#### In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib
import matplotlib.pyplot as plt
import re
%matplotlib inline
import pandas_profiling # утилита, удобна для знакомства с данными
# с её помощью можно получить кучу описательных статистик по датасету
from wordcloud import WordCloud
import os
from PIL import Image
from sklearn.model_selection import train_test_split
# Кодирование категориальных переменных
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import OneHotEncoder
import category_encoders as ce
# Шкалирование переменных
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import RobustScaler
from sklearn.metrics import classification report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import roc_auc_score, roc_curve
# Модели
from sklearn.linear_model import LogisticRegression, LogisticRegressionCV
from sklearn.model selection import StratifiedKFold
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
import xgboost as xgb
from xgboost import XGBClassifier
import time
from sklearn.metrics import cohen_kappa_score, make_scorer
from imblearn.over_sampling import SMOTE
from sklearn.linear_model import SGDClassifier, LogisticRegressionCV
# SGD - стохастический градиентный спуск
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import GradientBoostingClassifier
from graphviz import Source
```

```
import sklearn
import lightgbm as lgb
from catboost import CatBoostClassifier
```

#### In [3]:

```
data = pd.read_csv("train/train.csv")

breeds = pd.read_csv('breed_labels.csv') # словарь пород
colors = pd.read_csv('color_labels.csv') # словарь окрасов шерсти
states = pd.read_csv('state_labels.csv') # словарь местоположения
data.shape
```

### Out[3]:

(14993, 24)

#### In [5]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14993 entries, 0 to 14992
Data columns (total 24 columns):
#
    Column
                    Non-Null Count Dtype
     ----
                    -----
                    14993 non-null
                                   int64
0
    Type
1
                   13736 non-null object
    Name
2
                                   int64
                    14993 non-null
    Age
 3
    Breed1
                    14993 non-null int64
4
    Breed2
                    14993 non-null int64
5
    Gender
                    14993 non-null
                                   int64
6
    Color1
                    14993 non-null
                                    int64
7
    Color2
                    14993 non-null int64
8
    Color3
                    14993 non-null
                                   int64
9
                    14993 non-null
                                   int64
    MaturitySize
10
    FurLength
                    14993 non-null
                                    int64
11
    Vaccinated
                    14993 non-null
                                   int64
12
    Dewormed
                    14993 non-null
                                   int64
13
    Sterilized
                    14993 non-null
                                    int64
 14
    Health
                    14993 non-null
                                    int64
15
    Quantity
                    14993 non-null
                                   int64
                    14993 non-null
                                   int64
16
    Fee
17
    State
                    14993 non-null
                                    int64
18
    RescuerID
                    14993 non-null object
    VideoAmt
                    14993 non-null
                                    int64
20
    Description
                    14981 non-null
                                    object
21
    PetID
                    14993 non-null
                                    object
                    14993 non-null
22
    PhotoAmt
                                    float64
    AdoptionSpeed 14993 non-null
                                   int64
dtypes: float64(1), int64(19), object(4)
```

memory usage: 2.7+ MB

# In [6]:

data.describe()

# Out[6]:

	Туре	Age	Breed1	Breed2	Gender	Color1	
count	14993.000000	14993.000000	14993.000000	14993.000000	14993.000000	14993.000000	14
mean	1.457614	10.452078	265.272594	74.009738	1.776162	2.234176	
std	0.498217	18.155790	60.056818	123.011575	0.681592	1.745225	
min	1.000000	0.000000	0.000000	0.000000	1.000000	1.000000	
25%	1.000000	2.000000	265.000000	0.000000	1.000000	1.000000	
50%	1.000000	3.000000	266.000000	0.000000	2.000000	2.000000	
75%	2.000000	12.000000	307.000000	179.000000	2.000000	3.000000	
max	2.000000	255.000000	307.000000	307.000000	3.000000	7.000000	
4							•

# In [7]:

```
missing = data.isnull().sum().to_frame(name = "count_of_missing_values")
missing["%"] = data.isnull().sum() / len(data)
missing
```

# Out[7]:

	count_of_missing_values						
Туре	0	0.000000					
Name	1257	0.083839					
Age	0	0.000000					
Breed1	0	0.000000					
Breed2	0	0.000000					
Gender	0	0.000000					
Color1	0	0.000000					
Color2	0	0.000000					
Color3	0	0.000000					
MaturitySize	0	0.000000					
Furl enath	n	0 000000					

### In [8]:

```
#correlation map
plt.figure(figsize=(14, 12))
sns.heatmap(data.corr(), annot=True, linewidths=.5, fmt= '.2f')
plt.show()
                                                                                                                                    - 1.0
          Type - 1.00 -0.15 0.06 -0.04 0.06
          Age --0.15 1.00 -0.31 -0.04
                                         0.09 -0.04 -0.05
                                                               0.15 -0.14
                                                                                    0.10 -0.11
                                                                                                         -0.02 -0.08 0.10
                                    0.07 -0.04 -0.01 -0.00 -0.01 -0.11 0.05
                                                                              0.05 -0.03 0.09 -0.19 -0.03 0.02 0.04 0.11
       Breed1 - 0.06 -0.31
                                                                                                                                    - 0.8
                          -0.16 1.00
                                    0.06
                                         -0.02 0.00 0.04
                                                         0.05
                                                               0.11 0.01
                                                                              -0.01
                                                                                   -0.03 0.04 0.01 -0.04 0.00 0.05 -0.02
                    -0.12
       Gender
                                    1.00 -0.12 0.03 0.26 -0.09 -0.03 0.08
                                                                              0.04 -0.05
                                                                                              -0.05 0.00 0.02 0.10 0.06
                          -0.04 -0.02
                                    -0.12
                                         1.00 -0.11 -0.28 -0.03
                                                               0.07 -0.02
                                                                              -0.04
                                                                                   0.02 -0.12
                                                                                              0.05
                                                                                                   0.02 -0.01 -0.04 -0.04
        Color1
                                                                                                                                    0.6
                                         -0.11 1.00 0.09 -0.07 -0.01 0.03 0.01
        Color2
                     -0.04
                          -0.01 0.00
                                    0.03
                                                                              0.01 -0.00 0.02 -0.02 0.03 0.02 0.06 -0.04
                          -0.00 0.04
                                         -0.28 0.09 1.00
                                                         -0.05 0.01 0.05 0.05
                                                                              0.04
                                                                                              -0.02 0.01 0.02 0.10 -0.01
        Color3 - 0.20
                                                                                   -0.02 0.27
   MaturitySize --0.17
                          0.01 0.05 0.09 0.03 0.07 0.05 1.00 0.10 0.09 0.07
                                                                              -0.07
                                                                                   -0.01 -0.04 0.04 -0.06 0.02 0.02 0.05
                                                                                                                                    - 0.4
                          -0.11 0.11
                                               -0.01 0.01
                                                         0.10 1.00 -0.01
     FurLength - 0.00
                                    -0.03
                                         0.07
                                                                                   0.03 -0.04
                                                                                                   -0.03
                                                                                                        -0.01 -0.03 -0.09
    Vaccinated - 0.10 -0.14
                          0.05 0.01
                                                               -0.01 1.00 0.72
                                                                                   0.08 0.13 -0.12
                                                                                                   0.03 -0.03 -0.05
                                    0.08
                                         -0.02 0.03 0.05 -0.09
                               -0.01
     Dewormed - 0.03
                                    0.09
                                         -0.02 0.01 0.05
                                                         -0.07
                                                               0.02
                                                                    0.72 1.00
                                                                                   0.07
                                                                                              -0.11
                                                                                                              -0.10 -0.01
                                                                                                                                     0.2
      Sterilized - 0.01 -0.19
                               -0.01
                                    0.04
                                         -0.04 0.01 0.04
                                                         -0.07
                                                                              1.00
                                                                                        0.10
                                                                                              -0.06
                                                                                                         -0.02
                                                                                                              -0.06
                                                                                                                   -0.08
                          -0.03 -0.03
                                               -0.00 -0.02
                                                                                              -0.01
        Health
               -0.01
                                                                                   1.00
                                                                                                    0.03
```

# In [9]:

```
data.columns
```

#### Out[9]:

# Тип животного:

1 - собака

2 - кот

# In [10]:

```
data["Type"] = data["Type"].apply(lambda x: "dog" if x == 1 else "cat")
animals = data["Type"].value_counts().to_frame("count")
animals["%"] = data["Type"].value_counts(normalize = True)
animals
```

# Out[10]:

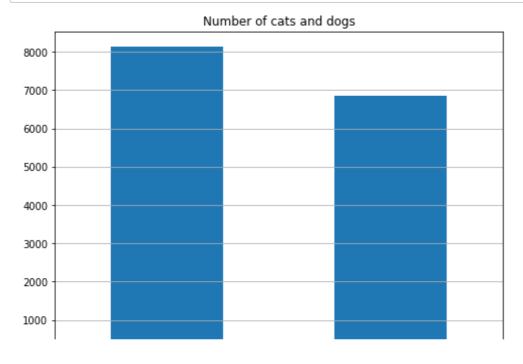
```
        count
        %

        dog
        8132
        0.542386

        cat
        6861
        0.457614
```

# In [11]:

```
data["Type"].value_counts().plot.bar(figsize=(8, 6), rot = 0)
plt.grid(axis='y')
plt.title('Number of cats and dogs');
```



# Имена

```
In [12]:
```

```
data["Name"]
Out[12]:
                 Nibble
0
            No Name Yet
1
2
                 Brisco
3
                   Miko
4
                 Hunter
14988
                     NaN
14989
         Serato & Eddie
                Monkies
14990
14991
                Ms Daym
14992
                   Fili
Name: Name, Length: 14993, dtype: object
In [13]:
data["Name"].values
Out[13]:
array(['Nibble', 'No Name Yet', 'Brisco', ..., 'Monkies', 'Ms Daym',
       'Fili'], dtype=object)
```

```
In [14]:
```

```
fig, ax = plt.subplots(figsize = (32, 24))
plt.subplot(1, 2, 1)
text_cat = ' '.join(data.loc[data['Type'] == 'cat', 'Name'].fillna('').values)
wordcloud = WordCloud(max_font_size=None, background_color='white',
                      width=1200, height=1000).generate(text_cat)
plt.imshow(wordcloud)
plt.title('Top cat names')
plt.axis("off")
plt.subplot(1, 2, 2)
text_dog = ' '.join(data.loc[data['Type'] == 'dog', 'Name'].fillna('').values)
wordcloud = WordCloud(max_font_size=None, background_color='white',
                      width=1200, height=1000).generate(text_dog)
plt.imshow(wordcloud)
plt.title('Top dog names')
plt.axis("off")
plt.show()
```

```
Snowy Antropalue ty-Cookie Miss ** Old Kitten Daisy Tom. Old Kitte
```



#### In [15]:

```
data.fillna('no_name', inplace = True)
```

#### In [16]:

#### In [17]:

```
for x in data["Name"]:
   if len(x) < 3 or re.search(r"\d+", x) is not None:
       names.add(x)
       # print(x)</pre>
```

```
In [18]:
```

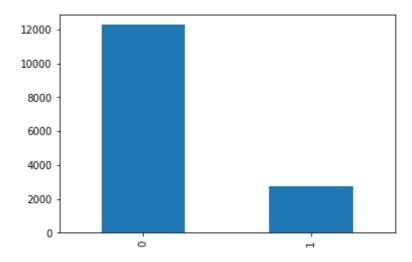
```
for x in names:
   data.loc[data['Name'] == x, 'Name'] = "no_name"
```

# In [19]:

```
data["No_name"] = 0
data.loc[data['Name'] == 'no_name', 'No_name'] = 1
data["No_name"].value_counts().plot.bar()
```

# Out[19]:

### <AxesSubplot:>



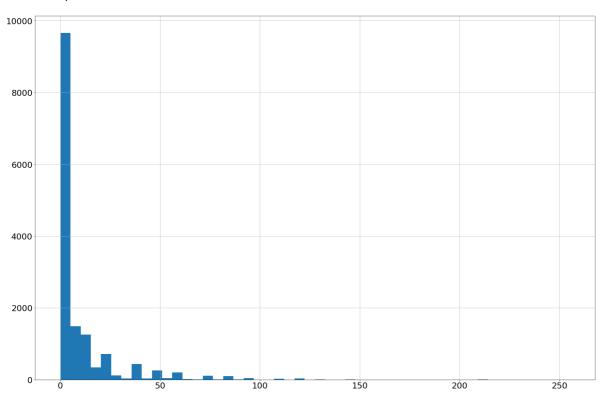
# Возраст (в месяцах)

# In [20]:

```
data["Age"].hist(bins = 50, figsize = (30, 20), xlabelsize = 25, ylabelsize = 25)
```

# Out[20]:

# <AxesSubplot:>



# In [21]:

data["Age"].value\_counts().sort\_index()

