

Conditional Generation with a Question-Answering Blueprint

Shashi Narayan¹, Joshua Maynez¹, Reinald Kim Amplayo¹, Kuzman Ganchev¹,
Annie Louis², Fantine Huot¹, Anders Sandholm², Dipanjan Das¹, Mirella Lapata¹

¹Google DeepMind, UK ²Google Research

shashinarayan@google.com, joshuahm@google.com, reinald@google.com,
kuzman@google.com, annielouis@google.com, fantinehuot@google.com,
sandholm@google.com, dipanjand@google.com, lapata@google.com

Abstract

The ability to convey relevant and faithful information is critical for many tasks in conditional generation and yet remains elusive for neural seq-to-seq models whose outputs often reveal hallucinations and fail to correctly cover important details. In this work, we advocate planning as a useful intermediate representation for rendering conditional generation less opaque and more grounded. We propose a new conceptualization of text plans as a sequence of question-answer (QA) pairs and enhance existing datasets (e.g., for summarization) with a QA *blueprint* operating as a proxy for content selection (i.e., what to say) and planning (i.e., in what order). We obtain blueprints automatically by exploiting state-of-the-art question generation technology and convert input-output pairs into input-blueprint-output tuples. We develop Transformer-based models, each varying in how they incorporate the blueprint in the generated output (e.g., as a global plan or iteratively). Evaluation across metrics and datasets demonstrates that blueprint models are more factual than alternatives which do not resort to planning and allow tighter control of the generation output.

1 Introduction

Neural generation models are often prone to hallucination (Song et al., 2018; Maynez et al., 2020; Kryscinski et al., 2020; Gabriel et al., 2021), repetition and redundancy (Li et al., 2018; Suzuki and Nagata, 2017), and struggle to identify which content units are salient (Tan et al., 2017a). These phenomena are amplified when generating long-form text, i.e., documents with multiple paragraphs (Wiseman et al., 2017), when dealing with non-linguistic data (e.g., database tables), or very long input—which is common when summariz-

ing multiple documents (Liu and Lapata, 2019; Perez-Beltrachini et al., 2019), books (Kryściński et al., 2021), or dialogue (Chen et al., 2022; Zhong et al., 2021). An additional challenge concerns the blackbox nature of deep learning systems, which hides the inherent complexity of modeling multiple interconnected linguistic phenomena in text generation, and makes it difficult to examine model decisions and attribute errors to specific components. The lack of modularity further affects controllability as these systems cannot be easily tailored to individual needs.

Attempts to remedy some of these issues focus on changing the way entities are represented (Puduppully et al., 2019b; Iso et al., 2019), allowing the decoder to skip low-confidence tokens to enhance faithful generation (Tian et al., 2019), modeling graph connections between document elements to better capture salience (Tan et al., 2017b; Liu and Lapata, 2019), encoding documents hierarchically (Celikyilmaz et al., 2018; Liu and Lapata, 2019; Rohde et al., 2021), learning latent alignments between the input and the target text (Xu et al., 2021), adopting sparse attention mechanisms (Child et al., 2019; Beltagy et al., 2020), and introducing content selection (Gehrmann et al., 2018; Dou et al., 2021) and planning components (Puduppully et al., 2019a; Moryossef et al., 2019b; Narayan et al., 2021; Wiseman et al., 2018).

In this paper we also aim to render conditional generation more modular via an intermediate, plan-based representation. While autoregressive models of language predict one token at a time, there is evidence that in humans some degree of planning occurs at a higher level than individual words (Levelt, 1993; Guhe, 2007). A long tradition in natural language generation views

Q ₁ : Who built the Shelby Mustang from 1969 to 1970?	A ₁ : Ford
Q ₂ : During what years was the Shelby Mustang built by Shelby American?	A ₂ : 1965 to 1968
Q ₃ : In what year was the fifth generation of the Ford Mustang introduced?	A ₃ : 2005
Q ₄ : What was the Shelby Mustang revived as?	A ₄ : a new high-performance model

The Shelby Mustang is a high performance variant of the Ford Mustang which was built by Shelby American from 1965 to 1968, and from 1969 to 1970 by Ford. Following the introduction of the fifth generation Ford Mustang in 2005, the Shelby nameplate was revived as a new high-performance model, this time designed and built by Ford.

Table 1: Question-answering (QA) blueprint for AQuaMuSe summary. QA pairs were obtained from a state-of-the-art question generation and answer identification system (Alberti et al., 2019).

planning as a central component to identifying important content and structuring it appropriately (Reiter and Dale, 2000), however, there is less agreement on how plans should be represented. Common examples include discourse trees (Mellish et al., 1998), entity transitions (Kibble and Power, 2004; Barzilay and Lapata, 2008), sequences of propositions (Karamanis, 2004), and schemas (McKeown, 1985).

Our work proposes a new conceptualization of text plans as a sequence of *question-answer* pairs. Specifically, we draw inspiration from the ‘‘Questions under Discussion’’ (QUD) theory of discourse structure, which posits that one way of articulating the structure of a text is to identify the questions and sub-questions that are raised and answered by subsequent spans of text (Carlson, 1983; Ginzburg, 1994; Van Kuppevelt, 1995; Larson, 2002; Roberts, 2012; Riester, 2019). Theoretical models of QUD assume that discourse contains *implicit* questions for each of the assertions made, which are thereby turned into answers. These questions and answers can be understood in terms of their use in moving a discourse forward to achieve communicative goals. We propose to make QUDs *explicit* by exploiting state-of-the-art question generation technology (Alberti et al., 2019; Lu and Lu, 2021) and use them as an intermediate representation layer for conditional generation, i.e., a question-answering (QA) *blueprint* operating as a proxy for both content selection (i.e., what to say) and planning (i.e., in what order).

Table 1 illustrates a plan for generating a Wikipedia abstract from the AQuaMuSe dataset (Kulkarni et al., 2020). We enhance existing datasets (e.g., for summarization) with similar blueprints which we obtain automatically. We then convert input-output pairs into input-blueprint-output tuples and propose to learn encoder-decoder models from these augmented annotations. We

develop three models that vary in how they integrate blueprints in the generation process and their ability to handle long outputs. Aside from generating blueprints and their corresponding text in one go, we propose a new architecture that iteratively plans and generates a sentence at a time, conditioning on the input *and* the output sentences generated so far. We do not generate a *global* blueprint, rather, our planning process is *incremental* and informed by generation, which we argue affords greater control over the output and its fluency. Moreover, the model is better equipped for long-form generation, since it does not have to (autoregressively) decode the blueprint and its summary in one go, avoiding the risk of exceeding the maximum decoder length.

We instantiate our models with a Transformer (Vaswani et al., 2017) encoder-decoder architecture and perform experiments on summarization datasets representing different information seeking tasks, application domains, and user requirements.¹ In all cases, we empirically demonstrate that blueprint models are more factual than alternatives which do not resort to planning; we also observe that QA blueprints are a better representation compared to plans based on entity chains (Narayan et al., 2021), allowing tighter control of the output, and providing a comprehensive explanation for model predictions (if the plan is erroneous, then the summary will be too).

2 Related Work

Questions under Discussion The QUD-based approach to discourse structure assumes an open-ended inventory of possible questions and sub-questions (Van Kuppevelt, 1995). Recent efforts (De Kuthy et al., 2018; Westera et al., 2020;

¹Our models, training data and predictions are available at https://github.com/google-research/google-research/tree/master/text_blueprint.

