Appendix: Non-Monotonic Sequential Text Generation

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A. Additional Experiment Details and Results

A.1. Word Reordering

Model The decoder is a 2-layer LSTM with 1024 hidden units, dropout of 0.0, based on a preliminary grid search of $n_{\text{layers}} \in \{1, 2\}, n_{\text{hidden}} \in \{512, 1024, 2048\}$, dropout $\in \{0.0, 0.2, 0.5\}$. Word embeddings are initialized with GloVe vectors and updated during training. All presented Word Reordering results use greedy decoding.

Training Each model was trained on a single GPU using a maximum of 500 epochs, batch size of 32, Adam optimizer, gradient clipping with maximum ℓ_2-norm of 1.0, and a learning rate starting at 0.001 and multiplied by a factor of 0.5 every 20 epochs. For evaluation we select the model state which had the highest validation BLEU score, which is evaluated after each training epoch.

Oracle For π^*_{annealed}, β is linearly annealed from 1.0 to 0.0 at a rate of 0.05 each epoch, after a burn-in period of 20 epochs in which β is not decreased. We use greedy decoding when π^*_{coaching} is selected at a roll-in step; we did not observe significant performance variations with stochastically sampling from π^*_{coaching}. These settings are based on a grid search of $\beta_{\text{rate}} \in \{0.01, 0.05\}, \beta_{\text{burn-in}} \in \{0, 20\}$, coaching-rollin $\in$ {greedy, stochastic} using the model selected in the **Model** section above.

Example Predictions Figure 4 shows example predictions from the validation set, including the generation order and underlying tree.

A.2. Unconditional Generation

We use the same settings as the Word Reordering experiments, except we always use stochastic sampling from π^*_{coaching} during roll-in. For evaluation we select the model state at the end of training.

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Table 1. Unconditional generation BLEU for various top-k samplers and policies trained with the specified oracle.

Oracle	**k**	**BLEU-2**	**BLEU-3**	**BLEU-4**
$\pi^*_{\text{left-right}}$	10	0.905	0.778	0.624
	100	0.874	0.705	0.514
	1000	0.853	0.665	0.466
	all	0.853	0.668	0.477
π^*_{uniform}	10	0.966	0.906	0.788
	100	0.916	0.751	0.544
	1000	0.864	0.651	0.435
	all	0.831	0.609	0.395
π^*_{annealed}	10	0.966	0.895	0.770
	100	0.931	0.804	0.628
	1000	0.907	0.765	0.585
	all	0.894	0.740	0.549

Unconditional Samples Samples in Tables 3-4 are organized as 'short' ($\leq$ 5th percentile), 'average-length' (45-55th percentile), and 'multi-sentence' ($\geq$ 3 punctuation tokens). Each image in Figures 1, 2, and 3 shows a sampled sentence, its underlying tree, and its generation order.

Additional BLEU Scores Since absolute BLEU scores can vary by using a softmax temperature (Caccia et al., 2018) or top-k sampler, we report additional scores for $k \in \{10, 100, 1000\}$ and BLEU-$\{2, 3, 4\}$ in Table 1. Generally the policy trained with the annealed oracle achieves the highest metrics.

A.3. Machine Translation

Data and Preprocessing We use the default Moses tokenizer script (Koehn et al., 2007) and segment each word into a subword using BPE (Sennrich et al., 2015) creating 40k tokens for both source and target. Similar to (Bahdanau et al., 2015), during training we filter sentence pairs that exceed 50 words.

Transformer Policy The Transformer policy uses 4 layers, 4 attention heads, hidden dimension 256, feed-forward dimension 1024, and is trained with batch-size 32 and a

Oracle	Validation BLEU (BP)	Validation Meteor	Validation YiSi	Validation Ribes	Test BLEU (BP)	Test Meteor	Test YiSi	Test Ribes
left-right	29.47 (0.97)	29.66	52.03	82.55	26.23 (1.00)	27.87	47.58	79.85
uniform	14.97 (0.63)	21.76	41.62	77.70	13.17 (0.64)	19.87	36.48	75.36
+⟨end⟩-tuning	18.79 (0.89)	25.30	46.23	78.49	17.68 (0.96)	24.53	42.46	74.12
annealed	19.50 (0.71)	26.57	48.00	81.48	16.94 (0.72)	23.15	42.39	78.99
+⟨end⟩-tuning	21.95 (0.90)	26.74	49.01	81.77	19.19 (0.91)	25.24	43.98	79.24

Table 2. LSTM Policy results for machine translation experiments.

learning rate 1e^{-5}. For this model and experiment, we define an epoch as 1,000 model updates. The learning rate is divided by a factor of 1.1 every 100 epochs. For π^*_{annealed}, β is linearly annealed from 1.0 to 0.0 at a rate of 0.01 each epoch, after a burn-in period of 100 epochs. We compute metrics after each validation epoch, and following training we select the model with the highest validation BLEU.

