main

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1 Apple Brand Sentiment at South by Southwest

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2 Business Problem

Apple (fictitiously) wants me to create an explanatory model of positive and negative sentiment in tweets related to the South by Southwest (SXSW) conference in Austin, Texas, 2011. They are specifically interested in what people think about their company, products, and marketing efforts. They've provided me with a labeled Twitter dataset, obtained by one of my coworkers. My objectives are:

1. Build a sentiment classifier for explanatory purposes.
2. Find out what people are saying about Apple (at South by Southwest, 2011).
3. Make some PR recommendations for the period immediately following the event.

3 Imports

[2]:
```
import re
import string
import json
from pprint import pprint
from functools import partial

import joblib
import matplotlib.pyplot as plt
import nltk
import numpy as np
import scipy as sp
import pandas as pd
import seaborn as sns

from sklearn.base import clone
```

```python
from sklearn.linear_model import LogisticRegression
from sklearn.dummy import DummyClassifier

from sklearn.naive_bayes import ComplementNB, MultinomialNB, BernoulliNB
from sklearn.svm import SVC, LinearSVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from imblearn.pipeline import Pipeline
from sklearn.pipeline import FeatureUnion
from sklearn.metrics import (
    classification_report,
    PrecisionRecallDisplay,
    ConfusionMatrixDisplay,
)
from imblearn.over_sampling import (
    SMOTE,
    RandomOverSampler,
    ADASYN,
)
from imblearn.under_sampling import RandomUnderSampler
from imblearn.ensemble import BalancedRandomForestClassifier
import bert_sklearn
from bert_sklearn import BertClassifier
import lime
from lime.lime_text import LimeTextExplainer
from transformers import AutoTokenizer

# Set Seaborn theme and default palette
sns.set_theme(font_scale=1.25, style="darkgrid")
sns.set_palette("deep", desat=0.85, color_codes=True)

# Turn on inline plotting
%matplotlib inline

# Load Black auto-formatter
%load_ext nb_black

# Enable automatic reloading
%load_ext autoreload
%autoreload 2
```

```
The nb_black extension is already loaded. To reload it, use:
  %reload_ext nb_black
The autoreload extension is already loaded. To reload it, use:
  %reload_ext autoreload
```

```
<IPython.core.display.Javascript object>
```

3.1 My tools Package

I put a lot of time and energy into developing my own tools for analysis. It's probably my favorite part of this kind of work, and I (admittedly) tend to get carried away with it. I developed a lot in `tools.language` and `tools.sklearn.vectorizers` for this project in particular. I'll discuss important developments as they come up.

[2]:
```python
# Import my modules
from ndg_tools import cleaning, plotting, outliers, utils, language as lang
from ndg_tools.sklearn.vectorizers import FreqVectorizer, VaderVectorizer
from ndg_tools.sklearn import selection

FIT_BERT = False

# Run time-consuming grid searches
RUN_SWEEPS = False

# Set my default MPL settings
plt.rcParams.update(plotting.MPL_DEFAULTS)
```

```
[nltk_data] Downloading package averaged_perceptron_tagger to
[nltk_data]     C:\Users\ndgig\AppData\Roaming\nltk_data…
[nltk_data]   Package averaged_perceptron_tagger is already up-to-
[nltk_data]       date!
[nltk_data] Downloading package universal_tagset to
[nltk_data]     C:\Users\ndgig\AppData\Roaming\nltk_data…
[nltk_data]   Package universal_tagset is already up-to-date!
[nltk_data] Downloading package wordnet to
[nltk_data]     C:\Users\ndgig\AppData\Roaming\nltk_data…
[nltk_data]   Package wordnet is already up-to-date!
```

```
<IPython.core.display.Javascript object>
```

4 Overview of Dataset

Since Apple is interested in sentiment analysis on Twitter, I've found a Twitter dataset with crowd-sourced sentiment labels. It comes from CrowdFlower, which has released other similar datasets.

The tweets are related to South by Southwest, an annual conference and arts festival in Austin, Texas. They are from 2011, when Apple launched the iPad 2.

It has only three features: the tweet text, the brand object of the sentiment, and the sentiment. It has only about 9,100 tweets.

[3]:
```python
df = pd.read_csv(normpath("data/crowdflower_tweets.csv"), encoding="latin1")
df.head()
```

[3]:
```
                                          tweet_text  \
0  .@wesley83 I have a 3G iPhone. After 3 hrs twe…
1  @jessedee Know about @fludapp ? Awesome iPad/i…
```

```
2  @swonderlin Can not wait for #iPad 2 also. The…
3  @sxsw I hope this year's festival isn't as cra…
4  @sxtxstate great stuff on Fri #SXSW: Marissa M…

  emotion_in_tweet_is_directed_at  \
0                          iPhone
1              iPad or iPhone App
2                            iPad
3              iPad or iPhone App
4                          Google

  is_there_an_emotion_directed_at_a_brand_or_product
0                                   Negative emotion
1                                   Positive emotion
2                                   Positive emotion
3                                   Negative emotion
4                                   Positive emotion
```

```
<IPython.core.display.Javascript object>
```

The dataset contains one text feature and two categorical features, one of which has a lot of null values. The feature names are very long and wordy, presumably to reflect the actual language used by CrowdFlower in crowdsourcing the dataset. I'm going to rename those before I do anything else.

[4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9093 entries, 0 to 9092
Data columns (total 3 columns):
 #   Column                                              Non-Null Count  Dtype
---  ------                                              --------------  -----
 0   tweet_text                                          9092 non-null   object
 1   emotion_in_tweet_is_directed_at                     3291 non-null   object
 2   is_there_an_emotion_directed_at_a_brand_or_product  9093 non-null   object
dtypes: object(3)
memory usage: 213.2+ KB
```

```
<IPython.core.display.Javascript object>
```

5 Cleaning

5.1 Renaming

[5]:
```
# Assign new column names
df.columns = ["text", "object_of_emotion", "emotion"]
df.head()
```

[5]:
```
                                                text    object_of_emotion  \
0  .@wesley83 I have a 3G iPhone. After 3 hrs twe…               iPhone
1  @jessedee Know about @fludapp ? Awesome iPad/i…  iPad or iPhone App
2  @swonderlin Can not wait for #iPad 2 also. The…                 iPad
3  @sxsw I hope this year's festival isn't as cra…  iPad or iPhone App
4  @sxtxstate great stuff on Fri #SXSW: Marissa M…               Google

            emotion
0  Negative emotion
1  Positive emotion
2  Positive emotion
3  Negative emotion
4  Positive emotion
```

```
<IPython.core.display.Javascript object>
```

Next, I take a look at the values of the categorical variables. The categories make sense, although the names are longer than necessary. I'm going to shorten some of them as well.

[6]:
```python
cleaning.show_uniques(df)
```

```
<IPython.core.display.HTML object>
```

```
<IPython.core.display.Javascript object>
```

First, I convert the categorical columns to `CategoricalDtype`. This will make it easier to rename the categories, and is a convenient way to differentiate the categorical features from the text column.

[7]:
```python
# Convert categorical columns to categorical dtype
cat_cols = ["emotion", "object_of_emotion"]
df[cat_cols] = df.loc[:, cat_cols].astype("category")

# Delete temp variable
del cat_cols

# Display results
display(df["emotion"].head(3), df["object_of_emotion"].head(3))
```

```
0    Negative emotion
1    Positive emotion
2    Positive emotion
Name: emotion, dtype: category
Categories (4, object): ['I can't tell', 'Negative emotion', 'No emotion toward␣
 ↪brand or product', 'Positive emotion']
```

```
0                iPhone
1    iPad or iPhone App
2                  iPad
Name: object_of_emotion, dtype: category
Categories (9, object): ['Android', 'Android App', 'Apple', 'Google', …, 'Other␣
 ↪Google product or service', 'iPad', 'iPad or iPhone App', 'iPhone']
```

<IPython.core.display.Javascript object>

Next, I rename the categories for both categorical features.

I use a single `dict` mapping old category names to new ones. I only need one `dict` for both features because the method `Series.cat.rename_categories(...)` ignores irrelevant keys.

[8]:
```
# Create mapping of old categories to new ones
new_cats = {
    # New 'emotion' categories
    "Negative emotion": "Negative",
    "Positive emotion": "Positive",
    "No emotion toward brand or product": "Neutral",
    "I can't tell": "Uncertain",
    # New 'object_of_emotion' categories
    "iPad or iPhone App": "iOS App",
    "Other Google product or service": "Other Google Product",
    "Other Apple product or service": "Other Apple Product",
}

# Rename categories in-place (ignores irrelevant keys)
df["emotion"].cat.rename_categories(new_cats, inplace=True)
df["object_of_emotion"].cat.rename_categories(new_cats, inplace=True)

# Delete renaming dict
del new_cats

# Show results
cleaning.show_uniques(df)
```

```
C:\Users\ndgig\anaconda3\envs\nlp-nn\lib\site-
packages\pandas\core\arrays\categorical.py:2630: FutureWarning: The `inplace`
parameter in pandas.Categorical.rename_categories is deprecated and will be
removed in a future version. Removing unused categories will always return a new
Categorical object.
  res = method(*args, **kwargs)
```

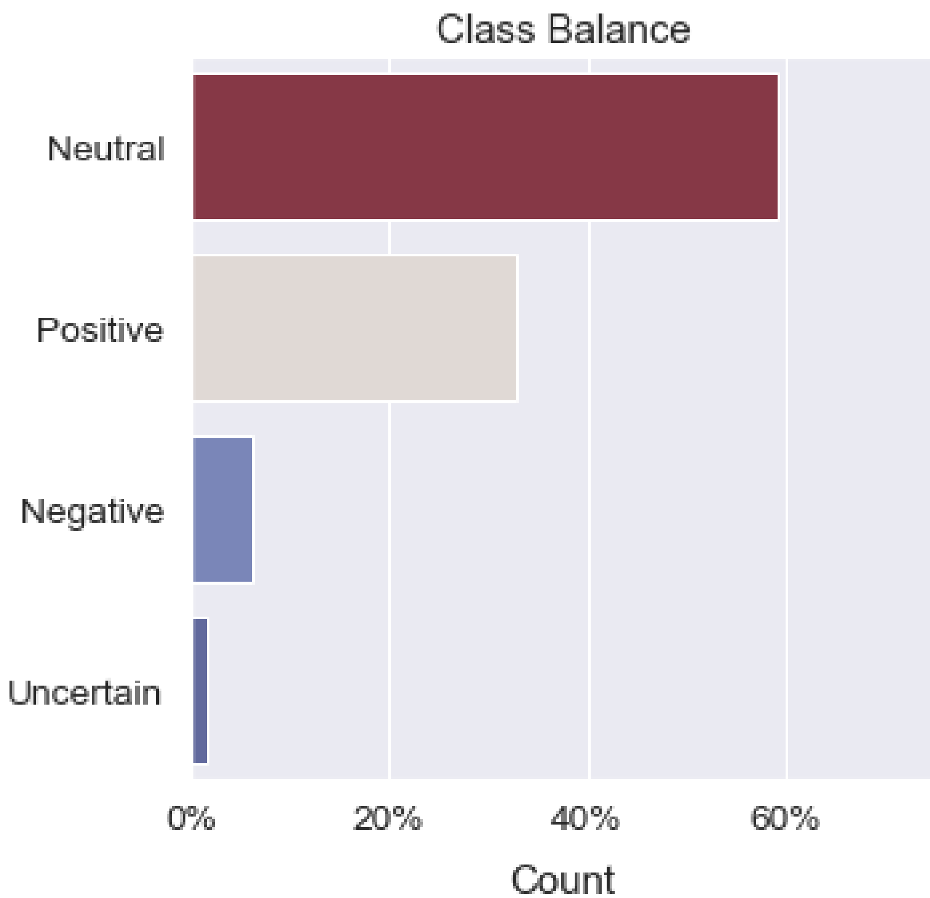
<IPython.core.display.HTML object>

<IPython.core.display.Javascript object>

The 'Neutral' category dominates the distribution, and 'Negative' is very underrepresented. 'Uncertain' is fortunately a very small 2% of the samples. That's good, because it's completely useless to me.

[9]:
```
ax = plotting.countplot(df["emotion"], normalize=True)
ax.set(title="Class Balance")
ax.set_xlim((0, 0.75))
```

[9]: (0.0, 0.75)




```
<IPython.core.display.Javascript object>
```

I drop the uncertain category, which doesn't have any clear value. I will have to cope with this imbalance later.

[10]:
```python
# Remove 'Uncertain' and 'Neutral' categories
df["emotion"] = df["emotion"].cat.remove_categories(["Uncertain", "Neutral"])
df
```

[10]:
```
                                                   text object_of_emotion  \
0     .@wesley83 I have a 3G iPhone. After 3 hrs twe…            iPhone
1     @jessedee Know about @fludapp ? Awesome iPad/i…           iOS App
2     @swonderlin Can not wait for #iPad 2 also. The…              iPad
3     @sxsw I hope this year's festival isn't as cra…           iOS App
4     @sxtxstate great stuff on Fri #SXSW: Marissa M…            Google
…                                                   …                 …
9088                      Ipad everywhere. #SXSW {link}              iPad
9089  Wave, buzz… RT @mention We interrupt your re…               NaN
9090  Google's Zeiger, a physician never reported po…               NaN
```

```
9091  Some Verizon iPhone customers complained their…                NaN
9092   Ï¡ Ïà ü_ Ê Î Ò £ Á ââ _ £  â_ ÛâRT ©…                NaN

       emotion
0     Negative
1     Positive
2     Positive
3     Negative
4     Positive
…         …
9088  Positive
9089       NaN
9090       NaN
9091       NaN
9092       NaN

[9093 rows x 3 columns]
```

```
<IPython.core.display.Javascript object>
```

[11]:
```
# Plot class balance
ax = plotting.countplot(df.emotion, normalize=True)
ax.set(title="Class Balance")
plotting.annot_bars(ax, format_spec="{x:.0%}")
ax.set_xlim((0, 1.1))
plotting.save(ax.figure, "images/class_balance.svg")
```

[11]:
```
'images\\class_balance.svg'
```

<IPython.core.display.Javascript object>

5.2 Missing Values

According to the table below, there are a lot of missing values in the 'object_of_emotion' category. I bet, however, that these NaN values correspond to the 'Neutral' category. If a tweet doesn't express a brand-emotion, then there shouldn't be any brand in the 'object_of_emotion' column.

There's also one null 'text' row, and a bunch of null 'emotion' rows where the 'Uncertain' category used to be.

[12]:
```
cleaning.info(df)
```

[12]:

	null	null_%	uniq	uniq_%	dup	dup_%
object_of_emotion	5802	63.81	9	0.10	22	0.24
emotion	5545	60.98	2	0.02	22	0.24
text	1	0.01	9065	99.69	22	0.24

<IPython.core.display.Javascript object>

I'll go ahead and drop the nulls in the 'text' and 'emotion' columns first.

[13]:
```
df.dropna(subset=["text", "emotion"], inplace=True)
cleaning.info(df)
```

[13]:

	null	null_%	uniq	uniq_%	dup	dup_%
object_of_emotion	357	10.06	9	0.25	9	0.25
text	0	0.00	3539	99.75	9	0.25
emotion	0	0.00	2	0.06	9	0.25

```
<IPython.core.display.Javascript object>
```

Since I don't have anymore null 'emotion' values, I'll go ahead and create a binary 'target' feature.

[14]:
```
df["target"] = df["emotion"].replace({"Positive": 1, "Negative": 0}).astype(np.
 ↪uint8)
df["target"]
```

[14]:
```
0       0
1       1
2       1
3       0
4       1
       ..
9077    1
9079    1
9080    0
9085    1
9088    1
Name: target, Length: 3548, dtype: uint8
```

```
<IPython.core.display.Javascript object>
```

[15]:
```
emotion_without_object = cleaning.null_rows(df)
display(emotion_without_object.head(), emotion_without_object.shape)
```

```
                                                  text object_of_emotion  \
46   Hand-Held  Û÷Hobo Ûª: Drafthouse launches  Û÷H…               NaN
64   Again? RT @mention Line at the Apple store is …                 NaN
68   Boooo! RT @mention Flipboard is developing an …                 NaN
103  Know that &quot;dataviz&quot; translates to &q…                 NaN
112  Spark for #android is up for a #teamandroid aw…                 NaN

      emotion  target
46   Positive       1
64   Negative       0
68   Negative       0
103  Negative       0
112  Positive       1

(357, 4)
```

<IPython.core.display.Javascript object>

Looks like some of the NaN values are associated with a positive or negative emotion. Also, it's important to note that some retweets, e.g. 64, 68, have sentimental content beyond that of the original tweet.

[16]:
```
lang.readable_sample(
    emotion_without_object.loc[emotion_without_object.target.astype(np.bool_),␣
↪"text"],
    random_state=456,
)
```

	text
6606	RT @mention RT @mention Shiny new @mention @mention @eightbit apps, a new @garyvee book, pop-up iPad 2 stores… #SXSW is Christmas for nerds.
4164	Mad long line for Google party at Maggie Mae's. Hope it's worth it.. but with 80s theme I am very optimistic #sxsw
3020	Apple offers original iPad donation program {link} #entry #friends #house #sxsw
8114	#touchingstories giving us the background to STARTING. Great to hear after yesterday's presos on #uncertainty #iPad and/or #tablet #SXSW
555	I have my golden tickets f 4sq party Day after the real party #Redbullbpm with Felix da Housecat playing on iPad! #SXSW {link}
5501	RT @mention At #sxsw even the cabbies are tech savvy. That's his iPhone streaming twitter. @mention {link}
6676	RT @mention Soundtrckr featured by @mention @mention as a Must-have for #SXSW {link}
157	@mention #SXSW LonelyPlanet Austin guide for #iPhone is free for a limited time {link} #lp #travel
5019	Here he comes ladies! @mention @mention RT @mention I'll be at Austin Convention Center w/ @mention showing my iPhone game. #SXSW
8025	Someone asks Leo about an iPad 2 at #SXSW, he says 'Email me, I'll send you one free'. O.o

<IPython.core.display.Javascript object>

These are positive tweets which are missing a brand label. Many of them seem positive—some towards a brand and some not. The original features names were 'emotion_in_tweet_is_directed_at' and 'is_there_an_emotion_directed_at_a_brand_or_product', which is not consistent with brandless positivity.

[17]:
```
# Create regex for finding each brand
re_apple = r"ipad\s*\d?\s*app|ipad|iphone\s*\d?\s*app|iphone|apple"
re_google = r"android\s*app|android|google"

