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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 data set and trained and evaluated a classifier for detecting nostalgic sentiment in the German language. 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-populist)—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

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Populist leaders and parties have enjoyed substantial electoral success around the globe in the second decade of the 21st century. Examples include political leaders such as Marine Le Pen in France, Donald Trump in the United States, and 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 (Schmuck & Hameleers, 2020; Wirz, 2018), which is rewarded by popularity cues such as likes and shares (Jost, Maurer, & Hassler, 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 U.S. 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). Yet, 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 right-wing populists use more nostalgic narratives in their Facebook communication than do left-leaning politicians.

Populism

The populist ideology is often defined as a "thin-centered" belief system (Mudde, 2004) around the core assumption that the good people are opposed to the malicious or incompetent elite, who fail to represent the people. 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, Wirth, & Müller, 2020); (b) *homogeneity assumptions*, that is 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 the *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, 2000, p. 274). The heartland denies historical facts and romanticizes the past, focuses on national in-groups that are considered native, and divides the population against those who migrated later. 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). Negative emotions such as anger and fear in particular 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 illustrated that the German 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 et al., 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 of 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, Gkinopoulos, 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 in-group 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 the heartland (Taggart, 2004). Collective nostalgia strengthens identification with the in-group (Smeekes et al., 2018), intentions to support the in-group (Wildschut et al., 2014), and favoritism toward the in-group (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. 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 in-group 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, Tausch, & Ayanian, 2017). Particularly, national nostalgia predicts prejudice (Smeekes et al., 2015).

Yet, people feel nostalgic for different aspects of their nation's past. For instance, conservatives in the United States feel more nostalgic for a homogenous past, such as that reflected in the concept of the 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, Turks who waxed nostalgic for the Ottoman empire (vs. the time of Kemal Atatürk) manifested more populist attitudes (Elçi, 2022).

Nostalgia and Populism

Populists 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 (Smeekes et al., 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 a discourse analysis, 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). German right-wing populists particularly seem to thrive on local narratives. For instance, the geographical distance to Nazi concentration camps predicts the success of the AfD decades later on 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. In addition, right-wing (compared to left-wing) candidates expressed more nostalgia. Finally, nostalgic (vs. non-nostalgic) posts elicited more emotional responses (e.g., likes, shares, emojis) from users. Building upon this work, we extend 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 (see Figure 1), a statistical model is trained on a data set (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. Afterward, 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).

The ground-truth data lie at the heart of the procedure, but scientific disciplines vary in the creation of these "gold standard" data. In computer science, the ground-truth data are usually annotated by three coders, 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. For instance, Azim and Bhuiyan (2018) annotated tweets using nine basic emotions as labels. Comparing different classifiers by relying on simple words showed that between 41.25% and 71.75% of the emotions were detected correctly. Similar rates were reported by Asghar and colleagues (2019).

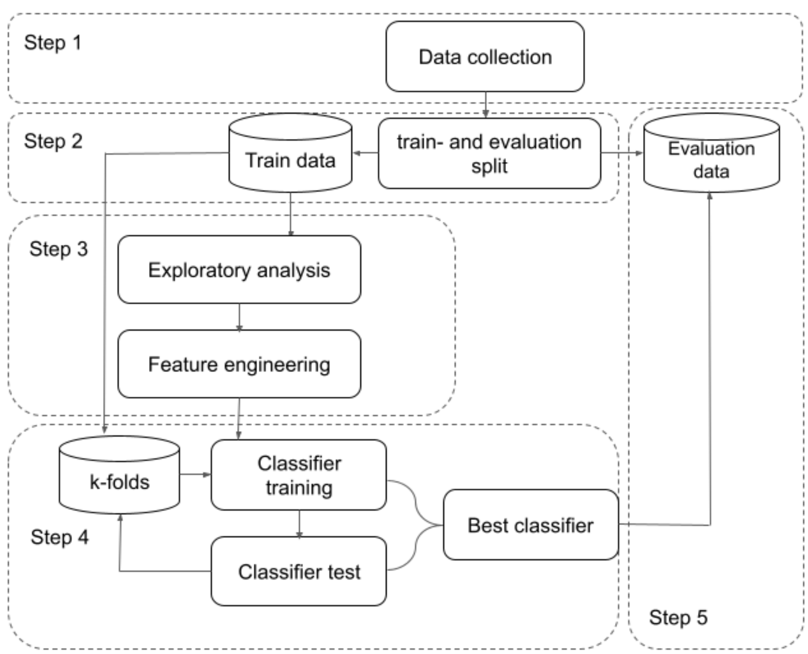

Figure 1. Typical procedure of supervised machine learning.

