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Machine Learning & Data Mining
Miniproject 3

Caltech Earthquakes
Caltech CS/CNS/EE 155
March 12^{th}, 2018

1 Introduction

- **Group members**
  Kelsi Riley
  Sakthi Vetrivel
- **Team name**
  Caltech Earthquakes
- **Division of labour**
  Kelsi implemented the HMM, and focused on improving it. She also did the preprocessing for the HMM, and was responsible for the unsupervised training of the HMM. Sakthi implemented the RNN and worked on improvements for it, as well and the visualization and interpretation of the HMM.

2 Pre-Processing

For our pre-processing of Shakespeare's sonnets, we started by converting each poem into a list, where the list contains the words of the poem in order of appearance, with a newline character between lines of the poem. Then because our HMM uses integer representations of emissions, we created two dictionaries: one mapping words to unique integer values and another mapping integers to unique words. This initial preprocessing was helpful, but when we looked at the values stored in our dictionaries, we realized that capitalized and lowercase words were considered different emissions with this processing, and if a word was followed by punctuation, it was considered a different emission than if it was not.

This prompted us to make each word lower case as we processed it, to ensure that words are considered the same emission regardless of their capitalization. We also decided to remove the characters '.', ',', ':', ';', '(', ')' and '?' from the poems we processed so that we didn't have many different emissions associated with the same word. We decided to leave in the apostrophe due to its presence in contractions, and actually being a part of the representation of the word. This updated preprocessing was an improvement from our initial attempt, but ultimately fell short of what we needed due to the presence of phrases in quotations in some of the poems (i.e. 'Will' in sonnets 135 and 136 and 'not you' and 'I hate' in sonnet 145). This lead us to need to adopt a somewhat more complicated process for removing quotations around words.

We ultimately ended up deciding to remove an apostrophe if it was in the beginning of a word and the word was not a word we recognized as beginning with an apostrophe. Then, we would remove the next apostrophe in the line. This allowed us to remove the quotations around certain words and phrases in the poems and simplified the number of observations of our model.

Because sonnets 126 and 99 adhered to the structure of a sonnet much less rigidly then the rest of Shakespeare's works, we decided not to train our models on them. While we were pre-processing the poems, we then did not represent these poems in our produced list of poems, where each poem was represented as a list of integers.

Also, as we suspected it would be useful to be able to easily assess if an integer emission mapped to the newline character, we decided to initialize our dictionaries mapping words to their unique integer representations and vice-versa with the newline-0 pair. This would allow us to easily identify when we had reached the end of the line when generating poems, instead of having to constantly use the dictionary mapping integer representations to strings to check if the string mapped to is the newline character.

Finally, we wanted to be able to generate sonnets that rhyme, so we ended up extending our preprocessing to enable doing so. To do this, we used our knowledge of the rhyme scheme of Shakespearian sonnets: abab cdcd efef gg. Then, as we processed our poems, we added the unique integer representations of last words of lines that rhyme to a rhyming dictionary. This rhyming dictionary mapped unique integer representations of words to a list of the integer representations of words that it rhymes with. We considered altering this so that if two words rhyme with each other, then every word that rhymes with either of them will rhyme with both of them, but ultimately decided against this implementation due to Shakespeare's liberal use of slant rhymes. We thought that generalizing rhyming this way could possibly produce "rhymes" that hardly resemble rhymes at all.

3 Unsupervised Learning

For our implementation of unsupervised learning for our Hidden Markov Model, we used the Homework 6 Solution Set. This implementation used the Baum-Welch algorithm to train on an unlabeled data set. We experimented with a variety of hidden state and iteration counts, and ultimately ended up deciding to choose these values to balance quality of poem emission with computation time. A greater number of hidden states seemed to yield more convincing imitation sonnets, but also produced very long run times. We ended up deciding to settle for 16 hidden states and modified our code so that trained Hidden Markov Models could be stored in text files and then accessed again later, so that we wouldn't have to wait for hours every time we wanted to generate poems.

