

# TELL YOUR WORDS

SPEECH TRAINER FOR CHILDREN

---

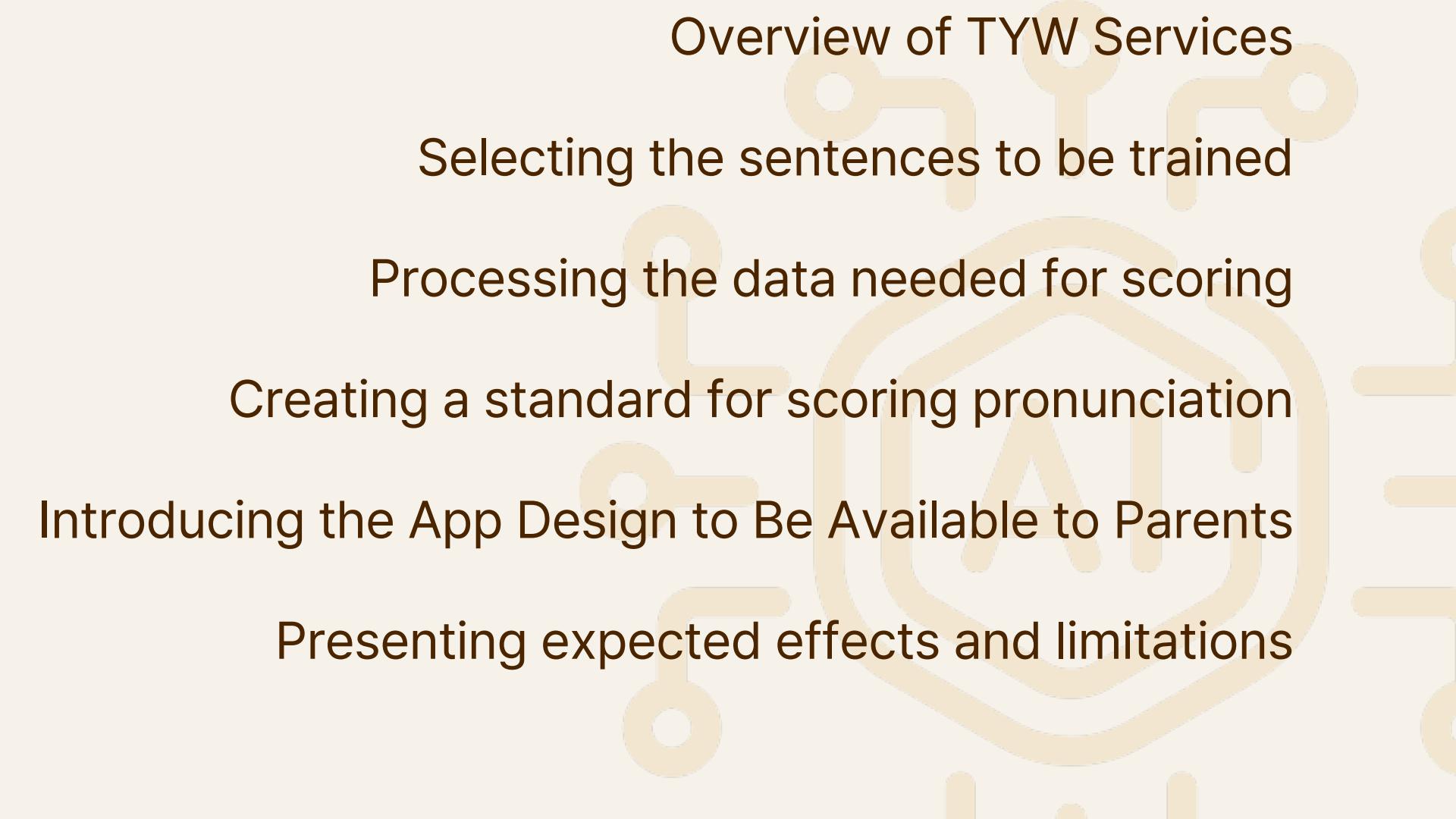
KIM JOONHEE, DEPT OF INFORMATION SYSTEM 18

MA YUDAM, DEPT OF KOREAN LANGUAGE & LITERATURE 19

PARK JUNHYEONG, DEPT OF BUSINESS ADMINISTRATION 18



# CONTENTS

- 
- 01 **Service Introduction** Overview of TYW Services
  - 02 **Sentence Selection** Selecting the sentences to be trained
  - 03 **Data Processing** Processing the data needed for scoring
  - 04 **Pronunciation score prediction** Creating a standard for scoring pronunciation
  - 05 **App UI Design** Introducing the App Design to Be Available to Parents
  - 06 **Conclusion & Suggestion** Presenting expected effects and limitations

## SERVICE INTRODUCTION

# WHAT KIND OF PROBLEM WE FACE?

## 46.1% OF DOUBLE-INCOME HOUSEHOLDS... HIGHEST EVER

THE PROPORTION OF DUAL-INCOME HOUSEHOLDS IS THE HIGHEST SINCE 2015 WHEN RELATED STATISTICS BEGAN TO BE COMPILED

# 46.1%

SOURCE) NATIONAL STATISTICAL OFFICE OF KOREA

## IN THE AFTERMATH OF COVID-19, 'I EXPERIENCED A CHILD-REARING GAP'

IN PARTICULAR, DUAL-INCOME OFFICE WORKERS WITH INFANTS (AGES 4 TO 7) WERE THE HIGHEST AT 90.4%

# 76.5%

SOURCE) INCRIUT X ALBACALL

## 'CHILDREN'S CHANCES OF DEVELOPING LANGUAGE SKILLS HAVE DECREASED'

75% OF OFFICIALS AT NATIONAL AND PUBLIC DAYCARE CENTERS RESPONDED, AND LANGUAGE DISORDERS INCREASED 30% COMPARED TO BEFORE COVID-19.

# 75%

SOURCE) EBS

# WHAT KIND OF PROBLEM WE FACE?



## COVID-19

DUE TO THE SOCIAL DISTANCE, CHILDREN HAVE A  
PROBLEM OF LACK OF LANGUAGE SKILLS

## DOUBLE-INCOME FAMILIES

FOR THESE CHILDREN, ADULTS HAVE TO SUPPORT THEM  
BUT IT'S HARD BECAUSE DOUBLE-INCOME FAMILIES ARE  
COMMON, ESPECIALLY IN KOREA

## THE DIRECTION OF PRIVATE EDUCATION

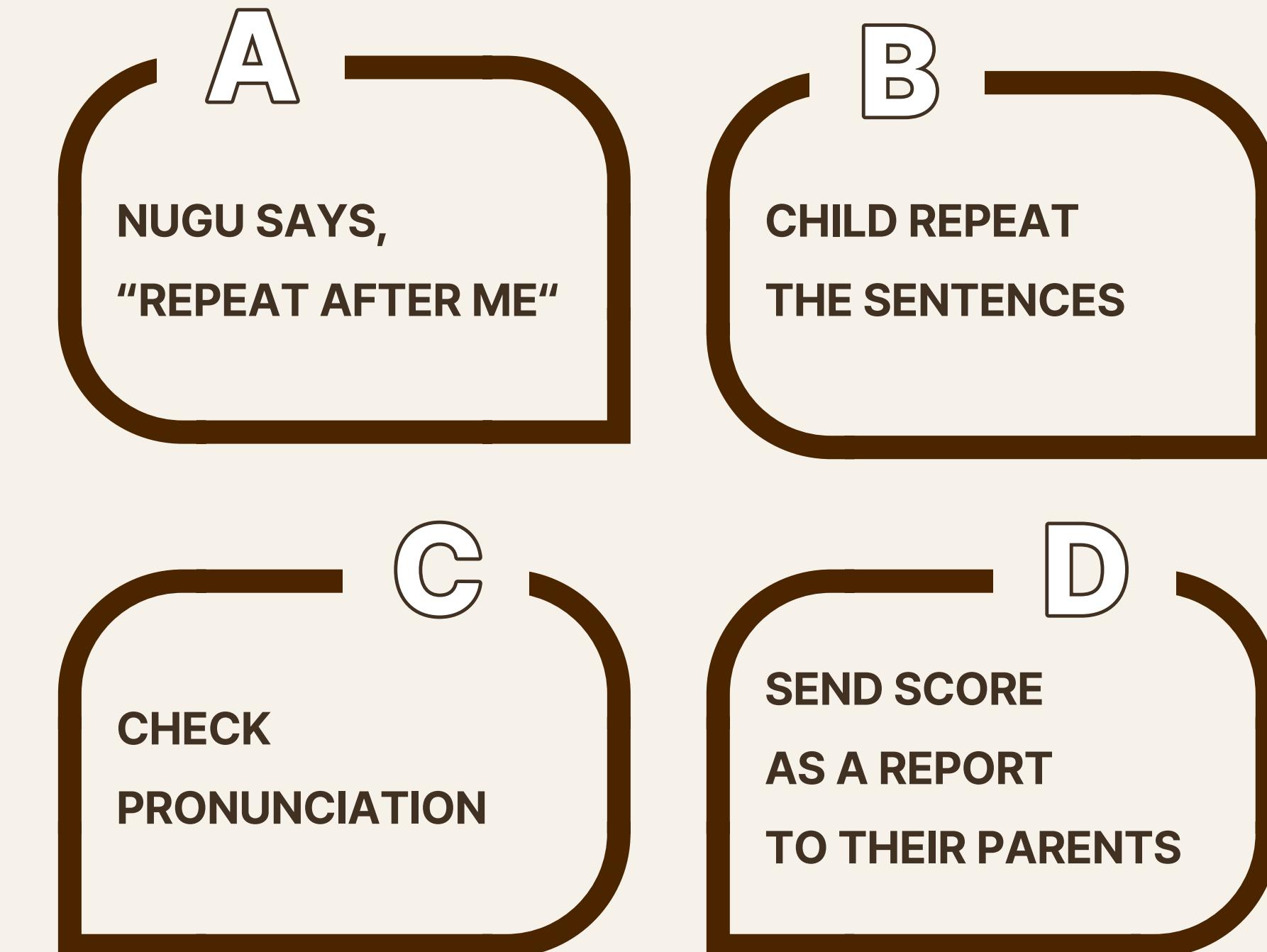
ACADEMIES ONLY DO FOCUS ON GRAMMAR AND  
UNIVERSITY ENROLLMENT EXAMS RATHER THAN  
CHILDREN'S PRONUNCIATION AND SPEAKING SKILLS

