

1 Thank reviewers for detailed comments. Our main contribution is the novel search-and-learning for
2 UnsupTextGen, achieving remarkable performance (sometimes even better than SupTextGen). Our
3 novelty, clarity, and performance are recognized by different reviewers. Despite some borderline score,
4 we find reviewers’ concerns can all be resolved and do not diminish our contributions, addressed below.

5 **R1:** Thanks for recognizing our novelty and performance. **3.1 (generic UnsupTextGen framework):**
6 By “generic” we mean the model can be applied to different tasks that share the same problem structure. In
7 fact, search-based UnsupTextGen has shown promising results for summarization^[36], simplification^[27,41],
8 grammar correction^[26]. Our framework differs from application-specific UnsupTextGen. For example,
9 the rules/heuristics in [18] only applies to sentiment style transfer. **Future work MT:** Thanks for
10 suggesting the future work. We are currently considering MT by using word-level dictionary and
11 performing search and learning. We’re happy to revise the terminology and highlight what applications
12 TGSL is appropriate for, namely, those where the input and output show certain resemblance. We expect,
13 however, this can be relaxed by using different search algorithms other than local search. **3.2 (SA+MM):**
14 We mentioned in Line 269 that SA+MM cannot achieve reasonable performance. This is because MM is
15 hard to train without warm start (training signal is too sparse merely by several negative samples).

16 **R2: 3 (Novelty):** Our main novelty is the search-and-learning framework TGSL for UnsupTextGen,
17 where our learning is non-trivial and involves two stages with different losses, well motivated and
18 supported by ablation study. To our best knowledge, we are the first to work in this direction. The scorers
19 highlighted by the reviewer are additional engineering contributions of this paper; TGSL also largely
20 differs from all previous RL models (see §2.4 for detailed discussion). **4 (no human eval):** human eval
21 is in Appendix D, summarized in Line 258, main paper. **6 (How...differs from previous unsupervised**
22 **search TextGen):** We propose a search-and-learning framework^{§2.2-2.3} for UnsupTextGen; previous
23 work is search only. **Component wise comparison of UnsupTextGen:** We’re unsure what “component
24 wise comparison” is; Tab 3 presents a rigorous ablation study of our model with previous work, where
25 model capacity is strictly controlled. **8 (future work MT/QuestionGen):** See response to R1. Thanks!

26 **R3: 1 (only replaces original scoring):** Our main contribution is the search-and-learning
27 framework^[§2.2-2.3]. Improving the original scorer^[§2.1] is our additional contribution. **3.1 (motivation):**
28 UnsupTextGen has wide applications, e.g., low-resource language and cold-start for new applications,
29 where large-scale parallel corpora are unavailable^[Line16]. Motivation for search-and-learning (main
30 contribution) is to improve efficiency by avoiding search and to improve performance by smoothing
31 out search noise^[Line30]. **3.2 (search-based UnsupTextGen):** Search component is simulated annealing
32 (SA)^[Line66]. UnsupTextGen is feasible with a manually defined objective function for the strong SA
33 search. We used SA but further proposed the novel search-and-learning framework. **3.3 Conclusion (and**
34 **clarity):** Thanks for saying the overall clarity is “very good.” Due to space limit, we omitted Conclusion
35 for submission. We’ll expand the details and include the conclusion should the paper be accepted.

36 **R4: 3.1 (additional compute/latency):** Our inference efficiency is as low as a conditional text generator,
37 but 5–10x faster than previous search UnsupTextGen_[Tab 3]; training efficiency $\approx 2 \times (\text{SA} + \text{finetuneGPT2})$.
38 **3.2 (controlling #parameters):** Yes, the number of parameters is strictly controlled in Tab 3; our 5–10x
39 speedup is under the same model capacity. **3.3 (inference times of other baseline methods):** In Tab 3,
40 we compared the efficiency with the SA algorithm^[20]. For other baselines, we either quoted results from
41 previous work or tested published output^[Appendex C]; thus, we don’t have the inference time. However,
42 our efficiency is comparable to any conditional text generator (when model capacity is controlled),
43 because we essentially distill the knowledge of searching into a conditional text generator. ♦While
44 our training efficiency is roughly $2 \times (\text{SA} + \text{finetuneGPT2})$, we do not view it as a disadvantage. First,
45 training is usually done off-line; when trained, our model is very efficient for deployment. Second, it’s
46 understandable that we sacrifice some training efficiency compared with supervised models, since we
47 do not have parallel data. In fact, our approach should be more efficient (and labor-saving) than data
48 collection plus human annotation in the supervised setting, as explained in “Broader Impact.” We hope
49 our explanation could address the review’s concern of efficiency. We will discuss this in the revision.

50 **R5: 3.1:** Thanks for understanding the significant substance of our work! See response to 5.1–5.4. **3.2**
51 **(search-based):** Yes, simulated annealing can be thought of as stochastic search, because it aims to
52 maximize a function. We’ll explain more. **3.3/3.4:** Ablation study is in Tab 3, showing SA performance
53 within TGSL. We briefly discussed StructuredPrediction (and RL) in §2.4: StructPredict in the supervised
54 setting requires expert demonstrations, but we only have pseudo-reference given by SA. We’ll include the
55 suggested papers and discuss StructPredict more in the revision. **4.1:** Thanks for pointing this out. Yes,
56 we’ve already realized this typo and corrected it in our local version. **4.2:** Energy $E(x) \in (-\infty, \infty)$ is
57 indeed unbounded and unnormalized. Probability is thus defined as $p(x) \propto \exp\{-E(x)\}$. We’ll present
58 it when revising the paper. **5.1:** $\Delta=1$ like most applications. **5.2:** Epoch=6^[Line233] by early stop on
59 validation. **5.3:** Beam size=5^[Line 285]. **5.4:** Yes. N is the length of y for a sample. Thanks! Will clarify.