Late hours used: 2 hour

1 Introduction

- **Group members**
  Zhewei Chen, Milad Taghavi, Yan Qi Huan
- **Team name**
  The Magic Marijuana Forest
- **Division of labour**
  Equal division of work
- **Team Code Repository**
  https://github.com/miladtaghavi/Miniproject3

2 Pre-Processing

Initially, in the naive HMM we tokenized the dataset by each single words, and for training, the words included in the whole poem chose as the singular sequence. Also the hyphenated words kept as single words to match with the Syllable dictionary. The punctuation is also omitted in pre-processing of the dataset.

For RNN model, in each poem, 40 consecutive characters were grouped as input and the next 10 characters grouped as labels. Here all punctuation kept intact, and the poem numbers are removed.

In the final model, the last words and the rhyming pair from each poem stored to train the HMM for rhyming. The dataset is also tokenized by single words. All punctuation is also omitted in pre-processing of the dataset expect the punctuation that appears in the hyphenated words. In this model, each singular sequence consists of the sequence of words in each line.

Also since sonnet 99 and 126 do not follow the same format as the rest of the sonnets in dataset, these two sonnets removed from the dataset to assure consistency.

To further analyze the emission matrices output from the final model(Section 8), the NLTK used to insert the part of speech (POS) on each word of the poems.

3 Unsupervised Learning

For our first model, we simply used the raw words from our preprocessing and trained it using the Hidden Markov Model (HMM) that was used in Homework 6. For simplicity, this model only learns the words and not punctuation or line spacing. The reason for this is that we believed that punctuation would be better learned by using the LSTM model that is described in section 5, while line spacing is constrained by the fact that each line must have 10 syllables in it.

The package used was the solutions to Homework 6 and we applied the function unsupervised_HMM() from the solution directly. Each input datapoint to the unsupervised HMM is simply a continous list of words from an individual poem, and thus the overall input has 152 entries that each have variable length since each poem has variable length (poems 99 and 126 were excluded due to their different format). The output of the HMM is simply a list of word emissions of any desired length. The number of hidden states was chosen to be 9 as we found that there are 9 general parts of speech in English, namely, noun, verb, adjective, adverb, pronoun, preposition, conjunction, interjection, and article. However, in section 4 below, we also did some systematic testing on the effects of varying the number of hidden states.

4 Poetry Generation, Part 1: Hidden Markov Models

Brief Description of Algorithm

As briefly described in section 3, each datapoint of input to the HMM is a list of words from each poem with the punctuations and linebreaks stripped. The HMM then runs the unsupervised algorithm that uses the EM algorithm for a fixed number of iterations. Next, it is asked to emit a certain number of words. In our case, we ask it to emit 140 words since we have 14 lines and each line has at most 10 syllables (and thus at most 10 words). Finally, in order to determine the linebreaks, we iterate through the chain of emitted words and break the lines at places where we get 10 syllables (or as close to 10 as possible, since sometimes we have a multisyllabic word at the boundary between 9 and 11 syllabes). The linebreak algorithm is chosen to biased to tiebreak towards a smaller number of syllables if we have a symmetric situation (i.e. it will choose 9 instead of 11 if we have a 2-syllable word at the boundary). Finally, we add commas at the end of each line except the final line where we add a period instead.

Sample Poem

The following is the raw 140-word emission output from a HMM model with 10 hidden states trained over 50 iterations.

```
the summer it annexed gold doth the used made depends i not stand
your day will torment when be buds another's great blame hues alone
let hath of penance thee shall by ignorance grew anticipate whether
shall have take say smother thy what is live beauty's for all the thee
of on to kind that force as than nourished dead affords give thy heart
nothing up the ambush me thou dost perfection dost me crowned thy
triumphant love must then from a with which in sweet and may such proof
marvel even can choose such won least for thou dost is need'st those do
```

```
wilt so still pattern my to yet now thee all which subsist with and hold
all my done my kind speak fear many mourn is most to my to i on give
my where and
```

We form lines by enforcing the restriction on 10 syllables per line (or closest approximation):

The summer it annexed gold doth the used,
Made depends I not stand your day will,
Torment when be buds another's great blame,
Hues alone let hath of penance thee shall,
By ignorance grew anticipate whether,
Shall have take say smother thy what is live,
Beauty's for all the thee of on to kind,
That force as than nourished dead affords give,
Thy heart nothing up the ambush me thou,
Dost perfection dost me crowned thy,
Triumphant love must then from a with which,
In sweet and may such proof marvel even,
Can choose such won least for thou dost is need'st,
Those do wilt so still pattern my to yet.