A B C

## WHAT'S NOT IN THE KOREAN ENGLISH EDUCATION MARKET

FURTHERMORE, THIS IDEA MAY TARGET THE RELATIVE  
LACK OF SPEAKING EDUCATION IN THE ENGLISH  
EDUCATION MARKET IN KOREA

# WE SUGGEST A SPEAKING PRACTICE SERVICE FOR CHILDREN



# WHICH SENTENCES DO WE TEACH?



LEARNING SOUNDS CAN BE DIFFERENT DEPENDING ON HOW WE STUDY AND WHAT SOUNDS WE'RE LOOKING AT

FOR EXAMPLE, THE SOUND /L/ IS LEARNED LATER  
USUALLY, LIQUIDS GET REPLACED BY GLIDES,  
IN ENGLISH WHERE /R/ BECOMES [W] AND /L/ BECOMES [W] OR [Y]

## FREQUENT PRONUNCIATION ERROR EXAMPLES IN ENGLISH

- [WÆBLT] 'RABBIT' ([R] -> [W])
- [Fɪt] 'PIT' ([P] -> [F])
- [Yɪf] 'LEAF' ([L] -> [Y])

# WHICH SENTENCES DO WE TEACH?

IN KOREAN, ALSO SIMILAR MISTAKES OCCUR.

BUT IN 'REPLACING', IT DEPENDS ON LANGUAGE STRUCTURE.

## FREQUENT PRONUNCIATION ERROR

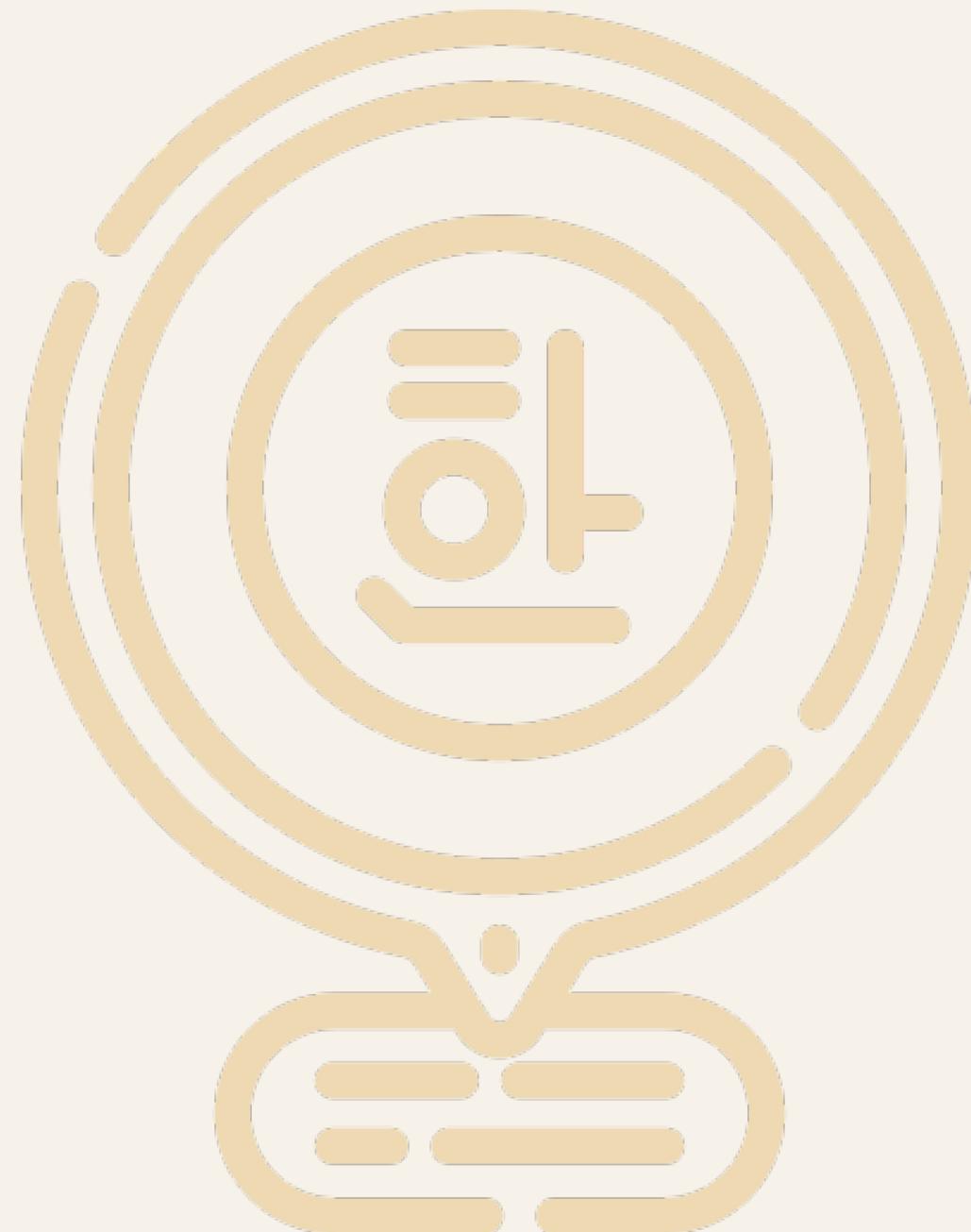
### EXAMPLES IN KOREAN

[POWICHA] /POLICHA/ '보리차' ([리] -> [위])

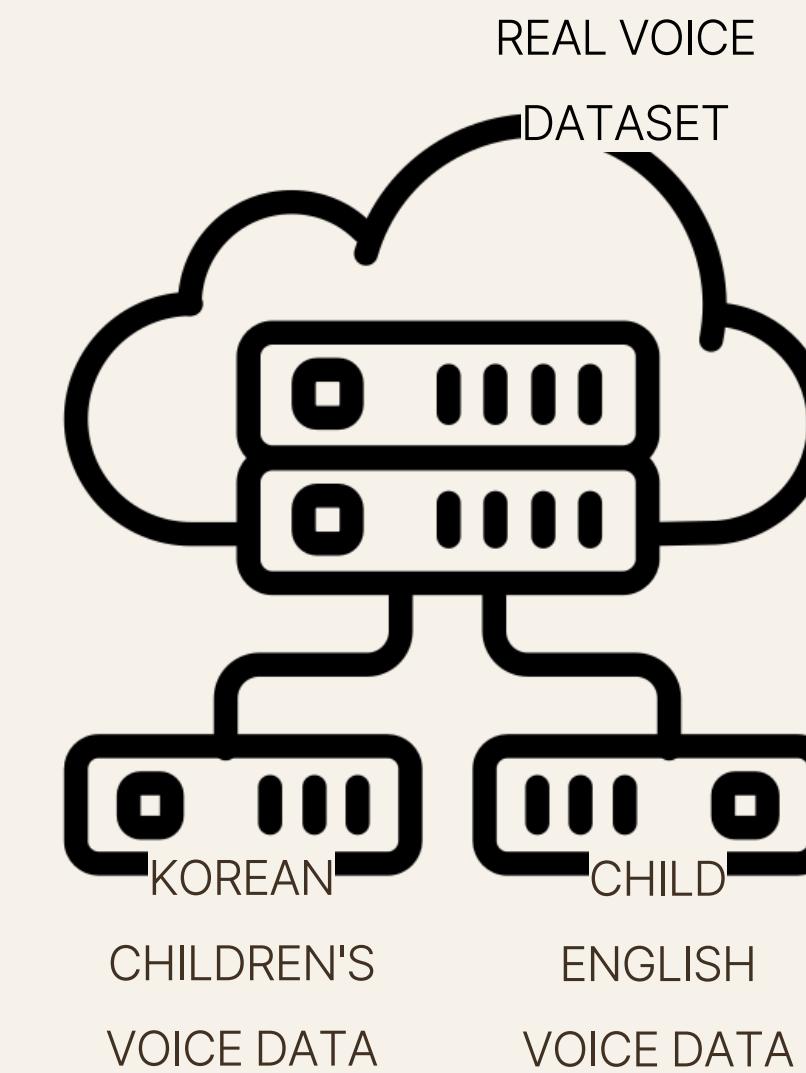
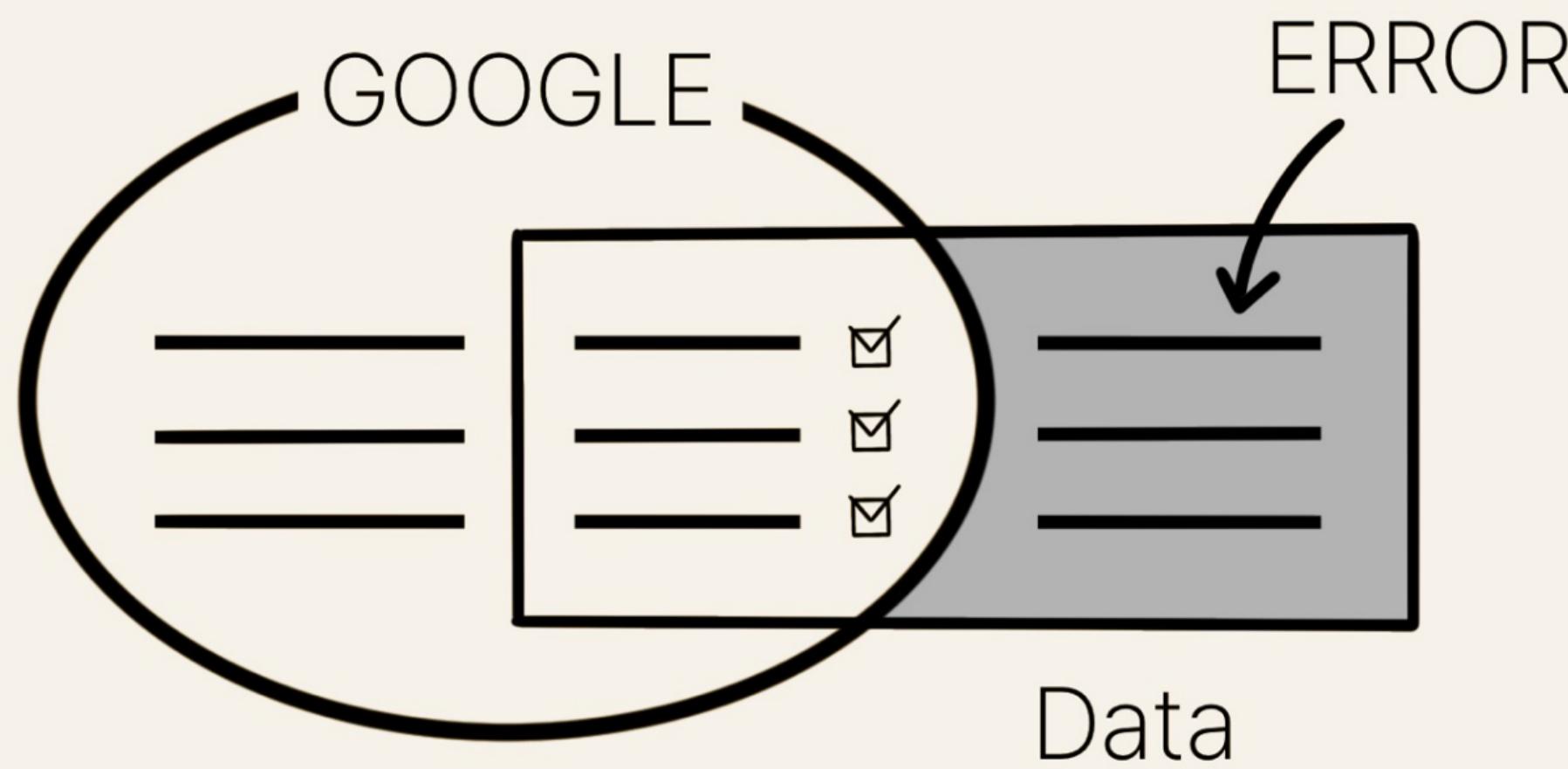
[YA:MCN] /LAMYƏN/ '라면' ([라] -> [야])

