24th STREET REALTY - MARKETING ANALYTICS

FIRM DESCRIPTION AND BACKGROUND

We began our search for data sets by reaching out to several local businesses—including Tiff's Treats, Verts, and 24th Street Realty—and gauging their interest in turning their raw data into valuable insights. We were pleased to find that 24th Street Realty, which had been collecting data for the past three years with the hopes of one day analyzing it, was both willing and eager to share its sales and marketing data with us.

As a real estate brokerage firm, 24th Street Realty offers a 100% free service to students, professors, and others looking to buy, sell, or lease in the Campus and Central Austin area. Its income comes primarily from referral fees, which are allocated according to property management companies' marketing budgets. As a free service, its success is heavily dependent on the quality of its agents and the connections they make. While 24th Street Realty's agents have been rated #1 by UT students since its founding in 2013, competition among both agents and brokerage firms remains high. Within the firm, "leads" are either generated personally by the agents or through the office. The firm defines a lead as anyone expressing interest in their services, whether that be a walk-in appointment, a client referral, or a completed interest form online. Personal leads belong to whoever generates them and office leads are distributed evenly among each agent through an automated, third-party system. On a larger scale, 24th Street Realty's competition includes West Campus Living, Property Management of Texas, Uptown Realty, 512 Realty, and individual leasing offices at various properties in the area. The firm's prime location in the offices above Starbucks, on the corner of 24th Street and San Antonio Street, gives it a competitive edge and has contributed to its success in garnering the highest number of walk-in clients in the campus area.

In addition to visibility, 24th Street Realty relies on several web-based promotions to generate leads including Twitter and Facebook accounts, a website, and a blog. Lori, the Marketing and Business Development Manager, posts leasing information as well as content relevant to college students--their largest demographic--on these platforms. While these accounts illicit a fair amount of engagement and reach to the firm's followers, its most popular form of promotion is word of mouth. Leasing agents still rely heavily on repeat clients and existing client referrals to generate new leads despite the firm's active presence on multiple social platforms.

DATA

Our data was given to us by Chris Zaiontz and Lori Kendall, the Leasing Manager and the Marketing and Business Development Manager at 24th Street Realty. They had been collecting data over the past three years, but were unsure how to analyze and learn from it. They shared two Dropbox folders with us containing "Leasing and Sales Numbers from 2013-2016" by month and a “Social Media Analytics” folder that contained reports generated by Sprout Social, a social media management tool, pulled monthly from Twitter and Facebook for 2016.

The social media analytics folder contained data counts such as: incoming messages, sent messages, new Twitter followers, new Facebook fans, post engagement, link clicks, and impressions. The average number of Twitter engagements per month is 282.6, while the average number of Facebook engagements per month is 162.4. Thus far in 2016, 24th Street Realty has tweeted an average of 46 tweets per month and posted an average of 21.9 Facebook posts per month. The average number of impressions per month for Facebook and Twitter had the highest counts, with 5,267.7 and 29,454.1 respectively. After removing outliers from the data though, the average number of impressions per month for Twitter lowered to 8,637.33.

The leasing and sales numbers contained data counts and percentages such as: number of leads, number of appointments, lead-to-appointment ratio, number of deals, close rate, and amount ($) invoiced. The average number of office leads per month is 269, while the average number of agent leads per month is 65. The average number of appointments made per month is 153, while the average number of deals made per month is 82. In relation to these numbers, the company was able to calculate lead-to-appointment ratios and close rate ratios, with their averages per month being 47.87% and 55.94% respectively. Lastly, the average invoice per month for 24th Street Realty is $53,314.

The data from the social media analytics folder was formatted as PDF reports with multiple graphics explaining the data. The leasing and sales numbers were formatted as CSV files organized by year, month, and agent. We combined all of this raw data manually in excel in multiple formats for ease of analysis when using Solver and the Data Analysis Toolpak.

