

TAILOR: Generating and Perturbing Text with Semantic Controls

Alexis Ross*[†] Tongshuang Wu*[◇] Hao Peng[◇] Matthew E. Peters[†] Matt Gardner[♣][†]

[†]Allen Institute for Artificial Intelligence, Seattle, WA, USA

[◇]Paul G. Allen School of Computer Science and Engineering, University of Washington

[♣]Microsoft Semantic Machines, USA

{alexisr, matthewp}@allenai.org

{wtshuang, hapeng}@cs.washington.edu

mattgardner@microsoft.com

Abstract

Controlled text perturbation is useful for evaluating and improving model generalizability. However, current techniques rely on training a model for every target perturbation, which is expensive and hard to generalize. We present TAILOR, a semantically-controlled text generation system. TAILOR builds on a pretrained seq2seq model and produces textual outputs conditioned on control codes derived from semantic representations. We craft a set of operations to modify the control codes, which in turn steer generation towards targeted attributes. These operations can be further composed into higher-level ones, allowing for flexible perturbation strategies. We demonstrate the effectiveness of these perturbations in multiple applications. First, we use TAILOR to automatically create high-quality contrast sets for four distinct natural language processing (NLP) tasks. These contrast sets contain fewer spurious artifacts and are complementary to manually annotated ones in their lexical diversity. Second, we show that TAILOR perturbations can improve model generalization through data augmentation. Perturbing just ~2% of training data leads to a 5.8-point gain on an NLI challenge set measuring reliance on syntactic heuristics.

1 Introduction

Semantic perturbation through controlled text generation modifies sentences to match certain target attributes, such as verb tense or sentiment (e.g., *positive*→*negative*). It has been widely applied to a variety of tasks, e.g., changing text style (Reid and Zhong, 2021), mitigating dataset biases (Gardner et al., 2021), explaining model behaviors (Ross et al., 2021), and improving model generalization (Teney et al., 2020; Wu et al., 2021). Existing efforts train task-specific generators, e.g., training

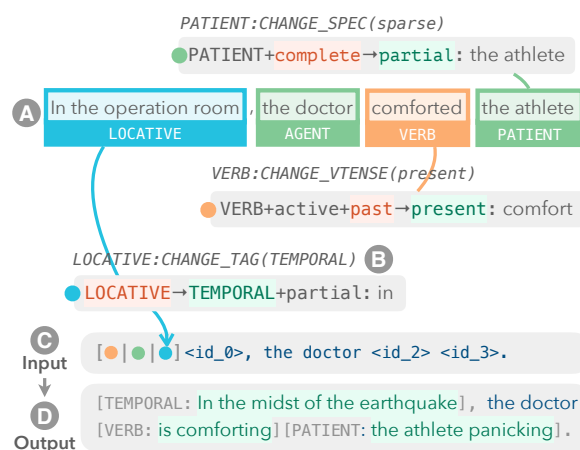


Figure 1: A compositional perturbation using TAILOR.¹ Given (A) an original sentence, we abstract each span into a structured *header* that contains its semantic roles and keywords. Arguments to preserve are included in the *context*, along with *blanks* (<id_*>) denoting where new generated text may be inserted. We specify desired perturbations by modifying each control code (e.g., changing role **LOCATIVE**→**TEMPORAL** in (B), verb tense **past**→**present**, and patient keyword specificity **complete**→**partial**). Given these *perturbed control codes* in the input (C), TAILOR generates a new sentence (D) that reflects the desired perturbations.

a sentiment style transferer requires instances annotated with *positive* and *negative* labels (Madaan et al., 2020b). As a result, they require costly annotated data and re-training for every task of interest.

This work introduces TAILOR, a system that supports application-agnostic perturbations. At its core is a *controlled generator* (§2) that flexibly generates outputs from target semantic attributes, which we represent through structured **control codes** in the inputs. As shown in Figure 1, these control codes build on the PropBank semantic analysis (Palmer et al., 2005) of the original sentence: For each argument span, the *semantic role* and *keyword* control codes specify the desired semantic content for the span at varying levels of granu-

* denotes equal contribution.

[†] Work done while at Allen Institute for AI

¹We open-source TAILOR and release TAILOR-generated contrast sets at <https://github.com/allenai/tailor>.

larity. To encourage control code following, we train the TAILOR generator with **unlikelihood training** (Welleck et al., 2020) to penalize generations that are not aligned with designated control codes.

The use of semantic role control codes allows TAILOR to perform fine-grained changes to individual arguments in a sentence (e.g., one can change only the **PATIENT** in Figure 1). Instead of specifying a perturbation with a generic target property (e.g., *positive*→*negative*), we can specify the linguistic transformation used to achieve the property (e.g., changing sentiment through negation or antonym replacement). Making such fine-grained perturbations allows for more careful evaluation and improvement of models’ language understanding (Kaushik et al., 2020; Wu et al., 2021).

To highlight the perturbations facilitated by TAILOR, we craft a list of primitive *perturbation operations* (§3) on inputs to the generator; these can be easily composed to achieve more complex perturbations. In Figure 1, TAILOR transforms sentence A to D through a series of perturbations: syntactic rewriting (changing verb tense), then sentence expansion (extending “the athlete”), and finally data recombination (i.e., generating new text that contains “in” but follows the **TEMPORAL** control). Compared to existing approaches that require training a separate model for every step or annotating a dataset that represents this transformation end-to-end, such compositions make TAILOR more cost-effective and generalizable. In fact, on nine fine-grained and compositional **STYLEPTB** perturbations (Lyu et al., 2021), TAILOR achieves performance compatible with task-specific baselines, and even outperforms them on five transfers (§F).

TAILOR’s flexible and human-readable control codes allow for broad, easily extendable applicability. We demonstrate its utility in evaluating and improving NLP model robustness, showing that TAILOR can help replicate existing **contrast sets** on four diverse tasks. By abstracting manual perturbation types in prior work into perturbation strategies with TAILOR, we can apply the changes to larger datasets while saving manual annotation efforts. Our analysis suggests that these contrast sets not only have high rates of validity, but also reduce spurious artifacts compared to the original evaluation datasets. In addition, TAILOR-produced contrast sets complement human annotated ones in terms of lexical diversity: only ~10% of their unique tokens overlap with manually created contrast sets. We

also explore TAILOR’s utility in data augmentation. We find that augmenting training data with just ~2% of TAILOR perturbations improves the **robustness** of natural language inference (NLI) models to inference heuristics, increasing performance on the HANS evaluation set (McCoy et al., 2019) by an average of 5.81 points and outperforming a previous syntactic augmentation method for NLI.

2 TAILOR’s Controllable Generator

Here, we provide an overview of the TAILOR generator. We first outline three types of **controls** (§2.1) that allow for specifying sentence meanings at varying granularity. Next, we explain how to embed them within **inputs** (§2.2) to the generator. We train the generator to follow control codes with **unlikelihood training** (§2.3).

2.1 Three Types of Controls

We use the following three types of controls to specify the shallow semantics, actual content, and ordering of various phrases in a sentence.

Semantic roles to denote shallow semantics. We rely on the PropBank semantic formalism (Palmer et al., 2005), as it provides well-established representations of meanings that are generalizable across different predicates and languages (Hajič et al., 2009). It represents sentence meanings with predicate-argument structures. Predicates (e.g., “comforted” in Figure 1) are usually evoked by verbs and reflect events (*what happened*). Arguments, usually spans of tokens, realize thematic roles of predicates; they include *core* arguments such as *who* did something (e.g., “the doctor” in Figure 1) and *to whom* (“the athlete”), as well as *adjunct* arguments like *where* something happened (“In the operation room”) and *how*.

Keywords for steering the actual generated content of predicates and arguments. The keywords can be *complete* and fully specify the target text of a given span (e.g., “the doctor” for the **AGENT** in Table 1A), *sparse* and add no constraints beyond the semantic role (e.g., * for **LOCATIVE**), or *partial* and specify some of the target text (e.g., “athlete” for **PATIENT**). As later shown in Table 3, these keyword controls are important for supporting a variety of perturbation strategies and applications.

