The Future of Meat: Sentiment Analysis of Food Tweets

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Abstract

The future of food largely depends on the future of meat, considering multiple policy recommendations that urge for a decrease in meat consumption due to its impact on human health and environmental sustainability. In view of the 'meat vs alternative protein' playing its own part in the overall polarisation of societal discourse, we explored the dynamics of sentiment related to meat and meat consumption on Twitter over a ten year period. Twitter is one of the best sources for tracing various food-related utterances in different cultures and societies since the food there is widely documented and discussed in multiple formats. We accumulate the necessary contextual knowledge of group dynamics in relation to the topic of meat consumption that can be useful when aspects influencing individual food choices are examined. In this paper, we analyse social media content written in a morphological complex and less-resourced language – Latvian.

1 Introduction

Food choice and food consumption play an important role in public health, as well as impact environmental sustainability profoundly. Obesity, type 2 diabetes and cardiovascular diseases are just a few of the health problems acquired due to the nutritional specifics of contemporary consumers (Min et al., 2019). While the impact of food on personal health is an area discussed by food policy makers and nutritionists globally, another new discourse has emerged in relation to food consumption, namely, the impact on planetary health or levels of biodiversity, pollution and CO2 that influence and shape climate change, as well as the planet's ecosystems overall (Grivins et al., 2020). One third of global carbon dioxide emissions are assigned to food systems, where the largest contribution comes from agriculture and land-use activities (estimated 71% of the total emissions), while the food supply chain – transport, consumption, retail and other related processes account for 29% respectively (Crippa et al., 2021). Meat production makes the largest impact when it comes to producing greenhouse gases, as it accounts for nearly 60% of all greenhouse gases from food production (Xu et al., 2021). Beef accounts for one quarter of the total emissions, and in general, the use of animals for meat causes twice the pollution of producing plant-based foods (Xu et al., 2021).

High emissions that meat production causes in the context of climate change have led to the current food start-up and innovation scene being dominated by ideas that focus on developing alternative plant-based proteins. Thus, the discourse on the future of food to a considerable extent consists of the future of meat. Alternative proteins, lab-grown meat, vegan diets, and flexitarian lifestyles – all of these concepts contribute to the discussion on how or if we will be consuming meat in the future. Despite a rather uniform policy push towards reduced meat consumption (Lancet, 2018), the issue is growing more polarised on the level of social sentiment (Grivins et al., 2020), while increasing amounts of investments flow into meat replacement innovation. Currently, however, there are no signs of a mass shift away from meat consumption worldwide.

One of the best venues for tracing sentiment towards particular food consumption is social media where food is widely documented and discussed in multiple formats (Min et al., 2019). In comparison to other sources of analysis, social media data allows us to trace spontaneous reactions when people tweet without delay, thus avoiding potential biases which might have arisen using other opinion-gathering methods, e.g., surveys and food diaries (Laguna et al., 2020). Social network data analysis has reached popularity in consumer studies, where food language data and images are analysed. Food turns out to be one of the key themes discussed on Twitter, the social network that we focus on in

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our work. As primarily a platform for text, not for images, and due to its accessibility for research purposes, Twitter is the digital space where it has become possible to follow the most random details of the everyday lives of tweeters – including the information on what, how and where they eat (Kāle et al., 2021).

We have chosen the Twitter social network for the analysis due to the availability of a large food-related data corpus in the Latvian language that was recently released – the Latvian Twitter Eater Corpus (LTEC (Sproģis and Rikters, 2020)). We focused on any entries concerning meat and meat products found in food-related tweets over a period of more than ten years. The tweet sentiment was then analysed in view of their positive, neutral or negative valence. Keeping in mind that social media are generally believed to showcase mostly positive experiences (Croijmans et al., 2020), we carried out a general sentiment analysis of the food tweets. We looked at the depiction of meat and meat products in temporal dynamics, thus trying to capture the historical as well as the contemporary 'Zeitgeist' in relation to meat consumption as it is depicted in the Latvian-speaking community. Besides an analysis of meat, we also looked into the depiction of vegan and vegetarian food on Twitter along with the debates about alternative proteins.

