MODEL SOLUTIONS

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Data Provided: None

DEPARTMENT OF COMPUTER SCIENCE Autumn Semester 2015-2016

TEXT PROCESSING 2 hours

Answer THREE questions.

All questions carry equal weight. Figures in square brackets indicate the percentage of available marks allocated to each part of a question.

1. In the context of Information Retrieval, given the following two documents:

   Document 1: Sea shell, buy my sea shell!

   Document 2: You can buy lovely SEA SHELL at the sea produce market.

   and the query:

   Query 1: buy lovely sea shell

   a) Explain three types of manipulations (except term weighting) that can be done on document terms before indexing them. What are the advantages of each of these manipulations? [20%]

ANSWER:

Term manipulations can include any of the following (answer only need 3): capitalisation, stemming, stop-word removal, indexing multi-terms, normalisation. Three exemplar definitions:

[P1](6%) A *stoplist* is a list of words ('stop-words') that are ignored when documents are indexed, and likewise discounted from queries. These are words that are so widespread in the document collection that they are of v.little use for discriminating between documents that are/are not relevant to a query. Their exclusion eliminates a large number of term occurrences that would need to be recorded, thereby reducing the size of indexes and saving computational effort during both indexing and retrieval.

[P1](8%) *Stemming* refers to the process of reducing words that are morphological variants to their common root or stem, e.g. so that variants *computer, computes, computed, computing*, etc. are reduced to a stem such as *compute*. For IR, stemming

is applied to documents before indexing and to queries. The effect of this is that when a query contains a term such as *computing*, retrieval can potentially return documents on the basis of their containing any of the morphological variants of the same root. This is the intended key benefit of using stemming. Stemming will also produce some reduction in the size of document indexes.

[P1](6%) *Capitalisation* refers to the process of normalising the case of words so that a single case is used, for example, all words are lowercased (e.g. SHELL = shell). This procedure makes indexing and retrieval more efficient by decreasing the number of terms that have to be represented. It also makes the term weighting more reliable, as higher frequency counts will be observed when putting together different variants of the term.

b) Applying stop word removal and capitalisation, show how Document 1 and Document 2 would be represented using an *inverted index*. Provide the stoplist used. [10%]

ANSWER:

[P1](3%) Based on *lowercasing* and *stopword removal* we assume a stoplist that includes the following terms: {`at, can, my, the, you, !, ,, .`}.

[P2](7%) As a result, we get the following inverted index:

term-id	word	docs
1	buy	d1:1, d2:1
2	lovely	d2:1
3	market	d2:1
4	produce	d2:1
5	sea	d1:2, d2:2
6	shell	d1:2, d2:1

c) Assuming *term frequency* (TF) is used to weight terms, compute the similarity between each of the two documents (Document 1 and Document 2) and Query 1. Compute this similarity using two metrics: Euclidean and cosine. Determine the ranking of the two documents according to each of these metrics and discuss any differences in the results. [40%]

ANSWER:

[P1](10%) Using the term order taken from the inverted index above, we can represent the two documents and the query as vectors as follows:

d1: $\langle 1, 0, 0, 0, 2, 2 \rangle$
d2: $\langle 1, 1, 1, 1, 2, 1 \rangle$
q: $\langle 1, 1, 0, 0, 1, 1 \rangle$

[P2](10%) **Ranking using cosine similarity**: The cosine between two vectors $\vec{x}$ and $\vec{y}$ is computed as:

$$cos(\vec{x}, \vec{y}) = \frac{\vec{x} \cdot \vec{y}}{|\vec{x}||\vec{y}|} = \frac{\sum_{i=1}^{n} x_i y_i}{\sqrt{\sum_{i=1}^{n} x_i^2} \sqrt{\sum_{i=1}^{n} y_i^2}}$$

