Improving scripts with a memory of natural feedback

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Abstract
How can an end-user provide feedback if a deployed structured prediction model generates incorrect output? Our goal is to allow users to correct errors directly through interaction, without retraining, by giving feedback on the model’s output. We create a dynamic memory architecture with a growing memory of feedbacks about errors in the output. Given a new, unseen input, our model can use feedback from a similar, past erroneous state. On a script generation task, we show empirically that the model learns to apply feedback effectively (up to 30 points improvement), while avoiding similar past mistakes after deployment (up to 10 points improvement on an unseen set). This is a first step towards strengthening deployed models, potentially broadening their utility.

1 Introduction
While language models have achieved remarkable performance on several reasoning tasks (Wang et al., 2018; Talmor et al., 2019), they are still prone to mistakes (Bender and Koller, 2020). This is especially true in structured prediction settings because models can ignore the structural complexity of human language, and rely on simplistic and error-prone greedy search procedures (Martins, 2020). As a result, these models typically produce syntactically correct output structures but have commonsense issues that degenerate the output (Sakaguchi et al., 2021). In deployed models, end-users can report such commonsense issues and inconsistency errors in the generated output structures, but retraining these models is prohibitively costly.

Our goal is to allow users to correct such errors directly through interaction, without retraining – by giving feedback on the model’s output or explanation. We consider the class of problems where the model’s structured output is a graph of nodes and edges. Graphs have a rich structure and capture complex interactions between nodes. Consequently, graphs generated by models often have issues that an end user can highlight. Specifically, we find that current seq2seq models typically produce syntactically correct output structure but have commonsense issues that degenerate the output (Sakaguchi et al., 2021), and end-users can critique such commonsense issues via natural feedback (Talmor et al., 2020). Given a partially incorrect structure and end-user feedback, we aim to localize an erroneous node or edge in the graph and generate a repaired graph. Learning to repair structure poses two major challenges: First, the system needs to connect and jointly reason over the incorrect source structure and the user feedback. Second, existing works that do structured generation do not account for end-user feedback after deployment (Yasunaga et al., 2021).
Our key innovation is doing structured output repair using feedback by an end-user.

Our approach loosely follows some early AI systems that maintained a memory of output problems and how to fix them (Sussman, 1973; Hammond, 1986; Riesbeck, 1981), but here we use neural methods and interact with a user to provide corrective feedback. More recently, it has been shown that neural methods can use expert feedback that guides the model towards the gold output in specialized domains (e.g., SQL experts’ feedback for natural language database query parsing (Elgohary et al., 2021); and compiler feedback for code fixing in Yasunaga and Liang (2020)). In contrast, in our work corrections by an end-user are expressed in a general way that also applies to new problems, as the model learns to operationalize those corrections.

Our approach is to add a corrector module, operating on the original model’s output. The corrector module is trained to interpret natural language feedback from the user and correct that output using it and do the original task of generating output structures (that can be noisy). In particular, our goal is for user feedback to be general, applied to multiple samples, rather than specific edit operations on particular model output. We address this by introducing a dynamic memory of user interactions for an error scenario, so that feedback on one problem can also be used to correct future, similar problems.

To validate our approach, we use a recently published dataset, INTERSCRIPT (Tandon et al., 2021), containing tuples of an imperfect generated script, a piece of user feedback, and a revised script, where a script is a graph of events and their temporal ordering describing how to achieve a given goal. On this challenging task, we show that FBNET can revise the scripts using natural feedback, leading to 10x improvement over a baseline that does not use feedback. We also show that our memory architecture is effective as it improves performance by 10% on unseen instances by growing and using the memory after deployment. The empirical evidence and ideas presented in this work are a first step towards strengthening deployed large-scale models, potentially broadening their utility.

2 Related work

Language-based interactive learning: Interactive learning involves a human in the loop, as opposed to learning from datasets collected offline. Language-based interactions typically involve controlled settings for simpler task setups and evaluation (Mehta and Goldwasser, 2019; Wang et al., 2016). However, they do not generalize to real-world settings because human feedback is rich and unrestricted.

Some approaches treat the model as a black box (e.g., machine teaching (Dasgupta et al., 2019; Talmor et al., 2020)). In such approaches when the model incorrectly answers a question like whether A whale has a belly button, then a user tells the model the explicit rule A mammal has a belly button. The model then corrects its answer by combining the feedback with its implicit knowledge, e.g., that A whale is a mammal. A downside is that it is not clear to the end-user what reasoning, if any, the model did to arrive at the answer.

In other approaches, the model’s reasoning is in some form exposed to critique. For example, Elgohary et al. (2021) fix natural sentences to SQL query parsing using feedback on the parsed structure – replace course id with program id. This feedback, given by domain experts is explicit, and can be parsed into structure edit commands that can be executed on the incorrect structure to fix it. However, this limits the generality of the approach.

