
⌵ :: SCRIPT AUTHORS ::

* Ademir Luiz do Prado

* Alexandre de Fátima Cobre

MACHINE LEARNING (ML)

Development of a Machine Learning model for the prognosis of COVID-19 in terms of SEVERITY using laboratory biomarkers. The data are from examinations of patients treated at the Hospital de Clínicas of the Federal University of Paraná

LEGEND:

Sex:

1=Female

2=Male

COVID:

* Total: 35,109 Positive Samples

* Non-Severe (Mild to Moderate): 7,719 samples

* Severe: 27,390 samples

Classification Severity:

* Severe (Serious - Inpatients)

* Non-Severe (Mild to Moderate - Outpatients)

Period of the Samples:

* March 2020 to September 2022

OBJECTIVE:

Develop a Machine Learning model to predict the severity of COVID-19 and identify biomarkers associated with this severity in order to optimize priority in hospital care.

```
# PHASES:
# 1: Import the DataSet
# 2: Import the Pandas library for handling the DataSet
# 3: Remove unnecessary columns (features) from DataSet
# 4: Exploratory Analysis
# 5: Install the Pycaret library to aid Auto-Machine Learn
# 6: Import the Pycaret library
# 7: Perform data pre-processing
# 8: Build and compare models
# 9: Train the best model based on predictive performance metrics
#10: Extract the metrics results from the model
#11: Write conclusions about the best identified model
#12: Save the model to make predictions in real analyzes (Deploy)
```

```
# Phase 1: Import the DataSet
```

```
from google.colab import files
uploaded = files.upload()
```

Escolher arquivos

COVID19 D...Severity.csv

- **COVID19 DataSetSeverity.csv**(text/csv) - 3610312 bytes, last modified: 26/12/2023 - 100% done

Saving COVID19 DataSetSeverity.csv to COVID19 DataSetSeverity.csv

```
# Phase 2: Import the Pandas library for handling the DataSet
import pandas as pd
DataSet = pd.read_csv("COVID19 DataSetSeverity.csv")
display (DataSet)
```



```
# Phase 4: Exploratory Analysis
## 4.1. DataSet Informations
DataSetSeverity.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 35109 entries, 0 to 35108
Data columns (total 51 columns):
```

#	Column	Non-Null Count	Dtype
---	-----	-----	-----
0	COVID	35109 non-null	object
1	Age	35109 non-null	int64
2	Sex	35109 non-null	int64
3	Erythrocytes	27977 non-null	float64
4	Haemoglobin	236 non-null	float64
5	Leukocytes	28100 non-null	float64
6	Mature Neutrophils	131 non-null	float64
7	Immature Neutrophils	23962 non-null	float64
8	Neutrophils	132 non-null	float64
9	Basophils	131 non-null	float64
10	Eosinophils	131 non-null	float64
11	Lymphocytes	28098 non-null	float64
12	Atypical Lymphocytes	23837 non-null	float64
13	Monocytes	28098 non-null	float64
14	Platelets	28219 non-null	float64
15	Prothrombin Time	8777 non-null	float64
16	Prothrombin Time - Relation*	8757 non-null	float64
17	Prothrombin Time - International Normalized Ratio	8785 non-null	float64
18	Partial Thromboplastin Time	2401 non-null	float64
19	Partial Thromboplastin Time - Relation*	2391 non-null	float64
20	D-Dimer	5102 non-null	float64
21	Glucose	6958 non-null	float64
22	HbA1c	1354 non-null	float64
23	Total Cholesterol	1738 non-null	float64
24	HDL-C	1424 non-null	float64
25	LDL-C	1378 non-null	float64
26	Triglycerides	1825 non-null	float64
27	Creatinine	26990 non-null	float64
28	Urea	23970 non-null	float64
29	Potassium	24510 non-null	float64
30	Sodium	24427 non-null	float64
31	Alanine transaminase	11570 non-null	float64
32	Aspartate transaminase	11538 non-null	float64
33	Albumin	7561 non-null	float64
34	Total Protein	587 non-null	float64
35	Globulin	587 non-null	float64
36	Ferritin	6185 non-null	float64
37	C-reactive protein	15689 non-null	float64
38	Amylase	896 non-null	float64
39	Lipase	907 non-null	float64
40	Troponin	3328 non-null	float64
41	pCO2	272 non-null	float64

42

pO2

269

non-null

float64

43

sO2

267

non-null

float64

44

pH

313

non-null

float64

45

HCO3 (standard)

246

non-null

float64

46

HCO3 (actual)

272

non-null

float64

47

BE(ECF)

268

non-null

float64

48

BE(B)

271

non-null

float64

49

CTCO2

269

non-null

float64

50

Procalcitonin

1922

non-null

float64

dtypes: float64(48), int64(2), object(1)

memory usage: 12.7 MB

4.2. Install and Import library for Descriptive Statistics

```
!pip install researchpy
import researchpy as rp
### 1: COVID Feature
rp.summary_cat(DataSetSeverity['COVID'])
```

Collecting researchpy

Downloading researchpy-0.3.5-py3-none-any.whl (33 kB)

Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-packages (from researchpy) (1.11.4)

Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from researchpy) (1.23.5)

Requirement already satisfied: pandas in /usr/local/lib/python3.10/dist-packages (from researchpy) (1.5.3)

Requirement already satisfied: statsmodels in /usr/local/lib/python3.10/dist-packages (from researchpy) (0.14.1)

Requirement already satisfied: patsy in /usr/local/lib/python3.10/dist-packages (from researchpy) (0.5.4)

Requirement already satisfied: python-dateutil>=2.8.1 in /usr/local/lib/python3.10/dist-packages (from pandas->researchpy) (2.8.2)



Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas->researchpy) (2023.3.post1)

Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages (from patsy->researchpy) (1.16.0)



Requirement already satisfied: packaging>=21.3 in /usr/local/lib/python3.10/dist-packages (from statsmodels->researchpy) (23.2)

Installing collected packages: researchpy

Successfully installed researchpy-0.3.5

	Variable	Outcome	Count	Percent	
0	COVID	Severe	27390	78.01	
1		Non-Severe	7719	21.99	

```
### 2: Sex Feature
rp.summary_cat(DataSetSeverity['Sex'])
```

	Variable	Outcome	Count	Percent	
0	Sex	2	19504	55.55	
1		1	15605	44.45	

```
### 3: Biomarkers Features
DescriptiveStat = DataSetSeverity
DataStatistics = DescriptiveStat.drop("COVID", axis = 1)
DataStatistics = DataStatistics.drop("Sex", axis = 1)
for statistical in DataStatistics.columns:
    display(rp.summary_cont(DataStatistics[statistical]))
```

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Age	35109.0	51.6917	20.7704	0.1109	51.4745	51.909



	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Erythrocytes	27977.0	3.7228	0.9563	0.0057	3.7116	3.734

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Haemoglobin	236.0	9.2301	2.5486	0.1659	8.9032	9.5569

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Leukocytes	28100.0	18.7901	311.2146	1.8566	15.1511	22.429

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Mature Neutrophils	131.0	51.7206	30.1088	2.6306	46.5162	56.925

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Immature Neutrophils	23962.0	8.2177	9.0723	0.0586	8.1028	8.3326

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Neutrophils	132.0	52.0864	30.2866	2.6361	46.8715	57.3012

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Basophils	131.0	0.3107	0.5819	0.0508	0.2101	0.4113

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Eosinophils	131.0	2.9733	8.0494	0.7033	1.5819	4.3646

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Lymphocytes	28098.0	18.3276	14.7855	0.0882	18.1547	18.5004

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Atypical Lymphocytes	23837.0	0.0842	0.3951	0.0026	0.0792	0.0892

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Monocytes	28098.0	6.8916	4.9824	0.0297	6.8334	6.9499

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Platelets	28219.0	251615.441	156999.4019	934.603	249783.5741	253447.3079

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Prothrombin Time	8777.0	15.4055	8.2819	0.0884	15.2322	15.5788

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Prothrombin Time – Relation*	8757.0	1.408	1.5861	0.0169	1.3748	1.4412

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Prothrombin Time - International Normalized Ratio	8785.0	1.4466	1.8551	0.0198	1.4078	1.4854

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Partial Thromboplastin Time	2401.0	32.9669	13.0154	0.2656	32.4461	33.4878

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Partial Thromboplastin Time – Relation*	2391.0	1.2919	1.547	0.0316	1.2298	1.3539

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	D-Dimer	5102.0	5.7938	66.6974	0.9338	3.9632	7.6244

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Glucose	6958.0	125.1138	72.5043	0.8692	123.4099	126.8177

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	HbA1c	1354.0	6.8219	2.075	0.0564	6.7113	6.9326

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Total Cholesterol	1738.0	169.4873	53.7783	1.29	166.9573	172.0174

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	HDL-C	1424.0	39.9185	14.4876	0.3839	39.1654	40.6716

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	LDL-C	1378.0	101.1627	39.9522	1.0763	99.0514	103.274

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Triglycerides	1825.0	159.7912	121.2147	2.8374	154.2263	165.3562

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Creatinine	26990.0	1.3944	1.469	0.0089	1.3768	1.4119

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Urea	23970.0	65.2884	53.4779	0.3454	64.6113	65.9654

	Variable	N	Mean	SD	SE	95% Conf.	Interval
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0 Potassium 24510.0 4.4125 0.7624 0.0049 4.403 4.4221

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Sodium	24427.0	139.3832	4.9508	0.0317	139.3211	139.4453

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Alanine transaminase	11570.0	62.3107	219.867	2.0441	58.304	66.3174

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Aspartate transaminase	11538.0	65.2683	392.5113	3.6542	58.1056	72.4311

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Albumin	7561.0	3.2091	0.774	0.0089	3.1917	3.2266

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Total Protein	587.0	5.7272	1.4442	0.0596	5.6101	5.8442

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Globulin	587.0	2.3336	0.8752	0.0361	2.2626	2.4045

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Ferritin	6185.0	5236.4282	244233.9427	3105.5331	-851.4965	11324.3529

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	C-reactive protein	15689.0	7.5842	7.5281	0.0601	7.4664	7.702

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Amylase	896.0	123.5301	855.65	28.5853	67.4282	179.6321

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Lipase	907.0	189.5899	2348.8678	77.9929	36.5221	342.6576

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	Troponin	3328.0	1789.749	26496.6591	459.3032	889.2037	2690.2943

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	pCO2	272.0	46.0662	18.3158	1.1106	43.8798	48.2526

	Variable	N	Mean	SD	SE	95% Conf.	Interval
0	pO2	269.0	79.7353	33.3306	2.0322	75.7342	83.7364

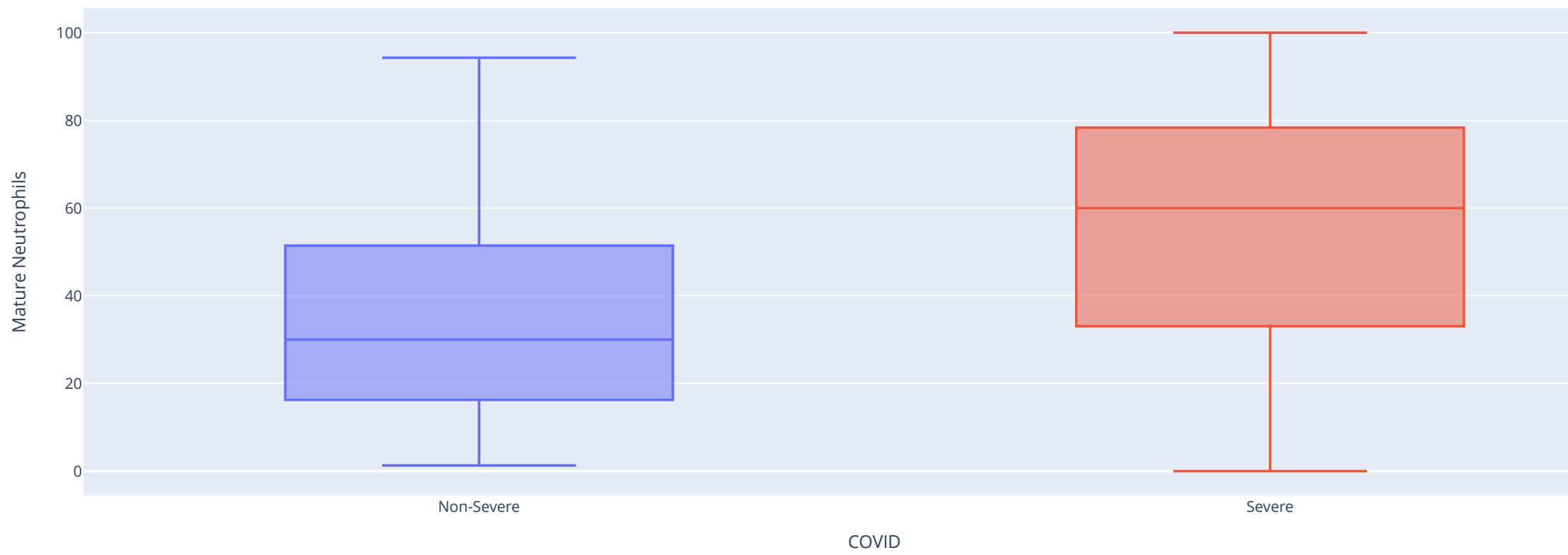
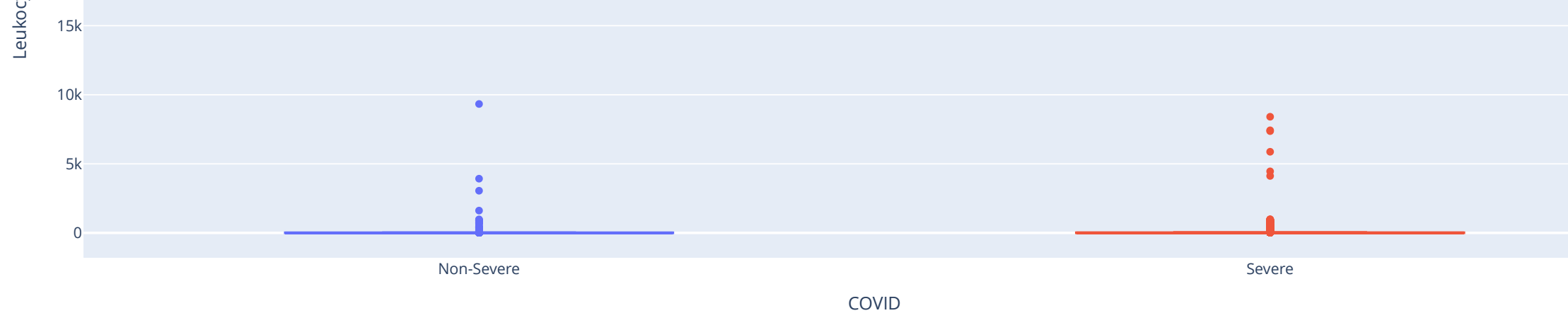
4.3. Analyzing the variation in biomarker levels between COVID-19 severity samples (SEVERE AND NON-SEVERE)

