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ETAL 2023: École d'été en Traitement Automatique des Langues

at CIRM: Centre International de Rencontres Mathématiques
Luminy, Marseille, June 12-16, 2023

Conférence invitée, June 13, 2023:

Speech & Language Technology (NLP):
Past, Present and Future

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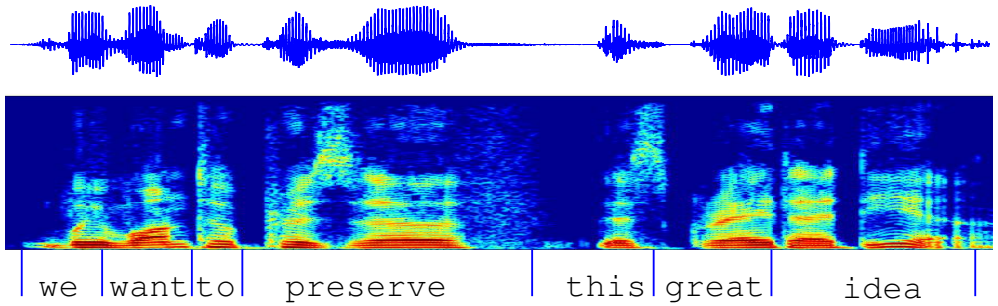
This Lecture

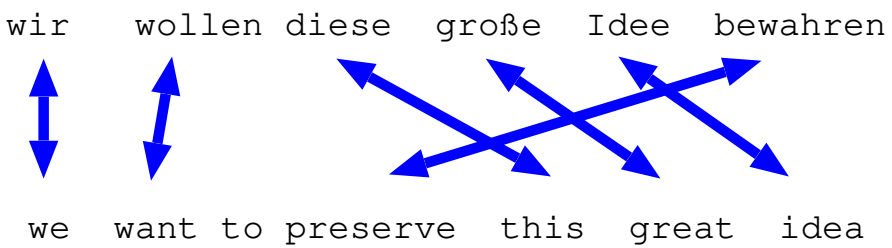
- my personal experience (1978-2023)
- my personal interpretation:
  - unifying framework: probabilistic models and Bayes decison theory
  - formal framework: mathematics (CIRM: rencontres mathématiques!)
  - deep learning is just one out of many machine learning approaches
  - experience: 'more data help'
- my personal messages:
  - success of data-driven approaches
  - NLP and AI: moving from rule-based to data-driven approaches
  - things started 40 years ago, not in 2013!
  - evolution from small to large language models

Speech & Language Technology: Sequence-to-Sequence Processing

Automatic Speech Recognition (ASR) (speech signal processing)



Machine Translation (MT) (symbol or text processing)



Handwriting Recognition (HWR) (text image processing)

common characteristics:

- **use of a 'small' language model (LM) to generate smooth fluent text (syntax, semantics, context)**
- **generative aspect of LM: unlike other NLP tasks (POS/synt./semant. labels, ...)**
- **LM is learned from text only (*without annotation, unsup. mode, pre-training)***

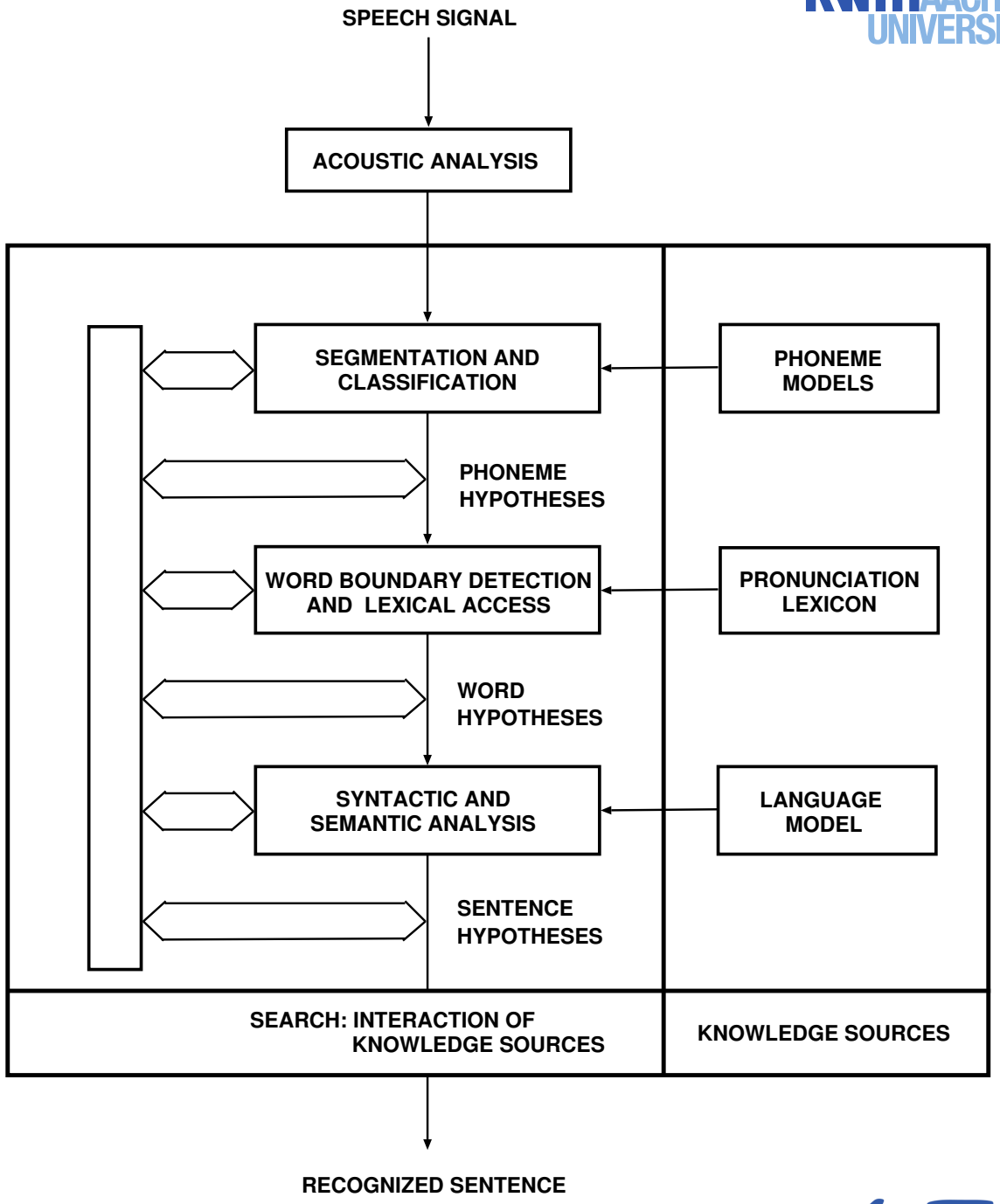
note: this is how (small) language models started (1980 - 2000)

ASR: first research 1975-1980

ASR is sequence-to-sequence processing at several levels:
10-ms vectors, phonemes, words

problems:
– ambiguities at/between all levels
– interdependencies of decisions

approach 1975-1980 (Baker/CMU and Jelinek/IBM):
– probabilitistic modelling
– holistic approach ('end-to-end'): single criterion for system design (Bayes decision rule)
– complex mathematical modelling