Loss with Auxiliary ⟨end⟩ Predictor A binary cross-entropy loss is used for the ⟨end⟩ predictor for all time-steps, so that the total loss is $\mathcal{L}_{\text{bce}}(\pi^*, \pi_{\text{end}}) + \mathcal{L}_{\text{KL}}(\pi^*, \pi)$ where $\mathcal{L}_{\text{KL}}$ is the loss from Section 3.2. For time-steps in which ⟨end⟩ is sampled, $\mathcal{L}_{\text{KL}}$ is masked, since the policy's token distribution is not used when a_t is ⟨end⟩. $\mathcal{L}_{\text{KL}}$ is averaged over time by summing the loss from unmasked time-steps, then dividing by the number of unmasked time-steps.

Tree Position Encodings We use an additional *tree position encoding*, based on (Shiv & Quirk, 2019), which may make it easier for the policy to identify and exploit structural relationships in the partially decoded tree. Each node is encoded using its path from the root, namely a sequence of left or right steps from parent to child. Each step is represented as a 2-dimensional binary vector ($[0,0]$ for the root, $[1,0]$ for left and $[0,1]$ for right), so that the path is a vector $e(a_i) \in \{0,1\}^{2*\text{max-depth}}$ after zero-padding. Finally, $e(a_i)$ is multiplied element-wise by a geometric series of a learned parameter p, that is, $e(a_i) \cdot \left[1, p, p, p^2, p^3, ...\right]$. We only use this approach with the Transformer policy.

Additional LSTM Policy Results are shown in Table 2. We use a bi-directional LSTM encoder-decoder architecture that has a single layer of size 512, with global concat attention (Luong et al., 2015). The learning rate is initialized to 0.001 and multiplied by a factor of 0.5 on a fixed interval.

References

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Table 3. **Short** (left) and **Average-Length** (right) unconditional samples from policies trained on Persona-Chat.

left-right	i can drive you alone . yeah it is very important . i am a am nurse . do you actually enjoy it ? what pair were you in ?	do you like to test your voice to a choir ? no pets , on the subject in my family , yes . cool . i have is also a cat named cow . i am doing good taking a break from working on it . i do not have one , do you have any pets ?
uniform	good just normal people around . you run the hills right ? i am great yourself ? i work 12 hours . do you go to hockey ?	just that is for a while . and yourself right now ? i am freelance a writer but i am a writer . that is so sad . do you have a free time ? yes i do not like pizza which is amazing lol . since the gym did not bother me many years ago .
annealed	are you ? i am . i like to be talented . how are you doing buddy ? i like healthy foods . i love to eat .	yeah it can be . what is your favorite color ? i do not have dogs . they love me here . no kids . . . i am . . you ? that is interesting . i am just practicing my piano degree . yea it is , you need to become a real nerd !

Table 4. **Multi-sentence** unconditional samples from policies trained on Persona-Chat.

left-right	nice ! i think i will get a jump blade again . have you done that at it ? great . what kinds of food do you like best ? i love italian food . wow . bike ride is my thing . i do nothing for kids . i am alright . my mom makes work and work as a nurse . that is what i do for work . that is awesome . i need to lose weight . i want to start a food place someday .
uniform	love meat . or junk food . i sometimes go too much i make . avoid me unhealthy . does not kill anyone that can work around a lot of animals ? you ? i like trains . baby ? it will it all here . that is the workforce . i am good , thank you . i love my sci fi stories . i write books . i am well . thank you . my little jasper is new .
annealed	i am definitely a kid . are you ? i am 10 ! i am in michigan state . . that is a grand state . that is good . i work as a pharmacist in florida . . . how are you ? wanna live in san fran ! i love it . well that is awesome ! i do crosswords ! that is cool .

Figure 1. Unconditional samples from a policy trained with π^*_{annealed}.

