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FROM WORDS TO PARAGRAPHS: MODELING SENTIMENT DYNAMICS IN 'NOTES FROM UNDERGROUND' WITH GPT-4 VIA DESCRIPTIVE METHODS AND DIFFERENTIAL EQUATIONS

Abstract

This study examines how the sentiment values in the first part of the book entitled as "Underground" of Fyodor Dostoevsky's "Notes from Underground" change from words to sentences to paragraphs. Using the GPT-4 language model, we conducted a descriptive analysis of standardized sentiment values and calculated cumulative sentiment trajectories over the text. We then created differential equation models to model the sentiment tones using regression analysis. Our findings suggest that sentiment becomes less negative from words to paragraphs, indicating that context moderates negativity. Paragraph sentiment was also more stable with lower variability. There was a narrative arc of initial decline followed by an upward turn in sentiment. Paragraphs had the highest baseline sentiment, suggesting that they are able to capture more nuanced context. Paragraphs lost short-term sentiment quickly but retained long-term sentiment longest, aligning with paragraphs maintaining overall text sentiment over time. These findings suggest that there are complex dynamics between linguistic units contributing to perceived stability of sentiment. Quantitative decay rates are useful indicators but do not fully characterize sentiment stability.

Key words: Sentiment analysis, differential equations, GPT-4, curve fitting, hierarchical regression analysis.

1. Introduction

Opinion mining or sentiment analysis (SA) examines opinions in text using a blend of mathematics and linguistics [1]. It offers valuable insights for enhancing educational practices [2]. SA operates mainly at four levels: Document, Sentence, Phrase, and Aspect [3, 4]. Document level classifies the overall sentiment of a text, while Sentence level focuses on individual sentences. Phrase level mines opinion words, and Aspect level analyzes the emotional components of phrases, assigning polarity to each.

Sentiment analysis is a multifaceted field involving various NLP tasks like aspect extraction and sarcasm detection [5]. It employs diverse techniques including machine learning, lexicon-based, rule-based, and statistical models [6, 7, 8, 9]. Specialized methods like aspect-based analysis and deep learning have also been developed [10, 11, 12, 13, 14]. Moreover, multi-modal algorithms are emerging that analyze not just text but also visual data [15]. Recent research suggests that keyword-based techniques may be inadequate for nuanced texts [16].

Although differential equations have previously been used in social sciences [17], the contribution of this research lies in building sentiment models through curve fitting and regression analysis. This approach not only enhances credibility but also allows for the study of complex sentiment relationships across various textual levels. It opens up avenues for predicting sentiment behavior in different contexts. Sentiment analysis is already applied in diverse sectors like marketing, politics, and healthcare [18, 19, 20, 21]. By fusing AI-driven sentiment analysis with mathematical models, this research sets the stage for deeper exploration into sentiment dynamics, enriching its application across various fields.

Given the intricacies of text sentiment representation and the intersection of AI-driven sentiment analysis with mathematical models, it is evident that understanding sentiment behavior in various contexts is not only crucial but intricate. Drawing on the principles of mathematical modeling and physics, this research takes innovative steps in employing techniques from stratified symbolic regression, genetic programming, and the finite difference method. Such techniques have proven instrumental in extracting differential equations from data, as showcased by many researches [22, 23, 24, 25]. By bridging the gap between AI sentiment analysis and mathematical modeling, this research promises to provide a more credible, predictive, and enriched understanding of sentiment behavior across textual forms. Therefore, research on the development of sentiment representation using AI-driven analysis combined with mathematical modeling is undeniably relevant.

2. Methodology

This study is based on quantitative research design. We analyzed the sentiments in the first part of the book entitled as "Underground". In the first part of the study, we descriptively investigated the general characteristics of the sentiments in standardized forms. Finally, we used regression models to get differential equations regarding the sentimental tones by using SPSS 25. We get the three given equations representing the sentiment points at different levels of text (word, sentence, and paragraph) as a function of x. The x variable could be interpreted as the position within the text.

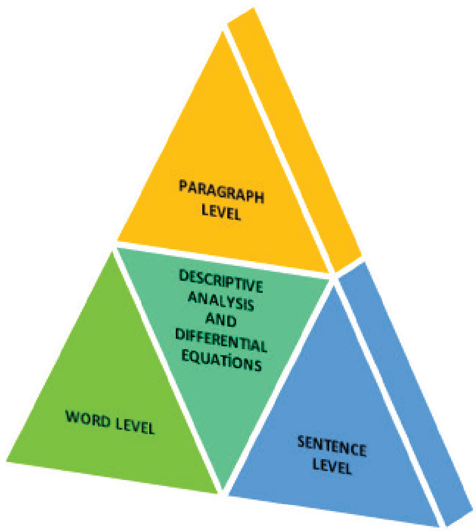

Figure 1– The main units of the analysis

We used GPT-4 which is a multimodal large language model created by OpenAI and the fourth in its GPT series to label sentiment values in word, sentence and paragraph levels. In this analysis we have three main units of the research as words, sentences and paragraphs (Figure 1) where GPT4 assigned sentiment scores between -1 and 0 (negative sentiments) and 0 and 1 (positive sentiments) to each word/phraseor to each sentence in a passage ot to an entire passage of text.

2.1 Analysis

In the first part of our study, we focused on a descriptive analysis of sentiments, standardized forms. Standardization—transforming data values to have a mean of zero and a standard deviation of one–is achieved by subtracting the dataset's mean from each value and dividing the result by the standard deviation. We used the cumulative sum of sentiment values to assess the overall sentiment trajectory over a text. This takes into account the sentiments expressed at each point, whether at the word, sentence, or paragraph level. This cumulative total can help us identify patterns, trends, or variations in sentiment over time, offering insights into the text's general tone and emotional content.

