Exam 2018-03-12

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This exam consists of three parts:

1. **Part A** consists of 5 items, each worth 3 points. These items test your understanding of the basic methods that are covered in the course. They require only compact answers, such as a short text, calculation, or diagram.

   Collected wildcards are valid for this part of the exam. The numbering of the questions corresponds to the numbering of the wildcards.

2. **Part B** consists of 3 items, each worth 6 points. These items test your understanding of the more advanced methods that are covered in the course. They require detailed and coherent answers with correct terminology.

3. **Part C** consists of 1 item worth 9 points. This item is an essay question that tests your understanding of the following article:

   Aylin Caliskan, Joanna J. Bryson, Arvind Narayanan. *Semantics Derived Automatically from Language Corpora Contain Human-Like Biases.* Science 356(6334):183–186, 2017.

Grade requirements 729G17: For grade G (Pass), you need at least 12 points in Part A. For grade VG (Pass with distinction), you additionally need at least 14 points in Part B, or at least 7 points in Part C.

Grade requirements TDP030: For grade 3, you need at least 12 points in Part A. For higher grades, you additionally need points in the other parts: for grade 4, at least 9 points in Part B; for grade 5, at least 14 points in Part B, or at least 7 points in Part C.

Note that surplus points in one part do not raise your score in another part.

Good luck!

Part A

Note: When instructed to 'answer with a fraction', you should provide a fraction containing concrete numbers and standard mathematical operations, but no other symbols. You do not need to simplify the fraction.

like this: $\frac{42+13}{100}$ not like this: $\frac{\#(a)+\#(b)}{N}$

01 Text classification (3 points)

a) The evaluation of a text classifier produced the following confusion matrix. The marked cell gives the number of times the system classified a document as class `C` whereas the gold-standard class for the document was `A`.

	A	B	C
A	58	6	1
B	5	11	2
C	0	7	43

Based on this confusion matrix, set up fractions for the following values:

i. recall with respect to class `B`

ii. precision with respect to class `A`

b) A certain Naive Bayes classifier has a vocabulary consisting of 48,359 unique words. We have the following counts for a collection of movie reviews:

$$\#(\text{pokemon}, \text{pos}) = 0 \qquad \#(\bullet, \text{pos}) = 712480$$
$$\#(\text{pokemon}, \text{neg}) = 20 \qquad \#(\bullet, \text{neg}) = 636767$$

Here $\#(w, c)$ denotes the number of occurrences of the word w in documents with class c, and $\#(\bullet, c)$ denotes the total number of tokens in documents with class c. Based on these counts, estimate the following probabilities using maximum likelihood estimation with add-one smoothing. Answer with fractions.

i. $P(\text{pokemon} \mid \text{pos})$

ii. $P(\text{pokemon} \mid \text{neg})$

c) Why do practical implementations of a Naive Bayes classifier often use log probabilities rather than standard probabilities? Answer with a short text.

Sample answers:

a) Fractions for recall and precision:

i. $\frac{11}{5+11+2}$ (recall with respect to class `B`)

ii. $\frac{58}{58+5+0}$ (precision with respect to class `A`)

b) Estimated probabilities:

i. $P(\text{pokemon} \mid \text{pos}) = \frac{\#(\text{pokemon},\text{pos})+1}{\#(\bullet,\text{pos})+|V|} = \frac{0+1}{712480+48359}$

ii. $P(\text{pokemon} \mid \text{neg}) = \frac{\#(\text{pokemon},\text{neg})+1}{\#(\bullet,\text{neg})+|V|} = \frac{20+1}{636767+48359}$

c) The main reason for using log probabilities is to avoid underflow during the computation of the probability of a document given a class c, where one has to multiply a potentially large number of small values (probabilities).

02 **Language modelling** **(3 points)**

The Corpus of Contemporary American English (COCA) is the largest freely-available corpus of English, containing approximately 560 million tokens. In this corpus we have the following counts of unigrams and bigrams:

snow	*white*	*white snow*	*purple*	*purple snow*
38,186	256,091	122	11,218	0

a) Estimate the following probabilities using maximum likelihood estimation without smoothing. Answer with fractions.

i. $P(\textit{snow})$ ii. $P(\textit{snow} \mid \textit{white})$

b) Explain why a bigram model trained on the COCA corpus using maximum likelihood estimation without smoothing may not be very useful. Use the following (preprocessed) sentence as an example to illustrate the problem.

a vibrant and colorful artist with a playful sense of humor known under the pseudonym purple snow , she was born in lithuania .

c) We use maximum likelihood estimation with add-k smoothing to train two trigram models on the COCA corpus: model A with $k = 0.1$, model B with $k = 0.01$. We compute the entropy of both models on the same data that we used for training. Which model has the higher entropy, and why? Anwer with a short text.