MARKETING ANALYTICS QUESTIONS

Our goal in this project was to determine if 24th Street Realty’s current marketing methods and lead allocation system contributed to the amount invoiced each month. We also wanted to create a model that would allow the firm to measure seasonality, predict future monthly invoices, and hire agents accordingly. By achieving these goals, we hoped to provide actionable recommendations supported by the firm’s own data. These are the specific questions that we sought to answer in our analysis:

1. What is the seasonality of sales?
2. What is the sales trend over time?
3. What are the projected sales for Q4 of 2016?
4. How well is each agent performing over time?
5. Are current social media efforts contributing to overall sales?

The first two questions pertain to seasonality and sales trend over time. As a newer company, we predicted that sales were increasing over time as the firm's agents gained experience and widened their consumer base. We also hypothesized that seasonality would reflect the school cycle, so we wanted to determine what specific months actually showed increases or decreases in sales. By quantitatively determining these spikes and dips, we hoped to provide suggestions as to how 24th Street Realty could allocate its marketing and labor resources more efficiently.

In addition, 24th Street Realty wanted to know what their sales would be for Q4 of 2016. By creating a forecasting model for future quarters, the firm can plan business logistics to ensure that they have enough leasing agents to respond to demand and continue providing top-quality service to their customers.

The last two questions relate to how individual leasing agents and current social media efforts contribute to overall sales. Close rates, or the rate at which agents convert appointments into a sale, are extremely important in real estate and management likes to see efficiencies. Because the skill and service level of an agent largely factors into closing a deal, answering this question can help 24th Street Realty determine if it needs to change its lead distribution system to account for the strengths/weaknesses of each agent.

For social media, we wanted to figure out if the company's Facebook and Twitter posts were actually helpful in leading customers to 24th Street Realty--whether that be generating leads or actual appointments. Because deals are the product of successful appointments, this metric directly affects overall sales. The results of this analysis will determine if 24th Street Realty needs to modify their social media strategy to drive more leads and ultimately sales.

MARKETING ANALYTICS TECHNIQUES AND RESULTS

We decided to use many different techniques that we had learned in class to answer the above marketing analytics questions. By using multiple techniques, we could diversify our analysis and create detailed visualizations for our client. Below, we have outlined the primary techniques we used: Multiplicative/Additive Models, Moving Averages, Ranked Averages with Sensitivity Analysis, and Multiple Linear Regression.

Multiplicative/Additive Models

As a neighborhood close to both campus and a major metropolitan area, there is a decent amount of seasonality in the Campus and Central Austin real estate business. Depending on the time in the year--or for many looking to lease, the semester--there are drops and spikes in the amount 24th Street Realty invoices each month. In order to gain a better understanding of these trends and their seasonality, we decided to look at the additive and multiplicative models for our data set. After using Solver to forecast sales and compare them against the actual sales figures, we found the multiplicative model was the best fit because it had a lower standard deviation of residuals than the additive model ($16,902.64 vs. $17,211.52).

The results of the multiplicative model can be found in *Figure 1,* along with a graphical representation in *Figure 2.* The base of $43,321.08 serves as the best estimate, without seasonality, invoiced at the beginning of the observed time period. The trend of 1.0111 in this model means that invoice amounts are increasing a rate of 1.11% per month. While we expected this percentage to be larger, it still confirms our prediction of overall growth and may be partially justified by the cyclical nature of student housing habits.

The seasonal indexes were more volatile, though. We found that the first four months of the year were by far the most successful, with April generating invoices 51% above an average month. This can be explained by the ending of the typical school year, and students' preparation for the following semester. Sales drop significantly below average during May (60% below) and June (20% below), presumably after most living arrangements for the next year have been made and students return home for the summer. We then see invoices rise 35% above average for July, possibly for transfer students and those who procrastinated making living arrangements during the spring. The following five months' percentages fluctuate below and above the average, reflecting the general volatility of the Campus and Central Austin housing market.

In addition to visualizing seasonality, we were able to use this analysis to create a predictive model for Q4 of this year. The forecasting equation is as follows:

*Forecasted Invoice = ($43,321.08) * (1.0111 ^ month #) * (seasonal index)*

While we already had sales figures for October 2016, our forecast predicted sales of $74,738.65 and $61,708.06 for November and December, respectively. These results can be seen in *Figure 1*.