Choosing Hidden States

Poem generated from HMM with 8 Hidden States:
Seen is when now pretty importune air
Even the dial in the and eye do
To in sadly amen telling lend fair
Needing them as the one of leisure too
Others himself whose much weary three cold
Own alteration urge torn is to thee
Best urge when heavily of my make old
Because loves see in end pyramids me
And my are mind of glass good your which jewel
Worth say few frequent thy in thy eyes those
Yet unlooked then to rehearse which that cruel
It away essays is with more strong grows
    Say to whom strongly drawn full things what fitted
    Blame sick of a prove of else crime committed

Poem Generated from HMM with 12 Hidden States:

Essays slay comment tear though all not show
Hours would neglected to beauty thou hearts
Boot to of the lives mad to in dost so
I thoughts interest of no thoughts is the line
Of that two authorizing no one her
Self-love simple being therein not truth this
End a thou that thy say when thy am her
Which said when your sweet shall love to see is
Beauty thinking since with to gain hours
I use did know with taste let wrongs thou one
My jade of soon so jewels be flowers
Alone confound without said thy alone
  Then flattery doth being an love deeds be
  You largess bid sums my self bad when I

Poem Generated from HMM with 16 Hidden States:

Far phrase unhappily whom high thou heart
Are and carve bareness fragrant not all make
Two lawful not remembrance herald art
By and wrinkles the welfare break sense take
Knows for tells false heart where eye hue and know
Ills and wink heart his being is catch be
Proved I of my assured moiety so
Live have was constancy doth think in I
I stay a for too you thy not self man
Heaven's age out thou I doth tell pilgrimage
Watch o in the time's fair with loving can
War for all a pent that when my you age
  Is saw is soul richly cannot days heart
  Or since the thy cloak we thou call wide art

As we increased the number of hidden states of our Hidden Markov Model, the quality of poem generated seemed to improve. Note: these poems were generated using our more sophisticated emission generation method, which enforces that lines must all be 10 syllables and that the produced poem must follow the proper rhyme scheme. We qualitatively decided that training with more hidden states improved the performance of our model, and ended up only using 16 hidden states instead of exploring the potential of using more because training the Hidden Markov Model with 16 hidden states already took hours. We thought training a Hidden Markov Model with any more hidden states would take too long to be practical.

4 Poetry Generation, Part 1: Hidden Markov Models

For our naive 14-line sonnet generation, we simply generated poems by randomly selecting a hidden state to start with, then randomly selecting the next observation and next state using the previous hidden state, as well as transition and emission probabilities stored in A and O of the Hidden Markov Model. We continued to do this until we had added 14 newline characters to our emission, so it would be 14 lines long. Poems generated this way were pretty terrible attempts at imitating sonnets. I have included a few examples of sonnets produced this way:

Poems Naively Generated from HMM with 8 Hidden States, Trained for 400 Iterations

Sonnet 1

Shines to
Wrong vanished when at and reason more had being and departest canst time in his tempteth
Painted goddess I
Said hours sight lesser the all to blessed suppose brief thy with lays lo in thine took I absent to
Age bosom aye or none
Name to of days with woe the keep even wit on from though
Making it sealed against
Grief to to those

Afterwards her but and
Hast I all
Ornament my
    Glass the her confined all longer not have as
    Sing it knife spite by love is

Sonnet 2

And the spurring and that and
Spirit in press I those brow a is the to you how and

Lies can doth sorrow to eager pluck bending
Iniquity course love she fiend sweet gain poor moon thy
Deeds born believe all as years fresh to the eternal interest but so glad be hath the sunset swear
Black put and that
Still have state my may do that such have no thou a sweet himself how salving
Is it hence secret purity thy unkind past read
Fresh shall as no or decease sun refined costly truth inward with
Sweet this what
    Saw so love lose wish wait who
    Thing my by shadow the I

As you can see, the syllable count of the lines is very inconsistent, ranging from 0 (in the case of the completely empty line) to nearly double the expected syllable count. On a similar note, the rhythm is inconsistent with the Shakespearian sonnets we used to train our HMM. This naive generation also fails to include any rhyming at all. Overall, these generations were largely nonsensical and fail to be very understandable. As such, they fail to retain Shakespeare's original voice very well and don't resemble his Sonnets closely at all. When we use this same generation method with a Hidden Markov Model with more hidden states we see similar results:

Poems Naively Generated from HMM with 16 Hidden States, Trained for 400 Iterations

Sonnet 3
Self of ere
Write silence sun worth things my in absence or

Sour account which love
Sake my blind therein he by by hand world's thy full
Rotten I not flowers then I I and err who I as
Rents wake and ere decease done lines every of simple and
Will to eyes moon incertainty king invent doth print a what like
Stands forgotten ever have thee poor
Verse false or
Possessing love's the and
Desired if
  See this in all my

Sonnet 4
Beams it but grace thee for but shore their make with thoughts than
Kept body hadst thou profitless
Be should pricked all to that
Thee the simply
Hid bath in despite worth his a true and learn be even when
Eclipses thee to sweetly themselves are
Show this of which farther moon
Acquainted all praise to
You their live
Loving tender your will as heart unkindness yet
Too true it deceive once friends all it she lose earth upon now he happy be
Is not may mistress' all from hath
  More so
  Jewel and

When we increase the number of hidden states, the length of the lines becomes more consistent, and there are fewer lines that don't contain any words at all, but the produced sonnets are still fail to meaningfully resemble Shakespearian sonnets. The quality improves with the increase in hidden states, but ultimately the problems of the generated sonnets failing to rhyme, have the correct number of syllables, and adhere to the standard rhythm of sonnets makes these generations lackluster. With more hidden states, Shakespeare's voice appears to show in the generation better, but it still isn't very accurately represented by our generations.

5 Poetry Generation, Part 2: Recurrent Neural Networks

Initial Implementation

For our preprocessing for the RNN, we decided to first break down the text file by line, and for each line we parsed, we made sure the line was not empty (not just an endline character) and removed any special characters from it. For example, we wanted to "Hello!" and "hello" to be processed as the same sequence of characters. We then finished each line with an endline character and added it to a accumulating string, which held the contents of the processed text file. After processing the input, we created dictionaries to convert each character found in the processed text to an integer, and a dictionary that converted integers to characters. We then generated a data set splitting this string into sequences of 40 consecutive characters, and converting the sequence of characters into a sequence of integers, and used the 41st character of the sequence as the y value, again, after converting it to an int.

We implemented a recurrent neural network using the Keras package for Python3. Using a sequential model, we had two dense LSTM layers of size 200, and one output layer. We calculated our loss using categorical cross-entropy loss, and 'adam' optimization. We also fine tuned our batch size, testing values of 32, 64, and 128. By observing the poems produced for these batch sized after 10 epochs of training, we settled on a batch size of 64. We also fine-tuned the size of the dense layers, trying sizes of 100, 150, and 200, as suggest in the project details, and settled of a size of 200. We then trained this model for 125 epochs, converging to a loss of 0.4146 from a loss of 3.45 after the first epoch. To improve our model, we also looked at more complex RNN, using two dropout layers between the dense layers, and fine tuned the dropout probability to eventually choose 0.4. Initially, the model was only trained for 20 epochs, but we found that the loss still hadn't converged so we continued training until the loss did not improve for 2 epochs. We used a window size of 40 as the instruction suggested, but later moved to smaller window size of 25 in our attempts to improve our model.

To generate our poems, we used our seed sequence "Shall I compare thee to a summer's day?" and processed it, and for a sliding window of 40 characters, predicted the next letter in the sequence. Our model gives us an array of probabilities for the next character, given the previous 40 characters, so using this array of probabilities, we sample from the population of characters accordingly for a given diversity value. We also counted the number of newline characters that were predicted in the entire generation process, stopping after 14 newline characters, giving us 14 lines in the poem.

Despite training for so many iterations, our LSTM did not successfully learn sentence structure or sonnet structure, as we see in the poems below, few of the words produced are real words. However, for the brief segments of the poems that contain real words, it seems to follow some loose sentence structure. For example: "i love you" and "of the braid". As a result, the poem quality seems fairly low, and this is a direct result of the character-based nature of the neural network resulting in jumbled English. Because there are so many more sequences of characters than sequences of words, the RNN takes more training data to train, but both sets of training data were still generated from the same text file. It took much longer to train the RNN than to train the HMM, again, because it starts from a lower level of understanding, since we are working with characters instead of words.

