PRODUCT CATEGORIZATION APPROACH

Product categorization is used in e-commerce to make easy to organize and find products in a shopping website. Using tags and keywords for product categorization reduce search time providing a good user experience. A correct match between products and categories is a challenging problem, especially for companies such as Amazon that host in their web page many retailers with millions of products, where each one has its own code of categorization and its own original and unique product name for products that may be similar or even the same.

Find a universal taxonomy for different retailers it is not a feasible task (manual mapping or rule-based categorization are not scalable and time consuming), so it is necessary to develop an automatic and scalable solution that helps to correctly categorize a new product in the available categories when it arrives

Problem formulation:

In this project we want to create a classifier that match the product name with the product category using mostly text features (our dataset contains product name, review, star rating, helpful votes and if the purchase was verified). For this prototype we consider only three categories of products that for its nature may be difficult to differentiate, these categories are: ‘Digital Software’, ‘Software’ and ‘Video Games’. The nature of these three categories along with other limitations in the data have to be considered during the modelling process in order to account them and found for them the best possible solution.

We have for this task mostly text data, so we have to trust that the text contains the necessary tags or keywords to make a correct classification of the products in our sample.

Some of the problems that we may find are the following:

1. **Not text information about the product:** text information of the product give it for the provider could be a feature of interest, because it gives more reliable information than the reviews made by users. Clients reviews do not always contain info related with the description of the product, but information related with quality of the product or if the user like or dislike the product received.
2. **Some products may not be well represented in the sample:** given the quantity of retailers and products with different names and characteristics or similar characteristics but with similar names we may have products with unique names that only appears one in the historical sample. Most of them may have keywords that help us to categorize them correctly but others may not. Also, this unique products that are not well represented may also have not enough information for the algorithm to learn from them. Eliminate these elements is not an option, because this represents a loss of information.
3. **Retailers and reviewers have their own way of name or describe a product:** the information given by the retailer (product name) and the info given by the reviewer (opinion about the product) do not necessarily describe the product category. This may be a problem when underrepresented products or new products are not similar to those that are in the historical data.
4. **Similar categories may be hard to classify due to the limitations described above**: the three categories considered here have similar characteristics, for example: ‘Digital Software’ and ‘Digital Video Games’ may have in common that they can be downloaded, while ‘Digital Software’ and ‘Software’ may be the same product with the difference that one may be downloaded and the other require a physical container (like a cd). This similarities along with the limitations discussed above may increment the rate of misclassifications.
5. **Unbalanced data:** for the three categories we have different sample sizes (‘Software’: 58%, ‘Digital Video Games’: 25%, ‘Software’: 17%) this means that the selected machine learning algorithm would have a tendency to predict the category that have majority (overfit), skewing the results. In these cases, measures like accuracy are not trustfull. To solve this problem we can use a cost or weight function or oversampling/undersampling alternatives as Smote. Additionally metrics as F1-scores, recall and precision are most trustworthy in these cases.

Implementing a solution

First, it is necessary to pre-process the data. In this case we have several text data columns, so the data processing step is different. Any text treatment will end up transforming the text features to its numeric representation before ML algorithms are applied to it. The methods that help with this task are called vectorization methods (Bag of words, TF-IDF and word2vec are the most popular). This includes the steps of removing text elements that are not useful like stop-words, accents, special characters, unusable numbers, etc.

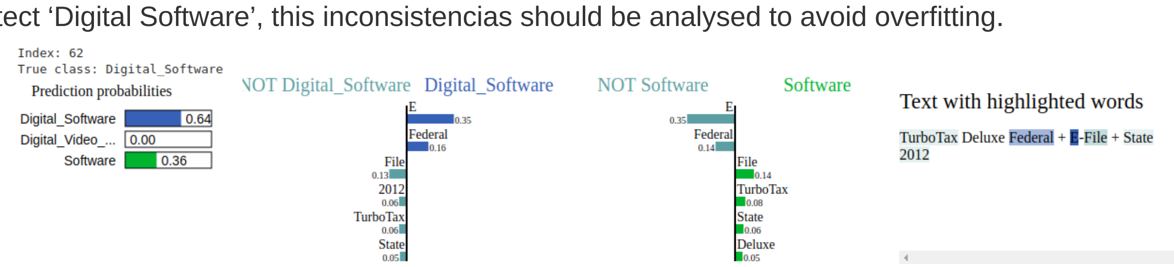
Our baseline model will use bag of words and we will look if the TF-IDF and word2vec improve the results of the most simple methodology. We are mainly looking for tags in the variables that help us to classify a product in the correct category for this reason we keep simple our approach and we are not looking for a deeper meaning or sentiment in the sentences.

Once the text data it is transformed into its numeric representation, we applied ML classification models. There are several models that we can use like multiclass Naive Bayes, Support Vector Machine, tree-models, multiclass logistic regression, deep learning. Here, we only use logistic regression for simplicity and time constraints, but these and other alternatives may be combined through ensemble methodologies (max voting, averaging, stacking, bagging or boosting) to improve the results. The natural process is to create several models and optimize the model parameters of each one (this can be done using grid search, random search or bayesian optimization)

Another reason to choose multiclass logistic regression it is because is useful to understand the contribution of each feature in the model. It is not always the most accurate model but it has high explicability and for a first approach may be of great help to create a better understanding of the data.

To validate our results we consider confusion matrix, F1-score, recall and precision as criteria for selecting the best method. These metrics were applied over a test sample that was not used during the training and that help us to understand how our model predict over a sample that did not see before (external validity).

Also, for each vectorization method used we analyse which words were the most important for each category in order to detect inconsistencies and eliminate that problem from the data. For example the name ‘E-File’ was separated becoming ‘E’ the most important word to detect ‘Digital Software’, this inconsistencias should be analysed to avoid overfitting.



Misclassification Problem:

Any machine learning model will have a rate of misclassification, this rate will be higher or lower depending of the overlapping that exist between the different categories. To reduce this rate is important to reduce this overlap. This can be done including more information about the product (as the description given by the retailer), creating a set of tags for each category that can be obtained from the most important words that represent each category. Additionally, from the test set results we can study the sample of misclassified products and study its patterns, in order to create a set of rules or features that identify those misclassified products in a sample without labels (real case) and later other set of rules or features that classify them in the correct category. These patterns may be found using clustering and identifying those points that have a distance too far from their centroids, then it is possible to use an ML model (with labels set using the results of the clustering) to predict again the correct category.

aws_product_class-Copy1

September 29, 2019

0.1 PRODUCT CATEGORY CLASSIFICATION

0.1.1 Here, we want to develop an automatic and scalable first prototipe that helps to correctly categorize a new product in the available categories when it arrives.

This first prototipe will help us to identify in what elements we have to go deeper in order to get the best model.

0.2 Summary of requirements

1. Train a model that predicts the product category for Software, Digital Software, and Digital Video Games products using the Amazon Customer Reviews dataset.
2. Evaluate and validate your model.

[1]:
```
# I checked warnings, but for the final report I prefer ignore those
#that really does not affect the results (warnings of libraries, etc)
import warnings
warnings.simplefilter('ignore')
#import platform
#platform.architecture()[0]
```

[2]:
```
#Further improvement: develop an enviroment
# Basic Modules
import os
import pandas as pd
import numpy as np
import boto3
import json
import matplotlib.pyplot as plt
#from sagemaker.predictor import json_deserializer
```

[3]:
```
#MOdels
from sklearn.linear_model import LogisticRegression
```

[4]:
```
# Modules for tokens
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences
```

```
from keras.utils import to_categorical
```

```
Using TensorFlow backend.
```

[5]:
```
#my own functions
%load_ext autoreload
%autoreload 2

from utils.py_functions import *
```

0.3 DATA

For our problem we use will three datasets from public datasets of Amazon. This datasets contains Customer Reviews fro three category of products.

- Software
- Digital Software
- Digital video games

[6]:
```
'''
!mkdir /tmp/recsys/
!aws s3 cp s3://amazon-reviews-pds/tsv/
↪amazon_reviews_us_Digital_Video_Games_v1_00.tsv.gz /tmp/recsys/
!aws s3 cp s3://amazon-reviews-pds/tsv/amazon_reviews_us_Software_v1_00.tsv.gz /
↪tmp/recsys/
!aws s3 cp s3://amazon-reviews-pds/tsv/amazon_reviews_us_Digital_Software_v1_00.
↪tsv.gz /tmp/recsys/
'''
```

[6]:
```
'\n!mkdir /tmp/recsys/\n!aws s3 cp s3://amazon-reviews-
pds/tsv/amazon_reviews_us_Digital_Video_Games_v1_00.tsv.gz /tmp/recsys/\n!aws s3
cp s3://amazon-reviews-pds/tsv/amazon_reviews_us_Software_v1_00.tsv.gz
/tmp/recsys/\n!aws s3 cp s3://amazon-reviews-
pds/tsv/amazon_reviews_us_Digital_Software_v1_00.tsv.gz /tmp/recsys/\n'
```

[7]:
```
df_video_games = pd.read_csv('data/amazon_reviews_us_Digital_Video_Games_v1_00.
↪tsv', delimiter = '\t', error_bad_lines = False)
print('Number of rows: ', df_video_games.shape)
df_software = pd.read_csv('data/amazon_reviews_us_Software_v1_00.tsv',␣
↪delimiter = '\t', error_bad_lines = False)
print('Number of rows: ', df_software.shape)
df_digital_software = pd.read_csv('data/
↪amazon_reviews_us_Digital_Software_v1_00.tsv', delimiter = '\t',␣
↪error_bad_lines = False)
print('Number of rows: ', df_digital_software.shape)
```

```
Number of rows:  (144724, 15)
```

```
b'Skipping line 8021: expected 15 fields, saw 22\nSkipping line 34886: expected
15 fields, saw 22\nSkipping line 49286: expected 15 fields, saw 22\n'
```

```
Number of rows:  (341249, 15)
Number of rows:  (101836, 15)
```

0.4 Dataset columns

- marketplace: 2-letter country
- customer_id: random identifier for a customer
- review_id: unique id for the review
- product_id: ASIN number. Unique id for product
- product_parent: the parent of that ASIN. Multiple ASINs (color or format variations of the same product) can roll up into a single parent parent.
- product_title: title/description of the product
- product_category: brad product category
- star_rating: 1 to 5 stars (review rating)
- helpful_votes: Number of helpful votes for the review
- total_votes: number of total votes the review received
- vine: Was the review written as part of the VIne program?
- verified_purchase: Was the review from a verified purchase?
- review_headline: the title of the review itself
- review_body: text of the review
- review_date: the date of the review was written.

[8]:
```
df_video_games.tail()
```

[8]:
```
       marketplace  customer_id       review_id  product_id  product_parent  \
144719          US     53011810  R2G7DI8NYXZB5R  B001AUEITS       163061733
144720          US     53094564  R3QRKP4DS759BP  B001AU6TQ8       801870836
144721          US     37181147  R24K4C0ZC3093U  B001AUEITS       163061733
144722          US     18614365  R13OA3TRCM8IBM  B001AUEITS       163061733
144723          US     28326760  R1PFDIHC9TM6V4  B000AQ7K4I        99419628

                                           product_title  \
144719                        Crazy Machines 2 [Download]
144720  Crazy Machines 1 - The Wacky Contraptions Game…
144721                        Crazy Machines 2 [Download]
144722                        Crazy Machines 2 [Download]
144723                         Emperor of the Fading Suns

          product_category  star_rating  helpful_votes  total_votes vine  \
144719  Digital_Video_Games            4              2            3    N
144720  Digital_Video_Games            1             13           16    N
144721  Digital_Video_Games            3              3            3    N
144722  Digital_Video_Games            1             20           22    N
144723  Digital_Video_Games            4              4            4    N
```

```
       verified_purchase                                    review_headline  \
144719                 N                              Worked first try for me
144720                 N      The Software May be Great, But I'll Never Know
144721                 N             Some install problems but good otherwise
144722                 N                                   Do Not Download This!
144723                 N   Suprisingly large scale and complex strategy game

                                              review_body review_date
144719  I was worried due to the 2 reviews I saw here,…  2008-12-25
144720  I downloaded this as a Christmas present for m…  2008-12-24
144721  The previous reviewer is correct in noting tha…  2008-09-10
144722  I downloaded this for my son's birthday yester…  2008-09-01
144723  This game has all the makings of a wonderful t…  2006-08-08
```

0.5 DROP SOME COLUMNS

[9]:
```python
df_digital_software = df_digital_software.drop(columns = ['marketplace',␣
↪'customer_id', 'product_parent', 'review_id', 'vine', 'review_date'])
df_software         = df_software.drop(columns = ['marketplace', 'customer_id',␣
↪'product_parent', 'review_id', 'vine', 'review_date'])
df_video_games      = df_video_games.drop(columns = ['marketplace',␣
↪'customer_id', 'product_parent', 'review_id', 'vine', 'review_date'])
```

[10]:
```python
df = pd.concat([df_digital_software, df_video_games, df_software], axis=0)
df.tail()
```

[10]:
```
        product_id                              product_title  \
341244  0877794618  Merriam-Webster's Medical Audio Dictionary
341245  0877794618  Merriam-Webster's Medical Audio Dictionary
341246  B00002SV6E                        Star Wars: Droid Works
341247  0671573535                              Star Trek Borg
341248  0877794618  Merriam-Webster's Medical Audio Dictionary

       product_category  star_rating  helpful_votes  total_votes  \
341244         Software            5              5            7
341245         Software            5              3            5
341246         Software            4              1            1
341247         Software            1              0            2
341248         Software            3             12           13

       verified_purchase                                    review_headline  \
341244                 N           My name is Maeda, and I love this CR-ROM.
341245                 N               I'd rather give 6 stars to this title
341246                 N                                     Droid building
341247                 N                                  don't buy this game
```

```
341248                 N  An Easy-to-Use Medical Dictionary with Excelle…

                                                     review_body
341244  I am a medical student.  I loved this CD-ROM v…
341245  I tried a Taber's, but was disappointed: he do…
341246  You get to build droids even ones in existence…
341247  We have not been able to even run this game be…
341248  Merriam-Webster's Medical Audio Dictionary is …
```

[11]:
```
df.dtypes
```

[11]:
```
product_id           object
product_title        object
product_category     object
star_rating           int64
helpful_votes         int64
total_votes           int64
verified_purchase    object
review_headline      object
review_body          object
dtype: object
```

0.5.1 We have products that only appears one. These products may be problematic if the text data does not describe the product correctly.

[12]:
```
df.groupby(['product_id', 'product_title', 'product_category'])['star_rating'].
    ↪count().reset_index().sort_values('star_rating').head(15)
```

[12]:
```
       product_id                                      product_title  \
0      0028650506                          BLACK MUSIC OF TWO WORLDS CD
13274  B000LP6JMM             Zonealarm Antivirus Small Business Ed 10U
13275  B000LPAGOY               Magic Math: Grades 1-2: Jacobson + Jennings
30638  B00B1PFFVC  Dell Inspiron 15R (N5110) Driver Recovery and …
30637  B00B1PF9KO  Dell Inspiron N5050 Driver Update and Drivers …
30636  B00B1PETSC  Dell Inspiron 8600 Driver Update and Drivers I…
13280  B000LRDOAA                                            MoviePlus
13281  B000LRGHBS                        ImpactPlus 5; High Impact Design
30635  B00B1PESDS  Dell Studio XPS 8100 Driver Update and Drivers…
30634  B00B1PEPJA  Dell Inspiron 660 Driver Update and Drivers In…
13284  B000LT158G                                      Pro Series Bridge
13285  B000LTM9ZO                                   North American Birds
13286  B000LTNVIS                                 3-D Web Animation Pack
13288  B000LU6M6K                  Pc-Cillin Antivirus 2007 (Tech Bench)
13290  B000LU6M8S                               pc-Cillin Antivirus 2007

      product_category  star_rating
```

```
0            Software          1
13274        Software          1
13275        Software          1
30638        Software          1
30637        Software          1
30636        Software          1
13280        Software          1
13281        Software          1
30635        Software          1
30634        Software          1
13284        Software          1
13285        Software          1
13286        Software          1
13288        Software          1
13290        Software          1
```

0.6 CHECK IF WE HAVE MISSING VALUES

We have missing data in review_headline, review_body. We have to eliminate it or fix this in order to keep going with the analysis.

