

COVID-19 VAERS ANALYSIS

Analyze & evaluate risk factors using adverse events based on age & gender to predict life-threatening risk probability of receiving a COVID-19 vaccine.

THE TEAM



Jesús M. Vera

github.com/jvera01



Dakota Dusold

github.com/Dakota-Dusold



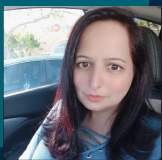
Daniel Gandía

github.com/DanielGandia



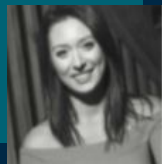
Justin Livingston

github.com/j89livingston



Hira Ayub

github.com/hira-ayub



Anna Stack

github.com/stackanna

BACKGROUND & TOPIC SELECTION

- US Citizens are concerned about the risk factors of taking the COVID-19 **vaccines**. We are playing the role of a team of data scientists hired by the government to analyze and assess the risk factors of receiving one of the three Emergency-Use Authorized COVID-19 **vaccines**.
- What is **VAERS**?
- How **VAERS** Reporting System help **CDC & FDA**?
- Why did we chose this **vaccine** analysis?
- The outcome of the analysis is to help citizens make a more informed decision when taking the **vaccine**. We will use **vaccine adverse event** data provided by the government from the **Vaccine Adverse Event Reporting System**. We will analyze and assess risk factors of taking the COVID19 **vaccine**.

TECHNOLOGIES AND RESOURCES



PostgreSQL



Python



Pandas Library

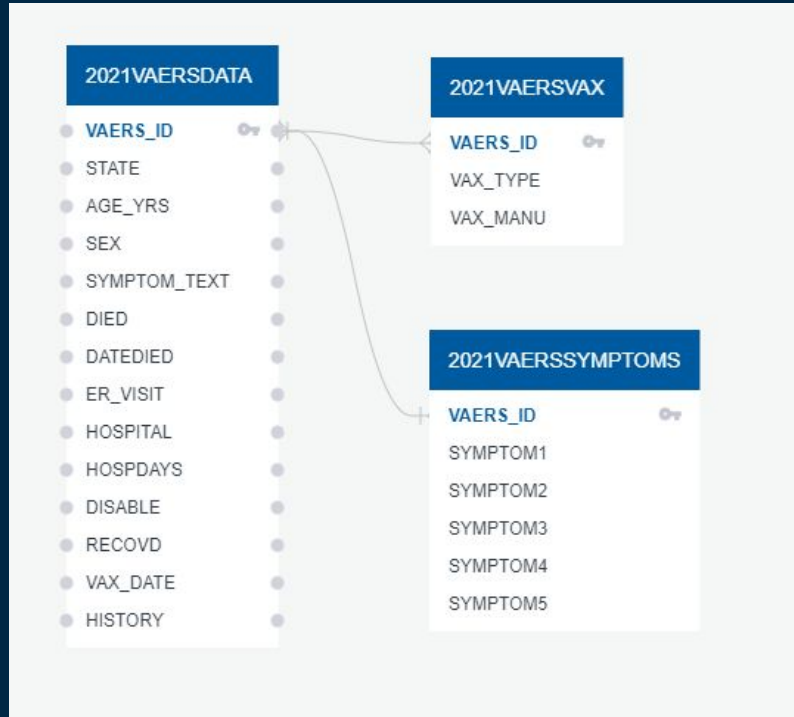


Scikit-Learn Library - Machine Learning



Tableau Public

DATA STRUCTURE & USER GUIDE



Header	Type	VAERS 2 Form	VAERS 1 Form	Description of Contents
VAERS_ID	Num(6)	✓	✓	VAERS Identification Number
RECVDATE	Date	✓	✓	Date report was received
STATE	Char(2)	Derived	Box 1	State
AGE_YRS	Num(xxx.x)	Item 6	Box 4	Age in Years
CAGE_YR	Num(xxx)	Derived	Derived	Calculated age of patient in years
CAGE_MO	Num(.x or 1)	Derived	Derived	Calculated age of patient in months
SEX	Char(1)	Item 3	Box 5	Sex
RPT_DATE	Date	Discontinued	Box 6	Date Form Completed
SYMPTOM_TEXT	Char(32,000)	Item 18	Box 7	Reported symptom text
DIED	Char(1)	Item 21	Box 8	Died
DATEDIED	Date	Item 21	Box 8	Date of Death
L_THREAT	Char(1)	Item 21	Box 8	Life-Threatening Illness
ER_VISIT	Char(1)	Discontinued	Box 8	Emergency Room or Doctor Visit
HOSPITAL	Char(1)	Item 21	Box 8	Hospitalized
HOSPDAYS	Num(3)	Item 21	Box 8	Number of days Hospitalized
X_STAY	Char(1)	Item 21	Box 8	Prolongation of Existing Hospitalization
DISABLE	Char(1)	Item 21	Box 8	Disability
RECOVD	Char(1)	Item 20	Box 9	Recovered
VAX_DATE	Date	Item 4	Box 10	Vaccination Date
ONSET_DATE	Date	Item 5	Box 11	Adverse Event Onset Date
NUMDAYS	Num(5)	Derived	Derived	Number of days (Onset date - Vax. Date)