Poems

—– diversity: 1.5
—– Generating with seed: " shall i compare thee to a summers day
"
shall i compare thee to a summers day
weat kerp tellv in these i would to hath
my self iil iiddsu your thlltt my self brane ereed
but ceatt that weal i love you be teildde
and me altereasonse of the braid and lind
which treals mind eye is is a lawvereo
at tenmn lines bety paming iimeshsy
or at dolg pdr tiat weadddleditg tiink
eor shamls iampeut sp will he's shcd might
sevoy seep tidu thou 'liserpeas nor
j thak oyck tine suelt so lem so ku haln
and nock i tas of fold cach or pattry
but be thy liate me thrnugh mights me sn botn
and in holaskeri hrln with the trwe doth green
and confoundane farth in thee tie live"

—– diversity: 0.75
—– Generating with seed: " shall i compare thee to a summers day
"
shall i compare thee to a summers day
when that wilt nottncry that fell asd feidt
that it 'bol gor moctatd i do dispilts
and diary my self i'ck tren to the most
but when your changent of this weil
byt sickt his tputatt mot i loow more eeee
to say toe borcmest whereup the bear
thy presclv ceauies ifart he lile artire
for whose winter's enoling on the rulp're
when sesimg a betteiry ocrure of thy deeds
therefo thy putlok dead trealed thou art
o what a worthsed wron delive no mane sehmnts
oo aly of these falsehe move's fresh ceserity
then the means me with vinter did stansed

and dotnt and in habkt and it gaults light"

—– diversity: 0.25
—– Generating with seed: " shall i compare thee to a summers day
"
shall i compare thee to a summers day
aid uosthfr this wirte doth beauty stail
thou mayst be thy oudsent'st a linit sade
but when your count in these cannot chind
o carve norer mine him though mews the even
but day doth daily draw my sorrows line
so thy freat gift woon be forgouingnl
for higheo of line ow well my heart deegines
so fotth the blow of with dupy steet selbit
ald my hoade fyen siln liss lysbs'bd and were orisit
oatt reason haved the stard or thy sweet graces
beauteous all fellls tine world have erreemed
more that my self but was donf iis oun
gow many lambs kild and they acvodance seegng
and all the dead no nore drtbl dole"

6 Additional Goals With RNN Model

Haikus

We adapted our RNN to compose haikus. To do this, we created an file of haikus, where each line in a haiku in separated by a tab character, and each haiku is separated by a newline character. We also changed our window size from 40 characters to 15, since haikus are much smaller, and a 40 character seed would make up a significant portion of the poem. We continued to use dense layers of size 200. We then trained the RNN on this data set for about 100 epochs with a batch size of 64 (the batch size we found was effective for our sonnets). To generate our haikus, we used the same skeleton as the sonnets, just adjusting the window size. The results for the haikus were much more promising than the sonnets, which was surprising considering the training set was smaller. Here are some of our favorite haikus that were generated:

light snowy breath to read
old tombstones hot wind shadows
the roadrunner's beak

furled umbrella
turns into a cane
chernobyl vells

Of course, many of the haikus we generated often contained just jumbled letters, and when they did contain words, they rarely made sense, much like the haikus above. However, the model was able to predict syllable count fairly accurately, as you can see the first haiku follows the 5-7-5 pattern, and the second haiku is close. Given more time, we would have liked to experiment with the Word2Vec package and worked to predict words that were similar to the previous words in the sequence.

More Complex RNNs

To improve our RNN, we decided to implement a more complex model. Instead of using two dense layers of size 200, we decided to include dropout layers as well to avoid overfitting.We also used a smaller window size of 25. Moreover, instead of predicting the character following a sequence, we trained the model to predict the character preceding the sequence. This was in preparation for us to generate rhyming poems.

