Linguistic calibration through metacognition: aligning dialogue agent responses with expected correctness

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Abstract

Open-domain dialogue agents have vastly improved, but still confidently hallucinate knowledge or express doubt when asked straightforward questions. In this work, we analyze whether state-of-the-art chit-chat models can express metacognition capabilities through their responses: does a verbalized expression of doubt (or confidence) match the likelihood that the model’s answer is incorrect (or correct)? We find that these models are poorly calibrated in this sense, yet we show that the representations within the models can be used to accurately predict likelihood of correctness. By incorporating these correctness predictions into the training of a controllable generation model, we obtain a dialogue agent with greatly improved linguistic calibration.

1 Introduction

Neural generative open-domain English-language dialogue agents have recently made progress towards the ability to carry on chit-chat conversations with humans (Adiwardana et al., 2020; Roller et al., 2020). Recent models—trained on large swaths of data from the internet to mimic human-human conversations—can name their favorite sports teams, describe what it’s like to be the owner of two dogs, or even share their opinions on tacos. However, ask a state-of-the-art chatbot “Which is heavier, 1 kg feathers or 1 kg stone?”, and it might confidently answer: “Feathers, because they are heavier than a kilogram of any other material.” Alternatively, it may express doubt and respond “I don’t know...” to an otherwise straightforward question as a result of a tendency to produce short, generic responses and overuse common phrases.

In this work, we seek to understand whether a model’s verbalized expression of confidence

1Answer generated by BST 2.7B (Roller et al., 2020).

“Obviously, ...”) or doubt (“I’m not sure, but...”) in its answer—which we refer to throughout as linguistic confidence—corresponds to the likelihood that the answer is correct, and if not, whether we can fine-tune the models with controlled generation techniques to achieve better alignment. In other words, do state-of-the-art open domain dialogue agents “know” what they do not know? If yes, can this knowledge inform their responses, to achieve better verbalized metacognition?

We thus make three main contributions. First, we annotate a state-of-the-art chit-chat model’s responses to a large-scale QA task for both factual correctness and linguistic confidence.² Next, us-
ing these annotations, we find that the model is poorly calibrated in the sense that linguistic confidence does not match factual correctness. On the other hand, we show that we can train a much better correctness predictor directly from the chit-chat model’s representations. Finally, we use this trained predictor within a controllable generation model to create a pipeline which greatly improves the calibration of a state-of-the-art chit-chat model.

2 Related Work

Knowledge in Open-Domain Chatbots This work focuses on neural generative open-domain dialogue agents, rather than general purpose language models or QA models trained to produce a factual answer given a question. Much progress has been made in recent years by training large-scale Transformer (Vaswani et al., 2017) encoder-decoder models for dialogue tasks (Roller et al., 2020; Adiwardana et al., 2020; Zhang et al., 2019). These sequence-to-sequence models are typically trained on large amounts of data from the internet to produce a conversational response given a dialogue history as input. Despite impressive performance on chit-chat tasks, these models are often prone to hallucinating knowledge (Roller et al., 2020). Dinan et al. (2019) and Gopalakrishnan et al. (2019) have proposed additional conditioning on a knowledge base to address this issue, but success is only partial, so we are far from being able to assume that even a knowledge-conditioned model reliably gives correct answers.

Overconfidence The Overconfidence effect is a well-studied phenomenon in humans which refers to the bias in which individuals’ assessments of their own accuracy (confidence) exceed their objective accuracy (correctness) (Pallier et al., 2002). It has been well-established in psychology research that humans tend to be overconfident—in other words, are poorly calibrated—when completing general knowledge tasks (Juslin, 1994; Kleitman and Stankov, 2001; Stankov and Crawford, 1996; Stankov, 1998). The work of Kamath et al. (2020) attempts to correct overconfidence in neural network models, by training QA models to abstain from answering questions in which they are likely to err, using probabilistic calibration (see next paragraph). We instead focus on getting conversational models to communicate their confidence verbally, so that they still produce an answer, but one that is not misleading as to how likely the answer is to be correct.

Probabilistic Calibration A large body of work has been dedicated to analysis (and correction of) the probabilistic calibration of deep neural networks. In particular, Guo et al. (2017) show that modern neural networks for classification tasks are poorly calibrated; in other words, the models’ confidence estimate ($\hat{P}$) that its answer ($\hat{Y}$) is correct ($\hat{Y} = Y^*$) is misaligned with the probability that it is indeed correct as measured by the joint distribution ($P(\hat{Y} = Y^*) \neq \hat{P}$). This contrasts with previous findings that show that (earlier) neural networks are well-calibrated on binary classification tasks (Niculescu-Mizil and Caruana, 2005). Throughout the rest of this paper, we refer to this notion of calibration as probabilistic calibration to distinguish it from linguistic calibration, which is the main focus of this work. In the latter, we measure linguistic confidence as opposed to the model’s probabilistic confidence estimates. More recently, probabilistic calibration has been explored in the space of large-scale language models (LMs). Desai and Durrett (2020) find that the pre-trained Transformers RoBERTa (Liu et al., 2019) and BERT (Devlin et al., 2019) are well-calibrated in-domain on the tasks Natural Language Inference (NLI), paraphrase detection, and commonsense reasoning. Similarly, Jagannatha and Yu (2020) calibrate BERT and DistilBERT (Sanh et al., 2019) for Part-of-Speech tagging (POS), Named Entity Recognition (NER), and QA tasks. As opposed to using LMs as target predictors on classification tasks like NLI and NER, Jiang et al. (2020) instead focus on LMs as natural language generators and analyze T5 (Raffel et al., 2020), a large scale Transformer with an encoder-decoder architecture. The authors find that it is poorly calibrated in its probability estimates on QA tasks. Conversely, Radford et al. (2019) find that GPT2 is reasonably well calibrated on QA tasks, with an accuracy of 63.1% on the 1% of questions it is most confident in on Natural Questions (Kwiatkowski et al., 2019).

