Deep Comedy 2.0

Generation of poetry in Dante's Divine Comedy style
through Deep Learning techniques

Francesco Ballerini
francesco.ballerini3@studio.unibo.it

Fabio Galvan
fabio.galvan@studio.unibo.it

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Abstract

We tackle the task of generating poetry in the style of Dante's Divine Comedy—with a focus on syllabification constraints—by deploying two distinct Transformer models, one trained to syllabify single verses and the other to generate group of tercets, with the output of the former dictating whether to accept or reject that of the latter during the generation process itself. Specifically, we show the results we obtained and justify the implementation choices we made by revisiting the alternatives that were explored and eventually discarded along the way.

1 Introduction

The *Divine Comedy* is an Italian narrative poem written by Dante Alighieri between 1308 and 1320. It is structured into three *cantiche*—*Inferno*, *Purgatorio*, and *Paradiso*—each one composed of 33 *canti*, plus an initial canto, traditionally considered as part of the Inferno. The verse scheme consists of tercets of hendecasyllables with rhyming scheme ABA BCB CDC . . . , also known as *terza rima* [1].

Differently from the quantitative verse of ancient Greek and Latin poetry, the hendecasyllable of Italian medieval—and modern—poetry is accentual. Its key characteristic is the *stress on the tenth syllable*: in the frequent case in which the final word is stressed on the penultimate syllable—as most Italian words are—such constraint produces verses of eleven syllables [1].

However, identifying syllables is not a trivial operation: in Italian, a sequence of vowels can be either pronounced as a single sound or as separate sounds. Therefore, one of the following linguistic phenomena can arise:

- *Syneresis*: consecutive vowels inside a word are pronounced as a single sound, and therefore belong to the same syllable.

E.g. ab|ban|do|n**ai**

- *Dieresis*: consecutive vowels inside a word are pronounced as different sounds, and therefore belong to different syllables.

  E.g. p**a**|**u**|ra

- *Synalephe*: consecutive vowels of adjacent words—i.e. a word ending with vowels is followed by a word beginning with vowels—are pronounced as a single sound, and therefore belong to the same syllable. The same syllable can thus span two adjacent words.

  E.g. sel|v**a o**|scu|ra

- *Dialephe*: consecutive vowels of adjacent words are pronounced as separate sounds, and therefore belong to different syllables.

  E.g. son|n**o** |**a**

What makes the syllabification of Italian poetry extremely challenging is that there are many exceptions to the rules that regulate the occurrences of these phenomena, and, most notably, Dante takes the liberty of bending those rules every time they get in the way of achieving the desired rhythmic effects [1].

2 Dataset

Luckily, we do not have to deal ourselves with syllabification rules applied to Dante's lexicon and style, since a syllabified version of the Divine Comedy—and the code used to generate it—is freely available on GitHub [2] as a repository containing the syllabification algorithm proposed in [1].

Although previous research work suggests training a generative model like ours on all non-Latin works by Dante—both poetry and prose—and on modern Italian corpora [3], we decided to rely on the Divine Comedy as our only source of data. The reason is that, as we wanted to focus on syllabification, we could have in principle applied the algorithm described in [1] to other works by Dante and to other authors; however, such algorithm relies on a data structure containing a word-level vocabulary of the Divine Comedy, enriched with metric information which is heavily dependent on the style of the Comedy itself. Therefore, applying the algorithm to a different text would require extending the vocabulary and possibly fine-tuning the information contained in the data structure [1], which seemed to go beyond the scope of this work.

Since our architecture consists of two interacting models—see Section 4—we built two distinct datasets for the syllabification and generation model, respectively.

2.1 Syllabification Dataset

The syllabification dataset consists of 14233—that is, the number of verses in the whole Comedy—samples of form `(input,target)`, where `input` is a non-syllabified verse and `target` the corresponding syllabified one. The rationale behind this choice is that the syllabification task is modeled as a Neural Machine Translation (NTM) task, where the input language is the non-syllabified Divine Comedy and the target language is its syllabified counterpart.

After being collected, the samples are shuffled and split into:

- Training set: 9963 samples (~70%).
- Validation set: 2846 samples (~20%).
- Test set: 1424 samples (~10%).

Each dataset is then divided into batches of size 64.

2.2 Generation Dataset

The generation dataset consists of 14230 samples of form `(input,target)`, where `input` are three consecutive verses and `target` is the verse following the last `input` verse. The rationale behind this choice is that the resulting four-verse window is arguably the smallest set of data capable of capturing the rhyming scheme ABA BCB CDC ... [4].

Once shuffled, the whole dataset is used as training set and divided into batches of size 64.

3 Tokenization

Being the focus of our generation on syllables, it seemed quite natural to choose syllables themselves as tokens for the generation dataset—an approach already proved to be successful in previous works of this kind [3, 4].

For the syllabification dataset, on the other hand, there was no immediate intuition about what the best choice would have been—between characters, syllables, and words—nor it was clear if input and target language should share the same kind of tokens.

3.1 Tokenization of the syllabification dataset

We experimented with the following input–target token combinations:

1. characters–characters.
2. characters–syllables.

```
['< N e l   m e z z o   d e l   c a m m i n   d i   n o s t r a   v i t a >',
 '< m i   r i t r o v a i   p e r   u n a   s e l v a   o s c u r a , >',
 '< c h é   l a   d i r i t t a   v i a   e r a   s m a r r i t a . >',
 '< A h i   q u a n t o   a   d i r   q u a l   e r a   è   c o s a   d u r a >',
 '< e s t a   s e l v a   s e l v a g g i a   e   a s p r a   e   f o r t e >',
 '< c h e   n e l   p e n s i e r   r i n o v a   l a   p a u r a ! >',
 '< T a n t ’   è   a m a r a   c h e   p o c o   è   p i ù   m o r t e ; >',
 '< m a   p e r   t r a t t a r   d e l   b e n   c h ’ i ’   v i   t r o v a i , >',
 '< d i r ò   d e   l ’ a l t r e   c o s e   c h ’ i ’   v ’ h o   s c o r t e . >',
 '< I o   n o n   s o   b e n   r i d i r   c o m ’   i ’   v ’ i n t r a i , >']
```

(a) Input

```
['< | N e l   | m e z | z o   | d e l   | c a m | m i n   | d i   | n o | s t r a   | v i | t a >',
 '< | m i   | r i | t r o | v a i   | p e r   | u | n a   | s e l | v a   o | s c u | r a , >',
 '< | c h é   | l a   | d i | r i t | t a   | v i a   | e | r a   | s m a r | r i | t a . >',
 '< | A h i   | q u a n | t o   a   | d i r   | q u a l   | e | r a   è   | c o | s a   | d u | r a >',
 '< | e | s t a   | s e l | v a   | s e l | v a g | g i a   e   | a | s p r a   e   | f o r | t e >',
 '< | c h e   | n e l   | p e n | s i e r   | r i | n o | v a   | l a   | p a | u | r a ! >',
 '< | T a n | t ’   è   | a | m a | r a   | c h e   | p o | c o   è   | p i ù   | m o r | t e ; >',
 '< | m a   | p e r   | t r a t | t a r   | d e l   | b e n   | c h ’   i ’   | v i   | t r o | v a i , >',
 '< | d i | r ò   | d e   | l ’   a l | t r e   | c o | s e   | c h ’   i ’   | v ’   h o   | s c o r | t e . >',
 '< | I o   | n o n   | s o   | b e n   | r i | d i r   | c o m ’   | i ’   | v ’   i n | t r a i , >']
```

(b) Target

Figure 1: First ten samples of the (unshuffled) syllabification dataset after character-level tokenization

3. words–syllables.

