Deep learning approach to automatic detection of language impairment in spontaneous speech

深度学习方法在言语障碍自动检测中的应用

Tan Lee 李丹

DSP and Speech Technology Laboratory

The Chinese University of Hong Kong

香港中文大学电子工程系

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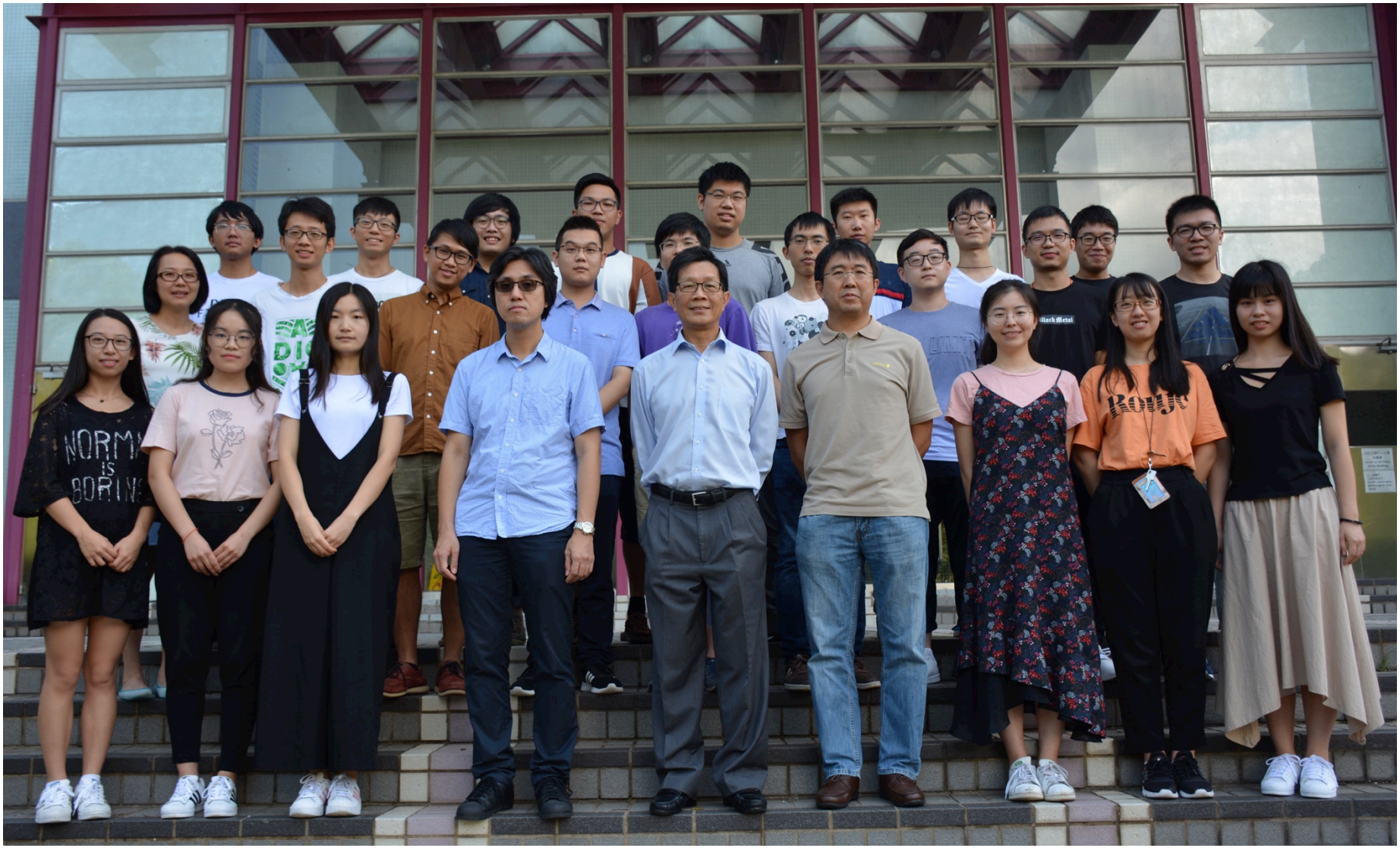
香港中文大学 CUHK

DSHLAB信号处理实验室



Speech Research @ CUHK

- Spoken language technology
  - ASR, TTS, Speaker ID, Language ID, …
  - Cantonese-focused, multilingual
  - Real-world and real-life speech
  - Deep learning approach

- Wide range of applications
  - Low-resource languages
  - Atypical speech
  - Hearing impairment
  - Music and audio classification

Perspectives

- With deep learning methods, high-performance systems depend on

  data data data data data data

- All about match and mismatch
- Typical vs. atypical
- Specificity vs. generalization

Atypical speech

- ✓ Unpopular languages: African languages, ethnic minority languages in China, regional dialects, ...
- ✓ Code-switching, code-mixing
- ✓ L2 speech
- ✓ Child voice
- ✓ Elderly voice
- ✓ Pathological
- ✓ Emotional
- ✓ Expressive

Atypical speech is meant to have little data.

Use of deep learning methods is not straightforward

Inter-disciplinary collaboration

Collaboration projects

Pathological voices

- CUHK Speech Therapy
- ENT, Sun Yat-Sen Memorial Hospital

Pathological speech (aphasia)

- University of Central Florida Speech and Language Pathology
- University of Hong Kong Speech and Hearing Science

Speech sound disorders of pre-school children

- CUHK Speech Therapy

Language acquisition of deaf children

- CUHK Linguistics

Speech perception of hearing impaired listeners

- CUHK Audiology
- CUHK Psychology

Behavior therapy: speech in motivational interviewing

- CUHK Educational Psychology

Pentatonic Scale Body Constitution (五音体质)

- CUHK School of Chinese Medicine

Speech and language impairment

- Difficulties and problems in production of spoken language
- Dysfunctions in linguistic-symbolic planning and/or speech motor control
- Outcome: atypical and abnormal speech
  - Poor voice quality, hoarseness
  - Articulatory deficiency, phonological errors
  - Unnatural, low intelligibility
  - Stuttering, dis-fluency, lacking intonation
  - Language deficits

Verbal language deficits

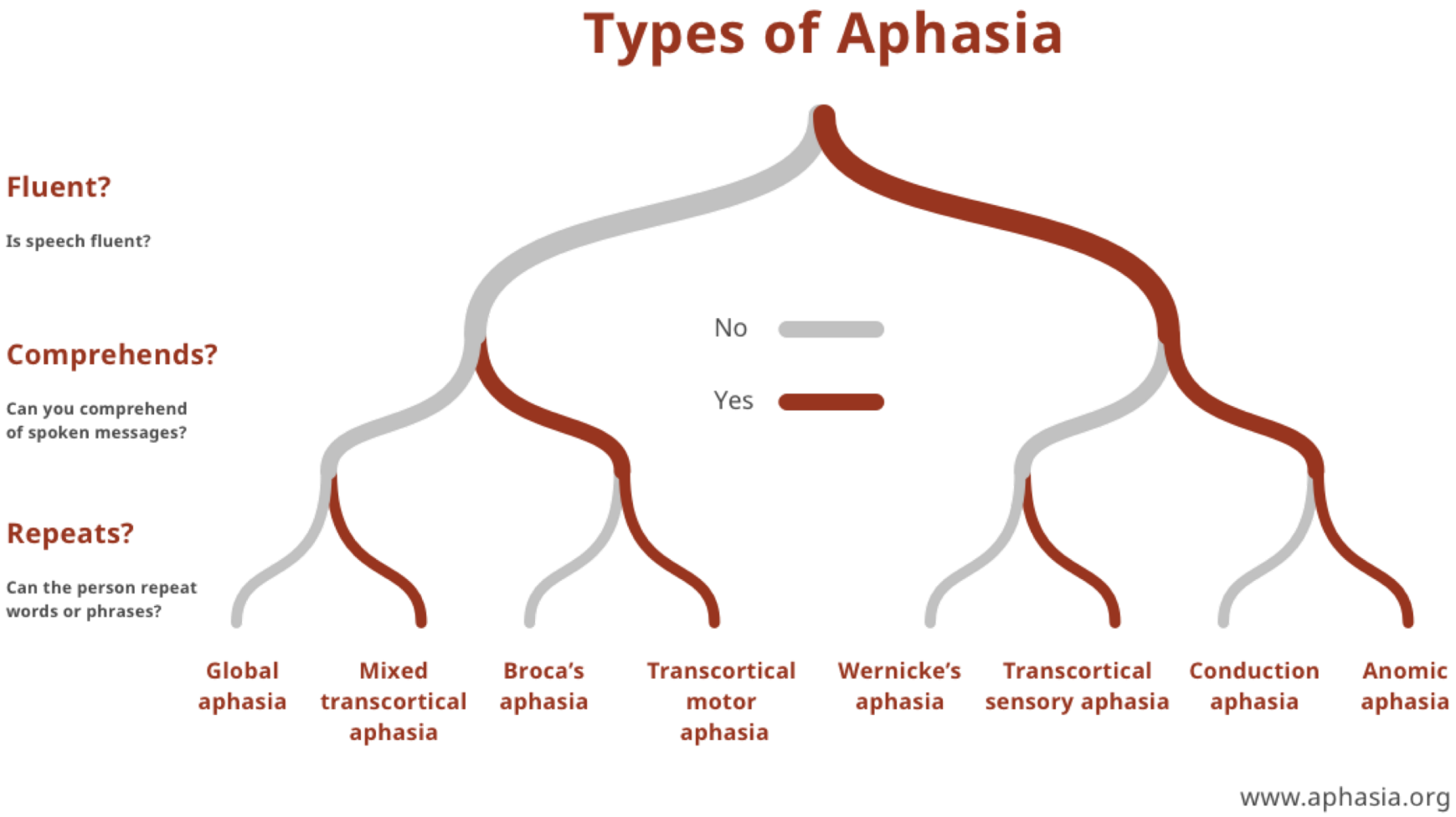
- Abnormality in language expressing in speech
- Not about voice and articulation problems
- Deficits in
  - Naming
  - Lexical representation
  - Semantic relation
  - Vocabulary coverage
  - Discourse organization

