In [50]:
```python
#importing python libraries and modules

#libraries & modules
import numpy as np #library for scientific computing
import pandas as pd #library for dataframes
import matplotlib.pyplot as plt #graphic library
import seaborn as sns #advanced graphic library based on matplotlib
import warnings #library to manage warnings
import scipy #library with algorithms for statistics and scientific computing
from sklearn.tree import DecisionTreeClassifier #classification algorithm
from sklearn.neighbors import KNeighborsClassifier #classification algorith
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV #optimization parameter algorithm
from sklearn.model_selection import cross_val_score #cross validation algorithm
from sklearn.model_selection import train_test_split #train test split
from sklearn import metrics
from sklearn.metrics import confusion_matrix #metrics tool
from sklearn.metrics import classification_report #metrics tool
from sklearn.preprocessing import StandardScaler #feature engineering tool
import category_encoders as ce #one hot encoding tool
from sklearn.ensemble import RandomForestClassifier
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer

warnings.filterwarnings('ignore')
```

EDA (Exploratory Data Analysis)

- we obtain a dataset from UCI (https://archive.ics.uci.edu/ml/index.php (https://archive.ics.uci.edu/ml/index.php))
- This data was extracted from the 1994 Census bureau database by Ronny Kohavi and Barry Becker
- The prediction task is to determine whether a person makes over $50K a year.

In [51]:
```python
#importing dataset

names = ['age', 'workclass', 'fnlwgt', 'education', 'education-num', 'marital-status',
         'occupation', 'relationship', 'race','sex','capital-gain',
         'capital-loss','hours-per-week','native-country','salary']
df_census = pd.read_csv('adult.data', names=names)
```

Dataset Explanation

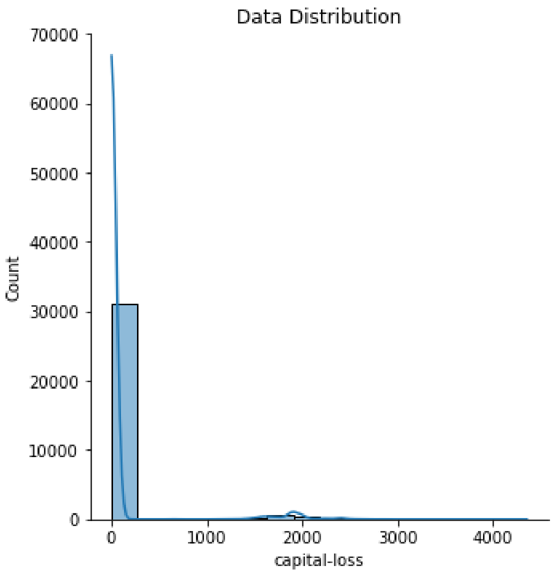
1. age: continuous.
2. workclass: Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked.
3. fnlwgt (Final weight): continuous. It is the number of people the census believes the entry represents.
4. education: Bachelors, Some-college, 11th, HS-grad, Prof-school, Assoc-acdm, Assoc-voc, 9th, 7th-8th, 12th, Masters, 1st-4th, 10th, Doctorate, 5th-6th, Preschool.
5. education-num: continous. It is the number of years spent in education.
6. marital-status: Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married-spouse-absent, Married-AF-spouse.
7. occupation: Tech-support, Craft-repair, Other-service, Sales, Exec-managerial, Prof-specialty, Handlers-cleaners, Machine-op-inspct, Adm-clerical, Farming-fishing, Transport-moving, Priv-house-serv, Protective-serv, Armed-Forces.
8. relationship: Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried.
9. race: White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other, Black.
10. sex: Female, Male.
11. capital-gain: continuous.
12. capital-loss: continuous.
13. hours-per-week: continuous.
14. native-country: United-States, Cambodia, England, Puerto-Rico, Canada, Germany, Outlying-US(Guam-USVI-etc), India, Japan, Greece, South, China, Cuba, Iran, Honduras, Philippines, Italy, Poland, Jamaica, Vietnam, Mexico, Portugal, Ireland, France, Dominican-Republic, Laos, Ecuador, Taiwan, Haiti, Columbia, Hungary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, El-Salvador, Trinadad&Tobago, Peru, Hong, Holand-Netherlands.
15. salary: If it is above 50k USD or equal or below