Riester, 2019) have nevertheless shown that it is possible to manually annotate documents with QUDs, i.e., to formulate a question for every assertion expressed in a text. De Kuthy et al. (2020) even go as far as to partially automate QUD annotation in German by automatically generating all potentially relevant questions for a given sentence. Related work (Ko et al., 2020) focuses on the generation of inquisitive questions that reflect general text understanding and free-form open-ended questions (Ko et al., 2021). Our work builds upon QUD and related discourse structure theories, although, we do not directly implement any of them in particular. We adopt question answering as a good way of spelling out the connection between the information structure of a sentence and the discourse in which the sentence can function.

QA Pairs as a Proxy for Annotation Labels

Question-answer pairs have been previously used as a proxy for expressing semantic content. QA-SRL (He et al., 2015) is a representation based on QA pairs that has been shown to capture the vast majority of arguments and modifiers in PropBank (Palmer et al., 2005) and NomBank (Meyers et al., 2004). Instead of using a pre-defined role lexicon, QA-SRL labels semantic roles with questions whose answers denote the argument bearing the role. Follow-on work uses QA pairs to represent discourse relations (Pyatkin et al., 2020) and to capture overlap or redundancy at the propositional level (Brook Weiss et al., 2021). We also employ QA pairs as an abstraction of propositional content, however, we do not target specific relation types, or make any linguistic assumptions about them (e.g., discourse relations vs semantic roles).

Question-Answering in Summarization

QA pairs have been used for evaluating summaries (Deutsch and Roth, 2021b; Eyal et al., 2019; Durmus et al., 2020; Wang et al., 2020), specifically as a means of estimating the information overlap between a reference summary and a system-generated one. QA-based signals have also been incorporated in the training of summarization models, using reinforcement learning (Arumae and Liu, 2018, 2019; Scialom et al., 2019) or as a way of identifying salient content in the input document (Deutsch and Roth, 2021a). Cao and Wang (2022) introduce the task of hi-

erarchical question-summary generation, where a source document is condensed into *multiple* summaries, each answering a different question. Questions are organized hierarchically into broad questions and more specific sub-questions that are learned from manual annotations. Our model outputs a QA-based plan and a *single* summary for a given document, although it is possible to generate different summaries from different plans for the same document. Our QA pairs are obtained automatically and they are not structured.

Planning in Encoder-Decoder Models

Various recent efforts have developed planning modules in the context of data-to-text generation. In most cases, the plans are specific to the input, which varies from tables and records to RDF tuples. For instance, Puduppully et al. (2019a) learn a plan corresponding to a sequence of records, and generate a summary conditioned on it. Narayan et al. (2020) treat content selection as a task similar to extractive summarization; they first extract sentence plans and then verbalize them one-by-one. Moryossef et al. (2019a,b) propose a symbolic planning stage followed by a neural realization stage. Other work (Puduppully and Lapata, 2021; Puduppully et al., 2022) advocates macro planning, where document content is organized into a sequence of paragraph plans which are verbalizations of tabular input. Our work is closest to Narayan et al. (2021), who also target summarization applications and learn an intermediate plan to guide generation. We adopt a more elaborate plan representation based on QA blueprints, and interface decoding with plan generation similarly to Narayan et al. (2020).

3 Text Generation with Blueprints

3.1 Problem Formulation

Let d denote the input to the model which could be a document (or multiple documents), a dialogue history, or even database tables. The model will learn to generate blueprint b for output s (e.g., a summary) and the output itself. The blueprint b is an ordered set of question-answer pairs $\{(q_1, a_1), (q_2, a_2), \dots, (q_m, a_m)\}$. Unsurprisingly, such blueprints are not naturally occurring in existing datasets that typically consist of (d, s) pairs. In the following we explain how we automatically augment training examples (d, s) into tuples (d, b, s) with blueprints (Section 3.2) and then

Overgenerated Question-Answer Pairs		RT	RH	CO
Q1: What is a high performance variant of the Ford Mustang?	A1: The Shelby Mustang	✓	✗	
Q2: What is the high performance variant of the Ford Mustang called?	A2: Shelby	✓	✗	
Q3: What is a high performance variant of the Ford Mustang?	A3: Shelby Mustang	✓	✗	
Q4: What is a Shelby Mustang?	A4: a high performance variant	✓	✗	
Q5: The Shelby Mustang is a high performance variant of what?	A5: the Ford Mustang	✓	✓	✗
Q6: The Shelby Mustang is a high performance variant of what?	A6: Ford Mustang	✓	✗	
Q7: The Shelby Mustang is a high performance variant of what Ford model?	A7: Mustang	✓	✗	
Q8: Who built the Shelby Mustang from 1965 to 1968?	A8: Shelby American	✓	✓	✗
Q9: During what years was the Shelby Mustang built by Shelby American?	A9: 1965 to 1968	✓	✓	✓
Q10: In what year did Ford take over production of the Shelby Mustang?	A10: 1969	✓	✗	
Q11: What was the final year that Shelby American built the Mustang?	A11: 1970	✗		
Q12: Who built the Shelby Mustang from 1969 to 1970?	A12: Ford	✓	✓	✓
Q13: What event in 2005 led to the revival of the Shelby Mustang?	A13: the introduction	✗		
Q14: What generation of Mustang was introduced in 2005?	A14: the fifth generation	✓	✗	
Q15: What generation of Mustang was introduced in 2005?	A15: fifth	✓	✗	
Q16: In what year was the fifth generation of the Ford Mustang introduced?	A16: 2005	✓	✓	✓
Q17: What name was brought back for the 2005 Ford Mustang?	A17: the Shelby nameplate	✓	✗	
Q18: What was the Shelby Mustang revived as?	A18: a new high-performance model	✓	✓	✓

[The Shelby Mustang is a high performance variant of the Ford Mustang]_{P1} which [was built by Shelby American]_{P2} [from 1965 to 1968.]_{P3} and [from 1969 to 1970 by Ford.]_{P4} [Following the introduction of the fifth generation Ford Mustang in 2005.]_{P5} [the Shelby nameplate was revived as a new high-performance model, this time designed and built by Ford.]_{P6}

Table 2: Generation of QA pairs for summary in Figure 1 and blueprint annotation. We split the summary into propositions P and select no more than one QA pair per proposition. RT, RH, and CO are shorthand for Round Trip, Rheme, and Coverage. Questions that pass/fail each filter are marked with ✓/✗, respectively.

describe how we devise blueprint models based on them (Section 3.3).

3.2 Blueprint Annotation

We first explain how question-answer pairs are automatically (over-)generated for output s , and subsequently filtered to create blueprint b . We illustrate the different filtering stages via the example in Table 2.

Question-Answer Generation We generate QA pairs following an approach similar to Honovich et al. (2021, 2022). We convert the SQuAD reading comprehension dataset (Rajpurkar et al., 2018b) to a question generation dataset by concatenating the answer and context (with separators) and fine-tuning a sequence-to-sequence transformer model to predict the question. Specifically, we fine-tune the T5-11B checkpoint from Raffel et al. (2020); questions are decoded with a beam size of 4. During training, answer candidates are the answers provided in the SQuAD annotation. At inference time, answer candidates (i.e., base noun phrases and named entities) are identified in the output s using SpaCy² and questions are generated with the SQuAD trained system. This procedure yields

²<https://spacy.io/>.

a large list of QA pairs (see in Table 2 the questions generated for the summary at the bottom), which we reduce using the filtering explained below.

Question-Answer Blueprints Initially, we apply a *Round-trip Consistency* check (Alberti et al., 2019), which discards questions if they yield answers different from those used to generate them. In Table 2, Q₁₁ is discarded as the answer it is paired with is wrong (*1968* was the final year that Shelby American built the Mustang, not *1970*). The same is the case for Q₁₃, where the answer to the question ought to have been *the introduction of the of the fifth generation Ford Mustang*.

