Multilingual and Low-Resource Speech Recognition

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Automatic Speech Recognition – ASR Lecture 14
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Languages of the World

- Over 6,000 languages globally....
- In Europe alone
  - 24 official languages and 5 “semi-official” languages
  - Over 100 further regional/minority languages
  - If we rank the 50 most used languages in Europe, then there are over 50 million speakers of languages 26-50 (Finnish – Montenegrin)
- 3,000 of the world’s languages are endangered
- Google cloud speech API covers over 98 languages and more than 300 accents/dialects of those languages; Apple Siri covers over 21 languages; Google assistant has over 30

Under-resourced languages

Under-resourced (or low-resourced) languages have some or all of the following characteristics

- limited web presence
- lack of linguistic expertise
- lack of digital resources: acoustic and text corpora, pronunciation lexica, ...

Under-resourced languages thus provide a challenge for speech technology

See Besaciera et al (2014) for more

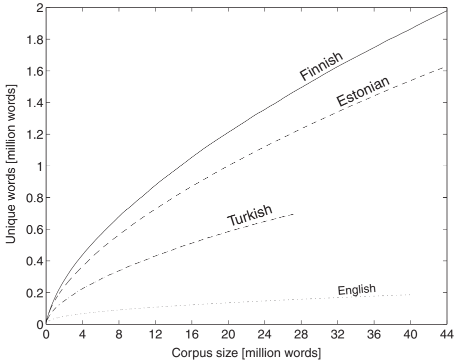
Speech recognition of under-resourced languages

- Training acoustic and language models with limited training data
- Transferring knowledge between languages
- Challenge of constructing pronunciation lexica
- Dealing with language specific characteristics (e.g. morphology)
- Prevalence of code-switching

Morphology

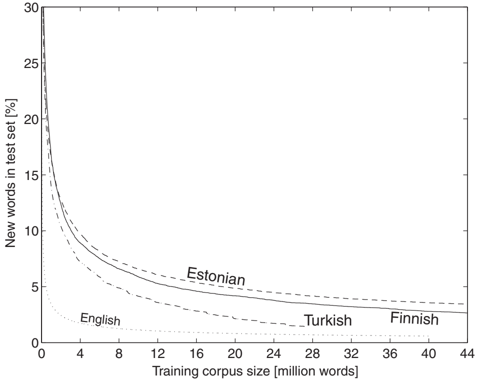
- Many languages are morphologically richer than English: this has a major effect of vocabulary construction and language modelling
- Compounding (eg German): decompose compound words into constituent parts, and carry out pronunciation and language modelling on the decomposed parts
- Highly inflected languages (eg Arabic, Slavic languages): specific components for modelling inflection (eg factored language models)
- Inflecting and compounding languages (eg Finnish, Estonian)
- All approaches aim to reduce ASR errors by reducing the OOV rate through modelling at the morph level; also addresses data sparsity

Vocabulary size for different languages



Creutz et al (2007)

OOV Rate for different languages



Creutz et al (2007)

Segmenting into morphs

- Linguistic rule-based approaches – require a lot of work for an under-resourced language!
- Automatic approaches – use automatically segment and cluster words into their constitutent morphs
- Morfessor (http://www.cis.hut.fi/projects/morpho/)
  - "Morfessor is an unsupervised data-driven method for the segmentation of words into morpheme-like units."
  - Aims to identify frequently occurring substrings of letters within either a word list (type-based) or a corpus of text (token-based)
  - Uses a probabilistic framework to balance between few, short morphs and many, longer morphs
- Morph-based language modelling uses morphs instead of words – may require longer context (since multiple morphs correspond to one word)

Code switching

- Code switching can be common in low-resource languages
- Hard to model if only monolingual training data is available
- Can interpolate monolingual language models, but how to predict likely switching points?
- Need to consider if there is a change in phonology

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"masithi 3 o'clock ke eclocktower mamela kyk hier ndiyamazi i know him i got him ... ndizithi kuye masiye e waterfront i wont tell him that i'm meeting a friend but ndiyayazi he wont mind xasidibana nawe he will buy us drinks and some lunch then sonwabe wethu"

Multilingual and cross-lingual acoustic models

How to share information from acoustic models in different languages?

