Automatic Speech Recognition

Acoustic Modelling

Decoding

Applications

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Speechly

Automatic Speech Recognition (ASR)

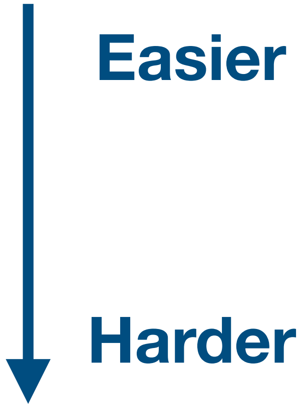
- Lecture goals: To understand…
  - … what is automatic speech recognition
  - … how statistical models are used to recognise speech
  - … what are the fundamentals of modelling speech acoustics
  - … how deep neural networks are used in speech recognition
  - … how different applications use speech recognition

- In some forms, automatic speech recognition has existed already for over 50 years

- In the past decade, the use of speech recognition in consumer devices has exploded

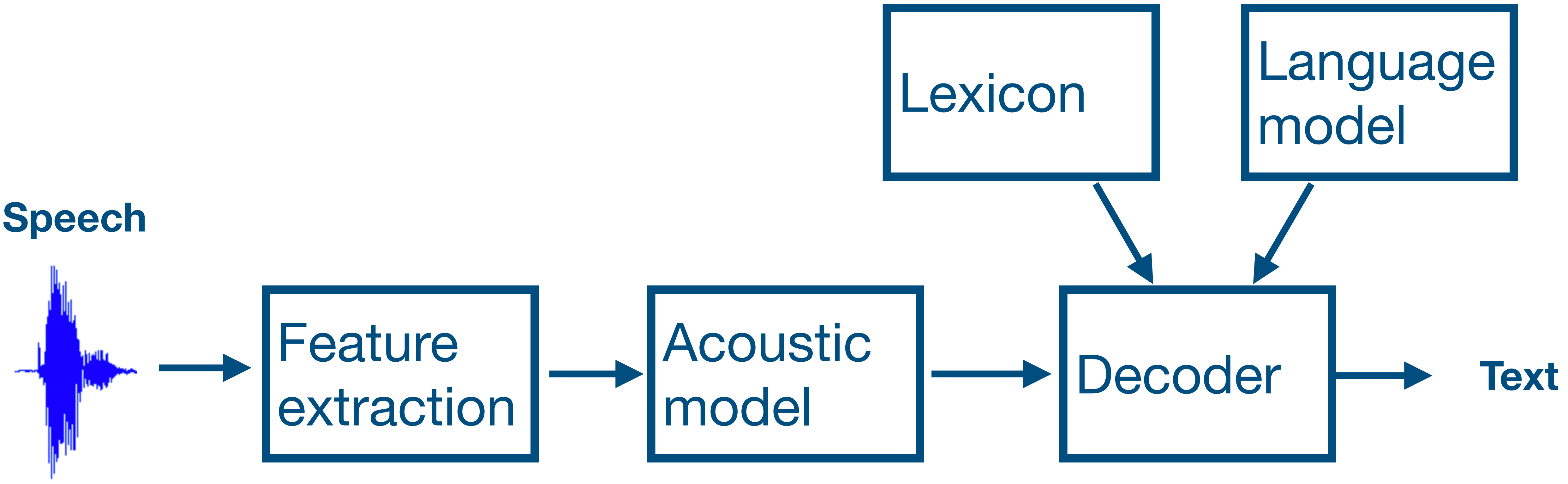
Speech Recognition Tasks

- Typical automatic speech recognition (ASR) tasks:
  - Keyword detection
  - Command-and-control
  - Search by speech
  - Dictation
  - Conversational interaction



- Speech characteristics relating to the recognition task:
  - Isolated words vs. continuous speech
  - Speaker dependent vs. independent
  - Vocabulary size
  - Read speech, planned speech, conversational speech
  - Environmental noise
  - Space and distance to the microphone: close-talk, near-field, far-field
- Recognising everyday speech around us is challenging because it is speaker independent, conversational, large vocabulary, continuous speech, mixed with various environmental noises!

Traditional Components of an ASR system



- Task of the automatic speech recognition: Find the most likely word sequence given the observations (speech) and the models for acoustics and language
- Speech acoustics are matched with a statistical model
- Language model is also typically a statistical model (n-gram, RNN), but in simple tasks it can be a fixed grammar or just a vocabulary

Statistical model of ASR

- **Find the most likely word sequence given the observations:**

$$\hat{\mathrm{W}} = \underset{\mathrm{W}}{\arg\max}\; p(\mathrm{W} \mid \boldsymbol{O}) = \underset{\mathrm{W}}{\arg\max}\; p(\boldsymbol{O} \mid \mathrm{W})\, p(\mathrm{W})$$

