

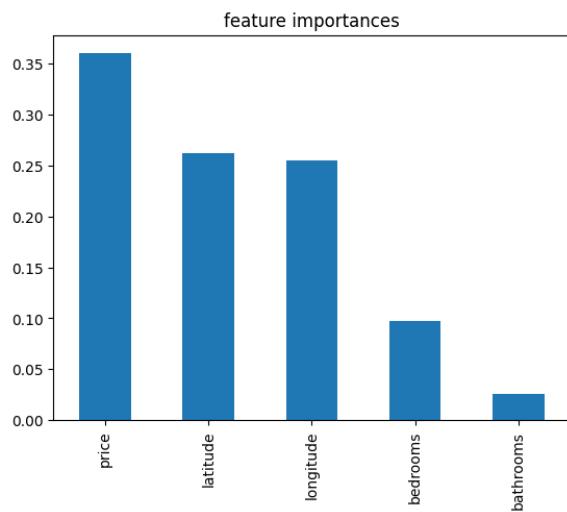
Отчет.

В ходе работы я провел эксперименты с feature importance и добавил все в библиотеку на python. Сравнил feature importance в реализации sklearn и R, а также сравнил sklearn с R-ranger.

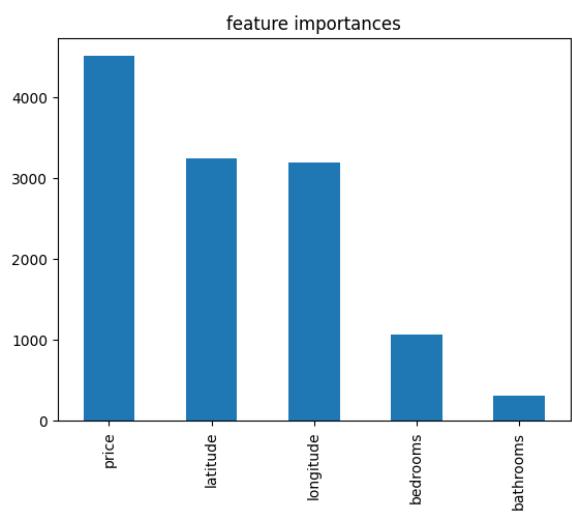
Эксперименты.

Использовал я датасет *rent.csv* из статьи, рассмотрел случаи, когда признаки: 1) разнородны, 2) присутствуют коррелированные признаки, 3) присутствуют нерелевантные признаки.

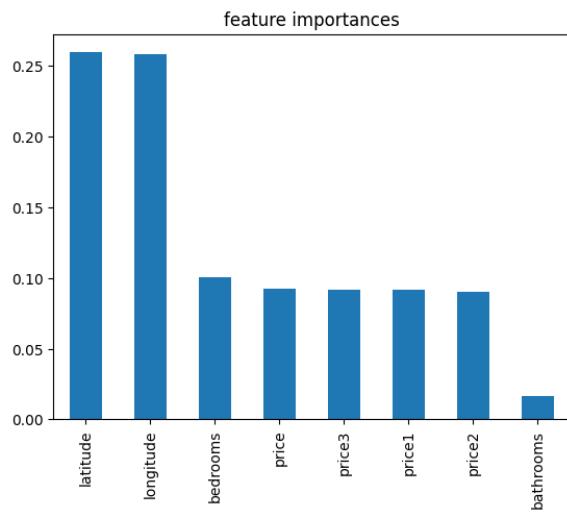
Подбор оптимальных гиперпараметров в реализации sklearn я осуществлял с помощью *Optuna*, и полученные параметры я использовал в реализации на R.



