SMARCO

SMARt COmmunities Skills Development in Europe

Urban Data Analytics

Dr. Assoc. Prof. Sotiris Kotsiantis

HELLENIC OPEN UNIVERSITY

Co-funded by the European Union

smarco

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

SMARCO

SMARt COmmunities Skills Development in Europe

Unit 3 – Visualization and outlier detection

Co-funded by the European Union

smarco

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

Unit 3 - Aim and objectives

- This unit introduces trainees to visualization of data. Trainees will also become familiar with outlier detection in data.

Co-funded by the European Union

smarco

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

Unit 3 - Learning outcomes

- Describe visualization techniques in data related to smart cities.
- Apply outlier detection in data related to smart cities.

Co-funded by the European Union

smarco

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

Table of contents

- Applications of visualization in the context of smart cities
- Visualizing air quality case study
- Outlier detection
- Outlier detection algorithms
- Applications of outlier detection in the context of smart cities

Co-funded by the European Union

smarco

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

Terms and keywords

- Visualization
- Line graphs, bar charts, and pie charts
- Outlier detection
- Isolation Forest

Co-funded by
the European Union

smarco

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

Applications of visualization in smart cities

- Network Visualization - Network Visualizations can be used to display the structure of the various digital infrastructures of a Smart City. This includes visualizing how the different systems and services are connected and how data flows throughout the city.
- Human Mobility Analysis - Smart cities often host a variety of connected devices that can detect physical movements such as taxi rides, public transportation usage or patterns of people moving around the city. Network visualizations can help to identify patterns in these movements or to identify potential problems in the structure of mobility choices or travel times.
- Air Quality Visualization - Smart cities have the ability to detect air quality and provide users with real-time data. This data can then be used to create visualizations that help analyze current air quality levels and observe potential changes over time.

Co-funded by the European Union

smarco

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

Applications of visualization in smart cities

- Traffic Data Visualization - Smart cities have a wealth of traffic data that can be used to develop visualizations that help identify issues in road structure or congestion problems.
- Energy Consumption Visualization - Smart cities can collect data on energy consumption to develop visualizations that allow energy-efficient optimization and better decision making. This can include visualizing electricity consumption within neighborhoods or across the city or mapping out patterns in resource utilization.

Co-funded by the European Union

smarco

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

Visualizing air quality

- Visualizing air quality can help people to have a better understanding of the pollution levels in their environment.
- Various graphical representations can be used to represent levels of air quality including line graphs, bar charts, and pie charts.
- Air quality open data often includes air quality indicators such as ozone (O3), nitrogen dioxide (NO2), particulate matter (PM2.5 and PM10), sulfur dioxide (SO2), lead (Pb), and volatile organic compounds (VOCs).

Co-funded by the European Union

smarco

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

Run Jupyter Online with Colab

- Google Colab is a cloud-based notebook environment that excels in collaborative work, data analysis, and machine learning tasks.
- You can write and execute python code, save and share your analyses, and access powerful computing resources, all for free from your browser.
- To start working with Colab you first need to log in to your google/gmail account, then go to this link https://colab.research.google.com.

Co-funded by the European Union

smarco

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

Visualization of air quality data

```python
import pandas as pd
!wget --no-check-certificate https://thalis.math.upatras.gr/~sotos/air-quality-india.csv
data = pd.read_csv('air-quality-india.csv',index_col=0, parse_dates=True)
data
```

	Year	Month	Day	Hour	PM2.5
Timestamp					
2017-11-07 12:00:00	2017	11	7	12	64.51
2017-11-07 13:00:00	2017	11	7	13	69.95
2017-11-07 14:00:00	2017	11	7	14	92.79
2017-11-07 15:00:00	2017	11	7	15	109.66
2017-11-07 16:00:00	2017	11	7	16	116.50
...	...	...	...	...	...