Moving Averages

By using moving averages, we were able to smooth out the data and determine a trend. We wanted to know whether there was a trend in sales throughout the year and also over the previous three years. This filtered out the noise of seasonality to make insights clearer visually. Since we had 37 months of sales data, as seen in *Figure 3,* Excel calculated the moving averages trendline using twelve month periods.

As can be seen in *Figure 4,* 2014 experienced a steady upward trend in sales. The beginning of 2015 then saw a sharp decline in invoices, likely because students had either already leased an apartment or were not interested in seeking 24th Street Realty's help. Later in 2015 there was a steady upward trend in the amount invoiced. However, in 2016 there has been another sharp drop in sales. Despite these fluctuations between years, overall sales have trended upward over time, increasing by an average of $15,000 between 2014 and 2016.

Ranked Averages with Sensitivity Analysis

24th Street Realty has been collecting performance data on its 23 real estate agents since the beginning of 2014. Data on each agent was collected during the following stages of the purchase funnel: number of self generated leads, lead-to-appointment ratio, and close rate. However, not all of the agents worked consistently each month since the beginning of 2014; some agents were hired on later and some agents took some time off. In order to accurately compare the performance of the agents, we decided to calculate the average of each performance statistic for each agent and then rank them. Sensitivity Analysis was applied to eliminate any outliers. *Figures 5-7* show the ranked averages for each stage of the purchase funnel and *Figure 8* shows an overall ranking of each agent by combining their ranks from the three statistics. *Figures 5-7* are more useful to understand each agent's strengths, while *Figure 8* highlights overall performance.

One limitation of this method is the seasonality of sales. For example, if an agent takes off during a peak month for business, their average could suffer compared to another agent who worked during the peak month. The agent who worked during a busier month would then have an inflated average despite the possibility of better performance from another agent in slower months. We hope that by breaking down the average ranks at each level of the funnel, in addition to ranking each agent overall, the agents' performances will be more accurately reflected.

Multiple Linear Regression

Since 24th Street Realty had been collecting social media and sales data separately, we decided to combine all of the data into one spreadsheet to determine if we could find a relationship between the amount of office leads the company gets and the amount of engagement 24th Street Realty has with its followers on social media. This would help tell us if 24th Street Realty's marketing strategies were actually effective at bringing clients in. The best way we could think to analyze this data was to run a multiple linear regression. If the p-values for each variable were significant and the overall Significance F test was lower than 0.05, we could then use the coefficients of each variable to determine which form of social media engagement had the biggest impact on bringing leads to the firm.

The first time we ran the multiple linear regression we used the number of office leads as the dependent y-variable and the following eight characteristics as the independent x-variables: lead-to-appointment ratio, close rate, Twitter reach, Twitter engagement, number of tweets, FB reach, FB engagement, and number of FB posts. The results of this initial regression can be seen in *Figure 9.* The only variables which we found to be significant, or close to being significant, were lead-to-appointment ratio, Twitter engagement, FB reach, and number of FB posts. The R-squared value was high at 0.99, but the overall Significance F test was not statistically significant so we decided to remove the insignificant variables and rerun the regression.

During the second regression we discovered that only Twitter engagements, number of FB posts, and FB reach were significant *(Figure 10)*. We continued this process until the only variables left in the regression were significant, and the Significant F test was below 0.05. Our final model can be seen in *Figure 11.* With a relatively high R-squared value of 0.82 and a Significant F test of 0.002, we believe our model is a good fit. According to our model, the only significant variables in bringing in office leads are Twitter engagements and FB reach. The coefficients for each variable suggest that FB reach has the highest impact on gaining new office leads. Holding all other variables constant, for every additional 100 impressions of FB posts for the month, 24th Street Realty gains three new office leads.

RECOMMENDATIONS

Drawing from the results of our multiplicative model, we suggest that 24th Street Realty take seasonality into account in both their marketing efforts and resource allocation. January through April proved to generate invoices above average, indicating that agents are in high demand during this period. It would benefit 24th Street Realty to ensure it has enough agents hired during this time to continue providing the high-quality service it prides itself on. It is also important to note that these above-average sales are happening regardless of the firm's marketing efforts. This is reflected in the lower Facebook reach and Twitter engagement for these months seen in *Figure 12*. Therefore, we suggest that 24th Street Realty continue posting to its social accounts during the first four months of the year to keep themselves top-of-mind, but allocate their marketing push to months where sales have consistently been below average (i.e. May, June, August, October, and December).

