LDA in Python – How to grid search best topic models?

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Python's Scikit Learn provides a convenient interface for topic modeling using algorithms like Latent Dirichlet allocation(LDA), LSI and Non-Negative Matrix Factorization. In this tutorial, you will learn how to build the best possible LDA topic model and explore how to showcase the outputs as meaningful results.

1.

Contents

How to build topic models with python sklearn. Photo by Sebastien Gabriel.

1. Introduction

In the last tutorial you saw how to build topics models with LDA using gensim. In this tutorial, however, I am going to use python's the most popular machine learning library – scikit learn.

With scikit learn, you have an entirely different interface and with grid search and vectorizers, you have a lot of options to explore in order to find the optimal model and to present the results.

In this tutorial, you will learn:

1. How to clean and process text data?
2. How to prepare the text documents to build topic models with scikit learn?
3. How to build a basic topic model using LDA and understand the params?

4. How to extract the topic's keywords?
5. How to gridsearch and tune for optimal model?
6. How to get the dominant topics in each document?
7. Review and visualize the topic keywords distribution
8. How to predict the topics for a new piece of text?
9. Cluster the documents based on topic distribution
10. How to get most similar documents based on topics discussed?

A lot of exciting stuff ahead. Let's roll!

2. Load the packages

The core package used in this tutorial is scikit-learn (**sklearn**).

Regular expressions **re** , **gensim** and **spacy** are used to process texts. **pyLDAvis** and **matplotlib** for visualization and **numpy** and **pandas** for manipulating and viewing data in tabular format.

Let's import them.

```
# Run in terminal or command prompt
# python3 -m spacy download en

import numpy as np
import pandas as pd
import re, nltk, spacy, gensim

# Sklearn
from sklearn.decomposition import LatentDirichletAllocation, TruncatedSVD
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
from sklearn.model_selection import GridSearchCV
from pprint import pprint

# Plotting tools
import pyLDAvis
import pyLDAvis.sklearn
import matplotlib.pyplot as plt
%matplotlib inline
```

3. Import Newsgroups Text Data

I will be using the 20-Newsgroups dataset for this. This version of the dataset contains about 11k newsgroups posts from 20 different topics. This is available as newsgroups.json.

Since it is in a json format with a consistent structure, I am using **pandas.read_json()** and the resulting dataset has 3 columns as shown.

```
# Import Dataset
df = pd.read_json('https://raw.githubusercontent.com/selva86/datasets/master/newsgroups.json')
print(df.target_names.unique())
```

```
['rec.autos' 'comp.sys.mac.hardware' 'rec.motorcycles' 'misc.forsale'
 'comp.os.ms-windows.misc' 'alt.atheism' 'comp.graphics'
 'rec.sport.baseball' 'rec.sport.hockey' 'sci.electronics' 'sci.space'
 'talk.politics.misc' 'sci.med' 'talk.politics.mideast'
 'soc.religion.christian' 'comp.windows.x' 'comp.sys.ibm.pc.hardware'
 'talk.politics.guns' 'talk.religion.misc' 'sci.crypt']
```

```
df.head(15)
```

