Automatic Speech Recognition: Introduction, Current Trends and Open Problems

Laurent Besacier

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1. The speech signal
2. 1990-2015: Bayes, HMMs, GMMs
3. 2015: neural nets to the rescue
4. 2020: 3 main ASR architectures used today
5. 2021: Self-Supervised Learning (SSL) for Speech
6. 2022: Multimodal Speech-Text Pre-trained Models
7. Future: is ASR a solved problem ?

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Speech facts

- Speech generally conveys a (linguistic) message (that can be reduced to a transcript)
- But not only (paralinguistics: speaker identity, speaker mood, speaker health condition, speaker accent, etc.)
- Variability at all levels (intra speaker, inter speaker, microphone, phone line, room acoustics, style)
- Speech is a continuous signal (no explicit word boundaries)
- May be decomposed into elementary units of sound (phonemes) that distinguish one word from another in a particular language (minimal pairs)
  - *kill* vs *kiss* - *pat* vs *bat*
  - phoneme set is language dependent
  - acoustic realization of the phoneme is dependent of its left and right neighbors (co-articulation)

(Main) Speech tasks

- Speech compression (solved)
- Speaker recognition (strong progresses over the last 10 years but still poor compared to other biometric modalities like fingerprint and iris)
- Text-to-speech synthesis (can still gain in naturalness but new progresses with DL: Wavenet, Tacotron2, VoiceLoop)
- **Speech-to-text (this talk)**
- Speech paralinguistics (early days): detection of gender, age, deception, sincerity, nativeness, emotion, sleepiness, cognitive disorders, (drug or alcohol) intoxication, pathologies, etc.
- Main speech conference: *Interspeech* (core A, every year)

Speech-to-text

- Automatic Speech Recognition (ASR)
- Ideally we want to have a system that deals with: spontaneous speech, multi-speakers, unlimited output vocabulary, any acoustic condition
- But performances differ greatly for different contexts (read vs spontaneous speech ; small vs large vocabulary ; quiet vs noisy; native vs non-native speech)

Figure: NIST ASR benchmark tests history (< 2015)

ASR as a partial task in a larger system

- ASR for spoken language processing (speech understanding, speech translation, speech summarization, etc.)
- Not just a problem of noisy transcripts
- No sentence boundaries, punctuation, case
- Disfluencies in spontaneous speech: false starts, fillers, repaired utterances
  - btw, should we keep them or remove them ?
  - some speech tasks are ill defined (ex: speech translation)
- Time to work on end-to-end approaches from speech ?

Speech representations

- Handcrafted feature vectors
  - standard extraction on sliding windows of 20-30ms at a frame rate of 10ms
  - filterbanks (signal energy in different frequency bands)
  - cepstral coefficients (inverse Fourier transform of the logarithm of the estimated spectrum of a signal)
  - linear predictive coding (a sample is predicted as a weighted sum of preceding samples and weights are used as features)
  - prosodic features (pitch, energy)
- Raw waveform ($>$ 2015)
  - bypass handcrafted preprocessing
  - preprocessing become part of the acoustic modeling and training
  - introducing convolutional layers in the first stages of the NN pipeline

Speech representations

- Spectrograms ($<$ 1990 and $>$ 2015!)
  - time-frequency representation that is actually similar to sequence of filterbanks ...
  - ... but processed as an image

Figure: Speech signal (top) and spectrogram (bottom)

- Self-supervised learnt representations ($>$ 2020 see next courses!)

Progresses over the years

Figure: ASR Performance[1] on English Conversational Telephony (Switchboard)

[1] Image from Bhuvana Ramabhadran' s presentation at Interspeech 2018

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Fundamental equation

x: observation (signal or features)
w: a word sequence

$$w^* = argmax_w p(w/x) = argmax_w p(x/w).p(w) \quad (1)$$

$p(x/w)$: acoustic model
$p(w)$: language model

Lexicons

- For acoustic modelling in large vocabulary speech recognition, we model phones instead of full words
- A pronunciation lexicon gives the decomposition of words into phonemes
- Adding a new word to the output vocabulary does not require retraining of the acoustic models
  - just add an entry to the pronunciation lexicon
  - *cat* /k a t/
- Hierarchical modelling of speech (signal/phones/words/utterance)

Hierarchical modelling of speech

Figure: From speech to utterances[2]

[2] Image from Steve Renals's lecture on ASR

ASR overview

Figure: ASR Overview

Acoustic modeling: HMM/GMM

- Complex sequential patterns of speech decomposed into piecewise stationary segments
- Sequential structure of the data described by a sequence of states
  - HMM (Hidden Markov Models) transitions
- Local characteristics of the data described by a distribution associated to each state
  - GMM (Gaussian Mixture Models) observations (outputs)

Figure: HMM/GMM approach

HMMs

- Well known algorithms for
  - *training* the model parameters (Baum-Welch algo.)
  - *decoding* the most probable hidden state sequence (Viterbi algo.)
  - *evaluate* the likelihood of an observation being generated by a HMM (Forward algo.)
- Phonemes are generally modeled in context (1 phoneme = N HMMs)
  - triphones or quintphones (model co-articulation)
  - state or parameter tying to reduce model complexity

