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Date: 2024-08-12

Poetry Across Multiple Languages

Introduction:

The reason I read, is because I am so fascinated with how writers manage to describe how they engage with the world. Every year or so I have these phases where I seek out poetry from various writers trying to expand my horizons and see how new experiences are described. During this summer I was also trying my hand in learning Spanish. So, when the two pursuits (one of the mind and one of the heart) come together in the form of a project, it is sort of like a solar eclipse. To expose myself to the beauty and awe of the Spanish literature I sought to find excerpts from some of the more recognizable poems in Spanish and try to learn from the poems, to improve my command of the Spanish language. However, I also relied on the English translations of these poems, but I felt almost unsatisfied with these translations as I know I am not reading these words in their original language, which the poet had in their mind. The goal of this paper is to compare the emotional affect scores of 3 human translated poems with 3 computer translations of the same poems to see how translation affects the emotion of the poems.

The poems I had decided to use for this analysis are from the anthology, *Selected poems [of] Pablo Neruda* (Neruda & Kerrigan, 1975). The specific poems I had decided to use are the following written by Pablo Neruda:

- *XIV Juegas todos los días…/ XIV Every Day You Play…* (Trans. W. S. Merwin)
- *XX Puedo escribir los versos…/ XX Tonight I Can Write… (*Trans. W.S. Merwin)
- *Oda al tomate/ Ode to the Tomato* (Trans. Nathaniel Tarn)

These poems and my findings are just a snapshot of the linguistic magic Neruda's poetry, and his fellow translators (both human and machine) have accomplished. I hope to carry this burden by presenting a potential tool that can be used by many in the field of Translation Studies to ensure the feelings of language continue to change and evolve over time.

Methodology:

The actual procedure of getting this NLP (Natural Language Processing) project from start to finish was met with some setbacks. The first step was copying the specific poems I wanted from the Neruda poem anthology, onto separate text files. I had typed out the poems in their original Spanish and English translation by translator. From there I then used python to help with my investigation into the NLP sentiment analysis scores of Neruda's poems in Translation. After sentiment analysis was complete further NLP procedures like Frequency Distribution plots and Lexical Dispersion plots also are generated for the well-rounded understanding of the kinds of words used between translations.

The first setback was that I wanted originally to compare the sentiment analysis scores of the Spanish poem translations by the professional translators with the original Spanish poems Neruda had written but I could not find a way to run the Spanish poems into the various sentiment analysis analyzers. The sentiment analysis analyzers I had used are: *TextBlob Sentiment Analysis*, *Naïve Bayes Sentiment Analysis*, and *Vader Sentiment Analysis*. The reason why I wanted to use three different sentiment analysis analyzers was to see if there were any differences in which analyzer I use to interpret the findings.

The second setback was trying to find a way to translate the original Spanish Poems to English (using python). This process was a bit tedious, so I had decided once the poems were translated, to write separate text files for each machine translation and save them as separate text files locally to ensure I was using the machine translated English text in the sentiment analysis part.

After I had gathered the machine translated poems and the human translations of the poems and ran sentiment analysis on them using the three various sentiment analysis analyzers: *TextBlob Sentiment Analysis*, *Naïve Bayes Sentiment Analysis*, and *Vader Sentiment Analysis.* The idea of which sentiment analyzer and code examples to use the TextBlob Sentiment Analysis and Naïve Bayes Sentiment Analysis were from Chapter 12. Natural Language Processing (NLP). In *Intro to Python - for Computer Science and Data Science: Learning to Program with AI, Big Data and the Cloud* by Peter and Harvey Deitel (Deitel & Deitel, 2020) as well as the online documentation from TextBlob itself. For the visualizations, I had decided for the analysis of the results to exclude the Naïve Bayes sentiment Analyzer as the values were not significant. The third sentiment analysis analyzer, Vader sentiment analysis was introduced to me by Professor Victoria Chui while in the course *INF1340 Introduction to Python*.

Results:

> *Exploratory data analysis can never be the whole story, but nothing else can serve as the foundation stone—as the first step.* – John, W. Tukey, Exploratory Data Analysis, 1977, p. 3

Table 1 Average Sentiment Analysis Score for each Translation Type (Without Naïve Bayes Analyzer)

Translation Type	TextBlob Sentiment Polarity Score	TextBlob Sentiment Subjectivity Score	Vader Analysis Positive Sentiment Score	Vader Analysis Negative Sentiment Score	Vader Analysis Neutral Sentiment Score	Vader Analysis Compound Sentiment Score
Human	0.1692	0.4966	0.1177	0.8040	0.0780	0.9130
Machine	0.1699	0.4908	0.1373	0.7823	0.0807	0.9963

Table 1 provides the average sentiment scores of each NLTK tool by translation type. The sentiment analysis scores range from (-1) to 1 for Polarity, and 0 to 1 for Subjectivity. In the Vader analysis depending on the Sentiment Analyzer used the results means something slightly different.

