PS5_AndrewYu

July 29, 2023

[1]:
```
from google.colab import drive

drive.mount('/content/drive')
FOLDERNAME = "Stanford Summer Session/SOC 128D"

#Packages for working with data
# !pip install "modin[dask]"
# import modin.pandas as pd
import pandas as pd
import matplotlib.pyplot as mplt
import seaborn as sb
import plotnine as pn
import numpy as np

mplt.style.use("ggplot")
```

```
Mounted at /content/drive
```

1. Run a topic model with 4 topics on the "guardian_co_river.csv" dataset.

[15]:
```
import json
import nltk
nltk.download('stopwords')
from nltk.corpus import stopwords
from nltk import word_tokenize
nltk.download('punkt')
from string import punctuation
from sklearn.feature_extraction.text import CountVectorizer
import regex as re
from nltk import pos_tag
nltk.download('averaged_perceptron_tagger')
from nltk.stem import WordNetLemmatizer
nltk.download('wordnet')

with open("stopwords_extra.json", "r") as file: stopwords_extra = set(json.
↪load(file))
stopwords_nltk = set(stopwords.words('english'))
punctuation += "–— ‘’‚“”„†‡•…‰ <> / "
```

```python
stopwords_punct = set(punctuation)
combined_stoplist = list(set.union(stopwords_extra, stopwords_nltk, stopwords_punct))

# I used the dataset with 18548 articles, for practice working with bigger datasets
df = pd.read_csv(f"drive/My Drive/{FOLDERNAME}/data/guardian_co_river.csv").dropna(subset=["body_text"])
# Unicode Categories C (Control), M (Mark), P (Punctuation), S (Symbol), Z (Separator) + emojis
df["body_text"] = df["body_text"].apply(lambda x: re.compile(r'[\p{C}|\p{M}|\p{P}|\p{S}|\p{Z}]+', re.UNICODE).sub(" ", x).strip())

# Lemmatization
def get_POS_tags(pos_tag):
  POS_tag = {'NN':'n', 'JJ':'a', 'VB':'v', 'RB':'r'}
  try:
    # Getting first 2 letters of pos_tag
    return POS_tag[pos_tag[:2]]
  except:
    # Fallback to noun (Default)
    return 'n'

# In doing this, token_pattern parameter in CountVectorizer won't work, so just add any patterns here
class LemmaTokenizer(object):
    def __init__(self):
        self.wnl = WordNetLemmatizer()
    def __call__(self, docs):
        return [self.wnl.lemmatize(word, pos=get_POS_tags(tag)) for word, tag in pos_tag(word_tokenize(docs)) if not re.search("\d+", word)]

# This python library automatically integrates anti-joining stopwords and takes in corpus as list of texts, converting into list of words via word_tokenize, to output DTM. Thus unnest_tokens not used
tf_vectorizer = CountVectorizer(stop_words=combined_stoplist, tokenizer=LemmaTokenizer(), strip_accents=None)
# tf is in the form (doc, word): freq
tf = tf_vectorizer.fit_transform(df["body_text"])

print(f"No. of words per topic: {len(tf_vectorizer.get_feature_names_out())}")
pd.DataFrame({"word": tf_vectorizer.get_feature_names_out()})
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data…
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to /root/nltk_data…
[nltk_data]   Package punkt is already up-to-date!
```

```
[nltk_data] Downloading package averaged_perceptron_tagger to
[nltk_data]     /root/nltk_data…
[nltk_data]   Package averaged_perceptron_tagger is already up-to-
[nltk_data]       date!
[nltk_data] Downloading package wordnet to /root/nltk_data…
[nltk_data]   Package wordnet is already up-to-date!
<ipython-input-15-ee2e12927e35>:22: DtypeWarning: Columns
(19,29,34,37,40,42,43,44,46,47,48) have mixed types. Specify dtype option on
import or set low_memory=False.
/usr/local/lib/python3.10/dist-packages/sklearn/feature_extraction/text.py:528:
UserWarning: The parameter 'token_pattern' will not be used since 'tokenizer' is
not None'
/usr/local/lib/python3.10/dist-packages/sklearn/feature_extraction/text.py:409:
UserWarning: Your stop_words may be inconsistent with your preprocessing.
Tokenizing the stop words generated tokens ["'d", "'ll", "'m", "'re", "'s",
"'ve", '``', 'accord', 'ai', 'associate', 'ca', 'change', 'concern',
'correspond', 'follow', 'give', 'greeting', 'ignore', "n't", 'place', 'provide',
'regard', 'sha', 'wo'] not in stop_words.
```

```
No. of words per topic: 157463
```

