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**Populists’ Use of Nostalgia: A Supervised Machine Learning Approach**

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An emotion that has recently gained traction in the context of populism is nostalgia, a sentimental longing or wistful affection for the past. Nostalgia can refer to the past of one’s group or nation, as reflected in populists’ narratives of the heartland—the vision of a utopian future based on an idealized past in which their country belonged to the ‘pure people.’ However, research on nostalgia in political communication across the political aisle is scarce. The current study aimed to fill this gap via supervised machine learning. First, we used an experimental approach established in psychology to create a ground-truth dataset and trained a classifier for detecting nostalgic sentiment in German language (with satisfactory reliability: *f1* = .79). We then applied this classifier to a large database (*N* = 4,022) of German political parties’ Facebook posts. We demonstrate that: (a) populist (vs. non-populists)—especially right-wing—parties employ nostalgia more frequently; (b) nostalgic narratives differ between parties, and (c) nostalgic (vs. non-nostalgic) posts are associated with more user engagement.

*Keywords: Automated text analysis, classifier development, German, Facebook, nostalgia, populism, political communication, supervised machine learning*

Populist leaders and parties have enjoyed substantial electoral success across the globe in the second decade of the 21st century. Examples include political leaders such as Marine Le Pen in France and Donald Trump in the US, Hugo Chávez in Venezuela, and parties such as Podemos in Spain. In Germany, the context of our study, the right-wing populist party *Alternative for Germany* (AFD) has become one of the strongest opposition parties in some federal states and even became the first-past-the-post party in the states of Thuringia and Saxony in the federal election of 2021.

There has been speculation about the role of social media in populists’ success (Engesser Fawzi, & Larsson, 2017). Populist communication is often highly charged, fueling negative emotions (Hameleers, Bos, & de Vreese, 2017; Schmuck & Hameleers, 2020; Wirz, 2018), which is rewarded by popularity cues such as likes and shares (Jost, 2020). Consequently, the algorithmic-recommendation logic of social media rewards populist communication.

An emotion that has recently gained traction in the context of populism is nostalgia—an ambivalent (albeit mostly positive) social emotion elicited by a sentimental longing for the past (Sedikides, Wildschut, Arndt & Routledge, 2008). Nostalgia can refer to the past of one’s group or nation (Sedikides & Wildschut, 2019). Former US president Donald Trump’s slogan ‘Make America Great Again’ exemplifies the use of this type of *national nostalgia* (Kenny, 2017). National nostalgia has been described as the “master-frame of populist radical right parties” (Smeekes, Wildschut & Sedikides, 2021, p. 90). It is less clear whether and how political parties beyond single populist actors use nostalgia in their discourse. A notable exception in a Hungarian context (Szabó & Kiss, 2022) showed that, during the 2019 election campaign for the EU parliament, right-wing populists used more nostalgic narratives in their Facebook communication than did left-leaning politicians.

**Populism**

The populist ideology is often defined as a “thin-centered” belief system (Mudde, 2004, p. 544) around the core assumption that the good people are opposed to the malicious or incompetent elite who fails to represent the people (Hameleers et al., 2017). This core assumption consists of three interwoven aspects: (a) anti-elitism, an antipathy toward political elites often accompanied by disappointment with legacy media and science (Mede & Schäfer, 2020; Schulz et al. 2020); (b) homogeneity, a homogenous conceptualization of ‘the people,’ referring to them as inherently good (Engesser et al., 2017) and as distinct from and opposed to ‘the others’; and (c) the vocal demand for people’s sovereignty, combined with the claim that elected representatives fail to execute the will of ‘the people’ (Hameleers & de Vreese, 2020). Jointly, these three aspects are considered a serious threat to liberal democracies (Galston, 2020; Schulze, Mauk & Linde, 2020).

Closely connected to the homogeneity assumption is the concept of *heartland*. The heartland is the “construction of an ideal world but, unlike utopian conceptions, it is constructed retrospectively from the past—it is, in essence, a past-derived vision projected onto the present as that which has been lost” (Taggart, 2004, p. 274). Heartland denies historical facts and romanticizes the past, focuses on national ingroups that are considered native, and divides the population against those who migrated to the heartland. In a nutshell, heartland represents “the good life but that, unlike utopias, it is a life that has already been lived and so shown to be feasible. It assumes or asserts that there was a good life before the corruptions and distortions of the present” (Taggart, 2004, p. 274).

The populist ideology is part of a larger populist communication logic (Engesser et al., 2017) that entails a political strategy (Weyland, 2016), specific actors (Aalberg & de Vreese, 2017), and an emotional communication style (Jagers & Walgrave, 2007). Particularly, negative emotions such as anger and fear have been linked to populist communication (Molek-Kozakowska & Wilk, 2021), although positive emotions such as joy or hope are also prevalent (Schmuck & Hameleers, 2020). The affect-oriented design of social media provides unique opportunity structures for this type of populist communication (Engesser et al., 2017). For instance, a content analysis of Facebook posts of leading German candidates before the 2017 general election illustrated that the right-wing populist AFD used the most populist message cues and that these cues were responded to with love and anger reactions among their audience (Jost, 2020). Evoked emotions, in turn, mediate the persuasiveness of populist appeals (Wirz, 2018). One emotion that is closely connected to heartland (Taggart, 2004), and thus might be of relevance to populists, is nostalgia (Menke & Wulf, 2021).

**Nostalgia**

Nostalgia is a sentimental longing for one’s past (Sedikides et al., 2008), a rose-tinted view on something that no longer is. It is a bittersweet (though predominantly positive) emotion triggered by personally meaningful memories such as those involving one’s childhood (Wildschut, Sedikides, Arndt & Routledge, 2006). Nostalgia is a social emotion (Sedikides & Wildschut, 2019), that is commonly understood and experienced by lay people across cultures (Hepper, Ritchie, Sedikides, & Wildschut, 2012, Hepper et al., 2014). Nostalgia is prevalent across ages albeit more so among older than younger people (Madoglou, Xanthopoulos & Kalamaras, 2017).

Nostalgia confers several psychological benefits. For instance, recalling nostalgic (vs. autobiographical control) memories strengthens the sense of being loved and protected (Wildschut et al., 2006). By fostering social connectedness (Sedikides & Wildschut, 2019), nostalgia galvanizes a sense of self-continuity (Sedikides, Wildschut, Routledge & Arndt, 2015) and meaning in life (Routledge et al., 2011), which elevates well-being (Sedikides & Wildschut, 2018).

