

Spoken Language Processing 2022/23

Second Exam

Duration: 90 minutes.

	Student number (6 digits):	First and last name:
A	nswers must be given exclusively or	the answer sheet. Answers given on other sheets will be ignored.
F O	ther incorrect answers, more than or	actly one correct answer. wer is worth 0.5 point. Very incorrect answers are worth -0.25 point are answer and questions left unanswered are worth 0 points. a each. Open questions 32 and 33 are worth 1.67 points.
Ques	tion 1 What is the distinguishing	feature of fricative consonants?
A	They are produced with complete c	losure of the vocal tract.
	They are produced with turbulent a	irflow through a narrow constriction in the vocal tract.
C	They are produced with rapid vibra	tion of the vocal folds.
D	They are produced with a burst of a	ir released from a complete stop.
Ques	tion 2 What are the differences b	etween vowel and consonant sounds in speech?
	Vowel sounds are produced with a degree of constriction in the vocal t	relatively open vocal tract, while consonant sounds involve some ract.
В	Consonant sounds are longer in dur	ation than vowel sounds.
C	Vowel sounds are louder than conso	onant sounds.
D	Vowel sounds are produced with vo	cal cord vibration while consonant sounds are not.
Ques	tion 3 Which of the following org	gans are included in the phonatory system?
A	Tongue, lips, and teeth.	C Nasal cavity, pharynx, and epiglottis.
В	Trachea, bronchi, and lungs.	Larynx, vocal folds, and glottis.
Ques	tion 4 What is the transfer function	on of an LTI system?
A	The Fourier transform of the output	signal divided by the Fourier transform of the input signal.
	The z-transform of the output signa	l divided by the z-transform of the input signal.
C	The inverse z-transform of the outp	ut signal divided by the inverse z-transform of the input signal.
D	The inverse Fourier of the output si	gnal divided by the inverse Fourier transform of the input signal.
•	tion 5 If $H(z)$ is a transfer function $X(z) = P(z)/Q(z)$. What are the roots	on of an LTI system with input $X(z)$ and output $Y(z)$ and $H(z)$ = s of the polynomial $Q(z)$ called?
A	Zeros of the transfer function $H(z)$.	Poles of the transfer function $H(z)$.
=	Zeros of the output signal $Y(z)$.	$\overline{\mathbb{D}}$ Poles of the input signal $X(z)$.
Ques	tion 6 A signal processing functi	on produced 101 signal frames that need to be recombined using a Lab1. If the window length is 512 samples and the hop length is
	A 25600 B	25856 26112 D 26368

	+1/2/59+
Question 7 In the source-filter model, the pulse tr	rain is used to model
A the spectral envelope of speech sounds. the filter excitation for voiced phonation.	C the filter excitation for unvoiced fricatives.D the resonances in the voiced phonation.
Question 8 Which of the following is a common cessing?	a application of linear prediction in speech signal pro
A Extracting the fundamental frequency from a s	speech signal.
B Removing background noise from a speech sig	gnal.
Estimating the spectral envelope of a speech si	ignal.
D Removing background noise from a speech sig	gnal.
Question 9 Two words that have the same spelling	g but sound differently are:
A non-homographs and homophones.	homographs and non-homophones.
B homographs and homophones.	D non-homographs and non-homophones.
Question 10 The Griffin-Lim algorithm is used to	D:
A estimate the original magnitude information ba	ased on the phase of the spectrum.
B estimate the original speech waveform based o	
	• •
estimate the original phase information based of	on the magnitude of the spectrum.
	on the complex cepstrum. del (GMM) of 16 mixtures with diagonal covariance
D estimate the original speech waveform based o	on the complex cepstrum. del (GMM) of 16 mixtures with diagonal covariance speech feature vectors of dimension 5. What is the
D estimate the original speech waveform based of Question 11 Consider a Gaussian mixture mode matrices. The model has been trained to fit MFCC model's total number of different parameters, including 176 B 240	on the complex cepstrum. del (GMM) of 16 mixtures with diagonal covariance. Speech feature vectors of dimension 5. What is thing weights, means, and covariances? C 96 D 80 N feature rows each with dimension D, that, is with the complex cepstrum.
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				be coarsely classified according not correspond to one of the	
A Sp	pectral	Global	C High-level	D Prosodic	
adapt it to the charact	teristics of each speaker. This ap	target speaker, proach introdu	in contrast to previo	a universal background model ous strategies that train a model s. Which of the following is n	lel
A It permits using	g larger GMM mo	odels.			
B It permits using		•			
= -	oarameters unchar oondence among		rant enagbare		
_			_		
		•	itomatic speech reco	_	
	•		odel trained on manu	•	
	1		els are provided by C decoder architecture.		
_	probabilities of the			conventional previously train-	ed
Question 18 In a (LVCSR), which of the				ous speech recognition system	ns
A Decoder			C Language mo	del	
B Pronunciation n	nodel		Speaker mode	el	
by an ASR system:	GNITON is know	vn as THE ta vn as ** ta		nce and the hypothesis generating audio INTO ** texting audio IN TO text	ed
A	23.1%	B 30.8%	33.3%	D 25.0%	
alignments. To do so	o, it defines the Ongth 15 frames, v	CTC alignment which of the following the contract of the following the contract of the contrac	concept. Considering	el without requiring frame-leving CTC alignment and an inpents is valid for the word part	out
ppeaaerrerreoet	t		C pppppppparrr	rot	
В рреаеаеттегеоо	ot		D ррааететегео:	ett	
8 multi-head self-atte	ention modules a	nd 4 attention l	neads. How many so	offormer encoder, with a stack offmax operations are compute en processing an input sequen	ed
	A 100	B 10	320	3200	