[13]:
```python
## check for missing values
df.isnull().sum()
```

[13]:
```
product_id          0
product_title       0
product_category    0
star_rating         0
helpful_votes       0
total_votes         0
verified_purchase   0
review_headline     5
review_body         4
dtype: int64
```

0.6.1 We can see that the na's are not at the same rows.

[14]:
```python
df[df.isnull().any(axis=1)]
```

[14]:
```
        product_id                                  product_title  \
3074    B00452VGXO                          The Sims 3 Late Night
11907   B008D7F47Q                                 FIFA Soccer 13
14470   B00S00IJH8                                         Sims 4
128119  B004VSTQ2A                         Xbox Live Subscription
21683   B00MUTB2SS          McAfee 2015 Antivirus Plus 3 PC (3-Users)
```

```
55474   B00EOI2ND6  HRB 2011 Basic FFP Test ASIN (Formerly: Micros…
76722   B001GL6QHS       TurboTax Deluxe Federal + State + eFile 2008
178530  B000M9DOTS                       MorphVOX Pro - Voice Changer
281897  B00008NNY0                                    Instant CD/DVD

           product_category  star_rating  helpful_votes  total_votes  \
3074    Digital_Video_Games            1              0            0
11907   Digital_Video_Games            5              0            0
14470   Digital_Video_Games            2              0            2
128119  Digital_Video_Games            1              1            8
21683              Software            1              1            1
55474              Software            4              0            0
76722              Software            4              0            0
178530             Software            4              0            1
281897             Software            1              0            4

       verified_purchase review_headline  \
3074                   Y             NaN
11907                  N      Five Stars
14470                  N       Two Stars
128119                 Y             NaN
21683                  Y             NaN
55474                  N      Four Stars
76722                  Y      Four Stars
178530                 Y             NaN
281897                 N             NaN

                                              review_body
3074                           Product code does not work.
11907                                                 NaN
14470                                                 NaN
128119  I DID NOT BUY THIS PRODUCT SO I AM CONFUSED AS…
21683   I am giving this one star because I am unable …
55474                                                 NaN
76722                                                 NaN
178530  Product worked was able to play with applicati…
281897  Shortly after buying the product I had to repl…
```

0.6.2 Fill values

[15]:
```
df.review_headline.fillna(df.review_body, inplace=True)
df.review_body.fillna(df.review_headline, inplace=True)
```

0.7 Check for white strings

[16]:
```
blanks = []  # start with an empty list

for i,lb,rv in df[['product_category','review_body']].itertuples():  # iterate␣
↪over the DataFrame , 'product_title', 'verified_purchase', 'review_headline'
    if type(rv)==str:            # avoid NaN values
        if rv.isspace():         # test 'review' for whitespace
            blanks.append(i)     # add matching index numbers to the list

print(len(blanks), 'blanks: ', blanks)
```

```
0 blanks:  []
```

[17]:
```
blanks = []  # start with an empty list

for i,lb,rv in df[['product_title', 'review_headline']].itertuples():  #␣
↪iterate over the DataFrame ,
    if type(rv)==str:            # avoid NaN values
        if rv.isspace():         # test 'review' for whitespace
            blanks.append(i)     # add matching index numbers to the list

print(len(blanks), 'blanks: ', blanks)
```

```
0 blanks:  []
```

0.8 IS BALANCED?

[18]:
```
df.groupby("product_category")['product_id'].count()/df.shape[0]
```

[18]:
```
product_category
Digital_Software       0.173247
Digital_Video_Games    0.246209
Software               0.580544
Name: product_id, dtype: float64
```

[19]:
```
dicti = {"Digital_Software": 0, "Digital_Video_Games": 1, "Software": 2}
df['product_category_label'] = df['product_category']
df = df.replace({"product_category": dicti})
```

[20]:
```
df.head()
```

[20]:
```
   product_id                                  product_title  \
0  B00U7LCE6A                           CCleaner Free [Download]
1  B00HRJMOM4                  ResumeMaker Professional Deluxe 18
2  B00P31G9PQ                           Amazon Drive Desktop [PC]
```

```
3  B00FGDEPDY         Norton Internet Security 1 User 3 Licenses
4  B00FZ0FK0U  SecureAnywhere Intermet Security Complete 5 De…

   product_category  star_rating  helpful_votes  total_votes  \
0                 0            4              0            0
1                 0            3              0            0
2                 0            1              1            2
3                 0            5              0            0
4                 0            4              1            2

  verified_purchase                              review_headline  \
0                 Y                                   Four Stars
1                 Y                                  Three Stars
2                 Y                                     One Star
3                 Y                          Works as Expected!
4                 Y  Great antivirus. Worthless customer support

                                        review_body product_category_label
0                                    So far so good       Digital_Software
1                     Needs a little more work…       Digital_Software
2                                    Please cancel.       Digital_Software
3                                Works as Expected!       Digital_Software
4  I've had Webroot for a few years. It expired a…       Digital_Software
```

0.9 CLEAN TEXT COLUMNS

[21]:
```python
#clean characters
df = standardize_text(df, "product_title")
df = standardize_text(df, "review_headline")
df = standardize_text(df, "review_body")
```

0.10 Eliminate stop words

[22]:
```python
#download stopwords
import nltk
nltk.download('stopwords')
nltk.download('wordnet')
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     /home/erikapat/nltk_data…
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to /home/erikapat/nltk_data…
[nltk_data]   Package wordnet is already up-to-date!
```

[22]: True

[23]:
```
df.tail(15).head()
```

[23]:
```
        product_id                            product_title  \
341234  B00002CEXA     email games  xcom first alien invasion
341235  B00002S6Z2               dimension   standard edition
341236  B00002S6EQ                                     unreal
341237  B00002JV50  microsoft windows  second edition upgrade
341238  B00002S9XK       sesame street get set to learn ages

        product_category  star_rating  helpful_votes  total_votes  \
341234                 2            4             25           26
341235                 2            5              9            9
341236                 2            4              6           12
341237                 2            2             21           25
341238                 2            5             48           59

       verified_purchase                                    review_headline  \
341234                 N                              old game but classic
341235                 N  d is e best relation database product on deskt…
341236                 N  wow!  so beautiful   you almost ate to blow it…
341237                 N                                  expensive bug fix
341238                 N          best introduction to games for  year old

                                              review_body  \
341234  aloug xcom lacks e wizbang grapics of e latest…
341235  e d world opens a pleora of opportunities to c…
341236  is is a great game!  a little lacking on story…
341237  for a company at as enoug revenue to run a sma…
341238  is game was e first game my son was able to pl…

       product_category_label
341234               Software
341235               Software
341236               Software
341237               Software
341238               Software
```

[24]:
```
# Import stopwords with nltk.
from nltk.corpus import stopwords
stop = stopwords.words('english')
# Exclude stopwords with Python's list comprehension and pandas.DataFrame.apply.
df['product_title'] = df['product_title'].apply(lambda x: ' '.join([word for␣
↪word in x.split() if word not in (stop)]))
df['review_headline'] = df['review_headline'].apply(lambda x: ' '.join([word␣
↪for word in x.split() if word not in (stop)]))
```

```
df['review_body'] = df['review_body'].apply(lambda x: ' '.join([word for word␣
↪in x.split() if word not in (stop)]))
#more cleaning
df['product_title'] = df['product_title'].map(lambda x : clean_text(x))
df['review_headline'] = df['review_headline'].map(lambda x : clean_text(x))
df['review_body'] = df['review_body'].map(lambda x : clean_text(x))
df['product_title'] = df['product_title'].map(lambda x : removeAscendingChar(x))
df['review_headline'] = df['review_headline'].map(lambda x :␣
↪removeAscendingChar(x))
df['review_body'] = df['review_body'].map(lambda x : removeAscendingChar(x))
```

0.11 Lemmatization

[25]:
```
#lemmatization
df['product_title'] = df['product_title'].map(lambda x : lemitizeWords(x))
df['review_headline'] = df['review_headline'].map(lambda x : lemitizeWords(x))
df['review_body'] = df['review_body'].map(lambda x : lemitizeWords(x))
```

[26]:
```
#eliminate single letters
df['product_title'] = df['product_title'].str.replace(r'\b\w\b','').str.
↪replace(r'\s+', ' ')
df['review_headline'] = df['review_headline'].str.replace(r'\b\w\b','').str.
↪replace(r'\s+', ' ')
df['review_body'] = df['review_body'].str.replace(r'\b\w\b','').str.
↪replace(r'\s+', ' ')
```

[27]:
```
df.tail(15).head()
```

[27]:
```
        product_id                                product_title  \
341234  B00002CEXA     email games xcom first alien invasion
341235  B00002S6Z2               dimension standard edition
341236  B00002S6EQ                                       unreal
341237  B00002JV50  microsoft windows second edition upgrade
341238  B00002S9XK          sesame street get set learn ages

        product_category  star_rating  helpful_votes  total_votes  \
341234                 2            4             25           26
341235                 2            5              9            9
341236                 2            4              6           12
341237                 2            2             21           25
341238                 2            5             48           59

       verified_purchase                                review_headline  \
341234                 N                               old game classic
341235                 N   best relation database product desktop macines
```

```
341236                 N                       wow beautiful almost ate blow
341237                 N                                   expensive bug fix
341238                 N                    best introduction games year old

                                               review_body  \
341234  aloug xcom lacks wizbang grapics latest games …
341235   world opens pleora opportunities create custo…
341236  great game little lacking story wat care got a…
341237  company enoug revenue run small country expect…
341238  game first game son able play age onwards exce…

       product_category_label
341234               Software
341235               Software
341236               Software
341237               Software
341238               Software
```

0.12 BASELINE MODEL

First we will develop a simple model, that we are going to use as Baseline.

For our baseline model we will do: * Tokenizing sentences to a list of separate words * Creating a train test split * Inspecting our data a little more to validate results

[28]:
```
from nltk.tokenize import RegexpTokenizer

tokenizer = RegexpTokenizer(r'\w+')

df["token_product_title"] = df["product_title"].apply(tokenizer.tokenize)
df["token_review_body"] = df["review_body"].apply(tokenizer.tokenize)
df["token_review_headline"] = df["review_headline"].apply(tokenizer.tokenize)
```

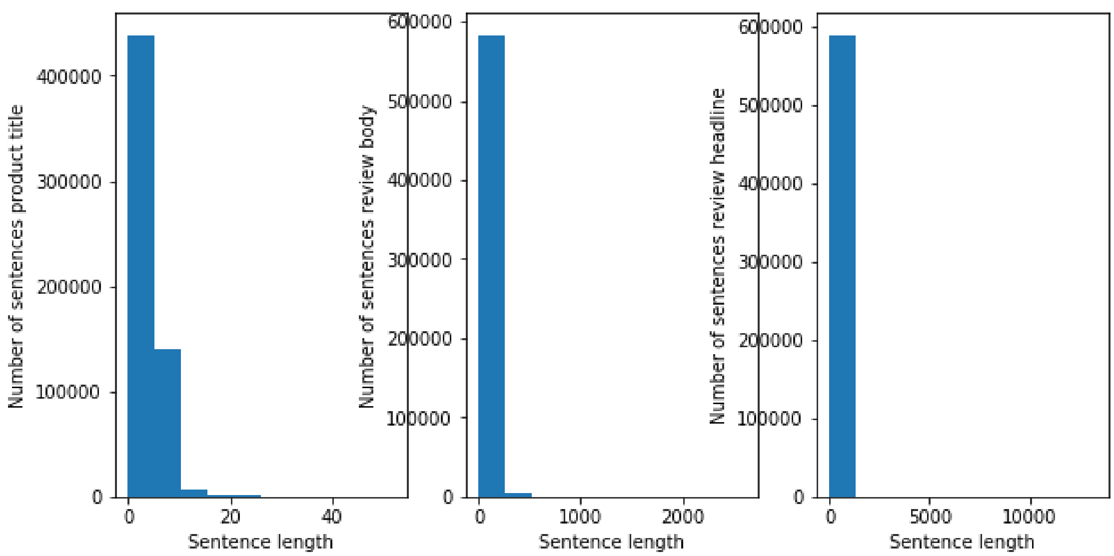
0.13 Inspecting tokens

[29]:
```
sentence_lengths_1 = descriptive_tokens(df, name = "token_product_title")
sentence_lengths_2 = descriptive_tokens(df, name = "token_review_body")
sentence_lengths_3 = descriptive_tokens(df, name = "token_review_headline")
```

```
Column  token_product_title  have 2637986 words total, with a vocabulary size of
16285
Max sentence length is 52
Column  token_review_body  have 22956901 words total, with a vocabulary size of
170124
Max sentence length is 2609
Column  token_review_headline  have 1670103 words total, with a vocabulary size
```

```
of 43088
Max sentence length is 13279
```

[30]:
```
%matplotlib inline
fig= plt.figure(figsize=(10, 5))
plt.subplot(1, 3, 1)
plt.xlabel('Sentence length')
plt.ylabel('Number of sentences product title')
plt.hist(sentence_lengths_1)
plt.subplot(1, 3, 2)
plt.xlabel('Sentence length')
plt.ylabel('Number of sentences review body')
plt.hist(sentence_lengths_2)
plt.subplot(1, 3, 3)
plt.xlabel('Sentence length')
plt.ylabel('Number of sentences review headline')
plt.hist(sentence_lengths_3)
plt.show()
```



[33]:
```
## **concatenate columns**

#We will use a concatination of columns, to see if we include review␣
↪information or not

#
#df['full_text'] = df["product_title"] + " " + df["review_body"]  + " " +␣
↪df["review_headline"]
```

```
df['product_title'] = df["product_title"] #+ " " + df["review_body"] #  + " " +␣
↪df["review_headline"] #
```

[34]:
```
df.head()
```

[34]:
```
   product_id                                  product_title  \
0  B00U7LCE6A                         ccleaner free download
1  B00HRJMOM4                 resumemaker professional deluxe
2  B00P31G9PQ                          amazon drive desktop pc
3  B00FGDEPDY             norton internet security user licenses
4  B00FZ0FK0U  secureanywere intermet security complete device

   product_category  star_rating  helpful_votes  total_votes  \
0                 0            4              0            0
1                 0            3              0            0
2                 0            1              1            2
3                 0            5              0            0
4                 0            4              1            2

  verified_purchase                           review_headline  \
0                 Y
1                 Y                                       ree
2                 Y
3                 Y                            works expected
4                 Y  great antivirus worless customer support

                                         review_body product_category_label  \
0                                           far good       Digital_Software
1                                  needs little work       Digital_Software
2                                      please cancel       Digital_Software
3                                     works expected       Digital_Software
4   ve ad webroot years expired decided purcase r…       Digital_Software

                              token_product_title  \
0                      [ccleaner, free, download]
1               [resumemaker, professional, deluxe]
2                       [amazon, drive, desktop, pc]
3       [norton, internet, security, user, licenses]
4  [secureanywere, intermet, security, complete, …

                                 token_review_body  \
0                                      [far, good]
1                             [needs, little, work]
2                                  [please, cancel]
3                                 [works, expected]
4  [ve, ad, webroot, years, expired, decided, pur…
```

```
                            token_review_headline
0                                              []
1                                           [ree]
2                                              []
3                               [works, expected]
4  [great, antivirus, worless, customer, support]
```

0.14 Enter embeddings

Machine Learning on images can use raw pixels as inputs. A way to represent text is to encode each character individually, this seems quite inadequate to represent and understand language. Our goal is to first create a useful embedding for each sentence in our dataset, and then use these embeddings to accurately predict the relevant category.