Nostalgia can also be a group-based emotion triggered by the past of one’s ingroup or country (i.e., collective nostalgia; Wildschut, Bruder, Robertson, van Tilburg & Sedikides, 2014), such as rosy memories of one’s nation’s past (Smeekes, Verkuyten, / Martinovic, 2015). These (envisioned) collective memories form the basis of heartland (Taggart, 2004). Collective nostalgia strengthens identification with the ingroup (Smeekes et al., 2018), intentions to support the ingroup (Wildschut et al., 2014), and favoritism toward the ingroup (Dimitriadou, Maciejovsky, Wildschut & Sedikides, 2019). Personal and collective nostalgia can be related. A thematic analysis of written nostalgic memories showed that collective memories, such as those elicited by historic buildings or movies about a distant past, are often interwoven with more personal stories, such as childhood memories of visiting historic places with one’s parents or listening to old songs (Holak & Havlena, 1992).

The social consequences of personal and collective nostalgia can differ substantially. Personal nostalgia has benign effects on intergroup relations: Inducing nostalgia about interacting with an older individual or a mentally ill person reduces prejudice toward the group “elderly” (Turner, Wildschut & Sedikides, 2018) while recalling nostalgic memories with an ingroup member who lives as an immigrant abroad reduces prejudice toward immigrants in one’s own country (Gravani, Soureti & Stathi, 2018). Collective nostalgia, in contrast, can have negative ramifications for intergroup relations (Sedikides & Wildschut, 2019). Specifically, it can fuel anger toward the outgroup and motivate collective action (Cheung, Sedikides & Wildschut, 2017). Also, national nostalgia predicts prejudice (Smeekes et al., 2015).

People feel nostalgic for different aspects of their nation’s past. For instance, conservatives in the US feel more nostalgic for a homogenous past such as reflected in the concept of heartland (Taggart, 2004), whereas liberals feel more nostalgic for a time when their country was more open to cultural diversity (Lammers & Baldwin, 2020; Stefaniak, Wohl, Sedikides, Smeesters & Wildschut, 2021). Individuals who feel more nostalgic about an open (vs. homogenous) society are less prejudiced (Wohl, Stefaniak & Smeesters, 2020). Similarly, in an online experiment, Turks who waxed nostalgic for the Ottoman empire (vs. the time of Kemal Atatürk) manifested more populist attitudes (Elçi, 2021).

**Nostalgia and Populism**

Populist political parties have been making use of nostalgic narratives in their campaigns. For example, right-wing populist politicians have been described as capitalizing on collective nostalgia to discredit the current political order and promote anti-elitism (Mols & Jetten, 2014). Moreover, nostalgia such as reflected in the heartland concept is commonly employed to romanticize the past for ingroup-members (Hameleers, 2018; Smeekes, 2015).

The heartland narrative is shaped by local context. Typical examples include ‘middle America’ and ‘la France Profonde.’ In Germany, the Nazi-past overshadows a national heartland (Engesser, Ernst, Esser & Büchl, 2016), but heartland narratives are found on the regional level such as that related to the former German Democratic Republic (GDR; Menke & Wulf, 2021). For example, according to discourse analyses, nostalgic reverie about the East German town of Dresden centering on its destruction by Allied bombing in World War II accounts for the far-right’s attraction to the city (Vees-Gulani, 2021). Particularly German right-wing populists seem to thrive on local narratives. For instance, the geographical distance to Nazi concentration camps predicts the success of the AFD decades later the municipality level (Jäckle, 2022).

So far, research has tested the relation between collective nostalgia and populism via artificial prompts in experimental settings (Lammers & Baldwin, 2020; Stefaniak et al., 2021) or via qualitative analyses of single populist campaigns (Menke & Wulf, 2021). In an exception, Szabó and Kiss (2022) relied on qualitative content analysis to examine nostalgia in the Facebook posts of Hungarian politicians. Both personal and collective nostalgia featured in political communication. Also, right-wing (compared to left-wing) candidates used more nostalgic themes. Finally, nostalgic (vs. non-nostalgic) posts elicited more emotional responses (e.g., likes, shares, emojis) from users. We extended the literature on populism and nostalgia by employing supervised machine learning.

**Supervised Machine Learning and Emotion Detection**

Supervised machine learning is a state-of-the-art approach recommended for the computational analysis of political communication (González-Bailón & Petchler, 2015; Stieglitz & Dang-Xuan, 2013). During supervised machine learning, a statistical model is trained on a dataset (called the ground-truth) for which the researcher knows which items belong to which class (Burger, 2018)—for instance, which posts are nostalgic, and which are not. Based on the ground-truth, the statistical model learns in an exploratory phase the text features (“the predictors”) that characterize the posts within each class. Usually, a test-and-train logic via k-fold cross-validation is employed to identify the best model. Afterwards, the best model is evaluated in confirmatory analysis of a hold-out evaluation data set to gauge the out-of-sample performance. If the performance is satisfactory, the classifier can be used to categorize new data (Scharkow, 2013), although it should always be validated after the application (Song et al., 2020). Figure 1 depicts the general procedure.

In computer science, the ground-truth data are usually annotated by three coders (often crowd-workers on platforms such as Amazon’s MTurk), who independently decide whether a text belongs to a certain class or not. The labels for the ground-truth data are assigned based on majority votes. That is, a text would be classified as nostalgic when two out of three independent coders think so. For instance, Azim and Bhuiyan (2018) annotated tweets using nine basic emotions as labels. Comparing different classifiers by relying on simple words (bag-of-words approach) showed that between 41.25% and 71.75% of the emotions were detected correctly. Similar rates were reported by Asghar et al. (2019).

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***Figure 1. Typical procedure of supervised machine-learning***

The ground-truth data lie at the heart of the procedure, but scientific disciplines vary in the creation of these ‘gold standard’ data. In communication science, the ground-truth data are typically human coded datasets created via manual content analysis (Scharkow, 2013). For instance, Burscher et al. (2015) had trained coders rate a large set of news articles and parliamentary questions for included policy issues. Similarly, Stoll et al. (2020) used a manually coded dataset of user comments and trained different models to detect incivility and impoliteness.

Recently, Çakar and Sengur (2021) implemented a different approach that did not rely on human coders. Participants selected one emotion that characterized best how they felt about the COVID-19 pandemic, described this emotion in an essay, and rated the emotion’s strength. The self-reported emotions served as labels for the participants’ essays which were then used to train the classifier. The classifier detected correctly between 63.7% and 75.7% of emotions. This use of self-report is compatible with psychological approaches. For instance, Meuleman and Scherer (2013) applied supervised machine learning on a dataset for which participants recalled emotional experiences, labeled these experiences on a set of basic emotions, and rated the experiences on 25 appraisal items. Classifiers trained on these data performed better than chance in distinguishing among discrete emotions.