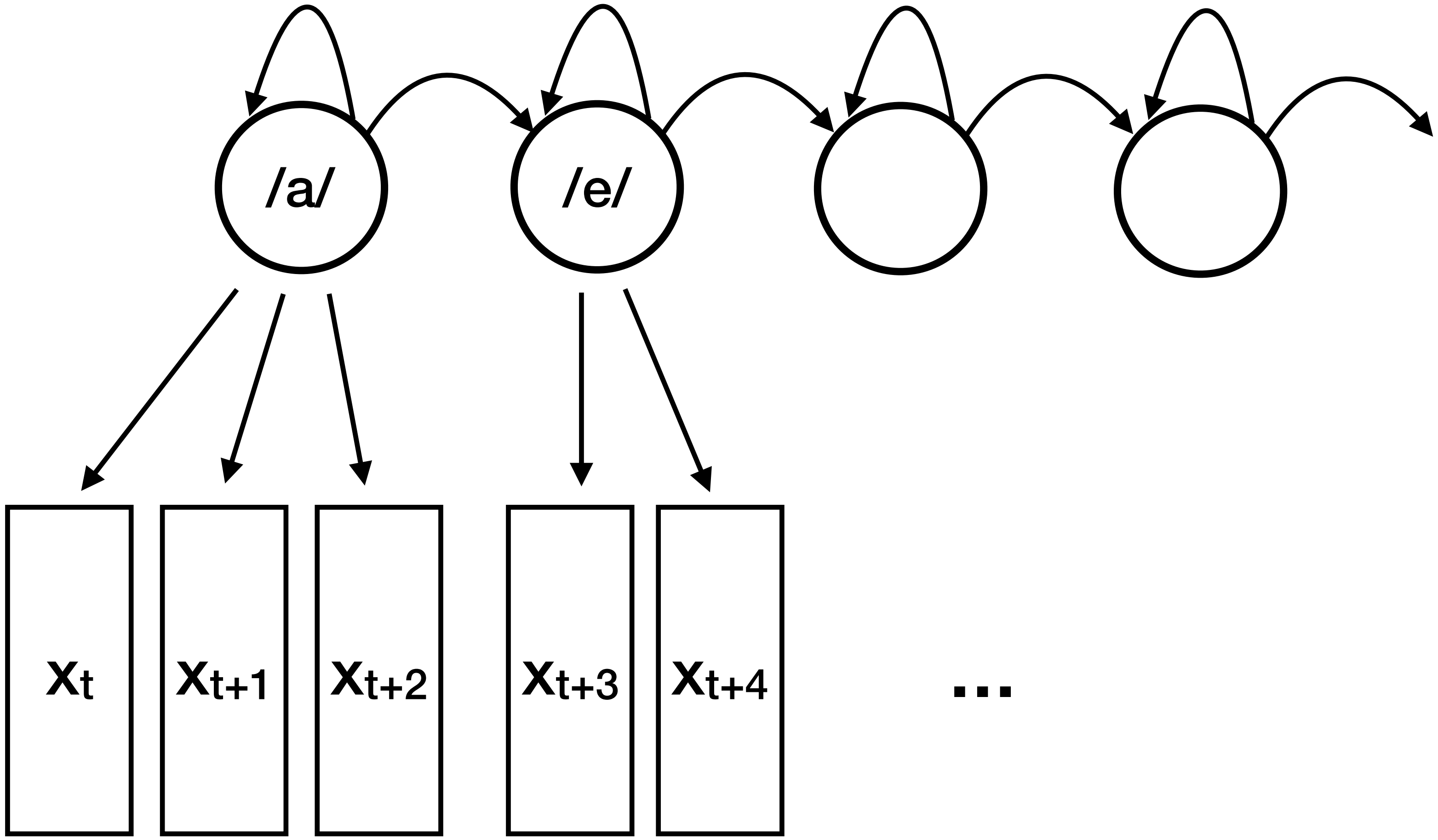
Language model:
Probability of the word sequence W

Acoustic model:
Likelihood of the observations O, given the word sequence W

- **Task of the decoder: Perform the search for the most likely word sequence**

Acoustic Model

- The information in speech signal is encoded in its time-varying properties
- The traditional model for the temporally varying speech signal is Hidden Markov Model (HMM): a sequence of states each coupled with a specific emission probability model for the distribution of the observations
- HMM states correspond to basic recognition units
  - Typical choices are phones, or context-dependent sub-phonemes, i.e. senones