Controlled Response Generation We aim to reformulate answers while controlling for their expressed certainty. This requires style transfer or controlled generation techniques, which encourage certain attributes to fit prescribed values, for example a given length or sentiment. Lample
et al. (2018) proposed a method to exert simultaneous control over multiple attributes based on concatenated learned control tokens. We similarly condition on an initial source text and concatenate multiple control tokens when generating responses. Keskar et al. (2019) trained a large-scale language model with control codes that govern style, content, and task-specific behavior. In the context of open-domain dialogue, See et al. (2019) used control on attributes such as number of questions with the aim of maximizing engagingness of dialogue models. Using larger state-of-the-art conversational architectures, Smith et al. (2020b); Madotto et al. (2020) compared several methods to achieve control in conversation; here, we use the simple method of training attribute-specific control tokens that was the most effective in Smith et al. (2020b) for a variety of styles. While our experiments in §5.3 suggest that good prediction performance can be achieved using just the question without yet committing to the substance of an answer, which would make less constrained text generation useful, the initial goal of this paper is to control the linguistic confidence of an answer without changing its substance. For this, techniques that condition on a source response are more relevant to us than less tightly constrained controlled techniques. Retrieve-and-refine generation (Weston et al., 2018; Roller et al., 2020) conditions on a possible answer, but does not control the style of the response. Here, we condition on the initial answer produced by a vanilla conversational model rather than a retrieval model, and then add additional control tokens to control the style.

3 Quantifying Linguistic Confidence

3.1 Linguistic Confidence

We aim to align a model’s expressed confidence with its actual correctness, rather than increase that correctness. We focus on models’ linguistic confidence, i.e., determined by its linguistic choices (e.g. “I don’t know, but...” vs. “Obviously, it’s…”). Do these models’ responses reflect whether they “know” what they do not know (metacognition)? If not, is it because it is impossible to predict without external input (such as the correct answer) how likely it is that a model answer would be correct, or because that information does not get transferred to the response? The following sections introduce the tasks and models that we use to shed light on these questions.

3.2 Closed-book QA as a testbed

The task of Question Answering (QA) traditionally has a model answer a general factoid question that a user might ask, allowing the model to consult given supporting evidence, e.g., search results or related Wikipedia articles, to give an answer. In this work, models do not have access to supporting evidence. Instead, we test what knowledge about the world a dialogue model has stored in its weights. Forcing a model to generate thus is called closed-book QA (Raffel et al., 2020) and any factoid-style question answering dataset can be used in this manner. Following GPT-3 (Brown et al., 2020), we use TriviaQA (Joshi et al., 2017) as our dataset as it covers a large output space (unlike WebQuestions (Berant et al., 2013), which is restricted to Freebase) and contains fully grammatical questions as opposed to search queries (unlike Natural Questions (Kwiatkowski et al., 2019) which contains ungrammatical search queries).

To convert it into a closed-book QA dataset we can use, we merge the “Web” and “Wikipedia” sections (including shared questions only once), remove all evidence, strip Wikipedia-based aliases of their “ (disambiguation)” suffix and use them to create a list of allowable gold answers. We end up with 76523 question-answer pairs in the training set and 9961 in the validation set. An example entry in this dataset looks like this:

What is the name of the tool used to sharpen a knife? (Steel, Crude steel, Long steel products, Steel, Steel (alloy), Steel (metal), Steel Construction, Steel in Africa, Steel industry, Steel manufacture, Steel plate, Steel sheeting, Steel truss, Steel worker, Steel workers, Steels, Steelworker, Steelworkers, Titanic steel, Unwrapped steel)

This example also illustrates that despite the list of aliases of the gold answer (“Steel,” given first in the otherwise alphabetically sorted list), evaluating correctness of answers may not always be so straightforward—consider this example answer:

 sometimes the task of Reading Comprehension is also referred to as QA, but there, models are given specific paragraphs of texts and asked to answer questions about that paragraph using that paragraph.

This answer was generated by the vanilla BST 2.7B model we consider in §3.5 and shows that human annota-
It is called a whetstone. It is a stone that is used for sharpening knives.