In [52]:
```python
#dataset information

print(df_census.head(3).transpose(),"\n")
print(df_census.info(null_counts=True))
print(df_census.describe().transpose())
```

```
                            0                   1                  2
age                        39                  50                 38
workclass           State-gov    Self-emp-not-inc            Private
fnlwgt                  77516               83311             215646
education           Bachelors           Bachelors            HS-grad
education-num              13                  13                  9
marital-status  Never-married  Married-civ-spouse           Divorced
occupation       Adm-clerical     Exec-managerial  Handlers-cleaners
relationship    Not-in-family             Husband      Not-in-family
race                    White               White              White
sex                      Male                Male               Male
capital-gain             2174                   0                  0
capital-loss                0                   0                  0
hours-per-week             40                  13                 40
native-country  United-States       United-States      United-States
salary                  <=50K               <=50K              <=50K

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   age             32561 non-null  int64 
 1   workclass       32561 non-null  object
 2   fnlwgt          32561 non-null  int64 
 3   education       32561 non-null  object
 4   education-num   32561 non-null  int64 
 5   marital-status  32561 non-null  object
 6   occupation      32561 non-null  object
 7   relationship    32561 non-null  object
 8   race            32561 non-null  object
 9   sex             32561 non-null  object
 10  capital-gain    32561 non-null  int64 
 11  capital-loss    32561 non-null  int64 
 12  hours-per-week  32561 non-null  int64 
 13  native-country  32561 non-null  object
 14  salary          32561 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
None
                  count           mean            std      min       25%  \
age             32561.0      38.581647      13.640433     17.0      28.0   
fnlwgt          32561.0  189778.366512  105549.977697  12285.0  117827.0   
education-num   32561.0      10.080679       2.572720      1.0       9.0   
capital-gain    32561.0    1077.648844    7385.292085      0.0       0.0   
capital-loss    32561.0      87.303830     402.960219      0.0       0.0   
hours-per-week  32561.0      40.437456      12.347429      1.0      40.0   

                     50%       75%        max  
age                 37.0      48.0       90.0  
fnlwgt          178356.0  237051.0  1484705.0  
education-num       10.0      12.0       16.0  
capital-gain         0.0       0.0    99999.0  
capital-loss         0.0       0.0     4356.0  
hours-per-week      40.0      45.0       99.0  
```

In [53]:
```python
#I have use this code to explore this dataframe
print(df_census['capital-loss'].value_counts())

fig1 = sns.displot(x=df_census['capital-loss'], kde=True)
fig1.set(title='Data Distribution', xlabel='capital-loss', ylabel='Count')

print(df_census['salary'].value_counts())
```

```
0       31042
1902      202
1977      168
1887      159
1848       51
        ...
2080        1
1539        1
1844        1
2489        1
1411        1
Name: capital-loss, Length: 92, dtype: int64
 <=50K    24720
 >50K      7841
Name: salary, dtype: int64
```



Conclusions:

- The dataset does not contain any NaN data.
- There are 9 categorical and 6 numerical features
- The column 'salary' is the dependant variable, the column we have to classify
- Class data is 24720 for below 50K and 7841 for above 50K. It is slightly imbalanced (aprox 1:3), so at the moment will use this data as that, if we want to improve results we can try to balance data.
- The column 'fnlwgt' does not give any useful information and does not have normal distribution.
- The column 'capital-loss' and 'capital-gain', almost all values are 0 and its distribution is not normal.

Exercici 1 (Nivell 1)

Agafa el conjunt de dades que vulguis i realitza un pipeline i un gridsearch aplicant l'algorisme de Random Forest.