[15]:

```
                                                      word
0                                                       aa
1                                                      aaa
2                                            aaaaaaaaaaaaa
3        aaaaaaaaaaarghhhheeeeiiiiiiiiuhhhhhhhhhhbyyyy…
4                                               aaaaaargh
…                                                      …
157458                                               ction
157459                                                 nal
157460                                               nding
157461                                                  re
157462                                                 rst

[157463 rows x 1 columns]
```

[17]:

```python
def get_model_topics(model, vectorizer, topics, n_top_words=10, detailed=False):
  word_dict = {}
  words = vectorizer.get_feature_names_out()
  if detailed:
    for topic_i, topic_freq in enumerate(model.components_):
      # Sorting indexes of words by top frequent topics
      top_freq_words_i = topic_freq.argsort()[:-n_top_words - 1:-1]
      # {topic: [(word, word_p), ...]}
      word_dict[topics[topic_i]] = [(words[i], topic_freq[i]/len(topic_freq))␣
↪for i in top_freq_words_i]
    return pd.DataFrame([(topic, word, freq) for topic, words in word_dict.
↪items() for word, freq in words], columns=["Topic", "Word", "Probability"])
```

```python
  else:
    for topic_i, topic_freq in enumerate(model.components_):
      top_freq_words_i = topic_freq.argsort()[:-n_top_words - 1:-1]
      # {topic: [word, ...]}
      word_dict[topics[topic_i]] = [words[i] for i in top_freq_words_i]
    return pd.DataFrame(word_dict)


from sklearn.decomposition import LatentDirichletAllocation as LDA
lda4 = LDA(n_components=4, random_state=1)
# probability of each (4) topic per (17982) document
topic_per_document = lda4.fit_transform(tf)
# Frequency of each (157463) word-term per (4) topic
word_per_topic = lda4.components_

# Log Likelihood:  Less negative
print("Log Likelihood: ", lda4.score(tf))

# Perplexity: exp(-1 * log likelihood),  Lower
print("Perplexity: ", lda4.perplexity(tf))

topics_words_df4 = get_model_topics(lda4, tf_vectorizer, ["Topic 1", "Topic 2",␣
↪"Topic 3", "Topic 4"])
topics_words_df4
```

```
Log Likelihood:  -86926244.37087119
Perplexity:  5463.206371294159
```

[17]:

	Topic 1	Topic 2	Topic 3	Topic 4
0	people	trump	year	year
1	water	state	make	day
2	year	republican	people	city
3	government	president	time	river
4	state	win	work	time
5	report	vote	life	world
6	country	make	river	park
7	river	year	find	make
8	case	time	child	run
9	make	election	film	back

2. Plot the top words for each topic, similar to what is done in section 5.2. What would you label these topics?

[104]:
```python
topics_words_df4 = get_model_topics(lda4, tf_vectorizer, ["Topic 1", "Topic 2",␣
↪"Topic 3", "Topic 4"], detailed=True)
topics_words_df4
```

