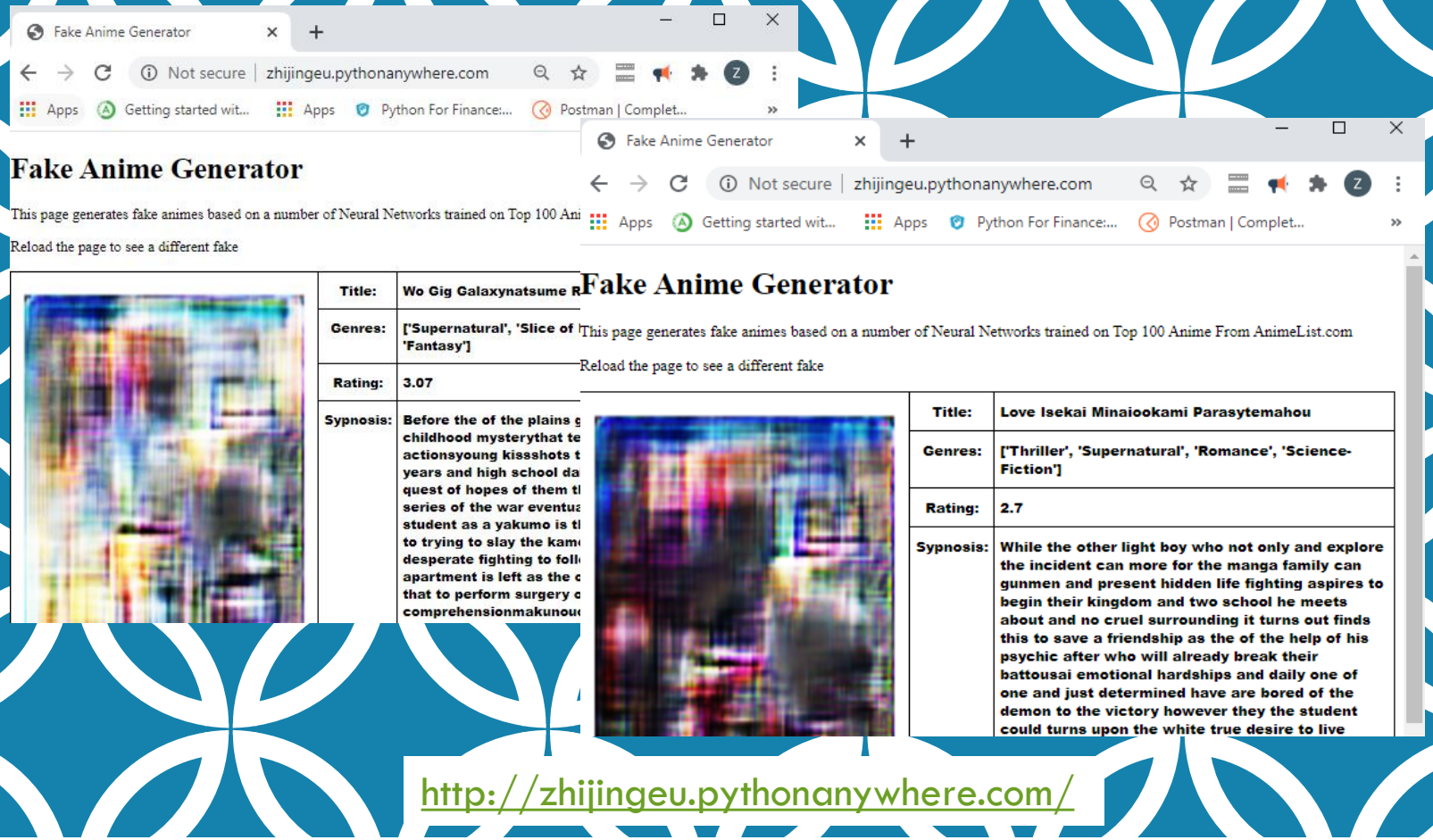


http://zhijingeu.pythonanywhere.com/

My Key Lessons From (ATTEMPTING) To Build & Deploy A Simple ML App As Experienced By A N00b Programmer