The vector magnitudes and cosine values are then:

$$|\mathrm{d1}| = \sqrt{1^2 + 0^2 + 0^2 + 0^2 + 2^2 + 2^2} = \sqrt{9} = 3$$

$$|\mathrm{d2}| = \sqrt{1^2 + 1^2 + 1^2 + 1^2 + 2^2 + 1^2} = \sqrt{9} = 3$$

$$|\mathrm{q}| = \sqrt{1^2 + 1^2 + 0^2 + 0^2 + 1^2 + 1^2} = \sqrt{4} = 2$$

$$cos(\mathrm{d1}, \mathrm{q}) = \frac{1.1 + 0.1 + 0.0 + 0.0 + 2.1 + 2.1}{3.2} = 5/6$$

$$cos(\mathrm{d2}, \mathrm{q}) = \frac{1.1 + 1.1 + 1.0 + 1.0 + 2.1 + 1.1}{3.2} = 5/6$$

Thus, the cosine values computed for the two documents are the same, and so the two are equally rated as relevant to the query.

[P3](10%) **Ranking using euclidean distance**: Euclidean distance is computed as $\sqrt{\sum_{i=1}^{n}(q_i - d_i)^2}$. In this case:

$$dis(\mathrm{d1}, \mathrm{q}) = \sqrt{(1-1)^2 + (0-1)^2 + (0-0)^2 + (0-0)^2 + (2-1)^2 + (2-1)^2} = \sqrt{3}$$

$$dis(\mathrm{d2}, \mathrm{q}) = \sqrt{(1-1)^2 + (1-1)^2 + (1-0)^2 + (1-0)^2 + (2-1)^2 + (1-1)^2} = \sqrt{3}$$

[P4](10%) **The difference between the two metrics**: while in this example the two metrics behave in the same way and they are not able to distinguish the two documents, in general cosine is a better metric for IR because it normalises the differences between the query and document vectors by the length of such vectors. This is important because documents can vary in size and a document should not be considered more relevant simply because it is closer in length to the query. Essentially the cosine metric computes the angle between two vectors, and therefore the length of such vectors is less relevant.

d) Explain TF.IDF. Include the formula (or formulae) for computing TF.IDF values as part of your answer. Discuss the expected effect of using TF.IDF to weight the terms in Document 1 and Document 2: would this be a better term weighting scheme than TF in this example?

[30%]

ANSWER:

[P1](15%) TF.IDF assigns weights to terms by taking into account two elements: the frequency of that term in a particular document (TF) and the proportion of documents in the corpus in which it occurs. The IDF for a term w is computed as follows, where D is the set of documents in the document collection and df_w is the document frequency of w (the count of documents in which w appears):

$$idf_{w,D} = log\frac{|D|}{df_w}$$

The TF.IDF value for a given term (w) in a given document (d) is:

$$tf.idf_{w,d,D} = tf_{w,d} \cdot idf_{w,D}$$

[P2](15%)
In this example, using TF.IDF would set the weight of three of the query terms to 0: buy, sea, $shell$, since they appear in all (two) documents in the collection and thus $log\frac{|D|}{df_w} = log\frac{2}{2} = log(1) = 0$. The only query term that receives a weight different from 0 is $lovely$, which only happens in Document 1, and therefore this document is ranked first. TF.IDF has a positive effect in this example and in general, since it disregards terms that are frequent across the whole collection of indexed documents.

2. a) Explain the differences between $rule\text{-}based$ and $empirical$ approaches to Machine Translation. Give the main advantage and disadvantage of each of these approaches. [20%]

ANSWER:

[P1](10%) Rule-based approaches are based on handcrafted rules designed by linguists, to translate from a language into a different language. Empirical approaches use examples of translations previously created (in general by human translators) and generate the translation of a new source segment by combining partial translations of words or sequences in the new segment to translate. The combination can be done in different ways, such as based on a model of translation probabilities.

[P2](5%) Advantage of rule-based approaches: rules can be very precise and generate good quality translation. Disadvantage (any of the three): 1) labour and time-intensive: there are often too many grammar rules to design, 2) it is hard to avoid contradiction and to maintain the grammar consistent over time. 3) Maintenance in general is an issue as changing one rule could have a knock on effect on many other rules.