Our work is uniquely positioned: we present the first system, with interactive feedback from end-users rather than experts on a real, structured task. Moreover, end-users use unrestricted language as a source of injecting commonsense to steer the model away from illogical output structures. Finally, differently from existing work, our model relies on a memory of past feedbacks in related scenarios to avoid repeating past mistakes. Such a “reminder” of a similar problem in the past can be seen as a modern approach to failure-driven reminding, an important theme in earlier AI and Cognitive Science research (Riesbeck, 1981; Schank and Leake, 1989; Ross, 1984).

Automatic feedback on model errors Recently, Yasunaga and Liang (2021) proposed a break-it-fix-it system (BIFI) to fix syntax errors in C and Python code automatically. Our work is different from theirs because: i) BIFI operates on a domain with well-defined syntax (Python or C code). This provides access to objective measures of evaluating correctness (i.e., compiler), which does not exist for us. ii) BIFI assumes access to a large corpus of real-
We make two assumptions on the characteristics of write operation is used whenever a user gives new world coding errors made by real people (allowing the training of a “breaker”). Such a corpus may not be readily available for many real-world scenarios.

3 FBNET

3.1 Input-output

In our setup, the input is a potentially noisy structure \( x \) generated by a base model \( B \) and the output \( y \) is a corrected structure. At inference time i.e., after deployment, a user can critique \( y \) by providing natural language feedback \( fb \) on an error state \( e \). As output, the model generates the corrected structure \( y \) that accounts for \( fb \). The structure can be expressed in a string representation using a graph description language such as DOT.

3.2 Assumptions

We make two assumptions on the characteristics of the feedback and the input.

A1. The base model \( B \) typically produces syntactically correct output structure but can have commonsense issues that degenerates the output, and end-users can critique on these issues via natural feedback.

A2. If two examples \( i, j \) have similar error states \( e_i \) and \( e_j \) then the feedback for one should apply to the other, i.e., \((e_i \sim e_j \Leftrightarrow f_{bi} \sim f_{bj})\)

3.3 Overview of the Architecture

Fig. 2 gives an overview of FBNET. The base model \( B \) is a frozen model capable of solving a (structured) task. It cannot take any user feedback. The corrector model is responsible for taking the feedback and the input.

3.4 Memory \( M \) and \( \Omega \)

The feedback is stored in a memory of key (x), value (fb) pairs. \( \Omega \) is a retrieval function that matches a query key (\( x_j \)) to a similar \( x_i \) in memory implicitly on the similarity of the error states \( e_i \) and \( e_j \). We use a BERT-based Sentence Transformer to encode \( x \) (Reimers and Gurevych, 2019), and we use cosine distance with a threshold of 0.9 to find a matching key \( x_m \). We leave investigation of more complex retrieval functions (e.g., using attention mechanism to future work.)

3.5 Corrector model

The graph corrector model \( G \) generates \( y \) given \( x \) and \( fb \). This is done in a two-step process, (i) learning to predict a graph edit operation \( y^e \) given \( x \) and \( fb \) (ii) using simple graph operations to apply \( y^e \) to \( x \) to produce \( y \). We find that edit operations are more usable than generating entire scripts for two reasons. First, generating edits is simpler for the model as compared to generating entire graphs. Second, it simplifies evaluation metrics as it is much simpler to compare two smaller generated edits. Note that given an edit we can deterministically fix a script, and thus the two-step process helps us in achieving the same end goal (corrected scripts from noisy scripts and feedback). To train the corrector, we require training examples in form of \((x, fb, y^e)\) triples. The input structure \( x \) can be expressed in a string representation using a graph description language such as DOT.

3.6 Training and Inference

As mentioned, the graph corrector \( G \) first generates an edit, which is applied to the incorrect graph \( x \) to generate the correct graph \( y \). We leverage a corpus
of \((x, fb, y)\) to train this system. Specifically, we extract an edit from each such tuple, where edit \(y^c\) is the difference between the output \(y\) and the input \(x\). We then train a language model to estimate \( P_\theta(y^c \mid x, fb)\), which allows us to generate an edit for a given \((x, fb)\) using greedy sampling, where \(\theta\) denotes the parameters of the language model.

We initialize \(\theta\) with a checkpoint from the text-to-text pretrained T5 transformer \(\text{(Raffel et al., 2020)}\) and fine-tune on our dataset. We use the default hyperparameters (including the Adafactor optimizer) in the T5 library.\(^1\) We fine-tune a T5-XXL model for the main results, fine-tuned for 5,000 steps (batch size 8), selecting the checkpoint with highest validation score (usually the final step).

**Generality of the method** In principle, we could apply our method to any structured prediction task. In this paper, we consider the challenging task of script generation where given a goal, we generate a partially ordered event sequence, the dataset and task is described next.