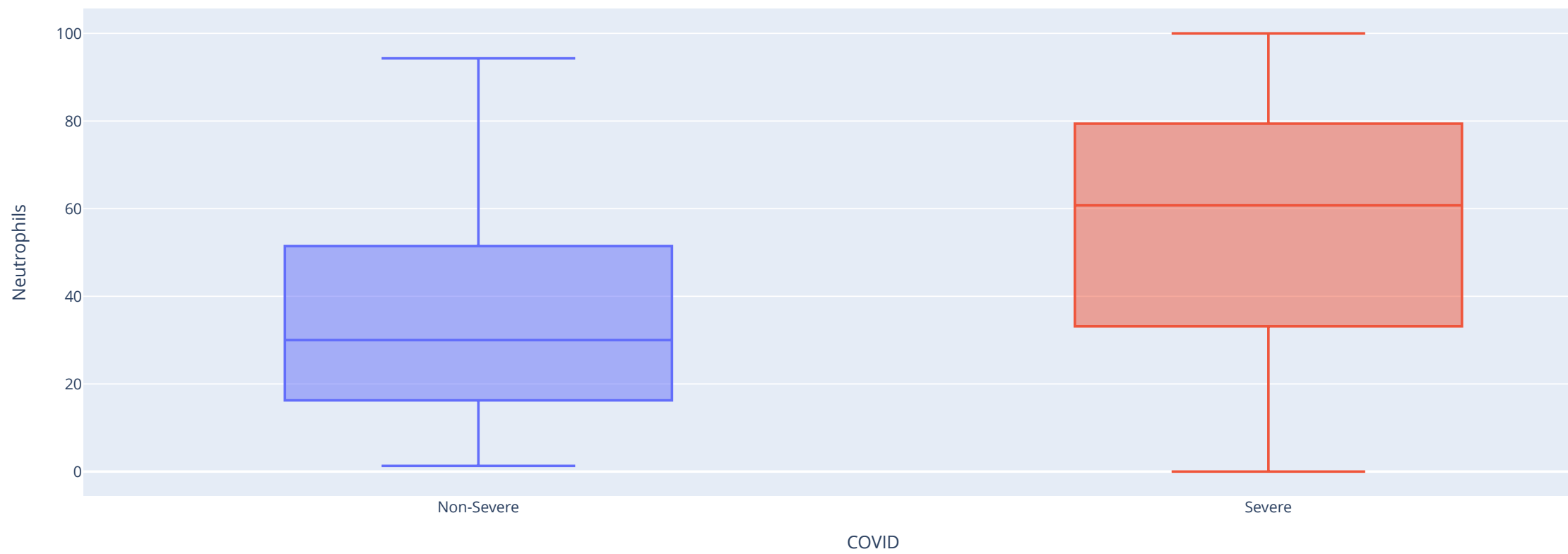
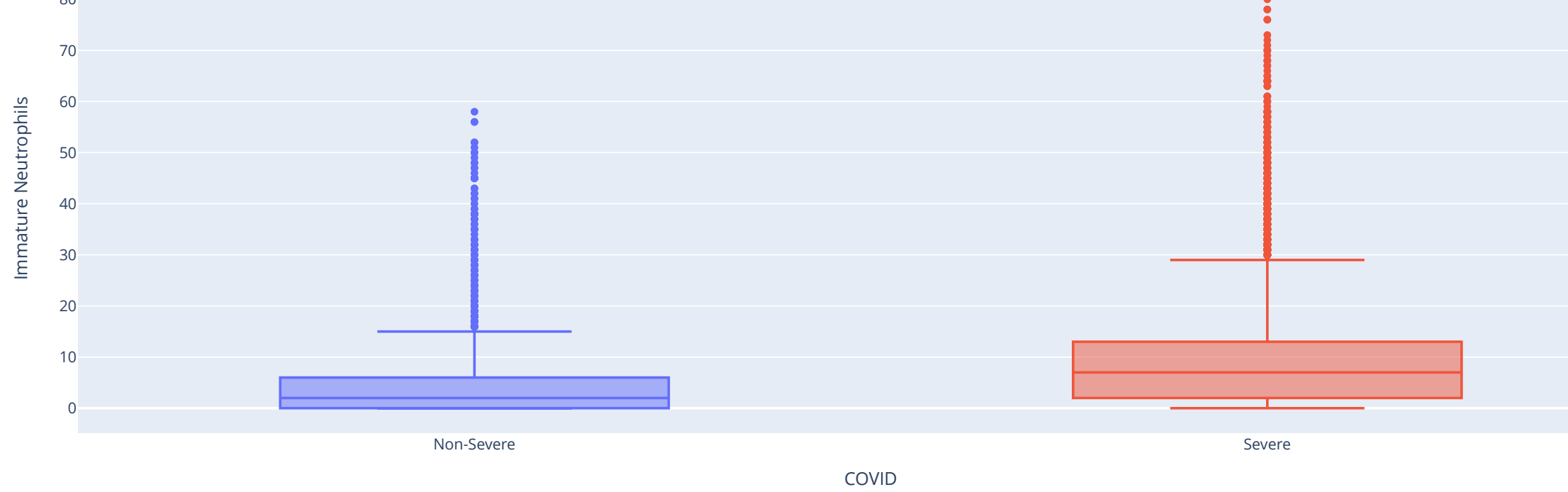
```
### 1: Import Plotly library to graphics
import plotly.express as px

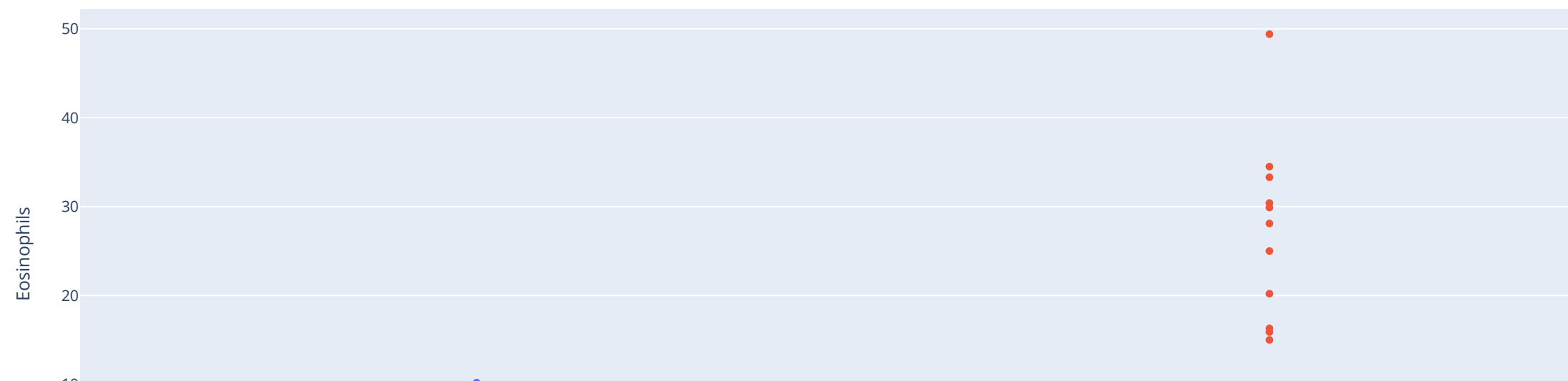
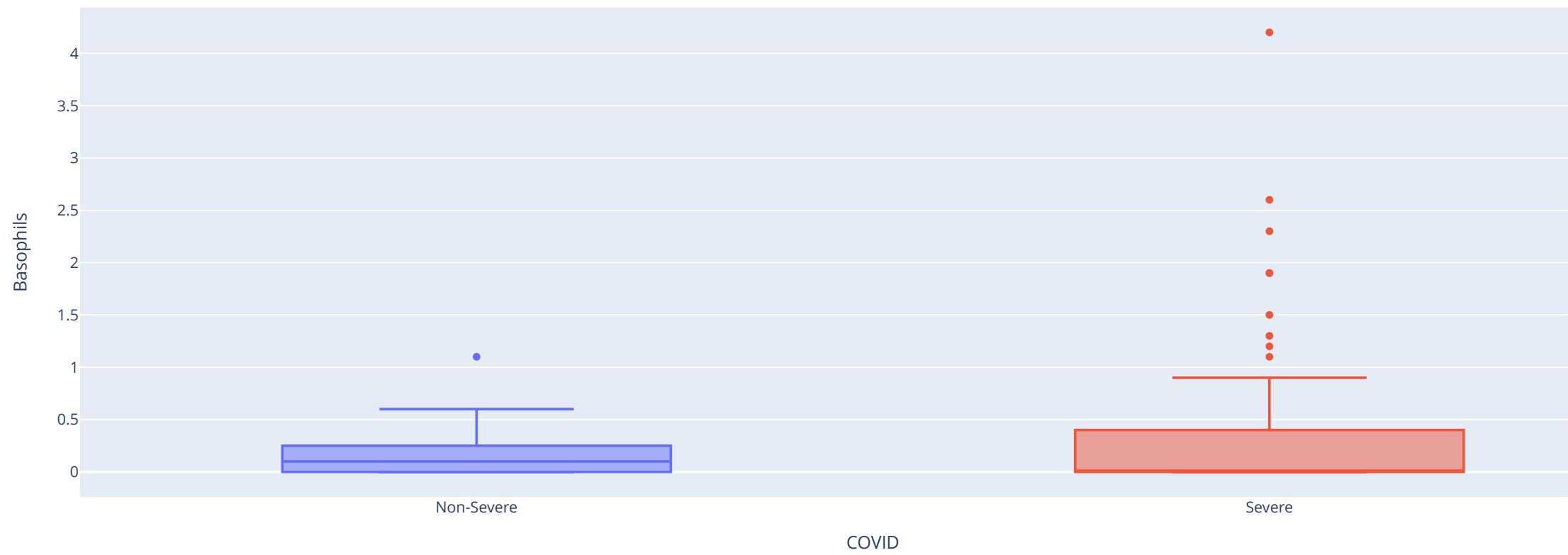
### 2: Create Graphics
# HISTOGRAM
#for biomarker in DataSetSeverity.columns:
#  if biomarker != 'COVID' and biomarker != 'Sex':
#    graphic = px.histogram(DataSetSeverity, x = biomarker, color = "COVID", text_auto = True)
#    graphic.show()

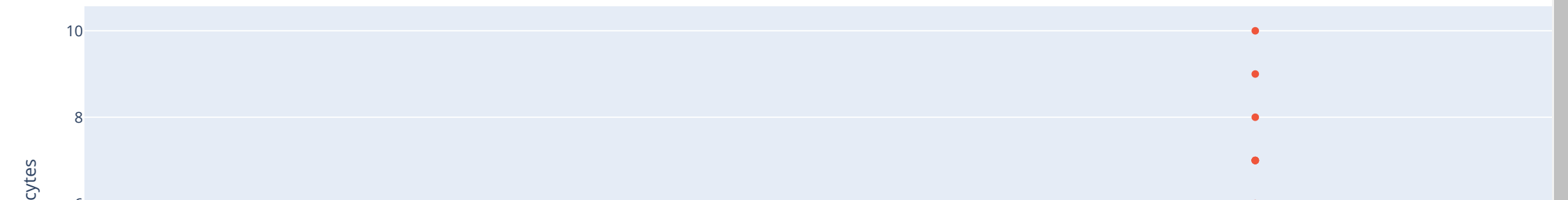
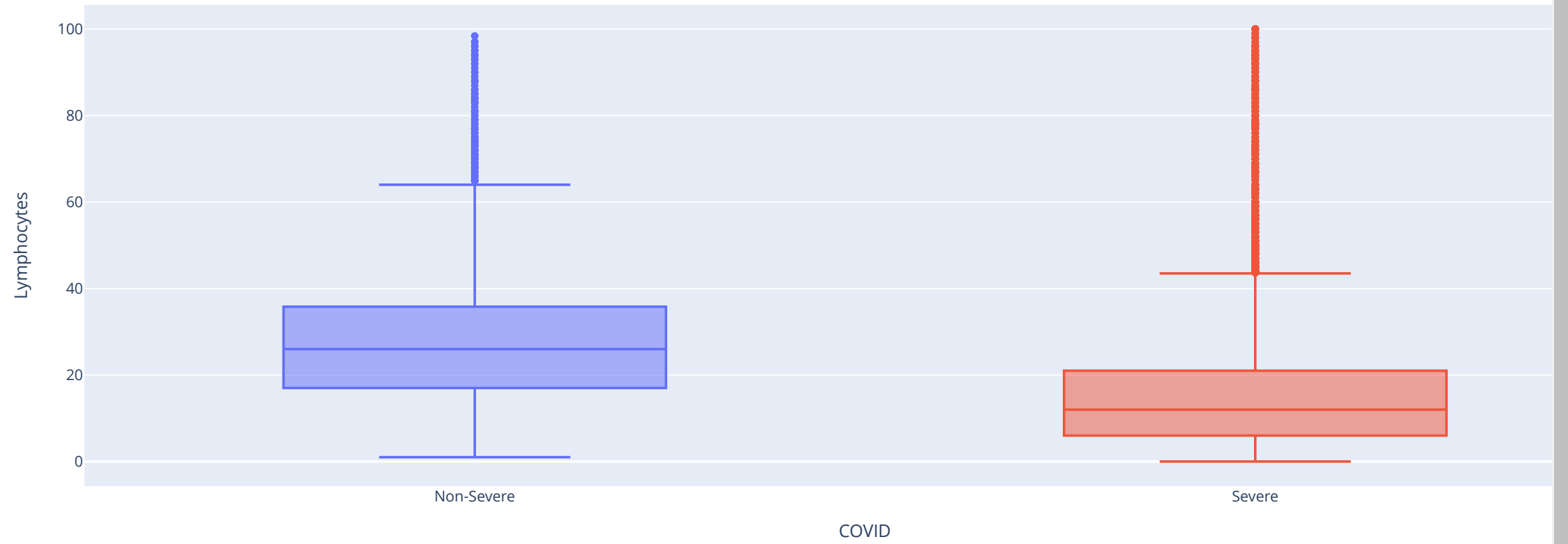
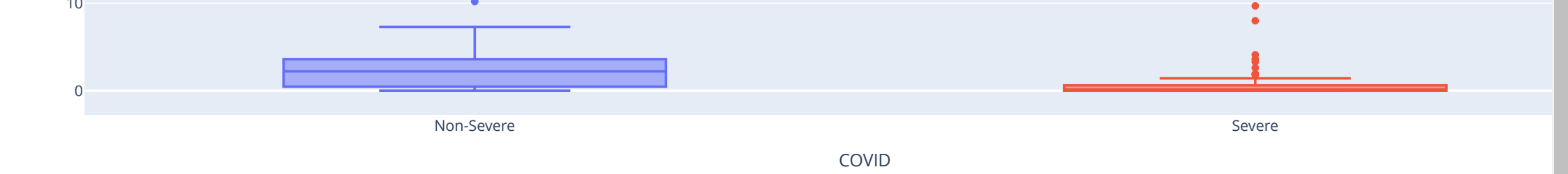
# BOXPLOT
for biomarker in DataSetSeverity.columns:
  if biomarker != 'COVID' and biomarker != 'Sex':
    graphic = px.box(DataSetSeverity, x = DataSetSeverity.columns[0], y=biomarker, color="COVID")
    graphic.show()
```

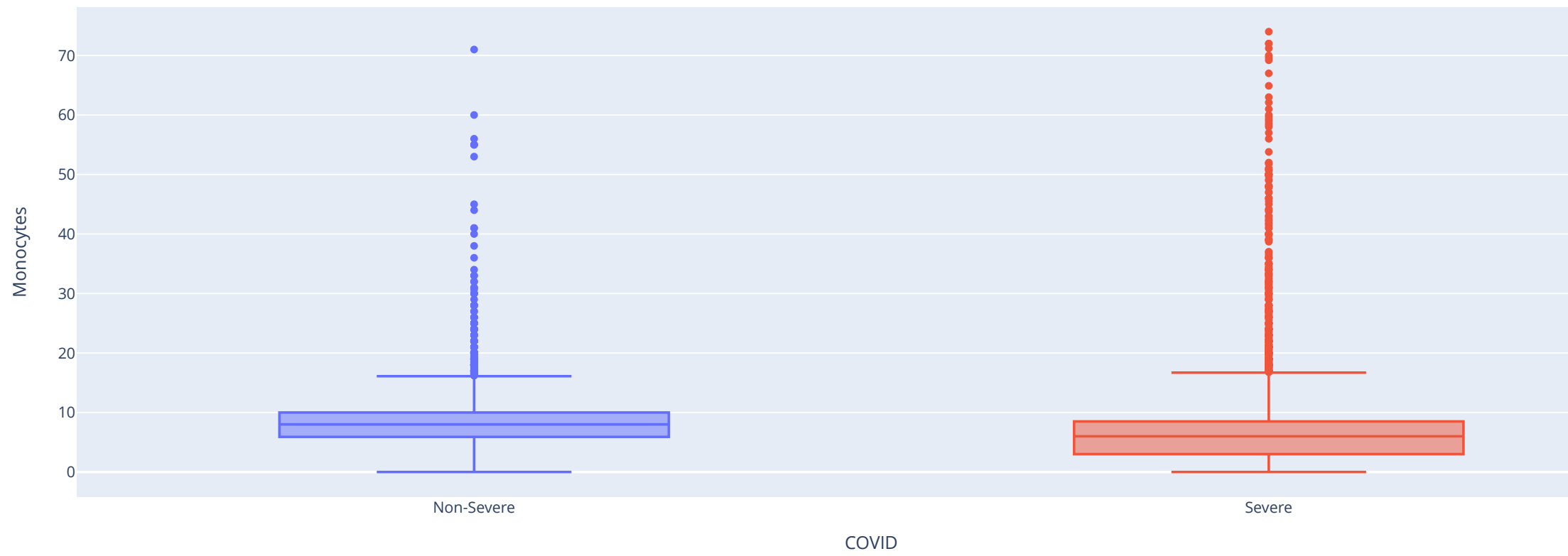
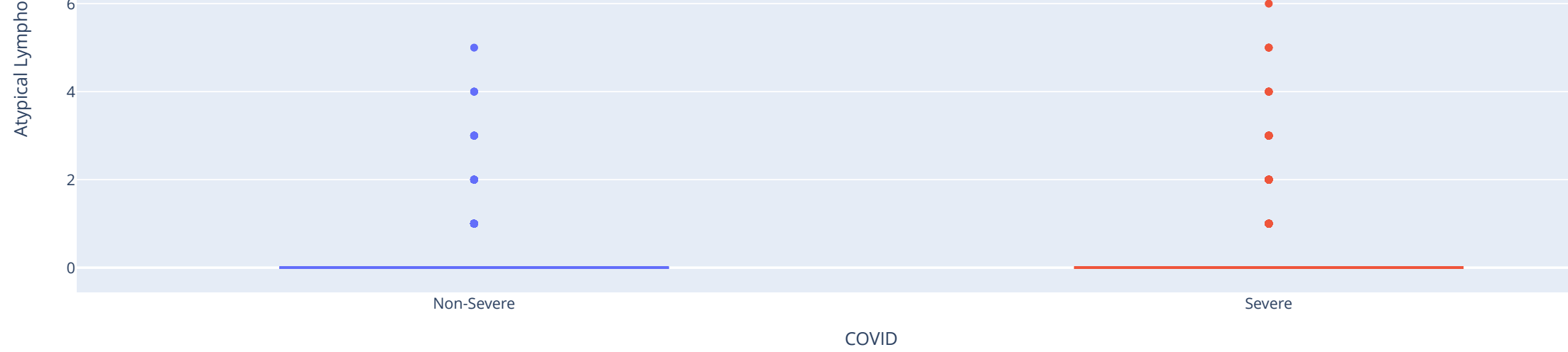