The AQI provides health categories corresponding to different concentration ranges of PM2.5. For example:

- 0-12 µg/m³: Good
- 12.1-35.4 µg/m³: Moderate
- 35.5-55.4 µg/m³: Unhealthy for sensitive groups
- 55.5-150.4 µg/m³: Unhealthy
- 150.5-250.4 µg/m³: Very Unhealthy
- 250.5 µg/m³ and above: Hazardous

- Adapted from https://www.kaggle.com/datasets/rohanrao/air-quality-data-in-india

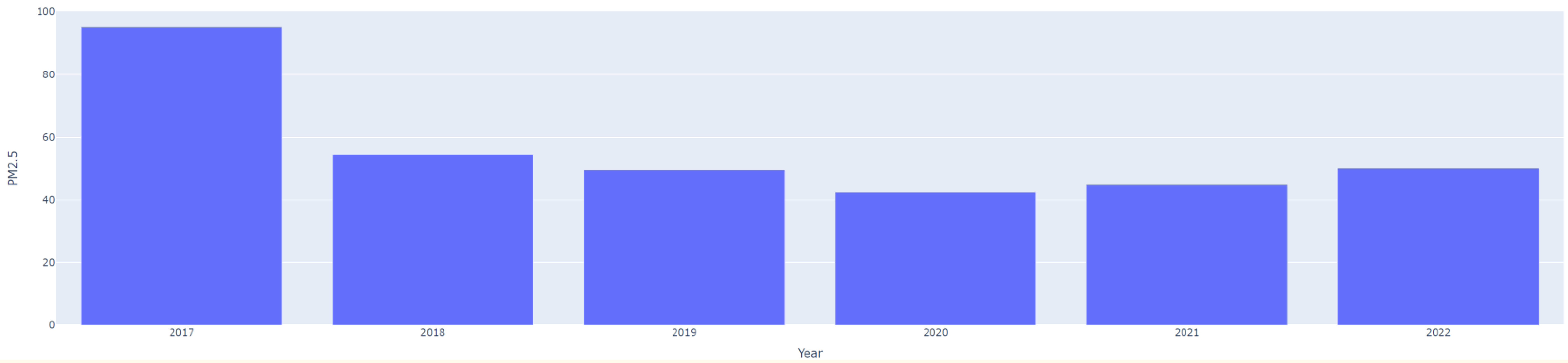
Co-funded by the European Union

smarco

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

Mean air quality per year

```
import plotly.express as px
fig = px.bar(data.groupby(["Year"])['PM2.5'].mean(), y="PM2.5")
fig.show()
```



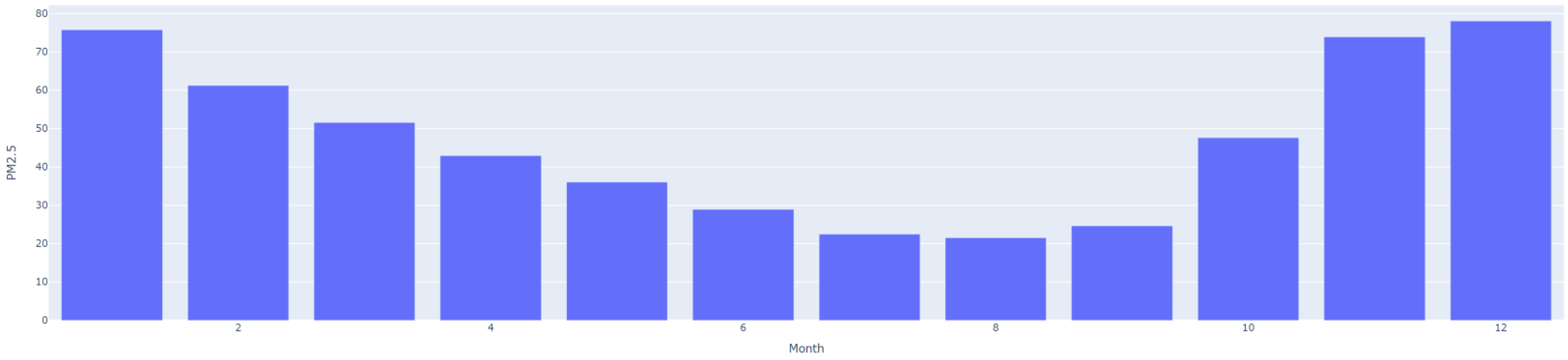
Co-funded by the European Union

smarco

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

Mean air quality per month

```
fig = px.bar(data.groupby(["Month"])['PM2.5'].mean(), y="PM2.5")
fig.show()
```



