# Cooperative Learning of Zero-Shot Machine Reading Comprehension

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#### **Abstract**

Pretrained language models have significantly improved the performance of down-stream language understanding tasks, including extractive question answering, by providing high-quality contextualized word embeddings. However, learning question answering models still need large-scaled data annotation in specific domains. In this work, we propose a cooperative, self-play learning framework, REGEX, for question generation and answering. REGEX is built upon a masked answer extraction task with an interactive learning environment containing an answer entity REcognizer, a question Generator, and an answer EXtractor. Given a passage with a masked entity, the generator generates a question around the entity, and the extractor is trained to extract the masked entity with the generated question and raw texts. The framework allows the training of question generation and answering models on any text corpora without annotation. We further leverage a reinforcement learning technique to reward generating high-quality questions and to improve the answer extraction model's performance. Experiment results show that REGEX outperforms the state-of-the-art (SOTA) pretrained language models and zero-shot approaches on standard question-answering benchmarks, and yields the new SOTA performance under the zero-shot setting.

#### 1 Introduction

Recent studies have shown that language model pretraining provides high-quality text representations and significantly improves neural networks' performance in a variety of natural language processing (NLP) tasks (Peters et al., 2018). Based the popular Transformer architecture (Vaswani et al.,



Tang Dynasty ... Chengdu became nationally known as a supplier of armies and the home of Du Fu, who is sometimes called China's greatest poet.



a supplier of armies and the home of Du Fu

What was Sichuan known for in the ancient world before 957?

QG Agent



A supplier of armies

Figure 1: The pipeline of zero-shot question answering (machine reading comprehension) by REGEX. AER (answer entity REcognition) agent recognizes answer entity from a given passage; QG (question Generation) generates a question based on the passage and recognized entity; QAE (question-answering EXtractor) extracts answer from the question and passage. In REGEX, the question-answer pairs for training the QA models (i.e., the QAE) are automatically generated and recognized by QG and AER models.

2017), various language models have been proposed (Devlin et al., 2018; Liu et al., 2019; Clark et al., 2020). These models are pretrained to predict a masked word in a given context from large corpora, and generate a contextual representation that encodes semantic and syntactic knowledge. The representation significantly improves performance in the downstream tasks after finetuning. Although masked language modeling is a powerful self-supervised training technique, annotation on large-scaled data is still necessary for finetuning in difficult downstream tasks, including extractive question answering (QA)<sup>1</sup> where a large number of labeled question-answer pairs are required as the training corpora.

To build a QA model achieving performance

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<sup>&</sup>lt;sup>1</sup>Also referred to as machine reading comprehension. The two terms are used interchangeably in this paper.

comparable to state-of-the-art (SOTA) approaches with limited data annotation efforts, we explore semi-supervised techniques to generate highquality question-answer pairs for training. We proposed a method consisting of two subtasks, answer entity recognition and question generation, to generate the pairs automatically. Both the entity recognizer and the question generator are pretrained on a limited number of labeled passage-answer-question triples from a seed QA corpus, and then adapted to other unlabeled corpora to generate more pairs. The recognizer aims to identify possible answer spans, including key-phrases and named entities, from input passages. We replace the spans with '[MASK]' tokens and feed the resulting passages into the generator. The generator is built to generate a fluent question that the passage and the masked entity can answer. With the entity recognizer and the question generator, we can automatically obtain labeled question-answer pairs from a text corpus in any target domain and enable the learning of high-performing QA models.

However, there is always a gap between the pretraining (i.e., seed) and the target corpus. We thus propose a reinforced training algorithm to better adapt the question generator and answer entity recognizer to the target domain and benefit the learning of the QA models. In the algorithm, we construct a cooperative environment where a question generator and an answer extractor work together to solve a masked entity prediction problem. The question generator first outputs a question based on the passage masked by the recognizer described above. With the generated question and the original, unmasked passage, we train the answer extractor to select the correct answer spans, which are the masked entity. The extractor is also the final model used for extractive QA. To extract the spans accurately, the generator has to provide a good question, and the extractor should select the most likely tokens. We design the reward functions to favor the questions leading to correct answers. We also gradually increase the difficulties of generated question (Karpukhin et al., 2020) by rewarding the questions that are not answered correctly but with low extraction losses via a stochastic expectationmaximization technique. The technique allows us to train the extractor with challenging examples incrementally. We denote our algorithm as REGEX for it is built with entity REcognizer, question Generator, and answer EXtractor.

With REGEX, we can train a QA model for any unlabeled target domain given the corresponding text corpora and a labeled QA corpus in the seed domain (either the same or different from the target). We show that REGEX yields the SOTA performance under the zero-shot setting in QA benchmark datasets. The pipeline of REGEX is illustrated in Figure 1. In this work, we make the following contributions,

- We propose a zero-shot extractive question answering solution, REGEX, which contains an answer entity recognition, question generation, and answer span extraction.
- We introduce a cooperative, reinforced selfplaying framework that adapts the models pretrained in the seed domain to the target and better trains the question generator and answer extractor jointly.
- We design a stochastic expectationmaximization algorithm that identifies difficult but answerable questions without supervision to incrementally train the QA model with challenging examples.