Question 22 Consider the computations associated with the dot-product self-attention operation. Consider also an input sequence of four vectors [2,0,0,1, 12,0,0,1], 12,0,0,8], [2,0,0,8]], and consider that queries, keys, and values are all computed through the projection matrix [1,0,0,0], [0,1,0,1], [0,0,1,0], [0,0,1,0]] (i.e., diagonal 4x4 matrices with the same values). What would be the result of the dot-product self-attention operation for the first element in the sequence? Recall that the softmax operation returns a uniform probability distribution when the input vectors have the same values in all dimensions.				-	+1/4/57+	
Question 23 Consider the original Transformer model, proposed for sequence-to-sequence NLP tasks like machine translation. Which of the following architectural components DOES NOT correspond to learned parameters in the model? A Projection matrices used to compute queries, keys, and value.s Feed-forward transformations after the multi-head attention operations. C Input and output token embeddings. Positional embeddings. Question 24 Which of the following architectures DOES NOT support Automatic Speech Recognition (ASR) tasks? A OpenAl Whisper VALL-E C SpeechT5 Wav2vec and other similar encoder models, combined with a downstream text decoder Question 25 Consider speech representation models like DiscreteBERT, pre-trained with objectives that resemble masked language modeling. Why is the pre-training of these models based on masking spans of consecutive tokens, rather than individual tokens? A Make the pre-training task simpler, this way facilitating training. Facilitate the combination with contrastive loss functions. C Improve computational efficiency in the computation of the loss function. Improve computational efficiency in the computation of the loss function. A void exploring local smoothness in nearby audio signals. Question 26 Consider encoder-decoder versus decoder-only transformer models. Which of the following architectural components is NOT COMMON to both families of models? A Embeddings and positional encodings. Cross-atte	sider also an ir queries, keys, [0,0,0,1]] (i.e., self-attention o	nput sequence of and values are a diagonal 4x4 m peration for the	four vectors [[2,0,0, ll computed through tatrices with the same first element in the se	0], [2,8,0,0], [2,0,8,0] the projection matrix values). What would quence? Recall that], [2,0,0,8]], and consider [[1,0,0,0], [0,1,0,0], [0,0,0], be the result of the dot-prothe softmax operation returns.	that 1,0], duct
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	-	_				f the
	A Domain	identification		C User intent det	tection	
	A Domain				•	



Question 28 Consider the OpenAI Whisper multitask speech model. Which of the following statements is false?

- A The system predicts the language being spoken through a specific output token.
- The system can predict the speaker of a given utterance (from a set of speakers) through a specific output token.
- The system can predict the start of a speech event through a token that encodes the time relative to the current audio segment.
- D The system predicts non-speech segments through a specific output token.

Question 29 Which of the following aspects corresponds to an advantage of BERTScore over BLEU?

- A Consider explicit penalties for very short generations.
- B Direct training to approximate human quality judgments for language generation.
- Consider semantic comparisons instead of exact word/n-gram matches.
- D Avoid the need for ground-truth references.

Question 30 Consider the Sparrow system introduced in the classes. Which of the following statements is **wrong**?

- A The system uses a large language model to guide the interaction with an external search engine.
- The system can interact with different external databases and tools.
- The system can consider a broad conversational domain.
- D The system uses a large language model for response generation.

