Holiday Kickoff in the Twittersphere

Analyzing tweets from Black Friday

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Project Background

- Use tweets to quantify various aspects of Black Friday and lead-up to Black Friday
- Collect tweets prior to and during holiday kickoff weekend (11/27 11/30)
- Examine popular brands to see how they compare to each other
 - Current idea is to examine consumer electronics brands
- Examine difference between consumer electronics brands, product categories, etc.
- Further opportunity to examine sentiment of tweets to gauge customers' attitudes towards brands

Architecture

Data Gathering:

Twitter API, SupervisorD, Kafka, Crontab, AWS CLI

Data Processing:

S3, EC2, EMR, GNU Parallel, Hive

Spark, Storm

Serving:

Tableau













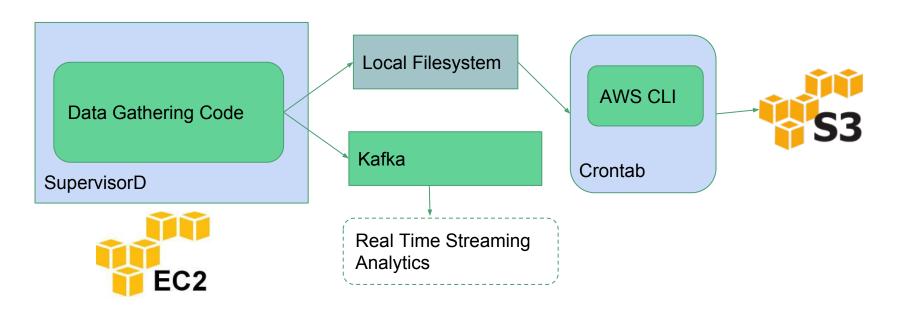




Data Collection Architecture

Code located here: https://github.com/mseltz/W205-

Project/tree/master/data_gathering



Data Gathering Results

Keywords:

```
4k
              machook
android
              microsoft
              nintendo
apple
beats
              panasonic
bluetooth
              philips
camera
              receiver
ds1r
              samsung
electronics
              sony
fithit
              speaker
              surface
gopro
headphones
              tablet
ipad
              theater
iphone
              visio
iawbone
              wii
laptop
              xbox
mac
```

Several overly broad keywords were removed early on, like 'pc'.

```
37M sample.data
                                                                                .gz 9.0G tweets-keywords-v1-2015-12-11.log
ic@sneed:/data/sard-twitters head -n 1 tweets-keywords-v1-2015-12-11.log | ig '.
"in_reply_to_user_id": null,
"created_at": "Fri Dec 11 04:59:19 +0000 2015",
"retweet count": 0,
"place": null,
"id_str": "675178022878711809",
"in reply to screen name": null,
"in reply to status id str": null,
"source": "<a href=\"http://twitter.com/download/iphone\" rel=\"nofollow\">Twitter for iPhone</a>",
"timestamp_ms": "1449809959512",
"filter level": "low",
"user": {
  "following": null,
  "default_profile": false,
  "profile_sidebar_border_color": "CODEED",
  "location": "Houston, Texas ",
  "contributors enabled": false,
  "created_at": "Mon Apr 04 17:00:15 +0000 2011",
  "listed count": 4.
  "default profile image": false,
  "id_str": "277073196",
```

Data Gathering Lessons

SupervisorD was absolutely critical when running for a long time. There were errors we were unable to plan for and latency/timeout issues that would cause the streaming API to disconnect. By being smart with our SupervisorD timeouts we were able to re-establish connectivity and also not burn out our Twitter API credentials by hitting the API too aggressively upon disconnect.

Avoid overly broad keywords.

The processing pipeline needs to be able to keep up with the velocity of data coming in.

Data Processing

Once the data was on S3, we had many options for processing it.

- EMR allows running Hive code directly on data stored in S3
 - http://docs.aws.amazon.com/ElasticMapReduce/latest/ReleaseGuide/emr-hive.html
- S3 allowed us to share large amounts of data within our team

To get to our end result, we applied filters and transforms using Python code and GNU Parallel to make it run faster, then loaded the filtered data into Hive for interaction and visualization. We've packaged these operations as runnable examples in the project's Github repository.

https://github.com/mseltz/W205-Project

Sentiment Analysis - Core

- Each tweet assigned a score based on message content
- Scores appended to the of tweet's JSON entry
- Score based on number of positive and negative words
 - Dictionary of terms retrieved from: Minqing Hu and Bing Liu. "Mining and Sumn Customer Reviews."

```
Toys R Us PS4 sale is <u>awesome!</u> +1
```

Sentiment score = 1

Time to <u>enjoy</u> my <u>great</u> new 55-inch Panasonic TV! +1 +1

Sentiment score = 2

I want to <u>like</u> Amazon's Black Friday deals, but I <u>hate</u> how they only put <u>cheap</u> stuff on sale.

Sentiment score = -1

Sentiment Analysis - Modifiers

- Added additional functionality to handle special terms that increase, decrease, or invert the meaning of the following word
- Increaser examples:
 - So, totally, completely, absolutely
- Decreaser examples:
 - o Sorta, a bit, a little
- Inverter examples:
 - O Not, isn't, lack of, didn't, don't

Wow, I don't like the deals this year at ALL.

-1x multiplier +1

Sentiment score = -1

Toys R Us PS4 sale is totally awesome!