Span ordering for determining how the thematic roles should be combined. We use predicate form to control the order of core arguments. For example, to distinguish “the athlete was comforted by

	Input	Target Output	Description
A	[VERB+active+past: comfort AGENT+complete: the doctor PATIENT+partial: athlete LOCATIVE+sparse: *] <id_0>, <id_1> <id_2> <id_3>.	[LOCATIVE: In the operating room], [AGENT: the doctor] [VERB: comforted] [PATIENT: the athlete].	Mask all roles
B	[VERB+active+past: comfort LOCATIVE+sparse: *] <id_0>, the doctor <id_1> <id_2> the athlete <id_3>.	[LOCATIVE: In the operating room], the doctor [VERB: comforted] the athlete.	Empty blanks
C	[VERB+active+past: comfort LOCATIVE+sparse: *] <id_0>, the doctor <id_1> the athlete.	[LOCATIVE: In the operating room], the doctor [VERB: comforted] the athlete.	Mask <i>subset</i> of arguments
N	[VERB+passive+present: comfort PATIENT+complete: the doctor AGENT+partial: athlete TEMPORAL+sparse: *] <id_0>, <id_1> <id_2> <id_3>.	[TEMPORAL: In the operating room], [PATIENT: the doctor] [VERB: comforted] [AGENT: the athlete].	Negative sample

Table 1: Example input/output formats for sentence “In the operating room, the doctor comforted the athlete.” A–C show different input formats the generator accepts. Each input (§2.2) contains a **header** (in brackets), which contains *control codes* (semantic role/keyword) for each span, as well as a **context**, which includes both original text to preserve and *blanks* (<id_*>) denoting where new text may be generated. The TAILOR generator outputs text that infills the context’s blanks with text following the header’s control codes. The last input (N) is a *negative* sample used for unlikelihood training, as described in §2.3.

Predicate control: VERB+active+past: comfort
Primary predicate label (Always VERB)
Lemma (Any verb lemma)
Voice (active, passive) ²
Tense (past, present, future)
Argument control: PATIENT+partial: athlete
Primary argument label (AGENT, PATIENT, TEMPORAL, LOCATIVE, MANNER, CAUSE, EXTENT, PURPOSE, etc.)
Keyword Content (* symbol or any text)
Keyword Specificity (complete, partial, sparse)

Table 2: TAILOR’s **control codes**. Primary controls build on predicate/argument labels, and others affect the form and content of generations (More in §A.1).

the doctor” from the semantically equivalent “the doctor comforted the athlete,” we target the former ordering through a *passive* control, and the latter through an *active* control. Additionally, we use the location of blank tokens (<id_*> in Figure 1 and Table 1) to determine the position of generated arguments (Wu et al., 2021) — e.g., where “in the operating room” appears in the generation.

2.2 Input Format Design

We integrate the aforementioned controls into the input format detailed in §A.1 and finetune seq2seq models to output corresponding full sentences.

As shown in Table 1, we start our input with a bracketed **header**, which contains a series of abstract *control codes* (Table 2) that denote the semantic role and keywords (content/specificity) to realize for each predicate and argument. For example, in Table 1A, the control codes for the predicate are “VERB+active: past” and the agent argument are “AGENT+complete: the doctor.” We

²We use <http://spacy.io/> for verb or POS detection.

map original semantic roles in PropBank to human-readable labels (i.e., ARG0 → AGENT) in order to leverage knowledge learned by pretrained models about roles’ meanings (Paolini et al., 2021).

After the header, we append the **context**, which consists of text to preserved and *blanks* specifying where new text should be generated. Given such inputs, we train our generator to output text augmented with control codes and brackets, which together specify which generated spans correspond to which controls. For example, in Table 1B, “[LOCATIVE: In the operating room]” represents the target span of control codes “LOCATIVE+sparse: *” and is generated at the location of *blank* <id_0> right before the preserved *context* “the doctor.”

We make three key design choices to allow TAILOR to generate roles fluently even when the optimal ordering of roles is unknown (e.g., when introducing a new argument). First, we explicitly separate signal about role placement (e.g., blanks in the context) from the role’s semantic controls (e.g., control codes in the header) such that we can specify the target semantic attributes for a role without tying them to a specific target placement. Second, we order the control codes in the header in an input-independent way (see §A.1) to discourage the generator from learning to rely on their relative orders. Third, we insert extra empty blanks into the context (e.g., <id_3> in Table 1B) such that the TAILOR generator can generate spans in the blank locations that result in the most fluent text.

With this flexibility in argument ordering comes the challenge of making strict controls on a single argument: Even if we only want to change verb tense, the generator may reorder other arguments.

To enable strict control over generations, which facilitates minimal perturbations (Ross et al., 2021), we further vary the number of arguments encoded in the header. As in Table 1C, our generator can take inputs that only mask a subset of arguments, such that, *e.g.*, any changes on the **LOCATIVE** argument or **VERB** do not affect the agent and patient.

2.3 Training

We finetune T5-BASE (Raffel et al., 2020) on input-output pairs derived from gold semantic roles in OntoNotes 5.0 train (Table 1; Pradhan et al., 2013).³ To train our generator to handle the different input formats described in §2.2, for each original input, we randomly sample the numbers of arguments to mask, number and placement of extra empty blanks, and keyword content/specificity for each role. See §A.2 for details.

Standard maximum likelihood estimation (MLE) is insufficient for training our generator to follow the controls, as there may exist signals beyond the given controls for the form of a generation. Consider the input: [VERB+active+past: comfort | AGENT+partial: athlete | PATIENT+complete: the doctor] In the operating room, <id_0>, <id_1> <id_2>. A generator trained with MLE may ignore controls **AGENT** and **PATIENT** and instead output text “The doctor comforted the athlete” rather than “The athlete comforted the doctor,” as the training data distribution may reflect that the former is more natural given context “in the operation room.”

To encourage reliance on controls, we incorporate **unlikelihood training** (Welleck et al., 2020) to penalize generations that conflict with input controls. That is, besides Table 1A–C which are used for MLE, we also create “negative” samples by randomly perturbing the control codes in our header (as in Table 1N, last row), such that most spans in the target output are not aligned with the control codes. We create up to three negative samples per input by randomly perturbing 1) verb voice/tense and primary controls for arguments, 2) keyword contents, and 3) keyword specificities (§A.1). Our final training data consists of 223K positive and 541K negative examples.

3 Creating Perturbations with TAILOR

With TAILOR, we can create diverse perturbations by modifying input controls. Given an original

³On par with T5, the blanks are in the form of <extra_id_*>; we refer them as <id_*> for simplicity.

sentence, we transform it to an input for TAILOR by extracting its semantic parses,⁴ masking spans we wish to modify, and providing their control codes. Then, we modify the control codes in the input to generate perturbed sentences with TAILOR, filtering out degenerate ones.

Primitive perturbation operations. We provide an easily-extendable set of perturbation macros, which capture three common types of perturbations in prior work, shown in Table 3: First, *syntactic rewriting* primarily involves shuffling text to create paraphrases (Zhang et al., 2019) or adversarial examples (Iyyer et al., 2018). We implement such shuffling through operations that perturb predicate forms, move blank tokens, and swap keyword contents of arguments. Second, *expansion and abstraction* add or remove text fragments from a sentence (Wu et al., 2021). We recreate these through operations on keywords (*e.g.*, deletion). Finally, *data recombination* involves recombining existing textual fragments, within or across inputs (Akyürek et al., 2021; Andreas, 2020). With **CHANGE_CONTENT**, we can integrate additional context (*e.g.*, from corresponding paragraphs in question answering tasks) into generations.

While our control codes are mostly derived from semantic roles, these primitive operations broadly cover both syntactic and semantic changes. They can also be used in conjunction with external knowledge bases to achieve targeted edits.⁵, or be composed to achieve more complex perturbation strategies as shown in §5, §6, and Appendix §F.

Filtering generations. We notice that the TAILOR generator produces degenerate outputs for some inputs; we exclude these heuristically based on content and perplexity scores (see §C for details).

4 Intrinsic Evaluation

Following previous work (Wu et al., 2021; Ross et al., 2021), we evaluate TAILOR generations on sentence likelihood, controllability, and closeness.⁶

⁴External semantic role labelers can be used when gold annotations are not available. Our experiments use the opensourced implementation of Shi and Lin (2019): demo.allennlp.org/semantic-role-labeling, with a test F1 of 86.5 on the Ontonotes 5.0 dataset (Pradhan et al., 2013).