1980-1990 Baseline Statistical Approach to ASR

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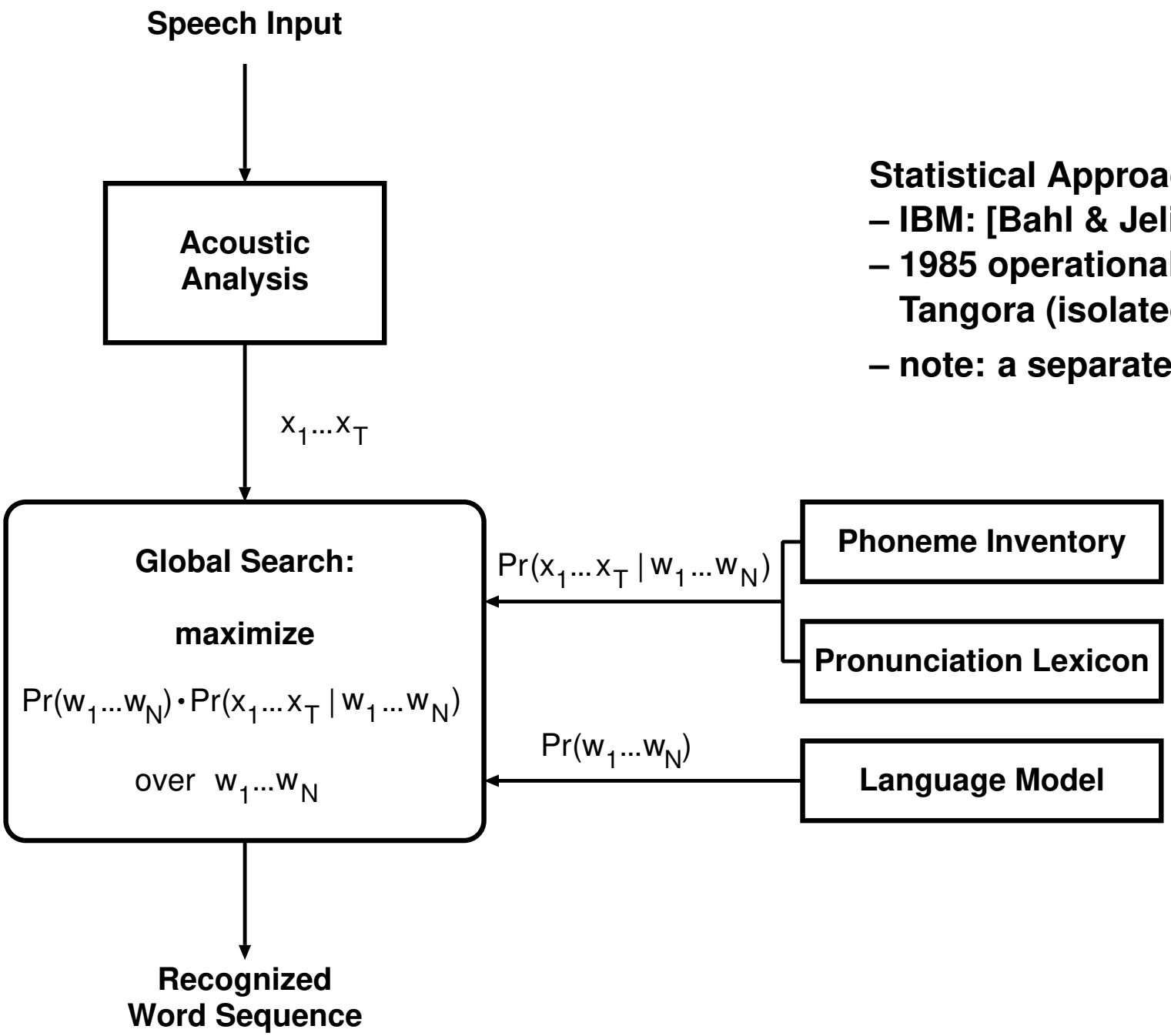
- modelling: probability distributions/data-driven approaches with

$$\text{10-msec vectors:} \quad x_1^T = x_1 ... x_t ... x_T \qquad x_t \in \mathbb{R}^D$$
$$\text{word string:} \quad w_1^N = w_1 ... w_n ... w_N$$

- consider joint generative model: $p(w_1^N, x_1^T) = p(w_1^N) \cdot p(x_1^T | w_1^N)$
- language model $p(w_1^N)$: based on word trigram counts, learned from text only $[w_1^N]$
- acoustic (-phonetic) model $p(x_1^T | w_1^N)$: learned from annotated audio $[x_1^T, w_1^N]$
  - generative hidden Markov model:
    discrete models/VQ, Gaussians, Gaussian mixtures, ...
  - structure: first-order dependence and mathematically nice
  - training: ('efficient') EM algorithm with sort of closed-form solutions
- clear difference to general machine learning:
  - well-known for isolated events (no context) $(x, c): \; x \rightarrow c = c(x)$
    class posterior $p(c|x)$ better than generative model $p(x|c)$
  - sequence-to-sequence problem: time alignment and language model context
- decoding/generation: Bayes decision rule (simplified form)
  = use single criterion and avoid local decisions



Statistical Approach to ASR

– IBM: [Bahl & Jelinek$^+$ 83]

– 1985 operational research system: Tangora (isolated words, speaker dep.)

– note: a separate LM

Operational ASR Systems

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ASR at Philips: Research Hamburg/Aachen and BU Dictation Systems Vienna:

- **1k-word continuous speech recognition: research prototype**
  SPICOS 1984-1989 (German BMBF): Siemens, Philips, German universities
- **10k-word continuous speech recognition: commercial Philips product**
  - **speaker dep., DP beam search and dynamic search space, real-time on Motorola 68020**
  - **presentation at Eurospeech 1993: medical text dictation**

speech translation at RWTH Aachen: research prototypes

- **Verbmobil 1993-2000 (German BMBF):**
  appointment scheduling/limited domain, German-English, 8k words
- **TC-STAR 2004-2007: domain: speeches given in EU parliament**
  - **challenge: MT robust wrt ASR errors $\rightarrow$ data-driven methods**
  - **approach to MT: phrase-based approach**
  - **first research prototype for unlimited domain and real-life data**
    - **fully automatic, not real time**
    - **without deep learning!**
  - **partners: KIT Karlsruhe, RWTH, CNRS Paris, UPC Barcelona, IBM-US Research, ...**

more research prototypes: GALE, BOLT, BABEL, QUAERO, EU-Bridge, Translectures, ERC
along with DARPA/NIST/project evaluations

ASR History: Operational Research Systems

- **steady improvement of data-driven methods:**
  HMMs with Gaussians and mixtures, phonetic CART, statistical trigram language model, speaker adaptation, sequence discriminative training, ANNs
- **methodology in ASR since 1990: standard public data:**
  TIMIT, RM/1k, WSJ/5k, WSJ/20k, NAB/64k, Switchboard/tel., Librispeech, TED-Lium
- **1993-2000 NIST/DARPA: comparative evaluation of operational systems:**
  – virtually all systems: generative HMMs and refinements
  – 1994 Robinson: hybrid HMM with RNN (singularity!)

alternative concepts (with less success):

- **1985-93: criticism about data-driven approach/machine learning**
  – acoustic model: too many parameters and saturation effect
  – concept of rule-based AI: acoustic-phonetic expert systems
  – language model: similar criticism (linguistic grammars)

- **SVM (support vector machines): never competitive in ASR**
  (ASR requires decisions in context!)

ASR: ANN in Acoustic Modelling

- 1987 [Bourlard & Wellekens 87]: MLP and ASR
- 1988 [Waibel & Hanazawa$^+$ 88]: phoneme recognition by TDNN (convol.NNs!)
- 1989 [Bourlard & Wellekens 89, Morgan & Bourlard 90]:
  – ANN outputs: can be interpreted as class posteriors
  – *hybrid HMM*: use ANN for frame label posteriors
- 1989 [Bridle 89]: softmax ('Gaussian posterior') for normalized ANN outputs
- 1991 [Bridle & Dodd 91] backpropagation for HMM discriminative training at word level
- 1993 [Haffner 93]: sum over label-sequence posterior probabilities in hybrid HMMs
  (*sequence discriminative training*)
- 1994 [Robinson 94]: RNN in hybrid HMM
  (operational system, DARPA evaluations)
- 1997 [Fontaine & Ris$^+$ 97, Hermansky & Ellis$^+$ 00]:
  tandem HMM: use ANN for feature extraction in a Gaussian HMM
- 2009 Graves: CTC for handwriting recognition
  (operational system, ICDAR competition 2009)

Neural ASR: Tandem vs. Hybrid HMM

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hybrid HMM: ANN-based feature extraction + Gaussian posterior + HMM

