



# Automated Assessment and Feedback: the Role of Spoken Grammatical Error Correction

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## **Cambridge Automated Language Teaching and Assessment Institute**



Virtual Institute for 

#### cutting-edge research on second language (L2) English assessment

- Machine Learning and Natural Language Processing •
- Develop technology to enhance assessment and learning

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Look to benefit learners and teachers worldwide 

http://mi.eng.cam.ac.uk/~mjfg/ALTA/index.html







#### Prof Mark Gales Yiting "Edie" Lu Stefano Bannò

#### Plus members of the ALTA Spoken Language Processing Technology Project, Cambridge University Engineering Department





#### Talk Outline

- Automated Learning and Assessment
- Spoken Grammatical Error Correction (GEC)
- Systems for Spoken GEC
- Using Spoken GEC in Automatic Assessment
- Using Spoken GEC for Learner/Teacher Feedback
- Open Challenges



#### **Growth in Automated Learning and Assessment**





## **Automated Learning and Assessment for English L2**

- Close to 2 billion people worldwide use and/or are learning English as a second language
  - Not enough teachers or examiners!
  - Automated assessment and Computer-Aided Language Learning (CALL) systems
  - Data-driven Integrated Learning and Assessment
- Speaking is key skill for communication
  - Many systems ignore or heavily restrict speech input not testing communication
  - Free speaking
    - Monologic e.g. giving a presentation
    - Dialogic e.g. discussing at a conference



## L2 learner speech data is challenging!





#### **Spoken Language Assessment and Feedback Pipeline**



Fine-grained – feedback on specific errors in words/phrases



## Speaking core skills





#### Language Resource: Grammar and Vocabulary





1. https://writeandimprove.com102. S.Bannò et al, "View-Specific Assessment of L2 Spoken English, INTERSPEECH 2022

#### **Spoken Grammatical Error Correction**



## **Grammatical Error Correction (GEC)**

• Aim of GEC is to produce the grammatically correct sentence from a sentence with mistakes

Original: The cat sit on the mat.

Corrected: The cat sat on the mat. The cat is sitting on the mat.

- 1:1 output assumption has relatively small effect on use of GEC
- Large pre-trained GEC models available for English L1 text
  - Lots of annotated L2 learner English writing for fine-tuning
  - But can we apply these to speech?



#### Challenges and advantages of spoken language

- Challenges for assessing and giving feedback on speech "grammatical" errors
  - We don't speak in sentences
  - We repeat ourselves, hesitate, mumble etc
  - No defined spoken grammar ... however there are phrases that a L1 speaker is highly unlikely to say
- Advantages of speech
  - No spelling or punctuation mistakes: over 25% written L2 English grammatical errors
  - We provide additional information about meaning of the text within the audio signal (and gestures)

Text + Pronunciation + Prosody (+Delivery)

Spoken Text ≠ Written Text



#### **Spoken Grammatical Error Correction (SGEC)**

#### Original speech: the cat si- sit on the um mat

Corrected: The cat sat on the mat.







#### **Challenges for automatic Spoken GEC**

• ASR errors are likely

the cat si- sit on the um mat ---- the cat si- see on the um mat ---- The cat saw on the mat.

- Increased for learner speech as harder to recognise
- Have to automatically segment data into "sentences"
- Lack of training data
  - Very little annotated speech data insufficient to train on
    - NICT-JLE<sup>1</sup> no audio samples
    - Linguaskill Speaking<sup>2</sup> (internal data set) approx. 3000 annotated responses
  - Written text data is mismatched to speaking e.g. no disfluencies, stricter grammar, different style



#### **Requirements for Spoken GEC for Assessment and Feedback**

#### Accurate

- Emphasis on precision with reasonable recall
- Feedback only on actual grammatical errors not errors made by the ASR system
  - Giving feedback on an ASR error is worse than giving no feedback
- Interpretable/explainable
  - Let the learner know why what they did was incorrect
- Reasonable computational load and time
  - Near real-time needed for practice apps



#### **Systems for Spoken GEC**



#### **Spoken GEC – End2end?**



Corpus	Audio	Text	DSF	GEC	L2?
ASR-Train <sup>1</sup>	$\checkmark$	$\checkmark$			$\checkmark$
Switchboard <sup>2</sup>	$\checkmark$	$\checkmark$	$\checkmark$		
$CLC^3 + BEA^4$		$\checkmark$		$\checkmark$	$\checkmark$

#### E2E not feasible (currently)

- > No paired training data
- Hard to give feedback to learners



 Y. Lu et al, "Impact of ASR Performance on Spoken Grammatical Error Detection", INTERSPEECH 2019
 M. Meteer, "Dysfluency Annotation Stylebook for the Switchboard Corpus", LDC Technical Report 1995
 D. Nicholls, "The Cambridge Learner Corpus: Error coding and analysis for lexicography and ELT", Corpus 18 Linguistics 2003 conference

