Predicting ethnicity with data on personal names in Russia[*]

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Abstract

In this paper we develop a machine learning classifier that predicts perceived ethnicity from data on personal names for major ethnic groups populating Russia. We collect data from VK, the largest Russian social media website. Ethnicity has been determined from languages spoken by users and their geographical location, with the data manually cleaned by crowd workers. The classifier shows the accuracy of 0.82 for a scheme with 24 ethnic groups and 0.92 for 15 aggregated ethnic groups. It can be used for research on ethnicity and ethnic relations in Russia, in particular with VK and other social media data.

Over the past decades, social scientists gained access to many large-scale data sets thanks to the proliferation of digital traces (Lazer and Radford, 2017). The explosive growth in new data even raised hopes that social science was entering its golden age (Buyalskaya et al., 2021). However, digital traces are typically not collected with a research purpose in mind and are framed by the needs of data providers. As a result, they often lack information on individuals that is important to researchers. One potential solution is to infer missing information using machine learning methods. For example, various socio-demographic characteristics were predicted from profile

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images (An and Weber, 2016), mobile phone metadata (Blumenstock et al., 2015), Facebook likes (Kosinski et al., 2013), and images of street scenes (Gebru et al., 2017).

One of important characteristics that is of great interest to social scientists but rarely present in digital traces is ethnicity. Taking ethnicity into account is important for analysing social inequalities in health (Khunti et al., 2021), political participation (Flesken and Hartl, 2020), the labour market and housing (Bertrand and Duflo, 2017), among other areas.

While lacking information on ethnicity, some large scale data sets have not been anonymised and include personal names. Examples of such data sets include US voter registration data (Imai and Khanna, 2016) or Twitter data (Wood-Doughty et al., 2018). Personal names can be used as a signal for ethnicity for many ethnic groups. Experimental studies of discrimination in the labour market and in housing have been using this feature (Bertrand and Duflo, 2017); it has also been applied to historic studies of social mobility (Clark, 2014). An ability to infer ethnicity from personal names allows social scientists to use new administrative and social media data.

While several ethnicity classifiers are already available to researchers, most of them are focusing on a few immigration destination countries and are limited to a small number of ethnic groups (Mateos, 2014). In this paper, we are addressing this gap by developing a machine learning approach to coding ethnicity from personal names for ethnic groups populating Russia, using data from VK, the largest Russian social media website.

1 Predicting ethnicity from personal names

There are several approaches to classifying ethnicity with data on personal names. Early studies employ a dictionary based method where names are compared to a reference list of names already classified by ethnicity. Coldman et al. (1988) is perhaps the first example of automatic name binary classification, developed to separate Chinese from non-Chinese names in Canada. Mateos (2007) offers a review of 13 studies published up to 2007 that use similar methodology. A successful application of this approach requires a large reference list that covers most ethnic first names and/or surnames. However, for many ethnic groups the reference lists of names do not exist or are incomplete. These classifiers also rely on the assumption that name/ethnicity distributions are similar for the reference list and the target population. As reference lists are often compiled from census data, it is not clear how well they will work with social media data.

The modern approach to ethnic name classification is based on machine learning (ML) algorithms. The main advantage of this approach is that it allows researchers to classify previously unseen names. Ambekar et al. (2009) develop a multiclass name classifier for 13 ethnic groups with the data from Wikipedia using hidden Markov models and decision trees. Lee et al. (2017) use recurrent neural networks to predict ethnicity from names from the Olympic records data. In other recent studies, Chaturvedi and Chaturvedi (2020) apply several machine learning algorithms to infer religion from personal names in South Asia, Ye et al. (2017) develop a multiclass classifier for 39 nationalities, Wood-Doughty et al. (2018) predict gender and ethnicity from Twitter usernames, etc.

None of the existing studies specifically focuses on Russian names. The most well known reference list of Russian surnames compiled by Unbegaun (1972) is incomplete and does not directly link surnames to ethnic groups. Karaulova et al. (2019) develop a method for identifying ethnically Russian surnames that uses suffix-based morphological regularities. ML based methods can achieve higher accuracy, and, besides, the method proposed by Karaulova et al. (2019) cannot distinguish between various ethnic groups populating Russia that is home to over 100 ethnic groups with often characteristic personal names.

2 Data collection and processing

We use data from VK (`www.vk.com`), a Russian social media website. VK was created in 2006 as a clone of Facebook and quickly became the most popular Russian social networking website. In December 2020 its user base in Russia consisted of 73 million people. [1] According to the VK Terms of Service, users understand and accept that information that they publish on their page becomes publicly available on the Internet. VK provides a public application programming interface (API) that allows downloading this information systematically in the open JSON format. In particular, it is possible to download user profiles from a selected region or VK community and

[1] VK press release. 4 March 2021. `https://vk.com/main.php?subdir=press&subsubdir=q4-2020-results`

access information on personal names and languages spoken by users. While users can provide false information the VK Terms of Service require the use of real names. VK has been shown to be a valuable source of data for social science research (Sivak and Smirnov, 2019; Smirnov, 2020).

VK does not directly collect information on user ethnicity. In order to infer ethnicity, we combine information on users' locations and the languages they speak, improving the quality of inference by manual checks via crowdsourcing. We use the resulting data on personal names (first name and surname) and inferred ethnicity as an input for machine learning (ML) algorithms. We apply the following protocol for collecting data and coding ethnicity.

