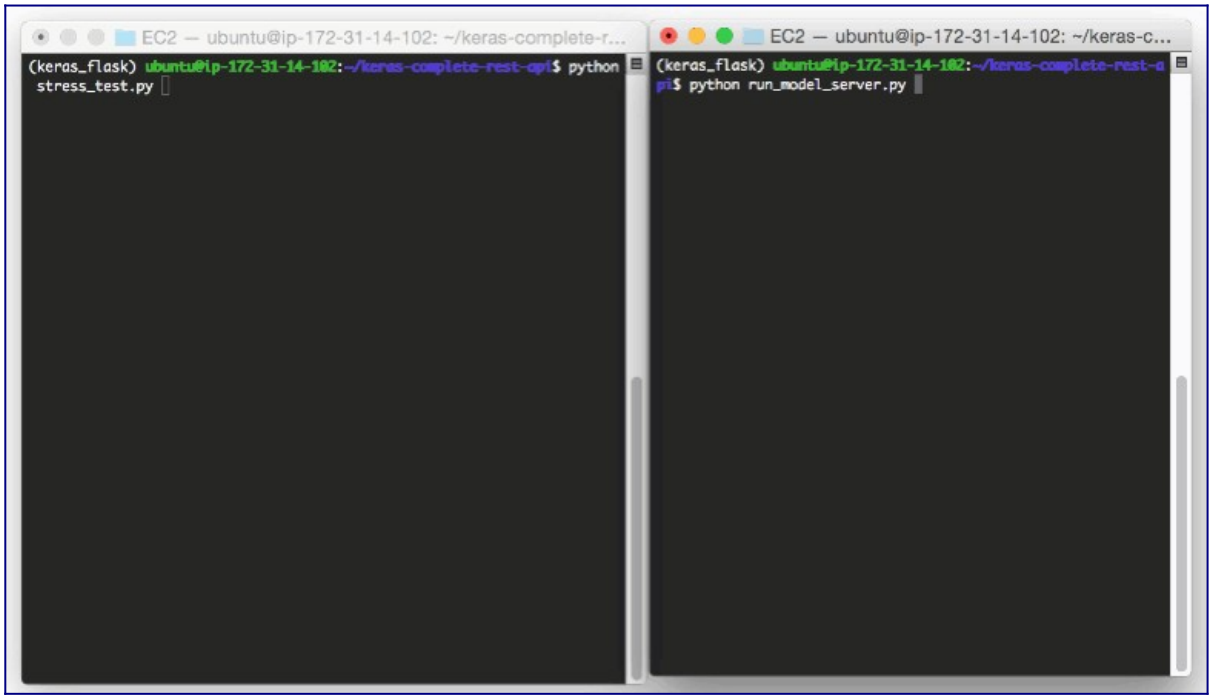
Deep learning in production with Keras, Redis, Flask, and Apache

By Adrian Rosebrock on in Deep Learning, Keras

https://www.pyimagesearch.com/2018/02/05/deep-learning-production-keras-redis-flask-apache/



Shipping deep learning models to production is a non-trivial task.

If you don't believe me, take a second and look at the "tech giants" such as Amazon, Google, Microsoft, etc. — *nearly all* of them provide some method to ship your machine learning/deep learning models to production in the cloud.

Going with a model deployment service is perfectly fine and acceptable…**but what if you wanted to *own the entire process* and *not rely on external services*?**

This type of situation is more common than you may think. Consider:

- An in-house project where you cannot move sensitive data outside your network
- A project that specifies that the entire infrastructure must reside within the company
- A government organization that needs a private cloud
- A startup that is in "stealth mode" and needs to stress test their service/application in-house

How would you go about shipping your deep learning models to production in these situations, and perhaps most importantly, **making it *scalable* at the same time?**

Today's post is the final chapter in our three part series on building a deep learning model server REST API:

1. Part one (**which was posted on the official Keras.io blog!**) is a simple Keras + deep learning REST API which is intended for single threaded use with no concurrent requests.

This method is a perfect fit if this is your first time building a deep learning web server or if you're working on a home/hobby project.
2. In part two we demonstrated how to leverage **Redis** along with **message queueing/message brokering** paradigms to efficiently batch process incoming inference requests (but with a small caveat on server threading that could cause problems).
3. In the final part of this series, I'll show you how to resolve these server threading issues, further scale our method, provide benchmarks, and **demonstrate how to efficiently scale deep learning in production using Keras, Redis, Flask, and Apache.**

As the results of our stress test will demonstrate, our single GPU machine can easily handle **500 concurrent requests** (0.05 second delay in between each one) without ever breaking a sweat — ***this performance continues to scale as well.***

To learn how to ship your own deep learning models to production using Keras, Redis, Flask, and Apache*, just keep reading.*

> **Looking for the source code to this post?**
> **Jump right to the downloads section.**

Deep learning in production with Keras, Redis, Flask, and Apache

The code for this blog post is primarily based on our previous post, but with some minor modifications — the first part of today's guide will review these changes along with our project structure.

From there we'll move on to configuring our deep learning web application, including installing and configuring any packages you may need (Redis, Apache, etc.).

Finally, we'll stress test our server and benchmark our results.

For a quick overview of our deep learning production system (including a demo) be sure to watch the video above!

Our deep learning project structure

Our project structure is as follows:

Deep learning in production with Keras, Redis, Flask, and Apache

Shell

```
├── helpers.py ├── jemma.png ├── keras_rest_api_app.wsgi ├── run_model_server.py ├── run_web_server.py ├── settings.py ├── simple_request.py └── stress_test.py
```

```
├── helpers.py
├── jemma.png
├──
keras_rest_api_a
pp.wsgi
├──
run_model_serv
er.py
├──
run_web_server.
py
├── settings.py
├──
simple_request.p
y
└──
stress_test.py
```

Let’s review the important files:

- `run_web_server.py` contains all our Flask web server code — Apache will load this when starting our deep learning web app.
- `run_model_server.py` will:
    - Load our Keras model from disk
    - Continually poll Redis for new images to classify
    - Classify images (batch processing them for efficiency)
    - Write the inference results back to Redis so they can be returned to the client via Flask
- `settings.py` contains all Python-based settings for our deep learning productions service, such as Redis host/port information, image classification settings, image queue name, etc.
- `helpers.py` contains utility functions that both `run_web_server.py` and `run_model_server.py` will use (namely `base64` encoding).
- `keras_rest_api_app.wsgi` contains our WSGI settings so we can serve the Flask app from our Apache server.
- `simple_request.py` can be used to programmatically consume the results of our deep learning API service.
- `jemma.png` is a photo of my family’s beagle. We’ll be using her as an example image when calling the REST API to validate it is indeed working.
- Finally, we’ll use `stress_test.py` to stress our server and measure image classification throughout.

As described last week, we have a single endpoint on our Flask server, `/predict` . This method lives in `run_web_server.py` and will compute the classification for an input image on demand. Image pre-processing is also handled in `run_web_server.py` .

