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Assignment Part 2

- Pleae Run All Cells ... the code will not take long to downlaod data 1:18 seconds to be exact.
- I have included a data sample in a zip file in a CSV format.
- The script will regenerate them as we.

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Part 1

Data collection

In [693]:

```
import pandas as pd
import numpy as np
import re
import csv
import os.path as pathFile
import os
import urllib.request as request
from bs4 import BeautifulSoup as bs

import matplotlib
import itertools
import matplotlib.pyplot as plt
%matplotlib inline
url = 'http://mlg.ucd.ie/modules/COMP41680/archive/index.html'
url_prefix = 'http://mlg.ucd.ie/modules/COMP41680/archive/'
```

Fetch All the Articales URLs

- I am using ***mode* = '*a*'** because I am writing data for each link. this might add new data to old ones if the file exist before.

In [694]:

```
# Article Category , Article Title
def write_Articles_to_CSV(fileName, key,link):
    for i,df in enumerate(pd.read_html(link)):
        sum_articles =+ len(df)
#         return sum_articles
#         print('{} {}'.format(key, sum))

# Drop the NaN Value from the table
        df = df.dropna(axis=0,how='any')
        df.to_csv(fileName, mode='a', index = False, header = False)
        return sum_articles
```

Parse each Month's URLs.

In [695]:

```
def fetch_data_from_url(prefix, url_to_fetch):

    try:
        html_page = request.urlopen(url_to_fetch)
        soup = bs(html_page, 'html.parser')
        main_page_months_links_keys = []
        main_page_months_links = []

        for link in soup.find_all('a', attrs={'href': re.compile('')}):
            newURL = url_prefix + link.get('href')
            if newURL in main_page_months_links:
                pass
            else:
                key = newURL.rsplit('/', 1)[1]
                main_page_months_links_keys.append(key)
                main_page_months_links.append(newURL)

        '''
        pop() => the last elements ... because it is the main url_prefixes URL
        '''
        main_page_months_links_keys.pop()
        main_page_months_links.pop()
        dictionary = dict(zip(main_page_months_links_keys, main_page_months_li
nks))
        return dictionary
    except Exception as e:
        print(e)
```

This block acts as the main

In [696]:

```
def main():
    all_articles_categories = 'all_articles_categories.csv'
    News_Article_Archive_linkes = fetch_data_from_url(url_prefix, url)
    print(len(News_Article_Archive_linkes))
    # if file is there delete it
    if pathFile.isfile(all_articles_categories):
            print('The file does exists')
            os.remove(all_articles_categories)

    print('Create a file')
    # create a file and poplaute it with data.
    overAllDict = []
    month_number_of_articles = []
    for key,link in News_Article_Archive_linkes.items():
    #     print('month: ', key)
    #     print('link: ',link)
       # Get the month and the total number of artiles published in it
        numer_of_articles = write_Articles_to_CSV(all_articles_categories,key,
link)
        month_number_of_articles.append({key : numer_of_articles})
        all_news_articles = fetch_data_from_url(url_prefix, link)
        # get all article links for each month
        # print(all_news_articles)
        overAllDict.append(all_news_articles)
    month_number_of_articles


if __name__ == '__main__':
    main()
```

```
12
Create a file
```

Write each article URLs in CSV file for later use

In [697]:

```
def write_articles_to_CSV(fileName,data_dict,operation = 'w'):
    try:
        with open(fileName, operation) as csvfile:
            fieldnames = ['Article', 'URL']
            writer = csv.DictWriter(csvfile, fieldnames=fieldnames)
            writer.writeheader()
            for key,values in enumerate(data_dict):
                for key,value in values.items():
                    # Pass the home page
                    if key == 'index.html':
                        pass
                    else:
                        newURL = url_prefix + key
                        writer.writerow({'Article': key , 'URL': newURL})
    except Exception as e:
        print('write_articles_to_CSV: {}'.format(e))
```

Write each article content:

- ***{key: title, vlaue: body}*** in CSV file for later use.
- I had to pass the acual extracted vlaues: title and body raw to the fucntion.

In [698]:

```
def write_articles_Contents_to_CSV(fileName,key,value,operation = 'w'):
    try:
        with open(fileName, operation) as csvfile:
            writer = csv.writer(csvfile)
            writer.writerow([key , value])
    except Exception as e:
        print('write_articles_Contents_to_CSV: {}'.format(e))
```

In [699]:

```
all_articles_URL_File = 'all_articles_URLs.csv'
write_articles_to_CSV(all_articles_URL_File,overAllDict)
```

Read the saved URLs back

In [700]:

```
get_all_Articles_URLs_from_CSV = []
def read_articles_from_CSV(fileName):
    try:
        with open(fileName) as csvfile:
            reader = csv.DictReader(csvfile)
            for row in reader:
                get_all_Articles_URLs_from_CSV.append((row['URL']))
        return get_all_Articles_URLs_from_CSV
    except Exception as e:
        print('read_articles_from_CSV: {}'.format(e))
```

read the html page content:

- Extract the title and body.

In [701]:

```
def read_html_page_Content(url):
    body_content = ''
    try:
        html_page = request.urlopen(url)
        soup = bs(html_page, 'html.parser')
        # get the article title:
        title = soup.find('h2').text
        # Remove the notice tag from the <div>
        soup.find('p',attrs={"class":"notice"}).decompose()
        # get the article body
        article = soup.find("div", {"class":"main"}).find_all('p')
        for element in article:
            body_content += '\n' + ''.join(element.find_all(text = True))
#         print(body_content)
        return title, body_content #dict(zip(title, body.getText()))
    except Exception as e:
        print('read_html_page_Content: {}'.format(e))
```

Get all the articles URLs for the CSV file

In [702]:

```
all_URLs = read_articles_from_CSV(all_articles_URL_File)
```

Number of Articles obtained

In [703]:

```
print(len(all_URLs))
```

```
1408
```

For Each Article Get its Conetents:

- H2 => header
- Body => text content

In [704]:

```
print('Scraping Articles Contents... please wait!')
articles_Contents = 'articles_Contents.csv'
if pathFile.isfile(articles_Contents):
        print('The file does exists')
        os.remove(articles_Contents)
for eachURL in all_URLs:
    title,body = read_html_page_Content(eachURL)
    write_articles_Contents_to_CSV(articles_Contents,title,body,'a')
#     print('Title: {}\nBody: {}\n-------------'.format(title,body))
print('Done Scraping Articles Contents.')
```

```
Scraping Articles Contents... please wait!
Done Scraping Articles Contents.
```

All the data collection is done above

++

Part 2

Analyse the collected data

Use panda to read all saved csv files

- add missing headers.

In [705]:

```
# read in all data from files
all_articles_categories_df = pd.read_csv(all_articles_categories, names = ['Ca
tegory','Titile'])
all_articles_URL_File_df = pd.read_csv(all_articles_URL_File)
articles_Contents_df = pd.read_csv(articles_Contents,names = ['Titile','Body']
)
```

In [706]:

```
all_articles_categories_df.head()
```

Out[706]:

	Category	Titile
0	technology	21st-Century Sports: How Digital Technology Is...
1	business	Asian quake hits European shares
2	technology	BT offers free net phone calls
3	business	Barclays shares up on merger talk
4	sport	Barkley fit for match in Ireland

In [707]:

```
# print the shape
all_articles_categories_df.shape
```

Out[707]:

```
(1408, 2)
```

In [708]:

```
# show the df frist 10 values
all_articles_URL_File_df.head(10)
```

Out[708]:

	Article	URL
0	article-jan-0418.html	http://mlg.ucd.ie/modules/COMP41680/archive/ar...
1	article-jan-0027.html	http://mlg.ucd.ie/modules/COMP41680/archive/ar...
2	article-jan-0631.html	http://mlg.ucd.ie/modules/COMP41680/archive/ar...
3	article-jan-2105.html	http://mlg.ucd.ie/modules/COMP41680/archive/ar...
4	article-jan-3300.html	http://mlg.ucd.ie/modules/COMP41680/archive/ar...
5	article-jan-4187.html	http://mlg.ucd.ie/modules/COMP41680/archive/ar...
6	article-jan-1974.html	http://mlg.ucd.ie/modules/COMP41680/archive/ar...
7	article-jan-3666.html	http://mlg.ucd.ie/modules/COMP41680/archive/ar...
8	article-jan-2629.html	http://mlg.ucd.ie/modules/COMP41680/archive/ar...
9	article-jan-2415.html	http://mlg.ucd.ie/modules/COMP41680/archive/ar...

In [709]:

```
all_articles_URL_File_df.shape
```

Out[709]:

```
(1408, 2)
```

In [710]:

```
articles_Contents_df.head(10)
```

Out[710]:

	Titile	Body
0	21st-Century Sports: How Digital Technology Is...	\n\nThe sporting industry has come a long way ...
1	Asian quake hits European shares	\nAsian quake hits European shares\n\nShares i...
2	BT offers free net phone calls	\n\nBT is offering customers free internet tel...
3	Barclays shares up on merger talk	\nBarclays shares up on merger talk\n\nShares ...
4	Barkley fit for match in Ireland	\n\nEngland centre Olly Barkley has been passe...
5	Bellamy under new fire	\nBellamy under new fire\n\nNewcastle boss Gra...
6	Benitez 'to launch Morientes bid'	\nBenitez 'to launch Morientes bid'\n\nLiverpo...
7	Benitez delight after crucial win	\n\nLiverpool manager Rafael Benitez admitted ...
8	Big war games battle it out	\n\nThe arrival of new titles in the popular M...
9	British Library gets wireless net	\n\nVisitors to the British Library will be ab...

In [711]:

```
articles_Contents_df.shape
```

Out[711]:

```
(1408, 2)
```

In [712]:

```
"""Slices the category colunm for later use"""
all_articles_Category_colm_df = all_articles_categories_df.iloc[:,0]
```

In [713]:

```
type(all_articles_Category_colm_df)
```

Out[713]:

```
pandas.core.series.Series
```

Merged two data frames togther:

- all_articles_Category_colm_df => ***which only contains the categoies column.***
- articles_Contents_df => ***which contains the article tilile and voday.***

In [714]:

```
"""Merge the sliced category df with the articles_Contents_df for easy readabi
lity"""
merged_df = pd.concat([all_articles_Category_colm_df, articles_Contents_df], a
xis=1)
```

In [715]:

```
merged_df.head(10)
```

Out[715]:

	Category	Titile	Body
0	technology	21st-Century Sports: How Digital Technology Is...	\n\nThe sporting industry has come a long way ...
1	business	Asian quake hits European shares	\nAsian quake hits European shares\n\nShares i...
2	technology	BT offers free net phone calls	\n\nBT is offering customers free internet tel...
3	business	Barclays shares up on merger talk	\nBarclays shares up on merger talk\n\nShares ...
4	sport	Barkley fit for match in Ireland	\n\nEngland centre Olly Barkley has been passe...
5	sport	Bellamy under new fire	\nBellamy under new fire\n\nNewcastle boss Gra...
6	sport	Benitez 'to launch Morientes bid'	\nBenitez 'to launch Morientes bid'\n\nLiverpo...
7	sport	Benitez delight after crucial win	\n\nLiverpool manager Rafael Benitez admitted ...
8	technology	Big war games battle it out	\n\nThe arrival of new titles in the popular M...
9	technology	British Library gets wireless net	\n\nVisitors to the British Library will be ab...

