SPEAKER AND LANGUAGE CLASSIFICATION

SPEAKER IDENTIFICATION (SID)

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More or less same toolkit used for both approaches.

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  - Phonetic context = what words/sounds are produced
  - Ex: Mark or Will saying “joint factor analysis” vs. Mark saying “let’s go to the beach”

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- I generally use 'SID' as a cover term for both unless otherwise specified

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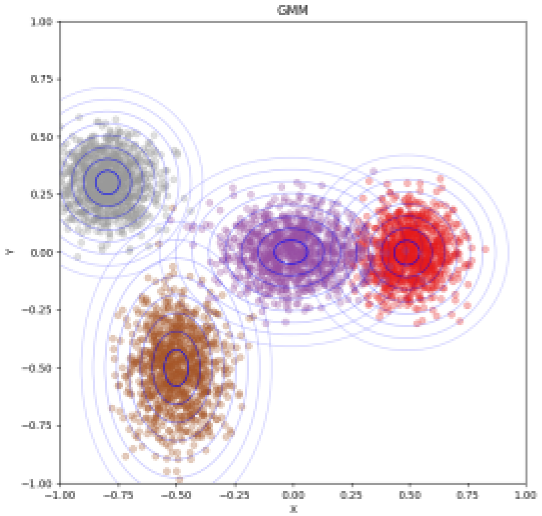

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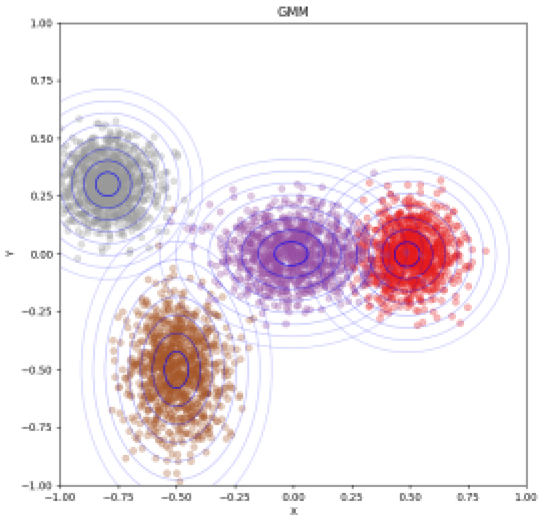

Image source: https://www.itzikbs.com/gaussian-mixture-model-gmm-3d-point-cloud-classification-primer

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This doesn't account for channel effects!

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If we know the channel and speaker for all utterances in our dataset, we can model the effects of both.

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- Take all recordings from a given channel (e.g. all phone conversations) and compute common factors
- Take all recordings from a given speaker and compute common factors
- In the process, learn matrices to **transform any vector** into its channel and speaker factors

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Intuition: once we learn the speaker vectors, we need to learn how to put them in categories.

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  - Good news: no need to train SID, bad news: need train ASR (TANSTAAFL)!!

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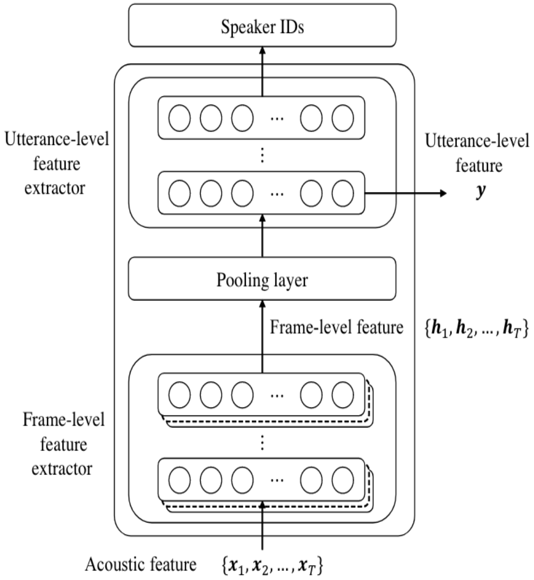

Figure 1: *DNNs for extracting utterance-level speaker features*

Okabe, Koji, Takafumi Koshinaka, and Koichi Shinoda. “Attentive Statistics Pooling for Deep Speaker Embedding.” In Interspeech 2018, 2252–56, 2018. https://doi.org/10.21437/Interspeech.2018-993.

