The Poetry Pioneer

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Abstract

Poetry is a popular linguistic art form whose works are succinct in length but dense in symbolism and meaning. While humans have been creating and studying poetry for millennia, computers have only recently attained the necessary syntactical control, semantic understanding and contextual awareness thanks to advances in computational linguistics.

Poems are usually of a particular type, defined by its form and use of mnemonic techniques such as rhyme and rhythm. These techniques have been passed on for generations without validation and previous attempts at automatic poetry generation have blindly hard-coded these rules, limiting the array of poems produced only to those studied by the programmer.

This thesis presents a full-spectrum implementation for automatic poetry analysis and composition. For any one poem, we extract form and usage of poetic techniques while attempting to build a semantic representation of how concepts mentioned in the poem relate to each other. We generalise the findings over large collections of each type, outlining a blueprint to the structure and content for generating that type of poem.

In addition, we endeavour to build an extensive source of common-sense knowledge to use as inspiration and ensure a cohesive topic flow. We couple this with third-party tools that provide control over grammatical structure, enabling us to take a content-first approach to the composition process. This helps retain the original message of the poem while we rephrase specifically to fit the required poetic structure.

Results show strong correlations between our derived blueprint and documented theory. Among the exceptions are cases where our blueprint provides significant evidence against theory, such as the strict adherence to iambic pentameter in Shakespearean sonnets. The poems generated by this system have shed light on the appropriateness and effectiveness of a knowledge-based, content-first approach to poetry generation that encourages further investigation.

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Introduction

1.1 Motivation

Alan Turing devised the Turing Test as a standard for a computer's ability to exhibit behaviour indistinguishable to that of a human. The original example that he used to indicate the requirements for passing the test included the following[54]:

Q: *Please write me a sonnet on the subject of the Forth Bridge.*
A: *Count me out on this one. I never could write poetry.*

Poetry is a linguistic art form whose works convey a particular message, often using symbolism and rhetoric. Writing poetry requires precise control over syntax, in-depth understanding of semantics and the contextual awareness to retain a coherent topic flow. They are often read out loud and use a number of mnemonic techniques based on the sound of speech, such as rhyme and rhythm. Poets break grammatical rules under a *"poetic license"* if it is believed that it will help their message resonate with the listener.

It's not unreasonable for Turing to have been pessimistic about the possibility of computers writing poetry. However, recent advances in Computational Linguistics and Creativity have made it worth investigation. In this paper, we attempt to create a system that can automatically generate poetry that makes sense grammatically, semantically and with some level of coherence.

Many types of poetry have spawned and evolved over millennia, each defined by the way it uses the aforementioned poetic techniques. We will not be able to write a variety of poems if we hard-code each style. Therefore, we aim that this system is able to learn the structure and typical content of classes of poems from examples and use this information to guide the generation process.

Poems are fundamentally *creative* works, and creativity is a behaviour exhibited particularly well by humans. For computer-generated poems to truly be indistinguishable from those created by humans, we want to demonstrate some element of imagination

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and originality. To investigate this, certain philosophies of creativity have been broken down into logical components and implemented in code by researchers of Computational Creativity. It will be fascinating to see how they perform in practice through creation of poetry.

Ultimately, poems are created to be enjoyed and to help people express themselves, while the purpose of computers is primarily to aid people in as many ways as possible. We intend that our system can be used to assist people either by creating poems for them, or as a tool for those who wish to write their own.

1.2 Objectives

We wish to create a system that:

- identifies the usage of a broad list of poetic and linguistic features in a single poem (Chapter 3).

- learns usage patterns of these features and typical content of any class of poems from examples (Chapter 4).

- produces poems (Chapter 5), spontaneously or using 'seeds' of inspiration, that are:

    - novel,
    - syntactically valid,
    - semantically interpretable,
    - contextually coherent,
    - evident of desire poetic techniques,
    - indicative of creativity and imagination.

- can be used to assist people in the creation of poems.

1.3 Contributions

This project makes contributions towards both Computational Creativity and Computational Linguistics.

- We demonstrate the ability for computer systems to assess written natural language works in terms of its structure, common words and phrases, rhetoric and poetic features such as rhyme, rhythm and alliteration.

- We validate the commonly taught expectations on structure and content of popular types of poetry.

- We will investigate the appropriateness of semantic networks of common sense as a representation of a written text's context in terms of objects and their descriptions, actions and relationships.

- We demonstrate the ability to learn usage patterns of written features from the analysis of a large number of comparable texts.

- We will investigate the appropriateness of semantic networks of common sense as a source of knowledge from which we can build sentences, retain a cohesive theme and demonstrate creativity.

- We explore the effectiveness of a content-first approach to poetry and applicability of third-party resources for Natural Language Generation.

Chapter 2

Background

This chapter gives a brief overview of the features and classes of poetry that exist, along with why people are interested in writing them. We will discuss, critique and gather inspiration from the related work in the area of poetry generation that most relate to the approach taken in this paper. We then give brief overviews into the fields of Computational Linguistics and Computational Creativity, both of which are involved in the task of automatic poetry generation. These overviews are by no means complete or comprehensive, but should provide enough information for those not familiar with the areas to understand and appreciate this paper.

2.1 Poetry Theory

To fully comprehend the task that we are about to undertake, we need to have an understanding of poetry as an art form. It is ever-evolving and different styles have emerged over the years. Here we discuss those styles and the underlying reason for why poetry is written.

2.1.1 The Purpose of Poetry

Merriam-Webster dictionary defines poetry as:
'writing that formulates a concentrated imaginative awareness of experience in language chosen and arranged to create a specific emotional response through meaning, sound, and rhythm.'

Let us break this down:

- ***Formulates*** implies that there is method to the process of writing a poem.

- ***Concentrated*** accentuates the fact that poems are generally short, as they are counted in stanzas in lines rather than paragraphs and pages.

- **Imaginative** confirms the fact that this is a creative act, that has a level of non-determinism and need not be entirely realistic.

- **Awareness of Experience** embodies the need for general background knowledge based on a particular set of experiences that surface when writing a poem.

- **Language Chosen and Arranged** reiterates that this is a methodical and systematic art - words are chosen carefully with precise intention.

- **Create a specific emotional response** gives the main purpose of the poem - to express a feeling or an idea and elicit emotion in the reader.

- **Through meaning, sound, and rhythm** describes that this purpose is not reached purely by words, but other language features.

To summarise, the purpose of poetry is to use one's imagination, knowledge and experience to trigger empathy about a particular subject matter. Poetry is a vehicle through which poets can share a very personal message that they want the reader to experience and remember. Poems are concise but have many layers of meaning that are subtle even to human readers and that only the best of poets can fully control.

We must keep this in mind throughout the project, as it is important to realise that the features of poetry discussed in the next section are not arbitrary rules on form but purposeful techniques used to make the language more concise and effective.

2.1.2 Features of Poetry

The earlier definition mentions the use of *meaning, sound and rhythm* in poetry. These add an extra layer of subtext to poems to help the author remain concise while still getting the complete message across. We call these techniques *features* of poetry throughout this paper. There are many features of poetry to address, but we have scoped this project down to concentrate on the following common ones.

2.1.2.1 Rhyme

Two words rhyme when they sound similar when spoken out loud. *Cat* and *fat* in figure 2.1 rhyme, as do *mice* and *nice*. Rhyming words need not be spelt similarly, for

*There once was a big brown **cat***
*That liked to eat a lot of **mice***
*He got all round and **fat***
*Because they tasted so **nice***

Figure 2.1: A rhyming quatrain often used in teaching poetry

example, *kite* and *height.*

Strict rhyme enforces the exact same sound while weak rhyme only requires that the vowel sounds are the same. Examples of weak rhyme are *turtle* with *purple* and *tragedy* with *strategy.*

A piece of text has a rhyme scheme if there is a pattern of rhyme between its lines. For example, the poem in Figure 2.1 has an *ABAB* rhyme scheme.

Rhyme can also occur within a line (internal rhyme) or between words in the middle of different lines.

Major Purposes

- Pleasant to hear, making the listener feel more comfortable and listen carefully.

- As a mnemonic device.

- Used at the end of lines of poetry and songs making the rhythmic structure more distinct.

2.1.2.2 Rhythm

Rhythm is the pattern of emphasis of syllables that occurs in a line of poetry. There are three major ways of measuring rhythm, often used in tandem - syllabic, quantitative and accentual.

The bartender said
to the neutron, 'For you, sir,
there will be no charge.'

Figure 2.2: A humourous Haiku

Syllabic rhythm enforces a certain number of syllables to be used in a particular line of poetry. Haikus, for example, are three lines long with the first and last lines

restricted to 5 syllables and the second to 7. An example is given in Figure 2.2.

Quantitative measures use the fact that some syllables *sound* longer than others when spoken out loud. Long sounding syllables are *stressed* while short ones are *unstressed*.

Accentual measures are similar to Quantitative, but they work on the *tendency to emphasize a particular syllable* when spoken out loud, rather than its length. It is important to note that a word's meaning can change depending on stress. For example, '**ob**ject' is a noun whereas 'ob**ject**' is a verb.

Lines of pre-defined patterns of stressed and unstressed syllables are called *meters*. Lines with meter are made up of individual units called *feet*. The five major foot types in poetry are given in Table 2.1.

Foot Type	Pattern	Example
iamb	unstressed - stressed	des**cribe**
trochee	stressed - unstressed	**po**em
spondee	stressed - stressed	**popcorn**
anapest	unstressed - unstressed - stressed	meta**phor**
dactyl	stressed - unstressed - unstressed	**po**etry

Table 2.1: The major poetic foot types with their corresponding pattern and an illustrative example.

The metre is formed by repeating feet, typically with up to six feet:

- Monometer: 1 foot

- Dimeter: 2 feet

- Trimeter: 3 feet

- Tetrameter: 4 feet

- Pentameter: 5 feet

- Hexameter: 6 feet

All Shakepeare's sonnets are written in iambic pentameter, i.e. five repetitions of unstressed-stressed syllables. The first line of his Sonnet II as an example:
*When **for**ty **win**ters **shall** be**siege** thy **brow**.*

Major Purposes

- Introduces a melody based on the natural intonations of speech.

- Adds a level of predictability and structure that resonates with readers and listeners.

- Emphasizes the message by putting stress on the words that matter.

2.1.2.3 Sound Devices

This project considers four types of sound devices.

The first is **onomatopoeia** - words that imitate or suggest sounds of particular sources. For example, the *pow* of a punch or the *tick-tock* of a clock. This technique has mostly been used in comic books to help the reader experience the sound of the scene to go with the image.

The next three devices are repetitions of a pattern of similar sounds. **Consonance** is the repetition of similar consonant sounds (e.g. *pitter patter* repeats the 'p', 't', and 'r' sounds), while **assonance** is that of vowels (e.g. *doom and gloom* repeats the 'oo' sound). **Alliteration** is a special case where the repeated sound occurs at the beginning of consecutive words. *Zany zebras zigzagged through the zoo* has alliteration on the letter 'z'.

Major Purposes

- Poets use onomatopoeia to help describe actions or atmosphere richly. A famous example is the nursery rhyme 'Old MacDonald', which uses onomatopoeia of the sounds that animals make to describe the farm, figuratively placing the reader or listener in the farm itself.

- Alliteration, consonance and assonance are pleasant to listen to when spoken out loud.

- Can be used to add drama to an action.

- Sometimes used to suggest danger.

2.1.2.4 Structure

The structure of the poem is the organisation of its lines in a poem. The main unit is the *stanza*, which is a fixed number of *lines* grouped by rhythmical pattern.

There are four major types of stanza:

- Couplet: 2 lines

- Tercet: 3 lines

- Quatrain: 4 lines

- Cinquain: 5 lines

Stanzas can also be called *verses*, which have the added property of a rhyme scheme. A *chorus* is a special type of verse that is repeated throughout a poem.

Features of the structure of a poem include:

- The number of stanzas.

- The number of lines per stanza.

- The number and positions of repeated lines.

- The number and positions of repeated stanzas.

- Enjambment; the continuation of a sentence over a line-break

The Haiku in Figure 2.2 has a single tercet structure with no repetitions. Songs are generally several stanzas long, with a chorus interleaving longer non-repeating verses.

Major Purposes

- Helps to guide the reader through the story.

- Forces the poet to be more succinct and purposeful.

- Manages the storyline - changes in stanza often suggest a change in perspective or message.

- Repetition helps drive home the main message.

- Ties several thoughts together into one continuous flow.

2.1.2.5 Symbolism and Imagery

Symbolism and imagery are general terms for creating an overall image in the reader's mind by describing a subject or object as something else with desired qualities.

Techniques include:

- **Metaphor**: an object is described as another object with a set of desirable characteristics. For example, saying someone is a lion immediately creates the image of bravery, intimidation and power.

- **Simile**: an object or action is specifically described using an adjective or adverb, but compared to another object that is a stereotypical example of that description. The phrases 'like a' and 'as a' are often used, e.g. *Runs like a cheetah*, *Slippery as an eel*.

- **Hyperbole**: unrealistic exaggeration, often used in tandem with metaphor e.g. *Cried a river of tears*.

- **Powerful Verb**: a more exciting way to describe an action using unusual verbs, e.g. *Wormed through the crowd*.

- **Personification**: using actions and properties associated with sentient objects to describe inanimate ones. Explained further in section 2.1.2.6

- **Onomatopoeia**: as explained in section 2.1.2.3, using imitations of known sounds to richly describe actions and atmosphere.

Major Purposes

- Explain complex concepts concisely.

- Induce empathy from the reader by relating it to something they understand.

2.1.2.6 Context and Personification

Poetry is similar to storytelling in that it has persona around whom the poem is written. Understanding who or what they are, their descriptions and their actions are all part of the underlying message that the poet wants to get across.

Personification is a technique used by poets to give inanimate objects life, expressing actions and descriptions as if it were sentient. This is a powerful technique that relates to imagery, helping poets make abstract messages clearer. For example, *the moon smiled* gives the moon life by describing it as having performed a sentient action with full intention of doing so. Noting the use of personification can make the context of the poem clearer, as inanimate objects are often the subject of the poem.

Major Purposes

Context is the underlying message in its bare form. It is the story that the poet wishes to tell and guides the use of all other features.

In this paper, we aim to extract characters and differentiate them by their descriptions and actions. This is vital in understanding the poem and can help us generalise the uses of features when attempting to produce a coherent story as the backbone to the generated poem. Furthermore, it will help determine the type of poem (narrative, lyrical, descriptive etc.) and will help guide generation of poems of a particular type.

2.1.3 Classification of Poetry

We define a type of poetry as a particular form of poem with a set of unique features, including those described in the previous section. Some types are very popular and have had their styles, features and purposes documented and taught. Out of these grew categories of different types that tend to be used for similar purposes.

This project attempts to derive these categories and some popular types of poetry by analysing many comparable poems.

2.1.3.1 Categories

There are many types of poem all with different form. However, there are only three main categories of purpose for a poem:

1. *Lyrical* poems have an identifiable speaker whose thoughts and emotions are being expressed in the poem. This means that poems of this category have very few characters, a song-like structure and tend to be in a reflective tone, generally using a lot of symbolism. Maya Angelou's *I Know Why The Caged Bird Sings* is an example of this, along with many songs.

2. *Descriptive* poems describe the surroundings of the speaker. This is identifiable by the use of adjectives and complex imagery. Many objects may appear in this type of poem to be able to give an in-depth description of the environment and atmosphere. There will be very few action verbs used.

3. *Narrative* poems concentrate on telling a story. It therefore has a coherent plot line, several characters with explicit relationships between them, action and climax. Ballads and Epics are types of narrative poems.

Some popular poem types do not fall under any one bracket as they can be used in any of the above categories. Examples include Haikus and Limericks.

2.1.3.2 Popular Types

As well as determining the category of poems, we aim to be able to detect and reproduce some popular types of poetry. For this project, we will concentrate on:

- *Haiku:* single tercet structure with 5-7-5 syllabic rhythm.

- *Limerick:* single cinquain structure with AABBA rhyme scheme. Lines 1, 2 and 5 have 7-10 syllables, while lines 3 and 4 have 5-7 syllables. The first line tends to begin with "There was a..." and ending with a person or location. Limericks are usually used for humour as the last line is generally a punchline.

- *Sonnet:* 14 lines, each in iambic pentameter with an ABAB CDCD EFEF GG rhyme scheme, i.e. three quatrains followed by a rhyming couplet.

- *Elegy:* usually used to mourn the dead, its lines alternates between dactylic hexameter and pentameter in rhythm. It has no particular rhyme scheme, although does still use rhyme.

- *Ode:* Description of a particular person or thing, using plenty of similes, metaphors and hyperbole.

- *Ballad:* Tells a story and has a number of quatrains, each with an AABB rhyme scheme. Lines alternate between iambic tetrameter and iambic trimeter.

- *Cinquain:* as the name suggests, this has 5 lines. They are not rhymed, but have a 2-4-6-8-2 syllabic pattern.

- *Riddle:* Riddles describe things without telling what it is, using anaphora to refer to it. Ususally told in a number of rhyming couplets.

- *Free Verse:* No particular features attached to this type.

2.2 Lessons from Related Work

This section looks at six important previous attempts at automatic poetry generation. They each have some aspect of investigation or experimentation that have influenced this project. Conversely, each of these attempts has its limitations that we look to overcome in this project.

2.2.1 Actively Gather Inspiration

Colton et al. published a paper in the International Conference of Computational Creativity 2012[21], whose main objective was to describe the first poetry generation system that satisfied the FACE Descriptive model[22]. It is a *Form Aware*[43] implementation that constructs templates of poems based on constraints of poetic features.

The most interesting point of this paper was its admission that inspiration cannot come from the technology and must come from the user. By taking this into account, it now takes inspiration from news articles as seen in Figure 2.3. However, since its objective was focused on passing a particular evaluation model, the poems created by this system are relatively simple and the processes rudimentary - using randomness rather than semantic applicability in word selection.

2.2.2 Constrain to Improve Creativity

Recently, Toivanen et al. attempted a solution that used off-the-shelf constraint solvers[53] to produce poetry. Their solution, illustrated in figure 2.4, also received inspiration from external sources. This is used to build the set of candidate words, form requirements and content requirements that are passed into a constraint solver

It was generally a bad news day. I read an article in the Guardian entitled: "Police investigate alleged race hate crime in Rochdale". Apparently, "Stringer-Prince, 17, has undergone surgery following the attack on Saturday in which his skull, eye sockets and cheekbone were fractured" and "This was a completely unprovoked and relentless attack that has left both victims shocked by their ordeal". I decided to focus on mood and lyricism, with an emphasis on syllables and matching line lengths, with very occasional rhyming. I like how words like attack and snake sound together. I wrote this poem.

Relentless attack
a glacier-relentless attack
the wild unprovoked attack of a snake
the wild relentless attack of a snake
a relentless attack, like a glacier
the high-level function of eye sockets
a relentless attack, like a machine
the low-level role of eye sockets
a relentless attack, like the tick of a machine
the high-level role of eye sockets
a relentless attack, like a bloodhound

Figure 2.3: The Guardian article used for inspiration(left) and the resulting poem(right).

with a manually encoded static constraint library powered by Answer Set Programming.
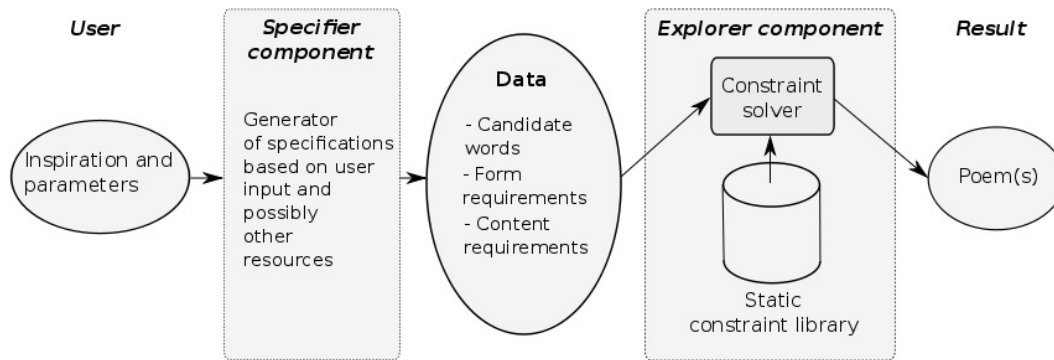
Figure 2.4: Complete poetry composition workflow.

The idea that constraints do not hinder but rather help the creative process is an attractive one for Computational Creativity research. Constraining words and other requirements for each particular word position is a natural technique for constraint programming, but extremely restrictive. First, the size of each line must be defined by number of words *and then* by rhythm and other poetic features. Secondly, once the candidate words are chosen there is no scope for further filtering. Finally, the

N SG VB, N SG VB, N SG VB!
PR PS ADJ N PL ADJ PRE PR PS N SG:
– C ADV, ADV ADV DT N SG PR VB!
DT N SG PRE DT N PL PRE N SG!

Music swells, accent practises, theatre hears!
Her delighted epiphanies bent in her universe:
– And then, singing directly a universe she disappears!
An anthem in the judgements after verse!

Figure 2.5: The POS template used for constraint input(left) and the resulting poem(right).

structure of the poem in terms of its parts-of-speech (section 2.4.2) tags must be defined beforehand and is taken from previous poems of the same type, as seen in Figure 2.5. Even though this is an efficient method that has produced impressive results, it is too restricted to produce truly creative work.

2.2.3 Learn from Experience

Ray Kurtzweil Cybernetic Poet (RKCP), created by Kurtzweil himself[40], addresses the issue of having a predefined template. He uses a stochastic approach that utilises of n-grams to build lines from words. The system was trained on a selection of poems that created a template and n-gram corpus from those poems. RKCP would use this to create similar types of poems. Some heuristics were employed to ensure that poems were not exact copies of other poems and to maintain a coherent theme.

> *Scattered sandals*
> *a call back to myself,*
> *so hollow I would echo.*

Figure 2.6: A haiku written by Ray Kurzweil's Cybernetic Poet after reading poems by Kimberly McLauchlin and Ray Kurzweil

This method is more flexible and has granular word selection. However, the vocabulary would still be limited and the form of the poem is not well defined due to being probabilistic. We can see that in Figure 2.6, the attempted Haiku has a syllabic rhythm is 4-6-7 as opposed to the required 5-7-5. A specific purpose or storyline is not definable and the use of imagery is only probabilistic. A lot also depends on the poems in the corpus, limiting semantic capabilities and word selection quality.

2.2.4 Choose Words Carefully

MCGONAGALL[43] takes a semantic representation of a sentence, called *semantic expressions*, as input into an NLG system. For example, the semantic expression of *"John loves Mary"* would be {*john(j), mary(m), love(l, j, m)*}

These are used as starting points for initialisation of his evolutionary system that uses stochastic methods to determine the best values to be carried forward to further iterations.

> *They play. An expense is a waist.*
> *A lion, he dwells in a dish.*
> *He dwells in a skin.*
> *A sensitive child,*
> *he dwells in a child with a fish.*

Figure 2.7: Resulting MCGONNAGAL poem when seeded with a couple of lines of Hilaire Belloc.

Of particular note is the structure of a lexical entry into the system. It is enriched with much semantic information, as in Figure 2.8, that backs up the fitness score and helps MCGONAGALL form syntactically and semantically correct sentences. We will use much of his ideas in this area. However, contextual coherence is lacking because of the restrictions imposed on evolution. It does not take particular types of poetry into account and there is little scope for creativity due to the strictness of grammar generated.

2.2.5 Derive Insight from Worldly Knowledge

Tony Veale's daring approach to knowledge-based poetry generation[55] concentrates on symbolism and imagery - arguably the hardest tasks in automatic poetry generation. He uses norms and stereotypes to build a structure that uses various words to describe objects and derive stereotypical characteristics. Out of this grew a very useful tool - Metaphor Magnet[56], which was used to create the impressive poetry shown in Figure 2.9.

His methods have obvious limitations in that they do not consider rhyme, rhythm or any other poetic feature other than symbolism. However, we will take advantage

Field	Value
Key	`lion_n`
Orthographic spelling	*lion*
Phonetic spelling	`[L,AY1,AH0,N]`
Semantic expression	lion(X,Y)
Semantic signature	$\boxed{X,Y}$
Anchored trees	`I_N_N`, `I_C_NP`, `A_R_C_NP`
Feature structure	$\begin{bmatrix} \text{CAT} & n \\[4pt] \text{AGR} & \begin{bmatrix} \text{NUM} & sg \\ \text{PERS} & 3 \\ \text{3RDSG} & + \end{bmatrix} \\[4pt] \text{PRON} & - \\ \text{PROP} & - \\[4pt] \text{SUB} & \begin{bmatrix} \text{ANIM} & + \end{bmatrix} \end{bmatrix}$

Figure 2.8: Semantically enriched lexical entry for *lion* in MCGONNAGAL

inspiration from the idea of using norms and stereotypes to give this system more symbolic choices of words and phrases.

2.2.6 Dare to be Different

WASP is one of the first attempts at an automatic poetry generator. It is a rule based system that takes a set of words, a set of verse patterns and returns a set of verses[35]. It uses heuristics to guide the construction to fit structure, but no semantic limitations are enforced.

This has obvious limitations but Gervas, the creator of this system, does make a good

My marriage is an emotional prison
Barred visitors do marriages allow
The most unitary collective scarcely organizes so much
Intimidate me with the official regulation of your prison
Let your sexual degradation charm me
Did ever an offender go to a more oppressive prison?
You confine me as securely as any locked prison cell
Does any prison punish more harshly than this marriage?
You punish me with your harsh security
The most isolated prisons inflict the most difficult hardships
O Marriage, you disgust me with your undesirable security

Figure 2.9: 'The legalized regime of this marriage', a poetic view of marriage as a prison

point that poetry's creativeness is somewhat down to daringness of transgression. We keep this in mind to allow some level of randomness and mutation from expected norms in this project.

2.3 Brief Overview of Computational Creativity

Simon Colton and Geraint Wiggins define research in this area as:
The philosophy, science and engineering of computational systems which, by taking on particular responsibilities, exhibit behaviours that unbiased observers would deem to be creative.[23]

In the context of automatic poetry generation, we are creating a system that *takes on the responsibility* of generating aesthetically pleasing, meaningful and novel poems. The poems still need to be sufficiently similar to existing works created by humans such that it *exhibits behaviour* to which *unbiased observers* can relate and recognise.

This definition has evolved from one where behaviour was *deemed creative if and only if it can be exhibited by humans*[58]. However, recent developments in the area have lead to the requirement of more quantitative measures for evaluation than Turing-style tests, such as the FACE and IDEA descriptive models[22].

This area of research has come under scrutiny for philosophical reasons, but has had support from Alan Turing and other pioneers of Artificial Intelligence. It has since been accepted as a valid area of research, with the annual International Conference on

Computational Creativity heading into its fifth year.

Successes of Computational Creativity:

- Simon Colton's *Painting Fool*[20] produced paintings that managed to trick art lovers into believing that it was the work of a talented human artist. An example is given in Figure 2.10.

- *JAPE*[14], created by Ritchie and Binsted in 1994 was given a general, non-humorous lexicon and generated puns as answers to questions. For example:
  Q:What do you call a strange market?
  A: A bizarre bazaar.

- *Iamus* by Gustavo Diaz-Jerez[28], which composed music entirely on its own that was then recorded by London Symphony Orchestra.

- *The Policeman's Beard is Half Constructed*[17] is recognised for being the first book, which included some poetry, to have been written entirely by a computer program, RACTER.

Figure 2.10: Chair #17 at the Performing Sciences Exhibition, La Maison Rouge, Paris, Sept 2011

2.3.0.1 Semantic Networks of Common Sense

Tom De Smedt uses the idea that the mind can be modelled as a search space of *concepts* and relations between them. to model creativity[26]. He proposes a network with concepts at the nodes and relations between them, perhaps of a specific type, are the edges.

In our case, these concepts are represented by words or phrases that have literal and symbolic meaning. The number of concepts in the space and how words relate to each other are determined by knowledge and experience.

If we think of a *cat* as a concept, it would be directly related to other concepts such as *dog* and *mouse*. These are *mundane* associations between concepts.

Concepts are defined in this network by looking at the outgoing neighbours of its node. This is called the concept *halo*. Conversely, the *field* of a concept acts as a classification by finding all neighbours that relate to it, rather than from it. A subgraph of the halo and field of the concepts *cat* and *feed.v* respectfully are shown in Figure 2.11.
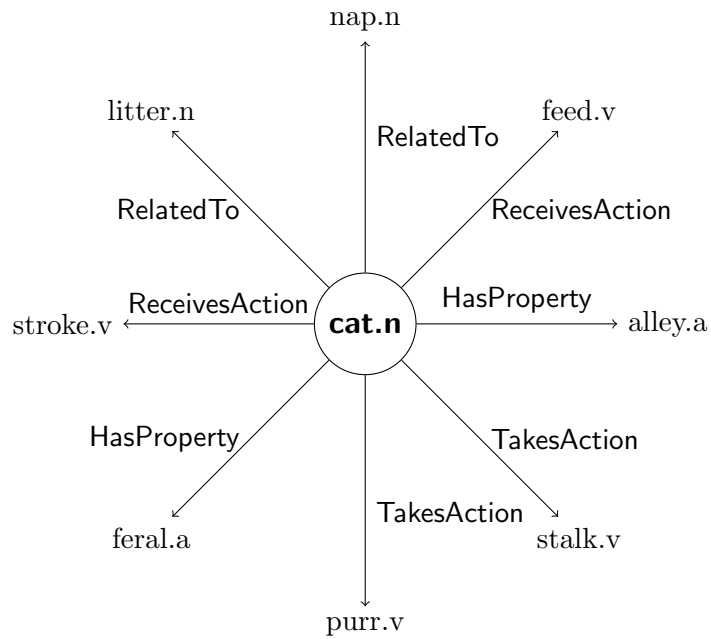
(a) Concept halo for 'cat.n'
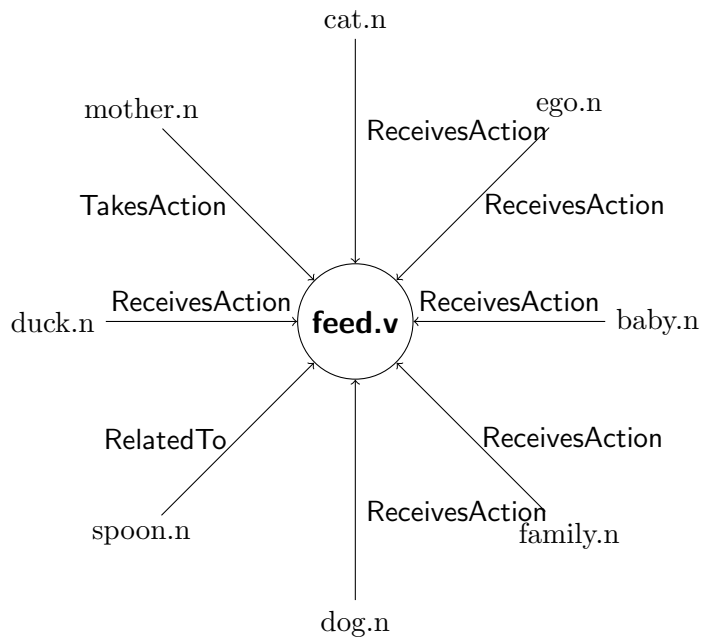
(b) Concept field for 'feed.v'

Figure 2.11: Example concept halo and field

If we were to look at *paths* in the network, we can realise relationships between concepts that are less mundane, and therefore more creative.

For example, we may travel along the path *cat → meow → loud → fire alarm* to create an analogy between the cats and fire alarms.

Since this knowledge is modelled as a graph, we are able to use standard graph algorithms such as Dijkstra's shortest path[29] to find similarity between concepts.

2.3.0.1.1 ConceptNet ConceptNet[42] is an attempt to build a single source of *'things computers should know about the world'* using the idea of a semantic network of concepts.

It gathers its knowledge from an array of sources but large amounts come from Wikipedia. Edges represent *relations* between concepts and come in various types including:

It also provides functional interfaces such as finding the closest concept to a given number of concepts and similarity between concepts.

2.4 Brief Overview of Computational Linguistics

Computational Linguistics is a wide area of research, covering Speech Recognition, Natural Language Processing and Generation and with overlaps in several other areas such as Machine Learning and Knowledge Representation. In fact, Daniel Jurafsky and James H. Martin needed almost a thousand pages to cover the foundations of this area[36].

Automatic poetry generation borrows many techniques and terminology from Computational Linguistics. Here we will briefly discuss the major ones in general and in the context of machine poetry analysis and generation. For an in depth general study of Computational Linguistics, we refer the interested reader to Jurafsky and Martin's book.

2.4.1 Words

Words are the fundamental building blocks of language. They have been studied for the creation of spell-checkers, text-to-speech synthesis and automatic speech recognition. Two major subsets where poetry is concerned is the study of pronunciation and morphology.

The CMU Pronunciation Dictionary[57] has taken steps towards computationally modelling the phonetics of words, using the ARPAbet phoneme set (see Table A.2 in the Appendix). It is highly important for poetry generation as it helps machines reason about rhyme and sound devices by simply comparing phonemes. It has over 133,000 words mapped to corresponding pronunciations.

To illustrate how this works, let us take two words that are spelled differently but pronounced the same - *kite* and *height*. The Jaro-Winkler distance, a normalised score of similarity between strings, for the tail of these words (in search of rhyme) gives 51.11%, indicating that it is barely probable that they rhyme if we only looked at spelling. Their corresponding phoneme sets are *'K AY1 T'* and *'HH AY1 T* respectively. Now it is trivial to compare them computationally and see that the tails are exactly the same and the words therefore rhyme.

Notice the '1' appended to the 'AY' phonemes. Vowel phonemes come with a digit appended to them that defines the emphasis placed on this syllable:

- 0: unstressed

- 1: stressed

- 2: light/secondary stress

Morphology of words is the study of putting words together with *morphemes*, the smallest unit of grammar. To use Jarufsky and Martin's example, the word *fox* consists of a single morpheme that is itself, but *cats* has two morphemes, *cat* and *-s*. This is of vital importance in our project as we need to understand the difference between different forms of the same word and how they relate to context. Furthermore, when generating text we wish to produce coherent grammar with consistent tense and perspective.

The CLiPS Pattern library has a number of tools for morphology of words. It provides a method of changing a word into its first, second or third person version, pluralisation and finding superlatives.[27]

2.4.2 Syntax

Syntax is the glue that binds words together. It gives us an understanding of the grammatical relationship between words and guides the building of phrases and sentences.

2.4.2.1 The Penn Treebank Tagset

Core to this area of research is *part-of-speech (POS)* analysis, which provides a model for grouping words together correctly, taking into account how words depend on each other. The big success story in this area is The Penn Treebank Tagset, an enormous corpus of annotated POS information [44]. The full tagset is given in Table A.3 in the Appendix. This accelerated progress of research in the area, as the paper had expected.

From these POS tags, we are able to create *grammars*, the structural rules of phrases and sentences, and *parsers* for those grammars that are able to extract grammatical structure from unstructured text.

For example, the phrase *John loves Mary* would be represented as in Figure 2.12 if parsed with a grammar based on The Penn Treebank tagset.
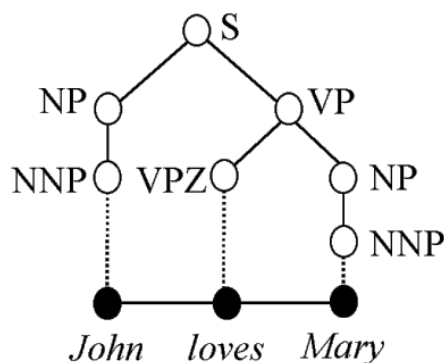
Figure 2.12: Parse tree of *'John loves Mary'*

Python's Natural Language Toolkit (NLTK)[15] is a suite of text processing libraries, corpora and lexical resources that is heavily used in this project, particularly for syntactical purposes. It will allow us to use The Penn Treebank tags as well as produce our own grammar and parser that can be used to parse most poetry. This is a challenge because we cannot expect poetry to follow grammatical rules as strictly as discourse. However, the pay-off will be that we can model the context of the poem, leading to better analysis of semantics and pragmatics of poetry.

2.4.2.2 Stanford Dependencies

The Stanford Dependencies[25] is another representation based around the relationships between words. All dependency relations are strictly binary and come in various

types depending on the participants, called the *governor* and the *dependent*.

It aims to make extraction of textual relationships more approachable to those without linguistic expertise by using more colloquial relationships, such as subjects and objects of a sentence. We represent the dependencies of a sentence as directed graphs with words at the nodes and the dependency relations as the edges between them. Figure 2.13 shows this for the sentence *'The shopkeeper told the customer to have a nice day'*
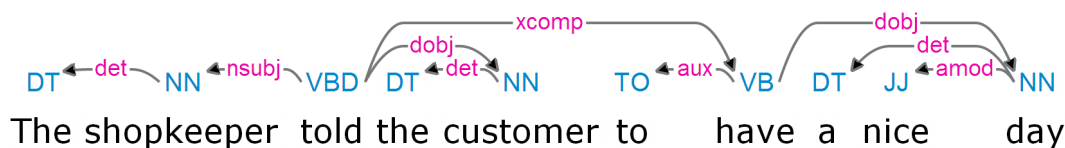
Figure 2.13: TurboParser Semantic Dependency parse for the shopkeeper example.

This was parsed using TurboParser[6].

2.4.3 Semantics

Noam Chomsky used the famous example *'Colourless green ideas sleep furiously'* to show that a valid grammatical syntax can be completely nonsensical[19]. This illustrates the importance of the study of semantics; the meaning of words and phrases, as well as pragmatics; the way context affects semantics. Suppose the context around Chomsky's example was a person with old (black-and-white, colourless) ideas of making money (green) that he wants to bring back (was put to sleep, but not peacefully), then this line would make some sense in a poetic way.

We first introduce the concepts of *anaphora* and *presuppostions* and techniques for resolving them. We then move on to discussing two current methods of understanding semantics in natural language; Discourse Representation Theory and Semantic Role Labelling.