⁵For example, if combined with WordNet (Miller, 1998), TAILOR perturbations may be able to incorporate a subset of natural logic (MacCartney and Manning, 2014): In Figure 1, we can create an entailment relationship by replacing **doctor** with its hyponym **adult**.

⁶We omit the diversity evaluation in POLYJUICE, as the keyword content control inherently impacts lexical diversity.

(a) Syntactically controlled rewriting		(b) Sentence expansion and abstraction	
Strategy	CHANGE_VTENSE(present) → [VERB+active+past→present: comfort]	Strategy	LOCATIVE:CHANGE_SPEC(partial) → [LOCATIVE+complete→partial: in the operation room]
Perturb.	In the operation room, the doctor comforts the athlete.	Perturb.	Under the dim light in the operation room, the doctor comforted the athlete.
Strategy	CHANGE_VVOICE(passive) → [VERB+active→passive+past: comfort]	Strategy	LOCATIVE:DELETE → [LOCATIVE+complete: in the operation room]
Perturb.	In...room, the athlete was comforted by the doctor.	Perturb.	In the operation room, the doctor comforted the athlete.
Strategy	CHANGE_IDX(4:0) → <id_0> In the operation room <id_0>		
Perturb.	The doctor comforted the athlete in the operation room.		
Strategy	CORE(SWAP_CORE) → [AGENT+complete: the athlete→doctor PATIENT+complete: the doctor→athlete]		
Perturb.	In the operation room, the athlete comforted the doctor.		
		(c) Data recombination (with external labels and/or contents)	
Strategy		Strategy	CAUSE:CHANGE_CONTENT(because he was in pain) → [CAUSE+complete: because he was in pain]
Perturb.		Perturb.	In the operation room the doctor comforted the athlete because he was in pain.

Table 3: We design a list of primitive operations on input controls to guide perturbations with the TAILOR generator.

Generator	Closeness			Pred. Controllability			Arg. Controllability		
	F1	Precision	Recall	Lemma	Tense	Voice	Role	Content	Spec.
TAILOR	64.3	66.5	73.4	74.3	80.3	81.6	70.5	64.5	64.5
TAILOR _{MLE}	58.5	59.5	68.6	72.2	70.2	76.1	60.3	45.1	45.1

Table 4: Intrinsic evaluation performance in percentage. TAILOR generates perturbations that are close to the original sentence, while reasonably following all the controls specified in Table 2. Ablating unlikelihood training (TAILOR_{MLE}) hurts all metrics across the board.

We additionally evaluate TAILOR’s unique ability to make fine-grained and compositional perturbations.

Metrics. *Likelihood* measures whether the generated text is grammatically correct and semantically meaningful. Following Ross et al. (2021), we ask whether perturbing a sentence with TAILOR drastically changes its likelihood. Using a pretrained GPT-2, we compute language modeling losses for both the original and edited texts and report the ratio of edited / original. We desire a value of 1.0, which indicates equivalent losses for the two.

Controllability measures if the generator responds to the controls given in inputs. We rely on cycle consistency to evaluate the controls in Table 2: For a given generation, we check whether the predicted semantic roles from an SRL system match the control codes in the input (e.g., whether “in the midst of the earthquake” in Figure 1 gets detected with a TEMPORAL tag). Since SRL predictions can be noisy, we manually inspect a subset of 98 generated spans and verify that cycle consistency measures positively correlate with ground-truth controllability, with Matthews correlation coefficient $\phi = 0.49$ (more details in §B).

Closeness captures whether the generated sentence involves only necessary changes. Since our generator takes controls at the argument level, we measure closeness with a weighted F1 score on the expected-to-change and actually-changed spans in the original sentence. We identify expected-to-

change spans from perturbation operations; in Figure 1A, all spans should be changed except for agent “the doctor.” Then, we deem a span actually edited if $\geq 50\%$ tokens within a span are changed (e.g., “operation room” in LOCATIVE).⁷ We weigh spans by their lengths to arrive at the final F1 score.

Compositionality. We evaluate TAILOR without any finetuning on the STYLEPTB benchmark (Lyu et al., 2021), which builds on the Penn Treebank and assesses both *single*, fine-grained transfers (e.g., *To Future Tense*) and *compositional* ones that concurrently edit multiple dimensions (e.g., *To Future Tense+ Active To Passive*). We report mean BLEU scores and compare to the transfer-specific baselines reported in the STYLEPTB paper (See §F).

Data. We use STYLEPTB (Lyu et al., 2021) to evaluate compositionality. For other metrics, we perturb 1,000 randomly selected sentences from the OntoNotes 5.0 validation dataset, created the same way as negative samples during training (§A.1), and evaluate on these perturbations.⁸

⁷We empirically tune the threshold to be 50%, as it tolerates cases where we do not know exactly how the tokens should change (e.g., when changing keyword sparsity, we do not know exactly how many new tokens should be generated; when changing semantic role controls, we may want to allow some tokens, like particles, to reoccur, while expecting others in the span to change.)

⁸Because these perturbations are generated randomly, some result in sets of controls that are *impossible* to follow. Thus, these results represent a lower bound on TAILOR’s controllability in downstream applications, for which strategies would be designed in a more principled, targeted manner, re-

4.1 Results

TAILOR generates perturbations with a loss ratio of 0.982, indicating no notable change in language modeling loss after perturbation. As shown in Table 4, TAILOR perturbations also tend to be close to the original sentence ($F1 = 64.3\%$), with reasonably correct predicates (74.3%-81.6% of the time) and arguments (70.5% controllability on semantic roles and 64.5% on contents.) TAILOR also demonstrates the ability to make compositional changes; it achieves results comparable to those of fine-tuned baselines on 8/9 tested transfers, and even outperforms the fine-tuned baseline on 5 of them (See §F and Table 11 for more details).

Effect of Unlikelihood Training. We compare TAILOR with a baseline that is finetuned on T5 *without* unlikelihood training (called TAILOR_{MLE} in Table 4). Across all metrics, unlikelihood training outperforms TAILOR_{MLE}, with more controllable and closer perturbations (up to a 20% increase).

Modulating likelihood and closeness. As mentioned in §2.2, our input format supports modulating likelihood and closeness. We can increase closeness by only masking the arguments we want to perturb. To quantify this effect, we randomly select a single argument to perturb for 1K sentences, but vary the number of masked arguments and number of inserted blanks. As desired, closeness is maximized when we mask only the argument we wish to perturb, as in Table 1B (with $F1 = 67.4\%$), whereas masking two extra arguments and inserting six extra blanks decreases closeness by 3% and 6%, respectively. On the other hand, we can prioritize likelihood (at the cost of closeness) by adding more blanks (e.g., insert extra roles whose optimal locations are not known in advance). On another 1K sentences, we observe that adding six extra blanks increases the likelihood ratio from 0.93 to 0.95.

5 Contrast Set Creation

Manually creating contrast sets is expensive, e.g., Gardner et al. (2020) reported spending 10-15 minutes per perturbation for UD Parsing, whereas labeling existing data is more efficient (Wu et al., 2021). We show that TAILOR can reduce human labor by automatically generating contrast set instances such that annotators only have to label them. We create TAILOR-generated contrast sets for four

stricting the perturbations to result in more plausible sets of controls. See §B for more details.

tasks: boolean question answering (BoolQ: Clark et al., 2019), extractive QA (SQuAD: Rajpurkar et al., 2016), dependency tree parsing (UD English: Nivre et al., 2016), and temporal relation extraction (MATRES: Ning et al., 2018).⁹

5.1 Replicating Contrast Sets with TAILOR

We take advantage of two key properties of TAILOR: First, TAILOR can make **context-dependent** changes. To recreate the *BoolQ* contrast set, we replicate *Entity Change* in Gardner et al. (2020) by replacing content keywords in questions with words in the paragraph that have the same semantic roles. For example, the paragraph in Table 5 indicates that “his bride” can serve as an AGENT. Second, TAILOR allows for **compositional** changes. For example, as in Table 5, we change prepositional phrase (PP) attachments from *noun*→*verb* to recreate the *UD Parsing* contrast set through the following composition of perturbation operations: remove the prepositional phrase from the patient keyword (e.g., “a diverse range of food **at all prices and styles**”), and introduce an adjunct argument with the preposition as partial keyword (e.g., LOCATIVE “at”). More details are in §D.1.

