Detecting Syntactic Violations from Single-trial EEG using Recurrent Neural Networks

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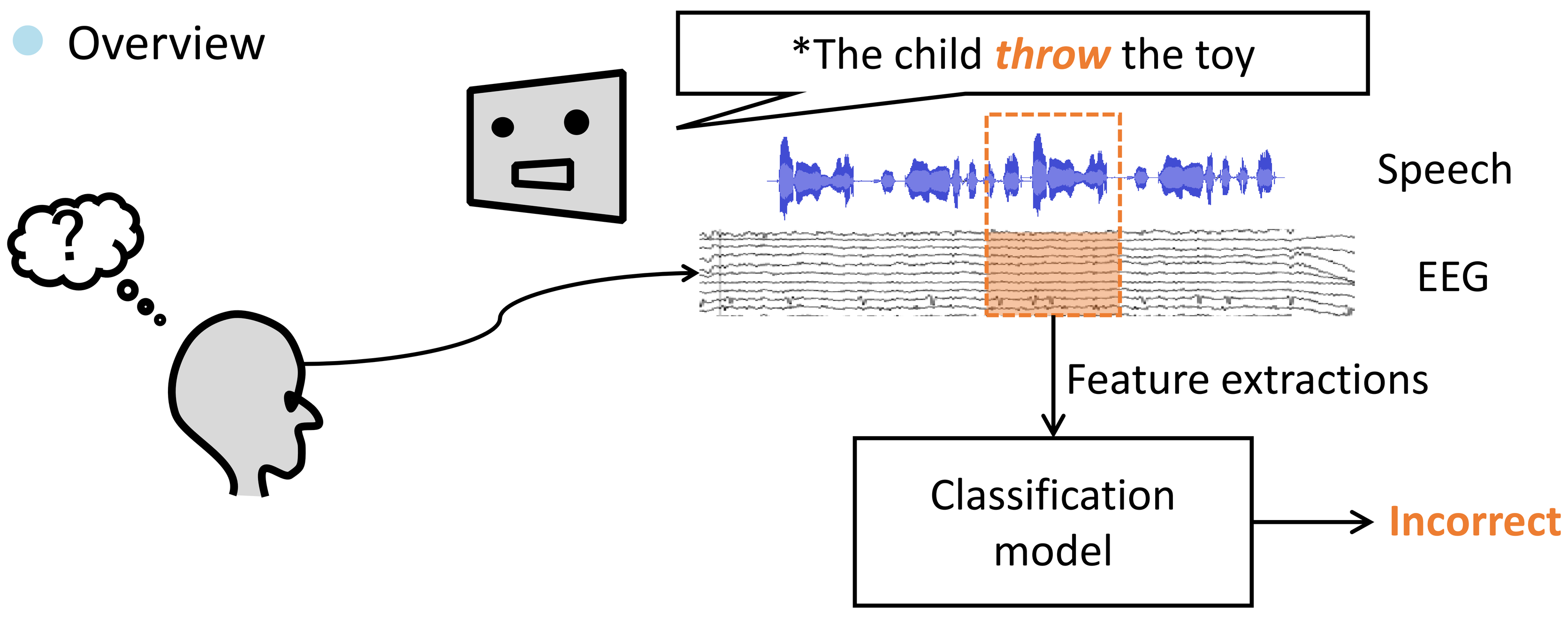
ICMI 2019 ACM International Conference on Multimodal Interaction - Late Breaking Results

Introduction

- Research goal
  - **Automatic evaluations** of sentences for machine translation / dialog. system
    Subjective evaluations are biased & ambiguous by human evaluators
- Research purpose
  - Detecting syntactic violations in spoken sentences with **single-trial EEG**
    Language-related EEG is usually studied by **averaging multiple-trials** due to it's low signal-to-noise ratio
- Overview



- **Single-trial** EEG classification
  - We have to evaluate **each sentence** -> single-trial classification
  - [Tanaka H, et.al, 2019] achieved **57.7%** acc. for detecting syntactic violations
    -> More accurate methods are necessary
  - Some **Neural network (NN) models** well performed
    - Stacked autoencoders (**SAE**) [Vareka L, et.al, 2017]
    - Long short-term memory (**LSTM**) [Alhagry S, et.al, 2017]
  - In this work, neural network models (SAE and LSTM) were applied to classify single-trial EEG signals for **syntactic violations**

Materials

- Syntactic violations
  - Japanese sentences manually crafted refering to [Takazawa S, et.al, 2002]
  - **Repetition of nominative case** violates Japanese grammar