In order to make our server production-ready, I’ve pulled out the `classify_process` function from last week’s single script and placed it in `run_model_server.py` . This script is very important as it will load our Keras model and grab images from our image queue in Redis for classification. Results are written back to Redis (the `/predict` endpoint and corresponding function in `run_web_server.py` monitors Redis for results to send back to the client).

But what good is a deep learning REST API server unless we know its capabilities and limitations?

In stress_test.py , we test our server. We'll accomplish this by kicking off 500 concurrent threads which will send our images to the server for classification in parallel. I recommend running this on the server localhost to start, and then running it from a client that is off site.

Building our deep learning web app

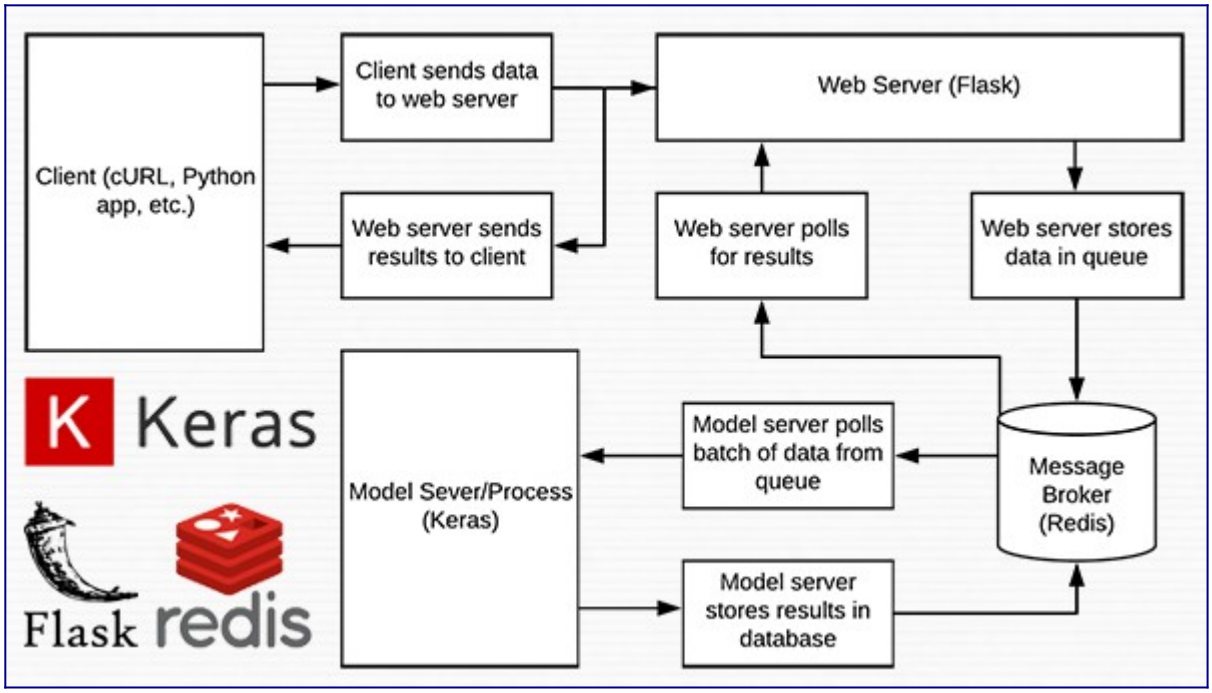


Figure 1: Data flow diagram for a deep learning REST API server built with Python, Keras, Redis, and Flask.

Nearly every single line of code used in this project comes from our previous post on building a scalable deep learning REST API — **the only change is that we are moving some of the code to *separate files* to facilitate scalability in a production environment.**

As a matter of completeness I'll be including the source code to each file in this blog post (and in the ***"Downloads"*** section of this blog post). **For a detailed review of the files, please see the previous post.**

Settings and configurations

Deep learning in production with Keras, Redis, Flask, and Apache

Python

```
# initialize Redis connection settings REDIS_HOST = "localhost" REDIS_PORT = 6379 REDIS_DB = 0 # initialize constants used to control image spatial dimensions and # data type IMAGE_WIDTH = 224 IMAGE_HEIGHT = 224 IMAGE_CHANS = 3 IMAGE_DTYPE = "float32" # initialize constants used for server queuing IMAGE_QUEUE = "image_queue" BATCH_SIZE = 32 SERVER_SLEEP = 0.25 CLIENT_SLEEP = 0.25
```

```
# initialize Redis connection settings
REDIS_HOST = "localhost"
REDIS_PORT = 6379
REDIS_DB = 0

# initialize constants used to control
image spatial dimensions and
# data type
IMAGE_WIDTH = 224
IMAGE_HEIGHT = 224
IMAGE_CHANS = 3
IMAGE_DTYPE = "float32"

# initialize constants used for server
queuing
IMAGE_QUEUE = "image_queue"
BATCH_SIZE = 32
SERVER_SLEEP = 0.25
CLIENT_SLEEP = 0.25
```

In settings.py you'll be able to change parameters for the server connectivity, image dimensions + data type, and server queuing.

Helper utilities

Deep learning in production with Keras, Redis, Flask, and Apache

Python

import the necessary packages import numpy as np import base64 import sys def base64_encode_image(a): # base64 encode the input NumPy array return base64.b64encode(a).decode("utf-8") def base64_decode_image(a, dtype, shape): # if this is Python 3, we need the extra step of encoding the # serialized NumPy string as a byte object if sys.version_info.major == 3: a = bytes(a, encoding="utf-8") # convert the string to a NumPy array using the supplied data # type and target shape a = np.frombuffer(base64.decodestring(a), dtype=dtype) a = a.reshape(shape) # return the decoded image return a

```
# import the necessary packages
import numpy as np
import base64
import sys

def base64_encode_image(a):
# base64 encode the input
NumPy array
return
base64.b64encode(a).decode("ut
f-8")

def base64_decode_image(a,
dtype, shape):
# if this is Python 3, we need the
extra step of encoding the
# serialized NumPy string as a
byte object
if sys.version_info.major == 3:
a = bytes(a, encoding="utf-8")

# convert the string to a NumPy
array using the supplied data
# type and target shape
a =
np.frombuffer(base64.decodestri
ng(a), dtype=dtype)
a = a.reshape(shape)

# return the decoded image
return a
```

The helpers.py file contains two functions — one for base64 *encoding* and the other for *decoding*.

Encoding is necessary so that we can serialize + store our image in Redis. Likewise, decoding is necessary so that we can deserialize the image into NumPy array format prior to pre-processing.