To decrease the number of QA pairs further, we chunk the text (bottom block in Table 2) into *propositions*—a proposition is a sub-sentential unit which represents a single claim or fact (Stanovsky et al., 2018; Ernst et al., 2022). We use propositions instead of sentences since the latter can be too long and contain multiple facts. We split text into propositions based on punctuation (period, comma, and semicolon), coordination (e.g., *and*, *but*), relative pronouns (e.g., *that*, *who*), and prepositions (e.g., *at*, *by*). Following this simple approach, the summary in Table 2 is split into six propositions, shown within square brackets. We next match each proposition to a

single QA pair heuristically, following a two-stage approach.

We first find the question whose answer is at the rightmost position within a proposition. If there are multiple such questions, we select the one with the longest answer. This first stage, which we call *Rheme*, is motivated by the theme-rheme structure (Vallduví and Vilkkuna, 1998) of natural language sentences: Already known information (i.e., the theme) is usually placed first while new information (i.e., the rheme) is placed later in a sentence or phrase (Kruijff-Korbayová and Steedman, 2003). Following this idea, Rheme selection prioritizes new-information seeking questions. As can be seen in Table 2, it eliminates several questions (e.g., Q₁–Q₄) as their answers are not the right most element in the obtained propositions. Questions Q₅ and Q₆ are identical, however we retain Q₅ as it yields the longest answer.

The second stage, which we call *Coverage*, prioritizes the selection of informative QA pairs by selecting non-overlapping ones. Specifically, we first convert s to a bag of tokens and select the QA pair with the highest lexical overlap. We then remove the overlapping tokens from s , and repeat this greedy selection process until the bag is empty or the overlap is zero. Table 2 shows how Coverage further eliminates QA pairs Q₅ and Q₈. The remaining four QA pairs constitute the final blueprint b . Rather than defaulting to a random order, we sort these based on the location of the answer spans in s (see the final order in Table 1).

3.3 Blueprint Models

We devised three seq-to-seq models, which differ in the way the output and its blueprint are generated.

End-to-End Model A straightforward approach would be to take d as input and learn to first predict blueprint b as $p(b|d)$, and then generate output s as $p(s|b)$. However, this approach crucially relies on the blueprint being accurate and capturing all required information, which might be overly optimistic, given that blueprints (for training) are generated automatically. Moreover, pipeline architectures are known to suffer from error propagation, which in our case would undoubtedly affect generation performance, the final stage of the pipeline.

Rather than modeling the blueprint and output generation stages separately, we train an encoder-decoder model to encode d and generate $b; s$ (i.e., the concatenation of the blueprint and output sequence) in one go. Essentially, the decoder first predicts blueprint b and then continues to generate output s , using both b and d . We prefix b and s with special markers “*Plan:*” and “*Summary:*”, respectively. In particular, we predict b as $a_1; q_1; \dots; a_m; q_m$, namely, a (concatenated) sequence of answer-question pairs.³ The model is trained with the standard maximum-likelihood objective to generate the augmented target $b; s$. Interestingly, in this end-to-end model the blueprint functions as a *macro-plan*, i.e., a *global* sketch of the content and organization of the output.

Multi-task Model It is generally challenging for encoder-decoder models to generate long output sequences (Ko and Li, 2020; Tan et al., 2021). The end-to-end model sketched above further amplifies this problem because it ultimately aims to generate sequence $b; s$ rather than just s , increasing the sequence length by 220% (see Table 3).

To mitigate this problem, we propose a multi-task model optimized to perform two separate tasks. Let a and q denote an ordered sequence of answers (a_1, \dots, a_m) and corresponding questions (q_1, \dots, q_m), in blueprint b . The model is trained to generate (a) the answer plan concatenated with output sequence $a; s$, and (b) the answer plan concatenated with questions $a; q$. In particular, we train a single encoder-decoder model to encode input d , while the decoder first predicts answer plan a (as $p(a|d)$) and then continues to generate output s (as $p(s|a, d)$) or corresponding questions q (as $p(q|a, d)$), depending on the task. We prefix a , q , and s with special markers “*Plan:*”, “*Questions:*”, and “*Summary:*”, respectively. We further prefix input d with “*Generate Summary:*” or “*Generate Questions:*” to instruct our model to generate output s or questions q , respectively. We sample data points from these two tasks with equal probability and train the model with the standard maximum-likelihood objective.

During inference, we use a two-step process to generate output s' and its blueprint b' for input d .

³Predicting b as $q_1; a_1; \dots; q_m; a_m$ is more natural, but, it led to inferior performance. See the ablation experiments in Section 5.3.

	AQuM	WCSum	SS-FD
# queries	8,162	—	—
# examples			
train	6,599	165,000	3,673
dev	714	8,723	338
test	849	9,166	337
source			
# docs	6.46	135.56	1.00
# words	12,986.88	7455.75	8051.74
# sentences	339.62	307.80	804.01
# words/doc	2,008.38	52.02	8051.74
target (original)			
# words	114.07	115.61	126.73
# sentences	3.65	4.74	5.26
novel unigrams	0.02	0.13	0.17
novel bigrams	0.13	0.54	0.66
novel trigrams	0.24	0.78	0.92
novel 4-grams	0.31	0.86	0.98
target (+blueprint)			
# QA-Pairs	8.16	9.56	28.10
# words	272.68	291.28	597.90

Table 3: Summary statistics for the datasets used in this work (AQuM, WCSum, and SS-FD are shorthands for AQuaMuse, WikiCatSum, and ScreenSumm-FD, respectively). We report on the number of queries, size of training, development, and test set, and average source and target length (in terms of documents, words, sentences, and words per document). We quantify the abstractiveness of the target by measuring the proportion of n -grams unseen in the source. We also report statistics on the target length augmented with the blueprint (number of QA pairs and words in total).

We first prefix d with “*Generate Summary:*” and generate a' ; s' , i.e., answer plan a' followed by output sequence s' . We then prefix d with “*Generate Questions:*”, prompt our decoder with the predicted answer plan a' and generate corresponding questions q' for blueprint b' . The multi-task model alleviates the length issue discussed above by learning to generate a ; s instead of b ; s . However, this comes at the expense of generation quality, since the model now conditions on the answers only, not question-answer pairs. As such, it can be viewed as an extension of FROST (Narayan et al., 2021) with the plan being a sequence of *answer spans* rather than *entity chains*. This model also creates a macro-plan of the output, however, less detailed compared to the end-to-end model.

Iterative Model Rather than predicting a global plan (i.e., answer plan a or blueprint b) prior

to generating output s , we employ an incremental approach that interleaves planning with text generation. Let output s consist of n sentences $\{s_1, s_2, \dots, s_n\}$; then, the corresponding blueprint b can be represented as $\{b_1, b_2, \dots, b_n\}$, where $b_i : \{(a_{j+1}^i, q_{j+1}^i), \dots, (a_{j+k}^i, q_{j+k}^i)\}$ consists of k question-answer pairs for sentence s_i . We train our model to iteratively plan and generate one sentence at a time, conditioning on the input and the output sentences generated so far. In particular, we train an encoder-decoder model where the encoder first encodes input d , while the decoder takes summary $\{s_1, \dots, s_i\}$ generated so far as a prompt and generates blueprint b_{i+1} for next sentence s_{i+1} , followed by sentence s_{i+1} itself.