Effects of number of hidden states

In order to determine the number of hidden states that we should use for this HMM, we decided to do experimentation over a wide number of models. Each state was trained for 50 iterations. We print 4 lines of output from each HMM.

<u>1 hidden state</u>
War in with my shall love is I physic,
Thine heart windows plead since that with successive,
Eyes my poor fade concord ride herd my,
Shadow my swift-footed yet thy owner's,

<u>2 hidden states</u>
They your harsh still aye who I my verse in,
Forests nurseth maiden of not was,
Solemn walls open with being doth a,
More in featureless beauty's acquainted,

<u>10 hidden states</u>
The summer it annexed gold doth the used,
Made depends I not stand your day will,

Torment when be buds another's great blame,
Hues alone let hath of penance thee shall,

25 hidden states
Eyes my respose a time's him forbid hath,
Who advocate fair valley-fountain to,
The edge by himself have not or in fool,
Fair question love how fingers knows some of,

As a qualitative observation, we generally see that with a lower number of hidden states, it is more common to see words that are rarely seen next to one another being placed together, such as "is I physic" or "who I my". This makes sense because when we have too few states, we do not have sufficient model complexity to sort the words into meaningful categories, leading to words that should have been separate being forced into the same category and thus nonsensical word combinations appearing since we are drawing vastly different words that have been placed into the same bin.

This appears to be somewhat improved in the 10 and 25 hidden states case, although it is still difficult to make a clear-cut judgment. By observation of about 10-20 poems generated, we found that 10 and 25 states produced qualitatively the same poems. Therefore, as mentioned in section 3 above, we decided to use 9 states as there are 9 general parts of speech in English. Therefore, since 9 states showed (from our testing) appeared to be approximately as expressive as 10 and 25 states, we decided on 9 states based on this theoretical justification.

Evaluation

We first look at some of the good qualities of the poems generated by this first attempt HMM model. Firstly, each line has 9-11 syllables as we enforced this syllable requirement when we split the paragraph of emitted text into separate lines. However, we were unable to ensure that each line has exactly 10 syllables since we could have multisyllabic words appearing on the boundary between below and above 10 syllables. One possible solution could have been to keep regenerating the paragraph of words until we get that all the lines have exactly 10 syllables, but this is potentially time-consuming. A second good quality that we see is that the poems sound somewhat like Shakespeare in terms of phrases that appear in the poem, since the HMM tends to learn word correlations of words that tend to appear adjacent to each other in the original training set.

However, these poems appear to be not particularly coherent in terms of whether each line stands on its own as an individual sentence/clause. The words at the end of each line are often unnatural-sounding, such as "whether" and "will". This is due to the fact that we learned and emitted text as a single paragraph for the entire poem, and arbitrarily forced each sentence to start a new line once we hit the syllable quota without regard for the contents of that line. We also see that this model fails to predict rhyme in the poem, which is expected since rhyme requires long-range correlations across two lines that inherently cannot be captured in the HMM model which only learns correlations between adjacent words. Both of these issues will be address in section 7 where we build a better multi-stage HMM.

5 Poetry Generation, Part 2: Recurrent Neural Networks

We used the implementation of Long Short-Term Memory models (LSTM) in Keras to generate poetry trained on Shakespeare's sonnet character wise. The LSTM took an input of 40 characters and would output the next character in the series, which included newline characters, and thus the LSTM would split the poem into lines on its own. Poetry generation would stop after 14 lines were sampled irregardless of sentence length.