DATA STRUCTURE & USER GUIDE

Header	Type	Description of Contents
VAERS_ID	Num(6)	VAERS Identification Number
VAX_TYPE	Char(15)	Administered Vaccine Type
VAX_MANU	Char(40)	Vaccine Manufacturer
VAX_LOT	Char(15)	Manufacturer's Vaccine Lot
VAX_DOSE_SERIES	Char(3)	Number of doses administered
VAX_ROUTE	Char(6)	Vaccination Route
VAX_SITE	Char(6)	Vaccination Site
VAX_NAME	Char(100)	Vaccination Name

Header	Type	Description of Contents
VAERS_ID	Num(6)	VAERS Identification Number
SYMPTOM1	Char(100)	Adverse Event MedDRA Term 1
SYMPTOMVERSION1	Num(XX.XX)	MedDRA dictionary version number 1
SYMPTOM2	Char(100)	Adverse Event MedDRA Term 1
SYMPTOMVERSION2	Num(XX.XX)	MedDRA dictionary version number 2
SYMPTOM3	Char(100)	Adverse Event MedDRA Term 3
SYMPTOMVERSION3	Num(XX.XX)	MedDRA dictionary version number 3
SYMPTOM4	Char(100)	Adverse Event MedDRA Term 4
SYMPTOMVERSION4	Num(XX.XX)	MedDRA dictionary version number 4
SYMPTOM5	Char(100)	Adverse Event MedDRA Term 5
SYMPTOMVERSION5	Num(XX.XX)	MedDRA dictionary version number 5

TABLEAU COVID-19 VAERS ANALYSIS

- Created a page to display the most frequent **symptoms** that were reported with life threatening risks.
- Total number of **adverse events** by **vaccines**.
- Most frequent **symptoms** reported by gender
- Most frequent **hospitalizations** reported by gender
- Total number of **adverse events** for ER visits, **hospitalizations**, life threatening events.

