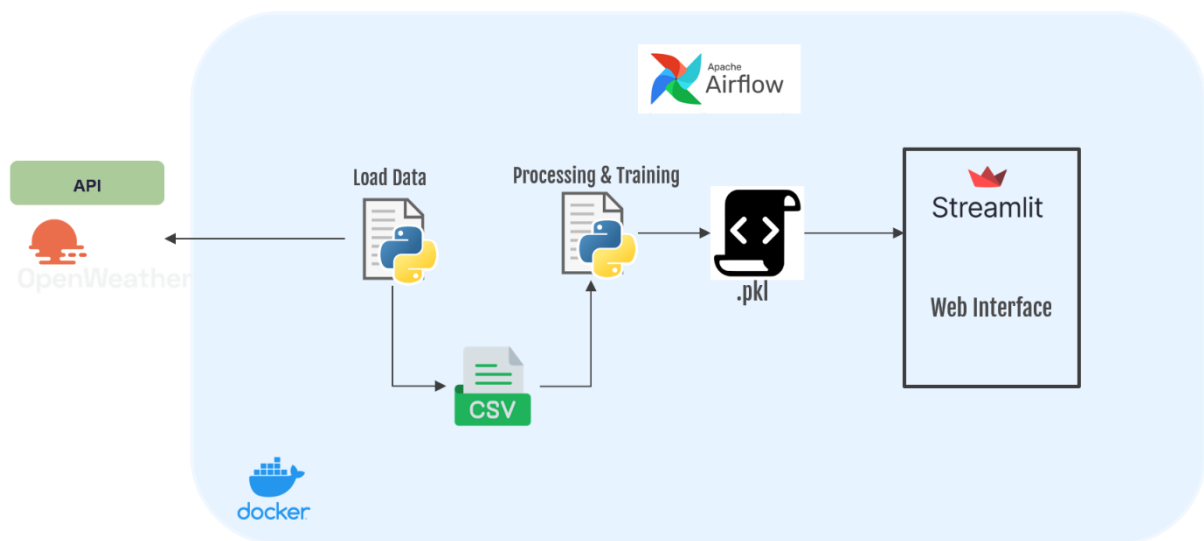


Projet3 :

Mise en place d'un pipeline d'entraînement continu en utilisant Apache Airflow et Streamlit



Professeur : F.KALLOUBI

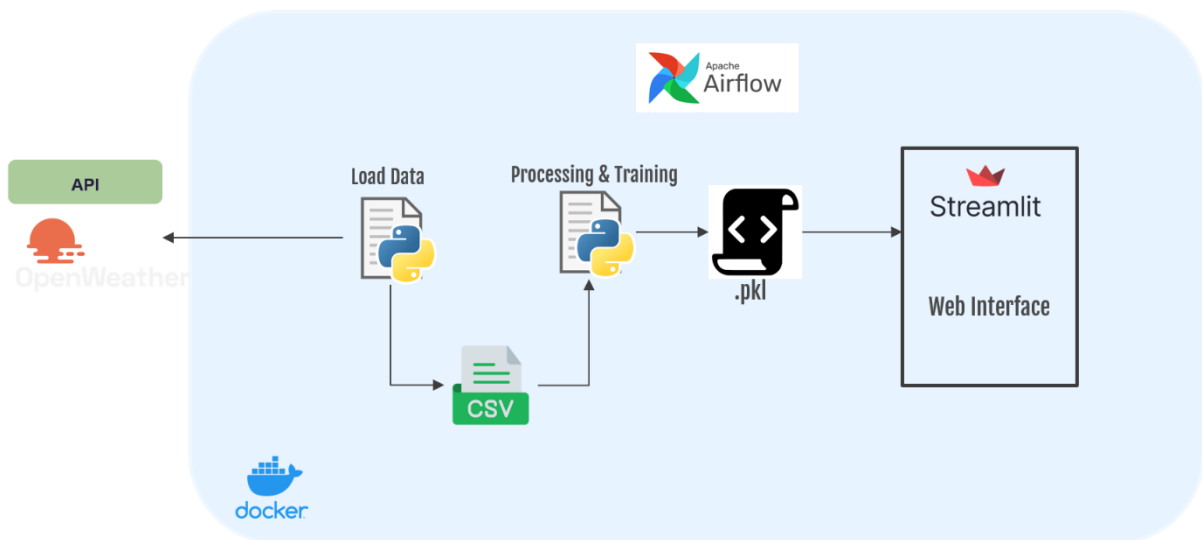
Réalisé par : O.OUHAYOU

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1) Objectif du projet :

