Controllable Text Generation with Language Constraints

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Abstract

We consider the task of text generation in language models with constraints specified in natural language. To this end, we first create a challenging benchmark COGNAC^1 that provides as input to the model a *topic* with example text, along with a constraint on text to be avoided. Unlike prior work, our benchmark contains knowledge-intensive constraints sourced from databases like Wordnet and Wikidata, which allows for straightforward evaluation while striking a balance between broad attribute-level and narrow lexicallevel controls. We find that even state-of-theart language models like GPT-3 fail often on this task, and propose a solution to leverage a language model's own internal knowledge to guide generation. Our method, called COG-NACGEN, first queries the language model to generate guidance terms for a specified topic or constraint, and uses the guidance to modify the model's token generation probabilities. We propose three forms of guidance (binary verifier, top-k token, textual example), and employ prefix-tuning approaches to distill the guidance to tackle diverse natural language constraints. Through extensive empirical evaluations, we demonstrate that COGNACGEN can successfully generalize to unseen instructions and outperform competitive baselines in generating constraint conforming text.²

1 Introduction

As language models (LMs) become increasingly good at generating text indistinguishable from human writing, a key question emerges: 'How can we best control them to produce what is required while preventing unwanted generations?' This is especially critical for reducing issues of toxicity and bias (Gehman et al., 2020; Xu et al., 2021; Input Instructions (w/ Demonstrations):

Write down examples of people who are citizens of UK. - David Lloyd George was Prime Minister of the United Kingdom from 1916 to 1922.

- Herbert Henry Asquith was a British statesman and Liberal politician who served as Prime Minister.

- Peter Edward Cook was an English satirist and comedic actor.

Continue listing them but avoid mentioning any politician.

<u>GPT-3 Output:</u>

William Lamb, 2nd Viscount Melbourne, served as Home Secretary and Prime Minister.

CognacGen Output (Ours):

George Orwell was an English novelist, essayist, journalist, and essayist laureate.

Figure 1: Constraining instructions and model generations. Green highlight specifies the topic to be covered. Red highlight specifies the constraint to conform to. GPT-3 generates continuation that mentioned a politician, thus violating the constraint. COGNACGEN generates continuation that satisfies both the topic requirement and the constraint.

Perez et al., 2022) and misinformation (Taylor et al., 2022) in applications that build on these models. Prior work has used special control codes (Keskar et al., 2019) to steer the model towards generating text on certain topics, explored the use of classifiers at inference time to modify the LM's probability distribution (Dathathri et al., 2020; Krause et al., 2021; Liu et al., 2021a), or prompting the LM itself to diagnosis and remove bias (Schick et al., 2021). While the former requires additional training with control codes, the other two approaches have only been shown to work with a small set of attributes as constraints.

In this work, we consider the problem of controlling generation in LMs with constraints specified in natural language (Figure 1). Our framework allows for the use of both guidance *topics* that instructs the model on *what to generate*, as well as *constraints* that specifies *what not to generate*, all described in

¹COGNAC stands for **Co**ntrollable generation with language constraints.

²Code and data are available at https://github.com/ princeton-nlp/Cognac.

Dataset	Instruction w/ Demonstrations	Topic / Constraint
WordNet	 Talk about motor vehicle: A cruiser is a type of warship. In motorsport, a safety car, or a pace car, is an automobile which [] A gas guzzler, in informal language, is a vehicle that is [] Do not talk about car: 	Topic : motor vehicle Constraint : car
Wikidata	 Arthur Neville Chamberlain [] was a British politician [] Maurice Harold Macmillan, [] was a British Conservative statesman [] Peter Edward Cook [] was an English satirist and comedic actor [] The above are sentences describing people who are citizens of United Kingdom. Now write similar sentences as the above while omitting any mention of politician. 	Topic : citizenship = UK Constraint : occupation = politician

Table 1: Examples of the instruction task for WordNet and Wikidata. The instruction is specified by a topic (green), a constraint (red), and a set of demonstration examples that are examples under the topic. The topic and constraint are specified by the corresponding entities (see details in §2.2). Note that the position of the topic and the constraint with regard to the demonstrations may vary.

plain English.³ The use of natural language allows for better scalability (since new concepts can be expressed in English), ease of specification by end users of the model, and coverage of knowledgeintensive concepts, while not requiring any special retraining of the LM itself. We create a new benchmark called COGNAC for this task containing two datasets based on WordNet (Miller, 1995) and Wikidata (Vrandečić and Krötzsch, 2014). These datasets contain knowledge-focused constraints that strike a balance between broad attribute-level and narrow lexical-level controls, while allowing for easy evaluation of constraint conformation. We find that even state-of-the-art LMs fail to follow simple language constraints. Figure 1 shows an example of how GPT-3 (Brown et al., 2020) ignores the directive of not mentioning politicians (in red).

To mitigate this failure, we develop COGNAC-GEN, a language model generation method that can follow linguistic guidance and does not require any retraining of off-the-shelf LMs. COGNACGEN uses prefix-tuning (Li and Liang, 2021) over a copy of the same LM to distill from a guidance model that can generate both topic- and constraint-related words given natural language specifications, which can then be used at inference time to modify the output probabilities of the LM for controlled generation. We develop three types of guidance modelsbinary verifier, top-k token generator, and textual example generator-that provide various levels of guidance to the LM. To handle the multi-token nature of the guidance examples, we also utilize a trie-based generation mechanism to track the guidance progress and ensure faithful guidance.