# Find brand/product name occurrences for each brand
findings = lang.locate_patterns(
    [re_apple, re_google],
    docs=emotion_without_object["text"],
```

```
    exclusive=True,
    flags=re.I,
)

# Convert to lowercase
findings = findings.str.lower()

# View results
display(
    findings.value_counts(),
    findings.size,
)
```

```
ipad           125
google         122
apple           76
iphone          57
android         19
iphone app       8
ipad app         4
android app      1
Name: locate_patterns, dtype: int64
```

```
412
```

```
<IPython.core.display.Javascript object>
```

[18]:
```
# Rename Apple apps to match categories defined previously
findings = findings.str.replace(
    r"ipad\s+app|iphone\s+app", "ios app", case=False, regex=True
)

# Fuzzy match with previously defined categories
findings = lang.fuzzy_match(findings, df["object_of_emotion"].cat.categories)

# View results
findings.sort_values("score")
```

[18]:

	original	match	score
46	ios app	iOS App	100
6220	iphone	iPhone	100
6202	iphone	iPhone	100
6180	apple	Apple	100
6180	ipad	iPad	100
…	…	…	…
3055	ipad	iPad	100
3055	ipad	iPad	100
3040	ipad	iPad	100
3269	android	Android	100

```
9054      ipad      iPad     100

[412 rows x 3 columns]
```

```
<IPython.core.display.Javascript object>
```

[19]:
```
# Define sort order, i.e. fill priority
order = [
    "iOS App",
    "Android App",
    "iPhone",
    "iPad",
    "Android",
    "Apple",
    "Google",
]

# Sort values in reverse order
utils.explicit_sort(
    findings,
    order=order,
    by="match",
    ascending=False,
    inplace=True,
)

# Fill in reverse, overwriting lower priority values
for i, brand in findings.match.items():
    df.at[i, "object_of_emotion"] = brand
df.loc[findings.index].sample(10, random_state=4564)
```

[19]:
```
                                                   text object_of_emotion  \
646   ÛÏ@mention I'll be at the Austin Convention C…            iPhone
7285  Google showing off google places with hotpot a…            Google
4870  Excited to say that I haven't used Foursquare,…            Google
1805  #sxsw: #15slides: Gruber: keeps on desk Apple …             Apple
4976  @mention Oh, oh, oh! Does the iPad come with m…              iPad
6996  RT @mention Zazzle is officially at #SXSW! Com…            iPhone
4536  Whoa - line for ipad2 is 3blks long!!! #apple …              iPad
2572  That sounds…fantastic. RT @mention At the Go…            Google
3861  Bad news is it costs $1,000? RT @mention Louis…           iOS App
7990  Apple to sell iPads in &quot;pop-up&quot; Appl…              iPad

       emotion  target
646   Positive       1
7285  Positive       1
4870  Positive       1
1805  Positive       1
```

```
4976  Positive       1
6996  Positive       1
4536  Positive       1
2572  Positive       1
3861  Negative       0
7990  Positive       1
```

```
<IPython.core.display.Javascript object>
```

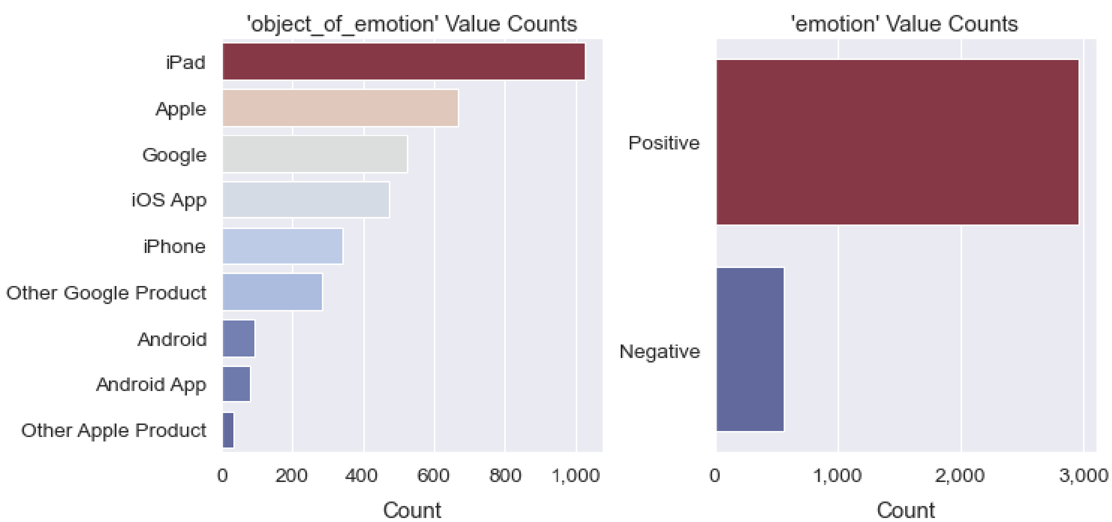
[20]:
```
# Get indices which were not filled
emotion_without_object.drop(findings.index, inplace=True)

# Drop unfilled observations
df.drop(emotion_without_object.index, inplace=True)

print(f"{emotion_without_object.shape[0]} observations dropped.")

del emotion_without_object
```

```
24 observations dropped.
```

```
<IPython.core.display.Javascript object>
```

Here's a look at the distributions.

[21]:
```
fig = plotting.countplot(df.select_dtypes("category"))
```




```
<IPython.core.display.Javascript object>
```

5.3 Initial Preprocessing

I do some minimal preprocessing on the text before I begin modeling. I transliterate the symbols to ASCII in order to remove accents and remove strange symbols which cannot be decoded properly. Unfortunately there are a lot of strange symbols in this dataset which I can't find a way to decode. I also decode HTML entities like `—` or `&`, and remove extra space.

[22]:
```
df["text"] = lang.force_ascii(df["text"])
df["text"] = lang.decode_html_entities(df["text"])
df["text"] = lang.strip_extra_space(df["text"])
df["text"]
```

```
HBox(children=(FloatProgress(value=0.0, description='force_ascii', max=3524.0,␣
↪style=ProgressStyle(description…
```

```
HBox(children=(FloatProgress(value=0.0, description='decode_html_entities',␣
↪max=3524.0, style=ProgressStyle(de…
```

```
HBox(children=(FloatProgress(value=0.0, description='strip_extra_space',␣
↪max=3524.0, style=ProgressStyle(descr…
```

[22]:
```
0       .@wesley83 I have a 3G iPhone. After 3 hrs twe…
1       @jessedee Know about @fludapp ? Awesome iPad/i…
2       @swonderlin Can not wait for #iPad 2 also. The…
3       @sxsw I hope this year's festival isn't as cra…
4       @sxtxstate great stuff on Fri #SXSW: Marissa M…
                                …
9077    @mention your PR guy just convinced me to swit…
9079    "papyrus…sort of like the ipad" - nice! Lol!…
9080    Diller says Google TV "might be run over by th…
9085    I've always used Camera+ for my iPhone b/c it …
9088                        Ipad everywhere. #SXSW {link}
Name: text, Length: 3524, dtype: object
```

```
<IPython.core.display.Javascript object>
```

5.4 Duplicates

There are several duplicate rows, and even more when only the text is considered. I don't want to get rid of all retweets, but I do want to get rid of those which don't have novel content.

[23]:
```
cleaning.dup_rows(df["text"]).sort_values()
```

[23]:
```
7       #SXSW is just starting, #CTIA is around the co…
3962    #SXSW is just starting, #CTIA is around the co…
1690    #pubcamp #kirkus #sxsw download Qrank on your …
```

```
1691    #pubcamp #kirkus #sxsw download Qrank on your …
466        Before It Even Begins, Apple Wins #SXSW {link}
468        Before It Even Begins, Apple Wins #SXSW {link}
9       Counting down the days to #sxsw plus strong Ca…
2559    Counting down the days to #sxsw plus strong Ca…
7493    Google Maps Street View car sighting!!! #SXSW …
7492    Google Maps Street View car sighting!!! #SXSW …
812     Google to Launch Major New Social Network Call…
813     Google to Launch Major New Social Network Call…
17      I just noticed DST is coming this weekend. How…
8483    I just noticed DST is coming this weekend. How…
8747    Need to buy an iPad2 while I'm in Austin at #s…
20      Need to buy an iPad2 while I'm in Austin at #s…
4897    Oh. My. God. The #SXSW app for iPad is pure, u…
21      Oh. My. God. The #SXSW app for iPad is pure, u…
6292    RT @mention Marissa Mayer: Google Will Connect…
6296    RT @mention Marissa Mayer: Google Will Connect…
6298    RT @mention Marissa Mayer: Google Will Connect…
6343    RT @mention New #UberSocial for #iPhone now in…
6353    RT @mention New #UberSocial for #iPhone now in…
6986    RT @mention YES! updated iPhone app has song i…
6987    RT @mention YES! updated iPhone app has song i…
24      Really enjoying the changes in Gowalla 3.0 for…
3950    Really enjoying the changes in Gowalla 3.0 for…
Name: text, dtype: object
```

<IPython.core.display.Javascript object>

[24]:
```python
dups = df["text"].str.replace(r"\bRT\s+", "", regex=True).duplicated()
display(len(df))
df = df.loc[~dups].copy()
df
```

3524

[24]:
```
                                                   text      object_of_emotion  \
0     .@wesley83 I have a 3G iPhone. After 3 hrs twe…                iPhone
1     @jessedee Know about @fludapp ? Awesome iPad/i…               iOS App
2     @swonderlin Can not wait for #iPad 2 also. The…                  iPad
3     @sxsw I hope this year's festival isn't as cra…               iOS App
4     @sxtxstate great stuff on Fri #SXSW: Marissa M…                Google
…                                                   …                     …
9077  @mention your PR guy just convinced me to swit…                iPhone
9079  "papyrus…sort of like the ipad" - nice! Lol!…                    iPad
9080  Diller says Google TV "might be run over by th…  Other Google Product
9085  I've always used Camera+ for my iPhone b/c it …               iOS App
9088                      Ipad everywhere. #SXSW {link}                  iPad
```

```
       emotion  target
0     Negative       0
1     Positive       1
2     Positive       1
3     Negative       0
4     Positive       1
…          …       …
9077  Positive       1
9079  Positive       1
9080  Negative       0
9085  Positive       1
9088  Positive       1

[3510 rows x 4 columns]
```

```
<IPython.core.display.Javascript object>
```

Next, I save the data for use in `exploratory.ipynb`, where I conduct an exploratory analysis. I'll proceed directly to modeling in this notebook.

[25]:
```
df.to_json("data/processed_tweets.json")
```

```
<IPython.core.display.Javascript object>
```

6 Modeling

6.1 Train-Test-Split

I perform the train-test split which I'll use throughout my modeling process.

[26]:
```
# Define X and y
X = df["text"].copy()
y = df["target"].copy()

# Perform the split
X_train, X_test, y_train, y_test = train_test_split(
    X,
    y,
    random_state=15,
    stratify=y,
    shuffle=True,
)

X_train.shape, y_train.shape, X_test.shape, y_test.shape
```

[26]:
```
((2632,), (2632,), (878,), (878,))
```

```
<IPython.core.display.Javascript object>
```

6.2 Preparing the Diagnostics

I choose to optimize macro average recall in order to compensate for the class imbalance. It is equivalent to Scikit-Learn's "balanced accuracy" metric, which is equivalent to the arithmetic mean of recall scores. I also plot a confusion matrix and precision-recall curve for each model. Confusion matrices are one of the best all-around diagnostic plots for classification, and precision-recall curves are particularly useful when dealing with class imbalance.

I'll need to define a couple functions for diagnostic purposes. I'll start by defining a function that returns a standard classification report as a `DataFrame`.

[27]:
```
def classif_report(
    y_true,
    y_pred,
    *,
    labels=[0, 1],
    target_names=None,
    sample_weight=None,
    zero_division=0,
):
    """Returns a classification report as a DataFrame."""
    if target_names is not None:
        target_names = [x.lower() for x in target_names]
    report = classification_report(
        y_true,
        y_pred,
        labels=labels,
        target_names=target_names,
        sample_weight=sample_weight,
        output_dict=True,
        zero_division=zero_division,
    )
    return pd.DataFrame(report)
```

```
<IPython.core.display.Javascript object>
```

I also define a function for evaluating each model I train. It will get the classification report, highlight my target metric (macro average recall), plot a confusion matrix, and plot precision-recall curves.

[28]:
```
def eval_model(
    estimator,
    name,
    X_test=X_test,
    y_test=y_test,
    display_labels=["Negative", "Positive"],
    highlight=("recall", "macro avg"),
    compare_curves=None,
    palette="deep",
```

```
    desat=0.85,
):
    # Make predictions
    y_true = y_test
    y_pred = estimator.predict(X_test)
    y_proba = estimator.predict_proba(X_test)

    # Get classification report (table)
    rep = classif_report(y_true, y_pred, target_names=display_labels)

    # Plot confusion matrix
    display_labels = [x.title() for x in display_labels]
    fig, (ax1, ax2) = plt.subplots(ncols=2, figsize=(12, 5))
    cm = ConfusionMatrixDisplay.from_predictions(
        y_true,
        y_pred,
        normalize="true",
        display_labels=display_labels,
        cmap=plotting.get_desat_cmap("Blues", desat=desat),
        colorbar=False,
        ax=ax1,
    )
    ax1.grid(False)
    ax1.set(title=f"{name} Confusion Matrix")

    # Plot main precision-recall curve
    n_colors = 1 if not compare_curves else 1 + len(compare_curves)
    colors = sns.color_palette(palette, n_colors=n_colors, desat=desat)
    prc = PrecisionRecallDisplay.from_predictions(
        y_true,
        y_proba[:, 1],
        pos_label=1,
        name=name,
        ax=ax2,
        c=colors[0],
    )
    # Plot comparison curves
    if compare_curves is not None:
        for color, curve in zip(colors[1:], compare_curves):
            curve.plot(ax2, c=color)
    ax2.set(xlabel="Recall", ylabel="Precision", title=f"{name}␣
↪Precision-Recall Curve")
    fig.tight_layout()

    # Display classification report, highlighting chosen metric
    display(
        rep.style.background_gradient(
```

```
            cmap=plotting.get_desat_cmap("coolwarm"),
            subset=highlight,
            vmin=0.0,
            vmax=1.0,
        )
    )
    return rep, cm, prc
```

```
<IPython.core.display.Javascript object>
```

6.3 Dummy Model

I begin by creating a dummy model as an ultimate baseline. Testing the dummy model will reveal how an extremely dumb algorithm performs on the metrics I'm using.

[29]:
```
fv = FreqVectorizer()
fv
```

[29]:
```
FreqVectorizer()
```

```
<IPython.core.display.Javascript object>
```

6.3.1 My `FreqVectorizer`

For vectorization, I'll primarily use my custom `FreqVectorizer`, which is an extension of Scikit-Learn's `TfidfVectorizer` with additional preprocessing options. It's called `FreqVectorizer` to emphasize that, like its parent class, it offers several different word-frequency-based vectorization algorithms. Among these algorithms are term frequency (count) vectorization and TF*IDF (term frequency * inverse document frequency) vectorization. By default, `FreqVectorizer` is set to perform **count vectorization**.

I'll discuss more details of my `FreqVectorizer` class as they become relevant. Feel free to look through the help page below.

[30]:
```
help(FreqVectorizer)
```

```
Help on class FreqVectorizer in module ndg_tools.sklearn.vectorizers:

class FreqVectorizer(sklearn.feature_extraction.text.TfidfVectorizer,
VectorizerMixin)
 |  FreqVectorizer(*, input='content', encoding='utf-8', decode_error='strict',
strip_accents=None, decode_html_entities=True, lowercase=True,
strip_extra_space=False, strip_numeric=False, strip_non_word=False,
strip_punct=False, strip_twitter_handles=False, strip_html_tags=False,
limit_repeats=False, uniq_char_thresh=None, mark_negation=False, stemmer=None,
preprocessor=None, tokenizer=None, token_pattern='\\b\\w\\w+\\b',
analyzer='word', stop_words=None, process_stop_words=True, ngram_range=(1, 1),
max_df=1.0, min_df=1, max_features=None, vocabulary=None, binary=False,
dtype=<class 'numpy.float64'>, norm=None, use_idf=False, smooth_idf=True,
sublinear_tf=False)
```

```
 |
 |  Convert a collection of raw documents to a matrix of word-frequency
features.
 |
 |  Extends Scikit-Learn's `TfidfVectorizer` with advanced preprocessing
options.
 |  These include numerous filters, stemming/lemmatization, and markers such as
PoS tags.
 |  Some preprocessing options are applied before tokenization, and some, which
require
 |  tokens, are applied during the tokenization step.
 |
 |  There are now a wider selection of built-in stopwords sets, and these
include the NLTK
 |  sets for many different languages. Complex stopwords queries are now also
supported.
 |
 |
 |  Parameters
 |  ----------
 |  input : {'filename', 'file', 'content'}, default='content'
 |      If 'filename', the sequence passed as an argument to fit is
 |      expected to be a list of filenames that need reading to fetch
 |      the raw content to analyze.
 |
 |      If 'file', the sequence items must have a 'read' method (file-like
 |      object) that is called to fetch the bytes in memory.
 |
 |      Otherwise the input is expected to be a sequence of items that
 |      can be of type string or byte.
 |
 |  encoding : str, default='utf-8'
 |      If bytes or files are given to analyze, this encoding is used to
 |      decode.
 |
 |  decode_error : {'strict', 'ignore', 'replace'}, default='strict'
 |      Instruction on what to do if a byte sequence is given to analyze that
 |      contains characters not of the given `encoding`. By default, it is
 |      'strict', meaning that a UnicodeDecodeError will be raised. Other
 |      values are 'ignore' and 'replace'.
 |
 |  strip_accents : {'ascii', 'unicode'}
 |      Remove accents and perform other character normalization
 |      during the preprocessing step.
 |      * 'ascii' is a fast method that only works on characters that have
 |          an direct ASCII mapping.
 |      * 'unicode' is a slightly slower method that works on any characters.
 |      *  None (default) does nothing.
```