3.3 Annotation scheme

The answers that a chatbot gives for a question are full-length sentences that may or may not answer the question, may or may not do so correctly, and may or may not express confidence linguistically. We settle on relating such generations to the gold answer aliases in our dataset by having humans annotate generations according to the annotation scheme shown in Table 1. Unless the question is not even acknowledged as such (EVA, short for “evasive”), the chatbot’s response is judged for linguistic confidence and for correctness with respect to the provided gold answers. Figure 4 in the appendix illustrates all 13 resulting classes with example answers in the GUI that is presented to human annotators.

The fine-grained 4-way splitting of correctness is designed to provide guidance to human annotators and reduce ambiguity. After the initial annotation, we simplify all correctness annotations to binary correctness that better aligns with the type of linguistic framing we would like the model to be able to express, mapping OTHER and WRONG to incorrect (x) and EXTRA and RIGHT to correct (✓).

The 3-way splitting of confidence is intuitively richer than simply splitting along confident vs. not confident (YEA vs. not), however many responses were of the kind “I don’t know, but I know that...,” which makes them ambiguous. Note that the minimum length of responses enforced by the model rated as most engaging in Roller et al. (2020) precludes responding with a straight “I don’t know,” which likely makes the ambiguity more salient (see discussion of minimum length in §3.5). We nevertheless release the full 3-way annotations in case they are useful for further research.

3.4 Automatic annotation

Noting predictability in patterns of human annotation, we seek to quantify whether automatic annotation would be an adequate substitute. Table 2 indeed confirms that the simplified binary correctness annotations are highly predictable by simply checking whether any of the answer aliases appear in the generation (tokenized). We will refer to this way of scoring correctness as match-based and use it as an automatic proxy for human annotations when the latter is cost-prohibitive.

Linguistic confidence is harder to automatically

| Axis: correctness | human-annotated correctness |
|-------------------|-----------------------------|
| OTHER             | 4-way                     |
| WRONG             | binary                     |
| EXTRA             |                            |
| RIGHT             |                            |
| gold in           |
| answer?           | EVA | 0.56 | 0.28 | 0.11 | 0.67 |
|                    | IDK | 0.17 | 7.81 | 7.81 | 0.06 |
|                    | TRY | 0.06 | 14.67 | 34.63 | 0.11 |
|                    | YEA | 2.73 | 0.11 | 0.33 | 29.89 |

Table 2: Composition of the VALID SET (in % of total): comparing BERT-based linguistic confidence scoring to human annotations. Binarizing linguistic confidence into YEA and not-YEA, the classifier has 0.90 precision and 0.97 recall for detecting linguistic confidence.
infer using template- and match-based methods, as there are many ways to express doubt or confidence. Nevertheless, we find that we obtain usable predictions by training a BERT-based classifier on a set of 2000 annotated question-prediction pairs. We will refer to this way of classifying 4-way certainty (IDK, TRY, YEA, and EVA) as BERT-based and likewise use it extensively for training. This classifier works well (see Table 3) for distinguishing IDK/TRY from YEA, but struggles to discern between IDK and TRY (likely due to inconsistency in human annotation for this distinction, as noted above) and to a lesser degree EVA and YEA.

3.5 Models

Our base model is the state-of-the-art open-domain English-language dialogue system BlenderBot from Roller et al. (2020). “BlenderBot” refers to a suite of models of varying sizes which employ a Seq2Seq Transformer architecture (Vaswani et al., 2017). These models were pretrained on 1.5B training examples using an existing Reddit dataset extracted and obtained by a third party and made available on pushshift.io (Baumgartner et al., 2020). We consider both 2.7B parameter and 9.4B parameter variants, as well as models trained solely on the pretraining data (Reddit) vs. those finetuned on the Blended Skill Talk tasks (BST; Smith et al., 2020a).

Throughout, we consider the outputs of beam search using the models’ recommended standard parameters, unless otherwise noted: we refer to removing the minimum length requirement (20 tokens) and the blocking of generations that repeat 3-grams from the prompt or past generation as the “free” variant.7

In Table 4, we show the correctness (using the match-based correctness scoring) and linguistic confidence (using the BERT-based classifier) for each of these models as well as our final calibrator-controlled chatbot on the held-out questions of the TriviaQA test set (more details on why we only use 3793 held-out questions in §5.5). We observe some gains in accuracy using the “free” decoding setup, but as we are interested in improving models that are more likely to be used in practice, we decide to conduct all remaining experiments on the vanilla BST 2.7B model (referred to as “vanilla” from here on) that Roller et al. (2020) recommend as most engaging. For this vanilla model, we observe that it attains an accuracy of only 4.96% on the test set, and yet it answers 29.45% of questions confidently (YEA).

4 Re-calibrating chatbots’ language

Having observed that BST 2.7B and all other BlenderBot variants are poorly linguistically calibrated (specifically, overconfident in answers to TriviaQA questions), we introduce a pipeline for improving calibration.

