$\text{CQM}_{\text{robust}}$: A Chinese Dataset of Linguistically Perturbed Natural Questions for Evaluating the Robustness of Question Matching Models

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Abstract

In this paper, we focus on studying robustness evaluation of Chinese question matching. Most of the previous work on analyzing robustness issue focus on just one or a few types of artificial adversarial examples. Instead, we argue that it is necessary to formulate a comprehensive evaluation about the linguistic capabilities of models on natural texts. For this purpose, we create a Chinese dataset namely **$\text{CQM}_{\text{robust}}$** which contains natural questions with linguistic perturbations to evaluate the robustness of question matching models. $\text{CQM}_{\text{robust}}$ contains 3 categories and 13 subcategories with 32 linguistic perturbations. The extensive experiments demonstrate that $\text{CQM}_{\text{robust}}$ has a better ability to distinguish different models. Importantly, the detailed breakdown of evaluation by linguistic phenomenon in $\text{CQM}_{\text{robust}}$ helps us easily diagnose the strength and weakness of different models. Additionally, our experiment results show that the effect of artificial adversarial examples does not work on the natural texts. The dataset and baseline codes will be publicly available in the open source community.

1 Introduction

The task of *Question Matching (QM)* aims to identify the question pairs that have the same meaning, and it has been widely used in many applications, e.g., community question answering and intelligent customer services, etc. Though neural QM models have shown compelling performance on various datasets, including Quora Question Pairs (QQP) (Iyer et al., 2017), LCQMC (Liu et al., 2018), BQ (Chen et al., 2018) and AFQMC[1], neural models are often not robust to adversarial examples, which means that the neural models predict unexpected outputs given just a small perturbations on the inputs. As the example 1 in Tab. 1 shows, a model might not distinguish the minor difference ("面 *noodles*") between the two sentences, and thus predicts the two questions semantically equivalent.

Recently, it attracts a lot of attentions from the research community to deal with the robustness issues of neural models on various NLP tasks, such as question matching, natural language inference and machine reading comprehension. Early works examine the robustness of neural models by creating a certain types of artificial adversarial examples (Jia and Liang, 2017; Alzantot et al., 2018; Ren et al., 2019; Jin et al., 2020), and involving human-and-model-in-the-loop to create dynamic adversarial examples (Nie et al., 2020; Wallace et al., 2019). Further studies discover that a few types of superficial cues (i.e. shortcuts) in the training data, are learned by the models and hence affect the model robustness (Gururangan et al., 2018; McCoy et al., 2019; Lai et al., 2021). Besides, several studies try to improve the robustness of the neural models by adversarial data augmentation (Min et al., 2020) and data filtering (Bras et al., 2020). All these efforts lead us to better find and fix the robustness issues to some extends.

However, there are several limitations in previous studies. First, the analysis and evaluation in previous work focus on just one or a few types of adversarial examples or shortcuts, but we need normative evaluation (Linzen, 2020; Ettinger, 2020; Phang et al.). The goal of the normative evaluation is not to fool a system by exploiting its particular weaknesses, but using systemically controlled datasets to comprehensively evaluate the basic linguistic capabilities of the models in a diverse way. Checklist (Ribeiro et al., 2020) and Textflint (Wang et al., 2021) are great attempts of normative evaluation. However, it is not clear that if the effects of the artificial adversarial methods on artificial examples are still shown on natural texts from real-world applications (Morris et al., 2020). Moreover, to the best of our knowledge, there are few Chinese datasets for QM robustness evaluation.

[1] It is from Ant Technology Exploration Conference (ATEC) Developer competition, which is no longer available.

Towards this end, we create a open-domain Chinese dataset namely **CQM$_{\text{robust}}$** contains natural questions with linguistic perturbation for evaluating the robustness of QM models. (1) By *linguistic*, we mean this systematically controlled dataset provides a detailed breakdown of evaluation by linguistic phenomenon. As shown in Tab. 1, there are 3 categories and 13 subcategories with 32 linguistic perturbation in CQM$_{\text{robust}}$, which enables us to evaluate the model performance by each category instead of just a single metric. (2) By *natural*, we mean all the questions in CQM$_{\text{robust}}$ are natural and issued by the users in a commercial search engine. This design can help us to properly evaluate the progress of a model's robustness on natural texts rather than artificial texts which may not preserve semantics and introduce grammatical errors.

The contributions of this paper can be summarized as follows:

- We construct a Chinese dataset namely CQM$_{\text{robust}}$ that contains linguistically perturbed natural questions from a commercial search engine. It is a systemically controlled dataset to test the basic linguistic capabilities of the models in a diverse way. (see Sec. 2 and Sec. 3)
- Our experimental results show that 3 characteristics of CQM$_{\text{robust}}$: (1) CQM$_{\text{robust}}$ is challenging, and has better discrimination power to distinguish the models that perform comparably on other datasets (see Sec. 4.2). (2) The detailed breakdown of evaluation by linguistic phenomena in CQM$_{\text{robust}}$ helps diagnose the advantages and disadvantages of different models (see Sec. 4.3). (3) Extensive experiment shows that the effect of artificial adversarial examples does not work on natural texts of CQM$_{\text{robust}}$. CQM$_{\text{robust}}$ can help us properly evaluate the models' robustness. (see Sec. 4.4).

The remaining of this paper is organized as follows. Sec. 2 describes the 3 categories and 13 subcategories with 32 linguistic perturbation in CQM$_{\text{robust}}$. Sec. 3 gives the construction process of CQM$_{\text{robust}}$. In Sec. 4, we conduct experiments to demonstrate 3 characteristics of CQM$_{\text{robust}}$. We conclude our work in Sec. 5.

2 Linguistic Perturbations in CQM$_{\text{robust}}$

The design of CQM$_{\text{robust}}$ is aimed at a detailed breakdown of evaluation by linguistic phenomenon. Hence, we create CQM$_{\text{robust}}$ by introducing a set of linguistic features that we believe are important for model diagnosis in terms of linguistic capabilities. Basically, 3 categories of linguistic features are used to build CQM$_{\text{robust}}$, i.e., lexical features (see Sec. 2.1), syntactic features (see Sec. 2.2), and pragmatic features (see Sec. 2.3). We list 3 categories, 13 subcategories with 32 operations of perturbation in Tab. 1. The detailed descriptions of all categories are given in this section.