## 4 Experiments

We now present the results of applying FBNET to a structured prediction task of script generation, where the input is a goal and output is a script. A script is a graph of events and their temporal ordering which describes how to achieve a given goal. Our objective is to improve the output of an existing script generation model, by feedback from end users. See Figure 1 for an example. We empirically evaluate two questions: 1) how effectively does the model react to feedback? and 2) To what extent does the memory improve performance on unseen examples by using past feedback on related inputs.

### 4.1 Experimental setup

**Dataset** We use a recently published dataset, InterScript \(\text{(Tandon et al., 2021)}\), containing tuples of an imperfect generated script, a piece of user feedback, and a revised script. Table 1 shows some examples in the dataset. This dataset lends itself to our task of given \(x\) and \(fb\), generate \(y\). This dataset also satisfies the assumptions in §3.2 on the B (T5-XXL model was the base model for InterScript which exhibits the desired properties), and the nature of the feedback (feedbacks in InterScript are general principle in nature so they would transfer across examples). The input scripts are syntactically valid and the dataset provides the differences between the output script and input script in the form of a graph edit operation (insert node, delete node, change edge order). The dataset contains 1,566 data points, randomly split into train (843 points), validation (154 points), test (545 points). \(x\) can be present in more than data points as there can be a diverse set of \(fb\) that apply to \(x\) see Table 4 that illustrates different natural feedbacks for the same error and possibly correcting various errors present in the script.

**Metrics:** We compare the gold edit \(y^c^*\) and the generated \(y^c\) edit. For example, the gold edit for example 1 in Table 1 will be: “insert node *wake up* and *turn off the alarm* before *get out of bed*”. We use two different metrics:

- **Exact match:** This metric gives a score of 1 if \(y^c^*\) is equal to \(y^c\) and 0 otherwise.
- **Human:** Sampled human evaluation to account for any lexically similar edits that do not exactly match.

We also provide scores for fine-grained evaluation comparing the components of \(y^c\) because the edit template looks like: [EDIT TYPE] over \([ARG]\) [NODE/EDGE] at \([LOCATION]\).

**Baseline** As baseline, we use the model that does not use any feedback (NO-FB) and is trained only with \(input = \) erroneous script and \(output = \) edit. The language model used in this baseline and FBNET is the same (T5-XXL), allowing a meaningful comparison.

### 4.2 Main result 1

**Does FBNET react to feedback?** Table 2 shows that FBNET learns to react to the feedback. There is an order of magnitude improvement over the baseline trained on the same setup as FBNET but without any feedback. We find that the model is good at identifying the error type that the feedback indicates, but it is difficult for the model to localize the error in the graph, probably because the location is not explicitly mentioned in the feedback, and the model needs to infer it.

### 4.2.1 Error analysis

We randomly sampled 50 instances from the test set where the model generates an incorrect edit (judged by exact match). Since automated metrics are limited in their ability to reflect the strengths and weaknesses of a generation model, our goal is to under-

\(^1\)https://github.com/google-research/text-to-text-transfer-transformer
1. decided to do yoga in the morning
2. set alarm for early morning
3. get out of bed;
4. prepare for yoga;
5. go to the bathroom;
6. do yoga;
7. do yoga in the morning

People don’t leave their alarms ringing all day.

1. decided to do yoga in the morning;
2. set alarm for early morning;
3. wake up and turn off the alarm;
4. get out of bed;

... 3. put on shoes; ...
5. open the door;
6. drive to the train station; ...
7. get into the car
8. reach the train station

You don’t need to look for a butterfly if it’s already in a container.

1. ...
3. pick up the butterfly;
4. put the butterfly in a container;
5. look for a butterfly; ...
6. Take the butterfly home ...

You don’t need to look for a butterfly if it’s already in a container.

1. ... 3. pick up the butterfly;
4. put the butterfly in a container;
5. Take the butterfly home ...

Table 1: Task: examples from the InterScript dataset. The task contains errors where there are obvious missing steps, wrong order, or, wrong steps.

| Input script | Feedback | Output fixed script |
|--------------|----------|---------------------|
| 1. decided to do yoga in the morning 2. set alarm for early morning 3. get out of bed; 4. prepare for yoga; 5. go to the bathroom; 6. do yoga; 7. do yoga in the morning | People don’t leave their alarms ringing all day. | 1. decided to do yoga in the morning; 2. set alarm for early morning; 3. wake up and turn off the alarm; 4. get out of bed; ...

... 3. put on shoes; ...
5. open the door;
6. drive to the train station; ...
7. get into the car
8. reach the train station

You don’t need to look for a butterfly if it’s already in a container.

1. ... 3. pick up the butterfly;
4. put the butterfly in a container;
5. Take the butterfly home ...