```
 |
 |      Both 'ascii' and 'unicode' use NFKD normalization from
 |      :func:`unicodedata.normalize`.
 |
 |  decode_html_entities : bool
 |      Decode HTML entities such as '&mdash;' or '&lt;' or '&gt;' into symbols,
 |      e.g. '-', '<', '>'. True by default.
 |
 |  lowercase : bool
 |      Convert all characters to lowercase before tokenizing. True by default.
 |
 |  strip_extra_space: bool
 |      Strip extra whitespaces (including tabs and newlines). False by default.
 |
 |  strip_numeric: bool
 |      Strip numerals [0-9] from text. False by default.
 |
 |  strip_non_word: bool
 |      Strip all non-alphanumeric characters (except underscore). False by
default.
 |
 |  strip_punct: bool or str of punctuation symbols
 |      If True, strip all punctuation. If passed a string of punctuation
symbols, strip
 |      only those symbols. False by default.
 |
 |  strip_twitter_handles: bool
 |      Strip Twitter @mentions. False by default.
 |
 |  strip_html_tags: bool
 |      Strip HTML tags such as '<p>' or '<div>'. False by default.
 |
 |  limit_repeats: bool
 |      Limit strings of repeating characters, e.g. 'zzzzzzzzzzz', to length 3.
 |
 |  uniq_char_thresh: float
 |      Remove tokens with a unique character ratio below threshold. Useful for
removing
 |      repetitive strings like 'AAAAAAAAAAARGH' or 'dogdogdog'. None by
default.
 |
 |  mark_negation: bool
 |      Mark tokens with '_NEG' which appear between a negation word and
sentence
 |      punctuation. Useful for sentiment analysis. False by default.
 |
 |  stemmer: {'porter', 'wordnet'}
 |      Stemming or lemmatization algorithm to use. Both implement caching in
```

```
order to
 |      reuse previous computations. Valid options:
 |      * 'porter' - Porter stemming algorithm (faster).
 |      * 'wordnet' - Lemmatization using Wordnet (slower).
 |      * None - Do not stem tokens (default).
 |
 |  preprocessor : callable, default=None
 |      Override the preprocessing (string transformation) stage while
 |      preserving the tokenizing and n-grams generation steps.
 |      Only applies if ``analyzer is not callable``.
 |
 |  tokenizer : callable, default=None
 |      Override the string tokenization step while preserving the
 |      preprocessing and n-grams generation steps.
 |      Only applies if ``analyzer == 'word'``.
 |
 |  analyzer : callable, default=None
 |      If a callable is passed it is used to extract the sequence of features
 |      out of the raw, unprocessed input.
 |
 |  stop_words : str or list of str
 |      If a string, it is passed to `tools.language.fetch_stopwords` and
 |      the appropriate stopword list is returned. Valid strings:
 |      * 'sklearn_english' - Scikit-Learn's English stopwords.
 |      * 'nltk_LANGUAGE' - Any NLTK stopwords set, where the fileid (language)
follows the underscore.
 |          For example: 'nltk_english', 'nltk_french', 'nltk_spanish'.
 |      * Supports complex queries using set operators, e.g. '(nltk_french &
nltk_spanish) | sklearn_english'.
 |
 |      If a list, that list is assumed to contain stop words, all of which
 |      will be removed from the resulting tokens.
 |      Only applies if ``analyzer == 'word'``.
 |
 |      If None, no stop words will be used. max_df can be set to a value
 |      in the range [0.7, 1.0) to automatically detect and filter stop
 |      words based on intra corpus document frequency of terms.
 |
 |  token_pattern : str, default=r"\b\w\w+\b"
 |      Regular expression denoting what constitutes a "token", only used
 |      if ``analyzer == 'word'``. The default regexp selects tokens of 2
 |      or more alphanumeric characters (punctuation is completely ignored
 |      and always treated as a token separator).
 |
 |      If there is a capturing group in token_pattern then the
 |      captured group content, not the entire match, becomes the token.
 |      At most one capturing group is permitted.
 |
```

```
 |  ngram_range : tuple (min_n, max_n)
 |      The lower and upper boundary of the range of n-values for different
 |      n-grams to be extracted. All values of n such that min_n <= n <= max_n
 |      will be used. For example an ``ngram_range`` of ``(1, 1)`` means only
 |      unigrams, ``(1, 2)`` means unigrams and bigrams, and ``(2, 2)`` means
 |      only bigrams. Defaults to (1, 1).
 |      Only applies if ``analyzer is not callable``.
 |
 |  max_df : float or int
 |      When building the vocabulary ignore terms that have a document
 |      frequency strictly higher than the given threshold (corpus-specific
 |      stop words). Defaults to 1.0.
 |      If float in range [0.0, 1.0], the parameter represents a proportion of
 |      documents, integer absolute counts.
 |      This parameter is ignored if vocabulary is not None.
 |
 |  min_df : float or int
 |      When building the vocabulary ignore terms that have a document
 |      frequency strictly lower than the given threshold. This value is also
 |      called cut-off in the literature. Defaults to 1.
 |      If float in range of [0.0, 1.0], the parameter represents a proportion
 |      of documents, integer absolute counts.
 |      This parameter is ignored if vocabulary is not None.
 |
 |  max_features : int
 |      If not None, build a vocabulary that only consider the top
 |      max_features ordered by term frequency across the corpus.
 |      None by default.
 |
 |      This parameter is ignored if vocabulary is not None.
 |
 |  vocabulary : Mapping or iterable
 |      Either a Mapping (e.g., a dict) where keys are terms and values are
 |      indices in the feature matrix, or an iterable over terms. If not
 |      given, a vocabulary is determined from the input documents. None by
default.
 |
 |  binary : bool
 |      If True, all non-zero term counts are set to 1. This does not mean
 |      outputs will have only 0/1 values, only that the tf term in tf-idf
 |      is binary. (Set idf and normalization to False to get 0/1 outputs).
 |      False by default.
 |
 |  dtype : dtype
 |      Type of the matrix returned by fit_transform() or transform().
 |      'float64' by default.
 |
 |  norm : {'l2', 'l1'}
```

```
 |      Each output row will have unit norm, either:
 |      * 'l2': Sum of squares of vector elements is 1. The cosine
 |      similarity between two vectors is their dot product when l2 norm has
 |      been applied. None by default.
 |      * 'l1': Sum of absolute values of vector elements is 1.
 |      See :func:`preprocessing.normalize`.
 |
 |  use_idf : bool
 |      Enable inverse-document-frequency reweighting. False by default.
 |
 |  smooth_idf : bool
 |      Smooth idf weights by adding one to document frequencies, as if an
 |      extra document was seen containing every term in the collection
 |      exactly once. Prevents zero divisions. True by default.
 |
 |  sublinear_tf : bool
 |      Apply sublinear tf scaling, i.e. replace tf with 1 + log(tf).
 |      False by default.
 |
 |  Attributes
 |  ----------
 |  vocabulary_ : dict
 |      A mapping of terms to feature indices.
 |
 |  fixed_vocabulary_: bool
 |      True if a fixed vocabulary of term to indices mapping
 |      is provided by the user
 |
 |  idf_ : array of shape (n_features,)
 |      The inverse document frequency (IDF) vector; only defined
 |      if ``use_idf`` is True.
 |
 |  stop_words_ : set
 |      Terms that were ignored because they either:
 |
 |        - occurred in too many documents (`max_df`)
 |        - occurred in too few documents (`min_df`)
 |        - were cut off by feature selection (`max_features`).
 |
 |      This is only available if no vocabulary was given.
 |
 |  Method resolution order:
 |      FreqVectorizer
 |      sklearn.feature_extraction.text.TfidfVectorizer
 |      sklearn.feature_extraction.text.CountVectorizer
 |      VectorizerMixin
 |      sklearn.feature_extraction.text._VectorizerMixin
 |      sklearn.base.BaseEstimator
```

```
 |      builtins.object
 |
 |  Methods defined here:
 |
 |  __init__(self, *, input='content', encoding='utf-8', decode_error='strict',
strip_accents=None, decode_html_entities=True, lowercase=True,
strip_extra_space=False, strip_numeric=False, strip_non_word=False,
strip_punct=False, strip_twitter_handles=False, strip_html_tags=False,
limit_repeats=False, uniq_char_thresh=None, mark_negation=False, stemmer=None,
preprocessor=None, tokenizer=None, token_pattern='\\b\\w\\w+\\b',
analyzer='word', stop_words=None, process_stop_words=True, ngram_range=(1, 1),
max_df=1.0, min_df=1, max_features=None, vocabulary=None, binary=False,
dtype=<class 'numpy.float64'>, norm=None, use_idf=False, smooth_idf=True,
sublinear_tf=False)
 |      Initialize self.  See help(type(self)) for accurate signature.
 |
 |  get_keywords(self, document, top_n=None)
 |
 |  ----------------------------------------------------------------------
 |  Class methods defined here:
 |
 |  from_sklearn(vectorizer, transfer_fit=True) from builtins.type
 |
 |  ----------------------------------------------------------------------
 |  Methods inherited from sklearn.feature_extraction.text.TfidfVectorizer:
 |
 |  fit(self, raw_documents, y=None)
 |      Learn vocabulary and idf from training set.
 |
 |      Parameters
 |      ----------
 |      raw_documents : iterable
 |          An iterable which generates either str, unicode or file objects.
 |
 |      y : None
 |          This parameter is not needed to compute tfidf.
 |
 |      Returns
 |      -------
 |      self : object
 |          Fitted vectorizer.
 |
 |  fit_transform(self, raw_documents, y=None)
 |      Learn vocabulary and idf, return document-term matrix.
 |
 |      This is equivalent to fit followed by transform, but more efficiently
 |      implemented.
 |
```

```
 |      Parameters
 |      ----------
 |      raw_documents : iterable
 |          An iterable which generates either str, unicode or file objects.
 |
 |      y : None
 |          This parameter is ignored.
 |
 |      Returns
 |      -------
 |      X : sparse matrix of (n_samples, n_features)
 |          Tf-idf-weighted document-term matrix.
 |
 |  transform(self, raw_documents)
 |      Transform documents to document-term matrix.
 |
 |      Uses the vocabulary and document frequencies (df) learned by fit (or
 |      fit_transform).
 |
 |      Parameters
 |      ----------
 |      raw_documents : iterable
 |          An iterable which generates either str, unicode or file objects.
 |
 |      Returns
 |      -------
 |      X : sparse matrix of (n_samples, n_features)
 |          Tf-idf-weighted document-term matrix.
 |
 |  ----------------------------------------------------------------------
 |  Data descriptors inherited from
sklearn.feature_extraction.text.TfidfVectorizer:
 |
 |  idf_
 |      Inverse document frequency vector, only defined if `use_idf=True`.
 |
 |      Returns
 |      -------
 |      ndarray of shape (n_features,)
 |
 |  norm
 |      Norm of each row output, can be either "l1" or "l2".
 |
 |  smooth_idf
 |      Whether or not IDF weights are smoothed.
 |
 |  sublinear_tf
 |      Whether or not sublinear TF scaling is applied.
```

```
 |
 |  use_idf
 |      Whether or not IDF re-weighting is used.
 |
 |  ----------------------------------------------------------------------
 |  Methods inherited from sklearn.feature_extraction.text.CountVectorizer:
 |
 |  get_feature_names(self)
 |      DEPRECATED: get_feature_names is deprecated in 1.0 and will be removed
in 1.2. Please use get_feature_names_out instead.
 |
 |      Array mapping from feature integer indices to feature name.
 |
 |          Returns
 |          -------
 |          feature_names : list
 |              A list of feature names.
 |
 |  get_feature_names_out(self, input_features=None)
 |      Get output feature names for transformation.
 |
 |      Parameters
 |      ----------
 |      input_features : array-like of str or None, default=None
 |          Not used, present here for API consistency by convention.
 |
 |      Returns
 |      -------
 |      feature_names_out : ndarray of str objects
 |          Transformed feature names.
 |
 |  inverse_transform(self, X)
 |      Return terms per document with nonzero entries in X.
 |
 |      Parameters
 |      ----------
 |      X : {array-like, sparse matrix} of shape (n_samples, n_features)
 |          Document-term matrix.
 |
 |      Returns
 |      -------
 |      X_inv : list of arrays of shape (n_samples,)
 |          List of arrays of terms.
 |
 |  ----------------------------------------------------------------------
 |  Methods inherited from VectorizerMixin:
 |
 |  build_analyzer(self)
```

```
 |      Return the complete text preprocessing pipeline as a callable.
 |
 |      Handles decoding, character filtration, tokenization, word filtration,
 |      marking, and n-gram generation. Alternatively, returns a callable
 |      wrapping the custom analyzer passed via the `analyzer` parameter.
 |
 |      Returns
 |      -------
 |      analyzer: callable
 |          A function to handle decoding, character filtration, tokenization,
 |          word filtration, n-gram generation, and marking.
 |
 |  build_preprocessor(self)
 |      Return a function to preprocess the text before tokenization.
 |
 |      Returns
 |      -------
 |      preprocessor: callable
 |            A function to preprocess the text before tokenization.
 |
 |  get_stop_words(self)
 |      Build or fetch the effective stop words set.
 |
 |      Returns
 |      -------
 |      stop_words: frozenset or None
 |              A set of stop words.
 |
 |  ----------------------------------------------------------------------
 |  Methods inherited from sklearn.feature_extraction.text._VectorizerMixin:
 |
 |  build_tokenizer(self)
 |      Return a function that splits a string into a sequence of tokens.
 |
 |      Returns
 |      -------
 |      tokenizer: callable
 |            A function to split a string into a sequence of tokens.
 |
 |  decode(self, doc)
 |      Decode the input into a string of unicode symbols.
 |
 |      The decoding strategy depends on the vectorizer parameters.
 |
 |      Parameters
 |      ----------
 |      doc : str
 |          The string to decode.
```

```
 |
 |      Returns
 |      -------
 |      doc: str
 |          A string of unicode symbols.
 |
 |  ----------------------------------------------------------------------
 |  Data descriptors inherited from
sklearn.feature_extraction.text._VectorizerMixin:
 |
 |  __dict__
 |      dictionary for instance variables (if defined)
 |
 |  __weakref__
 |      list of weak references to the object (if defined)
 |
 |  ----------------------------------------------------------------------
 |  Methods inherited from sklearn.base.BaseEstimator:
 |
 |  __getstate__(self)
 |
 |  __repr__(self, N_CHAR_MAX=700)
 |      Return repr(self).
 |
 |  __setstate__(self, state)
 |
 |  get_params(self, deep=True)
 |      Get parameters for this estimator.
 |
 |      Parameters
 |      ----------
 |      deep : bool, default=True
 |          If True, will return the parameters for this estimator and
 |          contained subobjects that are estimators.
 |
 |      Returns
 |      -------
 |      params : dict
 |          Parameter names mapped to their values.
 |
 |  set_params(self, **params)
 |      Set the parameters of this estimator.
 |
 |      The method works on simple estimators as well as on nested objects
 |      (such as :class:`~sklearn.pipeline.Pipeline`). The latter have
 |      parameters of the form ``<component>__<parameter>`` so that it's
 |      possible to update each component of a nested object.
 |
```

```
|      Parameters
|      ----------
|      **params : dict
|          Estimator parameters.
|
|      Returns
|      -------
|      self : estimator instance
|          Estimator instance.
```

```
<IPython.core.display.Javascript object>
```

I choose the ‘stratified’ dummy algorithm, which makes predictions according to the class support. The predictions will be as imbalanced as the classes.

[31]:
```python
pipe = Pipeline(
    [
        ("vec", fv),
        ("cls", DummyClassifier(strategy="stratified")),
    ],
    memory="pipe_cache",
    verbose=True,
)
pipe
```

[31]:
```
Pipeline(memory='pipe_cache',
         steps=[('vec', FreqVectorizer()),
                ('cls', DummyClassifier(strategy='stratified'))],
         verbose=True)
```

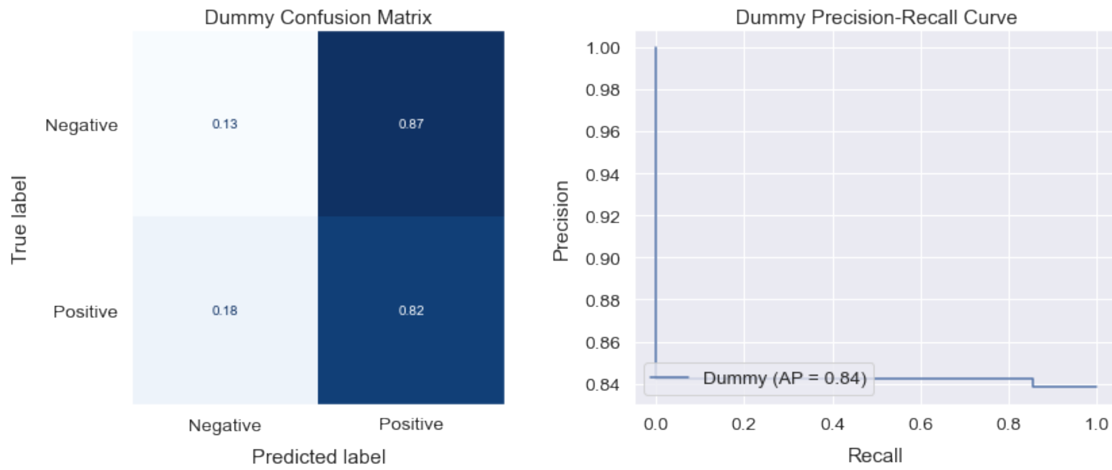
```
<IPython.core.display.Javascript object>
```

6.3.2 Fitting the Dummy

[32]:
```python
pipe.fit(X_train, y_train)
dummy_rep, dummy_cm, dummy_prc = eval_model(pipe, "Dummy")
```