Our results show that COGNACGEN outperforms prior methods and other strong baselines by a significant margin in our instruction conformance score metric, while keeping the generations fluent. When the topic and constraint are explicitly given (e.g., *UK* and *politican*; see Table 1), COGNAC-GEN outperforms previous methods for controlled generation by up to 12 points. Furthermore, COG-NACGEN leads 10 points ahead of the prominent GPT-3 (davinci) model on both datasets when evaluating with natural language instructions. Our analysis shows that COGNACGEN is able to improve generation even with imperfect guidance and can successfully generalize to unseen instructions.

2 The COGNAC Benchmark

2.1 Task Setup

We study the problem of conditional text generation with topics and constraints provided in natural language. As input, each context includes 1) a *topic* to generate text on (e.g., "List examples of people who are citizens of United Kingdom"), 2) a number of example generations under that topic (demonstrations) and 3) a *constraint* that specifies what the model should not generate (e.g. "Keep listing examples below, but do not mention any politician.")—all specified in natural language. The goal is to train LMs to generate fluent on-topic content while respecting the specified constraint.

LMs typically learn a probability distribution $p_{\theta}(x)$ on sequences of tokens. An autoregressive LM can generate text by predicting the probability of the next token conditioned on the previous

³Although we focus on English, our techniques should generalize to other languages too.

tokens: $p_{\theta}(x_j \mid x_{< j})$. In our task, we consider the previous tokens in the context to include a task specification t, demonstrations $E = \{e_k\}_{k=1}^K$, and a constraint c. We assume that the task description t is based on a topic entity \bar{t} . For example, "Talk about sports" is based on the topic entity "sports". Similarly, the constraint text c is generated based on a constraint entity \bar{c} . The topic and constraint entities are added to the demonstrations using a template (§2.2) into a full instruction $\mathcal{I} = \mathcal{G}(t, c, E)$. ⁴ This allows us to check the validity of each generation using a constraint checker $\mathcal{C}(x, \bar{c}) \in \{0, 1\}$ and a topic checker $\mathcal{T}(x, \bar{t}) \in \{0, 1\}$. Specifically, a sequence x generated by the LM is deemed valid when $x \sim p_{\theta}(x \mid \mathcal{I})$ such that $\mathcal{C}(x, c) = 1$ (constraint conformed) and $\mathcal{T}(x,t) = 1$ (on topic). We show in Table 1 examples of instructions and their corresponding topic and constraint entities.

Our task is challenging for three key reasons: 1) the model has to understand the topic and constraint specified in natural language, and 2) the topics and constraints are knowledge-intensive—broader than lexical-level constraint (e.g., 'Include words "car" and "drive" in a sentence.') yet more specific than broad attributes such as toxicity or sentiment, and 3) it has to respect both the topic (which specifies what to generate) and the constraint (which specifies what not to generate) simultaneously.

2.2 Dataset Collection

To our knowledge, there do not exist datasets for our task that contain topic and constraint specifications in natural language. Therefore, we create two new datasets based on WordNet and Wikidata for our COGNAC benchmark.

WordNet. We use WordNet (Miller, 1995) and its hypernymy relation to construct a hierarchical constraint dataset. We select five root nodes "animal", "vehicle", "art", "food", and "sport" from which the hierarchical structure is constructed. The leaf nodes are instances of their ancestors and are used as the topic and the constraint checker. Concretely, when evaluating the generated text x against a constraint entity \bar{c} using the Word-Net constraint checker: $C^{\text{wordnet}}(x, \bar{c}) = \mathbb{1}[\exists s \in$ leaf-nodes $(\bar{c}) : \mathcal{M}(s, x) = 1]$, where $\mathcal{M}(\cdot)$ denotes whether s is a substring of x.⁵ We sample two nodes as the topic and the constraint entities within the same subtree (higher-level : "vehicle", lower-level : "car") from the Word-Net hierarchy, where the higher-level node is the topic and the lower-level node is the constraint. We collect a total of 221 unique topics, 1, 440 unique constraints, and they form 3,073 unique topicconstraint pairs. We sample three leaf nodes under the topic node and use them as demonstrations (|E| = 3), where the demonstration is the first sentence from its Wikipedia page. We collect a dataset of train/develop/test split of 3,000/500/500.

Wikidata. We also use Wikidata (Vrandečić and Krötzsch, 2014) to construct a second dataset. Each property and value pair (e.g., property : "citizenship", value : "United Kingdom"; shown in Table 1) contains a set of names (e.g., Winston Churchill). We use 5 properties: occupation, citizenship, education, birthplace, and deathplace from Wikidata. In each instance, the topic entity is a sampled property-value pair and the demonstraitons |E| = 3 are from the propertyvalue name set. The constraint entity is selected by choosing what the GPT2-XL (Radford et al., 2019) most likely to generate. When evaluating a generation x with constarint entity \bar{c} , the Wikidata constraint checker $\mathcal{C}^{\text{wikidata}}(x, \bar{c}) = \mathbb{1}[\exists s \in$ name-set (\bar{c}) : $\mathcal{M}(s, x) = 1$]. We scrape from Wikipedia the corresponding first sentence of each entity. We collect a total of 150 unique topics, 261 unique constraints, and they form 540 unique topic-constraint pairs. We collect a dataset of train/develop/test split of 1500/500/198 examples.

We provide detailed data generation procedure for WordNet and Wikidata in A.1. Using the Word-Net and Wikidata databases for the checker functions enjoys the benefit of straightforward and automatic evaluation. However, we recognize the knowledge bases come with their fundamental limits to capture all relevant entities.