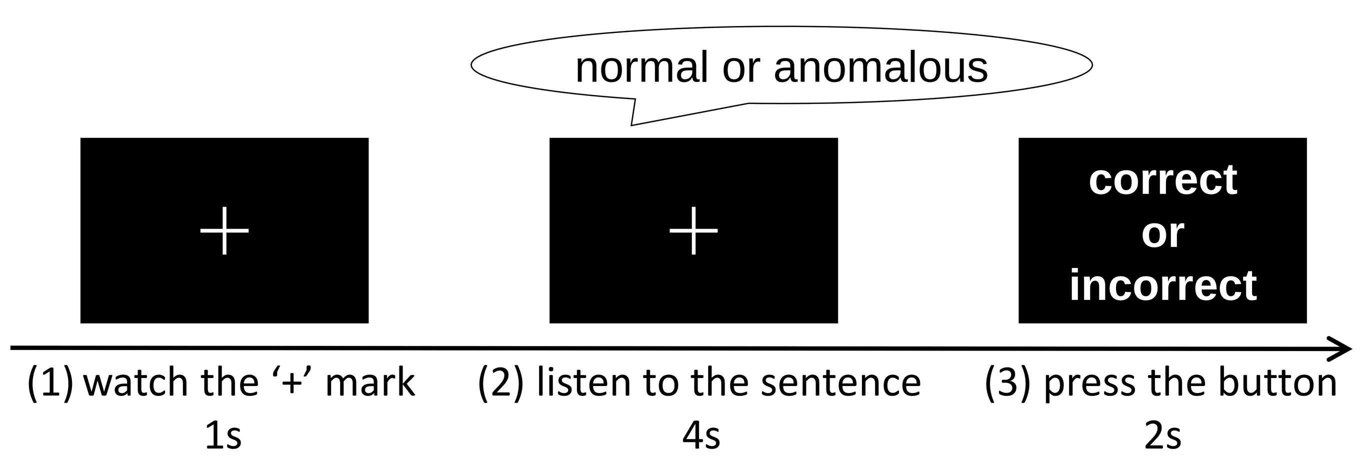
a.	tori-ga	sora-o	ton-da
	bird-NOM	sky-ACC	fly-PAST
	(The bird flew in the sky.)		
b.	*tori-ga	sora-**ga**	ton-da (* means syntactic incorrectness)
	bird-NOM	sky-**NOM**	fly-PAST

NOM : nominative case marker
ACC : accusative case marker
PAST : past tense morpheme

- **The nominative case of second phrase** as synchronous **onset** (t=0ms)
- **40 sentences** for syntactic correct and incorrect condition respectively
- **Speech** by a professional female narrator was used for stimulus

EEG Data Acquisition

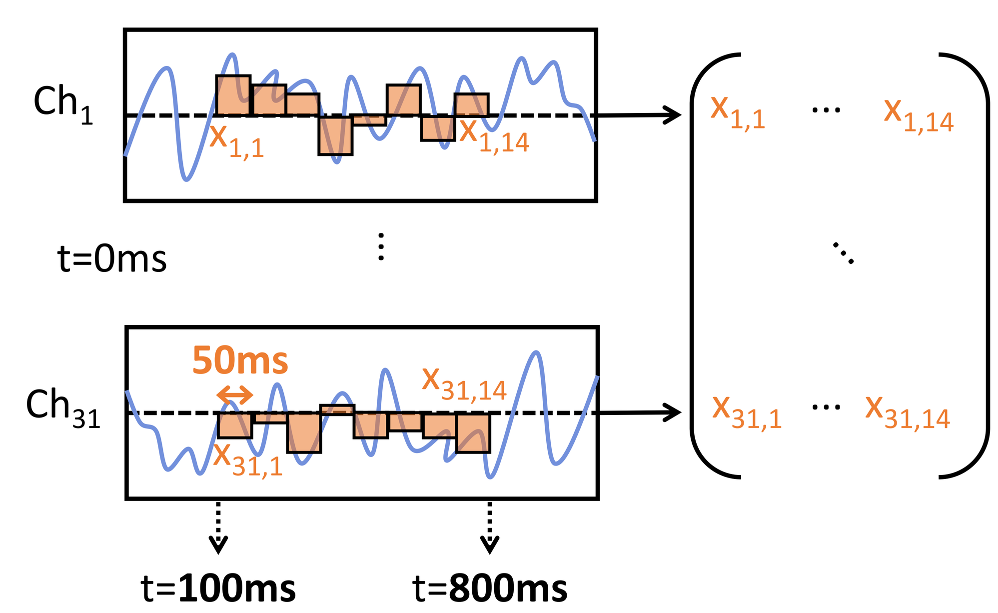
- Experimental procedure
  - Carried out in a soundproof room

