ASR, …, transformers, … explainability

Short bio

- Mathematics in Leiden, NL
- PhD at University of Amsterdam, Louis Pols
  - Structure of vowel systems
  - Phonetics - phonology
- Postdoc at Institute of Perception Research, Eindhoven
  - Intonation
- ASR department of a Belgium-based speech technology company
- Since 2002: Radboud University, Nijmegen, NL
  - Computational models of human speech processing
  - Computational cognition (learning, language acquisition)
  - Phonetics, morphology
  - Explainable AI, InDeep

InDeep

Interpreting Deep Learning Models for Text and Sound

nationale
wetenschaps
agenda

Radboud University

Shoebox 2, 1961/2, IBM

Four ways to look at ASR

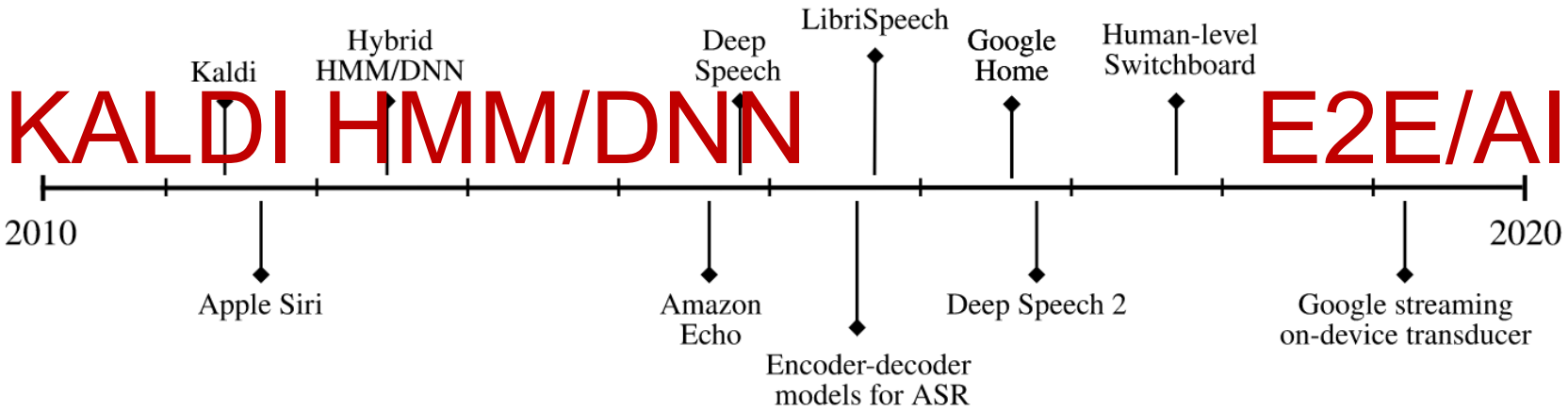
- ASR as a research topic itself
  - Word error rate (WER) minimization, latency, robustness, network architectures (KALDI vs Whisper), training regimes, transfer learning, etc.
- ASR as black box module in larger system
  - In a dialogue system
  - As a tool for the hearing-impaired
  - In cases where typing is dangerous/impossible
- ASR as a tool to unravel the structure in the speech signal
  - Biomarking
  - 'Computational lens'
  - CAPT etc.
- ASR as proxy for computational simulation for human speech processing
  - Plausibility issues, ecology

Key applications of ASR

- **Video:** Real-time and asynchronous video captioning
- **Audio** annotation (verbatim, summarizing), (speaker diarization)
- **Meeting** transcriptions
- **Media monitoring:** Speech-to-Text can help broadcast TV, podcasts, radio, and more quickly and accurately detect brand keyword spotting
- **Command and control** (robots)
- **Telephony:** Call tracking, accurate transcriptions, call analytics, speaker diarization, and more.

- **E-health:** Medical analyses of patients' audio (COPD, Alzheimer, Parkinson etc.). **Speech as biomarker. Verbatim or corrected output??**

ASR
2010-now

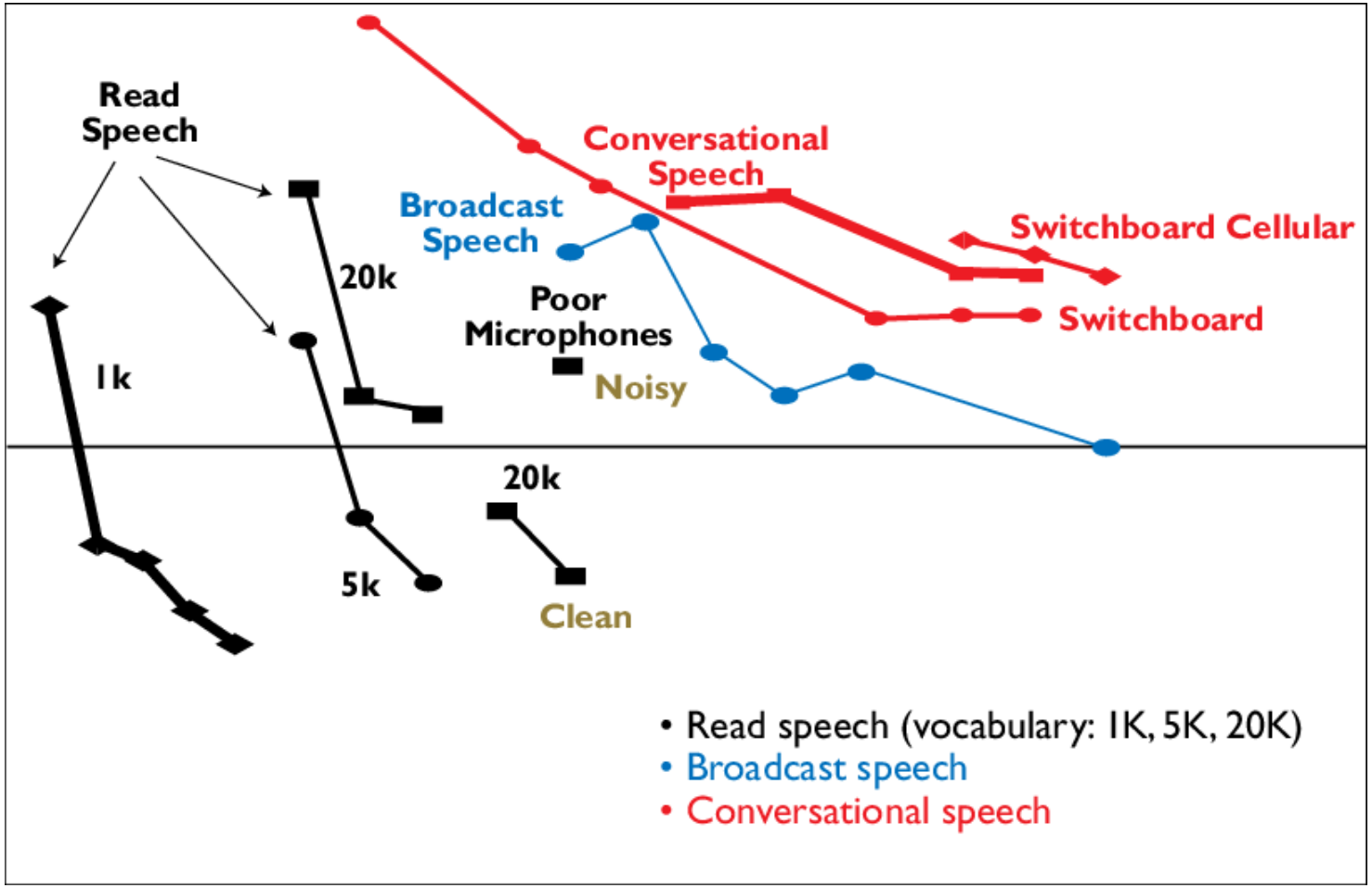


A timeline of some of the major developments in speech recognition from the years 2010 to 2020. The decade saw the launch of voice-based devices and voice assistants, open-source and widely used speech recognition software like Kaldi, and larger benchmarks like LibriSpeech. We also saw speech recognition models improve starting from hybrid neural network architectures to more end-to-end models including Deep Speech, Deep Speech 2, encoder-decoder models with attention, and transducer-based speech recognition.

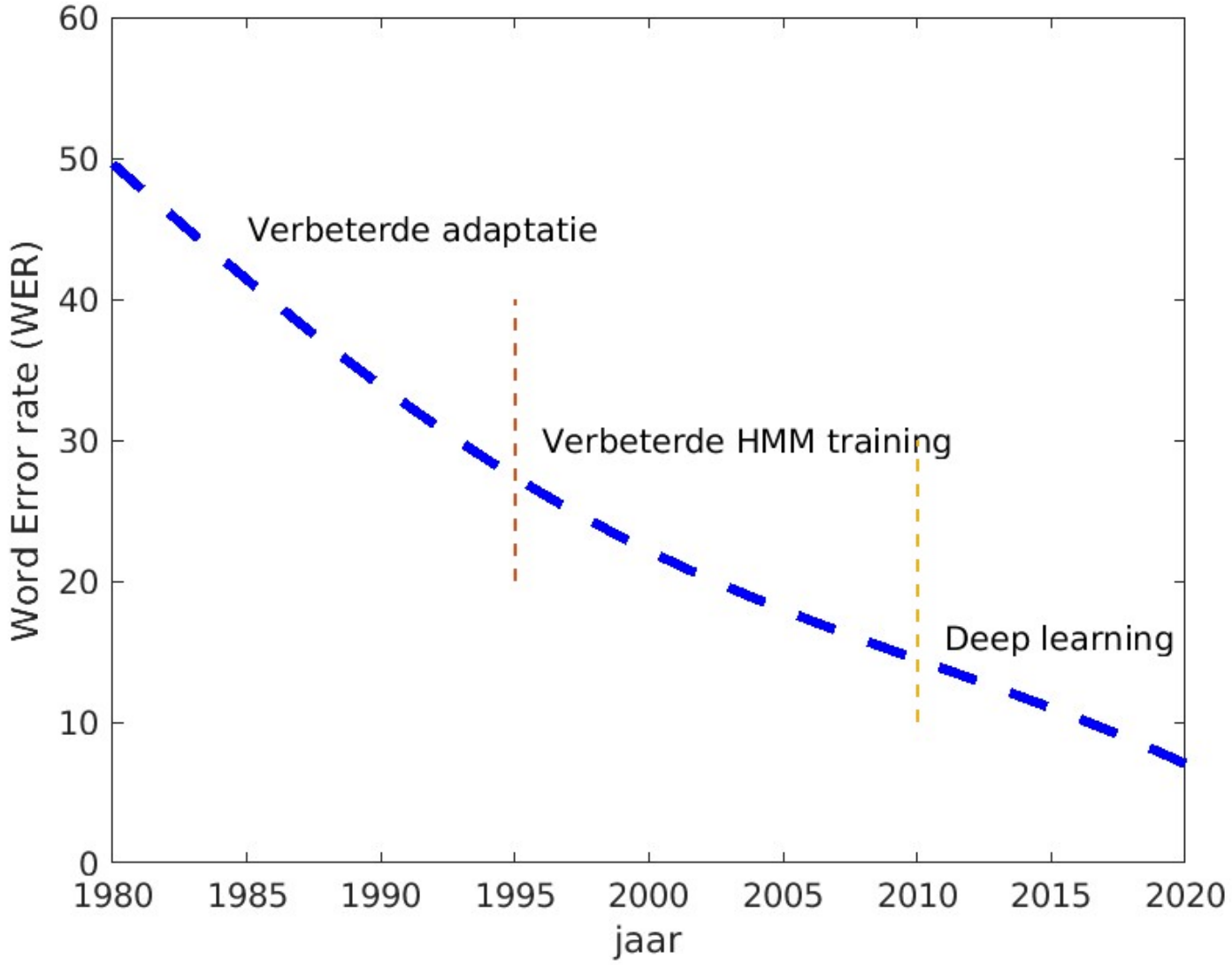
From https://awni.github.io/future-speech/

ASR techniques, overview

- Template matching (’70)
  - Representative speech patterns (e.g. words, syllables) are stored and labeled
  - New unknown data identified by comparison
- Probabilistic matching (’80-now)
  - Often by Hidden Markov Modeling (HMM)
  - An HMM is characterized by hidden states graph + state-state transition probabilities
  - Characterized by a (statistical) distribution in the acoustic space
  - Knowledge based
- ANN-based (2013-now)
  - Many directions
  - Mapping oriented: audio → orthography
  - Data based
- AI, Deep Learning (2020-now)

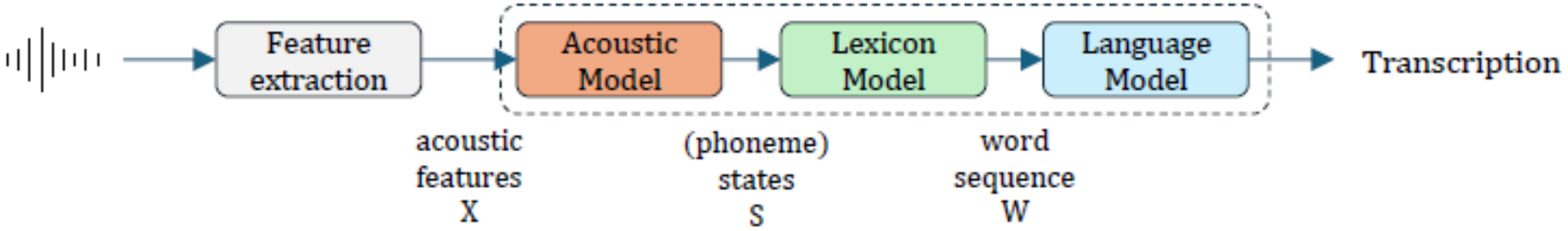


(By Xuedong Huang, 2016)


60
50
40
30
20
10
0
Word Error rate (WER)
Verbeterde adaptatie
Verbeterde HMM training
Deep learning
1980
1985
1990
1995
2000
2005
2010
2015
2020
jaar

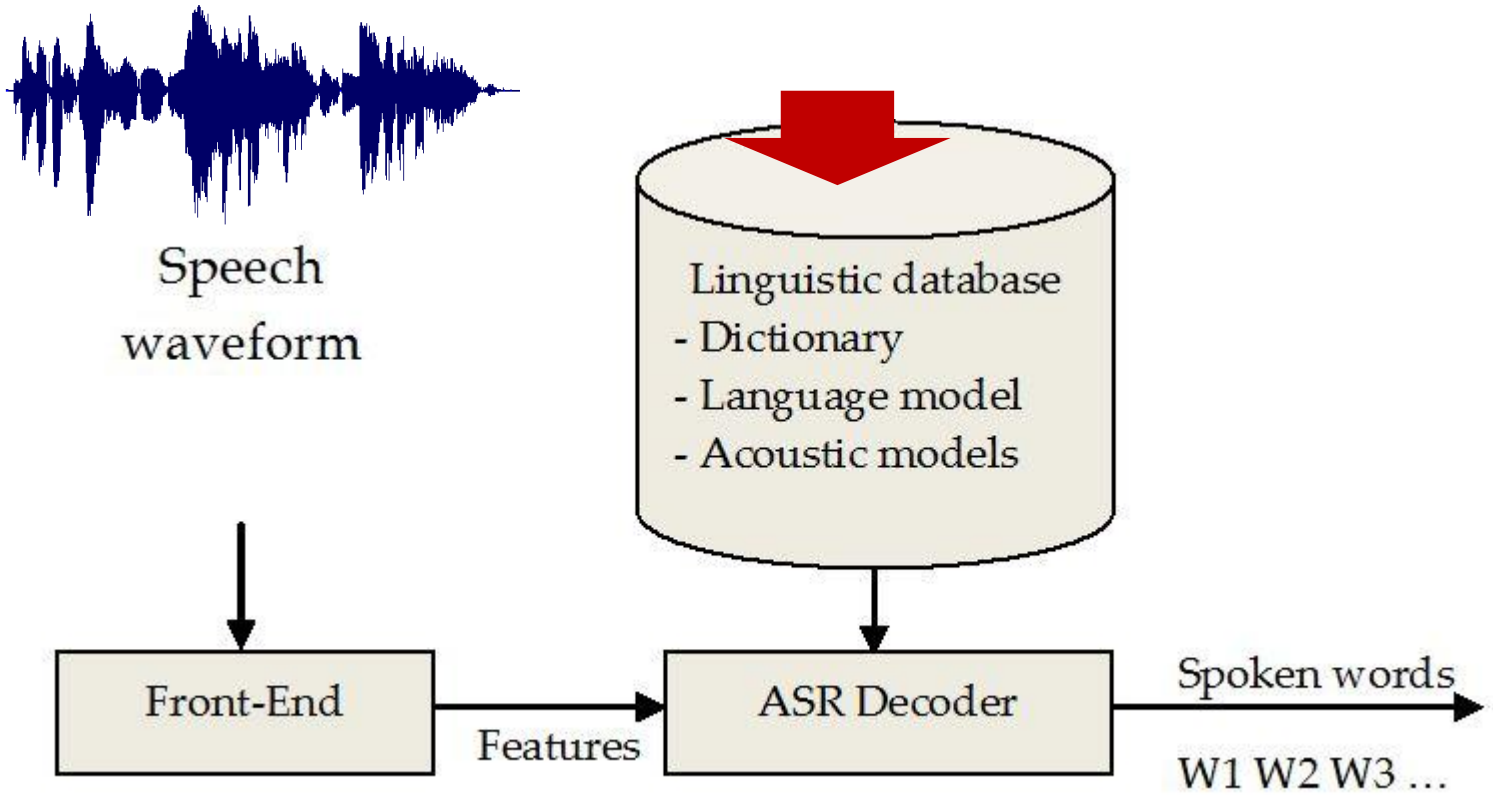
Overview

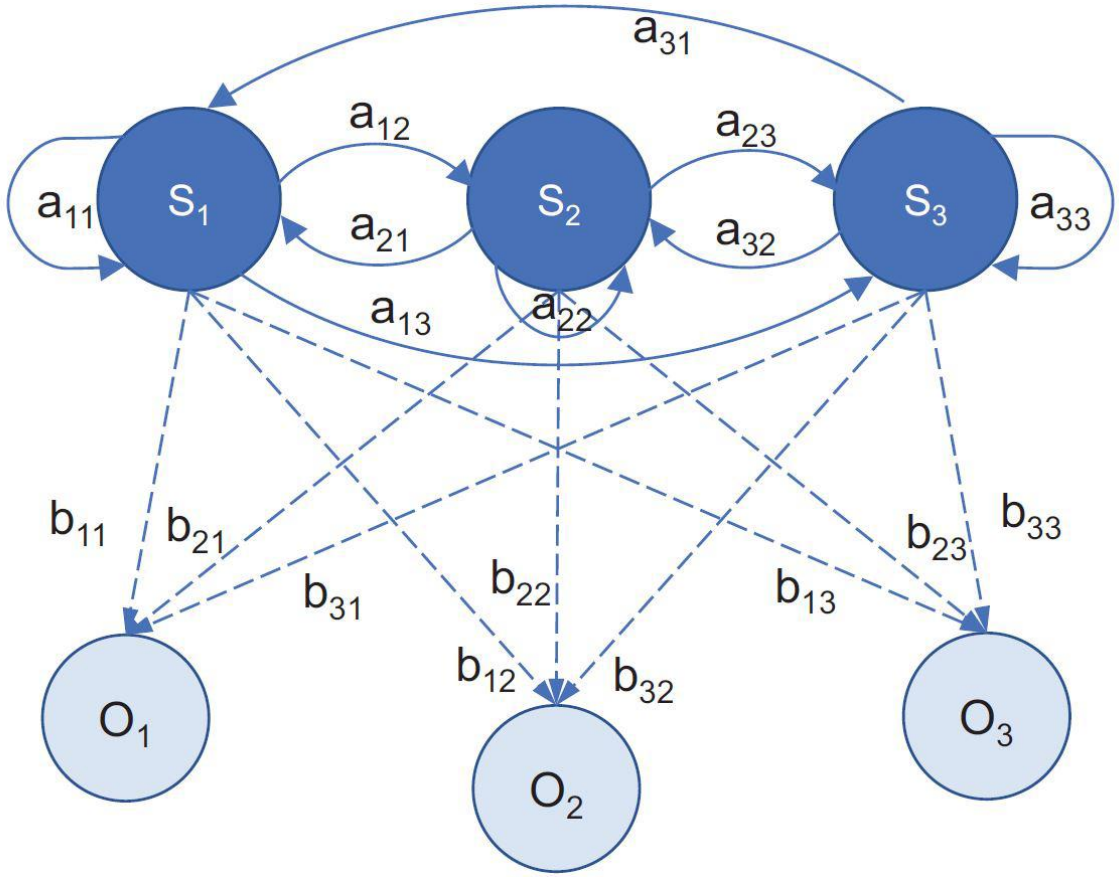
- 1952 “Audrey” (Bell Labs), numbers 0- 9, reported acc 97% , single speaker
- 1961-2: Shoebox (IBM), 16 English words on top of digits, single speaker
- 1993-5 (IBM) first commercial speech recognition product for personal dictation
- 1970’s, **hyrid speech recognition** combining acoustic models, pronunciation dictionaries and language models



- Since 2019/20 or so: **end-to-end speech recognition:** Vectorization of everything!
- Today: Transformer-like architectures and large-scale data.