2.1 Lexical Features

Lexical features are associated with vocabulary items, i.e. words. As a word is the smallest independent but meaningful unit of speech , an operation on a single word may change the meaning of the entire sentence. It is a basic but crucial capability for models to understand word and perceive word-level perturbations. To provide a fine-grained evaluation for model's capability of lexical understanding, we further consider 6 subcategories:

Part of Speech. Parts of speech (POS), or word classes, describe the part a word plays in a sentence. CQM$_{\text{robust}}$ considers 6 POS in Chinese grammar, including noun, verb, adjective, adverb, numeral and quantifier, which are content words that carry most meaning of a sentence. In this subcategory, we aim to test whether models can handle the word-level perturbations of these POS. As the example 1 in Tab. 1 [2] shows, inserting only one noun "面 *noodles*" makes the sentence meaning different. Furthermore, in this subcategory we provides a set of examples focusing on phrase-level perturbations to check model's capability on understanding word groups that act collectively as a single part of speech (see example 11).

Named Entity. Different from common nouns that refer to generic things, a named entity (NE) is a proper noun which refers to a specific real-world object. The close relation to world knowledge makes NE ideal for observing models' understanding of the meaning of names and background knowledge about entities. In CQM$_{\text{robust}}$, we include *Named Entity* an independent subcategory to test the model's behavior of named entity recognition, and focus on 4 types of NE most commonly seen, i.e., location, organization, person and product. Example 12 is a search query and its perturbation on NE. The two named entities, *"*山西 *Shanxi"* and *"*陕西 *Shaanxi"*, are similar at character level but

[2] All examples discussed in this section are presented in Column *Example and Translation* of Tab. 1.