Diverse natural language instructions. Our goal is to assess the model's ability to understand instructions that are diversely verbalized. For example, templates include instructions where the order of the topic and constraint vary and the lexical context differs. We collect 35 unique templates. to reflect the diverse nature of the instructions and generate a total of 107, 555 and 18, 900 unique instructions for WordNet and Wikidata, respectively. We split them across train/develop/test as 3/3/29

⁴In our task, the demonstrations E always share the same topic \bar{t} , yet they may violate the constraint \bar{c} .

⁵We implement the checks using exact match including multi-token entities.

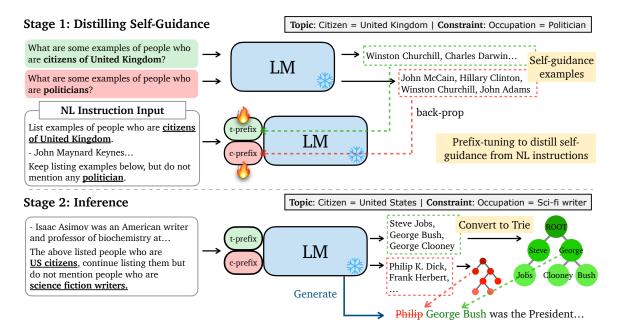


Figure 2: The two stages of COGNACGEN with textual example as guidance. Stage 1: the LM generates a list of guidance examples from the queries that specify the topic and constraint. During self-guidance distillation, the topic and constraint prefixes are tuned using the guidance example as target and the instruction with demonstrations as input. Stage 2: The guidance model (blue LM & the tuned prefixes) generates guidance examples from the test instance. The guidance examples are used to construct trie trees for both the topic (green) and the constraint (red). The generation (blue) LM's next token probability is modified by the tries.

templates. The templates are collected by PhD students writing the first nine seed templates, which are then expanded by paraphrasing using GPT-3 (Brown et al., 2020). The paraphrased templates were edited through human inspection to ensure quality. We provide examples in §A.2.

2.3 Evaluation Metrics

To evaluate different generation methods of LMs, we use metrics that test for correctness and fluency of the generations. Correctness is measured by the model's ability to generate text that conforms to the constraint while staying on topic. Fluency is measured by the model's ability to generate text that is coherent and not overly repetitive or simply copying from the input.

Instruction Conformance (IC). The main metric we use is whether the generation x conforms to the constraint c while staying on topic t:

$$\mathrm{IC} = \sum_{(\bar{t}, \bar{c}, E) \in \mathcal{D}} \frac{\mathbb{1}[\mathcal{T}(x, \bar{t}) = 1 \cap \mathcal{C}(x, \bar{c}) = 1]}{|\mathcal{D}|},$$

where \mathcal{D} is the evaluation dataset. A higher IC score indicates that the model can generate text that conforms to the constraint while staying on topic. We also report the on-topic score $\sum_{x \in \mathcal{D}} \frac{\mathbb{1}[\mathcal{T}(x,t)=1]}{|\mathcal{D}|}$ (higher is better) and the constraint violation score $\sum_{x \in D} \frac{\mathbb{1}[\mathcal{C}(x,\bar{c})=1]}{|\mathcal{D}|}$ (lower is better).

Copy-BLEU. We report the extent to which the generation undesirably copies from the demonstrations. The Copy-BLEU score is calculated by taking the maximum BLEU score between the generated text and the |E| demonstrations. The lower the Copy-BLEU, the less the generation copies from the demonstrations, hence more desirable.

Repetition (Rep-n). We report the ratio of the n-gram repetition (lower is better) in the generated text (**Rep-n**) proposed in Welleck et al. (2020).

Perplexity (PPL). The perplexity of the generated text is calculated with respect to a pre-trained GPT2-XL model (Radford et al., 2019) on the generated sentence (lower is better).

3 Method

3.1 Overview

We posit that the due to the knowledge-intensive nature of COGNAC, the model will benefit from an explicit use of its own knowledge by querying itself. To this end, we explicitly factorize the conditional probability as opposed to leaving the onus of inference to the LM. The desired distribution:

$$p(x \mid E, t, c) \propto p(x \mid E)p(t, c \mid x, E)$$
$$= p(x \mid E)p(t \mid x)p(c \mid x)$$

can be modeled by three components: 1) p(x | E), which is the probability conditioned only on the demonstrations E and 2) p(t | x) that evaluates if the task is performed, and 3) p(c | x) that evaluates if the constraint is conformed. The former is the *generation model*, which be modeled with the original pre-trained LM reasonably well, as recent work demonstrates LMs' ability to perform in-context learning with task specification and incontext demonstrations. We use the latter as a *guidance model* to steer generation explicitly.

3.2 Guided Generation

COGNACGEN updates the next token prediction probability from the generation model by modifying the logits using the guidance (the "Generate" step in Figure 2). Specifically, the next token probability is modified as

$$p(x_j \mid x_{< j}, \mathcal{I}) = \operatorname{softmax}(o_j + \alpha o_j^t - \beta o_j^c),$$

where s_j is the logits corresponding to the original probability $p(x_j | x_{< j}, E)$, $o_j^t, o_j^c \in \{0, 1\}^{|V|}$ are the guidance logits provided by the guidance model at each generation step j, and α and β are the hyperparameters that control the strength of the guidance. We use greedy decoding to generate from the above probability for COGNACGEN in our experiments. We describe how guidance logits are obtained in the following sections.

3.3 Guidance Model

Given a topic t or a constraint c, we construct a guidance model that modify the guidance probabilities $p(t \mid x)$ or $p(c \mid x)$. The guidance model has the same architecture as the generation language model. We use the guidance model to produce a *guidance logits* that modifies the next token logits of the language model at subword token indicies described in §3.2.