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- Predict who's speaking for each turn

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  - (During training) use 'oracle VAD' (cheating)

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- Problem: what if there's a speaker change within the window length?

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- Model rewarded so long as each speaker is distinguished from each other within the utterance

	1	**2**	**3**	**4**	**5**	**6**	**7**
Prediction	A	A	A	C	C	C	E
Label	Sally	Sally	Sally	Bob	Bob	Bob	J

	1	2	3	4	5	6	7
Prediction	A	A	A	C	C	C	B
Label	Sally	Sally	Sally	Bob	Bob	Bob	J

Correct: A=Sally, B=John, C=Bob, model is rewarded

	1	**2**	**3**	**4**	**5**	**6**	**7**
Prediction	B	B	A	C	C	C	B
Label	Vlad	Vlad	Jane	Kim	Kim	Kim	Vl

	1	2	3	4	5	6	7
Prediction	B	B	A	C	C	C	B
Label	Vlad	Vlad	Jane	Kim	Kim	Kim	Vl

Also correct: A=Jane, B=Vlad, C=Kim, model is rewarded

	1	**2**	**3**	**4**	**5**	**6**	**7**
Prediction	B	A	A	C	C	A	A
Label	Jo	Jo	Dan	Dan	Miguel	Dan	Dan

	1	2	3	4	5	6	7
Prediction	B	A	A	C	C	A	A
Label	Jo	Jo	Dan	Dan	Miguel	Dan	Dan

Incorrect: A={Jo,Dan}, B={Jo}, C={Dan,Miguel}, model fails

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- we can add in class D = silence to perform VAD alongside diarization!

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- E.g. speaker A from window 1 sure sounds a lot like speaker C from window 5, maybe they're the same person?

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- 'What language is this audio in?'
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- I use SLI b/c LID can also be classifying language of text

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- More likely that you will do inference on same subset of categories you train on
  - E.g. if you're identifying Spanish and English sentences in bilingual movies, you just need to train on Spanish and English

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  - Doesn’t work well-a single HMM state isn’t good at modeling a whole language

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  - Works much better, but now we need phonemic labels for each language!

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- Phonotactic LMs are easy to train as long as we have a decent chunk of text in the language
- We can even use a language-independent phone recognizer and get language ID solely from the phonotactic LMs!

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  - Like SID, SLI x-vectors can distinguish unseen languages
  - Use multilingual DNN BNFs as input features.

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- There is way less work done on LD relative to any other task discussed today.

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- (Languages can change much faster than participants in a conversation)

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- "Hey bro, you gave me this audio to stare at for hundreds of hours, here's the language and speaker identity of each utterance" - unsupervised NN