When analysing the discourse of meat in social media, it is important to be aware of the context the particular society is operating in. Regarding Latvian food culture and national cuisine general agreement is that the basis of Latvian cuisine is potato, dairy products, fish and meat, and pork in particular. It has formed as a heritage of peasant food in melange with aristocratic influence, similarly as in other European countries.[1] Somewhat better understanding of food consumption can be based on different seasons that Latvian society lives through during the year. As a Northern European country, Latvia has four distinct seasons where autumn and winter are relatively cold, dark and rainy, while summers are short and warm. What regards food choices, any society is sensitive to temperature and weather fluctuations, which is particularly evident in countries with greater seasonal variations in temperature (Spence, 2021). Latvia is a country with great seasonal variation in temperature, and thus, serves as good sandbox for weather related food data analysis. As previous research illustrates, Latvia also has its seasonal food preferences as depicted in social media: grey peas, tangerines and gingerbread during Christmas time, and cold soup strawberries and ice cream during hot spring and summer time (Kāle et al., 2021).

The driving motivation of this research has been to build a better understanding of the world, in particular looking into food consumption and food-related information sharing on social media. Food choices that consumers make affect public health and the planet's sustainability to a large extent, however, due to the interdisciplinary nature of food, many important topics have been under-researched in narrow scope research disciplines. This research aims to fill the gap and provide a methodology focused on sentiment analysis on how to understand food consumers given the role that social media play in modern lifestyles. With our approach, we aim to contribute to a growing research area that focuses on interdisciplinary research inquiries and insights into future of the food (Velasco et al., 2021). Collecting food-related data poses a yet unsolved challenge, thus, innovative ways to use social media and other large-scale data are the key innovative approach that this research offers.

2 Related Work

Food computing, a field that our research belongs to, is a novel, interdisciplinary, and future-oriented research area aiming to improve public health through a better understanding of food consumers. Empowered by new technology-based solutions, this interdisciplinary research area is expanding within the academic research that deals with food consumption, public health issues, and increasingly so – also within the environmental well-being of the planet. The term 'food computing' describes the use of computational methods when analysing different food-related data. The focus lies on large-scale data or 'big data' and the opportunities to collect the data in order to analyse food perception, recognition, and retrieval, as well as devise recommendations for prediction and monitoring. Food computing is an interdisciplinary field which in a broad sense encompasses food-related studies performed via computer science. In order to understand the rationale behind various food-related issues, food computing has grasped the opportunities opened through the web revolution: social networks, mobile networks, and the internet of things

[1] News portal of Latvian Radio and Latvian Television https://eng.lsm.lv/article/culture/food-drink/traditional-and-national-latvian-foods-whats-the-difference.a466155/

(IoT), which allow their users to easily share food images, recipes, cooking videos, or record food diaries, creating large-scale food data sets (Min et al., 2019). The rationale for food computing development has been an inquiry to design food recommendation systems. Such food recommendation systems, in turn, must understand users and their food choices in context. This research contributes to understanding this context.

There have been high expectations for the utility of large-scale data in food research, although a developed framework for its applicability is still lacking. Large-scale data or ‘big data’ are typically referred to large amounts of data produced very quickly by a high number of diverse sources. Other definitions related to big data highlight their unprecedented scale (volume), fragmentation (high variety), and real-time increase (velocity). While the use of big data is under increasing academic scrutiny, the field holds vast potential for opening new research areas in terms of food-related studies. Thus, for example, the term ‘big data’ is seldom used in relation to food safety, mainly because food safety data and information are scattered across the food, health, and agriculture sectors (Marvin et al., 2017).

The interdisciplinary characteristic of food-related data is also an issue in consumer research when it comes to utilising social network data. There are limitations concerning the fragmented nature of social media data: for example, Twitter users are digitally active and a relatively wealthy part of the population, thus, the results cannot be generalised by referring to the whole society. Nevertheless, even acknowledging the fragmentation, new research inquiries in using social media data can be of value for policymakers and those nudging particular behaviours among food consumers (Kāle and Rikters, 2021). Another research direction that proves the utility of social media analysis is looking at how digital food affects our analogue lives and eating behaviour in particular (Andersen et al., 2021). Correlating social media results related to food in a particular region with the sales data could be the next step in our analytical approach, as there is a common agreement that digital content impacts purchasing behaviours in our analogue lives, however, this lacks granularity when it comes to exact correlations and proof of statements.

As the research illustrates, food is bound by culture and climate, and the language employed in tweets within a geographic region reveals certain specifics that should be taken into account (Metcalfe, 2019). By analysing the frequency rates of food-related tweets, it has been possible to detect seasonality as well as to identify certain cultural aspects related to traditional Latvian cuisine. It has also revealed food-related tweeting activity in relation to particular days of the week and particular times of the day, uncovering the tweeting activity concerning specific foods during specific times of the day (Kāle et al., 2021). Knowledge and higher levels of precision about certain foods that are susceptible to seasonality peaks can help policymakers to shape their stories that will resonate on social media and lead to better public health through more healthy food choices. Meanwhile, the very same knowledge can also be used by food marketers who do not necessarily promote the most healthy food options for consumers (Velasco et al., 2021).