Finally, we used regression models to get differential equations regarding the sentimental tones. Creating a differential equation model using the difference method of variables, curve fitting, and linear regression involves several steps by using IBM SPSS 25 and Wolfram Alpha online. Here's a general outline of the process:

1. Data Collection: We collected sentiment data generated by GPT-4, where the variable x can be interpreted as the position within the text.
2. Calculation of Differences: We computed the differences between consecutive data points to approximate derivatives such as the first and second derivatives. We used the finite forward difference method to calculate these numerical derivatives, denoted as metrics.
3. Curve Fitting: Curve fitting was performed on both the original sentiment data and the calculated differences.
4. Linear Regression Analysis: If the relationship between the original data and the calculated differences appeared to be linear, linear regression was used to find the best-fit line. The aim was to minimize the sum of the squared differences between the observed and predicted values. Hierarchical linear regression analysis was used to identify functions that could represent differential equations.
5. Formulation of the Differential Equation: Based on the results of curve fitting and linear regression, a differential equation model was formulated. Coefficients from the regression were used to define the relationship between the dependent variable(s) and their derivatives in the differential equation.
6. Final Equations: We derived three equations representing sentiment at different textual levels (word, sentence, and paragraph) as functions for the position within the text.

2.2 Limitations

- The main limitation of this study is that we chose theEnglish translation of book rather than original one (Notes from Underground (Vintage Classics) by Fyodor Dostoevsky (Author), Richard Pevear (Translator), Larissa Volokhonsky (Translator). Although GPT-4 works well with russian, it is supposed that it can analyze the results best in English since the main aim is to analyze sentiments.
- The second limitation is that we use GPT-4 model since there are a lot of different libraries and algorithms for this so that our results are restricted within the capabilities of GPT-4 chatbot.
- Sentiment analysis and NLP face a number of obstacles, including idiosyncrasies in writing style, sarcasm, irony, and linguistic peculiarities. Many terms in many languages have nuanced or shifting meanings based on the specific setting or field in which they are used.
- Performing regression analysis on a variable and its numerical derivative based on a difference method might not be ideal for several reasons like loss of ınformation, amplification of noise, data requirements, assumption violations, non-stationarity, causality and ınterpretation ıssues. However, there are cases where using derivatives in a regression analysis could be beneficial. For example, if someone is interested in the rate of change or if the relationship between variables is best modeled by considering rates of change, then the derivative might be appropriate.

3. Findings

3.1 The Descriptive Interpretation of the Sentiment Values at Word Level

The descriptive values of the sentiment values at word level shows a generally negative sentiment at the word level (Table 1, p.13). Most descriptive statistics, like mean, median, and confidence intervals, are also in the negative range, confirming the same. here is a lot of variation in the standardized values, and the distribution is negatively skewed.

Table 1– The descriptive values of tstandardized values of the cumulative sum chart of the sentiments of the words

Cumtopnor	Mean		-35,7602	,72815
	95% Confidence Interval for Mean	Lower Bound	-37,1887	
		Upper Bound	-34,3317	
	5% Trimmed Mean		-34,8997	
	Median		-28,8500	
	Variance		673,360	
	Std. Deviation		25,94918	
	Minimum		-96,86	
	Maximum		8,10	
	Range		104,96	
	Interquartile Range		43,14	
	Skewness		-,533	,069
	Kurtosis		-,811	,137

The standardized values of the waterflow chart (cumulative sum) chart of the sentiments of the words show that at the beginning of the graph, there is a decline in the sentiment values (Figure 2). The initial decline in the graph suggests that the initial words have a largely negative sentiment. This could indicate that the subject matter or tone at the beginning is unfavorable or pessimistic. However there's a point at which the graph starts to curve upwards. This could signify a turning point in the sentiment– perhaps where the content starts to become less negative. This could indicate a shift in the subject or a change in the narrative tone, perhaps offering solutions, resolutions, or a more optimistic outlook.

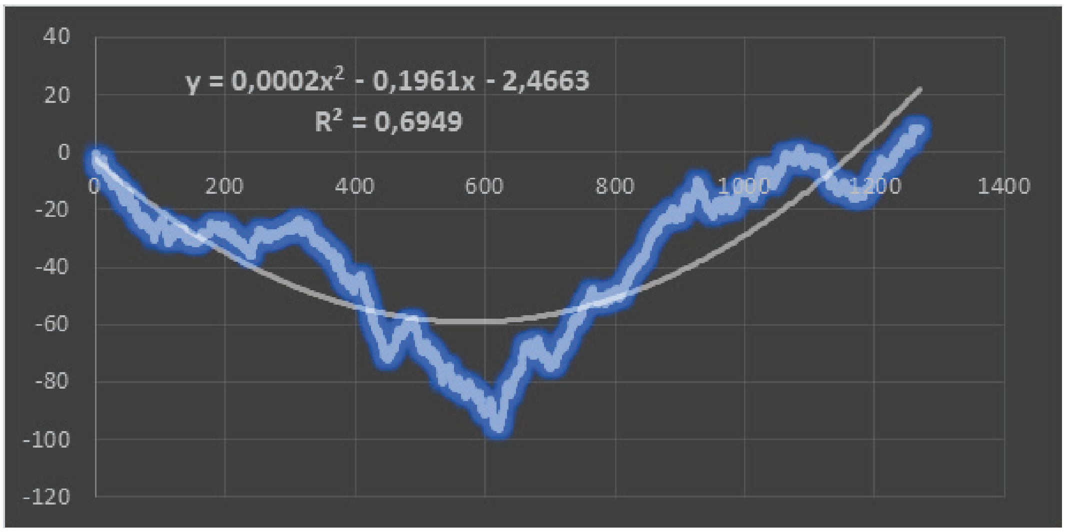

Figure 2 – The standardized values of the waterflow chart (cumulative sum) chart of the sentiments of the words and the relevant equation

3.2 The Descriptive Interpretation of the Sentiment Values at Sentence Level

The descriptive statistics indicate the cumulative sentiment trend in sentence level is negative on average, with a wide spread and skew towards more negative values with a lot of variation (Table 2, p. 14). There are some sentences with very negative sentiments, but there are also some sentences with relatively neutral sentiments.

