Analysis 1.1

January 13, 2019

1 Data Science Popularization

Dataset: DSP Master version-1

Relevant Information: The dataset contains instances of reporters from various fields of expertise with relevant information of the reporters which are sparse, repetitive and often missing.

Number of instances : 3316

Number of attributes : 16

Attributes : Country, Province, Category, Newspaper, Newspaper Website, Magazine, Magazine Website, Reporter Name, Reporter Email Reporter Phone, Reporter Twitter, Reporter Linkedin, Technology Health&Medical, Environment, Others

Missing Attribute values : Abundant

1.1 The journey with the master dataset :

1. Primarily we preprocessed the master dataset by dropping the duplicates
2. To classify names with respective gender scraped the possible Gender attributed names from various sites (viz, https://www.familyeducation.com/baby-names/browse-names/first-name/) and stored it in a github repo for reference (https://github.com/adjunctexorcist01/namesdb).
3. To verify the data, we checked the user twitter profiles wherever applicable
4. We filled the missing Location values from the data collected from twitter. The resulting dataset had 2972 datapoints
5. Next, we scraped google scholar for the reporter names to extract their Interests, Affiliation, Citation Count, Titles of their publications, and 10 publications by each reporter.The resulting dataset had 600 datapoints
6. We preprocessed the textual data by removing html tags and stop-words.

Problems we faced: - Many of the scraped names were of unisex in nature and it was hard to classify it under a particular gender - We saw a huge drop in valid datapoints as ~2372 datapoints threw exception while scraping from scholarly

2 Enter the revised dataset

Dataset: Final-DSP

Relevant Information: The dataset is a final version of the dataset provided, which is truncated and filled with information specific to analysis.

Missing values: Minimal

2.1 Importing relevant libraries

```
In [1]: %matplotlib inline
        import warnings
        warnings.filterwarnings("ignore")
        warnings.filterwarnings("ignore", category=DeprecationWarning)

        import pandas as pd
        import numpy as np
        import nltk
        import string
        import matplotlib.pyplot as plt
        import seaborn as sns
        from sklearn.feature_extraction.text import TfidfTransformer, TfidfVectorizer, CountVe


        from sklearn import metrics
        from sklearn.manifold import TSNE
        from nltk.stem.porter import PorterStemmer
        from sklearn.preprocessing import Normalizer

        import re
        from nltk.corpus import stopwords
        from nltk.stem.wordnet import WordNetLemmatizer
        from nltk.corpus import wordnet

        from gensim.models import Word2Vec
        from gensim.models import KeyedVectors
        import pickle
        from tqdm import tqdm
        import os
        import bokeh.plotting as bp
        from bokeh.models import HoverTool, BoxSelectTool
        from bokeh.plotting import figure, show, output_notebook, reset_output
        from bokeh.palettes import d3
        import bokeh.models as bmo
        from bokeh.io import save, output_file
        from sklearn.decomposition import TruncatedSVD
        from sklearn.cluster import MiniBatchKMeans, KMeans
        from sklearn.metrics import silhouette_score

        from sklearn.pipeline import make_pipeline
        from sklearn.preprocessing import Normalizer
```

```
In [3]: df = df = pd.read_excel("/home/ae/Documents/Work/Publications/Final-DSP.xlsx") #data f
```

2.2 Shape of the dataset

```
In [4]: df.shape
```

```
Out[4]: (600, 31)
```

```
In [5]: df.columns
```

```
Out[5]: Index(['Category', 'Reporter Name', 'Technology', 'Health&Medical',
               'Environment', 'Others', 'Country', 'Province', 'Newspaper',
               'NewspaperWebsite', 'Magazine ', 'Magazine Website', 'ReporterEmail',
               'Reporter Phone', 'ReporterTwitter', 'ReporterLinkedin', 'Gender',
               'Twitter Link', 'Location', 'User Url', 'Bio', 'Affiliation', 'Citedby',
               'Email', 'Interests', 'Publication Titles', 'CleanedText', 'Cleaned',
               'Name', 'Publications', 'Cleaned Publications'],
              dtype='object')
```

NB : - CleanedText and Cleaned Publications are Publication Titles and Publications respectively, which have undergone stop word, punctuation and html tag removal - Reporter Name is name from the provided Dataset and Name is the profile names resulted from the twitter scrape - Country is the location provided in the inital file and Location is derived from the twitter scrape - Bio is the twitter bio of individuals resulted from the scrape the importance of which seems negligible

2.3 Comparing the number of missing values between the provided and scraped data (location)

```
In [6]: df["Country"].describe()
```

```
Out[6]: count      583
        unique      42
        top        USA
        freq       270
        Name: Country, dtype: object
```

```
In [7]: #data entries having no known value for countries
        df["Country"].isna().sum()
```

```
Out[7]: 17
```

```
In [8]: df["Location"].describe()
```

```
Out[8]: count      585
        unique     141
        top        USA
        freq       237
        Name: Location, dtype: object
```

```
In [9]: #data entries having no known value for their present location
        df["Location"].isna().sum()
```

```
Out[9]: 15
```

Inference

- Since there is a marginal difference between the provided location and the scraped ones, we are choosing the provided ones(Country) due to it's refined formatting, for analysis.

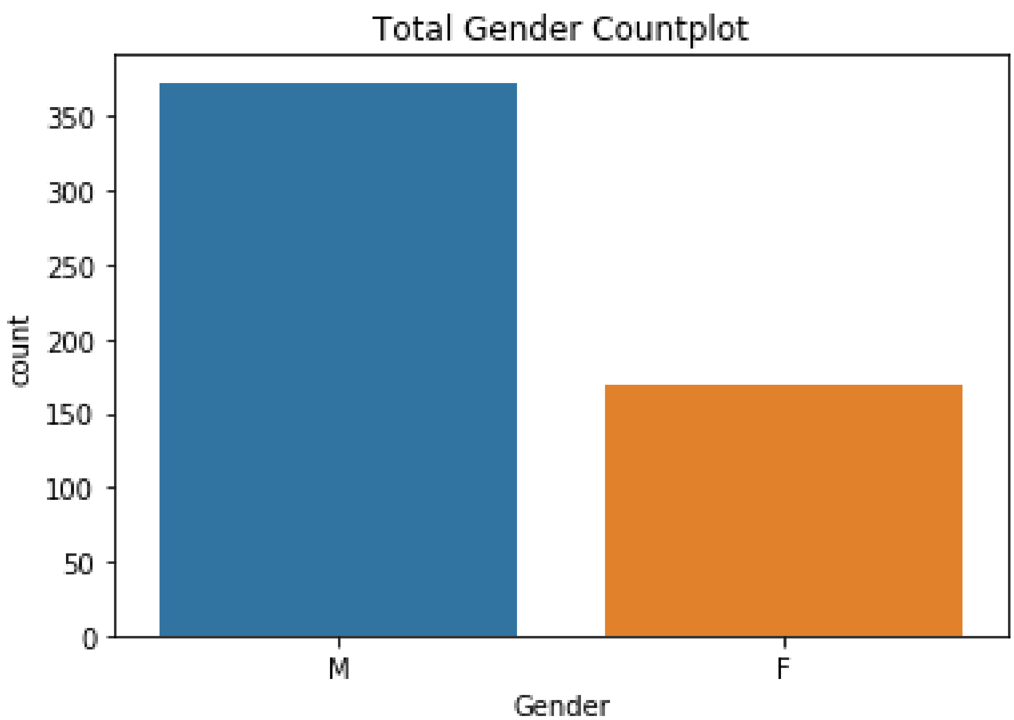
2.4 EDA on the final Dataset

2.4.1 Ratio of male/female reporters

In [10]:
```
#count of male(M) and female(F) reporters
df["Gender"].value_counts()
```

Out[10]:
```
M    373
F    169
Name: Gender, dtype: int64
```

In [11]:
```
sns.countplot(x="Gender", data=df).set_title("Total Gender Countplot")
plt.show()
```