Language models: from N-grams to RNNs

For a sequence of T words $W = w_1, w_2, ..., w_T$

$$P(W) = \prod_{k=1}^{T} P(w_k | w_1, w_2, ..., w_{k-1}) \tag{2}$$

$$P(W) = \prod_{k=1}^{T} P(w_k | h) \tag{3}$$

n-gram LM: $h = w_{k-n+1}, w_{k-n+2}, ..., w_{k-1}$
recurrent neural network LM: $h = rnn_state(E(w_1), E(w_2), ..., E(w_{k-1}))$

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NNs in the 90s and 00s

- Introduced in the 80s and 90s to speech recognition, but extremely slow and poor in performance compared to the state-of-the-art HMM/GMM
- Several papers published by ICSI, CMU, IDIAP several decades ago!
- Pros: no assumption about a specific data distribution
- Cons: slow and do not scale to large tasks

NNs for acoustic modeling (1990-2010)

- In most approaches, NNs model the posterior probability $p(s|x)$ of an HMM state s given an acoustic observation x
- Existing HMM speech recognizers can be used
- This model is known as hybrid NN-HMM and was introduced by Renals et al. (1994)

Figure: Hybrid NN-HMM

NNs for language modeling (1990-2010)

- Rescoring a lattice of output hypotheses using NN LM instead of N-gram
- Introduced by Bengio et al. (2003)
- Extended to large vocabulary speech recognition (Schwenk, 2007)
- Reducing computational complexity
  - using shortlist at output layer (Schwenk, 2007)
  - hierarchical decomposition of output probabilities (Morin and Bengio, 2005; Mnih and Hinton, 2008; Le et al., 2011)
- Recurrent neural networks were used in LM training (Mikolov et al., 2010)

Deep learning breakthrough

Like in vision, due to

- More data
  - ex: (2015) Librispeech (en) 1,000h (Panayotov et al., 2015)
  - ex: (2016) Baidu Deep Speech 2 (en) 12,000h (Amodei et al., 2016)
  - ex: (2017) Google Home (en) 18,000h (from a Google presentation)
  - ex: (2018) Google wav2words (en) >100.000h (informal discussion)
  - ex: (2021) Meta XLS-R >436,000h (Babu et al., 2021) (self-supervised)
  - ex: (2022) OpenAI Whisper model trained on 680,000 hours of multilingual speech[3] (Alec Radford, 2022)
- Computation (ex: GPU)
- Better optimization algorithms and training objectives
- ASR Toolkits (ex: Kaldi (Povey et al., 2011) and DL frameworks (Tensorflow, Pytorch)

[3] >75 years of speech !

End-to-end ASR (get rid of HMMs)

Approaches for end-to-end ASR

- Connectionist Temporal Classification (CTC)
  - Solves the problem of unaligned input and output sequences by marginalizing the conditional likelihood of the output sequence given the input over all possible alignments
- Attention Modeling
  - Simultaneously optimize alignment and grapheme (or word) decoding using attention weights (linear combination of hidden states) to influence the generated output
- Transducer-based
  - Allow to decouple the acoustic model from the language model; elegant to leverage larger amounts of raw text (for LM)

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CTC loss function

Figure: CTC Overview [4]

CTC overview

- Connectionist Temporal Classification
- Model will learn to align the transcript itself during training (Graves et al., 2006)
- Defined over a label sequence z (of length M)
- *blank or* _ symbol allows M-length target sequence to be mapped to a T-length sequence x[5]
- z can be represented by a set of all possible CTC paths (sequence of labels, at frame level) that are mapped to z
  - ex: M=2 ($z = hi$) and T=3 (3 frames): possible sequences are 'hhi', 'hii', '_hi', 'h_i', 'hi_'
- Probability $p(z/x)$ evaluated as sum of probabilities over all possible CTC paths (using Forward-Backward)
- Generate frame posteriors at decoding time

[5] gives the model the ability to say that a certain audio frame did not produce a character

CTC loss function

$$p(Y \mid X) = \sum_{A \in \mathcal{A}_{X,Y}} \prod_{t=1}^{T} p_t(a_t \mid X)$$

The CTC conditional **probability** | **marginalizes** over the set of valid alignments | computing the **probability** for a single alignment step-by-step.

Figure: CTC Loss [6]

- CTC loss can be very expensive to compute
- The problem is there can be a massive number of alignments
- We can compute the loss much faster with a dynamic programming algorithm

[6] from https://www.assemblyai.com/blog/end-to-end-speech-recognition-pytorch

CTC inference

- Greedy decoding

$$Y^* = \underset{Y}{\operatorname{argmax}}\ p(Y \mid X)$$

One heuristic is to take the most likely output at each time-step. This gives us the alignment with the highest probability:

$$A^* = \underset{A}{\operatorname{argmax}} \prod_{t=1}^{T} p_t(a_t \mid X)$$

We can then collapse repeats and remove ϵ tokens to get Y.