Emotion detection is a challenging task. Academic disciplines use supervised learning for emotion detection relying on differing standards for ground-truth creation. Here, we adopted the psychological approach capitalizing on essays and self-reported nostalgia as ground-truth. Emotional essays are classifiable by algorithms trained on Facebook posts (Jaidka et al., 2020), and so it is plausible that essays can also be used to train Facebook classifiers. We evaluated our approach by applying manual validation (as is common in communication science) and statistical performance measures (as is common in computer science).

We formulated the following three research questions (RQs):

RQ1. How prevalent is nostalgia in political communication across the political spectrum, that is, both by populist and non-populist parties?

RQ2. How does the content of nostalgic narratives differ between parties?

RQ3. How is nostalgia related to user-engagement with political communication?

**Classifier Development**

To create a ground-truth dataset, we used a vivid autobiographical writing task for the induction of nostalgia (Verplanken, 2012; based on Wildschut et al., 2006), a task well-established in psychology. According to the cognitive-functional model of emotions (Nabi, 1999), media content that touches upon an emotion’s core relational themes—its typical elicitors—triggers the respective emotion (de los Santos & Nabi, 2019; Nabi, 2002). Using a pre-defined set of elicitors to investigate emotions can rapidly become overly complex (Meulemann & Scherer, 2013). Our bottom-up approach (i.e., asking participants to write about their nostalgic memories) allowed us to capture variance in the themes of nostalgic narratives—variance that likely capture not only personal but also collective and geographically situated memories of a positive past that has been lost.

***Methods and Measurements***

We collected nostalgic essays in two experiments (NExp.1=295 of whom 170 were women and 125 men; NExp.2=261 of whom 179 were women, 80 men, and 2 nonbinary). We randomly assigned participants to write either about a nostalgic (nExp.1=161, nExp.2=135) or control memory (nExp.1=159, nExp.2=135) before they reported their state (i.e., subjective) nostalgia, answered socio-demographic questions, and expressed their political attitudes. All materials, training data, and analysis scripts are publicly available via the Open Science Framework: https://osf.io/gu92j/.

*Writing Instructions*

Given the relevance of locality for German populism, we aimed to collect memories on local contexts (Jäckle, 2022). In Experiment 1, participants in the experimental condition wrote about a nostalgic memory, whereas those in the control condition wrote about an ordinary memory, pertaining to their homeland. In Experiment 2, we replaced reference to participants’ “homeland” with reference to their “place of residence” to increase variance in nostalgic reveries.

*State Nostalgia*

Next, participants reported their current level of nostalgia (i.e, the subjective state nostalgia) on three validated items (Wildschut et al., 2006; e.g., “Right now, I am feeling quite nostalgic”; 1 = not at all, 7 = very much). We aggregated responses to form an index (Cronbach’s ɑExp.1=.96, Cronbach’s ɑExp.2=.96).

*Database Construction*

A preliminary analysis (i.e., Welch’s *t*-test) of Experiment 1 data showed that participants in the experimental (*M* = 4.63, *SD* = 1.83) and control (M=4.26, *SD* = 1.82) condition did not differ significantly on state nostalgia, *t*(312) = 2.00, *p* *=* .08, although the means were in the expected direction. Memories about one’s homeland (German: “Heimat”) were imbued with nostalgia in both conditions. In Experiment 2, participants in the experimental condition (*M* = 4.90, *SD* = 1.69) felt more nostalgic than those in the control condition (*M* = 3.38, *SD* = 1.95), *t*(234) = 7.00, *p* < .001.

To ascertain that text classes in the ground-truth reflected the expression of nostalgia, we followed Çakar and Sengur’s (2021) procedure and focused on self-reported nostalgia as labels. Specifically, we labeled essays as “nostalgic” when state nostalgia was above the scale mean of 3.5 (*n* = 363), and we labeled essays as “non-nostalgic” when state nostalgia was below the scale mean (*n* = 157). We excluded essays from participants with average levels of nostalgia to ensure class discrimination. Accordingly, class assignment in the ground-truth data was based on state nostalgia (for a comparison of this class assignment, which is based on self-reported affect, to human coders’ perception of the essays, see Supplementary material S1). We also excluded all essays with meaningless text (e.g., “fssdffz”), corrected all essays for typos via Microsoft Excel’s spellcheck function, and transformed all text to lowercase for the final database.

*Test-and Training Split*

We used 80% of the data as training and 20 % as evaluation. The purpose of that split was to separate strictly the exploratory phase (training) from the confirmatory phase (evaluation), allowing for an estimation of the out-of-sample prediction error (i.e., the classifiers’ ability to predict new data correctly; Yarkoni & Westfall, 2017). In both data sets, more texts were labelled as nostalgic (70 %) than control (30 %).

*Feature Engineering.*

Non-nostalgic essays (*Md* = 100 words) were shorter than nostalgic essays (*Md* = 132 words), Wilcoxon rank sum *w* = 16,458.00, *p* = .01, underlining the richness of nostalgic memories. We analyzed the essays’ linguistic content via the Linguistic Inquiry and Word Count (LIWC) dictionary (Pennebaker, Both & Francis, 2007, Pennebaker, Boyd, Jordan & Blackburn, 2015), a psychologically grounded dictionary that assigns words to pre-defined categories. Here, we employed a revised version of the German LIWC (Wolf et al., 2008), in which we removed category labels for 137 words (0.02% of all words) that had been identified by two human coders as not representing the respective category. We focused our analysis on the following theoretically derived categories: positive and negative emotions, personal pronouns, references to friends, family, the past (Davalos, Merchant & Rose 2015; Wildschut, Sedikides & Robertson, 2018), and space.

A series of two-sided Wilcoxon rank sum tests indicated that nostalgic (versus non-nostalgic) essays did not include more negative emotions, *w* = 10,766,075.00, *p* = .99, but were more positive, *w* = 10,640,910.00, *p* < .001. Non-nostalgic essays featured the pronoun ‘I’ more often than nostalgic essays, *w* = 11,201,087.50, *p* < .001, whereas nostalgic essays referred more often to ‘we’, *w* = 10,533,337.50, *p* < .001 (see also Wildschut et al., 2018). Nostalgic essays were also more likely to mention the past, *w* = 10,595,272.50, *p* = .003 (Davalos et al., 2015). All other ps > .20 (see Figure 2).