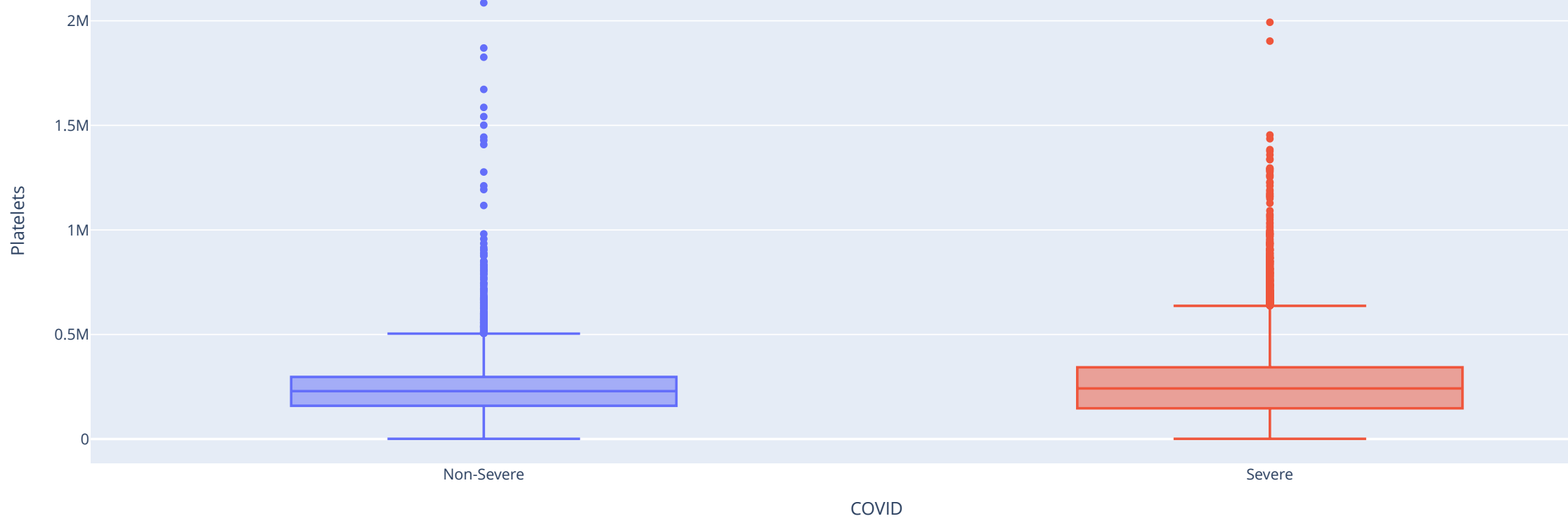









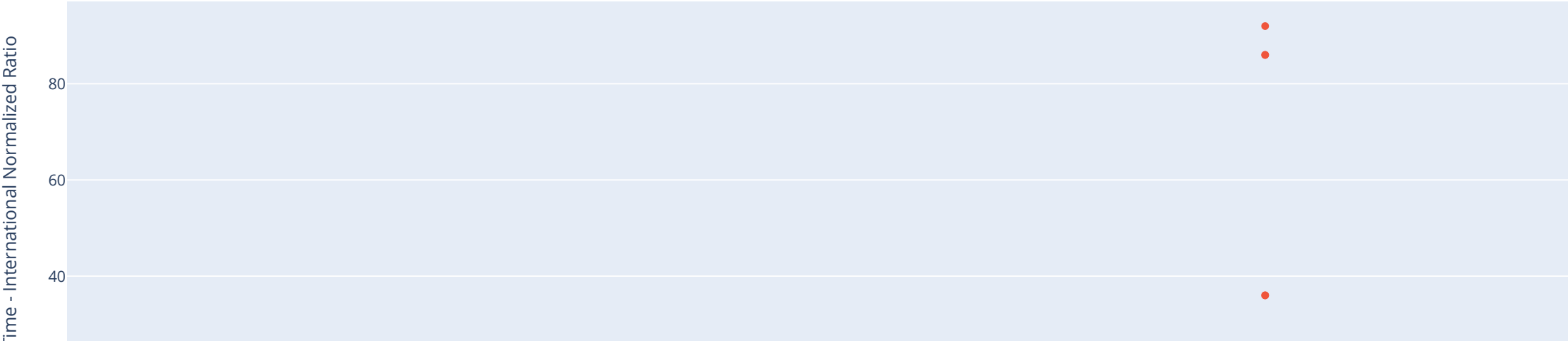


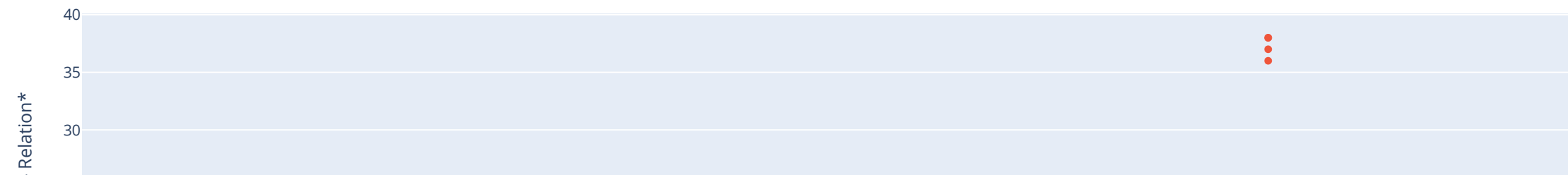
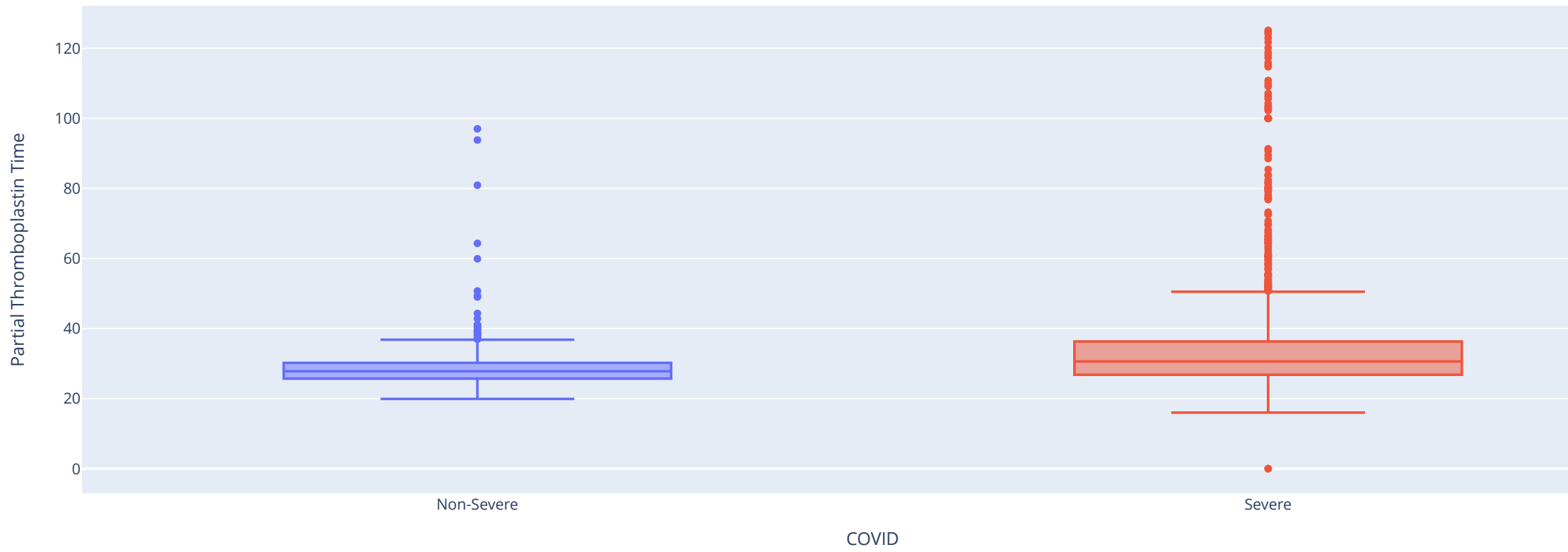
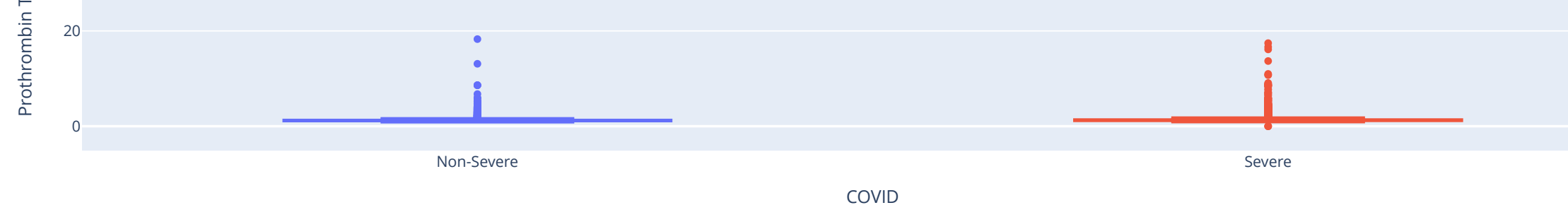


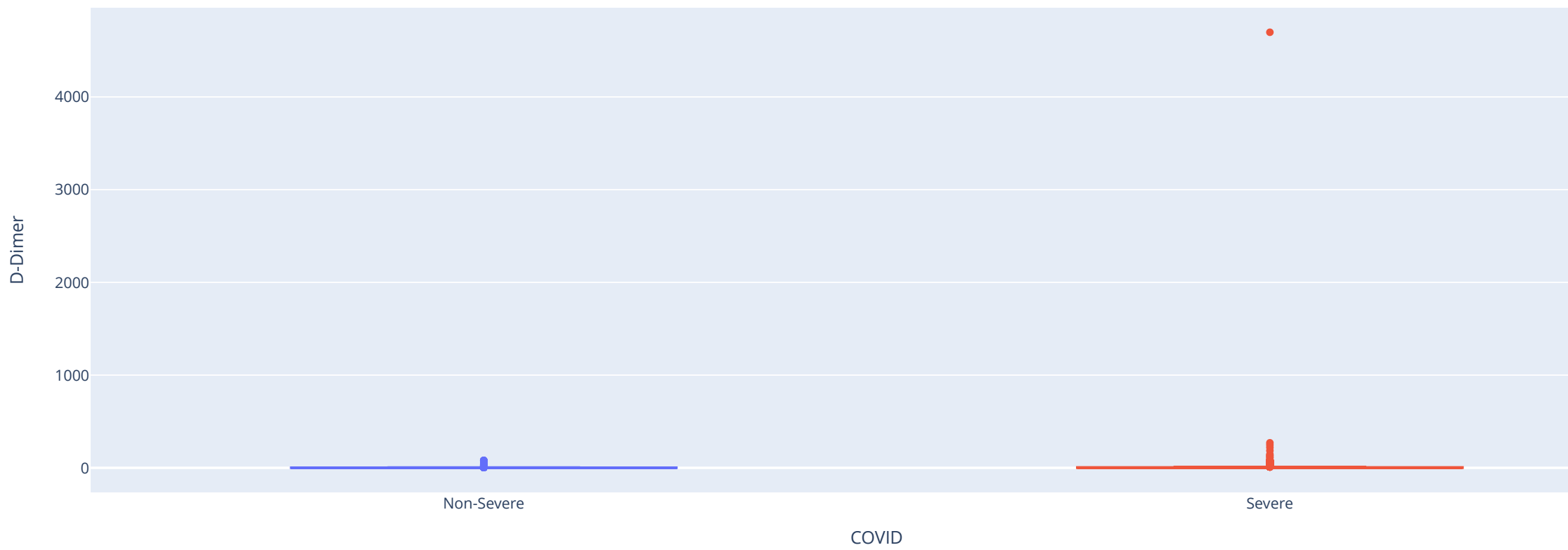
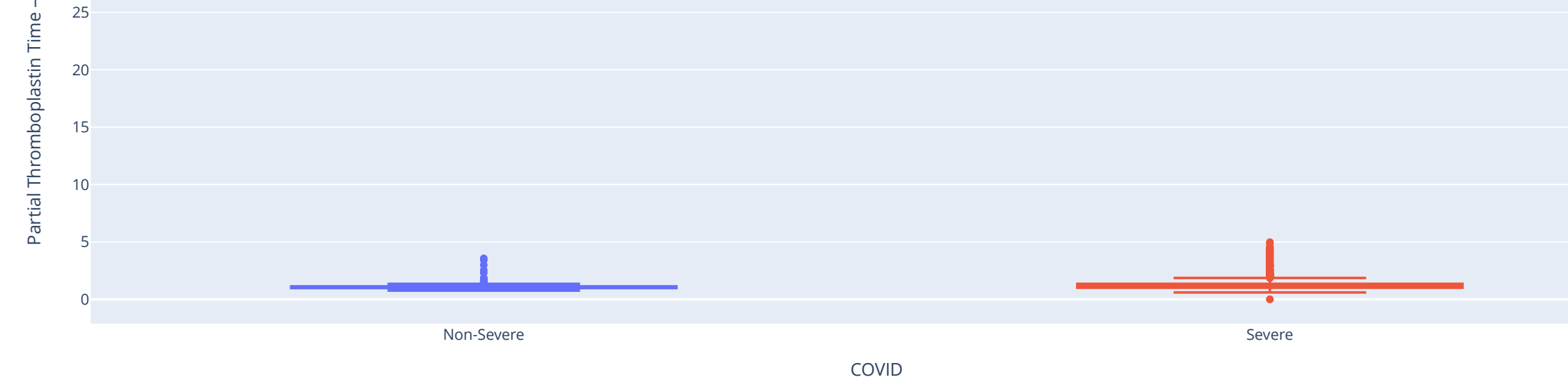
COVID

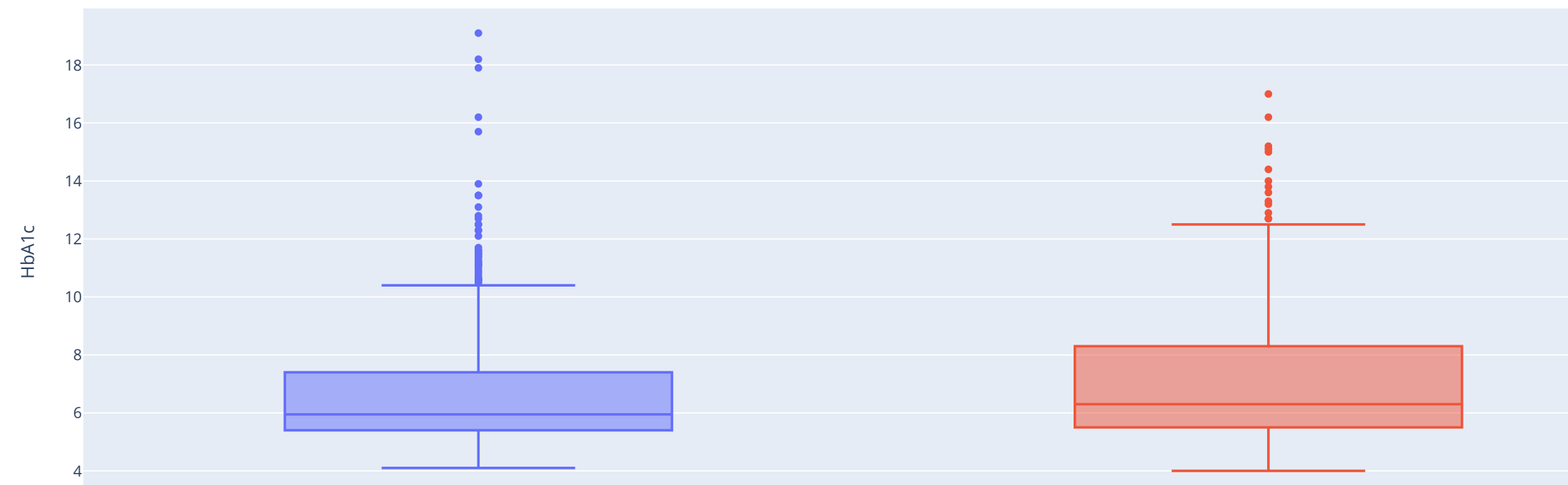
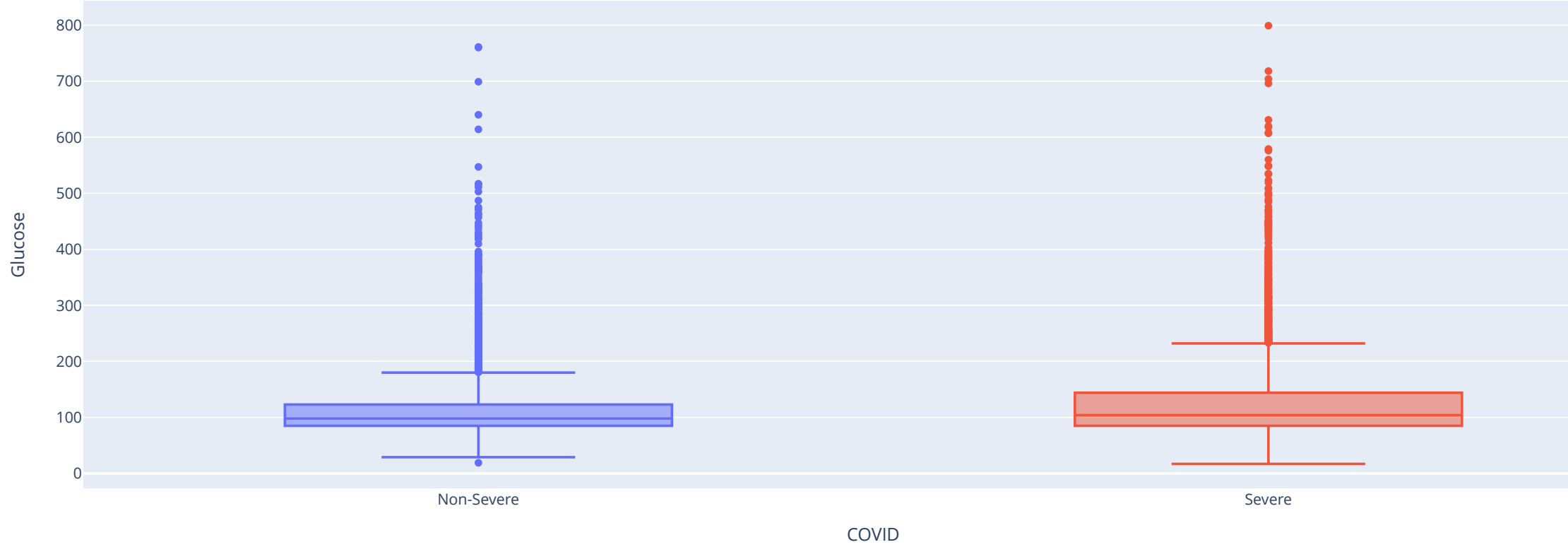


