Quiz 9: Topic Modeling for Fun and Profit

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April 18, 2024

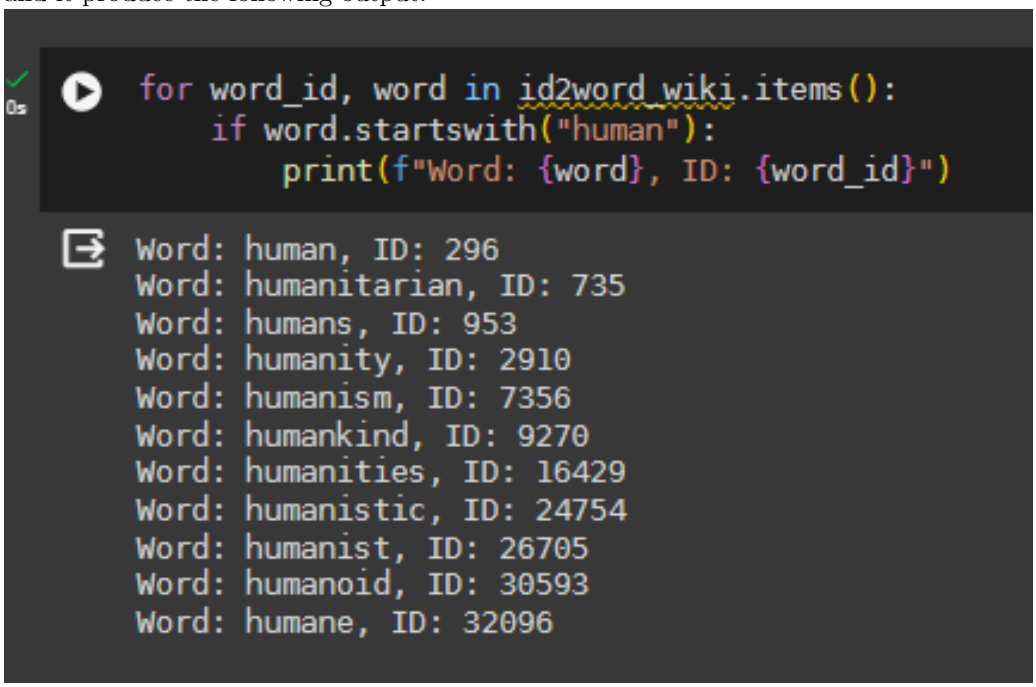
1 Question 1

Print all words and their ids from id2word_wiki where the word starts wtih "human".

To print the words and ids from id2word_wiki, I use the following code:

```
for word_id, word in id2word_wiki.items():
    if word.startswith("human"):
        print(f"Word: {word}, ID: {word_id}")
```

and it produce the following output:



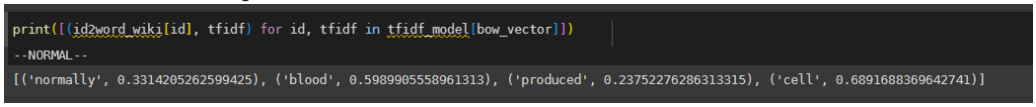
2 Question 2

Print text transformed into TFIDF space.

To print the text transformed into TFIDF space, I use the following code:

```
print([(id2word_wiki[id], tfidf) for id, tfidf in tfidf_model[bow_vector]])
```

and below is the output:



3 Question 3

Identify the source of difference and change it so they are equivalent.