- 2009 [Graves 09]: CTC - good results on LSTM RNN for handwriting task
- 2010 [Dahl & Ranzato$^+$ 10]: improvement in phone recognition on TIMIT
- 2011 [Seide & Li$^+$ 11, Dahl & Yu$^+$ 12]: Microsoft Research
  - fully-fledged hybrid HMM
  - 30% rel. WER reduction on Switchboard 300h
- since 2012: other teams confirmed reductions of WER by 20% to 30%

tandem HMM: ANN-based feature extraction + generative Gaussian + HMM

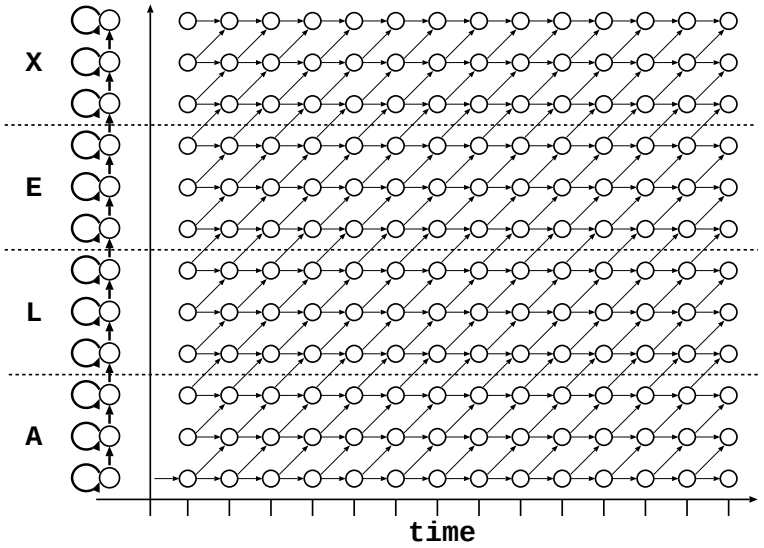
- 2006 [Stolcke & Grezl$^+$ 06]: cross-domain and cross-language portability
- 2007 [Valente & Vepa$^+$ 07]: 8% rel. WER reduction on LVCSR
- 2011 [Tüske & Plahl$^+$ 11]: 22% rel. WER reduction on LVCSR/QUAERO

experimental observation for hybrid and tandem HMM:
progress by using *deep* MLPs

Finite-State Transducer: Hidden Markov Model (similar: CTC and RNN-Transducer)

– **sequence of acoustic vectors:**
$X = x_1^T = x_1 ... x_t ... x_T$ **over time** $t = 1, ..., T$

– **sequence of states** $s = 1, ..., S$
$s_1^T = s_1 ... s_t ... s_T$ **over time** t
with phonetic labels:
$a_1^S = a_1 ... a_s ... a_S$
$= W$: **word sequence**



- **classical HMM: generative model for input sequence** x_1^T**:**

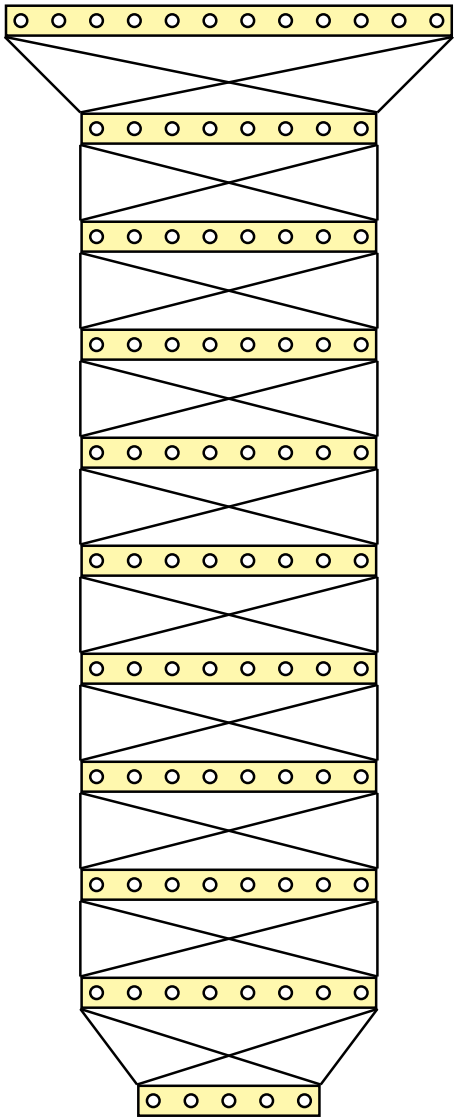
$$q_\vartheta(x_1^T | W = a_1^S) = \sum_{s_1^T} \prod_t q_\vartheta(s_{t+1} | s_t, a_{s_t}) \cdot q_\vartheta(x_t | a_{s=s_t})$$

- **hybrid HMM: discriminative model for output sequence** a_1^S
using $q(x_t | a_s) = q(a_s | x_t) \cdot q(x_t) / q(a_s)$**:**

$$q_\vartheta(W = a_1^S | x_1^T) = \sum_{s_1^T} \prod_t q_\vartheta(s_{t+1} | s_t, a_{s_t}) \cdot q_\vartheta(a_{s=s_t} | x_t)$$

[Bourlard & Wellekens 89] machine learning point-of-view:
it is much(!) easier to model $q_\vartheta(a_s | x_t)$ **than** $q_\vartheta(x_t | a_s)$

Artificial Neural Networks (ANN) and Deep Learning:



question: what is different now after 30 years?

answer: we have learned how to (better) handle a complex numerical optimization problem:

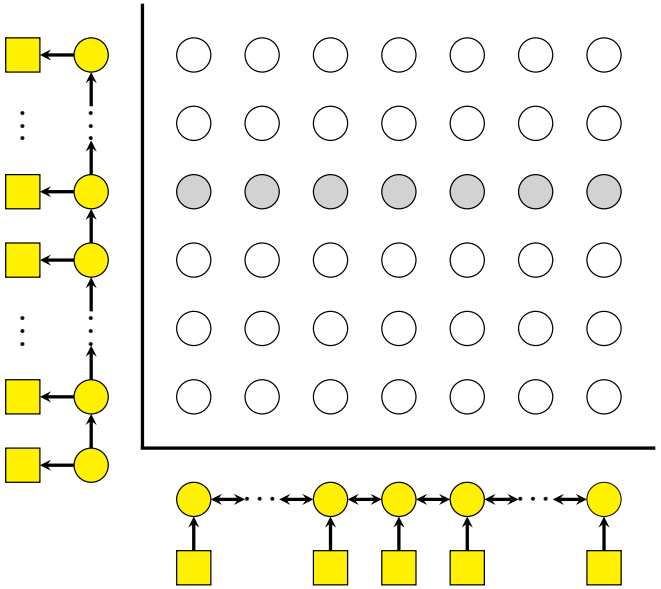
- **more powerful hardware (e. g. GPUs)**
- **empirical recipies for optimization: practical experience and heuristics, e.g. layer-by-layer pretraining**
- **result: we are able to handle more complex architectures (deep MLP, RNN, attention, transformer, etc.)**

my interpretation: 2022's most advanced ASR systems:

$=$ sophisticated feature extraction/representation

$+$ softmax (= Gaussian posterior)

common properties:
– input: acoustic encoder: representation/state vectors $h_t = h_t(x_1^T), t = 1, ..., T$
– output: (phoneme) labels $a_s,\ s = 1, ..., S$ with/without integrated language model



representation/state vectors h_t:
– deep MLP: finite window
– RNN and LSTM-RNN
– self-attention (transformer)

similar: output string

- **(cross-) attention: direct factorization:**

$$p(a_1^S|x_1^T) = \prod_s p(a_s|a_0^{s-1}, x_1^T) = \prod_s p(a_s|a_{s-1}, r_{s-1}, c_s)$$

$$c_s := \sum_t p(t|a_0^{s-1}, x_1^T) \cdot h_t$$

with context vector c_s and output state vector r_s

criticism for ASR: lack of strict monotonicity and localization

- **finite-state transducer (post. HMM, CTC, RNN-T, ...): introduce hidden paths and then factorize:**

$$p(a_1^S|x_1^T) = \sum_{s_1^T} p\left(s_1^T, a_1^S|h_1^T(x_1^T)\right)$$

$$= \sum_{s_1^T} \prod_t p\left(s_{t+1}, y_t = a_{s_t} \middle| s_t, a_0^{s_t-1}, h_1^T(x_1^T)\right)$$

