Operationalizing an AWS ML Project

The goal of this project will be to use several important tools and features of AWS to adjust improve, configure, and prepare a machine-learning model for production-grade deployment.

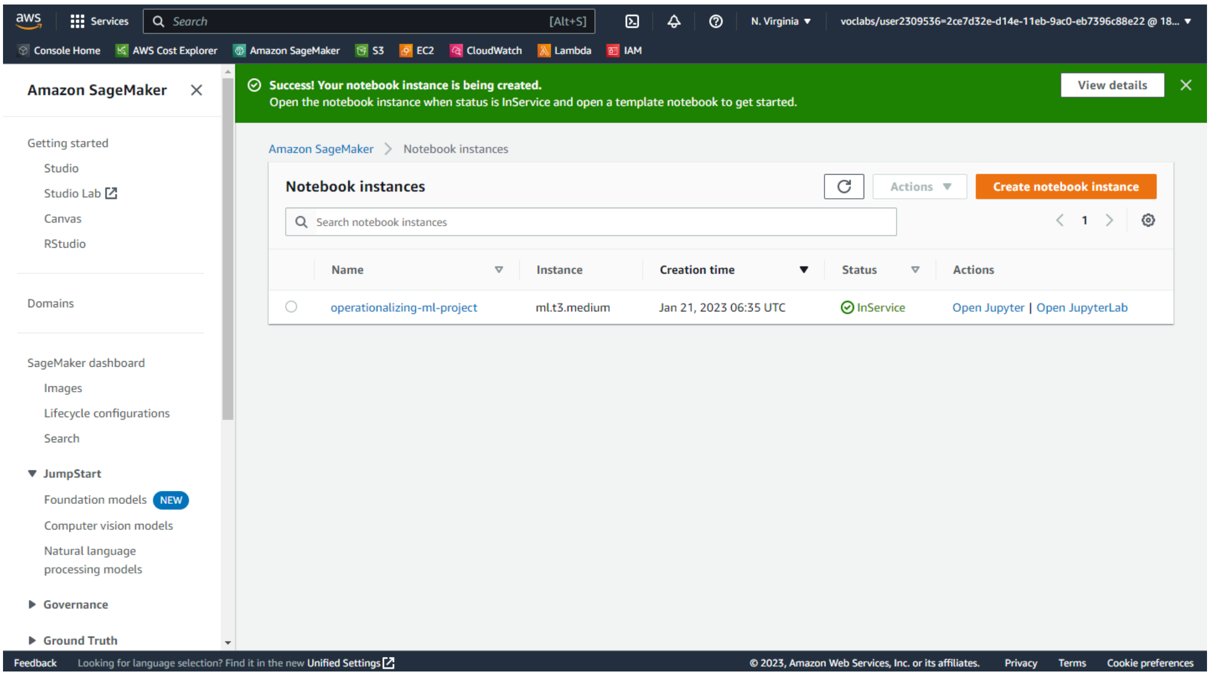
Training and Deployment on Sagemaker

Initial Setup

1. Create and open a sagemaker notebook instance
2. Install unzip command

```
sudo yum install unzip -y
```

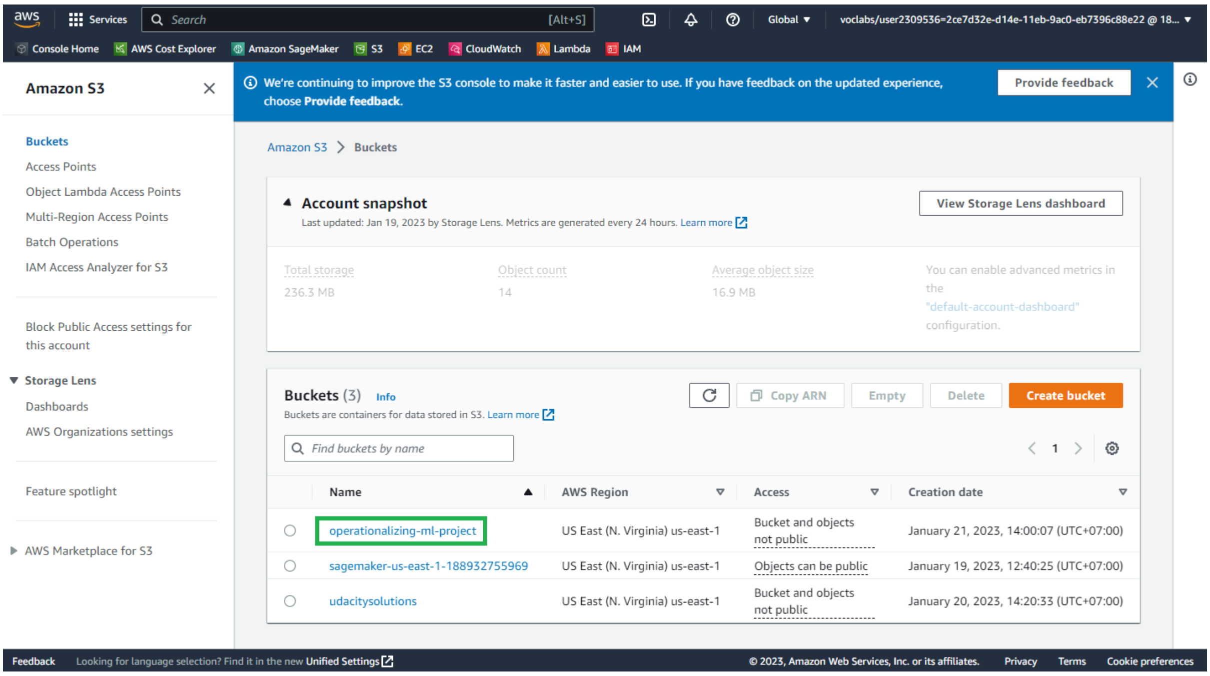
I choose `ml.t3.medium` as the cheapest compute instance just for running the jupyter notebook.