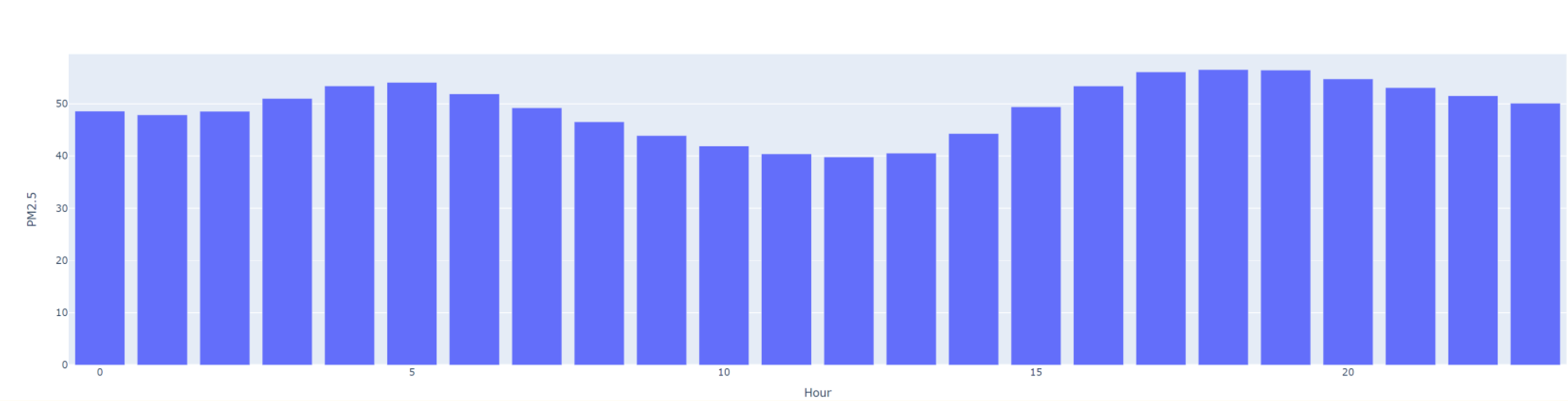
Co-funded by the European Union

smarco

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

Mean air quality per hour

```
fig = px.bar(data.groupby(["Hour"])['PM2.5'].mean(), y="PM2.5")
fig.show()
```



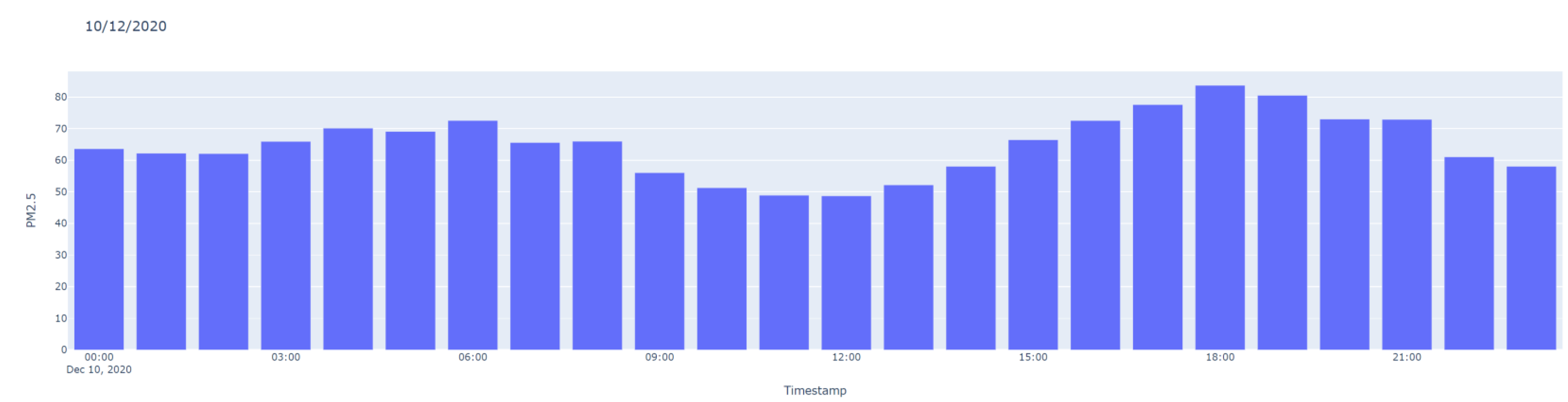
Co-funded by
the European Union

smarco

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

Air quality per hour a specific date

```
fig = px.bar(data.loc['2020-12-10'], y="PM2.5",title='10/12/2020')
fig.show()
```