4.1 Pipeline overview

We propose training a calibrator and using controllable generation techniques to create a pipeline such that generative dialogue agents are better able to “own their ignorance,” i.e., such that the models’ linguistic confidence in its answers better aligns with the probability that the answers are correct. The overall pipeline is illustrated8

| model                  | acc | EVA | IDK | TRY | YEA |
|------------------------|-----|-----|-----|-----|-----|
| Reddit 2.7B free       | 6.85| 2.22| 42.53| 14.87| 40.36|
| Reddit 9.4B free       | 6.99| 1.40| 8.28 | 39.60| 50.73|
| BST 2.7B               | 4.96| 1.03| 16.87| 52.65| 29.45|
| BST 2.7B free          | 6.43| 0.84| 8.15 | 15.53| 75.48|
| BST 9.4B              | 8.49| 1.24| 17.56| 51.46| 29.74|
| calibrator-controlled chatbot | 5.09 | 0.18| 12.02| 85.90| 1.90 |

Table 4: Match-based accuracies and automatically classified linguistic confidence (both in %) for different BlenderBot (Roller et al., 2020) variants’ responses to TriviaQA questions from the final 4000 question from the TEST SET. Free refers to no minimum length and n-gram blocking for the generation beam search. Bold: best accuracy, best engagingness in Roller et al. (2020), and our proposed system derived from BST 2.7B.

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5These samples come from the TRAIN SET (see §5.1); the classifier is the bert_classifier that is part of ParlAI (Miller et al., 2017), fine-tuning the final layer and predicting output classes from the [CLS] token. We did not tune this model heavily or try other tricks like averaging embeddings as we were satisfied with performance.

6https://files.pushshift.io/reddit/

7We did experiment with top-k and nucleus sampling, which slightly reduced accuracies; we also looked at correctness of the top few beams instead of just the single most likely generation, but those usually were similar to the top-1 answer in terms of correctness.

8The robot emoji in this figure and the annotation emoji throughout are distributed as part of the OpenMoji project under CC-BY-SA 4.0; the robot emoji is drawn by Mariella Steeb, the shrug, raised, and tipping hand, and the running person by Johanna Wellnitz, the muted speaker by Rana Cakir, the cross by Hilda Kalyoncu, the yarn by Nicole Kornhaas, and the 100 by Jose Avila. The crystal ball illustration was drawn by Vincent Le Moign and is distributed as part of
in Figure 1. We first train a calibrator to return the empirical probability that the model’s answer is correct (without seeing the gold answer; §4.2), and finetune the generative dialogue model to enable control over linguistic confidence (§4.3). Using the calibrator and the controllable generation model, we adjust the dialogue agent’s response by choosing linguistic confidence control tokens that align with the probability returned by the calibrator, resulting in a calibrator-controlled chatbot.

4.2 Training a calibrator

The first step of the pipeline involves training a calibrator that predicts the probability that the model’s response is correct, given the question and answer, as well the vanilla model’s internal representations corresponding to each. We choose an architecture which transforms the vanilla model’s encoder and decoder hidden states into logits corresponding to our two classes (correct and incorrect). The model is trained using 50,000 questions from the full TriviaQA training split with the vanilla model’s corresponding responses, automatically annotated for correctness using the match-based annotation scheme (see §3.4). Ablations in §5.3 show that different models for the calibrator, some not using the answer, some not using the internal representations, yield similar results.

4.3 Training a controllable generation model

The next step of the pipeline involves training a generative model that will adjust the linguistic confidence of a response, provided the original response and a control token representing the chosen linguistic confidence: <IDK>, <TRY>, or <YEA>. We achieve this by fine-tuning the generative dialogue model in two steps using controllable conditioned generation techniques.

Stage 1: confidence controllable model

We first train a linguistic confidence controllable generative dialogue model following the method in Smith et al. (2020b). We fine-tune the vanilla model on the original BST tasks, augmented with an additional task constructed from TriviaQA to incorporate confidence signals: 25000 questions.

from the TriviaQA training split are augmented with a control token capturing the vanilla model response’s linguistic confidence, as given by the BERT-based classifier (§3.4). The expected output is the vanilla model’s response to the question. All incorrectly answered examples and examples with the EVA label are discarded, and remaining examples are oversampled to have the same overall certainty distribution as we see on the VALID SET. The model thus learns to associate the linguistic confidence of the response with the control tokens and can generate responses with a desired degree of confidence at inference time by setting appropriate control tokens. We refer to this model as the intermediate model.