# Out[21]:

0	179
1	2304
2	3503
3	1966
4	1109
168	1
	_
180	2
180 212	_
	2

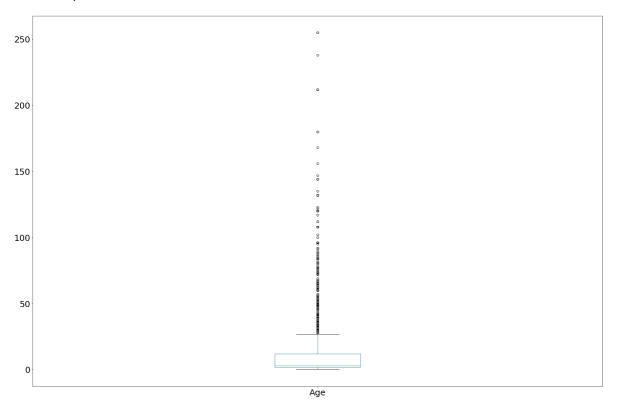
Name: Age, Length: 106, dtype: int64

#### In [22]:

```
data["Age"].plot.box(figsize = (30, 20), fontsize = 25)
```

### Out[22]:

#### <AxesSubplot:>



### In [31]:

```
def outlier_detect_IQR(data,col,threshold=3):
    IQR = data[col].quantile(0.75) - data[col].quantile(0.25)
    lower = data[col].quantile(0.25) - (IQR * threshold)
    upper = data[col].quantile(0.75) + (IQR * threshold)
    borders = (upper, lower)
    emiss = pd.concat([data[col] > upper, data[col] < lower],axis=1)
    outlier_index = emiss.any(axis=1)
    print('Количество выбросов в данных:', outlier_index.value_counts()[1])
    print('Доля выбросов:',outlier_index.value_counts()[1]/len(outlier_index))
    return outlier_index, borders</pre>
```

```
In [32]:
index,para = outlier_detect_IQR(data=data,col='Age',threshold=1)
print('Верхняя граница:',para[0],'\nНижняя граница:',para[1])
Количество выбросов в данных: 2200
Доля выбросов: 0.1467351430667645
Верхняя граница: 22.0
Нижняя граница: -8.0
In [33]:
data.loc[index,'Age'].sort_values()
Out[33]:
2180
          23
10492
          23
834
          23
14182
          23
9425
          23
        . . .
3998
         212
11087
         212
         238
13398
         255
5160
11172
         255
Name: Age, Length: 2200, dtype: int64
In [34]:
data["Age"].min()
Out[34]:
0
Заменим выбросы выборочным значением
In [35]:
def impute_outlier_with_arbitrary(data,outlier_index,value,col=[]):
```

```
def impute_outlier_with_arbitrary(data,outlier_index,value,col=[]):
    data_copy = data.copy(deep=True)
    for i in col:
        data_copy.loc[outlier_index,i] = value
    return data_copy
```

### In [36]:

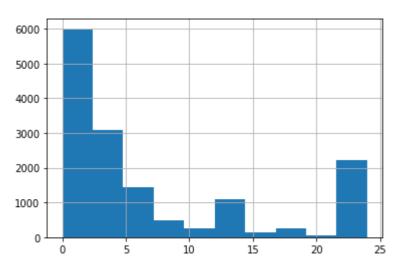
```
data = impute_outlier_with_arbitrary(data=data,outlier_index=index, value= 24, col=['Age'])
```

# In [37]:

```
data["Age"].hist()
```

### Out[37]:

# <AxesSubplot:>



# Порода

# In [40]:

```
data['Pure_breed'] = 0
data.loc[data['Breed2'] == 0, 'Pure_breed'] = 1
print(f"Доля чистокровных животных = {round(data['Pure_breed'].sum()/len(data), 2)} %")
```

Доля чистокровных животных = 0.72 %

#### In [41]:

```
breeds_dict = {k: v for k, v in zip(breeds['BreedID'], breeds['BreedName'])}
breeds_dict
Out[41]:
{1: 'Affenpinscher',
 2: 'Afghan Hound',
 3: 'Airedale Terrier',
4: 'Akbash',
 5: 'Akita',
 6: 'Alaskan Malamute',
7: 'American Bulldog',
8: 'American Eskimo Dog',
9: 'American Hairless Terrier',
 10: 'American Staffordshire Terrier',
 11: 'American Water Spaniel',
 12: 'Anatolian Shepherd',
 13: 'Appenzell Mountain Dog',
 14: 'Australian Cattle Dog/Blue Heeler',
15: 'Australian Kelpie',
 16: 'Australian Shepherd',
 17: 'Australian Terrier',
 18: 'Basenii'.
```

# In [42]:

```
data['Breed1_name'] = data['Breed1'].apply(lambda x: '_'.join(breeds_dict[x].split()) if x
data['Breed2_name'] = data['Breed2'].apply(lambda x: '_'.join(breeds_dict[x].split()) if x
data
```

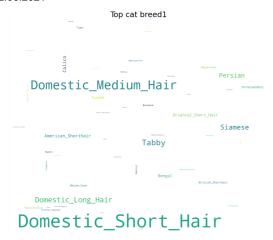
# Out[42]:

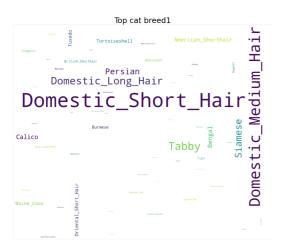
	Туре	Name	Age	Breed1	Breed2	Gender	Color1	Color2	Color3	MaturitySize	
0	cat	Nibble	3	299	0	1	1	7	0	1	
1	cat	no_name	1	265	0	1	1	2	0	2	
2	dog	Brisco	1	307	0	1	2	7	0	2	
3	dog	Miko	4	307	0	2	1	2	0	2	
4	dog	Hunter	1	307	0	1	1	0	0	2	
14988	cat	no_name	2	266	0	3	1	0	0	2	
14989	cat	Serato & Eddie	24	265	264	3	1	4	7	2	
14990	cat	Monkies	2	265	266	3	5	6	7	3	
14991	cat	Ms Daym	9	266	0	2	4	7	0	1	
14992	dog	Fili	1	307	307	1	2	0	0	2	

14993 rows × 28 columns

#### In [43]:

```
fig, ax = plt.subplots(figsize = (40, 36))
plt.subplot(2, 2, 1)
text cat1 = ' '.join(data.loc[data['Type'] == 'cat', 'Breed1_name'].fillna('').values)
wordcloud = WordCloud(max_font_size=None, background_color='white', collocations=False,
                      width=1200, height=1000).generate(text cat1)
plt.imshow(wordcloud)
plt.title('Top cat breed1', fontdict={'fontsize': 30})
plt.axis("off")
plt.subplot(2, 2, 2)
text_dog1 = ' '.join(data.loc[data['Type'] == 'dog', 'Breed1_name'].fillna('').values)
wordcloud = WordCloud(max_font_size=None, background_color='white', collocations=False,
                      width=1200, height=1000).generate(text_dog1)
plt.imshow(wordcloud)
plt.title('Top dog breed1', fontdict={'fontsize': 30})
plt.axis("off")
plt.subplot(2, 2, 3)
text_cat2 = ' '.join(data.loc[data['Type'] == 'cat', 'Breed2_name'].fillna('').values)
wordcloud = WordCloud(max_font_size=None, background_color='white', collocations=False,
                      width=1200, height=1000).generate(text_cat2)
plt.imshow(wordcloud)
plt.title('Top cat breed1', fontdict={'fontsize': 30})
plt.axis("off")
plt.subplot(2, 2, 4)
text_dog2 = ' '.join(data.loc[data['Type'] == 'dog', 'Breed2_name'].fillna('').values)
wordcloud = WordCloud(max_font_size=None, background_color='white', collocations=False,
                      width=1200, height=1000).generate(text_dog2)
plt.imshow(wordcloud)
plt.title('Top dog breed2', fontdict={'fontsize': 30})
plt.axis("off")
plt.show()
```







#### In [44]:

```
no_pure_breeds = ['Mixed_Breed', 'Domestic_Long_Hair', 'Domestic_Medium_Hair', 'Domestic_Sh

for x in no_pure_breeds:
   data.loc[data['Breed1_name'] == x, 'Pure_breed'] = 0
   data.loc[data['Breed2_name'] == x, 'Pure_breed'] = 0
```

### In [45]:

```
print(f"Доля чистокровных животных = {round(data['Pure_breed'].sum()/len(data), 2)} %")
```

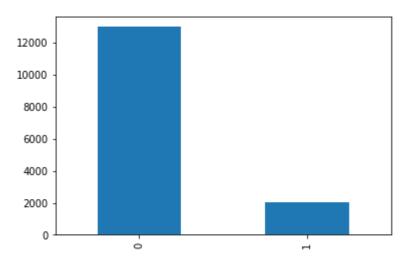
Доля чистокровных животных = 0.13 %

# In [46]:

data['Pure\_breed'].value\_counts().plot.bar()

# Out[46]:

# <AxesSubplot:>



# Пол

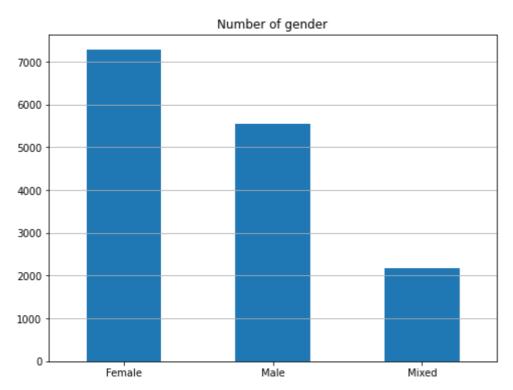
Пол питомца (1 = мужской, 2 = женский, 3 = смешанный, если в записи несколько животных)

# In [47]:

```
graph_data = data['Gender'].apply(lambda x: 'Male' if x == 1 else ('Female' if x == 2 else
graph_data.value_counts().plot.bar(figsize=(8, 6), rot = 0)
plt.grid(axis='y')
plt.title('Number of gender')
```

# Out[47]:

Text(0.5, 1.0, 'Number of gender')



### In [48]:

```
graph_data.value_counts().to_frame("count")
```

# Out[48]:

	count
Female	7277
Male	5536
Mixed	2180

# Окрас

### In [49]:

```
colors_dict = {k: v for k, v in zip(colors['ColorID'], colors['ColorName'])}
data['Color1_name'] = data['Color1'].apply(lambda x: colors_dict[x] if x in colors_dict els
data['Color2_name'] = data['Color2'].apply(lambda x: colors_dict[x] if x in colors_dict els
data['Color3_name'] = data['Color3'].apply(lambda x: colors_dict[x] if x in colors_dict els
colors_dict
```

# Out[49]:

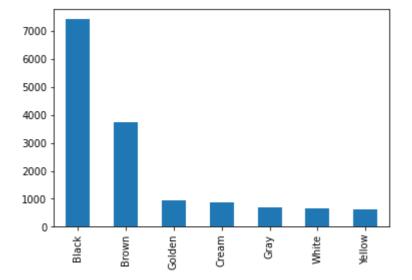
```
{1: 'Black',
2: 'Brown',
3: 'Golden',
4: 'Yellow',
5: 'Cream',
6: 'Gray',
7: 'White'}
```

#### In [50]:

```
data["Color1_name"].value_counts().plot.bar()
```

#### Out[50]:

#### <AxesSubplot:>

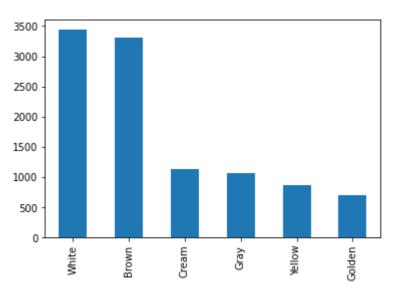


# In [51]:

data["Color2\_name"].value\_counts().drop(index='').plot.bar()

# Out[51]:

# <AxesSubplot:>

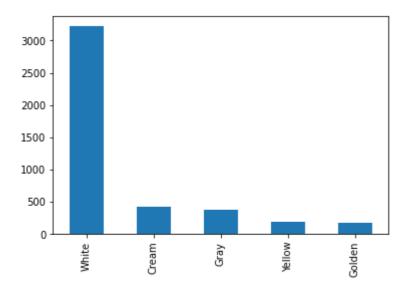


# In [52]:

data["Color3\_name"].value\_counts().drop(index='').plot.bar()

# Out[52]:

# <AxesSubplot:>



# In [53]:

data['full\_color'] = (data['Color1\_name'] + '\_\_' + data['Color2\_name'] + '\_\_' + data['Color

# In [54]:

data

# Out[54]:

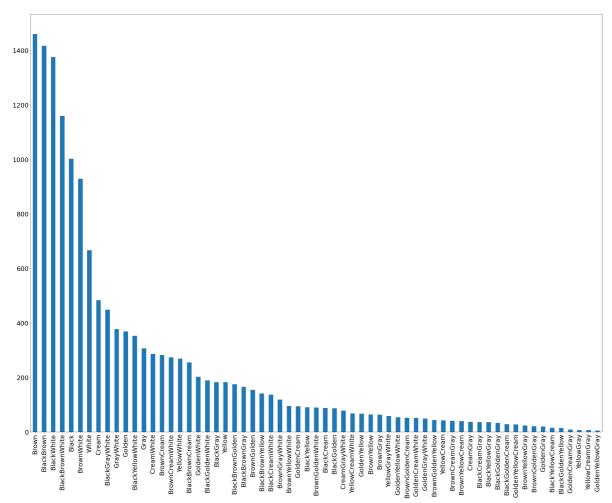
	Type	Name	Age	Breed1	Breed2	Gender	Color1	Color2	Color3	MaturitySize	
0	cat	Nibble	3	299	0	1	1	7	0	1	
1	cat	no_name	1	265	0	1	1	2	0	2	
2	dog	Brisco	1	307	0	1	2	7	0	2	
3	dog	Miko	4	307	0	2	1	2	0	2	
4	dog	Hunter	1	307	0	1	1	0	0	2	
14988	cat	no_name	2	266	0	3	1	0	0	2	
14989	cat	Serato & Eddie	24	265	264	3	1	4	7	2	
14990	cat	Monkies	2	265	266	3	5	6	7	3	
14991	cat	Ms Daym	9	266	0	2	4	7	0	1	
14992	dog	Fili	1	307	307	1	2	0	0	2	
14993 rows × 32 columns											

# In [55]:

data["full\_color"].value\_counts().plot.bar(figsize = (40, 30), fontsize=25)