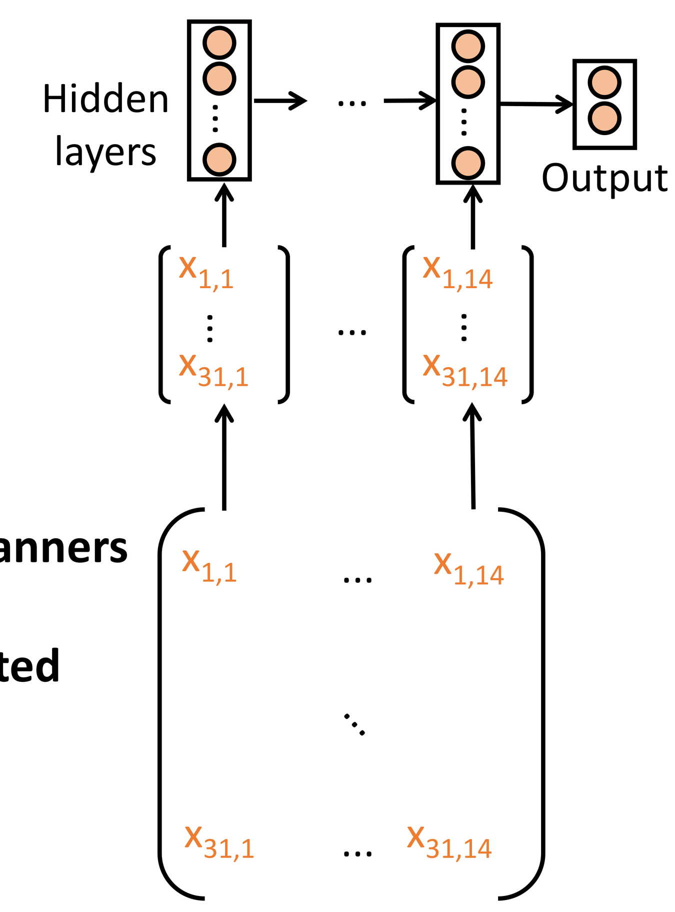


- Participants: **19 Japanese speakers** (16 males & 3 females, mean age: 24.2)
- EEG recording and preprocessings
  - EEG cap: ActiCap by Brain Products (**32 channel** electrodes)
  - Preprocessings
    1. Re-referencing
    2. High-pass filtering
    3. Epoching at synchronous onsets
    4. Reject artifacted epochs and removing muscle/eye-blink artifacts
    -> 1 participant was rejected (more than 30% epochs were rejected)

Features & Models

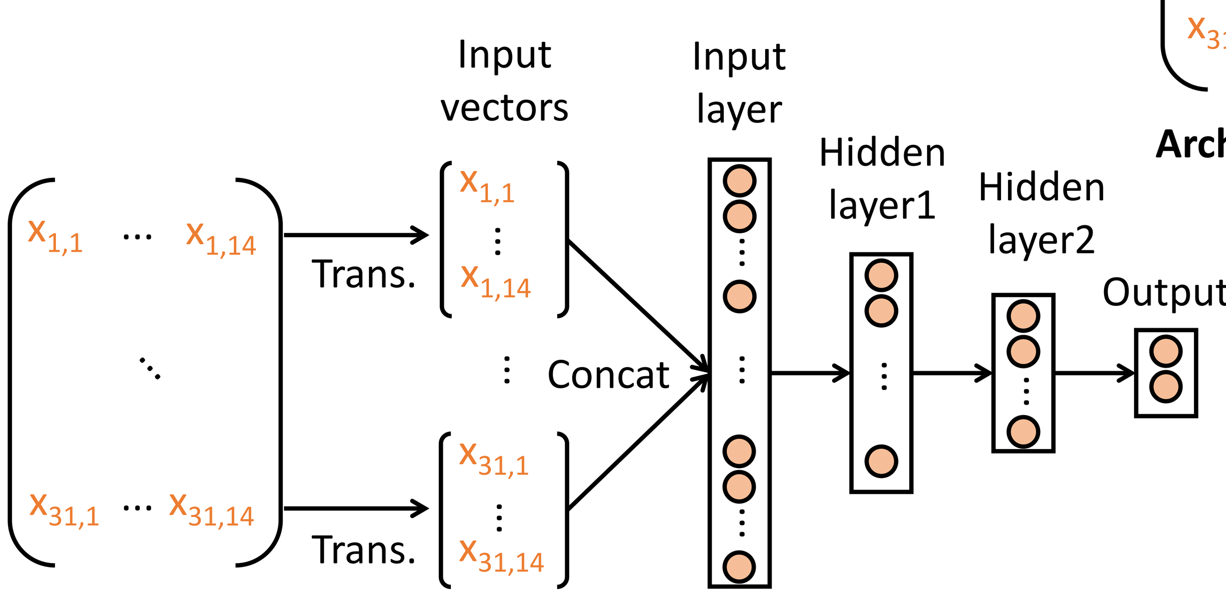
- Feature extraction [Vareka L, et.al, 2017]
  - **Average amplitudes** b/w **100 ms** and **800 ms** per each **50 ms** time window