Sample answers:

a) Maximum likelihood estimation without smoothing:

i. $P(snow) = \frac{38186}{560 \cdot 10^6}$

ii. $P(snow \mid white) = \frac{122}{256091} = 0$

b) Under a bigram model, to compute the probability of a sentence, one has to multiply the relevant bigram probabilities. For the given sentence this involves the probability $P(snow \mid purple)$, which is zero. This means that the model will assign zero probability to the given sentence – it is infinitely surprised by the sentence, even though most of the bigrams were probably observed during training.

c) Model A has higher entropy than model B. Add-k smoothing *increases* the total probability of trigrams that do *not* occur in the training data but *decreases* the total probability of the trigrams that *do* occur – and the more so the higher the k.

03 Part-of-speech tagging (3 points)

a) The following matrices specify (parts of) a hidden Markov model. The marked cell specifies the probability for the transition from `BOS` to `AB`.

	AB	PN	PP	VB	EOS
BOS	1/11	1/10	1/12	1/11	1/25
AB	1/11	1/11	1/11	1/10	1/14
PN	1/11	1/12	1/12	1/10	1/16
PP	1/13	1/11	1/12	1/14	1/18
VB	1/11	1/10	1/10	1/13	1/15

	she	got	up
AB	1/25	1/25	1/14
PN	1/13	1/25	1/25
PP	1/25	1/25	1/13
VB	1/25	1/14	1/19

Which probability does this model assign to the following tagged sentence (word/tag)? Answer with a fraction.

she/PN got/VB up/AB

b) One difference between greedy tagging with the multi-class perceptron and tagging with hidden Markov models based on the Viterbi algorithm is in the features that the two models have access to. Which of the following features would you have to choose to provide the greedy tagger with the same information that the hidden Markov model has access to, and which features go beyond what can be expressed in a hidden Markov model? Answer with a short text.

i. current word

ii. word to the left of the current word

iii. word to the right of the current word

iv. part-of-speech tag of the word to the left of the current word

c) State at least two other differences between greedy tagging with the multi-class perceptron and tagging with hidden Markov models based on the Viterbi algorithm, apart from the aforementioned differences in the feature models.

Sample answers:

a) $\frac{1}{10} \cdot \frac{1}{13} \cdot \frac{1}{10} \cdot \frac{1}{14} \cdot \frac{1}{11} \cdot \frac{1}{14} \cdot \frac{1}{14}$

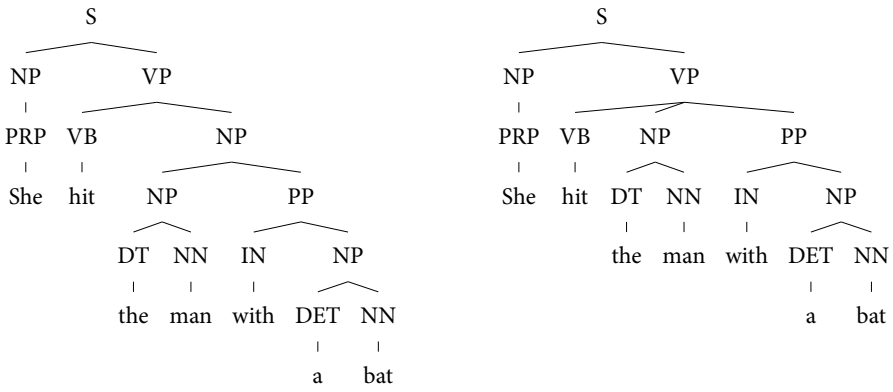
b) Feature (i) corresponds to the output probabilities of the hidden Markov model, and feature (iv) corresponds to the transition probabilities. Features (ii) and (iii) go beyond what can be captured with these probabilities.

c) Some differences:

- The hidden Markov model has a probabilistic interpretation, the multi-class perceptron does not.
- Different computational complexities. Let m and n denote the number of tags and the length of the input sentence, respectively. Then greedy tagging with the multi-class perceptron runs in time $O(mn)$, whereas the Viterbi algorithm needs time $O(m^2 n)$.