### Out[55]:

### <AxesSubplot:>

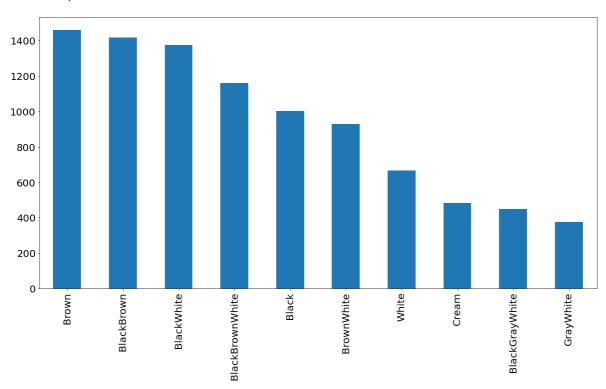


# In [56]:

data["full\_color"].value\_counts()[:10].plot.bar(figsize = (20, 10), fontsize=20)

# Out[56]:

# <AxesSubplot:>



# Размер животного в зрелом возрасте

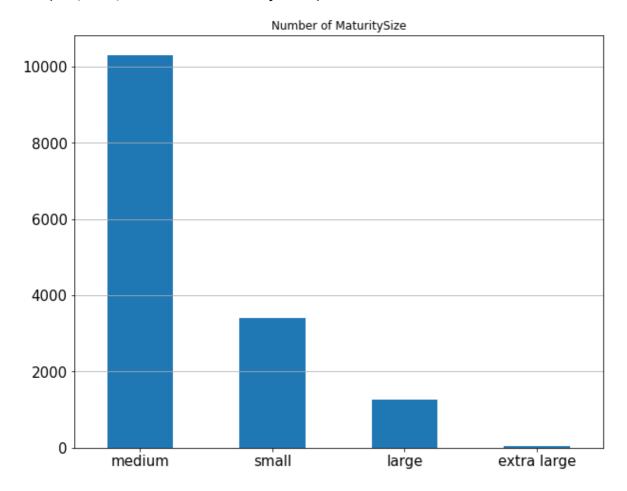
1 = маленький, 2 = средний, 3 = большой, 4 = очень большой, 0 = не указано

# In [57]:

```
graph_data = data['MaturitySize'].apply(lambda x: 'small' if x == 1 else ('medium' if x ==
graph_data.value_counts().plot.bar(figsize=(10, 8), rot = 0, fontsize=15)
plt.grid(axis='y')
plt.title('Number of MaturitySize')
```

# Out[57]:

Text(0.5, 1.0, 'Number of MaturitySize')

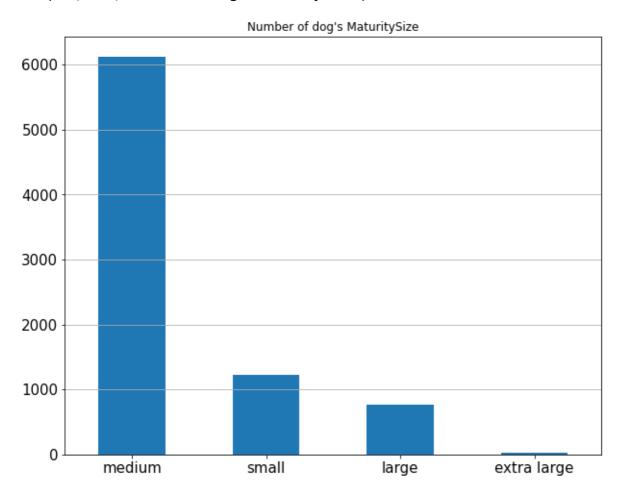


# In [58]:

```
graph_data = data[data['Type'] == 'dog']['MaturitySize'].apply(lambda x: 'small' if x == 1
graph_data.value_counts().plot.bar(figsize=(10, 8), rot = 0, fontsize=15)
plt.grid(axis='y')
plt.title("Number of dog's MaturitySize")
```

# Out[58]:

Text(0.5, 1.0, "Number of dog's MaturitySize")

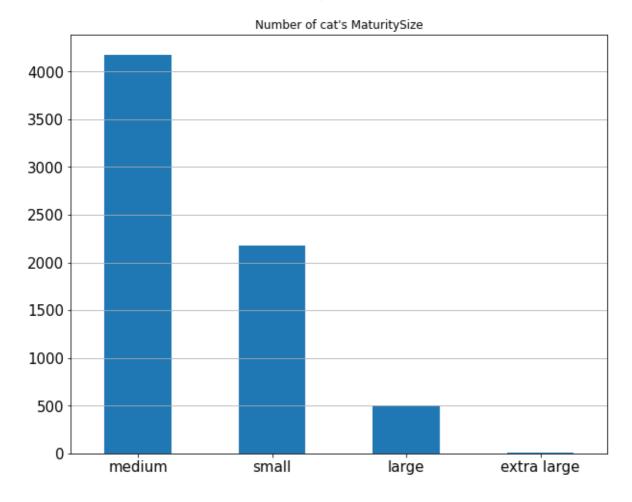


### In [59]:

```
graph_data = data[data['Type'] == 'cat']['MaturitySize'].apply(lambda x: 'small' if x == 1
graph_data.value_counts().plot.bar(figsize=(10, 8), rot = 0, fontsize=15)
plt.grid(axis='y')
plt.title("Number of cat's MaturitySize")
```

### Out[59]:

Text(0.5, 1.0, "Number of cat's MaturitySize")



# Длина шерсти

1 = короткая, 2 = средняя, 3 = длинная, 0 = не указано

### In [60]:

```
data["FurLength"].value_counts()
```

# Out[60]:

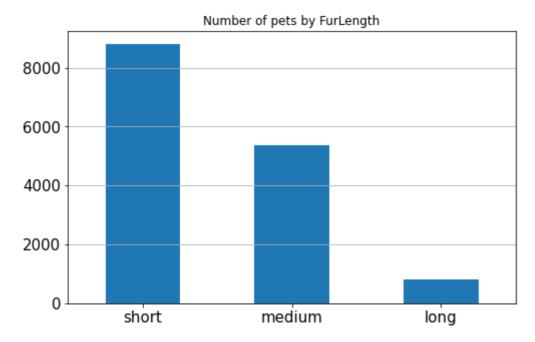
- 8808
   5361
   824
- Name: FurLength, dtype: int64

# In [61]:

```
graph_data = data['FurLength'].apply(lambda x: 'short' if x == 1 else ('medium' if x == 2 e
graph_data.value_counts().plot.bar(figsize=(8, 5), rot = 0, fontsize=15)
plt.grid(axis='y')
plt.title('Number of pets by FurLength')
```

### Out[61]:

Text(0.5, 1.0, 'Number of pets by FurLength')



# 3доровье

Есть 4 признака, относящиеся к здоровью питомца

- Vaccinated вакцинировано ли домашнее животное (1 = да, 2 = нет, 3 = не уверены)
- Dewormed избавлено ли животное от глистов (гельминтов) (1 = да, 2 = нет, 3 = не уверены)
- Sterilized стерилизовано ли животное (1 = да, 2 = нет, 3 = не уверены)
- Health состояние здоровья (1 = здоровый, 2 = легкая травма, 3 = серьезная травма)

#### In [62]:

```
data["Vaccinated"].value_counts()
```

### Out[62]:

2 72271 5898

1868

3

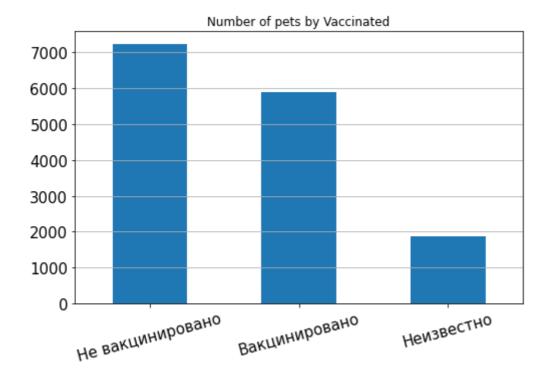
Name: Vaccinated, dtype: int64

### In [63]:

```
graph_data = data['Vaccinated'].apply(lambda x: 'Вакцинировано' if x == 1 else ('He вакцини graph_data.value_counts().plot.bar(figsize=(8, 5), rot = 15, fontsize=15) plt.grid(axis='y') plt.title('Number of pets by Vaccinated')
```

### Out[63]:

Text(0.5, 1.0, 'Number of pets by Vaccinated')



#### In [64]:

```
data["Dewormed"].value_counts()
```

# Out[64]:

1 8397

2 4815

3 1781

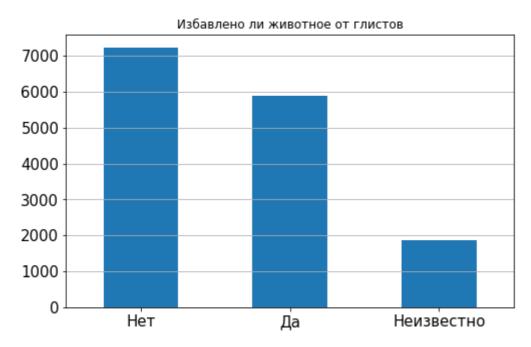
Name: Dewormed, dtype: int64

#### In [65]:

```
graph_data = data['Vaccinated'].apply(lambda x: 'Да' if x == 1 else ('Heт' if x == 2 else 'graph_data.value_counts().plot.bar(figsize=(8, 5), rot = 0, fontsize=15)
plt.grid(axis='y')
plt.title('Избавлено ли животное от глистов')
```

### Out[65]:

Text(0.5, 1.0, 'Избавлено ли животное от глистов')



# In [66]:

data["Sterilized"].value\_counts()

### Out[66]:

2 10077

1 3101

3 1815

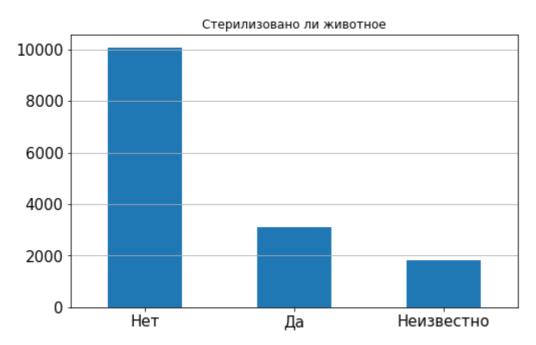
Name: Sterilized, dtype: int64

#### In [67]:

```
graph_data = data['Sterilized'].apply(lambda x: 'Да' if x == 1 else ('Heт' if x == 2 else 'graph_data.value_counts().plot.bar(figsize=(8, 5), rot = 0, fontsize=15)
plt.grid(axis='y')
plt.title('Стерилизовано ли животное')
```

# Out[67]:

Text(0.5, 1.0, 'Стерилизовано ли животное')



### In [68]:

```
data["Health"].value_counts()
```

# Out[68]:

1 14478 2 481 3 34

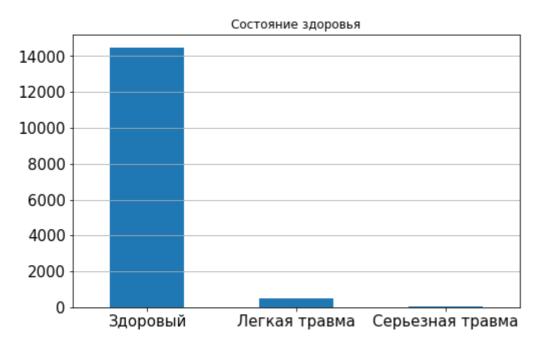
Name: Health, dtype: int64

### In [69]:

```
graph_data = data['Health'].apply(lambda x: 'Здоровый' if x == 1 else ('Легкая травма' if x graph_data.value_counts().plot.bar(figsize=(8, 5), rot = 0, fontsize=15) plt.grid(axis='y') plt.title('Состояние здоровья')
```

### Out[69]:

Text(0.5, 1.0, 'Состояние здоровья')

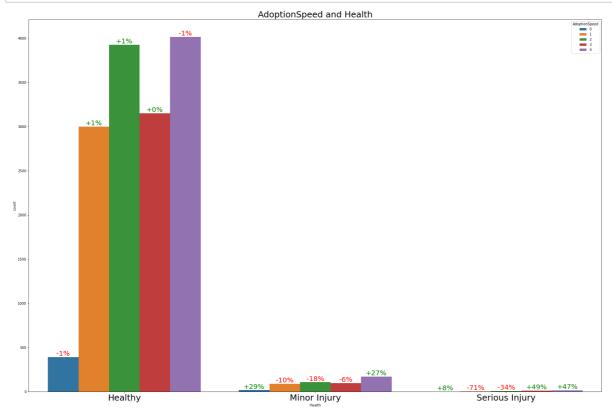


#### In [70]:

```
main count = data['AdoptionSpeed'].value counts(normalize=True).sort index()
def prepare_plot_dict(df, col, main_count):
    Preparing dictionary with data for plotting.
    I want to show how much higher/lower are the rates of Adoption speed for the current co
    At first I calculate base rates, then for each category in the column I calculate rates
    main_count = dict(main_count)
    plot_dict = {}
    for i in df[col].unique():
        val_count = dict(df.loc[df[col] == i, 'AdoptionSpeed'].value_counts().sort_index())
        for k, v in main count.items():
            if k in val count:
                plot_dict[val_count[k]] = ((val_count[k] / sum(val_count.values())) / main_
            else:
                plot_dict[0] = 0
    return plot_dict
def make_count_plot(df, x, hue='AdoptionSpeed', title='', main_count=main_count):
    Plotting countplot with correct annotations.
    g = sns.countplot(x=x, data=df, hue=hue);
    plt.title(f'AdoptionSpeed {title}', fontsize=20);
    ax = g.axes
    plot_dict = prepare_plot_dict(df, x, main_count)
    for p in ax.patches:
        h = p.get_height() if str(p.get_height()) != 'nan' else 0
        text = f"{plot_dict[h]:.0f}%" if plot_dict[h] < 0 else f"+{plot_dict[h]:.0f}%"</pre>
        ax.annotate(text, (p.get_x() + p.get_width() / 2., h),
             ha='center', va='center', fontsize=20, color='green' if plot_dict[h] > 0 else
             textcoords='offset points')
```

