Abstract

In this paper, we study the effects of incorporating timestamps, such as document creation dates, into generation systems. Two types of time-aware prompts are investigated: (1) textual prompts that encode document timestamps in natural language sentences; and (2) linear prompts that convert timestamps into continuous vectors. To explore extrapolation to future data points, we further introduce a new data-to-text generation dataset, TEMPWIKIBio, containing more than 4 millions of chronologically ordered revisions of biographical articles from English Wikipedia, each paired with structured personal profiles. Through data-to-text generation on TEMPWIKIBio, text-to-text generation on the content transfer dataset, and summarization on XSum, we show that linear prompts on encoder and textual prompts improve the generation quality on all datasets. Despite having less performance drop when testing on data drawn from a later time, linear prompts focus more on non-temporal information and are less sensitive to the given timestamps, according to human evaluations and sensitivity analyses. Meanwhile, textual prompts establish the association between the given timestamps and the output dates, yielding more factual temporal information in the output.

1 Introduction

Temporal information, such as publication and modification dates of documents, is an inherent attribute of documents. Both document writers and readers are aware of this information when organizing and consuming document content. For example, an event reported by a news article is likely to happen right on the publication date. However, state-of-the-art generation models are fine-tuned from large pre-trained models without incorporating temporal information (Lewis et al., 2020; Zhang et al., 2020), creating a gap between document processing by humans and automatic models. Though previous work has split datasets according to temporal information and shown deteriorated performance of large pre-trained models as knowledge becomes outdated on future data (Lazaridou et al., 2021; Jang et al., 2022), it is unclear how informing models of temporal information affects generation tasks.

Therefore, this work aims to study the effects of presenting temporal information to generation models. Concretely, to include timestamps in model inputs, we consider prepending two types of time-aware prompts to the encoder or the decoder. First, textual prompts encode timestamps within natural language descriptions, as commonly used by the recent prompt engineering work (Radford et al., 2019; Raffel et al., 2019). We further explore linear prompts that map timestamps to continuous vectors via linear projections.

Concretely, we fine-tune BART (Lewis et al., 2020) with time-aware prompts and conduct experiments on two text-to-text generation tasks: (1) content transfer (Prabhumoye et al., 2019) that generates the continuation of a passage using information from a given document, and (2) summarizing news articles with XSum (Narayan et al., 2018). To study time-aware prompts’ capability of extrapolating to future dates, we introduce TEMPWIKIBio, a data-to-text dataset containing timestamped revisions of biographical articles from English Wikipedia, each paired with an infobox as input. The revisions record changes of personal profiles from 2004 to 2021. For all experimented datasets, dated events are critical. We first evaluate model outputs with automatic metrics to examine the effects of temporal information on output informativeness. Human judges are then asked to additionally rate the factuality of model outputs and determine if the improvement or degradation is due to date changes.

1Our data and code are available at https://shuyangcao.github.io/projects/temporal_prompt_generation.
BART: Joseph Melville Broughton Jr. (November 17, 1888 – March 6, 1949) was the 60th Governor of the U.S. state of North Carolina from 1941 to 1945.

Linear Prompt: Joseph Melville Broughton Jr. (November 17, 1888 – March 6, 1949) was the 60th Governor of the U.S. state of North Carolina from 1941 to 1945 and a United States Senator from 1948 until his death in 1949.

Figure 1: Sample system outputs on TempWikiBio for data-to-text generation and on XSum for summarization. We highlight relevant temporal information in the input and corresponding correct (incorrect) information in the model outputs. Linear prompts could encourage selecting important dates on TempWikiBio, but the temporal information encoded in the linear prompts can not be captured by the model, leading to incorrect dates when resolving with the provided dates is required on XSum; while the model with textual prompts is sensitive to the provided dates and generates correct date, it lacks world knowledge (e.g., seasonal earning is only reported after the season) to handle the last case after perturbing the original publication date.

in the outputs. Finally, we perform a sensitivity analysis by making perturbations to the original dates (e.g., setting the dates to one year before) and providing models with the perturbed dates, and then inspect the changes of outputs. We find that:

- Time-aware prompts improve the model performance over the no-prompt baseline in 87.5% of comparisons on different metrics and datasets. Linear prompts work better on the data-to-text dataset, while textual prompts work better on the text-to-text datasets, partly due to modal compatibility.

- The improvement in output informativeness and factuality by linear prompts is less frequently related to modifying temporal information in the outputs than textual prompts, according to human judges. Moreover, models with linear prompts are less sensitive to the given temporal information, suggesting that linear prompts assist the processing of non-temporal content.

- Textual prompts associate the provided dates with the dates to be generated in the outputs, producing more factual time-related information. However, models with textual prompts could generate incorrect dates when complicated world knowledge is required to perform reasoning, as shown in the last example in Figure 1.

