UNIVERSITY OF CAMBRIDGE

Machine Learning of Level and Progression in Spoken EAL

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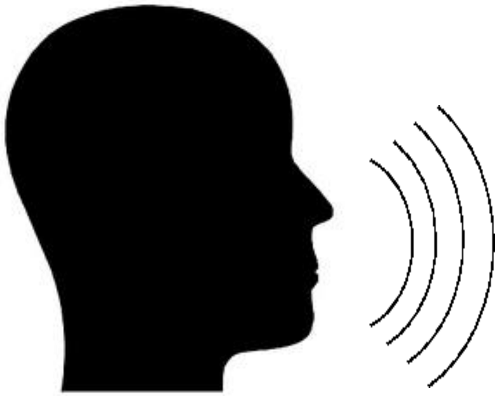
Cambridge ALTA

Institute for Automated Language Teaching and Assessment

Spoken Communication



Speaker Characteristics
Environment/Channel

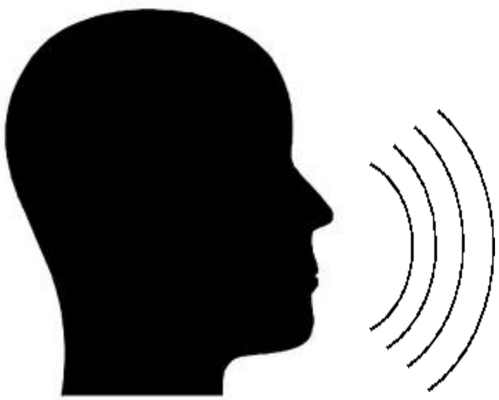
Pronunciation
Prosody

Message Construction

Message Realisation

Message Reception

Spoken Communication



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Message Construction | Message Realisation | Message Reception

Spoken communication is a very rich communication medium

Spoken Communication Requirements

- Message Construction should consider:
  - Has the speaker generated a coherent message to convey?
  - Is the message appropriate in the context?
  - Is the word sequence appropriate for the message?

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Spoken Language Versus Written

ASR Output

okay carl uh do you exercise yeah actually um i belong to a gym down here gold’s gym and uh i try to exercise five days a week um and now and then i’ll i’ll get it interrupted by work or just full of crazy hours you know

Spoken Language Versus Written

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Meta-Data Extraction (MDE) Markup

Speaker1: / okay carl {F uh} do you exercise /
Speaker2: / {DM yeah actually} {F um} i belong to a gym down here /
/ gold's gym / / and {F uh} i try to exercise five days a week {F um} /
/ and now and then [REP i'll + i'll] get it interrupted by work or just full of crazy hours {DM you know } /

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Written Text

Speaker1: Okay Carl do you exercise?
Speaker2: I belong to a gym down here, Gold's Gym, and I try to exercise five days a week and now and then I'll get it interrupted by work or just full of crazy hours.

Business Language Testing Service (BULATS) Spoken Tests

- Example of a test of communication skills
  A. Introductory Questions: where you are from
  B. Read Aloud: read specific sentences
  C. Topic Discussion: discuss a company that you admire

  D. Interpret and Discuss Chart/Slide: example above
  E. Answer Topic Questions: 5 questions about organising a meeting

Automated Assessment of One Speaker

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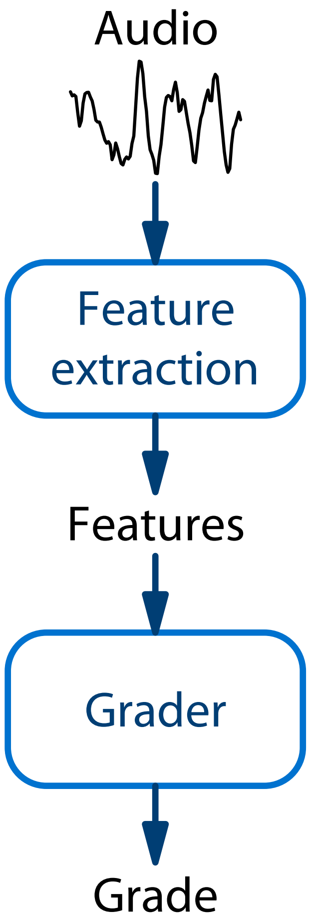

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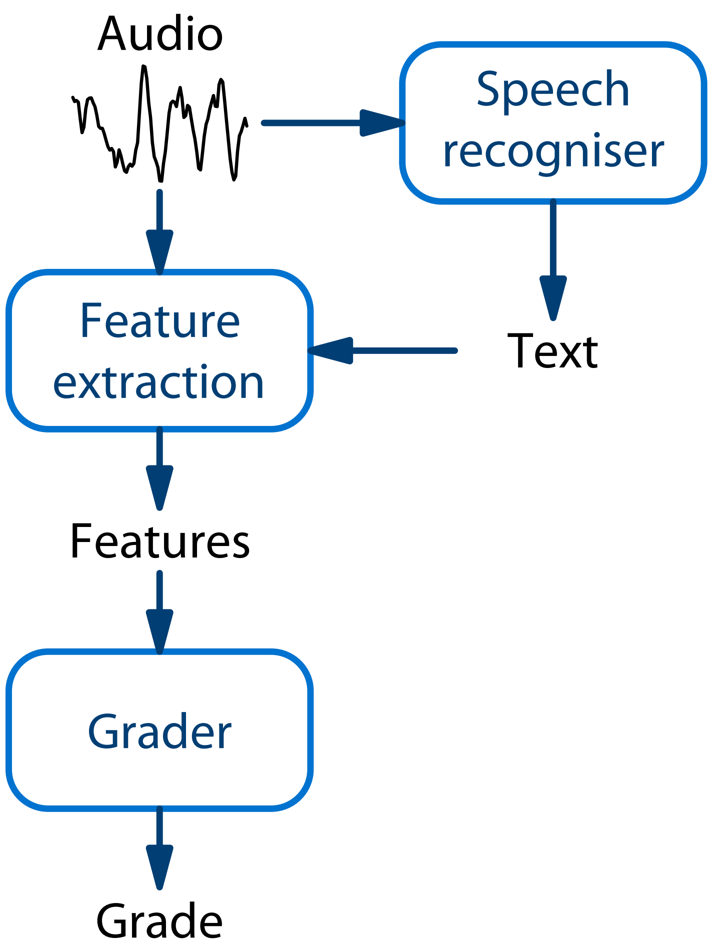
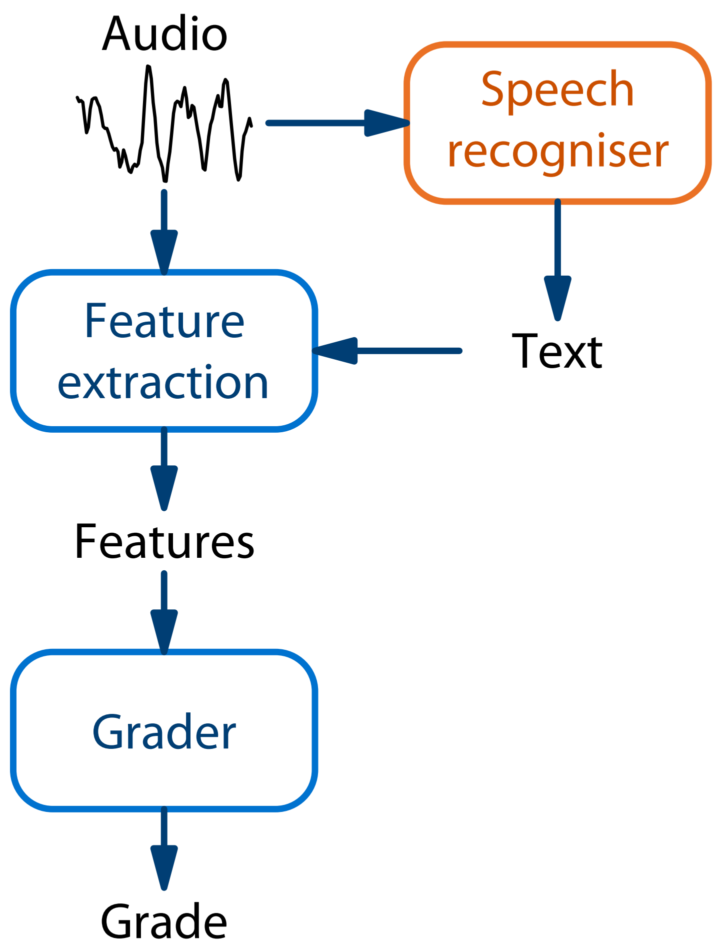