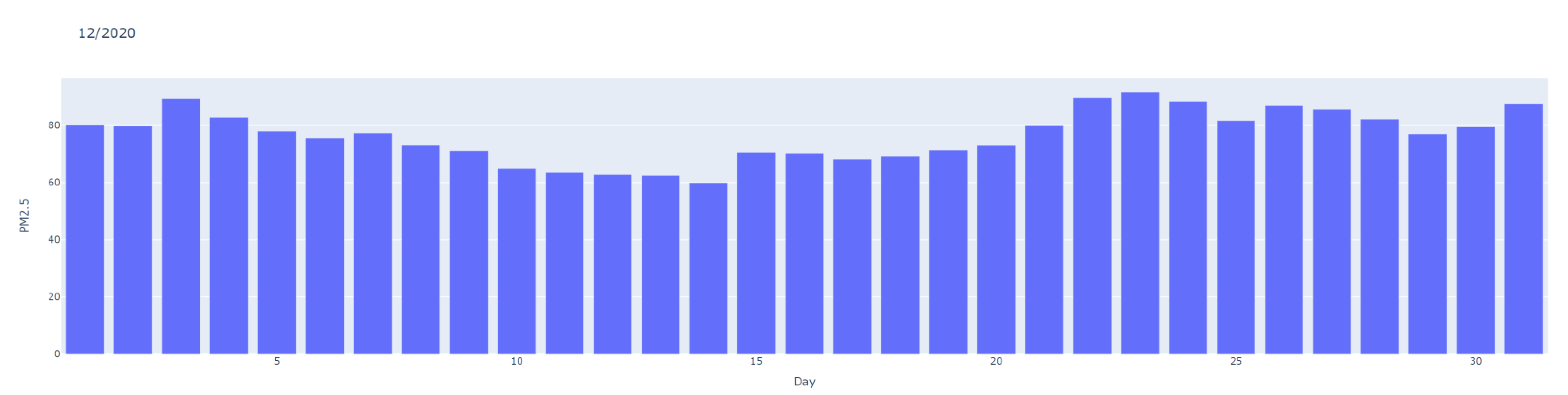
Co-funded by
the European Union

smarco

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

Air quality per day a specific month

```
fig = px.bar(data.loc['2020-12'].groupby(["Day"])['PM2.5'].mean(), y="PM2.5",title='12/2020')
fig.show()
```



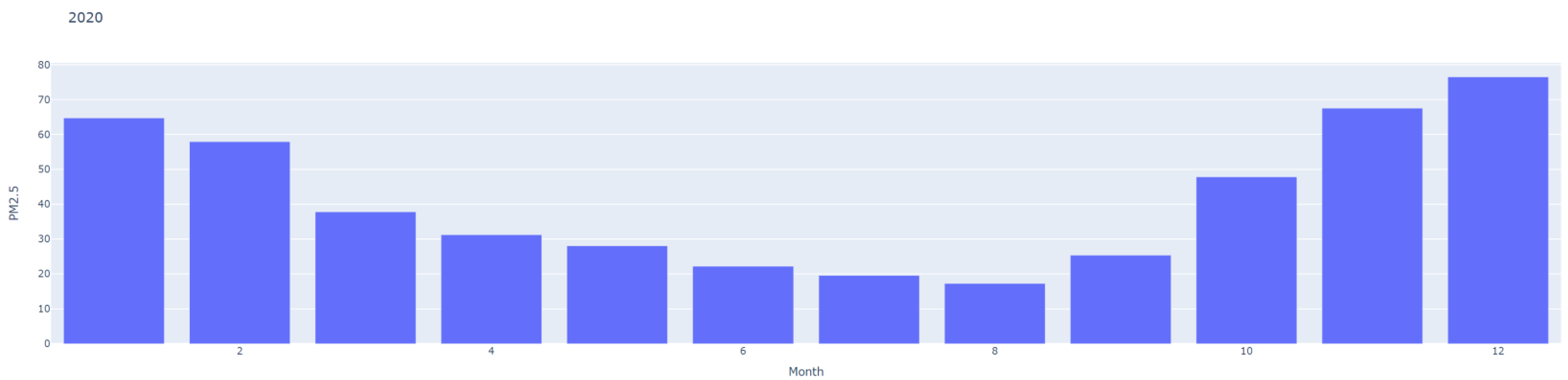
Co-funded by
the European Union

smarco

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

Air quality per month a specific year

```
fig = px.bar(data.loc['2020'].groupby(["Month"])['PM2.5'].mean(), y="PM2.5",title='2020')
fig.show()
```