In communication science, the ground-truth data are typically human-coded data sets created via manual content analysis (Scharkow, 2013). For instance, Burscher and colleagues (2014) had trained coders rate a large set of news articles and parliamentary questions for included policy issues. Similarly, Stoll, Ziegele, and Quiring (2020) used a manually coded data set 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 data set for which participants recalled emotional experiences, labeled these experiences on a set of basic emotions, and rated the experiences on 25 items. Classifiers trained on these data performed better than chance.

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 (developed 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 data set, 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 on an emotion's core relational themes—its typical elicitors—triggers the respective emotion (de los Santos & Nabi, 2019; Nabi, 2002). Using a predefined 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 captures not only personal, but also collective and geographically situated memories.

Methods and Measurements

We collected nostalgic essays in two experiments (*$N_{Exp.1}$* = 295, 170 women and 125 men; *$N_{Exp.2}$* = 261,179 women, 80 men, and two nonbinary). We randomly assigned participants to write about either a nostalgic memory (*$n_{Exp.1}$* = 161, *$n_{Exp.2}$* = 135) or a control memory (*$n_{Exp.1}$* = 159, *$n_{Exp.2}$* = 135) before they reported their state (i.e., subjective) nostalgia and answered some sociodemographic and other questions. All materials, training data, analysis scripts, and supplementary materials are openly available via the Open Science Framework: https://osf.io/gu92j/.

Writing Instructions

Given the relevance of locality for German populism (Jäckle, 2022), we aimed to collect memories on local contexts. 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 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 $\alpha_{Exp.1}$ = .96, Cronbach's $\alpha_{Exp.2}$ = .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), $t(234) = 7.00$, $p < .001$. Essays were thus collapsed across experiments.

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: https://osf.io/vb4qu/). We excluded all essays with meaningless text (e.g., "fssdffz"), corrected all 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 data set. The purpose of this split was to separate 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 labeled as nostalgic (70%) than control (30%).

Feature Engineering

Non-nostalgic essays (*Mdn* = 100 words) were shorter than nostalgic essays (*Mdn* = 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 dictionary* (LIWC, Pennebaker, Booth, & Francis, 2007; Pennebaker, Boyd, Jordan, & Blackburn, 2015). 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 on the following theoretically derived categories: terms reflecting positive and negative emotions; personal pronouns; and references to friends, family, the past (Davalos, Merchant, & Rose, 2015; Wildschut, Sedikides, & Robertson, 2018), and space (e.g., locations).

A series of two-sided Wilcoxon rank sum tests indicated that nostalgic (vs. 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, Merchant, Rose, 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.

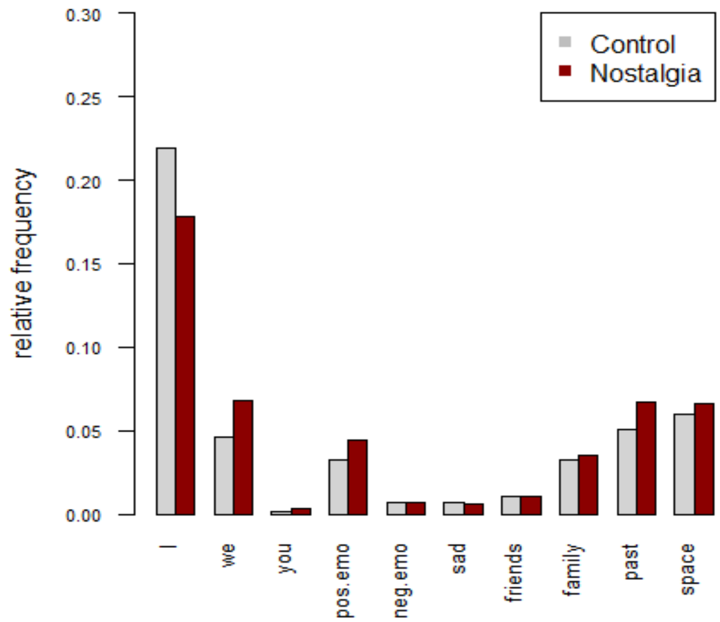

Figure 2. Relative frequencies of selected linguistic categories in the training data.