[THAYAM] /SALAM/ '사람' ([사] -> [따])

[KITA] /KICHA/ '기차' ([차] -> [타])



# GETTING SENTENCES THAT ARE WORTH REPEATING TO CHILDREN



# GETTING SENTENCES THAT ARE WORTH REPEATING TO CHILDREN

```
recognizer = sr.Recognizer()
recognized_texts = []

# Load wav files
for wav_file in glob.glob(wav_files_path):
    try:
        with sr.AudioFile(wav_file) as source:
            audio_data = recognizer.record(source)
        # STT by Google Web Speech API
        text = recognizer.recognize_google(audio_data, language="default")
        # language = 'ko-KR' when you want to use for korean sentences

        recognized_texts.append({'filename': wav_file, 'text': text})
    except sr.RequestError as e:
        print(f"Google Web Speech API request error: {e}")
    except Exception as e:
        print(f"Error processing {wav_file}: {e}")

# Create a DataFrame from the list of recognized texts
recognized_texts_df = pd.DataFrame(recognized_texts)
```

SINCE 'CHILDREN'S VOICE DATA' HAS BEEN CALIBRATED AND LABELED BY HUMANS,

THE TRANSCRIPT DATA MADE FROM THIS DATA IS VIEWED AS 'CORRECTED\_TEXT'

AND COMPARED WITH THE SENTENCES RECEIVED BY THE STT MODEL.

# GETTING SENTENCES THAT ARE WORTH REPEATING TO CHILDREN

```
json_texts_df = pd.DataFrame()

# Load json files
for json_file in glob.glob(json_files_path):
    with open(json_file, 'r') as file:
        data = pd.json_normalize(json.load(file))
    json_texts_df = json_texts_df.append(data, ignore_index=True)

json_texts_df.head()
corrected_texts_df = json_texts_df[['File.FileName', 'Transcription.LabelText']]
corrected_texts_df = corrected_texts_df.rename(columns={'File.FileName': 'filename', 'Transcription.LabelText': 'text'})

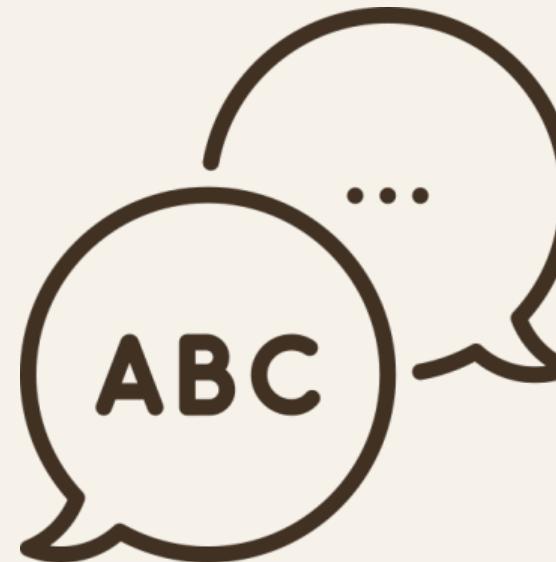
merged_df = pd.merge(corrected_texts_df, recognized_texts_df, on=['filename'], how='inner')

merged_df['corrected_text_cleaned'] = merged_df['corrected_text'].str.replace(r'[\s\W_]+', '')
merged_df['text_cleaned'] = merged_df['text'].str.replace(r'[\s\W_]+', '')
```

LOADING JSON FILES AND MAKE DATAFRAME WITH ONLY THE SENTENCES WITH THE ERROR CORRECTED IN THE JSON FORMAT FILE

IT IS NECESSARY TO PREPROCESS DATA FRAMES MADE USING GOOGLE API AND JSON FILES SO THAT THEY CAN BE PROCESSED

# THESE SENTENCES COULD BE REASONABLE ONES



## ENGLISH SENTENCE EXAMPLES

- A. THE HAPPY CAT SAT ON THE MAT
- B. HE HAS A BIG BLUE BALL TO PLAY
- C. THE LITTLE DUCK QUACKS IN THE POND
- D. THE SUN SHINES IN THE SKY
- E. TIM'S TOY TRUCK IS GREEN

## ENGLISH SENTENCE EXAMPLES

- A. 오리도 만들고 기차도 만들었다
- B. 아침에 라면을 먹어 행복했다
- C. 공연하는 사람들은 다 키가 엄청나게 컸다
- D. 코끼리 미끄럼틀을 탔다
- E. 구름 사이로 우리 비행기가 승 지나갔다

# DATA DESCRIPTION

The screenshot shows the homepage of the Speech Accent Archive. It features a large image of a human ear on the left and a stylized illustration of lips on the right. The main title "the speech accent archive" is centered above a navigation menu with links for "how to browse search resources about". Below the menu, a text block explains the archive's purpose: "The speech accent archive uniformly presents a large set of speech samples from a variety of language backgrounds. Native and non-native speakers of English read the same paragraph and are carefully transcribed. The archive is used by people who wish to compare and analyze the accents of different English speakers." At the bottom, it says "last updated: 24 july 2021 2959 samples". On the right, there is a detailed "Overview" section with tabs for "Overview", "Alerts", and "Reproduction". The "Overview" tab is selected, showing "Dataset statistics" and "Variable types". The "Dataset statistics" table includes rows for Number of variables (9), Number of observations (2172), Missing cells (9), Missing cells (%) (< 0.1%), Duplicate rows (0), Duplicate rows (%) (0.0%), Total size in memory (138.0 KB), and Average record size in memory (65.1 B). The "Variable types" section lists Numeric, Categorical, and Boolean.

