

# Milestone1

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CIS 700 Machine Learning and Security

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## Theme:

“Adversarial Text Generation: Adversarial Machine Learning Applications in Text Analysis”

## Purpose:

The purpose of this lab is to successfully run a new text dataset to generate synthetic data using an existing GAN project framework.

## Project:

Texygen is the name of the project selected. This project is a benchmarking tool that aids in text generation model research and testing. This tool allows for ease of various model testing to compare accuracy and synthetic data generation of models using same training baseline.

## (Hard/Soft)ware:

Google Colaboratory <https://colab.research.google.com/>

GPU Python 3 Google Compute Engine backend

Github [https://github.com/eordanis/CIS-700/tree/main/Project/Milestone1/Milestone1\\_test](https://github.com/eordanis/CIS-700/tree/main/Project/Milestone1/Milestone1_test)

## Resources:

Original Source: <https://github.com/geek-ai/Texygen>

Modified Sources Acquired: 2SU Course Files Section -> Texygenmaster\_Python\_3.6.zip

## Data:

The data for the selected project is setup as follows:

- Generated data training: 5000 word and 20 sentence count
- Oracle data generation: 10,000 sentence generation
- Real data training:

```
* image_coco : 20,000 sentences chosen from the image COCO captions data.  
10,000 of which are used as training set while other 10,000 used as test set  
* eapoe : 266 sentences chosen from the seinfeld script data. 133 of  
which are used as training set while other 133 used as test set  
          Compiled from various Edgar Allan Po Poems found on  
referenced poem sight [4].
```

## Modifications:

To begin, the modified source code acquired from the 2SU application was further modified to combine the original intention of the origin source authors as well as professor modification. If no arguments are passed, all models/data are run. Note, the order or model generation is done by first iterating over the GAN model type, then data type. If arguments are passed, those arguments will be validated and run accordingly to run a more targeted model test. Addition modifications were applied to eliminate much library warnings and informational messages as to keep output as clean as possible. Furthermore, file path naming was updated to be compliant with Google Colaboratory environment. All epoch time elapse console printing has been commented out for cleaner output reading.

## Setup:

Due to the heft of processor/gpu usage, it was deemed necessary to run the project in the Google Colaboratory. Original attempt to run was done via Pycharm IDE Professional Edition with Anaconda derived environments, however this proved too great of a strain on the accessible workstation.

### Step 1

A new Google Colaboratory workspace was setup, titled “Milestone1”. This workspace was run using the hosted runtime environment. This document is the current document being read.

In order to run against provided code base, it was necessary to sync the colab workspace the github repository files as follows

```
!git clone https://$GITHUB_AUTH@github.com/eordanis/CIS-700/
```

Running this command from the first cell in the workbook syncs the drive to the github repo location of project location

In [ ]:

```
!git clone https://$GITHUB_AUTH@github.com/eordanis/CIS-700/
```

## Step 2

Now the directory was changed to the folder needed to run the project

```
%cd CIS-700/Project/Milestone1/Milestone1_test
```

In [ ]:

```
%cd CIS-700/Project/Milestone1/Milestone1_test
```

## Step 3

Now it was necessary to import and download any missing libraries the hosted colaborartoy runtime did not have readily available via the following commands:

```
!pip install -r "requirements.txt"
import nltk
nltk.download('punkt')
```

Running this command from the next cell in the workbook installed the necessary libraries and at specified versions for the project.

In [ ]:

```
!pip install -r "requirements.txt"
import nltk
nltk.download('punkt')
```

## Step 4

Now it is time to run the application. Below are two examples of commands to run the application.

```
!python3 "main.py"
```

This first command was run without parameters. In the case of this command, all trainings (SeqGAN, Gsgan, TextganMmd, Leakgan, Rankgan, Maligan, Mle) were run on all available defaulted training data (oracle LSTM, real data, CFG). Running this command can take around 2+ hours to complete.

```
!python3 "main.py" -g seqgan -t real
```

This second command was run with parameters. In the case of this command, main was run with SeqGAN training on image\_coco. Running targeted trainings take less time to run, on average

completing in 5-15 minutes depending on selected parameters. With the above selection, runtime was run above 10 minutes.

```
!python3 "main.py" -g seqgan -t real -d data/eapoe.txt
```

This third command was run with parameters. In the case of this command, main was run with SeqGAN training on eapoe. Running targeted trainings take less time to run, on average completing in 5-15 minutes depending on selected parameters. With the above selection, runtime was run above 10 minutes.

