Feature Engineering on Twitter US Airline Dataset

Methods Used:

1. Bag of Words
2. Bag of N-Grams
3. TF-IDF
4. Cosine Document Similarity
5. word2vec trained on our dataset with tensorflow
6. word2vec trained on our dataset with gensim
7. word2vec trained by Google on News dataset

Import common packages

In [5]:
```
import pandas as pd
import numpy as np
import nltk
```

Load Cleaned Data Set

See previous code submission from project proposal for extensive data cleaning steps.

In [6]:
```
cleanDF = pd.read_csv("C:\git\CSML1010-Group_11-Final-Project\proposal\Tweets_cleaned.csv")
cleanDF.columns
```

Out[6]:
```
Index(['tweet_id', 'airline_sentiment', 'airline_sentiment_confidence',
       'negativereason', 'negativereason_confidence', 'airline', 'text',
       'text_cleaned', 'emojis_flag', 'emojis', 'emoticons_flag', 'emoticons',
       'text_cleaned_without_emojis_emoticons', 'hashtags',
       'text_cleaned_without_emojis_emoticons_hashtags', 'hashtags_flag',
       'text_cleaned_lower_case', 'text_cleaned_no_abbreviations',
       'text_list_no_stop_words', 'lemmas_list'],
      dtype='object')
```

Bag of Words Model

A bag of words model is a simpleway to represent text data as numeric vectors.

Each column is a word from our data set, each row is a single tweet and the value in each row is the number of occurrences of that word in the tweet.

In [3]:
```
from sklearn.feature_extraction.text import CountVectorizer

cv = CountVectorizer(min_df=0., max_df=1.)
cv_matrix = cv.fit_transform(cleanDF['lemmas_list'].values.astype('U'))
#.values.astype('U') converts the column of words to a unicode string
cv_matrix = cv_matrix.toarray()
cv_matrix
```

Out[3]:
```
array([[0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
       ...,
       [0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0]], dtype=int64)
```

In [4]:
```
# get all unique words in the corpus
vocab = cv.get_feature_names()
# show document feature vectors
pd.DataFrame(cv_matrix, columns=vocab)

#pd.options.display.max_columns = 100
#pd.set_option('display.max_rows', 100)

#pd.DataFrame(cv_matrix, columns=vocab).to_csv("bagofwords.csv")
```

Out[4]:

	00	000	000114	000lb	00a	00am	00p	00pm	01	01pm	...	zambia	zcc82u	zero	zig	zip	zipper	zone	zoom	z
0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
14635	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	
14636	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	
14637	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	
14638	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	
14639	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	

14640 rows × 8669 columns

Bag of N-Grams

A bag of n-grams model is similar to the bag of words model, but here we extend it to include a "bi-gram" of two words. This allows us to see the number of occurrences of two-word pairs in each of our tweets as a numeric vector.

In [5]:

```python
# you can set the n-gram range to 1,2 to get unigrams as well as bigrams
bv = CountVectorizer(ngram_range=(2,2))
bv_matrix = bv.fit_transform(cleanDF['lemmas_list'].values.astype('U'))

bv_matrix = bv_matrix.toarray()
vocab = bv.get_feature_names()
pd.DataFrame(bv_matrix, columns=vocab)

#pd.DataFrame(bv_matrix, columns=vocab).to_csv("bagofngrams.csv")
```

Out[5]:

	00 27	00 bag	00 check	00 don	00 flight	00 goodwill	00 happy	00 phone	00 pm	00 say	...	zone precious	zone space	zone thank	zoom sauce	zoom scroll	zuke non	zuric b
0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
14635	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
14636	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
14637	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
14638	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	
14639	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	

14640 rows × 62070 columns

TF-IDF Model

The TF-IDF model is a slightly more complicated way of vectorizing our text data. It combines two different ways of looking at our text. *term frequency* and *inverse document frequency*.

A more details explanation of how TF-IDF works is available elsewhere. For our purposes, it outputs scaled and normalized values which are more easily comparable and usable than bag of words-based models.