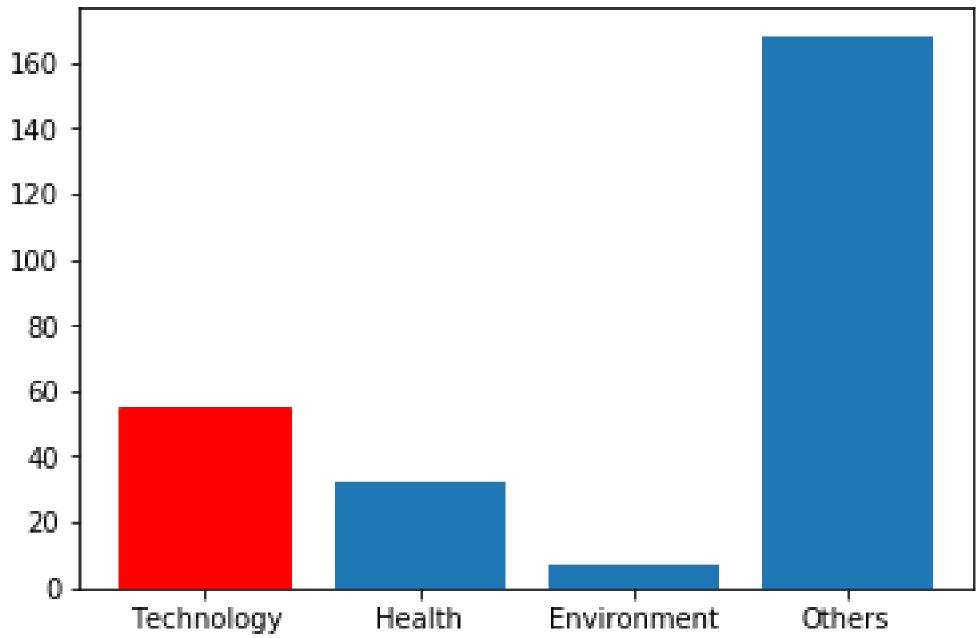
Observation:

- For the final dataset, we see the count of male reporters is more than twice the number of female reporters. (For the case of successful gender label)

2.4.2 Reporters on the various domains

The data includes categories of reporting as : 1. Technology 2. Environment 3. Health 4. Others
In the analysis below, we can compare the popularity of each domain among reporters.

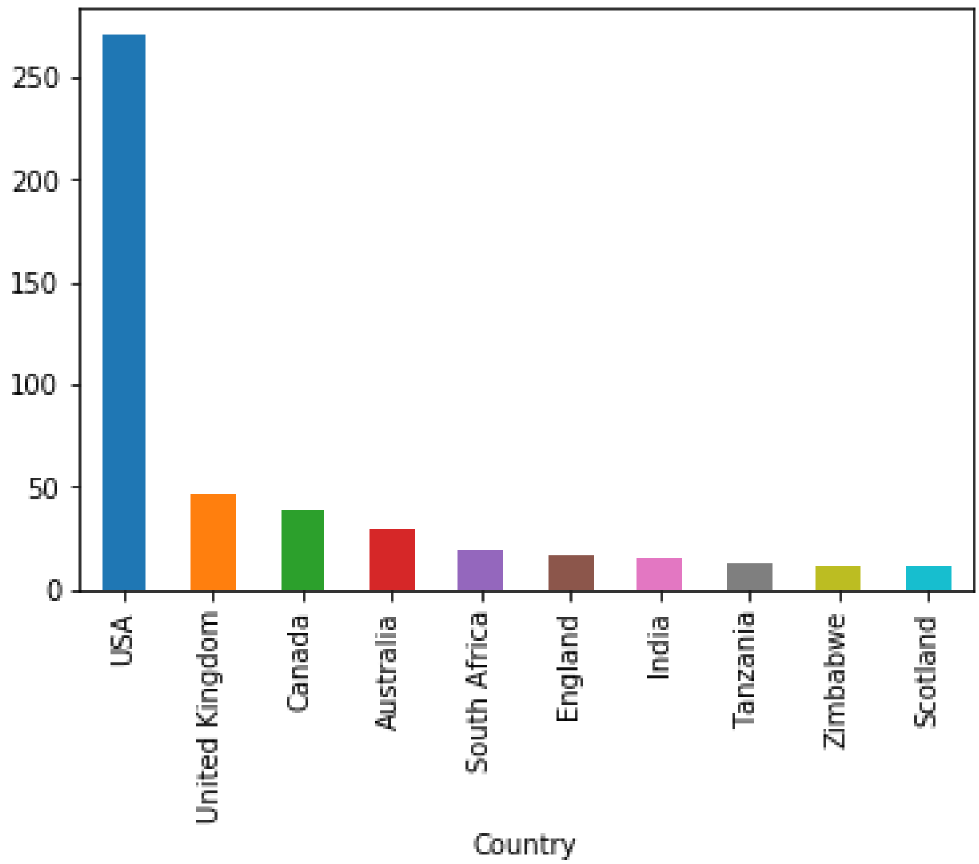
```
In [12]: x = ['Technology','Health','Environment','Others']
         y = [df['Technology'].sum(),df['Health&Medical'].sum(),df['Environment'].sum(),df['Ot
         barlist = plt.bar(x,y)
         barlist[0].set_color("r")

         plt.show()
```



From Observing the graph it is clear that the most of them are reporting on random or uncategorized issues.

2.4.3 Top 10 countries with highest number of reporters

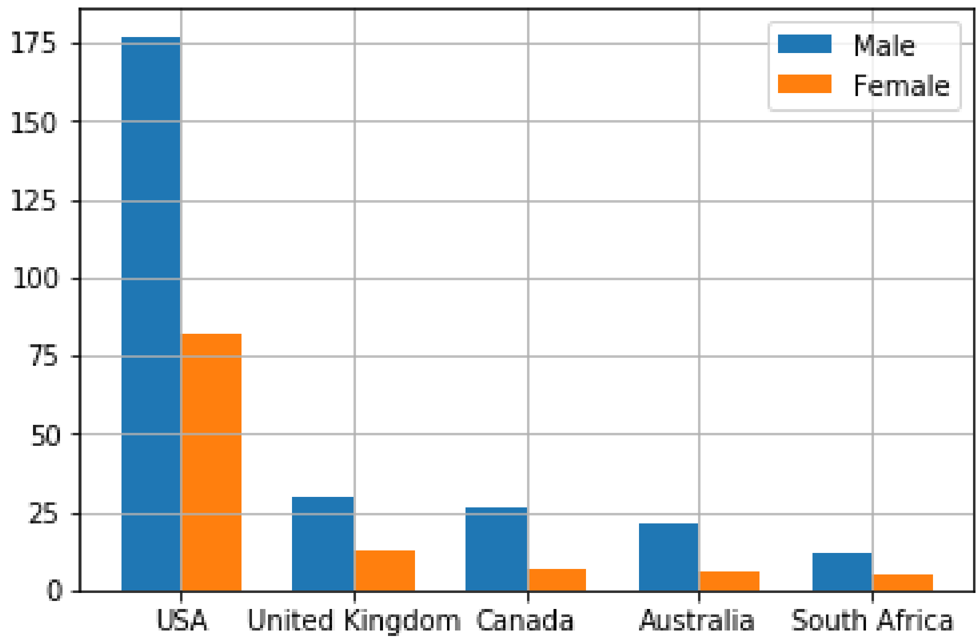
```
In [13]: df.groupby(['Country'])["Reporter Name"].count().sort_values(ascending = False).head(

Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x7f844f153630>
```



USA has the highest number of reporters with around ~45% of the share in the total data.

2.4.4 Gender ratio in the top 5 countries with the maximux number of reporters

In [14]:
```
w=0.35
ind = np.arange(5)
male = df[(df["Gender"]=="M")].groupby(["Country"])["Reporter Name"].count().sort_valu
female = df[(df["Gender"]=="F")].groupby(["Country"])["Reporter Name"].count().sort_va
plt.bar(ind, male, w, label="Male")
plt.bar(ind+w, female, w, label="Female")
plt.xticks(ind+w/2, male.keys())
plt.legend()
plt.grid()
plt.show()
```