4. words–words.

The best results on the syllabification task were given by far by combination 1, and got worse as tokens got “bigger”—with the worst results given by combination 4. Therefore, we opted for tokenization 1.

On the other hand, when we were still experimenting with the architecture, we initially tried to let the syllabification model handle the generation by itself, and, for that task, we observed the opposite behavior: the more complex the tokens, the better the quality of the generation. Still, the generated verse were far from satisfying; also, since the syllabification task as we defined it operates on a single-verse level, the model could only generate one isolated verse at a time, hence no rhyming scheme could be captured. For all these reasons, we finally decided to deploy two specialized models for the two tasks at hand—syllabification and generation—and work on their interaction.

In order to encode the information about how to initialize and when to stop the syllabification loop—see Section 6.1—each verse is enriched with a *start-of-verse* and an *end-of-verse* token, denoted with `<` and `>`, respectively.

The final result of the tokenization process is shown in Figure 1.

```
['<t> <v> nel  mez zo  del  cam min  di  no stra  vi ta </v> <v> mi  ri tro vai  per  u na  sel va o scu ra </v> <v> ché  la  di rit ta  via  e ra  smar ri ta </v> </t>',
 '<v> mi  ri tro vai  per  u na  sel va o scu ra </v> <v> ché  la  di rit ta  via  e ra  smar ri ta </v> </t> <t> <v> ahi  quan to a  dir  qual  e ra è  co sa  du ra </v>'
 '<v> ché  la  di rit ta  via  e ra  smar ri ta </v> </t> <t> <v> ahi  quan to a  dir  qual  e ra è  co sa  du ra </v> <v> e sta  sel va  sel vag gia e  a spra e  for te <
 '<t> <v> ahi  quan to a  dir  qual  e ra è  co sa  du ra </v> <v> e sta  sel va  sel vag gia e  a spra e  for te </v> <v> che  nel  pen sier  ri no va  la  pa u ra </v> <
 '<v> e sta  sel va  sel vag gia e  a spra e  for te </v> <v> che  nel  pen sier  ri no va  la  pa u ra </v> </t> <t> <v> tan t’ è  a ma ra  che  po co è  più  mor te </v>
 '<v> che  nel  pen sier  ri no va  la  pa u ra </v> </t> <t> <v> tan t’ è  a ma ra  che  po co è  più  mor te </v> <v> ma  per  trat tar  del  ben  ch’ i’  vi  tro vai </
 '<t> <v> tan t’ è  a ma ra  che  po co è  più  mor te </v> <v> ma  per  trat tar  del  ben  ch’ i’  vi  tro vai </v> <v> di rò  de  l’ al tre  co se  ch’ i’  v’ ho  scor
 '<v> ma  per  trat tar  del  ben  ch’ i’  vi  tro vai </v> <v> di rò  de  l’ al tre  co se  ch’ i’  v’ ho  scor te </v> </t> <t> <v> io  non  so  ben  ri dir  com’  i’  v
 '<v> di rò  de  l’ al tre  co se  ch’ i’  v’ ho  scor te </v> </t> <t> <v> io  non  so  ben  ri dir  com’  i’  v’ in trai </v> <v> tan t’ e ra  pien  di  son no  a  quel
 '<t> <v> io  non  so  ben  ri dir  com’  i’  v’ in trai </v> <v> tan t’ e ra  pien  di  son no  a  quel  pun to </v> <v> che  la  ve ra ce  via  ab ban do nai </v> </t>']
```

(a) Input

```
['<t> <v> ahi  quan to a  dir  qual  e ra è  co sa  du ra </v>',
 '<v> e sta  sel va  sel vag gia e  a spra e  for te </v>',
 '<v> che  nel  pen sier  ri no va  la  pa u ra </v> </t>',
 '<t> <v> tan t’ è  a ma ra  che  po co è  più  mor te </v>',
 '<v> ma  per  trat tar  del  ben  ch’ i’  vi  tro vai </v>',
 '<v> di rò  de  l’ al tre  co se  ch’ i’  v’ ho  scor te </v> </t>',
 '<t> <v> io  non  so  ben  ri dir  com’  i’  v’ in trai </v>',
 '<v> tan t’ e ra  pien  di  son no  a  quel  pun to </v>',
 '<v> che  la  ve ra ce  via  ab ban do nai </v> </t>',
 '<t> <v> ma  poi  ch’ i’  fui  al  piè  d’ un  col le  giun to </v>']
```

(b) Target

Figure 2: First ten samples of the (unshuffled) generation dataset after syllable-level tokenization

3.2 Tokenization of the generation dataset

The generation dataset is tokenized by syllables, both in its input and target component. Differently from the syllabification dataset, the text is converted to lowercase and punctuation is removed—except for apostrophes and accented characters—so as to avoid meaningless redundancies in the vocabulary.

The following special tokens are added to the dataset [3, 4]:

- `<v>`: start-of-verse token.
- `</v>`: end-of-verse token.
- `<t>`: start-of-tercet token.
- `</t>`: end-of-tercet token.

The final result of the tokenization process is shown in Figure 2.

4 Architecture

Our architecture consists of two full Transformer models, i.e. with both and encoder and a decoder, as in the original definition [5]. From now on, we will refer to them as *syllabifier* and *generator*, respectively.

While most NTM approaches deploy, in fact, an encoder–decoder architecture [6], recent successful application of Transformers to text generation rely on decoder-only models—most notably, GPT-3 [7]. However, based on the experience of last year's students, who

	Syllabifier	Generator	Base Model in [5]
N	2	2	6
d_{model}	128	128	512
d_{ff}	32	256	2048
h	2	2	8
P_{drop}	0.1	0.1	0.1

Table 1: Hyperparameter values (third column given for reference)

observed that GPT-3-like models were struggling to grasp the rhyming scheme [4], we decided to adopt a full Transformer architecture for both syllabification and generation.

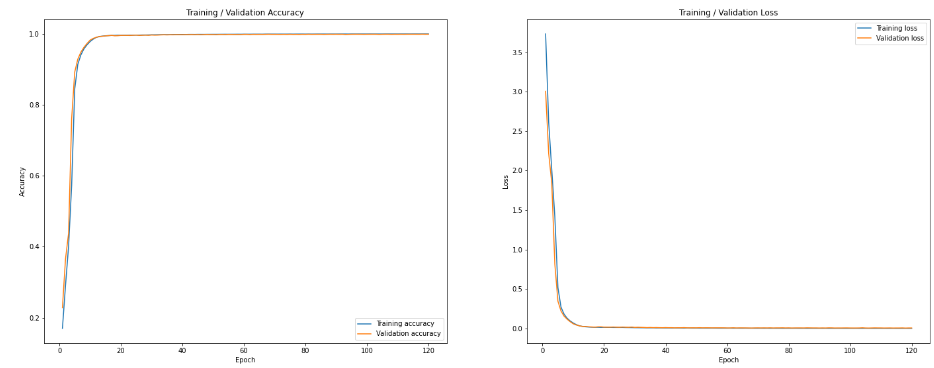
The tunable hyperparameters of the models are—see [5] for details:

- N: number of encoder (resp. decoder) layers in the encoder (resp. decoder).
- d_{model}: dimension of the outputs of all sub-layers in the model.
- d_{ff}: dimension of the inner layer of the feed-forward sub-layer.
- h: number of attention heads.
- P_{drop}: dropout rate.