Co-funded by the European Union

smarco

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

You can run the full example code

- https://colab.research.google.com/drive/10eg8RJ0ubUXwEgO-Qpm2EKY2Yij5lUg4?usp=sharing

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

Other applications of visualization

- Visualizing open data in smart cities can be done through a variety of methods.
  - One of the most common methods is to create maps of city data using geographic information systems (GIS) such as Esri ArcGIS Suite. Maps can illustrate a wide range of data points, from foot traffic to air quality, and provide insight into how a city is functioning.
  - Another popular method of visualization is to use interactive data visualizations or online dashboards to represent data. These visualizations often show data in real time and allow users to explore data sets in more detail.

Co-funded by the European Union

smarco

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

Outlier detection

- Outlier detection is the process of finding and analyzing data points that are significantly different from the rest of the data in a dataset.
- It is used to identify errors, inconsistent data or any type of unusual behavior that may be present in the data.
- Common approaches for outlier detection involve calculating summary statistics such as mean and standard deviation, using graphical techniques and using statistical models to identify outliers.

Co-funded by the European Union

smarco

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

Outlier detection algorithms

- Isolation Forest: Isolation Forest is an anomaly detection algorithm that isolates observations by randomly selecting a feature and then randomly selecting a split value between the maximum and minimum values of the selected feature. Isolation forest works by isolating observations away from the norm.
- DBSCAN: DBSCAN (Density-Based Spatial Clustering of Applications with Noise) is a data clustering algorithm that can identify outliers. It works by grouping together observations that are close together in terms of density. Outliers are, by definition, those that are too far away from the rest of the observations.
- One-Class Support Vector Machine: One-class support vector machine (OCSVM) is an unsupervised learning algorithm that can be used for outlier detection. It works by constructing a decision boundary around the data points that describe the normal behavior of the system. Data points outside the decision boundary are then identified as potential outliers.

Co-funded by the European Union

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

Outlier detection - case study

```
import pandas as pd
!wget --no-check-certificate https://thalis.math.upatras.gr/~sotos/Smart_City_index_headers.csv
data = pd.read_csv('Smart_City_index_headers.csv')
data
```

	Id	City	Country	Smart_Mobility	Smart_Environment	Smart_Government	Smart_Economy	Smart_People	Smart_Living	SmartCity_Index	SmartCity_Index_relative_Edmonton
0	1	Oslo	Norway	6480	6512	7516	4565	8618	9090	7138	666
1	2	Bergen	Norway	7097	6876	7350	4905	8050	9090	7296	823
2	3	Amsterdam	Netherlands	7540	5558	8528	8095	7098	7280	7311	839
3	4	Copenhagen	Denmark	7490	7920	8726	5580	5780	7200	7171	698
4	5	Stockholm	Sweden	6122	7692	8354	4330	6743	7730	6812	340
...	...	...	...	...	...	...	...	...	...	...	...

Co-funded by
the European Union

smarco

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

Dataset columns description

- Smart Mobility refers to the use of technology and data to improve transportation systems within a city.
- Smart Environment focuses on leveraging technology and data to monitor, manage, and improve environmental sustainability within a city.
- Smart Government involves the application of technology to enhance the efficiency, transparency, and responsiveness of government services.
- Smart Economy refers to the use of technology and innovation to drive economic development within a city.
- Smart People focus on initiatives that empower and engage citizens through technology.
- Smart Living involves using technology to enhance the overall quality of life for residents.
- A Smart City Index is a comprehensive assessment tool that evaluates and ranks cities based on various criteria related to their smart city initiatives. These indices typically cover multiple aspects, including technology, sustainability, governance, innovation, and quality of life.
- Smart City Index relative to Edmonton involve evaluating how well Edmonton performs compared to other cities in terms of its smart city initiatives across different categories.