Clean data before saving them

- ***Remove NaN***

In [716]:

```
"""Drop any row missing data"""
fileName = 'merged_contents.csv'
merged_df = merged_df.dropna(axis=0,how='any')
merged_df.to_csv(fileName, mode='w', index = False, header = True)
```

In [717]:

```
# check size
merged_df.size
```

Out[717]:

```
4224
```

In [718]:

```
# check type
type(merged_df)
```

Out[718]:

```
pandas.core.frame.DataFrame
```

Double check for missing vlaues if any

In [719]:

```
all_articles_categories_df.head().isnull
```

Out[719]:

```
<bound method NDFrame.isnull of      Category
Titile
0  technology  21st-Century Sports: How Digital Technology Is...
1    business                   Asian quake hits European shares
2  technology                     BT offers free net phone calls
3    business                  Barclays shares up on merger talk
4       sport                   Barkley fit for match in Ireland>
```

In [720]:

```
all_articles_URL_File_df.head().isnull
```

Out[720]:

```
<bound method NDFrame.isnull of                    Article
URL
0  article-jan-0418.html  http://mlg.ucd.ie/modules/COMP41680/arch
ive/ar...
1  article-jan-0027.html  http://mlg.ucd.ie/modules/COMP41680/arch
ive/ar...
2  article-jan-0631.html  http://mlg.ucd.ie/modules/COMP41680/arch
ive/ar...
3  article-jan-2105.html  http://mlg.ucd.ie/modules/COMP41680/arch
ive/ar...
4  article-jan-3300.html  http://mlg.ucd.ie/modules/COMP41680/arch
ive/ar...>
```

In [721]:

```
articles_Contents_df.head().isnull
```

Out[721]:

```
<bound method NDFrame.isnull of
Titile  \
0  21st-Century Sports: How Digital Technology Is...
1                   Asian quake hits European shares
2                     BT offers free net phone calls
3                  Barclays shares up on merger talk
4                   Barkley fit for match in Ireland

                                                Body
0  \n\nThe sporting industry has come a long way ...
1  \nAsian quake hits European shares\n\nShares i...
2  \n\nBT is offering customers free internet tel...
3  \nBarclays shares up on merger talk\n\nShares ...
4  \n\nEngland centre Olly Barkley has been passe...  >
```

Get classes labels:

In [722]:

```
lables = [] # we expect those 3 ['technology', 'business', 'sport']
for cat,title in all_articles_Category_colm_df.items():
#     print(title)
    if title in lables:
        pass
    elif title != 'Article Category':
        lables.append(title)
```

In [723]:

```
lables
```

Out[723]:

```
['technology', 'business', 'sport']
```

In [724]:

```
type(merged_df)
```

Out[724]:

```
pandas.core.frame.DataFrame
```

Check the Category distribution

In [725]:

```
merged_df.Category.value_counts()
```

Out[725]:

```
sport          526
business       491
technology     391
Name: Category, dtype: int64
```

Labels Mapping:

we assigned each category a value:

- 0 => technology.
- 1 => business.
- 2 => sport.

Convert Category to a numerical variable

In [726]:

```
merged_df['Category_num'] = merged_df.Category.map({lables[0]: 0.0, lables[1]:
1.0, lables[2] : 2.0})
```

In [727]:

```
# check that the conversion worked
merged_df.head(10)
```

Out[727]:

	Category	Titile	Body	Category_num
0	technology	21st-Century Sports: How Digital Technology Is...	\n\nThe sporting industry has come a long way ...	0.0
1	business	Asian quake hits European shares	\nAsian quake hits European shares\n\nShares i...	1.0
2	technology	BT offers free net phone calls	\n\nBT is offering customers free internet tel...	0.0
3	business	Barclays shares up on merger talk	\nBarclays shares up on merger talk\n\nShares ...	1.0
4	sport	Barkley fit for match in Ireland	\n\nEngland centre Olly Barkley has been passe...	2.0
5	sport	Bellamy under new fire	\nBellamy under new fire\n\nNewcastle boss Gra...	2.0
6	sport	Benitez 'to launch Morientes bid'	\nBenitez 'to launch Morientes bid'\n\nLiverpo...	2.0
7	sport	Benitez delight after crucial win	\n\nLiverpool manager Rafael Benitez admitted ...	2.0
8	technology	Big war games battle it out	\n\nThe arrival of new titles in the popular M...	0.0
9	technology	British Library gets wireless net	\n\nVisitors to the British Library will be ab...	0.0

In [728]:

```
"""store the feature matrix (X) and response vector (y)"""
X = merged_df.Body
y = merged_df.Category_num
```

In [729]:

```
# check the shapes of X and y
print(X.shape)
print(y.shape)
```

```
(1408,)
(1408,)
```

Using the 20 to 80 precent ration to slices the data.

In [730]:

```
# split X and y into training and testing sets
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=1,test_
size=0.2)
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(1126,)
(282,)
(1126,)
(282,)
```

Vectorizing our dataset

- user some weighing and filtering matrix

In [731]:

```
"""import and instantiate CountVectorizer (with the default parameters)"""
from sklearn.feature_extraction.text import CountVectorizer,TfidfVectorizer
"""remove English stop words and include ngram_range=(1, 2) companation"""
# vect = CountVectorizer(stop_words='english',max_df=0.5,min_df=2)
vect = TfidfVectorizer(stop_words='english', ngram_range=(1, 2),max_df=0.5)
```

In [732]:

```
# learn training data vocabulary, then use it to create a document-term matrix
X_train_dtm = vect.fit_transform(X_train)
```

In [733]:

```
# examine the document-term matrix
X_train_dtm
```

Out[733]:

```
<1126x195019 sparse matrix of type '<class 'numpy.float64'>'
        with 382177 stored elements in Compressed Sparse Row forma
t>
```

In [734]:

```
# display some sample weighted values
print(X_train_dtm[0])
```

```
(0, 44556)    0.0326243689375
(0, 160670)   0.032915747617
(0, 164101)   0.143480996178
(0, 72805)    0.110873577225
(0, 120019)   0.0204972851684
(0, 182398)   0.0363512826902
(0, 121739)   0.0217573787296
(0, 64112)    0.0900302035998
(0, 100346)   0.0461318862802
(0, 57652)    0.0301420514658
(0, 65947)    0.0391535824889
(0, 8573)     0.0157380722513
(0, 114144)   0.0220253590954
(0, 42311)    0.032915747617
(0, 74667)    0.0263645580952
(0, 59661)    0.472566674972
(0, 55211)    0.309060884293
(0, 102509)   0.0301420514658
(0, 81321)    0.0363512826902
(0, 19900)    0.0198354462464
(0, 193960)   0.0328199626268
(0, 192034)   0.0101403604364
(0, 97147)    0.0173213083189
(0, 106539)   0.0274705533562
(0, 62175)    0.0190967619183
:     :
(0, 177110)   0.0343416235025
(0, 159581)   0.0363512826902
(0, 29259)    0.0363512826902
(0, 70352)    0.0363512826902
(0, 72732)    0.0363512826902
(0, 17250)    0.0363512826902
(0, 157123)   0.0363512826902
(0, 132541)   0.0363512826902
(0, 103035)   0.0363512826902
(0, 162434)   0.0343416235025
(0, 100691)   0.031809752356
(0, 180384)   0.0363512826902
(0, 115982)   0.0363512826902
(0, 61117)    0.0343416235025
(0, 184233)   0.0363512826902
(0, 72872)    0.0363512826902
(0, 44594)    0.032915747617
(0, 69633)    0.0363512826902
(0, 36090)    0.0363512826902
(0, 55215)    0.0363512826902
(0, 59727)    0.0363512826902
(0, 24726)    0.0363512826902
(0, 134758)   0.0363512826902
(0, 179479)   0.0363512826902
(0, 69822)    0.0363512826902
```

In [735]:

```
# transform testing data (using fitted vocabulary) into a document-term matrix
X_test_dtm = vect.transform(X_test)
X_test_dtm
```

Out[735]:

```
<282x195019 sparse matrix of type '<class 'numpy.float64'>'
        with 57351 stored elements in Compressed Sparse Row format
>
```

In [736]:

```
"""Get the some of the vocabualry we have"""
terms = vect.get_feature_names()
vocab = vect.vocabulary_
print("Vocabulary has %d distinct terms" % len(terms))
```

```
Vocabulary has 195019 distinct terms
```

In [737]:

```
"""show some of the vocabualry we have"""
print(terms[500:600])
```

```
['100 baikal', '100 bonds', '100 britain', '100 cent', '100 chosen
', '100 companies', '100 countries', '100 date', '100 debt', '100
debts', '100 december', '100 decline', '100 depending', '100 diffi
cult', '100 don', '100 employees', '100 exchange', '100 fighting',
'100 firms', '100 foreign', '100 fresh', '100 gazprom', '100 gigab
ytes', '100 guarantee', '100 hard', '100 home', '100 hours', '100
iconic', '100 ids', '100 include', '100 index', '100 january', '10
0 jobs', '100 kfb', '100 km', '100 lawsuits', '100 lifetime', '100
list', '100 meet', '100 mentally', '100 metres', '100 million', '1
00 month', '100 multilateral', '100 new', '100 nigerian', '100 pag
e', '100 parent', '100 people', '100 points', '100 popular', '100
portability', '100 really', '100 record', '100 rupees', '100 said'
, '100 server', '100 seven', '100 size', '100 staff', '100 sure',
'100 telecom', '100 times', '100 trillion', '100 uk', '100 worth',
'100 years', '1000', '1000 web', '1000m', '1000m major', '1000m sw
edish', '100bn', '100bn proving', '100bn red', '100m', '100m 120m'
, '100m 20', '100m 200m', '100m 38m', '100m 52m', '100m analysts',
'100m champion', '100m deal', '100m euros', '100m final', '100m go
ld', '100m hurdles', '100m new', '100m personal', '100m represents
', '100m scheme', '100m silver', '100m steal', '100m title', '100m
withdrew', '100m world', '100s', '100s 000s', '101']
```

In [738]:

```
# what column is the term '2003 records' on?
vocab_nb['2003 records']
```

Out[738]:

```
2670
```

Building and evaluating a model

The multinomial Naive Bayes classifier is suitable for classification with **discrete features** (e.g., word counts for text classification). The multinomial distribution normally requires integer feature counts. However, in practice, fractional counts such as tf-idf may also work.

In [739]:

```
# import and instantiate a Multinomial Naive Bayes model
from sklearn.naive_bayes import MultinomialNB
nb = MultinomialNB()
```

In [740]:

```
# train the model using X_train_dtm (timing it with an IPython "magic command"
)
%time nb.fit(X_train_dtm, y_train)
```

```
CPU times: user 34.9 ms, sys: 16.8 ms, total: 51.8 ms
Wall time: 52.2 ms
```

Out[740]:

```
MultinomialNB(alpha=1.0, class_prior=None, fit_prior=True)
```

In [741]:

```
# make class predictions for X_test_dtm
y_pred_class_nb = nb.predict(X_test_dtm)
y_pred_class_nb
```

