Analyzing LIAR Plus Data Set

DataSet Visualization

Loading Training Data Set

In [33]:

```
import pandas as pd
# Read data from file 'filename.csv'
# (in the same directory that your python process is based)
# Control delimiters, rows, column names with read_csv (see later)
data = pd.read_csv("LIAR-PLUS-master/dataset/train2.tsv",sep='\t',
                   names=["Statement ID", "Label", "Statement", "Subject", "Speaker", "Speaker Job's title", "State in
fo",
                          "Party Affiliate", "barely true counts", "false counts", "half true counts", "mostly true co
unts", "pants on fire counts", "venue", "Extracted Justification"])
# Preview the first 5 lines of the loaded data
data.head()
```

Out[33]:

	Statement ID	Label	Statement	Subject	Speaker	Speaker Job's title	State info	Party Affiliate	barely true counts	false counts	half true counts	mostly true counts	pants on fire counts
0	2635.json	false	Says the Annies List political group supports ...	abortion	dwayne-bohac	State representative	Texas	republican	0.0	1.0	0.0	0.0	0.0
1	10540.json	half-true	When did the decline of coal start? It started...	energy,history,job-accomplishments	scott-surovell	State delegate	Virginia	democrat	0.0	0.0	1.0	1.0	0.0
2	324.json	mostly-true	Hillary Clinton agrees with John McCain "by vo...	foreign-policy	barack-obama	President	Illinois	democrat	70.0	71.0	160.0	163.0	9.0
3	1123.json	false	Health care reform legislation is likely to ma...	health-care	blog-posting	NaN	NaN	none	7.0	19.0	3.0	5.0	44.0

	Statement ID	Label	Statement	Subject	Speaker	Speaker Job's title	State info	Party Affiliate	barely true counts	false counts	half true counts	mostly true counts	pants on fire counts
4	9028.json	half-true	The economic turnaround started at the end of ...	economy,jobs	charlie-crist	NaN	Florida	democrat	15.0	9.0	20.0	19.0	2.0

DataSet Available at Tariq/LIAR-Plus (https://github.com/Tariq60/LIAR-PLUS)

- Column 1: the ID of the statement ([ID].json).
- Column 2: the label.
- Column 3: the statement.
- Column 4: the subject(s).
- Column 5: the speaker.
- Column 6: the speaker's job title.
- Column 7: the state info.
- Column 8: the party affiliation.
- Columns 9-13: the total credit history count, including the current statement.
  - 9: barely true counts.
  - 10: false counts.
  - 11: half true counts.
  - 12: mostly true counts.
  - 13: pants on fire counts.
- Column 14: the context (venue / location of the speech or statement).
- Column 15: the extracted justification

In [34]:
```
print(data.dtypes)
print(data.shape)
```

```
Statement ID                 object
Label                        object
Statement                    object
Subject                      object
Speaker                      object
Speaker Job's title          object
State info                   object
Party Affiliate              object
barely true counts          float64
false counts                float64
half true counts            float64
mostly true counts          float64
pants on fire counts        float64
venue                        object
Extracted Justification      object
dtype: object
(10240, 15)
```

In [35]:
```
import pandas as pd
# Read data from file 'filename.csv'
# (in the same directory that your python process is based)
# Control delimiters, rows, column names with read_csv (see later)
test_data = pd.read_csv("LIAR-PLUS-master/dataset/train2.tsv",sep='\t',
                   names=["Statement ID", "Label", "Statement", "Subject", "Speaker", "Speaker Job's title", "State in
fo",
                          "Party Affiliate", "barely true counts", "false counts", "half true counts", "mostly true co
unts", "pants on fire counts", "venue", "Extracted Justification"])
# Preview the first 5 lines of the loaded data
test_data.head()
```

Out[35]:

	Statement ID	Label	Statement	Subject	Speaker	Speaker Job's title	State info	Party Affiliate	barely true counts	false counts	half true counts	mostly true counts	pants on fire counts
0	2635.json	false	Says the Annies List political group supports ...	abortion	dwayne-bohac	State representative	Texas	republican	0.0	1.0	0.0	0.0	0.0
1	10540.json	half-true	When did the decline of coal start? It started...	energy,history,job-accomplishments	scott-surovell	State delegate	Virginia	democrat	0.0	0.0	1.0	1.0	0.0
2	324.json	mostly-true	Hillary Clinton agrees with John McCain "by vo...	foreign-policy	barack-obama	President	Illinois	democrat	70.0	71.0	160.0	163.0	9.0
3	1123.json	false	Health care reform legislation is likely to ma...	health-care	blog-posting	NaN	NaN	none	7.0	19.0	3.0	5.0	44.0

	Statement ID	Label	Statement	Subject	Speaker	Speaker Job's title	State info	Party Affiliate	barely true counts	false counts	half true counts	mostly true counts	pants on fire counts
4	9028.json	half-true	The economic turnaround started at the end of ...	economy,jobs	charlie-crist	NaN	Florida	democrat	15.0	9.0	20.0	19.0	2.0

In [5]:
```
data["Label"].head(20)
```

Out[5]:
```
0           false
1       half-true
2     mostly-true
3           false
4       half-true
5            true
6     barely-true
7       half-true
8       half-true
9     mostly-true
10    mostly-true
11      half-true
12          false
13    mostly-true
14    barely-true
15      half-true
16           true
17    barely-true
18      half-true
19    mostly-true
Name: Label, dtype: object
```

Binary Classification

As we see from the data its a multi-class data having 6 classes namely "false", ""mostly-true", "barely-true", "half-true", "true" , "pants-fire"

For the purpose of Binary Classification, we simply consider labels ""mostly-true", "barely-true", "half-true", "true" as "true" and "false" "pants-fire" as false

Converting Training Data to Binary Labelled Data

In [6]:
```
bin_data = data
```

In [7]:
```
bin_data['Label'] = bin_data['Label'].replace(['false', 'pants-fire'], 0)
```

In [8]:
```
bin_data['Label'] = bin_data['Label'].replace(['mostly-true', 'half-true', 'barely-true', 'true'], 1)
```

In [9]:
```
bin_data['Label'].head(10)
```

Out[9]:
```
0    0
1    1
2    1
3    0
4    1
5    1
6    1
7    1
8    1
9    1
Name: Label, dtype: int64
```

Converting Test Data to Binary Labelled Data

In [10]:
```
test_bin_data = test_data
```

In [11]:
```
test_bin_data['Label'] = test_bin_data['Label'].replace(['false', 'pants-fire'], 0)
test_bin_data['Label'] = test_bin_data['Label'].replace(['mostly-true', 'half-true', 'barely-true', 'true'], 1)
```