```
[Pipeline] … (step 2 of 2) Processing cls, total=   0.0s
```

```
<pandas.io.formats.style.Styler at 0x17487a81250>
```




```
<IPython.core.display.Javascript object>
```

It looks as bad as it should, with predictions as imbalanced as the classes. The precision-recall curve, if it can be called a "curve," is especially bad.

6.4 Baseline Model: Random Forest

I begin by training a `BalancedRandomForestClassifier` from the the Imbalanced-Learn toolkit. I've chosen this classifier as a baseline because of its unique potential to deal with the class imbalance. It's the standard random forest algorithm with a twist: when bootstrapping datasets for each decision tree, it uses **random undersampling** instead of standard random sampling. This means that it balances the classes for each subsample by drawing fewer samples from the majority class.

The weakness of undersampling is that it potentially throws away a large amount of data from the majority class. However, since undersampling is performed for each tree in the forest, observations from the majority class have multiple chances to be selected and taken into consideration.

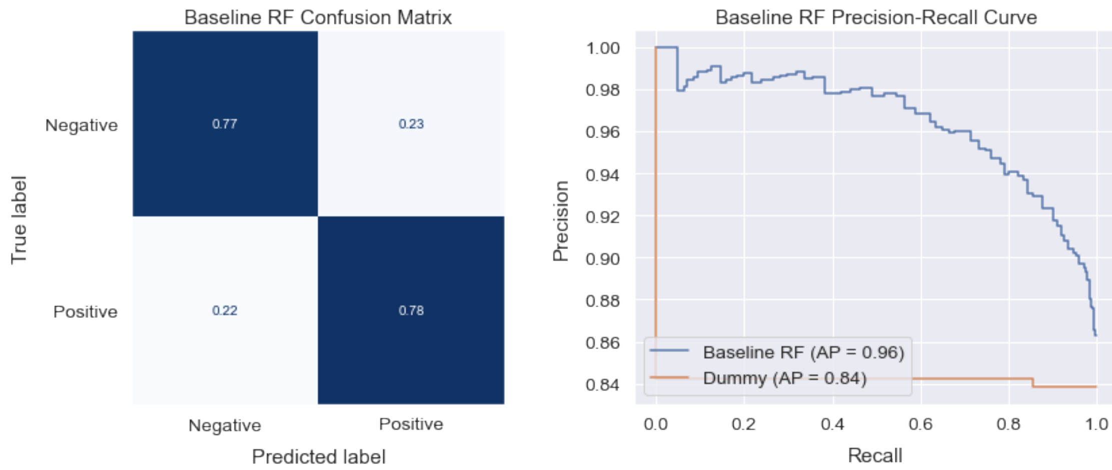
[33]:
```
pipe.set_params(cls=BalancedRandomForestClassifier(random_state=53))
```

[33]:
```
Pipeline(memory='pipe_cache',
         steps=[('vec', FreqVectorizer()),
                ('cls', BalancedRandomForestClassifier(random_state=53))],
         verbose=True)
```

```
<IPython.core.display.Javascript object>
```

[34]:
```
pipe.fit(X_train, y_train)
base_rep, base_cm, base_prc = eval_model(
    pipe, "Baseline RF", compare_curves=[dummy_prc]
)
```

```
[Pipeline] … (step 2 of 2) Processing cls, total=   0.9s
<pandas.io.formats.style.Styler at 0x17487c31790>
```




```
<IPython.core.display.Javascript object>
```

Not bad for a baseline! Note that the confusion matrix has a strong diagonal with strong negative recall in particular. It couldn't contrast more with the dummy model's confusion matrix. Accordingly, it also has much higher macro-average recall than the dummy, and a healthy precision-recall curve.

6.5 Adding `VaderVectorizer`

Next, I create a `FeatureUnion` which concatenates the output of `FreqVectorizer` with that of my custom `VaderVectorizer`.

`VaderVectorizer` extracts VADER (Valence Aware Dictionary and Sentiment Reasoner) polarity scores from documents and turns them into short vectors of shape (n_samples, 4). It's essentially a wrapper around the VADER tools found in NLTK. VADER analysis produces 4 scores: positive, neutral, negative, and compound. These are the 4 features in the matrix output by the vectorizer.

[35]:
```
fu = FeatureUnion(
    [
        ("frq", FreqVectorizer()),
        ("vad", VaderVectorizer()),
    ],
    verbose=True,
)

pipe.set_params(vec=fu)
```

```
[nltk_data] Downloading package vader_lexicon to
[nltk_data]     C:\Users\ndgig\AppData\Roaming\nltk_data…
[nltk_data]   Package vader_lexicon is already up-to-date!
```

[35]:
```
Pipeline(memory='pipe_cache',
         steps=[('vec',
```

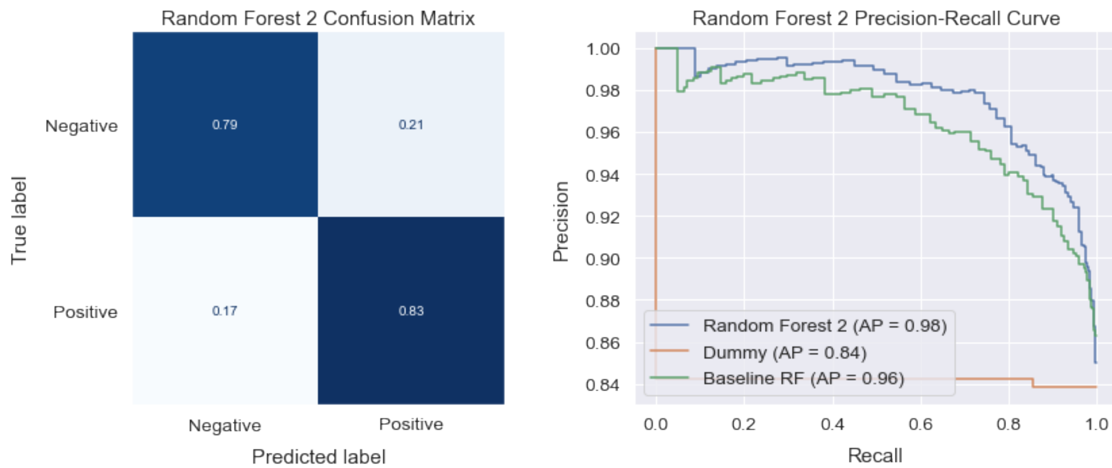
```
                    FeatureUnion(transformer_list=[('frq', FreqVectorizer()),
                                                    ('vad', VaderVectorizer())],
                                 verbose=True)),
                ('cls', BalancedRandomForestClassifier(random_state=53))],
         verbose=True)
```

```
<IPython.core.display.Javascript object>
```

[36]:

```python
pipe.fit(X_train, y_train)
rf_rep, rf_cm, rf_prc = eval_model(
    pipe,
    "Random Forest 2",
    compare_curves=[dummy_prc, base_prc],
)
```

```
[nltk_data] Downloading package vader_lexicon to
[nltk_data]     C:\Users\ndgig\AppData\Roaming\nltk_data…
[nltk_data]   Package vader_lexicon is already up-to-date!

[Pipeline] … (step 2 of 2) Processing cls, total=   0.7s

<pandas.io.formats.style.Styler at 0x1748956b2b0>
```




```
<IPython.core.display.Javascript object>
```

The macro-average recall is notably higher and the precision-recall curve is significantly wider than the baseline. As expected, the addition of `VaderVectorizer` is a major improvement.

6.6 Selecting the Best Classifier

I started with `BalancedRandomForestClassifier` because I intuitively thought it would perform well, and it has. Nevertheless, I want to run a broad search over the hyperparameter space of multiple different classifiers. I will also try random undersampling and random oversampling with each of them.

The first step is to extend the pipeline to contain a resampler slot.

[37]:
```python
pipe = Pipeline(
    [
        ("vec", fu),
        ("res", "passthrough"),
        ("cls", BalancedRandomForestClassifier()),
    ],
    memory="pipe_cache",
    verbose=True,
)
pipe
```

[37]:
```
Pipeline(memory='pipe_cache',
         steps=[('vec',
                 FeatureUnion(transformer_list=[('frq', FreqVectorizer()),
                                                ('vad', VaderVectorizer())],
                              verbose=True)),
                ('res', 'passthrough'),
                ('cls', BalancedRandomForestClassifier())],
         verbose=True)
```

```
<IPython.core.display.Javascript object>
```

I'll also include the basic `FreqVectorizer` options in the search space. This will determine whether the vectors are binary occurrence, count, TF*IDF, binary*IDF, or some other variant.

[38]:
```python
tfidf_grid = {
    "vec__frq__binary": [True, False],
    "vec__frq__norm": ["l2", None],
    "vec__frq__smooth_idf": [True, False],
    "vec__frq__sublinear_tf": [True, False],
    "vec__frq__use_idf": [True, False],
}
tfidf_grid
```

[38]:
```
{'vec__frq__binary': [True, False],
 'vec__frq__norm': ['l2', None],
 'vec__frq__smooth_idf': [True, False],
 'vec__frq__sublinear_tf': [True, False],
 'vec__frq__use_idf': [True, False]}
```

```
<IPython.core.display.Javascript object>
```

Next, I lay out the parameter space for four types of classifiers: random forest, logistic regression, support-vector machine, and naive bayes.

Notes on the Parameter Space Due to the negative range of VADER's 'Compound' score, `VaderVectorizer` must be turned off for the naive bayes classifiers. Since `VaderVectorizer` has the option of rounding scores to the nearest integer, I'll include that as an option for the other classifiers.

I only try `RandomUnderSampler` and `RandomOverSampler` for now. If one of these finds its way into the best pipeline, I'll try out more sophisticated methods like `SMOTE`.

I opt to use 'liblinear' as the solver for `LogisticRegression` because it works well on small datasets and offers both L1 and L2 regularization.

[39]:
```
classif_grid = [
    {
        "cls": [BalancedRandomForestClassifier()],
        "cls__n_estimators": sp.stats.randint(100, 1000),
        "cls__criterion": ["gini", "entropy"],
        "cls__max_depth": sp.stats.randint(10, 2000),
        "cls__min_samples_split": sp.stats.uniform(),
        "cls__min_samples_leaf": sp.stats.loguniform(1e-4, 0.25),
        "cls__replacement": [True, False],
        "res": ["passthrough"],
        "vec__vad__round_scores": [True, False],
        **tfidf_grid,
    },
    {
        "cls": [LogisticRegression(solver="liblinear")],
        "cls__C": sp.stats.loguniform(1e-4, 1e4),
        "cls__penalty": ["l1", "l2"],
        "cls__fit_intercept": [True, False],
        "cls__class_weight": ["balanced", None],
        "res": [RandomUnderSampler(), RandomOverSampler(), "passthrough"],
        "vec__vad__round_scores": [True, False],
        **tfidf_grid,
    },
    {
        "cls": [SVC()],
        "cls__C": sp.stats.loguniform(1e-4, 1e4),
        "cls__kernel": ["linear", "poly", "rbf", "sigmoid"],
        "cls__shrinking": [True, False],
        "cls__break_ties": [True, False],
        "cls__class_weight": ["balanced", None],
        "res": [RandomOverSampler(), RandomUnderSampler(), "passthrough"],
        "vec__vad__round_scores": [True, False],
        **tfidf_grid,
    },
    {
        "cls": [ComplementNB(), MultinomialNB(), BernoulliNB()],
        "cls__alpha": sp.stats.loguniform(1e-4, 1e4),
        "res": [RandomOverSampler(), RandomUnderSampler(), "passthrough"],
        "vec__vad": ["drop"],
```

```
        **tfidf_grid,
    },
]
classif_grid
```

[39]:
```
[{'cls': [BalancedRandomForestClassifier()],
  'cls__n_estimators': <scipy.stats._distn_infrastructure.rv_frozen at
0x1748953fa60>,
  'cls__criterion': ['gini', 'entropy'],
  'cls__max_depth': <scipy.stats._distn_infrastructure.rv_frozen at
0x1748953fc70>,
  'cls__min_samples_split': <scipy.stats._distn_infrastructure.rv_frozen at
0x1748953fdf0>,
  'cls__min_samples_leaf': <scipy.stats._distn_infrastructure.rv_frozen at
0x174898b3100>,
  'cls__replacement': [True, False],
  'res': ['passthrough'],
  'vec__vad__round_scores': [True, False],
  'vec__frq__binary': [True, False],
  'vec__frq__norm': ['l2', None],
  'vec__frq__smooth_idf': [True, False],
  'vec__frq__sublinear_tf': [True, False],
  'vec__frq__use_idf': [True, False]},
 {'cls': [LogisticRegression(solver='liblinear')],
  'cls__C': <scipy.stats._distn_infrastructure.rv_frozen at 0x174898b3370>,
  'cls__penalty': ['l1', 'l2'],
  'cls__fit_intercept': [True, False],
  'cls__class_weight': ['balanced', None],
  'res': [RandomUnderSampler(), RandomOverSampler(), 'passthrough'],
  'vec__vad__round_scores': [True, False],
  'vec__frq__binary': [True, False],
  'vec__frq__norm': ['l2', None],
  'vec__frq__smooth_idf': [True, False],
  'vec__frq__sublinear_tf': [True, False],
  'vec__frq__use_idf': [True, False]},
 {'cls': [SVC()],
  'cls__C': <scipy.stats._distn_infrastructure.rv_frozen at 0x174898b36a0>,
  'cls__kernel': ['linear', 'poly', 'rbf', 'sigmoid'],
  'cls__shrinking': [True, False],
  'cls__break_ties': [True, False],
  'cls__class_weight': ['balanced', None],
  'res': [RandomOverSampler(), RandomUnderSampler(), 'passthrough'],
  'vec__vad__round_scores': [True, False],
  'vec__frq__binary': [True, False],
  'vec__frq__norm': ['l2', None],
  'vec__frq__smooth_idf': [True, False],
  'vec__frq__sublinear_tf': [True, False],
```

```
  'vec__frq__use_idf': [True, False]},
 {'cls': [ComplementNB(), MultinomialNB(), BernoulliNB()],
  'cls__alpha': <scipy.stats._distn_infrastructure.rv_frozen at 0x174898b3af0>,
  'res': [RandomOverSampler(), RandomUnderSampler(), 'passthrough'],
  'vec__vad': ['drop'],
  'vec__frq__binary': [True, False],
  'vec__frq__norm': ['l2', None],
  'vec__frq__smooth_idf': [True, False],
  'vec__frq__sublinear_tf': [True, False],
  'vec__frq__use_idf': [True, False]}]
```

```
<IPython.core.display.Javascript object>
```

Next I run the search using Scikit-Learn's `RandomizedSearchCV`. My `selection.sweep` function is a wrapper around all of the Scikit-Learn search estimators which allows for easily switching between them and saving the results. Here I've specified `kind='rand'` to fit a `RandomizedSearchCV` with 10,000 candidates.

I typically prefer `RandomizedSearchCV` to `GridSearchCV` because I like to specify the number of candidates to try. Adding inconsequential hyperparameters to the parameter space has no effect on the number of candidates tried.

[40]:
```python
if RUN_SWEEPS:
    search = selection.sweep(
        pipe,
        classif_grid,
        n_jobs=-1,
        kind="rand",
        X=X_train,
        y=y_train,
        n_iter=10 ** 4,
        scoring="recall_macro",
        cv_dst="sweeps/classifier.joblib",
    )
    classifier_results = search.cv_results_
else:
    classifier_results = joblib.load("sweeps/classifier.joblib")

classifier_results = selection.prune_cv(classifier_results)
```

```
<IPython.core.display.Javascript object>
```

[41]:
```python
classifier_results.head(10)
```

[41]:
```
  param_cls           C  alpha break_ties class_weight criterion  \
0     SVC()  108.387623    NaN       True         None       NaN
1     SVC()   19.703076    NaN       True     balanced       NaN
2     SVC()   75.553489    NaN      False         None       NaN
3     SVC()    3.595819    NaN       True     balanced       NaN
```

```
4    SVC()    3.370624   NaN     False    balanced      NaN
5    SVC()  118.422907   NaN      True        None      NaN
6    SVC()  624.686785   NaN     False    balanced      NaN
7    SVC() 3101.865661   NaN     False    balanced      NaN
8    SVC() 8454.321014   NaN     False        None      NaN
9    SVC()  102.164007   NaN      True    balanced      NaN

  fit_intercept kernel  max_depth  min_samples_leaf  …  norm  smooth_idf  \
0           NaN    rbf        NaN               NaN  …    l2        True
1           NaN    rbf        NaN               NaN  …    l2        True
2           NaN   poly        NaN               NaN  …    l2        True
3           NaN   poly        NaN               NaN  …    l2       False
4           NaN    rbf        NaN               NaN  …    l2       False
5           NaN   poly        NaN               NaN  …    l2        True
6           NaN   poly        NaN               NaN  …    l2       False
7           NaN   poly        NaN               NaN  …    l2       False
8           NaN   poly        NaN               NaN  …    l2        True
9           NaN   poly        NaN               NaN  …    l2        True

  sublinear_tf use_idf  vad round_scores  \
0         True    True  NaN        False
1         True    True  NaN        False
2         True    True  NaN        False
3        False   False  NaN        False
4        False    True  NaN         True
5         True   False  NaN        False
6        False   False  NaN        False
7        False   False  NaN        False
8        False   False  NaN        False
9         True    True  NaN        False

                                              params mean_fit_time  \
0  {'cls': SVC(), 'cls__C': 108.3876234609627, 'c…      0.330799
1  {'cls': SVC(), 'cls__C': 19.703075707568555, '…      0.337223
2  {'cls': SVC(), 'cls__C': 75.55348904699694, 'c…      0.286599
3  {'cls': SVC(), 'cls__C': 3.595818511081092, 'c…      0.323740
4  {'cls': SVC(), 'cls__C': 3.370623837810783, 'c…      0.324798
5  {'cls': SVC(), 'cls__C': 118.42290693610798, '…      0.310527
6  {'cls': SVC(), 'cls__C': 624.6867851737038, 'c…      0.317598
7  {'cls': SVC(), 'cls__C': 3101.865660946222, 'c…      0.328406
8  {'cls': SVC(), 'cls__C': 8454.321013802326, 'c…      0.343416
9  {'cls': SVC(), 'cls__C': 102.16400718875725, '…      0.362909

   mean_score  rank_score
0    0.782379           1
1    0.781011           2
2    0.780357           3
```

```
3     0.779486           4
4     0.778957           5
5     0.778491           6
6     0.778491           6
7     0.778491           6
8     0.778491           6
9     0.777823          10

