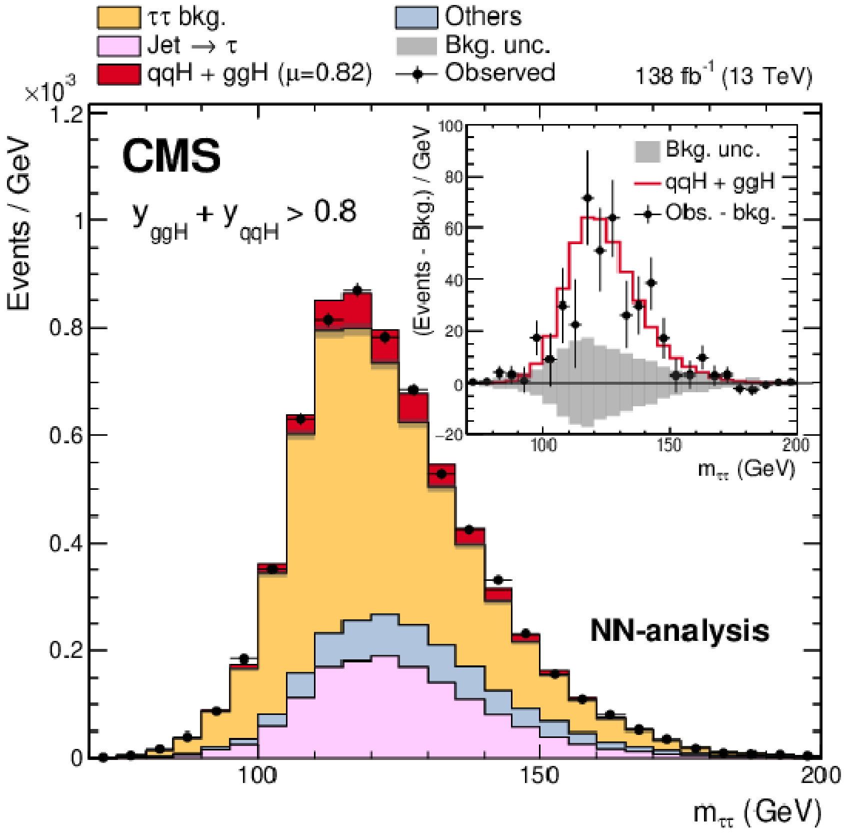
$$\mathcal{L}_{\mathrm{Y}} = -\sum_{f} \frac{g\, m_f}{2\, m_{\mathrm{W}}}\, \bar{f}\, f\, H$$

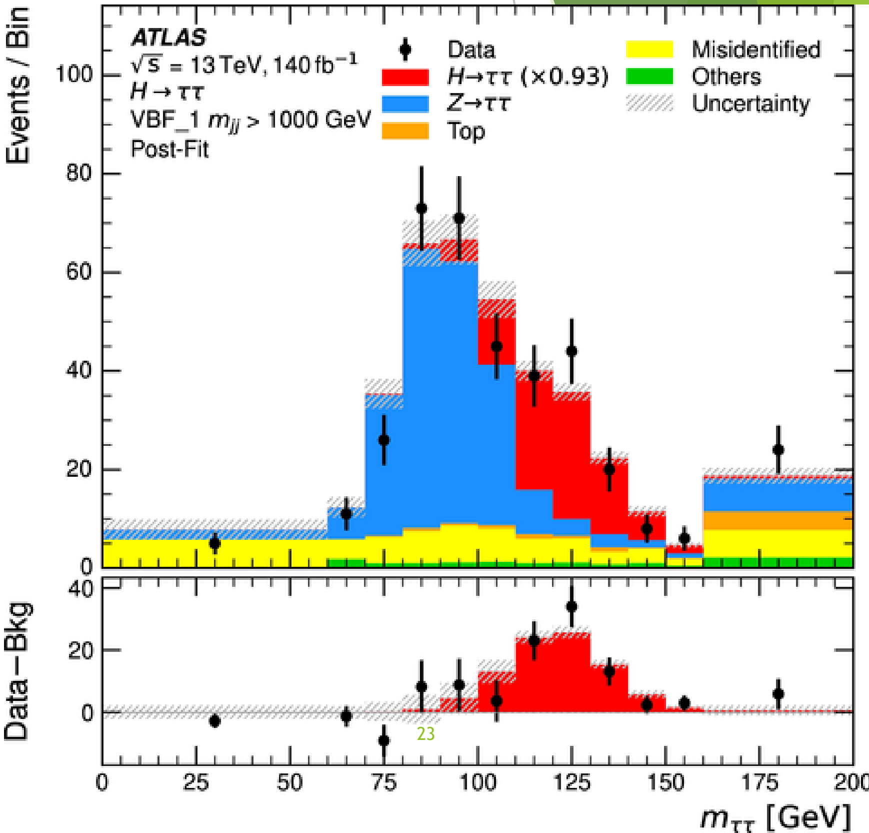




Studies of the Higgs boson by the ATLAS Collaboration

Experimental results on H->tautau decays



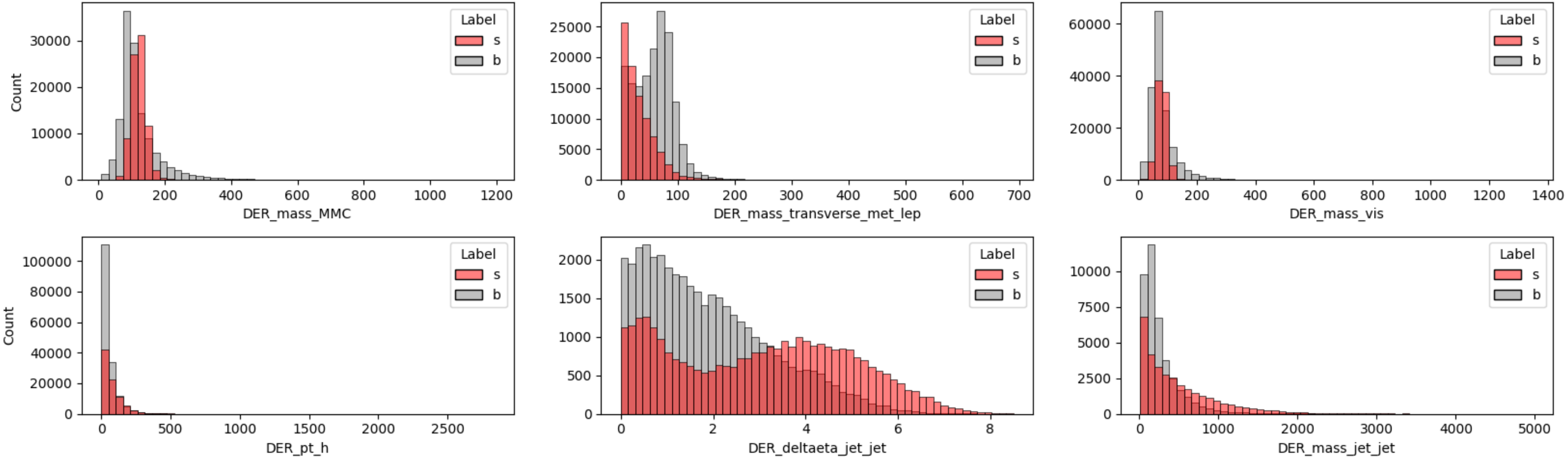


Higgs decay event shapes

- Read `higgs-boson/training/training.csv` into pandas dataframe
- Inspect dataframe using describe() and head()
- Plot several distributions

- Higgs Boson Machine Learning Challenge | Kaggle

Example distribution of Higgs boson and background event shapes


Label
s
b
Count
DER_mass_MMC
DER_mass_transverse_met_lep
DER_mass_vis
Count
DER_pt_h
DER_deltaeta_jet_jet
DER_mass_jet_jet