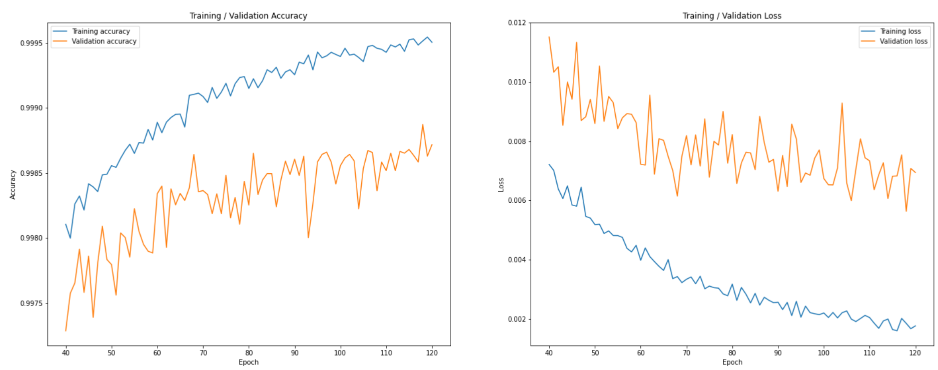
For the syllabifier, we initially experimented—as suggested in [8]—with a reduced version of the base model described in [5]; since we got excellent results almost right away, we fine-tuned the number of epochs of training instead of the single hyperparameters and temporarily kept this model.

However, when we tried to set those same hyperparameter values in the generator, we noticed that, although the generated verses were quite satisfying from a lexical perspective, the rhyming scheme was very inconsistent—probably because the model had learned the Comedy's vocabulary very well and was trying to fit words into verses even when they where not rhyming. Furthermore, we observed occasional generations of entire verses copied directly from the original text. By reducing N, d_{model}, d_{ff}, and h we obtained much more reliable rhymes, at the cost of generating words which are not always drawn from Dante's vocaboulary—or any vocabulary, for that matter. Also, the generation of non-original verses ceased to happen. We chose to prioritize the rhyming structure and adopted the less powerful model, since our focus was already on metric constraints anyway.

In light of the analysis of simpler models for the generative task, we decided to keep experimenting with the syllabifier, and discovered that we could achieve the same excellent quality of results by choosing hyperparameter values as small as those set in generator, thus accomplishing a better computational efficiency.



(a) 120 epochs



(b) Last 80 epochs

Figure 3: Syllabifier's accuracy and loss during training

As a final note, both models exploit the fixed sinusoidal positional encodings described in [5].

The chosen values of the hyperparameters are shown in Table 1.

5 Training

We trained our models on the free GPU runtime environment of Google Colab. We used the Adam optimizer with a learning rate varying over the course of training, as described in [5], and sparse categorical cross-entropy as loss function.

For both the syllabifier and the generator, the training process works as follows: for each sample `(input,target)`

1. Let `tar_input` be a copy of `target` excluding its last token and let `tar_real` be a copy of `target` excluding its first token, i.e. `tar_real` is `tar_input` shifted to the right by one token.
2. Give `input` as input to the encoder and `tar_input` as input to the decoder.
3. Compute the decoder output; call it `pred`.
4. Give `tar_real` and `pred` as inputs to the loss function.

When training the syllabifier, we observed essentially no overfitting—as shown in Figure 3—possibly thanks to its dropout sub-layers. We therefore opted for a number of epochs such that the validation loss reduction after that point seemed not to be worth the additional computing time, and performed a final training—on both training and validation set combined—of 60 epochs.

The generator, on the other hand, was trained on the whole generation dataset for 80 epochs. With a longer training we noticed—similarly to what we already observed when setting the hyperparameters—that the model was slightly improving its lexicon but losing the ability to generate correctly rhyming verses.

6 Results

Some examples of the outputs of our models are shown in Figures 4, 9, 10, and 11. In Sections 6.1 and 6.2 we get into the details of how such results were obtained.

The syllabification task resulted in a very successful outcome: in the experiment showed in Figure 4, the model reached an accuracy of 99.9% on the test set with its 60 epochs of training[1]. The syllabification mistakes are shown in Figures 5, 6, 7, and 8.

On the other hand, the lexicon of the generated verses could definitely be improved; however, as we already pointed out in Section 4, more powerful models struggle to satisfy the rhyming constraints, especially between verses belonging to different tercets, and the same behavior can be observed when training the same model for a grater number of epochs. There seems to be an inherent trade-off between word quality and correct rhyming scheme—which, in our opinion, is the most interesting open question this work points towards.

The final point worth discussing is that, even though the generation loop relies on the syllabifier to enforce the metric constraints, the experiments show that the generator, if left unchecked, produces verses whose number of syllables oscillates between 10 and 12; also, the corrections made by the syllabifier are never too dramatic, and often involve unusual combination of syllables that end up forming made-up words—see Figure 10. This suggest

[1]The accuracy we are referring to is measured in terms of correctly predicted tokens, i.e. characters.

that the generator was able to grasp the hendecasyllable structure quite effectively, even though not explicitly trained to syllabify verses, which it is a testament to the effectiveness of training our models on a correctly and exhaustively syllabified text, as the one available at [2].

6.1 Syllabification Procedure

The syllabification process works as follows:

1. Give a non-syllabified verse as input to the syllabifier's encoder.

2. Give < as input to the syllabifier's decoder.

3. Compute the decoder output, i.e. the prediction for the next token[2]:

   - If the predicted character is >, stop.
   - Otherwise, concatenate the predicted character to the decoder input and go back to Step 3.

6.2 Generation Procedure

The generation process, partially inspired by [4], works as follows:

1. Give the first tercet of the Divine Comedy—*Nel mezzo* ... *smarrita.*—as input to the encoder.

2. Give <t> as input to the decoder.

3. Compute the decoder output, i.e. the prediction for the next token[3].

4. Once a whole verse has been generated, pass it as input to the syllabifier:

   - If the syllabification returned by the syllabifier matches the one produced by the generator, count the syllables:
     - If there are 11 of them[4] , go to Step 5.
     - Otherwise, reset the generator's decoder input to its first token—either <t> or <v>—and go back to Step 3.
   - Otherwise, reset the generator's decoder input to its first token—either <t> or <v>—and go back to Step 3.

[2]Greedy sampling is used as sampling technique.

[3]Top-k sampling with $k = 10$ is used as sampling technique.

[4]Although, as pointed out in Section 1, the number of syllables is not part of the definition of hendecasyllable—rather, a consequence—we decided to embrace this simplifying assumption in order to further ensure the metric quality of the generated verses without having to deal with accent constraints.

5. Remove the first verse from the generator's encoder input.

6. Append the newly generated verse to the generator's encoder input.

7. Reset the generator's decoder input to to its first token—either `<t>` or `<v>`—and go back to Step 3.

References

[1] Andrea Asperti and Stefano Dal Bianco. Syllabification of the Divine Comedy. In *Journal on Computing and Cultural Heritage*, volume 14, issue 3. July 2021.

[2] `Dante` GitHub repository. `https://github.com/asperti/Dante`

[3] Andrea Zugarini, Stefano Melacci, and Marco Maggini. Neural Poetry: Learning to Generate Poems using Syllables. ICANN 2019.

[4] Riccardo Cozzi and Alessandro Liscio. Deep Comedy (project report). AY 2019–2020.

[5] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention Is All You Need. NeurIPS 2017.

[6] Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. Neural Machine Translation by Jointly Learning to Align and Translate. ICLR 2015.

[7] Tom B. Brown et al. Language Models are Few-Shot Learners. NeurIPS 2020.

