Data Science Solution Implementation

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Agenda

1. Deploy Model as an API with Plumber
2. Deploy Model as an API with FastAPI
3. Deploy a Machine Learning application with Streamlit

Deploy Model as an API with Plumber

Prerequisites

Ensure the following installations and setup:

- R and RStudio
- Docker Desktop
- Visual Studio Code

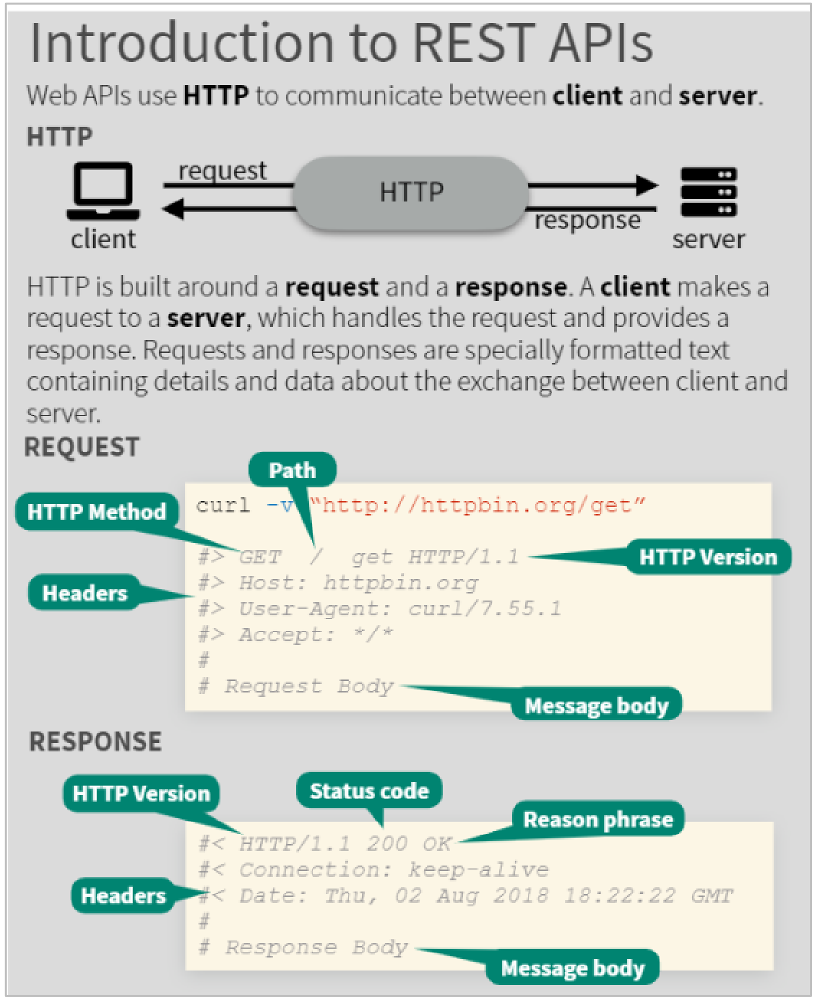
Learning Milestones

You will learn how to:

1. Persist a ML model.
2. Create an API service for the model.
3. Serve model predictions from a Docker container.

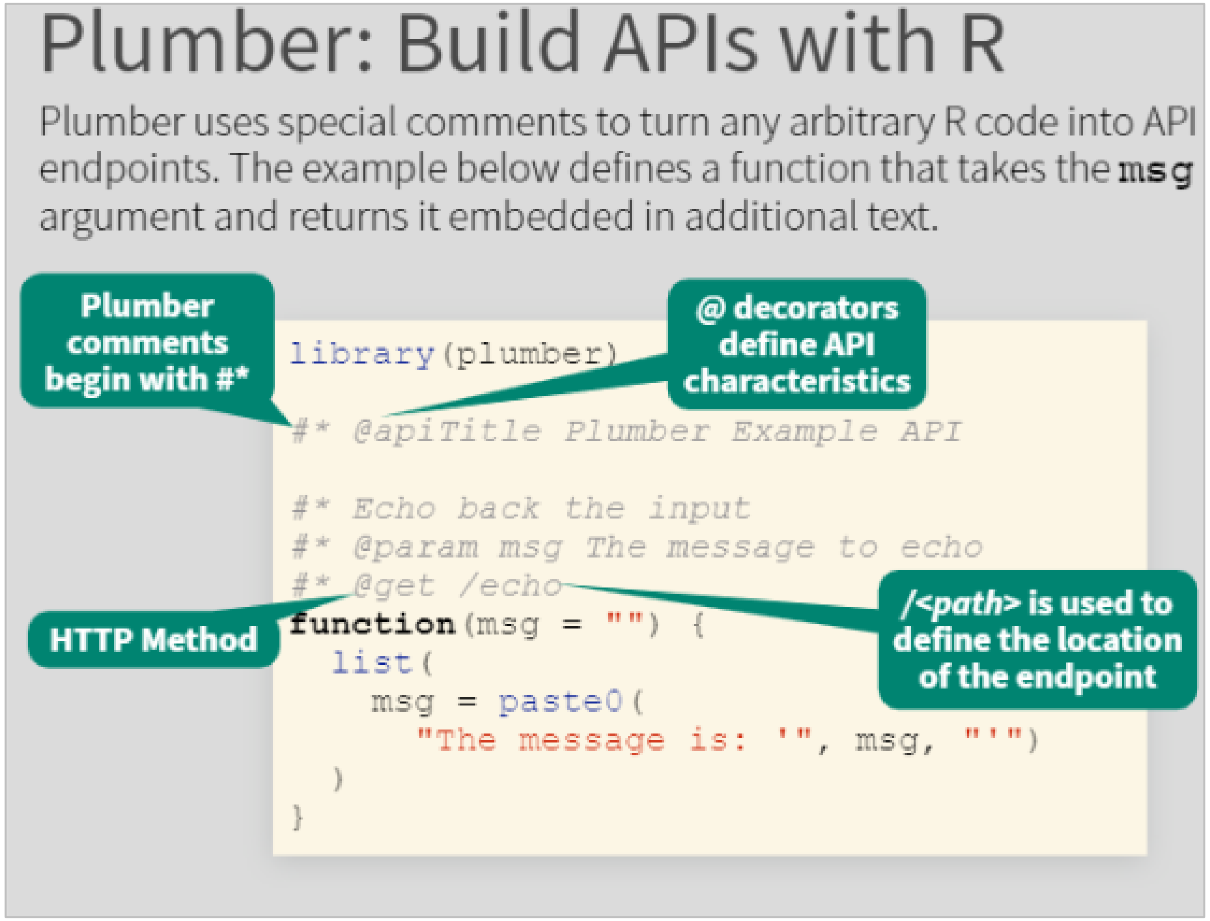
Primer: RESTful APIs

Application programming interfaces that enable applications to exchange information securely over the internet.



