

Predicting US Presidential Election'16



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Introduction

The **United States presidential election of 2016**, was scheduled on Tuesday, November 8, 2016.

Primary elections were held in the month of May.

Twitter – a dominant social medium for people to express their views and support their desired candidates.



Hillary Clinton
Democratic



Donald Trump
Republican



Project Aim

- To study election patterns using the primary election results and predict the next President.
- To study the trends in election by analyzing the tweets and sentiments for the candidates.

Datasets Overview

We have done our analysis on the below :-

- Primary Election Results
- Tweet Results

Primary Results Dataset

- The data set obtained from Kaggle.
- Total of 24612 instances and 8 attributes
- Target Variable : votes

state	state_abbreviation	county	fips	party	candidate	votes	fraction_votes
Alabama	AL	Autauga	1001	Democrat	Bernie San...	544	0.182
Alabama	AL	Autauga	1001	Democrat	Hillary Clint...	2387	0.8
Alabama	AL	Baldwin	1003	Democrat	Bernie San...	2694	0.329
Alabama	AL	Baldwin	1003	Democrat	Hillary Clint...	5290	0.647
Alabama	AL	Barbour	1005	Democrat	Bernie San...	222	0.078
Alabama	AL	Barbour	1005	Democrat	Hillary Clint...	2567	0.906
Alabama	AL	Bibb	1007	Democrat	Bernie San...	246	0.197
Alabama	AL	Bibb	1007	Democrat	Hillary Clint...	942	0.755
Alabama	AL	Blount	1009	Democrat	Bernie San...	395	0.386
Alabama	AL	Blount	1009	Democrat	Hillary Clint...	564	0.551
Alabama	AL	Bullock	1011	Democrat	Bernie San...	178	0.066
Alabama	AL	Bullock	1011	Democrat	Hillary Clint...	2451	0.913
Alabama	AL	Butler	1013	Democrat	Bernie San...	156	0.065
Alabama	AL	Butler	1013	Democrat	Hillary Clint...	2196	0.921
Alabama	AL	Calhoun	1015	Democrat	Bernie San...	1425	0.218
Alabama	AL	Calhoun	1015	Democrat	Hillary Clint...	5011	0.765
Alabama	AL	Chambers	1017	Democrat	Bernie San...	312	0.095
Alabama	AL	Chambers	1017	Democrat	Hillary Clint...	2899	0.886
Alabama	AL	Cherokee	1019	Democrat	Bernie San...	268	0.249
Alabama	AL	Cherokee	1019	Democrat	Hillary Clint...	712	0.661
Alabama	AL	Chilton	1021	Democrat	Bernie San...	888	0.346

Dataset for Democrats- County Wise

	A	B	C	D	E	F	G	H
1	state	state_abb	county	fips	party	candidate	votes	fraction_votes
2	Alabama	AL	Autauga	1001	Democrat	Bernie Sanders	544	0.182
3	Alabama	AL	Autauga	1001	Democrat	Hillary Clinton	2387	0.8
4	Alabama	AL	Baldwin	1003	Democrat	Bernie Sanders	2694	0.329
5	Alabama	AL	Baldwin	1003	Democrat	Hillary Clinton	5290	0.647
6	Alabama	AL	Barbour	1005	Democrat	Bernie Sanders	222	0.078
7	Alabama	AL	Barbour	1005	Democrat	Hillary Clinton	2567	0.906
8	Alabama	AL	Bibb	1007	Democrat	Bernie Sanders	246	0.197
9	Alabama	AL	Bibb	1007	Democrat	Hillary Clinton	942	0.755
10	Alabama	AL	Blount	1009	Democrat	Bernie Sanders	395	0.386
11	Alabama	AL	Blount	1009	Democrat	Hillary Clinton	564	0.551
12	Alabama	AL	Bullock	1011	Democrat	Bernie Sanders	178	0.066
13	Alabama	AL	Bullock	1011	Democrat	Hillary Clinton	2451	0.913
14	Alabama	AL	Butler	1013	Democrat	Bernie Sanders	156	0.065
15	Alabama	AL	Butler	1013	Democrat	Hillary Clinton	2196	0.921
16	Alabama	AL	Calhoun	1015	Democrat	Bernie Sanders	1425	0.218
17	Alabama	AL	Calhoun	1015	Democrat	Hillary Clinton	5011	0.765
18	Alabama	AL	Chambers	1017	Democrat	Bernie Sanders	312	0.095
19	Alabama	AL	Chambers	1017	Democrat	Hillary Clinton	2899	0.886
20	Alabama	AL	Cherokee	1019	Democrat	Bernie Sanders	268	0.249
21	Alabama	AL	Cherokee	1019	Democrat	Hillary Clinton	712	0.661
22	Alabama	AL	Chilton	1021	Democrat	Bernie Sanders	289	0.246
23	Alabama	AL	Chilton	1021	Democrat	Hillary Clinton	860	0.731

Dataset for Republicans-County Wise

280	Alabama	AL	Fayette	1057	Republican	Ted Cruz	1043	0.21
281	Alabama	AL	Franklin	1059	Republican	Ben Carso	388	0.093
282	Alabama	AL	Franklin	1059	Republican	Donald Tr	2155	0.515
283	Alabama	AL	Franklin	1059	Republican	John Kasic	107	0.026
284	Alabama	AL	Franklin	1059	Republican	Marco Ruk	562	0.134
285	Alabama	AL	Franklin	1059	Republican	Ted Cruz	892	0.213
286	Alabama	AL	Geneva	1061	Republican	Ben Carso	592	0.093
287	Alabama	AL	Geneva	1061	Republican	Donald Tr	3106	0.486
288	Alabama	AL	Geneva	1061	Republican	John Kasic	146	0.023
289	Alabama	AL	Geneva	1061	Republican	Marco Ruk	829	0.13
290	Alabama	AL	Geneva	1061	Republican	Ted Cruz	1517	0.237
291	Alabama	AL	Greene	1063	Republican	Ben Carso	19	0.07
292	Alabama	AL	Greene	1063	Republican	Donald Tr	147	0.538
293	Alabama	AL	Greene	1063	Republican	John Kasic	10	0.037
294	Alabama	AL	Greene	1063	Republican	Marco Ruk	33	0.121
295	Alabama	AL	Greene	1063	Republican	Ted Cruz	59	0.216
296	Alabama	AL	Hale	1065	Republican	Ben Carso	88	0.078
297	Alabama	AL	Hale	1065	Republican	Donald Tr	590	0.521
298	Alabama	AL	Hale	1065	Republican	John Kasic	24	0.021
299	Alabama	AL	Hale	1065	Republican	Marco Ruk	132	0.117
300	Alabama	AL	Hale	1065	Republican	Ted Cruz	283	0.25
301	Alabama	AL	Henry	1067	Republican	Ben Carso	436	0.115
302	Alabama	AL	Henry	1067	Republican	Donald Tr	1778	0.468

Twitter Dataset

- Created using the tweets in twitter
- Extracted using open source real time Twitter Scraper and python
- Hashtags used are #Hillary, #Trump, #USelection2016
- Targeted handles : @realdonaldtrump and @hillaryclinton
- Total of 3 attributes and 2219 instances of trump tweets
- Total of 3 attributes and 5001 instances of Hillary tweets

Tweet Dataset for Trump

	created_at	text						
7.94E+17	01-11-2016 22.53	RT @bfraser747: δΥ'¥δΥ'¥ #Abortion						
7.94E+17	01-11-2016 22.53	RT @mmpadellan: OH SNAP! Ladies on "The View" working it OUT!						
7.94E+17	01-11-2016 22.53	Bill Clinton was impeached on two charges: perjury and obstruction of justice.						
7.94E+17	01-11-2016 22.53	#TedCruz casts early ballot and votes #TRUMP #CruzCrew https://t.co/X2syBHkasV						
7.94E+17	01-11-2016 22.53	Ce que #Trump a dit...						
7.94E+17	01-11-2016 22.53	RT @ResistTyranny: Three reasons why #Trump will be a GREAT President:						
7.94E+17	01-11-2016 22.53	RT @johneric2004: There Are Pro-Trump Planes Flying Around Center City Philly #Trump						
7.94E+17	01-11-2016 22.53	@realDonaldTrump #Trump lied about giving to 9/11 fund https://t.co/Lj0CzqhZw5 #NeverTrump						
7.94E+17	01-11-2016 22.53	RT @mmpadellan: OH SNAP! Ladies on "The View" working it OUT!						
7.94E+17	01-11-2016 22.53	Check out this cartoon! The REAL #Trump Tower... @JeffSantosShow @buell003 @seattletimes @SeattleBernie #hillaryâ€¦ https://t.co/nk9WrkOuC3						
7.94E+17	01-11-2016 22.53	From the abuse I've seen and gotten on Twitter from #Trump folks I think its hostility to all "others" as well asâ€¦ https://t.co/gNUSHXNWX7						
7.94E+17	01-11-2016 22.53	*sigh* Listen here if you have any questions about how #Dangerous #Trump is... https://t.co/fj6RcaFpDB https://t.co/FQL7nuK0A4						
7.94E+17	01-11-2016 22.53	Trump says he knows more about war then generals #USA2016 #Trump https://t.co/VxzQpp2luo						
7.94E+17	01-11-2016 22.53	RT @esneet4113: WTF? #Trump IS IN TROUBLE!! Judge orders RNC to detail voter fraud pacts with Trump campaign https://t.co/7POGp5Pwn1						
7.94E+17	01-11-2016 22.53	RT @SS9Jonathan: Je kiff @OFNIW9 avec @steevy_boulay #C'estPasUneBoiteAPute 20\20 la vanne #OFNI #Trump						
7.94E+17	01-11-2016 22.53	RT @CorrectRecord: There's really no comparison between the #Trump and Clinton Foundations. https://t.co/Qy2ynv0bDU						
7.94E+17	01-11-2016 22.53	RT @JohnLeguizamo: Sorry a vote for #JillStein is a vote for #trump. U r being cavalier w th future of our country @SusanSarandon @MarkRuffâ€¦						
7.94E+17	01-11-2016 22.53	RT @Amaka_Ekwo: President #Trump https://t.co/CPXSHfi1U						
7.94E+17	01-11-2016 22.53	RT @tombermanap: Unpopularity of #Trump & #Arpaio with #Latinos could be key in #Arizona #election results. https://t.co/NKZJtpfh60 #hispanâ€¦						
7.94E+17	01-11-2016 22.53	RT @BethWeber1: Are you Jewish? A vote for #Trump is a vote for the most antisemitic candidate in our lifetime. #NeverForget what we haveâ€¦						
7.94E+17	01-11-2016 22.53	RT @DeFotis: #Mexico: For Peso, Oil Matters More Than #Trump https://t.co/4GQGKWN1rC #EmergingMarket #energy #Pemex \$EWW #currency @barron:						
7.94E+17	01-11-2016 22.53	RT @ElectionLawCtr: #Trump now beating #Hillary in #iowa #ohio and #Florida. #gators #hawkeyes #cyclones #buckeyes #seminoles #bengals #indâ€¦						





