In [1]:
```
import math
import matplotlib as mpl
from matplotlib import cm
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from pprint import pprint
import re
import seaborn
import time
import warnings

import nltk
#nltk.download()
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
nltk.download('stopwords')
stop_words = set(stopwords.words('english'))

from sklearn.decomposition import NMF
from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, make_scorer, accuracy_score, con
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.svm import SVC
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\jftgxfjxg\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

EDA

First, the training data is examined to see what columns exist and what type of information they hold. Each column is then check for common bad values: empty, NaN, or null, of which none are found.

In [2]:
```
df_train = pd.read_csv('https://raw.githubusercontent.com/obbrown1/Unsupervised-Alg
df_test = pd.read_csv('https://raw.githubusercontent.com/obbrown1/Unsupervised-Algo
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1490 entries, 0 to 1489
Data columns (total 3 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   ArticleId  1490 non-null   int64 
 1   Text       1490 non-null   object
 2   Category   1490 non-null   object
dtypes: int64(1), object(2)
memory usage: 35.0+ KB
```

In [3]:
```python
df_train.head()
```

Out[3]:

	ArticleId	Text	Category
0	1833	worldcom ex-boss launches defence lawyers defe...	business
1	154	german business confidence slides german busin...	business
2	1101	bbc poll indicates economic gloom citizens in ...	business
3	1976	lifestyle governs mobile choice faster bett...	tech
4	917	enron bosses in $168m payout eighteen former e...	business

In [4]:
```python
# Check for empty values
empty_columns = df_train.columns[df_train.isnull().all()]
print("Empty columns:", empty_columns)

# Check for null values
null_columns = df_train.columns[df_train.isnull().any()]
print("Null columns:", null_columns)

# Check for NaN values
nan_columns = df_train.columns[df_train.isna().any()]
print("NaN columns:", nan_columns)

# Check for missing values
missing_columns = df_train.columns[df_train.isnull().any() | df_train.isna().any()]
print("Missing value columns:", missing_columns)
```

```
Empty columns: Index([], dtype='object')
Null columns: Index([], dtype='object')
NaN columns: Index([], dtype='object')
Missing value columns: Index([], dtype='object')
```

A few calculated columns are added to further explore the data.

In [5]:
```python
def count_words(text):
    words = text.split()
    return len(words)

def len_text(text):
    return len(text)

# Apply the count_words function to each row of the 'text' column
df_train['word count'] = df_train['Text'].apply(count_words)
df_train['len'] = df_train['Text'].apply(len_text)
df_train['avg_word_length'] = df_train['len'] / df_train['word count']
df_train
```

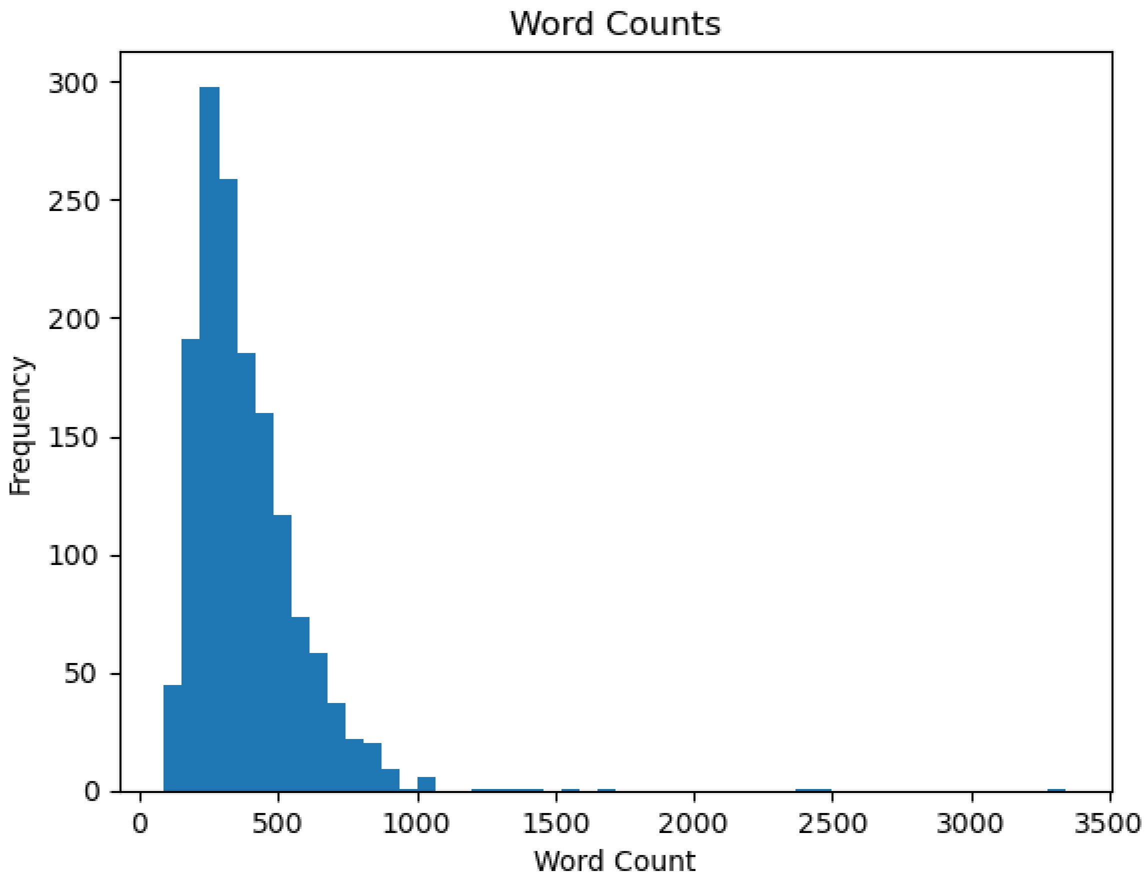
Out[5]:

	ArticleId	Text	Category	word count	len	avg_word_length
0	1833	worldcom ex-boss launches defence lawyers defe...	business	301	1866	6.199336
1	154	german business confidence slides german busin...	business	325	2016	6.203077
2	1101	bbc poll indicates economic gloom citizens in ...	business	514	3104	6.038911
3	1976	lifestyle governs mobile choice faster bett...	tech	634	3618	5.706625
4	917	enron bosses in $168m payout eighteen former e...	business	355	2190	6.169014
...	...	...	...	...	...	...
1485	857	double eviction from big brother model caprice...	entertainment	223	1266	5.677130
1486	325	dj double act revamp chart show dj duo jk and ...	entertainment	558	3111	5.575269
1487	1590	weak dollar hits reuters revenues at media gro...	business	237	1370	5.780591
1488	1587	apple ipod family expands market apple has exp...	tech	560	3242	5.789286
1489	538	santy worm makes unwelcome visit thousands of ...	tech	295	1723	5.840678

1490 rows × 6 columns

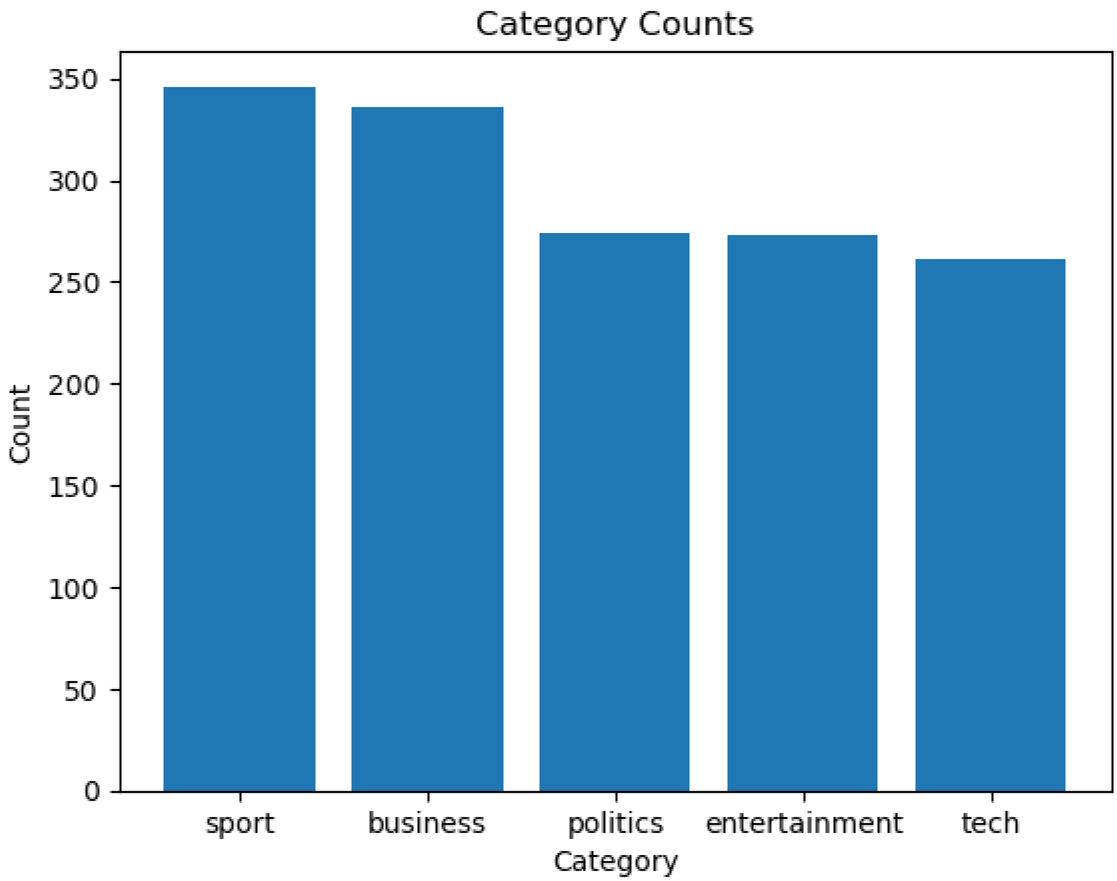
In [6]:

```
#Plot word counts
plt.hist(df_train['word count'], bins = 50)
plt.xlabel('Word Count')
plt.ylabel('Frequency')
plt.title('Word Counts')
plt.show()
```



In [7]:
```
category_counts = df_train['Category'].value_counts()

#Plot category counts
plt.bar(category_counts.index, category_counts.values)
plt.xlabel('Category')
plt.ylabel('Count')
plt.title('Category Counts')
plt.show()
```

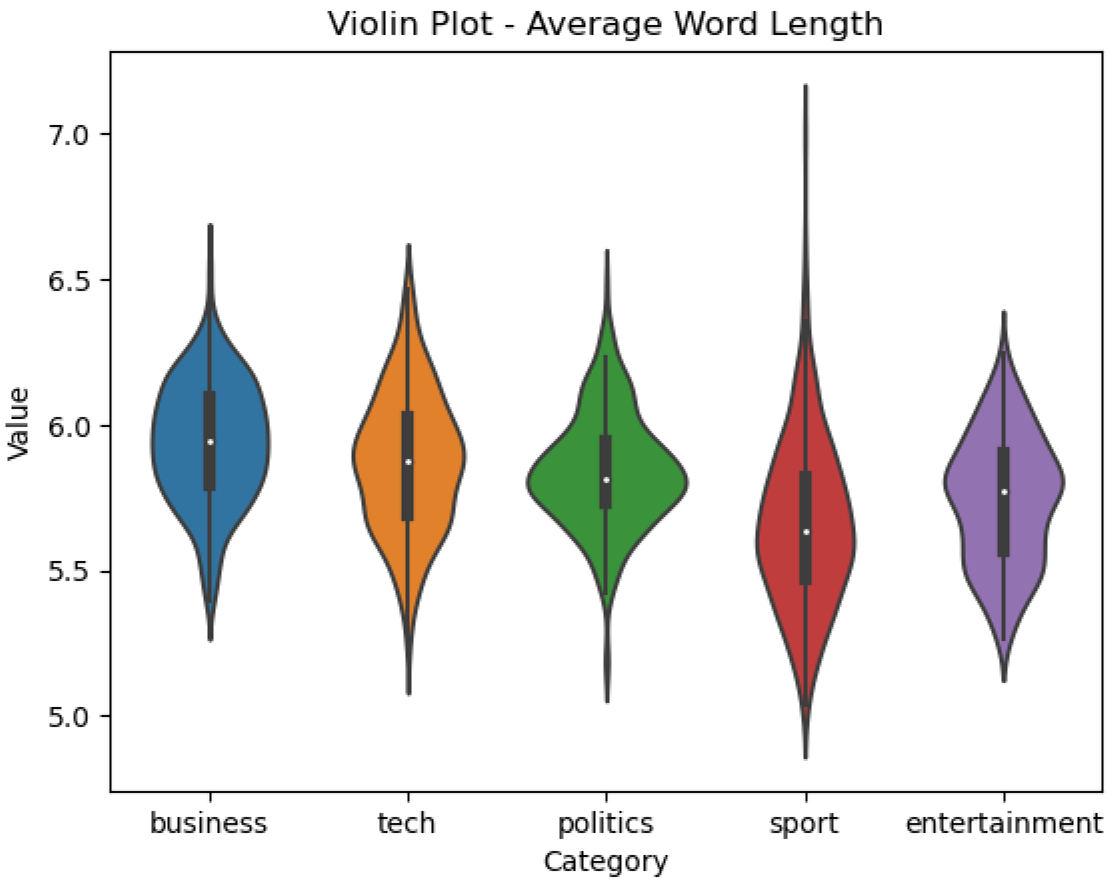


In [8]:

```
#Violin plot of word counts
seaborn.violinplot(x='Category', y='avg_word_length', data=df_train)

# Set labels and title
plt.xlabel('Category')
plt.ylabel('Value')
plt.title('Violin Plot - Average Word Length')

# Show the plot
plt.show()
```



In [9]:
```
filtered_df = df_train[df_train['avg_word_length'] > 6]
sorted_df = filtered_df.sort_values(by='avg_word_length', ascending=False)
sorted_df
```

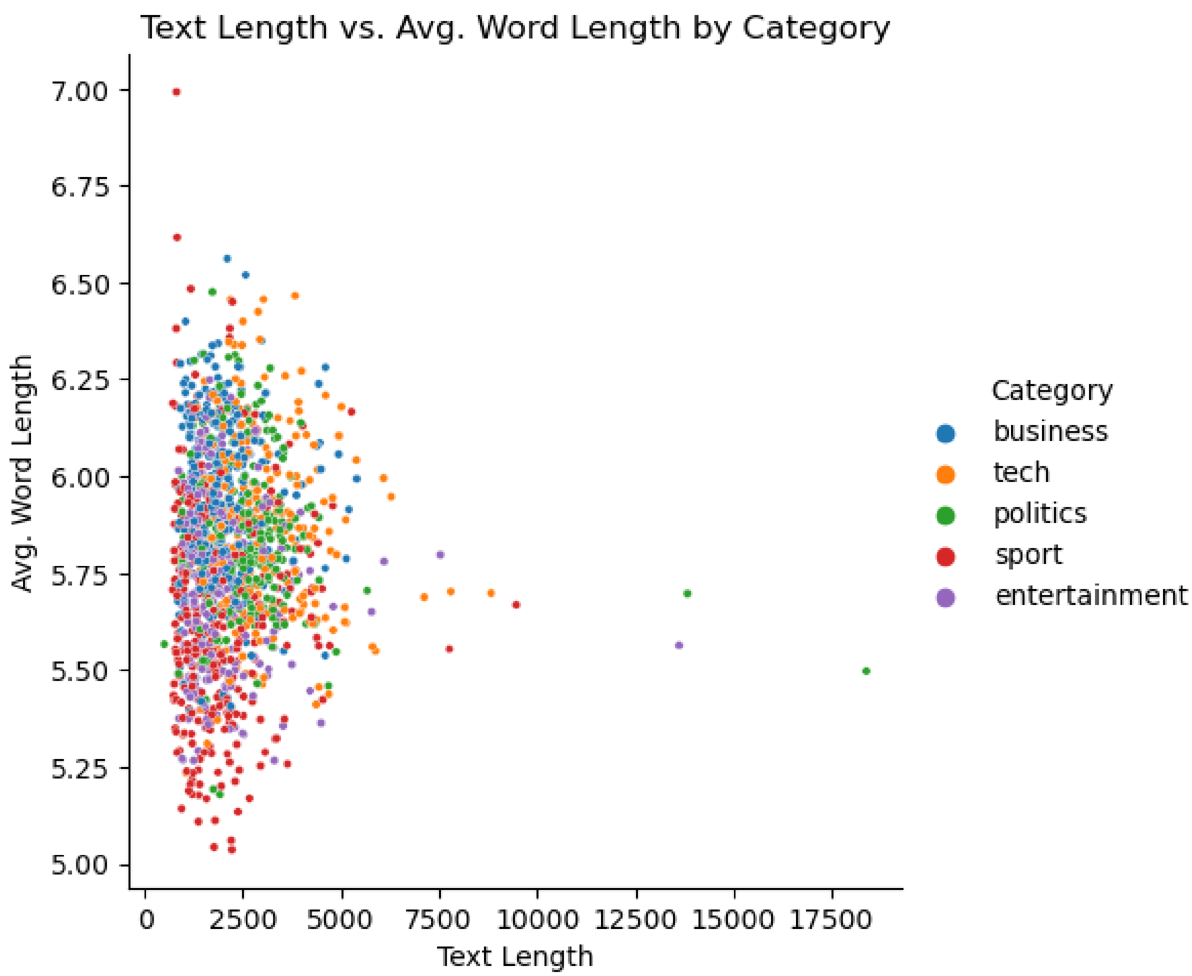
Out[9]:

	ArticleId	Text	Category	word count	len	avg_word_length
657	2111	worcester v sale (fri) sixways friday 25 feb...	sport	116	811	6.991379
852	1320	hereford 1-1 doncaster hereford win 3-1 on pen...	sport	125	827	6.616000
115	461	monsanto fined $1.5m for bribery the us agroch...	business	321	2106	6.560748
769	984	india seeks to boost construction india has cl...	business	395	2575	6.518987
1201	1808	english clubs make euro history all four of en...	sport	182	1180	6.483516
...	...	...	...	...	...	...
284	727	merritt close to indoor 400m mark teenager las...	sport	243	1460	6.008230
1106	1950	huge rush for jet airways shares indian airlin...	business	215	1291	6.004651
1129	801	more women turn to net security older people a...	tech	615	3692	6.003252
711	500	argentina closes $102.6bn debt swap argentina ...	business	321	1927	6.003115
486	2021	ad sales boost time warner profit quarterly pr...	business	426	2557	6.002347

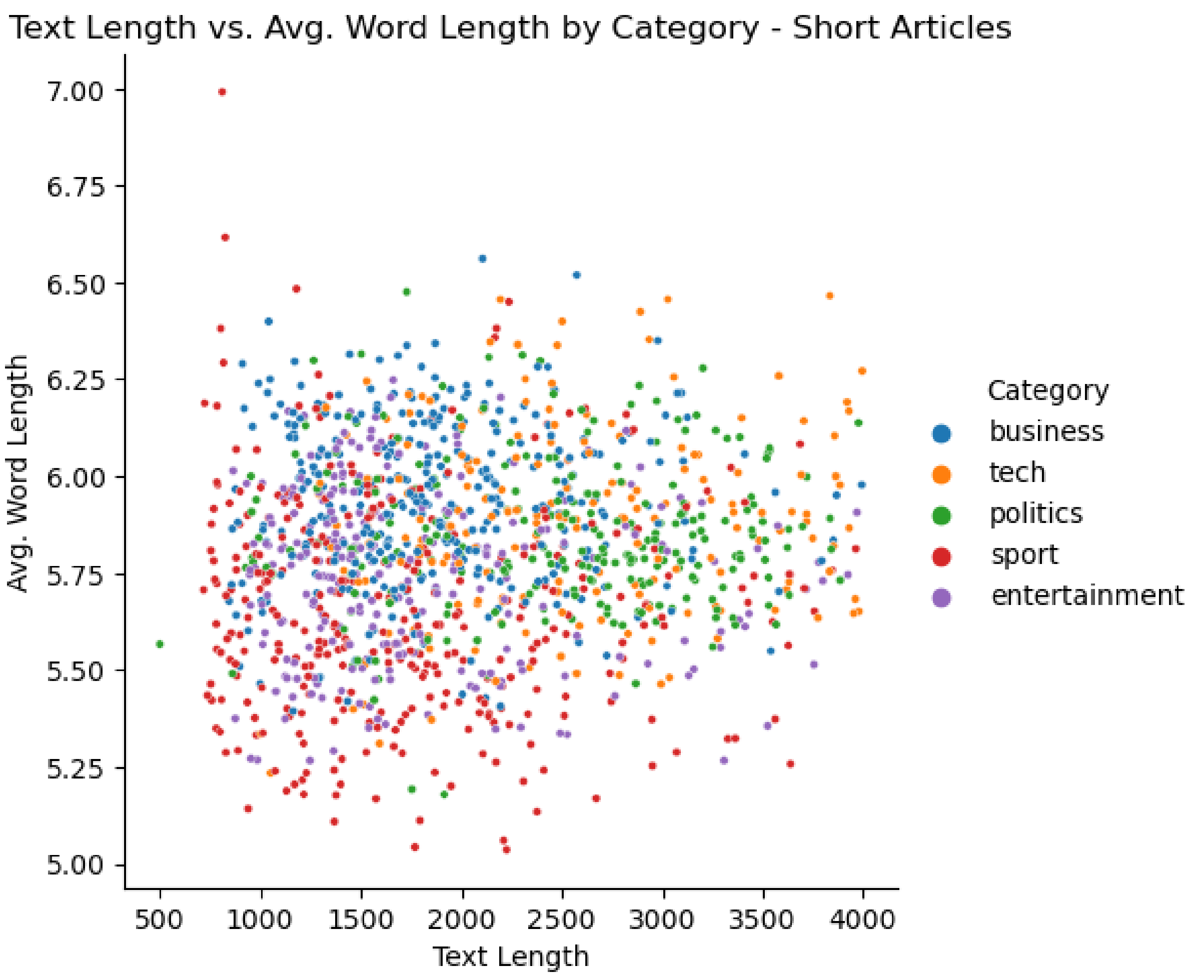
325 rows × 6 columns

In [10]:

```
seaborn.relplot(data=df_train, x='len', y='avg_word_length', hue='Category', s=10)
plt.xlabel('Text Length')
plt.ylabel('Avg. Word Length')
plt.title('Text Length vs. Avg. Word Length by Category')
plt.show()
```



In [11]:
```
df_short = df_train[df_train['len'] < 4000]
seaborn.relplot(data=df_short, x='len', y='avg_word_length', hue='Category', s=10)
plt.xlabel('Text Length')
plt.ylabel('Avg. Word Length')
plt.title('Text Length vs. Avg. Word Length by Category - Short Articles')
plt.show()
```



Data Cleaning

Below is an example of a single text field. The data cleaning function is then applied to the training data, which removes stop words, punctuation, and blank spaces. Stop word are extremely common words such as "a", "and", and "the", which do little to discriminate one piece of text from another. Removing them, along with punctuation and blank spaces, increases the signal-to-noise ratio of the text, speeds up algorithm runtimes, and makes workflows more portable across different datasets.

As shown below, applying the cleaning function significantly reduces the word count and text length, and slightly increases the average word length, as would be expected. It shifts average word counts up across all categories, and removes some many of the outliers on the low end of the average word length measure.

In [12]:

```
print(df_train['Text'][0][:500])
print('\nText length: ', df_train['len'][0])
print('Word count: ', df_train['word count'][0])
print('Average word length: ', df_train['avg_word_length'][0])
```

```
worldcom ex-boss launches defence lawyers defending former worldcom chief bernie ebb
ers against a battery of fraud charges have called a company whistleblower as their
first witness.  cynthia cooper  worldcom s ex-head of internal accounting  alerted d
irectors to irregular accounting practices at the us telecoms giant in 2002. her war
nings led to the collapse of the firm following the discovery of an $11bn (£5.7bn) a
ccounting fraud. mr ebbers has pleaded not guilty to charges of fraud and conspi

Text length:  1866
Word count:  301
Average word length:  6.1993355481727574
```

In [13]:
```python
def clean_text(text):

    text = re.sub(r'[^\w\s]', '', text)
    text = re.sub(r'\d+', '', text)
    words = text.split()
    filtered_words = [word for word in words if word.lower() not in stop_words]
    filtered_text = ' '.join(filtered_words)
    return filtered_text