Out[741]:

```
array([ 2.,  0.,  2.,  2.,  1.,  1.,  2.,  0.,  1.,  1.,  0.,  1.,
2.,
        2.,  1.,  0.,  0.,  1.,  0.,  2.,  1.,  1.,  2.,  2.,  2.,
2.,
        2.,  2.,  2.,  2.,  2.,  1.,  0.,  0.,  1.,  2.,  2.,  0.,
1.,
        2.,  1.,  0.,  1.,  0.,  0.,  2.,  1.,  1.,  0.,  2.,  2.,
0.,
        1.,  1.,  2.,  0.,  1.,  0.,  2.,  0.,  1.,  2.,  2.,  0.,
1.,
        0.,  1.,  0.,  1.,  2.,  1.,  2.,  1.,  2.,  2.,  2.,  1.,
2.,
        2.,  0.,  1.,  2.,  0.,  2.,  2.,  2.,  2.,  2.,  0.,  0.,
1.,
        0.,  2.,  0.,  0.,  1.,  0.,  1.,  0.,  1.,  1.,  2.,  2.,
1.,
        1.,  1.,  2.,  2.,  2.,  1.,  2.,  1.,  2.,  0.,  1.,  2.,
1.,
        2.,  1.,  0.,  2.,  1.,  1.,  2.,  0.,  2.,  2.,  2.,  1.,
2.,
        2.,  1.,  1.,  0.,  1.,  0.,  1.,  2.,  2.,  2.,  2.,  1.,
0.,
        2.,  2.,  2.,  2.,  2.,  2.,  1.,  0.,  0.,  2.,  0.,  0.,
1.,
        1.,  1.,  0.,  1.,  2.,  2.,  0.,  2.,  0.,  1.,  1.,  0.,
1.,
        2.,  1.,  1.,  0.,  2.,  2.,  0.,  1.,  0.,  2.,  2.,  0.,
1.,
        2.,  1.,  1.,  0.,  0.,  1.,  1.,  2.,  0.,  2.,  1.,  1.,
1.,
        0.,  0.,  1.,  1.,  1.,  0.,  0.,  0.,  0.,  2.,  1.,  0.,
2.,
        2.,  2.,  2.,  0.,  2.,  2.,  0.,  1.,  1.,  0.,  1.,  1.,
2.,
        0.,  2.,  1.,  2.,  0.,  1.,  1.,  0.,  0.,  2.,  2.,  0.,
1.,
        2.,  2.,  1.,  0.,  2.,  0.,  0.,  2.,  0.,  1.,  2.,  2.,
0.,
        1.,  1.,  2.,  1.,  0.,  1.,  2.,  1.,  0.,  0.,  0.,  2.,
1.,
        0.,  0.,  1.,  2.,  2.,  2.,  1.,  1.,  0.,  0.,  2.,  1.,
2.,
        2.,  1.,  2.,  0.,  2.,  1.,  0.,  1.,  2.])
```

In [742]:

```
# print the size of the y_pred
y_pred_class_nb.size
```

Out[742]:

282

In [743]:

```
# calculate accuracy_nb of class predictions
from sklearn import metrics
accuracy_nb = metrics.accuracy_score(y_test, y_pred_class_nb)
print("Accuracy_nb = %.3f%%" % accuracy_nb)
```

```
Accuracy_nb = 0.982%
```

NB Classification Error: classifier incorrect %?

In [744]:

```
print('Incorrect accuracy_nb = %.3f%%' % (1 - accuracy_nb))
```

```
Incorrect accuracy_nb = 0.018%
```

In [745]:

```
# calculate null accuracy_nb (for multi-class classification problems)
y_test.value_counts().head() / len(y_test)
```

Out[745]:

```
2.0    0.372340
1.0    0.333333
0.0    0.294326
Name: Category_num, dtype: float64
```

In [746]:

```
# I took this code form this API: https://github.com/scikit-learn/scikit-learn
/blob/master/examples/model_selection/plot_confusion_matrix.py
def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Purples):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
        print('Confusion matrix, without normalization')

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
```

Confusion matrix MultinomialNB

In [747]:

```
# print the confusion matrix
cm_nb = metrics.confusion_matrix(y_test, y_pred_class_nb)
cm_nb
```

Out[747]:

```
array([[ 79,   1,   3],
       [  1,  93,   0],
       [  0,   0, 105]])
```

N=282	Predict 0	Predict 1	Predict 2
Actual: 0	79	1	3
Actual: 1	1	93	0
Actual: 2	0	0	105

In [748]:

```
# get the lables
target_names = [lables[0], lables[1],lables[2]]
```

In [749]:

```
from sklearn.metrics import classification_report
target_names = [lables[0], lables[1],lables[2]]
print(classification_report(y_test, y_pred_class_nb, target_names=target_names
))
```

```
             precision    recall  f1-score   support

 technology       0.99      0.95      0.97        83
   business       0.99      0.99      0.99        94
      sport       0.97      1.00      0.99       105

avg / total       0.98      0.98      0.98       282
```

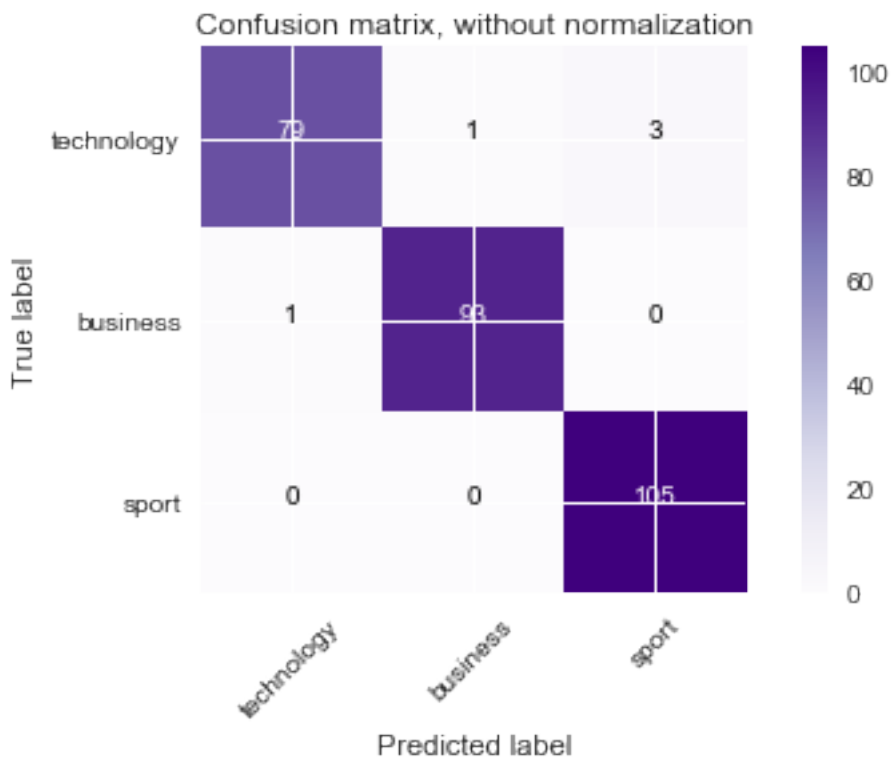
Analyse the Results Above:

- We can see that we were able to predict most of the tags correctlly from the table.
- ***For class 0 (technology)*** -> 79 out 83 were correcttly predicted. Only 4 were predicted wrong. 1 predicted as 1 (business) and 3 as 2 (sport).
- ***For class 1 (business)*** -> 93 out 94 were correcttly predicted. Only 1 was predicted wrong. 1 predicted as 0 (technology).
- ***For class 2 (sport)*** -> 105 out 105 were correcttly predicted.

In [750]:

```
# plot non-normalized confusion matrix
plot_confusion_matrix(cm_nb, lables, title='Confusion matrix, without normaliz
ation')
```

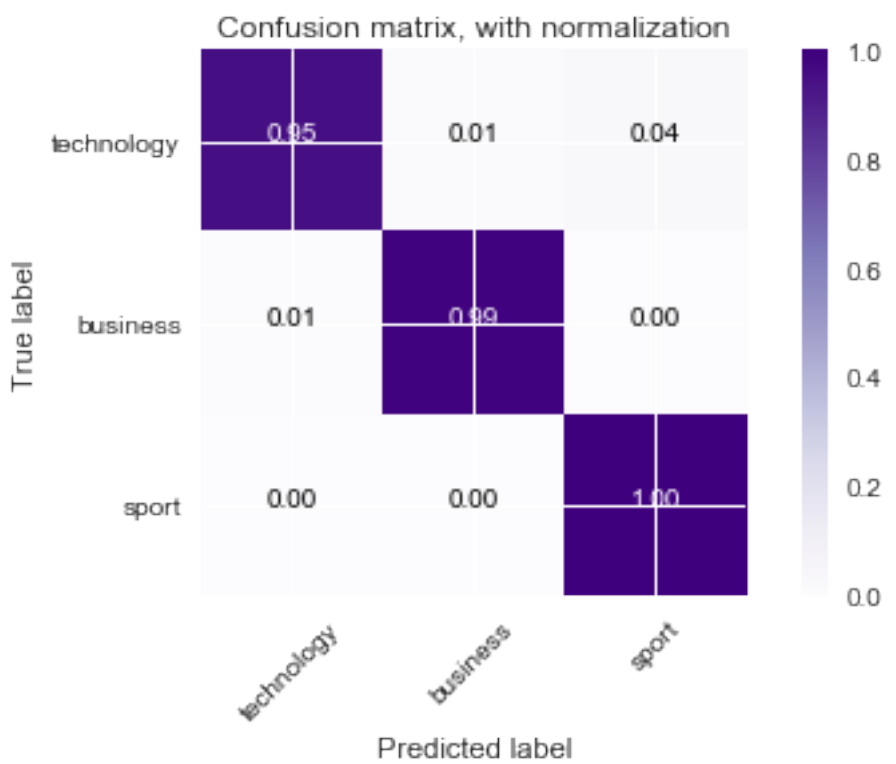
```
Confusion matrix, without normalization
```



In [751]:

```
# normalized confusion matrix
plot_confusion_matrix(cm_nb, lables, normalize=True, title='Confusion matrix,
with normalization')
```

```
Normalized confusion matrix
```



Analyse Results Above:

1. We can see that we were able to

In [752]:

```
# print message text for the false positives
X_test[y_test < y_pred_class_nb]
```

Out[752]:

```
1369    \nReport: Benitez delight after crucial win\n\...
866     \n\nSix years ago, Intercom invented business ...
777     \n\nCould Half-Life 2 possibly live up to the ...
1366    \nPlayers sought for $1m prize\n\nUK gamers ar...
Name: Body, dtype: object
```

In [753]:

```
# print message text for the false negatives
X_test[y_test > y_pred_class_nb]
```

Out[753]:

```
529    \nMaking your office work for you\n\nOur missi...
Name: Body, dtype: object
```

Labels meaning:

we assigned each category a value:

- 0 => technology.
- 1 => business.
- 2 => sport.

In [754]:

```
lables
```

Out[754]:

```
['technology', 'business', 'sport']
```

In [755]:

```
y_test[:10]
```

Out[755]:

```
1112    2.0
1256    0.0
177     2.0
101     2.0
1037    1.0
616     1.0
767     2.0
546     0.0
1163    1.0
283     1.0
Name: Category_num, dtype: float64
```

In [756]:

```
y_pred_class_nb
```

```
Out[756]:

array([ 2.,  0.,  2.,  2.,  1.,  1.,  2.,  0.,  1.,  1.,  0.,  1.,
2.,
        2.,  1.,  0.,  0.,  1.,  0.,  2.,  1.,  1.,  2.,  2.,  2.,
2.,
        2.,  2.,  2.,  2.,  2.,  1.,  0.,  0.,  1.,  2.,  2.,  0.,
1.,
        2.,  1.,  0.,  1.,  0.,  0.,  2.,  1.,  1.,  0.,  2.,  2.,
0.,
        1.,  1.,  2.,  0.,  1.,  0.,  2.,  0.,  1.,  2.,  2.,  0.,
1.,
        0.,  1.,  0.,  1.,  2.,  1.,  2.,  1.,  2.,  2.,  2.,  1.,
2.,
        2.,  0.,  1.,  2.,  0.,  2.,  2.,  2.,  2.,  2.,  0.,  0.,
1.,
        0.,  2.,  0.,  0.,  1.,  0.,  1.,  0.,  1.,  1.,  2.,  2.,
1.,
        1.,  1.,  2.,  2.,  2.,  1.,  2.,  1.,  2.,  0.,  1.,  2.,
1.,
        2.,  1.,  0.,  2.,  1.,  1.,  2.,  0.,  2.,  2.,  2.,  1.,
2.,
        2.,  1.,  1.,  0.,  1.,  0.,  1.,  2.,  2.,  2.,  2.,  1.,
0.,
        2.,  2.,  2.,  2.,  2.,  2.,  1.,  0.,  0.,  2.,  0.,  0.,
1.,
        1.,  1.,  0.,  1.,  2.,  2.,  0.,  2.,  0.,  1.,  1.,  0.,
1.,
        2.,  1.,  1.,  0.,  2.,  2.,  0.,  1.,  0.,  2.,  2.,  0.,
1.,
        2.,  1.,  1.,  0.,  0.,  1.,  1.,  2.,  0.,  2.,  1.,  1.,
1.,
        0.,  0.,  1.,  1.,  1.,  0.,  0.,  0.,  0.,  2.,  1.,  0.,
2.,
        2.,  2.,  2.,  0.,  2.,  2.,  0.,  1.,  1.,  0.,  1.,  1.,
2.,
        0.,  2.,  1.,  2.,  0.,  1.,  1.,  0.,  0.,  2.,  2.,  0.,
1.,
        2.,  2.,  1.,  0.,  2.,  0.,  0.,  2.,  0.,  1.,  2.,  2.,
0.,
        1.,  1.,  2.,  1.,  0.,  1.,  2.,  1.,  0.,  0.,  0.,  2.,
1.,
        0.,  0.,  1.,  2.,  2.,  2.,  1.,  1.,  0.,  0.,  2.,  1.,
2.,
        2.,  1.,  2.,  0.,  2.,  1.,  0.,  1.,  2.])
```

