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IMPROVING PREDICTION OF STOCK MARKET INDICES BY ANALYZING THE PSYCHOLOGICAL STATES OF TWITTER USERS

In our paper, we analyze the possibility of improving the prediction of stock market indicators by conducting a sentiment analysis of Twitter posts. We use a dictionary-based approach for sentiment analysis, which allows us to distinguish eight basic emotions in the tweets of users. We compare the results of applying the Support Vector Machine algorithm trained on three sets of data: historical data, historical and “Worry”, “Fear”, “Hope” words count data, historical data and data on the present eight categories of emotions. Our results suggest that the Twitter sentiment analysis data provides additional information and improves prediction as compared to a model based solely on information on previous shifts in stock indicators.

JEL Classification: G17, G02

Keywords: stock market; forecast; Twitter; mood; psychological states; Support Vectors Machine; machine learning,

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Introduction

Predicting financial markets is an interesting task from both practical and theoretical perspectives. By offering users a wide range of opportunities to express themselves, new information technologies make publicly available a huge amount of data about the emotions, moods, and psychological states of Internet citizens. In the U.S.A., which has a profound influence on the global economy, the Internet penetration rate is 78.3%, and active Internet users are also active financially. We think, therefore, that Twitter is a major additional resource of information that may help us improve forecasts of financial market. Although this idea was formulated several years ago, there is still no coherent opinion as to how this could be done (Bollen, Mao, and Zeng, 2011).

Over the past few years, significant progress has been achieved in using Twitter as an additional source of information (O'Connor, Balasubramanyan, Routledge, and Smith, 2010; Paul, and Dredze, 2011; Ruiz, Hristidis, Castillo, Gionis, and Jaimes, 2012). Bollen et al. (2011) reported that analyzing the text content of daily Twitter feeds increased the accuracy of DJIA predictions up to 87.6%. Zhang, Fuehres, and Gloor (2001) analyzed Twitter posts to predict stock market indicators such as the DJIA, S&P500, NASDAQ, and VIX, and found a high negative correlation (0.726, significant at level $p<0.01$) between the Dow Jones index and the presence of the words "hope", "fear", and "worry" in tweets (Zhang, Fuehres, and Gloor, 2011).

Chen and Lazer demonstrated that, using the approach proposed by Bollen, Mao, and Zeng, it is possible to create a more profitable trading strategy, but in their paper they did not provide information about the accuracy of prediction (Chen, Ray, Lazer, and Marius, 2013).

Regarding the application of sentiment analysis as a money generator, we did not find examples of successful projects. Derwent Capital Markets, a hedge fund, was the first to try applying sentiment analysis data, but their attempt proved inefficient (Malakian, 2013). Later the fund was rebranded into DCM Capital and presented a sentiment-based trading platform to retail investors (Malakian, 2013). Since a second attempt delivered no better results, DCM Capital's CEO, Paul Hawtin, put the sentiment-based platform up for auction. Starting at $7.9 million, the auction closed with a winning bid of $186,000 (Malakian, 2013). Yet, in his article, Malakian admits that there is no evidence to conclude that the failure of Derwent Capital Markets was due to poor technology (Malakian, 2013). The question of the applicability of sentiment analysis for real business has yet to be investigated.

There are two signs suggesting that this story is unfinished. The first is that Dow Jones and NYSE Technologies became partners aiming to improve prediction accuracy (Malakian, 2013). Second, according to Seth McGuire, director of Asset Management and Financial Technology, a few funds are now purchasing Twitter analyses, and social media aggregator Gnip will be one of the first to catch shifts in sentiment and capitalize on the market's wild swings (Or, 2011).

This leads us to the main hypothesis of our research, which is that analyzing tweets increases the accuracy of predicting stock market indicators. It is worth noting that analyzing Twitter-usage reliability is no easy task, as analysis algorithms are proprietary and their direct evaluation is impossible. To test our main hypothesis, we had to accomplish the following tasks:

1. Download a representative amount of raw data from Twitter.
2. Develop a sentiment analysis algorithm based on a psychological classification of emotions.
3. Analyze the prediction accuracy for machine-learning algorithms using data obtained from market and sentiment analyses.

Methodology

In our research, we faced two challenges: Twitter sentiment analysis and a prediction of the stock market based on sentiment analysis information.

Twitter sentiment analysis

A sentiment analysis of tweets could be conducted by training machine-learning algorithms on human-developed gold standards (Pang, Lee, and Vaithyanathan, 2002), or by calculating word frequencies from specially compiled dictionaries, which can include a group of n-grams words. In its simplest form, the lexicon approach was used by Zhang, Fuehres, and Gloor, who measured the quantity of tweets with the words "hope", "worry", and "fear" (Zhang et al., 2011). As we implemented the lexicon approach in our study, we found its application to be much faster than applying machine-learning algorithms to sentiment analysis. It allowed us to analyze a huge amount of tweets within reasonable time: it took us less than two days to analyze 288 million Tweets.

First, we used a Brief Mood Introspection Scale, with 8 scales and 2 adjectives representing each mood state as the starting point in creating dictionaries (Mayer and Gaschke, 1988). We also added all the synonyms of the selected adjectives from the WordNet dictionary (Miller, 1995). For example, we measured the presence of an energetic state in tweets by the occurrence of the following words: *animate, animated, athletic, brisk, chipper, emphatic, enterprising, exuberant, fresh, lusty, passionate, robust, sprightly, spry, strenuous, strong, tireless, trenchant, warming party, honor, vote.*

In total, our dictionaries of emotional words consist of 217 words, allowing us to recognize eight psychological states. To recognize derived words like "happyyy" or “happpppppyyyyyyy”, we use not just an exact word form, but regular expressions. For example, the expression [hap*y*] is used for the word “happy”. The entire content of tweets was entirely transferred to the lower case before analysis.

Second, we tested the quality of the sentiment analysis by applying the developed algorithms to the gold standard of 270 tweets (created by a professional translator with a specialist degree in the English language). For the quality test we used the standard measures of recall, precision, and F-measure (Jurafsky and Martin, 2008).

$$Recall_{\mathrm{energetic}} = \frac{A}{A+C}, \tag{1}$$

where A is the amount of tweets correctly recognized as falling within the “energetic” class, and C is the amount of tweets unrecognized by our algorithm, but marked as inherent to this class in the gold standard.

$$Precision_{\mathrm{energetic}} = \frac{A}{A+B}, \tag{2}$$

where A is the amount of tweets correctly recognized as falling within the “energetic” class, and B is the amount of tweets recognized by our algorithm, but marked as not inherent to this class in the gold standard.

$$F - measure_{cal} = \frac{2}{\frac{1}{Precision_{calm}} + \frac{1}{Recall_{calm}}} \tag{3}$$

Tab. 1. Measurement of performance for sentiment analysis

	happy	loving	calm	energetic	fearful	angry	tired	sad
Recall	93%	87%	57%	63%	70%	77%	73%	80%
Precision	90%	84%	71%	63%	70%	79%	79%	89%
F-measure	92%	85%	63%	63%	70%	78%	76%	84%

The results demonstrated a sufficient level of accuracy, and the F-measure for all categories was higher than 63% (Chen, Ray, Lazer, and Marius, 2013). The F-measure varied between 63% for two categories (“calm” and “energetic”) and 92% (“happy”). The achieved level of classification accuracy helped us obtain a fast and reliable algorithm for sentiment analysis.

Machine learning algorithms for stock market prediction

To test our main hypothesis, we used the Support Vector Machine algorithm, which helped us to classify days according to shifts in stock market indices and use the created model for prediction. The Support Vector Machine was chosen as it demonstrated the best performance in our preliminary research.

In order to understand whether a sentiment analysis of tweets provides any additional information, we used the SVM algorithm on three datasets. The first dataset characterized the stock market over the three previous days and was termed the basic set (Basic). The second set was created by adding to the basic set a normalized number of tweets with the words “Worry”, “Hope”, and “Fear” (Basic&WHF). The third set was formed by adding a normalized number of tweets from each of eight categories of the following emotions: “happy”, “loving”, “calm”, “energetic”, “fearful”, “angry”, “tired”, and “sad” (Basic&8EMO). We expect that the comparison between prediction accuracies based on our three learning sets will be different. According to our hypothesis about additional information available in Twitter, we expect the first set to provide the lowest accuracy level, the second set to provide a somewhat higher accuracy, while the highest prediction accuracy will be achieved by using the Basic&8EMO dataset.

In their work, Bollen and his co-authors found better predictions based on data from the four previous days, and adding data from extra days led to an overtraining model (Bollen et al., 2011). To test these findings, we trained the Support Vector Machine on datasets, including different periods from the previous days (from one to seven days).

Data description

By making use of Twitter API, we managed to download more than 700 million tweets (example of tweets could be found in Appendix I) from the period of 13/02/2013 to 29/09/2013 (we downloaded an average of 3,483,642 tweets per day). All the tweets were sorted by day, analyzed automatically according to data counts of the words “Worry”, “Hope”, and “Fear” (WHF dataset), and assigned by the developed sentiment analyzer counting tweets in the following categories: “happy”, “loving”, “calm”, “energetic”, “fearful”, “angry”, “tired”, and “sad” (8EMO dataset).

For the stock market data (S&P500, DJIA) we used the Yahoo finance website (http://finance.yahoo.com), which provides opening and closing historical prices as well as the volume for any given trading day (example of dataset provided in Appendix II). To apply the Support Vector Machine algorithm, we divided the days into two groups by adding a variable growth (0.1): 1 when the opening price was lower than the price at close, and 0 when the opening price was higher than or equal to the price at close. As a result, the Basic dataset consisted of 16 columns.

The first column provided information about index shift (1 or 0), then presented the opening price, closing price, maximum price, minimum price, and volume for three previous days. The Basic&WHF dataset, created by adding columns for the frequencies of the words "worry", "hope", and "fear" for the previous day (one day – three columns) or for several days (3 x number of days). For example, the Basic&WHF dataset for the previous 7 days consisted of 37 columns (16+3x7, example of dataset presented in Appendix III). While the Basic&8EMO dataset is formed in the same way, the three columns with word frequencies are replaced by 8 columns with frequencies of the words from the developed dictionary of emotional states. For example, the Basic&8EMO set with data from the sentiment analysis of the previous 7 days is composed of 72 columns (16+8x7, example presented in Appendix IV).