For the TextBlob Sentiment Analyzer, the scores come in two categories, “Polarity” and “Subjectivity”. Polarity is the overall emotional score; the Analyzer calculates based on the corpora (text input). If the sentiment score is closer to 1 this means that the text was extremely emotional. The reverse is also true if the polarity score is closer to 0, then the text does not have much emotion. And if the text is negative, it would receive a score of -1. Subjectivity score measures how "personal" the text is received, if a text has a sentiment score closer to 1 it means the text was extremely subjective and if the sentiment score is closer to 0 it means the text is more objective.

As for the Vader Analysis, depending on the exact category it describes what the sentiment score is measuring. But the ranges typically seem to have a larger score for the Vader Neutral and Compound sentiment elements compared to Vader Negative and Positive which produce low sentiment results. Below is Figure 1 that visualizes the findings from Table 1.

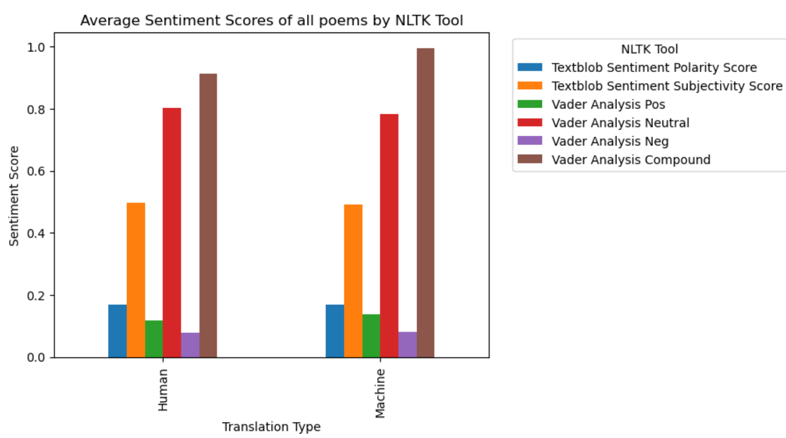

Figure 1 Bar plot of Table 1

I then decided to see among each poem how the various sentiment scores varied, and so Figure 2 captures the six different sentiment Analyzer's and their score for each of the poems. The data used to create Figure 3 can be found in Appendix A Tables. One sentiment tool I do want to focus on is the TextBlob Polarity Sentiment analysis scores among the three poems.

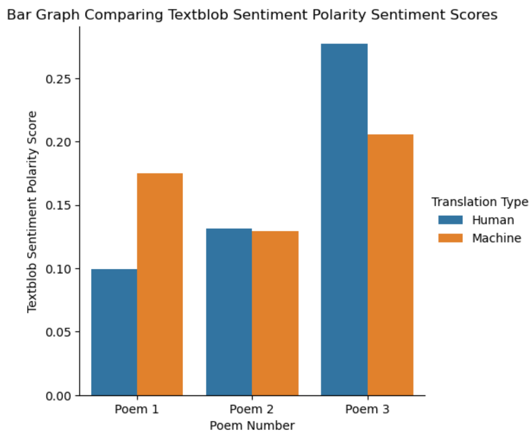

Figure 2 TextBlob Polarity Scores Among Poems and Translation Type

The reason why I decided to select Figure 2 to be closely examined is because of the stories this graph tells. In this graph we see three separate paths, the first path, is Poem 1: *Ode to the Tomato* is that sometimes the machine translation for a poem can prove to have a larger emotional score than the human translation. The second clue is that for Poem 2: *XIV Every Day You Play…* the polarity score is practically identical and finally the third path is Poem 3*: XX Tonight I Can Write…* where the human translation has a polarity score than the machine translation of the poem.

With these three different stories presented in Figure 2, I then did more NLP tasks like generating Frequency Plots and Lexical Dispersion plots for all 3 poems and their versions of translation (6 in total). To get a better sense of how these scores could possibly have changed. But the best tool to compare between the two poems, is to manually read among the groupings of poems and generate some meaning behind the plots. To see this, please check out the python file with all the plots and charts.