Outline

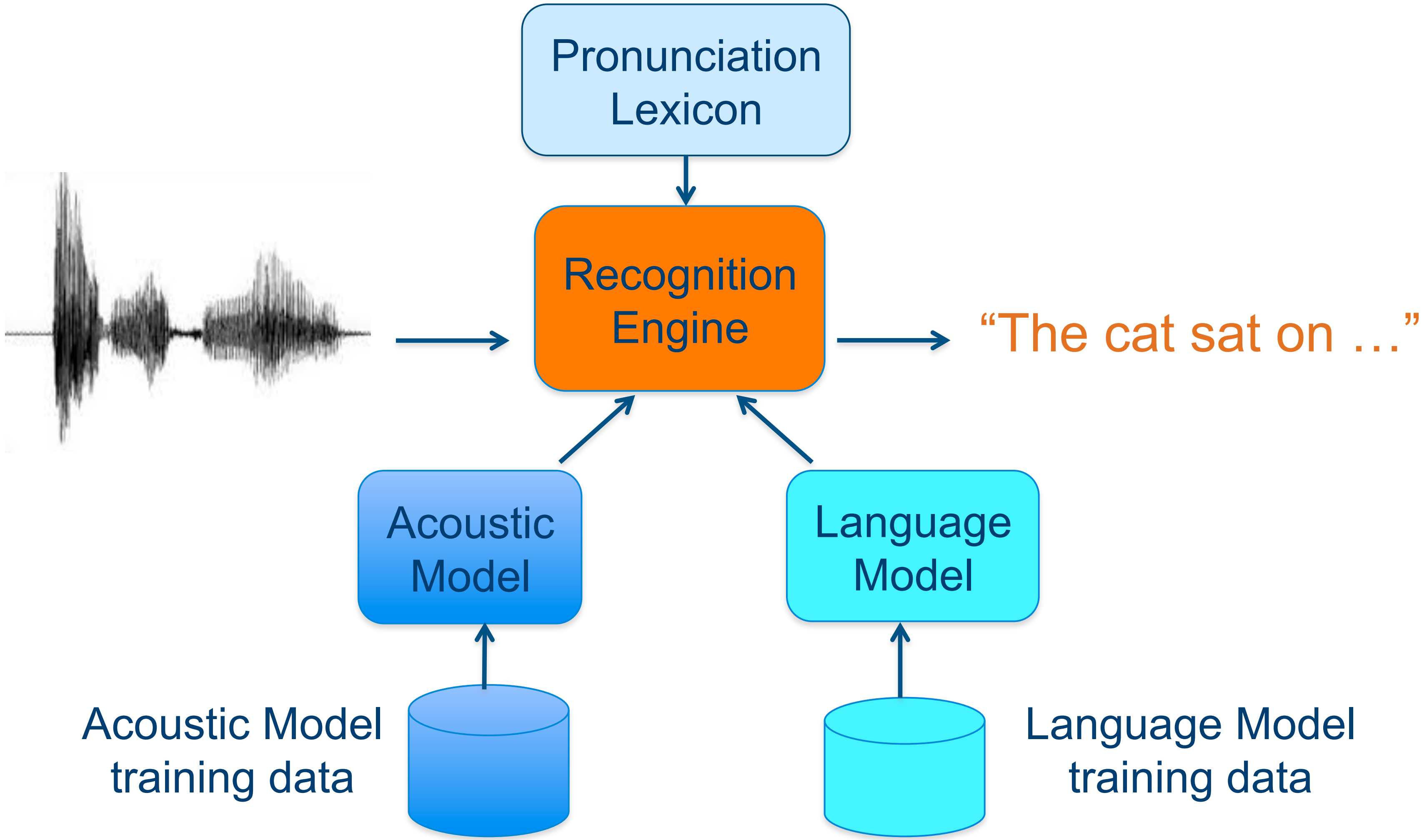

Audio
Speech
recogniser
Feature
extraction
Text
Features
Grader
Grade

Speech Recognition Challenges

- Non-native ASR highly challenging
  - Heavily accented
  - Pronunciation dependent on L1
- Commercial systems poor!
- State-of-the-art CUED systems

Training Data	Word error rate
Native & C-level non-native English	54%
BULATS speakers	30%

Automatic Speech Recognition Components



Forms of Acoustic and Language Models

Used to recognise L2 speech

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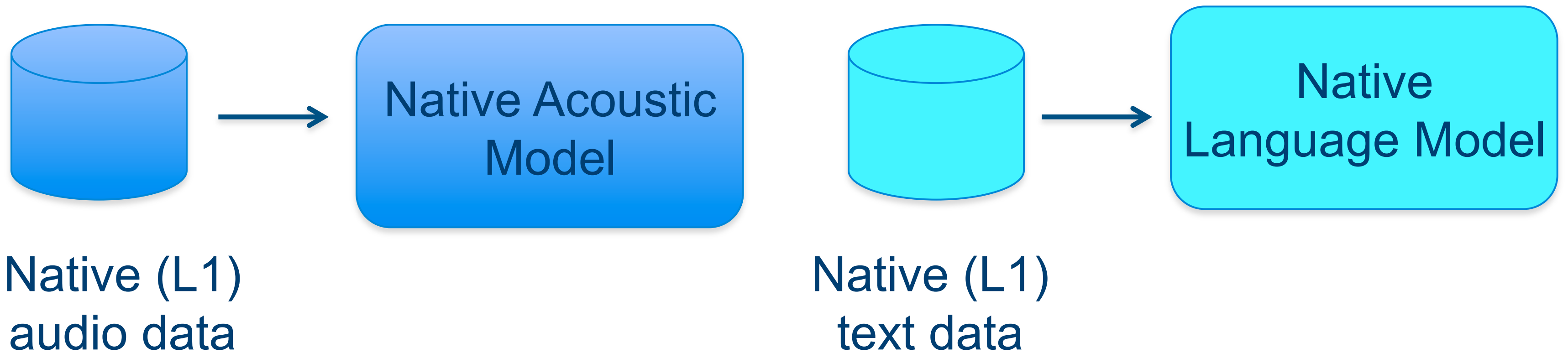
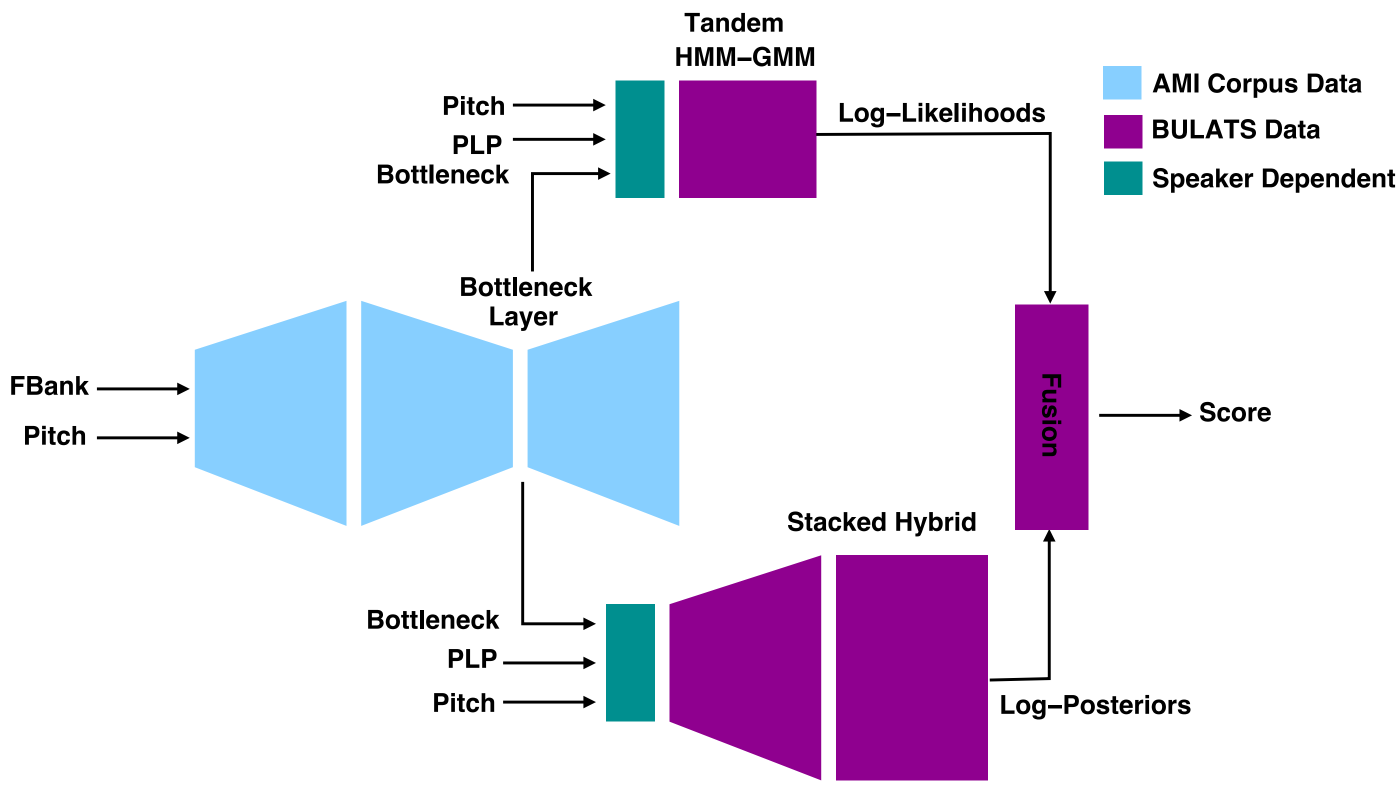


