Homework 4

Due: Sun Dec. 15 @ 11:59pm

In this homework we will covering NLP, Topic Modeling, Recommendation Engines and Timeseries Data

In Part 1 we will generate recommendations on products from a department store based on product descriptions. We'll first transform the data into topics using Latent Dirichlet Approximation, and then generate recommendations based on this new representation.

In Part 2 we will perform some timeseries transformations on weather data to create a simple model for predicting temperature.

Instructions Follow the comments below and fill in the blanks (__) to complete.

Please 'Restart and Run All' prior to submission.

When submitting to Gradescope, please mark on which page each question is answered.

Out of 59 points total.

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
warnings.simplefilter(action='ignore', category=DeprecationWarning)

%matplotlib inline
np.random.seed(123)
```

Part 1 : LDA and Recommendation Engine

We are going to create a recommendation engine for products from a department store.
The recommendations will be based on the similarity of product descriptions.
We'll query a product and get back a list of products that are similar.
Instead of using the descriptions directly, we will first do some topic modeling using LDA to transform the descriptions into a topic space.

Transform product descriptions into topics and print sample terms from topics

In [2]:
```
# 1.  (2pts) Load the Data

# The dataset we'll be working with is a set of product descriptions from JCPenney.

# Load product information from ../data/jcpenney-products_subset.csv.zip
# This is compressed version of a csv file.
# Use pandas read_csv function with the default parameters.
# read_csv has a parameter compression with default value 'infer' that will handle unzi
pping the data.
# Store the resulting dataframe as df_products.
df_products = pd.read_csv('../data/jcpenney-products_subset.csv.zip')

# print a summary of df_products using .info, noting the number of records (should be 5
000)
df_products.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 6 columns):
uniq_id          5000 non-null object
sku              5000 non-null object
name_title       5000 non-null object
description      5000 non-null object
category         4698 non-null object
category_tree    4698 non-null object
dtypes: object(6)
memory usage: 234.5+ KB
```

In [3]:
```
# 2.  (2pts) Print an Example

# The two columns of the dataframe we're interested in are:
#   name_title which is the name of the product stored as a string
#   description which is a description of the product stored as a string
#
# We'll print out the product in the first row as an example
# If we try to print both at the same time, pandas will truncate the strings
#   so we'll print them seperately

# print the product name_title in row 0 of df_products
print(df_products .name_title[0])

# print the product desciption in row 0 of df_products
print(df_products .description[0])
```

```
Alfred Dunner® Essential Pull On Capri Pant
You'll return to our Alfred Dunner pull-on capris again and again when you want an up
dated, casual look and all the comfort you love.     elastic waistband approx. 19-21"
inseam slash pockets polyester washable imported
```

In [4]:
```
# 3.  (4pts) Transform Descriptions using TfIdf

# In order to pass our product descriptions to the LDA model, we first need to vectoriz
e from strings to
#   fixed vectors of floats.
# To do this we will transform our documents into unigrams using Tf-Idf,
#    use both unigrams and bigrams
#    excluding terms which appear in less than 10 documents
#    excluding common English stop words and

# Import TfidfVectorizer from sklearn.feature_extraction.text
from sklearn.feature_extraction.text import TfidfVectorizer


#  Instantiate a TfidfVectorizer with
#   ngram_range=(1,2),
#   min_df=10,
#   stop_words='english'
# Store as tfidf
tfidf = TfidfVectorizer(ngram_range=(1,2),
                        stop_words='english',
                        min_df=10
                       )

# fit_transform tfidf on the descriptions column of our dataframe, creating the transfo
rmed dataset X_tfidf
# Store as X_tfidf
X_tfidf = tfidf.fit_transform(df_products.description)

# Print the shape of X_tfidf (should be 5000 x 3979)
X_tfidf
```

Out[4]:
```
<5000x3979 sparse matrix of type '<class 'numpy.float64'>'
        with 182556 stored elements in Compressed Sparse Row format>
```

In [5]:
```
# 4.  (3pts) Format Bigram Labels and Print Sample of Extracted Vocabulary

# The extracted vocabulary cat be retrieved from tfidf as a list using get_feature_name
s()
# Store the extracted vocabulary as vocabulary
vocabulary = tfidf.get_feature_names()

# Sklearn joins bigrams with a space character.
# To make output easier to read, replace all spaces in our vocabulary list with undersc
ores.
# To do this we can use the string replace() method.
# For example x.replace(' ','_') with replace all ' ' in x with '_'.
# Store the result back in vocabulary.
for i in range(len(vocabulary)):
    vocabulary[i] = vocabulary[i].replace(' ','_')