Architecture of LSTM

- Models:
  - Long short-term memory (LSTM)
    Feature vectors were inputted in **sequential manners**
  - Stacked autoencoders (SAE)
    Feature vectors of all channels were **concatenated** into one column vector



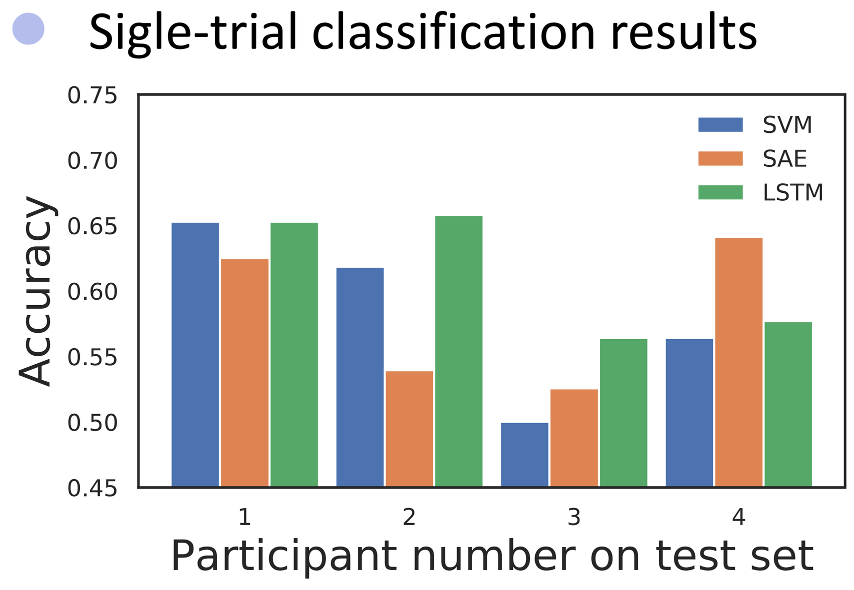
Architecture of SAE

Classifications

- Baseline model: linear-kernel support vector machine (SVM)
- Data
  - Training :**14** participants' data (1040 sentences)
  - Test :**4** participants' data (314 sentences)
  - Correct sentence: 50% / incorrect: 50% -> **chance level: 0.5**
- Optimization of **hyper-parameters**
  - Grid-searching with **10-hold cross validation** in the training data
  - SVM
    - C = {0.001, 0.01, 0.1, 1, 10, 100}
  - SAE
    - Number of hidden units: {10, 50, 100, 200, 300}
    - Number of hidden layers: {1, 2, 3}
    - Activation functions: {sigmoid, rectified linear unit}
  - LSTM
    - Number of hidden units: {5, 10, 15, 20, 25, 30}, others are the same as SAE
- Multiple-trials averaged analysis
  - We also investigated classification performances on **averaging multiple-trials** EEG signals

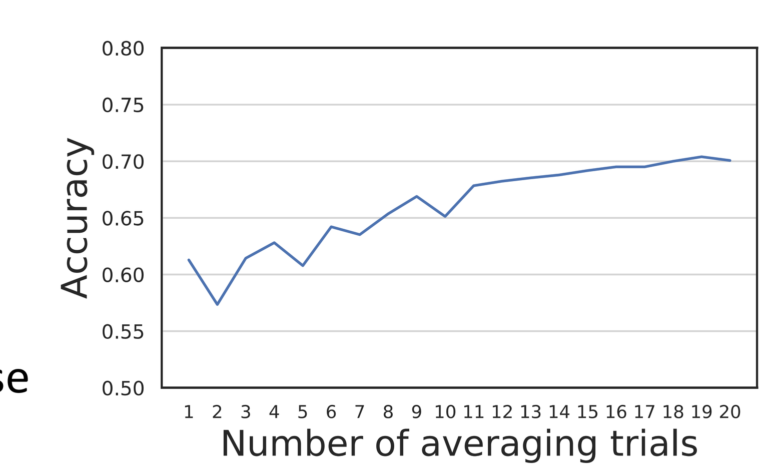
Results & Conclusions

- Sigle-trial classification results



Model	Accuracy
SVM	0.584
SAE	0.583
LSTM	**0.613**

- Multiple-trials averaged accuracies
  - Gradually **increasing** while the number of averaging trials increase



- Conclusions
  - LSTM could achived over 60% accuracy higher than chance level (p<0.01)
    -> **Sequential** models are feasible to properly classify high-dimensional sequential EEG signals
- In future
  - **Raw EEG** as features: NN can learn without specific feature extractions
  - Detection of **semantic violations** in sentences for evaluations of sentences

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