**NOTE:** For above estimates, based around 5 epochs. Additionally, CFG training appears to have stopped working suddenly, unsure why broken. Therefore running without that option for the time being. Additionally, the LeakGAN model failed entirely to run now due to flag errors, so this model was discarded from testing.

## Process

When running the various models, there are similar steps for each.

1. Beginning Training – begin model training(s)
2. Set training - sets the desired model training method
3. Start model pre-train generator – uses the training data to pre-train the generator model
4. Start model pre-train discriminator - – uses the training data to pre-train the discriminator model
5. Model adversarial training – runs the model to generate results based on the test data and metrics applied
6. Finish Training – end of model training(s)

During training, each model training runs through several passes or epochs. For simplicity, base epoch is set to 5, with model training running thrice for 15 total epochs thereabouts for each model trained on a particular data set.

## Metrics

### Abbreviations:

- BLEU - BiLingual Evaluation Understudy
- GAN - Generative Adversarial Network
- NLL - Negative Log-Likelihood
- RL - Reinforcement Learning

### Definitions

- EmbSim – influenced by BLEU, used instead to compare the word embeddings vs BLEU's comparison of word similarity between two sentences or documents.

- NLL-oracle : applied to synthetic data to determine fitting via oracle language model standards.
- NLL-test : dual to NLL-Oracle, used to determine a model's capability to fit to real test data

These measurement standards and more are discussed In the project directory's `"/docs/evaluation.md"` location.

## Models

For this report, the TextGAN and SeqGAN models were run on oracle and real training types. The real training types essentially runs the data against the `image_coco.txt` caption data. The TextGAN and SeqGAN was developed by the source project team to improve on existing GAN networks.

With regards to TextGan, the goal of this model is to generate high quality realistic synthetic data while overcoming the convergence dilemma by using a generator that runs as a long short-term memory network and its discriminator a convolutional network. By matching high-dimension laten feature distributions of the testing and training data, this model over longer epochs has shown demonstrate a higher performance in quantitative evaluation, showing the TextGAN model can produce sentences that appear to have been written by a human, and not AI generated.

For the SeqGAN model, this also proved successful in generating realistic looking sentences via this generator process. A second model was selected for comparison purposes. SeqGAN's generator is based off the reinforcement learning stochastic policy, allowing SeqGAN to performing gradient policy update in order to circumvent differentiation issues in the generation. Its discriminator is run on complete sentences, and its results used as the reinforcement learning reward signal. According to source authors, this model boasted higher performance over others run.

## Testing

Epochs were increased left to run at 5 for the sake of time. However, it is noted that as according to original project sourcing,  $\geq 45$  epochs for the models display the best NLL loss results on epochs  $> 40$ , prior to that point results would be poorer. NLL loss values are indicated to be better the lower they are, so if these values trend downward, the models are improving. For EmbeddedSimilarity, higher values are desired for better results.

## TextGAN

The following commands are to run TextGAN model on both oracle and real trainings.

**NOTE:** The real data essentially trained the model on the `eapoe.txt` data.

```
!python3 "main.py" -g textgan -t oracle
!python3 "main.py" -g textgan -t real
```

In [ ]:

```
!python3 "main.py" -g textgan -t oracle
```

Out [ ]:

```
***** Beginning Training *****
set training
oracle
start pre-train generator:
nll-oracle
time elapsed of nll-oracle: 1.0739710330963135
nll-test
time elapsed of nll-test: 1.2133264541625977
EmbeddingSimilarity
time elapsed of EmbeddingSimilarity: 88.22535681724548
epoch:1 nll-oracle:12.198931    nll-test:40.538124    EmbeddingSimilarity:-
0.19819031171098683
start pre-train discriminator:
adversarial training:
nll-oracle
time elapsed of nll-oracle: 1.081681489944458
nll-test
time elapsed of nll-test: 1.2737576961517334
EmbeddingSimilarity
time elapsed of EmbeddingSimilarity: 43.726564168930054
epoch:6 nll-oracle:11.897842    nll-test:36.785576    EmbeddingSimilarity:-
0.309232358180863
nll-oracle
time elapsed of nll-oracle: 1.0407702922821045
nll-test
time elapsed of nll-test: 1.1645281314849854
EmbeddingSimilarity
time elapsed of EmbeddingSimilarity: 43.738325357437134
epoch:10    nll-oracle:11.898141    nll-test:36.8766
EmbeddingSimilarity:-0.3125717377492794
***** Completed Training *****
```