[8] Transformer model for language understanding (TensorFlow tutorial). `https://www.tensorflow.org/text/tutorials/transformer`

```
Syllabifier input:       caduto se’ di quella dolce terra
Syllabifier output:      |ca|du|to |se’ |di |quel|la |dol|ce |ter|ra
Correct syllabification: |ca|du|to |se’ |di |quel|la |dol|ce |ter|ra

Syllabifier input:       «O frate mio, ciascuna è cittadina
Syllabifier output:      « |O |fra|te |mio, |cia|scu|na è |cit|ta|di|na
Correct syllabification: « |O |fra|te |mio, |cia|scu|na è |cit|ta|di|na

Syllabifier input:       sotto l’ombra perpetüa, che mai
Syllabifier output:      |sot|to |l’ om|bra |per|pe|tü|a, |che |mai
Correct syllabification: |sot|to |l’ om|bra |per|pe|tü|a, |che |mai

Syllabifier input:       ma per la vista che s’avvalorava
Syllabifier output:      |ma |per |la |vi|sta |che |s’ av|va|lo|ra|va
Correct syllabification: |ma |per |la |vi|sta |che |s’ av|va|lo|ra|va

Syllabifier input:       sopra la quale ogne virtù si fonda,
Syllabifier output:      |so|pra |la |qua|le o|gne |vir|tù |si |fon|da,
Correct syllabification: |so|pra |la |qua|le o|gne |vir|tù |si |fon|da,

Syllabifier input:       «Non so», rispuos’ io lui, «quant’ io mi viva;
Syllabifier output:      « |Non |so», |ri|spuo|s’ io |lui,« |quan|t’ io |mi |vi|va;
Correct syllabification: « |Non |so», |ri|spuo|s’ io |lui,« |quan|t’ io |mi |vi|va;

Syllabifier input:       per ch’io te sovra te corono e mitrio».
Syllabifier output:      |per |ch’ io |te |so|vra |te |co|ro|no e |mi|trio».
Correct syllabification: |per |ch’ io |te |so|vra |te |co|ro|no e |mi|trio».

Syllabifier input:       Deh, frate, or fa che più non mi ti celi!
Syllabifier output:      |Deh, |fra|te, or |fa |che |più |non |mi |ti |ce|li!
Correct syllabification: |Deh, |fra|te, or |fa |che |più |non |mi |ti |ce|li!

Syllabifier input:       per essere ad acquisto d’oro usata;
Syllabifier output:      |per |es|se|re ad |ac|qui|sto |d’ o|ro u|sa|ta;
Correct syllabification: |per |es|se|re ad |ac|qui|sto |d’ o|ro u|sa|ta;

Syllabifier input:       cose che torrien fede al mio sermone».
Syllabifier output:      |co|se |che |tor|rien |fe|de al |mio |ser|mo|ne».
Correct syllabification: |co|se |che |tor|rien |fe|de al |mio |ser|mo|ne».
```

Figure 4: Syllabifier output on the first 10 verses of the test set

```
|io |di|co |d’ A|ri|sto|ti|le e |di |Pla|to
|E |non |e|r’ an|co |del |mio |pet|to es|sau|sto
|fic|ca|va |ï|o |sì |co|me |far |suo|le
|ve|di og|gi|mai |quan|t’ es|ser |dee |quel |tut|to
|Io |a|vea |già il |mio |vi|so |nel |suo |fit|to;
|più |nel |suo a|mor, |più |mi |si |fé |ne|mi|ca.
|so|ve|nha |vos |a |temps |de |ma |do|lor!».
|Cu|rï|o, |ch’ a |dir |fu |co|sì |ar|di|to!
|si |ve|de |di |giu|sti|zia or|ri|bil |ar|te.
|par|le|rei |a |quei |due |che ’n|sie|me |van|no,
|Ca|i|na at|ten|de |chi a |vi|ta |ci |spen|se».
|fu |il |can|tor |de |lo |Spi|ri|to |San|to,
|Gran|di|ne |gros|sa, |ac|qua |tin|ta e |ne|ve
|Po|co |por|tä|i in |là |vol|ta |la |te|sta,
|Qui|vi è |la |sa|pï|en|za e |la |pos|san|za
|L’ ac|qua e|ra |bu|ia |as|sai |più |che |per|sa;
|co|min|ciò, |‘glo|ria! ’, |tut|to ’l |pa|ra|di|so,
|co|min|ciò ’l |Man|to|an |che |ci a|vea |vòl|ti,
|Tre |pas|si |ci |fa|cea il |fiu|me |lon|ta|ni;
|do|v’ E|te|ò|cle |col |fra|tel |fu |mi|so?».
|pen|sa |che |Pie|tro e |Pau|lo, |che |mo|ri|ro
|di |Io|sü|è |in |su |la |Ter|ra |San|ta,
|pen|sa |chi |e|ra, e |la |ca|gion |che ’l |mos|se,
|e |ve|dra’ |il |cor|règ|ger |che ar|go|men|ta
|che |d’ ac|qua |fred|da |In|do o |E|tï|o|po.
|In|fin |là |sù |la |vi|de il |pa|tri|ar|ca
|E ’l |fra|te:« Io |u|di’ |già |di|re a |Bo|lo|gna
|a|vean |le |lu|ci |mie |sì i|ne|brï|a|te,
|si |vi|der |mä|i in |al|cun |tan|to |cru|de,
|lo |sfa|vil|lar |de |l’ a|mor |che |lì |e|ra
|Di |quel |che |fé |col |bai|u|lo |se|guen|te,
|co|sì |in|tram|mo |noi |per |la |cal|laia,
|che |do|vria |l’ uom |te|ner |den|tro a |sua |me|ta.
|Or |per|ché |in |cir|cui|to |tut|to |quan|to
|che a’ |miei |pro|pin|qui |tu |ben |mi |rin|fa|mi.
|e |l’ a|li |d’ o|ro, e |l’ al|tro |tan|to |bian|co,
|con |l’ a|li a|per|te |li |gia|cea |un |dra|co;
|lo |dol|ce |ber |che |mai |non |m’ a|vria |sa|zio;
|Poi |dis|se:« |Più |pen|sa|va |Ma|ria |on|de
|che |quel|la |di |co|lui |che |li è |da|van|te;
```