The most simplest approach is to use a **bag of words model**, and apply a machine learning algorimth (like, logistic, naive bayes, between others). A bag of words just associates an index to each word in our vocabulary, and embeds each sentence as a list of 0s, with a 1 at each index corresponding to a word present in the sentence.

0.15 Bag of Words

[35]:
```
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer

def cv(data):
    count_vectorizer = CountVectorizer()

    emb = count_vectorizer.fit_transform(data)

    return emb, count_vectorizer

df_corpus = df['product_title'] #df['review_headline']#df['full_text']
#df_corpus = df['review_body', 'review_headline']
df_labels = df["product_category"]

X_train, X_test, y_train, y_test = train_test_split(df_corpus, df_labels,␣
 ↪test_size=0.2,                                                              ␣
 ↪random_state=40)
```

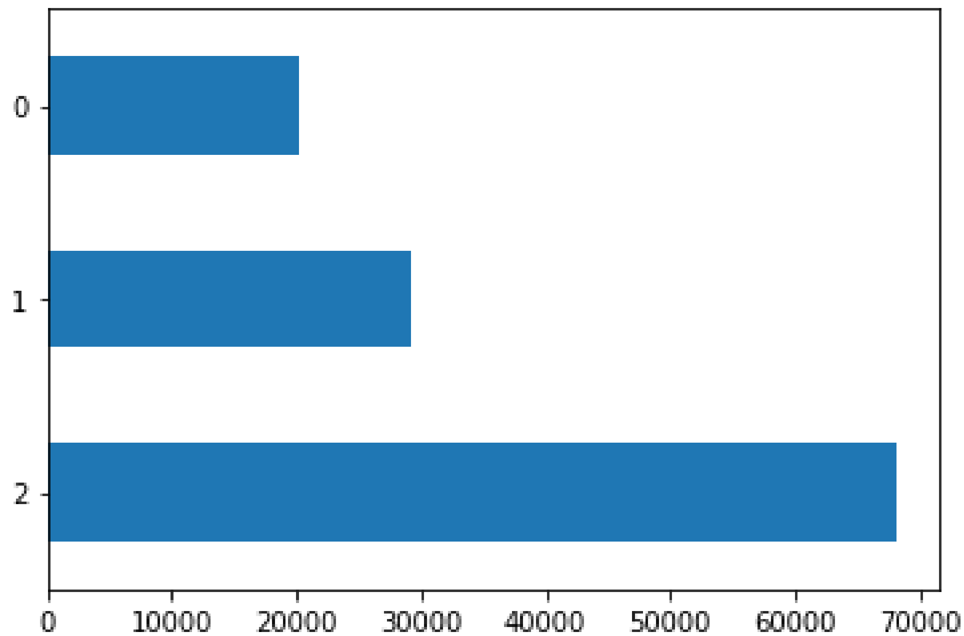
[36]:
```
y_test.value_counts()
```

[36]:
```
2    68194
1    29104
0    20264
```

Name: product_category, dtype: int64

[37]:
```
y_test.value_counts().plot('barh')
```

[37]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc3a06c2050>



[38]:
```
X_train_counts, count_vectorizer = cv(X_train)
X_test_counts = count_vectorizer.transform(X_test)
```

[39]:
```
print(X_train_counts.shape)
```

(470247, 15354)

[40]:
```
#print(X_train_counts.todense())
```

0.16 CHI-SQUARED

We've constructed a matrix, that have a lot of unique words/columns. This data configuratio will take a very long time to make predictions. We want to speed it up, so we'll need to cut down the column count somehow. One way to do this is to pick a subset of the columns that are the most informative.

[41]:
```
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
# Find the 1000 most informative columns
```

```
selector = SelectKBest(chi2, k=1000) #further work:check other alternatives
selector.fit(X_train_counts, y_train)
top_words = selector.get_support().nonzero()

# Pick only the most informative columns in the data.
chi_matrix = X_train_counts[:,top_words[0]]
```

[42]:
```
print(chi_matrix.shape)
```

```
(470247, 1000)
```

[43]:
```
X_train_counts = chi_matrix.copy()
```

[44]:
```
print(X_train_counts.shape)
```

```
(470247, 1000)
```

[45]:
```
#TOP WORDS FOR TEST
X_test_counts = X_test_counts[:,top_words[0]]
```

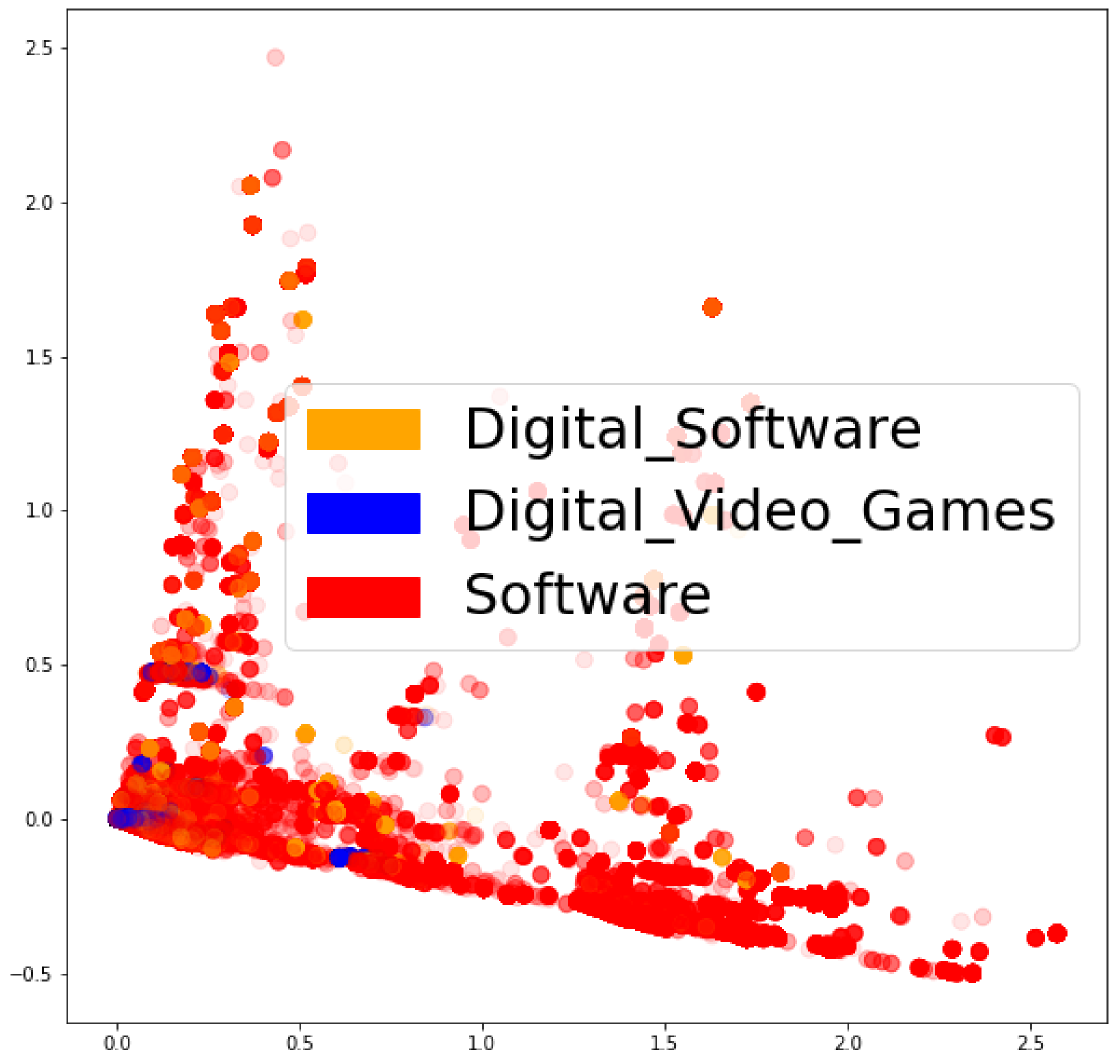
[46]:
```
print(X_test_counts.shape)
```

```
(117562, 1000)
```

0.17 Visualizing the embeddings

Here, we apply linear dimensionality reduction to see if we can find separations between the groups.

[47]:
```
fig = plt.figure(figsize=(10, 10))
plot_LSA(X_train_counts, y_train)
plt.show()
```



These embeddings don't look very cleanly separated. Let's see if we can still fit a useful model on them.

0.17.1 Fitting a classifier

Starting with a logistic regression is a good idea. It is simple, often gets the job done, and is easy to interpret.

0.17.2 Logistic regression

[48]:
```
# balance classes
from sklearn.utils import class_weight
class_weights = class_weight.compute_class_weight('balanced',
                                                  np.unique(y_train),
                                                  y_train)
classes = np.unique(y_train)
class_weights = dict(zip(classes, class_weights))
class_weights
```

[48]:
```
{0: 1.9216030010297651, 1: 1.355725653001211, 2: 0.574056508761971}
```

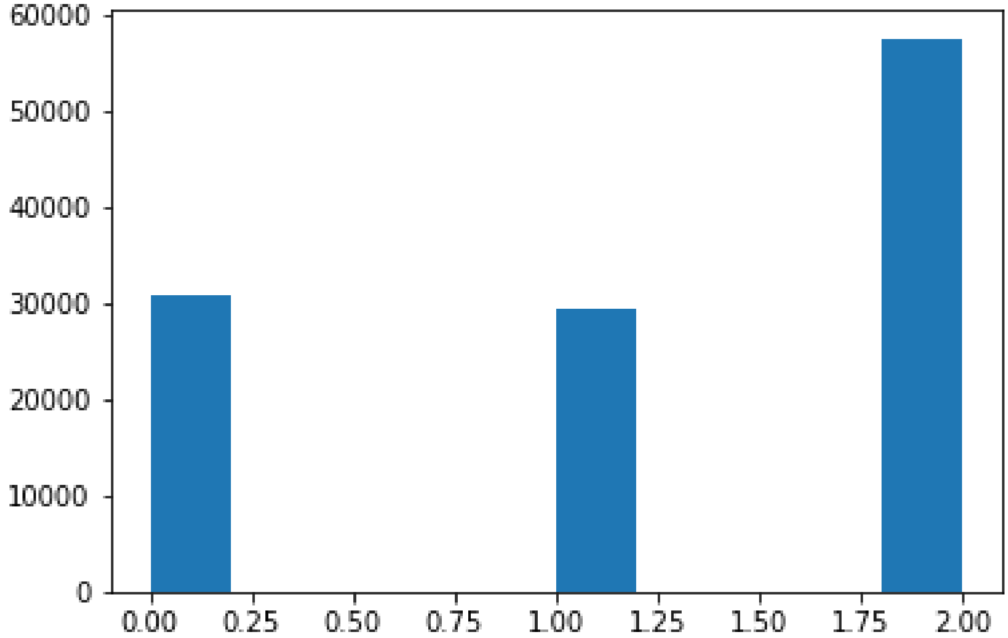
[49]:
```
from sklearn.linear_model import LogisticRegression
clf = LogisticRegression(C=30.0, class_weight=class_weights, #class_weight =␣
↪'balanced',
                         solver='newton-cg',
                         multi_class='multinomial', n_jobs=1, random_state=40)␣
↪#, n_jobs=-1 (default) all, -2 all cpus but one are used
clf.fit(X_train_counts, y_train) #, class_weight=class_weights to balance data
```

[49]:
```
LogisticRegression(C=30.0,
                   class_weight={0: 1.9216030010297651, 1: 1.355725653001211,
                                 2: 0.574056508761971},
                   dual=False, fit_intercept=True, intercept_scaling=1,
                   l1_ratio=None, max_iter=100, multi_class='multinomial',
                   n_jobs=1, penalty='l2', random_state=40, solver='newton-cg',
                   tol=0.0001, verbose=0, warm_start=False)
```

[50]:
```
y_predicted_counts = clf.predict(X_test_counts)
```

[51]:
```
plt.hist(y_predicted_counts)
```

[51]:
```
(array([30698.,     0.,     0.,     0.,     0., 29282.,     0.,     0.,
            0., 57582.]),
 array([0. , 0.2, 0.4, 0.6, 0.8, 1. , 1.2, 1.4, 1.6, 1.8, 2. ]),
 <a list of 10 Patch objects>)
```



0.17.3 Evaluation

Let's start by looking at some metrics to see if our classifier performed well at all.

[52]:
```
accuracy, precision, recall, f1 = get_metrics(y_test, y_predicted_counts)
print("accuracy = %.3f, precision = %.3f, recall = %.3f, f1 = %.3f" %␣
 ↪(accuracy, precision, recall, f1))
```

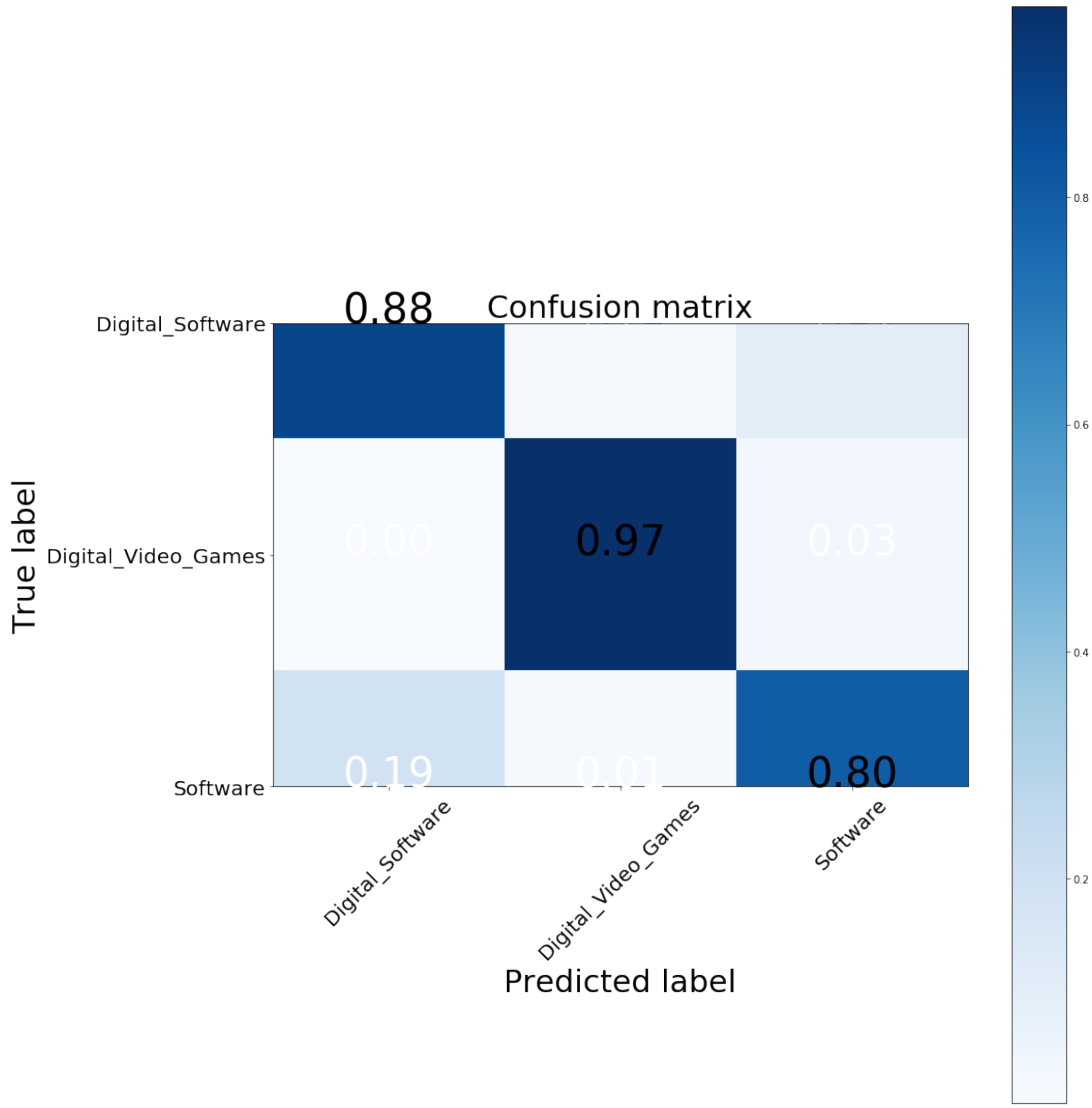
```
accuracy = 0.856, precision = 0.888, recall = 0.856, f1 = 0.863
```

0.17.4 Inspection

A metric is one thing, but in order to make an actionnable decision, we need to actually inspect the kind of mistakes our classifier is making. Let's start by looking at the confusion matrix.