Contrast set validity. We consider our perturbation strategies successful if they help reduce human labor, i.e., a contrast set author can easily label or take inspiration from TAILOR’s generations. Two authors sampled 100 original instances per task, inspected the *top-K* TAILOR perturbations, and labeled an instance to be **valid** if there is at least one perturbation that changes the groundtruth answer while being fluent or requiring only minor fixes.¹⁰ Table 5 shows that these TAILOR perturbation strategies generate contrast sets with high validity.¹¹

5.2 Measuring Contrast Set Quality

We sanity check that TAILOR-generated contrast sets can be used to reveal model errors. For example, a T5-BASE model finetuned on BoolQ (with test accuracy 83%) has a performance of 65% on both TAILOR-generated contrast sets and Gardner et al. (2020)’s (more in §D.2). However, this metric is

⁹TAILOR-generated contrast sets are available at <https://github.com/allenai/tailor>.

¹⁰Because we exercised controls at different granularity (i.e., UD requires sourcing contents from the generator while others mostly require syntactic rewrites with predetermined content), we set $k = 10$ for UD—an upper bound for not overloading the human inspector—and $k = 1$ for other tasks.

¹¹TAILOR achieves higher validity changing attachment from *noun*→*verb* (82%) than *verb*→*noun* (48%). Discussion in §D.

Dataset & Task		Top-K validity
BoolQ contrast set (Gardner et al., 2020)		82% (k=1)
Original	Paragraph: ...his bride was revealed...Deadpool also discovers that he has a daughter...from a former flame. Question: does [AGENT: Deadpool] [VERB: have] [PATIENT: a kid in the comics]? (Answer: True)	
Strategy	Change entity (AGENT: CHANGE_CONTENT(his bride))	
Perturb.	Question: does [AGENT: his bride] [VERB: have] [PATIENT: a kid in the comics]? (Answer: False)	
UD parsing contrast set (Gardner et al., 2020)		65% (k=10)
Original	Sentence: [AGENT: It] [VERB: has] [PATIENT: a diverse range of food at all prices and styles]. PP attachment: Noun (“at all prices and styles” attaches to “food”)	
Strategy	Swap attachment from noun to verb (<i>noun</i> → <i>verb</i>) PATIENT: CHANGE_CONTENT(a diverse range of food) LOCATIVE: CHANGE_CONTENT(at), CHANGE_SPEC(partial)	
Perturb.	Sentence: [AGENT: It] [VERB: has] [PATIENT: a diverse range of food] [LOCATIVE: at every turn]. PP attachment: Verb (“at every turn” attaches to “has”)	
MATRES contrast set (Gardner et al., 2020)		71% (k=1)
QA implication (Ribeiro et al., 2019)		81% (k=1)

Table 5: A demonstration of how we recreate contrast sets. Using primitive operations in Table 3, TAILOR supports context-aware and compositional changes. More examples (e.g., changing PP attachment *noun*→*verb*) are in §D.

only a proxy for the quality of evaluation data, since it can be made intentionally low if we generate all examples to target a known model error. Thus, we directly analyze the quality of TAILOR contrast sets by measuring their **lexical diversity** and impact on token-level **dataset artifacts**, both of which play important roles in dataset debiasing.

We measure lexical diversity on UD Parsing contrast sets because it involves sufficient generation of new content. We compare TAILOR- and human-generated (Gardner et al., 2020) contrastive edits for the same 100 UD instances: we randomly sample one edit for each valid instance, heuristically extract modified PPs, and compute diversity as the ratio of unique to total new tokens in the PPs, filtering stopwords. For *noun*→*verb*, the ratios are respectively 0.78 and 0.99 for TAILOR and humans; for *verb*→*noun*, both are 1.0. Thus, TAILOR can help generate contrast sets without significantly reducing lexical diversity. Furthermore, TAILOR outputs are distinguishable from humans’: their unique tokens only overlap for < 15% in *verb*→*noun*, and ~6% for *noun*→*verb*, suggesting that TAILOR can be used as a collaborative tool to diversify generation.

We also ask whether TAILOR perturbations can reduce dataset artifacts. Gardner et al. (2021) devise a statistical test for dataset artifacts that builds on the argument that no simple feature (e.g., single token) should show statistically significant correlation with labels in a language understanding problem. In Figure 2, we display the results: We plot the numbers of occurrences of each token against the conditional probability of the positive label given that token for both the BoolQ validation

data (red dots) and the contrast created by TAILOR (green dots). All tokens above or below the blue line show statistically significant correlation with positive labels and thus are considered dataset artifacts in Gardner et al. (2021)’s framework. While many tokens in the original BoolQ data exhibit significant correlations, most in the TAILOR contrast set fall within the confidence region. Thus, TAILOR can help create less evaluation data with fewer artifacts.

5.3 Discussion

Across the four tasks, we are able to replicate all perturbation strategies described by authors of the original contrast sets. While TAILOR requires manual effort to implement perturbation strategies, we believe the overall saved annotation effort outweighs this initial cost. First, once implemented, TAILOR perturbations can be applied to large datasets without requiring additional annotation effort. This large-scale applicability is especially useful for tasks whose single-instance annotation time is significant (e.g., UD Parsing). Second, given that TAILOR generations are distinguishable from human ones, they may have the potential to compensate for human omissions and thereby increase test case variety, which has been shown to be beneficial in prior work (Ribeiro et al., 2020); an interesting direction for future work would be to investigate this hypothesis in more detail. Third, the implementation overhead itself diminishes as more strategies are implemented. In BoolQ, while Gardner et al. (2020) manually created “a diverse set of perturbations, including adjective, entity, and event changes” (see their Appendix B.9), these are

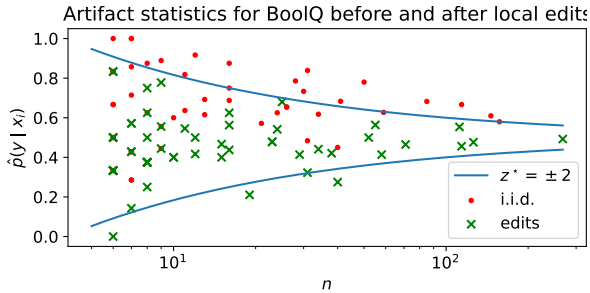


Figure 2: Dataset artifacts in original BoolQ validation set vs. contrast set created with TAILOR using (Gardner et al., 2021)’s statistical test.

all a type of *data recombination* in Table 3, and we can unify their implementations with TAILOR into the aforementioned keyword replacement in §5.1.

6 Data Augmentation

We explore whether TAILOR can be combined with noisy automated labeling for data augmentation. For the Stanford Natural Language Inference (SNLI) task (Bowman et al., 2015), we show that data augmentation with TAILOR perturbations increases model robustness to inference heuristics.

Min et al. (2020) find that augmenting SNLI training data by swapping hypotheses’ subject/objects (e.g., *This collection contains 16 El Grecos.* → *16 El Grecos contain this collection*) improves performance on HANS, a challenge set for diagnosing fallible syntactic heuristics in NLI models (McCoy et al., 2019). Following this, we use TAILOR to perturb hypotheses with the SWAP_CORE operation such that *original hypothesis* → *premise* and *perturbed hypothesis* → *new hypothesis*.

We finetune RoBERTA-BASE (Liu et al., 2019) on different training datasets: original SNLI train data (unaugmented baseline), SNLI train augmented with Min et al. (2020) (augmented baseline, referred to as *Syntactic Perturb.* in Table 6), and SNLI train augmented with TAILOR perturbations. We augment ~2% of SNLI train.¹² For each subset, we train 20 models with different random seeds. We evaluate each classifier on the in-domain SNLI test set and the out-of-domain HANS test set.¹³

As shown in Table 6, augmentation with TAILOR leads to 5.8-point gain on HANS overall, HANS and a 29.2-point gain on “non-entailment,” compared to the unaugmented baseline. The improvements are significant, with $t = -6.42$, $p < 10^{-3}$

¹²We augment the 549,367 SNLI train instances with 10,987 new instances. See §E for more details.

