

# LARGE LANGUAGE MODELS AS A PROXY FOR HUMAN EVALUATION IN ASSESSING THE COMPREHENSIBILITY OF DISORDERED SPEECH TRANSCRIPTION

Katrin Tomanek<sup>1</sup>, Jimmy Tobin<sup>1</sup>, Subhashini Venugopalan<sup>1</sup>, Richard J.N. Cave<sup>1,2</sup>, Katie Seaver<sup>1,3</sup>, Jordan Green<sup>1,3</sup>, Rus Heywood<sup>1</sup>,  
<sup>1</sup>Google Research, <sup>2</sup>Language and Cognition, UCL, <sup>3</sup>MGH Institute of Health Professions,  
[{katrintomanek, jtobin}@google.com](mailto:{katrintomanek, jtobin}@google.com)

## Introduction

### WER treats all errors the same

- Word Accuracy and Word Error Rate (WER) are measures of syntactic accuracy and errors of an automatic speech recognition (ASR) model, but they don't measure comprehensibility.
- On atypical speech (e.g. disordered speech), WER is often >20 and sometimes >60 for certain etiologies and severities.
- Individuals with disordered speech may still benefit from an ASR model with relatively high WER, provided that meaning is preserved.
- We aim to create a system that will automatically assess the ability of an ASR model to convey the user's intended message.

Error Type	Predicted Transcript	Actual Transcript	Word Acc.
Deletion	Come right back - I have a <b>head</b> -	Come right back please I have a headache	0.75
Contraction	I'm a bit overwhelmed	I am a bit overwhelmed.	0.60
Normalization	play Beyoncé Okay 9:30 five	play Beyonce Okay, nine thirty five.	0.50
Proper Noun	Here are TV shows by Hugh <i>Griffiths</i> First do you know how the story ends	Here are TV shows by Hugh Griffith Faust, do you know how the story ends?	0.86 0.88
Repetition	What <i>are you</i> are you trying to say to me	What are you trying to say to me?	0.75

## Method

### Classifiers Predicting Meaning Preservation

- Logistic Regression model on BERTScore+WER
- Logistic Regression model on cosine similarity of sentence embeddings (SentT5, 11b)
- Prompt-tuned LLMs: Flan-T5-XXL (11b) and Flan-cont-PaLM (62b)

<b>Example 1</b>
<b>Input Sequence</b>
Ground truth: {no no there are fifteen hundred total}.
Transcription: {no no there are 50 energy total}.
Transcript preserves the meaning of the ground truth: {
<b>Target Sequence</b>
no}
<b>Example 2</b>
<b>Input Sequence</b>
Ground truth: {He's huggable and lovable and a good with people}.
Transcription: {He's huggable and laughable and a good with people}.
Transcript preserves the meaning of the ground truth: {
<b>Target Sequence</b>
yes}

## Model Deployment Decisions

- Personalized ASR models [2] need to be quality checked (usually manually by Speech & Language Pathologists) before deploying to users.
- Word Accuracy does not distinguish well between high and low quality models.
- LATTEScore (LLMs to Assess Transcription Error Score) gives better model quality assessment.

$$\text{LATTEScore} = \frac{\# \text{ Predicted Meaning Preserved}}{\# \text{ Total Examples}} \times 100$$

## References

[1] MacDonald et al. Disordered Speech Data Collection: Lessons Learned at 1 Million Utterances from Project Euphonia. Interspeech 2021  
[2] Green et al. Automatic Speech Recognition of Disordered Speech: Personalized Models Outperforming Human Listeners on Short Phrases. Interspeech 2021

## Dataset

### Transcript Comprehensibility Dataset

- 4731 tuples of ground truth (from Euphonia corpus [1]) and (erroneous) ASR transcript along with human-rated meaning preservation label
- Significant inter-annotator agreement when assessing meaning preservation, Cohen's  $\kappa = 0.7$