[53]:
```
cm = confusion_matrix(y_test, y_predicted_counts)
fig = plt.figure(figsize=(15, 15))
plot = plot_confusion_matrix(cm, classes=['Digital_Software',␣
 ↪'Digital_Video_Games', 'Software'], normalize=True, title='Confusion matrix')
plt.show()
print(cm)
```

```
Normalized confusion matrix
```




```
[[17864   293  2107]
 [   74 28161   869]
 [12760   828 54606]]
```

[54]:
```
#IMPORTANCE OF WORDS
importance = get_most_important_features(count_vectorizer, clf, 10)
```

[55]:
```
importance[1]['tops'] #tops for video games
```

[55]:
```
[(5.8721997659747975, 'advertisement'),
 (6.056004926710933, 'auriculoerapy'),
 (6.067608435417419, 'acpa'),
```

```
 (6.189084280002864, 'armonica'),
 (6.366940460936444, 'anniilation'),
 (6.654794575584947, 'anvil'),
 (6.662276675378382, 'ajq'),
 (6.749679684006429, 'aboard'),
 (6.856134258149394, 'al'),
 (8.879801571394873, 'arcxt')]
```

[56]:
```
importance[0]['tops'] #digital software
```

[56]:
```
[(4.732064914147096, 'arcticlean'),
 (4.916537265320087, 'accessory'),
 (5.022995206385733, 'annie'),
 (5.149171414134906, 'abuse'),
 (5.250643295788913, 'albian'),
 (5.3368857002896295, 'anywere'),
 (5.450814857466169, 'ability'),
 (5.960461665146921, 'accurate'),
 (6.0128726237316785, 'amorpium'),
 (6.061294136122159, 'auorware')]
```

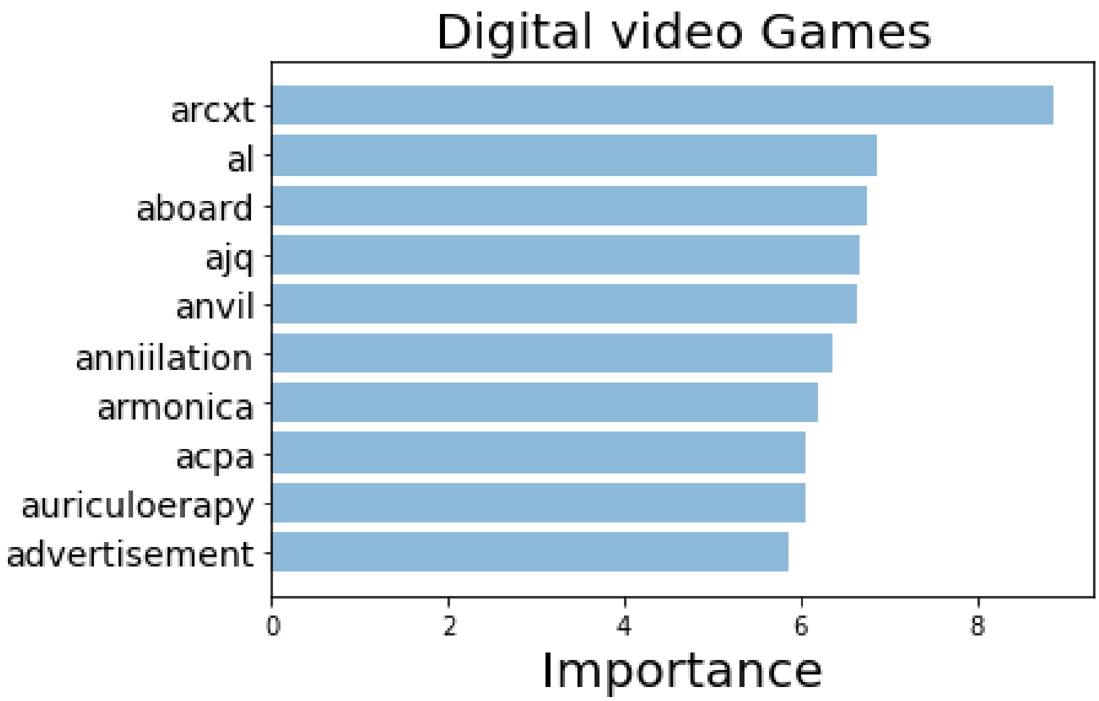
[57]:
```
importance[2]['tops'] #software
```

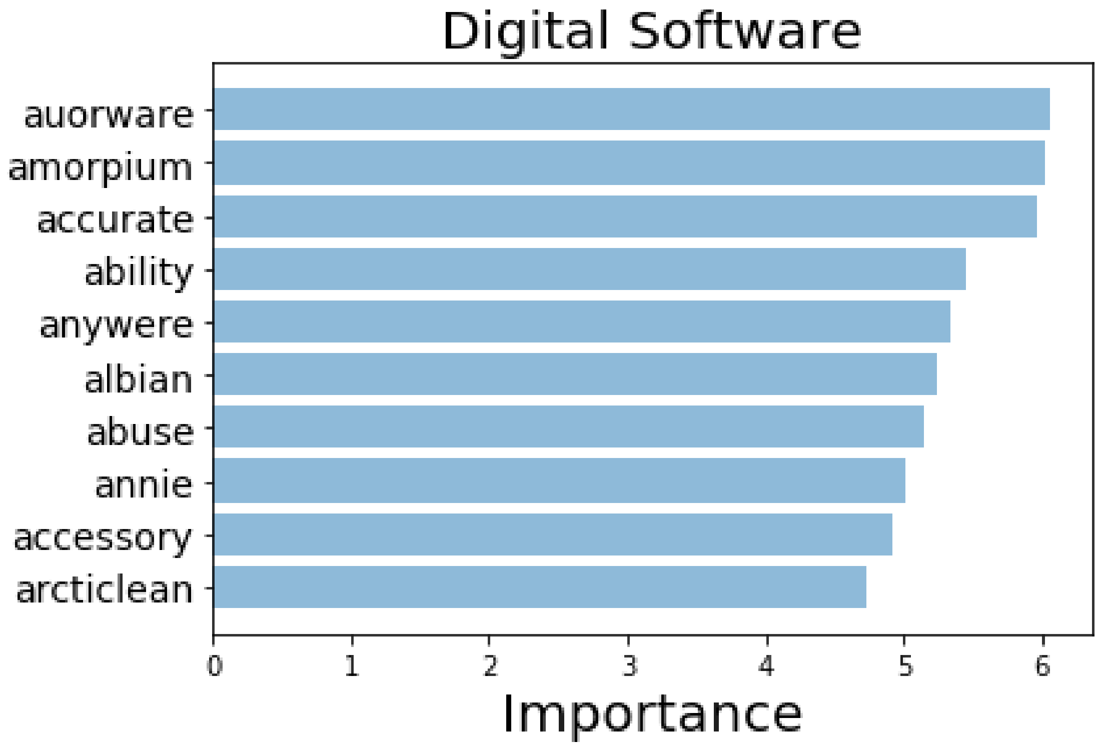
[57]:
```
[(4.728202879859752, 'accountz'),
 (4.747692774415891, 'amapi'),
 (4.798641640556464, 'amr'),
 (4.84254274779429, 'admirals'),
 (4.855943234965648, 'atari'),
 (5.335865550472419, 'adapter'),
 (5.635358372442225, 'arrangement'),
 (5.651636066332626, 'affiliate'),
 (5.92872288647246, 'artsy'),
 (6.144311096751719, 'attack')]
```

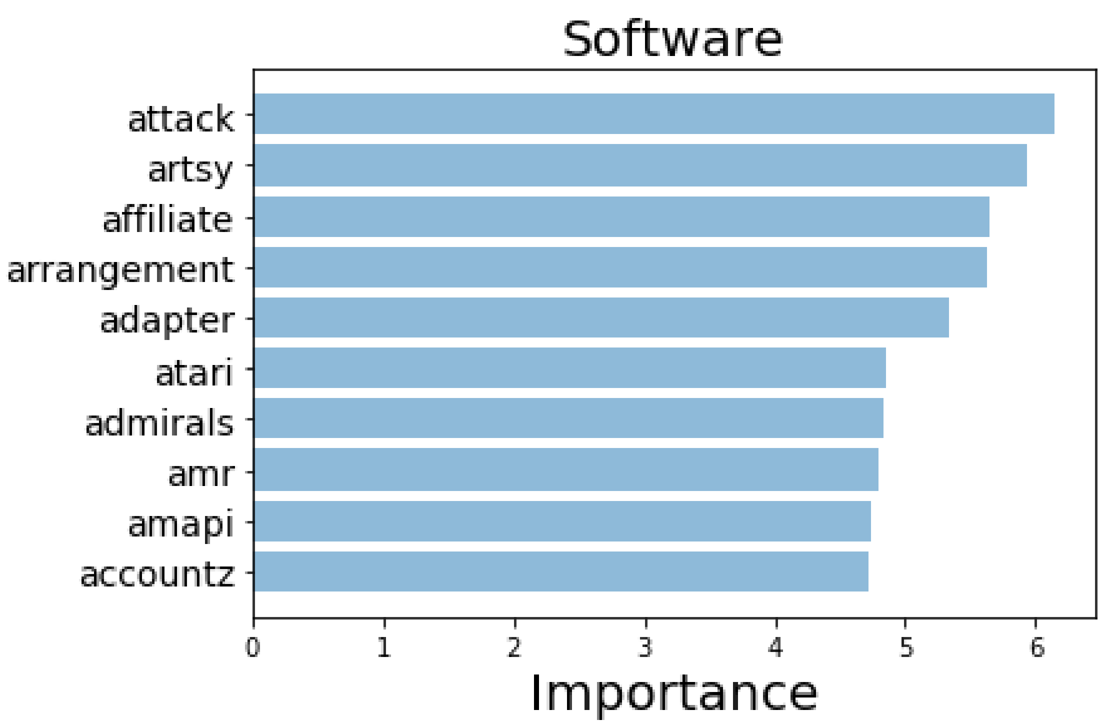
[58]:
```
#video games (1)
top_scores_video = [a[0] for a in importance[1]['tops']]
top_words_video = [a[1] for a in importance[1]['tops']]
#digital software (0)
top_scores_digital = [a[0] for a in importance[0]['tops']]
top_words_digital = [a[1] for a in importance[0]['tops']]
##software
top_scores_software = [a[0] for a in importance[2]['tops']]
top_words_software = [a[1] for a in importance[2]['tops']]

print("Most important words")
plot_important_words(top_scores_video, top_words_video, name = 'Digital video␣
 ↪Games')
```

```
plot_important_words(top_scores_digital, top_words_digital, name = 'Digital␣
 ↪Software')
plot_important_words(top_scores_software, top_words_software, name = 'Software')
```

Most important words




Digital Software
auorware
amorpium
accurate
ability
anywere
albian
abuse
annie
accessory
arcticlean
0
1
2
3
4
5
6
Importance


Software
attack
artsy
affiliate
arrangement
adapter
atari
admirals
amr
amapi
accountz
0
1
2
3
4
5
6
Importance

0.18 TFIDF Bag of Words

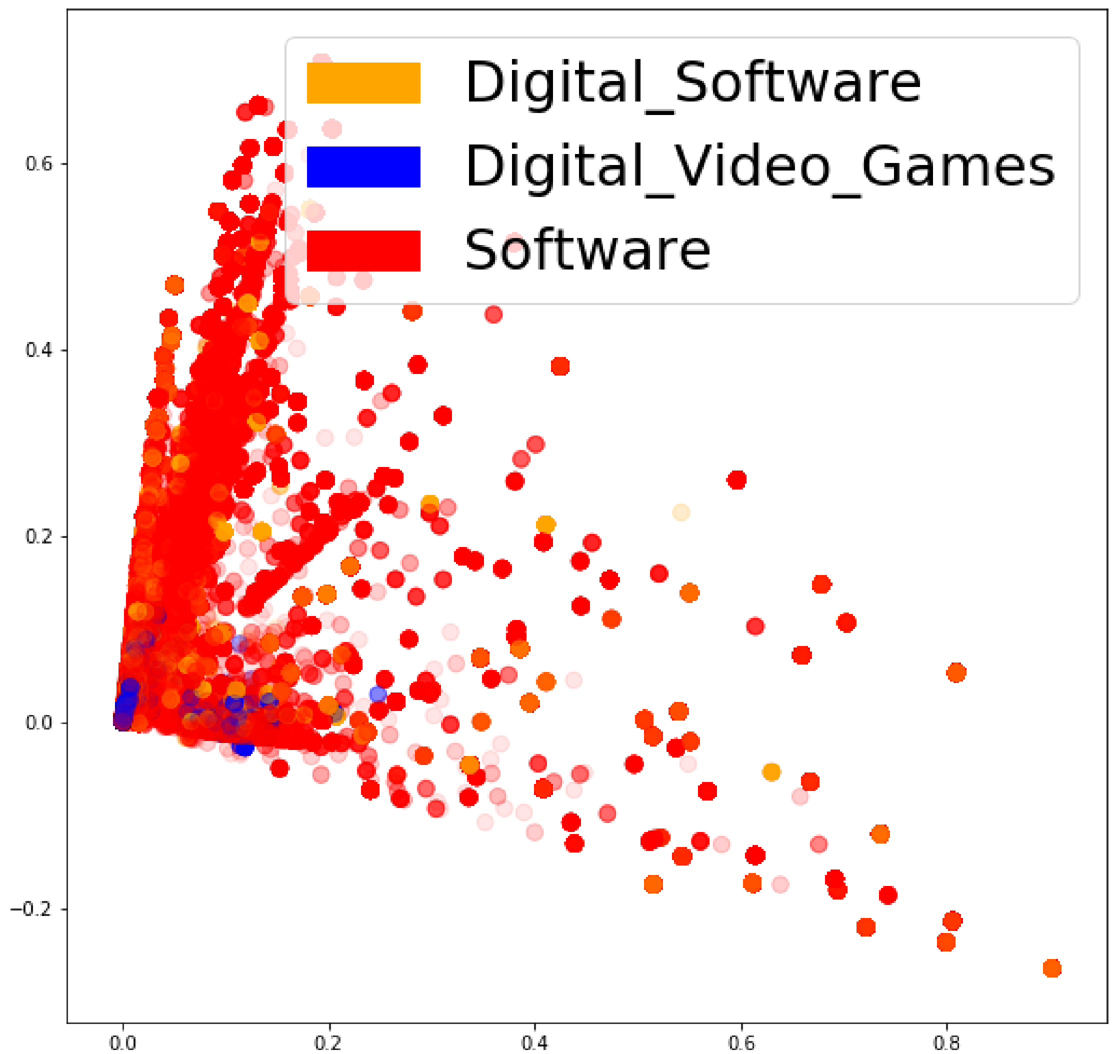
Let's try a slightly more subtle approach. Now, we will use a TF-IDF (Term Frequency, Inverse Document Frequency) which means weighing words by how frequent they are in our dataset, discounting words that are too frequent (as of, the and others), because they just add noise.

