MIS 375 Project

NIKE: What to do with the sneaker

resale market?

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Truncated Proposal

After a relatively unclear proposal submission, we determined that we will be looking for a way to track the influence Twitter buzz has on the resale value of a shoe. Fundamentally, Nike has created a culture of "sneakerheads" that buy shoes right at the drop time and resell them on eBay for substantially more. Each shoe has a different mark up value and a different amount of buzz on Twitter. Using Twitter as proxy data for public sentiment, we searched for a correlation between the change in price between the original and resale price compared to the amount of Twitter buzz. Our hypothesis was that we would find a correlation to help Nike change the original pricing of their shoe during the drop to increase profitability.

Data Collection Process and Challenges

We used the search function within the Tweepy API to filter historical tweets by date and keyword (shoe name), and exported the tweets to Excel to sum the tweets and retweets for the pre-buzz and post-buzz data points (*Figure 1*). Tweets made two days before the shoe release were considered pre-buzz, and tweets made up to one day after were considered post-buzz.

We used an average of the first 20 listings per shoe on eBay along with a dummy variable for celebrity endorsement, pre-buzz, post-buzz, and original price as independent variables in a multiple linear regression with resale price as the dependent variable (*Figure 2*).

The main challenges encountered during this project were the limitations of the Tweepy API, such as the rate limit and historical date limits. Because some of our trial shoe releases were highly anticipated, over one thousand tweets were often returned for one day, which limited the amount of data we could grab continuously. We limited the number of tweets grabbed by adding a count parameter to the function, but because we could not anticipate the popularity of each

shoe, we removed the count parameter and waited fifteen minutes for the rate limit to reset, in the event that a shoe was more popular than anticipated. This method worked because most shoes did not reach an exorbitant number of tweets.

Additionally, the search function could only accept a date parameter, not a time, thus we were unable to compile pre-buzz and post-buzz data that was within a few hours of the drop. A pseudo-fix was to find a specific tweet on an account's timeline that had a created_at time close to the specific time we desired and grab the tweet ID to be used as the max_ID or since_ID of the search function. In the end, we resorted to using the standard parameters because the bulk of the buzz was dispersed over multiple days rather than in the few hours surrounding the release time.

Lastly, the inability to grab tweets older than one week with the search function limited the number of data points we were able to collect, forcing us to miss one of the more significant releases in the past month, the Kobe Mamba XI.

Data Analysis and Methodology

After running the multiple linear regression the first time, we found that celebrity endorsements were statistically insignificant (*Figure 3*). We removed this variable from our model and took the log of our pre-buzz and post-buzz data points to improve the model's fit (*Figure 4*). Then we ran a regression with the net change in price versus the logs of pre and post-buzz, ignoring all other factors, to corroborate our findings (*Figure 5*). The final model we decided to use can be seen in *Figure 4*.

We decided to use a multiple linear regression to analyze our data because we predicted that there would be a linear relationship between the reseller's price of a shoe and multiple other variables (i.e. pre-buzz, post-buzz, celebrity endorsements, and original price). We found that, if

holding all other variables constant, an increase in the amount of pre-buzz surrounding a shoe drop reflected the largest increase in the amount a shoe will be resold for. This can be seen by analyzing the coefficient of the "Log pre-buzz" variable in *Figure 4*. This result proves the relationship between public sentiment and resell price, using Twitter data as a proxy for public sentiment. Twitter buzz including tweets, retweets and favorites mirrors the general public sentiment by encompassing all aspects of the shoe (style, color, celebrity affiliation). All of our variables are statistically significant and with a high r-squared value we can assure the accuracy of our model.

Insights and Recommendations

Initially, our goal was to create a pricing model Nike could use to predict the resale value of their shoes, and thus determine if they should increase the retail price of each shoe before the drop to increase their profits. After subsequent research though, it was determined that Nike has a unique and precise algorithm to maximize their share in the resale market (Highsnobiety). Nike releases shoes in quantities that never quite meet demand, intensifying brand exclusivity and generating large profits. Through this, Nike has created a continual demand for their shoes. To take complete advantage of this demand, Nike conducts spontaneous re-releases of existing shoe models at the same price. For example, a pair of highly sought Air Jordans could be re-released with a different color or pattern, allowing those who were unable to snag a pair from the original release to purchase and also allowing those who were on the fence to buy as well.

