Thought Flow Nets: From Single Predictions to Trains of Model Thought

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Abstract

When humans solve complex problems, they typically create a sequence of ideas (involving an intuitive decision, reflection, error correction, etc.) in order to reach a conclusive decision. Contrary to this, today’s models are mostly trained to map an input to one single and fixed output. In this paper, we investigate how we can give models the opportunity of a second, third and k-th thought. Taking inspiration from Hegel’s dialectics, we propose the concept of a thought flow which creates a sequence of predictions. We present a self-correction mechanism that is trained to estimate the model’s correctness and performs iterative prediction updates based on the correctness prediction’s gradient. We introduce our method at the example of question answering and conduct extensive experiments that demonstrate (i) our method’s ability to correct its own predictions and (ii) its potential to notably improve model performances. In addition, we conduct a qualitative analysis of thought flow correction patterns and explore how thought flow predictions affect human users within a crowdsourcing study. We find that (iii) thought flows enable improved user performance and are perceived as more natural, correct, and intelligent as single and/or top-3 predictions.

1 Introduction

Today’s classification models map a specific input x, e.g., a token or a sentence, to an output \( \hat{y} \) [Bishop, 2006] where \( \hat{y} \) can be, e.g., a class, a sequence (e.g., a generated text) or an answer span extracted from a context. This mapping \( x \rightarrow \hat{y} \) might involve various modulations and abstractions of \( x \) in a latent space, e.g., hidden layers of a neural network, but typically does not allow variations or trajectories of \( \hat{y} \). Humans, on the other hand, rarely come to a single decision right-away but follow a complex thought process which involves reflecting on initial decisions, comparing different hypotheses or resolving contradictions. While humans’ trains of thought are extensively studied in cognitive sciences and philosophy—one particular example being Hegel’s dialectics [Maybee, 2020]—such theories are rarely explored in machine learning. However, with increasingly complex tasks that have large output spaces, such as question answering (QA)¹, or tasks that require multiple reasoning steps such as multi-hop QA, learning to directly hit the right prediction in one shot might be more difficult than to learn to iteratively self-correct an initial prediction.

In this paper, we propose the concept of a thought flow as a sequence of inter-dependent probability distributions. Furthermore, we propose a simple correction module to implement this concept. It can be used on top of any model that provides output logits of one or multiple distributions. In particular, it is inspired by the three moments of Hegel’s dialectics which it relates to forward and backward passes of the model and is trained to judge whether the predicted class distribution corresponds to a correct prediction.

In our experiments on question answering, we demonstrate our method’s ability to self-correct flawed answer span predictions and identify qualitative patterns of self-correction, such as span reductions/extensions. Figure 1 shows a real example of a thought flow that corrects a prediction \( y^{(0)} \) that would be the output of a standard model to a new prediction \( y^{(2)} \).

¹A Longformer QA model can output 16M possible spans.
within two steps, namely a shrinkage of the answer span and a cross-sentence answer jump. We find that our method can achieve performance improvements up to 9.6% $F_1$ (absolute) on a question answering dataset.

Finally, we assess the impact of thought-flow predictions on human users within a crowdsourcing study. We find that thought-flow predictions are perceived as significantly more correct, understandable, helpful, natural, intelligent than single-answer predictions and/or top-3 predictions and result in the overall best user performance without increasing completion times or mental effort.

To sum up, our contributions are (i) a formalization of a thought flow inspired from human thinking and Hegel’s dialectics, (ii) a novel correction module and a corresponding gradient-based update scheme to generate a thought flow in a state-of-the-art transformer network, (iii) experiments on question answering that demonstrate its strong correction capabilities and identify qualitative patterns of self-correction, (iv) a crowdsourcing user study that demonstrates that thought flows can improve perceived system performance as well as actual user performance using the system.

2 Thought Flow Networks

In this section, we present background on Hegel’s dialectics (Section 2.1), formalize thought flows based on it (Section 2.2), and present a concrete implementation for question answering (Section 2.3).

2.1 Inspiration: Hegel’s Dialectics

To give models the opportunity to reflect and refine their pre-view’s one-sidedness or restrictedness and the initial determination 

As argued by, e.g., Mueller [1958], necessity be equated to it as argued by, e.g., Mueller [1958]. While the thesis-antithesis-synthesis triad can suggest the notion of a “one pass” process, the dialectical process in Hegel’s dialectic does not have to end after a single iteration, but can go through several iterations [Maybee, 2020]. The possibility for iteration is an essential property of our thought flow.

2.2 Formalization of Thought Flow Concept

We now translate the abstract description of these three moments into a simplified mathematical setting that can be implemented in any (neural) model that uses a vector-valued representation of the input (such as an embedding) and outputs (tuples of) logits. In particular, we embed Hegel’s dialectics in a framework of obtaining an initial “thought” vector and iteratively updating it in the three “moments”. Note that our formalization is not to be understood as an accurate reflection of Hegel’s dialectics but serves as a useful inspiration to enable the development of a novel machine learning model.

Thought. We model a thought with $\hat{z} \in Z$, the logits corresponding to a model’s prediction and $Z \subseteq \mathbb{R}^c$ being the logit space. This $\hat{z}$ serves as a representation of the model’s “decision state” as it captures information about the most probable output as well as possible alternatives and uncertainty.