The deep learning web server

Deep learning in production with Keras, Redis, Flask, and Apache

Python

import the necessary packages from keras.preprocessing.image import img_to_array from keras.applications import imagenet_utils from PIL import Image import numpy as np import settings import helpers import flask import redis import uuid import time import json import io # initialize our Flask application and Redis server app = flask.Flask(__name__) db = redis.StrictRedis(host=settings.REDIS_HOST, port=settings.REDIS_PORT, db=settings.REDIS_DB) def prepare_image(image, target): # if the image mode is not RGB, convert it if image.mode != "RGB": image = image.convert("RGB") # resize the input image and preprocess it image = image.resize(target) image = img_to_array(image) image = np.expand_dims(image, axis=0) image = imagenet_utils.preprocess_input(image) # return the processed image return image @app.route("/") def homepage(): return "Welcome to the PyImageSearch Keras REST API!" @app.route("/predict", methods=["POST"]) def predict(): # initialize the data dictionary that will be returned from the # view data = {"success": False} # ensure an image was properly uploaded to our endpoint if flask.request.method == "POST": if flask.request.files.get("image"): # read the image in PIL format and prepare it for # classification

image = flask.request.files["image"].read() image = Image.open(io.BytesIO(image)) image = prepare_image(image, (settings.IMAGE_WIDTH, settings.IMAGE_HEIGHT)) # ensure our NumPy array is C-contiguous as well, # otherwise we won't be able to serialize it image = image.copy(order="C") # generate an ID for the classification then add the # classification ID + image to the queue k = str(uuid.uuid4()) image = helpers.base64_encode_image(image) d = {"id": k, "image": image} db.rpush(settings.IMAGE_QUEUE, json.dumps(d)) # keep looping until our model server returns the output # predictions while True: # attempt to grab the output predictions output = db.get(k) # check to see if our model has classified the input # image if output is not None: # add the output predictions to our data # dictionary so we can return it to the client output = output.decode("utf-8") data["predictions"] = json.loads(output) # delete the result from the database and break # from the polling loop db.delete(k) break # sleep for a small amount to give the model a chance # to classify the input image time.sleep(settings.CLIENT_SLEEP) # indicate that the request was a success data["success"] = True # return the data dictionary as a JSON response return flask.jsonify(data) # for debugging purposes, it's helpful to start the Flask testing # server (don't use this for production if __name__ == "__main__": print("* Starting web service...") app.run()

```
# import the necessary packages
from keras.preprocessing.image
import img_to_array
from keras.applications import
imagenet_utils
from PIL import Image
import numpy as np
import settings
import helpers
import flask
import redis
import uuid
import time
import json
import io

# initialize our Flask application
and Redis server
app = flask.Flask(__name__)
db =
redis.StrictRedis(host=settings.R
EDIS_HOST,
port=settings.REDIS_PORT,
db=settings.REDIS_DB)

def prepare_image(image,
target):
# if the image mode is not RGB,
convert it
if image.mode != "RGB":
image = image.convert("RGB")

# resize the input image and
preprocess it
image = image.resize(target)
image = img_to_array(image)
image = np.expand_dims(image,
axis=0)
image =
imagenet_utils.preprocess_input
(image)

# return the processed image
return image

@app.route("/")
def homepage():
return "Welcome to the
PyImageSearch Keras REST
API!"

@app.route("/predict",
methods=["POST"])
```

Here in run_web_server.py , you'll see predict , the function associated with our REST API /predict endpoint.

The predict function pushes the encoded image into the Redis queue and then continually loops/polls until it obains the prediction data back from the model server. We then JSON-encode the data and instruct Flask to send the data back to the client.

The deep learning model server

Deep learning in production with Keras, Redis, Flask, and Apache

Python

```
# import the necessary packages from keras.applications import ResNet50 from keras.applications import imagenet_utils import numpy as np import settings import helpers import redis import time import json # connect to Redis server db = redis.StrictRedis(host=settings.REDIS_HOST, port=settings.REDIS_PORT, db=settings.REDIS_DB) def classify_process(): # load the pre-trained Keras model (here we are using a model # pre-trained on ImageNet and provided by Keras, but you can # substitute in your own networks just as easily) print("* Loading model...") model = ResNet50(weights="imagenet") print("* Model loaded") # continually pool for new images to classify while True: # attempt to grab a batch of images from the database, then # initialize the image IDs and batch of images themselves queue = db.lrange(settings.IMAGE_QUEUE, 0, settings.BATCH_SIZE - 1) imageIDs = [] batch = None # loop over the queue for q in queue: # deserialize the object and obtain the input image q = json.loads(q.decode("utf-8")) image = helpers.base64_decode_image(q["image"], settings.IMAGE_DTYPE, (1, settings.IMAGE_HEIGHT, settings.IMAGE_WIDTH, settings.IMAGE_CHANS)) # check to see if the batch list is None if batch is None: batch = image # otherwise, stack the data else: batch = np.vstack([batch, image]) # update the list of image IDs imageIDs.append(q["id"]) # check to see if we need to process the batch if len(imageIDs) > 0: # classify the batch print("* Batch size: {}".format(batch.shape)) preds = model.predict(batch) results = imagenet_utils.decode_predictions(preds) # loop over the image IDs and their corresponding set of # results from our model for (imageID, resultSet) in zip(imageIDs, results): # initialize the list of output predictions output = [] # loop over the results and add them to the list of # output predictions for (imagenetID, label, prob) in resultSet: r = {"label": label, "probability": float(prob)} output.append(r) # store the output predictions in the database, using # the image ID as the key so we can fetch the results db.set(imageID, json.dumps(output)) # remove the set of images from our queue db.ltrim(settings.IMAGE_QUEUE, len(imageIDs), -1) # sleep for a small amount time.sleep(settings.SERVER_SLEEP) # if this is the main thread of execution start the model server # process if __name__ == "__main__": classify_process()
```

```
# import the necessary packages
from keras.applications import
ResNet50
from keras.applications import
imagenet_utils
import numpy as np
import settings
import helpers
import redis
import time
import json

# connect to Redis server
db =
redis.StrictRedis(host=settings.R
EDIS_HOST,
port=settings.REDIS_PORT,
db=settings.REDIS_DB)

def classify_process():
# load the pre-trained Keras
model (here we are using a
model
# pre-trained on ImageNet and
provided by Keras, but you can
# substitute in your own
networks just as easily)
print("* Loading model...")
model =
ResNet50(weights="imagenet")
print("* Model loaded")

# continually pool for new
images to classify
while True:
# attempt to grab a batch of
images from the database, then
# initialize the image IDs and
batch of images themselves
queue =
db.lrange(settings.IMAGE_QUE
UE, 0,
settings.BATCH_SIZE - 1)
imageIDs = []
batch = None

# loop over the queue
for q in queue:
# deserialize the object and
obtain the input image
q = json.loads(q.decode("utf-8"))
image =
helpers.base64_decode_image(q
```

The run_model_server.py file houses our classify_process function. This function loads our model and then runs predictions on a batch of images. This process is ideally excuted on a GPU, but a CPU can also be used.

In this example, for sake of simplicity, we'll be using ResNet50 pre-trained on the ImageNet dataset. You can modify classify_process to utilize your own deep learning models.

The WSGI configuration

Deep learning in production with Keras, Redis, Flask, and Apache

Python

add our app to the system path import sys sys.path.insert(0, "/var/www/html/keras-complete-rest-api") # import the application and away we go... from run_web_server import app as application

```
# add our app to the system path
import sys
sys.path.insert(0,
"/var/www/html/keras-complete-
rest-api")

# import the application and
away we go...
from run_web_server import app
as application
```

Our next file, keras_rest_api_app.wsgi , is a new component to our deep learning REST API compared to last week.