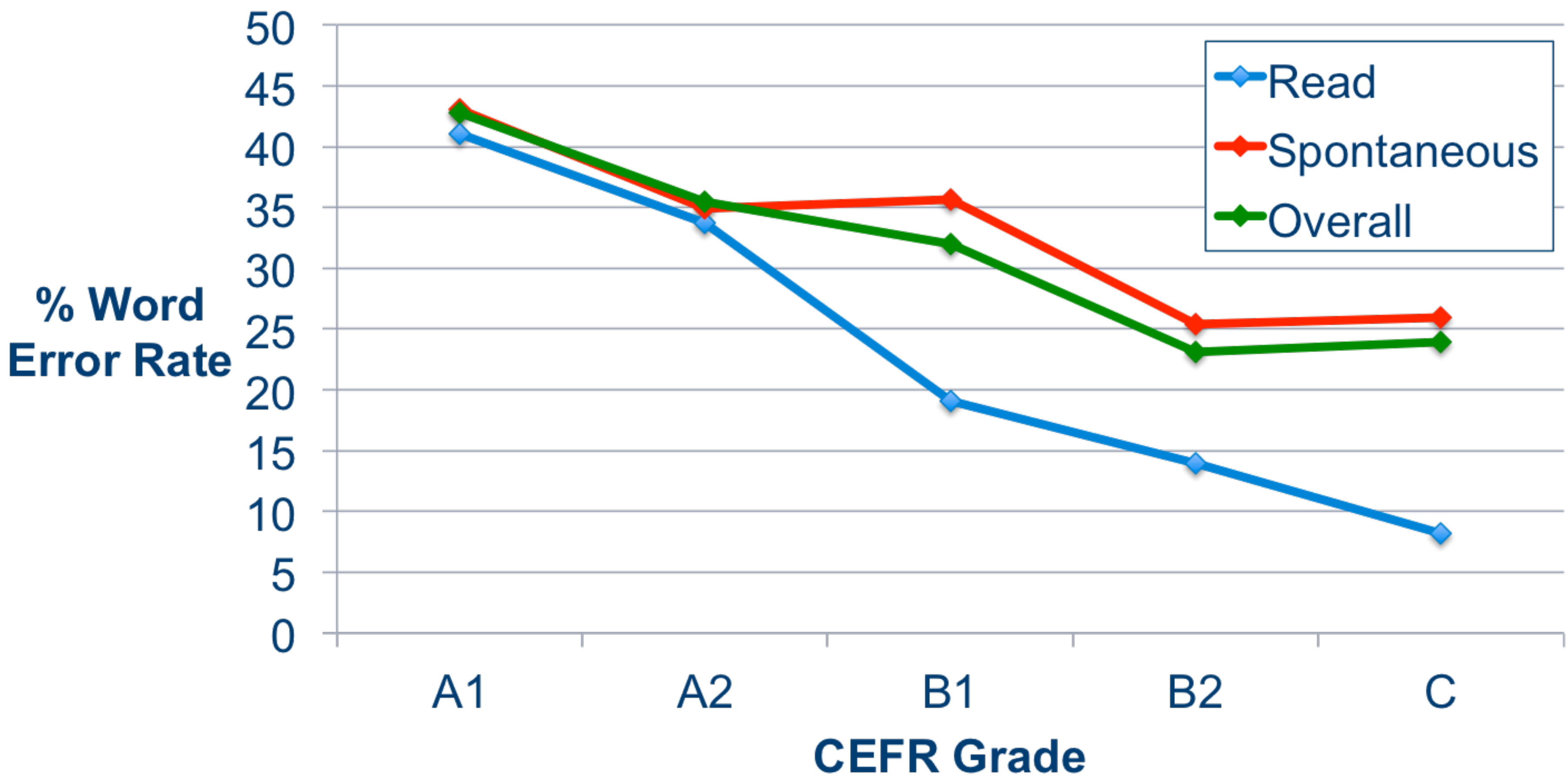
Useful to extract features

Deep Learning for Speech Recognition



- Fusion of HMM deep neural network and Gaussian mixture models
    - trained on BULATS data

