```
from google.colab import drive
drive.mount('/content/drive')
```

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

Assignment 1 for FIT5212, Semester 1, 2021

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Load packages

```
import nltk
import time
import torch
import random
!pip install pyLDAvis==2.1.2
import nltk
from gensim.corpora import Dictionary
import spacy
from gensim.models import LdaModel
from spacy.lang.en import English
import pyLDAvis.gensim
from nltk.stem.wordnet import WordNetLemmatizer
from gensim.models import Phrases
import torch.nn as nn
import torch.optim as optim
import matplotlib.pyplot as plt
import pandas as pd
nltk.download('stopwords')
random.seed(222)
nltk.download('wordnet')
from torchtext.legacy import data
from sklearn.linear_model import LogisticRegression
from sklearn.feature_extraction.text import TfidfVectorizer
from torchtext.legacy.data import TabularDataset
from nltk.stem import SnowballStemmer
stemmer = SnowballStemmer("english")
from sklearn.model_selection import cross_val_score
from nltk.stem import WordNetLemmatizer
from nltk import word_tokenize
from nltk.tokenize import RegexpTokenizer
from nltk.corpus import stopwords
import warnings
warnings.filterwarnings('ignore')
from sklearn.metrics import plot_precision_recall_curve, average_precision_score, p
import numpy as np
```

```
Requirement already satisfied: pyLDAvis==2.1.2 in /usr/local/lib/python3.7/di
Requirement already satisfied: joblib>=0.8.4 in /usr/local/lib/python3.7/dist
Requirement already satisfied: scipy>=0.18.0 in /usr/local/lib/python3.7/dist
Requirement already satisfied: numexpr in /usr/local/lib/python3.7/dist-packa
Requirement already satisfied: future in /usr/local/lib/python3.7/dist-packag
Requirement already satisfied: numpy>=1.9.2 in /usr/local/lib/python3.7/dist-
Requirement already satisfied: jinja2>=2.7.2 in /usr/local/lib/python3.7/dist
Requirement already satisfied: funcy in /usr/local/lib/python3.7/dist-package
Requirement already satisfied: wheel>=0.23.0 in /usr/local/lib/python3.7/dist
Requirement already satisfied: pandas>=0.17.0 in /usr/local/lib/python3.7/dis
Requirement already satisfied: pytest in /usr/local/lib/python3.7/dist-packag
Requirement already satisfied: MarkupSafe>=0.23 in /usr/local/lib/python3.7/d
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.7/dist-
Requirement already satisfied: python-dateutil>=2.7.3 in /usr/local/lib/pytho
Requirement already satisfied: more-itertools>=4.0.0 in /usr/local/lib/python
Requirement already satisfied: pluggy<0.8,>=0.5 in /usr/local/lib/python3.7/d
Requirement already satisfied: py>=1.5.0 in /usr/local/lib/python3.7/dist-pac
Requirement already satisfied: atomicwrites>=1.0 in /usr/local/lib/python3.7/
Requirement already satisfied: attrs>=17.4.0 in /usr/local/lib/python3.7/dist
Requirement already satisfied: setuptools in /usr/local/lib/python3.7/dist-pa
Requirement already satisfied: six>=1.10.0 in /usr/local/lib/python3.7/dist-p
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
```

Part 1: Text Classification

General comments and any shared processing here.

Timer

```
def epoch_time(start_time, end_time):
    elapsed_time = end_time - start_time
    elapsed_mins = int(elapsed_time / 60)
    elapsed_secs = int(elapsed_time - (elapsed_mins * 60))
    return elapsed_mins, elapsed_secs
```

Accuracy calculation

```
def binary_accuracy(preds, y):
    """
    Returns accuracy per batch, i.e. if you get 8/10 right, this returns 0.8, NOT 8
    """
    #round predictions to the closest integer
    rounded_preds = torch.round(torch.sigmoid(preds))
    correct = (rounded_preds == y).float() #convert into float for division
    acc = correct.sum() / len(correct)
    return acc
```

2 types of text preprocessing

1: [to lower, remove numbers, remove stop words, stemming]

For Stemming I use the SnowballStemmer from from nltk.stem.

2: [to lower, remove numbers, remove stop words, lemmatisation, remove rare tokens]

For lammatising, I use the WordNetLemmatizer.

```
def prep1(text):
    # get only word in the text, this step can remove number
    tokenizer = RegexpTokenizer(r'\w+')
    # get the stop words list for english
    stopwords_list = stopwords.words('english')
    tokens = tokenizer.tokenize(text.lower())
    # remove stop word
    rm_stop = [w for w in tokens if w not in stopwords_list]
    # stemming
    stem = [stemmer.stem(w) for w in rm_stop]
    return stem


def prep2(text):
    Lemmatizer = WordNetLemmatizer()
    # get only word in the text, this step can remove number
    tokenizer = RegexpTokenizer(r'\w+')
    stopwords_list = stopwords.words('english')
    #tokenizer.tokenize('Eighty-seven miles to go, yet.  Onward!')
    tokens = tokenizer.tokenize(text.lower())
    # remove those words which word length < 3
    rm_rare_token = [w for w in tokens if len(w) > 3]
    # remove stop word
    rm_stop = [w for w in rm_rare_token if w not in stopwords_list]
    # lemmatizing
    Lemma = [Lemmatizer.lemmatize(w) for w in rm_stop]
    return Lemma
```

Prepare data

Separate the first 1000 row from trainning set, and write to a new .csv file.

```
# read
train_1000 = pd.read_csv('axcs_train.csv')
# write
train_1000[:1000].to_csv('train1000.csv', index=False)
```

Print result

```
def print_result(train_acc, accuracy, precision, recall, f1score, attr):
  print('--------------------------------------------------------------------------------
  print('The Train Accuracy of ' + attr + f' is : {train_acc*100:.2f}%')
```

```
    print('The Test Accuracy of ' + attr + f' is : {accuracy*100:.2f}%')
    print('The Macro Precision of ' + attr + ' is: '+ str(precision))
    print('The Macro Recall of ' + attr + ' is : '+ str(recall))
    print('The Macro F1 score of ' + attr + ' is :'+ str(f1score))
    print('-----------------------------------------------------------------------
    return None
```

Part 1A: Statistical Method

Logistical regression model

Load data

```
# Load the dataset into a pandas dataframe.
def read_data(traindata):
  names = ['Abstract', 'InfoTheory', 'CompVis', 'Math']
  df_train = pd.read_csv(traindata)
  df_test = pd.read_csv('axcs_test.csv')
  # get the useful info
  train_data = df_train[names]
  test_data =  df_test[names]
  return train_data, test_data
```

process data

```
def process_data(df_train, df_test, attr, prep):
  attr = attr
  # get the docs and the label
  trainDocs = df_train.Abstract.tolist()
  testDocs = df_test.Abstract.tolist()
  trainLabels = eval('df_train.' + attr + '.tolist()')
  testLabels = eval('df_test.' + attr + '.tolist()')
  # define the vevtorizer
  vectorizer=TfidfVectorizer(analyzer='word')
  # do the preprocessing to text
  train_text = [prep(i) for i in trainDocs]
  test_text = [prep(i) for i in testDocs]
  # vevtorize the word in the abstract
  x_train = vectorizer.fit_transform([' '.join(i) for i in train_text])
  x_test = vectorizer.transform([' '.join(i) for i in test_text])
  y_train = np.asarray(trainLabels)
  y_test = np.asarray(testLabels)
  return x_train, y_train, x_test, y_test, attr
```

Logistical regression model

```
def log_reg(x_train, y_train, x_test, y_test, attr):
  lr = LogisticRegression()
```

```
  lr.fit(x_train, y_train)
  # Do the prediction
  y_predict=lr.predict(x_test)

  train_predict = lr.predict(x_train)
  train_acc = accuracy_score(y_train,train_predict)
  recall=recall_score(y_test,y_predict,average='macro')
  precision=precision_score(y_test,y_predict,average='macro')
  f1score=f1_score(y_test,y_predict,average='macro')
  accuracy=accuracy_score(y_test,y_predict)
  # print out the result
  print_result(train_acc, accuracy, precision, recall, f1score, attr)
  return lr, accuracy, precision, recall, f1score
```

Part 1B: RNN Method (Bi-direction)

Details of method

As well as having an RNN processing the words in the sentence from the first to the last (a forward RNN), we have a second RNN processing the words in the sentence from the last to the first (a backward RNN). At time step t, the forward RNN is processing word x_t, and the backward RNN is processing word x_{T-t+1}.

"Cited from https://github.com/bentrevett/pytorch-sentiment-analysis/blob/master/2%20-%20Upgraded%20Sentiment%20Analysis.ipynb"

prepare data

for different size of training data and preproccessing method

```
MAX_VOCAB_SIZE = 25_000
BATCH_SIZE = 64
EMBEDDING_DIM = 50
HIDDEN_DIM = 256
OUTPUT_DIM = 1
N_LAYERS = 2
BIDIRECTIONAL = True
DROPOUT = 0.5
# set a random seed
SEED = 1234

def preparedata(trainfile, prep):
  # axcs_train.csv & train1000.csv
  # set a random seed

  torch.manual_seed(SEED)
  torch.backends.cudnn.deterministic = True
  TEXT = data.Field(sequential=True, tokenize = prep, include_lengths = True)
  LABEL = data.LabelField(dtype = torch.float)

  tv_datafields = [("ID", None), # we won't be needing the source and notes, so we
                   ("URL", None),
```

```
                ('Date',None),
                ('Title',None),
                ('InfoTheory',LABEL),
                ('CompVis',LABEL),
                ('Math',LABEL),
                ("Abstract", TEXT)]
# read the data
train_data, test_data = TabularDataset.splits(
    # path='cola_public/for_torch_text', train='in_domain_train.tsv',
    path='',
    train=trainfile,
    test='axcs_test.csv',
    format='csv',skip_header=True,
    fields=tv_datafields)
# split the train data to train data, split ratio = 0.7
train_data, valid_data = train_data.split(random_state = random.seed(SEED))

# get the size
print(f'Number of testing examples: {len(test_data)}')
print(f'Number of training examples: {len(train_data)}')
print(f'Number ofa validation examples: {len(valid_data)}')

# build vocab using golve.6b.100d, need to download every time dont know why
TEXT.build_vocab(train_data,
                max_size = MAX_VOCAB_SIZE,
                vectors = "glove.6B.100d",
                unk_init = torch.Tensor.normal_)
LABEL.build_vocab(train_data)
# for the rnn we use gpu, more faster
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')

# get the iterator, it has sequence
train_iterator, valid_iterator, test_iterator = data.BucketIterator.splits(
    (train_data, valid_data, test_data),
    batch_size = BATCH_SIZE,
    # set sequence is true
    sort_key = lambda x: len(x.Abstract),
    sort_within_batch = True,
    device = device)
# set the next batch
batch = next(train_iterator.__iter__())

# create model
INPUT_DIM = len(TEXT.vocab)
PAD_IDX = TEXT.vocab.stoi[TEXT.pad_token]
model = RNN(INPUT_DIM,
            EMBEDDING_DIM,
            HIDDEN_DIM,
            OUTPUT_DIM,
            N_LAYERS,
            BIDIRECTIONAL,
            DROPOUT,
            PAD_IDX)
pretrained_embeddings = TEXT.vocab.vectors
# use Adam as the optimizer method
```

```
    optimizer = optim.Adam(model.parameters())
    UNK_IDX = TEXT.vocab.stoi[TEXT.unk_token]
    model.embedding.weight.data[UNK_IDX] = torch.zeros(EMBEDDING_DIM)
    model.embedding.weight.data[PAD_IDX] = torch.zeros(EMBEDDING_DIM)
    criterion = nn.BCEWithLogitsLoss()
    model = model.to(device)
    criterion = criterion.to(device)

    return train_iterator, valid_iterator, test_iterator, model, optimizer, criterion
```