Moment of Understanding. The first moment relates to an initial, seemingly stable view. We model this with the initial value of $\hat{z}(0)$, obtained from applying the prediction function $f_{\text{pred}} : \Phi \to Z$ to the model to the encoded input $\phi(x)$ with an encoding function $\phi : \mathbb{R} \to \Phi$ and the encoding space $\Phi \subseteq \mathbb{R}^c$ (see Figure 2a).

Dialectical Moment. In the second moment, the stability breaks down due to the view’s one-sidedness or restrictedness. To model this, we first introduce a new function $f_{\text{corr}} : Z \times \Phi \to \mathbb{R}$ that differentiably maps $\hat{z}(0)$ to a correctness score $s \in \mathbb{R}$ that is an estimate of the quality of the model prediction corresponding to $\hat{z}(0)$ while being conditioned on $\phi(x)$. Intuitively, $f_{\text{corr}}(\hat{z}(0), \phi(x))$ scores how good the current prediction corresponding to $\hat{z}(0)$ is given the model input corresponding to $\phi(x)$. Next, we formalize the dialectical moment with the gradient of the correctness score with respect to $\hat{z}(0)$, i.e., $\nabla_{\hat{z}(0)} s$ (see Figure 2b). Thus, we ask “How does the thought $\hat{z}(0)$ have to change in order to be more correct?” This gradient represents the view’s instability: As it creates a tension away from the current $\hat{z}(0)$ towards a new one, it destroys its stability and thus negates the initial view.

Speculative Moment. The third moment unites the initial view with the negation from the dialectical moment. We formalize this by modifying $\hat{z}(0)$ with a step into the gradient’s direction that yields

$$\hat{z}(1) := \hat{z}(0) + \alpha(0) \cdot \nabla_{\hat{z}(0)} s$$

A particular example of such an iterative process within Hegel’s work can be found in the dialectical development of Hegel’s logic regarding the concepts of “Abstract Purpose” and “Realized Purpose” [Maybee, 2020].

We choose $\hat{z}$ over $\hat{y}$ because we can modify logits in energy space without having to normalize in probability space.
we choose the element-wise product of the predicted start and end probabilities. We thus define $\phi(x) \in \mathbb{R}^d$ with $d$ denoting the dimension of the embeddings as:

$$\tilde{w}^{(i)} := \left(\hat{y}_\text{start}^{(i)} \odot \hat{y}_\text{end}^{(i)} + \epsilon \cdot \mathbf{1}\right) \in \mathbb{R}^L \quad (2)$$

$$\phi(x)^{(i)} := [e_1, e_2, \ldots, e_L] \cdot \frac{\tilde{w}^{(i)}}{\sum_j \tilde{w}^{(j)}_j} \in \mathbb{R}^d \quad (3)$$

where $\epsilon$ is a small constant that ensures that we do not divide by zero, $e_i$ is the embedding of the $i$-th token and $\odot$ is element-wise multiplication. The intuition behind this is that the correction module should have access to all information about the context that the prediction model focused on.

**Choosing $f_{\text{corr}}$.** We use a two-layer MLP with SELU activation [Klambauer et al., 2017] to map the concatenated vector

$$\left[\text{dropout}(\phi(x)^{(i)}) \hat{z}_\text{start}^{(i)} \hat{z}_\text{end}^{(i)}\right]^T \in \mathbb{R}^{d+2L} \quad (4)$$

to a correctness score $s$. Note that $f_{\text{corr}}$ does not receive the decoded answer text but directly uses the start and end logits to provide differentiability.

**Correctness Score $s$.** Following standard evaluation metrics for question answering, we use the $F_1$-score of the predicted answer as the correctness score that $f_{\text{corr}}$ is trained to predict.

**Training**

To train $f_{\text{corr}}$, we freeze the parameters of $f_{\text{pred}}$. Then, we pass the training instances through the whole model (including $\phi$, $f_{\text{pred}}$ and $f_{\text{corr}}$) as shown in Figure 2a to obtain the predicted correctness score $s$ (i.e., $f_{\text{corr}}$ predicts an $F_1$-score estimate without access to the ground-truth answer span). We determine the ground-truth correctness score by calculating the $F_1$-score between the ground truth answer and the answer prediction from $f_{\text{pred}}$. We define the correction prediction loss as the mean squared error between the calculated score and the predicted $s$ and train $f_{\text{corr}}$ to minimize it.

**Inference**

At inference time, we encode a new input and predict (i) the answer start and end logits using $f_{\text{pred}}$ and (ii) an estimated $F_1$-score $s$ of the predicted answer span using the correction module $f_{\text{corr}}$ as shown in Figure 2a. Instead of directly using the initial logits as the model’s prediction — as would be done in a standard model — we iteratively update the logits w.r.t. the estimated correctness score’s gradient following our formalization from Section 2.2 as shown in Figures 2b and 2c.