After analyzing our survey results (*Figure 6*) and leaning on our research, we recommend that Nike increase the price of the subsequent shoe drop only if adequate pre-buzz is created.

They could use the model we created to predict if increasing the shoe price would be profitable.

For example, if Nike collects historical Twitter data showing large amounts of buzz regarding the shoe drop, they would then be able to increase the subsequent shoe drop's price knowing that there is a market out there willing to pay a higher price for the shoe. We recommend that if substantial buzz is recorded for the initial release, Nike should increase the price of the shoe by 10% for the re-release. In *Figure 5*, one can see that of the 296 respondents around 46% are willing to pay at least the original price plus 10% if the shoe could not be bought elsewhere.

In addition to benefiting Nike, our insights have massive ramifications for resellers or sneakerheads. Essentially if a person is attempting to decide whether or not to flip a specific shoe, they can look at the buzz on Twitter and determine what the resale value will be using our model; this will allow them to determine whether or not the shoe will generate a profit.

SWOT Analysis

Strengths: Our model uses Twitter data as a proxy for current sentiment, which includes overall opinion on the color, style, celebrity endorsement, etc. Because the data is public and easily accessible, this is a convenient way to access a comprehensive analysis of sentiment.

Weaknesses: Our analysis was conducted with data from eight shoe releases over a two-month

period. The most obvious weakness is that the sample size is not statistically significant to the population of shoe drops per year. Secondly, our primary source of resale price data was eBay, despite the variety of platforms that are used in the resale market.

Opportunities: This model is a good starting point for analyzing whether Nike should release the shoe again, but it has the potential to include more factors outside of Twitter buzz.

Threats: Currently Nike uses a highly detailed, incredibly accurate model taking many more variables into account to determine the best original sale price for the shoe. We assumed they

were leaving a large majority of revenue on the table by not taking advantage of the resale market, but in reality only 4% of the shoes that are originally released are resold, so raising the price could deter the 96% away.

References

Leach, Alec. "The Ingenious Methods Nike Uses to Control the Sneaker Resell Market." Highsnobiety. Title Media UG, 9 June 2015. Web. 1 May 2016. http://www.highsnobiety.com/2015/06/09/sneaker-resell-market/.

