Proto-Gen: An end-to-end neural generator for persona and knowledge grounded response generation

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Abstract
In this paper we detail the implementation of Proto-Gen, an end-to-end neural response generator capable of selecting appropriate persona and fact sentences from available options, and generating persona and fact grounded responses. Incorporating a novel interaction layer in an encoder-decoder architecture, Proto-Gen facilitates learning dependencies between facts, persona and the context, and outperforms existing baselines on the FoCus dataset for both the sub-tasks of persona and fact selection, and response generation. We further fine tune Proto-Gen’s hyperparameters, and share our results and findings.

1 Introduction
With the growth of neural methods for language modelling, the task of response generation in the field of open domain dialogue and interactive systems have witnessed significant improvements. Incorporating transformer (Vaswani et al., 2017) based architectures with billions of parameters, and trained on large training corpora, such models (Radford et al., 2019; Zhang et al., 2020; Roller et al., 2021; Xu et al., 2022) have advanced the state-of-the-art in response generation. However, trained with the objective of generating the next response by conditioning only on the context, such models often result in unnatural and hallucinated responses (Rashkin et al., 2021), which if not addressed appropriately, hampers its usefulness in practical settings (Saha et al., 2021).

Although recent years have witnessed advancements in response generators which can factor in external knowledge (Dinan et al., 2019; Gopalakrishnan et al., 2019) and exhibit certain human-like features like personality traits, emotions, etc (Mairesse and Walker, 2007; Zhang et al., 2018; Rashkin et al., 2019; Saha et al., 2022), research in response generators that can generate user-centric responses by factoring both user persona and external knowledge is still an unsolved problem. In this paper we propose Proto-Gen, an end-to-end response generator that can select the most appropriate fact and user persona sentences based on the conversation context, and generate a response customized for the user.

2 Task an Data Description
The task aims at engendering intelligent response generators that can generate appropriate response to user queries by factoring in the user’s persona along with available external facts. It is further divided into two sub-tasks:

- Personality sentences and knowledge prediction: With the inputs being 5 persona candidates of the user, 10 knowledge candidates pertaining to the topic of discussion, and the conversation context, this sub-task requires predicting the correct persona and knowledge sentence which can be used for generating the response.
- Response generation: This sub-task requires generating the agent response to the user query in natural language, using persona and knowledge sentences.

The dataset (Jang et al., 2022) comprises 14,452 persona-knowledge dialogues (11,562 training, 1,445 validation, and 1,445 testing) pertaining to discussions about landmarks such as Statue of Liberty, Eiffel Tower, The Great Wall, etc.

3 Methods
As illustrated in Figure 1, we implement an end-to-end encoder-decoder based architecture for jointly performing all sub-tasks. Below we discuss each component in detail.

3.1 Encoding
The encoding layer comprises two BART (Lewis et al., 2020) based encoders: (i) Query Encoder
for encoding the conversation context and query. (ii) **Persona/Fact Encoder** for sequentially encoding the available persona and fact sentences. First the query encoder $Q_{\text{Enc}}$ encodes the context CTX, which comprises the last 128 tokens of the concatenated previous turns and the current user query (Equation 1). The persona and fact encoder $PF_{\text{Enc}}$ sequentially encodes each of the 5 persona and 10 knowledge sentences, which are further combined with the encoded context $E_{CTX}$ using multi-headed attention $\text{MHA}$ followed by dropout $\text{Drop}$ (Equations 2 to 5), to yield the final persona and fact encodings $E_{PER}$ and $E_{FCT}$.

$$E_{CTX} = Q_{\text{Enc}}(CTX)$$  
(1)

$$E_{PER} = PF_{\text{Enc}}(P_i)_{i=1}^{5}$$  
(2)

$$E_{FCT} = PF_{\text{Enc}}(F_i)_{i=1}^{10}$$  
(3)

$$E_{PER} = E_{PERS} + \text{Drop}(\text{MHA}(E_{PER}, E_{CTX}))_{i=1}^{5}$$  
(4)

$$E_{FCT} = E_{FCTS} + \text{Drop}(\text{MHA}(E_{FCT}, E_{CTX}))_{i=1}^{10}$$  
(5)

### 3.2 Interaction Layer

The interaction layer captures interactions between the context and the presented persona and fact sentences, for determining the best suited persona and fact sentences for generating the current response. The layer inputs the encoded context $E_{CTX}$, persona $E_{PER}$ and fact sentences $E_{FCT}$, and outputs a final concatenated representation $E_{ENC}$ for the decoder.

