Machine Learning on Kubernetes

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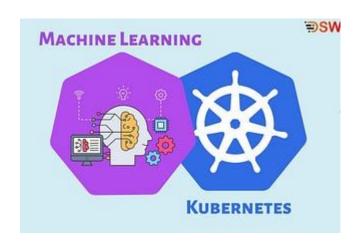


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Introduction

Project Overview

- This project demonstrates the deployment of a machine learning model using Flask API on a Kubernetes cluster.
- The model predicts customer behavior based on input features using logistic regression.

Technologies Used

- Google Cloud Platform (GCP): Provides the infrastructure for running Kubernetes.
- **Kubernetes:** Manages containerized applications in a clustered environment.
- **Docker:** Containerizes the Flask application and its dependencies.
- Flask: A lightweight web framework for building the API.
- Python: The programming language used for the model and API implementation.
- Minikube: Local Kubernetes cluster setup tool used for development and testing.

Design: Main Components

- Flask API: Handles incoming requests, loads the pre-trained machine learning model, and returns predictions.
- **Docker Image:** Contains the Flask application and its dependencies.
- **Swagger-UI:** Provides an interactive interface for testing the API endpoints.





Design: Project Workflow

- Model Training: Logistic regression model trained on customer data.
- API Development: Flask API developed to serve model predictions.
- Containerization: Flask application containerized using Docker.
- Deployment: Docker container deployed on a Kubernetes cluster using Minikube.
- Testing: API endpoints tested using Swagger-UI to ensure correct functionality.







Start minikube.

```
nhaile96456@cloudshell:~ (cs570-big-data-analytics) $ minikube start
* minikube v1.33.1 on Ubuntu 22.04 (amd64)
  - MINIKUBE FORCE SYSTEMD=true
  - MINIKUBE HOME=/google/minikube
  - MINIKUBE WANTUPDATENOTIFICATION=false
* Using the docker driver based on existing profile
 Starting "minikube" primary control-plane node in "minikube" cluster
* Pulling base image v0.0.44 ...
* Updating the running docker "minikube" container ...
* Preparing Kubernetes v1.30.0 on Docker 26.1.1 ...
  - kubelet.cgroups-per-gos=false
  - kubelet.enforce-node-allocatable=""
* Verifying Kubernetes components...
  - Using image gcr.io/k8s-minikube/storage-provisioner:v5
* Enabled addons: storage-provisioner, default-storageclass
* Done! kubectl is now configured to use "minikube" cluster and "default" namespace by default
nhaile96456@cloudshell:~ (cs570-big-data-analytics)$
```

- Create requirements.txt.
 - Start Minikube in Google Cloud Platform to create a local Kubernetes cluster.

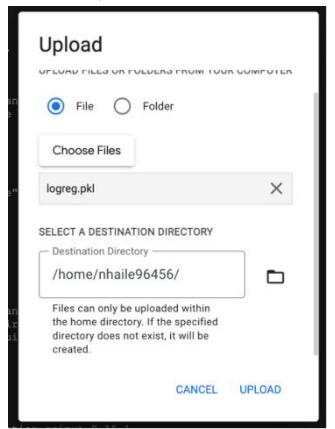
```
nhaile96456@cloudshell: (cs570-big-data-analytics) vi requirements.txt
nhaile96456@cloudshell: (cs570-big-data-analytics) $ cat requirements.txt
Flask==1.1.1
qunicorn==19.9.0
itsdangerous==1.1.0
Jinja2==2.10.1
MarkupSafe==1.1.1
Werkzeug==0.15.5
numpy==1.19.5 # Adjusted to a version before np.float deprecation scipy>=0.15.1
scikit-learn==0.24.2 # Ensure compatibility with numpy version matplotlib>=1.4.3
pandas>=0.19
flasgger==0.9.4
nhaile96456@cloudshell:~ (cs570-big-data-analytics)$
```

- Create requirements.txt.
 - List the necessary Python packages required for the project.

```
nhaile96456@cloudshell: (cs570-big-data-analytics) vi requirements.txt
nhaile96456@cloudshell: (cs570-big-data-analytics) $ cat requirements.txt
Flask==1.1.1
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Jinja2==2.10.1
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numpy==1.19.5 # Adjusted to a version before np.float deprecation scipy>=0.15.1
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pandas>=0.19
flasgger==0.9.4
nhaile96456@cloudshell:~ (cs570-big-data-analytics)$
```

Upload Model

 Upload the pre-trained logistic regression model (logreg.pkl) to the working directory.