Source: Posit. 2023. *REST APIs with plumber::CHEATSHEET.* https://github.com/rstudio/cheatsheets/blob/main/plumber.pdf

Primer: Plumber

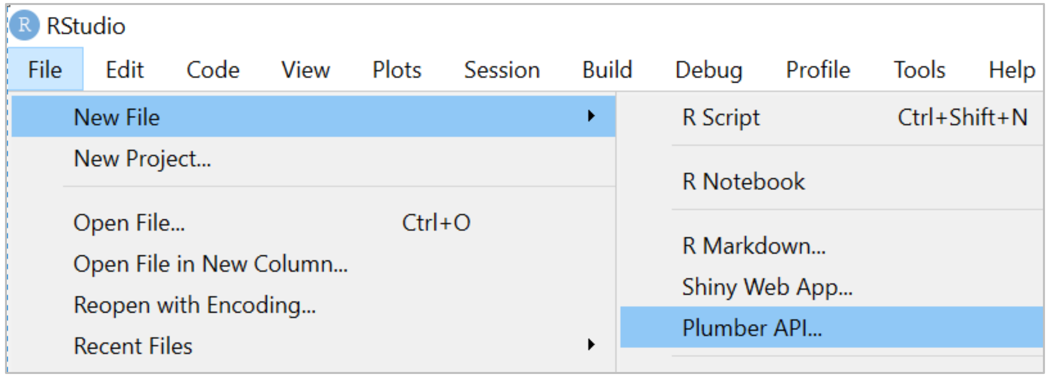


Source: Posit. 2023. *REST APIs with plumber::CHEATSHEET.*
https://github.com/rstudio/cheatsheets/blob/main/plumber.pdf

Primer: Plumber

Try Plumber

1. Launch RStudio.
2. Create a plumber file.
3. Create a function that takes a pair of random number sets (rnorm(100)) to generate a scatterplot at API endpoint ‘/scatter’.
4. Create a function that takes weight and height as inputs to compute bmi at API endpoint ‘/bmi’.



Primer: Plumber

Solution

GET is used to request data from a specified resource.

Develop API

```
#* Plot a scatter plot
#* @serializer jpeg
#* GET is used to request data from a specified resource.
#* @get /scatter
function(){
        rand = rnorm(100)
        rand2 = rnorm(100)
        plot(rand, rand2, main='Scatter Plot')
}

#* compute and return BMI given weight and height
#* @param ht height of a person in meters
#* @param wt weight of a person in kilograms
#* @post /bmi
function(ht, wt){
  as.numeric(wt)/(as.numeric(ht)**2)
}
```

Develop API

POST is used to send (large) data in the request body to a server to create/update a resource.

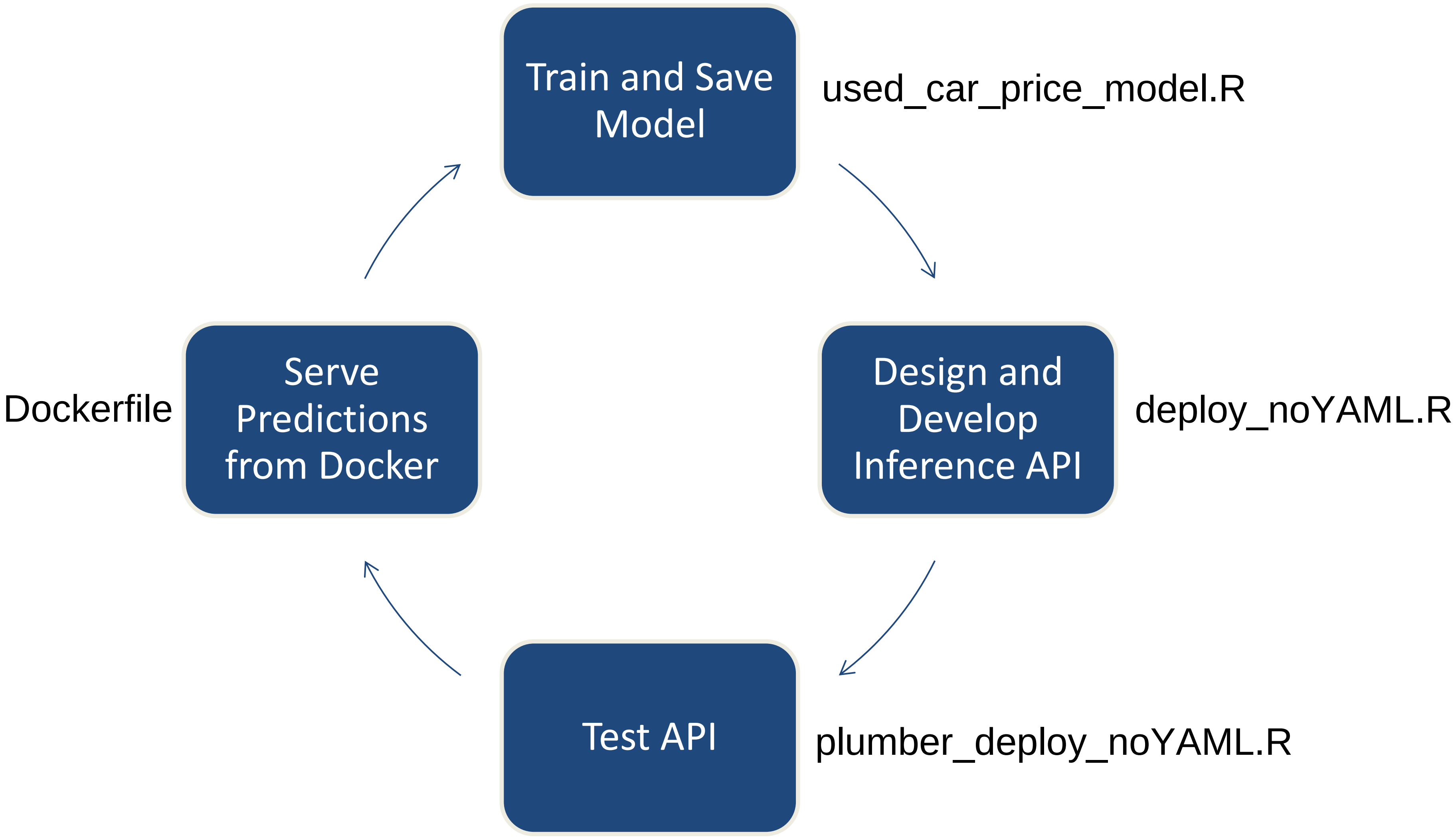
Call API

```
> library(httr)
> headers = c('Content-Type'='application/json')
> data = '{"ht":1.78,"wt":75}'
> url = 'http://127.0.0.1:7922/bmi'
> resp = httr::POST(url=url,httr::add_headers(.headers=headers), body=data)
> content(resp)
[[1]]
[1] 23.6713
```

Call API

```
D:\workspace\R>curl -X POST -H "Content-Type: application/json" -d "{\"ht\":1.78,\"wt\":74}" http://127.0.0.1:4325/bmi
[23.3556]
```

Process Flow



Process Flow

Step 1: Train and Save Model

1. Train a model that predicts the price of a used car.
2. Persist trained model as a RDS (R Data Serialisation) file.

Sample training script: *used_car_price_model.R*

```
# set path to folder containing the source codes
setwd("D:/Workspace/R/dssi-plumber")

# read the data file & inspect it's structure
cars = read.csv('data/cars.csv')
summary(cars)

#set initial seed for reproducibility
set.seed(123)

# train-test split
inds = createDataPartition(cars$Price, p=0.7, list=FALSE,times=1)
train_set = cars[inds,]
test_set = cars[-inds,]

# train model
model = lm(Price ~. , data = train_set)
# feature select
final_model = stepAIC(model)
summary(final_model)

# save final model
saveRDS(final_model, "models/car_price.rds")
```

Train model

Persist trained model

Process Flow

```r
model = readRDS("../models/car_price.rds")
```

Load trained model

Step 2: Design and Develop Inference API

1. Using Plumber, create a function that takes features/covariates as input parameters, loads the trained model and output predicted price at API endpoint '/api/v1/used-car/price'.