#### 2 Related Work

Representation learning has been an important topic in NLP area since neural language models were proposed (Bengio et al., 2003). Based on word co-occurrence, Mikolov et al. (2013) and Pennington et al. (2014) proposed language embedding algorithms to model word-level semantics. Recent studies have focused on pretraining contextualized word representations with large-scaled corpora (Peters et al., 2018). State-of-the-art representation models are pretrained with the masked language modeling task (Devlin et al., 2018; Liu et al., 2019; Clark et al., 2020) using the Transformer architecture (Vaswani et al., 2017).

Different variants of masked language models have been investigated to improve performance in downstream tasks. Joshi et al. (2020) leveraged a masked span generation task instead of word prediction. Fei et al. (2020) and Shen et al. (2020) proposed models that learns better syntax knowledge with syntactic distances (Shen et al., 2018) and heights (Luo et al., 2019). Henderson et al. (2019) and Humeau et al. (2019) showed that pretraining language models on dialog corpora perform better on dialog-related downstream tasks, as

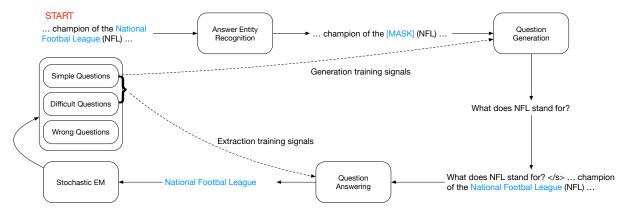


Figure 2: The cooperative learning pipeline for question answering. The pipeline starts from a passage and follows the steps: (1) recognizing a potential answer entity, (2) generating a question asking about the answer entity, and (3) answering the question by extracting the answer span in the passage.

compared to pretraining on Wikipedia. A span selection pretraining objective is proposed in Glass et al. (2019) to reduce the gap between the pretraining and downstream finetuning stages and to improve the performance on the QA task.

New training strategies, including reinforcement learning and self-training, have emerged recently for learning language generation in addition to maximum likelihood training. To optimize text generation models directly with non-differentiable objective functions, Rennie et al. (2017) proposed self-critical sequence training (SCST) using policy gradient (Kakade, 2001; Silver et al., 2014). On the other hand, self-training has been proved effective in various tasks, such as machine translation (He et al., 2019), image classification (Xie et al., 2020), and structured database-grounded question answering (Xu et al., 2020).

In contrast to self-training methods that usually adopt a teacher-student learning strategy, cooperative learning pipelines contain several agents working together to learn as much knowledge as possible. A typical cooperative learning framework is generative adversarial networks (GAN) (Goodfellow, 2016; Goodfellow et al., 2014), where a generator is optimized to confuse a discriminator, and a discriminator is trained to distinguish real examples from generated ones. Sequence GAN is further designed for learning diverse text generation (Yu et al., 2017). Unlike the adversarial learning method where two networks work for opposite goals, other studies proposed learning environments in which different agents learn the same objective functions for language emergence (Lazaridou et al., 2016; Mordatch and Abbeel, 2018; Havrylov and Titov, 2017), including simple natural language, compositional language, and symbolic language. In the domain of question answering, Shakeri et al. (2020) proposed to generate synthetic question-answer pairs with an end-to-end model simultaneously. Lee et al. (2020) introduced a model generating question-answer pairs with VAE and achieved the previous SOTA performance in zero-shot machine reading comprehension.

# 3 Zero-Shot Question Answering

In this work, we propose a cooperative, zero-shot question answering learning algorithm, REGEX, that enables training question answering agents on knowledge bases without large-scale data annotation. In this section, we first introduce the zero-shot question answering with pretrained models on the seed corpora and then propose a cooperative question answering learning environment for further improving the performance. We also illustrate the pipeline of REGEX in Figure 2.

#### 3.1 Zero-Shot QA with Pretrained Models

A fully supervised question answering learning task requires a large number of annotated question-answer pairs. However, the annotation process is usually both expensive and biased. To address the issue, we explore the possibility of reducing the data annotation efforts by training an answer entity recognition model and a question generator on an annotated seed corpus, and generating new question-answer pairs with unlabeled corpora. Then we can train question answering models with SOTA approaches using generated pairs.

## 3.1.1 Answer Entity Recognition

We first train an answer entity recognition (AER) model on a seed QA corpus. We specially build this recognizer because we found it performs poorly to get answer candidates simply with an off-the-shelf named entity recognition (NER) model pretrained on CONLL 2003 shared task (Bender et al., 2003), as shown in our experiment results later. To learn the recognizer, given a passage p, annotated question q, and the annotated answer entity e in the seed corpus, we first randomly select a sentence s containing e from p. We train a BERT-based BIO sequence tagging model that takes s as input, with cross-entropy loss and the labeled answer e. We use this method as a baseline (denoted as AER-Tag).

We also investigated an extraction-based AER model, which is similar to an extractive question answering model. Given a randomly selected sentence s, we train a model that predicts the start and end position of the answer entity e. With this method, we get potential answer entities by sorting the sum of start and end scores of all candidate spans. We further re-rank the entities by selecting those leading to low question generation perplexities (denoted as AER-Search).