2 Related Work

Temporal Generalization in NLP. Early work on temporal generalization focuses on detecting the shifts of n-gram frequencies over time (Michel et al., 2011) and detecting word meaning changes (Wijaya and Yeniterzi, 2011; Kulkarni et al., 2015). Besides linguistic shifts, model degradation on downstream tasks has been reported when tested on samples at a different time from the training data (Huang and Paul, 2018; Lukes and Søgaard, 2018; Lazaridou et al., 2021; Agarwal and Nenkova, 2021). In this work, we study the temporal generalization of our time-aware prompts, since they are constructed with temporal information.

Prompt Engineering. Prompts have been a common tool for controllable generation (Fan et al., 2018; Radford et al., 2019; Keskar et al., 2019; Raffel et al., 2019). Instructions are also constructed as prompts to allow large models to perform new tasks that are unseen in training (Brown et al., 2020; Sanh et al., 2022). More recently, prompts, either hand-crafted (Schick and Schütze, 2021; Gao et al., 2021) or learned (Li and Liang, 2021), are found to benefit model learning and improve few-shot performance on downstream tasks. Our textual time-aware prompts extend the year-level prompts in Dhingra et al. (2021) with months and days to incorporate fine-grained temporal information, and we further explore representing timestamps with linear prompts which have been mainly used for length-controlled generation (Kikuchi et al., 2016).
3 Time-aware Prompts

We study two types of prompts that are prepended to the encoder/decoder of a seq2seq model, to inform the model of temporal information.

**Textual Prompt.** Given a document’s timestamp, we first convert it to “day month year” with the day and the year in digits and the month in its textual form (e.g., “18 January 2015”), a format commonly used by mainstream media such as BBC news. We test three textual prompts and use the one that results in the highest ROUGE score on the development set of XSum, i.e., “Today is [timestamp].” (“Today is 18 January 2015.”) Other textual prompts are detailed in Appendix A. Compared to only inserting the year information (Dhingra et al., 2021), textual prompts in our paper provide more fine-grained temporal information.

**Linear Prompts** treat the concept of time as an axis, with each timestamp being mapped to a point on it. Concretely, we use the year, month, and day as scalars and transform them into prompt vectors through linear projections, as illustrated in Figure 2. The process of linear projections can also be viewed as changing the scales of vectors for the year, month, and day. While prior work has controlled the output lengths by changing the scales of memory cells in an LSTM (Kikuchi et al., 2016), representing temporal information with scales of vectors has yet been studied.

Figure 3: Numbers of samples and the corresponding time periods of revisions in different splits of TEMPWikiBIO. Changed attributes of the sample revisions are shaded in yellow. There is no overlapping subject between training/development sets and the two test sets.

4 TEMPWikiBIO Data Collection

To study how well time-aware prompts can extrapolate to future data, we collect TEMPWikiBIO, which has 4,277,450 revisions of infobox-paragraph pairs from 2004 to 2021 for 695,929 Wikipedia biography articles, extending WikiBIO (Lebret et al., 2016), which only includes the latest revision per article by 2015. Importantly, the profile (e.g., titles, awards, etc) of a person shown in the infobox changes over time (Figure 3).

Concretely, for each biography, we pick its latest revision every X days since the first revision, where X is sampled uniformly from [270, 450], to diversify the timestamps included in the data. We then extract the infobox and the lead paragraph per revision. As illustrated in Figure 3, two test sets are created: test–same time contains articles that are published at the same time as the training set, while test–future consists of samples that are created (or revised) after training and development sets. We further ensure that the subjects of biographies in both test sets are not in training or development sets. On average, each revision has 15.3 attributes in the infobox and 43.2 words in the first paragraph. Details of data collection are included in Appendix B.

5 Experiments and Results

For data-to-text generation on TEMPWikiBIO, we linearize the infobox and use it as the input to BART. Common data-to-text metrics (Gehrmann et al., 2021) are used, including BLEU-4 (Papineni et al., 2002), METEOR (Lavie and Agarwal, 2007), TER (Snover et al., 2006), and BERTScore (Zhang et al., 2020). For text-to-text summarization on XSum (Narayan et al., 2018) that consists of news articles and their corresponding summaries from BBC News, we report ROUGE scores (Lin, 2004)
Table 1: Results on TEMPWIKIBIO. Textual (T) and linear (L) prompts are used on encoder (ENC) or decoder (DEC). B: BLEU; MTR: METEOR; BS: BERTScore. The best result per metric is in boldface and the second best is in italics. Improvement over the no-prompt baseline is shaded. ∗: significantly better than the baseline (p < 0.001).

| Prompt | Content Transfer | XSum |
|--------|------------------|------|
|        | R-L              | R-1  | QEval |
|        | MTR             | BS   | R-2   |
| ENCT:T | -               | 27.52| 27.55 |
| ENCL:L | 28.15           | 28.40| 30.59 |
| DEC:T  | 28.41           | 28.84| 30.90 |
| DEC:L  | 27.62           | 27.68| 30.13 |
| ENCT:L | 28.15           | 28.40| 30.59 |
| ENCL:T | 27.82           | 27.99| 30.33 |
| DEC:T  | 28.84           | 30.90| 45.59 |
| DEC:L  | 27.62           | 27.68| 30.13 |