- General principle: share model parameters across languages, learning a multilingual representation of speech
- In neural network acoustic models, share hidden layers between languages
- Can share phone sets or map them between languages...
- ... but output layers are often monolingual, language specific

Multilingual and cross-lingual acoustic models

Methods to avoid a shared phoneme inventory

- General principle: share model parameters across languages, learning a multilingual representation of speech
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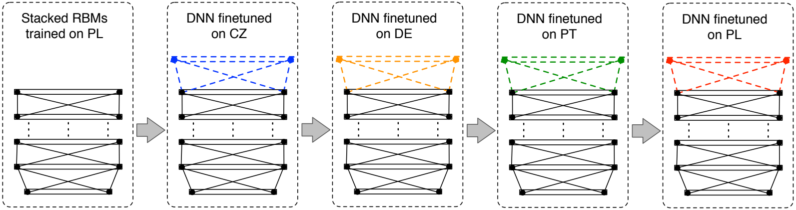
- Can share phone sets or map them between languages...
- ... but output layers are often monolingual, language specific

Multilingual and cross-lingual acoustic models

- **Multi-lingual phone sets** – use a network with multilingual hidden representations directly in a hybrid DNN/HMM system
- **Hat-swap/multi-task** – train a network with an output layer for each language, but shared hidden layers
- **Multilingual bottleneck** – use a bottleneck hidden layer (trained in a multilingual) way as features for either a GMM- or NN-based system
- **Pre-train** without phonetic labels in a language-independent manner

Hat Swap – architecture

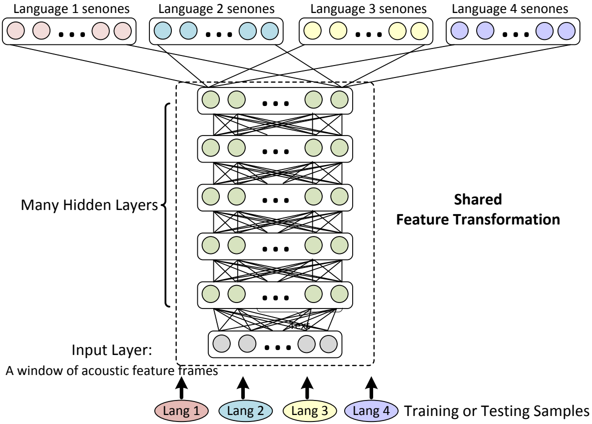


Ghoshal et al, 2013

Multi-lingual networks ("block softmax")

- Train one network for all languages:
  - separate output layer for each language
  - shared hidden layers
- Each training input is propagated forward to the output layer of the corresponding language – only that output layer is used to compute the error used to train the network for that input
- Since the hidden layers are shared, they must learn features relevant to all the output layers (languages)
- Can view this as a parallel version of hat swap