¹³For HANS, we follow the standard practice and collapse *neutral* and *contradiction* predictions to *non-entailment*.

Training Data	HANS Subset			
	SNLI	All	Entail.	Non-entail.
SNLI Train	91.1	64.7	99.0	30.5
+ Syntactic Perturb.	91.0	67.5	95.8	39.2
+ TAILOR Perturb.	91.1	70.5	81.3	59.7

Table 6: TAILOR augmentations lead to statistically significant gains on the HANS challenge set, without decreasing in-domain accuracy.

using Student’s t-test. Thus, TAILOR perturbations decrease reliance on the lexical-overlap-based inference heuristic for NLI.

Furthermore, TAILOR outperforms *Syntactic Perturb.*, an augmented baseline designed specifically for NLI. We hypothesize that although they create augmentations through similar transformations, Min et al. (2020)’s approach is limited to inputs with specific syntactic configurations, whereas TAILOR’s SWAP_CORE argument is applicable to any AGENT and PATIENT arguments. Thus, TAILOR is useful for improving model robustness – more so than template-based approaches.

7 Related Work

Controllable text generation has been widely used to influence various properties of generated text for text summarization (Peng et al., 2019), data augmentation (Lee et al., 2021), style transfer (Reid and Zhong, 2021; Madaan et al., 2020a), adversarial example generation (Iyyer et al., 2018), etc. Most generators take simple controls like tense (Hu et al., 2017), topic (Keskar et al., 2019), or sentiment polarity (Dathathri et al., 2020), which underspecify desired transformations. In contrast, TAILOR concretizes otherwise sparse controls (e.g., we can specify making a sentence more negative *through negation*.) Recent works incorporating syntactic structures for paraphrasing (Iyyer et al., 2018; Chen et al., 2019; Bao et al., 2019; Kumar et al., 2020; Sun et al., 2021; Huang and Chang, 2021) or discrete semantic signatures for diverse generation (Weir et al., 2020) are similar to TAILOR in their high-dimensional specification.

Also closely related are methods that reconstruct sentences from structured semantic representations. The most similar related work is InFillmore (Ou et al., 2021), which uses semantic representations derived from FrameNet with constrained decoding to guide generation. While InFillmore tunes the higher-level semantics of a sentence, TAILOR’s semantic controls incorporate fine-grained information about the location and semantics of tex-

tual phrases; in addition, we demonstrate two new applications for semantically-guided generation, contrast set generation and data augmentation. Abstract Meaning Representation (Banarescu et al., 2013; Mager et al., 2020) is an alternative semantic representation worth exploring for data perturbation, as it may further enable controls on entity recursions (Damonte and Cohen, 2019), though expressing such relationships is nontrivial.

Controlled generators have also been successfully used to perturb text for model training, evaluation, and explanation. They usually rely on application-specific labels (Ross et al., 2021; Madaan et al., 2020b; Sha et al., 2021; Akyürek et al., 2021) or require pairs of original and perturbed sentences (Wu et al., 2021), which are expensive to generalize.

Also related are the creation of minimally edited datasets, either through manual rewriting (Gardner et al., 2020; Kaushik et al., 2020), or creating perturbation templates (Andreas, 2020; Li et al., 2020; Ribeiro et al., 2020; Wu et al., 2019); TAILOR reduces the human efforts these studies require.

8 Discussion

We propose TAILOR, a system that enables task-agnostic, complex and context-aware perturbations. TAILOR demonstrates that it is possible to drive fine-grained perturbations with semantic features directly derived from an instance. Crucially, it shows that incorporating classical linguistic structures with modern large-scale neural architectures is feasible: With the help of modern pretrained large models, PropBank-style shallow semantic representations can help steer generation towards desired meanings.

Factors that affect TAILOR’s capability. Though broadly applicable, TAILOR’s controllability and effectiveness vary for different inputs. First, creating automatic perturbations with TAILOR requires external SRL predictors, which can be noisy on rare semantic roles or low-resource languages.¹⁴ Empirically, this did not seem to be a bottleneck, as exposing biases in downstream tasks does not usually require rarity at the semantic role level (*e.g.*, testing syntactic heuristics in NLI requires swapping only agents and patients). However, perturbing more challenging linguistic phenomena may re-

¹⁴Note that while TAILOR is designed to be language agnostic, we only evaluated it on English.

quire careful SRL predictor augmentation or even manual semantic role annotation.

We also notice TAILOR can sometimes produce degenerate outputs. We hypothesize that this is a byproduct of unlikelihood training — *i.e.*, the generator learns to reduce the likelihood of negative sequences by generating tokens that are very unlikely to appear in natural text. Generation hyperparameters (*e.g.*, number of beams) can reduce the number of degenerate outputs. While we perform unlikelihood training at the sequence level, future work can investigate the effect of penalizing generation at the level of tokens or spans, which may provide finer-grained signals for which spans should be considered unlikely, as well as more strategically balancing positive and negative samples.

Extending TAILOR. We believe the TAILOR generator is well-suited for controlled generation tasks beyond the perturbation-based tasks we explore. Given key entities or arguments as keywords and fully masked contexts, we envision TAILOR can help generate arguments (Schiller et al., 2021), compositionally augment data (Akyürek et al., 2021), or generate captions (Chen et al., 2020). In particular, as shown in §5, TAILOR’s human-readable controls can support humans on data curation, which suggests that designing NLP models for augmenting human capabilities is a promising direction.

The design of controls is also worthy of in-depth exploration. As mentioned in §7, AMR might be an alternative for semantic representation, if our primary goal is to express non-sequential relations. On the other hand, dependency parsing labels are useful for syntactic changes; future work may try to balance syntactic and semantic controls.

Having noted these opportunities, we believe TAILOR is already a powerful tool for perturbation, particularly for tasks where compositional changes are required. TAILOR is open-source, and available at <https://github.com/allenai/tailor>.

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Appendices

A TAILOR Generator Details

A.1 Input and Output Formats

All headers in inputs to the TAILOR generator begin with predicate controls, followed by core argument controls (first AGENT, then PATIENT), and then randomly ordered adjunct argument controls (LOCATIVE, TEMPORAL, etc.). Secondary controls are always given in the order of *control code+voice+tense:lemma* for verbs and *control code+keyword specificity:keyword content* for arguments. We also blank the auxiliary verbs of the predicate in an input, using `spacy` to detect them. We exclude discontinuous arguments (e.g., those with raw SRL labels B-C-*), as well as those with referents (e.g., those with raw SRL labels B-R-*), from input headers. We map ARG0 → AGENT and ARG1 → PATIENT. For other numbered arguments, we create human-readable labels by using argument functions included in the PropBank frame for the given predicate (Palmer et al., 2005).

On the output side, we ask the model to generate the full sentence (Table 1). We add the semantic roles for all the generated arguments, to help the generator build explicit mappings between the input control codes and the output spans – this can be important when the input codes are ambiguous (e.g., a TEMPORAL argument and a LOCATIVE argument that both have keywords “in”). To use generations in downstream applications, we remove these control codes to obtain cleaned outputs using regular expression matching.

A.2 Training details

Training inputs. During training, we randomly select, with equal probabilities, whether to mask all arguments or a subset. If a subset, we uniformly select the proportion of arguments to mask. To determine the number of extra blanks, we uniformly select a value less than 10 and set the number of blanks to be the maximum of that selected value and the number of arguments to mask. Any extra blanks (i.e., remaining after masking arguments) are inserted between subtrees of the predicate.