Tweet Dataset for Hillary

id	created_at	text
7.94E+17	01-11-16 19:40	Iraqi Army Officials Discover US-Made Missiles in ISIS's Military Base in Mosul #Clinton2016 https://t.co/pccDXsN7SG
7.94E+17	01-11-16 19:35	RT @chrischilds911: â #NAZI â ITEMS W/#SWASTIKA ON #EBAY! Visit: https://t.co/l5g7mPXP6j @eBay #Trump2016 #Trump #Republicans #Clinton2016â
7.94E+17	01-11-16 19:28	Even the @mike_pence rally was bigger. #clinton2016 #MAGA #lockherupðŸ¸ðŸ¸, @ Sanford Civic Center https://t.co/OUd2PSvoJT
7.94E+17	01-11-16 19:24	Remember back when Sarah Palin was the rock bottom of the Republican candidate barrel? #lovetrumpshate #Clinton2016
7.94E+17	01-11-16 19:16	The #HillaryClinton lemmings and suckers heading to jump off the #Clinton2016 cliff. https://t.co/CuyBQwyYKU
7.94E+17	01-11-16 18:52	Hoy Washington Post publica sondeo nacional que sitÃa a #TrumpPence2016 un punto por delante de #Clinton2016 46-45 https://t.co/fr1RkA2GZF
7.94E+17	01-11-16 18:39	RT @chrischilds911: â #NAZI â ITEMS W/#SWASTIKA ON #EBAY! Visit: https://t.co/l5g7mPXP6j @eBay #Trump2016 #Trump #Republicans #Clinton2016â
7.94E+17	01-11-16 18:27	RT @chrischilds911: â #NAZI â ITEMS W/#SWASTIKA ON #EBAY! Visit: https://t.co/l5g7mPXP6j @eBay #Trump2016 #Trump #Republicans #Clinton2016â
7.94E+17	01-11-16 18:19	RT @raixvenignacia: I just made the irrational decision and voted for #clinton2016 yes I'm that dumb
7.94E+17	01-11-16 18:17	@nytimesworld We are NOT #TrumpPoison. We are a nation of diversity & we are #StrongerTogether. We will survive this nightmare. #Clinton2016
7.94E+17	01-11-16 18:16	RT @countryqueen623: Still waiting for EVEN ONE reason #HillaryClinton #HillYes #ImWithHer #Clinton2016 #ClintonKaine #Hillary #Trump2016 #â
7.94E+17	01-11-16 18:10	#GetOutandVote #ImWithHer #Clinton2016 #MadamPresident #VoteBlueDownBallot #DontBeComplacent #UniteBlueâ https://t.co/1anSXR6NtV
7.94E+17	01-11-16 18:01	Poor WikiDrips and the Original G #Putin they thought they could bring @HillaryClinton down! fuck both of them! #Clinton2016
7.94E+17	01-11-16 17:59	RT @chrischilds911: â #NAZI â ITEMS W/#SWASTIKA ON #EBAY! Visit: https://t.co/l5g7mPXP6j @eBay #Trump2016 #Trump #Republicans #Clinton2016â
7.94E+17	01-11-16 17:47	Unintended campaign slogan of the day (...or of the campaign)... #Clinton2016 https://t.co/r7e0QExuEM
7.94E+17	01-11-16 17:44	@SophiaBush is going off with her retweets! #Clinton2016
7.94E+17	01-11-16 17:36	I just made the irrational decision and voted for #clinton2016 yes I'm that dumb
7.94E+17	01-11-16 17:30	Good information. We faced intimidation when we were voting. It's happening everywhere. Be vigilant and determined!â https://t.co/b3wLmoUBlg
7.94E+17	01-11-16 17:25	Look at how many people are here, he said sarcastically. #clinton2016 #election2016 #MAGAâ https://t.co/uexPDKWg6v
7.94E+17	01-11-16 17:21	On it! #imwithHer #soishe #clinton2016 https://t.co/BoBFBIg8E
7.94E+17	01-11-16 17:15	@realDonaldTrump #Clinton2016 #TrumpPence2016 30 yrs corruption, collusion and controversy is more than enough
7.93E+17	01-11-16 16:58	@GOPPollAnalyst @Trump_nc madnes did the email come from Hillary or her ppl? READ! ðŸ¸ #ImWithHer #HillaryClinton #clinton2016 #StillWithHer #