4. C. Bryant et al, "The BEA-2019 shared task on grammatical error correction". BEA Workshop 2019

#### **Spoken GEC – Cascade pipeline**



Train/fine-tune each module on different data sets

Various sources of information for feedback



#### **Spoken GEC – Cascade pipeline challenges**





## **Automatic Speech Recognition (ASR)**

- Hybrid ASR<sup>1</sup>
  - Acoustic model:
    - Kaldi LF-MMI TDNN-F<sup>2</sup> on L2 learner speech (ASR-Train) and AMI
  - Language model:
    - Trigram LM trained on ASR L2 manual transcriptions and Broadcast News English
    - su-RNNLM<sup>3</sup> trained on semi-supervised ASR L2 transcriptions
- Key features:
  - L2 speech from over 25 L1s
  - Explicitly model partial words and map all hesitations to a single word label
  - Word level confidence scores



1. Y. Lu et al, "Impact of ASR Performance on Spoken Grammatical Error Detection", INTERSPEECH 2019 2. D. Povey et al, "Purely sequence-trained neural networks for{ASR based on lattice-free MMI", INTERSPEECH 2016 3. X. Chen et al, "Future word contexts in neural network language models", ASRU 2017

#### **Spoken Disfluencies**

Typical disfluency reperandum interregnum repair I want a taxi [ to Marina Bay uh I mean + to Sentosa ] I want a taxi to Sentosa

- Interregnum regions easy to detect using rule-based methods
- Reparandum regions → focus of automatic disfluency detection



## **Automatic Disfluency Detection (DD)**

• Sequence tagging models

$$\hat{d}_{1:L} = \operatorname{argmax}_{d_{1:L}} P(d_{1:L}|w_{1:L};\boldsymbol{\theta}_{\mathrm{DD}})$$

• Non auto-regressive tagger

$$P(d_{1:L}|w_{1:L}; \boldsymbol{\theta}_{\text{DD}}) = \prod_{l=1}^{L} P(d_l | d_{1:l-1}, w_{1:L}; \boldsymbol{\theta}_{\text{DD}}) \approx \prod_{l=1}^{L} P(d_l | w_{1:L}; \boldsymbol{\theta}_{\text{DD}})$$

- Performance largely dependent on quality of tagger's internal feature representations
  - Depends on training criteria and framework<sup>1</sup>

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## Sequence Tagging DD Models

• Recurrent neural network (RNN)<sup>1,2</sup>



- $\vec{h}_{l} = \text{LSTM}(\boldsymbol{e}_{l}, \vec{h}_{l-1}; \vec{\theta}) \quad \overleftarrow{h}_{l} = \text{LSTM}(\boldsymbol{e}_{l}, \overleftarrow{h}_{l+1}; \overleftarrow{\theta})$  $h_{l} = [\vec{h}_{l}, \overleftarrow{h}_{l}]$ 
  - Reasonable good quality feature reps
  - Training scales with sequence lengths

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• Large pre-trained model: BERT<sup>3</sup>



- Capable of high quality feature reps
- Fine-tune BERT using DD objective

 X. Qian and Y. Liu, "Disfluency detection using multi-step stacked learning", NAACL HLT 2013
 V. Zayats et al, "Disfluency detection using bidirectional LSTM", zrXiv, 2016
 J. Kenton and L. Toutanova, "BERT: Pre-training of deepbidirectional transformers for language Understanding", NAACL-HLT 2019





 $\hat{y}_{1:N} = \operatorname{argmax}_{y_{1:N} \in \mathcal{Y}} P(y_{1:N} | w_{1:L}; \boldsymbol{\theta}_{\text{GEC}})$ 



#### seq2seq GEC

#### Treat GEC as a machine translation problem i.e. seq2seq

- **Encoder-decoder architecture**
- RNN-based  $\rightarrow$  Transformer-based encoder-decoder models
  - Large pretrained e.g. T5 'Text-to-Text Transfer Transformer'<sup>1</sup> ullet
- Gramformer<sup>2</sup>: T5-based fine-tuned for GEC on various corpora ۲
  - Can further fine-tune to target domain GEC
  - 223M parameters



ChatGPT<sup>3</sup>: generative autoregressive large language model [CGPT] ۲

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 $y_2$ (EOS . . . Feed forward Feed forward Cross attention Self attention Self attention . . . Feed forward Feed forward Self attention Cross attention Self attention  $e_2$  $e_1$ . . .  $(y_1)$ (BOS  $w_1$  $w_2$  $(w_L$ ...  $(y_N)$ Encoder Decoder