ENGLISH SPEECH DATA RECORDED BY PEOPLE OF DIFFERENT COUNTRIES, GENDERS, AND AGES. CONTAINING **2,140** SPEECH SAMPLES

RESEARCHERS CONSTRUCTED AN ELICITATION PARAGRAPH AND EACH SUBJECT'S PRONUNCIATION IS RECORDED

SINCE THE SAME PARAGRAPH WAS RECORDED BY MULTIPLE PEOPLE WITH DIFFERENT ENGLISH LEARNING BACKGROUNDS, THIS DATASET IS FIT TO OUR TASK

HOWEVER, IT LACKS PRONUNCIATION SCORE

- READING-PASSAGE.TXT: AN ELICITATION PARAGRAPH
- SPEAKERS\_ALL.CSV: DEMOGRAPHIC INFORMATION ON EVERY SPEAKER  
(DETAILED INFORMATION IN SPEECH\_DATASET\_PROFILE.HTML)
- RECORDING: A ZIPPED FOLDER CONTAINING .MP3 FILES WITH SPEECH

# LABELING VIA FEW SHOT LEARNING

SINCE THE DATASET LACKS THE PRONUNCIATION SCORE,  
WE DECIDED TO UTILIZE **\*FEW SHOT LEARNING** TECHNIQUE  
TO LABEL THE PRONUNCIATION SCORE OF EACH SPEECH DATA

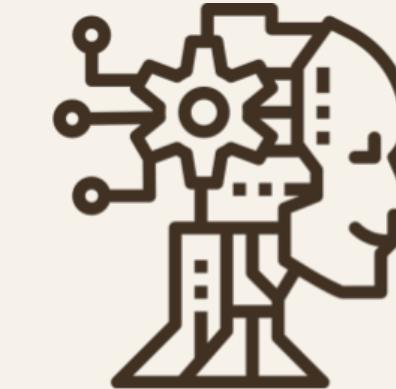
\*FEW SHOT LEARNING: A MACHINE LEARNING PARADIGM  
WHERE A MODEL IS TRAINED TO MAKE ACCURATE PREDICTIONS  
WITH ONLY A SMALL NUMBER OF EXAMPLES PER CLASS

## 1) MANUAL LABELING



MANUALLY LABELED  
THE PRONUNCIATION SCORE  
OF SAMPLE DATA AS 0, 1, 2

## 2) TRAIN FEW SHOT MODEL



USING THE MANUALLY  
LABELED DATA,  
TRAIN THE FEW SHOT MODEL

## 3) LABELING VIA FEW SHOT MODEL



TRAINED FEW SHOT MODEL  
PREDICTS PRONUNCIATION SCORE  
OF EACH SPEECH DATA

# LABELING VIA FEW SHOT LEARNING

## 1) MANUAL LABELING

MANUALLY LABELED SAMPLE SPEECH DATA AS 0(BAD), 1(NORMAL), 2(GOOD)  
FOR EACH OF FOUR METRICS

WE MANUALLY LABELED 10 SAMPLE DATA FOR EACH EVALUATION METRIC  
AND PRONUNCIATION LEVEL, TOTAL 120 SAMPLE DATA

ONLY LABELED DATA WITH CLEAR CLASSIFICATIONS

# LABELING

# VIA FEW SHOT LEARNING

## 1) MANUAL LABELING

### FOUR REPRESENTATIVE PRONUNCIATION METRICS

Metrics	Description
Accuracy	The level of the learner pronounce each word in the utterance correctly
Completeness	The percentage of the words that are actually pronounced
Fluency	Does the speaker pronounce smoothly and without unnecessary pauses?
Prosodic	Does the speaker pronounce in correct intonation, stable speaking speed and rythm?

# LABELING VIA FEW SHOT LEARNING

2) TRAIN FEW SHOT MODEL &

3) LABELING VIA FEW SHOT MODEL

USING THE MANUALLY LABELED DATA, WE TRAINED THE FEW SHOT MODEL

SET THE LABELED DATA AS TRAIN SET, AND NOT LABELED DATA SET AS TEST SET

FOR REAL WORLD SERVICES, IT WOULD BE USEFUL USE FEW-SHOT LEARNING  
BASED ON DATA LABELED BY EXPERTS

# LABELING VIA FEW SHOT LEARNING

1

```
class Audio_Encoder(nn.Module):
    def __init__(self, num_heads, num_layers):
        super().__init__()
        self.sentecne_level = nn.TransformerEncoder(nn.TransformerEncoderLayer(
            d_model=768, nhead=num_heads, dim_feedforward=3072, dropout=0.1), num_layers)

    def forward(self, batch):
        max_len = max([e.size(0) for e in batch])
        padded_embeddings = torch.zeros(len(batch), max_len, batch[0].size(-1))
        for i, emb in enumerate(batch):
            seq_len = emb.size(0)
            padded_embeddings[i, :seq_len, :] = emb
            random_tensor = torch.randn(padded_embeddings.size(0), 1, max_len, 768).float()
            batch_tensor = torch.cat((random_tensor, padded_embeddings), 1)
            batch_tensor = batch_tensor.permute(1, 0, 2).float()
            padding_mask = batch_tensor.sum(dim=-1).permute(1, 0) == 0
            output_batch = self.sentecne_level(batch_tensor.float(), padding_mask)
            output_batch = output_batch.permute(1, 0, 2)
            feature_vecs = output_batch[:, :, :]
        return feature_vecs
```

2) TRAIN FEW SHOT MODEL &  
3) LABELING VIA FEW SHOT MODEL

DEFINE A CUSTOMIZED

ENCODER CLASS THAT LEVERAGES

TRANSFORMER'S ENCODER TO

EXTRACT HIGH-DIMENSIONAL

FEATURE VECTORS

# LABELING VIA FEW SHOT LEARNING

2

```
class few_shot_Model(nn.Module):
    def __init__(self, encoder):
        super().__init__()
        self.encoder = encoder
        self.fc1 = nn.Linear(768, 768)
        self.ac = nn.ReLU()
        self.fc2 = nn.Linear(768, 256)
        self.sigmoid = nn.Sigmoid()

    def forward(self, voice_pair):
        voice_pair = self.encoder(voice_pair)
        voice_pair = self.fc1(voice_pair)
        voice_pair = self.ac(voice_pair)
        voice_pair = self.fc2(voice_pair)
        similarity = torch.cosine_similarity(voice_pair[0],
                                             voice_pair[1])
        out = similarity
        return out
```

- 2) TRAIN FEW SHOT MODEL &
- 3) LABELING VIA FEW SHOT MODEL

BUILDING A FEW SHOT MODEL

USING THE ENCODER CLASS

IT CONSISTS OF ONE ENCODER LAYER

AND TWO FULLY CONNECTED LAYERS

# LABELING VIA FEW SHOT LEARNING

- 2) TRAIN FEW SHOT MODEL &
- 3) LABELING VIA FEW SHOT MODEL

3

```
data with same classes
for epoch in range(10) :
    epoch_loss = 0
    target = torch.tensor([1.0]).to(device)

    total_loss = 0
    optimizer.zero_grad()
    for i,j in combinations(g1,2) :
        f_model.train()
        data = df.iloc[[i,j],2]
        data = tuple(d.to(device) for d in data)
        output = f_model(data).unsqueeze(0)
        loss = criterion(output, target)
        total_loss += loss
    total_loss.backward()
    optimizer.step()
    epoch_loss += total_loss
```

TRAIN THE MODEL ON  
DATA OF SAME CLASS  
AND DATA OF DIFFERENT CLASS

# LABELING VIA FEW SHOT LEARNING

4

```
for idx in tqdm(tests):
    f_model.eval()
    s1 = 0
    for i1 in g1:
        data = df.iloc[[idx, i1], 2]
        data = tuple(d.to(device) for d in data)
        s1 += torch.sigmoid(f_model(data)).detach().i

    s2 = 0
    for i1 in g2:
        data = df.iloc[[idx, i1], 2]
        data = tuple(d.to(device) for d in data)
        s2 += torch.sigmoid(f_model(data)).detach().i

    s3 = 0
    for i1 in g3:
        data = df.iloc[[idx, i1], 2]
```