# In [71]:

```
plt.subplots(figsize=(30,20))
make_count_plot(df=data, x='Health', title='Health')
plt.xticks([0, 1, 2], ['Healthy', 'Minor Injury', 'Serious Injury'], fontsize=25);
plt.title('AdoptionSpeed and Health', fontsize=25);
```

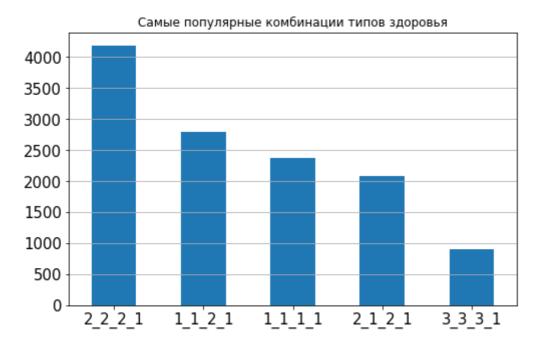


#### In [72]:

```
data['full_health'] = data['Vaccinated'].astype(str) + '_' + data['Dewormed'].astype(str) +
data['full_health'].value_counts()[:5].plot.bar(figsize=(8, 5), rot = 0, fontsize=15)
plt.grid(axis='y')
plt.title('Самые популярные комбинации типов здоровья')
```

#### Out[72]:

Text(0.5, 1.0, 'Самые популярные комбинации типов здоровья')



- 1\_1\_1\_1 вакцинировано, избавлено от глистов, стерилизовано и здорово
- 1\_1\_2\_1 вакцинировано, избавлено от глистов, не стерилизовано и здорово
- 2 1 2 1 не вакцинировано, избавлено от глистов, не стерилизовано и здорово
- 2\_2\_2\_1 не вакцинировано, не избавлено от глистов, не стерилизовано и здорово
- 3\_3\_3\_1 животное здорово, но информации о вакцинации, стерилизации и об избавлении от глистов нет

```
In [73]:
```

```
data['full_health'].value_counts()[:5]
```

### Out[73]:

2\_2\_2\_1 4189 1\_1\_2\_1 2786 1\_1\_1\_1 2377 2\_1\_2\_1 2081 3\_3\_3\_1 907

Name: full\_health, dtype: int64

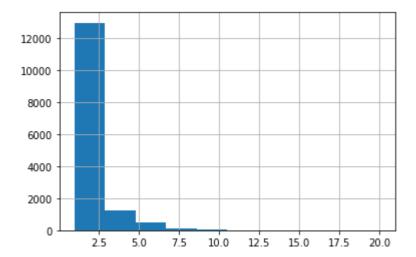
# Количество животных в одном профиле

# In [74]:

```
data['Quantity'].hist()
```

# Out[74]:

# <AxesSubplot:>



```
In [75]:
```

```
data['Quantity'].value_counts().sort_index()
Out[75]:
1
      11565
2
       1422
3
         726
4
         531
5
         333
6
         185
7
          84
8
          52
9
          33
          19
10
11
          10
12
           6
13
           2
14
           2
15
           4
           3
16
17
           3
18
           1
20
          12
Name: Quantity, dtype: int64
```

# In [76]:

# Стоимость

Некоторых животных отдают бесплатно, а за некоторых требуют плату

data['one\_pet'] = data["Quantity"].apply(lambda x: 1 if x==1 else 0)

#### In [78]:

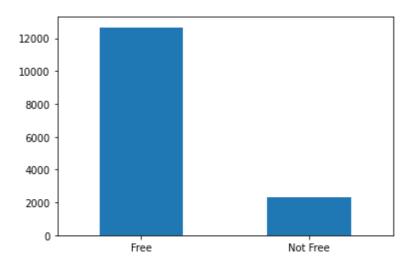
```
data['Free'] = data['Fee'].apply(lambda x: 'Free' if x == 0 else 'Not Free')
print(data["Free"].value_counts())
data["Free"].value_counts().plot.bar(rot = 0)
```

Free 12663 Not Free 2330

Name: Free, dtype: int64

#### Out[78]:

#### <AxesSubplot:>



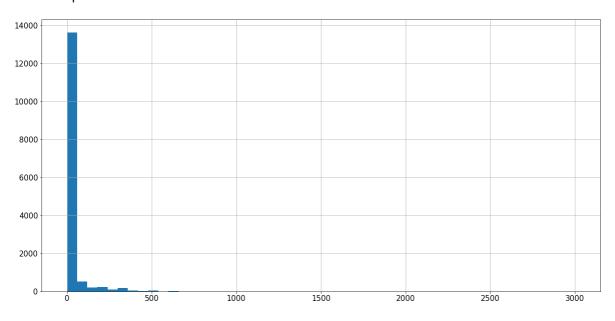
#### In [79]:

```
data['Free'] = data['Fee'].apply(lambda x: 1 if x == 0 else 0)
```

#### In [80]:

```
data['Fee'].hist(figsize = (20, 10), xlabelsize = 15, ylabelsize = 15, bins = 50)
```

#### Out[80]:



## In [81]:

data["Fee"].max()

## Out[81]:

3000

#### In [82]:

data.sort\_values('Fee', ascending=False)[['Name', 'Description', 'Fee', 'Breed1\_name', 'Age

## Out[82]:

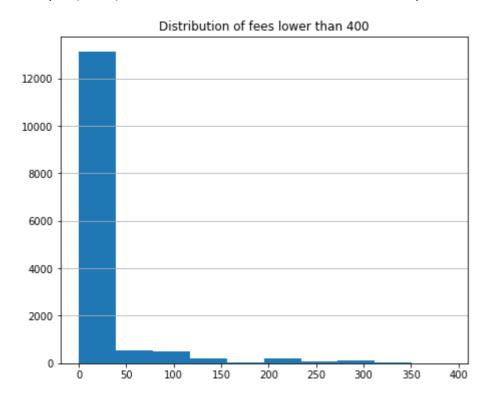
	Name	Description	Fee	Breed1_name	Age
8722	Khaleesi And Drogo	Both pups are family home trained. They love t	3000	German_Shepherd_Dog	4
10477	Bull Dog	Found this bull dog near my neighbourhood for	2000	English_Bulldog	24
8879	Rottweiler Semi-Adult - Adoption	Looking for new lovely home due to owner lack	1000	Rottweiler	8
2078	Rottweiler - Adoption	Open for Adoption with Fees Looking for new lo	1000	Rottweiler	8
8834	Adpoted	adpoted	1000	Shih_Tzu	24
4844	Coda	She is pure breed Siberian husky. Born at July	1000	Siberian_Husky	7
9745	Oscar	Oscar was found in Ara Damansara recently. My	800	Rottweiler	24
9782	no_name	Available open for booking cute kitten Solid w	800	Persian	1
14454	no_name	Looking for serius buyer Only female 2 month p	750	Persian	2
11687	no_name	Open for adoption! They are a family of a set	750	Dilute_Tortoiseshell	12

#### In [83]:

```
plt.figure(figsize=(16, 6));
plt.subplot(1, 2, 1)
plt.hist(data.loc[data['Fee'] < 400, 'Fee'])
plt.grid(axis='y')
plt.title('Distribution of fees lower than 400')</pre>
```

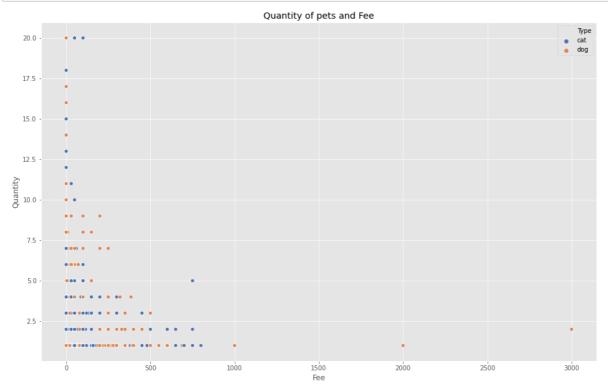
#### Out[83]:

Text(0.5, 1.0, 'Distribution of fees lower than 400')



#### In [84]:

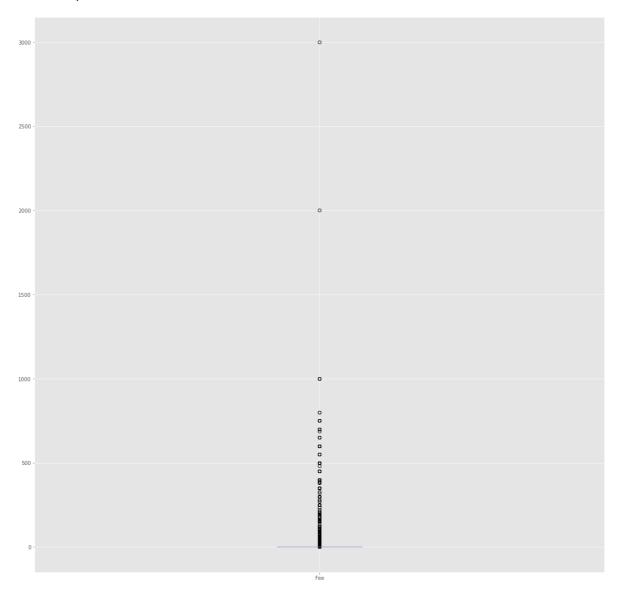
```
plt.style.use('ggplot')
plt.figure(figsize=(16, 10));
sns.scatterplot(x="Fee", y="Quantity", hue="Type",data=data, palette = "deep");
plt.title('Quantity of pets and Fee');
```



## In [85]:

```
data["Fee"].plot.box(figsize=(20,20))
# Что делать в этом случае?
```

## Out[85]:

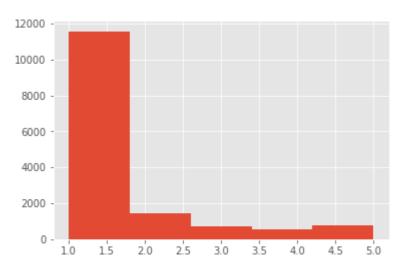


#### In [86]:

```
data["Quantity"] = data["Quantity"].apply(lambda x: x if x <= 5 else 5)
data["Fee"] = data["Fee"].apply(lambda x: x if x <= 500 else 500)
data["Quantity"].hist(bins=5)</pre>
```

#### Out[86]:

#### <AxesSubplot:>

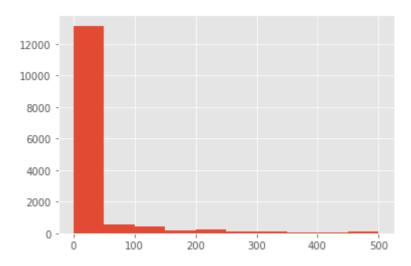


#### In [87]:

```
data["Fee"].hist()
```

#### Out[87]:

#### <AxesSubplot:>



# Месторасположение

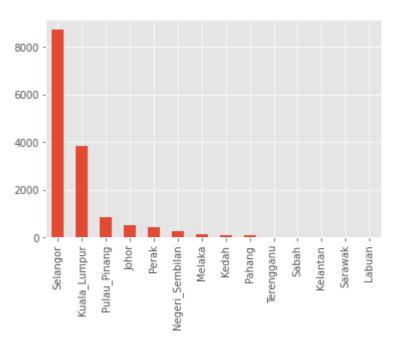
```
In [88]:
data["State"].value_counts()
Out[88]:
41326
         8714
41401
         3845
41327
          843
41336
          507
41330
          420
41332
          253
41324
          137
41325
          110
41335
           85
41361
           26
41345
           22
           15
41367
41342
           13
41415
            3
Name: State, dtype: int64
In [89]:
states_dict = {k: v for k, v in zip(states['StateID'], states['StateName'])}
states_dict
Out[89]:
{41336: 'Johor',
41325: 'Kedah',
 41367: 'Kelantan',
 41401: 'Kuala Lumpur',
41415: 'Labuan',
 41324: 'Melaka',
 41332: 'Negeri Sembilan',
 41335: 'Pahang',
 41330: 'Perak',
41380: 'Perlis',
 41327: 'Pulau Pinang',
 41345: 'Sabah',
 41342: 'Sarawak',
 41326: 'Selangor',
 41361: 'Terengganu'}
In [90]:
data['State_name'] = data['State'].apply(lambda x: '_'.join(states_dict[x].split()) if x in
```

#### In [91]:

```
data['State_name'].value_counts().plot.bar()
```

## Out[91]:

#### <AxesSubplot:>



## In [92]:

data['State\_name'].value\_counts()

#### Out[92]:

Selangor	8714
Kuala_Lumpur	3845
Pulau_Pinang	843
Johor	507
Perak	420
Negeri_Sembilan	253
Melaka	137
Kedah	110
Pahang	85
Terengganu	26
Sabah	22
Kelantan	15
Sarawak	13
Labuan	3