	content	target	target_names
0	From: lerxst@wam.umd.edu (where's my thing)\nSubject: WHAT car is this!?\nNn...	7	rec.autos
1	From: guykuo@carson.u.washington.edu (Guy Kuo)\nSubject: SI Clock Poll - Fin...	4	comp.sys.mac.hardware
10	From: irwin@cmptrc.lonestar.org (Irwin Arnstein)\nSubject: Re: Recommendatio...	8	rec.motorcycles
100	From: tchen@magnus.acs.ohio-state.edu (Tsung-Kun Chen)\nSubject: ** Software...	6	misc.forsale
1000	From: dabl2@nlm.nih.gov (Don A.B. Lindbergh)\nSubject: Diamond SS24X, Win 3....	2	comp.os.ms-windows.misc
10000	From: a207706@moe.dseg.ti.com (Robert Loper)\nSubject: Re: SHO and SC\nNntp-...	7	rec.autos
10001	From: kimman@magnus.acs.ohio-state.edu (Kim Richard Man)\nSubject: SyQuest 4...	6	misc.forsale
10002	From: kwilson@casbah.acns.nwu.edu (Kirtley Wilson)\nSubject: Mirosoft Office...	2	comp.os.ms-windows.misc
10003	Subject: Re: Don't more innocents die without the death penalty?\nFrom: bobb...	0	alt.atheism
10004	From: livesey@solntze.wpd.sgi.com (Jon Livesey)\nSubject: Re: Genocide is Ca...	0	alt.atheism
10005	From: dls@aeg.dsto.gov.au (David Silver)\nSubject: Re: Fractal Generation of...	1	comp.graphics
10006	Subject: Re: Mike Francesa's 1993 Predictions\nFrom: gajarsky@pilot.njin.net...	9	rec.sport.baseball
10007	From: jet@netcom.Netcom.COM (J. Eric Townsend)\nSubject: Re: Insurance and l...	8	rec.motorcycles
10008	From: gld@cunixb.cc.columbia.edu (Gary L Dare)\nSubject: Re: ABC coverage\nN...	10	rec.sport.hockey
10009	From: sehari@iastate.edu (Babak Sehari)\nSubject: Re: How to the disks copy ...	12	sci.electronics

Input – 20Newsgroups

You can see many emails, newline characters and extra spaces in the text and it is quite

4. Remove emails and newline characters

distracting. Let's get rid of them using regular expressions.

```
# Convert to list
data = df.content.values.tolist()

# Remove Emails
data = [re.sub('\S*@\S*\s?', '', sent) for sent in data]

# Remove new line characters
data = [re.sub('\s+', ' ', sent) for sent in data]

# Remove distracting single quotes
data = [re.sub("\'", "", sent) for sent in data]

pprint(data[:1])
```

```
['From: (wheres my thing) Subject: WHAT car is this!? Nntp-Posting-Host: '
 'rac3.wam.umd.edu Organization: University of Maryland, College Park Lines: '
 '15 I was wondering if anyone out there could enlighten me on this car I saw '
 'the other day. It was a 2-door sports car, looked to be from the late 60s/ '
 'early 70s. It was called a Bricklin. The doors were really small. In '
 'addition, the front bumper was separate from the rest of the body. This is '
 'all I know. If anyone can tellme a model name, engine specs, years of '
 'production, where this car is made, history, or whatever info you have on '
 'this funky looking car, please e-mail. Thanks, - IL ---- brought to you by '
 'your neighborhood Lerxst ---- ']
```

5. Tokenize and Clean-up using gensim's simple_preprocess()

The sentences look better now, but you want to tokenize each sentence into a list of words, removing punctuations and unnecessary characters altogether.

Gensim's `simple_preprocess()` is great for this. Additionally I have set `deacc=True` to remove the punctuations.

```
def sent_to_words(sentences):
    for sentence in sentences:
        yield(gensim.utils.simple_preprocess(str(sentence), deacc=True))  # deacc=True removes punc

data_words = list(sent_to_words(data))

print(data_words[:1])
```

```
[['from', 'wheres', 'my', 'thing', 'subject', 'what', 'car', 'is', 'this', 'nntp', 'posting', 'hos
```

6. Lemmatization

Lemmatization is a process where we convert words to its root word.

For example: 'Studying' becomes 'Study', 'Meeting becomes 'Meet', 'Better' and 'Best' becomes 'Good'.

The advantage of this is, we get to reduce the total number of unique words in the dictionary. As a result, the number of columns in the document-word matrix (created by CountVectorizer in the next step) will be denser with lesser columns.