The iterative model is trained on quadruples $\{(d, \phi, b_1, s_1), \dots, (d, s_{1,i}, b_{i+1}, s_{i+1}), \dots, (d, s_{1,n-1}, b_n, s_n), (d, s, b_{end}, s_{end})\}$, where ϕ is an empty context placeholder used to predict the first blueprint b_1 and corresponding first sentence s_1 , $(n+1)$ is the blueprint length, and $s_{1,i} = \{s_1, \dots, s_i\}$ are the output sentences generated so far; b_{end} and s_{end} are special tokens marking the end of the output prediction. We prefix $s_{1,i}$, b_i , and s_i with special markers “*Context:*”, “*Plan:*”, and “*Next Sentence:*”, respectively. We train the model with the standard maximum-likelihood objective to predict $s_{1,i}$; b_i ; s_i , however, we do not compute the loss for predicting context $s_{1,i}$ to avoid over-optimizing for sentences that appear at the beginning of the output.

The iterative approach does not create a global macro plan. Rather, it learns *micro* content plans and verbalizes them one-by-one, conditioning on previously generated sentences but not on previously generated QA pairs. Although it does not have a global document view like the end-to-end model, the iterative decoder cannot exceed the output sequence length as it plans and predicts one sentence at a time as b_i ; s_i , instead of generating b ; s in one go. And unlike the multi-task model, each sentence s_i is generated by conditioning on the full blueprint b_i (consisting of questions *and* answers).

4 Experimental Setup

4.1 Datasets

We evaluated our model on benchmarks representative of long-form question answering and summarization. Our datasets vary in terms of the

input given to the generation model (e.g., multiple documents or one, web pages, or dialogue transcripts), the user’s information need (e.g., answering a question or aggregating information), and summary style (e.g., genuinely abstractive vs extractive). Common features among them are very long inputs and multi-sentence output summaries. We summarize various dataset statistics in Table 3.

AQuaMuSe (Kulkarni et al., 2020, 2021) is a query-focused multi-document summarization dataset; it was created with the intent of simulating how a search engine might synthesize documents of high relevance to a user query. It consists of Google Natural Questions (Kwiatkowski et al., 2019) paired with web documents extracted from Common Crawl and long-form answers from Wikipedia. We approach this task as a generative QA problem where we take the query and associated web documents and generate a long-form answer to the query. We work on the split from Kulkarni et al. (2021); on average, each instance has 6.46 web documents (2,008 tokens per document), leading to very long input (12,987 tokens).

WikiCatSum (Perez-Beltrachini et al., 2019) is a topic-focused multi-document summarization dataset where the goal is to generate Wikipedia abstracts (i.e., lead article sections) from a large set of webpages related to an entity or a topic. It focuses on three entities, namely, Films (59,973 instances), Companies (62,545 instances), and Animals (60,816 instances). In experiments, we collate the different data subsets into one, which we refer to collectively as WikiCatSum. The input webpages are truncated to the first 800 tokens.

SummScreen-FD (Chen et al., 2022) is a recently released dialogue summarization dataset. It contains transcripts of TV episodes (e.g., Game of Thrones, CSI Las Vegas) and corresponding (community authored) summaries. The original dataset is divided into two complementary subsets; we use the ForeverDreaming (FD) subset released as part of the SCROLLS benchmark (Shaham et al., 2022), which incorporates episodes from 88 different shows. SummScreen-FD is a challenging testbed for several reasons. Plot details are often expressed indirectly in conversations between characters and are scattered across the entire tran-

script. The summarization task is highly compressive, a transcript the size of a book (on average 8,000 tokens; see Table 3) is condensed into a few sentences, and the evaluation of such summaries comes with its own challenges (e.g., it is not realistic to expect humans to read the transcript to be able to assess their quality).

We further analyze the characteristics of these datasets in Table 3. Long-form answers in AQuaMuSe are mostly extractive with only 2%, 13%, 24%, and 31% novel unigrams, bigrams, trigrams, and 4-grams, respectively. In comparison, summaries in WikiCatSum and SummScreen-FD are more abstractive; WikiCatSum abstracts have 13% novel unigrams, 54% bigrams, 78% trigrams, and 86% 4-grams, whereas in SummScreen-FD summaries 17% unigrams, 66% bigrams, 92% trigrams, and 98% 4-grams were not seen in the training. Interestingly, SummScreen-FD summaries have far more propositions than AQuaMuSe or WikiCatSum targets, leading to a much higher number for QA pairs in their blueprints (28.10 vs 8.16 or 9.56). This in turn makes the generation task for end-to-end models very challenging. The average summary length together with the blueprint annotations (i.e., b ; s) for SummScreen-FD is almost twice the size of WikiCatSum and AQuaMuSe (597.90 vs 291.28 and 272.68). The majority of questions in AQuaMuSe and WikiCatSum are *what* questions (76.0% and 74.2%, respectively), followed by *who*, *where*, *when*, and *how* questions. For SummScreen-FD, *what* and *who* questions are most popular (50.1% and 42.9%, respectively).

4.2 Comparison Systems

All our experiments used LONGT5 (Guo et al., 2021), an extension of the original T5 *encoder* (Raffel et al., 2020) with global-local attention sparsity patterns to handle long inputs. We compared a vanilla LONGT5⁴ model (xl, 3B parameters) fine-tuned on our datasets (with a maximum input sequence length of 4,096 tokens and a maximum output length of 512 tokens) against several blueprint variants. These include an end-to-end LONGT5 model (E2E) which first decodes blueprint b and then continues to decode output s ; a LONGT5 multitask model (MULTITASK) which jointly learns to predict the answer plan

⁴We used the publicly released checkpoints from <https://github.com/google-research/longt5>.

followed by either the output s or the questions in b ; and a LONGT5 iterative model (ITERATIVE) which plans and generates one sentence at a time.

In addition, we implemented a two-stage model (2-STAGE), which first creates blueprint b given input d and then generates output s given b and d as input. Finally, we also fine-tuned T5 (xl, 3B parameters) on our datasets with a maximum input sequence length of 1,024 tokens and a maximum output length of 256 tokens, as a baseline. We present these comparisons in Table 4 together with the performance of various state-of-the-art systems.

We fine-tuned all our models with a learning rate of 0.001 and a batch size of 128, for 50K steps. We select best checkpoints using average Rouge performance on validation sets. During inference, we use beam search with size 5 and alpha 0.8.

5 Automatic Evaluation

In this section we present experimental results using automatic evaluation metrics that assess overall summary (and blueprint) quality. Moreover, we quantify the extent to which automatically generated output is grounded to the blueprint and faithful to the input document/s.

5.1 Metrics

Summary and Blueprint Quality We evaluate summary quality automatically using (summary-level) Rouge F1 (Lin and Hovy, 2003). We report only RougeLSum⁵ in Table 4 for the sake of brevity. We also use RougeLSum to evaluate the quality of the automatically generated blueprint, i.e., the QA pairs and their order against the reference blueprint.

Informativeness and Grounding We evaluate informativeness using QA-based metrics. Specifically, following the reading comprehension literature (Rajpurkar et al., 2016, 2018b), we quantify the extent to which the generated text can answer all questions from its reference (*Informativeness*) and predicted blueprint (*Grounding*). Following Stelmakh et al. (2022), we use a RoBERTa model (Liu et al., 2019) fine-tuned on SQuAD-V2 for question-answering in both cases.⁶

⁵RougeLSum is very similar to ROUGE-L; while the latter is calculated on the summary as a whole, RougeLSum interprets newlines as sentence boundaries.

⁶This is a high performing model reaching 86.8% exact-match accuracy and 89.8% F1 on SQuAD.