#### 3.1.2 Question Generation

With AER, we replace the answer entity e in the passage p with a [MASK] token and obtain the masked passage  $p^*$ . We then build a question generator Q (denoted as QG interchangeably) that outputs answerable questions q in natural language with the concatenation of  $p^*$  and e as input, i.e.,

$$q = Q([p^*, e]) \tag{1}$$

We adopt the BART sequence-to-sequence model (Lewis et al., 2019) as the architecture of Q in our implementation, and we train Q on the question-answer pairs of the Natural Questions corpus (Kwiatkowski et al., 2019) by maximizing the likelihood of annotated questions.

#### 3.1.3 Question Answering

After pretraining the answer entity recognition and question generation models, we apply them to the target, unlabeled text corpora by recognizing answer entities and generating corresponding questions for training the answer extraction model. The answer extraction model A (denoted as QAE, question answering extractor, in the following) takes generated question q and the original, un-masked

passage p as inputs. Following the standard extractive QA method, we concatenate q and p, and train the network to locate the answer in p, which is the answer entity e automatically labeled by AER. That is

$$I_{st}, I_{ed} = A([q, x]) \tag{2}$$

where  $I_{st}$  and  $I_{ed}$  stand for the start and end positions of e in p, respectively. In implementation, we train the model A to predict  $I_{st}$  and  $I_{ed}$  separately with cross entropy losses.

## 3.2 Zero-shot QA with Cooperative Learning

Although the pretrained models can generate answer entity and questions from corpora in different target domains, there is always a domain shift from the seed QA corpus for pretraining to the target. To efficiently adapt the pretrained models to the new domains, we propose a cooperative learning algorithm that allows finetuning the models on the target corpora without additional annotations. The finetuning is based on a two-agent cooperative environment, REGEX. The two agents, namely the question generator (QG) and answer extractor (QAE), work together to predict a target answer entity. To build the environment, we need an answer extraction model pretrained on the seed QA corpus, and a cooperation pipeline processes the input passages from the target domain to self-train the QAE and QG models. The pipeline is illustrated in Figure 2 and comprises the following steps,

- Produce a masked passage by replacing an answer entity selected by AER with the "[MASK]" token.
- Generate a question asking about the masked entity with QG.
- Feed the generated question and the original passage into the QAE to predict the span of the selected answer entity from the original passage.
- Optimize the QAE with the ground-truth of the selected answer entities.
- Optimize the QG with self-critical sequence training.

In the proposed pipeline, all the AER, QG, and QAE models need pretraining to provide a reasonable start point for the cooperative self-training. However, the domain gap between the pretraining and the target corpus causes concern in performance. To mitigate the gap, we propose to measure

the quality of generated questions and incorporate the measurement in loss functions. The quality is defined in two folds, fluency and relevance. Firstly, the question should be fluent and understandable, and secondly, it should ask about the selected answer entity instead of the others. One method to identify the quality of questions is human-in-loop training. In other words, when a new question is generated, a human scorer is assigned to the question and decides if the question is fluent and asking about the selected entity. However, this method is both inefficient and expensive. To solve this problem, we introduce a stochastic expectation-maximization (SEM) method that learns the question quality without supervision.

## 3.2.1 Stochastic Expectation-Maximization

To improve the cooperative self-training, we first divide the generated questions based on the QAE loss each question yielding into three groups: low-, medium-, and high- loss questions. We can interpret questions with low loss as simple ones that the QAE model can easily answer. Medium-loss questions are challenging for the QAE, while those with high loss usually contain noise (e.g., containing grammatical errors or asking about incorrect answers other than the masked ones since the questions are automatically generated). If we train the answering model with all questions, the training signal would be very noisy due to the high-loss questions. Thus, we only train the QAE model with the low- and medium- loss questions, and we reward the QG model for generating only the lowloss questions and the medium-loss ones that QAE answers correctly. For the entire pipeline to be fully-unsupervised, we classify a given question into one of the three types described above by setting thresholds on the loss. Note that simply setting the thresholds as hyper-parameters does not work since the loss decreases as the QAE model being trained. In order to find the thresholds adaptively, we propose the SEM algorithm.

Like the standard EM, the SEM algorithm starts with a set of initial parameters  $\mu_i^0$ ,  $\sigma_i^0$ , and  $i \in [0,2]$  stands for one of the three types of questions.  $\mu_i$  is the mean value of the extraction loss led by the questions of type i, and  $\sigma_i$  stands for the standard variance of the losses of type-i questions. We update the values of  $\mu_i$  and  $\sigma_i$  in each training step. Assume the QAE model's extraction loss is  $l_j^t$ , where j stands for the j-th sample in the current training batch, and t is the current training step. We

decide the type of question j by

$$c_j = argmin_i \frac{|l_j^t - \mu_i|}{\sigma_i} \tag{3}$$

where  $c_j$  is the predicted question type of training example j. We then calculate the mean  $\hat{\mu}_i$  and standard variance  $\hat{\sigma}_i$  of the extraction losses for each question type over all the question-answer pairs in the current training batch, and update the global mean and standard variance of each type with