Sample Plumber file: *deploy_noYAML.R*

```r
## Model: Price ~ Age + KM + FuelType + HP + Automatic + CC + Weight

#* predict the price of a used car
#*
#* @param Age this is the age of the car as input by the user
#* @param KM distance ran in kms
#* @param FuelType takes one of the 3 values out of Diesel/Petrol/CNG
#* @param HP horsepower
#* @param Automatic 1 or 0
#* @param CC vehicle fuel capacity
#* @param Doors 2/3/4/5 doors
#* @param Weight weight of vehicle

#* @post /api/v1/used-car/price
function(Age, KM, FuelType, HP, Automatic, CC, Doors, Weight){
  newdata = data.frame(Age = as.numeric(Age), KM = as.numeric(KM),
                       FuelType = FuelType, HP = as.numeric(HP),
                       Automatic = as.numeric(Automatic),
                       CC = as.numeric(CC), Doors = as.numeric(Doors),
                       Weight = as.numeric(Weight))

  # predict car price using predict function in R
  return(list(price = jsonlite::unbox(predict(model, newdata))))
}
```

API parameters

API endpoint

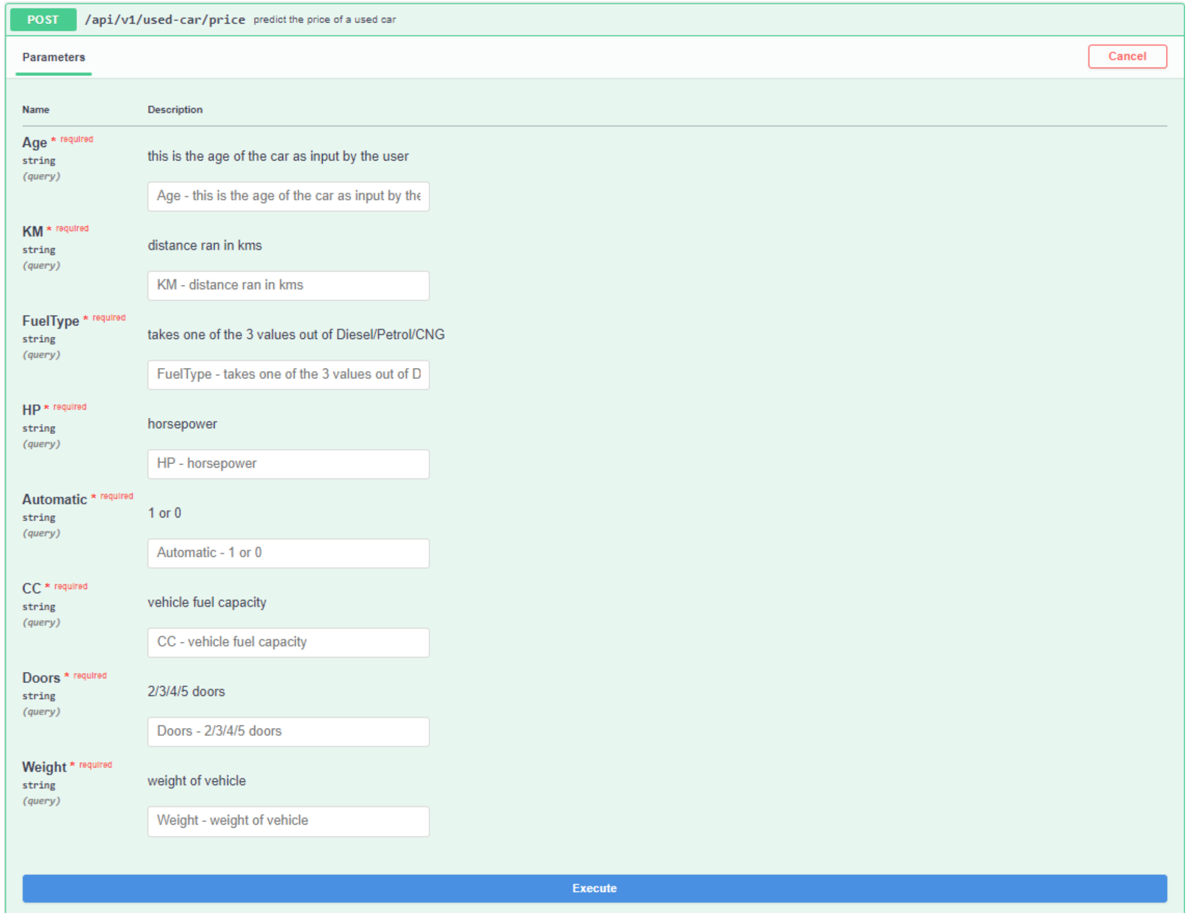
API function: Perform prediction on new inputs

Process Flow

Step 3: Test API

1. Create a wrapper R script that runs the Plumber API with a user-defined port.
2. Run the wrapper script.
3. In Swagger UI, fill in the parameter values and test the '/api/v1/used-car/price' API response.

Sample wrapper script: *plumber_deploy_noYAML.R*



Process Flow

Step 4: Serve Predictions from Docker

1. Start Docker Engine.
2. Create a Dockerfile that uses a Plumber API server image.
3. Specify the instructions to copy source files and running Plumber file.
4. Build the Docker image:

```
> docker build -t dssi-plumber-docker:1.0 .
```

5. Start the application container:

```
> docker run --rm -d -p 80:8000/tcp dssi-plumber-docker:1.0
```

Sample Dockerfile: *Dockerfile*

```
FROM trestletech/plumber

# copy necessary files
RUN mkdir /models
RUN mkdir /src
COPY models/car_price.rds /models/car_price.rds
COPY src/deploy_noYAML.R /src/plumber.R
WORKDIR /src

# plumber instructions to run
EXPOSE 8000
ENTRYPOINT ["R", "-e",  "pr <- plumber::plumb('/src/plumber.R'); \
    pr$run(host='0.0.0.0', port=8000)"]
```

Deploy Model as an API with FastAPI

Prerequisites

Ensure the following installations and setup:

- Docker Desktop
- Anaconda/Python Software
- Python virtual environment [Recommended]
- Install additional Python packages:

```
> pip install -r requirements.txt
```

Learning Milestones

You will learn how to:

1. Persist a ML model.
2. Create an API service for the model.
3. Serve model predictions from a Docker container.

Primer: FastAPI

FastAPI - Web framework for building APIs with Python

```python
from fastapi import FastAPI

app = FastAPI()


@app.get("/")
async def root():
    return {"message": "Hello World"}
```