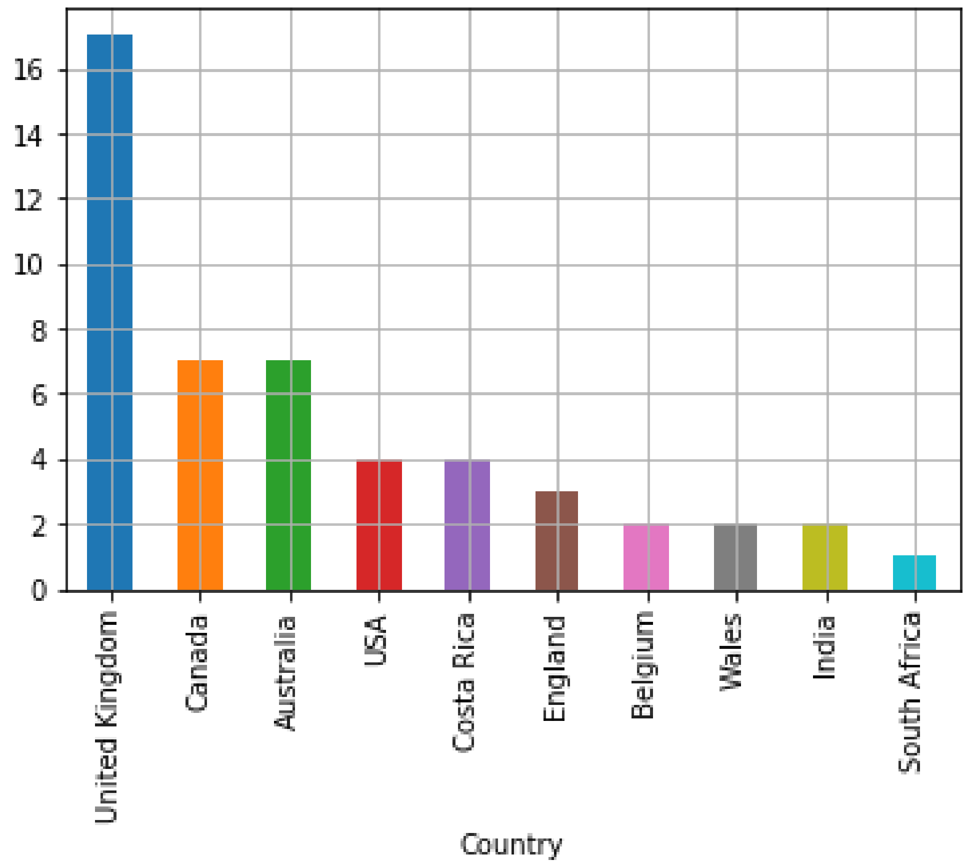


Most of the countries have female:male ratio as less than half.

2.4.5 Top 5 countries with the highest number of reports in the Technology domain

```
In [15]: df[df["Technology"]==1].groupby(['Country'])["Reporter Name"].count().sort_values(asce
```

```
Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x7f844f0ca128>
```



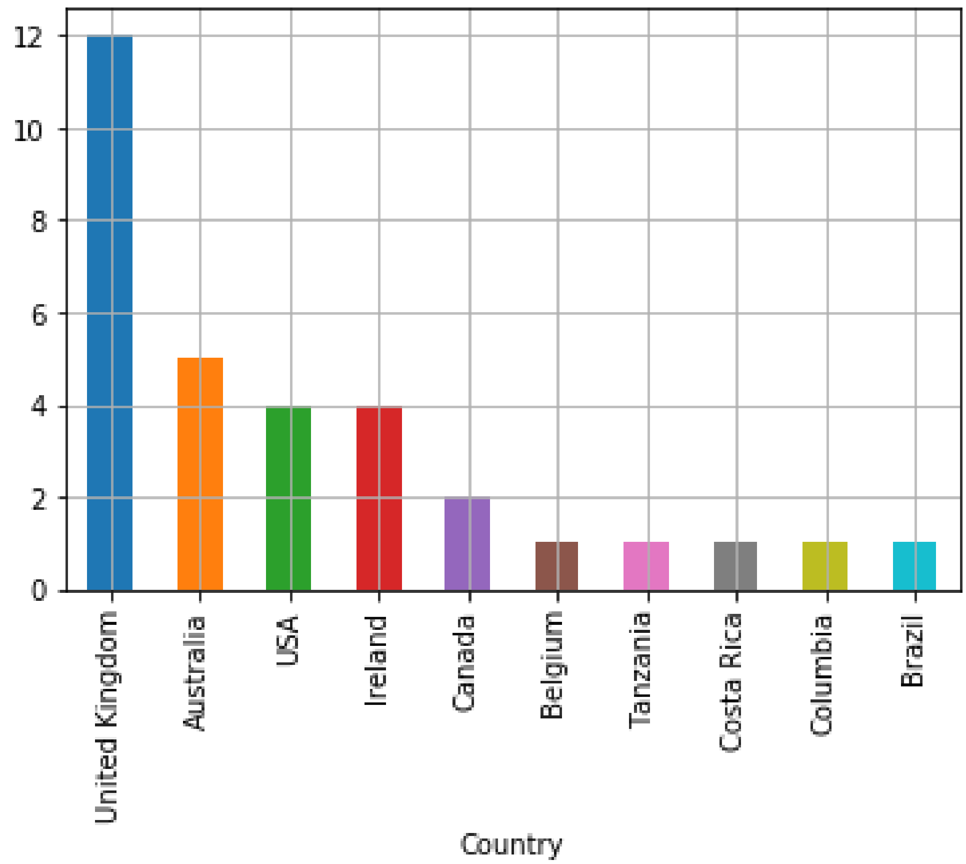
Top Countries in technology reporting are United Kingdom, Canada, Australia , USA(surprisingly, it ranks 4th despite having maximum reporters in the world) .

(The actual count of reporter for each country is significantly less as compared to the entire data, thus this is not a strong conclusion)

2.4.6 Top 5 countries with the highest number of reports in the Health and Medicine domain

```
In [16]: df[df["Health&Medical"]==1].groupby(['Country'])["Reporter Name"].count().sort_values
```

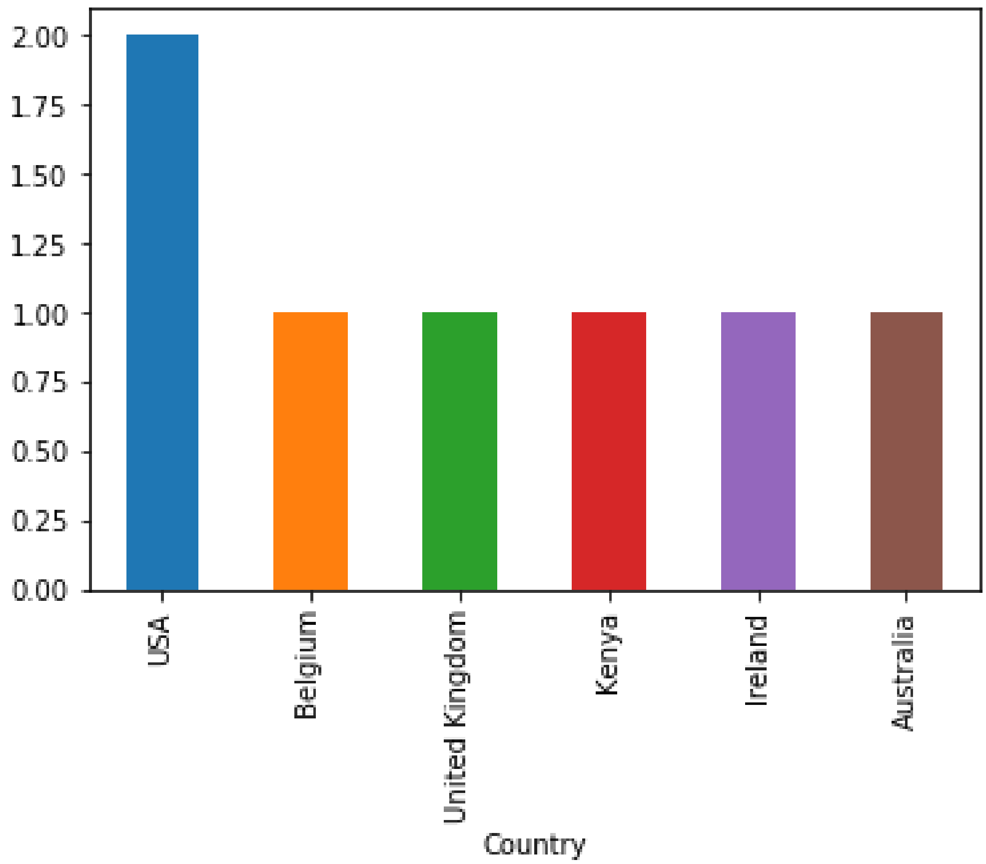
```
Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x7f844efc5438>
```



2.4.7 Top 5 countries with the highest number of reports in the Environment domain

```
In [17]: df[df["Environment"]==1].groupby(['Country'])["Reporter Name"].count().sort_values(asc
```

```
Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x7f844ef4a470>
```