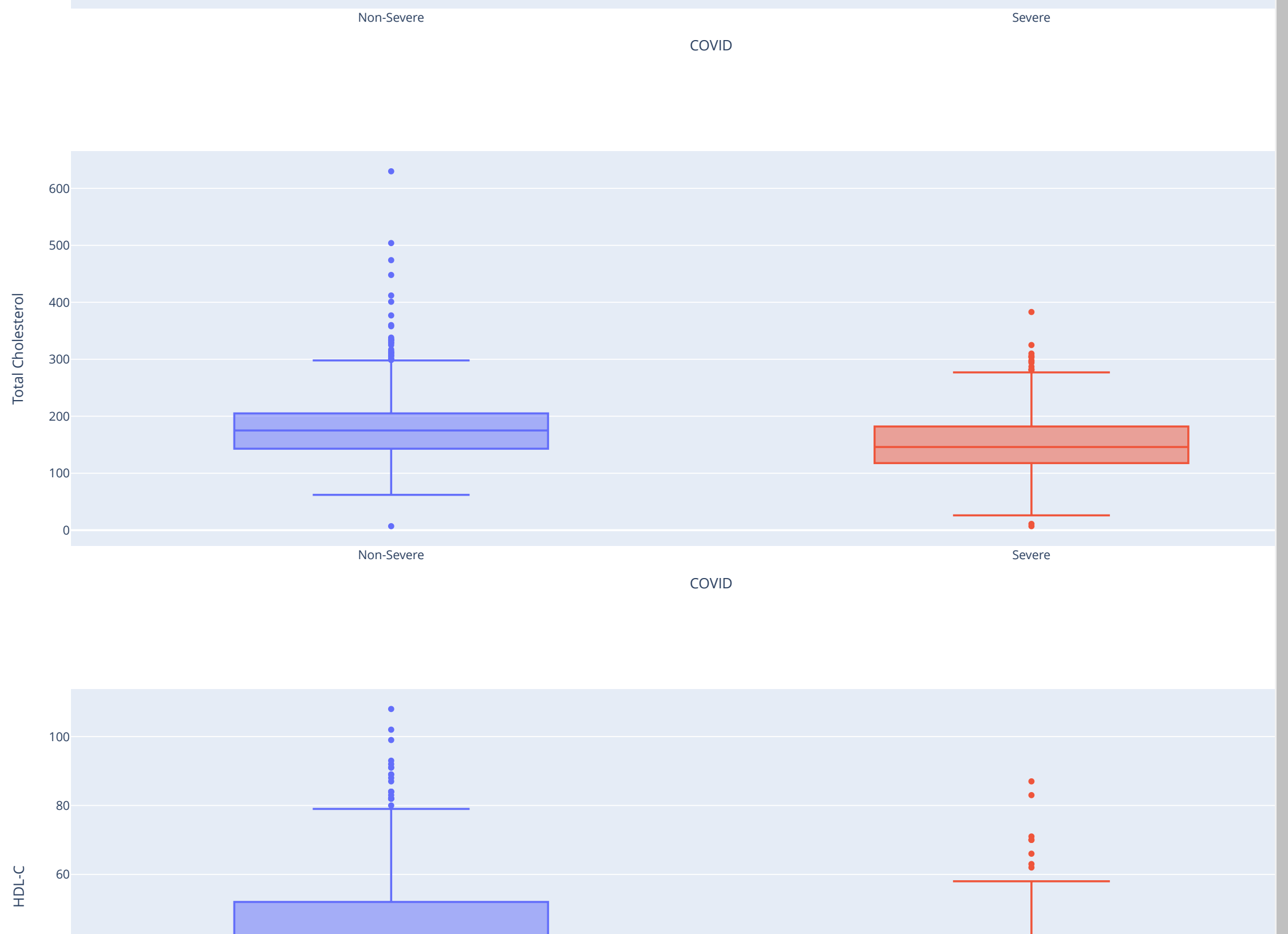
COVID

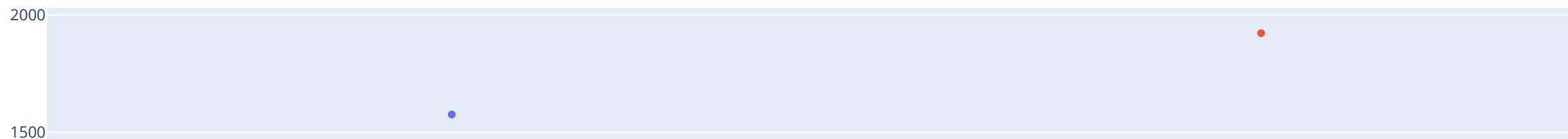
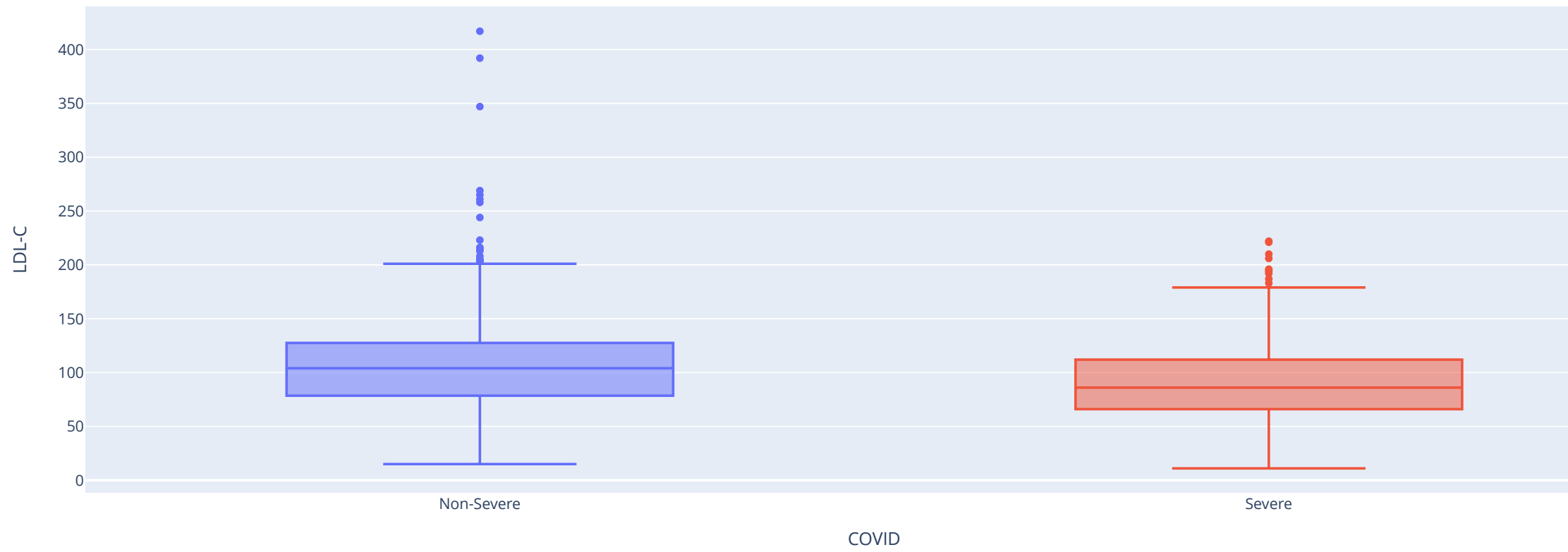
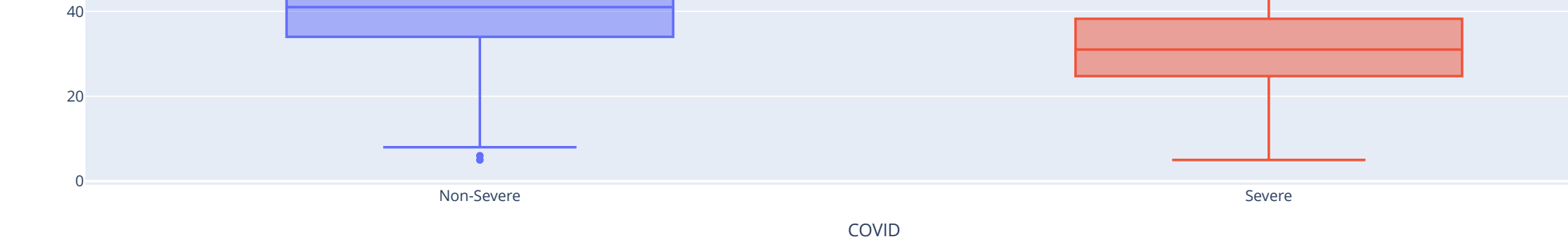


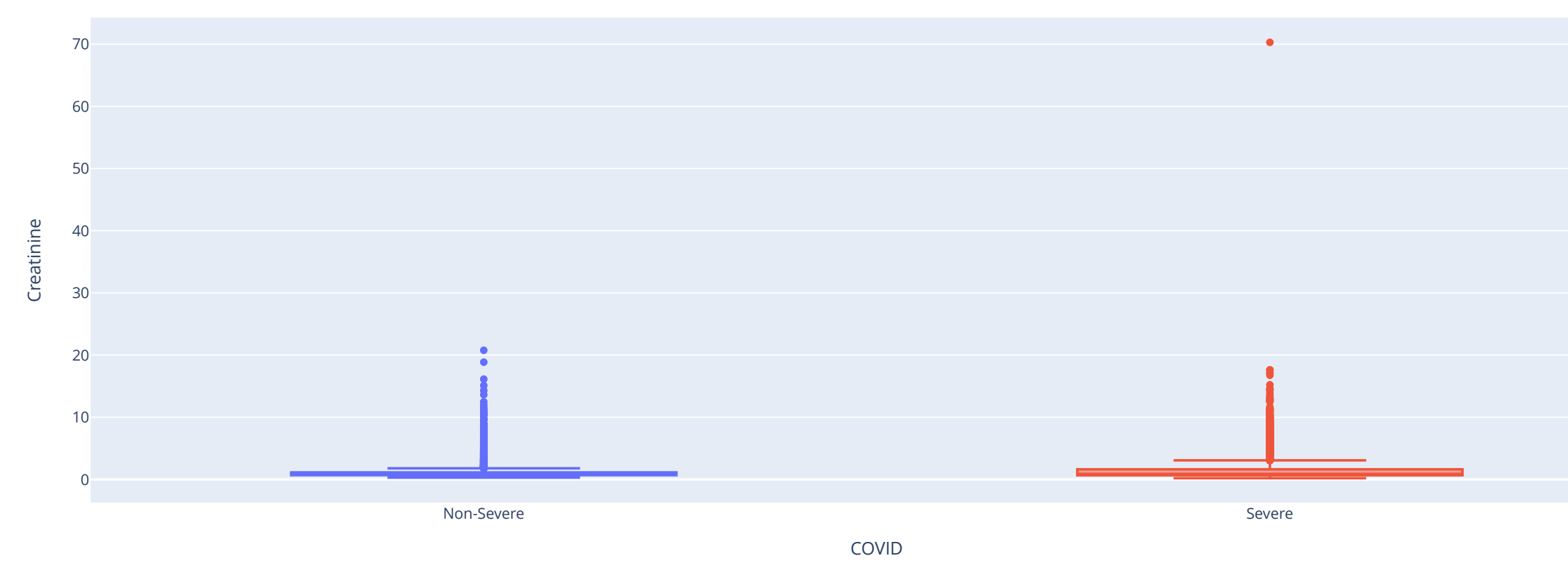
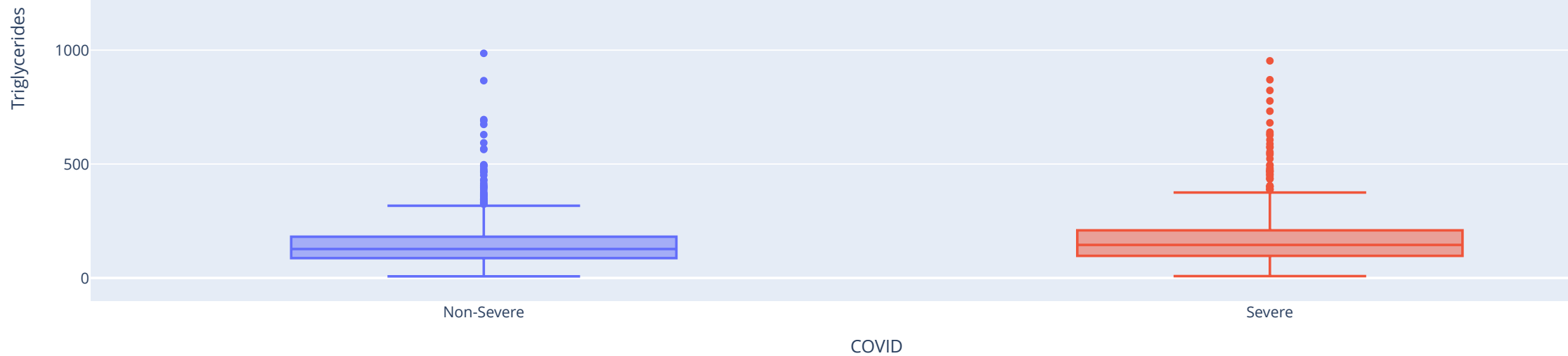


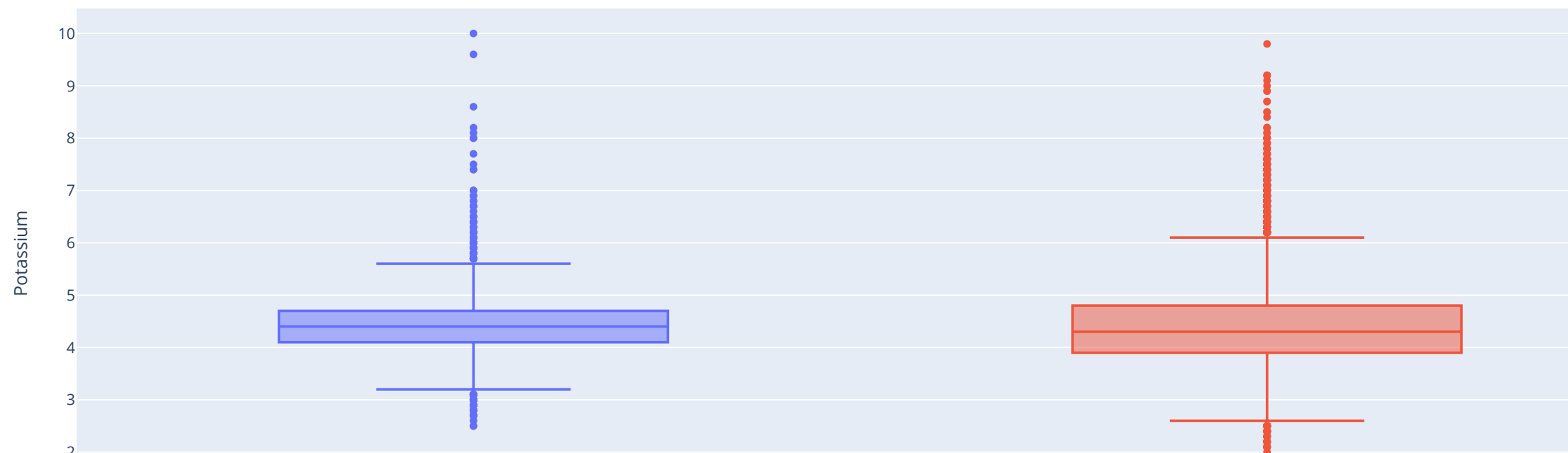
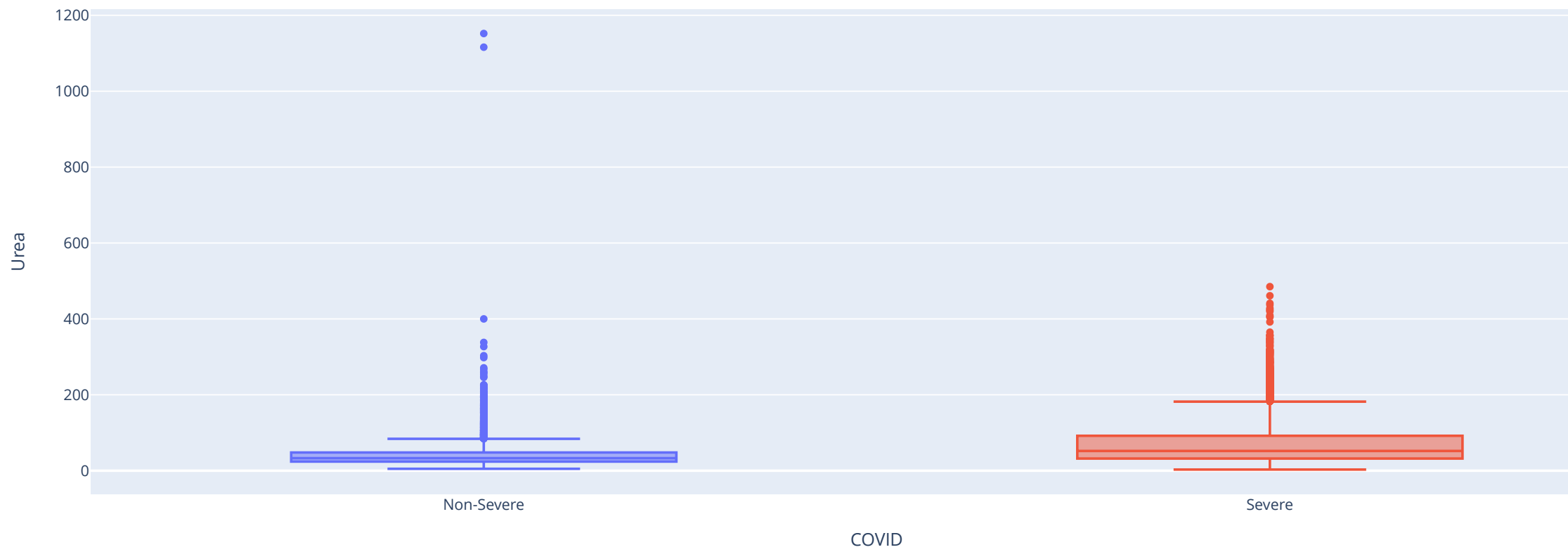