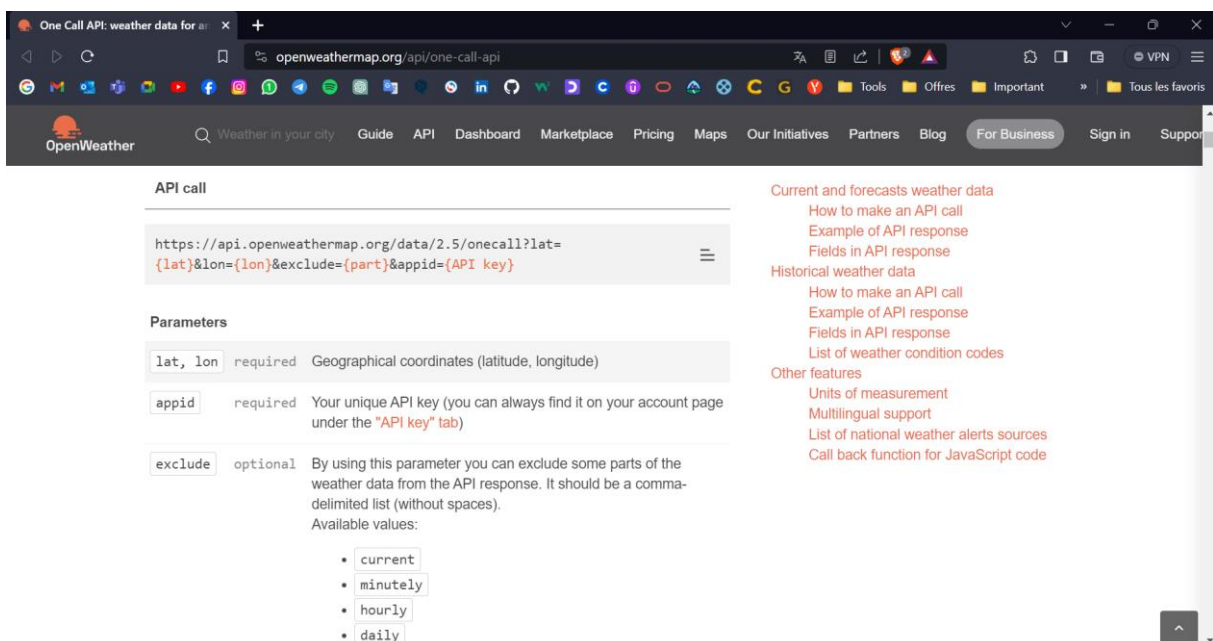
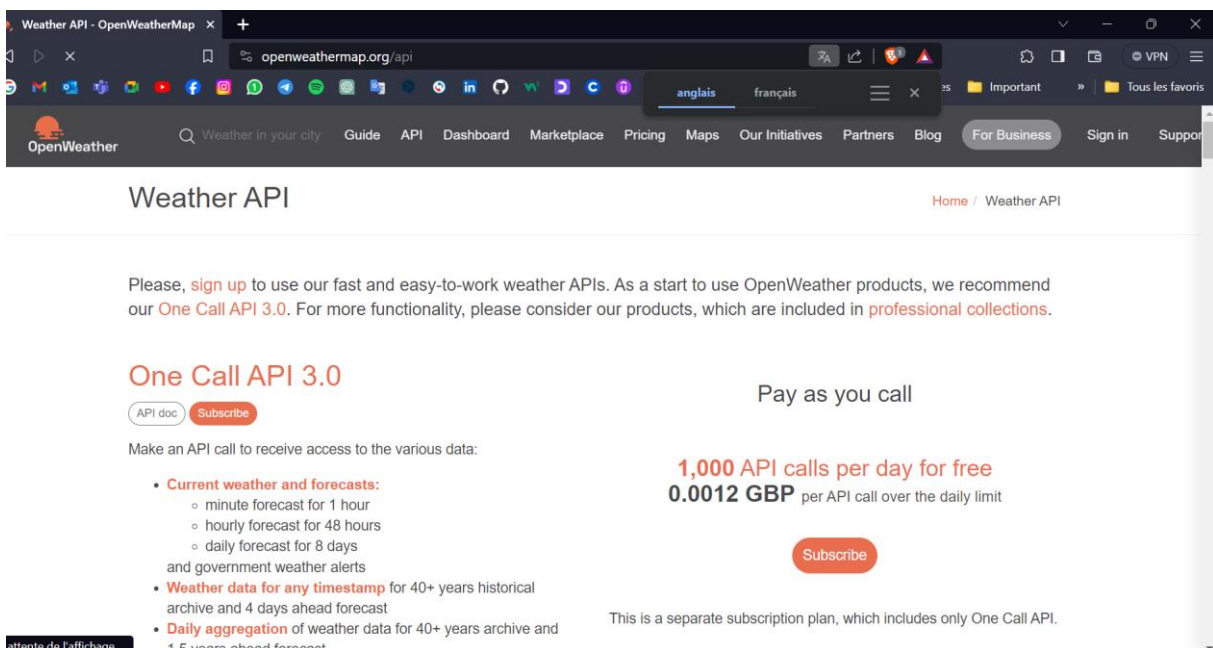
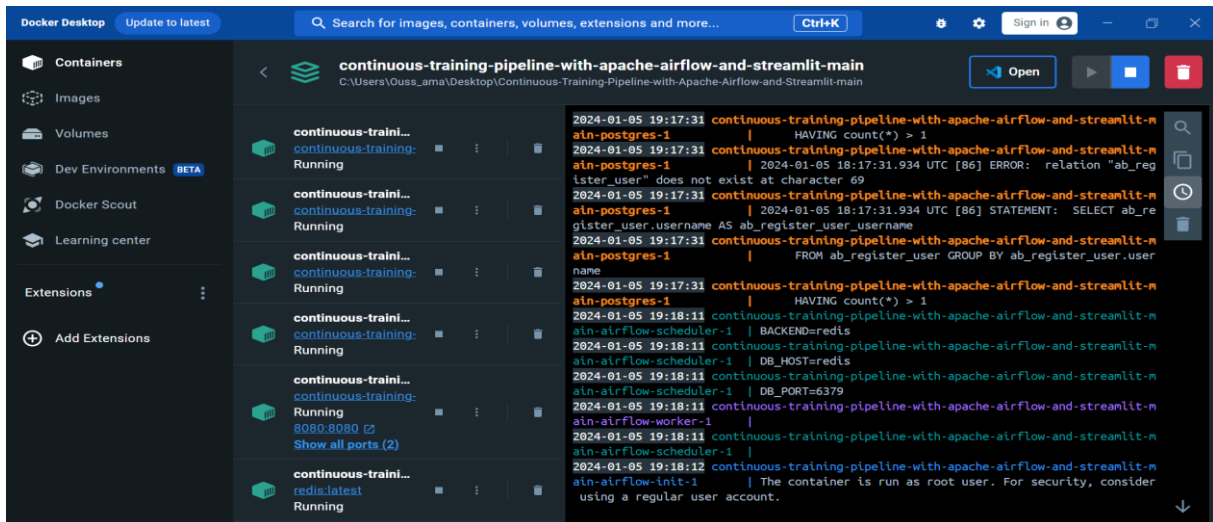
L'objectif de ce projet est de mettre en place un pipeline d'entraînement continu en utilisant Apache Airflow et Streamlit ce projet couvre plusieurs aspects liés à la collecte de données météorologiques via l'API **OpenWeatherMap** à l'application des techniques de prétraitement sur les données collectées (nettoyage, gestion des valeurs manquantes, conversion de types). à l'entraînement de modèles prédictifs sur ces données, à la mise en oeuvre d'une application web pour consommer le modèle, et à l'automatisation du processus à l'aide d'Apache Airflow. L'objectif global de ce projet est d'introduire et de mettre en pratique plusieurs concepts et compétences.