Recognition Error Rate Versus Learner Progression



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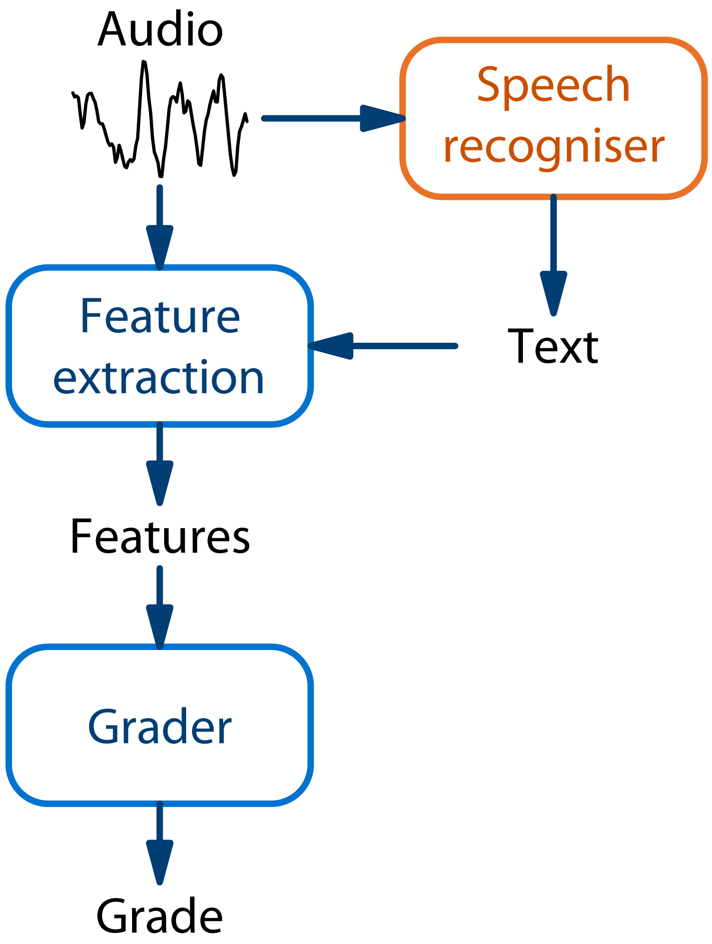
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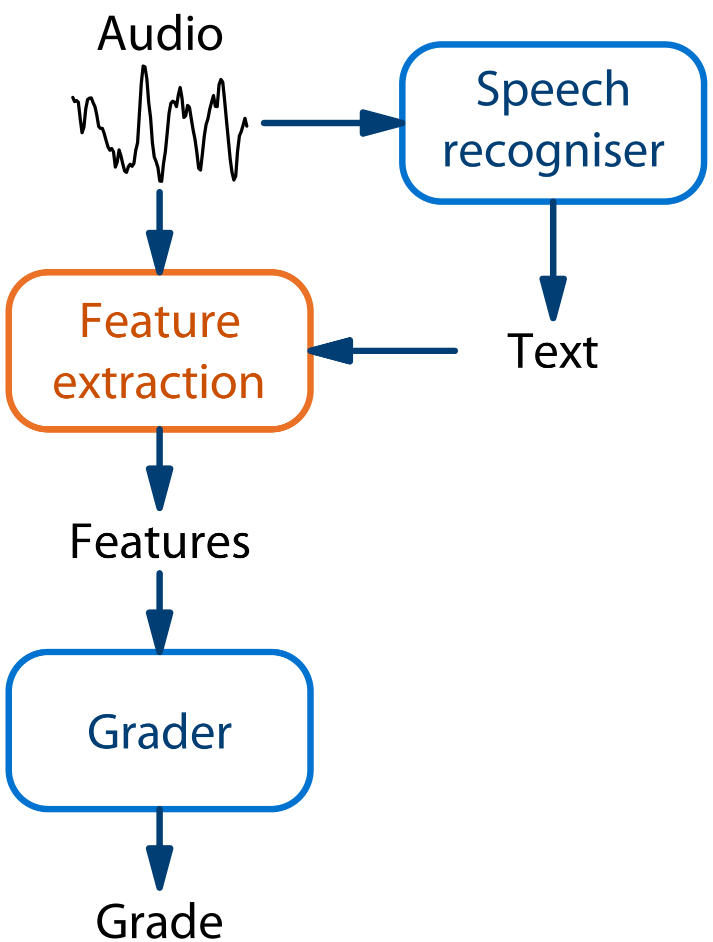
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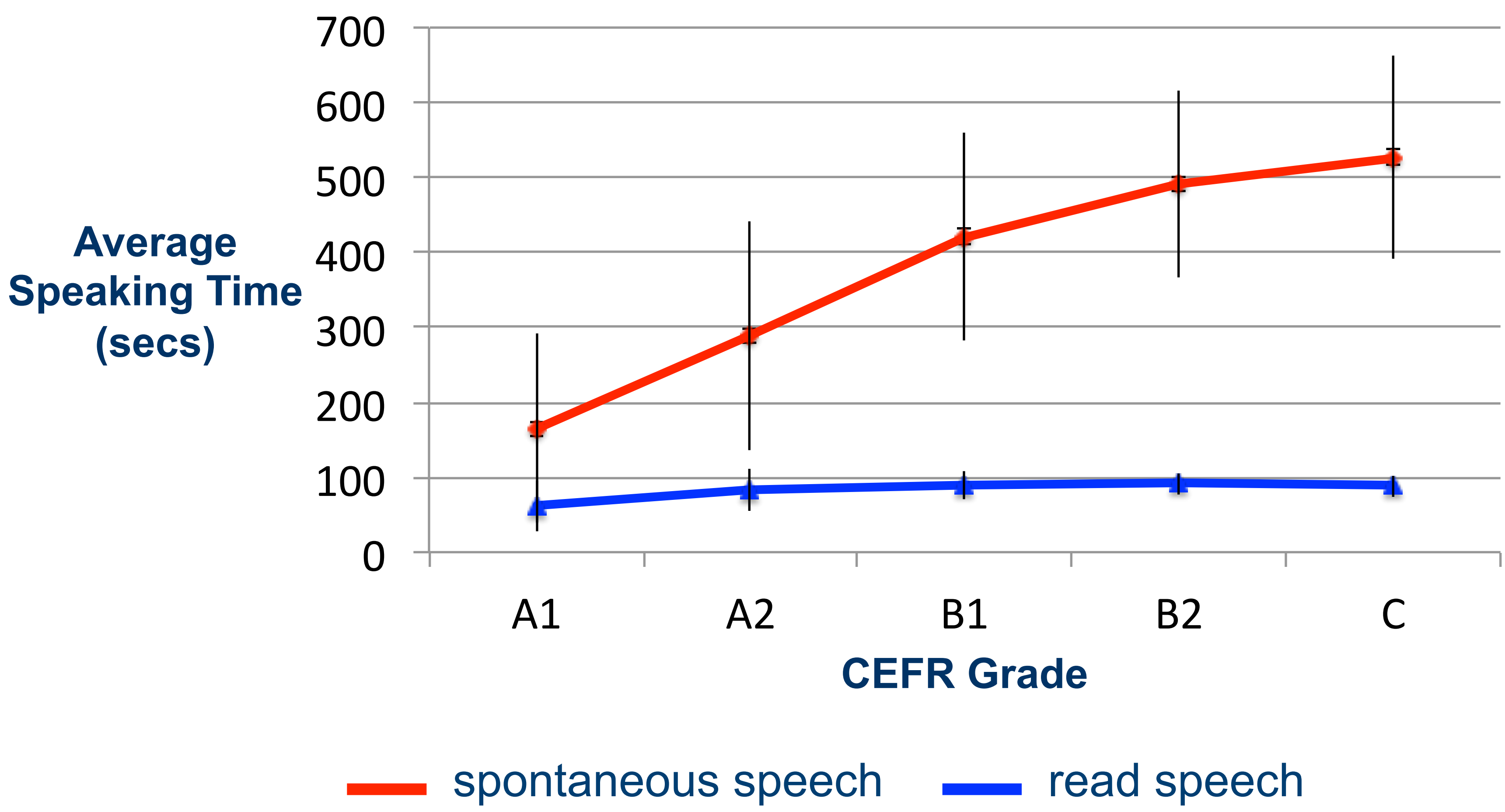
Baseline Features

- Mainly fluency based:
- Audio Features: statistics about
  - fundamental frequency (f0)
  - speech energy and duration
- Aligned Text Features: statistics about
  - silence durations
  - number of disfluencies (um, uh, etc)
  - speaking rate
- Text Identity Features:
  - number of repeated words (per word)
  - number of unique word identities (per word)

Speaking Time Versus Learner Progression



Pronunciation Features

- Hypothesis: poor speakers are weaker at making phonetic distinctions
  - Statistical approach – learn phonetic distances from graded data