Name: State\_name, dtype: int64

```
In [93]:
print(data['State_name'].value_counts(normalize=True).head(6).sum())
data['State_name'].value_counts(normalize=True).head(6)
0.9725872073634363
Out[93]:
Selangor
                   0.581205
Kuala_Lumpur
                   0.256453
Pulau_Pinang
                   0.056226
Johor
                   0.033816
Perak
                   0.028013
Negeri_Sembilan
                   0.016875
Name: State_name, dtype: float64
In [94]:
data.shape
14993*0.9725872073634363
Out[94]:
14582.0
In [95]:
state_in = ['Selangor', 'Kuala_Lumpur', 'Pulau_Pinang', 'Johor', 'Perak', 'Negeri_Sembilan'
data["State_name"] = data["State_name"].apply(lambda x: np.nan if x not in state_in else x)
In [96]:
data.dropna(inplace=True)
In [97]:
data.shape
Out[97]:
(14582, 36)
In [98]:
data['State_name'].value_counts()
Out[98]:
Selangor
                   8714
Kuala_Lumpur
                   3845
                    843
Pulau_Pinang
Johor
                    507
Perak
                    420
Negeri Sembilan
                     253
Name: State_name, dtype: int64
```

## ID тех, кто отдаёт питомцев

#### In [99]:

```
data["RescuerID"].value_counts()
```

#### Out[99]:

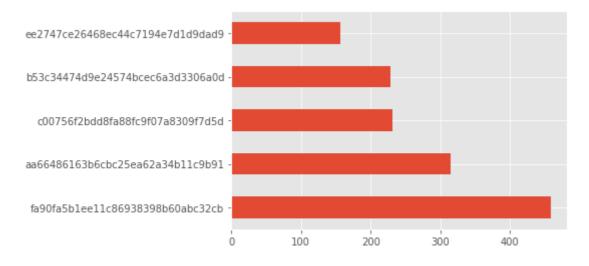
```
fa90fa5b1ee11c86938398b60abc32cb
                                     459
aa66486163b6cbc25ea62a34b11c9b91
                                     315
c00756f2bdd8fa88fc9f07a8309f7d5d
                                     231
b53c34474d9e24574bcec6a3d3306a0d
                                     228
ee2747ce26468ec44c7194e7d1d9dad9
                                     156
22414cc92d4bbd1571fa0cd246cb591b
                                       1
93f135ddaf72b4ed1b60521fdeab9426
                                       1
e928450b5c3ee09ec5c378459a043916
                                       1
566ba0fd7393d94d0a98df0354be3b5c
                                       1
7e1b8f045013ae6e1cd40f5cca103d9f
                                       1
Name: RescuerID, Length: 5415, dtype: int64
```

#### In [100]:

```
data["RescuerID"].value_counts().head().plot.barh()
```

#### Out[100]:

#### <AxesSubplot:>



#### In [101]:

```
st = set(data["RescuerID"].value_counts().values)
dict_resc = dict(data["RescuerID"].value_counts())
st = list(st)
st.sort(reverse=True)
dict_rank = dict()
i = 1
for x in st:
    dict_rank[x] = i
    i += 1
data["RankRescuer"] = data["RescuerID"].apply(lambda x: dict_rank[dict_resc[x]])
```

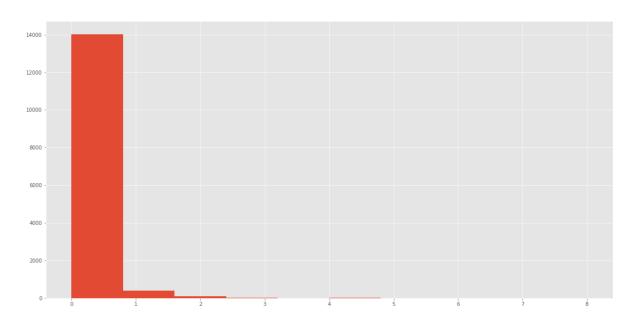
## Количество видео

#### In [102]:

```
data['VideoAmt'].hist(figsize=(20,10))
```

## Out[102]:

#### <AxesSubplot:>



## In [103]:

data["VideoAmt"].value\_counts(normalize=True)

## Out[103]:

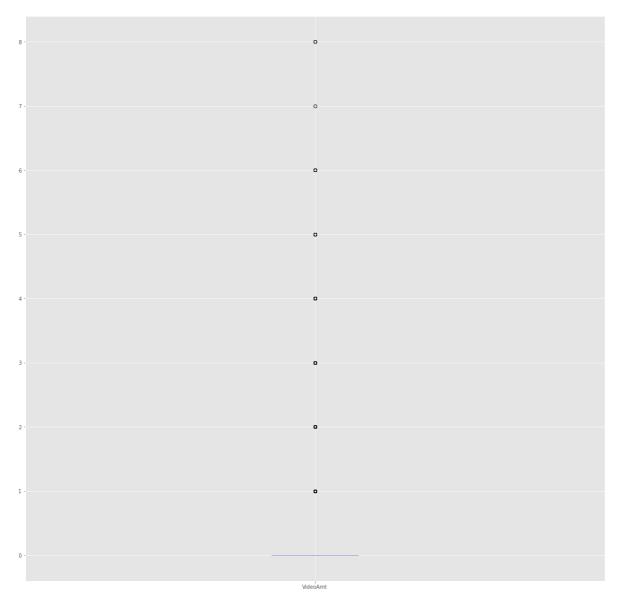
- 0 0.961185
- 1 0.028323
- 2 0.006241
- 3 0.002400
- 4 0.001029
- 5 0.000343
- 6 0.000274
- 8 0.000137
- 7 0.000069

Name: VideoAmt, dtype: float64

## In [104]:

```
data["VideoAmt"].plot.box(figsize=(20,20))
```

## Out[104]:



#### In [105]:

```
data["has_video"] = data["VideoAmt"].apply(lambda x: 1 if x > 0 else 0)
data[data["has_video"] == 1][["VideoAmt", "has_video"]]
```

#### Out[105]:

	VideoAmt	has_video
76	1	1
88	3	1
89	4	1
125	1	1
153	1	1
14892	1	1
14897	2	1
14950	1	1
14960	1	1
14966	1	1

566 rows × 2 columns

# Количество фото

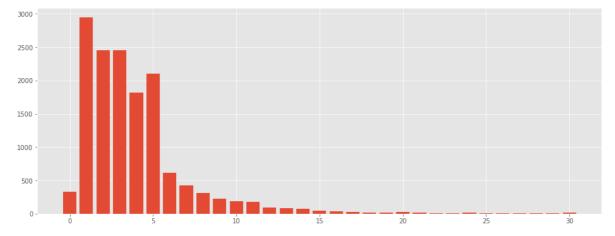
#### In [106]:

```
print(F'Maximum amount of photos in {data["PhotoAmt"].max()}')
```

Maximum amount of photos in 30.0

## In [107]:

```
index = range(0, 31)
values = data['PhotoAmt'].value_counts().sort_index().to_numpy()
plt.figure(figsize=(16, 6));
plt.bar(index,values)
plt.show()
```

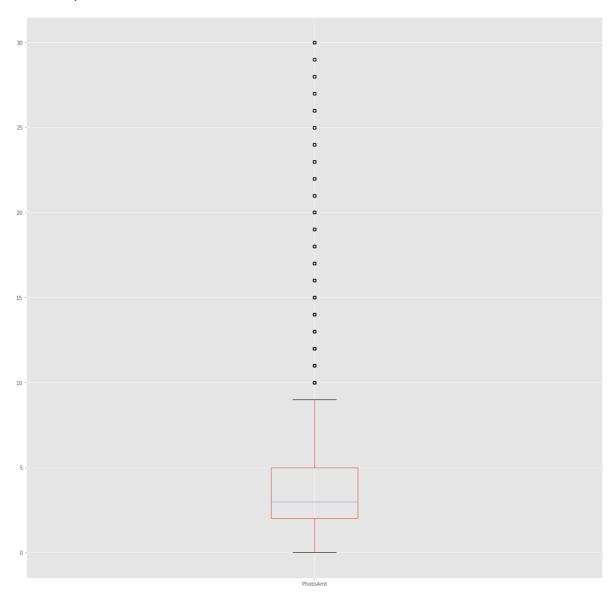


#### In [108]:

```
data["PhotoAmt"].plot.box(figsize=(20,20))
```

#### Out[108]:

#### <AxesSubplot:>



#### In [109]:

```
index,para = outlier_detect_IQR(data=data,col='PhotoAmt',threshold=1)
print('Верхняя граница:',para[0],'\nНижняя граница:',para[1])
```

Количество выбросов в данных: 1131 Доля выбросов: 0.07756137704018654

Верхняя граница: 8.0 Нижняя граница: -1.0

#### In [110]:

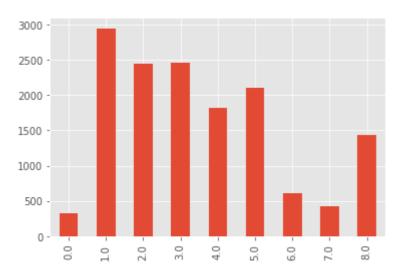
data = impute\_outlier\_with\_arbitrary(data=data,outlier\_index=index, value= 8, col=['PhotoAm

#### In [111]:

```
data['PhotoAmt'].value_counts().sort_index().plot.bar()
```

## Out[111]:

#### <AxesSubplot:>

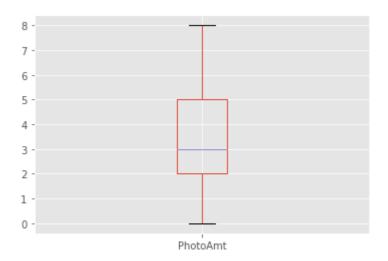


## In [112]:

```
data['PhotoAmt'].plot.box()
```

## Out[112]:

## <AxesSubplot:>



## Описание

#### In [113]:

#### Top words in description food gentle live 🛮 care ase contact really friend make ıve $oldsymbol{\circ}$ adorable orever alr eady home place o ed sibling dewormed JSe stray pt acium eadv back look 8 name care Le play currently pet male abandoned area eat goods much due born ea⊥ home email pupple good interested

## In [103]:

```
sentiment_dict = {}
for filename in os.listdir('../petfinder/train_sentiment/'):
    with open('../petfinder/train_sentiment/' + filename, 'r', errors='ignore') as f:
        sentiment = json.load(f)
    pet_id = filename.split('.')[0]
    sentiment_dict[pet_id] = {}
    sentiment_dict[pet_id]['magnitude'] = sentiment['documentSentiment']['magnitude']
    sentiment_dict[pet_id]['score'] = sentiment['documentSentiment']['score']
    sentiment_dict[pet_id]['language'] = sentiment['language']
```

#### In [104]:

data['lang'] = data['PetID'].apply(lambda x: sentiment\_dict[x]['language'] if x in sentimen
data['magnitude'] = data['PetID'].apply(lambda x: sentiment\_dict[x]['magnitude'] if x in se
data['score'] = data['PetID'].apply(lambda x: sentiment\_dict[x]['score'] if x in sentiment\_
data

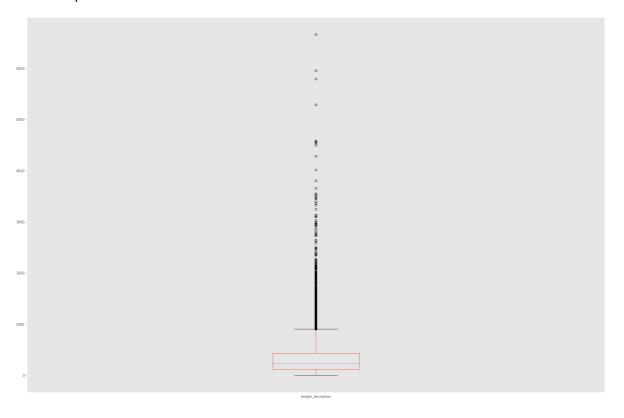
## Out[104]:

	Туре	Name	Age	Breed1	Breed2	Gender	Color1	Color2	Color3	MaturitySize	 full_c
0	cat	Nibble	3	299	0	1	1	7	0	1	 BlackV
1	cat	no_name	1	265	0	1	1	2	0	2	 BlackB
2	dog	Brisco	1	307	0	1	2	7	0	2	 Brown√
3	dog	Miko	4	307	0	2	1	2	0	2	 BlackB
4	dog	Hunter	1	307	0	1	1	0	0	2	 E
14988	cat	no_name	2	266	0	3	1	0	0	2	 E
14989	cat	Serato & Eddie	24	265	264	3	1	4	7	2	 BlackYellow\
14990	cat	Monkies	2	265	266	3	5	6	7	3	 CreamGray\
4											•

#### In [105]:

```
data["lenght_decription"] = data["Description"].apply(lambda x: len(x))
data["lenght_decription"].plot.box(figsize = (30, 20))
```

#### Out[105]:



#### In [106]:

```
index,para = outlier_detect_IQR(data=data,col='lenght_decription',threshold=1)
print('Верхняя граница:',para[0],'\nНижняя граница:',para[1])
```

Количество выбросов в данных: 1334 Доля выбросов: 0.0914826498422713

Верхняя граница: 748.0 Нижняя граница: -197.0

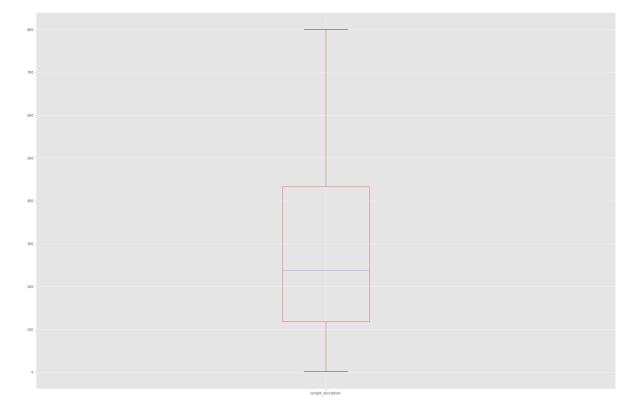
#### In [107]:

data = impute\_outlier\_with\_arbitrary(data=data,outlier\_index=index, value= 800, col=['lengh