2x multiplier +1

Sentiment score = 2

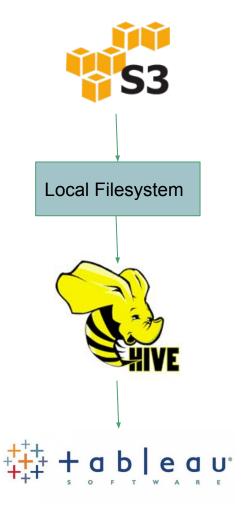
Toys R Us PS4 sale is <u>sorta good</u>, I guess.

0.5x multiplier +1

Sentiment score = 0.5

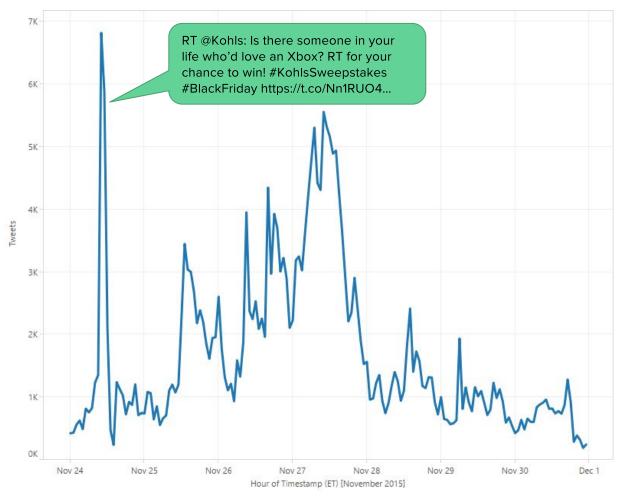
Serving Layer

- Tweets stored in Hive table
- Options to pull insights:
 - Query directly in Hive
 - Use Hiveserver2 to connect to Tableau
- Advantages:
 - Tableau has rich visualization capabilities
 - Can store queries to Hive tables for faster rendering in Tableau
- Disadvantages:
 - Live connection between Hive and Tableau limits speed
 - o Tableau cannot handle "big" data



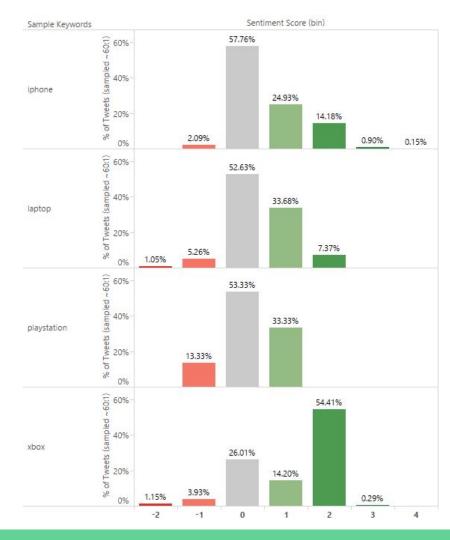
Analysis Results

- Tweets containing consumer electronics keywords and "Black Friday" start to ramp up starting Wed Nov 25
- Large spike in tweets on Nov 24 @ 10am ET (Kohl's Sweepstakes)
- Black Friday (Nov 27)
 has largest volume of tweets, then tapers
 down



Analysis Results - Sentiment

- We can look at the breakdown of sentiment of a particular keyword
- Sample keywords for products are given in the image to the right
 - Most terms have the majority of tweets as neutral
 - Keyword "xbox" has large percentage of fairly positive sentiment



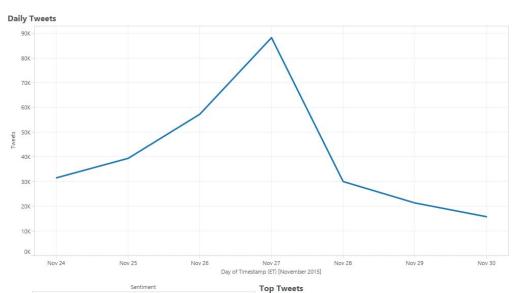
Analysis Results - Sentiment

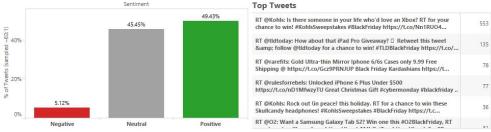
- We can look at the breakdown of sentiment of a particular keyword
- Sample keywords for brands are given in the image to the right
 - Most terms have the majority of tweets as neutral
 - Keyword "sony" has both mildly negative sentiment and mildly positive sentiment
 - Keywords "microsoft" and "samsung" have only neutral and positive sentiments



Analysis Results - Simple Dashboard

- Volume of tweets per day
- Sentiment of tweets (sampled)
- Top tweets (sampled)
- Interactive
 - When user clicks on any element of the dashboard, the other modules are updated to reflect only the selected data





Considerations for Scaling

- All filtering should be done at time of collection
 - We chose to collect more data than necessary, but chose to filter later -- filtering earlier would cut down on storage needs, allowing for more efficient data collection
- Sentiment analysis should be parallelized and run at time of collection
 - Currently, sentiment analysis is done as a batch process on a small subset of data
 - Current sentiment analysis algorithm is not optimized to be applied to streaming data -- scoring takes too long
 - We might be able to make this work with a larger cluster, Kafka and balanced consumers, Storm, or Spark Streaming.

Architecture Overview