details: RWTH papers at ICASSP and Interspeech

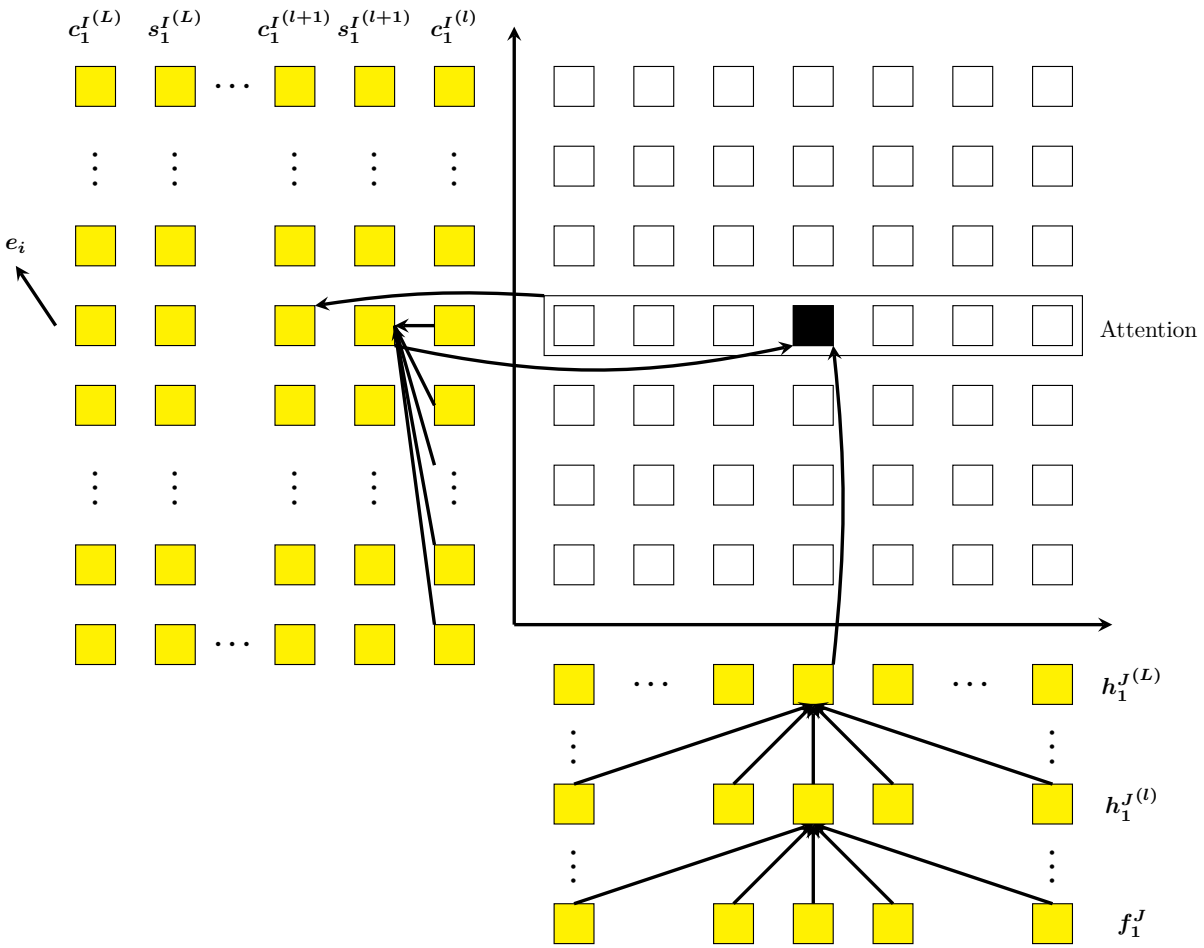
Sequence-to-Sequence Processing: Transformer Approach (Google [Vaswani & Shazeer+ 17])

designed for a 'two-dim.' problem with input and output sequences:

- **keep the *cross-attention* between output and input as in RNN attention [Bahdanau & Cho+ 15]**
- **for input and output sequence: replace RNN structure by *self-attention*, i. e. pair-wise associations**

2020 OpenAI: transformer GPT-3:
– 96 layers, each with 12.288 nodes
– 96 attention heads
in total: 175 Bio parameters

use LM concept for MT:
1 rather than 2 sequences
2013 [Kaltenbrenner & Blunsom 13]
2014 [Sutskever & Vinyals+ 14]
today: most successful with GPTs



Machine Translation (MT): History

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statistical approaches were controversial in MT (and other NLP tasks):

- **1969 Chomsky:**
  ... the notion 'probability of a sentence' is an entirely useless one, under any known interpretation of this term.
- **result: strict dichotomy until (around) 2000:**
  – speech = spoken language: signals, subsymbolic, machine learning
  – language = written text: symbols, grammars, rule-based AI
- **until 2000: mainstream approach was rule-based**
  – result: huge human effort required in practice
  – problems: coverage and consistency of rules
- **1989-93: IBM Research: statistical approach to MT**
  1994: key people (Mercer, Brown) left for a hedge fund
- **1996-2002 RWTH: improvements beyond IBM's approach:**
  HMM alignments, log-linear modelling, phrases as basic units
- **around 2004: from singularity to mainstream**
  F. Och (and more RWTH PhD students) joined Google
  2008: service *Google Translate*
- **since 2014: neural MT (unlike count-based MT):**
  attention mechanism [Bahdanau & Cho$^+$ 15]

Unifying Framework: Statistical Decision Theory and Bayes Decision Rule

- so far: historical review of ASR (along with MT) and ANNs
  covering a variety of ANN models and training criteria
- what about training criteria?
  (e. .g. cross-entropy, seq.disc. training, min. Bayes risk, expected loss, ...)

  ultimate justification should be based on performance
  – consequence: re-visit Bayes decision rule und its framework
  – example: textbook by Duda & Hart 1973, pp. 11-16
  – originally not explicitly meant for ASR or string processing
- what is not well covered in textbooks or papers:
  – mathematical relation between training criteria and loss function/performance
  – practical implications for training criteria

references, mostly RWTH:
[Ney 03, Schlüter & Scharrenbach$^+$ 05, Xu & Povey$^+$ 10, Schlüter & Nussbaum$^+$ 11],
[Schlüter & Nussbaum$^+$ 12, Schlüter & Nussbaum-Thom$^+$ 13, Schlüter & Beck$^+$ 19]

Bayes Decision Theory and Machine Learning (Puristic Mathematical View)

simplified notation: input string $x = x_1^T$ and output string $c = c_1^N$

- **define performance criterion: loss function $L[\tilde{c}, c]$, e. g. edit distance (WER) in ASR**
- ***true* Bayes decision rule:**
  theoretical assumption for guaranteed optimal performance:
  use TRUE (unknown) posterior distribution $pr(c|x)$ of the input data:

$$\textbf{general loss:} \quad x \rightarrow c_*(x) := \arg\min_c \Big\{ \underbrace{\sum_{\tilde{c}} pr(\tilde{c}|x) \cdot L[\tilde{c}, c]}_{\textbf{expected loss}} \Big\}$$

- ***pseudo* Bayes decision rule:**
  replace $pr(c|x$ by a MODEL $p_\vartheta(c|x)$ to generalize to unseen input x:

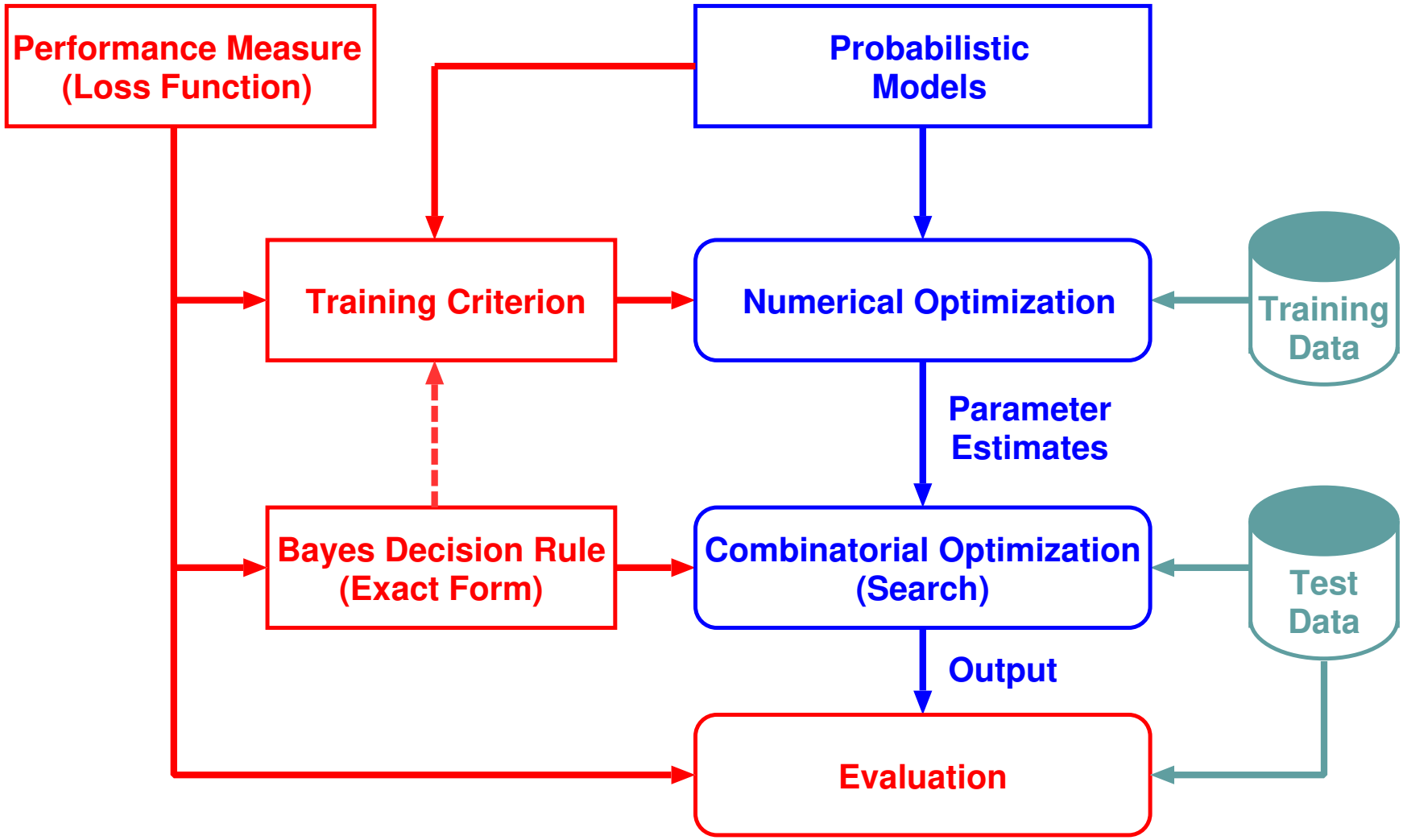
$$\textbf{general loss:} \quad x \rightarrow c_\vartheta(x) := \arg\min_c \Big\{ \sum_{\tilde{c}} p_\vartheta(\tilde{c}|x) \cdot L[\tilde{c}, c] \Big\}$$