Table 2 – The descriptive values of tstandardized values of the cumulative sum chart of the sentiments of the sentences

Snormcumsum	Mean		-14,5014	,57995
	95% Confidence Interval for Mean	Lower Bound	-15,6401	
		Upper Bound	-13,3627	
	5% Trimmed Mean		-13,5815	
	Median		-9,9024	
	Variance		228,379	
	Std. Deviation		15,11220	
	Minimum		-51,00	
	Maximum		4,56	
	Range		55,56	
	Interquartile Range		19,05	
	Skewness		-,929	,094
	Kurtosis		-,319	,187

The standardized values of the waterflow chart (cumulative sum) chart of the sentiments of the sentences show that at the beginning of the graph, there is a decline in the sentiment values (Figure 3). The initial decline in the graph suggests that the initial sentences have a largely negative sentiment. This could indicate that the subject matter or tone at the beginning is unfavorable or pessimistic. However there's a point at which the graph starts to curve upwards. This could signify a turning point in the sentiment–perhaps where the content starts to become less negative. This could indicate a shift in the subject or a change in the narrative tone, perhaps offering solutions, resolutions, or a more optimistic outlook. The leveling off at the end suggests that the change in sentiment is not a temporary spike but possibly a new sustained mood or theme possibly showing that the negative trend has plateaued and reached a steady state.

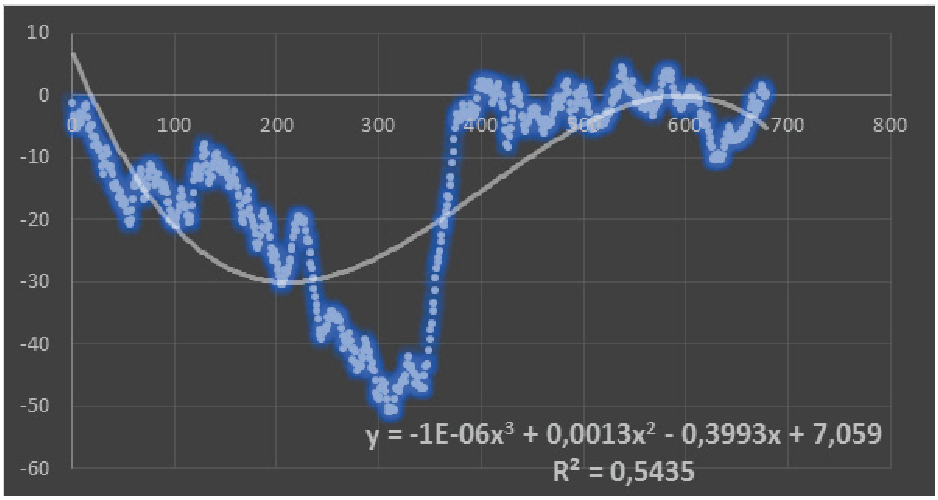

Figure 3 – The standardized values of the waterflow chart (cumulative sum) chart of the sentiments of the sentences and the relevant equation

3.3 The Descriptive Interpretation of the Sentiment Values at Paragraph Level

The descriptive statistics of the standardized values of the cumulative sum chart of the sentiments of the paragraphs suggest that the sentiments of the paragraphs are, on average, negative (Table 3, p. 15). Overall, the data suggests that the sentiments of the paragraphs are predominantly negative with a high degree of variability.

Table 3 – The descriptive values of tstandardized values of he cumulative sum chart of the sentiments of the paragraphs

			Statistic	Std. Error
Pnormcumsum	Mean		-8,1190	1,05517
	95% Confidence Interval for Mean	Lower Bound	-10,2289	
		Upper Bound	-6,0091	
	5% Trimmed Mean		-7,1696	
	Median		-5,6889	
	Variance		69,029	
	Std. Deviation		8,30839	
	Minimum		-32,50	
	Maximum		-,38	
	Range		32,12	
	Interquartile Range		3,46	
	Skewness		-2,472	,304
	Kurtosis		4,966	,599

The graph below represents the standardized values of the waterflow chart (cumulative sum) of the sentiments of the paragraphs (Figure 4). The initial decline in the graph suggests that the initial paragraphs have a largely negative sentiment. This could indicate that the subject matter or tone at the beginning is unfavorable or pessimistic. The stabilization at a lower level could mean that the negative sentiment is sustained over a period, but without worsening. This could represent a consistent theme or mood. The upward curve towards the end suggests a change in sentiment in the later paragraphs. This could indicate a shift in the subject or a change in the narrative tone, perhaps offering solutions, resolutions, or a more optimistic outlook.