Download and Upload Data to an S3 Bucket

I create an s3 bucket with the name `operationalizing-ml`.

```
wget -nc https://s3-us-west-1.amazonaws.com/udacity-aind/dog-project/dogImages.zip
unzip -q dogImages.zip
aws s3 cp ./dogImages s3://operationalizing-ml/dataset
```



Training and Deployment

Single Instance

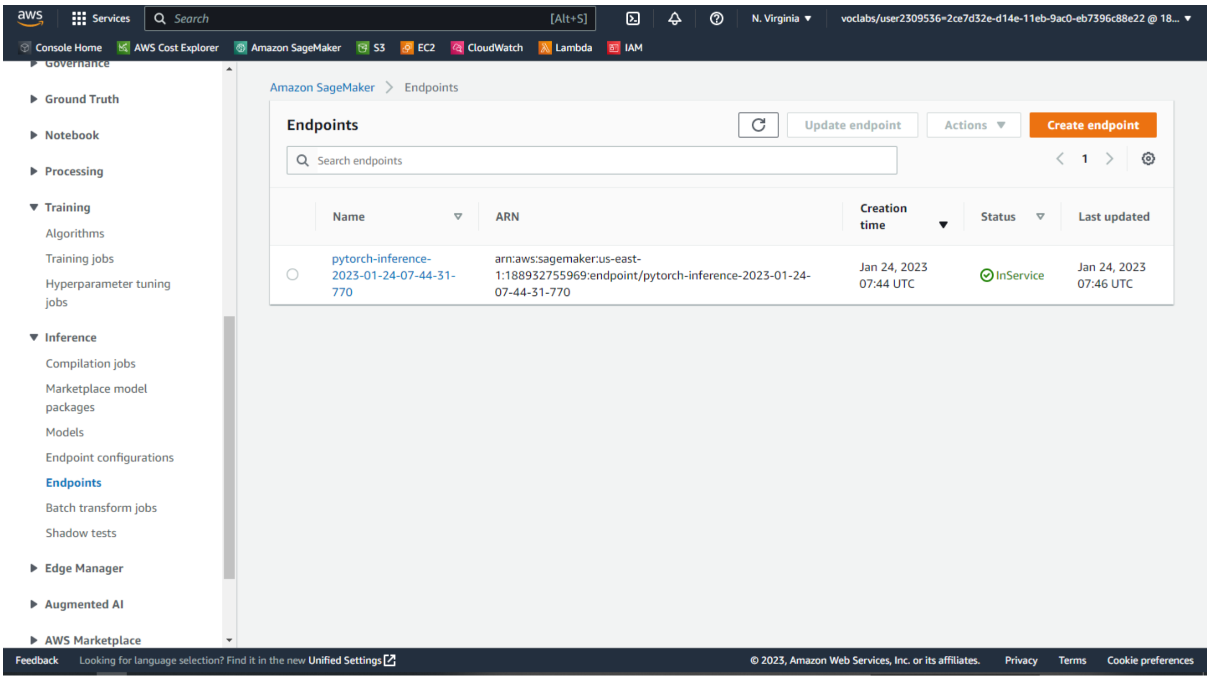
In my opinion because this training uses a small epoch, I don't need to spend more for a GPU instance, and a CPU-optimised instance like `ml.c5.2xlarge` is enough. It charges **$0.408/hour** and took **11 minutes and 3 seconds** to finish training.