$$\textbf{0/1 loss:} \quad x \rightarrow c_\vartheta(x) := \arg\max_c \Big\{ p_\vartheta(c|x) \Big\}$$

  textbooks: 0/1 loss widely used, i. e. optimal for minimum string error

- **principal questions:**
  – optimality: is it preserved when replacing $pr(c|x$ by $p_\vartheta(c|x)$?
  – exact loss function: how much does it matter ? in training/testing ?
  – what are suitable training criteria for learning $p_\vartheta(c|x)$?

Unifying View:
Bayes Decision Theory and Machine Learning
(*Why are we doing what we are doing?)*



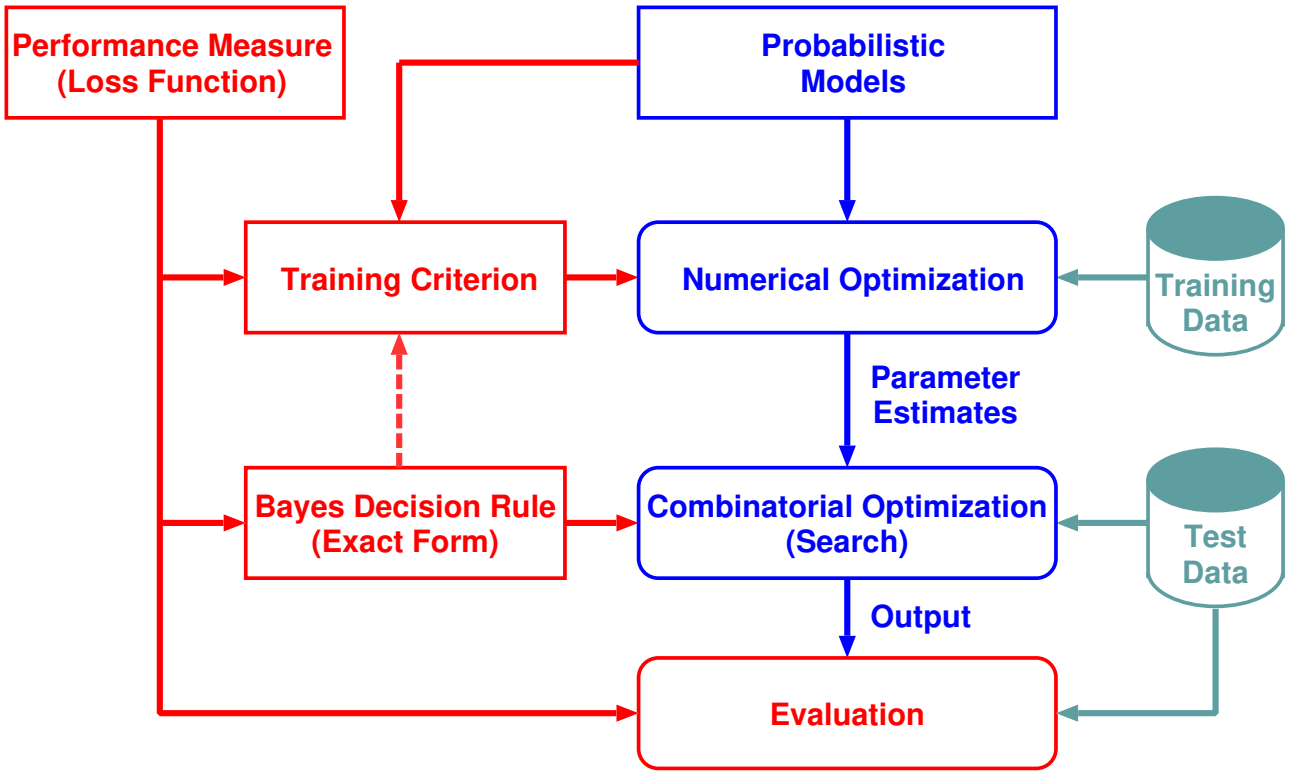
mathematical analysis (omitting details):

- optimality of pseudo Bayes decision rule: yes
  analysis: distinguish expected loss (error rate) for true and pseudo Bayes rules
- type of loss in Bayes decision rule:
  – compare 0/1 loss with general loss $L[\tilde{c}, c]$
  – identical results for metric loss function (e. g. edit distance)
  if $\max_c p_\vartheta(c|x) \geq 0.5$
- training criteria:
  – can be derived from expected loss
  – can be formulated as a function of model $p_\vartheta(c|x)$
  – training in practice: HUGE numerical optimization problem
  (many shortcuts and approximations beyond CE training)

Statistical Decision Theory for NLP: Where do we stand ?

- exact loss function:
  - not so important in testing
  - more important in training
- probabilistic models:
  - are most important: caused progress 1980-2023
  - dependencies and synchronization between input/output strings
  - often (e. g. ASR): separate LM
- training criterion:
  - is important
  - depends on prob. models
- numerical optimization:
  - hard math. problem
  - all variants of backpropagation
  - important in practice (1990 vs. 2022!)
- decision rule: search/generation: today's models: more important for low-accuracy conditions

this lecture:
- statistical decision theory defines a perfect framework
- its principles go beyond NLP and ANN



ASR Modelling: String Posterior Probability

- complete model for [input,output] pair $[x_1^T, W = a_1^S]$
  consists of language model (LM) and acoustic (-phonetic) model (AM):

$$p_\vartheta(W|x_1^T) := \frac{q_\vartheta^\alpha(W) \cdot q_\vartheta^\beta(W = a_1^S|x_1^T)}{\sum_{\tilde{W}} q_\vartheta^\alpha(\tilde{W}) \cdot q_\vartheta^\beta(\tilde{W} = \tilde{a}_1^S|x_1^T)}$$

  with model parameters ϑ (and exponents α, β)

- motivation: the log-linear combination mimicks the generative approch:

$$p_\vartheta(W|x_1^T) := \frac{p_\vartheta(x_1^T, W)}{\sum_{\tilde{W}} p_\vartheta(x_1^T, \tilde{W})} = \frac{p_\vartheta(W) \cdot p_\vartheta(x_1^T|W)}{\sum_{\tilde{W}} p_\vartheta(\tilde{W}) \cdot p_\vartheta(x_1^T|\tilde{W})}$$

- language model $q_\vartheta(W)$
  learned from text data only (without annotation) (e. g. 100 Mio words)
- acoustic model (AM): finite-state transducer (CTC, RNN-T, post.HMM, ...):

$$q_\vartheta(W = a_1^S|x_1^T) = \sum_{s_1^T} \prod_t q_\vartheta(s_{t+1}|s_t, a_{s_t}) \cdot q_\vartheta(a_{s=s_t}|x_1^T)$$

  learned from (manually) transcribed audio data (e. g. 500 hours = 5 Mio words)