In [12]:
```
def evaluate(model, test_set, model_name):

    y_pred = model.predict(test_set['Subject'].values.astype('U'))
    y_true = test_set['Label']
    f1 = f1_score(y_true, y_pred)
    precision = precision_score(y_true, y_pred)
    recall = recall_score(y_true, y_pred)
    accuracy = accuracy_score(y_true, y_pred)

    print('::::: Evaluation Results :::: {}'.format(model_name))
    print('Accuracy is: {}'.format(accuracy))
    print('F1 score is: {}'.format(f1))
    print('Precision score is: {}'.format(precision))
    print('Recall score is: {}'.format(recall))
    return accuracy
```

In [92]:
```
import pandas as pd
from nltk.corpus import stopwords
from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import (accuracy_score, f1_score, precision_score,
                             recall_score)

from sklearn.pipeline import Pipeline
```

Linear Regression

In [15]:
```
lr_pipeline = Pipeline([
    ('lrCV', CountVectorizer(stop_words="english", lowercase=True, ngram_range=(1, 1))),
    ('lr_clf', LogisticRegression(C=0.0001,random_state=42, n_jobs=-1))
])
```

```
In [16]: lr_pipeline.fit(bin_data['Subject'].values.astype('U'), bin_data['Label'])
```

```
C:\Users\pratik\Anaconda2\lib\site-packages\sklearn\linear_model\logistic.py:1228: UserWarning: 'n_jobs' > 1 does not
have any effect when 'solver' is set to 'liblinear'. Got 'n_jobs' = -1.
  " = {}.".format(self.n_jobs))
```

```
Out[16]: Pipeline(memory=None,
     steps=[('lrCV', CountVectorizer(analyzer=u'word', binary=False, decode_error=u'strict',
        dtype=<type 'numpy.int64'>, encoding=u'utf-8', input=u'content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1), preprocessor=None, stop_words='english',
     ...alty='l2', random_state=42,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False))])
```

```
In [17]: lr_acc = evaluate(lr_pipeline, test_bin_data, 'Logistic Regression')
```

```
::::: Evaluation Results :::: Logistic Regression
Accuracy is: 0.7232421875
F1 score is: 0.839397030488
Precision score is: 0.7232421875
Recall score is: 1.0
```

Support Vector Machine

```
In [18]: from sklearn.feature_extraction import text
         from sklearn.svm import SVC
```

```
In [19]: svm_pipeline = Pipeline([
             ('svm_CV', CountVectorizer(stop_words="english", lowercase=False, ngram_range=(1, 1))),
             ('svm_clf', SVC(random_state=42, gamma=1.0, kernel='rbf'))
         ])
```

In [20]:
```
svm_pipeline.fit(bin_data['Subject'].values.astype('U'), bin_data['Label'])
```

Out[20]:
```
Pipeline(memory=None,
     steps=[('svm_CV', CountVectorizer(analyzer=u'word', binary=False, decode_error=u'strict',
        dtype=<type 'numpy.int64'>, encoding=u'utf-8', input=u'content',
        lowercase=False, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1), preprocessor=None, stop_words='english',
  ...f',
  max_iter=-1, probability=False, random_state=42, shrinking=True,
  tol=0.001, verbose=False))])
```

In [21]:
```
svm_acc = evaluate(svm_pipeline, test_bin_data, 'SVM Count Vectorizer')
```

```
::::: Evaluation Results :::: SVM Count Vectorizer
Accuracy is: 0.80400390625
F1 score is: 0.879336259244
Precision score is: 0.792565297496
Recall score is: 0.987442614097
```

Naive Bayes Classification

In [22]:
```
from sklearn.naive_bayes import MultinomialNB
```

In [23]:
```
nb_pipeline = Pipeline([
    ('nb_CV', CountVectorizer(stop_words="english", lowercase=True, ngram_range=(1, 10))),
    ('nb_clf', MultinomialNB(alpha=6.8))
])
```

In [24]:
```
nb_pipeline.fit(bin_data['Subject'].values.astype('U'), bin_data['Label'])
```

Out[24]:
```
Pipeline(memory=None,
     steps=[('nb_CV', CountVectorizer(analyzer=u'word', binary=False, decode_error=u'strict',
        dtype=<type 'numpy.int64'>, encoding=u'utf-8', input=u'content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 10), preprocessor=None, stop_words='english',
        strip_accents=None, token_pattern=u'(?u)\\b\\w\\w+\\b',
        tokenizer=None, vocabulary=None)), ('nb_clf', MultinomialNB(alpha=6.8, class_prior=None, fit_prior=True))])
```

In [25]:
```
nb_acc = evaluate(nb_pipeline, test_bin_data, 'Naive Bayes Count Vectorizer')
```

```
::::: Evaluation Results :::: Naive Bayes Count Vectorizer
Accuracy is: 0.7287109375
F1 score is: 0.842015468608
Precision score is: 0.727353114561
Recall score is: 0.999594923035
```

Random Forest Classifier

In [26]:
```
rf_pipeline = Pipeline([
    ('rf_CV', CountVectorizer(stop_words="english", lowercase=False, ngram_range=(1, 1))),
    ('rf_clf', RandomForestClassifier(max_depth=12, n_estimators=300, n_jobs=-1, random_state=42))
])
```

In [30]:
```
rf_pipeline.fit(bin_data['Subject'].values.astype('U'), bin_data['Label'])
```

Out[30]:
```
Pipeline(memory=None,
     steps=[('rf_CV', CountVectorizer(analyzer=u'word', binary=False, decode_error=u'strict',
        dtype=<type 'numpy.int64'>, encoding=u'utf-8', input=u'content',
        lowercase=False, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1), preprocessor=None, stop_words='english',
   ...imators=300, n_jobs=-1,
            oob_score=False, random_state=42, verbose=0, warm_start=False))])
```

In [32]:
```
rf_acc = evaluate(rf_pipeline, test_data, 'Random Forest')
```

```
::::: Evaluation Results :::: Random Forest
Accuracy is: 0.72685546875
F1 score is: 0.841106629552
Precision score is: 0.725997842503
Recall score is: 0.999594923035
```

Multi Classification

In [36]:
```python
def accuracy(model, test_set, model_name):

    y_pred = model.predict(test_set['Subject'].values.astype('U'))
    y_true = test_set['Label']
    #f1 = f1_score(y_true, y_pred)
    #precision = precision_score(y_true, y_pred)
    #recall = recall_score(y_true, y_pred)
    accuracy = accuracy_score(y_true, y_pred)

    print('::::: Evaluation Results :::: {}'.format(model_name))
    print('Accuracy is: {}'.format(accuracy))
    return accuracy
```

Linear Regression

In [37]:
```python
lr_pipeline.fit(data['Subject'].values.astype('U'), data['Label'])
```

