Workshop 3: Machine learning and Data streaming

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https://github.com/SEBASBELMOS/workshop-003

Overview

This project implements a machine learning pipeline to predict happiness scores for different countries using data from five CSV files, as part of Workshop 3: Machine Learning and Data Streaming.

Project Structure

Folder/File	Description
assets/	Static resources (images, documentation, etc.)
data/	Data used in the project (ignored in .gitignore)
├── database/	Database Script
├── raw/	World Happiness CSV files
├── processed/	World Happiness Report file
docs/	Documentation, Guides and workshop PDFs
env/	Environment variables (ignored in .gitignore)
├── .env	Stores credentials and paths
kafka/	Python scripts for Apache Kafka
model/	AI Model
notebooks/	Jupyter Notebooks

Folder/File	Description
├── 01_EDA.ipynb	Exploratory Data Analysis of CSV files
├── 02_model-training.ipynb	Model Selection and Training
├── 03_model-performance.ipynb	Model Performance / Metrics
utilities/	Python scripts for Data processing
docker-compose.yml	Docker configuration
pyproject.toml	Poetry dependency management file
README.md	This file

Tools and Libraries

- Python 3.13 → Download here
- PostgreSQL → Download here
- Power BI Desktop → Download here
- Jupyter Notebook → VSCode tool used
- Docker → Documentation here

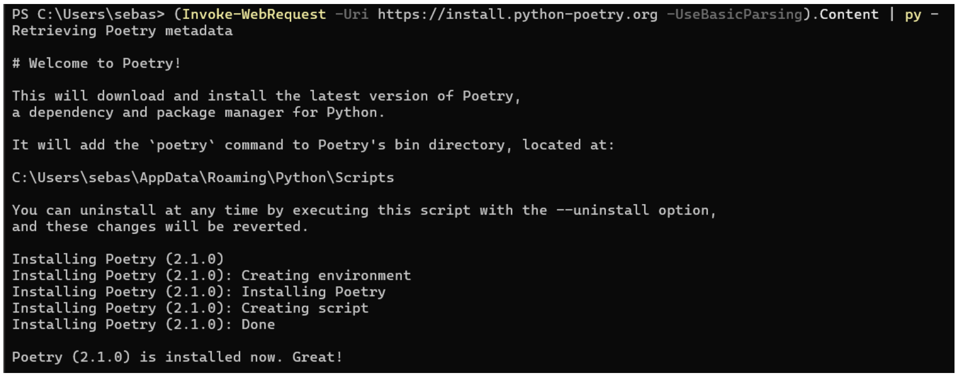
All the libraries are included in the Poetry project config file (*pyproject.toml*).

Installation and Setup

1. **Clone the Repository:**

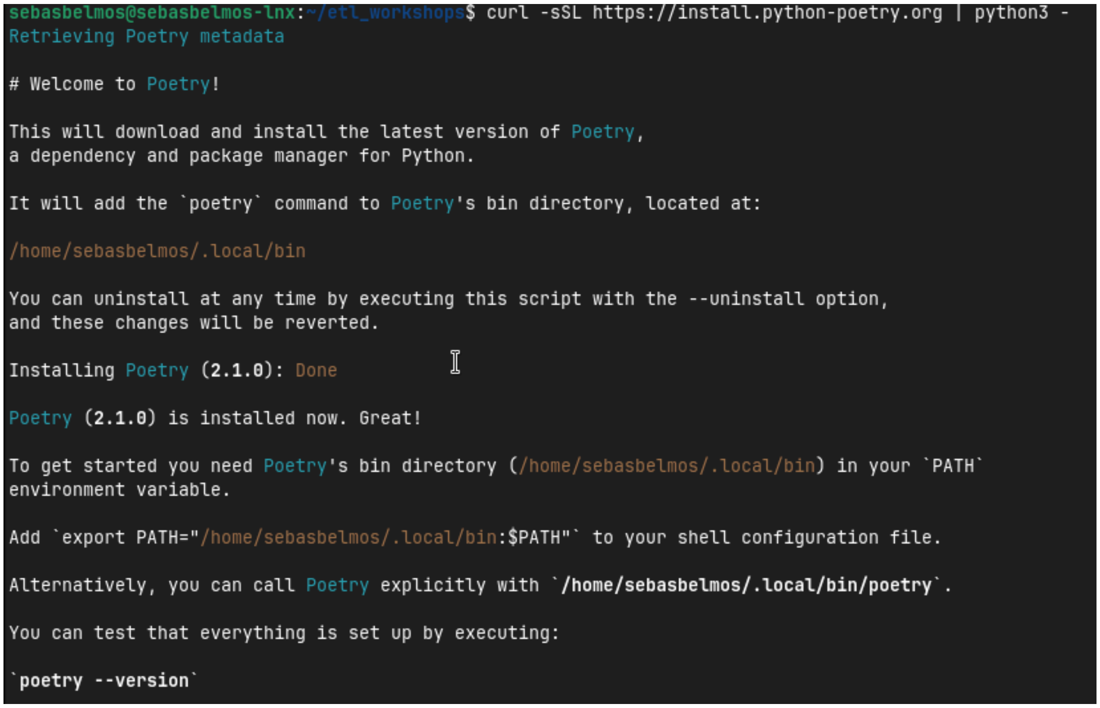
```
git clone <https://github.com/SEBASBELMOS/workshop-003.git>
cd workshop-001
```