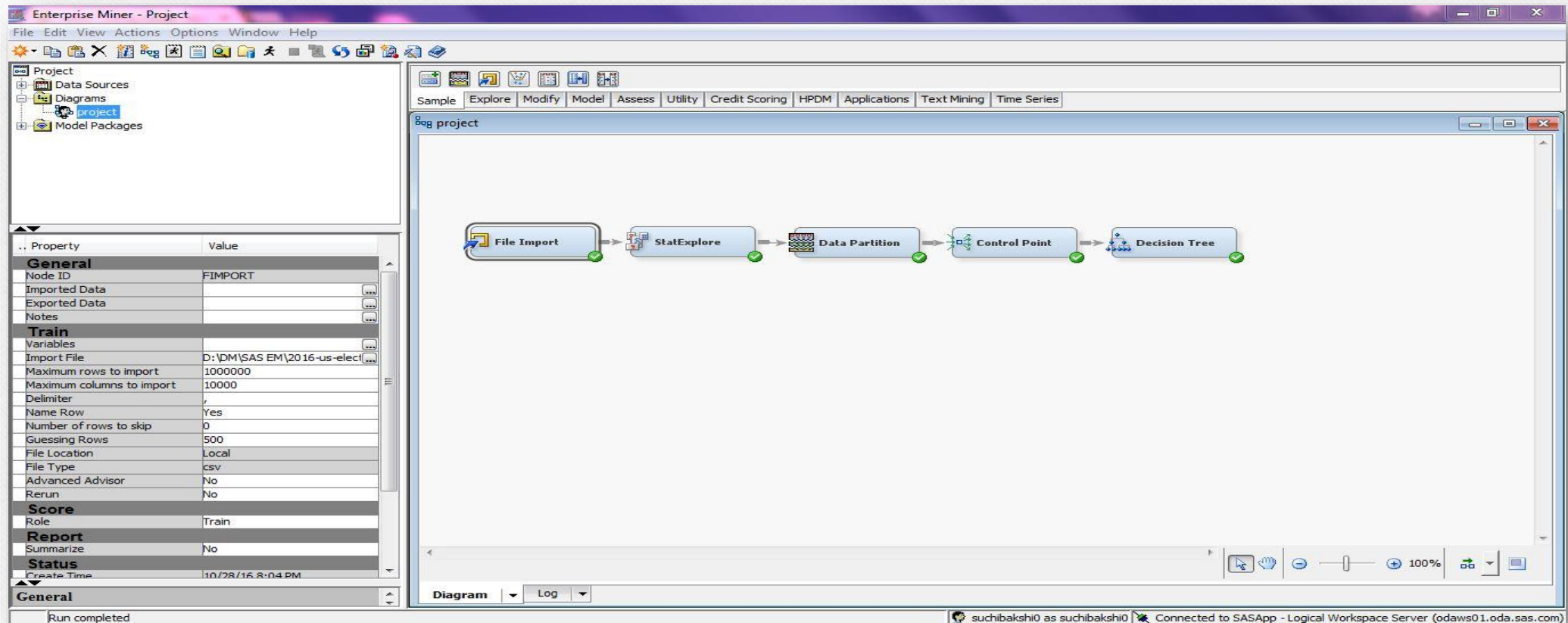
Objective 1

**Predicting the election result from
primary results**

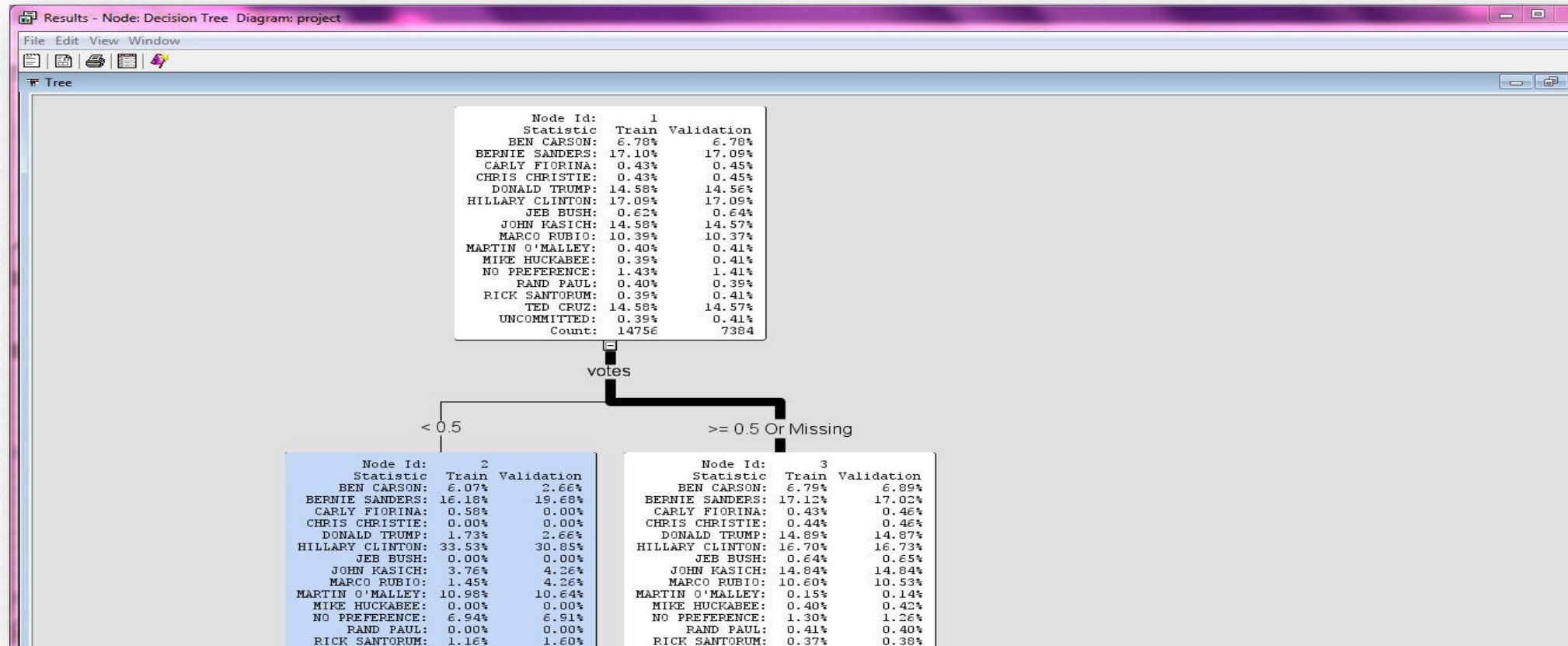
Data Partition

General	
Node ID	Part
Imported Data	
Exported Data	
Notes	
Train	
Variables	
Output Type	Data
Partitioning Method	Default
Random Seed	12345
<input type="checkbox"/> Data Set Allocations	
Training	60.0
Validation	30.0
Test	10.0
Report	
Interval Targets	Yes
Class Targets	Yes
Status	
Create Time	10/28/16 8:05 PM
Run ID	7011321e-03fb-1940-a7ce-70f1
Last Error	
Last Status	Complete
Last Run Time	11/1/16 8:15 PM

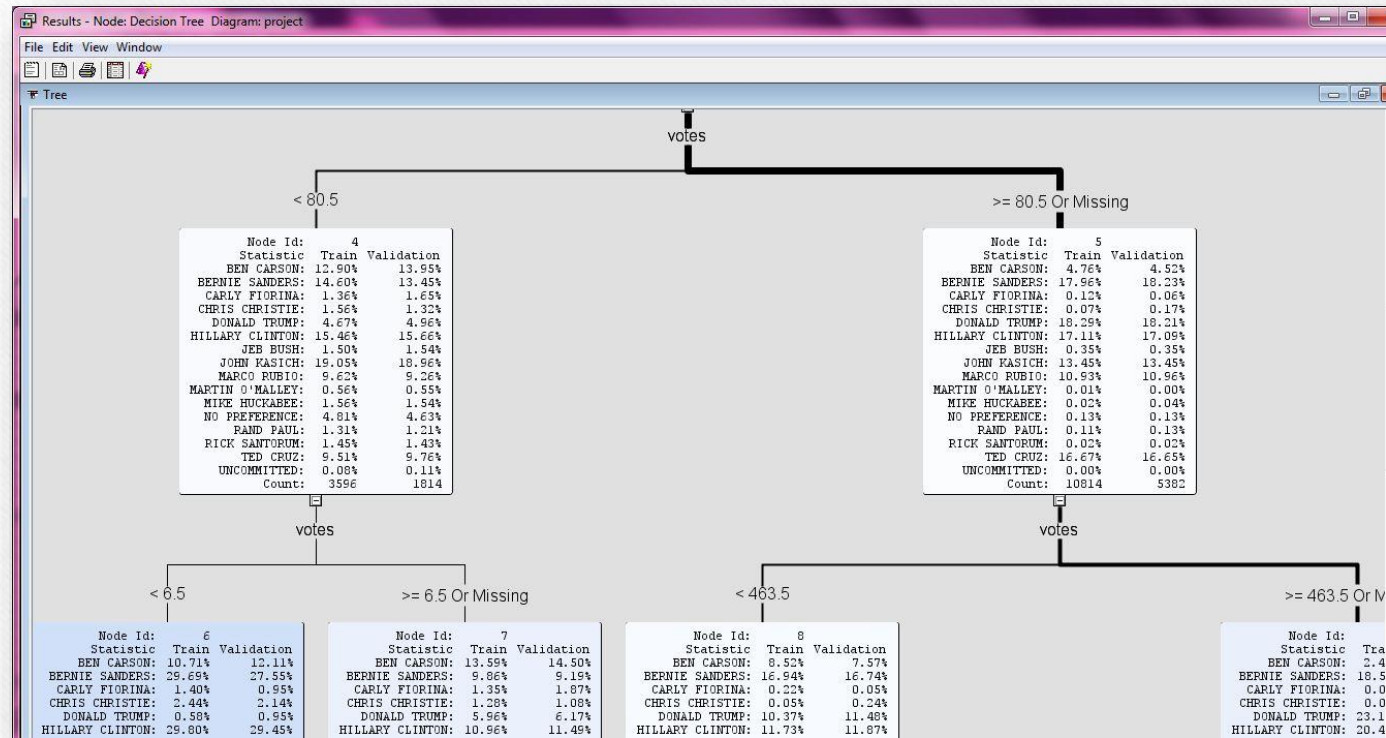
Decision Tree Model



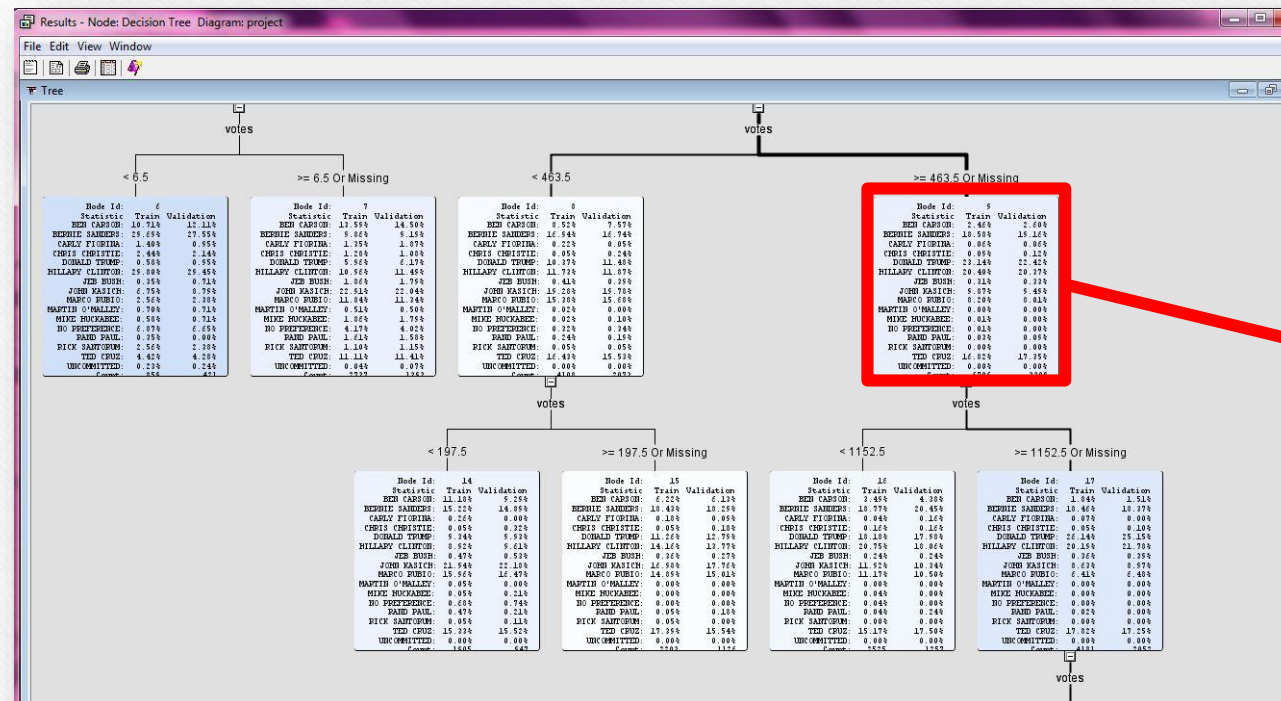
Decision Tree Output



Decision Tree Output - contd.