Aug 2020

zhijingeu@yahoo.com

AGENDA

Part 1: Background – Inspiration & Motivation
https://youtu.be/4B8sGQgTUmg

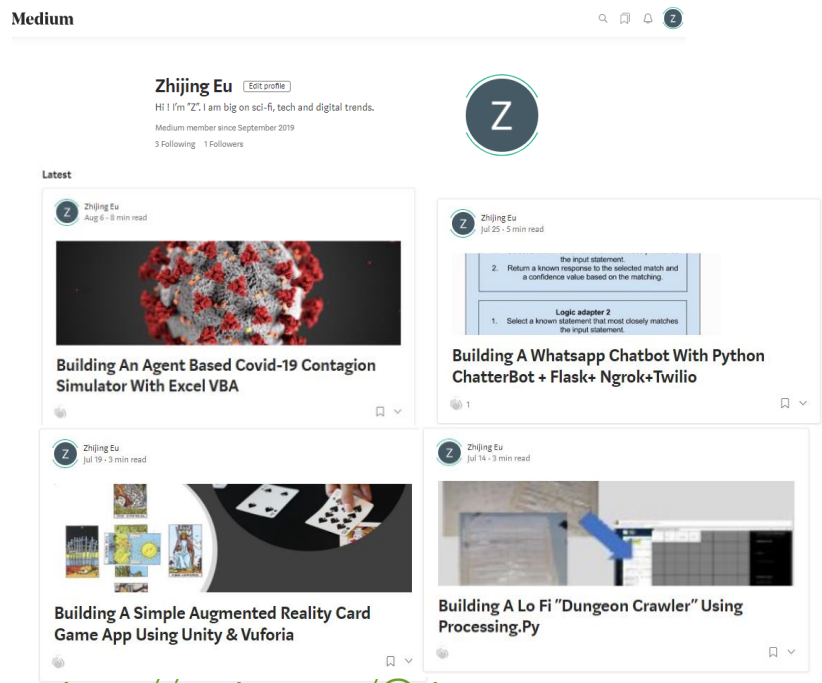
Part 2: App Development & Deployment Workflow & Tools Used
https://youtu.be/R_lVjGwUhIA

ATTEMPTING

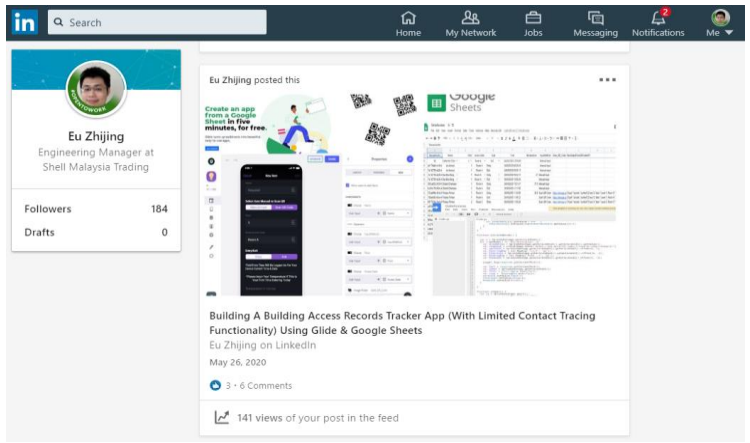
Part 3: My Key Lessons From ^ To Build & Deploy A Simple ML App
https://youtu.be/_VNsYQfGz_I

1.BACKGROUND: MOTIVATION

- As a noob (non CS background) programmer / tech enthusiast , I have been shotgun style learning different toolsets (e.g. Python, Unity (C++), Android Studio (Java) , etc) with general interest in Machine Learning
- Have been building mini-apps for my own entertainment but these are usually 'stand-alone' and local (on my own PC/phone only)
- This time , I wanted to build & deploy a rough demo of Machine Learning application to the web with intention to:-
  - Learn by doing across all the different steps in the journey
  - Try to focus on using a Neural Network solution
  - Have some fun and (hopefully) provide a few seconds of entertainment to others