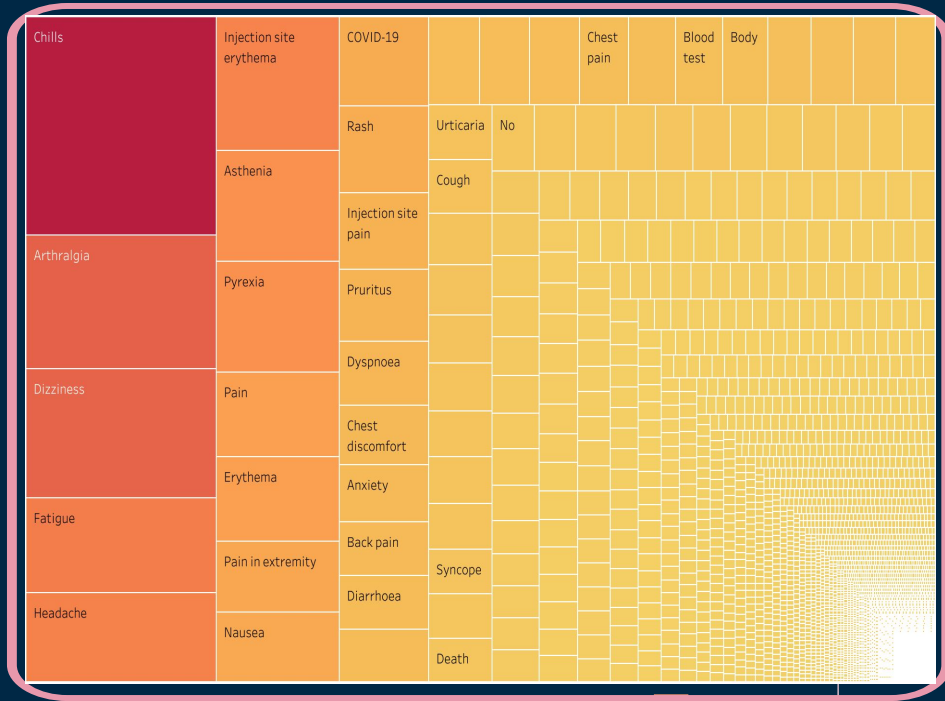


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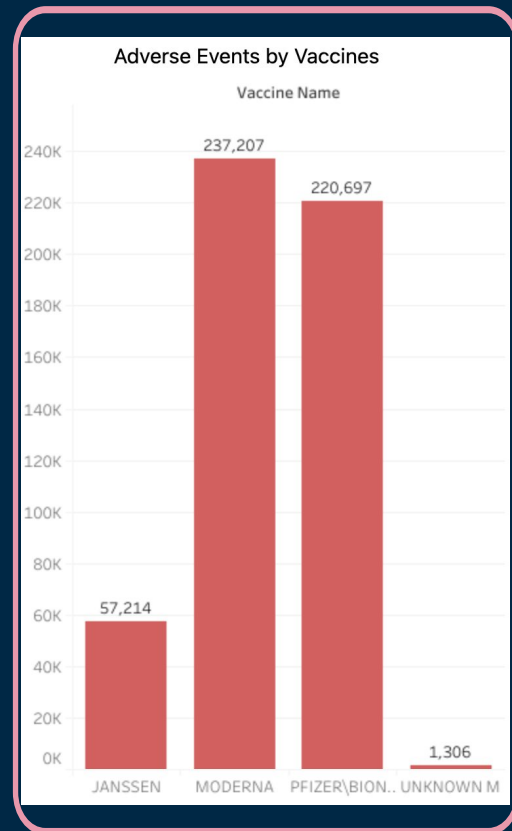


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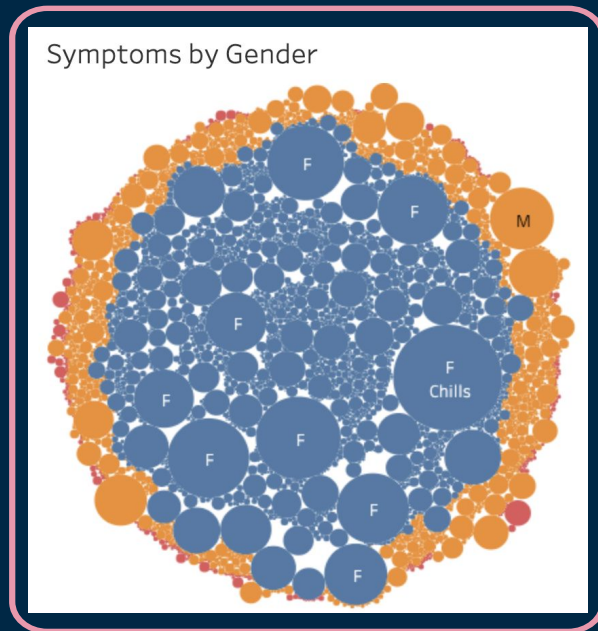


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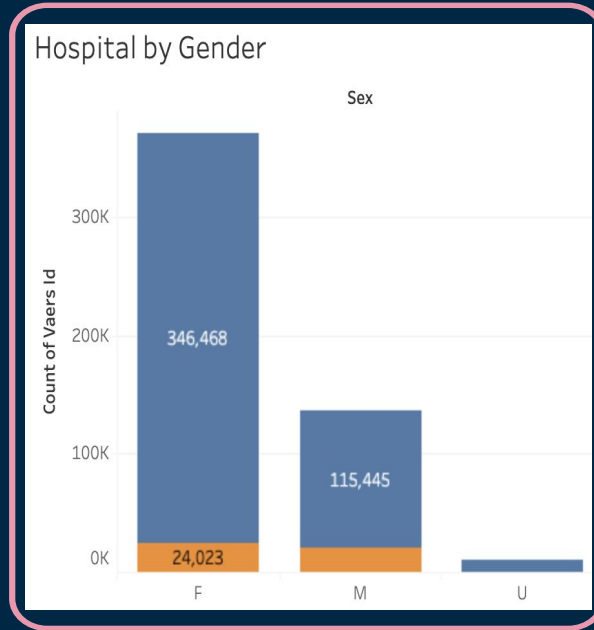