2.4.3.1 Anaphora Resolution and Presupposition Projection

In linguistics, *anaphora* is the technique of using words that are used to refer to another object within a specific context. For example, the sentences *'Joe put on a coat because he felt cold'* and *'Because he felt cold, Joe put on a coat'* are both anaphoric, with *'he'* being the anaphor that refers to 'Joe', who in the earlier sentence is referred to as the

antecedent and in the latter as the *postcedent* because of the relative ordering of the word and its anaphor.

Presupposition is a similar technique, except that it works on implicit assumptions about the context. For example, the sentence *'The cat chased the mouse, but it managed to evade the feline.'* uses the assumption that the cat is a feline. It then projects this as a presupposition to avoid re-using the same word or introducing anaphora, while still indicating to the same object. This is a very useful linguistic technique, especially when used to make temporal inferences. The sentence *'Joe stopped playing the piano'* has the implicit assumption that Joe once played the piano.

Resolving anaphora and presupposition in text is an ongoing research area in Computational Linguistics. Various tools have been developed using a variety of techniques that are not discussed here. It is worth noting, though, that existing solutions generally do not use domain-specific or linguistic knowledge.

2.4.3.2 Discourse Representation Theory

Discourse Representation Theory (DRT)[37] is a framework for investigating semantics of natural language proposed by Hans Kamp. Abstract mental representations of DRT are Discourse Representation Structures (DRSs), which are designed to combine meaning across sentences and cope with anaphora (e.g. using pronouns in place of nouns, see Section 2.4.3.1).

Using Kamp's example, if we take the sentence *A farmer owns a donkey* and convert it into a DRS, we get the following notation:
`{[x,y: farmer(x), donkey(y), own(x,y)]}`

If we then say *He beats it.*, it will produce:
`{[x,y,z,w: farmer(x), donkey(y), own(x,y), PRO(z), PRO(w), beat(z,w)]}`

We can then use anaphora resolution on this DRS to produce:
`{[x,y: farmer(x), donkey(y), own(x,y), beat(x,y)]}`

We can see that this is similar to the notation used by Manurung in MCGONNAGAL, described in section 2.2.4.

This method has evolved over the years to take tense and aspect into account, providing temporal reasoning in natural language sentences. Accuracy of anaphora and

presupposition (e.g. saying 'animal' instead of 'cat', see Section 2.4.3.1) resolution
has improved with the use of the third-party tools in combination with the ideas of
Blackburn and Bos[16].

Extending this example, we may wish to model the sentence *Every farmer who owns a
donkey beats it.*. DRT provides an elegant solution for this using first order logic style
'for all':

`{[x][y][farmer(x), donkey(y), own(x,y)` $\rightarrow$ `beat(x,y)]}`

This allows us to provide background knowledge to the system and make inferences
on it. As a result of its usefulness in many applications, NLTK has included DRS
manipulation and anaphora resolution into its core semantics package.

Johan Bos and his team have begun the Groningen Meaning Bank (GMB) project[**BasileBosEvangVer**
], a large semantically annotated corpus in lieu of The Penn Treebank, in the attempt
to bring the same success and acceleration to this sub-field of research. They use DRT
as the backbone to an assembly of third-party tools to annotate semantics, as can be
seen in Figure 2.14. However, the GMB project is still in early stages and has only
annotated open license news articles up until now, which is not a suitable corpus for
many use-cases, including poetry generation.
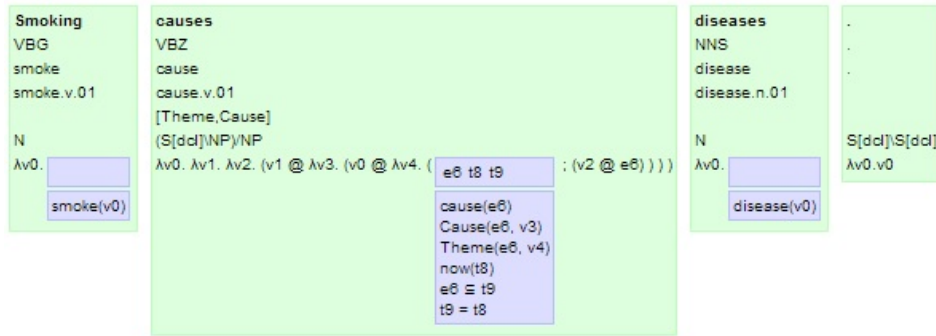
Figure 2.14: Semantic structure of the sentence *Smoking causes diseases.*

DRT in general is very effective when dealing with rule-based knowledge bases, in lieu
of declarative logic programming. Its proficiency at anaphora and presupposition res-
olution and handling "donkey phrases" make it applicable to question-answer systems,
where usefulness comes in determining truth or falsity of sentences.

However, it may not be an effective model for semantic relations that require classifi-
cation of different types of phrases and the roles of words in a sentence. It also requires

a very comprehensive and flexible grammar to be able to convert a large variety of English sentences into Discourse Representation Structures, especially if the sentences may not have perfect grammar as in poetry. For this, we use a method called Semantic Role Labelling.

2.4.3.3 Semantic Role Labelling

Semantic Role Labelling (SRL) is best described with an example. Take the sentence: *"The shopkeeper told the customer to have a nice day"* We wish to recognise the verb *'to tell'* as the coordinating word (called the **target**), *'the shopkeeper'* as the speaker, *'have a nice day'* as the message and *'the customer'* as the addressee. This output can be seen clearly in Figure 2.15, along with other potential labels.
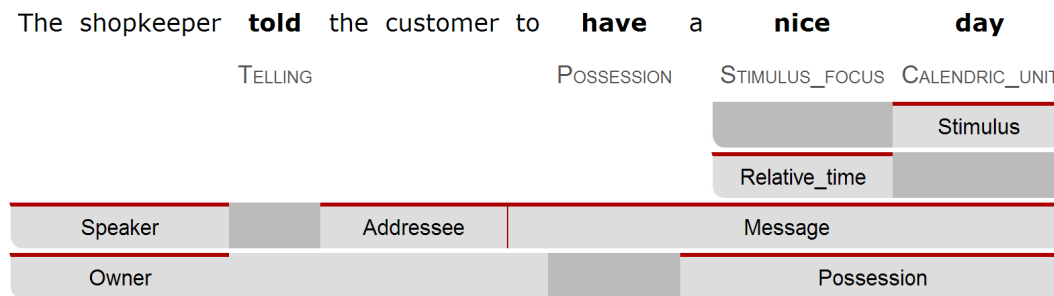
Figure 2.15: SEMAFOR frame-semantic parse for the shopkeeper example

This can be quite flexible as it can adapt to the syntactic structure of the sentence and does require absolute grammatical correctness. The SRL for the *"Yoda-speak"* equivalent will remain the same, as shown in Figure 2.16.
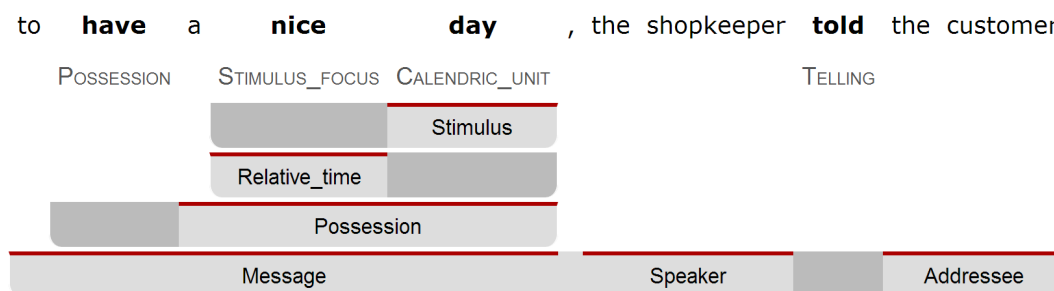
Figure 2.16: SEMAFOR frame-semantic parse for a grammatically incorrect sentence.

These examples are retrieved through the SEMAFOR tool[ref], which is one of a number of available SRLs[http://www.kenvanharen.com/2012/11/comparison-of-semantic-

role-labelers.html]. SEMAFOR was trained on FrameNet data (see 2.4.3.4.2) to determine the frame-semantic structure of the text.

While SRL may not be able to handle "donkey phrases" and does not inherently resolve anaphora or presuppositions, it is a much more effective method of extracting roles and relationships between words. The biggest benefit is that it is not entirely dependent on perfect grammar, which will be very useful in poetry analysis.

2.4.3.4 Semantic Knowledge Resources

There are various sources of different types of semantic information that are used to improve the quality of computational semantic understanding. Here we discuss those that are use heavily in this project and could potentially be used in the future.

2.4.3.4.1 WordNet WordNet is a widely used, high quality lexical database that provides hierarchical, conceptual-semantic and lexical relations of 155,287 English words[48].

Synsets in WordNet are sets of cognitive synonyms, e.g. *car* and *automobile* are in the same synset, but not *cable car*. The noun *bear* and it's verbal namesake are in separate synsets, aiding in word sense disambiguation.

A *hypernym* of a synset is a **type-of** relation. For example, the synset *mammal* is a hypernym of *cat* because cats are types of mammals. Similarly, *animal* is also a hypernym of *cat*, as well as being a hypernym of *mammal*. The *direct hypernym* of a synset is the synset directly above it in the hypernym tree; *feline* in the case of the cat. The *inherited hypernym* of a word refers to any word that appears in its *hypernym tree* as seen in Figure 2.17.

A *meronym* of a synset is a **part-of** relation. It denotes member constituents of other synsets. For example, the *wheel* synset is a meronym of *car*.

2.4.3.4.2 FrameNet FrameNet[10] is a lexicon with framing semantics to *define and constrain* the building of clauses around individual words. It describes the meaning of a word based on the words that typically participate with it, known as *frame elements* or *FEs*.

```
cat
  └ feline
      └ carnivore
          └ placental
              └ mammal
                  └ vertebrate
                      └ chordate
                          └ animal
                              └ organism
                                  └ living thing
                                      └ whole
                                          └ object
                                              └ physical entity
                                                  └ entity
```
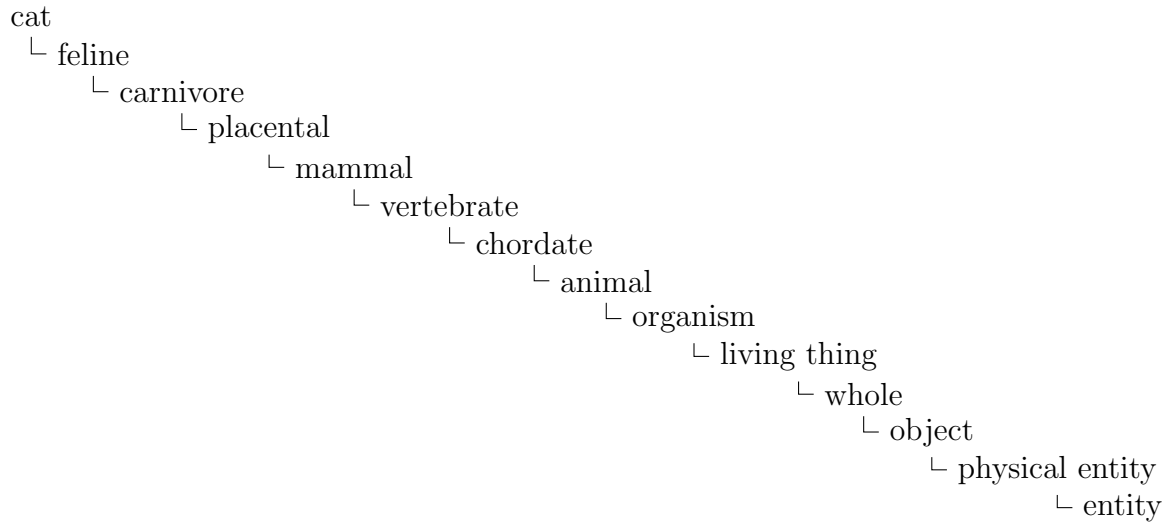
Figure 2.17: Full inherited hypernym tree for 'cat' synset according to WordNet

Frame Element	Number Annotated	Realisation(s)
Duration	1	PP[for].Dep(1)
Event AVP.Dep(1) PP[for].Dep(6)	16	VPto.Dep(9)
Experiencer	29	NP.Ext(29)
Focal_participant PP[for].Dep (9) PP[of].Dep (2) PP[over].Dep (1)	13	PP[after].Dep (3)
Time	1	NP.Dep (1)

Table 2.2: Frame elements for *yearn* lexical unit

Take the Desiring frame for example, which has a list of words, referred to as *lexical units* or *LUs* - that are used in statements that indicate desire, e.g. want, lust, yearn etc. Each of these LUs come with their own *lexical entries* that describe the FEs and *Valence patterns*. These define the types of phrases that can be built around a particular LU.

Take the *yearn* LU. It's FEs and Valence Patterns are shown in Tables 2.2 and 2.3.

Valence patterns are grouped by the permutation of FEs, e.g. *Event* and *Experiencer*, or *Experiencer* and *Focal_participant*. Each group comes with one or more Valence Patterns that indicate the type of phrase (NP means noun phrase, VP means verb

30

Number Annotated	Pattern 1	Pattern 2	Pattern 3	Pattern 4
1 TOTAL	Duration	Event	Experiencer	Experiencer
1	PP[for]			
Dep	VPto			
Dep	NP			
Ext	NP			
Ext				
15 TOTAL	Event	Experiencer		
1	AVP			
Dep	NP			
Ext				
6	PP[for]			
Dep	NP			
Ext				
8	VPto			
Dep	NP			
Ext				
10 TOTAL	Experiencer	Focal_participant		
3	NP			
Ext	PP[after]			
Dep				
7	NP			
Ext	PP[for]			
Dep				
2 TOTAL	Experiencer	Focal_participant	Focal_participant	
2	NP			
Ext	PP[for]			
Dep	PP[of]			
Dep				
1 TOTAL	Experiencer	Focal_participant	Time	
1	NP			
Ext	PP[over]			
Dep	NP			
Dep				

Table 2.3: Valence patterns for *yearn* lexical unit

phrase etc.), as well as the role in the clause - Ext (Subject), Obj (Object) and Dep (Dependency or Indirect Object).

FrameNet also provides *semantic types* with every FE of a frame. This indicates the required animation of any noun in all Valence patterns of the LU. For example, the *Experiencer* FE is a *Sentient* semantic type, while the *Event* FE has the *State_of_affairs* semantic type.

2.4.3.4.3   Oxford Collocations Dictionary   The Oxford Collocations Dictionary[24] is a source of word combinations. For any given word, it provides the set of words and POS commonly occur in relation to it.

The dictionary entry for *custard* can be seen in Figure 2.18. It gives common adjectives that are used to describe custard and the verbs that use custard as the subject or object. It also shows that we can make more complex nouns by appending the words *powder* and *pie*.

custard *noun*

ADJ. **creamy, thick | thin | smooth | lumpy | banana, egg, vanilla**

VERB + CUSTARD **make | pour | strain** *Strain the custard to remove lumps.*

CUSTARD + VERB **thicken | set**

CUSTARD + NOUN **powder | pie**

PHRASES **and/with custard** *some apple pie and custard* > Special page at FOOD

Figure 2.18: Oxford Collocations Dictionary entry for *'custard'*

2.4.3.4.4   Associations   The University of South Florida Free Associated Norms[49] provides associations collected directly from human participants. It is used by the Department of Psychology, and is therefore another high quality source of associated words that can be depended on for quality as it was collected in a scientifically sound manner.

2.4.3.4.5   NodeBox Perception   The NodeBox Perception model includes the data used in De Smedt's attempt to model common sense as a network, as discussed

in Section 2.3.0.1. This data was manually entered into the system and continues to be used for research, which means that it is a dependable source of data.

2.4.3.4.6   Google Search Suggestions   Tony Veale's attempt at modelling metaphors[56] introduced a clever use of Google's search suggestions as a method of finding associations between words and ultimately build Metaphor Magnet. While we may not use Metaphor Magnet, we take inspiration from his use of Google's search suggestions.

This is the least dependable source of information that we use because it is dependant on search suggestions rather than structured sentences. Therefore we will use this method with caution.

2.4.3.4.7   Noah's ARK Informal Research   Noah's ARK is an informal research group run by Noah Smith at Carnegie Mellon University[4] whose research focuses on problems of *ambiguity* and *uncertainty* in natural language processing. They provide online API access to two tools for linguistic structure analysis:

1. **SEMAFOR**[18] for SRL using FrameNet.

2. **TurboParser**[6] for Standford Dependency parsing.

SEMAFOR is particularly resource heavy, requiring a minimum of 8 gigabytes of random access memory. However, the request response from the online API is fairly quick - typically 1.24 seconds for simple sentences and 1.61 seconds for complex ones, tested using the specifications in Appendix A.4.

Noah's ARK request response is in JSON format and includes data from both SEMAFOR and TurboParser. TurboParser returns the Semantic Dependency Parse in CoNLL data format, whose structure can be seen in Table 2.4.

2.4.4   Natural Language Generation

Natural Language Generation is the term for putting some non-linguistic form of content into understandable text in a human language. Reiter and Dale give the framework[51] illustrated in Figure 2.19 for the process of generating natural language.

A similar model was propsed by Bateman and Zock[13], which includes four stages:

Field Number	Field Name	Description
1	ID	Token counter, starting at 1 for each new sentence.
2	FORM	Word text form or punctuation symbol
3	LEMMA	Lemma or stem of FORM
4	CPOSTAG	Coarse-grained part-of-speech tag
5	POSTAG	Fine-grained part-of-speech tag
6	FEATS	Unordered set of syntactic and/or morphological features
7	HEAD	ID of the parent of the current token ('0' if root)
8	DEPREL	Dependency relation to the HEAD
9	PHEAD	Projective head of current token
10	PDEPREL	Dependency relation to the PHEAD

Table 2.4: The CoNLL data format output by TurboParser.

Goal

Text
Planner

Text Plan

Sentence
Planner

Sentence Plans

Linguistic
Realiser
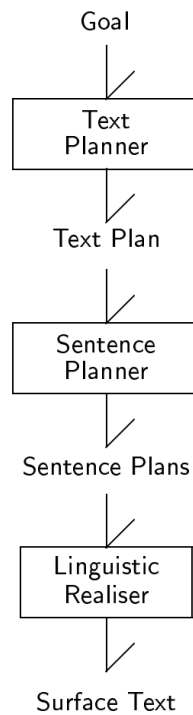
Surface Text

Figure 2.19: Reiter and Dale Natural Language Generation process

1. *Macro Planning:* Overall content of the text is structured.

2. *Micro Planning:* Specific words and expressions are decided.

3. *Surface Realisation:* Grammatical constructs and order are selected.

4. *Physical Presentation:* Final articulated text is presented.

SimpleNLG[34] is a Java library that provides useful functionality for natural language generation using the ideas of Reiter and Dale. In particular, it enables us to build *phrases* for nouns, verbs, prepositions, adjectives and adverbs that can be enriched with grammatical metadata such as tense, aspect and perspective (for verbs), as well as plurality, gender and animation for nouns.

These phrases can then be put together into *clauses* that define the roles of each phrase in the desired sentence, for example by specifying the subject and object noun phrases. It then *realises* a grammatically correct natural language sentence taking all of the provided information into account.

There are others, such as grammar generation implemented by NLTK (similar to the one used in MCGONNAGAL) or the constraint programming technique used by Toivanen et al. explained in section 2.2.2. However, we find that this process is not granular enough, jumping from the goal to the surface text without enough consideration for the individual words used.

More elaborate tools exist, such as KPML[12] and FUF[32]/SURGE[33], that have greater grammatical coverage than SimpleNLG. However, they are either no longer maintained or too complex for our purposes.

Chapter 3

Poem Analysis

The first phase of implementation involves writing a suite of algorithms to analyse a single poem in terms of the features mentioned in section 2.1.2. The aim is to run a large collection of poems through this analysis to learn the usage patterns of poetic features for any collection of poems. This is in line with the ultimate aim of generating poems without hard-coded rules for different types of poems.

The algorithms will cover the detection of the use of:

- Rhyme and internal rhyme
- Rhythm, including meter and syllable count
- Alliteration, assonance, consonance, onomatopoeia and other sound devices
- Structure, tense, point of view and repetition

Other algorithms will attempt to understand the context of the poem to extract:

- Characters
- Objects
- Locations
- Descriptions
- Relationships
- Actions
- Symbolism including metaphors, similes and personification

The output of this phase is a full analysis of a single poem. In lieu of this, we will walk through the implementations of each of these algorithms using the poems in Figures 3.1 and 3.2 as case studies.

There once was a big brown cat
That liked to eat a lot of mice.
He got all round and fat
Because they tasted so nice.

Figure 3.1: A rhyming quatrain often used in teaching poetry

The limerick packs laughs anatomical
Into space that is quite economical.
But the good ones I've seen,
So seldom are clean,
And the clean ones so seldom are
comical.

Figure 3.2: A limerick about limericks

[DH EH1 R]
[W AH1 N S]
[W AA1 Z], [W AH1 Z], [W AH0 Z], [W AO1 Z]
[AH0], [EY1]
[B IH1 G]
[B R AW1 N]
[K AE1 T]

Figure 3.3: The different ways of pronouncing the first line of the cat poem

3.1 Obtaining Phonetic Structure

Poets choose words based the *sound* when spoken out loud as well as their (literal or symbolic) meaning. As explained in section 2.4.1, we can use Carnegie Mellon University Pronounciation Dictionary (CMUPD) to get around the difficulty of determining phonetic structure. A word in the CMUPD is mapped to a list of different pronunciations for the same word. Each pronunciation is a list of phonemes that make up that particular pronunciation of that word, including indication of emphasis on the syllables.

We want to convert the poems into their pronunciations for use by the detection algorithms. This needs to be done word by word, so we first need to *tokenise* the sentence. Tokenisation involves splitting each sentence into a list of its basic components; words and punctuation. Once we have that, we iterate through the list and run each word through the CMUPD. Some words have multiple pronunciations, so we consider each possible permutation of pronouncing each line of the poem. Each of the pronunciations of the first line of Figure 3.1 is shown in Figure 3.3.

Unfortunately, the CMUPD only has about 133,000 words. This means that we are occasionally unable to translate to the phonetic structure, particularly in Shakespearean

poems. We get around this by temporarily converting the word into its closest match that exists in the dictionary and returning the phonetic structure in its place.

Python *difflib*[3] provides a function to find the closest matches of a word to a list of words, based on the Ratcliff/Obershelp pattern recognition algorithm. The complexity of this algorithm is quadratic in the worst and average case, linear in the best case.

The behaviour is based on how many subsequences the words have in common. Since we are only dealing with single words at a time, we have a higher chance of the best case.

We could use a variety of other techniques to get around this problem other than string matching:

- Break many syllable words into likely part-words, e.g. *'thrift'* and *'less'* instead of *'thriftless'*.

- Try all combinations of stress and syllables.

- Train a finite-state transducer model as in Dobrivsek et al. 2010[30].

The first option only works in a limited number of situations, most of which are handled by the string matching solution. For example, *'thriftless'* would become *'shiftless'*, which has an identical phonetic structure. The second option can result in poor performance and more false negatives or false positives than would be worth the added processing.

The final option is the most viable and would be used if the generation phase depended on perfect readings of the poems, such as in the stochastic n-gram methodology of RKCP (section 2.2.3). We only need an approximation for each individual poem because our results will depend on the analysis of a large number of poems, which will reduce the bias caused by any anomalies.

3.2 Rhyme

We want to detect end-line and internal rhyme, as described in section 2.1.2.1. We want to be able to build a normalised rhyme scheme representation for easy analysis in the abstraction phase.

First we collect the pronunciations of the words for which we wish to build a rhyme scheme. For end-line, we collect the last word of each line of the poem. For internal rhyme, we collect the all the words in a particular stanza.

Once we have our list, we can run it through the following algorithm:

```
1 for each word in the list:
2   for each pronunciation of the word:
3     for each phoneme in the pronunciation:
4     if this phoneme is stressed:
5       get the tail of the pronunciation from this phoneme onwards
6       get the rhyme phoneme pattern of this tail
7       if we have seen this pattern before:
8         assign it the corresponding rhyme token
9       else:
10         assign this pattern a new rhyme token
11
12       append this token to a set of possible tokens for this word
13   append the set of possible tokens for this word to the unzipped rhyme scheme
14 build all possible permutations of rhyme scheme from they unzipped rhyme scheme
15 normalise the rhyme schemes
```

There are a few tricks to this algorithm, namely obtaining the rhyme phoneme pattern on line 6 and the process of building and normalising the rhyme scheme in lines 12 to 15. These processes are explained in the coming sections.

3.2.1   Obtaining the Rhyme Phoneme Pattern

Words rhyme when both of the following conditions are met:

- the last phoneme of each word match

- the vowel sounds from the first *stressed* syllable match **in order**

The algorithm finds the first stressed syllable in lines 3 and 4. Once it is found, we iterate through the rest of the pronunciation, checking the *vowel* sounds and the *last* phoneme. Putting them together, in order, gives the rhyme phoneme pattern, which we can compare directly to find matching rhymes. Examples are illustrated in Figure 3.4.

Kite: K **AY1 T**

Height: H **AY1 T**

(a) Kite and Height

Turtle: T **ER1** T **AH0 L**

Purple: P **ER1** P **AH0 L**

(b) Turtle and Purple

Strategy: S T R **AE1** T **AH0** JH **IY0**

Tragedy: T R **AE1** JH **AH0** D **IY0**

(c) Strategy and Tragedy

Figure 3.4: Pairs of matching rhyme phoneme patterns

3.2.2 Building and Normalising the Rhyme Scheme

Each unique rhyme phoneme pattern is represented by a single capital letter starting with 'A'. This is the standard convention for rhyme schemes used in literary theory.

The fact that a single word may have several pronunciations creates a complication. To cope with it, we create a tuple for every possible rhyme pattern for a each word. The list of these tuples is what the algorithm refers to as the 'unzipped' rhyme scheme on line 12 and 13. Table 3.1 shows the unzipped rhyme scheme for the limerick in Figure 3.2. Note that the word *'anatomical'* has two pronunciations that affect the rhyme pattern, according to the CMUPD.

We then build every possible permutation of this list, which then gives us all of the possible rhyme schemes for the given words. We leave this list as it is and do not make a claim for any rhyme scheme to be more likely than any other at this stage.

(A,B)	(B)	(C)	(C)	(B)
anatomical	economical	seen	clean	comical

Table 3.1: Unzipped rhyme scheme for the limerick

The only possible rhyme scheme for the cat poem is $ABAB$, while the limerick could be either $AABBA$ or $ABCCB$ (equivalently, $CABBA$ so just the first word is ambiguous).

3.3 Rhythm

We attempt to recognise all three types of rhythm described in 2.1.2.2.

3.3.1 Detecting Syllabic Rhythm

The number of syllables in a word is equal to the number of vowel phonemes it has. We know that all vowel phonemes have a stress marker appended to them so counting the number of stress markers in the word will give us the number of syllables.

Syllabic rhythm is done on a line-by-line basis, so we tokenise each line and aggregate the syllables across all words in the line.

If we take one permutation of the line in Figure 3.3, we can see that each word has one vowel phoneme, i.e. each word in that sentence is monosyllabic. Therefore the number of syllables in the line is 7.

The full syllabic rhythm for the poems in Figure 3.1 and 3.2 are 7-8-6-7 and 11-6-5-11-11 respectively. We represent these as a tuple of integers and create a separate list of them for each stanza.

3.3.2 Detecting Quantitative and Accentual Rhythm

While theory counts rhythm in terms of metre and feet, as described in 2.1.2.2, some poems might have rhythm without following one of these pre-defined popular styles. Instead of searching for them specifically, we will extract the pattern of stressed and unstressed syllables for each line without making a claim on how it matches to theory.

We choose to do this mainly because there could be multiple possibilities for the stress pattern of a line due to variations in emphasis for particular words, e.g. *'**ob**ject'* and *'ob**ject**'*. The variability of possible stress patterns is compounded by limitations of the CMUPD:

- Some words are restricted to a single stress pattern even though it does not lose or change the meaning of the word if it was emphasised differently. For example, *'**quan**tity'*, *'quan**ti**ty'* and *'quanti**ty**'* are all valid, but the CMUPD only recognises the first because the other two are unusual in normal speech, but not necessarily for poetry.

- Similarly, the CMUPD fixes monosyllabic words to one of stressed or unstressed as in Figure 3.3. In poetry, however, they can be either so we need to allow for both possibilities.

- Stresses on some words have changed over time. For example ***prov**ed* was pronounced *prov**ed*** in Shakespeare's era.

- Though not necessarily a limitation, we do not recognise light or secondary stress in a word (the '2' stress marker). We therefore assume it could be either '1' or '0'.

- Poetic license often allows words to be pronounced with an entire extra syllable. For example *'de-served'* could be pronounced as *'de-ser-ved'*.

We account for these by manually increasing the possible phonetic stress marker readings. Unfortunately, this will lead to an unrealistically large number of possibilities. For example, the line in Figure 3.3 will give us all combinations of '1's and '0's.

We narrow this down by taking away any occurrences of the same stress three or more times in a row in the same line because it will never be read this way.

Like with rhyme, we do not make a claim for any stress pattern to be more likely than any other at this stage.

(1,0)	(1,0)	(1,0)	(1,0)	(1,0)	(1,0)	(1,0)
There	once	was	a	big	brown	cat

Table 3.2: All permutations of stress pattern are possible for the first line of the cat poem

(1,0)	(100)	(1,0)	(1,0)	(00100, 10100)
The	limerick	packs	laughs	anatomical

Table 3.3: Any permutation of these stress patterns are possible for the first line of the limerick

3.4 Sound Devices

We aim to detect each of the sound devices described in 2.1.2.3; alliteration, assonance and consonance.

The implementation for all three of them is very similar. For each line, we map each phoneme to the number of times it occurs and return those that occur more than once.

The only difference is that assonance only looks at *vowel* phonemes (i.e. with a stress marker) and consonance only looks at *non-vowel* phonemes. Alliteration only looks at either the *first* phoneme of each word in the line, or the *first stressed* phoneme and the one *immediately before* that.

For example, take the phrase *"Slither slather"*:

- **Consonance**: The phonemes *S*, *L* and *DH* occur twice.

- **Assonance**: The phoneme *ER0* occurs twice.

- **Alliteration**: The phonemes *S* and *L* occur twice each at the start of the word.

Common phrases like *'take away'* would give an assonance score on the *EY1* phoneme, which may not be intended. Therefore, we put a condition that we the occurrence counts for each sound device must be greater than 2. For example, consonance has a total occurrence score of six, assonance of two and alliteration of four. Therefore, the assonance would not be recognised.

Take another example: *"Mammals named Sam are clammy"*

- **Consonance**: *M* occurs five times while *L* occurs twice.

- **Assonance**: The phoneme *AE1* occurs thrice.

- **Alliteration**: None.

3.5 Form

We implement some detectors for the form and structure of the poem.

3.5.1 Structure and Repetition

The algorithms for detecting the features of structure described in section 2.1.2.4 are:

Number of stanzas

Count blank lines and add 1

Number of lines per stanza

Count new line characters of each stanza

Number of distinct sentences

The number of sentences returned when parsed using the CLiPS[27] *parsetree* function. More lines than sentences indicates **enjambment**.

Number and location of repeated lines

Find the list of non-unique lines. For each of those lines, find its line number locations in the poem.

The poem in Figure 3.1 has one stanza, four lines, no repeated lines and two distinct sentences, indicating enjambment.

The poem in Figure 3.2 has one stanza, five lines, no repeated lines and four distinct sentences, indicating enjambment.

3.5.2 Point of View

We can also determine the point of view of the speaker, i.e. whether it is in first or third person. If we find the word *'I'* anywhere in the poem and as long as it is outside speech marks, we say that the entire poem is in first person. Otherwise we default to third person. Figure 3.1 is written in third person but Figure 3.2 is in first person.

3.5.3 Tense

The tense of each line can be found by analysing the verb in that sentence. CLiPS pattern library provides a method of doing this using their *'tenses'* function. It also gives us the *aspect*, e.g. perfect, progressive. However, tests found this to be less accurate so we will settle for just the tense.

We record the tense of each line as well as the overall tense of the poem. Each line in the cat poem in Figure 3.1 is in past tense giving a past tense overall. The limerick in Figure 3.2 is in present tense overall because all but one line, is in present tense.

3.5.4 N-Grams

Python NLTK provides functionality for breaking up text into constituent *n-grams*, consecutive words of length `n`. We cover all lengths of `n` up to the size of the each line and count the frequency of occurrence of these n-grams across all poems for each particular line. The n-grams for all `n` in the first line of the cat poem are shown below.

1-grams
> *There, once, was, a, big, brown, cat*

2-grams
> *There once, once was, was a, a big, big brown, brown cat*

3-grams
> *There once was, once was a, was a big, a big brown, big brown cat*

4-grams

There once was a, once was a big, was a big brown, a big brown cat

5-grams

There once was a big, once was a big brown, was a big brown cat

6-grams

There once was a big brown, once was a big brown cat

7-grams

There once was a big brown cat

The unique n-grams with highest **n** that occur with significant frequency in a particular line across all poems are recorded. This will help us identify phrases commonly used for a single type of poetry and their location in the poem. For example, the perception that limericks starting with *'There was a'*.

3.5.5 Topics

Limericks typically talk about people and places, haikus about nature and seasons, sonnets about thoughts and emotions. We need to recognise the topics that poems cover so that our poems can follow suit, especially when there is no other source of inspiration.

We use the hypernym relation provided by WordNet to find the categories of the nouns used in the poem. We save the entire inherited hypernym tree (see Section 2.4.3.4.1) for each noun in each poem as a list of synsets. This list is compared with other poems in the interpretation stage, where we record the synsets that occur with significant frequency.

3.6 Characters and Context

Here we describe our approach to determining the context of the poem in terms of its characters and their relationships as described in section 2.1.2.6. The aim is to

build a representation of the characters much like the conceptual networks described in Section 2.3.0.1. This will then be compared in the abstraction phase to find a correlation between these representations and collections of poetry.

3.6.1 Semantic Relations

The semantic relations between persona in this project are based on those used in ConceptNet, the semantic network of and general knowledge described in Section 2.3.0.1.1. We can use the following relations to build our desired representation.

MadeOf

What is it made of?

E.g. tree - MadeOf → wood

IsA

What kind of thing is it?

E.g. banana - IsA → fruit

AtLocation

Where would you find it?

E.g. priest - AtLocation → church

CapableOf

What can it do?

bird - CapableOf → sing

Desires

What does it want?

banker - Desires → his loan to be repay

HasA

What does it have in its possession?

old person - HasA → white hair

HasProperty

What properties does it have?

doctor - HasProperty → smart

PartOf

What is it part of?

player - PartOf → team

ReceivesAction

What can you do to it?

book - ReceivesAction → read

CreatedBy

How do you bring it into existence?

sound - CreatedBy → vibration

UsedFor

What do you use it for?

guitar - UsedFor → make music

MotivatedByGoal

Why would you do it?

learn - MotivatedByGoal → knowledge

Believes

What does the character perceive to be true?

Little Red Riding Hood - Believes → Wolf is her grandma

SendMessage

What did the character say or write?

Little Red Riding Hood - SendMessage → What a big mouth you have

ReceiveMessage

What did the character hear or read?

Little Red Riding Hood - ReceiveMessage → The better to eat you with!

TakesAction

What did the character do?

Wolf - TakesAction → Swallow Little Red Riding Hood

Named

What is the name of the character?

Gotham Vigilante - Named → Batman

MakesSound

What sound does the character make? Used for onomatopoeia detection 3.7.2

bird - MakesSound → tweet

Each of these relationships has its corresponding inverse, e.g. *NotIsA*.

We want to use this representation to guide the generation process. To do this, we must analyse these relationships in existing poems and find correlations between them in the interpretation phase. For example, we may find that *Named* relations tend to occur in the first line of a poem, or what relation should be created if we need to extend the content of the poem.

To do this, we need to be able to extract the aforementioned relationships between concepts in a particular poem. If done correctly, the poem in Figure 3.1 will give us:

- cat - HasProperty → big

- cat - HasProperty → brown

- cat - Desires → eat a lot of mice

- cat - HasProperty → round

- cat - HasProperty → fat

- lot of mice - HasProperty → tasted so nice

- lot of mice tasted so nice - Causes → cat got all round and fat

The poem in Figure 3.2 will give us:

- limerick - TakesAction → packs

- laughs - ReceivesAction → packs

- laughs - HasProperty → anatomical

- space - HasProperty → quite economical

- laughs - AtLocation → space

- ones - HasProperty → good

- ones - NotHasProperty → clean

- ones - ReceivesAction → seen

- I - TakesAction → seen

- ones - ReceivesAction → seen

- ones - HasProperty → clean

- ones - NotHasProperty → comical

3.6.2 Semantic Labelling using Noah's ARK

We cannot determine these relationships from a syntactical parse alone due to the complex nature of the English language, in particular verb usage. For example, the phrase *tasted so nice* is a description rather than an action because the word *tasted* in this case is being used as a linking verb, where it is usually an action verb.

These complexities are further compounded by the fact that we cannot rely on correct grammar in poems. We therefore need a *semantic* parse.

We use SEMAFOR and TurboParser in conjunction via Noah's ARK to extract semantic relations from natural language.

3.6.2.1 FrameNet Semantic Role Labelling using SEMAFOR

We can use the SEMAFOR tool to derive the semantic relations by looking for the occurrence of corresponding FrameNet frames, and elements therein. The manually chosen list of frames and elements that translate directly into a particular relation is given in the Appendix, section A.5.

Each list may not be exhaustive for its corresponding semantic relation and there are some relations that will not be picked up by this method.