2) Installation et configuration :

```
C:\Windows\System32\cmd.exe
Microsoft Windows [version 10.0.22621.2861]
(c) Microsoft Corporation. Tous droits réservés.

C:\Users\Ouss_ama\Desktop\Continuous-Training-Pipeline-with-Apache-Airflow-and-Streamlit-main>docker-compose up -d
[+] Building 1.8s (8/8)
=> [airflow-init internal] load .dockerignore                                docker:default 0.1s
=> == transferring context: 2B                                                docker:default 0.0s
=> [airflow-init internal] load build definition from Dockerfile              docker:default 0.1s
[+] Building 2.1s (8/8)
=> [airflow-init internal] load .dockerignore                                docker:default 0.1s
=> == transferring context: 2B                                                docker:default 0.0s
=> [airflow-init internal] load build definition from Dockerfile              docker:default 0.1s
=> == transferring dockerfile: 121B                                           docker:default 0.0s
=> [airflow-scheduler internal] load metadata for docker.io/apache/airflow:2.6.1 1.8s
=> [airflow-init internal] load build context                                docker:default 0.0s
=> == transferring context: 37B                                               docker:default 0.0s
=> [airflow-webserver 1/3] FROM docker.io/apache/airflow:2.6.1@sha256:213aaled99052d9db4006c6813b3ffdbd0b529557f 0.0s
=> CACHED [airflow-init 2/3] ADD requirements.txt .                          0.0s
=> CACHED [airflow-init 3/3] RUN pip install -r requirements.txt              0.0s
=> [airflow-init] exporting to image                                         0.0s
=> == exporting layers                                                         0.0s
=> == writing image sha256:62ba7737a42cb26b3cff8bb50051a6d83e5eaa10533c2df432fdb009f2ed65d1 0.0s
```



3) Stockage des Données dans un Dataset:

```
jupyter Untitled Dernière Sauvegarde : il y a 6 minutes (auto-sauvegardé) Python 3 (ipykernel)

File Edit View Insert Cell Kernel Widgets Help

Entrée [8]: import os

import requests
import pandas as pd
from datetime import datetime
#7c0f631168d840e542618054bb96059e
api_key = '2a258b2fa442fb8d6f8be3014c88c57a'
endpoint = 'https://api.openweathermap.org/data/2.5/forecast'

existing_data = pd.read_csv('/opt/airflow/dags/scripts/dataset/Weather_Data.csv')
existing_data['Date'] = pd.to_datetime(existing_data['Date'], errors='coerce')

cities = [
    "Tokyo", "Mexico", "Séoul", "Jakarta", "New Delhi", "Le Caire", "Moscou", "Buenos Aires",
    "Manille", "Londres", "Dhâkâ", "Paris", "Pékin", "Bangkok", "Lima", "Bogotá", "Téhéran",
    "Kinshasa", "Santiago", "Madrid", "Naypyidaw", "Damas", "Singapour", "Ankara", "Luanda",
    "Bagdad", "Riyad", "Caracas", "Athènes", "Berlin", "Accra", "Hanoï", "Kiev", "Rome",
    "Addis-Abeba", "Guatemala", "Pyongyang", "Tachkent", "Saint-Domingue", "Brasilia",
    "Nairobi", "San José", "Tunis", "Alger", "Bucarest", "Budapest", "Conakry", "La Havane",
    "Port-au-Prince", "Dakar", "Amman", "Lisbonne", "Stockholm", "Kaboul", "Bakou",
    "San Salvador", "Minsk", "Varsovie", "Vienne", "Astana", "Harare", "Katmandou",
    "Khartoum", "Montevideo", "Quito", "Rabat", "Tananarive", "Colombo", "Kuala Lumpur",
    "Erevan", "Tripoli", "Bruxelles", "Phnom Penh", "Sofia", "Belgrade", "Mogadiscio",
    "Prague", "Tegucigalpa", "Yaoundé", "Maputo", "Tbilissi", "Pretoria", "Kampala",
    "Ottawa", "Abou Dabi", "Bamako", "Beyrouth", "Lusaka", "Managua", "Ndjamena",
    "Ouagadougou", "Sanaa", "Mascate", "Lomé", "Panamá", "Brazzaville", "Islamabad",
    "Kigali", "Zagreb", "Jerusalem", "Monrovia", "Riga", "Amsterdam", "Niamey", "Tirana",
    "Oulan-Bator", "Bangui", "Libreville", "Chişinău", "Vientiane", "Kingston", "Bichkek",
    "Achgabat", "Skopje", "Washington", "Helsinki", "Nouakchott", "Vilnius", "Freetown",
    "Asunción", "Oslo", "Douchanbé", "Copenhague", "Dublin", "Asmara", "Bratislava",
    "Koweït", "Lilongwe", "Tallinn", "Sarajevo", "Djibouti", "Doha", "Wellington",
    "Canberra", "Port Moresby", "Bujumbura", "Port-d'Espagne", "Porto-Novo",
    "Sucre (Bolivie)", "Bissau", "Ljubljana", "Georgetown", "Paramaribo", "Windhoek",
    "Massau", "Nicosie", "Dodoma", "Gaborone", "Maseru", "Suva", "Manama", "Port-Louis",
    "Podgorica", "Berne", "Reykjavík", "Yamoussoukro", "Praia", "Abuja",
    "Bandar Seri Begawan", "Luxembourg", "Malé", "Castries", "Dili", "Mbabwe",
    "Thimphou", "Malabo", "São Tomé", "Banjul", "Apia", "Nuku'alofa", "Saint-Georges",
    "Monaco", "Honiara", "Moroni", "Port-Vila", "Saint John's", "Tarawa", "Victoria",
    "Delap-Uliga-Darrit", "Andorre-la-Vieille", "Kingstown", "Roseau", "Basseterre",
    "Palikir", "Belmopan", "La Valette", "Bridgetown", "Vaduz", "Funafuti", "Saint-Marin",
    "Cité du Vatican", "Melekeok"
]

new_data_list = []

for city in cities:
    url = f'{endpoint}?q={city}&APPID={api_key}'
    response = requests.get(url)
```

```

        "Palikir", "Belmopan", "La Valette", "Bridgetown", "Vaduz", "Funafuti", "Saint-Marin",
        "Cité du Vatican", "Melekeok"
    ]

    new_data_list = []

    for city in cities:
        url = f'{endpoint}?q={city}&APPID={api_key}'
        response = requests.get(url)

        if response.status_code == 200:
            weather_data = response.json()

            if 'list' in weather_data:
                city_forecast = weather_data['list']

                for forecast in city_forecast:
                    timestamp = forecast['dt']
                    date = datetime.utcfromtimestamp(timestamp).strftime('%Y-%m-%d %H:%M:%S')

                    forecast_date = pd.to_datetime(date)

                    if forecast_date > existing_data['Date'].max():
                        city_info = {
                            'City': city,
                            'Date': date,
                            'Temperature': forecast['main']['temp'],
                            'Temp_Min': forecast['main']['temp_min'],
                            'Temp_Max': forecast['main']['temp_max'],
                            'Pressure': forecast['main']['pressure'],
                            'Sea_Level': forecast['main']['sea_level'] if 'sea_level' in forecast['main'] else None,
                            'Humidity': forecast['main']['humidity'],
                            'Description': forecast['weather'][0]['main'],
                            'Wind Speed': forecast['wind']['speed'],
                            'Country': weather_data['city']['country'],
                            'Lon': weather_data['city']['coord']['lon'],
                            'Lat': weather_data['city']['coord']['lat'],
                        }
                        new_data_list.append(city_info)
                    else:
                        print(f"No forecast data for {city}")
            else:
                print(f"Error {city}: {response.status_code}")