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Adverse Events to Hospital

All Symptoms	Hospital Y
COVID-19	1,196
Unevaluable event	1,060
Asthenia	1,059
Blood test	765
Cerebrovascular accident	731
Chest pain	656
Dyspnoea	642
Acute kidney injury	630
Abdominal pain	567
Pyrexia	502
Anticoagulant therapy	407
Headache	393
Acute myocardial infarcti..	392
Arthralgia	367
Fatigue	338
Atrial fibrillation	333
Nausea	330
Angiogram	327
Pulmonary embolism	324
Dizziness	313
Death	312
Computerised tomogram	311

Adverse Events to Life Threat Events

All Symptoms	L Threat Y
Blood test	318
Anticoagulant therapy	267
Cerebrovascular accident	232
Asthenia	225
Anaphylactic reaction	216
Dyspnoea	212
Pulmonary embolism	172
Abdominal pain	164
Chest pain	162
Deep vein thrombosis	153
Angiogram	151
Angiogram pulmonary ab..	142
Acute myocardial infarcti..	141
Pyrexia	126
Headache	121
Fatigue	113
Computerised tomogram	110
COVID-19	103
Atrial fibrillation	102
Nausea	101
Arthralgia	100

Adverse Events to ER Visits

All Symptoms	Er Ed Visit Y
Dizziness	3,194
Asthenia	1,959
Blood test	1,897
Dyspnoea	1,761
Arthralgia	1,467
Chest discomfort	1,433
Chills	1,350
Chest pain	1,337
Headache	1,288
Nausea	1,039
Abdominal pain	1,021
Blood pressure increased	998
Anxiety	993
Pyrexia	981
Bell's palsy	964
Fatigue	941
Pain	839
COVID-19	826
Anaphylactic reaction	773
Unevaluable event	721
Rash	687
Hypoaesthesia	675

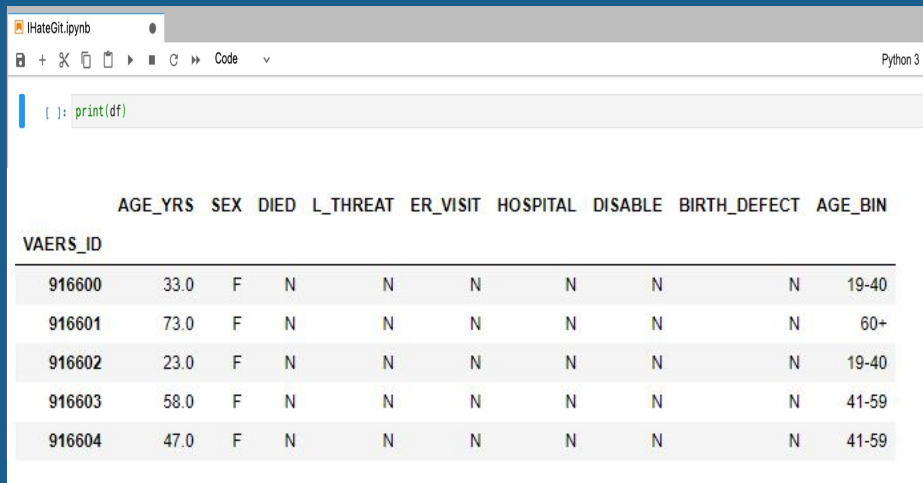
Can we predict the probability of a person over the age of 60 receiving a life threatening **symptom**?

From analyzing our data, we found a spike of life threatening symptoms in older patients. Using python's pandas and scikit-learn libraries, we can seek out the answer to our prediction.

CLEANING DATA USING PYTHON

For the 2021 VAERS Data file:

- Dropped the unnecessary columns.
- Replaced null values several columns to “N” to be fed into the machine learning.
- Null values on the age column were replaced with the median age for the provided gender.
- We created bins for ages to group them for the machine learning.



The image shows a Jupyter Notebook window titled 'IHateGit.ipynb' with a toolbar and 'Python 3' indicator. A code cell contains the command `print(df)`. Below the code, a preview of a DataFrame is displayed with columns: VAERS_ID, AGE_YRS, SEX, DIED, L_THREAT, ER_VISIT, HOSPITAL, DISABLE, BIRTH_DEFECT, and AGE_BIN. The data is as follows:

VAERS_ID	AGE_YRS	SEX	DIED	L_THREAT	ER_VISIT	HOSPITAL	DISABLE	BIRTH_DEFECT	AGE_BIN
916600	33.0	F	N	N	N	N	N	N	19-40
916601	73.0	F	N	N	N	N	N	N	60+
916602	23.0	F	N	N	N	N	N	N	19-40
916603	58.0	F	N	N	N	N	N	N	41-59
916604	47.0	F	N	N	N	N	N	N	41-59