3.6.2.2 Semantic Dependency Relations using TurboParser

SEMAFOR is trained on FrameNet. As explained in Section 2.4.3.4.2, FrameNet is still in ongoing research and may not find all of the semantic relations between words. In this case, we use the Stanford Dependencies syntactical parse to infer semantic information in attempt to fill the gaps left by the frame-semantic parse. We use the following heuristics:

governor - HasProperty → dependent

If the dependency relation is *'amod'*, *'conj'* or *'poss'* or if the dependent is an adjective.

governor - atLocation → dependent

If the dependency relation is *'agent'*, *'nsubj'* or *'prep'*, dependent is not a preposition, verb or 'WH' word and is a *location preposition* (in, at etc.).

governor - IsA → dependent

If the dependency relation is *'agent'*, *'nsubj'* or *'prep'*, dependent is not a preposition, verb or 'WH' word and is not a preposition itself.

governer - ReceivesAction → dependent

If the dependency relation is *'nusbjpass'* or *'dobj'* and the dependent is a verb.

governer - CapableOf → dependent

If the dependency relation is *'xsubj'* or *'rcmod'*.

governer - TakesAction → dependent

If the dependency is a verb whose lemma is not 'be' and no other relation has been found for this dependency.

Together, these tools provide fairly comprehensive coverage of the desired semantic relations.

3.6.3 Extracting and Binding Relations to Characters

If we were to use the methods described above as they are, the derived semantic relations would only be a set of abstracted frames and matched dependencies. This

(a) Hub for the 'shopkeeper' persona

(b) Hub for 'customer' persona
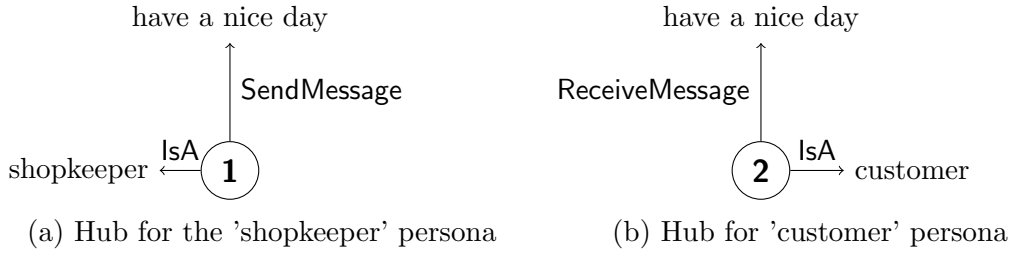
Figure 3.5: Persona hubs diagram for shopkeeper example

(a) Hub for the 'cat' persona

(b) Hub for the 'lot of mice' persona
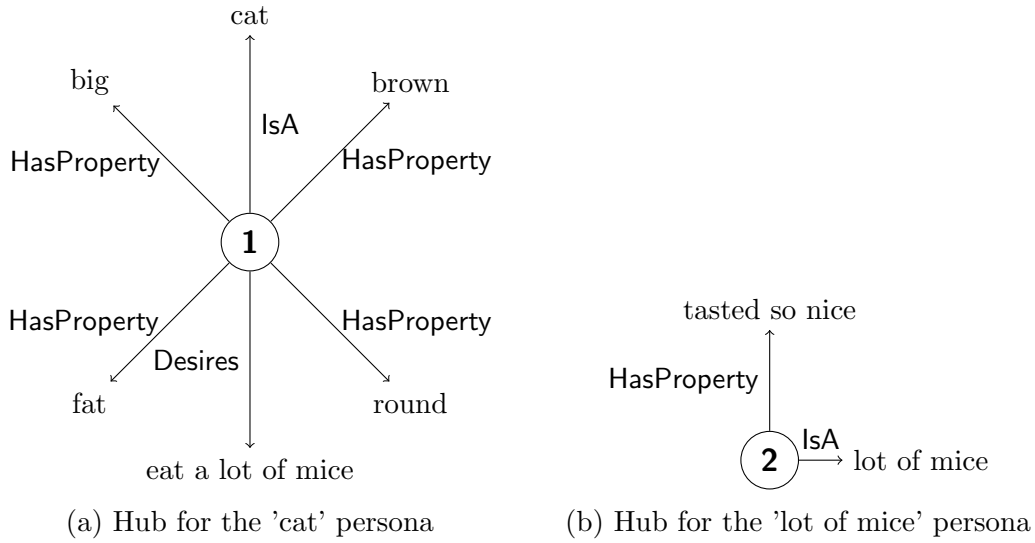
Figure 3.6: Persona hubs diagram for cat poem example

alone does not give us much more information than if we were to use the frame-semantic parse on its own. The true usefulness of this approach arises when the relations can are **bound** to persona in the poem.

For the shopkeeper example, we would recognise *'the shopkeeper'* and *'the customer'* as persona with *SendMessage* and *ReceiveMessage* relations bound to each of them with respect to the *'have a nice day'* message.

To accentuate the persona-centred structure, we can represent the desired output as a set of *hubs*, with each persona at the centre of the hub. Figures 3.5, 3.6 and 3.7 show this for the shopkeeper, cat poem and limerick examples respectively.

This will help guide the generation phase because we will know the *number of persona* typical for a collection of poems, the *number and type of relations* associated with *each* persona, as well as allow us to find commonalities in the types of persona themselves.

packs

TakesAction

limerick ←―― IsA ―(**1**)

(a) Hub for the 'limerick' persona

quite economical

HasProperty

(**2**) ―― IsA ―→ customer

(b) Hub for 'space' persona

packs

ReceivesAction

(**3**) ― IsA ―→ laughs

HasProperty

anatomical

(c) Hub for the 'laughs' persona

seen

TakesAction

(**4**) ― IsA ―→ I

(d) Hub for 'I' persona

good   limericks

HasProperty   IsA

(**5**)

ReceivesAction   NotHasProperty

seen   clean

(e) Hub for the persona represented by the first occurrence of 'ones'

clean   limericks

HasProperty   IsA

(**6**)

ReceivesAction   NotHasProperty

seen   comical

(f) Hub for the persona represented by the second occurrence of 'ones'

Figure 3.7: Persona hubs diagram for limerick example

To reach the desired representation, we execute this algorithm:

```
1 for each sentence in the poem:\\

2   get the dependency relations and frame-semantic parse\\

3   collapse loose leaves of the dependency relations\\

4   find and create possible persona objects\\

5   find candidate semantic relations from the frame-semantic parse\\

6   for each character object:\\

7       get all associated dependency relations\\
```

```
8      for each associated dependency relation:\\
9        if the dependent is involved in a candidate relation from the frame-semanti
10         bind the relation to the current character object and continue\\
11  else:\\
12         use the heuristics for dependency relations to find possible semantic rel
13 bind any that are found to the current character object and continue\\
```

We will describe each step in detail.

3.6.3.1 Obtaining the Semantic Dependency Relations and Frame-Semantic Parse from Noah's ARK

We leave the frame-semantic parse from SEMAFOR in its original JSON format because we only need to access this data once when finding the candidate relations on line 5 of Algorithm BLAH. We parse the CoNLL data format of the dependencies into a dictionary shown in Table 3.4 for easy access and processing downstream.

3.6.3.2 Collapsing Loose Leaves of Dependency Relations

In a lot of cases, the persona or relation that we look for are represented by phrases, not just a words. For example in Figure 3.8 the character should be *'a lot of mice'* rather than just the noun *'mice'*. In fact if we skipped this step of the algorithm, we would get two characters - *'lot'* and *'mice'* - which is obviously wrong.
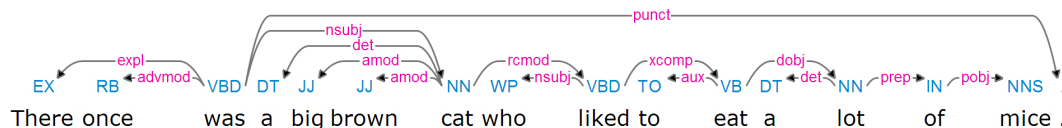
Figure 3.8: TurboParser Semantic Dependency parse for the first sentence of the cat poem.

Another example is the phrase *'tasted so nice'* as in Figure 3.9. If we did not collapse the tree, we would have that *'they'* can be described as *'nice'* and took the action of *'taste'*, both of which are wrong again.

ID	FORM	CPOSTAG	POSTAG	HEAD	DEPREL
1	There	EX	EX	3	expl
2	once	RB	RB	3	advmod
3	was	VB	VBD	0	null
4	a	DT	DT	7	det
5	big	JJ	JJ	7	amod
6	brown	JJ	JJ	7	amod
7	cat	NN	NN	3	nsubj
8	who	WP	WP	9	nsubj
9	liked.	VB	VBD	7	rcmod
10	to	TO	TO	11	aux
11	eat	VB	VB	9	xcomp
12	a	DT	DT	13	det
13	lot	NN	NN	11	dobj
14	of	IN	IN	13	prep
15	mice	NN	NNS	14	pobj
16	.	.	.	3	punct

Table 3.4: The dependencies dictionary data structure for the first sentence of the cat poem.
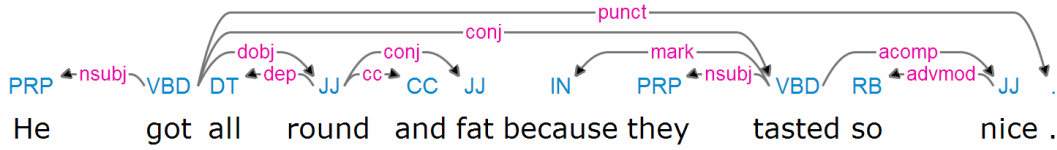
Figure 3.9: TurboParser Semantic Dependency parse for the second sentence of the cat poem.

To solve this, we merge leaves of the tree together if the dependency is 'collapsable' as per a set of conditions listed in the Appendix, section A.6.

By default, the parent of the dependency keeps all its attributes unchanged except for merging its form with that of the leaf, e.g. 'of' and 'mice' becomes 'of mice'. However, there are some cases where we wish to retain the part-of-speech (POS) tag of the leaf and overwrite the parent's POS tag:

- If the leaf is an adjective, the parent is a verb and the dependency relation is *dep* then we retain the adjective POS tag. These conditions usually imply a *linking verb*, generally used to describe a property; not an action. For example, *tasted so nice* is an adjectival phrase despite the use of a verb.

- Collapsing an *acomp* dependency relation should also retain the child POS tag because it too is evidence of a linking verb.

- The *pobj* and *prep* dependency relations are evidence of prepositions, which often link words together that lose meaning when separated. For example, *'of mice'* should retain the 'NNS' POS tag of *'mice'* rather than keep the 'PRP' POS tag of *'of'*.

Then we follow this algorithm:

```
1 get a list of all the leaves in the graph.\\

2 for each leaf in the reverse of this list:\\

3   if the dependency relation of this leaf (i.e. from its parent to it) is collapsab

4     get the parent\\

5     merge the form of the parent and the leaf\\

6     if necessary, the parent retains the part-of-speech tag of the leaf\\

7     the leaf is destroyed and the parent becomes the leaf.\\

8     loop back to line 3.\\
```

Figure 3.10 shows a dry run of this algorithm on the first line of the cat poem as shown in Figure 3.8.

The final diagrams of the collapsed dependencies for the full cat poem example can be seen in 3.11

(a) First sentence.

(b) Second sentence.
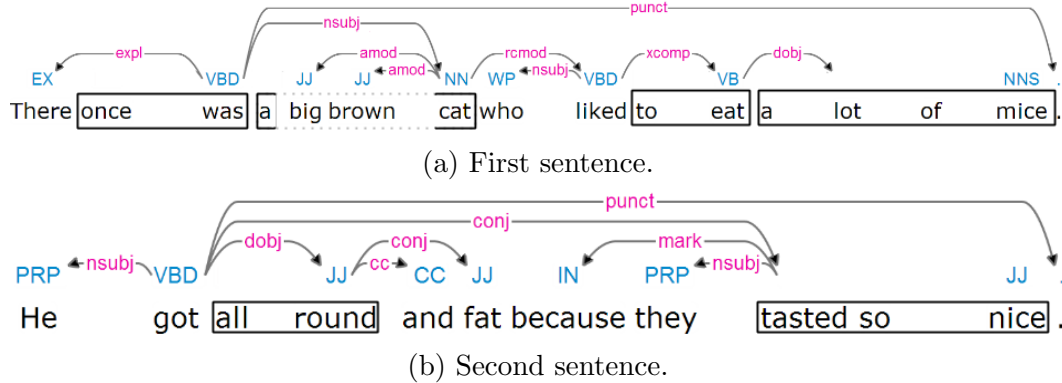
Figure 3.11: Final collapsed dependency diagrams for full cat poem example.

3.6.3.3 Finding and Creating Persona

A naive method for finding persona would be to simply extract nouns and pronouns. This would actually be sufficient for a basic level of analysis, but this does not account for anaphora and presuppositions (see Section 2.4.3.1). Notice that in the second half of the cat poem, the pronoun 'he' is used to refer to the 'cat' persona and 'they' to the 'a lot of mice' persona.

I will not be using any out-of-the box anaphora resolution tools like the ones mentioned in 2.4.3.1. Instead, I will take advantage of the persona creation to create a bespoke solution.

The solution requires some basic semantic information about the persona. We would like to determine whether the phrase representing the character:

1. is plural or singular.

2. is male, female, neutral or unknown.

3. is a living object, an inanimate physical object or a non-object.

Determining the first point is the most straightforward:

- if it is a noun and the POS tag ends in an 'S', it is plural (see 'mice' tag in 3.8).

- if it is a pronoun, check for membership in a manually built list of plural pronouns (e.g. 'they', 'them').

The pronoun case for the second point is similar; we check for membership in the manually built list of male pronouns (e.g. 'he', 'him') and the separate list of female pronouns (e.g. 'she', 'her').

The noun case is trickier. First we need to find the *synset* of the noun. Once we have this, we can use the *hypernym* relationships between synsets. Finally, we can check for whether a noun is male or female by looking for the existence of particular synsets that imply a gender. For example, the *'female'* synset would be an inherited hypernym of the synset *'cow'*. Therefore we know that cows are female. Similarly, *'maharaja'* has the hypernym *'prince'*, which we know to be male.

We can extend this practice to the final point of determining the animation of the character by checking if the *'living thing'* and *'physical object'* synsets are inherited hypernyms of the synset of the noun concerned.

Anaphora and presuppositions can be matched with their antecedents by comparing these semantic attributes with that of potential antecedents.

For example, we know that the persona represented by *'he'* must be resolved to refer to either the *'a cat'* or *'a lot of mice'* persona. The *'he'* persona is singular, so it can only match with the *'a cat'* object, and we resolve accordingly.

More complex examples may need to take gender and animation into account in a similar way.

3.6.3.4 Extracting Candidate Relations from the Frame-Semantic Parse

Using the map between FrameNet frames and semantic relations mentioned in section 3.6.2.1, we can carry out the following algorithm.

```
1 for each frame found in the frame-semantic parse:\\

2   look up the target of the frame in the map\\

3   if it can help build a relation: \\

4     retrieve the frame elements\\

5     match the frame elements with the corresponding text from the poem\\

6       if we cannot find all the elements we are looking for, we leave it blank\\
```

7   `add mapping from the text of the target to the newly built relation so we can f`

Figure 3.12 show a dry run of this algorithm using the first half of the cat poem in Figure 3.1.
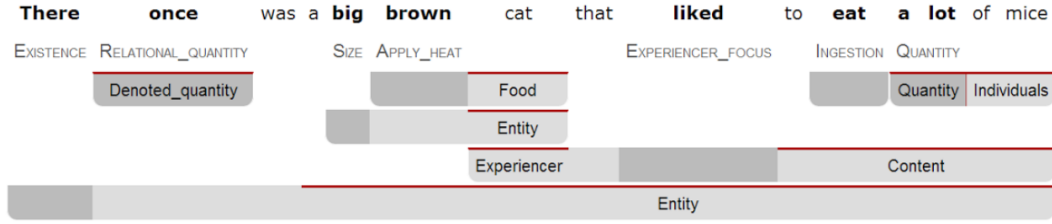
(a) Get all the frames found by the frame-semantic parse

(b) The only one that we can convert to a relation is the Experiencer_Focus frame

(c) Retrieve the frame elements with an anchor on the target text, *'liked'*

(d) Create the corresponding relation and map it to the target

Figure 3.12: Execution on the first half of the cat poem example.

No frames could be converted into relations for the second half of the cat poem example.

3.6.3.5   Obtaining the Associated Dependency Relations for each Persona

This step breaks up the semantic dependency tree and flattens it into the character-centric hubs like the ones in Figure 3.6. We start from Figure 3.10g.

First, we want to identify the persona in the dependency tree. All of the relations going out from it are naturally related dependencies of the persona, so they get added

to the hub.

The single relation coming into this character is also a related dependency. We reverse the direction of the branch and add it to the hub. The hub so far is more like a spider diagram, as shown in Figure 3.13.
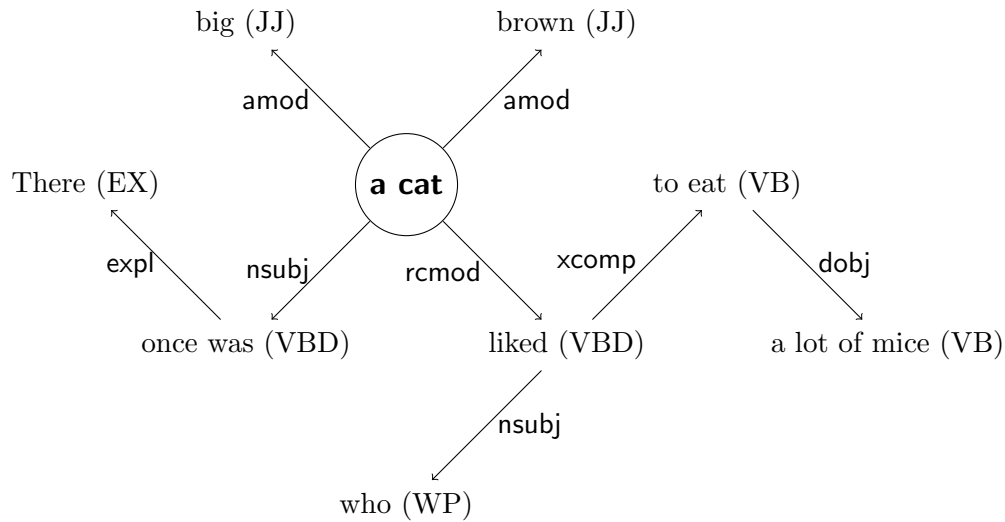
Figure 3.13: Initial dependency hub for the 'cat' persona.

Now we have a tree with the character as the root. The next step is to flatten it so that all nodes are directly related to the character. We do this by recursively converting all the grandchildren of the character root node to a direct child node until there are no more grandchildren. This is shown in Figure 3.14.

We repeat this process for each persona starting from the leftmost character in the sentence. The persona hubs for the second half of the poem is shown in Figure 3.15.

big (JJ)　　　　　　brown (JJ)

amod　　　　　　　amod

expl　　　　　　　xcomp
There (EX) ←　　**a cat**　　→ to eat (VB)

nsubj　　　　　rcmod　　dobj

once was (VBD)　　　liked (VBD)　　　a lot of mice (VB)

nsubj

who (WP)

(a) Persona: 'cat'

a lot of mice　　dobj　　→ to eat (VB)

(b) Persona: 'a lot of mice'
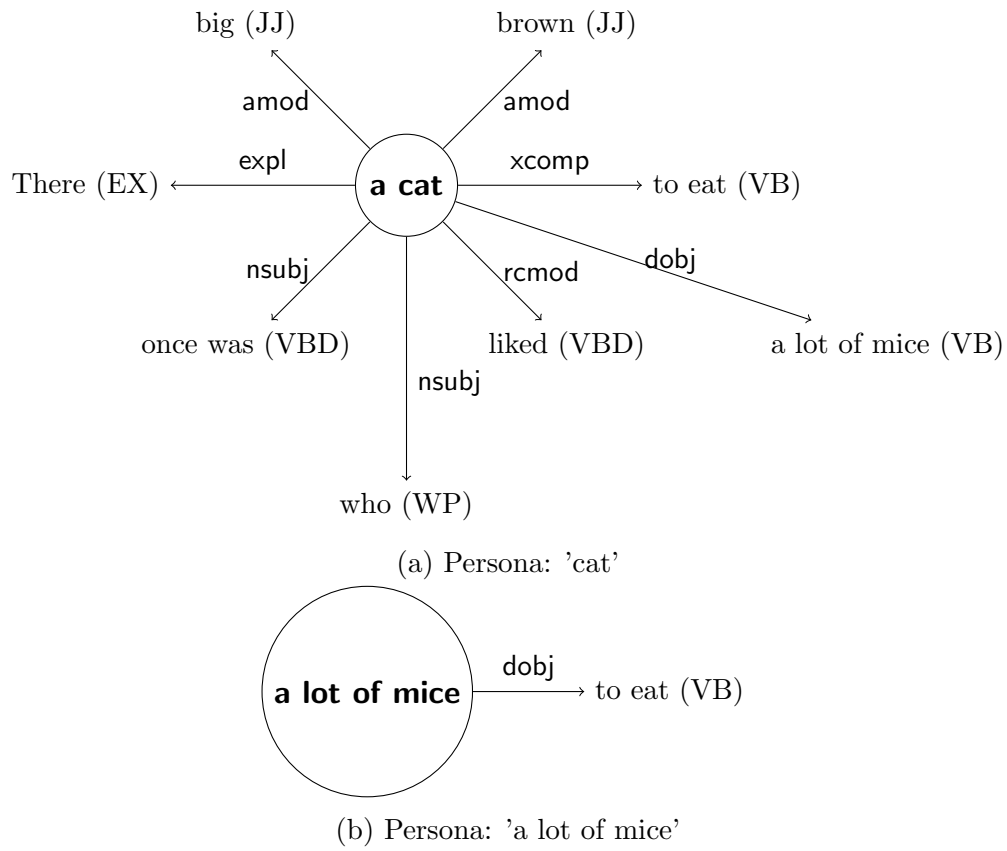
Figure 3.14: All persona hubs for the first sentence of the cat example.

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(a) Persona: 'he' before flattening.

(b) Persona: 'he' after flattening.

(c) Persona: 'they' before flattening   (d) Persona: 'they' after flattening

Figure 3.15: All persona hubs for the second sentence of the cat example.

Notice that the same *mark* dependency with node *because (IN)* is associated to both *'he'* and *'they'*. The *tasted so nice (JJ)* node is also involved with both of them, although the type of dependency differs.

In most cases, we do not want either of these duplicated dependencies as it can lead

to redundant relations. We will deal with this in the next step where we convert these dependencies into relations.

3.6.3.6 Binding ConceptNet Relations to Characters

Now that we have our hub data structure for all persona, we now need to look at each branch of each hub and decide if it can be converted into a semantic relation.

First, we check if the text of the child maps to the target of one of the candidate relations we extracted from the frame-semantic parse in section 3.6.3.4. If it does, then we accept that and move on to the next child without checking the dependency relation since it is likely to be the less accurate or redundant.

Sometimes the dependant of the relation will be blank because we could not find the right frame element as explained earlier. In this case, we just assume that this is a relation to the next persona in the list. This is a fair assumption given the limited number of persona per sentence, the probable forward reference structure of sentences and the fact that most of the relations we look to build are between persona.

If there is no candidate relation for this child, we then look at the type of the dependency between it and the persona. We use the heuristics described in section 3.6.2.2 to convert it into a semantic relation.
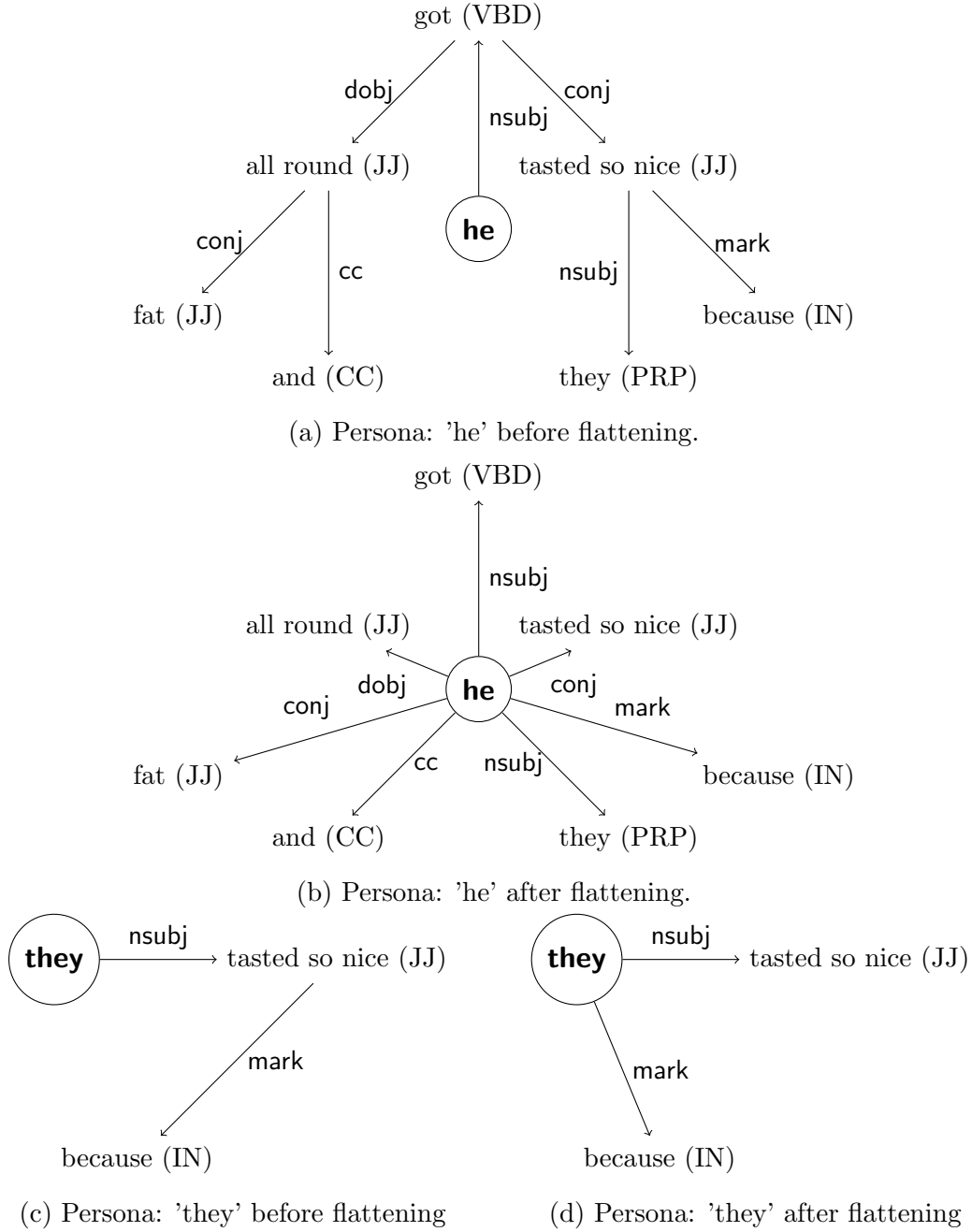
If we cannot find a relation using either of the above methods then it is unlikely that one exists, so we remove it from the hub and move on to the next child.

In all of those steps, we need to look out for negative adverbs such as 'not', 'seldom', 'rarely' etc. which we use to negate the relation found. We also need to look out for antonyms in the target word in the frame-semantic parse. For example, the *Experiencer-focus* frame helps us find *Desires* and *NotDesires* ConceptNet relations depending on whether the target word is synonymous with 'love' or 'hate'.

To avoid the aforementioned duplication problem, we prune these hubs by working backwards through the persona (i.e. starting from the rightmost in the sentence) and removing any relations that occur in earlier persona. So in fact the *'lot of mice'* persona has no relations (before anaphora resolution).

The duplication is mostly due to reversing the direction on incoming dependencies (heads). This pruning method works because the head of the last persona will be lower

down in the dependency tree than the head of any other persona. Duplicated relations are removed such that it is solely associated to the one it was closest to in the original tree.

We can see this entire process being applied step-by-step to the 'cat' persona in our ongoing example in Figure 3.16. The final hubs for all persona can be seen in Figure 3.17.

3.7 Symbolism and Imagery

This particular poetic technique can be very subtle and difficult to detect. Of the ones listed in section 2.1.2.5, we are able to recognise the use of three, similes; onomatopoeia and personification.

3.7.1 Personification

We used the animation of persona for anaphora resolution. We can take this idea further to detect the use of personification in poetry.

The following relations are symptomatic of a sentient being:

- 'Named' and 'NotNamed'

- 'Desires' and 'NotDesires'

- 'Believes' and 'NotBelieves'

- 'SendMessage' and 'NotSendMessage'

- 'ReceiveMessage' and 'NotReceiveMessage'

Therefore, if a character that is marked as an inanimate object has any of these relations, it is likely that the author of the poem was using personification to give the object human-like behaviour.

3.7.2 Onomatopoeia

Some onomatopoeia are recognised in traditional dictionaries, while some are not. There are also many variations of the same sound, e.g. 'Aah' versus 'Aaah'. New onomatopoeia can be created at any point depending on the sound the writer wants to portray. This range of variation and lack of consistency makes it difficult to detect all occurrences of onomatopoeia.

WrittenSound.com[2] is an online dictionary devoted to onomatopoeia. We use this to recognise the most common ones. A word in the poem is an onomatopoeia if the closest matching word in the dictionary, using *difflib* as in Section 3.1, has a similarity score of greater than 0.9

We check for onomatopoeia while building semantic relations. If we detect onomatopoeia, we add the MakesSound relation to the character with respect to the onomatopoeia. For example *"the window rattled"* would add the relation *MakesSound →rattled* to the *'window'* character object.

Furthermore, WrittenSound provides mappings between the onomatopoeia and the type of sound they represent. For example, *'ding'* is mapped to *'hard hit'* and *'metal'*. We add extra bonus relations by making deductions on this. For example, if the character makes a *'ding'*, sound, we can deduce and add the relations *ReceivesAction → hard hit* and *MadeOf → metal*.

These deductions are chosen manually. The full list is in the Appendix section A.7

3.7.3 Simile

Similes are relatively easy to detect because they often use the phrases 'like a' or 'as a' and 'than'.

A particular symptom of simile use is that the aforementioned phrases will be involved in a prepositional noun phrase, or *PNP Chunk* to use the parser terminology.
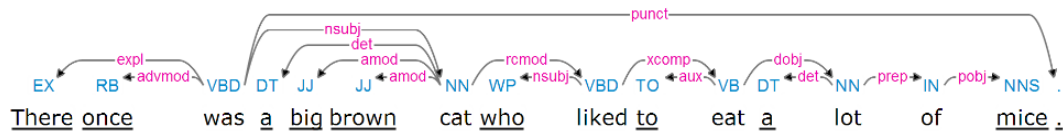
(a) Identify all of the leaves
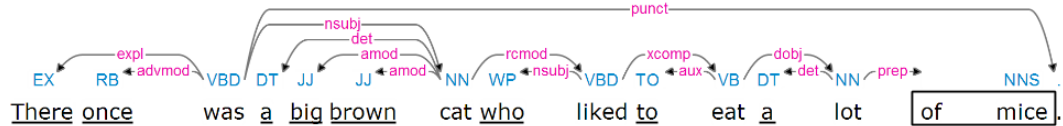
(b) Start from the rightmost leaf, *'mice'* (ignore punctuation). Dependency *'pobj'* is collapsable and we inherit the child POS tag.
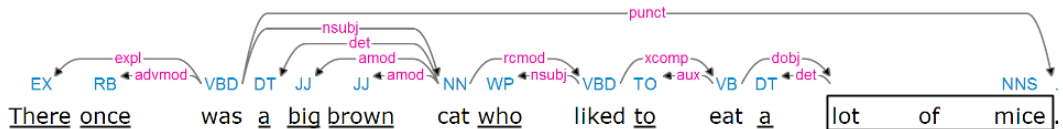
(c) Because we collapsed a leaf in the previous step and it remained a leaf, we see if we can collapse the same leaf further. Dependency *'prep'* is collapsable and we inherit the child POS tag once again.
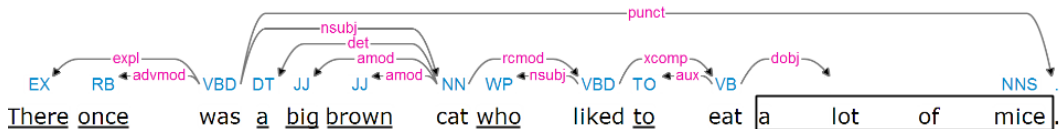
(d) The leaf we collapsed is now a parent so we move left to the next leaf *'a'*. Dependency *'det'* is collapsable and we retain the parent POS tag this time.
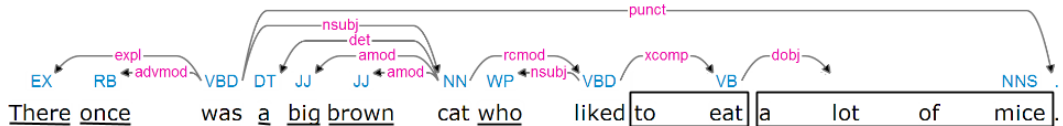
(e) We have a leaf again, but we cannot collapse any further. We move on to the next leaf, *'to'*. Dependency *'aux'* is collapsable and we retain the parent POS tag.
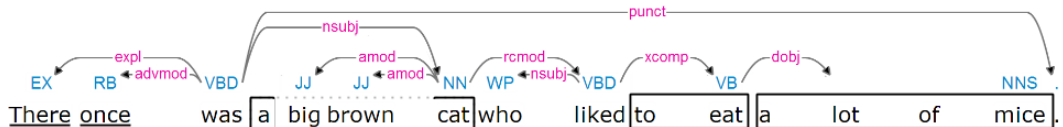
(f) Move on to next leaves. Dependencies *'nsubj'* and *'amod'* are not collapsable, but *'det'* is so we collapse leaf *'a'* with its parent *'cat'*.
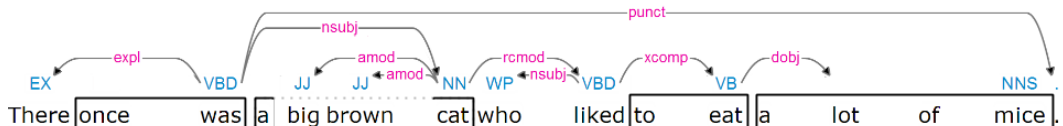
(g) Dependency *'advmod'* is collapsable and *'expl'* is not. Collapse accordingly and finish.

Figure 3.10: Execution of Algorithm BLAH on the first half of the cat poem example.

There (EX)

a lot of mice (NNS)   once was (VBD) a lot of mice (NNS)

expl

dobj   nsubj   dobj

to eat (VB) ← **a cat** → big (JJ) to eat (VB) ← **a cat** → big (JJ)

xcomp   xcomp

amod   amod

rcmod   amod   rcmod   amod

nsubj   nsubj

liked (VBD)   brown (JJ)   liked (VBD)   brown (JJ)

who (WP)   who (WP)
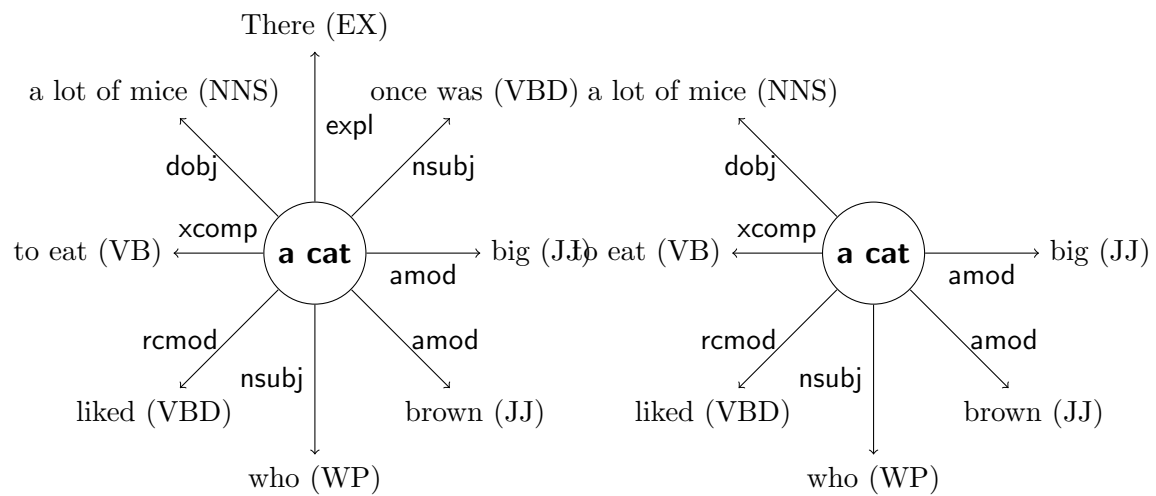
(a) Dependency hub for the 'cat' character, rearranged such that the children appear in the order they do in the original sentence, starting from *'There'* in the 12 o'clock position in a clockwise direction.

(b) Dependency *expl* does not map to any relation and the child *'There (EX)'* does not map to any relation via the frame-semantic parse. It is removed. Similarly remove the *'once was (VB)'* child because it is a verb but the lemma includes the verb 'be'.

Figure 3.16: Full binding process for the 'cat' character

(c) Dependency *'amod'* maps directly to a HasProperty relation for both the *'big (JJ)'* and *'brown (JJ)'* children.

(d) Remove the *'who (WP)'* child because it has a POS tag starting with W so the *'nsubj'* relation does not matter.

(e) In this case, *'liked (VBD)'* is a target mapped to a relation found from the frame-semantic parse. It gets replaced by this relation with no further consideration.