Table 2: Results on the content transfer and XSum datasets. R: ROUGE; QEval: QuestEval.

and QuestEval (Scialom et al., 2021), a QA-based faithfulness evaluation metric that checks if questions created from the summary can be addressed by reading the document with a QA model, and vice versa. The content transfer dataset (Prabhu-moye et al., 2019) considers sentences containing citations of news sources in Wikipedia articles as the target for generation. Many target sentences incorporate important dates from the cited articles, thus making it suitable to test our time-aware prompt design. To generate each target sentence, the context passage, which contains three sentences preceding the target sentence, and the cited news article are provided as input. ROUGE-L, METEOR, and BERTScore are computed for evaluation on the content transfer dataset.

**Automatic Evaluation.** Overall, models with time-aware prompts obtain better performance than the no-prompt baseline. Models with time-aware prompts win 49 of all 56 comparisons against the baseline on different metrics and datasets, indicating that adding time-aware prompts encourages the models to generate more informative outputs.

Linear prompts tend to work better on the encoder when the input is structured data, achieving the best overall performance on TEMPWIKIBIO (Table 1). Linear prompts also show less performance degradation than textual prompts when testing future samples. However, the better extrapolation performance by the model with linear prompts might be due to its lower sensitivity to the provided dates, as later revealed in our analysis.

When the input and output are both in natural language, textual prompts are more suitable, as evidenced by the better performance than linear prompts on all metrics on both the content transfer dataset and XSum (Table 2). We think that on text-to-text generation tasks, textual prompts benefit from modal compatibility and have an advantage of connecting the salient content with the timestamps.

**Human Evaluation.** We hire three fluent English speakers to evaluate 80 sets of paragraphs generated for TEMPWIKIBIO samples at a future time and 80 sets of sentences generated for content transfer samples by two models with time-aware prompts. The judges compare the output by each model against the output by the no-prompt baseline on two aspects: **informativeness** — whether the model output covers salient information in the input; and **factuality** — whether the model output is factually correct. For each set, the judges only know which output is generated by the baseline, and outputs by other models are randomly sorted. Besides the three-way label (win/tie/lose), we ask the judges to determine if the difference in each aspect between each pair of comparisons is date-related.

As shown in Figure 4, only a small portion of improvements by linear prompts is date-related, especially on the content transfer dataset where none of the outputs by the model with linear prompts is rated as having better factuality due to the inclusions or changes of dates, suggesting that linear prompts might help process other content. By contrast, the model with textual prompts focuses more on the temporal information and brings more factual dates into the outputs on the content transfer dataset.

**Analysis via Date Perturbation.** We probe into date sensitivity, to understand the mechanisms behind the two types of prompts. Specifically, the original timestamps of 2000 samples randomly selected from the test set of each dataset are per-
Figure 4: Percentages of samples that win or lose over the no-prompt baseline, on Test-Future of TempWikiBio and the content transfer dataset. While both time-aware prompts improve informativeness and factuality on TempWikiBio, textual prompts are more often rated as having date-related improvements in informativeness and factuality on the content transfer dataset. Krippendorff’s $\alpha$: 0.85 (informativeness); 0.64 (factuality).

Figure 5: Edit distances and differences of BLEU-4/ROUGE-L between outputs with perturbed dates and original dates on TempWikiBio and content transfer. Linear prompts are not sensitive to the given dates. Results on XSum are in Appendix C.

between the given temporal information and the generated temporal information, producing outputs with more factual dates.

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Ethical Consideration

Our work assumes the timestamps of documents can be accurately obtained and the models are always provided with the accurate creation dates. However, this might not be the case for some documents, especially the ones that are first published in a paper format and later digitized into electronic versions. Informing generation models of inaccurate timestamps could lead to incorrect content generation and other unpredictable behaviors, where fabricated facts might be picked up by end users, potentially causing harm to the public.
Limitation

Though we show that textual time-aware prompts help models generate more factually consistent outputs, we find that models with temporal prompts could generate incorrect temporal information due to the lack of world knowledge (Figure 9 of Appendix G). In this work, we do not further study methods that can incorporate extra world knowledge to address this issue.

During model evaluation, we investigate the effects of time-aware prompts on the generated temporal information via human evaluation, which includes 160 outputs by each model (320 in total). We believe automatic metrics that verify the correctness of temporal information in the outputs can better validate the improvements by our models. However, such automatic metrics do not exist. A potential design of temporal information evaluation metrics is to combine event and temporal expression extraction systems. We made several attempts at this design, but the performance of the event and temporal expression extraction systems we tested needs further improvement.

To obtain the timestamp of each sample, we rely on the automatic web archive (Appendix B). However, this approach for timestamp retrieval only applies to datasets that are based on web sources (e.g., news articles and blog posts). In addition, less popular web sources are less likely to be archived by automatic web archive service, which makes retrieving their timestamps more complicated and prevents the adoption of our methods.