Sample test:

In [757]:

```
merged_df[1112:1113]
```

Out[757]:

	Category	Titile	Body	Category_num
1112	sport	Leeds v Saracens (Fri)	\nLeeds v Saracens (Fri)\n\nHeadingley\n\nFrid...	2.0

Create a df with y_pred_class_nb and X_test

In [758]:

```
X_test_df = X_test.to_frame()
y_pred_class_df_nb = pd.DataFrame({'Predicted Category': y_pred_class_nb,
                   "Body":  X_test})
```

In [759]:

```
y_pred_class_df_nb.head()
```

Out[759]:

	Body	Predicted Category
1112	\nLeeds v Saracens (Fri)\n\nHeadingley\n\nFrid...	2.0
1256	\n\nThe Online News's online search engine was...	0.0
177	\n\nJuninho's agent has confirmed that the pla...	2.0
101	\nSports Stock Tips\n\nSports stocks are the b...	2.0
1037	\n\nUK house prices dipped slightly in Novembe...	1.0

Test the Category prediction for NB

In [760]:

```
# merge thme for readiblity
overAll_pred_class_df_nb = pd.concat([merged_df, y_pred_class_df_nb], axis=1)
# Drop NaN values
overAll_pred_class_df_nb = overAll_pred_class_df_nb.dropna(axis=0,how='any')
overAll_pred_class_df_nb
```

Out[760]:

	Category	Titile	Body	Category_num	

3	business	Barclays shares up on merger talk	\nBarclays shares up on merger talk\n\nShares ...	1.0	\nBarclays on merger talk\n\nSh
12	business	Bush to get 'tough' on deficit	\nBush to get 'tough' on deficit\n\nUS preside...	1.0	\nBush to on deficit\n preside...
19	sport	Charvis set to lose fitness bid	\n\nFlanker Colin Charvis is unlikely to play ...	2.0	\n\nFlanke Charvis is play ...
37	business	Fannie Mae 'should restate books'	\n\nUS mortgage company Fannie Mae should rest...	1.0	\n\nUS mo company F should res
47	technology	Gangsters dominate gaming chart	\n\nVideo games on consoles and computers prov...	0.0	\n\nVideo consoles a computers
48	sport	Gardener wins double in Glasgow	\nGardener wins double in Glasgow\n\nBritain's...	2.0	\nGardene double in Glasgow\n
49	business	Gazprom 'in $36m back-tax claim'	\n\nThe nuclear unit of Russian energy giant G...	1.0	\n\nThe nu Russian er G...
51	business	Germany calls for EU reform	\nGermany calls for EU reform\n\nGerman Chance...	1.0	\nGermany reform\n\n Chance...
56	sport	Henman decides to quit Davis Cup	\nHenman decides to quit Davis Cup\n\nTim Henm...	2.0	\nHenman quit Davis Henm...
58	sport	Hodgson shoulders England blame	\n\nFly-half Charlie Hodgson admitted his wayw...	2.0	\n\nFly-hal Hodgson a wayw...
60	sport	Holmes secures comeback victory	\nHolmes secures comeback victory\n\nBritain's...	2.0	\nHolmes comeback victory\n\n
65	sport	Jansen suffers a further setback	\nJansen suffers a further setback\n\nBlackbur...	2.0	\nJansen s further setback\n\
73	technology	Mobile games come of age	\n\nThe Online News News website takes a look ...	0.0	\n\nThe On News web look ...
75	sport	Mourinho sends out warning shot	\n\nChelsea boss Jose Mourinho believes his te...	2.0	\n\nChelse Mourinho b te...

80	sport	Off-colour Gardener storms to win	\n\nBritain's Jason Gardener shook off an upse...	2.0	\n\nBritain Gardener s upse...
81	business	Oil companies get Russian setback	\n\nInternational oil and mining companies hav...	1.0	\n\nInterna and mining hav...
87	technology	Remote control rifle range debuts	\nRemote control rifle range debuts\n\nSoon yo...	0.0	\nRemote range debu yo...
88	sport	Robinson ready for difficult task	\n\nEngland coach Andy Robinson faces the firs...	2.0	\n\nEnglan Andy Robi the firs...
91	business	S Korean lender faces liquidation	\nS Korean lender faces liquidation\n\nCredito...	1.0	\nS Korear faces liquidation\
94	sport	Safin plays down Wimbledon hopes	\n\nNewly-crowned Australian Open champion Mar...	2.0	\n\nNewly- Australian champion
98	business	Senior Fannie Mae bosses resign	\n\nThe two most senior executives at US mortg...	1.0	\n\nThe tw senior exe US mortg..
101	sport	Sports Stock Tips	\nSports Stock Tips\n\nSports stocks are the b...	2.0	\nSports S Tips\n\nSp are the b...
107	technology	US peer-to-peer pirates convicted	\nUS peer-to-peer pirates convicted\n\nThe fir...	0.0	\nUS peer- pirates convicted\
108	technology	US top of supercomputing charts	\n\nThe US has pushed Japan off the top of the...	0.0	\n\nThe US pushed Ja top of the..
111	sport	Williams says he will never quit	\n\nDefiant Matt Williams says he will not qui...	2.0	\n\nDefian Williams sa not qui...
115	technology	Xbox power cable 'fire fear'	\nXbox power cable 'fire fear'\n\nMicrosoft ha...	0.0	\nXbox po 'fire fear'\n ha...
119	sport	A November to remember	\nA November to remember\n\nLast Saturday, one...	2.0	\nA Novem remember\ Saturday, c
120	technology	A question of trust and	\nA question of trust and technology\n\nA	0.0	\nA questi and techn

		technology	majo...		majo...
131	technology	Blogs take on the mainstream	\nBlogs take on the mainstream\n\nWeb logs or ...	0.0	\nBlogs tal mainstrear logs or ...
133	business	Bush to outline 'toughest' budget	\n\nPresident Bush is to send his toughest bud...	1.0	\n\nPresid to send his bud...
...	...	...	...	...	...
1232	business	IMF 'cuts' German growth estimate	\nIMF 'cuts' German growth estimate\n\nThe Int...	1.0	\nIMF 'cuts growth estimate\n
1233	business	Indonesians face fuel price rise	\n\nIndonesia's government has confirmed it is...	1.0	\n\nIndone governmer confirmed
1241	technology	Junk e-mails on relentless rise	\nJunk e-mails on relentless rise\n\nSpam traf...	0.0	\nJunk e-m relentless rise\n\nSp
1251	sport	Mourinho defiant on Chelsea form	\nMourinho defiant on Chelsea form\n\nChelsea ...	2.0	\nMourinh Chelsea form\n\nCl
1256	technology	Online News web search aids odd queries	\n\nThe Online News's online search engine was...	0.0	\n\nThe Or online sear was...
1280	technology	Toxic web links help virus spread	\n\nVirus writers have begun using the power o...	0.0	\n\nVirus w begun usir o...
1286	business	US to probe airline travel chaos	\nUS to probe airline travel chaos\n\nThe US g...	1.0	\nUS to pr travel chac US g...
1291	technology	Windows worm travels with Tetris	\nWindows worm travels with Tetris\n\nUsers ar...	0.0	\nWindows travels with Tetris\n\nU
1293	business	Worldcom ex-boss launches defence	\n\nLawyers defending former WorldCom chief Be...	1.0	\n\nLawye former Wo Be...
1295	business	Absa and Barclays talks continue	\n\nSouth Africa biggest retail bank Absa has ...	1.0	\n\nSouth biggest ret Absa has .
1301	sport	Barbarians 19-47 New Zealand	\n\nNew Zealand proved too strong for an Austr...	2.0	\n\nNew Z proved too an Austr...

1302	sport	Big guns ease through in San Jose	\n\nTop-seeded Americans Andy Roddick and Andr...	2.0	\n\nTop-se Americans Roddick ar
1313	sport	D'Arcy injury adds to Ireland woe	\n\nGordon D'Arcy has been ruled out of the Ir...	2.0	\n\nGordor been ruled Ir...
1325	business	France Telecom gets Orange boost	\n\nStrong growth in subscriptions to mobile p...	1.0	\n\nStrong subscriptic p...
1329	technology	Gizmondo gadget hits the shelves	\nGizmondo gadget hits the shelves\n\nThe Gizm...	0.0	\nGizmonc hits the sh Gizm...
1331	technology	Global digital divide 'narrowing'	\nGlobal digital divide 'narrowing'\n\nThe "di...	0.0	\nGlobal d 'narrowing "di...
1333	sport	Hamm bows out for US	\n\nWomen's football legend Mia Hamm has playe...	2.0	\n\nWomer legend Mia playe...
1341	business	Irish markets reach all-time high	\n\nIrish shares have risen to a record high, ...	1.0	\n\nIrish sh risen to a r ...
1353	technology	Microsoft plans 'safer ID' system	\n\nMicrosoft is planning to make Windows and ...	0.0	\n\nMicros planning to Windows a
1357	sport	Moya fights back for Indian title	\n\nCarlos Moya became the first man to succes...	2.0	\n\nCarlos became th to succes..
1359	sport	Munster Cup tie switched to Spain	\nMunster Cup tie switched to Spain\n\nMunster...	2.0	\nMunster switched t Spain\n\nM
1366	technology	Players sought for $1m prize	\nPlayers sought for $1m prize\n\nUK gamers ar...	0.0	\nPlayers s $1m prize\ gamers ar.
1367	sport	QPR keeper Day heads for Preston	\nQPR keeper Day heads for Preston\n\nQueens P...	2.0	\nQPR kee heads for Preston\n\
1368	business	Renault boss hails 'great year'	\n\nStrong sales outside western Europe helped...	1.0	\n\nStrong outside we Europe hel
1369	technology	Report: Benitez delight after crucial win	\nReport: Benitez delight after crucial win\n\...	0.0	\nReport: E delight afte win\n\...
1353	technology	Microsoft plans 'safer ID' system	\n\nMicrosoft is planning to make Windows and ...	0.0	\n\nMicros planning to Windows a

1370	technology	Rings of steel combat net attacks	\nRings of steel combat net attacks\n\nGamblin...	0.0	\nRings of combat ne attacks\n\r
1378	technology	Sony PSP tipped as a 'must-have'	\nSony PSP tipped as a 'must-have'\n\nSony's P...	0.0	\nSony PS a 'must-have'\n\nS
1380	technology	T-Mobile bets on 'pocket office'	\n\nT-Mobile has launched its latest "pocket o...	0.0	\n\nT-Mobi launched it "pocket o..
1386	technology	UK gets official virus alert site	\n\nA rapid alerting service that tells home c...	0.0	\n\nA rapic service tha c...
1388	business	US company admits Benin bribery	\n\nA US defence and telecommunications compan...	1.0	\n\nA US c telecommu compan...