[10 rows x 27 columns]
```

```
<IPython.core.display.Javascript object>
```

6.7 Fitting an SVM

[42]:
```
pipe.set_params(**classifier_results.loc[1, "params"], cls__probability=True)
```

[42]:
```
Pipeline(memory='pipe_cache',
         steps=[('vec',
                 FeatureUnion(transformer_list=[('frq',
                                                 FreqVectorizer(binary=True,
                                                                norm='l2',
sublinear_tf=True,
                                                                use_idf=True)),
                                                ('vad', VaderVectorizer())],
                              verbose=True)),
                ('res', RandomUnderSampler()),
                ('cls',
                 SVC(C=19.703075707568555, break_ties=True,
                     class_weight='balanced', probability=True))],
         verbose=True)
```

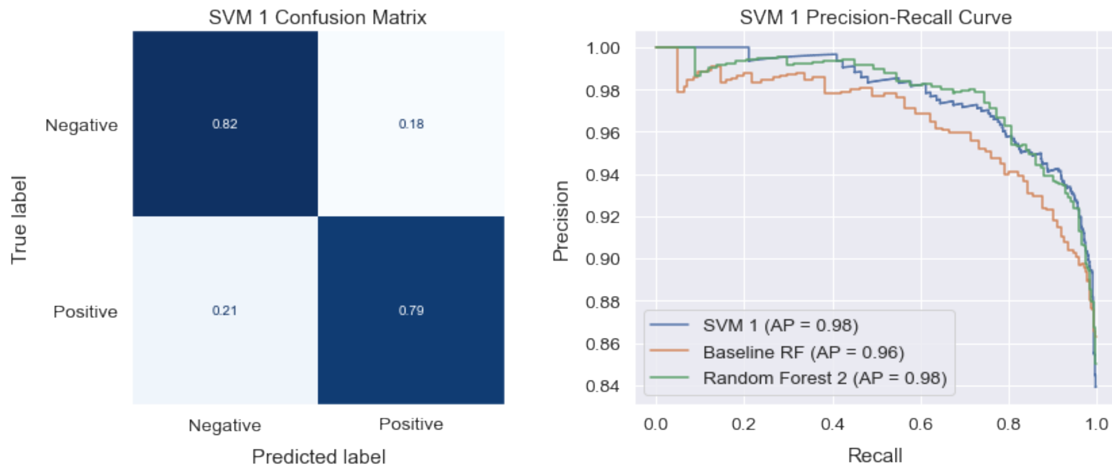
```
<IPython.core.display.Javascript object>
```

[43]:
```
pipe.fit(X_train, y_train)
svm1_rep, svm1_cm, svm1_prc = eval_model(
    pipe, "SVM 1", compare_curves=[base_prc, rf_prc]
)
```

```
[nltk_data] Downloading package vader_lexicon to
[nltk_data]     C:\Users\ndgig\AppData\Roaming\nltk_data…
[nltk_data]   Package vader_lexicon is already up-to-date!
```

```
[Pipeline] … (step 3 of 3) Processing cls, total=   0.6s
```

```
<pandas.io.formats.style.Styler at 0x174880cc8e0>
```



<IPython.core.display.Javascript object>

It's pretty similar to Random Forest 2. The biggest change seems to be the high negative recall. It also has a marginally wider precision-recall curve.

6.8 Tuning the Preprocessing

First I define some stopwords for this particular dataset which I'd like to try out.

[44]:
```
my_stop = {
    "america",
    "austin",
    "link",
    "mention",
    "southbysouthwest",
    "sxsw",
    "sxswi",
    "tweet",
    "twitter",
}

my_stop
```

[44]:
```
{'america',
 'austin',
 'link',
 'mention',
 'southbysouthwest',
 'sxsw',
 'sxswi',
 'tweet',
 'twitter'}
```

<IPython.core.display.Javascript object>

Next I lay out the preprocessing hyperparameter space for `FreqVectorizer`. My `FreqVectorizer` has built-in lemmatization with NLTK's `WordnetLemmatizer`, as well as the ability to mark words between a negation term and sentence punctuation. I'll try both of these options as well as others which I've added to Scikit-Learn's `TfidfVectorizer`.

[45]:
```
preproc_grid = {
    "vec__frq__stop_words": [my_stop, "nltk_english", None],
    "vec__frq__tokenizer": [
        nltk.word_tokenize,
        nltk.casual_tokenize,
        nltk.wordpunct_tokenize,
        None,
    ],
    "vec__frq__ngram_range": [(1, 1), (1, 2)],
    "vec__frq__max_df": sp.stats.uniform(0.05, 0.95),
    "vec__frq__strip_numeric": [True, False],
    "vec__frq__strip_twitter_handles": [True, False],
    "vec__frq__limit_repeats": [True, False],
    "vec__frq__mark_negation": [True, False],
    "vec__frq__stemmer": ["wordnet", None],
}
preproc_grid
```

[45]:
```
{'vec__frq__stop_words': [{'america',
   'austin',
   'link',
   'mention',
   'southbysouthwest',
   'sxsw',
   'sxswi',
   'tweet',
   'twitter'},
  'nltk_english',
  None],
 'vec__frq__tokenizer': [<function nltk.tokenize.word_tokenize(text,
language='english', preserve_line=False)>,
  <function nltk.tokenize.casual.casual_tokenize(text, preserve_case=True,
reduce_len=False, strip_handles=False, match_phone_numbers=True)>,
  <bound method RegexpTokenizer.tokenize of
WordPunctTokenizer(pattern='\\w+|[^\\w\\s]+', gaps=False, discard_empty=True,
flags=re.UNICODE|re.MULTILINE|re.DOTALL)>,
  None],
 'vec__frq__ngram_range': [(1, 1), (1, 2)],
 'vec__frq__max_df': <scipy.stats._distn_infrastructure.rv_frozen at
0x17489e4f460>,
 'vec__frq__strip_numeric': [True, False],
```

```
 'vec__frq__strip_twitter_handles': [True, False],
 'vec__frq__limit_repeats': [True, False],
 'vec__frq__mark_negation': [True, False],
 'vec__frq__stemmer': ['wordnet', None]}
```

<IPython.core.display.Javascript object>

Next I run a randomized search over `preproc_grid` with 1000 candidates. That should be enough to optimize the preprocessing.

[46]:
```python
if RUN_SWEEPS:
    search = selection.sweep(
        pipe,
        preproc_grid,
        n_jobs=-1,
        kind="rand",
        X=X_train,
        y=y_train,
        n_iter=1000,
        scoring="recall_macro",
        cv_dst="sweeps/preproc.joblib",
    )
    preproc_results = search.cv_results_
else:
    preproc_results = joblib.load("sweeps/preproc.joblib")

preproc_results = selection.prune_cv(preproc_results)
```

<IPython.core.display.Javascript object>

[47]:
```python
preproc_results.head(10)
```

[47]:
```
   limit_repeats  mark_negation    max_df ngram_range  stemmer  \
0           True           True  0.452590      (1, 1)     None
1           True           True  0.977528      (1, 1)  wordnet
2           True           True  0.811677      (1, 1)  wordnet
3           True           True  0.773526      (1, 1)  wordnet
4          False           True  0.249638      (1, 1)  wordnet
5           True           True  0.126879      (1, 1)  wordnet
6           True           True  0.315786      (1, 1)  wordnet
7          False           True  0.526762      (1, 1)  wordnet
8           True           True  0.945616      (1, 1)     None
9          False           True  0.758515      (1, 1)     None

                                          stop_words  strip_numeric  \
0                                       nltk_english          False
1  {sxswi, america, twitter, link, sxsw, mention,…          True
2  {sxswi, america, twitter, link, sxsw, mention,…         False
3  {sxswi, america, twitter, link, sxsw, mention,…         False
```

```
4  {sxswi, america, twitter, link, sxsw, mention,…         False
5  {sxswi, america, twitter, link, sxsw, mention,…         False
6                                               None          False
7                                               None          False
8                                       nltk_english           True
9  {sxswi, america, twitter, link, sxsw, mention,…         False

   strip_twitter_handles                                          tokenizer  \
0                  False     <function word_tokenize at 0x00000174F8AD78B0>
1                  False     <function word_tokenize at 0x00000174F8AD78B0>
2                   True     <function word_tokenize at 0x00000174F8AD78B0>
3                   True     <function word_tokenize at 0x00000174F8AD78B0>
4                  False     <function word_tokenize at 0x00000174F8AD78B0>
5                   True  <bound method RegexpTokenizer.tokenize of Word…
6                  False   <function casual_tokenize at 0x00000174F7A99940>
7                  False   <function casual_tokenize at 0x00000174F7A99940>
8                   True     <function word_tokenize at 0x00000174F8AD78B0>
9                   True   <function casual_tokenize at 0x00000174F7A99940>

                                              params  mean_fit_time  \
0  {'vec__frq__limit_repeats': True, 'vec__frq__m…       3.326375
1  {'vec__frq__limit_repeats': True, 'vec__frq__m…       9.399600
2  {'vec__frq__limit_repeats': True, 'vec__frq__m…       9.205640
3  {'vec__frq__limit_repeats': True, 'vec__frq__m…       9.219135
4  {'vec__frq__limit_repeats': False, 'vec__frq__…       8.764399
5  {'vec__frq__limit_repeats': True, 'vec__frq__m…       8.180685
6  {'vec__frq__limit_repeats': True, 'vec__frq__m…       8.840783
7  {'vec__frq__limit_repeats': False, 'vec__frq__…       8.368999
8  {'vec__frq__limit_repeats': True, 'vec__frq__m…       3.332243
9  {'vec__frq__limit_repeats': False, 'vec__frq__…       2.919505

   mean_score  rank_score
0    0.802835           1
1    0.799584           2
2    0.798919           3
3    0.798919           3
4    0.798651           5
5    0.798255           6
6    0.796869           7
7    0.795950           8
8    0.795445           9
9    0.795048          10
```

```
<IPython.core.display.Javascript object>
```

Looks like `mark_negation=True` won out pretty robustly, which doesn't surprise me. `nltk.word_tokenize` is also a clear winner, as is `ngram_range=(1, 1)`.

6.9 Fitting a Second SVM

Next I set the best parameters and fit another model. I'm anticipating some improvement.

[48]:
```
pipe.set_params(**preproc_results.loc[0, "params"])
```

[48]:
```
Pipeline(memory='pipe_cache',
         steps=[('vec',
                 FeatureUnion(transformer_list=[('frq',
                                                FreqVectorizer(binary=True,
limit_repeats=True,
mark_negation=True,
max_df=0.4525897144046643,
                                                               norm='l2',
stop_words='nltk_english',
sublinear_tf=True,
tokenizer=<function word_tokenize at 0x00000174F8AD78B0>,
                                                               use_idf=True)),
                                               ('vad', VaderVectorizer())],
                              verbose=True)),
                ('res', RandomUnderSampler()),
                ('cls',
                 SVC(C=19.703075707568555, break_ties=True,
                     class_weight='balanced', probability=True))],
         verbose=True)
```

```
<IPython.core.display.Javascript object>
```

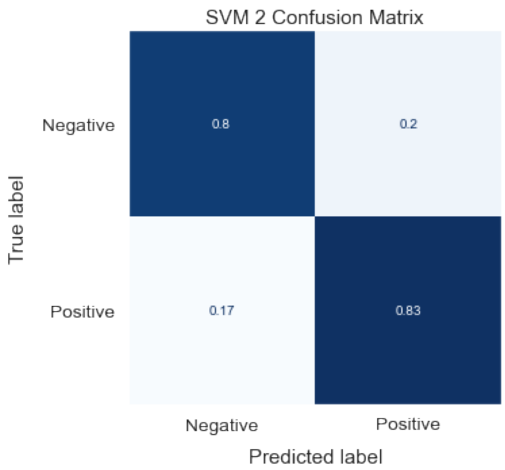
[49]:
```
pipe.fit(X_train, y_train)
svm2_rep, svm2_cm, svm2_prc = eval_model(
    pipe, "SVM 2", compare_curves=[svm1_prc, base_prc]
)
```

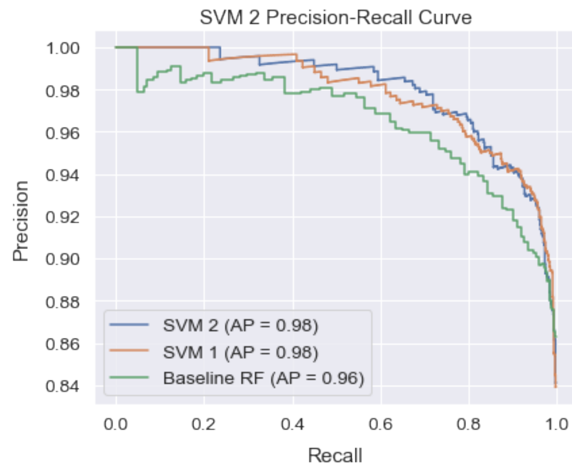
```
[nltk_data] Downloading package vader_lexicon to
[nltk_data]     C:\Users\ndgig\AppData\Roaming\nltk_data…
[nltk_data]   Package vader_lexicon is already up-to-date!
```

```
[Pipeline] … (step 3 of 3) Processing cls, total=   0.5s
```

```
C:\Users\ndgig\anaconda3\envs\nlp-nn\lib\site-
packages\sklearn\feature_extraction\text.py:396: UserWarning: Your stop_words
may be inconsistent with your preprocessing. Tokenizing the stop words generated
tokens ["'d", "'ll", "'re", "'s", "'ve", 'could', 'might', 'must', "n't",
'need', 'sha', 'wo', 'would'] not in stop_words.
  warnings.warn(
```

```
<pandas.io.formats.style.Styler at 0x1748a087e20>
```






```
<IPython.core.display.Javascript object>
```

There's a significant increase in macro recall, and the precision-recall curve is slightly wider than that of SVM 1.

It doesn't seem like I'm going to be able to improve much over this model, at least by conventional means. One possibility would be to use a `StackingClassifier` to combine the results of multiple different classifiers. Rather than go down that rabbit hole, I think I'll try fine-tuning a pre-trained neural network. The latter seems more promising, especially given the small size of the dataset. A pre-trained network will bring additional information with it, in a sense.

I go ahead and refit the final conventional model on the full `X` and save it.

[50]:
```
pipe.fit(X, y)
joblib.dump(pipe, "models/final_svm.joblib", compress=True)
```

```
[nltk_data] Downloading package vader_lexicon to
[nltk_data]     C:\Users\ndgig\AppData\Roaming\nltk_data…
[nltk_data]   Package vader_lexicon is already up-to-date!

[Pipeline] … (step 3 of 3) Processing cls, total=   0.8s
```

[50]:
```
['models/final_svm.joblib']
```

```
<IPython.core.display.Javascript object>
```

6.10 Fine-Tuning a BERT

I'm going to try using transfer learning to improve upon my previous model, and in particular, I'm going to fine-tune a pre-trained BERT model. BERT (Bidirectional Encoder Representations from Transformers) is a state of the art language understanding model trained on the union of the Toronto Book Corpus and Wikipedia. It's "bidirectional" in the sense that it takes both left and right context into account during training. It can be fine-tuned for a specific task (such as the present task) using one additional layer of neurons.

Before training the model, I need to find out the maximum sequence length for my dataset. I do this by tokenizing it with the BERT tokenizer and finding the maximum length.

[51]:
```
bert_tokenizer = AutoTokenizer.from_pretrained("bert-base-uncased",␣
 ↪use_fast=False)
df["text"].map(bert_tokenizer.tokenize).str.len().max()
```

[51]:
```
50
```

```
<IPython.core.display.Javascript object>
```

I use this Scikit-Learn wrapper for the Huggingface Transformers port of Google's BERT. The underlying model is a PyTorch model.

I start with the default hyperparameters, except for a few which I set in advance. I arrive at the training batch size through a process of trial and error with my GPU.

[52]:
```
bert = BertClassifier(
    do_lower_case=True,
    train_batch_size=28,
    max_seq_length=50,
)
bert.get_params()
```

```
Building sklearn text classifier…
```

[52]:
```
{'bert_config_json': None,
 'bert_model': 'bert-base-uncased',
 'bert_vocab': None,
 'do_lower_case': True,
 'epochs': 3,
 'eval_batch_size': 8,
 'fp16': False,
 'from_tf': False,
 'gradient_accumulation_steps': 1,
 'ignore_label': None,
 'label_list': None,
 'learning_rate': 2e-05,
 'local_rank': -1,
 'logfile': 'bert_sklearn.log',
 'loss_scale': 0,
 'max_seq_length': 50,
 'num_mlp_hiddens': 500,
 'num_mlp_layers': 0,
 'random_state': 42,
 'restore_file': None,
 'train_batch_size': 28,
 'use_cuda': True,
 'validation_fraction': 0.1,
 'warmup_proportion': 0.1}
```

<IPython.core.display.Javascript object>

6.10.1 Fitting a Baseline BERT

I fit the model with mostly default hyperparameters, then evaluate the result.

[53]:
```
if FIT_BERT:
    bert.fit(X_train, y_train)
    bert.save("models/bert_baseline.bin")
else:
    bert = bert_sklearn.load_model("models/bert_baseline.bin")

bert
```

```
Loading model from models/bert_baseline.bin…
Defaulting to linear classifier/regressor
Building sklearn text classifier…
```

[53]:
```
BertClassifier(bert_config_json={'architectures': ['BertForMaskedLM'],
                                 'attention_probs_dropout_prob': 0.1,
                                 'hidden_act': 'gelu',
                                 'hidden_dropout_prob': 0.1, 'hidden_size': 768,
                                 'initializer_range': 0.02,
                                 'intermediate_size': 3072,
                                 'layer_norm_eps': 1e-12,
                                 'max_position_embeddings': 512,
                                 'model_type': 'bert',
                                 'num_attention_heads': 12,
                                 'num_hidden_layers': 12, 'pad_token_…
                                       ('[unused15]', 16), ('[unused16]', 17),
                                       ('[unused17]', 18), ('[unused18]', 19),
                                       ('[unused19]', 20), ('[unused20]', 21),
                                       ('[unused21]', 22), ('[unused22]', 23),
                                       ('[unused23]', 24), ('[unused24]', 25),
                                       ('[unused25]', 26), ('[unused26]', 27),
                                       ('[unused27]', 28), ('[unused28]', 29),
…]),
               do_lower_case=True, label_list=array([0, 1], dtype=uint8),
               max_seq_length=50, train_batch_size=28)
```

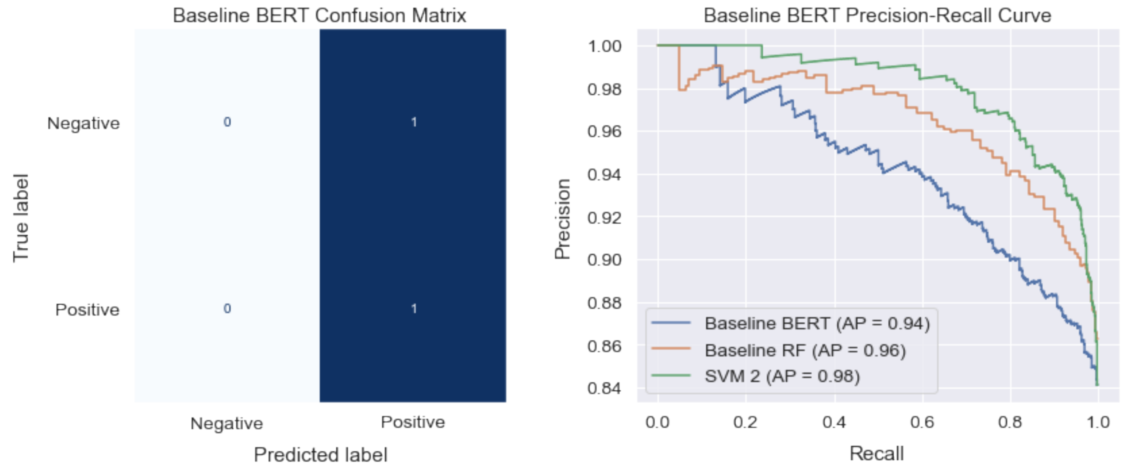
<IPython.core.display.Javascript object>

[54]:
```
bert1_rep, bert1_cm, bert1_prc = eval_model(
    bert,
    "Baseline BERT",
    compare_curves=[base_prc, svm2_prc],
)
```