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| Prompt Design             | R-1  | R-2  | R-L  |
|---------------------------|------|------|------|
| 1 (Date: ...)             | 45.70| 22.57| 37.47|
| 2 (Today is ...)          | 45.71| 22.55| 37.49|
| 3 (The following ...)     | 45.61| 22.54| 37.32|

Table 3: ROUGE scores on the dev set of XSum by models with different textual prompts on the encoder. Textual prompt “Today is [converted timestamp].” achieves the highest average ROUGE score and is used in our main experiments.

Tianyi Zhang*, Varsha Kishore*, Felix Wu*, Kilian Q. Weinberger, and Yoav Artzi. 2020. Bertscore: Evaluating text generation with bert. In International Conference on Learning Representations.

A Details of Prompts

Other Textual Prompts. The three designs of textual prompts we try in our pilot study are:

1. Date: [converted timestamp].
2. Today is [converted timestamp].
3. The following text is written on [converted timestamp].

As shown in Table 3, the second design “Today is [converted timestamp].” yields the highest average ROUGE score on the development set of XSum. Note that performances by the three prompt designs do not vary greatly.

B Details of Datasets

B.1 TempWikiBio

Data Collection. We use the English Wikipedia dump processed on February 1, 2022 and collect revisions before 2021 that have complete infoboxes. To identify biographies from all articles, we use the article titles and IDs in WikiBio (Lebret et al., 2016), which are originally from WikiProject for biographies. We then extract attributes of the infobox and the first paragraph of the article from each remaining revision with mwparserfromhell. Revisions that do not contain complete infoboxes are discarded. We further discard the first five revisions of each article to avoid including revisions with less comprehensive information about the person. To limit the number of revisions for each

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2https://dumps.wikimedia.org/
3https://en.wikipedia.org/wiki/Wikipedia:WikiProject_Biography
4https://github.com/earwig/mwparserfromhell
### Table 4: The numbers of TEMPWIKIBIO revisions made in different years, grouped by different splits.

| Year | Train | Dev | Test-Same Time | Test-Future |
|------|-------|-----|----------------|-------------|
| 2004 | 56    | 3   | 1              | -           |
| 2005 | 2,167 | 118 | 10             | -           |
| 2006 | 24,509| 1,234| 132           | -           |
| 2007 | 76,637| 3,794| 421           | -           |
| 2008 | 133,467| 6,770| 802           | -           |
| 2009 | 194,504| 9,882| 1,209         | -           |
| 2010 | 248,768| 12,578| 1,685         | -           |
| 2011 | 309,642| 15,801| 2,266         | -           |
| 2012 | 371,008| 18,893| 2,927         | -           |
| 2013 | 365,260| 18,619| 3,039         | -           |
| 2014 | 397,155| 20,572| 3,531         | -           |
| 2015 | 441,800| 22,597| 4,286         | -           |
| 2016 | 535,693| 27,771| 5,462         | -           |
| 2017 | 460,233| 23,733| 4,602         | -           |
| 2018 | 445,955| 22,872| 4,169         | -           |
| 2019 | -     | -   | -             | 11,698      |
| 2020 | -     | -   | -             | 11,998      |
| 2021 | -     | -   | -             | 11,132      |

### Table 5: Numbers of source documents for content transfer published in different years, grouped by different splits.

| Year | Train | Dev | Test |
|------|-------|-----|------|
| unknown | 1,719 | 14 | 250 |
| 1996 | 186 | 1 | 19 |
| 1997 | 100 | 1 | 8 |
| 1998 | 34 | 0 | 3 |
| 1999 | 399 | 3 | 29 |
| 2000 | 1,012 | 13 | 92 |
| 2001 | 831 | 11 | 99 |
| 2002 | 3,561 | 57 | 294 |
| 2003 | 6,672 | 150 | 553 |
| 2004 | 4,119 | 63 | 443 |
| 2005 | 4,112 | 66 | 441 |
| 2006 | 7,323 | 89 | 581 |
| 2007 | 12,398 | 151 | 937 |
| 2008 | 17,920 | 176 | 1,562 |
| 2009 | 26,090 | 298 | 2,499 |
| 2010 | 30,505 | 311 | 2,612 |
| 2011 | 40,035 | 400 | 3,256 |
| 2012 | 71,152 | 708 | 6,219 |
| 2013 | 94,216 | 799 | 7,274 |
| 2014 | 84,661 | 830 | 7,193 |
| 2015 | 55,248 | 588 | 5,229 |
| 2016 | 49,927 | 572 | 4,455 |
| 2017 | 44,243 | 509 | 3,489 |
| 2018 | 22,200 | 215 | 2,316 |
| 2019 | 1,337 | 22 | 147 |
| Total | 580,000 | 5,000 | 50,000 |

For the test split, the number of articles is downsampled to 10% of the original number of articles created in the test time period to achieve a reasonable running time of decoding.