For determining the most appropriate persona and fact sentences for the current turn’s response, the interaction layer utilizes fully-connected neural networks (FNN) which input a concatenated representation of:

1. **Biaffine Interaction Logits**: The logits $sc$ from a biaffine classifier which captures the interactions between the input persona and fact sentences. Biaffine classifiers are generalizations of linear classifiers, which include multiplicative interactions between two vectors (Dozat and Manning, 2016). Hence, we incorporate a biaffine layer for jointly determining the most appropriate persona and fact sentences for the current turn. Using layers of FNNs, the embedding of the start-of-sequence (SOS) token of both the fact and persona sentences are transformed to a reduced hidden size, which in turn are passed through a biaffine classifier to predict the most appropriate pair of persona and fact sentences for response generation (Equations 6 to 9). This layer is trained by minimizing the binary cross-entropy (BCE) loss between the predicted logits and the actual labels (Equation 16).

2. **Persona & Fact Prior Logits**: Depicted in Equations 10 and 11, FNNs are used to compute the prior probability of independently selecting each persona and fact sentence in the current turn. The FNNs inputs the representative persona and fact vectors $E_P$ and $E_F$ and yields the logits $\text{FNN}(E_P)$ and $\text{FNN}(E_F)$ for each sentence.

3. **Pre-computed Similarity Vector**: We input two additional vectors comprising normalized Levenshtein based similarity scores $^1$, which act as biases. (i) $F_{\text{sim}}$: A vector comprising unit normalized similarity scores between each factual sentence and the available Wikipedia knowledge for the landmark of discussion. (ii) $P_{\text{sim}}$: A vector comprising unit normalized similarity scores between the most similar fact from step (i), and the available persona sentences.

Equations 10 and 11 details the fact and persona prediction sub-tasks, which are trained by minimiz-

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1[https://pypi.org/project/fuzzywuzzy/]
We reuse BART’s decoder layers for decoding, which are pre-computed using Spacy.

\[
\lambda E = \text{Spacy}(\text{golden response})
\]

We experiment with different hyperparameter settings to engender multiple variants of the model. Specifically, we experiment with (i) Adding/removing the additional persona and fact similarity score vector as inputs in the interaction layer, (ii) Adding/removing the keyword based similarity score vector as inputs in the interaction layer, (iii) Using both the base and large versions of pre-trained BART, (iv) Adding dropout with a probability of 0.1 for regularization post concatenating the biaffine interaction logits, persona & fact prior logits and the pre-computed similarity vector in the interaction layer, (v) Sharing the same base encoder for encoding fact and persona sentences, (vi) Different values of the interpolation factor. Table 1 lists all the different hyperparameter settings that we experiment with, along with the resultant model ids.

### 4.3 Results and Observations

We train and evaluate all the model variants on the standard training and evaluation splits of the FocuS (Jang et al., 2022) dataset. For persona and knowledge selection (sub-task 1), we report overall accuracy scores-Persona Accuracy and Knowledge Accuracy, as well as Average Grounding-an average of the two accuracy scores. For response generation (sub-task 2), we report SacreBLEU (Post, 2018), CharF++ (Popović, 2015) and ROUGE-L.
| Model ID | Similarity Scores | Keyword Penalty | Base Model | Add Dropout | Persona & Fact Shared Encoder | Interpolation Factors |
|----------|------------------|----------------|-----------|-------------|-------------------------------|----------------------|
| 1        | yes              | no             | bart-base | yes         | yes                           | 0.7, 0.05, 0.15, 0.1, 0.0 |
| 2        | yes              | no             | bart-base | yes         | yes                           | 0.6, 0.2, 0.1, 0.1, 0.0 |
| 3        | yes              | no             | bart-base | yes         | no                            | 0.6, 0.2, 0.1, 0.1, 0.0 |
| 4        | yes              | no             | bart-base | no          | yes                           | 0.6, 0.2, 0.1, 0.1, 0.0 |
| 5        | yes              | no             | bart-large| no          | yes                           | 0.6, 0.2, 0.1, 0.1, 0.0 |
| 6        | yes              | yes            | bart-base | no          | yes                           | 0.6, 0.1, 0.1, 0.1, 0.1 |
| 7        | no               | yes            | bart-base | no          | yes                           | 0.6, 0.1, 0.1, 0.1, 0.1 |