Multi Instance

For the multi-instance training, I used spot instances. And the cheapest spot instance available in this account is ml.c5.2xlarge. It provides an affordable price of **$0.174/hour**. I used 2 instances and took **22 minutes and 33 seconds** to finish training in total.

Endpoint

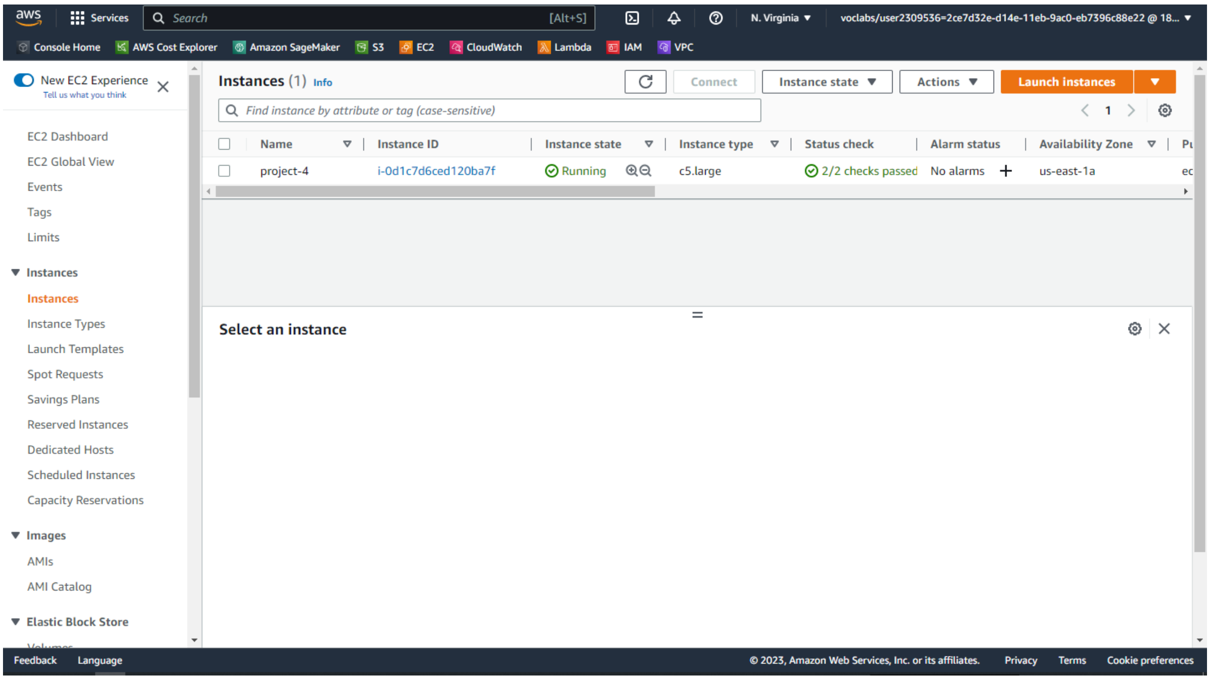
I created an endpoint from muli-instance estimator