First, we compile a list of 40 ethnic groups that, according to the 2010 Russian census, count more than 100,000 people. We exclude 9 groups in cases where either personal names are almost indistinguishable from ethnic Russian (Chuvash, Mordvin, Udmurt, Mari, Komi) or where it is not possible to assign ethnicity using the combination of the language spoken and location (Germans, Koreans, Roma, Turks). For the remaining ethnic groups we collect data on names and sex from user profiles in the cities where these groups are geographically concentrated and from thematic ethnic communities. This is facilitated by the fact that many ethnic groups in Russia have their "titular" regions where most of their members live (such as Chechnya for Chechens, Tatarstan for Tatars, etc.).

At the next stage we filter the data by the language spoken, only keeping the profiles of people who indicate that they can speak the language of the ethnic group they are intended to represent. Thus, someone who lives in Kazan (the capital of the Republic of Tatarstan) and can speak Tatar is assumed to be ethnically Tatar. At this stage we combine together the ethnic groups who share the same language (Kabardin and Adyghe; Karachay and Balkar) or the ethnic groups with similar personal names who share the same locations (the Avar, Dargin, Kumyk, Lezgian, Laki, Tabasaran and Nogai into the Dagestani).

Then we manually clean the data at Yandex.Toloka, a crowdsourcing platform similar to Amazon Mechanical Turk. For most ethnic groups, we employ data cleaners from locations where the group is geographically concentrated. We ask the data cleaners to select only the names that belong to required ethnic groups. To improve data quality, we implement several quality control checks. Our aim is to collect about 10,000 personal names for each ethnic group, although in some cases this is not possible.

In the resulting data set some of the names are spelled in Cyrillic and others in Latin alphabet. We transliterate all the names to Cyrillic using the **transliterate** package in Python. We make some manual adjustments, such as replacing the Ukrainian letter ‘i’ with the Russian ‘и’. Then we remove all the names containing non-Cyrillic characters other than ‘-’ and concatenate first names and surnames with the ‘#’ delimiter. The final sample consists of 172,280 names for 24 ethnic groups.

Table 1 shows the list of ethnic groups and their population and sample sizes. We make the data set with personal names linked to ethnicity publicly available on Github at `https://github.com/abessudnov/ruEthnicNamesPublic`.

3 Mapping text to vectors

In order to apply ML algorithms, text must be transformed into numerical vectors. We use three different vectorisation methods (Bag of Words, TFIDF, and fastText) and compare their performance with different ML algorithms.

The Bag of Words (BoW) converts text into a vector with dimensionality equal to the size of the vocabulary formed with unique tokens (extracted n-grams in our case) from a corpus. n-gram is a sequence of n characters from a name: for example, 3-grams of the name «Alice» are «Ali», «lic», «ice». Vectorisation is then performed according to the token (n-gram) frequency. As an example, if a corpus contains only tokens ‘A’, ‘T’, ‘G’, ‘C’, then «AATGA» would be converted to $<3, 1, 1, 0>$.

TFIDF (term frequency-inverse document frequency) shares the same idea but it uses the tf-idf function of a token, i.e. normalise the token frequency by the share of all words that contain the token .The motivation for this transformation is to decrease the impact of frequent tokens that often provide little information and to increase the impact of rare tokens that are more informative (Manning et al., 2009).

Finally, the fastText model (FT) (Joulin et al., 2016) is a method that transforms words into a vector of real values (so called word embeddings) using n-grams. It was trained on a large corpus to efficiently represent words as vectors. We pass the first names and surnames independently through the model that was trained on Russian texts[2] and then concatenate the pairs of vectors resulting in the vectors of dimensionality 600.

[2] https://fasttext.cc/docs/en/crawl-vectors.html

Table 1: Ethnic groups and their population and sample sizes

Ethnic group	**Data source (cities)**	**Population size (2010 census, thousand)**	**Sample size**
Ethnic Russian	Tambov, Vladimir, Vologda	111,000	11,879
Tatar	Kazan	5,300	9,862
Dagestani*	Makhachkala, Khasavyurt, Derbent, Kaspiysk	2,900	9,555
Ukrainian	VK Ukraine	1,900	8,377
Bashkir	Ufa	1,600	13,462
~~Chuvash~~	not selected	1,400	
Chechen	Grozny, Urus-Martan, Gudermes	1,400	5,257
Armenian	Yerevan	1,200	9,269
~~Mordvin~~	not selected	740	
Kazakh	Nur-Sultan	650	9,733
Adyghe / Kabardin	Nalchik, Baksan, Nartkala, Terek, Chegem, Maykop, Adygeysk	640	1,240
Azerbaijani	Baku	600	7,922
~~Udmurt~~	not selected	550	
~~Mari~~	not selected	550	
Ossetian	Vladikavkaz, Mozdok, Beslan	530	4,834
Belarusian	Minsk	520	13,393
Yakut	Yakutsk	480	1,604
Buryat	Ulan-Ude	460	7,691
Ingush	Nazran, Sunzha, Karabulak	440	1,315
~~German~~	not selected	390	
Balkar / Karachay	Cherkessk, Ust-Dzheguta, Karachaevsk, Nalchik, Tyrnauz	331	1,264
Uzbek	Tashkent	290	8,709
Tuvan	Kyzyl	260	3,556
~~Komi~~	not selected	230	
~~Roma~~	not selected	200	
Tajik	Dushanbe	200	10,636
Kalmyk	Elista	180	1,745
Georgian	Tbilisi	160	9,306
Jewish	Tel-Aviv, Jerusalem, Haifa	160	4,054
Moldovan	Kishinev	160	8,059
~~Korean~~	not selected	150	
~~Turkish~~	not selected	105	
Kyrgyz	Bishkek	100	9,558

Notes: The Dagestani include the Avar, Dargin, Kumyk, Lezgian, Laki, Tabasaran and Nogai ethnic groups. For Ukrainians we only use the data from the largest Ukrainian VK community. Data from VK communities are used for some other ethnic groups as well. Some of the cities in the table are outside of Russia.