(a) Correct syllabification

```
|io |di|co |d’ A|ri|sto|ti|le |di |Pla|to
|E |non |e|r’ an|co |del |mio |pet|to es|sa|u|sto
|fic|ca|va ï|o |sì |co|me |far |suo|le
|ve|di og|gi|mai |quan|t’ es|ser |de |quel |tut|to
|Io |a|vea |già |il |mio |vi|so |nel |suo |fit|to;
|più |nel |suo |a|mor, |più |mi |si |fé |ne|mi|ca.
|so|ve|nha |vos |a |tem|ps |de |ma |do|lor!».
|Cu|rï|o, |ch’ a |dir |fu |co|sì ar|di|to!
|si |ve|de |di |giu|sti|zia or|ri|bil ar|te.
|par|le|rei a |quei |due |che ’n|sie|me |van|no,
|Ca|i|na at|ten|de |chi |a |vi|ta |ci |spen|se».
|fu il |can|tor |de |lo |Spi|ri|to |San|to,
|Gran|di|ne |gros|sa, ac|qua |tin|ta e |ne|ve
|Po|co |por|tä |in |là |vol|ta |la |te|sta,
|Qui|vi è |la |sa|pï|pan|za e |la |pos|san|za
|L’ ac|qua e|ra |bu|ia as|sai |più |che |per|sa;
|co|min|ciò, |‘lo|ria!’, |tut|to ’l |pa|ra|ra|di|so,
|co|min|ciò ’l |Man|toan |che |ci a|vea |vòl|ti,
|Tre |pas|si |ci |fa|cea |il |fiu|me |lon|ta|ni;
|do|v’ E|teò|cle |col |fra|tel |fu |mi|so?».
|pen|sa |che |Pie|tro e |Pa|u|lo, |che |mo|ri|ro
|di |Io|sü|è in |su |la |Ter|ra |San|ta,
|pen|sa |chi e|ra, e |la |ca|gion |che ’l |mos|se,
|e |ve|dra’ |il |cor|règ|ger |che |ar|go|men|ta
|che |d’ ac|qua |fred|da In|do o |E|tï|o|po.
|In|fin |là |sù |la |vi|de il |pa|triar|ca
|E ’l |fra|te:« |Io |u|di’ |già |di|re a |Bo|lo|gna
|a|vean |le |lu|ci |mie |sì |i|ne|brï|a|te,
|si |vi|der |mäi |in |al|cun |tan|to |cru|de,
|lo |sfa|vil|lar |de |l’ a|mor |che |lì e|ra
|Di |quel |che |fé |col |ba|iu|lo |se|guen|te,
|co|sì in|tram|mo |noi |per |la |cal|la|ia,
|che |dov|ria |l’ uom |te|ner |den|tro a |sua |me|ta.
|Or |per|ché in |cir|cu|i|to |tut|to |quan|to
|che |a’ |miei |pro|pin|qui |tu |ben |mi |rin|fa|mi.
|e |l’ a|li |d’ o|ro, e |l’ al|tro |tan|tian|co,
|con |l’ a|li a|per|te |li |gia|cea un |dra|co;
|lo |dol|ce |ber |che |mai |non |m’ av|ria |sa|zio;
|Poi |dis|se:« |Più |pen|sa|va |Ma|ria on|de
|che |quel|la |di |co|lui |che |li |è |da|van|te;
```

(b) Syllabifier output

Figure 5: Incorrectly syllabified verses from the test set. The number of correctly syllabified verses is 1384/1424 (~97% of the test set)

```
|e |che |s’ in|con|tran |con |sì |as|pre |lin|gue,
|vol|gen|do|m’ io |con |li et|ter|ni |Ge|mel|li,
« |O|san|na, |sanc|tus |De|us |sa|ba|òth,
|a |le |cu|ru|le |Si|zii |e Ar|ri|guc|ci.
|l’ o|nor |d’ A|gob|bio e |l’ o|nor |di |quel|l’ ar|te
|che ’l |tien |le|ga|to, o |a|ni|ma |con|fu|sa,
|che |cre|de e |non, |di|cen|do« El|la è... |non |è...»,
|sci|as |quod |e|go |fui |suc|ces|sor |Pe|tri.
|co|min|ciò |el,« |se |non... |Tal |ne |s’ of|fer|se.
|l’ a|iu|ta |sì |ch’ i’ |ne |sia |con|so|la|ta.
|ri|co|min|ciò il |cor|te|se |por|ti|na|io:
|la |re|ve|sti|ta |vo|ce al|le|lui|an|do,
|S’ ï|o a|ves|si |le |ri|me |as|pre e |chioc|ce,
|Cer|to |tra |es|so e ’l |gau|dio |mi |fa|cea
|e |Gal|li e |quei |ch’ ar|ros|san |per |lo |staio.
|vol|se|si in |su i |ver|mi|gli e in |su |i |gial|li
|al|lor |che |ben |co|nob|be il |ga|le|ot|to,
« |O |fron|da |mia |in |che io |com|pi|a|cem|mi
|ché |se |che|li|dri, |ia|cu|li e |fa|ree
|con |ar|chi e |as|tic|ciuo|le |pri|ma e|let|te;
|ma |già |vol|ge|va il |mio |di|sio |e ’l |vel|le,
|ve|nim|mo o|ve |quel|l’ a|ni|me |ad |u|na
|Pon|tì |e |Nor|man|dia |pre|se e |Gua|sco|gna.
|qua |den|tro |è ’l |se|con|do |Fe|de|ri|co
|di|co |nel |cie|lo, |io |me |ne |glo|riai.
|qu’ ieu |no |me |puesc |ni |voill |a |vos |co|bri|re.
|tut|to, |qual |che |si |sia, |il |mio |in|ge|gno,
```

(a) Correct syllabification

```
|e |che |s’ in|con|tran |con |sì |a|spre |lin|gue,
|vol|gen|dom’ |io |con |li et|ter|ni |Ge|mel|li,
« |O|san|na, |sanc|cus |De|us |sa|ba|òth,
|a |le |cu|ru|le |Si|ziii e |Ar|ri|guc|ci.
|l’ o|nor |d’ A|gob|bio e |l’ o|n |di |quel|l’ ar|te
|che ’l |tien |le|ga|to, o |o |a|ni|ma |con|fu|sa,
|che |cre|de e |non, |di|cen|do« El|la è... |non |è....
|scias |quod |e|go |fui |suc|ces|sor |Pe|tri.
|co|min|ciò |el,« |se |non.. |Tal |ne |s’ of|fer|se.
|l’ ai|ta |sì |ch’ i’ |ne |sia |con|so|la|ta.
|ri|co|min|ciò |il |cor|te|se |por|ti|naio:
|la |re|ve|sti|ta |vo|ce al|le|lu|ian|do,
|S’ ï|o a|ves|si |le |ri|me a|spre e |chioc|ce,
|Cer|to |tra es|so e ’l |gau|dio |mi |fa|cea
|e |Gal|li e |quei |ch’ ar|ros|san |per |lo |sta|io.
|vol|se|si in |su i |ver|mi|gli e in |su i |gial|li
|al|lor |che |ben |co|nob|be il |ga|leot|to,
« |O |fron|da |mia |in |che |io |com|pia|cem|mi
|ché |se |che|li|dri, |ia|cu|li e |fa|re
|con |ar|chi e |a|stic|ciuo|le |pri|ma e|let|te;
|ma |già |vol|ge|va il |mio |di|sio e ’l |vel|le,
|ve|nim|mo o|ve |quel|l’ a|ni|me ad |u|na
|Pon|tì e |Nor|man|dia |pre|se e |Gua|sco|gna.
|qua |den|tro è ’l |se|con|do |Fe|de|ri|co
|di|co |nel |cie|lo, io |me |ne |glo|riai.
|qu’ ieu |no |me |puesc |ni |voil |a |vos |co|bri|re.
|tut|to, |qual |che |si |sia, il |mio |in|ge|gno,
```