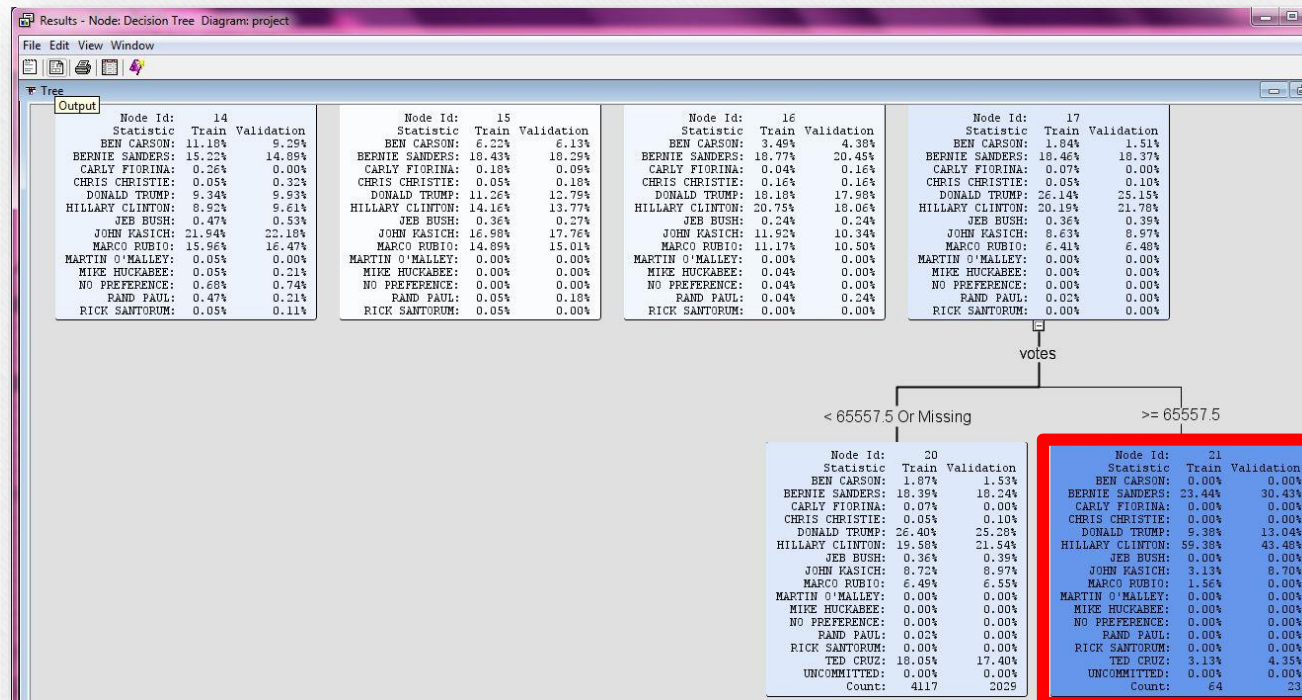
Decision Tree Output - contd.



>= 463.5 Or Missing

Node Id:	9	
Statistic	Train	Validation
BEN CARSON:	2.46%	2.60%
BERNIE SANDERS:	10.50%	10.16%
CARLY FIORINA:	0.06%	0.06%
CHRIS CHRISTIE:	0.05%	0.12%
DONALD TRUMP:	23.14%	22.42%
HILLARY CLINTON:	20.40%	20.37%
JEB BUSH:	0.31%	0.32%
JOHN KASICH:	9.87%	9.49%
MARCO RUBIO:	8.20%	8.01%
MARTIN O'MALLEY:	0.00%	0.00%
MIKE HUCKABEE:	0.01%	0.00%
NO PREFERENCE:	0.01%	0.00%
PAUL PAUL:	0.03%	0.05%
RICK SANTORUM:	0.00%	0.00%
TED CRUZ:	16.02%	17.35%
UNCOMMITTED:	0.00%	0.00%
Count:	6206	2200

Decision Tree Output - contd.



>= 65557.5

Node Id:	21
Statistic	Train Validation
BEN CARSON:	0.00% 0.00%
BERNIE SANDERS:	23.44% 30.43%
CARLY FIORINA:	0.00% 0.00%
CHRIS CHRISTIE:	0.00% 0.00%
DONALD TRUMP:	9.38% 13.04%
HILLARY CLINTON:	59.38% 43.48%
JEB BUSH:	0.00% 0.00%
JOHN KASICH:	3.13% 8.70%
MARCO RUBIO:	1.56% 0.00%
MARTIN O'MALLEY:	0.00% 0.00%
MIKE HUCKABEE:	0.00% 0.00%
NO PREFERENCE:	0.00% 0.00%
RAND PAUL:	0.00% 0.00%
RICK SANTORUM:	0.00% 0.00%
TED CRUZ:	3.13% 4.35%
UNCOMMITTED:	0.00% 0.00%
Count:	64 23