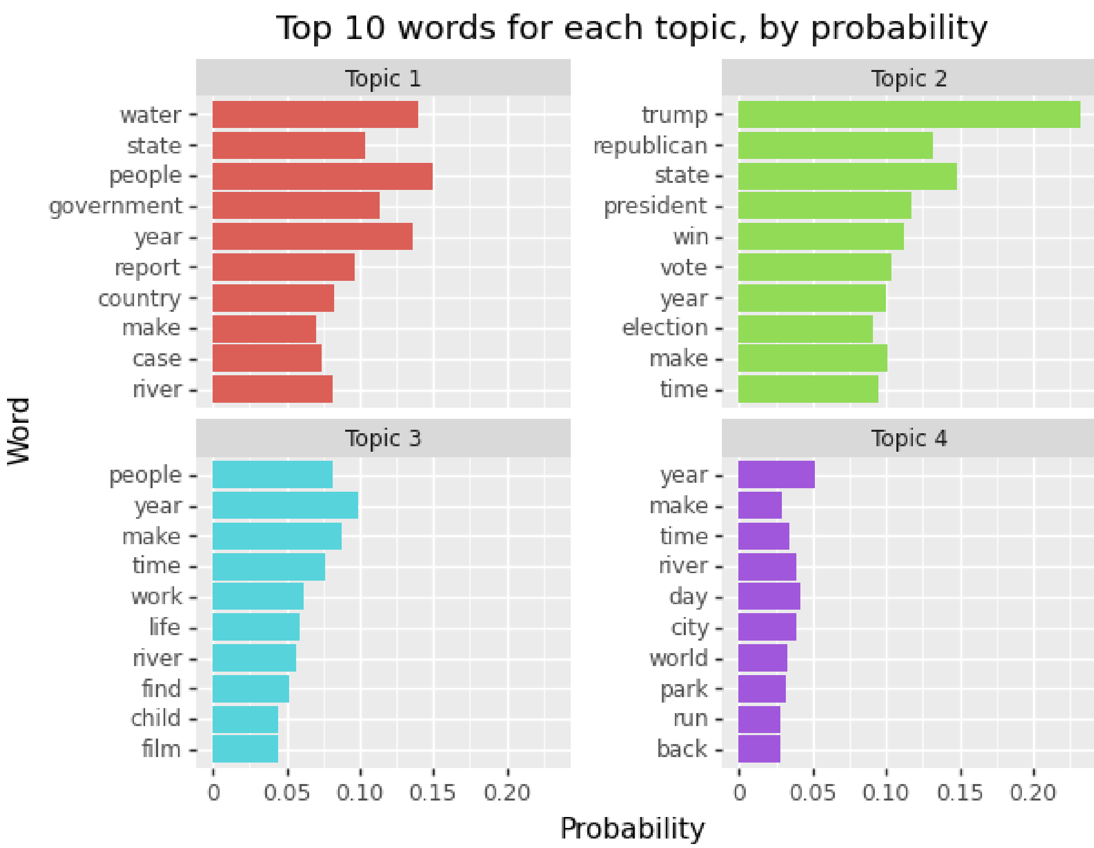
[104]:

	Topic	Word	Probability
0	Topic 1	people	0.150188
1	Topic 1	water	0.139437
2	Topic 1	year	0.135564
3	Topic 1	government	0.113529
4	Topic 1	state	0.104199
5	Topic 1	report	0.096412
6	Topic 1	country	0.082658
7	Topic 1	river	0.081916
8	Topic 1	case	0.074222
9	Topic 1	make	0.070491
10	Topic 2	trump	0.232615
11	Topic 2	state	0.147654
12	Topic 2	republican	0.132483
13	Topic 2	president	0.117492
14	Topic 2	win	0.112478
15	Topic 2	vote	0.102859
16	Topic 2	make	0.101298
17	Topic 2	year	0.099786
18	Topic 2	time	0.095326
19	Topic 2	election	0.091645
20	Topic 3	year	0.098372
21	Topic 3	make	0.087154
22	Topic 3	people	0.081191
23	Topic 3	time	0.076403
24	Topic 3	work	0.061427
25	Topic 3	life	0.059303
26	Topic 3	river	0.057298
27	Topic 3	find	0.051575
28	Topic 3	child	0.044530
29	Topic 3	film	0.044246
30	Topic 4	year	0.051727
31	Topic 4	day	0.041634
32	Topic 4	city	0.039051
33	Topic 4	river	0.038604
34	Topic 4	time	0.033675
35	Topic 4	world	0.033473
36	Topic 4	park	0.031982
37	Topic 4	make	0.028890
38	Topic 4	run	0.028120
39	Topic 4	back	0.027374

[105]:

```
# I've tried searching but I'm not sure why the sorting is not working, df is␣
↪sorted, and x is also reordered within
plot = (pn.ggplot(topics_words_df4, pn.aes(x='reorder(Word, Probability)',␣
↪y='Probability', fill='Topic')) +
        pn.geom_col(show_legend=False) +
```

```
        pn.coord_flip() +
        pn.facet_wrap('Topic', scales = "free_y") +
        pn.theme(subplots_adjust={'wspace': 0.4}) +
        pn.labs(title="Top 10 words for each topic, by probability", x="Word",␣
 ↪y="Probability")
        )

print(plot)
```



They are words are not very distinct, due to choice of number of topics, but I would label them

Topic 1: Government

Topic 2: Politics

Topic 3: Work

Topic 4: Time

3. Try running the LDA again, this time with a different number of topics. Does the new topic model make more or less sense to you?