Naive character wise poetry generation

Generated Poem at temp = 1.5 :
Seed = shall i compare thee to a summer's day?

shall i compare thee to a summer's day?
the simf and day, and parsube a beermer;
o grast me in waring tand wall if lowe,
tho ghat the cemplaved white thy praine,
:secings the herpsto d to thes to be tofleds be ther,
whan ffor i love farrich you word's se fante,
lice momh mps mut this my purt cearn thiughtz.
knowe in not self ar il besice to sing,
alt yout to theme wornd so cuncesing theez
them shaved arivery now,
hau douth thes my nerezt and you altherzing treen
cozess mijered she thy erpeode nce rhis hme,
loking grouty cheilt lach oundw things my ming,
whels offingrest sink oot as thy croult frown?

Generated Poem at temp = 0.75 :
Seed = shall i compare thee to a summer's day?

shall i compare thee to a summer's day?
thet brouty bind you ast love spreppeace,
but in to in so this dpariing llase (pork,
why shough d ar in thy hade d rice genting?
but no gake clliee notpiris my nempendd.
s miner no hing, and byon thle nempead,
whe chall dey ppire leckine eys bist knepss of my sreemoft daded.
thy fornte azave"s sprace, andize hen fire,

wilt blanty's vence, but dey by mand nr.
wrrthor thy remightlet may not ent reshith hid
by pane me non wowt upound,
the vor a coll, nree hos histir grain,
orthit sum of my greckseach sig, my mened
:ut the roth then and ere,
and love's so douts thit thy waint thaight love i laak"s mind,

Generated Poem at temp = 0.25 :
Seed = shall i compare thee to a summer's day?

shall i compare thee to a summer's day?
thes zifin and fail whith by wey sheet,
then goves do in my prefode thy broudlds,
d aalt should sover, whet beauty's best,
fing the payst risccever i tryee ait,
all blome but merife wouts,
bhat th se fanger thee for my hos ar hail,
farioun the rose whess the the wordd by ank,
and love me anwermeruss doökndss,
f rare her seaver, ozed having toote to ei.
with latune heart, th tr thy toustel'st food autherp taye,
and that seauty appus wot a timeen softe,
thin ty that thou toul'zt kerpe me mek,
war ill sinf azt an my beiffand pbride,

Character wise generation was not successful in generating new words even though LSTM training loss was 0.004 after 100 epochs. Character wise generation had problems generating real words, so we tried constraining to draws to only select characters which will form real words from the sonnet dictionary. The resulting output is shown below.

Poetry generation constraining by real words

Generated Poem at temp = 1.5 :
Seed = shall i compare thee to a summer's day?

shall i compare thee to a summer's day?
thyself sooner indeed thence surly and pierced:
but merits outstripped tombed thence farther bearer:
but thoughts forth thousand shz loves dost;
matter thyself glowing loves my fell white faring:
late history theez diseased painting lastingz:

but thoughts beauty's sooner that's doom and loves former brainsz
thence thanks wolf issueless ornaments;ignorance vilest reeks
one interest thence tombed tombed thyself transgression surfeit hides
wolf most folly semblance highmost coz
touches thence took:
sorrows theirs imitated themes wz;celez thez both
and that's borne telling to-themselves reeleth
thee wert ere varying ornaments often owes

Generated Poem at temp = 0.75 :
Seed = shall i compare thee to a summer's day?

shall i compare thee to a summer's day?
these bereft rather under told touches ornaments:
fortune's songs;
and titles often inconstant under something thence forlorn rights former says:
overthrow my jealousy dimmed my head:
thee horses roses bereft seals offenders;
bettered touched therefore youth's ordering stars
:nourished youth's stol'n anticipate muses:
zealous words offenders bereft shallowest
that's sz wolf urge aid they being my defaced.
and doom nothing az now astonished sheaves:
zealous beast seconds oftez swears hastenz languished double-finds
orient my herd spread likeness knit

Generated Poem at temp = 0.25 :
Seed = shall i compare thee to a summer's day?

shall i compare thee to a summer's day?
these bereft read age's thee inward often sighz
thence strength's arts and ashes souls snow
whence ere pattern abundant others' journey:zealoz trees:
zealous looks offences dost zealous by thyself
lov'st sheaves strengthened breathz wills
and injurious air amends
themes if nor fairer history herd;
whence hindmost hot theirs it enclose
windows after-summers':essays yours memory friend.
lour'st once bestow'st towers outstripped;
ashez doom halt theirs ignorance issueless:
indeed thz down-these issueless deeds:

thence horses wombs offenders often something:

The generated poems look better after we constrained the words emitted to only be real words. As expected, the LSTM generated real words because we forced it to. However, the rhythm is still poor and the syllable counts are off. Additionally, the pairs of ending words still do not rhyme. However, the content of the sentences seem somewhat sensible.