Given the chance to do this again, we would have liked to also train with a validation set, and have stopped training when the validation loss stopped improving, instead of depending of the training loss. Here are the poems generated with this approach:

—– Generating with end: ue by the grave and thee
—– Diversity: 0.25

and in this cold complaining
she would have trained crie
and in his and he like again
my art thou art in me must roves to side thy state
and in your offences fived in your devory
of fathered bester and with dinkilling eye
that she more living so offence alove
in either kill of beauty tend
and with a concestion makes her wind
and with your shame to supretise is scapening on to love my love
that my after for my days dad make the mettle wit
against my valthough it should nor gistless
cinfounded in a mined eyes
the tongue by the grave and thee

—– Diversity: 0.75

but loves her painted hend
with whose what eyes now love to my
and that can men shall heavenly for see only most to shows and toney
to make the mudder's grace
for thy sweet to time's eyes to hast
but no so is my love to cay
and to the humbers at the spirit on thee
'didst thou the sefle but in his rain
to from the best this true for then the eye alone
even in my love com from that at the reason
to lives my sorrow nature had't teou poy
to fair thy loses she lacks and unneed the bound to make their sidness
fit and the trembling eyes
the tongue by the grave and thee

—– Diversity: 1.5

i should in cartle's dame
was fined in lidob giden kies
then boldness her beauteous i will
hinour to elmantinal condensmaking
with those and burd nor let
to prubify to leave th from it
when shalt thou my have be end
so do am state at living eye and heart it may be gone lix
the other hours are so co civitate
the colous o'erds to hell for love and bift from this all treed
and when that gave to trespect thy state
but were the had taught the cloud or all apay
and in her hourffece baskys-are tongue by the grave and thee

Rhyming

For our rhyming using the RNN, we used this implementation of the more complex RNN. Our first step was to generate a rhyming dictionary using the CMU dictionary and parsing each line of the sonnets. Using the CMU dictionary, we generated the pronunciations of each of the words in the Shakespearean texts, and compared the pronunciations of the ending of each of the words, so each word mapped to the pronunciation of its ending, and each pronunciation mapped to a list of words with that ending.

Now to generate the rhyming poem, we find the endings of each line and generate the preceding characters based on the word. First, we find 7 random words in the sonnets, and make these the ends of lines 1, 2, 5, 6, 9, 10, and 13. Then, we use our rhyming dictionary to choose a word that rhymes with the line endings of the aforementioned lines and make these words the endings of lines 3, 4, 7, 8, 11, 12, and 14, such that we have a $ababcdcdefefgg$ rhyme scheme.

Below is one of the poems generated through this process:

Have women witagainst the cause but in the horn,
The sparm'dall wither yet love me all contented stair,
To beand croused could back their mildress' sky forlorn,
Effects and dischance andmore beauty of thyself all stair.
But his smokest love some is and now appear,
With that praise for living chance or thy burn,
Friendand for thee and steared berience more you peer,
Lively and confounds his artand heavenly one can spurn.
That true whan attening of her lind and horse,
Thas thoosebut if the would be maunt the heart,
Of all love's sout'st she dings with thy scarce,
Eyesand never was so watch the for both's transport.
To the priseand sily burupt make tears they sphere,
Thoutment on that gave darefrown from the dangerous year.

7 Additional Goals with HMM Model

Syllable Count

To generate emissions that more closely resembled sonnets, we decided the first thing that we needed to do would be to make sure generated lines have the proper number of syllables. To do this, we created a new poem generation function that produced lines that were all 10 syllables. To do this, we simply generated the beginning of lines as usual, but kept track of the syllable count of our line. We would not add the newline character until our line contained exactly 10 syllables, and would not add a word to our line if it would cause us to surpass 10 syllables. This implementation would also "backtrack" or remove words we already added to the line if it could not find a word to add to the end of the line after many attempts.