## Oracle Output

As we can see from the output above, over several loopthroughs, or epochs, the accuracy of the nll oracle and test values varied but appeared to having an upward trend in accuracy over epoch runs when running TextGAN with oracle training. However, it is noted the embedded fell over time during the runs. For training, it would yeild better results to run higher epochs, such as 40, however for testing sake only 5 were run.

## Best Values

- NLL-oracle: 11.898141 @epoch 10
- NLL-test: 36.785576 @epoch 6
- EmbeddingSimilarity: -0.198190311710986 @epoch 1

```

In [ ]:
!python3 "main.py" -g textgan -t real -d data/eapoe.txt
Out [ ]:
***** Beginning Training *****
set training
real
start pre-train generator:
EmbeddingSimilarity
time elapsed of EmbeddingSimilarity: 44.0513916015625
nll-test
time elapsed of nll-test: 0.07195925712585449
epoch:1 EmbeddingSimilarity:-0.36917074786673465      nll-test:37.6523
start pre-train discriminator:
adversarial training:
EmbeddingSimilarity
time elapsed of EmbeddingSimilarity: 43.88083100318909
nll-test
time elapsed of nll-test: 0.013695955276489258
epoch:6 EmbeddingSimilarity:-0.3965602633631248      nll-test:37.735287
EmbeddingSimilarity
time elapsed of EmbeddingSimilarity: 43.74346661567688
nll-test
time elapsed of nll-test: 0.013765573501586914
epoch:10      EmbeddingSimilarity:-0.4435325866887675      nll-
test:37.640396
***** Completed Training *****

```

## Real Output

As we can see from the output above, over several loopthroughs, or epochs, the accuracy of the nll values are also increase when running TextGAN with real training. However, it is noted the embedded similarity fell over the course of the run. This indicates to us that the test\_text.txt data generated should have closer similarity to the original eapoe.txt data file used to train the models.

For training, it would yeild better results to run higher epochs, such as 40, however for testing sake only 5 were run.

## Best Values

- NLL-test: 37.6404 @epoch 10
- EmbeddingSimilarity: -0.369170747866734 @epoch 1

## SeqGAN

The following commands are to run SeqGAN model on both oracle and real trainings.

**NOTE:** The real data essentially trained the model on the eapoe.txt data.

```

!python3 "main.py" -g seqgan -t oracle
!python3 "main.py" -g seqgan -t real

```

In [ ]:

```
!python3 "main.py" -g seqgan -t oracle
```

Out [ ]:

```
***** Beginning Training *****
set training
oracle
start pre-train generator:
nll-oracle
time elapsed of nll-oracle: 1.0661637783050537
nll-test
time elapsed of nll-test: 1.1655919551849365
EmbeddingSimilarity
time elapsed of EmbeddingSimilarity: 88.71221280097961
epoch:1 nll-oracle:10.742874    nll-test:7.5933557    EmbeddingSimilarity:-
0.2093585259617846
start pre-train discriminator:
adversarial training:
nll-oracle
time elapsed of nll-oracle: 1.042651653289795
nll-test
time elapsed of nll-test: 1.1159939765930176
EmbeddingSimilarity
time elapsed of EmbeddingSimilarity: 44.104719400405884
epoch:6 nll-oracle:10.199376    nll-test:7.031317    EmbeddingSimilarity:-
0.20886221700123014
nll-oracle
time elapsed of nll-oracle: 1.058502197265625
nll-test
time elapsed of nll-test: 1.109898567199707
EmbeddingSimilarity
time elapsed of EmbeddingSimilarity: 44.02372622489929
epoch:10    nll-oracle:10.114458    nll-test:7.057727
EmbeddingSimilarity:-0.2076366993211025
***** Completed Training *****
```

## Oracle Output

As we can see from the output above, over several loopthroughs, or epochs, the accuracy of the nll oracle and test values varied but leaned toward improvment when running SeqGAN with oracle training. Additionally, it is noted the embedded similarity is improving as well.