EC2 Training

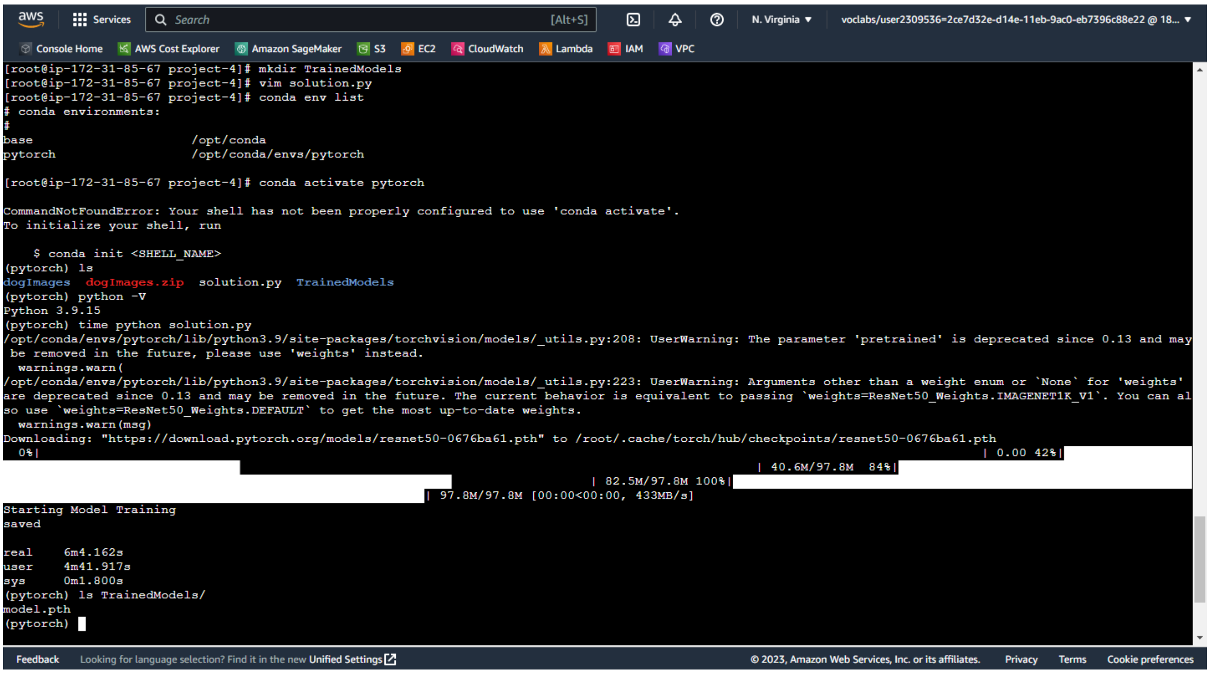
EC2 Setup

From previous training on Sagemaker, I used ml.c5.2xlarge. When I take a look at CloudWatch data. It shows me that the training doesn't use that much storage. So I choose `ml.c5.large` with **Amazon Deep Learning AMI PyTorch 1.13.1 (Amazon Linux 2)**.



EC2 Model training

Unlike training on sagemaker, the data preparation has to be set up manually.



Sagemaker Training vs EC2 Training

sagemaker:

- invoke a training job
- input data from s3
- save model data to s3

ec2:

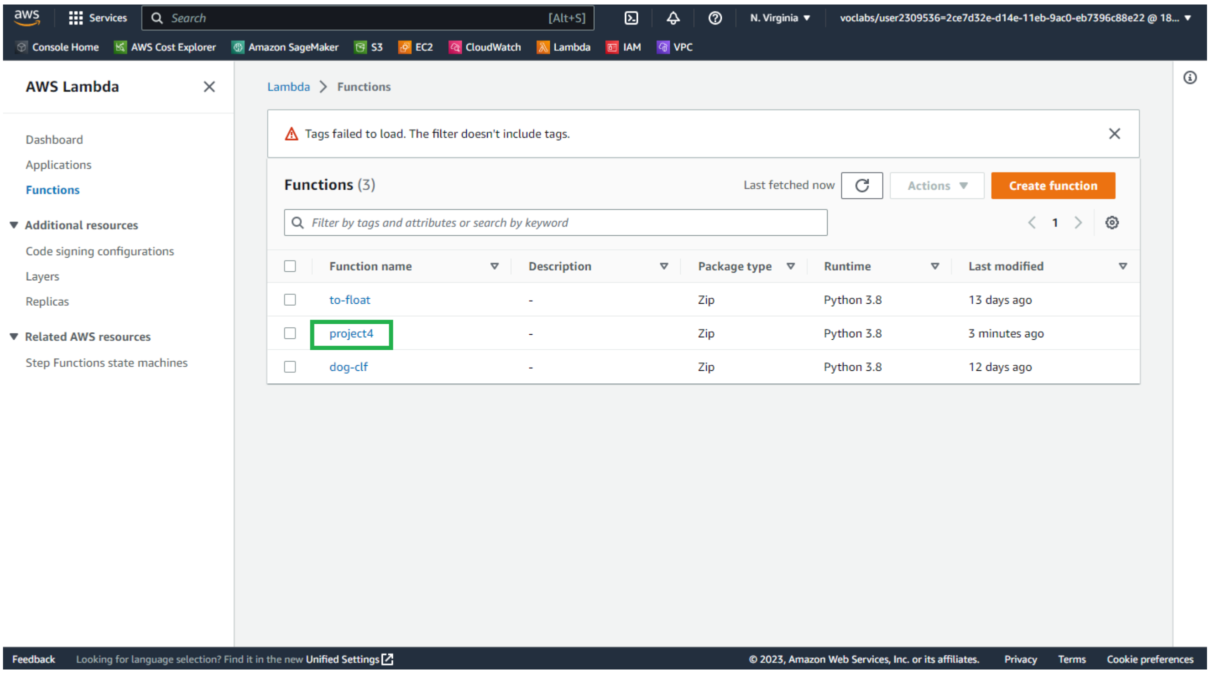
- training on local instance
- load data from local instance directory
- save model data to local directory

Lambda Function

This lambda function will invoke an endpoint `pytorch-inference-2023-01-24-07-44-31-770`. It only accepts a request with content type `application/json` and returns data with the following format:

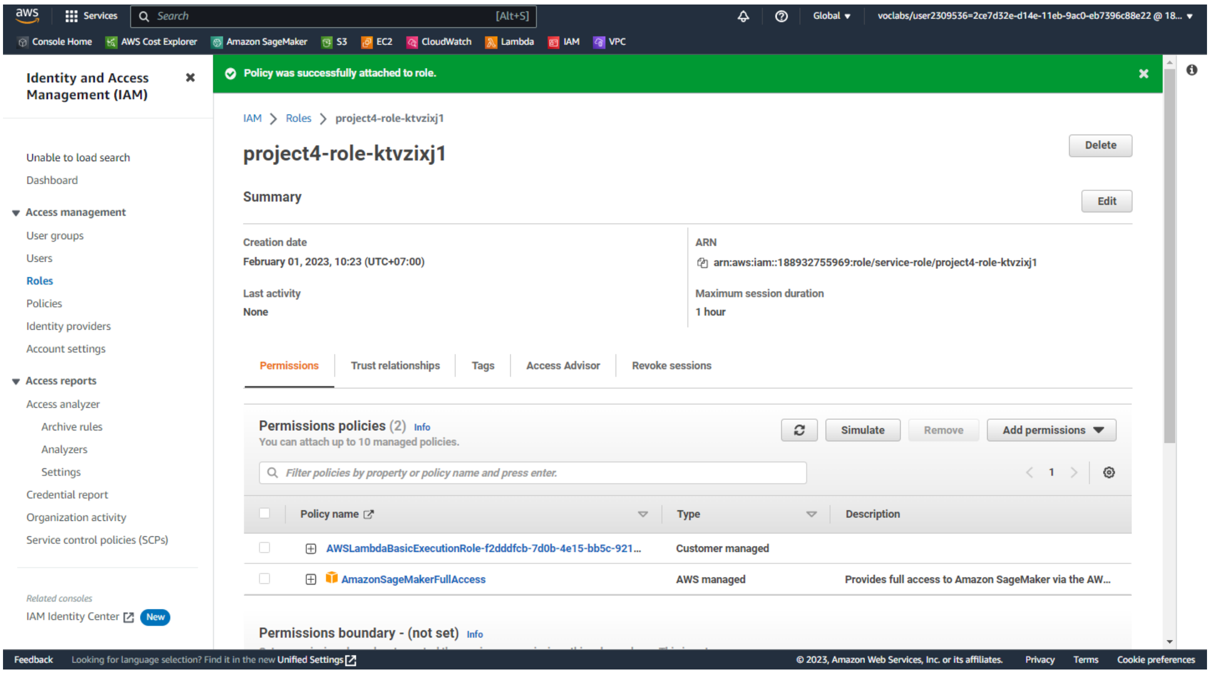
```
{
    'statusCode': 200,
    'headers': { 'Content-Type': 'text/plain', 'Access-Control-Allow-Origin':
'*' },
    'type-result':str(type(result)),
    'COntent-Type-In':str(context),
    'body': json.dumps(sss)
}
```