```
Predicting: 100%|
```

```
      | 110/110 [00:14<00:00,  7.69it/s]
Predicting: 100%|

      | 110/110 [00:13<00:00,  8.32it/s]
```

```
<pandas.io.formats.style.Styler at 0x174899dc3d0>
```




```
<IPython.core.display.Javascript object>
```

Looks terrible! It's worse than Baseline RF because it almost always predicts the positive class. Perhaps with some hand-tuning of the hyperparameters, this can be improved.

6.10.2 Fitting a Second BERT

I hand-tune the hyperparameters until I'm able to create a high quality model.

[55]:
```python
bert.set_params(
    num_mlp_hiddens=750,
    num_mlp_layers=2,
    epochs=4,
)
```

[55]:
```
BertClassifier(bert_config_json={'architectures': ['BertForMaskedLM'],
                                 'attention_probs_dropout_prob': 0.1,
                                 'hidden_act': 'gelu',
                                 'hidden_dropout_prob': 0.1, 'hidden_size': 768,
                                 'initializer_range': 0.02,
                                 'intermediate_size': 3072,
                                 'layer_norm_eps': 1e-12,
                                 'max_position_embeddings': 512,
                                 'model_type': 'bert',
                                 'num_attention_heads': 12,
                                 'num_hidden_layers': 12, 'pad_token_…
```

```
                                      ('[unused17]', 18), ('[unused18]', 19),
                                      ('[unused19]', 20), ('[unused20]', 21),
                                      ('[unused21]', 22), ('[unused22]', 23),
                                      ('[unused23]', 24), ('[unused24]', 25),
                                      ('[unused25]', 26), ('[unused26]', 27),
                                      ('[unused27]', 28), ('[unused28]', 29),
…]),
               do_lower_case=True, epochs=4,
               label_list=array([0, 1], dtype=uint8), max_seq_length=50,
               num_mlp_hiddens=750, num_mlp_layers=2, train_batch_size=28)
```

```
<IPython.core.display.Javascript object>
```

I find that using a multi-layer perceptron classifier with 2 hidden layers of 750 neurons each results in a much better model. I also set it to traverse the corpus 4 times.

[56]:
```python
if FIT_BERT:
    bert.fit(X_train, y_train)
    bert.save("models/bert_train.bin")
else:
    bert = bert_sklearn.load_model("models/bert_train.bin")

bert
```

```
Loading model from models/bert_train.bin…
Using mlp with D=768,H=750,K=2,n=2
Building sklearn text classifier…
```

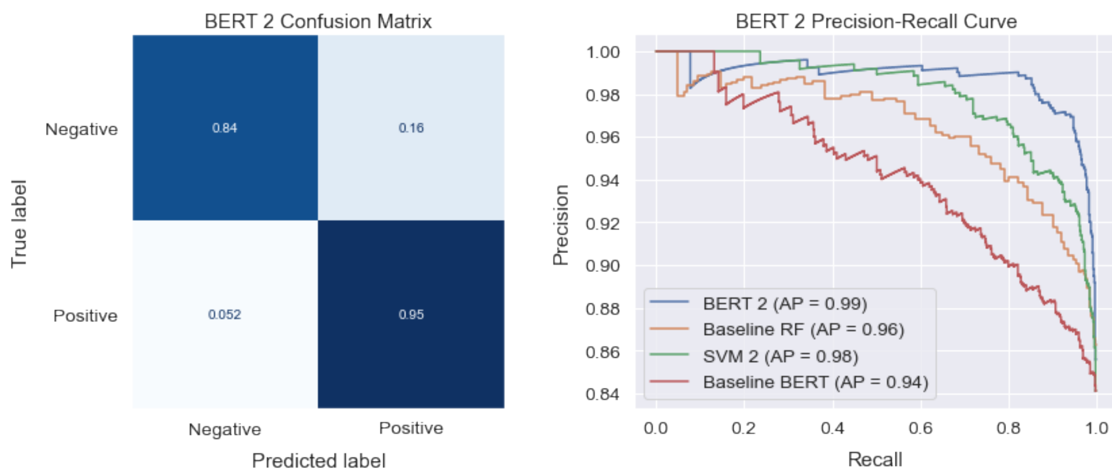
[56]:
```
BertClassifier(bert_config_json={'architectures': ['BertForMaskedLM'],
                                 'attention_probs_dropout_prob': 0.1,
                                 'hidden_act': 'gelu',
                                 'hidden_dropout_prob': 0.1, 'hidden_size': 768,
                                 'initializer_range': 0.02,
                                 'intermediate_size': 3072,
                                 'layer_norm_eps': 1e-12,
                                 'max_position_embeddings': 512,
                                 'model_type': 'bert',
                                 'num_attention_heads': 12,
                                 'num_hidden_layers': 12, 'pad_token_…
                                      ('[unused17]', 18), ('[unused18]', 19),
                                      ('[unused19]', 20), ('[unused20]', 21),
                                      ('[unused21]', 22), ('[unused22]', 23),
                                      ('[unused23]', 24), ('[unused24]', 25),
                                      ('[unused25]', 26), ('[unused26]', 27),
                                      ('[unused27]', 28), ('[unused28]', 29),
…]),
               do_lower_case=True, epochs=4,
               label_list=array([0, 1], dtype=uint8), max_seq_length=50,
               num_mlp_hiddens=750, num_mlp_layers=2, train_batch_size=28)
```

```
<IPython.core.display.Javascript object>
```

[57]:
```python
bert2_rep, bert2_cm, bert2_prc = eval_model(
    bert,
    "BERT 2",
    compare_curves=[base_prc, svm2_prc, bert1_prc],
)
```

```
Predicting: 100%|

      | 110/110 [00:13<00:00,  8.40it/s]
Predicting: 100%|

      | 110/110 [00:13<00:00,  8.38it/s]
```

```
<pandas.io.formats.style.Styler at 0x1748a0defa0>
```




```
<IPython.core.display.Javascript object>
```

It's a major improvement, with the highest macro recall I've seen yet. The precision-recall curve is much wider than the final conventional model, SVM 2, and the average precision is up to 0.99. The model's accuracy score is also a nice 0.95.

6.10.3 Refitting the Final Model

I'm so impressed with this last BERT model that I'll consider it my final model. Now I simply need to refit using the full `X` and `y`.

[58]:
```python
if FIT_BERT:
    bert.fit(X, y)
    bert.save("models/bert_final.bin")
else:
    bert = bert_sklearn.load_model("models/bert_final.bin")
```

```
bert
```

```
Loading model from models/bert_final.bin…
Using mlp with D=768,H=750,K=2,n=2
Building sklearn text classifier…
```

[58]:
```
BertClassifier(bert_config_json={'architectures': ['BertForMaskedLM'],
                                 'attention_probs_dropout_prob': 0.1,
                                 'hidden_act': 'gelu',
                                 'hidden_dropout_prob': 0.1, 'hidden_size': 768,
                                 'initializer_range': 0.02,
                                 'intermediate_size': 3072,
                                 'layer_norm_eps': 1e-12,
                                 'max_position_embeddings': 512,
                                 'model_type': 'bert',
                                 'num_attention_heads': 12,
                                 'num_hidden_layers': 12, 'pad_token_…
                                       ('[unused17]', 18), ('[unused18]', 19),
                                       ('[unused19]', 20), ('[unused20]', 21),
                                       ('[unused21]', 22), ('[unused22]', 23),
                                       ('[unused23]', 24), ('[unused24]', 25),
                                       ('[unused25]', 26), ('[unused26]', 27),
                                       ('[unused27]', 28), ('[unused28]', 29),
…]),
               do_lower_case=True, epochs=4,
               label_list=array([0, 1], dtype=uint8), max_seq_length=50,
               num_mlp_hiddens=750, num_mlp_layers=2, train_batch_size=28)
```

```
<IPython.core.display.Javascript object>
```

7 Interpretation

Artificial neural networks are the most difficult type of model to interpret because they are comprised of interconnected layers of neurons, and the neurons have no meaning—they are just neurons. They are difficult to interpret and explain in much the same way that a biological brain would be. Perhaps experts can glean something from the activity inside a neural network in a controlled setting, but in typical practice, they are treated as black boxes.

There are many indirect approaches to explaining the output of a neural network. One approach is to create a global surrogate model by training a conventional machine learning model on the output of a neural network. Another approach is to create local surrogate models which approximate the neural network's behavior in the vicinity of a particular example. There are many other approaches as well.

Bigram Analysis For my purposes, I am much more interested in what the model says about the data than in the model itself. I will take the simple approach of searching for bigrams in the text and predicting probabilities for them.

[59]:
```python
# Add some hashtags to stopwords
my_stop |= {"#sxsw", "#sxswi", "#austin", "#america"}
ngrams = lang.scored_bigrams(
    df["text"],
    stopwords=my_stop | lang.fetch_stopwords("nltk_english | sklearn_english"),
    tokenizer=partial(nltk.casual_tokenize, preserve_case=False,␣
 ↪strip_handles=True),
    min_freq=5,
    metric="pmi",
)

ngrams = ngrams.loc[lambda x: x > x.quantile(0.75)].copy()
ngrams.index = ngrams.index.str.join(" ")
ngrams
```

```
HBox(children=(FloatProgress(value=0.0, max=3510.0), HTML(value='')))
```

[59]:
```
bigram
ice cream                13.143096
interrupt regularly      13.143096
league extraordinary     12.880062
lustre pearl             12.880062
speech therapy           12.880062
                           …
2 takes                   5.687769
long line                 5.680389
new version               5.676397
/ bing                    5.665743
drivers 2                 5.635302
Name: score, Length: 229, dtype: float64
```

```
<IPython.core.display.Javascript object>
```

[60]:
```python
ngram_proba = pd.DataFrame(
    bert.predict_proba(ngrams.index.to_list()),
    columns=["neg", "pos"],
    index=ngrams.index,
)
ngram_proba
```

```
Predicting: 100%|

      | 29/29 [00:10<00:00,  2.73it/s]
```

[60]:

bigram	neg	pos
ice cream	0.262451	0.737549

```
interrupt regularly   0.263221  0.736779
league extraordinary  0.095287  0.904713
lustre pearl          0.558731  0.441269
speech therapy        0.454237  0.545763
…                          …         …
2 takes               0.618104  0.381896
long line             0.306551  0.693449
new version           0.840470  0.159530
/ bing                0.637566  0.362434
drivers 2             0.664487  0.335513

[229 rows x 2 columns]
```

```
<IPython.core.display.Javascript object>
```

Before moving on, I define a function for displaying a readable sample of tweets containing a certain regex pattern. There is an option to specify a particular brand.

[61]:
```python
def read_tweets(
    pattern,
    data=df,
    brand=None,
    text_col="text",
    brand_col="object_of_emotion",
    case=False,
    max_sample=10,
    random_state=578,
):
    """Show a readable sample of tweets containing a match for `pattern`."""
    if brand is None:
        text = data[text_col].copy()
    else:
        text = data.loc[data[brand_col] == brand, text_col].copy()
    contains_pat = text.loc[lambda x: x.str.contains(pattern, case=case)]
    return lang.readable_sample(contains_pat, n=max_sample,␣
 ↪random_state=random_state)
```

```
<IPython.core.display.Javascript object>
```

7.1 Top Bigrams for the Positive Class

I make a wordcloud below using the positive class probabilities.

[62]:
```python
ax = plotting.wordcloud(
    ngram_proba["pos"],
    cmap="Greens",
    size=(15, 8),
    desat=0.7,
    random_state=35,
```

```
)
ax.set(title="Top Bigrams for Positive Class")
fig = ax.get_figure()
```

Top Bigrams for Positive Class

<IPython.core.display.Javascript object>

I notice phrases like "free food" and "free drinks", which I don't think I've seen before. Some of the other phrases are familiar from `exploratory.ipynb`, such as "shiny new" and "cool technology". There is also positive talk about Apple's pop-up shop.

[63]:
```
read_tweets("free drinks|free food")
```

	text
482	Badgeless event! Free Drinks! UI@mention Heading to free Google-sponsored happy hour for Semantic Web Austin @mention Fogo de ChIAo #sxswU
5851	RT @mention Google Party is at GSD&M (Google Map it). #SXSW badge gets u in. Free food, drinks, music. Big place. No line. Great party. Come!
7181	Come! "@mention Google Party is at GSD&M #SXSW badge gets u in. Free food, drinks, music. Big place. No line. Great party. Come!"
7796	Google party, don't think they are checking for badges if you say your on list. Free food and booze. #frood #sxsw CC @mention
2846	Free coffee by company a, free drinks on company b, free food at company c. All money saved goes to Apple. Life at #SXSW. ;)
5542	RT @mention Badgeless event! Free Drinks! UI@mention Heading to free Google-sponsored happy hour for Semantic Web Austin @mention Fogo de ChIAo #sxswU
2097	I go to bars and get free drinks because I have an iPhone. #doesdroid #SXSW

	text
7795	Google Party is at GSD&M (Google Map it). #SXSW badge gets u in. Free food, drinks, music. Big place. No line. Great party. Come!
7550	Thanks for the free drinks Google! #sxsw (@mention Speakeasy w/ 47 others) {link}

```
<IPython.core.display.Javascript object>
```

Looks like Google had a party with free food and drinks, and people really liked it.

I'll use LIME to examine one of these tweets. LIME is a tool which creates a local surrogate model to approximate a model's predictions around a particular example.

[64]:
```
expl = LimeTextExplainer(
    class_names=["Negative", "Positive"],
    # I use nltk.casual_tokenize because BERT tokenizer raises errors
    split_expression=nltk.casual_tokenize,
    # Consider word order
    bow=False,
    # Mask string from BERT tokenizer
    mask_string="[MASK]",
)
expl_free_food = expl.explain_instance(df.at[7796, "text"].lower(), bert.
 ↪predict_proba)
expl_free_food.show_in_notebook()
```

```
Predicting: 100%|

     | 625/625 [00:28<00:00, 21.65it/s]
```

```
<IPython.core.display.HTML object>
```

```
<IPython.core.display.Javascript object>
```

It looks like the word "free" is especially associated with the positive class. That's hardly surprising. LIME doesn't seem to provide much additional insight for my purposes. Anyway, I'll definitely recommend that Apple give away free food and drinks, as Google did at this party.

[65]:
```
read_tweets("64gig wifi")
```

	text
2596	Only white #ipad2 64gig wifi available at #Austin #SXSW #Apple popup store right now, but no wait!
149	UI@mention #sxsw ipad store sold out of everything except 64gig wifi only whiteU @mention Did you manage to get yours?
4031	now I feel better (#106 1st day) @mention #sxsw ipad store sold out of everything except 64gig wifi only white
1530	@mention (via @mention #sxsw ipad store sold out of everything except 64gig wifi only white
150	UI@mention #sxsw ipad store sold out of everything except 64gig wifi only whiteU also known as the white jeans configuration.

	text
5303	RT @mention #sxsw ipad store sold out of everything except 64gig wifi only white

<IPython.core.display.Javascript object>

Looks like Apple sold out of every iPad 2 except the white 64gb model with wifi only (i.e. no mobile service). This is good news for Apple.

7.2 Top Bigrams for the Negative Class

Next, I plot the top bigrams for the negative class.

[66]:
```python
ax = plotting.wordcloud(
    ngram_proba["neg"],
    cmap="Reds",
    size=(15, 8),
    desat=0.7,
    random_state=5,
)
ax.set(title="Top Bigrams for Negative Class")
fig = ax.get_figure()
```

<IPython.core.display.Javascript object>

As in the EDA notebook, we see that people were talking about Apple being a "fascist company". This began with tech journalist Kara Swisher, who provoked a flurry of tweets by saying that Apple was the "classiest fascist company in America".

Again phrases show up related to sending iPad 2 money to Japan instead of spending it on an iPad. This is in response to the Fukushima Daiichi nuclear disaster.

Negative talk about the iPhone's battery life shows up again, as does talk about Josh Clark's presentation on iPad Design Headaches. There also is some negativity associated with Apple selling out of everything but 64gb iPads.

As in the EDA notebook, the phrase "fades fast" is related to talk about novelty iOS news apps having a short lifespan.

[67]:
```python
read_tweets("march 9-15")
```

	text
5786	RT @mention Going to #SXSW? The new iPhone guide to #Austin by @mention is free March 9-15. Hard to beat free. #lp
1205	Excellent tip from @mention Going to #SXSW? The new iPhone guide to #Austin by @mention is free March 9-15. Hard to beat free. #lp
5787	RT @mention Going to #SXSW? The new iPhone guide to #Austin by @mention is free March 9-15. Hard to beat free. #lp #mobile
2010	Lonely Planet's new iPhone Austin city guide is free March 9-15 for those going to #SXSW! {link} #travel
1748	Going to #SXSW? The new iPhone guide to #Austin by @mention is free March 9-15. Hard to beat free. #lp