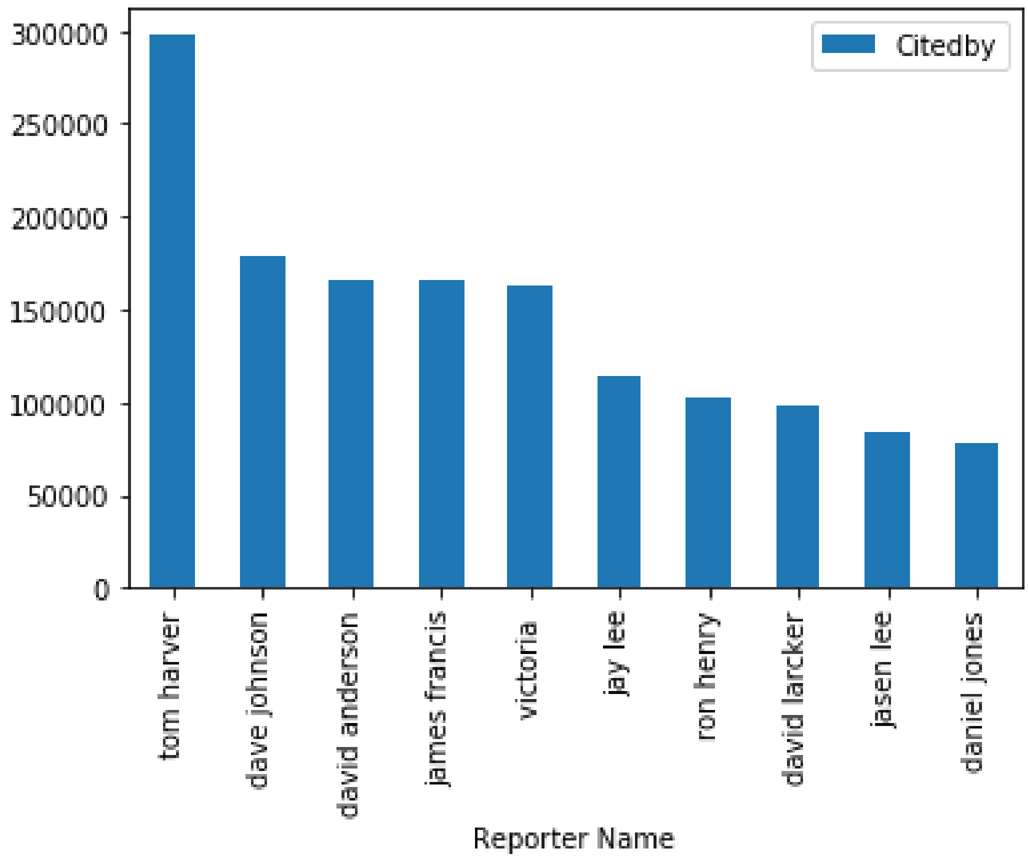
The count of reporters in Environment domain is low, thus we can't really confirm a pattern.

2.4.8 People getting cited the most and their respective countries

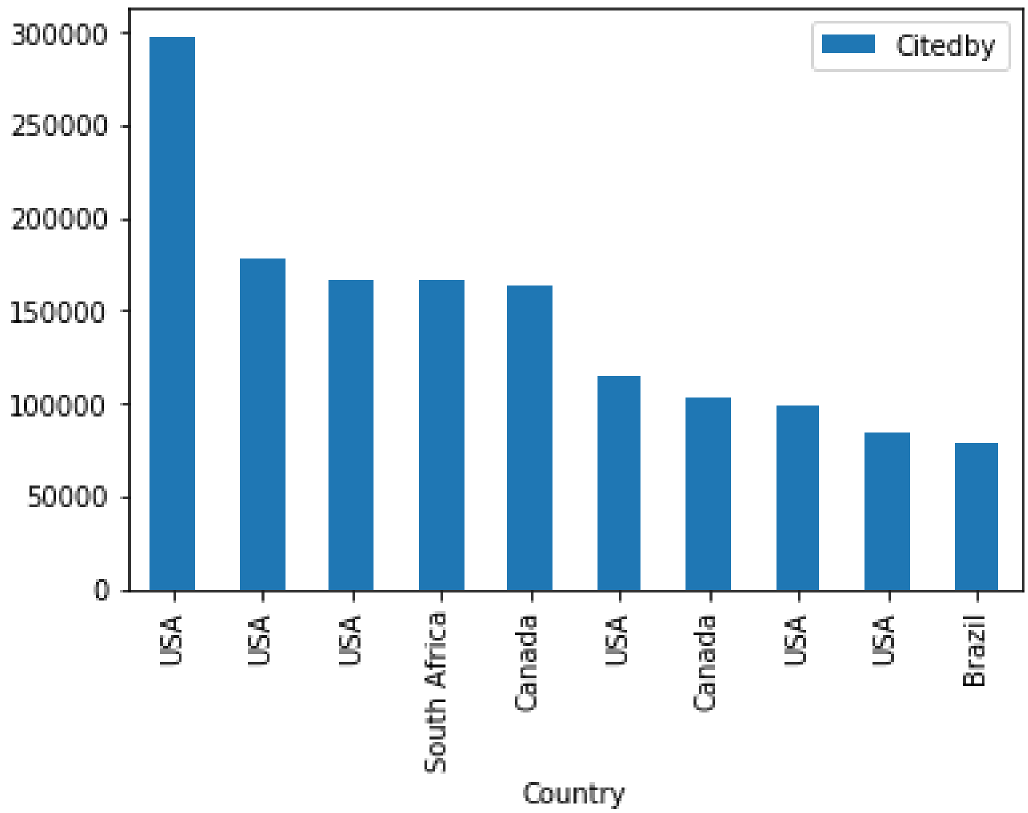
Most Active Reporters On the basis of number of citations on google scholar authored by a reporter , we estimated the activity of a reporter and how frequently they indulge .

```
In [18]: df[(df["Citedby"].notnull())][["Reporter Name", "Citedby", "Country"]].sort_values(by
```

```
Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x7f844ef317b8>
```




```
In [19]: df[(df["Citedby"].notnull())][["Reporter Name", "Citedby", "Country"]].sort_values(by

Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x7f844ee3b3c8>
```



Tom Harver being the reporter with highest citations (close to 0.3 million)

Further, we have grouped them on the basis of country, to deduce the country most active in reporting. Top 3 actively reporting countries being:

1. United States of America
2. Canada
3. South Africa

2.5 Analysing the Textual data

2.5.1 Final preprocessing of Publication Text for exceptions

```
In [20]: #function to remove stopwords
         def secondClean(text):
             cleaned = firstClean(text)
             filtered_words = []
             for x in cleaned.split():
                 if x not in stop_words:
                     filtered_words.append(x)
             return " ".join(filtered_words).strip()

         #conversion to processable string
```

```
def toString(x):
    try:
        return str(x)
    except:
        return 0

#cleaning html tags from text
def firstClean(text):
    return re.sub(r"[^A-Za-z\u00C0-\u00D6\u00D8-\u00f6\u00f8-\u00ff\s]","",text)
stop_words = stopwords.words('english')
```

```
In [21]: df['Cleaned Publications'] = df['Cleaned Publications'].apply(lambda x:toString(x))
```

```
In [22]: df['Cleaned Publications'] = df['Cleaned Publications'].apply(lambda x:secondClean(x)
```

```
In [23]: #tfidf used to find relevant words in text
         vectorizer = TfidfVectorizer(min_df=5, analyzer='word', ngram_range=(1, 2), stop_words
         vz = vectorizer.fit_transform(list(df['Cleaned Publications']))

         vz.shape
```

```
Out[23]: (600, 8966)
```

```
In [24]: tfidf = dict(zip(vectorizer.get_feature_names(),vectorizer.idf_))
```

```
In [25]: tfidf = pd.DataFrame(columns=['tfidf']).from_dict(dict(tfidf), orient='index')
```

```
In [26]: tfidf.columns = ['tfidf']
```

2.5.2 Visualizing the textual data using Word Cloud

```
In [27]: #higher tfidf score, more relevant words is to the context
         tfidf.head()
```

Out[27]:

	tfidf
abandoned	5.452685
abdominal	5.096010
aberrant	5.452685
aberrations	5.452685
abilities	4.508223

```
In [28]: from wordcloud import WordCloud

         def plot_word_cloud(terms):
             text = terms.index
             text = ' '.join(list(text))
             wordcloud = WordCloud(max_font_size=40).generate(text)
             plt.figure(figsize=(25, 25))
             plt.imshow(wordcloud, interpolation="bilinear")
             plt.axis("off")
             plt.show()
```

```
In [29]: plot_word_cloud(tfidf.sort_values(by=['tfidf'], ascending=False).head(40))
```

Inference: This shows the TF-IDF cloud words based on the text of publications for each records,it is interesting to see that even though the data is dominated by tech reporters, TF-IDF shows words which are related to Health domains - cell - dna - renal - microbiota are some of such words