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4E.g., 768 for BERT-base [Devlin et al., 2019].
Update Rule. As described in Section 2.2, we aim at modifying \( \hat{z}^{(i)} \) such that the correction module assigns an increased correctness (i.e., \( F_1 \)-score in this application to QA). To apply Equation (1), we have to define how the step size \( \alpha \) is chosen in our QA application. We choose a time-independent \( \alpha \) such that a predefined probability mass \( \delta \) is expected to move. To this end, we first take a probing step of length one, calculate the distance as the \( L_1 \) norm between the initial distribution and the probe distribution and choose the step width \( \alpha \in \mathbb{R}^+ \) such that it scales the linearized distance to the hyperparameter \( \delta \):

\[
\alpha := \left[ \frac{\delta}{||\sigma(\hat{z}^{(i)}) - \sigma(\hat{z}^{(i)} + \nabla \hat{z}^{(i)} s)||_1 + \epsilon} \right] (5)
\]

where \( \sigma(\cdot) \) denotes the softmax function and \( \epsilon \in \mathbb{R}^+ \) is a small constant for numerical stability.

Monte Carlo Dropout Stabilization. The gradient \( \nabla \hat{z}^{(i)} s \) is deterministic but can — as we find in preliminary experiments — be sensitive to small changes in the input representation \( \phi(x) \). We therefore stabilize our correction gradient estimation by sampling and averaging gradients instead. For this, we use the dropped-out input encoding from Equation (4) and sample five gradients for every step using MCDrop [Gal and Ghahramani, 2016].

3 Question Answering Experiments

3.1 Data, Model and Training

Dataset. We choose the HOTPOTQA dataset (distractor setting) [Yang et al., 2018] to evaluate our models because it contains complex questions that require multi-hop reasoning over two Wikipedia articles. In the distractor setting, the model is “distracted” by eight irrelevant articles that are passed to the model in addition to the two relevant articles. In addition to yes/no/answer span annotations, HOTPOTQA also provides explanation annotations in the form of binary relevance labels over the paragraphs of the relevant articles which we do not use when training our models. As the public test set is secret, we use the official validation set as test set and sample a custom validation set of size 10k from the training set leaving 80,564 training instances.

Base model. We use a Longformer-large [Beltagy et al., 2020] model with a linear layer on top that maps token embeddings to start and end logits as our underlying question answering model. The model reaches 63.5% \( F_1 \) (SD=0.6) on the HOTPOTQA validation set averaged over three random seeds and can handle input lengths up to 4096 tokens which enables us to feed-in the entire context as a single input without truncation. The model’s input is a single token sequence that contains the question followed by the answer context (i.e., the 10 concatenated Wikipedia articles). The model’s output are two distributions over the input tokens (i.e., two 4096-dimensional distributions), one for the answer start position and one for the answer end position. This allows the model to choose its answer from any text span within the context. We prepend a “yes” and a “no” token to the context, that offers the advantage of modeling these answer options within the same distributions as the text span answers. In total, this model has 435M parameters compared to the additional 331k parameters our MLP implementation of \( f_{corr} \) adds.

Training Details. We first train the base models on for five epochs on a single V100 GPU using a learning rate of \( 10^{-5} \), an effective batch size of 64 using an AdamW optimizer [Loshchilov and Hutter, 2019], early stopping and a cross entropy loss on the start/end logits. We subsequently train the correction modules using the same setting but the mean squared error loss function for \( F_1 \)-score prediction training. Training one model each took approximately three days. In the following, we report all results as averages over three random seeds including standard deviations.

3.2 Performance Improvements

How does Performance Vary Over Steps? Figure 3a shows how \( F_1 \)-scores per gradient scaling target \( \delta \) evolve over 100 steps. We observe that small \( \delta \) values enable small \( F_1 \) improvements. While \( \delta = 0.1 \) consistently improves \( F_1 \)-scores, all other \( \delta \) values eventually deteriorate \( F_1 \)-scores. The higher the \( \delta \) value, the quicker the \( F_1 \) decrease. We conclude that (i) very small \( \delta \) values are not sufficient to reach notable performance gains and that (ii) larger \( \delta \) can initially improve performance but then “overshoot” with their corrections. We hypothesize that a remedy to this trade-off is to use larger \( \delta \) values but stop the corresponding flows at the right time.

What if We Had a Stopping Oracle? To test this hypothesis, we introduce an oracle stopping function that stops the thought flow where it achieves it best \( F_1 \) performance. Figure 3b shows that, with this oracle function, thought flows can reach performance improvements up to 9.6% \( F_1 \) (SD=0.61).

Figure 3c shows that almost all performance improvements are due to the first decision change within the thought flows and answer spans constantly improve and do not randomly shift across the context. This observation shows that single thought flow changes are highly effective and can reach substantial corrections fast.

3.3 Thought Flow Patterns

In a qualitative evaluation, we identify thought flow patterns. We randomly sample 150 instances from the subset of the official validation split for which the thought flow changed the initial answer prediction. We identify six (non-exclusive) correction patterns and show selected examples in Table 1.

Cross-Sentence. With 52.7%, this is the most frequent type of correction. The thought flow shifts the predicted answer from one sentence to another.

Span Reduction. The thought flow can shorten the predicted answer span to correct the answer.

Span Extension. Similarly, the thought flow can also enlarge a predicted answer span to correct it.

In-Sentence. On top of in-sentence span reduction/extension, the thought flow can also jump between non-overlapping spans within a sentence.