- 2) TRAIN FEW SHOT MODEL &
- 3) LABELING VIA FEW SHOT MODEL

PREDICT THE PRONUNCIATION SCORE  
OF EACH SPEECH DATASET

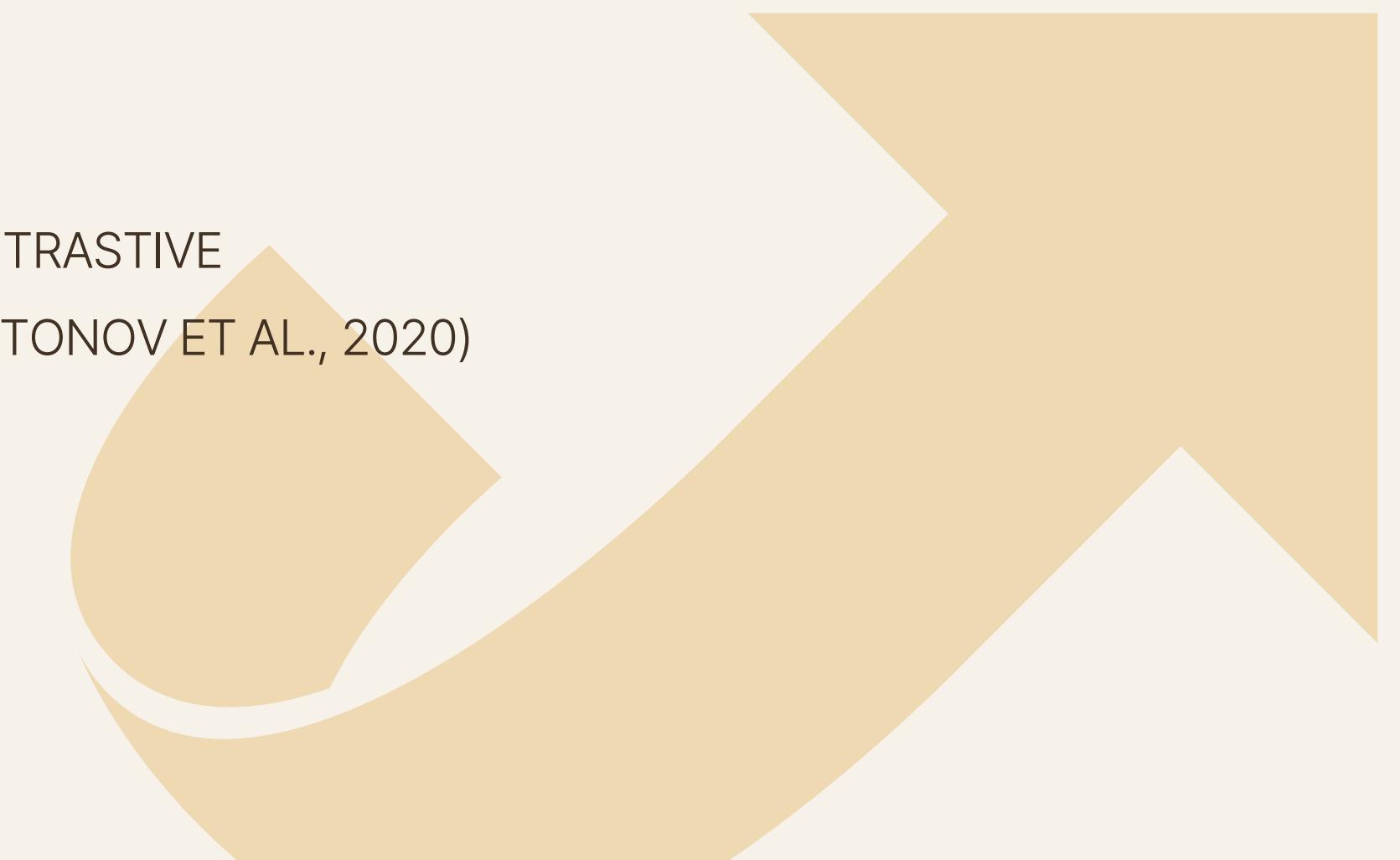
# AUDIO AUGMENTATION

**THE NUMBER OF OUR TOTAL SPEECH DATA WAS NEARLY 2,000,  
WE NEEDED MORE DATA TO TRAIN OUR DEEP LEARNING MODEL**

SINCE THE ORIGINAL DATASET WAS RECORDED IN A QUIET ROOM,  
AUDIO AUGMENTATION CAN IMPROVE THE MODEL PERFORMANCE

TO AUGMENT AUDIO FILES, WE REFERRED TO "DATA AUGMENTING CONTRASTIVE  
LEARNING OF SPEECH REPRESENTATIONS IN THE TIME DOMAIN" (KHARITONOV ET AL., 2020)  
FROM PAPERSWITHCODE" AND USED WAVAUGMENT LIBRARY

EXECUTED THE AUGMENTATION ONCE FOR EACH DATA,  
RESULTING IN A TOTAL OF NEARLY 4,000 DATASETS



# AUDIO AUGMENTATION

Modification	Description
Pitch shift	Make lower or higher the pitch of the voice
Reverberation	Add echo to a sound signal, conveying spatial depth and width to the sound
Noise	Applying additive noise In this case, we used generated uniform noise
Time dropout	Substituting a brief segment of audio with periods of silence This method is frequently employed in the literature

# APPROACH 1

WE TOOK TWO DIFFERENT APPROACHES TO PREDICT THE CHILDREN'S PRONUNCIATION  
ONE BASED ON THE COSINE SIMILARITY COMPARISON,  
AND THE OTHER BASED ON THE FINE-TUNED MODEL PREDICTION

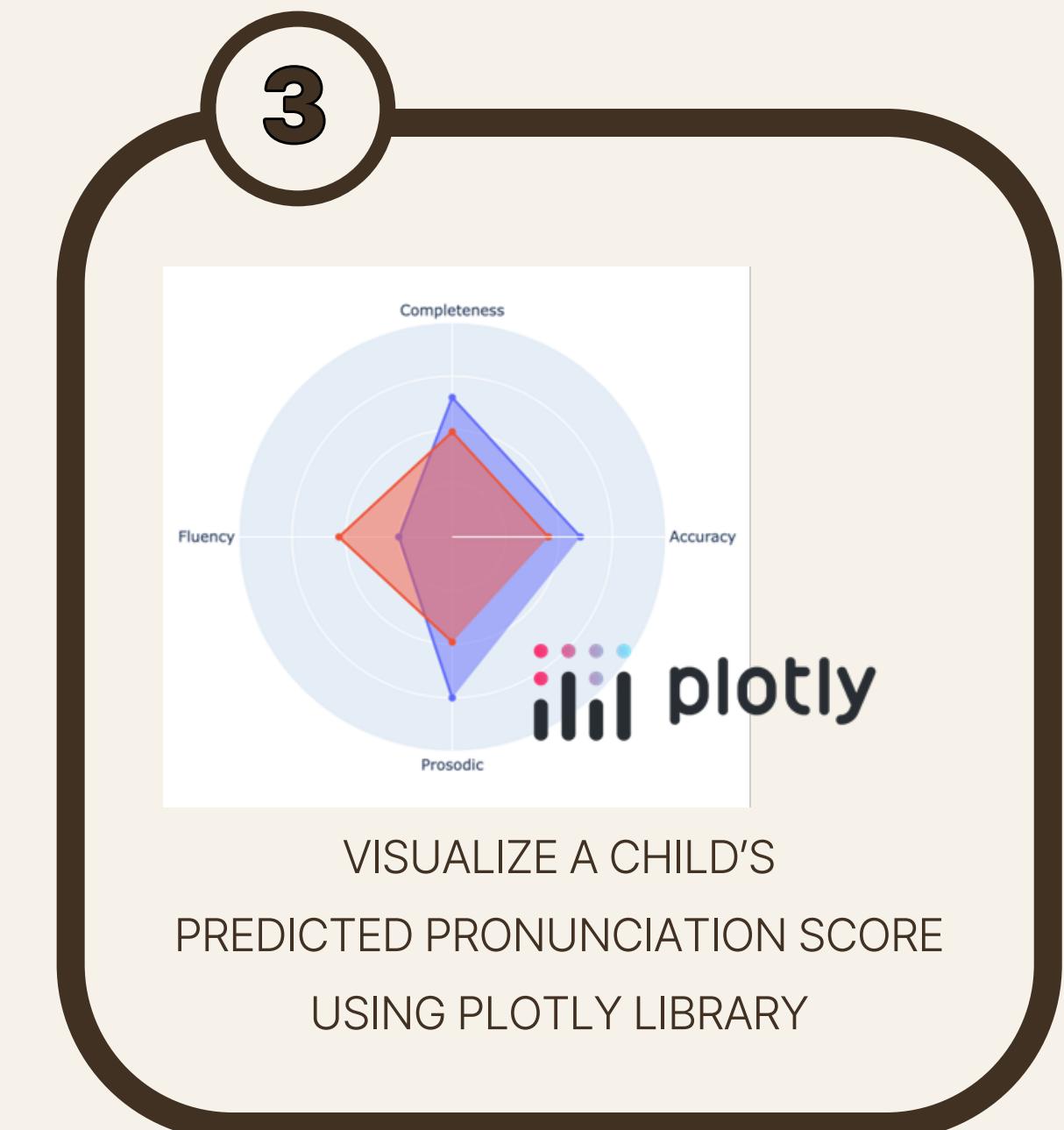
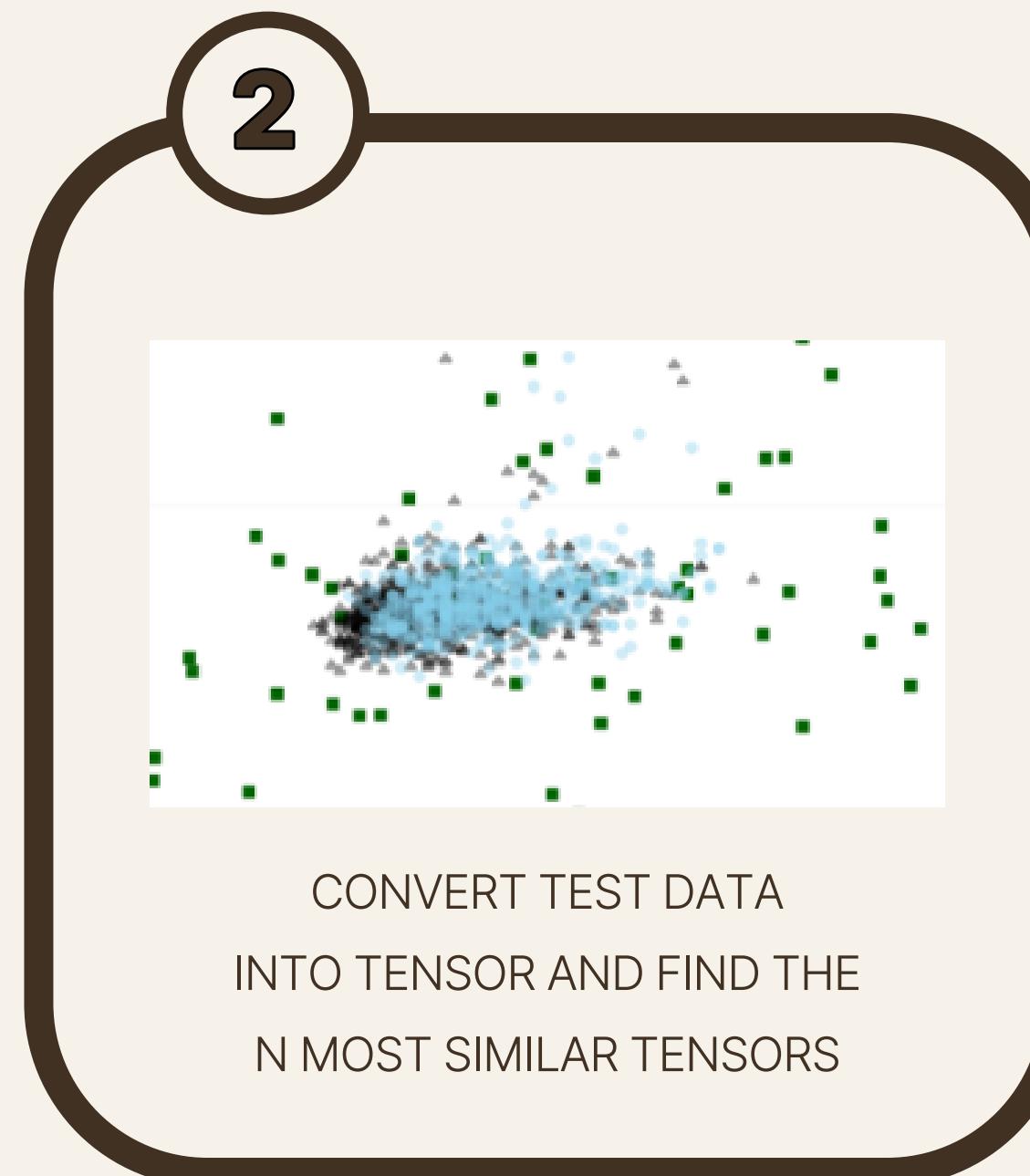
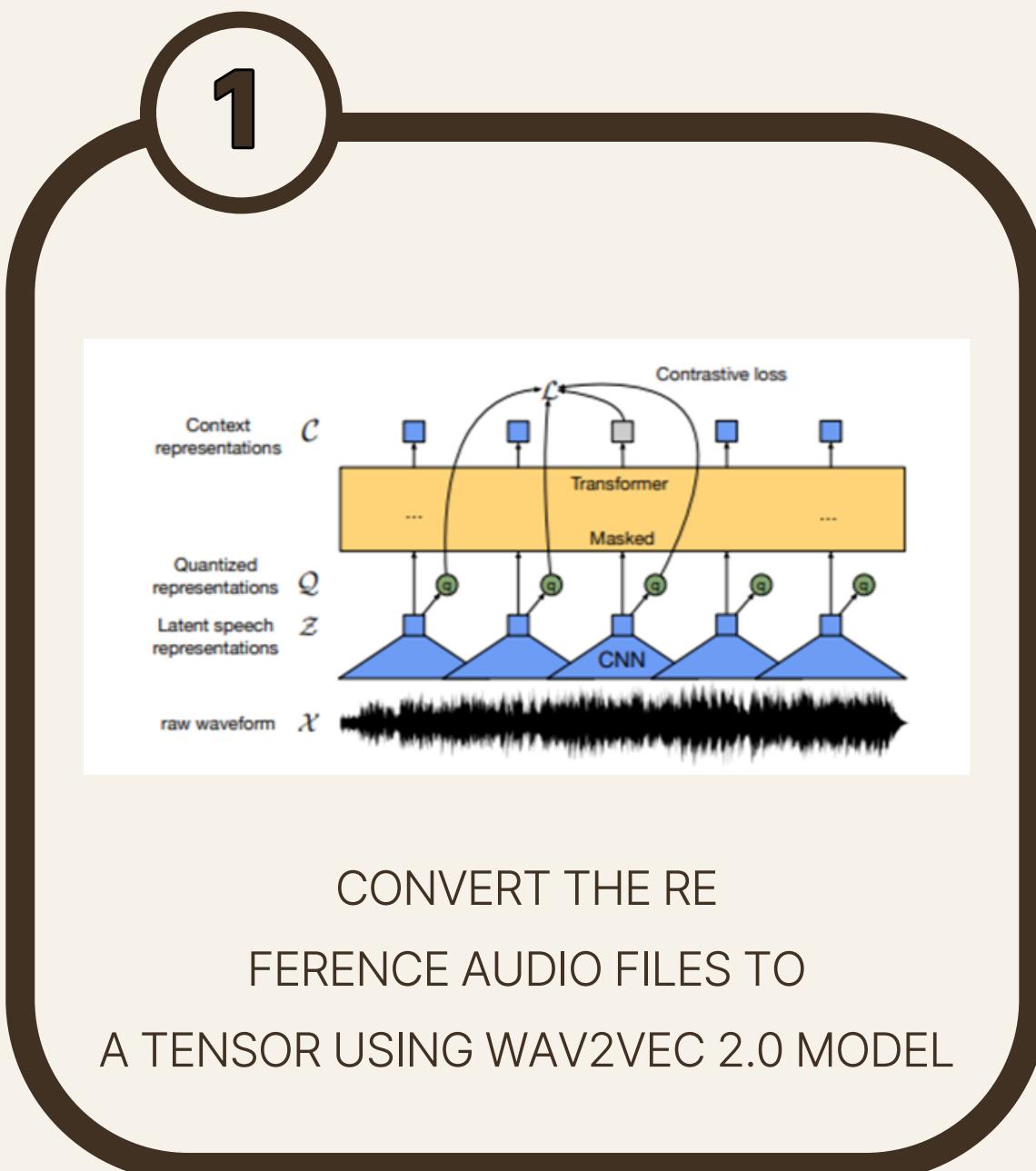
A BIG ASSUMPTION IS THAT AUDIO FILES WITH SIMILAR PRONUNCIATION  
WILL ALSO BE SIMILAR WHEN THEY ARE VECTORIZED