```

```

        "Asuncion", "Oslo", "Dushanbe", "Copenhagen", "Dublin", "Amman", "Bratislava",
        "Koweit", "Lilongwe", "Tallinn", "Sarajevo", "Djibouti", "Doha", "Wellington",
        "Canberra", "Port Moresby", "Bujumbura", "Port-d'Espagne", "Porto-Novo",
        "Sucre (Bolivie)", "Bissau", "Ljubljana", "Georgetown", "Paramaribo", "Windhoek",
        "Nassau", "Nicosie", "Dodoma", "Gaborone", "Maseru", "Suva", "Manama", "Port-Louis",
        "Podgorica", "Berne", "Reykjavik", "Yamoussoukro", "Praia", "Abuja",
        "Bandar Seri Begawan", "Luxembourg", "Malé", "Castries", "Dili", "Mbabane",
        "Thimphu", "Malabo", "São Tomé", "Banjul", "Apia", "Nuku'alofa", "Saint-Georges",
        "Monaco", "Honiara", "Moroni", "Port-Vila", "Saint John's", "Tarawa", "Victoria",
        "Delap-Uliga-Darrit", "Andorre-la-Vieille", "Kingstown", "Roseau", "Basseterre",
        "Palikir", "Belmopan", "La Valette", "Bridgetown", "Vaduz", "Funafuti", "Saint-Marin",
        "Cité du Vatican", "Melekeok"
    ]

    new_data_list = []

    for city in cities:
        url = f'{endpoint}?q={city}&APPID={api_key}'
        response = requests.get(url)

        if response.status_code == 200:
            weather_data = response.json()

            if 'list' in weather_data:
                city_forecast = weather_data['list']

                for forecast in city_forecast:
                    timestamp = forecast['dt']
                    date = datetime.utcfromtimestamp(timestamp).strftime('%Y-%m-%d %H:%M:%S')

                    forecast_date = pd.to_datetime(date)

                    if forecast_date > existing_data['Date'].max():
                        city_info = {
                            'City': city,
                            'Date': date,
                            'Temperature': forecast['main']['temp'],
                            'Temp_Min': forecast['main']['temp_min'],
                            'Temp_Max': forecast['main']['temp_max'],
                            'Pressure': forecast['main']['pressure'],
                            'Sea_Level': forecast['main']['sea_level'] if 'sea_level' in forecast['main'] else None,
                            'Humidity': forecast['main']['humidity'],
                            'Description': forecast['weather'][0]['main'],
                            'Wind Speed': forecast['wind']['speed'],
                            'Country': weather_data['city']['country'],
                            'Lon': weather_data['city']['coord']['lon'],
                            'Lat': weather_data['city']['coord']['lat'],
                        }
                        new_data_list.append(city_info)
                    else:
                        print(f"No forecast data for {city}")
            else:
                print(f"Error {city}: {response.status_code}")

    new_data_df = pd.DataFrame(new_data_list)

    if not new_data_df.empty:
        new_data_df.to_csv(os.path.abspath('/opt/airflow/dags/scripts/dataset/Weather_Data.csv'), index=False, mode='a', header=
    else:
        print("No new data to add.")