For training, it would yeild better results to run higher epochs, such as 40, however for testing sake only 5 were run.

## Best Values

- NLL-oracle: 10.114458 @epoch 10
- NLL-test: 7.031317 @epoch 6
- EmbeddingSimilarity: -0.207636699321102 @epoch 10



In [ ]:

```
!python3 "main.py" -g seqgan -t real -d data/eapoe.txt
```

Out [ ]:

```
***** Beginning Training *****
set training
real
start pre-train generator:
EmbeddingSimilarity
time elapsed of EmbeddingSimilarity: 44.03479051589966
nll-test
time elapsed of nll-test: 0.06215381622314453
epoch:1 EmbeddingSimilarity:-1.092657517043026nll-test:6.101324
start pre-train discriminator:
adversarial training:
92.44891
EmbeddingSimilarity
time elapsed of EmbeddingSimilarity: 44.07878828048706
nll-test
time elapsed of nll-test: 0.012879133224487305
epoch:6 EmbeddingSimilarity:-0.726695526133442nll-test:3.8079882
EmbeddingSimilarity
time elapsed of EmbeddingSimilarity: 43.626389265060425
nll-test
time elapsed of nll-test: 0.012568950653076172
epoch:10      EmbeddingSimilarity:-0.5105762563967318      nll-
test:3.4653516
***** Completed Training *****
```

## Real Output

As we can see from the output above, over several loopthroughs, or epochs, the accuracy of the nll values are also increase when running SeqGAN with real training. Additionally, it is noted the embedded similarity is improving as well. This indicates to us that the test\_text.txt data generated should have closer similarity to the original eapoe.txt data file used to train the models.

For training, it would yeild better results to run higher epochs, such as 40, however for testing sake only 5 were run.

## Best Values

- NLL-test: 3.4653516 @epoch 10
- EmbeddingSimilarity: 0.510576256396731 @epoch 10

## Data Comparision

### Oracle Data

Model comparison wise, SeqGAN performed better than TextGAN using a base of 5 epochs and under the testing done at this time. It would seem that using the SeqGAN model is superior to the

TextGAN model using these qualifying metrics. To see the best results under the SeqGAN model, it would require longer epoch testing.

### **TextGAN Best Values**

- NLL-oracle: 11.898141 @epoch 10
- NLL-test: 36.785576 @epoch 6
- EmbeddingSimilarity: -0.198190311710986 @epoch 1

### **SeqGAN Best Values**

- NLL-oracle: 10.114458 @epoch 10
- NLL-test: 7.031317 @epoch 6
- EmbeddingSimilarity: -0.207636699321102 @epoch 10

### **Real Data**

When comparing real data metrics between the two models, the results show SeqGAN to generate better values. Again, both models are running metrics on the real data with a base of 5 epoch, however incrementing this value and rerunning may generate different results.

### **TextGAN Best Values**

- NLL-test: 37.6404 @epoch 10
- EmbeddingSimilarity: -0.369170747866734 @epoch 1

### **SeqGAN Best Values**

- NLL-test: 3.4653516 @epoch 10
- EmbeddingSimilarity: 0.510576256396731 @epoch 10