IF WE HAVE A REFERENCE DATA THAT CONSISTS OF VARIOUS PRONUNCIATIONS ON THE SAME PHRASE,  
WE CAN DETERMINE THE SCORE OF NEW INPUT DATA BASED ON THE REFERENCE

FOR THE USE OF \*WAV2VEC2 MODEL, WE REFERED "WAV2VEC 2.0: A FRAMEWORK FOR SELF-SUPERVISED  
LEARNING OF SPEECH REPRESENTATIONS" (BAEVSKI ET AL., 2020) FROM PAPERWITHCODE

\*WAV2VEC 2.0: MODEL DEVELOPED BY FACEBOOK, THAT LEARNS POWERFUL REPRESENTATION FROM SPEECH AUDIO  
IT IS PRE-TRAINED WITH 53,000 HOURS OF SPEECH DATA, AND IT CAN BE FINE-TUNED FOR DOWNSTREAM TASKS

# APPROACH 1



# APPROACH 2

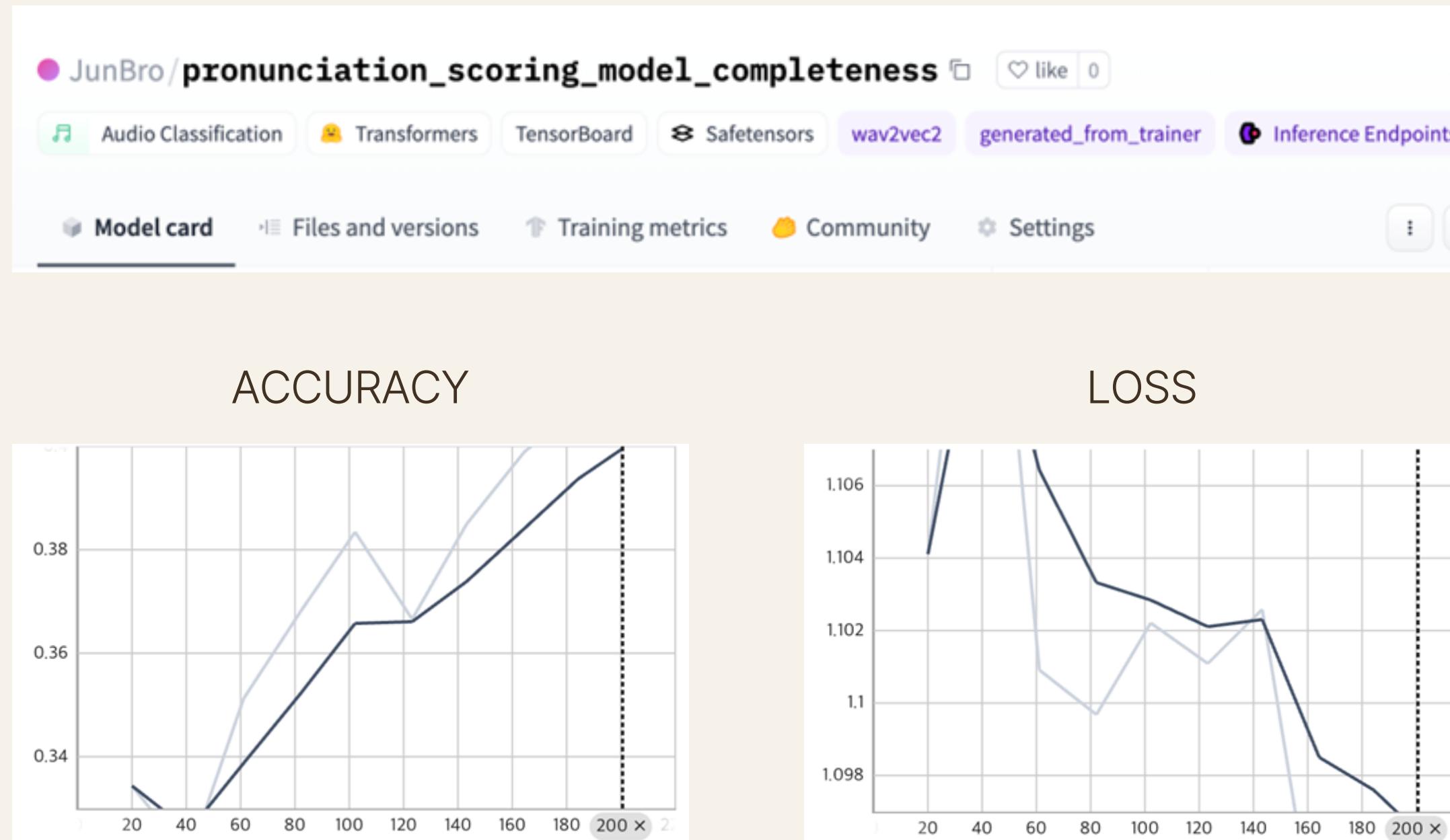
## FINE-TUNED WAV2VEC 2.0 MODEL FOR PRONUNCIATION SCORE PREDICTION

USED LABELED DATA FROM THE FEW SHOT LEARNING TO FINE TUNE THE WAV2VEC 2.0 MODEL  
AND SPLIT THEM INTO TRAIN, VALID AND TEST SET