Category	Subcategory	Perturbation Operation	Label #Y / #N	BERT base	ERNIE base	RoBERTa base	MacBERT base	RoBERTa large	MacBERT large	Examples and Translation
Lexical Feature	Part of Speech	insert n.	-/539	41.4±3.4	40.8±2.1	43.0±0.7	41.4±2.5	**45.4±4.1**	37.3±2.4	**E1**: 鸡蛋怎么炒好吃 / 鸡蛋 面 怎么炒好吃 how to fry eggs / how to fry egg noodles
		insert v.	-/131	39.4±0.4	33.8±2.6	37.4±2.0	35.9±2.7	**39.9±3.1**	29.5±3.8	**E2**: 伤口用什么好 / 伤口用什么 消毒 好 what is good for the wound / how to disinfect the wound
		insert adj.	-/458	23.5±1.9	19.2±3.7	**26.9±4.4**	23.9±4.2	18.1±2.4	10.4±2.1	**E3**: 有哪些类型的app / 有哪些类型的 移动 app what are types of apps / what are types of mobile apps
		insert adv.	-/302	3.7±0.5	4.2±0.5	3.8±0.6	4.4±1.2	**5.8±1.5**	3.1±1.1	**E4**: 为什么打嗝 / 为什么 老 打嗝 why burp / why always burp
		replace n.	-/702	86.6±0.3	86.7±0.1	88.3±0.3	88.8±1.2	**89.4±1.6**	87.8±0.7	**E5**: 申请美国 绿卡 流程 / 申请美国 签证 流程 U.S. green card application process / U.S. visa application process
		replace v.	-/466	71.7±1.1	77.6±0.8	76.9±0.4	76.5±1.2	81.0±1.6	**81.5±2.2**	**E6**: 为什么 下蹲 膝盖疼 / 为什么 下跪 膝盖疼 why knee pain when squatting / why knee pain when kneeling
		replace adj.	-/472	74.3±2.1	80.0±1.0	77.6±0.7	81.6±0.5	**82.7±1.1**	82.7±1.6	**E7**: 耳朵出血 严重 吗 / 耳朵出血 正常 吗 is the ear bleeding serious / is the ear bleeding normal
		replace adv.	-/188	19.1±6.1	19.3±4.4	16.3±3.8	23.9±4.6	**59.0±4.0**	56.2±2.0	**E8**: 为什么会 经常 头晕 / 为什么会 有点 头晕 why regularly feel dizzy / why slightly feel dizzy
		replace num.	-/1116	83.2±1.4	91.4±0.4	85.9±1.8	87.2±0.9	88.1±0.5	**91.9±1.1**	**E9**: 血压 130 /100高吗 / 血压 120 /100高吗 is blood pressure 130 /100 high / is blood pressure 120 /100 high
		replace quantifier	-/22	30.3±6.9	25.7±5.2	33.3±2.6	**34.9±2.6**	27.3±0.0	34.8±10.5	**E10**: 一 束 花多少钱 / 一 枝 花多少钱 how much is a bunch of flower / how much is a flower
		replace phrases	-/197	98.0±0.0	**98.1±0.2**	96.6±0.3	97.8±0.5	97.8±0.2	97.5±0	**E11**: 如何 提高自己的记忆力 / 如何 增加自己的实力 how to improve my memory / how to increase my strength
	Named Entity	replace loc.	-/458	**96.0±0.6**	95.7±0.2	95.4±0.4	95.0±0.4	94.7±0.4	94.5±0.5	**E12**: 山西 春节习俗 / 陕西 春节习俗 Shanxi spring festival customs / Shannxi spring festival customs
		replace org.	-/264	**94.9±0.2**	94.3±0.6	91.2±1.4	93.4±0.7	93.5±0.3	93.8±0.1	**E13**: 北京邮电大学 附近酒店 / 南京邮电大学 附近酒店 hotels near BUPT / hotels near NJUPT
		replace person	-/468	90.3±1.3	91.0±0.9	88.7±1.6	91.4±1.6	92.3±1.3	**93.2±1.1**	**E14**: 陈龙 的妻子 / 成龙 的妻子 wife of Long Chen / wife of Jackie Chan
		replace product	-/170	83.7±2.6	88.2±2.1	82.4±6.9	83.3±0.3	86.0±1.7	**88.8±4.4**	**E15**: iphone 6 多少钱 / iphone6x 多少钱 how much is iphone 6 / how much is iphone6x
	Synonym	replace n.	405/-	51.1±1.1	59.7±1.3	59.7±2.2	60.7±2.0	63.3±3.1	**71.6±4.0**	**E16**: 猕猴桃 的功效 / 奇异果 的功效 health benefits of Chinese gooseberry / health benefits of Kiwi
		replace v.	372/-	80.0±0.9	81.1±1.6	82.5±0.0	83.2±1.2	84.0±2.0	**88.1±1.4**	**E17**: 什么果汁可以 减肥 / 什么果汁可以 减重 what juice can lose weight / what juice can slim
		replace adj.	453/-	75.7±1.3	77.3±1.1	78.8±2.5	74.8±0.5	79.4±3.4	**88.5±1.3**	**E18**: 有趣 搞笑的广告词 / 幽默 搞笑的广告词 funny advertising words / humerous advertising words
		replace adv.	26/-	98.7±2.1	**100.0±0.0**	**100.0±0.0**	**100.0±0.0**	**100±0.0**	**100.0±0.0**	**E19**: 总是 想睡觉是为什么 / 老是 想睡觉是为什么 why always want to sleep / why repeatedly want to sleep
	Antonym	replace adj.	-/305	50.6±3.4	69.6±2.9	65.0±1.5	73.1±4.3	**91.7±2.3**	90.7±2.3	**E20**: 什么水果脂肪 低 / 什么水果脂肪 高 what fruit is low in fat / what fruit is high in fat
	Negation	negate v.	-/153	69.9±9.6	88.9±1.3	84.8±2.9	**93.3±1.3**	88.4±0.9	91.4±3.4	**E21**: 为什么宝宝哭 / 为什么宝宝 不 哭 why baby cries / why baby doesn't cry
		negate adj.	-/139	73.1±8.5	84.2±1.2	82.7±1.4	88.0±1.5	88.0±2.9	**89.4±1.0**	**E22**: 为什么苹果是红的 / 为什么苹果 不是 红的 why apple is red / why apple is not red
		neg.+antonym	59/-	29.9±2.5	34.4±2.5	39.0±1.7	31.1±2.5	40.7±1.7	**53.6±0.9**	**E23**: 激动 怎么办 / 无法 平静 怎么办 what to do if too excited / what to do if can't calm down
	Temporal word	insert	-/120	26.6±2.1	29.1±2.1	33.1±0.9	41.7±3.3	**47.5±5.4**	33.6±8.5	**E24**: 北京会下雨吗 / 北京 明天 会下雨吗 will it rain in Beijing / will it rain in Beijing tomorrow
		replace	-/114	44.1±6.1	67.8±2.6	55.0±0.5	53.8±1.3	70.4±6.1	**78.6±5.8**	**E25**: 昨天 下雪 了 吗 / 明儿 会下雪吗 was it snow yesterday / will it snow tomorrow
Syntactic Feature	Symmetry	swap	533/-	97.3±0.4	**98.0±0.1**	95.2±1.7	95.9±0.7	93.3±0.9	92.5±1.9	**E26**: 鱼 和 鸡蛋 能一起吃吗 / 鸡蛋 和 鱼 能一起吃吗 can I eat fish with egg / can I eat egg with fish
	Asymmetry	swap	-/497	14.5±2.0	18.3±3.7	26.8±3.2	26.4±2.5	**52.0±4.6**	49.1±10.8	**E27**: 北京 到 上海 航班 / 上海 到 北京 航班 Beijing to Shanghai flights / Shanghai to Beijing flights
	Negative Asymmetry	swap + negate	49/-	**47.6±3.4**	37.4±7.7	44.2±1.1	25.8±3.1	23.1±6.7	29.9±1.9	**E28**: 男人 比 女人 更 高 吗 / 女人 比 男人 更 矮 吗 are men taller than women / are women shorter than men
	Voice	insert passive word	94/37	76.8±1.4	72.5±0.0	77.4±0.9	74.0±0.7	**85.2±1.4**	74.8±2.2	**E29**: 梦见狗咬左腿 / 梦见 被 狗咬左腿 dreamed of being bitten by a dog / dreamed of being bitten by a dog
Pragmatic Feature	Misspelling	replace	468/-	**68.0±2.0**	65.1±0.2	64.2±0.6	65.0±2.3	63.5±1.8	63.2±1.6	**E30**: 什么 纹身 适合我 / 什么 文身 适合我 what tattoo suits me / what tatoo suits me
	Discourse Particle (Simple)	insert or replace	213/-	98.7±0.5	98.4±0.2	98.6±0.5	99.2±0.2	99.5±0.0	**99.8±0.2**	**E31**: 人为什么做梦 / 那么 人为什么做梦 why people dream / so why people dream
	Discourse Particle (Complex)	insert or replace	131/-	46.5±0.6	56.2±2.0	64.1±2.0	61.6±1.6	65.1±3.4	**68.4±0.3**	**E32**: 附近最好的餐厅 / 求助我旁边 哪家餐厅 最好吃 ? best restaurant nearby / heeelp!!! which restaurant is best in my area ?
Total	**13**	**32**	**2803/7318**	-						-

Table 1: Categories of $\mathrm{CQM}_{\mathrm{robust}}$ (described in Sec. 2) and performance of 6 models on $\mathrm{CQM}_{\mathrm{robust}}$ (discussed in Sec. 4). **Bold face** and underlined indicate the first and second highest accuracy for each testing scenario.

denote two different locations. We expect that the models can capture the subtle difference.

Synonym. A synonym is a word or phrase that means exactly or nearly the same as another word or phrase in a given language. This subcategory aims to test whether models can identify two semantically equivalent questions whose surface forms only differ in a pair of synonyms. As in example 16, the two sentences differ only in two words, both of which refer to Kiwifruit, so they have the same meaning.

Antonym. In contrast to synonyms, antonyms are words within an inherently incompatible binary relationship. This subcategory examines model's capability on distinguishing words with opposed meanings. We mainly focus on adjective's opposite, e.g., "高*high*" and "低*low*" (see example 20).

Negation. Negation is another way to express contradiction. To negate a verb or an adjective in Chinese, we normally put a negative before it, e.g., "不*not*" before "哭*cry*" (example 21), "不是*not*" before "红的*red*" (example 22). The negative before the verb or the adjective negates the statement. It is an effective way to analyze model's basic skill of figuring out the contradictory meanings even there is only a minor change.

Moreover, we include some equivalent paraphrases with negation in this subcategory. In example 23, "无法平静*can't calm down*" is the negative paraphrase of "激动*excited*", so that the paraphrase sentence is equivalent to the positive sentence. We believe that a robust QM system should be able to recognize this kind of paraphrase question pairs.