[ ]:
```python
from sklearn.model_selection import GridSearchCV

lda = LDA()
model = GridSearchCV(lda, param_grid={'n_components': [2, 4, 6, 8, 10]})
model.fit(tf)

print("Best Model's Params: ", model.best_params_)
print("Best Log Likelihood Score: ", model.best_score_)
print("Model Perplexity: ", model.best_estimator_.perplexity(tf))
```

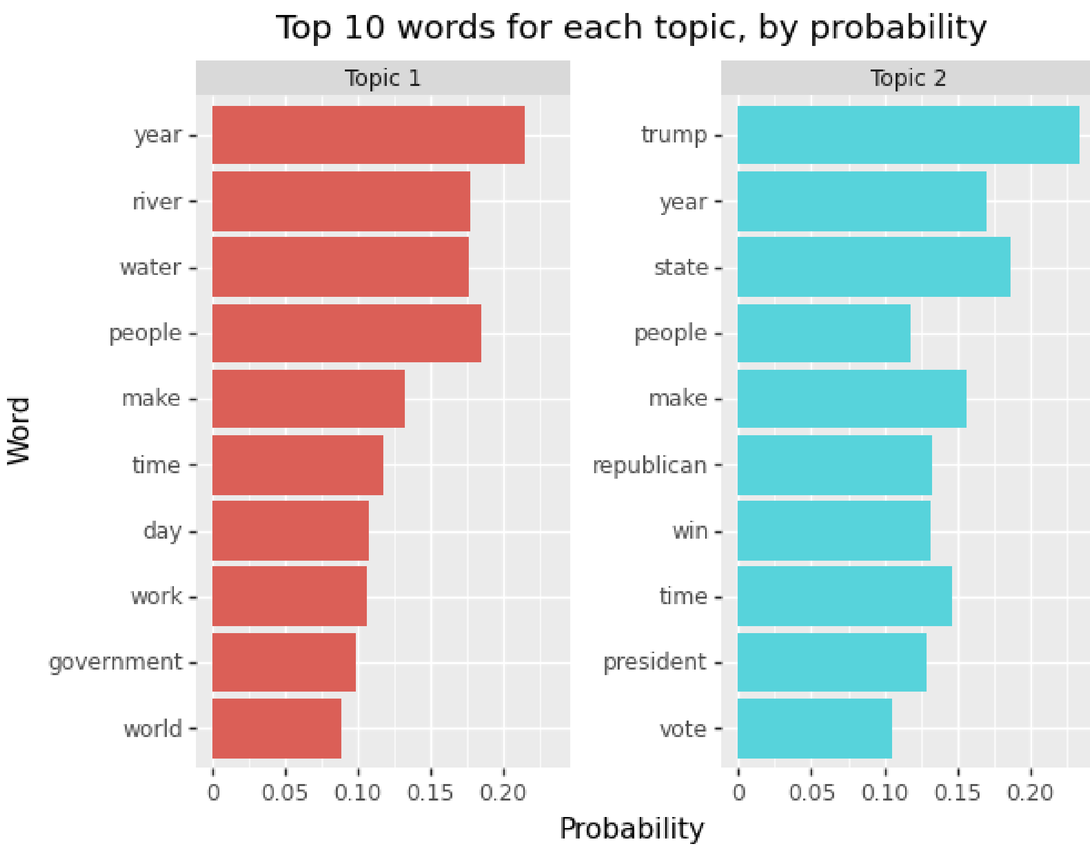
```
Best Model's Params:  {'n_components': 2}
Best Log Likelihood Score:  -20246738.786500275
Model Perplexity:  9943.179337936572
```

[19]:
```python
lda2 = LDA(n_components=2, random_state=1)
_ = lda2.fit_transform(tf)

topics_words_df2 = get_model_topics(lda2, tf_vectorizer, ["Topic 1", "Topic 2"])
topics_words_df2
```

[19]:

	Topic 1	Topic 2
0	year	trump
1	people	state
2	river	year
3	water	make
4	make	time
5	time	republican
6	day	win
7	work	president
8	government	people
9	world	vote

[107]:
```python
topics_words_df2 = get_model_topics(lda2, tf_vectorizer, ["Topic 1", "Topic␣
↪2"], detailed=True)
plot = (pn.ggplot(topics_words_df2, pn.aes(x='reorder(Word, Probability)',␣
↪y='Probability', fill='Topic')) +
        pn.geom_col(show_legend=False) +
        pn.coord_flip() +
        pn.facet_wrap('Topic', scales = "free_y") +
        pn.theme(subplots_adjust={'wspace': 0.4}) +
        pn.labs(title="Top 10 words for each topic, by probability", x="Word",␣
↪y="Probability")
        )

print(plot)
```



My intuition was 2 topics (based on the in-class materials), but I also wanted to test the optimal number using the GridSearch, which confirmed my intuition.