4 Machine learning algorithms and prediction accuracy

We apply several ML algorithms and compare their performance. These are complement Naive Bayes (CNB) and several versions of the Stochastic Gradient Descent (SGD) classifier: with the Log loss (LR, equivalent to logistic regression), with the Hinge loss (SVM, equivalent to linear Support Vector Machine), and with the modified Huber loss (MH, equivalent to quadratically smoothed Support Vector Machine) (Zhang, 2004), as well as the Gradient Tree Boosting (GB) (Friedman, 2001). The CNB and SGD models are implemented with **scikit-learn** (Pedregosa et al., 2011), and GB with **XGBoost** (Chen and Guestrin, 2016).[3]

We optimise the model hyperparameters with 3-fold cross-validation on the train data set (75% of the data), with F1 as the target metric. The model with the best hyperparameters is then evaluated on the test set (25% of the data). To prevent data leakage, we remove from the test set the names that are also present in the train set.

Table 2 reports the results for the five ML algorithms implemented with different vectorisation techniques, compared with a baseline random classifier that predicts ethnicity with a probability proportional to its frequency in the training set. We report four metrics: accuracy, precision, recall and F1. Accuracy is the proportion of correctly predicted names. Precision is the fraction of true positives among all positives (i.e. out of all names predicted to be ethnically Russian how many are actually ethnically Russian?). Recall is the fraction of true positives among true positives and false negatives (i.e. out of all ethnically Russian names how many did we label correctly?). F1 is a weighted average of precision and recall that provides a single measure of prediction accuracy.

With our data, the modified Huber (MH) model with TFIDF vectorisation shows the best fit and correctly classifies 82% of the names in the test set (see Table 2).

Figure 1 shows the confusion matrix for 24 ethnic groups based on the MH model. Table 3 shows the prediction metrics for each ethnic group. Prediction accuracy varies by group, from precision as high as 0.99 for Armenians and Georgians (two groups with very characteristic names that follow a simple pattern) to 0.68 for Tatars, 0.69 for

[3] We also implement several other approaches such as the Random Forest (RF), bidirectional Long Short Term Memory (LSTM), Multilayer Perceptron (MLP), and the one-dimensional Convolutional neural network (CNN). They perform worse with our data, and we only report the results from the five best algorithms.

Table 2: Model performance on the test set

Algorithm	Vectorisation	Accuracy	Precision	Recall	F1
Random		0.05	0.04	0.04	0.04
CNB	BoW	0.79	0.83	0.76	0.78
	TFIDF	0.78	0.82	0.74	0.76
SVM	BoW	0.80	0.82	0.80	0.81
	TFIDF	0.81	0.83	0.80	0.81
	fastText	0.71	0.70	0.67	0.68
LR	BoW	0.80	0.83	0.79	0.80
MH	BoW	0.80	0.82	0.80	0.81
	TFIDF	**0.82**	**0.84**	**0.81**	**0.82**
GB	fastText	0.78	0.80	0.75	0.77

Notes: CNB: complement Naive Bayes; SVM: linear Support Vector Machine; LR: logistic regression; MH: modified Huber, quadratically smoothed SVM; GB: Gradient Tree Boosting; BoW: Bag of Words; TFIDF: term frequency-inverse document frequency.

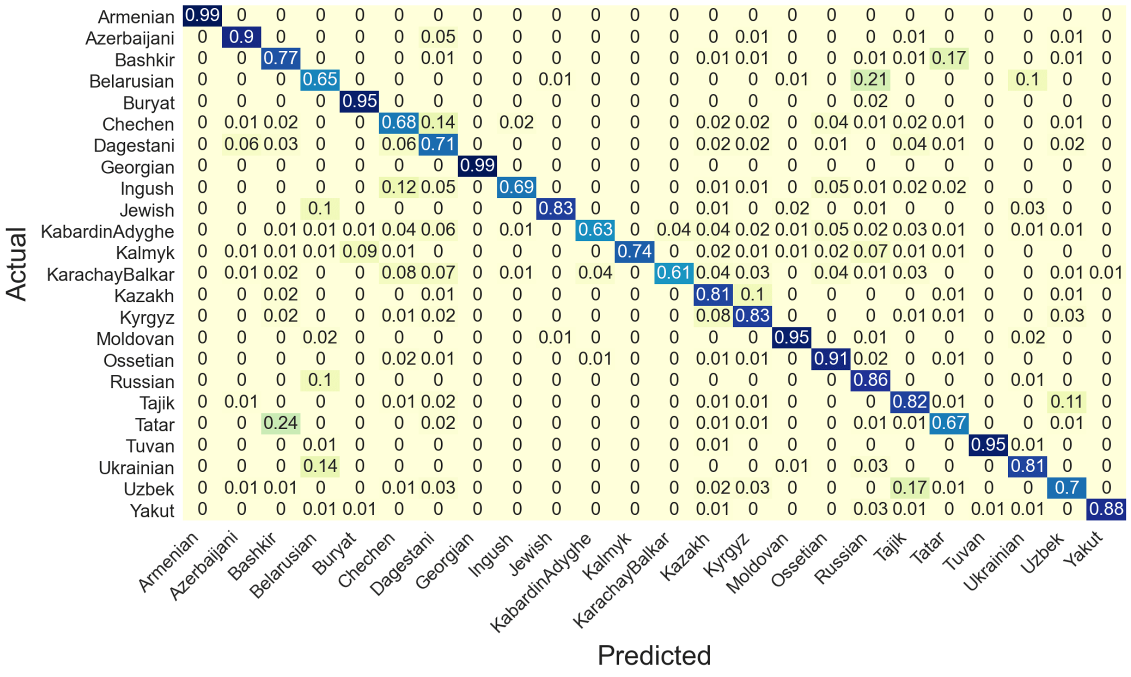


Figure 1: **Confusion matrix for 24 ethnic groups based on the MH model.** Prediction accuracy is high (0.99) for groups with names that follow a simple pattern (Armenians and Georgians) and low for groups such as Karachay / Balkar (0.61) and Kabardin / Adyghe (0.63), often classified as other North Caucasian groups, and Belarusians (0.65), often classified as ethnic Russians.