(b) Syllabifier output

Figure 6: Incorrectly syllabified verses from the validation set. The number of correctly syllabified verses is 12819/2846 (~99% of the validation set)

```
|leg|ge, |mo|ne|ta, of|fi|cio |e |co|stu|me
|di |No|stra |Don|na in |sul |li|to a|dri|a|no.
|nel |pros|si|mo |si |dan|no, e |nel |suo a|ve|re
|Già |e|ran |so|vra |noi |tan|to |le|va|ti
« |O |Vir|gi|lio, |Vir|gi|lio, |chi |è |que|sta?»,
|che |mo|rì |per |la |bel|la |Dei|a|ni|ra,
|s’ io |m’ in|tu|as|si, |co|me |tu |t’ in|mii».
|Ma io |veg|gi’ |or |la |tua |men|te |ri|stret|ta
|me|na|va |ï|o |li oc|chi |per |li |gra|di,
|a |tal |da |cui |la |no|ta |non |è in|te|sa,
|Io |non |E|në|a, |io |non |Pau|lo |so|no;
|ri|mon|tò ’l |du|ca |mio |e |tras|se |mee;
|pon |giù |il |se|me |del |pian|ge|re e a|scol|ta:
|per |che |no i |vol|le |Ge|de|on |com|pa|gni,
|ma |sa|pï|en|za, a|mo|re |e |vir|tu|te,
|ben |la |ru|i|na, e |die|de|mi |di |pi|glio.
|tra ’ |quai |co|nob|bi |Et|tòr |ed |E|nea,
|o|mai |la |na|vi|cel|la |del |mio in|ge|gno,
|Ve|de|va |Tro|ia in |ce|ne|re e in |ca|ver|ne;
|e or |s’ ac|co|scia e |o|ra è |in |pie|di |stan|te.
|e |quel|la |par|te on|de |pri|ma |è |pre|so
|chi ei |si |fos|ser |e |on|de |ven|ner |qui|vi,
|dal |suo |prin|ci|pio |ch’ è in |que|sto |tron|co|ne.
|di |tut|ta |l’ a|ni|mal |per|fe|zï|o|ne;
|e |cu’ |io |vi|di |su in |ter|ra |la|ti|na,
|di|nan|zi a |li oc|chi |mi |si |fu |of|fer|to
|sov|r’ al|trui |san|gue in |na|tu|ral |va|sel|lo.
|d’ in|fan|ti |e |di |fem|mi|ne e |di |vi|ri.
|cor|te|sia |e |va|lor |dì |se |di|mo|ra
|El |dis|se a |me:« |To|sto |ver|rà |di |so|vra
|guar|dan|do il |fo|co e i|ma|gi|nan|do |for|te
|fe|dir |tor|ne|a|men|ti e |cor|rer |gio|stra;
|Li|bi|coc|co |veg|n’ ol|tre e |Dra|ghi|gnaz|zo,
|tan|t’ e|ra |pien |di |son|no |a |quel |pun|to
|e |que|ste |co|se |pur |fu|ron |crea|tu|re;
|non |di|sdeg|nò |di |far|si |sua |fat|tu|ra.
|per |lei, |tan|to |che a |Dio |si |so|di|sfac|cia,
|e|ra o|no|ra|ta, es|sa |e |suoi |con|sor|ti:
|o |con |men |che |non |dee |cor|re |nel |be|ne,
|di|sce|se, a|vria |me|stier |di |tal |mi|li|zia
|il |qua|le e il |quan|to |de |la |vi|va |stel|la
|che al |giu|di|cio |di|vin |pas|sion |com|por|ta?
|Io |sta|va |so|vra ’l |pon|te a |ve|der |sur|to,
|ma |pa|ri in |at|to e |o|ne|sto |e |so|do.
|e |den|tro a |quei |che |più in|nan|zi ap|pa|ri|ro
|d’ u|na |di |lor |ch’ a|vea |tre |oc|chi in |te|sta.
|ché a |tut|ti un |fil |di |fer|ro i |ci|gli |fó|ra
```

(a) Correct syllabification

```
|leg|ge, |mo|ne|ta, of|fi|cio e |co|stu|me
|di |No|stra |Don|na in |sul |li|to a|dria|no.
|nel |pros|si|mo |si |dan|no, e |nel |suo |a|ve|re
|Già |e|ran |sov|ra |noi |tan|to |le|va|ti
« |O |Vir|gi|lio, |Vir|gi|lio, |chi è |que|sta?»,
|che |mo|rì |per |la |bel|la |De|i|a|ni|ra,
|s’ io |m’ in|tu|as|si, |co|me |tu |t’ in|miii».
|Ma |io |veg|gi’ or |la |tua |men|te |ri|stret|ta
|me|na|va ï|o |li oc|chi |per |li |gra|di,
|a |tal |da |cui |la |no|ta |non |è |in|te|sa,
|Io |non |E|në|a, |io |non |Pa|u|lo |so|no;
|ri|mon|tò ’l |du|ca |mio |e |tras|se |me;
|pon |giù |il |se|me |del |pian|ge|re e |a|scol|ta:
|per |che |no i |vol|le |Ge|deon |com|pa|gni,
|ma |sa|pï|en|za, a|mo|re e |vir|tu|te,
|ben |la |rui|na, e |die|de|mi |di |pi|glio.
|tra ’ |quai |co|nob|bi |Et|tòr |ed |E|E|nea,
|o|mai |la |na|vi|cel|la |del |mio |in|ge|gno,
|Ve|de|va |Troia |in |ce|ne|re e |in |ca|ver|ne;
|e |or |s’ ac|co|scia e |o|ra è |in |pie|di |stan|te.
|e |quel|la |par|te on|de |pri|ma è |pre|so
|chi |ei |si |fos|ser |e |on|de |ven|ner |qui|vi,
|dal |suo |prin|ci|pio |ch’ è |in |que|sto |tron|co|ne.
|di |tut|ta |l’ a|ni|mal |per|fï|o|ne;
|e |cu’ |io |vi|di |su |in |ter|ra |la|ti|na,
|di|nan|zi a |li oc|chi |mi |si |fu of|fer|to
|sov|r’ al|trui |san|gue |in |na|tu|ral |va|sel|lo.
|d’ in|fan|ti e |di |fem|mi|ne e |di |vi|ri.
|cor|te|sia e |va|lor |dì |se |di|mo|ra
|El |dis|se a |me:« |To|sto |ver|rà |di |sov|ra
|guar|dan|do il |fo|co e |i|ma|gi|nan|do |for|te
|fe|dir |tor|nea|men|ti e |cor|rer |gio|stra;
|Li|bi|coc|co |ve|gn’ ol|tre e |Dra|ghi|gnaz|zo,
|tan|t’ e|ra |pien |di |son|no a |quel |pun|to
|e |que|ste |co|se |pur |fu|ron |cre|a|tu|re;
|non |di|sde|gnò |di |far|si |sua |fat|tu|ra.
|per |lei, |tan|to |che |a |Dio |si |so|di|sfac|cia,
|e|ra o|no|ra|ta, es|sa e |suoi |con|sor|ti:
|o |con |men |che |non |de |cor|re |nel |be|ne,
|di|sce|se, av|ria |me|stier |di |tal |mi|li|zia
|il |qua|le e |il |quan|to |de |la |vi|va |stel|la
|che |al |giu|di|cio |di|vin |pas|sion |com|por|ta?
|Io |sta|va |sov|ra ’l |pon|te a |ve|der |sur|to,
|ma |pa|ri in |at|to e |o|ne|sto e |so|do.
|e |den|tro a |quei |che |più |in|nan|zi ap|pa|ri|ro
|d’ u|na |di |lor |ch’ a|vea |tre oc|chi in |te|sta.
|ché |a |tut|ti un |fil |di |fer|ro i |ci|gli |fó|ra
```