Entity Refinement. In this correction pattern, the thought flow keeps predicting the same entity but jumps to an alternative mention of the entity.
Logic Hops. The thought flow performs a step-wise reasoning that first resolves the first step of HotpotQA’s two-step reasoning structure before jumping to the second step, i.e., the correct answer.

Combinations. We observe various combinations of the aforementioned patterns. A model can, for instance, jump between sentences, refine entities and reduce the answer span.

Corrections can also occur sequentially. We provide detailed examples in the appendix. We additionally observe flow patterns with very high number of decision changes. These typically correspond to two- or three-cycles between answer spans or exhibit a seemingly chaotic behavior.

4 Human Evaluation

While the previous section showed that thought flows can enable complex self-correction and can reach promising performance gains, we now investigate how thought flow predictions affect human users in an AI-assisted question answering task.

4.1 Experiment Design

We choose a within-subject design in which each participant is exposed to three variations of a question answering system.

Conditions. We aim at assessing the effect of the thought flow concept on users and therefore present the outputs of the oracle-stopped thought flow in one condition (TF) and compare it to two baseline conditions. As baselines, we use top-1 predictions (SINGLE) (to compare against standard models) and top-3 predictions (TOP-3) (to compare to an alternative approach to show several predictions). For all conditions, we present the predicted answer(s) along with the sentence in which they appear in the context.

Dependent Variables. We study the effect of the condition (SINGLE, TF and TOP-3) on a set of dependent variables. We include variables on a per-question level (after each question) and on a per-system level (after all questions of one condition). The per-question variables include: (i) human answer correctness, (ii) perceived model correctness (iii) perceived understanding, (iv) perceived helpfulness and (v) completion time. The per-system variables include: (vi) usability using the UMUX questionnaire [Finstad, 2010; Finstad, 2013], (vii) mental effort using the Paas scale [Paas, 1992], (viii) anthropomorphism using the respective subscale of the Godspeed questionnaire [Bartneck et al., 2009], (ix) perceived intelligence using the subscale from the same questionnaire, (x) average completion time. We provide a list of all questionnaires in the appendix.

Apparatus. We sample 100 instances from the HotpotQA validation instances for which a thought flow using $\delta = 1$ causes at least one prediction change.7 From these, we sample 30 instances per participant and randomly assign the instances to three bins of 10 questions (one bin per condition).8 We balance the six possible condition orders across participants and include three attention checks per participant. We provide screenshots of the study interface in the appendix.

4.2 Quantitative Results

We use MTurk to recruit US crowdworkers with >90% approval rate and the MTurk Masters qualification an collect responses from 55 workers.9

Statistical Models.

Per-System Ratings. We analyze the per-system ratings using Friedman tests to account for the paired responses due to the within-subject design.10 We use Holm-corrected Conover post hoc tests to identify significant pairwise differences.

Per-Item Ratings. Note that the within-subject design of our study possibly introduces inter-dependencies within ratings that we have to account for using an appropriate statistical

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7We drop the robotics-specific item regarding “moving rigidly/elegantly” as it is not applicable to question answering.

8If there is no prediction change, TF is identical to SINGLE.

9We statistically account for random effects of single questions.

10Although aggregated Likert item scores are commonly considered interval responses, we use (non-parametric) Friedman tests that only require ordinal responses and are more conservative than their parametric counterparts RM-ANOVAs.
model. Additionally, our dependent variables are measured on different levels, e.g., completion time is measured on a ratio scale while human answer correctness is measured on a nominal (dichotomous) scale.\textsuperscript{11} We therefore use (generalized) linear mixed models (GLMM) and cumulative link mixed models (CLMM) to (i) account for random effects of question and subject IDs, and (ii) account for the variables’ respective measurement scales.\textsuperscript{12} We use LRT tests between the full model and the model without the condition variable to identify main effects of the condition variable and conduct Holm-corrected Tukey post-hoc tests.

Results.
We find significant differences for all dependent variables except usability and mental effort. We summarize the results of our statistical analysis in Table 2 using CLD codings [Piepho, 2004]. We provide the detailed $p$ values for main effects and each pairwise comparison in the appendix. In the following we discuss our findings for each dependent variable for which we found a significant main effect.

Perceived Answer Correctness. While there is no statistically significant difference between showing users single answers or top-3 predictions, displaying thought flows leads to significantly higher answer correctness ratings.

Understanding. Top-3 as well as thought flow predictions significantly increased the feeling understanding how the system came up with its answer compared to single predictions.

Helpfulness. Similarly, top-3 and the thought flow predictions significantly improve perceived system helpfulness compared to single predictions.

Anthropomorphism. While we observe no significant difference in antropomorphism ratings between single and top-3 predictions, the thought flow predictions are perceived significantly more human-like/natural than the single answers.

Perceived intelligence. Both, top-3 and the thought flow predictions, lead to an significantly increased perceived system intelligence.

Completion Time. We observe that the top-3 predictions significantly improve completion times compared to single answers, but there is no significant increase for thought flows.