Dagestani, and 0.71 for ethnic Russians. Recall is lowest for Karachay / Balkar (0.61) and Kabardin / Adyghe (0.63), often classified as other North Caucasian groups, and Belarusians (0.65), often classified as ethnic Russians.

Table 3: Prediction accuracy for ethnic groups

Ethnic group	**Precision**	**Recall**	**F1**
Armenian	0.99	0.99	0.99
Azerbaijani	0.87	0.90	0.89
Bashkir	0.76	0.77	0.76
Belarusian	0.74	0.65	0.69
Buryat	0.94	0.95	0.95
Chechen	0.74	0.68	0.71
Dagestani	0.69	0.71	0.70
Georgian	0.99	0.99	0.99
Ingush	0.86	0.69	0.76
Jewish	0.92	0.83	0.87
Kabardin / Adyghe	0.82	0.63	0.71
Kalmyk	0.94	0.74	0.83
Karachay / Balkar	0.85	0.61	0.71
Kazakh	0.82	0.81	0.82
Kyrgyz	0.81	0.83	0.82
Moldovan	0.94	0.95	0.94
Ossetian	0.86	0.91	0.88
Russian	0.71	0.86	0.78
Tajik	0.78	0.82	0.80
Tatar	0.68	0.67	0.68
Tuvan	0.97	0.95	0.96
Ukrainian	0.79	0.81	0.80
Uzbek	0.76	0.70	0.73
Yakut	0.97	0.88	0.93

Notes: Prediction accuracy estimated on the test set.

Can further improvements in prediction accuracy be made if we increase the sample size? Figure 2 demonstrates how the prediction metrics changes depending on the number of names in the training set. The steepest increase in accuracy occurs up to the point where we have approximately 50,000 to 60,000 names (i.e. about 2,500 names per group on average). Beyond this sample size the improvements are modest. We conclude that the training set with about 130,000 names is sufficient for classification purposes.

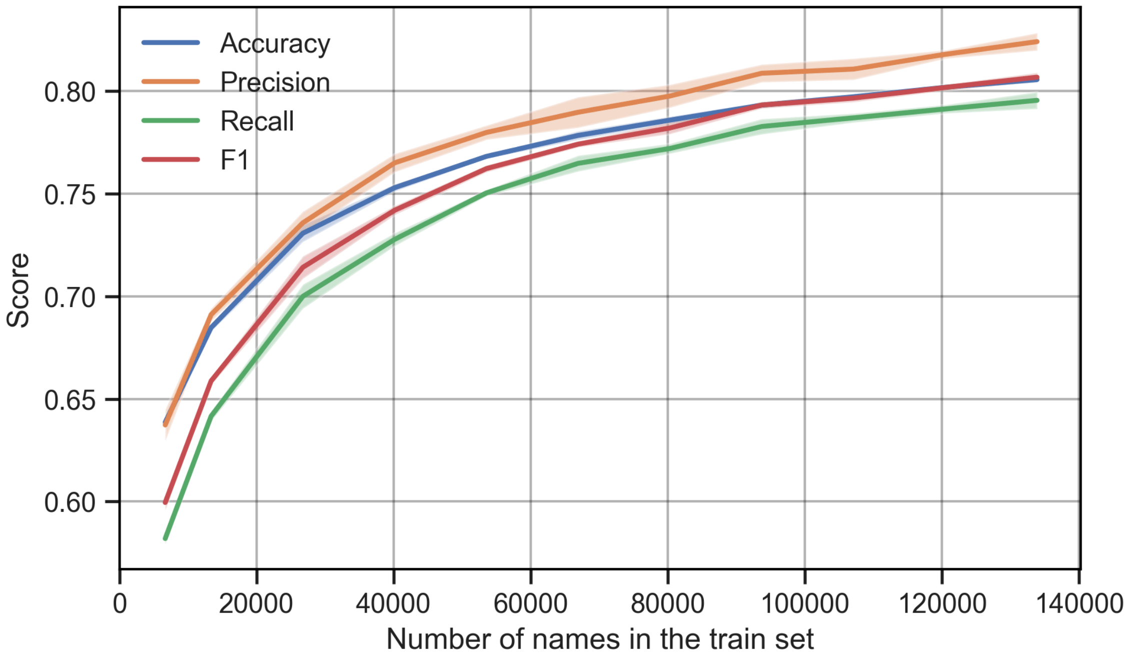


Figure 2: **Training set size and prediction accuracy**. The steepest increase in accuracy occurs up to the point of approximately 50,000 to 60,000 names (i.e. about 2,500 names per group on average). Further increase in sample size leads to only marginal improvements.

5 Classification with aggregated groups

Figure 1 shows that there is a pattern in the classification errors for several ethnic groups. For example, Tatar and Bashkir names often get confused by the algorithm. This can be explained by the characteristics of our data rather than by deficiencies of the classification tool. Indeed, Tatars and Bashkirs both are Turkic groups populating the Volga region who share common origins and culture. Historically, the boundaries between the Tatar and Bashkir identities were not always clear (Gorenburg, 1999). Some other ethnic groups in the data set also often share many common names.