A deeper understanding of language and how we describe foods is, however, a prerequisite to understanding the dynamics between the individual and the group when it comes to food choice. One of the most notable domains where individual and group behaviour can be traced via language is the domain of healthy vs tasty food. One of the most recognised challenges that hinder food consumers from choosing healthier food options is the strong tension between tastiness and healthiness that plays a decisive role in food choice and is important for obesity and other diseases, as well as environmental consciousness. This tension has been labelled as untasty = healthy intuition (Mai and Hoffmann, 2015). This tension is well seen in language differences in how people talk about comfort foods versus healthy foods, where comfort foods are described sensually – e.g. ‘broad-shouldered wine’ or ‘sexy dessert’ (Jurafsky, 2014), while healthy foods are depicted as rational, pragmatic and easy to cook items (Kāle and Agbozo, 2020). In particular, to the language of meat or vegetarian dishes as its opposite, there is a growing field of research looking into the language used for describing meat dishes versus vegan and vegetarian dishes. The same conclusions remain: the language of how the dish is described matters, and the taste of the dish can change just because the wording of how food is described, has been changed (Bacon et al., 2019). Instead of language analysis of how particular foods are described, we focus on sentiment analysis which can be of great use for food language analysts to gain a more holistic view of how particular foods are discussed in different societies.

Finally, we aim to illustrate the utility of data coming from languages less resourced and less spoken. Thus, the Latvian Twitter Eater Corpus (LTEC), a unique resource devised for the analysis of Latvian food-related tweets, has been used in this research. It might serve as a pilot corpus for other less-resourced languages and contribute to a better understanding of the differences in food narratives depending on the language we use (Fenko et al., 2010).

3 Methodology and Experiment Setup

Our analysis is based on inspecting the Latvian Twitter Eater Corpus (LTEC (Sproģis and Rikters, 2020)), which contains 2.4M tweets generated by 169k users collected for over 10 years by following 363 eating-related keywords in Latvian. The dataset provides some additional metadata about each tweet, such as location (when available), all food items mentioned in the tweet text, and a separate subset of tweets with manually annotated sentiment classes – positive, neutral and negative.

Since the corpus contains normalised versions of all food items in singular nominative form for each tweet, we used these to further select only the specific tweets for our analysis. This was done by firstly compiling a list of most used meat-related nouns (see Table 1), and then selecting only the very narrow subset which mentions either beef, chicken or pork.

3.1 Sentiment Analysis

We used the 5420 annotated tweets to fine-tune a pre-trained multilingual BERT (Devlin et al., 2019) model for the sentiment analysis task along with ∼20,000 sentiment-annotated Latvian tweets from other sources[2] so that the model would generalise better. We evaluated the sentiment model on the 743 tweet test set provided in LTEC and reached an accuracy of 74.06%. Our result outperforms the best accuracy reported by the authors of LTEC, who used a Naive Bayes model on stemmed data and reached 61.23%. However, this was expected since they used ∼20% less training data, and BERT or other transformer-based models have outperformed previous state-of-the-art methods in many language processing tasks, including classification. We then used the model to automatically classify all tweets in LTEC as positive, neutral or negative for further analysis.

3.2 Human Evaluation

To verify the quality of the sentiment analysis model, we selected 50 random automatically classified tweets from each year between 2011 and 2020 and performed a manual evaluation. Twelve human evaluators were asked to individually judge each of the 500 predictions by the model and provide a suggested alternative sentiment class for cases where they deemed the model to be incorrect. We used the majority vote of the human evaluators as the correct answer in cases where they disagreed on a particular evaluation and considered two classifications as correct in the 21 cases where the majority opinion was split in half (for example, 6 positive and 6 neutral). The overall agreement of the evaluators was 70.48% with a free marginal kappa (Randolph, 2005) of 0.56 (values from 0.40 to 0.75 are considered intermediate to good agreement).

The accuracy of the model according to the majority of human evaluators on this set was even higher, reaching 86.40%, while the accuracy of the average human evaluator compared to the majority was only 80.25%. This shows that 1) the tweet texts are not always trivial enough to be unequivocally classified into just one of the three sentiment classes, and 2) the model is good enough to be used on the scale of the whole dataset.