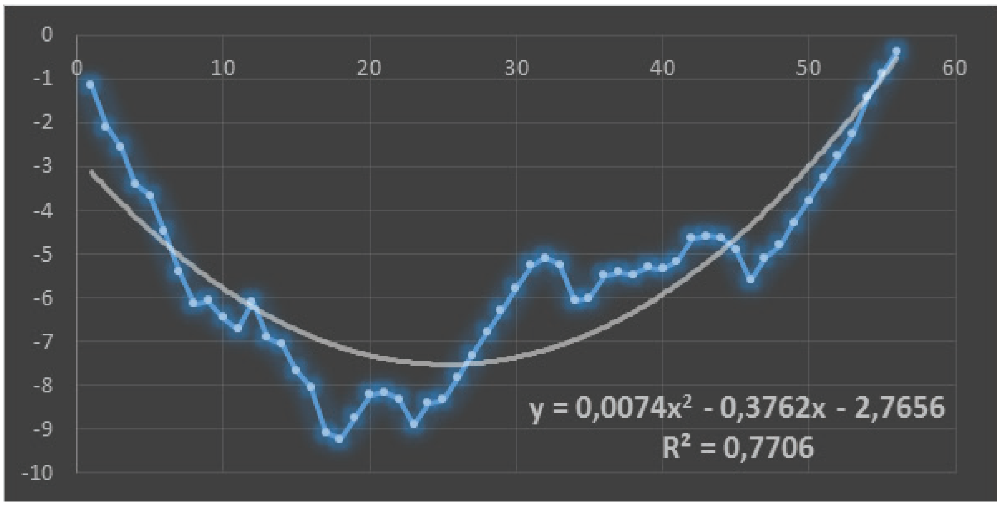

Figure 4 – The standardized values of the waterflow chart (cumulative sum) chart of the sentiments of the paragraphs and the relevant equation

3.4 The differential equations modelling for the words as the main unit of the research

In our sentiment analysis at the word level, we considered various models. The Cubic model has the highest R Square value (0.403) and a significant F statistic (284.935), making it the best fit among the models we could calculate (Table 4. p. 16). However, we opted for the linear model for its simplicity and because it also provided a good fit (R Square of 0.400). We plan to apply the same linear approach to sentence and paragraph levels but have omitted those results due to page constraints.

Table 4 – Model summary and parameter estimates for the sentiments in word level

Model Summary and Parameter Estimates									
Dependent Variable: dw/dx									
	Model Summary					Parameter Estimates			
Equation	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	,400	846,359	1	1268	,000	,006	-,800		
Logarithmica	.	.	.	.	.	.	.		
Inverse	,009	11,263	1	1268	,001	-,012	-,011		
Quadratic	,402	426,358	2	1267	,000	,057	-,798	-,066	
Cubic	,403	284,935	3	1266	,000	,063	-,868	-,075	,047
Compoundb	.	.	.	.	.	.	.		
Powera,b	.	.	.	.	.	.	.		
Sb	.	.	.	.	.	.	.		
Growthb	.	.	.	.	.	.	.		
Exponentialb	.	.	.	.	.	.	.		
Logisticb	.	.	.	.	.	.	.		
The independent variable is .									
a. The independent variable (wnormsent) contains non-positive values. The minimum value is -1,62. The Logarithmic and Power models cannot be calculated.									
b. The dependent variable (wnormderiv) contains non-positive values. The minimum value is -3,40. Log transform cannot be applied. The Compound, Power, S, Growth, Exponential, and Logistic models cannot be calculated for this variable.									

In a hierarchical regression analysis examining sentiments at the word and sentence levels, three models were built (Table 5). Model 1 used ‘wnormsent’ as a predictor and showed the highest explanatory power. Adding ‘snormsent’ in Model 2 and ‘snormder’ in Model 3 did not significantly improve the model, as indicated by non-significant Sig. F Change values (0.333 and 0.212). Therefore, we continue with the numerical derivatives of the variables in the same level.

Table 5 – Hierarchical regression analysis for the sentiments in word level and sentence level

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	,616a	,380	,379	,88553	,380	414,526	1	677	,000
2	,617b	,381	,379	,88557	,001	,939	1	676	,333
3	,618c	,382	,379	,88520	,001	1,564	1	675	,212
a. Predictors: (Constant), wnormsent b. Predictors: (Constant), wnormsent, snormsent c. Predictors: (Constant), wnormsent, snormsent, snormder d. Dependent Variable: wnormderiv									

In a hierarchical regression analysis focused on the second derivative of word-level sentiments, two models were compared. Model 2, which added ‘dwdt’ as a predictor, showed a significant improvement in predictive power, indicated by an Adjusted R Square of 0.792 and a Durbin-Watson statistic of 2.003, suggesting no autocorrelation in residuals (Table 6) The Standard Error of the Estimate also decreased in Model 2, confirming its efficiency. Thus, Model 2 is the more effective model for predicting the second derivative of word-level sentiments.

Table 6 – Model summary including the second derivative of the sentiments in word level as an additional predictor to Model 2.

					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,327[a]	,107	,106	1,78921	,107	151,392	1	1268	,000	
2	,890[b]	,793	,792	,86229	,686	4192,322	1	1267	,000	2,003
a. Predictors: (Constant), w b. Predictors: (Constant), w, dwdt c. Dependent Variable: d2wdt2										

The collinearity diagnostics table providing information about multicollinearity, which refers to a situation in regression analysis where predictor variables are highly correlated (Table 7). Belsley, Kuh, & Welsch [23] suggest that a condition index greater than 15 indicates a possible collinearity problem and a condition index greater than 30 indicates a serious problem. Even though the condition index for all dimensions is below 15, the variance proportions in Model 2 suggest that dwdt might be contributing to multicollinearity. Model 2 is more complex but may have multicollinearity issues, especially in Dimension 3.