Out[37]:
```
Pipeline(memory=None,
     steps=[('lrCV', CountVectorizer(analyzer=u'word', binary=False, decode_error=u'strict',
        dtype=<type 'numpy.int64'>, encoding=u'utf-8', input=u'content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1), preprocessor=None, stop_words='english',
     ...alty='l2', random_state=42,
          solver='liblinear', tol=0.0001, verbose=0, warm_start=False))])
```

In [38]:
```python
lr_mc_acc = accuracy(lr_pipeline, test_data, 'Logistic Regression ')
```

```
::::: Evaluation Results :::: Logistic Regression
Accuracy is: 0.20732421875
```

Support Vector Machine

```
In [39]: svm_pipeline.fit(data['Subject'].values.astype('U'), data['Label'])
```

```
Out[39]: Pipeline(memory=None,
              steps=[('svm_CV', CountVectorizer(analyzer=u'word', binary=False, decode_error=u'strict',
                 dtype=<type 'numpy.int64'>, encoding=u'utf-8', input=u'content',
                 lowercase=False, max_df=1.0, max_features=None, min_df=1,
                 ngram_range=(1, 1), preprocessor=None, stop_words='english',
           ...f',
           max_iter=-1, probability=False, random_state=42, shrinking=True,
           tol=0.001, verbose=False))])
```

```
In [40]: svm_mc_acc = accuracy(svm_pipeline, test_data, 'SVM Count Vectorizer')
```

```
::::: Evaluation Results :::: SVM Count Vectorizer
Accuracy is: 0.5267578125
```

Naive Bayes

```
In [41]: nb_pipeline.fit(data['Subject'].values.astype('U'), data['Label'])
```

```
Out[41]: Pipeline(memory=None,
              steps=[('nb_CV', CountVectorizer(analyzer=u'word', binary=False, decode_error=u'strict',
                 dtype=<type 'numpy.int64'>, encoding=u'utf-8', input=u'content',
                 lowercase=True, max_df=1.0, max_features=None, min_df=1,
                 ngram_range=(1, 10), preprocessor=None, stop_words='english',
                 strip_accents=None, token_pattern=u'(?u)\\b\\w\\w+\\b',
                 tokenizer=None, vocabulary=None)), ('nb_clf', MultinomialNB(alpha=6.8, class_prior=None, fit_prior=True))])
```

```
In [42]: nb_mc_acc = accuracy(nb_pipeline, test_data, 'Naive Bayes')
```

```
::::: Evaluation Results :::: Naive Bayes
Accuracy is: 0.3337890625
```

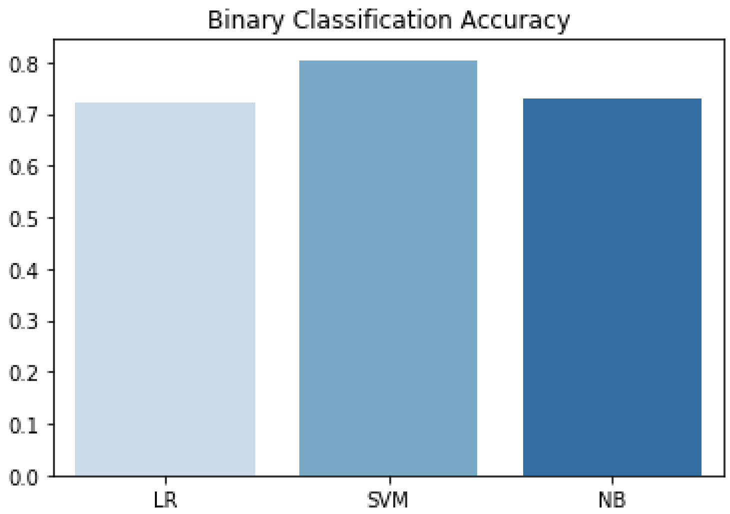
Classification Results

In [52]:
```
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

In [53]:
```
x_bin = ["LR", "SVM", "NB"]
y_bin = [lr_acc,svm_acc,nb_acc]
```

In [54]:
```
sns.barplot(x_bin, y_bin, palette="Blues")
plt.title("Binary Classification Accuracy")
```

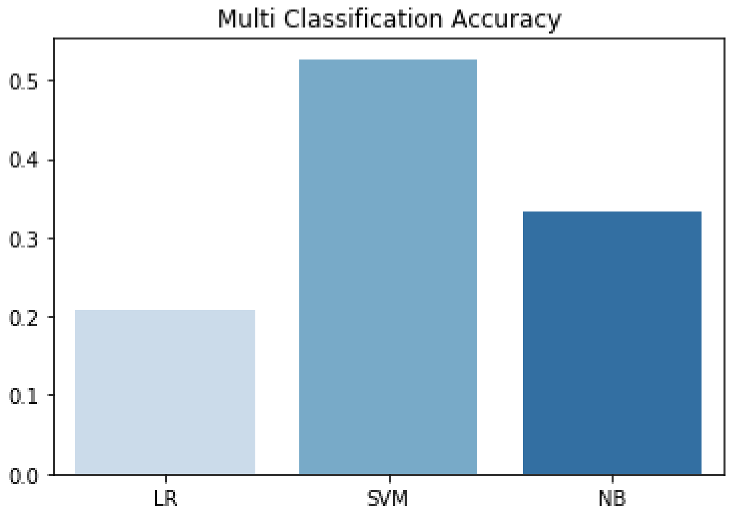
Out[54]:
```
Text(0.5,1,'Binary Classification Accuracy')
```



In [55]:
```
x_mc = ["LR", "SVM", "NB"]
y_mc = [lr_mc_acc,svm_mc_acc,nb_mc_acc]
```

In [56]:
```
sns.barplot(x_mc, y_mc, palette="Blues")
plt.title("Multi Classification Accuracy")
```

Out[56]: Text(0.5,1,'Multi Classification Accuracy')



As we see binary classification gives better results since we only want to label a statement as either true or false.

In case of six way classification, it gives worse results, due to the fact we have more restrictions in classifying within the 6 categories. Hence we need to analyse specific features to build a stronger classifier.

Analyzing Feature Set from the Data

Some of the features that define the data set include the Subject of the Statement, the Speaker of the statement, the speaker's job and the party affiliation.

Exploring the Subject / Topic Feature

The feature subject may be interesting in determining the truthfulness of a statement.

First, we see how many unique subjects or topics are present in the data and how the truthfulness of the statement depends on the topic of a statement.

In [57]:
```
data.columns
```

Out[57]:
```
Index([u'Statement ID', u'Label', u'Statement', u'Subject', u'Speaker',
       u'Speaker Job's title', u'State info', u'Party Affiliate',
       u'barely true counts', u'false counts', u'half true counts',
       u'mostly true counts', u'pants on fire counts', u'venue',
       u'Extracted Justification'],
      dtype='object')
```

In [58]:
```
def topic_data(df):

    df = df.copy()
    df["Subject"] = df["Subject"].apply(lambda x : str(x).lower().split(","))
    ## Create a dataframe of all subjects
    subjects = df.Subject.apply(pd.Series)
    cols = list(df.columns.values)
    cols.remove("Subject")

    df = subjects.merge(df, right_index = True, left_index = True) \
        .drop(["Subject"], axis = 1)


    lf = pd.melt(df, id_vars = cols, value_name = "Subject") \
        .drop("variable", axis = 1) \

    return lf
```

In [59]:
```
df_raw = data.sample(frac=1).reset_index()
topic_data = topic_data(df_raw)

set_of_subjects = set(topic_data['Subject'])

print("Total %d unique subjects" % len(set_of_subjects))
print("Sample subjects:\n", list(set_of_subjects)[:10])
```