We explore three variations of guidance model: 1) binary verifier, 2) top-k token, and 3) textual example. All guidance models compute the guidance probability $p_{guide}(\cdot | q)$, where q is a query based on a predefined template. The query template takes the constraint entity \bar{c} as input. We use $\bar{c} =$ 'wine' as an example throughout.

	Query q	Guidance Logit Tokens
Binary Verifier	Is [pinot noir] a type of [wine]?	$\label{eq:product} \begin{array}{l} \mbox{If $P(`yes' \mid q) > P(`no' \mid q)$,} \\ \mbox{then {pinot, noir}} \end{array}$
Top-K Token	What are some examples of [wine]?	$top-k(p_{guide}(\cdot q)) $ = {merlot, malbec}
Texual Example	What are some examples of [wine]?	Initialize Trie with: {merlot, cabernet, pinot noir, pinot gris} Trie(root) = {merlot, cabernet, pinot} Trie(pinot) = {noir, gris}

Table 2: Guidance types, the corresponding query, and the final tokens used to construct the guidance logits.

Binary verifier. The binary verifier evaluates the probability $p_{guide}("yes" | q)$, where q ="Is x_j a type of \bar{c} ?", where x_j is the token to generate at timestep j. Since sometimes x_j does not carry clear meaning as a single token, we first perform a greedy decoded look-ahead (Lu et al., 2021) using the generation LM to construct a multitoken $x_{j:j+M}$ and obtain guidance from the verifier model ⁶. Therefore, instead of using "noir" as the query word, we set w = "pinot noir" to construct the query and send to the verifier model. When $p_{guide}("yes" | q) > p_{guide}("no" | q)$, the generated entity w is tokenized to construct a verifier guidance logits o_j^c , where its *i*-th index is $\mathbb{1}[i \in \{x_j, x_{j+1}, \dots, x_{j+M}\}].$

The binary classifier guidance model can be viewed as an approximation of the constraint checker $C(\cdot, \cdot)$ but rely only on the existing knowledge in the LM.

Top-k token. The top-k token guidance uses the next token probability distribution from the guidance model $p_{guide}(\cdot | q)$, where q ="What are some examples of wine?". Concretely, we use the top-k tokens of this probability as guidance and construct the top-k guidance logits as o_j^c , where its *i*-th index is $\mathbb{1}[i \in top-k(p_{guide}(\cdot | q))]$. This variant falls short on providing guidance for multi-token entities due to its single-step nature (more discussion in §A.3).

Textual example. The textual example guidance model takes а query "What are some examples of wine?" and q= generates a set of guidance examples such as "cabernet", "merlot", "pinot noir", "pinot gris". We use top-p (Holtzman et al., 2019) sampling with beam search to generate a diverse set of guidance

⁶We use SpaCy part-of-speech parser to detect noun, noun phrase, or names. Therefore, M is determined by the parser.

examples. Directly tokenizing the examples into a set of subword tokens and use them to modify the logits might lead to suboptimal generation due to loss of order. For instance, a guidance example "pinot noir" may be split into "pinot" and "noir", and the probability of the two tokens will be modified in the same timestep.

To mitigate the issue, we propose a trie tree based approach to decide what guidance to apply at each step. We construct a trie tree Γ based on the generated guidance examples. With the above guidance examples, the root node will connect to its children nodes "cabernet", "merlot", and "pinot". The node "pinot" will connect to its children nodes "noir" and "gris". At each generation step j, the trie tree takes the last generated token and return only its children node tokens as guidance. For instance, if "pinot" is the current token to generate, the returned set of tokens are "noir" and "gris" as guidance. We show the same procedure in Figure 2 with names as an example. This set of tokens is used to construct the textual guidance logits o_i^c , where its *i*-th index is $\mathbb{1}[i \in \Gamma(x_{i-1})]$.

We summarize the different guidance models and their corresponding elements in Table 2 and provide a more detailed description for the textual example guidance in Algorithm 1 in A.

3.4 Tackling Diverse Natural Language Instructions

The method described so far assumes that the topic and constraint are given and can be used in a query template to obtain guidance. However, the full COGNAC task requires reading the entire instruction and demonstrations as input. We propose to train the model to take natural language instruction and demonstrations and generate the guidance directly. With the set of diverse instructions (described in §2.2), the model needs to infer the topic and the constraint entities from the full input containing the instruction and demonstrations. We finetune the generation model using prefix-tuning (Li and Liang, 2021) on the model's textual example generated examples. This can be thought of as distilling the model's own knowledge by mimicking the textual guidance as the output and generalizing the implicit topic and constraint inference to unseen instructions. Formally, we fine-tune the added prefix weights and save the prefix activations of the fixed guidance model $p_{guide}(y \mid [\mathcal{I}; P]; \theta, \phi)$, where y are the examples generated by the textual example model⁷, ϕ is the added fine-tuning weights to generate the activations (θ remains fixed throughout), and P is the added prefix tokens. The fine-tuning objective minimizes the loss $\mathcal{L}(\phi) = -\sum_t \log p_{guide}(y_t^* \mid [\mathcal{I}; P]; \theta, \phi)$. At the end of the training, only prefix activations $\phi(P)$ are saved. This step distills the model's own knowledge and generalizes the implicit topic and constraint inference to unseen natural language instructions (Figure 2 Stage 1).