3.3 Limitations and Assumptions

Our work has several important limitations that can be grouped into categories of 1) data availability, 2) tweet author's demographic profile, and 3) generalisation of the results. First, we cannot provide a specific demographic outlook of the usual tweet author from LTEC, and our analysis includes tweets by general digitally literate people active on Twitter. Second, while our sentiment analysis model is fairly accurate, misclassifications may still occur, especially in longer, multi-sentence tweets. Therefore, we use the automatically assigned sentiment classes only as an overview of the trend, but not for fine-grained analysis of specific tweets. Third, considering the limitations discussed, our results are not an exact extrapolation of meat-related food perception in Latvian society. Nevertheless, our approach utilises the growing LTEC and adds to

[2] https://github.com/Usprogis/Latvian-Twitter-Eater-Corpus/tree/master/sub-corpora/sentiment-analysis#other-latvian-twitter-sentiment-corpora

liver	sausage	chop	bacon
deer	bratwurst	ham	**beef**
steak	**pork**	cutlet	steak
meatball	turkey	ribs	goose
chicken	fillet	meat	salami
roast	schnitzel	lamb	gyros

Table 1: Meat products included in our experiment.

the understanding of the impact of meat on the part of the Latvian society, which tweets about food.

4 Experiment Results

Before turning to the sentiment analysis results regarding meat-related tweets, we first look at how sentiment is distributed in all food tweets of the dataset. In tweets from 2011-2020, we can observe an overall decrease in positive sentiment and a rise in negative sentiment, as well as a comparatively large share of neutral tweets. Figure 1 shows the overall sentiment distribution of that period. It is also visible that the number of positive tweets was decreasing until 2015, from 2015 onward there has been an increase in neutral tweets, and from around 2018 the amount of negative tweets has been increasing.

4.1 Meat-related

Figure 2 shows sentiment over time of meat-related tweets all together. Aside from selecting all inflections of the word "meat", we also include the specific meat products listed in Table 1 in this overview. Here we can see that up to 2016 Twitter users were not overly active in discussions around meat overall. The share of neutral sentiment tweets has significantly grown between 2016 and 2018 and has remained mostly stable since then, while the amount of more polarising opinions – positive and negative meat-related tweets seems to be still growing ever so slightly. Even though between 2011 and 2017 the level of negative tweets is mostly flat, the one spike in March of 2013 can be attributed to a scandal over the alleged use of horse meat in a popular butcher chain from Latvia[3]. Since 2016 tweets with negative sentiment have surpassed the positive ones, although the bulk of the meat-related food tweets can still be classified as neutral.

To have a more detailed look into specific meat products, Figure 3 illustrates the differences in sentiment related to chicken, beef and pork. Again, we can see a sharp rise in neutral tweets starting from 2016, which could be explained by the increase in popularity of publicly available lunch offers at local eateries and other types of food-specific advertising. A neutral tweet in this case is a tweet that simply informs about the daily offer at a cafe or restaurant without any emotional connotations to the food listed on those offers. With the onset of the Covid-19 pandemic, however, neutrality has given way to either positive or negative valence instead. One possible reason for this could be due to the closure of restaurants and other public spaces for food consumption, and accordingly less such neutral lunch-offer type tweets from the corporate sector players.

4.2 Vegans, Vegetarians and Alternative Proteins

In addition to posts directly mentioning meat-related products, we were also interested in exploring if any mentions of meat alternatives are mentioned and how they are perceived on Twitter. Figures 4 and 5 give an overview of tweets mentioning either 'vegan' or 'vegetarian' in any inflection in the Latvian language or any inflection of the word 'protein' in Latvian. We can observe overall lower amounts of tweets when compared to ones mentioning 'meat', as well as a higher tendency of positive sentiment tweets. The dominance of positive sentiment tweets over neutral tweets that dominate meat-related discourses can signify that there are few tweets by e.g. corporate sector in a form of lunch offers or sales of vegan/vegetarian food or any other marketing-related neutral tweets. Instead, veganism and vegetarianism as not yet a mainstream discourses are mostly discussed by people with strictly positive or negative attitudes towards them. Regarding negative sentiments, it should be noted that 'vegan' sometimes is used as a swearword in Latvian Twitter space, referring to a person that is weak, incapable of activities requiring physical strength and has not had job experience as belongs to younger generations. A new term 'soy latte drinkers' appeared during the debate when mandatory military service was renewed due to Russia's invasion of Ukraine. Young people who protested the mandatory military service were ironically called 'soy latte drinkers', implying their physical weakness due to vegetarian or vegan lifestyles. This signifies that social media sentiment

[3] https://www.theguardian.com/uk-news/2013/jul/19/horsemeat-scandal-meat-pies-latvia