UTILIZED HUGGING FACE'S LIBRARIES AND UPLOADED THE TRAINED MODEL  
TO OUR HUGGING FACE'S MODEL SPACE (REFER TO OUR TECH BLOG)

SINCE THERE ARE FOUR TARGET VARIABLES, THERE ARE FOUR DIFFERENT MODELS

# APPROACH 2



TRACKING THE TRAINING HISTORY

- 1) PREPROCESS THE DATASET IN SUITABLE FORMAT FOR MODEL TRAINING
- 2) FINE TUNING PRE-TRAINED MODEL IN FOUR DIFFERENT VERSIONS
- 3) USING FINE-TUNED MODELS, PREDICT THE PRONUNCIATION SCORE OF TEST FILE, AND VISUALIZE

# EVALUATION

WE EVALUATED THE MODEL PERFORMANCE  
AND VISUALIZED THE RESULT

COMPARING THE PREDICTION AND THE ORIGINAL LABELS,  
WE MADE CONFUSION MATRIX AND VISUALIZE IT AS A HEATMAP

TO CHECK VARIOUS CLASSIFICATION METRICS RESULTS,  
WE USED CLASSIFICATION REPORT METHOD FROM SCIKIT-LEARN

MODEL TENDS TO BE GOOD AT CATCHING 'BAD' PRONUNCIATION,  
SINCE IT IS VERY DISTINCTIVE FROM THE OTHERS

IF THE MANUAL LABELING STEP DONE THOROUGHLY BY EXPERTS,  
AND IF THE MANUALLY LABELED DATASET IS LARGE ENOUGH,  
THE MODEL CAN BE EXPECTED TO PERFORM BETTER

# EVALUATION

	precision	recall	f1-score	support
Bad	0.21	0.27	0.24	26
Normal	0.00	0.00	0.00	31
Good	0.40	0.53	0.46	43
accuracy			0.30	100
macro avg	0.21	0.27	0.23	100
weighted avg	0.23	0.30	0.26	100

ACCURACY

	precision	recall	f1-score	support
Bad	0.38	0.45	0.41	33
Normal	0.35	0.53	0.42	36
Good	0.50	0.10	0.16	31
accuracy			0.37	100
macro avg	0.41	0.36	0.33	100
weighted avg	0.41	0.37	0.34	100

COMPLETENESS

	precision	recall	f1-score	support
Bad	0.41	0.63	0.49	35
Normal	0.40	0.55	0.46	29
Good	0.17	0.03	0.05	36
accuracy			0.39	100
macro avg	0.32	0.40	0.34	100
weighted avg	0.32	0.39	0.32	100

FLUENCY

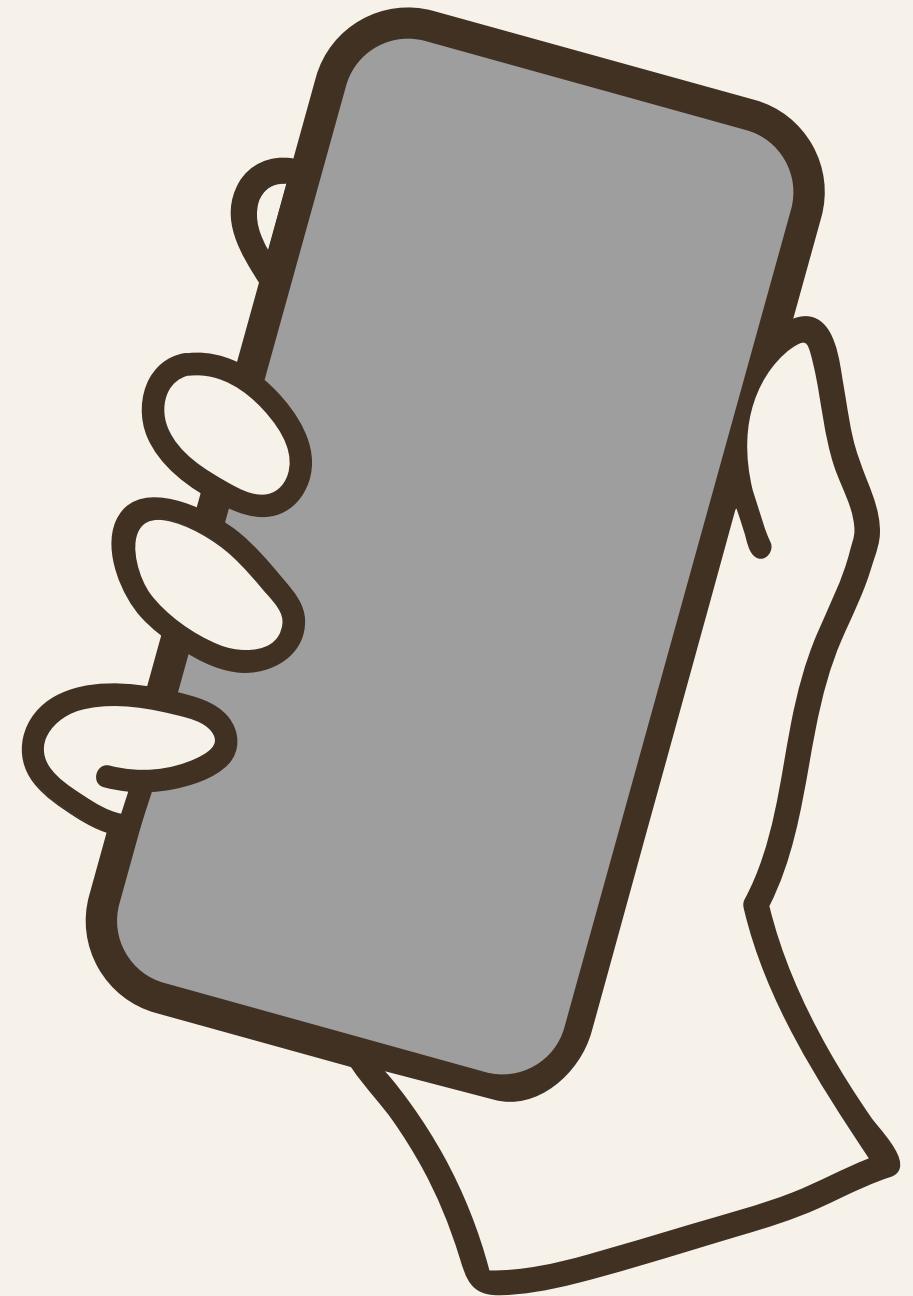
	precision	recall	f1-score	support
Bad	0.24	0.32	0.27	22
Normal	0.43	0.70	0.53	43
Good	0.00	0.00	0.00	35
accuracy			0.37	100
macro avg	0.22	0.34	0.27	100
weighted avg	0.24	0.37	0.29	100

PROSODIC

# APPLICATION GUIDE FOR PARENTS

THROUGH MANY OF THE ABOVE PROCESSES,  
WE HAVE HELPED CHILDREN LEARN MEANINGFULLY  
AND EVALUATED THEM BASED ON DATA

IT'S TIME TO SHARE THE RESULTS OF LEARNING  
WITH PARENTS TO MAKE YOUR CHILD'S LEARNING  
MORE EFFICIENT



# APPLICATION GUIDE FOR PARENTS

SCREEN THAT CONFIGURES THE APP CONSISTS OF SIX TYPES: LOGIN, HOME, STUDY LIST, AI REPORT, CHALLENGE AND PROFILE IN THE PRESENTATION, WE WILL INTRODUCE SOME SCREENS FOCUSING ON FUNCTIONS