Full content of the article

In [761]:

```
merged_df_index = merged_df.as_matrix()
merged_df_index[1112]
```

Out[761]:

```
array(['sport', 'Leeds v Saracens (Fri)',
       "\nLeeds v Saracens (Fri)\n\nHeadingley\n\nFriday, 25 Febru
ary\n\n2000 GMT\n\nThe Tykes have brought in Newcastle prop Ed Kal
man and Tom McGee from the Borders on loan while fly-half Craig Mc
Mullen has joined from Narbonne. Raphael Ibanez is named at hooker
for Saracens in one of four changes. Simon Raiwalui and Ben Russel
l are also selected in the pack while Kevin Sorrell comes in at ou
tside centre.\n\n- Friday's game at Headingley got the go-ahead on
Friday after passing an early pitch inspection. Leeds: Balshaw; Re
es, Christophers, Bell, Doherty; McMullen, Dickens; McGee, Rawlins
on, Gerber; Murphy, Palmer (capt), Morgan, Parks, Popham. Replacem
ents: Kalman, Regan, Hyde, Rigney, McMillan, Rock, Vickerman. Sara
cens: Bartholomeusz; Castaignede, Sorrell, Harris, Vaikona; Jackso
n, Bracken; Yates, Ibanez, Visagie; Raiwalui, Fullarton; Randell,
Russell, Vyvyan (capt). Replacements: Cairns, Lloyd, Broster, Ches
ney, Johnston, Rauluni, Little.",
       2.0], dtype=object)
```

In [762]:

```
# calculate predicted probabilities for X_test_dtm (poorly calibrated)
y_pred_prob = nb.predict_proba(X_test_dtm)[:, 1]
y_pred_prob[:10]
```

Out[762]:

```
array([ 0.13597069,  0.14699416,  0.04177381,  0.17840968,  0.9362
3811,
        0.76684104,  0.03832146,  0.0628393 ,  0.7258362 ,  0.9137
9836])
```

++

Comparing models

In [763]:

```
# import and instantiate a logistic regression model
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors  import KNeighborsClassifier
# logreg = LogisticRegression()
knn = KNeighborsClassifier(n_neighbors=len(lables))
```

In [764]:

```
# train the model using X_train_dtm
%time knn.fit(X_train_dtm, y_train)
```

```
CPU times: user 4.47 ms, sys: 2.54 ms, total: 7.02 ms
Wall time: 5.17 ms
```

Out[764]:

```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minko
wski',
           metric_params=None, n_jobs=1, n_neighbors=3, p=2,
           weights='uniform')
```

In [765]:

```
# make class predictions for X_test_dtm
y_pred_class_knn = knn.predict(X_test_dtm)
```

In [766]:

```
# calculate predicted probabilities for X_test_dtm (well calibrated)
y_pred_prob = knn.predict_proba(X_test_dtm)[:, 1]
y_pred_prob[:10]
```

Out[766]:

```
array([ 0.,  0.,  0.,  0.,  1.,  1.,  0.,  0.,  1.,  1.])
```

In [767]:

```
# calculate accuracy_knn
accuracy_knn = metrics.accuracy_score(y_test, y_pred_class_knn)
print("Accuracy = %.3f%%" % accuracy_knn)
```

```
Accuracy = 0.950%
```

In [768]:

```
print('Incorrect Accuracy = %.3f%%' % (1 - accuracy_knn))
```

```
Incorrect Accuracy = 0.050%
```

KNN Classification Error: classifier incorrect %?

In [769]:

```
# calculate null accuracy_nb (for multi-class classification problems)
y_test.value_counts().head() / len(y_test)
```

Out[769]:

```
2.0    0.372340
1.0    0.333333
0.0    0.294326
Name: Category_num, dtype: float64
```

In [770]:

```
# print the confusion matrix
cm_knn = metrics.confusion_matrix(y_test, y_pred_class_knn)
cm_knn
```

Out[770]:

```
array([[ 78,   4,   1],
       [  6,  87,   1],
       [  1,   1, 103]])
```

Confusion matrix KNeighborsClassifier

N=282	Predict 0	Predict 1	Predict 2
Actual: 0	78	4	1
Actual: 1	6	87	1
Actual: 2	1	1	103

In [771]:

```
print(classification_report(y_test, y_pred_class_knn, target_names=target_name
s))
```

```
             precision    recall  f1-score   support

 technology       0.92      0.94      0.93        83
   business       0.95      0.93      0.94        94
      sport       0.98      0.98      0.98       105

avg / total       0.95      0.95      0.95       282
```

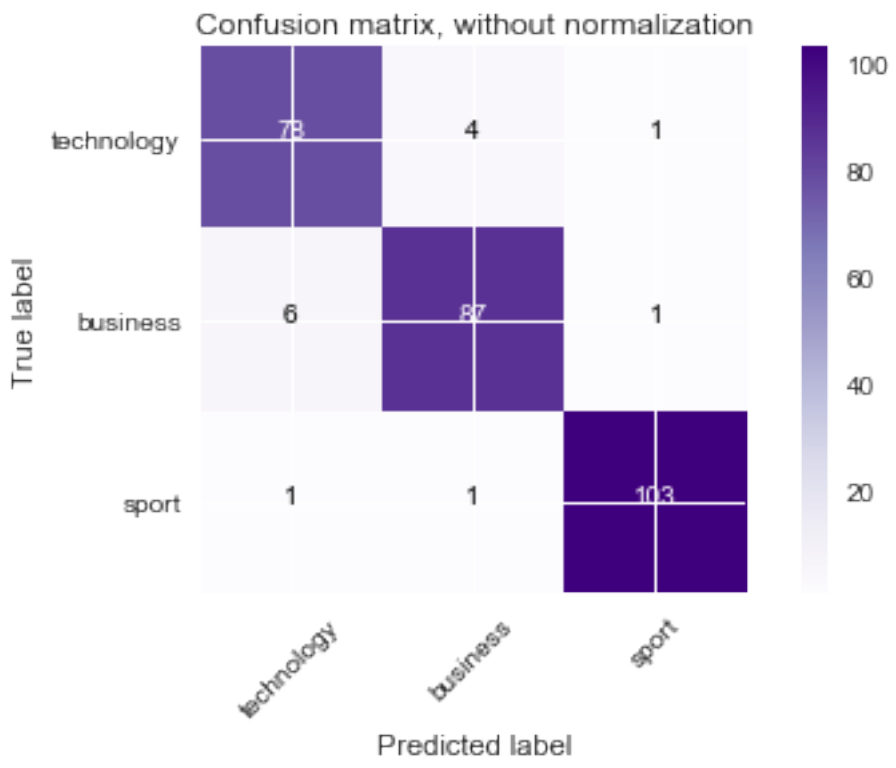
Analyse the Results Above:

- We can see that we were able to predict most of the tags correctlly from the table.
- ***For class 0 (technology)*** -> 78 out 83 were correcttly predicted. Only 5 were predicted wrong. 4 predicted as 1 (business) and 1 as 2 (sport).
- ***For class 1 (business)*** -> 87 out 94 were correcttly predicted. Only 7 were predicted wrong. 6 predicted as 0 (technology) and 1 as 2 (sport).
- ***For class 2 (sport)*** -> 103 out 105 were correcttly predicted. Only 2 were predicted wrong. 1 predicted as 0 (technology) and 1 as 1 (business).

In [772]:

```
# Plot non-normalized confusion matrix
plot_confusion_matrix(cm_knn, lables, title='Confusion matrix, without normali
zation')
```

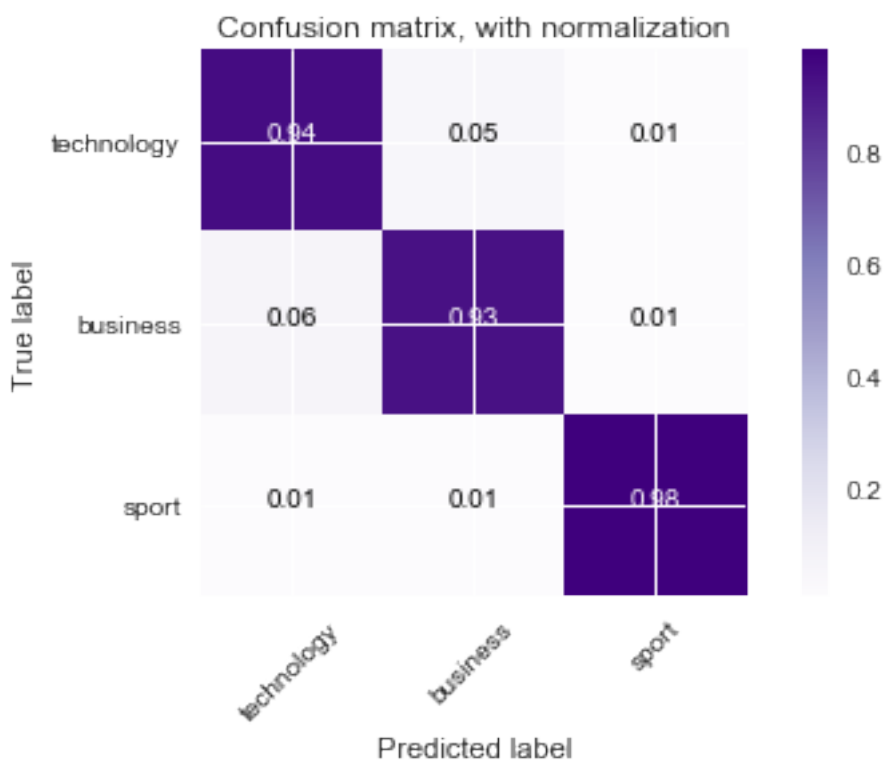
```
Confusion matrix, without normalization
```



In [773]:

```
# plot normalized confusion matrix
plot_confusion_matrix(cm_knn, lables, normalize=True, title='Confusion matrix,
with normalization')
```

```
Normalized confusion matrix
```



In [774]:

```
y_pred_class_df_knn = pd.DataFrame({'Predicted Category': y_pred_class_knn,
                    "Body":  X_test})
```

In [775]:

```
y_pred_class_df_nb.head()
```

Out[775]:

	Body	Predicted Category
1112	\nLeeds v Saracens (Fri)\n\nHeadingley\n\nFrid...	2.0
1256	\n\nThe Online News's online search engine was...	0.0
177	\n\nJuninho's agent has confirmed that the pla...	2.0
101	\nSports Stock Tips\n\nSports stocks are the b...	2.0
1037	\n\nUK house prices dipped slightly in Novembe...	1.0

Test the Category prediction for KNN

In [776]:

```
# merge thme for readiblity
overAll_pred_class_df_knn = pd.concat([merged_df, y_pred_class_df_knn], axis=1
)
# Drop NaN values
overAll_pred_class_df_knn = overAll_pred_class_df_knn.dropna(axis=0,how='any')
overAll_pred_class_df_knn
```

Out[776]:

	Category	Titile	Body	Category_num	
3	business	Barclays shares up on merger talk	\nBarclays shares up on merger talk\n\nShares ...	1.0	\nBarclays on merger talk\n\nSh
12	business	Bush to get 'tough' on deficit	\nBush to get 'tough' on deficit\n\nUS preside...	1.0	\nBush to on deficit\r preside...
19	sport	Charvis set to lose fitness bid	\n\nFlanker Colin Charvis is unlikely to play ...	2.0	\n\nFlanke Charvis is play ...
37	business	Fannie Mae 'should restate books'	\n\nUS mortgage company Fannie Mae should rest...	1.0	\n\nUS mo company F should res
47	technology	Gangsters dominate gaming chart	\n\nVideo games on consoles and computers prov...	0.0	\n\nVideo consoles a computers
48		Gardener wins	\nGardener wins		\nGardene

	sport	double in Glasgow	double in Glasgow\n\nBritain's...	2.0	double in Glasgow\n
49	business	Gazprom 'in $36m back-tax claim'	\n\nThe nuclear unit of Russian energy giant G...	1.0	\n\nThe nu Russian er G...
51	business	Germany calls for EU reform	\nGermany calls for EU reform\n\nGerman Chance...	1.0	\nGermany reform\n\n Chance...
56	sport	Henman decides to quit Davis Cup	\nHenman decides to quit Davis Cup\n\nTim Henm...	2.0	\nHenman quit Davis Henm...
58	sport	Hodgson shoulders England blame	\n\nFly-half Charlie Hodgson admitted his wayw...	2.0	\n\nFly-hal Hodgson a wayw...
60	sport	Holmes secures comeback victory	\nHolmes secures comeback victory\n\nBritain's...	2.0	\nHolmes s comeback victory\n\n
65	sport	Jansen suffers a further setback	\nJansen suffers a further setback\n\nBlackbur...	2.0	\nJansen s further setback\n\
73	technology	Mobile games come of age	\n\nThe Online News News website takes a look ...	0.0	\n\nThe On News web look ...
75	sport	Mourinho sends out warning shot	\n\nChelsea boss Jose Mourinho believes his te...	2.0	\n\nChelse Mourinho b te...
80	sport	Off-colour Gardener storms to win	\n\nBritain's Jason Gardener shook off an upse...	2.0	\n\nBritain Gardener s upse...
81	business	Oil companies get Russian setback	\n\nInternational oil and mining companies hav...	1.0	\n\nInterna and mining hav...
87	technology	Remote control rifle range debuts	\nRemote control rifle range debuts\n\nSoon yo...	0.0	\nRemote range debu yo...
88	sport	Robinson ready for difficult task	\n\nEngland coach Andy Robinson faces the firs...	2.0	\n\nEnglan Andy Robi the firs...
91	business	S Korean lender faces liquidation	\nS Korean lender faces liquidation\n\nCredito...	1.0	\nS Korean faces liquidation
94		Safin plays	\n\nNewly-crowned		\n\nNewly-

	sport	down Wimbledon hopes	Australian Open champion Mar...	2.0	Australian champion
98	business	Senior Fannie Mae bosses resign	\n\nThe two most senior executives at US mortg...	1.0	\n\nThe tw senior exe US mortg..
101	sport	Sports Stock Tips	\nSports Stock Tips\n\nSports stocks are the b...	2.0	\nSports S Tips\n\nSp are the b...
107	technology	US peer-to-peer pirates convicted	\nUS peer-to-peer pirates convicted\n\nThe fir...	0.0	\nUS peer- pirates convicted\
108	technology	US top of supercomputing charts	\n\nThe US has pushed Japan off the top of the...	0.0	\n\nThe US pushed Ja top of the..
111	sport	Williams says he will never quit	\n\nDefiant Matt Williams says he will not qui...	2.0	\n\nDefian Williams sa not qui...
115	technology	Xbox power cable 'fire fear'	\nXbox power cable 'fire fear'\n\nMicrosoft ha...	0.0	\nXbox po 'fire fear'\n ha...
119	sport	A November to remember	\nA November to remember\n\nLast Saturday, one...	2.0	\nA Novem remember\ Saturday,
120	technology	A question of trust and technology	\nA question of trust and technology\n\nA majo...	0.0	\nA questi and techn majo...
131	technology	Blogs take on the mainstream	\nBlogs take on the mainstream\n\nWeb logs or ...	0.0	\nBlogs tal mainstrea logs or ...
133	business	Bush to outline 'toughest' budget	\n\nPresident Bush is to send his toughest bud...	1.0	\n\nPresid to send his bud...
...	...	...	...	...	...
1232	business	IMF 'cuts' German growth estimate	\nIMF 'cuts' German growth estimate\n\nThe Int...	1.0	\nIMF 'cut growth estimate\n
1233	business	Indonesians face fuel price rise	\n\nIndonesia's government has confirmed it is...	1.0	\n\nIndone governme confirmed
1241	technology	Junk e-mails on relentless rise	\nJunk e-mails on relentless	0.0	\nJunk e-n relentless

			rise\n\nSpam traf...		rise\n\nSp
1251	sport	Mourinho defiant on Chelsea form	\nMourinho defiant on Chelsea form\n\nChelsea ...	2.0	\nMourinh Chelsea form\n\nCl
1256	technology	Online News web search aids odd queries	\n\nThe Online News's online search engine was...	0.0	\n\nThe Or online sear was...
1280	technology	Toxic web links help virus spread	\n\nVirus writers have begun using the power o...	0.0	\n\nVirus w begun usir o...
1286	business	US to probe airline travel chaos	\nUS to probe airline travel chaos\n\nThe US g...	1.0	\nUS to pr travel chac US g...
1291	technology	Windows worm travels with Tetris	\nWindows worm travels with Tetris\n\nUsers ar...	0.0	\nWindows travels with Tetris\n\nU
1293	business	Worldcom ex-boss launches defence	\n\nLawyers defending former WorldCom chief Be...	1.0	\n\nLawye former Wo Be...
1295	business	Absa and Barclays talks continue	\n\nSouth Africa biggest retail bank Absa has ...	1.0	\n\nSouth biggest ret Absa has .
1301	sport	Barbarians 19-47 New Zealand	\n\nNew Zealand proved too strong for an Austr...	2.0	\n\nNew Z proved toc an Austr...
1302	sport	Big guns ease through in San Jose	\n\nTop-seeded Americans Andy Roddick and Andr...	2.0	\n\nTop-se Americans Roddick ar
1313	sport	D'Arcy injury adds to Ireland woe	\n\nGordon D'Arcy has been ruled out of the Ir...	2.0	\n\nGordo been ruled Ir...
1325	business	France Telecom gets Orange boost	\n\nStrong growth in subscriptions to mobile p...	1.0	\n\nStrong subscriptic p...
1329	technology	Gizmondo gadget hits the shelves	\nGizmondo gadget hits the shelves\n\nThe Gizm...	0.0	\nGizmonc hits the sh Gizm...
1331	technology	Global digital divide 'narrowing'	\nGlobal digital divide 'narrowing'\n\nThe "di...	0.0	\nGlobal d 'narrowing "di...
1333	sport	Hamm bows	\n\nWomen's football legend Mia Hamm has	2.0	\n\nWome legend Mia

		out for US	playe...		playe...
1341	business	Irish markets reach all-time high	\n\nIrish shares have risen to a record high, ...	1.0	\n\nIrish sh risen to a r ...
1353	technology	Microsoft plans 'safer ID' system	\n\nMicrosoft is planning to make Windows and ...	0.0	\n\nMicros planning to Windows a
1357	sport	Moya fights back for Indian title	\n\nCarlos Moya became the first man to succes...	2.0	\n\nCarlos became th to succes..
1359	sport	Munster Cup tie switched to Spain	\nMunster Cup tie switched to Spain\n\nMunster...	2.0	\nMunster switched t Spain\n\nM
1366	technology	Players sought for $1m prize	\nPlayers sought for $1m prize\n\nUK gamers ar...	0.0	\nPlayers s $1m prize\ gamers ar.
1367	sport	QPR keeper Day heads for Preston	\nQPR keeper Day heads for Preston\n\nQueens P...	2.0	\nQPR kee heads for Preston\n\
1368	business	Renault boss hails 'great year'	\n\nStrong sales outside western Europe helped...	1.0	\n\nStrong outside we Europe hel
1369	technology	Report: Benitez delight after crucial win	\nReport: Benitez delight after crucial win\n\...	0.0	\nReport: E delight afte win\n\...
1370	technology	Rings of steel combat net attacks	\nRings of steel combat net attacks\n\nGamblin...	0.0	\nRings of combat ne attacks\n\r
1378	technology	Sony PSP tipped as a 'must-have'	\nSony PSP tipped as a 'must-have'\n\nSony's P...	0.0	\nSony PS a 'must-have'\n\nS
1380	technology	T-Mobile bets on 'pocket office'	\n\nT-Mobile has launched its latest "pocket o...	0.0	\n\nT-Mobi launched it "pocket o..
1386	technology	UK gets official virus alert site	\n\nA rapid alerting service that tells home c...	0.0	\n\nA rapic service tha c...
1388	business	US company admits Benin bribery	\n\nA US defence and telecommunications compan...	1.0	\n\nA US c telecommu compan...

282 rows × 6 columns

Test the prediction of the MultinomialNB.

In [777]:

```
predict = nb.predict(X_test_dtm)
num_tech = (predict == 0).sum()
num_business = (predict == 1).sum()
num_sport = (predict == 2).sum()
print("Tech : %d" % num_tech)
print("Business: %d" % num_business)
print("Sport: %d" % num_sport)
```

```
Tech : 80
Business: 94
Sport: 108
```

Test the prediction of the KNeighborsClassifier.

In [778]:

```
predict = knn.predict(X_test_dtm)
num_tech = (predict == 0).sum()
num_business = (predict == 1).sum()
num_sport = (predict == 2).sum()
print("Tech : %d" % num_tech)
print("Business: %d" % num_business)
print("Sport: %d" % num_sport)
```

```
Tech : 85
Business: 92
Sport: 105
```

Examining a model for further insight

We will examine our **trained Naive Bayes model** to calculate the approximate **"category" of each token**.

In [779]:

```
# store the vocabulary of X_train
X_train_tokens = vect.get_feature_names()
len(X_train_tokens)
```

Out[779]:

```
195019
```

In [780]:

```
# examine the first 50 tokens
print(X_train_tokens[:50])
```

```
['00', '00 early', '00 minute', '00 qualifying', '00 today', '000'
, '000 000', '000 100', '000 110', '000 133', '000 15', '000 198',
'000 2005', '000 2006', '000 2007', '000 2008', '000 30', '000 300
', '000 39', '000 425', '000 486', '000 82', '000 85', '000 accoun
ts', '000 added', '000 advertise', '000 advisers', '000 afford', '
000 american', '000 amf', '000 analysts', '000 announced', '000 an
nually', '000 apiece', '000 applicants', '000 august', '000 barrel
s', '000 battery', '000 bennett', '000 better', '000 books', '000
bpd', '000 bribe', '000 britannia', '000 broadband', '000 bsl', '0
00 bt', '000 business', '000 businesses', '000 bytes']
```

In [781]:

```
# examine the last 50 tokens
print(X_train_tokens[-50:])
```

```
['zola', 'zola absolutely', 'zola best', 'zola collapsed', 'zombie
s', 'zombies based', 'zombies bots', 'zombies giant', 'zombies mob
ile', 'zone', 'zone 1973', 'zone 85', 'zone countries', 'zone deal
er', 'zone forecast', 'zone georgewbush', 'zone hand', 'zone reten
tion', 'zone speed', 'zone substitute', 'zone time', 'zone world',
'zone written', 'zonealarm', 'zonealarm tools', 'zones', 'zones 16
', 'zones egypt', 'zones enjoy', 'zones player', 'zones scrum', 'z
ones stalled', 'zoom', 'zoom capability', 'zooms', 'zooms likely',
'zuluaga', 'zuluaga colombia', 'zurich', 'zurich according', 'zuri
ch financial', 'zurich london', 'zurich opera', 'zurich premiershi
p', 'zurich reported', 'zvonareva', 'zvonareva lost', 'zvonareva r
ussia', 'zvonareva struggled', 'zvonareva wimbledon']
```

In [782]:

```
# Naive Bayes counts the number of times each token appears in each class
nb.feature_count_
```

Out[782]:

```
array([[ 0.03753255,  0.        ,  0.04289114, ...,  0.        ,
         0.        ,  0.        ],
       [ 0.03492459,  0.        ,  0.        , ...,  0.        ,
         0.        ,  0.        ],
       [ 0.06542441,  0.03940521,  0.        , ...,  0.02927071,
         0.05725613,  0.05725613]])
```