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Candidate Grade A1

Candidate Grade C1

- Pattern of distances different between candidates of different levels

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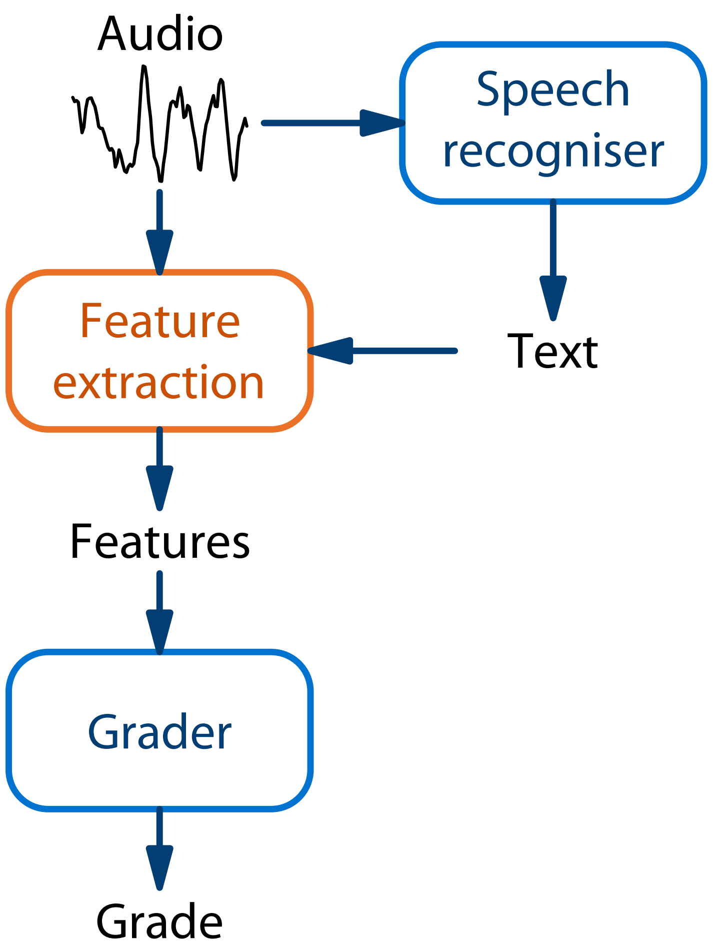
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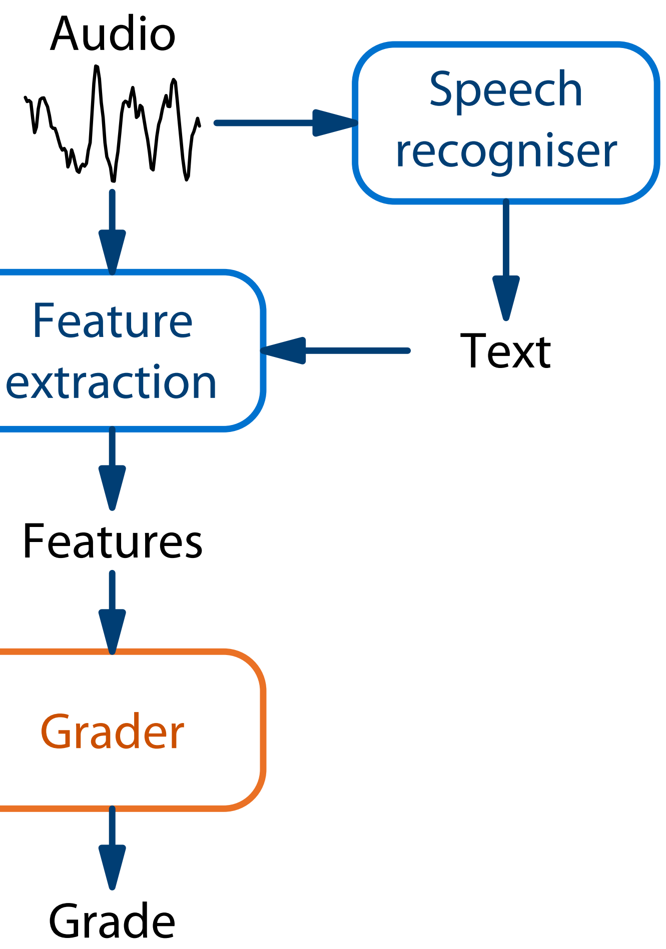
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Uses of Automatic Assessment

- Human graders

  ✔ very powerful ability to assess spoken language

  ✖ vary in quality and not always available

- Automatic graders

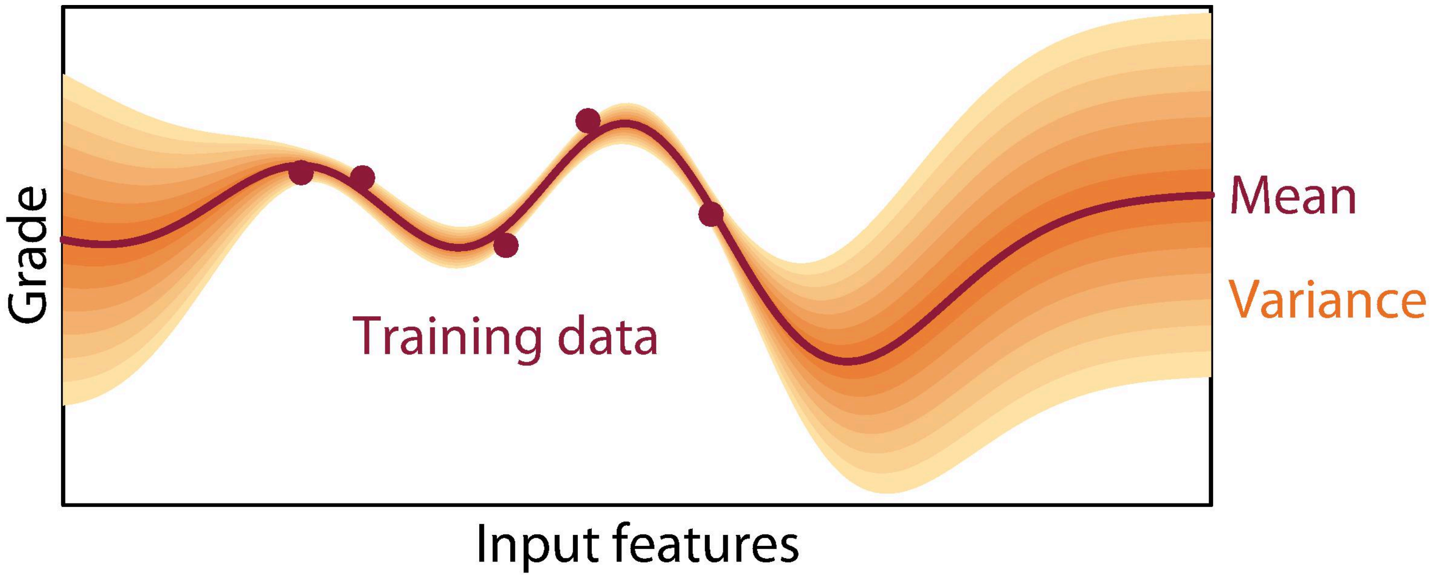
  ✔ more consistent and potentially always available

  ✖ validity of the grade varies and limited information about context

Uses of Automatic Assessment

- Human graders
  - ✔ very powerful ability to assess spoken language
  - ✖ vary in quality and not always available
- Automatic graders
  - ✔ more consistent and potentially always available
  - ✖ validity of the grade varies and limited information about context
- Use automatic grader
  - for grading practice tests/learning process
  - in combination with human graders
    - combination: use both grades
    - back-off process: detect challenging candidates

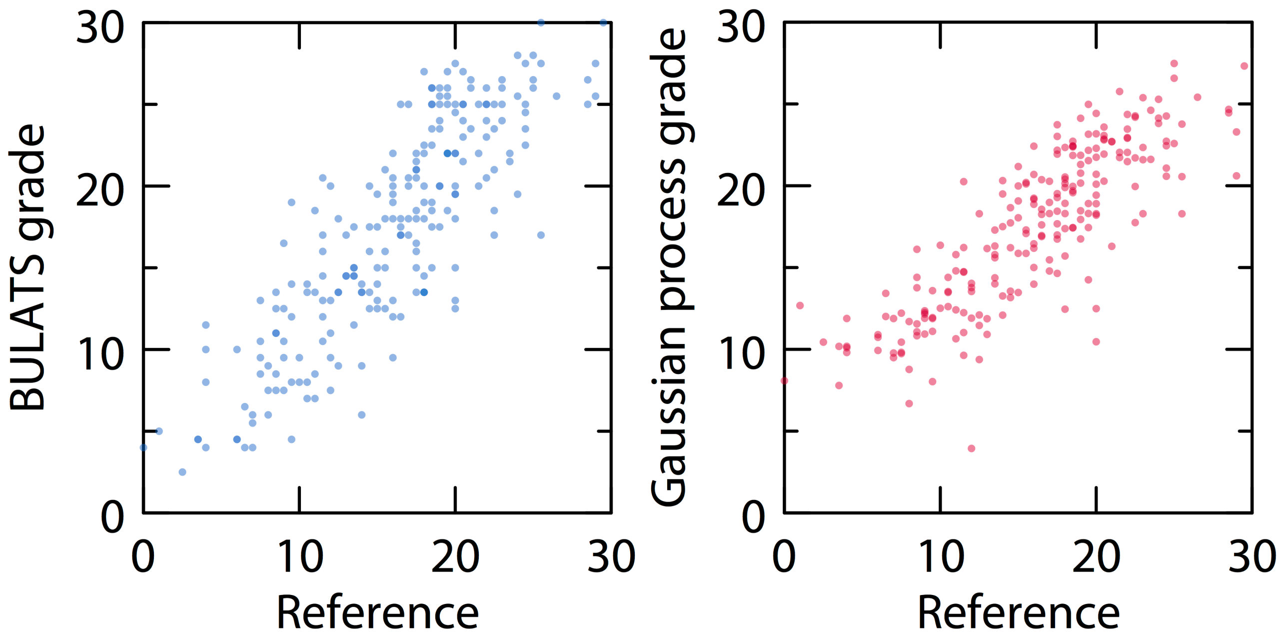
Gaussian Process Grader



- Currently have 1000s candidates to train grader
  - limited data compared to ASR frames (100,000s frames)
  - useful to have confidence in prediction