The whole period from 13/02/2013 to 29/09/2013 was divided into sets with data from 95 days. The period of 95 days was chosen to enable the use of 80 days for training and 15 days for prediction. Within that period we ran a minimum of 5 experiments with the dataset containing information from the previous 7 days (75 predictions) and a maximum of 40 experiments, with information just of the previous day (600 predictions). The 75 days given for prediction is a much longer period than the 19 days that Bollen and his colleagues had. The increased number of experiments helped us enhance the validity of findings.

Analysis

Stock market growth prediction

Applying the Support Vector Machine algorithm trained only on the Basic DJIA data provided an accuracy of 65.17%, which became the baseline for our analysis. We also tried to train the SVM on data with information from more than one day (from two to seven days), but it resulted in a less accurate forecast (Table 2). Prediction accuracy for the algorithm trained on the Basic dataset with one day's information was used as a baseline in further analysis.

Tab. 2. DJIA prediction. Accuracy of the Support Vector Machines algorithm trained on the Basic dataset.

Number of previous days included in dataset	**1 day**	**2 days**	**3 days**	**4 days**	**5 days**	**6 days**	**7 days**
Basic	**65.17%**	59.84%	60.00%	60.78%	57.93%	49.30%	48.68%
Number of days for prediction	600	645	630	645	675	645	645

The results presented in Table 3 demonstrate that using a more complex approach to extract emotional states does not provide more information than the basic method of relying on the appearance of the three words "worry", "hope", and "fear". Although the usage of the WHF dataset provided a better forecast, this improvement was not significant ($\chi^2(1)= 1.099$, $p=0.294$).

Tab. 3. DJIA prediction. Accuracy of the Support Vector Machines algorithm versus the training dataset.

	Number of previous days included in dataset						
Dataset	**1 day**	**2 days**	**3 days**	**4 days**	**5 days**	**6 days**	**7 days**
Basic&WHF	63.00%	61.01%	61.73%	66.35%	69.02%	**70.00%**	73.33%
Basic&8EMO	62.50%	60.20%	59.26%	65.40%	68.63%	**70.00%**	73.33%
Number of experiments	40	33	27	21	17	12	5
Number of days for prediction	600	495	405	315	255	180	75

Training the SVM algorithm on the Basic S&P500 dataset provided a baseline accuracy of 57.00%. Similarly, it is evident from Table 4 that applying the basic algorithm to sentiment analysis provided better information to improve forecasting (insignificant differences). The SVM algorithm trained on technical data and the number of instances of "fear", "hope", and "worry" in the previous five days demonstrated a higher accuracy of DJIA prediction (68.10%), and it was 10% more accurate than the baseline approach ($\chi^2(1)= 5.027$, $p<0.05$).

Table 4. S&P500 prediction. Accuracy of the Support Vector Machine algorithm versus the training dataset.

	Number of previous days included in dataset						
Dataset	**1 day**	**2 days**	**3 days**	**4 days**	**5 days**	**6 days**	**7 days**
Basic&WHF	59.33%	54.75%	54.07%	63.49%	**68.63%**	63.33%	60.00%
Basic&8EMO	56.67%	53.94%	58.77%	62.86%	67.84%	66.11%	56.00%
Number of experiments	40	33	27	21	17	12	5
Number of days for prediction	600	495	405	315	255	180	75

The baseline accuracy for the NASDAQ index was 50.67% (training on the Basic dataset). An analysis of the S&P500 prediction accuracy (Table 5) showed that both algorithms performed better if trained on datasets including information about the emotional states of Twitter users, but the accuracy differences were insignificant ($\chi^2(1)= 1.171$, $p=0.279$).

Tab. 5. NASDAQ prediction. Accuracy of the Support Vector Machine algorithm versus the training dataset.

	Information from previous						
Dataset	**1 day**	**2 days**	**3 days**	**4 days**	**5 days**	**6 days**	**7 days**
Basic&WHF	52.17%	50.30%	46.91%	47.62%	49.80%	45.00%	33.33%
Basic&8EMO	52.00%	49.90%	52.35%	52.70%	**56.08%**	52.78%	44.00%
Number of experiments	40	33	27	21	17	12	5
Number of days for prediction	600	495	405	315	255	180	75

Discussion

The application of Twitter data for stock market prediction looks like an attempt to use a magic crystal ball or unrelated data. However, it may not be as far-fetched as it appears at first sight. Impressed by the work of Bollen and his colleagues, we wanted to replicate and expand their results. Since 2008, when Bollen and his colleagues conducted their research, Twitter has changed dramatically. In 2008, the number of tweets from February 28 to December 19 was significant, amounting to 9,853,498 (Bollen, Mao, and Zeng, 2011). We now have to download much more. In the period from13/02/2013 to 29/09/2013 we downloaded 755,000,101 tweets – 76 times more than Bollen and his colleagues did, but within a shorter period of time.

Bollen, Mao, and Zeng reported that they had downloaded data for a period from February 28 to December 19, 2008, with the bulk of the data used for training and testing the algorithm (February 28 to November 28, 2008) and only 19 days spent for prediction (December 1 to 19, 2008). In our study the minimum number of days for prediction was 75 and the maximum number was 675, which enabled us to formulate more statistically valid statements.

The addition of sentiment analysis data to the training dataset for the SVM algorithm resulted in a 70% accuracy for the stock market predictions of the DJIA (previous 6 days included), 68.63% for the S&P500 (previous 5 days included), and 56.08% for NASDAQ (previous 5 days included). While these results do not outperform the accuracy achieved by

Bollen and his colleagues, the high prediction rate they demonstrated could have been achieved by chance, as they had a short testing period of 19 days. We asked the authors to send us their dataset, as it is no longer available on the web (http://terramood.informatics.indiana.edu/data), but have not yet received an answer.

However, we have a higher prediction accuracy for the S&P500 indicator, than that achieved by Ding et al (51.88%) (Ding, Fang, and Zuo, 2013) and the 68% reported by Mao et al (Mao, Wei, Wang, and Liu, 2012).

We found the Basic dataset to provide less information than the Basic&WHF. It supports the findings by Zhang, Fuehres, and Gloor, who maintain that calculation alone of the three words “Worry”, “Hope”, and “Fear” in tweets can provide additional information that increases prediction accuracy. We found it interesting that almost all sets of experiments with different amounts of information, included in the SVM dataset trained on Basic&WHF, on average performed better than SVM trained on Basic&8EMO. There are two possible explanations. First, Basic&8EMO provided more data that led to model overtraining. The second explanation is connected with the need to further improve sentiment analysis of tweets. The enhanced accuracy of sentiment analysis may deliver better results. Potential areas of improvement may be adding a weight to the words. For example, the word “*fear*” should weigh heavier in tweet analysis than, say, “*coward”*.

While collecting data, we downloaded about 1% of tweets published by users in historical order. That could not guarantee, however, that messages came from US citizens, even though 55% of them were in English. In order to improve prediction accuracy, we have to limit downloaded tweets only by analyzing user location, and we plan to continue in this manner in our future research.

Another point we found was a different baseline level for different indices. For example, we observed a maximum baseline accuracy of 65.17% for the DJIA, 57% for the S&P500, and only 50.67% for NASDAQ.

Analysis showed that even simple Twitter sentiment analysis data could significantly improve forecasting, which confirms our hypothesis (17 experiments within 15 days for predications, 255 days in total). It should be mentioned that we predicted the direction of change for stock market indices, but not the level of change, which may seriously limit the application of our findings to real-world trading strategy.

Conclusion

Our research sought to test the hypothesis that sentiment analysis of Twitter data may provide additional information, which may improve the accuracy of stock market prediction.

First, we created a server application to download and store tweets. Over the period from 13/02/2013 to 29/09/2013, we downloaded 755,000,101 tweets, with the daily average being 3,483,642. To analyze this huge amount of data, we needed a fast and reliable algorithm for sentiment analysis. To solve this task we used the lexicon-based approach that showed satisfactory performance.

Our results suggest that our hypothesis can be confirmed, at least for predicting the S&P500 index, for which we significantly improved forecasting accuracy. An accuracy of 57.00% provided by SVM, trained only on historical data, was increased to 68.63% through the use of Twitter sentiment analysis data.

In our further research, we plan to enhance accuracy by improving dictionaries and introducing word weights, to thoroughly check the reliability and validity of our dictionaries' algorithm, to continue data collection, and implement machine learning algorithms to predict the amount of change for chosen stock market indices.

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Appendices

Appendix I.

Example of tweets used for sentiment analysis. First four characters of twitter user name was removed to guarantee anonymity.