2.5.3 Clustering Publication Text

Purpose is to find similar reporters based on their publications through Clustering.

```
In [30]: # Single value reduction
         from sklearn.decomposition import TruncatedSVD
         svd = TruncatedSVD(n_components=50, random_state=0)
         svd_tfidf = svd.fit_transform(vz)

         svd_tfidf.shape

Out[30]: (600, 50)
```

```
In [31]: # T-distributed Stochastic Neighbor Embedding used. This helps in high level visualiz
         from sklearn.manifold import TSNE
         tsne_model = TSNE(n_components=2,perplexity=10, verbose=1, random_state=0, n_iter=200
         tsne_tfidf = tsne_model.fit_transform(svd_tfidf)
         print(tsne_tfidf.shape)
         tsne_tfidf_df = pd.DataFrame(tsne_tfidf)
         tsne_tfidf_df.columns = ['x', 'y']
         tsne_tfidf_df['Category'] = df['Category']
         tsne_tfidf_df['ReporterName'] = df['Reporter Name']
```

```
[t-SNE] Computing 31 nearest neighbors...
[t-SNE] Indexed 600 samples in 0.004s...
[t-SNE] Computed neighbors for 600 samples in 0.045s...
[t-SNE] Computed conditional probabilities for sample 600 / 600
[t-SNE] Mean sigma: 0.158728
[t-SNE] KL divergence after 250 iterations with early exaggeration: 79.166100
[t-SNE] KL divergence after 2000 iterations: 0.953784
(600, 2)
```

```
In [33]: output_notebook()
         plot_tfidf = bp.figure(plot_width=700, plot_height=600, title="tf-idf clustering of th
             tools="pan,wheel_zoom,box_zoom,reset,hover,previewsave",
             x_axis_type=None, y_axis_type=None, min_border=1)

         palette = d3['Category10'][len(tsne_tfidf_df['Category'].unique())]
         color_map = bmo.CategoricalColorMapper(factors=tsne_tfidf_df['Category'].map(str).uniq

         plot_tfidf.scatter(x='x', y='y', color={'field': 'Category', 'transform': color_map},
                            legend='Category', source=tsne_tfidf_df)
         hover = plot_tfidf.select(dict(type=HoverTool))
         hover.tooltips={"Reporter Name": "@ReporterName", "Category":"@Category"}

         show(plot_tfidf)
```

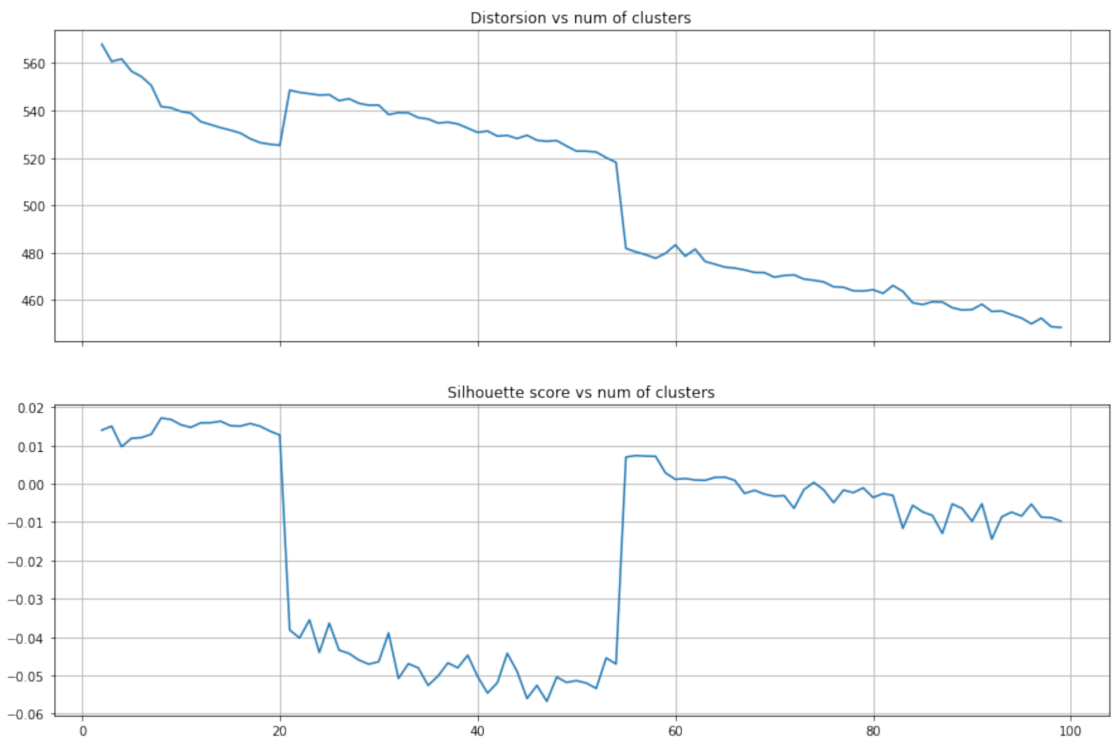
Inference: - Nearest Neighbour Clustering based on TSNE shows that there are small clusters scattered all over the place, hence reporters are fairly diverse in their style of publications. - The clusters are really small, thus it doesnt make sense to analyze each and every small cluster

Distorsion and Silhouette Score on Publication

```
In [34]: from tqdm import tqdm_notebook
         distorsions = []
         sil_scores = []
         k_max = 100
         for k in tqdm_notebook(range(2, k_max)):
             kmeans_model = MiniBatchKMeans(n_clusters=k, init='k-means++', n_init=1, random_st
                                      init_size=1000, verbose=False, max_iter=1000)
             kmeans_model.fit(vz)
             sil_score = silhouette_score(vz, kmeans_model.labels_)
             sil_scores.append(sil_score)
             distorsions.append(kmeans_model.inertia_)
```

```
HBox(children=(IntProgress(value=0, max=98), HTML(value='')))
```

```
In [35]: f, (ax1, ax2) = plt.subplots(2, 1, sharex=True, figsize=(15, 10))

         ax1.plot(range(2, k_max), distorsions)
         ax1.set_title('Distorsion vs num of clusters')
         ax1.grid(True)

         ax2.plot(range(2, k_max), sil_scores)
         ax2.set_title('Silhouette score vs num of clusters')
         ax2.grid(True)
```



Above graph shows Error to accuracy data points for each K in K-means till 100, there is an abnormality after 20 till around ~50 we dont know the reason of such abnormality, we also dont have an elbow curve to determine which K would be more suited Since the error is still decreasing even after we reach k=100. We cannot chose a large K because we dont have enough data for it cluster properly.if we choose k=100 it will select 6 datapoints in for each clusters (total records ~600). and analyzing those 100 clusters would not be feasible

2.6 Clustering on Affiliation

The Next interesting attribute to cluster on is on affiliation to find similarities, It includes Names of Universities, State etc

Preprocessing Affiliations

```
In [36]: df['Cleaned Affiliations'] = df['Affiliation'].apply(lambda x:secondClean(x))
```

```
In [37]: vectorizerAff = TfidfVectorizer(min_df=5, analyzer='word', ngram_range=(1, 2), stop_wo
         vz1 = vectorizerAff.fit_transform(list(df['Cleaned Affiliations']))
         df.reset_index(inplace =True)
         vz1.shape

Out[37]: (600, 98)

In [38]: #single value reduction
         svdAff = TruncatedSVD(n_components=50, random_state=0)
         svd_tfidfAff = svdAff.fit_transform(vz1)
         svd_tfidfAff.shape

Out[38]: (600, 50)

In [39]: tsne_modelAff = TSNE(n_components=2,perplexity=10, verbose=1, random_state=0, n_iter=2
         tsne_tfidfAff = tsne_modelAff.fit_transform(svd_tfidfAff)
         print(tsne_tfidfAff.shape)
         tsne_tfidf_dfAff = pd.DataFrame(tsne_tfidfAff)
         tsne_tfidf_dfAff.columns = ['x', 'y']
         tsne_tfidf_dfAff['Category'] = df['Category']
         tsne_tfidf_dfAff['ReporterName'] = df['Reporter Name']
         tsne_tfidf_dfAff['Affiliations'] = df['Cleaned Affiliations']

[t-SNE] Computing 31 nearest neighbors...
[t-SNE] Indexed 600 samples in 0.002s...
[t-SNE] Computed neighbors for 600 samples in 0.036s...
[t-SNE] Computed conditional probabilities for sample 600 / 600
[t-SNE] Mean sigma: 0.000000
[t-SNE] KL divergence after 250 iterations with early exaggeration: 70.454361
[t-SNE] KL divergence after 2000 iterations: 0.576950
(600, 2)


In [40]: output_notebook()
         plot_tfidf = bp.figure(plot_width=700, plot_height=600, title="tf-idf clustering of th
             tools="pan,wheel_zoom,box_zoom,reset,hover,previewsave",
             x_axis_type=None, y_axis_type=None, min_border=1)

         palette = d3['Category10'][len(tsne_tfidf_dfAff['Category'].unique())]
         color_map = bmo.CategoricalColorMapper(factors=tsne_tfidf_dfAff['Category'].map(str).u

         plot_tfidf.scatter(x='x', y='y', color={'field': 'Category', 'transform': color_map},
                            legend='Category', source=tsne_tfidf_dfAff)
         hover = plot_tfidf.select(dict(type=HoverTool))
         hover.tooltips={"Reporter Name": "@ReporterName", "Category":"@Category","Affiliations

         show(plot_tfidf)
```