Based on these preliminary analyses, we used single words (unigrams) as features to train our classifier. Although this bag-of-words approach is unsuitable for examining deeper argument structures, it does mirror typical manual content analysis focused on emotion detection (Heiss, Schmuck & Matthes, 2019; Schmuck & Hameleers, 2020). Also, terms for themes of nostalgia are likely to be similar in essays and political Facebook posts—for example, referring to one’s childhood and to the imagined ideal childhood in the heartland, respectively.

***Figure 2. Relative frequencies of selected linguistic categories in the training data***

*Preprocessing*

We used the *recipe* package (Kuhn & Wickham, 2020) and the *textrecipe* package (Hitveld, 2020) to formalize the following pre-processing steps. First, we split the text into single words (tokenization; Benoit & Matsuo, 2020) and removed punctuation marks and numbers from the text. We implemented the German stopword dictionary provided by the *snowball* package (Bouchet-Valat, 2020) to exclude words that are frequent in German language but have no interpretative value (e.g., “and” or “then”). To reduce the number of features, we removed words that appeared less than 10 times or more than 500 times. We expressed the remaining words (or tokens) as frequencies. To account for the larger number of nostalgic as compared to non-nostalgic essays, we used *synthetic minority oversampling* (SMOTE, Chawla, Bowyer, Hall & Kegelmeyer, 2002), which randomly increases minority examples of the training set by replicating them through linear interpolation and the *k*-nearest-neighbor algorithm. Oversampling increases the performance of supervised machine learning models when the data are imbalanced (Stoll, 2020).

*Classifier Training*

Following best practices in computer science (Hastie Tibshirani & Friedman, 2009), we compared four classifiers that are well-established in text classification and suitable for small datasets (Forman, 2003), involving the *parsnip* and *discrim* packages (Kuhn, 2020; Kuhn & Vaughan, 2021). We employed *regularized logistic regression* (Cooper, Gey & Dabney, 1992) to detect linear associations in the data, *random forest* (Breiman, 2001) to detect non-linear associations, and *naïve Bayes* (Lewis, 1998) and *support vector machine* (Suthaharan, 2016) to detect probabilistic associations.

We tuned each classifier using grid search within the *tune* package (Kuhn, 2021) and ten-fold cross validation. During cross-validation, the data are randomly split in *k* subsamples (here 10), which are statistically recycled to serve either as training data to train the classifier, or as test data to evaluate the out-of-sample performance therewith identifying the optimal parameter solution for the classifier (Yarkoni & Westfall, 2017). Performance can be evaluated using different statistical metrics. All of them rely on weighting the share of true positive cases (i.e., the nostalgic essays classified as nostalgic) and/or true negative cases against misclassifications (Burger, 2018). Here we used the *f*1 measure for tuning, as this metric can handle imbalanced classes. *F*1 represents the weighted average of precision (the share of true positive cases in all cases classified as positive) and recall (the share of true negative cases in all cases classified as negative). We further considered the detection of nostalgia (indicated by the recall or sensitivity measure, that is, the share of actual nostalgic essays among all essays classified as being nostalgic) as more relevant than the detection of expressions of non-nostalgic memories (indicated by the specificity measure, that is, the share of actual non-nostalgic essays among all essays classified as being non-nostalgic). Although high recall and sensitivity are desirable, the distinction between non-nostalgic and nostalgic memories is challenging even for human coders (Szabó & Kiss, 2022); for that reason, we clarified our priorities in advance.

The classifiers varied substantially in their performance (Table 1). The best performing classifier was logistic regression (*f*1 = .80). However, the logistic regression model classified only 57 out of 291 (20 %) of the nostalgic essays correctly. Naïve Bayes and support vector machine both performed worse. The second-best classifier, the random forest (*f*1 = .79), detected 252 out of 291 nostalgic essays correctly (87%), suggesting non-linear relations between the terms in the essays and participants’ state nostalgia. The random forest classifier was also better than the null model and more accurate than all the other classifiers, evaluating correctly 67 % of all essays accurately. Further, its recall was substantially better than its specificity.

To judge the interpretability of the random forest, we inspected the top-10 features (i.e., words) via the *vip* package (Greenwell & Boehmke, 2020). Nostalgic (vs. non-nostalgic) essays referred more often to endurance (“forever”, “often”, many”), childhood memories (“childhood,” “small,” “parents”), “people,” and pleasant times (“summer”). These findings dovetail with the view that nostalgia is a social emotion involving a sentimental affection and longing for the past (Sedikides, et al., 2015). Due to its good performance on the *f*1 measure, superior performance in detecting nostalgia, overall accuracy, and interpretability, we proceeded with the random forest classifier.

***Table 1. Performance of the top Classifiers with their best Parameter Solution Based on Tuning***

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Null model | regularized logistic regression (with λ = .32, mixture = .60)  | naïve Bayes (with Smoothness = .50 Laplace = 1.38) | random forest (mtry = 12, min n *n =*5) | support vector machine (cost = 1.25) |
| **Sensitivity (or recall)** | **1** | **.20** | **.06** | **.87** | **.56** |
| Specificity | 0 | .80 | .99 | .23 | .52 |
| Accuracy | .30 | .37 | .33 | .67 | .55 |
| ***F*1** | **.46** | **.80** | **.12** | **.79** | **.63** |
| ROC auc | .50 | .50 | .61 | .56 | .55 |
| PR auc | .65 | .85 | .79 | .75 | .78 |
| *Notes*. ROC = receiver operating characteristic, PR=precision-recall curve, auc = area under the curve. Optimal parameters were identified via tuning. λ=regularization rate. *M*try = number of randomly sampled parameters at each split when trees are created. Min\_*n*=minimum number of cases per split.All classifiers can range from 0 - 1, with 1 corresponding to a perfect classifier. Values of .50 represent a chance classification for all classifiers except the PR auc, here a chance classification corresponds to the ratio of the positive to the negative class (in this database, this would be a PR auc of .70). Central evaluation criteria used here to account for the imbalanced data set and the theoretical priorities are marked in boldface.  |

**Classifier Evaluation**

Thirteen essays were classified as non-nostalgic and *n* = 88 as nostalgic by the random-forest classifier in the hold-out evaluation data set. The accuracy measure indicated that 79 % of the essays were classified correctly, and the area under the receiver operating characteristic (ROC) curve showed an overall good performance of the classifier (ROC auc = .76). The confusion matrix demonstrated that the overall good performance was due to success in detecting nostalgic compared to control essays: 70 out of 72 nostalgic essays (97%) were classified correctly, whereas only 11 out of 31 control essays (35%) were classified correctly. The overall accuracy (.78) was within the range described for other emotion classifiers in the literature (Ashgar et al., 2019; Azim & Bhuiyan, 2018), and both the accuracy and *f*1 measure (.50) outperformed the null model (accuracyNull=.30, *f*1null=.46) in the evaluation data.