**Time Statistics.** The numbers of revisions made in different years are shown in Table 4.

**Copyright Policy.** We comply with the Wikipedia copyright policy to collect the TEMPWIKIBIO. TEMPWIKIBIO will be released under the CC BY-SA 3.0 license. The usage of TEMPWIKIBIO is limited by the copyright policy of Wikipedia.

### B.2 Content Transfer

The content transfer dataset (Prabhumoye et al., 2019) extracts sentences with citations to news outlets in Wikipedia as the sentences to be generated. The cited source documents then become the external source documents where the generation should be grounded. The three sentences preceding each sentence to be generated in the original Wikipedia article are taken as the context passage. As the source documents come from many different news sources, instead of constructing an extraction template for each new source, we query the Wayback Machine for the date when each source document was first archived to obtain the timestamp.

**Time Statistics.** In Table 5, we report the numbers of source documents in the content transfer dataset published in different years.

**Copyright Policy.** The content transfer dataset is publicly available with the usage limited by the MIT License.

### B.3 XSum

We conduct experiments on text summarization with XSum (Narayan et al., 2018), which contains articles from BBC News. During the construction of the dataset, the first sentence of each article is taken as the summary of the remaining content. The timestamp of each news article is extracted from its corresponding HTML file.

**Time Statistics.** In Table 6, we report the numbers of articles in XSum published in different years.

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5. [https://en.wikipedia.org/wiki/Wikipedia:Copyrights](https://en.wikipedia.org/wiki/Wikipedia:Copyrights)
6. [https://creativecommons.org/licenses/by-sa/3.0/](https://creativecommons.org/licenses/by-sa/3.0/)
7. [https://web.archive.org](https://web.archive.org)
8. [https://www.microsoft.com/en-us/research/project/content-transfer](https://www.microsoft.com/en-us/research/project/content-transfer)
9. [https://opensource.org/licenses/MIT](https://opensource.org/licenses/MIT)
Table 6: Numbers of XSum articles published in different years, grouped by different splits.

| Year | Train | Dev | Test |
|------|-------|-----|------|
| 2009 | 0     | 0   | 1    |
| 2010 | 1,142 | 60  | 62   |
| 2011 | 2,820 | 154 | 153  |
| 2012 | 5,450 | 304 | 319  |
| 2013 | 7,939 | 409 | 420  |
| 2014 | 15,409| 810 | 855  |
| 2015 | 49,041| 2,792| 2,736|
| 2016 | 70,922| 3,928| 3,983|
| 2017 | 51,322| 2,875| 2,805|
| Total| 204,045| 11,332| 11,334|

Table 7: Additional results on TEMPWIKIBIO. Textual (T) and linear (L) prompts are used on the encoder (ENC) or decoder (DEC). The best result is in **boldface** and the second best is in *italics*. Improvement over the no-prompt baseline is shaded. *: significantly better than the baseline with approximate randomization test ($p < 0.001$).

| Prompt | Parent | # Date |
|--------|--------|--------|
| **Test** | ENC:T | 56.30  | 1.33  |
|         | ENC:L | 56.57  | 1.33  |
|         | DEC:T | 56.52  | 1.35  |
|         | DEC:L | 56.36  | 1.32  |
| **Future** | ENC:T | 56.40  | 1.33  |
|         | ENC:L | 56.74  | 1.25  |
|         | DEC:T | 56.82  | 1.25  |
|         | DEC:L | 57.88  | 1.26  |

Table 8: Additional results on the content transfer and XSum datasets.

| Prompt | Content Transfer | XSum |
|--------|-----------------|------|
| **Test** | ENC:T | 71.52  | 37.04  | 0.275 |
|         | ENC:L | 11.27  | 37.15  | 0.272 |
|         | DEC:T | 11.66  | 37.34  | 0.293 |
|         | DEC:L | 11.40  | 36.84  | 0.287 |

Table 8. Textual prompts yield the best performance on the two datasets.

Sensitivity Analyses. We show the results of sensitivity analyses with date perturbation on XSum in Figure 6. Linear prompts again do not show sensitivity to the given dates. Compared to feeding the model with dates that are a year later or earlier, greater drops of ROUGE-2 are observed when feeding the models with dates that are 6 months later or earlier. This suggests that XSum emphasizes resolving date relations of months and days.

D Experiments with T5

We also conduct experiments with the T5 pre-trained model (Raffel et al., 2019). As T5-large has 370 million more parameters than bart.large that has 400 million parameters, we use T5-base, which has 220 million parameters. We do not experiment on XSum, where the performance by T5 is shown to be much lower than BART (Gehrmann et al., 2021).