@****ree: Happy birthday @MistahhCarter !! Miss you! Thank you miss you too!
@****impson9 when's your house warming party
@****ahAhmed nd surprisingly no anger..infact i was enjoying it..tum log discussion mn lage we the . Sb chilla tha.:D
@****a_ lol I would love to see that dance one day
@****thorne Bella love you so much please give me RT!в™Ґ
@****en19 hes gonna have to work hard to get under 300 pounds though #builtlikealineman
@****champion haha the funniest bit as thet we didnt qualify for the next round. i bet that 3-0 defeat to JUVE made them mentally disabled
@****ng_mks: Cewe canti' itu nda pernah meliat cowok dari wajah dan gaya..!! tapi meliat dari jumlah ban kendaraannya #Kehidupangaa
@****kelidster SORRY :-(
@****ogueiraa enjoy that while I freeze my butt off
@****eytaborn @tyler_tennant I just pictured that, seriously! Lolol
@****sHansenNFL Size wise does he look the part? Watched him live at OSu for years but always thought he was to small for next level.
@****orne123 hi love bug! рџ’‹
@****en13 I seriously despise the Chinese New Year now.
@****y_Var lol you Fufu for that
@****pinay ooh sounds interesting? I'm a civil servant we're not allowed to use social media on work pc's but we all have smart phonesрџ“±Yey
@****37 southapton made 10m offer for him,the higher so far
@****sorenson @addictedd2dance GYM IS FOREVER DONE!!!! #happytweet
@****72 @jacob_putney @alex_westra ill whoop all them asses all day sonnies
@****ezan haha. i'm afraid the toughest person will fall first :(
@****ealhadeff nice!! i'm a peruvian sociology student wondering about the lack of serious games for latin america.
@****s18_242 direct your tweet to @btchelp for assistance on this matter
@****res sorry mate be in tomz
@****_Service I DM'ed my info to Shay yesterday re: this issue. Still no call. Ridiculous!
@****H I cant see you crying :(I love you so much вќ¤
@****xxen but aren't all their shows like that anyways and people still watch it
@****V No, DC is not Alaska! But when i lived Va there were many colds i know if i stood out the cold long enough i wouldn't want to sing.
@****mun wah going oip this sem break ah! nice! #highflyer
@****ybaby Really happy to hear that. So where are u based?
@****4P4YN3 haha I was just guessing! He's always wearing that yellow wolf pack shirt of his
@****Dx: w/ me wifeyy @NATALiiEKiiMMx , #france '12 #opa&ampoma http://t.co/361U86pi hihi loveeee :*
@****yth77 can you not handle the image of a girl Sittin there having a poop? Aww sorry for puttin that image in your head
@****aga love your voice...
@****Abrielle No joke? I'm really talking bout it lol
@****ForNayaArmy fo'real. Where you been? Did tumblr swallowed you up? poor thing haha
@****nghua its an honour..

@****ie_noelll just the truth girl
RT @****nazi: Happy birthday to @DHoodJetLife (:
RT @****robzz: Fight breaks out in upstairs A hall? Gotta be the black girls at it again..
RT @****shogg: вЂњ@EmmasDaisyDukes: I start school today. Yippyyy ! :)вЂќgood luck
RT @****FishAA: Happy Birthday Girl @BeccaClepper рџЋЉрџЋ€рџЋ‰
RT @****rsln: RT @Natasyachnrsyt: 00:00 HappyBirthday coy @KuntoeWibie panjang umur,makin endut,semoga cintanya ga diphp in lagi eaa)w ...
@****ee: Happy birthday @MistahhCarter !! Miss you! Thank you miss you too!
@****mun wah going oip this sem break ah! nice! #highflyer
@****ld Children's television programs make me happy. They have the best soundtracks.
@****Man I swear I needa go into isolation for awhile &amp change my bloodclaut number, I'm liable to break someones neck .
@****hittakerx hahahahaha aw she text me going 'sorry rang u by mistake darling x' or something awwwwww cute
@****llenShow Please RT Share Your Love Story Contest! from Davids Bridal http://t.co/GuN5AMPG Keep Austin Weird!
@****ahAhmed nd surprisingly no anger..infact i was enjoying it..tum log discussion mn lage we the . Sb chilla tha.:D
@****Abrielle No joke? I'm really talking bout it lol listened to that new Prince track half a dozen times or so now. Love it. I love being able to see.
@****Dx: w/ me wifeyy @NATALiiEKiiMMx , #france '12 #opa&ampoma http://t.co/361U86pi hihi loveeee :*
@****elTsui good morning and I love you!! looking forward to checking out your album x))
@**** Dear @SenRandPaul: Don't worry about what you'd do if you were president. You'll never be president unless you do a lot of growing up. #GOP
@****H I cant see you crying :(I love you so much вќ¤
@****a_ lol I would love to see that dance one day
@****ud i hate hoes. Needy hoes, ratchet Hoes, sideline hoes, Beggin' hoes, dumb hoes, looking for love on Facebook hoes.
@****orNayaArmy fo'real. Where you been? Did tumblr swallowed you up? poor thing haha
Love is a weakness рџ’¬
@****orne123 hi love bug! рџ’‹
@****aga love your voice...
@****riaHutton love you xxx
@****horne Bella love you so much please give me RT!в™Ґ
@****ogueiraa enjoy that while I freeze my butt off
@****impson9 when's your house warming party
@****usijs What doesn't kill you makes you stronger
@****s_ All she did was Read and Gamble..lmao! #ItsAProblem Ima Smart ass by nature!
RT @****chny: Exhilarating to see liberated post-election Hillary, like Obama, finally pushing back hard at the GOP radicals http://t ...
RT @****onRipples: AIN'T NO BODY FRESHA THAN MA MO'FUCKIN CLIQUE
@****aj Its hard to eat with someone who won't feed they mind
@****js AYE!!! You in the front with them fresh ass J's....hey daddy)
RT @****axo27: ATTENTION ALL FRESHMAN IN HONORS GLOBAL : DROP IT WHILE YOU HAVE THE CHANCE #wordofadvice
@****ks Stay strong. Even when it feels like everything is falling apart. #Yes
RT @*****atic: @NanaKobra honestly haven't laughed that hard in a minute. Much needed.
@****len19 hes gonna have to work hard to get under 300 pounds though #builtlikealineman
RT @****dlerfun: The ultimate question... is Petsmart supposed to be "Pet smart" or "Pets mart"

Appendix II.

Table with example of DJIA historical data dataset (out of 40 used in our study) with data from three previous days

Day	DJIA	-1 day					-2 day					-3 day				
#	Direction	Open	High	Low	Close	Volume	Open	High	Low	Close	Volume	Open	High	Low	Close	Volume
1.	up	13973.39	13981.76	14001.93	13906.73	1956700	13982.91	13973.39	13990.36	13921.94	1148000	14018.7	13982.91	14029.35	13945.78	1305200
2.	down	13981.76	14035.67	14044.82	13977.9	1364100	13973.39	13981.76	14001.93	13906.73	1956700	13982.91	13973.39	13990.36	13921.94	1148000
3.	down	14035.67	13927.54	14058.27	13919.28	1385400	13981.76	14035.67	14044.82	13977.9	1364100	13973.39	13981.76	14001.93	13906.73	1956700
4.	up	13927.54	13880.62	13927.54	13834.4	1314100	14035.67	13927.54	14058.27	13919.28	1385400	13981.76	14035.67	14044.82	13977.9	1364100
5.	down	13880.62	14000.57	14001.19	13880.62	1398500	13927.54	13880.62	13927.54	13834.4	1314100	14035.67	13927.54	14058.27	13919.28	1385400
6.	up	14000.57	13784.17	14081.58	13784.01	1521900	13880.62	14000.57	14001.19	13880.62	1398500	13927.54	13880.62	13927.54	13834.4	1314100
7.	up	13784.17	13900.13	13918.44	13784.17	1325800	14000.57	13784.17	14081.58	13784.01	1521900	13880.62	14000.57	14001.19	13880.62	1398500
8.	down	13900.13	14075.37	14104.86	13880.19	1070100	13784.17	13900.13	13918.44	13784.17	1325800	14000.57	13784.17	14081.58	13784.01	1521900
9.	up	14075.37	14054.49	14149.15	14050.18	1771500	13900.13	14075.37	14104.86	13880.19	1070100	13784.17	13900.13	13918.44	13784.17	1325800
10.	up	14054.49	14089.66	14107.09	13937.6	1259200	14075.37	14054.49	14149.15	14050.18	1771500	13900.13	14075.37	14104.86	13880.19	1070100
11.	up	14089.66	14127.82	14128.21	14030.37	1108100	14054.49	14089.66	14107.09	13937.6	1259200	14075.37	14054.49	14149.15	14050.18	1771500
12.	up	14127.82	14253.77	14286.37	14127.82	1121000	14089.66	14127.82	14128.21	14030.37	1108100	14054.49	14089.66	14107.09	13937.6	1259200
13.	up	14253.77	14296.24	14320.65	14253	1165100	14127.82	14253.77	14286.37	14127.82	1121000	14089.66	14127.82	14128.21	14030.37	1108100
14.	up	14296.24	14329.49	14354.69	14296.24	1170800	14253.77	14296.24	14320.65	14253	1165100	14127.82	14253.77	14286.37	14127.82	1121000
15.	up	14329.49	14397.07	14413.17	14329.49	1156300	14296.24	14329.49	14354.69	14296.24	1170800	14253.77	14296.24	14320.65	14253	1165100
16.	up	14397.07	14447.29	14448.06	14373.32	948800	14329.49	14397.07	14413.17	14329.49	1156300	14296.24	14329.49	14354.69	14296.24	1170800
17.	up	14447.29	14450.06	14478.8	14412.06	1021000	14397.07	14447.29	14448.06	14373.32	948800	14329.49	14397.07	14413.17	14329.49	1156300
18.	up	14450.06	14455.28	14472.8	14411.66	839200	14447.29	14450.06	14478.8	14412.06	1021000	14397.07	14447.29	14448.06	14373.32	948800
19.	down	14455.28	14539.14	14539.29	14455.28	1173900	14450.06	14455.28	14472.8	14411.66	839200	14447.29	14450.06	14478.8	14412.06	1021000
20.	down	14539.14	14514.11	14539.14	14470.5	4077700	14455.28	14539.14	14539.29	14455.28	1173900	14450.06	14455.28	14472.8	14411.66	839200
21.	up	14514.11	14452.06	14521.59	14404.21	1196400	14539.14	14514.11	14539.14	14470.5	4077700	14455.28	14539.14	14539.29	14455.28	1173900
22.	up	14452.06	14455.82	14514.34	14382.09	1221700	14514.11	14452.06	14521.59	14404.21	1196400	14539.14	14514.11	14539.14	14470.5	4077700
23.	down	14455.82	14511.73	14546.82	14455.82	1212400	14452.06	14455.82	14514.34	14382.09	1221700	14514.11	14452.06	14521.59	14404.21	1196400
24.	up	14511.73	14421.49	14511.73	14383.02	1104500	14455.82	14511.73	14546.82	14455.82	1212400	14452.06	14455.82	14514.34	14382.09	1221700
25.	down	14421.49	14512.03	14519.95	14421.49	1014500	14511.73	14421.49	14511.73	14383.02	1104500	14455.82	14511.73	14546.82	14455.82	1212400
26.	up	14512.03	14447.75	14563.75	14395	1248400	14421.49	14512.03	14519.95	14421.49	1014500	14511.73	14421.49	14511.73	14383.02	1104500