This WSGI configuration file adds our server directory to the system path and imports the web app to kick off all the action. We point to this file in our Apache server settings file, /etc/apache2/sites-available/000-default.conf , later in this blog post.

The stress test

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Python

USAGE # python stress_test.py # import the necessary packages from threading import Thread import requests import time # initialize the Keras REST API endpoint URL along with the input # image path KERAS_REST_API_URL = "http://localhost/predict" IMAGE_PATH = "jemma.png" # initialize the number of requests for the stress test along with # the sleep amount between requests NUM_REQUESTS = 500 SLEEP_COUNT = 0.05 def call_predict_endpoint(n): # load the input image and construct the payload for the request image = open(IMAGE_PATH, "rb").read() payload = {"image": image} # submit the request r = requests.post(KERAS_REST_API_URL, files=payload).json() # ensure the request was sucessful if r["success"]: print("[INFO] thread {} OK".format(n)) # otherwise, the request failed else: print("[INFO] thread {} FAILED".format(n)) # loop over the number of threads for i in range(0, NUM_REQUESTS): # start a new thread to call the API t = Thread(target=call_predict_endpoint, args=(i,)) t.daemon = True t.start() time.sleep(SLEEP_COUNT) # insert a long sleep so we can wait until the server is finished # processing the images time.sleep(300)

```
# USAGE
# python stress_test.py

# import the necessary packages
from threading import Thread
import requests
import time

# initialize the Keras REST API endpoint URL along with the input
# image path
KERAS_REST_API_URL = "http://localhost/predict"
IMAGE_PATH = "jemma.png"

# initialize the number of requests for the stress test along with
# the sleep amount between requests
NUM_REQUESTS = 500
SLEEP_C
```

Our `stress_test.py` script will help us to test the server and determine its limitations. I always recommend stress testing your deep learning REST API server so that you know *if* (and more importantly, *when*) you need to add additional GPUs, CPUs, or RAM. This script kicks off `NUM_REQUESTS` threads and POSTs to the `/predict` endpoint. It's up to our Flask web app from there.

Configuring our deep learning production environment

This section will discuss how to install and configure the necessary prerequisites for our deep learning API server.

We'll use my PyImageSearch Deep Learning AMI (freely available to you to use) as a base. I chose a **p2.xlarge** instance with a single GPU for this example.

You can modify the code in this example to leverage multiple GPUs as well by:

1. Running multiple model server processes
2. Maintaining an image queue for *each* GPU and corresponding model process

However, keep in mind that your machine will still be limited by I/O. It may be beneficial to instead utilize multiple machines, each with 1-4 GPUs than trying to scale to 8 or 16 GPUs on a single machine.

Compile and installing Redis

Redis, an efficient in-memory database, will act as our queue/message broker.

Obtaining and installing Redis is very easy:

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Shell

$ wget http://download.redis.io/redis-stable.tar.gz $ tar xvzf redis-stable.tar.gz $ cd redis-stable $ make $ sudo make install

```
$ wget http://download.redis.io/redis-stable.tar.gz
$ tar xvzf redis-stable.tar.gz
$ cd redis-stable
$ make
$ sudo make install
```

Create your deep learning Python virtual environment

Let's create a Python virtual environment for this project. Please see last week's tutorial for instructions on how to install `virtualenv` and `virtualenvwrapper` if you are new to Python virtual environments.

When you're ready, create the virtual environment:

Deep learning in production with Keras, Redis, Flask, and Apache

Shell

$ mkvirtualenv keras_flask -p python3

```
$ mkvirtualenv keras_flask -p python3
```

From there, let's install the necessary packages:

Deep learning in production with Keras, Redis, Flask, and Apache

Shell

$ pip install numpy $ pip install scipy h5py $ pip install tensorflow==1.4.1 # tensorflow-gpu==1.4.1 for GPU machines $ pip install keras $ pip install flask gevent $ pip install imutils requests $ pip install redis $ pip install Pillow

```
$ pip install numpy
$ pip install scipy
h5py
$ pip install
tensorflow==1.4.1
# tensorflow-
gpu==1.4.1 for
GPU machines
$ pip install keras
$ pip install flask
gevent
$ pip install imutils
requests
$ pip install redis
$ pip install Pillow
```

***Note:** We use **TensorFlow 1.4.1** since we are using **CUDA 8**. You should use TensorFlow 1.5 if using CUDA 9.*

Install the Apache web server

Other web servers can be used such as nginx but since I have more experience with Apache (and therefore more familiar with Apache in general), I'll be using Apache for this example.

Apache can be installed via:

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Shell

$ sudo apt-get install apache2

```
$ sudo apt-get install apache2
```

If you've created a virtual environment using **Python 3** you'll want to install the Python 3 WSGI + Apache module:

Deep learning in production with Keras, Redis, Flask, and Apache

Shell

$ sudo apt-get install libapache2-mod-wsgi-py3 $ sudo a2enmod wsgi

```
$ sudo apt-get install libapache2-mod-wsgi-py3
$ sudo a2enmod wsgi
```

Otherwise, **Python 2.7** users should install the Pytohn 2.7 WSGI + Apache module:

Deep learning in production with Keras, Redis, Flask, and Apache

Shell

$ sudo apt-get install libapache2-mod-wsgi $ sudo a2enmod wsgi

```
$ sudo apt-get install libapache2-mod-wsgi
$ sudo a2enmod wsgi
```

To validate that Apache is installed, open up a browser and enter the IP address of your web server. If you can't see the server splash screen then be sure to open up Port 80 and Port 5000.

In my case, the IP address of my server is `54.187.46.215` (yours will be different). Entering this in a browser I see:

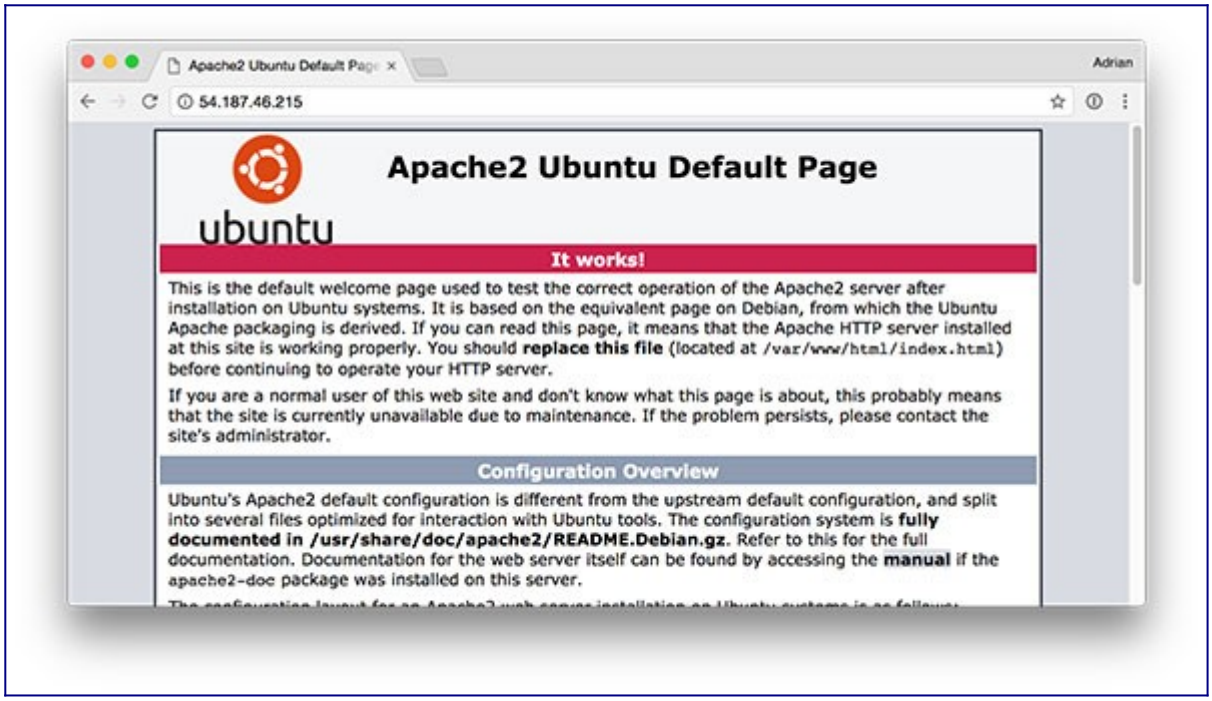

Figure 2: The default Apache splash screen lets us know that Apache is installed and that it can be accessed from an open port 80.

…which is the default Apache homepage.

Sym-link your Flask + deep learning app

By default, Apache serves content from `/var/www/html` . I would recommend creating a *sym-link* from `/var/www/html` to your Flask web app.

I have uploaded my deep learning + Flask app to my home directory in a directory named `keras-complete-rest-api` :

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Shell

```
$ ls ~ keras-complete-rest-api
```

```
$ ls ~
keras-
compl
ete-
rest-
api
```

I can sym-link it to `/var/www/html` via:

Deep learning in production with Keras, Redis, Flask, and Apache

Shell

```
$ cd /var/www/html/ $ sudo ln -s ~/keras-complete-rest-api keras-complete-rest-api
```

```
$ cd /var/www/html/
$ sudo ln -s ~/keras-
complete-rest-api
keras-complete-rest-
api
```

Update your Apache configuration to point to the Flask app

In order to configure Apache to point to our Flask app, we need to edit `/etc/apache2/sites-available/000-default.conf` .

Open in your favorite text editor (here I'll be using `vi`):

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Python

```
$ sudo vi /etc/apache2/sites-available/000-default.conf
```

```
$ sudo vi /etc/apache2/sites-available/000-default.conf
```

At the top of the file supply your WSGIPythonHome (path to Python bin directory) and WSGIPythonPath (path to Python site-packages directory) configurations:

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Apache

WSGIPythonHome /home/ubuntu/.virtualenvs/keras_flask/bin WSGIPythonPath /home/ubuntu/.virtualenvs/keras_flask/lib/python3.5/site-packages <VirtualHost *:80> ... </VirtualHost>

```
WSGIPythonHome /home/ubuntu/.virtualenvs/keras_flask/bin
WSGIPythonPath
/home/ubuntu/.virtualenvs/keras_flask/lib/python3.5/site-
packages

<VirtualHost *:80>
...
</VirtualHost>
```

Since we are using Python virtual environments in this example (I have named my virtual environment keras_flask), we supply the path to the bin and site-packages directory for the Python virtual environment.

Then in body of <VirtualHost> , right after ServerAdmin and DocumentRoot , add:

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Apache

<VirtualHost *:80> ... WSGIDaemonProcess keras_rest_api_app threads=10 WSGIScriptAlias / /var/www/html/keras-complete-rest-api/keras_rest_api_app.wsgi <Directory /var/www/html/keras-complete-rest-api> WSGIProcessGroup keras_rest_api_app WSGIApplicationGroup %{GLOBAL} Order deny,allow Allow from all </Directory> ... </VirtualHost>

```
<VirtualHost *:80>
    ...
    WSGIDaemonProcess keras_rest_api_app threads=10
    WSGIScriptAlias / /var/www/html/keras-complete-rest-api/keras_rest_api_app.wsgi
    <Directory /var/www/html/keras-complete-rest-api>
        WSGIProcessGroup keras_rest_api_app
        WSGIApplicationGroup %{GLOBAL}
        Order deny,allow
        Allow from all
    </Directory>
    ...
</VirtualHost>
```

Sym-link CUDA libraries (optional, GPU only)

If you're using your GPU for deep learning and want to leverage CUDA (and why wouldn't you), Apache unfortunately has no knowledge of CUDA's `*.so` libraries in `/usr/local/cuda/lib64` .

I'm not sure what the "most correct" way instruct to Apache of where these CUDA libraries live, but the "total hack" solution is to sym-link *all* files from `/usr/local/cuda/lib64` to `/usr/lib` :

Deep learning in production with Keras, Redis, Flask, and Apache

Shell

$ cd /usr/lib $ sudo ln -s /usr/local/cuda/lib64/* ./

```
$ cd /usr/lib
$ sudo ln -s /usr/local/cuda/lib64/* ./
```

If there is a better way to make Apache aware of the CUDA libraries, *please let me know in the comments.*

Restart the Apache web server

Once you've edited your Apache configuration file and optionally sym-linked the CUDA deep learning libraries, be sure to restart your Apache server via:

Deep learning in production with Keras, Redis, Flask, and Apache

Shell

```
$ sudo service apache2 restart
```

```
1 $ sudo service apache2 restart
```

Testing your Apache web server + deep learning endpoint

To test that Apache is properly configured to deliver your Flask + deep learning app, refresh your web browser:

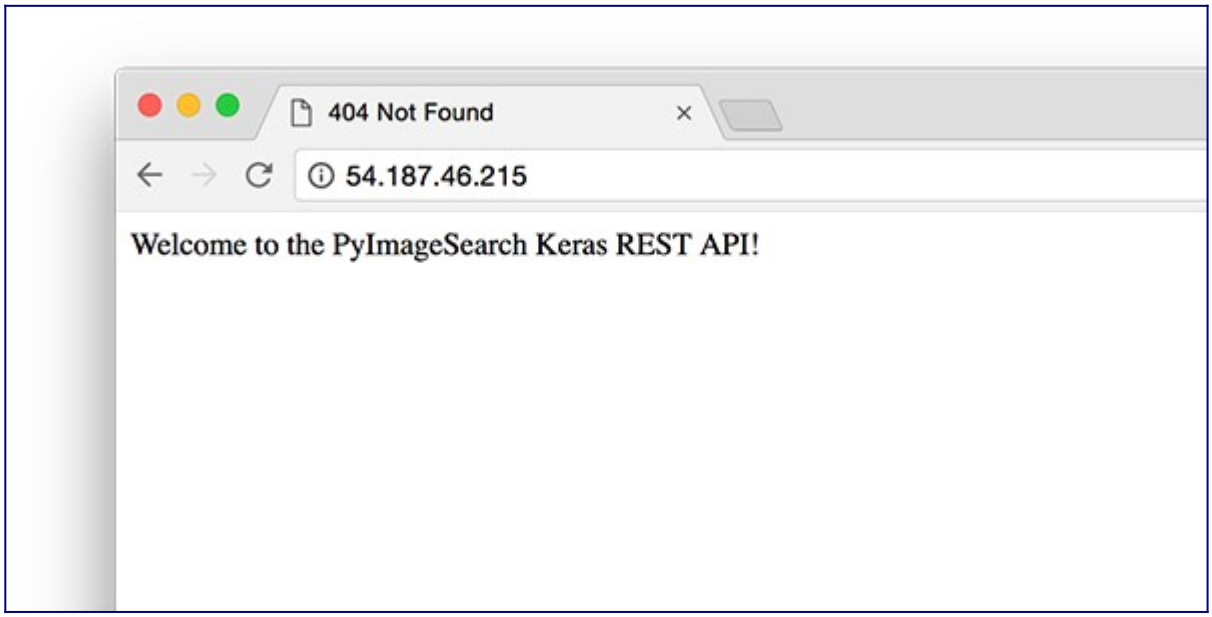


Figure 3: Apache + Flask have been configured to work and I see my welcome message.

You should now see the text *"Welcome to the PyImageSearch Keras REST API!"* in your browser.

Once you've reached this stage your Flask deep learning app should be ready to go.

All that said, if you run into any problems make sure you refer to the next section…

TIP: Monitor your Apache error logs if you run into trouble

I've been using Python + web frameworks such as Flask and Django for *years* and I still make mistakes when getting my environment configured properly.

While I wish there was a bullet proof way to make sure everything works out of the gate, the truth is something is likely going to gum up the works along the way.

The good news is that WSGI logs Python events, including failures, to the server log.

On Ubuntu, the Apache server log is located in `/var/log/apache2/` :

Deep learning in production with Keras, Redis, Flask, and Apache

Shell

```
$ ls /var/log/apache2 access.log error.log other_vhosts_access.log
```

```
$ ls /var/log/apache2
access.log error.log
other_vhosts_access.
log
```

When debugging, I often keep a terminal open that runs:

Deep learning in production with Keras, Redis, Flask, and Apache

Shell

```
$ tail -f /var/log/apache2/error.log
```

```
$ tail -f /var/log/apache2/error.log
```

…so I can see the *second* an error rolls in.

Use the error log to help you get Flask up and running on your server.

Starting your deep learning model server

Your Apache server *should* already be running. If not, you can start it via:

Deep learning in production with Keras, Redis, Flask, and Apache

Python

```
$ sudo service apache2 start
```

```
$ sudo service apache2 start
```

You'll then want to start the Redis store:

Deep learning in production with Keras, Redis, Flask, and Apache

Shell

```
$ redis-server
```

```
$ redis-server
```

And in a separate terminal launch the Keras model server:

Deep learning in production with Keras, Redis, Flask, and Apache

Shell

$ python run_model_server.py * Loading model... ... * Model loaded

```
$ python run_model_server.py
* Loading model...
...
* Model loaded
```

From there try to submit an example image to your deep learning API service:

Deep learning in production with Keras, Redis, Flask, and Apache

Shell

$ curl -X POST -F image=@jemma.png 'http://localhost/predict' { "predictions": [{ "label": "beagle", "probability": 0.9461532831192017 }, { "label": "bluetick", "probability": 0.031958963721990585 }, { "label": "redbone", "probability": 0.0066171870566904545 }, { "label": "Walker_hound", "probability": 0.003387963864952326 }, { "label": "Greater_Swiss_Mountain_dog", "probability": 0.0025766845792531967 }], "success": true }

```
$ curl -X POST -F image=@jemma.png 'http://localhost/predict'
{
  "predictions": [
    {
      "label": "beagle",
      "probability": 0.9461532831192017
    },
    {
      "label": "bluetick",
      "probability": 0.031958963721990585
    },
    {
      "label": "redbone",
      "probability": 0.0066171870566904545
    },
    {
      "label": "Walker_hound",
      "probability": 0.003387963864952326
    },
    {
      "label": "Greater_Swiss_Mountain_dog",
      "probability": 0.0025766845792531967
    }
  ],
  "success": true
}
```

If everything is working, you should receive formatted JSON output back from the deep learning API model server with the class predictions + probabilities.

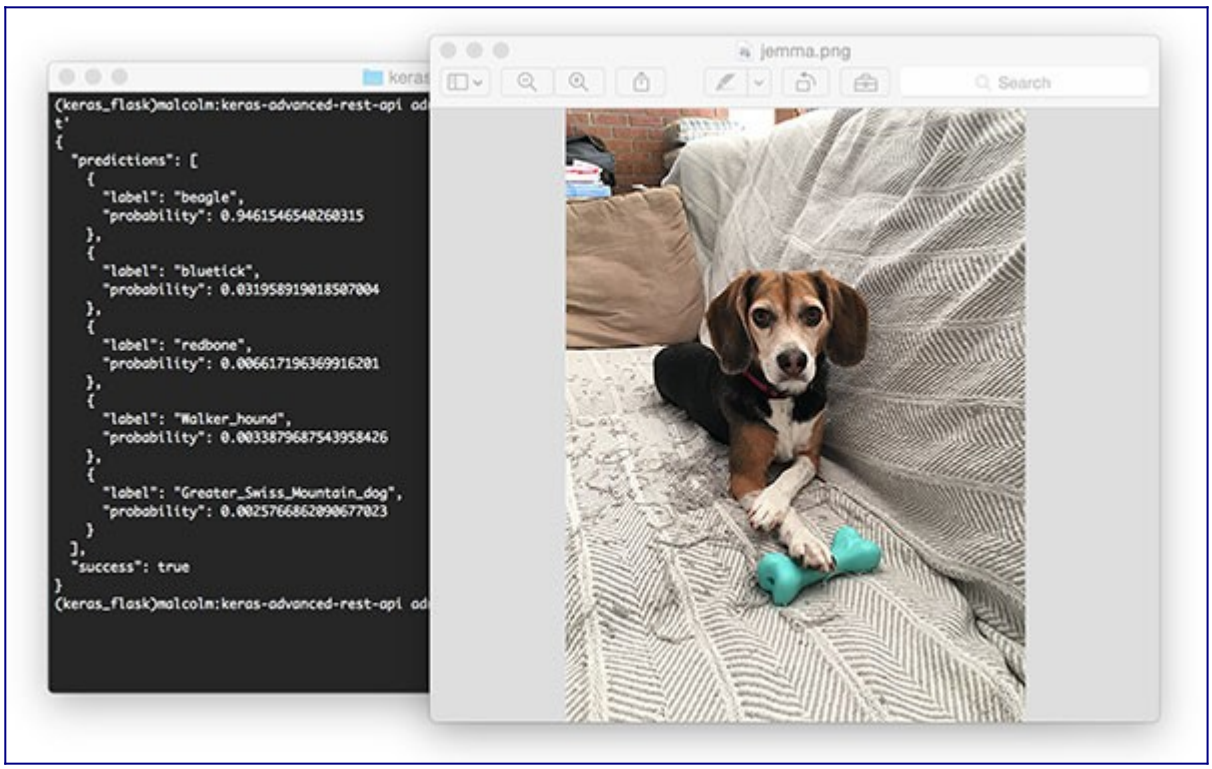


Figure 4: Using cURL to test our Keras REST API server. Pictured is my family beagle, Jemma. She is classified as a beagle with 94.6% confidence by our ResNet model.