Language disorders & brain condition

- Speech and language difficulties reflect the neurological conditions
- Aphasia: acquired language impairment caused by injury or pathology of certain brain areas
- Neurological injury: stroke or traumatic injury
- Neurodegeneration:
  - Primary Progressive Aphasia (PPA)
  - Parkinson's disease
  - Alzheimer's disease (AD)
- Spontaneous speech starts to deteriorate at very early stage of AD progression

Type	Language	Task	Demo
Aphasia	Cantonese	monologue	
	English	conversation	
	English	dialogue	
MCI	Cantonese	Picture description	

Aphasia

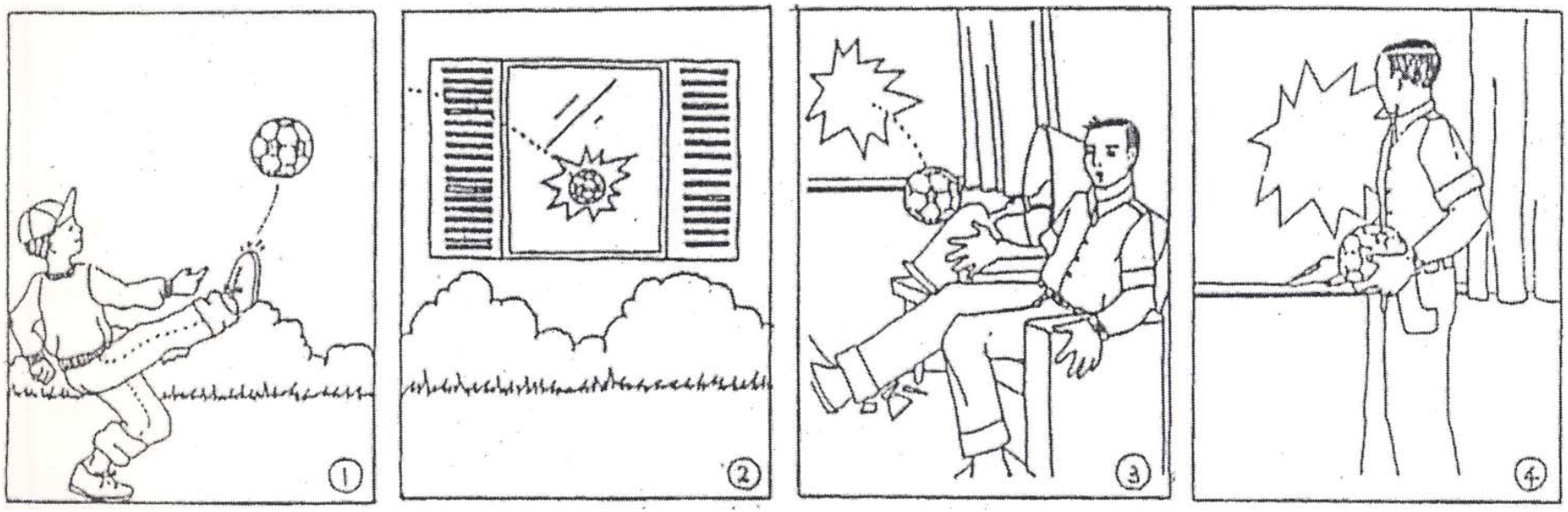

Types of Aphasia
Fluent?
Is speech fluent?
Comprehends?
Can you comprehend of spoken messages?
Repeats?
Can the person repeat words or phrases?
No
Yes
Global aphasia
Mixed transcortical aphasia
Broca's aphasia
Transcortical motor aphasia
Wernicke's aphasia
Transcortical sensory aphasia
Conduction aphasia
Anomic aphasia
www.aphasia.org

Cantonese AphasiaBank

- A large-scale multi-modal database created to support research on Cantonese-speaking aphasia population
- Audio recordings of spontaneous speech of native Cantonese speakers
- 104 aphasic and 149 unimpaired subjects
- Prescribed speech tasks: picture descriptions, procedure description, story telling, monologue

Task	Recording	Description
Single picture description	CatRe	Black and white drawing of a cat on a tree being rescued
	Flood	A colour photo showing a fireman rescuing a girl
Sequential picture description	BroWn	Black and white drawing of a boy accidentally break a window
	RefUm	Black and white drawing of a boy refusing an umbrella from his mother
Procedure description	EggHm	Procedures of preparing a sandwich with egg, ham and bread
Story telling	CryWf	Telling a story from a picture book "The boy who cried wolf"
	TorHa	Telling a story from a picture book "The tortoise and the hare"
Personal monologue	ImpEv	Description of an important event in life

Picture description



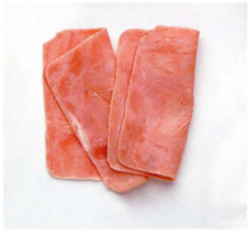
“Now I’m going to show you these pictures."

“Take a little time to look at these pictures. They tell a story. Take a look at all of them, and then I’ll ask you to tell me the story with a beginning, a middle, and an end. You can look at the pictures as you tell the story.”

Procedure description

麵包

雞蛋



火腿

“Let’s move on to something a little different.”

“Tell me how you would make an egg and ham sandwich.”

Subjective assessment

- All subjects were assessed using Cantonese Aphasia Battery (CAB)
- Comprehensive assessment: sub-tests on *comprehension*, *repetition* and naming abilities, information content, fluency
- Each sub-test results in a numerical score
- Sum of sub-test scores = Aphasia Quotient (AQ)
- AQ ranges from 0 to 100,
- 11 to 99 in Cantonese AphasiaBank

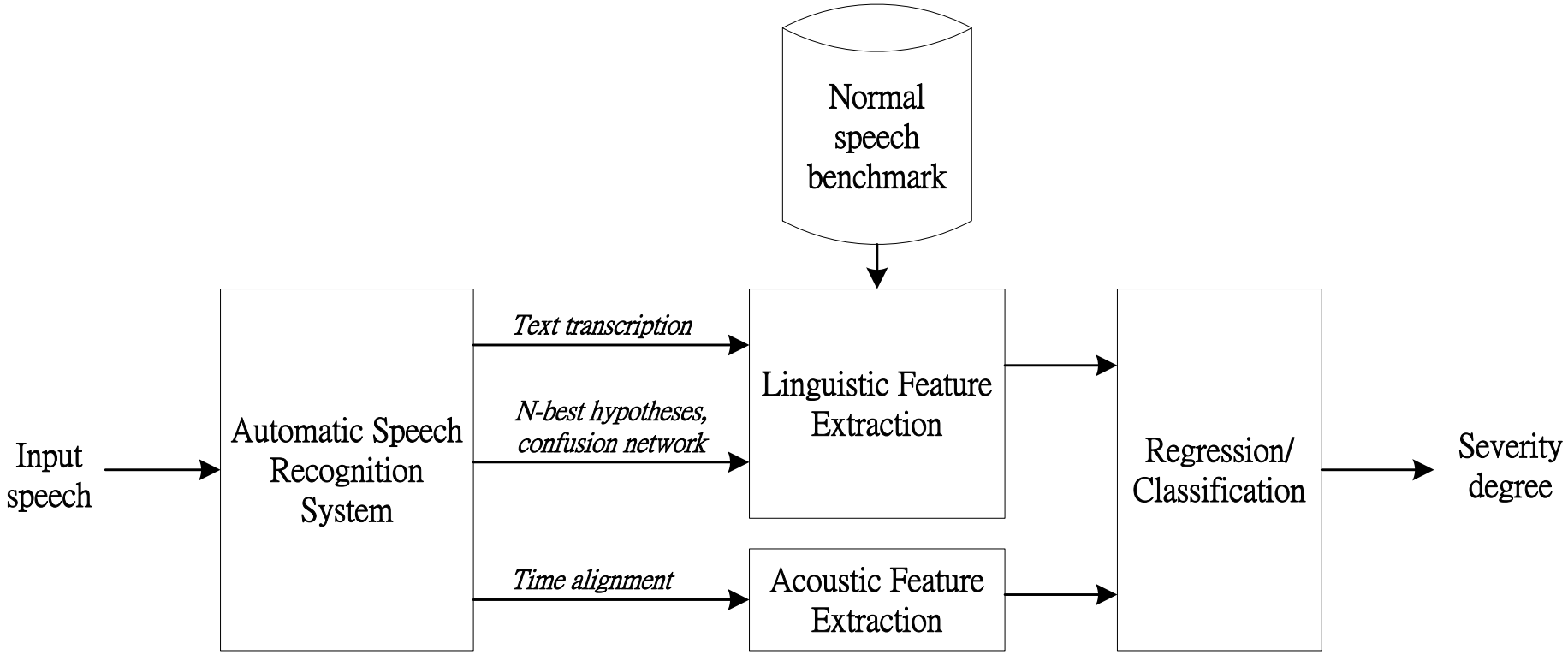
ID	Type	AQ	Information	Fluency	Comprehension	Demo
A003	Anomia	95.8	10	10	10	
A020	Broca's	65.0	9	4	7	
A088	Broca's	27.0	1	1	4.9	