To better track when appointments lead to deals, we suggest that 24th Street Realty survey their clients after they sign a deal to find which factors most influenced them to sign. One's purchase decision could be influenced by a variety of factors such as a referral from a friend, the level of service from the agent, or something else entirely. This allows the firm to see where opportunities exist to make improvements and ensure that they stay competitive in the future. They could even add these variables (i.e. count of referrals from friend, internet, etc.) to a multiple linear regression model to see if they have a significant impact on the amount invoiced per month.

We also suggest that 24th Street Realty attempt to utilize each agent's individual strengths. As shown in *Figure 5*, Agent Q has the most self-generated leads by far. However, *Figure 6* shows that he ranks 16th in the lead-to-appointment ratio. This could indicate that Agent Q has been unable to give an adequate amount of attention to the large number of leads that he has generated, thus hurting his ability to schedule appointments and ultimately close more deals. For this reason, 24th Street Realty should consider either changing the automated lead distribution system to take agents with too many leads out of the rotation, or incentivize agents to hand-off leads to agents with higher close rates (*Figure 7*). The firm could do this by setting a limit that once reached, allows agents to transfer their lead to a strong closer in exchange for a portion of the generated profit (given the agent is able to close the deal). This would encourage agents to work together rather than compete with each other. Further, in a service-based industry their success relies heavily on word of mouth. By investing their efforts in providing quality service from skilled professionals, both agents and clients benefit in the long run.

Lastly, data shows that 24th Street Realty's current social media strategy is in need of a revamp. Our analysis found that only Twitter engagements and FB reach were statistically significant in increasing the company's office leads. Rather than posting memes and movie quotes, 24th Street Realty should focus its content on information relevant to its services, such as customer testimonials or apartment listings around West Campus that new clients would find interesting. It could even incentivize people to follow its account or share its posts by hosting contests for 24th Street Realty swag. This would both increase engagement online and serve as free advertising around campus. Another simple way to increase the amount of impressions on a post is to "boost" its visibility (specifically to those who may not already follow you) by paying a small amount of money to Facebook. In combination, we feel these strategies could positively impact 24th Street Realty's social presence and generate more potential leads.