Here we will take a look at the first 15 lines of the real data files, both training/test [eapoe.txt / test\_eapoe.txt] and synthetic data generation from the model labeled test\_file.txt

test_eapoebd	eapoebd
1 Lo! Death has reared himself a throne	1 Once upon a midnight dreary, while I pondered, weak and weary,
2 In a strange city lying alone	2 Over many a quaint and curious volume of forgotten lore,
3 Far down within the dim West,	3 While I nodded, nearly napping, suddenly there came a tapping,
4 Where the good and the bad and the worst and the best	4 As of some one gently rapping, rapping at my chamber door.
5 Have gone to their eternal rest.	5 "'Tis some visitor," I muttered, "tapping at my chamber door--
6 There shrines and palaces and towers	6 Only this, and nothing more."
7 (Time-eaten towers that tremble not!)	7
8 Resemble nothing that is ours.	8 Ah, distinctly I remember it was in the bleak December,
9 Around, by lifting winds forgot,	9 And each separate dying ember wrought its ghost upon the floor.
10 Resignedly beneath the sky	10 Eagerly I wished the morrow;-- vainly I had sought to borrow
11 The melancholy waters lie.	11 From my books surcease of sorrow-- sorrow for the lost Lenore--
12 No rays from the holy heaven come down	12 For the rare and radiant maiden whom the angels name Lenore--
13 On the long night-time of that town;	13 Nameless here for evermore.
14 But light from out the lurid sea	14
15 Streams up the turrets silently--	15 And the silken, sad, uncertain rustling of each purple curtain
16 Gleams up the pinnacles far and free--	16 Thrilled me-- filled me with fantastic terrors never felt before;
17 Up domes-- up spires-- up kingly halls--	17 So that now, to still the beating of my heart, I stood repeating,
18 Up fanes-- up Babylon-like walls--	18 "'Tis some visitor entreating entrance at my chamber door--
19 Up shadowy long-forgotten bowers	19 Some late visitor entreating entrance at my chamber door;--
20 Of sculptured ivy and stone flowers--	20 This it is, and nothing more."
21 Up many and many a marvellous shrine	21
22 Whose wreathed friezes intertwine	22 Presently my soul grew stronger; hesitating then no longer,
23 The viol, the violet, and the vine.	23 "Sir," said I, "or Madam, truly your forgiveness I implore;
24 Resignedly beneath the sky	24 But the fact is I was napping, and so gently you came rapping,
25 The melancholy waters lie.	25 And so faintly you came tapping, tapping at my chamber door,
26 So blend the turrets and shadows there	26 That I scarce was sure I heard you"-- here I opened wide the door;--
27 That all seem pendulous in air,	27 Darkness there, and nothing more.
28 While from a proud tower in the town	28
29 Death looks gigantically down.	29 Deep into that darkness peering, long I stood there wondering, fearing,
30 There open fanes and gaping graves	30 Doubting, dreaming dreams no mortal ever dared to dream before;
31 Yawn level with the luminous wains;	31 But the silence was unbroken, and the stillness gave no token,
32 But not the riches there that lie	32 And the only word there spoken was the whispered word, "Lenore?"
33 In each idol's diamond eye--	33 This I whispered, and an echo murmured back the word, "Lenore!"--
34 Not the gaily-jewelled dead	34 Merely this, and nothing more.
35 Tempt the waters from their bed;	35
36 For no ripples curl, alas!	36 Back into the chamber turning, all my soul within me burning,
37 Along that wilderness of glass--	37 Soon again I heard a tapping somewhat louder than before.
38 No swellings tell that winds may be	38 "Surely," said I, "surely that is something at my window lattice:
39 Upon some far-off happier sea--	39 Let me see, then, what thereat is, and this mystery explore--
40 No heavings hint that winds have been	40 Let my heart be still a moment and this mystery explore;--

This figure is representative of a side by side comparison between the TextGAN test\_file.txt and SeqGAN test\_file.txt files. Although the sentence structures appear lacking, the sentence formulation was well developed. if you compare the full synthetic sentences, SeqGAN appears to have more realistic sentence generation:

textgan_test_file.txt	seqgan_test_file.txt
1 Depth dirges dirges haunted- footfalls bust footfalls thee- followed stately footfalls footfalls yore- mortal	1 nameless which sky stormy bore- explore heaven gently press louder lov his flint ,
2 for lies curious denser curious cushion curious ember curious further denser ember grim ! ember burning sorro	2 before- silence now press doubtless is quit made distant of chamber -- did and
3 yore- whether footfalls yore- lies lies our sent echo sorrow- 's visitor ehony sorrow- plutonian plainly sorz	3 stood countenance black burning rustling shroves explore lent he word of above sought by
4 silken shore- parting sent footfalls yore- curtain yore- louder haunted- gently answer answer an	4 divining scarcely by him explore implore- countenance reclining is : dreary answer " not
5 yore- his footfalls ehony above sorrow- been gently hesitating ember 'never- 'never- to hesitating lady adun	5 off sinking but plume burned bust same thy fearing perfumed now countenance i " me
6 answer whom with denser denser depth ember both tempter ashore ember tempter ember ember to ember both	6 me- 's his moment wandering sent - source tapping said raven here seat , nevermore ,
7 him guessing lies cushion hesitating broken ember ease ashore surcease cushion plume ember both ember 3	7 art cushion lightning were now grew ominous have again tone fiery eagerly
8 have whom denser our all ember december further broken tempter hesitating ashore hesitating tempter there- "n	8 implore- bends again eyes which whom frown forgiveness , eagerly then " and the 's
9 shutter dirges denser guessing storm obelance window explore good faster faster followed sorrow- sorrow- bet	9 fast i had bespelling hear respite , , this unseen living this . . . a frown
10 lies sorrow- denser denser felt implore- broken both ! denser help tempter ashore ember ashore footfalls bust	10 terrors ashore flitting gently perched me leave lightning dream whom laden
11 gently denser both ember felt air ember both ember ember hesitating ember hesitating ember both plainly	11 of friends frown sorrow nodded quit guessing is unseen now explore- screaming nothing
12 both bosom tempter long good sad devil door depth echo silken grim tempter sorrow- tempter hesitating 'never-	12 or forgiveness and parting 's forget linking , syllable perched hear dared ev'ry nothing be quoth soon
13 lies master fantastic sent sorrow- agreeing tempter ! madan above silken decorum lov silken sorrow- surcease	13 flint implore you blessed laden grim came heart whom though i never devil burning , this
14 answer gently dirges to master footfalls utters seraphim ! head such tempter bust 'never- than sorrow- 'never	14 disaster desolate me that we lies chamber he long . cushion . door what faster , laden
15 shore- yore- o's purple betook betook it explore stayed help bust 'never- volume curtain surcease cried dirg	15 being me- tinkled ember sat decorum relevancy . more is it yore- by with shore
16 door master surcease sorrow depth there- yore- binds silken for there- lady ! demon horror upon for horror do	16 tossed lie my echo tone your tempter eagerly , bust rustling velvet ever december murmured one
17 shore- horror purple ! lenore methought implore- broken ehony sorrow- broken betook wrought hopes broken befo	17 cliff louder living to ' burned velvet dreams is i ' grew faster the
18 lies our ember stayed ember token ashore help help spoken master bring forget plutonian decorum air help temp	18 : store broken pallas have alone wished ev'ry these perched laden .
19 answer gently door gently temptest louder just door louder gently footfalls footfalls yore- ehony cushion just	19 ev'ry than respite sung angels wheeled syllable cried god torrent a store temptest temptest
20 answer deep ease broken denser ember hesitating ember hesitating both cushion ember broken ember surcease xuz	20 bird he little over eyes is entrance tempter unseen evil on explore and rustling same
21 have curious presently sorrow- sorrow- agreeing footfalls madan sent deep both dirges dirges both ember ember	21 little the least 'never- floor there- fearing till eagerly syllable sad me long that with
22 answer master both cushion sent purple stately beast stately tempter stately surcease flirt door nameless doo	22 said utters this flirt smiling scarcely me evil louder lov grew ev'ry take
23 door bust footfalls songs curtain o's yore- echo but ancient nameless sorrow- silken token token broken 'nev	23 sinking binds peering again by door on . and . .
24 shore- bust nevermore 'never- 'never- gently madan divining for for for morrow louder louder hopes bust bust	24 burned no not your cushioned my whispered " temptest 's the bird
25 there- door surcease denser surcease ! dirges both broken help stayed tempter tempter ashore tempter bust	25 she fantastic stood lent fact more much not back disaster word
26 footfalls whether footfalls thee- lies broken hesitating smiling "d flirt surcease binds ashore sent sorrow-	26 wrought yore countenance sidenn engaged thinking chamber much cushion nightly on he ever . from
27 door depth utters guessing ' ! visitor lifted- whether help help silken visitor stayed eagerly surcease meani	27 flutter discourse heard store , pondered ; most utters blessed yet sad entreating burned
28 lies so streaming sent door agreeing sad ehony december enchanted- yore- louder agreeing dirges ehony ehony so	28 with bust minute purple one what my discourse whippet unseen ever a flirt till chamber burned
29 kind master lies both fantastic echo pallid ember both whether denser ember silken ember air if startled ash	29 expressing window sorrow- if rapping lov was common my yore- your i fast will
30 hesitating both surcease just plainly surcease burning sent both such denser ember a denser denser wandering	30 feather store doubtless above other let such unhappy me nevermore . is 's into again quaff many
31 shore- both broken ember tempter master broken hesitating before- lov tempter 'never- 'never- 'never- help me	31 wheeled shall pondered wide footfalls heart back placid it implore only lost , is agreeing to rustling
32 kind tutted dirges ember thee- ember shrieked master tempter master stepped purple purple what bust stayed he	32 flirt to countenance again art plainly and bird lightning nenpenhe as clasp . land --
33 depth there- betook to bust eagerly silken silken louder louder hesitating surcease silken ashore- to di	33 mourn purple ghastly relevancy ominous . filled placid muttered let tone 's plutonian
34 lies horror denser sorrow- answer hesitating sorrow- volume ancient ehony ehony bust answer yore- dirges loud	34 scarce surcease smiling volume violet name if upon flirt all violet nothing - and my distant
35 lies dirges denser depth depth ashore core tempter lies ember both sorrow- grave press stayed horror above at	35 bring taken press i the before see but . velvet hesitating
36 whom yore- gently ehony for ehony yore- depth denser tempter more hesitating hesitating both broken purple he	36 flirt to countenance again art plainly and bird lightning nenpenhe as clasp . land --
37 just just both implore- whether depth above nameless eagerly silken ashore- gaunt ashore stayed stayed bust gu	37 halm silken cushion whispered . radiant . me he " now . not ; shorn
38 kind denser yore- divining in denser broken sorrow- shutter footfalls eagerly broken denser eagerly to denser	38 wished faster something days spring whispered 's blessed my and the with is dreams further and thy more
39 bosom there- both denser both whether plutonian just whether felt lies depth eagerly ember whether whether an	39 vind felt surcease respite friends a me stood , this divining burning
40 gently yore- divining before shore- just chamber broken sorrow- see sorrow- answer louder answer louder 'never	40 or black let 's silence ominous plume an hopes chamber an upon .