- first we build a prototype machine learning model on the exisiting data before we create a pipeline

In [311]:
```
#adding a new column 'Over 50K' for classes
df_census.loc[df_census['salary'].str.contains('<=50K'), 'Over_50K'] = 1
df_census.loc[df_census['salary'].str.contains(">50K"), 'Over_50K'] = 0

#deleting features that are not important
columns_del = ['fnlwgt','capital-gain', 'capital-loss','salary']
df_census.drop(columns=columns_del, inplace=True)

#if we want to balance data
#we wil apply the method sample disproportionate to each stratum
#sample_stratum = 7841
#df_census = df_census.groupby('Over_50K', group_keys=False).apply(lambda x: x.sample(sample_stratum))
```

In [312]:
```
#pre-processing

#feature engineering: one-hot encoding
#selecting categorical features
columns_1 = ['workclass','education','marital-status',
             'occupation','relationship','race','sex','native-country']
#creating instance and applying to features
OHE = ce.OneHotEncoder(cols = columns_1,use_cat_names=True)
df_census_1 = OHE.fit_transform(df_census)


#feature engineering: standardization, as we assume Gaussian distribution
#selecting features to standardize
columns_2 = ['age','education-num','hours-per-week']
#creating instance and applying scalar
scaler = StandardScaler()
df_census_2 = df_census_1[columns_2].copy()
columns_sd = scaler.fit_transform(df_census_1[columns_2])
df_census_2[columns_2] = columns_sd

df_census_ok = pd.concat([df_census_1, df_census_2], axis=1)
```

In [313]:
```
#selecting variables X (aka predictors, independent or feature)
#selecting variable y (aka target or dependant)

X = df_census_ok.drop(columns=['Over_50K'])
y = df_census_ok['Over_50K']

#splitting in train and test dataset
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size=0.3, random_state=42)
```

In [314]:
```
#model Random Forest Classifier
model_name = 'Random Forest Classifier'
model = RandomForestClassifier().fit(X_train, y_train)

#we obtain predicted values from test data
y_pred = model.predict(X_test)

#Accuracy
acc = round(metrics.accuracy_score(y_test, y_pred),3)

#Confusion Matrix
confMatrix = confusion_matrix(y_test, y_pred)

TN = confMatrix[0,0]
TP = confMatrix[1,1]
FN = confMatrix[1,0]
FP = confMatrix[0,1]

#Other metrics
target_names = ['Below 50K (0)', 'Over 50K (1)']
classReport = classification_report(y_test, y_pred, target_names=target_names, output_dict=True)

pre = round(classReport['Over 50K (1)'].get('precision'),3)
sen = round(classReport['Over 50K (1)'].get('recall'),3)
f1s = round(classReport['Over 50K (1)'].get('f1-score'),3)
spe = round(classReport['Below 50K (0)'].get('recall'),3)
```

Random Forest Classifier	Predicted (Below 50K)	Predicted (Over 50K)
Actual (Below 50K)	TN	FP
Actual (Over 50K)	FN	TP

Random Forest Classifier	Predicted (0)	Predicted (1)
Actual (0)	1309	1005
Actual (1)	762	6693

model_name	Accuracy	Precision	F1 Score	Sensitivity	Specifity
RandomForestClassifier()	0.819	0.869	0.883	0.898	0.566

In [315]:
```
#we apply GridSearch to find the best parameters

#Random forest estimator
model_est = RandomForestClassifier()

#default parameters
print(model_est.get_params())

#selection of parameters and creating a dict for grid tool
n_estimators = [100, 300, 500]
max_depth = [5, 8, 15]
min_samples_split = [2, 5, 10]
min_samples_leaf = [1, 2, 5]

hyperF = dict(n_estimators = n_estimators, max_depth = max_depth,
             min_samples_split = min_samples_split,
            min_samples_leaf = min_samples_leaf)

model_grid = GridSearchCV(estimator=model_est,
                         param_grid=hyperF, n_jobs = -1)

model_hyper = model_grid.fit(X_train, y_train)
print('\nBest Parameters:\n ', model_hyper.best_params_)
```

```
{'bootstrap': True, 'ccp_alpha': 0.0, 'class_weight': None, 'criterion': 'gini', 'max_depth': None, 'max_feature
s': 'auto', 'max_leaf_nodes': None, 'max_samples': None, 'min_impurity_decrease': 0.0, 'min_impurity_split': Non
e, 'min_samples_leaf': 1, 'min_samples_split': 2, 'min_weight_fraction_leaf': 0.0, 'n_estimators': 100, 'n_job
s': None, 'oob_score': False, 'random_state': None, 'verbose': 0, 'warm_start': False}
```