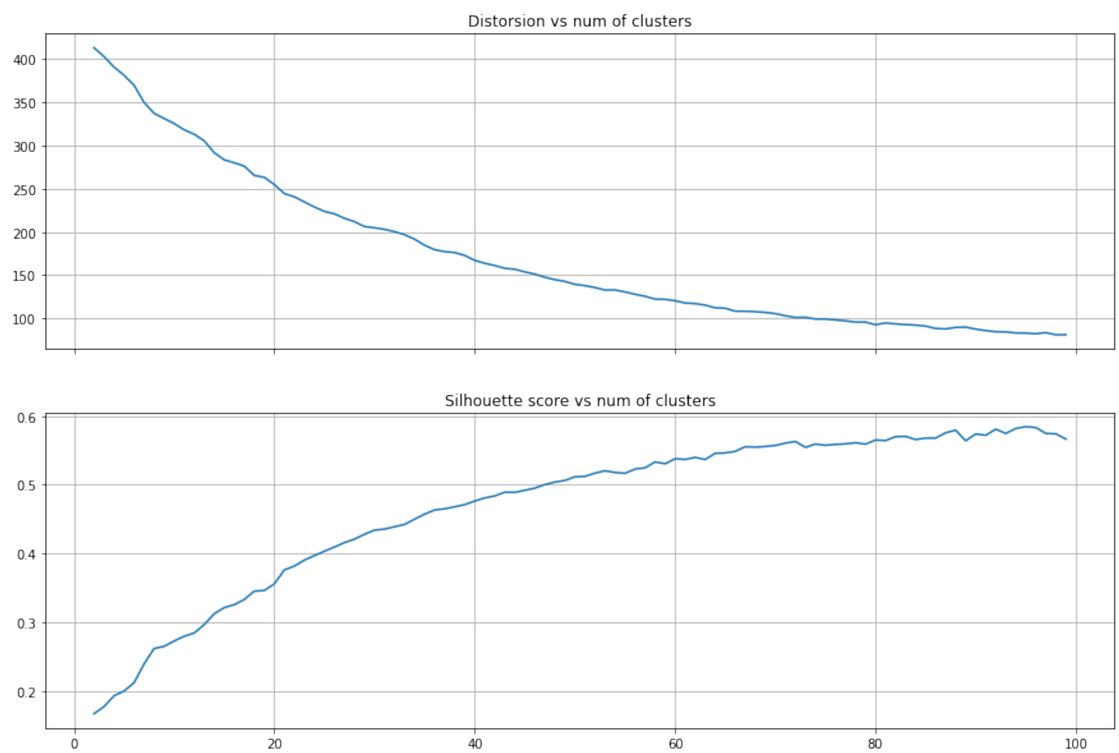
Observation: The bottom most cluster are associated to unknown attributes. And the right-most cluster belongs to PHDs and Stanford university.

Finding Distorsion and Silhouette Scores for Affiliations

In [41]:
```
distorsions = []
sil_scores = []
k_max = 100
for k in tqdm_notebook(range(2, k_max)):
    kmeans_model = MiniBatchKMeans(n_clusters=k, init='k-means++', n_init=1, random_s
                                   init_size=1000, verbose=False, max_iter=1000)
    kmeans_model.fit(vz1)
    sil_score = silhouette_score(vz1, kmeans_model.labels_)
    sil_scores.append(sil_score)
    distorsions.append(kmeans_model.inertia_)
```

```
HBox(children=(IntProgress(value=0, max=98), HTML(value='')))
```

In [42]:
```
f, (ax1, ax2) = plt.subplots(2, 1, sharex=True, figsize=(15, 10))

ax1.plot(range(2, k_max), distorsions)
ax1.set_title('Distorsion vs num of clusters')
ax1.grid(True)

ax2.plot(range(2, k_max), sil_scores)
ax2.set_title('Silhouette score vs num of clusters')
ax2.grid(True)
```



There isnt a elbow curve which would tell us the optimal K, And since the error keeps on reducing it difficult to know whats the correct K. Hence we have choose the ratio of errors in the interval of K values, The error rate curve decreases less lower in between 20-40 as compared to the interval below 20. and hence k is selected as 20 to make sure there are good number of clusters aswell.

```
In [43]: num_clusters = 20
         kmeans_model = MiniBatchKMeans(n_clusters=num_clusters, init='k-means++', n_init=1, ra
                                        init_size=1000, batch_size=1000, verbose=False, max_iter=100(
         kmeans = kmeans_model.fit(vz1)
         kmeans_clusters = kmeans.predict(vz1)
         kmeans_distances = kmeans.transform(vz1)
```

2.6.1 Affiliations : Clusters key words

```
In [44]: sorted_centroids = kmeans.cluster_centers_.argsort()[:, ::-1]
         terms = vectorizerAff.get_feature_names()
         all_keywords = []
         for i in range(kmeans.n_clusters):
             topic_keywords = []
             for j in sorted_centroids[i, :10]:
                 topic_keywords.append(terms[j])
             all_keywords.append(topic_keywords)

         keywords_df = pd.DataFrame(index=['cluster_{0}'.format(i) for i in range(num_clusters)
                                    columns=['keyword_{0}'.format(i) for i in range(10)],
                                    data=all_keywords)
         keywords_df
```

```
Out[44]:                       keyword_0            keyword_1         keyword_2  \
         cluster_0            university            professor  state university
         cluster_1            university                texas              york
         cluster_2           universidad                  del        researcher
         cluster_3           affiliation  unknown affiliation           unknown
         cluster_4  professor university            professor        university
         cluster_5                center       medical center           medical
         cluster_6             professor           university              york
         cluster_7             scientist               senior         assistant
         cluster_8       research fellow               fellow          research
         cluster_9              hospital           university            oxford
         cluster_10              science           technology        university
         cluster_11           department           university          medicine
         cluster_12       north carolina             carolina             north
         cluster_13            institute             research        university
         cluster_14             research  research associate         associate
         cluster_15              studies            professor        university
```

cluster_16	newcastle	university	york
cluster_17	college	professor	hunter college
cluster_18	postdoctoral	fellow	university
cluster_19	associate	associate professor	professor

	keyword_3	keyword_4	keyword_5	\
cluster_0	state	school	engineering	
cluster_1	harvard	doctoral	economics	
cluster_2	professor	york	george	
cluster_3	harvard	doctoral	economics	
cluster_4	associate professor	associate	columbia	
cluster_5	university	professor	columbia	
cluster_6	harvard	economics	engineering	
cluster_7	international	computer	science	
cluster_8	university	hospital	newcastle	
cluster_9	professor	department	center	
cluster_10	professor	institute	engineering	
cluster_11	professor	york	engineering	
cluster_12	university north	university	anthropology	
cluster_13	technology	new	biology	
cluster_14	national	university	center	
cluster_15	management	school	lecturer	
cluster_16	harvard	economics	engineering	
cluster_17	hunter	school	medicine	
cluster_18	researcher	university oxford	cancer	
cluster_19	university	state university	state	

	keyword_6	keyword_7	keyword_8	\
cluster_0	laboratory	student	stanford	
cluster_1	engineering	environmental	faculty	
cluster_2	doctoral	economics	engineering	
cluster_3	engineering	environmental	faculty	
cluster_4	germany	michigan	colorado	
cluster_5	harvard	washington	george	
cluster_6	environmental	faculty	federal	
cluster_7	university	york	florida	
cluster_8	national	stanford university	postdoctoral	
cluster_9	york	germany	engineering	
cluster_10	phd	computer science	computer	
cluster_11	mathematics	biology	university california	
cluster_12	state university	state	environmental	
cluster_13	director	oxford	professor	
cluster_14	germany	medical	laboratory	
cluster_15	international	assistant professor	assistant	
cluster_16	environmental	faculty	federal	
cluster_17	science	university	director	
cluster_18	oxford	associate	center	
cluster_19	physics	sciences	management	

```
                     keyword_9
cluster_0                  phd
cluster_1              federal
cluster_2        environmental
cluster_3              federal
cluster_4        distinguished
cluster_5             national
cluster_6               fellow
cluster_7            economics
cluster_8             stanford
cluster_9        environmental
cluster_10  professor computer
cluster_11          california
cluster_12             federal
cluster_13            medicine
cluster_14              cancer
cluster_15             germany
cluster_16              fellow
cluster_17           economics
cluster_18            research
cluster_19          washington
```