You can expect better topics to be generated in the end.

```
def lemmatization(texts, allowed_postags=['NOUN', 'ADJ', 'VERB', 'ADV']):
    """https://spacy.io/api/annotation"""
    texts_out = []
    for sent in texts:
        doc = nlp(" ".join(sent))
        texts_out.append(" ".join([token.lemma_ if token.lemma_ not in ['-PRON-'] else '' for toker
    return texts_out

# Initialize spacy 'en' model, keeping only tagger component (for efficiency)
# Run in terminal: python3 -m spacy download en
nlp = spacy.load('en', disable=['parser', 'ner'])

# Do lemmatization keeping only Noun, Adj, Verb, Adverb
data_lemmatized = lemmatization(data_words, allowed_postags=['NOUN', 'ADJ', 'VERB', 'ADV'])

print(data_lemmatized[:2])
```

```
['where s  thing subject what car be nntp post host rac wam umd edu organization university maryla
```

7. Create the Document-Word matrix

The LDA topic model algorithm requires a document word matrix as the main input.

You can create one using **CountVectorizer** . In the below code, I have configured the **CountVectorizer** to consider words that has occurred at least 10 times (**min_df**), remove built-in english stopwords, convert all words to lowercase, and a word can contain numbers and alphabets of at least length 3 in order to be qualified as a word.

So, to create the doc-word matrix, you need to first initialise the **CountVectorizer** class with the required configuration and then apply **fit_transform** to actually create the matrix.

Since most cells contain zeros, the result will be in the form of a sparse matrix to save memory.

If you want to materialize it in a 2D array format, call the **todense()** method of the sparse matrix like its done in the next step.

```
vectorizer = CountVectorizer(analyzer='word',
                             min_df=10,                        # minimum reqd occurences of a word
                             stop_words='english',             # remove stop words
                             lowercase=True,                   # convert all words to lowercase
                             token_pattern='[a-zA-Z0-9]{3,}',  # num chars > 3
                             # max_features=50000,             # max number of uniq words
                            )

data_vectorized = vectorizer.fit_transform(data_lemmatized)
```

8. Check the Sparsicity

Sparsicity is nothing but the percentage of non-zero datapoints in the document-word matrix, that is `data_vectorized` .

Since most cells in this matrix will be zero, I am interested in knowing what percentage of cells contain non-zero values.

```
# Materialize the sparse data
data_dense = data_vectorized.todense()

# Compute Sparsicity = Percentage of Non-Zero cells
print("Sparsicity: ", ((data_dense > 0).sum()/data_dense.size)*100, "%")
```

```
Sparsicity:  0.775887569365 %
```

9. Build LDA model with sklearn

Everything is ready to build a Latent Dirichlet Allocation (LDA) model. Let's initialise one and call `fit_transform()` to build the LDA model.

For this example, I have set the n_topics as 20 based on prior knowledge about the dataset. Later we will find the optimal number using grid search.

```
# Build LDA Model
lda_model = LatentDirichletAllocation(n_topics=20,               # Number of topics
                                      max_iter=10,               # Max learning iterations
                                      learning_method='online',
                                      random_state=100,          # Random state
                                      batch_size=128,            # n docs in each learning iter
                                      evaluate_every = -1,       # compute perplexity every n iters
                                      n_jobs = -1,               # Use all available CPUs
                                     )
lda_output = lda_model.fit_transform(data_vectorized)

print(lda_model)  # Model attributes
```

```
LatentDirichletAllocation(batch_size=128, doc_topic_prior=None,
             evaluate_every=-1, learning_decay=0.7,
             learning_method='online', learning_offset=10.0,
             max_doc_update_iter=100, max_iter=10, mean_change_tol=0.001,
             n_components=10, n_jobs=-1, n_topics=20, perp_tol=0.1,
             random_state=100, topic_word_prior=None,
             total_samples=1000000.0, verbose=0)
```