We also randomly select keyword contents and keyword specificities. For each argument span, we extract, using `spacy`, four keyword types from the span: *noun chunks*, *random subtrees*, *exact* keywords, and *prefixes*. For prefixes, we uniformly

select a number of tokens to include as the keyword (from 1 to the entire span). Once we extract all keyword candidates, we create corresponding keyword specificities: A keyword is *complete* if it contains all tokens in the original span, *partial* if it contains at least all but 5 tokens, and *sparse* otherwise. Then, we uniformly select a keyword content/specificity pair for each span from the set of keyword candidates (including the * symbol).¹⁵

To generate unlikelihood samples, we use three perturbation strategies on inputs: 1) Change *semantic roles* by swapping thematic role control codes (agent/patient), changing adjunct argument control codes to a uniformly selected other adjunct control code, and changing verb tense/voice. We swap verb tense/voice because the control code VERB does not have natural candidate swaps, given that predicates are the building block for semantic parses. We also swap the control codes in the target output. 2) Change keyword *contents* by replacing verb lemmas and keywords for both the predicate and all arguments. To make content swaps, we first gather the most commonly occurring keyword contents for each argument and predicate in Ontonotes 5.0 train, extracted according to the same process as described above for creating training inputs. For each primary control code and keyword specificity (e.g., TEMPORAL+partial), we store the 15 most commonly occurring keyword contents. To create the negative inputs, for each span, we uniformly sample from these stored keywords given the span’s control code and keyword specificity. This perturbation is designed to discourage the generator from ignoring the keyword content and merely generating commonly occurring text for particular semantic roles. 3) Change keyword *specificities* by uniformly selecting a different specificity. We weight each unlikelihood sample equally, with a reward of -1 (vs +1 for positive samples).

Hyperparameters. We train the TAILOR generator using Transformers (Wolf et al., 2020) for 10

¹⁵Because of how keywords are sampled, we notice that the generator is sensitive to the case of keyword contents. For example, if the keyword for a temporal span is *In 1980* instead of *in 1980*, TAILOR is biased towards generating it at the beginning of the sentence. We hypothesize that because some of the keywords we sample during training are cased (e.g., *exact* will lead to a cased keyword for a capitalized span beginning a sentence), the generator learns a bias towards generating spans with uppercase keyword at the beginning of the sentence. In applying the generator to perturbations, the case of keyword contents can be used to manipulate the order of generated roles when a certain order of generated contents is desired; otherwise, uncased keywords can be used.

epochs with early stopping. We use batch size 4 and default values for other parameters (learning rate of $5e-5$, Adam optimizer).

B Intrinsic Evaluation Details

Effectiveness of cycle consistency. To evaluate to what extent cycle consistency reflects true controllability, we conducted additional manual annotation on role-following. We sampled 25 sentences from the Ontonotes 5.0 development set, transformed them into inputs with varying numbers of masked arguments and blank tokens, and created up to two perturbed inputs per sentence by randomly replacing their blanked adjunct arguments with other candidate semantic roles (using `CHANGE_TAG`). The candidate roles were extracted from the frameset for each predicate verb. We also changed the keyword specificity to `SPARSE`, to make these role swaps more plausible.

We collected `TAILOR` and `TAILORMLE` generations from both the original and perturbed inputs, and one author manually validated the generated span for each specified argument (98 in total). Our annotations were *following* or *not following* the control (*i.e.*, the span matches/does not match the designated semantic role), or the set of controls can be *impossible to follow* if the human annotator could not think of any generation that would satisfy the control codes, due to a conflict between the role, keywords, and blank placement. We then computed the Matthews correlation coefficient (MCC) between the controllability of the role label as measured by the SRL predictor with the gold controllability annotations for the subset of roles without annotation *impossible*. The MCCs are 0.49 and 0.51 for `TAILORMLE` and `TAILOR`, respectively, suggesting that the cycle consistency measures positively correlate with true controllability measures.

Additionally, we measure to what extent the controllability measures from cycle consistency correlate with whether a set of controls is *impossible to follow*. The MCCs are -0.33 for both `TAILOR` and `TAILORMLE`; thus, incorrect role-following as measured by cycle consistency is positively correlated with controls that are impossible to follow. 14/98 instances were manually annotated as having impossible-to-follow controls, suggesting that a nontrivial proportion of the generations for which our intrinsic evaluation measures in §4 found to be unaligned with designated role control codes may be explained by impossible-to-follow controls.

C Degenerate Outputs

We observe that `TAILOR` produces degenerate outputs for some inputs, as shown in Table 8. We hypothesize that this is a byproduct of unlikelihood training: The generator may learn to reduce the likelihood of negative sequences by generating tokens that are very unlikely to appear in natural text. Certain generation hyperparameters, such as the number of beams, can reduce the number of degenerate outputs. While we perform unlikelihood training at the sequence level, future work can investigate the effect of penalizing generation at the level of tokens or spans, which may provide finer-grained signals for which spans should be considered unlikely, as well as more strategically balancing positive and negative samples.

Filtering. To exclude degenerations when using `TAILOR` generations in downstream applications, we employ a combination of heuristics and perplexity-based filtering. As shown by the examples in Table 8, degenerate outputs are easy to detect: We can simply search for whether the output includes “sanatate.” We also use cutoffs in perplexity scores computed with GPT-2 to filter degenerations, as degenerations have significantly lower perplexities than non-degenerate outputs: For generations for 300 randomly sampled validation inputs, the `TAILOR` generator produced generations with a mean perplexity of -346.46 for degenerate outputs (12/300) compared to -86.747 for others.

D Contrast Set Details (§5)

D.1 Perturbation Strategies

In Table 7, we illustrate our perturbation strategies for creating contrast sets. Besides BoolQ, already introduced in §5, the *Matres contrast set* Gardner et al. (2020) relies on within-sentence context: As a task that requires detecting and changing the temporal order of two verbs, our perturbations heavily rely on their syntactic relationships. For example, to change the *appearance order* of verbs in text (as described in (Gardner et al., 2020)), we would take the parent verb as the base predicate, and `MOVE` the text span containing the child verb.

For *QA implication* (Ribeiro et al., 2019), we combine `TAILOR` with semantic heuristics: by defining mappings between WH-words and answer types (*e.g.*, “who” and “the Huguenots”), we can easily create new questions about different targets.

Dataset & Task		Top-K validity
MATRES contrast set (Gardner et al., 2020)		71% (k=1)
Original	Sentence: Volleyball is a popular sport in the area, and [AGENT: more than 200 people] would be [VERB: watching] [PATIENT: the game], the chief <u>said</u> . Order: <u>watching</u> happens <i>after</i> <u>said</u>	
Perturbation strategy: Change tense		
Edits	VERB: CHANGE_VFORM(past) → [VERB+active+present→past: watch] Volleyball is...200 people <id_0> the game, the chief said.	
Perturbed	Sentence: Volleyball is a popular sport in the area, and [AGENT: more than 200 people] [VERB: <u>watched</u>] [PATIENT: the game], the chief <u>said</u> . Order: <u>watched</u> happens <i>before</i> <u>said</u>	
Perturbation strategy: Change order		
Edits	PATIENT: MOVE → [VERB+active+past: say AGENT+complete: Volleyball...the game] <id_0>, the chief said <id_0> .	
Perturbed	Sentence: [AGENT: the chief] [VERB: <u>said</u>] [PATIENT: <u>Volleyball is a popular sport in the area, and more than 200 people would be watching the game</u>]. Order: <u>said</u> happens <i>before</i> <u>watch</u>	
BoolQ contrast set (Gardner et al., 2020)		82% (k=1)
Original	Paragraph: ...his bride was revealed in the webcomic...Deadpool also discovers that he has a daughter by the name of Eleanor, from a former flame of Deadpool named Carmelita. Q: does [AGENT: Deadpool] [VERB: have] [PATIENT: a kid in the comics]? (A: True)	
Perturbation strategy: Change entity		
Edits	AGENT: CHANGE_CONTENT(his bride); → [VERB+active+present: have AGENT+complete: <u>Deadpool</u> → <u>his bride</u>] does <id_0> <id_1> a kid in the comics?	
Perturbed	Q: does [AGENT: <u>his bride</u>] [VERB: have] [PATIENT: a kid in the comics]? (A: False)	
UD parsing contrast set (pp attachment) (Gardner et al., 2020)		65% (k=10)
Original	Sentence: Do [AGENT: you] [VERB: prefer] [PATIENT: ham, bacon or sausages] [ADVERBIAL: with your breakfast]? PP attachment: Verb (“with your breakfast” attaches to “prefer”)	
Perturbation strategy: Swap attachment to Noun		
Edits	PATIENT: CHANGE_CONTENT(ham, bacon or sausages with), CHANGE_SPEC(partial) ADVERBIAL: DELETE → [VERB+active+present: prefer PATIENT+complete→partial: ham, bacon or sausages <u>with</u> ADVERBIAL+complete: with your breakfast] <id_0> you <id_1> <id_2> <id_3>?	
Perturbed	Sentence: Do [AGENT: you] [VERB: prefer] [PATIENT: ham, bacon or sausages <u>with bacon on them</u>]? PP attachment: Noun (“with bacon them” attaches to “sausages”)	
Original	Sentence: [AGENT: It] [VERB: has] [PATIENT: local boutiques and a diverse range of food at all prices and styles]. PP attachment: Noun (“at all prices and styles” attaches to “food”)	
Perturbation strategy: Swap attachment to Verb		
Edits	PATIENT: CHANGE_CONTENT(local boutiques and a diverse range of food) LOCATIVE: CHANGE_CONTENT(at), CHANGE_SPEC(partial) → [VERB+active+present: have PATIENT+complete: local boutiques and a diverse range of food <u>at all prices and styles</u> <u>LOCATIVE+partial: at</u>] <id_0> you <id_1> <id_2> <id_3>?	
Perturbed	Sentence: [AGENT: It] [VERB: has] [PATIENT: local boutiques and a diverse range of food] [LOCATIVE: <u>at every turn</u>]. PP attachment: Verb (“at every turn” attaches to “has”)	
QA implication (Ribeiro et al., 2019)		81% (k=1)
Original	Q: [MANNER: How] did [AGENT: the Huguenots] [VERB: defend] [PATIENT: themselves]? A: their own militia	
Perturbation strategy: Swap answer to be agent		
Edits	AGENT: CONTENT(who); MANNER: CONTENT(their own militia), SPEC(partial) → [VERB+active+past: defend AGENT+complete: <u>the Huguenots</u> → <u>who</u> PATIENT+complete: themselves MANNER+complete→partial: <u>how</u> → <u>their own militia</u>] <id_0> <id_1> <id_2> <id_3>?	
Perturbed	Q: [AGENT: <u>Who</u>] <u>has</u> [VERB: defended] [PATIENT: themselves] [MANNER: <u>by setting up their own militia</u>]? A: the Huguenots	