# Print the last 5 terms in the vocabulary
vocabulary[-5:]
```

Out[5]:
```
['zipper_pockets', 'zippered', 'zippers', 'zirconia', 'zone']
```

In [6]:
```
# 5. (4pts) Perform Topic Modeling with LDA

# Now that we have our vectorized data, we can use Latent Direchlet Allocation to learn
#   per-document topic distributions and per-topic term distributions.
# Though there are likely more, we'll model our dataset using 20 topics to keep things
 small.
# We'd like the model to run on all of the cores available in the machine we're using.
#    `n_jobs` tells the model how many cores to use, while `n_jobs=-1` indicates use al
l available.
# We'd also like the results to always be the same, so set random_state=123

# Import LatentDirichletAllocation from sklearn.decomposition
from sklearn.decomposition import LatentDirichletAllocation

# Instantiate a LatentDirichletAllocation model with
#    n_components=20, n_jobs=-1, random_state=123
# Store as lda
lda = LatentDirichletAllocation(n_components=20,  # the number of topics
                                n_jobs=-1,         # use all cpus
                                random_state=123) # for reproducability

# Run fit_transform on lda using X_tfidf.
# Store the output (the per-document topic distributions) as X_lda
# NOTE: this step may take a minute or more depending on your setup.
X_lda = lda.fit_transform(X_tfidf)

# Print the shape of the X_lda (should be 5000 x 20)
X_lda.shape
```

Out[6]:
```
(5000, 20)
```

In [7]:
```
# 6. (4pts) Print Top Topic Terms

# To get a sense of what each topic is composed of, we can print the most likely terms
 for each topic.
# We'd like a print statement that looks like this:
#    Topic #0 upper sole rubber synthetic rubber_sole
#
# For each topic print 'Topic #{idx} ' followed by the top 5 most likely terms in that
 topic.
# Hints:
#   Use vocabulary created above, but first convert from a list to np.array to make ind
exing easier
#   The per topic term distributions are stored in model.components_
#   np.argsort returns the indices of an np.array sorted by their value, in ascending o
rder
#   [::-1] reverses the order of an np.array

def print_top_words(model, vocabulary, n_top_words):
    for topic_idx, topic in enumerate(model.components_):
        message = "Topic {:#2d}: ".format(topic_idx)
        message += " ".join([vocabulary[i]
                             for i in topic.argsort()[:-n_top_words - 1:-1]])
        print(message)

print_top_words(lda,vocabulary,5)
```

```
Topic  0: technology construction sole_details comfort details
Topic  1: shaft shaft_height vary measurements slightly
Topic  2: length wash dry polyester dress
Topic  3: cotton crewneck tee sleeves crewneck_short
Topic  4: seat upholstery seat_height low frame
Topic  5: sheet fitted upper_lace fitted_sheet pillowcases
Topic  6: elastane nylon swim nylon_spandex tummy
Topic  7: clean skin hair brush plastic
Topic  8: set safe stoneware includes microwave
Topic  9: sleeves short washable_imported cotton washable
Topic 10: strap case bra dial straps
Topic 11: clean_imported clean polyester spot_clean spot
Topic 12: spandex spandex_washable washable_imported washable wicking
Topic 13: pockets fit cotton waist inseam
Topic 14: king sold comforter shams queen
Topic 15: rug resistant yes indoor backing
Topic 16: steel stainless_steel stainless glass measures
Topic 17: upper sole rubber synthetic rubber_sole
Topic 18: eye_catching catching eye ll_ready yoga
Topic 19: jewelry metal photos photos_enlarged enlarged
```

Generate recommendations using topics

In [8]:
```
# 7.  (3pts) Generate Similarity Matrix

# We'll use Content Filtering to make recommendations based on a query product.
# Each product will be represented by its LDA topic weights learned above.
# We'd like to recommend similar products in LDA space.
# We'll use cosine_similarity as measure of similarity.

