Natural Language Processing – Part 2

Now that we have some basics of text processing, and retrieving basic information such as named entities and part-of-speech tags, we can look into more advanced modelling for information retreival.
To be able to use modelling to extract meaning and information from text, you need a numerical representation of your texts. So we transform our words to vectors.

One hot encoding

The simpelest way of making a vector representation is by using one-hot ecoding. In one hot encoding you give a number to each unique word you have in your corpus.

For example, let's say my entire dataset consist of these two sentences:

In [3]:

```
sentences = ["We will stick to natural language processing in this class",
             "Bert found a stick in the forest"]
```

In [4]:

```
words = [w.lower() for sentence in sentences for w in sentence.split(' ')]
words = list(np.unique(words))
words.sort()
print(len(words),'unique words')
words
```

```
15 unique words
```

Out[4]:

```
['a',
 'bert',
 'class',
 'forest',
 'found',
 'in',
 'language',
 'natural',
 'processing',
 'stick',
 'the',
 'this',
 'to',
 'we',
 'will']
```

In [5]:

```python
# I can give each of these words a number
word_index ={}
for i, w in enumerate(words):
    word_index[w] = i
    print(w, ':', i)
```

```
a : 0
bert : 1
class : 2
forest : 3
found : 4
in : 5
language : 6
natural : 7
processing : 8
stick : 9
the : 10
this : 11
to : 12
we : 13
will : 14
```

Each of these words now has a one-hot encoded represenation, which are vectors that are **13** zeros, with **one** 1, at the index of the word. So, Bert would have:

In [6]:

```
v_bert = np.zeros((len(words),)).astype(int)
v_bert[word_index['bert']] = 1
v_bert
```

Out[6]:

```
array([0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0])
```

And for language it would be:

In [7]:

```
v_lang = np.zeros((len(words),)).astype(int)
v_lang[word_index['language']] = 1
v_lang
```

Out[7]:

```
array([0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0])
```

We an also use this method to create a representation of our sentences.

In [8]:

```
vectors = []
for sentence in sentences:
    vector = np.zeros((len(words), )).astype(int)
    idx = [word_index[w.lower()] for w in sentence.split(' ')]
    vector[idx] = 1
    vectors.append(vector)
    print(sentence)
    print('\t', vector)
    print()
```

```
We will stick to natural language processing in this class
	 [0 0 1 0 0 1 1 1 1 1 0 1 1 1 1]

Bert found a stick in the forest
	 [1 1 0 1 1 1 0 0 0 1 1 0 0 0 0]
```

Stacking these into a matrix, is called a document term count. The 'documents' are then the sentences. This is called a **Document Term Matrix** (DTM) or **Document Term Count** (DTC).

In [9]:

```
np.stack(vectors)
```

Out[9]:

```
array([[0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1],
       [1, 1, 0, 1, 1, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0]])
```

Obviously this is a small dataset, so the 'matrix' is tiny. In addtition the name *Docment Term Count* implies that it shows a count of the number of words. SInce our example sentences (or documents) only have unique words in them, the count is always one. So let's look at a larged dataset.

Luckly, we can use different pre existing python packages to create a document term matrix, without doing all the manual steps like we did above. For this example I will be using scikit-learn (sklearn) and nltk.

In [10]:

```
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.datasets import fetch_20newsgroups
from nltk.stem import SnowballStemmer
from nltk.corpus import stopwords
```

In [11]:

```
# Grab an example dataset of old newsgroups
newsgroups = fetch_20newsgroups()
print(newsgroups.data[0])
print(f"There are {len(newsgroups.data)} newsgroup postings in this dataset")
```

```
From: lerxst@wam.umd.edu (where's my thing)
Subject: WHAT car is this!?
Nntp-Posting-Host: rac3.wam.umd.edu
Organization: University of Maryland, College Park
Lines: 15

 I was wondering if anyone out there could enlighten me on this ca
r I saw
the other day. It was a 2-door sports car, looked to be from the l
ate 60s/
early 70s. It was called a Bricklin. The doors were really small.
In addition,
the front bumper was separate from the rest of the body. This is
all I know. If anyone can tellme a model name, engine specs, years
of production, where this car is made, history, or whatever info y
ou
have on this funky looking car, please e-mail.

Thanks,
```

- IL
   ---- brought to you by your neighborhood Lerxst ----

There are 11314 newsgroup postings in this dataset

We now use the `CountVectorizer` from sklearn to create a *DTC*. To ensure that we don't create a giant matrix, and we only want relevant words we use some techniques from the previous section as preprocessig steps:

- We filter out stopwords
- We set a minumum word count per document to no lower than 2
- We set a maximum appearance of a word to 90% of all documents
- We stem our words to combine different conjugations

In [12]:

```
# Define the stemmer
stemmer = SnowballStemmer(language='english')
# Define a list of stopwords. Note we need to stem these as well!
input_stopwords = [stemmer.stem(w) for w in stopwords.words('english')]
# Define the vectorizer
vectorizer = CountVectorizer(preprocessor=stemmer.stem, stop_words=input_stopwords, min_df=2,
                              max_df=0.9,
                             token_pattern=r"[a-zA-Z]{2,}")
```

In [13]:

```
dtc = vectorizer.fit_transform(newsgroups.data)
print(len(newsgroups.data))
dtc.shape
```

```
11314
```

Out[13]:

```
(11314, 46689)
```

In [59]:

```
vectorizer.get_feature_names()[:20]
```

Out[59]:

```
['aa',
 'aaa',
 'aaah',
 'aaahhhh',
 'aachen',
 'aad',
 'aaf',
 'aaldoubo',
 'aamir',
 'aammmaaaazzzzzziinnnngggg',
 'aamrl',
 'aao',
 'aardvark',
 'aargh',
 'aarghhhh',
 'aarhus',
 'aario',
 'aarnet',
 'aaron',
 'aas']
```

In [15]:

```
doc_nr = 0

words = np.array(vectorizer.get_feature_names())[dtc.toarray()[doc_nr, :]>1]
counts = dtc.toarray()[doc_nr, :][dtc.toarray()[doc_nr, :]>1]
for i, word in enumerate(words):
    print(word, counts[i])
```

```
anyone 2
car 5
edu 2
lerxst 2
umd 2
wam 2
```