Stress testing your deep learning REST API

Of course, this is just an example. Let's stress test our deep learning REST API.

Open up another terminal and execute the following command:

Deep learning in production with Keras, Redis, Flask, and Apache

Shell

$ python stress_test.py [INFO] thread 3 OK [INFO] thread 0 OK [INFO] thread 1 OK ... [INFO] thread 497 OK [INFO] thread 499 OK [INFO] thread 498 OK

```
$ python stress_test.py
[INFO] thread 3 OK
[INFO] thread 0 OK
[INFO] thread 1 OK
...
[INFO] thread 497 OK
[INFO] thread 499 OK
[INFO] thread 498 OK
```

In your run_model_server.py output you'll start to see the following lines logged to the terminal:

Deep learning in production with Keras, Redis, Flask, and Apache

Shell

* Batch size: (4, 224, 224, 3) * Batch size: (9, 224, 224, 3) * Batch size: (9, 224, 224, 3) * Batch size: (8, 224, 224, 3) ... * Batch size: (2, 224, 224, 3) * Batch size: (10, 224, 224, 3) * Batch size: (7, 224, 224, 3)

```
* Batch size: (9, 224, 224, 3)
* Batch size: (9, 224, 224, 3)
* Batch size: (8, 224, 224, 3)
```

Even with a new request coming in every 0.05 seconds our batch size never gets larger than ~10-12 images per batch.

Our model server handles the load easily without breaking a sweat and it can easily scale beyond this.

If you do overload the server (perhaps your batch size is too big and you run out of GPU memory with an error message), you should stop the server, and use the Redis CLI to clear the queue:

Deep learning in production with Keras, Redis, Flask, and Apache

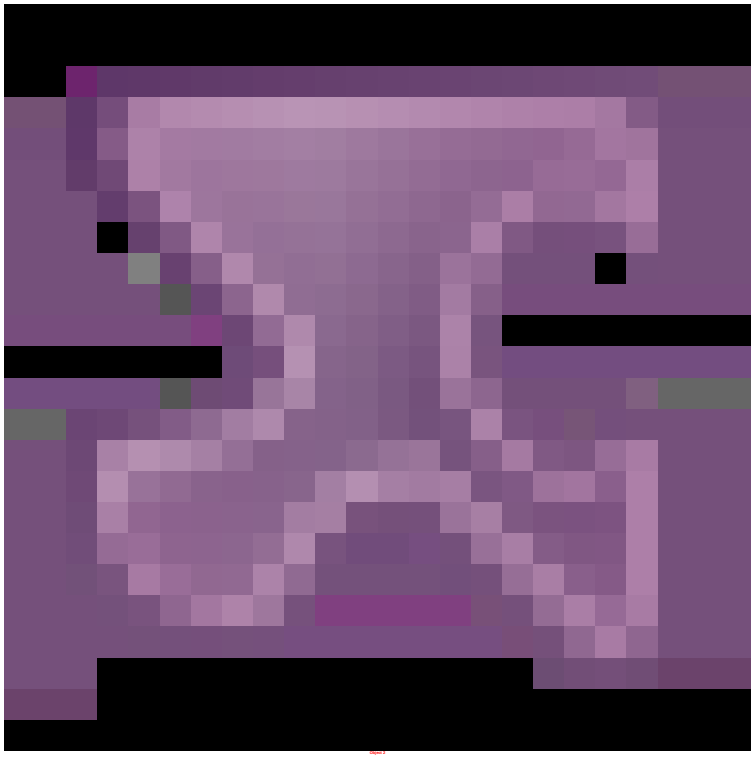
Shell

```
$ redis-cli > FLUSHALL
```

```
$ redis-cli
>
FLUSHALL
```

From there you can adjust settings in `settings.py` and `/etc/apache2/sites-available/000-default.conf`. Then you may restart the server.

For a full demo, please see the video below:



Recommendations for deploying your own deep learning models to production

One of the best pieces of advice I can give is to keep your data, in particular your Redis server, close to the GPU.

You *may* be tempted to spin up a giant Redis server with hundreds of gigabytes of RAM to handle multiple image queues and serve multiple GPU machines.

The problem here will be I/O latency and network overhead.

Assuming *224 x 224 x 3* images represented as float32 array, a batch size of 32 images will be ~19MB of data. This implies that for each batch request from a model server, Redis will need to pull out 19MB of data and send it to the server.

On fast switches this isn't a big deal, but you should consider running *both* your model server *and* Redis on the same server to keep your data close to the GPU.

Summary

In today's blog post we learned how to deploy a deep learning model to production using Keras, Redis, Flask, and Apache.

Most of the tools we used here are interchangeable. You could swap in TensorFlow or PyTorch for Keras. Django could be used instead of Flask. Nginx could be swapped in for Apache.

The only tool I would *not* recommend swapping out is Redis. Redis is arguably the best solution for in-memory data stores. Unless you have a specific reason to not use Redis, I would suggest utilizing Redis for your queuing operations.

Finally, we stress tested our deep learning REST API.

We submitted a total of 500 requests for image classification to our server with 0.05 second delays in between each — our server was not phased (the batch size for the CNN was never more than ~37% full).

Furthermore, this method is easily scalable to additional servers. If you place these servers behind a load balancer you can easily scale this method further.

I hope you enjoyed today's blog post!

To be notified when future blog posts are published on PyImageSearch*, be sure to enter your email address in the form below!*

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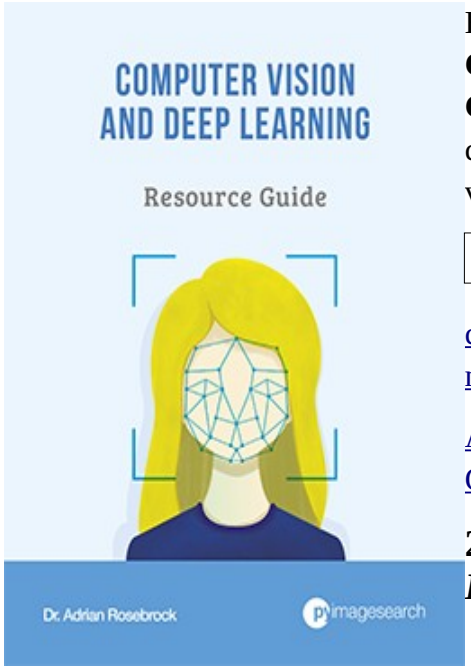
If you would like to download the code and images used in this post, please enter your email address in the form below. Not only will you get a .zip of the code, I'll also send you a **FREE 17-page Resource Guide on Computer Vision, OpenCV, and Deep Learning.** Inside you'll find my hand-picked tutorials, books, courses, and libraries to help you master CV and DL! Sound good? If so, enter your email address and I'll send you the code immediately!