According to GridSearch algorithm, the best parameters for this algorithm are:

- max_depth: 15
- min_samples_leaf: 1
- min_samples_split: 10
- n_estimators: 500

Once we know the ML structure we can make the pipeline

In [316]:
```
#pre-processsing step
#dropping columns
#one-hot encoding
#scaling data

columns_drop = ['fnlwgt','capital-gain','capital-loss','salary']
columns_scale = ['age','education-num','hours-per-week']
columns_ohe = ['workclass','education','marital-status',
             'occupation','relationship','race','sex','native-country']

transformers=[('drop_columns', 'drop', columns_drop),
              ('scale_data', StandardScaler(), columns_scale),
              ('categorical transformer', ce.OneHotEncoder(), columns_ohe)]

pre_process = ColumnTransformer(remainder='passthrough',
                                transformers=transformers)
```

In [317]:
```
steps = [('pre-processing', pre_process),
         ('RandomForest', RandomForestClassifier())]

#creating pipeline object
model_pipeline = Pipeline(steps)
```

In [318]:
```python
#importing dataset

names = ['age', 'workclass', 'fnlwgt', 'education', 'education-num', 'marital-status',
         'occupation', 'relationship', 'race','sex','capital-gain',
         'capital-loss','hours-per-week','native-country','salary']
df_census_pln = pd.read_csv('adult.data', names=names)

#adding a new column 'Over 50K' for classes
df_census_pln.loc[df_census_pln['salary'].str.contains('<=50K'), 'Over_50K'] = 1
df_census_pln.loc[df_census_pln['salary'].str.contains('>50K'), 'Over_50K'] = 0
```

In [319]:
```python
X = df_census_pln.drop(columns=['Over_50K'])
y = df_census_pln['Over_50K']

#splitting in train and test dataset
X_train,X_test,y_train,y_test = train_test_split(X, y,
                                                    test_size=0.3, random_state=42)

model_pipeline.fit(X_train,y_train)
```

Out[319]:
```
Pipeline(steps=[('pre-processing',
                 ColumnTransformer(remainder='passthrough',
                                   transformers=[('drop_columns', 'drop',
                                                  ['fnlwgt', 'capital-gain',
                                                   'capital-loss', 'salary']),
                                                 ('scale_data',
                                                  StandardScaler(),
                                                  ['age', 'education-num',
                                                   'hours-per-week']),
                                                 ('categorical transformer',
                                                  OneHotEncoder(),
                                                  ['workclass', 'education',
                                                   'marital-status',
                                                   'occupation', 'relationship',
                                                   'race', 'sex',
                                                   'native-country'])])),
                ('RandomForest', RandomForestClassifier())])
```

In [320]:
```python
#we obtain predicted values from test data
y_pred = model_pipeline.predict(X_test)

#Accuracy
acc = round(metrics.accuracy_score(y_test, y_pred),3)

#Confusion Matrix
confMatrix = confusion_matrix(y_test, y_pred)

TN = confMatrix[0,0]
TP = confMatrix[1,1]
FN = confMatrix[1,0]
FP = confMatrix[0,1]

#Other metrics
target_names = ['Below 50K (0)', 'Over 50K (1)']
classReport = classification_report(y_test, y_pred, target_names=target_names, output_dict=True)

pre = round(classReport['Over 50K (1)'].get('precision'),3)
sen = round(classReport['Over 50K (1)'].get('recall'),3)
f1s = round(classReport['Over 50K (1)'].get('f1-score'),3)
spe = round(classReport['Below 50K (0)'].get('recall'),3)
```

Random Forest Classifier	Predicted (Below 50K)	Predicted (Over 50K)
Actual (Below 50K)	TN	FP
Actual (Over 50K)	FN	TP