[59]:
```
def tfidf(data):
    tfidf_vectorizer = TfidfVectorizer()

    train = tfidf_vectorizer.fit_transform(data)

    return train, tfidf_vectorizer

X_train_tfidf, tfidf_vectorizer = tfidf(X_train)
X_test_tfidf = tfidf_vectorizer.transform(X_test)
```

[60]:
```
print(X_train_tfidf.shape)
```

```
(470247, 15354)
```

[61]:
```
fig = plt.figure(figsize=(10, 10))
plot_LSA(X_train_tfidf, y_train)
plt.show()
```



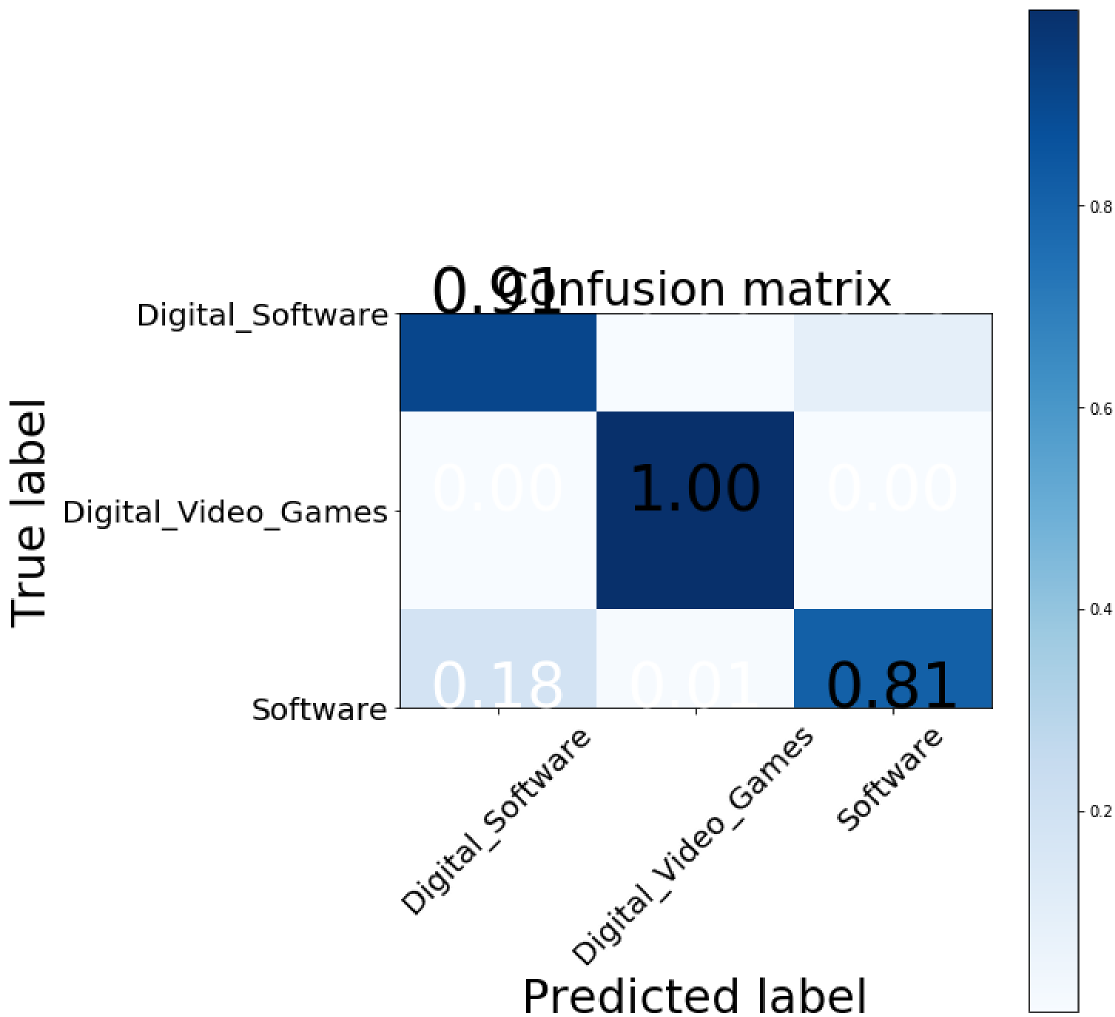
[62]:
```
clf_tfidf = LogisticRegression(C=30.0, class_weight= class_weights,#␣
↪'balanced',
                               solver='newton-cg',
                         multi_class='multinomial', n_jobs=1, random_state=40)
clf_tfidf.fit(X_train_tfidf, y_train)

y_predicted_tfidf = clf_tfidf.predict(X_test_tfidf)
```

[63]:
```
accuracy_tfidf, precision_tfidf, recall_tfidf, f1_tfidf = get_metrics(y_test,␣
↪y_predicted_tfidf)
print("accuracy = %.3f, precision = %.3f, recall = %.3f, f1 = %.3f" %␣
↪(accuracy_tfidf, precision_tfidf, recall_tfidf, f1_tfidf))
```

```
accuracy = 0.873, precision = 0.907, recall = 0.873, f1 = 0.881
```

[64]:
```
cm2 = confusion_matrix(y_test, y_predicted_tfidf)
fig = plt.figure(figsize=(10, 10))
plot = plot_confusion_matrix(cm2, classes=['Digital_Software',␣
↪'Digital_Video_Games', 'Software'], normalize=True, title='Confusion matrix')
plt.show()
print("TFIDF confusion matrix")
print(cm2)
print("BoW confusion matrix")
print(cm)
```

```
Normalized confusion matrix
```




```
TFIDF confusion matrix
[[18421    55  1788]
 [   21 28962   121]
 [12482   411 55301]]
```

```
BoW confusion matrix
[[17864   293  2107]
 [   74 28161   869]
 [12760   828 54606]]
```

0.18.1 Looking at important coefficients of the model

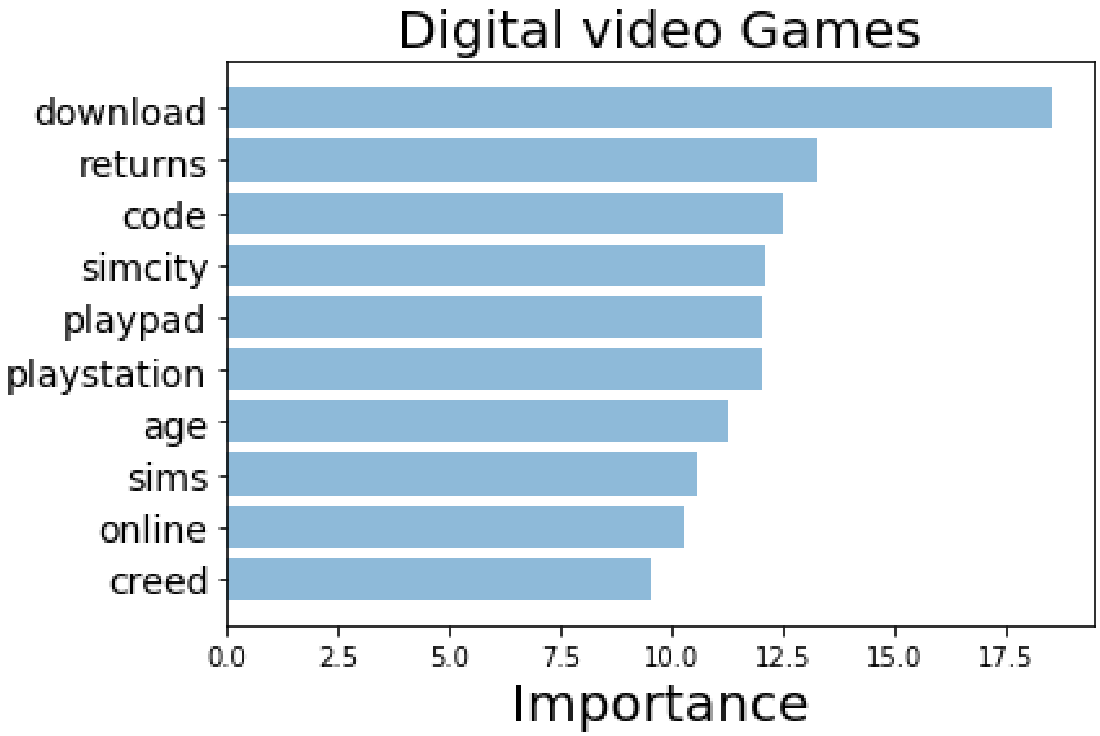
[65]:

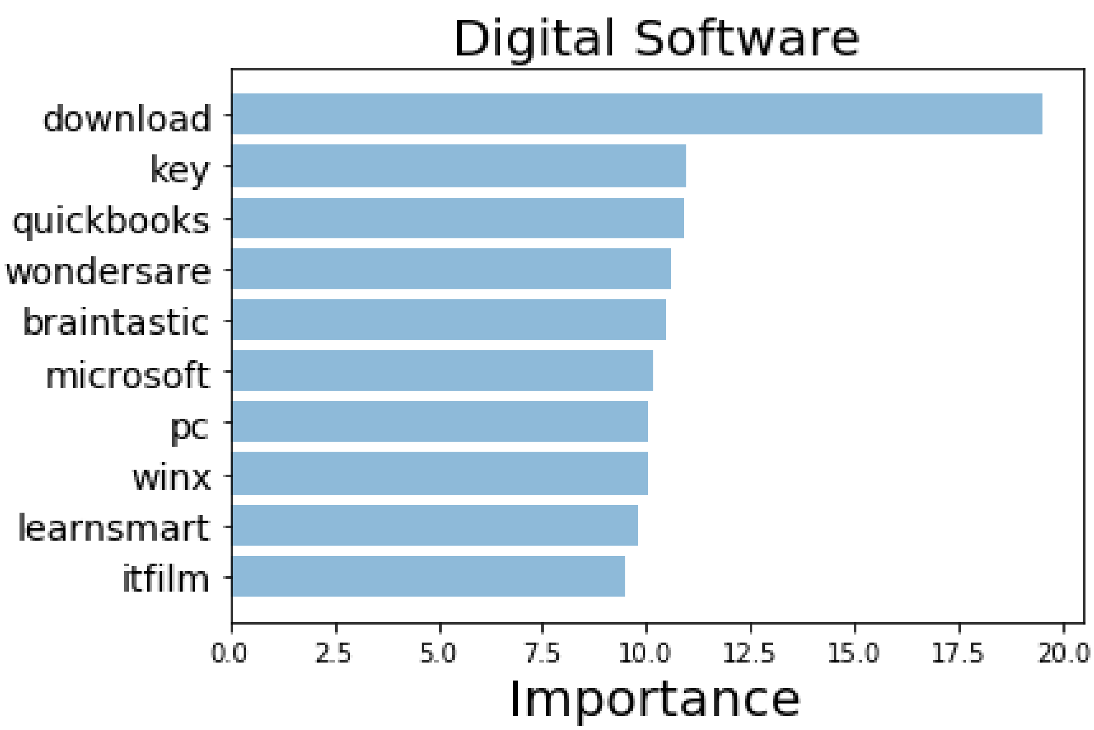
```python
importance_tfidf = get_most_important_features(tfidf_vectorizer, clf_tfidf, 10)
```

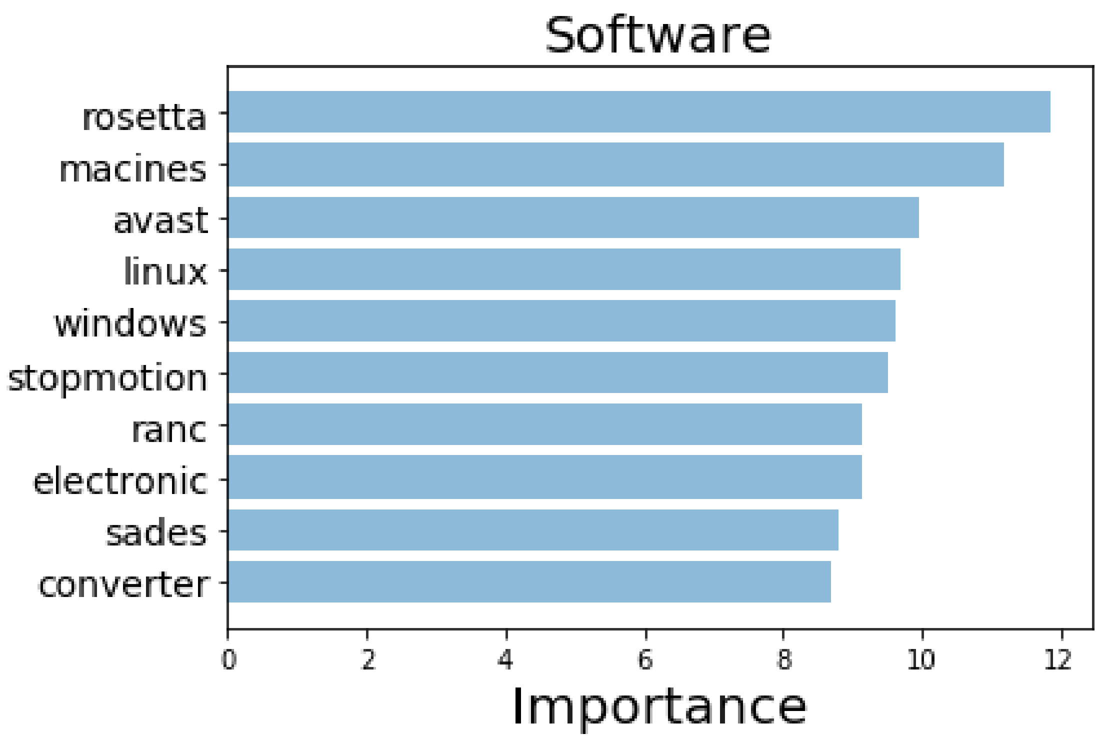
[66]:

```python
#video games (1)
top_scores_video = [a[0] for a in importance_tfidf[1]['tops']]
top_words_video = [a[1] for a in importance_tfidf[1]['tops']]
#digital software (0)
top_scores_digital = [a[0] for a in importance_tfidf[0]['tops']]
top_words_digital = [a[1] for a in importance_tfidf[0]['tops']]
##software
top_scores_software = [a[0] for a in importance_tfidf[2]['tops']]
top_words_software = [a[1] for a in importance_tfidf[2]['tops']]

print("Most important words")
plot_important_words(top_scores_video, top_words_video, name = 'Digital video␣
 ↪Games')
plot_important_words(top_scores_digital, top_words_digital, name = 'Digital␣
 ↪Software')
plot_important_words(top_scores_software, top_words_software, name = 'Software')
```

```
Most important words
```


Digital video Games
download
returns
code
simcity
playpad
playstation
age
sims
online
creed
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
Importance


Digital Software
download
key
quickbooks
wondersare
braintastic
microsoft
pc
winx
learnsmart
itfilm
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Importance



The words the model picked up look much more relevant! Although our metrics on our held out validation set haven't increased much, we have much more confidence in the terms our model is using.