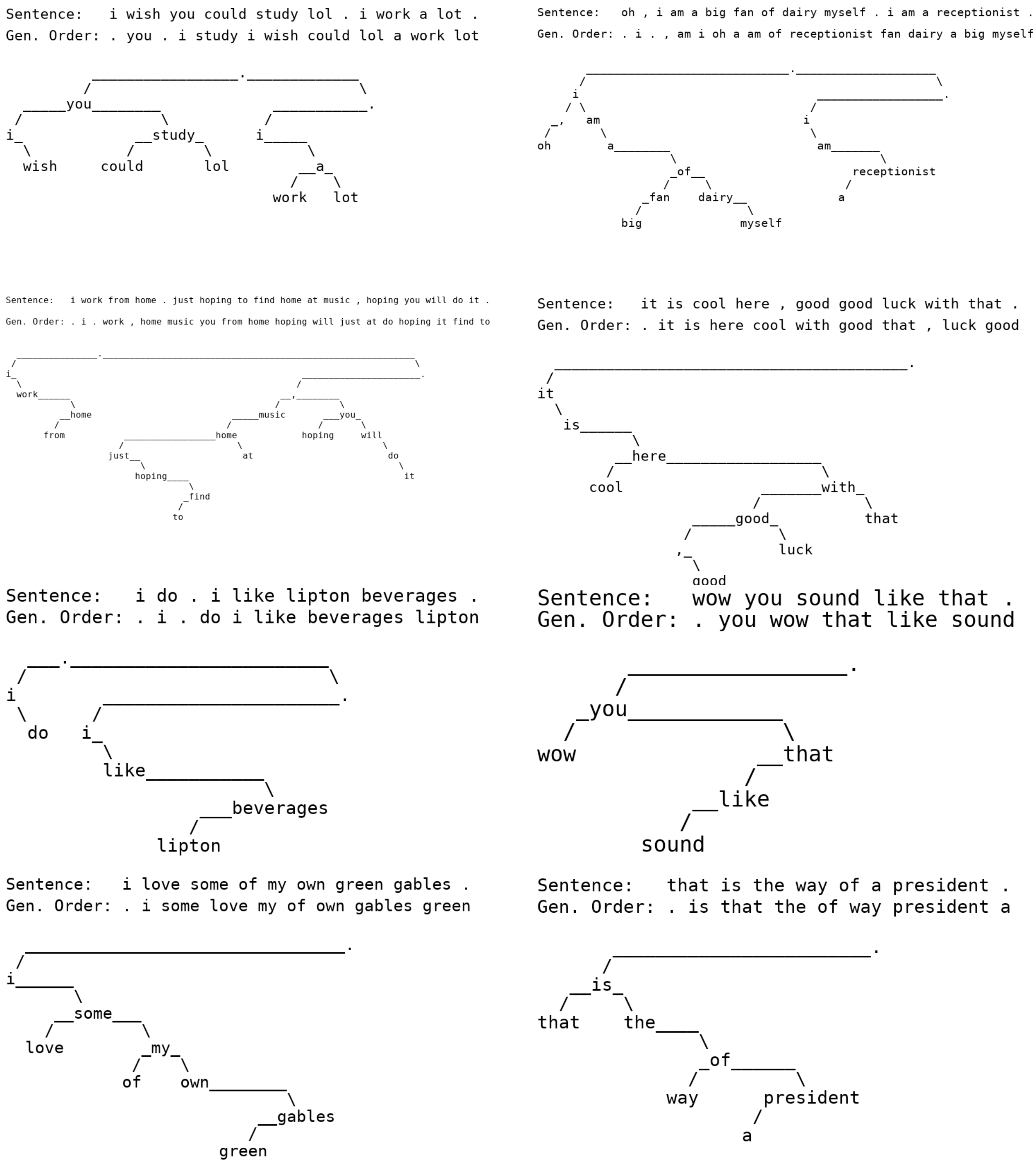


Figure 2. Unconditional samples from a policy trained with π^*_{uniform}.