```
<IPython.core.display.Javascript object>
```

The phrase "march 9-15" is evidently related to a free iPhone app giveaway—Lonely Planet's city guide to Austin, TX. This doesn't seem like a big deal for Apple, although it's unclear why it's associated with the negative class.

[68]:
```python
expl_march_915 = expl.explain_instance("march 9-15", bert.predict_proba)
expl_march_915.show_in_notebook()
```

```
Predicting: 100%|

      | 625/625 [00:28<00:00, 22.15it/s]

<IPython.core.display.HTML object>

<IPython.core.display.Javascript object>
```

Even after using LIME, it's still unclear why "march 9-15" is associated with the negative class. What is clear is that is has something to do with "9-15". Anyway, I'll move on to investigating "mistakes building."

[69]:
```python
read_tweets("mistakes made building")
```

	text
2735	Looks like this was a fun session at #SXSW: “Mistakes Made Building Nextflix for iPhone”: {link}
8098	#SXSW: Mistakes Made Building Netflix for iPhone (Plus, How to See Its Source Code!) {link} via @mention
8096	#SXSW: Mistakes Made Building @mention for iPhone (Plus, How to See Its Source Code!) {link}
6274	RT @mention Looks like this was a fun session at #SXSW: “Mistakes Made Building Nextflix for iPhone”: {link}

```
<IPython.core.display.Javascript object>
```

The phrase “mistakes building” is related to a talk about mistakes made building the iPhone Netflix app. This seems relatively benign as far as Apple is concerned.

[70]:
```python
read_tweets("steve jobs")
```

	text
6069	RT @mention I wonder if Apple intentionally scheduled the #iPad2 release to coincide with #SXSW. Steve Jobs, you crafty genius, youU_
2341	#sxsw #enchantment: @mention ”Sell your dream. Steve Jobs doesn’t say: iPhone is $188 of parts+AT&T, made by ppl in suicidal Chinese
7851	Steve Jobs doesn’t position the iPhone as a device made in China where suicide rates are high He sells dreams #Kawasaki #thisisdare #SXSW
3617	I wonder if Apple intentionally scheduled the #iPad2 release to coincide with #SXSW. Steve Jobs, you crafty genius, youU_
2818	Apple cited as the opposite of crowdsourcing - proprietary, Steve Jobs tells you what you want #csuitecsourcing #sxsw

```
<IPython.core.display.Javascript object>
```

There seems to be sarcastic talk about Steve Jobs, who was CEO of Apple during SXSW, 2011. This was a period of transition between Jobs and Tim Cook, as Jobs was having health difficulties at the time. Steve Jobs resigned later that year, and passed away shortly afterward.

Some of the talk is about unethical manufacturing practices related to Chinese factories with poor working conditions and high suicide rates.

7.3 Searching by Brand

Next, I extract the top 25% of bigrams for each brand (considered as an independent corpus).

[71]:
```python
# Find bigrams with brand-wise grouping
brand_ngrams = lang.stratified_ngrams(
    df,
    tokenizer=partial(nltk.casual_tokenize, preserve_case=False,␣
↪strip_handles=True),
    text="text",
```

```python
    stopwords=my_stop | lang.fetch_stopwords("nltk_english | sklearn_english"),
    cat="object_of_emotion",
    min_freq=3,
    select_best=0.25,
    metric="pmi",
)

# Drop duplicates and index by bigram
brand_ngrams = (
    brand_ngrams.sort_values("score", ascending=False)
    .drop_duplicates(subset=["bigram"])
    .set_index("bigram")
)

# Join tuples with space
brand_ngrams.index = brand_ngrams.index.str.join(" ")
brand_ngrams
```

```
HBox(children=(FloatProgress(value=0.0, max=92.0), HTML(value='')))

HBox(children=(FloatProgress(value=0.0, max=80.0), HTML(value='')))

HBox(children=(FloatProgress(value=0.0, max=666.0), HTML(value='')))

HBox(children=(FloatProgress(value=0.0, max=522.0), HTML(value='')))

HBox(children=(FloatProgress(value=0.0, max=34.0), HTML(value='')))

HBox(children=(FloatProgress(value=0.0, max=281.0), HTML(value='')))

HBox(children=(FloatProgress(value=0.0, max=1024.0), HTML(value='')))

HBox(children=(FloatProgress(value=0.0, max=468.0), HTML(value='')))

HBox(children=(FloatProgress(value=0.0, max=343.0), HTML(value='')))
```

[71]:

	score	object_of_emotion
bigram		

```
shameless promotion  12.063283                iPad
tests muro           12.063283                iPad
resulting shameless  12.063283                iPad
muro drawing         12.063283                iPad
deviantart buys      12.063283                iPad
…                        …                   …
sampler itunes        4.877744  Other Apple Product
awards .              4.460826          Android App
new #android          4.360063          Android App
+ android             3.951609              Android
android tablet        3.951609              Android

[470 rows x 2 columns]
```

```
<IPython.core.display.Javascript object>
```

I define a function below for plotting positive and negative wordclouds for a particular brand. It's similar to the one I use in the EDA notebook.

[72]:
```
def plot_brand_clouds(
    brand,
    model=bert,
    brand_ngrams=brand_ngrams,
    dst_schema="images/{brand}_bigram_proba.svg",
    cmap=("Reds", "Greens"),
    size=(10, 4),
    ncols=1,
    max_font_size=None,
    random_state=156,
    **kwargs,
):
    """Predict probabilities and plot positive and negative wordclouds."""
    scored_ngrams = brand_ngrams.loc[
        lambda x: x.object_of_emotion == brand, "score"
    ].copy()

    columns = [f"{brand}: Negative", f"{brand}: Positive"]
    ngram_proba = pd.DataFrame(
        model.predict_proba(scored_ngrams.index.to_list()),
        columns=columns,
        index=scored_ngrams.index,
    )

    fig = plotting.wordcloud(
        ngram_proba,
        cmap=list(cmap),
        size=size,
        ncols=ncols,
```

```
            repeat=True,
            max_font_size=max_font_size,
            random_state=random_state,
            **kwargs,
        )
        fig.savefig(dst_schema.format(brand=brand))
        return fig
```

<IPython.core.display.Javascript object>

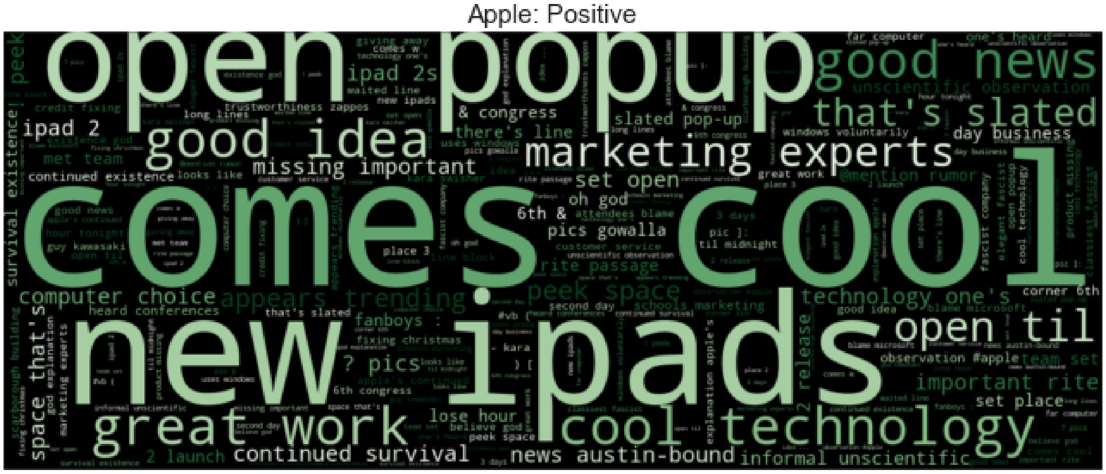
7.3.1 Top Apple Bigrams

[73]:
```
fig = plot_brand_clouds("Apple")
```

```
Predicting: 100%|

     | 11/11 [00:10<00:00,  1.05it/s]
```

Apple: Negative

Apple: Positive



<IPython.core.display.Javascript object>

Phrases like "fascist company" and "kara swisher" show up again, as expected. There's positive talk about the new iPads and the popup store selling them, which is also expected. What's this "blame microsoft" thing, I wonder?

[74]:
```
read_tweets("blame microsoft", brand="Apple")
```

	text
4426	We lose an hour tonight. #SxSW attendees will blame Microsoft, Apple will get credit for fixing it before Christmas.
6888	RT @mention We lose hour 2nite. #SxSW attendees will blame Microsoft, Apple will get credit 4 fixing it b4 Christmas.
6887	RT @mention We lose an hour tonight. #SxSW attendees will blame Microsoft, Apple will get credit for fixing it before Christmas.
6621	RT @mention RT @mention We lose an hour tonight. #SxSW attendees will blame Microsoft, Apple will get credit for fixing it before Christmas.

<IPython.core.display.Javascript object>

This appears to be a joke about daylight savings time. The suggestion is that Microsoft gets undeserved blame at SXSW, and Apple gets undeserved praise.

[75]:
```
read_tweets("product you're missing", brand="Apple")
```

	text
8770	If you haven't waited in line for an Apple product you're missing out on an important rite of passage. #sxsw
1598	Haha! RT @mention If you haven't waited in line for an Apple product you're missing out on an important rite of passage. #sxsw
8739	geeking out? RT @mention If you haven't waited in line for an Apple product you're missing out on an important rite of passage. #sxsw

<IPython.core.display.Javascript object>

The phrase "product missing" should actually be "product you're missing," and the tweets containing it are positive.

[76]:
```
read_tweets("marketing experts", brand="Apple")
```

	text
5171	RT @mention "At #SXSW, Apple schools the marketing experts" {link}
283	At #SXSW, Apple schools the marketing experts {link}
2046	At SXSW, Apple schools the marketing experts {link} #SXSW
2047	At SXSW, Apple schools the marketing experts {link} /via @mention #SXSW #Apple
1737	#tech At #SXSW, Apple schools the marketing experts {link}
1736	"At #SXSW, Apple schools the marketing experts" {link}

	text
7694	Social marketing experts at #SXSW: Everyone has to face facts & admit that Apple again showed everyone how marketing is done. #CNET
8162	"At SXSW, Apple schools the marketing experts" {link} #sxsw
116	At #SXSW, #Apple schools the marketing experts - {link}
5524	RT @mention At SXSW, Apple schools the marketing experts: {link} via @mention #sxsw #apple #marketing

<IPython.core.display.Javascript object>

The phrase "marketing experts" is related to tweets praising Apple's marketing strategies. That's definitely good to see.

[77]:
```
read_tweets("god", brand="Apple")
```

	text
5271	RT @mention #sxsw #enchantment: @mention "Bright spot for Apple: Pagemaker saved Apple. I believe in God b/c no other explanation of Apple survival
109	Kawasaki: "Not C.S. Lewis level reasoning, but Apple's continued existence is evidence for the existence of God" #bawling #sxsw
4026	"Desktop publishing saved Apple. Pagemaker was a gift from God." @mention #sxsw
5197	RT @mention "There is no other explanation for Apple's continued survival than the existence of God" #GuyKawasaki #sxsw
1923	Guy Kawasaki "I believe in God because there is no other explanation for the continuous survival of Apple over the years.". LOL #SXSW
7093	Apple is opening a temporary store in downtown Austin for March 11 to accommodate #SXSW attendees. God they are so fucking smart.
7186	"No other reason for Apple's continued survival than the existence of God" - @mention #enchantment #SXSW #sxswi
6403	RT @mention Oh My God! RT @mention It's not a rumor: Apple opening up a temporary store in downtown Austin for #SXSW &iPad 2 launch {link}
1452	Oh My God! RT @mention It's not a rumor: Apple opening up a temporary store in downtown Austin for #SXSW &iPad 2 launch {link}
5182	RT @mention "I believe in God because there is no other explanation for Apple's continued existence." Guy Kawasaki #enchantment #sxsw

<IPython.core.display.Javascript object>

The phrase "god explanation" is related to Guy Kawasaki saying:

> I believe in God because there is no other explanation for Apple's continued existence.

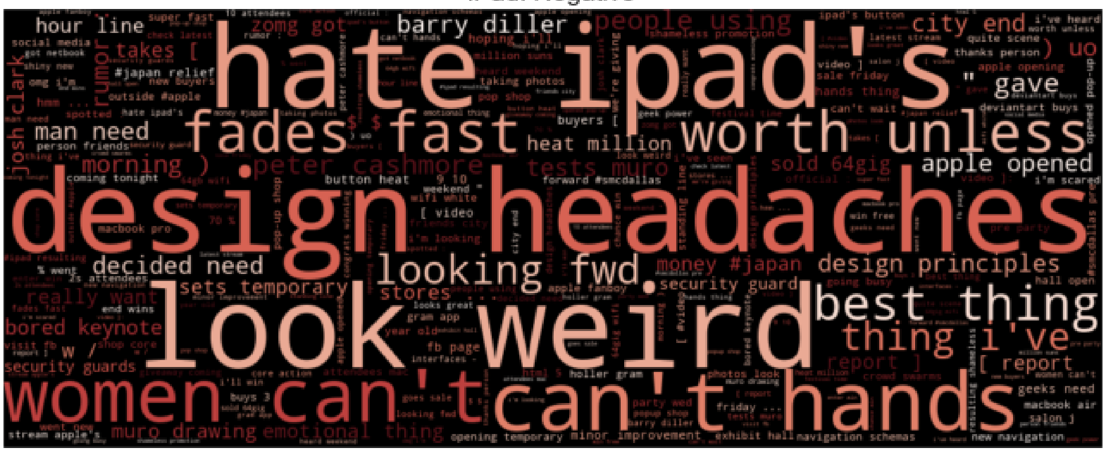
Kawasaki was Apple's Chief Evangelist, which is a marketing position. He seems to talk about God quite a bit, though. I think in this instance he was making a kind of self-deprecating joke.

7.3.2 Top iPad Bigrams

[78]:
```
fig = plot_brand_clouds("iPad")
```