Co-funded by the European Union

smarco

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

Outlier detection - case study

```
data = data.replace(" ", "")
data.columns = data.columns.str.replace(' ', '')
data = data.drop(columns='Id', errors='ignore')
scimean = (data.groupby('Country').median(numeric_only=True).astype(int).sort_values('SmartCity_Index', ascending=False).head(10))
scimean.style.background_gradient(cmap="GnBu")
```

Country	Smart_Mobility	Smart_Environment	Smart_Government	Smart_Economy	Smart_People	Smart_Living	SmartCity_Index	SmartCity_Index_relative_Edmonton
Netherlands	7540	5558	8528	8095	7098	7280	7311	839
Norway	6486	6989	7018	4925	7822	9090	7088	616
Canada	6727	4780	6510	6782	6930	9920	6866	394
Singapore	5790	4344	5560	5535	9695	10000	6813	341
Denmark	5876	8207	7540	5182	6386	7200	6803	330
Austria	5683	7608	6232	5415	8580	7500	6771	298
Sweden	4683	8296	7840	5980	6743	7730	6771	299
Switzerland	5326	8775	5591	6265	6425	7960	6707	235
Finland	5124	6519	6121	8155	5944	8710	6689	217
United States	7607	4800	5356	7265	6610	6220	6437	-35