In [16]:

```
newsgroups.data[doc_nr]
```

Out[16]:

```
"From: lerxst@wam.umd.edu (where's my thing)\nSubject: WHAT car is
this!?\nNntp-Posting-Host: rac3.wam.umd.edu\nOrganization: Univers
ity of Maryland, College Park\nLines: 15\n\n I was wondering if an
yone out there could enlighten me on this car I saw\nthe other da
y. It was a 2-door sports car, looked to be from the late 60s/\nea
rly 70s. It was called a Bricklin. The doors were really small. In
addition,\nthe front bumper was separate from the rest of the bod
y. This is \nall I know. If anyone can tellme a model name, engine
specs, years\nof production, where this car is made, history, or w
hatever info you\nhave on this funky looking car, please e-mail.\n
\nThanks,\n- IL\n   ---- brought to you by your neighborhood Lerxs
t ----\n\n\n\n\n"
```

In [17]:

```
from sklearn.metrics.pairwise import cosine_similarity

similar = cosine_similarity(dtc)

sim_dtc = similar[0, :].argsort()[::-1][:20]

df_dtc = pd.DataFrame(dtc[sim_dtc, :].toarray())
df_dtc[df_dtc==0] = float('nan')
df_dtc = df_dtc.dropna(axis=1, how='all')
df_dtc.columns = np.array(vectorizer.get_feature_names())[df_dtc.columns.values]
df_dtc.index = sim_dtc
most_common = df_dtc.sum(0).sort_values(ascending=False)[:20].index.values
df_dtc = df_dtc.loc[:, most_common]
```

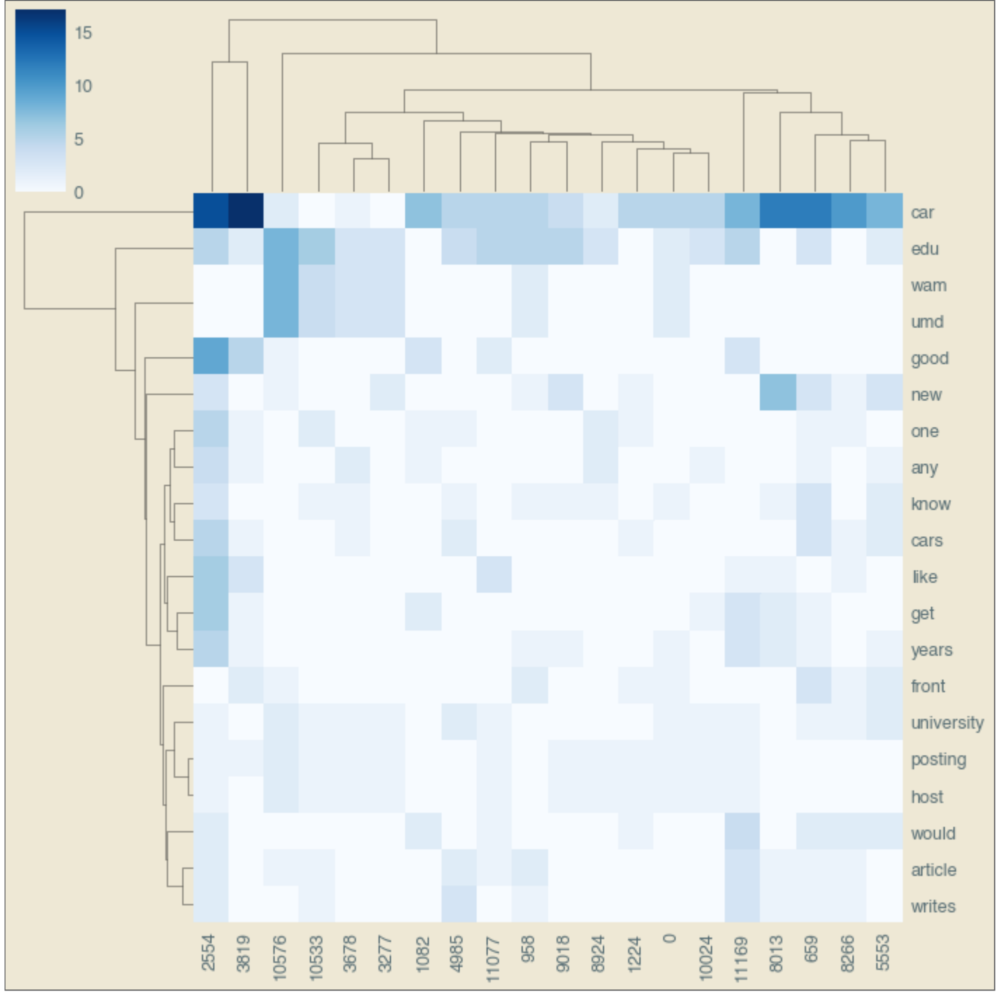
In [18]:

```
import matplotlib.pyplot as plt
plt.figure(figsize=(20,8))
sns.clustermap(df_dtc.fillna(0).T, cmap='Blues')
```

Out[18]:

```
<seaborn.matrix.ClusterGrid at 0x125a60a90>
```

```
<Figure size 1440x576 with 0 Axes>
```



TFIDF

Tf-idf stands for term frequency-inverse document frequency, and the tf-idf weight is a weight often used in information retrieval and text mining. This weight is a statistical measure used to evaluate how important a word is to a document in a collection or corpus. The importance increases proportionally to the number of times a word appears in the document but is offset by the frequency of the word in the corpus.
source **tfidf.com**

In [19]:

```
from sklearn.feature_extraction.text import TfidfVectorizer
# Define the stemmer
stemmer = SnowballStemmer(language='english')
```

```python
# Define a list of stopwords. Note we need to stem these as well!
input_stopwords = [stemmer.stem(w) for w in stopwords.words('english')]
# Define the vectorizer
vectorizer = TfidfVectorizer(preprocessor=stemmer.stem, stop_words=input_stopwords, min_df=2,
                              max_df=0.9,
                             token_pattern=r"[a-zA-Z]{2,}")
```

In [20]:

```python
tfidf = vectorizer.fit_transform(newsgroups.data)
print(len(newsgroups.data))
tfidf.shape
```

```
11314
```

