

Mitigating Temporal Misalignment by Discarding Outdated Facts

Michael J.Q. Zhang and Eunsol Choi

Department of Computer Science
The University of Texas at Austin
{mjqzhang, eunsol}@utexas.edu

Abstract

While large language models are able to retain vast amounts of world knowledge seen during pretraining, such knowledge is prone to going out of date and is nontrivial to update. Furthermore, these models are often used under temporal misalignment, tasked with answering questions about the present, despite having only been trained on data collected in the past. To mitigate the effects of temporal misalignment, we propose *fact duration prediction*: the task of predicting how long a given fact will remain true. In our experiments, we demonstrate how identifying facts that are prone to rapid change can help models avoid from reciting outdated information and identify which predictions require seeking out up-to-date knowledge sources. We also show how modeling fact duration improves calibration for knowledge-intensive tasks, such as open-retrieval question answering, under temporal misalignment by discarding volatile facts. Our data and code will be released publicly at https://github.com/mikejqzhang/mitigating_misalignment.

1 Introduction

A core challenge in deploying NLP systems lies in managing *temporal misalignment*, where a model that is trained on data collected in the past is evaluated on data from the present (Lazaridou et al., 2021). Temporal misalignment causes performance degradation in a variety of NLP tasks (Luu et al., 2021; Dhingra et al., 2022; Zhang and Choi, 2021). This is particularly true for knowledge-intensive tasks, such as open-retrieval question answering (QA) (Chen et al., 2017), where models must make predictions based on world knowledge which can rapidly change. Furthermore, such issues are only exacerbated as the paradigm for creating NLP systems continues to shift toward relying on large pre-trained models (Zhang et al., 2022; Chowdhery et al., 2022) that are prohibitively expensive to re-train and prone to reciting outdated facts.

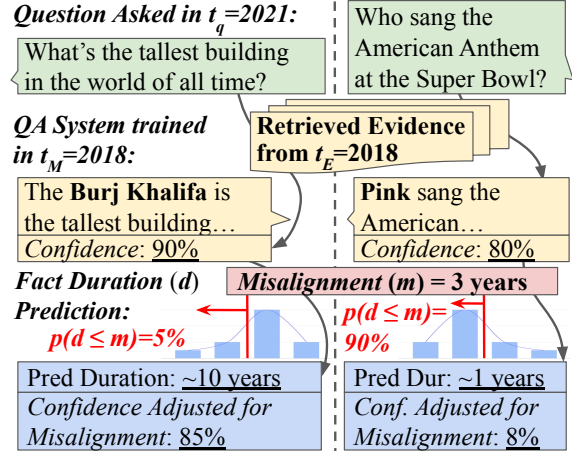


Figure 1: We depict the critical timestamps at play in open-retrieval QA systems. In the example on the left, the temporal misalignment between when the system was trained and evaluated has no affect on the answer. On the right, the answer has changed, causing the system to output an outdated answer with high confidence. To account for this, we apply our fact duration prediction system to adjust the system’s confidence accordingly.

Prior work has attempted to address these issues by updating the knowledge stored within the parameters of an existing pretrained model (Cao et al., 2021; Mitchell et al., 2022; Onoe et al., 2023). Another line of work has proposed using retrieval-based systems, which utilize a non-parametric corpus of facts that can be updated over time (Karpukhin et al., 2020; Guu et al., 2020; Lewis et al., 2021). Both methods, however, are incomplete solutions as they rely on an oracle to identify which facts need to be updated and to continuously curate a corpus of up-to-date facts.

Given the difficulty of keeping existing models up-to-date, we propose an alternative solution where we *abstain* from presenting facts that we *predict* to be out of date. To accomplish this, we introduce **fact duration prediction**, the task of predicting how frequently a given fact changes, and establish several classification and regression-based baselines. We also explore large-

scale sources of distant supervision for our task, including fact durations extracted from temporal knowledge bases (Chen et al., 2021b) and duration-related news text (Yang et al., 2020). We provide rich discussion on this challenging, new task, including exploring the relationship between fact duration prediction and temporal common-sense (Zhou et al., 2020; Qin et al., 2021).

We provide two sets of evaluations for our fact duration prediction systems. First, as our intrinsic evaluations, we report how close our systems’ duration estimates are to ground truth labels. We find that models that are trained with only distant supervision can predict the duration of 65% of temporally dependent facts from real search queries in NaturalQuestions (Kwiatkowski et al., 2019) to within 3 years, compared to 11% from a simple average-duration baseline. Second, as extrinsic evaluations, we study how predicted fact duration can improve the open-retrieval QA system’s predictions under temporal misalignment. We mainly focus on improving calibration (as depicted in Figure 1). Our approach can reduce expected calibration error by 50-60% over using system confidence alone on two QA systems (Roberts et al., 2020; Karpukhin et al., 2020) on SituatedQA dataset (Zhang and Choi, 2021).

We also explore other ways of applying our fact duration systems in QA, such as in ensembling close/open book systems to decide when retrieval is necessary due to temporal misalignment. Lastly, we apply fact duration prediction in a scenario where retrieval is performed over heterogeneous corpus containing both outdated and recent articles, and systems must weigh the relevance of an article against its recency. In summation, we present the first focused study on temporal misalignment in QA, and utilize fact duration prediction to mitigate model degradation over time.

2 Settings

2.1 Motivation

We aim to address temporal misalignment (Luu et al., 2021) in knowledge-intensive tasks, such as open-retrieval QA. Figure 1 illustrates our setting. We assume a QA model that is developed in the past and is evaluated on a query from a later date. This system suffers from temporal misalignment, returning outdated answers for some questions whose answer has changed in the meantime.

