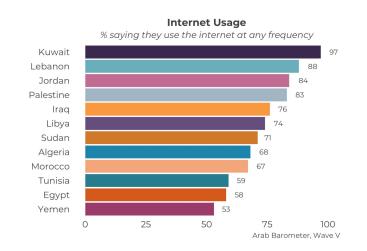
Arabic Spoken Dialect Identification (ASDI - قصدي)

Abir Messaoudi, Mayssa Kchaou and Chayma Fourati

Mentor: Desh Raj

Motivation

- Many different dialects/sub-dialects.
- Similarities and difference between dialects.
- On digital channels, Arabic speakers express
 themselves better in their own local dialect & by their
 own voices instead of textual comments.



it is important that this large part of the population understands the transmitted content!

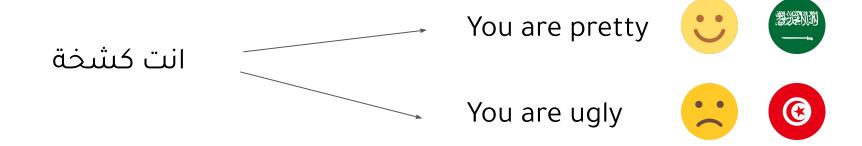
What is this?

ما هذا؟ :Modern Standard Arabic





Different meanings when switching dialects!



Challenges Automatic Speech recognition

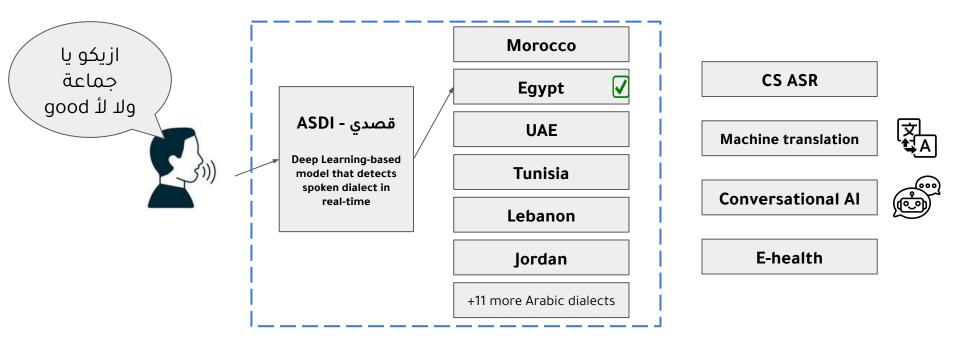
Arabic speakers tend to use **code-switching** in their daily conversation.

Existing ASR models (on Facebook, TikTok..):

- skip code-switching speech,
- Wrong transcription.

Automatically generated transcripts and subtitles can be almost error-free if we recognize dialects.

Solution



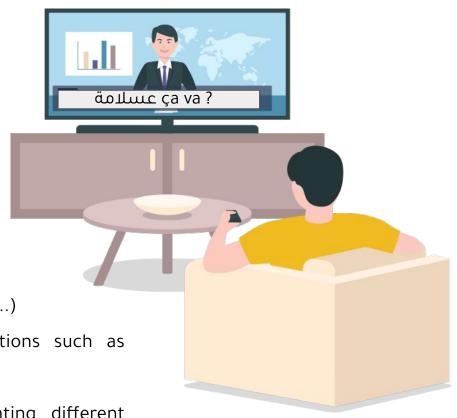
- Facilitate the speech interaction between arab nations by recognizing the speaker's dialect!
- It will be the front of multidialectal applications including: ASR, machine translation, voicebots and e-health applications!

Impact





- 2. Enhance customer services (banks, hotels, airports..)
- 3. Overcome language barriers in high-risk situations such as hospitals and courts.
- 4. Dialect maintenance: Identifying and documenting different dialects can help to preserve linguistic diversity and **prevent**Arabic dialects from dying out!





Up-to-date:

- Dialects are not static; they vary across space and time.
- New generations use phrases and vocabulary that were not in existence or use in the past.



Code-switching:

- Different accents of English and French.
- More than 30% of CS data. (Intra, inter-Sentential and intra-word.)



- Reliable:

- Didn't rely on automatic annotation.
- Annotated by Arabic native speakers!

- Sources:

- Podcast platforms,
- Youtube (vlogs, podcasts..)
- Series and movies.
- Public Arabic Speech datasets (MGB-3, Dvoice..).





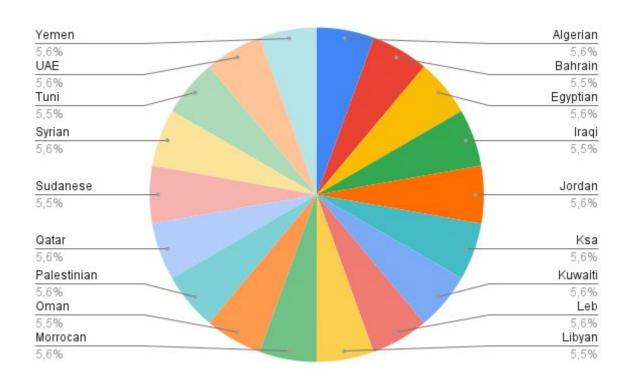


- Domains:

- Politics
- Entertainment
- Education
- Culture
- Sports
- Customer services

Total size: over **250** hours.

Balanced dataset with ~ 10 hours per dialect.

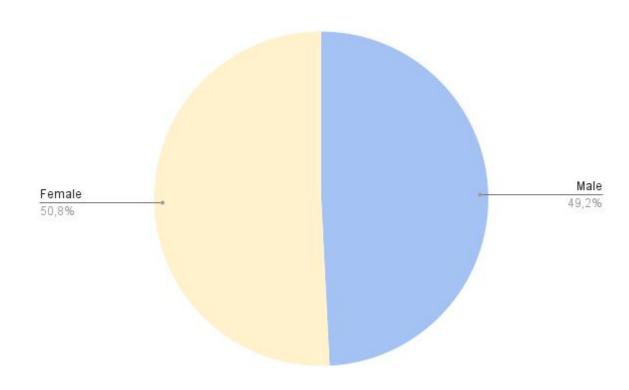


Distribution of dialects in ASDI dataset.

- 937 speakers

- 137k audios, between 2sec and 10 sec.

 Splitted into Train and validation sets.



Distribution of and Male/Female in ASDI dataset

ASDI system Roadmap

1. Finetune ASDI dataset using an already fine-tuned Arabic wav2vec 2.0 model on ASR, to better determine the context representations for the input audios.

WER	CER
23.4995	8.7133

Results of fine-tuning on Arabic ASR

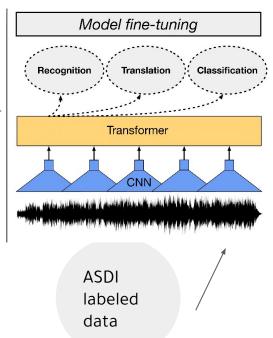
- a. Using Noisy data. (background music, noise..)
- b. Using Clean data.

ASDI system Roadmap

2. Pre-train a Multidialectal Acoustic model.

Self-supervised pre-training Wav2vec 2.0 / XLS-R Unlabeled Transformer speech: ADI 17 Masked + common voice

Finetune it on ASDI For dialect Identification



Wav2vec 2.0 architecture [1]

Thank you.

Code switching snapshot from dataset

Algerian English



Algerian French



Lebanese English



Tunisian French