10. Diagnose model performance with perplexity and log-likelihood

A model with higher log-likelihood and lower perplexity (exp(-1. * log-likelihood per word)) is considered to be good. Let's check for our model.

```
# Log Likelyhood: Higher the better
print("Log Likelihood: ", lda_model.score(data_vectorized))

# Perplexity: Lower the better. Perplexity = exp(-1. * log-likelihood per word)
print("Perplexity: ", lda_model.perplexity(data_vectorized))

# See model parameters
pprint(lda_model.get_params())
```

```
 Log Likelihood:  -9965645.21463
Perplexity:  2061.88393838
{'batch_size': 128,
 'doc_topic_prior': None,
 'evaluate_every': -1,
 'learning_decay': 0.7,
 'learning_method': 'online',
 'learning_offset': 10.0,
 'max_doc_update_iter': 100,
 'max_iter': 10,
 'mean_change_tol': 0.001,
 'n_components': 10,
 'n_jobs': -1,
 'n_topics': 20,
 'perp_tol': 0.1,
 'random_state': 100,
 'topic_word_prior': None,
 'total_samples': 1000000.0,
 'verbose': 0}
```

On a different note, perplexity might not be the best measure to evaluate topic models because it doesn't consider the context and semantic associations between words. This can be captured using topic coherence measure, an example of this is described in the gensim tutorial I mentioned earlier.

11. How to GridSearch the best LDA model?

The most important tuning parameter for LDA models is **n_components** (number of topics). In addition, I am going to search **learning_decay** (which controls the learning rate) as well.

Besides these, other possible search params could be **learning_offset** (downweigh early iterations. Should be > 1) and **max_iter**. These could be worth experimenting if you have enough computing resources.

Be warned, the grid search constructs multiple LDA models for all possible combinations of param values in the param_grid dict. So, this process can consume a lot of time and resources.

```
# Define Search Param
search_params = {'n_components': [10, 15, 20, 25, 30], 'learning_decay': [.5, .7, .9]}

# Init the Model
lda = LatentDirichletAllocation()

# Init Grid Search Class
model = GridSearchCV(lda, param_grid=search_params)

# Do the Grid Search
model.fit(data_vectorized)
```

```
GridSearchCV(cv=None, error_score='raise',
       estimator=LatentDirichletAllocation(batch_size=128, doc_topic_prior=None,
             evaluate_every=-1, learning_decay=0.7, learning_method=None,
             learning_offset=10.0, max_doc_update_iter=100, max_iter=10,
             mean_change_tol=0.001, n_components=10, n_jobs=1,
             n_topics=None, perp_tol=0.1, random_state=None,
             topic_word_prior=None, total_samples=1000000.0, verbose=0),
       fit_params=None, iid=True, n_jobs=1,
       param_grid={'n_topics': [10, 15, 20, 25, 30], 'learning_decay': [0.5, 0.7, 0.9]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring=None, verbose=0)
```

12. How to see the best topic model and its parameters?

```
# Best
best_ld

# Model
print("

# Log L
print("

# Perpl
print("
```

```
Best Model's Params:  {'learning_decay': 0.9, 'n_topics': 10}
Best Log Likelyhood Score:  -3417650.82946
Model Perplexity:  2028.79038336
```

13. Compare LDA Model Performance Scores

Plotting the log-likelihood scores against num_topics, clearly shows number of topics = 10 has better scores. And `learning_decay` of 0.7 outperforms both 0.5 and 0.9.