df_train_c = df_train
df_train_c['Text'] = df_train_c['Text'].apply(clean_text)
df_test_c = df_train
df_test_c['Text'] = df_train_c['Text'].apply(clean_text)
df_train_c['word count'] = df_train_c['Text'].apply(count_words)
df_train_c['len'] = df_train_c['Text'].apply(len_text)
df_train_c['avg_word_length'] = df_train_c['len'] / df_train_c['word count']
```

In [14]:
```python
print(df_train_c['Text'][0][:500])
print('\nText length: ', df_train_c['len'][0])
print('Word count: ', df_train_c['word count'][0])
print('Average word length: ', df_train_c['avg_word_length'][0])
```

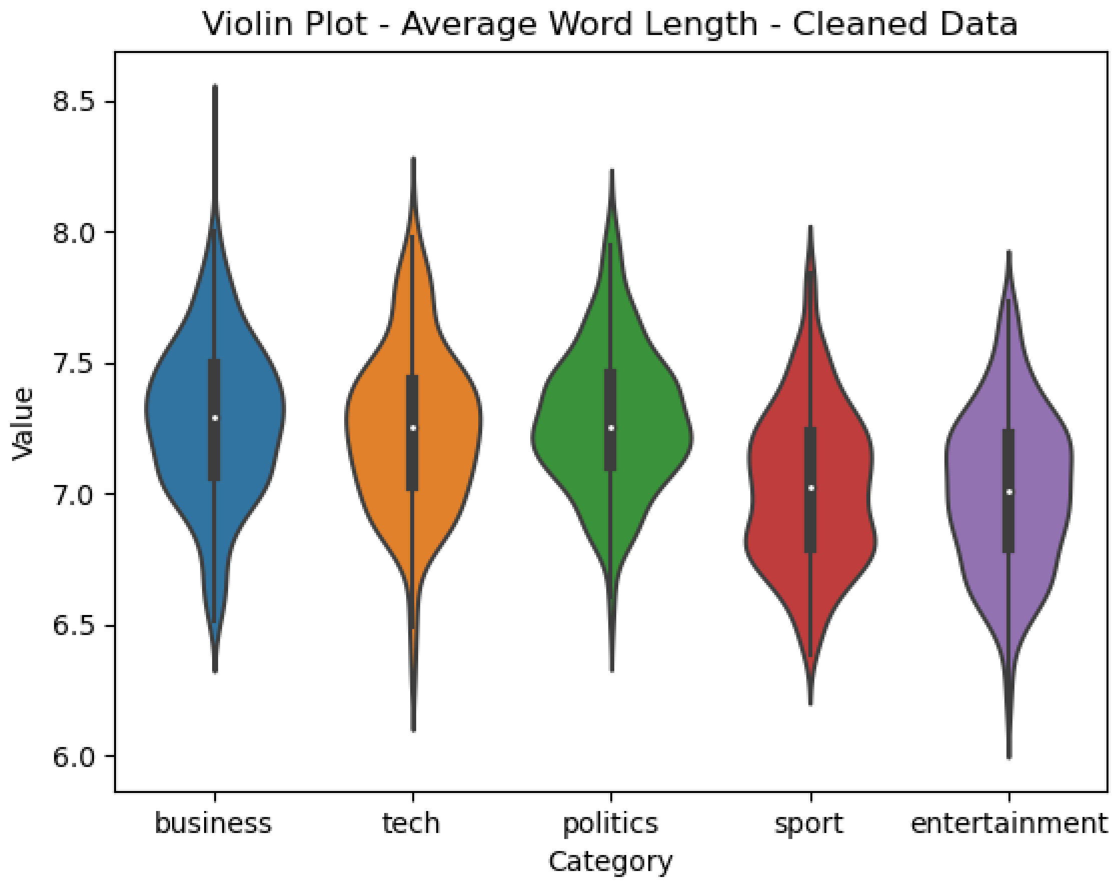
```
worldcom exboss launches defence lawyers defending former worldcom chief bernie ebbe
rs battery fraud charges called company whistleblower first witness cynthia cooper w
orldcom exhead internal accounting alerted directors irregular accounting practices
us telecoms giant warnings led collapse firm following discovery bn bn accounting fr
aud mr ebbers pleaded guilty charges fraud conspiracy prosecution lawyers argued mr
ebbers orchestrated series accounting tricks worldcom ordering employees hide ex

Text length:  1388
Word count:  185
Average word length:  7.5027027027027025
```

In [15]:
```python
#Violin plot of word counts
seaborn.violinplot(x='Category', y='avg_word_length', data=df_train_c)

# Set labels and title
plt.xlabel('Category')
plt.ylabel('Value')
plt.title('Violin Plot - Average Word Length - Cleaned Data')

# Show the plot
plt.show()
```



Analysis - Feature Extraction

I will use term frequency-inverse document frequency (TF-IDF) to extract features from the text data and prepare it to be used as input for non-negative matrix factorization (NMF). At a high level, TF-IDF is an algorithm to assign weights to words within documents which themselves appear within a larger corpus of many such documents. It assigns a heavier weight to a word that appears more frequently in a document, and offets that weight based on how frequently it appears in the whole of the corpus. Therefore, words that are more unique to and characteristic of a given document will be weighted more heavily.

Having explored the data, it is clear that removing stop words and extraneous characters like punctuation and white space has improved the data and better prepared it for analysis using TF-IDF and NMF. Removing stop words not only increases efficiency by condensing the corpus of text, it also increases the signal to noise ratio of the text by removing words that do little to differentiate documents from eachother and gives the TF-IDF algorithmm a better chance at capturing characteristic words.

Capturing characteristic words is crucial for NMF to effectively identify latent topics and extract meaningful features. Applying TF-IDF first ensures that NMF operates on a representation of the data that captures the relative importance of terms, enabling the discovery of underlying semantic structures and patterns in the text corpus.

In [16]:
```
#Train data only
tvec = TfidfVectorizer()
train_vec = tvec.fit_transform(df_train_c['Text'])

nmf_model = NMF(n_components=5)
train_nmf = nmf_model.fit_transform(train_vec)

classifier = LogisticRegression()
classifier.fit(train_nmf, df_train_c['Category'])

pred_train = classifier.predict(train_nmf)

acc = accuracy_score(df_train_c['Category'], pred_train)
print('Training accuracy: ', acc)
```

```
Training accuracy:  0.8932885906040269
```

In [17]:
```
#Train and test data
#tvec = TfidfVectorizer()
text_data = pd.concat([df_test_c['Text'], df_train_c['Text']], ignore_index=True)
category_data = pd.concat([df_test_c['Category'], df_train_c['Category']], ignore_i
train_vec = tvec.fit_transform(text_data)

#nmf_model = NMF(n_components=5)
train_nmf = nmf_model.fit_transform(train_vec)

classifier = LogisticRegression()
classifier.fit(train_nmf, category_data)

pred_train = classifier.predict(train_nmf)

acc = accuracy_score(category_data, pred_train)
print('Training accuracy: ', acc)
```

```
Training accuracy:  0.9053691275167786
```

Matrix Factorization

When you train the unsupervised model for matrix factorization, should you include texts (word features) from te test dataset or not as the input matrix? Why or why not?

As shown above, using the entirety of the text corpus does improve the training accuracy, likely because it allows the TF-IDF algorithm to create a larger set of vocabulary that can be used to distinguish documents. With other machine learning algorithms, using all of the data to train the model can be problematic, as it may lead to overfitting. In this case, however, that is not a concern, as the target labels are not included in the text data and therefore no overfitting can occur.

In [18]:
```
nmf_model = NMF(n_components=5)
train_nmf = nmf_model.fit_transform(train_vec)

classifier = LogisticRegression()
```

```
classifier.fit(train_nmf, category_data)

pred_train = classifier.predict(train_nmf)