(f) The final *'a lot of mice (NNS)'* child is not a verb so the *'dobj'* relation has no effect.
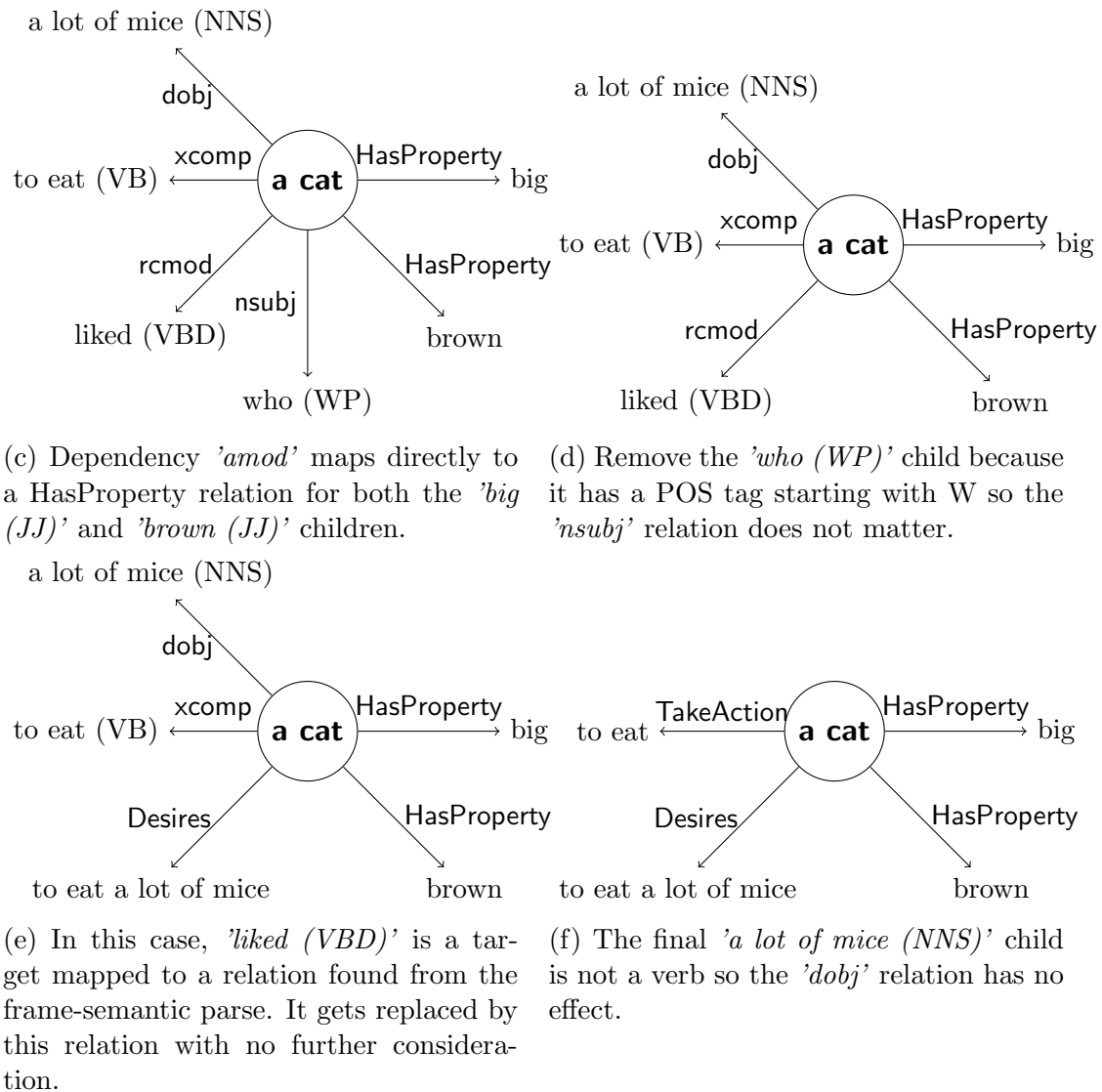
Figure 3.16: Full binding process for the 'cat' character
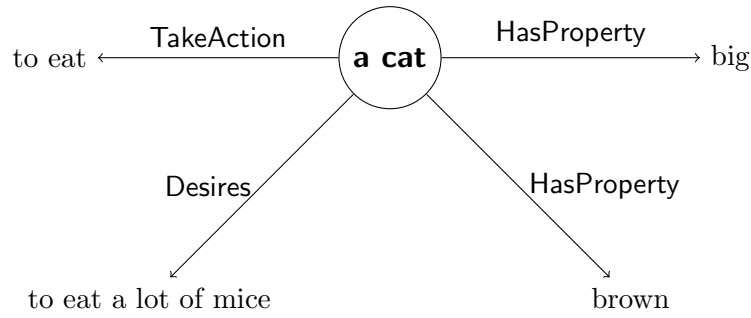
(a) Bindings for 'cat' persona.
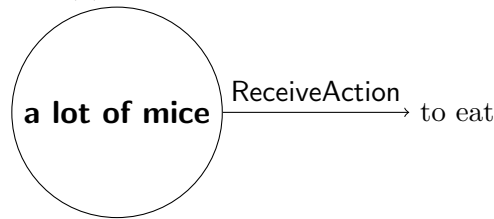
(b) Bindings for 'lot of mice' persona.
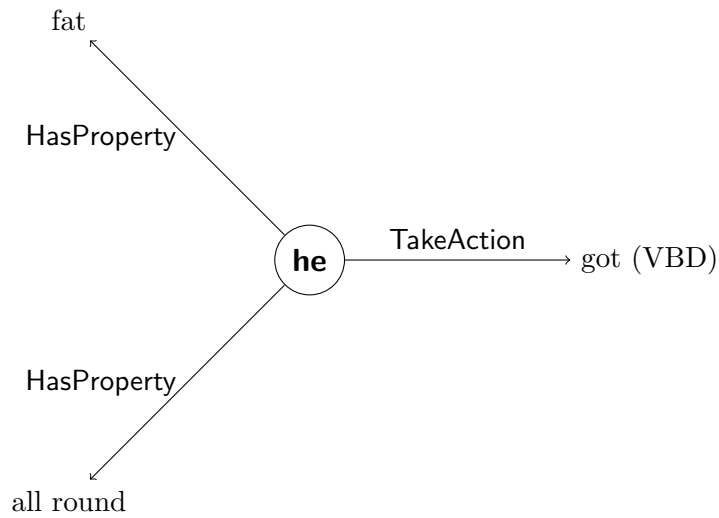
(c) Bindings for 'he' persona. Notice *'tasted so nice (JJ)'* was removed from here because of duplication with *'they'* persona below. We get one anomaly with *'got'* because we were unable to distinguish between definitions of 'became' and 'retrieved'.
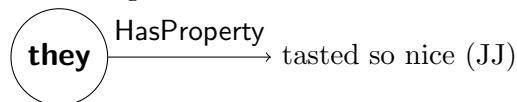
(d) Bindings for 'they' persona.

Figure 3.17: Complete bindings for all persona

Chapter 4

Analysis Interpretation

The second phase of implementation involves interpreting the results of the analysis phase. The goal is that these interpretations can be used to template the structure and outline the content for certain collections of poems, ultimately guiding the generation of novel and authentic poetry in the final phase.

4.1 Approach

In deciding how to approach this phase, we need to make predictions about the usage of the final interpretation and assumptions about the quality, or lack thereof, of the corpus and analysis.

4.1.1 The Corpus

The corpus is a large collection of poems. We may assume that each poem is already marked with the *type* of the collection - limerick, haiku, riddle etc. - much like data in a supervised machine learning problem. However, the poems should otherwise be *unseen* before analysis; we know nothing else about them.

Poems are most easily obtained from anthologies. This works very well with our assumptions as the data is already labelled with the type of poem, but we know nothing else about the content.

Another way to gather poems is by looking for those freely available on the Internet. However, the corpus obtained from an Internet search will likely be of lower quality than directly from a published anthology. For example, we may get the limerick in Figure 4.1, which is clearly very awkward. We can immediately see that it does not follow the typical *AABBA* rhyme scheme, and even more so that it doesn't have a fifth

line!

A limerick fan from Australia
regarded his work as a failure:
his verses were fine
until the fourth line
?

Figure 4.1: A very awkward limerick for analysis

Nevertheless, our blindness to the content of the corpus means the system must be robust to such outliers. Therefore, we *will* get anomalous results and need to be able to cope with them.

4.1.2   Subcategories of Collections

The first two stages aim to be an exhaustive analysis of any type of poem. The first stage achieves this by detecting as many features in a single poem as possible. The second stage does this not only by finding highlights among features of homogeneous poems, but correlations between them as well.

For example, limericks that start with *'There was a...'* may have a very distinctive rhythm pattern for the first line that is otherwise not strictly followed. Therefore, when generating new poetry in the next phase that starts with *'There was a...'*, we want to make sure we abide by this correlation.

There will be many correlations with more than two variables that may be more difficult to spot, but the complexity of finding all of them is exponential. We need to find a balance between the usefulness of this data and the complexity in obtaining it.

4.1.3   Novel and Creative Generation

There is another catch to the correlation problem - red herrings. Some features can be taken as law; 5 lines in a limerick, 5-7-5 syllable pattern in Haiku, iambic pentameter in Shakespearean Sonnets. However, some may be coincidences or the result of a very biased corpus.

Furthermore, we want to be able to generate poems that are *novel* and *creative*. So while we need to be guided by prior art on structure and content to create authentic pieces of literary art, we need to balance that with freedom of creativity.

4.2 A Stochastic Approach

The most suitable implementation that meets the priorities listed above is:

- Analyse each poem individually as planned.

- Store collections of poems by type (limerick, haiku etc.). This avoids extra filtering and repeated memory persistence downstream.

- Put the analysis results of each poem in a particular collection together, keeping each feature independent. For example, we put all of the rhyme schemes for all limericks in one big list, saving it separately from the list of stanza lengths. I will refer to this step as *'aggregation'* from now on.

- For each feature, create a probability distribution of the results that represents the likelihood of any particular value occurring for each feature. If 95 out of 100 limericks have an *AABBA* rhyme scheme, then we consider the probability of an *AABBA* rhyme scheme in a limerick to be 95%.

The aggregation step is bespoke to each feature. For example, we aggregate the tenses for each line of each poem differently to the way we would aggregate the overall tense for each poem. This enables us to handle outliers on a case-by-case basis since they are defined differently for every feature.

We can also decide how to *interpret* the data on a case-by-case basis, helping us handle the varying error bands for each feature. For example, detecting the rhyme scheme is more error-prone than detecting the number of syllables so we may round a 95% result for rhyme scheme up to 100%, but take it literally for syllable pattern.

This implementation also gives an effective way of finding correlations. We take a value for one of the features as a *given*, filter the store of analysed poems by this value and

aggregate. We can take any number of given values and of any permutation since each feature is aggregated and interpreted in isolation.

As a bonus, this implementation quite efficient both in terms of time and space (see Section 6.1.4). By storing the original poem analysis results, we can apply given values and find correlations *lazily*, i.e. only when needed.

4.3 Algorithms

All features can be aggregated using some variant of one of four algorithms, with slight feature-specific amendments so to have the flexibility and precision mentioned in the previous sections.

4.3.1 List Comprehension

The simplest of the four algorithms utilises Python's built in functional programming feature; list comprehensions. In a single line of code we put all of the results for a particular feature from all poems in the collection into one big list. The following algorithm shows the code for aggregating the number of stanzas.

```
1. num_stanzas = [poem.n_stanzas for poem in poems]
2. return Count(num_stanzas)
```

The second line gets the frequency distribution of this list, which can easily be turned into a probability distribution as required.

4.3.2 Line by Line

Sometimes we can gain more insight by interpreting patterns in a feature for **each line** rather than the poem altogether. In these cases, the analysis result is usually saved in the form of a tuple, one entry for each line.

Take stress patterns for example. The analysis of a single poem will store the result as $(x_1, x_2, \ldots, x_n)$ where x_i is the stress pattern for line `i` up to the total number of lines in that poem, `n`.

Suppose we have three poems in the corpus altogether. Then we have three tuples to aggregate: $(x_1, x_2, \ldots, x_n)$, $(y_1, y_2, \ldots, y_n)$ and $(z_1, z_2, \ldots, z_n)$.

If we are looking generalise the results on a line by line basis, we want to **transpose** the data to group each line together and put them in a list with the format $[(x_1, y_1, z_1), (x_2, y_2, z_2), \ldots, (x_n, y_n, z_n)]$.

Once this is done, we can apply the list comprehension algorithm described in Section 4.3.1 to each tuple in the list. The following algorithm outlines this full process with the stress pattern example.

```
1. stress_patterns = [poem.stress_patterns for poem in poems]

2. stress_patterns_all_lines = transpose(stress_patterns)

3. return [Count(stress_pattern_single_line) for stress_pattern_single_line in stress
}
```

4.3.3 Pick the Most Popular

The analysis of a single poem often has some ambiguities. For example, the rhyme scheme for a collection can never be decided by looking at just one poem because words can be pronounced in more than one way. The limerick in Figure 4.2 could either be *AABBA* or *AABBC* because *invited* can be pronounced as *[IH N V AY T **AH** D]* or *[IH0 N V AY T **IH**, D]* according to the CMU pronunciation dictionary.

> *There was a young man so benighted*
> *He never knew when he was slighted;*
> *He would go to a party*
> *And eat just as hearty,*
> *As if he'd been really invited.*

Figure 4.2: A limerick with more than one possible rhyme scheme

The analysis phase does not make a claim on which rhyme scheme is accepted and

instead stores all possibilities in a list [x_1, x_2, $\ldots$, x_n], where x_i is the ith rhyme scheme possibility up to n possibilities for the particular poem being analysed.

Let's assume again that we only have three poems in the corpus. Once they are all analysed, we get three lists [x_1, x_2, $\ldots$, x_n], [y_1, y_2, $\ldots$, y_n] and [z_1, z_2, $\ldots$, z_n] of possible rhyme schemes for each poem.

We illustrate what we want to happen by taking four cases:

- All possibilities across all poems are unique. Therefore, all are equally probable and that gives us our probability distribution.

- There is *one* set of indices (p, q, r) such that $x_p == y_q == z_r$. Then we take that to be the rhyme scheme and no other possibility is considered.

- There is *m>1* sets of indices $(p_1, q_1, r_1), (p_2, q_2, r_2), ..., (p_m, q_m, r_m)$ such that for all i up to m, $x_{p_i} == y_{q_i} == z_{r_i}$. Then all **sets** are candidate rhyme schemes where each rhyme scheme has a probability of $1/m$.

- There is a p and a q such that $x_p == y_q$, but no r such that $y_q == z_r$. In this case, the rhyme scheme x_p has a probability of two thirds, while every rhyme scheme z_i has the probability of one third each.

An iterative implementation makes this process simple. We first find the most popular rhyme scheme among all poems in a set and save its frequency. We then remove all poems that contain the most popular rhyme scheme from the set and repeat on the remaining poems until there are no more poems in the set.

The pseudo-code for this implementation is:

```
1. rhyme_scheme_counts = {}

2. possible_rhyme_scheme_lists = [poem.rhyme_schemes for poem in poems]

3. all_possible_rhyme_schemes = flatten(possible_rhyme_schemes)

4. most_popular_rhyme_schemes = most_common(all_possible_rhyme_schemes)

5. for each rhyme_scheme in most_popular_rhyme_schemes

6.   rhyme_scheme_counts[most_popular_rhyme_scheme)] = all_possible_rhyme_schemes.co
```

```
 7. for each possible_rhyme_scheme_list in possible_rhyme_scheme_lists

 8.    if possible_rhyme_scheme_list contains any of  most_popular_rhyme_schemes

 9.      remove possible_rhyme_scheme_list from possible_rhyme_scheme_lists

10. if possible_rhyme_scheme_lists is not empty, go to 3.

11. return rhyme_scheme_counts
```

4.3.4   Filter Below Threshold

This algorithm deals mostly with content-based features such as n-grams, persona relations and types of persona. These features are varied, unpredictable, error-prone and highly sensitive to bias in the corpus. However, they can still provide very interesting and useful data to guide generation and create authentic poems. For example, starting a limerick with *'There was a...'* and talking about nature in Haikus.

In this case, we perform the most suitable of the three aforementioned algorithms to collect all possible results. We then apply a filter so that only results that occur with *significant frequency* can be taken into account.

Unfortunately, there is no way to tell what frequency can really be counted as significant. It will vary greatly between types and subcategories of poems and is prone to many red-herrings. Trial and error has given the optimal threshold of 9% of the corpus, but this will need further research to refine.

4.4   Testing and Validation by Inspection

We test and validate this phase by looking at two factors:

1. Accuracy of the assumptions and predictions made at the start of this chapter.

2. Comparison of results with known poetry theory.

While some automated tests can be written to make sure that the algorithms above are implemented correctly, there is no desired output against which to compare. We
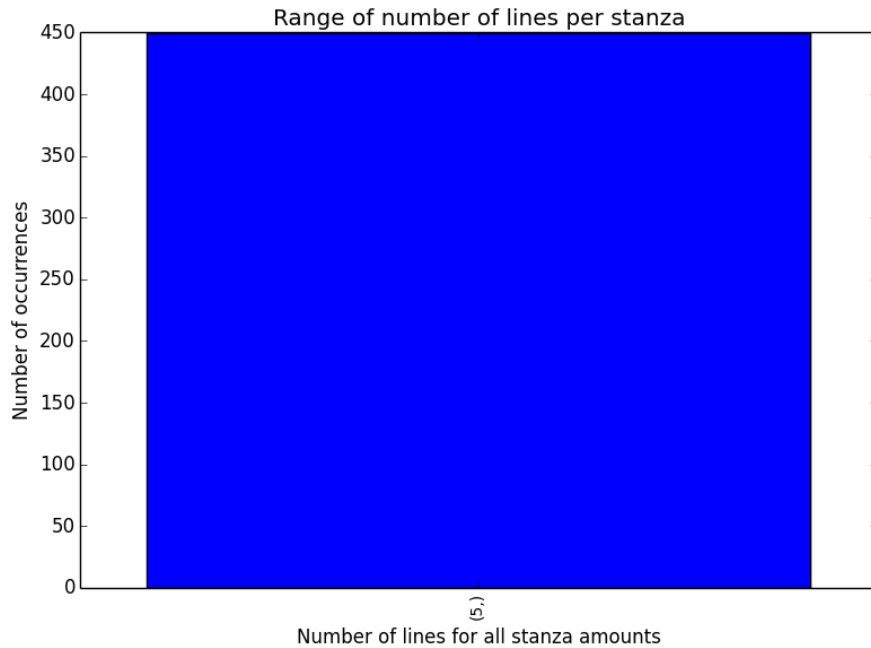
Figure 4.3: Five lines long, one stanza

cannot check for exact matches with poetry theory because this is an *investigation* where known theory is the hypothesis. Writing tests that fail if the hypothesis is not correct is an investigative fallacy.

Therefore, the best way to test and validate the results of this stage is by inspection. Python provides a convenient interface for graphing large sets of data, which also make it easy to inspect by eye.

The corpus used to test the system comprises of 450 limericks scrounged from the Internet. As mentioned earlier, poems gathered from the Internet are likely to have more outliers and anomalies, which makes for a more rigorous examination of the quality of our analysis and interpretation.

A noteworthy subset of the results are shown in Figures 4.4 through 4.9. The y-axis is given in raw values instead of probabilities for this testing stage.

The results of these and other corpora will be explored fully in the Evaluation. It is sufficient for the moment to say that these results are usable in the generation phase to apply rules but also guides us on the strength of these rules, suggesting where divergence may be applicable.

Figure 4.4: AABBA rhyme scheme by far the most common

(a) Limericks talk a lot about people
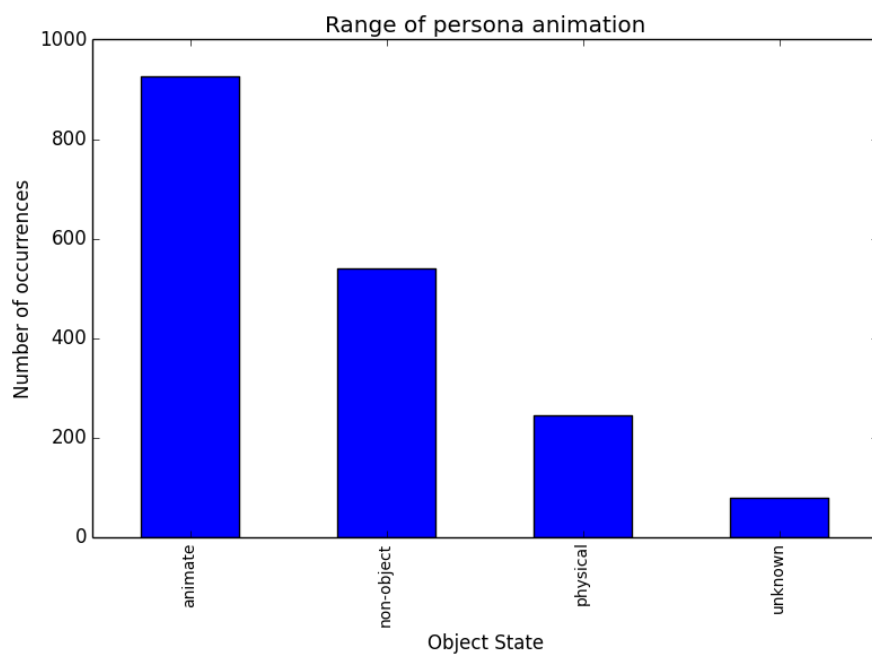
(b) Most persona are either animate objects or 'concepts' such as places

Figure 4.5: Limericks generally talk about people and other animate objects
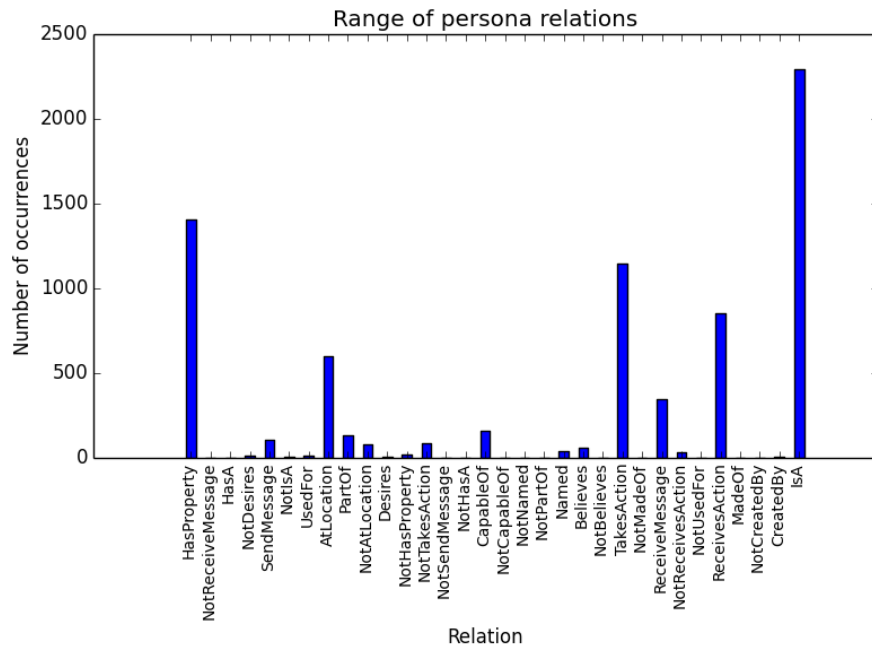
Figure 4.6: Limericks talk about who these people are, what properties they have, what they are named, where they are, their capabilities, what they do, what is done to them etc.
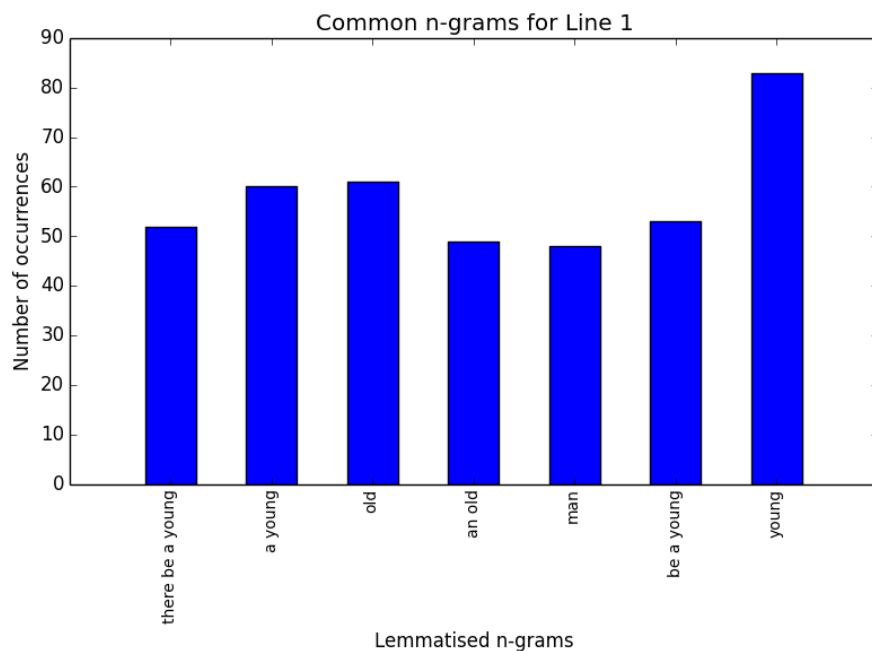
Figure 4.7: The first line often introduces the person, usually as either old or young
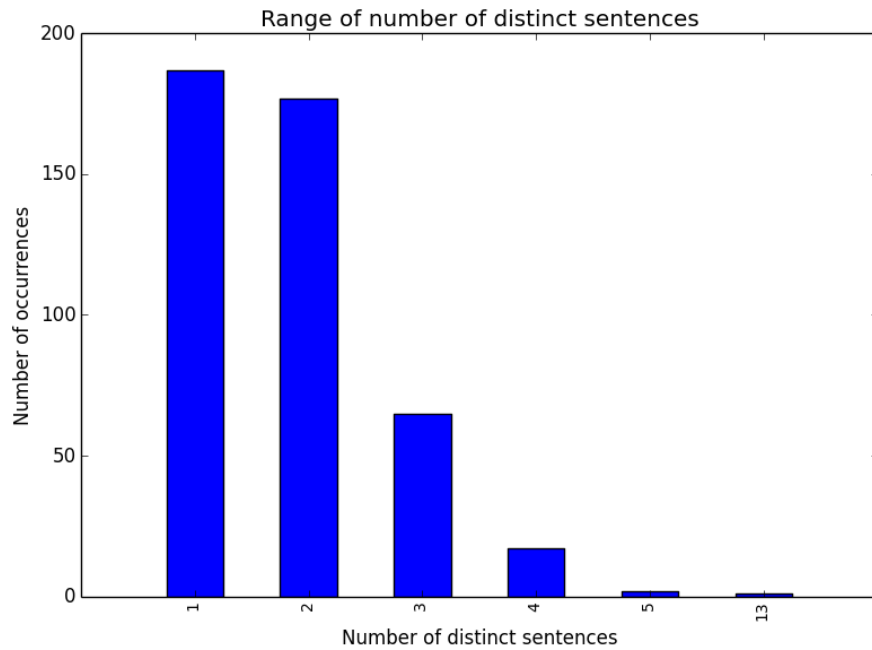
Figure 4.8: Whole poem seems to be either one or two sentences. This actually tells us that full stops are not needed, but if they are used then the whole poem is generally two sentences long.
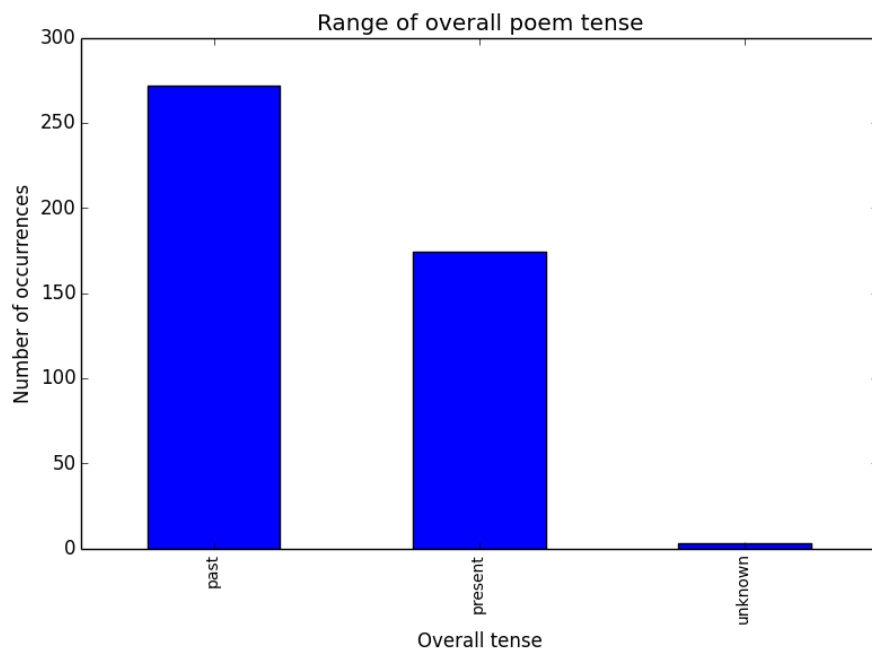
Figure 4.9: Never in future tense, mostly in past an sometimes in present

Chapter 5

Generation

The final stage of development involves generating new, novel and creative poetry by utilising the information gathered in the previous analysis and interpretation sections.

5.1 Approach

Most previous attempts at automatic poetry generation, including ones mentioned in Section 2.2, prioritise adherence to poetic features and structure above all else. This is done with the justification that:

- poetry rarely follows syntactical rules of English grammar.

- readers of poems, as humans, are extremely apt at finding subtle meaning in language, even if it was not intended by the author.

Veale argues that 'poetic licence' is not a licence but a contract that allows a speaker to take liberties in language in exchange for real insight[55]. We are in support of Veale's argument that grammatical rules in poetry are only broken for *some purpose* like matching a rhyme scheme or rhythm pattern. They are broken with precision and intention, not arbitrarily or randomly.

Furthermore, we discussed in Section 2.4.3 that even grammatically correct sentences can be completely nonsensical. We require understanding of the semantic relationships between words to be able to write with intention and in a way that can be understood by the reader. As discussed in Section 2.1.1, the purpose of poetry is to deliver a specific, intentional message. This cannot be done without control over language both syntactically and semantically.

Therefore, our approach will be **content first**. We aim to produce poetry that follow syntax and semantics as far as possible and only make specific exceptions for the sake

of poetic features.

Finally, this implementation should be able to produce any type of poem in accordance with the information gathered in the analysis and interpretation. We cannot make any assumptions on the length of the lines, the existence of rhyme or the topics covered by the poems.

5.2 Generating Simple Sentences

We attempted to recognise the existence of semantic relations during the analysis phase. Our interpretation of the results generalises the use of these relations with the intention of guiding the generation process. If we intend to write a poem describing a woman named Mary who wants a monkey, we would start with the persona relation hubs in Figure 5.1.

(a) First persona

(b) Second Persona
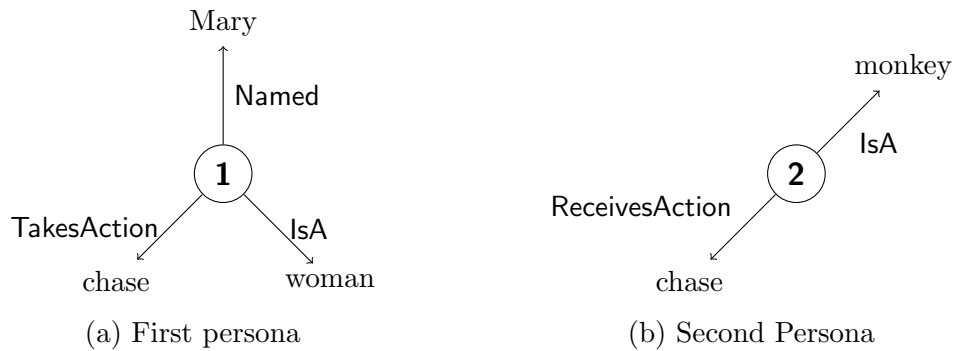
Figure 5.1: Starting relations for generation

These relations outline the context of the poem. In lieu with our *content first* approach, we begin by directly translating these relations into syntactically correct natural language *clauses*, which can be organised into lines in a poem. We make use of two tools to do this; **SimpleNLG** (Section 2.4.4) and **FrameNet** (Section 2.4.3.4.2).

We choose to use SimpleNLG because it provides an almost bespoke interface into the features of the sentence that we picked out in the analysis stage, allowing us to apply the results directly to our new poems.

These features include:

- Tense

- Aspect

- Perspective

- Negation

- Animation, Gender, Plurality

- Determiners

5.2.1 Translating Relations into Clauses

We used FrameNet when deriving relations with SEMAFOR in Section 3.6 by checking for the existence of certain frames. Now we reverse the process; use selected frames that correspond to particular relations to define the type and roles of phrases during generation.

Take the Desire relation for example. The corresponding frame in FrameNet would be *Desiring*. The general translation process follows this algorithm:

```
1 look up LUs from given Frames/IDs/Word

2 select a Valence Pattern

3 order phrases in Valence Pattern so that subjects come first, then the target, then

4 fill in the phrases with relevant words
```

Suppose we take the *1-Named→Mary* relation in Figure BLAH above. We have a character whose ID is 1 and has the name 'Mary'. The corresponding frame for the 'Named' relation is *Referring_by_name*.

However, it is not quite a perfect match because we only want verbs, whereas this frame includes Lexical Units (LUs) of other parts of speech as well. Each LU gives indication of its part-of-speech (POS) so we can filter by that.

Another complication is that the verb 'to name' does not exist in the FrameNet lexicon at all. The closest match is the adjective 'named' found in the *Being_named* frame. So we need to be able to look up this LU manually as well.

Number Annotated	Pattern part 1	Pattern part 1	Pattern part 1
19 TOTAL	Entity	Name	
(1)	CNI,–	NP,Obj	
(1)	NP,Ext	AVP,Dep	
(11)	NP,Ext	NP,Dep	
(6)	NP,Ext	NP,Obj	
16 TOTAL	Entity	Name	Speaker
(1)	NP,Ext	NP,Dep	CNI,–
(1)	NP,Ext	NP,Obj	CNI,–
(1)	NP,Ext	PP[by],Dep	CNI,–
(5)	NP,Obj	NP,Dep	NP,Ext
(1)	NP,Obj	PP[by],Dep	CNI,–
(5)	NP,Obj	PP[by],Dep	NP,Ext
(2)	NP,Obj	QUO,Dep	NP,Ext
1 TOTAL	Name	Name	
(1)	NP,Dep	NP,Ext	

Table 5.1: Valence patterns for the *call.v* LU

Yet another issue is that not all of these LUs come with full and accurate Valence patterns. FrameNet is an ongoing project with more data being added continuously so we do not want to use a word that does not have an accurate set of Valence patterns. Thankfully, the status of every LU is provided, so we only look up those that have the *Finished_Initial* annotation.

It is important to note that all relation translations may have their own set of similar caveats that are to be considered on a case by case basis to improve the quality of lines generated. Furthermore, while the TakesAction and ReceivesAction phrases enable us to use any verb in the FrameNet lexicon, having specific builder algorithms for as many relations as possible will greatly increase the quality and variation of language capabilities.

Back to our example, after dealing with all issues we are left with two LUs; *call.v* and *named.a*, where the string after the full stop in the LU indicates the word's POS. We choose one randomly with equal weights. We use *call.v* for this example.

This LU has three groups of Valence patterns, as can been seen in Table 5.1. Each group of patterns has an *TOTAL* count, indicating the occurrence frequency of this pattern in their annotated corpus. We assume that these are representative for our purpose and choose the group with the highest total occurrences.

Each pattern within a group also includes an occurrence count. However, the phrases produced by the system would be predictable and mundane if we always choose the most popular again. Instead we select randomly, weighted for occurrence scores. Let our selected Valence pattern be the third one from the top in Figure BLAH.

We then order the phrases according to how they would appear in a sentence; subjects first (*Ext*), then the target word, followed by the dependencies (*Dep*) and objects (*Obj*).

The Valence pattern does not include the LU itself so we add it as a verb phrase immediately after the subject.

Finally, we fill in the gaps by adding carefully selected words to each phrase. We discuss word selection in Sections 5.3 and 5.5.2.

5.2.2 Semantic Network of Common Sense

We discussed the idea of modelling the mind as a search space by connecting related concepts together in a network in Section 2.3.0.1. We gathered inspiration from ConceptNet and discussed Tom De Smedt's attempt to model creativity with such a construct.

We aim to replicate the experiment bespoke to our purposes, outlined in this section.

5.2.2.1 The Network

The primary purpose of our network is to help us build clauses out of one or two words. For this, we require our semantic network to give indications of **actions** that nouns take and receive, as well as **properties** they have.

The secondary purpose of the network is to provide associative data so to maintain a cohesive topic flow through the poem, rather than jumping between a variety of topics.

5.2.2.1.1 Nodes As with previous attempts, the nodes of the network are the *concepts*, represented by words. We take a step further by enriching these nodes with the POS of the word so to disambiguate between different meanings (e.g. *bear* the noun and *bear* the verb).

5.2.2.1.2   Edges   The edges of the network indicate the relationship between concepts. They are *directed* in our graph. The types of edges are:

HasProperty

>   Stereotypical descriptions of the head of the relation.
>   doctor.n - HasProperty → smart.a
>   run.v - HasProperty → quickly.adv

IsA

>   Taxonomy of the head of the relation (hypernymy).
>   E.g. banana.n - IsA → fruit.n

PartOf

>   The head of the relation is typically a constituent or member of the tail.
>   finger.n - PartOf → hand.n

TakesAction

>   The head of the relation typically performs the action in the tail.
>   lion.n - TakesAction → roar.v

ReceivesAction

>   The head of the relation typically has the action in the tail done unto it.
>   book.n - ReceivesAction → read.v

RelatedTo

>   Any non-specific, reversible association.
>   fat.a - RelatedTo → eat.v
>   eat.v - RelatedTo → food.n
>   food.n → RelatedTo

All edges are of equal weight at this stage. There is potential for prioritising certain types of relations or concepts to bias the vocabulary. For example, we could weight scientific words higher than regular ones to make the program lean towards a more advanced vocabulary.