- Beam-Search decoding

Figure: from https://www.assemblyai.com/blog/

Attention modeling

- Architecture similar to neural machine translation
- Speech encoder based on CNNs or pyramidal LSTMs **?**

Image from Alexandre Berard's thesis

Attention modeling

Initially proposed for (neural) machine translation (Bahdanau et al., 2014) and introduced for ASR by Chorowski et al. (2015)

- A context (attention) model is a function of the encoder codes and of the previous decoded tokens
- A speech encoder is defined (CNNs, pyramidal LSTMs)
- While CTC generates frame-level posteriors, attention models generate L predictions until the end-of-sequence symbol (no posterior for a given frame)
- Well-known issue with attention and CTC models is the thin lattices we end up with

Attention modeling (different view)

- Also called LAS: **L**isten (encode) ; **A**ttend (attention) and **S**pell (decode)

Image from
https://lorenlugosch.github.io/posts/2020/11/transducer/

Attention modeling (alignment)

- Allows non-monotonic alignements
- As opposed to CTC (monotonic)

Image from
https://lorenlugosch.github.io/posts/2020/11/transducer/

CTC versus Attention

- CTC provides monotonic alignements while attention allows non-monotonic alignements
  - Attention more suitable for speech translation
- Attention will induce Auto-Regressive decoding (one token at a time) as attention depends on decoder's state
  - slow inference
- CTC does not have this constraint and is much simpler
  - faster inference
- Can we do better ?
  - Yes, transducer models

Transducer models

- Problems with CTC
  - The output sequence length M has to be smaller than the input sequence length T (prevents models that do a lot of input pooling)
  - The outputs are assumed to be independent of each other. CTC models often produce wrong outputs like "I eight food"

Transducer models

- Solve both problems
- Predictor is a language model
- Joiner is a simple feed-forward network

Image from https://lorenlugosch.github.io/posts/2020/11/transducer/

Transducer: Search

1. Start by setting $t := 1$, $u := 0$, and $\mathbf{y} :=$ an empty list.
2. Compute f_t using $\mathbf{x}$ and g_u using $\mathbf{y}$.
3. Compute $h_{t,u}$ using f_t and g_u.
4. If the argmax of $h_{t,u}$ is a *label*, set $u := u + 1$, and output the label (append it to $\mathbf{y}$ and feed it back into the predictor).

   If the argmax of $h_{t,u}$ is $\varnothing$, set $t := t + 1$ (in other words, just move to the next input timestep and output nothing).
5. If $t = T + 1$, we're done. Else, go back to step 2.

Image from `https://lorenlugosch.github.io/posts/2020/11/transducer/`

Transducer models

- Interesting features
  - If encoder is causal (not using something like a bidirectional RNN), then search can run in online/streaming fashion
  - The predictor only has access to y (not x) unlike the decoder in an attention model, so we can easily pre-train the predictor on text-only data
  - Naturally defines alignment between x and y

Here's one alignment: $\mathbf{z} = \varnothing, C, A, \varnothing, T, \varnothing, \varnothing$

Transducer models

- Training using a forward-backward algorithm
- Memory usage is a strong issue
  - If we have $T = 1000$; $U = 100$; $L = 1000$ different tokens
  - If batch size $B = 32$ to store $h_{t,u}$ we need $BxTxUxL = 3,200,000,000$ or 12.8 GB if we're using single-precision floats
  - RAM limitation on GPU nodes !!!
  - need to find some way to reduce memory consumption during training—e.g., by pooling in the encoder to reduce T or by using a smaller batch size B

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Self supervised representation learning

- Using huge unlabeled data for training ; targets are computed from the signal itself
  - *"learn representations using objective functions similar to those used for supervised learning, but train networks to perform pretext tasks where both the inputs and labels are derived from an unlabeled dataset"* (from Chen et al. (2020))
- Introduced for vision: see for instance (Chen et al., 2020)
  - learn representations by contrasting positive pairs against negative pairs
- Introduced also in NLP: see for instance (Devlin et al., 2018)
  - learn representations by predicting tokens that were masked in an input sequence

Pre-trained language models

- Leverage large amount of freely available unlabeled text to facilitate transfer learning in NLP
- Yield state-of-the-art results on a wide range of NLP tasks + save time and computational resources
- Example of BERT (Devlin et al., 2018) based on the Transformer model (Vaswani et al., 2017)

Self supervised representation learning from speech

- Autoregressive predictive coding (APC) (Chung et al., 2019; Chung and Glass, 2020)
  - Considers the sequential structure of speech and predicts information about a future frame
- Contrastive Predictive Coding (CPC) (Baevski et al., 2019; Schneider et al., 2019a; Kahn et al., 2019)
  - Easier learning objective which consists in distinguishing a true future audio frame from negatives
- Other approaches for feature representation learning using multiple self supervised tasks (Pascual et al., 2019; Ravanelli et al., 2020) or bidirectional encoders (Song et al., 2019; Liu et al., 2020; Wang et al., 2020)

Autoregressive predictive coding (APC)

- Predicting the spectrum of a future frame (rather than a wave sample) (Chung et al., 2019)
- Somewhat inspired by language models (LMs) for text, which are typically a probability distribution over sequences of T tokens $(t_1, t_2, ..., t_T)$

$$P(sequence) = \prod_{k=1}^{T} P(t_k | t_1, t_2, ..., t_{k-1}) \tag{4}$$

$$P(sequence) = \prod_{k=1}^{T} P(t_k | h) \tag{5}$$

- Recurrent neural network LM: $h = rnn_state(E(t_1), E(t_2), ..., E(t_{k-1}))$
- For speech, each token t_k corresponds to a frame rather than a word or character token

Autoregressive predictive coding (APC)