**175B** parameters 

1. Raffel et al, "Exploring the limits of transfer learning with a unified text-to-text", Journal of Machine Learning Research, 2020

2. P. Damodaran, Gramformer. 2021 https://github.com/PrithivirajDamodaran/Gramformer 3. https://chat.openai.com/

#### Treat GEC as a sequence tagging problem<sup>1,2</sup>

- For each token in the source sequence GEC should produce a tag (edit) for required correction operation
  - e.g. GECToR by Grammarly (138M parameters)



GECToR architecture (from O. Skurzhanskyi and K. Omelianchuk<sup>3</sup>)



1. K. Omelianchuk et al, "GECTOR - Grammatical Error Correction: Tag, Not Rewrite", BEA Workshop, 2020 2. A. Awasthi et al, "Parallel Iterative Edit Models for Local Sequence Transduction", EMNLP-IJCNLP, 2019 3. O. Skurzhanskyi and K. Omelianchuk, "Building sequence tagging approach to Grammatical Error Correction" and Text Simplification", talk at Riken Japan, 2022

#### SGEC System Corpora

Corpus	Spoken?	#sents	#words	% disfluencies		
Training						
CLC <sup>1</sup>	X	1.9M	25.2M	-		
BEA <sup>2</sup>	X	1M	11.5M	-		
Evaluation						
FCEtst <sup>3</sup>	X	2681	37k	-		
LIN <sup>4</sup>	$\checkmark$	3361	38k	5%		



1. D. Nicholls, "The Cambridge Learner Corpus: Error coding and analysis for lexicography and ELT", Corpus Linguistics 2003 conference

2. C. Bryant et al, "The BEA-2019 shared task on grammatical error correction". BEA Workshop 2019
3. H. Yannakoudakis et al, "A new dataset and method for automatically grading ESOL texts", NAACL-HLT 2011
4. Y. Lu et al, "On Assessing and Developing Spoken 'Grammatical Error Correction' Systems", BEA Workshop 2022

#### SGEC training data pre-processing

- Convert written text corpora for training to "speechify" it
  - Correct any spelling errors
  - Remove punctuation
  - Upper (or lower) case all text to match ASR
  - Adding speech-like disfluencies through a masked LM can help (not used here)





#### **SGEC** spoken evaluation data

#### • LIN: Linguaskill Speaking L2 learner speech from multi-level English test

- 3361 grammatically corrected 'sentences' from 972 question responses
- 340 speakers from over 30 L1s
- Approximately equal distribution over grades A1-C1
- ASR and Manual transcriptions available
  - With/out disfluencies
  - Manually annotated by English Language iTutoring (ELiT) Ltd





#### **Phase 2 annotation**





#### Annotation phase 2 to phase 3





#### **Annotation phase 3**

#### ✓ Question

#### Long turn 1

Talk about a piece of technology you would like to own. You should say: • which piece of technology you would like to have • why you would like this technology • whether you think you will have this technology one day.

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- Minimal edit corrections made
- Type of error not marked



## **Measuring SGEC performance**

- Align and classify GEC edits with ERRor ANnotation Toolkit (ERRANT)<sup>1,2</sup>
  - Automatically extracts edits from parallel original and corrected sentences
  - Classifies them according to a dataset-agnostic rule-based framework
  - Facilitates error type evaluation at different levels of granularity

Auto:	the	cat	sit	on		mat
Reference:	the	cat	sat	on	the	mat
Edit:			R:VERB		M:DET	

- Spoken language differences to written text
  - Alignment will change depending on if Manual or ASR reference
  - Edit classification rules do not take speech effects into account such as disfluencies and partial phrases



- 1. C. Bryant et al, "Automatic annotation and evaluation oferror types for grammatical error correction", ACL 2017
- 2. M. Felice et al, "Automatic extraction of learner errors in ESL sentences using linguistically enhanced alignments", COLING 2016

### **Spoken GEC Performance**

• Manual, Fluent speech transcripts → Gramformer

	FCEtst	LIN
$M^{2} F_{0.5} \uparrow$	56.6	53.6

- Spoken GEC can match performance of Written GEC L2 English learner task
- Cascade GEC system: TDNN-F ASR → BERT DSF → Gramformer

	LIN		
Input to Gramformer	Manual	ASR+DD+GEC	
SER ↓	43.3	76.8	
TER $\downarrow$	8.3	27.9	

> Need to mitigate for ASR error progagation and domain mismatch



#### **GEC** system analysis

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• Over prediction of OTHER due to ERRANT missing speech-based rules

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\* This system did not have DD module

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## **Integrated Spoken GEC Training**



- Semi-supervised ASR error mitigation
- Reranking
- Embedding passing

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#### **Using Spoken GEC in Assessment**