(b) Syllabifier output

Figure 7: Incorrectly syllabified verses from the training set. The number of correctly syllabified verses is 9870/9963 (~99% of the training set)

```
|tras|si|mi |so|vra |quel|la |cre|a|tu|ra
|On|de, |se ’l |mio |di|sir |dee |a|ver |fi|ne
|Tu |non |se’ in |ter|ra, |sì |co|me |tu |cre|di;
|su |per |lo |suol |che |d’ o|gne |par|te au|li|va.
|s’ e|ra al|lun|ga|ta, u|nì |a |sé in |per|so|na
|e in |quel|la |for|ma |ch’ è |in |lui |sug|gel|la
|che |li as|seg|nò |set|te e |cin|que |per |die|ce,
|co|me |fa |don|na |che in |par|tu|rir |sia;
|che i |tre |a’ |tre |pu|gnar |per |lui |an|co|ra.
|che a|ver|le |den|tro e |so|ste|ner |lo |puz|zo
|che |quel |che |vo|le Id|dio, |e |noi |vo|le|mo».
|ri|spuo|s’ io |lui,« |mi smar|ri’ |in |u|na |val|le,
|ch’ a |la |pri|m’ ar|te |deg|nò |por|re |ma|no.
|le |la|gri|me |tra |es|si e |ri|ser|rol|li.
|che a |pe|na |po|scia |li av|rei |ri|te|nu|ti;
|che |nul|la |vo|lon|tà |è |di |più a|u|sa,
|e a|vea |in |at|to im|pres|sa e|sta |fa|vel|la
|Io |co|min|ciai:« |O |fra|ti, i |vo|stri |ma|li...»;
|co|sì |tut|ta |la |gen|te |che |lì |e|ra,
“ |Glo|rï|a |in |ex|cel|sis” |tut|ti“ |Deo”
|ma |per |sé |stes|sa |pur |fu el|la |sban|di|ta
|più |che |in |al|tra |con|vien |che |si |mo|va
|si |sta|va in |pa|ce, |so|bria |e |pu|di|ca.
|sì |che ’n |po|c’ o|ra a|vria |l’ o|rec|chia of|fe|sa.
|E |già il |po|e|ta in|nan|zi |mi |sa|li|va,
|giu|ra|to a|vria |po|co |lon|ta|no a|spet|to
« |Man|tü|a...», e |l’ om|bra, |tut|ta in |sé |ro|mi|ta,
|es|so |li|ta|re |sta|to ac|cet|to e |fau|sto;
|ri|com|pie |for|se |ne|gli|gen|za e in|du|gio
|se o|ra|zï|o|ne in |pri|ma |non |m’ a|i|ta
|nu|vo|le |spes|se |non |pai|on |né |ra|de,
|mi |dis|se:« |Non |sai |tu |che |tu |se’ in |cie|lo?
« |Qui |li |tro|vai— |e |poi |vol|ta |non |dier|no—»,
|qui|vi |sto |io |con |quei |che |le |tre |san|te
|ché |Bran|ca |Do|ria |non |mo|rì |un|quan|che,
|Bug|ge|a |sie|de e |la |ter|ra on|d’ io |fui,
|nel |qual |non |si |dee |cre|der |che |s’ in|vii
|ri|ma|sa |è |per |dan|no |de |le |car|te.
|che |ri|ce|ve |da |Eu|ro |mag|gior |bri|ga,
|i’ |di|co |di |Trai|a|no im|pe|ra|do|re;
|ri|spon|di |a |me |che ’n |se|te e ’n |fo|co ar|do.
|Lo |re|ge |per |cui |que|sto |re|gno |pau|sa
|pe|ne|ia, |quan|do al|cun |di |sé |as|se|ta.
|In |es|sa |ge|rar|cia |son |l’ al|tre |dee:
|del |bel|lo o|vi|le o|v’ io |dor|mi’ |a|gnel|lo,
|del |di|re e |del |ta|cer, |si |sta; |on|d’ io,
```

(a) Correct syllabification

```
|tras|si|mi |sov|ra |quel|la |cre|a|tu|ra
|On|de, |se ’l |mio |di|sir |de |a|ver |fi|ne
|Tu |non |se’ |in |ter|ra, |sì |co|me |tu |cre|di;
|su |per |lo |suol |che |d’ o|gne |par|te a|u|li|va.
|s’ e|ra al|lun|ga|ta, u|nì |a |sé |in |per|so|na
|e |in |quel|la |for|ma |ch’ è |in |lui |sug|gel|la
|che |li as|se|gnò |set|te e |cin|que |per |die|ce,
|co|me |fa |don|na |che |in |par|tu|rir |sia;
|che i |tre a’ |tre |pu|gnar |per |lui |an|co|ra.
|che |a|ver|le |den|tro e |so|ste|ner |lo |puz|zo
|che |quel |che |vo|le Id|dio, e |noi |vo|le|mo».
|ri|spuo|s’ io |lui,« |mi |smar|ri’ |in |u|na |val|le,
|ch’ a |la |pri|m’ ar|te |de|gnò |por|re |ma|no.
|le |la|gri|me |tra es|si e |ri|ser|rol|li.
|che |a |pe|na |po|scia |li av|rei |ri|te|nu|ti;
|che |nul|la |vo|lon|tà |è |di |più |a|u|sa,
|e |a|vea |in |at|to im|pres|sa e|sta |fa|vel|la
|Io |co|min|ciai:« |O |fra|ti, i |vo|stri |ma|li..
|co|sì |tut|ta |la |gen|te |che |lì e|ra,
“ |Glo|rï|a in |ex|cel|sis” |tut|ti“ |Deo”
|ma |per |sé |stes|sa |pur |fu |el|la |sban|di|ta
|più |che in |al|tra |con|vien |che |si |mo|va
|si |sta|va in |pa|ce, |so|bria e |pu|di|ca.
|sì |che ’n |po|c’ o|ra av|ria |l’ o|rec|chia of|fe|sa.
|E |già |il |po|e|ta in|nan|zi |mi |sa|li|va,
|giu|ra|to av|ria |po|co |lon|ta|no a|spet|to
« |Man|tü|a....», e |l’ om|bra, |tut|ta in |sé |ro|mi|ta,
|es|so |li|ta|re |sta|to ac|cet|to e |fa|u|sto;
|ri|com|pie |for|se |ne|gli|gen|za e |in|du|gio
|se |o|ra|zï|o|ne in |pri|ma |non |m’ a|i|ta
|nu|vo|le |spes|se |non |pa|ion |né |ra|de,
|mi |dis|se:« |Non |sai |tu |che |tu |se’ |in |cie|lo?
« |Qui |li |tro|vai— |poi |vol|ta |non |dier|no—»,
|qui|vi |sto io |con |quei |che |le |tre |san|te
|ché |Bran|ca |Do|ria |non |mo|rì un|quan|che,
|Bug|gea |sie|de e |la |ter|ra on|d’ io |fui,
|nel |qual |non |si |de |cre|der |che |s’ in|viii
|ri|ma|sa è |per |dan|no |de |le |car|te.
|che |ri|ce|ve |da E|u|ro |mag|gior |bri|ga,
|i’ |di|co |di |Tra|ia|no im|pe|ra|do|re;
|ri|spon|di a |me |che ’n |se|te e ’n |fo|co ar|do.
|Lo |re|ge |per |cui |que|sto |re|gno |pa|u|sa
|pe|neia, |quan|do al|cun |di |sé |as|se|ta.
|In |es|sa |ge|rar|cia |son |l’ al|tre |de:
|del |bel|lo o|vi|le o|v’ io |dor|mi’ a|gnel|lo,
|del |di|re e |del |ta|cer, |si |sta; on|d’ io,
```

(b) Syllabifier output

Figure 8: Incorrectly syllabified verses from the training set. The number of correctly syllabified verses is 9870/9963 (~99% of the training set)