```

	A	B	C	D	E	F	G	H	I	J
1	City,Date,Temp	erature,Temp_Min,Temp_Max,Pressure,Sea_Level,Humidity,Description,W								
2	Tokyo,2023-12-08 21:00:00,	283.15,283.15,284.43,1019,1019,62,Clear,1.72,JP,139.6917,35.6895								
3	Tokyo,2023-12-09 00:00:00,	283.99,283.99,285.67,1020,1020,55,Clear,0.87,JP,139.6917,35.6895								
4	Tokyo,2023-12-09 03:00:00,	286.54,286.54,288.24,1019,1019,47,Clear,2.16,JP,139.6917,35.6895								
5	Tokyo,2023-12-09 06:00:00,	289.61,289.61,289.61,1019,1019,36,Clear,1.34,JP,139.6917,35.6895								
6	Tokyo,2023-12-09 09:00:00,	288.8,288.8,288.8,1020,1020,39,Clouds,0.52,JP,139.6917,35.6895								
7	Tokyo,2023-12-09 12:00:00,	287.76,287.76,287.76,1020,1020,40,Clouds,1.63,JP,139.6917,35.6895								
8	Tokyo,2023-12-09 15:00:00,	286.83,286.83,286.83,1020,1020,40,Clouds,2.13,JP,139.6917,35.6895								
9	Tokyo,2023-12-09 18:00:00,	285.81,285.81,285.81,1020,1020,41,Clouds,2.41,JP,139.6917,35.6895								
10	Tokyo,2023-12-09 21:00:00,	285.04,285.04,285.04,1021,1021,41,Clear,2.42,JP,139.6917,35.6895								
11	Tokyo,2023-12-10 00:00:00,	286.53,286.53,286.53,1023,1023,37,Clear,2.83,JP,139.6917,35.6895								
12	Tokyo,2023-12-10 03:00:00,	289.59,289.59,289.59,1021,1021,32,Clear,2.25,JP,139.6917,35.6895								
13	Tokyo,2023-12-10 06:00:00,	290.78,290.78,290.78,1021,1021,31,Clear,1.78,JP,139.6917,35.6895								
14	Tokyo,2023-12-10 09:00:00,	289.66,289.66,289.66,1023,1023,35,Clear,2.39,JP,139.6917,35.6895								
15	Tokyo,2023-12-10 12:00:00,	288.01,288.01,288.01,1025,1025,49,Clear,2.61,JP,139.6917,35.6895								
16	Tokyo,2023-12-10 15:00:00,	287.33,287.33,287.33,1025,1025,67,Rain,3.88,JP,139.6917,35.6895								
17	Tokyo,2023-12-10 18:00:00,	286.44,286.44,286.44,1025,1025,69,Rain,4.18,JP,139.6917,35.6895								
18	Tokyo,2023-12-10 21:00:00,	286.3,286.3,286.3,1025,1025,73,Rain,4.12,JP,139.6917,35.6895								
19	Tokyo,2023-12-11 00:00:00,	285.8,285.8,285.8,1027,1027,79,Rain,4.44,JP,139.6917,35.6895								

4) Prétraitement des données

Prétraitement des données

Entrée [1]:

```
import seaborn as sns
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

Entrée [2]:

```
# Chargement du jeu de données
data = pd.read_csv("Weather_Data.csv")
data.head()
data.tail()
data.info()
```

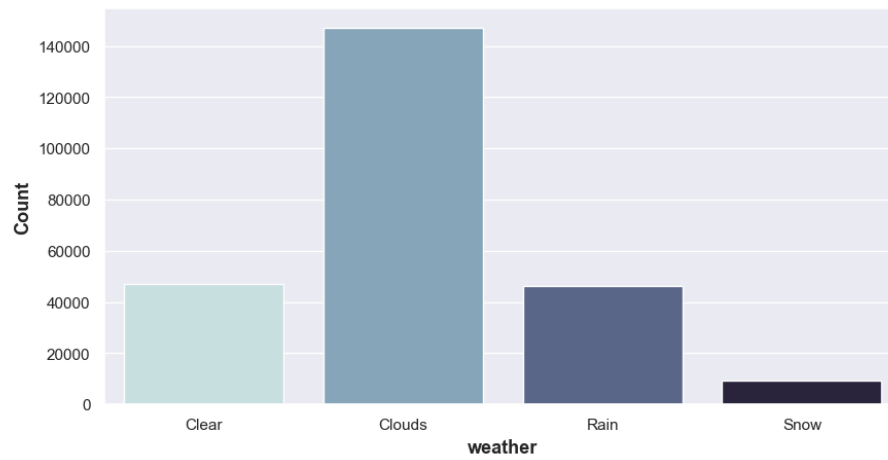
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 249850 entries, 0 to 249849
Data columns (total 13 columns):
#   Column      Non-Null Count  Dtype
---  -
0   City         249850 non-null  object
1   Date         249850 non-null  object
2   Temperature  249850 non-null  float64
3   Temp_Min    249850 non-null  float64
4   Temp_Max    249850 non-null  float64
5   Pressure     249850 non-null  int64
6   Sea_Level   249850 non-null  int64
7   Humidity     249850 non-null  int64
8   Description  249850 non-null  object
9   Wind Speed  249850 non-null  float64
10  Country      249163 non-null  object
11  Lon          249850 non-null  float64
12  Lat          249850 non-null  float64
dtypes: float64(6), int64(3), object(4)
memory usage: 24.8+ MB
```

Entrée [3]:

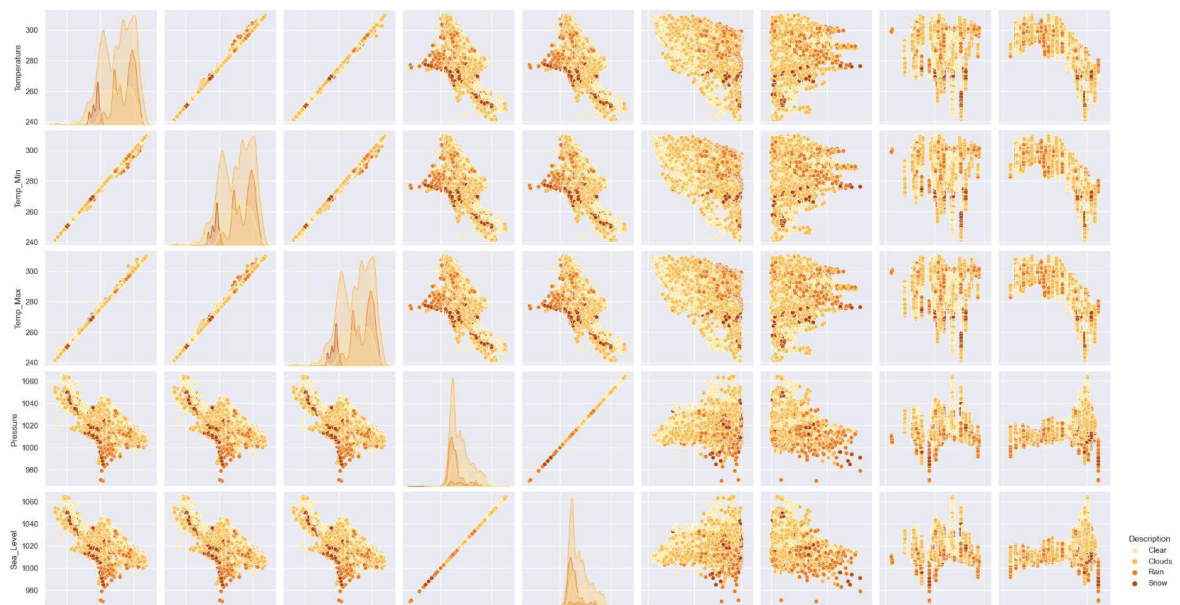
```
plt.figure(figsize=(10,5))
sns.set_theme()
sns.countplot(x = 'Description',data = data,palette="ch:start=.2,rot=-.3")
plt.xlabel("weather",fontweight='bold',size=13)
plt.ylabel("Count",fontweight='bold',size=13)
plt.show()
```

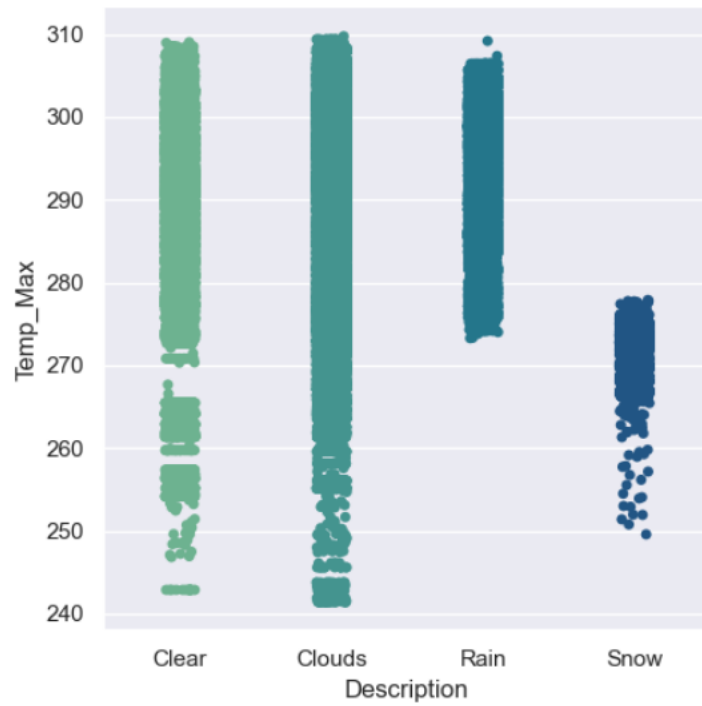
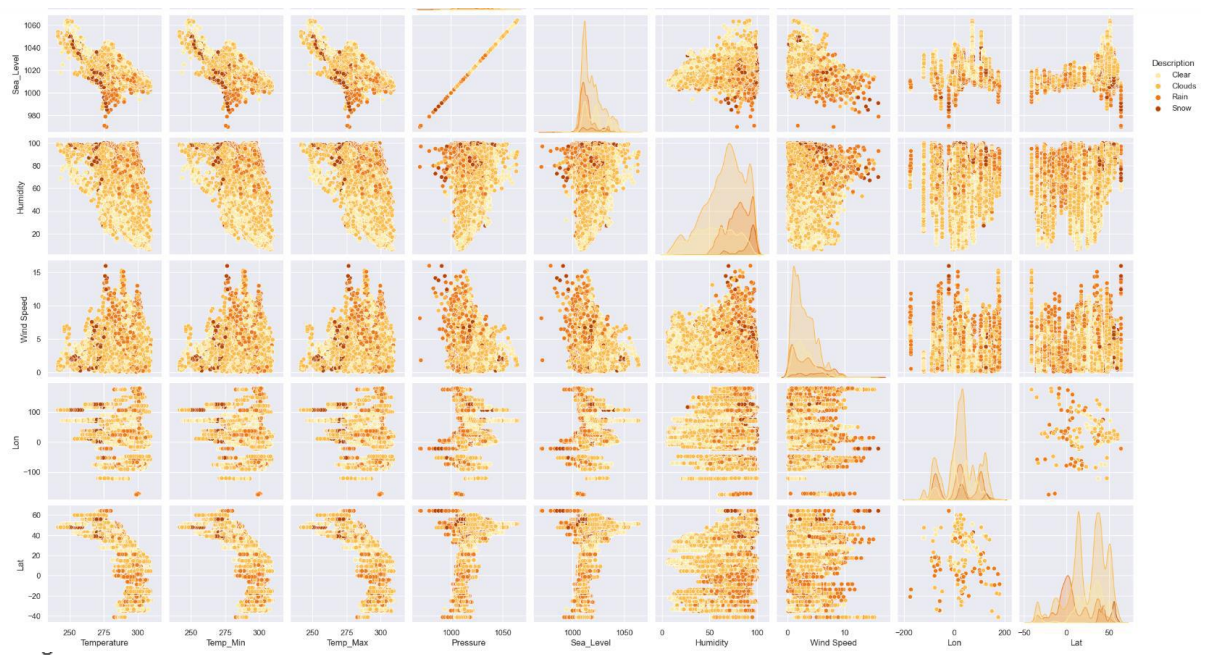


```
Entrée [3]: plt.figure(figsize=(10,5))
sns.set_theme()
sns.countplot(x = 'Description', data = data, palette="ch:start=.2,rot=-.3")
plt.xlabel("weather", fontweight='bold', size=13)
plt.ylabel("Count", fontweight='bold', size=13)
plt.show()
```



```
Entrée [4]: plt.figure(figsize=(14,8))
sns.pairplot(data.drop('Date',axis=1),hue='Description',palette="YlOrBr")
plt.show()
```





```

Entrée [ ]: import pandas as pd
from sklearn.model_selection import train_test_split
from imblearn.under_sampling import RandomUnderSampler
from collections import Counter
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score
import pickle

# Encode the target variable 'Description'
label_encoder = LabelEncoder()
data['Description'] = label_encoder.fit_transform(data['Description'])

# Separate features and target
X = data.drop('Description', axis=1)
y = data['Description']

# Split the dataset into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.5, random_state=42)

# Specify the merge parameters
new_data = pd.merge(X_train, y_train, how='inner', on=None, left_index=True, right_index=True, validate=None)

# Undersample the majority class using RandomUnderSampler
undersampler = RandomUnderSampler(sampling_strategy='not minority', random_state=42)
X_train_balanced, y_train_balanced = undersampler.fit_resample(X_train, y_train)

# Display class distribution after balancing
print("Class distribution after balancing:", Counter(y_train_balanced))

# Scale numerical features
scaler = StandardScaler()
X_train_balanced_scaled = scaler.fit_transform(X_train_balanced)

# Scale numerical features
scaler = StandardScaler()
X_train_balanced_scaled = scaler.fit_transform(X_train_balanced)
X_test_scaled = scaler.transform(X_test)

# Save the LabelEncoder
with open('label_encoder.pkl', 'wb') as encoder_file:
    pickle.dump(label_encoder, encoder_file)

# Train different models on the balanced and scaled dataset
models = {
    "Logistic Regression": LogisticRegression(max_iter=1000, random_state=42),
    "SVM": SVC(kernel='linear', random_state=42),
    "KNN": KNeighborsClassifier(n_neighbors=5),
    "Naive Bayes": GaussianNB(),
    "Decision Tree": DecisionTreeClassifier(criterion='entropy', random_state=42),
    "Random Forest": RandomForestClassifier(n_estimators=40, random_state=42),
    "XGBoost": XGBClassifier()
}

results = {}

for model_name, model in models.items():
    model.fit(X_train_balanced_scaled, y_train_balanced)
    y_pred = model.predict(X_test_scaled)
    accuracy = accuracy_score(y_test, y_pred)
    results[model_name] = accuracy





# Find the best model
best_model_name = max(results, key=results.get)
best_accuracy = results[best_model_name]

print("Results:")
for model, accuracy in results.items():
    print(f"{model}: {accuracy:.2%}")

print(f"Best Model: {best_model_name} with Accuracy: {best_accuracy:.2%}")

# Save the best model as a pickle file with a new name
new_file_name = 'dags\\scripts\\pickle_files\\modele_classification13.pkl'
with open(new_file_name, 'wb') as file:
    pickle.dump(models[best_model_name], file)