We attempted to validate our machine classification by creating a fully classified essay data set for manual validation. Thus, we ran the classifier on all essays (training and evaluation data) to obtain classification estimates for each essay (for similar approaches, see Giorgi et al., 2022; YouYou, Kosinski & Stillwell, 2015). We classified essays when the classifier considered the respective class to be at least 70% likely. This practice allowed us to obtain a large enough database to compare essays classified as non-nostalgic (*n*=68) and nostalgic (*n*=321) with the manual coding of the same essays as nostalgic or not (human-human intercoder agreement: 95%; see Supplementary material). The machine classification and the human classification were significantly associated, χ²(1)=36.10, *p*<.001. Posts perceived as non-nostalgic by the human coder had 2.01­times higher odds of being classified as such, whereas posts perceived as nostalgic by the human coder had 2.05­times higher odds of being classified as such, percentage agreement=67%. Performance of the classifier was consistent with prior research on emotion detection (e.g., Asghar et al., 2019; Azim & Bhuiyan, 2018).

Despite the unsatisfactory specificity, we deemed our classifier applicable for three reasons. (1) prior qualitative work (Szabó & Kiss, 2022) and (2) our own comparison between the perception of the essays as being nostalgic (or not) and a manual coding of the essays (Supplementary material S.1) demonstrated that the task of recognizing non-nostalgic essays is challenging even for humans. (3) Our actual application context included substantially more heterogenous content in which memories (nostalgic or not) likely stand out more clearly. Thus, we continued with answering our research questions in the next step ,but engaged in additional validation (see below).

**Nostalgia in Populist Discourses**

***Database***

We employed our classifier on a dataset with 4,022 Facebook posts uploaded by the seven German parliamentary parties during 2019 (1 January-31 December). We obtained data via *CrowdTangle*, a public insights tool owned and operated by Meta. We collapsed post text, links, and image text for analyses, set all text to lowercase, and removed emojis. We also collected aggregated user engagement (i.e., likes, love emojis, comments, and shares) per post. We provided the absolute count of posts per party in Supplementary Material S.5. We identified posts as nostalgic or non-nostalgic when they were classified with probabilities > .70. Of all posts, *n* = 646 (16.01%) were classified as nostalgic and *n* = 1,857 as non-nostalgic (46.17%).

***Validation***

For manual validation, we selected 5% of all Facebook posts classified as nostalgic and non-nostalgic, respectively (*n* = 125). A trained human coder then classified each of them as nostalgic or non-nostalgic. Agreement between the classifier and the human coder was reached in 82% of the cases. Of the 104 posts classified as non-nostalgic by the human coder, 87 were classified as non-nostalgic by the classifier (specificity = .84%). Of the 21 posts classified as nostalgic by the human coder, 15 were classified as nostalgic by the classifier (sensitivity = .71); *f*1=.57. Thus, the classifier performed even better in the application phase than in the development phase – likely due to the more heterogenous content within political Facebook posts compared to the essays. Further, the classifier did not simply classify all texts as nostalgic, but did indeed distinguish between nostalgic and non-nostalgic themes.

An inspection of the posts that were classified as nostalgic by the algorithm perceived as such by the human coder indicated that the classifier detected a wide range of nostalgic themes. Nostalgic posts included personal recollections of deceased party members, personal memories on famous politicians of the past, as well as collective issues such as the alleged loss of the ‘free Internet’ due to European policy reforms, increased forest dieback, or far-right narratives of immigrants allegedly “overflooding” the heartland (see Supplementary Material S.4 for additional explorations). We thus felt confident to proceed with the interpretation of our findings.

***Results***

RQ1 refers to whether the prevalence of nostalgia in political Facebook posts differs between political parties. The share of posts classified as nostalgic varied depending on party, χ²(6) )=346.43, *p<*.001 (Figure 3). Posts by the right-wing populist AFD (*z*)=15.85, *p* < .001) and the left-wing party The Left (*z)=*5.85, *p<*.001), which has been described as ‘partially populist’ by political scientists (Walter, 2007), were more frequently nostalgic than expected by chance. In contrast, posts by the eco-friendly, center left The Greens party (*z=*-3.40, *p<*.05) and the conservative CSU (*z=*-9.96, *p<*.001) were less frequently nostalgic than expected by chance (all other |*z|<*1.96, *p*s*>.*05). Only posts by the AFD were more frequently classified as nostalgic (*n=*149) than non-nostalgic (*n=*58), Odds-Ratio (*OR*)*=*2.57. For all other parties, posts were more likely to be classified as non-nostalgic than nostalgic, all *OR*s*<*0.29

RQ2 refers to whether there are differences in the content of nostalgic narratives between political parties. We used term-frequency/inverse-document-frequency analysis (*tf-idf;* Silge & Robinson, 2017) to address this question. This analysis yielded the most frequent terms contained in the nostalgic posts of each party that are not contained in the nostalgic posts of the other parties (i.e., the unique nostalgic terms).

Only nostalgic posts by the AFD referred to asylum-seekers and perpetrators, tapping into homogenous national nostalgia narratives around the heartland (see Figure 4). In contrast, nostalgic posts by The Left party were characterized by references to a more caring time with social housing and calls for a rental cap. Nostalgic posts by all parties referred to their own (present and past) politicians and the EU Parliament election of 2019. Some also referred to political programs such as basic pensions (i.e., liberal FDP, social-democratic SPD). Posts by the conservative Bavarian party CSU mentioned the state of Bavaria frequently, and posts by The Greens uniquely mentioned traditional craftmanship.