Table 1 reports the QA performance of existing

Eval. Year	Model	EM	AUC-ROC \uparrow	ECE \downarrow	RC@55 ($ \Delta $ \downarrow)
2018	① T5	36.0	0.82	0.13	55.0 (0.0)
	② DPR	37.9	0.74	0.22	55.0 (0.0)
2021	① T5	17.4	0.77	0.26	27.2 (27.8)
	② DPR	17.1	0.63	0.43	22.4 (32.6)
<i>Adjusting Confidence With Oracle Misalignment Info.</i>					
2021	① T5	17.4	0.75	0.12	47.8 (7.2)
	② DPR	17.1	0.71	0.17	38.7 (16.3)

Table 1: SituatedQA performance evaluated against answers from 2018 and 2021. Confidence estimates from a trained calibrator for each QA system. All models are trained on 2018 answers from NQ-Open. On the bottom, we present an oracle system which zeros the confidence of predictions whose answers have changed between 2018 and 2021.

systems on SituatedQA (Zhang and Choi, 2021), a subset of questions from NQ-Open (Kwiatkowski et al., 2019; Lee et al., 2019) that has been re-annotated with the correct answer as of 2021. In this dataset, 48% of questions are updated within the temporal gap (2018 to 2021). We can see that the current models, without considering temporal misalignment, experience performance degradation on both answer accuracy (EM drops from 37 to 17) and calibration metrics.¹

Can we improve QA system if we know which facts are outdated? We study this with an oracle setting, where we zeros the confidence of predictions whose answers have changed between 2018 and 2021 and report its performance in Table 1. While this cannot change answer accuracy, it can help models identify incorrect examples, improving calibration metrics across the board. In real scenarios, we do not know which facts are outdated. Thus, we build a fact duration model which predicts facts that are likely to be outdated, and use it to re-adjust the confidence of the QA model. We introduce both settings in detail below.

2.2 Fact Duration Prediction

We define the fact duration prediction task as follows: given a fact f , systems must predict its duration d , the amount of time that the fact remained true for. We consider datasets that represent facts in a variety of formats: QA pairs, statements, knowledge-base relations. For modeling purposes, we convert all facts to statements. For example, the fact $f = \text{“The last Summer Olympic Games were$

¹QA Model details can be found in Section 5.2 and calibration metrics are explained in Section 2.3.

held in Athens.” has a duration of $d = 4$ years.

Error Metrics We evaluate fact duration systems by measuring error compared to the gold reference duration: **Year MAE** is the mean absolute error in their predictions in years and **Log-Sec MSE** is mean squared error in log-seconds.

2.3 QA under Temporal Misalignment

The open-retrieval QA task is defined as follows: Given a question q^i , a system must produce the corresponding answer a , possibly relying on retrieved knowledge from an evidence corpus E . When taking temporal misalignment into consideration, several critical timestamps affects performance:

1. **Model Training Date** (t_M): When the training data for M was collected or annotated.
2. **Evidence Date** (t_E): When E was authored.²
3. **Query Date** (t_q): When q was asked.

For studying QA under temporal misalignment, we further specify that systems must produce appropriate answer at the time of the query a_{t_q} . For example, the question $q = \text{“Where are the next Summer Olympics?”}$ asked at $t_q = 2006$ has answer $a_{2006} = \text{“Beijing”}$. We define the magnitude of the temporal **misalignment** (m) to be the amount of time between a model’s training date and the query date ($m = t_M - t_q$). We will compare this with the duration of the fact being asked $d = f(q, a_{t_q})$. If $m > d$, we should **lower** the confidence of the model on this question.

For simplicity, we do not take an answer’s start date into account. Ideally, determining whether a given QA pair (q, a) has gone out of date should also consider the answer’s start date (t_s) and a model’s training date (t_m), and confidence can be lowered if $t_s + d < t_m + m$. While we expect this approximation to have less of an impact when settings where the misalignment period is small with respect to the distribution of durations, we perform error analysis on examples where considering start date hurts performance in Appendix C.

Calibration Metrics Even without temporal misalignment, models will not know the correct answer

²We primarily study settings where the evidence corpus does not change between training and inference ($t_E = t_M$), but also explore the effects of updating the evidence corpus ($t_E = t_q$) in Section 6. Training corpora and evidence corpora can contain documents authored over a large span of time. For t_M , we use the date its *latest* document was authored. For t_E , we studying using Wikipedia as our evidence corpus, and therefore all evidence is up-to-date as of t_E .

to every question. Well calibrated model predictions, however, allow us to identify low-confidence predictions and thereby avoid presenting users with incorrect information (Kamath et al., 2020). Under temporal misalignment, calibration further requires identifying which predictions should receive reduced confidence because the answer has changed. We consider following calibration metrics:

- **AUCROC**: Area under the ROC curve evaluates a calibration system’s performance at classifying correct and incorrect predictions over all possible confidence thresholds (Tran et al., 2022).
- **Expected Calibration Error (ECE)**: Computed by ordering predictions by estimated confidence then partitioning into equally sized 10 buckets. ECE is then macro-averaged mean absolute error each bucket’s average confidence and accuracy.
- **Risk Control (RC@XX)**: Uncertainty estimates are often used for selective-prediction, where models withhold low-confidence predictions below some threshold ($< \tau$), where τ is set to achieve a target accuracy (XX%) on some evaluation set. This metric measures τ generalizes across a new dataset (Angelopoulos et al., 2022). To compute RC@XX, we set τ based on predictions from t_M , then compute the accuracy on predictions t_q with confidence $\geq \tau$. In the ideal case, the difference $|\Delta|$ between RC@XX and XX should be zero.

3 Data

We first describe datasets that are used strictly for evaluation, split by task. We then describe our two large-scale sources for distant supervision.