In [783]:

```
# rows represent classes, columns represent tokens
nb.feature_count_.shape
```

Out[783]:

```
(3, 195019)
```

In [784]:

```
# number of times each token appears across all technology messages
# ['technology', 'business', 'sport']
technology_token_count = nb.feature_count_[0, :]
technology_token_count
```

Out[784]:

```
array([ 0.03753255,  0.        ,  0.04289114, ...,  0.        ,
        0.        ,  0.        ])
```

In [785]:

```
# number of times each token appears across all business messages
business_token_count = nb.feature_count_[1, :]
business_token_count
```

Out[785]:

```
array([ 0.03492459,  0.        ,  0.        , ...,  0.        ,
        0.        ,  0.        ])
```

In [786]:

```
# number of times each token appears across all sport messages
sport_token_count = nb.feature_count_[2, :]
sport_token_count
```

Out[786]:

```
array([ 0.06542441,  0.03940521,  0.        , ...,  0.02927071,
        0.05725613,  0.05725613])
```

In [787]:

```
# create a DataFrame of tokens with their separate technology, business, and s
port
tokens = pd.DataFrame({'token':X_train_tokens, lables[0]:technology_token_coun
t, lables[1]:business_token_count,lables[2]:sport_token_count}).set_index('tok
en')
tokens.head()
```

Out[787]:

	business	sport	technology
token			
00	0.034925	0.065424	0.037533
00 early	0.000000	0.039405	0.000000
00 minute	0.000000	0.000000	0.042891
00 qualifying	0.000000	0.035360	0.000000
00 today	0.039911	0.000000	0.000000

In [788]:

```
# examine 5 random DataFrame rows ... random_state = 6 so we get the same samp
le again
tokens.sample(5, random_state=6)
```

Out[788]:

	business	sport	technology
token			
revenue worth	0.0	0.000000	0.035173
releasing contamination	0.0	0.069304	0.000000
rensing jeremies	0.0	0.038929	0.000000
resurgence season	0.0	0.046488	0.000000
attacks involving	0.0	0.000000	0.076944

In [789]:

```
# Naive Bayes counts the number of observations in each class
nb.class_count_
```

Out[789]:

```
array([ 308.,  397.,  421.])
```

Before we can calculate the "category" of each token, we need to avoid dividing by zero and account for the class imbalance.

In [790]:

```
# add 1 to avoid dividing by 0
tokens[lables[0]] = tokens.technology + 1
tokens[lables[1]] = tokens.business + 1
tokens[lables[2]] = tokens.sport + 1
tokens.sample(5, random_state=6)
```

Out[790]:

	business	sport	technology
token			
revenue worth	1.0	1.000000	1.035173
releasing contamination	1.0	1.069304	1.000000
rensing jeremies	1.0	1.038929	1.000000
resurgence season	1.0	1.046488	1.000000
attacks involving	1.0	1.000000	1.076944

In [791]:

```
# calculate the ratio of business_to_sport_ratio, sport_to_technology_ratio,
# and business_to_technology_ratio for each token
tokens['business_to_sport_ratio'] = tokens.business / tokens.sport
tokens['sport_to_technology_ratio'] =  tokens.sport /  tokens.technology
tokens['business_to_technology_ratio'] =  tokens.business / tokens.technology
tokens.sample(5, random_state=6)
```

Out[791]:

	business	sport	technology	business_to_sport_ratio	sport_to_t
token					
revenue worth	1.0	1.000000	1.035173	1.000000	0.966022
releasing contamination	1.0	1.069304	1.000000	0.935188	1.069304
rensing jeremies	1.0	1.038929	1.000000	0.962529	1.038929
resurgence season	1.0	1.046488	1.000000	0.955577	1.046488
attacks involving	1.0	1.000000	1.076944	1.000000	0.928554

In [792]:

```
# examine the DataFrame sorted by business_to_sport_ratio
tokens.sort_values('business_to_sport_ratio', ascending=False)
```

Out[792]:

	business	sport	technology	business_to_sport_ratio	sport_to_tec
token					
bank	8.115480	1.000000	1.102348	8.115480	0.907155
sales	7.827708	1.000000	2.081174	7.827708	0.480498
growth	7.383704	1.000000	1.875627	7.383704	0.533155
economy	7.371425	1.000000	1.039611	7.371425	0.961898
oil	7.035165	1.000000	1.112411	7.035165	0.898948
yukos	6.632378	1.000000	1.000000	6.632378	1.000000
mr	8.175543	1.294586	6.203406	6.315181	0.208690
economic	6.363782	1.020761	1.067414	6.234350	0.956293
market	6.918792	1.128751	3.606844	6.129597	0.312947
shares	6.178675	1.046113	1.090022	5.906317	0.959717

prices	5.873443	1.000000	1.598560	5.873443	0.625563
dollar	5.752069	1.000000	1.027736	5.752069	0.973012
government	6.154691	1.119733	1.632736	5.496572	0.685801
company	7.122247	1.393415	3.163323	5.111362	0.440491
firm	6.098994	1.221062	3.158772	4.994825	0.386562
analysts	4.570639	1.000000	2.164630	4.570639	0.461973
stock	4.974026	1.109353	1.064383	4.483717	1.042250
profits	4.395555	1.000000	1.129556	4.395555	0.885303
china	5.479528	1.270010	1.930817	4.314554	0.657758
companies	4.413850	1.023089	3.436295	4.314239	0.297730
tax	4.211970	1.000000	1.028342	4.211970	0.972439
business	4.783769	1.158219	2.110355	4.130280	0.548827
euros	4.044923	1.000000	1.257229	4.044923	0.795400
rates	4.358673	1.086562	1.171230	4.011437	0.927710
india	4.253042	1.069576	1.513895	3.976383	0.706506
trade	4.061843	1.024177	1.520721	3.965959	0.673481
demand	4.186388	1.065940	1.862083	3.927416	0.572445
state	4.425056	1.138345	1.720889	3.887271	0.661487
rate	4.210376	1.093659	1.697357	3.849807	0.644331
financial	4.286305	1.113658	1.453113	3.848851	0.766395
...	...	...	...	...	...
victory	1.122958	4.609659	1.000000	0.243610	4.609659
robinson	1.026490	4.218434	1.023863	0.243334	4.120116
champions	1.000000	4.178405	1.039140	0.239326	4.021021
champion	1.071368	4.510203	1.046019	0.237543	4.311780
player	1.154169	4.913590	2.622400	0.234893	1.873700
old	1.179969	5.113595	1.945697	0.230751	2.628156
year old	1.097005	4.820635	1.165062	0.227564	4.137662
squad	1.000000	4.473274	1.021067	0.223550	4.380981
ve	1.175529	5.263109	1.488627	0.223353	3.535545
season	1.390883	6.294191	1.068208	0.220979	5.892288
got	1.152368	5.308126	1.518255	0.217095	3.496202
goal	1.099787	5.322652	1.244032	0.206624	4.278549
team	1.419890	6.925466	1.572495	0.205024	4.404125

ball	1.000000	4.949968	1.185814	0.202022	4.174319
ireland	1.248058	6.233374	1.071196	0.200222	5.819081
rugby	1.044277	5.467715	1.149052	0.190990	4.758460
league	1.112339	6.050703	1.080094	0.183836	5.602015
england	1.797005	9.914736	1.141243	0.181246	8.687667
coach	1.000000	5.589545	1.000000	0.178905	5.589545
match	1.091424	6.139487	1.169570	0.177771	5.249354
injury	1.000000	5.628347	1.077793	0.177672	5.222105
wales	1.162146	6.616722	1.074537	0.175638	6.157742
liverpool	1.000000	5.754935	1.021452	0.173764	5.634075
play	1.175666	6.837398	2.450516	0.171946	2.790187
arsenal	1.077527	6.269416	1.000000	0.171870	6.269416
chelsea	1.103382	6.926522	1.021230	0.159298	6.782527
players	1.100208	7.052917	3.499492	0.155993	2.015412
cup	1.028416	7.186205	1.036971	0.143110	6.929999
win	1.170653	8.191980	1.263275	0.142902	6.484714
game	1.126725	8.941256	4.490691	0.126014	1.991064

195019 rows × 6 columns

In [793]:

```
# look up the table for a given token
tokens.loc['ebbers', 'business_to_sport_ratio']
```

Out[793]:

```
2.7512942626191821
```

Graphs Plotting

In [794]:

```
merged_df.Category.value_counts()
```

Out[794]:

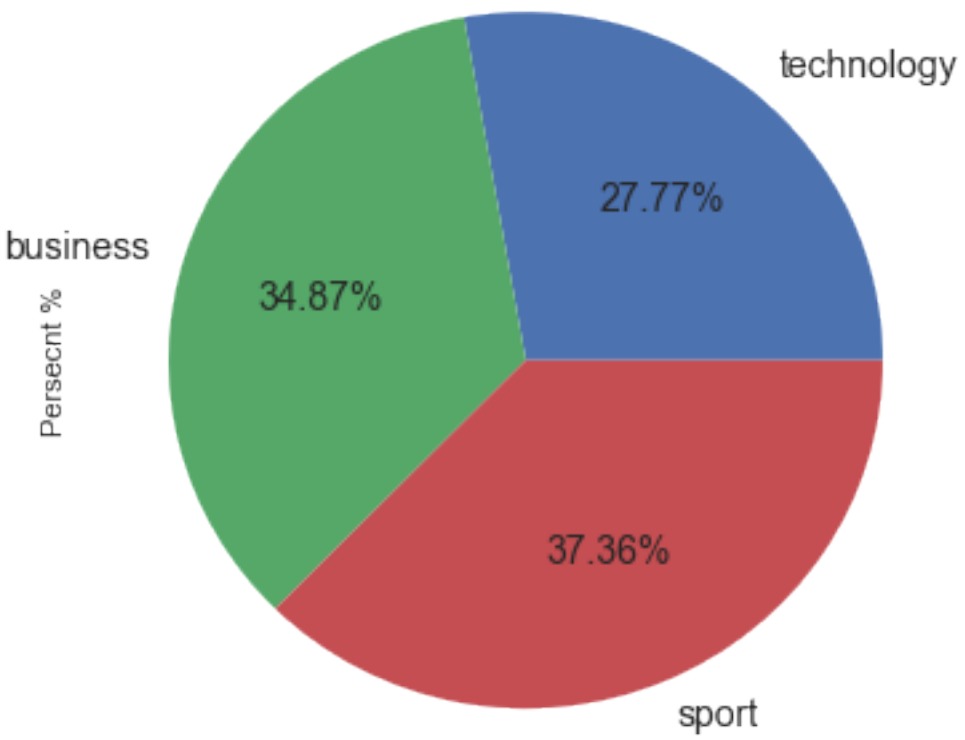
```
sport         526
business      491
technology    391
Name: Category, dtype: int64
```

In [795]:

```
# create three lists to hold the data for each category
counts = merged_df.Category.value_counts().tolist()
series = pd.Series([counts[2], counts[1], counts[0]],
                   index=lables,
                   name='Persecnt %')
#  Display Pie chart:
series.plot.pie(fontsize=14, autopct='%.2f%%', figsize=(6, 6))
```

Out[795]:

<matplotlib.axes._subplots.AxesSubplot at 0x1a2e1e9630>



In [796]:

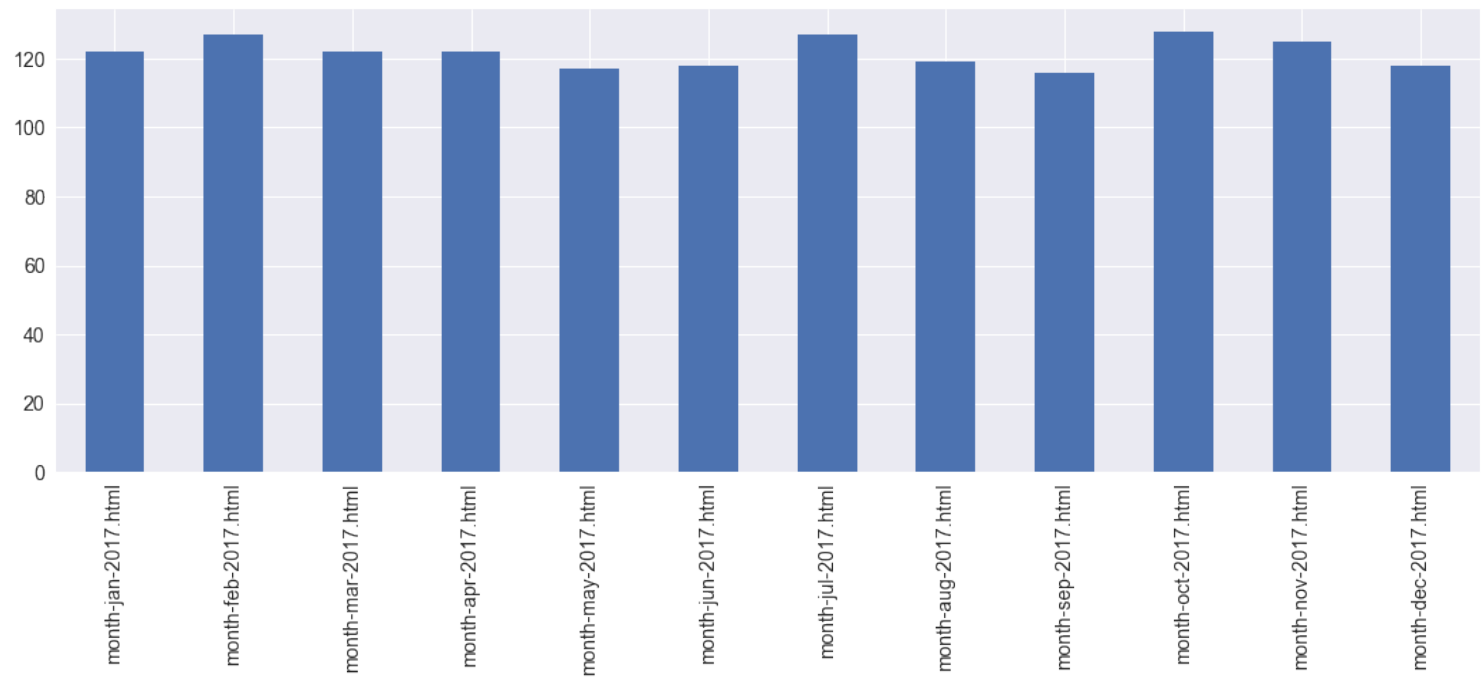
```
months = []
articles_count = []
for item in month_number_of_articles:
    for month,count in item.items():
        months.append(month)
        articles_count.append(count)
        print('{} {}'.format(month, count))

series = pd.Series(articles_count, index=months)
# #  Display Pie chart:
series.plot.bar(fontsize=14, figsize=(18, 6))
```

```
month-jan-2017.html 122
month-feb-2017.html 127
month-mar-2017.html 122
month-apr-2017.html 122
month-may-2017.html 117
month-jun-2017.html 118
month-jul-2017.html 127
month-aug-2017.html 119
month-sep-2017.html 116
month-oct-2017.html 128
month-nov-2017.html 125
month-dec-2017.html 118
```

Out[796]:

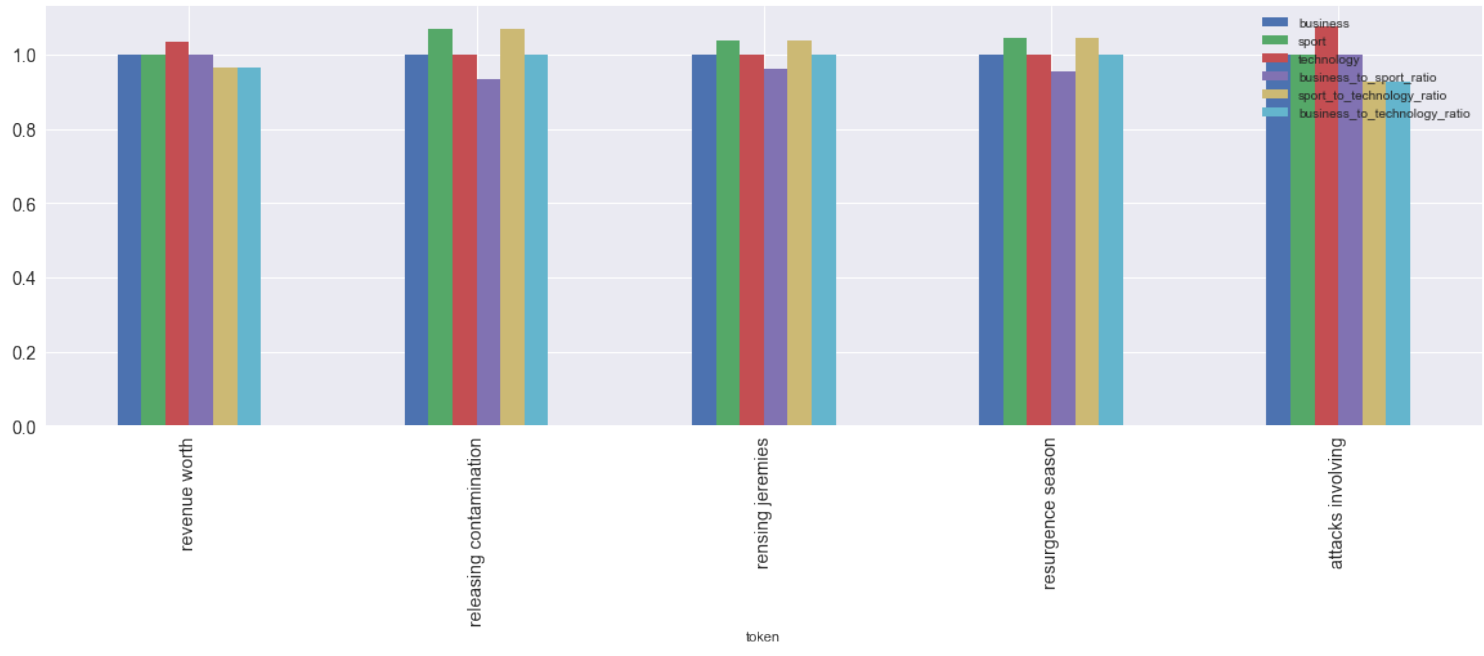
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a2eed5be0>
```



In [797]:

```
plt.figure()
data = tokens.sample(5, random_state=6)
data.plot.bar(fontsize=14,figsize=(20, 6))
plt.show()
```

```
<matplotlib.figure.Figure at 0x1a33bd2cc0>
```



Tentative Conclusion

Further in-depth studies and tests could be carried out to make statistically significant results. However, there doesn't seem to be much of a differen tbetween:

- The **MultinomialNB and KNeighborsClassifier** in the accurcy. Both gave us very good ones **98% and 95%**.
- **MultinomialNB** is very fast time: **39.3 ms** compared to **KNeighborsClassifier** time: **3.7 ms**. it worth to note that using **MultinomialNB** for intial testing is a good idea when you have a large data set and limited time. However, others might provide better results but takes longer time.
- The prediction accuracy is almost identical in our case. The only different is the speed and times to train the data.
- **"The sport category"** is the mosdt predicted documents overall with **100% MultinomialNB and 98% KNeighborsClassifier**

Despiset the differences between the two, thir prections is very similar in our case using this specific data set and accuracy is very accurate.

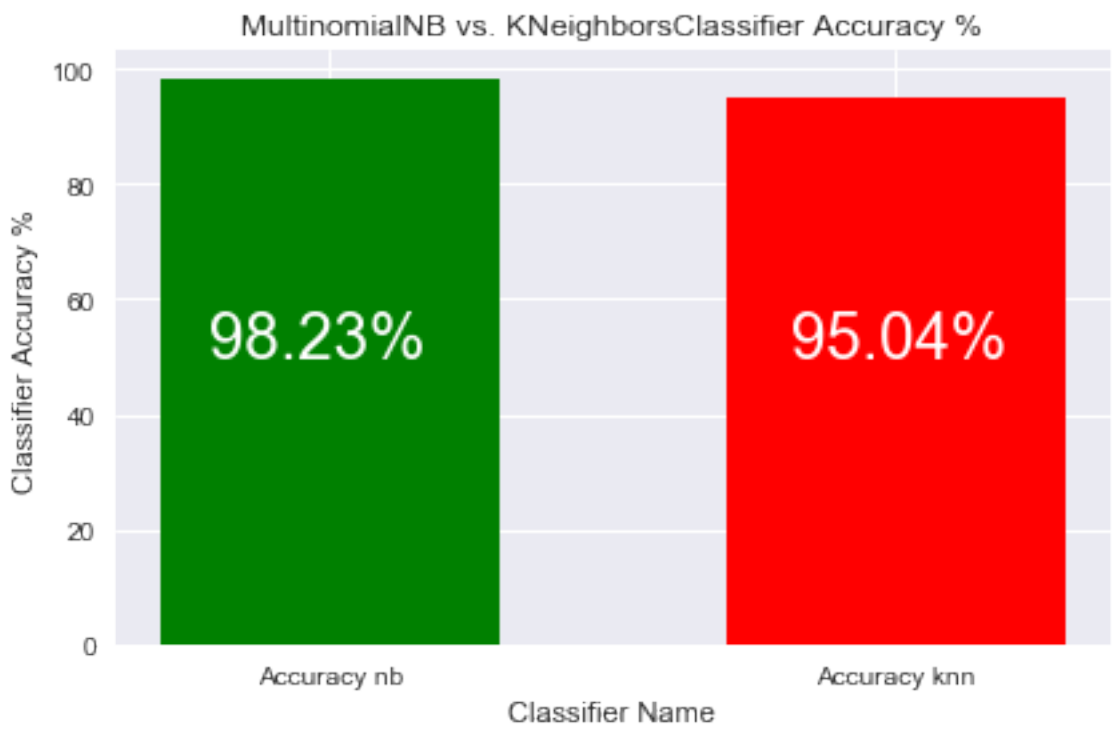
Accuracy for both Classifier

In [798]:

```
acc_nb = float(accuracy_nb * 100)
acc_knn = float(accuracy_knn * 100)
data = {'Accuracy nb': acc_nb, 'Accuracy knn': acc_knn}
plt.bar(range(len(data)), data.values(), width=0.6, align='center',color='gr')
plt.title('MultinomialNB vs. KNeighborsClassifier Accuracy %')
plt.xlabel('Classifier Name')
plt.ylabel('Classifier Accuracy %')
plt.tight_layout()
plt.text(0.2,0.5, s= str('%.2f%%' % acc_nb),fontsize=24,horizontalalignment='c
enter',transform=ax.transAxes, color='w')
plt.text(0.85,0.5, s= str('%.2f%%' % acc_knn),fontsize=24,horizontalalignment=
'center',transform=ax.transAxes, color='w')
plt.xticks(range(len(data)), data.keys())
```

Out[798]:

```
([<matplotlib.axis.XTick at 0x1a33866b70>,
  <matplotlib.axis.XTick at 0x1a2c8883c8>],
 <a list of 2 Text xticklabel objects>)
```



Finally:

- Further analysis can be done to pair the most freacunet terms/words to see how they are assosiate with each other and do they state positive or negative meanings.
- Different weighting and stop word filtering metrics could be used to further enhance the accuracy of the words-bag.
- Experiment with different models to intermes of accuracy and speed to see which is the most fitting one for our useage.