# From sklearn.metrics.pairwise import cosine_similarity
from sklearn.metrics.pairwise import cosine_similarity

# Use cosine_similarity to generate similarity scores on our X_lda data
# Store as similarities.
# NOTE: we only need to pass X_lda in once,
#   the function will calculate pairwise similarity for all elements in that matrix
similarities = cosine_similarity(X_lda)

# print the shape of the similarities matrix (should be 5000x5000)
similarities.shape
```

Out[8]:
```
(5000, 5000)
```

In [9]:
```
# 8. (4pts) Generate Recommendations

# Let's test our proposed recommendation engine using the product at row 0 in df_produc
ts.
#   The name of this product is "Alfred Dunner® Essential Pull On Capri Pant"

# Print the names for the top 10 most similar products to this query.
# Suggested way to do this is:
#   get the cosine similarities from row 0 of the similarities matrix
#   get the indices of this array sorted by value using np.argsort
#   reverse the order of these indices (remember, we want high values and np.argsort ev
aluates ascending)
#   get the first 10 indexes from this reversed array
#   use those indices to index into df_products.name_title and print the result

# HINT: The first two products should be:
#   'Alfred Dunner® Essential Pull On Capri Pant', (the original query product)
#   'Alfred Dunner® Pull-On Pants - Plus',
df_products.name_title[similarities[0].argsort()[::-1][:10]]
```

Out[9]:
```
0             Alfred Dunner® Essential Pull On Capri Pant
2091                  Alfred Dunner® Pull-On Pants - Plus
662                        Alfred Dunner® Pull On Pant
2973                Levi's® 511™ Slim Fit Jeans - Boys 4-7x
3251    Arizona Twill Camo Cargo Shorts - Boys 8-20, S...
3637               Love Indigo Turquoise Back Pocket Capris
858                  Liz Claiborne® Emma Ankle Pants - Plus
2562                   Liz Claiborne® Pajama Pants - Petite
4814                              adidas® 3G Speed Shorts
83                           Stylus™ Crossover Ankle Pants
Name: name_title, dtype: object
```

Part 2 : Timeseries Data

We are going to create a very simple model to predict average daily temperature at Laguardia Airport 2 days in the future. This point here isn't to generate a great model, but instead to get some practice with timeseries transformations and model evaluation.

This data was collected from https://rp5.ru/Weather_archive_in_New_York,_La_Guardia_(airport (https://rp5.ru/Weather_archive_in_New_York,_La_Guardia_(airport))

Before we do any modeling we need to resample and visualize the data.

In [10]:
```
# 9. (3pts) Load Weather Data

# Read in the our historical Laguardia weather data from '../data/weather_lga.csv.zip'.
# The data includes a column 'timestamp' that we'll use as our index.
# Use read_csv with default parameters except:
#   set index_col to 'timestamp'
#   pass 'timestamp' as the only element of a list to parse_dates
# Store the result as df_weather
df_weather = pd.read_csv('../data/weather_lga.csv.zip',index_col='timestamp')
df_weather.index = pd.to_datetime(df_weather.index)
# Print the info of df_weather
#   Should be 14600 rows by 10 columns with no missing values)
df_weather.shape
```

Out[10]:
```
(14600, 10)
```

In [11]:
```
# 10. (1pt) Examine Index

# Print out the first 5 elements of the index of df_weather.
# Note that there is more than one observation per day
df_weather.index[:5]
```

Out[11]:
```
DatetimeIndex(['2014-11-28 01:00:00', '2014-11-28 04:00:00',
               '2014-11-28 07:00:00', '2014-11-28 10:00:00',
               '2014-11-28 13:00:00'],
              dtype='datetime64[ns]', name='timestamp', freq=None)
```

In [12]:
```
df_weather.head()
```

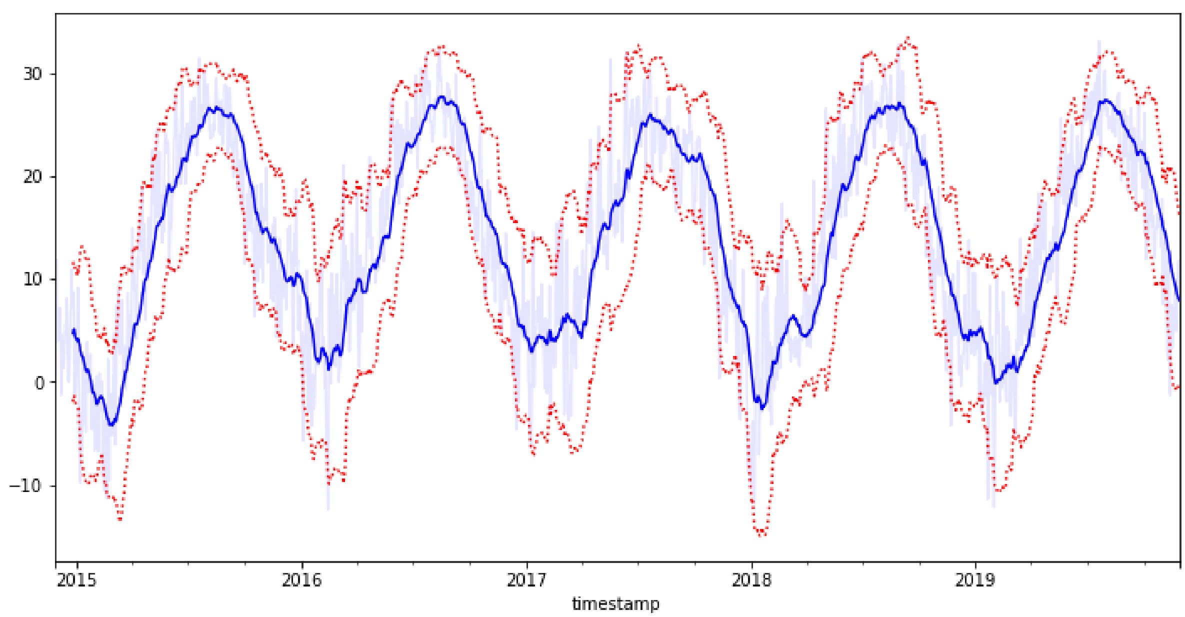
Out[12]:

	temperature	pressure	pressure_sealevel	pressure_changeslast3hours	relativehumidit
timestamp					
2014-11-28 01:00:00	1.1	762.5	763.5	0.3	70.
2014-11-28 04:00:00	0.0	763.0	764.0	0.5	69.
2014-11-28 07:00:00	0.0	764.2	765.2	1.2	73.
2014-11-28 10:00:00	1.1	765.5	766.4	1.3	59.
2014-11-28 13:00:00	2.2	764.8	765.8	-0.7	55.

In [13]:
```
# 11.  (3pts) Downsample and Aggregate