27.	down	14447.75	14559.65	14561.54	14447.75	960300	14512.03	14447.75	14563.75	14395	1248400	14421.49	14512.03	14519.95	14421.49	1014500
28.	up	14559.65	14526.16	14559.65	14439.55	926800	14447.75	14559.65	14561.54	14447.75	960300	14512.03	14447.75	14563.75	14395	1248400
29.	down	14526.16	14578.54	14585.1	14520.86	1537100	14559.65	14526.16	14559.65	14439.55	926800	14447.75	14559.65	14561.54	14447.75	960300
30.	up	14578.54	14572.85	14605.72	14531.48	914000	14526.16	14578.54	14585.1	14520.86	1537100	14559.65	14526.16	14559.65	14439.55	926800
31.	down	14572.85	14662.01	14684.49	14572.85	984200	14578.54	14572.85	14605.72	14531.48	914000	14526.16	14578.54	14585.1	14520.86	1537100
32.	up	14662.01	14550.35	14683.13	14525.36	1271400	14572.85	14662.01	14684.49	14572.85	984200	14578.54	14572.85	14605.72	14531.48	914000
33.	down	14550.35	14606.11	14625.24	14538.72	1047900	14662.01	14550.35	14683.13	14525.36	1271400	14572.85	14662.01	14684.49	14572.85	984200
34.	up	14606.11	14565.25	14606.11	14434.43	1312500	14550.35	14606.11	14625.24	14538.72	1047900	14662.01	14550.35	14683.13	14525.36	1271400
35.	up	14565.25	14613.48	14613.48	14497.8	1066800	14606.11	14565.25	14606.11	14434.43	1312500	14550.35	14606.11	14625.24	14538.72	1047900
36.	up	14613.48	14673.46	14716.46	14598.5	1285800	14565.25	14613.48	14613.48	14497.8	1066800	14606.11	14565.25	14606.11	14434.43	1312500
37.	up	14673.46	14802.24	14826.66	14673.46	1205200	14613.48	14673.46	14716.46	14598.5	1285800	14565.25	14613.48	14613.48	14497.8	1066800
38.	down	14802.24	14865.14	14887.51	14785.36	1445700	14673.46	14802.24	14826.66	14673.46	1205200	14613.48	14673.46	14716.46	14598.5	1285800
39.	down	14865.14	14865.06	14865.21	14790.57	1195700	14802.24	14865.14	14887.51	14785.36	1445700	14673.46	14802.24	14826.66	14673.46	1205200
40.	up	14865.06	14599.2	14865.06	14598.58	1616800	14865.14	14865.06	14865.21	14790.57	1195700	14802.24	14865.14	14887.51	14785.36	1445700
41.	down	14599.2	14756.78	14761.73	14599.2	1263200	14865.06	14599.2	14865.06	14598.58	1616800	14865.14	14865.06	14865.21	14790.57	1195700
42.	down	14756.78	14618.59	14756.78	14560.81	1680100	14599.2	14756.78	14761.73	14599.2	1263200	14865.06	14599.2	14865.06	14598.58	1616800
43.	up	14618.59	14537.14	14650.26	14495.29	1580500	14756.78	14618.59	14756.78	14560.81	1680100	14599.2	14756.78	14761.73	14599.2	1263200
44.	up	14537.14	14547.51	14553.73	14444.03	2072000	14618.59	14537.14	14650.26	14495.29	1580500	14756.78	14618.59	14756.78	14560.81	1680100
45.	up	14547.51	14567.17	14588.83	14457.6	1468900	14537.14	14547.51	14553.73	14444.03	2072000	14618.59	14537.14	14650.26	14495.29	1580500
46.	down	14567.17	14719.46	14721.42	14554.29	1373200	14547.51	14567.17	14588.83	14457.6	1468900	14537.14	14547.51	14553.73	14444.03	2072000
47.	up	14719.46	14676.3	14747.42	14666.54	1380200	14567.17	14719.46	14721.42	14554.29	1373200	14547.51	14567.17	14588.83	14457.6	1468900
48.	up	14676.3	14700.8	14768.05	14665.45	1296000	14719.46	14676.3	14747.42	14666.54	1380200	14567.17	14719.46	14721.42	14554.29	1373200
49.	down	14818.75	14839.8	14839.8	14734.47	1482500	14712.55	14818.75	14844.96	14712.55	970600	14700.8	14712.55	14743.49	14684.82	1289100
50.	up	14839.8	14700.95	14839.8	14687.05	1126200	14818.75	14839.8	14839.8	14734.47	1482500	14712.55	14818.75	14844.96	14712.55	970600
51.	up	14700.95	14831.58	14834.63	14700.95	911800	14839.8	14700.95	14839.8	14687.05	1126200	14818.75	14839.8	14839.8	14734.47	1482500
52.	down	14831.58	14973.96	15009.59	14831.58	1198900	14700.95	14831.58	14834.63	14700.95	911800	14839.8	14700.95	14839.8	14687.05	1126200
53.	up	14973.96	14968.89	14988.87	14941.09	1161600	14831.58	14973.96	15009.59	14831.58	1198900	14700.95	14831.58	14834.63	14700.95	911800
54.	down	15056.2	15105.12	15106.81	15021.87	1135100	14968.89	15056.2	15056.67	14968.89	1172300	14973.96	14968.89	14988.87	14941.09	1161600
55.	up	15105.12	15082.62	15144.83	15046.87	978100	15056.2	15105.12	15106.81	15021.87	1135100	14968.89	15056.2	15056.67	14968.89	1172300
56.	down	15082.62	15118.49	15118.49	15038.18	989800	15105.12	15082.62	15144.83	15046.87	978100	15056.2	15105.12	15106.81	15021.87	1135100
57.	up	15113.42	15091.68	15113.42	15053.46	942800	15082.62	15118.49	15118.49	15038.18	989800	15105.12	15082.62	15144.83	15046.87	978100

58.	up	15091.68	15215.25	15219.55	15089.3	1245900	15113.42	15091.68	15113.42	15053.46	942800	15082.62	15118.49	15118.49	15038.18	989800
59.	down	15234.75	15354.4	15357.4	15234.75	1757500	15273.92	15233.22	15302.49	15215.82	1450900	15211.87	15275.69	15301.34	15175.39	1240300
60.	up	15348.33	15335.28	15391.84	15314.15	1164200	15234.75	15354.4	15357.4	15234.75	1757500	15273.92	15233.22	15302.49	15215.82	1450900
61.	down	15334.97	15387.58	15434.5	15325.68	1229700	15348.33	15335.28	15391.84	15314.15	1164200	15234.75	15354.4	15357.4	15234.75	1757500
62.	down	15387.12	15307.17	15542.4	15265.96	1718500	15334.97	15387.58	15434.5	15325.68	1229700	15348.33	15335.28	15391.84	15314.15	1164200
63.	up	15300.57	15294.5	15348.41	15180.23	1488100	15387.12	15307.17	15542.4	15265.96	1718500	15334.97	15387.58	15434.5	15325.68	1229700
64.	up	15290.74	15303.1	15306.71	15199.63	1056600	15300.57	15294.5	15348.41	15180.23	1488100	15387.12	15307.17	15542.4	15265.96	1718500
65.	down	15307.33	15409.39	15521.49	15307.33	1306800	15290.74	15303.1	15306.71	15199.63	1056600	15300.57	15294.5	15348.41	15180.23	1488100
66.	up	15399.94	15302.8	15400.25	15229.53	1140200	15307.33	15409.39	15521.49	15307.33	1306800	15290.74	15303.1	15306.71	15199.63	1056600
67.	down	15306.02	15324.53	15398.7	15280.99	1211500	15399.94	15302.8	15400.25	15229.53	1140200	15307.33	15409.39	15521.49	15307.33	1306800
68.	up	15322.22	15115.57	15392.38	15115.57	2088300	15306.02	15324.53	15398.7	15280.99	1211500	15399.94	15302.8	15400.25	15229.53	1140200
69.	up	15168.1	14960.59	15168.63	14945.57	1414000	15255.22	15177.54	15304.98	15100.78	1342800	15123.55	15254.03	15254.11	15123.55	1479800
70.	down	15231.38	15122.02	15251.07	15086.09	1016100	15247.81	15238.59	15300.64	15211.25	942500	15044.46	15248.12	15255.58	15044.46	1373800
71.	up	15130.39	14995.23	15241.28	14981.21	1057700	15231.38	15122.02	15251.07	15086.09	1016100	15247.81	15238.59	15300.64	15211.25	942500
72.	down	14992.54	15176.08	15202.27	14953.45	1044900	15130.39	14995.23	15241.28	14981.21	1057700	15231.38	15122.02	15251.07	15086.09	1016100
73.	up	15178.08	15070.18	15205.92	15044.8	1074300	14992.54	15176.08	15202.27	14953.45	1044900	15130.39	14995.23	15241.28	14981.21	1057700
74.	up	15078.71	15179.85	15261.71	15078.71	1392500	15178.08	15070.18	15205.92	15044.8	1074300	14992.54	15176.08	15202.27	14953.45	1044900
75.	down	15315.47	15112.19	15322.07	15112.11	1113800	15186.3	15318.23	15340.09	15186.3	992100	15078.71	15179.85	15261.71	15078.71	1392500
76.	down	14760.62	14799.4	14858.56	14688.43	4200800	15105.51	14758.32	15105.51	14732.03	1726300	15315.47	15112.19	15322.07	15112.11	1113800
77.	up	14795.79	14659.56	14795.79	14551.27	1586700	14760.62	14799.4	14858.56	14688.43	4200800	15105.51	14758.32	15105.51	14732.03	1726300
78.	up	14669.69	14760.31	14812.03	14669.69	1359400	14795.79	14659.56	14795.79	14551.27	1586700	14760.62	14799.4	14858.56	14688.43	4200800
79.	up	14769.99	14910.14	14938.98	14769.68	1332300	14669.69	14760.31	14812.03	14669.69	1359400	14795.79	14659.56	14795.79	14551.27	1586700
80.	down	14911.6	14974.96	15083.28	14911.6	1205700	15016.58	14909.6	15034.63	14884.8	2300000	14921.28	15024.49	15075.01	14921.28	1136500
81.	up	14974.96	14932.41	15049.22	14870.51	1166100	14911.6	14974.96	15083.28	14911.6	1205700	15016.58	14909.6	15034.63	14884.8	2300000
82.	up	14923.73	14988.37	15025.9	14858.93	610000	14974.96	14932.41	15049.22	14870.51	1166100	14911.6	14974.96	15083.28	14911.6	1205700
83.	up	14995.46	15135.84	15137.51	14971.2	945600	14923.73	14988.37	15025.9	14858.93	610000	14974.96	14932.41	15049.22	14870.51	1166100
84.	up	15137.22	15224.69	15262.72	15137.22	1368200	14995.46	15135.84	15137.51	14971.2	945600	14923.73	14988.37	15025.9	14858.93	610000
85.	up	15298.03	15291.66	15348.95	15258.89	1050500	15228.46	15300.34	15320.42	15228.46	1092700	15137.22	15224.69	15262.72	15137.22	1368200
86.	up	15298	15460.92	15483.55	15298	1249500	15298.03	15291.66	15348.95	15258.89	1050500	15228.46	15300.34	15320.42	15228.46	1092700
87.	up	15460.69	15464.3	15498.39	15410.27	1301400	15298	15460.92	15483.55	15298	1249500	15298.03	15291.66	15348.95	15258.89	1050500
88.	down	15459.69	15484.26	15509.48	15455.77	994300	15460.69	15464.3	15498.39	15410.27	1301400	15298	15460.92	15483.55	15298	1249500