Describe how to make an egg and ham sandwich

Automatic assessment

- Based on analysis of speech signals
- Evidence-based
- Non-invasive, objective and repeatable
- Applying signal processing and machine learning techniques
- Spontaneous and free-style speech is a big challenge

Our approach

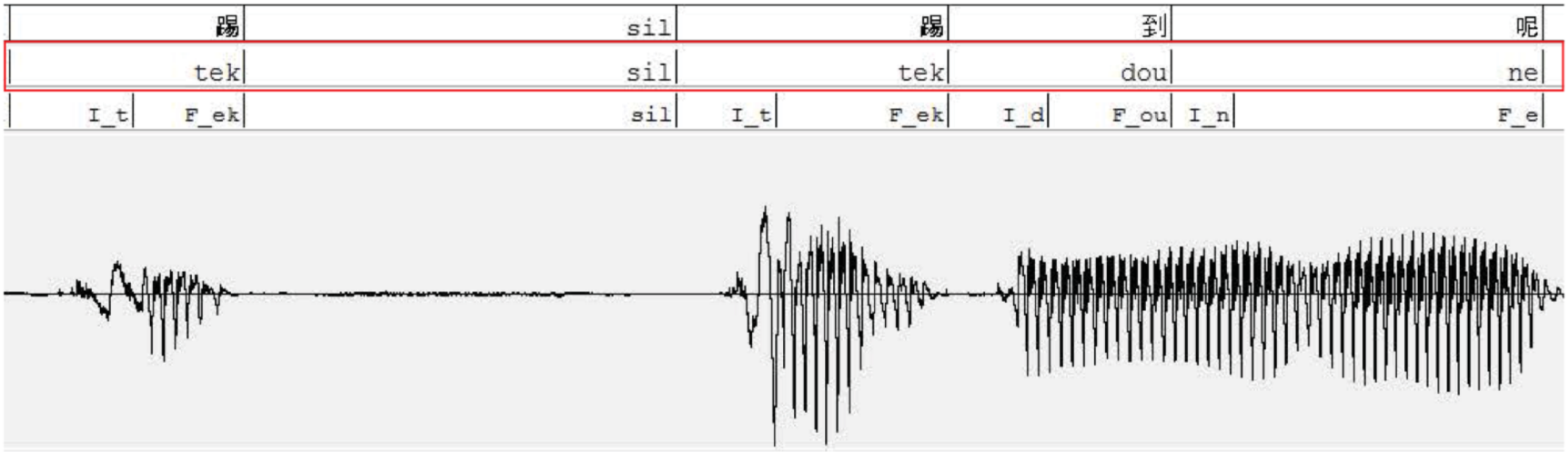


Goals

- **Prediction of AQ**
  - **Automatically generate AQ to measure the severity of impairment**
- **Binary classification**
  - **High-AQ: AQ ≥ 90 (mild/normal)**
  - **Low-AQ: AQ < 90 (severe)**

ASR

- Provide a range of information to facilitate extraction of speech and language features
- Linguistic features computed from text
- Duration features derived from time alignment
- Phone posteriors: data-model matching degree



ASR performance

- ASR for spontaneous and impaired speech is not straightforward
- DNN acoustic models trained by multi-task learning
  - Domain-matched data: unimpaired speech in Cantonese AphasiaBank
  - Domain-mismatched data: CUSENT and K086
- Test data: 7 stories from 82 impaired speakers

Acoustic model	Training data	Syllable error rate %
Conventional DNN	CanAB	48.08
TDNN-BLSTM	CanAB	43.35
MT-TDNN-BLSTM	CanAB, K086,CUSENT	**38.05**

Design of text features

To compute feature from ASR output text to robustly reflect topic-specific content of a story and differentiate unimpaired story from impaired ones

Cont102 (control)	A023_ANM (impaired)
aa6 有 個 男仔 踢波. 踢爛 咗 個 玻璃 窗. gam2 個 玻璃 窗 有 個 男人. 同埋 有 個 燈. 跟住 有 個 男人 攞 住 個 波. 就 望 出去 個 爛 咗 個 玻璃 窗 出 便 嘞. m6.	喇 個 就 xxx 空地 度 踢波. gam2 直至 有 日 佢 踢波 嘅 時候. 就 食 咗 個 e6 喺 邊 度 去 咗 個 咩 個 gam2zau6 波 呢 入 咗 去 個 窿 嗰 度. gam2 xxx 嗰 個 人 就 攞 住 個 波 响度 鬧.

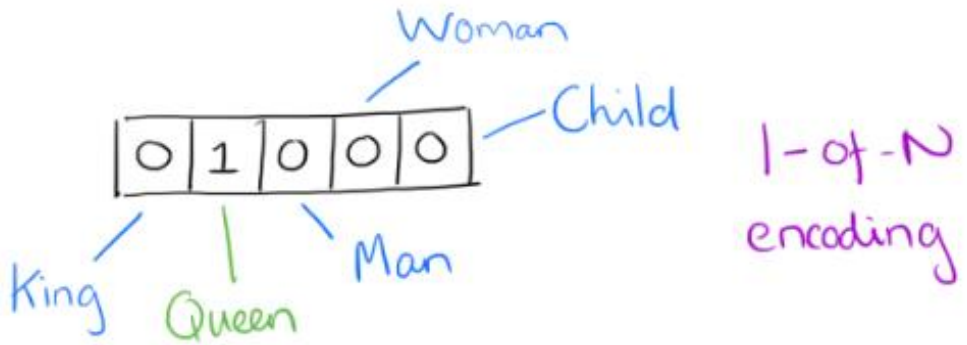
Vector representation of word

- Word transcription is discrete representation, not good for similarity measuring
- Word-embedding: to learn low-dimension continuous-value representation of discrete linguistic units
- Semantic relation learned from data

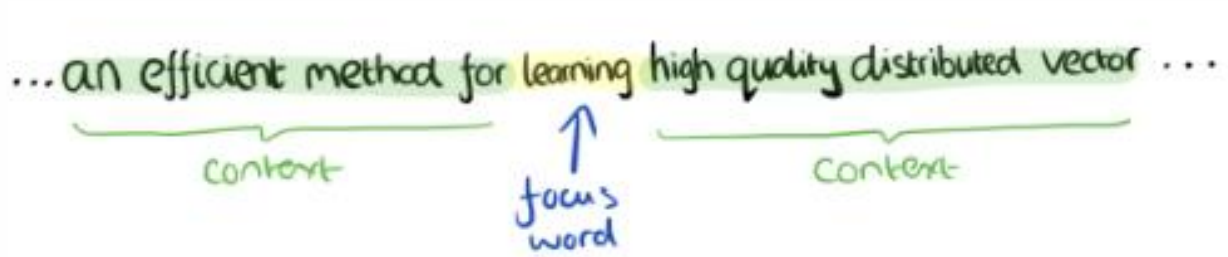
  e.g., “King”- “Man” + “Woman” = “Queen”