Schick et al. (2021) share a similar high-level idea to use the same model's ability to identify bias and modify its generation. The authors propose to self-debias by prompting the model to obtain a biased probability, and subtract the probability from the original generation probability. However, our method focuses on a more knowledge-intensive task, which requires the guidance to provide specific knowledge instead of a broader detection of biases. Our task also requires staying on topic and avoid constraints at the same time. This warrants a different design for $p(t \mid x)$ and $p(c \mid x)$, which leads to developing the three guidance models and their tailored decoding design (e.g., incorporating trie). Finally, our setting expands to inferring topic and constraint (not given as control codes or attributes) from natural language instructions.

4 Experimental Setup

Evaluation We perform evaluations under two settings for both datasets in COGNAC:

- 1. Both the topic and the constraint are specified using a **control code** each;
- 2. The topic and the constraint are specified in the form of a **natural language instruction**.

The control code setting allows us to better compare with prior work, which mostly uses a small set of attributes to steer generation. In this setting, we examine COGNACGEN with all three guidance types: binary verifier, top-k token, and textual example. We adapt COGNACGEN to this setting by skipping the self-guidance distillation step and use the topic and constraint directly as control code.

However, the NL instruction setting is more realistic and closer to the real-world use case, where a user can control the LM with natural language. For this setting, the test set split (§2) contains a set

⁷We only show results for textual example since it works best in our experiments, but the distillation procedure can be applied to all three guidance models.

Evaluation with Control Codes							
		We	ordNet	Wikidata			
	Correctness		Fluency		orrectness	Fluency	
Model	$\mathrm{IC}\uparrow$	On-Topic \uparrow / Violation \downarrow	Rep-1 / Rep-2 / Copy-BLEU / PPL ↓	$IC\uparrow$	On-Topic \uparrow / Violation \downarrow	Rep-1 / Rep-2 / Copy-BLEU / PPL ↓	
Fine-Tuning	10.2	77.6 / 67.4	0.19/0.04/0.10/58.9	9.6	29.8 / 34.3	0.21 / 0.09 / 0.06 / 42.4	
Self-Debiasing	24.2	50.8 / 26.6	0.27 / 0.14 / 0.01 / 51.4	19.8	35.6 / 29.6	0.27/0.15/0.05/ 8.0	
CognacGen							
- binary verifier	28.0	67.6 / 39.8	0.30/0.11/0.02/65.2	22.8	34.2 / 23.6	0.29 / 0.15 / 0.04 / 12.1	
- top-k token	36.0	53.8 / 17.8	0.28 / 0.11 / 0.06 / 53.4	25.4	41.2 / 27.0	0.25/0.11/0.06/ 9.8	
- textual example	36.2	61.8 / 25.6	0.30 / 0.12 / 0.06 / 47.9	35.8	43.8 / 14.2	0.17/0.06/0.05/ 6.4	

Table 3: Evaluation results on the control code setting on the development set of WordNet and Wikidata. We report Correctness and Fluency metrics for both datasets and IC is the Instruction Conformance score. The Fine-Tuning baseline use CTRL-style (Keskar et al., 2019) training and Self-Debiasing is adapted from Schick et al. (2021).

Evaluation with Natural Language Instructions							
WordNet						Wi	kidata
Correctness Fluency		Fluency	Correctness Fluency		Fluency		
Model	Size	$\mathrm{IC}\uparrow$	On-Topic \uparrow / Violation \downarrow	Rep-1 / Rep-2 / Copy-BLEU / PPL ↓	$\mathrm{IC}\uparrow$	On-Topic \uparrow / Violation \downarrow	Rep-1 / Rep-2 / Copy-BLEU / PPL ↓
GPT-2 XL	1.5B	12.0	86.8 / 74.8	0.18 / 0.03 / 0.10 / 57.7	18.4	38.6 / 37.0	0.15 / 0.04 / 0.26 / 33.8
GPT-3 (davinci)	175B	22.4	57.0 / 34.8	0.20 / 0.04 / 0.01 / 39.9	20.2	25.2 / 11.1	0.08 / 0.01 / 0.01 / 22.2
CognacGen	1.5B	32.4	54.8 / 22.4	0.29 / 0.13 / 0.02 / 51.7	31.8	43.9 / 19.7	0.22/0.10/0.02/ 9.6
InstructGPT	175B	49.0	82.6 / 33.6	0.20 / 0.05 / 0.02 / 28.3	41.9	52.5 / 16.7	0.07 / 0.01 / 0.02 / 15.7

Table 4: Results on the NL instruction setting on the test set of WordNet and Wikidata. We report Correctness and Fluency metrics for both datasets and IC is the Instruction Conformance score. The natural language instruction templates do not overlap across train/development/test splits. COGNACGEN uses textual example guidance.

of unseen instruction templates that are never seen in the train set (details in §2.2). We use textual example guidance for COGNACGEN in this setting because we observe its superior performance across the board in the control code setting.

Baselines When evaluating with control codes, we compare COGNACGEN to a fine-tuned model baseline built on CTRL (Keskar et al., 2019), where the topic and the constraint are provided as control codes that are appended at the beginning of the input text. We also compare to the self-debiasing technique proposed in (Schick et al., 2021), as it is the only method in the recent controllable generation approach that can apply to arbitraty number of control codes/attributes without fine-tuning. To adapt COGNACGEN to the control code setting, we can simply skip the self-guidance distillation stage and use the topic and constraint as control.

When evaluating with natural language instructions, we compare with two large language models (175B parameters): GPT-3 (davinci) (Brown et al., 2020), and InstructGPT (text-davinci-002) (Ouyang et al., 2022).