Preprocessing

We used the recipe package (Kuhn & Wickham, 2020) and the textrecipe package (Hitveld, 2020) to formalize the following preprocessing steps. First, we split the text into single words (tokenization; Benoit & Matsuo, 2020) and removed punctuation marks and numbers. We implemented the German stopword dictionary provided by the snowball package (Bouchet-Valat, 2020) to exclude words that are frequent in the German language, but have no interpretative value (e.g., "and" or "then"). To reduce the number of features, we removed words that appeared fewer 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 with non-nostalgic essays, we used *synthetic minority oversampling* (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 data sets (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 nonlinear 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 tenfold 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 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 because this metric can handle imbalanced classes. The *f*1 measure 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 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 of 291 nostalgic essays correctly (87%), suggesting nonlinear 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 67% of all essays accurately. Further, its recall was substantially better than its specificity.

To judge the interpretability of the classifier, 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, Wildschut, Routledge, et al., 2015). Because of 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

Note. 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 to 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 are used here to account for the imbalanced data set, and the theoretical priorities are in boldface.

Classifier Evaluation

Thirteen essays were classified as non-nostalgic and 88 as nostalgic by the random-forest classifier in the holdout 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 with control essays: A total of 70 of 72 nostalgic essays (97%) were classified correctly, whereas only 11 of 31 control essays (35%) were classified correctly. The overall accuracy (.78) was within the range described for other emotion classifiers in the literature (Asghar et al., 2019; Azim & Bhuiyan, 2018), and both the accuracy and *f*1 measure (.50) outperformed the null model ($accuracy_{null}$ = .30, $f1_{null}$ = .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 the supplementary material: https://osf.io/vb4qu). The machine classification and the human classification were significantly associated, $\chi^2(1) = 36.10$, $p < .001$. Posts perceived as non-nostalgic by the human coder had 2.01 times higher odds of being classified as such by the algorithm, whereas posts perceived as nostalgic by the human coder had 2.05 times 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 indicated that the recognition of non-nostalgic memories is challenging even for humans (Szabó & Kiss, 2022); (2) our own comparison between the perception of the essays as being nostalgic (or not) and a manual coding of the essays (supplementary material: https://osf.io/vb4qu) demonstrated that the task of recognizing non-nostalgic essays is challenging even for humans; and (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 added an extra step of additional manual validation (discussed next).

Nostalgia in Populist Discourses

Database

We employed our classifier on a data set 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 S5 (https://osf.io/vb4qu). 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), $f1$ = .57. Thus, the classifier performed even better in the application phase than in the development phase—likely due to the more heterogenous content within the political posts compared with the essays. 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 and 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, memories of famous politicians of the past, as well as collective issues such as the alleged loss of the "free Internet" resulting from European policy reforms, increased forest dieback, or far-right narratives of immigrants allegedly "overflooding" the heartland (see Supplementary Material S4, at https://osf.io/vb4qu, for additional explorations).

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, $\chi^2(6) = 346.43$, $p < .001$ (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 $|z| < 1.96$, ps > .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 ORs < 0.29.

RQ2 refers to potential differences 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).

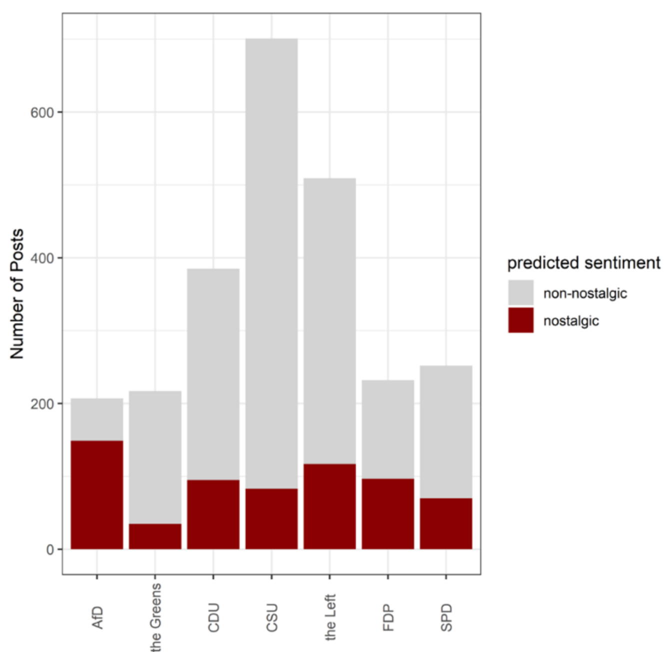

Figure 3. Nostalgic sentiment in German parties' Facebook posts.
Note. AfD = Alternative for Germany; CDU = Christian Democratic Union of Germany; CSU = Christian-Social Union in Bavaria; FDP = Free Democratic Party; SPD = Social Democratic Party Germany.