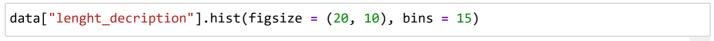
#### In [108]:

```
data["lenght_decription"].plot.box(figsize = (30, 20))
```

#### Out[108]:

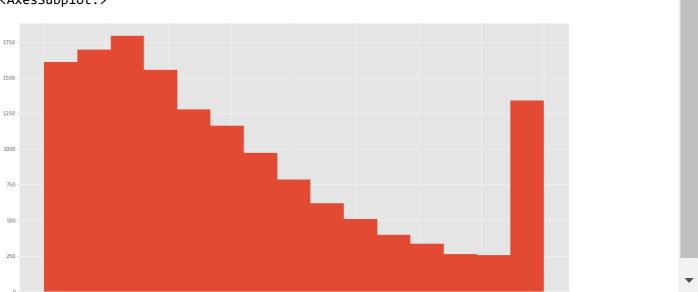


#### In [109]:



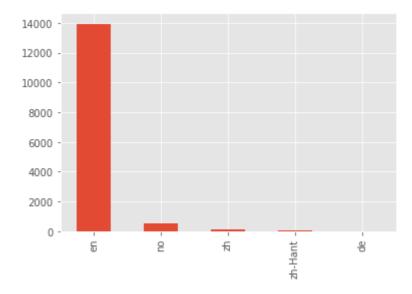
## Out[109]:

## <AxesSubplot:>



## In [110]:

## Out[110]:



```
In [111]:
```

```
data["lang"].value_counts()
```

#### Out[111]:

en 13939 no 511 zh 94 zh-Hant 36 de 2

Name: lang, dtype: int64

#### In [112]:

```
data[data["lang"] == 'zh']["Description"][1002] # китайский (упрощенный)
```

#### Out[112]:

'小豹纹是一只两个月大的女生。她的性格非常活泼可爱。现在寻找一个有爱心,有耐心和有经济能力的有缘人来领养她。请一定要带她打三支预防针,过后每年打一支以及每个月放猫虱药。 漂亮可爱的她在等着你带她回去哦!'

#### In [113]:

```
data[data["lang"] == 'en']["Description"][4] # английский
```

#### Out[113]:

"This handsome yet cute boy is up for adoption. He is the most playful pal we've seen in our puppies. He loves to nibble on shoelaces, Chase you at such a young age. Imagine what a cute brat he will be when he grows. We are looking for a loving home for Hunter, one that will take care of him and give him the love that he needs. Please call urgently if you would like to adopt this cutie."

#### In [114]:

```
data[data["lang"] == 'zh-Hant']["Description"][571] # китайский (традиционный)
```

#### Out[114]:

'有人可以給孩子們一個家嗎? 有養貓經驗者優先... Whatsapp 救起來時,滿身黑油,好可 憐,可以給孩子一個家嗎? Puchong area..... 性格比较害怕人,只可以养在室内, 要有养猫经验,要有耐心和他接触。。......'

#### In [115]:

```
data[data["lang"] == 'de']["Description"][14314] # немецкий
```

#### Out[115]:

'Kiki Sgt manja dan aktiv.'

#### In [116]:

```
data.shape
```

#### Out[116]:

(14582, 42)

#### In [117]:

```
data["lang"] = data["lang"].apply(lambda x: np.nan if x == 'de' else x)
data.dropna(inplace=True)
data.shape
```

#### Out[117]:

(14580, 42)

#### In [118]:

```
data["lang"].value_counts()
```

#### Out[118]:

en 13939 no 511 zh 94 zh-Hant 36

Name: lang, dtype: int64

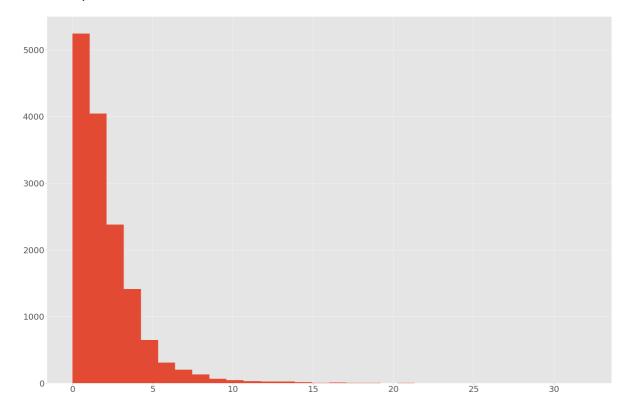
#### In [119]:

```
data["lang"] = data["lang"].apply(lambda x: 'zh' if x == 'zh-Hant' else x)
```

#### In [120]:

```
data["magnitude"].hist(bins = 30, figsize = (30, 20), xlabelsize=25, ylabelsize=25)
```

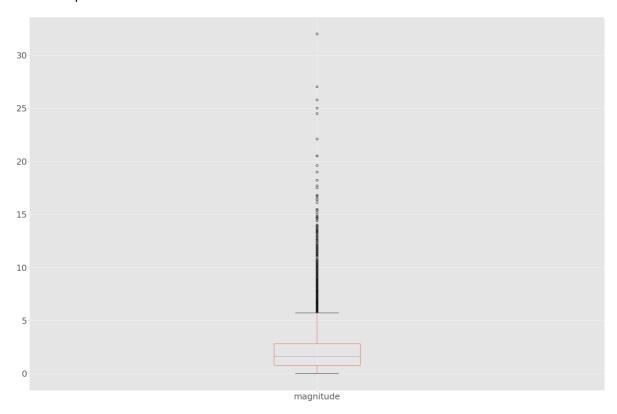
## Out[120]:



## In [121]:

```
data["magnitude"].plot.box(fontsize=25, figsize=(30,20))
```

## Out[121]:



#### In [122]:

```
d_neg = data[data["score"] < -0.25][["Description", "score", "magnitude"]]
d_neg[d_neg["magnitude"] > 2]
```

#### Out[122]:

	Description	score	magnitude
540	Meet Baby Rosemary, one of the puppies that we	-0.4	4.1
1544	Her name is Nicky She was dumped by her owner	-0.3	2.1
1981	please help me rescue this little babyhe's a	-0.3	3.5
2603	I found these poor kittens in Taipan, Subang	-0.3	4.0
4561	Sep SPCA Ampang is relocating to a smaller pla	-0.3	2.9
7271	I found her & her brother wandering about near	-0.3	2.5
7566	Latte is one of three kittens that were rescue	-0.3	4.6
8046	suspected 2b lost, but posted everywhere tryin	-0.3	3.0
8668	4 year old female siberian husky for adoption	-0.3	4.1
8915	I found him when he was about 4 months, at our	-0.3	2.7
10583	A mother cat gave birth to six kittens near my	-0.3	2.5
10631	I found these poor kittens in Taipan, Subang	-0.3	4.0
10744	My friend rescued a toy poodle from drainage n	-0.4	3.2
12431	Found this little baby running on the road whe	-0.4	2.3
12958	Spotty is a beige color local female puppy. Va	-0.5	3.0
14541	***11 days left!!! ***The time is running out	-0.3	6.3
14688	Her name is White She was dumped by her owner $\dots$	-0.3	2.1
14827	Coffee, 9 months old Doberman mix. Male. 2 mon	-0.3	2.9

#### In [123]:

```
index,para = outlier_detect_IQR(data=data,col='magnitude',threshold=1)
print('Верхняя граница:',para[0],'\nНижняя граница:',para[1])
```

Количество выбросов в данных: 1078 Доля выбросов: 0.07393689986282578

Верхняя граница: 4.8

Нижняя граница: -1.199999999999997

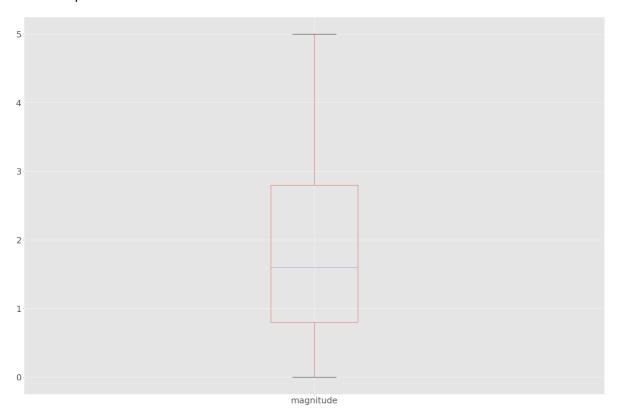
#### In [124]:

```
data = impute_outlier_with_arbitrary(data=data,outlier_index=index, value= 5, col=['magnitu
```

## In [125]:

```
data["magnitude"].plot.box(fontsize=25, figsize=(30,20))
```

## Out[125]:



#### In [126]:



# Информация с Google Vision API

#### In [127]:

```
metadata dict = {}
i = 0
for filename in os.listdir('../petfinder/train metadata/'):
     with open('../petfinder/train metadata/' + filename, 'r', errors='ignore') as f:
          metadata = json.load(f)
     pet id = filename.split('.')[0]
     if pet_id[-1] == '1':
          metadata_dict[pet_id[:-2]] = {}
          if 'labelAnnotations' in metadata:
                index = 0
               for i in range(0, len(metadata['labelAnnotations'])):
                     desc = metadata['labelAnnotations'][i]['description']
                     if desc.find('dog') != -1 or desc.find('cat') != -1:
                          index = i
                          break
               metadata_dict[pet_id[:-2]]['object_in_img'] = metadata['labelAnnotations'][inde
               metadata_dict[pet_id[:-2]]['score_in_img'] = metadata['labelAnnotations'][index
               metadata_dict[pet_id[:-2]]['object_in_img'] = 'no'
               metadata_dict[pet_id[:-2]]['score_in_img'] = 0
metadata_dict
Out[127]:
{'0008c5398': {'object_in_img': 'cat', 'score_in_img': 0.9943703},
 '000a290e4': {'object_in_img': 'dog', 'score_in_img': 0.96414083}, '000fb9572': {'object_in_img': 'dog', 'score_in_img': 0.97213346}, '0011d7c25': {'object_in_img': 'cat', 'score_in_img': 0.9923178},
 '00156db4a': {'object_in_img': 'dog', 'score_in_img': 0.95605063},
 '001a1aaad': {'object_in_img': 'cat', 'score_in_img': 0.97333777},
 '001b1507c': {'object_in_img': 'cat', 'score_in_img': 0.99399006},
 '002230dea': {'object_in_img': 'cat', 'score_in_img': 0.6242952}, '002278114': {'object_in_img': 'skin', 'score_in_img': 0.9343813}, '002278114-': {'object_in_img': 'cat', 'score_in_img': 0.99444574}, '0025a8313': {'object_in_img': 'cat', 'score_in_img': 0.97613597}, '0038234c6': {'object_in_img': 'dog', 'score_in_img': 0.9712321},
 '0038c9343': {'object_in_img': 'dog', 'score_in_img': 0.9496203},
 '003dd2e26': {'object_in_img': 'cat', 'score_in_img': 0.91389936},
 '0045ed62a': {'object_in_img': 'cat', 'score_in_img': 0.99238837},
 '004709939': {'object_in_img': 'cat', 'score_in_img': 0.9907051}, '004a26127': {'object_in_img': 'dog', 'score_in_img': 0.9645945},
 '004c2f355': {'ohiect in img': 'cat'. 'score in img': 0.9947366}.
```

#### In [128]:

```
data['object_in_img'] = data['PetID'].apply(lambda x: metadata_dict[x]['object_in_img'] if
data['score_in_img'] = data['PetID'].apply(lambda x: metadata_dict[x]['score_in_img'] if x
data
```

#### Out[128]:

	Туре	Name	Age	Breed1	Breed2	Gender	Color1	Color2	Color3	MaturitySize	
0	cat	Nibble	3	299	0	1	1	7	0	1	
1	cat	no_name	1	265	0	1	1	2	0	2	
2	dog	Brisco	1	307	0	1	2	7	0	2	
3	dog	Miko	4	307	0	2	1	2	0	2	
4	dog	Hunter	1	307	0	1	1	0	0	2	
14988	cat	no_name	2	266	0	3	1	0	0	2	
14989	cat	Serato & Eddie	24	265	264	3	1	4	7	2	
14990	cat	Monkies	2	265	266	3	5	6	7	3	
14991	cat	Ms Daym	9	266	0	2	4	7	0	1	
14992	dog	Fili	1	307	307	1	2	0	0	2	

14580 rows × 44 columns

**→** 

#### In [129]:

```
data["object_in_img"].value_counts()
```

#### Out[129]:

```
cat
                     6273
                     5875
dog
dog breed
                     1193
dog like mammal
                      646
no
                      333
clothing
                         1
hair
                         1
hand
                         1
                         1
meal
                        1
road
```

Name: object\_in\_img, Length: 64, dtype: int64

#### In [130]:

```
data["object_in_img"] = data["object_in_img"].apply(lambda x: "cat" if x.find("cat") != -1
```

## In [131]:

```
data["object_in_img"].value_counts()
```

## Out[131]:

Out[131]:		
dog	7802	
cat	6323	
no	333	
fauna	23	
mammal	11	
cage	8	
plant	5	
floor	4	
furniture	4	
structure	4	
yellow		
blue	2	
skin	2	
car	2	
	) )	
text	כ ז	
face	3	
textile	2	
grass	2	
black	2	
light	3 3 3 3 3 2 2 2 2 2 2 2 2	
animal shelter	2	
product	2	
vertebrate	2	
fur	2	
hand	1	
rock	1	
window	1	
plush	1	
leg	1	
fashion accessory	1	
photo caption	1	
wheel	1	
footwear	1	
white	1	
iron	1	
facial hair	1	
wildlife	1	
room	1	
stairs	1	
collage	1	
road	1	
whiskers	1	
property	1	
pink	1	
people	1	
nature reserve	1	
red	1	
hair	1	
stuffed toy	1	
meal	1	
wood	1	
clothing	1	
snout	1	
Name: object in imp	_	int