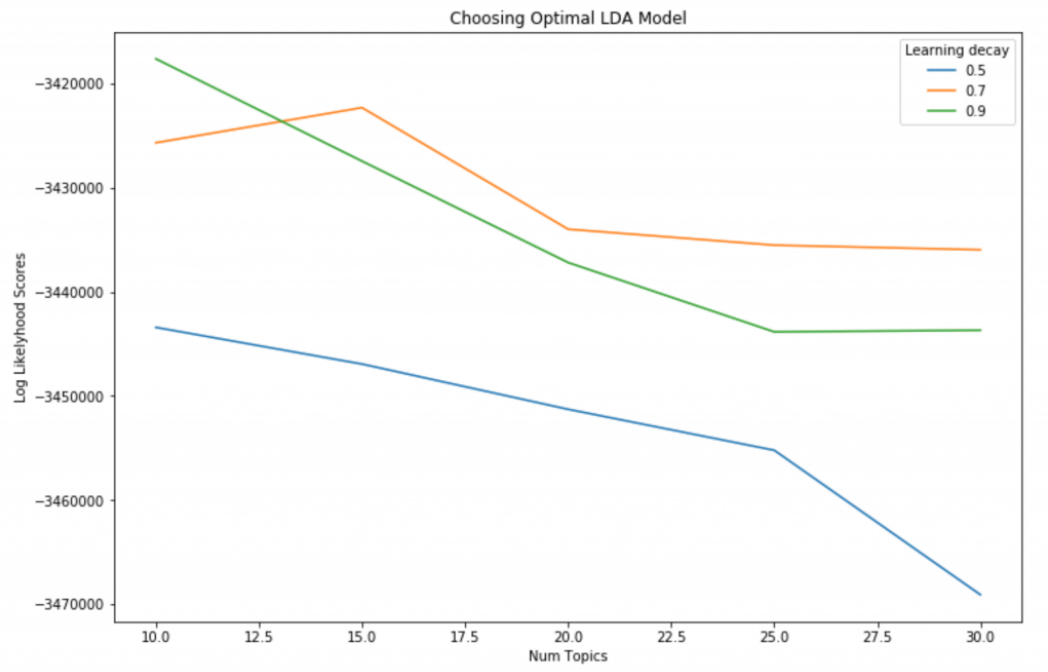
This makes me think, even though we know that the dataset has 20 distinct topics to start with, some topics could share common keywords. For example, 'alt.atheism' and 'soc.religion.christian' can have a lot of common words. Same with 'rec.motorcycles' and 'rec.autos', 'comp.sys.ibm.pc.hardware' and 'comp.sys.mac.hardware', you get the idea.

To tune this even further, you can do a finer grid search for number of topics between 10 and 15. But I am going to skip that for now.

So the bottom line is, a lower optimal number of distinct topics (even 10 topics) may be reasonable for this dataset. I don't know that yet. But LDA says so. Let's see.

```
# Get Log Likelyhoods from Grid Search Output
n_topics = [10, 15, 20, 25, 30]
log_likelyhoods_5 = [round(gscore.mean_validation_score) for gscore in model.grid_scores_ if gscore
log_likelyhoods_7 = [round(gscore.mean_validation_score) for gscore in model.grid_scores_ if gscore
log_likelyhoods_9 = [round(gscore.mean_validation_score) for gscore in model.grid_scores_ if gscore

# Show graph
plt.figure(figsize=(12, 8))
plt.plot(n_topics, log_likelyhoods_5, label='0.5')
plt.plot(n_topics, log_likelyhoods_7, label='0.7')
plt.plot(n_topics, log_likelyhoods_9, label='0.9')
plt.title("Choosing Optimal LDA Model")
plt.xlabel("Num Topics")
plt.ylabel("Log Likelyhood Scores")
plt.legend(title='Learning decay', loc='best')
plt.show()
```



Grid Search Topic Models

14. How to see the dominant topic in each document?

To classify a document as belonging to a particular topic, a logical approach is to see which topic has the highest contribution to that document and assign it.

In the table below, I've greened out all major topics in a document and assigned the most dominant topic in its own column.

```
 # Create Document - Topic Matrix
lda_output = best_lda_model.transform(data_vectorized)

# column names
topicnames = ["Topic" + str(i) for i in range(best_lda_model.n_topics)]

# index names
docnames = ["Doc" + str(i) for i in range(len(data))]

# Make the pandas dataframe
df_document_topic = pd.DataFrame(np.round(lda_output, 2), columns=topicnames, index=docnames)

# Get dominant topic for each document
dominant_topic = np.argmax(df_document_topic.values, axis=1)
df_document_topic['dominant_topic'] = dominant_topic

# Styling
def color_green(val):
    color = 'green' if val > .1 else 'black'
    return 'color: {col}'.format(col=color)

def make_bold(val):
    weight = 700 if val > .1 else 400
    return 'font-weight: {weight}'.format(weight=weight)

# Apply Style
df_document_topics = df_document_topic.head(15).style.applymap(color_green).applymap(make_bold)
df_document_topics
```