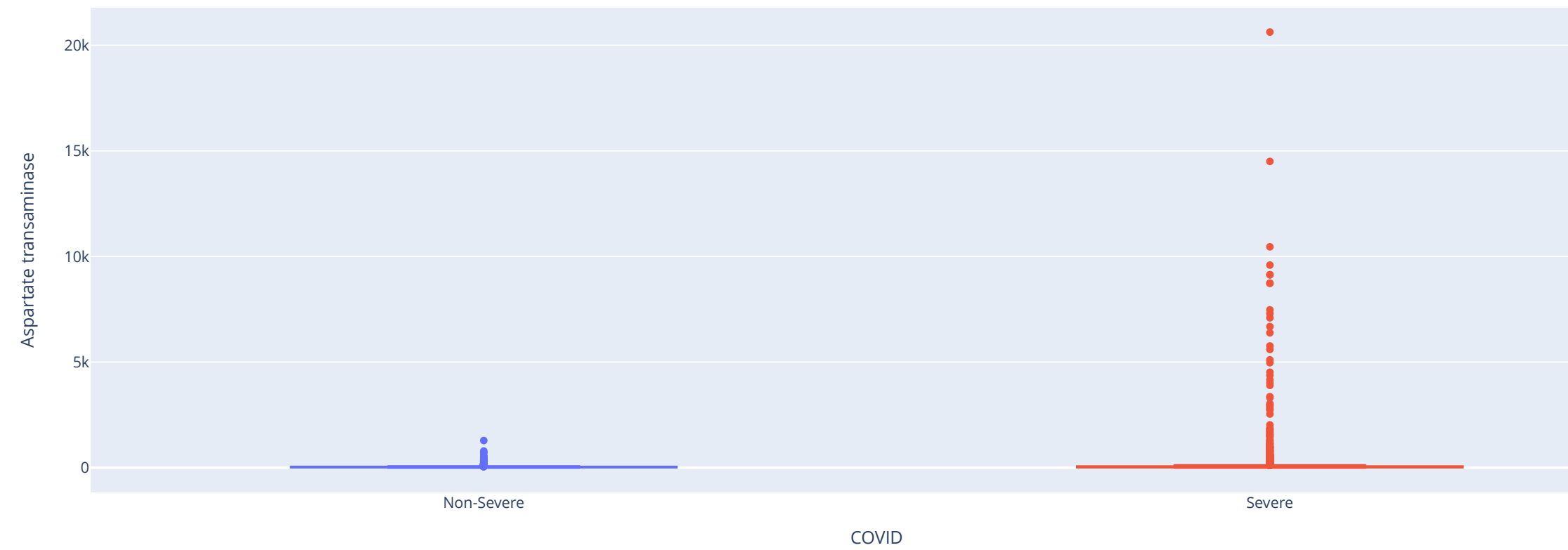
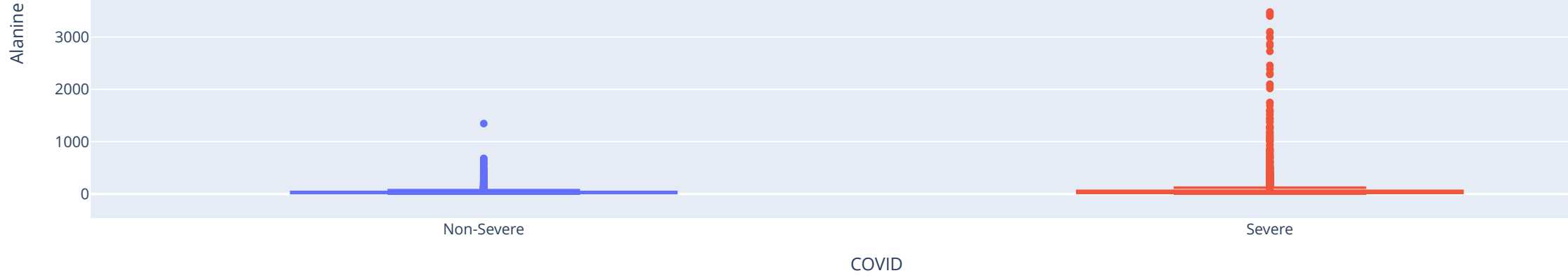


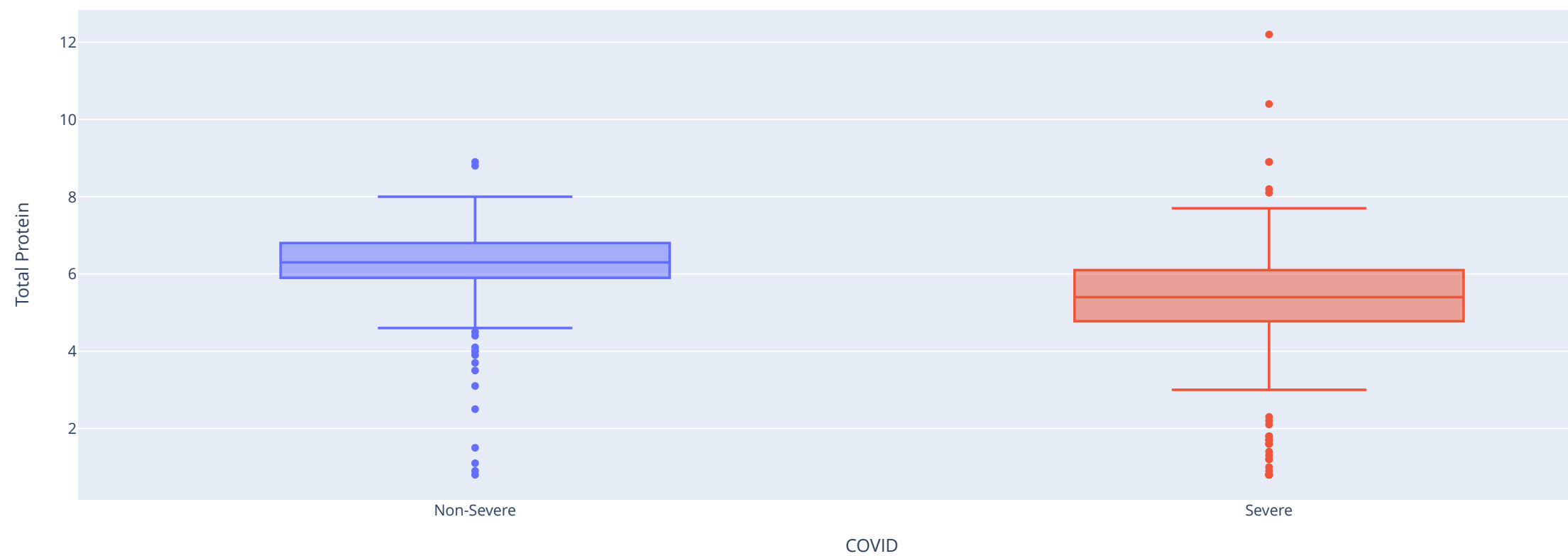
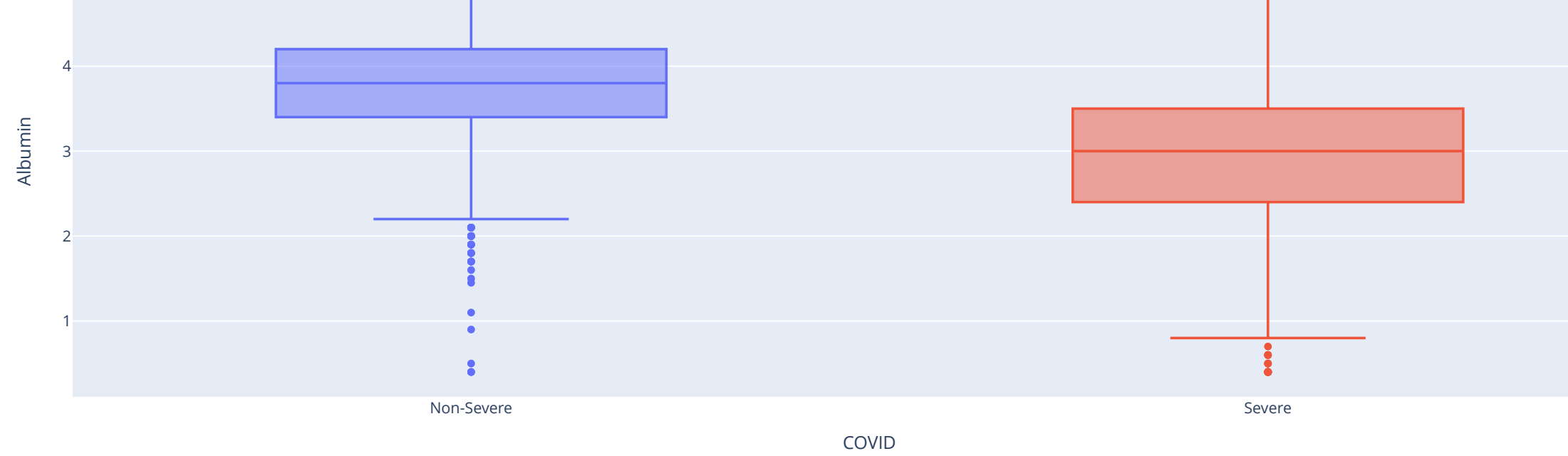


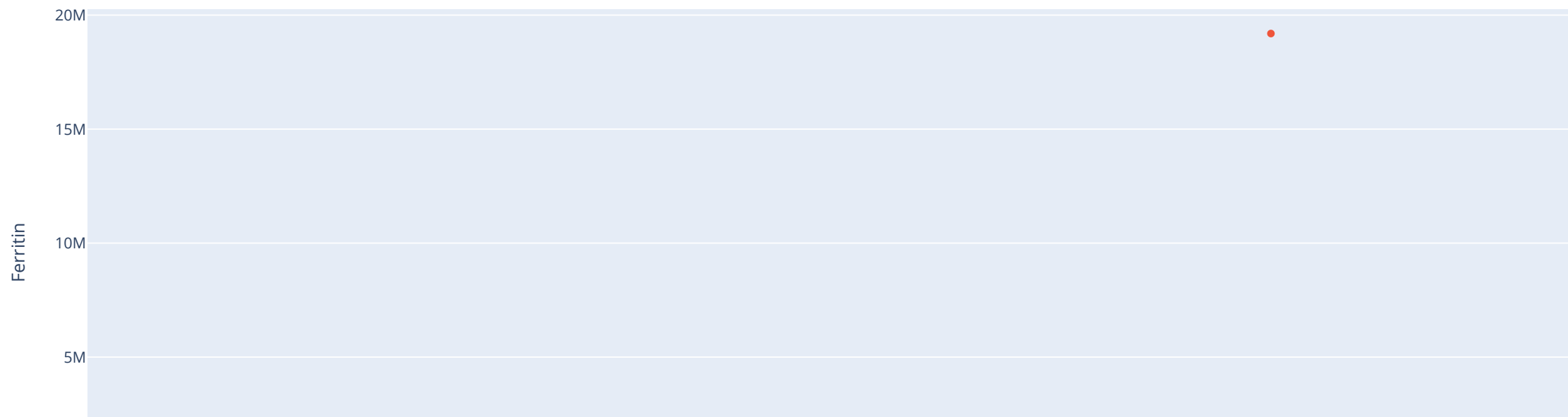
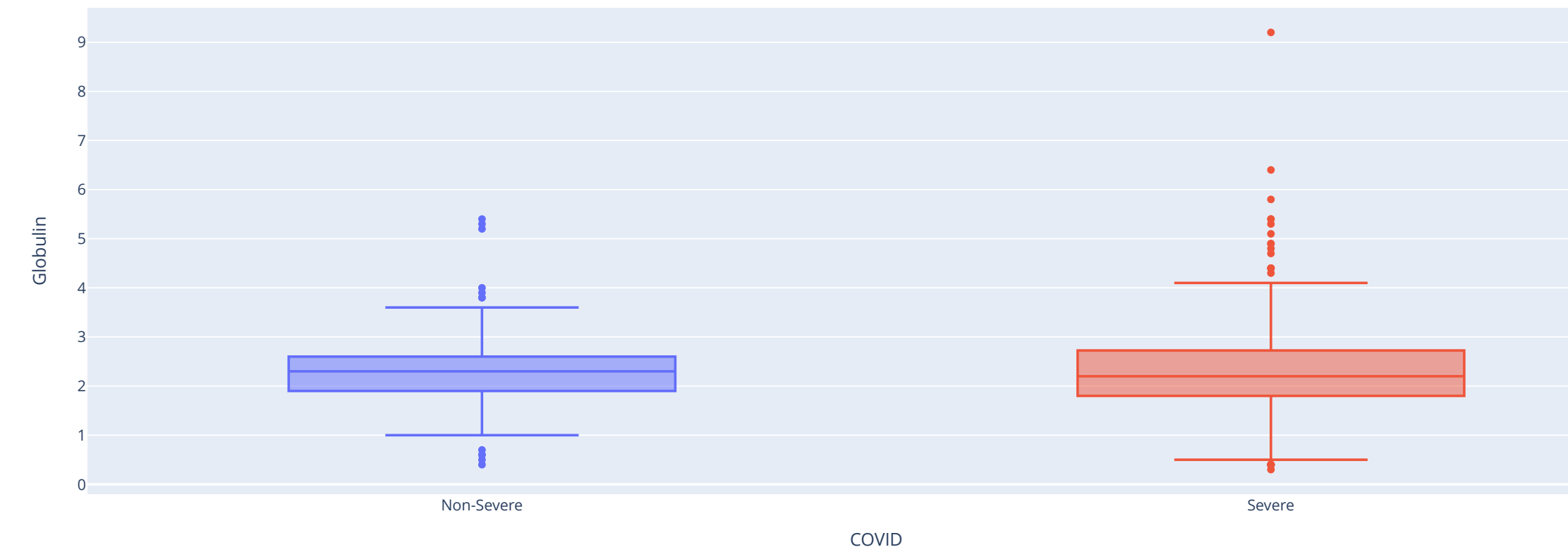