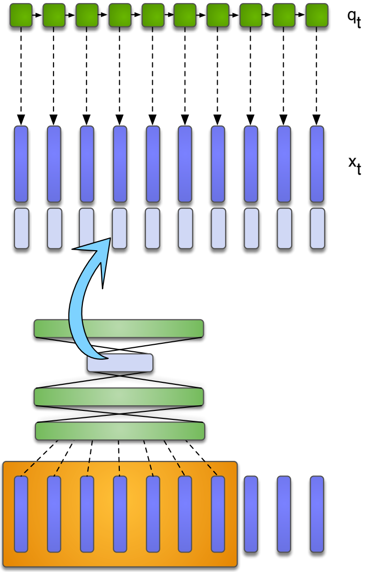
Multi-lingual networks – architecture



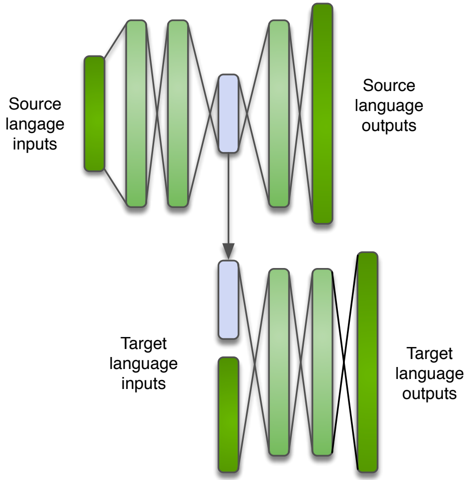
Huang et al, 2013

NB: A senone is a context-dependent tied state

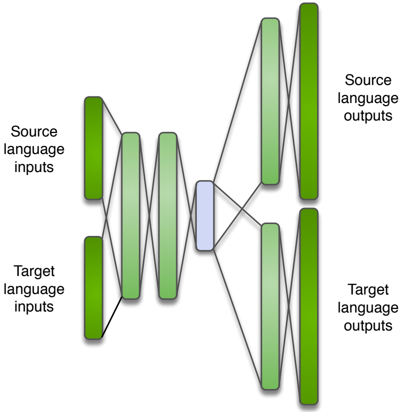
Bottleneck features



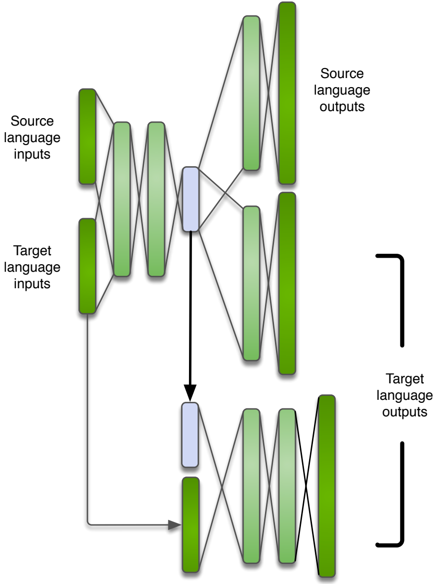
Cross-lingual bottleneck features



Multi-lingual bottleneck network



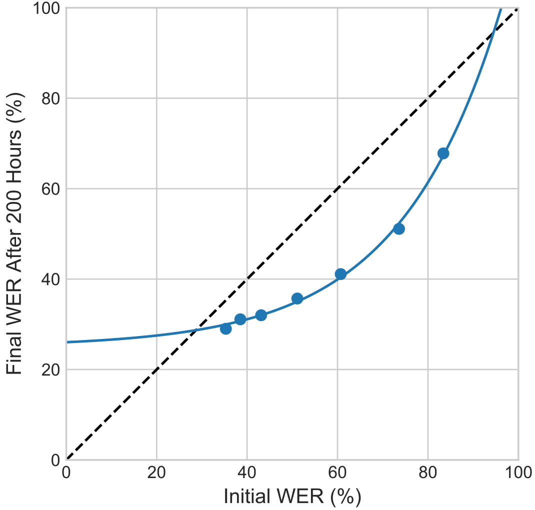
Use of BN features in HMM/DNN systems



Semi-supervised training

- Assume we only have a only a small amount of data is transcribed, but much more untranscribed data $\rightarrow$ train a seed model and use it to transcribe more data
- But don't want to train further on incorrect captions
- Traditional solution: apply data filtering based on confidence scores
- This can select out the harder data that is most useful for refining the system
- Solution (Manohar, 2018): use a lattice to incorporate uncertainty about the transcription, train with MMI criterion (see next lecture)
- Requires a strong language model for the best performance (Wallington et al, 2021)

Example: Tagalog



From Wallington et al (2021)

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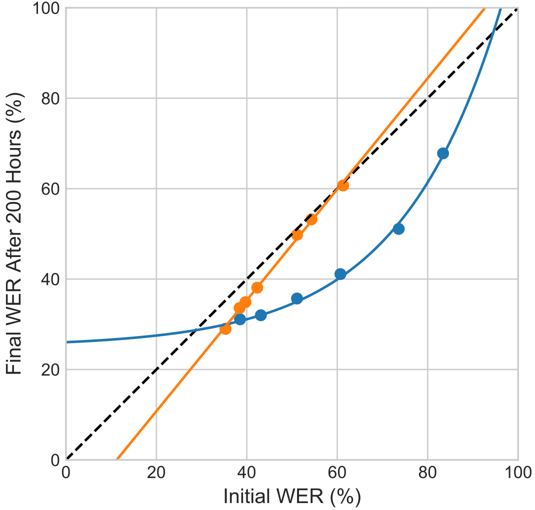

