Examples of Questions and Answers

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Examples of closed questions

Which of the following statements holds true for the BERT pre-training phase?

- It uses a context window to define positive examples.
- Self-supervised training with masked language modeling and next sentence prediction is used in the training phase.
- The model is trained using Next Word Prediction task
- It is trained by corrupting text with an arbitrary noising function, and learning a model to reconstruct the original text.
- None of the above.

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The Negative Sampling

- Can be used for bootstrapping supervised classification models.
- Can be used to avoid data overfitting.
- Can be used to find negative words in sentiment analysis.
- Can be used to select negative examples while training a Word2Vec model.
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Considering the one-hot encoding representation

- Each textual unit is represented by a dense vector consisting of real-valued elements
- Each textual unit is represented by a sparse vector consisting of boolean elements.
- Each textual unit is weighted by its number of occurrences in the input corpus.
- It varies according to the size of the context window.
- None of the above.

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Considering the HITS algorithm, during the hub update step

- Each node relevance score is normalized by the number N of nodes.
- Each link relevance score is normalized by the number N of nodes.
- For each node, the hub score is the sum of the authority scores of each node that it points to.
- For each node, the hub score is the sum of the hub scores of each node that points to it.
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In the self-attention mechanism implemented in BERT

- The attention score of a reference token is computed separately for each token in the sequence, including the reference token itself.
- The attention score of a reference token is computed separately for each token in the sequence, except for the reference token itself.
- The attention score of a reference token is computed by attending only part of the sequence according to the positional encoding.
- The attention score of special tokens (e.g., SEP) is computed by attending only other special tokens (e.g., CLS).
- None of the above.

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- Syntactic Parsing.
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- Lexical databases.
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- Stemming.

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Which of the following is a valid definition of n-gram?

- A set of n sentences that are part of a document.
- A bag of words describing a document topic.
- A contiguous sequence of n characters that are part of a word.
- A set of n phonemes that are part of a phrase.
- None of the above.

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Examples of open questions

Explain the PageRank algorithm

- $1.\,\,$ Enumerate and explain the main algorithm steps.
- 2. Exemplify at least one context of usage in NLP.
- 3. Specify the conditions under which PageRank can be applied to a given graph. Explain how to proceed when the conditions are not satisfied.

Solution 8.1

- Rule 1. Links from a graph node to itself are ignored.
- Rule 2. Multiple outgoing edges from one node to another are treated as a single edge.
- Rule 3. Set the same initial value for all nodes (e.g.,
- Apply the Pagerank formula to all vertices at each s $P(x) = \frac{1}{N}$

$$P(x) = \frac{1 - \lambda}{N} + \lambda \sum_{y \to x} \frac{P(y)}{out(y)}$$

lambda: damping factor

N: number of vertices

 $y \rightarrow x$: node x's incoming edge

Solution 8.2

- It is used in information retrieval to get an estimation of the overall importance of a node in the graph.
- It can be used as additional relevance score for building search engines.

Solution 8.3

- The graph must not have sinks (i.e., vertices with only incoming edges).
- To solve this problem it is possible to add an outgoing edge from the sink vertex to every other node in the graph.

Explain the Latent Dirichlet Allocation

- $1.\;\;$ Elaborate on the steps required to generate an LDA model.
- 2. Describe the Author-Topic Model (ATM) and its similarities/differences with LDA.
- 3. Enumerate <u>at least</u> two practical examples of application of ATM.

Solution 9.1

- Generative topic model.
- Each word in a document is assumed to be generated either by sampling a topic from a document-specific distribution over topics and by sampling a word from the distribution over words that characterizes that topic.
- For each document in the corpus and for each term, a topic is chosen accordingly to the document-topic distribution.
- Words are extracted from the input vocabulary V by taking into account the terms probabilities for each given topic in the document mixture.

Solution 9.2

- It is a Generative model for documents and extends the Latent Dirichlet Allocation to include authorship information.
 - Each author is associated with a multinomial distribution over topics
 - Each topic is associated with a multinomial distribution over words
 - A document with multiple authors is modeled as a distribution over topics that is a mixture of the distributions associated with the authors

Solution 9.3

ATM can be used for

- Who is the most authoritative author on a given topic?
- What are the topic covered by a given author?
- What is the most authoritative paper of an author?

Elaborate on the Recommendation task

- $1.\,\,$ Formulate the task and clarify the main goals.
- 2. Illustrate at least two business scenarios of usage for a recommender system.
- 3. Compare content-based and collaborative filtering systems by highlighting pros and cons of each of the above-mentioned strategies.

Solution 10.1

- Let U be a set of users, I be a set of recommendable items, R an ordered set of ratings
- The task is to find $F(\cdot): U \times I \to R$
- The goal is to generate user-specific item rankings.

Solution 10.2

- NetFlix users receive movie recommendations based on their previous interactions with the platform.
- Travelers of a tourism agency receive hotel recommendations based on the census data (e.g., age, gender, job, salary, etc.)

Solution 10.3

- Collaborative filtering: recommend to a given user those items that were selected by similar users.
 - Pros: no need for content-level explorations (more efficient).
 - Cons: popularity bias, cold start.
- Content-based approaches: recommend items that are most similar to those previously selected by the same user.
 - Pros: solves the cold start and the first rater problems.
 - Cons: filter bubble. Need for content-level explorations (more computationally intensive).

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Affiliation

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 - https://dbdmg.polito.it
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Thank you!