Models	RougeLSum		QA-F1		ANLI
	summ.	bluepr.	inform.	ground.	entail.
HiBERT*	27.11	—	—	—	—
TextRank*	31.07	—	—	—	—
SiBERT*	30.79	—	—	—	—
AQuaMuse					
T5	41.53	—	19.77	—	70.01
LONGT5	61.43	—	39.22	—	82.52
2-STAGE	46.34	36.61	24.10	64.22	61.40
E2E	58.96 [†]	54.16 [†]	34.59	69.53	83.64 [†]
MULTITASK	59.24 [†]	54.88	37.87 [†]	52.01	83.37
ITERATIVE	56.48	52.92 [†]	36.04	69.37 [†]	84.77
WikiCatSum					
BART	39.73	—	—	—	—
REFLECT	42.17	—	—	—	—
T5	40.17	—	18.79	—	46.21
LONGT5	41.00	—	22.97	—	56.11
2-STAGE	37.84	24.27	17.78	79.48	49.68
E2E	39.78	45.40	19.22	82.88	60.56
MULTITASK	42.34	46.95	20.55 [†]	62.14	52.09
ITERATIVE	39.53	46.35 [†]	18.75	80.35 [†]	64.37
SummScreen					
R2T-BART	23.30	—	—	—	—
T5	25.84	—	3.31	—	0.78
LONGT5	31.22 [†]	—	7.59	—	8.40
2-STAGE	19.07	21.63	2.70	54.22	1.24
E2E	28.22	34.49	6.13	54.53	8.53
MULTITASK	31.88	35.23	7.06 [†]	21.15	9.57
ITERATIVE	29.86 [†]	39.36	7.55 [†]	70.83	20.84

Table 4: Results on AQuaMuSe, WikiCatSum, and SummScreen-FD test sets. Baseline and earlier SOTA models are presented in the top block and all blueprint models are shown in the bottom block. Models marked with * generate extractive summaries. HiBERT, TextRank, and SiBERT results on AQuaMuSe are taken from Kulkarni et al. (2021). BART and REFLECT (extract-then-abstract) results are taken from Song et al. (2022). Hybrid R2T-BART (content selection + generation) results are taken from Chen et al. (2022). Best results for each task are **boldfaced**. Scores that are not significantly different (using paired bootstrap resampling; $p < 0.05$) from the best score in each column are marked with a dagger (†).

Given generated text s' and question-answer pair (q_i, a_i) from the (reference or predicted) blueprint, we apply our question-answering model to s' to predict answer a'_i to question q_i . We then compute the token-level F1 score between predicted answer a'_i and ground truth answer a_i , and report the average.

Faithfulness Hallucinations are a widely known issue with neural abstractive summarization (Song et al., 2018; Maynez et al., 2020; Kryscinski et al.,

2020; Gabriel et al., 2021), especially when a sentence combines content from multiple sources (Lebanoff et al., 2019).

Following previous work (Maynez et al., 2020; Falke et al., 2019; Narayan et al., 2022; Honovich et al., 2022; Dušek and Kasner, 2020), we quantify the extent to which generated summaries are faithful to their input using textual entailment. We resort to textual entailment for two reasons; firstly, it is a relatively intuitive metric, all information in a summary should be entailed by the source or at least not conflict with it; secondly, recent studies (Maynez et al., 2020; Fischer et al., 2022) have shown that it correlates with human judgments of faithfulness across summarization datasets and tasks.

Following Honovich et al. (2022), we trained an entailment model by fine-tuning T5-11B (Raffel et al., 2020) on the Adversarial NLI dataset (ANLI; Nie et al., 2020). For each sentence (hypothesis) in the summary, we compute its entailment probability given the input (premise) and report the average across all sentences to obtain an overall score (Maynez et al., 2020).

More formally, let E denote a textual entailment model that predicts $E(a, b)$, namely, that text b is entailed by text a . The faithfulness score F of summary s containing sentences s_1, \dots, s_2 with respect to input D is computed as:

$$F(s) = \frac{1}{n} \sum_{i=1}^n E(D, s_i)$$

where n is the number of sentences in the summary. If the input is longer than the T5 maximum encode length, we split it, calculate the entailment probability per split, and take the maximum. We convert probabilities to binary labels using a threshold (1 if > 0.5 , and 0, otherwise).

We further validated our ANLI entailment scores against human judgments of faithfulness elicited as part of SummEval (Fabbri et al., 2021), a recently released dataset for assessing automated summarization metrics. Our entailment predictions correlate well with human ratings, achieving a Spearman’s rank correlation of $\rho = 0.774$.

5.2 Results

Why LONGT5 for Blueprint Models All the tasks we are dealing with require modeling input of highly complex nature, which is often very long (see Table 3). Our results in Table 4

(see Rouge/summary column) demonstrate that T5 models always fall behind LONGT5, underscoring the importance of sparse attention mechanisms for modeling long inputs. In fact, LONGT5 sets a new state of the art on AQUaMuSe and SummScreen-FD. On WikiCatSum, it is slightly worse than REFLECT (Song et al., 2022), an extract-then-abstract model which has a dedicated content selection module. Similar content selection techniques could also benefit LONGT5, however, we leave this to future work. We henceforth use LONGT5 as a base model for fine-tuning our blueprint models.

Blueprint Models and Rouge Compared to LONGT5, blueprint variants slightly underperform on AQUaMuse, but score better on WikiCatSum and SummScreen-FD (see MULTITASK model). All differences between LONGT5 and blueprint models are statistically significant using paired bootstrap resampling; $p < 0.05$). For a fair comparison, we always use a maximum decoder length of 512 tokens. With the exception of AQUaMuse, E2E is inferior to other blueprint models, which is not surprising since it has to generate much longer text (recall it predicts $b; s$ rather than simply s). Overall, MULTITASK is significantly better than other blueprint models on WikiCatSum but on par with ITERATIVE on SummScreen-FD.

Similar patterns emerge when evaluating the predicted blueprints against reference QA pairs, with ITERATIVE significantly outperforming the other two variants on SummScreen-FD. This could be due to the fact that SummScreen-FD summaries have far more propositions than AQUaMuSe or WikiCatSum targets; it is better to predict them one sentence at a time, rather than all together. With regard to WikiCatSum, the difference between MULTITASK and ITERATIVE is not significant (although MULTITASK has a slight numerical advantage) and both systems are significantly better than E2E. On AQUaMuSe, MULTITASK is significantly better than E2E and ITERATIVE.

Note that all 2-STAGE models are significantly worse in comparison to blueprint variants, when evaluating either their blueprints or summaries (in terms of Rouge). While our models learn to optimize blueprints and summaries *together*, 2-STAGE models are faced with the harder task of predicting the blueprint solely based on the input (text-to-data). Since the blueprints learned by the

first stage are of poor quality, the summaries generated in the second stage are also inferior.

Blueprint Models and Informativeness Our blueprint annotation of reference summaries naturally provides a more principled alternative to Rouge. We can now use QA pairs in *reference* blueprints to evaluate the informativeness of *predicted* summaries. Results follow a pattern overall similar to Rouge, however, this approach reveals the complexity of the different generation tasks better than Rouge. While we were able to achieve reasonably high Rouge across datasets, we are far from generating informative summaries. On SummScreen-FD, in particular, we achieve a maximum Rouge score of 31.88, but are able to answer correctly only 7.59% of reference questions using the predicted summaries.

Across datasets, LONGT5 performs on par with MULTITASK, the difference between the two models is not statistically significant, and the same is true of ITERATIVE on SummScreen.

Blueprint Models and Grounding The E2E and ITERATIVE variants are significantly better than MULTITASK in generating texts grounded to their predicted blueprints (see ground. column in Table 4). This is because both models generate text *conditioned* on their blueprints; E2E first predicts blueprint b and then continues to generate output s using both b and the input, whereas ITERATIVE plans and generates one sentence at a time as $b_i; s_i$. This is not the case with MULTITASK, which generates s conditioned on answer spans only. E2E performs slightly better than ITERATIVE on AQuaMuSe and WikiCatSum (differences are not statistically significant) but struggles on SummScreen-FD, where summaries are longer with more facts/propositions, requiring inference over long-range dependencies, and common sense reasoning. ITERATIVE seems the best option for grounded generation without sacrificing informativeness (ITERATIVE is most informative amongst blueprint models on SummScreen-FD, second best on AQuaMuSe, and third best on WikiCatSum).