3.1 Evaluation Data

QA under Misalignment We evaluate on SituatedQA (Zhang and Choi, 2021), a dataset of questions from NQ-Open (Kwiatkowski et al., 2019) with temporally or geographically dependent answers. We use the temporally-dependent subset, where each question has been annotated with a brief timeline of answers that includes the correct answer as of 2021, the prior answer, and the dates when each answer started to be true. We evaluate misalignment between $t_M = 2018$ and $t_q = 2021$ using the answers from NQ-Open for a_{2018} and answers from SituatedQA as a_{2021} .

While several recent works have proposed new datasets for studying temporal shifts in QA (Kasai et al., 2022; Livska et al., 2022), these works focus

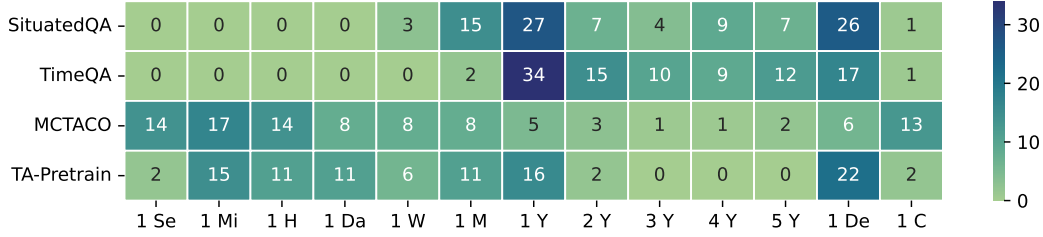


Figure 2: Duration statistics on each dataset’s training set (development set for MC-TACO). Each column represents a different duration class used by our classification model, with units abbreviated as **S**econds, **M**inutes, **D**ays, **W**eeks, **M**onths, **Y**ears, **D**ecades, and **C**enturies. Each row represents each dataset’s duration distribution, where each cell contains the % of examples in each class.

on questions about new events, where answers do not necessarily change (e.g., “how much was the deal between Elon Musk and Twitter worth?”). We do not study such shifts in the input distribution over time. We, instead, study methods for managing the shift in the output distribution (i.e., answers changing over time). Adjusting model confidence due to changes in input distribution has been explored (Kamath et al., 2020); however, to the best of our knowledge, this is the first work on calibrating over shifts in output distribution in QA.

Fact Duration Following our “QA under temporal misalignment” evaluations above, we also evaluate fact duration prediction on SituatedQA. To generate fact-duration pairs, we use the annotated previous answer as of 2021, converting the question/answer pair into statement using an existing T5-based (Raffel et al., 2020) conversion model (Chen et al., 2021a). We then use distance between the 2021 and previous answer’s start date as the fact’s duration, d .

Temporal Commonsense Temporal commonsense evaluations focus on inference about generic events (e.g., identifying that glaciers move over the course of centuries and a typical college campus tour lasts a few minutes or hours). In contrast, fact duration prediction requires making inferences about specific entities. For instance, determining the duration of an answer to a question like “Who does *Lebron James* plays for?” requires using both entity knowledge to determine that *Lebron James* is a basketball player, and applying commonsense knowledge to determine that basketball players can change teams every few years. Previous work (Onoe et al., 2021) has demonstrated the non-trivial nature of combining such knowledge.

Due to the differences in task definition described above, we do not use temporal commonsense datasets for evaluating fact duration predic-

tion. We, however, still evaluate on them explore how these tasks compare. In particular, we evaluate our fact duration predictions systems on the typical event duration subset of MCTACO (Zhou et al., 2019). Each MCTACO example consists of a multiple-choice question about the duration of some event in a provided context sentence, which we convert into duration statements following steps outlined in Appendix B (examples in Table 2).

During preprocessing, we use the same question conversion model as above to transform each QA pair into a statement and prepend the context sentence onto each question. We use the metrics proposed by the original authors, and we select all multiple choice options whose duration falls within some absolute threshold of predicted duration, measured in log seconds. This threshold is selected based on development set performance. **Strict Accuracy** evaluates whether systems correctly label all multiple-choice options for a given context-question pair, and **F1** measures the average F1 between the gold and predicted answer sets.

3.2 Distant Supervision Sources

Temporal Knowledge Bases are a rich resource for studying how facts change over time, and numerous prior works have created datasets from them for studying temporal dynamics in language. TimeQA (Chen et al., 2021b) is one such dataset that curates 70 different temporally-dependent relations from Wikidata and uses handcrafted templates to convert into decontextualized QA pairs, where the question specifies the time period in question. To convert this dataset into fact-duration pairs (f, d), we first convert their QA pairs into a factual statements, f , by removing the date and using a QA-to-statement conversion model (Chen et al., 2021a). We then determine the duration of each facts, d , to be the length of time between the start date of one answer to the question and the next.

Dataset	Example
SituatedQA	Q: Who are the judges on Asia Got Talent? / A: Vanness Wu / Start: 2015, End: 2017 MI: Vanness Wu is the judge on Asia Got Talent , lasting [MASK] [MASK] . / TD: 2 Years
MCTACO	Context: About 30% of Ratners’s profit already is derived from the U.S. Q: How long did it take to make profit? / A: 3 Months MI: About 30% of Ratners’s profit already is derived from the U.S. It took [MASK] [MASK] to make profit. / TD: 3 Months
TimeQA	Subj: Patrick Burns (businessman) Rel: Lives in Obj: Oshawa, Ontario Start: 1856 End: 1878 MI: Patrick Burns (businessman) lived in Oshawa, Ontario , lasting [MASK] [MASK] . / TD: 22 years
TA-Pretrain	MI: Jorge Ramos has been the face of Univision’s News broadcast for [MASK] [MASK] . TD: 24 Years

Table 2: Fact duration prediction input examples. We standardize formats to predict target duration (**TD**) from the masked input (**MI**). The top row(s) in each cell represents the original data, and the bottom row shows our setting.