User Performance. While top-3 predictions already improve user performance in terms of $F_1$-score of the user’s given answer, thought flow predictions enable even higher performances, that are significantly higher than answers given in the single answer or top-3 conditions. We additionally analyze user answers using exact match scores and find the same effects and model orders.

Overall, our results indicate that thought flows are better or equally good than single answer or top-3 predictions regarding all evaluated dimensions. In particular for perceived answer correctness, humanlikeness and user performance, thought flows are significantly better than both, the single answers and the top-3 predictions. While comparable (statistically indistinguishable) improvements of understanding, helpfulness, naturalness and intelligence can also be achieved using top-3 predictions, these come at the cost of significantly increased completion times compared to single answers. In contrast, we do not find a significant time increase using thought flows.

\begin{table}[h]
\centering
\begin{tabular}{lcl}
\hline

Pattern & Freq. & Example \\
\hline

cross-sent. & 52.7\% & Question: Who is older Danny Green or James Worthy?  
(1) Daniel Richard "Danny" Green, Jr. (born June 22, 1987) is an American professional basketball player for the San Antonio Spurs of the National Basketball Association (NBA).  
(2) James Ager Worthy (born February 27, 1961) is an American professional basketball coach and former player, commentator, television host, and analyst.  

span reduction & 23.3\% & Question: What philosophy related to creationism is Paul Nelson noted for?  
(1) Paul A. Nelson (born 1958) is an American philosopher of science noted for his advocacy of young earth creationism and intelligent design  
(2) Paul A. Nelson (born 1958) is an American philosopher of science noted for his advocacy of young earth creationism and intelligent design  

span extension & 21.3\% & Question: Ronald Reagan and George H. W. Bush both held which position in office?  
(1) The presidency of Ronald Reagan began on January 20, 1981, when Ronald Reagan was inaugurated as President of the United States, and ended on January 20, 1989.  
(2) The presidency of Ronald Reagan began on January 20, 1981, when Ronald Reagan was inaugurated as President of the United States, and ended on January 20, 1989.  

in-sent. & 7.3\% & Question: When was the stadium that held the 2015 Magyar Kupa demolished?  
(1) The stadium was closed in 2016 and demolished in 2017 to give place to the new Ferenc Puskas Stadium.  
(2) The stadium was closed in 2016 and demolished in 2017 to give place to the new Ferenc Puskas Stadium.  

age_info & 4\% & Question: Is the Pakistan fast bowler who joined the Kent County Cricket Club in June, 2011 a left-hand or right-hand batsmans?  
(1) Wahab Riaz (Punjabi, Urdu: ; born 28 June 1985) is a Pakistani cricketer.  
(2) He is a left-arm fast bowler and a right-hand batsman.  

\hline
\end{tabular}
\caption{A subset of correction Patterns identified in 150 randomly sampled thought flows using $\delta = 1$. The correct answer is marked bold, the predicted answer per flow step is marked in orange. We provide the full list of identified patterns in the appendix.}
\end{table}
Variables for which it is found to be the sole superior system are marked cyan, variables for which it is found to be better than others are marked green.

Table 2: Statistical results of our human evaluation ($N = 55$). "*" marks dependent variables on which a significant effect of the system condition was observed (Friedman tests and LRT tests for GLMM/CLMM). Pairwise differences between conditions (Holm-adjusted Tukey/Conover tests) are reported as compact letter display codings. E.g., the “humanlike” column shows that the post hoc test detected a significant difference between SINGLE and TF but no significant difference between any other pair. Similarly, the last column shows pairwise differences between all conditions and the TF condition reaches significantly higher human answer F1-scores than any other conditions. Variables for which TF is among the best performing models are marked cyan, variables for which it is found to be the sole superior system are marked green.

5 Related Work

Cognitive Modeling and Systems. The fields of cognitive modeling and cognitive systems provide numerous models of human thinking [Rupert, 2009; Busemeyer and Diederich, 2010; Levine, 2018; Lake et al., 2017]. While work in these fields often orient towards accurate descriptions of human cognition, our method does not aim to provide a plausible description of cognitive process but, instead, aims to apply a philosophical concept to machine learning in order to improve classification performance and user utility.

Confidence Estimation and Model Corrections. Estimating a model’s confidence and the correctness of its predictions is addressed with various methods, including the training of secondary models for predicting the main model’s uncertainty [Blatz et al., 2004; DeVries and Taylor, 2018]. Among those, ConfidNet is particularly related to our approach as it predicts the true-class probability of the main model [Corbière et al., 2019]. In contrast, our correction module receives the class probabilities of the main model as an input and predicts a correctness score. In difference to methods aiming at estimating accurate confidence scores, we predict such scores only as an auxiliary task in order to generate a gradient that allows us to update the model prediction. Regarding model correction, the arguably most established approach to learn corrections of model predictions is gradient boosting [Friedman, 2001] including its popular variant XGBoost [Chen and Guestrin, 2016]. In contrast to those works, we do not use an ensemble of weak learners but propose a lightweight correction module that is applicable on top of any existing classification model. Further, in our method, the correction module receives the main model’s predictions and is able to directly adapt them.