Model details All of our COGNACGEN variants use GPT-2 XL (1.5B parameters) (Radford et al., 2019) for both generation and guidance models. The top-k token uses top 20 tokens for topic and top 40 tokens for the constraint. The textual example guidance generates 200 tokens for building the trie. For both GPT-3 and InstructGPT, we use top-p = 0.95 and temperature $\tau = 0.9$. We provide more details about self-guidance distillation training details in §A.3.

5 Results

Main results. Tables 3 and 4 display the results for the two evaluation settings, respectively. In the control code setting (Table 3), COGNACGEN (textual example) achieves the best instruction conformance (IC) scores, outperforming the self-debiasing baseline by 12 points on WordNet and by 16 points on Wikidata. The fine-tuned baseline achieves the lowest IC scores across both datasets. Among COGNACGEN's variants, textual example

Template Position	WordNet	Wikidata
Beginning: topic; End: constraint	33.2	32.6
Beginning: topic & constraint	31.2	17.4
End: topic & constraint	36.6	11.4

Table 5: Instruction Conformance for different natural language templates using COGNACGEN textual example. These three templates are applied to all the instances in the development set.

guidance performs better than top-k token guidance and the binary verifier. All model variants of COGNACGEN seem to be equally fluent, with COGNACGEN textual example having a desirable slightly lower 47.9 perplexity.

In the NL instruction setting (Table 4), COG-NACGEN textual example achieves a higher performance than GPT-3 (legacy) by 10.0 points on WordNet and 11.6 points on Wikidata, despite having much fewer parameters (1.5B vs 175B). InstructGPT achieves much higher scores (49 IC on Wordnet and 41.9 IC on Wikidata), but it is also a much larger model(175B) and is also fine-tuned on instruction following using human feedback (RLHF) (Ouyang et al., 2022).

To analyse model performance on different kinds of templates, we report IC scores for each of the three templates in development sets in Table 5. We observe that performance among different templates stays about the same for WordNet, but for Wikidata, the template with the topic and constraint specified at the end proves to be more challenging than others. This highlights challenges due to structural variations in instruction templates and how this may manifest differently in each dataset.

Performance analysis by category. We analyze the performance of COGNACGEN (textual example) by category for both WordNet (Table 6) and Wikidata (Table 7), revealing how each category provides different challenges. We observe that COGNACGEN struggles to avoid violating constraints for the 'Art' category at a IC of 15.0, a much lower score compared to other categories which all have > 30.0 IC. Moreover, for knowledge-heavy categories such as 'Art' in Word-Net and 'birthplace'/'deathplace' (as topic) in Wikidata, COGNACGEN struggles to stay on topic.

Model ablations. To provide more insight into the workings of COGNACGEN, we ablate away the trie-based generation and also compare with a database oracle model on Wikidata, which provides an upper bound on IC score when using the

	WordNet		
	$\mathrm{IC}\uparrow$	On-Topic \uparrow	Violation \downarrow
Animal	33.9	62.8	29.0
Vehicle	43.0	78.0	35.0
Food	36.0	64.6	28.7
Sport	36.4	66.7	30.3
Art	15.0	55.0	40.0

Table 6: WordNet performance breakdown by category. In every example, the topic and constraint are coming from the same category.

		Wikidata	
	$IC\uparrow$	On-Topic ↑	Vio. \downarrow
When Used as Topic			
- Occupation	32.8	44.4	20.0
- Citizen	46.2	55.5	12.6
- Education	33.3	33.3	33.3
- Birthplace	0.0	0.0	18.2
- Deathplace	4.4	4.4	20.0
When Used as Constraint			
- Occupation	15.8	29.0	23.7
- Citizen	14.1	26.3	37.4
- Education	44.4	44.4	5.6
- Birthplace	40.7	50.3	12.4
- Deathplace	25.5	29.1	3.6

Table 7: Wikidata performance breakdown by category. In Wikidata, topic and constraint are often from different categories. On-topic only accounts for when the category is used as topic. Vio.: violation only accounts for when the category is used as constraint.

proposed decoding method proposed in §3.2. This oracle model has access to the knowledge base, and hence can provideperfect guidance (Table 8). The oracle achieves an IC of 73, compared to COGNAC-GEN's 35.8, indicating that there is quite a bit of room for improvement on our task, both in terms of generating more on-topic text and avoiding violations. Further, both COGNACGEN and the oracle degrade in performance drastically when the tries are removed, highlighting the effectiveness of using tries to guide generation. This degradation is particularly pronounced due to the need for generating multi-token names in Wikidata.

Qualitative examples. Finally, Table 10 shows example generations from COGNACGEN and GPT-3 (davinci) on WordNet and Wikidata. For Word-Net, COGNACGEN generates constraint comforming output yet GPT-3's generation violates the constraint by generating examples including scallop. On Wikidata, COGNACGEN is able to follow the

Model	$\mathrm{IC}\uparrow$	On-Topic ↑	Vio. \downarrow	$\mathrm{PPL}\downarrow$
COGNACGEN - w/o trie	35.8 10.4	43.8 11.2	14.2 3.2	6.4 5.0
Oracle - w/o trie	73.0 13.2	73.4 12.6	0.4 2.0	9.9 3.8

Table 8: Ablation on trie between COGNACGEN (textual example) and the oracle which assumes access to the knowledge base, instead of relying on the LM's internal knowledge. The ablation is on Wikidata.

instructions and generate a sentence about a journalist, while GPT-3 fails to stay on topic.