Out[20]:

```
(11314, 46689)
```

In [21]:

```python
similar = cosine_similarity(tfidf)

sim_tfidf = similar[0, :].argsort()[::-1][:20]

df_tfidf = pd.DataFrame(tfidf[sim_tfidf, :].toarray())
df_tfidf[df_tfidf==0] = float('nan')
df_tfidf = df_tfidf.dropna(axis=1, how='all')
df_tfidf.columns = np.array(vectorizer.get_feature_names())[df_tfidf.columns.values]
df_tfidf.index = sim_tfidf
most_common = df_tfidf.sum(0).sort_values(ascending=False)[:20].index.values
df_tfidf = df_tfidf.loc[:, most_common]
```

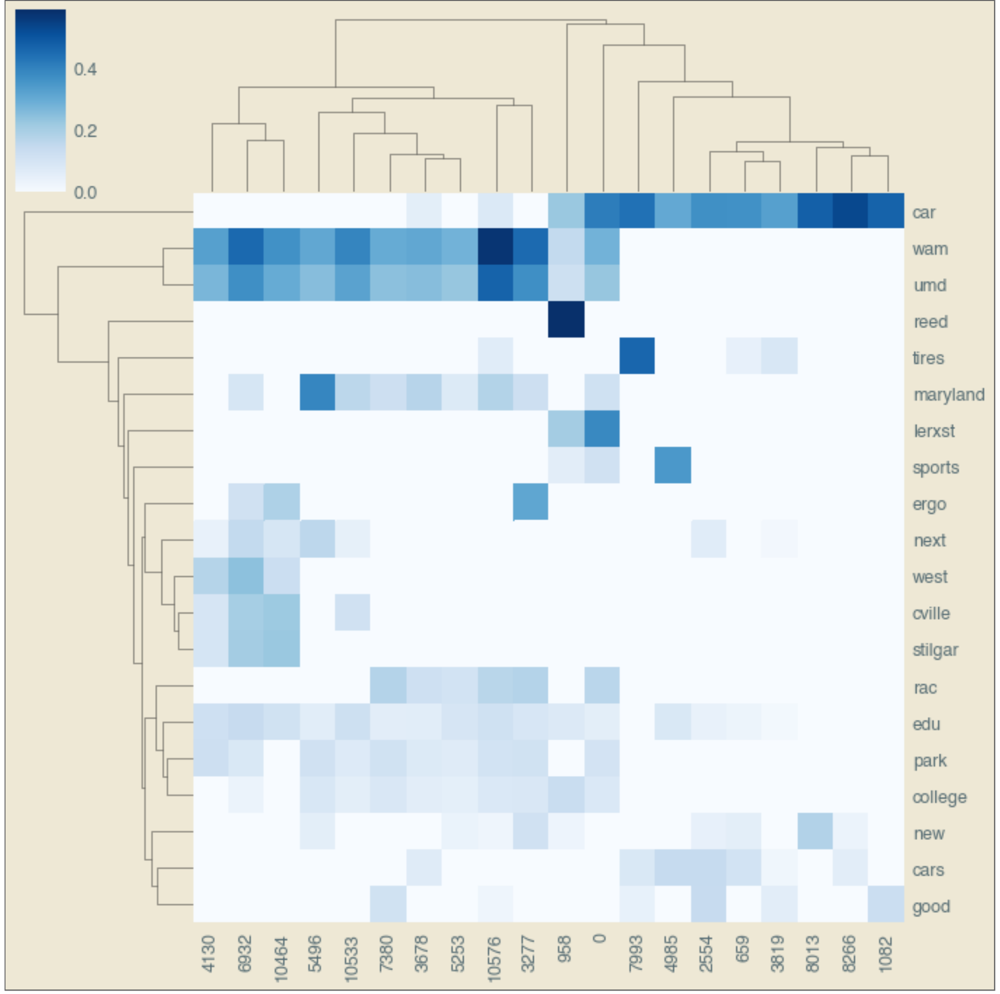
In [22]:

```python
plt.figure(figsize=(20,8))
sns.clustermap(df_tfidf.fillna(0).T, cmap='Blues')
```

Out[22]:

```
<seaborn.matrix.ClusterGrid at 0x12514c210>
```

```
<Figure size 1440x576 with 0 Axes>
```


0.4
0.2
0.0
car
wam
umd
reed
tires
maryland
lerxst
sports
ergo
next
west
cville
stilgar
rac
edu
park
college
new
cars
good
4130
6932
10464
5496
10533
7380
3678
5253
10576
3277
958
0
7993
4985
2554
659
3819
8013
8266
1082

Train a classifier using TFIDF

In [23]:

```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix, f1_score, precision_score, recall_score
```

In [24]:

```
X = newsgroups.data
y = newsgroups.target

# Split into train and test set
X_train_text, X_test_text, y_train, y_test = train_test_split(X, y)
```

In [25]:

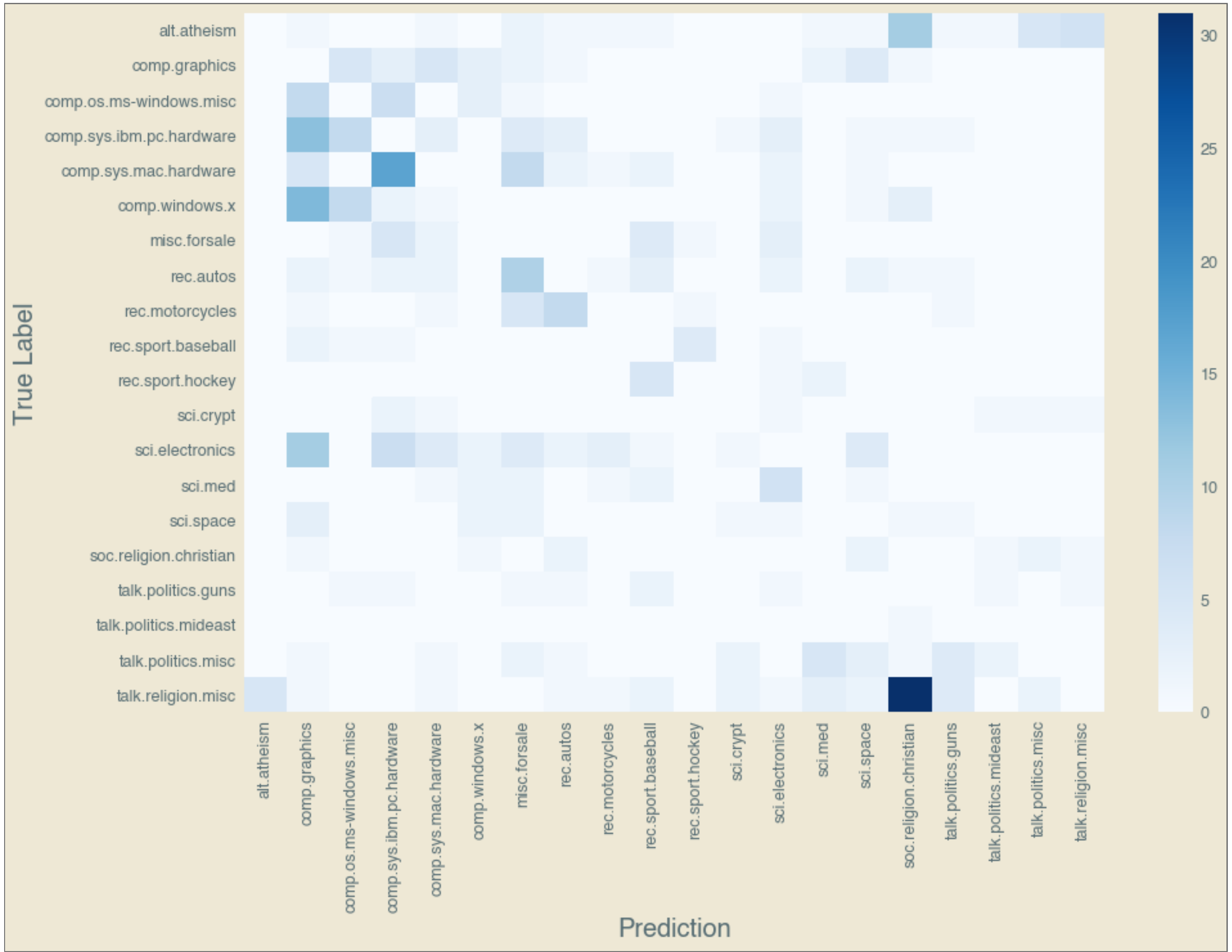
```
vectorizer = TfidfVectorizer(preprocessor=stemmer.stem, stop_words=input_stopwords, min_df=2,
                             max_df=0.9,
                            token_pattern=r"[a-zA-Z]{2,}")
X_train = vectorizer.fit_transform(X_train_text)
X_test = vectorizer.transform(X_test_text)

# Train classifier
model = RandomForestClassifier()
model.fit(X_train, y_train)

# Predict on test class
y_pred = model.predict(X_test)
y_proba = model.predict_proba(X_test)

# Show scores
print("accuracy", (y_pred == y_test).mean())
print('F1', f1_score(y_test, y_pred, average='weighted'))
print('recall', recall_score(y_test, y_pred, average='weighted'))
print('precision', precision_score(y_test, y_pred, average='weighted'))
```

```
accuracy 0.8469423824673029
F1 0.8454934852767634
recall 0.8469423824673029
precision 0.8536500645165409
```

Plot the confusion matrix

In [26]:

```
mat = confusion_matrix(y_test, y_pred) * (np.identity(len(newsgroups.target_names))!=1).astype(int)
mat = pd.DataFrame(data=mat, columns=newsgroups.target_names, index=newsgroups.target_names)
plt.figure(figsize=(15, 10))
sns.heatmap(mat, cmap='Blues')
plt.xlabel("Prediction", fontsize=20);
plt.ylabel("True Label", fontsize=20);
```



We can also plot the vectors in a 2-D space

In [46]:

```
from sklearn.manifold import TSNE
target_names = {i:k for i, k in enumerate(newsgroups.target_names)}
x_plot = TSNE().fit_transform(X_test)
df_v = pd.DataFrame(x_plot, columns=['x','y'])
df_v['target'] = [target_names.get(x) for x in y_test]
df_v['pred'] = [target_names.get(x) for x in y_pred]
```

In [47]:

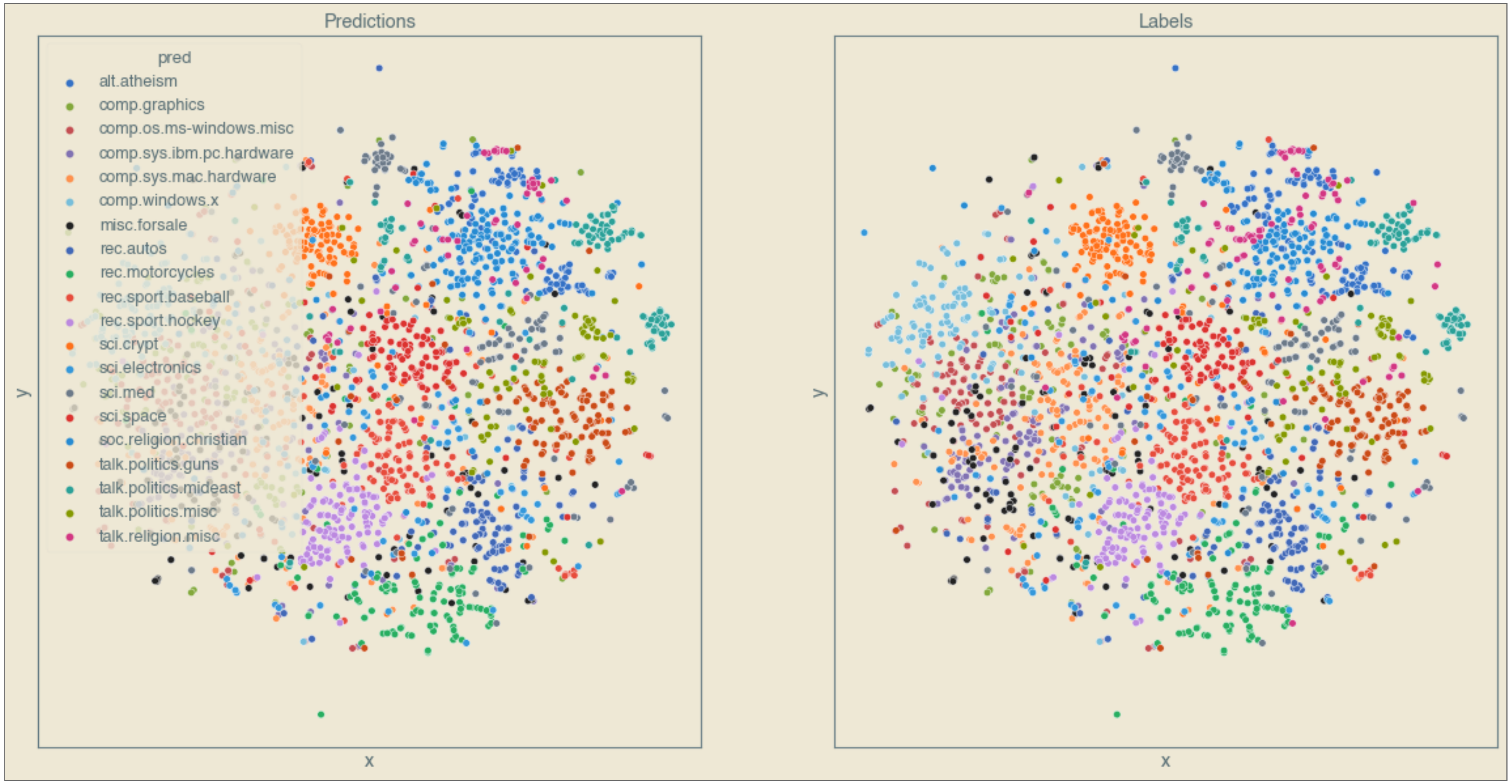
```
df_v.head()
```

Out[47]:

	x	y	target	pred
0	-13.426824	9.467989	comp.sys.ibm.pc.hardware	comp.sys.ibm.pc.hardware
1	5.348517	-42.748169	comp.sys.ibm.pc.hardware	comp.sys.ibm.pc.hardware
2	49.850338	31.386789	alt.atheism	alt.atheism
3	-28.125605	1.156664	comp.sys.mac.hardware	comp.sys.mac.hardware
4	44.419605	7.453356	talk.politics.misc	talk.politics.misc

In [55]:

```
plt.figure(figsize=(20,10))
plt.subplot(121)
sns.scatterplot(data=df_v.sort_values('pred'), x='x', y='y', hue='pred')
plt.title('Predictions');
plt.xticks([]); plt.yticks([]);
plt.subplot(122)
sns.scatterplot(data=df_v.sort_values('target'), x='x', y='y', hue='target', legend=None)
plt.title('Labels');
plt.xticks([]); plt.yticks([]);
```



Word 2 vec

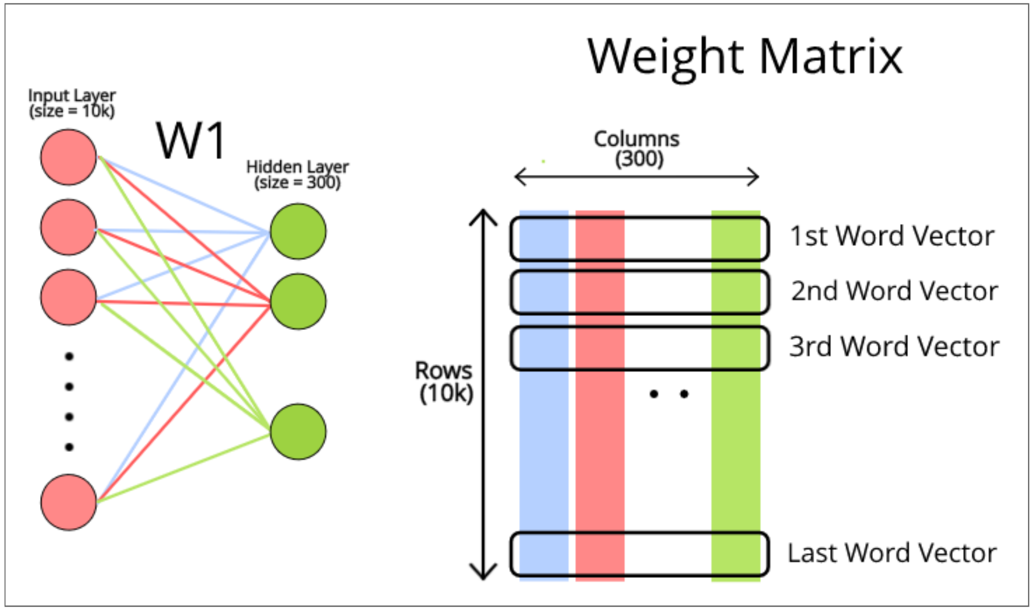
In [32]:

```
print(sentences)
vectors
```

```
['We will stick to natural language processing in this class', 'Be
rt found a stick in the forest']
```

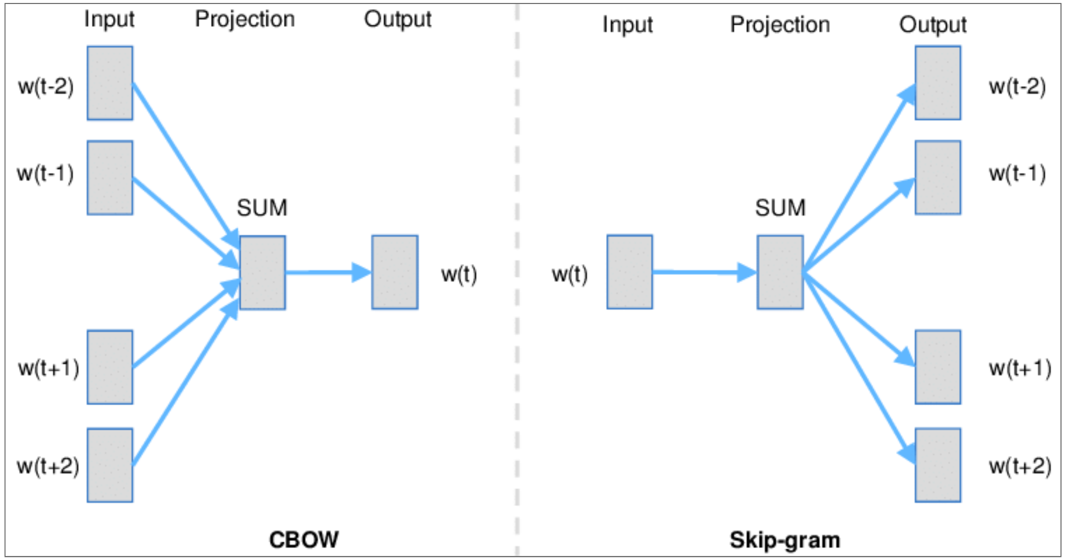
Out[32]:

```
[array([0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1]),
 array([1, 1, 0, 1, 1, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0])]
```



Source: **https://mc.ai/deep-nlp-word-vectors-with-word2vec/**

There are two types of W2V models, CBOW (Continuous Bag of Words) and Skip-gram



CBOW

The CBOW method, tries to predict the target word based on the context.

We will stick to Natural language processing in this class

Average of context words: ('we', 'will' 'to', 'natural') -> 'stick'

CBOW is faster and has slightly better accuracy for frequent words

Skip-gram

The skip-gram method tries to predict the context, based on the input word.

We will stick to Natural language processing in this class

Word 'stick' -> ('we', 'will' 'to', 'natural')

Skip-gram works well with small datasets, and has better representation for rare words or phrases

Training a w2v model

A w2v model can easily be trained using the gensim package

In [56]:

```
model = Word2Vec(sentences, min_count=5, sg=0, window=5)
model.wv.most_similar('computers', topn=10)
```

Out[56]:

```
[('platforms', 0.8607274889945984),
 ('machines', 0.8510891199111938),
 ('packages', 0.829599916934967),
 ('workstations', 0.8101068139076233),
 ('applications', 0.8040137887001038),
 ('pcs', 0.7959615588188171),
 ('workstation', 0.7937494516372681),
 ('silicon', 0.7891894578933716),
 ('capabilities', 0.7720874547958374),
 ('models', 0.7720366716384888)]
```

In [57]:

```
model = Word2Vec(stemmed, min_count=5, sg=0, window=5)
model.wv.most_similar('comput', topn=10)
```

Out[57]:

```
[('engin', 0.7261886596679688),
 ('network', 0.6091169118881226),
 ('research', 0.6016672849655151),
 ('tech', 0.5968046784400940),
 ('system', 0.5861861705780029),
 ('electron', 0.5841708779335022),
 ('carnegi', 0.5837568044662476),
 ('academ', 0.5775421857833862),
```

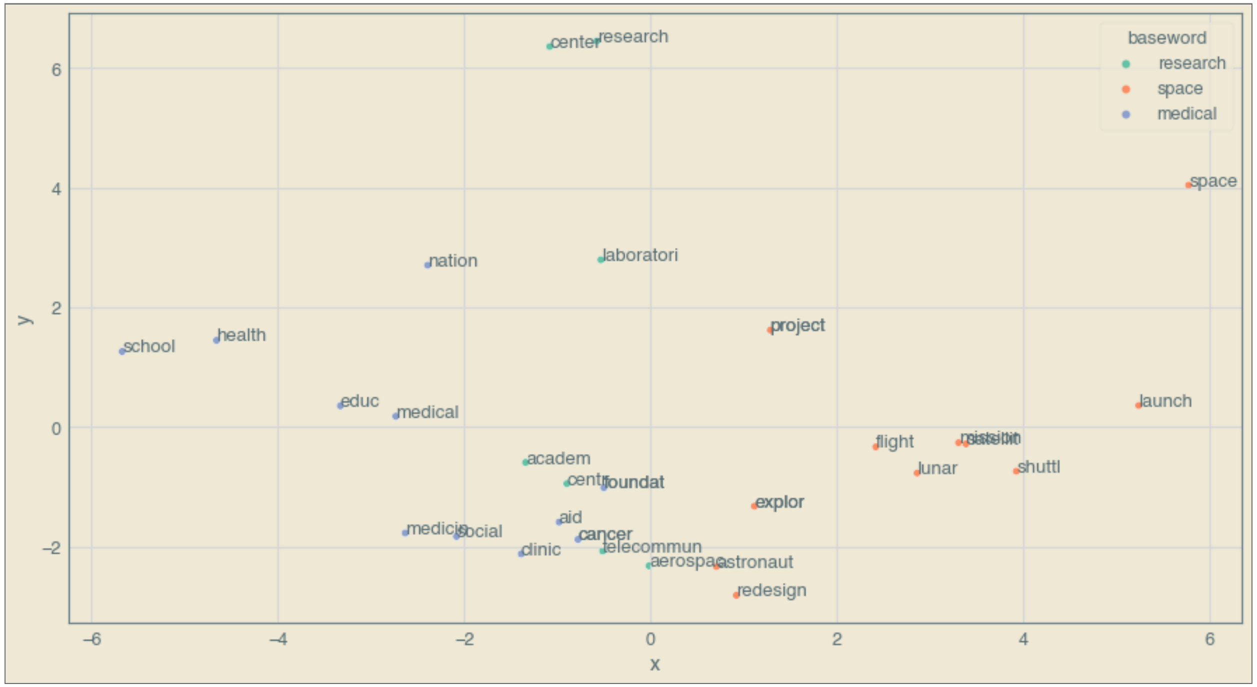
```
 ('depart', 0.5755692720413208),
 ('centr', 0.5711894631385803)]
```

In [36]:

```
from sklearn.decomposition import PCA
words = ['research', 'space', 'medical']

N = 10
un_words = []
basew = []
for word in words:

    un_words.extend([x[0] for x in model.wv.most_similar(stem.stem(word), topn=N)])
    un_words.append(word)
    basew.extend([word for n in range(N+1)])

X = PCA(2).fit_transform(np.stack([model.wv[stem.stem(w)] for w in un_words]))
df = pd.DataFrame(X, columns=['x', 'y'])
df['word'] = un_words
df['baseword'] = basew
```

In [37]:

```
plt.figure(figsize=(15, 8))
sns.scatterplot(data=df, x='x', y='y', hue='baseword', palette='Set2')
for row in df.itertuples():
    plt.annotate(row.word, (row.x, row.y))
```



Topic modelling

There are different ways of obtaining topics from a corpus.

- **Supervised**
  - Classification: Like the tfidf example we saw above. However this requires you to know the topics beforehand, and train a classifier to recognize them.
- **Semi-supervised**
  - Query: Using a vectorizer like the tfidf method, you can use similarity metrics to find documents close to a query
- **Unsupervised**
  - LDA: Unsupervised methods use propabilistic calculations to find common topics in text.