Results on TEMPWIKIBIO and content transfer are shown in Tables 9 and 10. While linear prompts still work better on TEMPWIKIBIO samples drawn...
Table 9: Results on TempWikiB10 with T5 as the base model. Textual (T) and linear (L) prompts are used on encoder (ENC) or decoder (DEC). B: BLEU; MTR: METEOR; BS: BERTScore. The best result per metric is in boldface. Improvement over the no-prompt baseline is shaded.

| Prompt | R-L | B-4 | MTR | BS |
|--------|-----|-----|-----|----|
| ENC:T  | 17.27 | 8.00 | 23.11 | 24.73 |
| ENC:L  | 22.68 | 7.61 | 22.30 | 23.96 |

Table 10: Results on the content transfer dataset with T5 as the base model. R: ROUGE. *: significantly better than the baseline with approximate randomization test (p < 0.001).

at a future time and textual prompts work better on text-to-text content transfer, the improvements by linear prompts are less substantial. We conjecture that T5 is pre-trained with natural language prefixes for multiple tasks and prefers textual prompts.

E Details of Human Evaluation

Figures 10 and 11 include the instructions provided to annotators for our human evaluation. All annotators are college students based in the U.S. The purpose of the annotation study and the usage of collected data are explained to the annotators before the annotation begins. We compensate each annotator with $15 per hour.

F Details of Implementation

For experiments with BART (Lewis et al., 2020), we use bart.large.11 For experiments with T5 (Raffel et al., 2019), we use T5-base.12 Fairseq (Ott et al., 2019)13 is used for model training and decoding with BART. HuggingFace Transformer (Wolf et al., 2020) is used for decoding with T5. Experiments are conducted with NVIDIA A6000 GPU with 48GB memory.

Training Settings. For training on all datasets with BART, we first follow the hyperparameter setting provided by the original BART training script for XSum14 except that we set the total number of update steps to 30,000 for TempWikiB10 and 35,000 for the content transfer dataset. In addition, we adjust the accumulated batch size for training on TempWikiB10 to have 65,536 tokens in each batch. We then tune the learning rates on TempWikiB10 and the content transfer dataset by searching through $1 \times 10^{-5}$, $3 \times 10^{-5}$, and $5 \times 10^{-5}$ with the model without prompts. Based on the BLEU-4 scores on the development sets, we choose $5 \times 10^{-5}$ for TempWikiB10 and $3 \times 10^{-5}$ for the content transfer dataset. Each model is trained for one run with one random seed due to the high computational cost of fine-tuning large models. For experiments with T5, we follow the default parameters suggested by HuggingFace.

Decoding Settings. We use beam search with beam sizes of 4, 4 and 6 for decoding on TempWikiB10, content transfer, and XSum. The maximum decoding lengths are set to 100, 100, and 60 for TempWikiB10, content transfer, and XSum.

Running Time. When using 4 GPUs, training on TempWikiB10, content transfer, and XSum takes 11, 7, and 2 hours. Meanwhile, decoding on TempWikiB10, content transfer, and XSum respectively takes 2 hours, 1 hour, and 15 minutes with 1 GPU.

Evaluation. We use sacreBLEU (Post, 2018)15 for calculating the BLEU and TER scores. To obtain the METEOR (Lavie and Agarwal, 2007) score, we use NLTK (Bird et al., 2009). The official BERTScore (Zhang* et al., 2020),16 QuestEval (Scialom et al., 2021),17 and PARENT (Dhingra et al., 2019)18 libraries are used. For ROUGE scores (Lin, 2004), we use the Python implementation by Google.19

11https://github.com/pytorch/fairseq/tree/main/examples/bart
12https://huggingface.co/t5-base
13https://github.com/pytorch/fairseq/tree/2380a6e4
14https://github.com/pytorch/fairseq/blob/main/examples/bart/README.summarization.md
15https://github.com/mjpost/sacrebleu
16https://github.com/Tiiiger/bert_score
17https://github.com/ThomasScialom/QuestEval
18https://github.com/google-research/language/tree/master/language/table_text_eval
19https://github.com/google-research/google-research/tree/master/rouge
G Example Outputs

In Figures 7, 8, and 9, we show example outputs by different systems on TEMPWikiBio, content transfer, and XSum.
The second season of "Faking It", an American single-camera romantic comedy, premiered on September 23, 2014, and concluded on November 2, 2015, on the MTV network. MTV is going to be Faking It for another year. The youth-skewing cable network has renewed the comedy starring Katie Stevens and Rita Volk, The Hollywood Reporter has confirmed. MTV will unspool 10 new episodes – up two from season one – in 2015. From showrunner Carter Covington, the half-hour comedy series was the first new scripted entry picked up to series under new network topper Susanne Daniels. "Faking It has proved to be the perfect companion show to Awkward, retaining nearly 90 percent of its lead in each week," Daniels said in a release announcing the news Monday. “We’re excited about Carter Covington’s delicious plans for season two.” The comedy, which centers on two best friends who are mistakenly outed as lesbians and catapult to instant popularity, opened in April to 1.17 million total viewers. Through its first seven episodes, the comedy has averaged 948,000 total viewers. MTV says the show is the highest-rated new series launch this year with a 1.5 rating among viewers 12-34 and 1.4 million viewers each week when factoring in three days of delayed viewing. The season finale airs Tuesday. For MTV, Faking It comes as Daniels is looking to double the network’s roster of original scripted series. In addition to veterans Awkward and Teen Wolf, MTV will also launch comedy Happyland and dramas Finding Carter and Eye Candy. On the pilot side, MTV is readying its adaptation of Scream and buzzy book adaptation Shannara development.