Table 7: A demonstration of how we recreate contrast sets for different tasks (§5). Using primitive operations in Table 3, TAILOR supports context-aware and compositional changes.

Input	Degenerate Output
[VERB+passive+past: lower AGENT: * PATIENT+partial: corporate bonds TEMPORAL+complete: this year] One indication of a growing number of junk defaults , Mr. Asquith says , is that about half of the \$ 3 billion of <id_0> that <id_1> <id_2> <id_3> to a default rating <id_4> <id_5> are junk bonds sold during the market 's big issue years of 1984 through 1986 ..	pastra pastra sanatate sanatate pastraurmatoarele sanataurmatoarele pastradatorita sanatedatorita pastracresterea sanatate urmeaza sanateinformatiile sanatacresterea pastra urmeaza urmeaza pastrainformatiileinformatiiledatoritadatoritaurmatoarele.
[VERB+active+present: visit AGENT: * PATIENT+partial: Galilee TEMPORAL: *] <id_0> went to <id_1> <id_2> <id_3> .	AG pastra pastra sanatate sanatate pastraurmatoarele sanataurmatoareleurmatoarele pastrainformatiile sanateinformatiileinformatiile pastradatorita sanatedatoritadatoritaurmatoareleatoritainformatiile dumneavoastra sanatate urmeaza sanatacresterea

Table 8: Example inputs from the validation set for which the TAILOR generator outputs degenerate text.

For *UD English* (Nivre et al., 2016), we use constrained decoding (Hokamp and Liu, 2017) to prevent generation of the original prepositional phrase. Our strategy for changing prepositional phrase (PP) attachments from *verb*→*noun* is similar to that of *noun*→*verb*, introduced in §5. We use the following composition of perturbation operations: append the preposition to the patient keyword (e.g., “ham or sausages **with**”), change patient keyword specificity from **complete**-**partial** (to generate a new PP attaching to the patient), and delete the argument with original verb attachment (e.g., **ADVERBIAL** “with your breakfast”).

We note that TAILOR achieves higher validity changing attachment from *noun*→*verb* (82%) than *verb*→*noun* (48%). This result is expected, as all semantic role labeling arguments attach to verb predicates; thus, introducing controls for an SRL argument (e.g., **LOCATIVE** with keyword content “at”) to generate a prepositional phrase with verb attachment (“at every turn”) reflects the training objective of the generator. On the other hand, our *verb*→*noun* strategy involves appending the preposition to the keyword control for an argument, and none of our controls explicitly reflect the target attachment of a prepositional phrase within an argument (e.g., keyword controls do not specify whether “with” should attach to “sausages” vs “ham”). Furthermore, preposition keywords within an SRL argument do not deterministically lead to noun attachments in our training data—Sometimes a preposition within an argument may reflect verb attachment (e.g., in the case of “Do [AGENT: you] [VERB: prefer] [PATIENT: eating with a fork or eating with a knife]?”; here, “eating with a fork or eating with a knife” is the patient of “prefer” but prepositional phrase “with a fork” attaches to verb “eating.”) Because the training objective of our generator does not provide deterministic signal for

Dataset	Task Eval Original	Contrast Set	
		Human ↓	Tailor ↓
BoolQ	82.8	64.8 (-17.5)	64.7 (-17.6)
SQuAD	91.8	66.1 (-25.7)	55.3 (-36.5)
MATRES	70.3	49.4 (-20.9)	42.3 (-28.0)

Table 9: Accuracies of predictors on original task evaluation data and contrasts sets. The performance drops on contrast sets (vs. original test accuracies), shown in parentheses, are similar for TAILOR-generated contrast sets and expert-created sets (Gardner et al., 2020; Ribeiro et al., 2019).

noun attachment outputs, we do not expect our *verb*→*noun* strategy to always result in generations with noun attachment. Our *verb*→*noun* strategy is instead intended to *facilitate* the collection of text with noun attachment. Future work can investigate incorporating auxiliary signals about target configurations of keyword contents in outputs (e.g., that a preposition should depend on a particular word in the span).

D.2 Predictor Performance Evaluation

The performances of downstream predictors on original task evaluation data and contrast sets, both TAILOR-generated and human-expert-generated, are shown in Table 9.¹⁶ For SQuAD, we evaluate a fine-tuned RoBERTa, the most downloaded model hosted on Huggingface,¹⁷ and use the QA implication challenge set (Rajpurkar et al., 2016) as the human contrast set. Since we could not find readily available predictors for BoolQ and MATRES, we formulate these tasks as a text-to-text task and fine-tune T5-BASE for 10 epochs; we evaluate the

¹⁶We report accuracy on the test set for MATRES and held-out validation sets for BoolQ and SQuAD, which do not have publicly available test sets.

¹⁷<https://huggingface.co/deepset/roberta-base-squad2>

Premise	TAILOR-Generated Hypothesis
A lady in shorts is riding a bike.	A bike is riding a lady in shorts.
A band plays drums in the parade.	Drums are playing a band in the parade.
A young woman eating doritos on mars.	Doritos is eating a young woman on mars
A crowd of people is outside watching a surfer.	A surfer is outside watching a crowd of people.
A lady is holding a viola in the woods.	A viola is holding a lady in the woods.
A girl in striped swimsuit is jumps into the ocean to catch fish	Fish is jumps into the ocean to catch a girl in striped swimsuit
A person is training a choir for the upcoming competition.	For the upcoming competition is training a choir has been person
The photographer gathers the bridal party before the ceremony.	The bridal party is gathering the photographer before the ceremony

Table 10: Examples of augmented data in NLI augmentation experiments (§6). We use original SNLI hypotheses as premises in the augmented data and use `SWAP_CORE` with TAILOR to generate new hypotheses.

checkpoint with the lowest validation loss.¹⁸

The drops in predictors’ accuracies on the TAILOR-generated contrast sets (compared to original test accuracies) show that they can be used to reveal model errors not reflected in original validation data. However, this result should be interpreted with caution, as it is not directly reflective of dataset quality. For instance, if the contrast data tests one error type or is adversarially constructed to include instances where predictors fail, then lower accuracy does not necessarily mean exposing more model errors. Thus, we treat these performance metrics as secondary to other direct metrics of dataset quality, discussed in §5, and run this analysis on a small number of contrast set instances as a sanity check. That said, the fact that predictors perform poorly on TAILOR-generated contrast sets even without including an adversarial component in our contrast set creation suggests that TAILOR can be useful for creating evaluation data to find model errors.