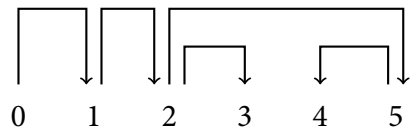
04 **Syntactic analysis** **(3 points)**

a) Below is a small phrase structure treebank, consisting of just two trees. Read off all rules whose left-hand sides are either NP or VP and estimate their rule probabilities using maximum likelihood estimation.



b) How do probabilistic context-free grammars help address the computational problems that arise from syntactic ambiguity? Answer with a short text.

c) State a sequence of transitions that make an transition-based dependency parser produce the following dependency tree:



Sample answers:

a) Rules and probabilities:

$$\text{NP} \rightarrow \text{PRP}\ \tfrac{2}{7} \quad \text{NP} \rightarrow \text{NP PP}\ \tfrac{1}{7} \quad \text{NP} \rightarrow \text{DT NN}\ \tfrac{2}{7} \quad \text{NP} \rightarrow \text{DET NN}\ \tfrac{2}{7}$$

$$\text{VP} \rightarrow \text{VB NP}\ \tfrac{1}{2} \quad \text{VP} \rightarrow \text{VB NP PP}\ \tfrac{1}{2}$$

b) Probabilistic context-free grammars allow us to model the fact that not all possible parse trees for a given sentence are equally relevant or likely. Given such a grammar, we can find the most probable parse tree for a given sentence efficiently, even though the total number of trees is very large.

c) SH SH SH SH RA SH SH LA RA RA RA

05 **Semantic analysis** **(3 points)**

a) Choose the correct semantic relation: synonym, antonym, hyponym, hypernym?

purchase	is a/an … of	buy
chair	is a/an … of	furniture
liberty	is a/an … of	freedom
bird	is a/an … of	eagle
synonym	is a/an … of	antonym

b) Here are three signatures (glosses and examples) from Wiktionary for different senses of the word *colour*:

1 The spectral composition of visible light. *Humans and birds can perceive colour.* **2** A particular set of visible spectral compositions, perceived or named as a class. *Most languages have names for the colours black, white, red, and green.* **3** Hue as opposed to achromatic colours (black, white, and grays). *He referred to the white flag as one 'drained of all colour'.*

Based on these signatures, which of the three senses of the word *colour* does the Lesk algorithm predict in the following sentence? Ignore the word *colour*, stop words, and punctuation.

As the large flag of red and blue colour was raised in a highly visible spot at the top of the mountain, a light rain began to fall.

c) We read off word vectors from the following co-occurrence matrix (target words correspond to rows, context words correspond to columns):

	HuSHa'	*Ha'DIbaH*
qa'vIn	5	1
qurgh	5	5
jonta'	1	0
Dargh	1	4

Sort the four words in decreasing degree of semantic similarity to the word *Dargh*, assuming that semantic similarity is measured as the angle between word vectors.

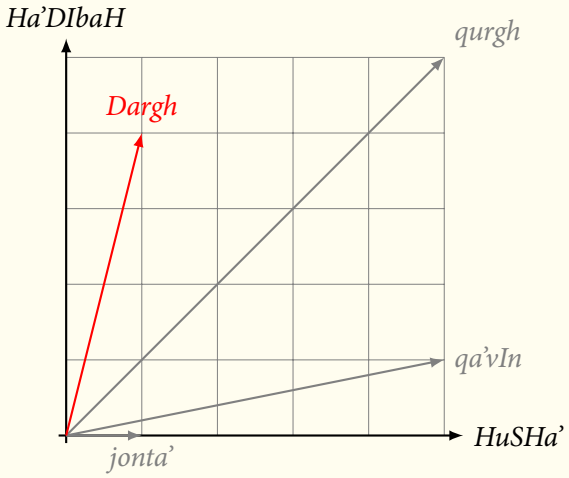
Sample answers:

a) Semantic relations:

purchase	is a synonym of	buy
chair	is a hyponym of	furniture
liberty	is an synonym of	freedom
bird	is a hypernym of	eagle
synonym	is an antonym of	antonym

b) sense 1 (match with *visible* and *light*), sense 2 (match with *visible* and *red*)

c) From most similar to least similar: *Dargh*, *qurgh*, *qa'vIn*, *jonta'*. To see this, we draw the four vectors in a two-dimensional coordinate systems with coordinates *HuSHa'* and *Ha'DIbaH*:



Part B

06 **Levenshtein distance** **(6 points)**

The following matrix shows the values computed by the Wagner–Fischer algorithm for finding the Levenshtein distance between the two words *student* and *teacher*. Note that the matrix is missing a value (marked cell).

t	7	6	5	5	5	6	6	7
n	6	5	4	4	5	5	6	6
e	5	4	3	4	4	5	5	6
d	4	3	3		4	5	6	7
u	3	2	2	3	4	5	6	7
t	2	1	2	3	4	5	6	7
s	1	1	2	3	4	5	6	7
#	0	1	2	3	4	5	6	7
	#	t	e	a	c	h	e	r

a) Define the concept of the Levenshtein distance between two words. The definition should be understandable even to readers who have not taken this course.

b) Calculate the value for the marked cell. Explain your calculation. Show that you have understood the Wagner–Fischer algorithm.

c) It is much more likely for a user to mistype the word *student* as *stusent* than as *stulent*; this is because the keys for the letters *d* and *s* are much closer to each other on the keyboard than the keys for the letters *d* and *l*. Explain how the Wagner–Fischer algorithm could be adapted to take this information into account.