QA Calibration Under Temporal Misalignment	Total (Ch. / Unch. between $t_M = 2018$ and $t_q = 2021$)
SituatedQA	322 (157 / 165)
Duration Prediction	# Train / Dev / Test
SituatedQA	— / 377 / 322
TimeQA	11,708 / 2,492 / 2,461
MC-TACO (Duration)	— / 1,075 / 2,899
Time-Aware-Pretraining	24,089 / 5,686 / —

Table 3: Dataset statistics for our QA misalignment calibration and duration prediction tasks. We report the number of examples used in our QA calibration experiments along with how many examples have answers that have changed/unchanged between 2018 and 2021. **News Text** contains a vast array of facts and rich temporal information. Time-Aware Pretraining dataset (TA-Pretrain) (Yang et al., 2020) curates such texts from CNN and Daily Mail news articles using regular expressions to match for duration-specifying phrases (e.g., “Crystal Palace goalkeeper Julian Speroni has ended the uncertainty over his future by signing a new *12 month* contract to stay at Selhurst Park.”). Pretraining on this dataset has previously been shown to improve performance on temporal commonsense tasks.

3.3 Dataset Summary

Table 3 reports data statistics. In Figure 2, we show the distribution of durations from each dataset. While most facts in SituatedQA and TimeQA change over the course of months to decades, facts in MCTACO and TA-Pretrain cover a wider range.

4 Fact Duration Prediction

Before reporting our duration prediction results, we first describe our models for predicting duration.

4.1 Comparison Systems

Lowerbounds We include two simple baselines: *Random* samples a duration and *Average* uses the

average duration from each dataset.

Following prior work on temporal common sense reasoning (Yang et al., 2020), we develop BERT-based (Devlin et al., 2018) models.³ We frame fact duration prediction as cloze questions to more closely match the system’s pretraining objective (Schick and Schütze, 2020). To this end, we append “, **lasting** [MASK][MASK]” onto each fact,⁴ illicit the model to fill in the masked tokens with a duration. Similarly, for our TA-Pretrain and MCTACO datasets, we replace the target durations with two mask tokens. Table 2 contains examples. Predictions are made by encoding the input statement averaging the encoded representations of the two “[MASK]” tokens and using it as an input to a single hidden layer network. Using this same representation, we train two models with regression-based and classification-based learning objectives respectively.

Classification Model frames the task as a 13-way classification task where each class corresponds to a duration in Figure 2.⁵ We train using cross entropy loss, selecting the closest duration class as the pseudo-gold label for each fact. Because this model can only predict a limited set of durations, we report its upperbound by always selecting the class closest to the gold duration.

Regression Model uses the mean squared error loss in units of log seconds, where the output from the hidden layer predicts a scalar value.

³We explore using other pretrained models in Appendix C.

⁴We use two mask tokens as typically duration information requires at least two tokens, one for value and another for unit.

⁵We select these duration classes based on frequency across all datasets.

Model	Training Data	SituatQA		TimeQA		MCTACO	
		LS-MSE	Y-MAE	LS-MSE	Y-MAE	EM	F1
Random	—	7.14	13.44	2.22	6.96	20.3	38.1
Average	—	5.42	10.61	1.65	5.41	23.8	41.3
Classification Upperbound	—	0.28	4.18	0.12	1.66	8.0	37.2
Classification	TimeQA	4.20	8.45	1.55	4.80	20.3	41.3
	TA Pretrain	40.51	8.77	9.36	7.85	28.3	57.7
	TimeQA + TA Pretrain	6.28	8.37	1.70	4.66	28.3	57.2
Regression	TimeQA	3.75	8.40	0.97	4.22	21.2	41.0
	TA Pretrain	38.48	8.99	32.10	5.70	33.1	57.8
	TimeQA + TA Pretrain	3.58	8.15	0.97	4.19	31.8	57.8

Table 4: Fact Duration Prediction Results.

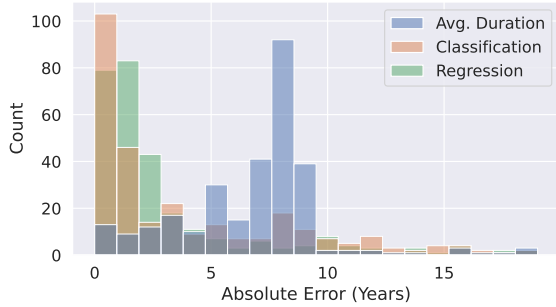


Figure 3: Histogram of errors from fact duration systems trained on TimeQA + TA-Pretrain and evaluated on SituatedQA. We truncate errors > 20 years.

4.2 Results

We experiment with training on TimeQA and TA-Pretrain individually and on the union of both datasets. Table 4 reports duration prediction and temporal commonsense performance. Overall, we find that our trained systems outperform simple random and average baselines on SituatedQA. This is indicative of strong generalizability from our distantly-supervised fact-duration systems, even when baselines benefit from access to the gold label distribution. We also provide a histogram of errors from our systems in Figure 3 where we can see that over 60% of our classification-based system’s predictions are within 3 years of the gold duration, while predicting the exact duration remains challenging. Below, we reflect the impact of our different modeling choices and research questions.

Regression vs. Classification Regression-based models tend to outperform their classification-based counterparts. The instances where this is not true can be attributed to an insufficient amount of training data. In Figure 3, we can see the different types of errors each model makes. The classification-based system predicts duration within 1 year more frequently, but is off between by 2-3 years more frequently than our regression-based system.