ITERATIVE Is Most Faithful Model As far as faithfulness is concerned, ITERATIVE performs consistently better than E2E and MULTITASK, as well as T5 and LONGT5 models where text is gener-

Reference Summary
Grissom and Catherine investigate the death of a man found in a dumpster, who is found to have had a severe eating disorder. Meanwhile, Nick and Sara investigate the death of a couple at the brink of a bitter divorce, in which evidence seems to point to the couple's dog.
R2T-BART
Catherine Catherine, Sara and Grissom investigate the death of a man who was found dead in a garbage bin. The victim's wife, Lori Tinsley, was a poker player. The man's brother, Jesse Menyel, was also found dead. The case is complicated by the fact that the victim had a gun in his apartment. Meanwhile, Nick and Warrick investigate the murder of a woman who died in a car crash. The woman's husband, Greg Colletti, is the suspect.
LONGT5
Grissom and Catherine investigate when a man is found dead in a dumpster. They soon discover a lot more went on in the kitchen than cooking. Meanwhile Nick and Sara are called to the scene of a double homicide. The victims are a husband and his wife who were both in the process of selling off their rare records. Suspicion quickly falls on the wife's ex-boyfriend, but the evidence increasingly points to the husband.
E2E
Grissom, Nick and Catherine investigate when a man is found dead in a dumpster. Meanwhile a couple are found dead in their home. Sara and Nick investigate a case involving a record collection.
MULTITASK
Grissom and Catherine investigate when a man is found dead in the garbage. Their investigation leads to Jackpot's pretzels as the killer. Meanwhile Sara and Nick are called to a double murder when a husband and his wife are found dead in their home. When the husband and wife were found dead, their extensive record collection was also missing.
ITERATIVE
Grissom, Catherine and David investigate when a man is found dead in a dumpster. The man had been eating at a restaurant called Aunt Jackpot's Pretzels. They discover that he ate himself to death. Meanwhile Nick and Sara look into the disappearance of a husband and wife who are found dead in their home. Also missing is a record collection that the husband had been collecting. They discover that the wife's neck was slashed in the attack. CSIs track down Missy Halter, a woman who helped them find the records.

Table 5: System output and reference summary for SummScreen-FD (CSI S6.E9, “Dog Eat Dog”). Propositions which are not grounded to the input are in **red**. Generated questions from blueprint models are not shown due to space constraints.

ated from scratch without any planning (pairwise differences between ITERATIVE and comparison systems are all significant with the exception of E2E on AQuaMuse). On SummScreen-FD, ITERATIVE brings large gains on faithfulness without sacrificing informativeness (both in terms of Rouge and QA-F1). The ANLI score for ITERATIVE is 20.84, whereas it is below 10 for E2E and MULTITASK. E2E outperforms LONGT5 on AQuaMuSe and WikiCatSum, but gains are smaller compared to ITERATIVE.

We show examples of system output in Table 5, highlighting propositions that are *not* grounded to the input in **red**. E2E summaries are shorter, which is somewhat expected; the model has to decode both the plan and the summary and in cases where the blueprint is large (e.g., in SummScreen-FD),

Q1:	What breed existed but is no longer extinct? now extinct?
A1:	Old English Bulldogs
Q2:	Along with the Old English Bulldog and Toy Bulldog, what breed was considered extinct at the end of the 19th century? What was the Old English Bulldog bred for?
A2:	Bullenbeisser Fighting in public arenas
Old English Bulldogs refers to a breed of dog that once existed but is no extinct. At the end of the 19th century, three breeds – the Old English Bulldog, Toy Bulldog, and Bullenbeisser – were considered extinct.	
Old English Bulldogs refers to a breed of dog that existed but is now extinct. It was bred for fighting in public arenas.	

Table 6: Example of plan/summary generated by our E2E blueprint model as answer to the question ‘‘What is the difference between an Old English Bulldog and an English Bulldog?’’ (AQuaMuse test set); user edits to the plan and updated summary are shown in **red**.

there is no more room to decode the summary. MULTITASK is more verbose, however, the plan (a sequence of answer spans) is less detailed and as a result the summary less accurate (Jackpot’s pretzels is a restaurant, not a killer). ITERATIVE contains many details in the summary, more than the reference, which are *not* hallucinations. Both R2T-BART and LONGT5 are rather loose with the facts and generate multiple hallucinations.

Blueprint Models are Controllable Our conceptualization of text plans as QA pairs brings inherent controllability to the generation process. By changing the blueprint, we can control content selection (i.e., what to say) and planning (i.e., in what order) without retraining the model or introducing additional control mechanisms. We provide an example in Table 6 where the plan predicted by the E2E model has been edited to render it more coherent and factual. As can be seen, the model is able to change its output according to the modified plan. Another example is shown in Table 7, where the output is rendered shorter by removing QA pairs from the predicted plan.

We are also able to control the faithfulness of predicted summaries as follows. We take the predicted plan and remove question-answer pairs (E2E, ITERATIVE) or answer spans (MULTITASK) that cannot be answered based on the input. We then prompt our decoder with the modified plan and generate a new summary (or sentence for ITERATIVE). In Table 8, we quantitatively evaluate +drop variants, which are controlled for faithfulness against vanilla blueprint models. We observe improvements in entailment scores across

Q1:	Hinduism is an Indian religion and what else? A1: dharma
Q2:	Hinduism is a way of what? A2: life
Q3:	Hinduism has been called what in the world? A3: the oldest religion
Q4:	Who call Hinduism Sanatana Dharma? A4: some practitioners
Q5:	What does Sanatana Dharma mean? A5: the eternal tradition
Q6:	Scholars regard Hinduism as a fusion of various Indian cultures and what else? A6: traditions
Q7:	Hinduism has no founder and what else? A7: diverse roots
Q8:	What started to develop between 500 BCE and 300 CE? A8: This Hindu synthesis
Q9:	When did the Vedic period end? A9: 500 BCE

Hinduism is an Indian religion and dharma, or a way of life, widely practiced in the Indian subcontinent. Hinduism has been called the oldest religion in the world, and some practitioners and scholars refer to it as Santāna Dharma, ‘‘the eternal tradition’’, or the ‘‘eternal way’’, beyond human history. Scholars regard Hinduism as a fusion or synthesis of various Indian cultures and traditions, with diverse roots and no founder. This ‘‘Hindu synthesis’’ started to develop between 500 BCE and 300 CE, following the Vedic period (1500 BCE to 500 BCE).

Hinduism is an Indian religion and dharma, or a way of life, widely practiced in the Indian subcontinent.

Table 7: Example of plan/summary generated by the E2E blueprint model as answer to the question ‘‘What section of the world or country is hinduism usually found in?’’ (AQuaMuse test set); the part of the plan which is removed by the user is highlighted in **■**; the shorter summary generated from the elided plan is shown in **red**.

the board (see column entail. in the table), with the ITERATIVE+drop performing best. Improvements on abstractive datasets (WikiCatSum and SummScreen-FD) are larger compared to AQuaMuSe which is mostly extractive (see Table 3). The minor drop in Rouge and informativeness is somewhat expected as the models now zoom in on information they can *reliably* talk about, improving the consistency of the output.