Word embedding

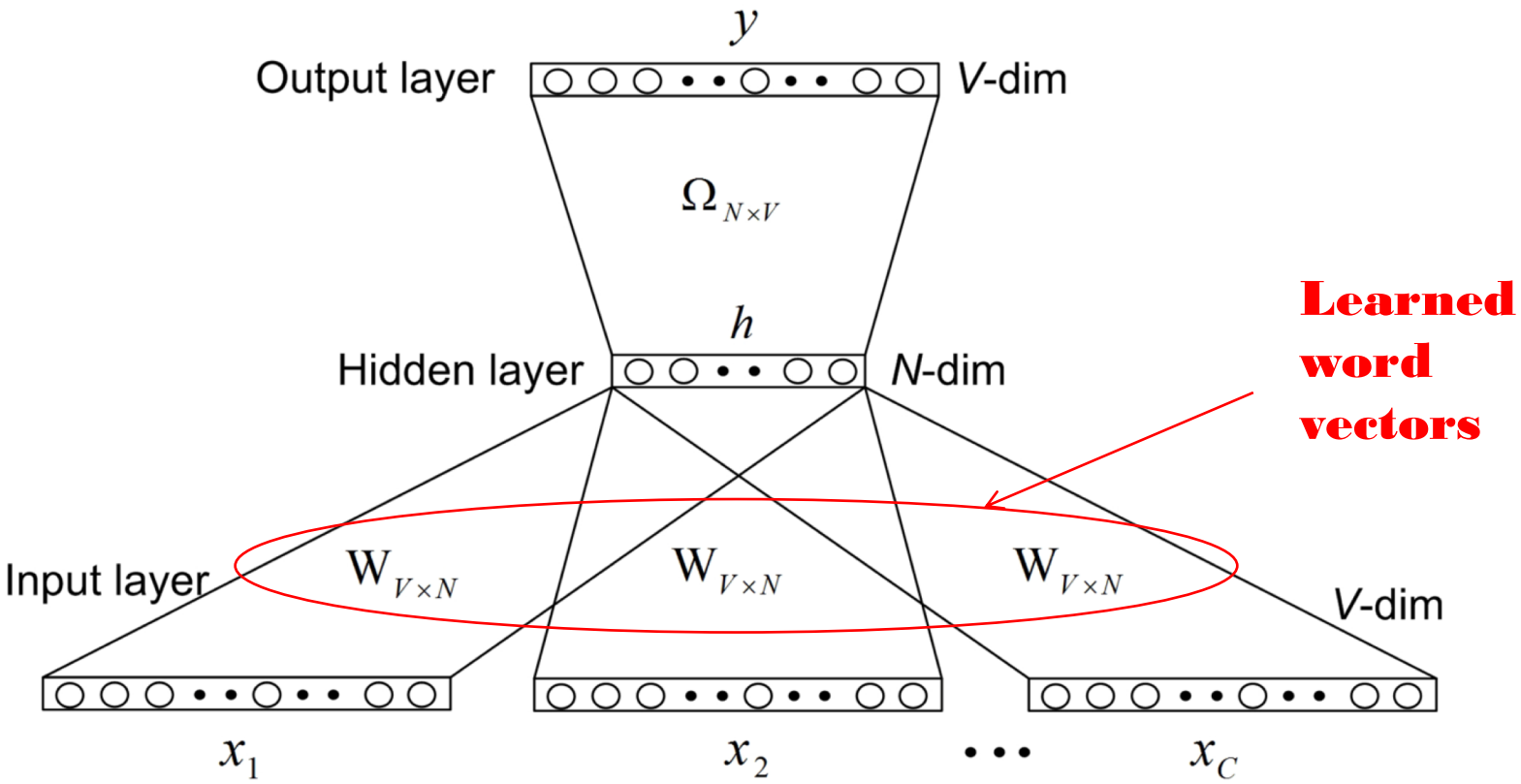
- Initially each word represented by a 1-hot vector



- The 1-hot word vectors are used as input to a neural network
- A NN model is trained to predict central word from context words

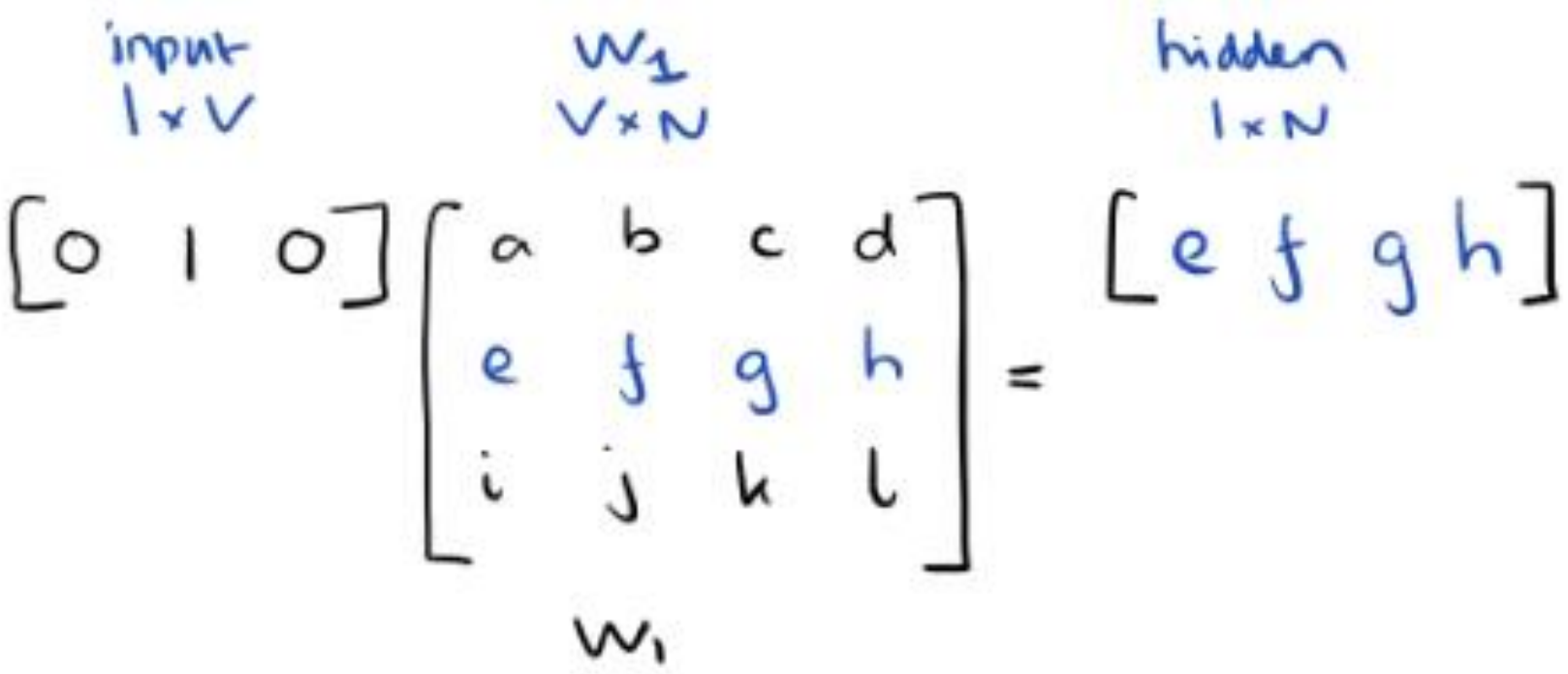


Continuous bag-of-words (CBOW)



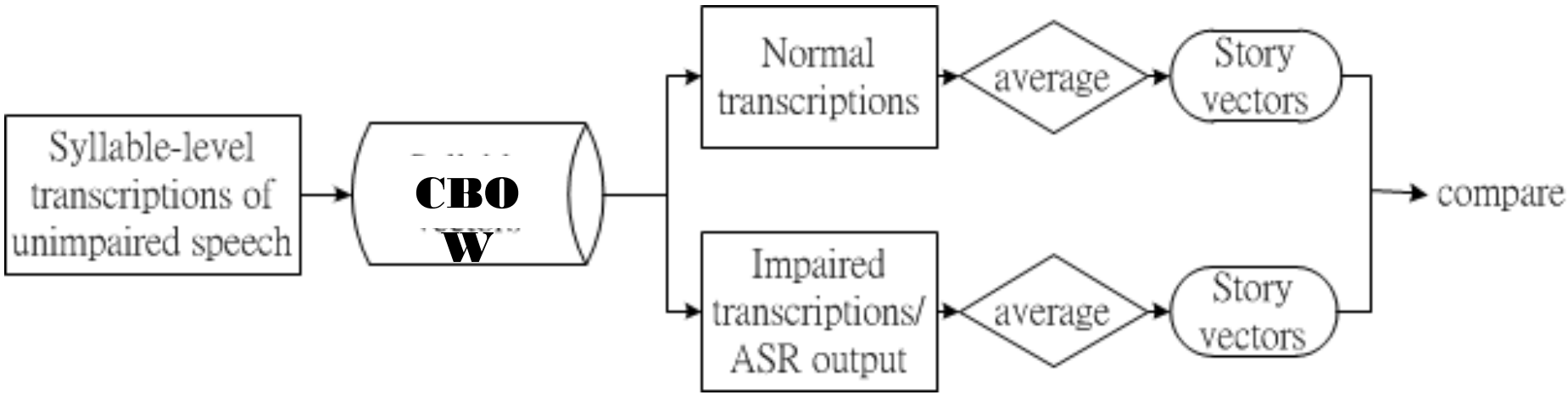
Word embedding

After training, each row of matrix W gives a continuous-value word vector representation