For many social research questions the classification we developed is too detailed and a schema with a smaller number of aggregated ethnic groups would be preferable. At the next step of the analysis we merge several ethnic groups together. We take into account the confusion matrix (Figure 1), as well as the historical and cultural factors and likely applications of the classification tool in social science research. We combine together the following groups: 1) Tatars and Bashkirs (two Turkic groups populating the Volga region), 2) ethnic Russians, Belarusians and Ukrainians (eastern Slavic groups), 3) Chechens, Dagestanis and Ingushes (ethnic groups populating the Eastern part of the North Caucasus), 4) Kabardins, Adyghe, Karachays, Balkars and Ossetians (ethnic groups populating the Western part of the North Caucasus), 5) Kazakhs and Kyrgyz (two Central Asian groups with nomadic origins), 6) Tajiks and Uzbeks (two Central Asian groups with settled agricultural origins). The aggregated classification has 15 groups.

Table 4 shows prediction accuracy metrics for several ML models fitted to the aggregated data. The MH algorithm with the TFIDF vectorisation again provides the best model fit, with the overall accuracy increasing from 0.82 in the original classification with 24 ethnic groups to 0.92 in the aggregated classification with 15 groups.

Table 5 shows prediction accuracy for each ethnic group with the aggregated classification. Figure 3 shows the confusion matrix. Prediction accuracy for several ethnic groups has improved, in particular for eastern Slavic names (ethnic Russians, Belarusians and Ukrainians, now predicted with the precision of 0.94), Bashkirs / Tatars (0.92), Kazakhs / Kyrgyz (0.91) and Uzbeks / Tajiks (0.91). Precision is the lowest for Chechens / Dagestani / Ingush (0.81), due to the confusion with similar names of neighbouring Caucasian ethnic groups (mainly Western North Caucasian and Azerbaijani).

Table 4: Model performance with the aggregated classification

Algorithm	**Vectorisation**	**Accuracy**	**Precision**	**Recall**	**F1**
Random		0.11	0.07	0.07	0.07
CNB	BoW	0.89	0.92	0.85	0.88
SVM	TFIDF	0.91	0.92	0.90	0.91
LR	BoW	0.92	0.93	0.89	0.91
MH	TFIDF	**0.92**	**0.94**	**0.90**	**0.92**

Notes: CNB: complement Naive Bayes; SVM: linear Support Vector Machine; LR: logistic regression; MH: modified Huber, quadratically smoothed SVM; BoW: Bag of Words; TFIDF: term frequency-inverse document frequency. Model accuracy evaluated on the test set.

Recall is the lowest for Kalmyks (0.74) where a fraction of names gets classified as either Slavic or Buryat. Kalmyks and Buryats are two Buddhist groups with common Mongolian origins, although populating the opposite ends of Russia. Recall is also lower for Jewish names (0.79) where many names get classified as Slavic. Note that many Ashkenazi Jews have surnames with German and Slavic origins.

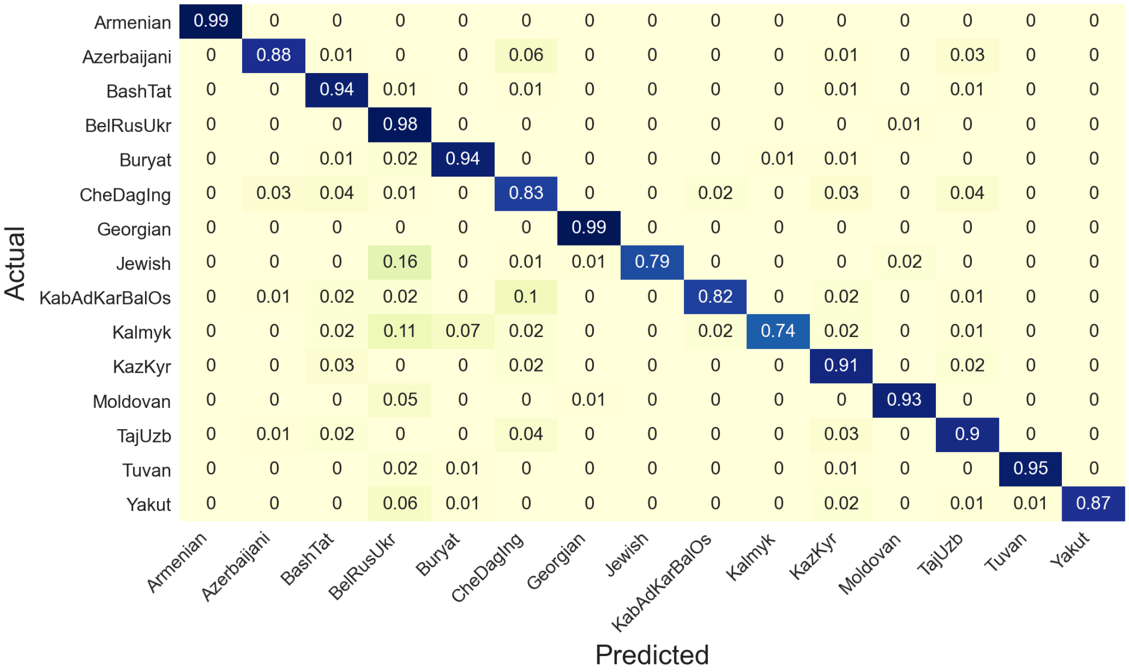
To validate the classifier, we apply it to two random samples of names collected on VK in Moscow and Kazan, two Russian cities with different ethnic structure of the populations (2,000 names in each city), and compare the ethnic distributions with the data from the 2010 Russian census. There are many limitations to this approach. The census and VK represent different populations (VK's being considerably younger). VK data were collected in 2021, and the census was conducted in 2010. The census likely under counts many immigrant groups, especially from Central Asia, as well as internal immigrants from the North Caucasus. However, while we should not expect the VK and census data to have the same ethnic distributions, we would still hope to see some consistency.