Import FastAPI

Create a FastAPI instance

Path operation decorator

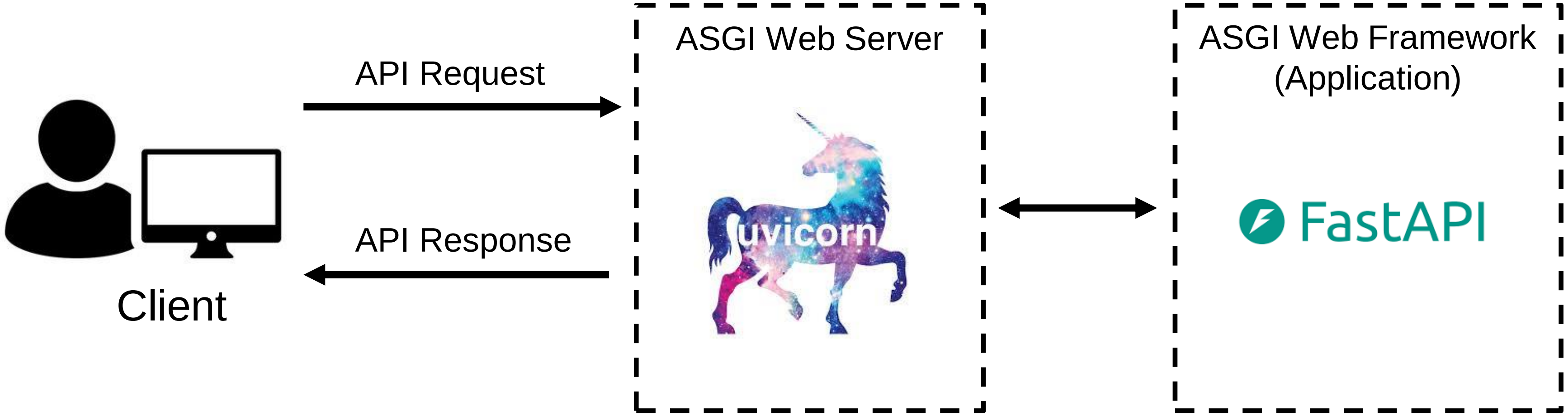
Path operation function

API Response

Source: https://fastapi.tiangolo.com/tutorial/first-steps/

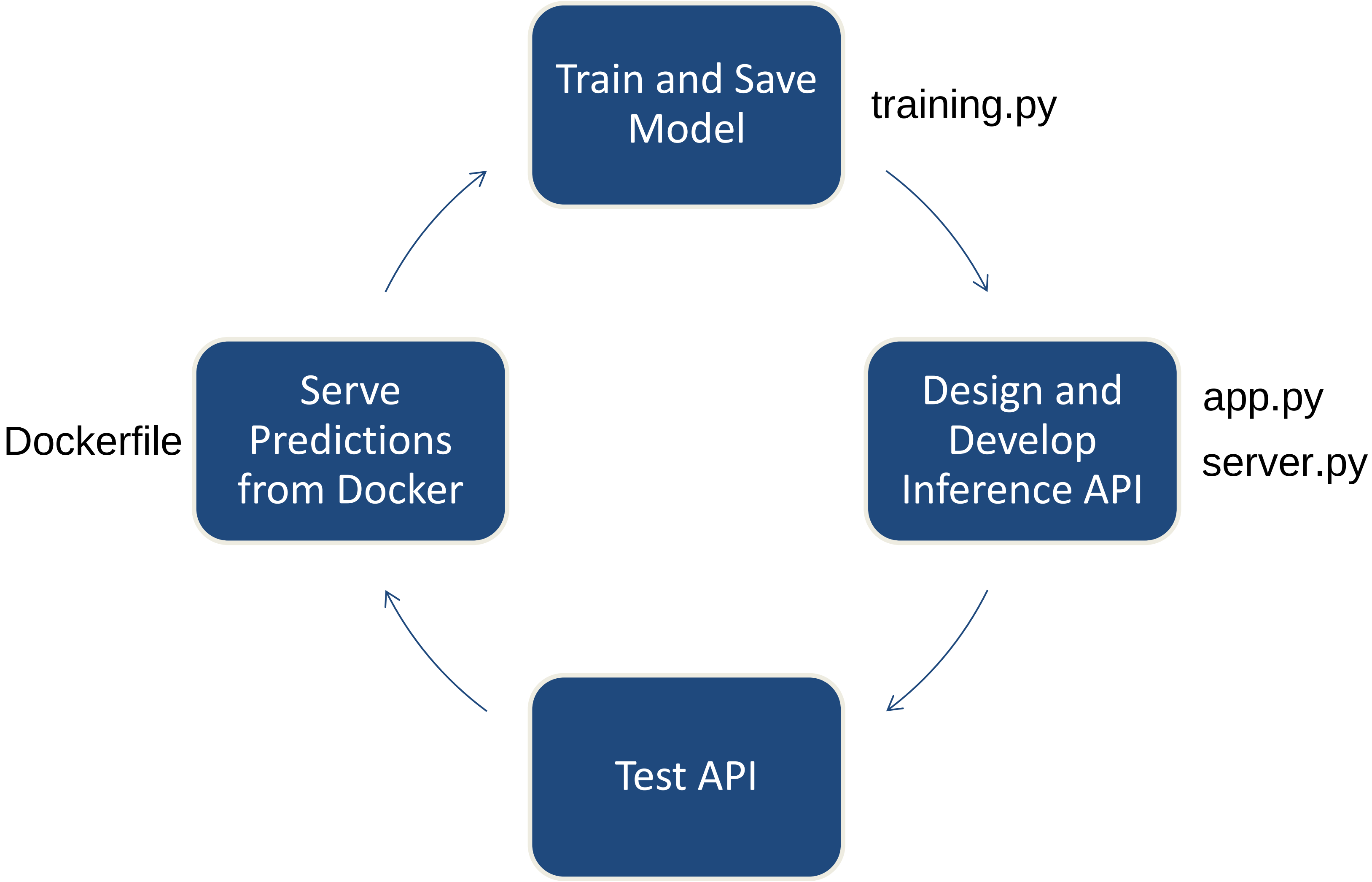
Primer: FastAPI

FastAPI - Web framework for building APIs with Python



Source: https://www.uvicorn.org/

Process Flow



Process Flow

Step 1: Train and Save Model

1. Run the training module to train and persist model:

```
> python –m src.training --data_path data/cars.csv --r2_criteria 0.8
```

Sample training script: *training.py*

Process Flow

Step 2: Design and Develop Inference API

1. Using FastAPI, develop an API that takes new data for inference as input and outputs predicted value at endpoint '/api/v1/used-car/price'.
2. Implement ASGI server using Uvicorn for the APIs.

Sample application code: *app.py*
Sample server code: *server.py*

```python
from fastapi import FastAPI
from fastapi.responses import JSONResponse
import pandas as pd
from src.model_registry import retrieve
from src.config import appconfig

app = FastAPI()

model, features = retrieve(appconfig['Model']['name'])

@app.get("/")
def home():
    return {"message": "Welcome to DSSI!"}

@app.post(appconfig['API']['used_car_price'])
def predict(data: dict):
    pred_df = pd.DataFrame.from_dict([data])
    pred = model.predict(pred_df[features])
    return {"price": pred[0]}
```

```python
import uvicorn
import src

if __name__ == '__main__':
    uvicorn.run("src.app:app",host="0.0.0.0",port=8000)
```