E Data Augmentation Details (§6)

Augmented data. To create our augmented data, we filter generations by perplexity scores from GPT-2 such that we retain 75% of generations. Examples of augmented inputs are shown in Table 10.

Classifiers. We train all SNLI classifiers, which build on RoBERTA-BASE (Liu et al., 2019), using AllenNLP (Gardner et al., 2018). We train for 10 epochs using the Adam optimizer with a learning rate of 2e-05 and batch size 32; we use early stopping with a patience of 3.

¹⁸For MATRES, we format inputs by surrounding verbs with marker “<el>” and “</el>” and train the predictor to output the label in natural language, e.g., “Mr. Erdogan has long <el> sought </el> an apology... After that raid An Israeli raid on this ship <el> left </el> nine passengers dead...” → “before”.

F TAILOR’s fine-grained and compositional perturbations on STYLEPTB

Here, we show how TAILOR can be applied to fine-grained style transfer. We evaluate TAILOR without any finetuning¹⁹ on the STYLEPTB benchmark (Lyu et al., 2021), which builds on the Penn Treebank and assesses fine-grained stylistic changes, both on *single* transfers (e.g., *To Future Tense*) and compositional ones that concurrently edit multiple stylistic dimensions (e.g., *To Future Tense+ Active To Passive*).

Transfers Evaluated. We evaluate on the transfers in STYLEPTB for which Lyu et al. (2021) report results, as their baselines require training separate models for each transfer. Within this subset of transfers, we exclude *PP Back to Front* and *Passive to Active* from evaluation, as they contain < 5 test inputs. We also exclude the transfers *Substatement Removal*, *Information Addition*, *Adjective Emphasis*, and *Verb/Action Emphasis*, for which our semantic-role-derived inputs are not well-suited. For example, *Substatement Removal* involves removing substatements that represent “referring” and “situations,” both of which are technical philosophical concepts that cannot be straightforwardly detected through semantic roles. As another example, *Information Addition* requires adding unordered keyword contents to a sentence (eg *the work force provides the third arm of the alliance*; add keywords: *force black* → *the work force pro-*

¹⁹This evaluation is zero-shot in spirit, as TAILOR is not trained on any paired transfers present in STYLEPTB. However, it is unclear if the test inputs in STYLEPTB overlap with the Ontonotes 5.0 training data, since the two do share some data points (van Son et al., 2018), and STYLEPTB does not seem to preserve original PTB splits. This leakage may advantage the external SRL predictor in parsing STYLEPTB test inputs. Still, this advantage should be minor, as the evaluated transfers do not require complex semantic role parsing.

(a) Single transfers	Single Finetune		Compos. Finetune		No Finetune	
	GPT-2	RETRIEVEEDIT	CS-GPT-TV	CS-GPT-TP	TAILOR	TAILOR, Filtered
To Future Tense	89.5	89.9	72.7	81.0	87.3	88.9, 357/364
To Past Tense	83.6	93.5	69.4	83.4	88.4	89.3, 216/218
To Present Tense	75.4	90.9	73.3	82.6	71.0	84.7, 175/209
ADJ or ADV Removal	64.7	89.7	—	—	78.1	84.3, 224/243
PP Front to Back	39.8	54.1	—	—	84.2	96.9, 20/23
PP Removal	76.3	79.8	—	76.0	71.7	85.7, 199/238
Active to Passive	47.6	68.1	47.2	—	55.6	77.8, 98/137

(b) Compositional transfers		Compos. Finetune	Multi-Single Finetune	No Finetune	
		CS-GPT*	CS-SYS-GEN*	TAILOR	TAILOR, Filtered
Tense + Voice	ToPast+ActiveToPassive	40.9	33.7	66.0	66.0, 30/30
	ToFuture+ActiveToPassive	49.6	41.9	46.8	67.0, 90/131
	ToFuture+PassiveToActive	52.8	39.9	68.3	68.3, 131/131
	ToPast+PassiveToActive	47.4	36.5	70.2	70.2, 65/65
	ToPresent+PassiveToActive	52.3	42.4	69.9	69.9, 95/95
	ToPresent+ActiveToPassive	50.3	44.5	31.5	61.4, 43/84
Tense + PPRemoval	ToFuture+PPRemoval	73.8	46.5	74.3	79.2, 215/229
	ToPast+PPRemoval	77.2	54.2	73.8	79.7, 100/108
	ToPresent+PPRemoval	70.9	54.5	69.1	70.4, 153/156

Table 11: BLEU scores for single and compositional style transfers in STYLEPTB. Baseline results are taken from Tables 14-16 and 19-20 in Lyu et al. (2021). * represents the same type of models finetuned on different subsets of styles, e.g., CS-GPT* in (b) includes CS-GPT-TV, trained on all *Tense+Voice* compositional transfers, and CS-GPT-TP, on *Tenses+PP Removal*. A single TAILOR model helps achieve comparable performance on single transfers compared to finetuned baselines, and is more capable on multiple compositional transfers.

vides the third arm of the **black alliance force**. While the TAILOR generator was only trained with ordered arguments, one could extend the keyword contents to also include unordered target tokens.

Perturbation strategies. For transfers modifying only verb tense (e.g., *To Future Tense*), we mask the verb, modal arguments, and negation arguments, as these are relevant to verb conjugations, and make relevant perturbations on the secondary verb control specifying tense. For transfers modifying verb voice, we mask the verb, agent, and patient. For transfers requiring removal of certain parts of speech (POS)—i.e., *ADJ or ADV Removal*, *PP Removal*, and all compositional *Tense + PP Removal* sub-transfers—we first use spacy to detect such POS, next mask all arguments containing them, and finally perturb the keyword contents to remove the POS for these arguments. For *PP Front to Back*, we mask the argument at the beginning of the original text and implement the change using CHANGE_IDX.

We use cased keywords (A.2) to encourage generations with similarly ordered arguments as the original sentence, except for the *PP Front to Back* transfer, which calls for differently ordered arguments. For transfers modifying verb form only, we set the number of extra blanks to be 2 to allow for generation of helper verbs; for other transfers, we

allow for 0 extra blanks to preserve the original order of generated spans. We decode perturbed sentences greedily using beam search (with beam width 10) and preventing repeated bigrams.

For each transfer, we create perturbations for each predicate in the original input, and report mean BLEU scores.²⁰ Because this process results in multiple perturbations (one per verb), we choose the one with the lowest perplexity from GPT-2 to represent the transfer. Unsuccessful transfers, either due to a failure of perturbation strategy (e.g., no verbs are found by our SRL predictor) or due to a degenerate output (see §C), are given a BLEU score of 0.0.

Baselines. We work with baselines reported by Lyu et al. (2021): GPT-2 and RETRIEVEEDIT are the best-performing single-transfer models evaluated but require separate models to be trained for each transfer. CS-GPT* are models trained on compositional subsets of data (e.g., *Tense+Voice*, detailed in Table 11 caption). CS-SYS-GEN are ablations of CS-GPT* trained only on corresponding individual changes but evaluated on compositional transfers.²¹

Result. On compositional transfers, we find that TAILOR outperforms the baseline system trained

²⁰We report Bleu_1 from nlg-eval (Sharma et al., 2017).

²¹CS-SYS-GEN refers to CS-GPT-ZERO in Lyu et al. (2021).

without compositional fine-tuning, CS-SYS-GEN, on 8/9 compositions, and even outperforms CS-GPT* (models with compositional finetuning) on 5 cases. It also achieves compatible or better results than GPT-2 and RETRIEVEDIT on single transfers. Low TAILOR performance on some transfers (*e.g.*, *ToFuture+ActiveToPassive*) appears to be driven by unsuccessful transfers, rather than generations that do not follow controls, as indicated by the higher performances on the subset where unsuccessful transfers are removed (*Filtered Test*). Importantly, TAILOR achieves these gains with a *single model* and *without any transfer-specific finetuning*.