CSE 546 — Project1 Report

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1. Problem statement

In this project, we aim to build an elastic application which can automatically scale out and in on demand and cost-effectively by using the laaS cloud resources from Amazon Web Services (AWS). AWS is the most widely used laaS provider and offers a variety of compute, storage, and message services. Our application will offer a meaningful cloud service to users, and the technologies and techniques that we learn will be useful for us to build many others in future.

In this project, we aim to build a scalable face recognition service on the cloud which has all the software components loosely coupled. Every component of AWS used is elastic and hence, the project can be scaled up and down as per the number of requests coming in.

- Our cloud application performs face recognition on user-provided images using the provided deep learning model, which then returns the recognition result as output to the users.
- Each image input through the website is a request to our application and our application can handle multiple requests concurrently.
- It automatically scales out when the request demand increases, and automatically scales in when the demand drops.
- The application should handle all the requests as fast as possible, and it should not miss any requests. In addition, the recognition requests should all be correct.

2. Design and implementation

2.1 Architecture

We have built a Flask application for the web tier so that the user can upload multiple images. The web tier always runs on an AWS instance which sends messages with image information (encoded image and image name) to the Request queue (FIFO SQS). App instances created, polls for a message from the request queue and processes the same to get the recognition results. Each of these results is then sent back to the web tier using a Response queue (FIFO SQS) and these results are then displayed in a tabular format on the web tier.

 The SQS is responsible for maintaining two communication channels between the web tier instance and application tier instances. The FIFO queues will result in each message

- being processed exactly once by the app instances so that there is no duplication of the recognition results.
- The controller is a part of the web tier and is responsible for scaling in and scaling out the number of instances based on the load of requests.
- An app tier instance is spawned by the controller based on the auto scaling parameters
 that have been set. Each such instance contains a face recognition model and a python
 script that perpetually polls the request queue for incoming requests. Once a request is
 detected, it begins processing it in a series of steps.
 - Consume a message from request queue
 - Use the provided face recognition model to get a classification result
 - Send the response to the response queue
 - Write the input and outputs to their respective S3 buckets
 - Delete the message from the request queue

Now, the python script returns to its polling state and waits for the next request

The high-level architecture of the cloud-application is shown in Fig. 1.

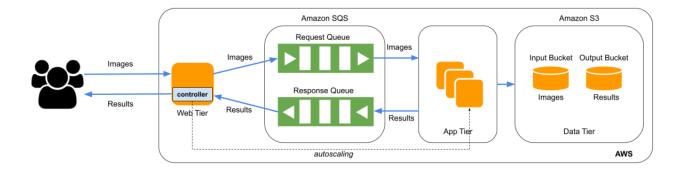


Fig. 1

2.2 Autoscaling

Autoscaling is one of the crucial reasons for hosting applications on the cloud. This project utilizes the Auto Scaling property of the cloud, so that the application resources are used efficiently. The web tier instance takes care of scaling up the instances, based on the number of requests made, considering one image is equal to a request. We will be using at most x app instances in this project and each instance processes the images to get the recognition result. If the number of requests is more than 100 at a particular time, the request-messages are held in the Request queue until there is an app instance available to pick up the request. The code embedded in each of the app instances will poll the SQS request queue, in order to check if there are messages in the Request queue. If there are no messages left in the Request queue,

the app instance will stop itself automatically, so that the resources are not wasted and thus the application is scaled down by the app instance itself.

3. Testing and evaluation

Testing is an important part of building a cloud application, where you check if the application handles the requests concurrently and if it auto-scales, so that minimum resources are used to maximize the efficiency of the final product.

In this project, we tested our application for stress (work load) and also efficient auto-scaling of the EC2 instances. The images below portray that the application works as expected and the deployed product is efficient and fast.

A workload generator is used to replicate concurrent requests. Our system was tested on this and successfully executed the load of 100 requests in 130 seconds.

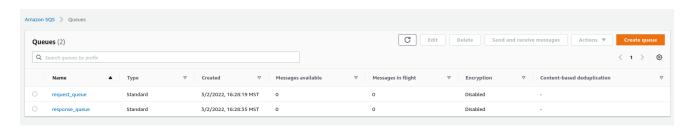


Fig. 2 SQS set-up.



Fig. 3 SQS messages sent

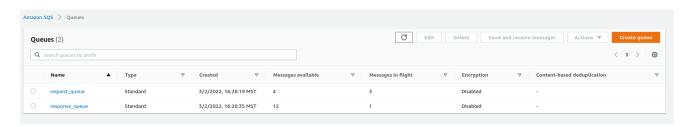


Fig. 4 SQS messages processed.

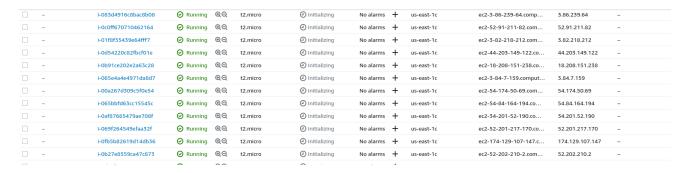


Fig. 5 App tier instances running.