APPENDIX

Figure 1

Month #	Month	Year	Month	Invoiced	Forecast	Sq. Error	error		base	$43,321.08
1	October	2013	10	$14,337	$28,985.46	$214,577,429.64	-$14,648.46		trend	1.01113837
2	November	2013	11	$50,091	$50,160.75	$4,864.76	-$69.75			
3	December	2013	12	$51,186	$41,415.28	$95,466,886.51	$9,770.72		1	1.20
4	January	2014	1	$36,297	$54,210.46	$320,892,026.57	-$17,913.46		2	1.23
5	February	2014	2	$61,073	$56,446.71	$21,402,514.97	$4,626.29		3	1.00
6	March	2014	3	$11,631	$46,443.55	$1,211,913,908.4	-$34,812.55		4	1.51
7	April	2014	4	$61,125	$70,844.17	$94,462,356.21	-$9,719.17		5	0.40
8	May	2014	5	$29,528	$19,099.24	$108,759,001.46	$10,428.76		6	0.80
9	June	2014	6	$56,751	$38,248.38	$342,346,790.56	$18,502.62		7	1.35
10	July	2014	7	$63,039	$65,237.44	$4,833,128.82	-$2,198.44		8	0.72
11	August	2014	8	$47,844	$35,206.82	$159,698,375.04	$12,637.18		9	1.06
12	September	2014	9	$57,100	$52,673.15	$19,596,963.38	$4,426.85		10	0.66
13	October	2014	10	$40,853	$33,106.05	$60,015,298.96	$7,746.95		11	1.13
14	November	2014	11	$64,997	$57,291.62	$59,372,902.63	$7,705.38		12	0.924761117
15	December	2014	12	$24,556	$47,302.90	$517,421,306.61	-$22,746.90		mean	0.99999991
16	January	2015	1	$69,886	$61,917.04	$63,504,344.49	$7,968.96			
17	February	2015	2	$24,877	$64,471.20	$1,567,700,752.	-$39,594.20		SSE	$10,285,397,935
18	March	2015	3	$87,219	$53,045.99	$1,167,794,817.	$34,173.01		Stdev errors	$16,902.64
19	April	2015	4	$83,309	$80,915.41	$5,729,276.87	$2,393.59			
20	May	2015	5	$22,419	$21,814.40	$365,544.80	$604.60			
21	June	2015	6	$39,619	$43,685.79	$16,538,772.16	-$4,066.79			
22	July	2015	7	$102,025	$74,511.62	$756,986,269.80	$27,513.38			
23	August	2015	8	$42,233	$40,211.83	$4,085,119.18	$2,021.17			
24	September	2015	9	$75,118	$60,161.19	$223,706,175.02	$14,956.81			
25	October	2015	10	$62,269	$37,812.41	$598,124,610.25	$24,456.59			
26	November	2015	11	$58,742	$65,436.22	$44,812,536.71	-$6,694.22			
27	December	2015	12	$66,451	$54,027.49	$154,343,495.59	$12,423.51			
28	January	2016	1	$77,473	$70,719.19	$45,613,973.67	$6,753.81			
29	February	2016	2	$104,754	$73,636.45	$968,301,842.96	$31,117.55			
30	March	2016	3	$57,354	$60,587.02	$10,452,447.29	-$3,233.02			
31	April	2016	4	$97,773	$92,418.37	$28,672,016.97	$5,354.63			
32	May	2016	5	$16,390	$24,915.54	$72,684,830.29	-$8,525.54			
33	June	2016	6	$39,269	$49,896.18	$112,936,893.65	-$10,627.18			
34	July	2016	7	$62,697	$85,104.22	$502,083,328.49	-$22,407.22			
35	August	2016	8	$34,471	$45,928.36	$131,271,130.98	-$11,457.36			
36	September	2016	9	$52,224	$68,713.73	$271,911,098.23	-$16,489.73			
37	October	2016	10	$25,666	$43,187.84	$307,014,902.98	-$17,521.84			
38	November	2016	11	-	$74,738.65	-	-			
39	December	2016	12	-	$61,708.06	-	-			