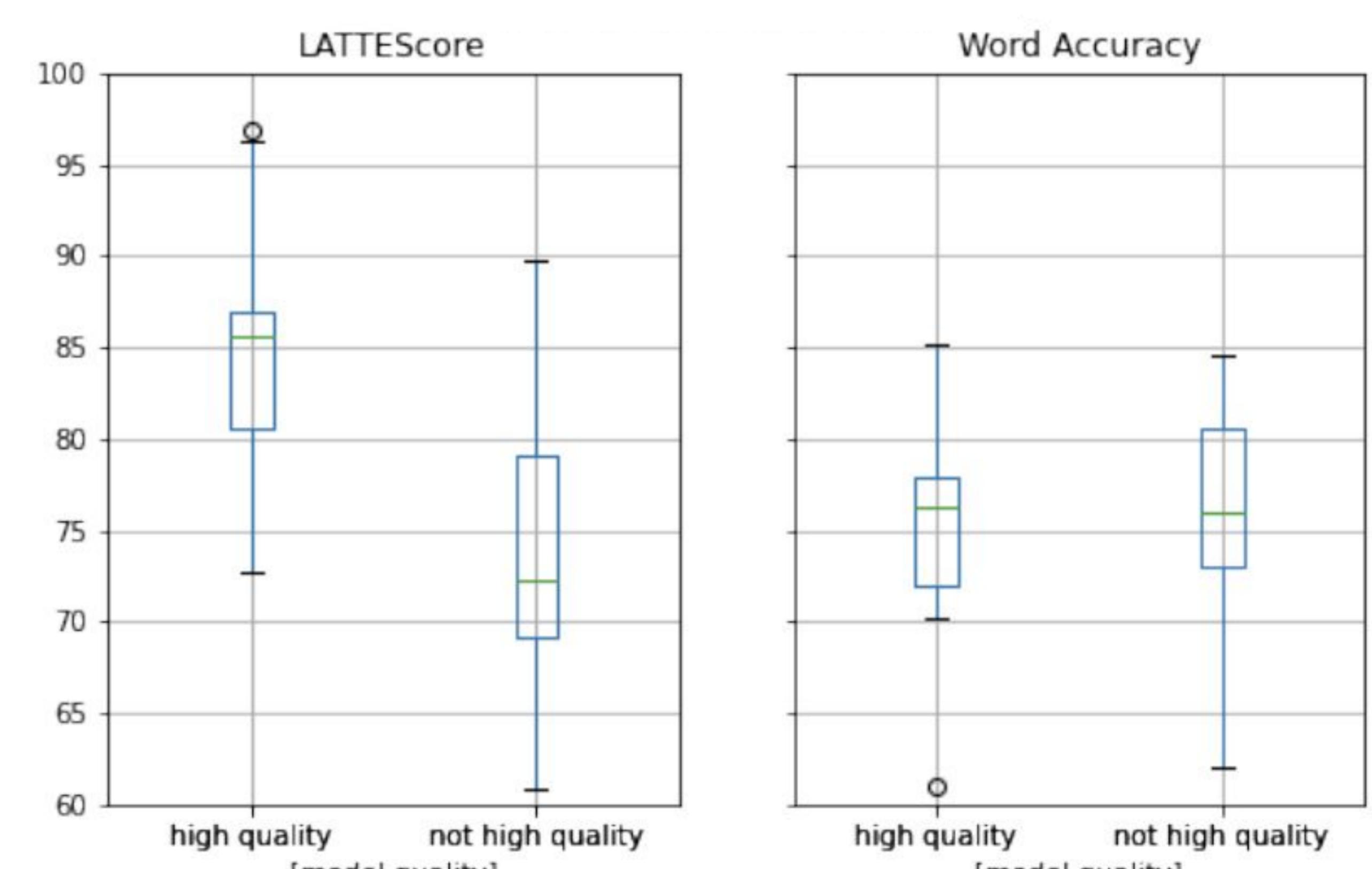
Error Severity	Meaning Preserved	Description	# Examples (%)	Example
0	yes	Meaning is completely preserved	900 (19%)	G: I would be fascinated to know your answers. T: I will be fascinated to know your answers.
1	yes	Some errors, but meaning is mostly preserved.	1145 (24%)	G: Yeah I have one basically every day. T: Yeah I have I'm basically every day.
2	no	Major errors, significant loss of intended meaning.	2686 (57%)	G: How large is that file? T: How large is a funnel?

## Results

### Classifiers Performance (ROC-AUC)

Approach	Full set (940)	Sliced by severity		
		SEV (467)	MOD (302)	MILD (149)
BERTScore+WER	0.791	0.753	0.791	0.856
SentT5 Emb Sim	0.857	0.813	0.879	0.899
Flan-T5 XXL	0.878	0.836	0.923	0.890
Flan-cont-PaLM	<b>0.900</b>	<b>0.863</b>	<b>0.944</b>	<b>0.903</b>

### LATTEScore to Distinguish Model Quality



## Conclusion

- We propose a new approach to assess ASR model performance based on comprehensibility rather than syntax preservation.
- LLM-based classifiers perform very well in this task and outperform other classifiers.
- LATTEScore better predicts how useful a model will be to the end user.
- Beyond speech impairment, LLM-based classifiers can be useful for low-resource languages where human evaluation is challenging.
- Future work will explore using multi-lingual LLMs for zero-shot performance in other languages.