6 Related Work

Constrained text generation. Prior approaches to constrained text generation fall into several categories. First, works like CTRL (Keskar et al., 2019), GeDi (Krause et al., 2021) and Neurologic decoding (Lu et al., 2021, 2022b) use additional context information such as control codes, attributes or word lists to condition their generations. Second, papers like PPLM (Dathathri et al., 2020) and DExperts (Liu et al., 2021a) modify the model's output probabilities during inference using classifiers and auxiliary models, respectively. Along the same lines, Unlikelihood training (Welleck et al., 2020) and CRINGE (Adolphs et al., 2022) use auxiliary token-level and sequence-level objectives to discourage models from assigning high probabilities to certain tokens or sequences, while Quark (Lu et al., 2022a) and Liu et al. (2021b) use reinforcement learning to do the same. All these approaches are limited by the type of control they exert over the language model, restricted to high-level concepts like sentiment, toxicity or repetition and usually employing a fixed set of predetermined binary or categorical codes.

The third category consists of methods that use a language model's own knowledge to guide its generations, which is probably most similar to our work. This includes self-debiasing (Schick et al., 2021), which reduces toxicity by prompting the model to generate toxic content and offset this behavior from the main generation LM. This method works is limited to a single high-level attribute (e.g. toxicity) that needs to be suppressed while COG-NACGEN can handle a composition of attributes (topic + constraints) based on precise factual knowledge. More recently, Self-correction (Welleck et al., 2022) learns a correction module that iteratively edits generated text and is trained using scalar or language feedback. Their method requires progressively training and updating the corrector module and the generation uses multiple iterations, whereas our guidance module is only prefix-tuned once and can generate text in one pass.

Instruction following. A large body of literature in embodied agent learning has focused on following instructions or constraints in a grounded setting (Vogel and Jurafsky, 2010; Chen and Mooney, 2011; Artzi and Zettlemoyer, 2013; Luketina et al., 2019; Misra et al., 2018; Yang et al., 2021). These papers focus on instruction understanding that maps to actions in an external environment, as opposed to text generation. More recently, papers have looked explored finetuning language models to follow instructions in natural language for various NLP tasks (Ouyang et al., 2022; Mishra et al., 2022; Wang et al., 2022; Wei et al., 2021; Bach et al., 2022). In contrast to our work, these methods do not focus on using language to control the generated text in a fine-grained manner and require costly fine-tuning or large-scale prompt creation.

7 Conclusion

We have introduced a new task for controllable generation in language models with constraints specified in natural language. We developed COGNAC, a new benchmark containing knowledge-based constraints using data from Wordnet and Wikidata and showed that even state-of-the-art language models like GPT-3 fail to conform to the provided instructions. We then develop COGNACGEN, a method to use knowledge internal to a language model to guide its own generations. Our approach involves several key innovations such as guidance self-distillation using prefix-tuning and a trie-based decoding scheme based on the guidance of textual examples. This helps the model generate on-topic text that violates constraints less frequently compared to several baselines, including much larger models like GPT-3. More importantly, our method require training only the prefix parameters and can easily be scaled to larger models without requiring significant computational overhead. Our analysis also revealed that there is still significant room to improve on COGNAC and we hope future approaches will find the benchmark useful for developing better methods to control language models.

Limitations

Our work is aimed at reducing undesirable generations in LMs while promoting desirable text. A successful scenario would increase the instruction conformance score when our method is applied. However, our benchmark is limited by the comprehensiveness of the underlying knowledge bases (KB) used. Any generation that goes beyond the factual knowledge present in the KB would be deemed incorrect, which may amplify any bias existing in the KB, e.g., people with certain background or ethnicity might be underrepresented. Furthermore, even when the generation is within the scope of the KB, the model might still have a tendency to choose certain types of knowledge over another. These implicit biases might cause unfairness to the end users of the model.

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A Appendix

A.1 Data Generation Process

Table 3 shows how the topic and constraint are sampled from the two datasets WordNet and Wikidata.

WordNet. Each example is constructed by: 1) sampling a node as the topic, 2) sampling |E| = 3 nodes under the topic node, and 3) generating a continuation from GPT2-XL (Radford et al., 2019) and using the generated node as the constraint. Note that both the topic and the constraint are within the same category.

Wikidata. Each example is constructed by: 1) first sample a property and a value as the topic, 2) sample |E| = 3 entities from the property-value name set, and 3) generate a continuation from GPT2-XL and use the generated entity as a constraint. In contrast to WordNet, the topic and constraint are from different categories. To ensure their information does not update over time, we use only names of deceased people.

A.2 Natural Language Instruction Templates

We provide the natural language instruction template examples in Table 9 for training (template 0-2) and development sets (template 3-5). The templates vary in their instruction positions. In template 0 and 3, the topic and constraint specification is added to the beginning and the end, respectively, with demonstration examples in the middle. On the other hand, template 1 and 4 put demonstrations to the bottom and specify the topic and constraint at once in the beginning. Note that the word use also differs between templates, sometimes

A.3 Method Details

Training and inference details. During selfguidance distillation, we add for each topic and constraint 10 prefix tokens and the MLP with hidden size 512, and save only the activation for inference. We train with batch size of 16 using the AdamW optimizer (Loshchilov and Hutter, 2017) with learning rate 3e - 5 for 20 epochs. During guided generation, we set $\alpha = 5.0$ and $\beta = 100.0$ and use greedy decoding. The binary verifier guidance uses 8 tokens for greedy look-ahead.

We provide a complete algorithm for textual example in Algorithm 1.