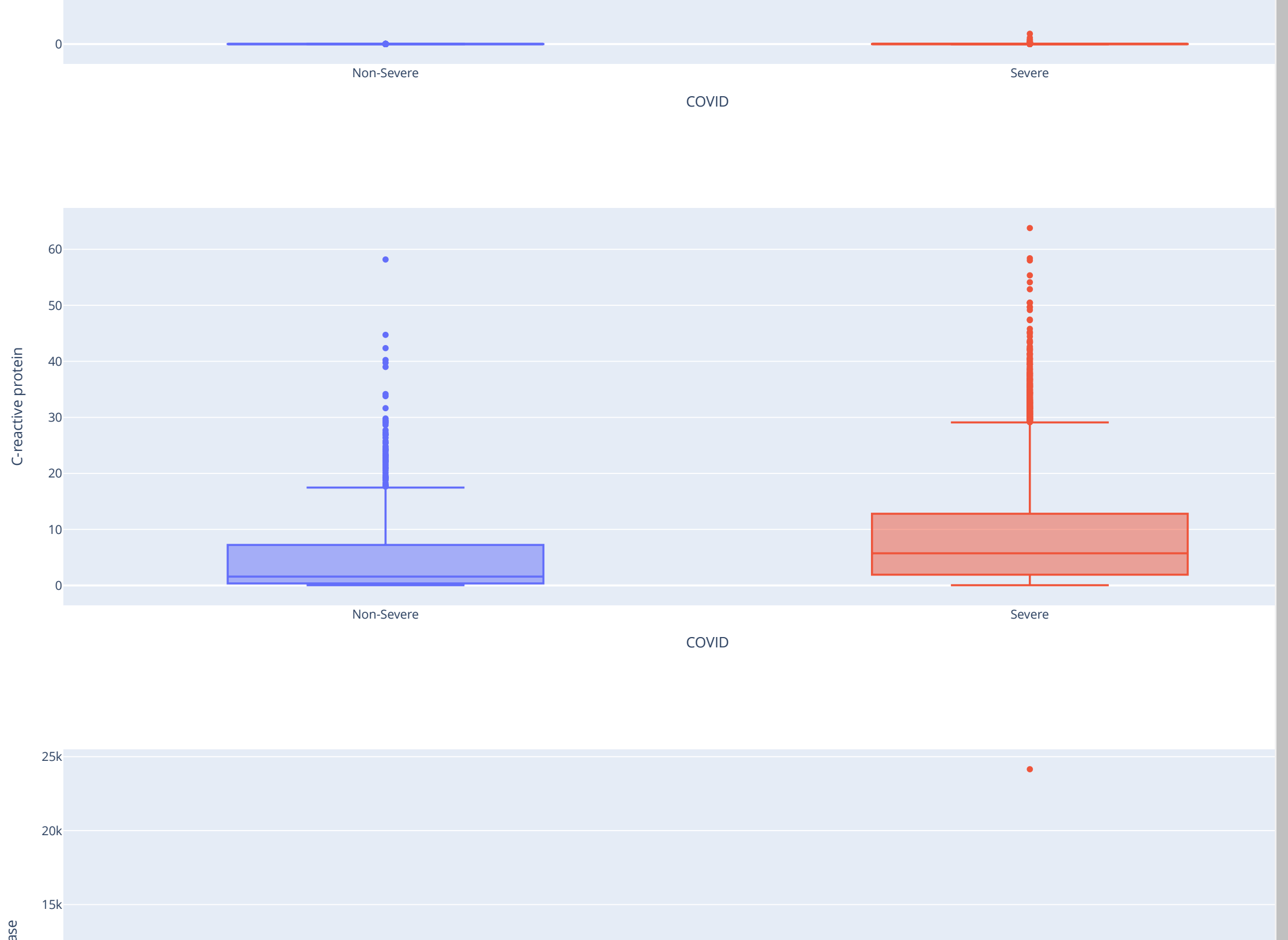










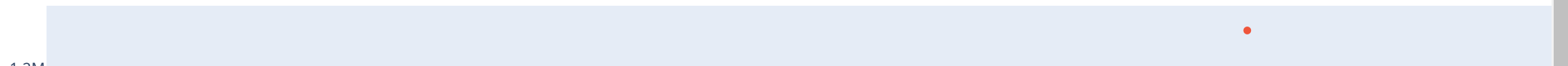


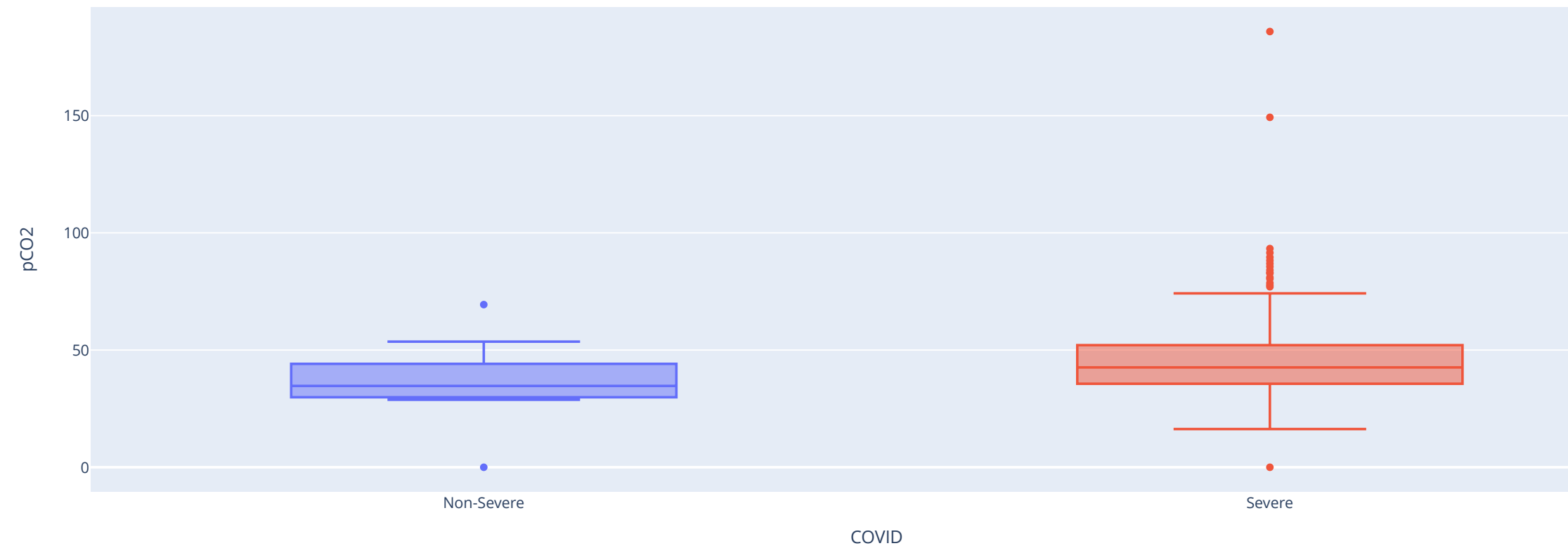
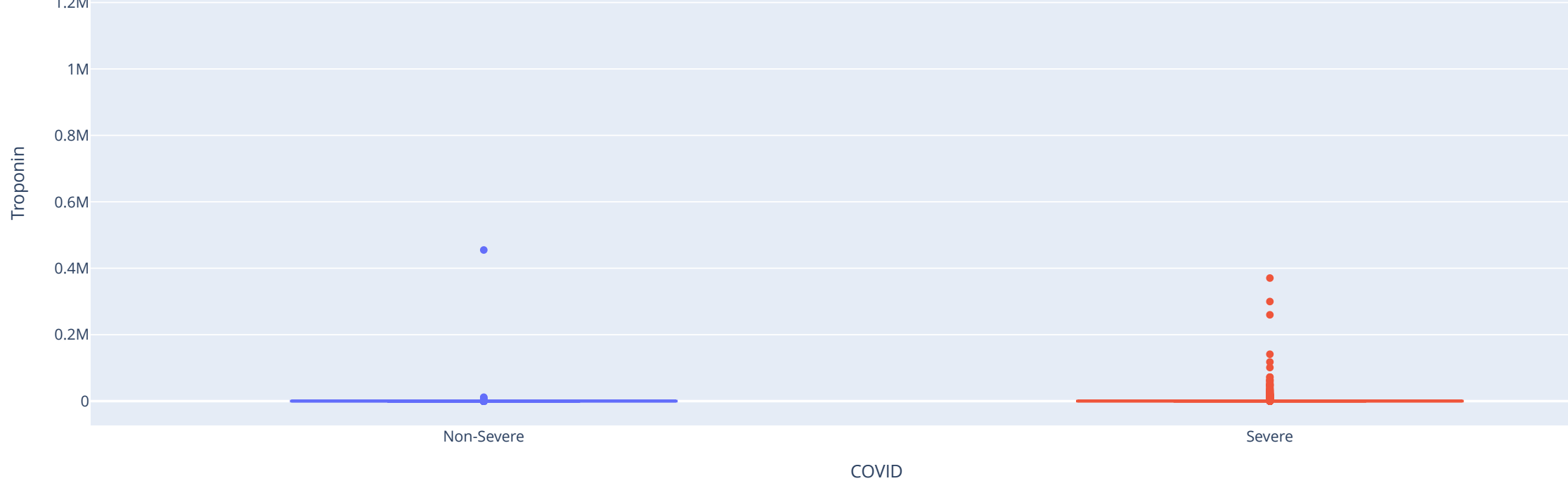


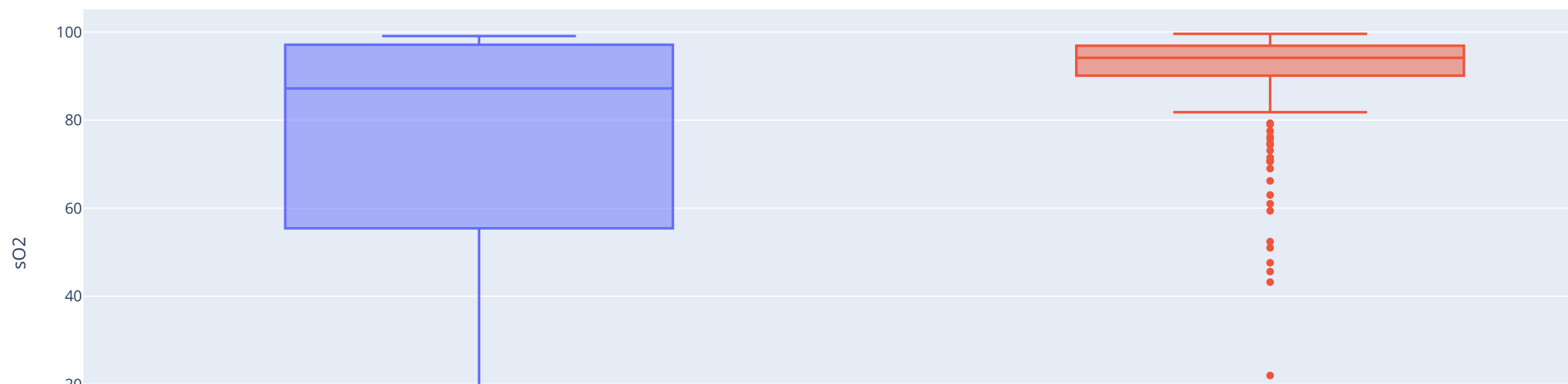
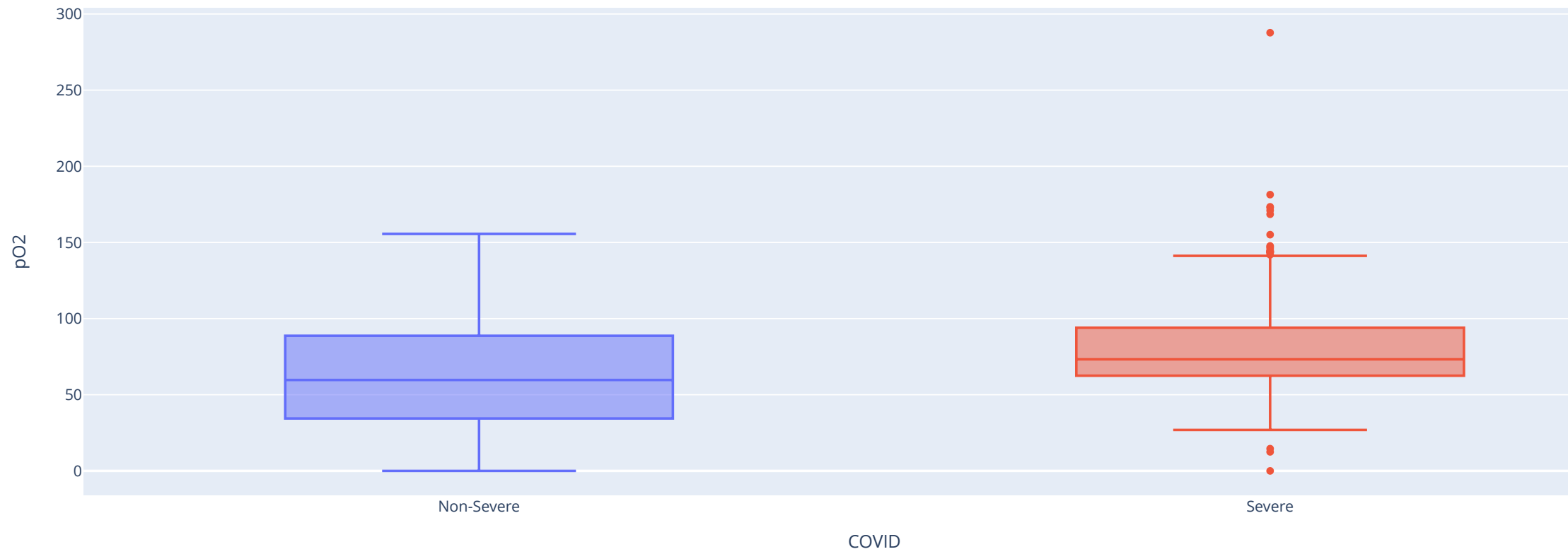
COVID



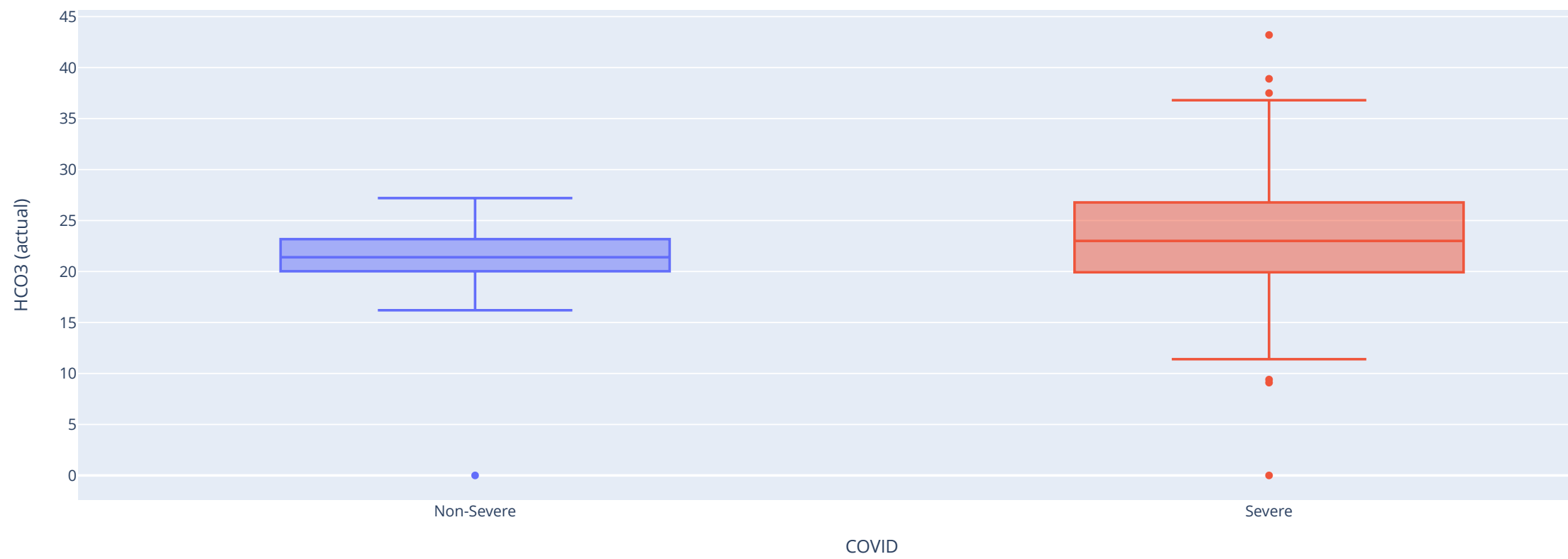
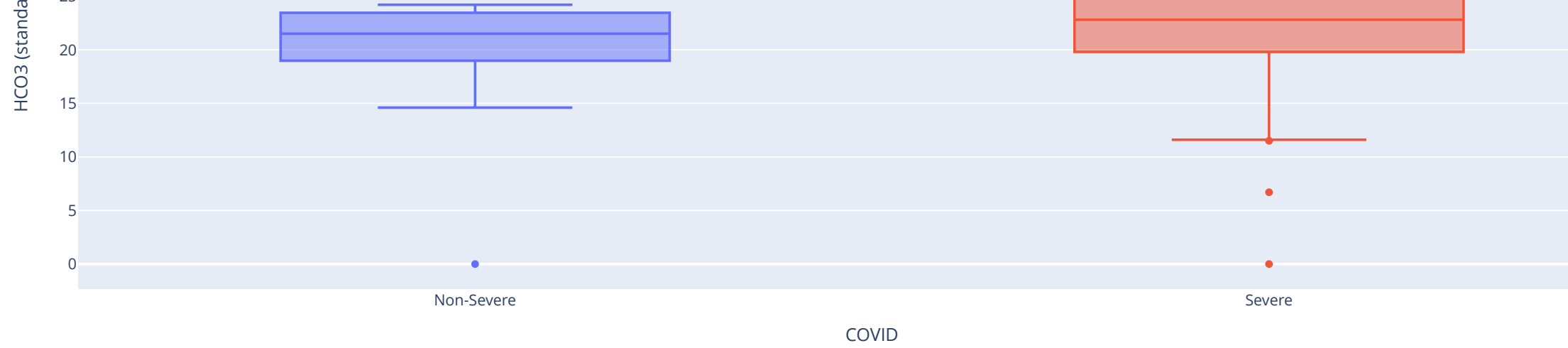
COVID



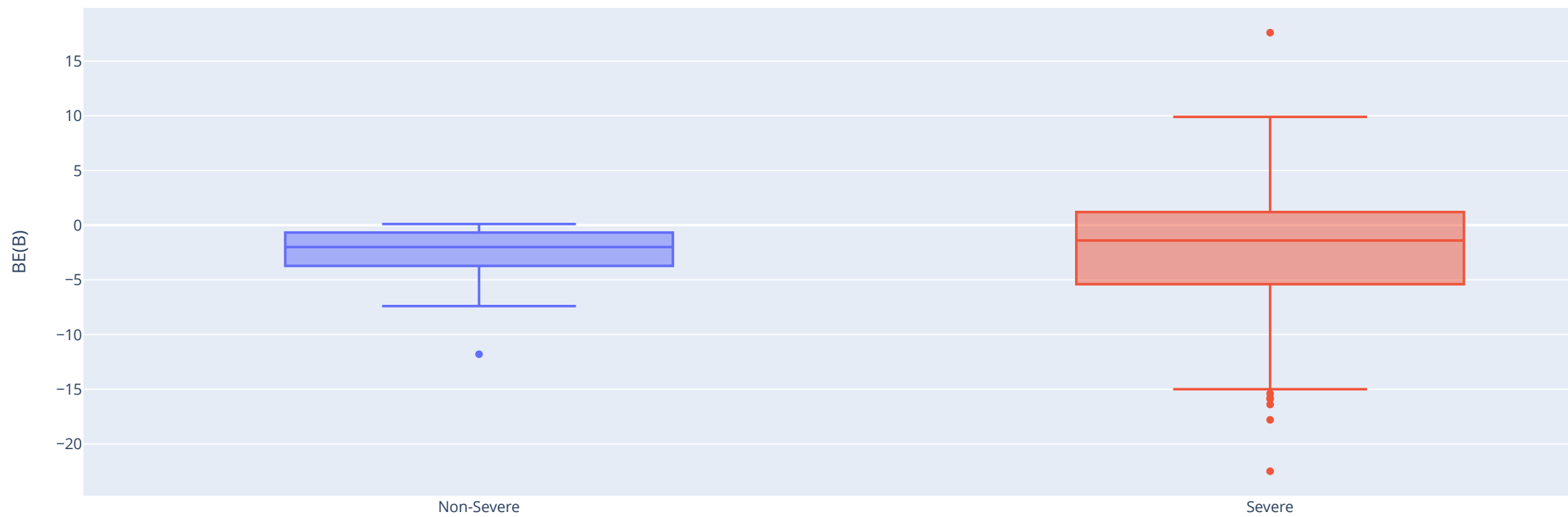
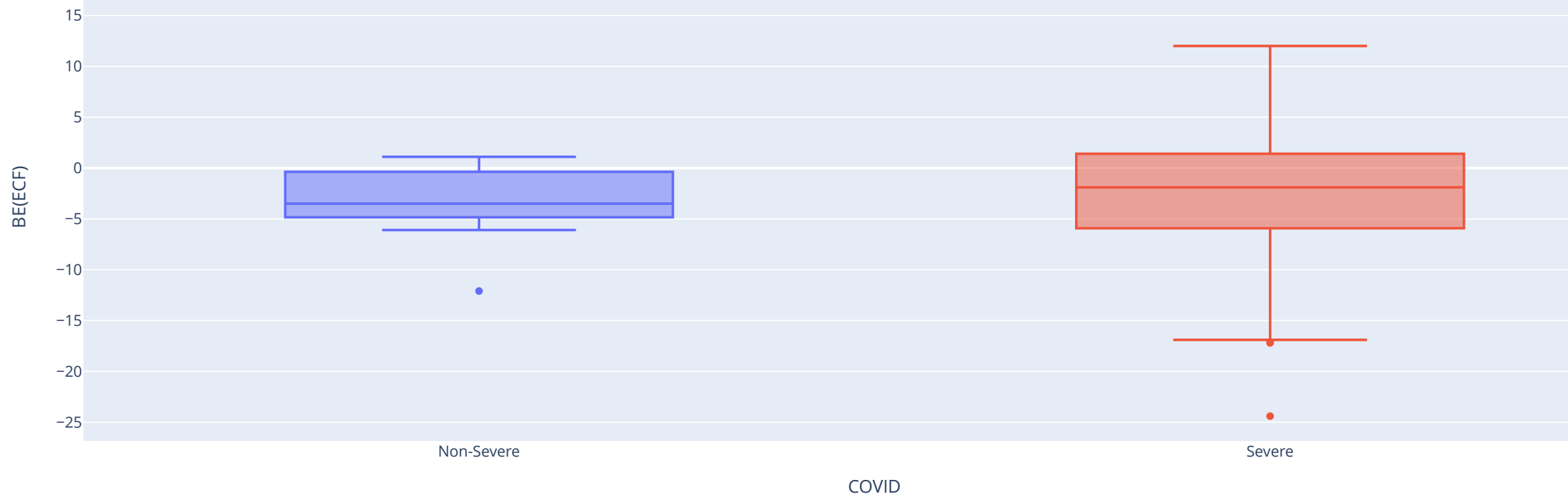