2. **Installing the dependencies with *Poetry***
    - Windows:
        - In Powershell, execute this command:




```
(Invoke-WebRequest -Uri <https://install.python-poetry.org> -UseBasicParsing).Content | py -
```

  - Press Win + R, type *sysdm.cpl*, and press **Enter**.
  - Go to the *Advanced* tab, select *environment variable*.
  - Under System variables, select Path → Click Edit.
  - Click *Edit* and set the path provided during the installation in **PATH** so that the `poetry` command works. ("C:\Users\username\AppData\Roaming\Python\Scripts")
  - Restart Powershell and execute *poetry --version*.
- Linux
  - In a terminal, execute this command:

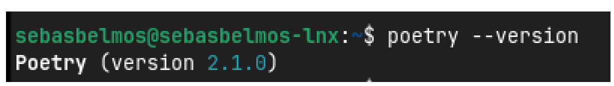



```
curl -sSL <https://install.python-poetry.org> | python3 -
```

- Now, execute:

```
export PATH = "/home/user/.locar/bin:$PATH"
```

- Finally, restart the terminal and execute *poetry --version*.



3. **Poetry Shell**

- Enter the Poetry shell with *poetry shell*.
- Then, execute *poetry init*, it will create a file called *pyproject.toml*
- To add all the dependencies, execute this:

```
poetry add pandas matplotlib psycopg2-binary sqlalchemy python-dotenv seab
orn ipykernel dotenv kafka-python
```

- Install the dependencies with:
  In case of error with the .lock file, just execute

poetry lock to fix it.

```
poetry install
```

- Create the kernel with this command (You must choose this kernel when running the notebooks):

```
poetry run python -m ipykernel install --user --name workshop-003 --display-name "Python (workshop-003)"
```

4. **Enviromental variables**

> Realise this in VS Code.

1. Inside the cloned repository, create a new directory named *env/*.
2. Within that directory, create a file called *.env*.
3. In the *.env file*, define the following six environment variables (without double quotes around values):

```
PG_HOST = #host address, e.g. localhost or 127.0.0.1
PG_PORT = #PostgreSQL port, e.g. 5432

PG_USER = #your PostgreSQL user
PG_PASSWORD = #your user password

PG_DATABASE = #your database name, e.g. postgres
```

4. Create the database with this command:

```
psql -U your_username -c "CREATE DATABASE happiness_db;"
```

5. **Execution**

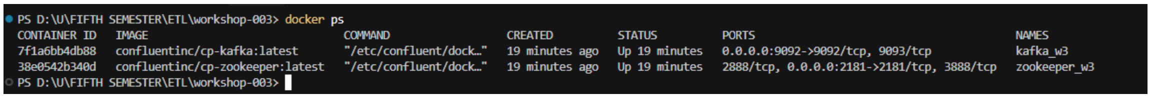
a. Run all the notebooks to create the EDA, transformations and model.

b. Run this command to start the Docker Containers for Kafka and Zookeeper.

```
docker-compose up -d
```

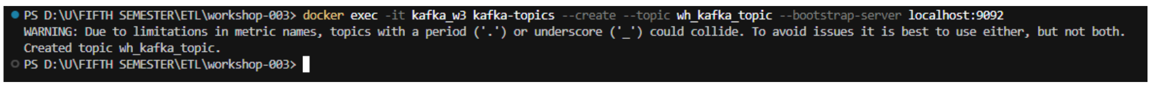
c. To check if the containers are correctly running, use this command:

```
docker ps
```



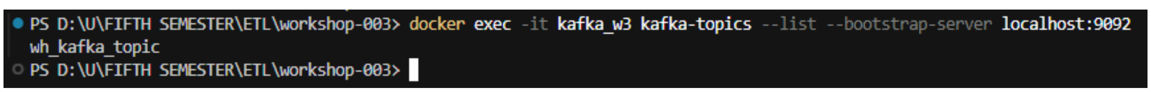
d. Now we can create a `Kafka Topic` with this command:

```
docker exec -it kafka_w3 kafka-topics --create --topic wh_kafka_topic --bootst
rap-server localhost:9092
```



e. To check if it was created, run this command:

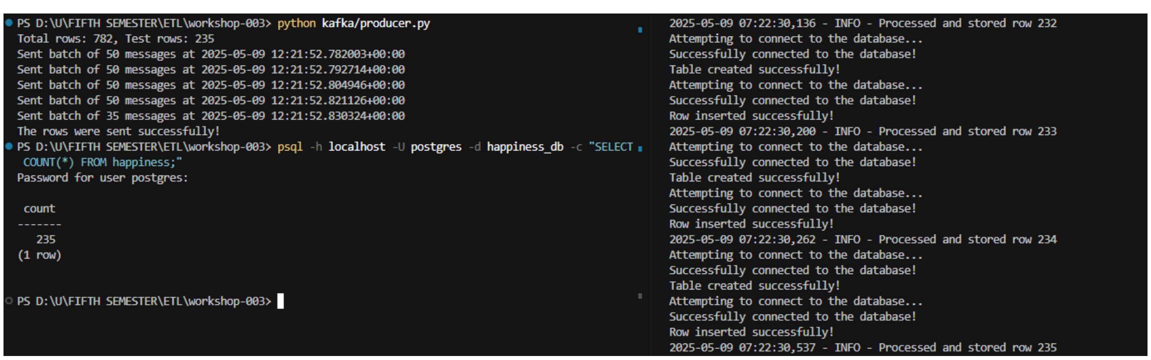
```
docker exec -it kafka_w3 kafka-topics --list --bootstrap-server localhost:9092
```



f. Finally, run the files from the kafka directory (`producer.py` and `consumer.py` , in the same order) with the following commands:

```
python kafka/producer.py
```

```
python kafka/consumer.py
```



g. Optional Cleanup (After executing everything)

```
docker-compose down
psql -h localhost -U postgres -d happiness_db -c "DELETE FROM happiness;"
psql -h localhost -U postgres -d happiness_db -c "ALTER SEQUENCE happines
s_id_seq RESTART WITH 1;"
```

Conclusions

This project successfully implemented a machine learning pipeline to predict happiness scores, fulfilling the objectives of Workshop 3: Machine Learning and Data Streaming. The pipeline integrated exploratory data analysis (EDA), model training, data streaming with Apache Kafka, and performance evaluation, with predictions stored in a PostgreSQL database.

Model Performance

- Four regression models were evaluated: Linear Regression, Random Forest Regressor, an Alternative Random Forest Regressor, and Gradient Boosting Regressor. The Alternative Random Forest Regressor, configured with 100 estimators and a random state of 0, achieved the best performance with a Mean Squared Error (MSE) of 0.1721, a Mean Absolute Error (MAE) of 0.3246, and a Coefficient of Determination (R^2) of 0.8639. This indicates that the model explains 86.39% of the variance in happiness scores, outperforming the other models and demonstrating the effectiveness of ensemble techniques with increased estimators.
- The Linear Regression model produced an MSE of 0.2103 and an R^2 of 0.8337, explaining 83.37% of the variance, which is a reasonable but improvable fit. The Random Forest Regressor (50 estimators) improved upon this with an MSE of 0.1755 and an R^2 of 0.8612, while the Gradient Boosting Regressor achieved an MSE of 0.1749 and an R^2 of 0.8617, both showing strong performance but falling short of the Alternative Random Forest Regressor.
- The Root Mean Squared Error (RMSE) of the Alternative Random Forest Regressor, at approximately 0.4149, suggests an average prediction error of 0.4149 on a 0–10 scale, which is reasonable for this dataset. The Explained Variance Score of 0.8650 further confirms the model's ability to capture the variance in the target variable.

Data Streaming and Storage

- The pipeline streamed the 30% test set (235 rows) from a total dataset of 782 rows, aligning with the 70/30 train-test split. The Kafka producer and consumer successfully processed and stored these predictions in the `happiness` database table, with each row including input features, actual happiness scores, and predicted happiness scores.

Visual and Analytical Insights

- **Actual vs Predicted Happiness Scores**: A scatter plot of actual versus predicted happiness scores closely follows the ideal line (y=x), indicating high predictive accuracy. Most predictions deviate by less than 0.5 points from the actual scores, consistent with the RMSE of 0.4149, demonstrating the model's reliability.
- **Average Predicted Happiness Score by Continent**: Analysis by continent revealed distinct regional patterns. North America exhibited the highest average predicted happiness score at 7.2, reflecting better socio-economic conditions, followed by South America at 6.1 and Central America at 5.8. The "Other" category, encompassing regions not explicitly classified, averaged 5.5, suggesting potential areas for further investigation into happiness factors.
- **Original vs Predicted Happiness Scores by Continent**: A comparison of original and predicted average happiness scores by continent showed strong alignment, confirming the model's generalisation capability. For instance, North America's original average score of 7.3 was predicted as 7.2, Central America's 5.9 as 5.8, and South America's 6.2 as 6.1, with the "Other" category aligning at 5.6 and 5.5, respectively. These minor differences (less than 0.1 on average) highlight the model's robustness across diverse regions.
- **Feature Importance**: The model identified `social_support`, `gdp_per_capita`, and `healthy_life_expectancy` as the most influential predictors, aligning with real-world expectations where social and economic factors heavily influence happiness. Features like `government_corruption` and continent-specific dummy variables had less impact, suggesting that while regional differences exist, universal socio-economic factors dominate happiness predictions.

Author

Created by **Sebastian Belalcazar Mosquera**.

Connect with me on LinkedIn for feedback, suggestions, or collaboration opportunities!