Top-k token guidance. While we only use top-k of the next token probability from the guidance dis-

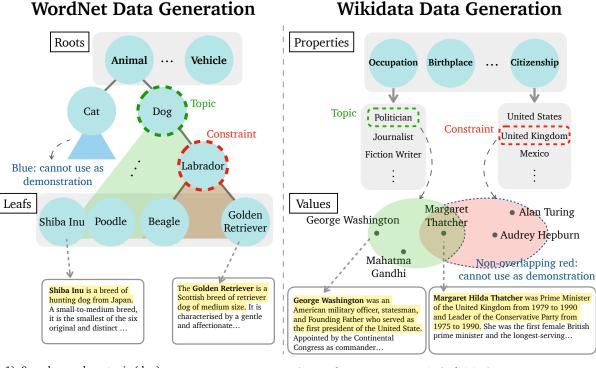
Algorithm 1 COGNACGEN (Textual Example Guidance)

Ou	idanee)
1:	Initialize $p_{gen}(x; \theta)$ > Pre-trained generation LM
2:	$p_{\text{guide}}(x;\theta) \leftarrow p_{\text{gen}}(x;\theta) \qquad \triangleright \text{ Same LM for guidance}$
3:	
4:	Stage 1 – Distilling Self-Guidance
5:	Initialize parameters ϕ and prefix P
6:	for $\mathcal{I} = (t, c, E) \in \mathcal{D}_{\text{train}}$ do
7:	$y^* = p_{ ext{guide}}(y \mid ext{query-template}(ar{t}); heta)$
8:	
9:	return $\phi(P)$ \triangleright Only saving the activations
10:	
11:	Stage 2 – Guided Generation
12:	Sample guidance $x^g \sim p_{guide}(x^g \mid \mathcal{I}; \phi(P))$
13:	Initialize trie Γ using guidance x^g
14:	Set trie tree level $l = 1$
15:	for $t = 1 \dots T$ do
16:	$\{w_k\} = \Gamma(l)$ \triangleright Retrieve a set of tokens
17:	$s' = Bag-of-Tokens(\{w_k\})$
18:	Obtain s'' for constraint following same steps
19:	\triangleright Logits s comes from $p_{gen}(x_j \mid x_{< j}) = \operatorname{softmax}(s)$
20:	$p'_{\text{gen}}(x_j \mid x_{< j}) = \operatorname{softmax}(s + \alpha s' - \beta s'')$
21:	$x_t \sim p_{ ext{gen}}'(x_j \mid x_{\leq j})$
22:	if $x_i \in \{w_k\}$ then
23:	l = l + 1
24:	return x_1, \ldots, x_T

tribution, we could decode multiple steps to handle multi-token entities. To encourage only generating one entity, the query template can be modified to "What is *one* example of \vec{c} ". We leave this to future exploration and research.

A.4 Qualitative Examples

We show qualitative example of input instance and model generated output in Table 10.



1) Sample a node as topic (dog)

- 2) Sample nodes: Shiba Inu & Golden Retriever
- 3) Take first sentence from Wikipedia as demonstration

4) Select a constraint node in the topic subtree

1) Sample a property as topic (politician)

- 2) Sample examples: George Washington & Margaret Thacher
- 3) Take first sentence from Wikipedia as demonstration
- 4) Select a constraint property based on model generation

Figure 3: Data generation process for WordNet (left) and Wikidata (right). Note that in WordNet, the topic and constraint need not be connected.

ID	Template	Instruction Position
0	Write down examples of [topic]. [Demonstrations] Continue listing them but do not include examples of [constraint].	Begin & End
1	Below we show examples of [topic]. Following these examples, keep listing but don't mention [constraint]. [Demonstrations]	Begin
2	[Demonstrations] Below we show examples of [topic]. Following these examples, keep listing but don't mention [constraint].	End
3	Generate examples that are under the category of [topic]. [Demonstrations] Now keep generating but exclude anything that's in the category of [constraint].	Begin & End
4	List out examples of [topic]. Right after these examples, continue listing but avoid mentioning [constraint]. [Demonstrations]	Begin
5	[Demonstrations] The above are sentences describing [topic]. Now write similar sentences as the above while omitting any mention of [constraint].	End

Table 9: Natural language instruction templates in training (0-2) and development (3-5) sets.

Wikidata Data Generation

Dataset	Input Instructions and Demonstrations	Generation
WordNet	List out examples of bivalve. Right after these examples, continue listing but avoid mentioning scallop. - [] "ark shells" because species such as arca have a large flat area between the umbones [] - Placopecten magellanicus, previously listed as pecten tenuicostatus and as pecten grandis and once referred to as the "giant scallop", [] - Argopecten irradians, [], common names atlantic bay scallop []	GPT-3 Output: Aequipecten irradians, common names atlantic bay scallop or bay scallop, is a marine bivalve mollusk in the family pectinidae. COGNACGEN Output (Ours): Clams are a group of bivalve mollusks that are found in the northern Atlantic Ocean.
Wikidata	Generate examples that are under the category of journalist. - Michael Mackintosh Foot was a British Labour Party politician who served as Labour Leader from 1980 to 1983. [] - Henry George was an American political economist and jour- nalist. [] - John Griffith London was an American novelist, journalist and social activist. [] Now keep generating but exclude anything that's in the category of people who were born in Cambridge.	 GPT-3 Output: Elizabeth Gurley Flynn (May 30, 1890 – September 5, 1964) was an American labor activist, anarchist and socialist/communist organizer born in Concord, New Hampshire. COGNACGEN Output (Ours): William F. Buckley Jr. (born William F. Buckley; June 18, 1925 – February 3, 2015) was an American conservative political commentator, author, and publisher. He was the editor of National Review []

Table 10: Example natural language instruction input and model output comparison between COGNACGEN textual example and GPT-3 (davinci).