Supervision from KB vs. News Text We find that training on temporal knowledge-base relations (TimeQA) alone vastly outperforms training on news text (TA Pretrain) alone for fact-duration prediction; however, the opposite is true when comparing performance on temporal commonsense (MCTACO). Training on both datasets tends to improve our regression-based system, but yields mixed results for our classification-based system. We hypothesize that the closeness in label distribution (see Figure 2) between the training and evaluation sets impacts the performance significantly.

Fact Duration vs. Temporal Commonsense

While fact duration prediction and temporal commonsense are conceptually related, we find that strong performance on either task does not necessarily transfer to the other. As discussed above, this can be attributed to differences in label distributions; however, label distribution also serves as a proxy variable for the type of information being queried for in either task. Commonsense knowledge primarily differentiates events that take place over different orders of magnitude of time (e.g., seconds versus years). Differentiating whether an event takes place over finer-grained ranges (e.g., one versus two years), however, cannot be resolved with commonsense knowledge alone, and further require fact retrieval. We find that NQ contains queries for facts that change over a smaller range of durations (between 1-10 years), and, therefore, commonsense knowledge alone is insufficient.

5 Calibrating QA under Temporal Misalignment

In this section, we return our motivating use-case of using fact duration prediction to calibrate open-retrieval QA systems under temporal misalignment.

QA Model	Fact Dur. Model	AUCROC \uparrow	ECE \downarrow	RC@55 ($ \Delta \downarrow$)	Avg Conf % Δ
① T5 36.0 \rightarrow 17.4	N / A	0.766	0.265	27.2 (27.8)	0.0
	Oracle	0.749	0.116	47.8 (7.2)	-25.8
	Regression	0.709	0.185	32.4 (22.6)	-23.2
	Classification	0.765	0.131	29.3 (25.7)	-15.1
② DPR ($t_e = 2018$) 37.9 \rightarrow 17.1	N / A	0.629	0.433	22.4 (32.6)	0.0
	Oracle	0.708	0.172	38.7 (16.3)	-36.9
	Regression	0.601	0.268	26.1 (28.9)	-34.0
	Classification	0.654	0.235	43.5 (11.5)	-20.9
③ DPR ($t_e = 2021$) — \rightarrow 19.6	N / A	0.636	0.370	25.4 (29.6)	-3.8

Table 5: Results for calibrating QA under temporal misalignment on SituatedQA. All systems’ training dates are 2018 and evaluation dates are 2021. We report each system’s EM accuracy, evaluated against the answers from 2018 and 2021, in the first column. We also report how much model confidence changes on average (Avg Conf Δ) with each adjustment method (for DPR with $t_e = 2021$ we compare average confidence against using $t_e = 2018$).

5.1 Calibrating with Fact Duration Prediction

We begin by assuming access to some existing base calibration system, $c(q, a) \in [0, 1]$ that has the same training date as the QA system its calibrating. We then use fact duration to generate our misalignment-aware confidence score c_m through simple post-hoc augmentation, scaling **down** the existing confidence score by a discount factor based on the degree of misalignment and the predicted fact duration. We compute this factor differently for each of our fact duration systems.

- **Classification:** Here, the output is a probability distribution over our different duration classes ($p(d|q, a)$). We set the discount factor to be the CDF of this distribution evaluated at m :

$$c_m = c(q, a) \sum_{d \leq m} P(d|q, a)$$

- **Regression:** Here, the output is a single predicted duration d . We set the discount factor to the binary value indicating whether or not the misalignment period has exceeded the predicted duration:⁶

$$c_m = c(q, a) \mathbb{1}\{d < m\}$$

5.2 Models

Base QA and Calibration Systems We experiment with three QA systems throughout our study:

⁶We also experiment with using our classification-based system’s predicted class or the expected duration as the duration for adjusting confidence, but find that both methods underperform compared to using the system’s CDF. We include these results in Appendix C.

- ① T5: We use T5-large (Roberts et al., 2020) which has been pretrained with salient-span-masking objective as a closed-book system on NQ-Open dataset.
- ② DPR ($t_e=2018$): We use DPR (Karpukhin et al., 2020) which retrieves passages from a $t_e = 2018$ Wikipedia snapshot as an open-book system. The model is also trained on the NQ-Open dataset.
- ③ DPR ($t_e=2021$): We use the same model from ②, but swap the retrieval corpus with an updated Wikipedia snapshot that matches query timestamp ($t_e = 2021$) following Zhang and Choi (2021), which showed partial success in returning up-to-date answers.

For each QA system, we train a calibrator that predicts the correctness of the QA system’s answer. We follow Zhang et al. (2021) for the design and input features to calibrator, using the model’s predicted likelihood and encoded representations of the input (details in Appendix A).

Fact Duration Systems For both our regression and classification based models, we use the systems trained over both with TimeQA. We also include results using an oracle fact duration system, which zeroes the confidence for all questions that have been updated since the training date.

5.3 Results

Table 5 the results from our calibration experiments. As discussed in 2.1, both models suffer from temporal degradation, and zero-ing out the confidence of outdated facts with oracle information improves the calibration performance. Using the duration predicted from our model also shows

Model	Adj.	AUCROC	ECE	RC@55 (Δ)
① T5	Uniform Per-Ex	0.757 0.765	0.180 0.131	30.5 (24.5) 29.3 (25.7)
② DPR	Uniform Per-Ex	0.627 0.654	0.259 0.235	25.6 (29.4) 43.5 (11.5)

Table 6: Ablating per-example calibration: We first adjust confidence **Per-Example**, which is our full system. We then adjust confidence **Uniformly** across all examples, such that the net decrease in confidence across the test set is equivalent.

similar gains. Both regression and classification model lowers the confidence of models, improving calibration metrics across the board. We find that our classification-based model consistently outperforms our regression-based model on our calibration task, despite the opposite being true for our fact-duration evaluations. We attribute this behavior to our classification-based system’s error distribution, as it gets more examples correct to within 1 year (Figure 3). Classification-based system can also hedge its predictions over different duration classes by predicting a distribution, which we use to compute the CDF over.