- No final set of target tokens (softmax layer replaced by a regression layer)
- Learnable parameters in APC are the RNN parameters θ_{rnn} and the regression layer parameters θ_r
- Encourage APC to infer more global structures rather than the local information in the signal
  - ask the model to predict a frame n steps ahead of the current one
- Model is optimized by minimizing the L1 loss between sequence $(x_1, x_2, ..., x_T)$ and the predicted sequence $(y_1, y_2, ..., y_T)$:

$$\sum_{i=1}^{T-n} |t_i - y_i|, t_i = x_{i+n} \tag{6}$$

Autoregressive predictive coding (APC)

- Chung et al. (2019) models APC with a multi-layer unidirectional LSTM with residual connections
- After training, RNN hidden states are taken as the learned representations
- A follow-up work (Chung and Glass, 2020) adds an auxiliary objective that serves as regularization to improve generalization

Feature	ASR (WER ↓)	ST (BLEU ↑)
log Mel	18.3	12.9
APC w/ L_f	15.2	13.8
APC w/ L_m	14.2	14.5

Table 2: Automatic speech recognition (ASR) and speech translation (ST) results using different types of features as input to a seq2seq with attention model. Word error rates (WER, ↓) and BLEU scores (↑) are reported for the two tasks, respectively.

Differences between speech and text SSL

- Input speech representations (MFCCs for instance) are already in a vector form (no embedding layer)
- More uncertainty
  - text (discrete): finite number of possible outcomes (target tokens)
  - speech and video (continuous): infinite number of frames that can plausibly follow a given audio (or video) clip

Figure: Figure from `https://ai.facebook.com/blog/self-supervised-learning-the-dark-matter-of-intelligence`

Contrastive Predictive Coding (CPC)

- Maybe an easier learning objective (classification instead of regression)
- Use of a contrastive loss that distinguishes a true future audio sample from negatives
- Example of *wav2vec* (Schneider et al., 2019b) that relies on a fully convolutional architecture
- Applied the learned representations to improve a supervised ASR system

Figure: Figure from (Schneider et al., 2019b)

Contrastive Predictive Coding (CPC)

- Encoder network $Z = f(X)$; 5 (causal) convolution layers ; local feature representations z_i encode 30 ms of audio every 10ms
- Context network $C = g(Z)$; 9 (causal) convolution layers ; mix multiple z_i (receptive field of dimension v corresponding to 210ms) into a single contextualized representation c_i
- Model trained to distinguish a sample z_{i+k} that is k steps in the future from distractor samples $\tilde{z}$ drawn from a proposal distribution p_n by minimizing a contrastive loss for each step $k = 1, ..., K$
- Negatives examples sampled by uniformly choosing distractors from each audio sequence: is $p_n(z) = 1/T$ where T is the sequence length

Representation learning with multiple self-supervised tasks

- Problem-agnostic speech encoder (PASE) (Pascual et al., 2019)
- PASE+: robust speech recognition in noisy and reverberant environments (Ravanelli et al., 2020)

Representation learning with multiple self-supervised tasks

- Problem-agnostic speech encoder (PASE) (Pascual et al., 2019)
- Jointly tackle multiple self-supervised tasks using an ensemble of neural networks that cooperate to discover good speech representations
- Approach requires consensus across tasks, more likely to learn general, robust, and transferable features
- Authors find that such representations outperform more traditional hand-crafted features in different speech classification tasks such as speaker identification, emotion classification, and ASR

Problem-agnostic speech encoder (PASE)

- Encoder: SincNet (Ravanelli and Bengio, 2018) + Convblocks (receptive field 150ms)
- Workers: one for each task (see next slide)

Figure 1: *The PASE architecture, with the considered workers.*

Figure: Figure from (Pascual et al., 2019)

Problem-agnostic speech encoder (PASE)

- Regression workers that solve 7 self-supervised tasks
- Trained to minimize the mean squared error (MSE) between the target features and the network predictions
  - **Waveform** learns to reconstruct waveforms
  - **LPS** reconstruct log power spectrum
  - **MFCC** reconstruct mel-frequency cepstral coefficients
  - **Prosody** predicts 4 basic prosodic features per frame
  - **LIM** (local info max) contrastive task where positive sample is drawn from the same utterance and a negative sample is drawn from another random utterance (that likely belongs to a different speaker)
  - **GIM** (global info max) similar to LIM using global representations (averaged over 1s) instead of local ones
  - **SPC** sequence predicting coding: similar to contrastive predictive coding (CPC) introduced earlier

Problem-agnostic speech encoder (PASE)

- Experiments on speaker identification, emotion recognition and ASR

Table 2: *Accuracy comparison on the considered classification tasks using MLPs and RNNs as classifiers.*

Model	Classification accuracy [%]					
	Speaker-ID *(VCTK)*		Emotion *(INTERFACE)*		ASR *(TIMIT)*	
	MLP	RNN	MLP	RNN	MLP	RNN
MFCC	96.9	72.3	90.8	91.1	81.1	84.8
FBANK	98.4	75.1	94.1	92.8	80.9	85.1
PASE-Supervised	97.0	80.5	93.8	92.8	82.1	84.7
PASE-Frozen	97.3	82.5	91.5	92.8	81.4	84.7
PASE-FineTuned	**99.3**	**97.2**	**97.7**	**97.0**	**82.9**	**85.3**