Sequences of Predictions. The idea of iteratively predicting and correcting has been explored for a long time. Early work includes Mori et al. who present a non-neural iterative correction method tailored to estimate elevation maps from aerial stereo imagery [Mori et al., 1973]. Katupitiya et al. propose to iterate two neural networks to address the problem of predicting inputs of a mechanical process given the outputs of the process [Katupitiya and Gock, 2005]. While their method is specifically designed for the task of input prediction, our work presents a general-purpose classification model that iterates class label predictions. Besides those task-specific methods, there are models and inference methods that make use of an iterative prediction process by design, such as Hopfield networks [Hopfield, 1982] and their modern variants [Barra et al., 2018; Ramsauer et al., 2020], or Loopy Belief Propagation, Markov Chain Monte Carlo or Gibbs sampling [Bishop, 2006; Koller and Friedman, 2009]. While these techniques can be linked to our work conceptually, they all require to train a new model. In contrast, our approach can be applied to an existing neural model as well. Another related approach is chain-of-thought prompting [Wei et al., 2022] in which a language model is prompted with demonstrations of problem decomposition/reasoning in a few-shot manner and subsequently can be observed to show similar behavior in its answer. While this method yields impressive model answers, it predicts one answer that contains information on its deduction without changing or correcting its answer. In contrast, our method is not targeted towards decomposition/reasoning but predicts a sequence of answers with the goal of iteratively improving it.

Learning to Stop. A further line of work, ACT [Graves, 2016] and PonderNet [Banino et al., 2021], trains recurrent networks to learn when to stop applying recurrent transformations within the model. While their approaches require the model to contain recurrent modules and to retrain the base model, our method only requires the model to yield output logits and leaves the base model unchanged.

6 Conclusion

In this paper, we introduced a task-agnostic self-correction formalism that turns a model’s single output prediction into an evolving sequence of predictions—the thought flow. We take inspiration from Hegel’s dialectics and propose a correction module along with a gradient-based update rule that sequentially updates a model’s output distributions in the direction of an increasing self-estimate of correctness. We apply our method to question answering models and conduct extensive experiments including human evaluation. We find that thought flows (i) can increase F1-scores up to 9.3%, (ii) exhibit complex self-correction patterns and (iii) provide significant improvements in human interaction and system perception including task performance and perceived system correctness and naturalness. A potential next step to further improve performance is learning to stop.
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A Question Answering Experiments

A.1 Dataset Details.
We use the HOTPOTQA dataset [Yang et al., 2018], which is an English multi-hop question answering data set. It covers 90,564 training instances, 7,405 test validation instances and 7,405 test instances per setting (there are a distractor and a fullwiki setting). Training instances are grouped by difficulty and cover 18,089 easy, 56,814 medium and 15,661 hard questions. We refer to [Yang et al., 2018] for more details.

A.2 Thought Flow Patterns
We provide an extended list of patterns and examples from our qualitative thought flow analysis in Table 3. In addition Table 4 shows additional thought flow examples using three correction steps.

B User Study

B.1 Questionnaire Items

Per-System Questionnaires

Usability. The UMUX usability scale [Finstad, 2010; Finstad, 2013] uses the following four 5-point Likert items:

• This system’s capabilities meet my requirements.
• Using this system is a frustrating experience.
• This system is easy to use.
• I have to spend too much time correcting things with this system.

Mental Effort. The Pass mental effort scale usability scale [Paas, 1992] uses a single 9-point Likert item:

• Please rate the mental effort required to decide if the system’s answer is correct. (The 9 points are labeled from “very, very low mental effort” to “very, very high mental effort”.)

Anthropomorphism. The Godspeed anthropomorphism subscale [Bartneck et al., 2009] use five 5-point semantic differential scales that ask the user to rate the system in a spectrum of:

• fake – natural
• machinelike – humanlike
• unconscious – conscious
• artificial – lifelike
• (moving rigidly – moving elegantly) (We exclude this item as it is not applicable to question answering systems.)

Perceived Intelligence. The Godspeed perceived Intelligence subscale [Bartneck et al., 2009] use five 5-point semantic differential scales that ask the user to rate the system in a spectrum of:

• incompetent – competent
• ignorant – knowledgeable
• irresponsible – responsible
• unintelligent – intelligent
• foolish – sensible

Per-Item Questionnaires

Perceived Answer Correctness. We use a single binary item to collect perceived answer correctness ratings:

• I think the system’s answer is correct.

Perceived Helpfulness. We use a single 5-point Likert item to collect helpfulness ratings:

• I think the system’s answer enables me to give the correct answer.

Perceived Understanding. We use a single 5-point Likert item to collect understanding ratings:

• I understand how the system came up with its answer.

B.2 Interface

Figures 4 to 6 show screenshots of our experiment interface for the three studied prediction conditions TF, TOP-3 and SINGLE. Figure 7 depicts an attention check question.