# We'll downsample our data to a daily frequency.
# Since we're downsampling, we need to aggregate observations.
# For this exercise, we'll aggregate using mean.
# Store the result of the downsample and aggregation as df_daily
df_daily = df_weather.resample('D', level=0).mean()

# Print the info of df_daily.
#    Should be 1827 rows by 10 columns with an index with daily frequency
df_daily.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 1827 entries, 2014-11-28 to 2019-11-28
Freq: D
Data columns (total 10 columns):
temperature                   1827 non-null float64
pressure                      1827 non-null float64
pressure_sealevel             1827 non-null float64
pressure_changeslast3hours    1827 non-null float64
relativehumidity              1827 non-null float64
windspeed                     1827 non-null float64
maxwindgust_prior10minutes    1827 non-null float64
horizontalvisibility          1827 non-null float64
temperature_dewpoint          1827 non-null float64
precipitation_amount          1827 non-null float64
dtypes: float64(10)
memory usage: 157.0 KB
```

In [14]:
```
# 12. (6pts) Visualize Temperature

# We'd like to plot temperature over time as well as a smoothed version with standard a
eviation

# First, create a fig,ax using subplots with figsize=(12,6)
fig,ax = plt.subplots(figsize=(12,6))

# On ax, plot the temperature column of df_daily, use a solid blue line with alpha valu
e 0.1
ax = df_daily.temperature.plot(alpha = 0.1,c = 'b')

# Create a rolling object for a 30 window on temperature
#   All parameters of rolling default except for the window size
# Store as rolling_temp
rolling_temp = df_daily.temperature.rolling(30)

# On ax, plot the mean of rolling_temp, use a solid blue line
ax = rolling_temp.mean().plot(c = 'b')

# On ax, plot the mean of rolling_temp plus 2 standard deviations, use a dotted red lin
e
ax = (rolling_temp.mean() + 2 * rolling_temp.std()).plot(style=':',c='r')
# On ax, plot the mean of rolling_temp minus 2 standard deviations, use a dotted red li
ne
ax = (rolling_temp.mean() - 2 * rolling_temp.std()).plot(style=':',c='r')
```



Create Model to Predict Temperature

Now we'll create a very simple model to predit temperature 2 days in the future. This is the same as saying we'd like to predict today's temperature using data 2 days in the past.

We'll create two models

1. using only the temperature from 2 days in the past
2. using the full set of features from 2 days in the past joined with all features from 1 year in the past

In [15]:
```
# For use in this section
from sklearn.linear_model import Lasso
from sklearn.feature_selection import SelectFromModel
from sklearn.model_selection import cross_val_score
```

In [16]:
```
# 13. (2pts) Create Dataset of 2 days ago

# We need to align the temperature on the current date with data from 2 days prior.
# To do this we'll shift all data 2 days forward