Develop Flask API

Create flask_api.py to handle API requests and return model predictions.

```
nhaile96456@cloudshell:~ (cs570-big-data-analytics) $ vi flask api.py
nhaile96456@cloudshell:~ (cs570-big-data-analytics)$ cat flask api.py
from flask import Flask, request
import numpy as np
import pickle
import pandas as pd
from flasgger import Swagger
app = Flask( name )
Swagger (app)
# Load the logistic regression model
pickle in = open("logreq.pkl", "rb")
model = pickle.load(pickle in)
@app.route('/')
def home():
    return "Welcome to the Flask API!"
@app.route('/predict', methods=["GET"])
def predict class():
    11 17 11
```

Create Dockerfile

Define the Dockerfile to containerize the Flask application and its dependencies.

```
nhaile96456@cloudshell:~ (cs570-big-data-analytics) $ vi Dockerfile
nhaile96456@cloudshell:~ (cs570-big-data-analytics) $ cat Dockerfile
# Use the official Python image from the Docker Hub
FROM python: 3.8-slim
# Set the working directory in the container
WORKDIR /app
# Copy the current directory contents into the container at /app
COPY . /app
# Install any needed packages specified in requirements.txt
RUN pip install --no-cache-dir -r requirements.txt
# Make port 5000 available to the world outside this container
EXPOSE 5000
# Define environment variable to prevent Python from writing .pyc files to disk
ENV PYTHONUNBUFFERED=1
# Run flask api.py when the container launches
CMD ["python", "flask api.py"]
nhaile96456@cloudshell:~ (cs570-big-data-analytics)$
```

Build Docker Image

- Use Docker to build an image from the Dockerfile.
 - sudo docker build -t ml_app_docker .

```
nhaile96456@cloudshell:- (cs570-big-data-analytics) $ sudo docker build -t ml app docker .
[+] Building 39.0s (9/9) FINISHED
                                                                                                                                                         docker:default
nhaile96456@cloudshell:- (cs570-big-data-analytics)$
```

Run Docker Container

Debugger PIN: 269-833-583

• Run the Docker container, exposing the Flask API on port 5000.

nhaile96456@cloudshell:~ (cs570-big-data-analytics)\$ docker container run -p 5000:5000 ml app docker

docker container run -p 5000:5000 ml_app_docker

```
/usr/local/lib/python3.8/site-packages/sklearn/base.py:310: UserWarning: Trying to unpickle estimator LogisticRegression from version 0.23.2 when using version 0.24.2. This might lead to breaking code or invalid results. Use at your own risk.

warnings.warn(

* Serving Flask app "flask_api" (lazy loading)

* Environment: production

WARNING: This is a development server. Do not use it in a production deployment.

Use a production WSGI server instead.

* Debug mode: on

* Running on http://0.0.0.0:5000/ (Press CTRL+C to quit)

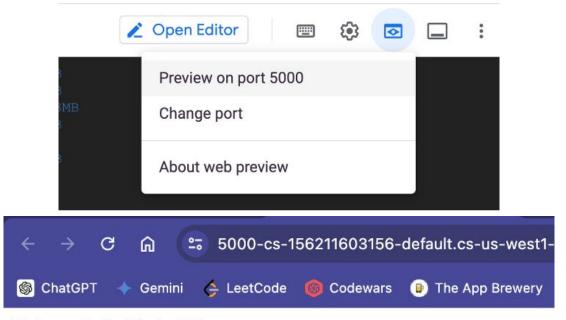
* Restarting with stat

/usr/local/lib/python3.8/site-packages/sklearn/base.py:310: UserWarning: Trying to unpickle estimator LogisticRegression from version 0.23.2 when using version 0.24.2. This might lead to breaking code or invalid results. Use at your own risk.

warnings.warn(

* Debugger is active!
```

- Expose Port in Cloud Shell
 - Configure port forwarding in Google Cloud Shell to access the Flask API.



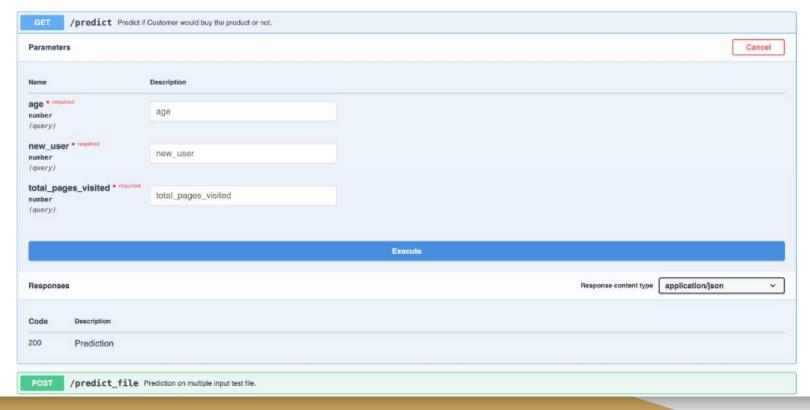
Welcome to the Flask API!

- Access Swagger-Ul
 - Add /apidocs/ at the end of the URL and you will see the home page of Swagger-UI.