Table 3: *Word error rate (WER) obtained on the DIRHA corpus.*

	WER [%]
MFCC	35.8
FBANK	34.0
PASE-Supervised	33.5
PASE-Frozen	32.5
PASE-FineTuned	**29.8**

Figure: Table from (Pascual et al., 2019)

Many follow-up approaches

- Speech-XLNet: Unsupervised Acoustic Model Pretraining For Self-Attention Networks (Song et al., 2019)
- Mockingjay: Unsupervised speech representation learning with deep bidirectional transformer encoders (Liu et al., 2020)
- Unsupervised pre-training of bidirectional speech encoders via masked reconstruction (Wang et al., 2020)
- **Wav2vec 2.0: A Framework for Self-Supervised Learning of Speech Representations (Baevski et al., 2020)**
- **HuBERT: Self-Supervised Speech Representation Learning by Masked Prediction of Hidden Units (?)**

Speech-XLNet

- Speech-XLNet (Song et al., 2019)
- Learn speech representations with self-attention networks
- BERT-like autoencoding (AE) scheme to train a bi-directional speech representation model (not only left-to-right)
- Mask and reconstruct speech frames rather than word tokens (regression instead of classification task)
- Encourage network to learn global structures by shuffling speech frame orders (can be also seen as dynamic data augmentation)
- Training using a Mean Absolute Error (MAE) loss over several permutations of the input frames
- (Unfortunately) not compared with previous APC and CPC approaches

Speech-XLNet

- Experiments on Hybrid and end-to-end ASR
- Results of Hybrid ASR on TIMIT are reported below

Table 2: *PER comparison with previous pretrain methods. We approximate the number of parameters based on the description in the previous studies.*

Pretrain Method	Pretrain Data	Pretrain Params	Dev/Test PER(%)
VQ-Wav2vec ([8])	libri (960h)	34M	15.34 / 17.78
RBM-DBN ([21])	timit (8h)	$\approx$ 34.2M	15.90 / 16.80
Ours (Randomly Init)	-	19.9M	13.20 / 15.10
Wav2vec ([7])	libri+wsj (1041h)	34M	12.90 / 14.70
Ours (Pretrained)	libri+wsj+ted (1248h)	19.9M	11.70 / 12.80
VQ-Wav2vec+BERT ([8])	libri (960h)	$\approx$ 71.8M	9.64 / 11.64

Figure: Table from (Song et al., 2019)

Unsupervised speech representation learning with deep bidirectional transformer encoders

- Predict the current frame through jointly conditioning on both past and future contexts (Mockingjay (Liu et al., 2020))
- Masked acoustic modeling task (rand. mask 15% of input frames)[7]
- Use multi-layer transformer encoders and multi-head self-attention
- Add a prediction head (2 layers of feed-forward network with layer-norm) using last encoder layer as input

Figure: Table from (Liu et al., 2020)

[7] Use of additional consecutive masking where they mask consecutive frames C_{num} to zero. The model is required to infer on global rather than local structure

Unsupervised speech representation learning with deep bidirectional transformer encoders

- Experiments on phoneme classification
- With different amount of annotated data for training

Figure: Figure from (Liu et al., 2020)

Unsupervised Pre-training of Bidirectional Speech Encoders via Masked Reconstruction

- Pre-training speech representations via a masked reconstruction loss (Wang et al., 2020)
- Masking in both frequency and time to encourage model to exploit spatio-temporal info
- Elegant extension of data augmentation technique SpecAugment (Park et al., 2019)

Figure: Figure from (Wang et al., 2020)

Unsupervised Pre-training of Bidirectional Speech Encoders via Masked Reconstruction

Table 3: Dev set %CERs of character-based systems pre-trained on LibriSpeech, and fine-tuned with different amounts of supervised data.

	Baseline	Pre-train *Libri.* w/o LIN	Pre-train *Libri.* w/ LIN
si84	15.23	14.02	**13.29**
+ SpecAug	12.98	12.26	**11.70**
si284	7.01	6.90	**6.48**
+ SpecAug	6.29	6.19	**5.61**

Fig. 2: Dev set learning curves (%CER and CTC loss) of different systems pre-trained on *LibriSpeech*. The first 5 epochs of fine-tuning update only the LIN and softmax layers.

Figure: From (Wang et al., 2020)

Wav2vec 2.0: A Framework for Self-Supervised Learning of Speech Representations

- Encode speech with CNN layers and then mask spans of the resulting latent speech representations (cf masked LM)
- Learn *discrete* speech units as latent representations[8]
- Latent representations fed to a Transformer network to build contextualized representations
- Model trained with a contrastive task (true latent to be distinguished from distractors)

Figure: Figure from (Baevski et al., 2020)

[8] Authors found this more effective than non-quantized targets

HuBERT: Self-Supervised Speech Representation Learning by Masked Prediction of Hidden Units

- Similar Conv+Transf encoder but
- Uses cross-entropy loss (same as BERT) instead of contrastive loss
- Discrete targets are built through a separate clustering process
- Learnt *discrete* speech units are refined at each iteration (3 iterations for large models)
- X-LARGE version of HuBERT as 1 billion parameters
- Model recently outperformed SOTA techniques for speech recognition, generation, and compression

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SpeechT5 (Ao et al., 2021)

- A multimodal extension of transformer encoder-decoder models such as T5
- Encode or decode both speech and text with a single model
- Maps both acoustic and text information in a shared vector space
- Used to initialize ASR (speech-to-text), TTS (text-to-speech), Voice Conversion (VC – speech-to-speech), etc.