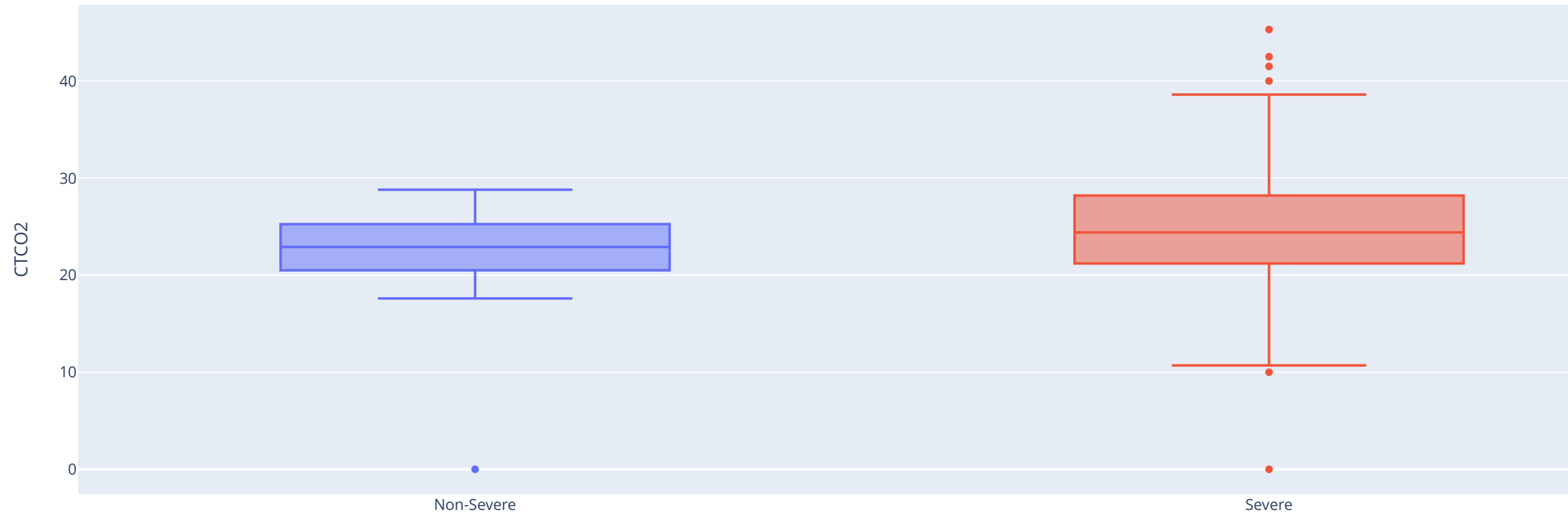




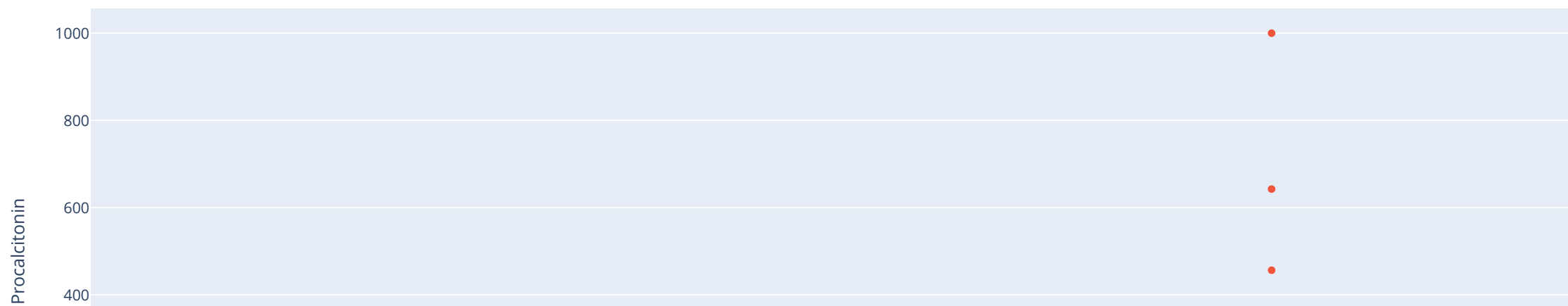
20



COVID



COVID



Insights:

In general, the levels of all biomarkers varied between SEVERE and NON-SEVERE samples for COVID-19.
In general, SEVERE samples for COVID-19 had altered laboratory measurements compared to NON-SEVERE samples for COVID-19.
SEVERE samples for COVID-19 demonstrate changes in laboratory measurements.
All variables are important for analyzing the two groups of samples.
The differences between the groups show that an in-depth study of supervised Machine Learning is justifiable.

Phase 5: Install the Pycaret library to aid Auto-Machine Learn

!pip install pycaret

```
Requirement already satisfied: pycaret in /usr/local/lib/python3.10/dist-packages (3.2.0)
Requirement already satisfied: category-encoders>=2.4.0 in /usr/local/lib/python3.10/dist-packages (from pycaret) (2.6.3)
Requirement already satisfied: cloudpickle in /usr/local/lib/python3.10/dist-packages (from pycaret) (2.2.1)
Requirement already satisfied: deprecation>=2.1.0 in /usr/local/lib/python3.10/dist-packages (from pycaret) (2.1.0)
Requirement already satisfied: imbalanced-learn>=0.8.1 in /usr/local/lib/python3.10/dist-packages (from pycaret) (0.10.1)
Requirement already satisfied: importlib-metadata>=4.12.0 in /usr/local/lib/python3.10/dist-packages (from pycaret) (7.0.0)
Requirement already satisfied: ipython>=5.5.0 in /usr/local/lib/python3.10/dist-packages (from pycaret) (7.34.0)
Requirement already satisfied: ipywidgets>=7.6.5 in /usr/local/lib/python3.10/dist-packages (from pycaret) (7.7.1)
Requirement already satisfied: jinja2>=1.2 in /usr/local/lib/python3.10/dist-packages (from pycaret) (3.1.2)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.10/dist-packages (from pycaret) (1.3.2)
Requirement already satisfied: kaleido>=0.2.1 in /usr/local/lib/python3.10/dist-packages (from pycaret) (0.2.1)
Requirement already satisfied: lightgbm>=3.0.0 in /usr/local/lib/python3.10/dist-packages (from pycaret) (4.1.0)
Requirement already satisfied: markupsafe>=2.0.1 in /usr/local/lib/python3.10/dist-packages (from pycaret) (2.1.3)
Requirement already satisfied: matplotlib<=3.6,>=3.3.0 in /usr/local/lib/python3.10/dist-packages (from pycaret) (3.6.0)
Requirement already satisfied: nbformat>=4.2.0 in /usr/local/lib/python3.10/dist-packages (from pycaret) (5.9.2)
Requirement already satisfied: numba>=0.55.0 in /usr/local/lib/python3.10/dist-packages (from pycaret) (0.58.1)
Requirement already satisfied: numpy<1.27,>=1.21 in /usr/local/lib/python3.10/dist-packages (from pycaret) (1.23.5)
Requirement already satisfied: pandas<2.0.0,>=1.3.0 in /usr/local/lib/python3.10/dist-packages (from pycaret) (1.5.3)
Requirement already satisfied: plotly-resampler>=0.8.3.1 in /usr/local/lib/python3.10/dist-packages (from pycaret) (0.9.1)
Requirement already satisfied: plotly>=5.0.0 in /usr/local/lib/python3.10/dist-packages (from pycaret) (5.15.0)
Requirement already satisfied: pmdarima!=1.8.1,<3.0.0,>=1.8.0 in /usr/local/lib/python3.10/dist-packages (from pycaret) (2.0.4)
Requirement already satisfied: psutil>=5.9.0 in /usr/local/lib/python3.10/dist-packages (from pycaret) (5.9.5)
Requirement already satisfied: pyod>=1.0.8 in /usr/local/lib/python3.10/dist-packages (from pycaret) (1.1.2)
Requirement already satisfied: requests>=2.27.1 in /usr/local/lib/python3.10/dist-packages (from pycaret) (2.31.0)
Requirement already satisfied: schemdraw==0.15 in /usr/local/lib/python3.10/dist-packages (from pycaret) (0.15)
Requirement already satisfied: scikit-learn<1.3.0,>=1.0 in /usr/local/lib/python3.10/dist-packages (from pycaret) (1.2.2)
Requirement already satisfied: scikit-plot>=0.3.7 in /usr/local/lib/python3.10/dist-packages (from pycaret) (0.3.7)
Requirement already satisfied: scipy~=1.10.1 in /usr/local/lib/python3.10/dist-packages (from pycaret) (1.10.1)
Requirement already satisfied: sktime!=0.17.1,!0.17.2,!0.18.0,<0.22.0,>=0.16.1 in /usr/local/lib/python3.10/dist-packages (from pycaret) (0.21.1)
Requirement already satisfied: statsmodels>=0.12.1 in /usr/local/lib/python3.10/dist-packages (from pycaret) (0.14.1)
Requirement already satisfied: tbats>=1.1.3 in /usr/local/lib/python3.10/dist-packages (from pycaret) (1.1.3)
Requirement already satisfied: tqdm>=4.62.0 in /usr/local/lib/python3.10/dist-packages (from pycaret) (4.66.1)
Requirement already satisfied: xxhash in /usr/local/lib/python3.10/dist-packages (from pycaret) (3.4.1)
Requirement already satisfied: yellowbrick>=1.4 in /usr/local/lib/python3.10/dist-packages (from pycaret) (1.5)
Requirement already satisfied: wurlitzer in /usr/local/lib/python3.10/dist-packages (from pycaret) (3.0.3)
Requirement already satisfied: patsy>=0.5.1 in /usr/local/lib/python3.10/dist-packages (from category-encoders>=2.4.0->pycaret) (0.5.4)
```



```
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (from deprecation>=2.1.0->pycaret) (23.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from imbalanced-learn>=0.8.1->pycaret) (3.2.0)
Requirement already satisfied: zipp>=0.5 in /usr/local/lib/python3.10/dist-packages (from importlib-metadata>=4.12.0->pycaret) (3.17.0)
Requirement already satisfied: setuptools>=18.5 in /usr/local/lib/python3.10/dist-packages (from ipython>=5.5.0->pycaret) (67.7.2)
Requirement already satisfied: jedi>=0.16 in /usr/local/lib/python3.10/dist-packages (from ipython>=5.5.0->pycaret) (0.19.1)
Requirement already satisfied: decorator in /usr/local/lib/python3.10/dist-packages (from ipython>=5.5.0->pycaret) (4.4.2)
Requirement already satisfied: pickleshare in /usr/local/lib/python3.10/dist-packages (from ipython>=5.5.0->pycaret) (0.7.5)
Requirement already satisfied: traitlets>=4.2 in /usr/local/lib/python3.10/dist-packages (from ipython>=5.5.0->pycaret) (5.7.1)
Requirement already satisfied: prompt-toolkit!=3.0.0,!<3.0.1,<3.1.0,>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from ipython>=5.5.0->pycaret) (3.0.43)
Requirement already satisfied: pygments in /usr/local/lib/python3.10/dist-packages (from ipython>=5.5.0->pycaret) (2.16.1)
Requirement already satisfied: backcall in /usr/local/lib/python3.10/dist-packages (from ipython>=5.5.0->pycaret) (0.2.0)
Requirement already satisfied: matplotlib-inline in /usr/local/lib/python3.10/dist-packages (from ipython>=5.5.0->pycaret) (0.1.6)
Requirement already satisfied: pexpect>4.3 in /usr/local/lib/python3.10/dist-packages (from ipython>=5.5.0->pycaret) (4.9.0)
Requirement already satisfied: ipykernel>=4.5.1 in /usr/local/lib/python3.10/dist-packages (from ipywidgets>=7.6.5->pycaret) (5.5.6)
Requirement already satisfied: ipython-genutils~0.2.0 in /usr/local/lib/python3.10/dist-packages (from ipywidgets>=7.6.5->pycaret) (0.2.0)
Requirement already satisfied: widgetsnbextension~3.6.0 in /usr/local/lib/python3.10/dist-packages (from ipywidgets>=7.6.5->pycaret) (3.6.6)
Requirement already satisfied: jupyterlab-widgets>=1.0.0 in /usr/local/lib/python3.10/dist-packages (from ipywidgets>=7.6.5->pycaret) (3.0.9)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib<=3.6,>=3.3.0->pycaret) (1.2.0)
Requirement already satisfied: cycycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib<=3.6,>=3.3.0->pycaret) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib<=3.6,>=3.3.0->pycaret) (4.46.0)
Requirement alreadyv satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib<=3.6,>=3.3.0->pycaret) (1.4.5)
```

```
#Phase 6: Import the Pycaret library
from pycaret import classification
```

```
# Phase 7: Perform data pre-processing
classification_setup = classification.setup(data = DataSetSeverity, target = "COVID")
```

Description		Value
0	Session id	8801
1	Target	COVID
2	Target type	Binary
3	Target mapping	Non-Severe: 0, Severe: 1
4	Original data shape	(35109, 51)
5	Transformed data shape	(35109, 51)
6	Transformed train set shape	(24576, 51)
7	Transformed test set shape	(10533, 51)
8	Numeric features	50
# Phase 8: Build and compare models		
models = classification.compare_models()		

	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
lightgbm	Light Gradient Boosting Machine	0.8808	0.9177	0.8808	0.8757	0.8757	0.6250	0.6314	2.3050
xgboost	Extreme Gradient Boosting	0.8796	0.9153	0.8796	0.8747	0.8751	0.6247	0.6297	0.9890
rf	Random Forest Classifier	0.8786	0.9060	0.8786	0.8732	0.8725	0.6136	0.6220	5.0830
et	Extra Trees Classifier	0.8779	0.9047	0.8779	0.8726	0.8714	0.6098	0.6191	4.6190
gbc	Gradient Boosting Classifier	0.8636	0.8939	0.8636	0.8572	0.8525	0.5460	0.5645	6.4250
ada	Ada Boost Classifier	0.8481	0.8744	0.8481	0.8383	0.8375	0.5024	0.5153	1.5700
dt	Decision Tree Classifier	0.8144	0.7358	0.8144	0.8168	0.8155	0.4656	0.4658	0.7540
lda	Linear Discriminant Analysis	0.8087	0.7927	0.8087	0.7870	0.7780	0.3002	0.3373	0.4800
ridge	Ridge Classifier	0.8029	0.0000	0.8029	0.7818	0.7587	0.2326	0.2909	0.3030
lr	Logistic Regression	0.8011	0.7758	0.8011	0.7755	0.7634	0.2505	0.2942	2.1290
knn	K Neighbors Classifier	0.7882	0.6947	0.7882	0.7582	0.7616	0.2545	0.2740	1.1900
dummy	Dummy Classifier	0.7802	0.5000	0.7802	0.6086	0.6838	0.0000	0.0000	0.2790
svm	SVM - Linear Kernel	0.7059	0.0000	0.7059	0.7054	0.6286	0.0170	0.0361	1.1300
qda	Quadratic Discriminant Analysis	0.4920	0.6480	0.4920	0.7780	0.4170	0.0281	0.0930	0.2750
nb	Naive Bayes	0.2816	0.7064	0.2816	0.7608	0.2069	0.0263	0.0890	0.1950

```
# Phase 9: Train the best model based on predictive performance metrics
# First: The Light Gradient Boosting Machine (lightgbm) model achieved the best performance. We will create the Light Gradient Boosting Machine model
model_lightgbm = classification.create_model("lightgbm")
```

	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
Fold							
0	0.8763	0.9131	0.8763	0.8708	0.8692	0.6016	0.6123
1	0.8869	0.9166	0.8869	0.8825	0.8825	0.6461	0.6516
2	0.8853	0.9168	0.8853	0.8806	0.8803	0.6384	0.6451
3	0.8857	0.9281	0.8857	0.8812	0.8814	0.6436	0.6487
4	0.8747	0.9131	0.8747	0.8691	0.8695	0.6068	0.6127
5	0.8747	0.9128	0.8747	0.8690	0.8692	0.6057	0.6120
6	0.8889	0.9237	0.8889	0.8846	0.8846	0.6527	0.6581
7	0.8873	0.9295	0.8873	0.8833	0.8841	0.6540	0.6569
8	0.8738	0.9100	0.8738	0.8680	0.8681	0.6014	0.6082
9	0.8742	0.9130	0.8742	0.8684	0.8680	0.6000	0.6081
Mean	0.8808	0.9177	0.8808	0.8757	0.8757	0.6250	0.6314
Std	0.0061	0.0066	0.0061	0.0068	0.0070	0.0224	0.0211

```
# Second: The Extreme Gradient Boosting (xgboost) model second the best performance.
model_xgboost = classification.create_model("xgboost")
```

	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
Fold							
0	0.8788	0.9058	0.8788	0.8735	0.8736	0.6185	0.6247
1	0.8792	0.9149	0.8792	0.8745	0.8755	0.6275	0.6308
2	0.8820	0.9125	0.8820	0.8772	0.8776	0.6319	0.6368

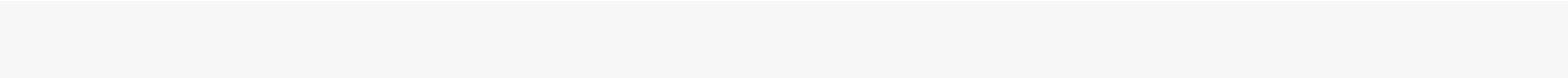
```
# Third: The Random Forest Classifier (rf) model third the best performance.
model_rf = classification.create_model("rf")
```

	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
Fold							
0	0.8714	0.9073	0.8714	0.8652	0.8641	0.5865	0.5966
1	0.8824	0.9112	0.8824	0.8776	0.8779	0.6324	0.6377
2	0.8804	0.9024	0.8804	0.8752	0.8749	0.6220	0.6290
3	0.8865	0.9146	0.8865	0.8822	0.8807	0.6384	0.6475
4	0.8808	0.8955	0.8808	0.8757	0.8752	0.6230	0.6305
5	0.8686	0.9034	0.8686	0.8621	0.8602	0.5734	0.5858
6	0.8856	0.9138	0.8856	0.8811	0.8808	0.6405	0.6468
7	0.8873	0.9178	0.8873	0.8829	0.8832	0.6491	0.6539
8	0.8718	0.8931	0.8718	0.8657	0.8642	0.5863	0.5972
9	0.8710	0.9004	0.8710	0.8647	0.8635	0.5843	0.5948
Mean	0.8786	0.9060	0.8786	0.8732	0.8725	0.6136	0.6220
Std	0.0068	0.0079	0.0068	0.0076	0.0082	0.0266	0.0244

```
# Fourth: The Extra Trees Classifier (et) model fourth the best performance.
model_et = classification.create_model("et")
```

	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
Fold							
0	0.8694	0.9029	0.8694	0.8629	0.8615	0.5778	0.5889
1	0.8779	0.9055	0.8779	0.8726	0.8729	0.6170	0.6227
2	0.8804	0.9043	0.8804	0.8752	0.8745	0.6198	0.6279
3	0.8873	0.9129	0.8873	0.8832	0.8812	0.6395	0.6496
4	0.8767	0.8945	0.8767	0.8712	0.8707	0.6090	0.6168
5	0.8674	0.9035	0.8674	0.8608	0.8584	0.5672	0.5808
6	0.8828	0.9101	0.8828	0.8779	0.8776	0.6302	0.6370
7	0.8864	0.9134	0.8864	0.8819	0.8815	0.6425	0.6491
# Fifth: The Gradient Boosting Classifier (gbc) model fifth the best performance. model_gbc = classification.create_model("gbc")							

	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC
Fold							
0	0.8641	0.8834	0.8641	0.8588	0.8514	0.5400	0.5636
1	0.8653	0.8987	0.8653	0.8591	0.8545	0.5521	0.5703
2	0.8621	0.8939	0.8621	0.8554	0.8505	0.5392	0.5583
3	0.8694	0.9031	0.8694	0.8635	0.8599	0.5709	0.5865
4	0.8621	0.8902	0.8621	0.8556	0.8503	0.5386	0.5586
5	0.8592	0.8897	0.8592	0.8519	0.8476	0.5308	0.5494
6	0.8649	0.9025	0.8649	0.8582	0.8547	0.5538	0.5699
7	0.8694	0.9058	0.8694	0.8632	0.8604	0.5727	0.5867
8	0.8641	0.8817	0.8641	0.8578	0.8528	0.5463	0.5654
9	0.8559	0.8903	0.8559	0.8481	0.8431	0.5154	0.5359
Mean	0.8636	0.8939	0.8636	0.8572	0.8525	0.5460	0.5645
Std	0.0039	0.0079	0.0039	0.0045	0.0050	0.0165	0.0147



```
# Phase 10: Extract the metrics results from the 5 top models
# First: lightgbm model metrics
classification.evaluate_model(model_lightgbm)
```

Plot Type:

Pipeline Plot

Hyperparameters

AUC

Confusion Matrix

Threshold

Precision Recall

Prediction Error

Class Report

Feature Selection

Learning Curve

Manifold Learning

Calibration Curve

Validation Curve

Dimensions

Feature Importance

Feature Importance...