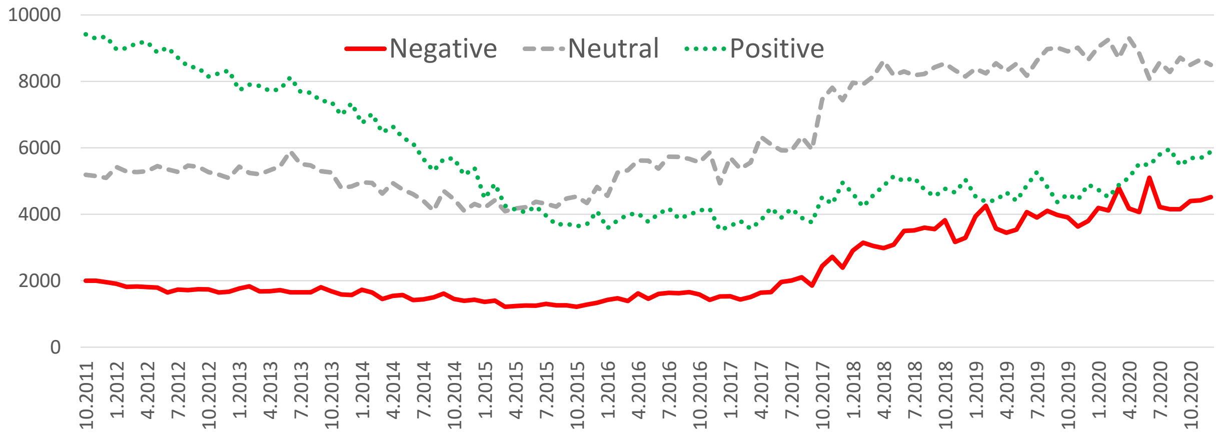

Figure 1: Distribution of overall tweet sentiment in LTEC over time from 2011 to 2020.

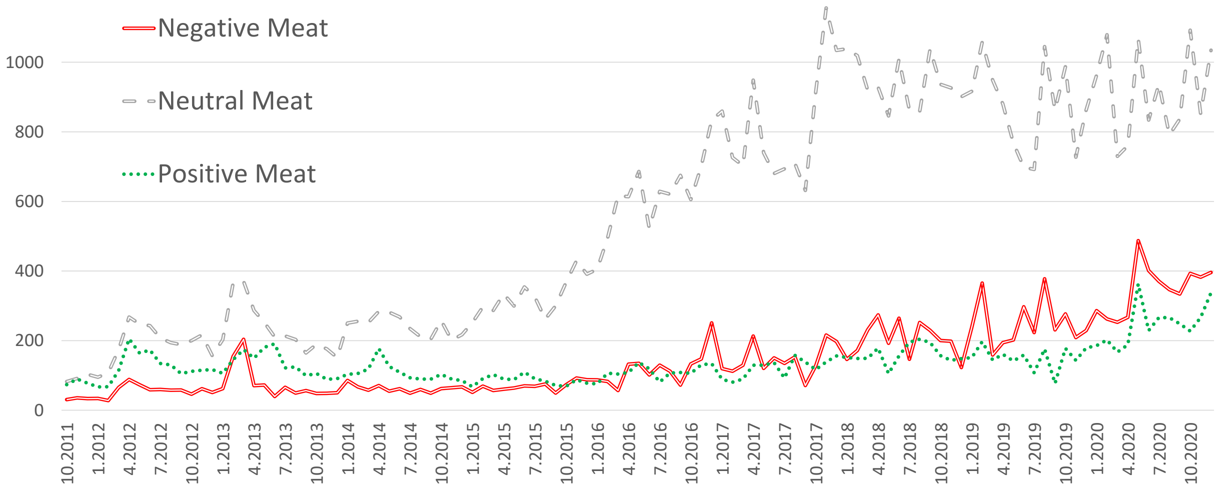

Figure 2: Temporal sentiment dynamics of meat-related tweets LTEC in 2011-2020.

analysis has also potential to reveal stereotypes existing in the particular societies in relation to food and health, and potentially serve as a litmus test for fake news spread in relation to lifestyles, health and food.

With regard to proteins, we see similar dynamics as to the vegan and vegetarian discourse, albeit with even fewer frequencies, which means that discussion on proteins in Latvian Twitter space is very low, and if it takes place, then it is mostly positive or neutral, with little generated, informative content. These results of low levels of frequencies signify that vegan, and vegetarian diets and the quest for alternative proteins remain marginal in everyday discussions of Twitter users in Latvia.