SpeechT5 (Ao et al., 2021)

- A single transformer encoder/decoder backbone
- Several modality-specific pre-post nets
  - standard for text
  - encoder pre-net for speech similar to the CNN blocks of wav2vec2.0
  - decoder pre-net for speech is different (fully connected net + ReLU) as the model will output slices of filterbank features (no speech directly)
  - a speaker embedding is concatenated to the output of the speech-decoder pre-net to support voice conversion and multi-speaker TTS

(a) The model architecture of SpeechT5

SpeechT5 (Ao et al., 2021)

- A composite loss with multiple pre-training objectives
  - a masked language modeling (MLM) loss on discrete latent speech representations (*à la HuBERT*)
  - a speech reconstruction L1 loss (in the continuous filterbank space)
  - a cross-entropy loss specific to the prediction of the stop token
  - a text denoising objective (*à la BART*)
  - a cross-modal objective to better align speech and text representations (unclear in the paper)

The final pre-training loss with unlabeled speech and text data can be formulated as

$$\mathcal{L} = \mathcal{L}^s_{mlm} + \mathcal{L}^s_1 + \mathcal{L}^s_{bce} + \mathcal{L}^t_{mle} + \gamma \mathcal{L}_d. \quad (6)$$

where γ is set to 0.1 during pre-training.

SpeechT5 Ao et al. (2021)

- Experiments on several downstream speech tasks (ASR, VC, TTS, speaker id.) show slightly better results than speech-only pre-training

Model	LM	dev-clean	dev-other	test-clean	test-other
wav2vec 2.0 BASE (Baevski et al., 2020)	-	6.1	13.5	6.1	13.3
HuBERT BASE (Hsu et al., 2021) †	-	5.5	13.1	5.8	13.3
Baseline (w/o CTC)	-	5.8	12.3	6.2	12.3
Baseline	-	4.9	11.7	5.0	11.9
SpeechT5 (w/o CTC)	-	5.4	10.7	5.8	10.7
SpeechT5	-	**4.3**	**10.3**	**4.4**	**10.4**
DiscreteBERT (Baevski et al., 2019)	4-gram	4.0	10.9	4.5	12.1
wav2vec 2.0 BASE (Baevski et al., 2020)	4-gram	2.7	7.9	3.4	8.0
HuBERT BASE (Hsu et al., 2021)	4-gram	2.7	7.8	3.4	8.1
wav2vec 2.0 BASE (Baevski et al., 2020)	Transf.	2.2	6.3	2.6	6.3
Baseline	Transf.	2.3	6.3	2.5	6.3
SpeechT5	Transf.	**2.1**	**5.5**	**2.4**	**5.8**

Table 1: Results of ASR (speech to text) on the LibriSpeech dev and test sets when training on the 100 hours subset of LibriSpeech. † indicates that results are not reported in the corresponding paper and evaluated by ourselves.

mSLAM Bapna et al. (2022)

- Extension of SLAM Bapna et al. (2021) architecture where speech and text unified in a common encoder model
  - Use of convolution-augmented transformer (conformer) blocks, introduced earlier for ASR Gulati et al. (2020)
  - Input is speech, text, or concatenated speech-text
  - Speech-text pre-training is a mix of self-supervised learning objectives (rather similar to SpeechT5) and supervised cross-modal learning objectives (which leverage aligned speech-text pairs)

mSLAM Bapna et al. (2022)

- SSL learning objectives for speech (*à la* HuBERT) and text (BERT)
- Speech-text objectives
  - translation language modeling (TLM): predicts masked text or speech spans from a concatenated speech-text input (to encourage use of cross-modal context)
  - Connectionist Temporal Classification (CTC) loss is applied on the speech part of concatenated speech-text using character transcript as a target (ASR loss to learn better speech-text

mSLAM Bapna et al. (2022)

- Massively multilingual (51 lang. speech; 101 lang. text), 2B param
- Downstream task experiments
  - ASR, speech translation, spoken lang. id., spoken intent classification and text classification
  - Speech-text pre-training better than speech-only pre-training for multilingual ASR and translation

mSLAM Bapna et al. (2022)

- Zero shot cross-modal properties
- Zero shot text translation from a fine-tuned speech translation model
- The model has never seen src-txt/tgt-txt parallel data but it has seen src-speech/tgt-text + monolingual src-txt
- ... but a system fine-tuned only on text cannot translate speech

Table 6: Zero-shot Performance - CoVoST 2 translation results with X→Y indicating X as the fine tuning modality and Y as the testing modality: S=Speech, T=Text. CAE is our CTC zero-shot character auto-encoding probe.