Stage 2: confidence-and-content controlled model

Adjusting the linguistic confidence of a generated response via control tokens with the intermediate model often also changes the content of the response. Simultaneous control over both linguistic confidence and content would be preferable, to allow changing the linguistic confidence of a given response without altering the provided answer for a question. We achieve this in a second stage of fine-tuning by constructing a task that simultaneously conditions on linguistic confidence and response content. Training prompts for this task are constructed by concatenating the same 25000 TriviaQA training split questions with the vanilla model’s response, a linguistic confidence control token as before, and also an additional control token capturing whether the content of the intermediate response when given that question and linguistic confidence control token is the same (<SAME>) or different (<DIFF>) from the vanilla model’s response. The expected output is the intermediate model’s response to the question with that linguistic confidence control token. The content control token is <SAME> if both the vanilla model and intermediate model’s responses to the question are correct, and <DIFF> if only one of them is correct. Examples where both the vanilla model and intermediate model’s responses are incorrect are discarded, because there are so many different ways to be incorrect. Choosing <SAME> at inference time yields a model which adjusts the linguistic confidence of the vanilla model’s response (provided as input) without changing the answer to the question. Henceforth, we refer to this model as our “controlled” model, to be used in the final pipeline.
5 Results

We describe data collection and annotation results, as well as experimental results and analysis on the vanilla model and each stage of the pipeline for the calibrator-controlled chatbot.

5.1 Data collection and annotation

We collect human annotation for both training data and for our final evaluation of the vanilla model and the calibrator-controlled chatbot. Question and response pairs are annotated for both correctness and linguistic confidence using the annotation scheme described in §3.3. Crowdsourcing annotators annotate questions in batches of nine questions, after completing an “onboarding” test of three questions.

Training data

We collect annotations for the vanilla model’s responses to 2000 questions each from the train and validation splits of TriviaQA. Each question and response pair is annotated by one crowdsource annotator for the training split and three crowdsource annotators for the validation split. We refer to these splits as the TRAIN SET and the VALID SET throughout; we use the TRAIN SET to train the BERT-based classifier (§3.4) and for early-stopping the calibrator training, we use the VALID SET for early-stopping the controllable generation model fine-tuning steps and for tuning hyperparameters for BERT-based classifier, calibrator, and the controllable generation models.

Final evaluation data

For our final evaluation of chatbots, we have three annotators label 5000 question and response pairs from the TriviaQA validation set (none of which overlap with the VALID SET) for each the vanilla model and the controlled model under all three linguistic confidence control settings (IDK, TRY, YEA). We refer to this size $3 \times 4 \times 5000$ set as the TEST SET throughout. Note that evaluating our calibrator-controlled chatbot would only require annotating responses generated with the one linguistic confidence control token dictated by the probability returned by the calibrator for each example. However, collecting annotations for all three linguistic confidence control settings allows future work to improve the calibrator in isolation, without having to re-train and re-label the controlled outputs.

Inter-annotator agreement

We analyze agreement between annotators using the question and response pairs from the VALID SET that were annotated three times each. For linguistic confidence, 43.60% of samples have all three annotators agree and 97.60% have at least two agree. For four-way correctness, these ratios are 69.15% and 97.90%; for binary correctness, they are 94.35% and 99.40%. We restrict to samples for which a majority exists and take the majority label, reducing the size of the VALID SET from 2000 to 1793 examples and the size of the TEST SET from 5000 to 4793 examples.

5.2 Evaluating the vanilla model

Table 5 shows the poor linguistic calibration of the vanilla model (BST 2.7B) on the VALID SET. As the highlighted cells show, a mere 14% of the model’s confident answers are actually correct. To examine whether some questions are intrinsically “difficult” in a way that can be detected by shallow features, we train a sparse logistic regression model on all 2–7-grams that appear at least 5 times in our human-annotated test set to predict binarized correctness and binarized certainty from questions (1166 such n-grams) or from answers (1882 such n-grams). These four regressions are performed independently and use sparsity-inducing $L_1$ regularization. This yields between 9 and 19 n-grams that are useful indi-

|        | 4-way | binary |
|--------|-------|--------|
|        | EXTRA | WRONG | RIGHT | OTHER |            |        |
|        |       |        |        |        |            |        |
| vanilla model |       |        |        |        |            |        |
| 2.4% EVA | —     | —      | —      | —      |            |        |
| 31.6% IDK | 96.86 | 2.96   | 0.09   | 0.09 | 99.67 | 0.33    |
| 38.1% TRY | 88.65 | 9.55   | 0.65   | 1.15 | 97.71 | 2.29    |
| 27.8% YEA | 33.80 | 54.10  | 3.60   | 8.50 | 86.25 | 13.75   |
| calibrator-controlled chatbot |       |        |        |        |            |        |
| 0.2% EVA  | —     | —      | —      | —      |            |        |
| 12.1% IDK | 75.79 | 22.40  | 0.68   | 1.13 | 98.03 | 1.97    |
| 85.9% TRY | 69.48 | 26.57  | 0.84   | 3.12 | 95.21 | 4.79    |
| 1.8% YEA  | 16.92 | 47.69  | 7.69   | 27.69 | 61.11 | 38.89   |

Table 5: Human majority annotations on the vanilla model’s and the calibrator-controlled chatbot’s answers to the held-out 4000 test questions, given as % of the total for which majorities exist. Gray highlight: confidently given answers that are actually correct, to capture calibration of confidence.
predict correctness as reliably as our full calibrator, and (2) empirical correctness can be predicted directly from words using an independent model (BERT) to a reasonable accuracy. So, while our existing set up achieves good results, there is probably room for improving the calibrator so it can make better use of the provided information.