$$\mu_i^{t+1} = \mu_i^t * \alpha + \hat{\mu}_i * (1 - \alpha) \tag{4}$$

and

$$\sigma_i^{t+1} = \sigma_i^t * \beta + \hat{\sigma}_i * (1 - \beta)$$
 (5)

where  $\mu_i^{t+1}$  and  $\sigma_i^{t+1}$  stands for the new mean and standard variance of extraction losses for each class. The questions from the next training batch will be classified with the updated parameters. We call this method stochastic EM because similar to stochastic gradient descent, the method updates trainable parameters batch-by-batch instead of observing all training data. In our implementation, we define i=0,1,2 as low-, medium-, and high-loss questions, respectively. Obviously, we have  $\mu_0^t < \mu_1^t < \mu_2^t$  for every time step t, and the constraint is guaranteed via value initialization.

## 3.2.2 Reinforced Question Generation

To improve the QG model on the target domain, we train the model using policy gradient with rewards obtained from the SEM algorithm. We reward QG when generating questions that yield low QAE losses or yield medium losses and correct QAE predictions. Besides, while optimizing the model, we compare the likelihood of the generated question q calculated by the optimized generator and the pretrained generator to keep the generated questions grammatically correct. To sum up, for q that should be rewarded, we calculate the rewards by

$$r_q = max(1 - \alpha \cdot D_{KL}(P(q)||P^*(q)), 0)$$
 (6)

where  $D_{KL}$  stands for the KL divergence, P stands for the likelihood of q based on the current generation model,  $p^*$  stands for the pretrained (initial) generation model, and  $\alpha$  is a positive coefficient tuned as a hyperparameter. From the equation, we can see that we do not reward any question yielding high perplexity measured by  $p^*$  since the question may contain grammar errors. With the rewards,

we train the QG model by maximizing the product of each generated question's likelihood and the corresponding reward

$$l_q = r_q \cdot P(q) \tag{7}$$

It is worth noting that rewarding questions with both low- and medium- losses makes training more robust. Rewarding only the low-loss ones likely leads to a trivial convergence, where the QG generates questions containing the answers and the QAE simply does sub-sequence matching. Training only with the medium-loss questions slows down the model convergence.

## **3.2.3** Cooperative Answer Entity Recognition

In addition to the AER-Tab and AER-Search strategies, we propose a cooperative AER model (AER-Coop) for the self-training pipeline. We first enumerate top N answer entities predicted by the pretrained extractive AER model. Instead of only sorting the answer entities by comparing the perplexities of questions they yield in QG, we also score the entities with the pretrained QAE model. If the QAE model successfully predicts the entity based on the generated question, we add a positive score to the entity for re-ranking. With this method, we sample top k answer entities for self-training, where k << N. We show the details of our AER methods in Appendix A.

## 4 Experiments

#### 4.1 Modules

In this work, we train three modules for building the cooperative self-training environment REGEX, i.e., the answer entity REcognizer (AER), the question Generator (QG), and the question-answering EXtractor (QAE). We used a BERT (Devlin et al., 2018) model for AER, a BART (Lewis et al., 2019) model for QG, and an ELECTRA (Clark et al., 2020) model for QAE.

#### 4.2 Data

In our experiment work, we leveraged the Natural Question (Kwiatkowski et al., 2019) dataset as the seed corpus for pretraining all modules introduced above. To evaluate the performance of the proposed REGEX on question answering tasks with different difficulty levels, we conduct experiments on both SQuAD v1.1 (Rajpurkar et al., 2016) and AdversarialQA corpora (Bartolo et al., 2020).

The SQuAD v1.1 is the easiest QA corpus used in this paper. The dataset contains 107, 785 question-answer pairs on 536 articles, which are split into passages. Each question is labeled with an answer that can be extracted from the given passage.

The Natural Questions dataset is a large-scale corpus designed for open-domain question answering. The dataset is more challenging than SQuAD. All questions are collected from human search queries and are annotated with long and abstractive answers. Some of the questions are also labeled with a short answer for learning answer-span extraction or reading comprehension. Focusing on the machine reading comprehension task, we select 106, 926 questions labeled with both long and short answers from the dataset for experiments.

AdversarialQA is the most challenging dataset evaluated in this work. The dataset is constructed by collecting natural-language questions that humans can correctly answer, but SOTA pretrained language models, including BERT (Devlin et al., 2018) and RoBERTa (Liu et al., 2019), cannot. The corpus contains 30,000 question-answer pairs for training. The size is smaller than the SQuAD, but the questions are more difficult for machine reading comprehension models. We evaluate REGEX on both SQuAD and AdversarialQA corpora to analyze the quality of the extracted answers and generated questions.

#### 4.3 Implementation Details

There are three phases of model training in this work: pretraining on the Natural Question corpus, cooperative adaptation with reinforcement learning on the target corpora, and final finetuning on the target corpora. We adopt most of the hyperparameters reported in the original BERT (Devlin et al., 2018), BART (Lewis et al., 2019), and ELEC-TRA (Clark et al., 2020) papers. However, we noticed that the ELECTRA model is not stable with our generated question-answer pairs at the final finetuning. As a result, we select the final finetuning learning rates from  $\{3e-5, 4e-5, 5e-5\}$ and report the highest performance. All the other hyper-parameters are the same as reported in the corresponding papers. For all the phases, we fix eps = 1e - 6 and  $s_w = 2000$ , where  $s_w$  is the number of warm-up steps, and we apply no weight decays. In the following sections, we describe the details of each training phase.