```
Total 144 unique subjects
('Sample subjects:\n', [nan, 'hunger', 'trade', 'welfare', 'homeland-security', 'children', 'occupy-wall-street', 'is
lam', 'retirement', 'workers'])
```

Finding unique subjects occuring more than 200 times

In [61]:
```
subject_counts = topic_data.groupby("Subject").count()
subjects_200 = subject_counts.where(subject_counts['Statement ID'] > 200).dropna().index
topic_data = topic_data[topic_data['Subject'].isin(subjects_200)]
```

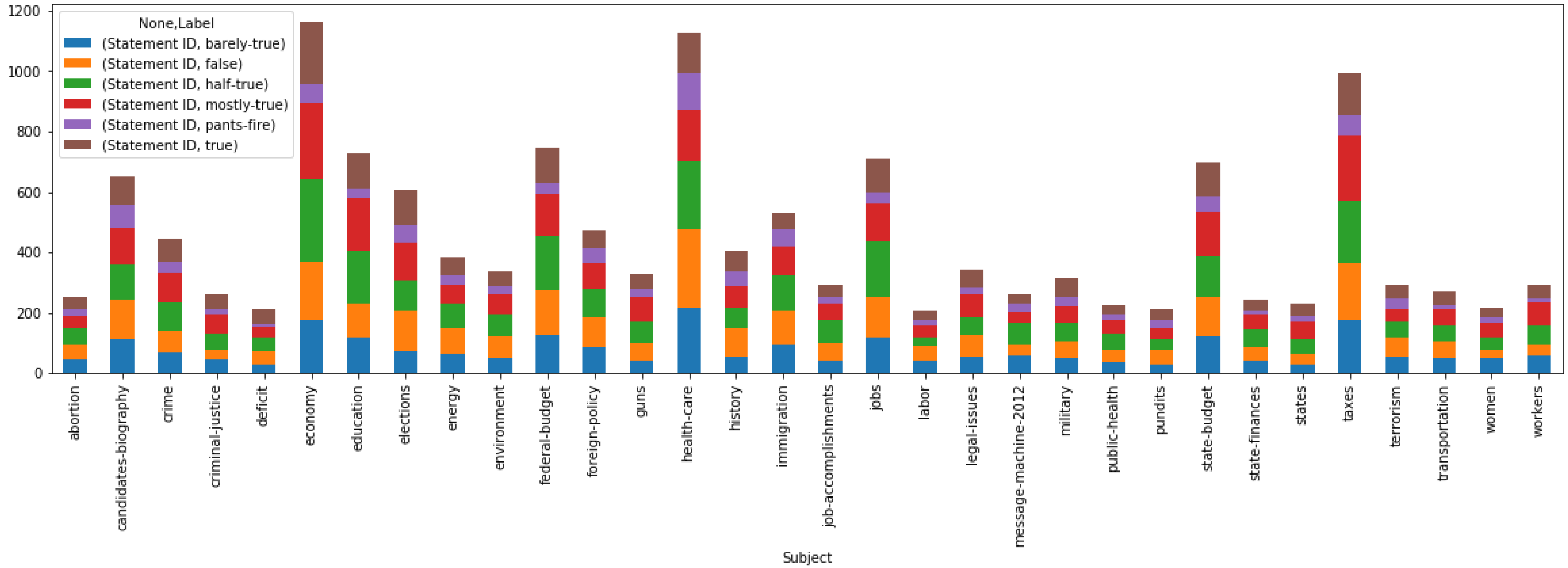
In [90]:
```
topic_data.head(5)
```

Out[90]:

	index	Statement ID	Label	Statement	Speaker	Speaker Job's title	State info	Party Affiliate	barely true counts	false counts	half true counts	mostly true counts	pants on fire counts	ve
0	1279	6291.json	half-true	Unemployment among Oregon high school graduate...	cascade-policy-institute	NaN	NaN	organization	0.0	0.0	1.0	0.0	0.0	a websi
1	4183	5385.json	true	Says Scott Walker enacted the biggest cuts to ...	kathleen-falk	NaN	NaN	democrat	1.0	3.0	3.0	1.0	0.0	a speec announ her candida
3	5969	2892.json	true	Said Republicans made historic gains in state ...	national-review	NaN	NaN	none	0.0	0.0	0.0	0.0	0.0	Nationa Review Online
4	7146	13399.json	barely-true	Says that hes responsible for Austinincluding ...	jimmy-flannigan	Small business owner	Texas	none	1.0	0.0	0.0	0.0	0.0	an Aust Monitor intervie that day plus for
5	8094	3556.json	mostly-true	Says an average of $4 billion is added to the ...	saxby-chambliss	U.S. Senator	Georgia	republican	1.0	1.0	3.0	4.0	1.0	an op-e

In [62]:
```
count_df = topic_data.groupby(["Subject","Label"]).agg({"Statement ID" : "count"})
count_df.unstack().plot(kind='bar', stacked=True, figsize=(20,5))
```

Out[62]: <matplotlib.axes._subplots.AxesSubplot at 0x1649b240>



Here, we find a distribution showing the relation between the truthfulness of a statement with its corresponding topic

Exploring the Speaker Feature

The feature speaker may also contribute significantly in determining the truthfulness of a statement.

First, we see how many unique speakers are there in the data.

Next we wish to see which speakers are more likely to make a false claim and which speakers are most truthful.

In [63]:
```
speakers_df = df_raw.copy()
speakers = speakers_df['Speaker'].unique()
print("Total %d unique speakers" % len(speakers))
print("Sample speakers:\n", speakers[:10])
```

```
Total 2911 unique speakers
('Sample speakers:\n', array(['cascade-policy-institute', 'kathleen-falk', 'glenn-beck',
       'national-review', 'jimmy-flannigan', 'saxby-chambliss',
       'josh-mandel', 'todd-tiahrt', 'ron-kind', 'barack-obama'],
      dtype=object))
```

In [64]:
```
speakers_cts = speakers_df.groupby("Speaker").Statement.count()
speakers = speakers_cts[speakers_cts > 20]
print("Total %d unique speakers who appear more than 20 times within the dataset" % len(speakers))
print("Sample speakers:\n", speakers[:10])
```