```
Predicting: 100%|

      | 18/18 [00:10<00:00,  1.71it/s]
```

iPad: Negative



iPad: Positive


```
<IPython.core.display.Javascript object>
```

A lot of familiar phrases appear hear, like "design headaches" and "64gig wifi". I haven't seen "look weird" before, though.

[79]:
```
read_tweets("look weird", brand="iPad")
```

	text
6189	RT @mention It's official: people using the iPad 2 to take photos just look weird. #SXSW

	text
2366	It's official: people using the iPad 2 to take photos just look weird. #SXSW
2711	LOL 2 true RT @mention It's official: people using the iPad 2 to take photos just look weird. #SXSW

<IPython.core.display.Javascript object>

These tweets say that people using the iPad 2 to take photos look weird. I can see that, because the iPad 2 is pretty large and unwieldy.

[80]:
```
read_tweets("women can't", brand="iPad")
```

	text
8256	In my next life I'm coming back as an iPad 2. Women can't keep their hands off this thing. #SXSW
6131	RT @mention In my next life I'm coming back as an iPad 2. Women can't keep their hands off this thing. #SXSW
6564	RT @mention RT @mention In my next life I'm coming back as an iPad 2. Women can't keep their hands off this thing. #SXSW

<IPython.core.display.Javascript object>

The phrase "women can't" actually comes from positive tweets.

[81]:
```
read_tweets("hate the ipad's", brand="iPad")
```

	text
3311	iPad design malady: iPad Elbow - I hate the iPad's back button with the heat of a million suns. #tapworthy #sxsw
6198	RT @mention Josh Clark: I hate the iPad's back button with the heat of a million suns. #tapworthy #SXSW
6155	RT @mention iPad design malady: iPad Elbow - I hate the iPad's back button with the heat of a million suns. #tapworthy #sxsw
3990	Josh Clark: I hate the iPad's back button with the heat of a million suns. #tapworthy #SXSW

<IPython.core.display.Javascript object>

The phrase "hate ipad's" is related to Josh Clark's talk about iPad design challenges. He says he hates the iPad's back button "with the heat of a million suns." This is just one guy's opinion on a very specific design choice, but it's interesting.

[82]:
```
read_tweets("worth it unless", brand="iPad")
```

	text
7367	@mention Peter Cashmore on the iPad 2: it's only a minor improvement. Not worth it unless you have money to burn. #SXSW
4347	just got mine & i disagree RT @mention Peter Cashmore on iPad 2 it's only a minor improvement Not worth it unless you've $ 2 burn #SXSW
5145	RT @mention @mention Peter Cashmore on the iPad 2: it's only a minor improvement. Not worth it unless you have money to burn. #SXSW

<IPython.core.display.Javascript object>

The phrase "worth unless" is related to Peter Cashmore's claim that the iPad 2 is only a minor improvement over the original iPad, and not worth the price. One person who bought an iPad 2 voices their disagreement.

[83]:
```
read_tweets("congrats to @mention", brand="iPad")
```

	text
8531	Congrats to @mention another @mention winner of an #iPad case, it's going on a mission trip with his sister in Haiti! #SXSW #cbatsxsw
3401	Awwww yeah!!! RT @mention Congrats to @mention on winning the last @mention #iPad case for her boyfriend aw :) #SXSW #cbatsxsw
8535	Congrats to @mention on winning the last @mention #iPad case for her boyfriend aw :) #SXSW #cbatsxsw
8333	I'm a captain penguin now! RT @mention congrats to @mention for getting to the next level in his fave iPad game PengAirborne #SXSWU
5641	RT @mention Congrats to @mention for winning the Ipad 2 raffled at the #SmileyParty. Check your inbox for details! #sxsw

<IPython.core.display.Javascript object>

The positive phrase "congrats winning" is related to tweets congratulating someone who won an iPad case giveaway.

[84]:
```
read_tweets("netbook", brand="iPad")
```

	text
8816	It's #SXSW Festival time… OMG I'm scared! Got my netbook, Firm's iPad and my droid!
1900	LoL U r gadgetzilla! Have fun! @mention It's #SXSW Festival time. OMG I'm scared! Got my netbook, #iPad & my droid!
2957	YES RT @mention LoL U r gadgetzilla! Have fun! @mention It's #SXSW Festival time. OMG I'm scared! Got my netbook, #iPad & my droid!

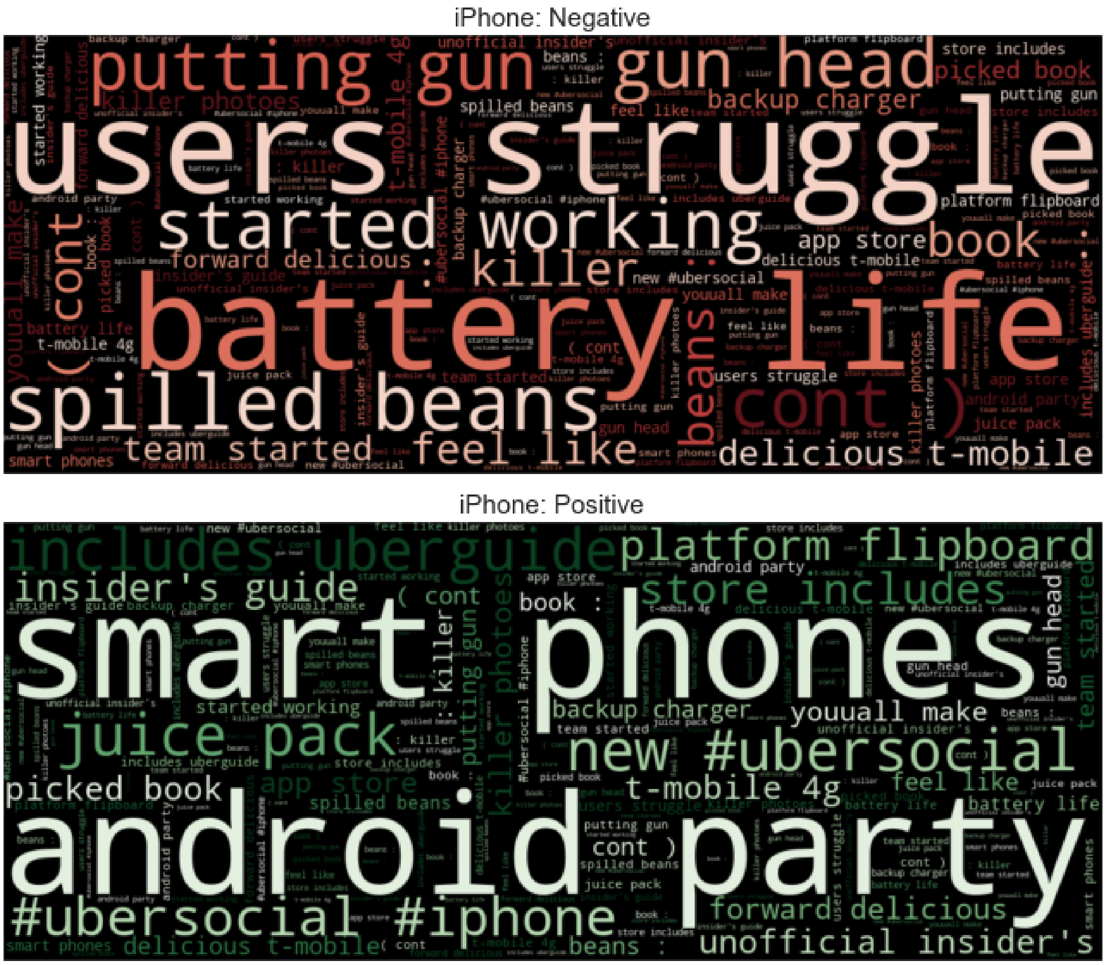
<IPython.core.display.Javascript object>

The phrase "got netbook" is related to tweets expressing excitement about the festival.

7.3.3 Top iPhone Bigrams

[85]:
```
fig = plot_brand_clouds("iPhone")
```

```
Predicting: 100%|

          | 4/4 [00:09<00:00,  2.48s/it]
```



<IPython.core.display.Javascript object>

[86]:
```
read_tweets("battery life", brand="iPhone")
```

	text
7671	@mention Respectfully disagree about the iphone. Battery life is a problem and it isn't as ubiquitous as it seems. #project314 #sxsw
1335	Disgusted with my iPhone's battery life. Already down to 11% at 3:30 pm while my blackberry is going strong. #Sxsw

	text
8820	This #SXSW I am grateful for: my bicycle, having a back-up Twitter app. Cursing: losing an hour of zzzs, iPhone battery life.
4397	Just got my Mophie Juice Pack plus for my iPhone 4! Now I'm ready for #sxsw. More than double the battery life #FTW
3121	#sxsw is exposing my iphone's horrendous battery life.

```
<IPython.core.display.Javascript object>
```

As discovered in the EDA notebook, there are complaints about the iPhone's battery life. I think this is important feedback for Apple to consider.

[87]:
```
read_tweets("gun to @mention head", brand="iPhone")
```

	text
7503	@mention putting a gun to @mention head. Give me your iPhone! #SXSW {link}
5146	RT @mention @mention putting a gun to @mention head. Give me your iPhone! #SXSW {link}
6488	RT @mention RT @mention @mention putting a gun to @mention head. Give me your iPhone! #SXSW {link}

```
<IPython.core.display.Javascript object>
```

The "gun head" tweets appear to be related to a joke about stealing someone's iPhone. Negative, perhaps, but not really of concern to Apple.

[88]:
```
read_tweets("spilled the beans", brand="iPhone")
```

	text
6220	So @mention just spilled the beans: next platform for Flipboard is the iPhone. Team started working on it. #sxflip #SXSW #SXSWi
1089	UI@mention So @mention just spilled the beans: next platform for Flipboard is the iPhone. Team started working on it. #sxflip #SXSW #SXSWiU Gr8!
1632	Woot! RT @mention So @mention just spilled the beans: next platform for Flipboard is the iPhone. Team started working on it. #sxflip #SXSW

```
<IPython.core.display.Javascript object>
```

The "spilled beans" tweets are actually positive, pertaining to the release of a Flipboard app for iPhone.

[89]:
```
read_tweets("users struggle", brand="iPhone")
```

	text
7158	Looking forward to delicious T-Mobile 4G here in Austin while iPhone users struggle to do anything. #SXSW
5737	RT @mention forward to delicious T-Mobile 4G here in Austin while iPhone users struggle to do anything. #SXSW
6529	RT @mention RT @mention forward to delicious T-Mobile 4G here in Austin while iPhone users struggle to do anything. #SXSW

```
<IPython.core.display.Javascript object>
```

The "users struggle" tweets are related to criticism of the iPhone's lackluster AT&T service, and the suggestion the T-Mobile is better. Presumably these are Android users.

[90]:
```
read_tweets("android party", brand="iPhone")
```

	text
2994	Mega tether iPhone/Android party with @mention and @mention . #chargin2diffphonesatonce #dorkinout #sxsw
2465	You should probably put that away… RT @mention at the Android party and kinda embarrassed by my iPhone #SXSW
2565	at the Android party and kinda embarrassed by my iPhone #SXSW

```
<IPython.core.display.Javascript object>
```

The "android party" tweets are related to someone being embarrassed to have an iPhone at the Android party at Lustre Pearl. This seems pretty benign.

[91]:
```
read_tweets("new #ubersocial", brand="iPhone")
```

	text
96	Yai!!! RT @mention New #UberSocial for #iPhone now in the App Store includes UberGuide to #SXSW sponsored by (cont) {link}
3838	Fuck the iphone! RT @mention New #UberSocial for #iPhone now in the App Store includes UberGuide to #SXSW … {link}
1370	@mention -> RT @mention New #UberSocial for #iPhone now in the App Store includes UberGuide to #SXSW (cont) {link}
6349	RT @mention New #UberSocial for #iPhone now in the App Store includes UberGuide to #SXSW {link} Got it now
3353	Whoohoo! Got it! ;) RT @mention New #UberSocial for #iPhone now in the App Store includes UberGuide to #SXSW (cont) {link}
1369	@mention –> RT @mention New #UberSocial for #iPhone now in the App Store includes UberGuide to #SXSW … {link}
6343	RT @mention New #UberSocial for #iPhone now in the App Store includes UberGuide to #SXSW sponsored by #Mashable {link}
4220	@mention look! RT @mention New #UberSocial for #iPhone now in the App Store includes UberGuide to #SXSW … {link}

```
&lt;IPython.core.display.Javascript object&gt;
```

There's a lot of positive talk about the new UberSocial app for iPhone. There's also one very negative retweet about it.

7.3.4 Top iOS App Bigrams

[92]:
```python
fig = plot_brand_clouds("iOS App")
```

```
Predicting: 100%|

    | 10/10 [00:09<00:00,  1.01it/s]
```

iOS App: Negative

iOS App: Positive


```
&lt;IPython.core.display.Javascript object&gt;
```

[93]:
```python
read_tweets("mistakes", brand="iOS App")
```

	text
3850	@mention is about to talk about the mistakes he made building Netflix for the iPhone. #SXSW #netflixiphone
1862	@mention about to talk at #sxsw on mistakes building #Netflix #iphone app
6274	RT @mention Looks like this was a fun session at #SXSW: "Mistakes Made Building Nextflix for iPhone": {link}
2735	Looks like this was a fun session at #SXSW: "Mistakes Made Building Nextflix for iPhone": {link}
2352	About to check out "mistakes I made building Netflix for iPhone." this is going to be cool -you should always learn from mistakes. #sxsw
8098	#SXSW: Mistakes Made Building Netflix for iPhone (Plus, How to See Its Source Code!) {link} via @mention

<IPython.core.display.Javascript object>

The phrase "mistakes building" is related to mistakes made building the Netflix app for iPhone. This is something I previously uncovered.

[94]:
```
read_tweets("vuvuzela", brand="iOS App")
```

	text
8231	Very smart from @mention #hollergram iPad app for #sxsw! {link} (may leave my vuvuzela at home now)
30	Very smart from @madebymany #hollergram iPad app for #sxsw! http://t.co/A3xvWc6 (may leave my vuvuzela at home now)
6843	RT @mention Very smart from @mention #hollergram iPad app for #sxsw! {link} (may leave my vuvuzela at home now)

<IPython.core.display.Javascript object>

The "leave vuvuzela" tweets are related to the Hollergram app, a custom social network app created for SXSW, 2011. The idea is that the app can be used to get people's attention and communicate, I think. There's nothing negative here.

[95]:
```
read_tweets("hard to beat", brand="iOS App")
```

	text
5787	RT @mention Going to #SXSW? The new iPhone guide to #Austin by @mention is free March 9-15. Hard to beat free. #lp #mobile
1748	Going to #SXSW? The new iPhone guide to #Austin by @mention is free March 9-15. Hard to beat free. #lp
5786	RT @mention Going to #SXSW? The new iPhone guide to #Austin by @mention is free March 9-15. Hard to beat free. #lp

<IPython.core.display.Javascript object>

The phrase "hard beat" is actually from positive tweets related to an LonelyPlanet's guide to Austin (an app). I've already uncovered similar tweets.

[96]:
```
read_tweets("louisiana", brand="iOS App")
```

	text
145	UI@mention #sxsw beta testing interactive book for iPad app by Moonbot studios out of Louisiana. Cool app.U
5284	RT @mention #sxsw beta testing interactive book for iPad app by Moonbot studios out of Louisiana. Cool app.
5063	RT @mention UI@mention #sxsw beta testing interactive book for iPad app by Moonbot studios out of Louisiana. Cool app.U
1847	#sxsw beta testing interactive book for iPad app by Moonbot studios out of Louisiana. Cool app.

```
<IPython.core.display.Javascript object>
```

The "studios louisiana" phrase is related to tweets about an interactive book app by Moonbot Studios. These are positive tweets, which also contain the positive phrase "interactive book."

[97]:
```
read_tweets("papa sangre", brand="iOS App")
```

	text
8269	First, get Papa Sangre on the iPhone. Their panel was amazing and the game is totally awesome. #sxsw #sxswi
6435	RT @mention Papa Sangre, an immersive audio game for IPhone, is free today. Highly recommended. #PapaSangre #SxSW
7637	Papa Sangre, an immersive audio game for IPhone, is free today. Highly recommended. #PapaSangre #SxSW

```
<IPython.core.display.Javascript object>
```

The phrase "papa sangre" is the title of a well-liked game for iPhone which was free one day during the festival. These are actually positive tweets. The phrase was most likely judged negative because of the term "sangre," which is Spanish for "blood."

[98]:
```
read_tweets("video streaming", brand="iOS App")
```

	text
2824	Our updated iPhone app has song info for select streams (incl. @mention 24/7) & live video streaming in time for #SXSW {link}
6985	RT @mention YES! updated #iPhone app has song info @mention 24/7 stream +others also live video streaming for #SXSW {link}
6986	RT @mention YES! updated iPhone app has song info @mention 24/7 stream +others also live video streaming for #SXSW {link}
8374	YES! updated iPhone app has song info @mention 24/7 stream +others also live video streaming for #SXSW {link}

	text
6630	RT @mention RT @mention YES! updated iPhone app has song info @mention 24/7 stream +others also live video streaming for #SXSW {link}
6832	RT @mention Updated NPR Music iPhone app has song info for All Songs 24/7 & live video streaming just in time for #SXSW {link}
6425	RT @mention Our updated iPhone app has song info for select streams (incl. @mention 24/7) & live video streaming in time for #SXSW {link}
7780	So cool! RT @mention Updated NPR Music iPhone app song info 4 All Songs 24/7 & live video streaming in time 4 #SXSW {link}
7463	Updated NPR Music iPhone app has song info for All Songs 24/7 & live video streaming just in time for #SXSW {link}

```
<IPython.core.display.Javascript object>
```

The phrases "video streaming" and "info 24/7" come from tweets celebrating the updated NPR Music app for iPhone.

[99]:
```python
read_tweets(r"#itunes.*#bbq", brand="iOS App")
```

	text
1050	Congrats! RT @mention Good News! Austin Eats: BBQ for iPhone is now available - {link} #iTunes #Austin #BBQ #SXSW #SXSWi
5795	RT @mention Good News! Austin Eats: BBQ for iPhone is now available - {link} #iTunes #Austin #BBQ #SXSW #SXSWi /via @mention
5794	RT @mention Good News! Austin Eats: BBQ for iPhone is now available - {link} #iTunes #Austin #BBQ #SXSW #SXSWi
1442	Good News! Austin Eats: BBQ for iPhone is now available - {link} #iTunes #Austin #BBQ #SXSW #SXSWi

```
<IPython.core.display.Javascript object>
```

The hashtag combination "#itunes #bbq" comes from tweets promoting the iPhone app, "Austin Eats: BBQ."

[100]:
```python
read_tweets(r"share photos", brand="iOS App")
```

	text
4464	RT@mention What's going on at #sxsw today? Share photos, video with iReport: {link} or through #CNN iPhone app!
8896	@mention What's going on at #sxsw today? Share photos, video with iReport: {link} or through CNN iPhone app!
7698	On the Early #nerdbird to #SXSW - get @mention iPhone app. Share photos of airport people. Like people of Wal-Mart, but at airports!
6410	RT @mention On the Early #nerdbird to #SXSW - get @mention iPhone app. Share photos of airport people. Like people of Wal-Mart, but at airports!

```
<IPython.core.display.Javascript object>
```

The phrase “share photos” seems to come from positive tweets promoting two different apps which support photo sharing.

8 Recommendations

See `exploratory.ipynb` for more of the investigation which led to my recommendations.

1. Try to shake your authoritarian image by ostensibly allowing end-users more freedom. People like that Apple products just work out of the box, but they find your paternalistic approach to managing your products off-putting. Send the message that when you buy an Apple product, you are free to do what you want with it. Keep control over the most important things, but relinquish control over the less important things. Make people feel like they have the freedom to customize your products as they see fit. Make some concessions to placate the majority, while allowing the elite techno-snobs to continue complaining on the fringe.

2. Do something to improve the iPhone’s battery life and turn it into a marketing campaign. There were a lot complaints about the iPhone’s battery life. One user suggested that their Blackberry was doing much better. There were also complaints about #batterykiller apps which use geolocation in the background. If you made a big publicized effort to increase the iPhone’s battery life, that would get people excited.

3. Open another temporary popup store for your next big product launch. The iPad 2 popup store was a roaring success, and people couldn’t stop talking about it. Terms like ‘shiny new’, ‘jealous’, and ‘cool technology’ were closely associated with the iPad 2 and popup store.

4. Provide free refreshments at your events. There was a lot of excitement about the free food and drinks Google offered at their party. Free refreshments go a long way to generate good will, so I recommend providing them at at least some of your events.

9 Future Work

9.0.1 Stacking Classifiers

After experimenting a little with Scikit-Learn’s `StackingClassifier`, it’s clear to me that I could develop a more accurate conventional model this way. The `StackingClassifier` trains several classifiers on the data and then trains a final classifier on the concatenated output of those classifiers. It also allows you to pass the training data to your final estimator, so the final estimator is trained both on prior data and the predictions of the classifier ensemble.

9.0.2 Bertweet

A variant of BERT exists which is designed specifically for English tweets. I have not had a chance to try it yet, but I suspect it could outperform my final model.

10 Conclusion

I created an accurate model, at around 93% accuracy. The dataset is small, noisy, and not particularly well labeled. Nevertheless, I'm confident that I can increase the accuracy by using Bertweet.

Through interpreting my model and conducting exploratory analysis in `exploratory.ipynb`, I arrived at four recommendations. First, you should publicly relinquish a small amount of control over your products to send the message that you care about individual freedom (and aren't a "fascist company"). Second, you should improve the iPhone's battery life and turn that into a rallying point for a marketing campaign. People are really concerned about the iPhone's battery life. Third, you should repeat the temporary popup store for your next big product launch. There was an overwhelming amount of chatter about the iPad 2 popup store. And fourth, you should provide free refreshments at some of your events.

[ ]:

```

```