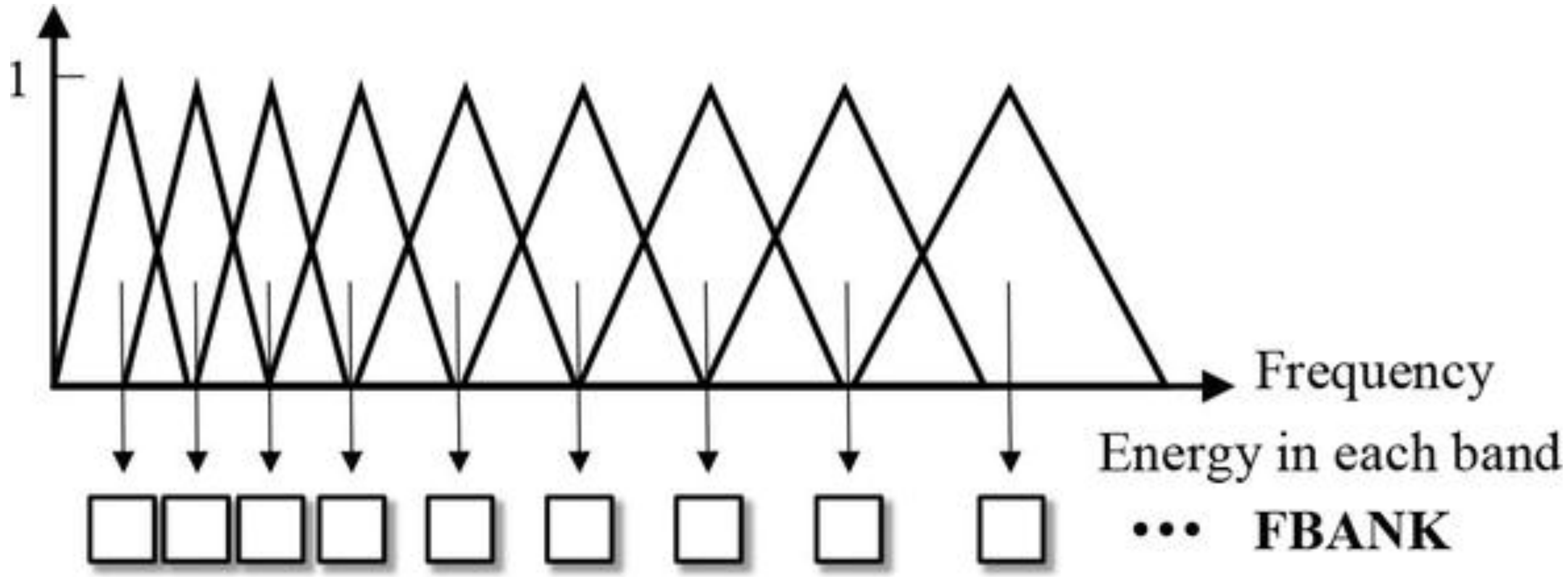


Phonemes, phones, triphones, senones

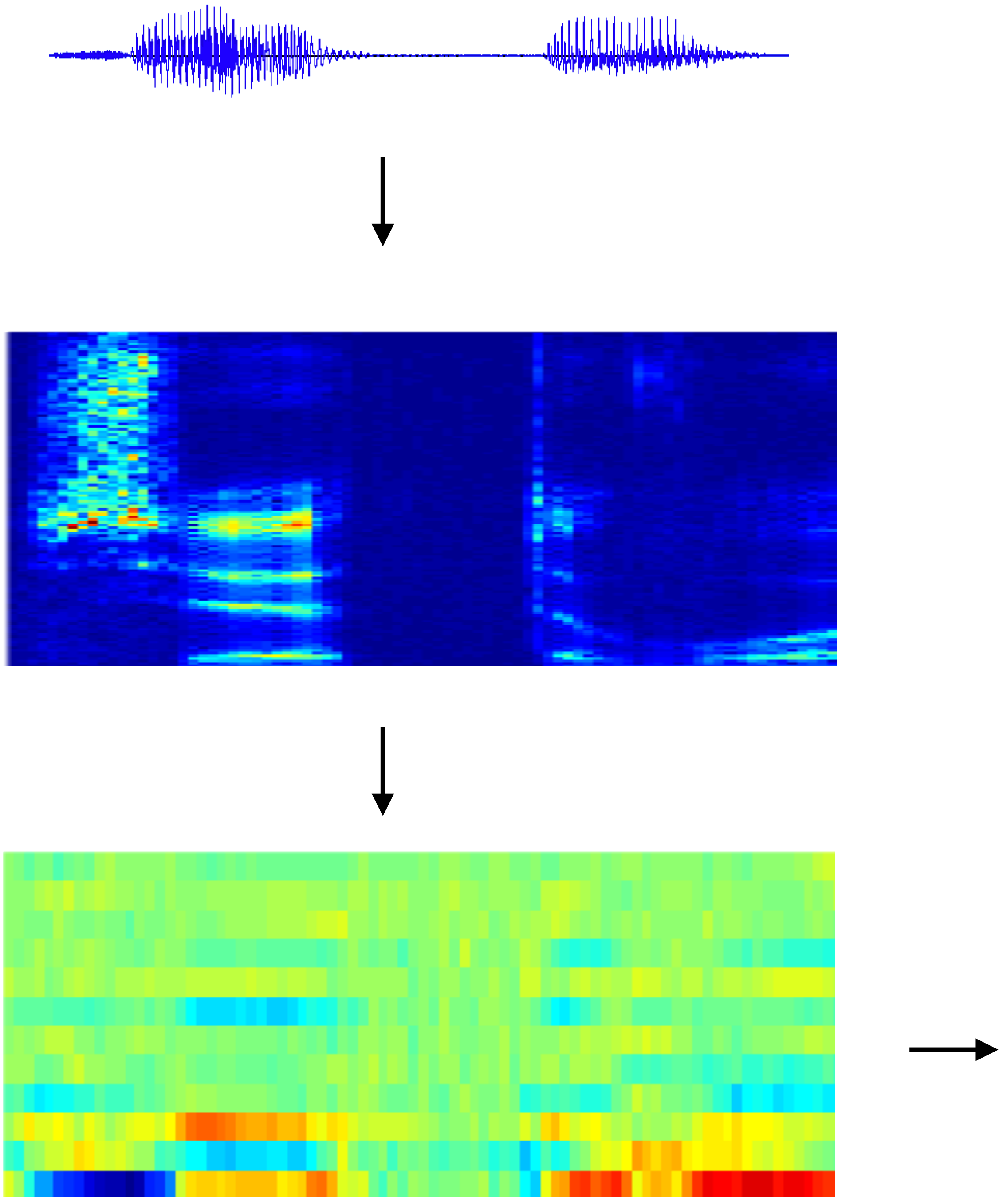
- *Phoneme -* The basic unit in spoken language, analogous to a letter in written text is.
- *Phone -* Spoken realisation of a phoneme
- *Lexicon -* Mapping between words and phoneme sequences
- *Context-dependent phone -* A phone model which takes the surrounding phonemes into account
  - A large proportion of the acoustic variation of phones is due to this phoneme context
- *Triphone -* Context dependent phone which considers both the previous and the next phone, i.e. the left and the right context
  - Notation: t-a+s means phone /a/ occurring between /t/ and /s/
- *Senone -* Part of a phone. Traditionally ASR systems have used 3 HMM states for modelling a single triphone. One state is then called a senone.

Features for Speech Acoustics

- To model the time varying speech signal with HMM-based acoustic models, the signal has to be converted into a sequence of short-time features
- The features need to retain the relevant information for the phone identities, while inhibiting unwanted variation (e.g. due to the speaker or environment)
- Extraction of speech features apply various non-linear processing steps, based on the knowledge of human hearing and psycho-acoustics
- Typical features for speech recognition:
  - Mel-Frequency Cepstral Coefficients (MFCCs)
  - Perceptual Linear Prediction (PLP)
  - Logarithmic Mel-Filterbank Energies