Hybrid ASR: modular architecture



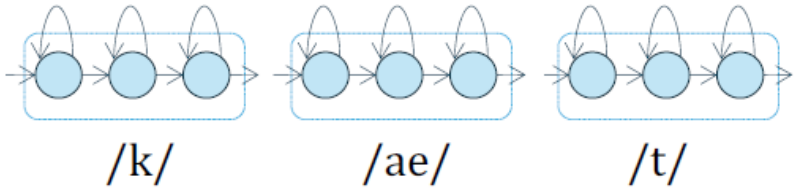


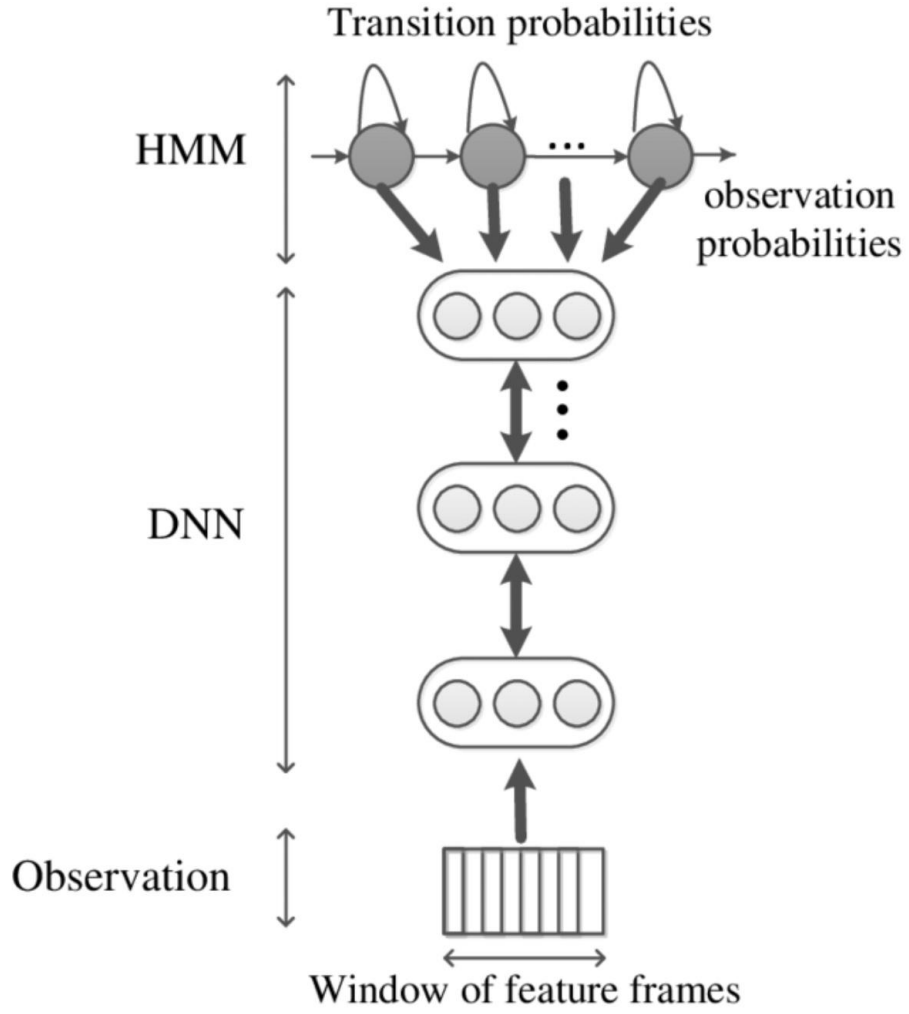
HMM

Forward backward
Expectation Maximization
Viterbi

Pos:
time warping
statistical underpinning

Neg:
Poor time resolution
State-state independence assumption


/k/
/ae/
/t/


Transition probabilities
HMM
observation probabilities
DNN
Observation
Window of feature frames

Deep Learning: a Very Short history …

- MLP (MultiLayer Perceptron): since 1958 (e.g. Rosenblatt)

- RNN (recurrent neural networks): (1925, Ising), 1980, various people (e.g. Elman)
- *Backpropagation: 1982, Werbos a.o.*

- LSTM (long-short term memory): 1995, Hochreiter et al.
- *Word2vec: 2013, Mikolov, Google team*
- Sequence to sequence: 2014, Sutskever et al. (now at OpenAI)

- Since 2006: theoretical development of training approaches deep models (Bengio, et al.)

- Transformers: 2017, Vaswani et al.
- BERT (Bidirectional Encoder Representations from Transformers), 2018, Google (and many variants)
- Audio, s2t: Wav2vec2.0, 2020: Whisper, 2022 (and variants), Conformers

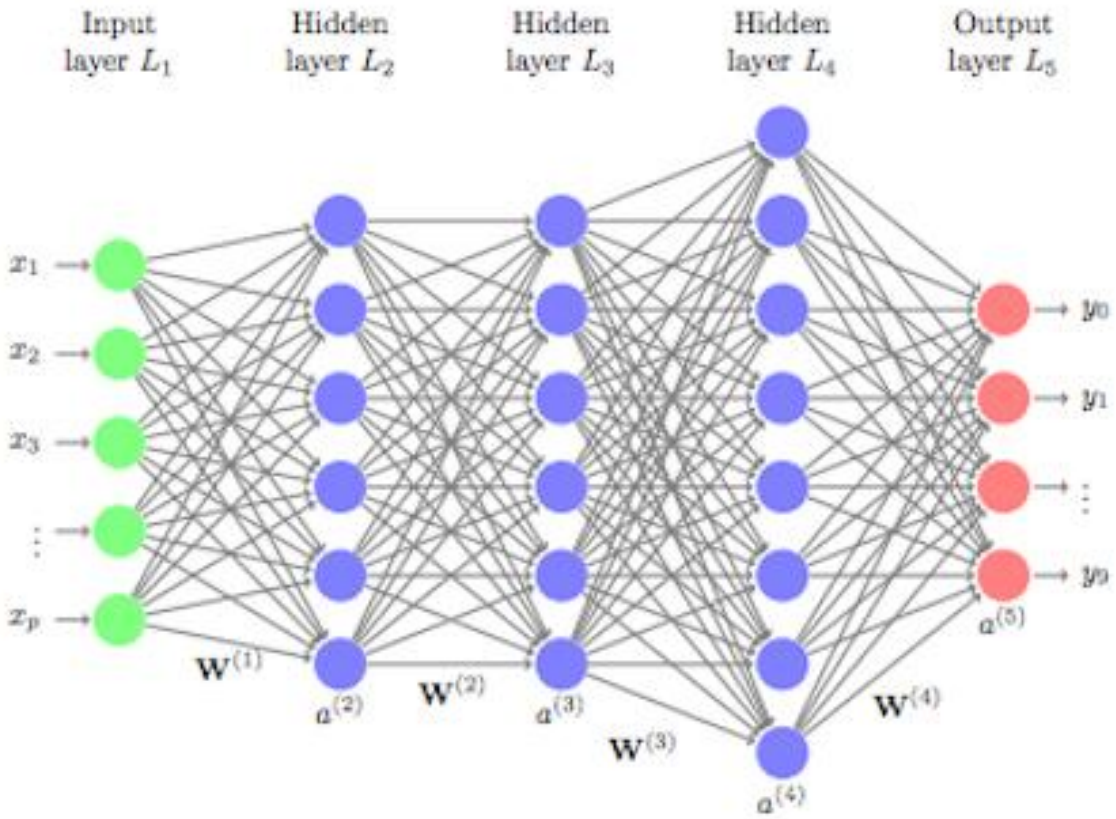
Speech and Language and AI

- Speech (and Language) Technology now

- Impact of Artificial Intelligence (AI)

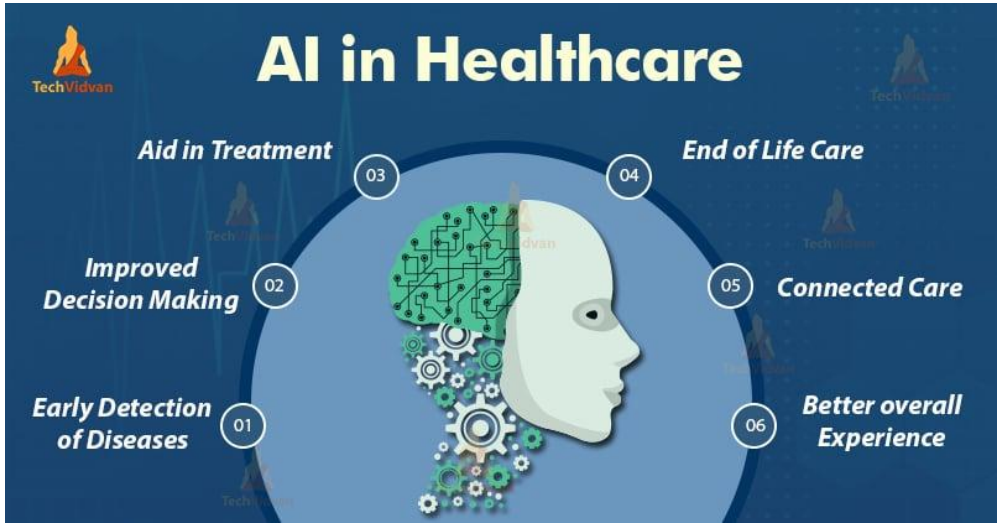
Speech and Language and AI

- Speech (and Language) Technology now
- Impact of Artificial Intelligence (AI)



What we now see is only the beginning…

- AI can be extremely useful:
  - pattern discovery
  - e.g., medical data
  - text generation
  - code generation



- But also risky:
  - spoofing
  - deep fakes, incl. fake audio
  - production of incorrect but convincing texts
  - large-scale pollution of social media eco-system

	pro	challenge
Classical approach	Insight-based, knowledge based	Lower performance
Recent deep learning approaches	Higher performance (relative 30-60% reduction of error rates)	Data hungry!! (But …!) Small data sets? What do ***we*** learn? Explainable, Responsible AI?

One of the KEY papers (2017)

Attention*1706.03762.pdf

Attention Is All You Need

Ashish Vaswani* Google Brain avaswani@google.com

Noam Shazeer* Google Brain noam@google.com

Niki Parmar* Google Research nikip@google.com

Jakob Uszkoreit* Google Research usz@google.com

Llion Jones* Google Research llion@google.com

Aidan N. Gomez* † University of Toronto aidan@cs.toronto.edu

Łukasz Kaiser* Google Brain lukaszkaiser@google.com

Illia Polosukhin* ‡ illia.polosukhin@gmail.com

Abstract

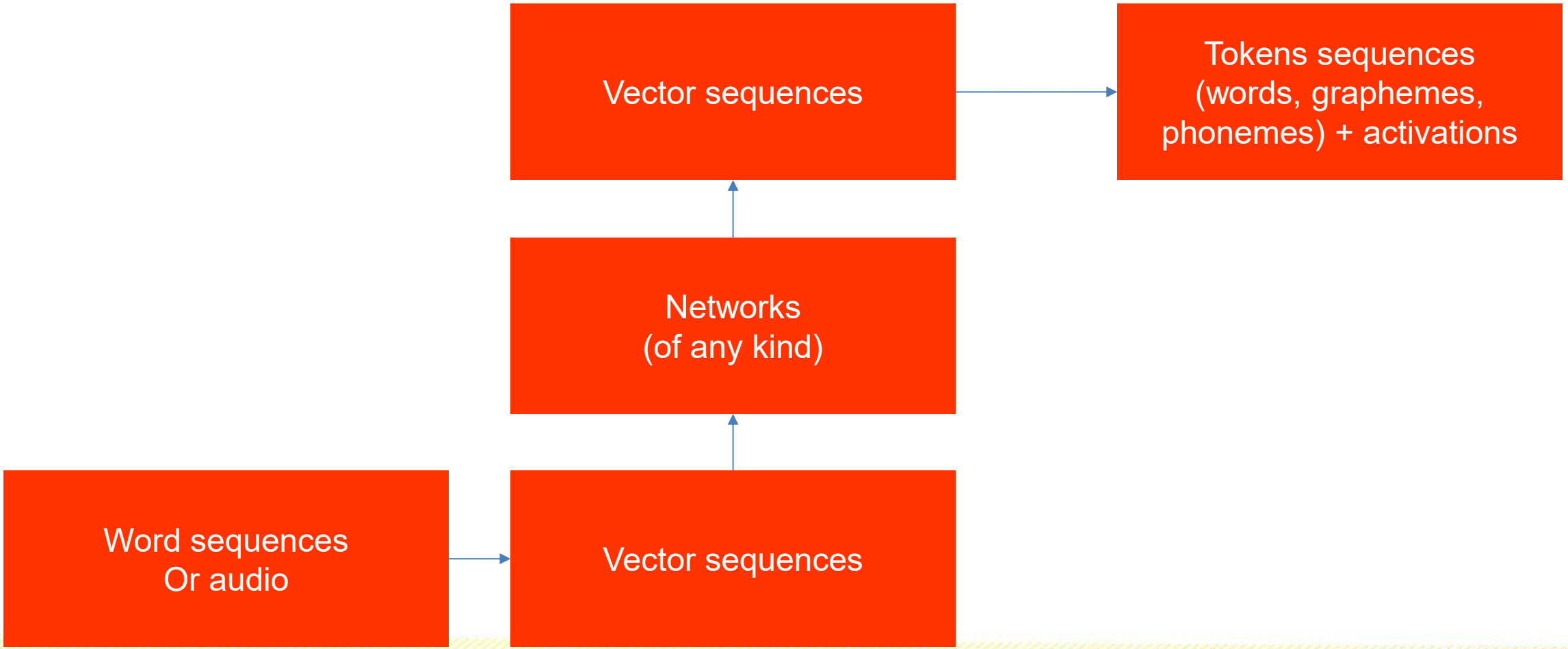
The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to be superior in quality while being more parallelizable and requiring significantly less time to train. Our model achieves 28.4 BLEU on the WMT 2014 English-to-German translation task, improving over the existing best results, including ensembles, by over 2 BLEU. On the WMT 2014 English-to-French translation task, our model establishes a new single-model state-of-the-art BLEU score of 41.8 after training for 3.5 days on eight GPUs, a small fraction of the training costs of the best models from the literature. We show that the Transformer generalizes well to

Vaswani et al. (2017)

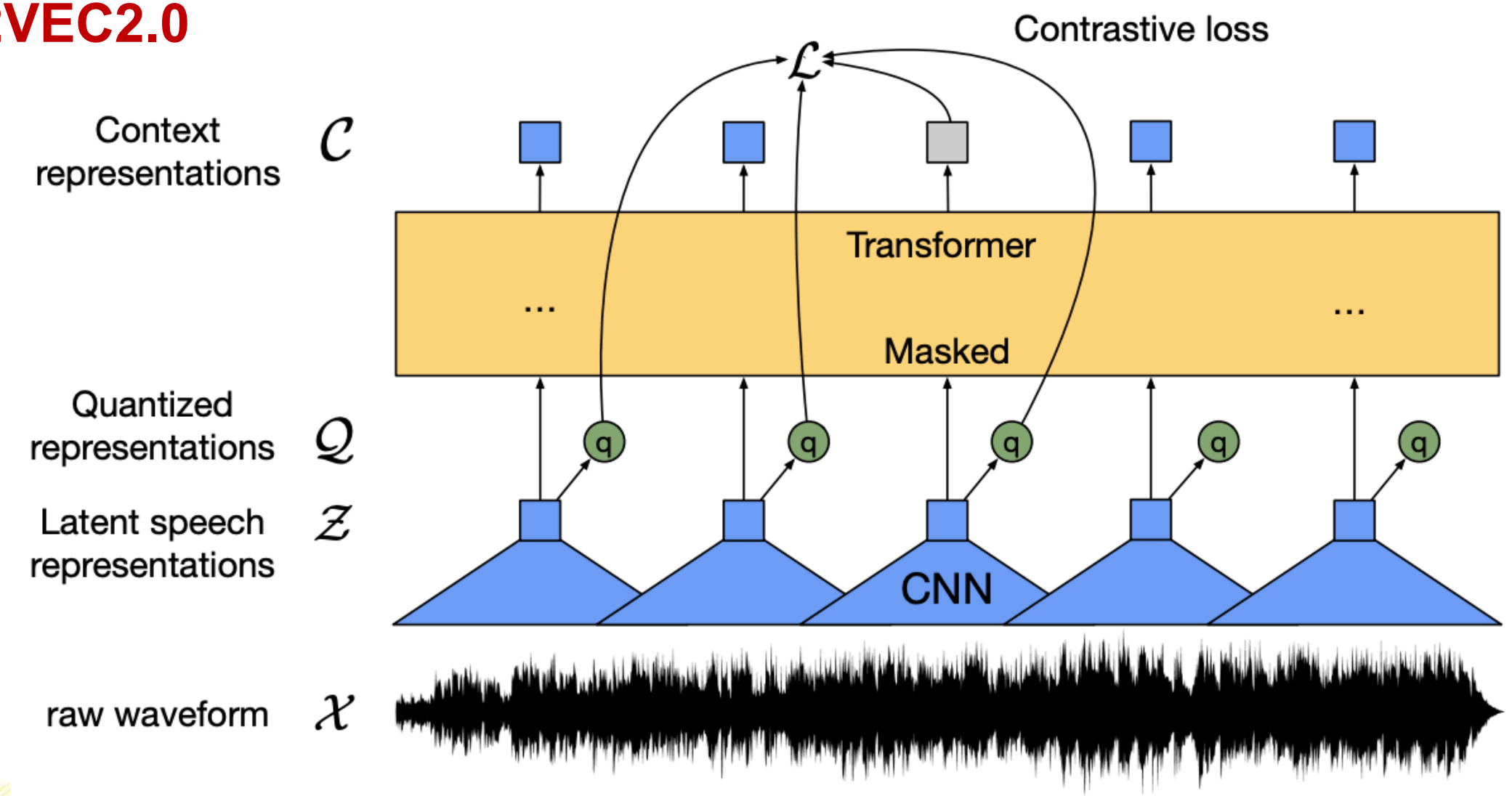
Abstract

The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to be superior in quality while being more parallelizable and requiring significantly less time to train. Our model achieves 28.4 BLEU on the WMT 2014 English-to-German translation task, improving over the existing best results, including ensembles, by over 2 BLEU. On the WMT 2014 English-to-French translation task, our model establishes a new single-model state-of-the-art BLEU score of 41.8 after training for 3.5 days on eight GPUs, a small fraction of the training costs of the best models from the literature. We show that the Transformer generalizes well to other tasks by applying it successfully to English constituency parsing both with large and limited training data.

VECTORS, NETWORKS



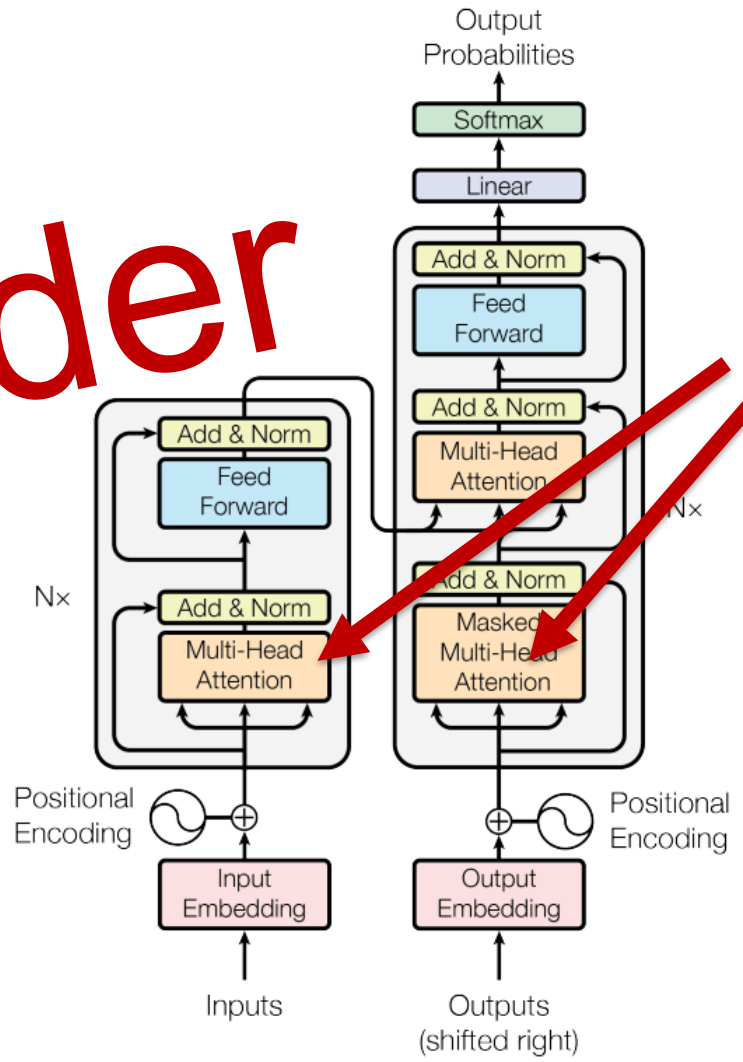
WAV2VEC2.0


Contrastive loss
$\mathcal{L}$
Context representations
$\mathcal{C}$
Transformer
...
...
Masked
Quantized representations
$\mathcal{Q}$
q
q
q
q
q
Latent speech representations
$\mathcal{Z}$
CNN
raw waveform
$\mathcal{X}$