Finally, we also experiment with creating simple summaries, by forcing the ITERATIVE model to generate from a *single* question-answer pair on each iteration (see +Q1 variant in Table 8). In the example shown in Table 9, ITERATIVE+Q1 produces simple summary sentences, each focusing on a single information element. Interestingly, as far as the ITERATIVE model is concerned, +Q1 variants are as faithful as +drop ones even if they do not explicitly control for faithfulness (across datasets the differences between the two models are not statistically significant). This suggests that controlling for simplicity might be sufficient to reduce hallucinations, however, at the expense of informativeness (Rouge scores for +Q1 variants

Models	Rouge (RLSum)		QA-F1	ANLI	
	summ.	bluepr.	inform.	entail.	
AQuaMuse	E2E	58.96 [†]	54.16 [†]	34.59	83.64 [†]
	+drop	58.74 [†]	52.71 [†]	34.64	83.98 [†]
	MULTITASK	59.24 [†]	54.88	37.87[†]	83.37 [†]
	+drop	59.25	53.79 [†]	37.57	84.98 [†]
	ITERATIVE	56.48	52.92 [†]	36.04	84.77 [†]
	+drop	56.30	46.62	36.03	85.50 [†]
	+Q1	55.57	52.29 [†]	34.97	85.74
WikiCatSum	E2E	39.78	45.40	19.22 [†]	60.56
	+drop	37.35	36.00	17.74	64.38
	MULTITASK	42.34	46.95	20.55	52.09
	+drop	40.65	36.45	19.29 [†]	56.71
	ITERATIVE	39.53	46.35 [†]	18.75	64.37
	+drop	38.80	41.78	18.14	66.56
	+Q1	38.80	43.81	18.91	65.42 [†]
SummScreen	E2E	28.22	34.49	6.13	8.53
	+drop	25.50	23.22	5.28	10.00
	MULTITASK	31.88	35.23	7.06 [†]	9.57
	+drop	30.40 [†]	24.75	6.10	12.23
	ITERATIVE	29.86 [†]	39.36	7.55	20.84 [†]
	+drop	28.10	32.25	6.43	24.12 [†]
	+Q1	27.94	29.47	6.63	24.80

Table 8: Controllability results on the AQuaMuSe, WikiCatSum and SummScreen-FD test sets. Lighter blue color means more control. Best results for each metric are **boldfaced**. Scores that are not significantly different (using paired bootstrap resampling; $p < 0.05$) from the best score for each column are marked with a dagger ([†]).

tend to be significantly worse compared to +drop counterparts).

Most of the controllability cases we illustrate here are fully automatic and could be conceptualized as system flags that users select according to requirements (e.g., low tolerance for hallucinations, shorter summaries for small screen displays). Another potential use case would be to generate summaries for a set of questions provided by the user. Their input might be articles retrieved as an answer to a query, or in an educational context several chapters on a topic (e.g., cell biology). However, we leave this to future work.

5.3 Ablation Studies

As described in Section 3.2, we construct blueprint annotations using the Rheme- and Coverage-based selection strategies. Table 10 presents various ablations that provide rationales for these

ITERATIVE	
Q ₁ : In what country was Abraham Verghese born? A ₁ : Ethiopia	Abraham Verghese was born in Ethiopia, while his parents, teachers from Kerala, India, lived there.
Q ₂ : From what country did Verghese’s parents come? A ₂ : India	
Q ₃ : Cutting for Stone is set in Ethiopia and what other country? A ₃ : the United States	The main characters in this gripping family saga, set in Ethiopia and the United States, are two physicians from India.
Q ₄ : What are the main characters in Cutting for Stone? A ₄ : two physicians	
Q ₅ : In what year did Cutting for Stone win the Man Booker Prize? A ₅ : 2007	Cutting for Stone won the Man Booker Prize in 2007.
Q ₆ : Who is the author of Cutting for Stone? A ₆ : Ethiopian-born Verghese	The author is Ethiopian-born Verghese.
ITERATIVE+Q1	
Q ₁ : In what country was Abraham Verghese born? A ₁ : Ethiopia	Abraham Verghese was born in Ethiopia.
Q ₂ : From what country did Verghese’s parents come? A ₂ : India	His parents were teachers from Kerala, India.
Q ₃ : Cutting for Stone is set in Ethiopia and what other country? A ₃ : the United States	Cutting for Stone is a gripping family saga, set in Ethiopia.
Q ₄ : What are the main characters in Cutting for Stone? A ₄ : two physicians	The main characters are two physicians from India.

Table 9: System output from ITERATIVE and ITERATIVE+Q1 generating WikiCatSum abstract on “Abraham Verghese.”

E2E	Rouge (RLSum)		
	summary	blueprint	both
QA Plan, Rheme, Covg, Sorted	48.75	39.06	44.31
AQ Plan, Rheme, Covg, Sorted	50.86	39.95	45.60
–Sorted, Random	50.79	36.08	43.43
–Rheme	47.16	40.70	44.19
–Coverage	47.02	41.37	44.79
–Rheme, –Coverage	18.05	42.54	40.90

Table 10: E2E model trained on AQuaMuSe with different selection and sorting (validation set).

annotation choices. For the sake of brevity, we report experiments with the E2E model trained (for 50,000 steps) on AQuaMuSe. We observe very similar trends on the other two datasets. As can be seen, it is empirically better to form blueprints from answer-question pairs rather than predicting the questions first and then their answers which is more natural (at least to humans). We further assessed whether sorting the QA pairs based on how they appear in the summary matters by defaulting to a random ordering (see –Sorted in the table). Removing either Rheme or Coverage has a small negative impact on the summaries but not their blueprints, while removing them both is detrimental to summary quality, while the absence of Sorting mostly affects the quality of the blueprint. It is not surprising that sorting is most important to generating a blueprint with correctly ordered propositions.

6 Human-based Evaluation

In addition to automatic evaluation, we conducted three human-based studies assessing different dimensions of output quality. Wishing to avoid well-documented issues⁷ with automated bots on Amazon Mechanical Turk and crowdworkers running through HITs as quickly as possible without paying attention to the tasks, we used a few trained annotators. They were given task-specific instructions and went through several pilots to iron out disagreements on edge cases.⁸

6.1 Summary Quality

Our first study assessed overall *summary quality*. Specifically, we asked our annotators to select the best among three system summaries taking into account how much they deviated from the reference in terms of *informativeness* (are the summaries on topic or emphasize irrelevant details?) and overall *fluency*. We adapted the definition of fluency provided in Howcroft et al. (2020): Does the text ‘flow well’ or is it a sequence of unconnected parts?

We conducted our annotation study on 100 instances, each randomly sampled from AQUaMuse, WikiCatSum, and SumScreen. We collected ratings from three annotators (after two rounds of pilot studies to improve agreement) for the output of seven systems. Overall, we obtained 100 (instances) x 3 (datasets) x 6 (systems) x 3 (annotators) = 5,400 annotations. Annotator agreement was 97.11%. Our results are presented in Table 11. We report on percentage of times each system was ranked best.

In general, we observe that LONGT5 and blueprint models based on it are perceived as significantly better than previous state-of-the-art models (i.e., SiBERT and R2T-BART). On AQUaMuse, LONGT5 is rated overall best, followed by E2E and MULTITASK (however, differences between them are not statistically significant). On WikiCatSum, E2E is rated best but is not significantly different compared to the other models. On SummScreen, our ITERATIVE variant is rated best followed by LONGT5. These results mirror the difficulty of the task (see Table 3), the longer the input/output, the better ITERATIVE performs.

⁷<https://stanforddaily.com/2020/06/21/>.

⁸We release our instructions and annotation templates together with our data and models.