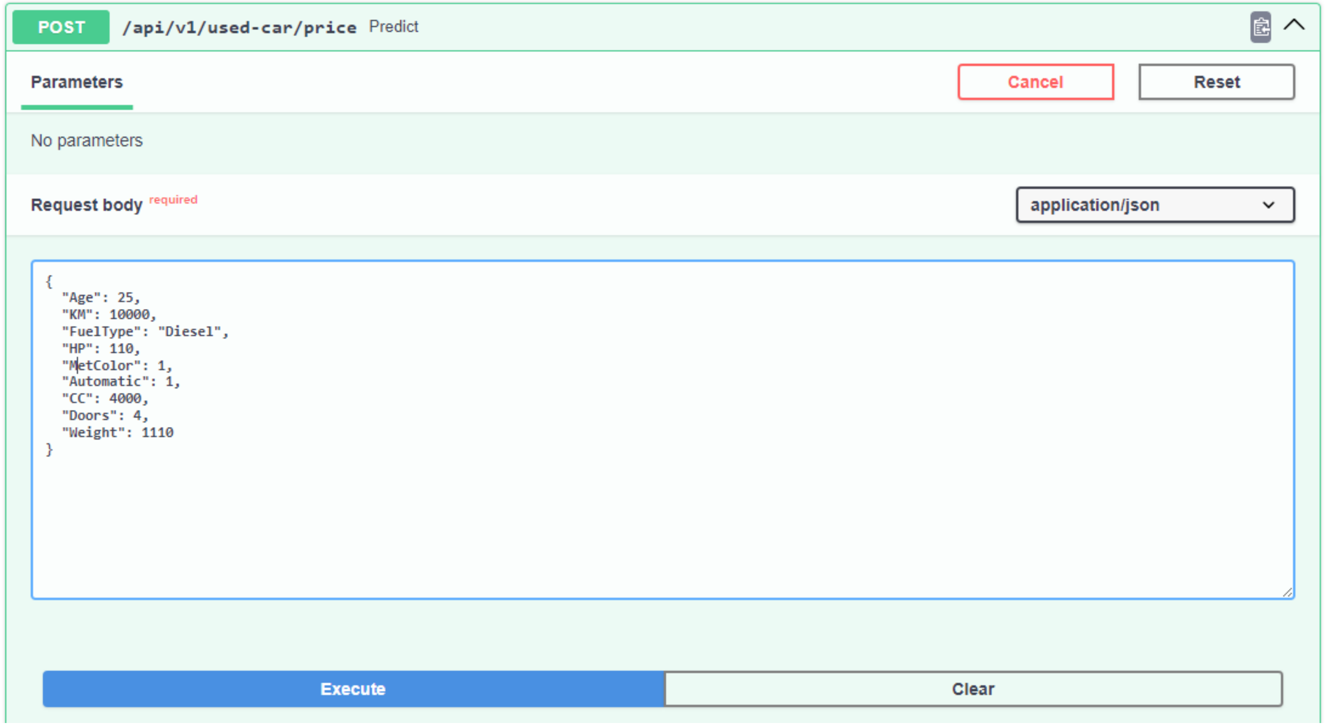
Process Flow

Step 3: Test API

1. Start API service:

```
> python server.py
```

2. Use Swagger UI (http://127.0.0.1:8000/docs) to test the response of the API.



Process Flow

Step 4: Serve Predictions from Docker

1. Start Docker Engine.
2. Create a Dockerfile that specifies the instructions to install required packages, copy source files and run the API service.
3. Build the Docker image:

```
> docker build -t dssi-fastapi-docker:1.0 .
```

4. Start the application container:

```
> docker run --rm -d -p 80:8000 dssi-fastapi-docker:1.0
```

```
FROM python:3.9

WORKDIR /dssi

COPY ./requirements.txt /dssi/requirements.txt

RUN pip install --no-cache-dir --upgrade -r /dssi/requirements.txt

COPY ./server.py ./server.py
COPY ./src ./src
COPY ./models ./models
COPY ./metadata ./metadata

CMD ["python", "server.py"]
```

Sample Dockerfile: *Dockerfile*

Access API

Access the deployed R mode via API call and perform exploration of predictions.

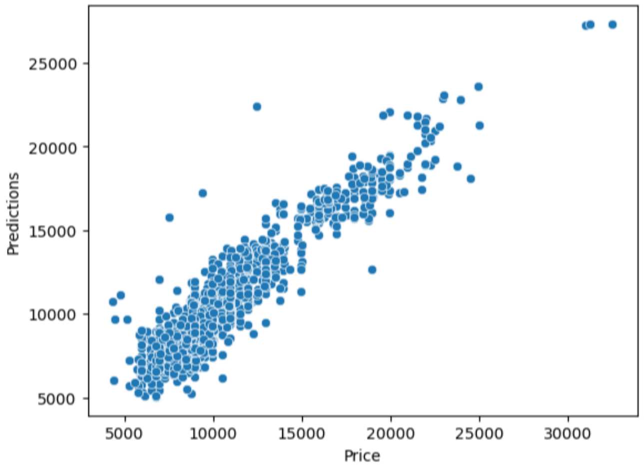
Sample Python notebook: *DSSI_TestAPI.ipynb*

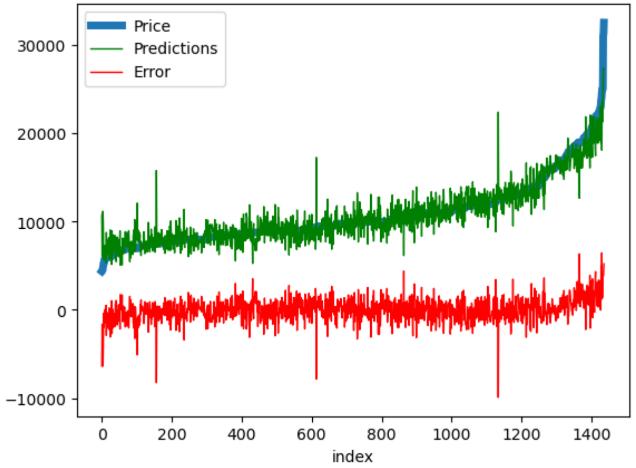
In [1]:
```python
import requests
import pandas as pd

new_data = {
  "Age": 25,
  "KM": 10000,
  "FuelType": "Diesel",
  "HP": 110,
  "MetColor": 1,
  "Automatic": 1,
  "CC": 4000,
  "Doors": 4,
  "Weight": 1110
}
```

In [2]:
```python
resp = requests.post("http://127.0.0.1/api/v1/usedcar/predict", json = new_data)
print("Predicted Price: ", resp.json()["price"])
```

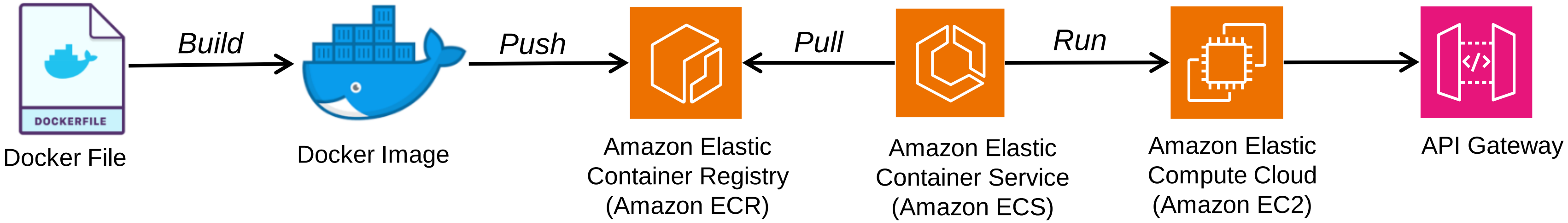
```
Predicted Price:  8878.829091562038
```