Bi-direction LSTM RNN model

```
# the LSTM returns the output and a tuple of the final hidden state and the final c
# the standard RNN only returned the output and final hidden state.
class RNN(nn.Module):
    def __init__(self, vocab_size, embedding_dim, hidden_dim, output_dim, n_layers,
                 bidirectional, dropout, pad_idx):

        super().__init__()
        # get the embedding for target word
        self.embedding = nn.Embedding(vocab_size, embedding_dim, padding_idx = pad_
        self.rnn = nn.LSTM(embedding_dim,
                           hidden_dim,
                           # Implementing bidirectionality and adding additional la
                           num_layers=n_layers,
                           bidirectional=bidirectional,
                           dropout=dropout)

        self.fc = nn.Linear(hidden_dim * 2, output_dim)
        self.dropout = nn.Dropout(dropout)
    def forward(self, text, text_lengths):
        embedded = self.dropout(self.embedding(text))
        #pack sequence make RNN to only process the non-padded elements of our sequ
        # lengths need to be on CPU!
        packed_embedded = nn.utils.rnn.pack_padded_sequence(embedded, text_lengths.
        packed_output, (hidden, cell) = self.rnn(packed_embedded)
        #unpack sequence
        output, output_lengths = nn.utils.rnn.pad_packed_sequence(packed_output)
        #concat the final forward (hidden[-2,:,:]) and backward (hidden[-1,:,:]) hi
        #and apply dropout
        hidden = self.dropout(torch.cat((hidden[-2,:,:], hidden[-1,:,:]), dim = 1))
        return self.fc(hidden)

def train(model, iterator, optimizer, criterion, attr):
    #initialization
    epoch_loss = 0
    epoch_acc = 0
    model.train()
    for batch in iterator:
        # the gradient
        optimizer.zero_grad()
        text, text_lengths = batch.Abstract
        predictions = model(text, text_lengths).squeeze(1)
```

```
        # get the loss and accuracy
        loss = eval('criterion(predictions, batch.' + attr + ')')
        acc = eval('binary_accuracy(predictions, batch.' + attr + ')')
        loss.backward()
        optimizer.step()
        # update the parametor
        epoch_loss += loss.item()
        epoch_acc += acc.item()
    return epoch_loss / len(iterator), epoch_acc / len(iterator)

def evaluate(model, iterator, criterion, attr):
    epoch_loss = 0
    epoch_acc = 0
    model.eval()
    with torch.no_grad():
        for batch in iterator:
            text, text_lengths = batch.Abstract
            predictions = model(text, text_lengths).squeeze(1)
            loss = eval('criterion(predictions, batch.' + attr + ')')
            acc = eval('binary_accuracy(predictions, batch.' + attr + ')')
            epoch_loss += loss.item()
            epoch_acc += acc.item()
    return epoch_loss / len(iterator), epoch_acc / len(iterator)
```

Get resualt function

```
def rnnresult(epochs, attr, train_iterator, valid_iterator, test_iterator, model, c
  N_EPOCHS = epochs
  best_valid_loss = float('inf')
  for epoch in range(N_EPOCHS):
      start_time = time.time()
      # train loss and acc
      train_loss, train_acc = train(model, train_iterator, optimizer, criterion, at
      # validation
      valid_loss, valid_acc = evaluate(model, valid_iterator, criterion, attr)
      # get the timer
      end_time = time.time()
      epoch_mins, epoch_secs = epoch_time(start_time, end_time)
      # use validation set to reduce overfitting
      if valid_loss < best_valid_loss:
          best_valid_loss = valid_loss
          torch.save(model.state_dict(), 'RNN-model-' + attr + '.pt')

  model.load_state_dict(torch.load('RNN-model-' + attr + '.pt'))

  test_loss, test_acc = evaluate(model, test_iterator, criterion, attr)

  y_predict = []
  y_test = []
  p_conf = []

  model.eval()
  with torch.no_grad():
      for batch in test_iterator:
```

```
    for batch in test_iterator:
        text, text_lengths = batch.Abstract
        predictions = model(text, text_lengths).squeeze(1)
        preds = torch.sigmoid(predictions)
        rounded_preds = torch.round(preds)
        y_predict += rounded_preds.tolist()
        y_test += eval('batch.' + attr + '.tolist()')
        p_conf += preds.tolist()

  test_list = y_test

  y_predict = np.asarray(y_predict)
  y_test = np.asarray(y_test)
  recall=recall_score(y_test,y_predict,average='macro')
  precision=precision_score(y_test,y_predict,average='macro')
  f1score=f1_score(y_test,y_predict,average='macro')
  accuracy=accuracy_score(y_test,y_predict)
  # print out the result
  print_result(train_acc, accuracy, precision, recall, f1score, attr)

  return accuracy, precision, recall, f1score, test_list, p_conf
```

Part 1C: Results for Methods

F1, precision, etc.

```
task = ['InfoTheory', 'CompVis', 'Math']
```

RNN result

```
accuracy_rnn_list, precision_rnn_list, recall_rnn_list, f1score_rnn_list, test_list
```

Using all of the data in the axcs_train.csv file +

[to lower, remove numbers, remove stop words, stemming]

```
train_iterator, valid_iterator, test_iterator, model, optimizer, criterion =  prepa
for t in task:
  accuracy, precision, recall, f1score, test_list, p_conf = rnnresult(5, t, train_i
  accuracy_rnn_list.append(accuracy)
  precision_rnn_list.append(precision)
  recall_rnn_list.append(recall)
  f1score_rnn_list.append(f1score)
  test_list_rnn_list.append(test_list)
  p_conf_rnn_list.append(p_conf)
```

```
    Number of testing examples: 19678
    Number of training examples: 38312
    Number ofa validation examples: 16419
    .vector_cache/glove.6B.zip: 862MB [02:41, 5.33MB/s]
    100%|███████████████| 398980/400000 [00:30<00:00, 26277.92it/s]-------------
```

```
The Train Accuracy of InfoTheory is : 94.63%
The Test Accuracy of InfoTheory is : 94.86%
The Macro Precision of InfoTheory is: 0.9305375268399492
The Macro Recall of InfoTheory is : 0.8935267293882223
The Macro F1 score of InfoTheory is :0.9105812637343471
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
The Train Accuracy of CompVis is : 97.61%
The Test Accuracy of CompVis is : 95.64%
The Macro Precision of CompVis is: 0.9371239379511578
The Macro Recall of CompVis is : 0.8279614949133459
The Macro F1 score of CompVis is :0.8724547531052609
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
The Train Accuracy of Math is : 88.54%
The Test Accuracy of Math is : 86.60%
The Macro Precision of Math is: 0.85828188038979
The Macro Recall of Math is : 0.8137129619589616
The Macro F1 score of Math is :0.8310311583350934
--------------------------------------------------------------------------------
```

Using all of the data in the axcs_train.csv file +

[to lower, remove numbers, remove stop words, lemmatisation, remove rare tokens]

```
train_iterator, valid_iterator, test_iterator, model, optimizer, criterion =  prepa
for t in task:
  accuracy, precision, recall, f1score, test_list, p_conf = rnnresult(5, t, train_i
  accuracy_rnn_list.append(accuracy)
  precision_rnn_list.append(precision)
  recall_rnn_list.append(recall)
  f1score_rnn_list.append(f1score)
  test_list_rnn_list.append(test_list)
  p_conf_rnn_list.append(p_conf)
```

```
Number of testing examples: 19678
Number of training examples: 38312
Number ofa validation examples: 16419
--------------------------------------------------------------------------------
The Train Accuracy of InfoTheory is : 94.65%
The Test Accuracy of InfoTheory is : 94.40%
The Macro Precision of InfoTheory is: 0.9036874864480935
The Macro Recall of InfoTheory is : 0.9115872240918212
The Macro F1 score of InfoTheory is :0.9075663379493254
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
The Train Accuracy of CompVis is : 97.71%
The Test Accuracy of CompVis is : 95.86%
The Macro Precision of CompVis is: 0.9203735906858208
The Macro Recall of CompVis is : 0.8567029940010529
The Macro F1 score of CompVis is :0.8850934239226673
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
The Train Accuracy of Math is : 88.70%
The Test Accuracy of Math is : 87.01%
The Macro Precision of Math is: 0.8583001489234061
The Macro Recall of Math is : 0.8245339135025496
```

```
The Macro F1 score of Math is :0.8384782794804984
--------------------------------------------------------------------------------
```

Using the first 1000 row of data in the axcs_train.csv file +

[to lower, remove numbers, remove stop words, stemming]

```
train_iterator, valid_iterator, test_iterator, model, optimizer, criterion =  prepa
for t in task:
  accuracy, precision, recall, f1score, test_list, p_conf = rnnresult(5, t, train_i
  accuracy_rnn_list.append(accuracy)
  precision_rnn_list.append(precision)
  recall_rnn_list.append(recall)
  f1score_rnn_list.append(f1score)
  test_list_rnn_list.append(test_list)
  p_conf_rnn_list.append(p_conf)
```

```
Number of testing examples: 19678
Number of training examples: 700
Number ofa validation examples: 300
--------------------------------------------------------------------------------
The Train Accuracy of InfoTheory is : 99.72%
The Test Accuracy of InfoTheory is : 81.62%
The Macro Precision of InfoTheory is: 0.40812074397804654
The Macro Recall of InfoTheory is : 0.5
The Macro F1 score of InfoTheory is :0.44941242305540013
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
The Train Accuracy of CompVis is : 100.00%
The Test Accuracy of CompVis is : 89.06%
The Macro Precision of CompVis is: 0.44531964630551885
The Macro Recall of CompVis is : 0.5
The Macro F1 score of CompVis is :0.4710783786689603
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
The Train Accuracy of Math is : 97.58%
The Test Accuracy of Math is : 69.86%
The Macro Precision of Math is: 0.3493241183047058
The Macro Recall of Math is : 0.5
The Macro F1 score of Math is :0.4112965954646084
--------------------------------------------------------------------------------
```