5 Conclusion

We started with a statement that the future of food will to a large extent be determined/dependent on the future of meat since policy recommendations urge for decreased meat consumption. This has paved the way for e.g. alternative protein development as more and more investments flow into this area, as well as vegetarian/vegan diet appreciation, which has come to shape the discourse in a stark conflict with the discourse of meat lovers. Social media in this case can serve as a litmus test for the public mood and attitudes towards meat consumption. Our research reveals that negative sentiment about meat on Latvian Twitter is steadily rising, although the neutral mood is still holding its fair share of dominance. The spread of the Covid-19 pandemic seems to have notably decreased neutrality towards certain meat types – chicken, beef and pork. All these data help us to trace the public attitude towards meat consumption and assess its readiness for change towards the future of less meat consumption as envisioned by policymakers. Looking at the sentiments and frequencies regarding vegan/vegetarian food and protein related, we con-

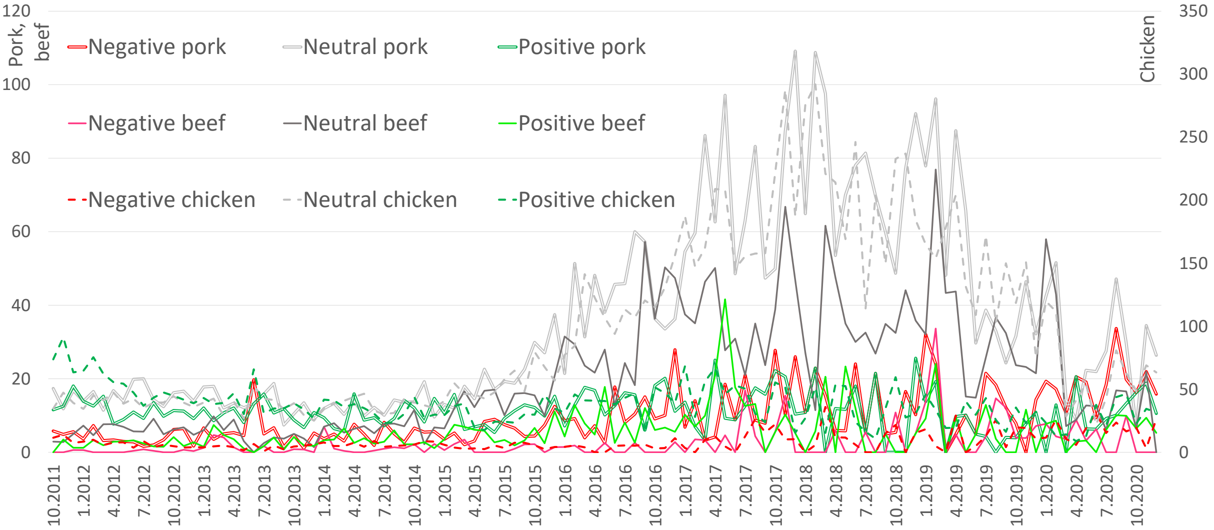

Figure 3: Temporal sentiment dynamics in 2011-2020: tweets mentioning beef, chicken or pork.

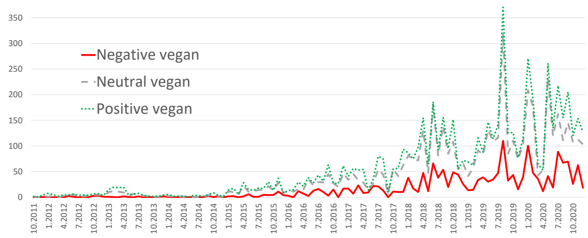

Figure 4: Distribution of tweet sentiment in LTEC over time from 2011 to 2020 of tweets mentioning vegan or vegetarian.

clude that there are not many discussions related to these themes on Twitter when compared to meat, especially in comparison to neutral, informative tweets about meat.

These data can be useful for policymakers working with the public diets' shift towards more environmentally conscious choices. Knowing the dominating discourse in the society related to meat and being able to trace the sentiment changes over time, can potentially best signify the society's maturity for change as suggested by public health policymakers. These data can be useful also for industry players, such as retailers and meat producers who shape their own discourse on meat consumption in particular markets. For marketers, temporal sentiment dynamics related to meat are valuable sales and marketing data and can be utilised in their promotional activities.