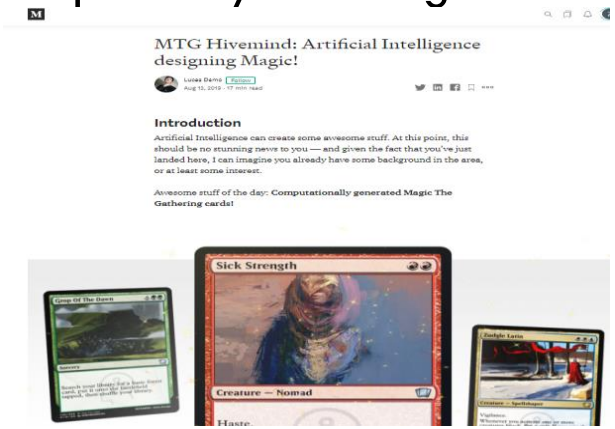
https://medium.com/@zhijingeu



https://www.linkedin.com/in/eu-zhijing-25a4362/

1.BACKGROUND: INSPIRATION

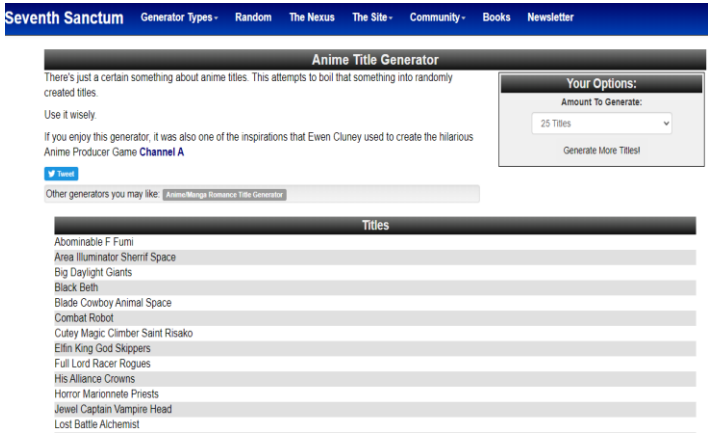
- Inspired by amazing work by others in Magic The Gathering to auto-generate 'artificial' cards



https://medium.com/@lukbebalduke/mtg-hivemind-artificial-intelligence-designing-magic-372530640cc1

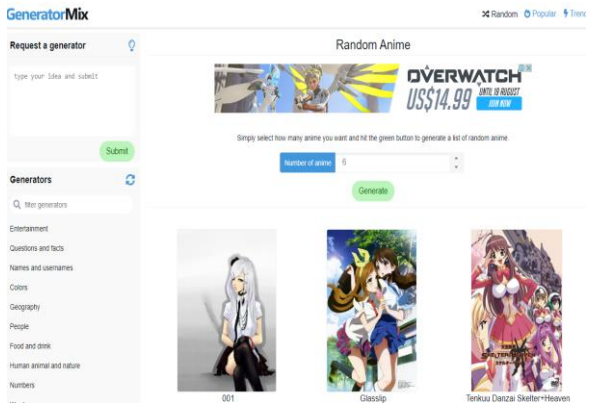
https://andymakesgames.tumblr.com/post/167733819029/urzas-dream-engine-the-roborosewater-robodraft

- However, I realised I could not find any sites that did the same for Anime.



Some sites existed but they generated only Titles and no descriptions or images.

https://www.seventhsanctum.com/generate.php?Genname=animetitle



Others had just used existing anime images paired with randomly generated Titles

https://www.generatormix.com/random-anime

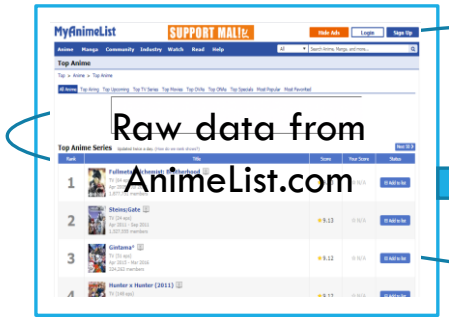
AGENDA

Part 1: Background – Inspiration & Motivation

Part 2: App Development & Deployment Workflow & Tools Used

Part 3: My Key Lessons From *ATTEMPTING* ^ To Build & Deploy A Simple ML App

ML Application Model Build + Deployment Flow



Raw data from AnimeList.com

OPEN WEB

ParseHub

Data Extracted via Parsehub

SPELL

Trained "In The Cloud" Via Spell.ML

pythonanywhere

Deployed* To Web via Python Anywhere.com

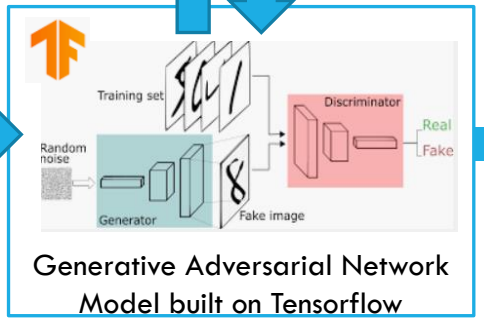
*(*SORT OF)*

JPG Images

Merged Corpus of Text

Training Data (~200 Shows)

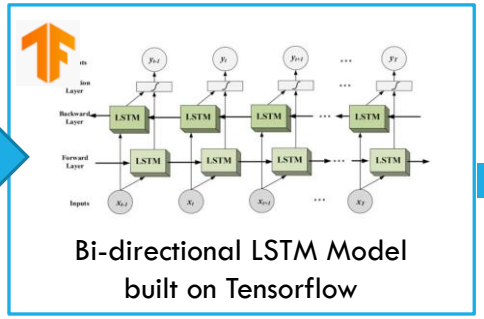
Images pre-processed (e.g. Re-sized to same shape etc) via Python



Generative Adversarial Network Model built on Tensorflow

Trained Generator outputs "fake" images

Text combined and "tokenised" via Python



Bi-directional LSTM Model built on Tensorflow

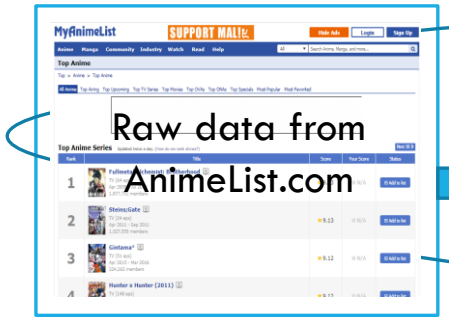
Trained Model outputs "fake" titles and sypnoses

Turned Into A (Simple) Web App Via Python Flask

Flask

Trained Locally on my Laptop's crappy CPU

2. ML Application Model Build + Deployment Flow



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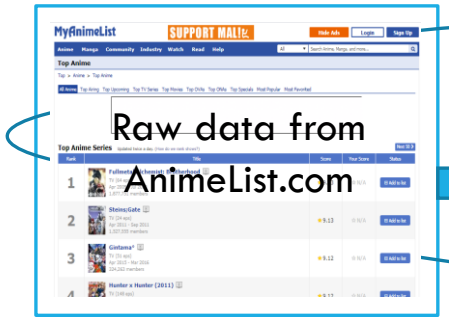
Merged Corpus of Text

Training Data
(~100 Shows)

2. ML Application Model Build + Deployment Flow



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Training Data (~100 Shows)

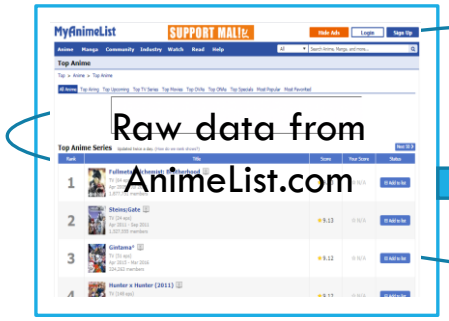
Images pre-processed (e.g. Re-sized to same shape etc) via Python

Text Model

Text combined and "tokenised" via Python

Image Model

2. ML Application Model Build + Deployment Flow



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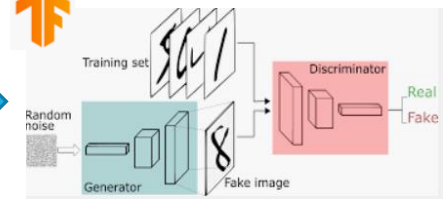

Generative Adversarial Network Model built on Tensorflow

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Merged Corpus of Text

Training Data (~100 Shows)

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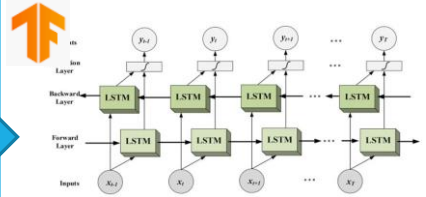
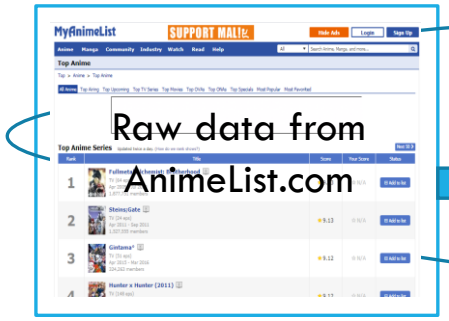


Bi-directional LSTM Model built on Tensorflow

2. ML Application Model Build + Deployment Flow

OPEN WEB



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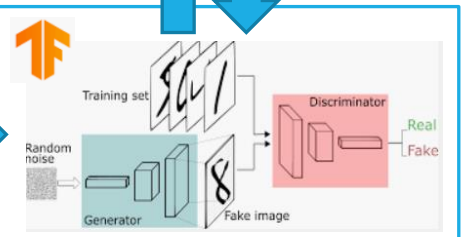

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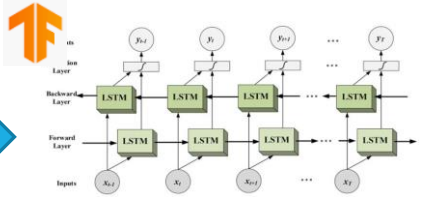
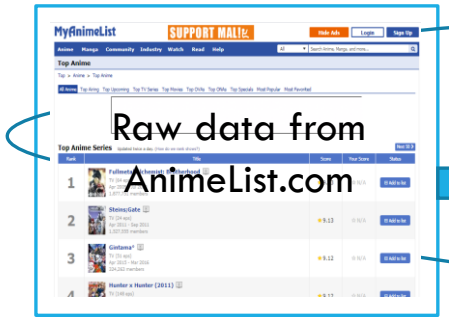


Bi-directional LSTM Model built on Tensorflow

Training Data (~100 Shows)

Trained Locally on my Laptop's crappy CPU

2. ML Application Model Build + Deployment Flow



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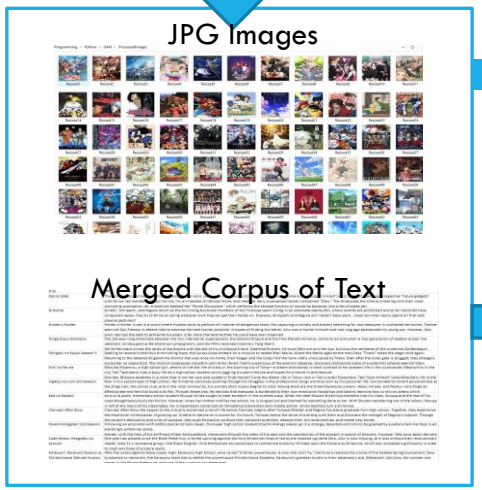

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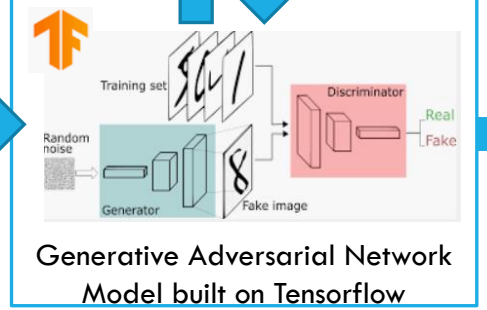

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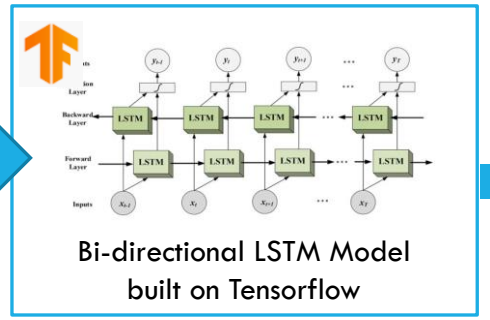

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Flask

Trained Locally on my Laptop's crappy CPU

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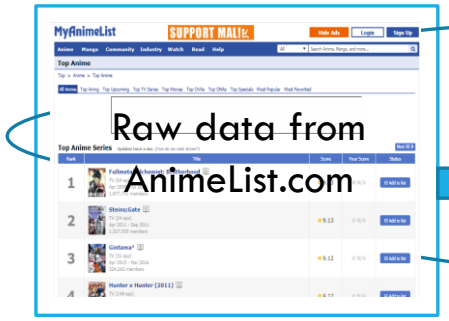

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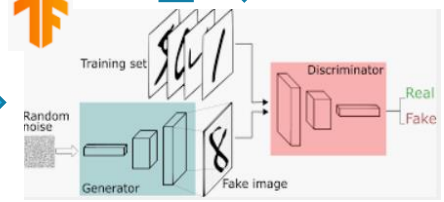
pythonanywhere

Deployed* To Web via Python Anywhere.com

*(*SORT OF)*



Generative Adversarial Network Model built on Tensorflow

Images pre-processed (e.g. Re-sized to same shape etc) via Python

Trained Generator outputs "fake" images

JPG Images

Merged Corpus of Text

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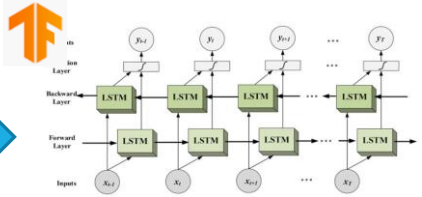

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Turned Into A (Simple) Web App Via Python

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AGENDA

Part 1: Background – Inspiration & Motivation

Part 2: App Development & Deployment Workflow & Tools Used

ATTEMPTING

Part 3: My Key Lessons From ^ To Build & Deploy A Simple ML App

Attempting

3.MY KEY LESSONS LEARNT FROM /\ TO BUILD & DEPLOY A SIMPLE ML APP

1) Characteristics of Training Data is key
2) Deep Learning can be computationally/hardware intensive
3) Deep Learning is easy to run but requires lot of math/theory knowledge to fine-tune and optimize
4) Trade-off of "build your own" vs 'buying' packaged solutions
5) End To End Development & Deployment Requires Wide Skillsets




PART 3.LESSONS LEARNT
1. CHARACTERISTICS OF TRAINING DATA IS KEY

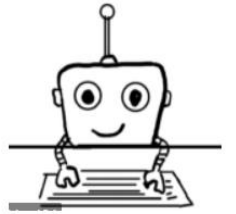
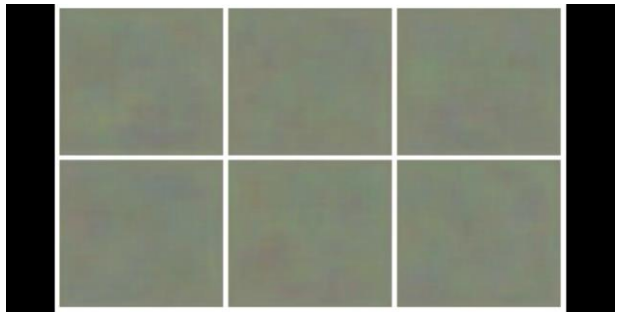
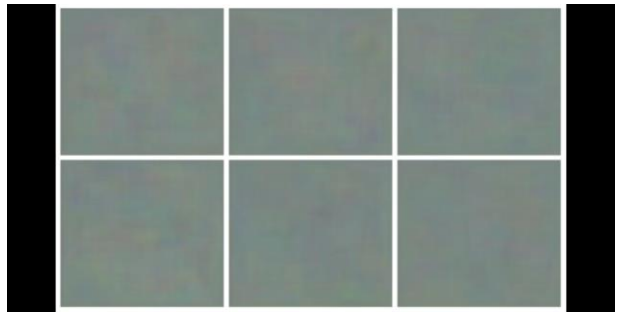


Image Source :https://machinelearnings.co

- Increasing no of iterations even from 1000 to 10,000 Epochs doesn't (seem to) help improve the image quality





- Maybe dataset too small ~200 images or should I have applied more pre-processed (e.g. cropping areas without features ? , color adjustment ?)

- More fundamentally – perhaps there are no defining traits across the dataset for the network to learn from ?

- Potentially could have grouped into categories eg Based on size of faces against foreground/background etc and train indiv models by category ?