In [7]:
```
from sklearn.feature_extraction.text import TfidfVectorizer

tv = TfidfVectorizer(min_df=0., max_df=1., use_idf=True)
tv_matrix = tv.fit_transform(cleanDF['lemmas_list'].values.astype('U'))
tv_matrix = tv_matrix.toarray()

vocab = tv.get_feature_names()
pd.DataFrame(np.round(tv_matrix, 2), columns=vocab)

#pd.DataFrame(np.round(tv_matrix, 2), columns=vocab).to_csv("tfidfmodel.csv")
```

Out[7]:

	00	000	000114	000lb	00a	00am	00p	00pm	01	01pm	...	zambia	zcc82u	zero	zig	zip	zipper	zone	zoom
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
14635	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
14636	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
14637	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
14638	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
14639	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

14640 rows × 8669 columns

Cosine Document Similarity

This measure of document similarity uses a distance function to compare the vectors of each document (aka tweet) in our TF-IDF model. A value closer to 1 indicates a more similar document and a value closer to 0 indicates a dissimilar document. The values represent the cosine angle between the vectors for each tweet.

In [8]:
```python
from sklearn.metrics.pairwise import cosine_similarity

similarity_matrix = cosine_similarity(tv_matrix)
similarity_df = pd.DataFrame(similarity_matrix)
similarity_df

#similarity_df.to_csv("documentsimilarity.csv")
```

Out[8]:

	0	1	2	3	4	5	6	7	8	9	...	14630	14631	14632	14633	14634	14635	1
0	1.0	0.0	0.000000	0.0	0.0	0.000000	0.0	0.0	0.0	0.0	...	0.00000	0.000000	0.0	0.000000	0.0	0.000000	0.00
1	0.0	1.0	0.000000	0.0	0.0	0.000000	0.0	0.0	0.0	0.0	...	0.00000	0.000000	0.0	0.000000	0.0	0.000000	0.00
2	0.0	0.0	1.000000	0.0	0.0	0.000000	0.0	0.0	0.0	0.0	...	0.00000	0.000000	0.0	0.084757	0.0	0.000000	0.00
3	0.0	0.0	0.000000	1.0	0.0	0.000000	0.0	0.0	0.0	0.0	...	0.00000	0.000000	0.0	0.000000	0.0	0.000000	0.00
4	0.0	0.0	0.000000	0.0	1.0	0.307344	0.0	0.0	0.0	0.0	...	0.00000	0.000000	0.0	0.000000	0.0	0.000000	0.00
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
14635	0.0	0.0	0.000000	0.0	0.0	0.028866	0.0	0.0	0.0	0.0	...	0.30427	0.188921	0.0	0.052285	0.0	1.000000	0.04
14636	0.0	0.0	0.000000	0.0	0.0	0.026716	0.0	0.0	0.0	0.0	...	0.00000	0.000000	0.0	0.098288	0.0	0.046479	1.00
14637	0.0	0.0	0.000000	0.0	0.0	0.000000	0.0	0.0	0.0	0.0	...	0.00000	0.000000	0.0	0.000000	0.0	0.000000	0.00
14638	0.0	0.0	0.000000	0.0	0.0	0.019337	0.0	0.0	0.0	0.0	...	0.00000	0.000000	0.0	0.035024	0.0	0.033641	0.03
14639	0.0	0.0	0.114465	0.0	0.0	0.116877	0.0	0.0	0.0	0.0	...	0.00000	0.000000	0.0	0.130844	0.0	0.070611	0.06

14640 rows × 14640 columns

Word2Vec Word Embedding Model

Training with CBOW (Continuous Bag of Words)

Now, we look at a more advanced model. Here, we implement a word embedding model. Word embedding is a way of representing individual words in such a way that words that are similar are represented similarly.

We do this using a word2vec model which represents words as multi-dimensional vectors (in this case 100 dimensions).

We build a model from scratch here using *keras* and *tensorflow* to build a *Continuous Bag of Words* (CBOW) model. A CBOW takes multiple words that surround a target word as input, and predicts the target word based on that input.