Ouestion 31

Consider the first utterance of the Harvard set:

The birch canoe slid on the smooth planks

with the phonetic transcription:

ða batt ka nu slid on ða smuð plænks

Considering that a voiced region is a sequence of voiced phones, how many voice regions are in the utterance? Identify the boundaries of each voiced region.

Question 32 In the lectures, automatic speech recognition (ASR) research was described as an open scientific field that has been the focus of remarkable developments since the 50s. Briefly describe the main generations of ASR systems. Mention their main characteristics. Finally, explain what the two main alternatives in current modern ASR systems are.

Question 33 Consider the BLEU metric, as used in the labs, for evaluating automatically generated responses in dialogue systems. Discuss the main problems and limitations associated with the use of this metric.

Student number (6 digits): 0 0 0 0 0 0 0 1 1 1 1 1 1 1 2 2 2 2 2 2 2 3 3 3 3 3 3 3 4 4 4 4 4 4 4 5 5 5 5 5 5 5 6 6 6 6 6 6 6 7 7 7 7 7 7 7 8 8 8 8 8 8 9 9 9 9 9 9 9	Answer Sheet Answers must be given exclusively on this sheet. Answers given on other sheets will be ignored. No corrections are allowed on this sheet. Encode your student number (6 digits) by selecting the digits on the left, starting with 0 if it has just 5 digits, and write your name below. First and last name:
QUESTION 1: A C QUESTION 2: B C QUESTION 3: A B C QUESTION 4: A C QUESTION 5: A B QUESTION 7: A C QUESTION 7: A C QUESTION 8: A B QUESTION 9: A B QUESTION 10: A B QUESTION 11: B C QUESTION 12: B C QUESTION 13: A B QUESTION 14: B C QUESTION 14: C C QUESTION 15: A C C	D QUESTION 16: A B □ D D QUESTION 17: A B C □ QUESTION 18: A B □ D QUESTION 19: A B □ D D QUESTION 20: □ B C D D QUESTION 21: A B □ D D QUESTION 22: A B □ D D QUESTION 23: A B □ D D QUESTION 24: A □ C D D QUESTION 25: A B □ C □ D QUESTION 26: A □ C D D QUESTION 28: A □ C D D QUESTION 29: A B □ D QUESTION 30: A □ C D
	n can be annotated in voiced (+) and unvoiced (-) phones: hirch cannot slid on the smooth planks

ne birch canoe slid on the smooth planks

ða ba:tf ka'nu: slid on ða smu:ð plæŋks

++ ++- -+++ ++ ++ ++ -+++

If the word boundaries are removed:

++++--++++++++-++--

It is now clear that there are 5 voiced regions in the utterance. The first region ends before the $\mathfrak f$ sound. The second starts in the $\mathfrak d$ of the word "canoe" and ends in the $\mathfrak s$ of "slid". The third starts at $\mathfrak l$ and runs until the $\mathfrak s$ of "slid". The fourth is the sequence mu: $\mathfrak d$ in the word "smooth". The last region is the læ $\mathfrak q$ in "planks".

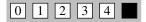


QUESTION 32:

0 1 2 3 4

We can distinguish 4 main generations in ASR development. The first systems were based on heuristics and on dedicated analog systems and hardware (1G: 1950-1970). The second generation corresponds to the introduction of non-statistical pattern-matching approaches, especially, dynamic time warping (DTW) (2G: 1970-1980). The great evolution of ASR came with the 3rd generation that tackled the problem as a statistical problem and introduced the extremely influential HMM/GMM approach (3G: 1980-2010). HMM-based systems have been the standard de facto in ASR until the arrival of more recent end-to-end approaches (4G: 2010-now), with systems such as the transformer. Nowadays, attention-encoder-decoder-based approaches dominate the field, however, in limited-resourced scenarios, HMM-based systems (using DNNs as the acoustic model) can still provide very competitive performances.

QUESTION 33:



The BLEU metric is based on comparisons against ground-truth references and, in the context of dialogue, this is a serious limitation because there are usually many acceptable responses to an input context, while only a few of these possibilities are collected as references. As a consequence, the BLEU metric is known to correlate poorly with human judgments of dialogue response quality, and recent developments have proposed the use of learned metrics that avoid the use of ground-truth references. Another problem relates to the fact that BLEU uses word/n-gram overlaps to assess similarity against the ground-truth references, which may be misleading due to the possibility of phrasing the same semantic content in different ways. Metrics based on assessing similarity through (contextual) word embeddings can offer an alternative that avoids this issue.