LDA

	🍞	🥑	🥓
Document 0	10	0	0
Document 1	0	10	0
Document 2	0	0	10
Document 3	10	10	10
	🍞	🥑	🥓

Document 0	🍞🍞🍞🍞🍞🍞🍞🍞🍞🍞	Remove Document
Document 1	🥑🥑🥑🥑🥑🥑🥑🥑🥑🥑	Remove Document
Document 2	🥓🥓🥓🥓🥓🥓🥓🥓🥓🥓	Remove Document
Document 3	🍞🍞🍞🍞🍞🍞🍞🍞🍞🍞🥑🥑🥑🥑🥑🥑🥑🥑🥑🥑🥓🥓🥓🥓🥓🥓🥓🥓🥓🥓	Remove Document

source: https://medium.com/@lettier/how-does-lda-work-ill-explain-using-emoji-108abf40fa7d

	Topic 0	Topic 1	Topic 2
🍞	0.000	0.000	0.999
🥑	0.999	0.000	0.000
🥓	0.000	0.999	0.000
	Topic 0	Topic 1	Topic 2

	Topic 0	Topic 1	Topic 2
Document 0	0.030	0.030	0.939
Document 1	0.939	0.030	0.030
Document 2	0.030	0.939	0.030
Document 3	0.333	0.333	0.333
	Topic 0	Topic 1	Topic 2

Document 0 🍞🍞🍞🍞🍞🍞🍞🍞🍞🍞 Remove Document

Document 1 🥑🥑🥑🥑🥑🥑🥑🥑🥑🥑 Remove Document

Document 2 🥓🥓🥓🥓🥓🥓🥓🥓🥓🥓 Remove Document

Document 3 🍞🍞🍞🍞🍞🍞🍞🍞🍞🍞🥑🥑🥑🥑🥑🥑🥑🥑🥑🥑🥓🥓🥓🥓🥓🥓🥓🥓🥓🥓 Remove Document

source: **https://medium.com/@lettier/how-does-lda-work-ill-explain-using-emoji-108abf40fa7d**

There are two main hypterparameters that are important in LDA.
The alpha Controls how many topics are in one document

> *Turn it down, and the documents is more likely to have one or few topics.*
> *Turn it up, and the documents will likely have more of a mixture of topics.*

The beta (or eta in gensim) hyperparameter controls the distribution of words per topic.

> *Turn it down, and the topics will likely have less words.*
> *Turn it up, and the topics will likely have more words.*

In [38]:

```
from sklearn.decomposition import NMF
from gensim.models import LdaModel
from gensim.corpora import Dictionary
```

In [58]:

```
fake_documents = [['bread']*10,
                  ['avocado']*10,
                  ['bacon']*10,
                  [*['bacon']*10, *['avocado']*10, *['bread']*10]]
dictionary = Dictionary(fake_documents)
corpus = [dictionary.doc2bow(doc) for doc in fake_documents]

lda = LdaModel(corpus, num_topics=3, id2word=dictionary, passes=100, alpha=.33, eta=.01)
print(lda.print_topics(num_words=1),'\n')
for i, doc in enumerate(corpus):
    t1, t2, t3 = lda.get_document_topics(doc)
    print('Document', i)
    print(dictionary.id2token[t1[0]], np.round(t1[1], 2),
    dictionary.id2token[t2[0]], np.round(t2[1], 2),
    dictionary.id2token[t3[0]], np.round(t3[1], 2))
```

```
[(0, '0.500*"bread"'), (1, '0.999*"bacon"'), (2, '0.333*"bacon"')]

Document 0
bread 0.94 avocado 0.03 bacon 0.03
Document 1
bread 0.94 avocado 0.03 bacon 0.03
Document 2
bread 0.03 avocado 0.94 bacon 0.03
Document 3
bread 0.66 avocado 0.33 bacon 0.01
```

Let's try and run this on the newsgroups dataset

In [40]:

```
# Tokenize the text
tok = RegexpTokenizer(r"[a-zA-Z]{3,}")
documents = [tok.tokenize(text.lower()) for text in newsgroups.data]

#check to see we're keeping the right shape
assert len(documents) == len(newsgroups.data)
```

In [41]:

```
dictionary = Dictionary(documents)
dictionary.filter_extremes(no_above=.1, no_below=150)
stopword_ids = [dictionary.token2id.get(w, None) for w in input_stopwords]
dictionary.filter_tokens(bad_ids=stopword_ids)
corpus = [dictionary.doc2bow(doc) for doc in documents]
lda = LdaModel(corpus, id2word=dictionary, num_topics = len(target_names), passes=10, chunksize=200,
              alpha=.4, eta=.8)
```

In [42]:

```
for i in range(20):
    terms = np.array(lda.get_topic_terms(i, topn=8))
    print(f'Topic {i}')
    print('\t',' '.join([str(dictionary.id2token[t[0]]) + '('+str(np.round(t[1], 2))+')' for t in terms]))
```

```
Topic 0
	 day(0.02) ago(0.02) told(0.02) went(0.01) days(0.01) left
(0.01) came(0.01) pitt(0.01)
Topic 1
	 tell(0.01) anything(0.01) bad(0.01) enough(0.01) little
(0.01) maybe(0.01) give(0.01) lot(0.01)
Topic 2
	 david(0.08) john(0.06) org(0.05) mark(0.05) jim(0.04) rob
ert(0.04) wrote(0.03) newsreader(0.03)
Topic 3
	 key(0.06) chip(0.04) netcom(0.04) clipper(0.03) encryptio
n(0.03) keys(0.02) att(0.02) security(0.02)
Topic 4
	 year(0.08) washington(0.04) andrew(0.04) cmu(0.03) chicag
o(0.03) san(0.02) mot(0.02) york(0.02)
Topic 5
	 inc(0.06) opinions(0.04) steve(0.04) uucp(0.03) corporati
on(0.03) corp(0.02) disclaimer(0.02) mine(0.02)
Topic 6
	 space(0.07) gov(0.06) nasa(0.05) research(0.05) technolog
y(0.04) institute(0.03) center(0.03) access(0.02)
Topic 7
	 evidence(0.02) however(0.01) science(0.01) example(0.01)
```

```
given(0.01) claim(0.01) non(0.01) argument(0.01)
Topic 8
         team(0.04) game(0.03) hockey(0.03) win(0.02) uiuc(0.02) g
ames(0.02) play(0.02) toronto(0.02)
Topic 9
         sun(0.03) information(0.03) list(0.03) email(0.03) intern
et(0.02) info(0.02) group(0.02) send(0.02)
Topic 10
         drive(0.11) ibm(0.04) mac(0.03) dos(0.03) disk(0.03) hard
(0.03) software(0.03) scsi(0.03)
Topic 11
         car(0.03) power(0.03) high(0.02) low(0.01) cars(0.01) buy
(0.01) columbia(0.01) cost(0.01)
Topic 12
         god(0.08) jesus(0.03) bible(0.02) christian(0.02) christi
ans(0.02) faith(0.02) life(0.02) religion(0.01)
Topic 13
         israel(0.04) israeli(0.02) war(0.02) turkish(0.02) jews
(0.02) men(0.02) government(0.01) jewish(0.01)
Topic 14
         card(0.05) bit(0.03) video(0.03) driver(0.03) windows(0.0
3) memory(0.03) drivers(0.02) mouse(0.02)
Topic 15
         max(0.37) bike(0.08) dod(0.07) dan(0.05) green(0.04) ray
(0.04) ride(0.03) daniel(0.03)
Topic 16
         file(0.03) program(0.03) files(0.02) window(0.02) windows
(0.02) mit(0.02) code(0.02) available(0.02)
Topic 17
```