Retrieval-Based QA: Update or Adjust In Table 5, we compare the performance of DPR with static and hot-swapped retrieval corpora from $t_e = 2018$ and $t_e = 2021$. While updating the retrieval corpus improves EM accuracy, adjusting model confidence using fact duration on a static corpus performs better on all calibration metrics. This suggests that, when users care about having accurate confidence estimates or only see high-confidence predictions, temporal adjustment can be more beneficial than swapping retrieval corpus.

Ablations: Per-Example vs Uniform Adjustment We compare our system, which adjusts confidence on a per-example basis, against one that uniformly decreases confidence by the same value v across the entire test set: $c_m = \max(c(q, a) - v, 0)$. These ablations still depend on our fact-duration systems to determine the v such that the total confidence over the entire test set is the same for both methods. Table 6 reports the results from this ablation study. We find that uniformly adjusting confidence improves ECE, which is expected given the decrease in the QA systems EM accuracy after misalignment. We find, however, that our per-example adjustment methods outperform uniform confidence adjustments.

Inference Ensemble	EM	%
① T5 + ⑧ DPR ($t_e = 2021$)	20.5	45.7
② DPR ($t_e = 2018$) + ⑧ DPR ($t_e = 2021$)	19.3	45.0

Table 7: Adaptive inference using temporal misalignment results: we use our duration prediction to decide whether to use the prediction from model with newer corpus (DPR $t_e = 2021$). In this data (SituatingQA), 48.8% of examples requires up-to-date knowledge.

6 Beyond Calibration: Adaptive Inference

In this section, we go beyond calibration and use the new misalignment-aware confidence score to decide **how** to answer the question. Concretely, we consider a system that is equipped with multiple paths to answer a question (i.e., three systems described in Section 5.2) and choose a path based on fact duration prediction. We motivate two adaptive inference scenarios and discuss the performances.

Hybrid: Closed + Open (①+⑧): Recent work has investigated the benefits of hybrid closed/open book QA systems: systems that perform closed-book QA when possible, but retrieve evidence when necessary. Besides the computational benefits of not always having to use retrieval, forgoing retrieval for popular questions only can also improve overall performance (Mallen et al., 2022). We use our fact duration predictions to decide when retrieval is necessary: we first predict an answer using T5 and run fact duration prediction using this answer. We then use the CDF of the predicted duration distribution to determine whether it is at least 50% likely that the fact has changed: $\sum_{d \leq m} P(d|q, a) \geq 0.5$. If so, we then run retrieval with DPR using the updated corpus $t_e = 2021$ and present the predicted answer. We report our results in the first row of Table 7, which shows that this outperforms either system on its own, while running retrieval on less than half of all examples.

Two Corpus: Relevancy vs. Recency (②+⑧): While most work for QA have focused on retrieving over Wikipedia, many questions require retrieving over other sources such as news or web text. One challenge in moving away from Wikipedia lies in managing *temporal heterogeneity* across different articles. Unlike Wikipedia, news and web articles are generally not maintained to stay current, requiring retrieval-based QA systems using such resources to identify out-of-date information in articles. Systems that retrieve such resources must consider the trade-off between the recency versus

relevancy of an article. In these experiments, we experiment with using fact duration prediction as a method for evaluating this trade-off in retrieval.

Our experimental setup is as follows: instead of computing misalignment from the model’s training date, we compute relative to when the article was authored ($m = 3$ years for retrieval over 2018 Wikipedia and $m = 0$ years for retrieval over 2021 Wikipedia). After predicting the best answers using either retrieval corpus, we re-rank answers according to their misalignment-adjusted confidence estimates, and select the answer with the greater confidence. We report results in Table 7. We find that our method is able to recover comparable performance to always using up-to-date articles, while using it just under half the time.

7 Related Work

Commonsense and Temporal Reasoning Recent works have proposed several forecasting benchmarks (Zou et al., 2022; Jin et al., 2021a) related to our fact duration prediction task. While our task asks models to predict *when* a fact will change, these forecasting tasks ask *how* a fact will change. Qin et al. (2021) studies temporal commonsense reasoning in dialogue settings with focus on numerical reasoning. Quantitative reasoning has been explored in other works as quantitative relations between nouns (Forbes and Choi, 2017; Bagherinezhad et al., 2016), distributions over quantitative attributes Elazar et al. (2019), and representing numbers in language models (Wallace et al., 2019).

Calibration Abstaining from providing a QA system’s predictions has been explored in several recent works. Chen et al. (2022) examines instances where knowledge conflicts exist between a model’s memorized knowledge and retrieved documents. As the authors note, such instances often arise due to temporal misalignment. Prior work (Kamath et al., 2020; Zhang et al., 2021; Varshney and Baral, 2023) has explored abstaining from answering questions by using a second model to predict whether the test question comes from the same training distribution of the QA system. While our fact duration is also being used to predict a shift in distribution, fact duration focuses on predicting a shift in a question’s *output* distribution of answers instead of a shift in *input* distribution of questions; therefore, these two systems are addressing orthogonal challenges in robustness to distribution shift and are complementary.