Table 1: List of experiments with different hyperparameter settings

| Model ID | Persona Accuracy | Knowledge Accuracy | Average Grounding | Sacre BLEU | Char F++ | ROUGE L | Average Generation | Average Score |
|----------|------------------|--------------------|-------------------|------------|----------|--------|-------------------|--------------|
| (Jang et al., 2022)* | 86.86 | 65.06 | 75.96 | 10.87 | 27.90 | 30.99 | 23.26 | 49.61 |
| 1        | 77.26            | 32.49              | 54.87             | 8.58       | 28.08   | 21.81 | 19.49 | 37.18 |
| 2        | 86.38            | 80.36              | 83.37             | 18.91      | 40.07   | 38.03 | 32.34 | 57.85 |
| 3        | 86.16            | 74.24              | 80.20             | 18.19      | 40.10   | 36.27 | 31.52 | 55.86 |
| 4        | 85.02            | 85.18              | 85.10             | 19.85      | 42.32   | 38.84 | 33.67 | 59.39 |
| 5        | 87.75            | 68.72              | 78.23             | 18.35      | 39.68   | 38.14 | 32.00 | 55.14 |
| 6        | 84.00            | 83.09              | 83.54             | 19.28      | 41.74   | 38.14 | 33.05 | 58.30 |
| 7        | 85.35            | 79.42              | 82.39             | 19.39      | 41.90   | 38.00 | 33.10 | 57.74 |

Table 2: Results of the experiments from Table 1. The best score for each metric is highlighted in bold. * lists the best scores from the external baseline.

Table 2 shares the results of the experiments listed in Table 1. We make the following observations: (i) Comparing models 4 and 5, we observe that using bart-base as the base model generally outperforms bart-large, which we attribute to the smaller size of training data in comparison to the larger number of parameter updates required to train the large model. (ii) Comparing models 6 and 7, we see that incorporating the persona and fact similarity scores as additional vectors mostly results in better scores. This intuitively makes sense, as the similarity vector acts as an additional bias term for the model, which facilitates learning. (iii) Comparing models 4 and 6, we observe that adding the keyword based penalty term to the loss function does not seem to help learning. (iv) In comparison to model 4, adding dropout to the concatenated representation of the interaction layer in model 2 does not yield better results. We reason that since the base architecture already includes multiple regularization constrains, adding additional dropout layers hinders learning, specially because the size of the training data is small compared to the pre-training data of BART. (v) Comparing models 2 and 3, we observe that sharing the base encoder for encoding both persona and fact sentences, results in better scores. We attribute this to the fewer parameter updates required for parameter sharing. (vi) Comparing models 1 and 2, we note that a higher interpolation factor for biaffine classifier yields better overall scores, in comparison to fact and persona selection. Overall, we observe that model 4, which uses bart-base as the base model, inputs the additional similarity vectors, shares encoder for encoding persona and fact, while not adding additional dropout and keyword penalty, yields best results on the validation set.

5 Conclusion

Here we detail Proto-Gen, an end-to-end neural response generator, that can not only select appropriate persona and fact sentences from available input options, but also generate persona and knowledge grounded responses. Incorporating a novel interaction layer which includes biaffine classifiers and trained on the FoCus dataset, Proto-Gen outperforms existing external baselines for all sub-tasks. We further perform experiments to fine tune Proto-Gen’s hyperparameters, and report our results.
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