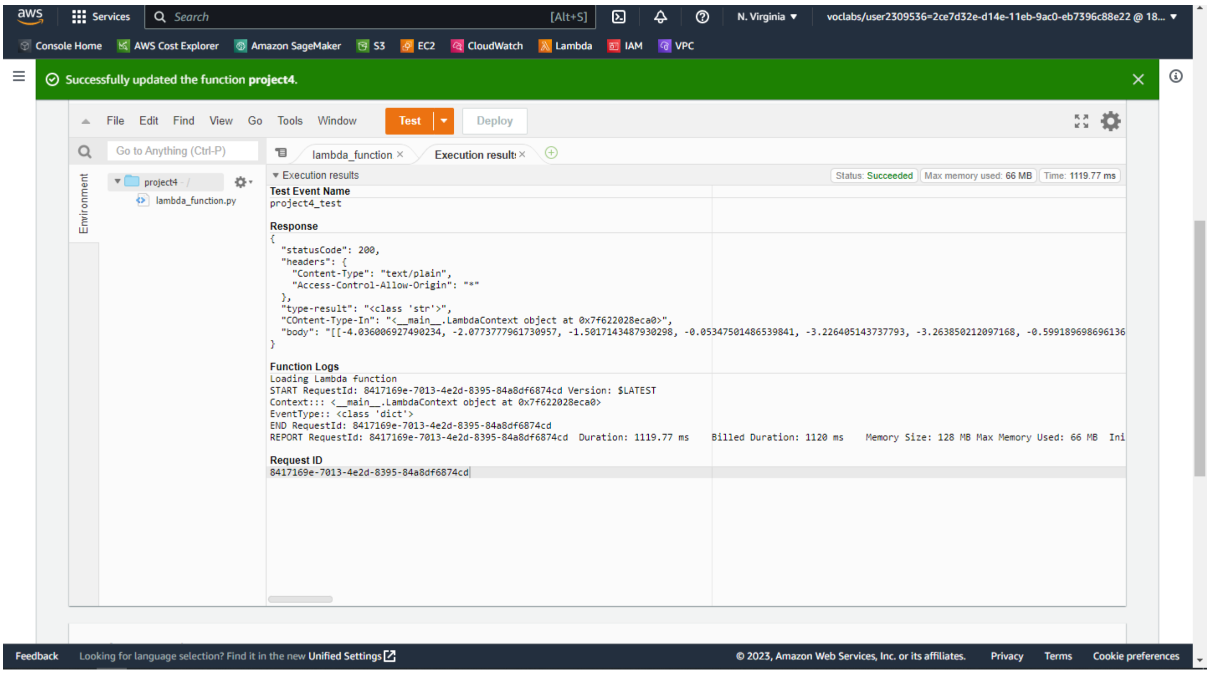
The detail about this lambda function can be found at `src/code/lamdafunction.py`.