Figure 2

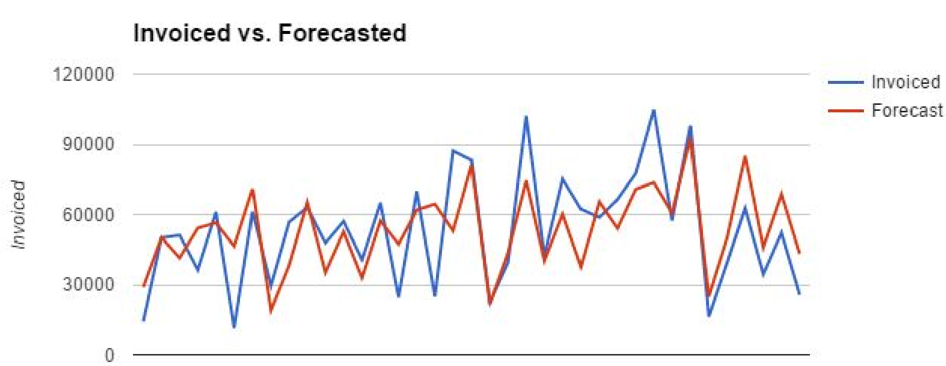

Figure 3

Month		Year	Office leads	Agent lea	# of app	Lead/Appt Rati	# of Deals	Close Rate	Invoiced
October	1	2013	93	49	79	55.60%	24	30.40%	$14,337
Novembe	2	2013	217	36	149	58.90%	79	53.00%	$50,091
Decembe	3	2013	172	48	112	50.90%	79	70.50%	$51,186
January	4	2014	225	12	130	49.40%	66	45.20%	$36,297
February	5	2014	271	64	165	49.30%	102	61.80%	$61,073
March	6	2014	21	27	29	60.40%	19	65.50%	$11,631
April	7	2014	282	57	143	42.20%	90	62.90%	$61,125
May	8	2014	201	7	100	48.10%	41	41.00%	$29,528
June	9	2014	214	58	143	61.40%	92	65.30%	$56,751
July	10	2014	195	56	107	42.60%	100	93.50%	$63,039
August	11	2014	232	29	108	42.90%	79	71.40%	$47,844
Septembe	12	2014	333	193	207	40.00%	99	49.20%	$57,100
October	13	2014	331	55	190	53.20%	69	47.30%	$40,853
Novembe	14	2014	285	10	153	48.70%	95	56.60%	$64,997
Decembe	15	2014	48	47	78	53.50%	44	55.80%	$24,556
January	16	2015	343	28	200	55.90%	119	58.60%	$69,886
February	17	2015	164	35	84	42.20%	41	48.80%	$24,877
March	18	2015	270	48	124	39.00%	109	87.90%	$87,219
April	19	2015	359	34	199	50.60%	124	62.30%	$83,309
May	20	2015	231	3	92	39.30%	33	35.90%	$22,419
June	21	2015	244	34	128	46.00%	61	47.70%	$39,619
July	22	2015	394	37	154	39.10%	136	93.00%	$102,025
August	23	2015	375	6	137	33.00%	50	44.90%	$42,233
Septembe	24	2015	206	593	234	29.10%	108	50.70%	$75,118
October	25	2015	350	56	222	55.60%	101	50.10%	$62,269
Novembe	26	2015	134	47	122	65.10%	86	72.00%	$58,742
Decembe	27	2015	367	49	185	43.90%	108	58.40%	$66,451
January	28	2016	370	46	222	53.40%	116	52.30%	$77,473
February	29	2016	349	30	284	74.90%	134	47.20%	$104,754
March	30	2016	280	61	114	33.40%	89	78.10%	$57,354
April	31	2016	445	66	277	54.20%	169	61.00%	$97,773
May	32	2016	229	15	96	39.30%	27	28.10%	$16,390
June	33	2016	122	34	94	60.30%	59	62.80%	$39,269
July	34	2016	227	108	149	44.50%	106	71.10%	$62,697
August	35	2016	359	9	139	37.80%	55	39.60%	$34,471
Septembe	36	2016	476	240	266	37.20%	87	32.70%	$52,224
October	37	2016	543	96	257	40.20%	44	17.10%	$25,666