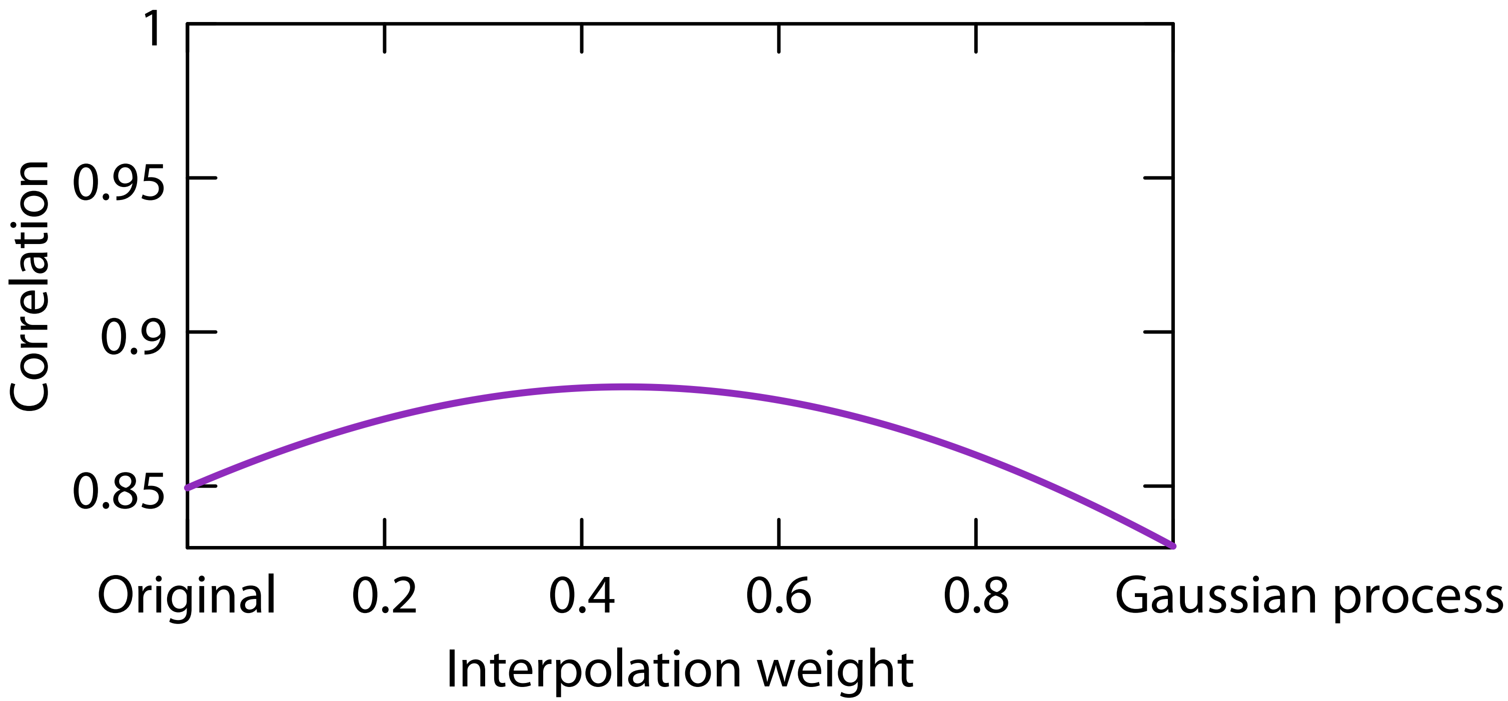
Gaussian Process is a natural choice for this configuration

Form of Output



Graders	Pearson Correlation
Human experts	0.85
Automatic GP	0.83 – 0.86

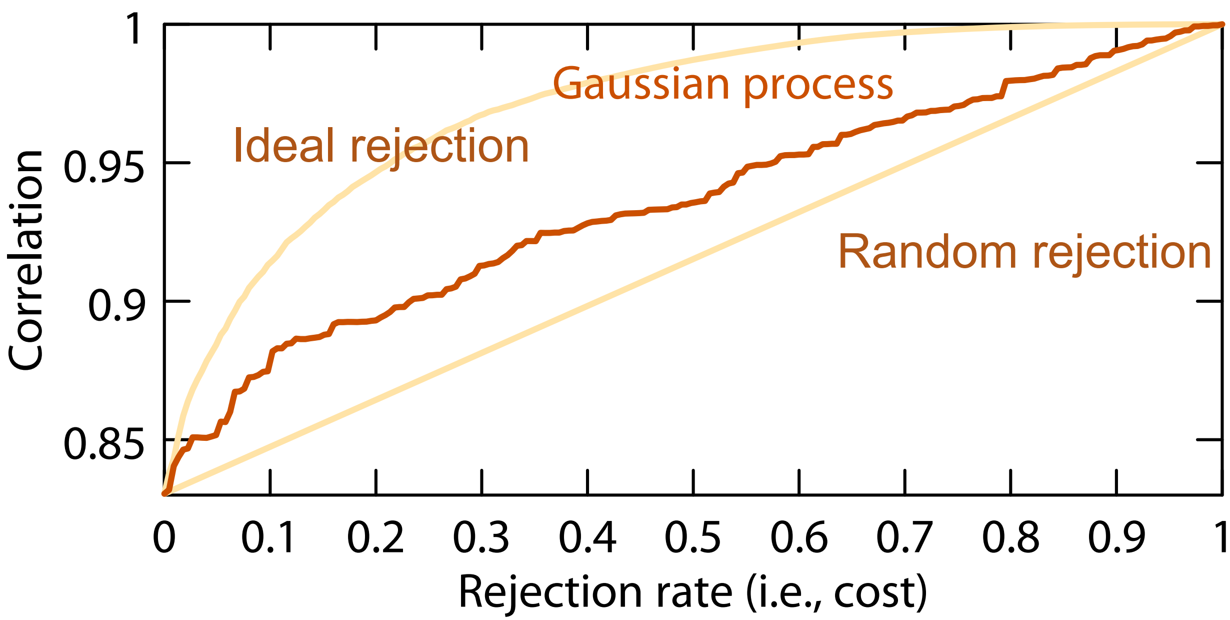
Combining Human and Automatic Graders



- Interpolate between human and automated grades
  - Higher correlation i.e. more reliable grade produced
- Content checking can be done by the human grader

Detecting Outlier Grades

- Standard (BULATS) graders handle standard speakers very well
  - non-standard (outlier) speakers less well handled
  - use Gaussian Process variance to automatically detect outliers