Taking into account the seldom use of social media data in academic research due to the fragmented nature – user demographics unknown, data only from the relatively wealthy and digitally active part of society, particular preferences of the social network in focus – Twitter, while other different social networks also of use, we consider that our research provides important encouragement to utilise social network data. The utility of our research results can be seen via creating valuable insights into group dynamics of the particular society, and while fragmented and in many ways incomplete, social media data of a particular social network Twitter, can to a large extent impact individual food choices. Group dynamics of social media can signify and determine the trends that impact individual preferences and ultimately food choices. Therefore, when developing individual food and health apps, it is of utmost importance to include the context data of the individual, society, national cuisine, weather and seasonality in their analysis. Social media data serve to signify those various influential context factors as can be seen also from our analysis of a particular focus on meat consumption sentiments in the Latvian Twitter community.

In future work we aim to refine our sentiment analysis approach – sometimes it was difficult to determine if the sentiment was positive or negative, especially if the tweet was ironic. Including more gradations of sentiments could be useful for us to trace the direction of morals when it comes to meat consumption. It could also allow us to separate better tweets, where 'vegan' or 'soy latte drinker' were used as allegories rather than food choices. This leads us to the necessity to collaborate with anthropologists and food historians on how food is used as an allegory to describe other processes in society instead of purely food perception and food

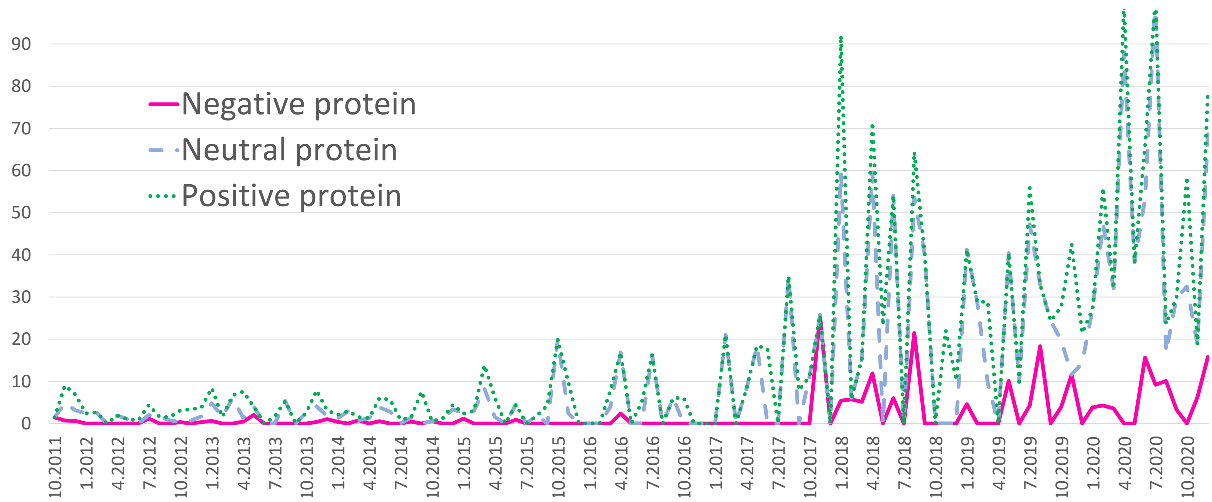

Figure 5: Distribution of tweet sentiment in LTEC over time from 2011 to 2020 of tweets mentioning protein.

choices from a dietary perspective. Furthermore, these data also invite for cross-checking spread of stereotypes and fake news related to food consumption and health aspects. This can be crucial for any public health policy strategic development – to know what kind of stereotypes and prejudices exist in certain groups, and how they are spread in social media.

As illustrated earlier, Latvia provides a good case of food-related tweet sentiment analysis due to its four seasons and rather different temperatures throughout the year. In the future, we aim to correlate the food sentiment data with the weather data to determine the impact that the weather has on our food choices. We also plan to carry out weather impact analysis on meat choices in particular.

We plan to release the additional data and models generated in this research publicly. The automatically assigned sentiment classes will be added to the main corpus data repository on GitHub[4], and publish the sentiment analysis model to Hugging Face's model hub[5].

Limitations

In this work, we only considered training our models on data that is publicly available to enable reproducibility. Also, since hyper-parameter tuning on training large models is computationally very costly, we opt for choosing mostly default parameters in our experiments.

We would further like to note that Twitter is a platform and resource for the relatively affluent and digitally well connected members of society. Thus, the population which is most vulnerable and most sensitive to food price fluctuations remain outside the scope of this analysis.

Ethics Statement

Our work fully complies with the ACL Code of Ethics[6]. We use only publicly available datasets and relatively low compute amounts while conducting our experiments to enable reproducibility. All human data annotators were fairly compensated in accordance with market rates.