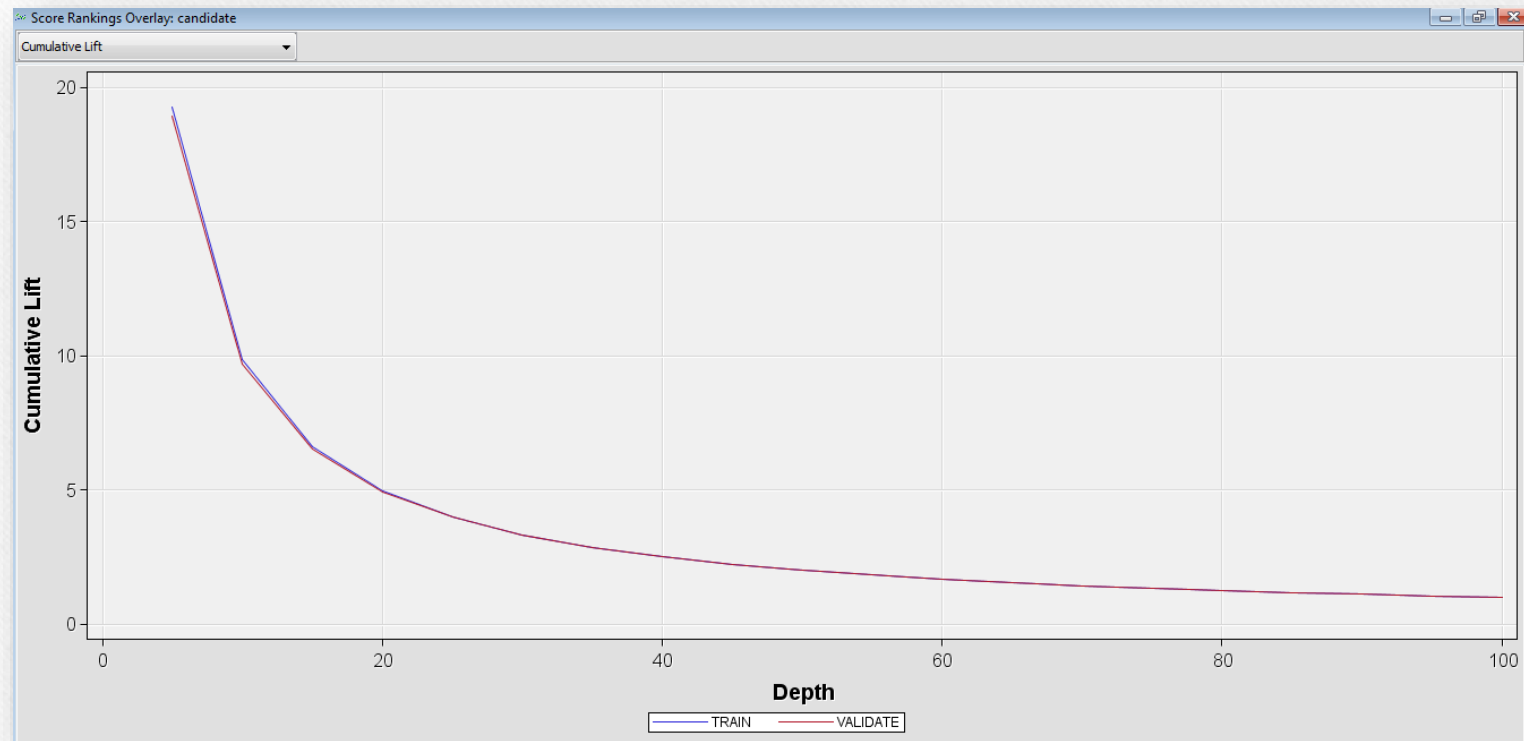
Decision Tree - Statistics

Fit Statistics

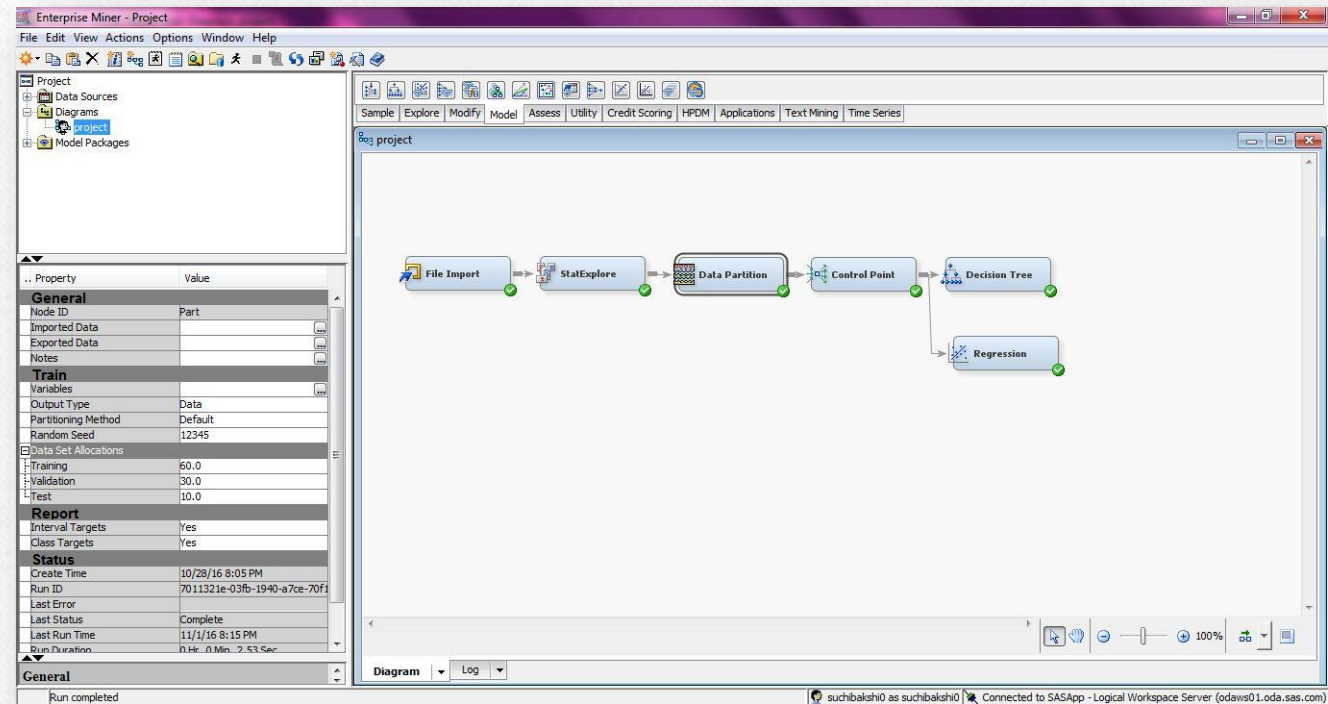
Target=candidate Target Label=' '

Fit Statistics	Statistics Label	Train	Validation	Test
NOBS	Sum of Frequencies	14756.00	7384.00	2471.00
MISC	Misclassification Rate	0.76	0.78	0.78
MAX	Maximum Absolute Error	1.00	1.00	1.00
SSE	Sum of Squared Errors	12349.65	6203.76	2077.66
ASE	Average Squared Error	0.05	0.05	0.05
RASE	Root Average Squared Error	0.23	0.23	0.23
DIV	Divisor for ASE	236096.00	118144.00	39536.00
DFT	Total Degrees of Freedom	221340.00	.	.

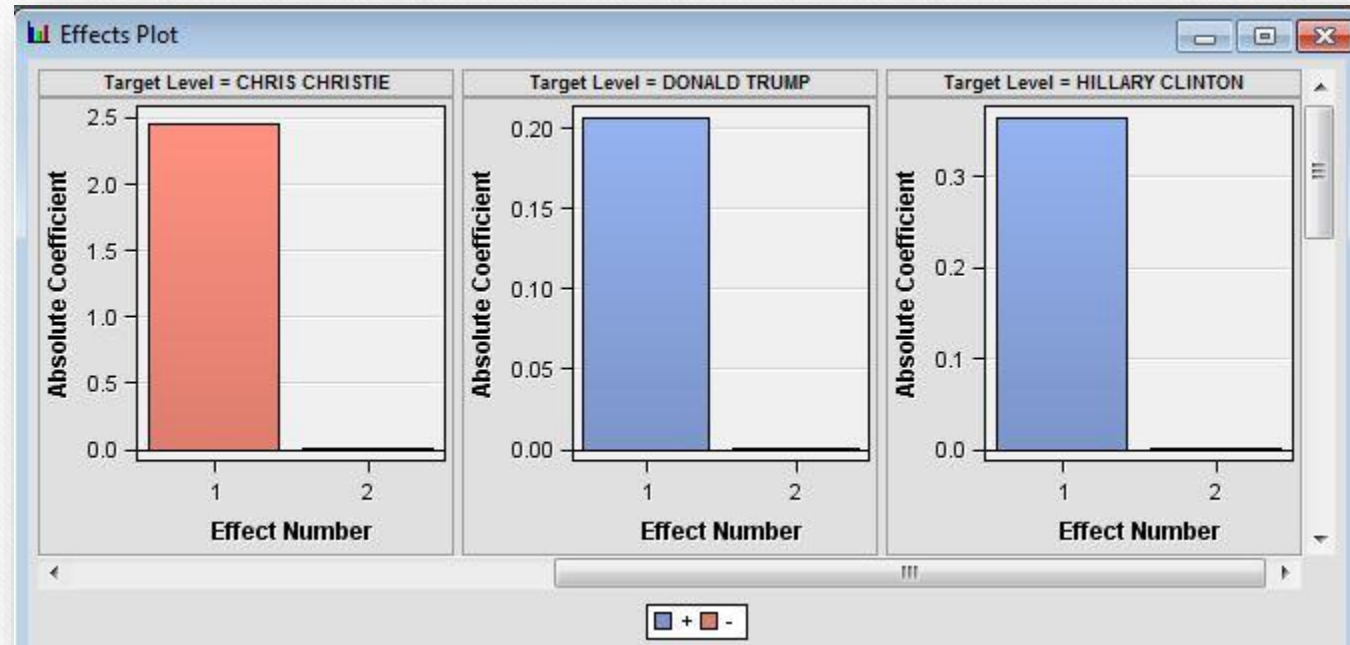
Decision Tree- Lift Curve



Regression Model



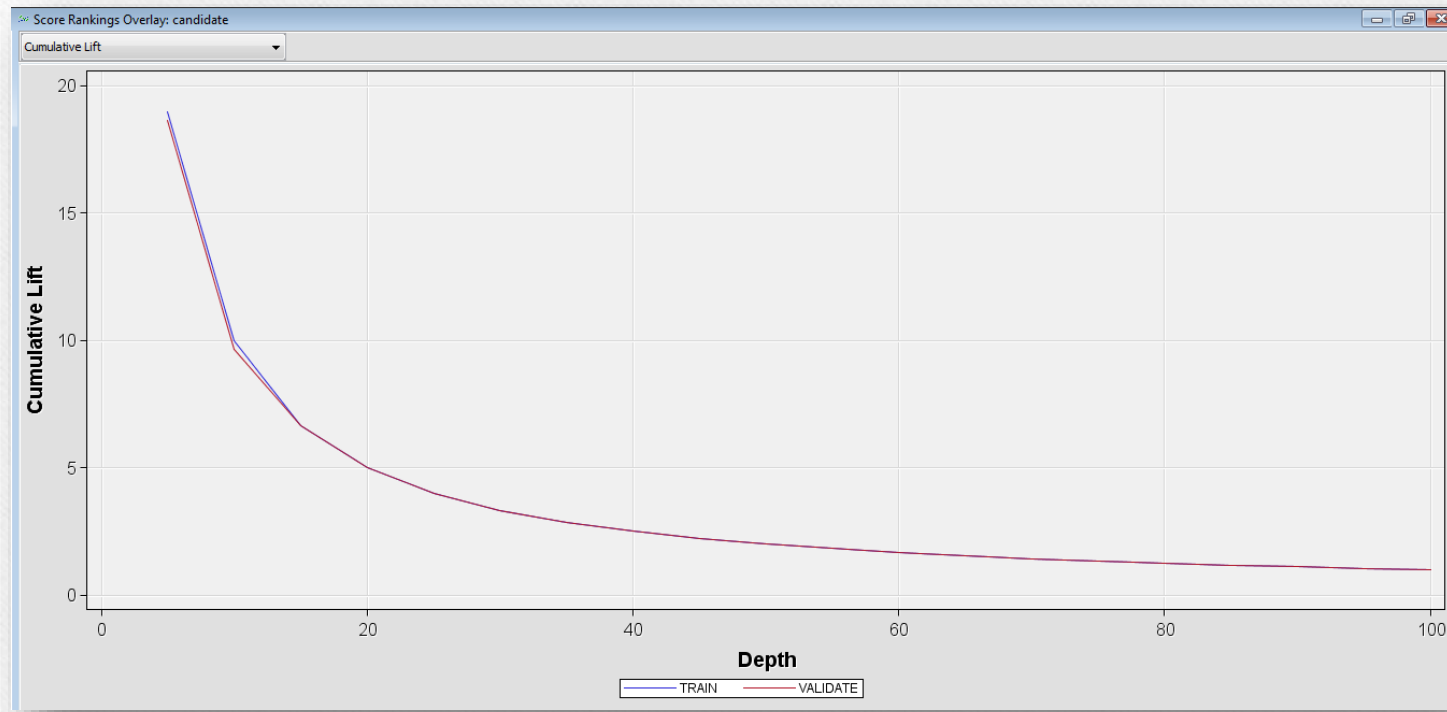
Regression Output



Regression – Statistics

Fit Statistics	Statistics Label	Train	Validation	Test
AIC	Akaike's Information Criterion	60171.62	.	.
ASE	Average Squared Error	0.05	0.05	0.05
AVERR	Average Error Function	0.25	0.25	0.26
DFE	Degrees of Freedom for Error	221310.00	.	.
DFM	Model Degrees of Freedom	30.00	.	.
DFT	Total Degrees of Freedom	221340.00	.	.
DIV	Divisor for ASE	236096.00	118144.00	39536.00
ERR	Error Function	60111.62	30089.40	10091.39
FPE	Final Prediction Error	0.05	.	.
MAX	Maximum Absolute Error	1.00	1.00	1.00
MSE	Mean Square Error	0.05	0.05	0.05
NOBS	Sum of Frequencies	14756.00	7384.00	2471.00
NW	Number of Estimate Weights	30.00	.	.
RASE	Root Average Sum of Squares	0.23	0.23	0.23
RFPE	Root Final Prediction Error	0.23	.	.
RMSE	Root Mean Squared Error	0.23	0.23	0.23
SBC	Schwarz's Bayesian Criterion	60480.84	.	.
SSE	Sum of Squared Errors	12611.40	6310.49	2116.60
SUMW	Sum of Case Weights Times Freq	236096.00	118144.00	39536.00
MISC	Misclassification Rate	0.83	0.83	0.83

Regression – Lift Curve



Model Comparison

- According to the results, Decision tree is preferred over Regression
- Comparison performed over factors -
 - Lift-curve graphs
 - Statistics

Objective 2

**Predicting the election result from
sentimental analysis of 'Tweets'**

Twitter Scraped Data

The screenshot displays a data analysis application with a central table of Twitter data and a sidebar repository.