```

Nom	Modifié le	Type	Taille
 encoder.pkl	16/12/2023 18:19	Fichier PKL	1 Ko
 label_encoder.pkl	16/12/2023 18:19	Fichier PKL	1 Ko
 <u>modele_classification13.pkl</u>	16/12/2023 18:19	Fichier PKL	5760 Ko
 new_model.pkl	16/12/2023 18:19	Fichier PKL	10729 Ko

5) Développement de l'application web

```
weather_dag.py streamlit_app.py x
1 import streamlit as st
2 import pickle
3 import pandas as pd
4 from sklearn import preprocessing
5 import numpy as np
6 import seaborn as sns
7 import matplotlib.pyplot as plt
8 import plotly.express as px
9 from matplotlib.ticker import MaxNLocator
10 import filter
11 import visualization as viz
12
13 # Load the pre-trained model
14 with open('/opt/airflow/dags/scripts/pickle_files/modele_classification13.pkl', 'rb') as model_file:
15     model = pickle.load(model_file)
16
17 label_encoder = preprocessing.LabelEncoder()
18
19 # num_samples = 400
20 # nouvelles_donnees1 = pd.DataFrame({
21 #     'Temperature': np.random.uniform(270, 300, num_samples),
22 #     'Temp_Min': np.random.uniform(270, 300, num_samples),
23 #     'Temp_Max': np.random.uniform(270, 300, num_samples),
24 #     'Pressure': np.random.uniform(990, 1020, num_samples),
25 # })
26
27
28
29
30
31
32
33
34 # Main Streamlit app
35 def main():
36     st.title("Weather Prediction App")
37
38     # Sidebar navigation
39     page = st.sidebar.selectbox("Choose a page", ["Home", "Prediction"])
40
41     if page == "Home":
42
43         data = pd.read_csv("/opt/airflow/dags/scripts/Weather_Data.csv")
44
45         cities = filter.get_unique_cities_and_countries(data)
46         city_selected = filter.create_city_country_dropdown(cities)
47
48         # Call the function to get filtered records
49         filtered_records = filter.filter_records_by_city(data, city_selected)
50
51         # Display the selected city in the map
52         viz.map(filtered_records)
53
54         # Dataset features
55         all_features = ['Temperature', 'Temp_Min', 'Temp_Max', 'Pressure', 'Humidity', 'Wind Speed']
56
```

```

56     viz.create_viz(filtered_records,all_features)
57
58
59
60     elif page == "Prediction":
61
62         st.write("Make a weather prediction:")
63         # User input for each feature
64         temperature = st.slider("Temperature", min_value=0.0, max_value=400.0)
65         temp_min = st.slider("Minimum Temperature", min_value=0.0, max_value=400.0)
66         temp_max = st.slider("Maximum Temperature", min_value=0.0, max_value=400.0)
67         pressure = st.slider("Pressure", min_value=900, max_value=1100)
68         sea_level = st.slider("Sea Level", min_value=900, max_value=1100)
69         humidity = st.slider("Humidity", min_value=0, max_value=100)
70         wind_speed = st.slider("Wind Speed", min_value=0.0, max_value=20.0)
71         lon = st.number_input("Longitude")
72         lat = st.number_input("Latitude")
73         # Create a DataFrame with user input
74         user_data = pd.DataFrame({
75             'Temperature': [temperature],
76             'Temp_Min': [temp_min],
77             'Temp_Max': [temp_max],
78             'Pressure': [pressure],
79             'Sea_Level': [sea_level],
80             'Humidity': [humidity],
81             'Wind Speed': [wind_speed],
82             'Lon': [lon],
83             'Lat': [lat]
84         })
85         # Load the label_encoder
86         with open('/opt/airflow/dags/pickle_files/label_encoder.pkl', 'rb') as label_encoder_file:
87             label_encoder1 = pickle.load(label_encoder_file)
88         # Make a prediction
89         if st.button("Predict"):
90             # scaler = preprocessing.StandardScaler()
91             # processed_data = scaler.fit_transform(nouvelles_donnees1)
92             print(user_data)
93             prediction = model.predict(user_data)
94             print("Raw predictions:",prediction)
95             st.success(f"Prediction: {prediction[0]}")
96
97     if __name__ == "__main__":
98         main()