Figure 4

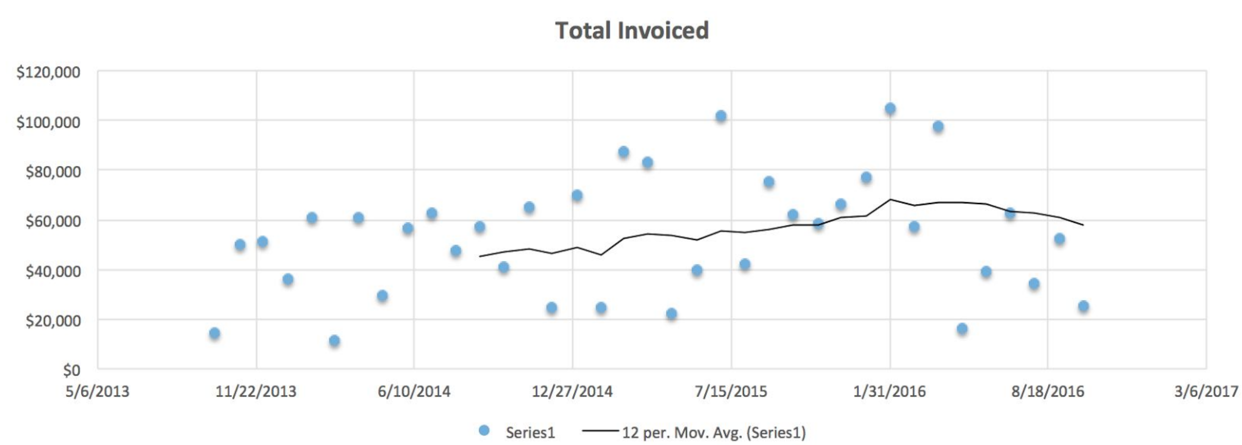

Figure 5

Self Generated Leads				
Agent	Sum	Count	Average	Rank
Agent Q	1048	34	30.82	1
Agent S	98	20	4.9	2
Agent V	34	7	4.86	3
Agent U	107	30	3.57	4
Agent H	112	34	3.29	5
Agent G	108	33	3.27	6
Agent D	99	33	3	7
Agent N	93	34	2.74	8
Agent C	10	4	2.5	9
Agent K	37	16	2.31	10
Agent B	49	22	2.23	11
Agent L	54	25	2.16	12
Agent F	22	11	2	13
Agent O	23	14	1.64	14
Agent W	11	7	1.57	15
Agent R	29	22	1.32	16
Agent M	13	10	1.3	17
Agent J	11	9	1.22	18
Agent T	9	11	0.82	19
Agent E	8	11	0.73	20
Agent P	16	28	0.57	21
Agent I	8	28	0.29	22
Agent A	1	4	0.25	23

Figure 6

Lead Appointment Ratio				
Agent	Sum	Count	Average	Rank
Agent L	16.9	25	68%	1
Agent E	7.25	11	66%	2
Agent C	2.42	4	61%	3
Agent S	11.81	20	59%	4
Agent B	12.39	22	56%	5
Agent D	18.36	33	56%	6
Agent H	16.99	34	50%	7
Agent F	5.39	11	49%	8
Agent R	9.32	22	42%	9
Agent V	2.89	7	41%	10
Agent N	13.21	34	39%	11
Agent G	12.74	33	39%	12
Agent A	1.49	4	37%	13
Agent O	5.17	14	37%	14
Agent W	2.48	7	35%	15
Agent Q	11.88	34	35%	16
Agent K	5.45	16	34%	17
Agent P	9.15	28	33%	18
Agent J	2.68	9	30%	19
Agent M	2.94	10	29%	20
Agent I	7.37	28	26%	21
Agent T	0	0	0	22
Agent U	0	0	0	23

Figure 7

Close Rate				
Agent	Sum	Count	Average	Rank
Agent N	28.07	34	82.60%	1
Agent G	26.528	33	80.40%	2
Agent D	23.651	33	71.70%	3
Agent S	13.195	20	66.00%	4
Agent U	19.755	30	65.90%	5
Agent O	9.072	14	64.80%	6
Agent T	6.145	11	55.90%	7
Agent H	18.911	34	55.60%	8
Agent L	13.028	25	52.10%	9
Agent V	3.604	7	51.50%	10
Agent B	11.166	22	50.80%	11
Agent W	3.321	7	47.40%	12
Agent Q	15.367	34	45.20%	13
Agent F	4.833	11	43.90%	14
Agent K	6.912	16	43.20%	15
Agent R	9.046	22	41.10%	16
Agent E	4.105	11	37.30%	17
Agent A	1.472	4	36.80%	18
Agent P	9.149	28	32.70%	19
Agent I	5.72	28	20.40%	20
Agent J	1.416	9	15.70%	21
Agent M	1.15	10	11.50%	22
Agent C	0.2	4	5.00%	23

Figure 8

Overall Rank					
Agent	Self Generated Lead	Lead to Appointmen	Close Rate	Average Rank	Overall Rank
Agent S	2	4	4	3.33	1
Agent G	6	12	2	6.67	2
Agent H	5	7	8	6.67	3
Agent N	8	11	1	6.67	4
Agent L	12	1	9	7.33	5
Agent V	3	10	10	7.67	6
Agent B	11	5	11	9	7
Agent Q	1	16	13	10	8
Agent U	4	23	5	10.67	9
Agent O	14	14	6	11.33	10
Agent C	9	3	23	11.67	11
Agent F	13	8	14	11.67	12
Agent E	20	2	17	13	13
Agent R	16	9	16	13.67	14
Agent K	10	17	15	14	15
Agent W	15	15	12	14	16
Agent T	19	22	7	16	17
Agent A	23	13	18	18	18
Agent J	18	19	21	19.33	19
Agent P	21	18	19	19.33	20
Agent M	17	20	22	19.67	21
Agent I	22	21	20	21	22