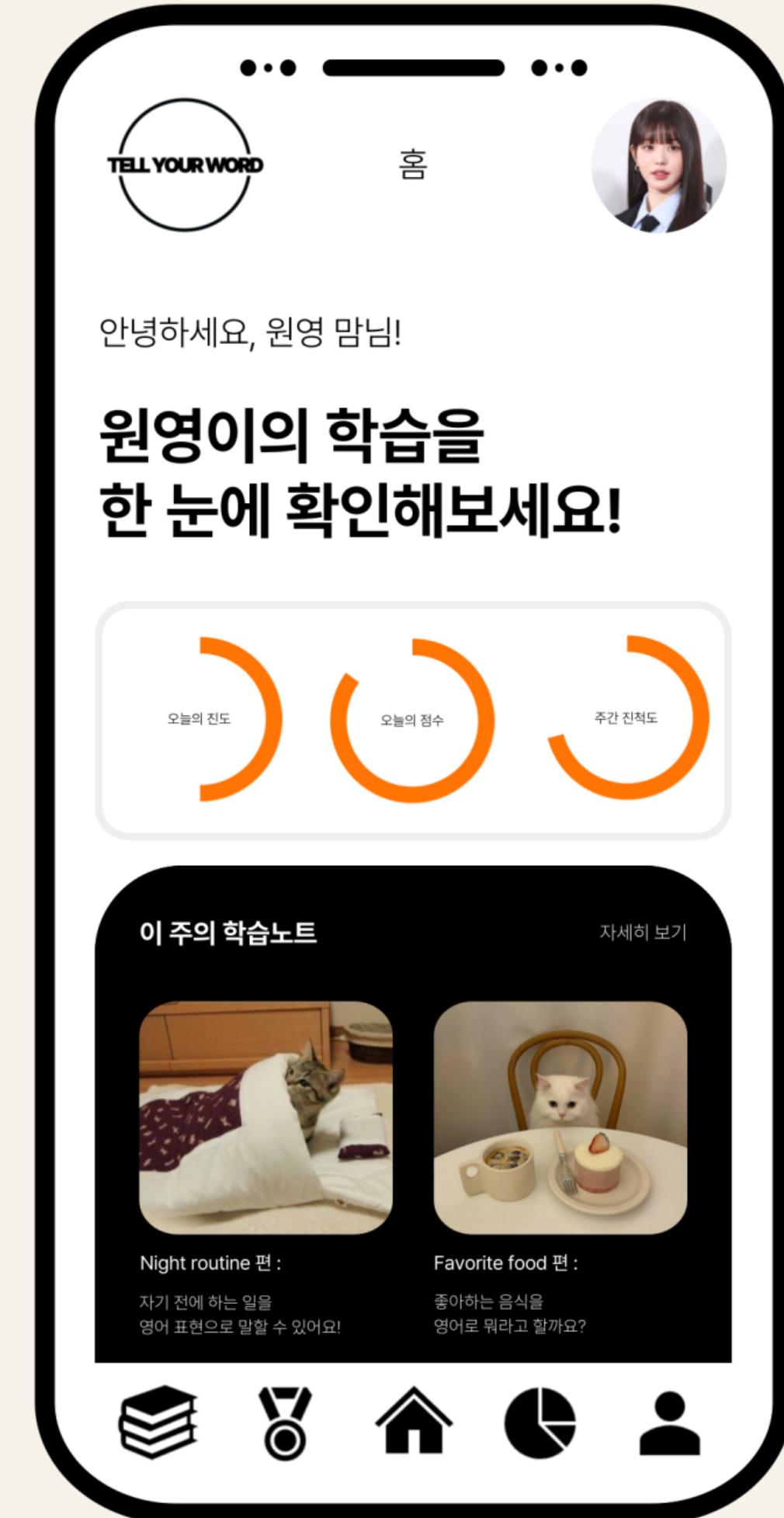


# HOME SCREEN

PROVIDE LEARNING DATA IN GRAPHS  
SO PARENTS CAN CHECK THEIR CHILD'S  
LEARNING STATUS AT A GLANCE

PROVIDE A SUMMARY OF WHAT THEIR CHILD  
LEARNED THIS WEEK

IF PARENTS WANT TO KNOW MORE,  
THEY CAN TOUCH AND GO TO  
THE LEARNING LIST SCREEN



# STUDY LIST SCREEN

PROVIDES SEARCH SERVICES BASED ON STUDY DATES OR KEYWORDS

HELP FACILITATE REVIEW BY PROVIDING WHAT THEIR CHILD HAS LEARNED IN A FILE

TO LEARN MORE ABOUT WHAT THEIR CHILD HAS LEARNED TODAY,

PARENTS CAN TOUCH THE LEARNING NOTES AND GO TO THE AI REPORT SCREEN



# AI REPORT SCREEN

DIGITIZE THE CHILD'S PRONUNCIATION,  
SCORE IT, AND VISUALIZE IT DIRECTLY  
TO HELP PARENTS UNDERSTAND IT EASILY

PROVIDES DATA SUCH AS  
VOICE SCORES BY INDICATOR,  
LEVEL COMPARED TO THE SAME AGE GROUP,  
AND INCREASE IN MONTHLY TOTAL SCORE

ADOPT A GRAPH TYPE THAT  
REPRESENTS EACH CHARACTERISTIC WELL

COMMENT AT THE BOTTOM OF THE GRAPH  
TO BRIEFLY EXPLAIN THE WEAKNESSES



# CHALLANGE SCREEN

NO MATTER HOW WELL THE CONDITIONS FOR LEARNING ARE,  
IT WILL BE DIFFICULT TO PARTICIPATE STEADILY WITHOUT  
ENCOURAGING PARTICIPATION

MOTIVATION BY PROVIDING REWARDS  
FOR LEARNING (EX) T MEMBERSHIP POINTS

REWARDED BY PERFORMING SIMPLE MISSIONS  
OR CONTINUING TO LEARN

IT'S NOT JUST A SERVICE, BUT IT GIVES YOU  
THE FEELING OF BEING A MEMBER OF YOUR CHILD'S GROWTH

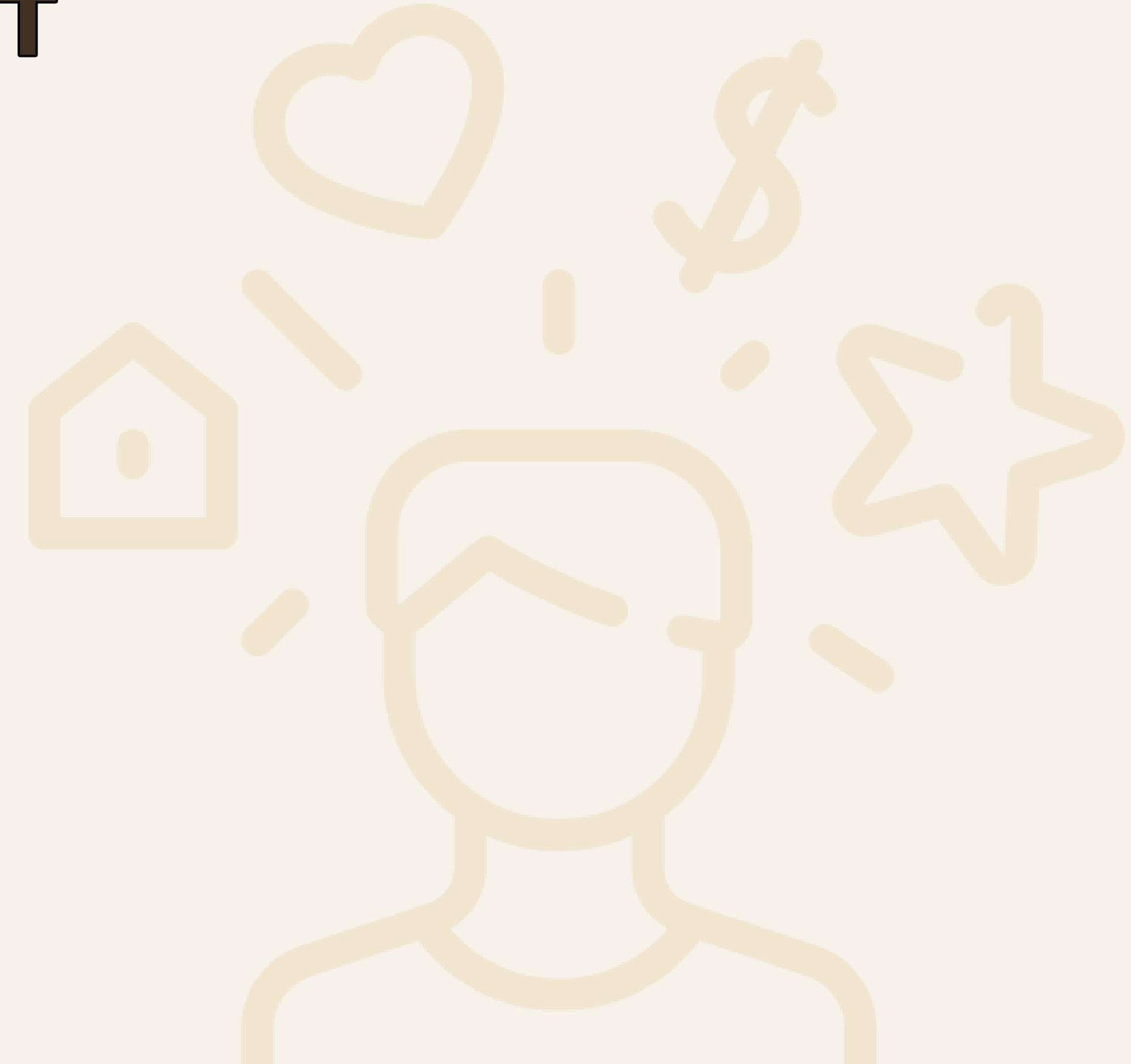


# EXPECTED ACHIEVEMENT

SUPPORTING CHILDREN TO IMPROVE  
THEIR PRONUNCIATION SKILLS

OFFERING MORE ACTIVE  
ENGLISH EDUCATION MATERIALS TO THE USERS

ANALYZING AND MAKING FUTURE WORK  
ABOUT CHILDREN'S LANGUAGE DEVELOPMENT



# LIMITATION



- NEED MORE LABELLED DATA FOR ACCURACY
- NEED PROFESSIONAL ANNOTATORS TO DETERMINE PRONUNCIATION SCORES
- NEED TO CHECK IF NUGU SPEAKER CAN SAVE SPEAKERS' .WAV DATA

THANK YOU  
FOR  
LISTENING

TELL YOUR WORDS

---

KIM JOONHEE, DEPT OF INFORMATION SYSTEM 18  
MA YUDAM, DEPT OF KOREAN LANGUAGE & LITERATURE 19  
PARK JUNHYEONG, DEPT OF BUSINESS ADMINISTRATION 18