89.	up	15485.03	15451.85	15498.16	15415.71	1059700	15459.69	15484.26	15509.48	15455.77	994300	15460.69	15464.3	15498.39	15410.27	1301400
90.	up	15456.92	15470.52	15502	15438.12	1262400	15485.03	15451.85	15498.16	15415.71	1059700	15459.69	15484.26	15509.48	15455.77	994300
91.	up	15465.91	15548.54	15589.4	15465.91	1362700	15456.92	15470.52	15502	15438.12	1262400	15485.03	15451.85	15498.16	15415.71	1059700
92.	up	15524.27	15543.74	15544.55	15491.96	2292600	15465.91	15548.54	15589.4	15465.91	1362700	15456.92	15470.52	15502	15438.12	1262400
93.	up	15543.97	15545.55	15576.21	15516.2	1809200	15524.27	15543.74	15544.55	15491.96	2292600	15465.91	15548.54	15589.4	15465.91	1362700
94.	down	15547	15567.74	15604.22	15544.06	987000	15543.97	15545.55	15576.21	15516.2	1809200	15524.27	15543.74	15544.55	15491.96	2292600
95.	up	15576.69	15542.24	15602.6	15496.84	993200	15547	15567.74	15604.22	15544.06	987000	15543.97	15545.55	15576.21	15516.2	1809200

Appendix III.

Table with example of WHF data (with data from seven previous days) added to DJIA Historical data to receive Basic&WHF dataset (one of five used in our study). All values multiplied by 10^3 to fit page.

Day	-1 day			-2 day			-3 day			-4 day			-5 day			-6 day			-7 day		
#	Worry	Hope	Fear	Worry	Hope	Fear	Worry	Hope	Fear	Worry	Hope	Fear	Worry	Hope	Fear	Worry	Hope	Fear	Worry	Hope	Fear
1.	0.708	3.017	0.424	0.655	2.904	0.467	0.651	2.781	0.417	0.536	2.623	0.353	0.531	2.759	0.380	0.577	3.471	0.352	0.700	3.440	0.393
2.	0.682	3.019	0.404	0.708	3.017	0.424	0.655	2.904	0.467	0.651	2.781	0.417	0.536	2.623	0.353	0.531	2.759	0.380	0.577	3.471	0.352
3.	0.636	3.050	0.590	0.682	3.019	0.404	0.708	3.017	0.424	0.655	2.904	0.467	0.651	2.781	0.417	0.536	2.623	0.353	0.531	2.759	0.380
4.	0.688	3.012	0.429	0.562	2.896	0.481	0.601	2.740	0.399	0.636	3.050	0.590	0.682	3.019	0.404	0.708	3.017	0.424	0.655	2.904	0.467
5.	0.621	2.931	0.432	0.688	3.012	0.429	0.562	2.896	0.481	0.601	2.740	0.399	0.636	3.050	0.590	0.682	3.019	0.404	0.708	3.017	0.424
6.	0.668	3.016	0.407	0.621	2.931	0.432	0.688	3.012	0.429	0.562	2.896	0.481	0.601	2.740	0.399	0.636	3.050	0.590	0.682	3.019	0.404
7.	0.683	3.022	0.421	0.668	3.016	0.407	0.621	2.931	0.432	0.688	3.012	0.429	0.562	2.896	0.481	0.601	2.740	0.399	0.636	3.050	0.590
8.	0.626	2.925	0.446	0.683	3.022	0.421	0.668	3.016	0.407	0.621	2.931	0.432	0.688	3.012	0.429	0.562	2.896	0.481	0.601	2.740	0.399
9.	0.667	2.874	0.444	0.565	2.679	0.421	0.527	2.974	0.378	0.626	2.925	0.446	0.683	3.022	0.421	0.668	3.016	0.407	0.621	2.931	0.432
10.	0.722	3.110	0.417	0.667	2.874	0.444	0.565	2.679	0.421	0.527	2.974	0.378	0.626	2.925	0.446	0.683	3.022	0.421	0.668	3.016	0.407
11.	0.614	3.012	0.352	0.722	3.110	0.417	0.667	2.874	0.444	0.565	2.679	0.421	0.527	2.974	0.378	0.626	2.925	0.446	0.683	3.022	0.421
12.	0.675	3.192	0.441	0.614	3.012	0.352	0.722	3.110	0.417	0.667	2.874	0.444	0.565	2.679	0.421	0.527	2.974	0.378	0.626	2.925	0.446
13.	0.747	3.068	0.430	0.675	3.192	0.441	0.614	3.012	0.352	0.722	3.110	0.417	0.667	2.874	0.444	0.565	2.679	0.421	0.527	2.974	0.378
14.	0.549	2.886	0.373	0.525	2.591	0.407	0.573	2.796	0.364	0.747	3.068	0.430	0.675	3.192	0.441	0.614	3.012	0.352	0.722	3.110	0.417

15.	0.620	2.986	0.406	0.549	2.886	0.373	0.525	2.591	0.407	0.573	2.796	0.364	0.747	3.068	0.430	0.675	3.192	0.441	0.614	3.012	0.352
16.	0.617	2.832	0.413	0.620	2.986	0.406	0.549	2.886	0.373	0.525	2.591	0.407	0.573	2.796	0.364	0.747	3.068	0.430	0.675	3.192	0.441
17.	0.625	2.998	0.392	0.617	2.832	0.413	0.620	2.986	0.406	0.549	2.886	0.373	0.525	2.591	0.407	0.573	2.796	0.364	0.747	3.068	0.430
18.	0.644	2.766	0.383	0.625	2.998	0.392	0.617	2.832	0.413	0.620	2.986	0.406	0.549	2.886	0.373	0.525	2.591	0.407	0.573	2.796	0.364
19.	0.553	2.839	0.372	0.502	2.621	0.376	0.517	3.030	0.423	0.644	2.766	0.383	0.625	2.998	0.392	0.617	2.832	0.413	0.620	2.986	0.406
20.	0.602	2.963	0.375	0.553	2.839	0.372	0.502	2.621	0.376	0.517	3.030	0.423	0.644	2.766	0.383	0.625	2.998	0.392	0.617	2.832	0.413
21.	0.625	2.906	0.399	0.602	2.963	0.375	0.553	2.839	0.372	0.502	2.621	0.376	0.517	3.030	0.423	0.644	2.766	0.383	0.625	2.998	0.392
22.	0.625	2.800	0.456	0.625	2.906	0.399	0.602	2.963	0.375	0.553	2.839	0.372	0.502	2.621	0.376	0.517	3.030	0.423	0.644	2.766	0.383
23.	0.558	2.858	0.391	0.625	2.800	0.456	0.625	2.906	0.399	0.602	2.963	0.375	0.553	2.839	0.372	0.502	2.621	0.376	0.517	3.030	0.423
24.	0.762	2.983	0.366	0.509	2.643	0.360	0.528	2.801	0.342	0.558	2.858	0.391	0.625	2.800	0.456	0.625	2.906	0.399	0.602	2.963	0.375
25.	0.613	2.874	0.386	0.762	2.983	0.366	0.509	2.643	0.360	0.528	2.801	0.342	0.558	2.858	0.391	0.625	2.800	0.456	0.625	2.906	0.399
26.	0.583	2.788	0.473	0.613	2.874	0.386	0.762	2.983	0.366	0.509	2.643	0.360	0.528	2.801	0.342	0.558	2.858	0.391	0.625	2.800	0.456
27.	0.615	2.844	0.386	0.583	2.788	0.473	0.613	2.874	0.386	0.762	2.983	0.366	0.509	2.643	0.360	0.528	2.801	0.342	0.558	2.858	0.391
28.	0.544	3.358	0.348	0.558	2.618	0.393	0.510	2.743	0.366	0.534	2.645	0.350	0.615	2.844	0.386	0.583	2.788	0.473	0.613	2.874	0.386
29.	0.581	2.869	0.376	0.544	3.358	0.348	0.558	2.618	0.393	0.510	2.743	0.366	0.534	2.645	0.350	0.615	2.844	0.386	0.583	2.788	0.473
30.	0.594	2.788	0.385	0.581	2.869	0.376	0.544	3.358	0.348	0.558	2.618	0.393	0.510	2.743	0.366	0.534	2.645	0.350	0.615	2.844	0.386
31.	0.720	2.973	0.430	0.594	2.788	0.385	0.581	2.869	0.376	0.544	3.358	0.348	0.558	2.618	0.393	0.510	2.743	0.366	0.534	2.645	0.350
32.	0.595	2.916	0.383	0.720	2.973	0.430	0.594	2.788	0.385	0.581	2.869	0.376	0.544	3.358	0.348	0.558	2.618	0.393	0.510	2.743	0.366
33.	0.610	2.818	0.367	0.488	2.555	0.335	0.546	2.653	0.376	0.595	2.916	0.383	0.720	2.973	0.430	0.594	2.788	0.385	0.581	2.869	0.376
34.	0.618	3.001	0.393	0.610	2.818	0.367	0.488	2.555	0.335	0.546	2.653	0.376	0.595	2.916	0.383	0.720	2.973	0.430	0.594	2.788	0.385
35.	0.613	3.021	0.384	0.618	3.001	0.393	0.610	2.818	0.367	0.488	2.555	0.335	0.546	2.653	0.376	0.595	2.916	0.383	0.720	2.973	0.430
36.	0.594	2.913	0.403	0.613	3.021	0.384	0.618	3.001	0.393	0.610	2.818	0.367	0.488	2.555	0.335	0.546	2.653	0.376	0.595	2.916	0.383
37.	0.621	2.923	0.382	0.594	2.913	0.403	0.613	3.021	0.384	0.618	3.001	0.393	0.610	2.818	0.367	0.488	2.555	0.335	0.546	2.653	0.376
38.	0.560	2.710	0.373	0.514	2.682	0.363	0.525	2.834	0.360	0.621	2.923	0.382	0.594	2.913	0.403	0.613	3.021	0.384	0.618	3.001	0.393
39.	0.630	3.659	0.537	0.560	2.710	0.373	0.514	2.682	0.363	0.525	2.834	0.360	0.621	2.923	0.382	0.594	2.913	0.403	0.613	3.021	0.384
40.	0.624	2.940	0.441	0.630	3.659	0.537	0.560	2.710	0.373	0.514	2.682	0.363	0.525	2.834	0.360	0.621	2.923	0.382	0.594	2.913	0.403
41.	0.588	3.018	0.459	0.624	2.940	0.441	0.630	3.659	0.537	0.560	2.710	0.373	0.514	2.682	0.363	0.525	2.834	0.360	0.621	2.923	0.382
42.	0.568	2.890	0.433	0.588	3.018	0.459	0.624	2.940	0.441	0.630	3.659	0.537	0.560	2.710	0.373	0.514	2.682	0.363	0.525	2.834	0.360
43.	0.538	2.737	0.377	0.503	2.595	0.336	0.544	3.167	0.398	0.568	2.890	0.433	0.588	3.018	0.459	0.624	2.940	0.441	0.630	3.659	0.537
44.	0.578	2.800	0.392	0.538	2.737	0.377	0.503	2.595	0.336	0.544	3.167	0.398	0.568	2.890	0.433	0.588	3.018	0.459	0.624	2.940	0.441
45.	0.595	2.756	0.401	0.578	2.800	0.392	0.538	2.737	0.377	0.503	2.595	0.336	0.544	3.167	0.398	0.568	2.890	0.433	0.588	3.018	0.459