Temporal Word. Temporal reasoning is the relatively higher-level linguistic capability that allows the model to reason about a mathematical timeline. Unlike English, verbs in Chinese do not have morphological inflections. Tenses and aspects are expressed either by temporal noun phrases like "明天*tomorrow*" (examples 24) or by aspect particles like "了*le*", which indicates the completion of an action (examples 25). This subcategory focuses on the temporal distinctions and helps us evaluate the models' temporal reasoning capability.

2.2 Syntactic Features

While single word sense is important to question meaning, how words composed together into a whole also affects sentence understanding. We believe the the relations among words in a sentence is important information for models to capture, so we focus on several types of syntactic features in this category. We pre-define 4 linguistic phenomena that we believe is meaningful to locate model's strength and weakness, and describe them here.

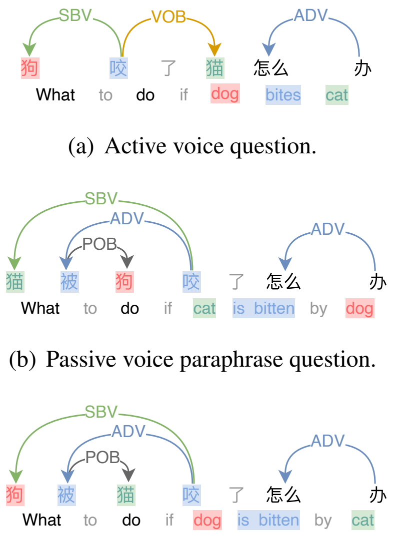
Symmetry. Sometimes paraphrases can be generated by only swapping the two conjuncts around in a structure of coordination. As shown in example 26, "鱼*fish*" and "鸡蛋*egg*" are joined together by the conjunction "和*and*", which have the symmetric relation to each other. Even if we swap them around, the sentence meaning will not change. We name this subcategory *Symmetry*, with which we aim to explore if a model captures the inherent dependency relationship between words.

Asymmetry. Some words (such as "和and") denote symmetric relations, while others (for example, preposition "到to") denote asymmetric. Example 27 shows a sentence pair in which the word before the preposition "到*to*" is an adverbial and the word after it is the object. Swapping around the adverbial and the object of the prepositional phrase will definitely leads to a nonequivalent meaning. If a model performs well only on subcategory *Symmetry* or *Asymmetry*, it may rely on shortcuts instead of the understanding of the syntactic information.

Negative Asymmetry. To further explore the syntactic capability of QM model, $\mathrm{CQM}_{\mathrm{robust}}$ includes a set of test examples which consider both syntactic asymmetry and antonym, and we name this category *Negative Asymmetry*. In example 28, the asymmetric relation between "男人*men*" and "女人*women*" and the opposite meaning of "高*taller*" and "矮*shorter*" resolve to an equivalent meaning. With this subcategory, we can better explore model's capability of inferring more complex syntactic structure.

Voice. Another crucial syntactic capability of models is to differentiate active and passive voices. In Chinese, the most common way to express the passive voice is using Bei-constructions which feature an agentive case marker "被*bei*". The subject of a Bei-construction is the patient of an action, and the object of the preposition "被*bei*" is the agent. Compared to Fig.1(a), the additional "被*bei*" and the change of word order of "猫*cat*" and "狗*dog*" in Fig.1(b) convert the sentence from active to passive voice, but the two sentences have the same meaning. If we further change the word order from Fig.1(b) to Fig.1(c), the sentence still uses passive voice but has different meaning.

Passive voice is not always expressed with an



(a) Active voice question.

(b) Passive voice paraphrase question.

(c) Passive voice non-paraphrase question.

Figure 1: The dependency relations of active voice and passive voice questions.

overt "被*bei*". Sometimes a sentence without any passive marker is still in passive voice. In example 29, although the first sentence is without "被*bei*", it expresses the same meaning as the second one. There are a set of active-passive examples in this category, which are effective to evaluate model's performance on active and passive voices.

2.3 Pragmatic Features

Lexical items ordered by syntactic rules are not all that make a sentence mean what it means. Context, or the communicative situation that influence language use, has a part to play. We include some pragmatic features in CQM$_{\text{robust}}$ so as to observe whether models are able to understand the contextual meaning of sentences.

Misspelling. Misspellings are quite often seen by search engines and question-answering systems, which are mostly unintentional. Models should have the capability to capture the true intention of the questions with spelling errors to ensure the robustness. In example 30, despite the misspelled word "文身*tatoo*" the two questions mean the same, In some real world situations, models should understand misspellings appropriately. For example, when users search a query but type in misspelling, a robust model will still give the correct result.

Discourse Particle. Discourse particles are words and small expressions that contribute little to the information the sentence convey, but play some pragmatic functions such as showing politeness, drawing attention, smoothing utterance, etc. As in example 32, the word "求助*help*" is used to draw attention and bring no additional information to the sentence. Whether using these little words do not change the sentence meaning. It is necessary to a model to identify the semantic equivalency when such words are used.

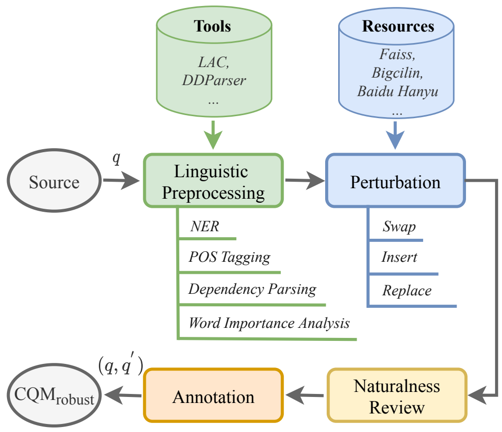


Figure 2: Construction process of CQM$_{\text{robust}}$.

3 Construction

We design CQM$_{\text{robust}}$ as a *diverse* and *natural* corpus. The construction process of CQM$_{\text{robust}}$ is divided into 4 steps and illustrated in Fig. 2. Firstly, we preprocess the source questions to obtain their linguistic knowledge, which will be used to perturb the source texts. Then we pair the source and perturbed question as an example. The examples' naturalness is reviewed by human evaluators. At last, the examples are annotated manually and CQM$_{\text{robust}}$ is finally constructed. We introduce the construction details in the following:

Linguistic Preprocessing. We collect a large number of source questions from the search query log of a commercial search engine. All the source questions are natural and then we perform several linguistic preprocessings on them: named entity recognition, POS tagging, dependency parsing, and word importance analysis. The linguistic knowledge about the source questions we obtained in this step will be used for perturbation.