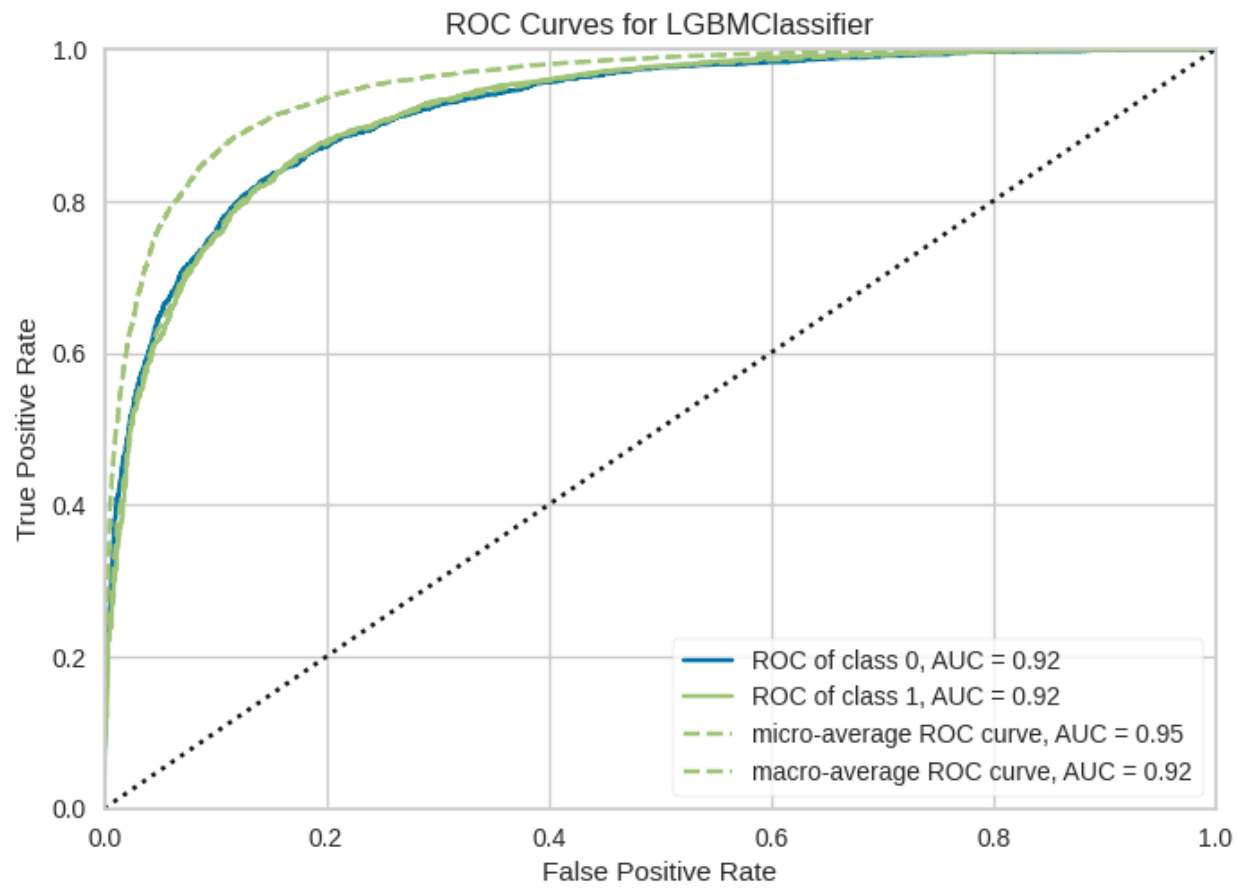
Decision Boundary

Lift Chart

Gain Chart

Decision Tree

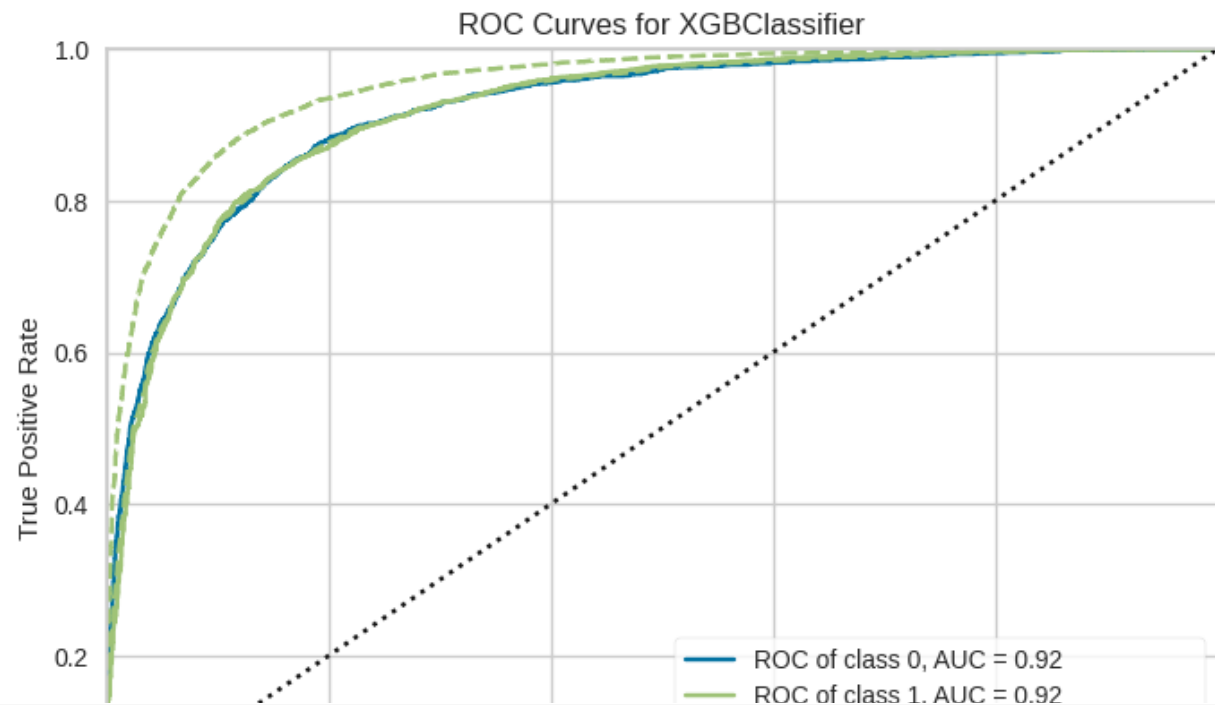
KS Statistic Plot



```
# Second: xgboost model metrics
classification.evaluate_model(model_xgboost)
```

Plot Type:

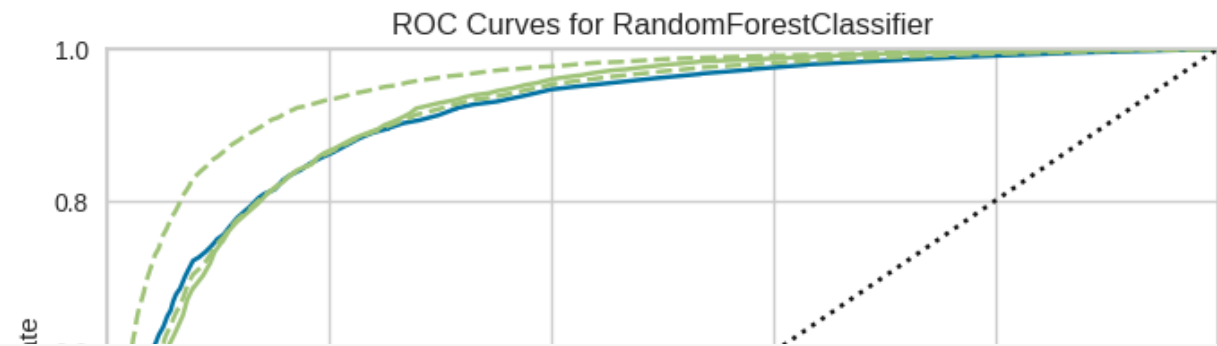
Pipeline Plot	Hyperparameters	AUC	Confusion Matrix	Threshold	Precision Recall	Prediction Error	Class Report
Feature Selection	Learning Curve	Manifold Learning	Calibration Curve	Validation Curve	Dimensions	Feature Importance	Feature Importance...
Decision Boundary	Lift Chart	Gain Chart	Decision Tree	KS Statistic Plot			



```
# Third: rf model metrics
classification.evaluate_model(model_rf)
```

Plot Type:

Pipeline Plot	Hyperparameters	AUC	Confusion Matrix	Threshold	Precision Recall	Prediction Error	Class Report
Feature Selection	Learning Curve	Manifold Learning	Calibration Curve	Validation Curve	Dimensions	Feature Importance	Feature Importance...
Decision Boundary	Lift Chart	Gain Chart	Decision Tree	KS Statistic Plot			



```
# Fourth: et model metrics
classification.evaluate_model(model_et)
```


Plot Type:

Pipeline Plot

Hyperparameters

AUC

Confusion Matrix

Threshold

Precision Recall

Prediction Error

Class Report

Feature Selection

Learning Curve

Manifold Learning

Calibration Curve

Validation Curve

Dimensions

Feature Importance

Feature Importance...

Decision Boundary

Lift Chart

Gain Chart

Decision Tree

KS Statistic Plot

Fifth: gbc model metrics
classification.evaluate_model(model_gbc)

Plot Type:

Pipeline Plot

Hyperparameters

AUC

Confusion Matrix

Threshold

Precision Recall

Prediction Error

Class Report

Feature Selection

Learning Curve

Manifold Learning

Calibration Curve

Validation Curve

Dimensions

Feature Importance

Feature Importance...

Decision Boundary

Lift Chart

Gain Chart

Decision Tree

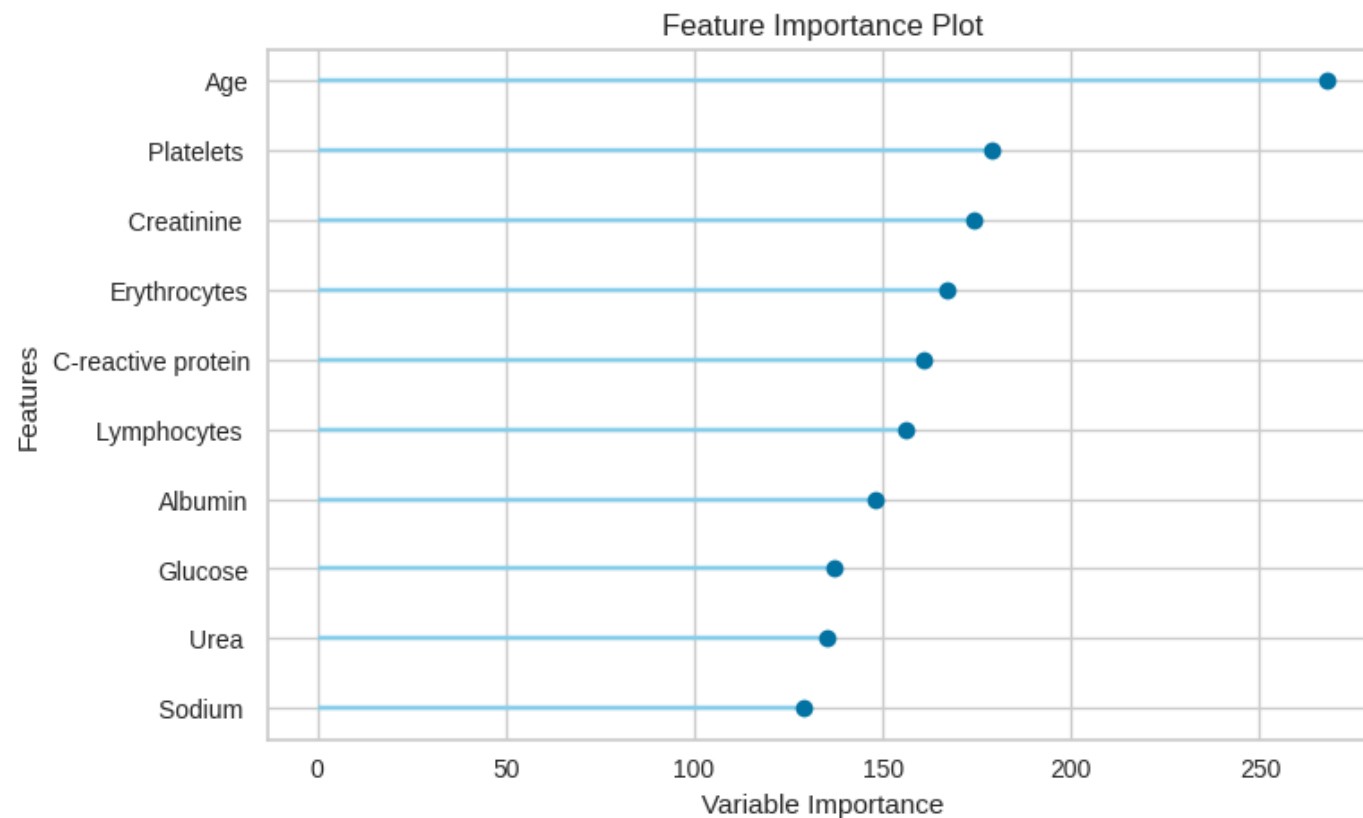
KS Statistic Plot

ROC Curves for GradientBoostingClassifier

The figure is a Receiver Operating Characteristic (ROC) curve plot titled "ROC Curves for GradientBoostingClassifier". The x-axis is labeled "False Positive Rate" and ranges from 0.0 to 1.0. The y-axis is labeled "True Positive Rate" and ranges from 0.0 to 1.0. A diagonal dotted line represents the performance of a random classifier. Four curves are plotted: a solid blue line for "ROC of class 0, AUC = 0.90", a solid green line for "ROC of class 1, AUC = 0.90", a dashed green line for "micro-average ROC curve, AUC = 0.94", and a dash-dot green line for "macro-average ROC curve, AUC = 0.90". All curves are significantly above the diagonal line, indicating good model performance.

Curve Type	AUC
ROC of class 0	0.90
ROC of class 1	0.90
micro-average ROC curve	0.94
macro-average ROC curve	0.90

Plotting only the 10 most important biomarkers for lightgbm model
classification.plot_model(model_lightgbm, plot ="feature")



```
# Phase 11: Write conclusions about the best identified model
# Several Machine Learning models were built to predict the diagnosis of COVID-19 using biomarker data from patients with COVID-19
# The Light Gradient Boosting Machine (lightgbm) model had the best predictive performance
# The 5 most important biomarkers for the prognosis of COVID-19, for the samples under study, were: C-reactive protein, Creatinine, Albumin, Lymphocytes and Erythrocytes
# The next step is to develop the App so that the model can be used in Health Institutions.
```

```
# Phase 12: Save the model to make predictions in real analyzes (Deploy)
classification.save_model(model_lightgbm, "BestModel-ML_LightGBM")

Transformation Pipeline and Model Successfully Saved
(Pipeline(memory=Memory(location=None),
  steps=[('label_encoding',
    TransformerWrapperWithInverse(exclude=None, include=None,
      transformer=LabelEncoder()))),
  ('numerical_imputer',
    TransformerWrapper(exclude=None,
      include=['Age', 'Sex', 'Erythrocytes',
        'Haemoglobin ', 'Leukocytes ',
        'Mature Neutrophils ',
        'Immature Neutrophils',
        'Neutrophils ', 'Basophils ',
```

```
        'Eosinophils ', 'Lym...
LGBMClassifier(boosting_type='gbdt', class_weight=None,
                colsample_bytree=1.0, importance_type='split',
                learning_rate=0.1, max_depth=-1,
                min_child_samples=20, min_child_weight=0.001,
                min_split_gain=0.0, n_estimators=100, n_jobs=-1,
                num_leaves=31, objective=None,
                random_state=8801, reg_alpha=0.0,
                reg_lambda=0.0, subsample=1.0,
                subsample_for_bin=200000, subsample_freq=0)],
        verbose=False),
'BestModel-ML_LightGBM.pkl')
```