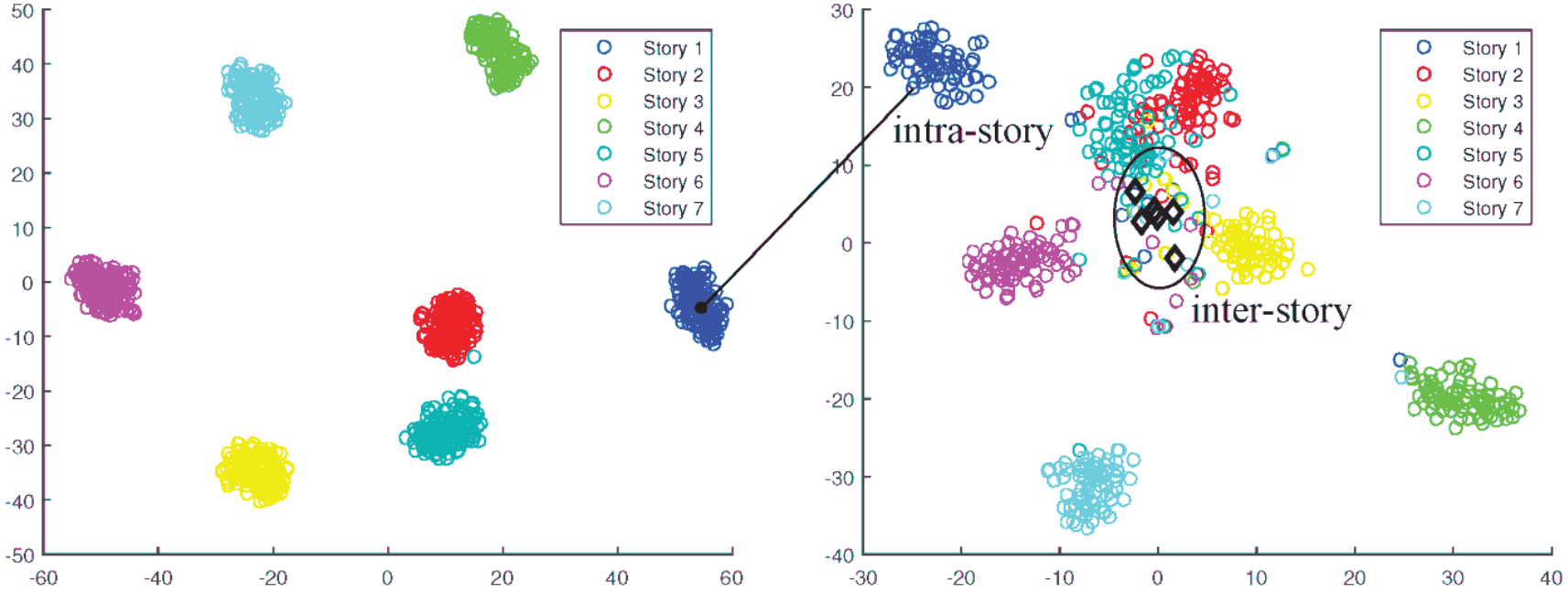
Vector representation of a story

- For Cantonese spontaneous speech, word transcriptions are unreliable and sometimes not attainable
- The 1-best ASR output is in the form of a syllable sequence
- Each syllable is represented by a 50-dimensional vector
- The whole story is represented by taking the average of all syllable vectors
- The story-level vector reflects topic and content
- Impaired speech have distorted story vectors


Syllable-level transcriptions of unimpaired speech
CBO
W
Normal transcriptions
average
Story vectors
Impaired transcriptions/ ASR output
average
Story vectors
compare

Effectiveness of story vectors

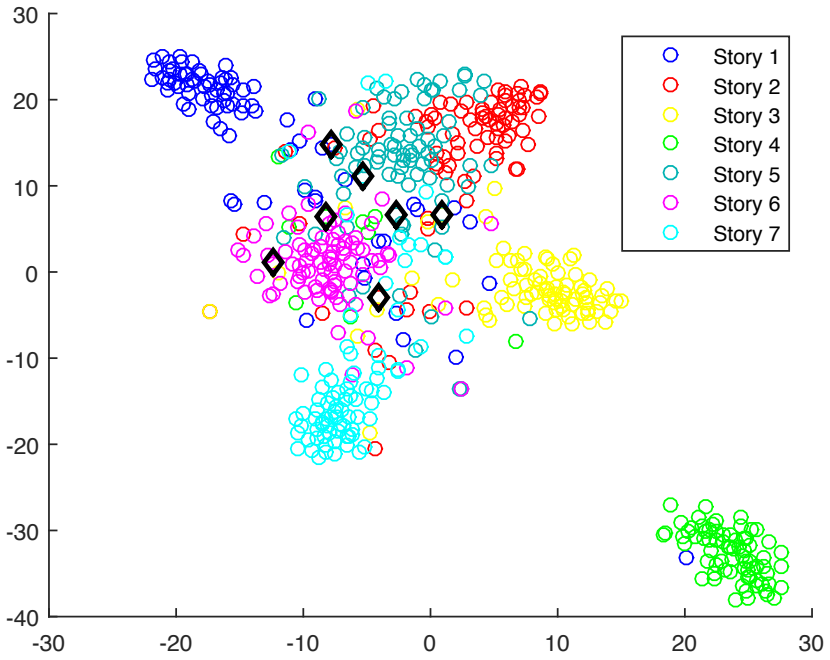
With ground-truth (manual) transcriptions, let us visualize the distributions of story vectors.



Unimpaired speech

Impaired speech

If ASR output transcriptions are used, story vectors of impaired speech are even confused



Quantifying the impairment

Intra-story feature: deviation from reference story vectors of impaired speech

→ **Correlation with AQ: 0.61**

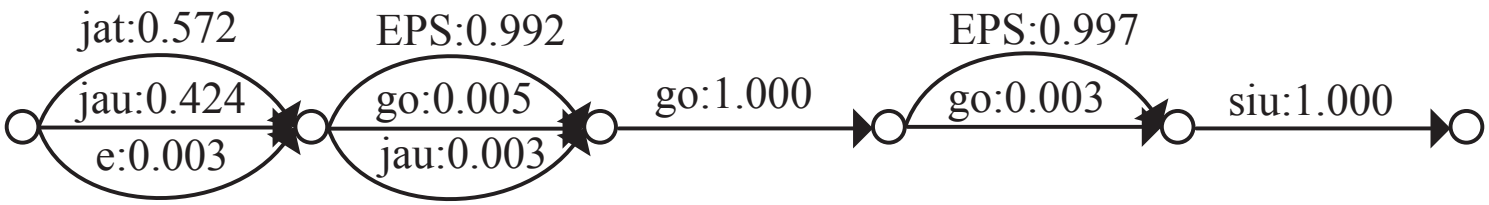
Inter-story feature: number of story vectors that are confused with other topics

→ **Correlation with AQ: 0.82**

More robust representation

- 1-best ASR output contains many errors (~38%)
- Richer and more inclusive representation from ASR

  n-best, *lattice*, *confusion network*
- More robust story vectors could be computed by taking weighted average of all syllable vectors
  1. in n-best output
  2. In confusion networks



Supra-segmental duration features

- **To capture dis-fluency of impaired speech**
- **Supra-segmental duration: time length of speech units beyond phonemes**

Description of features (correlation with AQ)
Non-speech-to-speech duration ratio (−0.684), # silence segments (−0.460), average duration of silence segments (−0.633), **average duration of speech segments** (0.655) # spoken syllables (0.448), **# syllable per speech chunk** (0.693), **ratio of # silence to # syllables** (−0.683), **average # syllable per second** (0.688), **ratio of aver. duration of silence to speech segments** (−0.667) ratio of # fillers to the length of speech segment (−0.368), # long silence segment (−0.420), # short silence segment (0.146), average syllable level confidence score from ASR (0.6328)

Prediction of AQ

Prediction of AQ: by applying linear regression and random forest (RF) regression to 2 text-based features and 4 best duration features

Correlation between predicted AQ and reference AQ

Text features	LR	RF
1-best of MT-TDNN-BLSTM	0.819	0.839
10-best of MT-TDNN-BLSTM	0.825	0.841
CNs of MT-TDNN-BLSTM	**0.827**	**0.842**

For 75.6% (62/82) subjects, prediction errors are smaller than 10, e.g., 45 predicted as 55

Classification: High-AQ vs. Low-AQ

F1 score

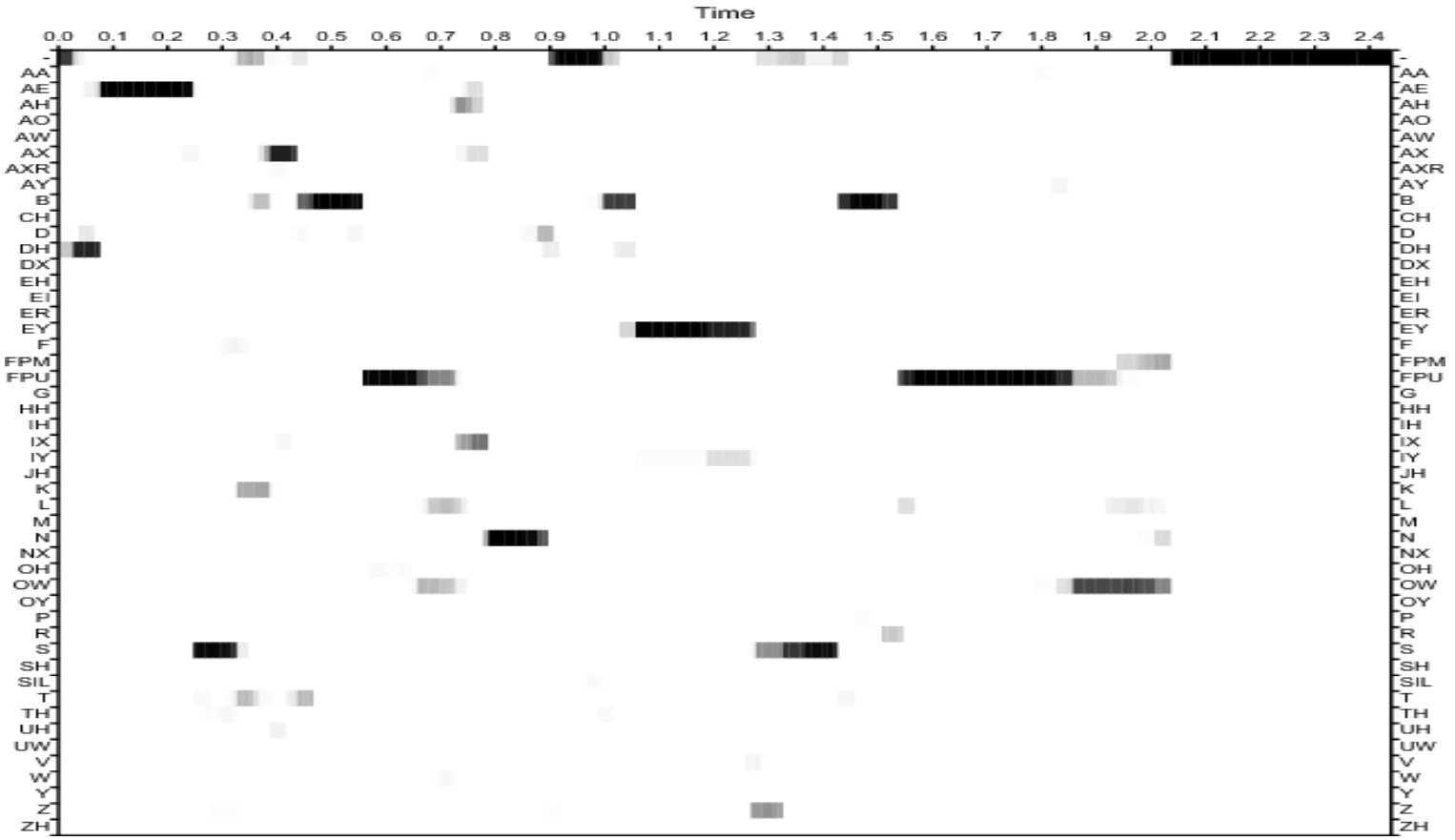
	Binary Decision Tree	Random Forest	SVM
Text features only	0.851	0.896	0.841
Acoustic features only	0.792	0.821	0.789
All features	**0.891**	**0.903**	**0.874**