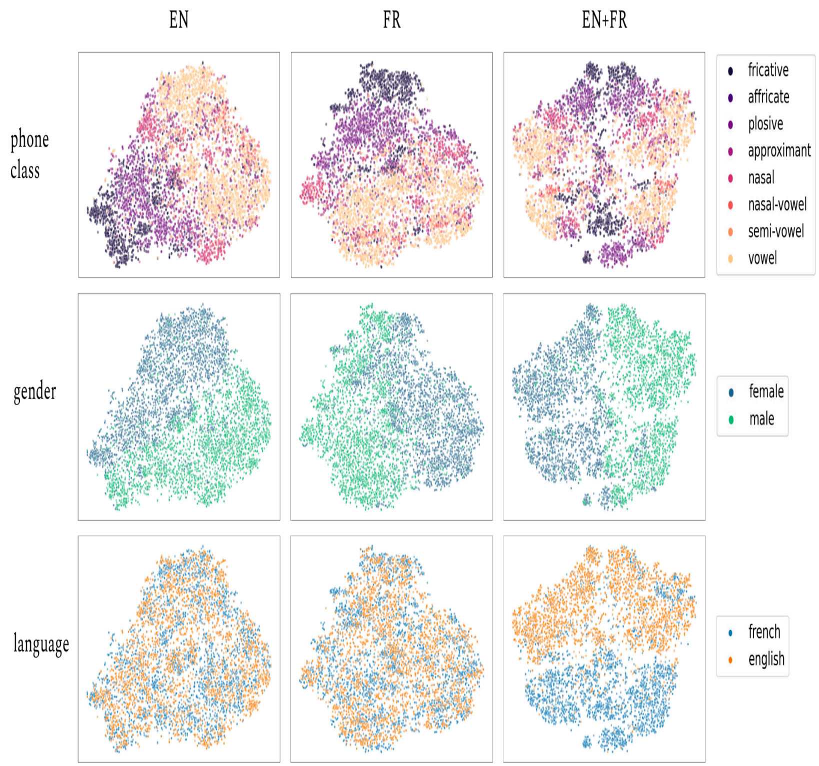

Figure 1: *T-SNE visualisation of English and French phone embeddings at the CPC level, for monolingual (EN and FR) and bilingual (EN+FR) models. Embeddings are colored based on their phone class label, gender label and language label.*

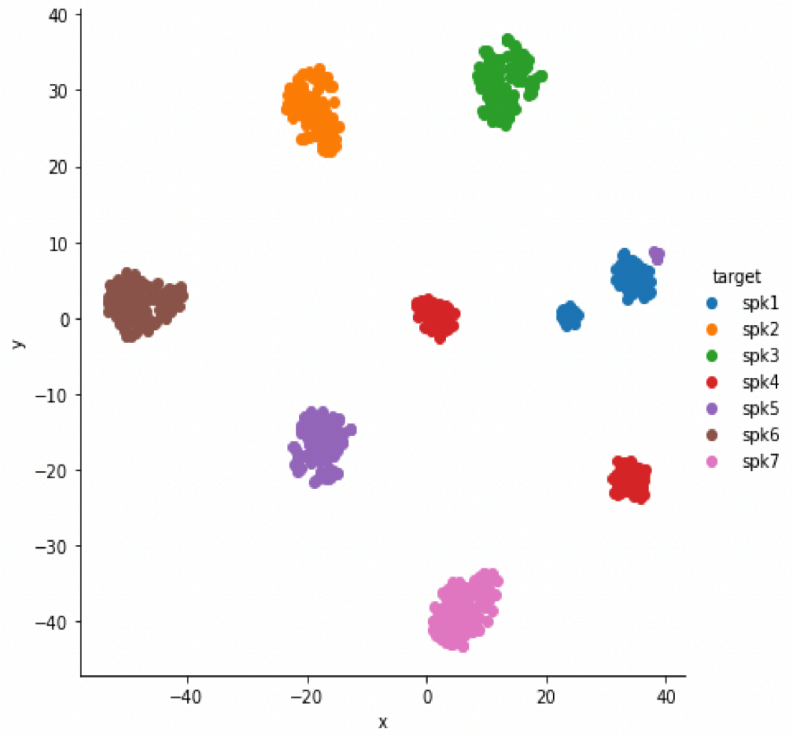

Fig. 2. t-SNE plot of the mean context vector, $\bar{c}^i$, computed for 50–10(
utterances each, from a set of 7 speakers in the LibriSpeech dataset.

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- SD and LD are ways of identifying speaker and language changes in continuous audio
- Standard method is to encode audio as some sort of vector which can be scored for its identity
- Neural networks allow us to engineer some fun end-to-end methods, and can also completely disrespect decades of feature engineering by performing SID and SLI *by accident.*

THANK YOU!