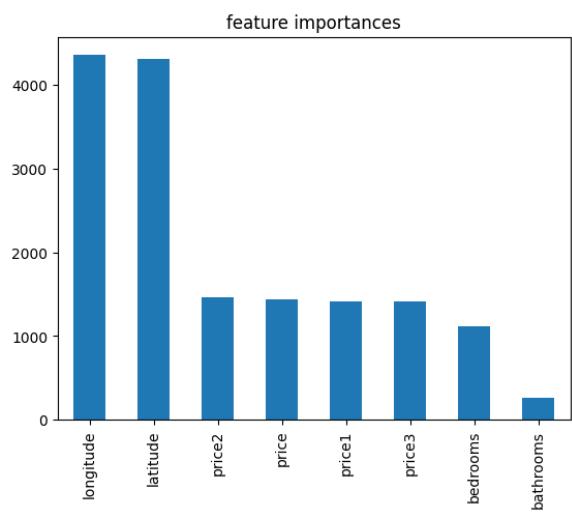
(a) Python: Исходный датасет



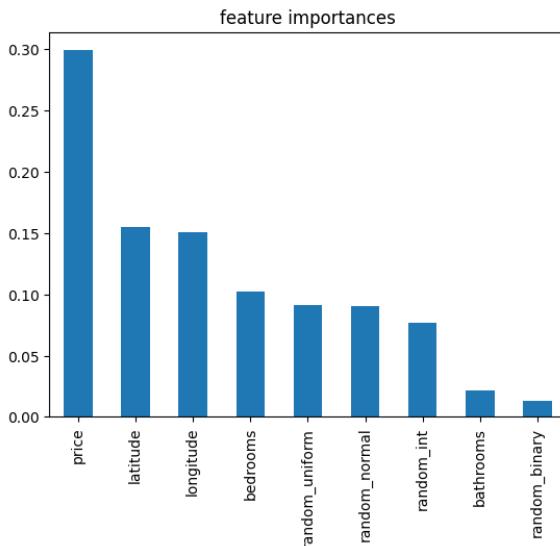
(a) R: Исходный датасет



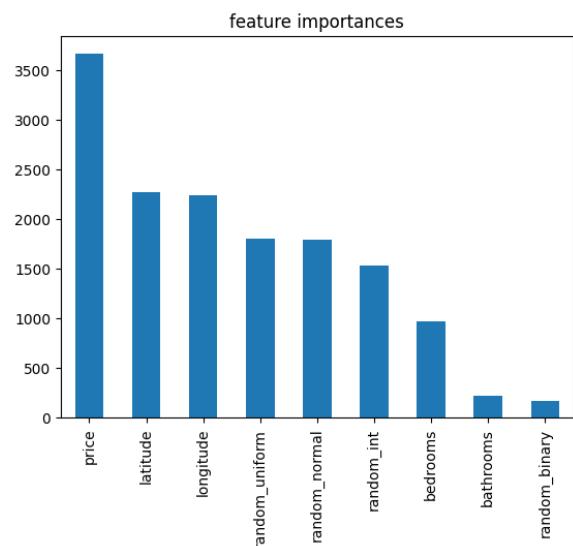
(b) Python: добавлены коррелированные признаки



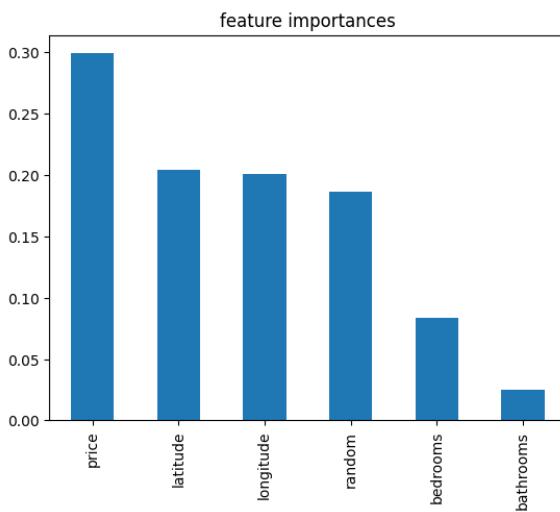
(b) R: добавлены коррелированные признаки



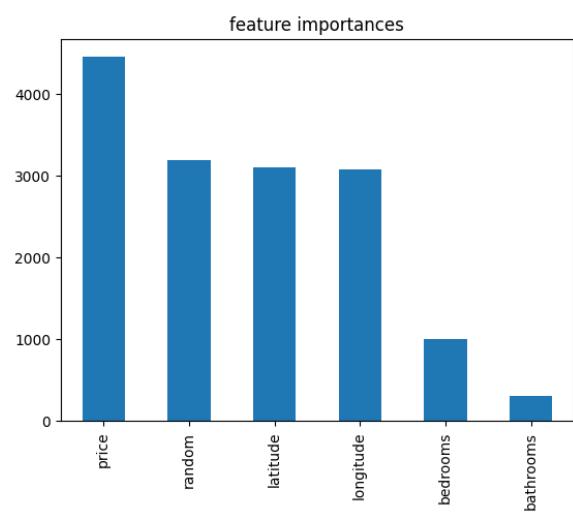
(c) Python: много нерелевантных признаков



(c) R: много нерелевантных признаков



(d) Python: 1 нерелевантный признак



(d) R: 1 нерелевантный признак

Как можно заметить, результаты в некоторых экспериментах неожиданные.

В примере (b) я скопировал признак *price* 3 раза, и получилось, что важность этого признака уменьшилась. Вообще, при добавлении коррелированных признаков, важности этих признаков будут уменьшаться.

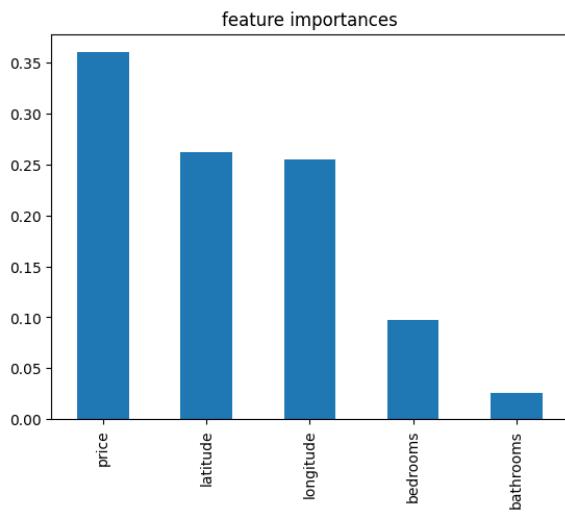
В примерах (c) и (d) я создал несколько признаков, которые никак не связаны с target.

Возникают вопросы, глядя на рисунки с нерелевантными признаками разного типа: 1) Почему эти признаки имеют важность? 2) Почему признаки *random_uniform*, *random_normal*, *random_int* имеют важность больше, чем признак *random_binary*?

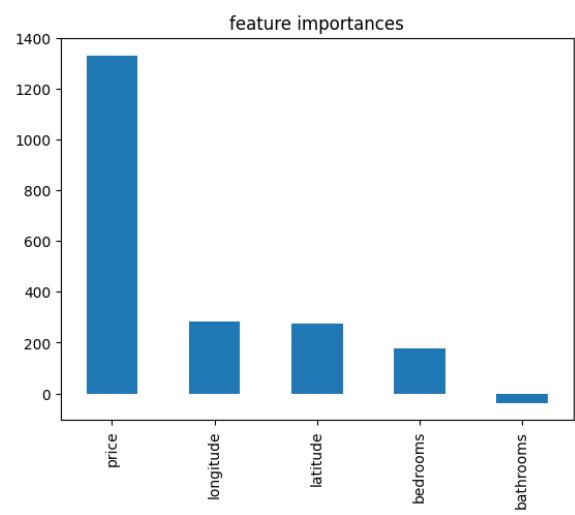
Ниже приведена таблица с оптимальными параметрами для каждого из примеров (a)-(d):

Пример	<i>n_estimators</i>	<i>max_depth</i>	<i>min_samples_leaf</i>	<i>max_features</i>
(a)	1760	26	5	<i>sqrt</i>
(b)	1289	14	3	1.0
(c)	1064	24	13	0.5
(d)	1096	19	3	0.3333333333333333

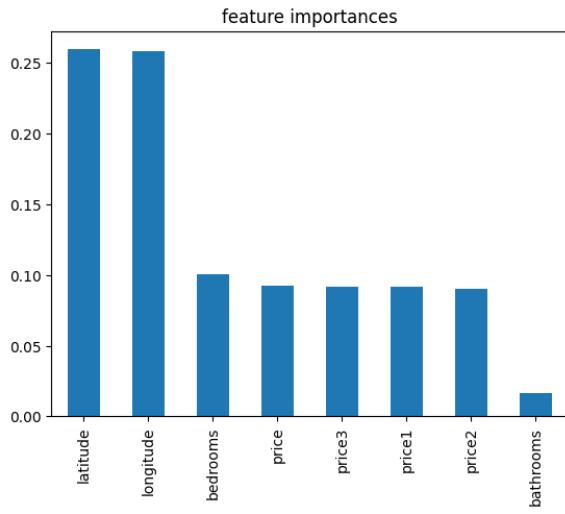
Sklearn vs R-ranger



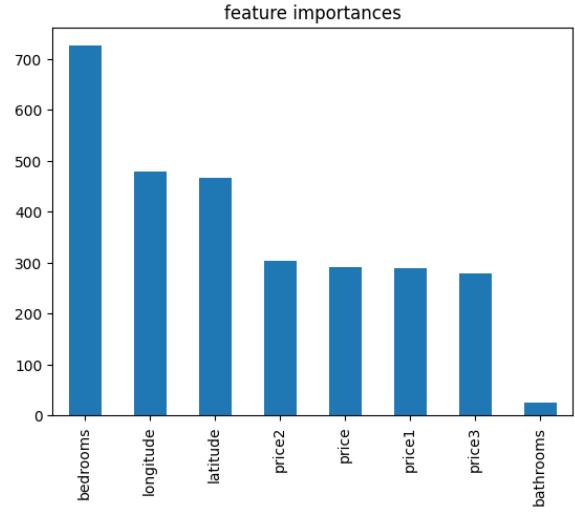
(a) Sklearn: Исходный датасет



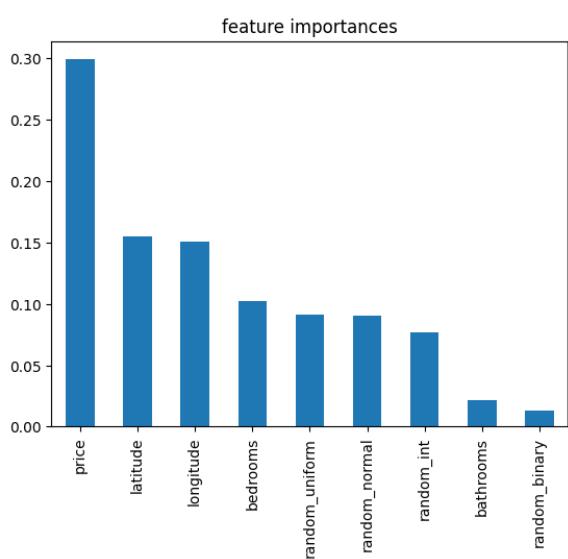
(a) R-ranger: Исходный датасет



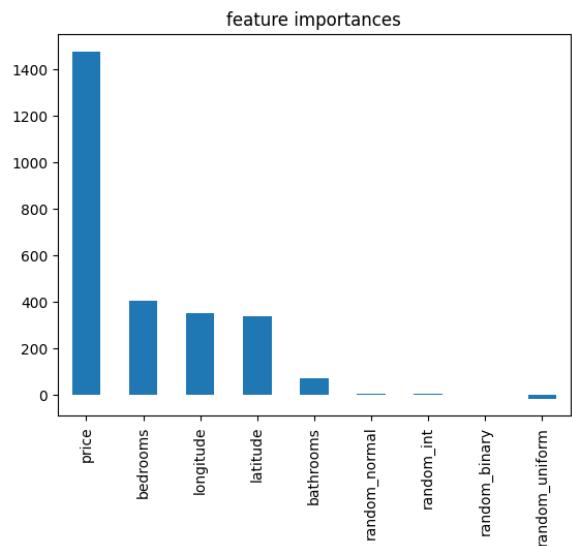
(b) Sklearn: добавлены коррелированные признаки



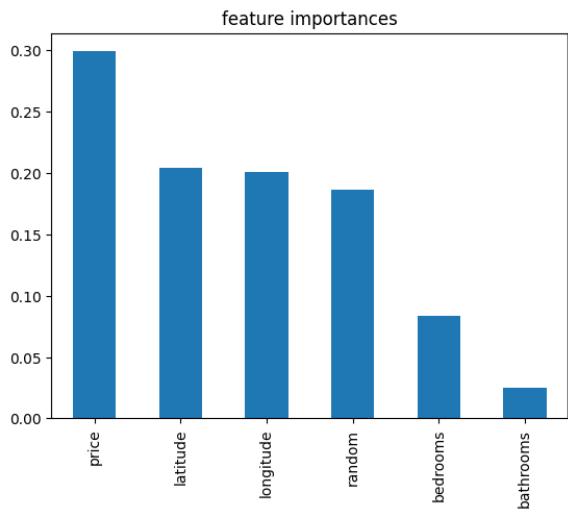
(b) R-ranger: добавлены коррелированные признаки



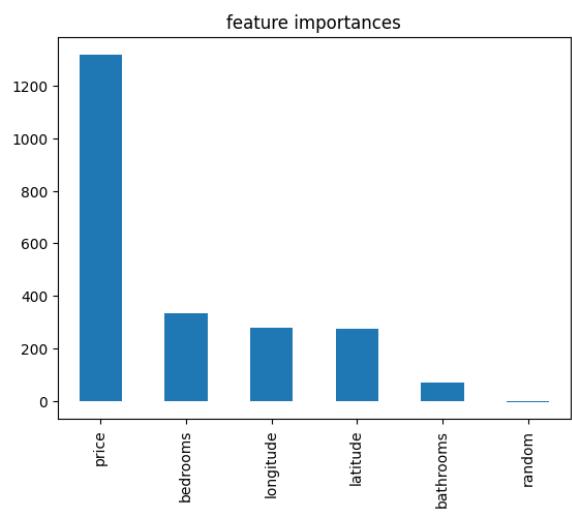
(c) Sklearn: много нерелевантных признаков



(c) R-ranger: много нерелевантных признаков



(d) Sklearn: 1 нерелевантный признак



(d) R-ranger: 1 нерелевантный признак

Код

```
1 from .python_implementations import (
2     sklearn_importance,
3     objective_classifier
4 )
5
6 from .r_implementations import (
7     r_randomforest_importance,
8     clean_feature_names
9 )
10
11 from .pic import (
12     picture
13 )
14
15
16 __version__ = "1.0.0"
17 __all__ = ['sklearn_importance', 'picture',
18             'r_randomforest_importance']
```

Листинг 1: Файл `__init__.py`

```
1 import matplotlib.pyplot as plt
2
3
4 def picture(fi):
5     fi.plot(kind='bar')
6     plt.title('feature importances')
7     plt.show()
8     return
```

Листинг 2: Файл `pic.py`

```
1 from sklearn.ensemble import RandomForestClassifier
2 import pandas as pd
3 import optuna
4 from sklearn.model_selection import train_test_split
5 from sklearn.metrics import accuracy_score
6
7
8 def objective_classifier(trial, X_train, y_train):
9     n_estimators = trial.suggest_int('n_estimators', 50, 2000)
10    max_depth = trial.suggest_int('max_depth', 5, 30, log=True)
11    min_samples_leaf = trial.suggest_int('min_samples_leaf', 1, 40)
12    max_features = trial.suggest_categorical(
13        'max_features', ["sqrt", 0.25, 1/3, 0.5, 0.7, 1.0])
14
15    model = RandomForestClassifier(
16        n_estimators=n_estimators,
17        max_depth=max_depth,
18        min_samples_leaf=min_samples_leaf,
19        max_features=max_features,
20        random_state=42,
21        oob_score=True,
22        bootstrap=True,
23        n_jobs=-1
24    )
25
26    model.fit(X_train, y_train)
```

```

27
28     return model.oob_score_
29
30
31 def sklearn_importance(X_train, y_train):
32     study = optuna.create_study(direction='maximize')
33     study.optimize(lambda trial: objective_classifier(
34         trial, X_train, y_train), n_trials=100)
35     best_params = study.best_params
36     rf = RandomForestClassifier(
37         **best_params,
38         random_state=42,
39         oob_score=True,
40         bootstrap=True,
41         n_jobs=-1
42     )
43     print(best_params)
44     rf.fit(X_train, y_train)
45     fi = pd.Series(rf.feature_importances_, index=X_train.columns)
46     return fi.sort_values(ascending=False)

```

Листинг 3: Файл python_implementations.py

```

1 from rpy2.robjects.vectors import StrVector
2 import pandas as pd
3 import numpy as np
4 import re
5 import rpy2.robjects as robjects
6 from rpy2.robjects import pandas2ri
7 from rpy2.robjects.packages import importr
8 import warnings
9 import traceback
10 from rpy2 import robjects
11
12
13 def clean_feature_names(names):
14     """
15         R. """
16     cleaned_names = [name.replace('.', '_').replace(
17         '_', '_').replace(' ', '_') for name in names]
18     return cleaned_names
19
20 def r_randomforest_importance(X, y, data_path=None, n_estimators=1760,
21     max_depth=26, min_samples_leaf=5, max_features='sqrt'):
22     try:
23         base = importr('base')
24         utils = importr('utils')
25         randomForest = importr('randomForest')
26
27         original_features = list(X.columns)
28         cleaned_features = clean_feature_names(original_features)
29
30         df_for_r = X.copy()
31         df_for_r.columns = cleaned_features
32         df_for_r['target'] = y.values
33
34         with robjects.conversion.localconverter(robjects.default_converter +
35             pandas2ri.converter) as cv:
36             r_df = robjects.conversion.py2rpy(df_for_r)

```

```

36     formula_str = "target ~ " + " + ".join(cleaned_features)
37     formula = robjects.Formula(formula_str)
38
39     print(f"Training R Random Forest with formula: {formula_str}")
40
41     n_samples = X.shape[0]
42     n_features = len(cleaned_features)
43     if max_features == 'sqrt':
44         max_features = round(np.sqrt(n_features))
45     else:
46         max_features = round(n_features * max_features)
47
48     rf_result = randomForest.randomForest(
49         formula,
50         data=r_df,
51         ntree=n_estimators,
52         nodesize=min_samples_leaf,
53         maxnodes=2**max_depth,
54         mtry=max_features,
55         importance=True
56     )
57
58     importance_r = randomForest.importance(rf_result, type=2, scale=False)
59
60     importance_matrix = np.array(importance_r)
61
62     feature_names_r = list(robj.r['rownames'](importance_r))
63
64     print(f"Importance matrix shape: {importance_matrix.shape}")
65     print(f"Feature names from R: {feature_names_r}")
66
67     if importance_matrix.ndim == 2:
68         importance_values = importance_matrix[:, 0]
69     else:
70         importance_values = importance_matrix
71
72     importance_series = pd.Series(
73         importance_values, index=original_features)
74
75     print("Successfully computed variable importance")
76     print(importance_series)
77
78     return importance_series.sort_values(ascending=False)
79
80 except Exception as e:
81     warnings.warn(f"R implementation failed: {e}")
82     import traceback
83     traceback.print_exc()
84     return None
85
86
87 def r_ranger_importance_air(X, y, n_estimators=1760, max_depth=26,
88                             min_samples_leaf=5, max_features='sqrt'):
89     try:
90         base = importr('base')
91         ranger = importr('ranger')
92
93         original_features = list(X.columns)

```

```

94     cleaned_features = clean_feature_names(original_features)
95
96     df_for_r = X.copy()
97     df_for_r.columns = cleaned_features
98
99     df_for_r['target'] = y.astype(str).values
100
101    name_map = dict(zip(cleaned_features, original_features))
102
103    with robjects.conversion.localconverter(robjects.default_converter +
104        pandas2ri.converter):
105        r_df = robjects.conversion.py2rpy(df_for_r)
106
107        r_target = base.factor(r_df.rx2('target'))
108
109        r_cleaned_features = StrVector(cleaned_features)
110
111        r_df_features_only = r_df.rx(True, r_cleaned_features)
112
113        r_df = base.cbind(r_df_features_only, target=r_target)
114
115        formula_str = "target ~ " + " + ".join(cleaned_features)
116        formula = robjects.Formula(formula_str)
117
118        print(f"Training R Ranger Forest with formula: {formula_str}")
119
120        target_type = robjects.r['class'](r_df.rx2('target'))
121        target_levels = robjects.r['levels'](r_df.rx2('target'))
122        print(f"Target type in R: {list(target_type)}")
123        print(f"Target levels: {list(target_levels)}")
124
125        n_features = len(cleaned_features)
126        if max_features == 'sqrt':
127            mtry_val = round(np.sqrt(n_features))
128        elif isinstance(max_features, float):
129            mtry_val = round(n_features * max_features)
130        else:
131            mtry_val = max_features
132
133        rf_result = ranger.ranger(
134            formula,
135            data=r_df,
136            num_trees=n_estimators,
137            min_node_size=min_samples_leaf,
138            mtry=mtry_val,
139            importance="impurity_corrected",
140            max_depth=max_depth,
141            classification=True
142        )
143
144        task_type = rf_result.rx2('treetype')[0]
145        print(f"Ranger task type: {task_type}")
146
147        importance_r = rf_result.rx2('variable.importance')
148        importance_values = np.array(importance_r)
149        feature_names_r = list(robjects.r['names'](importance_r))
150
151        importance_series = pd.Series(importance_values, index=
feature_names_r)
importance_series.index = importance_series.index.map(name_map)

```

```
152     print("Successfully computed variable importance for CLASSIFICATION"
153 )
154
155     return importance_series.sort_values(ascending=False)
156
157 except Exception as e:
158     warnings.warn(f"Ranger implementation failed: {e}")
159     traceback.print_exc()
160
161     return None
```

Листинг 4: Файл r_implementations.py