Using the first 1000 row of data in the axcs_train.csv file +

[to lower, remove numbers, remove stop words, lemmatisation, remove rare tokens]

```
train_iterator, valid_iterator, test_iterator, model, optimizer, criterion =  prepa
for t in task:
  accuracy, precision, recall, f1score, test_list, p_conf = rnnresult(5, t, train_i
  accuracy_rnn_list.append(accuracy)
  precision_rnn_list.append(precision)
  recall_rnn_list.append(recall)
  f1score_rnn_list.append(f1score)
  test_list_rnn_list.append(test_list)
```

```
  p_conf_rnn_list.append(p_conf)
```

```
.vector_cache/glove.6B.zip: 0.00B [00:00, ?B/s]Number of testing examples: 19
Number of training examples: 700
Number ofa validation examples: 300
.vector_cache/glove.6B.zip: 862MB [02:41, 5.35MB/s]
100%|████████████████| 398825/400000 [00:29<00:00, 25779.36it/s]------------
The Train Accuracy of InfoTheory is : 99.72%
The Test Accuracy of InfoTheory is : 81.62%
The Macro Precision of InfoTheory is: 0.40812074397804654
The Macro Recall of InfoTheory is : 0.5
The Macro F1 score of InfoTheory is :0.44941242305540013
------------------------------------------------------------------------------
------------------------------------------------------------------------------
The Train Accuracy of CompVis is : 100.00%
The Test Accuracy of CompVis is : 89.06%
The Macro Precision of CompVis is: 0.44531964630551885
The Macro Recall of CompVis is : 0.5
The Macro F1 score of CompVis is :0.4710783786689603
------------------------------------------------------------------------------
------------------------------------------------------------------------------
The Train Accuracy of Math is : 97.58%
The Test Accuracy of Math is : 69.86%
The Macro Precision of Math is: 0.3493241183047058
The Macro Recall of Math is : 0.5
The Macro F1 score of Math is :0.4112965954646084
------------------------------------------------------------------------------
```

Logistical regression result

```
# save record for plot
lr_list, x_test_list, y_test_list, accuracy_list, precision_list, recall_list, f1sc
```

Using all of the data in the axcs_train.csv file +

[to lower, remove numbers, remove stop words, stemming]

```
train_data, test_data = read_data('axcs_train.csv')
for t in task:
  x_train, y_train, x_test, y_test, attr = process_data(train_data, test_data, t, p
  lr, accuracy, precision, recall, f1score = log_reg(x_train, y_train, x_test, y_te
  lr_list.append(lr)
  x_test_list.append(x_test)
  y_test_list.append(y_test)
  accuracy_list.append(accuracy)
  precision_list.append(precision)
  recall_list.append(recall)
  f1score_list.append(f1score)
```

```
------------------------------------------------------------------------------
The Train Accuracy of InfoTheory is : 95.96%
The Test Accuracy of InfoTheory is : 94.80%
The Macro Precision of InfoTheory is: 0.9425963885881121
The Macro Recall of InfoTheory is : 0.8791932023916174
```

```
The Macro F1 score of InfoTheory is :0.9067483826731856
---------------------------------------------------------------------------
---------------------------------------------------------------------------
The Train Accuracy of CompVis is : 98.40%
The Test Accuracy of CompVis is : 96.06%
The Macro Precision of CompVis is: 0.9563872028665801
The Macro Recall of CompVis is : 0.8347847616308346
The Macro F1 score of CompVis is :0.8835760502007933
---------------------------------------------------------------------------
---------------------------------------------------------------------------
The Train Accuracy of Math is : 90.39%
The Test Accuracy of Math is : 87.23%
The Macro Precision of Math is: 0.8612369062993256
The Macro Recall of Math is : 0.8273212697256961
The Macro F1 score of Math is :0.8413474431046426
---------------------------------------------------------------------------
```

Using all of the data in the axcs_train.csv file +

[to lower, remove numbers, remove stop words, lemmatisation, remove rare tokens]

```
train_data, test_data = read_data('axcs_train.csv')
for t in task:
  x_train, y_train, x_test, y_test, attr = process_data(train_data, test_data, t, p
  lr, accuracy, precision, recall, f1score = log_reg(x_train, y_train, x_test, y_te
  lr_list.append(lr)
  x_test_list.append(x_test)
  y_test_list.append(y_test)
  accuracy_list.append(accuracy)
  precision_list.append(precision)
  recall_list.append(recall)
  f1score_list.append(f1score)
```

```
---------------------------------------------------------------------------
The Train Accuracy of InfoTheory is : 96.01%
The Test Accuracy of InfoTheory is : 94.74%
The Macro Precision of InfoTheory is: 0.9420436035202082
The Macro Recall of InfoTheory is : 0.8777793296551086
The Macro F1 score of InfoTheory is :0.9056437974025807
---------------------------------------------------------------------------
---------------------------------------------------------------------------
The Train Accuracy of CompVis is : 98.43%
The Test Accuracy of CompVis is : 95.85%
The Macro Precision of CompVis is: 0.9551910716178484
The Macro Recall of CompVis is : 0.8248511133962626
The Macro F1 score of CompVis is :0.8760619877930864
---------------------------------------------------------------------------
---------------------------------------------------------------------------
The Train Accuracy of Math is : 90.69%
The Test Accuracy of Math is : 87.22%
The Macro Precision of Math is: 0.8616797743857159
The Macro Recall of Math is : 0.8265293102881499
The Macro F1 score of Math is :0.8409721122828717
---------------------------------------------------------------------------
```

Using the first 1000 row of data in the axcs_train.csv file +

[to lower, remove numbers, remove stop words, stemming]

```
train_data, test_data = read_data('train1000.csv')
for t in task:
  x_train, y_train, x_test, y_test, attr = process_data(train_data, test_data, t, p
  lr, accuracy, precision, recall, f1score = log_reg(x_train, y_train, x_test, y_te
  lr_list.append(lr)
  x_test_list.append(x_test)
  y_test_list.append(y_test)
  accuracy_list.append(accuracy)
  precision_list.append(precision)
  recall_list.append(recall)
  f1score_list.append(f1score)
```

```
    ------------------------------------------------------------------------------
    The Train Accuracy of InfoTheory is : 99.80%
    The Test Accuracy of InfoTheory is : 81.62%
    The Macro Precision of InfoTheory is: 0.40812074397804654
    The Macro Recall of InfoTheory is : 0.5
    The Macro F1 score of InfoTheory is :0.44941242305540013
    ------------------------------------------------------------------------------
    ------------------------------------------------------------------------------
    The Train Accuracy of CompVis is : 99.90%
    The Test Accuracy of CompVis is : 89.06%
    The Macro Precision of CompVis is: 0.44531964630551885
    The Macro Recall of CompVis is : 0.5
    The Macro F1 score of CompVis is :0.4710783786689603
    ------------------------------------------------------------------------------
    ------------------------------------------------------------------------------
    The Train Accuracy of Math is : 97.60%
    The Test Accuracy of Math is : 69.86%
    The Macro Precision of Math is: 0.3493241183047058
    The Macro Recall of Math is : 0.5
    The Macro F1 score of Math is :0.4112965954646084
    ------------------------------------------------------------------------------
```

Using the first 1000 row of data in the axcs_train.csv file +

[to lower, remove numbers, remove stop words, lemmatisation, remove rare tokens]

```
train_data, test_data = read_data('train1000.csv')
for t in task:
  x_train, y_train, x_test, y_test, attr = process_data(train_data, test_data, t, p
  lr, accuracy, precision, recall, f1score = log_reg(x_train, y_train, x_test, y_te
  lr_list.append(lr)
  x_test_list.append(x_test)
  y_test_list.append(y_test)
  accuracy_list.append(accuracy)
  precision_list.append(precision)
  recall_list.append(recall)
  f1score_list.append(f1score)
```

```
--------------------------------------------------------------------------------
The Train Accuracy of InfoTheory is : 99.80%
The Test Accuracy of InfoTheory is : 81.62%
The Macro Precision of InfoTheory is: 0.40812074397804654
The Macro Recall of InfoTheory is : 0.5
The Macro F1 score of InfoTheory is :0.44941242305540013
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
The Train Accuracy of CompVis is : 99.90%
The Test Accuracy of CompVis is : 89.06%
The Macro Precision of CompVis is: 0.44531964630551885
The Macro Recall of CompVis is : 0.5
The Macro F1 score of CompVis is :0.4710783786689603
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
The Train Accuracy of Math is : 97.60%
The Test Accuracy of Math is : 69.86%
The Macro Precision of Math is: 0.3493241183047058
The Macro Recall of Math is : 0.5
The Macro F1 score of Math is :0.4112965954646084
--------------------------------------------------------------------------------
```

Part 1D: Plots for Methods

F1, precision, etc.