encoder

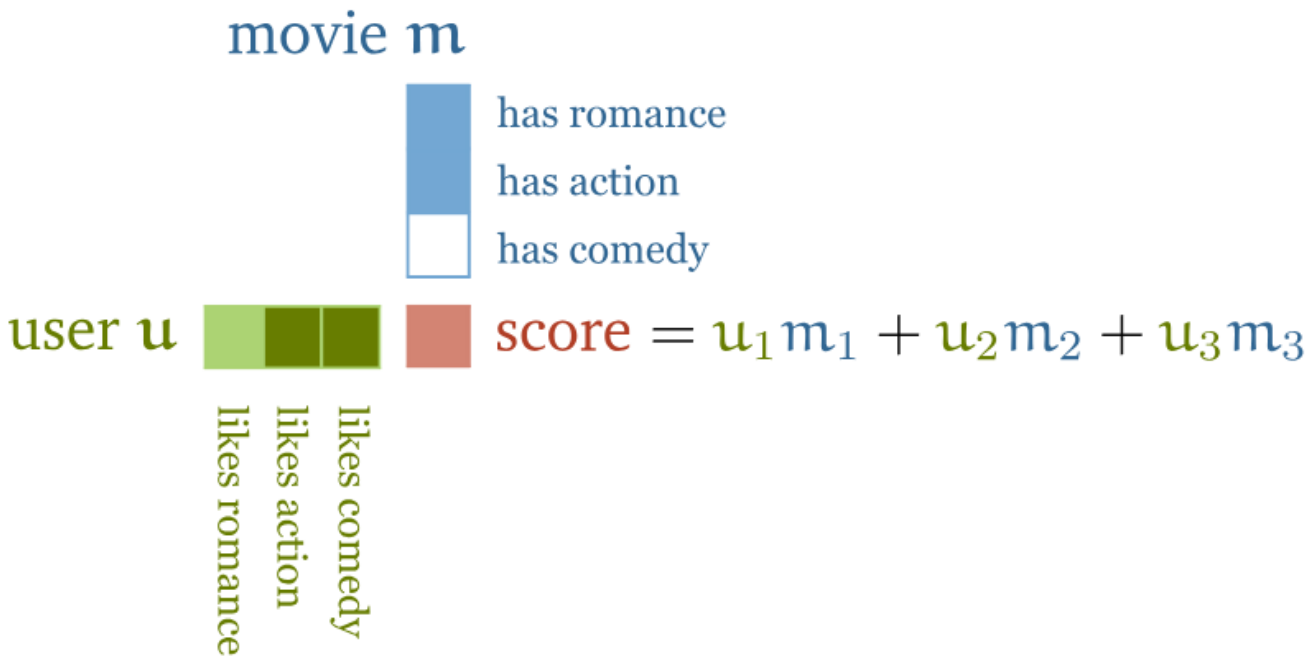
attention

decoder



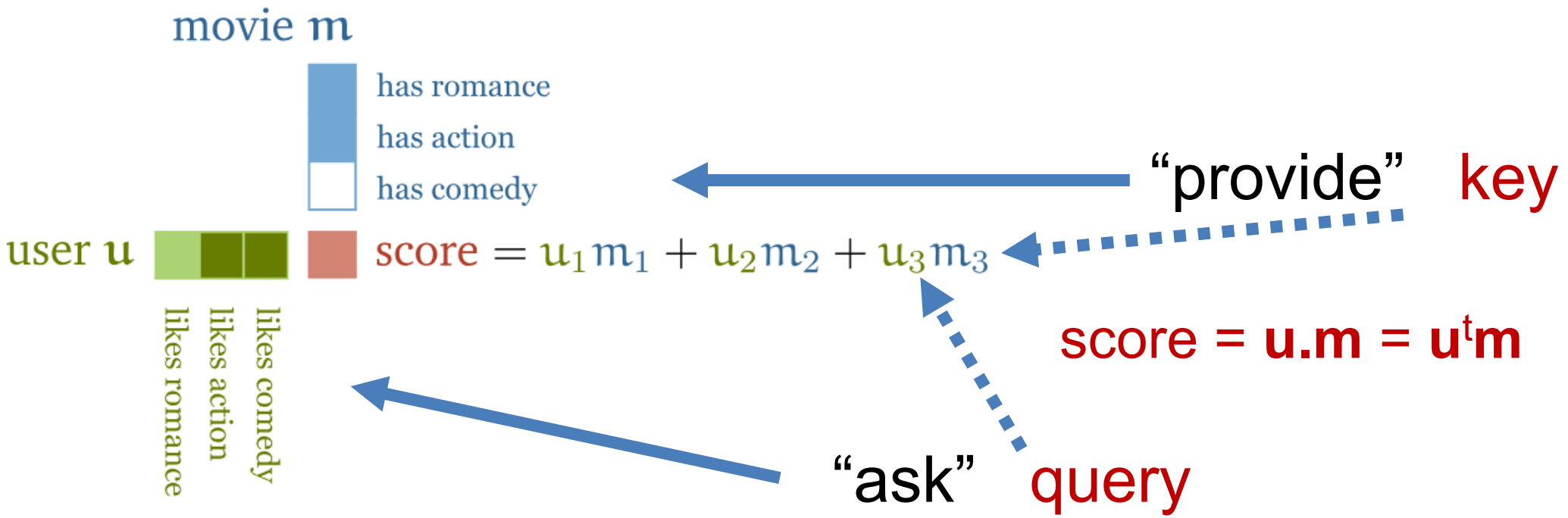
Understanding why self-attention works, in particular the dotprot construction

See https://peterbloem.nl/blog/transformers



Understanding why self-attention works, in particular the dotprot construction

See https://peterbloem.nl/blog/transformers



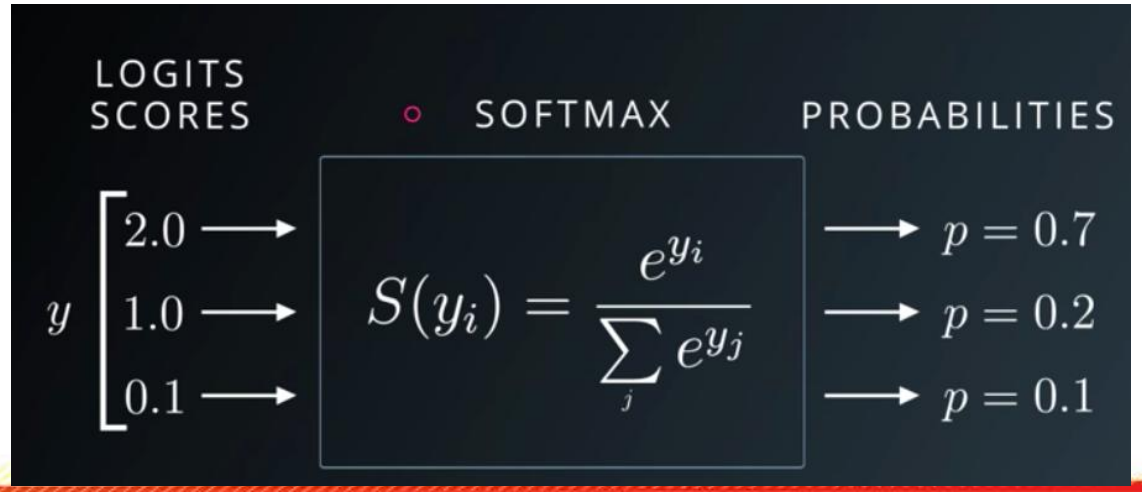
ATTENTION

- the dot product gives values anywhere between negative and positive infinity

- next, apply a softmax
  - to map all these values to [0,1] and
  - to ensure that they sum to 1 over the whole sequence

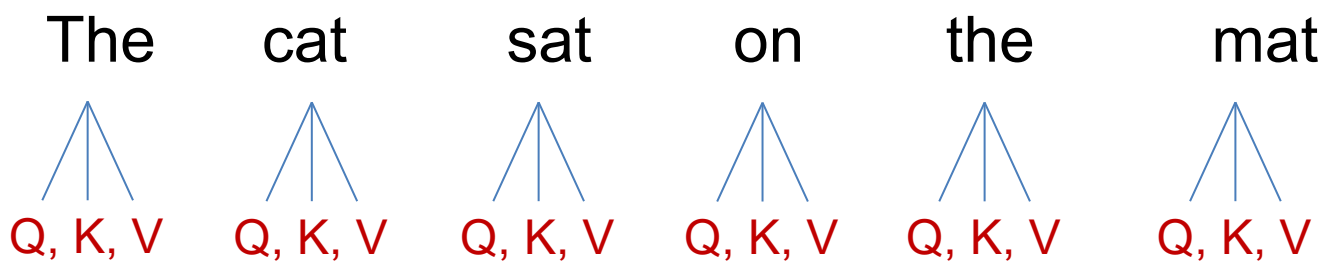
$$a_i = \frac{e^{x_i}}{\sum_{j=1}^{n} e^{x_j}}$$

This sequence is the basic operation of self attention.



Q, K, V

- Query: the degree a word looks for other words to pay attention to
- Key: the degree to which a word likes to be paid attention to
- Value: the value of the information of that word



A survey of transformers

Tianyang Lin, Yuxin Wang, Xiangyang Liu, Xipeng Qiu *

School of Computer Science, Fudan University, Shanghai, 200433, China
Shanghai Key Laboratory of Intelligent Information Processing, Shanghai, 200433, China

2.1.1. Attention modules

Transformer adopts attention mechanism with Query–Key–Value (QKV) model. Given the packed matrix representations of queries $\mathbf{Q} \in \mathbb{R}^{N \times D_k}$, keys $\mathbf{K} \in \mathbb{R}^{M \times D_k}$, and values $\mathbf{V} \in \mathbb{R}^{M \times D_v}$, the scaled dot-product attention used by Transformer is given by[1]

$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^\top}{\sqrt{D_k}}\right)\mathbf{V} = \mathbf{A}\mathbf{V}, \tag{1}$$

[1] If not stated otherwise, we use row-major notations throughout this survey (e.g., the ith row in $\mathbf{Q}$ is the query $\mathbf{q}_i$) and all the vectors are row vectors by default.

$$\text{MultiHeadAttn}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{Concat}(\text{head}_1, \ldots, \text{head}_H)\mathbf{W}^O, \tag{2}$$

$$\text{where head}_i = \text{Attention}(\mathbf{Q}\mathbf{W}_i^Q, \mathbf{K}\mathbf{W}_i^K, \mathbf{V}\mathbf{W}_i^V). \tag{3}$$

In Transformer, there are three types of attention in terms of the source of queries and key–value pairs:

- *Self-attention*. In Transformer encoder, we set $\mathbf{Q} = \mathbf{K} = \mathbf{V} = \mathbf{X}$ in Eq. (2), where $\mathbf{X}$ is the outputs of the previous layer.
- *Masked Self-attention*. In the Transformer decoder, the self-attention is restricted such that queries at each position can only attend to all key–value pairs up to and including that position. To enable parallel training, this is typically done by applying a mask function to the unnormalized attention matrix $\hat{\mathbf{A}} = \exp(\frac{\mathbf{Q}\mathbf{K}^\top}{\sqrt{D_k}})$, where the illegal positions are masked out by setting $\hat{A}_{ij} = -\infty$ if $i < j$. This kind of self-attention is often referred to as autoregressive or causal attention.[2]

FROM A MATHEMATICAL POINT OF VIEW

johnthickstun.com/docs/transformers.pdf

The Transformer Model in Equations

John Thickstun

Abstract

This document presents a precise mathematical definition of the transformer model introduced by Vaswani et al. [2017], along with some discussion of the terminology and intuitions commonly associated with the transformer. We also draw some connections between the transformer and lstm, based on observations by Levy et al. [2018].

1 Introduction

A **transformer block** is a parameterized function class $f_\theta : \mathbb{R}^{n\times d} \to \mathbb{R}^{n\times d}$. If $\mathbf{x} \in \mathbb{R}^{n\times d}$ then $f_\theta(\mathbf{x}) = \mathbf{z}$ where

$$Q^{(h)}(\mathbf{x}_i) = W_{h,q}^T \mathbf{x}_i, \quad K^{(h)}(\mathbf{x}_i) = W_{h,k}^T \mathbf{x}_i, \quad V^{(h)}(\mathbf{x}_i) = W_{h,v}^T \mathbf{x}_i, \qquad W_{h,q}, W_{h,k}, W_{h,v} \in \mathbb{R}^{d\times k}, \tag{1}$$

$$\alpha_{i,j}^{(h)} = \text{softmax}_j\left(\frac{\langle Q^{(h)}(\mathbf{x}_i), K^{(h)}(\mathbf{x}_j)\rangle}{\sqrt{k}}\right), \tag{2}$$

$$\mathbf{u}_i' = \sum_{h=1}^{H} W_{c,h}^T \sum_{j=1}^{n} \alpha_{i,j}^{(h)} V^{(h)}(\mathbf{x}_j), \qquad W_{c,h} \in \mathbb{R}^{k\times d}, \tag{3}$$

$$\mathbf{u}_i = \text{LayerNorm}(\mathbf{x}_i + \mathbf{u}_i'; \gamma_1, \beta_1), \qquad \gamma_1, \beta_1 \in \mathbb{R}^d, \tag{4}$$

$$\mathbf{z}_i' = W_2^T \text{ReLU}(W_1^T \mathbf{u}_i), \qquad W_1 \in \mathbb{R}^{d\times m}, W_2 \in \mathbb{R}^{m\times d}, \tag{5}$$

$$\mathbf{z}_i = \text{LayerNorm}(\mathbf{u}_i + \mathbf{z}_i'; \gamma_2, \beta_2), \qquad \gamma_2, \beta_2 \in \mathbb{R}^d. \tag{6}$$

The notation softmax_j indicates we take the softmax (defined in Equation 9) over the d-dimensional vector indexed by j. The LayerNorm function [Lei Ba et al., 2016] is defined for $\mathbf{z} \in \mathbb{R}^k$ by

$$\text{LayerNorm}(\mathbf{z}; \gamma, \beta) = \gamma\frac{(\mathbf{z} - \mu_\mathbf{z})}{\sigma_\mathbf{z}} + \beta, \qquad \gamma, \beta \in \mathbb{R}^k. \tag{7}$$

$$\mu_\mathbf{z} = \frac{1}{k}\sum_{i=1}^{k} \mathbf{z}_i, \quad \sigma_\mathbf{z} = \sqrt{\frac{1}{k}\sum_{i=1}^{k}(\mathbf{z}_i - \mu_\mathbf{z})^2}. \tag{8}$$

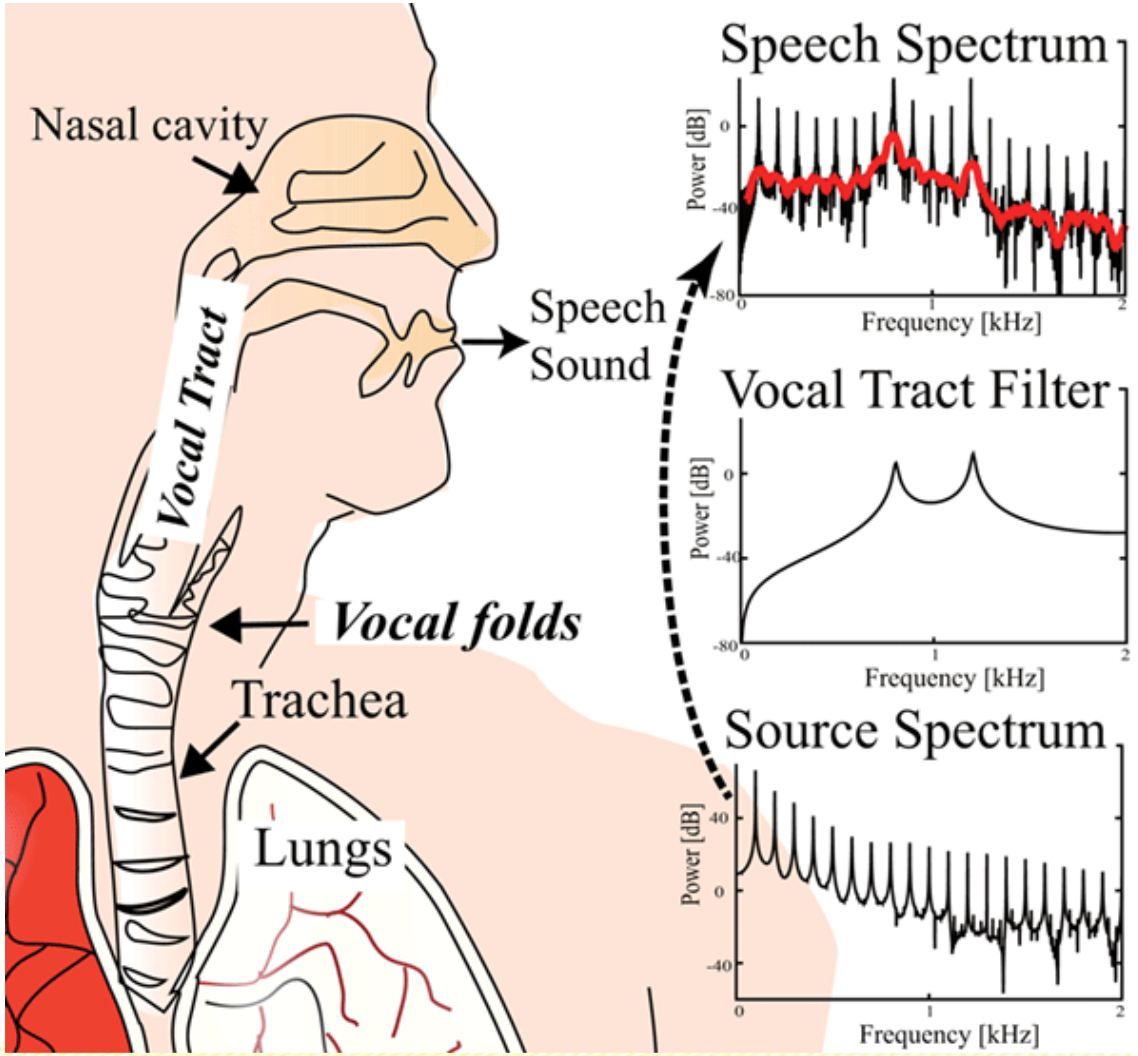
Many pretrained models available on HuggingFace

HuggingFace: repository with available models (from OpenAI, Meta, …, and other groups)

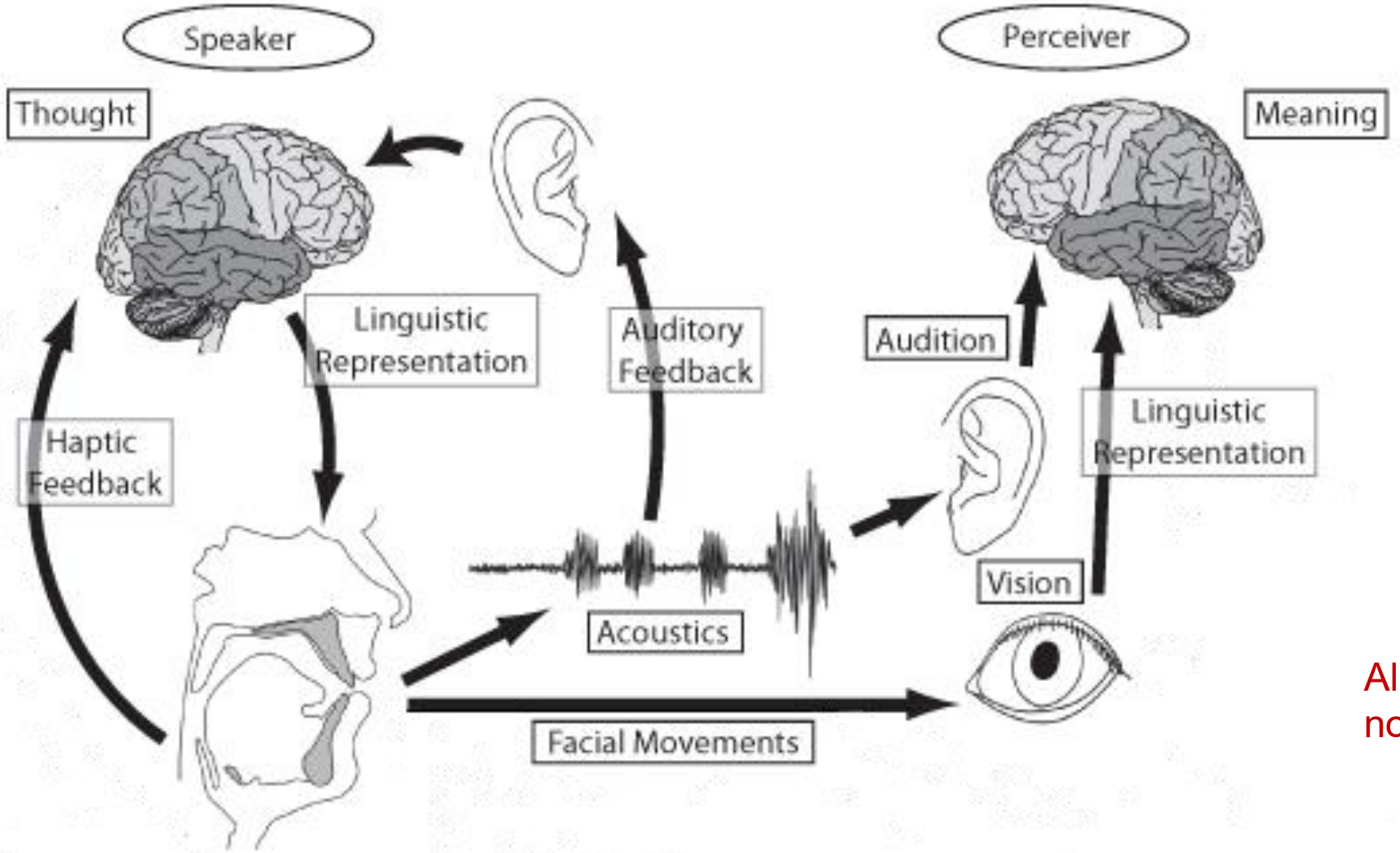
- April 9, 2025: 1,582,000 models (nearly 50 subcategories); 352000 datasets (8 different modalities)
- Sept 30, 2025: >2,000,000 models

Examples:

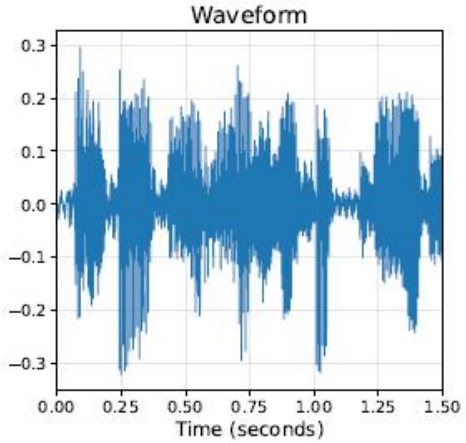
- A Wav2Vec2 model that is pretrained on relatively clean LibriSpeech data
- A Wav2Vec2 model that is pretrained and fine-tuned on noisy + clean data
- XLS-R: multilingual and multi-accent, pretrained on the CommonVoice corpus
- A huBERT model, improves or matches Wav2Vec2 performance and extends the Wav2Vec2 architecture, pretrained on LibriSpeech data
- Whisper, Whisper-large-v3, etc. etc.