Discussion:

The reason why I had decided to stick with the poems of Pablo Neruda was because of how influential his works are. When starting this project, I had heard of Pablo Neruda, but never read his poems (in either Spanish or English), but to my surprise his poetry is referenced quite a lot and for good reason. In the introduction for the anthology *Selected poems [of] Pablo Neruda* (Neruda & Kerrigan, 1975); Jean Franco highlights the overall feat and praise Neruda's poetry gets, he mentions in the later years of Neruda's career we can see the growth and attention to his audience is what makes Neruda a great poet (Franco, 1973). Franco wrote: "…Neruda who not only regards the word as a communication vessel with the past but also a giver of life…" (Franco, 1973, p.20).

What I had learned while on my journey understanding Neruda's poetry and his translations, is how translations should be understood. In the book *Translation: A Very Short Introduction* by Mattew Reynolds, he mentions that "Translation is not the same as communication. Instead, it is *part* of communication" (Reynolds, 2016, p. 25). To me after using NLP to begin to quantify the emotional impact words, I began to wonder about the kinds of ways words can change meaning. When comparing the text files of the human translation with the computer translation I had noticed there were slight differences in the poems themselves. For example, in both the poem translations by W. S. Merwin: *XIV Every Day You Play…* and *XX Tonight I Can Write…*, it seems to try to capture the clear language that Neruda had written in the original Spanish; However, when I had translated Neruda's poems using Machine Learning/Translation, the titles of the poems changed completely to: ***XIV You Play Every Day…*** and ***XX I Can Write the Verses…***. Now these subtle and slight changes in the title are not wrong, but they do change the meaning of the poems.

Ilya Kaminsky had written an Introduction for the poetry anthology, *The Ecco Anthology of International Poetry*, that "by translating, we learn how the limits of our English-speaking minds can be stretched to accommodate the foreign, and how there by we are able to make our own language more beautiful—to awaken it" (Kaminsky, 2009, p. xl). What I believe Kaminsky is alluding to is how the deliberate manoeuvring and change towards our approach to language can result in surprises beyond what we can fathom language becoming.

The machine translations I had generated with the help of the NLTK python, presented to me a firsthand example as to how machine translation works. Reynolds (2016) mentions that these translations executed by the machine are not bound by the same restrictions humans have. He states:

"In this method of translation, the computer does not apply rules for converting one language into another. It searches for all the ways a given phrase, and ones like it, have been translated in the past; and then it uses statistical techniques to determine which of the possibilities is likely to work best in the given context" (Reynolds, 2016, p. 95).

By physically reading the comparisons of the two types of translation, I began to wonder about if we will get to a point where we cannot tell the difference between a human translation of a poem and machine translation of a poem. Reynolds also written that:

"This extraordinary technology is advancing at speed. While it does so, it is radically changing our relationship to language. It enables communication where it was not possible before. And it is exposing people to strange versions of languages they do not know. Take 'Breakfast overslept, no experience.' You can see what it is getting at; but can also enjoy it as a piece of language. It has a kind of poetry" (Reynolds, 2016, p. 97).

This underlying optimism Reynolds has for language with machine translation as a tool is also a feeling I share as this could potentially mean a new way to exchange ideas and feelings. Yet at the same time, it goes to show even though a machine can translate text, it still requires a level of thinking to get at the heart of the words.

Conclusion:

If I had to present, my findings to Pablo Neruda I am sure he would be quite pleased with the insights I have made with his poems. From taking his words and translating them to seeing how similar the English translations of his poems are, I was able to understand translation by forging my own path with sentiment analysis. Now this is not the only way to understand text but given the tools I was provided with I was able to make my close readings of these poems (with the help of the NLP tools of course). Unfortunately, I could not have included all the plots and findings onto this report, it would have been way too long and not as exciting. So, consider this an effort to briefly present my findings as a mini checkpoint into a larger discussion I hope to have on this topic of translation and NLP soon. The results from this study are only considering the three poems I had typed out into text files, converted into English translations and performed basic NLP Sentiment analysis on. Some lingering questions I had, which I hope to solve too is if I could try to capture the sentiment scores of the original Spanish poem, which English translation would resemble the original poem? Another completely different tangent for a future project is to check the sounds of each poem and see if translation can capture elements of the poems that are not visible on a page/screen? In any case I am content with the project this far and I hope to return to Neruda's poems when I practice my Spanish or better yet to also expand on my English.