law(0.04) gun(0.03) colorado(0.02) government(0.02) bill (0.02) guns(0.02) control(0.02) rights(0.02)

Topic 18

president(0.03) michael(0.03) white(0.03) clinton(0.03) health(0.02) national(0.02) austin(0.01) press(0.01)

Topic 19

sale(0.04) price(0.03) apple(0.03) ohio(0.03) acs(0.03) college(0.03) book(0.02) berkeley(0.02)

In [43]:

```
pred = []
for i, doc in enumerate(corpus):
    pred.append(pd.DataFrame(lda.get_document_topics(doc)).set_index(0).idxmax().values[0])
```

In [44]:

```
df = pd.DataFrame([pred, newsgroups.target]).T
df.columns = ['pred', 'label']
df['label'] = df['label'].replace(target_names)
df['count'] = 1
df.head()
```

Out[44]:

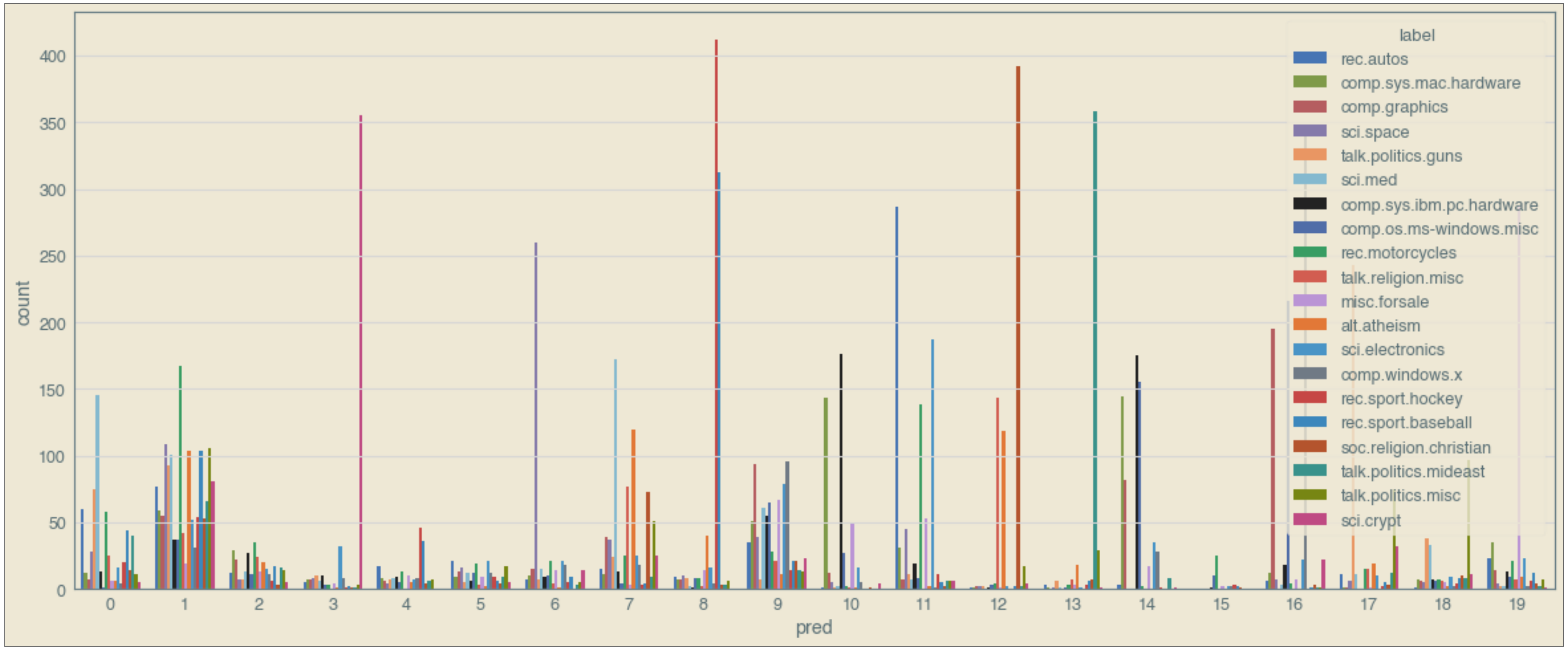
	pred	label	count
0	11	rec.autos	1
1	4	comp.sys.mac.hardware	1
2	1	comp.sys.mac.hardware	1
3	2	comp.graphics	1
4	7	sci.space	1

In [45]:

```
x, y = np.unique(pred, return_counts=True)
x2, y2 = np.unique(newsgroups.target, return_counts=True)
plt.figure(figsize=(20,8))
sns.barplot(data=df, y="count", x='pred', hue='label', estimator=sum)
```

Out[45]:

```
<AxesSubplot:xlabel='pred', ylabel='count'>
```



Exercise time

On datacamp, try **'Simple topic identification'** module. If you have time left, take a look at the **Named-entity recognition** module