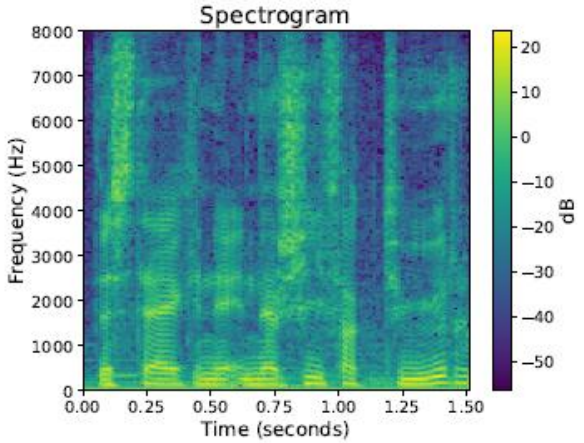
Borden & Harris (textbook)



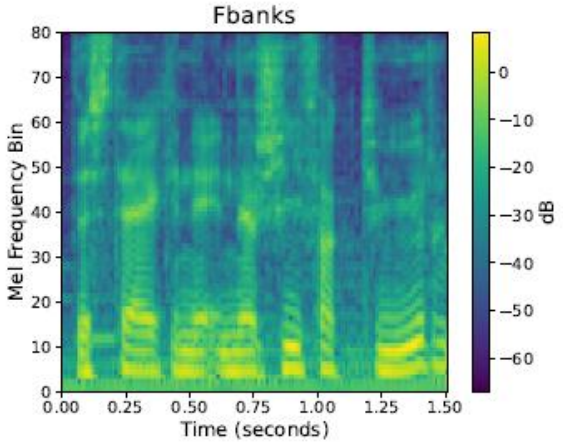
Almost all arrows involve non-linear processes



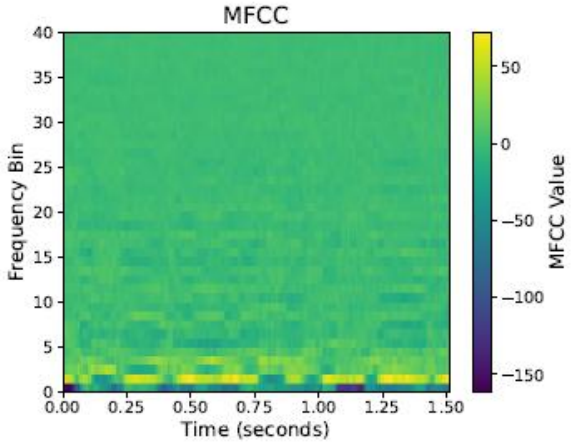
(a) raw waveform signal



(b) 256-dimensional spectrogram



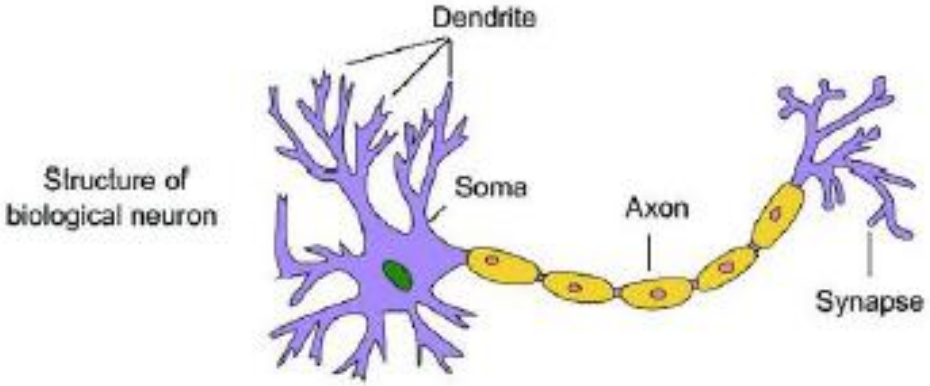
(c) 80-dimensional Fbanks



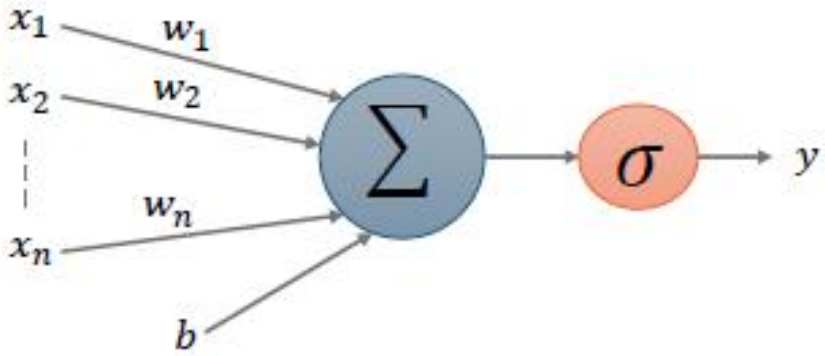
(d) 40-dimensional MFCCs

Optimal feature representation of audio depends on the task

Bengio et al., 2013: representation learning



(a) Brain neuron



(b) Perceptron

In a general neural network, such a building block is called a **neuron**. Like a perceptron, a neuron receives inputs, has a set of weights and a bias, and computes an activation (which is generally not constrained to 0 or 1). Mathematically, the output y of a **neuron** can be expressed in terms of its inputs x_i, weights w_i, bias term b and activation function σ as in Eq. 2.1.

$$y = \sigma(\sum_{i=1}^{n} w_i x_i + b) \tag{2.1}$$

MLPs are general approximators when #hidden layers ≥ 2 (already known in the late 80-ies)
Weakness: context

Multi-layer Perceptron

Typically, a neural network consists of multiple layers of neurons stacked on top of each other, which in its simplest form is referred to as **multi-layer perceptron (MLP)**. An MLP consists of several layers of neurons, where every neuron in a layer is connected to neurons in the layer before (i.e. a *fully connected* layer). Such a network is also called a **Feed-forward Neural Network**. The layers between the input layer and the output layer are called the **hidden layers**. Figure 2.6 shows a simple MLP with two hidden layers. In this example, there are four inputs and two outputs. In a speech recognition model (for which unfortunately for our environment, two hidden layers does not suffice), the input could for example be a time-frame of 80-dimensional fbanks (i.e. 80 input values), and the output could be for example 26 neurons, one for each letter of the alphabet.[5]

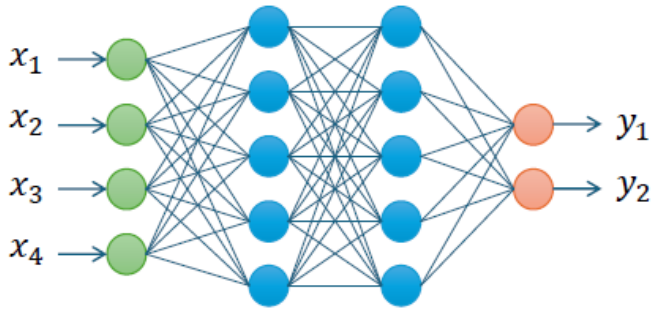
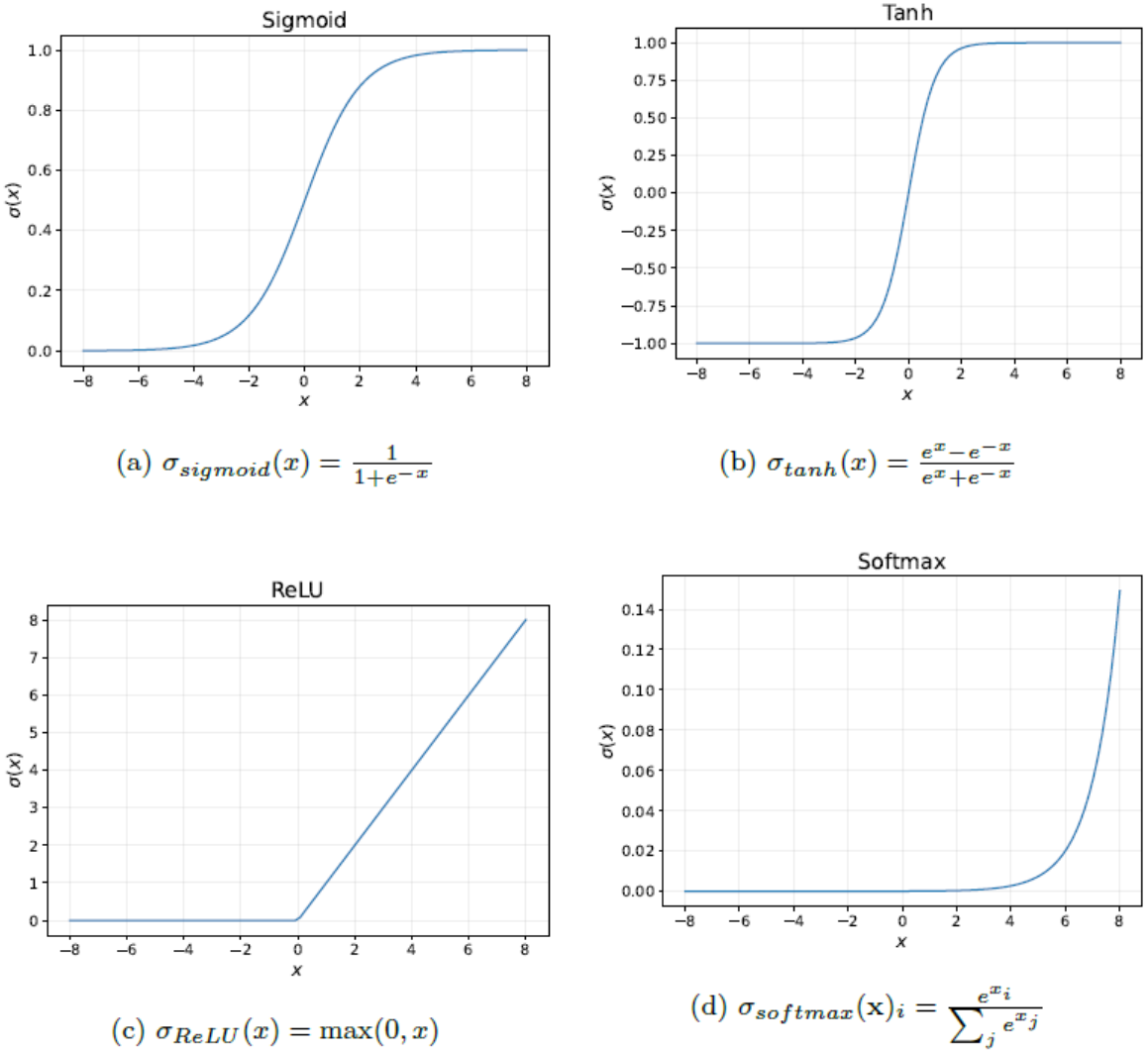


Figure 2.6: Multilayer Perceptron



(a) $\sigma_{sigmoid}(x) = \frac{1}{1+e^{-x}}$

(b) $\sigma_{tanh}(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}}$

(c) $\sigma_{ReLU}(x) = \max(0, x)$

(d) $\sigma_{softmax}(\mathbf{x})_i = \frac{e^{x_i}}{\sum_j e^{x_j}}$

Figure 2.4: Common activation functions used in neural networks.

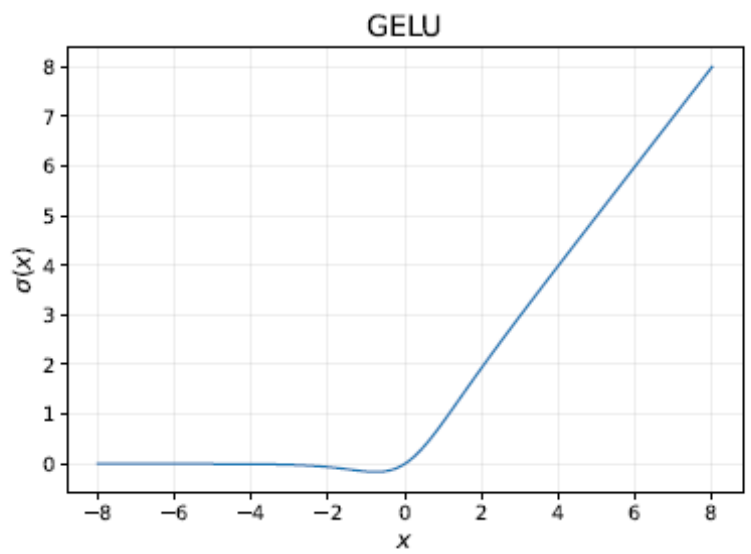
Classical:
- sigmoid
- tanh

(often problems with vanishing gradient)

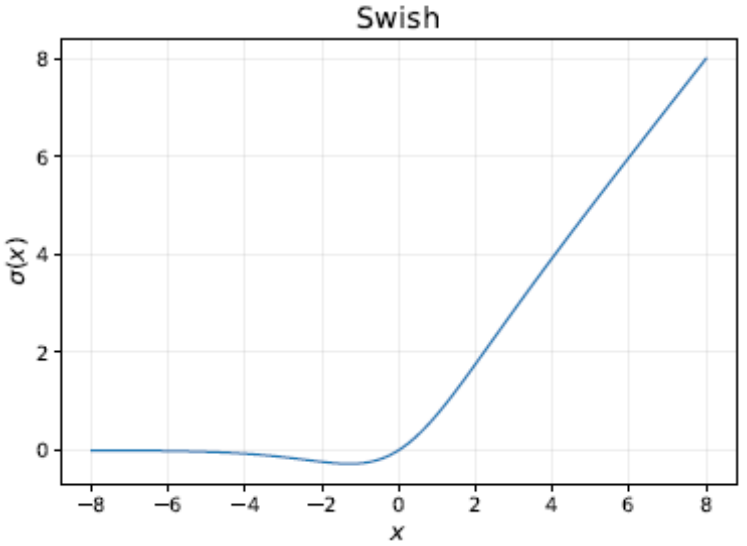
More recent:
- ReLU (rectified linear unit)
- GELU (Gaussian Error Linear Unit)
- … many more

- Softmax in the last layer

From Jakob Poncelet, Doct. Diss., 202



(a) $\sigma_{GELU}(x) = x\Phi(x)$



(b) $\sigma_{swish}(x) = \frac{x}{1+e^{-\beta x}}$

Figure 2.5: Common activation functions used in recent speech processing models.

(a) Standard layer

(b) Bottleneck layer

Figure 2.11: Example of a bottleneck layer. In the standard layer, there are $m \times n = 30$ connections. In the bottleneck layer, this is reduced to $(m \times k) + (k \times n) = 22$.

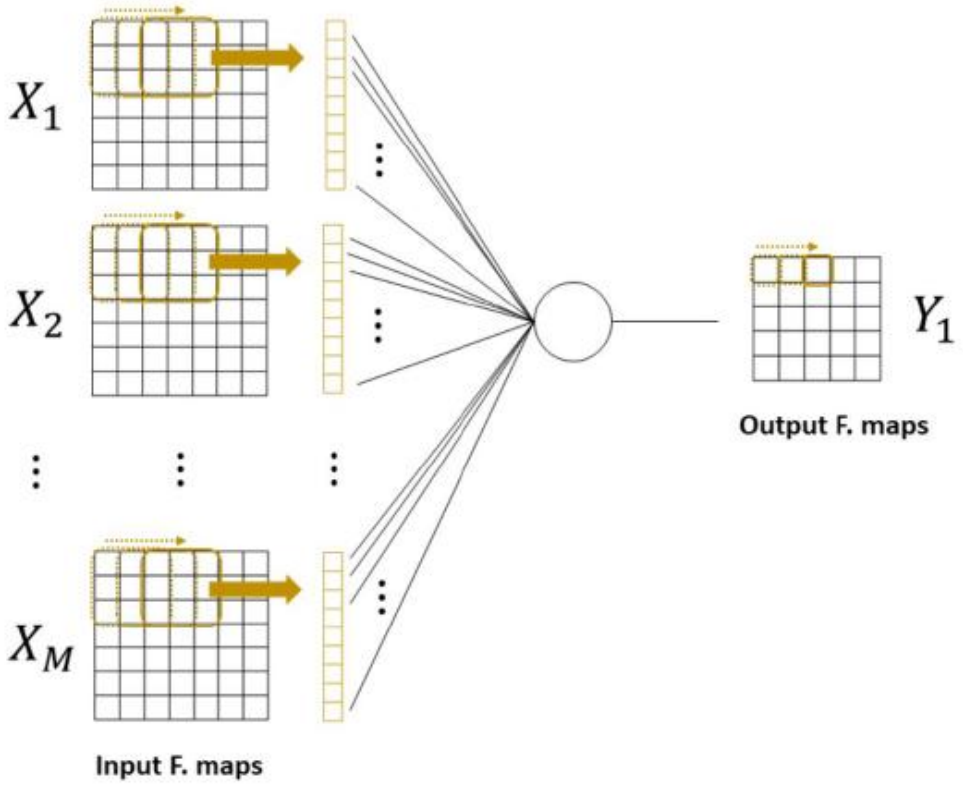
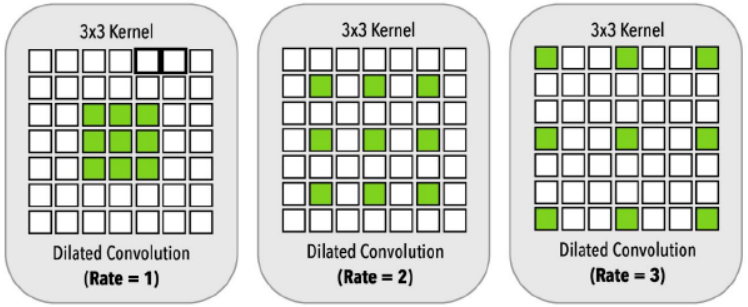
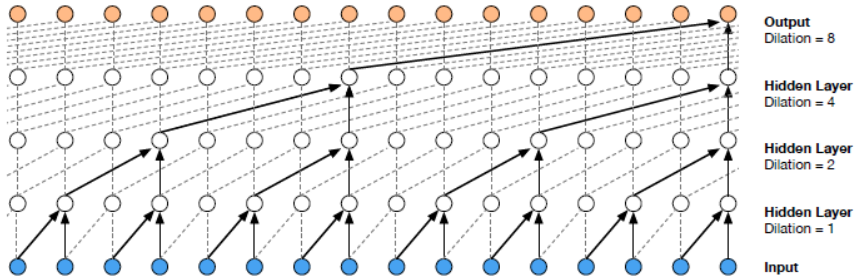


Figure 2.8: Illustration of a 2-dimensional convolutional layer. The filter is applied over the input by processing in a grid-like manner performing the multiplication and accumulation operation on local grids. Then the outputs of the filters are combined



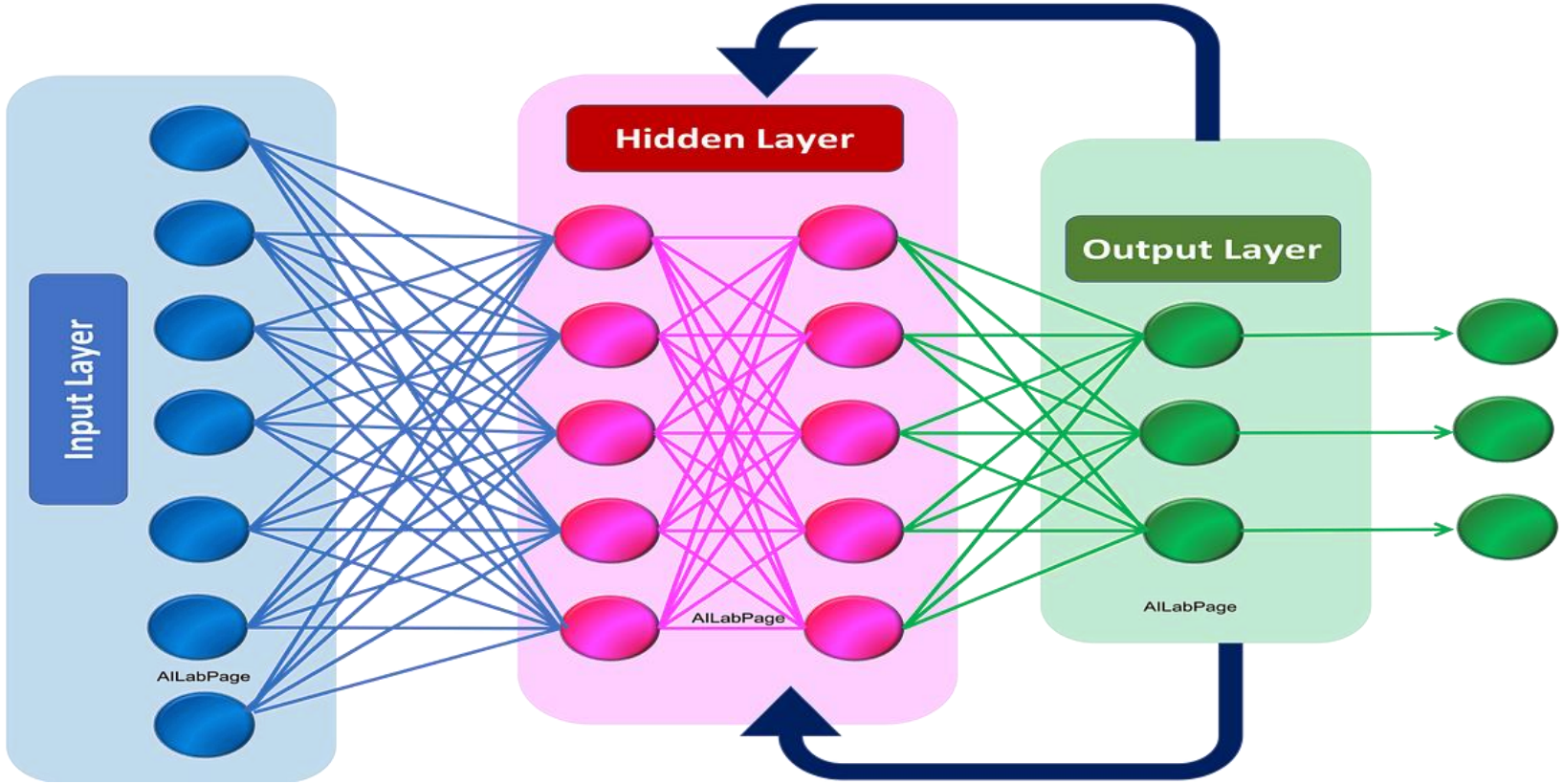
(a) 2D dilated convolution (from [102])



(b) 1D dilated convolution (from [101])

Figure 2.10: Illustration of dilated convolutions applied to (a) 2D convolutions and (b) 1D convolutions in WaveNet.

Recurrent Neural Networks

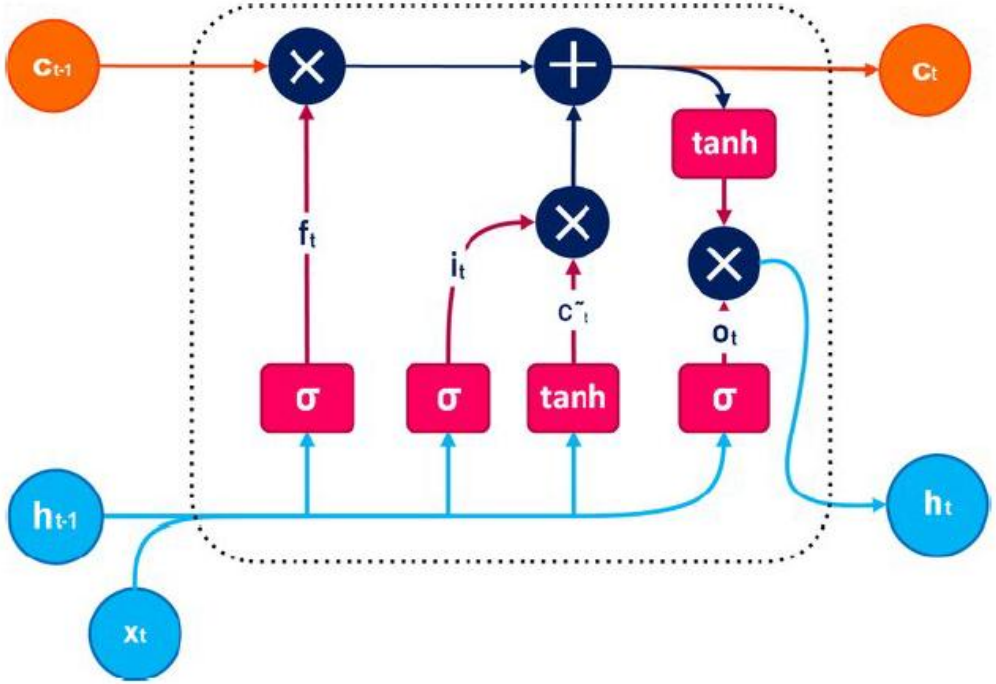


RNNs, LSTMs

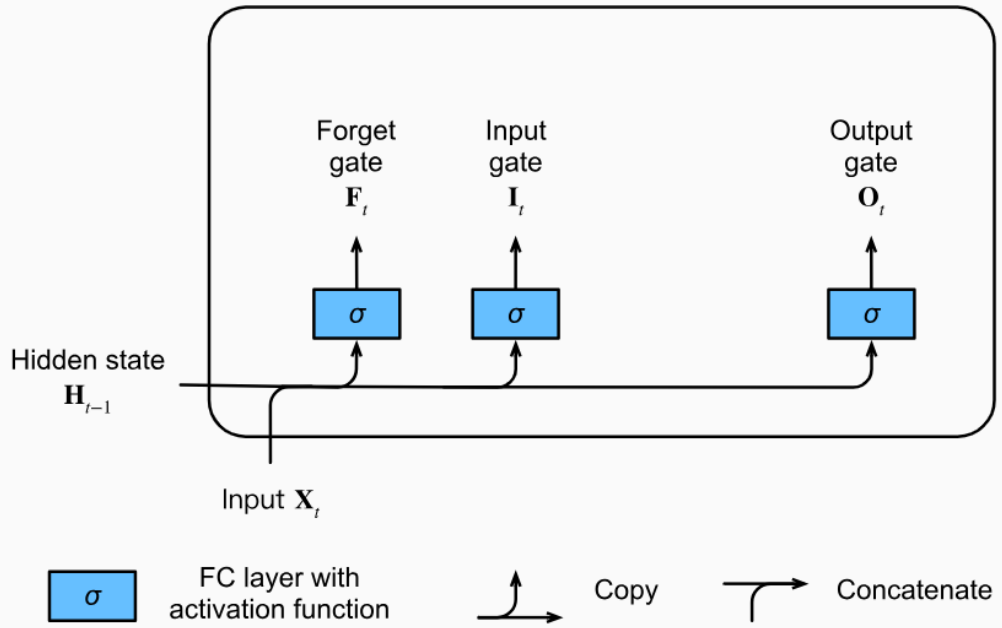
- RNNs: *vanishing gradients* and *exploding gradients*
  - *“vanishing gradient problem”*

- Improvement: **Long Short-Term Memory (LSTM)**
  - input gate, forget gate and output gate determine which information to store, discard and output respectively
  - LSTM can learn which information in the sequence might be required later on, and discard the rest, by separating the long-term and short-term memory
  - LSTMs may remember long-term dependencies

  The key distinction between vanilla RNNs and LSTMs is that the latter support gating of the hidden state



Long Short-Term Memory (LSTM)

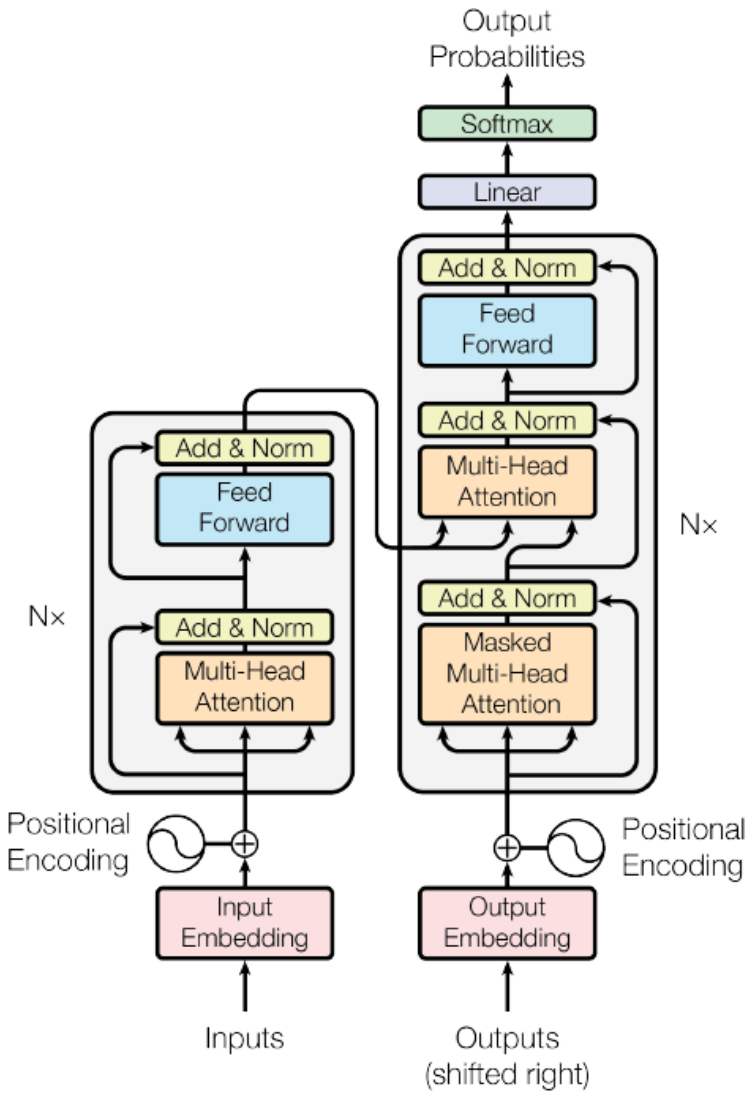


Computing the input gate, the forget gate, and the output gate in an LSTM model.

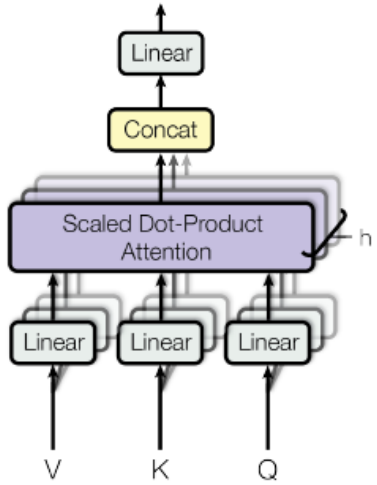
LSTMs are sometimes considered a member of the RNN family.
RNNs are still used for simpler sequential tasks in smaller, resource-constrained environments.

Transformers (2015-6-7)

- led to enormous breakthroughs in deep learning
- natural language processing, computer vision and speech processing
- uses parallellisation and attention mechanisms to improve upon RNNs for sequence modelling tasks
- encoder-decoder architecture



(a) Transformer Network



(b) Multi-head Attention

End-to-end (E2E)

- The first approach for E2E ASR is based on **Connectionist Temporal Classification (CTC)**
- CTC directly maps an input sequence to an output sequence, without requiring an alignment between the two.

- CTC predicts the output label probabilities for every input timestep, including the possibility of repetitions and a *blank* token (often '_') (**logit matrix**)
- CTC assumes that the relation between input and output is *monotonic*
  - i.e. if a word comes after another word in the output sequence, it must also come after this word in the input sequence

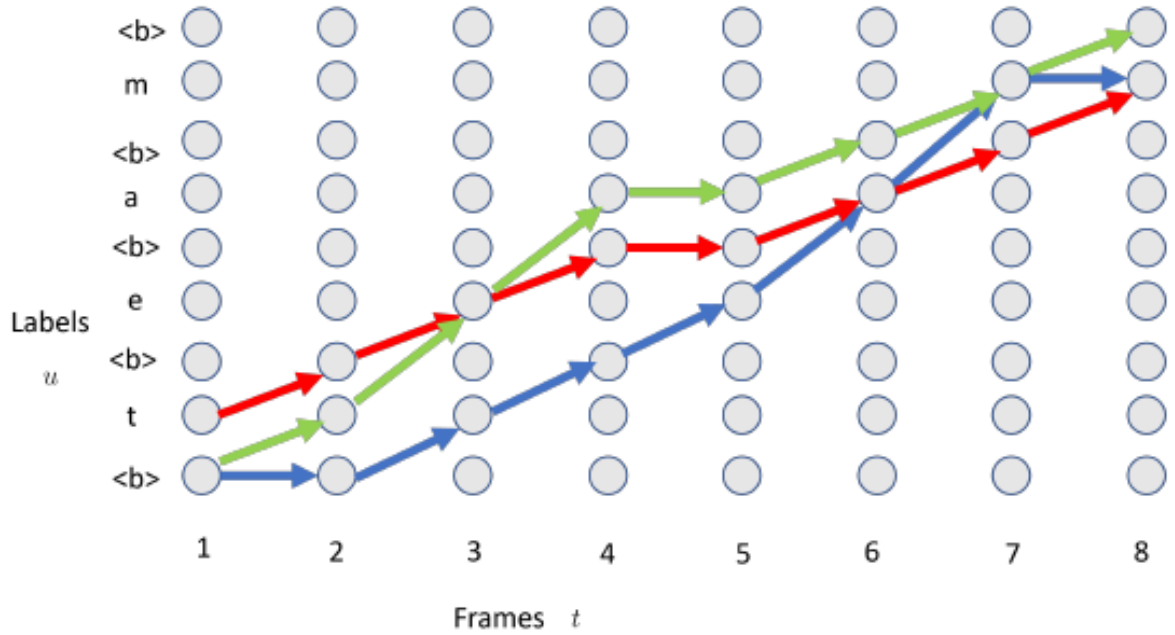


Figure 2.22: Example of CTC alignments. The figure shows three possible valid paths which make up the word "team". The acoustic frame indices are plotted on the horizontal axis and the output letters on the vertical axis. The $< b >$ represents the blank label '_'. The red path is ($t\_e\_\_\_a\_m$), the green path is ($\_teaa\_m\_$) and the blue path is ($\_\_\_t\_eamm$). Figure from [161].

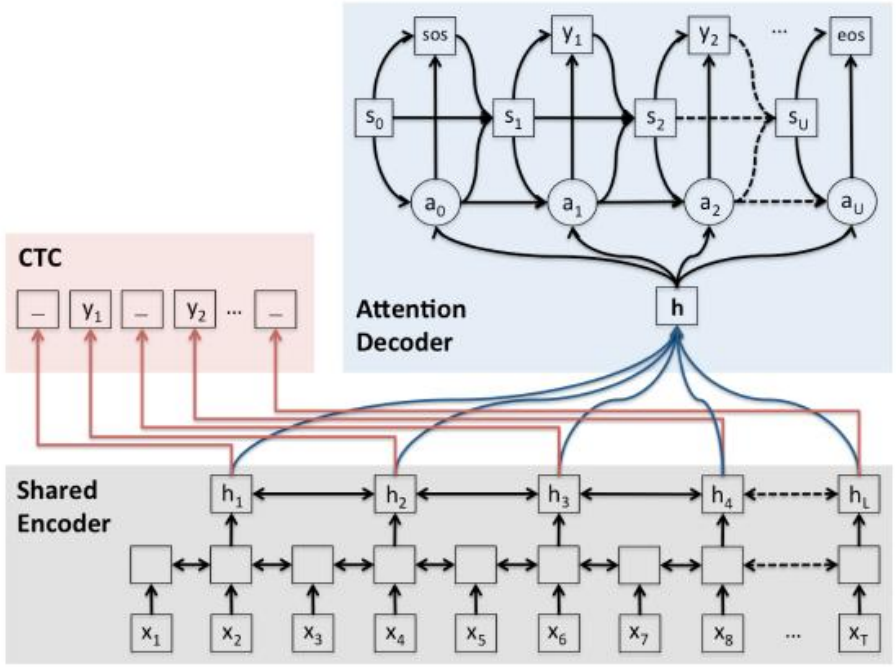


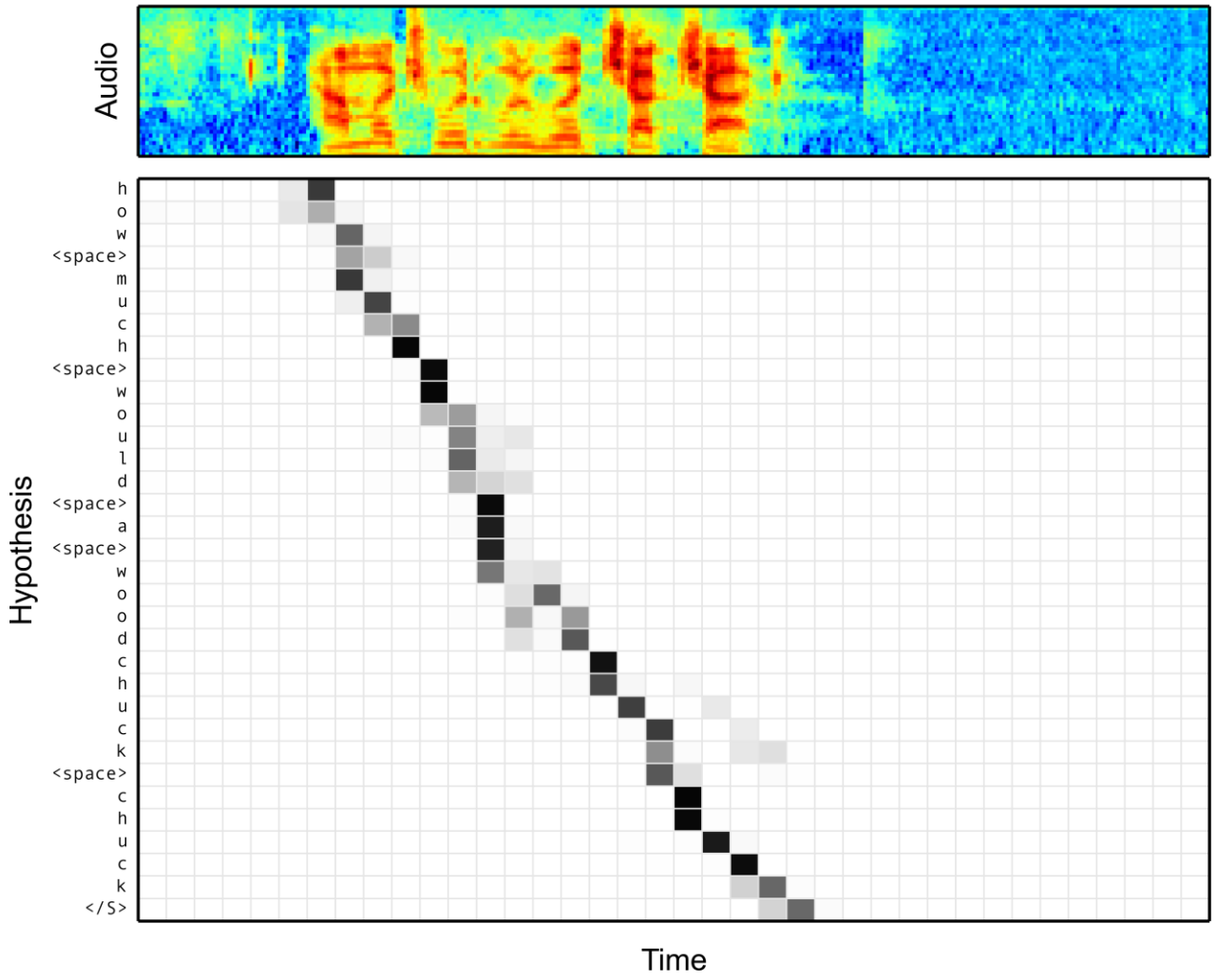
Figure 2.23: Schematic example of an RNN-based hybrid CTC/Attention model (CTC+AED) speech recognition model. Inputs and outputs are denoted x_i and y_i respectively, the decoder cell states are denoted s_i. a_i represents the context vector for step i which is computed from the encoder states h_t using the attention weights $\alpha_{i,t}$. Figure from [167].

Many combinations are possible.

Here an RNN in combination with CTC

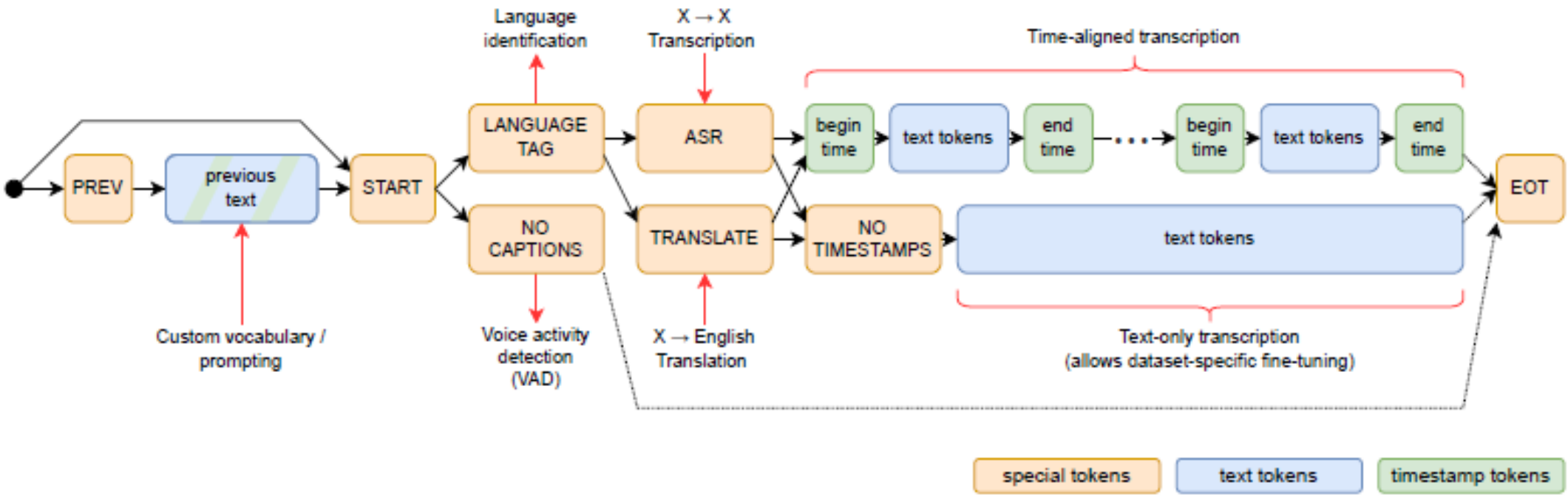
(see Jakob Poncelet's thesis for more details)

Alignment between the Characters and Audio



Whisper (2022) + several variants

- major impact
- speech recognition and speech translation model (680 thousand hours, 5 million hours of speech)
- training based on ***weak supervision*** (i.e., the transcripts not perfect)
- **robust** against various domain factors -- too robust?
- **decoder** is extended to many down-stream tasks, including language identification, timing generation, prompting, speech translation (to English), speech recognition.
- *task-specific tokens*: if the decoder has to transcribe, then the first token in the decoder is “|transcribe|”. If it has to translate, the first token is “|translate|”
- the decoder is conditioned on the previous sentence as a *prompt*


Language identification
X → X Transcription
Time-aligned transcription
PREV
previous text
START
LANGUAGE TAG
ASR
begin time
text tokens
end time
begin time
text tokens
end time
EOT
NO CAPTIONS
TRANSLATE
NO TIMESTAMPS
text tokens
Custom vocabulary / prompting
Voice activity detection (VAD)
X → English Translation
Text-only transcription (allows dataset-specific fine-tuning)
special tokens
text tokens
timestamp tokens

Dimension reduction, manifold learning

- Traditional methods in unsupervised learning mostly based dimensionality reduction
- Aim: ignore irrelevant information (e.g. noise-, speaker- and environment-induced variations)

- **Principal Component Analysis (PCA)**, SVD low-rank approximations

Dimension reduction, manifold learning

- Bottleneck layers
  - denoising

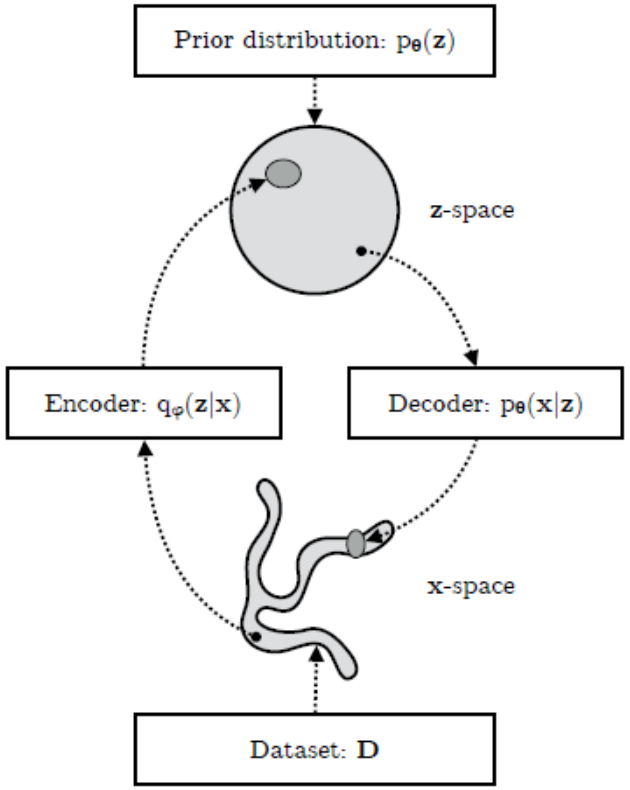
- **variational autoencoders (VAE)** have been proposed which combine the autoencoder with a probabilistic framework involving stochastic optimisation and variational Bayes techniques.

- latent variable can also be quantized: vector-quantized VAE (VQ-VAE)
- generative adversarial networks (GAN) utilize generator and discriminator networks to learn a data distribution

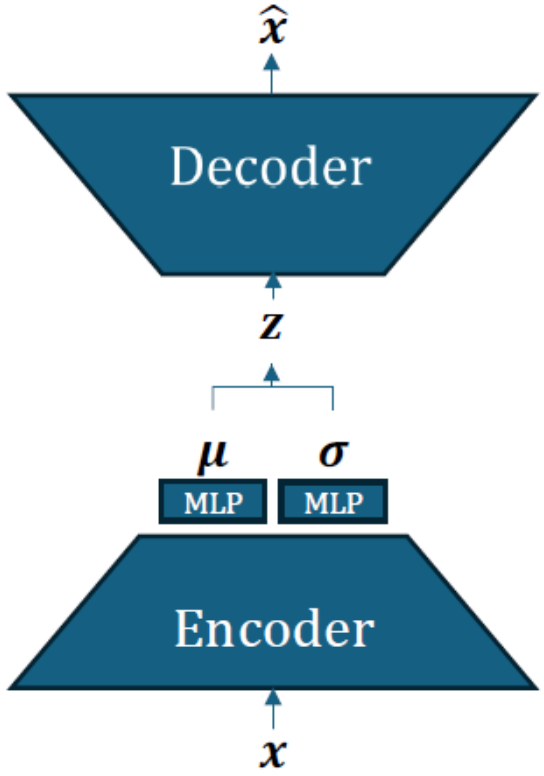
Extensions of VAE

- **Factorised Hierarchical Variational Autoencoder (FHVAE)** assumes that speech can be defined with a short-term segment-level latent variable and a long-term sequence-level latent variable.
- FHVAE tries to separate the speech content (short-term information) from speaker and environment related content (long-term information)

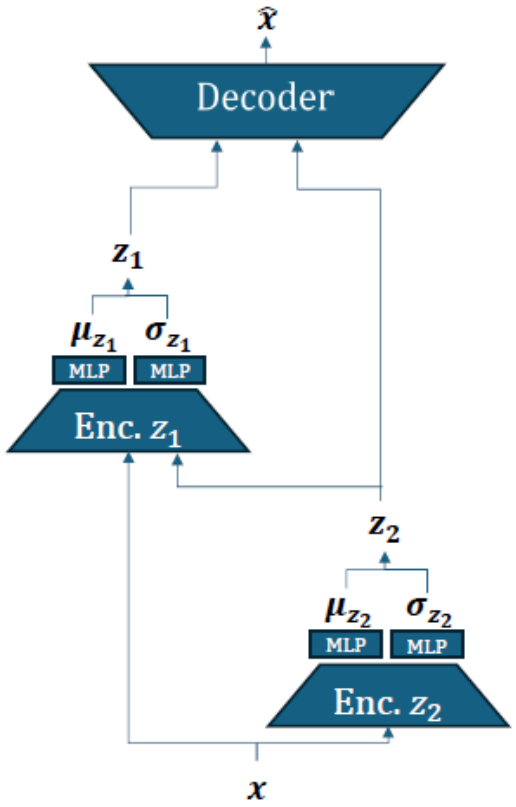
- **Stochastic Temporal Convolutional Networks (STCN)** explore a larger number of hierarchical latent variables.
- In STCNs, the lower-level latent variables have a small temporal receptive field and encode local information. The higher-level latent variables have a wide temporal receptive field and model long-term aspects.



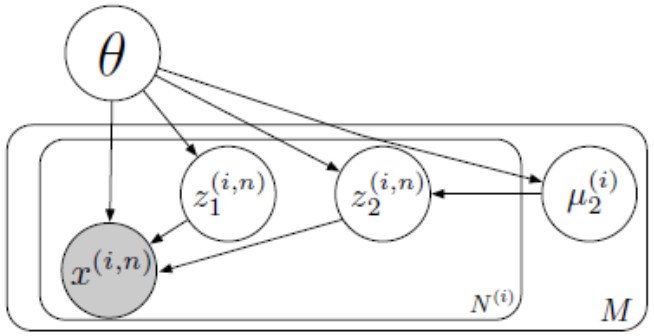
(a) Graphical Model



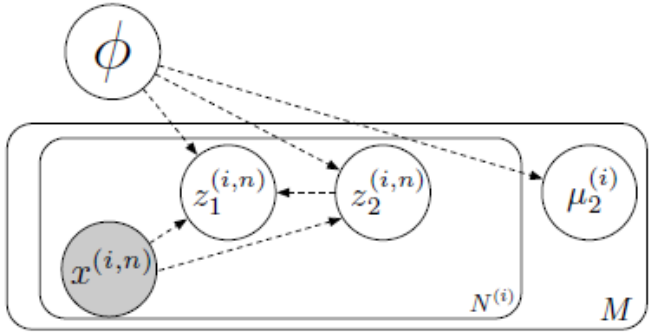
(b) Implementation



(a) FHVAE model schematic



(b) Generative model (graphical)

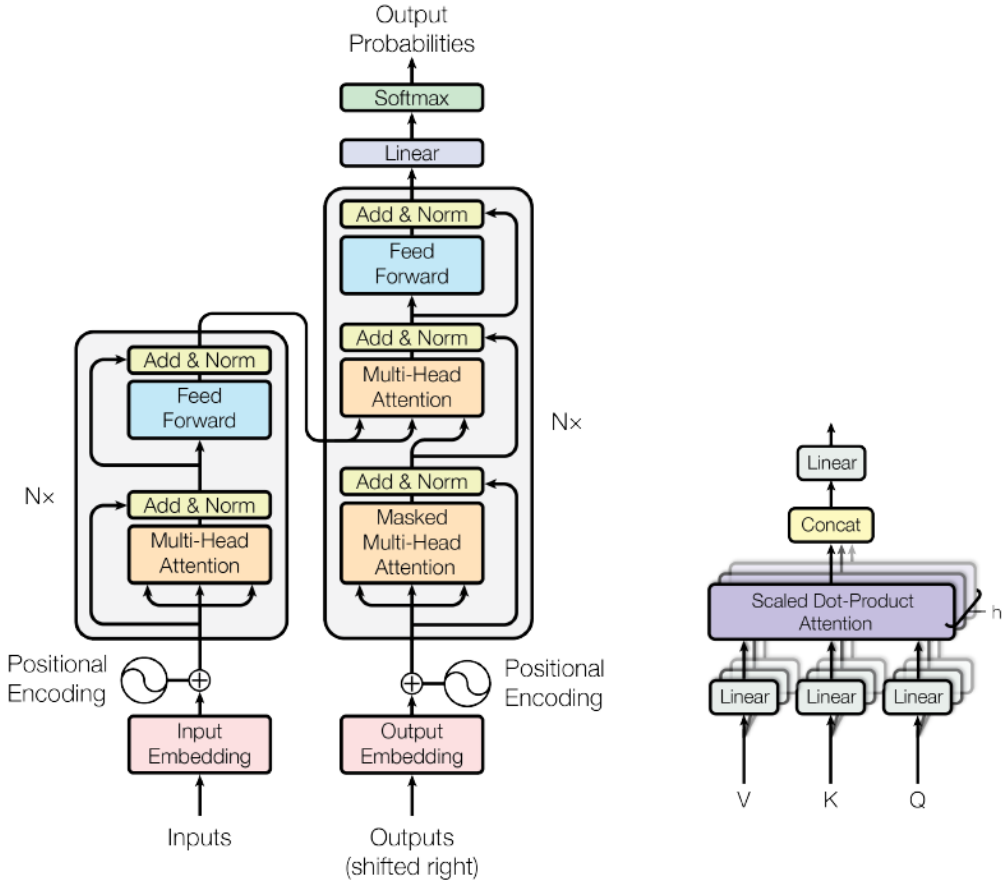


(c) Recognition model (graphical)

Figure 2.30: Overview of the FHVAE, detailing the full model in (a), and graphical representations of the conditional distributions in (b) and (c) for the generative and recognition model respectively. Figure (b) and (c) from [49].

How to find “explain” a DNN?

- Perturbation of input (classic)
  - I/O relation
  - Voronoi
- Probing classifiers, SHAP, LIME (fashion)
  - Feature attribution
- Mechanistic Interpretation (booming)
  - Responsible subgraphs
  - Usually difficult analysis



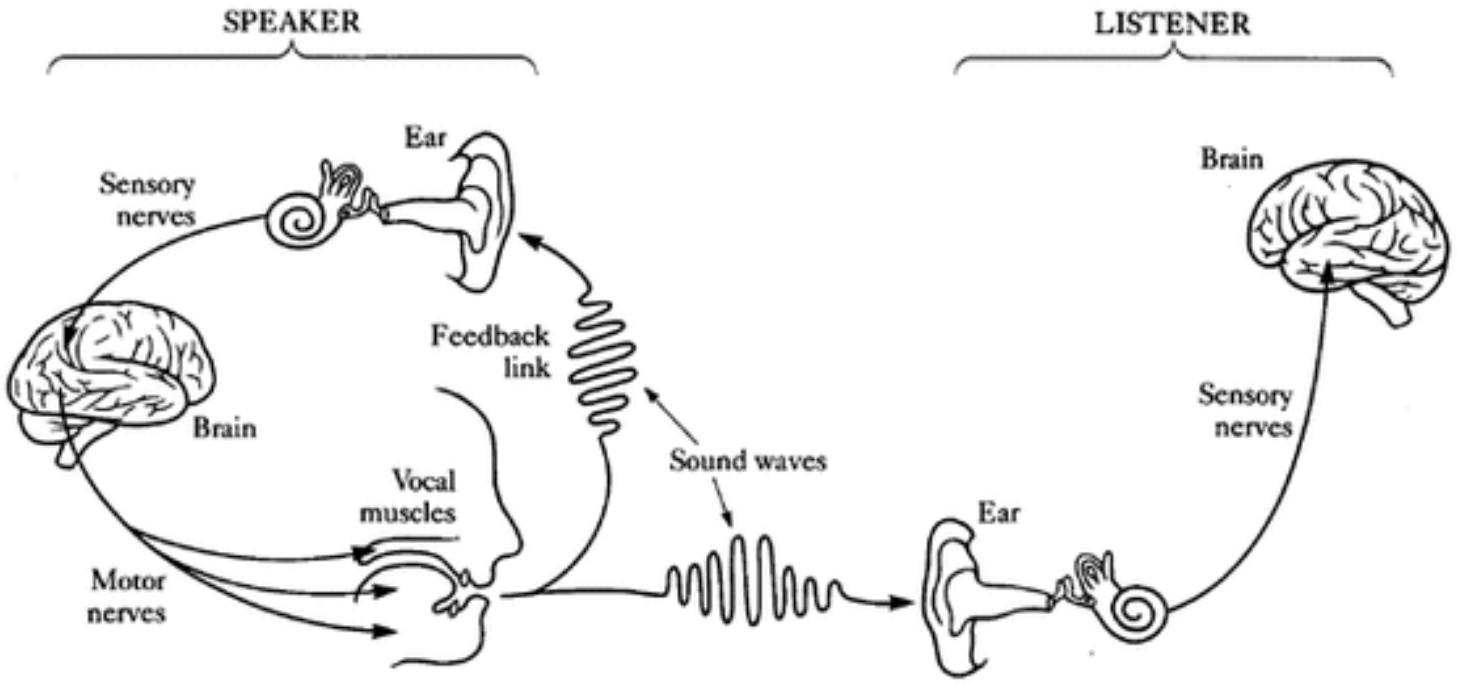
(a) Transformer Network

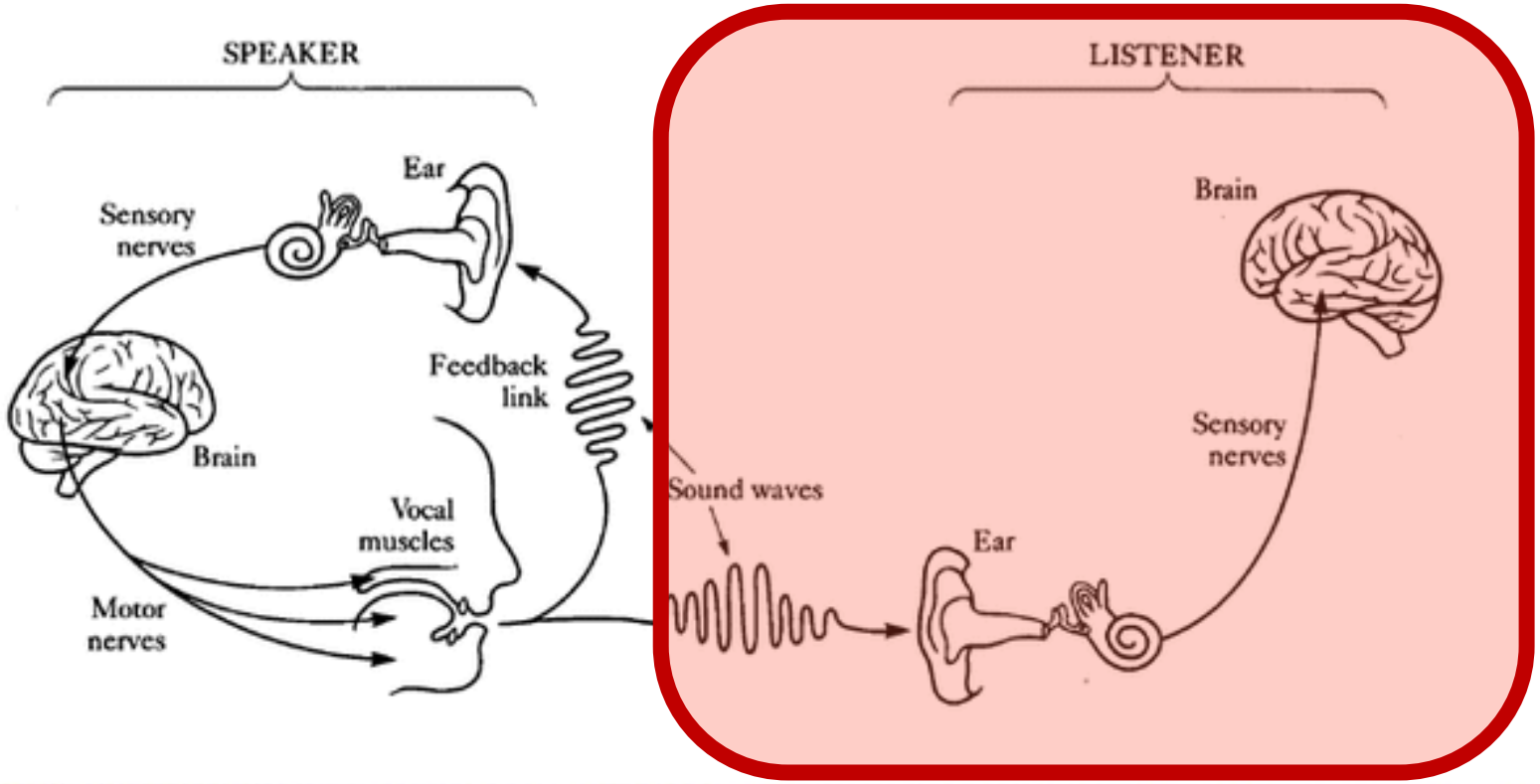
(b) Multi-head Attention

The following slides discuss the potential relation between ASR and Human Speech Recognition

What about humans?

Speaker-listener loop



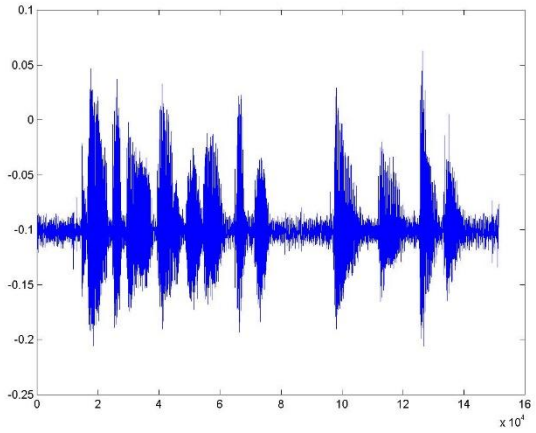

SPEAKER
LISTENER
Ear
Sensory nerves
Feedback link
Brain
Vocal muscles
Motor nerves
Sound waves
Brain
Sensory nerves
Ear

speaker

Concept

Grammar
Mental lexicon

Muscle
activation,
articulation



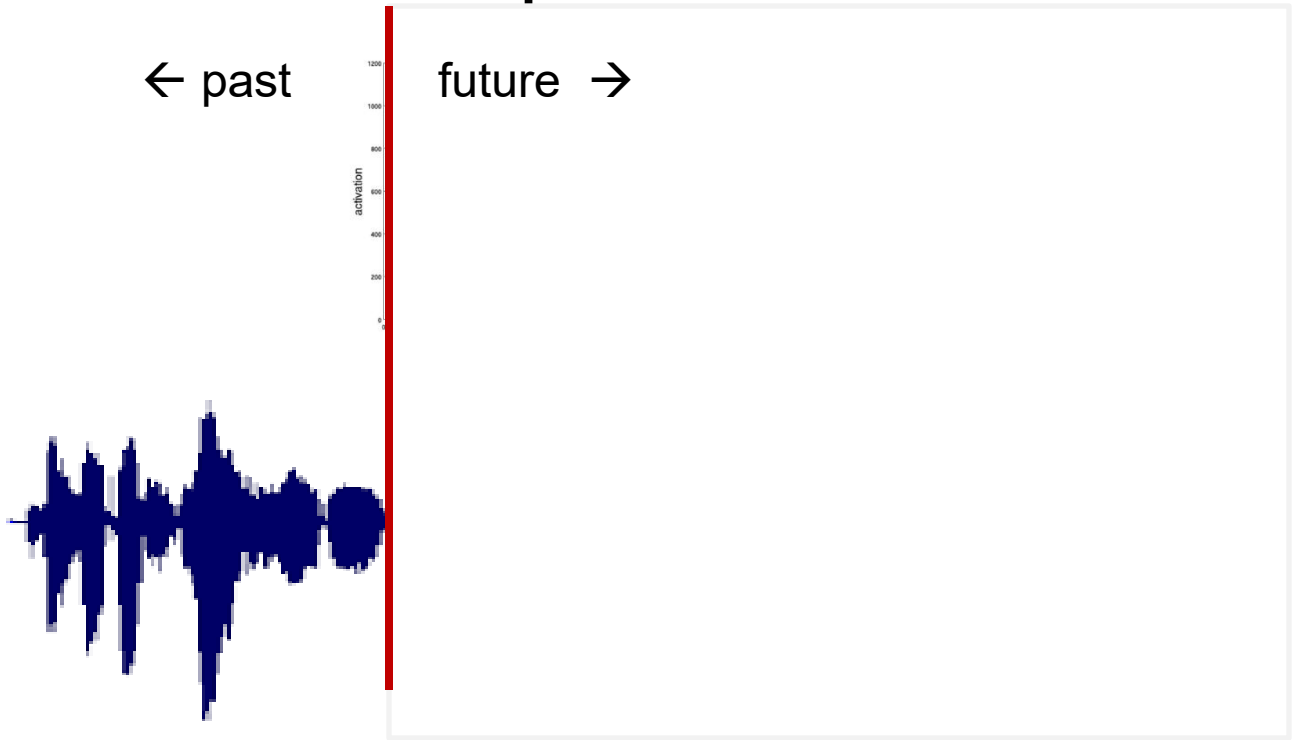
listener

Concept

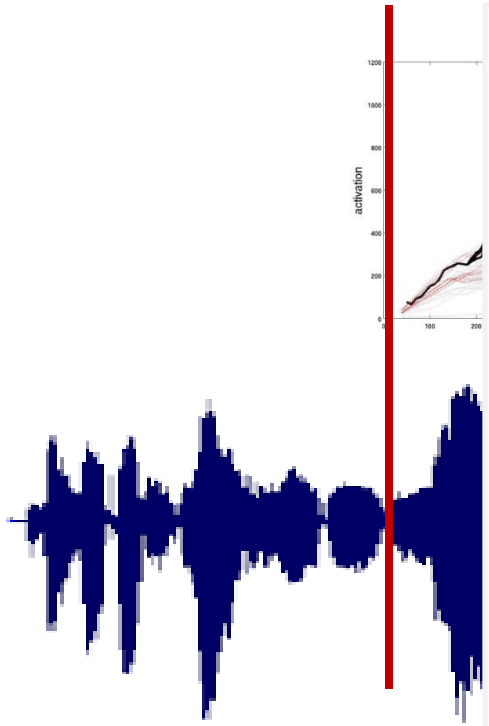
Grammar
Mental
lexicon

Auditory
pathway

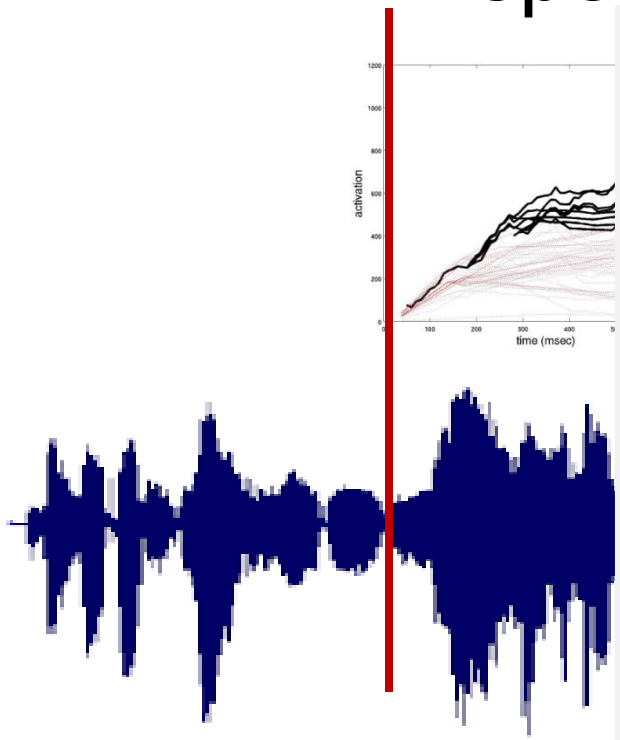
Comprehension of continuous speech



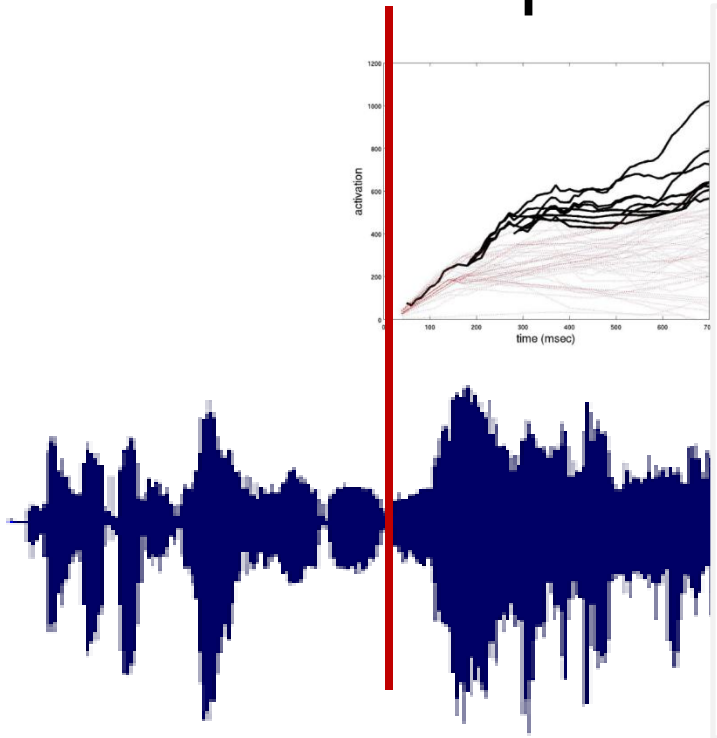
Comprehension of continuous speech



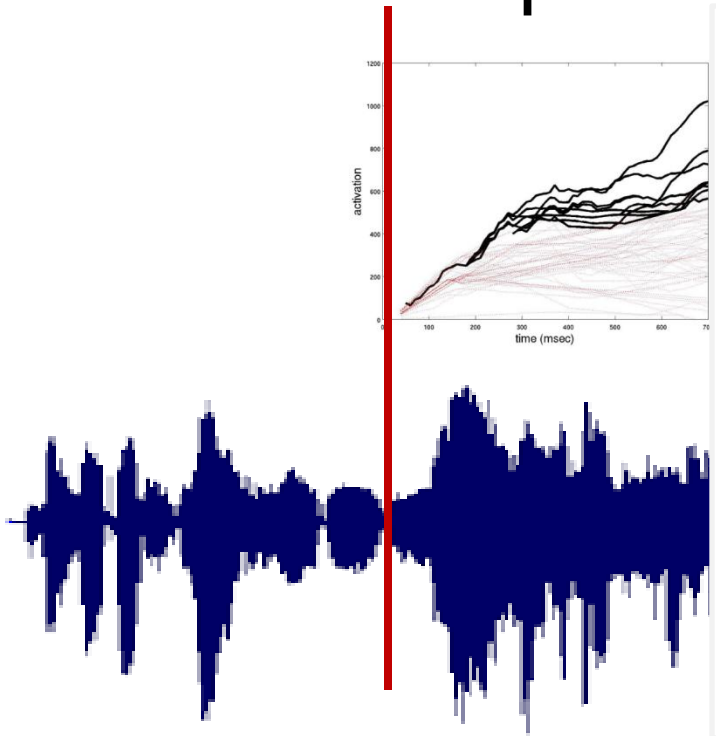
Comprehension of continuous speech



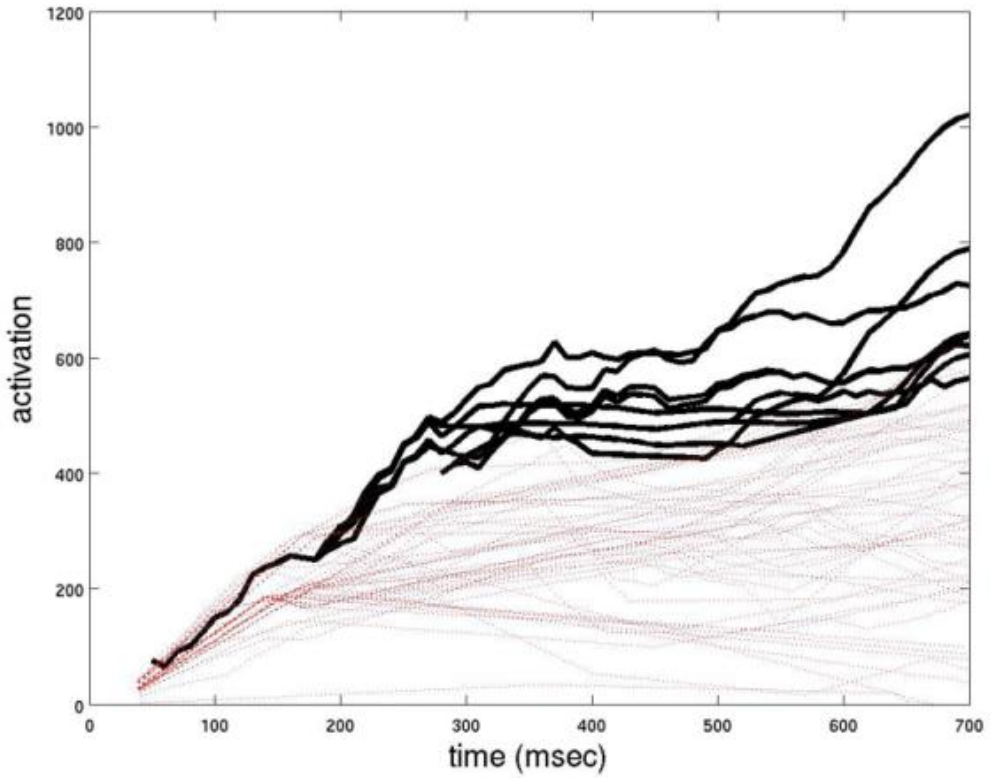
Comprehension of continuous speech



Comprehension of continuous speech



Activation

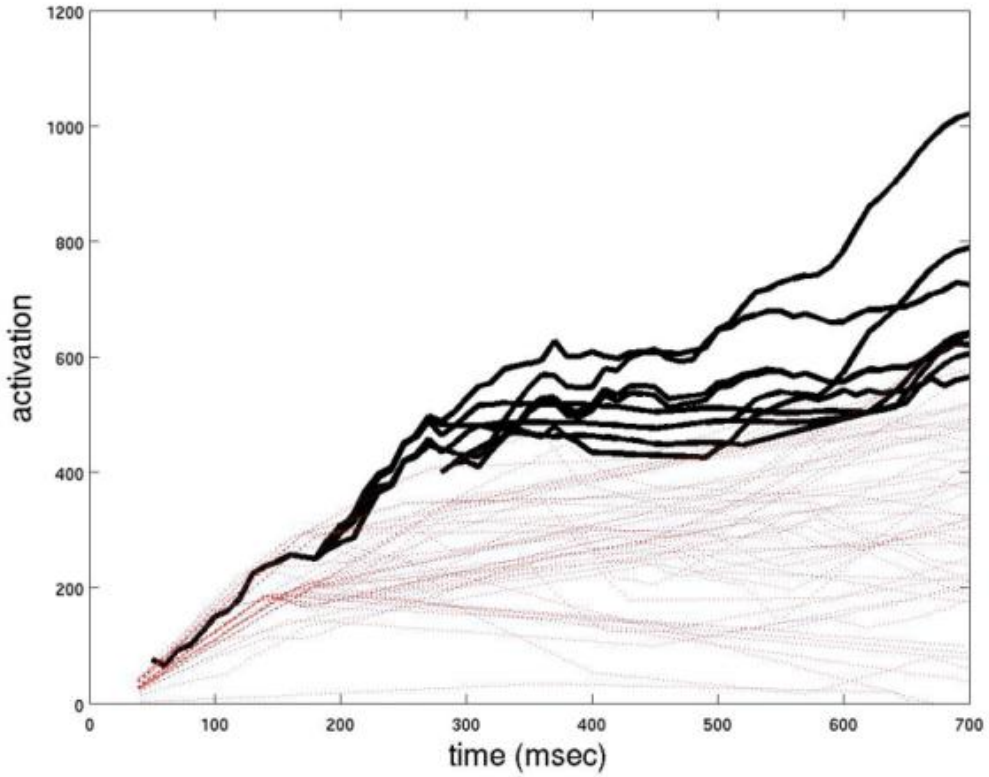


Words compete in the listener's head

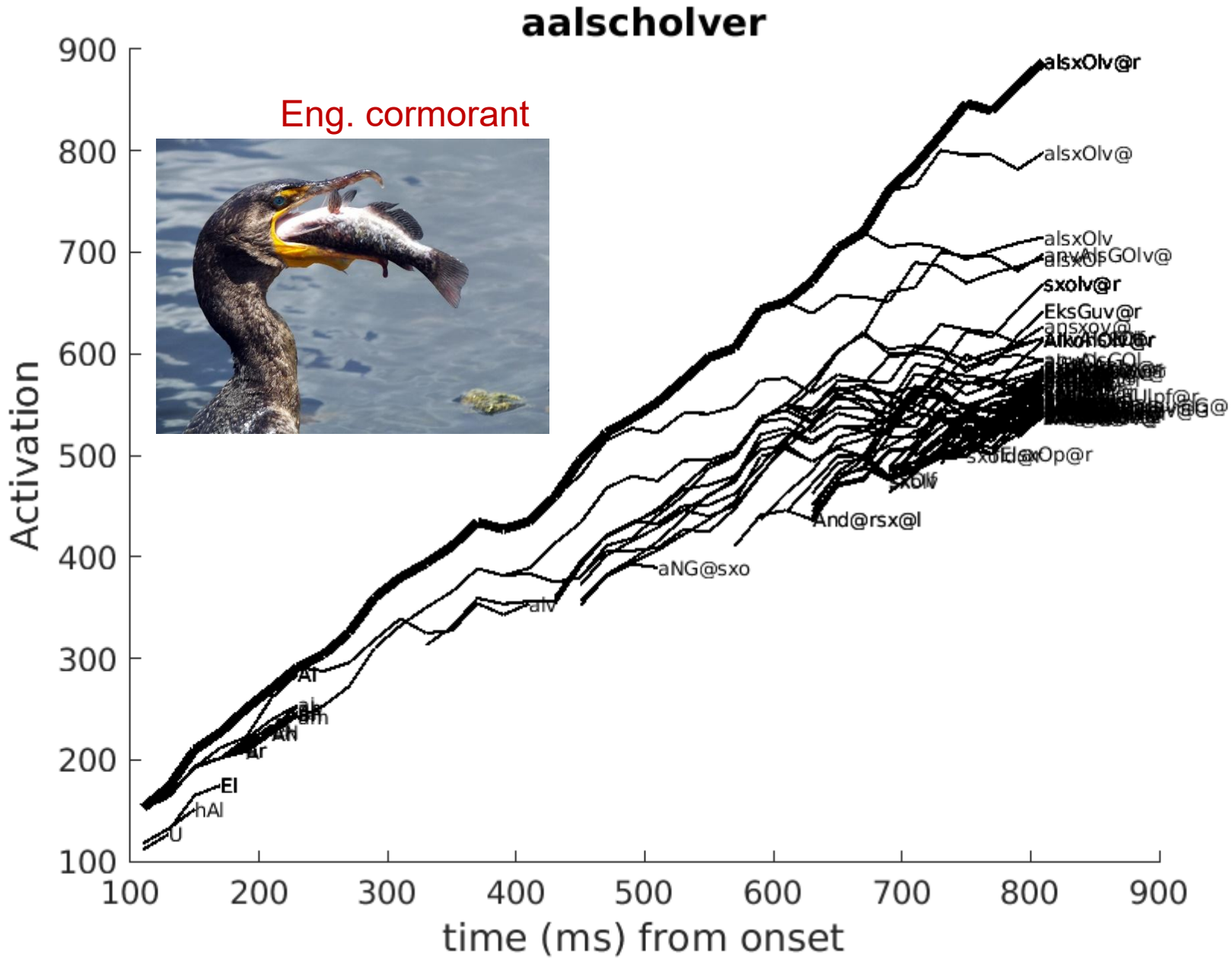
You have to select a winner 3 times a second