Build Vocabulary

In [9]:
```python
from keras.preprocessing import text
from keras.utils import np_utils
from keras.preprocessing import sequence

tokenizer = text.Tokenizer()
tokenizer.fit_on_texts(cleanDF['lemmas_list'].values.astype('U'))
word2id = tokenizer.word_index

word2id['PAD'] = 0
id2word = {v:k for k, v in word2id.items()}
wids = [[word2id[w] for w in text.text_to_word_sequence(doc)] for doc in cleanDF['lemmas_list'].values
.astype('U')]

vocab_size = len(word2id)
embed_size = 100
window_size = 2

print('Vocabulary Size:', vocab_size)
print('Vocabulary Sample:', list(word2id.items())[:10])
```

```
Using TensorFlow backend.

Vocabulary Size: 8872
Vocabulary Sample: [('flight', 1), ('thank', 2), ('hour', 3), ('cancel', 4), ('service', 5), ('time',
6), ('delay', 7), ('customer', 8), ('help', 9), ('get', 10)]
```

Build (context_words, target_word) pair generator

In [10]:
```python
def generate_context_word_pairs(corpus, window_size, vocab_size):
    context_length = window_size*2
    for words in corpus:
        sentence_length = len(words)
        for index, word in enumerate(words):
            context_words = []
            label_word   = []
            start = index - window_size
            end = index + window_size + 1

            context_words.append([words[i]
                                 for i in range(start, end)
                                 if 0 <= i < sentence_length
                                 and i != index])
            label_word.append(word)

            x = sequence.pad_sequences(context_words, maxlen=context_length)
            y = np_utils.to_categorical(label_word, vocab_size)
            yield (x, y)
```

In [11]:
```
i = 0
for x, y in generate_context_word_pairs(corpus=wids, window_size=window_size, vocab_size=vocab_size):
    if 0 not in x[0]:
        print('Context (X):', [id2word[w] for w in x[0]], '-> Target (Y):', id2word[np.argwhere(y[0])[
0][0]])

        if i == 10:
            break
        i += 1
```

```
Context (X): ['plus', 'add', 'experience', 'tacky'] -> Target (Y): commercial
Context (X): ['aggressive', 'blast', 'entertainment', 'guest'] -> Target (Y): obnoxious
Context (X): ['blast', 'obnoxious', 'guest', 'face'] -> Target (Y): entertainment
Context (X): ['obnoxious', 'entertainment', 'face', 'little'] -> Target (Y): guest
Context (X): ['entertainment', 'guest', 'little', 'recourse'] -> Target (Y): face
Context (X): ['seriously', 'pay', 'seat', 'playing'] -> Target (Y): flight
Context (X): ['pay', 'flight', 'playing', 'bad'] -> Target (Y): seat
Context (X): ['flight', 'seat', 'bad', 'thing'] -> Target (Y): playing
Context (X): ['seat', 'playing', 'thing', 'fly'] -> Target (Y): bad
Context (X): ['playing', 'bad', 'fly', 'va'] -> Target (Y): thing
Context (X): ['yes', 'nearly', 'fly', 'vx'] -> Target (Y): time
```

Build CBOW Deep Network Model

In [12]:
```
import keras.backend as K
from keras.models import Sequential
from keras.layers import Dense, Embedding, Lambda

import tensorflow as tf
with tf.device('/gpu:0'):

    cbow = Sequential()
    cbow.add(Embedding(input_dim=vocab_size, output_dim=embed_size, input_length=window_size*2))
    cbow.add(Lambda(lambda x: K.mean(x, axis=1), output_shape=(embed_size,)))
    cbow.add(Dense(vocab_size, activation='softmax'))

    cbow.compile(loss='categorical_crossentropy', optimizer='rmsprop')
    print(cbow.summary())
```