46.	0.569	2.915	0.384	0.595	2.756	0.401	0.578	2.800	0.392	0.538	2.737	0.377	0.503	2.595	0.336	0.544	3.167	0.398	0.568	2.890	0.433
47.	0.505	2.623	0.361	0.569	2.915	0.384	0.595	2.756	0.401	0.578	2.800	0.392	0.538	2.737	0.377	0.503	2.595	0.336	0.544	3.167	0.398
48.	0.592	2.780	0.389	0.567	2.627	0.369	0.448	2.587	0.319	0.490	2.653	0.328	0.536	2.688	0.373	0.563	2.703	0.358	0.586	2.717	0.360
49.	0.600	2.814	0.403	0.602	2.994	0.353	0.528	3.020	0.360	0.436	2.571	0.328	0.471	2.670	0.342	0.518	2.823	0.354	0.591	2.980	0.438
50.	0.593	2.757	0.409	0.599	2.752	0.413	0.615	2.719	0.380	0.578	2.876	0.362	0.513	2.567	0.376	0.492	2.443	0.338	0.516	2.477	0.344
51.	0.575	2.733	0.370	0.511	2.397	0.320	0.482	2.480	0.326	0.496	2.551	0.325	0.593	2.757	0.409	0.599	2.752	0.413	0.615	2.719	0.380
52.	0.585	2.734	0.398	0.575	2.733	0.370	0.511	2.397	0.320	0.482	2.480	0.326	0.496	2.551	0.325	0.593	2.757	0.409	0.599	2.752	0.413
53.	0.574	2.735	0.411	0.585	2.734	0.398	0.575	2.733	0.370	0.511	2.397	0.320	0.482	2.480	0.326	0.496	2.551	0.325	0.593	2.757	0.409
54.	0.540	2.684	0.368	0.574	2.735	0.411	0.585	2.734	0.398	0.575	2.733	0.370	0.511	2.397	0.320	0.482	2.480	0.326	0.496	2.551	0.325
55.	0.547	2.522	0.378	0.471	2.398	0.339	0.518	2.700	0.362	0.540	2.684	0.368	0.574	2.735	0.411	0.585	2.734	0.398	0.575	2.733	0.370
56.	0.586	2.575	0.323	0.527	2.618	0.316	0.424	2.432	0.314	0.557	2.567	0.327	0.609	2.789	0.378	0.558	2.714	0.348	0.563	2.743	0.378
57.	0.519	2.679	0.393	0.507	2.676	0.377	0.521	2.614	0.356	0.524	2.648	0.367	0.500	2.568	0.345	0.517	2.648	0.378	0.575	2.766	0.409
58.	0.498	2.524	0.392	0.519	2.679	0.393	0.507	2.676	0.377	0.521	2.614	0.356	0.524	2.648	0.367	0.500	2.568	0.345	0.517	2.648	0.378
59.	0.490	2.408	0.348	0.498	2.524	0.392	0.519	2.679	0.393	0.507	2.676	0.377	0.521	2.614	0.356	0.524	2.648	0.367	0.500	2.568	0.345
60.	0.495	2.420	0.345	0.449	2.227	0.320	0.487	2.487	0.364	0.490	2.408	0.348	0.498	2.524	0.392	0.519	2.679	0.393	0.507	2.676	0.377
61.	0.526	2.753	0.383	0.495	2.420	0.345	0.449	2.227	0.320	0.487	2.487	0.364	0.490	2.408	0.348	0.498	2.524	0.392	0.519	2.679	0.393
62.	0.537	2.694	0.403	0.526	2.753	0.383	0.495	2.420	0.345	0.449	2.227	0.320	0.487	2.487	0.364	0.490	2.408	0.348	0.498	2.524	0.392
63.	0.490	2.395	0.341	0.537	2.694	0.403	0.526	2.753	0.383	0.495	2.420	0.345	0.449	2.227	0.320	0.487	2.487	0.364	0.490	2.408	0.348
64.	0.496	2.477	0.322	0.490	2.395	0.341	0.537	2.694	0.403	0.526	2.753	0.383	0.495	2.420	0.345	0.449	2.227	0.320	0.487	2.487	0.364
65.	0.516	2.402	0.342	0.439	2.246	0.391	0.473	2.408	0.359	0.496	2.477	0.322	0.490	2.395	0.341	0.537	2.694	0.403	0.526	2.753	0.383
66.	0.604	2.506	0.362	0.516	2.402	0.342	0.439	2.246	0.391	0.473	2.408	0.359	0.496	2.477	0.322	0.490	2.395	0.341	0.537	2.694	0.403
67.	0.553	2.486	0.340	0.604	2.506	0.362	0.516	2.402	0.342	0.439	2.246	0.391	0.473	2.408	0.359	0.496	2.477	0.322	0.490	2.395	0.341
68.	0.516	2.594	0.350	0.553	2.486	0.340	0.604	2.506	0.362	0.516	2.402	0.342	0.439	2.246	0.391	0.473	2.408	0.359	0.496	2.477	0.322
69.	0.482	2.547	0.348	0.516	2.594	0.350	0.553	2.486	0.340	0.604	2.506	0.362	0.516	2.402	0.342	0.439	2.246	0.391	0.473	2.408	0.359
70.	0.462	2.466	0.336	0.478	2.372	0.330	0.469	2.486	0.341	0.482	2.547	0.348	0.516	2.594	0.350	0.553	2.486	0.340	0.604	2.506	0.362
71.	0.477	2.524	0.359	0.462	2.466	0.336	0.478	2.372	0.330	0.469	2.486	0.341	0.482	2.547	0.348	0.516	2.594	0.350	0.553	2.486	0.340
72.	0.581	2.621	0.364	0.477	2.524	0.359	0.462	2.466	0.336	0.478	2.372	0.330	0.469	2.486	0.341	0.482	2.547	0.348	0.516	2.594	0.350
73.	0.466	2.465	0.320	0.581	2.621	0.364	0.477	2.524	0.359	0.462	2.466	0.336	0.478	2.372	0.330	0.469	2.486	0.341	0.482	2.547	0.348
74.	0.573	2.725	0.381	0.466	2.465	0.320	0.581	2.621	0.364	0.477	2.524	0.359	0.462	2.466	0.336	0.478	2.372	0.330	0.469	2.486	0.341
75.	0.466	2.561	0.327	0.501	2.510	0.326	0.527	2.553	0.341	0.573	2.725	0.381	0.466	2.465	0.320	0.581	2.621	0.364	0.477	2.524	0.359
76.	0.500	2.587	0.340	0.466	2.561	0.327	0.501	2.510	0.326	0.527	2.553	0.341	0.573	2.725	0.381	0.466	2.465	0.320	0.581	2.621	0.364