Name: object\_in\_img, dtype: int64

```
In [132]:
```

```
data["object_in_img"].value_counts().drop('dog').drop('cat').drop('no').sum()
```

#### Out[132]:

122

#### In [133]:

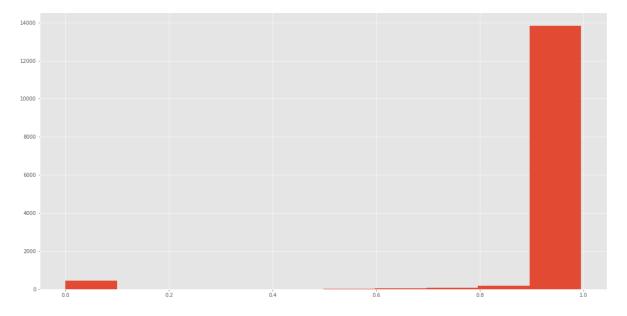
```
data["object_in_img"] = data["object_in_img"].apply(lambda x: "cat" if x.find("cat") != -1
data.loc[data["object_in_img"] == 'no', "score_in_img"] = 0
```

#### In [134]:

```
data["score_in_img"].hist(figsize=(20,10))
```

#### Out[134]:

#### <AxesSubplot:>

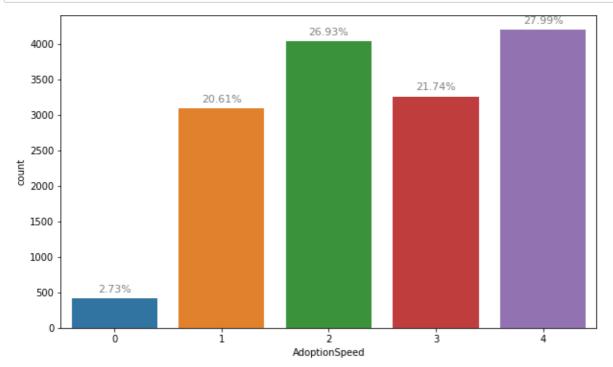


# **Целевая переменная (скорость, с которой заберут питомца)**

- 0 питомец был принят в семью в тот же день, как его занесли в список
- 1 животное было принято в семью в период от 1 до 7 дней (1 неделя) после внесения в список
- 2 животное было принято в семью в период от 8 до 30 дней (1 месяц) после внесения в список
- 3 животное было принято в семью в период от 31 до 90 дней (2-3 месяц) после внесения в список
- 4 животное не было принято в семью после 100 дней ожидания

#### In [10]:

```
plt.figure(figsize=(10, 6));
g = sns.countplot(x='AdoptionSpeed', data=data)
# plt.title('Количество животных в каждом из классов');
ax=g.axes
for p in ax.patches:
    ax.annotate(f"{p.get_height() * 100 / data.shape[0]:.2f}%", (p.get_x() + p.get_width() ha='center', va='center', fontsize=11, color='gray', rotation=0, xytext=(0, 10), textcoords='offset points')
```



#### In [11]:

```
data["AdoptionSpeed"].value_counts()
```

#### Out[11]:

- 4 4197 2 4037
- 3 3259
- 1 3090
- 0 410

Name: AdoptionSpeed, dtype: int64

# Выбираем признаки для обучения

#### Препроцессинг

#### In [136]:

```
data.columns
Out[136]:
Index(['Type', 'Name', 'Age', 'Breed1', 'Breed2', 'Gender', 'Color1', 'Color
```

```
'Color3', 'MaturitySize', 'FurLength', 'Vaccinated', 'Dewormed',
'Sterilized', 'Health', 'Quantity', 'Fee', 'State', 'RescuerID',
'VideoAmt', 'Description', 'PetID', 'PhotoAmt', 'AdoptionSpeed',
'No_name', 'Pure_breed', 'Breed1_name', 'Breed2_name', 'Color1_name',
'Color2_name', 'Color3_name', 'full_color', 'full_health', 'one_pet',
'Free', 'State_name', 'RankRescuer', 'has_video', 'lang', 'magnitud'
e',
'score', 'lenght_decription', 'object_in_img', 'score_in_img'],
dtype='object')
```

#### In [137]:

```
data_tree = data.copy()
```

#### In [138]:

```
data_tree["Gender"] = data_tree["Gender"].apply(lambda x: 'male' if x == 1 else ('female' i
data_tree["MaturitySize"] = data_tree["MaturitySize"].apply(lambda x: 'small' if x == 1 els
data_tree["FurLength"] = data_tree["FurLength"].apply(lambda x: 'short' if x == 1 else ('me
data_tree["Vaccinated"] = data_tree["Vaccinated"].apply(lambda x: 'yes' if x == 1 else ('no
data_tree["Dewormed"] = data_tree["Dewormed"].apply(lambda x: 'yes' if x == 1 else ('no' if
data_tree["Sterilized"] = data_tree["Sterilized"].apply(lambda x: 'yes' if x == 1 else ('no
data_tree["Health"] = data_tree["Health"].apply(lambda x: 'Healthy' if x == 1 else ('Minor
```

#### In [139]:

#### In [140]:

#### Out[140]:

	Type	No_name	Age	Breed1	Breed2	Gender	Color1_name	Color2_name	Color3_nan
0	0	0	3	164	0	1	0	5	
1	0	1	1	133	0	1	0	1	
2	1	0	1	172	0	1	1	5	
3	1	0	4	172	0	0	0	1	
4	1	0	1	172	0	1	0	0	
14988	0	1	2	134	0	2	0	0	
14989	0	0	24	133	99	2	0	6	
14990	0	0	2	133	101	2	2	4	
14991	0	0	9	134	0	0	6	5	
14992	1	0	1	172	132	1	1	0	

14580 rows × 28 columns

#### In [141]:

```
X = data_tree.drop('AdoptionSpeed', axis=1)
y = data_tree['AdoptionSpeed']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42, s
X_train.shape, X_test.shape, y_train.shape, y_test.shape
Out[141]:
```

# **Target Encoding + Normalization**

((11664, 27), (2916, 27), (11664,), (2916,))

```
In [142]:
```

```
In [143]:
```

```
ss = StandardScaler().fit(X_train_tar)
X_train_tar = ss.transform(X_train_tar)
X_test_tar = ss.transform(X_test_tar)
y_train_tar = y_train
y_test_tar = y_test
```

## One-Hot Encoding + Normalizaton

```
In [144]:
```

```
to_dummies = [ # переменные, которые сейчас не числовые
    'Gender', 'MaturitySize', 'FurLength', 'Vaccinated', 'Dewormed',
                      'Sterilized', 'Health', 'Color1_name', 'Color2_name', 'Color3_name',
                      'State_name', 'lang', 'object_in_img']
# Закодированные категориальные переменные методом OneHot Encoding
data_ohe = pd.get_dummies(data_tree, columns=to_dummies, drop_first=True)
data_ohe.shape
Out[144]:
(14580, 56)
In [145]:
X ohe = data ohe.drop('AdoptionSpeed', axis=1)
y_ohe = data_ohe['AdoptionSpeed']
X_train_ohe, X_test_ohe, y_train_ohe, y_test_ohe = train_test_split(X_ohe, y_ohe, test_size
X_train_ohe.shape, X_test_ohe.shape, y_train_ohe.shape, y_test_ohe.shape
Out[145]:
((11664, 55), (2916, 55), (11664,), (2916,))
In [146]:
ss = StandardScaler().fit(X_train_ohe)
X_train_ohe = ss.transform(X_train_ohe)
X test ohe = ss.transform(X test ohe)
```

## Построим baseline

Heoбходимо построить baseline. Хороший baseline копирует распределение целевой переменной на train.

#### In [147]:

y\_train.value\_counts(normalize=True) # смотрим изначальное распределение целевой переменной

#### Out[147]:

Name: AdoptionSpeed, dtype: float64

#### In [152]:

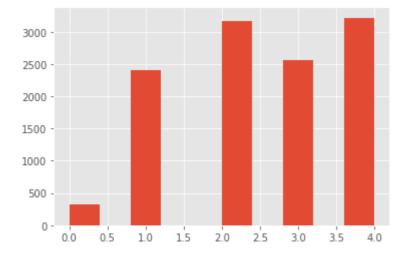
```
y_naive_pred = np.random.choice(
   [4., 2., 3., 1., 0.],
   len(y_test),
   p=y_train.value_counts(normalize=True).values) # р - вероятности
```

Наивное предсказание в точности повторяет распределение тренировочной выборки

#### In [153]:

```
y_train.hist()
```

#### Out[153]:

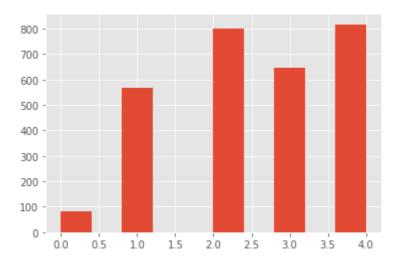


#### In [154]:

```
plt.hist(y_naive_pred)
```

## Out[154]:

(array([ 83., 0., 569., 0., 0., 799., 0., 648., 0., 817.]),
array([0., 0.4, 0.8, 1.2, 1.6, 2., 2.4, 2.8, 3.2, 3.6, 4. ]),
<BarContainer object of 10 artists>)



# In [155]:

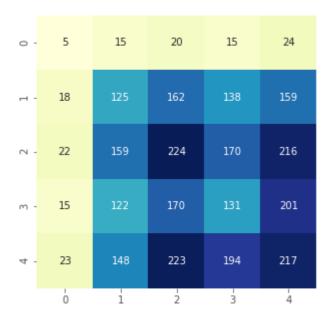
```
print(cohen_kappa_score(y_test, y_naive_pred, weights='quadratic'))

cm = confusion_matrix(y_test, y_naive_pred)

conf_matrix = pd.DataFrame(data = cm, index=range(0, 5), columns=range(0, 5))

plt.figure(figsize = (5,5))
sns.heatmap(conf_matrix, annot=True,fmt='d',cmap="YlGnBu", cbar=False);
# внизу предсказанные метки, слева - истинные метки
```

#### 0.021974708694860734



# Деревья решений

# In [156]:

```
tree_clf = DecisionTreeClassifier(max_depth=2, class_weight='balanced') # кол-во разбиений tree_clf.fit(X_train, y_train)
```

# Out[156]:

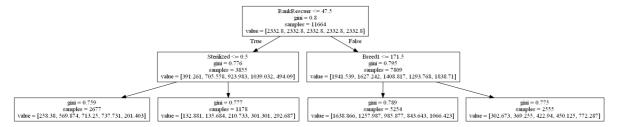
DecisionTreeClassifier(class\_weight='balanced', max\_depth=2)

## In [157]:

```
graph = Source(sklearn.tree.export_graphviz(tree_clf, out_file=None, feature_names=X.column
png_bytes = graph.pipe(format='png')
with open('dtree_pipe.png','wb') as f:
    f.write(png_bytes)

from IPython.display import Image
Image(png_bytes)
```

# Out[157]:



#### In [158]:

```
print(cohen_kappa_score(y_test, tree_clf.predict(X_test), weights='quadratic'))
```

#### 0.09047269931245372

#### In [159]:

```
tree_clf = DecisionTreeClassifier(max_depth=2, class_weight='balanced') # кол-во разбиений tree_clf.fit(X_train_ohe, y_train_ohe)
```

#### Out[159]:

DecisionTreeClassifier(class\_weight='balanced', max\_depth=2)

#### In [160]:

```
print(cohen_kappa_score(y_test_ohe, tree_clf.predict(X_test_ohe), weights='quadratic'))
```

#### 0.09047269931245372

## In [161]:

```
tree_clf = DecisionTreeClassifier(max_depth=2, class_weight='balanced') # кол-во разбиений tree_clf.fit(X_train_tar, y_train_tar)
```

#### Out[161]:

DecisionTreeClassifier(class\_weight='balanced', max\_depth=2)

#### In [162]:

```
print(cohen_kappa_score(y_test_tar, tree_clf.predict(X_test_tar), weights='quadratic'))
```

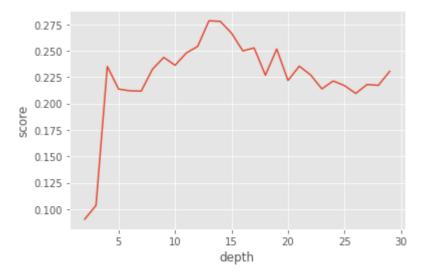
#### 0.09047269931245372

# In [163]:

```
scores =[]
for depth in range(2, 30):
    tree_clf = DecisionTreeClassifier(max_depth=depth, class_weight='balanced')
    tree_clf.fit(X_train, y_train)
    scores.append(cohen_kappa_score(y_test, tree_clf.predict(X_test), weights='quadratic'))
```

## In [164]:

```
plt.plot(range(2, 30), scores)
plt.xlabel('depth')
plt.ylabel('score')
plt.show()
```



# In [165]:

```
# функция для подбора наилучших параметров

def grid_search_cv(model, param_grid, x_train, y_train):
    kfold = StratifiedKFold(n_splits=10, shuffle=True, random_state=7)
    kappa_scorer = make_scorer(cohen_kappa_score, weights = 'quadratic')
    grid_search = GridSearchCV(model, param_grid, cv=kfold, scoring=kappa_scorer, verbose=4
    t_start = time.time()
    grid_search.fit(x_train, y_train)
    t_end = time.time()
    print('model {} best score is {}'.format(model.__class__.__name__, grid_search.best_sco
    print('time for training is {} seconds'.format(t_end - t_start))
    print(f"Best params = {grid_search.best_estimator_}")
    return grid_search.best_estimator_
```