I change the code section to below, basically only swapping "_, word" with "word, _":

```
# select top 50 words for each of the 20 LDA topics
top_words = [[word for word, _ in lda_model.show_topic(topicno, topn=50)] for topicno in
    range(lda_model.num_topics)]
print(top_words)
```

```
[
  ['actor', 'singer', 'politician', 'player', 'footballer', 'actress', 'german', 'writer', 'british',
      'french', 'president', 'italian', 'director', 'composer', 'canadian', 'musician', 'japanese',
      'songwriter', 'prime', 'minister', 'russian', 'poet', 'spanish', 'producer', 'james', 'movie',
      'australian', 'king', 'governor', 'killing', 'scottish', 'physicist', 'ii', 'ice', 'robert',
      'george', 'journalist', 'charles', 'football', 'david', 'baseball', 'dutch', 'painter',
      'general', 'battle', 'begins', 'hockey', 'france', 'television', 'austrian'],
  ['country', 'countries', 'league', 'government', 'water', 'capital', 'largest', 'population',
      'east', 'west', 'century', 'africa', 'land', 'union', 'sea', 'football', 'republic', 'cities',
      'language', 'power', 'river', 'million', 'region', 'air', 'empire', 'european', 'live', 'team',
      'central', 'important', 'france', 'large', 'international', 'independence', 'western',
      'premier', 'climate', 'cup', 'kingdom', 'nations', 'club', 'soviet', 'northern', 'army',
      'india', 'al', 'party', 'major', 'mount', 'economy'],
  ['body', 'light', 'earth', 'things', 'example', 'energy', 'water', 'cells', 'species', 'person',
      'animals', 'blood', 'usually', 'god', 'transmission', 'small', 'tower', 'mast', 'way', 'uhf',
      'word', 'cell', 'means', 'common', 'human', 'theory', 'makes', 'universe', 'living', 'object',
      'types', 'form', 'study', 'change', 'large', 'sun', 'live', 'right', 'chemical', 'fish',
      'great', 'evolution', 'space', 'temperature', 'important', 'mass', 'plants', 'inside', 'man',
      'humans'],
  ['rgb', 'hex', 'color', 'language', 'languages', 'blue', 'web', 'pink', 'red', 'usb', 'esperanto',
      'purple', 'green', 'software', 'ff', 'light', 'lake', 'heart', 'crayola', 'bytes', 'disease',
      'computers', 'violet', 'cancer', 'linux', 'alphabet', 'yellow', 'words', 'com', 'apple',
      'operating', 'magenta', 'data', 'colors', 'chinese', 'free', 'means', 'usually', 'memory',
      'drive', 'version', 'os', 'doctors', 'word', 'flash', 'spoken', 'mac', 'writing', 'letters',
      'latin'],
  ['president', 'river', 'jpg', 'bush', 'rural', 'file', 'london', 'reagan', 'york', 'germany',
      'government', 'party', 'chicago', 'election', 'house', 'capital', 'roman', 'town', 'st',
      'washington', 'presidential', 'china', 'bridge', 'famous', 'elected', 'ii', 'george', 'tower',
      'urban', 'county', 'great', 'german', 'republican', 'west', 'carter', 'century', 'cities',
      'important', 'museum', 'vice', 'virginia', 'office', 'center', 'largest', 'empire', 'dole',
      'said', 'bavaria', 'east', 'hugo'],
  ['island', 'church', 'jpg', 'islands', 'sea', 'king', 'europe', 'file', 'country', 'land',
      'countries', 'england', 'america', 'large', 'black', 'henry', 'china', 'largest', 'capital',
      'built', 'east', 'live', 'mario', 'birds', 'ocean', 'small', 'queen', 'usually', 'great',
      'australia', 'house', 'century', 'catholic', 'west', 'kansas', 'population', 'important',
      'mountains', 'famous', 'western', 'roman', 'asia', 'building', 'parts', 'px', 'popular',
      'cities', 'japan', 'bird', 'sonic'],
  ['music', 'movie', 'band', 'award', 'rock', 'series', 'television', 'movies', 'released', 'film',
      'love', 'album', 'played', 'guitar', 'songs', 'doctor', 'song', 'disney', 'awards', 'man',
      'popular', 'wrote', 'famous', 'episode', 'star', 'park', 'play', 'children', 'married',
      'voice', 'live', 'role', 'father', 'story', 'death', 'studios', 'animation', 'school', 'tv',
      'black', 'vocals', 'white', 'heart', 'career', 'nominated', 'lead', 'mother', 'young',
      'albums', 'actor'],
  ['game', 'number', 'person', 'example', 'windows', 'player', 'games', 'numbers', 'internet',
      'usually', 'way', 'word', 'microsoft', 'school', 'players', 'words', 'gender', 'means', 'ball',
      'things', 'sexual', 'play', 'team', 'information', 'version', 'study', 'change', 'autism',
      'common', 'children', 'problems', 'help', 'released', 'field', 'written', 'rules', 'nintendo',
      'mental', 'include', 'disorder', 'suicide', 'type', 'based', 'types', 'explorer', 'uses',
      'computers', 'data', 'social', 'special'],
  ['politician', 'actress', 'actor', 'french', 'german', 'footballer', 'singer', 'british', 'writer',
      'italian', 'player', 'president', 'minister', 'king', 'russian', 'ii', 'prime', 'musician',
      'canadian', 'scottish', 'composer', 'william', 'japanese', 'france', 'general', 'indian',
      'poet', 'governor', 'battle', 'england', 'spanish', 'australian', 'kingdom', 'emperor',
      'painter', 'director', 'dutch', 'pope', 'swedish', 'producer', 'paul', 'songwriter', 'george',
      'charles', 'author', 'polish', 'leader', 'army', 'henry', 'killed'],
  ['album', 'usually', 'things', 'food', 'bc', 'person', 'band', 'good', 'book', 'god', 'said',
      'way', 'money', 'word', 'human', 'countries', 'example', 'century', 'water', 'ancient',
      'means', 'making', 'song', 'man', 'fruit', 'milk', 'important', 'released', 'types', 'live',
      'books', 'popular', 'love', 'believe', 'right', 'include', 'music', 'death', 'art', 'men',
```

```
        'think', 'sold', 'metal', 'common', 'body', 'thought', 'gold', 'number', 'public', 'come']
]
```