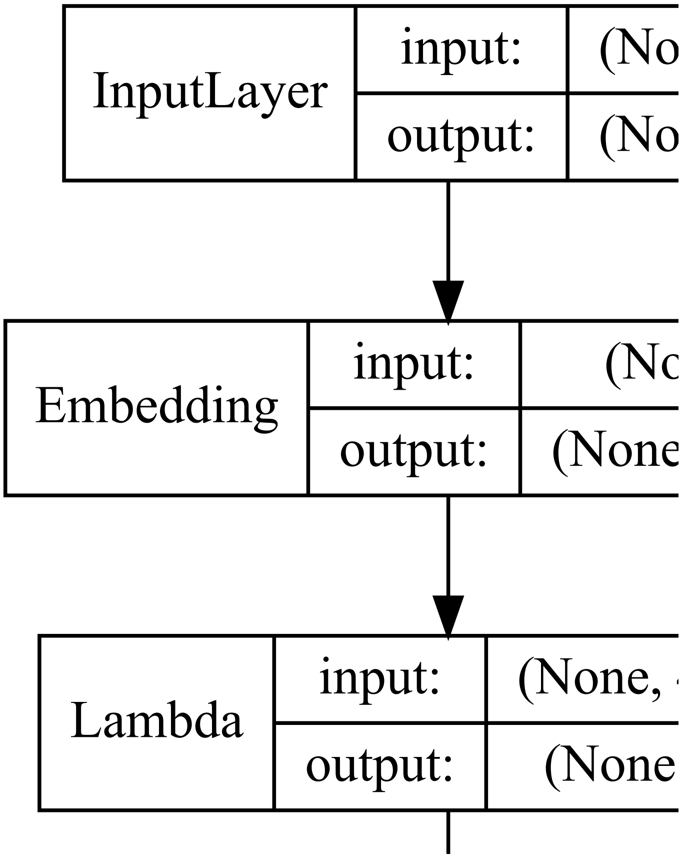
```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
embedding_1 (Embedding)      (None, 4, 100)            887200    
_________________________________________________________________
lambda_1 (Lambda)            (None, 100)               0         
_________________________________________________________________
dense_1 (Dense)              (None, 8872)              896072    
=================================================================
Total params: 1,783,272
Trainable params: 1,783,272
Non-trainable params: 0
_________________________________________________________________
None
```

Visualize Model

In [13]:
```python
from IPython.display import SVG
from keras.utils.vis_utils import model_to_dot

SVG(model_to_dot(cbow, show_shapes=True, show_layer_names=False,
                 rankdir='TB').create(prog='dot', format='svg'))
```

Out[13]:



Train model for 5 epochs

In [ ]:
```
with tf.device('/gpu:0'):
    for epoch in range(1, 6):
        loss = 0.
        i = 0
        for x, y in generate_context_word_pairs(corpus=wids, window_size=window_size, vocab_size=vocab
_size):
            i += 1
            loss += cbow.train_on_batch(x, y)
            if i % 100000 == 0:
                print('Processed {} (context, word) pairs'.format(i))

        print('Epoch:', epoch, '\tLoss:', loss)
        print()
```

```
C:\ProgramData\Anaconda3\envs\milestone1\lib\site-packages\tensorflow_core\python\framework\indexed_s
lices.py:433: UserWarning: Converting sparse IndexedSlices to a dense Tensor of unknown shape. This m
ay consume a large amount of memory.
  "Converting sparse IndexedSlices to a dense Tensor of unknown shape. "

Processed 100000 (context, word) pairs
Epoch: 1        Loss: 980699.2105463557

Processed 100000 (context, word) pairs
Epoch: 2        Loss: 1144282.866285345

Processed 100000 (context, word) pairs
Epoch: 3        Loss: 1337395.7755461363

Processed 100000 (context, word) pairs
Epoch: 4        Loss: 1453879.772978104
```

Get word embeddings

In [30]:
```
#load weights (COMMENT OUT BELOW if re-training)
weights = pd.read_csv("word2vecCBOWtrained.csv")
weights = cbow.get_weights()[0]
weights = weights[1:]

print(weights.shape)



#word2vecCBOWtrained = pd.DataFrame(weights, index=list(id2word.values())[1:]).head()

#pd.DataFrame(weights, index=list(id2word.values())[1:]).to_csv("word2vecCBOWtrained.csv")
```

```
(8871, 100)
```