In [45]:
```python
tsne_tfidf_dfAff['clusters'] = kmeans_clusters
kmeans.n_clusters
```

Out[45]:
```
20
```

In [46]:
```python
kmeans_clusters1 = list(map(str,kmeans_clusters))
tsne_tfidf_dfAff.head()
```

Out[46]:
```
           x          y   Category      ReporterName  \
0  -9.728665  -1.908636   Magazine  diego bernardini
1 -18.391047  -1.789205   Magazine       raquel beer
2  37.898724 -33.167332  Newspaper   conrado morenoã
3  38.114857 -33.231438  Newspaper    rosario medina
4  36.284264 -32.078583  Newspaper   javier sampedro

                                       Affiliations  clusters
0  Instituto Universitario de Ciencias Medicas Fu...         0
1  Teacher Department Nursing Faculty Health Scie...        11
2  Profesor del Centro de Estudio de Tecnologias ...         2
3  Universidad del Rosario Facultad de Jurisprude...         2
4                 Catedrático de ciencias del deporte         0
```

In [47]:
```python
color_lookup = dict(zip(set(kmeans_clusters),palette))
tsne_tfidf_dfAff['colors'] = tsne_tfidf_dfAff['clusters'].apply(lambda x:color_lookup
```

In [48]:
```python
output_notebook()
plot_tfidf = bp.figure(plot_width=700, plot_height=600, title="tf-idf clustering of th
```

```
            tools="pan,wheel_zoom,box_zoom,reset,hover,previewsave",
            x_axis_type=None, y_axis_type=None, min_border=1)

        palette = d3['Category20'][kmeans.n_clusters]
        color_map = bmo.CategoricalColorMapper(factors=list(set(kmeans_clusters1)), palette=pa

        plot_tfidf.scatter(x='x', y='y', color='colors',
                           legend='clusters', source=tsne_tfidf_dfAff)
        hover = plot_tfidf.select(dict(type=HoverTool))
        hover.tooltips={"Reporter Name": "@ReporterName", "Category":"@Category","Cluster#":"@

        show(plot_tfidf)
```

2.6.2 Clustering on Interests

Next interesting attribute to look at is interest , although this doesnt hold that much significance in terms of reporting, it could still give us a fair idea of how similar the interests of reporters are.

Preprocessing Text of Interests

```
In [49]: df['Interests'] = df['Interests'].apply(lambda x:toString(x))
         df['Cleaned Interests'] = df['Interests'].apply(lambda x:secondClean(x))
         vectorizer = TfidfVectorizer(min_df=5, analyzer='word', ngram_range=(1, 2), stop_words
         vz2 = vectorizer.fit_transform(list(df['Cleaned Interests']))

         vz2.shape

Out[49]: (600, 105)

In [50]: svd = TruncatedSVD(n_components=50, random_state=0)
         svd_tfidf = svdAff.fit_transform(vz2)
         svd_tfidf.shape

Out[50]: (600, 50)

In [51]: tsne_model = TSNE(n_components=2,perplexity=10, verbose=1, random_state=0, n_iter=2000
         tsne_tfidf = tsne_modelAff.fit_transform(svd_tfidf)
         print(tsne_tfidf.shape)

[t-SNE] Computing 31 nearest neighbors...
[t-SNE] Indexed 600 samples in 0.002s...
[t-SNE] Computed neighbors for 600 samples in 0.051s...
[t-SNE] Computed conditional probabilities for sample 600 / 600
[t-SNE] Mean sigma: 0.000000
[t-SNE] KL divergence after 250 iterations with early exaggeration: 75.665688
[t-SNE] KL divergence after 2000 iterations: 0.713738
(600, 2)
```

```
In [52]: tsne_tfidf_df1 = pd.DataFrame(tsne_tfidf)
         tsne_tfidf_df1.columns = ['x', 'y']
         tsne_tfidf_df1['Category'] = df['Category']
         tsne_tfidf_df1['ReporterName'] = df['Reporter Name']
         tsne_tfidf_df1['Interests'] = df['Interests']
```

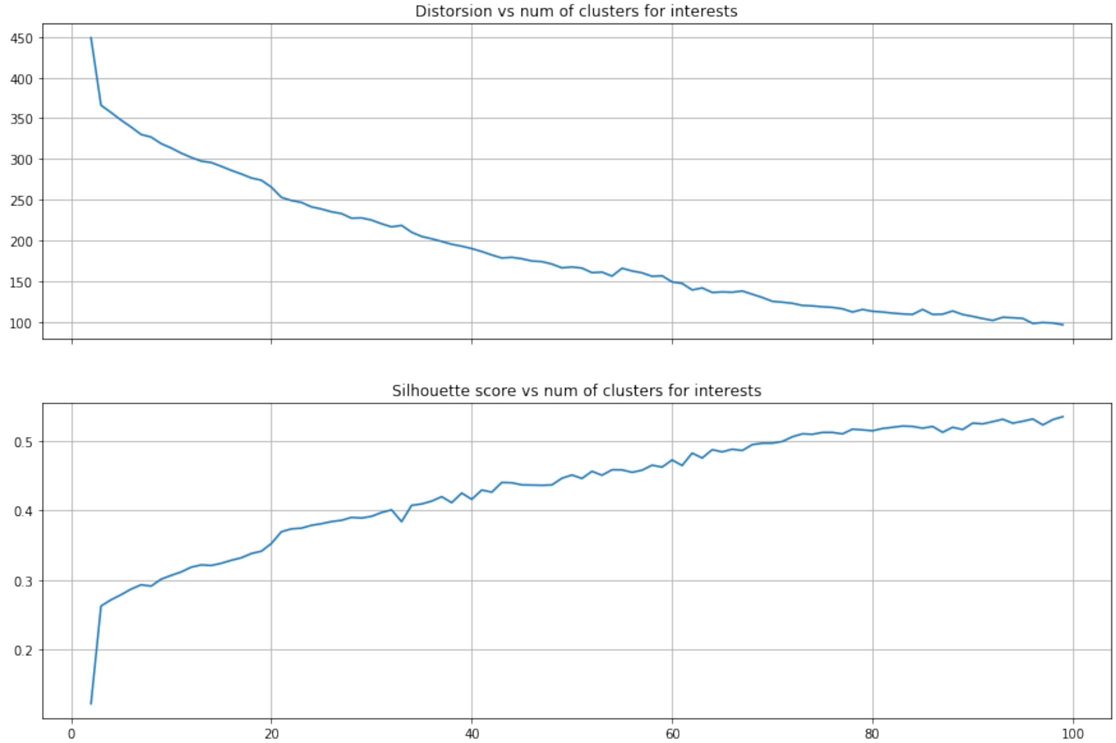
```
In [53]: output_notebook()
         plot_tfidf = bp.figure(plot_width=700, plot_height=600, title="tf-idf clustering of tl
             tools="pan,wheel_zoom,box_zoom,reset,hover,previewsave",
             x_axis_type=None, y_axis_type=None, min_border=1)

         palette = d3['Category10'][len(tsne_tfidf_df1['Category'].unique())]
         color_map = bmo.CategoricalColorMapper(factors=tsne_tfidf_df1['Category'].map(str).uni

         plot_tfidf.scatter(x='x', y='y', color={'field': 'Category', 'transform': color_map},
                            legend='Category', source=tsne_tfidf_df1)
         hover = plot_tfidf.select(dict(type=HoverTool))
         hover.tooltips={"Reporter Name": "@ReporterName", "Category":"@Category","Interests":'

         show(plot_tfidf)
```

Distorsion and Silhouette Scores for Interests

```
In [54]: distorsions = []
         sil_scores = []
         k_max = 100
         for k in tqdm_notebook(range(2, k_max)):
             kmeans_model = MiniBatchKMeans(n_clusters=k, init='k-means++', n_init=1, random_s
                                      init_size=1000, verbose=False, max_iter=1000)
             kmeans_model.fit(vz2)
             sil_score = silhouette_score(vz2, kmeans_model.labels_)
             sil_scores.append(sil_score)
             distorsions.append(kmeans_model.inertia_)
```

```
HBox(children=(IntProgress(value=0, max=98), HTML(value='')))
```

```
In [55]: f, (ax1, ax2) = plt.subplots(2, 1, sharex=True, figsize=(15, 10))

         ax1.plot(range(2, k_max), distorsions)
         ax1.set_title('Distorsion vs num of clusters for interests')
         ax1.grid(True)

         ax2.plot(range(2, k_max), sil_scores)
         ax2.set_title('Silhouette score vs num of clusters for interests')
         ax2.grid(True)
```