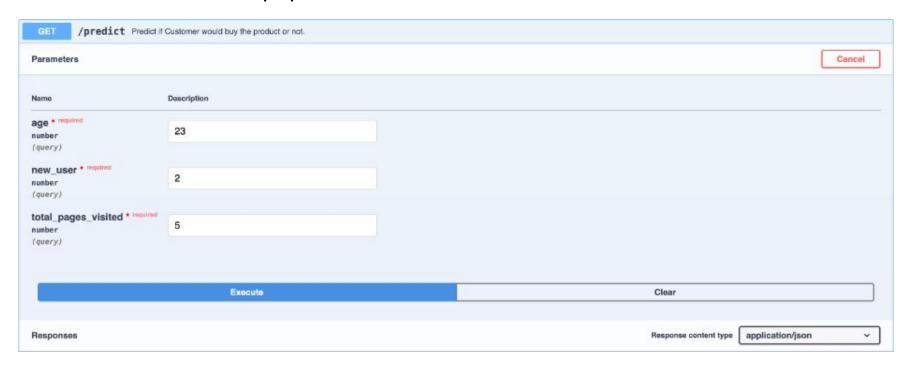
Test: GET

• Click 'Get' and 'Try it out' at the top right side to get the following page.



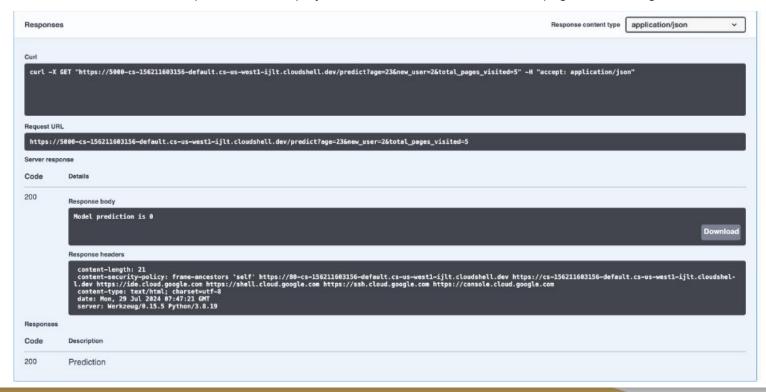
Test: GET

• Enter values for the input parameters and click 'Execute.'



Test: GET

- Upon the execution call, the request goes to the app and predictions are made by the model.
- The result of the model prediction is displayed in the Prediction section of the page as following



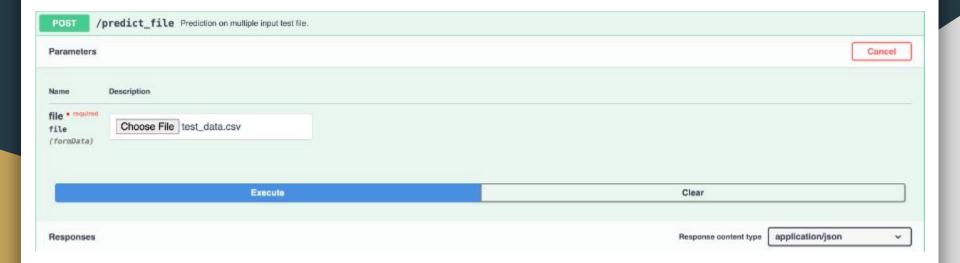
Test: POST

Next, the app can make predictions for a group of customers (test data) by clicking 'Post'.



Test: POST

• Upload the test_data.csv file and click 'Execute.'



Test: POST

The model would make the predictions, and the results would be displayed as shown below.



Test: Kill the Docker Container

- To list running docker containers to kill them, run the command docker ps.
- Then run 'docker kill <container_id>'.

```
nhaile96456@cloudshell:~ (cs570-big-data-analytics)$ docker kill 6393b5a57ff9 6393b5a57ff9 nhaile96456@cloudshell:~ (cs570-big-data-analytics)$
```

Enhancement Ideas



- Integrate CI/CD pipelines to automate testing, building, and deploying updates to the Kubernetes cluster.
- Implement model versioning to manage and deploy multiple versions of the machine learning model, ensuring seamless updates and rollbacks.
- Enhance the scalability of the system using Kubernetes features like Horizontal Pod Autoscaler (HPA) to automatically scale the number of pods based on demand.
- Integrate advanced monitoring and logging solutions, such as Prometheus and Grafana, to gain deeper insights into application performance and detect issues proactively.
- Implement enhanced security measures, including role-based access control (RBAC) and network policies, to secure the application and its deployment environment.

Conclusion

- The machine learning model was successfully deployed on a Kubernetes cluster using Flask and Docker, demonstrating a robust and scalable architecture.
- A functional Flask API was developed to handle prediction requests, providing accurate and timely responses based on the logistic regression model.
- Swagger-UI was integrated for interactive documentation and testing, making it easy for users to test API endpoints and understand the available functionalities.
- The Flask application and its dependencies were efficiently containerized using Docker, ensuring consistency across different deployment environments.
- The project lays a solid foundation for future enhancements, including automated CI/CD pipelines, model versioning, and scalability improvements.



References

Machine Learning on Kubernetes | Data | eBook

Machine Learning on Kubernetes, published by packt

What is Kubernetes for MLOps

GitHub Link

• https://github.com/cur10usityDrives/Cloud-Computing/tree/main/Kubernetes/Machine-Learning