Reference: On June, 2014, the series was renewed for a second season of 10 episodes, which was later extended to 20 episodes.

BART: The series was renewed for a second season of 10 episodes on September 23, 2014.

Textual Prompt: On June, 2014, MTV renewed "Faking It" for a second season of 10 episodes.

Linear Prompt: The series was renewed for a second season of 10 episodes on September 23, 2014.

Context: Furthermore, the magazine said of the phrase, “So when your square friend uses it, take a little bit of pleasure in knowing they’re referencing a stoner comedy – or a drag reality show referencing a stoner comedy – even if they have no idea.” In 2014, VH1 began airing a television show called "Bye Felicia". and pop singer Jordin Sparks released a mixtape titled "#ByeFelicia". According to Google Trends, the phrase reached its highest usage in mid-2015.

Date: 2017-12-15

Source Document: Outgoing White House official Omarosa Manigault Newman says Roberts’ "Bye, Felicia" dig was "petty" and a "black woman civil war." A link has been sent to your friend’s email address. A link has been posted to your Facebook feed. To find out more about Facebook commenting please read the Conversation Guidelines and FAQs Following an appearance on ‘Good Morning America’ about her resignation from the White House, anchor Robin Roberts muttered the phrase about Omarosa Manigault Newmans. USA TODAY Omarosa Manigault Newman clapped back at Robin Roberts after the Good Morning America host took a dig at her on Thursday’s show, telling Inside Edition that her comments were "petty" and akin to "a black woman civil war." The White House public liaison and assistant to the president, who is leaving her post on Jan. 20, had told GMA’s Michael Strahan, "When I can tell my story — and it is a profound story — I know the world will want to hear." Later, a skeptical Roberts commented, "She said she has a story to tell? I’m sure she’ll be selling that story." Then she invoked Friday’s classic two-word dismissal for persons unlikely to be missed by anyone: "Bye, Felicia." Do you know how awful you have to be to annoy Robin Roberts? pic.twitter.com/h0gxAhRFRD For anyone unfamiliar with the expression, we’ll let its inventor, Ice Cube, explain: "It’s the phrase to get ANYBODY out of your face that’s saying something stupid."

Reference: On December 14, 2017, Robin Roberts, a host of ABC TV’s “Good Morning America”, used the phrase to conclude a segment about Omarosa Manigault Newman’s departure from the Presidency of Trump administration staff.

BART: In January 2017, Omarosa Manigault Newman responded to Robin Roberts’ use of the phrase on "Good Morning America", calling it a "black woman civil war".

Textual Prompt: In December 2017, "Good Morning America" host Robin Roberts used the phrase during an interview with Omarosa Manigault Newman about her resignation from the White House.

Linear Prompt: In January 2017, "Good Morning America" host Robin Roberts used the phrase to refer to Omarosa Manigault Newman, who had just resigned from her position in the White House.

Figure 8: Example system outputs on the content transfer dataset. Textual prompts are on the decoder and linear prompts are on the encoder. The publication dates are frequently required in the outputs.
The cloning of the first animal from an adult cell was a remarkable scientific achievement. It promised new treatments for debilitating diseases. But it also raised fears of cloned human beings, designer babies and a dystopian future. Twenty years on, neither the hopes nor the fears have been realised. So what is Dolly’s legacy? I first saw Dolly in 1997 at the Roslin Institute just outside Edinburgh. She stood apart from the other sheep in the pens at this agricultural research centre. She stood prouder, her fleece seemed like a lion’s mane and there was an aura about her. Dolly’s creation had echoes of Mary Shelley’s classic novel Frankenstein, in which inanimate tissue was brought to life by electricity. Dolly was created from DNA taken from a cell taken from a sheep. The technique involved putting the DNA into an empty eggshell and then zapping it with electricity. This created an embryo. Researchers at Roslin then implanted the embryo into the womb of a sheep which grew into Dolly - an exact genetic copy of the sheep from which the skin cell was taken. It took 277 attempts to clone Dolly and there were many miscarriages on the way. There were also genuine concerns that it would not be long before cloned humans would be walking the Earth - people would try to clone themselves to achieve a kind of immortality or they might try to resurrect a beloved dead relative. The airwaves were filled with conversations about what it meant to be human, whether the clones would be exactly the same as the person from which they were cloned and what kind of world the scientists were tumbling us into. When I met the researchers at Roslin they were acutely aware of public suspicion. And they knew it was important to be clear, open and honest about their work. Dolly’s creator, Prof Sir Ian Wilmut, could not be any more different from fictional scientists such as Dr Frankenstein or indeed Dr Moreau, who developed human-like hybrids in a story by HG Wells. By contrast, Prof Wilmut is a quietly-spoken man whose motivation was to improve animal welfare and human health. This bespectacled scientist with his gentle candour was ideally complemented by the enthusiastic and eloquent Dr Simon Best, who was brought in to commercialise the technology to improve human health...