Figure 9

OFFICE LEADS VS. SOCIAL MEDIA (ROUND 1)

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.999714259
R Square	0.9994286
Adjusted R Square	0.994857396
Standard Error	9.204927113
Observations	10

ANOVA

	df	SS	MS	F	Significance F
Regression	8	148201.2693	18525.15866	218.635776	0.052260095
Residual	1	84.73068316	84.73068316		
Total	9	148286			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	-646.7102875	75.79116156	-8.532792929	0.074269818	-1609.728304	316.3077285	-1609.728304	316.3077285
Lead/Appt Ratio	639.487914	57.3617469	11.14833401	0.056952057	-89.36218608	1368.338014	-89.36218608	1368.338014
Close Rate	-69.94612536	25.36659084	-2.757411345	0.221484794	-392.259222	252.3669713	-392.259222	252.3669713
Twitter Reach	0.000596367	7.20E-05	8.280428906	0.076511934	-0.00031875	0.001511483	-0.00031875	0.001511483
Twitter Engagement	-0.736471767	0.051689016	-14.24812886	0.04460779	-1.393242992	-0.079700541	-1.393242992	-0.079700541
Number of Tweets	0.541273191	0.479485425	1.128862658	0.461511589	-5.551166783	6.633713165	-5.551166783	6.633713165
FB Reach	0.020764322	0.001407877	14.7486779	0.043098568	0.002875551	0.038653093	0.002875551	0.038653093
FB Engagement	-0.058641597	0.039759329	-1.47491416	0.379305432	-0.563831767	0.446548573	-0.563831767	0.446548573
FB Posts	35.74910143	2.251671174	15.8766972	0.040044847	7.138906497	64.35929636	7.138906497	64.35929636

Figure 10

OFFICE LEADS VS. SOCIAL MEDIA (ROUND 3)

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.909637018
R Square	0.827439505
Adjusted R Square	0.778136506
Standard Error	60.46050137
Observations	10

ANOVA

	df	SS	MS	F	Significance F
Regression	2	122697.6944	61348.84721	16.78274199	0.002134493
Residual	7	25588.30558	3655.472226		
Total	9	148286			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	313.9431166	33.62999687	9.335210998	3.36E-05	234.4208104	393.4654228	234.4208104	393.4654228
Twitter Engagement	-0.524453905	0.099811987	-5.254418044	0.001180512	-0.76047175	-0.28843606	-0.76047175	-0.28843606
FB Reach	0.033082286	0.006416419	5.155880086	0.001315431	0.017909866	0.048254705	0.017909866	0.048254705

Figure 11

Month	Year	Invoiced	Office leads	Agent leads	# of appts.	Lead/Appt Ratio	# of Deals	Close Rate	Twitter Reach	Twitter Engagement	Number of Tweets	FB Reach	FB Engagement	FB Posts
January	2016	$77,473	370	46	222	53.40%	116	52.30%	25928	14	22	1189	53	19
February	2016	$104,754	349	30	284	74.90%	134	47.20%	1998	9	17	887	182	15
March	2016	$57,354	280	61	114	33.40%	89	78.10%	8430	40	27	941	468	22
April	2016	$97,773	445	66	277	54.20%	169	61.00%	5493	165	24	6891	81	21
May	2016	$16,390	229	15	96	39.30%	27	28.10%	6392	192	41	2454	139	20
June	2016	$39,269	122	34	94	60.30%	59	62.80%	12239	816	85	7953	180	23
July	2016	$62,697	227	108	149	44.50%	106	71.10%	216805	518	68	5263	110	21
August	2016	$34,471	359	9	139	37.80%	55	39.60%	6724	417	77	7845	110	25
September	2016	$52,224	476	240	266	37.20%	87	32.70%	4183	318	43	6033	191	28
October	2016	$25,666	543	96	257	40.20%	44	17.10%	6349	337	56	13221	110	25