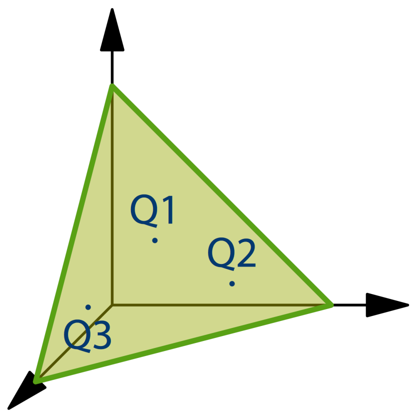


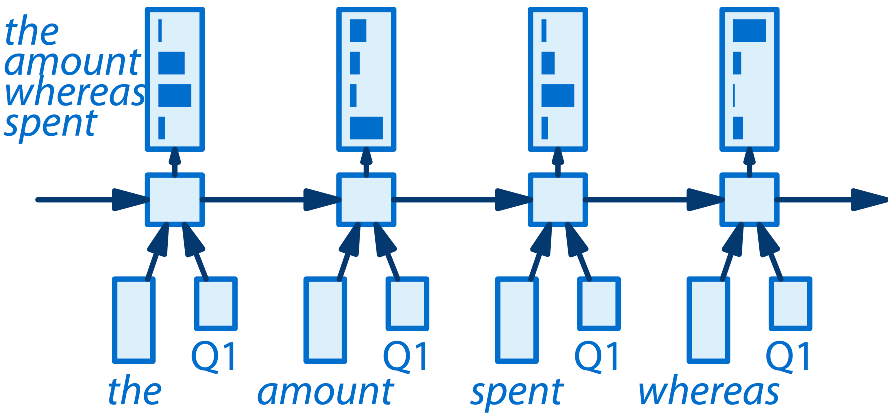
- Back-off to human experts
  - Reject 10%: performance 0.83 ➔ 0.88

Assessing Content

- Grader correlates well with expert grades
  - features do not assess content – primarily fluency features

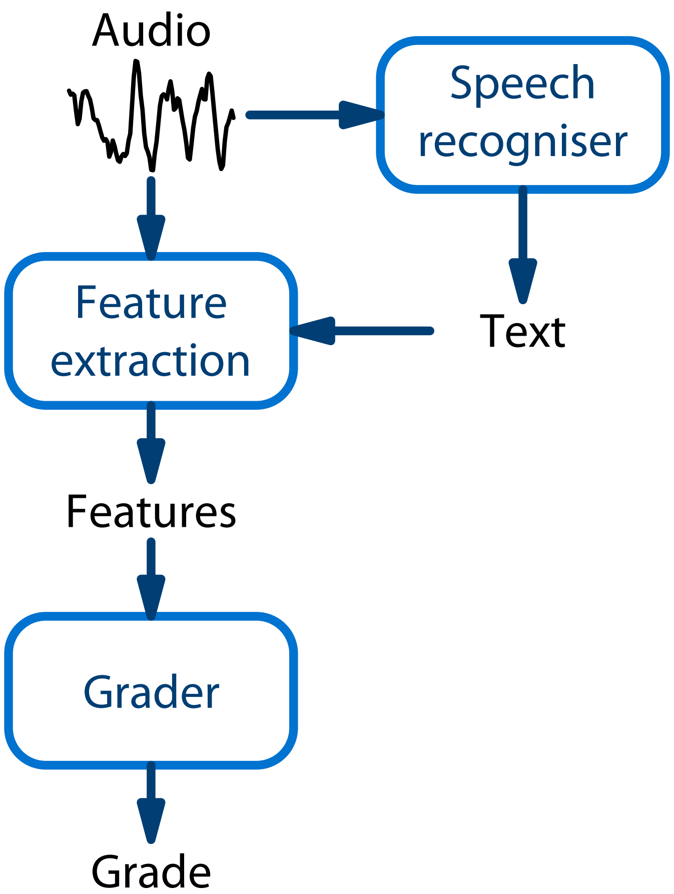
Topic space:





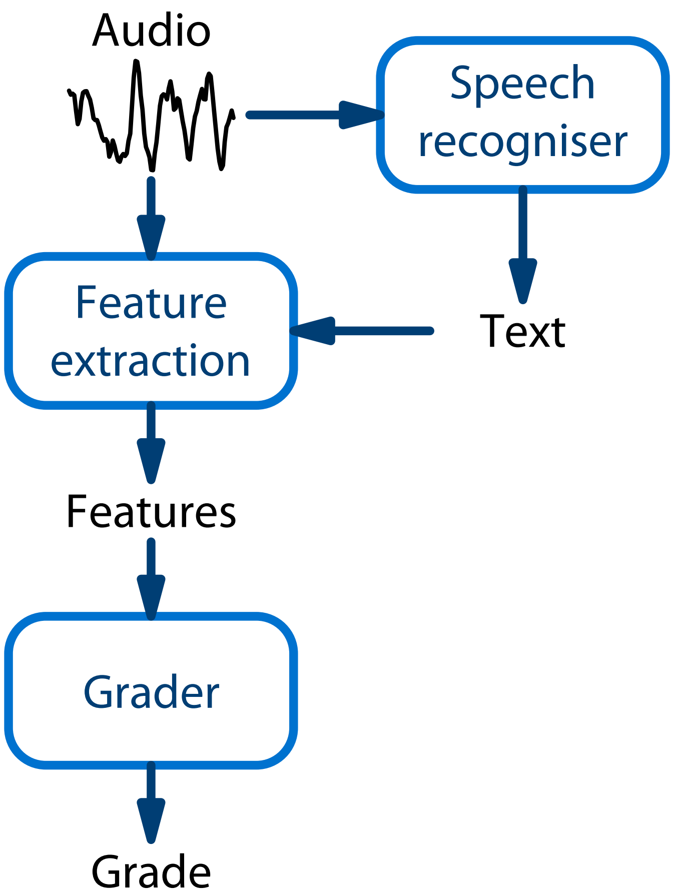
- Train a Recurrent Neural Network Language Model for each question
  - assess whether the response is consistent with example answers

Spoken Language Assessment



- Automatically assess:
  - Message realisation
    - Fluency, pronunciation
  - Message construction
    - Construction & coherence of response
    - Relationship to topic

Spoken Language Assessment

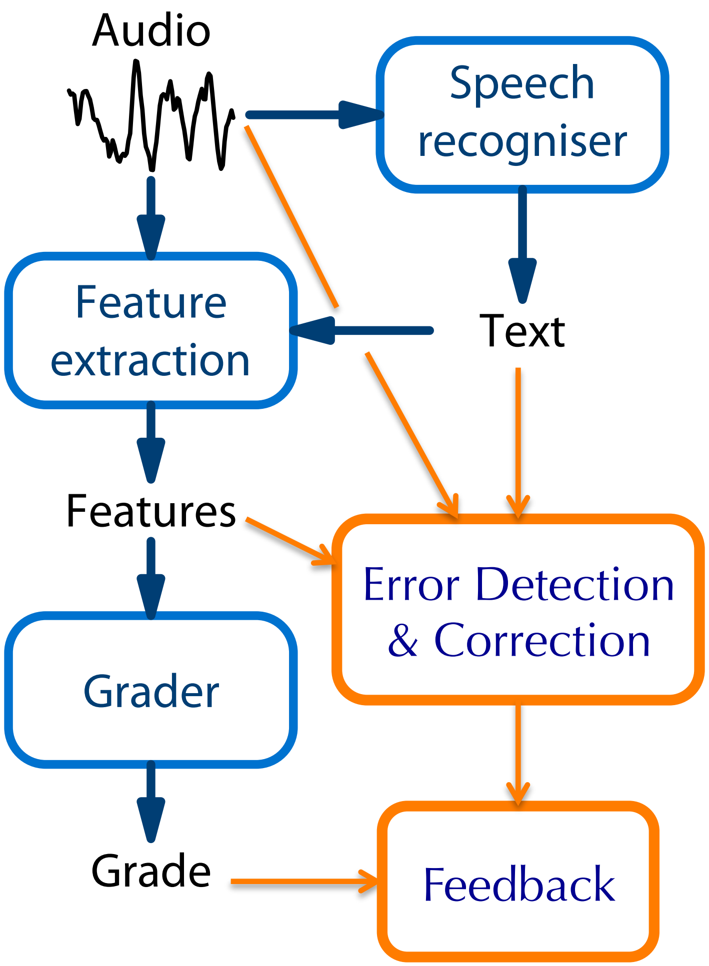


- Automatically assess:
  - Message realisation
    - Fluency, pronunciation

  Achieved (with room for improvement)
  - Message construction
    - Construction & coherence of response
    - Relationship to topic

  Unsolved – active research areas

Spoken Language Assessment and Feedback



- Automatically assess:
  - Message realisation
    - Fluency, pronunciation
  - Message construction
    - Construction & coherence of response
    - Relationship to topic
- Provide feedback:
  - Feedback to user: realisation, construction
  - Feedback to system: adjust to level