[P3](5%) Advantage of empirical approaches: no expert knowledge is necessary: models can be generated given data only (abundant for many language pairs and domains) and can be easily re-generated as new examples are collected. Disadvantage: the very little or inexistent linguistic information makes models far from precise generating garbled translations in many cases.

b) Describe the two main models of a standard *phrase-based* approach to statistical machine translation. Explain how these models are combined and how they are applied to generate a translation for a new segment. [30%]

ANSWER:

The two main models of a PBSMT system are $P(F|E)$ (translation model) and $P(E)$ (language model).

[P1](7%) $P(F|E)$: faithfulness model - will ensure that a translation E will have words that generally translate to words in F.

[P2](7%) $P(E)$: fluency model - will ensure that E reads well and is grammatical in the target language.

[P3](8%) These as well as the other models are computed as independent functions h and combined using a log-linear model of the type $\sum_{i=1}^{m} \lambda_i h_i$, where λ_i is the weight of each model.

[P4](8%) To translate a new source segment, a $decoder$ applies this combined model to find the translation that covers all source words and maximises the weighted joint translation probability $\sum_{i=1}^{m} \lambda_i h_i$ for that source segment.

c) Explain the intuition behind the IBM Model 1 in the context of Statistical Machine Translation (SMT). Give the most important outcome of this model for an SMT system. Give one direction in which this model can be improved. [30%]

ANSWER:

[P1](15%) IBM Model 1 is a model for word-alignment between bilingual segments, i.e. to identify likely correspondences between two languages at word level. The model is trained in an unsupervised way based on a (large) training parallel corpus where sentences have been aligned, i.e., a corpus of sentence pairs which are translation of each other. The algorithm is a direct application of the Expectation Maximization (EM) algorithm:

1) Initially consider all alternative word alignments as equally likely

2) Observe across sentences that (e.g.) source word 'x' often links to target word 'y'

3) Increase probability of this word pair aligning

4) Iteratively redistribute probabilities, until probabilities stop changing (convergence)

[P2](5%) Once the corpus is aligned, a dictionary of source-target word pairs with translation probabilities can be extracted by simply taking the output of the final iteration. This dictionary can then be used as the most basic component in SMT.

[P2](10%) Possible directions (only one necessary): 1) add a 'fertility' component, i.e., words in the source language can generate (align too) multiple words in the target language 2) Add component to model absolute position of the words in the two sentences, i.e., words in the certain positions in the source segment tend to align to words in certain positions in the target segment, for example, to learn that the first word in the source segment may be more likely to align to the first or one of the first words in the target language as opposed to one of the last words in the target language 3) Add a component to model word order dependencies, i.e., the fact the alignment of one source word to a given target word may be dependent on the neighboring words in one of both languages

d) Given the two scenarios:

Scenario 1: English-Chinese language pair, 300,000 examples of translations.

Scenario 2: Portuguese-Spanish, 50,000 examples of translations.

In which of these scenarios would Statistical Machine Translation work better and why? Would a rule-based transfer approach be a good solution in any of these scenarios?

[20%]

ANSWER:

[P1](10%) It is more likely that SMT would work better for Scenario 2, even with significantly fewer examples, given that the language pair is structurally very similar, and also uses many similar (sometimes identical) words. The relatively small number of examples in this case would probably lead to untranslated words in the target language, that is, Portuguese words in the Spanish translation. Because of the lexical overlap between these two languages and the large number of cognates (similar words with similar meanings), translations should still be understandable.

[P2](10%) For Chinese-English, a rule-based approach with manually designed rules allowing for long-distance reorderings could be more precise, however it would still be very costly.

3. a) Given sentences like the following:

- *My new phone works well and it is much faster than the old one.*
- *My new phone has 32GB of memory and can play videos.*

What is the first step to detect the sentiment in these two sentences? Should both these sentences be addressed in the same way by sentiment analysis approaches? [20%]

ANSWER:

[P1](10%) The first step is to run a subjectivity analysis. This has to do with detecting whether the text (word/phrase, sentence, document) contains opinions, emotions, sentiment, or simply facts. Only subjective sentences should then be put forward for sentiment analysis, which has to do with the actual polarity of the text (word/phrase, sentence, document): positive, negative, or more fine-grained distinctions.