acc = accuracy_score(category_data, pred_train)
print('Training accuracy: ', acc)
```

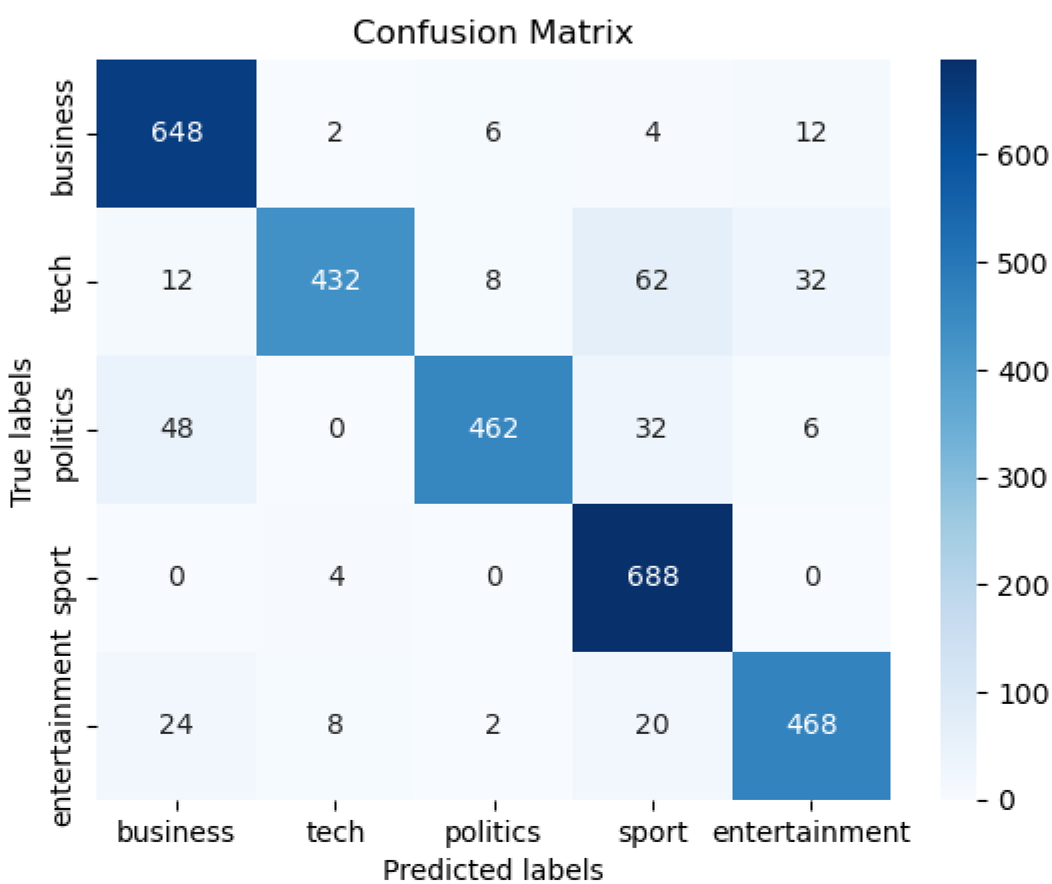
```
Training accuracy:  0.9053691275167786
```

In [19]:
```
cm = confusion_matrix(category_data, pred_train)

# Create a heatmap of the confusion matrix
categories = df_train_c['Category'].unique()
seaborn.heatmap(cm, annot=True, cmap='Blues', fmt='d', xticklabels = categories, yt

# Add labels, title, and ticks to the plot
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.title('Confusion Matrix')
#plt.xticks(ticks=1, labels = df_train_c['Category'].unique())

# Show the plot
plt.show()
```



Hyperparameter Tuning

In [20]:
```
def hyperparameter_tuning_NMF(df):
    pipeline = Pipeline([
        ('tfidf', TfidfVectorizer()),
        ('nmf', NMF()),
        ('classifier', LogisticRegression())
    ])

    param_grid = {
        'tfidf__norm': ['l1', 'l2'],
        'tfidf__max_df': [0.95],
        'tfidf__min_df': [1, 2],
        'nmf__n_components': [5],
        'nmf__solver': ['mu'],
        'nmf__beta_loss': ['frobenius', 'kullback-leibler'],
        'nmf__l1_ratio': [0, 0.5, 1]
    }

    scoring = make_scorer(accuracy_score)
    grid_search = GridSearchCV(pipeline, param_grid, cv=5, scoring=scoring)
    grid_search.fit(df['Text'], df['Category'])

    return (grid_search.best_estimator_, grid_search.best_params_)
```

In [21]:
```
st = time.time()
(best_model, best_params) = hyperparameter_tuning_NMF(df_train_c)
best_params = {key: [value] for key, value in best_params.items()}
pd.DataFrame(best_params)
nmf_pst = time.time() - st
print('Parameter search time: ', nmf_pst)
```

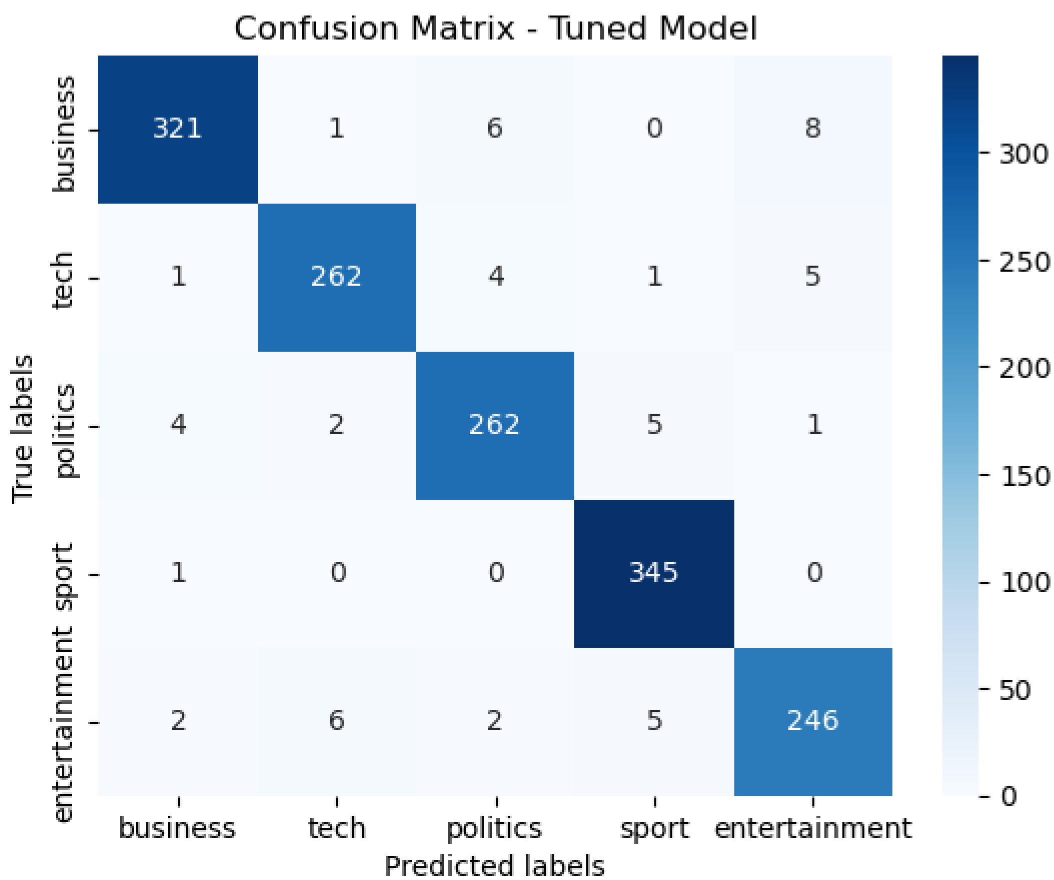
```
Parameter search time:  372.1904239654541
```

In [22]:
```
st = time.time()
pred = best_model.predict(df_test_c['Text'])
nmf_acc = accuracy_score(df_test_c['Category'], pred)
print('NMF accuracy: ', nmf_acc)
nmf_pt = time.time() -st
print('Prediction time: ', nmf_pt)
```