***Figure 3. Nostalgic sentiment in German parties’ Facebook posts.*** AFD = Alternative for Germany, CDU = Christian Democratic Union of Germany, CSU = Christian-Social Union in Bavaria, FDP = Free Democratic Party, SPD = Social Democratic Party Germany

***Figure 4. Most Frequent Terms in Nostalgic Posts Unique for Single Parties (TF-IDF).*** AFD = Alternative for Germany, CDU = Christian Democratic Union of Germany, CSU = Christian-Social Union in Bavaria, FDP = Free Democratic Party, SPD = Social Democratic Party Germany

**User Responses to Nostalgic Posts**

RQ3 pertained to the relation between nostalgia and user responses. A series of Wilcoxon’s tests indicated that posts which were classified as nostalgic with probabilities > .70, received more likes and love emojis, and were commented and shared more often, than posts that were classified as non-nostalgic (Table 2).

***Table 2. User Engagement with Nostalgic Versus Non-Nostalgic Posts***

|  |  |  |  |
| --- | --- | --- | --- |
|  | Non-nostalgic | Nostalgic | Wilcoxons' |
|   | *Md* | *MaD* | *Md* | *MaD* | *w* | *p* |
| Likes | 272,00 | 252,04 | 519,00 | 525,58 | 6263435 | <.001 |
| Love | 9,00 | 10,38 | 11,00 | 11,86 | 6245752 | <.001 |
| Comments | 139,00 | 149,74 | 248.5 | 257,23 | 6219873 | <.001 |
| Shares | 41,00 | 44,48 | 107,00 | 133,43 | 5987126 | <.001 |
| *Notes*. *Md* = Median, *MaD* = Mean average distance from the median |

**Discussion**

We broadened the literature by using supervised machine learning to investigate nostalgia in populist and non-populist political communication. Our results confirm both the close association between populism and nostalgia observed previously (Menke & Wulf, 2021; Mols & Jetten, 2014; Smeekes et al., 2021) and ideological asymmetries characterizing this association (Jost, 2017). Consistent with prior work in a Hungarian context (Szabó & Kiss, 2022), the right-wing populist AFD expressed the most nostalgia in its social media communication, although The Left party, which has been characterized as partially populist, also employed nostalgia frequently. Non-populist parties seldomly addressed nostalgic topics in their social media communication. Extending prior research on variation in the content of collective nostalgia (Lammers & Baldwin, 2020; Wohl & Stefaniak, 2021), we demonstrated that nostalgic narratives differed between parties. On the one hand, only the AFD referred to a more homogenous, nativist society—the heartland (Taggart, 2004). On the other hand, only The Left referred to a more pro-social and caring past. Consistent with prior experimental research in Germany (Menke & Wulf, 2021), users engaged more with nostalgic than non-nostalgic posts. Of note, nostalgia was unassociated with content sharing for Hungarian political Facebook posts (Szabó & Kiss, 2022), wherefore future research comparing the interplay of nostalgia in political communication and user responses in different contexts seems desirable.

 On a more abstract level, our study underlined the advantages of employing supervised machine learning in political-communication research, in accord with prior recommendation for automated text analysis (González-Bailón & Petchler, 2015; Scharkow, 2013; Stieglitz & Dang-Xuan, 2013). Extending relevant findings in communication science, we showed that using psychologically established procedures in line with functional and appraisal theories of emotions (Frijda, 1988; Nabi, 1999; Scherer, 2005) to build the ground truth for emotion detection allows a rich depiction of emotions and a classifier performance comparable to that observed for hand-coded data. Although human coding remains the gold-standard for perceived content in text data, vivid recall tasks, like the one used in our study, are used frequently in psychological science (Ferrer, Grenen & Taber., 2015), making them a valuable data source for future classifier developments.

***Limitations and Directions for Future Research***

Our study had certain limitations. The ground-truth database relevant to the development of our classifier was modest. Increasing this database is likely to strengthen the classifiers’ performance (González-Bailón & Petchler, 2015). Furthermore, such an increase would allow for more complex deep-learning algorithms, which might also boost performance.

Also, despite performing better than chance in detecting both nostalgic and non-nostalgic essays, our classifier performed overall unsatisfactorily regarding the detection of non-nostalgic text in the essay data. Although our induction procedure ensured internal validity, enhancing the database with unequivocally non-nostalgic content could strengthen classifier performance. Indeed, performance was better on the political dataset, which included a larger variety of topics than the evaluation data set. Here the classifier agreed in 82% of posts with a human coder. Nevertheless, classifier performance is best on the same type of input on which it was trained. Thus, retraining our model on political Facebook posts likely further strengthens its performance.

Finally, our examination of nostalgia in populist and non-populist communication pertained to a single country, Germany, and a single social network site, Facebook. Future investigations could focus on other countries and a larger variety of social media as well as on traditional political communication such as parliamentary speeches or political advertisements.

***Practical Implications and Conclusion***

Nostalgia confers several psychological benefits (Sedikides et al., 2015), ranging from individual well-being (Wildschut & Sedikides, 2022) to intragroup bonding (Wildschut et al., 2014). It also helps people to manage existential anxieties and imbues life with meaning (Sedikides & Wildschut, 2019), while acting as a motivational force (Sedikides & Wildschut, 2020). National nostalgia can have broad-ranging consequences, depending on how it is used (Sedikides & Wildschut, 2019). We discussed research documenting the pernicious influence of national nostalgia (e.g., increases in prejudice) as used by right-wing populist parties. To prevent or offset such influence, one could instill another type of national nostalgia, focusing on a diverse and open past (Stefaniak et al., 2021; Wohl et al., 2020) or on memories of democratic periods (Elçi, 2021). At the minimum, taking nostalgia into account might help democratic political parties to increase engagement with their social media campaigns.

Overall, we provided unique evidence for the interplay between populism and nostalgia and demonstrated the value of employing psychologically informed supervised machine learning in political communication research.

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**Supplementary Materials for:**

**Populists’ Use of Nostalgia: A Supervised Machine Learning Approach**

**Validation via Manual Content Analysis**

We applied manual coding for three reasons: To (1) scrutinize our ground-truth data construction, (2) test the validity of our classifier, and (3) explore themes of personal and collective nostalgia in the examined texts.

***Analytical Approach***

We employed a structuring qualitative content analysis (Mayring & Fenzl, 2014) for the manual coding of the data. In such an analysis, the communication content that is analyzed is systematically assigned to pre-defined categories in a codebook. The codebook is developed based on the literature. For each category, it includes a description together with prototypical examples for the respective category and coding rules guiding the assignment. The codebook can be refined in a pilot-phase to include categories or coding rules that emerge from the material. Before the actual coding, the intersubjective comprehensibility of the codebook must be established via intercoder reliability checks. To this end, different reliability coefficients exist that measure agreement between at least two coders on a randomly sampled subset of the material (Lacy et al., 2015).