[P2](10%) In the example, only the first sentence is subjective and therefore has a sentiment that can be analysed.

b) Explain two approaches for Subjectivity Analysis. [20%]

ANSWER:

[P1](10%) A simple rule-based subjectivity classifier can be built: a sentence/document is subjective if it has at least n (say 2) words that belong to an emotion words lexicon; a sentence/document is objective otherwise.

[P2](10%) A Naive Bayes classifier can be built with features that count emotion words from a lexicon, as well as other features, such as adjectives, negation words, etc. Training data with instances with binary labels (subjective vs objetive) would be required.

c) Explain the weighted lexical-based approach for Sentiment Analysis. Given the following sentences and opinion lexicon, apply this approach to classify *each* sentence in S1-S4 as **positive**, **negative** or **objective**. Show the final emotion score for each sentence and also how this score was generated. Give any general rules that you used to calculate this score as part of your answer. Explain these rules when they are applied. [30%]

Lexicon:

awesome	5
boring	-3
brilliant	2
funny	3
happy	4
horrible	-5

(S1) He is brilliant and funny.
(S2) I am not happy with this outcome.
(S3) I am feeling AWESOME today, despite the horrible comments from my supervisor.
(S4) He is extremely brilliant but boring, boring, very boring.

ANSWER:

[P1](10%) The general weighted lexical-based approach counts positive (Cpos) and negative (Cneg) words in the text and weights them using the weights in the lexicon given:
If Cpos $>$ Cneg then positive
If Cpos $<$ Cneg then negative
If Cpos $=$ Cneg $= 1$ then objective

[P2](5%) (S1) Emotion(brilliant) $= 2$; Emotion(funny) $= 3$. Therefore Cpos $= 2+3$ and Cneg $= 0$, so Cpos $>$ Cneg $=$ positive

[P3](5%) (S2) Emotion(happy)$= 4$; Rule $=$ "not" is detected in neighbourhood, so emotional valence of term is decreased by 1 and sign is inverted. Therefore Emotion(happy)=-3, and Cneg=-3, so Cneg $>$ Cpos $=$ negative

[P4](5%) (S3) Emotion(horrible) $=$ -5, Emotion(awesome) $= 5$. Rule $=$ "awesome" is intensified because it is in capital letters, and in this case it's intensified by 1 (because it's a positive word). Therefore, Cneg $=$ -5, Cpos $= 6$, so Cpos $>$ Cneg $=$ positive

[P5](5%) (S4) Emotion(brilliant) $= 2$; Emotion(boring) $=$ -3. Rules $=$ "boring" happens 3x, so Emotion(boring) $=$ -9. "extremely" is a (positive) intensifier in this case, with $+2$ added, so Emotion(brilliant) $= 4$. "very" is a (negative) intensifier in this case, with -2 subtracted from total. Cpos $= 4$ and Cneg $=$ -11, so Cneg $>$ Cpos $=$ negative

d) Give Bing Liu's model for an **opinion**. Explain each of the elements in the model and exemplify them with respect to the following text. Identify the features present in the text, and for each indicate its sentiment value as either *positive* or *negative*. Discuss two language processing challenges in automating the identification of such elements. [30%]

"I have just bought the new iPhone 5. It is a bit heavier than the iPhone 4, but it is much faster. The camera lenses are also much better, taking higher resolution pictures. The only big disadvantage is the cost: it is the most expensive phone in the market. Lucia Specia, 12/10/2015."

ANSWER:

[P1](20%) An **opinion** is a quintuple $(o_j, f_{jk}, so_{ijkl}, h_i, t_l)$, where:

- o_j is a target object: in the example, iPhone 5
- f_{jk} is a feature of the object o_j: in the example, weight, speed, camera/lenses/pictures, price
- so_{ijkl} is the sentiment value of the opinion: in the example, negative, positive, positive, negative
- of the opinion holder h_i (usually the author of the post): in the example, Lucia Specia
- on feature f_{jk} of object o_j at time t_l: in the example, 12/10/2015.