5.4 Controllable generation training results

The final controllable model\(^\text{10}\) shows convincing separation of confident from non-confident answers on the Test Set. Qualitatively, non-cherry-picked examples are shown in Table 7. Quantitatively, combining <IDK>- and <TRY>- categories (see discussion in §3.3), 98.79% and 99.12% of <IDK>- and <TRY>- forced are rated by humans as not belonging to the <YEA>- category, respectively, and 96.27% of <YEA>- forced generations are judged as <YEA> by humans. Furthermore, 88.46% of questions that the vanilla model answered correctly remain correct when letting the <YEA>-forced model answer the same questions. By contrast, the intermediate model (not conditioned on the initial answer itself) only maintains 56.81% of correct answers as correct when conditioned on the <YEA> token. This justifies the two-stage approach of conditioning over the first response. In fact, 61.65% of questions that were answered confidently and correctly by the vanilla model are given the word-for-word same answer by the calibrator-controlled chatbot. Finally, the controlled chatbot does not lose much performance on the original BST 2.7B training tasks: performance on these validation sets drops by less than one point of perplexity.

5.5 Evaluating the calibrator-controlled chatbot

The calibrator-controlled chatbot requires mapping the empirical correctness probabilities returned by the calibrator to the control tokens used by the controllable model. For this, we select thresholds on the calibrator outputs to map to IDK, TRY, and YEA by searching over all threshold values between 0 and 1 (with 0.025 steps) that maximize \(p(\text{\texttt{YEA}} | \text{\texttt{YEA}})\) using the first 1000 questions of each parameter set as in the vanilla BST 2.7B model, except for batch size 128, 4 training epochs, learning rate 7e-6, and dropout 0.2 for both stages. For stage 1, the new task has weight 5.0; for stage 2 the new task has weight 9.0 and we additionally drop the control token in 20% of training iterations.

### Table 6: Predictive \(n\)-grams in questions and answers with their associated weights, negative weights indicating a push towards “correct” and EVA/IDK/TRY, and positive weights counting towards “incorrect” and YEA.

| Correctness | from questions | from answers |
|-------------|----------------|--------------|
| ↑           | 1.098 city is  | 0.506 It is the |
| ↑           | 0.187 \(\Rightarrow\) What | 0.502 It was a |
| ✔           | 0.155 is the   | 0.375 used to  |

| Certainty (EVA/IDK/TRY ≤ YEA) | from questions | from answers |
|-------------------------------|----------------|--------------|
| ↑ 0.737 is a                   | 0.812 \(\Rightarrow\) It |
| YEA 0.193 in which             | 0.152 in the   |
| TRY -0.355 in the              | -2.459 \(\Rightarrow\) I |
| IDK -0.540 \(\Rightarrow\) Who | -2.750 but I    |
| EVA -0.782 \(\Rightarrow\) Which | -4.122 I’m not  |

\(^\text{10}\)All parameters are set as in the vanilla BST 2.7B model, except for batch size 128, 4 training epochs, learning rate 7e-6, and dropout 0.2 for both stages. For stage 1, the new task has weight 5.0; for stage 2 the new task has weight 9.0 and we additionally drop the control token in 20% of training iterations.
Figure 2: **Calibrator performance.** We evaluate the performance of our calibrator on the **TEST SET** by comparing the ratio of answers that were actually correct to the probability returned by the classifier (binned). The size and label indicate the number of question and answer pairs in each of 20 bins.

| question | How many Von Trapp children were there in the Sound of Music? |
|----------|---------------------------------------------------------------|
| vanilla  | I’m not sure, but I do know that the film was based on a novel by James Fenimore Cooper. |
| <IDK>    | I’m not sure, but I do know that there were eight children in the film. |
| <TRY>    | I’m not sure, but I do know that there were eight children in the film. |
| <YEA>    | There were eight Von Trapp children, including Sally Hemings, Sally Field, and Johnny Depp. |

| question | Who was the only British medal winner at the 2010 Winter Olympics? |
|----------|------------------------------------------------------------------|
| vanilla  | That would be Michael Phelps. He was born and raised in Birmingham, England. |
| <IDK>    | I’m not sure, but I do know that the winner of that event was Michael Phelps. |
| <TRY>    | I’m not sure, but I do know that the winner of that event was Michael Phelps. |
| <YEA>    | That would be Michael Phelps. He was born and raised in Birmingham, England. |

Table 7: Contrasting answers from the vanilla model and the controlled model with all three certainty control tokens, over a non-cherry-picked list of questions.

Figure 3: Average correctness for both the vanilla chatbot and the calibrator-controlled chatbot, grouped by their respective certainty as annotated by humans: the vanilla chatbot is rarely correct, even when it claims to be certain through language. The calibrator-controlled chatbot has more than double the chance of being correct when it expresses certainty linguistically, compared to the vanilla model. This comes with more selective use of that category (and also the ‘IDK’ category), as shown in Table 5. The data here is the set of 3793 examples from the clean test set (after discarding the examples used for tuning the thresholds) for which there was a majority-agreement on annotations.