Table 6 presents the results of the comparison between the VK and census data, with the aggregated ethnic classification. The distributions are generally consistent both in Moscow and Kazan. In Moscow, 86% of the names in the VK sample get classified as ethnic Russian (or Belarusian and Ukrainian), compared to 93% in the census data. The proportions of non-Slavic ethnic groups are higher in the VK sample than in the census data. This does not necessarily represent a bias in the classifier and may reflect the undercounting of non ethnically Russian groups in the census data for Moscow.

Table 5: Prediction accuracy for ethnic groups in the aggregate classification

Ethnic group	Precision	Recall	F1
Armenian	0.99	0.99	0.99
Azerbaijani	0.90	0.88	0.89
Bashkir / Tatar	0.92	0.94	0.93
Russian / Belarusian / Ukrainian	0.94	0.98	0.96
Buryat	0.96	0.94	0.95
Chechen / Dagestani / Ingush	0.81	0.83	0.82
Georgian	0.99	0.99	0.99
Jewish	0.94	0.79	0.86
Adyghe / Balkar / Kabardin / Karachay / Ossetian	0.90	0.82	0.86
Kalmyk	0.95	0.74	0.84
Kazakh / Kyrgyz	0.91	0.91	0.91
Moldovan	0.96	0.93	0.95
Tajik / Uzbek	0.91	0.90	0.91
Tuvan	0.97	0.95	0.96
Yakut	0.98	0.87	0.92

Notes: Prediction accuracy was estimated with the test set.



Actual \ Predicted	Armenian	Azerbaijani	BashTat	BelRusUkr	Buryat	CheDagIng	Georgian	Jewish	KabAdKarBalOs	Kalmyk	KazKyr	Moldovan	TajUzb	Tuvan	Yakut
Armenian	0.99	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Azerbaijani	0	0.88	0.01	0	0	0.06	0	0	0	0	0.01	0	0.03	0	0
BashTat	0	0	0.94	0.01	0	0.01	0	0	0	0	0.01	0	0.01	0	0
BelRusUkr	0	0	0	0.98	0	0	0	0	0	0	0	0.01	0	0	0
Buryat	0	0	0.01	0.02	0.94	0	0	0	0	0.01	0.01	0	0	0	0
CheDagIng	0	0.03	0.04	0.01	0	0.83	0	0	0.02	0	0.03	0	0.04	0	0
Georgian	0	0	0	0	0	0	0.99	0	0	0	0	0	0	0	0
Jewish	0	0	0	0.16	0	0.01	0.01	0.79	0	0	0	0.02	0	0	0
KabAdKarBalOs	0	0.01	0.02	0.02	0	0.1	0	0	0.82	0	0.02	0	0.01	0	0
Kalmyk	0	0	0.02	0.11	0.07	0.02	0	0	0.02	0.74	0.02	0	0.01	0	0
KazKyr	0	0	0.03	0	0	0.02	0	0	0	0	0.91	0	0.02	0	0
Moldovan	0	0	0	0.05	0	0	0.01	0	0	0	0	0.93	0	0	0
TajUzb	0	0.01	0.02	0	0	0.04	0	0	0	0	0.03	0	0.9	0	0
Tuvan	0	0	0	0.02	0.01	0	0	0	0	0	0.01	0	0	0.95	0
Yakut	0	0	0	0.06	0.01	0	0	0	0	0	0.02	0	0.01	0.01	0.87

Figure 3: **Confusion matrix for 15 aggregated ethnic groups based on MH model** Aggregation improves prediction accuracy for several ethnic groups, in particular for eastern Slavic names (0.94), Bashkirs / Tatars (0.92), Kazakhs / Kyrgyz (0.91) and Uzbeks / Tajiks (0.91). Precision is the lowest for Chechens / Dagestani / Ingush (0.81), due to the confusion with similar names of neighbouring Caucasian ethnic groups.

Table 6: Validation of the classifier with the census data for Moscow and Kazan

City	**Ethnic group**	**VK (%)**	**Census (2010, %)**
Moscow			
	Russians/Belarusians/Ukrainians	86.0	93.4
	Jews	2.9	0.5
	Tatars/Bashkirs	2.6	1.4
	Chechens/Dagestanis/Ingushes	1.6	0.4
	Tajiks/Uzbeks	1.4	0.6
	Armenians	1.2	1.0
	Kazakhs/Kyrgyz	1.2	0.3
	Moldovans	1.1	0.2
	Other	2.0	2.2
Kazan			
	Russians/Belarusians/Ukrainians	60.0	49.2
	Tatars/Bashkirs	30.6	47.7
	Jews	2.0	0.2
	Chechens/Dagestanis/Ingushes	1.5	<0.5
	Kazakhs/Kyrgyz	1.4	<0.5
	Tajiks/Uzbeks	1.3	0.4
	Moldovans	1.0	<0.1
	Other	1.2	<1.5

Notes: VK data include samples of 2,000 names in Moscow and Kazan each.

In Kazan, the VK classifier returns more ethnically Russian names compared to the census (60% compared to 49%) and fewer Tatar names (31% vs 48%). It may be the case that ethnic Russians are more likely to be VK users. It is also possible that some people who self-identify as Tatars may have ethnically Russian surnames, for example, as a result of ethnic intermarriage (Bessudnov and Monden, 2021).