***Database***

We manually coded two data sets. The essay data set included all 520 essays that were used to train and evaluate the classifier. The Facebook data set included 125 randomly sampled political Facebook posts from the classifier application study. These posts had been classified as nostalgic versus non-nostalgic by the classifier with a probability of > 70% (see main text).

***Codebook Development***

Our codebook had two aims. First, we aimed at obtaining an overall classification of the texts as being nostalgic or not – a human judgement comparable to the one by the supervised machine learning algorithm employed in this study. Second, we aimed to explore personal and collective nostalgia in the texts. This part of the codebook was guided by prior content analyses of nostalgia in everyday and political communication (Holak & Havlena, 1992; Menke & Wulf, 2021; Szabó & Kiss, 2022). We coded for the subject of the nostalgic memory (personal or collective) and a set of nostalgic objects (e.g., social relationships, media experiences) and restorative appeals (Table S1).

We established intercoder reliability based on an iterative refinement procedure. First, two independent coders coded 40 essays that were randomly selected to represent both nostalgic essays (i.e., written by participants whose self-reported state nostalgia was above the scale mean) and non-nostalgic essays (i.e., written by participants who reported state nostalgia below the scale mean). Then we checked the intercoder reliability via the tidycomm shinyapp (https://joone.shinyapps.io/icr\_web/). Given that we expected some categories to be infrequent in the essays, we used Brennan-Predigers’ κ (Brennan & Prediger, 1981) as a measure for intercoder reliability. We chose this coefficient because it outperforms Krippendorfs’ alpha in cases of imbalanced data (i.e., when the characteristic of interest is infrequent in the data). We considered values >.75 satisfactory.

Seven categories had κ values below this threshold. We discussed them in an extensive coding session in which we jointly coded five so-far unseen posts with a revised version of the codebook that included more detailed coding rules. Next, two independent coders coded another 40 posts with the revised categories resulting in a high intercoder-agreement for all categories, all Brennan-Prediger’s κ > .89. Table S1 shows the final categories and coding rules. We provide the German version of the codebook including the examples per category at the Open Science Framework (https://osf.io/gu92j/).

***Table S.1. Codebook for the Manual Content Analysis***

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Category** | **Definition** | **Coding rules** | **%** | **κ** |
| ID | Participant number of the essay respectively URL of the Facebook post |  |  |  |
| Coder Id | Initials of the coder |  |  |  |
| Theme | Keywords summarizing the content of the post | Open description of the content in a few keywords |  |  |
| Perceived nostalgia  | Global evaluation of the text as expressing or potentially eliciting nostalgia.  | Nostalgia is the bittersweet memory, the sentimental longing for a past, which is perceived as positive(er), beautiful(er), familiar(er), and possibly more glorious than the present. That is, the text must refer to an emotionally positive(er) past that seems desirable. This impression can also be conveyed by lamenting the comparably worse present.  | .95 | .90 |
| Past oriented | The text refers to the past | Code when the text refers to the past | .90 | .80 |
| Subjects: personal | The text entails personal memories or experiences | Code when the text describes personal memories or experiences | 1 | 1 |
| Subjects: A younger self | The text refers to a younger version of oneself | Coded when the text refers to a younger version of the author  | .75 | .93 |
| Objects: Social relationships | The text refers to social interactions with close others | Coded when one focus of the text is the interaction with close others such family, friends, partners | .78 | .94 |
| Objects: Setting | The text refers to specific settings | Coded when one focus of the text is the settings (e.g., because they are particularly positive, impressive, awe inducing or negative) | .73 | 1 |
| Objects: Animals | The text refers to pets or other animals | Coded when one focus of the text is on animals such as pets.  | .92 | .85 |
| Objects: Non-vivid objects | The text refers to non-vivid objects such as vehicles or food | Coded when one focus of the text are specific non-vivid objects (e.g., because they are particularly positive, impressive, awe inducing or negative), the category is not coded when these objects are only used (e.g., sitting in the car) but when they valuable (e.g., grandfathers’ old car). | .78 | 1 |
| Objects: Media | The text refers to specific media experiences | Coded when one focus of the text are specific media-related experiences, for instance specific devices, TV shows, games, beloved media characters and so on. | .90 | .80 |
| Subject: Collective  | The text entails collective memories | Coded when the text describes memories of the past of a stable collective/social identity (i.e., a social category such as “the Germans", "the Berlin people", "the students"). It is about identities one could use to describe him- or herself, e.g., I am XYZ. For instance, I am a fan of …, I am German, I am Muslim etc. | .78 | .89 |
| Collective Identity | Which collective is addressed? | Open description of the collective identity addressed. | 1 |  |
| Restorative nostalgia | Texts that present the past as an ideal time that should be restored | Coded when the text contains references to an ideal world ("heartland"), which―as opposed to utopian ideas―is constructed retroactively from the past. In other words, a vision derived from the past that is projected onto the present as "what has been lost". Often also: lamenting the present perceived as more negative. | 1 | 1 |
| Conservative nostalgia  | Texts that transmit restorative nostalgia for a more conservative time | Coded when the restorative nostalgia refers to a conservative past (e.g., more traditional gender roles, a more homogenous society with less diversity (e.g., less migration)).  | 1 | 1 |
| Liberal nostalgia  | Texts that transmit restorative nostalgia for a more liberal time | Coded when the restorative nostalgia refers to a liberal past (e.g., less social inequality, better nature, more liberal sexual norms (e.g., in the 70ths) | 1 | 1 |
| Explicit nostalgia expression | Texts that express bittersweet emotions about the past | Coded when the text contains descriptions of (a) positive (joy, pleasure, love, well-being) AND (b) negative (anger, sadness, disappointment, longing) emotions? | .98 | .95 |
| Explicit nostalgia: Word | Texts that include the word nostalgia | Coded when the text includes the word nostalgia | 1 | 1 |
| Miscellaneous | Open category for further comments |  |  |  |
| *Notes*. Translated for publication purposes and slightly edited for consistency in the descriptions. |

***Index Construction***

To test the prevalence of personal and collective nostalgia in our data, we calculated two indices based on the human coding that summarized personal and collective nostalgia, respectively. Both indices used the following formula:

$$index nostalgia=(Σx\_{i}×a×b)$$

$x\_{i}$ = the single themes of either personal or collective nostalgia

$a$ = references to the past

$b$ = the human perception of the text as being nostalgic (versus not).