Acoustic Model: Training Criterion and Procedure

suitable training criterion for (audio, text) pairs $[X_r, W_r],\ r = 1, ..., R$:

$$\max_{\vartheta} \left\{ \sum_r \log\ p_\vartheta(W_r|X_r) \right\} \qquad p_\vartheta(W|X) = \frac{q^\alpha(W) \cdot q_\vartheta^\beta(W|X)}{\sum_{\tilde{W}} q^\alpha(\tilde{W}) \cdot q_\vartheta^\beta(\tilde{W}|X)}$$

numerical optimization problem in training:

- **ignore denominator: simplified baseline**
  - **effect: decoupling of AM and LM**
    advantage: independent training of AM and LM
  - **variants for AM training: full sum or best path/Viterbi (frame-wise CE)**
    note: EM framework still works for neural HMM
- **keep denominator: *sequence discriminative training***
  - **0/1 loss: errors at sequence level (IBM 1986: MMI)**
    (see above: training criterion)
  - **exact loss (e. g. WER): errors at symbol level in sequence context**
    variants in ASR: Povey's phoneme/symbol error, sMBR, ...

  result: LM affects training of AM!

  denominator: how to approximate it?
  - **word hypothesis lattice**
  - **simplifed language model (lattice-free MMI, Povey 2016)**

history: Bahl/IBM 1986, Normandin 1991, Valtchev 1996, Povey 2002/16, Heigold 2005/12

reconsider training criterion for (audio,ctext) pairs $[X_r, W_r],\ r = 1, ..., R$:

$$\max_{\vartheta} \left\{ \sum_r \log\ p_\vartheta(W_r|X_r) \right\} \qquad p_\vartheta(W|X) := \frac{q^\alpha(W) \cdot q_\vartheta^\beta(W|X)}{\sum_{\tilde{W}} q^\alpha(\tilde{W}) \cdot q_\vartheta^\beta(\tilde{W}|X)}$$

terminology: What does *end-to-end* mean?

- **training criterion: a single global criterion for optimum performance, independent of model structure**
- **monolithic structure of a model: simplicity/elegance of programming? what about adequacy/performance?**

remarks:

- **ASR: training of acoustic model and language model:**
  - **transcribed audio: 500 hours = 5 Mio words**
  - **text (from press, books, internet,...): 100 Mio words and more**
- ***end-to-end* concept:**
  - **for training and search/generation: yes (? and robustness/easiness of training)**
  - **for the structure: can it reflect the training data situation?**

Effect of AM, Training Criterion and LM (Tüske et al. RWTH 2017)

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QUAERO task, English Eval 2013:
broadcast news/conversations, podcasts, TED lectures

Word error rates [%] on QUAERO English Eval 2013
(PP: perplexity of LM = power of LM ≅ effective vocab.size)

Acoustic Model (AM): hybrid HMM			Language Model (LM)	
Type		Training Criterion	Count	Count + ANN
			PP=131.1	PP=92.0
Gaussian mixtures		max.lik.	20.7	
		seq.disc. training	19.2	16.1
Neural Net	FF MLP	frame-wise CE	11.6	
		seq.disc. training	10.7	9.0
	LSTM RNN	frame-wise CE	10.6	
		seq.disc. training	9.8	8.2

observations:
– improvements by acoustic ANNs: 50% relative
– improvement by language model ANN: 15% relative
– total improvements by deep learning: 60% relative (from 19.2% to 8.2%)

Neural Language Modelling
[Sundermeyer et al.; RWTH 2012, 2015]

- important principle (undervalued!):
  - move away from count-based statistics for categorial random variables
  - instead: word/symbol embeddings and operations in a high-dim. vector space
- interpolation of TWO models (2015):
  count model (3 Bio words) + ANN model (60 Mio words)
- details and refinements:
  - use of word classes for softmax in output layer
  - unlimited history of RNN: requires re-design of ASR search
- perplexity (PP) and word error (WER) rate on test data (QUAERO)

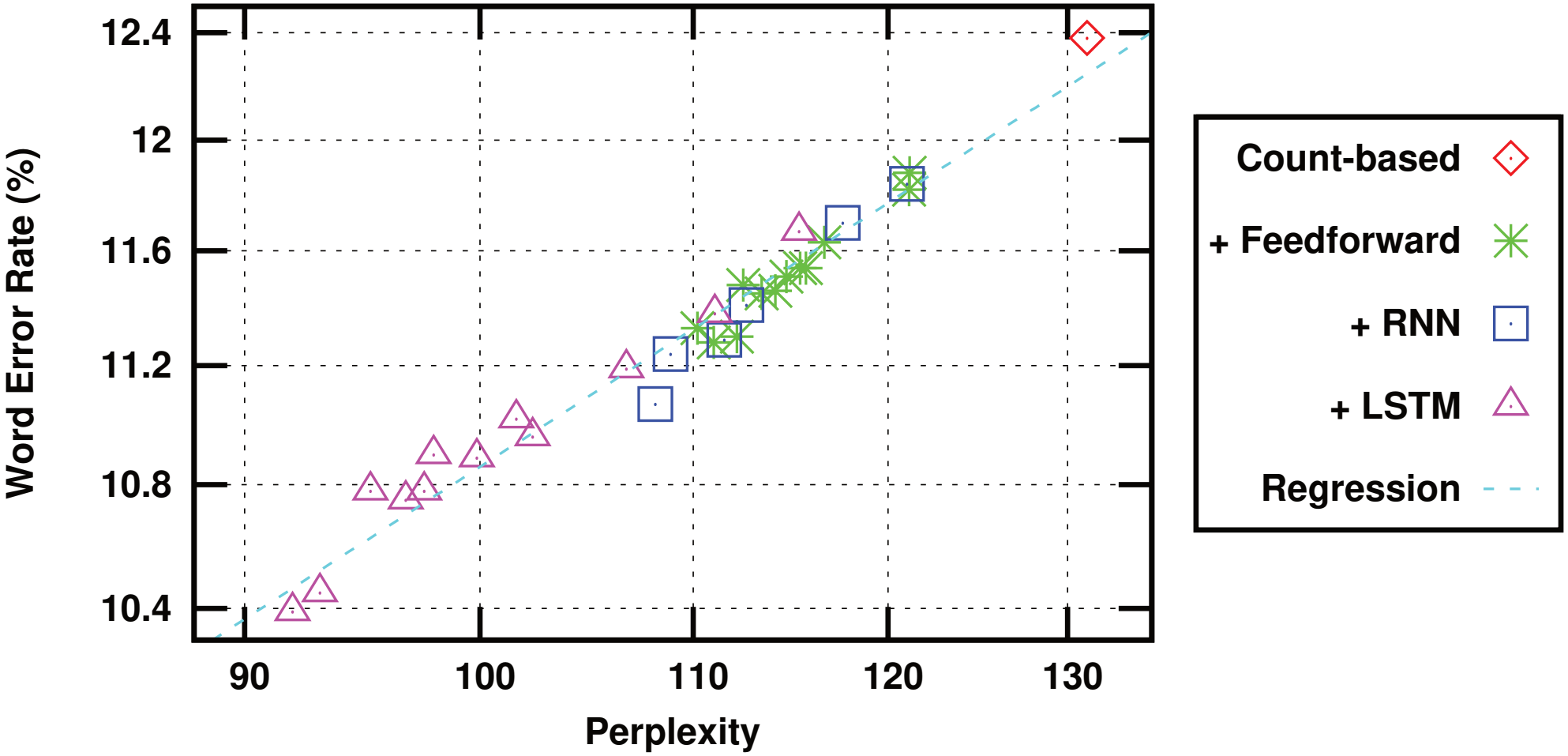
models	PP	WER[%]
count model	131.2	12.4
+ 10-gram MLP	112.5	11.5
+ Recurrent NN	108.1	11.1
+ LSTM-RNN	96.7	10.8
+ 10-gram MLP with 2 layers	110.2	11.3
+ LSTM-RNN with 2 layers	92.0	10.4

- improvements achieved:
  - perplexity: 30% reduction: from 131 to 92
  - WER: 15% reduction: from 12.4% to 10.4%