The **TEST SET**, which are therefore subsequently excluded from the final test set results. This results in thresholds of 0 and 0.375: in practice, the calibrator is never asked to produce IDK, even though the resulting sentence sometimes ends up being annotated as such (see also §3.3 about ambiguity between both categories).

Figure 3 shows that our calibrator-controlled chatbot displays much better linguistic calibration, with the correctness of linguistically confident answers jumping nearly threefold, from 13.7% to 38.9%. Note that this is achieved by answering much fewer questions confidently, which is a necessary side effect for a chatbot for which overall correctness is low. Table 5 shows in a more detailed way how the calibrator-controlled chatbot performs on our test set, with both correctness and certainty judged by humans. As a beneficial side effect, evasive answers (EVA) are greatly reduced.
in this calibrator-controlled chatbot. Qualitatively, these two cherry-picked examples illustrate how the calibrator-controlled chatbot improves over the vanilla model in the sense that it is able to “own its ignorance” and verbally express doubt when its answer is likely incorrect:

**What type of animal is a frogmouth?**

*vanilla:* Frogmouths are a type of amphisbaenia that live in freshwater.
*calibrator-controlled chatbot:* I’m not sure, but I think it’s a type of freshwater fish.

**What type of animal is a Garron?**

*vanilla:* A garron is a type of lizard. They are native to the Americas.
*calibrator-controlled chatbot:* I’m not sure, but I think it’s a type of lizard. It’s also the name of a town in France.

6 Conclusion

This work has shown that (1) state-of-the-art conversational model BlenderBot (Roller et al., 2020) is poorly linguistically calibrated, expressing confidence for answers that are very likely incorrect, but (2) correctness likelihood can be well predicted by a trained calibrator, and (3) using those predictions in a controlled generation architecture allows to greatly improve the linguistic calibration of the model. The inference-time control techniques we adopted are easy to turn on and off through the choice of control tokens. This allows for flexible adjustments depending on the conversation requirements, e.g., being very openly ignorant in settings that require higher sensitivity, or deliberately expressing uncertainty to allow space for the conversation partner to give their own answer, or committing to confident answers even if they are incorrect in low-stakes casual conversation settings where goofy mistakes are acceptable or even funny. If this flexibility is not required, future work could explore “baking in” the linguistic calibration so that a vanilla model directly expresses the correct level of confidence, e.g., through retraining as in Xu et al. (2020), or by training the model specifically not to output responses for which confidence and correctness don’t match through unlikelihood techniques (Welleck et al., 2019; Li et al., 2019). Another promising avenue is to consider the whole set of possible responses as a distribution before a specific decoding choice has committed to an answer, and try to leverage that to increase accuracy of the response, or indeed further improve calibration. Finally, focus on meta-level considerations of chatbot responses could be applied to domains other than accurate question answering, for example training a model to recognize when it is about to say something potentially insensitive, perhaps contradict itself, when it has repeated itself a lot, or shown any other measurable trait of interest in a conversation: openly acknowledging potential problems in a response might be an easier first step than fixing them.

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Appendix

A Calibrator Ablation Experiments

We also experimented with training calibrators with more limited inputs to the calibrator, which could potentially allow for controlled generation based merely on the question, which we leave for future work. Recall, the calibrator we use pools all encoder and decoder hidden states (§4.2): we denote this as “+enc +dec”. Table 8 shows results of ablations when omitting the encoder states (“-enc +dec”), all but the very first timestep’s decoder state (“+enc -dec”), or both (“-enc -dec”), proving that much can be achieved without ever seeing the full answer the model ended up giving. We further show that reasonable performance can be achieved without using the chatbot’s internal representations, and instead, by merely training an external model (here, BERT) to predict empirical correctness from the questions and answers themselves. However the performance does not appear as robust as that of the calibrators that use the chatbot’s internal representations.

B Qualitative analysis of calibrator output bins

Table 9 shows all question/answer pairs for which the calibrator believes the answers are more likely right than wrong. Note also that the questions and answers don’t seem to all be connected through some exploitable surface pattern, corroborating the findings from §5.3 that the calibrator really does use more interesting model-internal representations.

C Annotation GUI with examples

Figure 4 shows annotated examples for all 13 classes in the annotation scheme.

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Produced until 2001, what was the name of the 128-bit game console produced by Sega that has developed quite a cult following?

Correct answer: Dreamcast. Possible (sometimes incorrect) aliases: Dream Cast, DreamCast, Dreamcast, Dreamcast 2, Dreamcast Emulation, Katrina (console), SEGA Dreamcast

Table 8: Comparison of different calibrators via Expected Calibration Error (ECE), Maximum Calibration Error (MCE), and (Average) Negative Log Likelihood (Guo et al., 2017). Closer to zero is better for all metrics. Both calibration error metrics require binning the data by its calibration output probability. Threshold 0.375 means that we have only two bins, split on the threshold we end up choosing in the calibrator pipeline (§5.5)—note that this threshold was picked using results from the +enc +dec set up, so was not optimized for the other set ups. Note that the MCE in the 20 bin case is usually decided by a bin that contains a single incorrect example for which the calibrator happened to predict a high probability of being correct.