Table 2: FBNET learns to react to feedback: there is an order of magnitude improvement over the baseline trained on the same setup as FBNET but without any feedback. Two ablations (error location identification and error type identification) show that while error localization from implicit feedback is a hard subproblem, FBNET can perform error type identification given the feedback.

| NO-FB | FBNET |
|-------|-------|
| EM    | 3.54  | 38.6  |
| Err loc | 9.67  | 45.8  |
| Err type | 30.4  | 69.3  |

Table 2: FBNET learns to react to feedback: there is an order of magnitude improvement over the baseline trained on the same setup as FBNET but without any feedback. Two ablations (error location identification and error type identification) show that while error localization from implicit feedback is a hard subproblem, FBNET can perform error type identification given the feedback.

- **Challenging feedback (24%)** The second most common type of error occurs when the feedback is too challenging or abstract. For example, for the goal “go to locker room,” the generated script repeats the step “walk to the locker room.” The feedback is ‘can’t go where you already are’, and FBNET generates the edit “reorder edge between ‘( walk towards the locker room , walk to the locker room )’ ” which is incorrect.

- **Error not localized (20%)** A number of errors step from FBNET failing to locate the error location from the feedback. For example consider the input erroneous script about the goal buy an xbox: 1. go to the store 2. talk to the cashier 3. make the transaction 4. get the receipt 5. load the video game into the car 6. get into the car 7. take xbox home The feedback is after a person makes a transaction, they then head to their car. The expected edit is: insert node ‘walk to the car’ after ‘get the receipt’, but the predicted edit insert node ‘get into the car’ after ‘make the transaction’ does not correctly identify the erroneous node.

- **Alternative answers (16%)** We also encounter cases where there are multiple ways

• **Lexical variation (36%)** Exact match is strict and might underestimate the performance of a model on generation tasks. We find the same to be the case here; a large majority of the model predicted edits are actually correct and are different from the correct edit in benign ways. Common examples of such cases include the model generating picking a book vs, choosing a book to read, or suggesting a reordering of edges A and B vs. edges B and A.

• **Stand the typical errors made by the model and use the analysis to calibrate the findings in Table 2.**
Table 3: **Memory is effective in recalling past feedback on related scenarios**: FBNET can use past scenarios from test time, and leads to $\sim 10$ exact match points improvement on the challenging task. Two ablations (error location identification and error type identification) show that error localization is hard.

|       | NO-FB | FBNET | ORACLE-FB |
|-------|-------|-------|-----------|
| EM    | 6.94  | 16.72 | 22.2      |
| Err loc | 15.3  | 20.9  | 27.8      |
| Err type | 34.7  | 56.9  | 72.2      |

To correct a script. For example, an edit can be expressed as insert node ‘A’ before ‘step 4’ or insert node ‘A’ after ‘step 3’. Similar to errors caused by lexical variations, these errors show that exact match is too stringent.

Our error analysis found in about 32% of the cases, the model generated edit is correct, and is marked wrong by the strict exact match metric. Extrapolating this under-counting to the entire test set, the accuracy of FBNET in Table 2 increases to $\sim 70\% (+32\%)$.

### 4.3 Main result 2

We test performance over the interaction set which comprises of topics that are never seen during training. As the memory keeps building over test instances, we find that the accuracy over similar/analogous scripts and errors also improves. This is due to effective recall from the memory, thus leading to past feedback being applied on future instances in a zero shot setting. See Table 3 for the results.

#### How well can FBNET do retrieval?

The model was able to correctly retrieve relevant past entries from the memory, 80% of the times. As reported in Table 2, the model is not perfect at applying feedbacks, so the scores on the interaction set in Table 3 are relatively low. By improving the exact match performance of FBNET on applying feedbacks, the scores on the interaction set should also increase substantially. Note that many of the generated edits are still lexically similar to the expected edit.

#### How well can FBNET apply a retrieved feedback that is not directly applicable.

If we retrieve the most related entry in the memory, it may be applicable to the goal in the question at an abstract level. For example, to correct a mistake in a script that has an incorrectly generated step: a school door should be locked by a student upon leaving the school, the relevant retrieved feedback is *don’t lock the door when leaving the hotel - the staff will*. This retrieved feedback is not directly applicable but we find that the model is able to effectively apply such feedbacks 70% of the times - implying that to some extent, the model is able to use the general principle in a feedback.

### 5 Summary

Our goal is to create a system that can continuously improve the structured output of a model. Our approach is to train an error correction model that uses natural language (NL) feedback to correct errors in that output. We have presented the first step towards this goal, showing that an error correction module can learn to interpret NL feedback successfully, resulting in 40% fewer errors in script generation. We have also described ongoing work on the next step, namely adding a memory layer where human feedback is stored and later retrieved efficiently. Together, these offer a possible path to systems that can continuously improve their output over time, with progressively less feedback and without retraining.
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