```
Total 65 unique speakers who appear more than 20 times within the dataset
('Sample speakers:\n', Speaker
alan-grayson      30
barack-obama     488
ben-carson        25
bernie-s          88
bill-clinton      31
bill-nelson       23
blog-posting      59
bob-mcdonnell     37
chain-email      142
charlie-crist     70
Name: Statement, dtype: int64)
```

In [65]:
```
speakers_df = speakers_df[speakers_df['Speaker'].isin(speakers.keys())]
```

In [89]:
```
speakers_df.head(5)
```

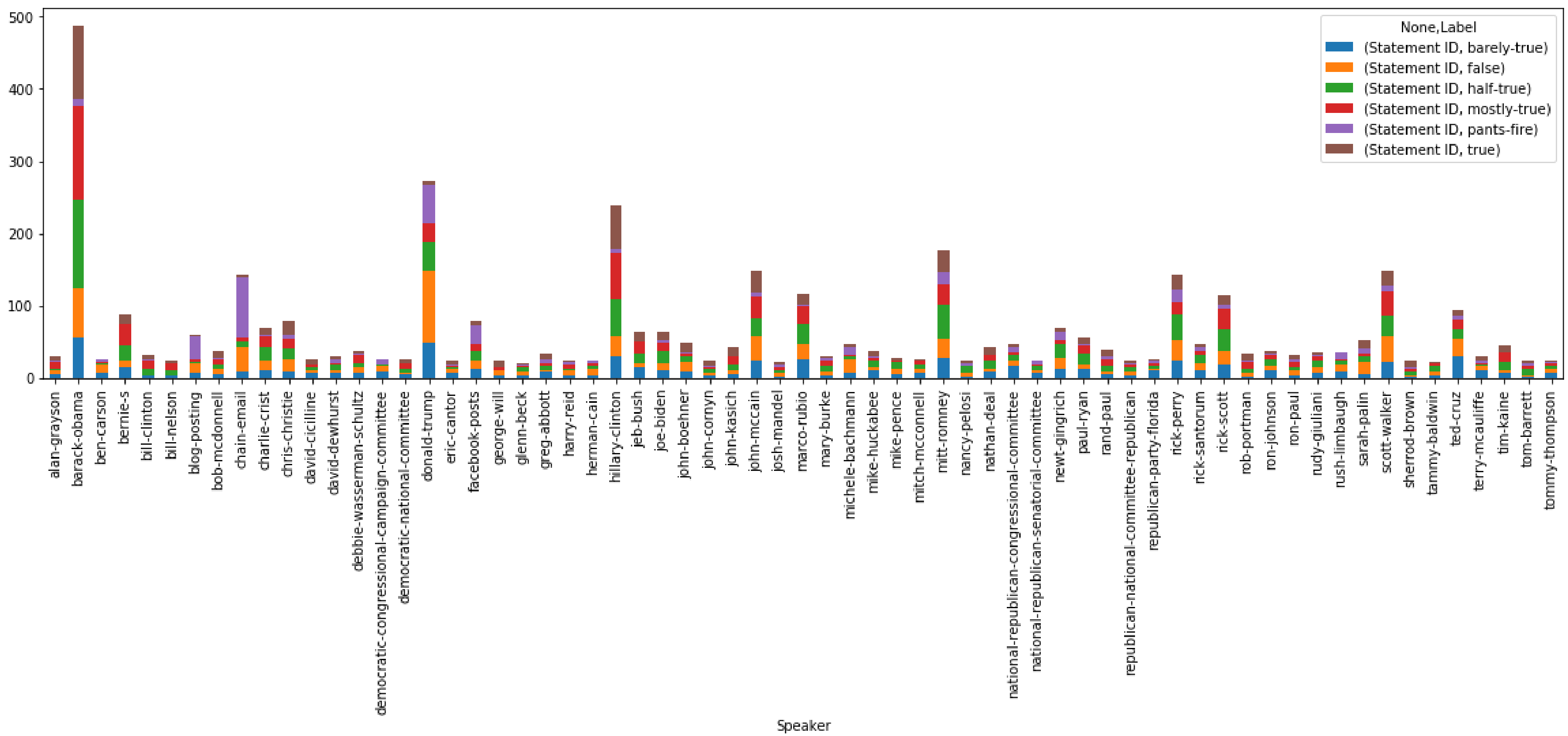
Out[89]:

	index	Statement ID	Label	Statement	Subject	Speaker	Speaker Job's title	State info	Party Affiliate	barely true counts	false counts	cou
2	5163	10876.json	barely-true	Says Hillary Clinton makes more per hour at a ...	income,wealth,workers	glenn-beck	NaN	NaN	none	5.0	7.0	7.0
6	9401	7048.json	false	Says that Sherrod Brown is an Obama rubber sta...	cap-and-trade,climate-change,environment,votin...	josh-mandel	Ohio treasurer	Ohio	republican	4.0	5.0	4.0
9	5782	13451.json	half-true	The list of voters that North Carolina Republi...	elections	barack-obama	President	Illinois	democrat	70.0	71.0	160
10	8669	6492.json	true	Says under Wisconsin law, he cannot remove his...	elections	paul-ryan	U.S. Representative	Wisconsin	republican	19.0	6.0	16.

	index	Statement ID	Label	Statement	Subject	Speaker	Speaker Job's title	State info	Party Affiliate	barely true counts	false counts	t cou
12	88	767.json	barely-true	Sen. McCain's tax plan provides "virtually not...	taxes	joe-biden	U.S. senator	Delaware	democrat	11.0	10.0	21.

In [66]:
```
count_speakers = speakers_df.groupby(["Speaker","Label"]).agg({"Statement ID" : "count"})
count_speakers.unstack().plot(kind='bar', stacked=True, figsize=(20,5))
```

Out[66]: <matplotlib.axes._subplots.AxesSubplot at 0x1454fa90>



For example, an interesting feature from the distribution is that **Donal Trump** is always making *false claims* most of the time. ["true" label is very less]

Exploring the Job Feature

The feature **Job** may also contribute significantly in determining the truthfulness of a statement.

Some speakers belonging to particular job may make more false claims while others may make more truthful claims

In [67]:
```
jobs_df = data.copy()
jobs = jobs_df['Speaker Job\'s title'].unique()
print("Total %d unique jobs" % len(jobs))
print("Sample jobs:\n", jobs[:10])
```