Table 7 – The collinearity diagnostics table

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions		
				(Constant)	W	Dwdt
1	1	1,007	1,000	,50	,50	
	2	,993	1,007	,50	,50	
2	1	1,633	1,000	,00	,18	,18
	2	1,000	1,278	1,00	,00	,00
	3	,367	2,108	,00	,82	,82
a. Dependent Variable: d2wdt2						

The table 8 presents the coefficients for each predictor in the regression models. In the context of a regression equation, these coefficients are the weights that are multiplied by the predictors to estimate the dependent variable. The collinearity statistics (Tolerance and VIF) indicate whether the predictors are highly correlated with each other. Tolerance close to 0 and VIF (Variance Inflation Factor) much greater than 10 can indicate a problem with multicollinearity [24]. No multicollinearity issues are indicated by the Tolerance and VIF statistics in this respect (Table 9, p. 17).

Table 8 – The table presenting the coefficients for each predictor in the regression models

Model B		Unstandardized Coefficients		Standardized Coefficients	T	Sig. Zero-order	Correlations			Collinearity Statistics	
		Std. Error	Beta				Partial	Part	Tolerance	VIF	
1	(Constant)	-,004	,050		-,083	,934					
	W	,700	,057	,327	12,304	,000	,327	,327	,327	1,000	1,000
2	(Constant)	,007	,024		,271	,786					
	W	-,751	,035	-,350	-21,194	,000	,327	-,512	-,271	,600	1,667
	Dwdt	-1,814	,028	-1,070	-64,748	,000	-,848	-,876	-,828	,600	1,667
a. Dependent Variable: d2wdt2											

We can write the significant model explaining % 79 of the variance of first derivative of sentiments in word level in a diferential equation like follows:

Equation 1:

$$\frac{d^2w}{dx^2} = 0.007 - 0.751w - 1.814\,\frac{dw}{dx} \qquad \textit{(explaining \%79 of the variance)}$$

3.5 The Differential Equations Modelling for the Sentences as the Main Unit Of The Research

Just as Word level analysis, we made curve fitting for sentiments in sentence level. Out of the available models, the Cubic model has the highest R Square value (0.330), indicating it explains the most variance in the dependent variable snormder compared to the other models. However, the improvement over the Linear and Quadratic models is relatively small, and depending on the specific context, a simpler model might be preferred for ease of interpretation and application. According to Table 9, Model 2 showed stronger predictive power with an R^2 value of 0.754, confirmed as statistically significant by a low p-value. The Durbin-Watson statistic of 2.003 supports the model's validity.

Table 9 – Model summary presenting the results of regression analyses for two models attempting to predict the variable ds2dt2

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,825[a]	,681	,680	1,07739	,681	1440,924	1	676	,000	
2	,868[b]	,754	,753	,94611	,073	201,619	1	675	,000	2,003
a. Predictors: (Constant), dsdt b. Predictors: (Constant), dsdt, s c. Dependent Variable: ds2dt2										

Since the condition index for all dimensions is below 15, the data suggests that Model 2 is more complex and better conditioned to explain the dependent variable, but it might also be more susceptible to multicollinearity, especially in Dimension 3 (Table 10).

Table 10 – Collinearity Diagnostics

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions		
				(Constant)	Dsdt	S
1	1	1,002	1,000	,50	,50	
	2	,998	1,002	,50	,50	
2	1	1,572	1,000	,00	,21	,21
	2	1,000	1,254	1,00	,00	,00
	3	,428	1,915	,00	,79	,79
a. Dependent Variable: ds2dt2						

Based on Model 2 in the table below, the equation for the dependent variable snormder in terms of the predictor variables snormsent and snormsecondder given as follows (Table 11):

Equation 2:

$$\frac{d^2s}{dx^2} = 0.004 - 0.622s - 1.673\,\frac{ds}{dx} \qquad \textit{(explaining \%75 of the variance)}$$

Table 11– Coefficients

Model B		Unstandardized Coefficients		Standardized Coefficients	T	Sig. Zero-order	Correlations			Collinearity Statistics	
		Std. Error	Beta				Partial	Part	Tolerance	VIF	
1	(Constant)	,004	,041		,091	,927					
	Dsdt	-1,361	,036	-,825	-37,960	,000	-,825	-,825	-,825	1,000	1,000
2	(Constant)	,004	,036		,121	,904					
	Dsdt	-1,673	,038	-1,014	-43,586	,000	-,825	-,859	-,832	,673	1,485
	S	-,622	,044	-,330	-14,199	,000	,249	-,480	-,271	,673	1,485
a. Dependent Variable: ds2dt2											

3.6. The Differential Equations Modelling for the Paragraphs as the main unit of the research

Table given below shows that Model 2 slightly improves upon Model 1, explaining 75.1% of the variance compared to 70.3% in Model 1 (Table 12).

Table 12 – Model summary including the second derivative of the sentiments in paragraph level as an additional predictor to Model 2

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	,838a	,703	,697	,46556	,703	122,974	1	52	,000	
2	,867b	,751	,742	,42998	,049	9,963	1	51	,003	2,010
a. Predictors: (Constant), dpdt b. Predictors: (Constant), dpdt, p c. Dependent Variable: dp2dt2										

Since the condition index for all dimensions is below 15, the data suggests that Model 2 is more complex and better conditioned to explain the dependent variable, but it might also be more susceptible to multicollinearity, especially in Dimension 3 (Table 13).