#### Holistic "hand-crafted" features-based auto-marker



Standard approach to speech auto-marking



#### View Specific and/or Multi-view auto-marker<sup>1</sup>



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## **Grammatical accuracy grader pipeline**



(no disfluency detection module used here)



#### **GEC Grader evaluation**

• ERRANT label distribution over grades



• Grader RMSE

Model	LinBus
holistic	0.406
GEC	0.495
text	0.409
pronunciation	0.451
5-way multi-view	0.386



#### **Using Spoken GEC for Learner/Teacher Feedback**



#### What and how to present?



https://liulishuo.com

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#### Improve feedback precision: remove 'OTHER'





1. Lu, Gales and Bannò, "On Assessing and Developing Spoken 'Grammatical Error Correction' Systems", BEA Workshop, 2022 45

#### Improve feedback precision: confidence filtering



 $\log P = \alpha \log P_{\rm ASR} + \beta \log P_{\rm DD} + \gamma \log P_{\rm GEC}$ 

Sentence level > edit level confidence filtering



	ELIT-ASR-AUTO		
Edit Type	None	Sent	
M:DET	19.12	27.42	
R:PREP	21.54	33.33	
R:NOUN:NUM	22.58	38.39	
R:VERB:TENSE	24.54	21.40	
U:DET	17.19	<b>21.85</b>	
R:VERB	22.61	<b>24.14</b>	
R:NOUN	27.87	12.46	
M:PREP	12.15	18.32	
R:VERB:FORM	22.37	29.93	
R:VERB:SVA	16.85	34.55	
TOTAL	20.89	24.28	



Fo.5 breakdown – top 10 edit types



## **Open Challenges for Spoken GEC**

- Increasing Accuracy
  - Tighter integration of modules
  - Data augmentation
  - Domain adaptation of GEC networks
  - Sequence uncertainty when was a good/bad GEC sequence generated?



Saliency: What caused the grammatical error?



#### ChatGPT: are huge amounts of data and compute "all we need"?

What about "your manager has asked you for the result of an internal staff survey on travelling to work the first chart shows how staff at your company travelled to work the second chart shows what improvements to company facilities the staff would like to see look at the chart and then talk about the information describing the survey results um by car forty percent by train thirty five thirty five percent by bus ten percent on foot five percent bicycle five percent motor bicycle motorbike five percent free company bus to and from station very many"

Here is a corrected version of the sentence:

\$

"Your manager has asked you for the result of an internal staff survey on travelling to work. The first chart shows how staff at your company travelled to work, and the second chart shows what improvements to company facilities the staff would like to see. Look at the chart and then talk about the information, describing the survey results: by car, 40%; by train, 35%; by bus, 10%; on foot, 5%; by bicycle, 5%; by motorbike, 5%; and a free company bus to and from the station is desired by many."

In this sentence, I made a few changes to improve the grammar and clarity. First, I added the missing article "the" before "first chart" and "second chart". I also added the article "a" before "free company bus" to make it clear that there is only one bus. I also changed the word "very" to "many" to better match the verb "desired". Finally, I added a few commas to make the sentence easier to make the sentence ea ଓ Try again



https://chat.openai.com/ 49

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#### ChatGPT: ASR errors are still an issue

Last one (for now ;-)): "i think my stall language skill is have fast range rate and experiences for quality control as we working for more than ten years"



Here is a corrected version of the sentence:

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"I think my language skills have a fast rate of improvement, and I have a lot of experience in quality control. I have been working in this field for more than ten years."

In this sentence, I made a few changes to improve the grammar and clarity. First, I changed "stall" to "skills" to correctly reflect the subject of the sentence. I also added the article "a" before "fast rate of improvement" to make it clear that we are talking about a specific rate. I also changed "experiences" to "experience" because "experiences" is a plural noun, while "experience" is a singular noun. Finally, I added the phrase "I have been working in this field for more than ten years" to clarify the subject's experience in quality control. Let me know if you have any other questions.

• ASR error: "I think my strongest skill..."  $\rightarrow$  "I think my stall language skill ..."



#### Conclusions

- Automated assessment and computer aided language learning is growly rapidly
  - Needed to cope with over 2Bn learners/speakers
- Learners increase in grammatical accuracy and range as they progress
  - Automatic Grammatical Error Correction (GEC) is very popular for Writing Assessment and Feedback
  - Automatic Spoken GEC (SGEC) shown to be of use to Speaking Assessment and Feedback
- Lots of open challenges in Automatic SGEC
  - Improving core accuracy whilst handling limited labelled training data
  - Increase robustness to and awareness of ASR errors
  - Add interpretability and explainability to give more in-depth feedback



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## **Questions?**

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