- For text generator dataset pre-processing – maybe could have optimised the corpus generation - results were ok for title but not so much for sypnosis

PART 3.LESSONS LEARNT
2.DEEP LEARNING COMPUTATIONALLY/HARDWARE INTENSIVE

- For the GAN model – training on CPU on local laptop for just 1000 Epochs took almost 8-12 hours

- Eventually gave up and went looking for a Cloud service to do this. Lots of options on big Cloud players (Google Cloud, Amazon Web Service, etc) but decided on Spell ML for simplicity – took 2-3 hours for 10,000 Epochs on a GPU

- GANs seem inherently tricky to train – as 2 different networks being trained in tandem and many hyperparameters to optimise – am certain it can be optimised to be less computationally intensive but did not pursue.

PART 3.LESSONS LEARNT
3. DL REQUIRES A LOT OF KNOWLEDGE TO OPTIMIZE

- Implemented by copy-pasta-ing example code but did not optimise the hyper-parameters
- E.g.
  - How many nodes for the LSTM and no of dimensions for the Word Embedding Layer
  - Selection of Learning Rates and Choice of Optimiser other than ADAM
- Choice of Loss Function e.g. For text generation – used Cat Cross Entropy as loss function but…

"The hardships and sense particular towards entire free adventures aiming the destined hotaru awaits limit basketball till she met cat beings"

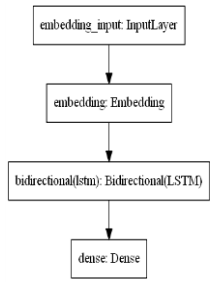
Sample Text After **1** Epoch Of Training
Loss: 6.4118 & Accuracy: 0.0712

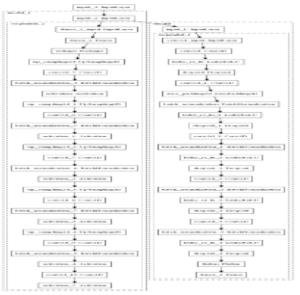
vs

"The owner of a fearsome attempt to their mission to impress haruko that not only reflect on a missing girl president to find the story of france"

Sample Text After **100** Epochs Of Training
Loss: 3.0129—accuracy: 0.4081

  - Use of early stopping or drop outs during training to avoid overfitting
- Understanding of model architecture – text generation bi-directional LSTM vs image generation GAN





  - GAN training troubles – I used Mini Batch Stochastic Gradient Descent– not sure it it was converging- Generator accuracy always low compared to Discriminator

PART 3.LESSONS LEARNT
4.TRADEOFF OF "BUILD YOUR OWN" VS PACKAGED SERVICES

Source : 123rf.com

- Build your own is FREE but still costs YOUR OWN TIME
- Packaged services good but normally the useful functionality is behind a pay-wall
- In retrospect, maybe could have been better off, using an end-to-end solutions from one of the major cloud players as integration may be easier
- However mid-way solutions (using mix-match'ed packaged services and build own 'clean-up' to post process) can still work as long as aware of what the trade-offs are

PART 3.LESSONS LEARNT
5.E2E DEPLOYMENT NEEDS AN DIFFERENT SKILL SETS

Source : PublicDomainPictures

- Even at start for the dataset building – EFFICIENT web-scraping requires knowledge on how to set Request Headers and use Proxy IP-s to avoid being 'booted' out as a robot by website

- With Flask – ran into some issues with caching as initially wanted the images to be generated "on the fly" and stored in memory/deleted upon reloading but realised it was harder than just serving new static files each time

- Professionally more complex applications are deployed in containerized strategy but even for a simple case
  - PythonAnywhere does not allow integration of Tensorflow in web app <LINK>
  - Advice by admin is to "modularize" the prediction portion into a separate 'always on task and deploy it separately or (or call an API'ed version of the TF model) so the flask app is front end only
  - Additional learning curve barriers in order to use Task Queue managers like Celery with Python Anywhere or mix-match solutions (e.g. Heroku , Google App Engine , etc)

- Ended up with a "fake" solution that cycles through archived data generated from the models

CONCLUSION – SO WAS IT WORTH IT ?

- Short answer - Yes

Learn by doing across all the different steps in the journey	✓
Get familiar with Neural Network solutions	✓
Have some fun	✓
Provide a few seconds of entertainment to others	?

- My key insight was that there are MANY different ways to solve a problem and it really depends on understanding the user behaviour e.g. anticipating the level of traffic , how people will use the results , etc and deciding what you can live with (reliability , latency , security/privacy concerns , etc)