# Shift all data in df_daily two days forward
# Store in df_twodaysprior
df_twodaysprior = df_daily.shift(2)

# Check that the data in df_twodaysprior is in fact the data in df_daily shifted two da
ys (provided)
assert np.all(df_twodaysprior.loc['2019-11-28'].values == df_daily.loc['2019-11-26'].v
alues)

# Print the shape of df_twodaysprior (should be the same as df_daily, 1827 x 10)
df_twodaysprior.shape
```

Out[16]: (1827, 10)

In [17]:
```
# 14. (4pts) Create Dataset of 1 Year Ago

# We'd also like to use data from 1 year ago.
# To do this we'll shift all data 365 days forward

# # Shift all data in df_daily two days forward
# Store in df_oneyearprior
df_oneyearprior = df_daily.shift(365)

# Check that the data in df_oneyearprior is in fact the data in df_daily shifted 365 da
ys
#   Use a similar assert statement to the one in Question 13
#   Compare date range '2019-11-27' to '2019-11-28' in df_oneyearprior
#       to the same dates one year prior in df_daily
assert np.all(df_oneyearprior.loc['2019-11-27':'2019-11-28'].values ==
              df_daily.loc['2018-11-27':'2018-11-28'].values)

# Print the shape of df_oneyearprior (should be the same as df_daily, 1827 x 10)
df_oneyearprior.shape
```

Out[17]: (1827, 10)

In [18]:
```
# 15. (2pts) Modify df_oneyearprior Column Names

# In order to make model interpretation easier later,
#   we'll modify the column names df_oneyearprior.

# Prepend all column names in df_oneyearprior with the string 'oneyearprior_'
df_oneyearprior = df_oneyearprior.add_prefix('oneyearprior_')

# Print out the first two column names in df_oneyearprior (first should be 'oneyearprio
r_temperature')
print(df_oneyearprior.columns[:2])
```

```
Index(['oneyearprior_temperature', 'oneyearprior_pressure'], dtype='object')
```

In [19]:
```
# 16. (4pts) Create Model Using df_twodaysprior

# Now we'll create and evaluate a Lasso model trained on df_twodaysprior to predict tem
perature in df_daily.
# In order to aviod any missing data due to shifting, we'll only be using data from
#   '2015-11-28' to '2019-11-28'

# Extract our target temperature from df_daily rows
#    corresponding to dates from  '2015-11-28' to '2019-11-28' inclusive
# Store in y
y = df_daily.loc['2015-11-28':'2019-11-28'].temperature

# Extract the temperature column from  df_twodaysprior as a dataframe
#    corresponding to dates from  '2015-11-28' to '2019-11-28' inclusive
# Recall that to extract a single column as a dataframe, we can pass a list with a sing
le value
# Store in X1
X1 = df_twodaysprior.loc['2015-11-28':'2019-11-28'][['temperature']]

# Generate 5-fold R^2 cross validation scores using Lasso with default values, X1 and y
# Store in scores
scores = cross_val_score(Lasso(), X1,y, cv=5)

# Print the mean of scores. (Note that this score may seem surprisingly high.)
scores.mean()
```

Out[19]:
```
0.7504069358404043
```

In [20]:
```
# 17. (4pts) Create Model Using df_twodaysprior and df_oneyearprior

# Now we'll create and evaluate a Lasso model trained on both df_twodaysprior and df_on
eyearlater.
# As before we'll only be using data from '2015-11-28' to '2019-11-28' inclusive
# We'll use the same y as in the questions above.

# Join the rows corresponding to the dates in our target y from df_twodaysprior with th
ose from df_oneyearprior
# Since the indices should be the same, we can use the join function.
# Store the result in X2
X2 = df_twodaysprior.join(df_oneyearprior).loc['2015-11-28':'2019-11-28']

# Generate 5-fold R^2 cross validation scores using Lasso with default values, X2 and y
# Store in scores
scores = cross_val_score(Lasso(), X2,y, cv=5)

# Print the mean of scores. You should see a slight improvement
scores.mean()
```

Out[20]: 0.7911960330948566

In [21]:
```
# 18. (4pts) Select Important Features From Second Model

# Instantiate SelectFromModel with a Lasso model, both with default values, and fit on
 X2 and y
# Store the result as sfm
sfm = SelectFromModel(Lasso()).fit(X2,y)

# Get the chosen features from sfm using get_support
feature_idx = sfm.get_support()

# Using the column names in X2 and support, print out each chosen featurename on a sepa
rate line
print(*X2.columns[feature_idx],sep = '\n')
```

```
temperature
pressure
relativehumidity
oneyearprior_temperature
oneyearprior_relativehumidity
```