	Topic0	Topic1	Topic2	Topic3	Topic4	Topic5	Topic6	Topic7	Topic8	Topic9	dominant_topic
Doc0	0	0	0	0	0	0.14	0	0	0	0.84	9
Doc1	0	0.05	0	0	0.05	0.24	0	0.65	0	0	7
Doc2	0	0	0	0	0	0.08	0.2	0	0	0.71	9
Doc3	0	0.55	0	0	0	0.44	0	0	0	0	1
Doc4	0.16	0.29	0	0	0	0.53	0	0	0	0	5
Doc5	0	0	0.05	0	0	0	0	0.12	0	0.83	9
Doc6	0	0	0	0	0	0.88	0.1	0	0	0	5
Doc7	0	0	0	0	0	0.99	0	0	0	0	5
Doc8	0	0	0.08	0.67	0	0	0	0	0.24	0	3
Doc9	0	0	0.74	0	0	0.14	0	0	0.11	0	2
Doc10	0	0	0	0	0.41	0.16	0	0.06	0	0.36	4
Doc11	0	0	0	0	0	0	0	0.97	0	0	7
Doc12	0	0	0	0.44	0	0.04	0	0.27	0	0.24	3
Doc13	0.14	0	0	0	0	0.07	0.57	0.08	0	0.13	6
Doc14	0	0	0	0	0.78	0.22	0	0	0	0	4

Document Topic Weights: df_document_topics

15. Review topics distribution across documents

```
df_top
df_topi
df_topi
```

	Topic Num	Num Documents
0	5	2979
1	2	1516
2	4	1286
3	9	1252
4	1	1024
5	7	976
6	3	930
7	8	607
8	0	428
9	6	316

Topic Document Distribution: df_topic_distribution

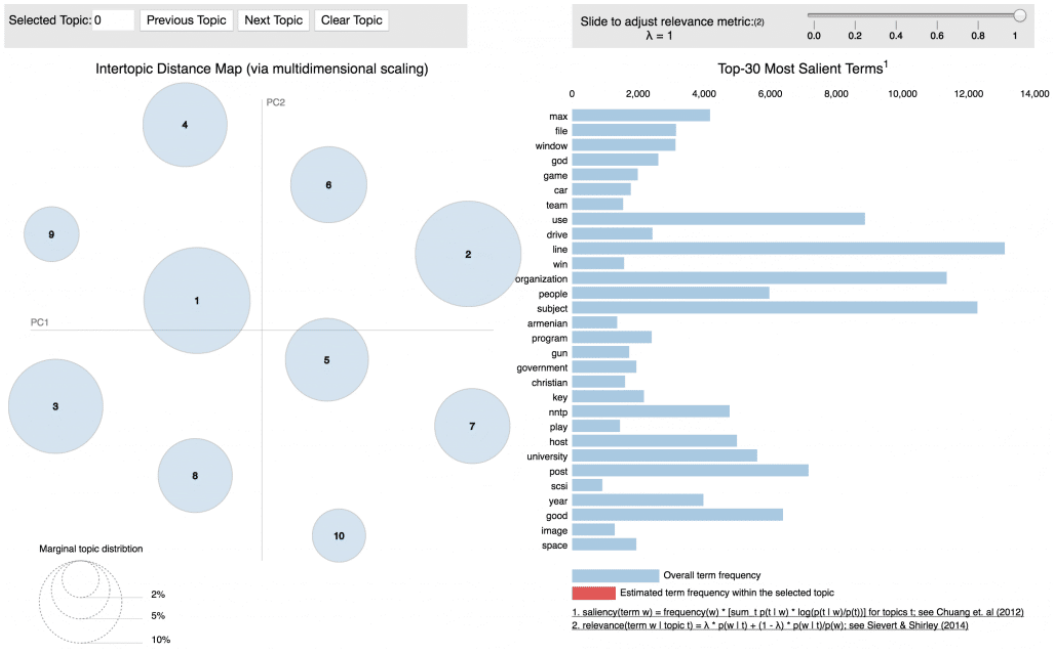
The

16. How to visualize the LDA model with pyLDAvis?

pyLDAvis offers the best visualization to view the topics-keywords distribution.