Example: MFCC feature extraction

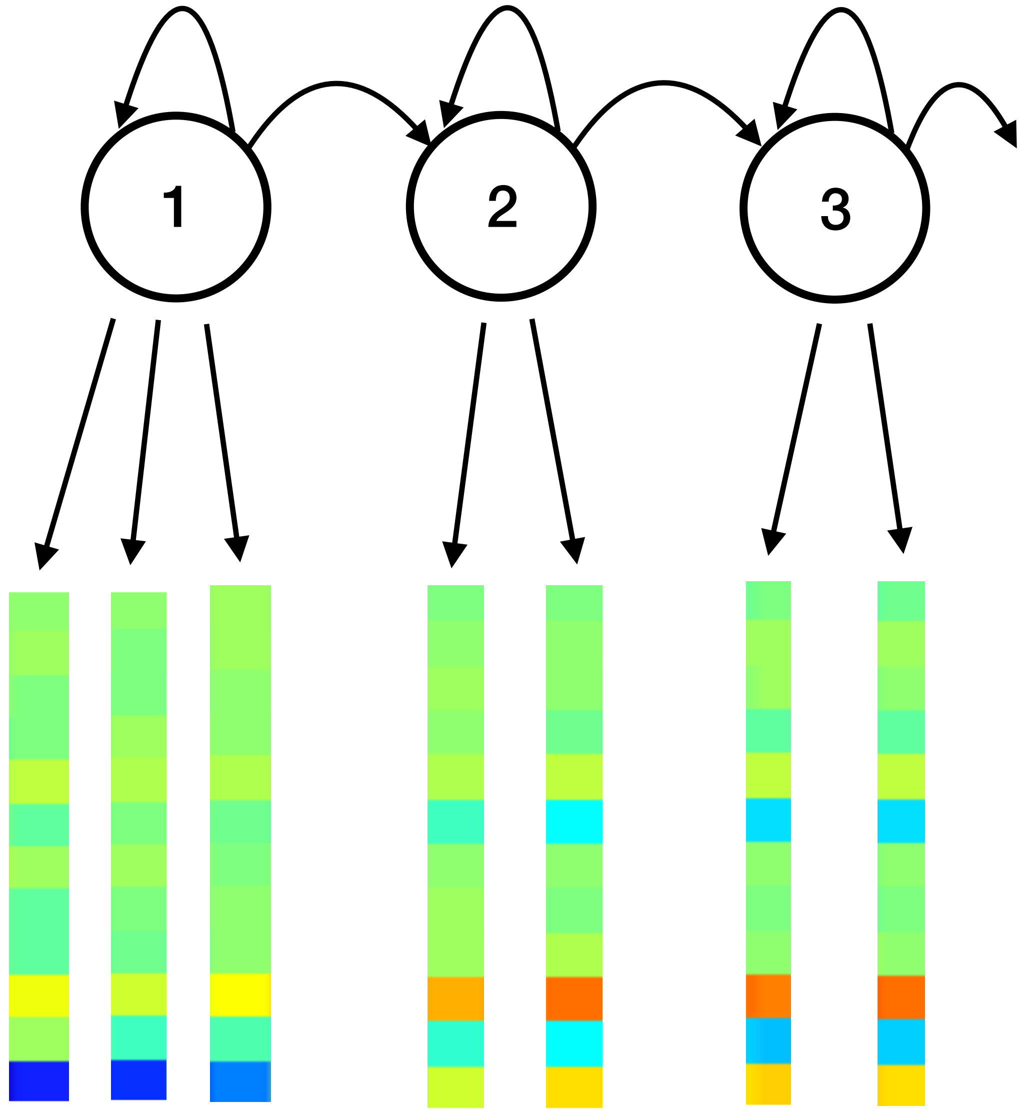


Typical properties of Mel-Frequency Cepstral Coefficient features in classical ASR:

- **Feature vectors are 13 dimensional**
- **Each feature vector is extracted from a 25ms spectral analysis window**
- **Windows overlap such that the feature extraction generates 100 feature vectors per second**

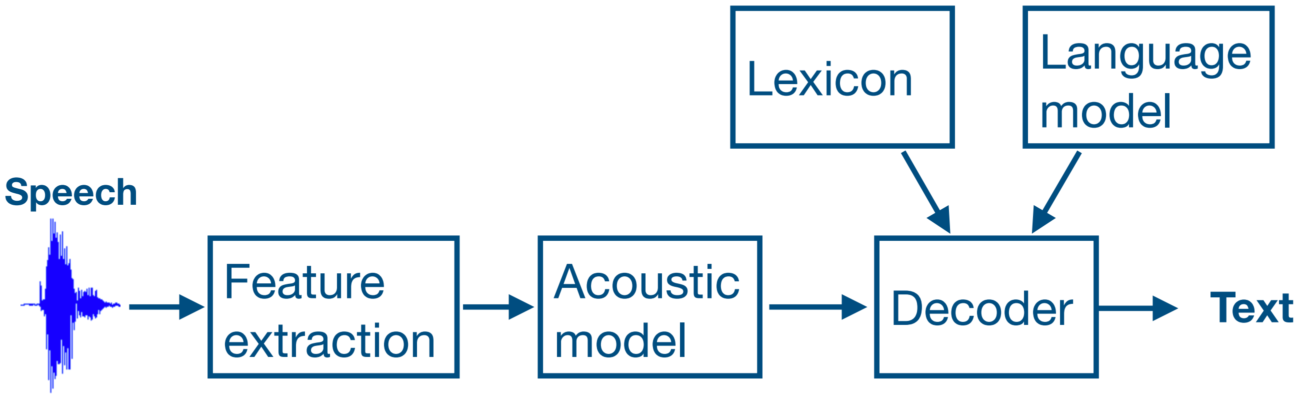
$$\begin{pmatrix} 2.3 \\ -4.2 \\ 0.8 \\ \vdots \\ 1.3 \end{pmatrix}\begin{pmatrix} 1.7 \\ -3.4 \\ 2.1 \\ \vdots \\ 0.2 \end{pmatrix}\cdots\begin{pmatrix} 0.9 \\ 1.4 \\ -1.5 \\ \vdots \\ -2.6 \end{pmatrix}$$