5.2.2.1.3   Concept Halos and Fields   The Concept Halo and Field work in the same way as described in Section 2.3.0.1. We use them to fill in the gaps in the sentence

with intelligent word selection. For example, if we are given a verb, we can lookup the concept field for that verb looking only at TakesAction and ReceivesAction edges to find possible subjects and objects for the verb. Similarly, we can find modifiers for verbs and nouns by looking up HasProperty edges their respective concept halos.

5.2.2.2 Sources

There are various sources for semantic relationships between words. Some are more applicable to our use case given the nature of relations that we desire and the quality of the source.

5.2.2.2.1 Collocations The Oxford Collocations Dictionary, as described in Section 2.4.3.4.3, provides the set of words and POS commonly occur in relation to any given word.

The dictionary entry for *custard* can be seen in Figure 5.2. It gives common adjectives that are used to describe custard, which can be converted into *HasProperty* relations. It also shows that custard receives the action of being made, poured and strained, while it takes the actions of thickening and setting. Furthermore, we can infer that it is closely related to *powder* and *pie*.

custard *noun*

ADJ. **creamy, thick | thin | smooth | lumpy | banana, egg, vanilla**

VERB + CUSTARD **make | pour | strain** *Strain the custard to remove lumps.*

CUSTARD + VERB **thicken | set**

CUSTARD + NOUN **powder | pie**

PHRASES **and/with custard** *some apple pie and custard* > Special page at FOOD

Figure 5.2: Oxford Collocations Dictionary entry for *'custard'*

We can extract relations directly by parsing this dictionary, which is freely available in compressed HTML format. As the dictionary is developed by Oxford and is used by students of English, its entries are very high quality and dependable.

5.2.2.2.2 Associations We discussed The University of South Florida Free Associated Norms in Section 2.4.3.4.4, which provides general associations between words. It continues to be used for research and is therefore another source that can be depended on for quality as it was collected in a scientifically sound manner.

The POS of each word is provided but no direction in the association can be determined. Therefore, we may be able to assume that a noun has the property of an associated adjective and that an adjective is a property of associated nouns. However, we cannot assume the whether a noun takes or receives the action of an associated verb. Therefore we use the more general *RelatedTo* relationship instead.

5.2.2.2.3 NodeBox Perception The NodeBox Perception model, as discussed in section 2.4.3.4.5, has plenty of overlap in the types of semantic relations used in Perception as we will be using for this project, including 'is-a' (*IsA*), 'is-property-of' (reversed HasProperty), 'is-part-of' (*PartOf*) and 'is-related-to' (*RelatedTo*). We generalise all other relations to our *RelatedTo* relation.

This data was manually entered into the system and continues to be used for research, which means that it is a high-quality source of data.

5.2.2.2.4 WordNet 2.4.3.4.1 As mentioned in Section, WordNet is very large and already has fast and simple interfaces from Python, so we do not merge its meronym (*PartOf*), hypernym and holonym (*IsA*) relations with our knowledge graph at this point. While it may prove useful to consolidate all data in a single graph in the future, it is not necessary at this stage as we can still benefit fully from its data without doing so.

5.2.2.2.5 Google Search Suggestions While we currently do not preprocess relations in the way Veale did to produce Metaphor Magnet (see Section 2.4.3.4.6), we do use a similar method to help complete sentences, particularly those with indirect objects.

For example, we would be able to produce a sentence like *'Mary hit the nail with'* but be unable to complete the sentence due to a lack of information of indirect objects. However, Google suggestions auto-complete *'hit the nail with'* with *'hammer'*, as one

might expect.

This is the least dependable source of information that we use, so we only use it for that specific case and do not add any to our knowledge network.

5.2.2.3 Concept Similarity

Similarity between concepts in the knowledge network is the primary method of guiding word choice throughout the poem. We deal with two main types of similarity; associative and symbolic.

5.2.2.3.1 Associative Similarity Associative similarity between concepts is represented by the length of the shortest past between them in our network. We use Dijkstra's Algorithm[29] as the underlying implementation of our shortest path algorithm.

Associative similarity helps us choose the best replacement word from a list of candidates. This is very useful when rephrasing to match rhyme and rhythm and will be explained in greater detail in Section 5.6.

It can also help us choose applicable words to start new lines of poetry that stay within context (see Section 5.5).

In both of these cases, we are finding the *most* similar concept from a list of candidates of unknown length. The brute force implementation can quickly increase both space and memory complexity. To fix this, we alter Dijkstra's Algorithm to have a limited search depth. This way, if we know the shortest path to one of the candidates is x, we can abort any further searches that go beyond length x for the shortest path.

5.2.2.3.2 Similarity Paths Paths from one concept do more than show the extent of the relationship - they also show intermediary concepts taken to get from one to the other. This can be a powerful way of joining two concepts together that may not be on consecutive lines.

For example, suppose the first line of a poem mentions the concept *'man.n'* and the third line *'myth.n'* (Section 5.5.1 explains how this scenario might arise). The path in the knowledge network between these two concepts goes via the concept *'mystery.n'*,

which we can use to seed the second line creating a smooth topic flow through the poem.

5.2.2.3.3   Symbolic Similarity   Symbolic similarity can be attained through inductive reasoning and substitution by concepts that have a very similar concept halo and field up to a certain depth. Simply put, we can find similarity with the *Duck Test*: if it looks like a duck, swims like a duck and quacks like a duck, it probably is a duck. Object-oriented programmers can relate this idea to the Liskov substitution principle[46].

Symbolic similarity has many use cases, including the new method of anaphora resolution to be proposed for future work. For this phase, it enables us to implement the following poetic features:

Similes

We can describe a property or an action of a persona in our poem by comparing the persona to an concept in our knowledge network that (stereotypically) has that property or takes/receives that action.

The relation *1- TakesAction → run quickly* can be built into the phrase 'runs like a cheetah' by recognising that cheetahs are stereotypically quick runners.

Metaphors

Similarly to Similes, we can find concepts in our network that share a number of semantic relations with the persona we are trying to describe.

Any persona with relations *1 - TakesAction → crawl, 1 - HasProperty → social* and *1 - HasProperty → small* is analogous to an insect because its concept in the graph shares those relations.

Personification

If we are given an inanimate object as a persona, we can describe it as if it were sentient by looking giving it relations that belong to a sentient being.

A car could be personified by giving it all the relations that a lion has in our concept network, to produce sentences like *'The car roared'*.

Irony

Our knowledge network is made up of semantic attributes that are expected for

each concept. Irony can be attained by producing lines of poetry that describe a concept doing the opposite of the concepts given in our graph.

5.3 Persona Creation and Management

5.3.1 Referencing Specific Persona

When we convert the relation *1-Named→Mary* in Figure BLAH to a phrase, we need to refer to the persona using *IsA* relations. The clause will be built with the verb 'named' and object 'Mary', and we look up the persona that this relation was taken from and find an *IsA* relation to use as the subject. In this example, we will find *'woman'* and when we add the determiner *'a'*, we get the clause *'a woman named Mary'*.

We follow a similar process when converting the *1-TA→chase* relation. The only difference is now that we can use the name of the persona as another candidate for the subject. This will give us either *'The woman chases'* or *'Mary chases'*.

5.3.2 Adding New Persona

The verb 'chase' is *transitive*, i.e. it requires a subject **and** an object, so we need a persona that receives the action 'chase'. If we look through the relations of the other known persona, we will find the relation *2-RA→chase* and we use *2-IsA→monkey* to derive the corresponding reference to that character. We complete the sentence by adding *'monkey'* to the end, giving us either *'The woman chases a monkey'* or *'Mary chases a monkey'*.

Suppose we could not find a corresponding ReceivesAction relation for 'chase' in any of the current set of persona. We must then find a concept in our knowledge network that receives the action 'chase' to use as the object of the clause. We do this by looking at the concept field of the *'chase.v'* concept in our knowledge graph for only the edges with type ReceivesAction. This gives us the required list of concepts from which to select the object of the clause. We use concept similarity to find the most applicable object given the current context of the poem; a process to be described in detail in

Section 5.5.2, but for now let's assume that we use the concept *'thief.n'*.

When we add a new noun to the poem, we need to create a new persona object so that we can refer back to it later. The new character is instantiated with an IsA relation to its noun word, i.e. *thief*. Its plurality, gender and animation are all derived from the word itself using the process described in Section 3.6.3.3.

5.3.3 Anaphora and Presupposition

So far we are only able to refer to persona by *Named* or *IsA* relations that are already part of the persona's hub. This leads to to combinations of clauses such as *'There was a woman named Mary. Mary chased the monkey'*, which is not natural speech.

The natural way to phrase it could be *'There was a woman named Mary. She chased the monkey'*. In this case, the introduction of the pronoun 'she' is a contextual reference back to the aforementioned persona. This is introduction of anaphora, described in Section 2.4.3.1.

Another option for variety in reference is to use *presuppositions*; implicit assumptions about context. This can give us clause combinations such as *'A woman named Mary. She chased the monkey. The animal stole her banana'*. Here we refer back to the monkey persona by looking for a hypernyms in WordNet and IsA relations in our knowledge network for the concept *'monkey.n'*. The implicit assumption made is that monkeys are animals, so the reader would understand the reference.

A more advanced method of presupposition introduction would be to look at stereotypical recipients (concept field) of the concept *'chase.v'* in our knowledge network. This may give us the clause combination *'A woman named Mary. She chased the monkey. The thief stole her banana'*. In this case, we are making an implicit assumption that the monkey is a thief because, according to our knowledge network, thieves stereotypically get chased. This assumption gets added to the context and can be used to develop the story, a process described in Section 5.5.

5.3.4 Semantic Types

Suppose we had the relations *2-RA→chase* and *2-IsA→monkey* but with no corresponding TakesAction relation in any other known persona. We would either need to create a new persona to be the subject of the clause or choose an already existing persona to be the subject.

In the former case we can simply look up our knowledge network in the same way we did when finding the object of the sentence. However, if we run across this case often (which we might, see Section 5.5.2), we could end up introducing a new persona every line, which can lead to a less cohesive poem. The latter case is preferable because we want to reuse persona that already exist.

There's a trap here though. What if the only other persona was an inanimate object like *a plate*? Or a non-object like *evolution*? To say *'A plate chases the monkey'* or *'Evolution chases the monkey'* makes no sense. Unless we are using personification, we would want a sentient being to be the subject of the 'chase' action.

This is where we use the semantic types provided in FrameNet, as discussed in Section 2.4.3.4.2. They indicate the required animation of any noun in all Valence patterns of the LU. We also store the animation of every persona in the system upon creation so that we can refer to it when deciding if a persona is a relevant match with a particular semantic type. If no existing persona are applicable, we can revert back to finding one from our knowledge network.

5.4 Poem Initialisation

Before we start building any poem, we need to construct the basic structure for the desired form of poetry. We also want to be able to take some *inspiration* to initialise the content that can either be sampled from the knowledge network or from the user.

5.4.1 Overall Structure

Our new poem first needs to be initialised with values of features that span across the entire poem, namely:

- Number of stanzas

- Number of lines per stanza

- Number and locations of repeated lines

- Tense

- Perspective

- Rhyme Scheme

All of these can be retrieved directly from the template developed in the previous chapter. The template is made up of probability distributions for the various values a feature can take on, so by default we get the value by sampling this distribution.

If one result is clearly more probably than the rest, we want to treat it as unambiguous. For example, more than half of the rhyme schemes found for limericks were *AABBA*, as pictured in figure 4.4. Each of the other values are some slight variation on *AABBA* (e.g. *AABCA*, *ABCCB* etc.) and occur less than a ninth of the *AABBA* frequency.

To generalise this, we try to match the frequency to Zipf's law - the most probable possibility has twice the probability of the second most probable, thrice the probability of the third most probable etc.[newman2005power]. We add the base threshold that the most probable possibility must be at least 50%. If any feature follows this rule and Zipf's law, we treat the most probable value as unambiguous and *always* apply it to the initial structure of this type of poem.

5.4.2 Inspiration

The poetry generation process can be seeded with *inspiration*, which can be in the form of words or relations. Inspiration can come from the user, or the program can come up with it itself. Inspiration from the user is input manually into the system.

When the program derives its own inspiration, it looks to the common hypernym ancestors of previous poems. It chooses a random hypernym and recursively looks for all holonyms in WordNet, out of which one will be randomly selected. A persona is then created and used as the single source of inspiration for the rest of the poem. Section 5.5.1 explains how.

5.5   Incremental Growth

To ensure some level of cohesion between lines in the poem, we will build line by line, choosing contextually relevant words and relations on the fly.

5.5.1   Applying Inspiration

As we know, new lines are created by taking a relation from a persona and building it using the process described in Section 5.2. If these relations are provided in the inspiration, we first allocate them to lines in the poem based on two factors; relation type and rhyme scheme.

5.5.1.1   Relation Ordering by Type

The template derived from the previous parts of the implementation tracks relation usage by line. We use this to decide the order that relations should appear. For example, the Named relation is most likely to appear in the first than any other line in a limerick, as shown in Figure BLAH. Therefore, if any Named relations exist among any persona, that relation comes first.

5.5.1.2   Allocating Relations by Rhyme Scheme

Rephrasing statements occurs when we need to adhere to a poetic feature such as rhyme or rhythm, a process described in Section 5.6. However, we want to stay as true to the initial inspiration as possible so we avoid rephrasing any clauses built from relations provided by the user whenever we can.

Therefore, we apply the simple heuristic that relations provided by the user should be allocated to lines that introduce a new rhyme token. These lines automatically bypass rephrasing for rhyme adherence. Naturally, this is only possible when the number of provided relations is less than or equal to the number of rhyme tokens so it is not always possible, but it provides the user with a useful guide on how many relations to input.

This ability to allocate relations to certain lines also provides flexibility of control for the user. If they *want* a relation to mark the ending of the poem, they can configure it to do so.

Once relations have been allocated to lines we can begin composing lines in natural language.

5.5.2   Creating New Lines

New lines are created by taking a relation from a persona and building it using the process described in Section 5.2. Even though inspiration may not be distributed consecutively through the poem, we always start with the first line and build linearly down to the last line.

Suppose we are building limericks with an *AABBA* rhyme scheme and that we are provided with one relation by the user, only providing content for the first line. That line would be built first without any rephrasing for rhyme. The process of building the rest of the lines are dependant on whether or not they should rhyme with a previous one.

5.5.2.1   Rhyming Lines

When the second line starts being built, we recognise that it is has not been allocated any relation so we must create one. We also know that it needs to rhyme with the first line so we can avoid rephrasing again by seeding the line with a word that rhymes, and then building the rest of the line backwards from it.

The process of finding rhyming words is outlined in Section 5.6.1.1. We select one within context (as described in 5.5.3), and build a relation according to its POS to

guarantee that it ends up at the end of the clause once it is built.

For example, if the rhyming word is an adjective we cannot build a TakesAction phrase from it because those phrases end in either a noun or a verb when created. We could rephrase for rhyme later but that would go against our 'context first' approach.

Once a relation of the chosen type and with the chosen rhyme word has been created, it is added to the most applicable persona based on semantic type and associative similarity (see Sections 5.3.4 and 5.2.2.3.1). This process is followed when building the fourth and fifth line of our limerick as well.

5.5.2.2 Blank Lines

The third line has no allocated relation and is the start of a new rhyme token. In this case we add any relation or word we want as long as it stays within context (Section 5.5.3).

We therefore choose any word that is associatively similar to those in context and then build a relation based on its POS as in the previous section.

5.5.3 Keeping in Context

We choose words based on context to achieve coherent topic flow throughout the poem. In our implementation, we define context as **the concepts mentioned in the current and immediately surrounding lines**, i.e. the context of line 2 is determined by the words used in line 1, so far in line 2 and the head and tail of the relation that is expected to be translated in line 3.

Whenever there is a choice between using any set of candidate concepts, we choose the one that is most associatively similar to the set of context concepts. For example, if we had the concepts 'man.n' and 'pizza.n' in our set of context concepts and 'fat.a' and 'cat.n' as our candidate concepts, we would choose to use 'fat.a' because it is more associatively similar to 'man.n' and 'pizza.n' than 'cat.n'.

5.6 Rephrase for Poetic Features

In lieu with our *content first* approach, we want to avoid rephrasing as much as possible. However, a poem is not a poem unless it adheres to rules of poeticness such as rhyme and rhythm. Therefore, rephrasing a clause will still happen frequently. The challenge is in keeping the phrase as true to the original as possible.

The main two cases where rephrasing is required is to match with rhyme and rhythm. We will look at the full tactics of each.

5.6.1 Rhyme

Rhyme is a very powerful poetic tool that comes naturally to many human authors. If a poem doesn't rhyme when it is supposed to, it is a big give-away that it may not have been created by a human at all. So while we will try to stay true to the original, it is vital that the poem rhymes when it is supposed to at any cost.

5.6.1.1 Finding Rhyming Words

Rhyming words are retrieved from the RhymeBrain API[5]. This tool accepts *any target string of letters* (not just words from a dictionary) and finds rhyming words. This works well with our high priority for strong rhyme because it rarely fails to give back rhyming words and tends to return more possibilities than alternatives like Wordnik[1]. It also means that even the most obscure names words input from the user can be used effectively.

Results from the API also come with a score, allowing us to balance strength of rhyme with applicability to content. For example, if we are looking to rhyme with the target word *'address'*, we get the results shown in Table 5.2.

'Misaddress' is the only word with the top rhyme score from RhymeBrain. However, if *'access'* is highly applicable in context, we may choose that instead despite the lower score. We do not consider any words lower than a score of 200.

The main drawback of the RhymeBrain API is that it tries to find rhyming words with

Word	Rhyme Score	Syllables
misaddress	300	3
access	228	2
assets	228	2
abscess	228	2
annex	228	2
annexe	228	2
mantes	228	2

Table 5.2: First 8 RhymeBrain results for *'address'*

Word	Rhyme Score	Syllables
less	300	1
yes	300	1
dress	300	1
guess	300	1
bless	300	1
mess	300	1
chess	300	1

Table 5.3: First 8 RhymeBrain results for *'ress'*

very strict rhyme; at least as many syllables as the target string with exactly matching emphasis. This is why **'dress'** and *'impress'* are not suggested as candidate rhymes for *'**add**ress'*.

To counter this, we try to find the rhymes of a suffix of the target string that most probably only contains the last syllable. To do this, we convert the word into its pronunciations as in Section 3.1. We then find the first consonant phoneme from the right with a vowel phoneme to its left. We then search for the probable letters in the original string corresponding to that consonant phoneme and take the suffix from that letter onwards.

For example, the word *'address'* has the pronunciations *[AH0 D R EH1 S]* and *[AE1 D R EH2 S]*. In both cases, we select the 'R' phoneme and match it up to the 'r' in 'address', giving us the suffix 'ress'. The results for words rhyming with 'ress' are shown in Table 5.3.

This gives us many more words that rhyme with 'address', including *'dress'* and *'impress'*.

100

5.6.1.2 Guaranteeing Rhyme

The general tactic is to only replace words with synonyms or very close associative similarity. For example, I could exchange the word 'horse' with 'pony' if I needed to rhyme with 'Tony'.

If that is not possible, we look to *extend* the clause by adding applicable adjectives or adverbs to the end of the sentence. SimpleNLG enables us to do this by adding *post modifiers* to noun and verb phrases. These are words that will appear immediately after the parent phrase.

We first find the final (target) word in the phrase of the clause that is being rephrased. If it is a noun, we filter out any non-adjective candidate rhymes. Similarly, if it is a verb we filter out non-adverbs. We then look up the concept halo for the target word, looking only at 'HasProperty' edges. This gives us a list of words that are commonly used to describe the target word. We then compare this list to the candidate rhyming words, find the most associatively similar pair and add it as a post modifier to the phrase of the target word.

This process guarantees that the final word in the clause will have the necessary rhyme when realised, but also keeps the added or replaced word in very close context to the original statement.

5.6.2 Rhythm

Rhythm is much less stringent than rhyme because most words can be mispronounced without changing their meaning. For example, in the fifth line of Shakespeare's Sonnet 116 he pronounces the monosyllabic word *'fixed'* as *'fix-**ed**'*, essentially adding a syllable and changing the stress.

Given this flexibility, we stick to our *content first* approach and only try to find a best match for rhythm without compromising content.

5.6.2.1 Syllabic

Syllabic rhythm, as described in Section 2.1.2.2, defines the number of syllables each line should contain. After we have created phrases for the line and matched any rhyme scheme correctly, we can extend or reduce the syllable length of the line to match syllabic rhythm.

5.6.2.1.1 Extending If the number of syllables in the line is fewer than the required amount, we must add syllables to the line. The simplest way to do this is to add more modifiers.

We randomly choose a phrase from those that make up the line. We then look up the knowledge network for modifiers by looking the target word's concept halo for the *HasProperty* relation. We randomly select one and add it as a modifier to the phrase of the target word as long as does not add more syllables than required to make up the deficit.

We repeat this process, expanding the depth of the halo to incorporate more words when necessary, until we have *exactly* the right number of syllables.

SimpleNLG chooses where the modifier should appear in the sentence unless explicitly told to where to put them. This can be done by adding it as a *pre-modifier* to the phrase, enforcing the word to appear *before* the target word, or a *post-modifier* to enforce appearance after the target word.

To ensure that we do not tamper with the rhyming word, we explicitly instruct to only ever add pre-modifiers to the phrase of the rhyming word.

5.6.2.1.2 Reducing Occasionally the syllabic length of the line exceeds the required number of syllables. In this case, replacement of words is our only option. We utilise our knowledge graph to find replacements with close associative similarity, but there is still a risk of losing coherence. We never replace the rhyming word.

The process involves finding the longest word in the sentence and replacing it with the most applicable word with fewer syllables. We repeat until we either have exactly the right number of syllables or if we overshoot and have too few, we using the extending process to get it back up to the exact required amount.

0....1	**0**	**0**	**1...0**	**0.....1**
Wo-man	chased	the	hai-ry	mon-key

Table 5.4: Line paired with desired rhyme scheme

5.6.2.2 Accentual

Any poem with accentual rhythm has, by definition, syllabic rhythm. Therefore we rephrase to match syllabic rhythm before we fit to accentual rhythm. That way we know that we have exactly the right number of syllables at the beginning of the rephrasing process.

Let's take *'Woman chased the hairy monkey'* as our line and '01001001' as our required stress pattern. If we put one on top of the other as in Figure 5.4, we can pair up each word with its required pattern.

Start from the rightmost word; *'monkey'*. Since we do not want to tamper with rhyme, we disregard this pattern-word pair. Moving along to the left we get the word 'hairy', which has the required pattern of '10'. This matches with the actual stress pattern for 'hairy', so nothing needs to be done and move along again. The same happens for the words 'the' and 'chased' because they are both monosyllabic and can be either stressed or unstressed.

Finally, the word 'woman' is paired with the stress pattern '01'. We have a mismatch because, according to the CMU Pronunciation Dictionary, the stress pattern for 'woman' is '10'. We need to replace the word.

There are three approaches to this problem:

1. The simple and naive method would be to choose any random word that fits the required pattern, but that contradicts the *content first* approach.

2. We could only look at synonyms and hypernyms/*IsA* relations and replace with any that have the required pattern, but there is a risk that none of them do, in which case we do not replace the word at all, keeping the incorrect pattern.

3. The final approach involves indexing all words in the knowledge network by possible stress patterns. We select the most associatively similar word from the values of the required stress pattern. However, this again leads to the possibility

of finding a poor replacement word in terms of preserving the integrity of the content.

We choose to use the second method given our priorities for this project. In our example we would replace the word with 'adult' as it is a hypernym of woman.

Chapter 6

Evaluation

6.1 Comparison of Analysis Results to Theory

A major goal of this project is to show that the structure and content of types of poetry can be derived by analysing corpuses of collections. We would like to investigate how our results matches up with those documented in literary theory, as described by Young Writers[8], a poetry and creative writing resource for UK schools, and poets.org[9], supported by the Academy of American Poets.

We evaluate the results of analysing 450 limericks, 718 haiku and all 154 of Shakespeare's sonnets. These three types of poetry cover a large range of techniques and are of varying lengths, enabling us to evaluate more completely.

6.1.1 Limericks

One stanza, five lines, no repetition

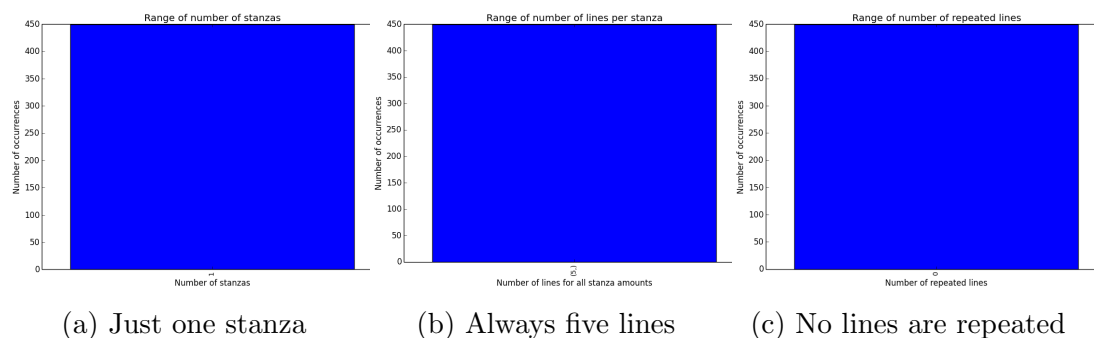All of the poems in our corpus follow this rule, as seen in Figure 6.1.

(a) Just one stanza   (b) Always five lines   (c) No lines are repeated

Figure 6.1: One stanza, five lines, no repetition.

Usually begins with *'There was a...'* and ends with a name, person or place

Figure 6.2 shows the N-Grams for line 1. We can see that *'There be a young'*, the lemmatised version of *'There was a'* with the added *'young'* adjective is used with significant frequency (any substring is also considered a significantly frequent n-gram). We can also see in Figure 6.3 that limericks largely talk about animate objects (such as people) or non-objects (such as places). Furthermore, Figure 6.4 confirms that the type of persona are people, organisms and animals.
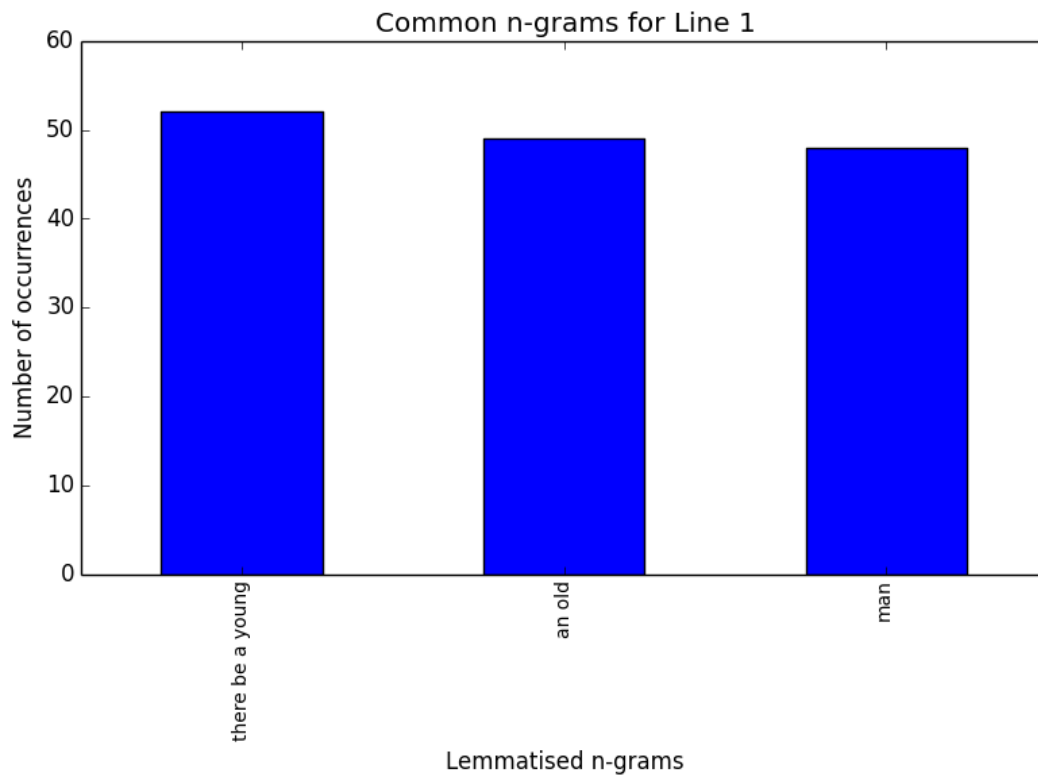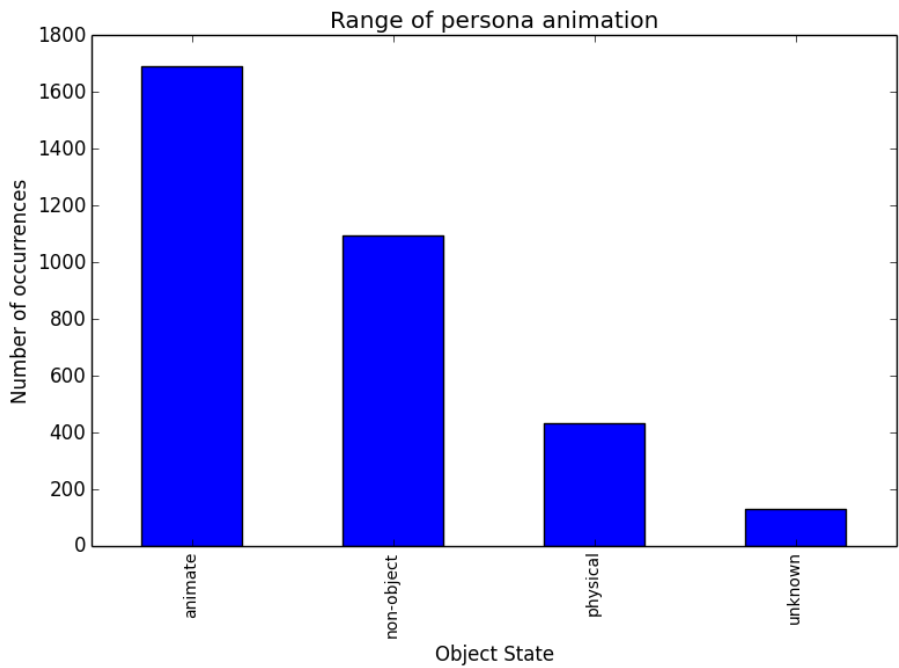

Figure 6.2: N-grams for Line 1
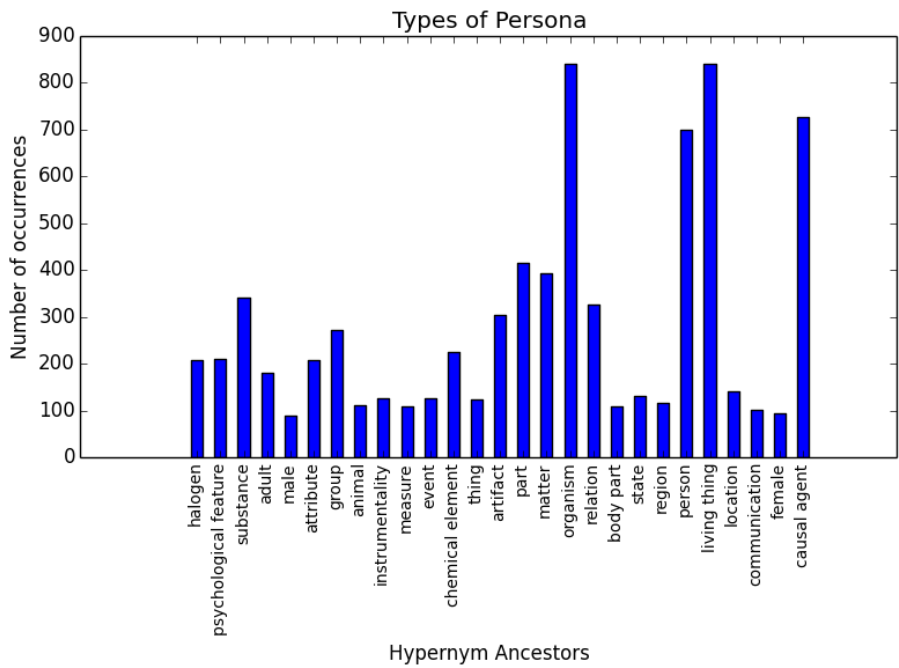
Figure 6.3: Animation of nouns

Figure 6.4: Types of persona

Overall, our results supports the theory. However, since the analysis omits Named

Entity Recognition, we are unable to specifically say whether or not it was a person or a place.

Furthermore, our results only show that 52 poems have this n-gram, which is only 11.6% of the corpus. We suspect this discrepancy comes from the popularity of Edward Lear poems, of which most start with *'There was a...'*, but poems by other authors do not generally use this as a rule. This comes down to the contents of the corpus. Since it was a collection of previously unseen poems from various sources across the Internet, we do not know the proportion of Edward Lear poems in the corpus before analysis (as required to avoid biasing the corpus as mentioned in Section 4.1.1). If the poem had a higher proportion of Edward Lear limericks, the frequency of this property would probably increase. However, since we are analysing limericks in general, our result may be representative.

Last line is farfetched or unusual

We have no way of determining this from our analysis or results because the social context of the poem was never considered. As a result this feature will only occur by chance during generation, not intention.

Usually nonsense or humour

As above.

$AABBA$ rhyme scheme

Our results show that this is by far the most probable rhyme scheme, as seen in Figure 6.5. The other possibilities are close variations of $AABBA$, eluding to the limitations of the CMU Pronunciation Dictionary and our method of handling words unknown to it, as described in Section 3.1. The results may yet improve if we were to build a state transducer model to predict the most likely rhythm pattern for words that are not in the dictionary.
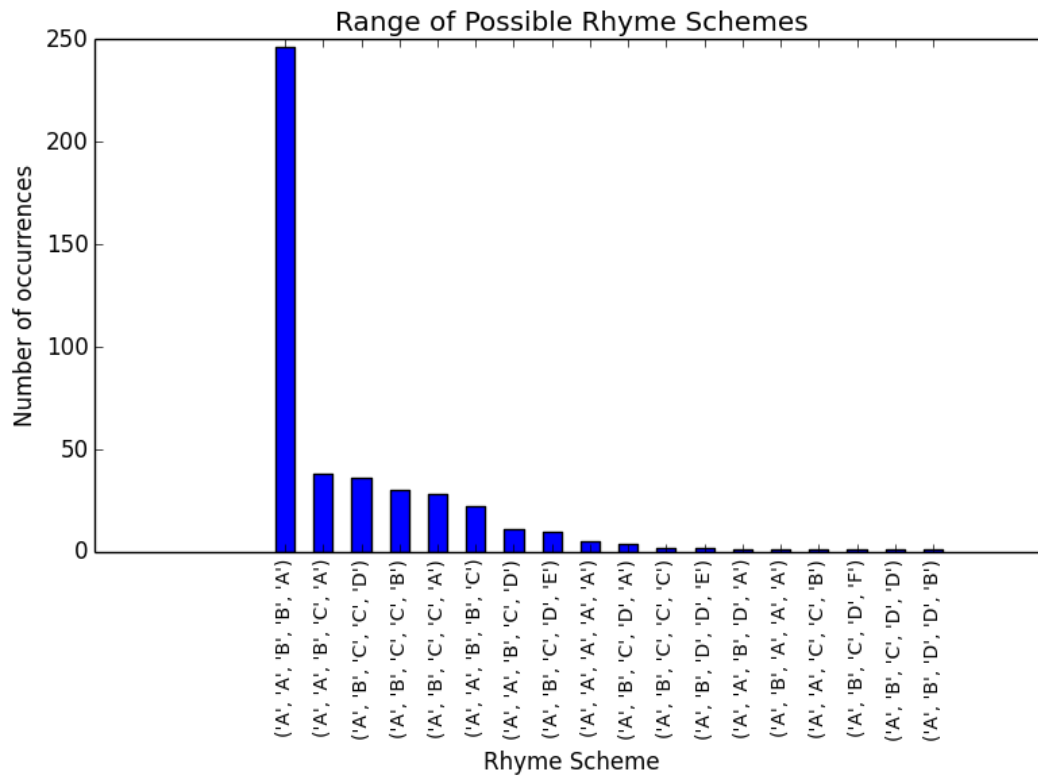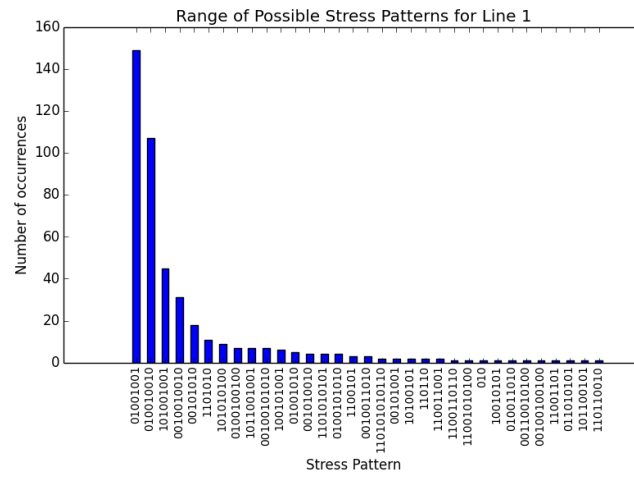
Figure 6.5: Rhyme Scheme

Despite those shortcomings the results follow Zipf's law as discussed in Section 5.4.1, which means that we can treat the top result as unambiguous. Therefore, all limericks generated by the system will aim to have the $AABBA$ rhyme scheme.
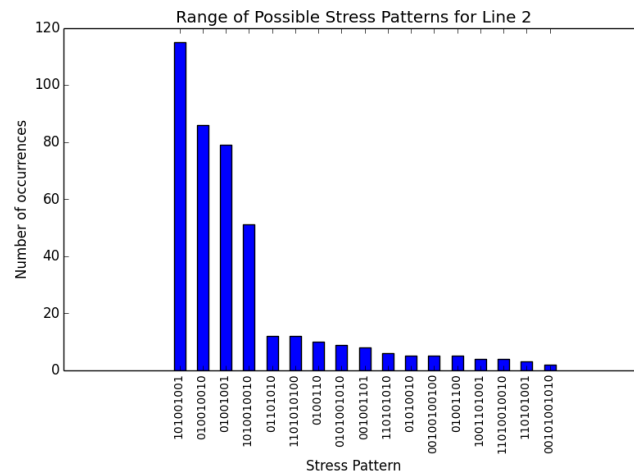
Lines 1, 2 and 5 have 01001001 meter, while lines 3 and 4 have 01001 meter
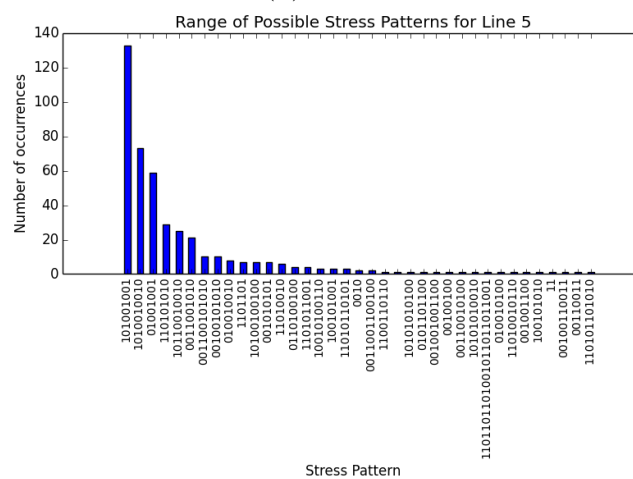
Figure 6.6 show the stress patterns of lines 1, 2 and 5.

(a) Line 1

(b) Line 2

(c) Line 5

Figure 6.6: Stress patterns for lines 1, 2 and 5

The most popular rhyme scheme in line 1 is the expected one. However, it does not follow Zipf's law because the second option - the expected pattern with an appended unstressed syllable - is not significantly less probable.

The results for the second line are worse because the expected pattern is only third most probable. The others are variations on the expected pattern - first prefixed with a stressed syllable and then appended with an unstressed syllable. However, given the relative proportions of these three, it is not unlikely that the expected pattern will be selected.

The analysis of the fifth line is the worst. Not only is the expected pattern the third most popular, the graph follows Zipf's law, which means that the first, incorrect pattern (expected pattern prefixed with a stressed syllable) will be treated as unambiguous.

In all cases, the most probable patterns include the expected one or variations thereof. This is likely caused by the limitations of the CMU Pronunciation Dictionary again. We do not suspect it is our methodology because we try to accommodate for as many rhythm possibilities during analysis and we make no claims or filters along the way.

Since our generation phase tries for a best fit rather than strictly the same pattern, this is not a damaging result in that respect.

Figures 6.7a and 6.7b show the stress patterns of lines 3 and 4.
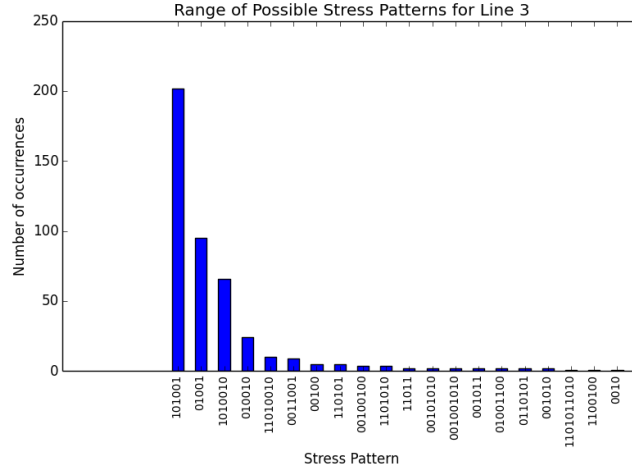
(a) Line 3
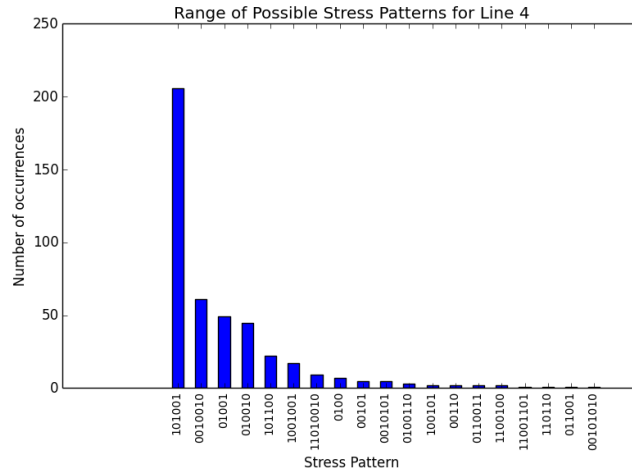
(b) Line 4

Figure 6.7: Stress patterns for lines 3 and 4

In both of these lines, the expected pattern is the third most popular and the most popular is the expected pattern prefixed with a stressed syllable. The most interesting thing is the relative proportions - both times the 101001 pattern would be treated as unambiguous. The reasoning for this comes down to three possibilities:

- The limitations of the CMU Pronunciation Dictionary are greater than expected, but consistent. The syllable count is consistently one too high and happens to lead with the added stressed syllable very often as its mistake.

- Our algorithms for detecting rhythm are flawed.

- The corpus is very biased to this particular mistake.

- Limericks actually have 101001 as the expected rhythm so our sources are wrong and perhaps this was never noticed.

The first two are unlikely because the results for lines 1 and 2 as well as for other poems (see following sections) are generally as expected. If either of those were in fact the problem, we would expect many more anomalous results.

The third is a possibility. The corpus of poems was collected from various sources across the Internet, but some websites provided more than others. It is likely that the same author who consistently made the same mistake was published on the same website that made up a large proportion of the corpus.

The fourth possibility requires further investigation into high quality limericks written by well known authors and more sources for the rhythm of limericks. Poets.org credits Edward Lear's *Book of Nonsense*[41] as the defining anthology for modern limericks.

The first 10 poems of that very book are shown in Appendix A.8.1. If we analyse them by eye, the third line has six syllables 5 times and the fourth line has six syllables 8 times. From this we can assume that the expected rhythm of 01001 is actually not that common.

The Book of Limericks (Wordsword Reference)[45] is a published anthology of over 1,800 limericks. This book was not used to build the corpus so it is unlikely that any of them would have been part of the original analysis. We select the first 10 from this analogy, as seen in Appendix A.8.2, and perform the same analysis by eye. In this case, the third line has six syllables 8 times and the fourth line has six syllables all 10 times.

This suggests that the standard is in fact to have six syllables, so the expected rhythm of 01001 is not correct. Therefore, we look to other sources of literary theory in case this has been pointed out.

Nowhere is it mentioned that the rhythm should be 101001. The five sources in Appendix A.8.3 teach the rhythm of limericks, but their teachings vary and the examples they use often do not match up with what they preach.

We therefore conclude that more investigation needs to be done to decide what is the *actual* expected rhythm of the third and fourth line or limericks, and we

further propose that based on our analysis it should be 101001.

Other Noteworthy Results

Figure 6.8 shows that limericks are usually written in past tense and occasionally in present tense.

A very large proportion are written in third person, as seen in Figure 6.9.
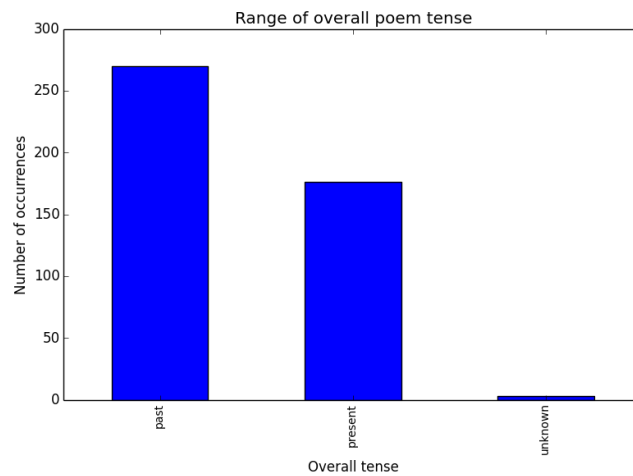
Figure 6.8: Probability distribution of overall poem tense
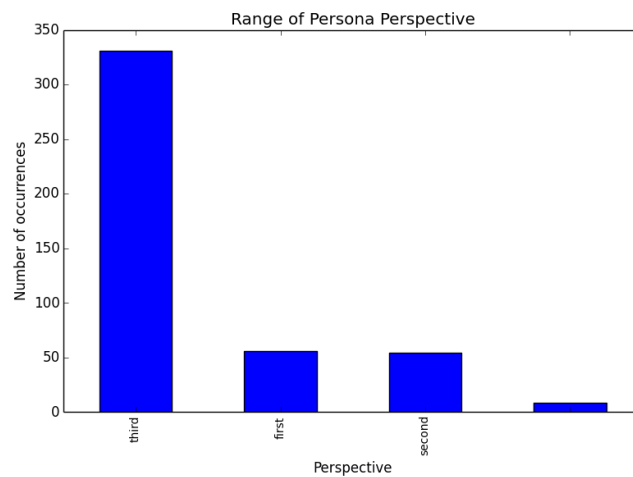
Figure 6.9: Probability distribution perspective across poem

6.1.2 Haiku

One stanza, three lines, no repetition

All of the poems in our corpus follow this rule, as seen in Figure 6.10.

(a) Just one stanza (b) Always five lines (c) Negligible number of lines are repeated
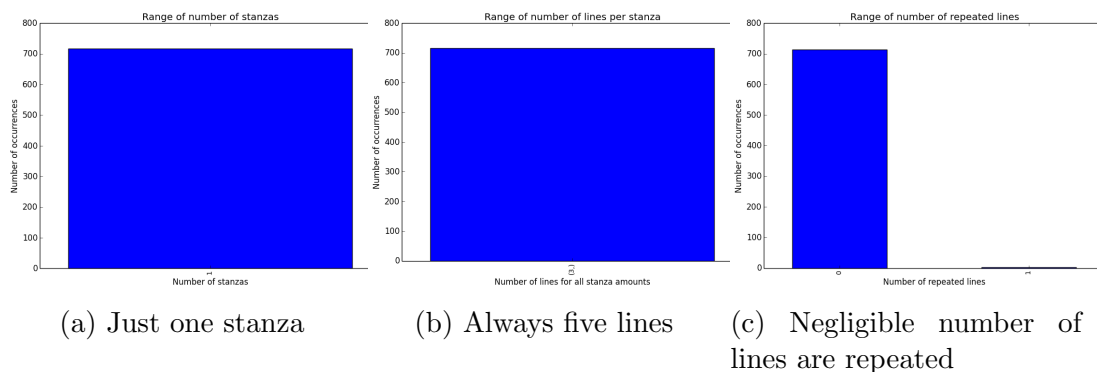
Figure 6.10: One stanza, three lines, no repetition.

Topic ranges widely, *nature* is very common

Figure 6.11 shows that there is indeed a wide range of topics including halogen (light), living thing, natural object, cognition, chemical element, organism, body part, atmospheric phenomenon, weather and natural phenomenon; all of which elude to nature.

Figure 6.12 also shows that it generally talks about non-objects, i.e. nouns that do not cast a shadow. This includes nature and weather.
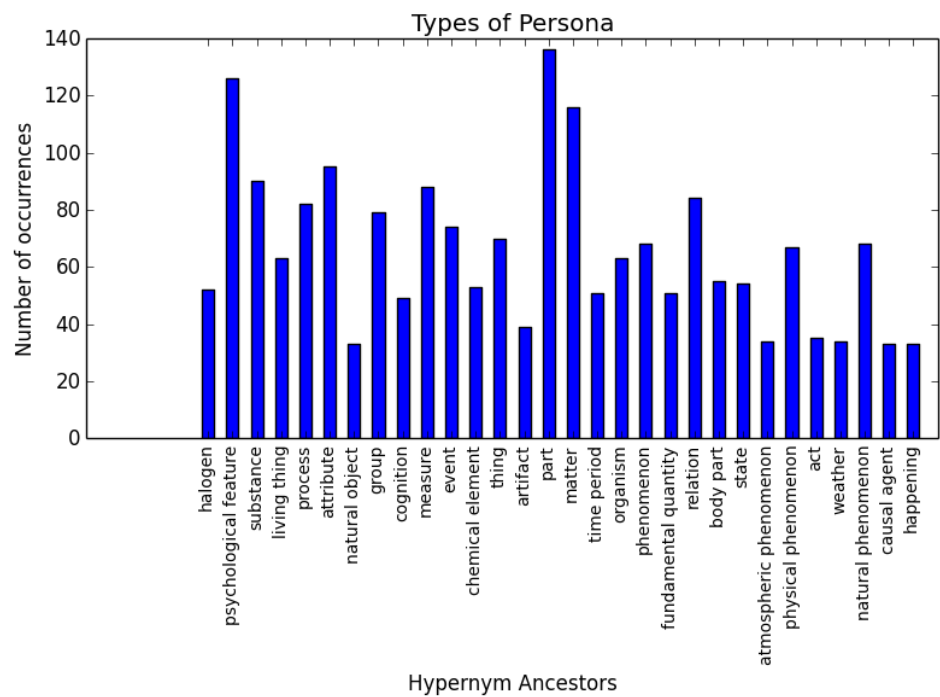
Figure 6.11: Animation of nouns in haiku
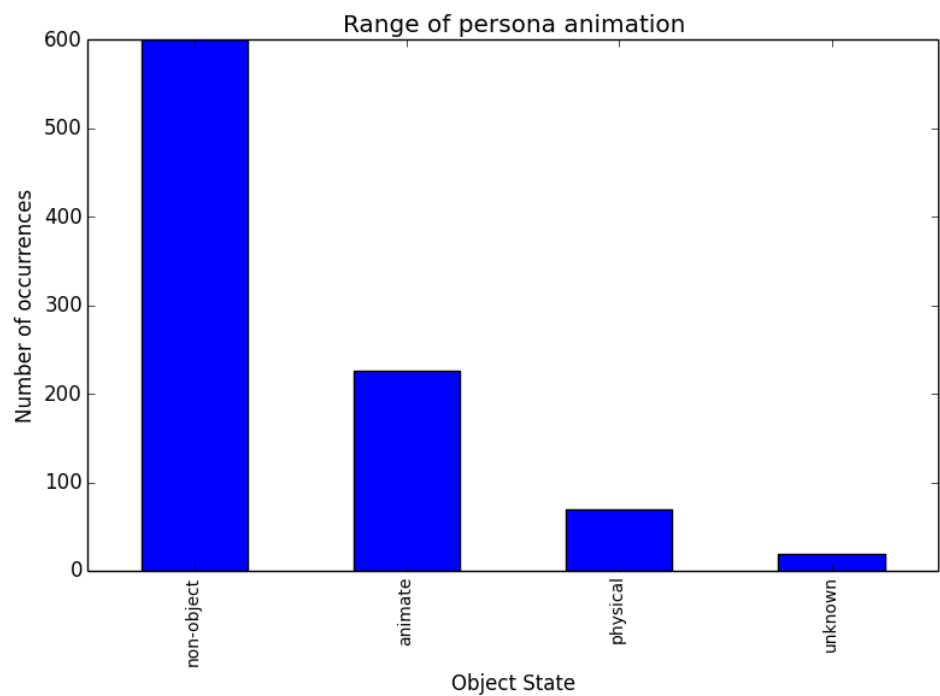
Figure 6.12: Types of persona in haiku

5-7-5 syllabic rhythm

Figures 6.13a through 6.13c show the syllabic rhythm of each line. It is clear that 5-7-5 is a most popular and is taken as unambiguous.
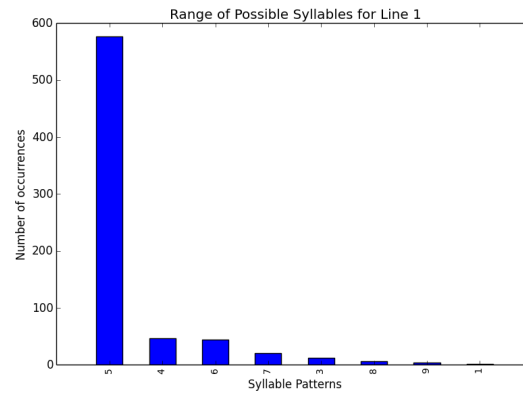
(a) Line 1
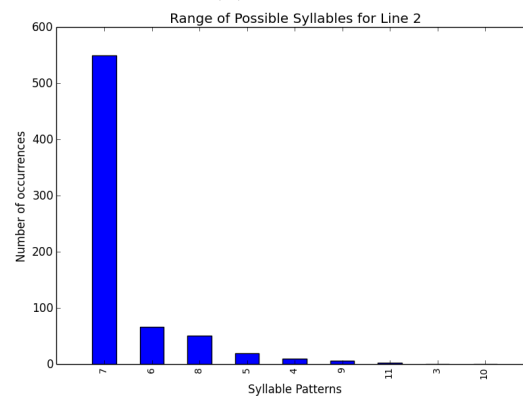
(b) Line 2
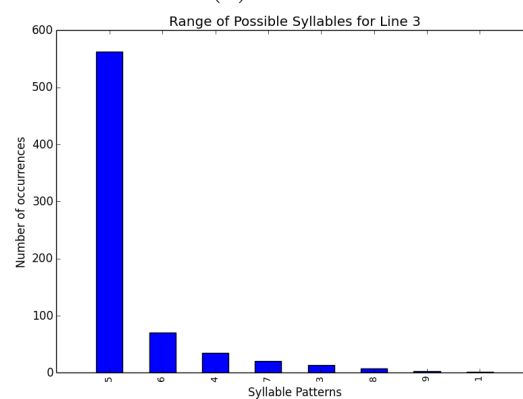
(c) Line 3

Figure 6.13: Syllable counts for each line

No rhyme scheme

Figure 6.14 shows that haiku is most likely to not have any specific rhyme scheme (equivalently, an ABC rhyme scheme). The candidate rhyme schemes occur with low frequency, so the lack of rhyme scheme is treated as unambiguous and any rhyme only occurs by chance during generation.
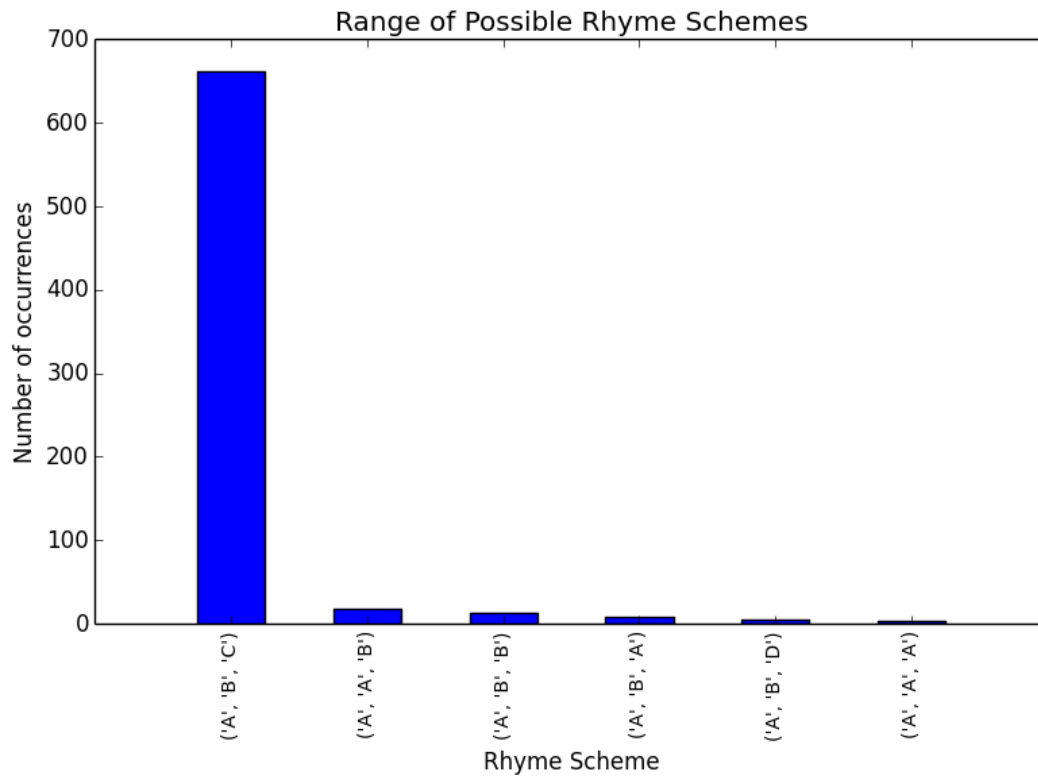
Figure 6.14: ABC implies no rhyme scheme

Other Noteworthy Results

Conversely to limericks, Figure 6.15 shows that haikus are usually written in the present tense and occasionally in past tense.
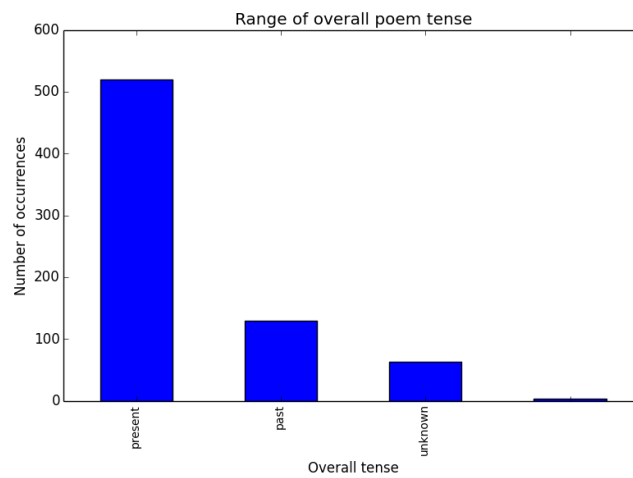
Figure 6.15: Probability distribution of overall poem tense
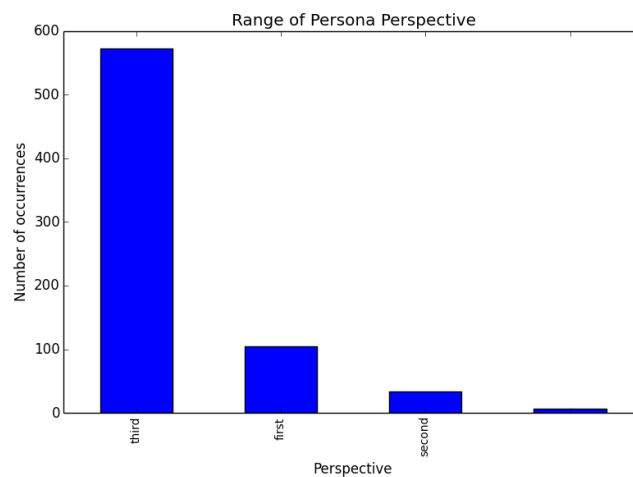
Figure 6.16: Probability distribution perspective across poem

As with limericks, most haiku are written in third person, as seen in Figure 6.16.

6.1.3 Shakespearean Sonnets

One stanza, fourteen lines, no repetition
All of the poems in our corpus follow this rule, as seen in Figure 6.17.

(a) Just one stanza

(b) Negligible number are not fourteen lines

(c) No lines are repeated
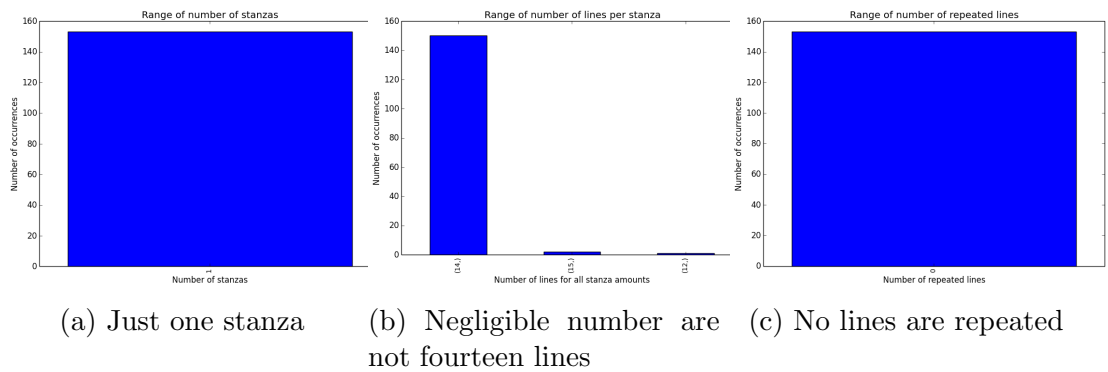
Figure 6.17: One stanza, five lines, no repetition.

Topic is usually of thought, emotion and ideas

This is evident from Figure 6.18, which shows the topics covered are related to similar concepts, such as psychological feature, cognition, emotion, feeling, relation, state and communication.
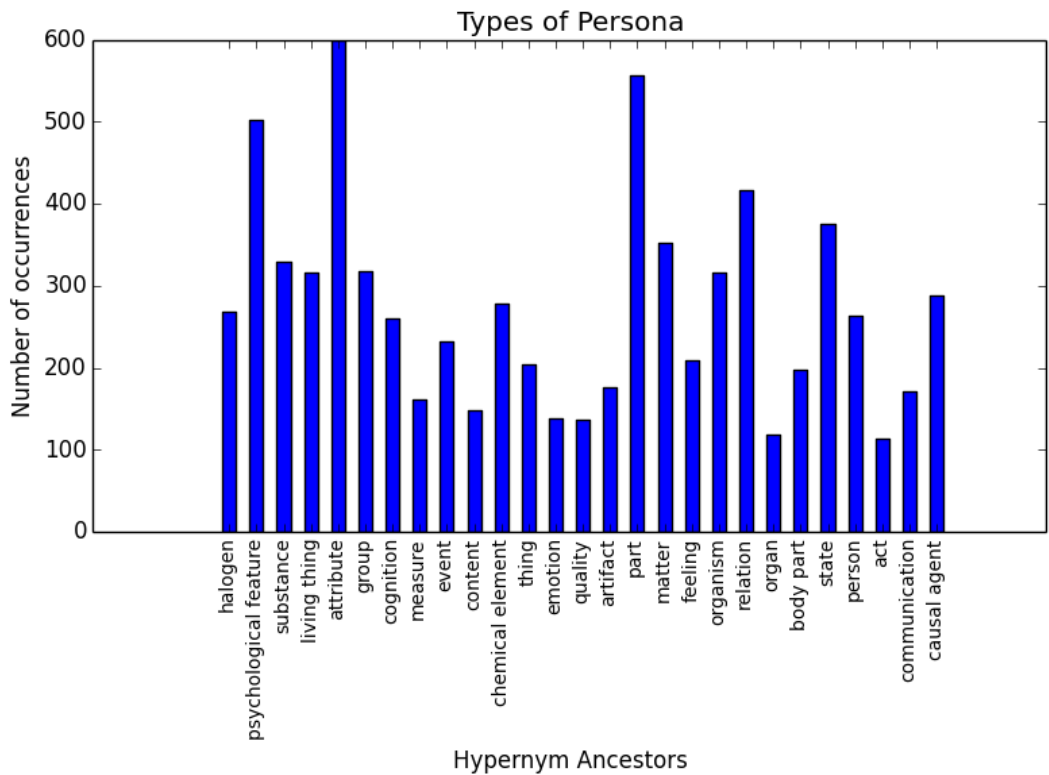
Figure 6.18: Topics covered in sonnets

Figure 6.19 supports this, showing that non-objects were often discussed more

than animate and inanimate objects.
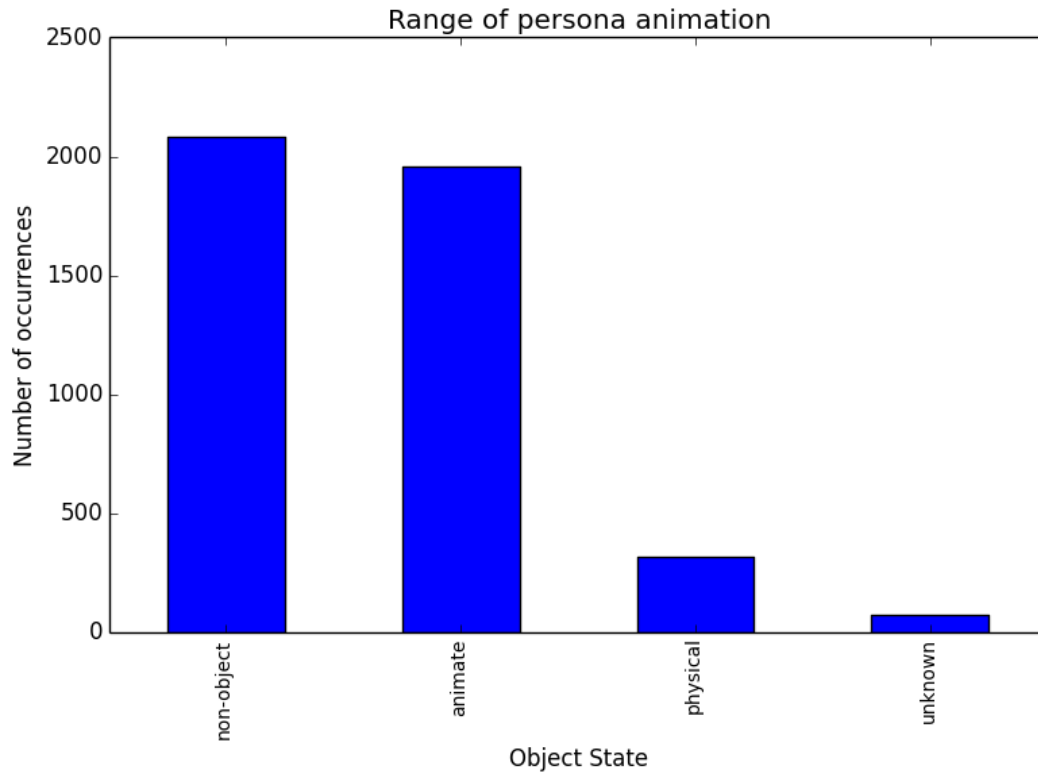
Figure 6.19: Types of persona in sonnets are non-objects

Figure 6.20 also shows that Shakespeare mentioned words such as *'love'*, *'beauty'*, *'fair'* and *'think'* a significant number of times across his sonnets.
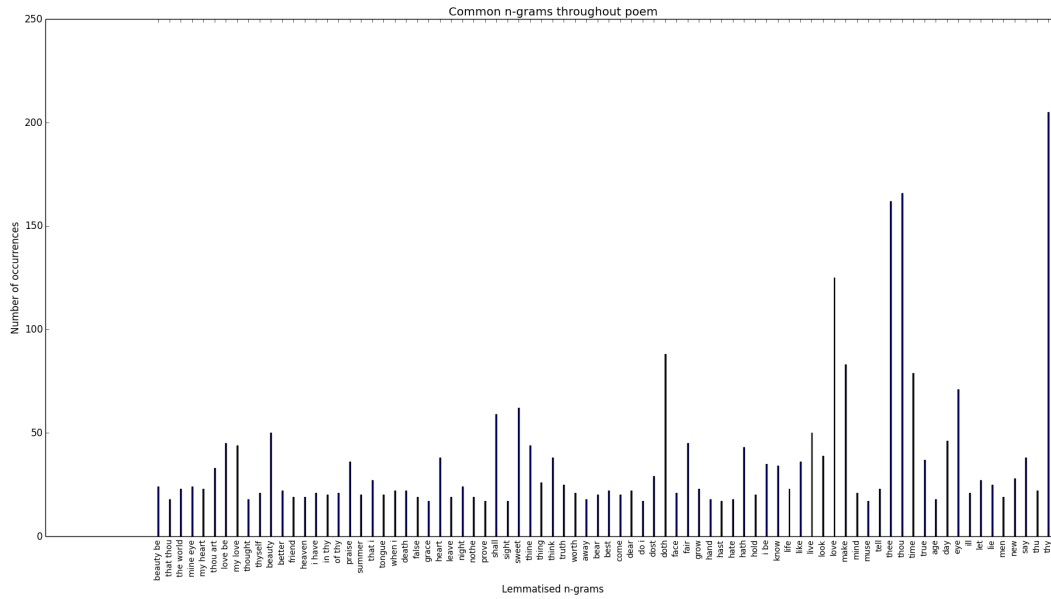
Figure 6.20: Words used in sonnets with significant frequency

ABABCDCDEFEFGG rhyme scheme

Figure 6.21 shows that the most probable rhyme scheme is as expected. However, because of the Shakesperean vocabulary that is not in the CMU Pronunciation Dictionary, it often failed to complete analysis for certain poems if there were too many potential permutations (see Section 3.2).
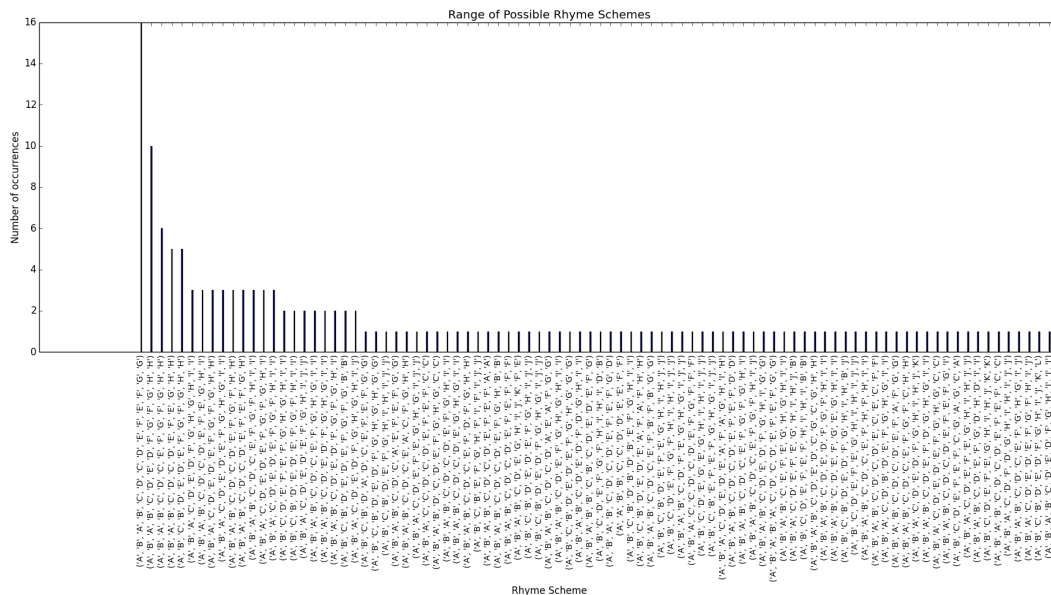
Figure 6.21: Possible rhyme schemes for the Shakespearean sonnet

This exposes a limitation on this system that each extra line of the poem potentially increases the number of rhyme permutations exponentially, risking incomplete analyses. A simple solution to this would be to leave the rhyme schemes in their unzipped form as in Figure 3.1 and counting the frequency of possible permutations iteratively.

Iambic pentameter for every line

Figure 6.22 show that each line is unambiguously iambic pentameter (0101010101) **except** for the 13th line, which unambiguously starts with a stressed syllable instead of an unstressed one.

This is a very exciting result because it is unlikely to be caused a limitation of the CMU Pronunciation Dictionary or our implementation because this discrepancy is so consistent and specific. This is also the *"perfect"* corpus, containing all 154 of Shakespeare's original sonnets.

Most research says that every line of every Shakespearean Sonnet is iambic pentameter. No research could be found to support the stressed first syllable of the 13th line, however, we propose that it is a significant result and not a coincidence.

Firstly, iambic pentameter is not even a possibility in our analysis. Secondly, the thirteenth line of the poem is the start of the *'heroic couplet'*, marking a change in the previous quatrains and signalling the impending end of the sonnet. Therefore, there is a motivation to break the monotony and add the extra stress, acting as the start of a strong conclusion.

If analyse the sonnets by eye for this specific aspect, we can find examples where the first syllable **cannot** be unstressed, either due to the starting word needing two stressed syllables or use of punctuation (particularly exclamation marks) following the first syllable.

Sonnet I: *Pity the world, or else this glutton be,*

Sonnet XIII: *O, none but unthrifts! Dear my love, you know*

Sonnet XIX: *Yet, do thy worst, old Time: despite thy wrong,*

Sonnet XXIII: *O, learn to read what silent love hath writ:*

Sonnet XXVII: *Lo! thus, by day my limbs, by night my mind,*

Sonnet XXXIV: *Ah! but those tears are pearl which thy love sheds,*

Sonnet XXXVII: *Look, what is best, that best I wish in thee:*

Sonnet XLVII: *Or, if they sleep, thy picture in my sight*

Sonnet LII: *Blessed are you, whose worthiness gives scope,*

Sonnet LV: *So, till the judgment that yourself arise,*

Sonnet LIX: *O, sure I am, the wits of former days*

Sonnet LXV: *O, none, unless this miracle have might,*

Sonnet LXVII: *O! him she stores, to show what wealth she had*

Sonnet XCI: *Wretched in this alone, that thou mayst take*

Sonnet XCVII: *Or, if they sing, 'tis with so dull a cheer*

Sonnet CV: *'Fair, kind, and true,' have often lived alone,*

Sonnet CXXV: *Hence, thou suborn'd informer! a true soul*

Sonnet CXLIX: *But, love, hate on, for now I know thy mind;*

We use these unambiguous examples to guide how the rest of the ambiguous lines should be interpreted. We also argue that stressing the first syllable is more natural when spoken out loud in all cases.

Given the evidence and motivations explained above, we claim that it was Shakespeare's intention to start the 13th line of his sonnets with a stressed syllable, which means that it is **not iambic pentameter**, contrary to current literacy theory.
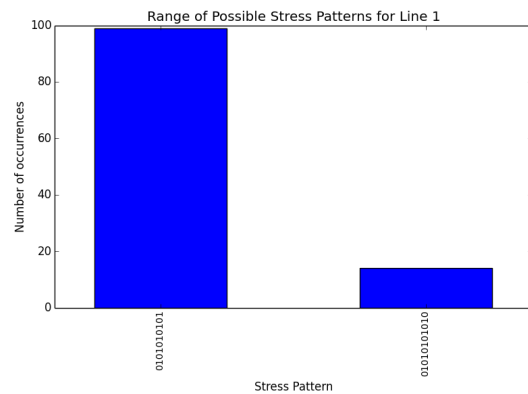
(a) Line 1 stress patterns
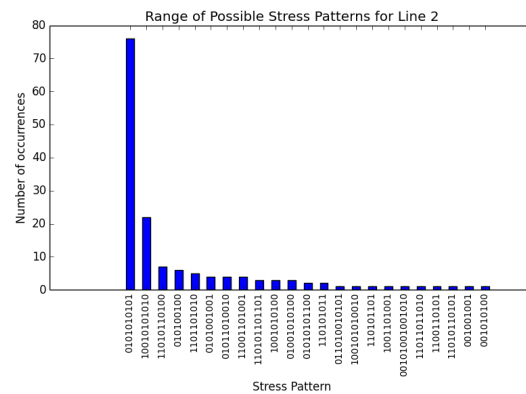
(b) Line 2 stress patterns
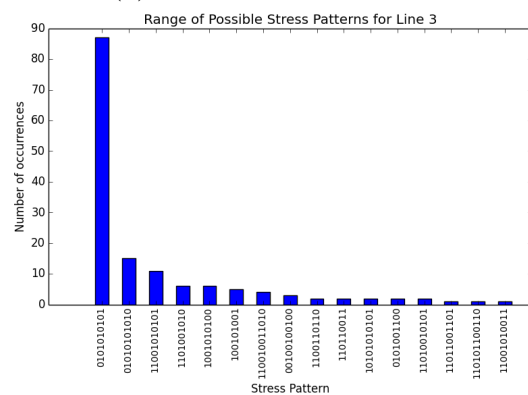
(c) Line 3 stress patterns
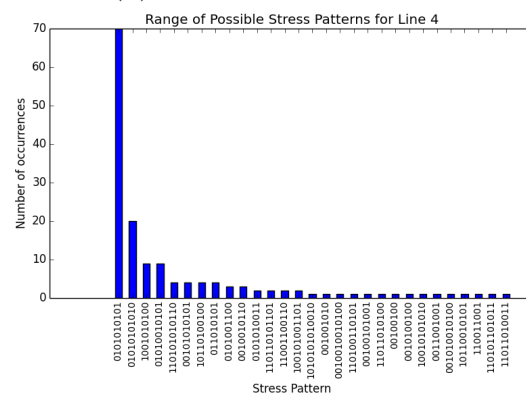
(d) Line 4 stress patterns
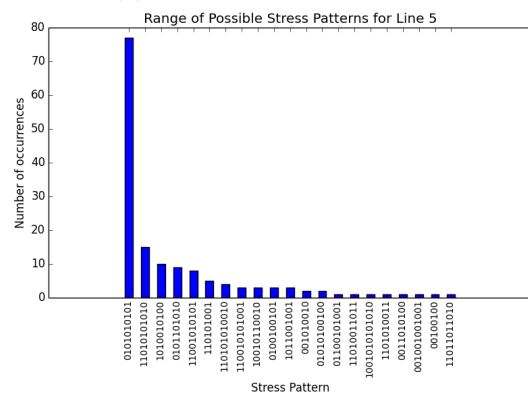
(e) Line 5 stress patterns
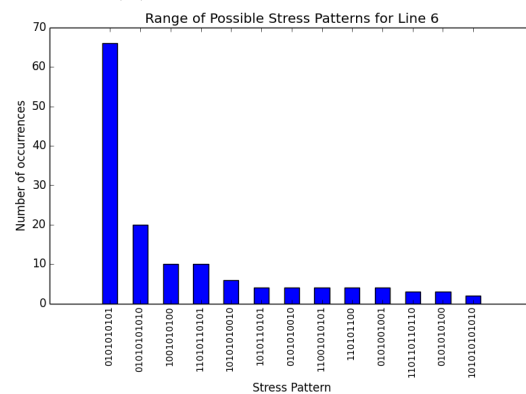
(f) Line 6 stress patterns
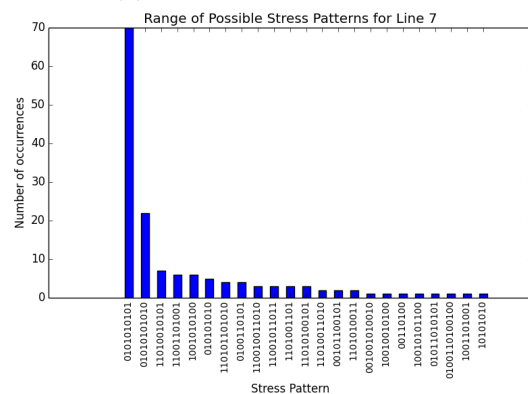
(g) Line 7 stress patterns
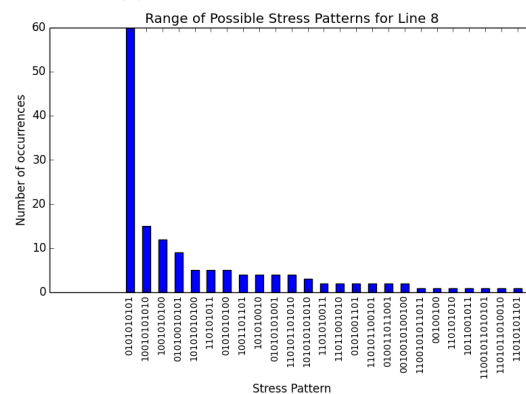
(h) Line 8 stress patterns

Figure 6.22: Sonnet stress patterns for each line

(i) Line 9 stress patterns

(j) Line 10 stress patterns

(k) Line 11 stress patterns

(l) Line 12 stress patterns

(m) Line 13 stress patterns

(n) Line 14 stress patterns
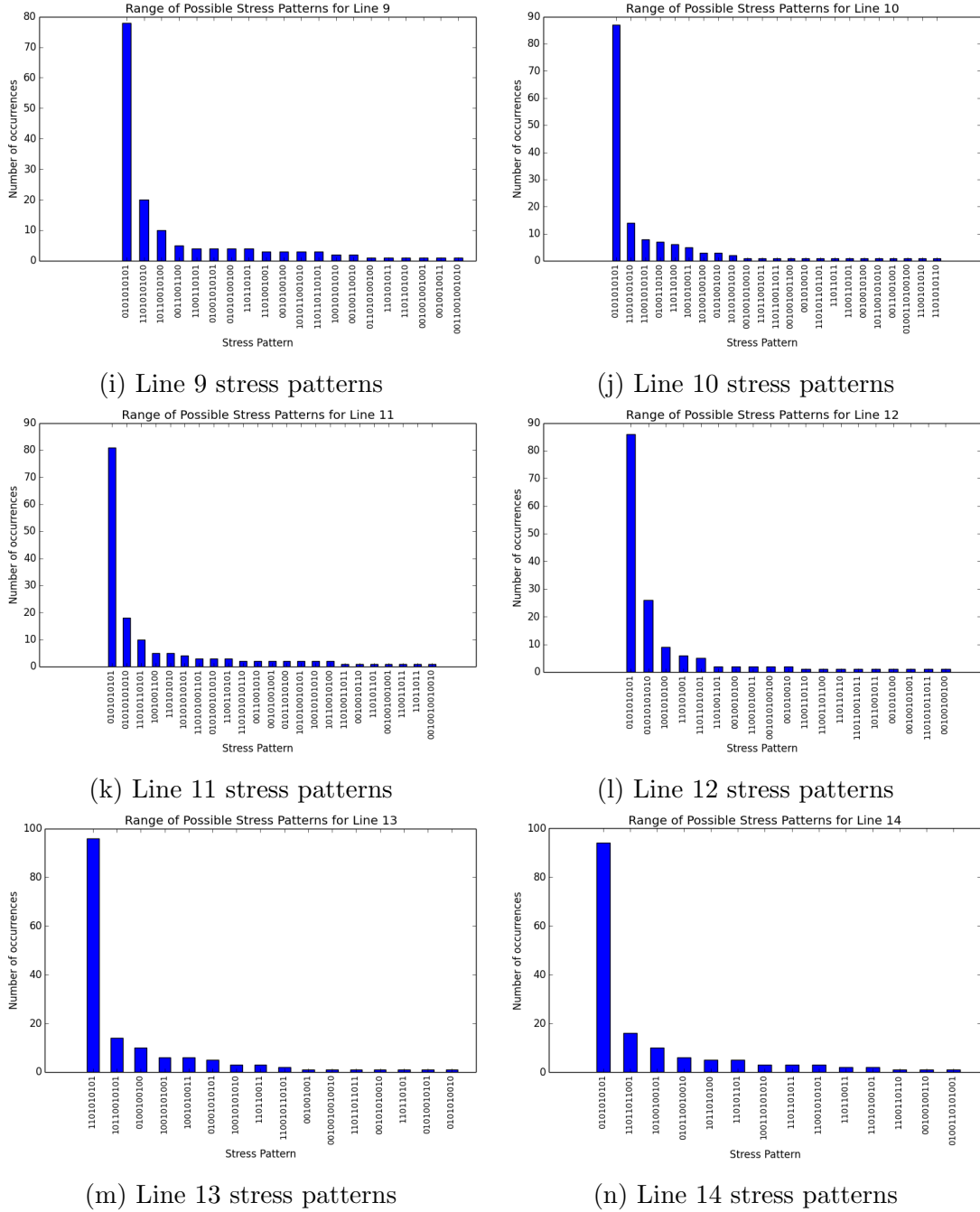
Figure 6.22: Sonnet stress patterns for each line

Other Noteworthy Results

Most sonnets are written in first or second person as seen in Figure 6.24 and almost all are written in the present tense, shown in Figure 6.23.
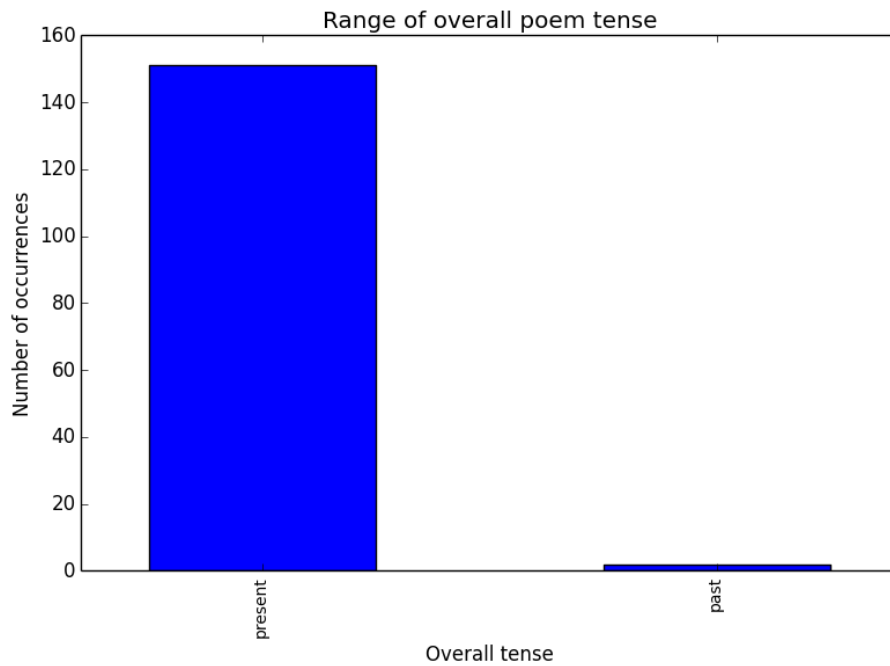
Figure 6.23: Probability distribution of overall poem tense
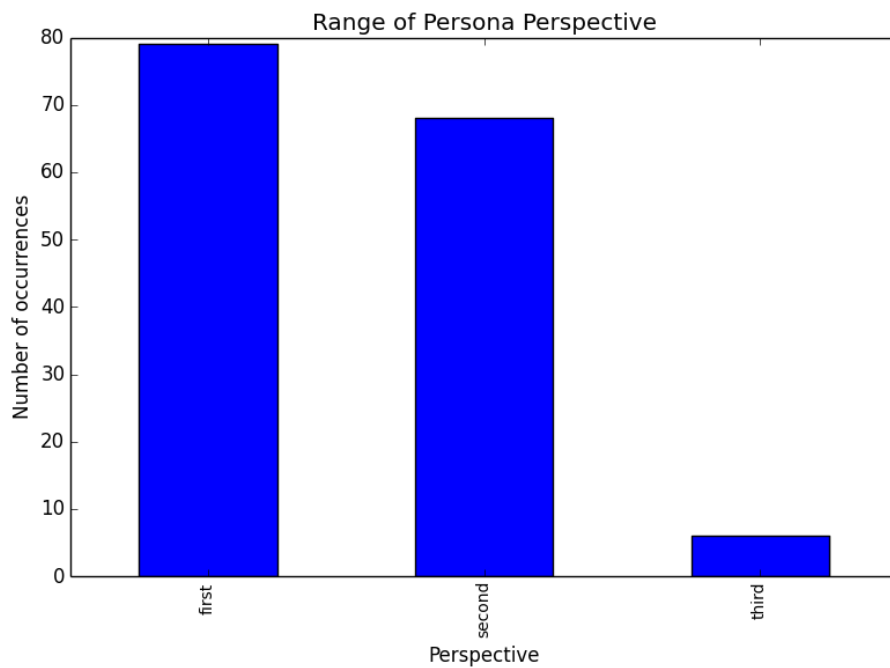
Figure 6.24: Probability distribution perspective across poem

It's also worth noting that similes are used in almost every other sonnet, evident

Poem Type	Corpus size	Analysis (s)	Aggregation (s)
Limerick	450	8040	40.1
Haiku	718	2808	45.7
Sonnet	154	12004	51.7

Table 6.1: Speed of analysis and aggregation by poem type

from Figure 6.25.
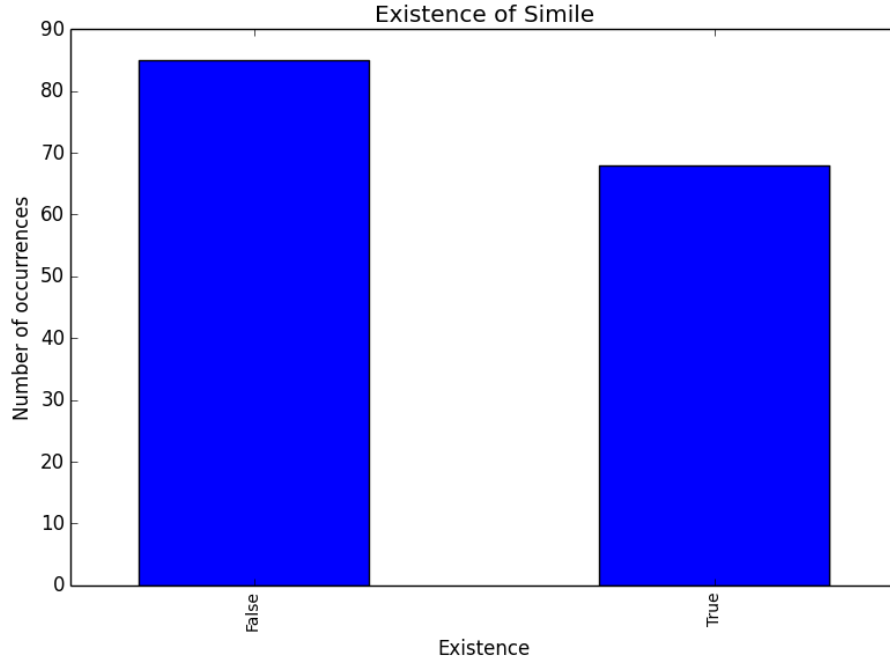
Figure 6.25: Evidence of frequent use of analogies

6.1.4 Concurrency and Performance

The timing of the analysis and interpretation is shown in Table 6.1 using machine specifications given in Appendix A.4.

We can see that the length of the poem has more impact on performance than the size of the corpus. The unusual words used in Shakespearean sonnets that would not have been in the CMU Pronunciation Dictionary would have also contributed to the slow speed of analysis. This is because we find the most similar word that is in the dictionary as described in Section 3.1. On average, it takes 0.81 seconds to look up a

4-letter word and 1.09 seconds to look up a 10-letter word.

Since poems are analysed and features are aggregated *in isolation*, there is plenty of scope for concurrency.

For the poem analysis, a thread pool managed the concurrent execution of 10 workers, each analysing one poem. Trial and error showed 10 to be the optimal number of worker threads for limericks and 12 for haiku. Large resources such as the CMU Pronouncing Dictionary and WordNet were created once and shared amongst the threads. Due to the aforementioned scaling issues with sonnets analysis was done *serially*, further contributing to the discrepancy in speed.

This was sufficiently fast for this corpus and since this is data is pre-processed and stored. However, we use Python's Pool Executor library rather than the Threading module, enabling us to move over to processes instead of threads with minimal effort if we need multi-core parallelism. It should be noted that this might be slower due to larger overhead and the need for large resources to be created in multiple locations since memory cannot be shared.

The generalisation process was actually fastest without the overhead of constructing the thread pool. With a thread pool of any number of workers, the average processing time is above 42 seconds for the results of the 450 analysed limericks. Without threading, the process took 40.1 seconds on average.

This generalisation process is fast enough for it to be done over again with different given values as discussed in Section 4.2.

6.1.5 Summary

Overall, our results show that the system's interpretation of poetic structure and content matches with literary theory on many occasions, despite relatively low quality corpuses. This shows that there is no need to hard-code any rules of poetry, as was done in previous attempts.

In fact, we have even found two cases where our program is contrary to literacy theory that may be true findings, not errors. It is exciting to see computerised poetry analysis become involved in furthering our understanding of a literary art such as poetry.

The major shortcomings of the current implementation are:

- The omission of any Named Entity Recognition limits not only the specific recognition of names and places, but also the general contextual understanding of the poem.

- Our attempt to patch up the limitations of the CMU Pronunciation Dictionary by finding the closest matching word (see Section 3.1) is not as reliable as expected and should be replaced with a state transducer model implementation.

- The memory and time complexity rises exponentially with the length of the poem in the current implementation. As seen with the sonnets compared to the haiku and limericks, the quality of analysis falls as the poems get longer.

- The sentiment of the poem has not been considered at all in this project, but it is an important factor because, for example, limericks are meant to be humorous.

- Using our own algorithms for anaphora resolution and presupposition projection is not effective at the moment, so we end up finding more persona than expected. We propose a new method in Section **??** that utilises our contextual awareness and semantic understanding of persona.

6.2 Analysis of Generated Poetry

We evaluate the generation phase with limericks and haikus, as they are sufficient to show the positives and negatives of this project. The assessment is done on poems that were created from scratch, i.e. without inspiration from the user. This is because cohesiveness, creativity and vocabulary all naturally improve when seeded with inspiration, which is not a true test of the system.

For completeness, Figures 6.26 through 6.29 are examples of limericks generated with inspiration from the user. In each of these cases, note that the persona was initiated as *singular, male and animate*.

Rohith

Named

1

Desires   IsA
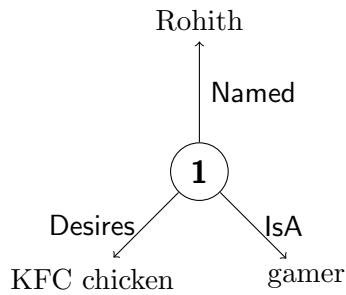
KFC chicken   gamer

an early man allegedly named Rohith

a gamer securely established in myth

he aspired as KFC chicken

he smarted with gamer thicken

a noticeable, asleep gamer silversmith

Figure 6.26: Limerick seeded with inspiration

Umar

Named

1

Desires   IsA
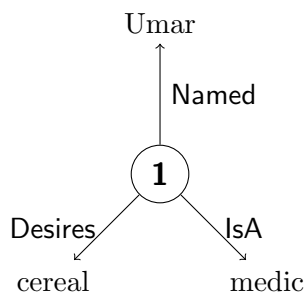
cereal   medic

there be a young medic named Umar

the attractive man serves behind bar

say he longs for cereal

publishes material

the successful launch washes vintage car

Figure 6.27: Limerick seeded with inspiration

Mat

Named

1

Desires   IsA
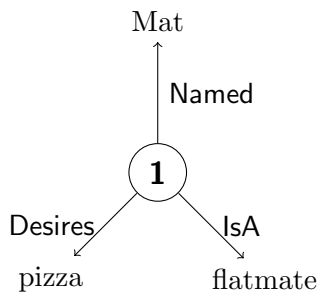
pizza   flatmate

there be a young man named Mat

long-standing flatmate trims excess fat

he ambitions vanishes of pizza

he enters arena

it all but, humanely, destroys habitat

Figure 6.28: Limerick seeded with inspiration

William

Named

1

Desires   IsA

success   supervisor
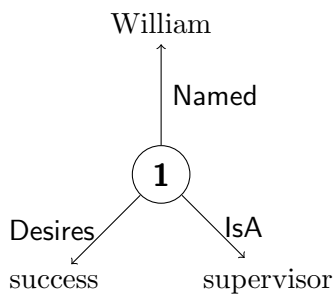
there was a primitive man called William

supervisor thirsted for civilian million

he interested in success

a thin man concisely assess

the father divines man vermilion

Figure 6.29: Limerick seeded with inspiration

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The point about improving cohesiveness is evident from the second lines of the last penultimate example. Since we knew that the third line would use *'pizza'* in the first of them, the rhyming word chosen for the second line was *'fat'* because it is the most associatively similar. The same goes with *'success'* and *'million'* in the last example and *'cereal'* and *'bar'* in the second example. In the first example, *'myth'* was chosen because it knows that the persona is male and the concept *'man.n'* is two hops away from *'myth.n'* on our knowledge graph (via *'mystery.n'*).

6.2.1 Turing-style Tests

We employ Turing-style tests to assess whether participants can tell human poems apart from ones generated by our system. Five haiku and five limericks were generated *without* inspiration. They were each then shuffled together with five poems sampled from their respective corpora, which were written by humans.

The poems were put in a survey with answer options as *"Human"*, *"Computer"* and *"Can't tell"*. We also leave space for participants to give their feedback on their decision, which is extremely valuable because it tells us how we can improve for the future.

Overall the results are promising - every poem generated by our system was thought to have been written by a human by more than 10% of participants.

For the haiku, the worst result had 82.16% of participants realising that it was created by a computer (Figure 6.34). The best result had only 34.34% realised that it was generated by a computer (Figure 6.33). However, some of the human written poems were also mostly thought to be computer generated. This reduces the integrity of the test because it could mean that the participants were not qualified to take the test due to lack of knowledge about haiku or poor command English. Alternatively, it could be that the human-generated poems were of a relatively poor quality as they were randomly selected.

The limericks results did not look as good. The worst result had 86.99% of participants realising that it was created by a computer (Figure 6.44). The best result had 73.17% realised that it was generated by a computer (Figure 6.48). The main reasons for this are that even thought the words were related, the limericks were not cohesive and did not tell a story. We discuss this further in later sections.

The results of the Haiku test are shown in Figures 6.30 through 6.39 and the limerick test in Figures 6.40 through 6.49. The correct answer is shown in **blue** on the pie charts.

shape taps on window

the brightness flares upon

it causes concern
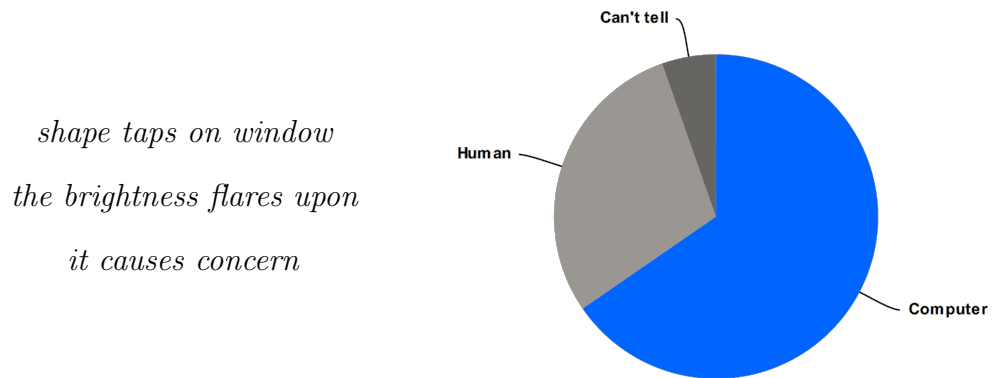
Figure 6.30: Haiku Turing Test Question 1

met on September

she melts frozen me

like how rain soaks into sea
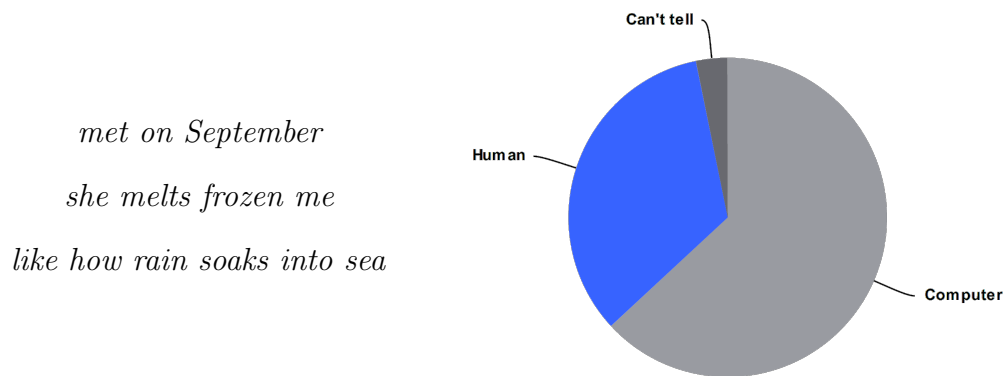
Figure 6.31: Haiku Turing Test Question 2

silly confused plants

harbinger an early spring

fifty eighth more to come
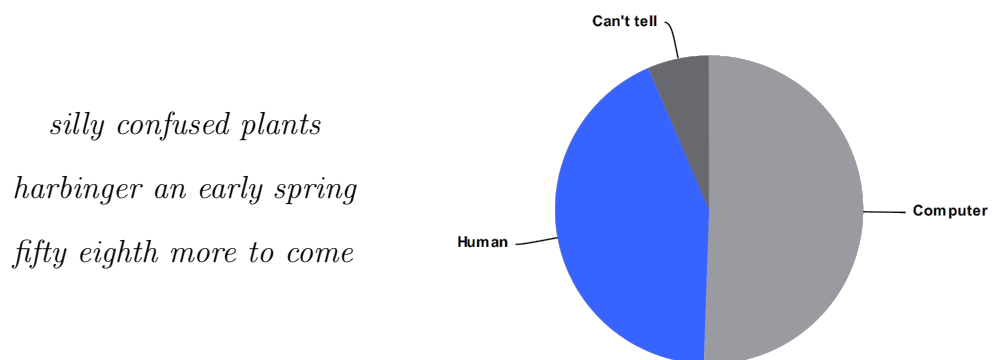
Figure 6.32: Haiku Turing Test Question 3

chlorine bleach critique

element abject force out

a military source
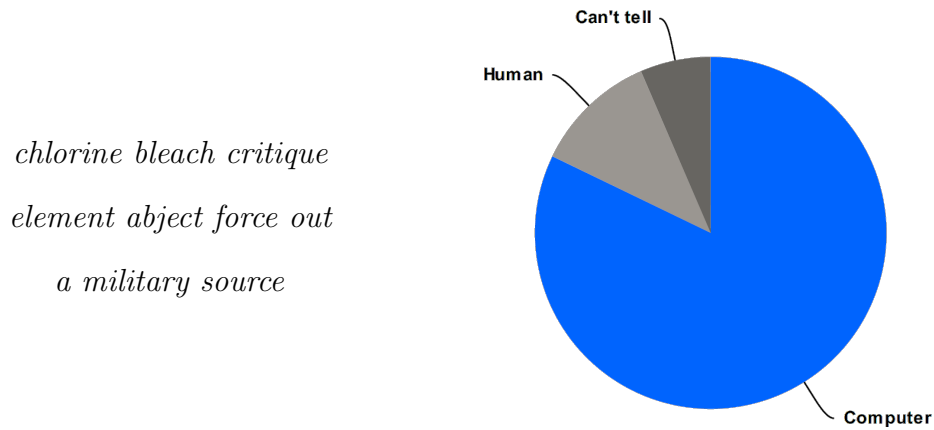
Figure 6.33: Haiku Turing Test Question 4

oblong, homeless box

the dialog like a script

packs sound in a box
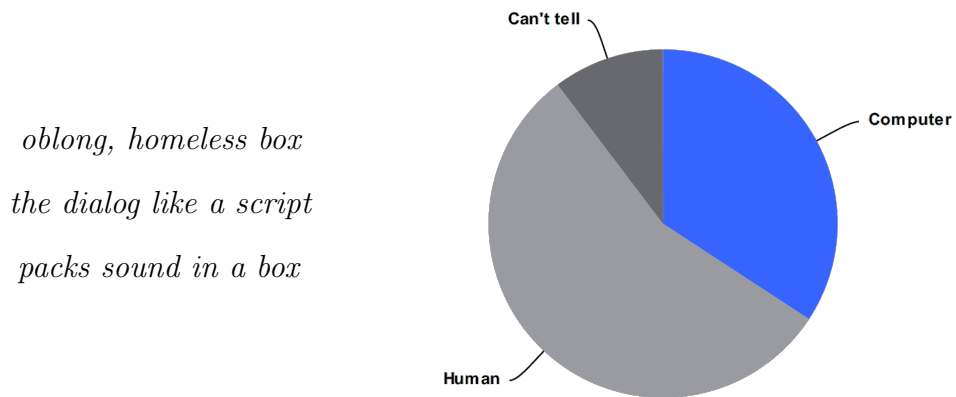
Figure 6.34: Haiku Turing Test Question 5

summer's solstice

the voice of the cormorant

dreams of yesterday
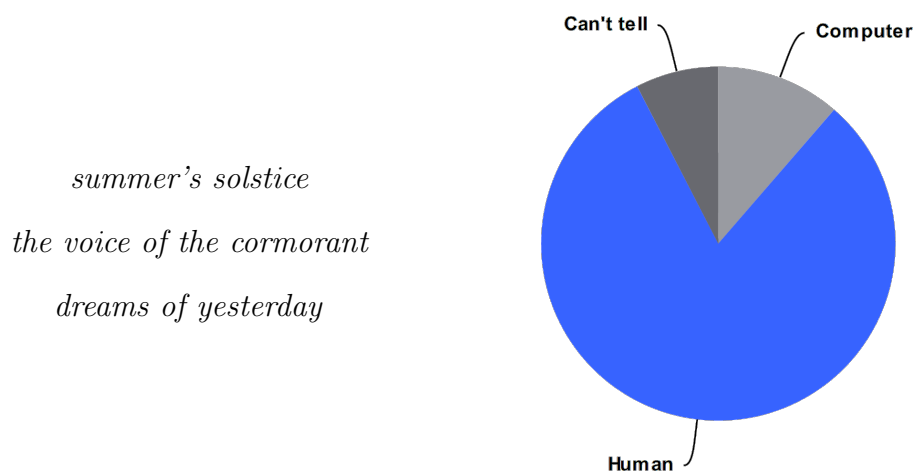
Figure 6.35: Haiku Turing Test Question 6

an education

funding university

a pre-school playgroup

Figure 6.36: Haiku Turing Test Question 7

unstable condition

political like a watershed

state turns to ferment
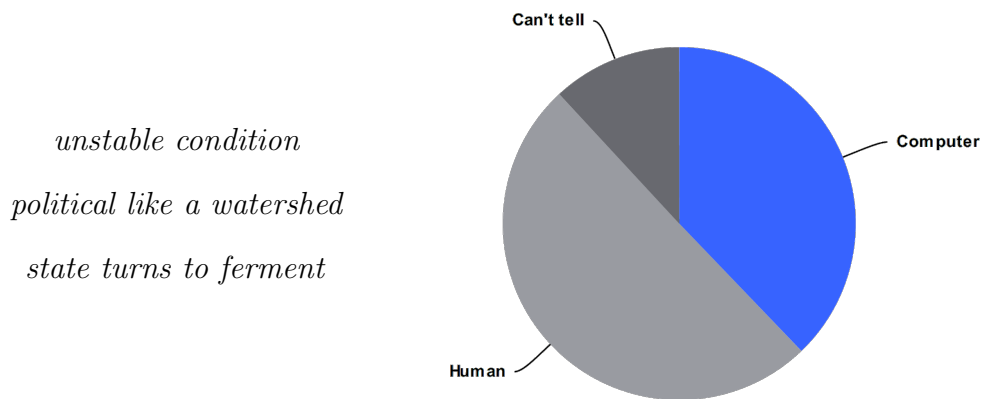
Figure 6.37: Haiku Turing Test Question 8

foaming white horses

rolling in collapse on dunes

look a jellyfish
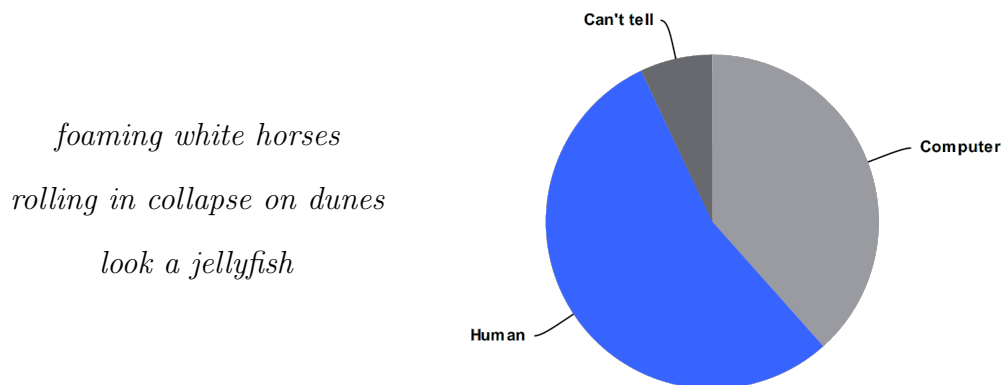
Figure 6.38: Haiku Turing Test Question 9

135

today was lovely

i worked and walked carefully

happened this lately
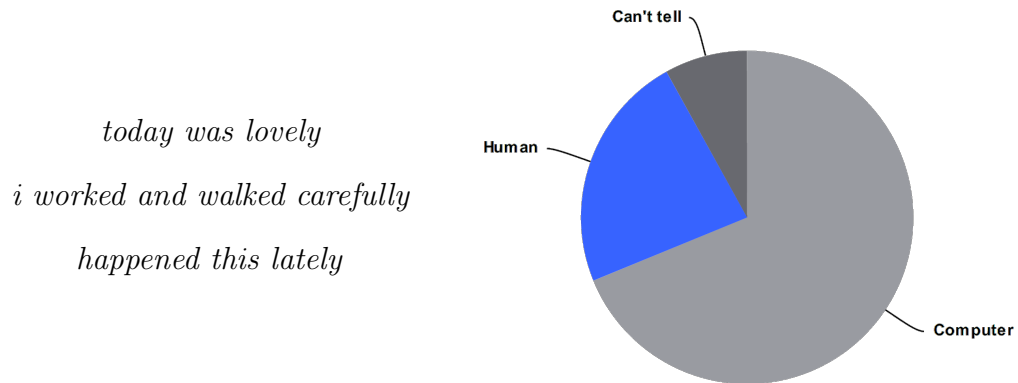
Figure 6.39: Haiku Turing Test Question 10

amazingly, antelope stew

is supposedly better for you

than a goulash of rat

or Hungarian cat

but I guess that you probably gnu
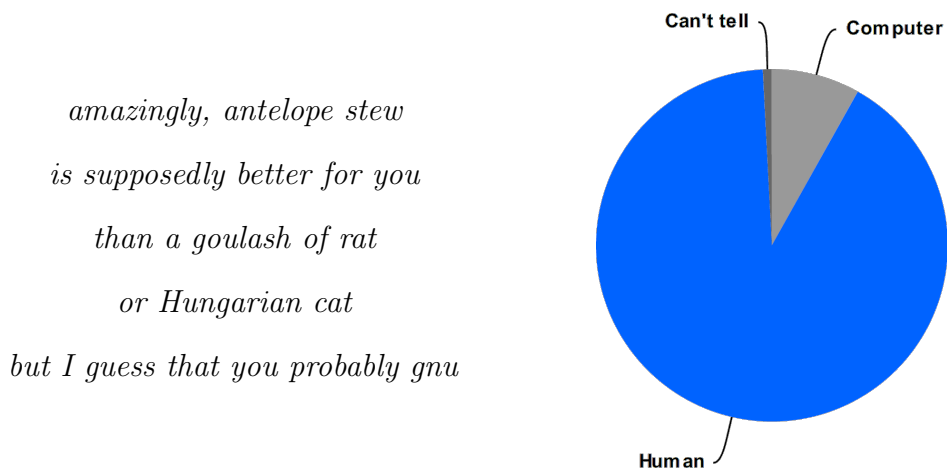
Figure 6.40: Limerick Turing Test Question 1

there was a strange man named

Einstein

the genius scientist followed the line

central overtakes the leader

he polishes off a reader

a rational person imposes fine
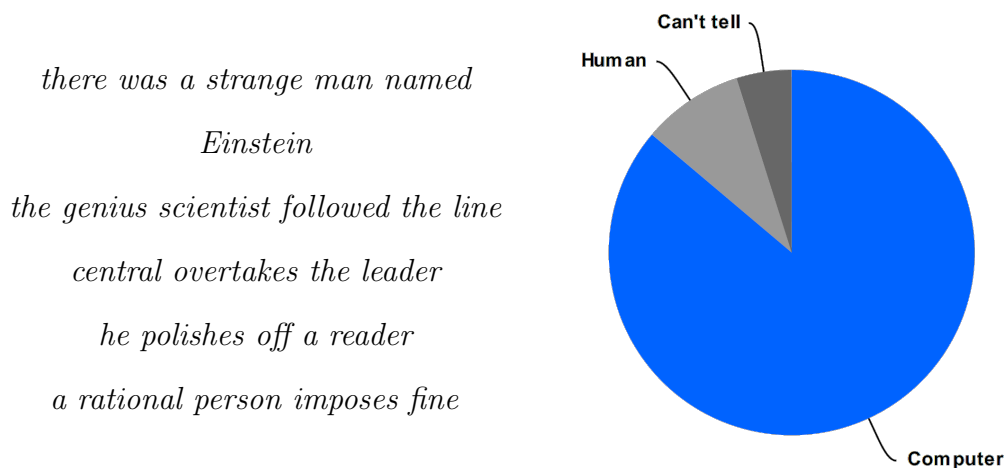
Figure 6.41: Limerick Turing Test Question 2

at I sighed as I hoped

for a bike like a Harley I groped

in my pocket for cash

and bought something less flash

then I sat on my moped and moped
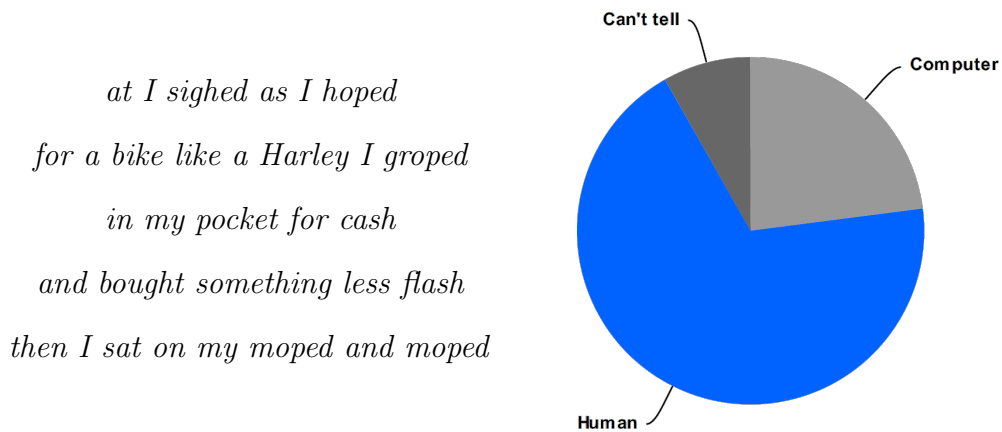
Figure 6.42: Limerick Turing Test Question 3

to compose a sonata today

don't proceed in the old fashioned way

with your toes on the keys

bang the floor with your knees

oh how modern critics will say
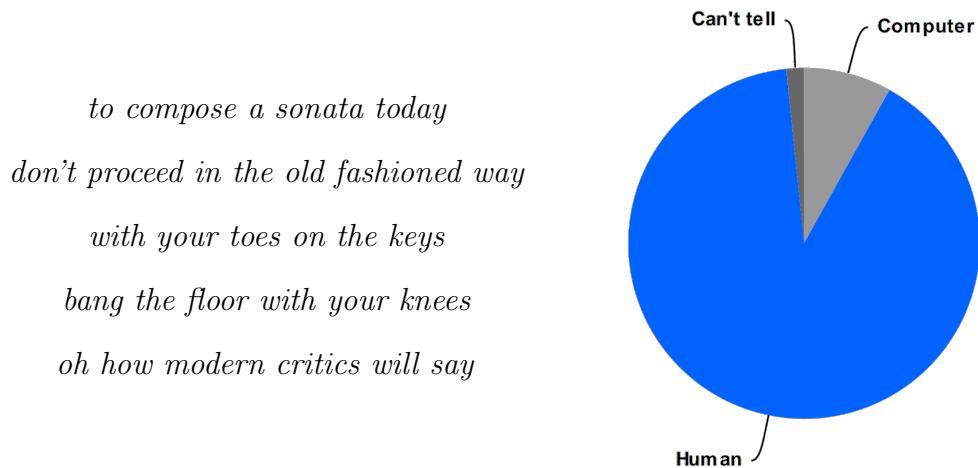
Figure 6.43: Limerick Turing Test Question 4

the weather uproots devilwood

evergreen roots autumn bulb wood

it maintains stance

has one clear-cut chance

possibility strengthens position good
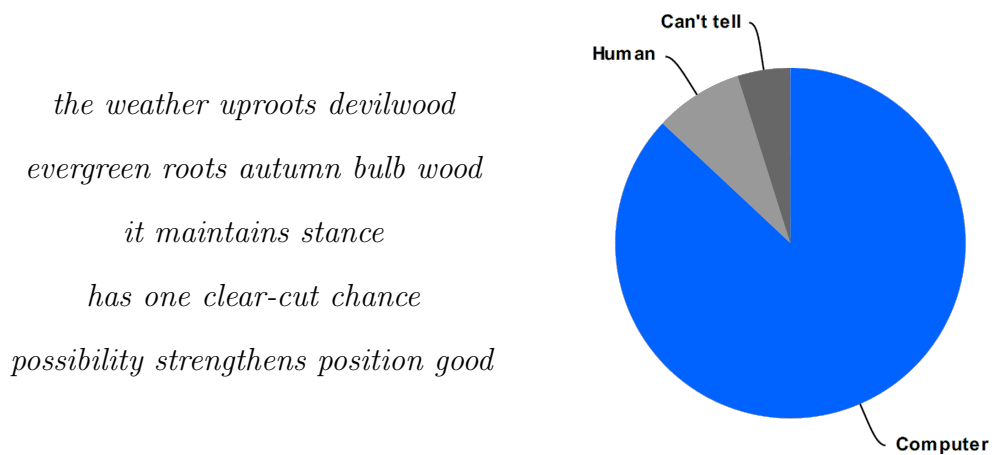
Figure 6.44: Limerick Turing Test Question 5

137

there was a young person called

Smarty

who sent out his cards for a party

so exclusive and few

were the friends that he knew

that no one was present but Smarty
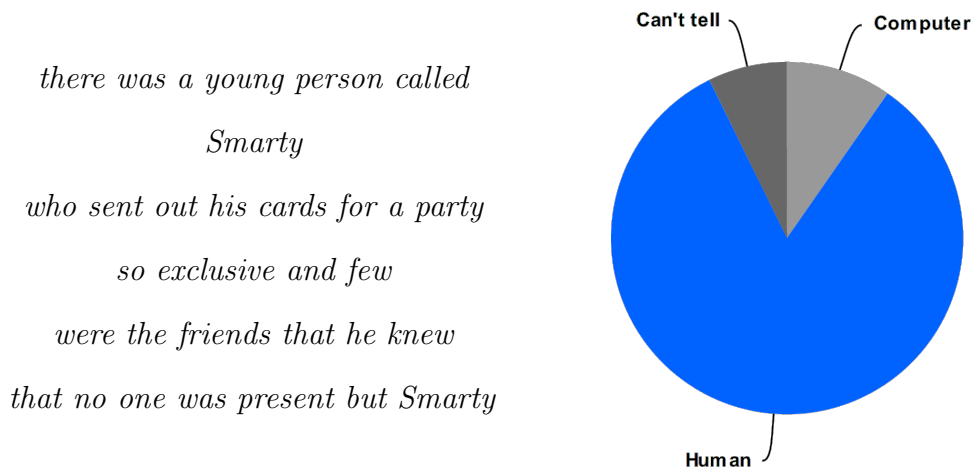
Figure 6.45: Limerick Turing Test Question 6

the middle-aged man from France

while communication keeps his stance

his position is in love

emotion is ugly like a cancer above

he logically does not advance
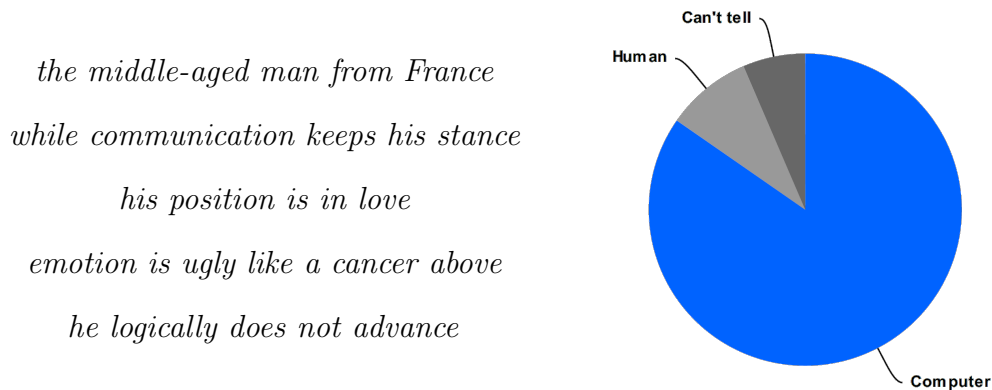
Figure 6.46: Limerick Turing Test Question 7

the bold chlorine contaminates water

the landscape gives short birth to

daughter

binary compounds crosses lagoon

chemical element goes up in balloon

derives inspiration underwater
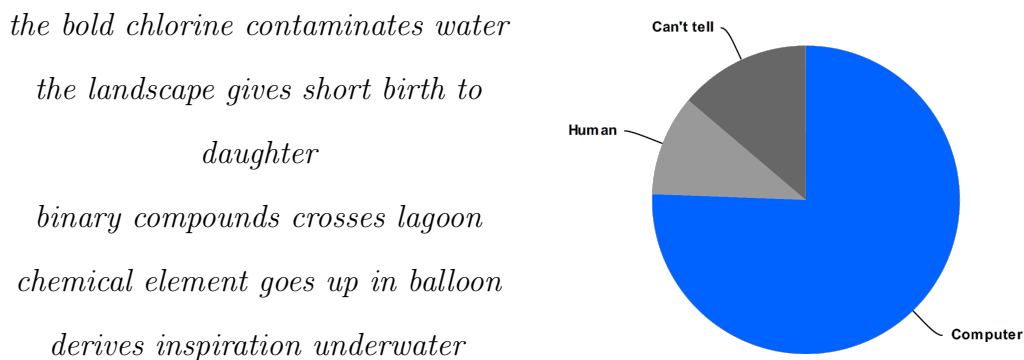
Figure 6.47: Limerick Turing Test Question 8

138

there is a young, fine man called Ricky

he is as dark-haired as a trainer sticky

he wants to slumber

he gets a wrong number

deep sleeps quite tricky
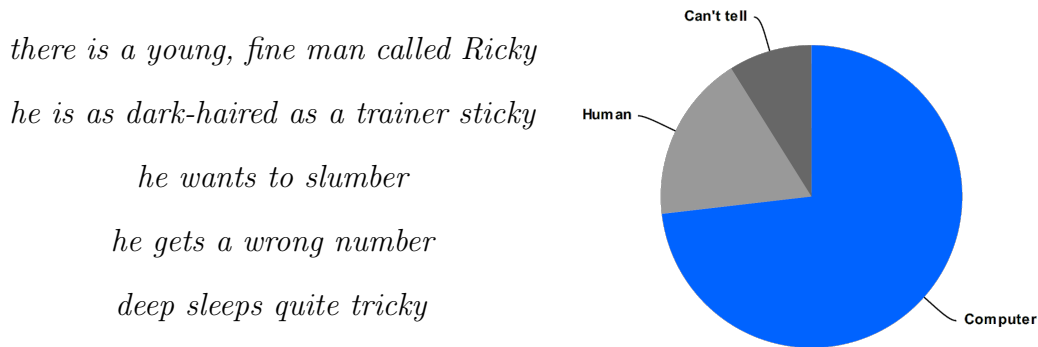
Figure 6.48: Limerick Turing Test Question 9

a talkative tourist named Margot

was handed a plate of escargot

at a fancy French feast

then her chattering ceased

and the whole crowd soon heard her

new car go

Figure 6.49: Limerick Turing Test Question 10

6.2.2 Quality of English

We mentioned at the start of this paper that poetry is meant to convey a particular message. We argued that we need control over syntax and semantics of language to achieve this goal, and that it comes before attempting to use poetic features.

6.2.2.1 Vocabulary and Word Selection

The vocabulary of the system is dispersed among the third-party and internal sources used.

WordNet 117,000 words

CMUPD 133,000 words

FrameNet 13,000 words

Knowledge Network 28,802 words

SimpleNLG Lexicon : 6317 words

The most important of these are the last three in the list because they come with semantic information on the usage, inflections and associations of words. The average vocabulary of native English speakers is 20,000-35,000[7], so there is still plenty of room for improvement.

It is worth noting that there is little to no scientific or colloquial vocabulary. Names of people and places in our knowledge network is also limited.

Given the limited repetition of words in the poems, this vocabulary size is sufficient. The Turing Test results did not indicate any issues with vocabulary being too basic for a human author.

6.2.2.2 Grammar and Sentence Structure

The grammatical capabilities are mainly governed by FrameNet and SimpleNLG. FrameNet gives the instruction on how to build a sentence from a single word, while SimpleNLG can be used to follow those instructions. This approach enables us to build upwards from words to phrases to complex sentences based on first principles of structuring a sentence with subjects, actions, objects and indirect objects.

This gives us the ability to generate many types of sentences for any purpose. The initial structure of every line of poetry created by this system has correct grammar and is only broken for poetic license. As a result, the grammar produced by this system is of a higher quality compared to many previous works (see Section 2.2) and yet is flexible enough to be unpredictable.

Comments on the Turing Tests did not condemn the grammar of the computer generated poetry. Some comments did admonish the grammar of human generated poetry, indicating that it was a factor that participants looked out for. One comment even

said *"The grammar seems too off to be poetic license."* about a human generated poem. This justifies our content-first approach.

The amount of vocabulary used effectively is somewhat limited by the fact that we translate a relation (of which there are relatively few types) to phrases. We use the general takes and receives action relations to spread our usable vocabulary as wide as possible, but quality will significantly improve if we get more relations like in Concept-Net[42].

One major point of feedback from the Turing Tests was the inability for this system to carry out *enjambment* - letting sentences overflow into multiple lines. Given our process of building from first principles, we build noun phrases and verb phrases that get *realised* into a full sentence. We can simply split these phrases over multiple lines to achieve enjambment. This is particularly important for poems with very short syllable counts, such as haikus.

6.2.3 Creativity and Cohesiveness

Poems are *creative* works, which means that they should at least be *non-deterministic.*

We generated 100 poems where 50 were given the same *word* as inspiration and 50 the same *relation* as inspiration.

Each poem was very different in the case of the single word inspiration. When given the same relation as inspiration, the first line was always a direct translation as per Section 5.2, which means that there was *some* overlap in that line, but little in the others.

Furthermore, if the tail of the given relation is a word with very few rhyming candidates then following lines may end up being similar because of lack of choices for words. However, there is enough non-determinism, thanks to a large knowledge network and the randomness introduced in the rephrasing processes, for there to be consistent variation.

6.2.3.1 Knowledge as Creativity

One philosophy of creativity is that it is an amalgamation of knowledge and experience. Our system has its semantic network of common-sense (Section 5.2.2) that fills this

role. It has precisely 203,324 relations between 28,802 unique concepts (compared to de Smedt's Perception with 9,000 relations across 4,000 concepts) from high-quality and dependable sources. There are more resources, such as ConceptNet, that could be used to extend this knowledge base in the future.

A third of all relations are of the most general *RelatedTo* type, which is only really useful for cohesiveness throughout the poem and do not help building relations between persona. More specific understanding of the relations between words will increase the variation, and therefore creativity, of the system.

6.2.3.2 Cohesiveness

The problem of a cohesive theme is a very important one. Many decisions made by participants on the Turing test were based on the extent to which words in the poem were related to each other. The haiku in Figure 6.36 mentions words on the theme of education but are not related temporally or any other way. This haiku still fooled many, and the reason given was that they did not expect such cohesiveness from a computer. Human poems were also admonished for their lack of cohesiveness and therefore thought to be computer-generated.

Many human poems were lauded for their story-telling; a temporally consecutive series of events. Further investigation into strategies that utilise tense and aspect together with cohesiveness may be the final piece in the puzzle for automatic generation of poetry, especially if it is able to cope with long poems that include many stanzas.

6.2.4 Performance

The timings taken to generate 10 haikus and 10 limericks without inspiration are seen in Table 6.2. On average, a limerick takes **322.75** seconds and a haiku takes **12.53** seconds to create.

Limerick	Haiku
291.992	21.365
241.588	12.608
50.754	14.134
863.205	13.066
16.115	10.385
369.568	9.384
491.374	10.889
584.955	9.145
290.491	15.148
27.447	9.137

Table 6.2: Timings for generating 10 haikus and 10 limericks

6.2.4.1 Delay when Finding Rhymes

It is intuitive that longer poems take more time to compose. The less obvious trend is that adherence to a rhyme scheme greatly increases processing time because choosing the most associatively similar (see Section 5.2.2.3.1) pair of words when rephrasing for rhyme, as described in Section 5.6.1.2, causes the greatest delay.

Suppose we want to choose the best word in context to rhyme with *'cheese'*. The call to the RhymeBrain API[5] takes 0.599 seconds and returns 117 candidate rhymes. If we assume we have 10 contextual words to compare with then we require 1170 graph lookups. In most cases lookup converges to a maximum depth of 1 eventually, which has an average lookup time of 0.0043. However, there may be some lookups of maximum depth of 2 or 3 before converging, which have average times of 0.228 and 1.691 seconds respectively.

Therefore, the time to complete our *'cheese'* example is at best
$$1170 * 0.0043 + 0.599 = 5.63$$
seconds but could potentially take up to roughly
$$50 * 1.691 + 120 * 0.228 + 1000 * 0.0043 + 0.599 = 116.809$$
seconds just to choose one word with machine specifications in Appendix A.4.

There are several ways this can be improved with threading, caching, optimising the shortest path algorithm and reducing API calls. However, this implementation is inherently long-winded because we are getting the rhyme words *first*, and then finding the most contextually appropriate.

A more efficient implementation would be to store the rhyme phoneme patterns, as in Section 2.1.2.1, in each node of the knowledge network. We then start from each context node and do a breadth first search for the nearest node with the required rhyme phoneme pattern. For further optimisation, we could create a thread for each context node and perform this process concurrently.

This removes the need for an API call and for the shortest path associative similarity altogether, significantly reducing time and memory complexity.

6.2.4.2 SimpleNLG via JPype

Another sub-optimal implementation is that the Natural Language Generation library that we use in this project is SimpleNLG, a *Java* library. This is made possible by launching a JVM via JPype, which also allows us to run the library and access its objects. Naturally, it will be more efficient to use local Python implementation.

Chapter 7

Conclusion

7.1 Summary of Achievements

This project uses a suite of algorithms to analyse the structure, poetic techniques and typical content of any given poem in detail. Together they cover a large number of features and give as many options for each feature as possible.

We extract persona from the poems to give more contextual understanding in our readings. By peppering these persona with semantic information such as gender, animation and plurality, we are able to perform some basic anaphora and presupposition resolution. Semantic relationships between other persona and other concepts are extracted using Semantic Role Labelling and Dependency Parsing. These are used to help guide the construction of new poems.

The analysis results of several poems can be aggregated together to produce an overall blueprint of the class of poem. Each feature is aggregated in isolation, allowing for individual implementations resulting in higher quality interpretations of each feature. We automatically produce graphs for the results of this aggregation and interpretation based on probability distributions of each feature taking on a particular value.

Our blueprints for limericks, haiku and sonnets have largely validated the taught theory. Some parts of theory have been called into question due to inconsistencies with our results that may lead to further investigation of poetry theory.

We use the aforementioned blueprints to produce new poetry with the derived style. We are able to receive inspiration input from a user as well as extract inspiration from the blueprint.

Poems are built with a content-first approach from first principles; translating relations directly into phrases that are put together to form sentences. The large number grammatical structures provided by FrameNet, that together with the extensive vocabulary and the NLG engine SimpleNLG enable to produce a variety of grammatically correct sentences.

We built a semantic knowledge network and use it to find associative similarity between concepts, which is used to choose words carefully when building sentences and retain some amount of contextual coherence between different sentences. It is also used to find symbolic similarity between concepts in order to introduce analogies, demonstrating seemingly imaginative and creative capabilities.

The sentences built are converted into lines of poetry by rephrasing them to match rhyme, syllabic rhythm and accentual rhythm.

Turing-style tests were created to assess the extent to which poems produced by our system can be distinguished from human written poetry. It revealed that the major drawback of our system was keeping cohesiveness over large number of lines, as well as after rephrasing for rhyme and rhythm. It validated our content-first approach since there was minimal negative feedback on grammaticality and vocabulary in computer generated poems, but some in human written ones.

7.2 Applications

The system has the intended application of being able to learn the structure of and recreate any poem when provided with a number of examples. Users can add their own inspiration to the poems, which means that it is effective as a stand-alone product for creating poetry for enjoyment.

Most parts of this system have a general-purpose implementation. The analysis and interpretation algorithms can be used to build a blueprint of any kind of text if given sufficient examples, not just poetry. For example, we could give it the lyrics of all songs by 'The Beatles' and it should output a blueprint for creating new song lyrics.

The blueprint itself is based on probabilities and can be interpreted in various ways, which can be used for other applications such as teaching poetry to children.

Our semantic network of common sense can be used to build eloquent natural language sentences, not necessarily poetry, especially when combined with FrameNet and an NLG engine such as SimpleNLG in the way this project has done. It can also be used as the back end of a metaphorical search engine based on the symbolic similarity technique.

Our ability to extract persona and related semantic information has several use cases. Firstly, it can be used to expand our semantic knowledge network by feeding it large amounts of text, for example from Wikipedia. It can also be used as a stand-alone information extraction engine for other researchers of Natural Language Processing. It is particularly useful for the problem of anaphora and presupposition resolution, as well as deriving relations between the persona. Rephrasing the text from which it was extracted is another possibility since we showed that we can build a variety of sentences directly from relations without changing meaning.

The natural language generation module on its own has a large vocabulary and broad control over grammar. Since it is based on first principles of building a sentence, it can adapt to almost any situation.

7.3 Future Work

7.3.1 Deliverable as an App

This project has the potential to become a fun app that people can use to produce poems, probably about their friends. A polished front end and some ironing out of minor kinks would be all that is necessary to create the first deliverable.

7.3.2 Deriving Inspiration on Topics to Remain Cohesive

We discussed the positive effects on cohesiveness of starting the generation process with inspiration in Section 6.2. We can take advantage of this by deriving relations about the poem topic from natural text, for example on Wikipedia.

For example, if we did want to generate a sonnet on the subject of the Forth Bridge as in Turing's example dialogue for the Turing Test[54], we can look up Forth Bridge on Wikipedia, extract relations on the text in the way we did in the analysis stage and seed the generation process with that.

This has the advantage of preserving cohesiveness throughout the poem while using up-to-date and relevant information about a single topic.

This would be a fruitful next stage to the deliverable as all the components have been created already.

7.3.3 Rephrasing Module

The biggest culprit of ruining the fluency and cohesiveness of sentences was the rephrasing module. It was rare to find synonyms of the words that we wanted to replace that had the structure that we desired, and associative similarity often did not work well enough. The only other strategy was to expand the sentence by adding modifiers to verbs and nouns, which worked well but became predictable. Reducing the length of sentences and rephrasing to use enjambent (flowing sentences over into new lines) are the next challenges.

An alternative route would be to rephrase the whole sentence from scratch by going back to the original relation from which it was built. However, some forward-looking heuristics could be implemented to avoid this, for example by using intransitive verbs when we know that the sentence can only be five syllables long so not to need the added object of the sentence.

Rephrasing is an ongoing research topic in Computational Linguistics and effective rephrasing is probably a MPhil or PhD in itself.

7.3.4 Strategies for Retaining Coherence

Cohesiveness in this system is achieved on a word-by-word basis by finding associatively similar concepts in the knowledge graph. At the moment, the context concept nodes include those in the lines immediately surrounding the one being built. This gives a ladder effect to the cohesiveness; we can go from one topic to another but may end up far away from the original by the end of the poem. This is a big reason the limericks performed poorly compared to the haiku, according to feedback on the Turing test.

A better strategy could be to attain a circular effect, whereby we aim to return to the original concept that we started with by the end of the poem. Or we have a star effect, where one concept anchors the entire poem. Thorough experimentation with different strategies will be required to uncover a consistently effective approach.

Once again, this is likely to be an MPhil or PhD project.

7.3.5 Expanding the Knowledge and Use Cases of the Semantic Network

There are several sources of knowledge that were not used in building our semantic network.

- *VerbNet*: a lexical database that groups verbs by semantic and syntactic linking behaviour.[52]

- *ACE*: a classification of names, places and other proper nouns for Named Entity Recognition.[31]

- *PropBank*: an annotated corpus a million words defining and providing argument role labels for verbs[38]

- *NomBank*: similar to PropBank, but for nouns instead of verbs.[47]

- *Metaphor Magnet*: a web application that maps commonplace metaphors in everyday texts[56] Google Ngrams

- *LinguaTools DISCO*: a tool to derive semantic similarity between words based on statistical analysis of large text collections[39]

Combining these with ConceptNet and our ability to extract relations from any text can all be used to build and improve the knowledge network.

7.3.6 Context-Aware Anaphora and Presupposition Resolution

Combining the semantic network with our ability to identify persona and relations in text, we can make inferences on the properties and capabilities of the persona to resolve anaphora and presuppositions.

Suppose we take the cat poem in Figure 3.1, but the word *'he'* is replaced with *'the feline'*. Since they are represented by different nouns, we would not initially recognise that *'cat'* and *'feline'* refer to the same persona. Once all the persona were found, if we compared each pair using our knowledge network, we would find the relation *'cat.n'-IsA→'feline.n'*. We can therefore infer with some confidence that the persona represented by the words *'cat'* and *'feline'* are one and the same.

Take another example sentence:
There was a cat with a flea on his back. It chased the mouse.

In this situation, it is ambiguous whether *'It'* refers to the cat or the flea because they are both singular, animated and neutral gender. However, our semantic network of common sense would be able to reveal that *'It'* probably refers to the cat since it is common sense that cats take the action of chasing mice.

This is a new solution proposal for the research topic of anaphora and presupposition resolution that is likely to require an MPhil or PhD thesis to fully investigate.

Appendix A

A.1 Dry Run of Generation Phase with Commentary

Input seed: Limerick about a computer that is bored with data and finds poetry fun

1. *There once was (a/an) _____ named ____[A]*
_____[A]
_____[B]
_____[B]
_____[A]

This is a limerick template straight out of the generation phase.

2. *There once was a computer named ____ [data]*
That was bored with data [data]
It finds poetry fun [fun]
_____[fun]
_____ [data]

This step introduced the computer, the fact that it is bored with data and finds poetry fun. It does not take any structure into account when adding these.

3. *There once was a computer named Zeta*
That was bored to death with data
It finds poetry fun
_____ sun
_____ beta

This step filled in the name Zeta since it needed to rhyme with data. It rephrased 'bored' with 'bored to death' to fit the rhythm without losing meaning. Found third line to be complete. Added sun to end of next line since it is an association with fun and follows rhyme scheme. Added beta to end of last line since it rhymes with data (and Zeta)

4. *There once was a computer named Zeta*
That was bored to death with data
It finds poetry fun
Like the summer sun
The revolutionary new system goes into beta

This step added a simile to compare the fun of poetry to the sun since it fit the rhythm structure (alternatively, "like the scorching/setting/sinking sun", but summer sun has alliteration on 'su' rather than just 's'). A phrase was found that ends with beta and was arbitrarily added.

5. *There once was a computer named Zeta*
That was bored to death with data
It finds poetry fun
Like the summer sun
The new system goes into beta

Redundant adjective removed to fit structure in last line. Poem finished.

Note too that we added the input data to the first three lines. Separating them out will make it more coherent, especially in longer poems. Then the associations could be found with surrounding sentences, not just the previous one.

Further rephrasing of lifted sentences, such as the last one, could be beneficial to adding randomness and creativity.

Phoneme	Example	Tranlsation
AA	odd	AA D
AE	at	AE T
AH	hut	HH AH T
AO	ought	AO T
AW	cow	K AW
AY	hide	HH AY D
B	be	B IY
CH	cheese	CH IY Z
D	dee	D IY
DH	thee	DH IY
EH	Ed	EH D
ER	hurt	HH ER T
EY	ate	EY T
F	fee	F IY
G	green	G R IY N
HH	he	HH IY
IH	it	IH T
IY	eat	IY T
JH	gee	JH IY
K	key	K IY
L	lee	L IY
M	me	M IY
N	knee	N IY
NG	ping	P IH NG
OW	oat	OW T
OY	toy	T OY
P	pee	P IY
R	read	R IY D
S	sea	S IY
SH	she	SH IY
T	tea	T IY
TH	theta	TH EY T AH
UH	hood	HH UH D
UW	two	T UW
V	vee	V IY
W	we	W IY
Y	yield	Y IY LD
Z	zee	Z IY
ZH	seizure	S IY ZH ER

Table 1: ARPAbet phoneme set with corresponding examples

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Tag	
CC	Coordinating conjunction
CD	Cardinal number
DT	Determiner
EX	Existential there
FW	Foreign word
IN	Preposition or subordinating conjunction
JJ	Adjective
JJR	Adjective, comparative
JJS	Adjective, superlative
LS	List item marker
MD	Modal
NN	Noun, singular or mass
NNS	Noun, plural
NNP	Proper noun, singular
NNPS	Proper noun, plural
PDT	Predeterminer
POS	Possessive ending
PRP	Personal pronoun
PRP$	Possessive pronoun
RB	Adverb
RBR	Adverb, comparative
RBS	Adverb, superlative
RP	Particle
SYM	Symbol
TO	to
UH	Interjection
VB	Verb, base form
VBD	Verb, past tense
VBG	Verb, gerund or present participle
VBN	Verb, past participle
VBP	Verb, non-3rd person singular present
VBZ	Verb, 3rd person singular present
WDT	Wh-determiner
WP	Wh-pronoun
WP$	Possessive wh-pronoun
WRB	Wh-adverb

Table 2: Penn Treebank Tagset in alphabetical order

A.2 CMU Pronunciation Dictionary ARPABET Phoneme Set

A.3 Penn Treebank Tagset

A.4 Testing Specifications

- Processor: Intel Core i7-3612QM CPU @ 2.10 GHz

- RAM: 8GB

- Average round trip ping to demo.ark.cs.cmu.edu: 131 milliseconds

A.5 FrameNet Frames to ConceptNet Relations

PartOf

Frame	Character Frame Element	Whole Frame Element
Architectural_part	Part	Whole
Building_subparts	Building_part	Whole
Clothing_parts	Subpart	Clothing
Observable_body_parts	Body_part	Possessor
Part_edge	Part	Whole
Part_inner_outer	Part	Whole
Part_ordered_segments	Part	Whole
Part_orientational	Part	Whole
Part_piece	Piece	Substance
Part_whole	Part	Whole
Shaped_part	Part	Whole
Vehicle_subpart	Part	Whole
Wholes_and_parts	Part	Whole
Inclusion	Part	Whole

CreatedBy

Frame	Character Frame Element	Creator Frame Element
Creating	Created_Entity	Creator
Cooking_creation	Produced_food	Cook
Intentionally_create	Created_Entity	Creator
Text_creation	Text	Author
Manufacturing	Product	Producer/Factory

MadeOf

Frame	Character Frame Element	Substance Frame Element
Substance	[Noun After]	Substance

Causes

Frame	Character Frame Element	Effect Frame Element
Cause_to_start	Cause	Effect
Causation	Actor	Affected
Causation	Cause	Effect
Condition_Symptom_Relation	Medical_condition	Symptom
Cognitive_connection	Concept_1	Concept_2

Desire

Frame	Character Frame Element	Desirable Frame Element
Desiring	Experiencer	Event
Experiencer_focus	Experiencer	Content

CapableOf

Frame	Character Frame Element	Activity Frame Element
Capability	Entity	Event

UsedFor

MotivatedByGoal

Has

NotHas

Frame	Character Frame Element	Purpose Frame Element
Expend_resource	Resource	Purpose
Using	Instrument	Purpose
Tool_purpose	Tool	Purpose
Ingest_substance	Substance	Purpose
Using_resource	Resource	Purpose
Usefulness	Entity	Purpose

Frame	Character Frame Element	Goal Frame Element
Purpose	Means	Goal/Value

Frame	Character Frame Element	Possession Frame Element
Possession	Owner	Possession
Have_associated	Topical_entity	Entity
Inclusion	Total	Part
Containers	Container	Contents

Frame	Character Frame Element	Possession Frame Element
Used_up	[Character in view]	Resource
Expend_resource	[Character in view]	Resource
Abandonment	Agent	Theme

Frame	Character Frame Element	Name Frame Element
Being_named	Entity	Name

Named

Believes

Frame	Character Frame Element	Belief Frame Element
Awareness	Cognizer	Content
Certainty	Cognizer	Content
Religious_belief	Believer	Content
Trust	Cognizer	Information
Opinion	Cognizer	Opinion

SendMessage and ReceiveMessage

Frame	Speaker Character Frame Element	Message Frame Element	Addresse
Communication	Communicator	Message/Topic	Addressee
Telling	Speaker	Message	Addressee
Request	Speaker	Message	Addressee
Speak_on_topic	Speaker	Topic	Audience
Statement	Speaker	Message/Topic	Addressee
Prevarication	Speaker	Topic	Addressee
Reporting	Informer	Behaviour/Wrongdoer	Authorities
Text_creation	Author	Text	Addressee
Chatting	Interlocutor_1	Topic	Interlocuto

A.6 List of collapsable dependencies

- acomp

- advmod

- aux

- cop

- dep

- det

- measure

- neg

- nn

- num

- number

- preconj

- predet

- prep

- pobj

- quantmod

A.7 Onomatopoeia Types to ConceptNet Relations

- laughter: TakesAction → laugh

- laughing: TakesAction → laugh

- hit: ReceivesAction → hit

- hard hit: ReceivesAction → hard hit

- punch: TakesAction → punch

- fall: TakesAction → fall

- light hit: ReceivesAction → light hit

- liquid: HasProperty → wet

- water: HasProperty → wet

- wet: HasProperty → wet

- rain: HasProperty → wet

A.7. ONOMATOPOEIA TYPES TO CONCEPTNET RELATIONS

- coins: IsA → money

- weapon: IsA → weapon

- metal: MadeOf → metal

- rubber: MadeOf → rubber

- music: HasProperty → musical

- disease: HasProperty → ill

- surprise: HasProperty → surprised

- dismay: HasProperty → dismay

- pain: HasProperty → in pain

- telephone: IsA → telephone

- siren: HasA → siren

- electronic: HasProperty → electronic

- static: HasProperty → electronic

- electric: HasProperty → electronic

- television: HasProperty → electronic

- video games: HasProperty → electronic

- horn: HasA → horn

- clock: IsA → clock

- predator: IsA → predator

- animal: IsA → animal

- frog: IsA → frog

- bird: IsA → bird

- cat: IsA → cat

- dog: IsA → dog

A.8 Evaluation

A.8.1 Edward Lear

There was an old man with a beard
Who said, "It's just as I feared!
Two owls and a hen,
Four larks and a wren
Are making a nest in my beard!"

There was a Young Lady of Ryde,
Whose shoe-strings were seldom untied.
She purchased some clogs,
And some small spotted dogs,
And frequently walked about Ryde.

There was an Old Man with a nose,
Who said, 'If you choose to suppose,
That my nose is too long,
You are certainly wrong!'
That remarkable Man with a nose.

There was an Old Man on a hill,
Who seldom, if ever, stood still;
He ran up and down,
In his Grandmother's gown,
Which adorned that Old Man on a hill.

There was a Young Lady whose bonnet,
Came untied when the birds sate upon it;
But she said: 'I don't care!
All the birds in the air

Are welcome to sit on my bonnet!'

There was a Young Person of Smyrna,
Whose Grandmother threatened to burn her;
But she seized on the cat,
And said, 'Granny, burn that!
You incongruous Old Woman of Smyrna!'

There was an Old Person of Chili,
Whose conduct was painful and silly,
He sate on the stairs,
Eating apples and pears,
That imprudent Old Person of Chili.

There was an Old Man with a gong,
Who bumped at it all day long;
But they called out, 'O law!
You're a horrid old bore!'
So they smashed that Old Man with a gong.

There was an Old Lady of Chertsey,
Who made a remarkable curtsey;
She twirled round and round,
Till she sunk underground,
Which distressed all the people of Chertsey.

There was an Old Man in a tree,
Who was horribly bored by a Bee;
When they said, 'Does it buzz?'
He replied, 'Yes, it does!'
'It's a regular brute of a Bee!'

A.8.2   The Book of Limericks

There was an old woman of Lynn,
Whose nose very near reach'd her chin;
You may easy suppose
She had plenty of beaux,
This charming old woman of Lynn.

There was an old woman of Gloster,
Whose parrot two guineas it cost her;
But his tongue never ceasing,
Was vastly displeasing,
To that talkative woman of Gloster.

There was a sick man of Tobago,
Lived long on rice-gruel and sago;
But at last, to his bliss,
The physician said this:
'To a roast leg of mutton you may go.'

There was an old miser of Reading,
Had a house with a yard, with a shed in;
'Twas meant for a cow,
But so small that I vow
The poor creature could scarce get its head in.

There was a young person in pink,
Who called out for something to drink;
But they said, 'O my daughter,
There's nothing but water!'
Which vexed that young person in pink.

There was an old person of Sheen,
Whose expression was calm and serene;
He sat in the water,
And drank bottled porter,
That placid old person of Sheen.

There was an old person of Florence,
Who held mutton chops in abhorrence;
He purchased a bustard,
And fried him in mustard,
Which choked that old person of Florence.

There was an old person of Loo,
Who said, 'What on earth shall I do?'
When they said, 'Go away!'
She continued to stay,
That vexatious old person of Loo.

There was an old man of Spithead,
Who opened the window and said -
'Fil-jomble, fil-jumble,
Fil-rumble-come-tumble!'
That doubtful old man of Spithead.

There was an old person of Brigg,
Who purchased no end of a Wig;
So that only his nose
And the end of his toes
Could be seen when he waled about Brigg.

A.8.3   Limerick sources

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