As evident, 2 topics summarises all the documents more clearly and sensibly, with Topic 1 being about rivers and Topic 2 being more political

4. Using whichever topic model made the most sense to you, create a dataset similar to co_documents in section 5.3. Choose two articles to examine in more detail. Discuss the topic probabilities.

[123]:
```
def get_model_docs(model, dtm, detailed=False):
    topic_dict = {}
    doc_topic = model.transform(dtm)
    if detailed:
      for doc_i, topic_probs_of_doc in enumerate(doc_topic):
        num_topics = doc_topic.shape[1]
        # Sorting topics by top probabilities
        top_probable_topics = topic_probs_of_doc.argsort()[:-num_topics - 1:-1]
        topic_dict[f"Doc {doc_i}"] = [(topic+1, topic_probs_of_doc[topic]) for␣
↪topic in top_probable_topics]
```

```
        df = pd.DataFrame([(doc, topic, prob) for doc, topics_probs in topic_dict.
 ↪items() for topic, prob in topics_probs], columns=["Document", "Topic",␣
 ↪"Probability"])
        # Chaining doesn't work for some reason
        df['Dominant_topic'] = df[df.index % num_topics == 0]["Topic"]
        df['Dominant_topic'] = df['Dominant_topic'].fillna(method='ffill')
        df['Dominant_topic'] = df['Dominant_topic'].astype(int)
        return df

    else:
      for doc_i, topic_probs_of_doc in enumerate(doc_topic):
        num_topics = doc_topic.shape[1]
        top_probable_topics = topic_probs_of_doc.argsort()[:-num_topics - 1:-1]
        topic_dict[f"Doc {doc_i}"] = [topic for topic in top_probable_topics]
    return pd.DataFrame(topic_dict)

docs_topics_df = get_model_docs(lda2, tf, detailed=True)
docs_topics_df
# Probabilities of each topic add up to 1, which confirms this is simlar to␣
 ↪co_documents (gamma)
```

[123]:

```
         Document  Topic  Probability  Dominant_topic
0           Doc 0      1     0.645597               1
1           Doc 0      2     0.354403               1
2           Doc 1      1     0.999263               1
3           Doc 1      2     0.000737               1
4           Doc 2      1     0.921166               1
…               …    …           …               …
35959   Doc 17979      2     0.004749               1
35960   Doc 17980      2     0.987856               2
35961   Doc 17980      1     0.012144               2
35962   Doc 17981      1     0.952474               1
35963   Doc 17981      2     0.047526               1

[35964 rows x 4 columns]
```

[125]:

```
# To find a topic that has a very fair probability of belonging to either Topic
docs_topics_df[docs_topics_df["Probability"].between(0.45, 0.65)]
# I chose        Doc 17975
```

[125]:

```
         Document  Topic  Probability  Dominant_topic
0           Doc 0      1     0.645597               1
18          Doc 9      1     0.593177               1
48         Doc 24      1     0.539227               1
49         Doc 24      2     0.460773               1
56         Doc 28      2     0.571738               2
…               …    …           …               …
```

```
35902  Doc 17951      2     0.586099                2
35938  Doc 17969      2     0.555969                2
35946  Doc 17973      1     0.635390                1
35950  Doc 17975      2     0.506625                2
35951  Doc 17975      1     0.493375                2

[2900 rows x 4 columns]
```

[124]:
```python
chosen_docs_df = docs_topics_df[docs_topics_df["Document"].isin(["Doc 1", "Doc␣
↪17975", "Doc 17980"])]
chosen_docs_df
```

[124]:
```
         Document  Topic  Probability  Dominant_topic
2           Doc 1      1     0.999263               1
3           Doc 1      2     0.000737               1
35950  Doc 17975      2     0.506625               2
35951  Doc 17975      1     0.493375               2
35960  Doc 17980      2     0.987856               2
35961  Doc 17980      1     0.012144               2
```

The probabilities show that

- Doc 1 is extremely likely to be Topic 1 (Rivers)
- Doc 17975 is quite on the fence, but ultimately leans towards Topic 2 (Politics)
- Doc 17980 is extremely likely to be Topic 2 (Politics)

5. Considering what we know about the Colorado River and water rights in the U.S. (from readings and class), are we surprised by the topics generated by these news articles? Describe how your results compared to expectations.