References

Tjark Andersen, Derek Byrne, and Qian Wang. 2021. How digital food affects our analog lives: The impact of food photography on healthy eating behavior. *Frontiers in Psychology*, 12:634261.

Linda Bacon, Jonathan Sands Wise, Sophie Attwood, and Daniel Vennard. 2019. The language of sustainable diets: A field study exploring the impact of renaming vegetarian dishes on u.k. café menus. In *World Resources Institute*.

Monica Crippa, Efisio Solazzo, D. Guizzardi, Fabio Monforti, Francesco Tubiello, and Adrian Leip. 2021. Food systems are responsible for a third of global anthropogenic ghg emissions. *Nature Food*, 2:1–12.

Ilja Croijmans, Iris Hendrickx, Els Lefever, Asifa Majid, and Antal Van Den Bosch. 2020. Uncovering the language of wine experts. *Natural Language Engineering*, 26(5):511–530.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of

[4]https://github.com/Usprogis/Latvian-Twitter-Eater-Corpus/

[5]https://huggingface.co/models

[6]https://www.aclweb.org/portal/content/acl-code-ethics

deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Anna Fenko, Jacco J. Otten, and Hendrik N. J. Schifferstein. 2010. Describing product experience in different languages: The role of sensory modalities. *Fuel and Energy Abstracts*.

Mikelis Grivins, Afton Halloran, and Maija Kāle. 2020. *Eight megatrends in Nordic-Baltic food systems*. Nordisk Ministerråd.

Daniel Jurafsky. 2014. *The Language of Food: A Linguist Reads the Menu*. W. W. Norton, New York, New York, United States.

Maija Kāle and Ebenezer Agbozo. 2020. Tracing complexity in food blogging entries. *CEUR Workshop Proceedings*, abs/2007.05552.

Maija Kāle and Matīss Rikters. 2021. Fragmented and valuable: Following sentiment changes in food tweets. *Smell, Taste, and Temperature Interfaces CHI 2021 workshop*, abs/2106.04903.

Maija Kāle, Jurģis Šķilters, and Matīss Rikters. 2021. Tracing multisensory food experiences on twitter. *International Journal of Food Design*, 6:181–212.

Laura Laguna, Susana Fiszman, Patricia Puerta, C Chaya, and Amparo Tárrega. 2020. The impact of covid-19 lockdown on food priorities. results from a preliminary study using social media and an online survey with spanish consumers. *Food Quality and Preference*, 86:104028.

The Lancet. 2018. We need to talk about meat. *The Lancet*, 392(10161):2237. Publisher: Elsevier.

Robert Mai and Stefan Hoffmann. 2015. How to combat the unhealthy = tasty intuition: The influencing role of health consciousness. *Journal of Public Policy & Marketing*, 34(1):63–83.

Hans J. P. Marvin, Esmée M. Janssen, Yamine Bouzembrak, Peter J. M. Hendriksen, and Martijn Staats. 2017. Big data in food safety: An overview. *Critical Reviews in Food Science and Nutrition*, 57(11):2286–2295. PMID: 27819478.

Robyn Metcalfe. 2019. *Food Routes: Growing Bananas in Iceland and Other Tales from the Logistics of Eating*. MIT Press, London, England.

Weiqing Min, Shuqiang Jiang, Linhu Liu, Yong Rui, and Ramesh Jain. 2019. A survey on food computing. *ACM Computing Surveys*, 52(5):1–36.

Justus J Randolph. 2005. Free-marginal multirater kappa (multirater k [free]): An alternative to fleiss' fixed-marginal multirater kappa. *Online submission*.

Charles Spence. 2021. Explaining seasonal patterns of food consumption. *International Journal of Gastronomy and Food Science*, 24:100332.

Uga Sproģis and Matīss Rikters. 2020. What Can We Learn From Almost a Decade of Food Tweets. In *In Proceedings of the 9th Conference Human Language Technologies - The Baltic Perspective (Baltic HLT 2020)*, volume 328, pages 191 – 198, Kaunas, Lithuania. IOS Press.

Carlos Velasco, Charles Michel, and Charles Spence. 2021. Gastrophysics: Current approaches and future directions. *International Journal of Food Design*, 6:137–152.

Xiaoming Xu, Prateek Sharma, Shijie Shu, Tzu-Shun Lin, Philippe Ciais, Francesco N Tubiello, Pete Smith, Nelson Campbell, and Atul K Jain. 2021. Global greenhouse gas emissions from animal-based foods are twice those of plant-based foods. *Nature Food*, 2(9):724–732.