```
Total 1185 unique jobs
('Sample jobs:\n', array(['State representative', 'State delegate', 'President', nan,
       'Wisconsin Assembly speaker', 'U.S. Senator', 'Former governor',
       'Columnist', 'U.S. House member -- 4th District',
       'Treasury secretary '], dtype=object))
```

In [87]:
```
job_cts = jobs_df.groupby("Speaker Job\'s title").Statement.count()
jobs = job_cts[job_cts > 20]
print("There are %d unique jobs who appear more than 20 times within the dataset" % len(jobs))
print("Some sample jobs include:\n", jobs[:5])
```

```
There are 52 unique jobs who appear more than 20 times within the dataset
('Some sample jobs include:\n', Speaker Job's title
Attorney                                   81
Attorney General                           33
Businessman                                34
Candidate for U.S. Senate and physician    39
Co-host on CNN's "Crossfire"               73
Name: Statement, dtype: int64)
```

In [88]:
```
jobs
```

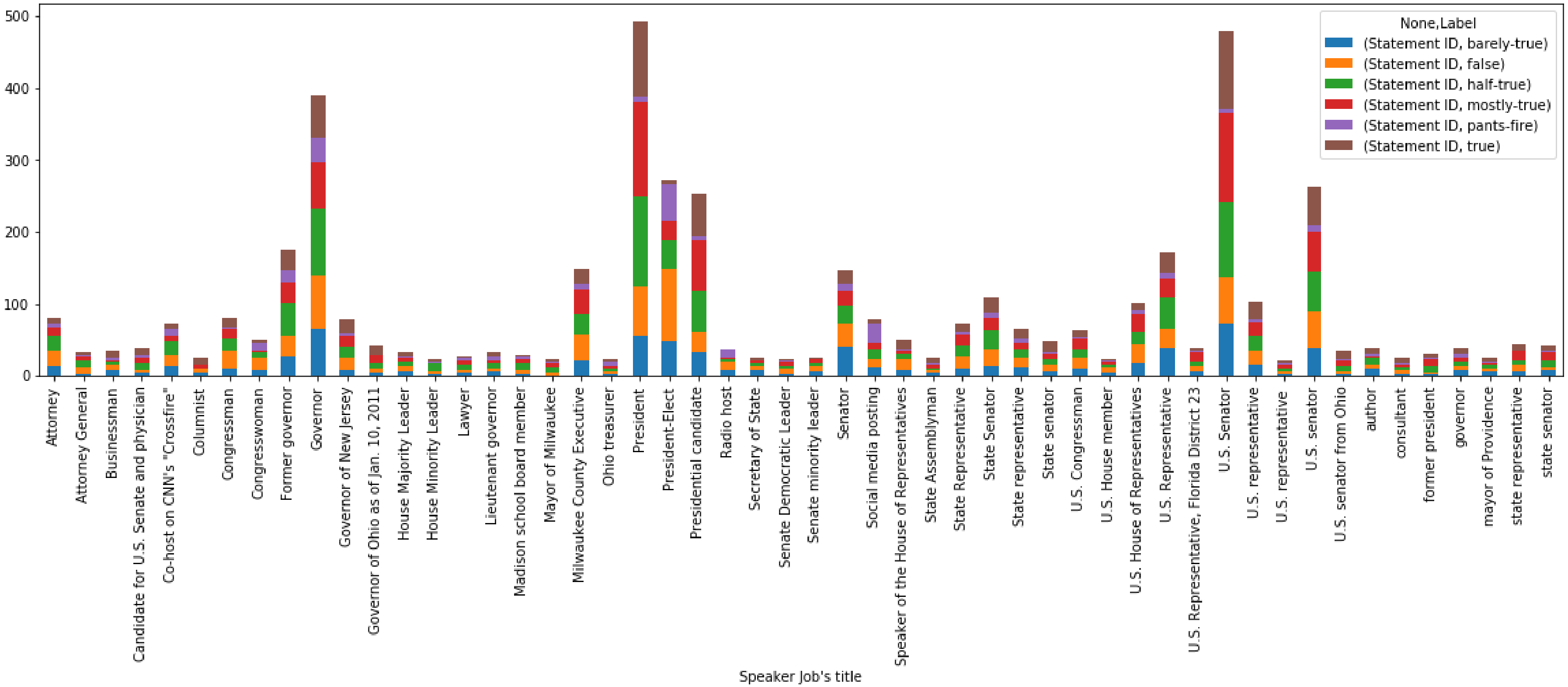
```
Out[88]:  Speaker Job's title
          Attorney                                        81
          Attorney General                                33
          Businessman                                     34
          Candidate for U.S. Senate and physician         39
          Co-host on CNN's "Crossfire"                    73
          Columnist                                       25
          Congressman                                     80
          Congresswoman                                   50
          Former governor                                176
          Governor                                       391
          Governor of New Jersey                          78
          Governor of Ohio as of Jan. 10, 2011            43
          House Majority Leader                           32
          House Minority Leader                           23
          Lawyer                                          28
          Lieutenant governor                             33
          Madison school board member                     29
          Mayor of Milwaukee                              23
          Milwaukee County Executive                     149
          Ohio treasurer                                  24
          President                                      492
          President-Elect                                273
          Presidential candidate                         254
          Radio host                                      36
          Secretary of State                              25
          Senate Democratic Leader                        23
          Senate minority leader                          25
          Senator                                        147
          Social media posting                            78
          Speaker of the House of Representatives         50
          State Assemblyman                               25
          State Representative                            72
          State Senator                                  108
          State representative                            66
          State senator                                   48
          U.S. Congressman                                63
          U.S. House member                               23
          U.S. House of Representatives                  102
          U.S. Representative                            172
          U.S. Representative, Florida District 23        38
```

```
U.S. Senator                                    479
U.S. representative                             103
U.S. representative                              21
U.S. senator                                    263
U.S. senator from Ohio                           34
author                                           38
consultant                                       26
former president                                 31
governor                                         39
mayor of Providence                              26
state representative                             44
state senator                                    42
Name: Statement, dtype: int64
```

In [84]:
```
jobs_df = jobs_df[jobs_df['Speaker Job\'s title'].isin(jobs.keys())]

jobs_count = jobs_df.groupby(["Speaker Job\'s title","Label"]).agg({"Statement ID" : "count"})
jobs_count.unstack().plot(kind='bar', stacked=True, figsize=(20,5))
```

Out[84]: <matplotlib.axes._subplots.AxesSubplot at 0x1065a6d8>



Interestingly **President-Elect** or president to be elected has the higher number of cases where he/she makes a false claim.

Exploring the Party Affiliation Feature

Members of a particular party may be more prone to making false claims than others. Hence an important step is to study such a relation between party affiliation and the truthfulness of their claims.

In [70]:
```
parties_df = df_raw.copy()
parties = jobs_df['Party Affiliate'].unique()
print("Total %d unique parties" % len(parties))
print("Sample parties:\n", parties)
```