[131]:
```python
for index, row in df.iloc[[1, 17975, 17980], df.columns.
↪get_indexer(['web_title', 'web_url'])].iterrows():
    print(f"Title: {row['web_title']}, URL:{row['web_url']}\n")
```

```
Title: The farmers dealing with water shortages even before historic Colorado
River deal, URL:https://www.theguardian.com/global/2023/may/31/arizona-farmers-
water-colorado-river-cuts

Title: Paraguayan dictator toppled in family coup,
URL:https://www.theguardian.com/theguardian/1989/feb/04/fromthearchive

Title: The American Presidency,
URL:https://www.theguardian.com/world/1912/nov/07/usa.fromthearchive
```

Upon reading the articles, the most probable topics mostly makes sense, as also suggested by the title of the article.

Doc 1 discusses the lives of the farmers near the Colorado River, which checks out with it being assigned Topic 1 (Rivers)

Doc 17975 discusses the the events surrounding the political party in Colorado, and has litle to nothing to do with the Colorado River, yet is assigned such a fair probability, which is confusing. This could be because even Topic 1 itself isn't such a clearly defined "Rivers" topic - there are also quite a lot of political terms. What is the true differentiating factor between Topic 1 and 2 is that 2 is more specific ("trump", "republican", "president"). However, the model did predict correctly that this article is more likely Topic 2 than 1 anyway.

Doc 17980 discusses mostly the American Presidency which checks out with it being assigned Topic 2 (Politics)

Doc 1, which talks the most regarding the Colorado River situation, aligns with what we learnt from the readings - Arizona is fighting for its rights to usage of the water from the river, with California and Nevada, aligning with the reading - The farmers were already struggling with water, in growing the most profitable and marketable commodity crops - alfalfa and cotton. This aligns with the reading that agriculture sucks up 79% of all water usage from the river.

[ ]:
```
# If it contains spaces, use '\ ' to represent each space E.g. 'Summer\ PSet\ 1.
↪ipynb'
FILENAME = "PS5_AndrewYu.ipynb"

%cd drive/My\ Drive
%cd $FOLDERNAME
!sudo apt-get install texlive-xetex texlive-fonts-recommended␣
↪texlive-plain-generic
!pip install PyPDF2

!jupyter nbconvert --log-level CRITICAL --to pdf $FILENAME
```

```
/content/drive/My Drive
/content/drive/My Drive/Stanford Summer Session/SOC 128D
Reading package lists… Done
Building dependency tree… Done
Reading state information… Done
The following additional packages will be installed:
  dvisvgm fonts-droid-fallback fonts-lato fonts-lmodern fonts-noto-mono
  fonts-texgyre fonts-urw-base35 libapache-pom-java libcommons-logging-java
  libcommons-parent-java libfontbox-java libfontenc1 libgs9 libgs9-common
  libidn12 libijs-0.35 libjbig2dec0 libkpathsea6 libpdfbox-java libptexenc1
  libruby3.0 libsynctex2 libteckit0 libtexlua53 libtexluajit2 libwoff1
  libzzip-0-13 lmodern poppler-data preview-latex-style rake ruby
  ruby-net-telnet ruby-rubygems ruby-webrick ruby-xmlrpc ruby3.0
  rubygems-integration t1utils teckit tex-common tex-gyre texlive-base
  texlive-binaries texlive-latex-base texlive-latex-extra
  texlive-latex-recommended texlive-pictures tipa xfonts-encodings
  xfonts-utils
Suggested packages:
  fonts-noto fonts-freefont-otf | fonts-freefont-ttf libavalon-framework-java
  libcommons-logging-java-doc libexcalibur-logkit-java liblog4j1.2-java
  poppler-utils ghostscript fonts-japanese-mincho | fonts-ipafont-mincho
```