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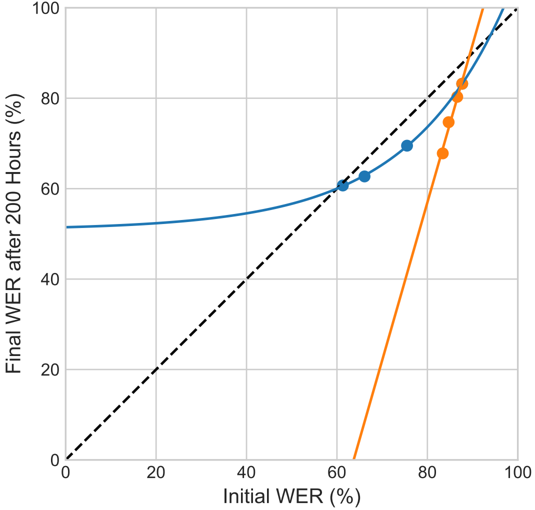
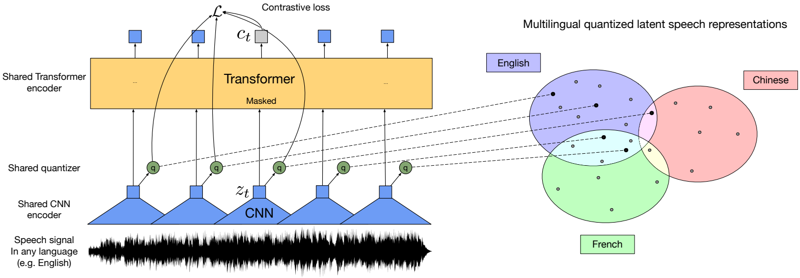


From Wallington et al (2021)

Pre-training

- Pre-train the network without using label information
- Can pre-train on multilingual or single language data, then fine tune on the target language
- Examples:
  - RBM pre-training (Swietojanski et al, 2012)
  - Self-supervised training (Conneau et al, 2020)

Self-supervised training



Conneau et al, 2020

Graphemes and phonemes

- Can represent pronunciations as a sequence of graphemes (letters) rather than a sequence of phones
- A standard feature of "end-to-end" ASR (see lectures 16 and 17)
- Advantages of grapheme-based pronunciations
  - No need to construct/generate phone-based pronunciations
  - Can use unicode attributes to assist in decision tree construction
- Disadvantages:
  - may not always be a direct link between graphemes and sounds (eg. in English)
  - Orthographic representation may not be very efficient (eg. Xhosa, Gaelic)

Grapheme-based ASR results for 6 low-resource languages

Language	ID	System	WER (%) tg	+cn	cnc
Kurmanji Kurdish	205	Phonetic	67.6	65.8	64.1
		Graphemic	67.0	65.3	
Tok Pisin	207	Phonetic	41.8	40.6	39.4
		Graphemic	42.1	41.1	
Cebuano	301	Phonetic	55.5	54.0	52.6
		Graphemic	55.5	54.2	
Kazakh	302	Phonetic	54.9	53.5	51.5
		Graphemic	54.0	52.7	
Telugu	303	Phonetic	70.6	69.1	67.5
		Graphemic	70.9	69.5	
Lithuanian	304	Phonetic	51.5	50.2	48.3
		Graphemic	50.9	49.5	

IARPA Babel, 40h acoustic training data per language, monolingual training; cnc is confusion network combination, combining the grapheme- and phone-based systems
Gales et al (2015)

Very large multilingual models

- Very recent systems are trained on massively multilingual speech data
- Eg. OpenAI's *Whisper* is trained on 680,000 hours from a set of 97 languages
  - 117,000 hours of non-English speech data
- Output is a universal grapheme set
- Whisper also integrates language detection and speech translation

Speech recognition systems for low-resource languages

- Morph-based language modeling
- Transferring data between acoustic models based on multilingual hidden representations
- Grapheme-based pronunciation lexica
- Massively multilingual models