Effect of Language Model: Word Error Rate vs. Perplexity

empirical law: $WER = \alpha \cdot PP^{\beta}$ **with** $\beta \in [0.3, 0.5]$

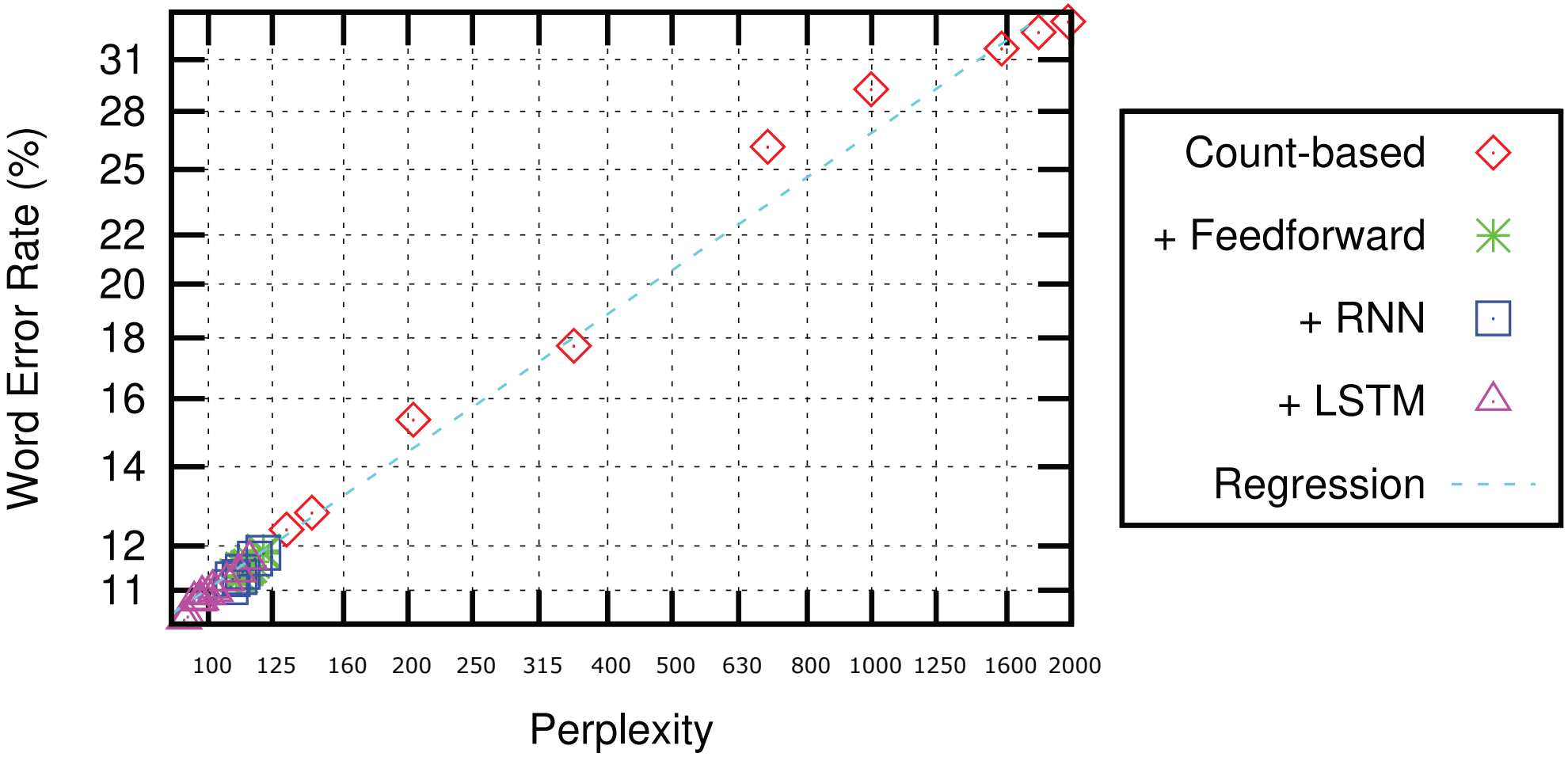
[Makhoul & Schwartz 94, Klakow & Peters 02]



Effect of Language Model: Word Error Rate vs. Perplexity

empirical law: $WER = \alpha \cdot PP^{\beta}$

open question: theoretical justification?



early work:

- **1989 [Nakamura & Shikano 89]:**
  English word category prediction based on neural networks.
- **1993 [Castano & Vidal$^+$ 93]:**
  Inference of stochastic regular languages through simple recurrent networks

important component in ANN-based LMs:
– word/symbol representations/embeddings: vectors in high-dim. space
– in addition to ANN structures (MLP, RNN, LSTM-RNN, transformer, ...)

since 2000 (mainly LM for ASR):

- **2000 [Bengio & Ducharme$^+$ 00]: A neural probabilistic language model**
- **2002 [Schwenk & Gauvain 02, Schwenk 07]:**
  Continuous space language models
- **2010 [Mikolov & Karafiat$^+$ 10]:**
  RNN based language model
- **2012 RWTH Aachen [Sundermeyer & Schlüter$^+$ 12]:**
  LSTM-RNN for language modeling

power of LMs and word representations (spirit of *distributional semantics*):

1954 Harris: Words are similar if they appear in similar contexts.

1957 Firth: You shall know a word by the company it keeps.

- papers by [Collobert & Weston 08, Collobert & Weston$^+$ 11]:

  2008: *A Unified Architecture for NLP: Deep Neural Networks with Multitask Learning.*

  2011: *NLP (almost) from Scratch.*

  use of word vectors for formal NLP tasks:

  POS/NER tagging, syntactic analysis, semantic role labeling, text classif., ...

- word vectors: (semantic) interpretations and calculations
  examples of relations between word vectors [Mikolov & Corrado$^+$ 13]:

$$Germany - Berlin \cong France - Paris$$
$$king - queen \cong man - woman$$

- 2013/2014: use LM concept for MT [Kaltenbrenner & Blunsom 13, Sutskever & Vinyals$^+$ 14]
- since 2019: LLMs (large-scale LMs) based on GPT architecture:
  - G: generative: generate text (as opposed to formal NLP tasks)
  - P: pre-trained: based on text without *any* annotation
  - T: transformer: ANN structure for sequence-to-sequence processing

  LLM implies: more data, more parameters (200 Bio), multi-lingual, multi-task, ...

Refining LLMs: *InstructGPT*

***InstructGPT* introduced by OpenAI, arxiv, 04-Mar-2022:**
Training language models to follow instructions with human feedback.

three levels of training:

- **pre-training or unsupervised training (using log perplexity):**
  - **training mode: raw text with no annotation**
  - **operation mode (surprising result !):**
    type of task (*prompt*): can be specified in plain language
    (e. g. summarization, story generation, translation, ...)
    full system operation is described by a triplet (in plain language!):
    triplet := [prompt, input, output]
    (typically used in so-called *few-shot learning/setting*)
- **supervised fine-tuning:**
  - **training data: based on (many) triplets of the above type**
  - **training criterion: (log) perplexity**
    all triplets are interpreted as a *single* sequence of text
- **human feedback and reinforcement learning:**
  - **starting point: system is used to generate the outputs for [prompt, input] pairs**
  - **human evaluation and ranking**
  - **reinforcement learning based on human scores**

Summary

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40 years of building operational systems for NLP:

- **success of data-driven vs. handcrafted rule-based approaches**
- **misconception: things started 40 years ago, not in 2013!**
- **persistent evolution of data-driven concepts:**
  - **signal-processing NLP: ASR and HWR**
  - **text-processing NLP:**
    - **language models for ASR (+ HWR + MT)**
    - **machine translation (MT)**
    - **large language models for NLU, e. g. Q&A, dialog management, ...**
- **additional success ('revolution'):**
  symbol embeddings/vectors in contrast to symbol count statistics
- **statistical decision theory:**
  unifying framework for data-driven approach and machine learning:
  - **distinguish ingredients:**
    loss function, prob.model, training criterion along with numerical optimization
  - **includes as a special case: ANNs and deep learning**
  - **most useful framework after 40 years of NLP**

What about the Future?