Random Forest Classifier	Predicted (0)	Predicted (1)
Actual (0)	1315	999
Actual (1)	778	6677

model_name	Accuracy	Precision	F1 Score	Sensitivity	Specifity
RandomForestClassifier()	0.818	0.87	0.883	0.896	0.568

In [321]:
```
#applying gridsearch

n_estimators = [100, 300, 500]
max_depth = [5, 8, 15]
min_samples_split = [2, 5, 10]
min_samples_leaf = [1, 2, 5]

hyperF = dict(RandomForest__n_estimators = n_estimators,
              RandomForest__max_depth = max_depth,
              RandomForest__min_samples_split = min_samples_split,
              RandomForest__min_samples_leaf = min_samples_leaf)

model_grid = GridSearchCV(model_pipeline, param_grid=hyperF)

model_hyper = model_grid.fit(X_train, y_train)

print(model_hyper.best_params_)
```

```
{'RandomForest__max_depth': 15, 'RandomForest__min_samples_leaf': 1, 'RandomForest__min_samples_split': 2, 'Rand
omForest__n_estimators': 500}
```

According to GridSearch algorithm, the best parameters for this algorithm are:

- max_depth: 15
- min_samples_leaf: 1
- min_samples_split: 2
- n_estimators: 500

Exercici 2 (Nivell 1)

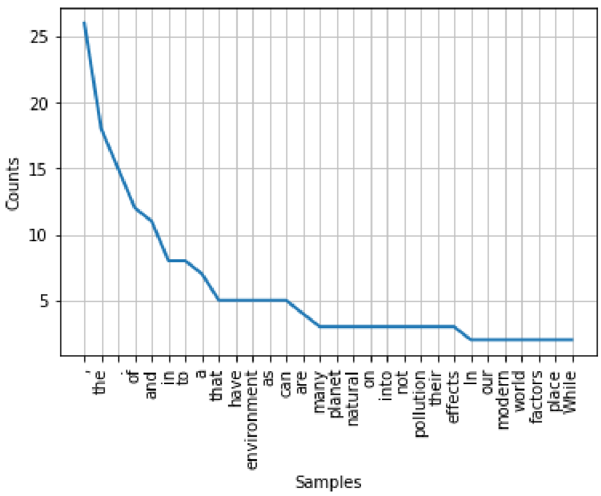
Agafa un text en anglès que vulguis, i calcula'n la freqüència de les paraules.

In [47]:
```
import nltk
from nltk.tokenize import sent_tokenize
from nltk.tokenize import word_tokenize
from nltk.probability import FreqDist
import matplotlib.pyplot as plt
```

In [48]:

```
#text from (https://lingua.com/english/reading/#exercises)

text="""In our modern world, there are many factors that place the wellbeing of the planet in jeopardy. While some
Global warming or climate change is a major contributing factor to environmental damage. Because of global warmin
Air pollution is primarily caused as a result of excessive and unregulated emissions of carbon dioxide into the a
In many areas, people and local governments do not sustainably use their natural resources. Mining for natural ga
Ultimately, the effects of the modern world on the environment can lead to many problems. Human beings need to co

#first we split the text in words
tokenized_word=word_tokenize(text)

#now we calculate frequency of words
fdist = FreqDist(tokenized_word)
print(fdist)

#5 most common words
print(fdist.most_common(30))

#plotting word distribution
fdist.plot(30,cumulative=False)
plt.show()
```

```
<FreqDist with 185 samples and 351 outcomes>
[(',', 26), ('the', 18), ('.', 15), ('of', 12), ('and', 11), ('in', 8), ('to', 8), ('a', 7), ('that', 5), ('hav
e', 5), ('environment', 5), ('as', 5), ('can', 5), ('are', 4), ('many', 3), ('planet', 3), ('natural', 3), ('o
n', 3), ('into', 3), ('not', 3), ('pollution', 3), ('their', 3), ('effects', 3), ('In', 2), ('our', 2), ('moder
n', 2), ('world', 2), ('factors', 2), ('place', 2), ('While', 2)]
```



Exercici 1 (Nivell 2)

Treu les stopwords i realitza stemming al teu conjunt de dades.