Resource Guide (it’s totally free).



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cnn, convolutional neural network, deep learning, keras, machine learning, neural nets, redis, rest api

A scalable Keras + deep learning REST API
Getting started with the Intel Movidius Neural Compute Stick

20 Responses to *Deep learning in production with Keras, Redis, Flask, and Apache*

1. Meng Lee February 7, 2018 at 1:15 am #
Hi Adrian,

Thanks for the post sharing a end-to-end workflow of shipping an app utilizing Deep Learning.

I have built a app recognizing cats using Flask, TensorFlow, CNN in similar way months ago but I decided to built another one by following your post to practice again. Thanks for the material again ??

Let me put the link of the app for anyone want further learning:

https://github.com/leemengtaiwan/cat-recognition-app

Reply

- Adrian Rosebrock February 8, 2018 at 8:36 am #
Great job, thanks for sharing! ??

Reply

2. Anastasios Selalmazidis February 8, 2018 at 6:34 am #
Great article Adrian, as always. I am a flask+ apache guy myself but I found out that flask works better with nginx+gunicorn. You can give it a try if you have the time and maybe benchmark those two to see which fits better fro production environments

Reply

- 

  Adrian Rosebrock February 8, 2018 at 7:45 am #
  Great suggestion, thanks Anastasios. I don't think I'll have the time to benchmark with nginx + gunicorn, but if any other readers would like to try and post the results in the comments that would be great!

  Reply

-

3. 

   Prakruti February 21, 2018 at 6:39 am #
   Hi Adrian,

   Thank you for the post ! Helped a lot !
   I replaced Resnet50 with InceptionV3 as I did not have good internet to download the Resnet weights then. Also changed the image size to 299. One thing I noticed is I got wrong prediction results when I execute the curl command to test the api. So, I checked by reading the image from file system in the function classify_process() itself, which gave correct results. My image size is about 409*560*3 and format is PNG. Something is getting changed in the image data when the image is serialized and encoded or decoded ?
   Can you help me with this ?

   Reply

   - 

     Adrian Rosebrock February 22, 2018 at 9:02 am #
     Hey Prakruti — I'm not sure why you would receive different predictions when using cURL vs. the standard Python script. The actual image dimensions should not matter as they will be resized to a fixed size prior to being passed through the .predict function. Which version of Keras and Python are you using?

     Reply

   -

4. 

   Marco March 8, 2018 at 8:47 am #
   What's the point of having the redis queue? If you removed it you would save the step of encoding/decoding everything into base64, which is faster.

   The only reason that I can imagine is for load balancing, but you're suggesting a load balancer at host level.

   Reply

   - 

     Adrian Rosebrock March 9, 2018 at 9:17 am #

You need a queue to handle incoming images, regardless of whether you are batch processing them or not. Neural networks + GPUs are most efficient when batch processing. Sure, we need to encode/decode images but if you don't you will have zero control over the queue size. Furthermore, you can easily run into situations where there is not enough memory on the GPU to handle all images. Queueing controls this.

Reply

5. Aniruddh March 16, 2018 at 3:17 am #
Hi Adrian,

Loved all three parts. I implemented the same following your blogs, however, I am curious to know how using Kafka would scale compared to Redis. Would you be interested in shedding some light on it?

Also, I tried replacing apache with just gunicorn and the response time wasn't great under the stress (used Jmeter) and there were many "connection failed exceptions" while running it on the local machine.

Reply

Adrian Rosebrock March 19, 2018 at 5:39 pm #
I haven't used Apache Kafka at scale before so I cannot provide any intuitive advise. But it would make for a great blog post. I will consider this for the future but I'm not sure if/when I'll be able to do it.

Reply

6. patrick March 17, 2018 at 3:21 am #
I try to set this on aws but i get "You don't have permission to access / on this server. Apache/2.4.18 (Ubuntu) Server at xx.xxx.xxx.xxx Port 80". if i remove the apache configuration, then the default Apache homepage shows. Is this apache configuration need to changed?

Reply

Adrian Rosebrock March 19, 2018 at 5:25 pm #
It sounds like you may need to edit your incoming port rules for your AWS instance to include your IP address and port 80 for Apache.

Reply

7. 

Andrew Copley March 19, 2018 at 7:53 pm #
Just a couple of notes for Ubuntu 14:04 that I picked up on my journey

1.

WSGIPythonHome /home/ubuntu/.virtualenvs/keras_flask/bin

should be, according to mod_wsgi documentation, in default site conf file

WSGIPythonHome /home/ubuntu/.virtualenvs/keras_flask/

2. if you run into redis memory errors you may want to run

echo ‘vm.overcommit_memory = 1’ >> /etc/sysctl.conf
sysctl vm.overcommit_memory=1

Otherwise..great tutorial !!

Reply

- 

  Adrian Rosebrock March 20, 2018 at 8:25 am #
  Thanks for sharing, Andrew.

  Reply

8. 

Rehan March 27, 2018 at 7:34 am #
i am trying to deploy the model on google cloud. my problem is that i don’t want to run the **run_model_server.py** file manually as my plan is to deploy the whole thins with model as a service. how can i avoid running the file manullay and seeing the prediction on the browser instead of terminal?

Reply

- 

  Adrian Rosebrock March 30, 2018 at 7:33 am #
  You can create a cronjob (or modify the init boot) that automatically launches run_model_server.py on boot.

  As for displaying the predictions in the browser you will need to modify the code to include a custom route that will interface with “predict” and return the results. If you’re new to Flask and web development, that’s okay, but you’ll want to do your research first and teach yourself the fundamentals of Flask.

  Reply

9. 

   Henrique April 20, 2018 at 4:06 pm #
   I'm getting this error after restarting apache2 and acessing the server

   Fatal Python error: Py_Initialize: Unable to get the locale encoding
   ModuleNotFoundError: No module named 'encodings'

   I'm trying to figure what what might be causing it but with no success.

   Reply

   - 

     laksh August 11, 2018 at 9:39 am #
     I'm getting the same error on ubuntu 18.04

     Reply

   - 

     vamsi October 29, 2018 at 2:54 pm #
     The below change worked for me in Ubuntu 18.04 and Python 3.6
     In the file /etc/apache2/sites-available/000-default.conf, change the line

     WSGIPythonHome /home/ubuntu/.virtualenvs/keras_flask/bin

     to

     WSGIPythonHome /home/ubuntu/.virtualenvs/keras_flask

     Hope that helps.

     Reply

   -

10. 

    pablo August 21, 2018 at 1:45 pm #
    For the ones using only CPUs I would suggest to try multiprocessing, celery is a good option.

11.