Exhibits

Figure 1

Date	Username	Tweet	# RT		
04/20/2016 @ 23:44	ALLKIX	#ALLKIX The Nike Sock Dart 'Hasta' and 'Black White' Are Releasing Tomorrow https://t.co/cUgrBzBJjL https://t.co/m575WEvUSN	0	Tweets	38
04/20/2016 @ 23:40	InsideSneakers	#Nike Sock Dart SE « Hasta »#Early #Links : https://t.co/P7FwIPIP8u #Inside #Sneakers https://t.co/m7fju2dpSR		RT	2:
04/20/2016 @ 23:28	mainframenyc	NIKE SOCK DARTDropping tomorrow 🚍 THURSDAY, 21 APRIL 2016 - 8:00 BST Black/White/Black, Hasta/White/Black 🚻 https://ti.co/ZmgXS0XXWR		Total	6
04/20/2016 @ 22:39	WildProgressive	https://t.co/U/UxGUSjDT Nike Sock Dart SE Hasta Black NikeLab	0		
04/20/2016 @ 21:59	devinQ_lgnd	@nikestore is the Nike Sock Dart "hasta" and "black" colorway releasing tomorrow?	0		
04/20/2016 @ 21:15	5PointzBristol	Nike Sock Dart SE "Hasta" - drops 8am tomorrow - full of premium details - £94.99 https://t.co/4WqkCzbm69 https://t.co/CFR3nVQHe2	0		
04/20/2016 @ 19:24	ninobrown_ETP	RT more_sneakers "The Nike Sock Dart SE "Hasta White" will be available tomorrow !Links:https://t.co/NzF6ZYxhS1 https://t.co/FF6K2IXyA3"	0		
04/20/2016 @ 19:07	more_sneakers	The Nike Sock Dart SE "Hasta White" will be available tomorrow !Links:https://t.co/ilxnFtSEe8 https://t.co/isBateRkH1	0		
04/20/2016 @ 17:41	TheShoeGame	Nike Sock Dart Hasta Release Date https://t.co/U01KQ2YbNy https://t.co/fjr.JvDtLYp	8		
04/20/2016 @ 17:01	Isdls	Les Nike Sock Dart Black & Dart	12		
04/20/2016 @ 16:40	thesolesupplier	RELEASE REMINDER I Launching at 8am GMTNike Sock Dart SE Hasta Whitehttps://t.co/dBjRQaRp55 https://t.co/HAorMBIYvM	0		
04/20/2016 @ 16:39	Kickz2fire	#SneakerBar These Two Nike Sock Dart Colorways Release Tomorrow https://t.co/8xfL5luWTt https://t.co/4hlG8PR00q	0		
04/20/2016 @ 16:15	KicksDealsCA	Also releasing Midnight PST tonight is the "hasta" colorway of the Nike Sock Dart for \$175 + free shipping. https://t.co/282EH91pVI	0		
04/20/2016 @ 16:12	RT_Kicks4Sale	These Two Nike Sock Dart Colorways Release Tomorrow https://t.co/l/MhtixQppt https://t.co/kb0E47L8Uw	0		
04/20/2016 @ 16:12	SBDetroit	These Two Nike Sock Dart Colorways Release Tomorrow https://t.co/DjsecQkDYw.https://t.co/LM5sWtGyGH	2		
04/20/2016 @ 15:30	Footpatrol_ldn	Nike Sock Dart Hasta/Black/White Released in-store & Dine on Friday 22nd April (available online from 8:00AM Bhttps://t.co/ZaEHMT2hY1	0		
04/20/2016 @ 13:57	sneakerzimmer	Nike Sock Dart SE "Hasta" dropping tomorrow at @NikeStoreEurope: https://t.ca/XUYhAjll14 #nike #sockdart https://t.ca/boEaE8K2CM	0		
04/20/2016 @ 11:04	YummyDestiny	https://t.co/UhzhaGxH2o PRE-DRDER Nike Sock Dart SE Hasta White Sz UK 6 7 8 9 10 11 833124-302 https://t.co/WyyyAV4dK6	0		
04/20/2016 @ 11:04	YummyDestiny	https://t.co/abTsHxy0gw#stylePRE-ORDER Nike Sock Dart SE Hasta White Sz UK 6 7 8 9 10 11 833124-302	0		
04/20/2016 @ 11:04	YummyDestiny	https://t.co/UhzhaGxH2o PRE-DRDER Nike Sock Dart SE Hasta White Sz UK 6 7 8 9 10 11 833124-302 https://t.co/c7bfiJ3KXm	0		
04/20/2016 @ 11:04	YummyDestiny	https://t.co/UhzhaGxH2o PRE-ORDER Nike Sock Dart SE Hasta White Sz UK 6 7 8 9 10 11 833124-302 https://t.co/S8acVX4b2E	0		
04/20/2016 @ 11:04	YummyDestiny	https://t.co/UhzhaGxH2o PRE-ORDER Nike Sock Dart SE Hasta White Sz UK 6 7 8 9 10 11 833124-302 https://t.co/uLSj.JerrKz	0		
04/20/2016 @ 11:04	YummyDestiny	https://t.co/UhzhaGxH2o PRE-ORDER Nike Sock Dart SE Hasta White Sz UK 6 7 8 9 10 11 833124-302 https://t.co/mgQBlsbFCa	0		
04/20/2016 @ 11:04	YummyDestiny	https://t.co/UhzhaGxH2o PRE-DRDER Nike Sock Dart SE Hasta White Sz UK 6 7 8 9 10 11 833124-302 https://t.co/xoUyq28Aa8	0		
04/20/2016 @ 11:04	YummyDestiny	https://t.cd/UhzhaGxH2o PRE-ORDER Nike Sock Dart SE Hasta White Sz UK 6 7 8 9 10 11 833124-302 https://t.cd/II/DccsJ2b	0		
04/20/2016 @ 11:03	YummyDestiny	https://t.co/UhzhaGxH2o PRE-ORDER Nike Sock Dart SE Hasta White Sz UK 6 7 8 9 10 11 833124-302 https://t.co/Zs1b7UKS4m	0		
04/20/2016 @ 11:01	ShoesSteals	https://t.co/tYmavaJ26L PRE-DRDER Nike Sock Dart SE Hasta White Sz UK 6 7 8 9 10 11 833124-302 https://t.co/ExU06KBIOs	0		
04/20/2016 @ 11:01	ShoesSteals	https://t.co/tYmavaJ26L PRE-ORDER Nike Sock Dart SE Hasta White Sz UK 6 7 8 9 10 11 833124-302 https://t.co/tYUeK3SDvEV	0		
04/20/2016 @ 11:01	ShoesSteals	https://t.co/tYmavaJ26L PRE-ORDER Nike Sock Dart SE Hasta White Sz UK 6 7 8 9 10 11 833124-302 https://t.co/ze4AlZje8q	0		
04/20/2016 @ 11:01	ShoesSteals	https://tt.co/tYmavaJ26L PRE-ORDER Nike Sock Dart SE Hasta White Sz UK 6 7 8 9 10 11 833124-302 https://tt.co/iUKcBkif9s	0		