Logistical regression precision-recall-curve plot

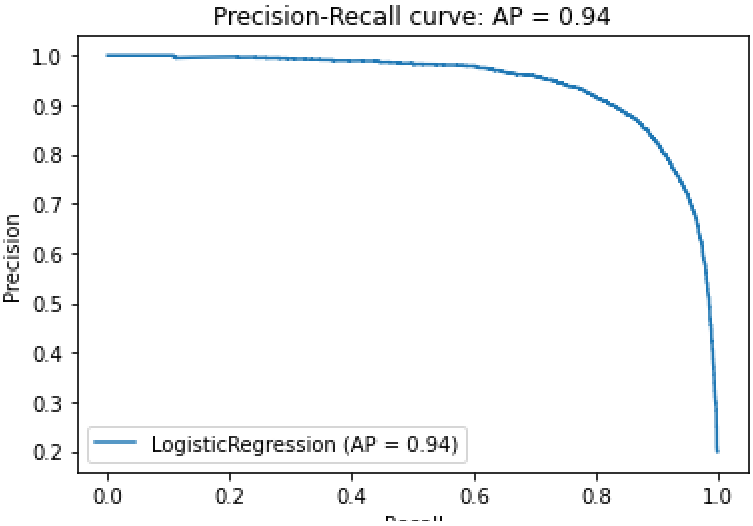
```
i = 0
def plot_lr(lr, x_test, y_test):
  # plot the precision recall curve
  y_score = lr.decision_function(x_test)
  average_precision = average_precision_score(y_test, y_score)
  disp = plot_precision_recall_curve(lr, x_test, y_test)
  disp.ax_.set_title('Precision-Recall curve: '
                     'AP = {0:0.2f}'.format(average_precision))
  return None
```

1. all data + [to lower, remove numbers, remove stop words, stemming] + InfoTheory

```
len(x_test_list)
```

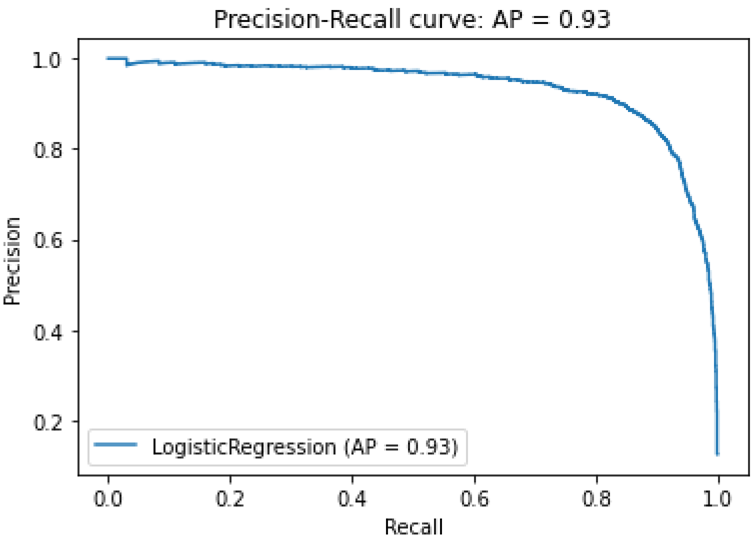
```
12
```

```
plot_lr(lr_list[i], x_test_list[i], y_test_list[i])
i+=1
```



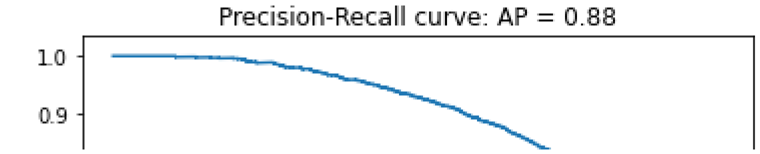
2. all data + [to lower, remove numbers, remove stop words, stemming] + CompVis

```
plot_lr(lr_list[i], x_test_list[i], y_test_list[i])
i+=1
```



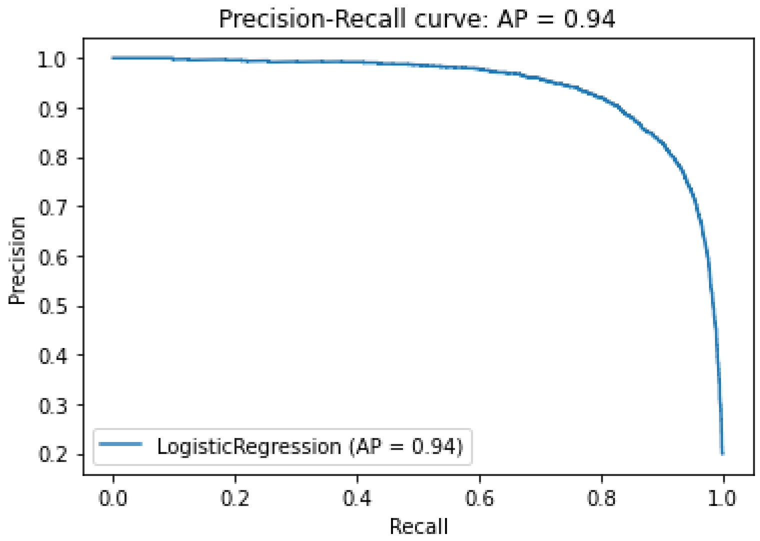
3. all data + [to lower, remove numbers, remove stop words, stemming] + Math

```
plot_lr(lr_list[i], x_test_list[i], y_test_list[i])
i+=1
```



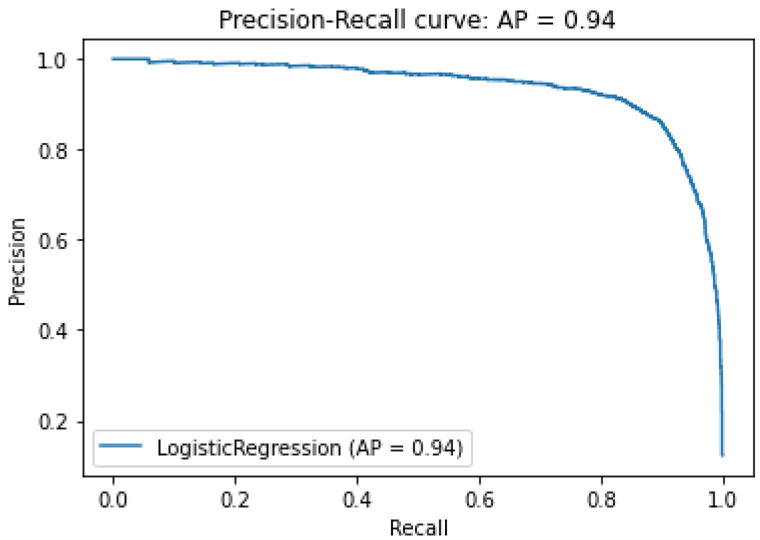
4. all data + [to lower, remove numbers, remove stop words, lemmatisation, remove rare tokens] + InfoTheory

```
plot_lr(lr_list[i], x_test_list[i], y_test_list[i])
i+=1
```



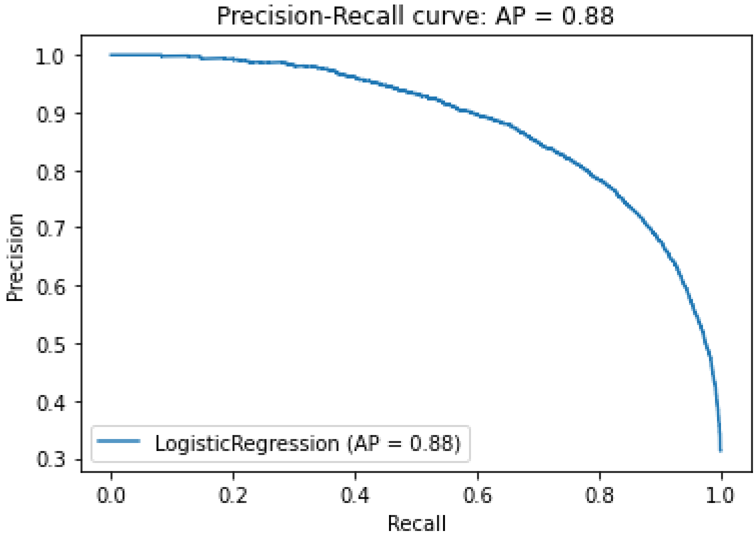
5. all data + [to lower, remove numbers, remove stop words, lemmatisation, remove rare tokens] + CompVis

```
plot_lr(lr_list[i], x_test_list[i], y_test_list[i])
i+=1
```



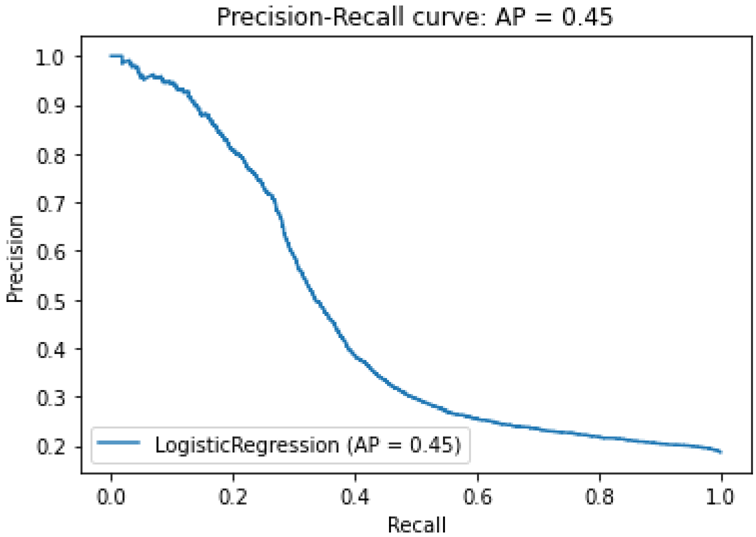
6. all data + [to lower, remove numbers, remove stop words, lemmatisation, remove rare tokens] + Math

```
plot_lr(lr_list[i], x_test_list[i], y_test_list[i])
i+=1
```



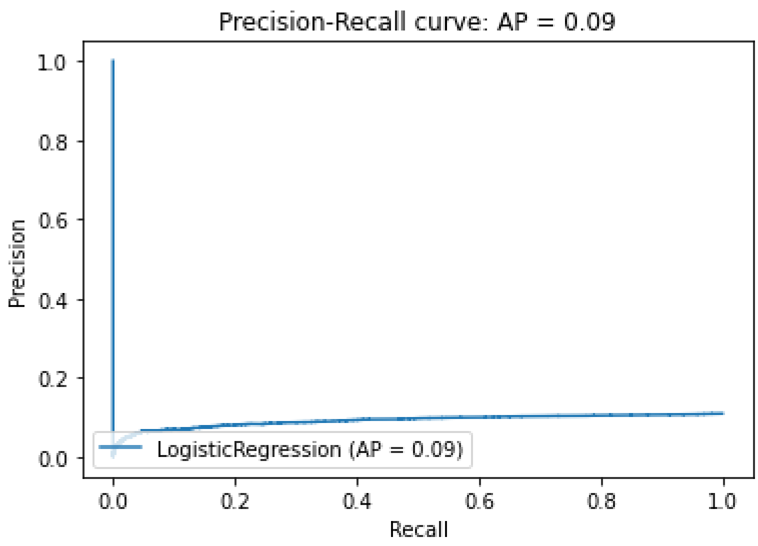
7. first 1000 row data + [to lower, remove numbers, remove stop words, stemming] + InfoTheory

```
plot_lr(lr_list[i], x_test_list[i], y_test_list[i])
i+=1
```