Build a distance matrix to view the most similar words (contextually)¶

In [40]:

```
#load word embeddings (COMMENT OUT BELOW if re-training)
word2vecCBOWtrained = pd.read_csv("word2vecCBOWtrained.csv")

from sklearn.metrics.pairwise import euclidean_distances

# compute pairwise distance matrix
distance_matrix = euclidean_distances(weights)
print(distance_matrix.shape)

# view contextually similar words
similar_words = {search_term: [id2word[idx] for idx in distance_matrix[word2id[search_term]-1].argsort
()[1:6]+1]
                   for search_term in ['flight', 'airline', 'good', 'bad', 'time', 'seat', 'amazing',
'experience']}

similar_words
```

```
(8871, 8871)
```

Out[40]:

```
{'flight': ['7hours', 'functionality', 'tvs', 'us2065', 'typical'],
 'airline': ['rocky', 'reduction', 'squeak', 'dedicated', 'prohibit'],
 'good': ['dnx58v', 'fog', 'fax', 'rr', '🤍'],
 'bad': ['ua1266', 'win', 'lekvhg', 'crucial', 'underserved'],
 'time': ['practice', 'm', 'aa3230', 'wifi', 'loading'],
 'seat': ['taiwan', 'bogota', 'brendan', 'fudgin', 'yaayy'],
 'amazing': ['steve', "nat'l", '24hours', 'row7', 'eyewitness'],
 'experience': ['jean', 'any1', 'attitude', 'baby', 'hayes']}
```

Visualize word embeddings

In [44]:

```
word2vecCBOWtrained.iloc[:, 0]
```

Out[44]:

```
0             thank
1              hour
2            cancel
3           service
4              time
           ...
8823         stuffy
8824    arbitrarily
8825    retribution
8826          aires
8827            PAD
Name: Unnamed: 0, Length: 8828, dtype: object
```

Word2Vec Word Embedding Model

Using gensim to train model

Now, to give us another feature to compare with, we will generate a similar word2vec model, using the Continuous Bag of Words model - this time, using gensim. We are again training this on our own data set, so we expect similar results. It will be a good double-check that both models are performing similarly.

In [46]:
```
from gensim.models import word2vec

# tokenize sentences in corpus
wpt = nltk.WordPunctTokenizer()
tokenized_corpus = [wpt.tokenize(document) for document in (cleanDF['lemmas_list'].values.astype('U'
))]

# Set values for various parameters
feature_size = 100    # Word vector dimensionality
window_context = 30          # Context window size
min_word_count = 1   # Minimum word count
sample = 1e-3   # Downsample setting for frequent words

w2v_model = word2vec.Word2Vec(tokenized_corpus, size=feature_size,
                          window=window_context, min_count=min_word_count,
                          sample=sample, iter=50)

# view similar words based on gensim's model
similar_words = {search_term: [item[0] for item in w2v_model.wv.most_similar([search_term], topn=5)]
                  for search_term in ['flight', 'airline', 'good', 'bad', 'time', 'seat', 'amazing',
'experience']}
similar_words
```

Out[46]:
```
{'flight': ['afternoon', 'flightr', 'proactively', 'fvf9yw', 'characterize'],
 'airline': ['saddening', 'investment', 'business', 'absolute', 'bmi'],
 'good': ['comfortable', 'appleton', 'surprised', 'lmaooo', 'bad'],
 'bad': ['horrible', 'terrible', 'awful', 'difficulty', 'archaic'],
 'time': ['min', 'ua51', 'gla', 'yeah', 'estimate'],
 'seat': ['economy', 'seating', 'leg', 'row', 'voluntarily'],
 'amazing': ['fantastic', '👍', '😊', 'awesome', '⤴⤴'],
 'experience': ['ua5184', 'confrontational', 'wpg', 'respect', 'guru']}
```

In [47]:
```
from gensim.models import KeyedVectors

#export model
#w2v_model.wv.save_word2vec_format(fname='gensim_word2vec_trained.bin', binary=True)
```