[P2](10%) Some of the challenges are (only two necessary):

- Need Named Entity Recognition to identify target objects.
- Need Information Extraction to extract features of the target object (properties of objects), as well as time and holder.
- Need co-reference resolution to know that "it" = iPhone.
- Need synonym match when words used do not belong to lexicon of opinion words, e.g. fast versus efficient

4. a) Sketch the algorithm for Huffman coding, i.e. for generating variable-length codes for a set of symbols, such as the letters of an alphabet. What does it mean to say that the codes produced are *prefix-free*, and why do they have this property? [30%]

ANSWER:

- To begin, we need to know the relative probabilities of all the symbols in the symbol set.
- We start the algorithm by creating a leaf node for each symbol, which is labelled with its associated probability.
- Then, iterate over this collection of nodes, until only one node remains, as follows:
  - with each iteration, select and remove two nodes, which are joined under a new parent node
  - crucially, the nodes selected must have the lowest associated probabilities (or strictly, there must be no other nodes that have lower probabilities)
  - the new parent node is labelled with a probability value that is the sum of probabilities of the two child nodes
  - the new node is added back into the collection of nodes
- The single node that remains represents a binary tree whose root should be labelled with probability 1.0, and whose leaf nodes store the full set of symbols.
- Finally, a code-tree is produced by labelling the left and right side of each branch within the tree with 0 or 1, respectively. Then, the path from the root to the symbol at any leaf node gives a unique sequence of 0s and 1s, which is the code for this symbol.

That codes are *prefix-free* means that no symbol has a code which is a prefix of any other code, e.g. as would hold if there were codes `110` and `1101`. This property follows from the fact that symbols only appear on the leaf nodes of code trees, as a consequence of the algorithm. There could only be a code that was the prefix of another if its symbol was labelled on a non-leaf node, i.e. so that the path from the root to this symbol's node then *continued on* to the node for the second symbol.

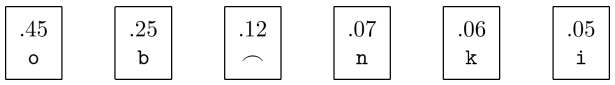
b) We want to compress a large corpus of text of the (fictitious) language *Bonobo*. The writing script of Bonobo uses only the letters {b, i, k, n, o} and the symbol ⌒ (which is used as a 'space' between words). Corpus analysis shows that the probabilities of these six characters are as follows:

Symbol	Probability
b	0.25
i	0.05
k	0.06
n	0.07
o	0.45
⌒	0.12

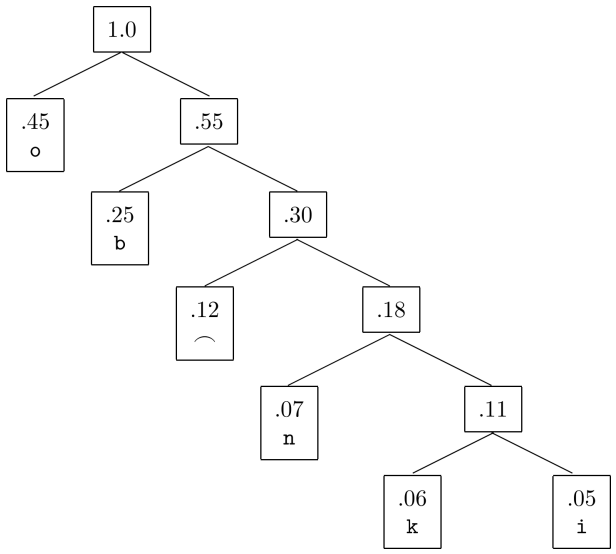
Apply the method you described in 4(a) to create a Huffman code for the Bonobo character set. [30%]

ANSWER:

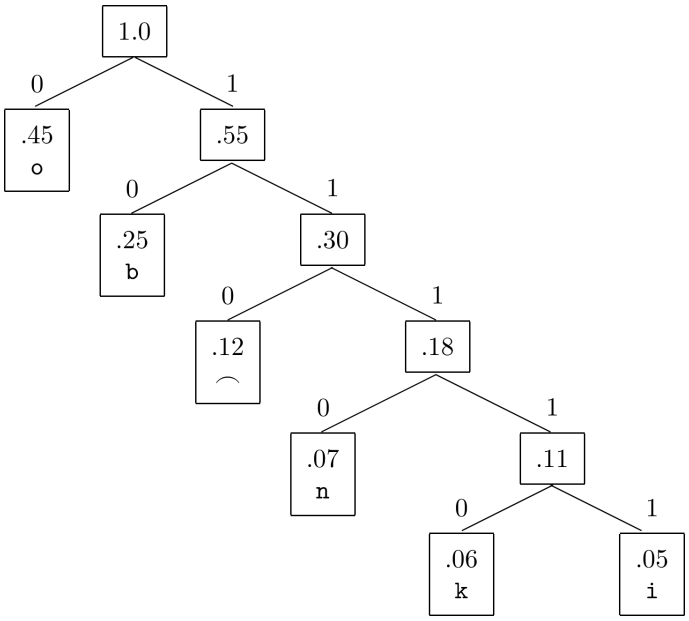
First create initial nodes as follows:



Running the algorithm produces tree:



and assigning 0s and 1s to branches gives:



This gives the following codes for the symbols:

Symbol	Probability	Code	Code length
o	0.45	0	1
b	0.25	10	2
⌒	0.12	110	3
n	0.07	1110	4
k	0.06	11110	5
i	0.05	11111	5

c) Given the code you have generated in 4(b), what is the average bits-per-character rate that you could expect to achieve, if the code was used to compress a large corpus of Bonobo text? How does this compare to a minimal fixed length binary encoding of this character set? [20%]

ANSWER:

we assume that the distribution of characters in the large corpus is the same as the one that we have been given from previous corpus analysis. Then, can calculate the average bits-per-character rate summing across symbols for the probability of that symbol times by its code length:

Symbol	Probability	Code	Code length	$p \times len$
o	0.45	0	1	0.45
b	0.25	10	2	0.50
⌒	0.12	110	3	0.36
n	0.07	1110	4	0.28
k	0.06	11110	5	0.30
i	0.05	11111	5	0.25
				2.14

giving a cost of 2.14 bits-per-character. A minimal fixed length binary encoding would requre 3 bits per character, i.e. this is sufficient to encode up to $2^3 = 8$ characters, whilst a 2 bit code would allow only $2^2 = 4$ characters, and we have 6 to encode. Using a 3 bit fixed-length code would result in corpus storage requiring about 40% more space than the Huffman codes.

Where the student has answered 4(b) of the question incorrectly (resulting in an incorrect code), they can still gain full marks on this part of the question, provided that their answer demonstrates the correct method for computing the required values, and illustrates it w.r.t. their (incorrect) code from 4(b).

d) Use your code for Bonobo to encode the following two messages, and compute for each message the average bits-per-character rate that results:

bonobo⌒okobo

iniko⌒nikoni

Discuss why the two bits-per-character rates achieved differ, comparing them also to the expected rate that you computed in 4(c). [20%]

ANSWER:

Encoding the first message we get:

```
b  o n    o b  o -   o k     o b  o
10 0 1110 0 10 0 110 0 11110 0 10 0 = 24 bits
```

as the original message has 12 chars, this give $24/12 = 2.0$ bits per character.

For the second message we get:

```
i     n    i     k     o -   n    i     k     o n    i
11111 1110 11111 11110 0 110 1110 11111 11110 0 1110 11111 = 47 bits
```

Again the message has 12 chars, giving $47/12 = 3.92$ bits per character.

The two bpc rates differ considerably. The first is slightly better than the expected rate for a large corpus, whilst the second is considerably worse — worse even than a fixed length encoding. This is due to the differential extents to which the distribution of chars within the two messages diverge from the distribution used when computing the Huffman codes. For the first message the distribution is close to the corpus

distribution: high frequency/probability letters predominate, so many short codes are assigned. The distribution in the second message runs contrary to the corpus distribution, with low frequency letters predominating, so that many long codes are assigned.

Where the student has answered 4(b) of the question incorrectly (resulting in an incorrect code), they can still gain full marks on this part of the question, provided that their answer demonstrates the correct method for computing the required values, and illustrates it w.r.t. their (incorrect) code from 4(b).

END OF QUESTION PAPER