In [40]:
```python
#removing stopwords

from nltk.corpus import stopwords

#we create a filter with stopwords in english
stop_words=set(stopwords.words("english"))
#print(stop_words)

#we tokenized text in sentences
tokenized_word=word_tokenize(text)
#print(tokenized_word)

#we create a list to keep text without stopwords
filtered_word=[]
stop_words_detected=[]
for w in tokenized_word:
    if w not in stop_words:
        filtered_word.append(w)
    else:
        stop_words_detected.append(w)

#we join the words
text_stopwords = ' '.join(filtered_word)

print("Text without stopwords:\n",text_stopwords)
print("\nStop words detected:\n",stop_words_detected)

#stemming

from nltk.stem import PorterStemmer

ps = PorterStemmer()

stemmed_words=[]
for w in filtered_word:
    stemmed_words.append(ps.stem(w))

text_stemmed = ' '.join(stemmed_words)
print("\nStemmed Text:\n",text_stemmed)
```

```
Text without stopwords:
 In modern world , many factors place wellbeing planet jeopardy . While people opinion environmental problems na
tural occurrence , others believe human beings huge impact environment . Regardless viewpoint , take considerati
on following factors place environment well planet Earth danger . Global warming climate change major contributi
ng factor environmental damage . Because global warming , seen increase melting ice caps , rise sea levels , for
mation new weather patterns . These weather patterns caused stronger storms , droughts , flooding places formerl
y occur . Air pollution primarily caused result excessive unregulated emissions carbon dioxide air . Pollutants
mostly emerge burning fossil fuels addition chemicals , toxic substances , improper waste disposal . Air polluta
nts absorbed atmosphere , cause smog , combination smoke fog , valleys well produce acidic precipitation areas f
ar away pollution source . In many areas , people local governments sustainably use natural resources . Mining n
atural gases , deforestation , even improper use water resources tremendous effects environment . While strategi
es often attempt boost local economies , effects lead oil spills , interrupted animal habitats , droughts . Ulti
mately , effects modern world environment lead many problems . Human beings need consider repercussions actions
, trying reduce , reuse , recycle materials establishing environmentally sustainable habits . If measures taken
protect environment , potentially witness extinction endangered species , worldwide pollution , completely uninh
abitable planet .

Stop words detected:
 ['our', 'there', 'are', 'that', 'the', 'of', 'the', 'in', 'some', 'have', 'the', 'that', 'are', 'just', 'a', 't
hat', 'have', 'a', 'on', 'the', 'of', 'your', 'into', 'the', 'that', 'our', 'as', 'as', 'the', 'in', 'or', 'is',
'a', 'to', 'of', 'we', 'have', 'an', 'in', 'a', 'in', 'and', 'the', 'of', 'have', 'and', 'in', 'that', 'they',
'did', 'not', 'is', 'as', 'a', 'of', 'and', 'of', 'into', 'the', 'from', 'the', 'of', 'in', 'to', 'and', 'are',
'into', 'the', 'and', 'they', 'can', 'a', 'of', 'and', 'in', 'as', 'as', 'in', 'from', 'the', 'and', 'do', 'no
t', 'their', 'for', 'and', 'of', 'can', 'have', 'on', 'the', 'these', 'to', 'their', 'can', 'to', 'and', 'the',
'of', 'the', 'on', 'the', 'can', 'to', 'to', 'the', 'of', 'their', 'to', 'and', 'while', 'are', 'not', 'to', 'th
e', 'we', 'can', 'the', 'of', 'more', 'and', 'a']

Stemmed Text:
 in modern world , mani factor place wellb planet jeopardi . while peopl opinion environment problem natur occur
r , other believ human be huge impact environ . regardless viewpoint , take consider follow factor place environ
well planet earth danger . global warm climat chang major contribut factor environment damag . becaus global war
m , seen increas melt ice cap , rise sea level , format new weather pattern . these weather pattern caus stronge
r storm , drought , flood place formerli occur . air pollut primarili caus result excess unregul emiss carbon di
oxid air . pollut mostli emerg burn fossil fuel addit chemic , toxic substanc , improp wast dispos . air pollut
absorb atmospher , caus smog , combin smoke fog , valley well produc acid precipit area far away pollut sourc .
in mani area , peopl local govern sustain use natur resourc . mine natur gase , deforest , even improp use water
resourc tremend effect environ . while strategi often attempt boost local economi , effect lead oil spill , inte
rrupt anim habitat , drought . ultim , effect modern world environ lead mani problem . human be need consid repe
rcuss action , tri reduc , reus , recycl materi establish environment sustain habit . if measur taken protect en
viron , potenti wit extinct endang speci , worldwid pollut , complet uninhabit planet .
```