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future: what time horizon: 3, 5, 10, 20 years?
e. g. difficult prediction: ANN around 1990

short-term horizon: low-hanging fruits
– more data, more complex models, more parameters, more computation
– 1989 R. Mercer/IBM: *There is no data like more data.*

long-term horizon: scientific challenges:
beyond more data, we need better mathematical frameworks:

- **back-propagation search:**
  beyond trial and error: better theory of numerical optimization
- **present ANN structures**
  – deep MLP, RNN, LSTM, self-embedding, transducer, transformer,...:
  – lack of principal mathematical justification:
  why are some structures better for modelling and learning?
- **beyond ANN structures:**
  – what about going beyond the present structures (matrix-vector product + nonlinearity)?
  – there is plenty of (data-driven) life outside and beyond deep learning!
  (but yes, it will be complex mathematical models)

What about the Future? (ctd)

- **word/symbol embeddings in NLP:**
  - **most important concept in lieu of count-based statistics**
  - **widely underrated in statistics and general NLP**

- **open research directions: beyond *supervised* machine learning:**
  strictly *unsupervised* machine learning,
  i. e. absolutely no parallel (input,output) pairs

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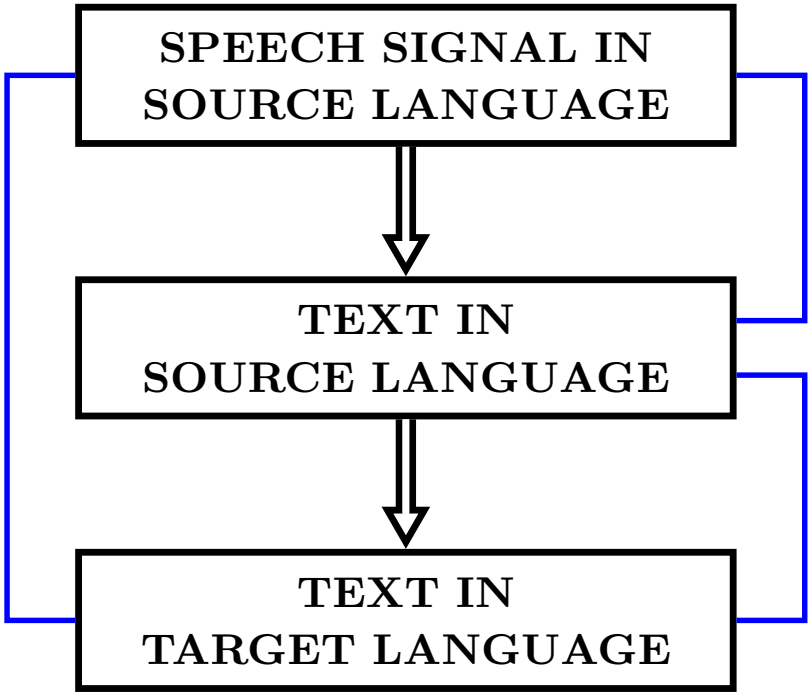
Speech Translation



source audio $X \rightarrow$ source text $F \rightarrow$ target text E

challenge: exploit three types of training data
– text MT: (F, E) sentence pairs (e. g. 100 Mio = 1-2 Bio words)
– ASR: (X, F) pairs (e. g. 5000 hours = 50 Mio words)
– speech-text MT: (X, E) (e. g. 1000 hours?)

Industry vs. Academia

most important contributions:

- **academia:**
  - **general HMM framework**
  - **RNN-HMM [Robinson 1994]**
  - **RNN-CTC [Graves 2009]**
  - **deep learning (in the narrow sense!) [Hinton 2011]**
  - **cross-attention [Montreal team 2014]**
- **industry:**
  - **self-attention and transformer**
  - **conformer**

APPENDIX: LLM and GPT

- large-scale language model (LLM) called *chatGPT*:
  - API introduced on 30-Nov-2022 by OpenAI
  - function: human-like conversational (text) dialog *(unlimited domain)*
  - CEO S. Altman: "costs are eye-watering"
  - operational loss in 2022: 540 Mio USD (416 on computing, 89 on staff)
- OpenAI's technology behind *chatGPT*:
  - baseline architecture *GPT: generative pre-trained transformer*
  - *GPT-3*: with 1.3 to 175 Bio parameters,
    trained on 300 Bio (subword) tokens (cut-off date: June 2020)
  - *InstructGPT* (sibling to *ChatGPT*): refinement with human feedback
- other types of dialog systems:
  - limited-domain, task-oriented dialog
  - explicit dialog strategy: manually designed and coded

  specific systems: *voice command and control*
  - Amazon's Alexa (loss in 2022: 10 Bio USD - 12 000 employees)
  - Apple's Siri
  - Google's (Digital) Assistant

LLM and GPT: Typical Tasks

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every-day NLP tasks with plain text for input and output:

- **conversational dialog (with many turns):**
  input: ***customer query/command***
  output: ***system response***
- **text summarization:**
  input: ***full text***
  output: ***text summary***
- **story generation:**
  input: ***key words***
  output: ***full text***
- **machine translation (with bilingual training data):**
  input: ***sentence in source language***
  output: ***sentence in target language***

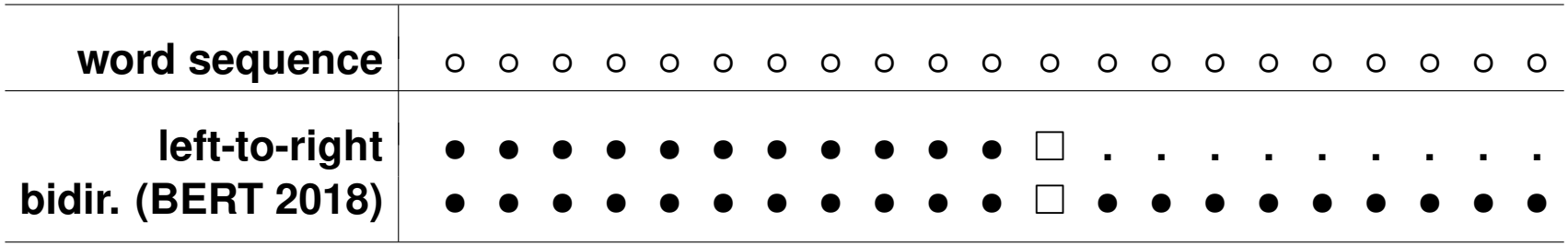
remarkable property (in contrast to formal NLP tasks):
everything is expressed in terms of plain every-day language:
– system input: formulated by the user
– type of task (*prompt/instruction*): specified by the user
– generated output: smooth fluent language
(primary goal which a language model is designed for)

History: How (Small) Language Models Started (1980-2000)

(small) language models:

- **introduced by IBM for ASR around 1980**
  - **key advantage: use of text data without annotation**
  - **statistics: based on counts of word trigrams (and higher order n-grams)**
  - **concept: sucessfully transferred from ASR to HWR and MT**
- **experimental conditions around 2000:**
  - **training: about 100 Mio running words (tokens)**
  - **model size: same order of magnitude**
- **training criterion: log perplexity (= cross-entropy), i. e. *predict next word***
  probability of a word sequence $w_1^N = w_1 ... w_n .... w_N$:

$$\log\, p_\vartheta(w_1^N) = \sum_{n=1}^{N} \log\, p_\vartheta(w_n | w_0^{n-1})$$



Some LLMs (until 2022)

- **OpenAI:**
  - **2018 GPT-1: 0,12 Bio**
  - **2019 GPT-2: 1,5 Bio**
  - **2020 GPT-3: 175 Bio (train: 300 Bio)**
  - **2022 *InstructGPT* and *ChatGPT***
- **Google:**
  - **2018 BERT: 3,3 Bio (train: 300 Bio, 40 epochs)**
  - **2019 T5: 11 Bio (train: 1000 Bio)**
  - **2020 Meena (for dialog): 2,6 Bio (train: 61 Bio)**
  - **2022 LaMDA: 137 Bio (train: 2810 Bio)**
  - **2022 PaLM: 540 Bio (train: 780 Bio)**
- **more LLMs:**
  - **2019 BART / Meta: 0,33 Bio (train: 55 Bio, 40 epochs)**
  - **2019 Megatron / Nvidia: 3,9 Bio (train: 366 Bio)**
  - **2020 DialoGPT / Microsoft: 0,76 Bio (train: 10 Bio)**
  - **2022 OPT / Meta: 175 Bio (train: 180 Bio)**
- **years 2021-2022: more than 50 LLMs**
  recent European activities:
  - **BLOOM / BigScience: 176 Bio (train: 366 Bio)**
  - **Luminous / Aleph Alpha (OpenGPT-X): 70 Bio (train: 588 Bio)**
  - **HPLT / EU project: major EU languages**

Conclusions

- large-scale language models:
  - primary design goal: to generate smooth fluent text
  - approach: data, but no manual design or coding
  - dialog management: learned by data-driven approach (unlike manually designed dialog strategies)
  - (hopeful) by-product: semantic correctness
- LLMs are part of data-driven machine learning:
  - more data, more complex models, more computation
  - 1989 R. Mercer/IBM: *There is no data like more data.*
- re-interpretation of neural LLM: operations in high-dim. vector space:
  - used for categorical data along with symbolic reasoning
  - useful for areas beyond NLP? general concept for categorical statistics?

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ChatGPT: From Small to Large Language Models

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