Estimating Emission Distribution Models



- If we know the alignment of the feature vectors to the HMM states, it is possible to estimate the emission distribution model to represent the distribution of the observations in that state
- Typically this alignment is NOT known, and instead the alignment and emission distributions are estimated iteratively using the Expectation-Maximization (EM) algorithm
- The alignment over the HMM states can be obtained using the Viterbi algorithm
- To improve the emission distribution models, it is coming to combine together multiple consecutive feature vectors, e.g. with a window of 5 feature vectors

Language Model and Decoder



- The output of the acoustic model is a sequence of probabilities of phones or senones
- That sequence needs to be decoded in order to find the most likely output message
- The phone sequences are converted to potential word sequences, or hypotheses, using the information from the lexicon
- Language model (LM) defines the allowed words and gives probabilities for their sequences, effectively defining the decoder search space
- The decoder then finds the most probable output text for the input signal, combining the probabilities from the acoustic and language models

Example on scoring alternative hypotheses:

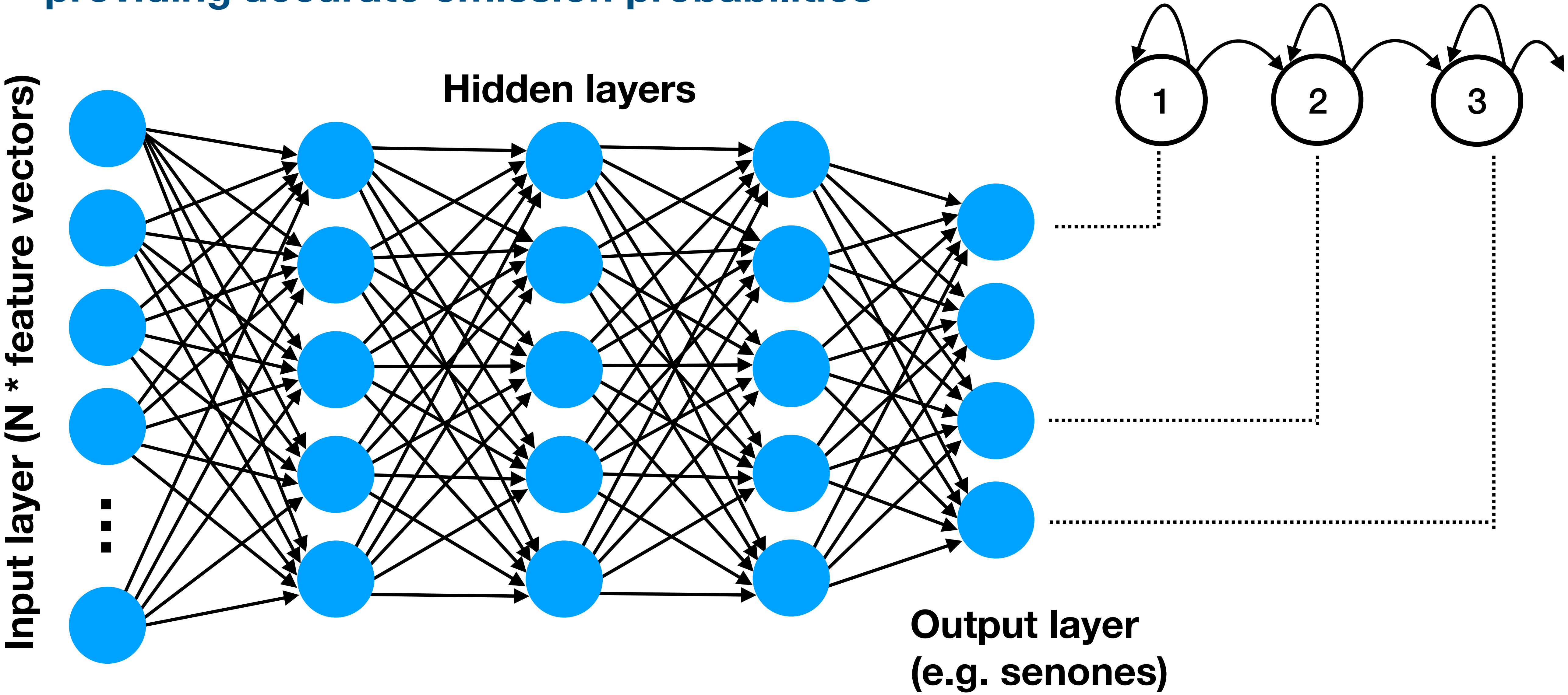
Wreck a nice beach → High AM score/Low LM score

Recognize speech → High AM score/High LM score → **Best hypothesis!**

Read the news → Low AM score/High LM score

Neural Networks for Acoustic Modelling

- Classical HMM-based ASR systems used Gaussian Mixture Models (GMMs) as the emission distribution models. Nowadays Deep Neural Networks (DNNs) are used instead.
- DNN-HMM hybrid systems use HMMs with DNNs for emission probabilities
- Neural networks are discriminative models, which can outperform GMMs in providing accurate emission probabilities



Neural Network Acoustic Models

- **Neural network acoustic models come in many flavours:**
  - **Feed-forward networks**
  - **Recurrent networks (RNNs, LSTMs, GRUs)**
  - **Convolutional input layers**
  - **Attention-based models**
- **Hybrid models often rely on HMM/GMM systems for initialisation and to define the DNN output layer**
- **Decoding relies on the acoustic model to produce likelihoods p(o|s):**

$$\hat{\mathrm{W}} = \arg\max_{\mathrm{W}} p(\boldsymbol{O} \mid \mathrm{W})\, p(\mathrm{W}) = \arg\max_{\mathrm{W}} \sum_{s_{1:T} \in W} \left(\prod_{t=1}^{T} p(o_t \mid s_t)\, p(s_t \mid s_{t-1}) \right) p(W)$$