4 Question 4: Evaluation using Misplaced words.

To test evaluate this, I myself haven't look at the next cell where it list out all the replacements and see if I can spotted the word that was misplaced.

The challenge were:

- 0 actor singer politician player footballer written german writer british french
- 1 country countries league government water temperature largest population east west
- 2 body light earth things married energy water cells species person
- 3 rgb hex color language languages blue king pink red usb
- 4 president light jpg bush rural file london reagan york germany
- 5 island church jpg young sea king europe file country land
- 6 music movie light award rock series television movies released film
- 7 game number person example latin player games numbers internet usually
- 8 politician actress actor french german footballer singer british god italian
- 9 album usually things food bc person band good president god

These are my results:

- topic 1: written becuase the other words were about profession or nationality
- topic 2: temperature because the other words were about coutnries and nature
- topic 3: earth because other things was about human and not nature
- topic 4: king because the other words were mostly about cameras and light
- topic 5: jpg because the others were about landscape, and regions
- topic 6: rock because the words were mostly about films and movies
- topic 7: latin because most of the words were about games and numbers
- topic 8: god because the other words were about professions and nationality
- topic 9: god because most of other words were food and stuff not something that was worship

While the actual replacements were:

```
[
  (0, ('actress', 'written')),
  (1, ('capital', 'temperature')),
  (2, ('example', 'married')),
  (3, ('web', 'king')),
  (4, ('river', 'light')),
  (5, ('islands', 'young')),
  (6, ('band', 'light')),
  (7, ('windows', 'latin')),
  (8, ('writer', 'god')),
  (9, ('book', 'president'))
]
```

Which I got 4 out of 9 right.

I didn't do this for LSI because LSI has almost 200 topics and using this for all of them is going to take a long time

5 Question 5: Evaluate using Half and Half

In order to see the topics assignments of each models, I've modified the code for intra_inter like below:

```
from collections import defaultdict
import re

def intra_inter(model, test_docs, num_pairs=10000):
    # split each test document into two halves and compute topics for each half
    half = int(len(test_docs)/2)
    part1 = [model[id2word_wiki.doc2bow(tokens[: half])] for tokens in test_docs]

    part2 = [model[id2word_wiki.doc2bow(tokens[half :])] for tokens in test_docs]
    # count the frequency of each topic across all documents
    topic_count1 = defaultdict(int)
    for i, doc_topics in enumerate(part1):
        if len(doc_topics) == 0:
          topic_count2["Unidentified"] +=1
          continue
        top_topic = max(doc_topics, key=lambda x: x[1])[0]
        topic_count1[top_topic] += 1

    topic_count2 = defaultdict(int)
    for i, doc_topics in enumerate(part2):
        if len(doc_topics) == 0:
          topic_count2["Unidentified"] +=1
          continue
        top_topic = max(doc_topics, key=lambda x: x[1])[0]
        topic_count2[top_topic] += 1

    print("Topic count for first part:")
    for topic, count in sorted(topic_count1.items(), key=lambda x: -1 if isinstance(x[0], str) else
        x[0]):
      print(f"Topic {topic}: {count}")

    print("Topic count for second part:")
    for topic, count in sorted(topic_count2.items(), key=lambda x: -1 if isinstance(x[0], str) else
        x[0]):
      print(f"Topic {topic}: {count}")
    # print computed similarities (uses cossim)
    print("average cosine similarity between corresponding parts (higher is better):")
    print(np.mean([gensim.matutils.cossim(p1, p2) for p1, p2 in zip(part1, part2)]))

    random_pairs = np.random.randint(0, len(test_docs), size=(num_pairs, 2))
    print("average cosine similarity between 10,000 random parts (lower is better):")
    print(np.mean([gensim.matutils.cossim(part1[i[0]], part2[i[1]]) for i in random_pairs]))
```

This code allows me to print out the topics that the model predict each document to be and then I'll count the occurence that each topic was assigned.