	Hours	BLEU ↑			CER ↓	
Lang	Paired	S→S	S→T	T→S	S→T	CAE
ar	0	13.3	0.0	0.0		82.6
fa	0	6.2	0.0	0.0		80.0
ja	0	1.6	0.0	0.0		100.0
zh	0	8.7	0.0	0.0		100.0
cy	0	6.1	0.1	0.0		24.3
mn	0	0.5	0.1	0.0		78.4
id	0	3.9	5.1	0.0		10.4
lv	0	19.4	8.2	0.0		18.4
et	0	17.2	8.3	0.0		16.5
sv	0	33.1	15.2	0.0		13.9
ca	0	33.4	16.7	0.0		10.0
ru	0	41.7	21.9	0.0		85.9
sl	6	24.9	7.8	0.0		10.6
pt	10	34.2	17.2	0.0		9.0
nl	41	32.6	16.8	0.0		11.3
ta	63	0.3	0.0	0.0		91.2
tr	69	11.7	1.7	0.0		12.6
it	79	35.0	19.7	0.0		11.2
es	140	39.1	21.2	0.0		7.9
fr	179	36.7	20.0	0.0		9.4
de	197	32.7	16.8	0.0		8.3

Data2Vec [Baevski et al., 2022]

- Data2vec is a framework for general self-supervised learning
  - works for all three modalities: images, speech and text
  - with a learning objective identical in each modality
  - based on masked predictions and latent representation learning
- Data2vec unifies the learning algorithm but still learns representations individually for each modality
  - a.k.a Data2vec Text model (~BERT), Data2vec Speech model (~HuBERT), Data2vec Image model (~BEiT)

Data2Vec [Baevski et al., 2022]

- The only modality-specific elements in the architecture are the feature encoders and masking strategies on the input data
- The model is an off-the-shelf Transformer network (Vaswani et al., 2017) working in a student/teacher mode
- The learning task for the student is to predict masked latent representations of the teacher
  - representations of the full input data are build to serve as targets in the learning task (teacher mode)
  - we encode a masked version of the input sample with which we predict the full data representations (student mode).

Data2Vec [Baevski et al., 2022]

Data2Vec [Baevski et al., 2022]

The model is trained to predict the model representations of the original unmasked training sample based on an encoding of the masked sample.

- only the masked time-steps are predicted
- these targets are the average of the top K blocks of the teacher [a]
- given contextualized training targets yt, we use a Smooth L1 loss to regress these targets: [b]

$$\mathcal{L}(y_t, f_t(x)) = \begin{cases} \frac{1}{2}(y_t - f_t(x))^2/\beta & |y_t - f_t(x)| \leq \beta \\ (|y_t - f_t(x)| - \frac{1}{2}\beta) & \text{otherwise} \end{cases}$$

[a] In preliminary experiments we found that averaging performed as well as predicting each block separately with a dedicated projection while enjoying the advantage of being more efficient.

[b] the beta parameter controls the transition from the squared loss to the L1 loss, supposedly for outliers sensitivity

Data2Vec [Baevski et al., 2022]

- Images: Vision Transformer Base and Large are tested for image classification on ImageNet-1k

Table 1. Computer vision: top-1 validation accuracy on ImageNet-1K with ViT-B (86M parameters) and ViT-L (307M parameters) models. Our results are based on training for 800 epochs while as several other well-performing models were trained for 1,600 epochs (MAE, MaskFeat).

	ViT-B	ViT-L
MoCo v3 (Chen et al., 2021b)	83.2	84.1
DINO (Caron et al., 2021)	82.8	-
BEiT (Bao et al., 2021)	83.2	85.2
MAE (He et al., 2021)	83.6	85.9
SimMIM (Xie et al., 2021)	83.8	-
MaskFeat (Wei et al., 2021)	84.0	85.7
data2vec	84.2	86.2

Data2Vec [Baevski et al., 2022]

- Speech: Data2vec is trained on the Librispeech dataset and evaluated on a ASR task

Table 2. Speech processing: word error rate on the Librispeech test-other test set when fine-tuning pre-trained models on the Libri-light low-resource labeled data setups (Kahn et al., 2020) of 10 min, 1 hour, 10 hours, the clean 100h subset of Librispeech and the full 960h of Librispeech. Models use the 960 hours of audio from Librispeech (LS-960) as unlabeled data. We indicate the language model used during decoding (LM). Results for all dev/test sets and other LMs can be found in the supplementary material (Table 5).

	Unlabeled data	LM	Amount of labeled data				
			10m	1h	10h	100h	960h
Base models							
wav2vec 2.0 (Baevski et al., 2020b)	LS-960	4-gram	15.6	11.3	9.5	8.0	6.1
HuBERT (Hsu et al., 2021)	LS-960	4-gram	15.3	11.3	9.4	8.1	-
WavLM (Chen et al., 2021a)	LS-960	4-gram	-	10.8	9.2	7.7	-
data2vec	LS-960	4-gram	12.3	9.1	8.1	6.8	5.5

Data2Vec [Baevski et al., 2022]

- Text: Data2vec is trained on the same setting as BERT and tested on the GLUE benchmark

Table 3. Natural language processing: GLUE results on the development set for single-task fine-tuning of individual models. For MNLI we report accuracy on both the matched and unmatched dev sets, for MRPC and QQP, we report the unweighted average of accuracy and F1, for STS-B the unweighted average of Pearson and Spearman correlation, for CoLA we report Matthews correlation and for all other tasks we report accuracy. BERT Base results are from Wu et al. (2020) and our baseline is RoBERTa re-trained in a similar setup as BERT. We also report results with wav2vec 2.0 style masking of spans of four BPE tokens with no unmasked tokens or random targets.