ExampleSet (1793 examples, 0 special attributes, 3 regular attributes)

Filter (1,793 / 1,793 examples): all

Row No.	id	created_at	text
1	7.93526E+17	01-11-2016 1...	We can wait f...
2	7.93526E+17	01-11-2016 1...	RT @vivelafra...
3	7.93526E+17	01-11-2016 1...	RT @slava38...
4	https://tâ€	?	?
5	7.93526E+17	01-11-2016 1...	RT @slava38...
6	7.93526E+17	01-11-2016 1...	?
7	7.93526E+17	01-11-2016 1...	RT @slava38...
8	7.93526E+17	01-11-2016 1...	RT @Stonew...
9	7.93526E+17	01-11-2016 1...	Make Salmon...
10	7.93526E+17	01-11-2016 1...	@JohnKasic...
11	7.93526E+17	01-11-2016 1...	RT @shad0w...
12	7.93526E+17	01-11-2016 1...	RT @cash_...
13	7.93526E+17	01-11-2016 1...	RT @slava38...
14	7.93526E+17	01-11-2016 1...	RT @vivelafra...
15	7.93526E+17	01-11-2016 1...	@carlquintan...
16	7.93526E+17	01-11-2016 1...	RT @slava38...

Repository

- ➕ Add Data
- 📁 Samples
- 📁 DB
- 📁 DM Project (ASUS)
 - 📁 Clinton (ASUS)
 - 📁 Hillary (ASUS)
 - 📄 Hillary (ASUS - v1, 11/13/16 9:58 PM)
 - 📁 Process (ASUS)
 - 📁 Trump 2016 Data (ASUS)
 - 📁 Trump Data (ASUS)
 - 📁 hillary2 (ASUS)
 - 📁 trump2 (ASUS)
 - 📄 #Trump2016_tweets (ASUS - v1, 11/13/16 9:58 PM)
- 📁 Data Mining Project (ASUS)
- 📁 Local Repository (ASUS)
- 📁 demo1 (ASUS)
- 📁 demo2 (ASUS)
- 📁 demo3 (ASUS)
 - 📁 Data (ASUS)
 - 📁 Process (ASUS)
- 📁 demo4 (ASUS)
- 📁 demos2 (ASUS)

```
1 import tweepy
2 import csv
3
4 #Twitter API credentials
5 consumer_key = "M4YE494z0hnnMgsyMfrQVoRgy"
6 consumer_secret = "fGL4tqw2Jmdqp0bLkXxIA7f3ZtWIAshn8Grdne1ibSTfsX3m2"
7 access_key = "1693425644-piiUDKvYv8P6Gug5KJzC85wvp3Lk4m611oarE0EU"
8 access_secret = "MTu308VvYsJwY2Uv0V1cmVev000jYZNLfDnVgqkq80SS"
9
10 def get_all_tweets(screen_name):
11     #Twitter only allows access to a users most recent 3240 tweets with this method
12
13     #authorize twitter, initialize tweepy
14     auth = tweepy.OAuthHandler(consumer_key, consumer_secret)
15     auth.set_access_token(access_key, access_secret)
16     api = tweepy.API(auth)
17
18     #initialize a list to hold all the tweepy Tweets
19     alltweets = []
20
21     #make initial request for most recent tweets (200 is the maximum allowed count)
22     new_tweets = api.search(q = screen_name,count=100)
23
24     #save most recent tweets
25     alltweets.extend(new_tweets)
26
27     #save the id of the oldest tweet less one
28     oldest = alltweets[-1].id - 1
29
30     #keep grabbing tweets until there are no tweets left to grab
31
32     i=0
33     while (i<150):
34         print "getting tweets before %s" % (oldest)
35
36         #all subsequent requests use the max_id param to prevent duplicates
37         new_tweets = api.search(q = screen_name,count=100,max_id=oldest)
38
39         #save most recent tweets
40         alltweets.extend(new_tweets)
41
42         #update the id of the oldest tweet less one
```

Line 62, Column 27

Tab Size: 4

Python

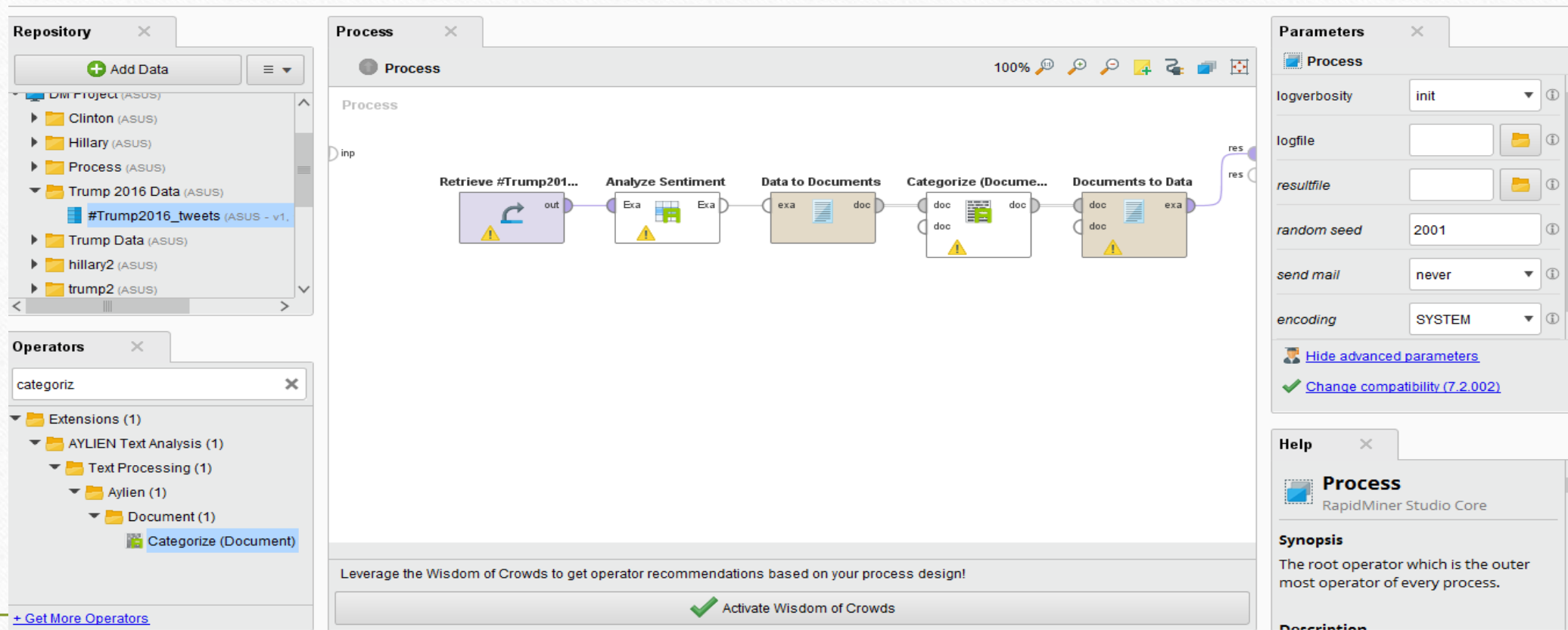
```
31
32
33
34     print "getting tweets before %s" % (oldest)
35
36     #all subsequent requests use the max_id param to prevent duplicates
37     new_tweets = api.search(q = screen_name,count=100,max_id=oldest)
38
39     #save most recent tweets
40     alltweets.extend(new_tweets)
41
42     #update the id of the oldest tweet less one
43     oldest = alltweets[-1].id - 1
44     i+=1
45
46     print "...%s tweets downloaded so far" % (len(alltweets))
47
48     #transform the tweepy tweets into a 2D array that will populate the csv
49     outtweets = [[tweet.id_str, tweet.created_at, tweet.text.encode('utf-8')] for tweet in alltweets]
50
51     #write the csv
52     with open('%s tweets.csv' % screen_name, 'wb') as f:
53         writer = csv.writer(f)
54         writer.writerow(["id","created_at","text"])
55         writer.writerows(outtweets)
56
57     pass
58
59
60 if __name__ == '__main__':
61     #pass in the username of the account you want to download
62     get_all_tweets("trump")
63
```

Line 62, Column 27

Tab Size: 4

Python

Model used for Sentiment Analysis



Result

ExampleSet (Retrieve #Trump2016_tweets)

ExampleSet (6206 examples, 4 special attributes, 3 regular attributes)

Filter (3,349 / 6,206 examples): no_missing_attrib...