Models	summary quality ↑		
	AQuaMuse	WikiCatSum	SummScreen
SiBERT	0.12	—	—
R2T-BART	—	—	0.10
LONGT5	0.49	0.35 [†]	0.42 [†]
E2E	0.39 [†]	0.40	0.26
MULTITASK	0.39 [†]	0.37 [†]	0.39 [†]
ITERATIVE	0.30	0.28 [†]	0.44
+drop	0.31	0.27 [†]	0.39 [†]

Table 11: Proportion of times each system was ranked best for summary quality (on AQUaMuse, WikiCatSum, and SummScreen test sets). Best results for each task are **boldfaced**. Systems in each column are marked with † when they are not significantly different from the best system; unmarked pairwise differences from the best system are significant ($p < 0.01$; using Friedman’s ANOVA test (with post-hoc Wilcoxon signed-rank test, Bonferroni corrected for multiple comparisons)).

Blueprint Models	AQuaMuse		WikiCatSum		SummScreen	
	Coh↑	Red↓	Coh↑	Red↓	Coh↑	Red↓
E2E	2.83	8.30	2.94	4.70	2.43	49.3 [†]
MULTITASK	2.58	16.00 [†]	2.84 [†]	6.30 [†]	2.28 [†]	33.0
ITERATIVE	2.51	40.00	2.64	31.00	2.09	81.7
+drop	2.56	36.70	2.66	27.30	2.28	63.7
Gold	2.85 [†]	7.00 [†]	2.67	14.30 [†]	2.02	95.7

Table 12: Blueprint quality human evaluation on AQUaMuse, WikiCatSum, and SummScreen-FD test sets. Mean scores for coherence (Coh; higher is better) and proportion of QA pairs deemed redundant (Red; lower is better). Best results for each task are **boldfaced**. Systems in each column are marked with † when they are not statistically significant from the best system; unmarked pairwise differences from the best system are significant ($p < 0.01$; using a Friedman’s ANOVA test with post-hoc Wilcoxon signed-rank test, Bonferroni corrected for multiple comparisons).

6.2 Blueprint Quality

We further evaluated the predicted plans more directly. Participants were shown QA blueprints and asked to assess whether they tell a coherent story (are they all relevant and ordered comprehensively?) using a 3-point scale (where 3 is best and 1 is worst). They were also asked to evaluate whether the plans have redundant QA pairs; a QA pair is redundant if it does not add new information to the plan. We collected judgments for

Models	AQuaMuse			WikiCatSum			SummScreen		
	Absent↓	Contra↓	NewInfo↓	Absent↓	Contra↓	NewInfo↓	Absent↓	Contra↓	NewInfo↓
E2E	6.30 [†]	4.10 [†]	1.79 [†]	2.00 [†]	0.40	1.74	26.60	5.30 [†]	1.76 [†]
MULTITASK	13.20 [†]	13.60	2.06	5.80 [†]	3.70 [†]	1.91 [†]	63.00	8.70	2.60
ITERATIVE	5.00 [†]	2.50 [†]	1.77	2.80	2.90 [†]	1.90 [†]	12.00	2.80	1.53
+drop	4.90	2.30 [†]	1.86 [†]	3.60 [†]	2.10 [†]	1.74	14.20 [†]	3.60 [†]	1.89
Gold	3.60 [†]	2.40 [†]	1.88 [†]	1.60 [†]	1.80	2.02	4.50	3.90	1.39

Table 13: Human evaluation results for blueprint grounded generation on AQuaMuse, WikiCatSum, and SummScreen-FD test sets. Proportion of QA pairs *not* mentioned in the summary (Absent; lower is better); proportion of QA pairs with information contradictory to the summary (Contra; lower is better), and mean scores for new information present in the summary (NewInfo; lower is better). The best results for each task are **boldfaced**. Systems in each column are marked with † when they are not statistically significant from the best system; unmarked pairwise differences from the best system are significant ($p < 0.01$; using a Friedman’s ANOVA test with post-hoc Wilcoxon signed-rant test, Bonferroni corrected for multiple comparisons).

the same instances used in our summary quality evaluation from three annotators whose overall agreement was 97.87% and obtained a total of 100 (instances) x 3 (datasets) x 5 (systems) x 3 (raters) = 4,500 annotations.

Table 12 shows the results of this study. We report mean scores per dataset for all blueprint models. As an upper bound, we further elicited annotations for blueprints automatically created from *gold* standard reference summaries (see row Gold in the table). E2E generates the most coherent blueprints: Differences between E2E and all comparison systems are statistically significant with the exception of the gold standard. This is not surprising, since all QA pairs in E2E are generated together, whereas in MULTITASK the spans and their corresponding questions are generated separately. ITERATIVE only generates QA pairs for a sentence at a time and thus we would not expect it to be more coherent than models which generate a global document plan. With regard to redundancy, ITERATIVE blueprints are generally most redundant, which is again down to not having a global view of previously generated QA pairs. ITERATIVE further underscores issues with our question generation technology which is far from perfect, for example, several QA pairs are different on the surface but actually semantically equivalent, however, we have no means of detecting this without robust coreference resolution.

6.3 Blueprint Grounded Generation

We next examine whether model summaries are grounded to their blueprints. Specifically, we

asked our annotators to decide whether each QA pair in the blueprint is mentioned in the summary, and report the number of times it isn’t. Ideally, we would like the summary to follow the blueprint as closely as possible. For QA pairs mentioned in the summary, we further asked our annotators to highlight whether the intent of the question was preserved or contradicted (we report the number of contradictions). Finally, we also asked participants to decide whether the summary has *additional* information which cannot be found in its blueprint, using a 3-point scale (where 3 is for summaries with lots of new information and 1 is for summaries with no new information). We elicited annotations for blueprint models, and, as an upper bound, for gold summaries and blueprints extrapolated from them. We obtained 100 (instances) x 3 (datasets) x 5 (systems) x 3 (raters) = 4,500 judgments.

The results of our grounding experiments are summarized in Table 13. Across datasets, we observe that ITERATIVE summaries are most grounded. ITERATIVE blueprints have the least number of questions that are absent from or contradict their generated texts. ITERATIVE summaries also display the least amount of new information in relation to their blueprints. ITERATIVE+drop is slightly less grounded compared to ITERATIVE, however, this is not entirely surprising since we prompt the ITERATIVE model with externally modified blueprints (see ITERATIVE+drop in Table 13). Note that ITERATIVE+drop summaries are deemed more faithful than ITERATIVE summaries in automatic evaluation. The entailment scores improve for all three datasets (see Table 4).

7 Conclusion

In this work we proposed a novel plan-based approach to conditional generation. We conceptualized text plans as a sequence of QA pairs operating as a proxy for what to say and in what order. We developed Transformer-based models that generate by conditioning on a global QA blueprint plan (E2E, MULTITASK) or iteratively by planning and generating one sentence at a time (ITERATIVE). Experimental results across three challenging datasets demonstrate that blueprint models are inherently more informative than vanilla sequence-to-sequence approaches without a planning component. Among the three presented here (E2E, MULTITASK, ITERATIVE), we find that ITERATIVE is the best choice for grounded generation and suggests a promising direction for long-form generation.

Blueprint models offer several advantages compared to blackbox generation. Model predictions can be examined, and errors can be traced back to the blueprint, which in turn can reveal whether the output is informative and faithful to its input. The formulation of the blueprint plan as question-answer pairs makes it intuitive and user-friendly. We have discussed how blueprint models might be used in a human-in-the-loop setting, where users interact with and influence model predictions directly, e.g., by editing the blueprint length and content (as different blueprints lead to different outputs). In the future, we would like to use blueprints more directly to advance methods for training language models using reward learning (Sutton and Barto, 2018), e.g., based on whether the output answers the blueprint questions. Rather than eliciting expensive human feedback (Stiennon et al., 2020), blueprints could provide a cheaper automatic alternative. Finally, although we focused primarily on the generation problem in this work, we believe blueprints might also be useful as a general-purpose approach to retrieving and organizing important content, especially when faced with many and very long inputs.

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