89.4% (42/47) Low-AQ speakers corrected classified

88.6% (31/35) High-AQ speakers correctly classified

Posteriorgram features

For each time frame of input speech, ASR acoustic models generate a time-posterior matrix known as "**posteriograms**"



What information posteriorgram features might represent

- Paraphasia: unintended words, extraneous substitutions, e.g., car → lar, cat → dog
- Voice disorder: change of voice leads mismatch between acoustic models and input speech
- Dis-fluency: inappropriate pauses, lengthening of phonemes

Feature design

- **Weakly constrained recognizer:**

  generating posteriograms only based on sounds

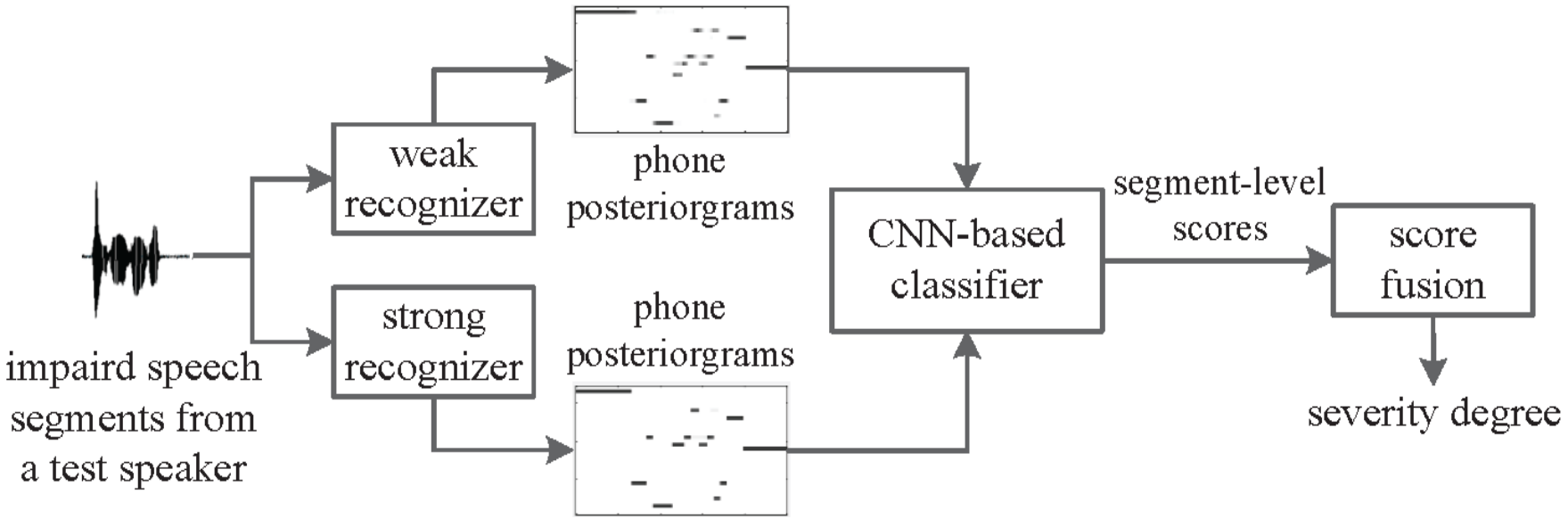
- **Strongly constrained recognizer:**

  generating posteriorgrams with domain-specific language models

Understandably the “strong” posteriorgram is closer to what is intended to be spoken

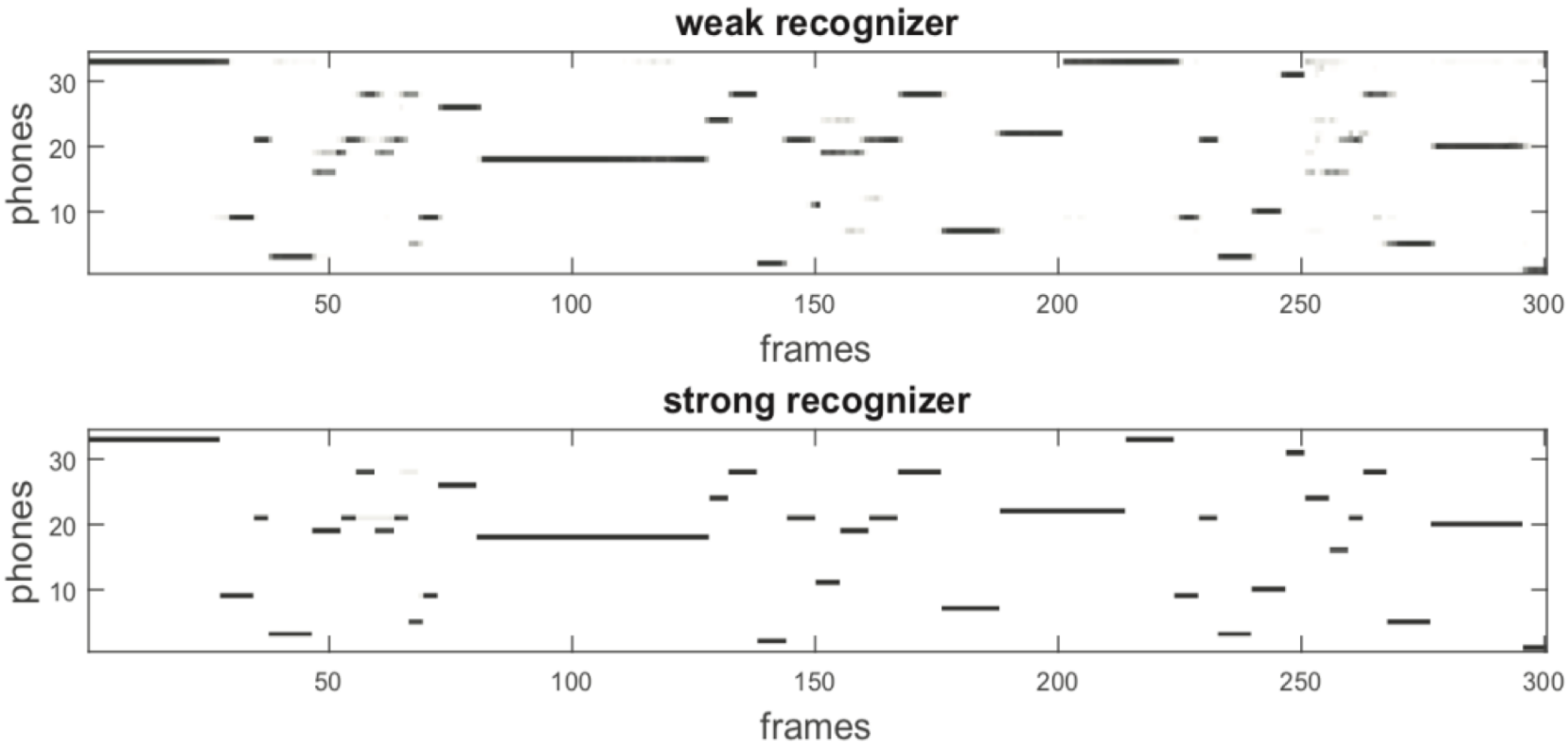
Deviation in the “weak” posteriorgram could be due to speech and language impairment