Clustering

```
In [56]: num_clusters = 20
         kmeans_model = MiniBatchKMeans(n_clusters=num_clusters, init='k-means++', n_init=1, ra
                                  init_size=1000, batch_size=1000, verbose=False, max_iter=1000
         kmeans = kmeans_model.fit(vz2)
         kmeans_clusters = kmeans.predict(vz2)
         kmeans_distances = kmeans.transform(vz2)

In [57]: tsne_tfidf_df1['clusters'] = kmeans_clusters
         tsne_tfidf_df1['colors'] = tsne_tfidf_df1['clusters'].apply(lambda x:color_lookup.get

In [58]: output_notebook()
         plot_tfidf = bp.figure(plot_width=700, plot_height=600, title="tf-idf clustering of tl
             tools="pan,wheel_zoom,box_zoom,reset,hover,previewsave",
             x_axis_type=None, y_axis_type=None, min_border=1)

         palette = d3['Category20'][kmeans.n_clusters]
         color_map = bmo.CategoricalColorMapper(factors=list(set(kmeans_clusters1)), palette=pa

         plot_tfidf.scatter(x='x', y='y', color='colors',
                            legend='clusters', source=tsne_tfidf_df1)
         hover = plot_tfidf.select(dict(type=HoverTool))
```

```
hover.tooltips={"Reporter Name": "@ReporterName", "Category":"@Category","Cluster#":"(

show(plot_tfidf)
```

Here, the majority of interests are included in cluster 0 and small clusters are scattered all over the place. Thus no strong similarity in interests noted.

Clusters of Keywords

In [59]:
```
sorted_centroids = kmeans.cluster_centers_.argsort()[:, ::-1]
terms = vectorizer.get_feature_names()
all_keywords = []
for i in range(kmeans.n_clusters):
    topic_keywords = []
    for j in sorted_centroids[i, :10]:
        topic_keywords.append(terms[j])
    all_keywords.append(topic_keywords)

keywords_df = pd.DataFrame(index=['cluster_{0}'.format(i) for i in range(num_clusters)
                           columns=['keyword_{0}'.format(i) for i in range(10)],
                           data=all_keywords)
keywords_df
```

Out[59]:
```
                keyword_0             keyword_1    keyword_2  \
cluster_0         science              learning       social
cluster_1             nan                theory       design
cluster_2     engineering  software engineering      systems
cluster_3          health         public health       public
cluster_4         ecology          evolutionary      biology
cluster_5       cognitive            psychology  recognition
cluster_6        genetics        bioinformatics     genomics
cluster_7    conservation               ecology      biology
cluster_8          cancer               biology     clinical
cluster_9        medicine                  care      nuclear
cluster_10        biology             molecular   structural
cluster_11   neuroscience               imaging      biology
cluster_12       modeling               science         care
cluster_13     psychology                social        media
cluster_14         theory               studies  development
cluster_15     management               capital     learning
cluster_16      education             sociology      medical
cluster_17            law             economics   management
cluster_18        climate                change      ecology
cluster_19      chemistry             materials   processing

                        keyword_3       keyword_4      keyword_5  \
cluster_0                 machine         physics       analysis
cluster_1                 digital        dynamics        ecology
```

cluster_2	software	human	management
cluster_3	global	medical	psychology
cluster_4	evolution	theory	digital
cluster_5	neural	law	theory
cluster_6	gene	research	biology
cluster_7	conservation biology	animal	marine
cluster_8	physics	research	digital
cluster_9	physics	health	global
cluster_10	plant	bioinformatics	physiology
cluster_11	cognitive	theory	evolution
cluster_12	quality	computer	theory
cluster_13	clinical	climate	risk
cluster_14	physics	innovation	social
cluster_15	systems	intelligence	economics
cluster_16	biology	psychology	technology
cluster_17	regulation	health	theory
cluster_18	marine	conservation	gene
cluster_19	structural	physics	environmental

	keyword_6	keyword_7	keyword_8 \
cluster_0	machine learning	systems	computer
cluster_1	economics	education	energy
cluster_2	programming	information	interaction
cluster_3	care	human	research
cluster_4	dynamics	economics	education
cluster_5	environmental	digital	dynamics
cluster_6	computational biology	nuclear	computational
cluster_7	science	management	materials
cluster_8	dynamics	ecology	economics
cluster_9	science	environmental	development
cluster_10	marine	cancer	computational biology
cluster_11	dynamics	ecology	economics
cluster_12	epidemiology	digital	dynamics
cluster_13	behavior	management	economics
cluster_14	sociology	organizational	science
cluster_15	mining	public	ecology
cluster_16	research	marine	medicine
cluster_17	digital	dynamics	ecology
cluster_18	dynamics	economics	education
cluster_19	nuclear	biology	dynamics

	keyword_9
cluster_0	information
cluster_1	engineering
cluster_2	computer
cluster_3	cancer
cluster_4	energy
cluster_5	ecology

```
cluster_6             human
cluster_7           natural
cluster_8         education
cluster_9           digital
cluster_10    computational
cluster_11        education
cluster_12          ecology
cluster_13        education
cluster_14           neural
cluster_15         dynamics
cluster_16          science
cluster_17        education
cluster_18           energy
cluster_19          imaging
```

Cluster 0 is the biggest cluster but after looking the most frequent keyword it is still difficult to form a judgement on the interests.

2.7 Bigram analysis on Affiliations

Since with single words it is difficult to form an opinion , bigrams would help us to form a better inference of the common context in various texts.

```
In [60]: text = list(df['Cleaned Affiliations'])

In [61]: bigrams = [b for l in text for b in zip(l.split(" ")[:-1], l.split(" ")[1:])]

In [62]: from collections import Counter
         counter = Counter()
         for l in text:
             for t in range(0,len(l.split(" "))-1):
                 counter.update([l.split(" ")[t]+" "+l.split(" ")[t+1]])
         counter.most_common(10)

Out[62]: [('Unknown affiliation', 26),
          ('State University', 21),
          ('Associate Professor', 20),
          ('Assistant Professor', 11),
          ('Medical Center', 10),
          ('Professor University', 10),
          ('University North', 9),
          ('North Carolina', 8),
          ('University California', 8),
          ('Computer Science', 8)]
```

There are around 600 records and within these records only 26 Unknown affiliations occur> like wise with other bigrams, it could mean the affiliations are varied. Though, State University and Associate/Assistant Professors seem to lead in the data.

2.8 Bigram Analysis on Interests

```
In [63]: InterestText = df['Cleaned Interests'].str.lower()
         InterestCounter = Counter()
         for l in InterestText:
             for t in range(0,len(l.split(" "))-1):
                 InterestCounter.update([l.split(" ")[t]+" "+l.split(" ")[t+1]])
         InterestCounter.most_common(10)
```

```
Out[63]: [('machine learning', 14),
          ('artificial intelligence', 7),
          ('software engineering', 6),
          ('natural language', 6),
          ('public health', 5),
          ('data science', 5),
          ('language processing', 5),
          ('conservation biology', 5),
          ('computational biology', 5),
          ('molecular biology', 4)]
```

The counts though insignificant in comparison to the total data, but we can identify a general trend Interests have a bend towards scientific topics like Machine Learning ,Natural Language Processing and Biology.

2.9 Bigram Analysis on Publication Text

```
In [64]: PublicationCounter = Counter()
         PublicationTexts = df['Cleaned Publications']
         for l in tqdm_notebook(PublicationTexts):
             for t in range(0,len(l.split(" "))-1):
                 PublicationCounter.update([l.split(" ")[t]+" "+l.split(" ")[t+1]])
```

```
HBox(children=(IntProgress(value=0, max=600), HTML(value='')))
```

```
In [65]: PublicationCounter.most_common(20)
```

```
Out[65]: [('united states', 136),
          ('present study', 82),
          ('results show', 81),
          ('paper presents', 77),
          ('climate change', 73),
          ('gene expression', 65),
          ('mental health', 64),
          ('risk factors', 61),
          ('case study', 59),
```

```
('health care', 57),
('age years', 57),
('purpose study', 55),
('wide range', 55),
('recent years', 53),
('older adults', 53),
('results indicate', 52),
('data collected', 49),
('aim study', 48),
('little known', 48),
('magnetic resonance', 47)]
```

No strong inference can be judged from here. Though, health and medicine seem to be a more commonly discussed subject.

```
In [ ]:
```

```
In [ ]:
```