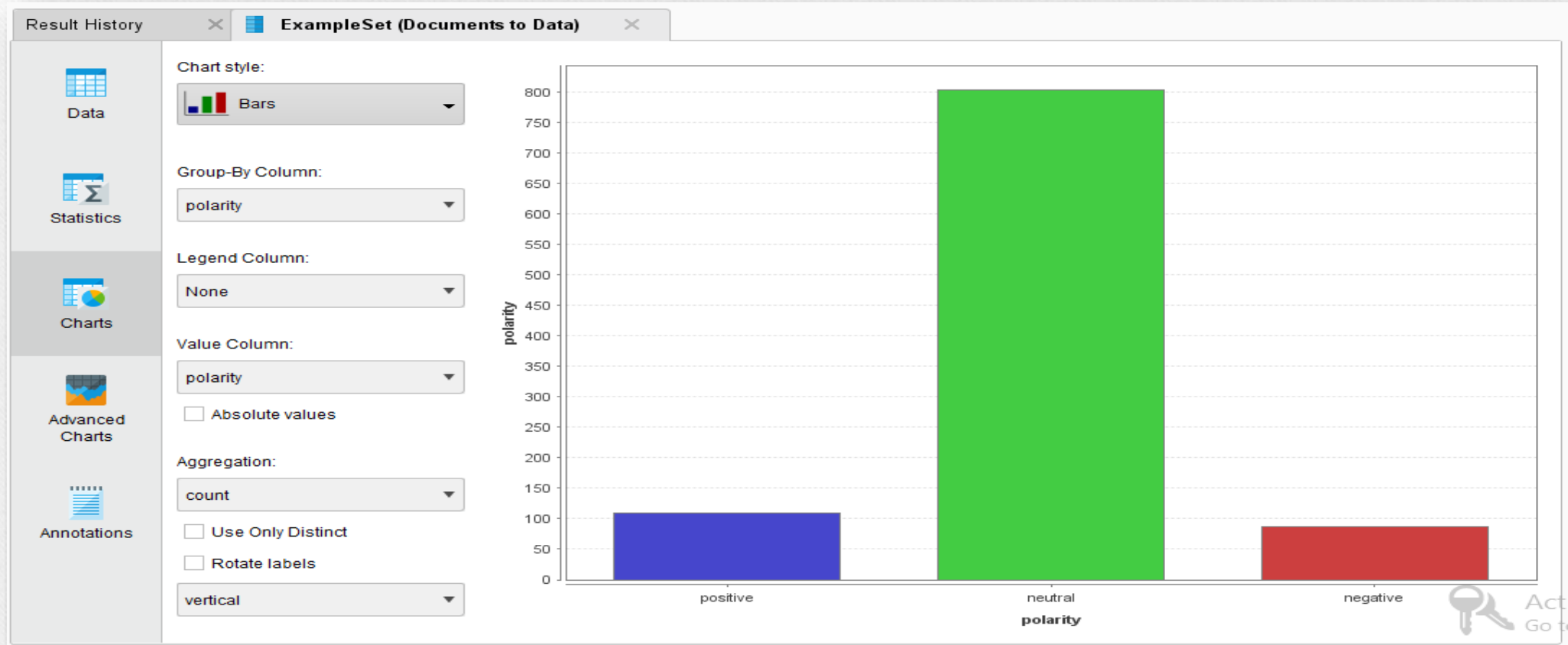
Row No.	polarity...	subjecti...	polarity	subjecti...	id	created...	text
1	0.913	0.993	positive	objective	7932119...	2016-10-...	RT @Ca...
2	0.461	1.000	neutral	objective	7932119...	2016-10-...	RT @jko...
3	0.828	1	neutral	subjective	7932119...	2016-10-...	RT @US...
4	0.509	1	neutral	subjective	7932119...	2016-10-...	@Gerile...
5	0.641	0.998	neutral	objective	7932119...	2016-10-...	RT @am...
6	0.828	1	neutral	subjective	7932119...	2016-10-...	RT @US...
7	0.980	0.999	neutral	objective	7932117...	2016-10-...	RT @dav...
8	0.688	0.901	neutral	objective	7932117...	2016-10-...	Trump g...
9	0.464	1	positive	objective	7932117...	2016-10-...	Brand ne...
10	0.813	1.000	neutral	objective	7932117...	2016-10-...	RT @am...
11	0.828	1	neutral	subjective	7932117...	2016-10-...	RT @US...
12	0.416	1	neutral	subjective	7932116...	2016-10-...	I'm votin...
13	0.828	1	neutral	subjective	7932116...	2016-10-...	RT @US...
14	0.761	0.741	negative	objective	7932115...	2016-10-...	RT @IA...
15	0.461	1.000	neutral	objective	7932115...	2016-10-...	RT @jko...
16	0.422	1.000	neutral	objective	7932115...	2016-10-...	@Hillary...
17	0.882	0.548	positive	objective	7932115...	2016-10-...	@shells...

Repository

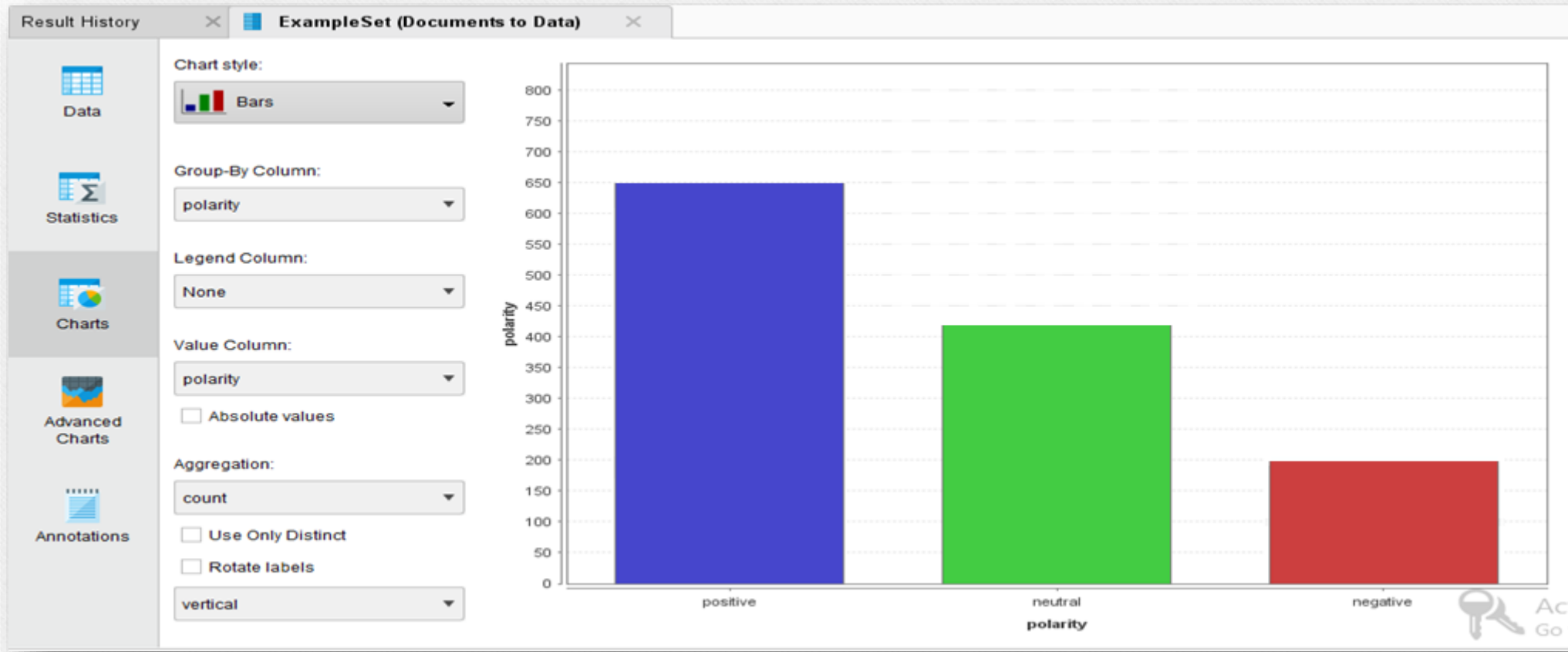
- Samples
- DB
- DM Project (ASUS)
 - Data (ASUS)
 - #Trump2016_tweets (ASUS - v1, 11/1...
 - Process (ASUS)
 - test (ASUS - v1, 11/4/16 4:32 PM - 2 kB)
- Local Repository (ASUS)
 - demo1 (ASUS)
 - demo2 (ASUS)
 - demo3 (ASUS)
 - demo4 (ASUS)
 - demos2 (ASUS)
- Cloud Repository (disconnected)

Activate Windows
Go to PC settings to activate Windows.