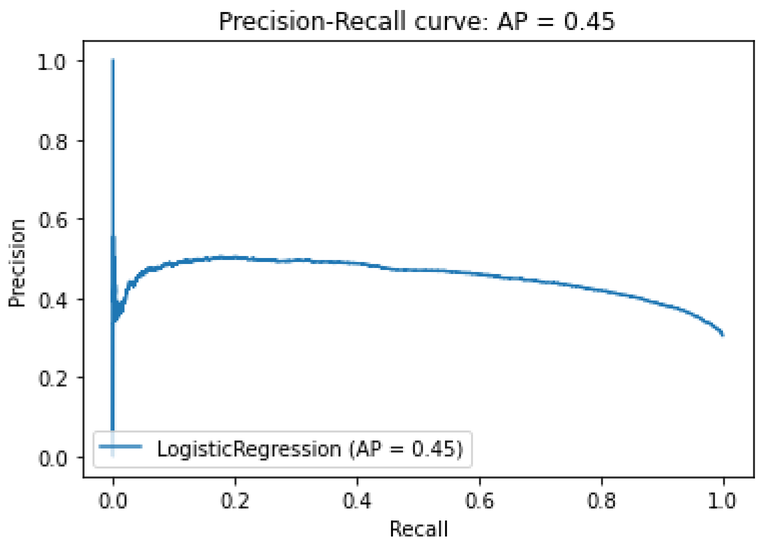
8. first 1000 row data + [to lower, remove numbers, remove stop words, stemming] + CompVis

```
plot_lr(lr_list[i], x_test_list[i], y_test_list[i])
i+=1
```



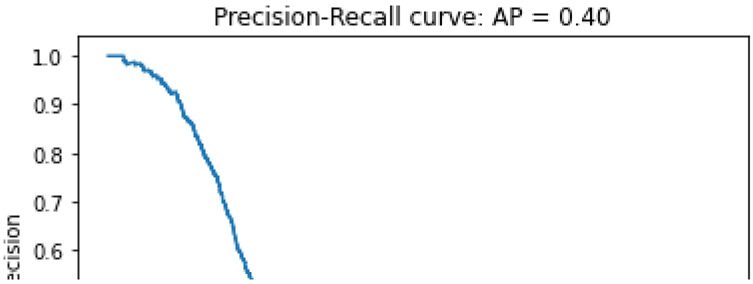
9. first 1000 row data + [to lower, remove numbers, remove stop words, stemming] + Math

```
plot_lr(lr_list[i], x_test_list[i], y_test_list[i])
i+=1
```

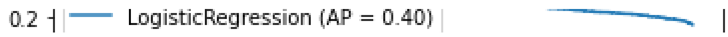


10. first 1000 row data + [to lower, remove numbers, remove stop words, lemmatisation, remove rare tokens] + InfoTheory

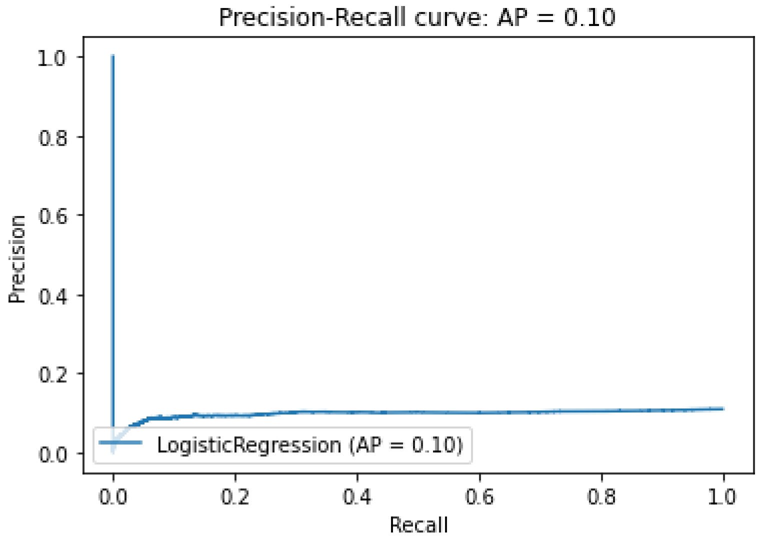
```
plot_lr(lr_list[i], x_test_list[i], y_test_list[i])
i+=1
```



11. first 1000 row data + [to lower, remove numbers, remove stop words, lemmatisation, remove rare tokens] + CompVis

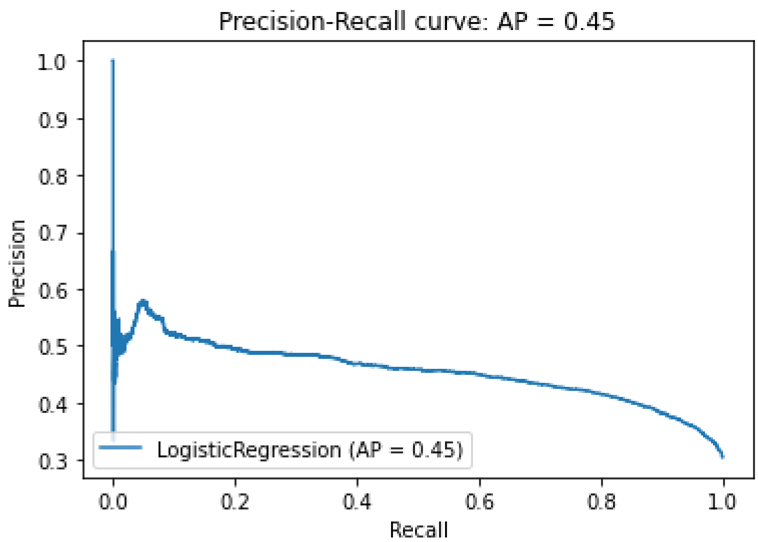



```
plot_lr(lr_list[i], x_test_list[i], y_test_list[i])
i+=1
```



12. first 1000 row data + [to lower, remove numbers, remove stop words, lemmatisation, remove rare tokens] + Math

```
plot_lr(lr_list[i], x_test_list[i], y_test_list[i])
```



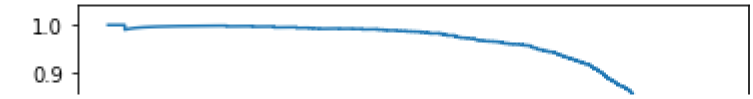
RNN precision-recall-curve plot

plot precision-recall-curve function for RNN model

```
i = 0
def rnn_plot(y_test_list, p_conf):
  # initializ the list
  P, R, sort = [], [], []
  # turn the list to a np array for use argsort function
  p_conf = np.array(p_conf)
  # sort the array big to small
  for i in np.argsort(-p_conf):
    sort.append([p_conf[i], y_test_list[i]])
  for i in range(len(sort)):
    TP, FP, FN = 0, 0, 0
    # positive and ture
    for j in sort[:i+1]:
      if int(j[1]) == 1:
        TP += 1
      else:
        FP += 1
    # nagitive and false
    for a in sort[i+1:]:
      if int(a[1]) == 1:
        FN +=1
    # calcualte the precision and recall
    P.append(TP/(TP+FP))
    R.append(TP/(TP+FN))
  # plot the curve
  plt.xlabel('Recall')
  plt.ylabel('Precision')
  plt.plot(R,P)
  return None
```

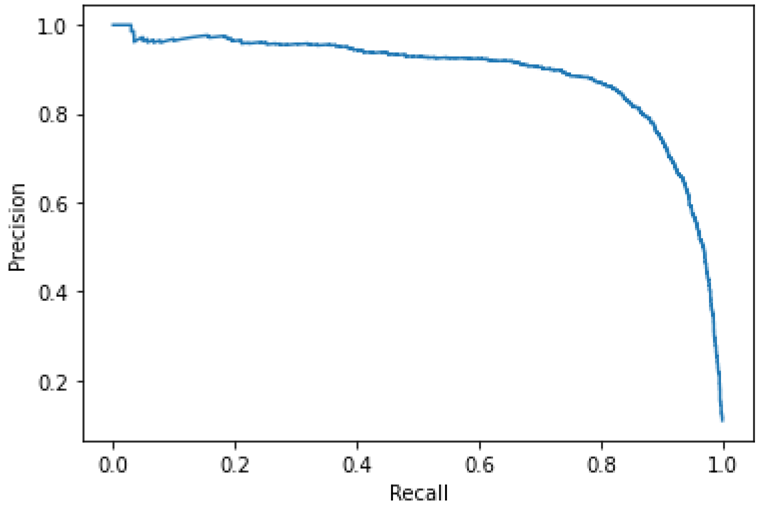
1. all data + [to lower, remove numbers, remove stop words, stemming] + InfoTheory

```
rnn_plot(test_list_rnn_list[i], p_conf_rnn_list[i])
i += 1
```



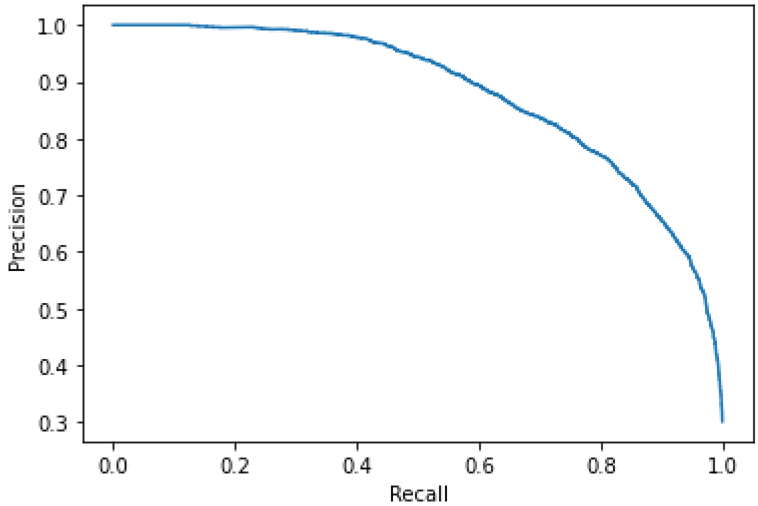
2. all data + [to lower, remove numbers, remove stop words, stemming] + CompVis

```
rnn_plot(test_list_rnn_list[i], p_conf_rnn_list[i])
i += 1
```



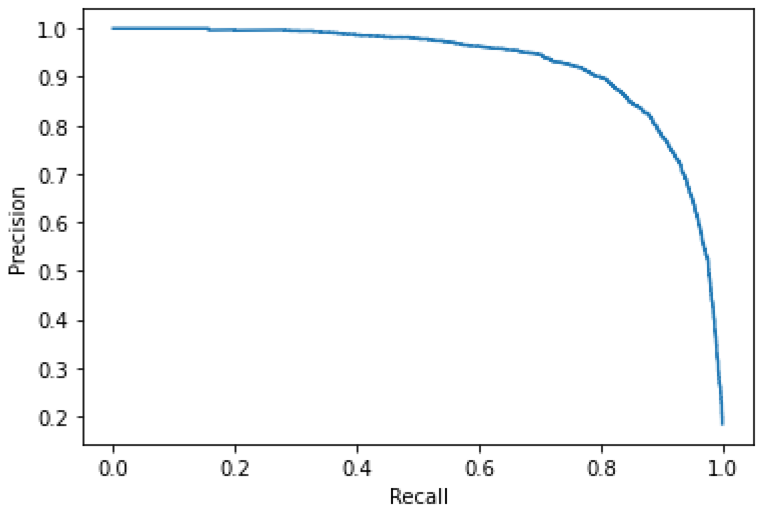
3. all data + [to lower, remove numbers, remove stop words, stemming] + Math

```
rnn_plot(test_list_rnn_list[i], p_conf_rnn_list[i])
i += 1
```