Keeping Systems Up-to-Date Several works have explored continuing pretraining to address temporal misalignment in pretrained models (Dhingra et al., 2022; Jin et al., 2021b). Other works have explored editing specific facts into models (Cao et al., 2021; Mitchell et al., 2022; Meng et al., 2022). These works, however, have only focused on synthetic settings and assume access to the updated QA pair. Furthermore, such systems have yet to be successfully applied to new benchmarks for measuring whether language models have acquired emergent information (Onoe et al., 2022). Recent work on retrieval-based QA systems have found improved adaptation when updated with up-to-date retrieval corpora (Izacard et al., 2022; Lazaridou et al., 2022).

Prompted LLMs We focus on fine-tuned QA models, but recent work has also explored prompting language models for QA. Calibration under this setting has been studied (Si et al., 2022; Kadavath et al., 2022). Recent products from OpenAI, such as ChatGPT (OpenAI, 2022) and GPT-4 (OpenAI, 2023), have also demonstrated the ability to identify when its predictions are based on temporally-volatile facts (see examples in the Appendix D); however, it’s not public knowledge how their system works. We find that GPT-4 abstains on 86% of all SituatedQA examples we study: on 95% of examples whose answers have been updated between 2018 and 2021 and on 79% of examples that have not (details in Appendix D). However, they do not provide users with estimates of how likely it is that a fact has changed, only that it does change over time. In contrast, our approach provides users with an interpretable duration estimate indicating why a prediction may not be trustworthy.

8 Conclusion

We improve QA calibration under temporal misalignment by introducing the fact duration prediction task, alongside several datasets and baseline systems for it. Future work may build upon this evaluation framework to further improve QA calibration under temporal misalignment. For instance, future work may examine modeling different classes distributions of fact duration distributions, like modeling whether a fact changes after a regular, periodic time interval.

Limitations

We only evaluate temporal misalignment between 2018 and 2021, a three-year time difference, on a relatively small scale SituatedQA dataset (N=322). This is mainly due to a lack of benchmark that supports studying temporal misalignment. Exploring this in more diverse setup, including different languages, text domains, wide range of temporal gaps, would be fruitful direction for future work.

As is the case with all systems that attempt to faithfully relay world knowledge, treating model predictions as fact runs the risk of propagating misinformation. While the goal of our fact duration prediction systems is to prevent models from reciting outdated facts, it does not always succeed and facts may change earlier than expected. Even though a given fact may be expected to only change once every decade, an improbable outcome may occur and the fact changes after only a year. In such an event, our misalignment-aware calibration system may erroneously maintain high confidence in the outdated answer.

Furthermore, our system, as it stands, does not take the answer start date into account. Our system also can make errors due to changes in the typical duration of a given fact. For instance “*What’s the world’s tallest building?*” changes more frequently over time as the rate of technological advances also increases. We explore such errors from our systems in Appendix C.

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A Implementation Details

A.1 QA Models

We use the T5⁷ and DPR⁸ checkpoints that have been finetuned on NQ-Open’s training set from the transformers library model hub.⁹ For DPR, we use the retrieval corpora from December 20, 2018 for $t_E = 2018$ and February 20, 2021 for $t_E = 2021$, following [Zhang and Choi \(2021\)](#).

A.2 Calibration Models

We implement our trained calibration systems using XGBoost ([Chen and Guestrin, 2016](#)) using the features for T5 and DPR outlined in [Zhang et al. \(2021\)](#). For T5, we concatenate (1) the averaged, encoded representations of the input question, and (2) the model likelihood. For DPR, we concatenate (1) the averaged, encoded representations of the input question and selected passage, (2) the averaged, encoded representations of the start and end tokens of the selected answer span, and (3) the likelihood of the answer span, computed as the product of the likelihoods of selecting the start index, end index, and passage index.

⁷<https://huggingface.co/google/t5-large-ssm-nqo>

⁸<https://huggingface.co/facebook/dpr-reader-single-nq-base>

⁹<https://huggingface.co/models>

Model	Training Data	SituatQA		TimeQA		MCTACO	
		LS-MSE	Y-MAE	LS-MSE	Y-MAE	EM	F1
Classification	TimeQA	8.5	4.18	4.7	1.47	20.6	41.2
	TA Pretrain	9.0	55.33	6.0	22.05	28.9	53.8
	TimeQA + TA Pretrain	8.2	7.58	5.1	1.56	28.0	56.9
Regression	TimeQA	8.4	3.76	4.6	1.18	25.1	41.3
	TA Pretrain	11.6	44.56	20.6	27.59	33.1	58.3
	TimeQA + TA Pretrain	8.7	7.66	4.6	1.23	32.2	57.3

Table 8: Fact Duration Prediction Results using DeBERTa-v3-base instead of BERT-base. All other settings are the same as in Table 4.

QA Model	Misalignment Adj.	AUCROC \uparrow	ECE \downarrow	RC@55 ($ \Delta \downarrow$)	Avg Conf % Δ	
① T5 36.0 \rightarrow 17.4	CDF	0.765	0.131	29.3	25.7	15.1
	Argmax	0.762	0.249	28.1	26.9	2.6
	Expectation	0.708	0.169	37.5	17.5	35.0
② DPR ($t_e = 2018$) 37.9 \rightarrow 17.1	CDF	0.654	0.235	43.5	11.5	20.9
	Argmax	0.650	0.403	23.8	31.2	3.9
	Expectation	0.641	0.177	38.2	16.8	49.2

Table 9: Additional calibration results on SituataQA, comparing different methods of adjusting model confidence for temporal misalignment using the output of our classification-based fact-duration system. All other settings are the same as in Table 5.

We train our systems on NQ-Open on a randomly sampled 60/40 training and development splits, following Zhang et al. (2021). We use a maximum depth of 10 and experiment with several values for the learning rate $\{0.01, 0.1, 0.2, 0.5\}$ and column sub-sampling ratio $\{0.0, 0.1, \dots, 0.9\}$, which we keep the for sampling by tree, level, and node. We train with early stopping after 10 epochs without improvement and select the best performing system as evaluated on the development split.