This new generation method ultimately improved the quality of our generated sonnets a lot. Having the lines of the generated poem each contain the correct number of syllables made them resemble Shakespearian sonnets much more closely. Below we have included a poem generated using this improved generation method:

Sonnet Generated with HMM with 16 Hidden States and 400 Training Iterations
Love and which away self the he let who
Same summer's to darkness lovers thy that
Inward the and on sight this I if thee
Hoisted woe see do let brow of on could
Impeached visage to unkind with for on
Conspire me me keeps will the fool I tanned
Thought ill the this which jewel men so my
A a world a did a horses and faults
Ransom and hearts my frame being it to
Tongue in you I love think looking if now
Thee deeds the pitying from alike saith by
Near your death's long sorrow more to that art
    Spirit this falsehood things I thee not me
    Were since red love love in envy well and

Rhyming

While altering our method of emission generation allowed our Hidden Markov Models to generate poems more closely resembling Shakespearian sonnets, they still failed to generate poems with any kind of rhyme scheme. We decided that we should further improve our emission generation method to ensure that the produced sonnets followed the abab cdcd efef gg rhyme scheme. To do this, we used the rhyming dictionary that we created when pre-processing the sonnets and generated lines of our emission backwards, starting with the last word of the last line of the poem.

Because we generated poems backwards in this implementation, we reversed the lists containing our training poems, and trained our Hidden Markov Model using the reversed lists of poems. Then, we started generation, selecting a word to rhyme with using the rhyming dictionary generated while pre-processing the data when we came across the later of two lines that would have to rhyme with each other. Then when we got to generating the earlier line to rhyme with a previous word we had chosen, we randomly chose a word that rhymed with it using the rhyming dictionary again. Unfortunately, because O is sparse, it is possible that when we are generating a line that must rhyme with a previously generated line, it is not possible to generate any of the words that would satisfy the rhyme. In this case, we would "backtrack" again, regenerating the previous line and hoping for better luck the next time. If this repeatedly fails, our generation algorithm backtracks further, reselecting the word to rhyme with and then regenerating subsequent lines.

In this implementation, we again enforced that each line must be exactly 10 syllables long, using the same underlying algorithm described above in the syllable count section. This improved generation method yielded poems that were much more similar to the Shakespearian sonnets which our HMM was trained on.

Sonnets Generated with HMM with 16 Hidden States and 400 Training Iterations

Far phrase unhappily whom high thou heart
Are and carve bareness fragrant not all make
Two lawful not remembrance herald art
By and wrinkles the welfare break sense take
Knows for tells false heart where eye hue and know
Ills and wink heart his being is catch be
Proved I of my assured moiety so
Live have was constancy doth think in I
I stay a for too you thy not self man
Heaven's age out thou I doth tell pilgrimage
Watch o in the time's fair with loving can
War for all a pent that when my you age
  Is saw is soul richly cannot days heart
  Or since the thy cloak we thou call wide art

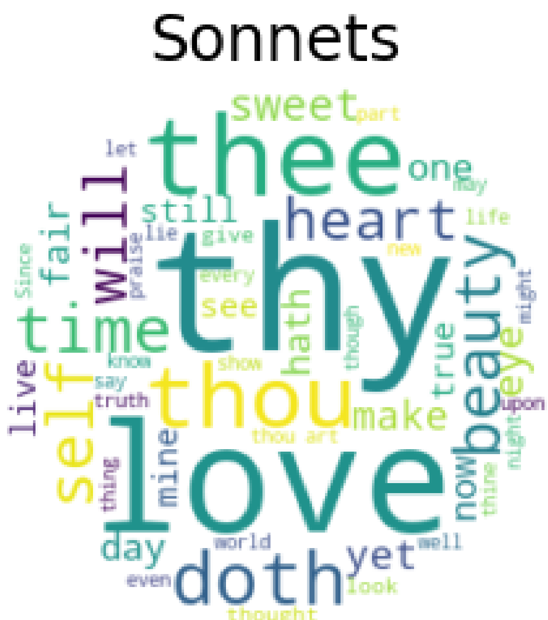
Faults if of ill me horse art it so her
With against second pay that and truth too
You desire exceeded think thou blood her
Be on than are so rich was can though do
Than air sense at body living their any
Me or you bring do of of this I find
Your days rise to gaze with to all many
Side remain weeds carve huge thee hath chide blind
Will your own stand gave still that then belied
The learned's and from less tell soul an there
Hath most varying as in time except wide
Are toil labouring thy clock our age where
  Live ruth whom I flattery tongue I and call
  His make thou ye assured her thought all