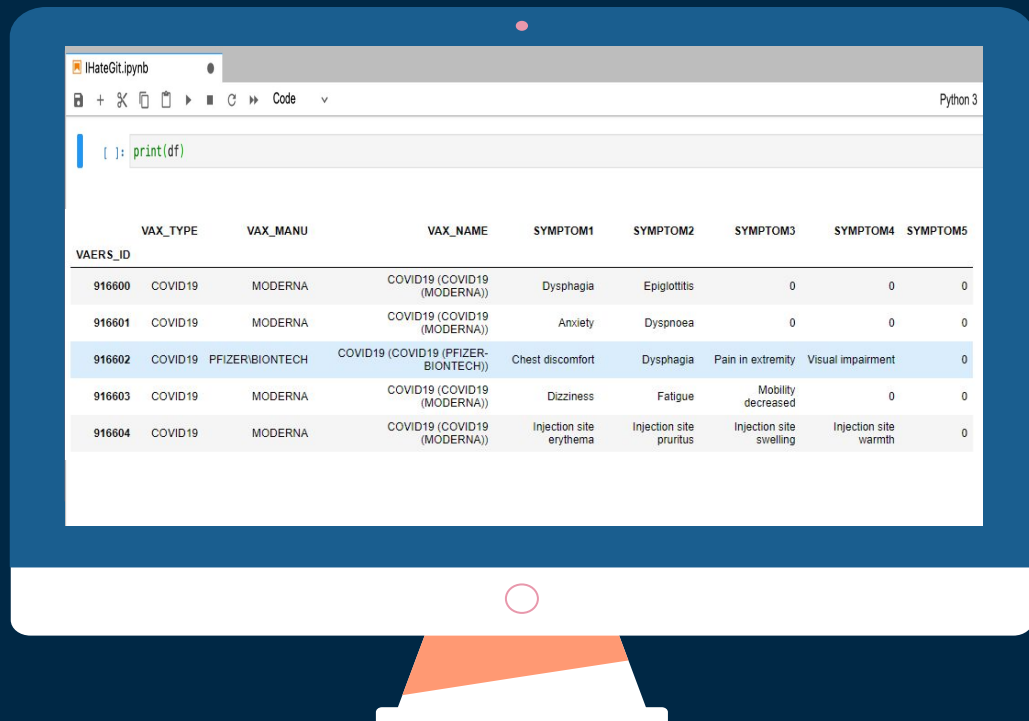
CLEANING DATA USING PYTHON

For the 2021 VAERS VAX file:

- Kept the columns with **vaccine** name and type in order to set as an unique ID and filter for COVID-19 **adverse events** only.

For the 2021 VAERS SYMPTOMS file:

- We grouped the values of each of the symptom columns to remove the multiple rows for those IDs that had more than 5 **symptoms**.