In [ ]:

## Notes

This project was a collaborative effort by all team members listed in top of document. Project was developed/run/tested while on video call as a team effort. All parties put forth equal effort in testing, data selection and stripping, as well as understanding content.

Given the short duration of setup, running, etc there was not sufficient time to truly understand each of the models under the project. 2 model were selected for study, however even these would require more than a week for all encompassing tasking to really dive in and understand. Additionally it should be noted the amount of time it takes to run these models with higher epoch values. Running the full models over and over can help training, however can take hours to complete. Furthermore, the .csv files were not populating. Given more time dedicate to this project, issues may have been able to be resolved

## Reference

- [1] Geek-Ai. "Texygen by Geek.AI." GitHub, 2017, [github.com/geek-ai/Texygen](https://github.com/geek-ai/Texygen).
- [2] Yu, Lantao, et al. "SeqGAN: Sequence Generative Adversarial Nets with Policy Gradient." ArXiv.org, 25 Aug. 2017, [arxiv.org/abs/1609.05473](https://arxiv.org/abs/1609.05473).
- [3] Zhang, Yizhe, et al. "Adversarial Feature Matching for Text Generation." ArXiv.org, 18 Nov. 2017, [arxiv.org/abs/1706.03850](https://arxiv.org/abs/1706.03850).
- [4] EA Poem Source. <https://poestories.com/read/valentine>

In [ ]:

```
#PDF/HTML conversion of notebook
!apt-get install texlive texlive-xetex texlive-latex-extra pandoc
!pip install pypandoc
!jupyter nbconvert --to PDF "Milestone1.ipynb"
!jupyter nbconvert --to HTML "Milestone1.ipynb"
```