77.	0.511	2.600	0.340	0.500	2.587	0.340	0.466	2.561	0.327	0.501	2.510	0.326	0.527	2.553	0.341	0.573	2.725	0.381	0.466	2.465	0.320
78.	0.537	2.650	0.350	0.511	2.600	0.340	0.500	2.587	0.340	0.466	2.561	0.327	0.501	2.510	0.326	0.527	2.553	0.341	0.573	2.725	0.381
79.	0.483	2.833	0.401	0.476	2.755	0.354	0.508	2.595	0.377	0.553	2.853	0.360	0.456	2.579	0.319	0.470	2.411	0.346	0.499	2.537	0.366
80.	0.586	3.000	0.372	0.509	2.604	0.311	0.435	2.410	0.309	0.460	2.494	0.316	0.483	2.833	0.401	0.476	2.755	0.354	0.508	2.595	0.377
81.	0.585	2.930	0.396	0.586	3.000	0.372	0.509	2.604	0.311	0.435	2.410	0.309	0.460	2.494	0.316	0.483	2.833	0.401	0.476	2.755	0.354
82.	0.537	2.716	0.382	0.585	2.930	0.396	0.586	3.000	0.372	0.509	2.604	0.311	0.435	2.410	0.309	0.460	2.494	0.316	0.483	2.833	0.401
83.	0.522	2.681	0.329	0.537	2.716	0.382	0.585	2.930	0.396	0.586	3.000	0.372	0.509	2.604	0.311	0.435	2.410	0.309	0.460	2.494	0.316
84.	0.501	2.749	0.341	0.461	2.462	0.307	0.429	2.716	0.313	0.522	2.681	0.329	0.537	2.716	0.382	0.585	2.930	0.396	0.586	3.000	0.372
85.	0.536	2.799	0.379	0.501	2.749	0.341	0.461	2.462	0.307	0.429	2.716	0.313	0.522	2.681	0.329	0.537	2.716	0.382	0.585	2.930	0.396
86.	0.525	2.710	0.378	0.536	2.799	0.379	0.501	2.749	0.341	0.461	2.462	0.307	0.429	2.716	0.313	0.522	2.681	0.329	0.537	2.716	0.382
87.	0.528	2.654	0.374	0.525	2.710	0.378	0.536	2.799	0.379	0.501	2.749	0.341	0.461	2.462	0.307	0.429	2.716	0.313	0.522	2.681	0.329
88.	0.587	3.037	0.456	0.528	2.654	0.374	0.525	2.710	0.378	0.536	2.799	0.379	0.501	2.749	0.341	0.461	2.462	0.307	0.429	2.716	0.313
89.	0.478	2.541	0.332	0.455	2.469	0.375	0.472	2.711	0.337	0.587	3.037	0.456	0.528	2.654	0.374	0.525	2.710	0.378	0.536	2.799	0.379
90.	0.511	2.672	0.327	0.478	2.541	0.332	0.455	2.469	0.375	0.472	2.711	0.337	0.587	3.037	0.456	0.528	2.654	0.374	0.525	2.710	0.378
91.	0.504	2.645	0.382	0.511	2.672	0.327	0.478	2.541	0.332	0.455	2.469	0.375	0.472	2.711	0.337	0.587	3.037	0.456	0.528	2.654	0.374
92.	0.511	2.569	0.356	0.504	2.645	0.382	0.511	2.672	0.327	0.478	2.541	0.332	0.455	2.469	0.375	0.472	2.711	0.337	0.587	3.037	0.456
93.	0.486	2.535	0.352	0.511	2.569	0.356	0.504	2.645	0.382	0.511	2.672	0.327	0.478	2.541	0.332	0.455	2.469	0.375	0.472	2.711	0.337
94.	0.504	2.514	0.366	0.447	2.351	0.317	0.419	2.460	0.324	0.486	2.535	0.352	0.511	2.569	0.356	0.504	2.645	0.382	0.511	2.672	0.327
95.	0.508	2.672	0.369	0.504	2.514	0.366	0.447	2.351	0.317	0.419	2.460	0.324	0.486	2.535	0.352	0.511	2.569	0.356	0.504	2.645	0.382

Appendix IV.

Table with example of eight emotional categories data (with data from two previous days) added to DJIA Historical data to receive Basic&8EMO dataset (one of for 33 used in our study). All values multiplied by 10^2 to fit the page.

Day	-1 day								-2 day							
#	happy	loving	calm	energetic	fearful	angry	tired	sad	happy	loving	calm	energetic	fearful	angry	tired	sad
96.	0.941	2.612	0.770	0.810	0.448	3.071	0.690	0.975	1.048	2.650	0.754	0.776	0.421	3.179	0.786	0.972
97.	0.930	2.644	0.778	0.877	0.462	3.218	0.710	1.020	0.941	2.612	0.770	0.810	0.448	3.071	0.690	0.975
98.	1.007	2.596	0.777	0.865	0.556	3.113	0.680	1.019	0.930	2.644	0.778	0.877	0.462	3.218	0.710	1.020
99.	0.943	2.551	0.774	0.847	0.442	3.030	0.705	0.990	1.007	2.596	0.777	0.865	0.556	3.113	0.680	1.019

100.	0.910	2.826	0.833	0.872	0.507	3.237	0.774	1.027	0.944	2.563	0.704	0.755	0.432	2.767	0.685	0.918
101.	0.921	2.477	0.769	0.843	0.450	3.113	0.691	0.993	0.910	2.826	0.833	0.872	0.507	3.237	0.774	1.027
102.	0.912	2.410	0.765	0.842	0.444	3.201	0.707	0.952	0.921	2.477	0.769	0.843	0.450	3.113	0.691	0.993
103.	0.952	2.395	0.757	0.828	0.435	3.015	0.678	0.956	0.912	2.410	0.765	0.842	0.444	3.201	0.707	0.952
104.	1.296	2.469	0.737	0.844	0.417	2.817	0.637	0.921	0.952	2.395	0.757	0.828	0.435	3.015	0.678	0.956
105.	0.927	2.645	0.796	0.928	0.450	3.118	0.782	0.984	1.102	2.517	0.681	0.758	0.410	2.733	0.650	0.885
106.	0.953	2.556	0.778	0.921	0.459	3.154	0.686	0.978	0.927	2.645	0.796	0.928	0.450	3.118	0.782	0.984
107.	0.871	2.142	0.738	0.816	0.406	3.182	0.625	0.856	0.953	2.556	0.778	0.921	0.459	3.154	0.686	0.978
108.	0.958	2.635	0.776	0.938	0.436	3.103	0.669	0.953	0.871	2.142	0.738	0.816	0.406	3.182	0.625	0.856
109.	0.973	2.363	0.730	0.894	0.417	2.782	0.613	0.908	0.958	2.635	0.776	0.938	0.436	3.103	0.669	0.953
110.	1.051	2.497	0.749	0.939	0.398	2.780	0.657	0.874	0.987	2.343	0.699	0.839	0.387	2.459	0.615	0.859
111.	0.938	2.422	0.741	0.955	0.418	2.885	0.649	0.915	1.051	2.497	0.749	0.939	0.398	2.780	0.657	0.874
112.	0.900	2.280	0.734	0.951	0.406	2.852	0.628	0.896	0.938	2.422	0.741	0.955	0.418	2.885	0.649	0.915
113.	0.923	2.286	0.716	0.959	0.407	2.782	0.616	0.888	0.900	2.280	0.734	0.951	0.406	2.852	0.628	0.896
114.	0.991	2.342	0.723	1.402	0.426	2.875	0.633	0.931	0.923	2.286	0.716	0.959	0.407	2.782	0.616	0.888
115.	1.191	2.427	0.703	1.176	0.409	2.717	0.661	0.904	0.955	2.258	0.673	1.182	0.383	2.584	0.643	0.872
116.	0.935	2.400	0.739	1.030	0.440	2.945	0.701	0.918	1.191	2.427	0.703	1.176	0.409	2.717	0.661	0.904
117.	0.916	2.310	0.727	1.001	0.427	2.818	0.686	0.908	0.935	2.400	0.739	1.030	0.440	2.945	0.701	0.918
118.	0.995	2.256	0.702	0.957	0.421	2.776	0.661	0.899	0.916	2.310	0.727	1.001	0.427	2.818	0.686	0.908
119.	0.997	2.351	0.712	1.093	0.395	2.797	0.669	0.912	0.995	2.256	0.702	0.957	0.421	2.776	0.661	0.899
120.	0.899	2.587	0.776	0.865	0.434	3.027	0.785	0.998	0.961	2.384	0.700	1.601	0.441	2.536	0.625	0.881
121.	0.995	2.485	0.739	0.849	0.418	2.809	0.684	0.953	0.899	2.587	0.776	0.865	0.434	3.027	0.785	0.998
122.	0.940	2.400	0.694	0.779	0.397	2.745	0.619	0.891	0.995	2.485	0.739	0.849	0.418	2.809	0.684	0.953
123.	0.962	2.418	0.755	0.834	0.403	2.838	0.629	0.922	0.940	2.400	0.694	0.779	0.397	2.745	0.619	0.891
124.	1.722	2.392	0.699	0.722	0.410	2.674	0.747	0.889	1.165	2.297	0.678	0.677	0.375	2.461	0.598	0.885
125.	0.978	2.338	0.713	0.746	0.430	2.707	0.650	0.884	1.722	2.392	0.699	0.722	0.410	2.674	0.747	0.889
126.	0.944	2.319	0.731	0.745	0.404	2.756	0.635	0.898	0.978	2.338	0.713	0.746	0.430	2.707	0.650	0.884
127.	0.951	2.464	0.756	0.785	0.449	3.053	0.658	0.985	0.944	2.319	0.731	0.745	0.404	2.756	0.635	0.898
128.	0.951	2.406	0.730	0.811	0.416	2.762	0.625	0.943	0.951	2.464	0.756	0.785	0.449	3.053	0.658	0.985
129.	0.880	2.526	0.787	0.766	0.444	2.911	0.644	0.932	0.939	2.189	0.674	0.760	0.372	2.439	0.598	0.837
130.	0.926	2.466	0.828	0.909	0.446	3.014	0.664	0.937	0.880	2.526	0.787	0.766	0.444	2.911	0.644	0.932