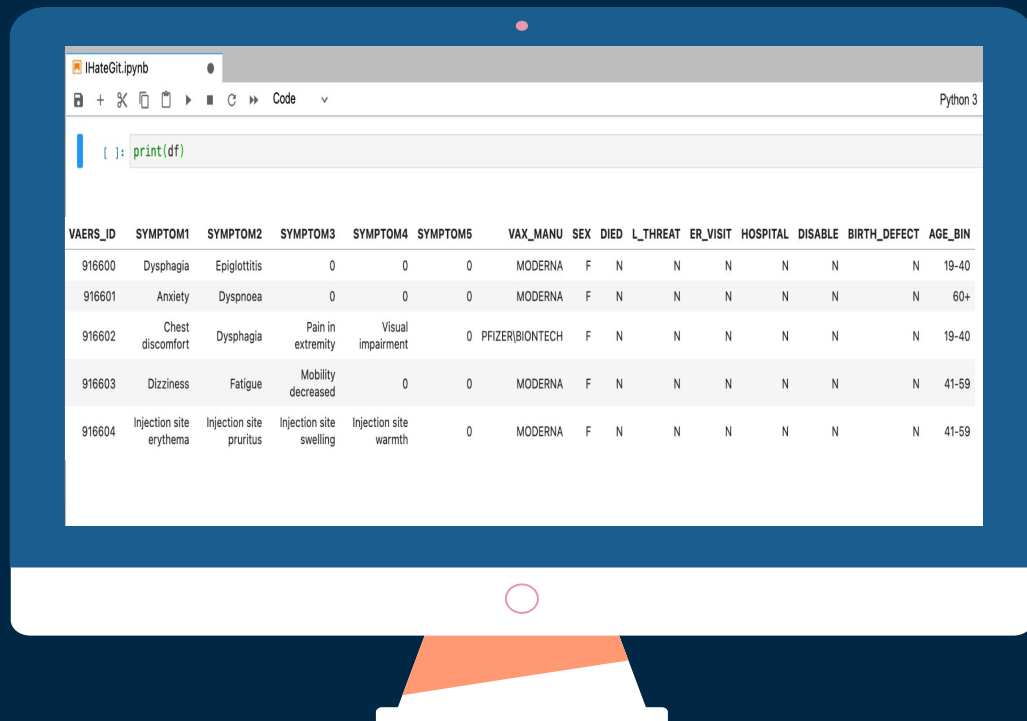


The image shows a computer monitor with a Jupyter Notebook interface. The notebook is titled 'IHateGit.ipynb' and shows a code cell with the command `print(df)`. Below the code, a table is displayed with the following columns: VAX_TYPE, VAX_MANU, VAX_NAME, SYMPTOM1, SYMPTOM2, SYMPTOM3, SYMPTOM4, and SYMPTOM5. The table contains 6 rows of data, each representing a different vaccine and its associated symptoms.

	VAX_TYPE	VAX_MANU	VAX_NAME	SYMPTOM1	SYMPTOM2	SYMPTOM3	SYMPTOM4	SYMPTOM5
VAERS_ID								
916600	COVID19	MODERNA	COVID19 (COVID19 (MODERNA))	Dysphagia	Epiglottitis	0	0	0
916601	COVID19	MODERNA	COVID19 (COVID19 (MODERNA))	Anxiety	Dyspnoea	0	0	0
916602	COVID19	PFIZERBIONTECH	COVID19 (COVID19 (PFIZER-BIONTECH))	Chest discomfort	Dysphagia	Pain in extremity	Visual impairment	0
916603	COVID19	MODERNA	COVID19 (COVID19 (MODERNA))	Dizziness	Fatigue	Mobility decreased	0	0
916604	COVID19	MODERNA	COVID19 (COVID19 (MODERNA))	Injection site erythema	Injection site pruritus	Injection site swelling	Injection site warmth	0

CLEANING DATA USING PYTHON

- We merged the Vax dataframe with the Symptoms dataframe.
- We drop the duplicates and fill the all null values with "0"
- Filtered for COVID-19 **vaccine** type only.
- Finally, the Data dataframe was merged with the Vax and Symptoms dataframe and it was exported to be used on the machine learning model.