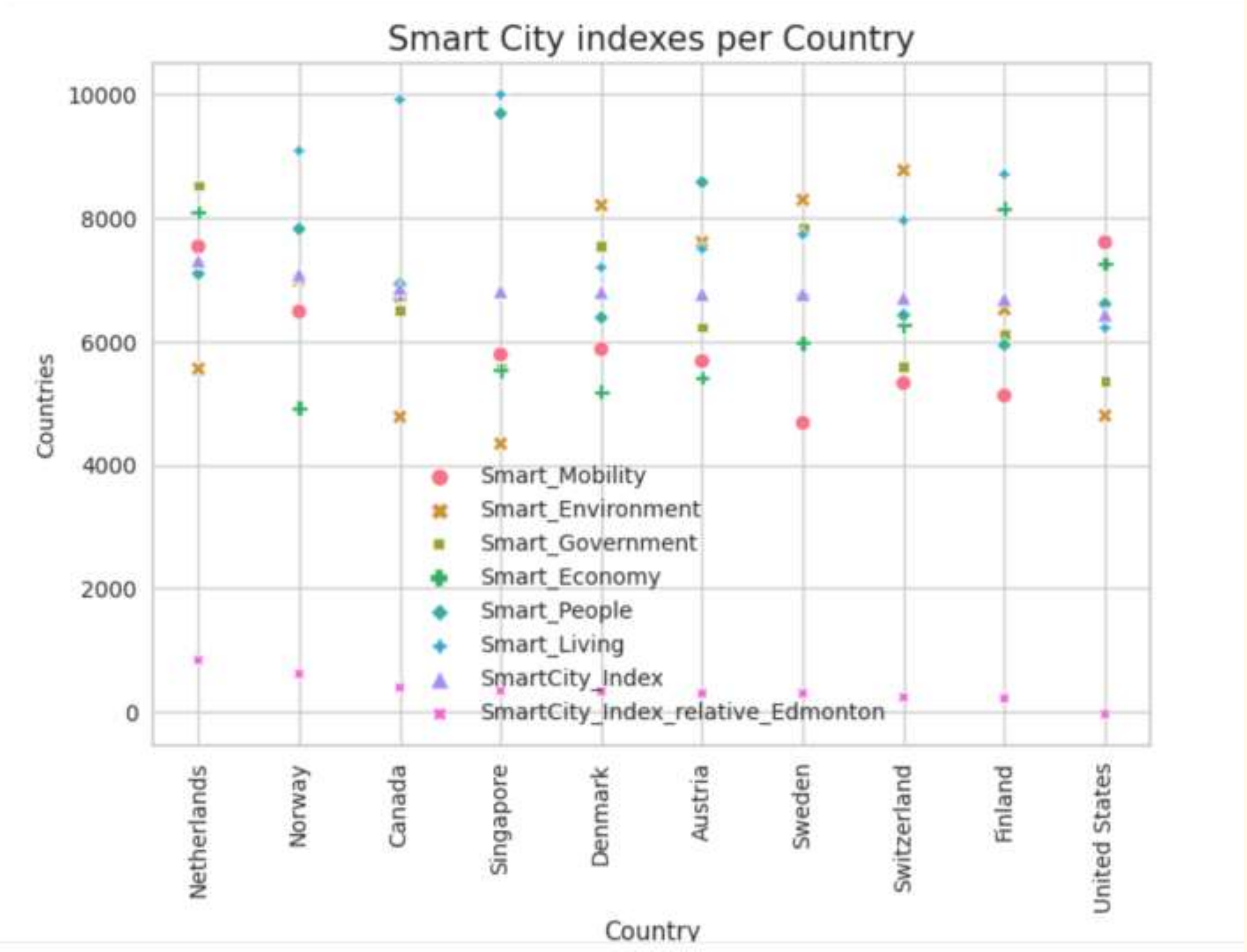
Co-funded by
the European Union

smarco

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

Visualization smart city indexes per Country

```
import seaborn as sns
import matplotlib.pyplot as plt
sns.scatterplot(data=scimean)
sns.set_style('whitegrid')
plt.ylabel('Countries', fontsize = 10)
plt.title('Smart City indexes per Country', fontsize = 15)
ticks=plt.xticks(rotation=90)
```



Seaborn is a Python data visualization library based on Matplotlib. It provides a high-level interface for creating attractive and informative statistical graphics. Seaborn simplifies the process of creating complex visualizations and is particularly well-suited for working with structured datasets such as Pandas DataFrames.

Co-funded by the European Union

smarco

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

Use Isolation Forest for outlier detection

```
!pip install git+https://github.com/pycaret/pycaret.git
from pycaret.anomaly import *
ano1 = setup(data)
iforest = create model('iforest')
```

PyCaret is an open-source, low-code machine learning library in Python that simplifies the end-to-end machine learning process. It provides a high-level interface for automating various steps in a typical machine learning workflow, including data preprocessing, feature engineering, outlier detection, model selection and model evaluation. PyCaret is designed to be user-friendly and efficient, making it especially useful for users who want to quickly experiment with different machine learning models without writing extensive code.

Co-funded by the European Union

smarco

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

Anomaly score computation using Isolation Forest

- **Isolation Forest Algorithm**: works by constructing a tree-based structure to isolate anomalies efficiently. It builds isolation trees, which are binary trees, in a recursive manner.
- **Random Feature Selection**: At each step of constructing a tree, Isolation Forest randomly selects a feature and then randomly selects a value within the range of that feature's values to create a split.
- **Recursive Partitioning**: The data points are recursively partitioned based on the randomly selected features and values. The process continues until each data point is isolated in its own leaf node or until a predefined maximum tree depth is reached.
- **Path Length Calculation**: The anomaly score for a data point is determined by the average path length in the trees needed to isolate that point. Anomalies are expected to have shorter path lengths because they are easier to isolate due to their uniqueness.

Co-funded by the European Union

smarco

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

Anomaly score computation using Isolation Forest

- **Normalization of Scores**: To obtain a normalized anomaly score, the average path length is compared to the expected average path length for a point in a well-distributed dataset. The expected average path length is obtained from the harmonic mean of the number of data points in the dataset.
- **Scoring Interpretation**: A lower anomaly score indicates a more anomalous data point. In other words, if a data point has a lower-than-expected average path length, it is considered more likely to be an anomaly.
- **Threshold Determination**: Users can set a threshold to determine which data points are considered anomalies. Points with anomaly scores below the threshold are labeled as anomalies, while those above the threshold are considered normal.