Perturbation. We conduct different perturbation operations for different subcategories. In general, we perturb the sentences in 3 ways:

- **replace**: replace a word with another word, e.g., for category *Synonym*, we replace one word with its synonym;

Category	Length		#		
	q	q'	Y	N	All
Lexical	8.58	8.89	1,315	6,784	8,099
Syntactic	9.86	9.89	678	532	1,210
Pragmatic	8.73	9.03	812	0	812
Avg / Total	8.74	8.90	2,805	7,316	1,0121

Table 2: Data statistics of $\mathrm{CQM}_{\mathrm{robust}}$.

Model	$\mathrm{LCQMC}_{\mathrm{test}}$	$\mathrm{CQM}_{\mathrm{robust}}$	$\triangle$
$\mathrm{BERT}_{\mathrm{b}}$	87.1±0.1	66.6±0.6	-20.5
$\mathrm{ERNIE}_{\mathrm{b}}$	87.3±0.1	69.8±0.3	-17.5
$\mathrm{RoBERTa}_{\mathrm{b}}$	87.2±0.4	69.5±0.1	-17.7
$\mathrm{MacBERT}_{\mathrm{b}}$	87.4±0.3	70.3±0.6	-17.1
$\mathrm{RoBERTa}_{\mathrm{l}}$	**87.7±0.1**	**73.8±0.3**	-13.9
$\mathrm{MacBERT}_{\mathrm{l}}$	87.6±0.1	73.8±0.5	-13.8

Table 3: Accuracy(%) on $\mathrm{LCQMC}_{\mathrm{test}}$ and $\mathrm{CQM}_{\mathrm{robust}}$. $_{\mathrm{b}}$ indicates base, and $_{\mathrm{l}}$ indicates large.

- **insert** : insert an additional word, e.g., for category *Temporal word*, we insert temporal word to the source question;
- **swap**: swap two words. This operation is only used in *Syntactic Feature*.

The perturbations of all categories are listed in column *Perturbation Operation* of Tab. 1, and the perturbation details will be given in Appendix A.
Naturalness Review. To ensure the generated sentences are natural, we examine their appearances in the search log and only retain the sentences which have been entered into the search engine.
Annotation. The source question and generated question are paired together as an example. Then the examples are evaluated by evaluators from our internal data team. They need to evaluate whether the examples are fluent, grammatically correct, and correctly categorized. The low-quality examples are discarded and the examples with inappropriate categories are re-classified.

Then the question pairs are annotated by the annotators from our internal data team. Semantically equivalent question pairs are positive examples, and inequivalent pairs are negative. The annotators are required a approval rate higher than 99% for at least 1,000 prior tasks. Each example is annotated by three annotators, and the examples will be tagged with the label which more than 2 annotators choose. To further ensure the annotation quality, 10% of the annotated examples are selected randomly and reviewed by a linguistic expert. If the review accuracy is lower than 95%, the annotators need to re-annotate all the examples until the accuracy is higher than 95%.

Eventually, we generate 10,121 examples for $\mathrm{CQM}_{\mathrm{robust}}$. The class distribution of all categories are given in Tab. 1. Additional data statistics are provided in Tab. 2.

4 Experiments

In this section, we conduct experiments to discuss 3 characteristics (char.) of $\mathrm{CQM}_{\mathrm{robust}}$. In Sec. 4.1, we provide the experimental setup and the evaluation metrics. In Sec. 4.2, Sec. 4.3 and Sec. 4.4, we give the experimental results and discussions.

4.1 Experimental Setup

Datasets. To evaluate the robustness of QM models, we select LCQMC to fine-tune the models and evaluate the models' performance on our $\mathrm{CQM}_{\mathrm{robust}}$ corpus. LCQMC is a large-scale Chinese QM corpus proposed by Harbin Institute of Technology in ***general domain*** and the source questions are collected from Baidu Knows (a popular Chinese community question answering website), which ***are similar to the search queries in form***. Specifically, we firstly fine-tune the models on $LCQMC_{train}$. Then we choose the model with the best performance on $LCQMC_{dev}$ and report the results of the chosen models on $LCQMC_{test}$ and $\mathrm{CQM}_{\mathrm{robust}}$. Tab. 8 presents the statistics of LCQMC. **Models.** We choose 6 popular pre-trained models to conduct experiments: $BERT_{\mathrm{b}}$ (Devlin et al., 2019), $ERNIE_{\mathrm{b}}$ (Sun et al., 2019), $RoBERTa_{\mathrm{b}}$, $RoBERTa_{\mathrm{l}}$ (Liu et al., 2019), $MacBERT_{\mathrm{b}}$, $MacBERT_{\mathrm{l}}$ (Cui et al., 2020). A detailed comparison is provided in Tab. 7 (in Appendix).
Evaluation Metrics. QM problem is normally formulated as a binary classification task. Like most classification tasks, we use accuracy to evaluate a single model's performance, which is the proportion of correct predictions among the total number of the examined examples. As CQM_{robust} is a fine-grained corpus consisting of a set of linguistic categories and each category differs in size, we use the ***micro-averaged*** and the ***macro-averaged accuracy*** to compare the models' performances on $\mathrm{CQM}_{\mathrm{robust}}$, which can help us better indicate the models' ability on different categories.

Training details about our experiments are described in Appendix B.1.1.