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 posts also referred to political programs such as basic pensions. Posts by the conservative Bavarian party CSU mentioned the state of Bavaria frequently, and posts by The Greens uniquely mentioned traditional craftmanship.

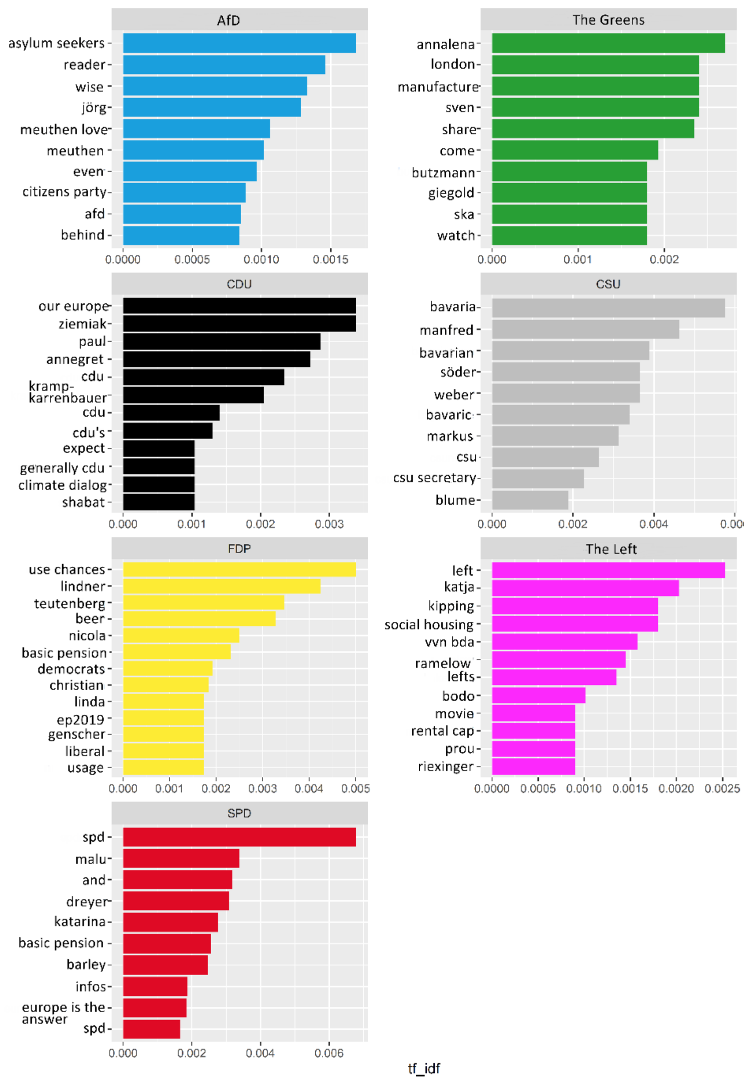

Figure 4. Most frequent terms in nostalgic posts unique for single parties (TF-IDF).

Note. 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 that were classified as nostalgic with probabilities > .70 received more likes and love emojis, and were commented on 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		Wilcoxon's	
	Mdn	*MaD*	*Mdn*	*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

Note. *Mdn* = median; *MaD* = mean average distance from the median.

Discussion

We broadened the literature by using supervised machine learning to investigate nostalgia in 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 Facebook communication, although The Left party also employed nostalgia frequently. Non-populist parties seldomly addressed nostalgic topics.

Extending prior research on variation in the content of collective nostalgia (Lammers & Baldwin, 2020; Wohl & Stefaniak, 2020), we demonstrated that nostalgic narratives differed between parties. Only the AfD referred to a more homogenous, nativist society—the heartland (Taggart, 2004). Only The Left referred to a more prosocial 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). Thus, future research comparing the interplay of nostalgia 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 (for similar arguments, see 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 with 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 research (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 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.

In addition, 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 data set, which included a larger variety of topics than the evaluation data set. Here the classifier agreed in 82% of posts with a human coder. Further, 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, Wildschut, Routledge, 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 a 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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