0.19 word2vec

0.19.1 Capturing semantic meaning

Our first models have managed to pick up on high signal words. However, it is unlikely that we will have a training set containing all relevant words. To solve this problem, we need to capture the semantic meaning of words.

0.19.2 Enter word2vec

Word2vec is a model that was pre-trained on a very large set of sentences, and provides embeddings that map words that are similar close to each other. A quick way to get a sentence embedding for our classifier, is to average word2vec scores of all words in our sentence.

[67]:
```
#!pip install gensim
#!pip install --upgrade pip
```

```
#!wget https://github.com/mmihaltz/word2vec-GoogleNews-vectors/blob/master/
↪GoogleNews-vectors-negative300.bin.gz
```

Note: The load_word2vec_format() method also has an optional limit argument which will only load the supplied number of vectors – so you could use limit=500000 to cut the memory requirements by about 5/6ths. (And, since the GoogleNews and other vector sets are usually ordered from most- to least-frequent words, you'll get the 500K most-frequent words. Lower-frequency words generally have much less value and even not-as-good vectors, so it may not hurt much to ignore them.)

[68]:
```
import gensim
word2vec = gensim.models.KeyedVectors.
↪load_word2vec_format('GoogleNews-vectors-negative300.bin', binary=True,␣
↪limit = 100000)
```

1 data to introduce in the model.

[69]:
```
df.head(2)
```

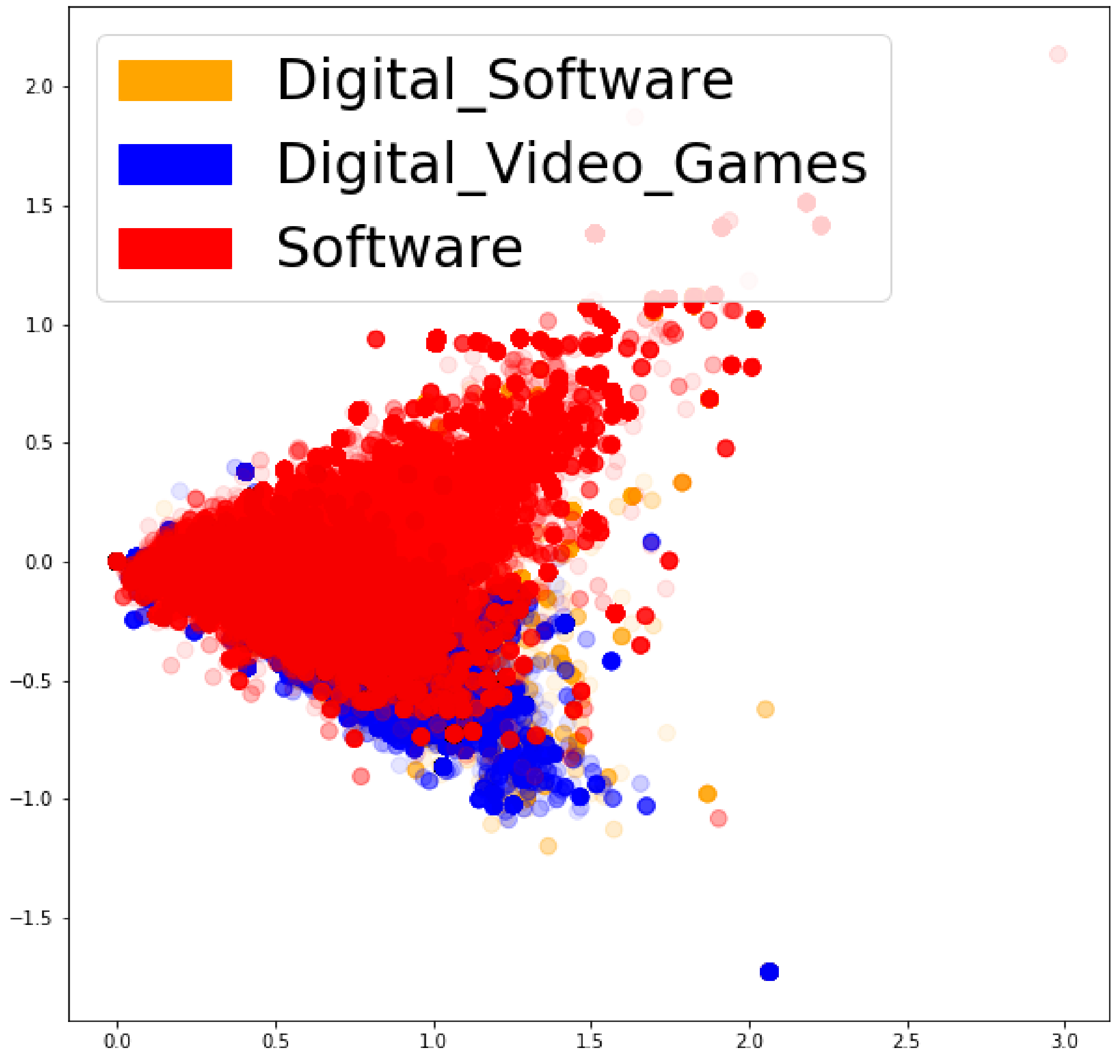
[69]:
```
   product_id                     product_title  product_category  star_rating  \
0  B00U7LCE6A            ccleaner free download                 0            4
1  B00HRJMOM4  resumemaker professional deluxe                 0            3

   helpful_votes  total_votes verified_purchase review_headline  \
0              0            0                 Y
1              0            0                 Y             ree

         review_body product_category_label  \
0           far good       Digital_Software
1  needs little work       Digital_Software

                   token_product_title      token_review_body  \
0            [ccleaner, free, download]            [far, good]
1  [resumemaker, professional, deluxe]  [needs, little, work]

  token_review_headline
0                    []
1                 [ree]
```

[70]:
```
list_labels = df["product_category"].tolist()
df_corpus2 = df[["product_category", 'product_title', 'token_product_title']] #␣
↪introduce more columns
```

[71]:
```
embeddings = get_word2vec_embeddings(word2vec, df_corpus2, name =␣
↪'token_product_title')
```

```
X_train_word2vec, X_test_word2vec, y_train_word2vec, y_test_word2vec =␣
↪train_test_split(embeddings, list_labels,
                                                                                   ␣
↪          test_size=0.2, random_state=40)
```

[72]:
```
fig = plt.figure(figsize=(10, 10))
plot_LSA(embeddings, list_labels)
plt.show()
```



These look a little bit more separated, let's see how our logistic regression does on them!

[73]:
```
clf_w2v = LogisticRegression(C=30.0, class_weight = class_weights,␣
↪#class_weight='balanced',
                             solver = 'newton-cg',
```

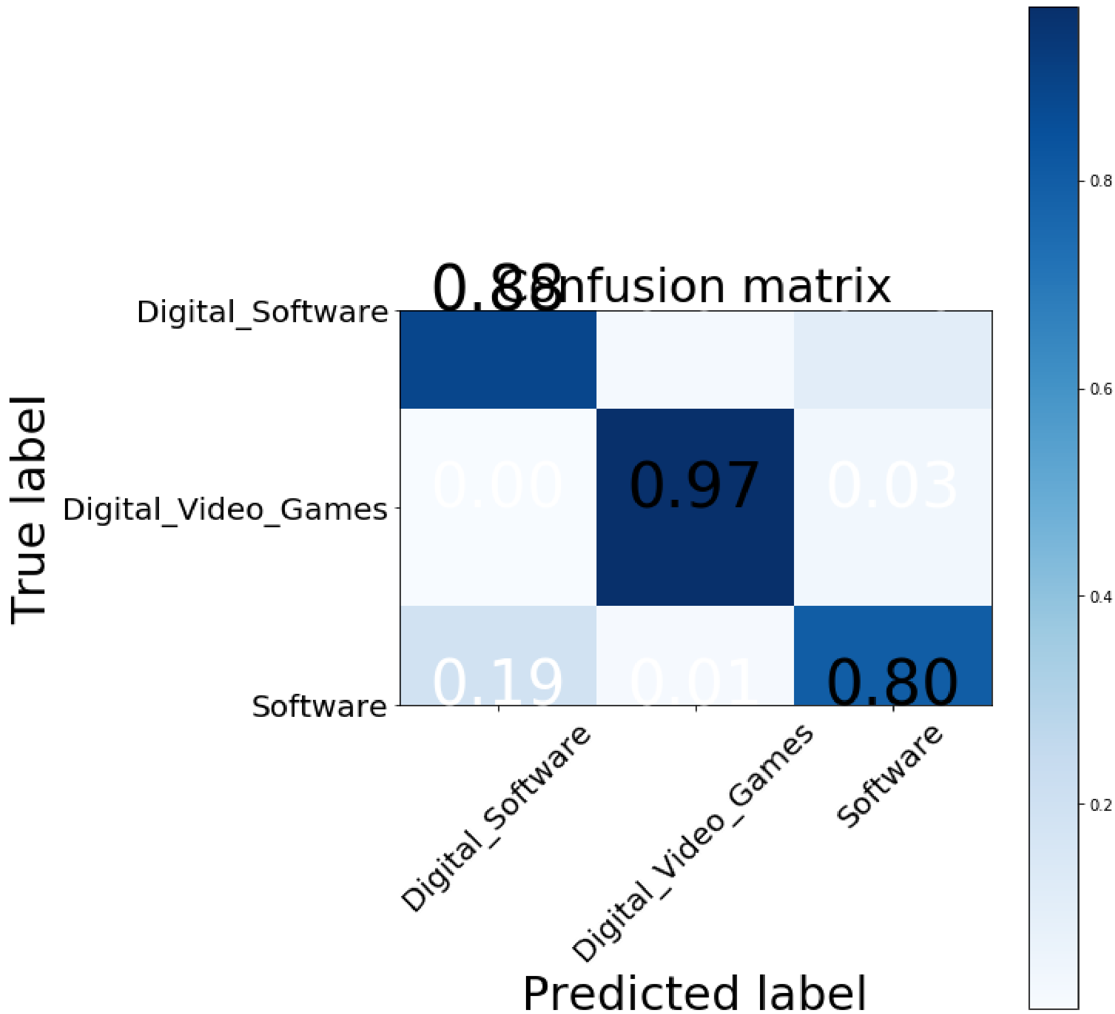
```
                             multi_class = 'multinomial', random_state = 40)
clf_w2v.fit(X_train_word2vec, y_train_word2vec)
y_predicted_word2vec = clf_w2v.predict(X_test_word2vec)
```

[74]:
```
accuracy_word2vec, precision_word2vec, recall_word2vec, f1_word2vec =␣
 ↪get_metrics(y_test_word2vec, y_predicted_word2vec)
print("accuracy = %.3f, precision = %.3f, recall = %.3f, f1 = %.3f" %␣
 ↪(accuracy_word2vec, precision_word2vec,
                                                                          ␣
 ↪recall_word2vec, f1_word2vec))
```

```
accuracy = 0.809, precision = 0.849, recall = 0.809, f1 = 0.814
```

[75]:
```
cm_w2v = confusion_matrix(y_test_word2vec, y_predicted_word2vec)
fig = plt.figure(figsize=(10, 10))
plot = plot_confusion_matrix(cm, classes=['Digital_Software',␣
 ↪'Digital_Video_Games', 'Software'], normalize=True, title='Confusion matrix')
plt.show()
print("Word2Vec confusion matrix")
print(cm_w2v)
print("TFIDF confusion matrix")
print(cm2)
print("BoW confusion matrix")
print(cm)
```

```
Normalized confusion matrix
```




```
Word2Vec confusion matrix
[[17182   682  2400]
 [  338 28115   651]
 [13552  4849 49793]]
TFIDF confusion matrix
[[18421    55  1788]
 [   21 28962   121]
 [12482   411 55301]]
BoW confusion matrix
[[17864   293  2107]
 [   74 28161   869]
 [12760   828 54606]]
```

[76]:

```
# **More values for the logistic**
```

[77]:
```
dicti_n = {0:"Digital_Software", 1:"Digital_Video_Games", 2:"Software"}
```

[78]:
```
#clf_w2v.score(X, y)
arr = clf_w2v.predict_proba(X_test_word2vec)
df_predict= pd.DataFrame(data=arr)
df_predict.columns = ["Digital_Software", "Digital_Video_Games", "Software"]
arr = clf_w2v.predict(X_test_word2vec)
df_predict['predicted_label'] = pd.DataFrame(data=arr.flatten())
df_predict['prediction_title'] = df_predict['predicted_label'].copy()
df_predict = df_predict.replace({"prediction_title": dicti_n})
arr = np.array(y_test_word2vec)
df_predict['real_label'] = pd.DataFrame(data=arr.flatten())
df_predict["max_pred"] = df_predict[['Digital_Software',␣
↪'Digital_Video_Games','Software']].max(axis=1)
print(df_predict.shape)
df_predict.head()
```

```
(117562, 7)
```

[78]:
```
   Digital_Software  Digital_Video_Games  Software  predicted_label  \
0          0.025940             0.000846  0.973214                2
1          0.162306             0.463053  0.374641                1
2          0.169370             0.000059  0.830571                2
3          0.528857             0.000017  0.471126                0
4          0.008877             0.004264  0.986858                2

      prediction_title  real_label  max_pred
0             Software           2  0.973214
1  Digital_Video_Games           2  0.463053
2             Software           2  0.830571
3     Digital_Software           2  0.528857
4             Software           2  0.986858
```