Security and Testing

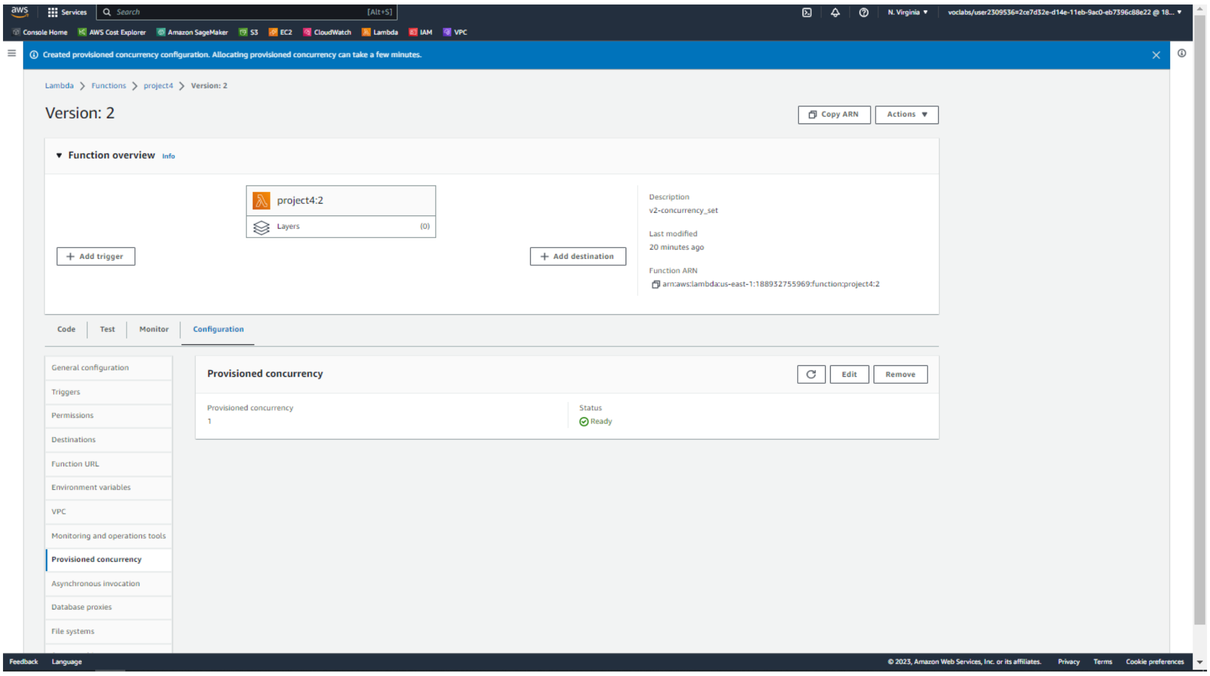
By default for security purposes, AWS Lambda does not have access to AWS Sagemaker. Certain authentication methods are required. One of the methods is by using the `IAM role` with the corresponding policies. In this case `AmazonSageMakerFullAccess` policy. It grants the lambda function broader permissions to access SageMaker services. This scenario will produce vulnerability because the lambda function only needs permissions to invoke an endpoint from Sagemaker. So using the principle of least privilege is recommended. The corresponding policy needs to be adjusted to limit the lambda function to invoke an endpoint only. Also, the old or unused roles need to be deleted to grant more security.





Concurrency and Auto-scaling

The main purpose of concurrency and auto-scaling are to reduce latency during high-traffic scenarios. In this project, I just worked with low-traffic situations. So a small amount of concurrency is acceptable. I configured concurrency after creating a version of the lambda function. The only concurrency setting available is provisioned concurrency.



For the same reason as concurrency, a small amount of instances is acceptable for auto-scaling. I choose **3** for the maximum instances. It will be triggered if **10** requests come simultaneously.