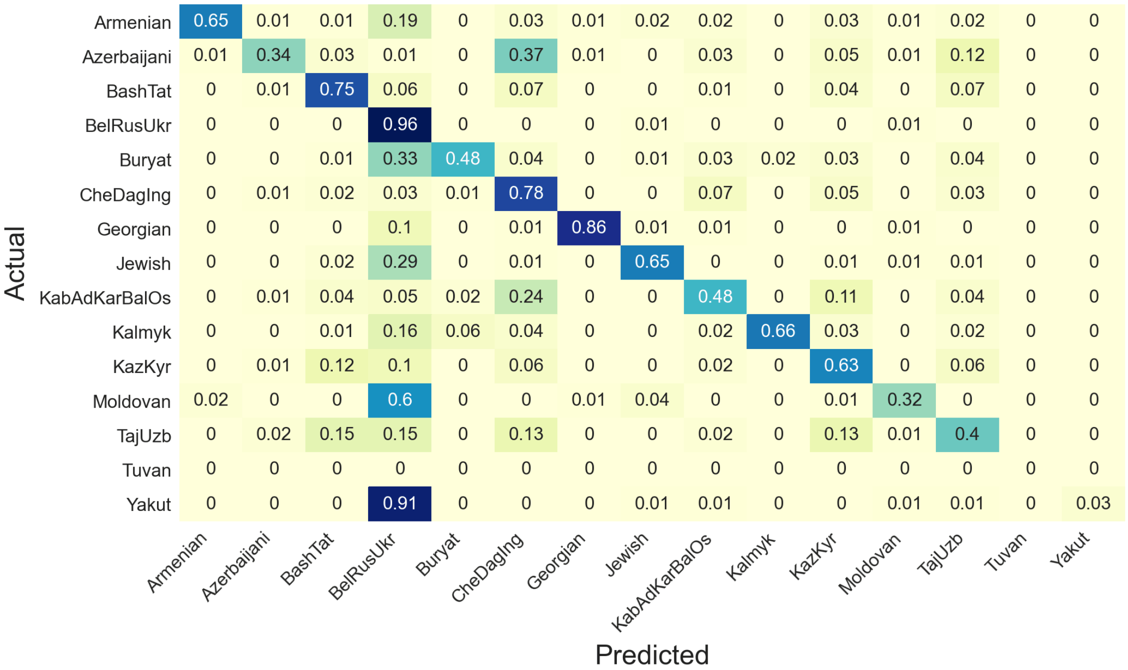
6 Validation with external historical data

So far we have only used VK data for designing and validating the classifier. One may wonder how it performs with external data where the data generating process is different. It is, however, difficult to find a data set that has both personal names and recorded ethnicity for Russian ethnic groups. The only data source that we identified is of historical nature. These are data on the victims of political repression campaigns in the USSR in the 1920-30s collected by the Memorial society from various published sources.[4] The data contain over 2.7 million individual records, often with assigned ethnicity. We remove records with missing ethnicity and from ethnic groups that are not part of our classification scheme (Poles, Germans, Latvians, etc.). The final analytic sample consists of 909,012 names with recorded ethnicity.

This data set is not ideal for our purposes. The data are about 100 years old; since then the naming conventions for some ethnic groups (as well as the boundaries between groups) have evolved. Data on ethnicity were mostly recorded by the Soviet secret police, with many possible sources of bias, and were not necessarily based on self-identification of individuals. Soviet political terror affected some ethnic groups stronger than others. However, the results from the application of the classifier are still informative.

As expected, the classifier performs worse with an external data set, compared to VK data (see Table 7 and Figure 4). Both precision and recall are very high for ethnic Russians (combined with Ukrainians and Belarusians) who represent about 78% of the data set. For some ethnic groups (Azerbaijanis, Moldovans, Tajiks / Uzbeks, Yakuts) both precision and recall are low. Other groups (Armenians, Bashkirs / Tatars, Georgians, Jews, Kalmyks) show high precision and recall even with historical and arguably not very reliable data.

[4] See `http://lists.memo.ru` and `https://github.com/nextgis/memorial_data`.



	Armenian	Azerbaijani	BashTat	BelRusUkr	Buryat	CheDagIng	Georgian	Jewish	KabAdKarBalOs	Kalmyk	KazKyr	Moldovan	TajUzb	Tuvan	Yakut
Armenian	0.65	0.01	0.01	0.19	0	0.03	0.01	0.02	0.02	0	0.03	0.01	0.02	0	0
Azerbaijani	0.01	0.34	0.03	0.01	0	0.37	0.01	0	0.03	0	0.05	0.01	0.12	0	0
BashTat	0	0.01	0.75	0.06	0	0.07	0	0	0.01	0	0.04	0	0.07	0	0
BelRusUkr	0	0	0	0.96	0	0	0	0.01	0	0	0	0.01	0	0	0
Buryat	0	0	0.01	0.33	0.48	0.04	0	0.01	0.03	0.02	0.03	0	0.04	0	0
CheDagIng	0	0.01	0.02	0.03	0.01	0.78	0	0	0.07	0	0.05	0	0.03	0	0
Georgian	0	0	0	0.1	0	0.01	0.86	0.01	0.01	0	0	0.01	0	0	0
Jewish	0	0	0.02	0.29	0	0.01	0	0.65	0	0	0.01	0.01	0.01	0	0
KabAdKarBalOs	0	0.01	0.04	0.05	0.02	0.24	0	0	0.48	0	0.11	0	0.04	0	0
Kalmyk	0	0	0.01	0.16	0.06	0.04	0	0	0.02	0.66	0.03	0	0.02	0	0
KazKyr	0	0.01	0.12	0.1	0	0.06	0	0	0.02	0	0.63	0	0.06	0	0
Moldovan	0.02	0	0	0.6	0	0	0.01	0.04	0	0	0.01	0.32	0	0	0
TajUzb	0	0.02	0.15	0.15	0	0.13	0	0	0.02	0	0.13	0.01	0.4	0	0
Tuvan	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Yakut	0	0	0	0.91	0	0	0	0.01	0.01	0	0	0.01	0.01	0	0.03