Table 13 – Collinearity Diagnosticsa

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions		
				(Constant)	Dpdt	p
1	1	1,062	1,000	,47	,47	
	2	,938	1,064	,53	,53	
2	1	1,522	1,000	,01	,24	,24
	2	,988	1,241	,99	,01	,01
	3	,490	1,762	,00	,76	,75
a. Dependent Variable: dp2dt2						

Based on Model 2 in the table, the equation for the dependent variable: Equation 3 (Table 14):

$$\frac{d^2p}{dx^2} = 0.035 - 1.622V\frac{dp}{dx} - 0.405p \qquad \textit{(explaining \%74 of the variance)}$$

Table 14 – Coefficients of the two hierarchical regression models with the dependent variable

Model B		Unstandardized Coefficients		Standardized Coefficients	T	Sig. Zero-order	Correlations			Collinearity Statistics	
		Std. Error	Beta				Partial	Part	Tolerance	VIF	
1	(Constant)	,039	,063		,618	,539					
	Dpdt	-1,404	,127	-,838	-11,089	,000	-,838	-,838	-,838	1,000	1,000
2	(Constant)	,035	,059		,605	,548					
	Dpdt	-1,622	,136	-,968	-11,944	,000	-,838	-,858	-,834	,741	1,349
	P	-,405	,128	-,256	-3,156	,003	,237	-,404	-,220	,741	1,349
a. Dependent Variable: dp2dt2											

3.7 The Analysis of the Differential Equations

We get three differential equations where each one describes how a specific dependent variable (w, s, p standing for word, sentence and paragraph) changes with respect to an independent variable (x).The coefficients (0.007, 0.751, 1.814 for the first equation, etc.) indicate the magnitude of the respective terms' contribution to the change of the dependent variable.

$\frac{d^2w}{dx^2} = 0.007 - 0.751w - 1.814\frac{dw}{dx}$ *(explaining %79 of the variance)* with the general solutions for the differential equations by wolfram alpha:

$w(x) = 0.00932091 + C[1]\cdot e^{-1.17467x} + C[2]\cdot e^{-0.639327x}$

$\frac{d^2s}{dx^2} = 0.004 - 0.622s - 1.673\frac{ds}{dx}$ *(explaining %75 of the variance)* with the general solutions for the differential equations by wolfram alpha:

$s(x) = 0.00643087 + C[1]\cdot e^{-1.11531x} + C[2]\cdot e^{-0.557695x}$

$\frac{d^2p}{dx^2} = 0.035 - 0.405p - 1.622\frac{dp}{dx}$ *(explaining %74 of the variance)* with the general solutions for the differential equations by wolfram alpha:

$p(x) = 0.0864198 + C[1]\cdot e^{-1.31371x} + C[2]\cdot e^{-0.308286x}$

In summary, the general solutions suggest that over time, all three sentiment measures w, s, and p will stabilize to slightly positive values, with the speed of stabilization depending on the specific decay rates. For $w(x)$, $s(x)$, and $p(x)$, the constant terms are 0.00932091, 0.00643087, and 0.0864198, respectively. These represent the base sentiment level for each. Among them, $p(x)$ has the highest base sentiment level. The finding that p(x) has the highest base sentiment level implies that, in the long run (as x approaches infinity), the sentiment score for paragraphs will stabilize at a higher level compared to words and sentences.

4. Discussion

The 1864 novella “Notes from Underground” by Fyodor Dostoevsky introduces the Underground Man, a cynical recluse living in St. Petersburg. In the philosophical first half, he contends that human nature is irrational, making ideal societies impossible. Overall, the sentiments in the “Underground” section are dark, complex, and fraught with tension. They reflect a deep sense of disillusionment with both society and the self, as well as a profound existential despair. The second half follows a more conventional format. The opening “Underground” section establishes a gloomy, contemplative mood through the protagonist’s cynical monologues on society, reason, and the meaning of life. He grapples with complex ideas that lead to dark, nihilistic conclusions about human nature and the pursuit of happiness. The tone reflects his mental agony and sense of estrangement. Both the beginning and the end of the “Underground” section are negative, but the nature of this negativity shifts. The beginning is more confrontational and critical, actively challenging societal norms and intellectual trends. The end, in contrast, is more resigned and reflective, focusing on the inescapable suffering and irrationality of the human condition.

When the comparisons of the sentiment values at word, sentence and paragraph level based on descriptive results for the first part of the book following results can be given as follows:

- Mean Sentiment: The mean sentiment value becomes less negative as we move from word to paragraph level. This could imply that while individual words may be negative, the sentences and paragraphs they form could be less negative in sentiment, possibly due to the context in which they are used.
- Variability: The standard deviation decreases from word level to paragraph level, suggesting that the sentiment is more stable at the paragraph level. Stability in sentiment analysis in this article refers to the consistency or steadiness of sentiment scores over a particular level of text.
- Trends: All three levels show an initial decline in sentiment but have an upward curve later on. This may indicate that the text starts with a negative tone but gradually becomes less negative.
- Skewness & Kurtosis: Word and sentence levels are negatively skewed, while the paragraph level is even more so. This again confirms a generally negative sentiment.
- Interquartile Range: This range is highest at the word level, indicating more variability in the middle 50% of the data compared to sentence and paragraph levels.

The text likely starts off with a negative or pessimistic tone but shows signs of becoming less negative or more neutral as it progresses. This could indicate a narrative structure that starts with a problem or issue and gradually moves towards solutions or resolutions.

In the context of differential equations, p(x) has the highest base sentiment level. The finding that p(x) has the highest base sentiment level implies that, in the long run (as x approaches infinity), the sentiment score for paragraphs will stabilize at a higher level compared to words and sentences. Paragraphs are generally more context-rich than individual words or sentences. They can provide a more nuanced and complete representation of sentiment. The higher base sentiment level might reflect this richness and complexity.