Thus, the *personal nostalgia index* counted personal nostalgia when the text referred to the past in a nostalgic manner *and* entailed any of the themes of personal nostalgia. Themes of personal nostalgia were counted, when the subject of the nostalgic memory was a personal experience or memories of a younger self or when typical objects of personal nostalgia—such as social relationships, animals, and pets, inanimate objects, or media experiences—were mentioned. The personal nostalgia index was zero when the respective text either did not refer to the past in a nostalgic manner or did not entail any of these personal nostalgia themes.

The *collective nostalgia index* counted collective nostalgia when the text referred to the past in a nostalgic manner *and* the subject of the text was a collective identity or the text expressed restorative appeals. The collective nostalgia index was zero when the texts either did not refer to the past in a nostalgic manner or did not include any of the themes of collective nostalgia.

**Results**

***S.1 Comparing Self-Reported and Manually Coded Nostalgia in the Essay Data***

 Our first analysis used self-reported nostalgia as label for the ground-truth data. As detailed in the main text, we labeled as nostalgic essays that were written by participants with self-reported state nostalgia above the scale midpoint, and we labeled as non-nostalgic essays that were written by participants with self-reported state nostalgia below the scale midpoint. We excluded essays written by participants with self-reported nostalgia corresponding to the scale midpoint. We compared these labels to the perception of the essays as nostalgic (vs. non-nostalgic) by the human coders. Essays labeled as nostalgic (vs. non-nostalgic) based on participants’ self-report were more likely to be perceived as nostalgic (vs. non-nostalgic) by the coder, χ²(1)=38.31, *p*<.001. Essays that were written by someone reporting above-mean levels of nostalgia had 2.12-times higher odds to be perceived as nostalgic (vs. not-nostalgic) by the human coder. Essays that were written by someone reporting below-mean levels of nostalgia had 1.63-times higher odds to be perceived as non-nostalgic (vs. nostalgic) by the human coder. Overall, the label based on self-reported nostalgic affect and the manual coding (i.e., perceived nostalgia in the essays) agreed in 66% of the essays (Table S2).

***Table S2. Confusion Matrix for Essays written by Someone Self-Identifying as Nostalgic respectively non-Nostalgic versus the Manual Coding of the Essays***

|  |  |  |  |
| --- | --- | --- | --- |
|   | Manually coded as non-nostalgic | Manually coded as nostalgic | Σ |
| self-reported affect: not nostalgic | 96 | 59 | 155 |
| self-reported affect: nostalgic | 113 | 239 | 352 |
| Σ | 209 | 298 | 507 |

**S.2 Comparing Machine Classified Nostalgia and Manually Coded Nostalgia in the Evaluation Data**

 This analysis compared the performance of our classifier to the human coding of the essays in the hold-out evaluation dataset. Human and algorithmic evaluation were marginally associated, in a Fischer’s test, *p* = .07. Essays that were deemed nostalgic by the classifier had 1.9-times higher odds to be perceived as nostalgic (vs. non-nostalgic) by the human coder. Essays that were deemed non-nostalgic by the classifier had 1.6-times higher odds to be perceived as non-nostalgic (vs. nostalgic) by the human coder (Table S3).

**Table S3**

*Confusion Matrix for Essays Classified as Nostalgic and Non-Nostalgic in the Evaluation Data Versus the Manual Coding of the Essays*

|  |  |  |  |
| --- | --- | --- | --- |
|  | Manually coded as non-nostalgic | Manually coded as nostalgic | Σ |
| Classified as non-nostalgic | 8 | 5 | 13 |
| Classified as nostalgic | 30 | 58 | 88 |
| Σ | 38 | 63 | 101 |

**S.3. Exploring Themes of Personal and Collective Nostalgia in the Essays**

To test whether essays classified as nostalgic (vs. non-nostalgic) by the random-forest classifier differed in their coverage of personal and collective nostalgia, we used the classification of the essays as nostalgic (vs. non-nostalgic) as independent variable and our indices of personal and collective nostalgia as dependent variables in two independent *t*-tests with Welch-correction.

Essays classified as nostalgic scored higher on the index of personal nostalgia (*M* = 2.21, *SD* = 2.05) than essays classified as non-nostalgic (*M* = 0.47, *SD* = 1.25), *t*(406.82) = 13.11, *p* < .001, *d* = 1.01. Essays classified as nostalgic also entailed more collective nostalgia (*M* = 0.13, *SD* = 0.39) than essays classified as non-nostalgic (*M* = 0.06, *SD* = 0.27), *t*(734.72) = 25.48, *p* < .001, *d* = 0.27.

**S.4. Exploring Themes of Personal and Collective Nostalgia in the Facebook Posts**

To test whether political Facebook posts classified as nostalgic (vs. non-nostalgic) by the random-forest classifier covered more themes of personal and collective nostalgia, we used the classification of the posts as nostalgic (vs. non-nostalgic) as independent variable and our indices of personal and collective nostalgia as dependent variables in two independent *t*-tests with Welch-correction.

Facebook posts classified as nostalgic included more personal nostalgia (*M* = 0.41, *SD* = 0.87) than posts classified non-nostalgic (*M* = 0.02, *SD* = 0.15), *t*(245.46) = 2.32, *p* = .02, *d* = 0.61. Facebook posts classified as nostalgic tended to include more collective nostalgia (*M* = 0.44, *SD* = 0.76) than posts classified as non-nostalgic (*M* = 0.05, *SD* = 0.23), although the difference was only marginally significant, *t*(247.47) = 1.83, *p* = .07, *d* = 0.69.

**S.5. Distribution of Facebook Posts Across Parties**

Most posts in our database were uploaded by the governing conservative parties CDU and CSU (Table S4). The Green party was least active on Facebook during the examined time period.

**Table S4**

*Absolute Number of Facebook Posts per Party*

|  |  |  |
| --- | --- | --- |
| **Party Ideology** | **Party Name** | ***n***  |
| Right-wing populist, far right | Alternative for Germany (AfD) | 405 |
| Green politics, center left | Alliance 90/The Greens (Bündnis 90/Die Grünen) | 334 |
| Christian democratic, liberal conservative | Christian Democratic Union (CDU) | 637 |
| Christian democratic, conservative | Christian Social Union (CSU) | 991 |
| Liberal, free democratic | Free Democratic Party (FDP) | 805 |
| Democratic socialism, left-wing populism | The Left (Die Linke) | 413 |
| Social-democratic | Social Democratic Party of Germany (SPD) | 437 |
| *Notes*. *N* = 4,022 Facebook posts uploaded to the official party pages between January 1st and December 31st, 2019. |

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