[79]:
```
df_predict[df_predict['max_pred'] <.60].tail(20)
```

[79]:
```
        Digital_Software  Digital_Video_Games  Software  predicted_label  \
117366          0.586714             0.000583  0.412702                0
117370          0.408311             0.104081  0.487608                2
117379          0.484080             0.004732  0.511189                2
117396          0.528857             0.000017  0.471126                0
117414          0.588009             0.411903  0.000087                0
117427          0.162306             0.463053  0.374641                1
117434          0.162306             0.463053  0.374641                1
117447          0.042814             0.385320  0.571866                2
117449          0.405033             0.004700  0.590267                2
117468          0.527834             0.015643  0.456522                0
117469          0.162306             0.463053  0.374641                1
```

```
117506          0.162306          0.463053  0.374641               1
117537          0.528857          0.000017  0.471126               0
117540          0.586714          0.000583  0.412702               0
117545          0.162306          0.463053  0.374641               1
117546          0.474616          0.000683  0.524701               2
117552          0.553615          0.000045  0.446340               0
117553          0.520785          0.012557  0.466657               0
117554          0.591094          0.000003  0.408903               0
117555          0.528857          0.000017  0.471126               0

           prediction_title  real_label  max_pred
117366     Digital_Software           2  0.586714
117370             Software           2  0.487608
117379             Software           2  0.511189
117396     Digital_Software           2  0.528857
117414     Digital_Software           0  0.588009
117427  Digital_Video_Games           1  0.463053
117434  Digital_Video_Games           1  0.463053
117447             Software           2  0.571866
117449             Software           2  0.590267
117468     Digital_Software           2  0.527834
117469  Digital_Video_Games           2  0.463053
117506  Digital_Video_Games           1  0.463053
117537     Digital_Software           2  0.528857
117540     Digital_Software           0  0.586714
117545  Digital_Video_Games           2  0.463053
117546             Software           2  0.524701
117552     Digital_Software           2  0.553615
117553     Digital_Software           0  0.520785
117554     Digital_Software           2  0.591094
117555     Digital_Software           2  0.528857
```

[80]:

```
df_predict_long = pd.melt(df_predict, id_vars=['predicted_label',␣
 ↪'prediction_title'])
df_predict_long.head()
```

[80]:

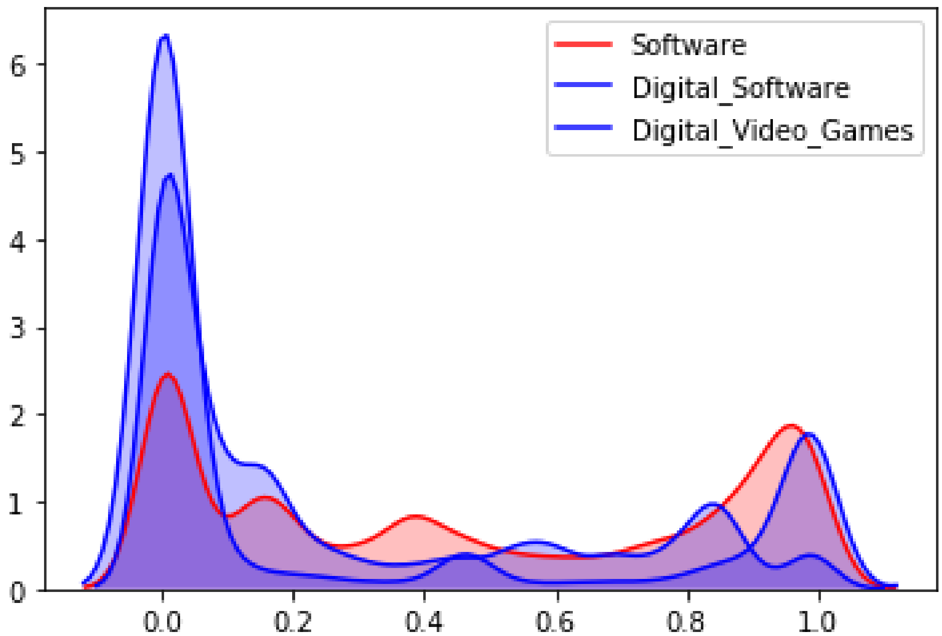
```
   predicted_label     prediction_title          variable     value
0                2             Software  Digital_Software  0.025940
1                1  Digital_Video_Games  Digital_Software  0.162306
2                2             Software  Digital_Software  0.169370
3                0     Digital_Software  Digital_Software  0.528857
4                2             Software  Digital_Software  0.008877
```

[81]:

```
import seaborn as sns
sns.kdeplot(df_predict_long.loc[(df_predict_long['variable']=='Software'),
            'value'], color='r', shade=True, Label='Software')
```

```
sns.kdeplot(df_predict_long.
 ↪loc[(df_predict_long['variable']=='Digital_Software'),
            'value'], color='b', shade=True, Label='Digital_Software')
sns.kdeplot(df_predict_long.
 ↪loc[(df_predict_long['variable']=='Digital_Video_Games'),
            'value'], color='b', shade=True, Label='Digital_Video_Games')
```

[81]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc2ed287950>



1.0.1 Further inspection

In order to provide some explainability, we can leverage a black box explainer such as LIME.

[82]:
```
from lime import lime_text
from sklearn.pipeline import make_pipeline
from lime.lime_text import LimeTextExplainer

df_corpus = df['product_title'] #df['review_headline']#df['full_text']
#df_corpus = df['review_body', 'review_headline']
df_labels = df["product_category"]


X_train_data, X_test_data, y_train_data, y_test_data =␣
 ↪train_test_split(df_corpus, df_labels, test_size=0.2,
```

```
↪random_state=40)
vector_store = word2vec
def word2vec_pipeline(examples):
    global vector_store
    tokenizer = RegexpTokenizer(r'\w+')
    tokenized_list = []
    for example in examples:
        example_tokens = tokenizer.tokenize(example)
        vectorized_example = get_average_word2vec(example_tokens, vector_store,␣
↪generate_missing=False, k=300)
        tokenized_list.append(vectorized_example)
    return clf_w2v.predict_proba(tokenized_list)

c = make_pipeline(count_vectorizer, clf)
```

[83]:

```
def explain_one_instance(instance, class_names):
    explainer = LimeTextExplainer(class_names=class_names)
    exp = explainer.explain_instance(instance, word2vec_pipeline,␣
↪num_features=6,  top_labels=2)
    return exp

def visualize_one_exp(features, labels, index, class_names):
    exp = explain_one_instance(features[index], class_names = class_names)
    print('Index: %d' % index)
    print('True class: %s' % class_names[labels[index]])
    exp.show_in_notebook(text=True)
```

[84]:

```
class_names = ['Digital_Software', 'Digital_Video_Games', 'Software']
visualize_one_exp(X_test_data, y_test_data, 65, class_names)
```

```
Index: 65
True class: Software

<IPython.core.display.HTML object>
```

[85]:

```
visualize_one_exp(X_test_data, y_test_data, 60, class_names)
```

```
Index: 60
True class: Digital_Software

<IPython.core.display.HTML object>
```

[86]:

```
visualize_one_exp(X_test_data, y_test_data, 62, class_names)
```

```
Index: 62
True class: Digital_Software
```

```
<IPython.core.display.HTML object>
```

[87]:
```
visualize_one_exp(X_test_data, y_test_data, 68, class_names)
```

```
Index: 68
True class: Digital_Video_Games
```

```
<IPython.core.display.HTML object>
```

[88]:
```
visualize_one_exp(X_test_data, y_test_data, 58, class_names)
```

```
Index: 58
True class: Software
```

```
<IPython.core.display.HTML object>
```

[89]:
```
visualize_one_exp(X_test_data, y_test_data, 56, class_names)
```

```
Index: 56
True class: Digital_Software
```

```
<IPython.core.display.HTML object>
```

[90]:
```
visualize_one_exp(X_test_data, y_test_data, 52, class_names)
```

```
Index: 52
True class: Software
```

```
<IPython.core.display.HTML object>
```

[91]:
```
label_to_text = {
    0: "Digital_Software",
    1: "Digital_Video_Games",
    2: "Software"
}
random.seed(40)
#importance of words
sorted_contributions = get_statistical_explanation(X_test_data.tolist(), 100, word2vec_pipeline, label_to_text)
```

[92]:
```
sorted_contributions
```

[92]:
```
{'Digital_Software': {'bottom': deluxe       -0.007775
  essentials   -0.006164
  quickbooks   -0.002955
  ome          -0.002803
```

```
turbotax     -0.002682
efile        -0.002677
publiser     -0.002596
potosop      -0.002360
openoffice   -0.002255
norton       -0.002086
internet     -0.001617
converter    -0.001433
back         -0.000929
wi           -0.000665
premiere     -0.000517
premier      -0.000449
programpc    -0.000447
basic        -0.000426
tax          -0.000378
software     -0.000306
mac           0.000513
avast         0.001191
video         0.001226
financial     0.001455
elements      0.001517
user          0.002185
federal       0.002207
pc            0.003165
industry      0.003212
adobe         0.003285
microsoft     0.005154
pro           0.005687
apace         0.006107
antivirus     0.011239
state         0.011652
security      0.012200
quicken       0.015116
free          0.017359
block         0.018185
fed           0.021634
download      0.022492
dtype: float64, 'tops': download      0.022492
fed           0.021634
block         0.018185
free          0.017359
quicken       0.015116
security      0.012200
state         0.011652
antivirus     0.011239
apace         0.006107
pro           0.005687
```

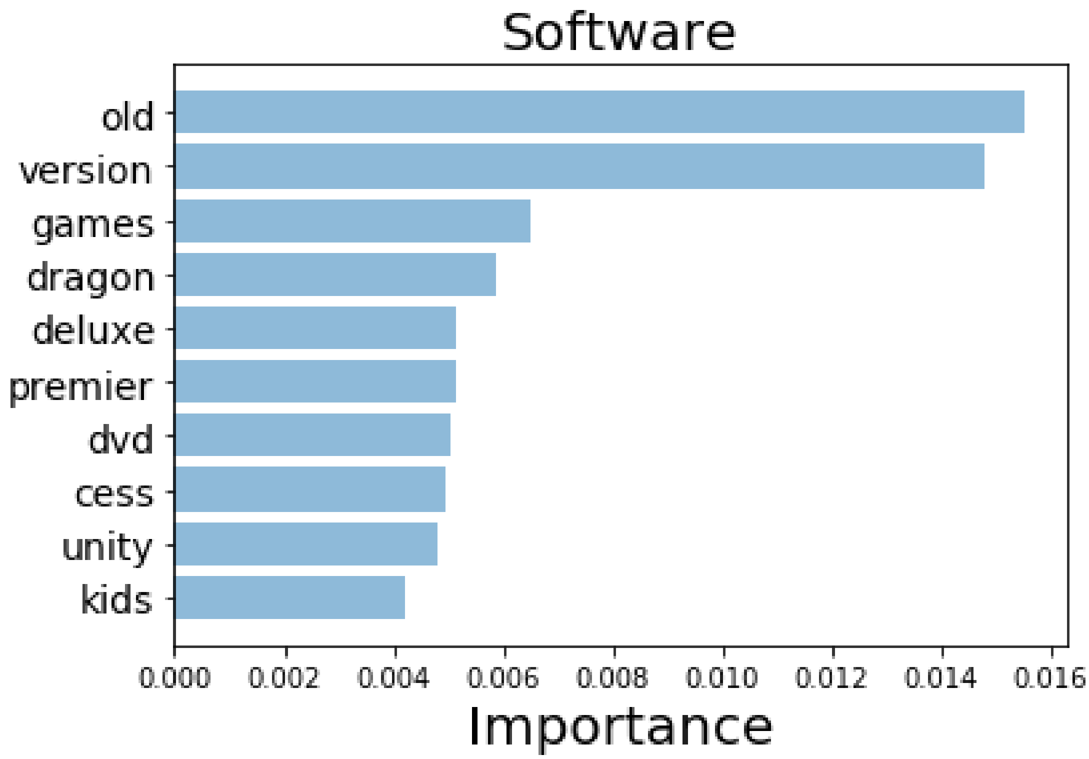
```
microsoft     0.005154
adobe         0.003285
industry      0.003212
pc            0.003165
federal       0.002207
user          0.002185
elements      0.001517
financial     0.001455
video         0.001226
avast         0.001191
mac           0.000513
software     -0.000306
tax          -0.000378
basic        -0.000426
programpc    -0.000447
premier      -0.000449
premiere     -0.000517
wi           -0.000665
back         -0.000929
converter    -0.001433
internet     -0.001617
norton       -0.002086
openoffice   -0.002255
potosop      -0.002360
publiser     -0.002596
efile        -0.002677
turbotax     -0.002682
ome          -0.002803
quickbooks   -0.002955
essentials   -0.006164
deluxe       -0.007775
dtype: float64}, 'Software': {'bottom': microsoft    -0.003474
command      -0.002850
contractor   -0.002428
middle       -0.002116
ome          -0.001500
                …
deluxe        0.005151
dragon        0.005897
games         0.006495
version       0.014777
old           0.015534
Length: 127, dtype: float64, 'tops': old           0.015534
version       0.014777
games         0.006495
dragon        0.005897
deluxe        0.005151
```

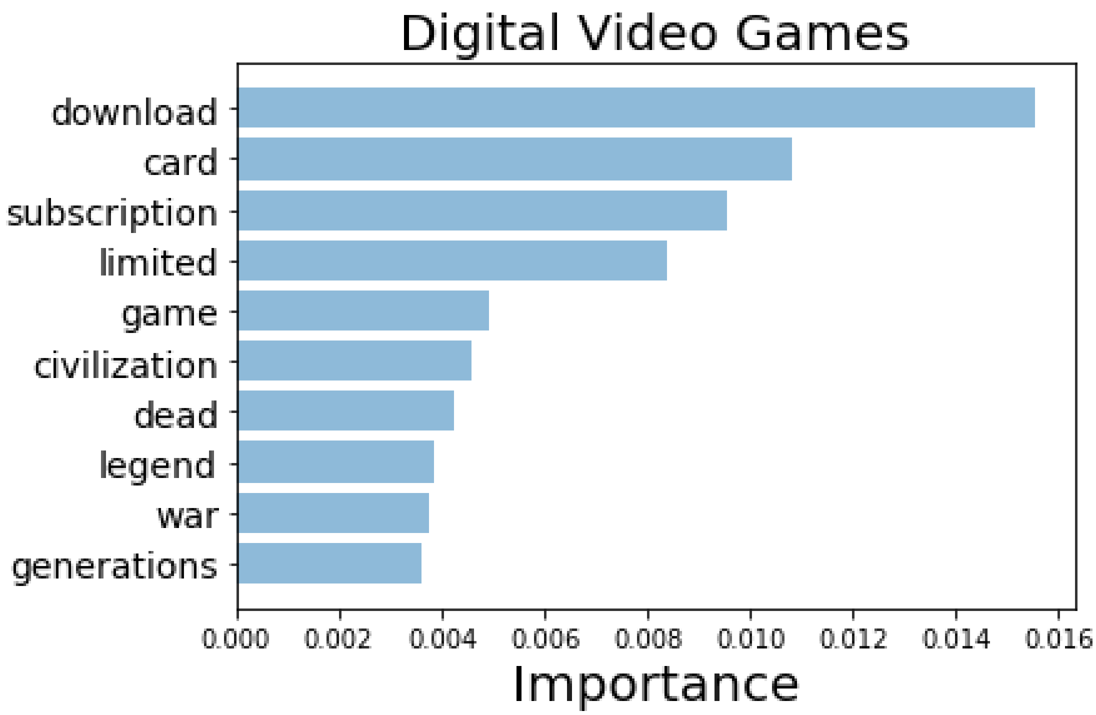
```
                 …
 ome           -0.001500
 middle        -0.002116
 contractor    -0.002428
 command       -0.002850
 microsoft     -0.003474
 Length: 127, dtype: float64}, 'Digital_Video_Games': {'bottom': typing
-0.005492
 year            -0.004149
 deluxe          -0.003546
 overkill        -0.002858
 sims            -0.001620
                   …
 game             0.004918
 limited          0.008361
 subscription     0.009551
 card             0.010809
 download         0.015530
 Length: 74, dtype: float64,
 'tops': download        0.015530
 card             0.010809
 subscription     0.009551
 limited          0.008361
 game             0.004918
                   …
 sims            -0.001620
 overkill        -0.002858
 deluxe          -0.003546
 year            -0.004149
 typing          -0.005492
 Length: 74, dtype: float64}}
```