In the context of decay components we found the following results:

Fast-Decay Component: The ranking in terms of losing fast-changing sentiment quickest is $p(x)>w(x)>s(x)$.

Slow-Decay Component: The ranking in terms of retaining slow-changing sentiment the longest is $p(x)<s(x)<w(x)$.

If we assume that the decay rates are indicative of the sentiments’ sensitivity to change and staying power. Sensitivity in sentiment analysis in this text refer to the degree to which the sentiment scores are affected by minor changes in the text.

p(x) is the most sensitive to immediate changes, which means that it will change quickly in response to new information. However, it is also the most likely to retain a base level of sentiment over the long term. This is because p(x) captures the overall sentiment of the text, which is not likely to change drastically unless there is a major event.

w(x) is moderately sensitive to both immediate and long-term changes. This means that it will be affected by new information, but it will also be influenced by the text's overall sentiment.

s(x) is the least sensitive to immediate changes, but it is moderately sensitive to long-term changes. This means that it will not be swayed by new information, but it will be affected by the text's overall sentiment over time.

It should be keep in mind that Slower decay rates don't necessarily mean greater stability. Magnitude of sentiment shifts also contributes to stability. Starting sentiment score provides context for subsequent shifts. Interactions between linguistic units affect overall stability. Operational definition of stability depends on application. Quantitative decay rates don't fully capture perceived stability

In this respect, based on the descriptive analysis and the results of differential equations, there are a couple reasons why paragraph-level sentiment analysis tends to be more stable and sensitive than word- or sentence-level analysis:

1) Paragraphs capture more context. Paragraphs contain multiple sentences and thus provide more context to interpret the sentiment of any given word or sentence. Paragraphs can be both stable and sensitive, depending on the nature of the changes they experience. They are stable against minor fluctuations but sensitive to major shifts that affect the broader context they encapsulate. A paragraph may be less sensitive to small, local changes that affect only one or a few words or sentences within it. This is because the broader context can absorb these fluctuations. A paragraph may be more sensitive to large, global changes that affect its overall sentiment. In such cases, the additional context provided by the paragraph actually amplifies the impact of the change.

2) Less sensitivity to order effects. The sentiment of a paragraph is less susceptible to the order in which words or sentences appear. The overall sentiment of a well-written paragraph remains largely the same regardless of structural variations. Word- or sentence-level analysis, on the other hand, is more prone to being influenced by the specific ordering of the text's components, reducing stability.

3) Aggregation Effects. When analyzing at the paragraph level, the sentiments of various sentences are aggregated. This aggregation could amplify sensitivity to changes if the new information significantly shifts the aggregated sentiment.

4) Complexity of Analysis. Sentiment analysis at the paragraph level may involve more complex linguistic features such as subjectivity, tone, and rhetorical devices, which could make it more sensitive to changes.

5) Order of Components. A single, strong sentence could potentially sway the sentiment of an entire paragraph.

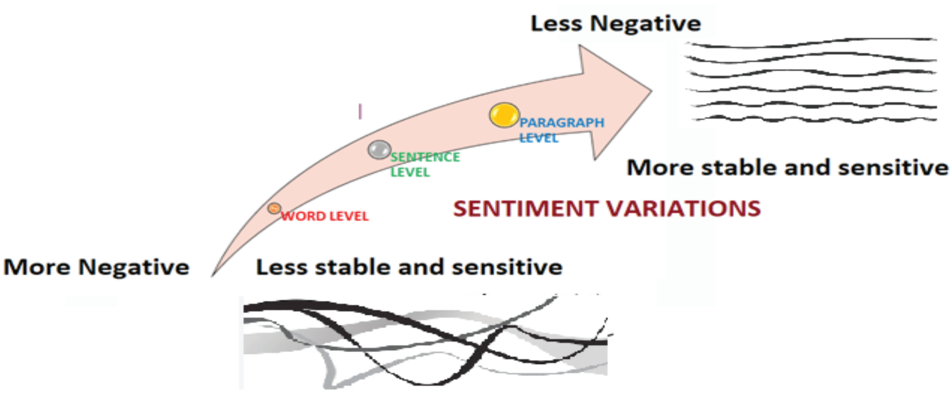

Figure 5 – The comparison shows that the sentiment variations are more rapid and decay faster at the word level, while they are slower and more stable at the paragraph level

5. Conclusion

This research aims to understand the dynamics of sentiment evolution in textual units ranging from individual words to expansive paragraphs. One of the most striking revelations is that sentiment becomes increasingly less negative as we traverse from the granularity of words to the complexity of paragraphs. This not only emphasizes the moderating role of context in toning down negativity but also spotlights the multi-layered intricacies of human language and sentiment.

The study also found that paragraph-level sentiment is more stable than word or sentence sentiment. This means that the sentiment of a paragraph is less likely to change over time than the sentiment of a word or sentence. This is because paragraphs are typically longer and contain more information, which makes them more resistant to change.

Our study also uncovers a general narrative arc in sentiment, characterized by an initial decline followed by an upward turn. This pattern is reflective of a common narrative structure, moving from a problem or conflict to a potential resolution. This observation can be particularly useful for literary analysis, scriptwriting, or even in the evaluation of user-generated content.

Finally, the study found that paragraphs lose short-term sentiment more quickly than words or sentences but are adept at retaining long-term sentiment. This nuanced behavior of paragraphs makes them uniquely suited for applications where both immediate and enduring sentiments are of interest. It suggests that paragraphs are more responsive to new or emerging information while also serving as a stable repository for the overall sentiment landscape over extended periods.