## 4.3.1 Pretraining

We pretrain the AER, QG, and QAE models on the Natural Questions (i.e., the seed) corpus. Since the corpus is designed for learning question-answering models and each passage only contains one answer entity, the training data is very sparse. To solve the problem, we only use the sentence containing the answer entity to balance the token classes.

## 4.3.2 Cooperative Learning

We follow the steps described in section 3.2 for the cooperative training phase. Since we pretrain the AER model on the sentence level, we first split input passages into sentences and then run the AER model on each sentence to predict the answer entities. With the recognized answer entities from each sentence, we randomly sample one entity to train the QG and QAE models.

## 4.3.3 Final Finetuning

For finetuning, we apply a similar method to preprocess the target corpus as we used in cooperative learning. We first recognize all possible answer entities in each passage in the target corpus' training set and then generate questions with all the recognized entities to construct the training question-answer pairs. AER and QG models are fixed here. With the training pairs, we finetune the QA model using the official Huggingface (Wolf et al., 2019) training scripts for question answering <sup>2</sup>.

## 4.4 Finetuning Performance

To evaluate the performance of REGEX, we train our models with the three phases using settings of both zero-shot and semi-supervised learning. In our semi-supervised setting, we use the annotated answer entities in the target corpora but utilize QG to generate questions for obtaining the training question-answer pairs. The labeled questions are not used. We employ no annotation from the target corpora for the zero-shot task but re-construct the question-answer label pairs with recognized answer entities and generated questions using AER and QG.

## 4.4.1 Semi-supervised QA

We first evaluate REGEX with the semi-supervised question answering task. Here we use the human-annotated answers and QG-generated questions for

cooperative training and final finetuning. The performance of models only with pretraining, REGEX, and SOTA trained with full-supervision is shown in Table 1 for both SQuAD and AdversarialQA.

Models	EM	F1
SQuAD 1.1		
PT	81.2	89.1
CT	83.1	90.7
Supervised ELECTRA-large	89.7	94.9
AdversarialQA		
PT	27.9	41.4
CT	30.3	43.9
Supervised ELECTRA-large	50.1	62.9

Table 1: The performance of the question answering models in the semi-supervised setting. PT is the pre-trained model, and REGEX stands for our cooperatively trained approach. Additionally, we also show the supervised SOTA results, which are trained with the Electra-large-discriminator model, for comparison.

Table 1 shows that REGEX yields improvement over pretrained models in both corpora. REGEX reaches over 90% F1 score in SQuAD. The performance approaches the SOTA, achieved by training an ELECTRA-large-discriminator model on the entire annotated training set. On the AdversarialQA corpus, REGEX also outperforms the pretraining method. However, there is a more significant gap between SOTA and REGEX, which only uses annotated answers but no questions. The experiment result suggests that the cooperative learning strategy improves the question generation model, but the quality and complexity of generated questions are still worse than ones composed by humans. Thus, we observe a more considerable performance drop in AdversarialQA than SQuAD.

## 4.4.2 Zero-Shot OA

We also evaluate the models under the zero-shot learning settings, where we do not use any annotated questions and answer entities. We first run the AER model to recognize answer entities and generate a question for each entity with the QG model. We train the QAE models based on the constructed question-answer pairs and evaluate the models on the original test set. We summarize the zero-shot experiment results and the SOTA performance in Table 2.

The results show that REGEX trained in zeroshot still achieves the high eighties F1 scores on

<sup>2</sup>https://github.com/huggingface/ transformers/tree/master/examples/ question-answering

Models	EM	F1			
SQuAD 1.1	SQuAD 1.1				
Info-HCVAE (Lee et al., 2020)	71.2	81.5			
PT + NER	18.4	25.7			
CT + NER	27.4	35.4			
PT + AER-T	60.8	75.7			
CT + AER-T	71.4	82.4			
PT + AER-S	70.2	83.8			
CT + AER-S	72.7	85.9			
PT + AER-C	75.9	86.9			
CT + AER-C	79.3	89.0			
Supervised ELECTRA-large	89.7	94.9			
AdversarialQA					
PT + AER-T	17.7	29.5			
CT + AER-T	21.8	34.4			
PT + AER-S	22.6	37.1			
CT + AER-S	24.1	38.7			
PT + AER-C	24.2	37.6			
CT + AER-C	25.7	40.0			
Supervised ELECTRA-large	50.1	62.9			

Table 2: The performance of the question answering models in the zero-shot setting. Info-HCVAE is the previous zero-shot SOTA in SQuAD 1.1. In the approaches denoted as NER, we utilize the BERT named entity recognition model pretrained on the CONLL 2003 shared task for AER. AER-T, AER-S, and AER-C stand for recognizing answer entities with the tagging models, the extractive AER-Search method, and the cooperative answer entity recognition. Similarly, we also report the supervised SOTA for comparison.