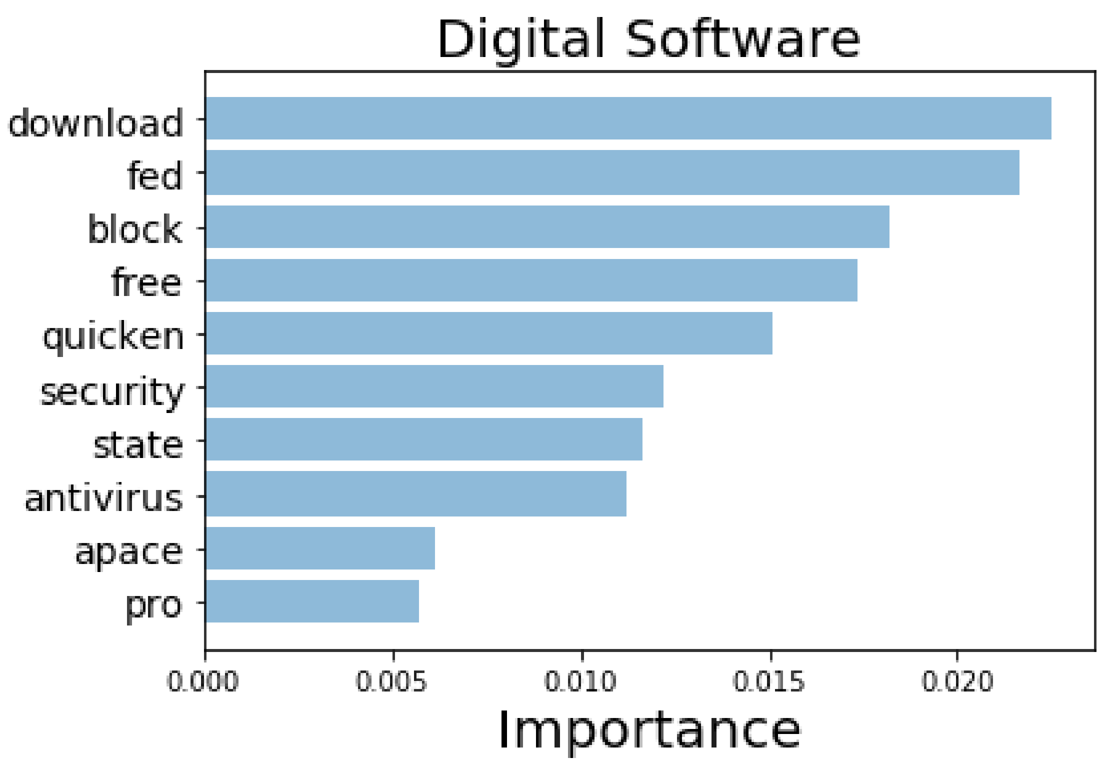
[93]:

```
#Software
top_words_Software = sorted_contributions['Software']['tops'][:10].index.
 ↪tolist()
top_scores_Software = sorted_contributions['Software']['tops'][:10].tolist()
top_words_GAMES = sorted_contributions['Digital_Video_Games']['tops'][:10].
 ↪index.tolist()
top_scores_GAMES = sorted_contributions['Digital_Video_Games']['tops'][:10].
 ↪tolist()
top_words_Digital = sorted_contributions['Digital_Software']['tops'][:10].index.
 ↪tolist()
top_scores_Digital = sorted_contributions['Digital_Software']['tops'][:10].
 ↪tolist()

plot_important_words(top_scores_Software, top_words_Software, "Software")
plot_important_words(top_scores_GAMES, top_words_GAMES, "Digital Video Games")
```

```
plot_important_words(top_scores_Digital, top_words_Digital, 'Digital Software')
```




Digital Video Games
download
card
subscription
limited
game
civilization
dead
legend
war
generations
0.000
0.002
0.004
0.006
0.008
0.010
0.012
0.014
0.016
Importance


Digital Software
download
fed
block
free
quicken
security
state
antivirus
apace
pro
0.000
0.005
0.010
0.015
0.020
Importance

1.1 Conclusion:

We get better results with **TFIDF Bag of Words** option. Also, aggregate review info to the model does not help to the improvement of the results of the model that only consider 'product title'. Further analysis are required to get a better model.

1.2 NEXT STEPS

1.2.1 Based in the results there are several things to do to improve the results:

1. Improve the text treatment, there are words that have misspelling or not sense. More time cleaning it is necessary. Also, it is necessary to spend more time cleaning reviews (eliminate adjectives, verbs, keep only noums that can help to identify the category).
2. Use n_grams > 1. A word by itself may mean nothing, specially when we are treating with names of products.
3. This first approach was mostly exploratory, for this reason we only use logistic regression, but there are models that may help to improve the results (based tree methodologies, deep leaning, bayesian methods, between others), aditionally would be interesting combine different methodolofies using emsemble methodologies like (max voting, averaging, bagging or boosting). Compare the results with ROC curves and information criteria as AIC and BIC.
4. We can try to improve the results combining text with numerical variables. Use number of votes to give more weights to those reviews with more votes may help to find better keywords for the products. Include a label for relevant/irrelenvant information based in the available information.
5. Use Spark to speed the results.
6. Use methodologies as SMOTE to balance the data.
7. Explore other alternative to Word2Vect like: fastText GloVe or ELMO. Consider other alternatives like pre-trained NLP models to get better results, as for example BERT, ULMFIT, between others.
8. Use BlazingText's implemetation of Word2Vec.
9. Use H2OAutoML algorithm to if we can improve the results.
10. INclude more categories to the analysis.
11. Implement the ideas wrote at the beggining to fight misclassification issues.
12. During the treatment we eliminate numbers, because we think this may aggregate noise to result. We may recheck this treatment and evaluate which may remain in the trining dataset.

[ ]:

```

```

[ ]:

```

```

[ ]:

```

```

[ ]:

```

```

```
# ---------------------------------------------- py_functions.py
-----------------------------------------------------------------------------------
######################################
#
#  Functions used for this project
#

def descriptive_tokens(df, name):
    '''
    '''
    all_words = [word for tokens in df[name] for word in tokens]
    sentence_lengths = [len(tokens) for tokens in df[name]]
    VOCAB = sorted(list(set(all_words)))
    print('Column ', name,  " have %s words total, with a vocabulary size of %s" %
(len(all_words), len(VOCAB)))
    print("Max sentence length is %s" % max(sentence_lengths))
    return sentence_lengths




from sklearn.decomposition import PCA, TruncatedSVD
import matplotlib
import matplotlib.patches as mpatches
import matplotlib.pyplot as plt


def plot_LSA(data, text_labels, plot = True):
    '''
    Dimensionality reduction using truncated SVD (aka LSA).

    This transformer performs linear dimensionality reduction by means of
truncated singular value decomposition (SVD).
    Contrary to PCA, this estimator does not center the data before computing the
singular value decomposition.
    This means it can work with scipy.sparse matrices efficiently.
    '''
    lsa = TruncatedSVD(n_components=2)
    lsa.fit(data)
    lsa_scores = lsa.transform(data)
    color_mapper = {label:idx for idx,label in enumerate(set(text_labels))}
    color_column = [color_mapper[label] for label in text_labels]
    colors = ['orange','blue','red']
    if plot:
        plt.scatter(lsa_scores[:,0], lsa_scores[:,1], s=75, alpha=.1,
c=text_labels, cmap=matplotlib.colors.ListedColormap(colors))
        orange_patch = mpatches.Patch(color='orange', label='Digital_Software')
        green_patch = mpatches.Patch(color='blue', label='Digital_Video_Games')
        red_patch = mpatches.Patch(color='red', label='Software')
        plt.legend(handles=[orange_patch, green_patch, red_patch], prop={'size':
30})


#### EVALUATION

from sklearn.metrics import accuracy_score, f1_score, precision_score,
recall_score, classification_report
def get_metrics(y_test, y_predicted):
    '''
    Evaluation metrics
    '''
    # true positives / (true positives+false positives)
    precision = precision_score(y_test, y_predicted, pos_label=None,
                                    average='weighted')
```

```
    # true positives / (true positives + false negatives)
    recall = recall_score(y_test, y_predicted, pos_label=None,
                          average='weighted')

    # harmonic mean of precision and recall
    f1 = f1_score(y_test, y_predicted, pos_label=None, average='weighted')

    # true positives + true negatives/ total
    accuracy = accuracy_score(y_test, y_predicted)
    return accuracy, precision, recall, f1


import numpy as np
import itertools
from sklearn.metrics import confusion_matrix

def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    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, fontsize=30)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, fontsize=20, rotation=45)
    plt.yticks(tick_marks, classes, fontsize=20)

    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", fontsize=40)

    plt.tight_layout()
    plt.ylabel('True label', fontsize=30)
    plt.xlabel('Predicted label', fontsize=30)

    return plt

###########
#Word2vect
############

def get_average_word2vec(tokens_list, vector, generate_missing=False, k=300):
    if len(tokens_list)<1:
        return np.zeros(k)
    if generate_missing:
        vectorized = [vector[word] if word in vector else np.random.rand(k) for
word in tokens_list]
    else:
        vectorized = [vector[word] if word in vector else np.zeros(k) for word in
tokens_list]
    length = len(vectorized)
    summed = np.sum(vectorized, axis=0)
    averaged = np.divide(summed, length)
```

```
    return averaged

def get_word2vec_embeddings(vectors, df, name = 'tokens', generate_missing=False):
    embeddings = df[name].apply(lambda x: get_average_word2vec(x, vectors,
generate_missing=generate_missing))
    return list(embeddings)


### IMPORTANCE OF WORDS

def get_most_important_features(vectorizer, model, n=5):
    index_to_word = {v:k for k,v in vectorizer.vocabulary_.items()}

    # loop for each class
    classes ={}
    for class_index in range(model.coef_.shape[0]):
        word_importances = [(el, index_to_word[i]) for i,el in
enumerate(model.coef_[class_index])]
        sorted_coeff = sorted(word_importances, key = lambda x : x[0],
reverse=True)
        tops = sorted(sorted_coeff[:n], key = lambda x : x[0])
        bottom = sorted_coeff[-n:]
        classes[class_index] = {
            'tops':tops,
            'bottom':bottom
        }
    return classes



def plot_important_words(top_scores, top_words, name = 'top_words_software'):
    y_pos = np.arange(len(top_words))
    top_pairs = [(a,b) for a,b in zip(top_words, top_scores)]
    top_pairs = sorted(top_pairs, key=lambda x: x[1])

    top_words = [a[0] for a in top_pairs]
    top_scores = [a[1] for a in top_pairs]

    plt.barh(y_pos,top_scores, align='center', alpha=0.5)
    plt.title(name, fontsize=20)
    plt.yticks(y_pos, top_words, fontsize=14)
    #plt.suptitle(name, fontsize=16)
    plt.xlabel('Importance', fontsize=20)
    plt.show()


#---------------------------
#### importance word2vec
#---------------------------

import random
from collections import defaultdict
from lime.lime_text import LimeTextExplainer
import pandas as pd

def get_statistical_explanation(test_set, sample_size, word2vec_pipeline,
label_dict):
    sample_sentences = random.sample(test_set, sample_size)
    explainer = LimeTextExplainer()

    labels_to_sentences = defaultdict(list)
    contributors = defaultdict(dict)

    # First, find contributing words to each class
    for sentence in sample_sentences:
        probabilities = word2vec_pipeline([sentence])
```

```
        curr_label = probabilities[0].argmax()
        labels_to_sentences[curr_label].append(sentence)
        exp = explainer.explain_instance(sentence, word2vec_pipeline,
num_features=6, labels=[curr_label])
        listed_explanation = exp.as_list(label=curr_label)

        for word,contributing_weight in listed_explanation:
            if word in contributors[curr_label]:
                contributors[curr_label][word].append(contributing_weight)
            else:
                contributors[curr_label][word] = [contributing_weight]

    # average each word's contribution to a class, and sort them by impact
    average_contributions = {}
    sorted_contributions = {}
    for label,lexica in contributors.items():
        curr_label = label
        curr_lexica = lexica
        average_contributions[curr_label] = pd.Series(index=curr_lexica.keys())
        for word,scores in curr_lexica.items():
            average_contributions[curr_label].loc[word] = np.sum(np.array(scores))/
sample_size
        detractors = average_contributions[curr_label].sort_values()
        supporters = average_contributions[curr_label].sort_values(ascending=False)
        sorted_contributions[label_dict[curr_label]] = {
            'bottom':detractors,
             'tops': supporters
        }
    return sorted_contributions


#### Cleaning text

def standardize_text(df, text_field):
    df[text_field] = df[text_field].str.replace(r"-", "")
    df[text_field] = df[text_field].str.replace(r",", "")
    df[text_field] = df[text_field].str.replace(r"?", "")
    df[text_field] = df[text_field].str.replace(r"\(.*\)","")
    df[text_field] = df[text_field].str.replace(r"http\S+", "")
    df[text_field] = df[text_field].str.replace(r"http", "")
    df[text_field] = df[text_field].str.replace(r"@\S+", "")
    df[text_field] = df[text_field].str.replace(r"\n", "")
    df[text_field] = df[text_field].str.replace(r"[^A-Za-z0-9(),!?@\'\`\"\_\n]", "
")
    df[text_field] = df[text_field].str.replace(r"@", "at")
    df[text_field] = df[text_field].str.replace('[0-9]+', "")
    df[text_field] = df[text_field].str.lower()
    df[text_field] = df[text_field].str.replace(r"th", "")
    df[text_field] = df[text_field].str.replace(r"h", "")
    df[text_field] = df[text_field].str.replace(r"stars", "")
    df[text_field] = df[text_field].str.replace(r"star", "")
    df[text_field] = df[text_field].str.replace(r"one", "")
    df[text_field] = df[text_field].str.replace(r"two", "")
    df[text_field] = df[text_field].str.replace(r"three", "")
    df[text_field] = df[text_field].str.replace(r"four", "")
    df[text_field] = df[text_field].str.replace(r"five", "")
    return df



import re
def clean_text(text):
    text = text.lower()
    text = re.sub(r"what’s", "what is ", text)
    text = re.sub(r"\’s", " ", text)
    text = re.sub(r"\’ve", " have ", text)
```

```
    text = re.sub(r"can’t", " can not ", text)
    text = re.sub(r"n’t", " not ", text)
    text = re.sub(r"i’m", "i am ", text)
    text = re.sub(r"\’re", " are ", text)
    text = re.sub(r"\’d", " would ", text)
    text = re.sub(r"\’ll", " will ", text)
    text = re.sub(r"\’scuse", " excuse ", text)
    text = re.sub('\W', ' ' , text)
    text = re.sub('\s+', ' ', text)
    text = text.strip(' ')
    return text


import nltk
from nltk.stem.wordnet import WordNetLemmatizer
from nltk.tokenize import ToktokTokenizer
lemma=WordNetLemmatizer()
token=ToktokTokenizer()


def lemitizeWords(text):
    words=token.tokenize(text)
    listLemma=[]
    for w in words:
        x=lemma.lemmatize(w,'v')
        listLemma.append(x)
    return text


import unicodedata
def removeAscendingChar(data):
    data=unicodedata.normalize('NFKD', data).encode('ascii',
'ignore').decode('utf-8', 'ignore')
    return data
```