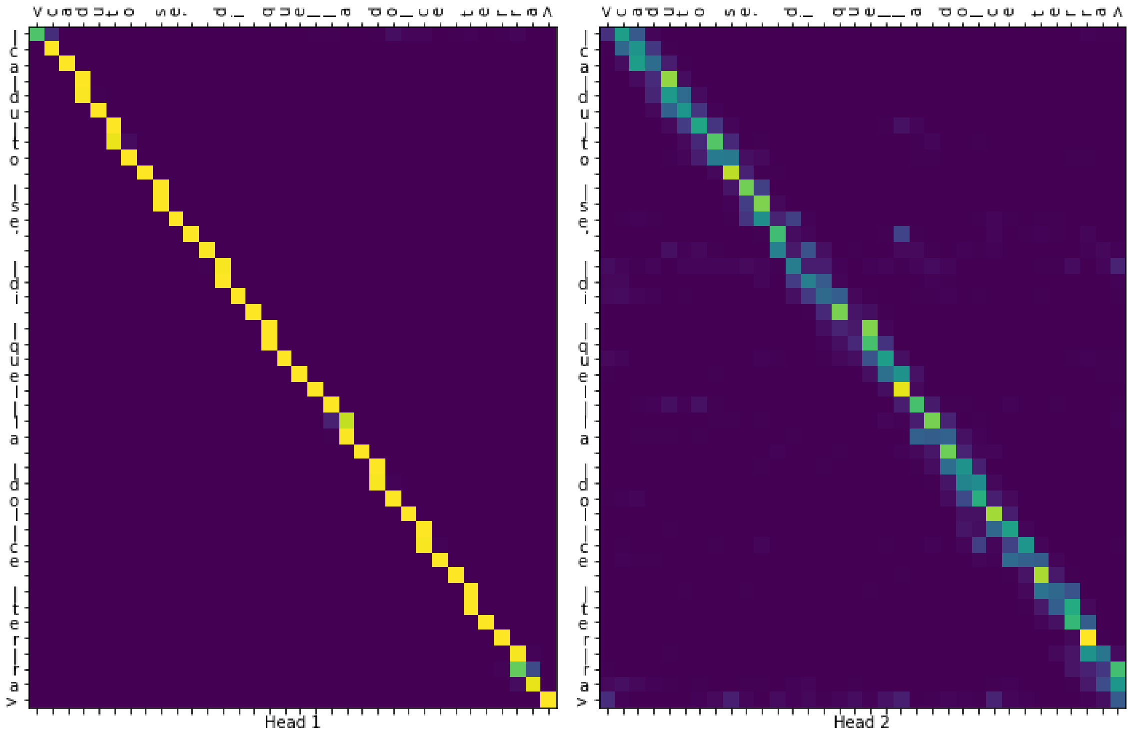


Figure 9: Syllabifier attention plots for input verse *caduto se' di quella dolce terra*

```
FOUND CONFLICT:
Generator output:    ch' i' |fos|si a|va|si |che |per |me |di |io
Syllabifier output:  ch' i' |fos|si |a|va|si |che |per |me |di |io

FOUND WRONG NUMBER OF SYLLABLES:
Generator output = Syllabifier output: ba|le|va |la |pre|di|cò |le |ter|re |mol|li
Number of syllables: 12

FOUND CONFLICT:
Generator output:    mo |ch' el|la |per |lo |tuo |pen|sa|ria |stes|na
Syllabifier output:  mo |ch' el|la |per |lo |tuo |pen|sa|ria |ste|sna

FOUND CONFLICT:
Generator output:    la |pi|sto|e|ta in |su |la |ru|i|na
Syllabifier output:  la |pi|sto|e|ta in |su |la |rui|na

FOUND WRONG NUMBER OF SYLLABLES:
Generator output = Syllabifier output: o|mai |ve|dë|a' |ne|re |san|gue in |sa
Number of syllables: 10
```

Figure 10: Constraint violations found by the syllabifier during the generation process

```
ahi |quan|to a |l’ o|ro e |tu ’l |sa|rà |di |pa|ra
e|ra|gian|do|mi |pria |di |dio |lau|da|to
la |sua |ve|du|ta |già |in |su |la |fo|ra

o |to|sco |ch’ al |pet|to |fu |de |la |mat|to
sì |co|me |tri|sce |di |cuor |de |la |val|le
e |non |ve|dea |io |ch’ io |non |so |di|sfat|to

e |tu |ve|drai |pa|rea |be|mie |pa|sto|le
e |te|sta o|ra|zion |pic|cio|la al |cam|mi|no
che a |pe|na |po|scia |li av|vin|le |sue |scu|le

e |no|stra |pop|pa |nel |no|stro |sof|fer|no
de’ |fa|re|mi |fa |la |som|mer|ce|ne|ra
fa |ve|der |noi |e |an|cor |fa |di|ser|no

e |voi |che ’l |scen|nir |fu |già |mai |o|ra|ra
li|be|re |sta|va e |non |la|scia |re|lit|ta
sì |che ’n|ver|so |noi |la |via |con |la |cu|ra

d’ un |pec|ca|tor |me|stier |più |non |fu |tol|ta
la |sca|la|zion |de |li al|tri |fa|cea |buo|ne
e |da |la |no|va |gra|ve |si |di|sciol|ta

sì |nel |fer|ro |mon|do e |io |per|ché |suo|ne
co|sì |quel |fu |fra|te |che |più |s’ ap|pa|da
la |piog|gia |con|nel |fon|do |che |na|ven|ne

le |do|lo|gi|gne |gra|zia |val|le |chia|da
so|vra |lo |qua|le an|dar |l’ et|ter|na |po|glie
di|sce|si |del |vo|la|re e |non |mi |ri|da

e |io |se |quei |che |com’ |io |ti |fa|vel|glie
ch’ i’ |stra|nï|as|se |me |con |la |tua |stan|za
per |gra|var |la |pa|ce e |da |no|vel|ra|glie

on|de |fu |det|to a |l’ o|pe|re |che a |men|za
po|scia |del |ciel |più |bel|la |sua |fi|gu|ra
ta|le |fac|cian |le |be|a|ti |mon|te|za

stel|li a |lui |se ’l |mon|do |sen|ten|za |fu|ra
fa|ce|va |pri|ma |chi |pa|ce e |re|tag|gio
tut|ti |le |gen|ti |tue |pa|ra|zion |gi|ra
```

(a) With syllabification marks

```
ahi quanto a l’ oro e tu ’l sarà di para
eragiandomi pria di dio laudato
la sua veduta già in su la fora

o tosco ch’ al petto fu de la matto
sì come trisce di cuor de la valle
e non vedea io ch’ io non so disfatto

e tu vedrai parea bemie pastole
e testa orazion picciola al cammino
che a pena poscia li avvinle sue scule

e nostra poppa nel nostro sofferno
de’ faremi fa la sommercenera
fa veder noi e ancor fa diserno

e voi che ’l scennir fu già mai orara
libere stava e non lascia relitta
sì che ’nverso noi la via con la cura

d’ un peccator mestier più non fu tolta
la scalazion de li altri facea buone
e da la nova grave si disciolta

sì nel ferro mondo e io perché suone
così quel fu frate che più s’ appada
la pioggia connel fondo che navenne

le dologigne grazia valle chiada
sovra lo quale andar l’ etterna poglie
discesi del volare e non mi rida

e io se quei che com’ io ti favelglie
ch’ i’ stranïasse me con la tua stanza
per gravar la pace e da novelraglie

onde fu detto a l’ opere che a menza
poscia del ciel più bella sua figura
tale faccian le beati monteza

stelli a lui se ’l mondo sentenza fura
faceva prima chi pace e retaggio
tutti le genti tue parazion gira
```

(b) Without syllabification marks

Figure 11: Generator output