Co-funded by the European Union

smarco

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

Presentation of possible outliers

```
iforest_results = assign_model(iforest)
iforest_results[iforest_results['Anomaly']==1].sort_values("Anomaly_Score", ascending=False)
```

	City	Country	Smart_Mobility	Smart_Environment	Smart_Government	Smart_Economy	Smart_People	Smart_Living	SmartCity_Index	SmartCity_Index_relative_Edmonton	Anomaly	Anomaly_Score
98	Beijing	China	7610	2998	2806	4905	5183	1980	4449	-2023	1	0.018435
5	Montreal	Canada	7490	4848	6624	6180	8465	9920	7353	880	1	0.008218
92	Shanghai	China	6870	2936	3842	4430	4423	1980	4228	-2244	1	0.004111
80	Budapest	Hungary	5313	3142	5732	2410	7260	3120	4453	-2019	1	0.001611
86	Hong Kong	China	6143	3340	4984	4780	4385	1980	4313	-2160	1	0.000278
11	Trondheim	Norway	6492	7102	6686	4945	7558	9090	7039	567	1	0.000046

Co-funded by the European Union

smarco

Project 101186291 — SMARCO

Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

You can run the full example code

https://colab.research.google.com/drive/1krbS_3MtrvVhFaVzLH_eAdSpl5_TnGqy?usp=sharing

Co-funded by the European Union

smarco

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

Other applications of outlier detection in smart cities

- Smart Traffic Systems: Outlier detection techniques can identify unusual behavior on the roads and inform traffic management decisions.
- Air Quality Monitoring: Outlier detection models can detect anomalous air quality values and alert city authorities to take necessary measures.
- Public Transportation: Outlier detection techniques can be used to identify riders who are deviating from normal patterns or performing some kind of suspicious activity.
- Waste Management: Outlier detection models can be used to detect unusual waste disposal patterns and inform city authorities to take measures to optimize waste disposal and recycling.

Co-funded by the European Union

smarco

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

List of references

- Lavalle, A., Teruel, M. A., MatÃ©, A., & Trujillo, J. (2020). Improving Sustainability of Smart Cities through Visualization Techniques for Big Data from IoT Devices. Sustainability, 12(14), 5595. https://doi.org/10.3390/su12145595
- Ahmed, U., Srivastava, G., Djenouri, Y., & Lin, J. C.-W. (2022). Knowledge graph based trajectory outlier detection in sustainable smart cities. Sustainable Cities and Society, 78, 103580. https://doi.org/10.1016/j.scs.2021.103580
- Belhadi, A., Djenouri, Y., Srivastava, G., Djenouri, D., Lin, J. C.-W., & Fortino, G. (2021). Deep learning for pedestrian collective behavior analysis in smart cities: A model of group trajectory outlier detection. Information Fusion, 65, 13-20. https://doi.org/10.1016/j.inffus.2020.08.003

Co-funded by the European Union

smarco

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

Further reading

- Ji, W., Xu, J., Qiao, H., Zhou, M., & Liang, B. (2019). Visual IoT: Enabling Internet of Things Visualization in Smart Cities. IEEE Network, 33(2), 102-110. https://doi.org/10.1109/mnet.2019.1800258
- Murshed, S., Al-Hyari, A., Wendel, J., & Ansart, L. (2018). Design and Implementation of a 4D Web Application for Analytical Visualization of Smart City Applications. ISPRS International Journal of Geo-Information, 7(7), 276. https://doi.org/10.3390/ijgi7070276
- Djenouri, Y., Djenouri, D., & Lin, J. C.-W. (2021). Trajectory Outlier Detection. ACM Transactions on Knowledge Discovery from Data, 15(2), 1-28. https://doi.org/10.1145/3425867
- Soomro, K., Bhutta, M. N. M., Khan, Z., & Tahir, M. A. (2019). Smart city big data analytics: An advanced review. WIREs Data Mining and Knowledge Discovery, 9(5). Portico. https://doi.org/10.1002/widm.1319

Co-funded by the European Union

smarco

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

Unit completed - What's next?

- To consolidate your learning and reflect on the key concepts covered, please take a moment to complete this quiz.
- Your feedback and results will help you track your progress and support continuous improvement of the training experience.
- By completing this quiz, you will also become eligible to receive a certificate of successful training completion.
- Click this link to begin the quiz!

Co-funded by the European Union

smarco

Project 101186291 — SMARCO
Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.

SMARCO

SMARt COmmunities Skills Development in Europe

www.smarco.eu

info@smarco.eu

We are social! Follow us on:

@smarcoproject

@smarcoproject

@smarcoproject

Co-funded by the European Union

smarco

Project 101186291 — SMARCO

Funded by the European Union. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union or the European Education and Culture Executive Agency (EACEA). Neither the European Union nor EACEA can be held responsible for them.