

ENGINEERING TRIPOS PART IIB

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Friday 23 April 2010 2.30 to 4.00

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Module 4F11

SPEECH AND LANGUAGE PROCESSING

*Answer not more than **three** questions.*

*All questions carry the same number of marks.*

*The **approximate** percentage of marks allocated to each part of a question is indicated in the right margin.*

*There are no attachments.*

STATIONERY REQUIREMENTS

Single-sided script paper

SPECIAL REQUIREMENTS

Engineering Data Book

CUED approved calculator allowed

**You may not start to read the questions  
printed on the subsequent pages of this  
question paper until instructed that you  
may do so by the Invigilator**

1 This question concerns the use of linear predictive coding (LPC) in modelling speech. The order of the LPC model is  $p$ . The  $n^{\text{th}}$  sample of the speech signal is  $s_n$ .

(a) Write an expression for the prediction error  $e_n$  in terms of the speech signal  $s_n$  and the linear prediction coefficients  $a_1, \dots, a_p$ . [15%]

(b) Show how the transfer function  $A(z)$  of the prediction error filter relates the speech spectrum  $S(z)$  to the transform of the prediction error  $E(z)$ . [15%]

(c) Derive the *normal equations*

$$\sum_n s_n s_{n-j} = \sum_{k=1}^p a_k \sum_n s_{n-k} s_{n-j} \quad j = 1, \dots, p$$

which are solved to obtain the optimum filter coefficients under the mean square error criterion. [20%]

(d) Explain the assumptions underlying the *autocorrelation method* and give the simplified form of the normal equations which result. [20%]

(e) Give Durbin's Algorithm for finding the optimum filter coefficients and explain how they guarantee that increasing the order of the LPC predictor reduces the mean square error. [30%]

- 2 (a) Draw a block diagram of the generic speech recognition architecture and give a brief description of each component. [20%]
- (b) A speech recognition system is to be constructed using Hidden Markov Models (HMMs). The HMMs will have Gaussian observation distributions and will be trained as whole-word models so that each word has its own HMM. A training set of  $R$  utterances for each word in the recognition vocabulary is available, and the Baum Welch algorithm is to be used to estimate the parameters of the HMM observation distributions.
- (i) Suggest an initialisation procedure for the parameters of the Gaussian observation distributions. [10%]
- (ii) Give the equations defining the forward and backward probabilities used in the Baum Welch algorithm. Derive the recursions for one of the probabilities. [20%]
- (iii) Give a relationship for the probability of being in state  $j$  at time  $t$ ,  $L_j(t)$ , in terms of the forward and backward probabilities. [10%]
- (iv) Give the Baum Welch reestimation formulae for the mean and variance parameters of the Gaussian observation distribution associated with each state. [20%]
- (c) A large-vocabulary isolated-word system is to be trained for use with the Google Maps application. It is decided to use HMMs based on word-internal triphones.
- (i) Discuss why word-internal triphones might be a better choice for this application than whole-word HMMs. [10%]
- (ii) Contrast the HMM training procedure for word-internal triphone models to the training procedure for whole-word acoustic models. [10%]

3 (a) What is a weighted finite state acceptor? What is the main difference between a weighted finite state acceptor (WFSA) and a weighted finite state transducer (WFST)? [20%]

(b) Weighted finite state acceptors assign a weight to a particular string by summation ( $\oplus$  operation) over the weights of all paths that generate the string, where the weight of each path is obtained as the product ( $\otimes$  operation) of the path arc weights and the path initial and final weights.

(i) Define a semiring in the context of WFSA. [10%]

(ii) Complete Table 1 to describe the attributes of three commonly used semirings. [20%]

Semiring	$\mathbb{K}$	$\oplus$	$\otimes$	$\bar{0}$	$\bar{1}$
Probability					
Log					
Tropical					

Table 1

(iii) A WFSA  $A$  can generate the sequence 'a b' via two alternative paths. What does the weight,  $\llbracket A \rrbracket('a b')$ , assigned to the sequence 'a b' by  $A$  represent in each of the three semirings of Table 1? [30%]

(c) Two WFSTs  $A$  and  $B$  are shown in Fig. 1, where  $A$  maps  $x$  to  $y$  and  $B$  maps  $y$  to  $z$ . Draw the transducer  $A \circ B$ , which maps  $x$  to  $z$ , that results from the composition of  $A$  with  $B$  in the tropical semiring. [20%]

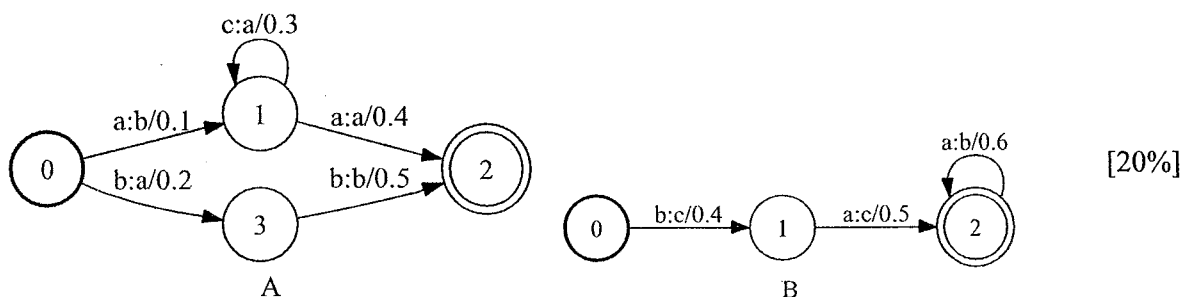


Fig. 1

4 This question concerns the use of alignment models in statistical machine translation. An English sentence of  $I$  words is denoted by the sequence  $e_0^I = e_0, e_1, \dots, e_I$ , where  $e_0$  is the additional NULL word added to the start of the sentence. A foreign sentence of  $J$  words is denoted  $f_1^J = f_1, \dots, f_J$ . Alignment between the two sentences is specified by the sequence  $a_1^J = a_1, \dots, a_J$ .

(a) By making simplifying conditional independence assumptions, describe the translation probability distribution  $P(f_1^J, a_1^J, J | e_0^I)$  in terms of its three component distributions: the sentence length distribution, the word translation distribution, and the word alignment distribution. [20%]

(b) Give the formulae of the alignment distribution under IBM models 1 and 2 and the HMM alignment model. Explain their differences. [20%]

(c) Alignment link sets  $B$  and  $B'$  are extracted from two different alignments. How is the alignment error between  $B$  and  $B'$  computed? Why is the alignment error useful for developing statistical machine translation systems? [20%]

(d) How are 'phrases' defined in the context of phrase-based statistical machine translation models? Describe the advantages of using phrases rather than words in a statistical machine translation system. [20%]

(e) Briefly describe how a word-based alignment model can be used to extract phrase pairs from a parallel corpus. [20%]

**END OF PAPER**