Intriguingly, our findings echo the famous quote: “Watch your thoughts, they become your words; watch your words, they become your actions; watch your actions, they become your habits; watch your habits, they become your character; watch your character, it becomes your destiny.” Just as the proverb underscores the progression from thoughts to destiny, our study reveals a similar progression in sentiment from isolated words to contextualized paragraphs. reme—a single word may express intense negativity. However, as these words come together into phrases, sentences, and paragraphs, the contextual relationships between them moderate the overall sentiment. The negativity of individual words becomes diluted within the broader meaning. Just as the proverb shows our habits and character evolving from small thoughts and words, our analysis reveals how the sentiment of language grows more nuanced as words gain context. The volatility of isolated words gives way to balanced, subtle shades of meaning in paragraph form. This parallels how fleeting thoughts solidify into steady character over time.

The insights from this research have broad implications, not just for the academic community but also for industries like marketing, journalism, and mental health services, where understanding sentiment can be pivotal. Future work could focus on expanding the dataset, incorporating multilingual texts, or even exploring how these findings translate to spoken language.

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СӨЗДЕРДЕН ПАРАГРАФТАРҒА: СИПАТТАМАЛЫҚ ӘДІСТЕР МЕН ДИФФЕРЕНЦИАЛДЫҚ ТЕҢДЕУЛЕР АРҚЫЛЫ GPT-4 КӨМЕГІМЕН «ЖЕР АСТЫНДАҒЫ ЖАЗБАЛАРДА» КӨҢІЛ-КҮЙ ДИНАМИКАСЫН МОДЕЛЬДЕУ

Андатпа

Бұл зерттеу Федор Достоевскийдің «Жер астындағы жазбалар» кітабының «Жер асты» деп аталатын бірінші бөліміндегі көңіл-күй мағынасының сөздерден сөйлемдерге, абзацтарға қалай өзгеретінін зерттейді. GPT-4 тіл үлгісін пайдалана отырып, біз стандартталған сезім мәндерінің сипаттамалық талдауын жүргіздік және мәтін бойынша жинақталған көңіл-күй траекторияларын есептедік. Содан кейін регрессиялық талдауды пайдалана отырып, көңіл-күй реңктерін модельдеу үшін дифференциалдық теңдеу үлгілерін жасадық. Біздің қорытындыларымыз сөздерден абзацтарға дейін көңіл-күйдің теріс болмайтынын, бұл контекст негативтілікті төмендететінін көрсетеді. Аз өзгергіштікпен параграфтың көңіл-күйі де тұрақталды. Бастапқы құлдыраудың баяндау доғасы болса, содан кейін көңіл-күй көтерілді. Параграфтар неғұрлым нюансты контекстті түсіре алатынын білдіретін ең жоғары негізгі ойға ие болды. Абзацтар қысқа мерзімді көңіл-күйді тез жоғалтты, бірақ уақыт өте келе жалпы мәтіндік сезімді сақтай отырып, абзацтармен сәйкестендірілген ұзақ мерзімді көңіл-күйді ұзаққа сақтады. Бұл тұжырымдар сезімнің тұрақтылығын қамтамасыз ететін тілдік бірліктер арасында күрделі динамика бар екенін көрсетті. Сандық ыдырау жылдамдығы – пайдалы көрсеткіштер, бірақ ол көңіл-күй тұрақтылығын толық сипаттамайды.

Тірек сөздер: көңіл-күйді талдау, дифференциалдық теңдеулер, GPT-4, қисық аппроксимация, иерархиялық регрессиялық талдау.

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ОТ СЛОВ К ПАРАГРАФАМ: МОДЕЛИРОВАНИЕ ДИНАМИКИ НАСТРОЕНИЙ В «ЗАПИСКАХ ИЗ ПОДПОЛЬЯ» С ПОМОЩЬЮ GPT-4 ЧЕРЕЗ ОПИСАТЕЛЬНЫЕ МЕТОДЫ И ДИФФЕРЕНЦИАЛЬНЫЕ УРАВНЕНИЯ

Аннотация

В данном исследовании рассматривается, как изменяются значения настроения в первой части книги «Записки из подполья» Федора Достоевского, озаглавленной как «Подполье», от слов к предложениям и абзацам. Используя языковую модель GPT-4, мы провели описательный анализ стандартизированных значений настроения и рассчитали кумулятивные траектории настроения по тексту. Затем мы создали модели дифференциальных уравнений для моделирования оттенков настроения с помощью регрессионного анализа. Полученные нами результаты свидетельствуют о том, что от слов к абзацам настроение становится менее негативным, что указывает на то, что контекст регулирует негативность. Настроение абзацев также было более стабильным и отличалось меньшей вариативностью. Наблюдалась дуга повествования с первоначальным снижением, за которым следовал подъем настроения. Абзацы имели самые высокие исходные настроения, что говорит о том, что они способны отражать более тонкий контекст. Абзацы быстро теряли краткосрочное настроение, но дольше всего сохраняли долгосрочное настроение, что согласуется с тем, что абзацы сохраняют общее настроение текста с течением времени. Полученные результаты позволяют предположить, что существует сложная динамика между языковыми единицами, способствующая ощутимой стабильности настроения. Количественные показатели распада являются полезными индикаторами, но не в полной мере характеризуют стабильность настроения.

Ключевые слова: анализ настроений, дифференциальные уравнения, GPT-4, аппроксимация кривой, иерархический регрессионный анализ.

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