Reference: The birth of Dolly the sheep seemed one of those moments in scientific research that would change the world forever.

BART: The birth of Dolly the sheep in 1997 sent shockwaves through the scientific community.

Textual Prompt: It is 20 years since the birth of Dolly the sheep.

Linear Prompt: It is 20 years since the birth of Dolly the sheep.
Annotation Instruction
The annotation task consists of 80 groups of paragraphs produced by two systems that briefly describe the career of a person. In addition to the paragraphs, each group includes a infobox listing out important information about the person. You will also find a reference paragraph and a baseline paragraph for each group.

Please read each system-produced paragraph and compare it with the baseline paragraph on two aspects: informativeness and factuality. For each aspect, if the system-produced paragraph is better, please label “win”; if the system-produced paragraph is worse, please label “lose”; if the two paragraphs are similar, please label “tie”.

When you label “win” or “lose”, if the better or worse aspect is due to date mentions, please label “win (date)” and “lose (date)” correspondingly.

The explanation of the two aspects is shown below along with an example.

Example

**Vincent Trapp**

| Personal information |
|----------------------|
| Born | 26 January 1861 |
|       | Melbourne, Australia |
| Died | 21 October 1929 (aged 68) |
|       | Melbourne, Australia |

| Domestic team information |
|---------------------------|
| Years | 1881-1884 |
| Team | Victoria |

**Baseline**: Vincent Trapp (26 January 1861) was an Australian cricketer. He played two first-class cricket matches for Victoria between 1881 and 1884.

**System1**: Vincent Trapp (26 January 1861 – 21 October 1929) was an Australian cricketer. He played two first-class cricket matches for Victoria between 1881 and 1884.

**System2**: Vincent Trapp (26 January 1861 – 21 October 1929) was an Australian cricketer. He played for Victoria between 1881 and 1884.

**System3**: Vincent Trapp (26 January 1861) was an Australian cricketer. He played two first-class cricket matches for Victoria between 1881 and 1884, according to Cricinfo.

**Informativeness**: Whether the paragraph synthesizes salient information about the person.

In this example, both system 1 and 2 are better than the baseline as they mention the death date of the person, which is an important information, while system 3 that additionally talks about the source of the information ties with the baseline. Moreover, system 1 and system 2 should be labeled with “win (date)” as the information is related to a date.

**Factuality**: Whether the content of the paragraph is factually correct.

In this example, both system 1 and 3 tie with the baseline. System 2 is better than the baseline as it avoids mentioning “two first-class cricket matches” which is an incorrect information. System 2 should only be labeled with “win”.

Figure 10: Guideline for human evaluation on WIKIREVISION.
Annotation Instruction

The annotation task consists of 80 groups of sentences produced by two systems that continue the given context passage using the information in the given source documents. In addition to the sentences, each group includes the context passage and the source document. You will also find a reference sentence and a baseline sentence for each group.

Please read each system-produced sentence and compare it with the baseline sentence on two aspects: informativeness and factuality. For each aspect, if the system-produced sentence is better, please label “win”; if the system-produced sentence is worse, please label “lose”; if the two sentences are similar, please label “tie”.

When you label “win” or “lose”, if the better or worse aspect is due to date mentions, please label “win (date)” and “lose (date)” correspondingly.

The explanation of the two aspects is shown below along with an example.

Example

Context Passage: The Burleigh Waters Library opened in 1991. For decades a local urban myth maintained that sharks were seen as far south in the canal waterways as Burleigh Waters. Alleged sightings and stories were locally spread, but balanced with scepticism.

Source Document: Publication date: 20 February 2003. The Queensland government has warned people not to swim in coastal canal systems after the second fatal shark attack in as many months on the Gold Coast yesterday. An 84-year-old man from Burleigh Waters died after he was attacked by a 2.5 metre bull whaler while swimming in Burleigh Lake just before 6.30am (AEST) ...

Baseline: An 84-year-old man from Burleigh Waters was attacked by a 2.5 metre bull whaler while swimming in Burleigh Lake.

System1: An 84-year-old man from Burleigh Waters died after he was attacked by a 2.5 metre bull whaler while swimming in Burleigh Lake.

System2: In February 2003, an 84-year-old man from Burleigh Waters died after he was attacked by a 2.5 metre bull whaler while swimming in Burleigh Lake.

System3: In 2013, an 84-year-old man from Burleigh Waters died after he was attacked by a 2.5 metre bull whaler while swimming in Burleigh Lake.

Informativeness: Whether the sentence synthesizes salient information of the source document. In this example, all systems are better than the baseline as they mention the man died after the attack, which is an important information. Moreover, system 2 should be labeled with “win (date)” as it also mentions the date of the event.

Factuality: Whether the content of the sentence is factually correct. In this example, both system 1 and 2 tie with the baseline. System 3 is worse than the baseline as it mentions an incorrect date. System 3 should be labeled with “lose (date)”.

Figure 11: Guideline for human evaluation on the content transfer dataset.