Exercici 1 (Nivell 3)

Realitza sentiment analysis al teu conjunt de dades.

I did not have enough time to finish this exercize :(

In [46]:
```
#Lemmatization
from nltk.stem.wordnet import WordNetLemmatizer
lem = WordNetLemmatizer()

lemma_words=[]
for w in filtered_word:
    lemma_word = lem.lemmatize(w)
    lemma_words.append(lemma_word)

text_lemmatized = ' '.join(lemma_words)
print("\nStemmed Text:\n",text_lemmatized,"\n")

#tokenizer to remove unwanted elements from out data like symbols and numbers
token = RegexpTokenizer(r'[a-zA-Z0-9]+')
cv = CountVectorizer(lowercase=True,stop_words='english',
                     ngram_range = (1,1),tokenizer = token.tokenize)
text_sentiment= cv.fit_transform(lemma_words)

#we will use the "Sentiment analysis of movies" from kaggle to train the model
data=pd.read_csv('train.tsv', sep='\t')

from sklearn.feature_extraction.text import CountVectorizer
from nltk.tokenize import RegexpTokenizer
#tokenizer to remove unwanted elements from out data like symbols and numbers
token = RegexpTokenizer(r'[a-zA-Z0-9]+')
cv = CountVectorizer(lowercase=True,stop_words='english',
                     ngram_range = (1,1),tokenizer = token.tokenize)
text_counts= cv.fit_transform(data['Phrase'])

X_train, X_test, y_train, y_test = train_test_split(
    text_counts, data['Sentiment'], test_size=0.3, random_state=1)

from sklearn.naive_bayes import MultinomialNB
#Import scikit-learn metrics module for accuracy calculation
from sklearn import metrics
# Model Generation Using Multinomial Naive Bayes
clf = MultinomialNB().fit(X_train, y_train)
predicted= clf.predict(X_test)
print("MultinomialNB Accuracy:",metrics.accuracy_score(y_test, predicted))
#print(X_test)
#print(predicted)

#we obtain predicted values from text
#predicted = clf.predict(text_sentiment)
#print(text_sentiment)
#print(predicted)
```

```
Stemmed Text:
 In modern world , many factor place wellbeing planet jeopardy . While people opinion environmental problem natu
ral occurrence , others believe human being huge impact environment . Regardless viewpoint , take consideration
following factor place environment well planet Earth danger . Global warming climate change major contributing f
actor environmental damage . Because global warming , seen increase melting ice cap , rise sea level , formation
new weather pattern . These weather pattern caused stronger storm , drought , flooding place formerly occur . Ai
r pollution primarily caused result excessive unregulated emission carbon dioxide air . Pollutants mostly emerge
burning fossil fuel addition chemical , toxic substance , improper waste disposal . Air pollutant absorbed atmos
phere , cause smog , combination smoke fog , valley well produce acidic precipitation area far away pollution so
urce . In many area , people local government sustainably use natural resource . Mining natural gas , deforestat
ion , even improper use water resource tremendous effect environment . While strategy often attempt boost local
economy , effect lead oil spill , interrupted animal habitat , drought . Ultimately , effect modern world enviro
nment lead many problem . Human being need consider repercussion action , trying reduce , reuse , recycle materi
al establishing environmentally sustainable habit . If measure taken protect environment , potentially witness e
xtinction endangered specie , worldwide pollution , completely uninhabitable planet .

MultinomialNB Accuracy: 0.6049169122986885
```