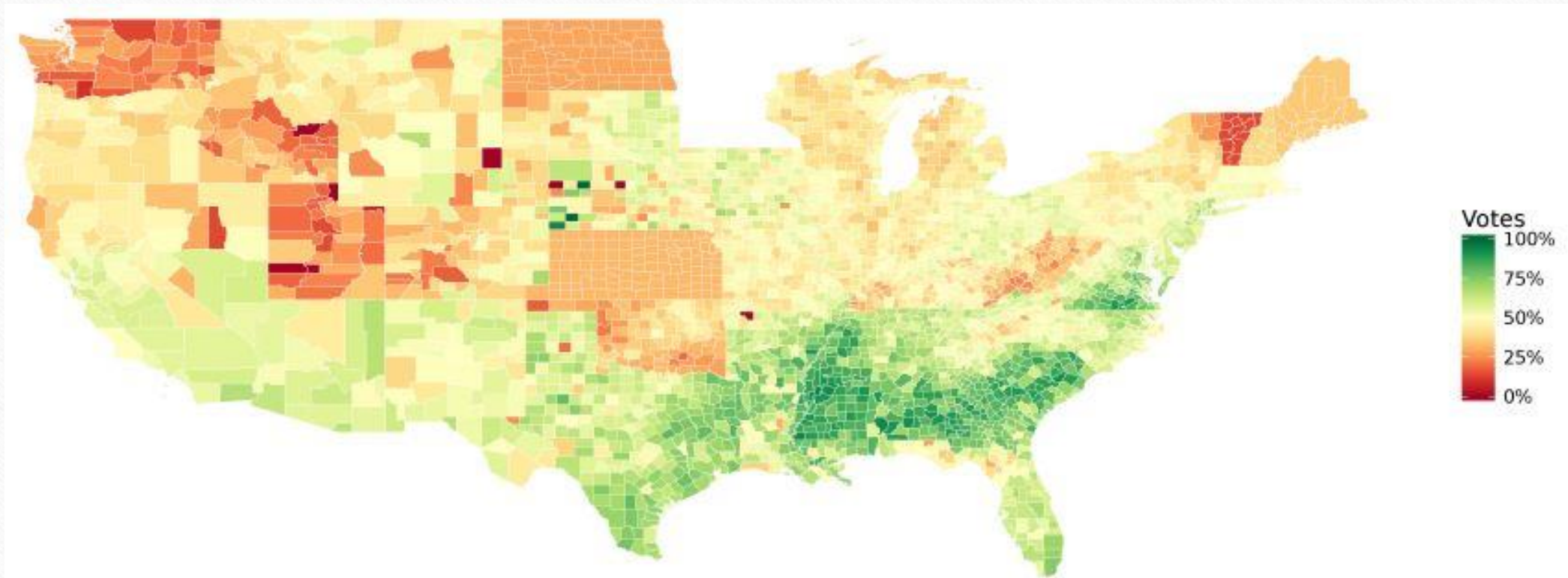
Trump – Tweets Sentiments



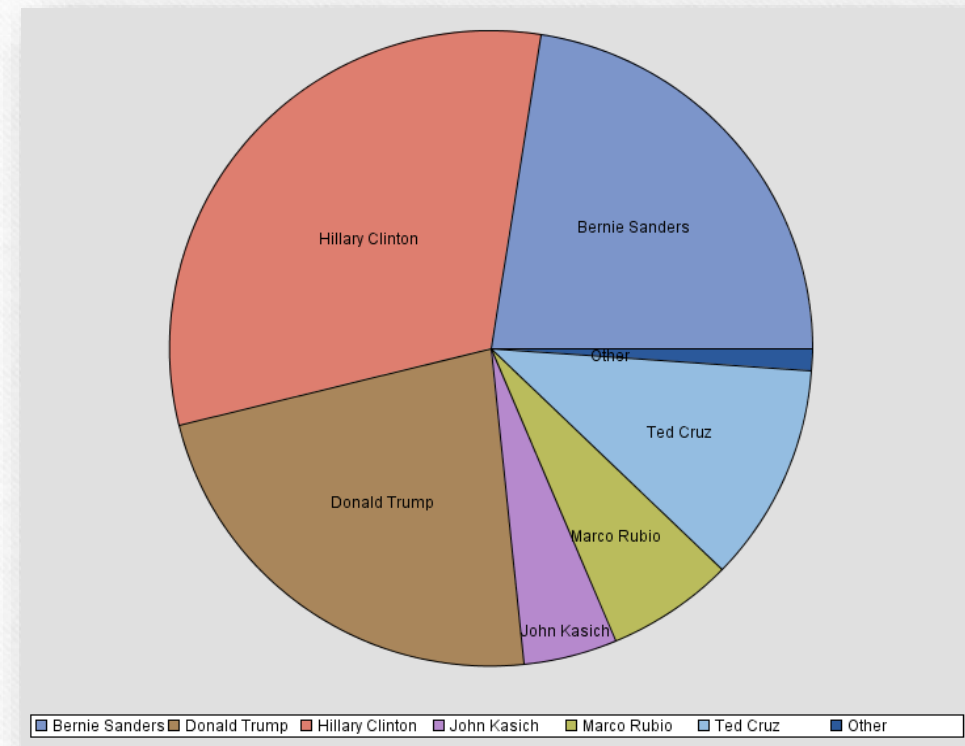
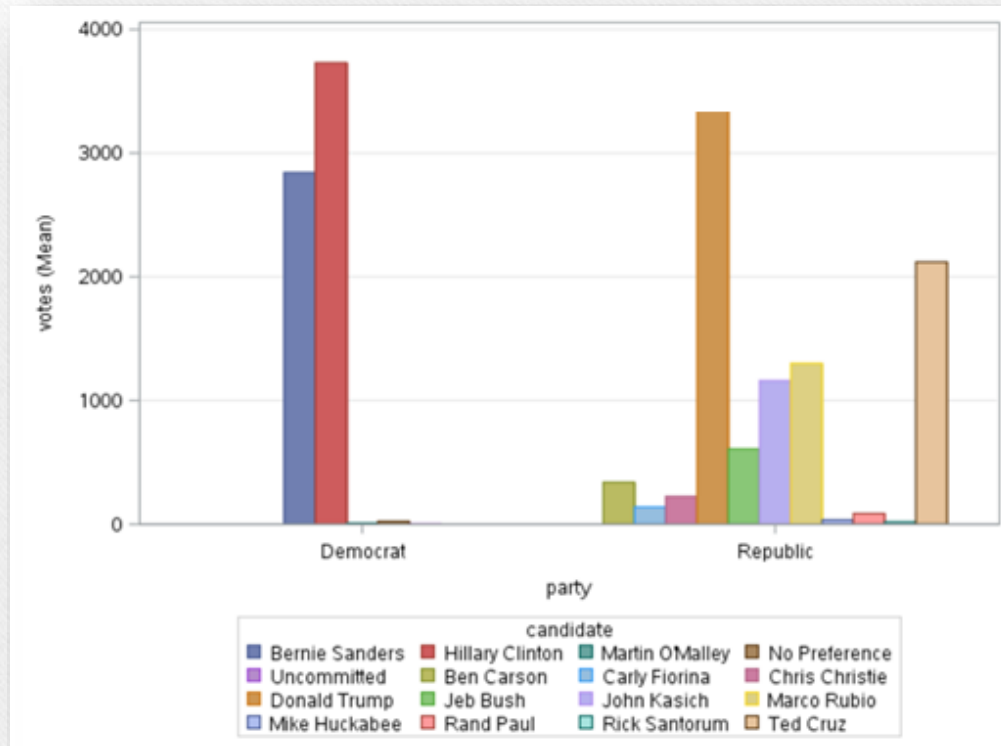
Hillary – Tweets Sentiments



Primary Votes distribution - Hillary



Visualization

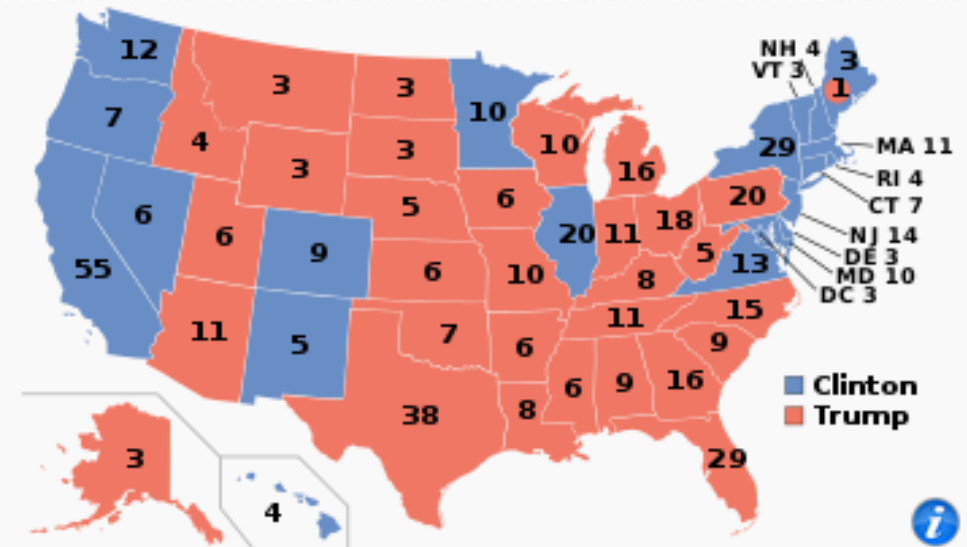


Analysis

- ❑ As per the Decision Tree and Regression Models, we can see Hillary is leading with greater number of votes.
- ❑ Tweeter data sets the trend showed, Trump had higher tweets mentioned about media and Hillary had more policy focused keywords.
- ❑ Trump tweets had an overall neutral sentiments.
- ❑ Hillary had higher tweets for positive sentiments.

Actual Election Results' 2016

Nominee	Donald Trump	Hillary Clinton
Party	Republican	Democratic
States carried	30 +	20 +
Popular vote	60,350,24	60,981,118
Percentage	47.30%	47.79%



Conclusion

- ❑ Comparing to Actual results and Data mining results,
 - Clinton received more number of votes (Predictive model)
 - Clinton received positive sentiments;
but fell short on media engagement (Text Mining)
 - Trump overall received negative sentiments;
but he was actively engaged (Text Mining)