- **However, discriminative DNNs produce posterior probabilities P(S|O)**
- **Solution to the mismatch: Apply Bayes rule to convert posteriors to “pseudo-likelihoods”, using state priors:**

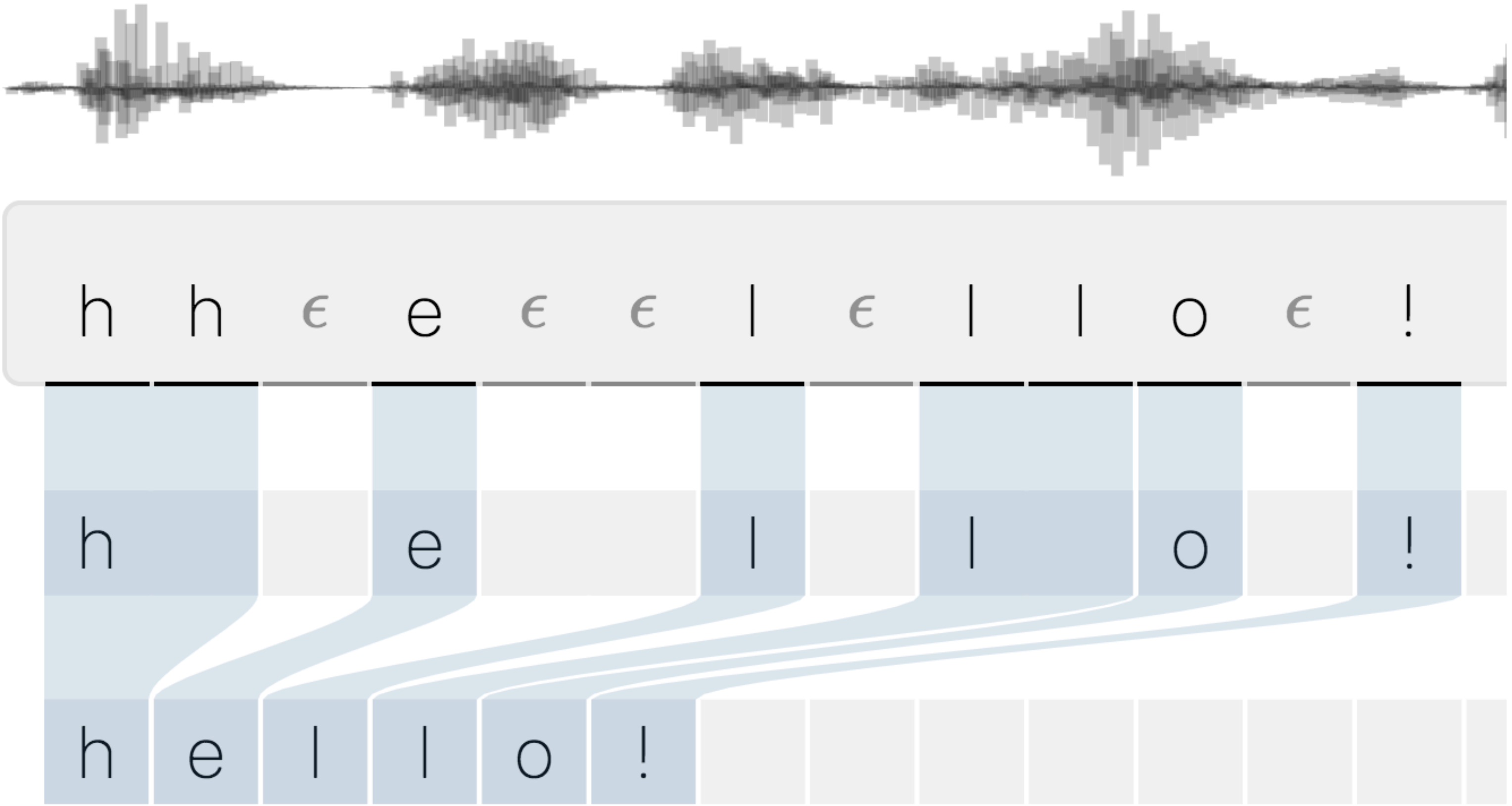
$$p(o \mid s) = \frac{P(s \mid o)\, p(o)}{P(s)} \propto \frac{P(s \mid o)}{P(s)}$$

End-to-End Models for ASR

- A growing trend in automatic speech recognition is to simplify the statistical modelling and decoding by using end-to-end models
- A sequence-to-sequence classifier can take speech features as input, and directly produce text as output
- Benefits:
  - Simpler training procedure (just one model to train)
  - Possibility for more accurate models than with separated AM, LM, and Lexicon
  - Decoding is significantly simpler and faster than with traditional ASR models
- Downsides:
  - Requires a lot of training data
  - Difficulty to adapt to new domains
  - Typically some language model is still needed for the best results

Connectionist Temporal Classification

- A relatively simple method for alignment-free sequence modelling is called CTC = Connectionist Temporal Classification
  - Introduces a special blank symbol ε, which allows (potential) direct usage of the network output as a recognition result
- CTC refers to an output encoding scheme and a loss function for sequence classification problems
- Typically CTC is applied for training deep neural networks with recurrent layers (RNNS, LSTMs)