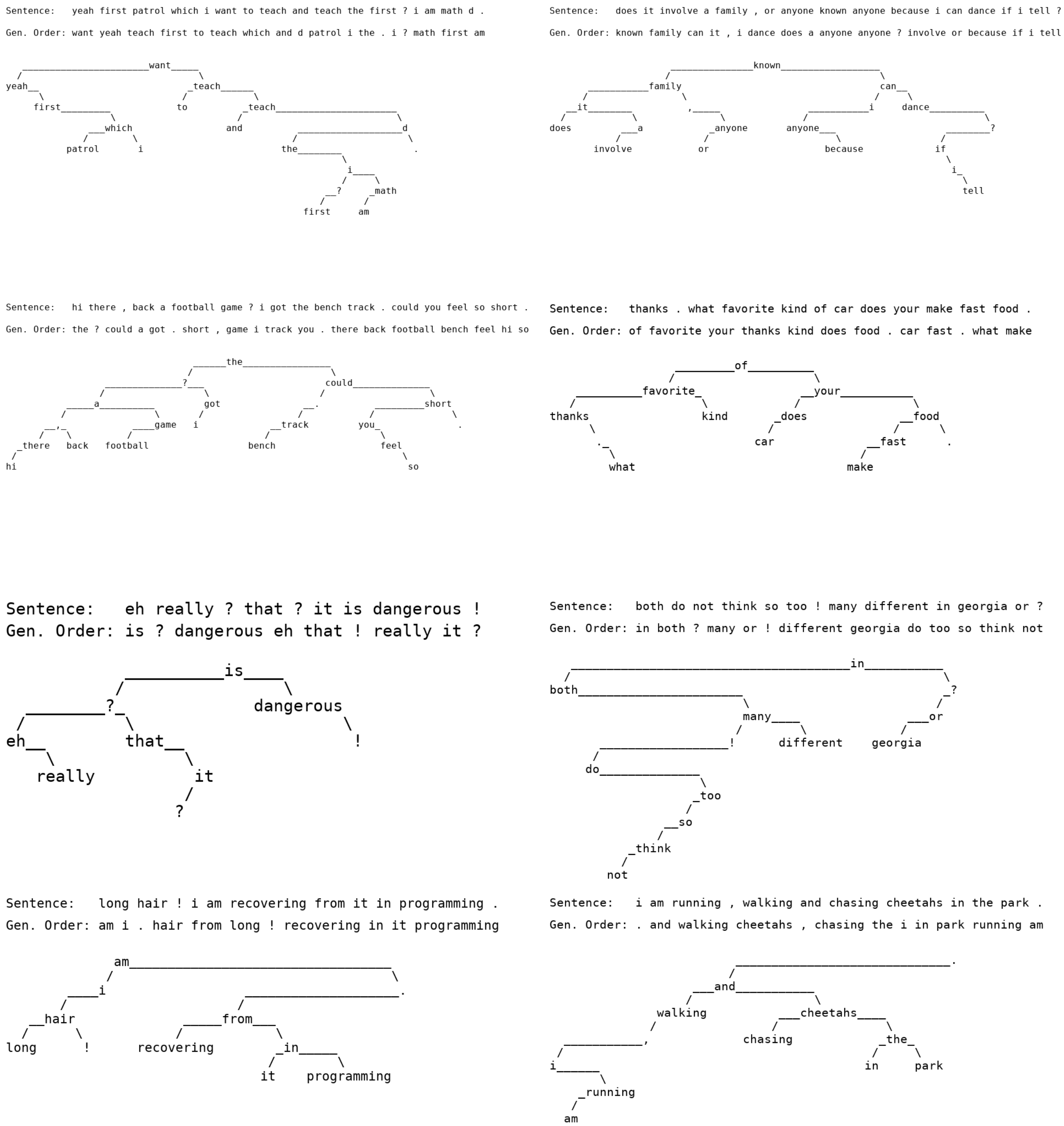


Figure 3. Unconditional samples from a policy trained with $\pi^*_{\text{left-right}}$.

```
Sentence:   fancy . do you have any hobbies ?
Gen. Order: fancy . do you have any hobbies ?

fancy
     \
      .
       \
        do_
           \
            you_
                \
                 have_
                      \
                       any___
                             \
                              hobbies
                                     \
                                      ?
```

```
Sentence:   mostly classical . it is very good in our lives .
Gen. Order: mostly classical . it is very good in our lives .

mostly____
          \
     classical
              \
               .
                \
                 it
                   \
                    is_
                       \
                        very_
                             \
                              good
                                  \
                                   in_
                                      \
                                       our__
                                            \
                                             lives
                                                  \
```

```
Sentence:   a little sick , but i am thinking about a new diet .
Gen. Order: a little sick , but i am thinking about a new diet .

a__
   \
  little_
         \
        sick
            \
             ,_
               \
               but
                  \
                   i
                    \
                    am___
                         \
                      thinking__
                                \
                              about
                                   \
                                    a_
                                      \
                                      new_
```

```
Sentence:   over being a lumberjack ? i love to be outdoors , its just me and listening to music .
Gen. Order: over being a lumberjack ? i love to be outdoors , its just me and listening to music .

over__
      \
     being
          \
           a____
                \
         lumberjack
                   \
                    ?
                     \
                      i_
                        \
                       love
                           \
                            to
                              \
                              be___
                                   \
                                 outdoors
                                         \
                                          ,_
                                            \
                                            its_
                                                \
                                               just
                                                   \
                                                    me_
                                                       \
                                                       and____
                                                              \
                                                          listening
```

```
Sentence:   she won more of work on yourself . made life down .
Gen. Order: she won more of work on yourself . made life down .

she_
    \
    won_
        \
        more
            \
             of_
                \
               work
                   \
                    on___
                         \
                      yourself
                              \
                               ._
                                 \
                                made_
                                     \
                                     life_
                                          \
                                          down
```