07 **Viterbi algorithm** **(6 points)**

The following matrices specify a hidden Markov model in terms of costs (negative log probabilities). The marked cell gives the transition cost from `BOS` to `AB`.

	AB	PN	PP	VB	EOS
BOS	11	10	12	11	25
AB	11	11	11	10	14
PN	11	12	12	10	16
PP	13	11	12	14	18
VB	11	10	10	13	15

	she	got	up
AB	25	25	14
PN	13	25	25
PP	25	25	13
VB	25	14	19

When using the Viterbi algorithm to calculate the least expensive (most probable) tag sequence for the sentence 'she got up' according to this model, we get the following matrix. Note that the matrix is missing three values (marked cells).

		she	got	up
BOS	0			
AB		A	59	72
PN		23	60	82
PP		37	B	70
VB		36	47	78
EOS				C

a) Calculate the missing values.

b) Starting in cell `C`, list the backpointers for the matrix and state the least expensive (most probable) tag sequence for the sentence.

c) Let m denote the number of tags in the hidden Markov model and let n denote the length of the input sentence. The memory required by the Viterbi algorithm is in $O(mn)$. The runtime of the Viterbi algorithm is in $O(m^2n)$. Explain what these statements mean and why they hold.

08 **Named entity tagging** **(6 points)**

Named entity tagging is the task of identifying entities such as persons, organisations, and locations in running text. One way to approach this task is to use the same techniques as in part-of-speech tagging. However, a complicating factor is that named entities can span more than one word. Consider the following sentence:

Alfred Nobel was an inventor from Sweden.

In this example, while the unigram 'Sweden' corresponds to one named entity of type 'location' (LOC), we would also like to identify the bigram 'Alfred Nobel' as a mention of *one* named entity, of type 'person' (PER).

To solve this problem, we can use the so-called IOB tagging. In this scheme we introduce a special 'part-of-speech' tag for the beginning (B) and inside (I) of each entity type, as well as one tag for words outside (O) any entity. Here is the example sentence represented with IOB tags:

$$\text{Alfred}_{\text{B-PER}}\ \text{Nobel}_{\text{I-PER}}\ \text{was}_{\text{O}}\ \text{an}_{\text{O}}\ \text{inventor}_{\text{O}}\ \text{from}_{\text{O}}\ \text{Sweden}_{\text{B-LOC}}$$

a) Named entity taggers often use *gazetteers*. Explain what a gazetteer is and how it can be integrated into a named entity tagger based on the multi-class perceptron.

b) In addition to gazetteers, named entity taggers often use *word shape features*, which represent the abstract letter pattern of a word. Give a concrete example of such a feature, and explain why word-shape features are especially useful in named entity tagging, compared to part-of-speech tagging.

c) Named entity taggers using the IOB tagging scheme can be evaluated at the level of words ('How many words were tagged with the correct IOB tag?') or at the level of entities ('How many *n*-grams were tagged with their correct entity type?'). Provide an example that shows that a named entity tagger can have a high word-level tagging accuracy but a low entity-level tagging accuracy. Explain.

Part C

09 **The limitations of word embeddings** **(9 points)**

This item is an essay question that tests your understanding of the following article:

Aylin Caliskan, Joanna J. Bryson, Arvind Narayanan. *Semantics Derived Automatically from Language Corpora Contain Human-Like Biases*. Science 356(6334):183–186, 2017.

a) Summarise the paper by Caliskan et al. in your own words.

b) Caliskan et al. investigate whether word vectors embed knowledge of the real-world properties associated with the words, or, as they put it, 'whether there is an algorithm that can extract of predict the property, given the vector'. Explain their approach using the example illustrated in Fig. 1 below (reproduced from the article).

Fig. 1. Occupation-gender association. Pearson's correlation coefficient $\rho = 0.90$ with $P < 10^{-18}$.

c) Caliskan et el. write: 'Our work has implications for AI and machine learning because of the concern that these technologies may perpetuate cultural stereotypes.' Explain this statement. Would you agree with the authors' concern?