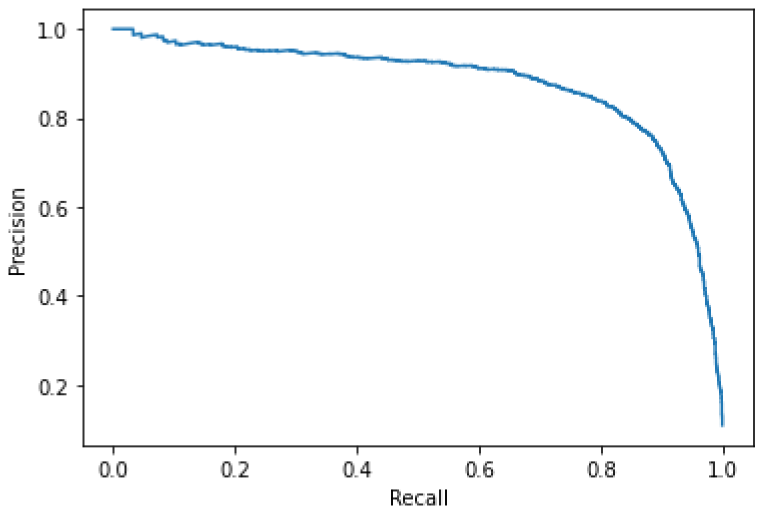
4. all data + [to lower, remove numbers, remove stop words, lemmatisation, remove rare tokens] + InfoTheory

```
rnn_plot(test_list_rnn_list[i], p_conf_rnn_list[i])
i += 1
```



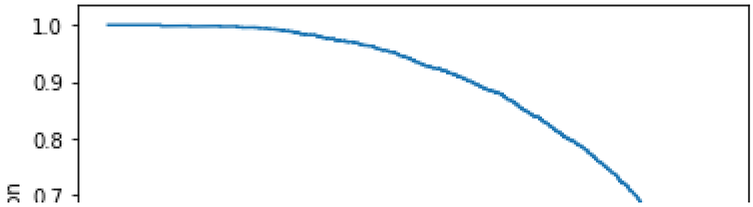
5. all data + [to lower, remove numbers, remove stop words, lemmatisation, remove rare tokens] + CompVis

```
rnn_plot(test_list_rnn_list[i], p_conf_rnn_list[i])
i += 1
```



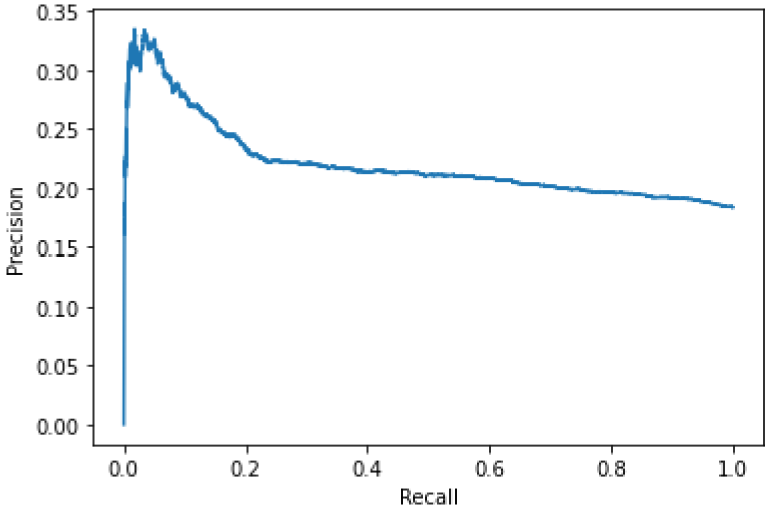
6. all data + [to lower, remove numbers, remove stop words, lemmatisation, remove rare tokens] + Math

```
rnn_plot(test_list_rnn_list[i], p_conf_rnn_list[i])
i += 1
```



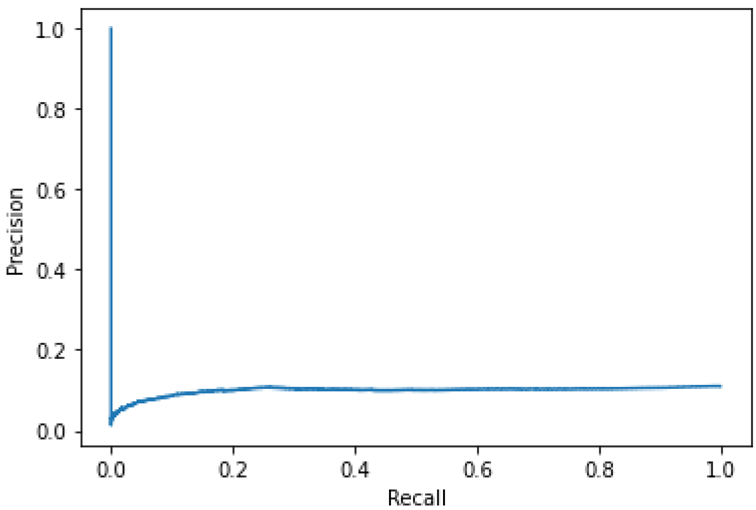
7. first 1000 row data + [to lower, remove numbers, remove stop words, stemming] + InfoTheory


```
rnn_plot(test_list_rnn_list[i], p_conf_rnn_list[i])
i += 1
```



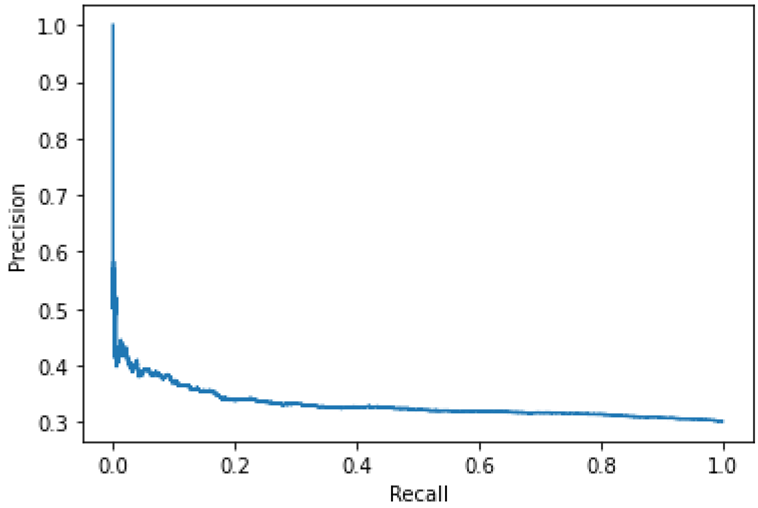
8. first 1000 row data + [to lower, remove numbers, remove stop words, stemming] + CompVis

```
rnn_plot(test_list_rnn_list[i], p_conf_rnn_list[i])
i += 1
```



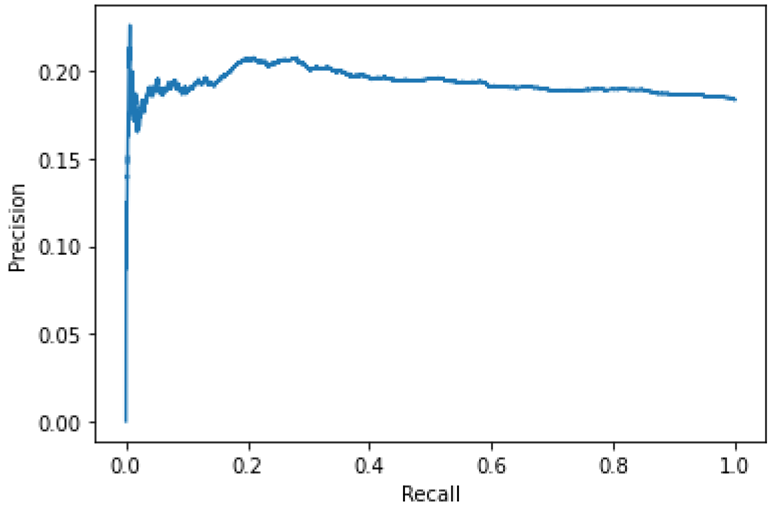
9. first 1000 row data + [to lower, remove numbers, remove stop words, stemming] + Math

```
rnn_plot(test_list_rnn_list[i], p_conf_rnn_list[i])
i += 1
```



10. first 1000 row data + [to lower, remove numbers, remove stop words, lemmatisation, remove rare tokens] + InfoTheory

```
rnn_plot(test_list_rnn_list[i], p_conf_rnn_list[i])
i += 1
```

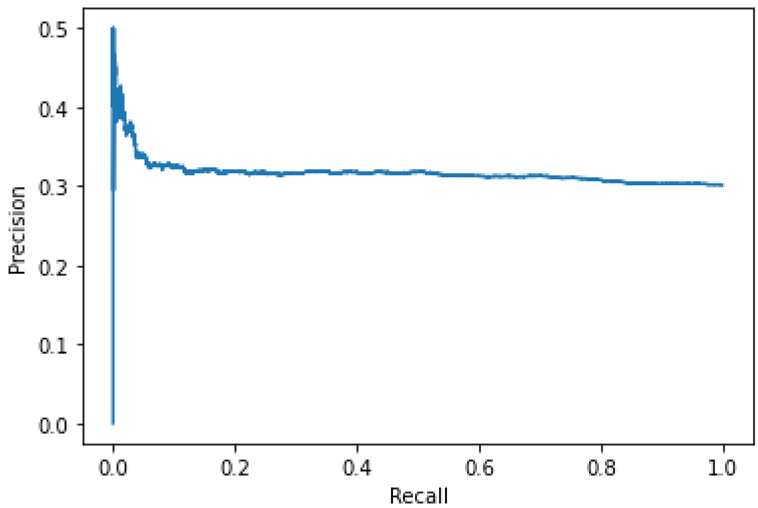


11. first 1000 row data + [to lower, remove numbers, remove stop words, lemmatisation, remove rare tokens] + CompVis

```
rnn_plot(test_list_rnn_list[i], p_conf_rnn_list[i])
i += 1
```

12. first 1000 row data + [to lower, remove numbers, remove stop words, lemmatisation, remove rare tokens] + Math

```
rnn_plot(test_list_rnn_list[i], p_conf_rnn_list[i])
i += 1
```



Part 2: Topic Modelling

General comments and any shared processing here.