Figure 4: **Confusion matrix for 15 ethnic groups based on the MH model applied to the Memorial data.** The classifier performs worse with an external data set, compared to VK data, with low precision for some ethnic groups (Azerbaijanis, Moldovans, Tajiks / Uzbeks, Yakuts). Precision is high for ethnic Russians combined with Ukrainians and Belarusians (0.97) and for some other groups (Armenians, Bashkirs / Tatars, Georgians, Jews, Kalmyks).

Table 7: Prediction accuracy with the Memorial data

Ethnic group	**Precision**	**Recall**	**F1**	**n**
Armenian	0.85	0.65	0.74	3,376
Azerbaijani	0.05	0.34	0.09	325
Bashkir / Tatar	0.78	0.75	0.76	41,282
Russian / Belarusian / Ukrainian	0.97	0.96	0.96	704,636
Buryat	0.38	0.48	0.42	5,690
Chechen / Dagestani / Ingush	0.06	0.78	0.10	1,986
Georgian	0.76	0.86	0.81	1,714
Jewish	0.74	0.65	0.69	43,883
Adyghe / Balkar / Kabardin / Karachay / Ossetian	0.88	0.48	0.62	59,753
Kalmyk	0.81	0.66	0.73	4,406
Kazakh / Kyrgyz	0.11	0.63	0.19	37,182
Moldovan	0.09	0.32	0.14	1,495
Tajik / Uzbek	0.01	0.40	0.01	1,568
Yakut	0.17	0.03	0.05	1,716

7 Conclusion and limitations

In this paper we develop a classifier that predicts ethnicity from data on personal names for major ethnic groups populating Russia. The multiclass classifier achieves the overall accuracy of 0.82 with 24 ethnic groups and 0.92 with 15 ethnic groups. It can be used in further studies of ethnic groups and relations in Russia, especially with VK and other social media data. We make the data and Python code for the classifier available in a Github repository at `https://github.com/abessudnov/ruEthnicNamesPublic`.

We acknowledge and discuss several limitations of the classifier.

First, while we include most major ethnic groups populating Russia, some groups are missing, as personal names of most members of these groups are indistinguishable from ethnic Russian. These groups are geographically concentrated in several Russian regions (Chuvashiya, Mordoviya, Udmurtiya, Mari El, and Komi) and the classifier is of limited used when applied to the data from these regions. It is not possible to differentiate between ethnic Russians and members of indigenous ethnic groups in these regions on the basis of personal names only.

Second, to increase the reliability of the classifier we create an aggregated ethnic classification scheme, combining some ethnic groups together, even when they are culturally and historically different. This applies, for example, to groups combining ethnic Russians, Ukrainians and Belarusians, or Chechens, Ingushes and Dagestanis (the latter also an aggregation of several ethnic groups with their own languages). Many personal names in these groups are of common origin and more nuanced analysis would have lower reliability. For many research purposes the aggregated classification offers enough precision, such as in the analysis of labour market discrimination where the main difference is between the groups of European andhttps://www.overleaf.com/project/606d70aeee6bd5aa528bd8a5 ‘Southern’ origin (Bessudnov and Shcherbak, 2020).

Third, the data cleaning procedure we use could introduce some bias in the data. Crowd workers on Yandex.Toloka could filter out names that do not look “ethnic enough", for example, by excluding names that look similar to ethnic Russian. This could affect ethnic groups with a large proportion of Russified personal names, such as Yakuts. Although the bias in crowdsourced data mining is usually recognized as an undesirable effect (Ghai et al., 2020; La Barbera et al., 2020), in our case it can have a mixed effect on the reliability of the classifier. Keeping in the data the names of the ethnic Russian origin for non-ethnically Russian groups would result in a higher proportion of false negatives for ethnic Russian individuals. At the same time, excluding these names leads to more false negatives for the members of non-ethnically Russian ethnic groups with ethnic Russian names. While the name can be a strong marker of ethnicity it cannot guarantee complete reliability.

Fourth, we develop and validate the classifier with VK data, and this is where we see its intended use. By extension, we assume that it should work well with other social media data, although this remains to be empirically proven. It may not work well with other types of data, especially for some ethnic groups, as our validation with the historic Memorial data set has demonstrated.

Fifth, determining ethnicity on the basis of personal names rather than self-identification may appear to be problematic. Having an ethnic name does not necessarily correspond to personal identification as a member of an ethnic group. Note, however, that even self-reported ethnicity is not error free, and people may have various reasons to misreport their ethnic origins in surveys. Besides, our classifier is designed to measure perceived rather than self-reported ethnicity. Perceived ethnicity has real consequences in many areas of social life.

Finally, we should emphasise the ethical aspect of this study. A tool that classifies ethnicity from personal names can be potentially misused by various actors ranging from state authorities to nationalist political movements (Mittelstadt et al., 2016). The issue of ethnicity in Russia, very sensitive in the Soviet times, remains significant today in interpersonal relations, as well as in the labour market and housing. It is important to recognise that our classifier cannot, and is not intended to unequivocally identify ethnicity at the individual level. While this tool can produce reliable distributions for ethnicity for data sets with hundreds and thousands names, for each individual name there remains a margin of error that does not let the classifier to be used for individual profiling.

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