SQuAD and significantly outperforms the previous zero-shot SOTA (Info-HCVAE). REGEX zero-shot also performs slightly worse than semi-supervised training in the AdversarialQA, but we did not find previous zero-shot studies to compare with our models. The cooperative learning models still yield significantly better performance than the pretrained models, and we notice that the improvement from the cooperative learning over the pretrained models is higher in the zero-shot setting than the semisupervised task for both datasets. The observation indicates that the model trained with the cooperative environment is more robust against the automatically recognized answer entities, which are noisier than the annotated ones. We also experiment with recognizing answer entities using the NER model pretrained on CONLL corpus. The setting yields low extraction performance, suggesting the importance of our AER module.

## 4.5 Analysis

#### 4.5.1 Case Study

An example of a SQuAD passage is shown in Table 3. We list the annotated and generated question-answer pairs by different models. The table shows that the models can recognize reasonable answer entities other than the annotated ones, and the REGEX generates more readable questions.

## 4.5.2 Diversity is Important

Question Generation. We further analyze the quality of generated questions on SQuAD and AdversarialQA. We compare the lengths and vocabulary sizes of the questions and summarize the statistics in Table 4. The statistics show that the ground-truth questions are longer and more diverse in vocabulary than the generated ones in both corpora. Under the zero-shot setting, generated questions have a significantly smaller vocabulary than ground-truth ones, and the vocabulary size of the generated questions is also smaller in a more difficult corpus (AdversarialQA). We observe a correlation between the vocabulary size and the QA performance reported in Table 1 and 2, presumably because the QAE model requires diverse knowledge during training. Thus, we believe generating more diverse question-answer pairs with good quality will be a critical next step to improve REGEX.

Answer Entity Recognition. We then analyze the AER model based on the ratio of human-annotated answers that AER successfully recognizes. We report the rate (denoted as hit rate) for both corpora in Table 5. We also summarize the number of answers in each passage, average answer lengths, and the vocabulary sizes of answers for both recognized and annotated ones. Like the generated questions, the recognized answers are less diverse than the annotated ones in terms of both vocabulary size and answer lengths. The vocabulary size of the recognized answers is significantly smaller in AdversarialQA than SQuAD, leading to less diverse question generation. We also notice that the hit rate is not high on both corpora but still results in promising zero-shot performance. Given that the diversity and quality of recognized answers decide the performance of generated questions and thus the final QAE results, we believe an improved AER allows us to better leverage the potential of REGEX.

Architecturally, the school has a Catholic character. Atop the Main Building's gold dome is a golden statue of the Virgin Mary. Immediately in front of the Main Building and facing it, is a copper statue of Christ with arms upraised with the legend "Venite Ad Me Omnes". Next to the Main Building is the Basilica of the Sacred Heart. Immediately behind the basilica is the Grotto, a Marian place of prayer and reflection. It is a replica of the grotto at Lourdes, France where the Virgin Mary reputedly appeared to Saint Bernadette Soubirous in 1858. At the end of the main drive (and in a direct line that connects through 3 statues and the Gold Dome), is a simple, modern stone statue of Mary.

Annotated	Pretrained	REGEX
Saint Bernadette Soubirous	a Marian place of prayer and reflection	a Marian place of prayer and reflection
To whom did the Virgin Mary allegedly appear in 1858 in Lourdes France?	what is the grotto at st bernadette's?	what is the grotto in st bernadette school?
a copper statue of Christ	the grotto at Lourdes, France	Venite Ad Me Omnes
What is in front of the Notre Dame Main Building?	where is the grotto located at st bernadette school?	what is the message on the statue in front of st bernadette school?
the Main Building	Immediately behind the basilica is the Grotto	1858
The Basilica of the Sacred heart at Notre Dame is beside to which structure?	what is the grotto in st peter's school?	when was the grotto at lourdes built?
a Marian place of prayer and reflection	copper statue of Christ with arms upraised	a simple, modern stone statue of Mary
What is the Grotto at Notre Dame?	what is it a statue of christ?	what is the statue at st bernadette school?
a golden statue of the Virgin Mary	a replica	the grotto at Lourdes, France
What sits on top of the Main Building at Notre Dame?	is the grotto at st bernadette school in paris a replica of which European landmark?	what is the replica of st bernadette's school in paris?

Table 3: An example of a passage in the training set of the Squad corpus. We list the annotated question-answer pairs, and the question-answer pairs generated by the pretrained and REGEX models. The bold texts are annotated or recognized answer entities.

Models	Mean Len.	Std Len.	Vocab		
	SQuAD				
Ground-truth	11.29	3.72	988703		
Semi-sup. PT	10.49	2.48	919105		
Semi-sup. CT	10.54	1.91	923191		
Zero-shot PT	10.57	2.63	789924		
Zero-shot CT	10.53	1.94	873300		
AdversarialQA					
Ground-truth	10.83	4.71	324919		
Semi-sup. PT	10.64	2.57	319144		
Semi-sup. CT	10.63	1.92	318978		
Zero-shot PT	10.56	2.65	108620		
Zero-shot CT	10.53	1.9	108270		

Table 4: The vocabulary sizes and lengths of questions annotated by humans or generated by different models. Results for both SQuAD 1.1 and AdversarialQA are showed.

