GEC Review

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1 Grammatical Error Correction

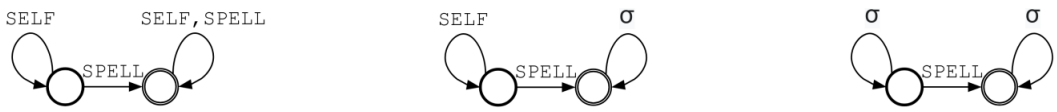
Grammatical error correction (GEC) aims to systematize writing errors to correct grammar and spelling errors. However, one of the biggest bottlenecks in GEC is data sparsity [Google], namely the need for more diverse and large exemplary data. Although there have been many attempts to generate synthetic data based on various models, such as heuristic-based random words, such models failed to represent the proper distribution of grammatical errors in the wild [Google]. We will explain tagged corruption models by [stahlberg-kumar-2021-synthetic] that enables a more flexible distribution of synthetic data and produces state-of-the-art results on GEC baselines.

1.1 Tagged Corruption Models

This section summarizes the paper [stahlberg-kumar-2021-synthetic]

Tagged corruption models create an ungrammatical (corrupt) sentence from a clean sentence based on an error tag $\tau \in T$, where T denotes 25 error tags supported by ERRANT.

The model is trained using Seq2Edits [stahlberg-kumar-2020-seq2edits], which can predict the error tags together with the edits. Additionally, Finite State Transducers (FST) are utilized to force to generate a particular error tag. The following figure shows the FSTs for the $SPELL$ tag.



(a) NoSigma (b) PostSigma (c) PrePostSigma

Figure 1: Image credit: [stahlberg-kumar-2021-synthetic]

In Fig 1, σ refers to any error tag and $SELF$ denotes the source spans that are not modified, i.e., the change points where corruption is applied. In Fig 1a,

only includes $SELF$ and $SPELL$, whereas Fig 1b can have any error tag after starting with $SELF$ and $SPELL$ tags. Fig 1c, however, can start and end with any error tags as long as including a $SPELL$ tag in between.

1.1.1 Synthetic Data Generation with Tagged Corruption Models

Let x_n ($n \in [1, N]$) and $y_{t,n}$ denote the input sentence and the corresponding corrupted sentence for a given tag $\tau \in T$, respectively. One of the goals is to only apply one tag per sentence and create a new corrupted corpus from the input data such that the distribution of the error tags are equal:

$$\forall \tau \in T : P(\tau) \approx= \frac{|\{\tau_n = \tau | n \in [1, N]|\}}{N} \tag{1}$$

Three methods are compared: Offline-Optimal, Offline-Probabilistic, Online

Offline-Optimal The offline-optimal model searches for the tag with the highest log-probability under the constraint that the distribution of the tags matches the desired distribution:

$$\max_{\tau^*} \sum_{n=1}^{N} log P(y_{\tau_n^*,n} | \tau_n^*, x_n) \tag{2}$$

It can be shown that this model can be solved with the minimum-cost solver.

Offline-Probabilistic In the offline-probabilistic model, the samples are created according to a given distribution, and then N sentences with the highest likelihood to contain a given tag is drawed:

$$P((x, y)|\tau) = \frac{P(\tau|(x, y)P(x, y)}{\sum_{n=1}^{N} P(\tau|(x_n, y_n))P(x_n, y_n)} \tag{3}$$

assuming each corrupted sentence sample for a given tag has equal probability, i.e., $P(x, y) = \frac{1}{N}$, we obtain

$$P((x, y)|\tau) = \frac{P(\tau|(x, y)}{\sum_{n=1}^{N} P(\tau|(x_n, y_n))} \tag{4}$$

Now,

$$P(\tau|(x, y)) = \frac{P(\tau, x, y)}{P(x, y)} = \frac{P(x)P(\tau|x)P(y|(\tau, x))}{P(x, y)} = \frac{\frac{1}{N}\frac{1}{|T|}P(y|(\tau, x))}{\frac{1}{N}} = \frac{1}{|T|}P(y|(\tau, x)) \tag{5}$$

Note that, since we draw the corrupted sentences with the highest probability to contain a given tag, the model may include corrupted sentences derived from the same sentence or exclude some sentences in the input data. This is not an issue in the offline-optimal model as the model already takes each input sentence as a supply node (in the minimum-cost problem terminology) and derive the optimal tag accordingly.

Online Both offline-optimal and offline-probabilistic models have to create $N * |T|$ corrupted sentences to find the optimal solutions, and hence each have $\Omega(N|T|)$ time-complexity. This issue can be optimized by assigning tags on the fly according to a given distribution and creating a model with $\Omega(N)$ time complexity.

2 ERRANT for Turkish

We give corresponding grammatical errors according to ERRANT error tags. Note that some tags don't have a Turkish example, i.e., CONTR (n't $\rightarrow$ not) or DET (the $\rightarrow$ a). The following table is taken from [UCAM-CL-TR-938] and adjusted for Turkish.

Code	Meaning	Description\Example
ADJ	Adjective	büyük adam oldun → koca adam oldun
ADJ:FORM	Adjective Form	→ Comparative or superlative adjective errors. Since the corresponding Turkish comparative and superlative adjectives (daha/en) are strict, it is unlikely to encounter errors here.
ADV	Adverb	çabukca → çabucak
CONJ	Conjunction	ve → ama
CONTR	Contraction	-
DET	Determiner	-
MORPH	Morphology	This can be tricky in Turkish. For instance, both hızlı (adj) and hızlıca (adv) can be used interchangeably: hızlı geldin ∼ hızlıca geldin
NOUN	Noun	kafam ağrıyor → başım ağrıyor
NOUN:INFL	Noun Inflection	We adjust the original definition to the correct use of "ler" or "lar" for plural words. Defterlar → defterler
NOUN:NUM	Noun Number	iki kişiydi → iki kişilerdi
NOUN:POSS	Noun Possessive	-
ORTH	Orthography	birşey → bir şey
OTHER	Other	Unclassified errors; e.g. paraphrases.
PART	Particle	-
PREP	Preposition	sen de kalalım → sende kalalım
PRON	Pronoun	bizimki çocuklar → bizim çocuklar
PUNCT	Punctuation	; → ,
SPELL	Spelling	entellektüel → entelektüel
UNK	Unknown	Detected but not corrected errors
VERB	Verb	geldim → gittim
VERB:FORM	Verb Form	gitme için bekledik → gitmek için bekledik
VERB:INFL	Verb Inflection	Misapplication of tense morphology. geldem → geldim
VERB:SVA	Subject-Verb Agreement	(Ben) geldin → (Ben) geldim
VERB:TENSE	Verb Tense	
WO	Word Order	hemen çocuk geldi → çocuk hemen geldi. Note: Turkish is more malleable against the word order.