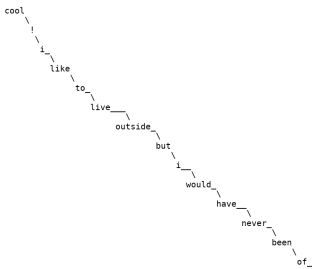
```
Sentence:   oh yeah that happens ! i always check the watch out .
Gen. Order: oh yeah that happens ! i always check the watch out .

oh_
   \
   yeah_
        \
        that___
               \
             happens
                    \
                     !
                      \
                       i__
                          \
                        always__
                                \
                               check_
                                     \
                                     the__
                                          \
                                         watch_
                                               \
                                               out
```

```
Sentence:   i do not wish i were a better person .
Gen. Order: i do not wish i were a better person .

i
 \
  do_
     \
     not_
         \
         wish
             \
              i_
                \
                were
                    \
                     a__
                        \
                       better__
                               \
                              person
                                    \
                                     .
```

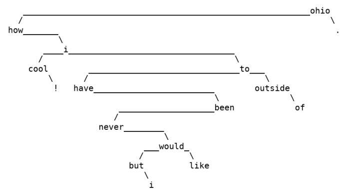
```
Sentence:   neat when i visit art school i hope i love them .
Gen. Order: neat when i visit art school i hope i love them .

neat_
     \
     when
         \
          i__
             \
            visit_
                  \
                  art__
                       \
                      school
                            \
                             i_
                               \
                               hope
                                   \
                                    i_
                                      \
                                      love_
                                           \
                                           them
                                               \
                                                .
```

Figure 4. Word Reordering Examples. The columns show policies trained with $\pi^*_{\text{left-right}}$, π^*_{uniform}, and π^*_{annealed}, respectively.

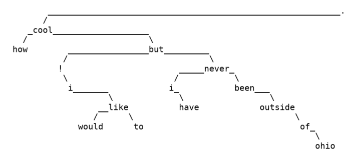
Actual: how cool ! i have never been outside of ohio but i would like to .
Predicted: cool ! i like to live outside but i would have never been of ohio .
Gen. Order: cool ! i like to live outside but i would have never been of ohio .



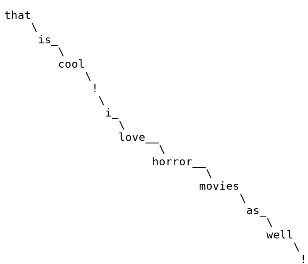
Actual: how cool ! i have never been outside of ohio but i would like to .
Predicted: how cool ! i have never but i would like been to outside of ohio .
Gen. Order: ohio how . i cool to ! have outside been of never would but like i



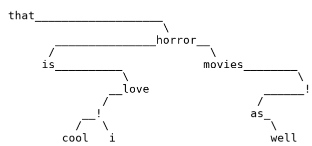
Actual: how cool ! i have never been outside of ohio but i would like to .
Predicted: how cool ! i would like to but i have never been outside of ohio .
Gen. Order: . cool how but ! never i i been like have outside would to of ohio



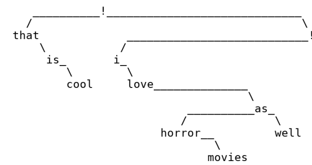
Actual: that is cool ! i love horror movies as well !
Predicted: that is cool ! i love horror movies as well !
Gen. Order: that is cool ! i love horror movies as well !