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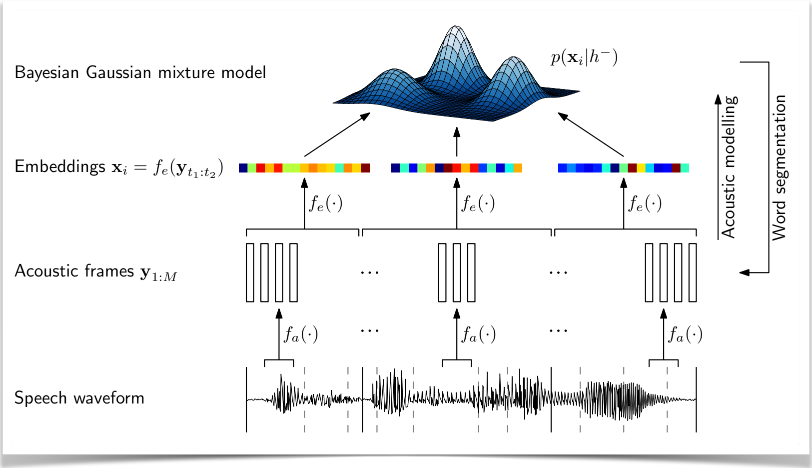
Ongoing work:

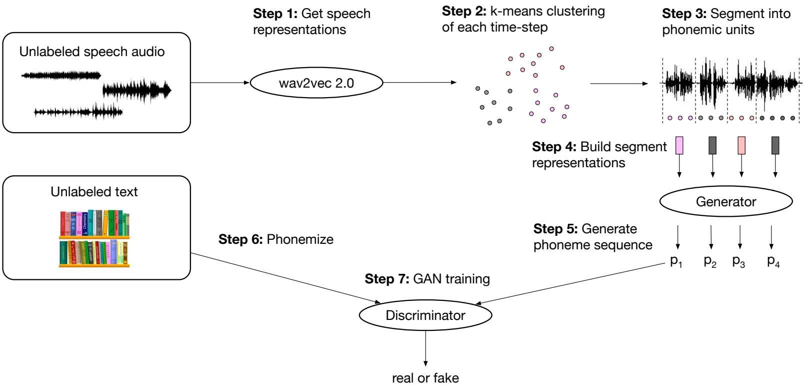
- "Zero-resource" ASR (no transcribed speech data at all)
- Languages without written forms
- Much active research in this area (including at Edinburgh)

Bottom-up approaches (1)



Kamper et al, 2017

Bottom-up approaches (2)



Baevski et al, 2021

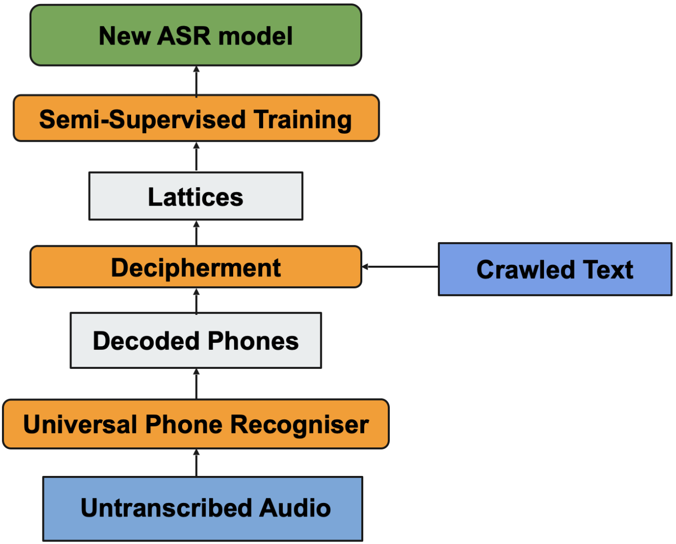
Top-down approaches

- Use a multilingual phone set
- Need a pronunciation model to map from words/graphemes to phones for each new language

$$P(X|W) = \underbrace{P(X|Q)}_{\text{Language universal}} \times \underbrace{P(Q|W)}_{\text{Learn for each language}} \times \underbrace{P(W)}_{\text{Train as normal}}$$

- Obtain pronunciation model in an unsupervised manner:
  - Universal grapheme-to-phoneme model with a phylogenetic tree to associate closely-related languages (Li et al, 2022)
  - Learn the mapping using a "decipherment" approach (Klejch et al, 2022)

Decipherment: full pipeline



Reading (1)

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Reading (2)

- M. Creutz et al (2007). "Morph-based speech recognition and modeling OOV words across languages", *ACM Trans Speech and Language Processing*, 5(1). http://doi.acm.org/10.1145/1322391.1322394
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Reading (3)

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