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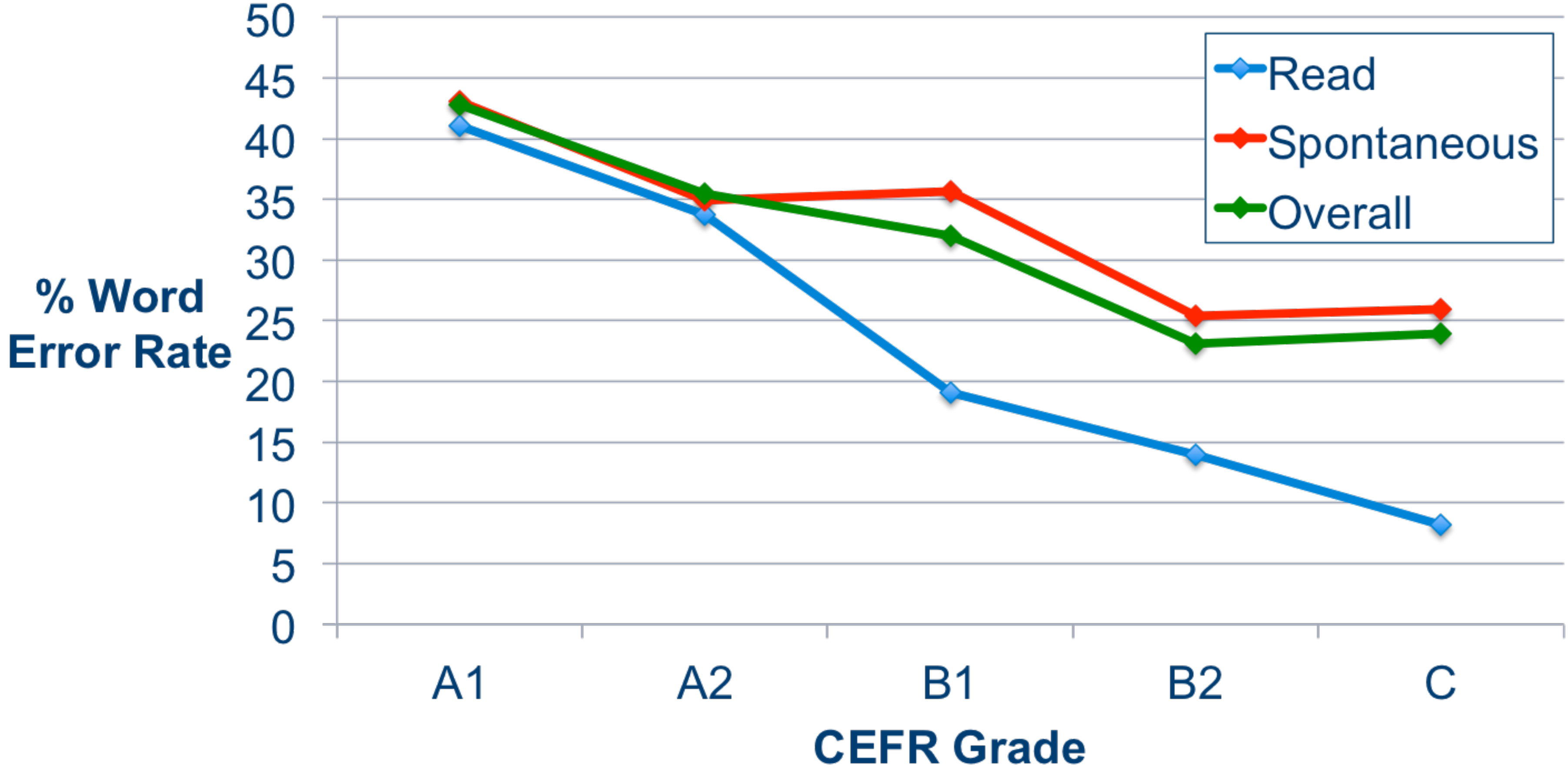
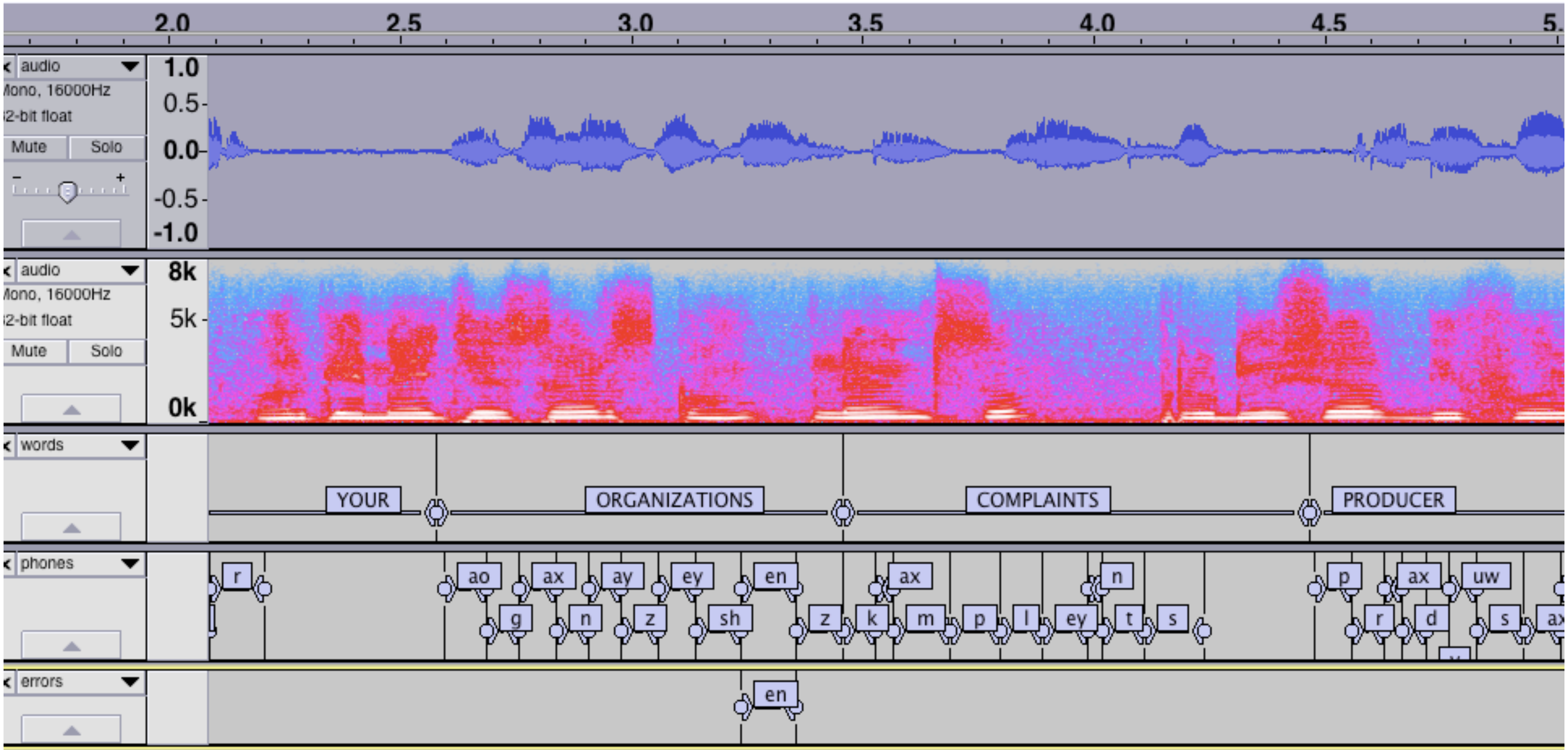


Time Alignment and Pronunciation Feedback



- Lightly supervised:
  - No pronunciation labelling required – trained just on grades

Conclusions

- Automated machine-learning for spoken language assessment
  - important to keep costs down
  - able to be integrated into the learning process
- Current level – assessment of fluency
  - ongoing research into assessing communication skills:
    - appropriateness and acceptability
- Error detection and feedback is challenging
  - high precision required in detecting where errors have occurred
  - supplying feedback in appropriate form for learner

Thank You

- Acknowledgement: members of CUED MIL ALTA team:
  - Rogier van Dalen, Kostas Kyriakopoulos, Andrey Malinin, Yu Wang