```

6) Mise en place avec Apache Airflow

```
weather_dag.py x
1 from datetime import datetime, timedelta
2 from pytz import timezone
3 from airflow import DAG
4 from airflow.operators.bash import BashOperator
5
6 # Set the timezone to Casablanca
7 casablanca_tz = timezone('Africa/Casablanca')
8
9 default_args = {
10     'owner': 'DUHAYOU_OUSSAMA',
11     'depends_on_past': False,
12     'start_date': datetime.now(casablanca_tz),
13     'email_on_failure': False,
14     'email_on_retry': False,
15     'retries': 0,
16     'retry_delay': timedelta(minutes=5),
17 }
18
19 dag = DAG(
20     'Weather_app',
21     default_args=default_args,
22     description='An Airflow DAG to fetch weather data and update the CSV file',
23     schedule_interval='0 */3 * * *', # Run every 3 hours
24     max_active_runs=1, # Ensure only one run at a time

```

```
weather_dag.py x
19 dag = DAG(
20     'Weather_app',
21     default_args=default_args,
22     description='An Airflow DAG to fetch weather data and update the CSV file',
23     schedule_interval='0 */3 * * *', # Run every 3 hours
24     max_active_runs=1, # Ensure only one run at a time
25     catchup=False, # Do not run backfill for the intervals between start_date and the current date
26 )
27
28
29
30 # Task to execute the Python script
31 execute_script_task_1 = BashOperator(
32     task_id='task_1',
33     bash_command='python /opt/airflow/dags/scripts/main.py',
34     dag=dag
35 )
36
37 # Task to execute the Python script
38 execute_script_task_2 = BashOperator(
39     task_id='task_2',
40     bash_command='python /opt/airflow/dags/scripts/Projet_ML2.py',
41     dag=dag
42 )

```

```
42 )
43
44 execute_script_task_3 = BashOperator(
45     task_id='task_3',
46     bash_command='streamlit run --server.address 0.0.0.0 --server.enableWebsocketCompression',
47     dag=dag
48 )
49
50 # Set task dependencies
51 execute_script_task_1 >> execute_script_task_2 >> execute_script_task_3
52

```

The screenshot displays the Apache Airflow web interface. At the top, there's a navigation bar with links for Airflow, DAGs, Security, Browse, Admin, and Docs. The current time is 22:55 UTC. Below the navigation bar, there's a header for 'DAG Import Errors (1)'. A yellow warning banner states: 'Do not use **SQLite** as metadata DB in production – it should only be used for dev/testing. We recommend using Postgres or MySQL. [Click here](#) for more information.' Another yellow banner below it says: 'Do not use **SequentialExecutor** in production. [Click here](#) for more information.'

The main section is titled 'DAGs'. It features a filter bar with 'All' (selected), 'Active', and 'Paused' tabs. A search bar for 'Filter DAGs by tag' and a 'Search DAGs' input field are present. Below this is a table listing DAGs with columns: DAG, Owner, Runs, Schedule, Last Run, Next Run, Recent Tasks, Actions, and Links. The table lists several DAGs, including 'Weather_Project_DAG', 'example_bash_operator', 'example_branch_datetime_operator', 'example_branch_datetime_operator_2', 'example_branch_dop_operator_v3', 'example_branch_labels', 'example_branch_operator', and 'example_branch_python_operator_decorator'. Each row shows the owner as 'airflow', the number of runs, the schedule, the last run time, the next run time, and a series of circles representing recent task instances. Action buttons (play, stop, refresh) are available for each DAG.

Below the DAGs table is a navigation bar with tabs: Grid, Graph (selected), Calendar, Task Duration, Task Tries, Landing Times, Gantt, Details, Code, and Audit Log. To the right of these tabs are play and stop buttons.

The 'Graph' tab is active, showing a task instance detail view for 'manual__2023-12-14T22:23:53Z'. The task instance is 'manual__2023-12-14T22:23:52.675341+00:00'. The layout is set to 'Left > Right'. A search bar for 'Find Task...' is present. Below the search bar, there's a legend for task states: deferred, failed, queued, removed, restarting, running, scheduled, shutdown, skipped, success, up_for_reschedule, up_for_retry, upstream_failed, and no_status. The 'running' state is highlighted in green. At the bottom, there's a diagram showing the task flow: 'task_1' (green box) → 'task_2' (green box) → 'task_3' (yellow box). An 'Auto-refresh' toggle is on the right.