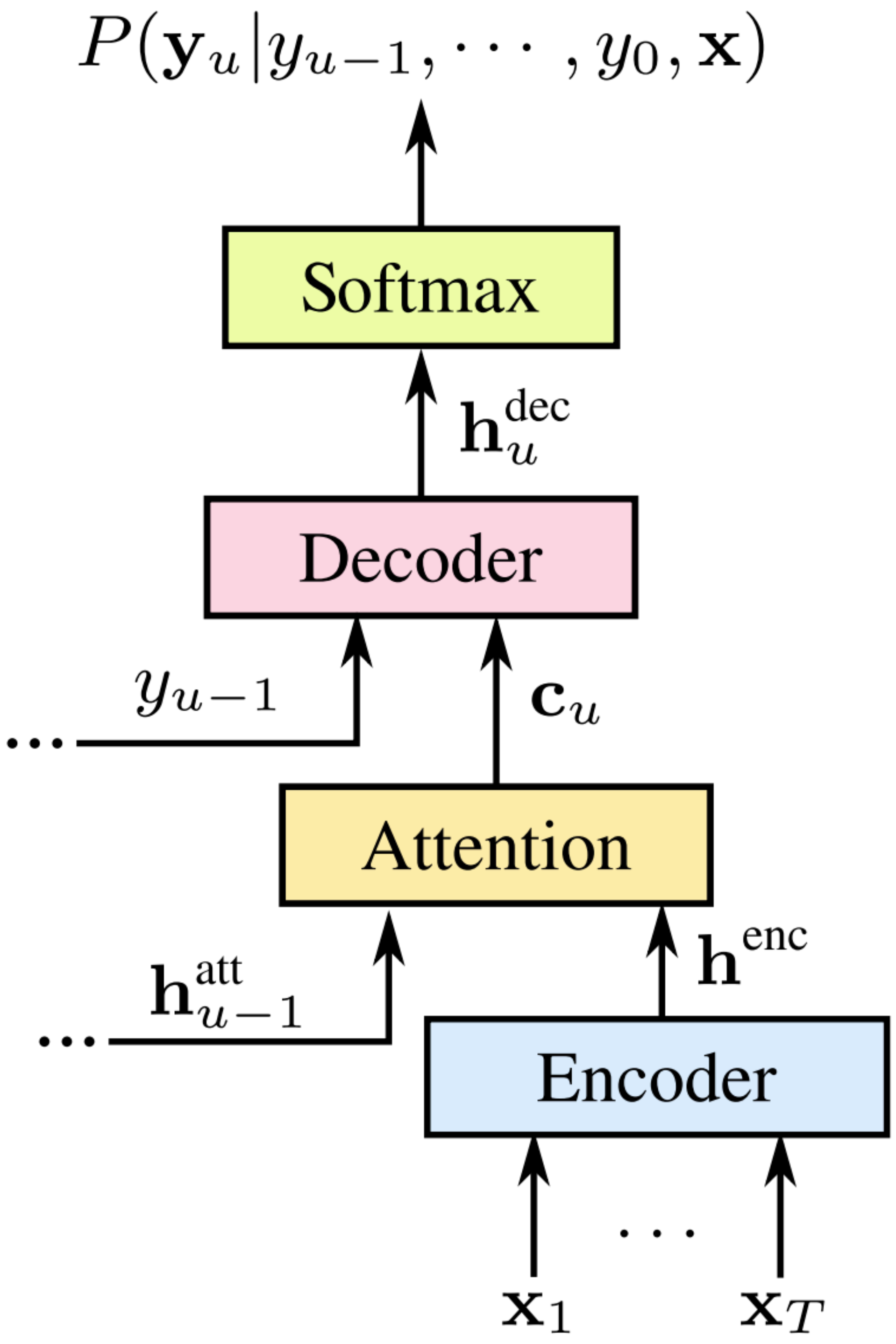


- CTC network outputs phones or letters (graphemes), instead of context-dependent senones
- In practice, a LM and a decoder is still needed

https://distill.pub/2017/ctc/

Encoder, Attention, Decoder

- Another type of end-to-end model uses an encoder-decoder approach with attention mechanism
- A complex neural network can output graphemes (letters) directly, without an explicit lexicon
- Listen, Attend and Spell by Google consists of:
  - Encoder (Listener) resembles traditional acoustic model
  - Attention mechanism resolves alignment between input frames and output symbols
  - Decoder (Speller) acts as a language model and constructs the output
  - All the model blocks are optimised jointly
  - An additional LM can still improve the accuracy