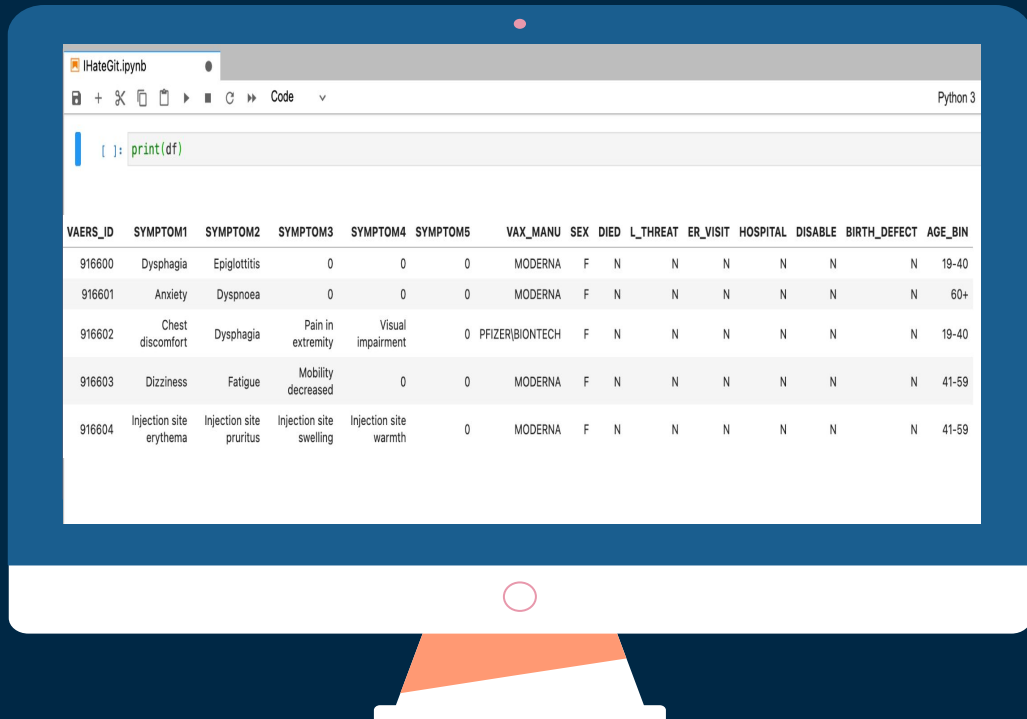


The image shows a Jupyter Notebook window titled 'IHateGit.ipynb' with a 'Code' tab selected. The code cell contains the command `print(df)`. Below the code, a data table is displayed, representing the contents of the dataframe 'df'. The table has 15 columns: VAERS_ID, SYMPTOM1, SYMPTOM2, SYMPTOM3, SYMPTOM4, SYMPTOM5, VAX_MANU, SEX, DIED, L_THREAT, ER_VISIT, HOSPITAL, DISABLE, BIRTH_DEFECT, and AGE_BIN. The table contains 5 rows of data, with the first row having missing values for SYMPTOM2, SYMPTOM3, SYMPTOM4, SYMPTOM5, and BIRTH_DEFECT.

VAERS_ID	SYMPTOM1	SYMPTOM2	SYMPTOM3	SYMPTOM4	SYMPTOM5	VAX_MANU	SEX	DIED	L_THREAT	ER_VISIT	HOSPITAL	DISABLE	BIRTH_DEFECT	AGE_BIN
916600	Dysphagia	Epiglottitis	0	0	0	MODERNA	F	N	N	N	N	N	N	19-40
916601	Anxiety	Dyspnoea	0	0	0	MODERNA	F	N	N	N	N	N	N	60+
916602	Chest discomfort	Dysphagia	Pain in extremity	Visual impairment	0	PFIZER(BIONTECH	F	N	N	N	N	N	N	19-40
916603	Dizziness	Fatigue	Mobility decreased	0	0	MODERNA	F	N	N	N	N	N	N	41-59
916604	Injection site erythema	Injection site pruritus	Injection site swelling	Injection site warmth	0	MODERNA	F	N	N	N	N	N	N	41-59

CLEANING DATA USING PYTHON

- To find which **symptoms** had the most life threatening, we had to filter down the dataset by **hospitalization**, life threatening, and death
- We took the remaining **symptoms** from all 5 columns and listed out the most frequent **symptoms**.
- Finally, we have created a dataset that contains all ID's with only the most life threatening **symptoms**.
- The dataframe is now ready for our machine learning model

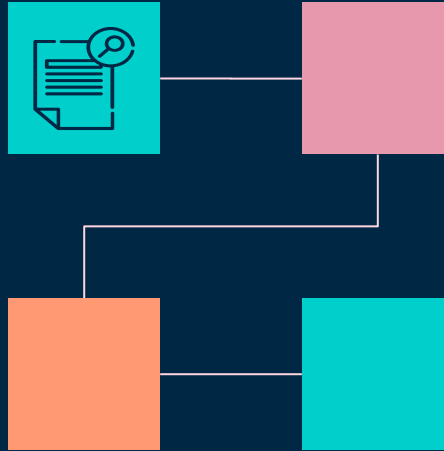


VAERS_ID	SYMPTOM1	SYMPTOM2	SYMPTOM3	SYMPTOM4	SYMPTOM5	VAX_MANU	SEX	DIED	L_THREAT	ER_VISIT	HOSPITAL	DISABLE	BIRTH_DEFECT	AGE_BIN
916600	Dysphagia	Epiglottitis	0	0	0	MODERNA	F	N	N	N	N	N	N	19-40
916601	Anxiety	Dyspnoea	0	0	0	MODERNA	F	N	N	N	N	N	N	60+
916602	Chest discomfort	Dysphagia	Pain in extremity	Visual impairment	0	PFIZER(BIONTECH	F	N	N	N	N	N	N	19-40
916603	Dizziness	Fatigue	Mobility decreased	0	0	MODERNA	F	N	N	N	N	N	N	41-59
916604	Injection site erythema	Injection site pruritus	Injection site swelling	Injection site warmth	0	MODERNA	F	N	N	N	N	N	N	41-59