#### 5 Conclusion

We propose a cooperative, self-play learning framework, REGEX, for question generation and answering in this work. REGEX contains an answer entity REcognizer, a question Generator, and an answer EXtractor. We also introduce in the framework a novel stochastic expectation-maximization method to measure the quality of generated questions. Ex-

Models	Mean Len.	Ans./Psg.	Vocab
SQuAD (hit rate: 15.35%)			
Ground-truth	3.38	4.64	295653
AER	2.63	4.20	208994
AdversarialQA (hit rate: 6.19%)			
Ground-truth	4.22	11.32	126731
AER	2.64	4.13	28954

Table 5: Statistics of annotated and recognized answer entities. Vocab is the vocabulary size in the entities; Ans/Psg is the average number of answers in a passage; the hit rate stands for the ratio of annotated answers that the AER model successfully recognizes.

periments show that REGEX significantly outperforms the pretrained model baselines in both zero-shot and semi-supervised settings, and the zero-shot SOTA in literature. Furthermore, the REGEX question-answering model achieves performance comparable to fully-supervised SOTA in SQuAD 1.1 dataset with automatically generated question-answer pairs. Experiments and analyses suggest that REGEX, which leveraging cooperative self-play learning, is a promising framework for making machine learning methods more scalable and less dependent on human annotation.

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## **A** Answer Entity Recognition Details

In this section, we describe details of the AER methods, which are not covered in detail in previous sections. All AER models are pretrained on the Natural Questions corpus. To solve the sparsity problem, in other words, the passages are long but not all potential question-answer pairs are annotated, we train all following AER models by using the sentence containing the annotated answer entities as inputs, instead of the whole passage. If a sentence in the passage does not contain an annotated answer entity, we do not use it for training.

In this work, we introduce two types of AER methods, tagging based AER (AER-tag) and extraction based AER (AER-Search and AER-Coop). We describe their training and how we use the trained model to recognize answer entities in our experiments.

#### A.1 AER-Tag

#### A.1.1 Training

We apply a BIO tagging model for answer entity recognition in the AER-Tab method. We train the model to classify all tokens in the input sentence into three classes,

- B(egin) the first token of the annotated answer entity
- I(nsize) other tokens of the annotated answer entity
- O(utside) tokens that are not a part of the annotated answer entity

#### A.1.2 Evaluation

Given an input passage, we run the trained BIO tagging model on each of its sentences and greedily predict answer entities. There might be more than one answer entities predicted in each sentence, and we only use the answer entities start with a predicted B tag.

#### A.2 AER-Search

#### A.2.1 Training

For AER-Search method, we need to pretrain an extraction-based AER model. We also take a sentence of L tokens containing an annotated answer entity as an example. Using an extraction model, which is similar as our question answering model, we train the model to predict the start and end location of the annotated answer entity. The model outputs a start score and an end score for each token, and predicts the start/end locations by selecting the tokens that are assigned with highest scores. The model is trained with cross-entropy loss, by regarding the extraction task as two L-class classification tasks.

#### A.2.2 Evaluation

In evalution, we first run the model on each sentence of the input passages and calculate the start and end scores for each token. For each span  $(x_i, x_{i+1}, \ldots, x_j)$  that is not longer than  $L_{span}$  tokens, we calculate the span score with

$$s_{ij} = s_{st}^i + s_{ed}^j \tag{8}$$

where  $s_{st}^i$  is the start score of the first token of span (i,j), and  $s_{ed}^j$  is the end score of the last token of the span. In pratice, we set  $L_{span}=10$ .

To re-rank all possible answer entities, we select top  $N_0=40$  spans according to  $s_{ij}$  for each passage. For all selected answer entities, we generated questions with a pretrained question generator and collect the generation perplexity of the questions. We select  $N_{search}=5$  question-answer pairs with lowest perplexities for the final question-answering finetuning.

## A.3 AER-Coop

In AER-Coop, we use the same extraction training method applied in AER-Search, and we also use the  $s_{ij}$  scores to select the top  $N_0=40$  preliminary answer entities for further search. The difference is that we search for final answer entities cooperatively with the pretrained question generator and question answering extractor.

With the question generator and question answering extractor, we re-rank the recognized answer entities with the following score

$$s_{ij}^c = \gamma \cdot I_c - p \tag{9}$$

where  $\gamma$  is a large, positive coefficient, p is the perplexity of generated question based on span (i, j),

and  $I_c = 1$  if the generated question is correctly answered, and otherwise  $I_c = 0$ .

## A.4 Answer Entity Overlapping

We found the extraction-based AER model leads to overlapping problems, since a large start or end score assigned to a token leads to many candidate answer entities start or end at the token. In practice, if an answer entity is selected by the AER-Search and AER-Coop method, we no longer consider any other answer entities that overlap with the selected ones.

## **B** REGEX Examples

In this section, we show some examples of our full model. The examples are contained in Table 6.