A good topic model will have non-overlapping, fairly big sized blobs for each topic. This seems to be the case here. So, we are good.

```
pyLDAvis.enable_notebook()
panel = pyLDAvis.sklearn.prepare(best_lda_model, data_vectorized, vectorizer, mds='tsne')
panel
```



Visualize Topic Distribution using pyLDAvis

17. How to see the Topic's keywords?

The weights of each keyword in each topic is contained in **lda_model.components_** as a 2d array. The names of the keywords itself can be obtained from **vectorizer** object using **get_feature_names()**.

Let's use this info to construct a weight matrix for all keywords in each topic.

```
# Topic-Keyword Matrix
df_topic_keywords = pd.DataFrame(best_lda_model.components_)

# Assign Column and Index
df_topic_keywords.columns = vectorizer.get_feature_names()
df_topic_keywords.index = topicnames

# View
df_topic_keywords.head()
```

	aaa	aaron	abandon	abbreviation	abc	abide	ability	able	abolish	abomination	...	zion	zionism	zionist	zip	zisfein	zone	zoology
Topic0	9.575406	0.359981	0.100651	0.101689	0.117518	0.103411	3.453262	0.191085	0.107853	0.101680	...	0.100883	0.100633	0.100840	0.104984	0.100637	0.138300	0.100731
Topic1	0.100890	0.105746	0.131275	1.755703	0.101024	0.100685	19.461132	120.830022	0.104326	0.100753	...	0.100750	0.100667	0.100638	153.218332	0.100576	0.101657	0.100688
Topic2	0.109275	18.638578	31.992522	0.109649	0.110307	0.109873	85.985221	163.572888	23.501138	2.393444	...	0.101008	0.100948	0.102842	0.299180	0.100691	0.303542	0.100890
Topic3	0.103078	0.179178	0.101424	0.106328	0.101892	0.134666	5.270624	65.015866	0.100779	0.102793	...	1.246157	0.100726	0.102040	0.103102	29.849950	0.249888	82.317755
Topic4	0.100805	0.101627	1.919950	0.409059	6.007337	75.657222	87.171712	198.055427	27.465725	0.210156	...	0.256475	0.121024	0.143113	16.549160	0.115601	2.433356	0.101339

Topic Word Weights: df_topic_keywords

18. Get the top 15 keywords each topic

From the above output, I want to see the top 15 keywords that are representative of the topic.

The `show_topics()` defined below creates that.

```
# Show top n keywords for each topic
def show_topics(vectorizer=vectorizer, lda_model=lda_model, n_words=20):
    keywords = np.array(vectorizer.get_feature_names())
    topic_keywords = []
    for topic_weights in lda_model.components_:
        top_keyword_locs = (-topic_weights).argsort()[:n_words]
        topic_keywords.append(keywords.take(top_keyword_locs))
    return topic_keywords

topic_keywords = show_topics(vectorizer=vectorizer, lda_model=best_lda_model, n_words=15)

# Topic - Keywords Dataframe
df_topic_keywords = pd.DataFrame(topic_keywords)
df_topic_keywords.columns = ['Word '+str(i) for i in range(df_topic_keywords.shape[1])]
df_topic_keywords.index = ['Topic '+str(i) for i in range(df_topic_keywords.shape[0])]
df_topic_keywords
```

	Word 0	Word 1	Word 2	Word 3	Word 4	Word 5	Word 6	Word 7	Word 8	Word 9	Word 10	Word 11	Word 12	Word 13	Word 14
Topic 0	game	team	win	play	year	line	organization	subject	league	season	fan	new	san	baseball	red
Topic 1	file	window	use	program	image	run	version	line	available	server	ftp	set	user	software	display
Topic 2	say	god	people	write	think	know	believe	christian	make	subject	line	good	just	organization	thing
Topic 3	people	gun	say	article	write	just	know	time	make	think	organization	line	subject	child	year
Topic 4	key	use	space	government	make	law	line	organization	write	subject	public	people	encryption	year	know
Topic 5	line	subject	organization	post	university	host	nntp	edu	thank	write	computer	article	know	use	distribution
Topic 6	max	use	bit	line	subject	wire	chip	bhj	organization	giz	power	signal	high	circuit	cable
Topic 7	drive	good	write	line	think	organization	subject	article	scsi	year	time	make	game	play	just
Topic 8	armenian	right	people	state	government	turkish	war	write	israeli	say	israel	article	arab	muslim	subject
Topic 9	car	write	line	article	subject	organization	good	just	post	bike	nntp	host	look	think	dod