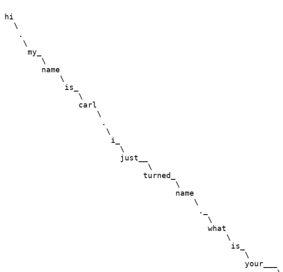
Actual: that is cool ! i love horror movies as well !
Predicted: that is cool ! i love horror movies as well !
Gen. Order: that horror is movies love ! ! as cool i well



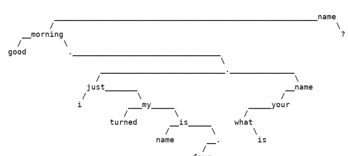
Actual: that is cool ! i love horror movies as well !
Predicted: that is cool ! i love horror movies as well !
Gen. Order: ! that ! is i cool love as horror well movies



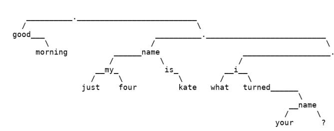
Actual: good morning . my name is sophie . i just turned four . what is your name ?
Predicted: hi . my name is carl . i just turned name . what is your favorite pub ?
Gen. Order: hi . my name is carl . i just turned name . what is your favorite pub ?



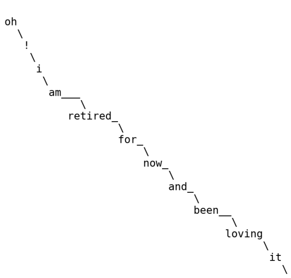
Actual: good morning . my name is sophie . i just turned four . what is your name ?
Predicted: good morning . i just turned my name is four . . what is your name name ?
Gen. Order: name morning ? good . . just name i my your turned is what name . is four



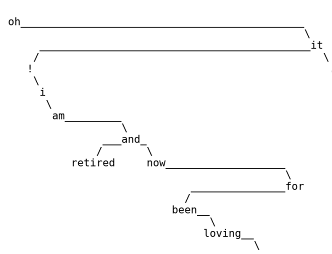
Actual: good morning . my name is sophie . i just turned four . what is your name ?
Predicted: good morning . just my four name is kate . what i turned your name ? .
Gen. Order: . good . morning name . my is i just four kate what turned name your ?



Actual: oh i am been retired now for years . and loving it !
Predicted: oh ! i am retired for now and been loving it .
Gen. Order: oh ! i am retired for now and been loving it .



Actual: oh i am been retired now for years . and loving it !
Predicted: oh ! i am retired and now been loving years for it .
Gen. Order: oh it ! . i am and retired now for been loving years



Actual: oh i am been retired now for years . and loving it !
Predicted: oh ! i am been retired for years and loving it now .
Gen. Order: . oh ! i am now retired been years for and loving it

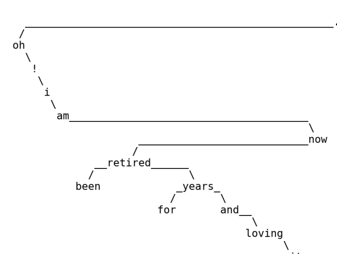


Figure 5. Translation outputs from a policy trained with π^*_{annealed} on the test set.

```
Source:     das führte mich dazu , Satellitenbilder zu benutzen
Target:     this is really what brought me to using satellite im
Predicted:  that led me to use satellite imagery .
Gen. Order: me that satellite led to . use imagery

   ______me___________
  /                   \
that_         _____satellite________
     \       /                      \
     led    to_                   ___.
               \                 /
               use           imagery
```

```
Source:     aber unsere Hände bleiben immer noch außerhalb des Bildschirms .
Target:     but our two hands still remain outside the screen .
Predicted:  but our hands still remain the screen of the screen .
Gen. Order: . but our hands still the remain screen of screen the

  _______________________________________.
 /
but_
    \
    our__
         \
        hands__
               \
              still________
                           \
                         ___the__
                        /        \
                     remain     screen
                                      \
                                       of______
                                               \
                                              _screen
                                             /
                                           the
```

```
Source:     als die Arbeiten zurückkamen , berechnete ich Noten
Target:     when the work came back , I calculated grades .
Predicted:  when this came back , I posed grades .
Gen. Order: I , . when grades came posed this back

                      I____________
                     /             \
   _________________,            ___.
  /                             /
when______                 __grades
          \               /
        __came_        posed
       /       \
     this      back
```

```
Source:     meine Eltern wollten , dass ich Ingenieur wie sie werde .
Target:     my parents wanted me to become an engineer like them .
Predicted:  my parents wanted me to like them .
Gen. Order: my parents to wanted . me like them

my___
     \
   parents_________
                   \
             ______to__________
            /                  \
         wanted             _______.
               \           /
               me     like_
                           \
                           them
```

```
Source:     und ich habe einen ganzen Haufen wirklich interessanter Dinge gelernt .
Target:     and I learned a whole bunch of really interesting stuff .
Predicted:  and I learned a whole lot of really interesting thing .
Gen. Order: I and interesting a . learned whole thing of lot really

  _I_____________________________
 /                               \
and           ____________________interesting______
             /                                     \
        ___a__                                    __.
       /      \                                  /
  learned   whole____                          thing
                     \
                     _of__
                    /     \
                  lot    really
```