B.3 Statistical Results

Table 5 provides the $p$ values for main effects and each pairwise comparison.
| Pattern       | Frequ. | Example                                                                                                                                                                                                 |
|--------------|--------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| cross-sentence | 52.7%  | Question: Who is older Danny Green or James Worthy?                                                                                                                                                    |
|              |        | (1) Daniel Richard "Danny" Green, Jr. (born June 22, 1987) is an American professional basketball player for the San Antonio Spurs of the National Basketball Association (NBA).                                      |
|              |        | (2) James Ager Worthy (born February 27, 1961) is an American professional basketball coach and former player, commentator, television host, and analyst.                                                        |
| span reduction | 23.3%  | Question: What philosophy related to creationism is Paul Nelson noted for?                                                                                                                               |
|              |        | (1) Paul A. Nelson (born 1958) is an American philosopher of science noted for his advocacy of young earth creationism and intelligence                                                                                                                     |
| span extension | 21.3%  | Question: Ronald Reagan and George H. W. Bush both held which position in office?                                                                                                                    |
|              |        | (1) The presidency of Ronald Reagan began on January 20, 1981, when Ronald Reagan was inaugurated as President of the United States, and ended on January 20, 1989.                                                                                          |
|              |        | (2) The presidency of Ronald Reagan began on January 20, 1981, when Ronald Reagan was inaugurated as President of the United States, and ended on January 20, 1989.                                                                                          |
| in-sent, entity ref. | 7.3%  | Question: When was the stadium that held the 2015 Magyar Kupa demolished?                                                                                                                             |
|              |        | (1) The stadium was closed in 2016 and demolished in 2017 to give place to the new Ferenc Puskas Stadium.                                                                                             |
|              |        | (2) The stadium was closed in 2016 and demolished in 2017 to give place to the new Ferenc Puskas Stadium.                                                                                             |
| entity-ref. hug | 8%     | Question: Which host of Sunday Night Safran has the hebrew first name Yehoshua?                                                                                                                        |
|              |        | (1) John Michael Safran (Hebrew: "Yehoshua Safran"); born 13 August 1972 is an Australian radio personality, satirist, documentary maker and author, known for combining humour with religious, political and ethnic issues. |
|              |        | (2) It was hosted by John Safran and Catholic priest, Bob Maguire.                                                                                                                                    |
| contrib, del. hug | 4%   | Question: Is the Pakistan fast bowler who joined the Kent County Cricket Club in June, 2011 a left-hand or right-hand batsmans?                                                                      |
|              |        | (1) Wahab Riaz (Punjabi, Urdu: ; born 28 June 1985) is a Pakistani cricketer.                                                                                                                          |
|              |        | (2) He is a left-arm fast bowler and a right-hand batsman.                                                                                                                                                 |
| contrib, del. hug | 9.3%  | Question: Who was born in 1922 and published a book in 1985 by Delacorte Press?                                                                                                                      |
|              |        | (1) Kurt Vonnegut Jr. (November 11, 1922; April 11, 2007) was an American writer.                                                                                                                    |
|              |        | (2) Galapagos is the eleventh novel written by American author Kurt Vonnegut.                                                                                                                          |

Table 3: Correction Patterns identified in 150 randomly sampled thought flows using $\delta = 1$. The correct answer is marked bold, the predicted answer per flow step is marked in orange.

**Examples**

Question: How many times did the man who coached the 1986-87 UNLV Runnin’ Rebels fail to win 20 games in a season?

(1) He spent the majority of his career coaching with the UNLV Runnin’ Rebels, leading them four times to the Final Four of the NCAA Men’s Division I Basketball Tournament, winning the national championship in 1990.

(2) Overall, he won over 700 games in his career, and only twice failed to win 20 games in a season.

(3) Overall, he won over 700 games in his career, and only twice failed to win 20 games in a season.

Question: Why did the CEO of the football team based in Denver, Colorado step down in 2014?

(1) He served as the Broncos CEO from his purchase of the club in 1984 until July 2014, when he stepped down as Broncos’ CEO due to the onset and progression of Alzheimer’s disease.

(2) He served [...], when he stepped down as Broncos’ CEO due to the onset and progression of Alzheimer’s disease.

(3) He served [...], when he stepped down as Broncos’ CEO due to the onset and progression of Alzheimer’s disease.

Table 4: Multi-step correction examples ($\delta = 1$).

| Method    | perceived quality | user performance | p-values | p-values | p-values | p-values |
|-----------|-------------------|------------------|----------|----------|----------|----------|
|           | correct*          | understand*      | helpful* | usability | mental effort | humanlike* | intelligent* | time* | answer F1* |
| TF - SINGLE | <0.0001           | <0.0001          | <0.0001  | 0.07968  | 0.6282   | 0.03575   | 0.00124   | <0.0001 | <0.0001 |
| TF - TOP-3 | 0.00891           | 0.8867           | 0.9994   | 0.84254  | 0.30556  | 1          | 0.06207   | 0.0001  | 0.0001  |
| TOP-3 – SINGLE | 0.51897           | <0.0001          | <0.0001  | 0.13653  | 0.25097  | 0.00586   | 0.00012   | <0.0001 | <0.0001 |

Table 5: Detailed p values for all main effects and pairwise comparisons shown in Table 2. Significant p values are marked bold. Cell colors follow the color coding on Table 2.
**Instructions:**
- We evaluate three systems that automatically answer questions.
- Each of the three systems has a different kind of answer output.
- We will show you 10 questions for each system. After each round of 10 questions, we kindly ask you to fill out a survey about the system (represented by all 10 questions) that you saw right before.
- Additionally, we ask you to rate your agreement to three statements for each question.
- You do not have to search for the correct answer in the internet. We kindly ask you to only rely on the systems' predictions.