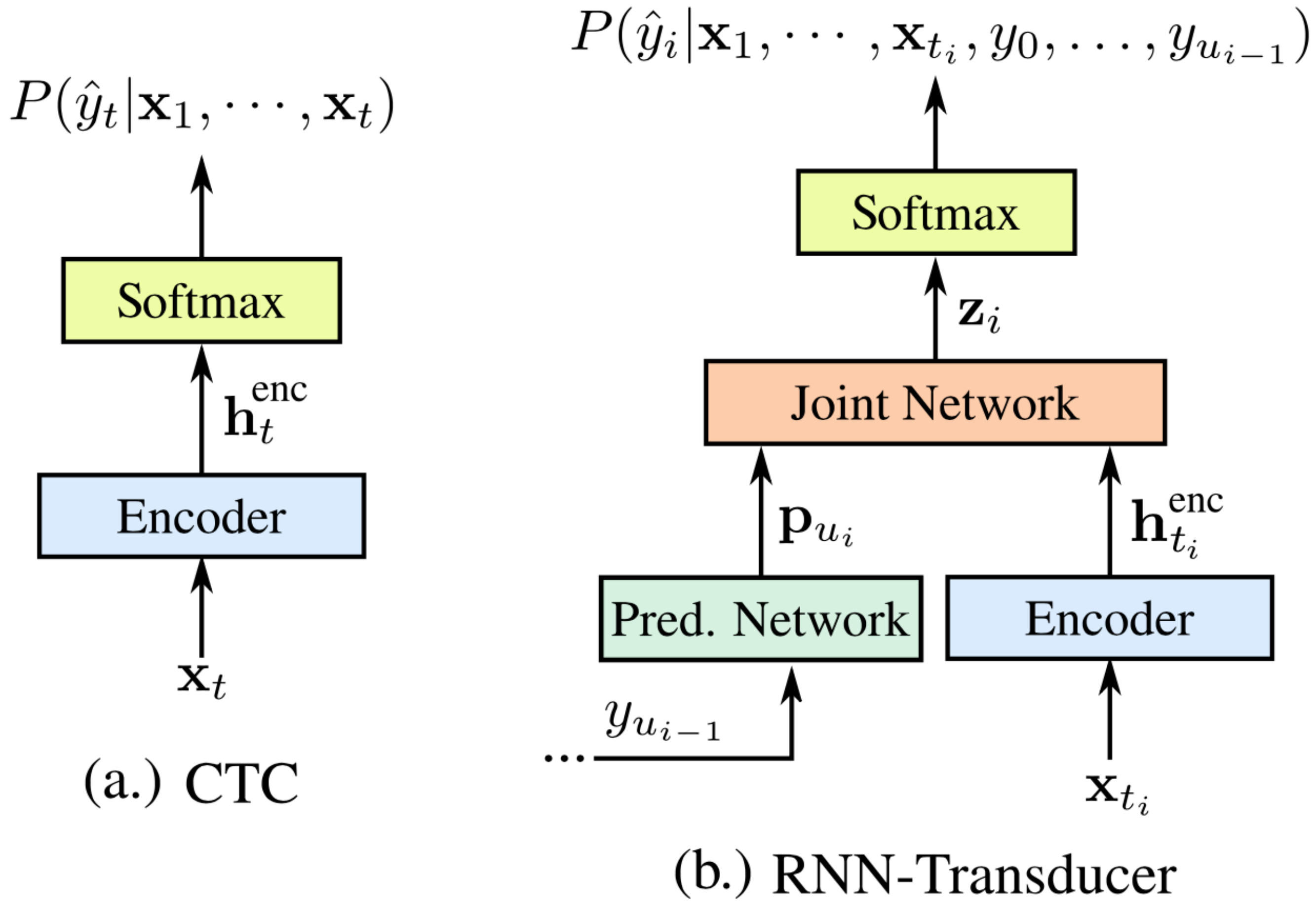


$P(\mathbf{y}_u | y_{u-1}, \cdots, y_0, \mathbf{x})$
Softmax
$\mathbf{h}_u^{\text{dec}}$
Decoder
y_{u-1}
$\mathbf{c}_u$
...
Attention
$\mathbf{h}_{u-1}^{\text{att}}$
$\mathbf{h}^{\text{enc}}$
...
Encoder
$\mathbf{x}_1$
...
$\mathbf{x}_T$

Prabhavalkar *et al*.: A Comparison of Sequence-to-Sequence Models for Speech Recognition (Interspeech 2017)

RNN Transducer

- A recurrent architecture that has recently gained popularity for real-time ASR
- Originally proposed by Graves et al. (2012, 2013), later used e.g. by Google for their on-device (mobile phone) ASR
- The network output is either letters or words/word-pieces
- The encoder in RNN-T is similar to the CTC models
- RNN-T architecture introduces a predictor, which is an integrated neural language model with a recurrent input signal
- The joint network combines the outputs of the encoder and the predictor to produce the probability distribution of the next letter or word



$P(\hat{y}_t|\mathbf{x}_1, \cdots, \mathbf{x}_t)$
Softmax
$\mathbf{h}_t^{\text{enc}}$
Encoder
$\mathbf{x}_t$
(a.) CTC
$P(\hat{y}_i|\mathbf{x}_1, \cdots, \mathbf{x}_{t_i}, y_0, \ldots, y_{u_{i-1}})$
Softmax
$\mathbf{z}_i$
Joint Network
$\mathbf{p}_{u_i}$
$\mathbf{h}_{t_i}^{\text{enc}}$
Pred. Network
Encoder
$\ldots$ $y_{u_{i-1}}$
$\mathbf{x}_{t_i}$
(b.) RNN-Transducer

He *et al.*: Streaming End-to-End Speech Recognition for Mobile Devices (ICASSP 2018)

Applications of Speech Recognition

- The improvement of automatic speech recognition accuracy has driven the adoption of ASR in various applications
- Speech recognition works well as an input method especially when typing is cumbersome, e.g. with mobile devices, or in-car applications
- Typical uses of ASR include
  - Command-and-control applications
  - Dictation
  - Automatic call center operation
  - Generating transcriptions and TV subtitles
- Smart speakers such as Amazon Echo and Google Home have popularised using speech to control simple tasks
  - Home automation can be controlled with speech, even if the devices themselves don’t have ASR capabilities: It is enough that they can communicate with the smart speaker.

Challenges in ASR

- Although automatic speech recognition accuracy is close to human performance in many practical tasks, there are still challenges that need constant attention:
  - Out-of-vocabulary words are difficult to recognise correctly
  - Varying environmental noises impair recognition accuracy
  - Overlapping speech or “babble noise” is especially problematic
  - Recognising child speech, or people with speech production disabilities, may perform poorly. Also heavily accented speech is typically causing difficulties.
- Often the key to a successful model is to obtain enough realistic, in-domain training data. Some data can be simulated if necessary.
- Many DNN-based models require huge amounts of data for training, in the order of thousands of hours. End-to-end models may need up to 100,000h of speech for the best performance!

ASR in Smart Speakers

- Smart speakers are always on, waiting for a dedicated wake word
- Once the wake word is detected, the speech is streamed to the cloud, where speech recognition, natural language understanding, and response generation takes place
- Special challenges:
  - Robust wake word detection on the device
  - Far-field speech recognition, possibly with a lot of background noise
  - Low-latency cloud-based ASR
  - Personalisation to match user's needs and habits, like recognising songs from a personal playlist
- ASR solutions:
  - Noise-robust feature extraction with beam-forming and acoustic echo cancellation
  - Complex DNN-based ASR models in the cloud, trained from tens of thousands of hours of speech, using real or simulated room acoustics

Group Discussion

- Think about an application where ASR would be useful, but where it is not yet commonly used. How would ASR change the user experience? What are the biggest challenges for ASR in that use case?

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