Models		Lexical							Syntactic	Pragmatic	CQM_{robust}
		POS	NE	Synonym	Antonym	Negation	Temporal	Lexical			
$BERT_b$	micro	62.1±1.1	92.3±0.5	69.5±0.4	50.6±3.4	64.4±5.9	35.1±3.3	67.2±0.7	59.1±0.4	72.6±1.6	66.6±0.6
	macro	51.9±1.5	91.2±0.7	76.4±0.6	50.6±3.4	57.6±4.4	35.5±3.3	61.4±1.2	59.1±0.7	71.1±1.1	62.0±0.9
$ERNIE_b$	micro	64.6±0.5	92.8±0.4	73.2±0.9	69.6±2.9	77.8±1.1	48.0±1.9	71.0±0.3	60.0±1.2	72.4±0.3	69.8±0.3
	macro	52.4±0.7	92.3±0.6	79.5±0.7	69.6±2.9	69.1±1.2	48.5±1.9	65.5±0.5	56.5±1.0	73.2±0.8	65.1±0.3
$RoBERTa_b$	micro	64.2±0.1	90.6±1.8	74.2±1.4	65.0±1.5	76.3±1.7	43.7±0.2	70.1±0.1	63.1±0.6	73.3±0.1	69.5±0.1
	macro	53.3±0.2	89.4±2.5	80.3±1.1	65.0±1.5	68.8±1.3	44.0±0.2	65.0±0.1	60.9±0.6	75.6±0.5	65.5±0.1
$MacBERT_b$	micro	64.8±1.1	92.0±0.7	73.3±1.1	73.1±4.3	80.7±0.5	47.6±1.3	71.2±0.7	62.1±1.0	73.4±1.5	70.3±0.6
	macro	54.2±0.9	90.7±0.6	79.7±0.5	73.1±4.6	70.7±0.1	47.7±0.2	66.3±0.2	55.5±0.7	75.2±1.1	65.8±0.1
$RoBERTa_l$	micro	**67.2±0.9**	92.5±0.3	76.0±2.1	**91.7±2.3**	80.2±0.8	**58.6±2.8**	74.1±0.3	**72.6±1.4**	73.2±1.9	**73.8±0.3**
	macro	**57.7±0.6**	91.6±0.3	81.7±1.6	**91.7±2.3**	72.3±0.6	**59.0±2.7**	70.2±0.3	**63.4±1.2**	76.0±2.0	69.8±0.2
$MacBERT_l$	micro	65.6±0.8	**93.2±0.6**	**83.2±1.6**	90.7±2.3	**84.3±1.3**	55.5±4.0	**74.4±0.4**	70.2±3.7	**73.7±1.1**	73.8±0.5
	macro	54.7±0.9	**92.6±0.9**	**87.1±1.2**	90.7±2.3	**78.1±0.9**	56.1±4.0	**70.7±0.5**	61.6±2.4	**77.1±0.6**	**70.2±0.5**

Table 4: The micro-averaged and macro-averaged accuracy are on each category of CQM_{robust}.

	PWWS	$PWWS_{nat}$	FOOLER	$FOOLER_{nat}$	$CHECKLIST_{nat}$
Train	159,503	-	64,086	-	
Test	400	200	400	200	400

Table 5: Statistics of the adversarial examples.

4.2 Char. 1: Challenging and with Better Discrimination Ability

Tab. 3 shows the performances of models on held-out set $LCQMC_{test}$ and our CQM_{robust}, which presents the primary characteristics of DuQM:

Challenging. Comparing to the *held-out test* on $LCQMC_{test}$, all models achieve lower performance on CQM_{robust}. As shown in Tab. 3, all models achieve accuracy higher than 87% on $LCQMC_{test}$, but show a significant performance drop on CQM_{robust}. Column $\triangle$ in Tab. 3 shows the differences between models' performances on $LCQMC_{test}$ and CQM_{robust}, which presents that the performance on CQM_{robust} is lower than on $LCQMC_{test}$ by at most 20.5%. CQM_{robust} is more **challenging**, and it can better reflect true capability of QM models.

Better Discrimination Ability. CQM_{robust} can better distinguish the models' performances. As shown in Tab. 3, all the models have similar performances on $LCQMC_{test}$ (around 87%), but different performances on CQM_{robust}: the accuracy of base models differ from 66.6% to 70.3%, and the large models show higher performance (73.8%). In conclude, CQM_{robust} shows a better discrimination ability to evaluate models.

It demonstrates that CQM_{robust} can better evaluate the robustness of QM models.

4.3 Char. 2: Diagnose Model in Diverse Way

CQM_{robust} corpus is a fine-grained corpus which has 3 linguistic categories and 13 subcategories and enables a detailed breakdown of evaluation on different linguistic phenomena. In Tab. 1 we give the performances of 6 models on all fine-grained categories of CQM_{robust}, and Tab. 4 reports the micro-averaged and macro-averaged accuracy. By comparing these results, we introduce the second characteristic of CQM_{robust}: it can diagnose the strengths and weaknesses of the models in a diverse way. Several interesting observations are noticed: (from Tab. 1 and 4):

1) *In most categories*, large models outperform base models. As the large models have more parameters and larger pre-training corpus, it is reasonable that they have better capabilities than relatively smaller models.
2) In *Named Entity*, all models show good performances (higher than 90%). Another interesting finding is that although $ERNIE_b$ is a relatively small model, it performs slightly better than $RoBERTa_l$ on this subcategory, which might attribute to the entity masking strategy for pre-training.
3) $MacBERT_l$ is significantly better than others in *Synonym*. We suppose that it benefits from using similar words instead of random words for masking when pre-training. Moreover, $RoBERTa_l$ and $MacBERT_l$ have remarkable better performance in *Antonym*.
4) The overall low performances in *Temporal word* represent that all models lack the capability of temporal reasoning.
5) All models have surprisingly poor performances on *Asymmetry* while good performances in *Sym-*

Training set	LCQMC	Attack test set				$\text{CHECKLIST}_{\text{nat}}$	$\text{CQM}_{\text{robust}}$	
		PWWS	PWWS_{nat}	FOOLER	$\text{FOOLER}_{\text{nat}}$		Micro	Macro
LCQMC	87.7	58.1	81.5	57.1	87.8	76.9	73.8	69.8
LCQMC+PWWS	87.7$_{+0.0}$	**97.6**$_{+39.5}$	81.8$_{+0.3}$	73.1$_{+16.0}$	87.6$_{-0.2}$	76.0$_{-0.9}$	**75.2**$_{+1.4}$	70.4$_{+0.6}$
LCQMC+FOOLER	87.5$_{-0.2}$	78.5$_{+20.4}$	**83.8**$_{+2.3}$	**80.8**$_{+23.7}$	82.0$_{-5.8}$	**79.2**$_{+2.3}$	71.4$_{-2.4}$	68.8$_{-1.0}$

Table 6: Adversarial training results of $\text{RoBERTa}_{\text{l}}$. 'FOOLER' refers to 'TEXTFOOLER'. We use green and red subscripts to represent a higher and lower accuracy respectively.

metry. We suppose that lack of learning word orders would result in a wrong prediction when the words orders are altered.