```
Total 7 unique parties
('Sample parties:\n', array(['republican', 'democrat', 'independent', 'columnist', 'none',
       'libertarian', 'constitution-party'], dtype=object))
```

In [71]:
```
parties_cts = parties_df.groupby("Party Affiliate").Statement.count()
parties = parties_cts[parties_cts > 30]
print("Total %d unique affiliations who appear more than 30 times" % len(parties))
print("Sample affiliations:\n", parties[:5])
```

```
Total 10 unique affiliations who appear more than 30 times
('Sample affiliations:\n', Party Affiliate
activist         39
columnist        35
democrat       3336
independent     147
journalist       38
Name: Statement, dtype: int64)
```

In [72]:
```
parties_df = parties_df[parties_df['Party Affiliate'].isin(parties.keys())]
```

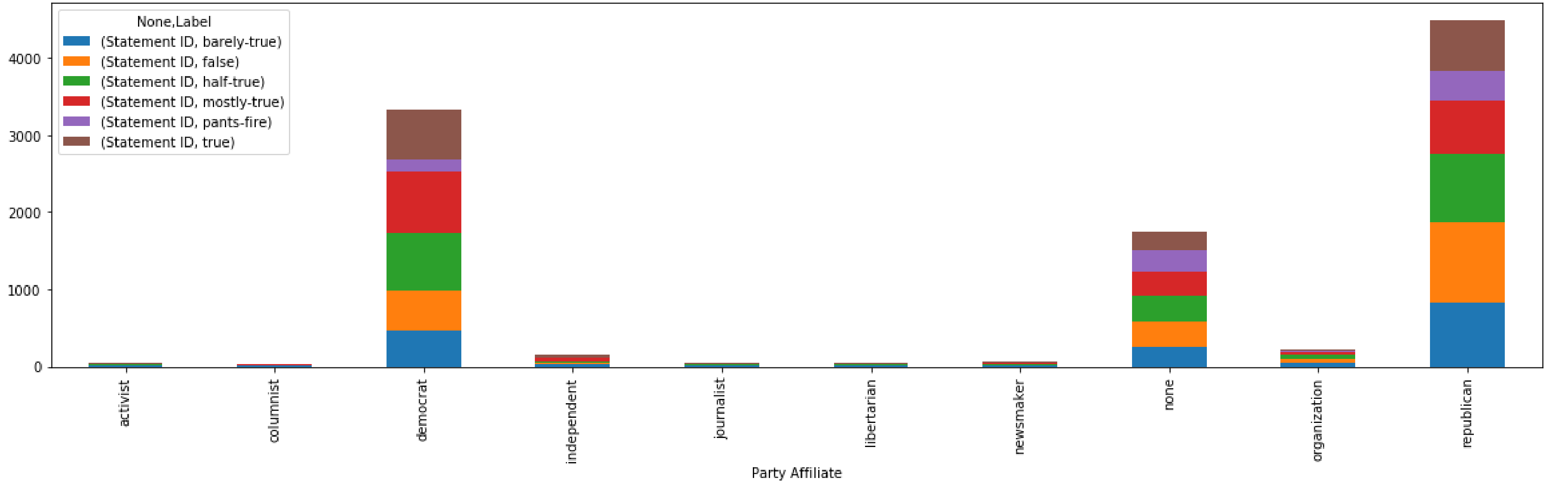
In [91]:
```
parties_df.head()
```

Out[91]:

	index	Statement ID	Label	Statement	Subject	Speaker	Speaker Job's title	State info	Party Affiliate	barely true counts	false counts	half true counts	mos tı couı
0	1279	6291.json	half-true	Unemployment among Oregon high school graduate...	economy,jobs,workers	cascade-policy-institute	NaN	NaN	organization	0.0	0.0	1.0	0.0
1	4183	5385.json	true	Says Scott Walker enacted the biggest cuts to ...	education,state-budget,state-finances	kathleen-falk	NaN	NaN	democrat	1.0	3.0	3.0	1.0
2	5163	10876.json	barely-true	Says Hillary Clinton makes more per hour at a ...	income,wealth,workers	glenn-beck	NaN	NaN	none	5.0	7.0	7.0	2.0
3	5969	2892.json	true	Said Republicans made historic gains in state ...	elections	national-review	NaN	NaN	none	0.0	0.0	0.0	0.0
4	7146	13399.json	barely-true	Says that hes responsible for Austinincluding ...	candidates-biography,city-budget,city-governme...	jimmy-flannigan	Small business owner	Texas	none	1.0	0.0	0.0	0.0

In [85]:
```
parties_count = parties_df.groupby(["Party Affiliate","Label"]).agg({"Statement ID" : "count"})
parties_count.unstack().plot(kind='bar', stacked=True, figsize=(20,5))
```

Out[85]: <matplotlib.axes._subplots.AxesSubplot at 0x111ec208>



Sentiment Analysis

An important analysis in this paper states that by considering the sentiment of the statement in question. The paper considers Sentistrength library for their purpose.

By ranking the sentiment of the statement from a range of 0 to 5 indicating negative to neutral and to positive, it may give some interesting insights as to whether a statement is truthful or not

In [74]:
```
import nltk
```

In [75]:
```
import vaderSentiment
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
```

In [76]:
```
analyzer = SentimentIntensityAnalyzer()
```

In [77]:
```
sentiments = pd.DataFrame([analyzer.polarity_scores(row) for row in df_raw.Statement]).join(df_raw)
```

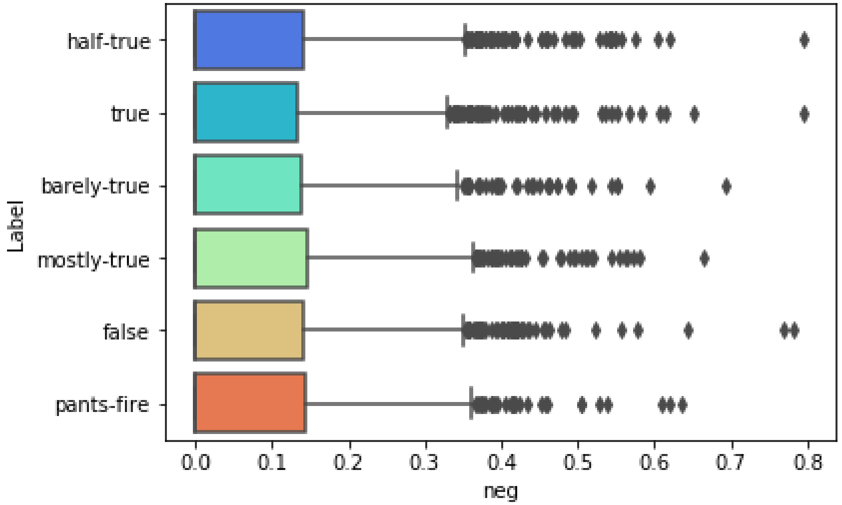
In [78]:
```
sentiments.head(5)
```

Out[78]:

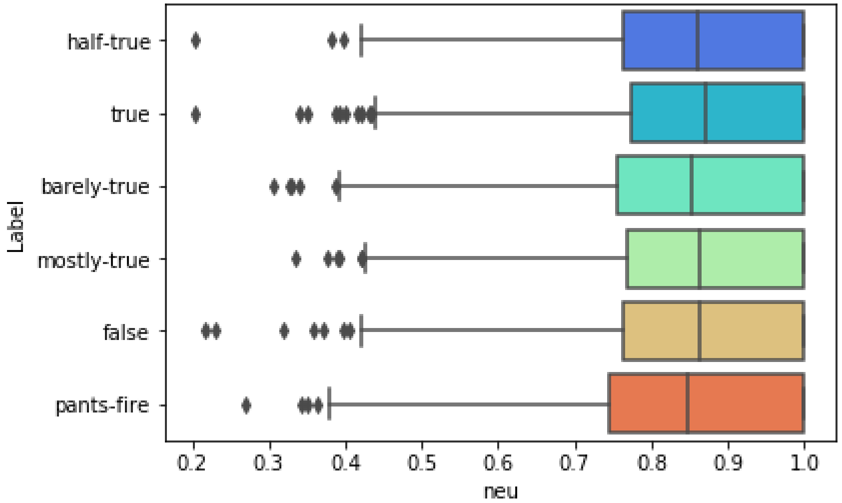
	compound	neg	neu	pos	index	Statement ID	Label	Statement	Subject	Speaker	Speaker Job's title	State info	Par Affilia
0	0.0772	0.093	0.772	0.135	1279	6291.json	half-true	Unemployment among Oregon high school graduate...	economy,jobs,workers	cascade-policy-institute	NaN	NaN	organizati
1	-0.2960	0.155	0.845	0.000	4183	5385.json	true	Says Scott Walker enacted the biggest cuts to ...	education,state-budget,state-finances	kathleen-falk	NaN	NaN	democrat