Appendix A Table:

Table 2 Sentiment Analysis Scores Long (Without Naive Bayes Analyzer)

ID	Translation Type	Poem Number	NLTK Tool	Sentiment Analysis Score
0	Human	Poem 1	Textblob Sentiment Polarity Score	0.0994
1	Machine	Poem 1	Textblob Sentiment Polarity Score	0.1750
2	Human	Poem 2	Textblob Sentiment Polarity Score	0.1312
3	Machine	Poem 2	Textblob Sentiment Polarity Score	0.1292
4	Human	Poem 3	Textblob Sentiment Polarity Score	0.2769
5	Machine	Poem 3	Textblob Sentiment Polarity Score	0.2056
6	Human	Poem 1	Textblob Sentiment Subjectivity Score	0.4937
7	Machine	Poem 1	Textblob Sentiment Subjectivity Score	0.5095
8	Human	Poem 2	Textblob Sentiment Subjectivity Score	0.4157
9	Machine	Poem 2	Textblob Sentiment Subjectivity Score	0.4633
10	Human	Poem 3	Textblob Sentiment Subjectivity Score	0.5804
11	Machine	Poem 3	Textblob Sentiment Subjectivity Score	0.4997
12	Human	Poem 1	Vader Analysis Pos	0.1030
13	Machine	Poem 1	Vader Analysis Pos	0.1180
14	Human	Poem 2	Vader Analysis Pos	0.1010
15	Machine	Poem 2	Vader Analysis Pos	0.1350
16	Human	Poem 3	Vader Analysis Pos	0.1490
17	Machine	Poem 3	Vader Analysis Pos	0.1590
18	Human	Poem 1	Vader Analysis Neutral	0.8410
19	Machine	Poem 1	Vader Analysis Neutral	0.8340
20	Human	Poem 2	Vader Analysis Neutral	0.8410
21	Machine	Poem 2	Vader Analysis Neutral	0.7810
22	Human	Poem 3	Vader Analysis Neutral	0.7300
23	Machine	Poem 3	Vader Analysis Neutral	0.7320
24	Human	Poem 1	Vader Analysis Neg	0.0550
25	Machine	Poem 1	Vader Analysis Neg	0.0480
26	Human	Poem 2	Vader Analysis Neg	0.0580
27	Machine	Poem 2	Vader Analysis Neg	0.0840
28	Human	Poem 3	Vader Analysis Neg	0.1210
29	Machine	Poem 3	Vader Analysis Neg	0.1100
30	Human	Poem 1	Vader Analysis Compound	0.8652
31	Machine	Poem 1	Vader Analysis Compound	0.9948
32	Human	Poem 2	Vader Analysis Compound	0.9451
33	Machine	Poem 2	Vader Analysis Compound	0.9975
34	Human	Poem 3	Vader Analysis Compound	0.9287
35	Machine	Poem 3	Vader Analysis Compound	0.9967

Appendix B Figures:

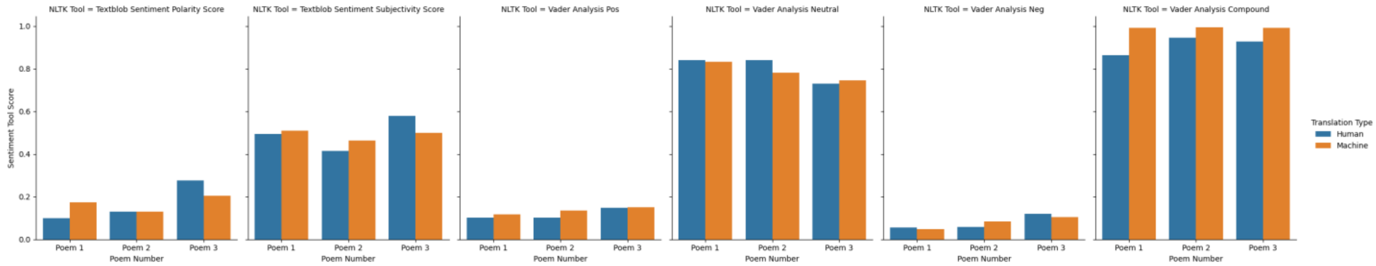

Figure 3 Collective Bar plot presenting sentiment scores by NLTK Tool

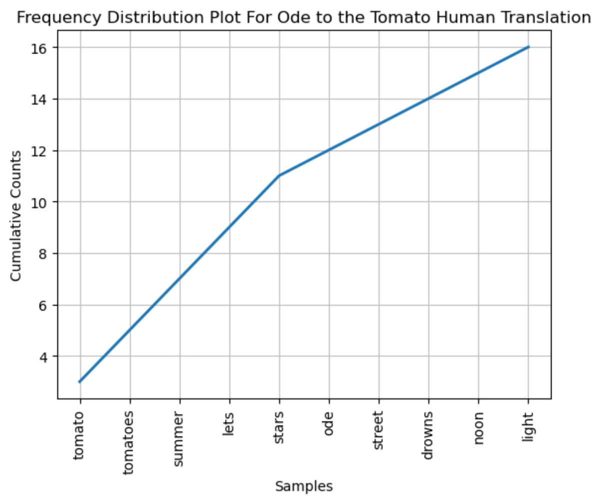

Figure 4 Frequency Plot Ode to the Tomato Human Translation

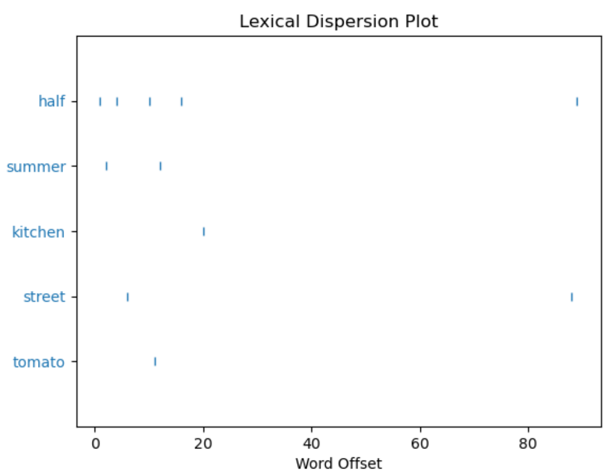

Figure 5: Lexical Dispersion Plot for Ode to the Tomato Human Translation

References:

Deitel, P., & Deitel, H. (2020). 12. Natural Language Processing (NLP). In *Intro to Python - for Computer Science and Data Science: Learning to Program with AI, Big Data and the Cloud* (1st ed.). chapter, Pearson.

Franco, J. (1975). Introduction. In *Selected Poems of Pablo Neruda* (pp. 13–23). introduction, Penguin Books Ltd.

Kaminsky, I. (2009). Introduction. In *The Ecco Anthology of International Poetry* (pp. xxxiii–li). introduction, Ecco.

Kaminsky, I., & Harris, S. (2010). *The Ecco Anthology of International Poetry*. Ecco.

Neruda, P. (1975). *Selected poems of Pablo Neruda* (A. Kerrigan, W. S. Merwin, A. Reid, & N. Tarn, Trans., N. Tarn, Ed.). Penguin.

XIV Juegas todos los días… In *Selected poems of Pablo Neruda* (A. Kerrigan, W. S. Merwin, A. Reid, & N. Tarn, Trans., N. Tarn, Ed.). Penguin. (pp.26, 28)

XIV Every Day you Play… In *Selected poems of Pablo Neruda* (A. Kerrigan, W. S. Merwin, A. Reid, & N. Tarn, Trans., N. Tarn, Ed.). Penguin. (pp.27, 29)

XX Puedo escribir los versos… In *Selected poems of Pablo Neruda* (A. Kerrigan, W. S. Merwin, A. Reid, & N. Tarn, Trans., N. Tarn, Ed.). Penguin. (pp.30, 32)

XX Tonight I Can Write… In *Selected poems of Pablo Neruda* (A. Kerrigan, W. S. Merwin, A. Reid, & N. Tarn, Trans., N. Tarn, Ed.). Penguin. (pp.31, 33)

Oda al tomate In *Selected poems of Pablo Neruda* (A. Kerrigan, W. S. Merwin, A. Reid, & N. Tarn, Trans., N. Tarn, Ed.). Penguin. (pp.160, 162, 164)

Ode to the Tomato In *Selected poems of Pablo Neruda* (A. Kerrigan, W. S. Merwin, A. Reid, & N. Tarn, Trans., N. Tarn, Ed.). Penguin. (pp.161, 163, 165)

Reynolds, M. (2016). *Translation: A very short introduction*. Oxford University Press.

Tukey, J. W. (1977). *Exploratory Data Analysis*. Addison-Wesley.

Tutorial: Quickstart. Tutorial: Quickstart - TextBlob 0.18.0.post0 documentation. (n.d.). https://textblob.readthedocs.io/en/dev/quickstart.html

Visualizing categorical data#. Visualizing categorical data - seaborn 0.13.2 documentation. (n.d.). https://seaborn.pydata.org/tutorial/categorical.html