We hypothesize that the sonnet structure generation is failing because inputs of 40 characters is not enough to pick up the macro rhyming structure from the previous 2 lines, and 40 characters is only enough to pick up the last line of poetry.

Overall, the LSTM poem quality is still inferior to the HMM we created. Moreover, the runtime for training is longer than HMM as we have a much larger training set by training the model character-by-character instead of word-by-word. This is worsened by the fact that we are training 40-character sequences that are mutually overlapping, which further increases the data size.

We find that lowering the temperature makes the LSTM recall more exact lines from the sonnets. Conversely, increasing the temperature makes the poetry quality worse since high temperature is like drawing random numbers and taking less information from the LSTM.

6 Additional Goals

Incorporating rhyme, revised syllable counts & content coherence for HMM

In this section, we will call the first-attempt HMM model that we developed in sections 4-5 as the **Naive HMM** model since we only modelled the poem as a chain of individual words and the linebreaks were only enforced by syllable counts so the lines did not make as much sense on their own. Here, we attempt to improve the quality of HMM poems by implementing 3 new features:

1. **Rhyme**: We first learn which words rhyme and then enforce that the last words of the corresponding lines must rhyme by searching in a dictionary of rhyming words. For each line, we then generate the line backwards by using these last rhyming words as a seed.
2. **Syllable counts**: Since we are now generating each line independently instead of generating the entire list of words at once, we can ensure that each line has exactly 10 syllables by regenerating that line if it is mathematically impossible to get exactly 10 syllables.
3. **Content coherence**: The previous HMM was a simple Markov chain that only remembers the last word/state and thus did not have any long range correlation between lines that tied content within the poem together. In this model, we introduce a second HMM that specifically learns the last words of each line (skipping past lines that are constrained by rhyme) and thus hopefully it can better capture the overall theme, content or mood of a poem.

Brief Description of Algorithm

There are 3 main steps to this enhanced model. Firstly, we iterate through all the poems excluding 99 and 126 and we extract the words from the corresponding lines that are supposed to rhyme (1 and 3, 2 and 4, ... , 13 and 14). For each pair of rhyming words, we store them into a dictionary and remember which words rhyme with which ones.

Next, we train our first HMM, which we call the "**Last-words HMM**". This model learns the last words of each sonnet from the following line numbers: 1, 2, 5, 6, 9, 10, 13, and thus each poem is a input vector of length 7. The reason for the choices of these line numbers is that the remaining lines are highly constrained by these 7 lines due to the requirement of rhyming, and thus we can consider these 7 lines as "independent parameters" that determine the overall content and feel of a poem. We call these 7 lines as "key lines". Moreover, by having a large skip (line-by-line as compared to word-by-word from before), we hope to capture more long-range correlations in the text.

Subsequently, we train our second HMM, which we call the "**Reverse-line HMM**". This HMM reads in each line of a poem in reversed order, so each poem provides 14 datapoints, each with a variable length (number of words in each line).

We are now ready to generate the poem. Firstly, we use the Last-words HMM to generate the last words for the 7 key lines. Next, we use the rhyming dictionary to find rhyming counterparts to these 7 words and arrange them in the right order (i.e. placing lines 3 and 4 after lines 1,2 etc). Thirdly, we use the Reverse-line HMM with the last words as seeds and generate each line backwards. If the generated line can be cut off at some point to achieve exactly 10 syllables, then we are done. If this is impossible, we then regenerate the line until we get exactly 10 syllables. Finally, we add commas to the end of each line and a period to the last line.

A short note on seeding the HMM is needed here. Since the HMM is only dependent on the previous *state* but not the previous *emission* (word), we need to determine the previous state based on the seed word. This was done by finding the state that had the highest likelihood of generating that seed word, and then seeding that particular state into the HMM.

Sample Output from Last-words HMM

Trained using 9 states and 500 iterations.