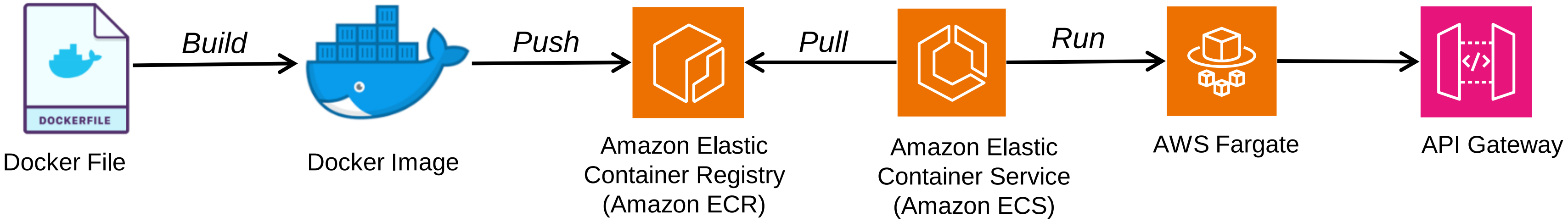


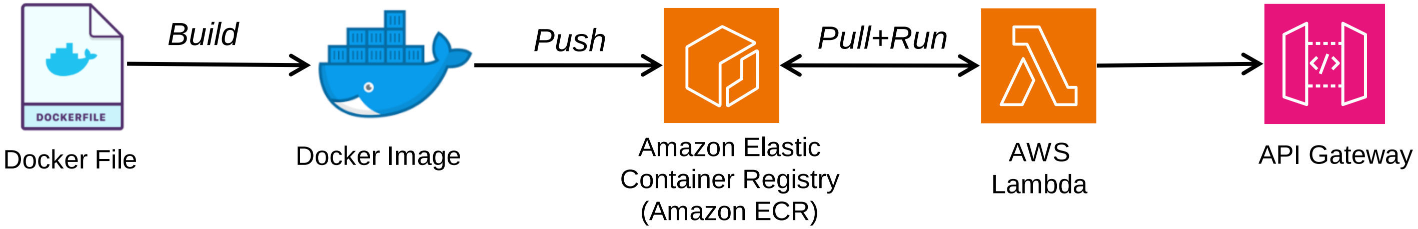
Deploy on AWS

Stateful Deployment (Large consistent workload)



Stateless Deployment (On-demand workload)





Deploy a Machine Learning Application with Streamlit

Prerequisites

Ensure the following installations and setup:

- GitHub Account
- Git and GitHub CLI
- Anaconda/Python Software
- Python virtual environment [Recommended]
- Install additional Python packages:

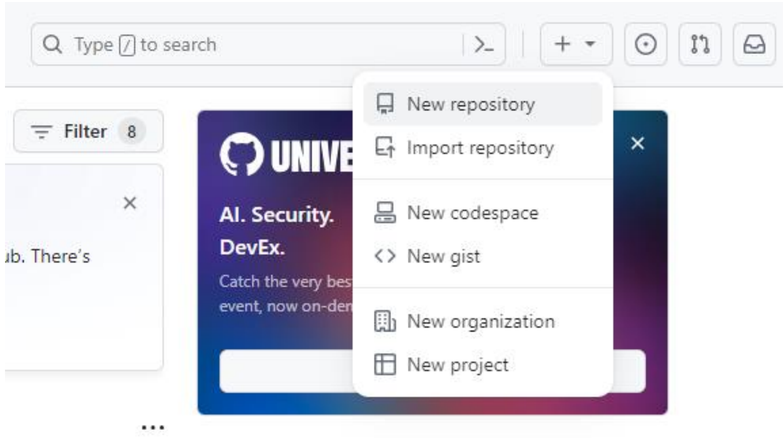
```
> pip install -r requirements.txt
```

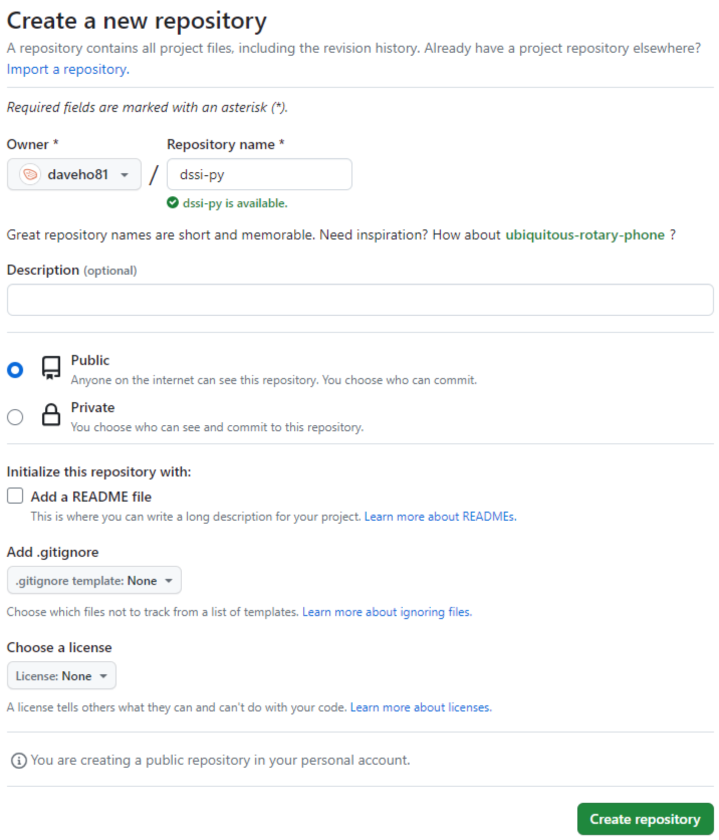
Learning Milestones

You will learn how to:

1. Create a web application that uses a trained ML model to automate decisions.
2. Deploy the web application online.

Step 1: Create a public repository on GitHub





Primer: Git

Step 2: Push remote repository to GitHub

1. Download and unzip the source code in local directory.
2. Open command prompt (or terminal) and navigate to the directory containing the unzipped source codes.
3. Authentication setup with GitHub (via HTTPS):

```
> gh auth login
```

4. Push repository to GitHub:

```
> git init
> git add .
> git commit -m "first commit"
> git branch –M main
> git remote add origin https://github.com/daveho81/dssi-py.git
> git push –u origin main
```

Include all the modified contents in the current directory

Direct copy-pasting of quotation marks can cause formatting issues in multi-lingual terminals

Change to your own repository URL

Primer: Streamlit

Try Streamlit

1. Display a dataframe table.

```
# Load diabetes dataset
st.subheader('**Diabetes Data**')
db = datasets.load_diabetes()

df = pd.DataFrame(db.data, columns=db.feature_names)

# Display dataframe as an interactive table
st.dataframe(df, use_container_width=True)
```

2. Run Streamlit application locally.

```
> streamlit run toy-app.py
```

Sample application code: *toy-app.py*

Primer: Streamlit

Try Streamlit

3. Add a plot.

```
# Plot histogram for age of patients
fig, ax = plt.subplots(figsize=(6, 3))
if 1==0: # Evaluate True to show plot
    df['age'].hist(bins = 10, ax=ax)
    fig.suptitle("Age Distribution")
    st.pyplot(fig)
```

4. Ensure requirements.txt specifies required packages.

5. Commit changes to GitHub repository.

```
> git status
> git add .
> git status
> git commit -m “Enable plot”
> git push –u origin main
```