2	0.0000	0.000	1.000	0.000	5163	10876.json	barely-true	Says Hillary Clinton makes more per hour at a ...	income,wealth,workers	glenn-beck	NaN	NaN	none
3	0.3400	0.000	0.821	0.179	5969	2892.json	true	Said Republicans made historic gains in state ...	elections	national-review	NaN	NaN	none
4	0.3182	0.000	0.867	0.133	7146	13399.json	barely-true	Says that hes responsible for Austinincluding ...	candidates-biography,city-budget,city-governme...	jimmy-flannigan	Small business owner	Texas	none

In [79]:
```
import seaborn as sns
```

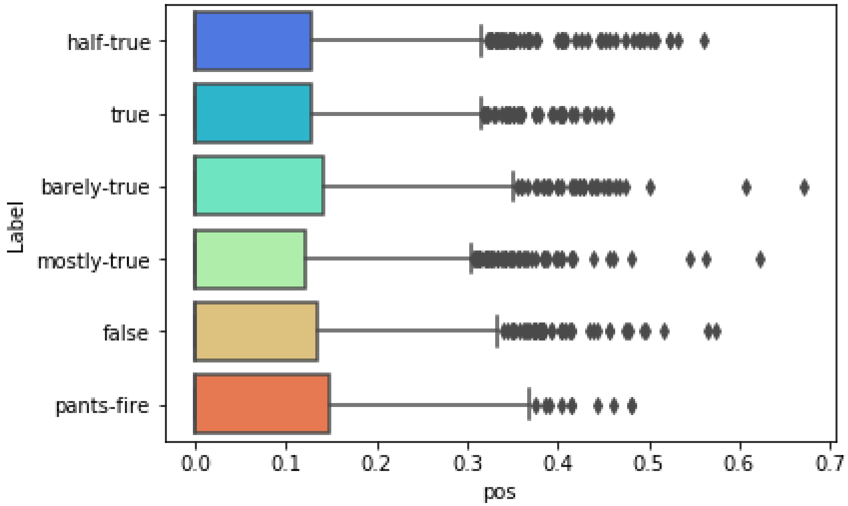
In [81]:
```
ax = sns.boxplot(x='neg', y='Label', data=sentiments , palette='rainbow')
```



In [82]:
```
ax = sns.boxplot(x='neu', y='Label', data=sentiments, palette='rainbow')
```



In [83]:
```
ax = sns.boxplot(x='pos', y='Label', data=sentiments, palette='rainbow')
```



For each statement, we can extract 4 metrics: negativity, positivity, neutrality and a compound value of all of these metrics.

An interesting observation is that for all 6 available truth labels, all the metrics follow the same distribution, suggesting that the dataset is well balanced in this regard.

Insights

As we see many of the features are important in determining the truthfulness of the statement.

Feature like Venue may also have a contributing factor. A interview may be more misleading than a state speech. Or the location may also determine it. A speech given in a remote location may be more misleading than otherwise.

Hence an important aspect is to study the importance of such features and its relationships to build a stronger classifier in future.

Along with that incorporating recent advances in natural language processing like sentiment analysis may also improve in classification results.

Libraries

- Matplotlib
- Scipy
- Seaborn
- Nltk
- Sklearn
- Pandas

Code

- https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LinearRegression.html (https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LinearRegression.html)
- https://stackoverflow.com/questions/29960558/creating-a-bar-plot-using-seaborn (https://stackoverflow.com/questions/29960558/creating-a-bar-plot-using-seaborn)
- https://datascienceplus.com/seaborn-categorical-plots-in-python/ (https://datascienceplus.com/seaborn-categorical-plots-in-python/)
- https://stackoverflow.com/questions/12541370/typeerror-encoding-is-an-invalid-keyword-argument-for-this-function/13867190 (https://stackoverflow.com/questions/12541370/typeerror-encoding-is-an-invalid-keyword-argument-for-this-function/13867190)
- https://stackoverflow.com/questions/45890328/sklearn-metrics-for-multiclass-classification (https://stackoverflow.com/questions/45890328/sklearn-metrics-for-multiclass-classification)
- https://stackoverflow.com/questions/45890328/sklearn-metrics-for-multiclass-classification (https://stackoverflow.com/questions/45890328/sklearn-metrics-for-multiclass-classification)
- https://scikit-learn.org/stable/modules/multiclass.html (https://scikit-learn.org/stable/modules/multiclass.html)
- https://stackoverflow.com/questions/39303912/tfidfvectorizer-in-scikit-learn-valueerror-np-nan-is-an-invalid-document (https://stackoverflow.com/questions/39303912/tfidfvectorizer-in-scikit-learn-valueerror-np-nan-is-an-invalid-document)
- https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.CountVectorizer.html (https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.CountVectorizer.html)

In [ ]: