Gender Profiling in Social Network

Dmitry Badeev

December 2021

Abstract

Six models for solving problem of Gender Profiling in Social Network for one- and multi-genre texts are presented in this work. All of them are based on *Russian SBERT NLU* model and one-genre training texts datasets of different size. Three models are constructed with the stylometric features of the Russian language. Final models achieved the best results in tests for both single-genre and multi-genre texts.

`https://github.com/dbadeev/gender_profiling`

1 Introduction

A goal of creating machine learning data driven models in computer linguistics is to construct the model most independent on genres, topics, and styles of text presented in training and testing sets. This fully concerns the task of gender identification of text author.
This theme was partly addressed at the PAN 2016 [F. Rangel and Stein, 2016], PAN 2019 [Francisco Rangel, 2019] competitions where Twitter was used for training, and different corpora from social media, blogs, essays, and reviews were used for evaluation. A similar competition on Forum for Information Retrieval Evaluation 2017 [Litvinova T, 2017a] was held for Russian texts.

In the studies conducted the topic for different languages, the authors identified four main approaches in building gender profiling models for one- and multi-genre texts from social networks.

They can be summarized as follows:

1. Stylometric methods (lexical, syntactic, structural), the purpose of which is to capture the author's writing style using various statistical characteristics.

2. Content-based techniques that are designed to identify author profiles based on the content of the text (BOW, n-grams of words, slang words, tf-idf, etc.).

3. Also, it is possible to apply the criteria for selecting characteristics that play the role of a filter. For each term, it calculates a distribution score across two categories. As criteria, you can use: odds ratio (OR), chi-square and correlation coefficient. Each of these functions usually finds different terms specific to this category.

4. Using deep learning methods ($CNN, LSTM, Bi-LSTM, GRU$) and ready-made pre-trained models ($GloVe, BERT, GPT, etc.$)

All the approaches results will be discussed in the 2.

The presented work is based on the use of the pre-trained language model of the Russian language $SBERT$, with further fine-tuning for the training set, in combination with the stylometric methods.

1.1 Team

Research was done by **Dmitry Badeev**.

2 Related Work

In gender profiling on single-genre and multi-genre texts of social networks for different languages (except Russian) the teams achieved the best results, mainly working with stylometric features.
According to the PAN'19 [Francisco Rangel, 2019] and PAN'17
[Francisco Rangel and Stein, 2017], results in works with traditional approaches have gained higher accuracy than deep learning methods:
[Matej Martinc and Pollak, 2017], [Alex I. Valencia Valencia and Pineda, 2019],
[Gishamer, 2019], [Joo and Hwang, 2019], [Pizarro, 2019],
[Srinivasarao and Manu, 2019], [Régis Goubin and Fossi, 2019],
[Angelo Basile and Nissim, 2017], [Yasuhide Miura and Ohkuma, 2017].
The top four teams used a combination of n-gramm and SVM, while the top team [Marco Polignano and Semeraro, 2019] using the deep learning model is 11-th.

In gender profiling of one-genre Russian-language texts of social networks the best result was achieved in 2013 [Korshunov, 2013]. However, as the same method was used in the works later (PAN FIRE '17), the achievement is possibly due to the specifics of the dataset and test cases on which the model's performance was evaluated.

Among the works where the PAN FIRE '17 [Litvinova T, 2017b] dataset was used, [Sboev, 2019] has the best result. Experiments were carried out with various models, including deep learning. The first place was taken by the Gradient Boosting model with symbolic n-gramm representation.

At the same time, in the work [Сбоев, 2020], the result was higher when using the model with GRU, CVAE. But in this work was not mentioned comparison with other models on the dataset used.

In gender profiling of one-genre Russian-language texts of social networks the *LDR* (Low Dimensionality Representation) [F. Rangel and Franco-Salvador., 2016] method, chosen as the baseline, was in the lead. This method represents documents on the basis of the probability distribution of occurrence of their words in the different classes. The key concept of *LDR* is a weight, representing the probability of a term to belong to one of the different categories (e.g. female vs. male). The distribution of weights for a given document should be closer to the weights of its corresponding category.

In gender profiling of multi-genre Russian-language texts of social networks among the *Essays*, the best result was shown in [R. Bhargava and Sharma, 2017], where a combination of rule-based classification and deep learning methods was applied.

Surprisingly, the results were quite high on a test sample from *Facebook*, which outperformed all other categories, including *Twitter*. The hypothesis of the authors of the review [Litvinova T, 2017b], this is due to the fact that *Facebook* posts are longer and grammatically richer, with fewer syntax errors and typos compared to *Twitter*.

According to the results, the models with the traditional approach turned out to be better than the models using deep learning methods.

3 Model Description

Model containing three fully connected layers was built for an experiment with the Gender Profiling in Social Network task.

The *Russian SBERT NLU* model (24 layers and 426.9 million parameters) was used as the base *BertLayer*.

Averaging of token embeddings is taken from the last *BERT layer* (masked mean pooling is used).

Next layer - the hidden one (*Dense*) with 1024 neurons and the *relu* activation function.

For regularization, between the last hidden layer and the output layer, $Dropout = 0.25$ is used.

The last layer *(classifier)* consists of a fully connected layer with two output neurons and a *sigmoid* activation function.

Since there are two classes in the target (male and female), *Binary Cross Entropy Loss* is used as the loss function:

$$BCE = -\frac{1}{N}\sum_{i=0}^{N}(y_i \cdot log(\hat{y}_i) + (1 - y_i) \cdot log(1 - \hat{y}_i))$$

Optimization algorithm - *Adam*, value $learning\_rate = 10^{-5}$.

The stylometric feature S of gender definition in Russian is also used:

S - the stylometric features of gender for the Russian language

In Russian, the singular forms of the past tense verbs change by gender (the masculine singular forms have the ending "- л", and the ending "- ла" is the indicator of the feminine singular forms). Also, reflexive verbs of the past tense differ in gender - for the feminine gender they have the ending "-лась", and for the masculine - "-лся". The described features of the verbs were used in combination with the subject of the sentence if the subject was the first person singular pronoun "я" (or "Я"), and if the subject came from the verb no more than within a 4-word window.

Thus, in total, four features are used: two for the masculine gender - "ІЯ(я) [0-4] -л" and "Я (я) [0-4] -лся", and two for the feminine gender - "Я (я) [0-4] -ла "and" Я (я) [0-4] -лась ".

4 Dataset

I planned to use data from the assignment for PAN at CLEF 2017, PAN at FIRE Track on Multi-genre Gender Identification in Russian. But links to datasets did not work, and a request to the organizers to give an opportunity to access the data remained unanswered.

Fortunately, I found the source - a common database of corpuses, from which datasets were formed for tasks at the conference. The structure of datasets, both training and test, is described detailly in [Litvinova T, 2017b]. I prepared datasets for my experiments similar to the data from the task on RusProfiling PAN '17 in accordance with that instructions.

Twitter dataset

Total

- Messages from 1000 authors were used, 500 of each gender
- All messages from one author were combined and treated as one text
- Text length of one author - about 500 words or about 1500 words
- The entire dataset was splitted into two: training dataset and testing dataset

Model training dataset (RuSb_base)

  - Contains texts of 600 authors, 300 for each gender

Dataset for testing single-genre texts

– Contains texts of 400 authors, 200 of each gender

Facebook dataset

Dataset for testing single-genre texts

- Contains the texts of 220 authors, 110 of each gender
- All messages from one author were combined and treated as one text
- Text size of one author is about 1000 words

The source for both Twitter and Facebook datasets was one text base, in which the source social network was not indicated. The division into different social networks was carried out according to the size of the text of one author, the only one criterion of difference mentioned in [Litvinova T, 2017b]. So, it is permissible to consider **all texts (Facebook and Twitter)** from the database **as one-genre**.

Essays dataset

Dataset for testing multi-genre texts

- Contains the texts of 370 authors, 185 of each gender
- One or two texts per author (in case of two texts they were merged together and considered as one text)
- The average text length in is 150 words.

Reviews dataset

Dataset for testing multi-genre texts

- Contains the texts of 776 authors, 388 of each gender
- One or two texts per author (in case of two texts they were merged together and considered as one text)
- The average text length in this dataset was 150 words.

Gender imitation dataset

Dataset for testing multi-genre texts

- Contains the texts of 94 authors, 47 of each gender
- Three texts from each author that were merged together and considered as one text

- All three texts have one theme (from a set of themes)
  - the first text is written in the usual way for the person who wrote it (without any deception)
  - the second is written from the person of the opposite sex ("imitation")
  - the third text should be as of author is the same gender, but personal writing style will not be recognized ("obfuscation")
- All texts from one author were combined and counted as one text
- Most of the texts are 80-150 words long

For experiments with models trained on datasets of different sizes, two additional single-genre datasets were formed.

The Medium dataset used the entire *Twitter dataset (training + test)* for training. *The Large Training Dataset* used the combined *Twitter Dataset (training + test)* with *the Facebook Dataset.*

Medium training dataset

- Contains texts of 1000 authors, 500 for each gender
- All texts from one author were combined and counted as one text
- Text length of one author - about 500 words or about 1500 words

Big training dataset

- Contains texts of 1220 authors, 610 for each gender
- All texts from one author were combined and counted as one text
- Text length of one author - evenly from about 500 words to 1500 words

All datasets are available at github.

5 Experiments

For the experiments, three models were prepared with the same parameters, but trained on datasets of different size:

- **RuSb_base** - 600 Twitter posts, 300 for each gender (*Base training dataset*)
- **RuSb_mid** - 1000 Twitter posts, 500 for each gender (*Average training dataset*)

- **RuSb_big** - 1220 Twitter posts, 610 for each gender (*Large training dataset*)

Three more models (**RuSb_base+S** , **RuSb_mid+S**, **RuSb_big+S**), additionally used S - the stylometric features of gender for the Russian language, described in 3[1].

5.1 Metrics

The quality of model predictions were be assessed by two metrics - *accuracy* and $F_1 score$.

5.2 Experiment Setup

Training parameters:

- Basic BertLayer - Russian SBERT NLU model;
- batch size = 24;
- seq_len = 256;
- N_tune_lrs = 24;
- Optimizer - Adam;
- Learning rate = 1e-5;
- Metrics - F1, Accuracy;
- Number of epochs = 3.

Model summary is presented in Table 1:

[1] S - the stylometric features of gender for the Russian language

```
Model:

_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 1)]               0

_________________________________________________________________
bert_layer (BertLayer)       (None, 1024)              426908672

_________________________________________________________________
dense (Dense)                (None, 1024)              1049600

_________________________________________________________________
dropout (Dropout)            (None, 1024)              0

_________________________________________________________________
dense_1 (Dense)              (None, 2)                 2050
=================================================================
Total params: 427,960,322
Trainable params: 303,361,026
Non-trainable params: 124,599,296

_________________________________________________________________
```

TABLE 1. Model summary

6 Results

Overall results

The Table 2 shows the results (*accuracy*) obtained for all six models for test single- and multi-genre sets.

RuSb_mid and **RuSb_mid** tested only on **Facebook** data test, as models **RuSb_big** and **RuSb_big+S** are more informative in other data test categories, in comparison with first two.

It makes no sense to use models **RuSb_base+S** and **RuSb_big+S** on **Gender Imitation**, since accounting for stylometric features will lead to a deliberately incorrect result.

The result for **Facebook** can be considered one-genre, as mentioned earlier 4[2].

[2]The source for both Twitter and Facebook datasets was one text base

	Twitter	Facebook	Essays	Reviews	Gender imitation
RuSb_base	0.87	0.85	0.86	0.80	0.93
RuSb_base+S	0.90	0.89	0.87	0.80	
RuSb_mid		0.85			
RuSb_mid+S		0.89			
RuSb_big			0.86	0.83	0.95
RuSb_big+S			0.86	0.83	

TABLE 2. Overall results

Comments:

1. Stylometric features for *Reviews* did not affect the result, while in other cases, both single and multigenre, there is a slight increase. Perhaps this is due to the brevity of messages in Reviews (up to 80 words), where the forms of presentation considered by stylometric features are used rarely.

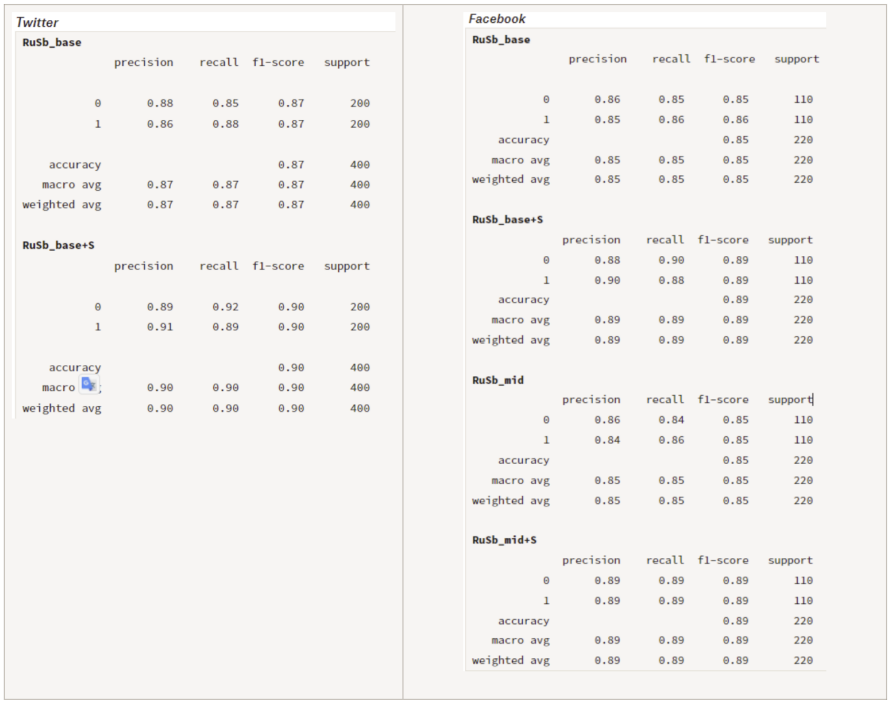
2. The lowest results in *Reviews* in comparison with other datasets - also, in my opinion, due to the brevity of messages.

3. Increasing the training dataset didn't have affect in two cases: *Facebook* and *Essays*. If in the one-genre *Facebook* case it can be assumed that the size of the base dataset was quite sufficient, then in the case of *Essays*, it seems logical to assume that the reason was the limited themes set as the basis for user texts.

4. The very high percentage of recognition shown in Gender Imitation is surprising. This phenomenon is beyond the scope of current work and deserves additional analysis.

More detailed information on the metrics of all experiments is given below in Table 3 and Table 4:

One-genre Gender Detection (Russian)



Twitter

RuSb_base

	precision	recall	f1-score	support
0	0.88	0.85	0.87	200
1	0.86	0.88	0.87	200
accuracy			0.87	400
macro avg	0.87	0.87	0.87	400
weighted avg	0.87	0.87	0.87	400

RuSb_base+S

	precision	recall	f1-score	support
0	0.89	0.92	0.90	200
1	0.91	0.89	0.90	200
accuracy			0.90	400
macro avg	0.90	0.90	0.90	400
weighted avg	0.90	0.90	0.90	400

Facebook

RuSb_base

	precision	recall	f1-score	support
0	0.86	0.85	0.85	110
1	0.85	0.86	0.86	110
accuracy			0.85	220
macro avg	0.85	0.85	0.85	220
weighted avg	0.85	0.85	0.85	220

RuSb_base+S

	precision	recall	f1-score	support
0	0.88	0.90	0.89	110
1	0.90	0.88	0.89	110
accuracy			0.89	220
macro avg	0.89	0.89	0.89	220
weighted avg	0.89	0.89	0.89	220

RuSb_mid

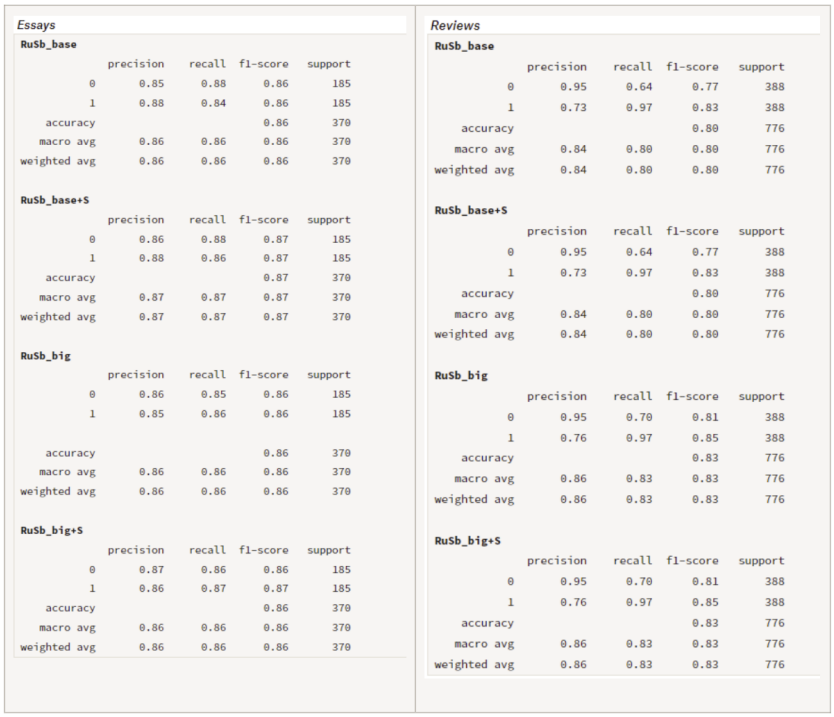
	precision	recall	f1-score	support
0	0.86	0.84	0.85	110
1	0.84	0.86	0.85	110
accuracy			0.85	220
macro avg	0.85	0.85	0.85	220
weighted avg	0.85	0.85	0.85	220

RuSb_mid+S

	precision	recall	f1-score	support
0	0.89	0.89	0.89	110
1	0.89	0.89	0.89	110
accuracy			0.89	220
macro avg	0.89	0.89	0.89	220
weighted avg	0.89	0.89	0.89	220

TABLE 3. Metrics on One-genre Gender Detection (Russian)

Cross-genre Gender Detection (Russian)



Essays

RuSb_base

	precision	recall	f1-score	support
0	0.85	0.88	0.86	185
1	0.88	0.84	0.86	185
accuracy			0.86	370
macro avg	0.86	0.86	0.86	370
weighted avg	0.86	0.86	0.86	370

RuSb_base+S

	precision	recall	f1-score	support
0	0.86	0.88	0.87	185
1	0.88	0.86	0.87	185
accuracy			0.87	370
macro avg	0.87	0.87	0.87	370
weighted avg	0.87	0.87	0.87	370

RuSb_big

	precision	recall	f1-score	support
0	0.86	0.85	0.86	185
1	0.85	0.86	0.86	185
accuracy			0.86	370
macro avg	0.86	0.86	0.86	370
weighted avg	0.86	0.86	0.86	370

RuSb_big+S

	precision	recall	f1-score	support
0	0.87	0.86	0.86	185
1	0.86	0.87	0.87	185
accuracy			0.86	370
macro avg	0.86	0.86	0.86	370
weighted avg	0.86	0.86	0.86	370

Reviews

RuSb_base

	precision	recall	f1-score	support
0	0.95	0.64	0.77	388
1	0.73	0.97	0.83	388
accuracy			0.80	776
macro avg	0.84	0.80	0.80	776
weighted avg	0.84	0.80	0.80	776

RuSb_base+S

	precision	recall	f1-score	support
0	0.95	0.64	0.77	388
1	0.73	0.97	0.83	388
accuracy			0.80	776
macro avg	0.84	0.80	0.80	776
weighted avg	0.84	0.80	0.80	776

RuSb_big

	precision	recall	f1-score	support
0	0.95	0.70	0.81	388
1	0.76	0.97	0.85	388
accuracy			0.83	776
macro avg	0.86	0.83	0.83	776
weighted avg	0.86	0.83	0.83	776

RuSb_big+S

	precision	recall	f1-score	support
0	0.95	0.70	0.81	388
1	0.76	0.97	0.85	388
accuracy			0.83	776
macro avg	0.86	0.83	0.83	776
weighted avg	0.86	0.83	0.83	776

TABLE 4. Metrics on Multi-genre Gender Detection (Russian)

Comments:

1. Brings to notice the imbalance of *precision* and *recall* in all models on the *Reviews* dataset - high accuracy to distinguish class 0 (female) with a low percentage to detect the class itself, and vice versa for class 1 (male).

Comparison with previous results

The *Table 5* and *Table 6* shows the rating of **RuSb_base**, **RuSb_base+S**, **RuSb_big+S**, **RuSb_big+S** models in comparison with other models 2, both in One- and Multi-Genre Genre Detection. No comparison was made on Facebook, because a relevant test dataset for this category was not found.

Work	Corpus	Features	Method used	Result
RuSb_base+S	[Litvinova T, 2017b]	Stylometric features	Russsian SBERT	**0.90**
RuSb_base	[Litvinova T, 2017b]		Russsian SBERT	**0.87**
[Korshunov, 2013]	self-made	word (3-grams)	SVM	0.86
[Sboev, 2019]	[T. Litvinova and Romanchenko, 2016] [Litvinova T, 2017b]	char n-grams	Gradient Boosting	0.79
[Сбоев, 2020]	[Litvinova T.A., 2018]		GRU, CVAE	0.76
[I. Markov and Gelbukh, 2017] - CIC3	[Litvinova T, 2017b]	statistical		0.6825
[F. Rangel and Franco-Salvador., 2016]	[Litvinova T, 2017b]	probability distribution of occurrence of tdoc's words in the different classes.		0.6759
[I. Markov and Gelbukh, 2017] - CIC2	[Litvinova T, 2017b]	BOW, word (suffix 3-grams), tf-idf	SVM	0.6650
[R. Bhargava and Sharma, 2017]	[Litvinova T, 2017b]	POS, rule-based classification	LSTM, Bi-LSTM	0.6525
[I. Markov and Gelbukh, 2017] - CIC1	[Litvinova T, 2017b]	POS combination, tf-idf	SVM	0.6525

TABLE 5. Comparison on One-genre Gender Detection (Russian)

Work	Corpus	Features	Method used	Test Corpus	Result
RuSb_base+S	[Litvinova T, 2017b] (Twitter - training)	Stylometric features	Russsian SBERT	Essays	**0.87**
RuSb_base	[Litvinova T, 2017b] (Twitter - training)		Russsian SBERT	Essays	**0.86**
RuSb_big	[T. Litvinova and Romanchenko, 2016] [Litvinova T, 2017b]		Russsian SBERT	Essays	**0.86**
RuSb_big+S	[T. Litvinova and Romanchenko, 2016], [Litvinova T, 2017b]	Stylometric features	Russsian SBERT	Essays	**0.86**
[F. Rangel and Franco-Salvador., 2016]	[Litvinova T, 2017b] (Twitter - training)	stylometric analysis		Essays	0.8141
[R. Bhargava and Sharma, 2017]	[Litvinova T, 2017b] (Twitter - training)	POS, rule-based classification	LSTM, Bi-LSTM	Essays	0.7838
[V. Vinayan and Amrita, 2017]	[Litvinova T, 2017b] (Twitter - training)	exotic stat (average word length, URL usage, etc), tf-idf	SVM	Essays	0.6811
RuSb_big+S	[T. Litvinova and Romanchenko, 2016], PAN FIRE '17 [d8]	Stylometric features	Russsian SBERT	Reviews	**0.83**
RuSb_big	[T. Litvinova and Romanchenko, 2016], [Litvinova T, 2017b]		Russsian SBERT	Reviews	**0.83**
RuSb_base+S	[Litvinova T, 2017b] (Twitter - training)	Stylometric features	Russsian SBERT	Reviews	**0.80**
RuSb_base	[Litvinova T, 2017b] (Twitter - training)		Russsian SBERT	Reviews	**0.80**
[Sboev, 2019]	[Litvinova T, 2017b] (Twitter - training)	char n-grams	Gradient Boosting	Reviews	0.79
[F. Rangel and Franco-Salvador., 2016]	[Litvinova T, 2017b] (Twitter - training)	stylometric analysis		Reviews	0.72
[I. Markov and Gelbukh, 2017] - CIC3	[Litvinova T, 2017b] (Twitter - training)	statistical		Reviews	0.6186
[I. Markov and Gelbukh, 2017] - CIC1	[Litvinova T, 2017b] (Twitter - training)	POS combination, tf-idf	SVM	Reviews	0.5979
[R. Bhargava and Sharma, 2017]	[Litvinova T, 2017b] (Twitter - training)	POS, rule-based classification	LSTM, Bi-LSTM	Reviews	0.5786
RuSb_base+S	[Litvinova T, 2017b] (Twitter - training)	Stylometric features	Russsian SBERT	Gender imitation	**0.95**
RuSb_base	[Litvinova T, 2017b] (Twitter - training)		Russsian SBERT	Gender imitation	**0.93**
[R. Bhargava and Sharma, 2017]	[Litvinova T, 2017b] (Twitter - training)	POS, rule-based classification	LSTM, Bi-LSTM	Gender imitation	0.6596
[F. Rangel and Franco-Salvador., 2016]	[Litvinova T, 2017b] (Twitter - training)	stylometric analysis		Gender imitation	0.6383

TABLE 6. Comparison on Multi-genre Gender Detection (Russian)

Models, based on *Russian SBERT* with further tuning, as well as similar models that take into account stylometric features S, showed better results compared to models from other works built on similar datasets.

7 Conclusion

As part of the project, the following tasks were implemented:

- a review of works on similar topics for Russian and other languages was prepared;
- datasets for training models and testing in four different genres based on the database and description of datasets were formed;
- the basic model was built and five more models were trained on the basis of datasets of different size and stylometric features;
- the comparison of the results shown by the trained models with the results obtained in previous works was performed;
- the analysis of the results obtained were realized.

Based on the research results, the following conclusions can be drawn:

1. The *Russian SBERT NLU* model, as a base, with further fine-tuning for the gender classification task, gives a model that exceeds the results of the models discussed above in 2 - both with a traditional approach and models using deep learning methods.
2. The results of prediction in gender profiling on single-genre and multi-genre datasets do not have significant differences, with the exception of specific requirements for texts if the genre of the tested datasets are differs from the one on which the training took place (message size, limited topics, etc.).
3. An increase in the training dataset gives a slight increase in the accuracy of prediction on one-genre and some multi-genre datasets. If there is a requirement to limit the size of messages in the dataset to a small value (less than 100 words), or the genre of the tested sample differs from the one used for training, the accuracy does not change.
4. The use of stylometric features makes it possible to improve the prediction results of the base model built on the *Russian SBERT NLU* model in gender profiling on single and multi-genre datasets. However, the difference in the results is insignificant.

References

[Alex I. Valencia Valencia and Pineda, 2019] Alex I. Valencia Valencia, Helena Gomez Adorno, C. S. R. and Pineda, G. F. (2019). Bots and gender identification based on stylometry of tweet minimal structure and n-grams model. In *In Linda Cappellato, Nicola Ferro, David E. Losada, and Henning Müller, editors, CLEF 2019 Labs and Workshops, Notebook Papers, September 2019. CEUR-WS.org.*

[Angelo Basile and Nissim, 2017] Angelo Basile, Gareth Dwyer, M. M. J. R. H. H. and Nissim, M. (2017). N-gram: New groningen author-profiling model—notebook for pan at clef 2017. In *In Linda Cappellato, Nicola Ferro, Lorraine Goeuriot, and Thomas Mandl, editors, CLEF 2017 Evaluation Labs and Workshop – Working Notes Papers, 11-14 September, Dublin, Ireland, September 2017. CEUR-WS.org.*

[F. Rangel and Stein, 2016] F. Rangel, P. Rosso, B. V. W. D. M. P. and Stein, B. (2016). Overview of the 4th author profiling task at pan 2016: cross-genre evaluations. In *Working Notes Papers of the CLEF 2016 Evaluation Labs. CEUR Workshop Proceedings/Balog, Krisztian [edit.]*, pages 750—784.

[F. Rangel and Franco-Salvador., 2016] F. Rangel, P. R. and Franco-Salvador., M. (2016). A low dimensionality representation for language variety identification. In *In 17th International Conference on Intelligent Text Processing and Computational Linguistics, CICLing. Springer-Verlag, LNCS, arXiv:1705.10754.*

[Francisco Rangel and Stein, 2017] Francisco Rangel, Paolo Rosso, M. P. and Stein, B. (2017). Overview of the 5th author profiling task at pan 2017: Gender and language variety identification in twitter. In *In Linda Cappellato, Nicola Ferro, Lorraine Goeuriot, and Thomas Mandl, editors, CLEF 2017 Evaluation Labs and Workshop – Working Notes Papers, 11-14 September, Dublin, Ireland, September 2017. CEUR-WS.org.*

[Francisco Rangel, 2019] Francisco Rangel, P. R. (2019). Overview of the 7th author profiling task at pan 2019: Bots and gender profiling in twitter.

[Gishamer, 2019] Gishamer, F. (2019). Using hashtags and pos-tags for author profiling. In *In Linda Cappellato, Nicola Ferro, David E. Losada, and Henning Müller, editors, CLEF 2019 Labs and Workshops, Notebook Papers, September 2019. CEUR-WS.org.*

[Joo and Hwang, 2019] Joo, Y. and Hwang, I. (2019). Steve martin at semeval-2019 task 4: Ensemble learning model for detecting hyperpartisan news. In *In Proceedings of the 13th International Workshop on Semantic Evaluation*, pages 990—994.

[Korshunov, 2013] Korshunov, A. (2013). Detection of demographic attributes of microblog users. In *Proceedings of the Institute for System Programming Volume 25.*

[Litvinova T, 2017a] Litvinova T, Rangel F, R. P. S. P. L. O. (2017a). Overview of the rusprofiling pan at fire track on cross-genre gender identification in russian. In *Notebook papers of FIRE 2017, FIRE-2017, Bangalore, India, December 8–11, CEUR Workshop Proceedings. CEUR-WS.org, vol 2036.*

[Litvinova T, 2017b] Litvinova T, Rangel F, R. P. S. P. L. O. (2017b). Overview of the rusprofiling pan at fire track on cross-genre gender identification in

russian. In *In Notebook papers of FIRE 2017, FIRE-2017, Bangalore, India, December 8–11, CEUR Workshop Proceedings. CEUR-WS.org, vol 2036*, pages 1—7.

[Marco Polignano and Semeraro, 2019] Marco Polignano, Marco Giuseppe de Pinto, P. L. and Semeraro, G. (2019). Identification of bot accounts in twitter using 2d cnns on user-generated contents. In *In Linda Cappellato, Nicola Ferro, David E. Losada, and Henning Müller, editors, CLEF 2019 Labs and Workshops, Notebook Papers, September 2019. CEUR-WS.org.*

[Matej Martinc and Pollak, 2017] Matej Martinc, Iza Škrjanec, K. Z. and Pollak, S. (2017). Pan 2017: Author profiling - gender and language variety prediction—notebook for pan at clef 2017. In *In Linda Cappellato, Nicola Ferro, Lorraine Goeuriot, and Thomas Mandl, editors, CLEF 2017 Evaluation Labs and Workshop – Working Notes Papers, 11-14 September, Dublin, Ireland, September 2017. CEUR-WS.org.*

[Pizarro, 2019] Pizarro, J. (2019). Using n-grams to detect bots on twitter. In *In Linda Cappellato, Nicola Ferro, David E. Losada, and Henning Müller, editors, CLEF 2019 Labs and Workshops, Notebook Papers, September 2019. CEUR-WS.org.*

[R. Bhargava and Sharma, 2017] R. Bhargava, G. Goel, A. S. and Sharma, Y. (2017). Gender identification in russian texts. In *In Working Notes for PAN-RUSProfiling at FIRE'17. Workshops Proceedings of the 9th International Forum for Information Retrieval Evaluation (Fire'17), Bangalore, India. CEUR-WS.org, 2017.*

[Régis Goubin and Fossi, 2019] Régis Goubin, Dorian Lefeuvre, A. A. J. M. E. E.-Z. and Fossi, L. G. (2019). Bots and gender profiling using a multi-layer architecture. In *In Linda Cappellato, Nicola Ferro, David E. Losada, and Henning Müller, editors, CLEF 2019 Labs and Workshops, Notebook Papers, September 2019. CEUR-WS.org.*

[Sboev, 2019] Sboev, D. Gudovskikh, . M. R. R. (2019). A gender identification of text author in mixture of russian multi-genre texts with distortions on base of data-driven approach using machine learning models. In *AIP Conference Proceedings 2116, 270006.*

[Srinivasarao and Manu, 2019] Srinivasarao, M. and Manu, S. (2019). Bots and gender profiling using character and word n-grams. In *In Linda Cappellato, Nicola Ferro, David E. Losada, and Henning Müller, editors, CLEF 2019 Labs and Workshops, Notebook Papers, September 2019. CEUR-WS.org.*

[Yasuhide Miura and Ohkuma, 2017] Yasuhide Miura, Tomoki Taniguchi, M. T. and Ohkuma, T. (2017). Author profiling with word+character neural attention network—notebook for pan at clef 2017. In *In Linda Cappellato, Nicola Ferro, Lorraine Goeuriot, and Thomas Mandl, editors, CLEF 2017*

Evaluation Labs and Workshop – Working Notes Papers, 11-14 September, Dublin, Ireland, September 2017. CEUR-WS.org.

[Сбоев, 2020] Сбоев (2020). ГЕНЕРАТИВНО-ДИСКРИМИНАТИВНАЯ НЕЙРОСЕТЕВАЯ МОДЕЛЬ ДЛЯ ЗАДАЧИ АВТОРСКОГО ПРОФИЛИРОВАНИЯ. *Вестник Национального исследовательского ядерного университета МИФИ*, 9(1):50–57.