Top 15 topic keywords

19. How to predict the topics for a new piece of text?

Assuming that you have already built the topic model, you need to take the text through the same routine of transformations and before predicting the topic.

For our case, the order of transformations is:

`sent_to_words()` –> `lemmatization()` –> `vectorizer.transform()` –> `best_lda_model.transform()`

You need to apply these transformations in the same order. So to simplify it, let's combine these steps into a `predict_topic()` function.

```
# Define function to predict topic for a given text document.
nlp = spacy.load('en', disable=['parser', 'ner'])

def predict_topic(text, nlp=nlp):
    global sent_to_words
    global lemmatization

    # Step 1: Clean with simple_preprocess
    mytext_2 = list(sent_to_words(text))

    # Step 2: Lemmatize
    mytext_3 = lemmatization(mytext_2, allowed_postags=['NOUN', 'ADJ', 'VERB', 'ADV'])

    # Step 3: Vectorize transform
    mytext_4 = vectorizer.transform(mytext_3)

    # Step 4: LDA Transform
    topic_probability_scores = best_lda_model.transform(mytext_4)
    topic = df_topic_keywords.iloc[np.argmax(topic_probability_scores), :].values.tolist()
    return topic, topic_probability_scores

# Predict the topic
mytext = ["Some text about christianity and bible"]
topic, prob_scores = predict_topic(text = mytext)
print(topic)
```

```
['say', 'god', 'people', 'write', 'think', 'know', 'believe', 'christian', 'make', 'subject', 'lin
```

`mytext` has been allocated to the topic that has religion and Christianity related keywords, which is quite meaningful and makes sense.

20. How to cluster documents that share similar topics and plot?

You can use k-means clustering on the document-topic probabilioty matrix, which is nothing but `lda_output` object. Since out best model has 15 clusters, I've set `n_clusters=15` in `KMeans()`.

Alternately, you could avoid k-means and instead, assign the cluster as the topic column number with the highest probability score.

We now have the cluster number. But we also need the X and Y columns to draw the plot.

For the X and Y, you can use SVD on the `lda_output` object with `n_components` as 2. SVD ensures that these two columns captures the maximum possible amount of information from `lda_output` in the first 2 components.

```
# Construct the k-means clusters
from sklearn.cluster import KMeans
clusters = KMeans(n_clusters=15, random_state=100).fit_predict(lda_output)

# Build the Singular Value Decomposition(SVD) model
svd_model = TruncatedSVD(n_components=2)  # 2 components
lda_output_svd = svd_model.fit_transform(lda_output)

# X and Y axes of the plot using SVD decomposition
x = lda_output_svd[:, 0]
y = lda_output_svd[:, 1]

# Weights for the 15 columns of lda_output, for each component
print("Component's weights: \n", np.round(svd_model.components_, 2))

# Percentage of total information in 'lda_output' explained by the two components
print("Perc of Variance Explained: \n", np.round(svd_model.explained_variance_ratio_, 2))
```

```
Component's weights:
 [[ 0.08  0.23  0.24  0.14  0.2   0.85  0.09  0.19  0.07  0.2 ]
 [ 0.02 -0.1   0.9   0.16  0.16 -0.32 -0.01 -0.01  0.13  0.09]]
Perc of Variance Explained:
 [ 0.09  0.21]
```

We have the X, Y and the cluster number for each document.

Let's plot the document along the two SVD decomposed components. The color of points represents the cluster number (in this case) or topic number.