The National History Museum of Montevideo is located in the historical residence of General Fructuoso Rivera. It exhibits artifacts related to the history of Uruguay. In a process begun in 1998, the National Museum of Natural History (1837) and the National Museum of Anthropology (1981), merged in 2001, becoming the National Museum of Natural History and Anthropology. In July 2009, the two institutions again became independent. The Historical Museum has annexed eight historical houses in the city, five of which are located in the Ciudad Vieja. One of them, on the same block with the main building, is the historic residence of Antonio Montero, which houses the Museo Romantico.

#### When was the national history museum of montevideo founded?

In the 1920s, John Maynard Keynes prompted a division between microeconomics and macroeconomics. Under Keynesian economics macroeconomic trends can overwhelm economic choices made by individuals. Governments should promote aggregate demand for goods as a means to encourage economic expansion. Following World War II, Milton Friedman created the concept of monetarism. Monetarism focuses on using the **supply and demand of money** as a method for controlling economic activity. In the 1970s, monetarism has adapted into supply-side economics which advocates reducing taxes as a means to increase the amount of money available for economic expansion.

#### Monarism focuses on the relationship between the?

Starting in 2006, Apple's industrial design shifted to favor aluminum, which was used in the construction of the first Mac-Book Pro. Glass was added in 2008 with the introduction of the unibody MacBook Pro. These materials are billed as environmentally friendly. The iMac, MacBook Pro, MacBook Air, and Mac Mini lines currently all use aluminum enclosures, and are now made of a single unibody. Chief designer **Jonathan Ive** continues to guide products towards a minimalist and simple feel, including eliminating of replaceable batteries in notebooks. Multi-touch gestures from the iPhone's interface have been applied to the Mac line in the form of touch pads on notebooks and the Magic Mouse and Magic Trackpad for desktops.

#### Who is the designer of the macbook pro?

The city's total area is 468.9 square miles (1,214 km2). 164.1 sq mi (425 km2) of this is water and 304.8 sq mi (789 km2) is land. The highest point in the city is Todt Hill **on Staten Island**, which, at 409.8 feet (124.9 m) above sea level, is the highest point on the Eastern Seaboard south of Maine. The summit of the ridge is mostly covered in woodlands as part of the Staten Island Greenbelt.

#### Where is the highest point in new york city?

In 1922, the number of supporters had surpassed 20,000 and by lending money to the club, Barça was able to build the larger Camp de Les Corts, which had an initial capacity of 20,000 spectators. After the Spanish Civil War the club started attracting more members and a larger number of spectators at matches. This led to several expansion projects: the grandstand in 1944, the southern stand in 1946, and finally the northern stand in 1950. After the last expansion, Les Corts could hold **60,000 spectators**.

#### What is the capacity of barcelona's stadium?

On 1 November 2013, international postal services for Somalia officially resumed. The Universal Postal Union is now assisting the Somali Postal Service to develop its capacity, including providing technical assistance and basic mail processing equipment.

## Who is responsible for supporting the somali postal service?

In addition to membership, as of 2010[update] there are 1,335 officially registered fan clubs, called penyes, around the world. The fan clubs promote Barcelona in their locality and receive beneficial offers when visiting Barcelona. Among the best supported teams globally, Barcelona has the highest social media following in the world among sports teams, with over 90 million Facebook fans as of February 2016. The club has had many prominent people among its supporters, including **Pope John Paul II**, who was an honorary member, and former prime minister of Spain José Luis Rodríguez Zapatero. FC Barcelona has the second highest average attendance of European football clubs only behind Borussia Dortmund.

#### Who was an honorary member of barcelona football club?

In April 1758, the British concluded the Anglo-Prussian Convention with Frederick in which they committed to pay him an annual subsidy of £670,000. Britain also dispatched 9,000 troops to reinforce Ferdinand's Hanoverian army, the first British troop commitment on the continent and a reversal in the policy of Pitt. Ferdinand had succeeded in driving the French from Hanover and Westphalia and re-captured the port of Emden in March 1758 before crossing the Rhine with his own forces, which caused alarm in France. Despite Ferdinand's victory over the French at the Battle of Krefeld and the brief occupation of Düsseldorf, he was compelled by the successful manoeuvering of larger French forces to withdraw across the Rhine.

## What did france pay to the prussian monarchy?

Executives at Trump Entertainment Resorts, whose sole remaining property will be the Trump Taj Mahal, said in 2013 that they were considering the option of selling the Taj and winding down and exiting the gaming and hotel business. What is the future of the trump taj mahal?

Vehicles typically include headlamps and tail lights. Headlamps are white or selective yellow lights placed in the front of the vehicle, designed to illuminate the upcoming road and to make the vehicle more visible. Many manufactures are turning to LED headlights as an energy-efficient alternative to traditional headlamps. Tail and brake lights are red and emit light to the rear so as to reveal the vehicle's direction of travel to following drivers. White rear-facing reversing lamps indicate that the vehicle's transmission has been placed in the reverse gear, warning anyone behind the vehicle that it is moving backwards, or about to do so. Flashing turn signals on the front, side, and rear of the vehicle indicate an intended change of position or direction. In **the late 1950s**, some automakers began to use electroluminescent technology to backlight their cars' speedometers and other gauges or to draw attention to logos or other decorative elements.

When did they start putting back up lights in cars?