	MNLI	QNLI	RTE	MRPC	QQP	STS-B	CoLA	SST	Avg.
Base models									
BERT (Devlin et al., 2019)	84.0/84.4	89.0	61.0	86.3	89.1	89.5	57.3	93.0	80.7
Baseline (Liu et al., 2019)	84.1/83.9	90.4	69.3	89.0	89.3	88.9	56.8	92.3	82.5
data2vec	83.2/83.0	90.9	67.0	90.2	89.1	87.2	62.2	91.8	82.7
+ wav2vec 2.0 masking	82.8/83.4	91.1	69.9	90.0	89.0	87.7	60.3	92.4	82.9

Data2Vec [Baevski et al., 2022]

- The method can be seen as a kind of generalization of the concept of masked language/speech/pixels modelling. It's a masked latent representation pretraining task.
- Experimental results show data2vec to be effective in all three modalities
- To explain these results the authors say that the fact the "Target representations being continuous and contextualized makes them richer than a fixed set of targets"
- Potential improvements and limitations: modality specific feature extractors amd masking strategies, potential representation collapse

Conclusion

- Training such models requires access to powerful computing platforms
- Simpler and more efficient pre-training approaches needed
- Standardization in the evaluation process also needed (need for a multimodal and multilingual GLUE)
- Only scratched the surface of zero-shot capabilities of these models (transfer from text to speech tasks)
- More research needed on the decoder side (especially to generate expressive speech with adequate prosody)

1 The speech signal

2 1990-2015: Bayes, HMMs, GMMs

3 2015: neural nets to the rescue

4 2020: 3 main ASR architectures used today

5 2021: Self-Supervised Learning (SSL) for Speech

6 2022: Multimodal Speech-Text Pre-trained Models

7 Future: is ASR a solved problem ?

On par with human transcription ?

Read Speech			
Test set	DS1	DS2	Human
WSJ eval'92	4.94	3.60	5.03
WSJ eval'93	6.94	4.98	8.08
LibriSpeech test-clean	7.89	5.33	5.83
LibriSpeech test-other	21.74	13.25	12.69

Figure: Comparison of WER for two speech systems and human level performance on **read** speech (from (Amodei et al., 2016)

Accented Speech			
Test set	DS1	DS2	Human
VoxForge American-Canadian	15.01	7.55	4.85
VoxForge Commonwealth	28.46	13.56	8.15
VoxForge European	31.20	17.55	12.76
VoxForge Indian	45.35	22.44	22.15

Figure: Comparison of WER for two speech systems and human level performance on **accented** speech (from (Amodei et al., 2016)

On par with human transcription ?

Noisy Speech			
Test set	DS1	DS2	Human
CHiME eval clean	6.30	3.34	3.46
CHiME eval real	67.94	21.79	11.84
CHiME eval sim	80.27	45.05	31.33

Figure: Comparison of WER for two speech systems and human level performance on **noisy** speech (from (Amodei et al., 2016)

Language coverage

- Google addresses (only) 100 languages (ASR)
- Language technology issues: 300 languages (95 % population)
- Language coverage / revitalisation / documentation issues: $>$ 6000 languages !

Figure: from Laura Welcher - Big Data for Small Languages The Rosetta Project

Low resource ASR

- Rapid development of ASR for new languages
- In low resource conditions
- For languages poorly described
- ex: DARPA Babel program

Language	ML-24		CTC		Attention	
	XE	ST	XE	ST	XE	ST
Pashto	54.5	51.5	51.5	49.5	50.6	50.1
Guarani	52.1	48.5	--	47.8	47.3	46.3
Igbo	63.4	60.2	61.4	59.2	59.6	58.8
Amharic	49.3	44.5	--	44.6	45.9	44.5
Mongolian	59.1	55.1	59.6	53.0	54.5	53.5
Javanese	60.1	55.3	57.5	54.1	55.4	54.2
Dholuo	43.7	40.5	--	40.0	40.7	39.9
Georgian	45.0	40.8	44.3	40.6	45.6	43.9

Figure: Performance of end-2-end models on Babel languages[9]

[9] from Bhuvana Ramabhadran' s presentation at Interspeech 2018

Zero resource ASR

In an unknown language, from unannotated raw speech, discover:[10]

- Invariant subword units (phone units ?)
- Words/terms (lexicon/semantic units ?)

Technological challenge

- Can we build useful speech technologies without any textual resources ?
- Unsupervised ASR / autonomous systems

Scientific challenge

- Can we build algorithms that learn languages like infants do ?
- Can we build algorithms that extract meaningful units from unknown languages ?

[10] The zero resource challenge: `http://zerospeech.com` (Dunbar et al., 2017)

Multilingual ASR

1 system - N languages

- In end-2-end ASR, acoustic, pronunciation and language model are integrated into a single neural network
- Makes them very suitable for truly multilingual ASR
- First attempts using hybrid CTC/attention ASR approaches (Watanabe et al., 2017)
- Similar in spirit to multilingual NMT (Johnson et al., 2016)
- Recent proposition using a transformer network (Zhou et al., 2018)

Other ASR challenges

- Can we leverage multiple sensors to design noise robust approaches ? (Barker et al., 2017)
- What do NNs learn ? (Belinkov and Glass, 2017)
- How can we can exploit adversarial examples to improve overall robustness ?
- Can we analyze (and deal with) biases between genders, dialects, regional accents ?
- How to deal with code-switching phenomena ?

Questions?

Thank you

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