```
NMF accuracy:  0.963758389261745
Prediction time:  2.8959975242614746
```

In [23]:
```
cm2 = confusion_matrix(df_train_c['Category'], pred)

seaborn.heatmap(cm2, annot=True, cmap='Blues', fmt='d', xticklabels = categories, y
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.title('Confusion Matrix - Tuned Model')
plt.show()
```



Supervised Learning - Logistic Regression

In [25]:

```
warnings.filterwarnings('ignore')
st = time.time()

LR_train_vec = tvec.fit_transform(df_train_c['Text'])

logreg = LogisticRegression()
param_grid = {'C': [0.1, 1, 10],
              'solver': ['newton-cg', 'lbfgs', 'liblinear'],
              'penalty':['l1', 'l2']
             }

st = time.time()
grid_search = GridSearchCV(logreg, param_grid, cv=5)
grid_search.fit(LR_train_vec, df_train_c['Category'])
best_params_lr = grid_search.best_params_

lr_pst = time.time() - st
print('Parameter search time: ', lr_pst)
params_lr = {key: [value] for key, value in best_params_lr.items()}
pd.DataFrame(params_lr)
```

```
warnings.filterwarnings('default')
```

```
Parameter search time:  73.70681476593018
```

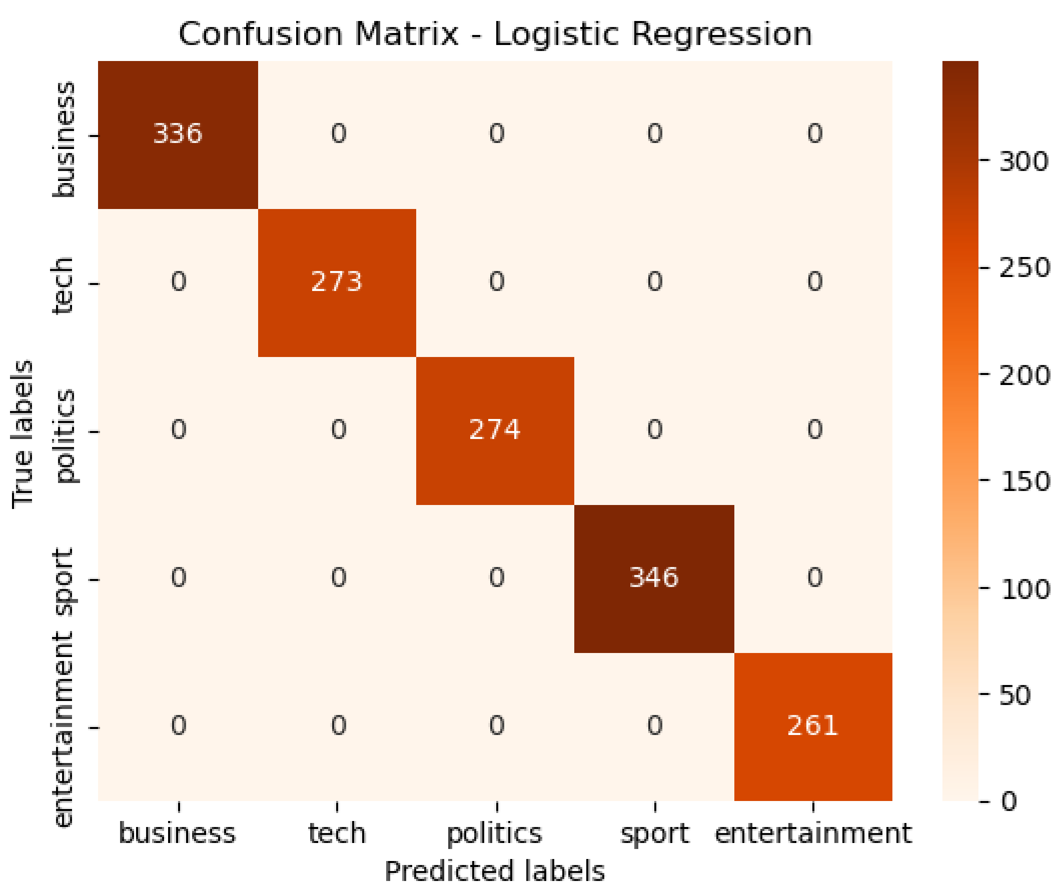
In [26]:
```
logreg_best = LogisticRegression(**best_params_lr)
logreg_best.fit(LR_train_vec, df_train_c['Category'])

LR_test_vec = tvec.fit_transform(df_test_c['Text'])
st = time.time()
y_pred = logreg_best.predict(LR_test_vec)
lr_pt = time.time() - st
print('Predict time: ', lr_pt)

lr_acc = accuracy_score(df_test_c['Category'], y_pred)
print("Accuracy:", lr_acc)
```

```
Predict time:  0.010003089904785156
Accuracy: 1.0
```

In [27]:
```
cm_lr = confusion_matrix(df_train_c['Category'], y_pred)
seaborn.heatmap(cm_lr, annot=True, cmap='Oranges', fmt='d', xticklabels = categorie
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.title('Confusion Matrix - Logistic Regression')
plt.show()
```



Supervised Learning - Logistic Regression - Random Subset

Below, we will see how logistic regression performs on a random subset of the combined train and test data.

In [28]:
```
df_all = pd.concat([df_train_c, df_test_c], ignore_index = 1)
df_rand = df_all.sample(int(len(df_all)*0.5))
LR_random_vec = tvec.fit_transform(df_rand['Text'])

logreg_rand = LogisticRegression(**best_params_lr)
logreg_rand.fit(LR_random_vec, df_rand['Category'])

st = time.time()
y_pred_rand = logreg_rand.predict(LR_random_vec)
lr_rand_pt = time.time() - st
print('Predict time: ', lr_rand_pt)

lr_rand_acc = accuracy_score(df_rand['Category'], y_pred_rand)
print("Accuracy:", lr_rand_acc)
```