**Question:** Which South African politician won the indirect presidential election with 277 votes?

1. The system found its first answer *Kgalema Motlanthe* in this context:

   The ruling party, the African National Congress (ANC), with a two-thirds majority in the National Assembly of South Africa, elected *Kgalema Motlanthe* as President.

2. The system reconsidered its answer and found its second and final answer *Jacob Zuma* in this context:

   *Jacob Zuma* of the ruling African National Congress won the election with 277 votes (13 more than the number of seats held by the ANC), while Mvume Dandala of the Congress of the People got 47 votes.

**What do you think is the correct answer to the question?** (only use the information on this page, please do not use Google etc.)

|   |   |   |   |   |
|---|---|---|---|---|
| no | 1 | 2 | 3 | yes |

**Please rate the following statements.**

1. I think the system’s final answer is correct.

|   |   |   |   |   |
|---|---|---|---|---|
| strongly disagree | 1 | 2 | 3 | 4 | 5 |

2. I think the system’s answers enable me to give the correct answer.

|   |   |   |   |   |
|---|---|---|---|---|
| strongly disagree | 1 | 2 | 3 | 4 | 5 |

3. I understand how the system came up with its answers.

|   |   |   |   |   |
|---|---|---|---|---|
| strongly disagree | 1 | 2 | 3 | 4 | 5 |

4. Why do you think the answer is correct/incorrect?

5. Do you have any additional comments? (optional)

---

*Figure 4: User study interface showing the TF condition (ours).*
Instructions:
- We evaluate three systems that automatically answer questions.
- Each of the three systems has a different kind of answer output.
- We will show you 10 questions for each system. After each round of 10 questions, we kindly ask you to fill out a survey about the system (represented by all 10 questions) that you saw right before.
- Additionally, we ask you to rate your agreement to three statements for each question.
- You do not have to search for the correct answer in the internet. We kindly ask you to only rely on the systems’ predictions.

Question: Angry Dad: The Movie was first introduced in what episode of “The Simpsons” That was the eighteenth episode of the thirteenth season

1. The system predicted *I Am Furious (Yellow)* as the most probable answer which it found in:
   *I Am Furious (Yellow)* *I Am Furious (Yellow)* is the eighteenth episode of “The Simpsons” thirteenth season.

2. The system predicted *The Boys of Bummer* as the 2. most probable answer which it found in:
   *The Boys of Bummer* *The Boys of Bummer* is the eighteenth episode of “The Simpsons” eighteenth season.

3. It predicted *the eighteenth episode* as the 3. most probable answer which it found in:
   *I Am Furious (Yellow)* is *the eighteenth episode* of “The Simpsons” thirteenth season.

What do you think is the correct answer to the question? (only use the information on this page, please do not use Google etc.)

Please rate the following statements.

I think the system’s most probable answer is correct.

|       | 1 | 2 | yes |
|-------|---|---|-----|
| no    |   |   |     |
| 1     |   |   |     |
| 2     |   |   |     |

I think the system’s answers enable me to give the correct answer.

| strongly disagree | 1 | 2 | 3 | 4 | 5 | strongly agree |
|-------------------|---|---|---|---|---|----------------|

I understand how the system came up with its answers.

| strongly disagree | 1 | 2 | 3 | 4 | 5 | strongly agree |
|-------------------|---|---|---|---|---|----------------|

Why do you think the answer is correct/incorrect?

Do you have any additional comments? (optional)

Figure 5: User study interface showing the TOP-3 condition.
Figure 6: User study interface showing the SINGLE condition.

**Instructions:**

- We evaluate three systems that automatically answer questions.
- Each of the three systems has a different kind of answer output.
- We will show you 10 questions for each system. After each round of 10 questions, we kindly ask you to fill out a survey about the system (represented by all 10 questions) that you saw right before.
- Additionally, we ask you to rate your agreement to three statements for each question.
- You do not have to search for the correct answer in the internet. We kindly ask you to only rely on the systems’ predictions.

**Question:** What profession does Kazuyuki Fujita and Gilbert Yvel have in common?

The system predicted **professional wrestler, mixed martial artist** as its answer which it found in:

Kazuyuki Fujita (Teng Tian He Zhi, Fujita Kazuyuki) (born October 16, 1970) is a Japanese **professional wrestler, mixed martial artist** and a former amateur wrestler.

**What do you think is the correct answer to the question?** (only use the information on this page, please do not use Google etc.)

**Please rate the following statements.**

| I think the system’s answer is correct. | no | 1 | 2 | yes |
|----------------------------------------|----|---|---|-----|

| I think the system’s answer enables me to give the correct answer. | strongly disagree | 1 | 2 | 3 | 4 | 5 | strongly agree |
|---------------------------------------------------------------|-------------------|---|---|---|---|---|----------------|

| I understand how the system came up with its answer. | strongly disagree | 1 | 2 | 3 | 4 | 5 | strongly agree |
|-----------------------------------------------------|-------------------|---|---|---|---|---|----------------|

**Why do you think the answer is correct/incorrect?**

**Do you have any additional comments?** (optional)
Figure 7: User study interface showing an attention check.