6) BERT_{b} and ERNIE_{b} perform better on *Misspelling*, and $\text{RoBERTa}_{\text{b}}$ and $\text{MacBERT}_{\text{b}}$ are relatively better on *Complex Discourse Particles*.

In general, $\text{CQM}_{\text{robust}}$ diagnoses models from a linguistic perspective and can help us identify the strengths and weaknesses of the models.

4.4 Char. 3: Natural Adversarial Examples

$\text{CQM}_{\text{robust}}$ is a dataset generating by linguistically perturbing natural questions. We argue that this kind of natural adversarial examples is beneficial to a *robustness evaluation*. To prove that, we conduct an experiment to compare the performances of 2 adversarial training (AT) methods PWWS (Ren et al., 2019) and TextFooler (Jin et al., 2020) on artificial and natural test examples:

- *Artificial examples*, which are generated *artificially* and may not preserve semantics and introduce grammatical errors. We employ 2 methods PWWS and TextFooler on $\text{LCQMC}_{\text{test}}$ to generate artificial adversarial examples. These two methods generate adversarial examples by replacing words with synonyms until models are fooled.
- *Natural examples* are texts within linguistic and semantics constraints. Our evaluators from the internal data team reviewed and annotated all the generated texts with methods PWWS, TextFooler and the translated texts of Checklist dataset, and we finally get three natural test sets, PWWS_{nat}, $\text{TextFooler}_{\text{nat}}$ and $\text{Checklist}_{\text{nat}}$.

Besides, we employ PWWS and TextFooler on $\text{LCQMC}_{\text{train}}$ to generate artificial adversarial examples, which are incorporated with original $\text{LCQMC}_{\text{train}}$ as training data (Row *LCQMC+PWWS* and *LCQMC+FOOLER* in Tab. 6).The detailed data statistics are shown in Tab. 5. AT details are in Appendix B.2. **Evaluation with artificial and natural adversarial examples.** We fine-tune $\text{RoBERTa}_{\text{l}}$ on LCQMC and the artificial adversarial examples generated by PWWS and TextFooler, and evaluate on the adversarial test sets. The results are shown in Tab. 6. Row *LCQMC* shows that only training with $\text{LCQMC}_{\text{train}}$ shows a low performance on *PWWS* and *TextFooler* (we provide a detailed analysis in Appendix B.3), and the performances on *PWWS* and *TextFooler* are significantly higher on $\textit{PWWS}_{nat}$ and $\textit{PWWS}_{nat}$. However, if we incorporate $\text{LCQMC}_{\text{train}}$ with the examples generated by PWWS and TextFooler, the model's performances on *PWWS* and *TextFooler* increase greatly (both methods achieve an great improvement of more than 16%) , but the effects on natural examples $\textit{PWWS}_{nat}$ and $\textit{TextFooler}_{nat}$ are not significant (-5.8% ~2.3%). On the other 2 natural test sets, $\text{Checklist}_{\text{nat}}$ and $\text{CQM}_{\text{robust}}$, the effects of 2 adversarial methods are also not obvious (-2.4% ~2.3%).

In conclusion, the common artificial AT methods are not so effective on the natural datasets. As a corpus consisting linguistically perturbed natural questions, $\text{CQM}_{\text{robust}}$ is beneficial to a robustness evaluation to help us mitigate models' undesirable performance in real-world applications.

5 Conclusion

In this work, we create a Chinese dataset namely $\mathbf{CQM}_{\textbf{robust}}$ which contains linguistically perturbed natural questions for evaluating the robustness of QM models. $\text{CQM}_{\text{robust}}$ is designed to be fine-grained, diverse and natural. Specifically, $\text{CQM}_{\text{robust}}$ has 3 categories and 13 subcategories with 32 linguistic perturbation. We conduct extensive experiments with $\text{CQM}_{\text{robust}}$ and the results demonstrate that $\text{CQM}_{\text{robust}}$ has 3 characteristics: 1) $\text{CQM}_{\text{robust}}$ is challenging and has more discrimination ability; 2) The fine-grained design of $\text{CQM}_{\text{robust}}$ helps to diagnose the strengths and weakness of models, and enables us to evaluate the models in a diverse; 3) The effect of artificial adversarial examples does not work on the natural texts of $\text{CQM}_{\text{robust}}$.

Ethical Considerations

This work presents $\mathrm{CQM}_{\mathrm{robust}}$, a diverse and natural dataset for the research community to evaluate the robustness of QM models. Data in $\mathrm{CQM}_{\mathrm{robust}}$ are collected from a commercial search engine (we are legally authorized by this company), the details are presented in Sec. 3. Since $\mathrm{CQM}_{\mathrm{robust}}$ do not have any user information, there is no privacy concerns. In addition, to ensure that the $\mathrm{CQM}_{\mathrm{robust}}$ is free potential biased and toxic content, we desensitize all the instances in it. Regarding to the issue of labor compensation, all the annotators and evaluators are employees from our internal data team and are fairly compensated.

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A Construction Details

Sec. 3 provides an overview of construction process[3] of $\text{CQM}_{\text{robust}}$. However, $\text{CQM}_{\text{robust}}$ is a diverse dataset with 3 categories and 13 subcategories. And they are constructed with different adversarial methods. Details about our construction approaches to different categories are described in this section.

Lexical Features. For each source question, we select the word with specific POS tagss or entity type and high word importance score as *target word*, and perturb the source questions with some other words we collect from following 4 sources:

- Elasticsearch[4]: to collect words which have high character overlap with *target words*;
- Faiss[5]: to collect words which are semantically similar to *target words*;
- Bigcilin[6]: to collect synonym of *target words*;
- Baidu Hanyu[7]: to collect antonym and synonym of *target words*;
- XLM-RoBERTa(Conneau et al., 2020): to insert additional words to source sentences[8];
- Vocabulary lists[9]: to insert some specific words, such as negation word and temporal word.

Syntactic Features. For *Symmetry* and *Asymmetry*, we retrieve the source questions in the search log and the returned questions whose edit distance to source question is equal to 4 are selected as candidate questions. Then we compare the dependency structures of the source question and candidate questions. Only the question pairs which contain symmetric or asymmetric relations (which swap the order of two symmetric / asymmetric words) are retained. To generate examples for *Negative Asymmetry*, we select some pairs from *Asymmetry* and negate one side of the pairs. The asymmetric syntactic structure of two sentences and one-sided negation resolves to a positive meaning. For *Voice*, we add "被*bei*" word to source questions to conduct a change of voice.