Load data

```
def lda_read_data(rows):
  # uncomment and run to load up this data
  text_data = []
  df = pd.read_csv('axcs_train.csv')
  df = df[:rows]
  docs = df['Abstract'].tolist()
  raw_docs = docs.copy()
  return raw_docs, docs
```

2 types of preprocessing

Preprocessing 1

lower + RegxpTokenizer + remove numbers + remove short word(len<1) + SnowballStemming + occur less than 50 or more than 50% of the documents

```
def preprocess1(docs):
  # Split the documents into tokens.
  tokenizer = RegexpTokenizer(r'\w+')
  for idx in range(len(docs)):
      docs[idx] = docs[idx].lower()  # Convert to lowercase.
      docs[idx] = tokenizer.tokenize(docs[idx])  # Split into words.
  # Remove numbers, but not words that contain numbers.
  docs = [[token for token in doc if not token.isnumeric()] for doc in docs]
  # Remove words that are only one character.
  docs = [[token for token in doc if len(token) > 1] for doc in docs]
  # Stemming the documents.
  stemmer = SnowballStemmer("english")
  docs = [[stemmer.stem(token) for token in doc] for doc in docs]
  # Remove rare and common tokens.
  # Create a dictionary representation of the documents.
  dictionary = Dictionary(docs)
  # Filter out words that occur less than 50 documents, or more than 50% of the doc
  dictionary.filter_extremes(no_below=50, no_above=0.5)
  # Bag-of-words representation of the documents.
  corpus = [dictionary.doc2bow(doc) for doc in docs]
  return corpus, dictionary
```

Preprocessing 2

lower + spacy tokenizer + remove short word(len<1) + lematizeing + bigram + occur less than 50 or more than 50% of the documents

```
def preprocess2(docs):
  nlp = spacy.load('en_core_web_sm')
  # Split the documents into tokens.
  for idx in range(len(docs)):
      docs[idx] = docs[idx].lower()  # Convert to lowercase.
      docs[idx] = nlp(docs[idx])  # Split into words.
  # Remove words that are only one character.
  docs = [[token for token in doc if len(token) > 1] for doc in docs]
  # Lemmatize the documents.
  docs = [[token.lemma_ for token in doc] for doc in docs]
  # Add bigrams and trigrams to docs (only ones that appear 20 times or more).
  bigram = Phrases(docs, min_count=20)
  for idx in range(len(docs)):
      for token in bigram[docs[idx]]:
          if '_' in token:
              # Token is a bigram, add to document.
              docs[idx].append(token)
  # Remove rare and common tokens.
  # Create a dictionary representation of the documents.
```

```
  dictionary = Dictionary(docs)
  # Filter out words that occur less than 20 documents, or more than 50% of the doc
  dictionary.filter_extremes(no_below=20, no_above=0.5)
  # Bag-of-words representation of the documents.
  corpus = [dictionary.doc2bow(doc) for doc in docs]
  return corpus, dictionary
```

Train and get the plot of LDA topic model

```
def LDA_topic(K, corpus, dictionary):
  # Train LDA model.
  # Set training parameters.
  NUM_TOPICS = K
  chunksize = 2000
  passes = 20
  iterations = 400
  eval_every = None  # Don't evaluate model perplexity, takes too much time.
  # Make a index to word dictionary.
  temp = dictionary[0]  # This is only to "load" the dictionary.
  id2word = dictionary.id2token

  model = LdaModel(
      corpus=corpus,
      id2word=id2word,
      chunksize=chunksize,
      alpha='auto',
      eta='auto',
      iterations=iterations,
      num_topics=NUM_TOPICS,
      passes=passes,
      eval_every=eval_every
  )
  top_topics = model.top_topics(corpus) #, num_words=20)
  # Average topic coherence is the sum of topic coherences of all topics, divided b
  avg_topic_coherence = sum([t[1] for t in top_topics]) / NUM_TOPICS
  lda_display = pyLDAvis.gensim.prepare(model, corpus, dictionary, sort_topics=Fals

  return lda_display, model
```

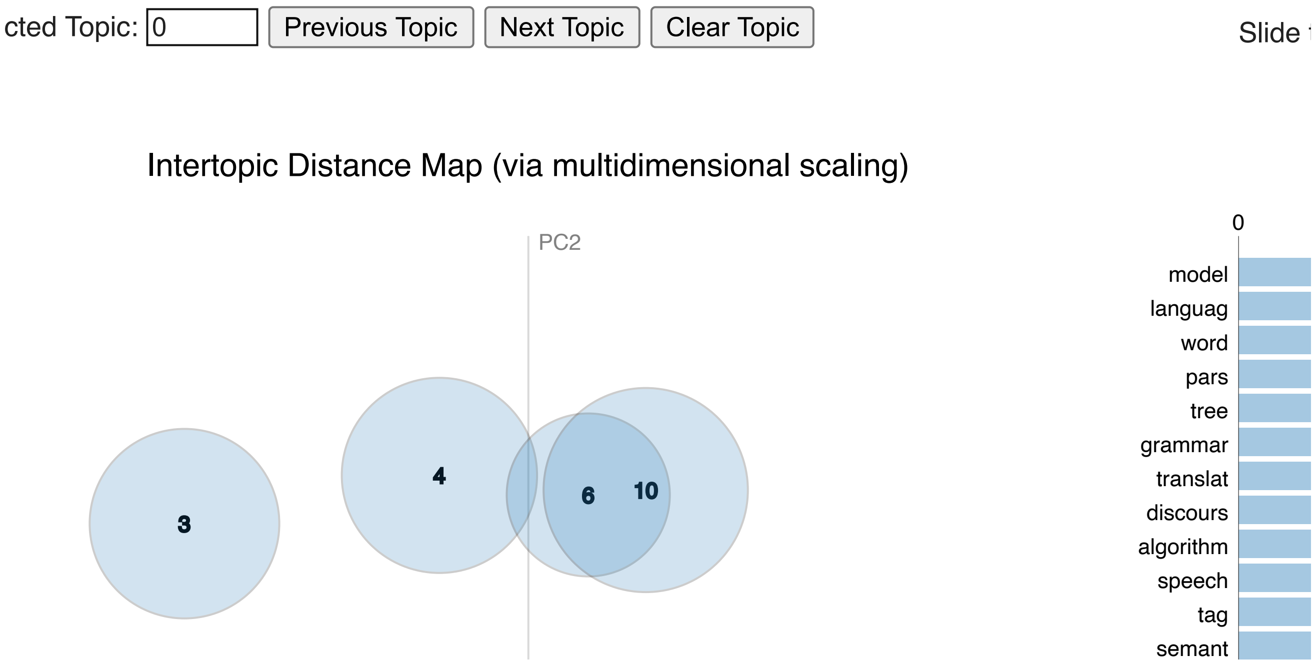
Visualisation

```
def get_document_topics(ldamodel, corpus, texts):
   # Init output
    document_topics_df = pd.DataFrame()

    # Get main topic in each document
    for i, row in enumerate(ldamodel[corpus]):
        row = sorted(row, key=lambda x: (x[1]), reverse=True)
        # Get the Dominant topic, Perc Contribution and Keywords for each document
        for j, (topic_num, prop_topic) in enumerate(row):
            if j == 0:  # => dominant topic
```

```
            if j == 0:  # => dominant topic
                wp = ldamodel.show_topic(topic_num)
                topic_keywords = ", ".join([word for word, prop in wp])
                document_topics_df = document_topics_df.append(pd.Series([int(topic
            else:
                break
    document_topics_df.columns = ['Dominant_Topic', 'Perc_Contribution', 'Topic_Key

    # Add original text to the end of the output
    contents = pd.Series(texts)
    document_topics_df = pd.concat([document_topics_df, contents], axis=1)

    document_topics_df.columns = ['Dominant_Topic', 'Perc_Contribution', 'Topic_Key

    return document_topics_df
```

Apply preprocessing 1, K = 10 to First 1000 rows data

```
# get the first 1000 rows data
raw_docs, docs = lda_read_data(1000)
corpus, dictionary = preprocess1(docs)
lda_display, model = LDA_topic(10, corpus, dictionary)
# get the plot
pyLDAvis.display(lda_display)
```




```
doc_topic_df = get_document_topics(ldamodel=model, corpus=corpus, texts=raw_docs)
doc_topic_df.head()
```