Scoring

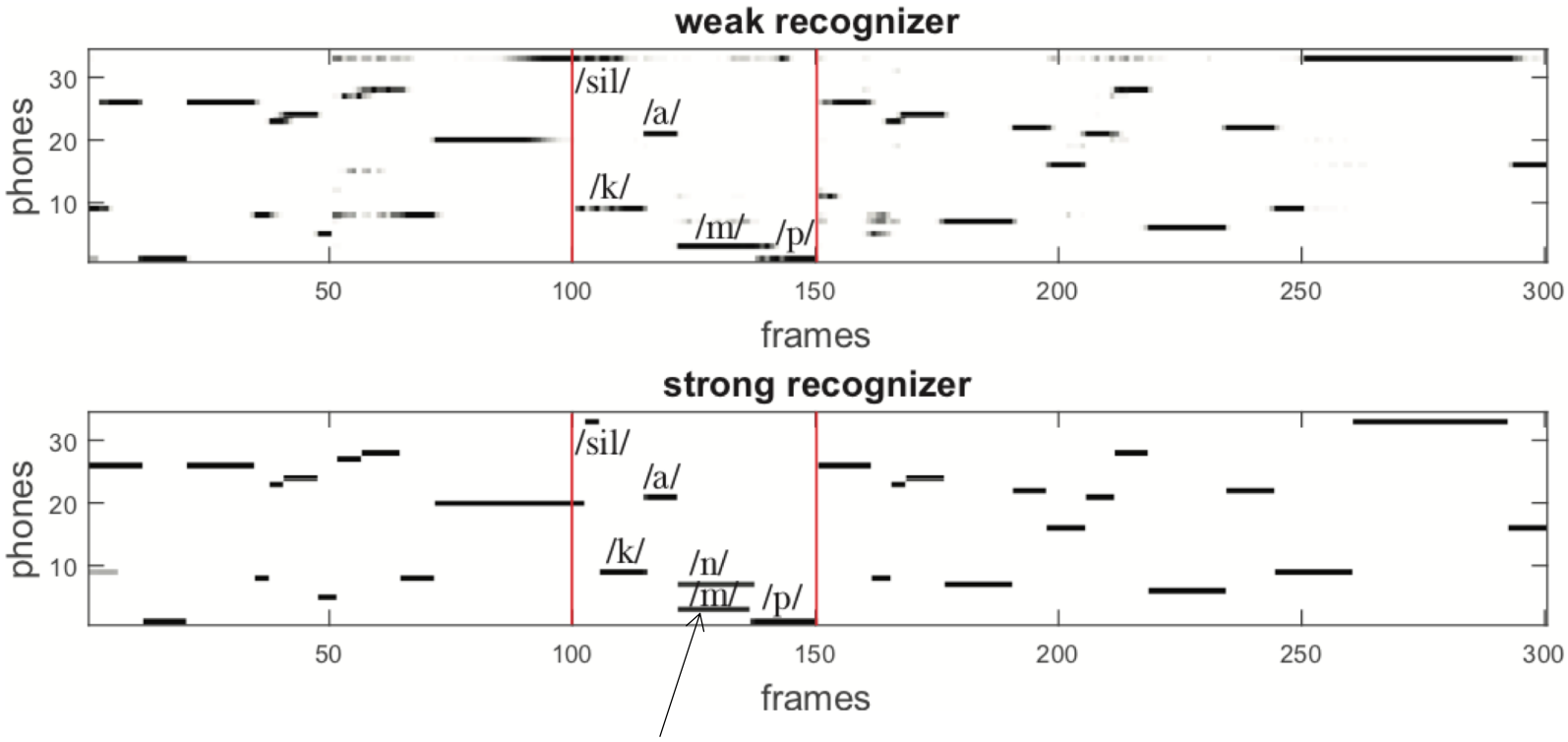


(Each segment is 3 second long)