```
Predict time:  0.006997823715209961
Accuracy: 1.0
```

Supervised Learning - Random Forest

In [29]:
```
rf = RandomForestClassifier()

param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [3, 5, 7]
}

rf_train_vec = tvec.fit_transform(df_train_c['Text'])
rf_test_vec = tvec.fit_transform(df_test_c['Text'])

st = time.time()
grid_search = GridSearchCV(rf, param_grid, cv=5)
grid_search.fit(rf_train_vec, df_train_c['Category'])
rf_pst = time.time() - st
print('Parameter search time: ', rf_pst)

best_params_rf = grid_search.best_params_
```

```
Parameter search time:  115.38959336280823
```

In [30]:
```
rf_params = {key: [value] for key, value in best_params_rf.items()}
pd.DataFrame(rf_params)
```

Out[30]:

	max_depth	n_estimators
0	7	200

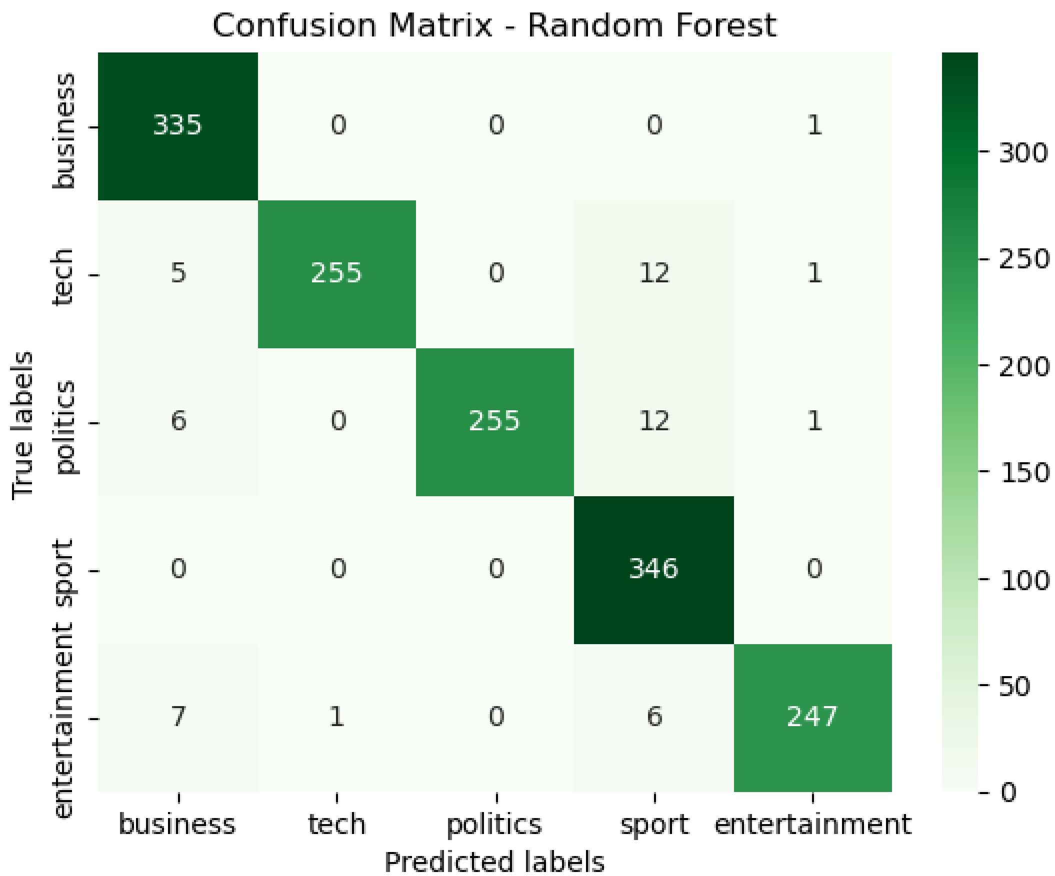
In [31]:
```
# Train the model with the best hyperparameters
rf_best = RandomForestClassifier(**best_params_rf)
rf_best.fit(rf_train_vec, df_train_c['Category'])
```

```
st = time.time()
y_pred_rf = rf_best.predict(rf_test_vec)
rf_pt = time.time() - st

rf_acc = accuracy_score(df_test_c['Category'], y_pred_rf)
print("Accuracy:", rf_acc)
print('Predict time: ', rf_pt)
```

```
Accuracy: 0.9651006711409396
Predict time:  0.5177068710327148
```

In [32]:
```
cm_rf = confusion_matrix(df_train_c['Category'], y_pred_rf)
seaborn.heatmap(cm_rf, annot=True, cmap='Greens', fmt='d', xticklabels = categories
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.title('Confusion Matrix - Random Forest')
plt.show()
```



Supervised Learning - Random Forest - Random Subset

Below, we will see how random forest performs on a random subset of the combined train and test data.

In [33]:
```
rf_rand = RandomForestClassifier(**best_params_rf)
rf_rand_vec = tvec.fit_transform(df_rand['Text'])
rf_rand.fit(rf_rand_vec, df_rand['Category'])
```

```
st = time.time()
y_pred_rf = rf_rand.predict(rf_rand_vec)
rf_pt = time.time() - st

rf_acc = accuracy_score(df_rand['Category'], y_pred_rf)
print("Accuracy:", rf_acc)
print('Predict time: ', rf_pt)
```

```
Accuracy: 0.9778523489932885
Predict time:  0.9708750247955322
```

Supervised vs. Unsupervised Learning

The table below shows that, while all models achieve good accuracy, the supervised methods achieve the best accuracy and in less time than the unsupervised NMF model. Logistic regression, in particular, is the most accurate method of the three, and also the fastest across both time dimensions. One advantage of the NMF model is that it is not prone to overfitting, while the supervised models are. This could become a more significant factor if the dataset were to increase in size or the analysis were to increase in complexity.

In [34]:
```
comparison = pd.DataFrame({
    'Model':['NMF', 'Logistic Regression', 'Random Forest'],
    'Accuracy':[nmf_acc, lr_acc, rf_acc],
    'Tuning Time':[nmf_pst, lr_pst, rf_pst],
    'Prediction Time':[nmf_pt, lr_pt, rf_pt]
})

comparison
```

Out[34]:

	Model	Accuracy	Tuning Time	Prediction Time
0	NMF	0.963758	372.190424	2.895998
1	Logistic Regression	1.000000	73.706815	0.010003
2	Random Forest	0.977852	115.389593	0.970875

References

https://en.wikipedia.org/wiki/Tf%E2%80%93idf

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https://towardsdatascience.com/mastering-random-forests-a-comprehensive-guide-51307c129cb1

https://www.kaggle.com/code/robinlutter/bbc-news-classification-nmf-vs-supervised