Pragmatic Features.

Misspelling. With the help of Chinese heteronym lists[10], we obtain a set of common typos and substitute the correct-spelling words with typos. To ensure the correctness, the perturbation should satisfy two constraints:

1) The typos should be commonly used Chinese characters;
2) Only one character in the source sentence is replaced with its typo.

Discourse Particle. We construct this category in 2 ways:

1) We replace or add some question words, auxiliary words or punctuation marks to generate *Simple Discourse Particle* examples (*Discourse Particle (Simple)* in Tab. 1);
2) For *Complex Discourse Particle* examples (*Discourse Particle (Complex)* in Tab. 1), we select some question pairs from a Frequently-Asked-Questions (FAQ) log, especially pairs with big differences in sentence length. Then the pairs are manually annotated and we retained the examples labeled with *Y*.

With above approaches, we perturb the source questions and obtain a large set of question pairs. Then the generated question pairs are reviewed naturalness and annotated manually.

B Supplementary Experiments

B.1 Additional Experimental Setting

B.1.1 Training Details

In the fine-tuning stage, we insert a $[SEP]$ between the question pairs. The pooled output is passed to a classifier. We use different different learning rates and epochs for different pre-trained. Specifically, for large models, the learning rate is 5e-6 and the number of epochs is 3. For base models, the learning rate is 2e-5, and we set the number of epochs as 2. The batch size is set as 64 and the maximal length of question pair is 64. We use early stopping to select the best checkpoint. Each model is fine-tuned 3 times on $\text{LCQMC}_{\text{train}}$ and we choose the model with the best performance on $\text{LCQMC}_{\text{dev}}$ to report test results.

[3] We use *Lexical Analysis of Chinese* (LAC) to do POS tagging, word importance analysis, and NER: https://github.com/baidu/lac. We use a dependency parsing tool: https://github.com/baidu/DDParser

[4] https://github.com/elastic/elasticsearch

[5] https://github.com/facebookresearch/faiss

[6] http://www.bigcilin.com/browser/

[7] https://hanyu.baidu.com/

[8] We add an additional $\{mask\}$ before target word, and use pre-trained language model to predict it. The prediction result of $\{mask\}$ is the word inserted to the source sentence.

[9] Vocabulary lists refer to some word lists containing specific words, such as negation word list and temporal word list.

[10] https://github.com/FreeFlyXiaoMa/pycorrector/blob/master/pycorrector/data/same_stroke.txt

Models	L	H	A	# of Parameters	Masking	LM Task	Corpus
BERT$_b$	12	768	12	110M	T	MLM	Wikipedia
ERNIE$_b$	12	768	12	110M	T/E/Ph	MLM	Wikipedia+Baike+Tieba, etc.
RoBERTa$_b$	12	768	12	110M	MLM	-	EXT[11]
MacBERT$_b$	12	768	12	110M	Mac	SOP	EXT
RoBERTa$_l$	24	1024	16	340M	MLM	-	EXT[12]
MacBERT$_l$	24	1024	16	340M	Mac	SOP	EXT

Table 7: The hyper-parameters of public pre-trained language models we use(L: number of layers, H: the hidden size, A: the number of self-attention heads, T: Token, E: Entity, Ph: Phrase, WWM: Whole Word Masking, NM: N-gram Masking, MLM: Masked LM, Mac: MLM as correction).

Corpus	Train	Dev	Test	Fine-grained
LCQMC	238,766	8,802	12,500	No

Table 8: Data statistics of LCQMC.

Data	BERT	RoBERTa
PWWS	<u>41.5</u>	<u>41.9</u>
PWWS$_{nat}$	23.0$_{-18.5}$	18.5$_{-23.4}$
TEXTFOOLER	**46.6**	**42.9**
TEXTFOOLER$_{nat}$	14.6$_{-32.0}$	12.2$_{-30.7}$
CQM$_{robust}$	33.4	26.2

Table 9: Attack success rate(%) on different test data.

B.1.2 Datasets Details

Tab. 8 gives a detailed description of LCQMC Corpus. And it is worth mentioning that LCQMC is in general domain and its source questions are similar to the search query, which are the form of source questions for CQM$_{robust}$. In other words, CQM$_{robust}$ is not a ood test set of LCQMC, so that the lower performance could not be attributed to being a ood test set.

B.2 Adversarial Training Details

Tab. 5 gives a detailed statistics of adversarial examples generated with TextFooler, PAWS. To generate training samples, we select a set of LCQMC training questions and apply the methods PWWS and TextFooler on them. The labels are same as original samples. To generate test samples and ensure a robust evaluation, we utilize 4 datasets, PWWS$_{nat}$, TextFooler$_{nat}$, Checklist$_{nat}$[13] and CQM$_{robust}$, which are natural adversarial examples. We conduct an experiment about adversarial training by feeding the models both the original data and the adversarial examples, and observe whether the original models become more robust. We use pre-trained model RoBERTa$_l$ (described in Tab. 7) for fine-tuning and the fine-tuning details are described in Sec. 4.1.

B.3 Results of Attacks

We give the main results of attacks to BERT$_b$ and RoBERTa$_l$ in Tab. 9. The results show that the un-natural attacks (on artificial adversarial samples, i.e. PWWS and TextFooler in Tab. 9) have higher success rate than CQM$_{robust}$. However, if we select the natural examples from the artificial adversarial samples (PWWS$_{nat}$ and TextFooler$_{nat}$ in Tab. 9), the attack success rate of PWWS and TextFooler is significantly decreasing by at least 18.5% on BERT$_b$ and 30.7% on RoBERTa$_l$ respectively. CQM$_{robust}$, in which all the samples are natural and grammarly correct, gets the best performance when black-box attacking (compare to PWWS$_{nat}$ and TextFooler$_{nat}$ in Tab. 9). In summary, the artificial adversarial examples training is not effective on natural texts, such as CQM$_{robust}$. It is reasonable that we should pay more attention to the naturalness when generating the adversarial examples.

[13] Before annotating, we translate original Checklist dataset into Chinese using a translation tool