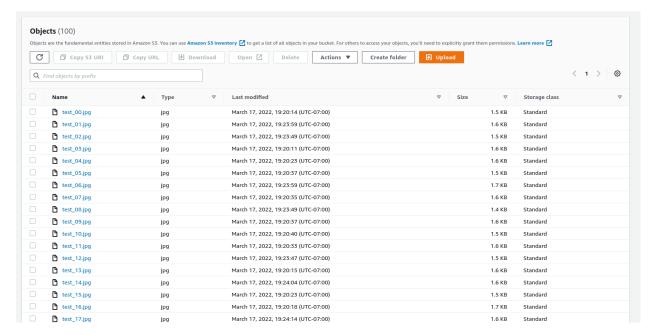


Fig. 6 S3 bucket storing input and output information.

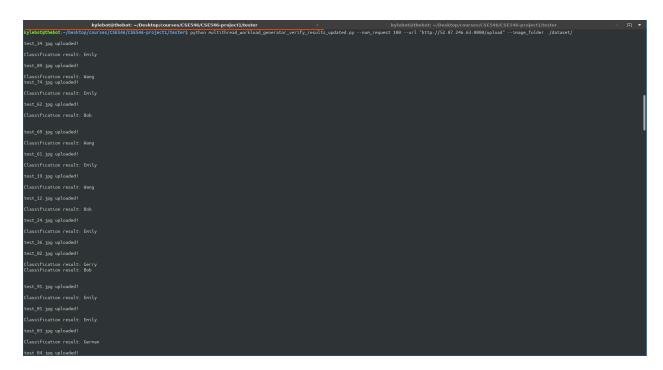


Fig. 7 Output terminal displaying results.

4. Code

The project uses python programs that implement the different abstractions of the boto3 services that have been used in the Flask app, which would run in the 'app.py' file. All the three services are independent of each other and from the main module. They are loosely coupled such that they could be reused in other projects too with minimal or no changes.

The three python modules using AWS SDKs in this project are:-

- Amazon Simple Queue Service It is a distributed message queuing service. We use methods that are required to perform basic operations on SQS Service like creating, deleting, sending, and receiving messages using 'sqs' resource of boto3 SDKs in Python.
- Amazon Simple Storage Service It is a service offered by Amazon Web Services that
 provides object storage through a web service interface. The boto3 SDKs also provide
 services to handle S3 buckets and their methods help in uploading and downloading
 files to and from the S3 buckets.
- Amazon Elastic Compute Cloud It allows users to rent virtual computers on which they
 can run their own computer applications. The boto3 SDKs contain methods that are
 required to perform basic operations on EC2, such as starting or terminating (stopping)
 an instance.

4.1 Web Tier

The web tier runs on a Flask application which is launched using the main.py script. In this application users can upload an image. This image is then encoded into a base64 format and passed as a message into the request queue along with the label of the image which serves as an identifier. Apart from this, the web tier keeps polling the response queue to identify the recognition results of the images that were pushed into the request queue and once it matches the result using the identifier, the results are displayed.

4.2 App Tier

1. Functions

• read_one_request() - It reads a message from the SQS Request Queue

Input - None

Returns - fname, content, msg

fname - This is the filename of the image sent in the request message. It is retrieved from the 'imageName' attribute of the message.

content - This is the base64 decoded message i.e. the actual image.

msg - This is the message metadata

• recognize() - It uses the deep learning model to get a prediction result

Input - content

content - This is the base64 decoded message i.e. the actual image.

Returns - label

label - This is the prediction result from the deep learning model. If no result is obtained, 'None' is returned instead.

send one response() - It sends a message to the SQS Response Queue

Input - fname, label

fname - This is the filename of the image sent in the request message. It is retrieved from the 'imageName' attribute of the message.

label - This is the prediction result from the deep learning model.

Returns - None

 delete_message() - deletes a message from the SQS Request Queue using the 'ReceiptHandle' attribute.

Input - msg

msg - This is the message metadata

Returns - None

It consumes a message from the Request Queue, uses the deep learning model to get a prediction result and sends the result to the SQS response queue. Processed messages are deleted from the Request Queue. Additionally, the input and output data is stored in separate S3 Buckets.

Steps to run our project :-

- to run the web_tier: cd web_tier; gunicorn --bind 0.0.0.0 -w 20 -t 1800 wsgi:app
- to run the controller: cd controller; python3 watchdog.py
- we created a AMI for app-tier
- controller will launch instances from the created AMI

5. Individual Contributions

5.1 Hemendu Roy

I primarily worked on designing the App Tier Instances. This entailed writing Python code as described in *Section 4.2*.

The script performs the following tasks,

- Consume a message from request queue
- Use the provided face recognition model to get a classification result
- Send the response to the response queue
- Write the input and outputs to their respective S3 buckets
- Delete the message from the request queue
- Continue polling the request queue for new messages

Once the app tier scripts were ready, I configured them to be run automatically upon instance startup. At first, I configured this using *cron*. Later, this was converted to a *systemd* service. Lastly, I created an AMI to be used by the controller to scale in/out the app tier instances. This AMI was subsequently modified during the integration and testing phases.

5.2 Radhika Ganapathy

I mainly worked on the web tier interface and built a flask application to implement the same.

- The web app has an interface that enables users to upload an image to the web application.
- The image uploaded is then encoded into base64 format.
- Created a Request Queue using Amazon's SQS Service.
- Every time an image is uploaded, a message containing the encoded image along with the label is sent to the queue.
- Web app keeps polling the response queue to see if the result is processed and ready to be displayed.
- Once the result is matched using an identifier, the result is displayed.