Figure 2

Shoe	Date	pre buzz dates	post buzz dates	Resale Price	Price	Pre Buzz	Post Buzz	Celebrity Endorsemen
NIKE AIR GRIFFEY MAX 1 "FRESH WATER"	4/21/2016	4/19 - 4/21	4/21 -4/22	\$143.07	\$150.00	21	208	1
UNDFTD X NIKE DUNK LUX HIGH	4/21/2016	4/19 - 4/22	4/21 -4/22	\$248.46	\$165.00	150	61	0
NIKE SOCK DART "HASTA"	4/21/2016	4/19 - 4/22	4/21 -4/22	\$147.50	\$150.00	61	433	0
NIKE AIR MORE UPTEMPO "WHITE/GYM RED"	4/23/2016	4/21-4/23	4/23 -4/24	\$244.85	\$160.00	292	332	0
AIR JORDAN 10 "NYC"	4/27/2016	4/25 - 4/27	4/27 -4/28	\$261.49	\$190.00	988	1501	1
NIKE KYRIE 2	4/28/2016	4/26-4/28	4/28-4//29	\$157.49	\$120.00	1610	1064	1
NIKE KOBE 11 LOW "Draft Day"	4/28/2016	4/26-4/28	4/28-4//29	\$169.93	\$160.00	100	439	1
* Pre Buzz = 2 day before				Resale Price	Original Price	Log Pre Buzz	Log Post Buzz	
*Post Buzz = 1 day after				\$143.07	\$150.00	1.322219295	2.318063335	
				\$248.46	\$165.00	2.176091259	1.785329835	
				\$147.50	\$150.00	1.785329835	2.636487896	
				\$244.85	\$160.00	2.465382851	2.521138084	
				\$261.49	\$190.00	2.994756945	3.176380692	
				\$157.49	\$120.00	3.206825876	3.026941628	
				\$169.93	\$160.00	2	2.64246452	

Figure 3

8								
Regression Sta	tistics							
Multiple R	0.987558138							
R Square	0.975271077							
Adjusted R Square	0.92581323							
Standard Error	14.38843794							
Observations	7							
ANOVA								
	df	SS	MS	F	Significance F			
Regression	4	16329.67065	4082.417663	19.71923845	0.048846327			
Residual	2	414.0542925	207.0271462					
Total	6	16743.72494						
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	-315.0227228	70.13926636	-4.491388906	0.046166432	-616.8076287	-13.23781694	-616.8076287	-13.23781694
Original Price	3.395130464	0.460899595	7.366312533	0.017934635	1.412039563	5.378221365	1.412039563	5.378221365
Pre Buzz	0.132853618	0.026143389	5.081728969	0.036610396	0.020367693	0.245339543	0.020367693	0.245339543
Post Buzz	-0.113358561	0.032365188	-3.502484294	0.072735069	-0.252614724	0.025897602	-0.252614724	0.025897602
Celebrity Endorsement	-27.50782126	13.81157183	-1.991650305	0.184644428	-86.9342185	31.91857599	-86.9342185	31.91857599

Figure 4

Regression S	tatistics							
Multiple R	0.972503261							
R Square	0.945762593							
Adjusted R Square	0.891525186							
Standard Error	17.39862277							
Observations	7							
ANOVA								
	df	SS	MS	F	Significance F			
Regression	3	15835.58872	5278.529573	17.43745962	0.021091211			
Residual	3	908.1362231	302.7120744					
Total	6	16743.72494						
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	-66.56482624	67.71619353	-0.982997165	0.398092772	-282.0679762	148.9383237	-282.0679762	148.9383237
Original Price	1.813086854	0.339049535	5.347557417	0.012789817	0.734079915	2.892093793	0.734079915	2.892093793
Log Pre Buzz	65.09417341	13.46919673	4.832817779	0.016891748	22.22917805	107.9591688	22.22917805	107.9591688
Log Post Buzz	-65.43825782	19.51392839	-3.35341283	0.043947412	-127.5402871	-3.336228525	-127.5402871	-3.336228525