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Figure 4: Human-written example answers to the question “Who was the US president during hurricane Katrina?” (correct answer: George W. Bush) annotated for both linguistic confidence and correctness using the taxonomy given in Table 1. Emoji in this figure only are Twitter Emoji (Twemoji), distributed under CC-BY 4.0.
| prediction | label | question / answer |
|------------|-------|-------------------|
| 0.782      | ✓     | **What part of the body produces insulin?** Insulin is produced in the pancreas, which is located in the abdomen. |
| 0.749      | ✓     | **Vishnu and Shiva are gods in which religion?** They are the gods of Hinduism, Buddhism, and Jainism. |
| 0.742      | ✓     | **Las Vegas is in which US State?** It is located in the state of Nevada in the southeastern region of the United States. |
| 0.732      | ✗     | **Who is Darth Vader’s son?** Anakin Skywalker, the main protagonist of the original Star Wars trilogy. |
| 0.727      | ✓     | **What city do The White Stripes and Kid Rock come from?** The white stripes are from Jackson-ville, Florida. Kid rock is from Detroit. |
| 0.714      | ✗     | **Which country will host the 2014 FIFA World Cup?** I think it will be hosted in Qatar, but I’m not 100% sure. |
| 0.707      | ✗     | **Kiel and Lübeck are cities in which German state?** Kiel is in Bavaria and Lubeck is in Lower Saxony. |
| 0.700      | ✗     | **Aladdin is a variety of which vegetable?** Yes, it is a type of cabbage. It is one of my favorite vegetables. |
| 0.665      | ✓     | **What does Mexican Coke have that American Coke doesn’t?** Mexican coke uses cane sugar instead of high fructose corn syrup. |
| 0.635      | ✗     | **Romansh is a native and official language of which country?** Romanian is a Romance language spoken in southern Italy and Greece. |
| 0.620      | ✗     | **What synthetic opioid is used to help treat heroin addiction?** Heroin is an opiate derived from the poppy plant. It is very addictive. |
| 0.611      | ✓     | **What video game series features an archaeologist named Lara Croft?** She is the protagonist of the video game franchise “The Tomb Raider” |
| 0.588      | ✓     | **What is Mexico’s most commonly used language?** I would have to say Spanish. It is the second most spoken language in the world after English. |
| 0.583      | ✗     | **Lynchburg the home of Jack Daniels whisky is in which US State?** It is located in Mount Vernon, Pennsylvania in the United States. |
| 0.577      | ✗     | **What is the surname of Django in the 2012 film ‘Django Unchained’?** It is Leonardo DiCaprio. He was nominated for an Academy Award for that role. |
| 0.577      | ✗     | **The world was first aware of the Chernobyl disaster after detectors were triggered at a nuclear plant in which country?** It was in Pripyat, Ukraine. It was a nuclear power plant. |
| 0.568      | ✓     | **Miami Beach in Florida borders which ocean?** The beach is located on the Atlantic Ocean side of the Florida Gulf of Mexico. |
| 0.561      | ✓     | **What is Brazil’s most widely-spoken language?** Brazilian Portuguese is the second most spoken language in the world after English. |
| 0.560      | ✓     | **What in the world of the internet is an ISP ?** ISP stands for Internet Service Provider. It is a company that provides internet service. |
| 0.560      | ✓     | **What video game, created by Notch, is the best-selling PC game of all-time?** Notch is the creator of Minecraft, which is one of the best selling PC games of all time. |
| 0.556      | ✗     | **What actor has played James Bond in the most movies?** Daniel Craig is the current Bond. He was born in 1962. |
| 0.552      | ✓     | **The Mossad is the intelligence agency of what country?** It is the Israeli Intelligence Service. It was founded in 1948. |
| 0.538      | ✗     | **What raw material is used for making glass?** Glass is a mixture of silicon dioxide and carbonate. |
| 0.536      | ✗     | **The naval base Pearl Harbour is in which US State?** It was in Pennsylvania, near Philadelphia. |
| 0.524      | ✓     | **Peter Parker alias Spiderman worked for which newspaper?** I think it was the Daily Bugle, but I’m not sure. It was a long time ago. |
| 0.522      | ✓     | **King Robert Baratheon and Queen Cersei Lannister are characters in which US television fantasy drama series?** The series is called “Game of Thrones” and is based on ”A Song of Ice and Fire” by George R. R. Martin. |
| 0.521      | ✗     | **Leonidas was the king of what city-state?** He was king of Greece. He was the ruler of the kingdom of Macedonia. |
| 0.509      | ✗     | **In which US city did the 2004 remake of the film Alfie take place?** It was in Las Vegas, Nevada. It was filmed on the Strip. |

Table 9: The 28 question/answer pairs from the TEST SET for which the calibrator believes answers are more likely to be correct than not, and their respective calibrator outputs and human-annotated binarized correctnesses.