Predicting Rain in Australia

Project Aim

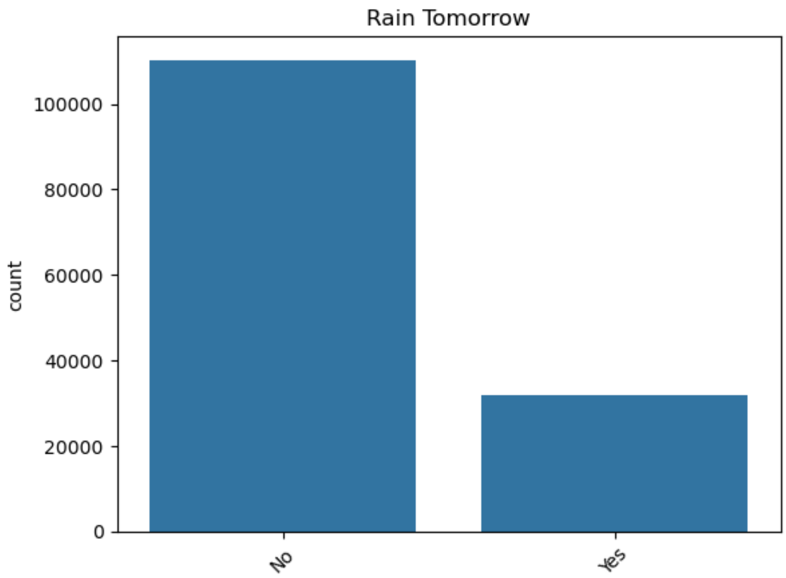
The aim of the project is to predict if it will rain tomorrow based on todays weather.

The data set contains data from Australia is can be downloaded here.

Data Exploration

The given Dataset from Australia has 23 different columns and contains 145460 data entrys.

The target column is RainTomorrow, which is a Boolean. The target is unevenly distibuted (fewer rainy days).



The Data for today contains information about the date, the city, temperature, humidity, pressure, wind, clouds, sunshine and rain. Most variables are numeric. Categorical values are the location , wind related values (e.g. wind direction). Rains today is a boolean. The dataset contains measurements from 49 citys/places.

Missing values in %	
Date	0.000000
Location	0.000000
MinTemp	1.020899
MaxTemp	0.866905
Rainfall	2.241853
Evaporation	43.166506
Sunshine	48.009762
WindGustDir	7.098859
WindGustSpeed	7.055548

Missing values in %	
WindDir9am	7.263853
WindDir3pm	2.906641
WindSpeed9am	1.214767
WindSpeed3pm	2.105046
Humidity9am	1.824557
Humidity3pm	3.098446
Pressure9am	10.356799
Pressure3pm	10.331363
Cloud9am	38.421559
Cloud3pm	40.807095
Temp9am	1.214767
Temp3pm	2.481094
RainToday	2.241853
RainTomorrow	2.245978

How to proceed with missing values:

- delete entrys with over 10% of missing values
- replace Nans for cateforical variables with mode
- replace Nans for numerical variables with median

First Observation

If it rains today, there is 50% chance that it also rains tomorrow. If it does not rain today, it will most likely also not rain tomorrow.

RainTomorrow

RainToday	No	Yes
No	92728	16604
Yes	16858	14597

Preprocessing data

- How to proceed with missing values:
  - delete entrys with over 10% of missing values
  - replace Nans for categorical variables with mode
  - replace Nans for numerical variables with median

- delete Date column since it is not used for modelling (note: The date is deleted for making the model easier. One should keep in mind that the seasons in fact have an influence on the weather. Therefore foradvanced modelling the date/month should be considered)
- encode RainToday and RainTomorrow in binary variable
- encode location and variables for wind direction with get_dummies (note: Since there are a lot of Locations in the dataset, this step leads to an enormous increase of the number of features)
- Scaling of numerical features by vector normalization

Modelling and Prediction

The modelling script does model 4 different modeltypes:

- KNeighbors
- Decision Tree
- Random Forest
- Gradient Boosting

The modeling script then stores the best model with MLFlow. The prediction script uses the best model stored in the previous step with MLFlow.