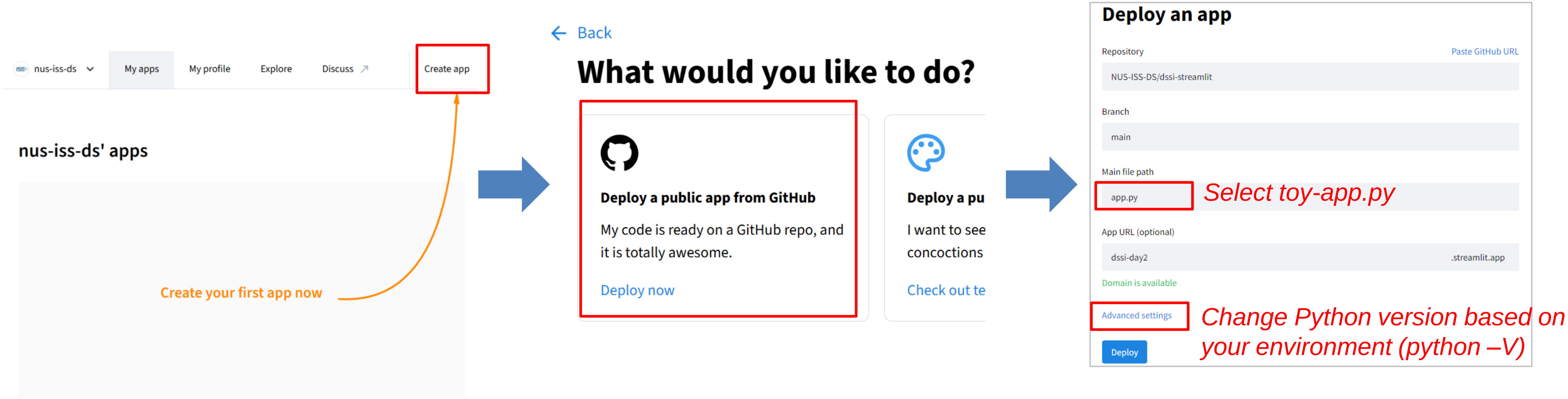
Primer: Streamlit

Try Streamlit

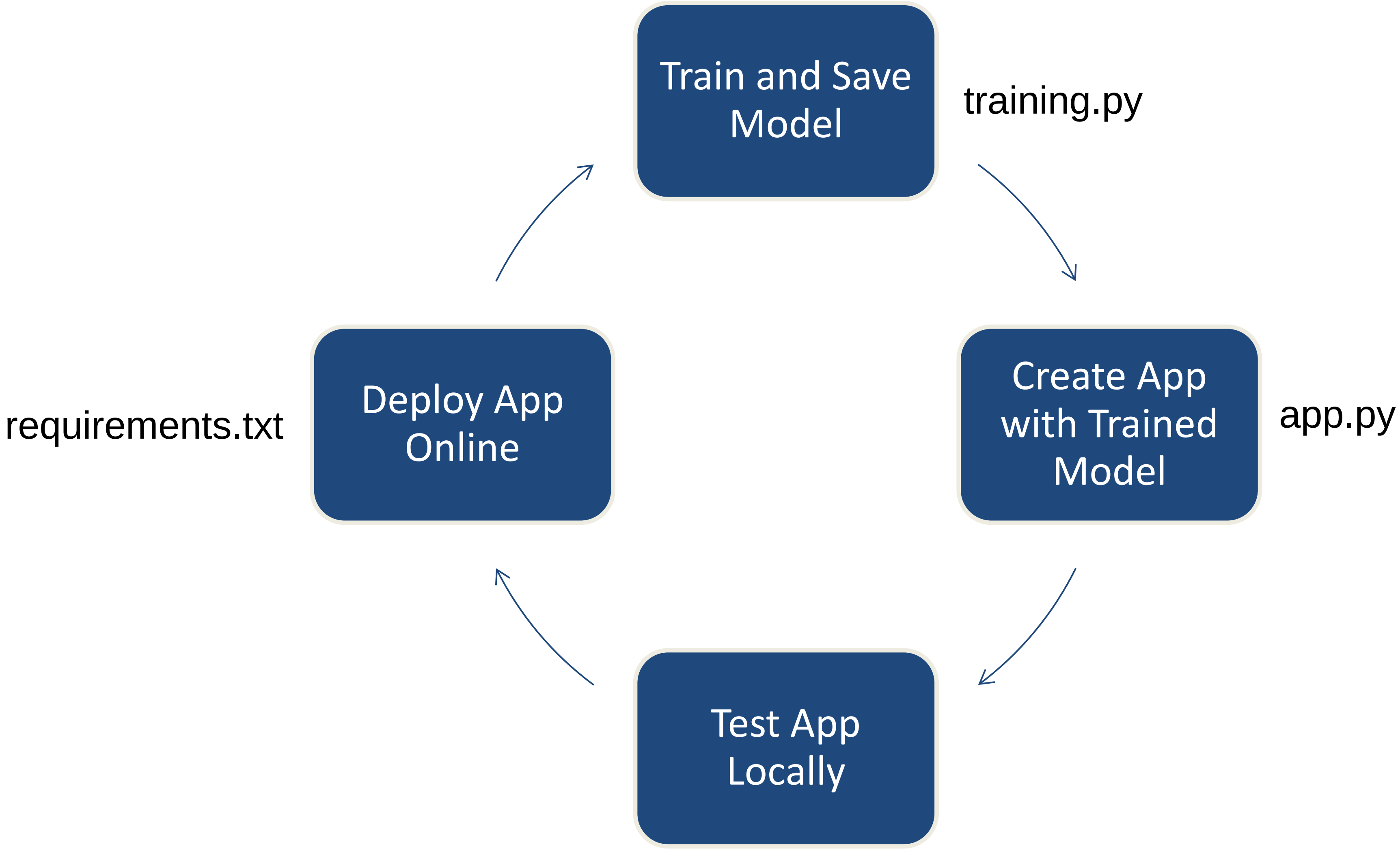
6. Deploy Toy Application on Streamlit Community Cloud.

    i. Sign up https://streamlit.io/cloud using GitHub account.

    ii. Deploy repository:



Process Flow



Process Flow

Step 1: Train and Save Model

1. Perform EDA and model development on Jupyter notebook.
2. Develop a training script to automate model training and persistence.
3. Run the training module:

```
> python –m src.training --data_path data/loan_dataset.csv --f1_criteria 0.6
```

Sample model training notebook: *DSSI_LoanModel.ipynb*
Sample training script: *training.py*

Process Flow

Step 2: Create App with Trained Model

1. Develop an inference script to load trained model and serve predictions.
2. Build an application with Streamlit that automates decisions with user inputs and trained model.