Visualize word embeddings

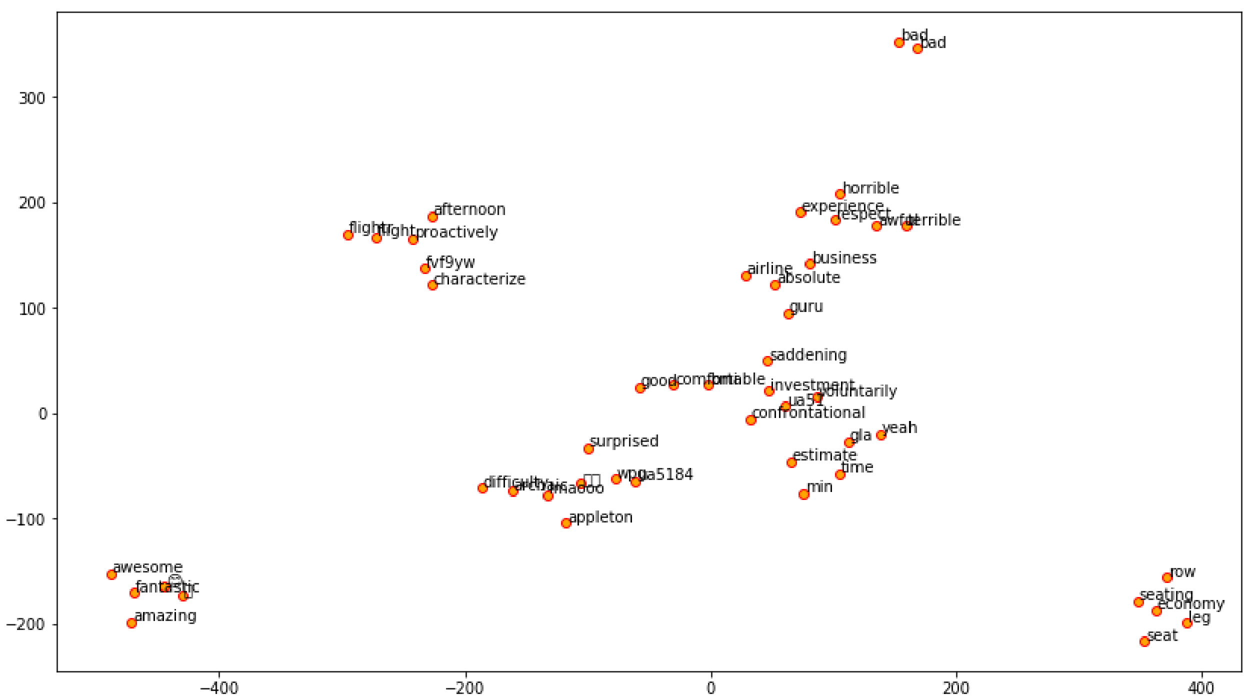
In [48]:
```python
import matplotlib.pyplot as plt
from sklearn.manifold import TSNE

words = sum([[k] + v for k, v in similar_words.items()], [])
wvs = w2v_model.wv[words]

tsne = TSNE(n_components=2, random_state=0, n_iter=10000, perplexity=2)
np.set_printoptions(suppress=True)
T = tsne.fit_transform(wvs)
labels = words

plt.figure(figsize=(14, 8))
plt.scatter(T[:, 0], T[:, 1], c='orange', edgecolors='r')
for label, x, y in zip(labels, T[:, 0], T[:, 1]):
    plt.annotate(label, xy=(x+1, y+1), xytext=(0, 0), textcoords='offset points')
```

```
C:\ProgramData\Anaconda3\envs\milestone1\lib\site-packages\matplotlib\backends\backend_agg.py:211: Ru
ntimeWarning: Glyph 55357 missing from current font.
  font.set_text(s, 0.0, flags=flags)
C:\ProgramData\Anaconda3\envs\milestone1\lib\site-packages\matplotlib\backends\backend_agg.py:211: Ru
ntimeWarning: Glyph 56397 missing from current font.
  font.set_text(s, 0.0, flags=flags)
C:\ProgramData\Anaconda3\envs\milestone1\lib\site-packages\matplotlib\backends\backend_agg.py:176: Ru
ntimeWarning: Glyph 128077 missing from current font.
  font.load_char(ord(s), flags=flags)
C:\ProgramData\Anaconda3\envs\milestone1\lib\site-packages\matplotlib\backends\backend_agg.py:211: Ru
ntimeWarning: Glyph 56842 missing from current font.
  font.set_text(s, 0.0, flags=flags)
C:\ProgramData\Anaconda3\envs\milestone1\lib\site-packages\matplotlib\backends\backend_agg.py:211: Ru
ntimeWarning: Glyph 10548 missing from current font.
  font.set_text(s, 0.0, flags=flags)
C:\ProgramData\Anaconda3\envs\milestone1\lib\site-packages\matplotlib\backends\backend_agg.py:180: Ru
ntimeWarning: Glyph 10548 missing from current font.
  font.set_text(s, 0, flags=flags)
```