MACHINE LEARNING IN PYTHON

IMPORT

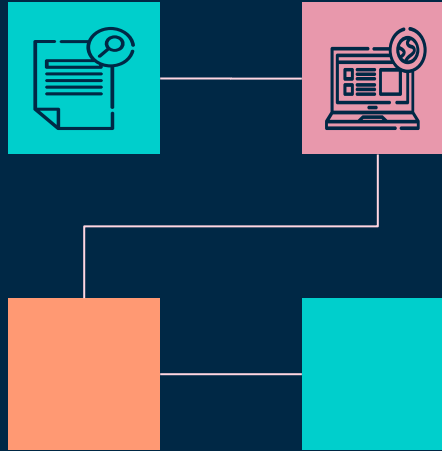
We imported the cleaned data file
for our machine learning



MACHINE LEARNING IN PYTHON

IMPORT

We imported the cleaned data file
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CONVERT

Next, we converted the symptom
list into unique numbers and the
rest of the categorical features into
a binary column

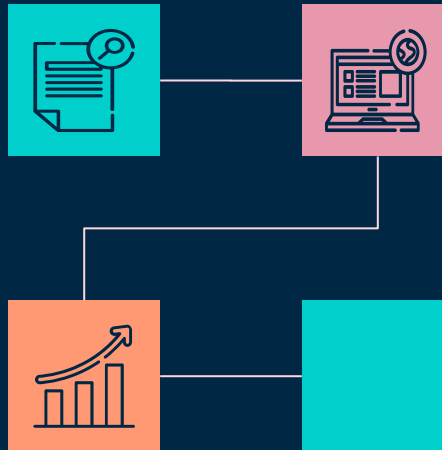
MACHINE LEARNING IN PYTHON

IMPORT

We imported the cleaned data file for our machine learning.

TRAIN AND TEST

The dataframe needed to be split into random train and test subsets, then scaled to unit variance.



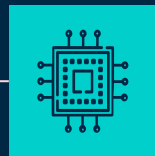
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Next, we converted the symptom list into unique numbers and the rest of the categorical features into a binary column.

MACHINE LEARNING IN PYTHON

IMPORT

We imported the cleaned data file for our machine learning.



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TRAIN AND TEST

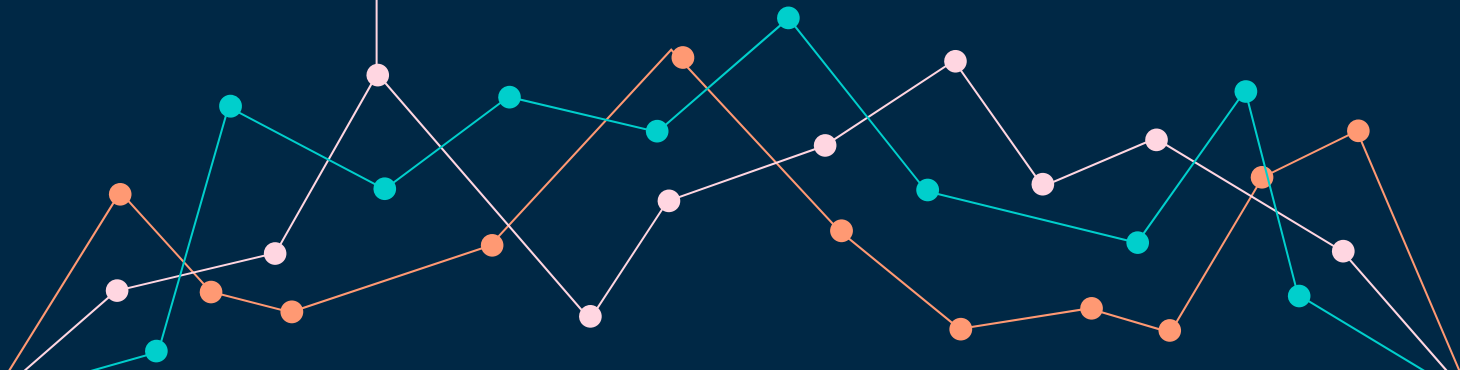
The dataframe needed to be split into random train and test subsets, then scaled to unit variance.

PREDICT

Using RandomForestClassifier, we were able to achieve a predictive accuracy with controlled over-fitting.

72%

Chance to get a symptom that was present during a life threatening adverse event if you are over the age of 60



CONCLUSION

Despite the heightened chance to get a life threatening symptom over the age of 60, our initial data found the death rate to be low. Even for the deaths reported, we lack the current resources to take pre-existing conditions into account. VAERS reports new data everyday, leaving more potential for unique questions to be asked, and more precise predictions to be answered.