Sample inference script: *inference.py*
Sample application code: *app.py*

```python
def app_sidebar():
    st.sidebar.header('Loan Details')
    emp_length_options = ['< 1 year','1 year','2 years','3 years','4 years','5 years',
                          '6 years','7 years','8 years','9 years','10+ years']
    emp_length = st.sidebar.selectbox("Employment Length", emp_length_options)
    int_rate = st.sidebar.slider('Loan Interest Rate', 5, 40, 10, 1)
    annual_inc = st.sidebar.text_input("Annual Income '000s", placeholder="in '000s")
    fico_range_high = st.sidebar.slider('FICO Upper Boundary', 600, 800, 700, 50)
    loan_amnt = st.sidebar.text_input('Loan Amount')
    def get_input_features():
        input_features = {'emp_length': emp_length,
                          'int_rate': int_rate,
                          'annual_inc': int(annual_inc)*1000,
                          'fico_range_high': fico_range_high,
                          'loan_amnt': int(loan_amnt)
                         }
        return input_features
    sdb_col1, sdb_col2 = st.sidebar.columns(2)
    with sdb_col1:
        predict_button = st.sidebar.button("Assess", key="predict")
    with sdb_col2:
        reset_button = st.sidebar.button("Reset", key="clear")
    if predict_button:
        st.session_state['input_features'] = get_input_features()
    if reset_button:
        st.session_state['input_features'] = {}
    return None
```

Capture user inputs

Persist user inputs for the session

Retrieve user inputs and perform prediction

```python
assessment = get_prediction(emp_length=st.session_state['input_features']['emp_length'],
                            int_rate=st.session_state['input_features']['int_rate'],
                            annual_inc=st.session_state['input_features']['annual_inc'],
                            fico_range_high=st.session_state['input_features']['fico_range_high'],
                            loan_amnt=st.session_state['input_features']['loan_amnt'])
```

Process Flow

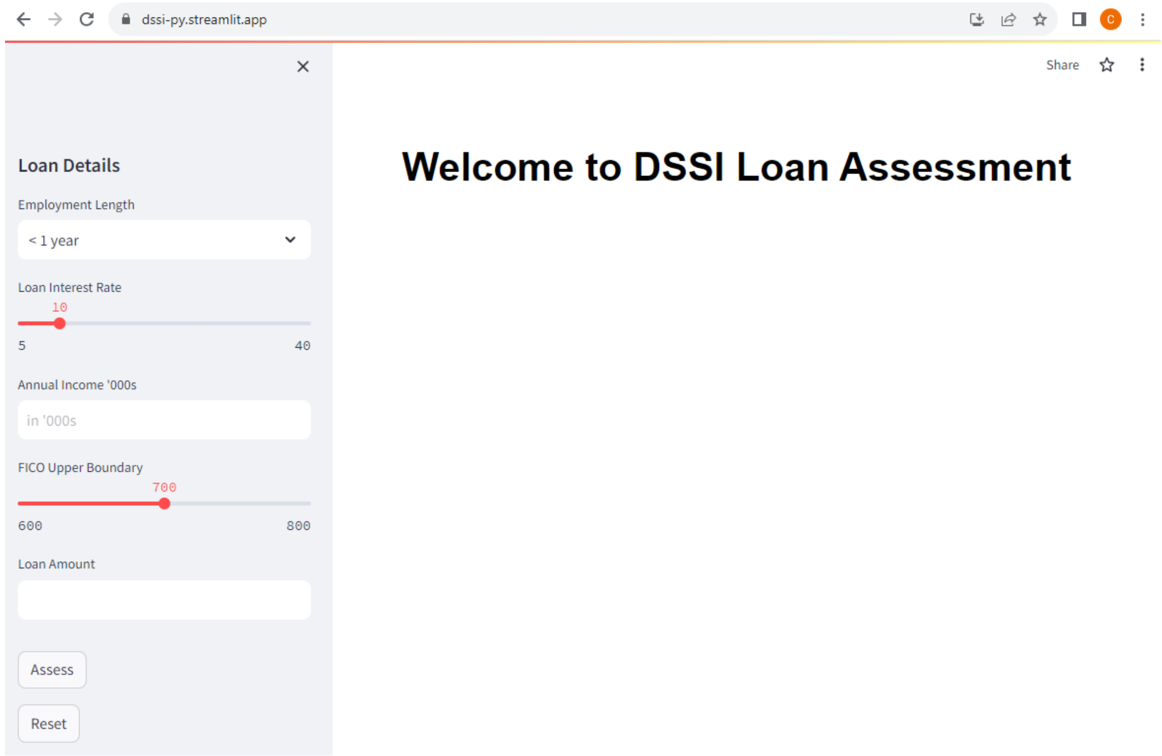
Step 3: Test App Locally

Run Streamlit application:

```
> streamlit run app.py --server.port 8080
```

Step 4: Deploy App Online

1. Commit repository to GitHub.
2. Deploy on Streamlit community cloud.



Process Flow

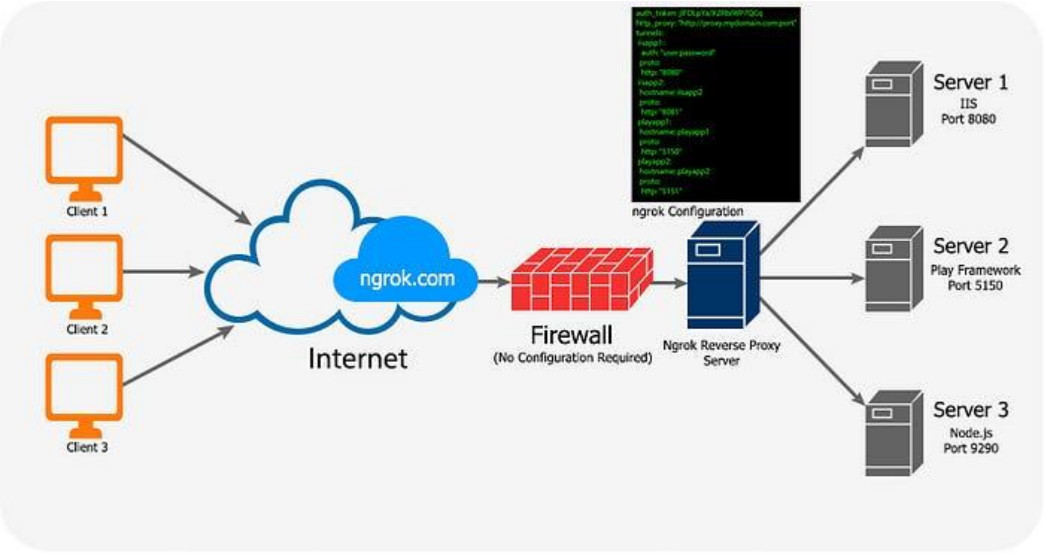
Step 4: Deploy App Online

Expose local service to internet using ngrok.

1. Sign up with https://ngrok.com/
2. Complete the instructions to install ngrok on your local machine and add authtoken.
3. Deploy:

```
> streamlit run app.py --server.port 8080
```

```
> ngrok http 8080
```



Note: All servers are in Internal Network running behind http proxy and not in DMZ

```
ngrok                                                          (Ctrl+C to quit)

Build better APIs with ngrok. Early access: ngrok.com/early-access

Session Status                online
Account                       daveho (Plan: Free)
Version                       3.5.0
Region                        Asia Pacific (ap)
Latency                       3ms
Web Interface                 http://127.0.0.1:4040
Forwarding                    https://6e4a-137-132-27-105.ngrok-free.app -> http://localhost:8080

Connections                   ttl     opn     rt1     rt5     p50     p90
                              9       1       0.02    0.02    1.20    90.01
```

Use static domains and configuration file to run multiple tunnels.

Ref: ngrok. 2023. *ngrok Agent Configuration File*. https://ngrok.com/docs/agent/config/

Workshop

1. In your group, develop and deploy a machine learning application of your choice with Streamlit Community Cloud.

2. Submit Powerpoint slides that contains:
   i. Group members name (Cover page)
   ii. Streamlit application URL (Enable sharing)
   iii. Screenshot of application

Thank You