Word2Vec Word Embedding Model

Using Pre-Trained Model from Google

Subet of Google's word2vec model for the 500,000 most frequent words

For our final model, instead of training our own word2vec model, we instead download Google's pre-trained word2vec model. Google has trained this model on articles from its news service and it includes 300 dimensions in almost 3.7 GB. This is not a manageable size, but we still want to load Google's model to compare to our custom-trained models.

To make this manageable, when loading the model we limit it to the first 500,000 rows. Google's model is organized with the most frequent words at the beginning of the dataset so this should be an effective reduction.

We save this reduced model to use in our benchmarking.

In [49]:
```
from gensim.models import KeyedVectors

w2v_model = KeyedVectors.load_word2vec_format(r'C:\Users\Patrick\gensim-data\word2vec-google-news-300
\word2vec-google-news-300\GoogleNews-vectors-negative300.bin', binary=True, limit=500000)

# view similar words based on gensim's model
similar_words = {search_term: [item[0] for item in w2v_model.wv.most_similar([search_term], topn=5)]
                  for search_term in ['flight', 'airline', 'good', 'bad', 'time', 'seat', 'amazing',
'experience']}
similar_words
```

```
C:\ProgramData\Anaconda3\envs\milestone1\lib\site-packages\ipykernel_launcher.py:7: DeprecationWarnin
g: Call to deprecated `wv` (Attribute will be removed in 4.0.0, use self instead).
  import sys
```

Out[49]:
```
{'flight': ['flights', 'plane', 'Flight', 'airplane', 'takeoff'],
 'airline': ['airlines', 'Airlines', 'Airline', 'Airways', 'Lufthansa'],
 'good': ['great', 'bad', 'terrific', 'decent', 'nice'],
 'bad': ['good', 'terrible', 'horrible', 'Bad', 'lousy'],
 'time': ['day', 'moment', 'days', 'period', 'periods'],
 'seat': ['seats', 'Seat', 'Seats', 'seat_vacated', 'seated'],
 'amazing': ['incredible',
  'awesome',
  'unbelievable',
  'fantastic',
  'phenomenal'],
 'experience': ['experiences',
  'expertise',
  'expereince',
  'experince',
  'knowledge']}
```

In [50]:
```
from gensim.models import KeyedVectors

#export model
#w2v_model.wv.save_word2vec_format(fname='gensim_word2vec_google_subset.bin', binary=True)
```