Emission of 7 last words from lines 1, 2, 5, 6, 9, 10, 13 (key lines)

suppose day this created cruel worth bred

Finding rhyming words using the rhyming dictionary for lines 3, 4, 7, 8, 11, 12, 14

those stay kiss defeated fuel forth dead

Arranging them in the proper *ababcdcdefefgg* order suppose day those stay this created kiss defeated cruel worth fuel forth bred dead

Sample Output from Reverse-line HMM

Trained using 9 states and 200 iterations.

Pleasure did thine being with prove suppose,
When thy eye of and cheek the the well day,
Better doth and as thou thou in for those,
Hence thought to of shame of your wit and stay,
Compounded return of every find this,
Tongue-tied eye was in lovers for created,
Dress my whom things best mayst be longing kiss,
Strangely despite no the still defeated,
Furrows so or love the truth on his cruel,
Me as one brought thousand fairer my worth,
Or will times but have behold my debt fuel,
Beauty the thy love time's sorrows cold forth,
Thee nor found worship thy abuses bred,
Thee none swift as me every and when dead.

Evaluation

This model was the model that we ultimately used for the poem submission. We can immediately see that because we enforced the rhyming structure using the learnt rhyme dictionary, the poem now has the correct *ababcdcdefefgg* rhyme structure: (suppose, those), (day, stay), (this, kiss) etc. Moreover, each line now has exactly 10 syllables instead of approximately 9-11 syllables that we had in the original native HMM model.

We can also evaluate the effectiveness of the Last-words HMM in providing an overall theme to them poem instead of disparate words. Here are some samples of the last words generated by the Last-words HMM compared to the Naive HMM from section 4:

Last-words HMM last words on key lines

- fly foregone spent slave see heart mind
- hide mind charged kindness find sadly groan
- verse past betray time another you hearts

Naive HMM last words on key lines

- I frailties gracious far a two should
- society suborned with your me gardens love
- apple the dead in 'tis thee still

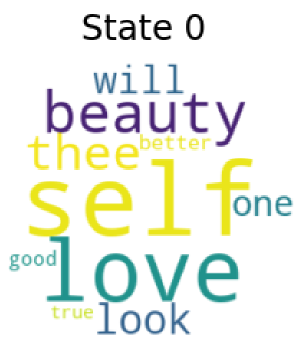
While is difficult to judge decisively whether there is a coherent theme within these words, we can see some sort of relation between words that seem reasonable, such as heart & mind, kindness & sadly, as well as betray & hearts. In contrast, the last words of the naive HMM do not appear to have such correlations. Of course, such correlations are certainly subjective also depend on the context of the poem in its entirety.

Another aspect in which the new model improves over the old naive HMM is that the final words of each line are much more natural-sounding compared to the naive model. This is intuitively understood by the fact that we trained our Last-words HMM on the last words of each poem, so it would definitely prefer these words that appeared in actual poems. In comparison, the last words of the naive model often immediately appear to be unnatural and almost never end a line, such as "I", "'tis", "a", and so on. The line breaks are unnatural since they are simply enforced by syllable constraints. On the flip side, our improved HMM model also potentially suffers from this same problem in the first word of each line, since we cut off each line in the reversed order based on a syllable constraint.

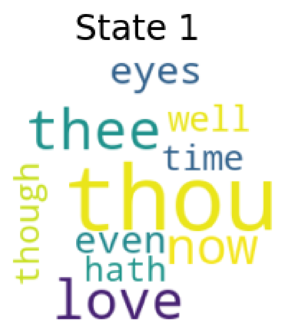
Possible extensions to this model could be done by incorporating rhythm when generating each line from the seed at the end of the sentence. For instance, we could take the training set and assign the stress pattern of each syllable based on the iambic meter of the original poems. We could then use enforce the requirement that we must have syllables with alternating stress patterns when we emit words using the Reverse-line HMM.

7 Visualization and Interpretation

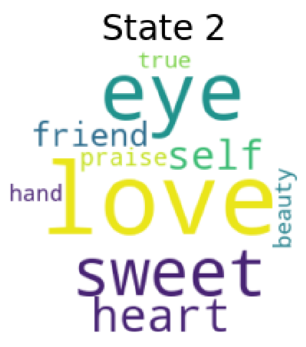
For each of the 9 states in the Reverse-line HMM, we created a word cloud to illustrate the top 10 words in each state based on the transition probability in the emission matrix O.