Project Organization

The Project structure is based on the cookiecutter data science project template. #cookiecutterdatascience

```
├── LICENSE
├── README.md          <- The top-level README for developers using this project.
├── data
│   └── raw            <- The original, immutable data dump.
│
├── docker               <- These two folders contain
├── docker_images        <- the docker files
│
├── models             <- Trained and serialized models, model predictions, or
model summaries
│
├── mysql               <- database
│
├── notebooks          <- Jupyter notebooks. Naming convention is a number (for
ordering),
│                         the creator's initials, and a short `-` delimited
description, e.g.
│                         `1.0-jqp-initial-data-exploration`.
│
├── reports            <- Generated analysis as HTML, PDF, LaTeX, etc.
│   └── figures        <- Generated graphics and figures to be used in reporting
│
├── requirements.txt   <- The requirements file for reproducing the analysis
environment, e.g.
│                         generated with `pip freeze > requirements.txt`
```

```
│
├── src                <- Source code for use in this project.
│   ├── __init__.py    <- Makes src a Python module
│   │
│   ├── data           <- Scripts to generate the database and preprocess the data
│   │   ├── make_dataset.py
│   │   └── preprocessing.py
│   │
│   ├── features       <- Scripts to turn raw data into features for modeling
│   │   └── mlflow_server.sh
│   │
│   ├── models         <- Scripts to train models and then use trained models to
make
│   │   │                 predictions
│   │   ├── predict_model.py
│   │   ├── train_model.py
│   │   └── weather_api.py
│   │
│   ├── visualization  <- Scripts to create exploratory and results oriented
visualizations
│       └── Streamlit.py
│
├── cron_pipeline.sh     <- cron pipeline to automate all steps
└── docker-compose.yml   <- docker-compose file to run all Docker containers
```

Automation with cron

Seperate Docker container to automate the process:

- calls cron_pipeline.sh every 10 minutes
- the script calls the FastAPI endpoints in the model container in the following order:
    - make dataset (chooses a random part of the original data to simulate changes in the data)
    - preprocess data
    - train model

SQL

Task: store data in a local database (SQL)

Solution:

src/data/convert_data_to_sql.py

- takes the big weatherAUS.cvs from this source: https://www.kaggle.com/datasets/jsphyg/weather-dataset-rattle-package?resource=download
- converts it into a table called weather_table in weather_australia.db and save it in data/raw

src/test.sql.py

- checks for missing/extra columns and the right data type in the table (so far float or string) src/data/make_dataset.py

- loads the sql, ignores specific columns and simply filter (e.g the location) the big database. The results will be saved in data/raw
- note: for first instances the data folder and the database are not gitignored!!
- make dataset filters the .db for e.g location or select a random amonúnt of data for the subset and save it as .csv with current date

Working with a real MySQL project:

- no databases are shared directly, raw data is weatherAUS.csv
- everybody needs to execute mySQL for database handling, either in docker or MYSQL workbench

STEP-BY-STEP guide

- install MYSQL
- initiating a MYSQL Connection (more infos on How To Do here: https://dev.mysql.com/doc/workbench/en/wb-getting-started-tutorial-create-connection.html)
- creating the schema: e.g. rain_australia
- running the script "create_table.sql" (change the first line (USE {your schema name}))
  - it creates the empty table
- running the script "import_data.sql" (change the third line (LOAD DATA INFILE 'your path', for me the table needed to be in the MY SQL SERVER folder))
  - it fills the empty table and can handle the 'NA' values from the raw data
- running the script "test_table.spl.sql" (change the first line (USE {your schema name}))
  - it should create an output with 145460 (number of rows in the table)
- probably more useful in containerization

MySQL dockerization:

- build Docker image:

```
docker build -t weather-mysql
```

- in another terminal `docker ps` for container ID

Enter MySQL client:

- e.g. docker exec -it c3ecfcd4a529 mysql -u root -proot (Container ID = c3ecfcd4a529, Password= root) check the table with USE weather_db;SELECT COUNT(*) FROM weather_data;SELECT * FROM weather LIMIT 5; -> Outcome: 14560
- exit with quit

MLFLOW

- mlflow_server.sh
  - sets up the mlflow server (http://localhost:8080)

- train model with simple mlflow architecture for tracking

Dockerization

four docker containers: `mysql`, `MLFlow`, `Streamlit` and `model` services are added to `docker-compose.yml`.

The mysql image is located at `mysql/Dockerfile`, the MLflow image is located at `docker_images/Dockerfile_mlflow`, the Streamlit image is located at `docker_images/Dockerfile_streamlit` while the model image is at `docker_images/Dockerfile_model`.

- `mysql` container hosts all the raw data
- `MLFlow` container hosts the mlflow server
- `model` container hosts the data substracting, data preprocessing, training, predicting, and FastAPI services
    - `test_model` container triggers the command to test the FastAPI service
- `Streamlit` container hosts the Streamlit app
    - `Make dataset` button triggers the command to substract the data from the whole data base (hosted by `mysql` container)
    - `Preprocess` button triggers the command to preprocesse the sub-dataset (created by `make dataset`)
    - `Train model` button triggers the command to train the model based on the preprocessed data (created by `preprocess`)
    - `Predict` button triggers the command to predict the value based on the model (trained by `training`)
- to start(or build if not exists) the docker compose:

```
docker-compose up --build
```

- to test the FastAPI:

```
# in a new terminal
docker-compose start test_model
```

- to open the Streamlit app, in your browser, go to http://localhost:8501/
- to visit the MLflow server, in your browser, go to http://localhost:8080/