A.3 Fact Duration Prediction Models

We use BERT-base from the transformers library for all duration prediction baselines, trained with a batch size in $\{32, 64\}$ and learning rate in $\{1e - 5, 5e - 5\}$. We train until convergence and select the best checkpoint as determined by development set performance. Due to computational resource constraints, we do not further tune hyperparameters. All models are trained once and results reflect a single run. All experiments took were performed Quadro RTX 8000 gpus and required less than one week’s worth of GPU hours.

B Datasets

B.1 Fact Duration Dataset Preprocessing

In TimeQA, several examples have answers that are simply the empty string. We remove all such examples from our preprocessed dataset. In SituataQA, several examples have answers that begin and end

in the same year, without further annotation determining the exact number of days or months. We simply assume that all such question answer pairs instances have a duration of 1 month.

B.2 Temporal Commonsense Datasets Preprocessing

As we noted above, each MCTACO example consists of a multiple-choice question about the duration of some event in a provided context sentence. During preprocessing, we use the same question conversion model as above to transform each QA pair into a statement and prepend the context sentence onto each question. We use the metrics proposed by the original authors, and we select all multiple choice options whose duration falls within some absolute threshold of predicted duration, measured in log seconds (Yang et al., 2020). This threshold is selected based on development set performance.

C Additional Results

Different Pretrained Models for Fact Duration Prediction In Table 8, we report our results from DeBERTa-v3-base (He et al., 2021) on our fact duration prediction system. We also experiment with using the large variants of both BERT and DeBERTa, but do not find substantial improvement.

Adjusting Confidence with Expected Duration In addition adjusting confidence using the CDF

User: Who is the current US president?
ChatGPT: As an AI language model, I don't have real-time information or the ability to browse the internet. My knowledge was last updated in September 2021, and at that time, the President of the United States was Joseph R. Biden Jr. However, please note that the political landscape can change, and there may have been a new election or other developments since then. To obtain the most accurate and up-to-date information, I recommend checking reliable sources such as official government websites or reputable news outlets.

User: Who won the last NBA Championship?
ChatGPT: As an AI language model, I don't have real-time data, and my knowledge was last updated in September 2021. Therefore, I cannot provide information on the winner of the most recent NBA Championship. However, as of my last update, the Milwaukee Bucks were the reigning NBA Champions, having won the championship in the 2020-2021 season. I recommend checking reliable news sources or conducting a quick online search to find the current champion.

Table 10: Example ChatGPT outputs to two temporally dependent questions with different answer durations. Predictions are taken from the May 12, 2023 ChatGPT version.

of the predicted duration distribution from our classification-based system, we also experiment with using the expected duration as our discounting factor. We incorporate this by zeroing the confidence estimate if the expected duration is exceeded by the degree of misalignment: $f(q, a) = \mathbb{1}\{\sum_{d \geq m} d \cdot P(d|q, a)\}$.

In Table 9, we report additional results on our calibration evaluation. We include calibration performance of our best performing fact duration models finetuned on SituatedQA: trained only on SituatedQA for our classification-based model and first trained on TimeQA + TA Pretrain for our regression-based model.

Error Analysis In Table 11, we highlight sampled errors from our fact duration system and discuss their causes and impact.

D ChatGPT and GPT-4 outputs

Table 10 includes two examples of ChatGPT informing users that the answers to a given question may have changed. It, however, does not provide users with an estimate of how likely it has changed, or how often the answer is expected to change. This lack of a duration estimate results in lesser transparency and interpretability for users. To get results on SituatedQA, we prompt GPT-4 with the following system prompt (recommended by their documentation): “You are ChatGPT, a large lan-

Question {2018 Answer / 2021 Answer}	{G / P} Dur
When did the last volcano erupt in Iceland? (2010 / March 19, 2021)	7 Y / 10 Y
How many episodes of Touching Evil are there? (16 / 16)	1 W / 1 Y
Who got the most passing yards in the NFL? (Peyton Manning / Drew Brees)	3 Y / 1 Y

Table 11: Example fact duration predictions errors from SituatedQA. We include the answers from $t_M = 2018$ and $t_q = 2021$, and the gold / predicted durations ($\{G / P\}$ Dur). In the first example, we see that our system correctly identified volcanic eruptions as an infrequent event; however, our system misses that the answer has changed within the misalignment period because it doesn't have access to the answer start date. In the second example, our system fails no longer changes since the show ended. In the last example, our model underestimates the fact's duration, but still correctly identifies that the answer has changed.

guage model trained by OpenAI. Answer as concisely as possible. Knowledge cutoff: September 2021. Current date: May 12, 2023.” We then present GPT-4 with the user's question from SituatedQA. We determine whether a systems abstains from a given prediction if it references its knowledge cutoff from the prompt September 2021 or if it mentions real-time information in its generated output.

E Licensing

Dataset Licensing TimeQA is licensed under the BSD 3-Clause License. SituatedQA and Wikipedia are both distributed under the CC BY-SA 4.0 license. MCTACO and TA-Pretrain are both unlicensed.

Model Licensing The transformers library, BERT model, T5 model, and question conversion model are all licensed under the Apache License v2.0. DPR is licensed under the Attribution-NonCommercial 4.0 International license. Our use of all these resources are in compliance with their licenses.

F Ethical Considerations

We do not collect any data in this paper. While we do generate a dataset, we visually inspect generated examples and do not find any cases of harmful or offensive content. The existing datasets used in this work have previously been vetted by their authors prior work. We also note that our work is only applied to English datasets and models.