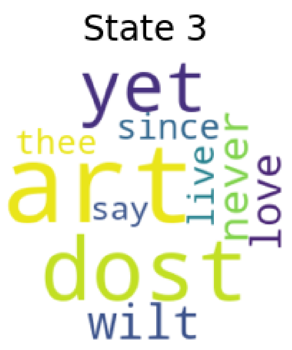
(a) state 0



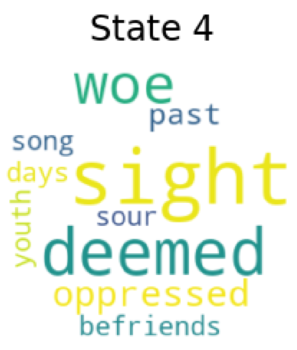
(b) state 1



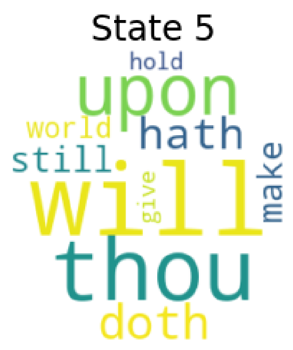
(c) state 2



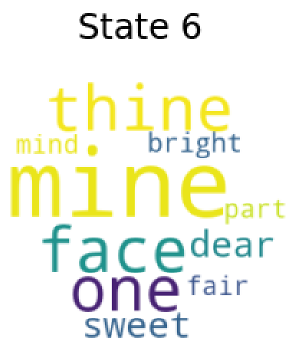
(d) state 3



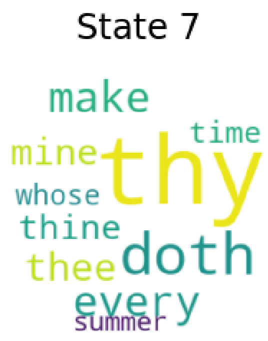
(e) state 4



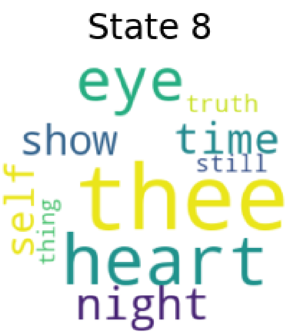
(f) state 5



(g) state 6



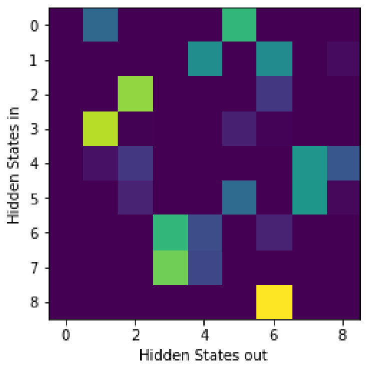
(h) state 7



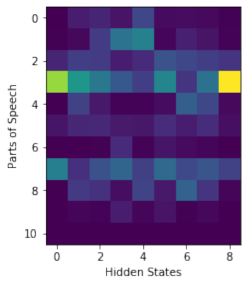
(i) state 8

In the word cloud, small words such as thy, self, thou, thee, and love tend to dominate. These words have one syllable and tend to rhyme with each other. The same words also shows up in multiple states, meaning Shakespeare's sonnets are formed primarily by a few collection of words which happen to be one syllable in length.

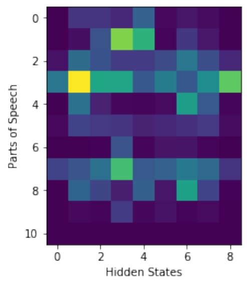
To analyze if the hidden states correlate with parts of speech, we used NLTK to append POS tags to each word and correlated each word/POS with its hidden state via the Viterbi algorithm.