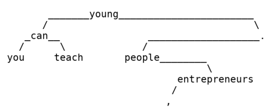
```
Source:     ich musste feststellen , dass es erstaunlich viel Spaß macht .
Target:     and I found that this was shockingly fun .
Predicted:  I had to tell you that it &apos;s amazing fun .
Gen. Order: to I fun had that . tell it you &apos;s amazing

  ____to________________________________
 /                                      \
I_                 _____________________fun
  \               /                        \
  had       ______that                      .
           /          \
       tell_          it___
            \              \
            you        &apos;s___
                                 \
                               amazing
```

```
Source:     wie halte ich sie für Distanzläufe motiviert ? &quot
Target:     how do I keep them motivated for the long run ? &quo
Predicted:  how do I motivated them for them ? &quot;
Gen. Order: ? I &quot; how them do motivated for them

         _______________________?__
        /                          \
   ____I____________________      &quot;
  /                         \
how               _____________them
   \             /
   do   motivated______
                       \
                     __for
                    /
                  them
```

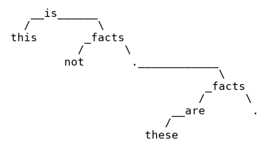
```
Source:     diese jungen Unternehmen haben eine enorme Auswirkung auf ihre Städte .
Target:     these young entrepreneurs are having a tremendous impact in their cities .
Predicted:  these young companies have a huge impact .
Gen. Order: . these young have companies impact a huge

    _____________________________________.
   /
these__
       \
      young___________
                      \
                  ____have_________
                 /                 \
            companies         _____impact
                             /
                            a_
                              \
                              huge
```

Figure 6. Translation outputs from a policy trained with π^*_{uniform} on the test set.

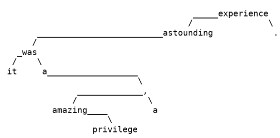
```
Source:     man kann jungen Leuten beibringen , Unternehmer zu sein .
Target:     and you can train young people to be entrepreneurs .
Predicted:  you can teach young people , entrepreneurs .
Gen. Order: young can . you teach people entrepreneurs ,
```



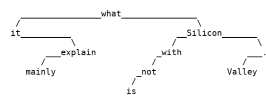

```
Source:     dies ist nicht meine Meinung . das sind Fakten .
Target:     this is not my opinion . these are the facts .
Predicted:  this is not facts . these are facts .
Gen. Order: is this facts not . facts are . these
```



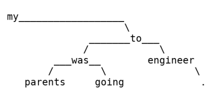

```
Source:     es war ein bemerkenswertes Privileg und eine aufregende Erfahrung .
Target:     it was a remarkable privilege and an amazing education .
Predicted:  it was a amazing privilege , a astounding experience .
Gen. Order: experience astounding . was it a , amazing a privilege
```



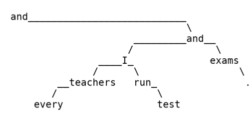

```
Source:     es erklärt hauptsächlich , was mit Silicon Valley nicht stimmt .
Target:     it mostly explains what &apos;s wrong with Silicon Valley .
Predicted:  it mainly explain what is not with Silicon Valley .
Gen. Order: what it Silicon explain with . mainly not Valley is
```



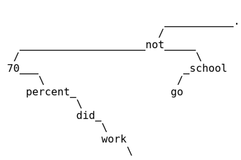

```
Source:     meine Eltern wollten , dass ich Ingenieur wie sie werde .
Target:     my parents wanted me to become an engineer like them .
Predicted:  my parents was going to engineer .
Gen. Order: my to was engineer parents going .
```




```
Source:     wie jeder Lehrer führte ich Tests und Prüfungen durch .
Target:     and like any teacher , I made quizzes and tests .
Predicted:  and every teachers I run test and exams .
Gen. Order: and and I exams teachers run . every test
```




```
Source:     70 % haben keine Arbeit , gehen nicht zur Schule .
Target:     70 percent don &apos;t work , don &apos;t go to scho
Predicted:  70 percent did work , not go school .
Gen. Order: . not 70 school percent go did work ,
```




```
Source:     wie halte ich sie für Distanzläufe motiviert ? &quot
Target:     how do I keep them motivated for the long run ? &quo
Predicted:  how do I give them to do ?
Gen. Order: ? do how I do to them give
```