Further Improvements

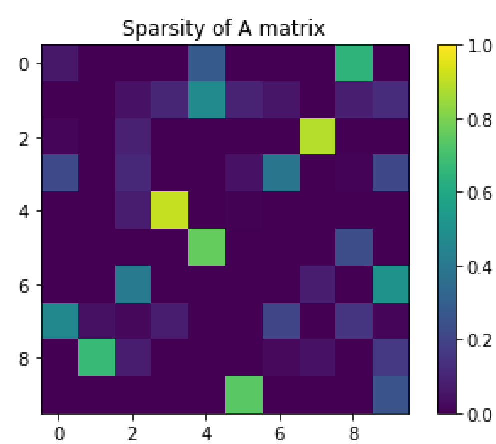
If we had more time to improve our Hidden Markov Model, we would have liked to reincorporate punctuation to our poem generation. The lack of punctuation is an aspect of the generated poems that obviously deviates from Shakespearian sonnets. Additionally, if we had more time, we would have enjoyed being able to experiment with the performance of Hidden Markov Models with more than 16 hidden states. Unfortunately, because training the Hidden Markov Models took a very long time, we were unable to explore models with very many hidden states. It also would have been interesting to explore Haiku generation with our Hidden Markov Model, although we were unable to do so in the scope of this project.

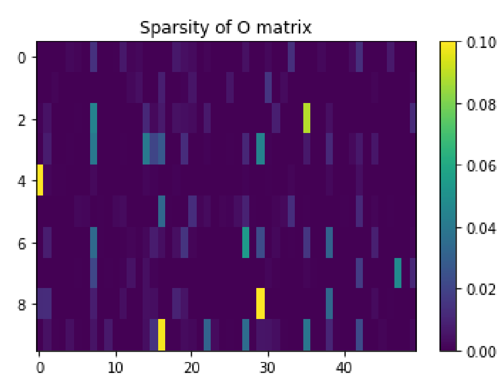
8 Visualization and Interpretation

Visualization of dataset



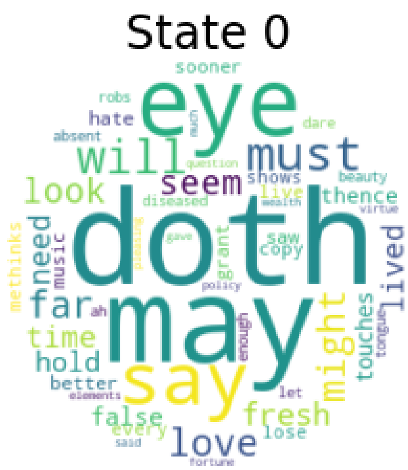
Visualization of the sparsities of A and O

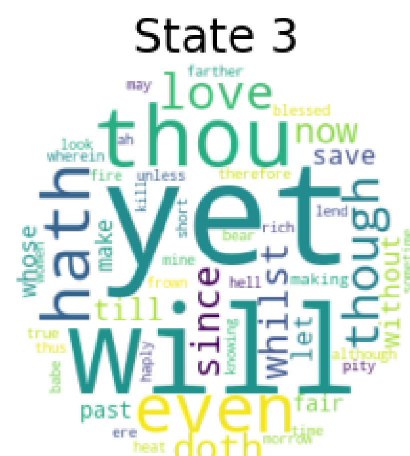


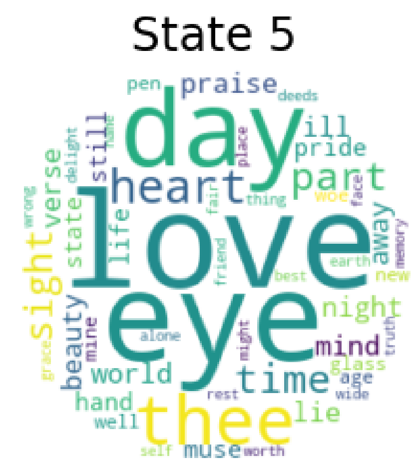


Most elements of A and O are very close to 0. For the A matrix, this implies that at each state, there are only a few states to which the HMM will likely transition. For the O matrix, this implies that at each state, a few key observations are likely to be emitted. Usually, these correspond to frequently occurring words like ”the”, ”and”, ”a”, etc.

Visualization of states







all night got
of deepest over-partial