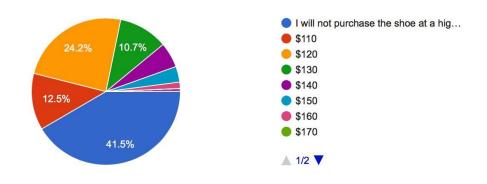
Figure 5

SUMMARY OUTPUT								
Regression St	tatistics							
Multiple R	0.854385867							
R Square	0.72997521							
Adjusted R Square	0.594962814							
Standard Error	25.73446242							
Observations	7							
ANOVA								
	df	SS	MS	F	Significance F			
Regression	2	7161.346148	3580.673074	5.406727351	0.072913387			
Residual	4	2649.050223	662.2625558					
Total	6	9810.396371						
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	63.51259808	59.96124361	1.059227499	0.349219829	-102.9665032	229.9916994	-102.9665032	229.9916994
Log Pre Buzz	65.03359073	19.92237729	3.264348916	0.030953581	9.720203808	120.3469777	9.720203808	120.3469777
Log Post Buzz	-66.50114734	28.85578456	-2.304603682	0.082520204	-146.6176491	13.61535445	-146.6176491	13.61535445

Figure 6

You have decided to purchase these shoes with a retail price of \$100 (disregard the actual selling price of this shoe). Unfortunately, Nike raises the price of the shoe, and you cannot find it for cheaper elsewhere. At what price will you no longer want to purchase the shoe?

(289 responses)



Code

```
#!/usr/bin/env python
# encoding: utf-8
import tweepy, csv, random, datetime, time, xlsxwriter
#Twitter API credentials
ckey="i14oaj5zZr5vlHahtB35U4pRm"
csecret="oKB3XSWYZ67yotPOIFT0ypPtU5i6eMTPa6T6NIXZG6sL01UgY1"
atoken="46006104-7rnN3dvCQE1Gq7zmzVQlkEEuvan8KKtZ8r07nXzuT"
asecret="DNGOQqhV8cHEOorojf5yJNnLFSkttP11XLcu8pjjkOUs2"
auth = tweepy.OAuthHandler(ckey, csecret)
auth.set_access_token(atoken, asecret)
api = tweepy.API(auth)
def convert_date(created_at):
      #2016-04-19 23:22:19
      time = str(created at)
      dt = datetime.datetime.strptime(time, '%Y-%m-%d %H:%M:%S')
      return dt
def grab_tweets(keywords, start, end):
      all tweets = []
      new tweets = tweepy.Cursor(api.search, q = keywords, since = start, until =
end).items()
      for obj in new_tweets:
             if not obj.retweeted and "RT @" not in obj.text:
                   tweet = []
                   tweet.append(obj.created_at.strftime('%m/%d/%Y @ %H:%M'))
                   tweet.append(obj.user.screen_name)
                   tweet.append(obj.text)
                   tweet.append(obj.retweet_count)
                   all_tweets.append(tweet)
      return(all_tweets)
def write_xls(all_tweets, search_terms, workbook):
      format01 = workbook.add format()
      format02 = workbook.add format()
      format03 = workbook.add_format()
```

```
format01.set_align('center')
format01.set_align('vcenter')
format02.set_align('center')
format02.set_align('vcenter')
format03.set align('center')
format03.set_align('vcenter')
format03.set_bold()
header = ['Date', 'Username', 'Tweet', '# RT']
title = "Keywords - "
for elt in search_terms:
      title += elt + ' '
worksheet = workbook.add_worksheet(title)
out1 = all_tweets
row = 0
col = 0
worksheet.set_column('A:A', 20)
worksheet.set_column('B:B', 20)
worksheet.set column('C:C', 100)
worksheet.set_column('D:D', 7)
for item in header:
      worksheet.write(row, col, item, format03)
      col = col + 1
row += 1
col = 0
for elt in out1:
      write = []
      write = [elt[0], elt[1], elt[2], elt[3]]
      format01.set_num_format('yyyy/mm/dd hh:mm:ss')
       worksheet.write(row, 0, write[0], format02)
      worksheet.write(row, 1, write[1], format02)
      worksheet.write(row, 2, write[2], format02)
       worksheet.write(row, 3, write[3], format02)
       row += 1
```

```
col = 0
```

```
def main():
```