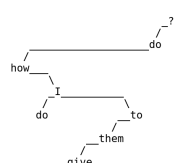


Figure 7. Translation outputs from a policy trained with $\pi^*_{\text{leftright}}$ on the test set.

```
Source:     mit diesem Werkzeug wurde die Grenze also durchbrochen .
Target:     so with this tool , this boundary has been broken .
Predicted:  so this instrument was taken through that motor limit .
Gen. Order: so this instrument was taken through that motor limit .

so_
  \
   this____
           \
            instrument_
                       \
                        was__
                             \
                              taken___
                                      \
                                       through_
                                               \
                                                that__
                                                      \
                                                       motor__
                                                              \
                                                               limit
                                                                    \
                                                                     .
```

```
Source:     aber jetzt müssen Sie sich darüber keine Sorgen mehr machen .
Target:     but now you don &apos;t have to worry about it .
Predicted:  but now you don &apos;t have to worry about that anymore .
Gen. Order: but now you don &apos;t have to worry about that anymore .

but_
    \
     now_
         \
          you_
              \
               don___
                     \
                      &apos;t_
                              \
                               have
                                   \
                                    to__
                                        \
                                         worry__
                                                \
                                                 about_
                                                       \
                                                        that___
                                                               \
                                                                anymore
                                                                       \
                                                                        .
```

```
Source:     einige meiner schlauesten Kinder schnitten nicht besonders gut ab .
Target:     some of my smartest kids weren &apos;t doing so well .
Predicted:  some of my smart kids don &apos;t run very well .
Gen. Order: some of my smart kids don &apos;t run very well .

some
    \
     of
       \
        my__
            \
             smart_
                   \
                    kids_
                         \
                          don___
                                \
                                 &apos;t_
                                         \
                                          run_
                                              \
                                               very_
                                                    \
                                                     well
                                                         \
                                                          .
```

```
Source:     für uns ist die Sonne die Quelle des Reichtums .
Target:     for us , the sun is the source of prosperity .
Predicted:  for us , the Sun is the source of the wealth .
Gen. Order: for us , the Sun is the source of the wealth .

for
   \
    us
      \
       ,_
         \
          the_
              \
               Sun
                  \
                   is_
                      \
                       the__
                            \
                             source
                                   \
                                    of_
                                       \
                                        the__
                                             \
```

```
Source:     diese jungen Unternehmen haben eine enorme Auswirkung auf ihre Städte .
Target:     these young entrepreneurs are having a tremendous impact in their cities .
Predicted:  these young companies have a tremendous impact on their cities .
Gen. Order: these young companies have a tremendous impact on their cities .

these__
       \
        young____
                 \
                  companies_
                            \
                             have
                                 \
                                  a____
                                       \
                                        tremendous__
                                                    \
                                                     impact
                                                           \
                                                            on__
                                                                \
                                                                 their__
                                                                        \
                                                                         cities
                                                                               \
                                                                                .
```

```
Source:     seit 1970 waren keine menschlichen Wesen mehr auf dem Mond .
Target:     since 1970 , no human beings have been back to the moon .
Predicted:  since 1970 , no human being had more on the moon .
Gen. Order: since 1970 , no human being had more on the moon .

since_
      \
       1970
           \
            ,
             \
              no__
                  \
                   human__
                          \
                           being_
                                 \
                                  had_
                                      \
                                       more
                                           \
                                            on_
                                               \
                                                the_
                                                    \
                                                     moon
                                                         \
                                                          .
```

```
Source:     wer wird mich versorgen , wenn ich Krebs habe ? &quot;
Target:     who &apos;s going to take care of me if I have cancer ? &
Predicted:  who will feed me when I have cancer ? &quot;
Gen. Order: who will feed me when I have cancer ? &quot;

who_
    \
     will_
          \
           feed
               \
                me_
                   \
                    when
                        \
                         I_
                           \
                            have__
                                  \
                                   cancer
                                         \
                                          ?__
                                             \
                                              &quot;
```

```
Source:     sogar ein zerplatzter Traum kann diesen Zweck erfüllen .
Target:     even a shattered dream can do that for you .
Predicted:  even a shattered dream can meet this purpose .
Gen. Order: even a shattered dream can meet this purpose .

even
    \
     a____
          \
           shattered__
                      \
                       dream_
                             \
                              can_
                                  \
                                   meet_
                                        \
                                         this___
                                                \
                                                 purpose
                                                        \
                                                         .
```