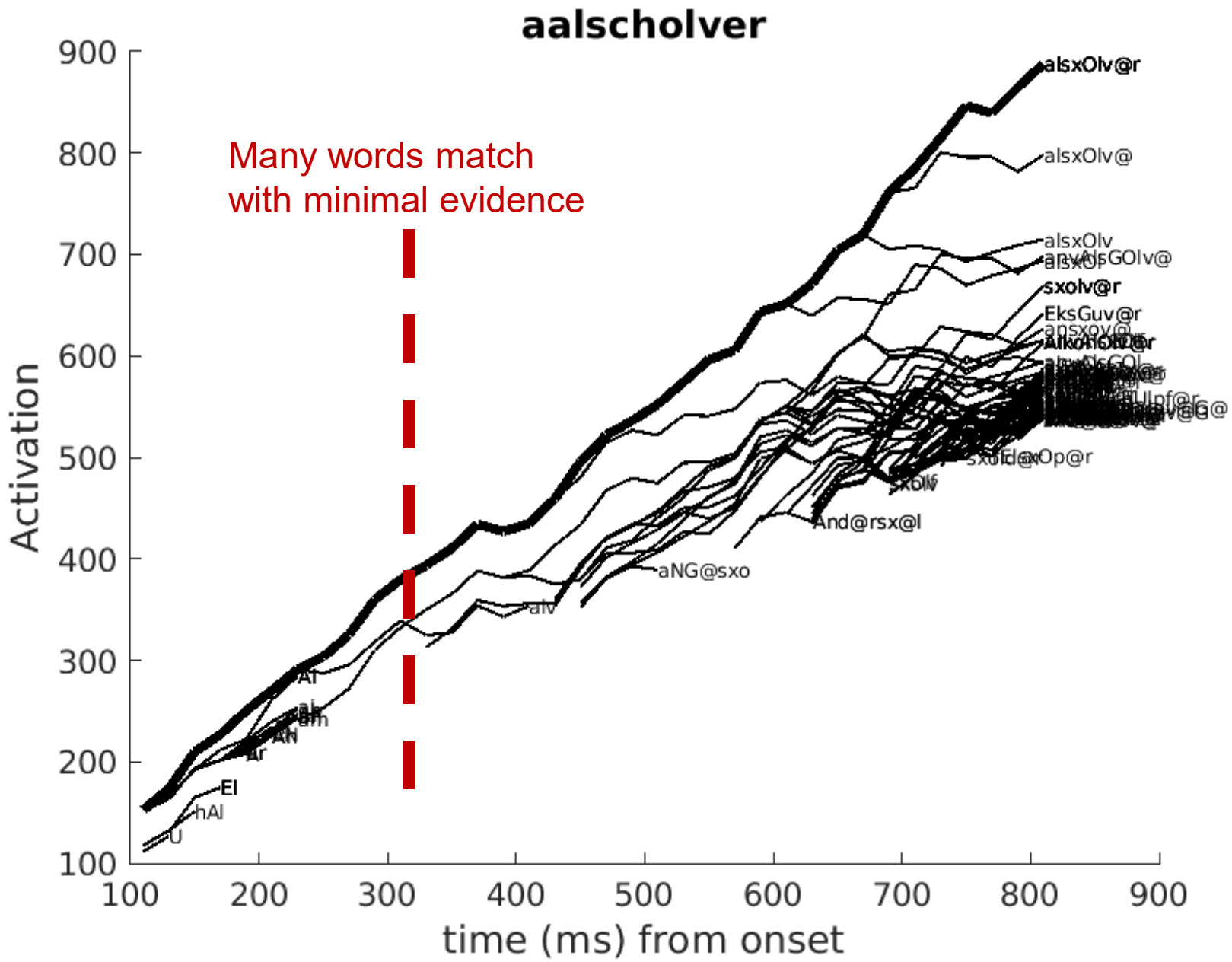
±60000 (±100) options per word

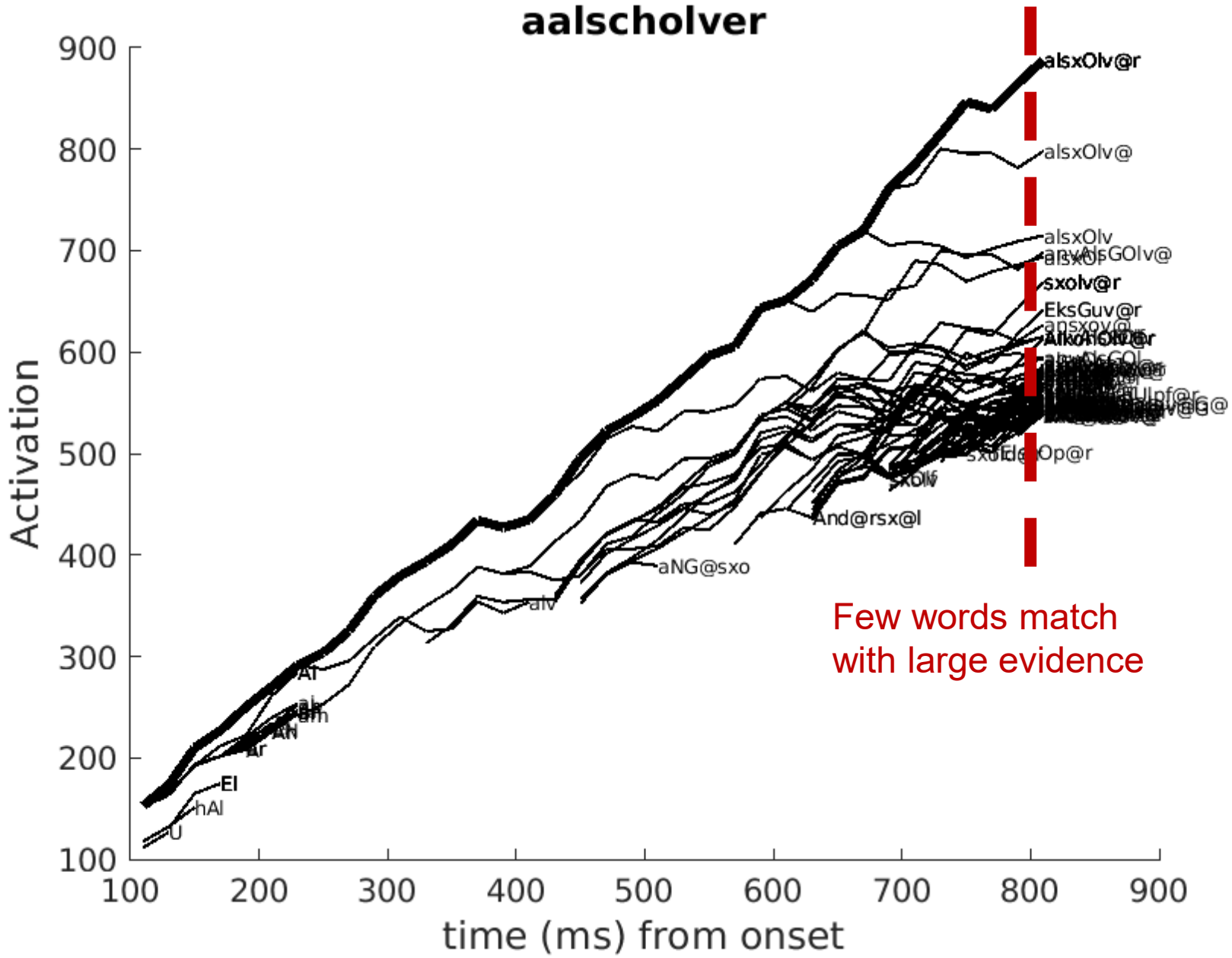
Activation

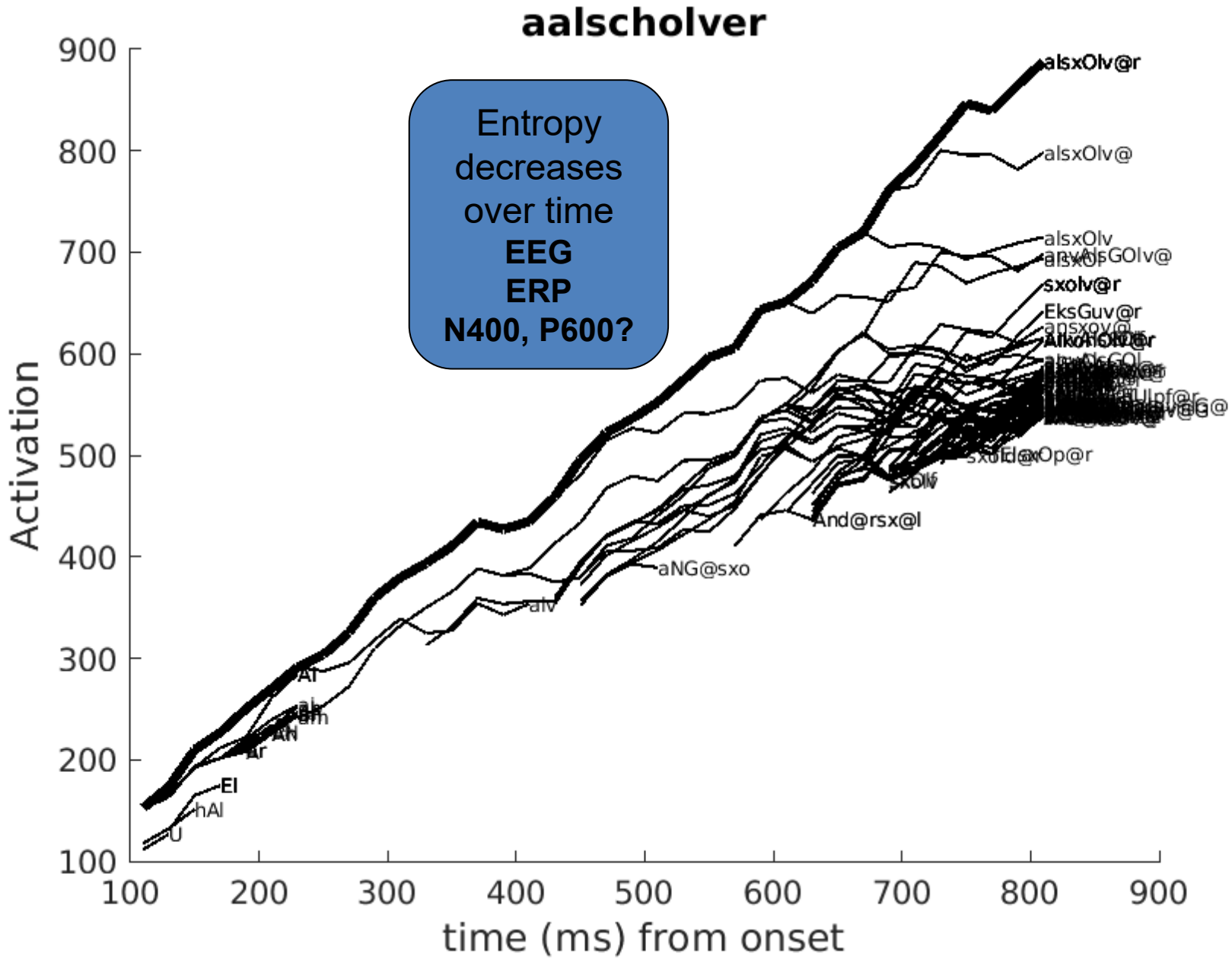


Activation = log(P(signal|word)) + λ log P(word)
Example here: duration 0.68 sec.
Shown: top 200 candidates, recomputed each 10 ms


aalscholver
Eng. cormorant
Activation
time (ms) from onset
100
200
300
400
500
600
700
800
900
alsxOlv@r
alsxOlv@
alsxOlv
sxolv@r
EksGuv@r
And@rsx@l
aNG@sxo
hAl
El


aalscholver
Many words match
with minimal evidence
Activation
time (ms) from onset
100
200
300
400
500
600
700
800
900
alsxOlv@r
alsxOlv@
alsxOlv
sxolv@r
EksGuv@r
aNG@sxo
And@rsx@l
hAl


aalscholver
Activation
time (ms) from onset
100
200
300
400
500
600
700
800
900
alsxOlv@r
alsxOlv@
alsxOlv
sxolv@r
EksGuv@r
aNG@sxo
And@rsx@l
Op@r
El
hAl
U
Few words match
with large evidence


aalscholver
Entropy decreases over time
EEG
ERP
N400, P600?
Activation
time (ms) from onset
100
200
300
400
500
600
700
800
900
alsxOlv@r
alsxOlv@
alsxOlv
sxolv@r
EksGuv@r
aNG@sxo
And@rsx@l
hAl

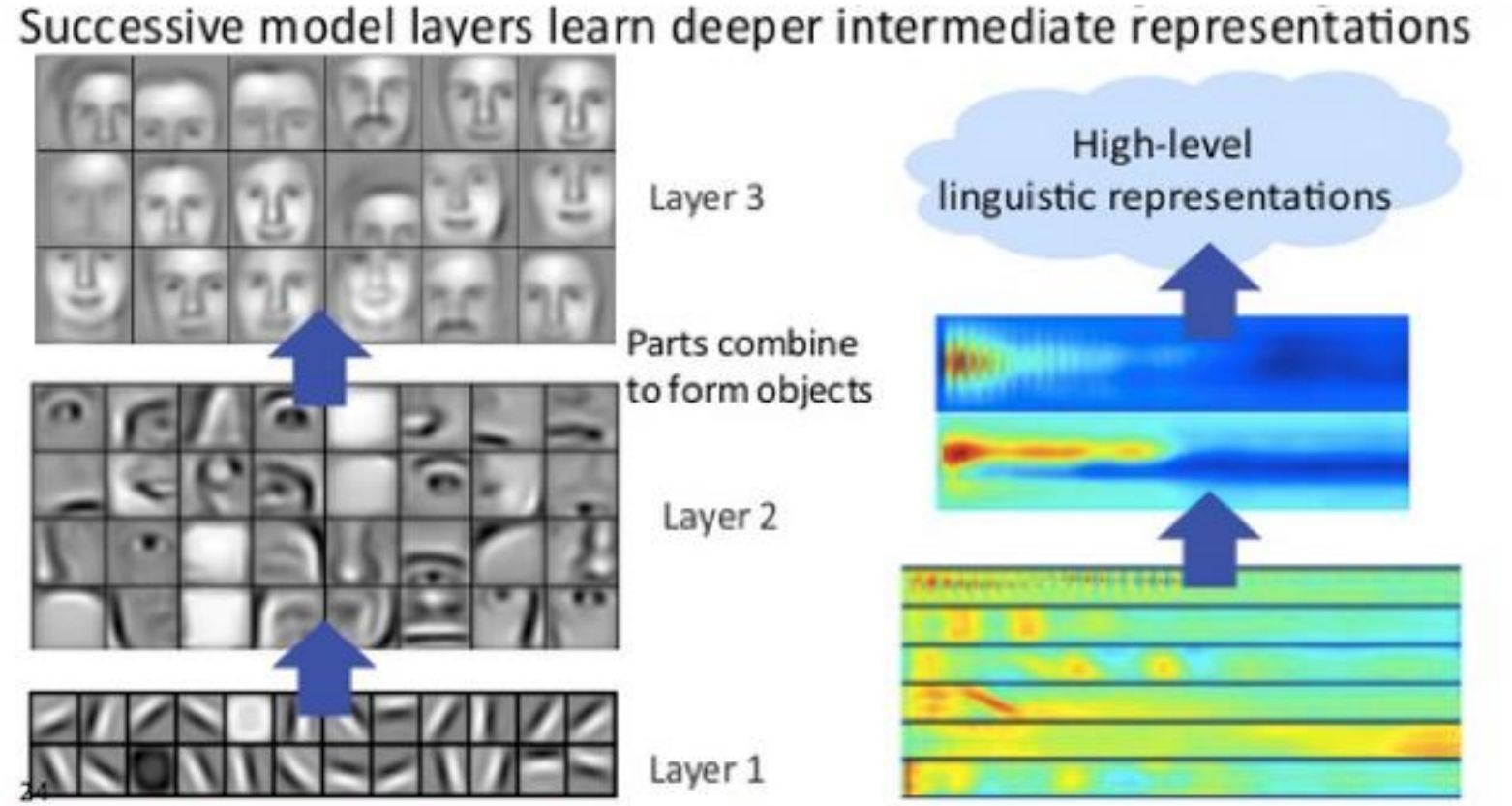
Four ways to look at ASR

- ASR as a research topic itself
  - Word error rate (WER) minimization, noise robustness, network architectures, training regimes etc.
- ASR as black box module in larger system
  - In a dialogue system
  - As a tool for the hearing-impaired
  - In cases where typing is dangerous/impossible
- ASR as a tool to unravel the structure in the speech signal
  - Biomarking
- ASR as a computational simulation for human speech processing
  - Plausibility issues, ecology

Why DNN are useful: view 1

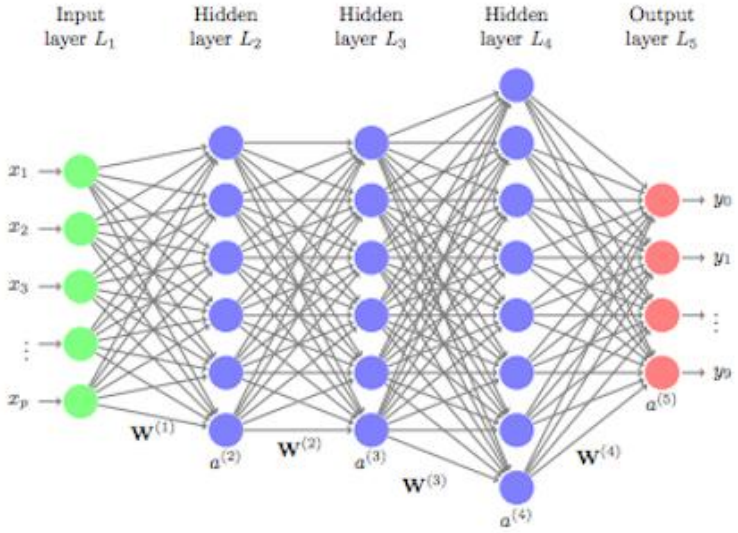
- DNNs may discover structure in data sets because subsequent layers ignore more and more details that are irrelevant for correctly predicting output labels
- Increasingly abstract representations emerge by cascading multiple (nonlinear) transformations

  - so far, most convincing in image classification


Successive model layers learn deeper intermediate representations
Layer 3
Parts combine
to form objects
Layer 2
Layer 1
High-level
linguistic representations
Prior: underlying factors & concepts compactly expressed w/ multiple levels of abstraction

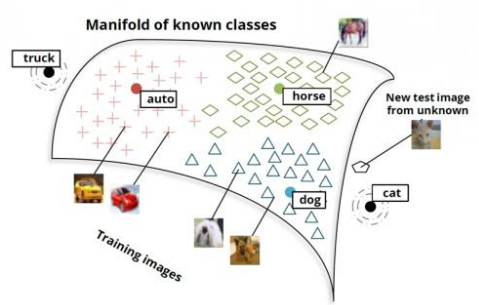
View 2

- focus on the role of DNNs to find optimal representations, in particular in the sense of features.
- learning of optimal representations can be achieved if the network is able to disentangle the underlying explanatory factors hidden in the observed data (Bengio et al., 2013)



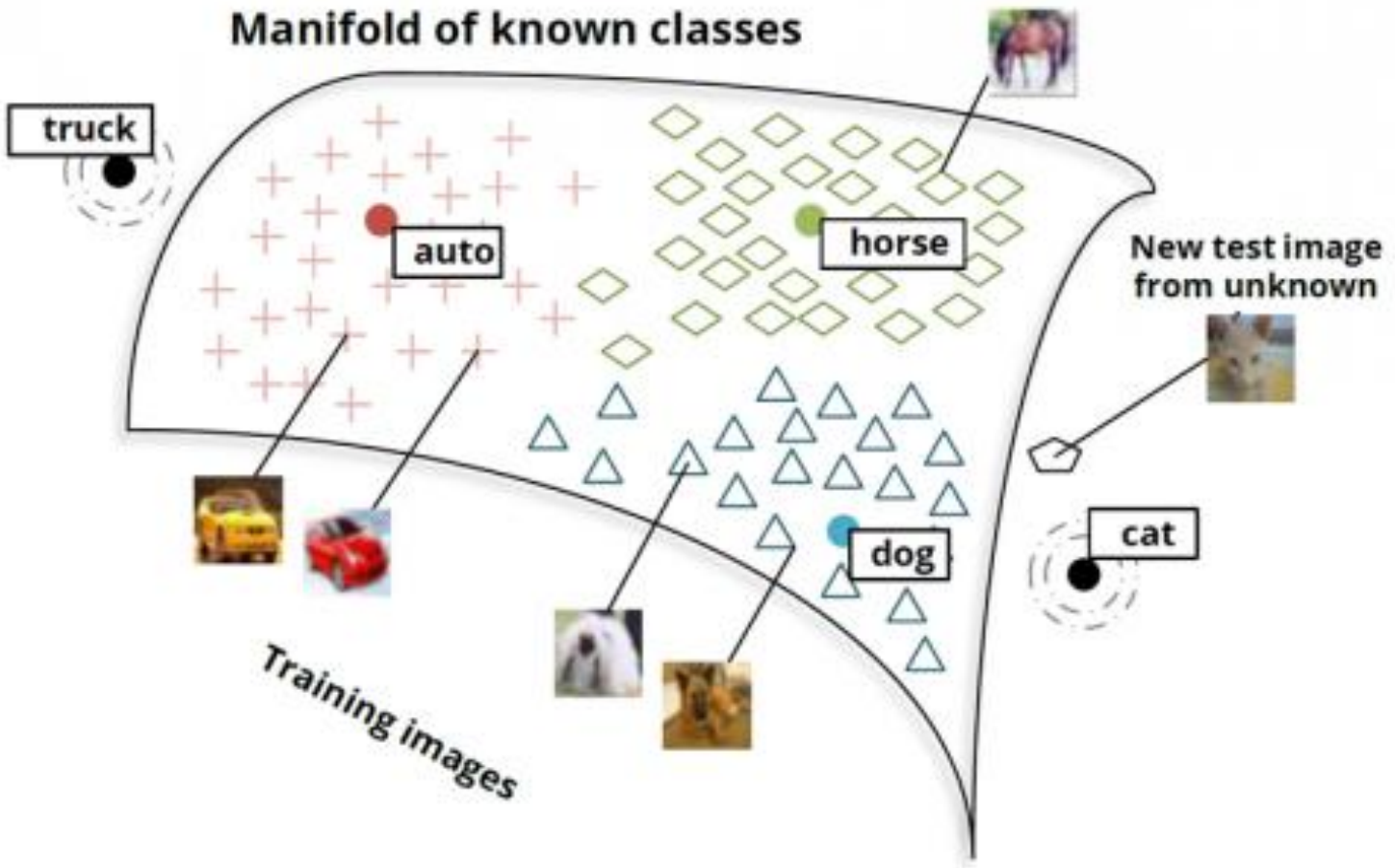
View 3

- more geometrically inspired interpretation of a DNN is based on the manifold assumption
  - the application of manifold learning methods on speech signals is (also) based on the relatively slow ballistic movements of articulators



- Deep networks may provide a very effective method for dimensionality reduction.
- directions tangent to the manifold are well preserved while directions orthogonal to the manifolds aren't
- DNNs are related to **manifold learning** (Tenenbaum, Bengio, Singh Tomar, ….).

A manifold


Manifold of known classes
truck
auto
horse
New test image
from unknown
cat
dog
Training images

View 4

- A fourth approach is more theoretical and analyzes DNNs on an ’information plane’ using ’information bottleneck’
- Any DNN can be characterized by the mutual information between a hidden layer and the input and output variables, as a function of hidden layer depth
- Tishby et al. argue that the optimal architecture (number of layers and features/connections at each layer) is related to the bifurcation points of the information bottleneck plane.

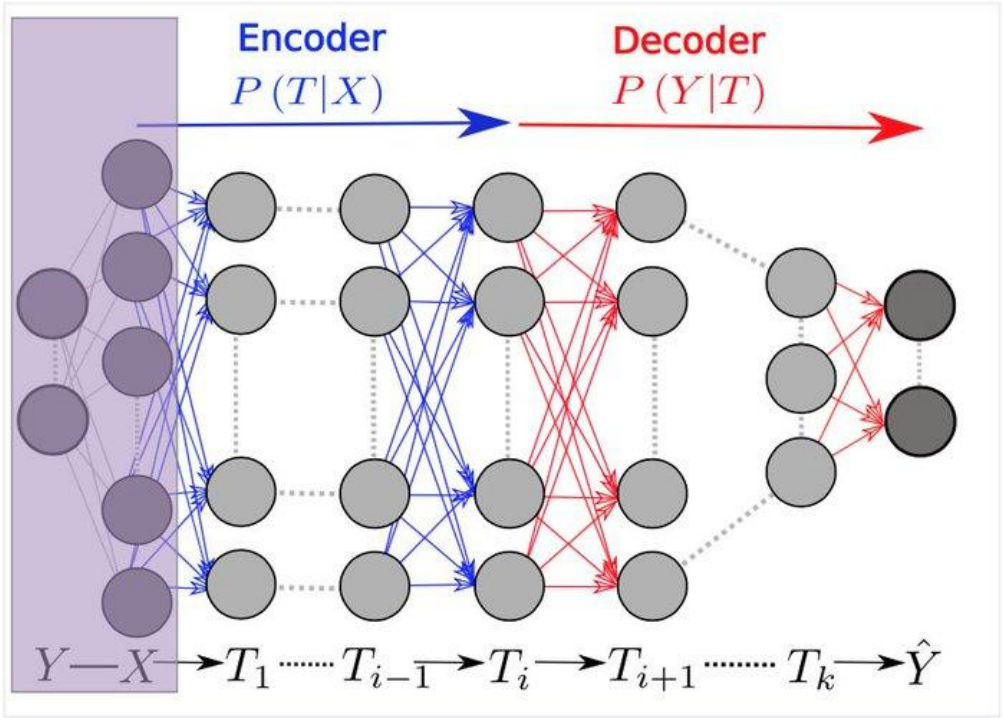


Figure 1: The DNN layers form a Markov chain of successive internal representations of the input layer X. Any representation of the input, T, is defined through an encoder, $P(T|X)$, and a decoder $P(\hat{Y}|T)$, and can be quantified by its *information plane* coordinates: $I_X = I(X;T)$ and $I_Y = I(T;Y)$. The Information Bottleneck bound characterizes the optimal representations, which maximally compress the input X, for a given mutual information on the desired output Y. After training, the network receives an input X, and successively processes it through the layers, which form a Markov chain, to the predicted output $\hat{Y}$. $I(Y;\hat{Y})/I(X;Y)$ quantifies how much of the relevant information is captured by the network.

Naftali Tishby 2017, 2018

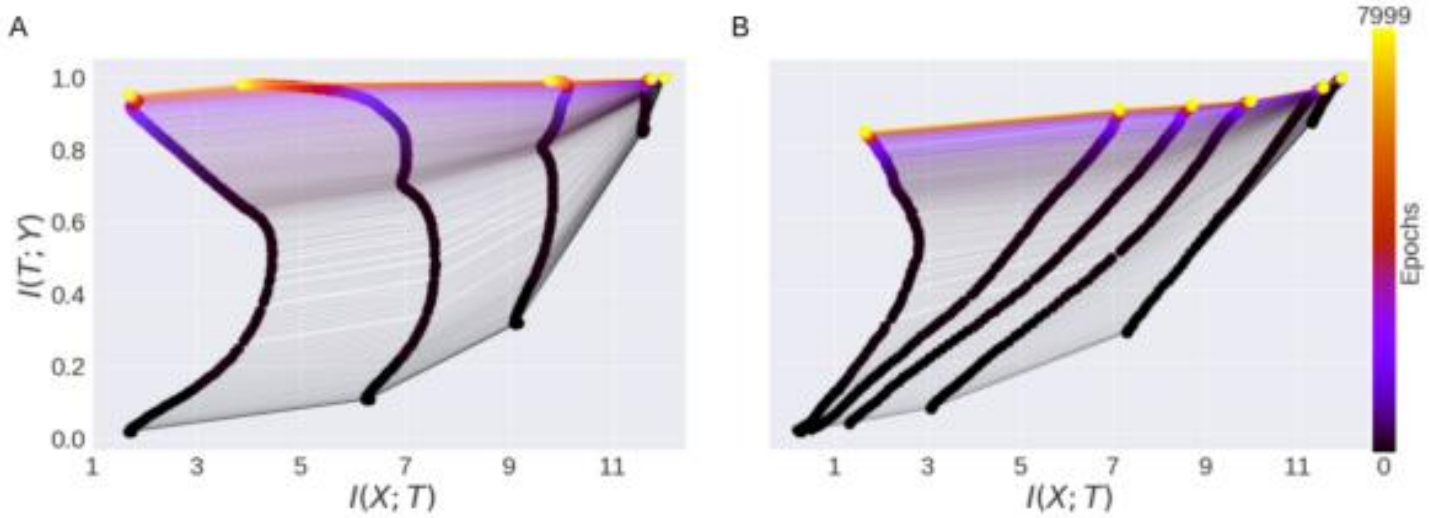


Figure 1: Information plane dynamics and neural nonlinearities. (A) Replication of Shwartz-Ziv & Tishby (2017) for a network with tanh nonlinearities (except for the final layer which contains sigmoidal neurons). The x-axis plots information between each layer and the input, while the y-axis plots information between each layer and the output. The color scale indicates training time in epochs. Each of the six layers produces a curve in the information plane with the input layer at far right, output layer at the far left. Different layers at the same epoch are connected by fine lines. (B) Information plane dynamics with ReLU nonlinearities (except for the final layer of 2 sigmoidal neurons). Here no compression phase is visible in the ReLU layers. For learning curves of both networks, see Appendix A

Thank you for your attention