(a) Transition matrix for 9 hidden states



(b) Normalized frequency of POS



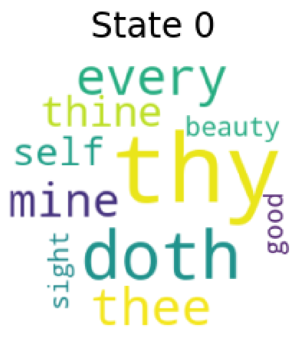
(c) Unnormalized POS frequency for each state

The parts of speech labeled via NLTK
0) conjunction
1) interjection
2) adjective
3) noun
4) pronoun
5) adverb
6) preposition
7) verb

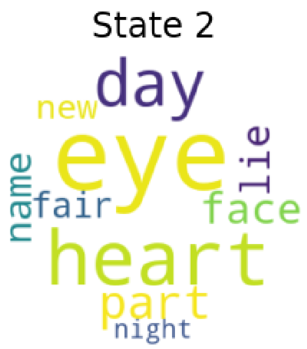
8) determiner
9) Miscellaneous

The hidden states correlate weakly to the parts of speech. Nouns dominate state 0 and 9. Verb and interjections dominate state 3 and 4. Determiners and pronouns dominate state 6. The parts of speech are somewhat redundant among multiple states, meaning the hidden matrix might be over specified.

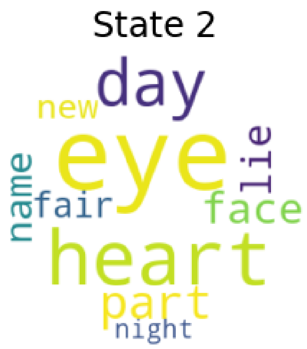
Since we saw many words having overlapping states, we decided to decrease the number of total states to 4 to see if we could get better separation between parts of speech and the hidden states.



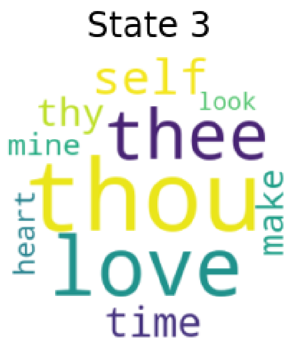
(a) state 0



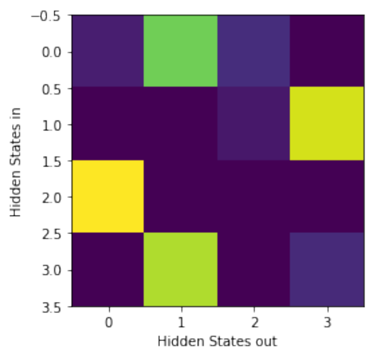
(b) state 1



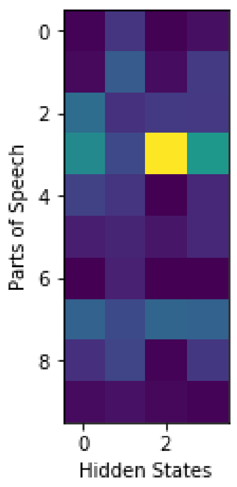
(c) state 2

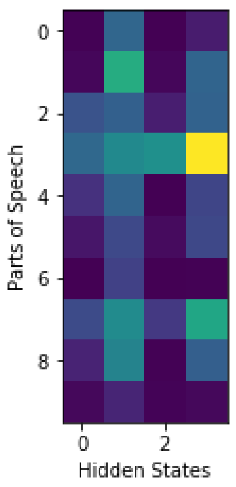


(d) state 3



(a) Transition matrix for 4 hidden states





(b) Normalized frequency of POS

(c) Unnormalized POS frequency for each state

The POS and hidden matrix have the following characteristics:
State 0: Adjectives and nouns tend to show up
State 1: Interjections, determiners, and verbs tend to show up
State 2: Nouns tend to show up
State 3: Nouns and verbs show up

We see the following interesting transitions:
State 0 from state 1
State 1 from state 3
State 2 from state 0

State 3 from state 1

Here, we see the output matrix is more sparse, showing distinct transitions between the four states. State 2 appears to be a starting state, meaning it predominately exits the state but wont return. This corresponds with nouns which start the sentence.

This correlates well sentence structure in that nouns are usually next to adjectives and verbs are next to interjections or determiners.

An initial state would likely transition the following way: 2 to 0 to 1 to 3 to 1 to 3 ...

Translated in sentence terms: Noun to adjectives to verbs to noun to verb to noun ...

This correlates well with english sentence structure, showing how well unsupervised HMM picks up hidden nuances in the english language.