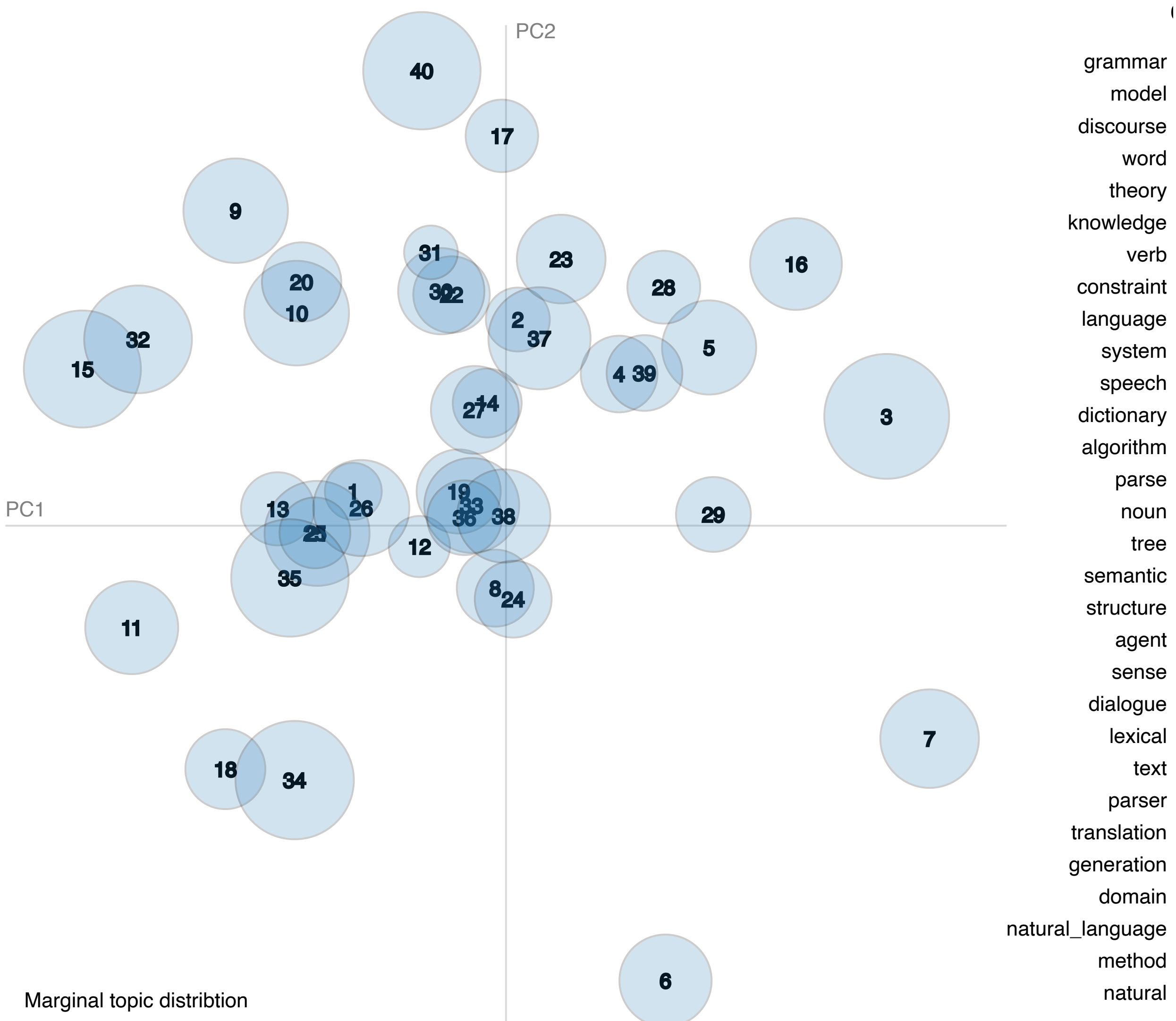
	Dominant_Topic	Perc_Contribution	Topic_Keywords	Original_Text
0	7.0	0.4980	algorithm, pars, grammar, parser, it, be, can,...	Nested satisfiability A special case of the s...
1	4.0	0.9244	text, word, method, from, by, corpus, lexic, b...	A note on digitized angles We study the confi...
2	5.0	0.9605	languag, natur, system,	Textbook examples of recursion We discuss

Apply preprocessing 2, K = 40 to First 1000 rows data

```
# get the first 1000 rows data
raw_docs, docs = lda_read_data(1000)
corpus, dictionary = preprocess2(docs)
lda_display, model = LDA_topic(40, corpus, dictionary)
# get the plot
pyLDAvis.display(lda_display)
```

Selected Topic: 0 Previous Topic Next Topic Clear Topic

Intertopic Distance Map (via multidimensional scaling)



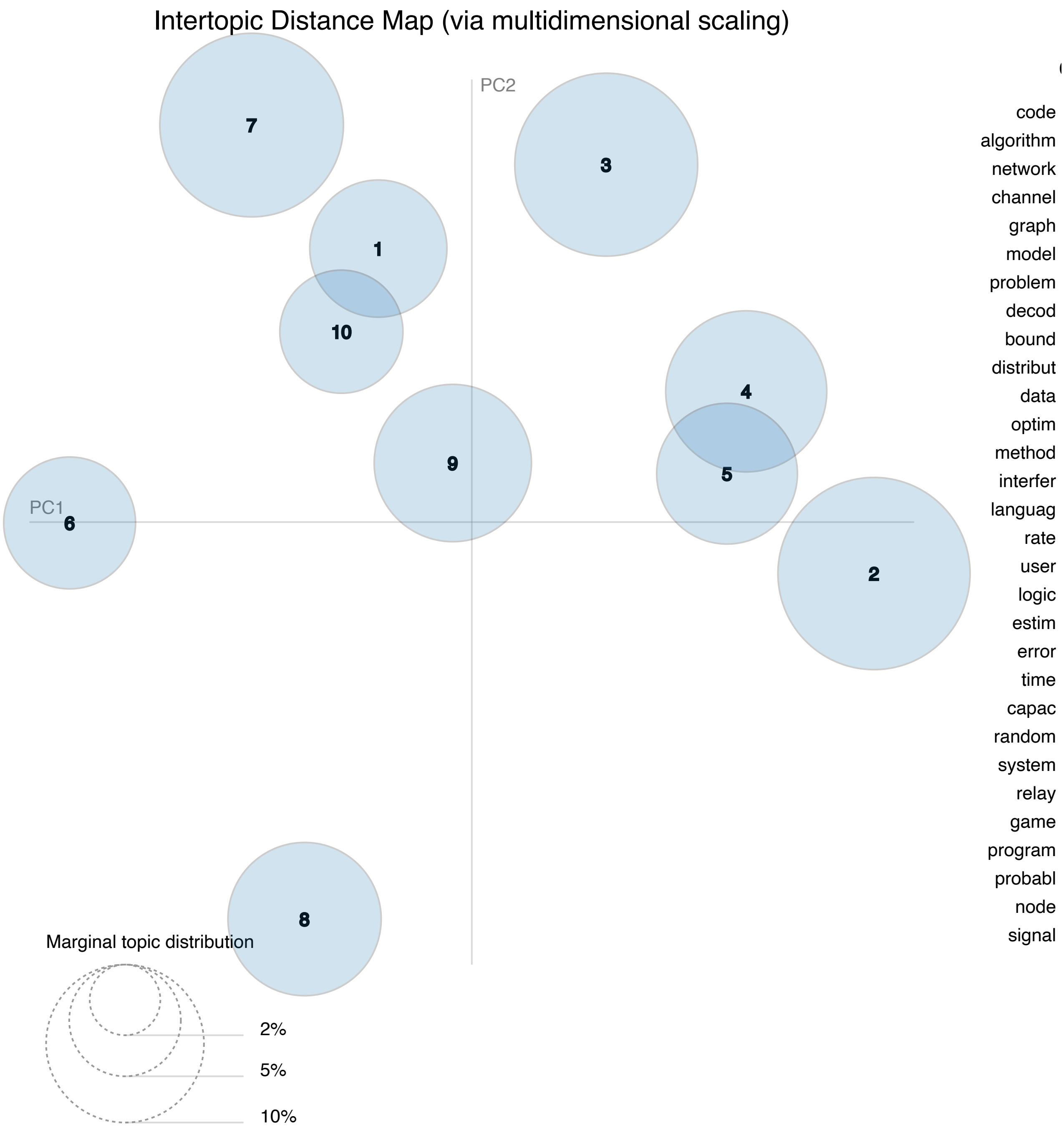

```
doc_topic_df = get_document_topics(ldamodel=model, corpus=corpus, texts=raw_docs)
doc_topic_df.head()
```

	Dominant_Topic	Perc_Contribution	Topic_Keywords	Original_Text
0	27.0	0.5620	discourse, structure, algorithm, as, which, co...	Nested satisfiability A special case of the s...
1	39.0	0.5486	algorithm, problem, time, by, show, can, searc...	A note on digitized angles We study the confi...
2	37.0	0.9472	english, tree, translation, machine	Textbook examples of recursion We discuss

Apply preprocessing 1, K = 10 to first 20000 rows data

```
# get the first 20000 rows data
raw_docs, docs = lda_read_data(20000)
corpus, dictionary = preprocess1(docs)
lda_display, model = LDA_topic(10, corpus, dictionary)
# get the plot
pyLDAvis.display(lda_display)
```

Selected Topic: 0 Previous Topic Next Topic Clear Topic




```
doc_topic_df = get_document_topics(ldamodel=model, corpus=corpus, texts=raw_docs)
```

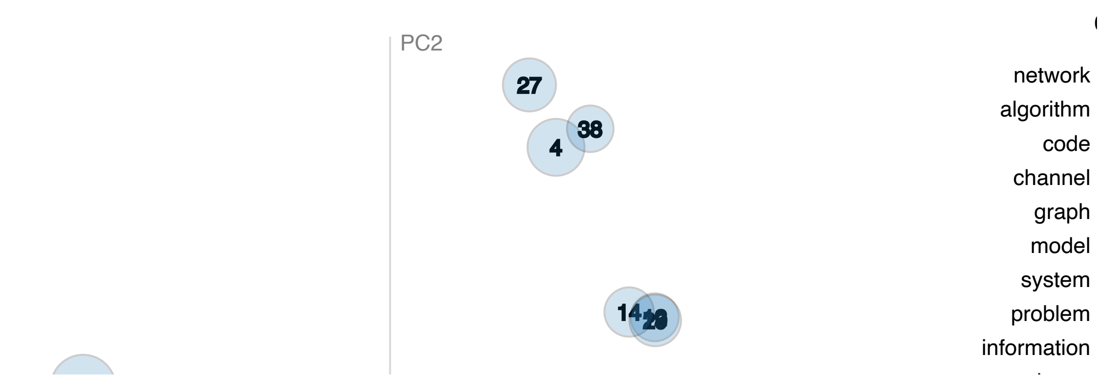
```
doc_topic_df = get_document_topics(ldamodel=model, corpus=corpus, texts=raw_docs)
doc_topic_df.head()
```

	Dominant_Topic	Perc_Contribution	Topic_Keywords	Original_Text
0	6.0	0.5979	graph, bound, set, problem, be, number, show, ...	Nested satisfiability A special case of the s...
1	6.0	0.4191	graph, bound, set, problem, be, number, show, ...	A note on digitized angles We study the confi...
2	2.0	0.9447	model, languag, as, program, logic, system, ...	Textbook examples of recursion We discuss ...

Apply preprocessing 2, K = 40 to first 20000 rows data

```
# get the first 20000 rows data
raw_docs, docs = lda_read_data(20000)
corpus, dictionary = preprocess2(docs)
lda_display, model = LDA_topic(40, corpus, dictionary)
# get the plot
pyLDAvis.display(lda_display)
```

Selected Topic: 0 Previous Topic Next Topic Clear Topic




```
doc_topic_df = get_document_topics(ldamodel=model, corpus=corpus, texts=raw_docs)
```

	Dominant_Topic	Perc_Contribution	Topic_Keywords	Original_Text
0	6.0	0.6005	problem, show, set, show_that, polynomial, giv...	Nested satisfiability A special case of the s...
1	38.0	0.3189	path, each, cost, multi, phase, two, player, h...	A note on digitized angles We study the confi...
2	30.0	0.2815	function, complexity, theory, proof, theorem	Textbook examples of recursion We discuss

```
doc_topic_df.head()
```

Reference

RNN code from https://github.com/bentrevett/pytorch-sentiment-analysis/blob/master/2%20-%20Upgraded%20Sentiment%20Analysis.ipynb

✓ 0 秒 完成时间：下午11:18