This is the output of running with lda model:

```
LDA results:
Topic count for first part:
Topic 0: 17
Topic 1: 115
Topic 2: 211
Topic 3: 13
Topic 4: 80
Topic 5: 90
Topic 6: 186
Topic 7: 98
Topic 8: 75
Topic 9: 115
Topic count for second part:
Topic 0: 907
Topic 1: 14
Topic 2: 9
Topic 3: 2
Topic 4: 9
Topic 5: 7
Topic 6: 28
Topic 7: 11
Topic 8: 5
Topic 9: 8
average cosine similarity between corresponding parts (higher is better):
0.5149764097900886
average cosine similarity between 10,000 random parts (lower is better):
0.46075469966823446
```

We can see that the amount of topics of both are the same.
And this is the output of running with lsi model:

```
LSI results:
Topic count for first part:
Topic 0: 502
Topic 2: 4
Topic 5: 3
Topic 6: 2
Topic 7: 9
Topic 9: 1
Topic 10: 5
Topic 11: 30
Topic 13: 3
Topic 14: 11
Topic 15: 1
Topic 17: 2
Topic 19: 7
Topic 20: 9
Topic 21: 31
Topic 22: 17
Topic 23: 2
Topic 24: 26
Topic 25: 1
Topic 27: 2
Topic 28: 4
Topic 29: 2
Topic 30: 7
Topic 31: 5
Topic 32: 17
Topic 33: 8
Topic 34: 9
Topic 35: 19
Topic 36: 19
Topic 38: 1
Topic 39: 1
```

```
.
Topic 60: 5
Topic 62: 6
Topic 63: 2
Topic 64: 8
Topic 65: 11
Topic 67: 1
Topic 69: 2
Topic 71: 1
Topic 72: 3
Topic 73: 3
Topic 74: 4
Topic 76: 1
Topic 77: 3
Topic 78: 1
Topic 80: 2
Topic 81: 2
Topic 82: 3
Topic 83: 4
Topic 86: 2
Topic 88: 9
Topic 92: 1
Topic 93: 2
Topic 94: 6
Topic 95: 12
Topic 96: 1
```

```
Topic 154: 3
Topic 156: 1
Topic 158: 1
Topic 162: 2
Topic 163: 2
Topic 165: 1
Topic 169: 1
Topic 170: 2
Topic 174: 2
Topic 175: 1
Topic 176: 1
Topic 178: 8
Topic 182: 1
Topic 184: 6
Topic 187: 3
Topic 188: 5
Topic 190: 2
Topic 193: 8
Topic 196: 1
Topic 197: 1
Topic count for second part:
Topic Unidentified: 903
Topic 0: 48
Topic 2: 1
Topic 10: 1
Topic 11: 3
Topic 13: 1
Topic 20: 1
Topic 21: 2
```

```
Topic 74: 1
Topic 77: 1
Topic 86: 1
Topic 99: 1
Topic 110: 1
Topic 126: 1
Topic 127: 1
Topic 160: 1
Topic 163: 1
Topic 170: 1
Topic 179: 1
Topic 187: 1
Topic 188: 1
average cosine similarity between corresponding parts (higher is better):
0.0647689533762877
average cosine similarity between 10,000 random parts (lower is better):
0.007668506642081885
```

However for LSI, we can see that there is a significance difference between the similar half and the dissimilar half.

Note that because for LSI, there are instances where it can't calculate the topic of a document and return an empty topic lists, in these instances, we coutn them as Unidentified.

6 Question 6: Comparing models

The intra_inter metrics for LSI are:

- Avg cosine similarity between halves of same doc: 0.0648
- Avg cosine similarity between random docs: 0.0082

For LDA the numbers are:

- Corresponding halves: 0.515
- Random halves: 0.462

Comparing the value for similar document, we can see that LDA achieves a far better value compares to LSI. This suggests that LSI failes to capture the content even within a single document. We can see this from the previous section where for LSI, we see a lot of Unidentified. Therefore, eventhough LSI produce lower similarity value for randomized half, it's poor performance against the similar document is troublesome. In conclusion, I believe that LDA would be a better choice for this dataset.