131.	0.928	2.367	0.773	0.780	0.439	2.884	0.645	0.902	0.926	2.466	0.828	0.909	0.446	3.014	0.664	0.937
132.	0.951	2.434	0.755	0.811	0.434	2.848	0.623	0.914	0.928	2.367	0.773	0.780	0.439	2.884	0.645	0.902
133.	0.972	2.343	0.755	0.782	0.439	2.801	0.616	0.935	0.951	2.434	0.755	0.811	0.434	2.848	0.623	0.914
134.	0.857	2.279	0.728	0.753	0.401	2.689	0.583	0.877	0.921	2.164	0.689	0.715	0.360	2.380	0.586	0.842
135.	0.894	2.293	0.789	0.783	0.494	2.925	0.748	0.868	0.857	2.279	0.728	0.753	0.401	2.689	0.583	0.877
136.	0.874	2.296	0.746	0.760	0.428	2.774	0.619	0.874	0.894	2.293	0.789	0.783	0.494	2.925	0.748	0.868
137.	0.955	2.276	0.731	0.838	0.422	2.731	0.624	0.870	0.874	2.296	0.746	0.760	0.428	2.774	0.619	0.874
138.	1.015	2.317	0.739	0.760	0.412	2.653	0.594	0.869	0.955	2.276	0.731	0.838	0.422	2.731	0.624	0.870
139.	0.938	2.374	0.748	0.737	0.386	2.648	0.589	0.881	1.202	2.140	0.659	0.621	0.354	2.281	0.553	0.798
140.	1.007	2.389	0.753	0.732	0.395	2.788	0.602	0.896	0.938	2.374	0.748	0.737	0.386	2.648	0.589	0.881
141.	0.981	2.355	0.733	0.744	0.401	2.754	0.610	0.885	1.007	2.389	0.753	0.732	0.395	2.788	0.602	0.896
142.	1.007	2.294	0.716	0.741	0.410	2.924	0.600	0.885	0.981	2.355	0.733	0.744	0.401	2.754	0.610	0.885
143.	0.977	2.001	0.657	0.665	0.338	2.142	0.502	0.795	1.007	2.294	0.716	0.741	0.410	2.924	0.600	0.885
144.	0.967	2.157	0.686	0.693	0.364	2.516	0.572	0.855	1.008	2.182	0.717	0.729	0.363	2.616	0.581	0.837
145.	1.017	2.303	0.731	0.664	0.377	2.678	0.598	0.860	0.987	2.046	0.650	0.612	0.373	2.258	0.570	0.787
146.	0.932	2.299	0.755	0.730	0.392	2.879	0.608	0.903	1.017	2.303	0.731	0.664	0.377	2.678	0.598	0.860
147.	1.676	2.727	0.769	0.765	0.379	2.674	0.595	0.867	1.120	2.248	0.675	0.652	0.355	2.282	0.575	0.803
148.	0.990	2.419	0.776	0.751	0.392	2.755	0.597	0.869	1.676	2.727	0.769	0.765	0.379	2.674	0.595	0.867
149.	0.943	2.242	0.763	0.737	0.398	2.689	0.583	0.879	0.990	2.419	0.776	0.751	0.392	2.755	0.597	0.869
150.	0.822	2.387	0.778	0.661	0.424	2.826	0.598	0.868	0.858	2.101	0.673	0.614	0.341	2.213	0.563	0.791
151.	0.870	2.355	0.769	0.708	0.411	2.783	0.595	0.881	0.822	2.387	0.778	0.661	0.424	2.826	0.598	0.868
152.	0.891	2.225	0.760	0.713	0.384	2.712	0.581	0.895	0.870	2.355	0.769	0.708	0.411	2.783	0.595	0.881
153.	0.870	2.153	0.774	0.701	0.394	2.810	0.596	0.890	0.891	2.225	0.760	0.713	0.384	2.712	0.581	0.895
154.	0.864	2.152	0.729	0.681	0.382	2.696	0.568	0.880	0.870	2.153	0.774	0.701	0.394	2.810	0.596	0.890
155.	1.000	2.370	0.771	0.649	0.396	2.735	0.582	0.910	0.854	2.198	0.713	0.594	0.344	2.546	0.594	0.858
156.	0.888	2.418	0.786	0.701	0.407	2.890	0.619	0.958	1.000	2.370	0.771	0.649	0.396	2.735	0.582	0.910
157.	0.915	2.313	0.769	0.678	0.394	2.752	0.594	0.928	0.888	2.418	0.786	0.701	0.407	2.890	0.619	0.958
158.	0.938	2.297	0.761	0.680	0.413	2.723	0.580	0.919	0.915	2.313	0.769	0.678	0.394	2.752	0.594	0.928
159.	0.870	2.266	0.752	0.624	0.480	2.689	0.553	0.873	0.913	2.054	0.677	0.573	0.481	2.296	0.533	0.785
160.	0.886	2.057	0.707	0.665	0.418	2.581	0.524	0.850	0.869	2.142	0.668	0.658	0.425	2.594	0.562	0.877
161.	1.439	2.446	0.721	0.611	0.379	2.642	0.559	1.052	1.041	2.164	0.635	0.566	0.389	2.219	0.527	0.813

162.	0.841	2.172	0.696	0.640	0.389	2.585	0.548	0.897	1.439	2.446	0.721	0.611	0.379	2.642	0.559	1.052
163.	0.865	2.239	0.704	0.616	0.407	2.521	0.555	0.896	0.828	2.116	0.658	0.594	0.347	2.295	0.532	0.839
164.	0.877	2.229	0.724	0.644	0.387	2.702	0.570	0.902	0.865	2.239	0.704	0.616	0.407	2.521	0.555	0.896
165.	0.890	2.249	0.750	0.693	0.404	2.593	0.576	0.887	0.877	2.229	0.724	0.644	0.387	2.702	0.570	0.902
166.	0.971	2.376	0.743	0.741	0.416	2.699	0.592	0.901	0.890	2.249	0.750	0.693	0.404	2.593	0.576	0.887
167.	1.650	2.043	0.662	0.551	0.330	2.297	0.504	0.776	0.944	2.192	0.700	0.651	0.378	2.552	0.556	0.861
168.	0.842	2.137	0.711	0.626	0.390	2.427	0.526	0.835	0.964	2.299	0.731	0.616	0.355	2.520	0.554	0.885
169.	0.860	2.766	0.891	0.704	0.390	2.408	0.633	0.935	0.886	2.269	0.807	0.633	0.383	2.606	0.616	0.843
170.	0.948	2.454	0.764	0.645	0.382	2.521	0.552	0.906	0.860	2.766	0.891	0.704	0.390	2.408	0.633	0.935
171.	0.991	2.291	0.755	0.662	0.383	2.491	0.551	0.889	0.948	2.454	0.764	0.645	0.382	2.521	0.552	0.906
172.	0.895	2.296	0.765	0.732	0.458	2.715	0.545	0.925	0.991	2.291	0.755	0.662	0.383	2.491	0.551	0.889
173.	0.911	2.314	0.725	0.659	0.389	2.531	0.535	0.882	0.895	2.296	0.765	0.732	0.458	2.715	0.545	0.925
174.	0.834	2.245	0.705	0.652	0.571	2.437	0.548	0.881	0.835	2.185	0.673	0.671	0.791	2.241	0.531	0.852
175.	0.977	2.314	0.723	0.721	0.509	2.527	0.531	0.868	0.834	2.245	0.705	0.652	0.571	2.437	0.548	0.881
176.	0.992	2.656	0.720	0.702	0.503	2.581	0.542	0.868	0.977	2.314	0.723	0.721	0.509	2.527	0.531	0.868
177.	0.845	2.267	0.699	0.674	0.459	2.478	0.535	0.852	0.992	2.656	0.720	0.702	0.503	2.581	0.542	0.868
178.	0.787	2.189	0.691	0.710	0.436	2.400	0.526	0.846	0.845	2.267	0.699	0.674	0.459	2.478	0.535	0.852
179.	0.857	2.350	0.733	0.642	0.407	2.525	0.553	0.883	0.860	2.074	0.667	0.595	0.385	2.261	0.523	0.820
180.	0.829	2.261	0.714	0.650	0.415	2.525	0.519	0.851	0.857	2.350	0.733	0.642	0.407	2.525	0.553	0.883
181.	0.876	2.231	0.719	0.677	0.407	2.542	0.540	0.857	0.829	2.261	0.714	0.650	0.415	2.525	0.519	0.851
182.	0.978	2.240	0.725	0.653	0.412	2.498	0.538	0.841	0.876	2.231	0.719	0.677	0.407	2.542	0.540	0.857
183.	0.954	2.324	0.728	0.681	0.440	2.557	0.544	0.862	0.978	2.240	0.725	0.653	0.412	2.498	0.538	0.841
184.	1.006	2.321	0.709	0.653	0.646	2.339	0.515	0.853	0.874	2.273	0.686	0.630	0.444	2.285	0.512	0.822
185.	0.895	2.460	0.702	0.785	0.685	2.390	0.508	0.846	1.006	2.321	0.709	0.653	0.646	2.339	0.515	0.853
186.	0.860	2.271	0.695	0.721	0.603	2.409	0.519	0.883	0.895	2.460	0.702	0.785	0.685	2.390	0.508	0.846
187.	0.999	2.024	0.650	0.632	0.452	2.200	0.489	0.805	0.860	2.271	0.695	0.721	0.603	2.409	0.519	0.883
188.	0.952	2.521	0.788	0.743	0.525	2.734	0.566	0.941	0.999	2.024	0.650	0.632	0.452	2.200	0.489	0.805
189.	0.868	2.363	0.742	0.909	0.547	2.472	0.521	0.881	0.865	2.248	0.683	0.663	0.455	2.368	0.530	0.850
190.	0.835	2.354	0.747	0.748	0.481	2.537	0.513	0.885	0.868	2.363	0.742	0.909	0.547	2.472	0.521	0.881

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