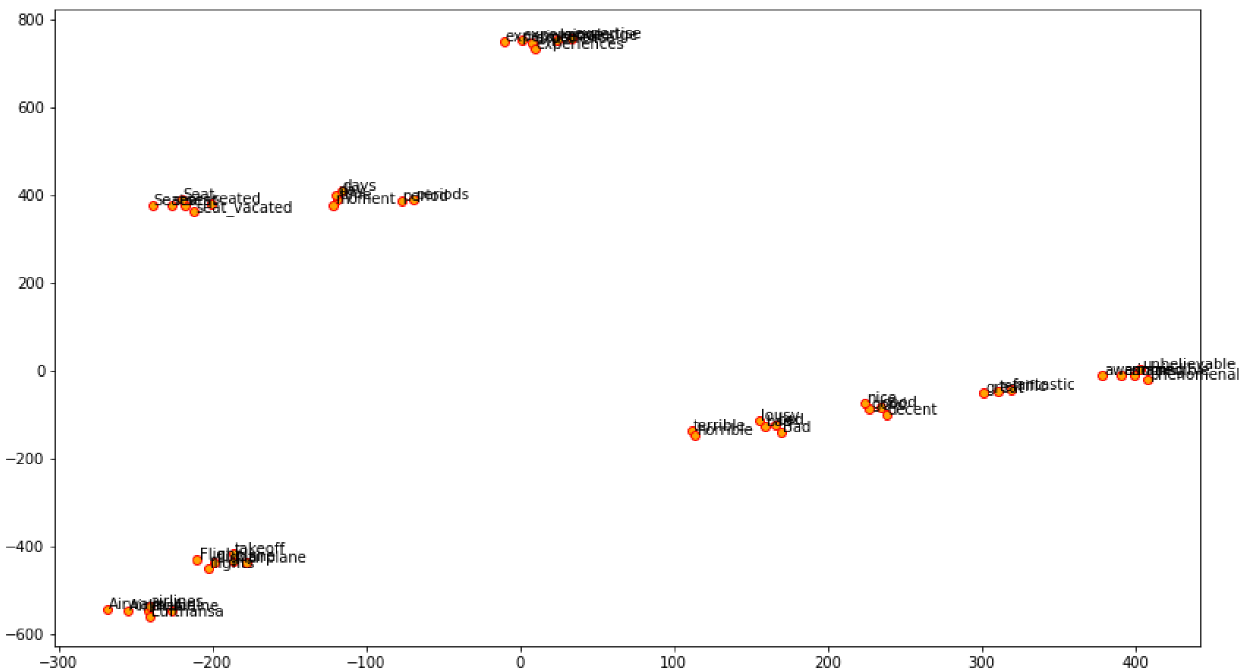
In [51]:
```
import matplotlib.pyplot as plt
from sklearn.manifold import TSNE

words = sum([[k] + v for k, v in similar_words.items()], [])
wvs = w2v_model.wv[words]

tsne = TSNE(n_components=2, random_state=0, n_iter=10000, perplexity=2)
np.set_printoptions(suppress=True)
T = tsne.fit_transform(wvs)
labels = words

plt.figure(figsize=(14, 8))
plt.scatter(T[:, 0], T[:, 1], c='orange', edgecolors='r')
for label, x, y in zip(labels, T[:, 0], T[:, 1]):
    plt.annotate(label, xy=(x+1, y+1), xytext=(0, 0), textcoords='offset points')
```

```
C:\ProgramData\Anaconda3\envs\milestone1\lib\site-packages\ipykernel_launcher.py:5: DeprecationWarnin
g: Call to deprecated `wv` (Attribute will be removed in 4.0.0, use self instead).
  """
```



In [ ]:

General Testing

In [52]:
```
#check if using GPU
import tensorflow as tf
if tf.test.gpu_device_name():
    print('Default GPU Device: {}'.format(tf.test.gpu_device_name()))
else:
    print("Please install GPU version of TF")
```

```
Default GPU Device: /device:GPU:0
```

In [ ]:
```
#test execution on GPU
import tensorflow as tf
with tf.device('/gpu:0'):
    a = tf.constant([1.0, 2.0, 3.0, 4.0, 5.0, 6.0], shape=[2, 3], name='a')
    b = tf.constant([1.0, 2.0, 3.0, 4.0, 5.0, 6.0], shape=[3, 2], name='b')
    c = tf.matmul(a, b)

with tf.Session() as sess:
    print (sess.run(c))
```

Reference:

Much of the example code is credited to Dipanjan (DJ) Sarkar at:

[https://towardsdatascience.com/understanding-feature-engineering-part-3-traditional-methods-for-text-data-f6f7d70acd41 (https://towardsdatascience.com/understanding-feature-engineering-part-3-traditional-methods-for-text-data-f6f7d70acd41)](https://towardsdatascience.com/understanding-feature-engineering-part-3-traditional-methods-for-text-data-f6f7d70acd41)

and

[https://towardsdatascience.com/understanding-feature-engineering-part-4-deep-learning-methods-for-text-data-96c44370bbfa (https://towardsdatascience.com/understanding-feature-engineering-part-4-deep-learning-methods-for-text-data-96c44370bbfa)](https://towardsdatascience.com/understanding-feature-engineering-part-4-deep-learning-methods-for-text-data-96c44370bbfa)