# ScHARe Data Management and Analysis in Python

September 18, 2024

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# SCHARE

# Workshop setup

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# We have registered you for ScHARe

To opt out, email us at schare@mail.nih.gov You have been:

registered for ScHARe

- added to a free temporary billing project that will allow you to run the event materials with your instructors
- You will be active on this billing project for the duration of the Think-a-Thon. If you want to access work-in-progress after this time, you will need to set up your own billing and copy your workspaces to it

# In preparation for the Think-a-Thon

Let's make sure that everyone:

- 1. has provided their Gmail address and has been registered for ScHARe
- 2. has created a Terra account
- 3. can access the tutorial we will be using today at: **bit.ly/schare-python-notebooks**
- 4. has configured their cloud environment
- 5. can run the tutorial in playground mode:



Please paste the address below in your browser:

# bit.ly/schare-python-notebooks-2

If you have already created a Terra account and are logged in, you will see this:

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If you have not logged in, or have not yet created a Terra account, you will see this:

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# Welcome to Terra Community Workbench

Terra is a cloud-native platform for biomedical researchers to access data, run analysis tools, and collaborate. <u>Learn more about Terra.</u>

If you are a new user or returning user, click log in to continue.

LOG IN

BETA

**Click on the login button:** 

BETA

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# Use the Gmail address you provided us with to log in:



## Input the password associated with your Gmail account:

G Sign in with Google
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Hi Luca
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Enter your password
Show password
To continue, Google will share your name, email address, language preference, and profile picture with Terra. Before using this app, you can review Terra's <b>privacy policy</b> and terms of service.

Forgot password?

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#### New User Registration

First Name *	Last Name *
Contact Email for Notifications	*



## **Accept the Terra Terms of Service:**

### Terra Terms of Service

Please accept the Terms of Service to continue.

#### **Terra Platform Terms of Service**

Last Modified: January 10th, 2023

Effective Date: January 10th, 2023

Certain terms (including capitalized terms) are defined in Section 13 (Definitions).

#### 1. Introduction

Thanks for using Terra! Terra is a platform developed by Verily, Microsoft and The Broad

DECLINE AND SIGN OUT

ACCEPT

# You will see this welcome page:



# Welcome to Terra Community Workbench

Terra is a cloud-native platform for biomedical researchers to access data, run analysis tools, and collaborate.

Find how-to's, documentation, video tutorials, and discussion forums

Learn more about the Terra platform and our co-branded sites  $\square$ 

### Paste this address in your browser: bit.ly/schare-pythonnotebooks-2



## Newly registered users might see this message:



#### This is normal: the message should go away in a few minutes

## Refreshing the page after a while, all users should see this:

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#### For example, if your last name starts with "S", click on the notebook highlighted above

## **Do you see a Playground mode button?**



#### If yes, click on it to start your virtual computer. You are done!

## If you don't see Playground mode, click on the Open button:

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# Note that you might encounter an error due to the large number of users – just try again in a few minutes:



# If all goes well, you will see this:



#### Click on Continue. You are all set!

# SCHARE

# Why Python?

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# What is Python?

Python is a computer programming language used in data science to:

- manipulate and analyze data and conduct statistical calculations
- create data visualizations
- build machine learning algorithms

Python's **data science libraries** are powerful. Examples include:

- **Numpy** for linear algebra and high-level mathematical functions
- **Pandas** for handling data structures and manipulating tables
- SciPy for data science tasks like interpolation and signal processing
- **Scikit-learn** a machine learning library that is useful for classification, regression, and clustering algorithms
- PyBrain for machine learning tasks and to test and compare algorithms



Sources www.quanthub.com/python-for-data-science/ coursera.org



R is a **programming language** for statistical computing and graphics

It is used by data miners, bioinformaticians and statisticians for data analysis

Users have created **packages** to augment its functions

Third-party **graphical user interfaces** are also available, such as Rstudio





supports **both Python and R** 

Source en.wikipedia.org

# Why Python?

#### According to SlashData:

- there are 8.2 million Python users
- 69% of machine learning developers and data scientists use Python (vs. 24% of them using R)

**Source** stackify.com/learn-python-tutorials/

# How to learn Python

#### How long does it take to learn Python?

It can take **2 to 5 months**, but you can write your first short program in **minutes** 

#### Can you learn Python with no experience?

Python is the **perfect** programming language **for people without any coding experience**, as it has a simple syntax and is very accessible to beginners

**Unfamiliar terminology** may be a barrier, which today's workshop will hopefully help you overcome

Links to additional **free learning resources** will be provided at the end

# SCHARE

Data Management and Analysis in Python

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# Schare



# **Guest expert Cindy Sheffield** NIH/OD/ORS



# **About Cindy**

Cindy is **Data Services Librarian** at the NIH Library.

She began her **library career** at the Johns Hopkins Medical Institutions with a focus on Evidenced Based Medicine. She progressed within the Welch Medical Library, leaving Hopkins as the Associate Director of Education Services.

Cindy has worked at several **federal agencies** including the Department of Homeland Security, the Department of Defense, and the Department of Health and Human Services. Within DHHS she was worked for both the National Institutes of Health and the Federal Drug Administration.

Her **focus** has always been on using key resources to identify the best evidence, and then to organize and manage that evidence in a way that makes sense for users. At the NIH she works with various user groups to support literature research and data science.

She is the Outreach Librarian for the NIH Clinical Centers, Pain and Palliative Care Team, the Eunice Kennedy Shriver, National Institute of Child and Human Development, the Administration for Children and Families, and the Office of the National Coordinator for Health Information Technology.

# Schare



**Guest expert** Sarvesh Soni NIH/NLM



# **About Sarvesh**

Dr. Sarvesh Soni is a Research Fellow with Dr. Dina Demner-Fushman at the National Library of Medicine.

Dr. Soni has a PhD in Biomedical Informatics from The University of Texas Health Science Center at Houston (UTHealth). He researches clinical natural language processing (NLP), focusing on question answering (QA) from both structured and unstructured data present in electronic health records (EHRs).

He implemented methods to generate paraphrases of clinical questions automatically and improve EHR QA and designed systems to automatically retrieve EHR text documents and underlying exact answer spans for given clinical information needs.




# ScHARe Think-a-Thon Series: An Introduction to Python for Data Science, Part 2

Cindy Sheffield, Biomedical Librarian, NIH Library Sarvesh Soni, Research Fellow, National Library of Medicine

NIH Library | nihlibrary.nih.gov

Office of Research Services National Institutes of Health U.S. DEPARTMENT OF HEALTH AND HUMAN SERVICES

#### Introduction



National Institutes of Health Office of Management NIH Library | nihlibrary.nih.gov

### Agenda



- Recap from August session 10 min
- Importance of data cleaning 10 min
- Tools for data cleaning 10 min
- How data impacts visualizations 10 min
- Machine Learning primer 10 min
- Examples of Visualizations, Data Cleaning, Machine Learning 80 min





- Know how to find Python libraries to help with code functionality
- Understand the importance of data cleaning
- Know what tools are available to help with data cleaning
- Visualizations and the importance of telling an accurate story
- Understand the mechanisms behind Machine Learning



# **Recap from Part 1:**



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# Slido quiz

#### What is a Python library?

□ A collection of books about Python programming

 $\Box$  Answer B A collection of related modules that provide specific functionality

 $\Box$  A place to store Python code

 $\Box$  A way to access Python from the command line



Python Libraries – a collection of related modules that provide more extensive functionality and solve specific problems

Sample libraries: Numpy Pandas Matplotlib How to find libraries: PyPI.org GitHub



# Slido quiz

Which of the following are examples of Python libraries?

 $\Box$  Excel, OpenRefine

□ Matplotlib, Pandas, Numpy

 $\Box$  R, SQL

□ GitHub, PyPI

# Data Cleaning / Data Wrangling



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# **Data Cleaning**



# Ensure:

- Data accuracy
- Data consistency
- Data quality
- Efficiency

# Processes:

- Parsing (First/Last Name)
- Correcting (Typos, errors)
- Standardizing (format)
- Match (id duplicates)
- Consolidating (clean presentation)



# Slido quiz

#### Why is clean data important?

 $\Box$  It allows for better decision-making and saves time

 $\Box$  It makes data look nice without adding any practical value

□ It removes all irrelevant information from public datasets

 $\Box$  It ensures that data can never be incorrect

# **Types of Dirty Data**



- Corrupted
- Inaccurate
- Duplicates
- Irrelevant information

Establish quality control standards:

- Account for missing values
- De-duplication / Consolidating
- Irrelevant information
- Normalize non-standard values
- Understand outliers vs. incorrect data
- Change case if needed
- Check for bad values in fields(i.e.: alpha vs. numeric, formatting, spacing)
- Ensure overall data quality



# **Data Wrangling**



Six step process:

- Explore
- Transform
- Clean
- Enrich
- Validate
- Store



### Data Wrangling –

Mapping, merging, concatenating, or converting data, to transform the content, so it can be used for algorithmic processing and analysis.



# Slido quiz

Which of the following is part of the data wrangling process?

- $\Box$  Transforming data to prepare it for analysis
- □ Writing code in a programming language
- $\Box$  Saving data as images
- $\Box$  Downloading data from the internet



### **Benefits of Clean Data**

- Allows for informed decision making, and it is the precursor to artificial intelligence.
- Enhances efficiencies by saving time, effort, and resources.
- Improves satisfaction for consumers and producers
- In Public Health and Regulatory environments, it helps to maintain trust and avoid legal actions.

#### Business Intelligence versus Data Science





### Tools



- Excel: Functions within Excel
- R: dplyr, tidyr, rrefine
- Python: Pandas, NumPy
- OpenRefine

#### Excel





# **Open Refine [openrefine.org]**



- Open Source
- Desktop application
- Data cleanup and transformation
- Faceting
- Clustering
- Reconciling

OpenRefine:

- is 'a tool for working with messy data'
- works best with data in tabular format
- can help split data into more granular parts
- can help match local data to other data sets
- can help enhance a data set with data from other sources

Tutorial: Library Carpentry: OpenRefine: https://librarycarpentry.org/lc-open-refine/instructor/aio.html





# Slido quiz

What is OpenRefine used for?

 $\Box$  Word processing

 $\Box$  Creating spreadsheets

 $\Box$  Data cleanup and transformation

□ Developing websites

 Buttrey S, Whitaker LR. A data scientist's guide to acquiring, cleaning and managing data in R. 1st edition ed. THEi Wiley ebooks. Wiley; 2017.

- 2. Gueta T, Carmel Y. Quantifying the value of user-level data cleaning for big data: A case study using mammal distribution models. *Ecological informatics*. 2016;34:139-145. doi:10.1016/j.ecoinf.2016.06.001
- Martin N, Martinez-Millana A, Valdivieso B, Fernández-Llatas C. Interactive Data Cleaning for Process Mining: A Case Study of an Outpatient Clinic's Appointment System. Springer International Publishing; 2019:532-544. *Lecture Notes in Business Information Processing*.
- 4. Mertz D. Cleaning data for effective data science : doing the other 80% of the work with Python, R, and command-line tools. Packt Publishing; 2021.
- 5. Van den Broeck J, Cunningham SA, Eeckels R, Herbst K. Data cleaning: detecting, diagnosing, and editing data abnormalities. *PLoS Med*. Oct 2005;2(10):e267. doi:10.1371/journal.pmed.0020267
- 6. Walker M. Python Data Cleaning Cookbook : Prepare Your Data for Analysis with Pandas, NumPy, Matplotlib, Scikit-Learn, and OpenAI. Packt Publishing, Limited; 2024.
- 7. Wang X, Wang C. Time Series Data Cleaning: A Survey. *IEEE access*. 2020;8:1866-1881.
   doi:10.1109/ACCESS.2019.2962152



#### Visualizations



- Use to better understand data
- Prepare the data so it tells an accurate story
- Understand the data and any potential bias



# Machine Learning



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## Machine Learning and Artificial Intelligence (AI)

- Machine Learning type of AI and CS
- Improves how software systems process and categorize data
   Artificial Intelligence
- Focuses on the use of data and algorithms
- Imitate human learning
- Gradually improving its accuracy
- ML algorithms imitate human learning
- ML algorithms improve over time as they take large data sets

https://bootcamp.berkeley.edu/blog/how-does-machine-learning-work/



Machine Learning

Deep Learning ibrarv

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### **Types of Machine Learning**





**Reinforcement Learning** 

Learns as it goes through trial and error, rather than being trained using sample data, like in supervised learning.



Office of Management

National Institutes of Health https://bootcamp.berkeley.edu/blog/how-does-machine-learning-work/ NIH Library | nihlibrary.nih.gov

# **Types of Machine Learning - Supervised**



- Taught by example
- Training data is fed into an algorithm and teaches to categorize based on pre-set characteristics
- Algorithm can similarly sort raw data
  - Good at classifying data into pre-set categories
     Example: identify spam emails or telling images
     apart





- Uses algorithms to sort unlabeled and unstructured data
- Algorithms discover data patterns without human intervention
- Good situations without clear delineations between different data categories
- Example:
  - Recommend similar types of research projects or publications



- NIH Library Office of Research Services Serving the NIH Community
- Combines supervised and unsupervised machine learning to sort or identify data
- Involves labeling some data
- Involves rules and structure for the algorithm to use to start sorting and identifying data
- A small amount of tagged data improves an algorithm's accuracy
- Example: classify content in scanned documents: typed and handwritten





- Used for decision-making in a complex, uncertain environment
- Game-like rules system designed to maximize algorithm's score
- Programmers define rules; computer starts without guidance
- Computer learns through trial and error for optimal solutions
  - Example: used for language processing, self-driving vehicles and game-playing Als

ational Institutes of Health https://bootcamp.berkeley.edu/blog/how-does-machine-learning-work/ NIH Library | nihlibrary.nih.gov



#### **Training Set and Test Set**



Training Data Set—a subset to train a model.
Test data set—a subset to test the trained model.





Test Data



National Institutes of Health Office of Management https://developers.google.com/machine-learning/crash-course/trainingand-test-sets/splitting-data

NIH Library | nihlibrary.nih.gov

# **Evaluating Machine Learning Performance**



		Actual (ex. Manual coding)		
		Positive	Negative	
ML model/ Algorithm Predictions	Positive	True Positive (TP)	False Positive (FP)	Positive Predictive Value
	Negative	False Negative (FN)	True Negative (TN)	Negative Predictive Value
		Sensitivity	Specificity	

- Accuracy: how much did the model get right; % of predictions the model or algorithm gets correct;
   = (TP + TN)/(TP+FN +FP+TN)
- **Precision:** also called positive predictive value (PPV); the quality of the positive predictions; % of positive predictions that were correct; =TP/TP+FP
- Sensitivity: also referred to as recall; measures how well a model can detect positive instances; =TP/TP+FN
- **Specificity:** measures how well the model identifies negatives instances; =TN/TN+FP
- F1 score: also used to assess accuracy of the model and it accounts for both precision and recall; =TP/TP + ½(FP+FN)



## Machine Learning Performance Example



tp = AI Model found true positive = 100 fp = AI Model marked as positive; but negative = 5 tn = AI Model found true negative = 50 fn = AI Model marked as negative; but positive = 10



•Accuracy: how much did model get right;

= (tp + tn)/(tp + fn + fp + tn) = 150 / 165 = .9091

•Precision: positive predictive value (PPV);

= *tp* / *tp* + *fp* = 100 / 105 = **.9523** 

•Sensitivity: recall; true positive instances;

*=tp/(tp+fn)* = 100/100 + 10 = 100/110 = **.9091** 

Specificity: negatives;

*=tn/tn+fp* = 50/50 + 5 = 50/55 = **.9091** 

•F1 Score: assesses accuracy; precision and recall; = 2 (precision \* recall / precision + recall) Or = TP/TP + ½(FP+FN) = 100/100 + .5(10 + 5) = 100/107.5 = .9302





Artificial Intelligence

Machine Learning

Deep Learning

- **Deep Learning**
- Subset of Machine Learning
- Teaches computers to process data similar to human brain
- Recognize picture patterns, text, sounds and other data
- Produce insights and predictions based on data
- Use to automate tasks typically done by humans:
  - describe images
  - transcribe files into text





### Deep Learning (Cont'd)

## Used in everyday products:

- •Digital assistants
- •Voice-activated television remotes
- Fraud detection
- Automatic facial recognition
- **Uses of Deep learning:**
- •Self-driving cars
- •Defense systems
- •Medical image analysis
- •Factories





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## Natural Language Processing (NLP)



- NLP is an artificial intelligence technique
- Subset of machine learning
- Allows machines to process and understand language like humans
- Uses computational linguistics combined with machine learning, deep learning and statistical modeling
- Understands intent and sentiment
- Stores information and context to strengthen future responses







- Text analysis and data mining
  - helps scientists extract valuable information from vast amounts of unstructured text data
- Automated Literature Review
  - allows for automated literature; speeds up gathering and summarizing research
- Semantic Search and Information Retrieval
  - enhances search engines, enabling more relevant results
- Language Translation
  - enables translation between different languages



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- Knowledge Representation
  - convert textual information into structured data
- Sentiment Analysis
  - understand public opinion and reactions to scientific breakthroughs or research findings.
- Question-Answering Systems
  - enables specific questions and receive relevant answers from large databases or scientific literature
- Automated Report Generation
  - generate summaries, abstracts, or reports automatically, reducing manual effort





#### **Clinical Applications**

- analyze electronic health records
- extract important medical information
- diagnosing patients
- identifying patterns in medical data

#### Data Interpretation and Visualization

- interpret and understand complex scientific data
- generate visualizations