Unimpaired speech

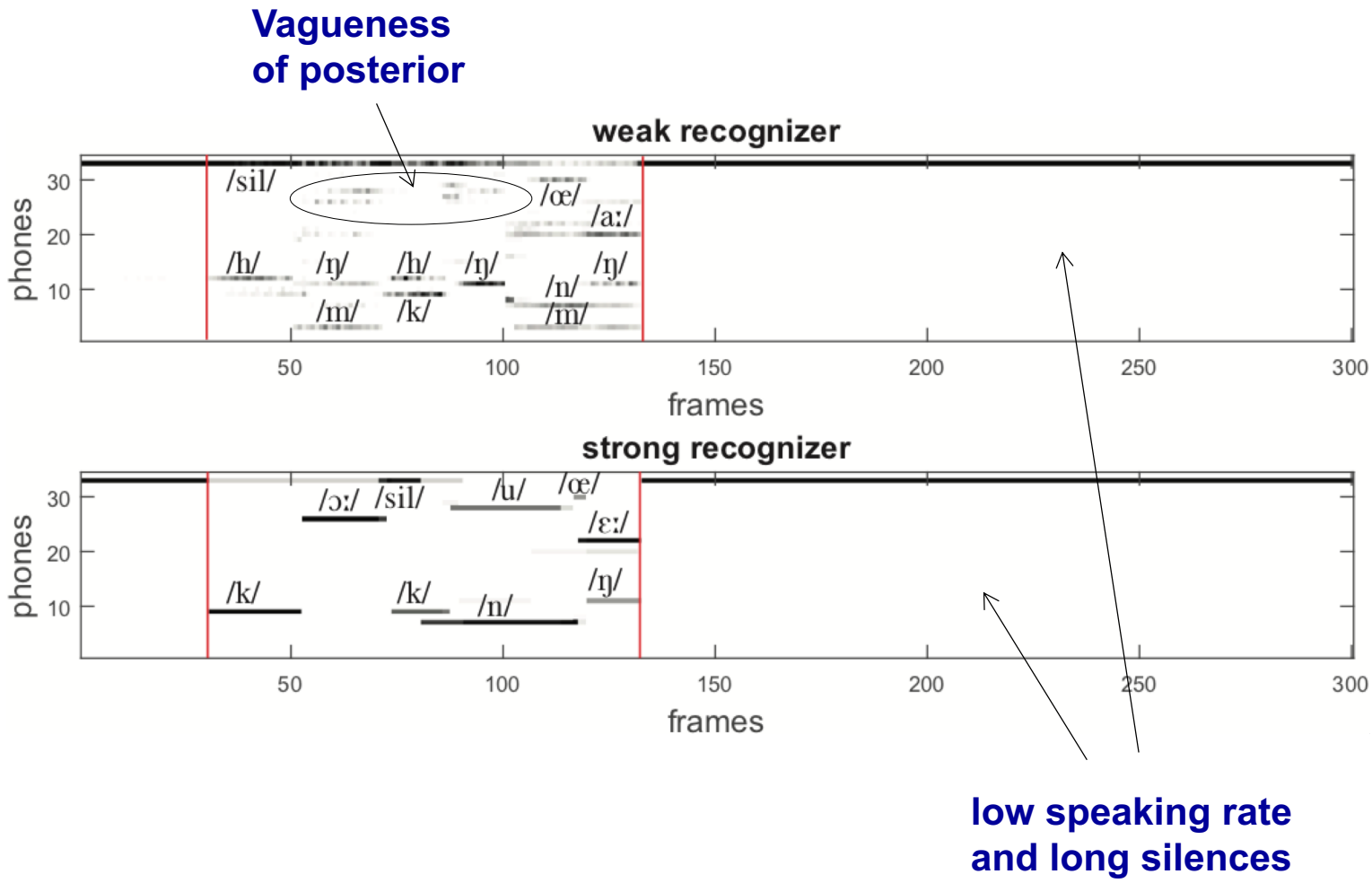


Mild impairment

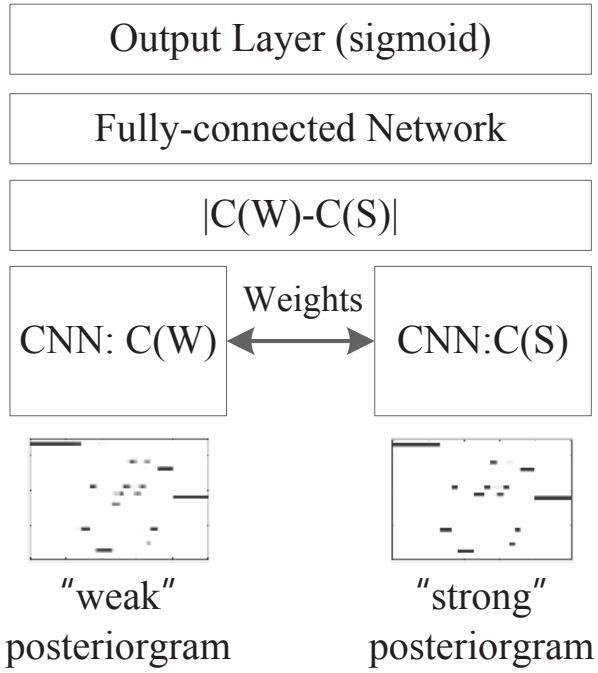


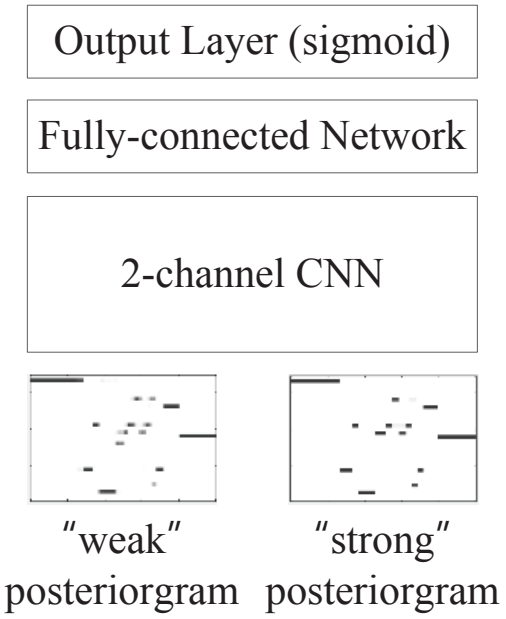
uncertainty of strong recognizer

Severe disorder



Classification by convolution NN

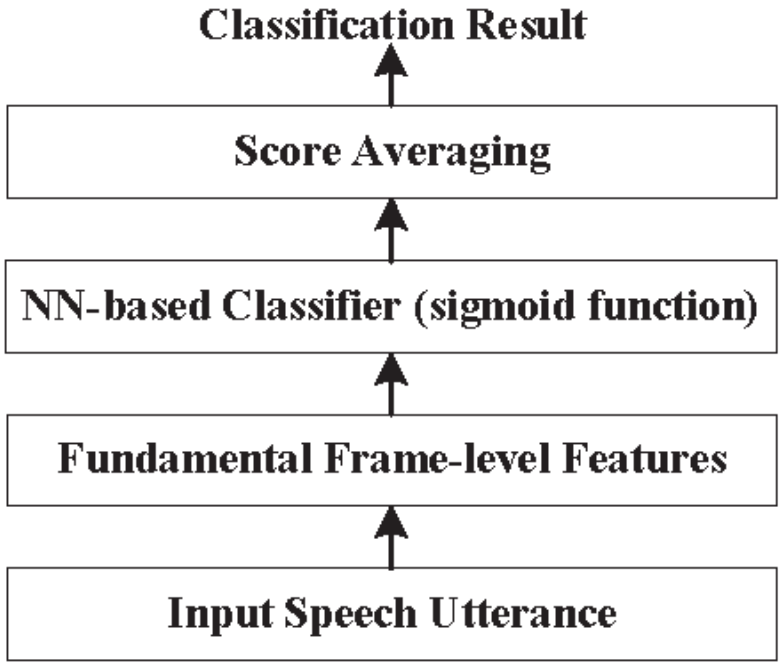




Binary classification F1 score: ~89%, comparable to the text+duration features

An end-to-end approach

- One single model directly from utterance to prediction score
- Speech features for assessment learned implicitly by neural networks without feature design



End-to-End framework

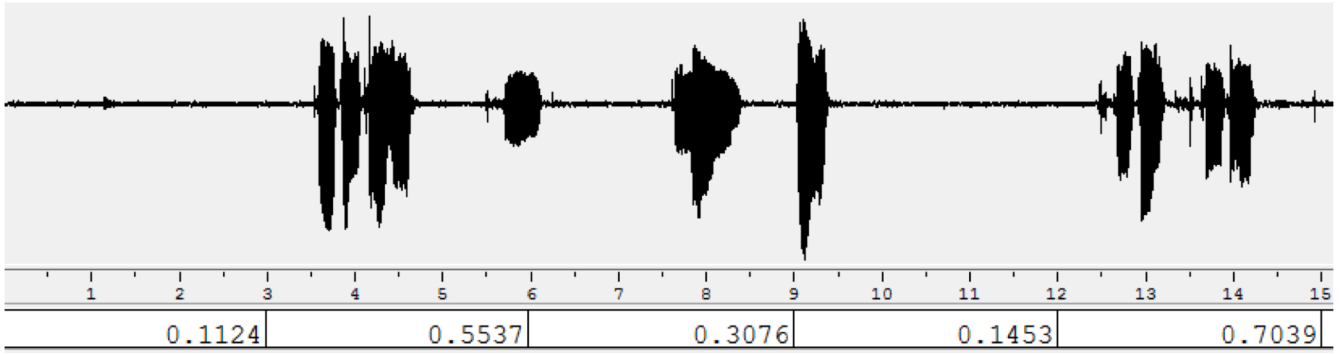
- Binary classification: High-AQ vs. Low-AQ
- Classifier: 2-layer unidirectional sequence-to-one GRU model and CNN model

	GRU-RNN	CNN
Accuracy (F1 score)	0.77	0.79

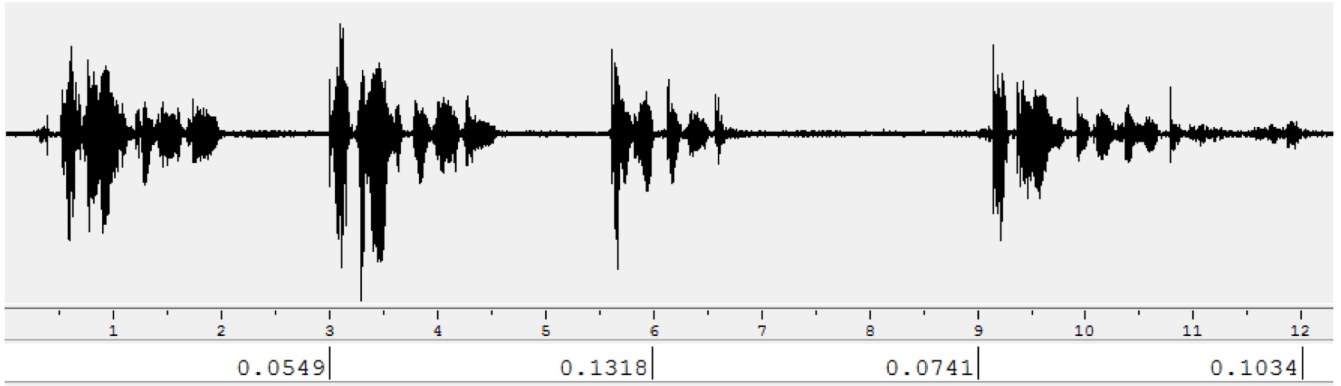
- The performance is slightly worse than ASR-generated features but is comparable
- It's much more efficient than ASR-generated features

End-to-end model is able to learn acoustic features:

Low-AQ speaker (AQ: 55.4)

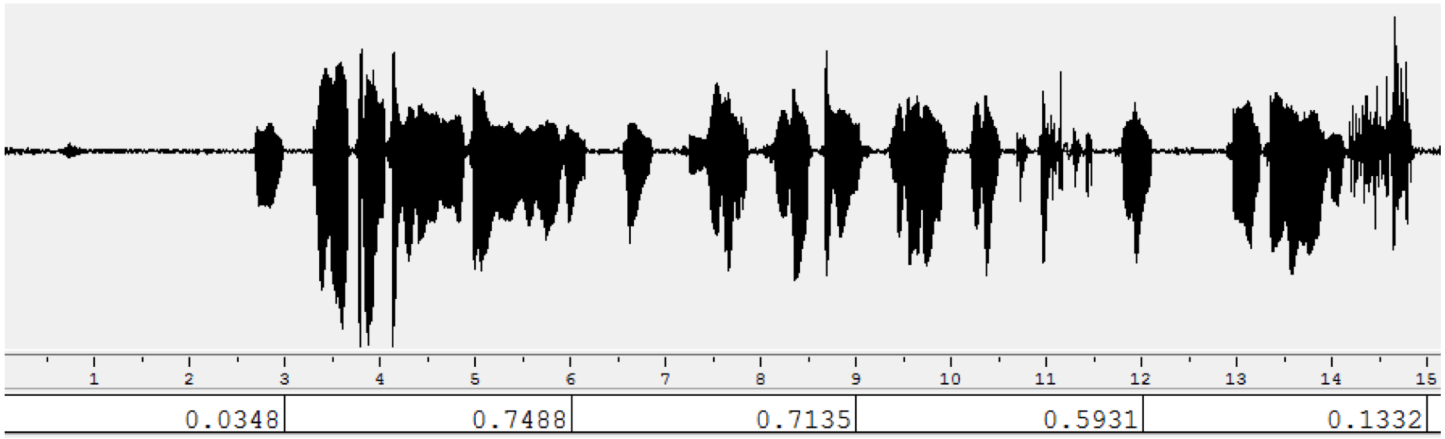


Low-AQ speaker (AQ: 11.0)



End-to-end model fails to learn linguistic features:

Low-AQ speaker (AQ: 41.3): misclassified to High-AQ



- This speaker has fluent speech but mostly function words with few content words

Data resource of pathological speech

Publicly available databases of pathological speech are scarce

Dimension of difficulty:

- **Language variation**
- **Variety of pathology**

Audio recording in regular clinical work has not become a standard practice in most places

Not just a matter of data …

- To speech technologists, clinical knowledge is often incomplete, inadequate, disconnected pieces, not well documented and continually evolving
- Clinical goals are diversified and may not be clearly described
- Reliable ground-truth are not available
- Large individual differences among patients
- Multiple types of disorders co-exist

Thank you !

tanlee@ee.cuhk.edu.hk

http://dsp.ee.cuhk.edu.hk