## In [166]:

```
# функция для подбора наилучших параметров

def randomized_cv(model, param_grid, x_train, y_train, n_iter = 20):
    kfold = StratifiedKFold(n_splits=10, shuffle=True, random_state=7)
    kappa_scorer = make_scorer(cohen_kappa_score, weights = 'quadratic')
    grid_search = RandomizedSearchCV(model, param_grid, cv=kfold, scoring=kappa_scorer, ver
    t_start = time.time()
    grid_search.fit(x_train, y_train)
    t_end = time.time()
    print('model {} best accuracy score is {}'.format(model._class_.__name__, grid_search
    print('time for training is {} seconds'.format(t_end - t_start))
    print(grid_search.best_score_)
    print(f"Best params = {grid_search.best_estimator_}")
    return grid_search.best_estimator_
```

# In [167]:

```
param grid = {
    'max_depth': range(2,30),
    'min_samples_leaf': list(range(3,11)), # минимальное количество наблюдений в листе
    'class_weight': [None, 'balanced'],
    'criterion': ["gini", "entropy"]
tree_model = grid_search_cv(DecisionTreeClassifier(random_state=42), param_grid, X_train, y
Fitting 10 folds for each of 896 candidates, totalling 8960 fits
[CV 1/10] END class_weight=None, criterion=gini, max_depth=2, min_samples_
leaf=3; total time=
                      0.0s
[CV 2/10] END class weight=None, criterion=gini, max depth=2, min samples
leaf=3; total time=
                     0.0s
[CV 3/10] END class_weight=None, criterion=gini, max_depth=2, min_samples_
leaf=3; total time=
                      0.0s
[CV 4/10] END class_weight=None, criterion=gini, max_depth=2, min_samples_
leaf=3; total time=
[CV 5/10] END class_weight=None, criterion=gini, max_depth=2, min_samples_
leaf=3; total time=
                      0.0s
[CV 6/10] END class_weight=None, criterion=gini, max_depth=2, min_samples_
leaf=3; total time=
[CV 7/10] END class_weight=None, criterion=gini, max_depth=2, min_samples_
leaf=3; total time=
[CV 8/10] END class weight=None, criterion=gini, max depth=2, min samples
leaf=3; total time=
[CV 9/10] END class_weight=None, criterion=gini, max_depth=2, min_samples_
leaf=3; total time=
                      0.0s
```

## In [168]:

```
Fitting 10 folds for each of 896 candidates, totalling 8960 fits
[CV 1/10] END class weight=None, criterion=gini, max depth=2, min samples
leaf=3; total time=
                      0.0s
[CV 2/10] END class_weight=None, criterion=gini, max_depth=2, min_samples_
leaf=3; total time=
                      0.0s
[CV 3/10] END class_weight=None, criterion=gini, max_depth=2, min_samples_
leaf=3; total time=
                      0.0s
[CV 4/10] END class weight=None, criterion=gini, max depth=2, min samples
leaf=3; total time=
                      0.0s
[CV 5/10] END class_weight=None, criterion=gini, max_depth=2, min_samples_
leaf=3; total time=
                      0.0s
[CV 6/10] END class_weight=None, criterion=gini, max_depth=2, min_samples_
leaf=3; total time=
                      0.0s
[CV 7/10] END class_weight=None, criterion=gini, max_depth=2, min_samples_
leaf=3; total time=
                      0.05
[CV 8/10] END class_weight=None, criterion=gini, max_depth=2, min_samples_
leaf=3; total time=
                      0.0s
[CV 9/10] END class_weight=None, criterion=gini, max_depth=2, min_samples_
leaf=3; total time=
                      0.0s
```

tree model = grid search cv(DecisionTreeClassifier(random state=42), param grid, X train oh

## In [169]:

```
tree_model = grid_search_cv(DecisionTreeClassifier(random_state=42), param_grid, X_train_ta
```

```
Fitting 10 folds for each of 896 candidates, totalling 8960 fits
[CV 1/10] END class_weight=None, criterion=gini, max_depth=2, min_samples_
leaf=3; total time=
                     0.0s
[CV 2/10] END class_weight=None, criterion=gini, max_depth=2, min_samples_
leaf=3; total time=
[CV 3/10] END class_weight=None, criterion=gini, max_depth=2, min_samples_
leaf=3; total time=
                     0.0s
[CV 4/10] END class_weight=None, criterion=gini, max_depth=2, min_samples_
leaf=3; total time=
                     0.0s
[CV 5/10] END class_weight=None, criterion=gini, max_depth=2, min_samples_
leaf=3; total time=
                     0.0s
[CV 6/10] END class_weight=None, criterion=gini, max_depth=2, min_samples_
leaf=3; total time=
                     0.0s
[CV 7/10] END class weight=None, criterion=gini, max depth=2, min samples
leaf=3; total time=
                     0.0s
[CV 8/10] END class_weight=None, criterion=gini, max_depth=2, min_samples_
leaf=3; total time=
                     0.0s
[CV 9/10] END class_weight=None, criterion=gini, max_depth=2, min_samples_
leaf=3; total time=
                     0.0s
```

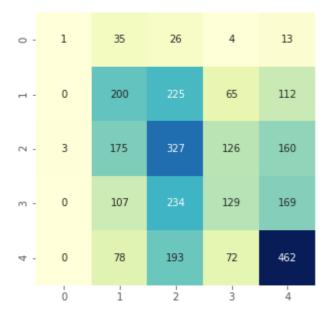
# In [195]:

```
t_start = time.time()
tree_clf = DecisionTreeClassifier(max_depth=8, min_samples_leaf=3, random_state=42) # κοπ-6
tree_clf.fit(X_train, y_train)
t_end = time.time()

print(f" Score = {cohen_kappa_score(y_test, tree_clf.predict(X_test), weights='quadratic')}
print(f"Time = {t_end - t_start} seconds")

cm = confusion_matrix(y_test, tree_clf.predict(X_test))
conf_matrix = pd.DataFrame(data = cm, index=range(0, 5), columns=range(0, 5))
plt.figure(figsize = (5,5))
sns.heatmap(conf_matrix, annot=True,fmt='d',cmap="YlGnBu", cbar=False);
```

Score = 0.3315742536320757 Time = 0.09474682807922363 seconds



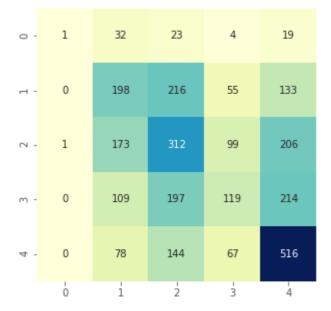
# In [196]:

```
t_start = time.time()
tree_clf = DecisionTreeClassifier(max_depth=8, min_samples_leaf=3, random_state=42)
tree_clf.fit(X_train_ohe, y_train_ohe)
t_end = time.time()

print(f" Score = {cohen_kappa_score(y_test_ohe, tree_clf.predict(X_test_ohe), weights='quad
print(f"Time = {t_end - t_start} seconds")

cm = confusion_matrix(y_test_ohe, tree_clf.predict(X_test_ohe))
conf_matrix = pd.DataFrame(data = cm, index=range(0, 5), columns=range(0, 5))
plt.figure(figsize = (5,5))
sns.heatmap(conf_matrix, annot=True,fmt='d',cmap="YlGnBu", cbar=False);
```

Score = 0.3350237954505293 Time = 0.14860272407531738 seconds



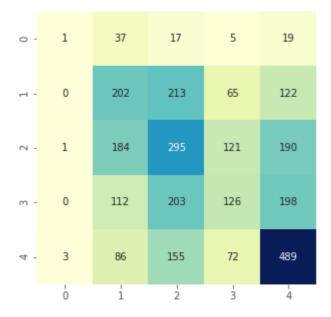
# In [197]:

```
t_start = time.time()
tree_clf = DecisionTreeClassifier(max_depth=8, min_samples_leaf=3, random_state=42)
tree_clf.fit(X_train_tar, y_train_tar)
t_end = time.time()

print(f" Score = {cohen_kappa_score(y_test_tar, tree_clf.predict(X_test_tar), weights='quad
print(f"Time = {t_end - t_start} seconds")

cm = confusion_matrix(y_test_tar, tree_clf.predict(X_test_tar))
conf_matrix = pd.DataFrame(data = cm, index=range(0, 5), columns=range(0, 5))
plt.figure(figsize = (5,5))
sns.heatmap(conf_matrix, annot=True,fmt='d',cmap="YlGnBu", cbar=False);
```

Score = 0.3218469396835203 Time = 0.09873580932617188 seconds



#### In [194]:

```
import warnings
warnings.filterwarnings("ignore")
```

# Логистическая регрессия

```
In [198]:
```

```
log_reg = LogisticRegression()
log_reg.fit(X_train, y_train)
print(cohen_kappa_score(y_test, log_reg.predict(X_test), weights='quadratic'))
```

#### 0.16762819323035805

### In [199]:

```
log_reg = LogisticRegression()
log_reg.fit(X_train_ohe, y_train_ohe)
print(cohen_kappa_score(y_test_ohe, log_reg.predict(X_test_ohe), weights='quadratic'))
```

#### 0.3127792475934328

#### In [200]:

```
log_reg = LogisticRegression()
log_reg.fit(X_train_tar, y_train_tar)
print(cohen_kappa_score(y_test_tar, log_reg.predict(X_test_tar), weights='quadratic'))
```

#### 0.3183727797097937

## In [201]:

```
param_grid = {
    'C': [0.1, 0.3, 0.5, 1.0],
    'class_weight': [None, 'balanced'],
    'solver': ['newton-cg', 'lbfgs', 'liblinear', 'sag']
}
log_reg_model = grid_search_cv(LogisticRegression(), param_grid, X_train, y_train)
```

```
Fitting 10 folds for each of 32 candidates, totalling 320 fits

[CV 1/10] END ....C=0.1, class_weight=None, solver=newton-cg; total time=
25.6s

[CV 2/10] END ....C=0.1, class_weight=None, solver=newton-cg; total time=
26.3s

[CV 3/10] END ....C=0.1, class_weight=None, solver=newton-cg; total time=
20.3s

[CV 4/10] END ....C=0.1, class_weight=None, solver=newton-cg; total time=
22.5s

[CV 5/10] END ....C=0.1, class_weight=None, solver=newton-cg; total time=
23.0s

[CV 6/10] END ....C=0.1, class_weight=None, solver=newton-cg; total time=
15.6s

[CV 7/10] END ....C=0.1, class_weight=None, solver=newton-cg; total time=
22.0s

[CV 8/10] END ....C=0.1, class_weight=None, solver=newton-cg; total time=
19.8s

[CV 9/10] END ....C=0.1, class_weight=None, solver=newton-cg; total time=
25.1s
```

# In [202]:

```
param grid = {
    'C': [0.1, 0.3, 0.5, 1.0],
    'class_weight': [None, 'balanced'],
    'solver': ['newton-cg', 'lbfgs', 'liblinear', 'sag']
}
log_reg_model = grid_search_cv(LogisticRegression(), param_grid, X_train_ohe, y_train_ohe)
Fitting 10 folds for each of 32 candidates, totalling 320 fits
[CV 1/10] END ....C=0.1, class weight=None, solver=newton-cg; total time=
1.1s
[CV 2/10] END ....C=0.1, class weight=None, solver=newton-cg; total time=
1.2s
[CV 3/10] END ....C=0.1, class_weight=None, solver=newton-cg; total time=
1.2s
[CV 4/10] END ....C=0.1, class_weight=None, solver=newton-cg; total time=
1.25
[CV 5/10] END ....C=0.1, class_weight=None, solver=newton-cg; total time=
1.2s
[CV 6/10] END ....C=0.1, class_weight=None, solver=newton-cg; total time=
[CV 7/10] END ....C=0.1, class_weight=None, solver=newton-cg; total time=
[CV 8/10] END ....C=0.1, class_weight=None, solver=newton-cg; total time=
[CV 9/10] END ....C=0.1, class_weight=None, solver=newton-cg; total time=
1.3s
FOY 40 /407 END
In [203]:
param_grid = {
    'C': [0.1, 0.3, 0.5, 1.0],
    'class_weight': [None, 'balanced'],
    'solver': ['newton-cg', 'lbfgs', 'liblinear', 'sag']
}
log_reg_model = grid_search_cv(LogisticRegression(), param_grid, X_train_tar, y_train_tar)
Fitting 10 folds for each of 32 candidates, totalling 320 fits
[CV 1/10] END ....C=0.1, class weight=None, solver=newton-cg; total time=
0.8s
[CV 2/10] END ....C=0.1, class_weight=None, solver=newton-cg; total time=
0.8s
[CV 3/10] END ....C=0.1, class_weight=None, solver=newton-cg; total time=
0.8s
[CV 4/10] END ....C=0.1, class_weight=None, solver=newton-cg; total time=
0.8s
[CV 5/10] END ....C=0.1, class_weight=None, solver=newton-cg; total time=
[CV 6/10] END ....C=0.1, class_weight=None, solver=newton-cg; total time=
0.8s
[CV 7/10] END ....C=0.1, class weight=None, solver=newton-cg; total time=
0.7s
[CV 8/10] END ....C=0.1, class_weight=None, solver=newton-cg; total time=
0.8s
[CV 9/10] END ....C=0.1, class_weight=None, solver=newton-cg; total time=
0.8s
```

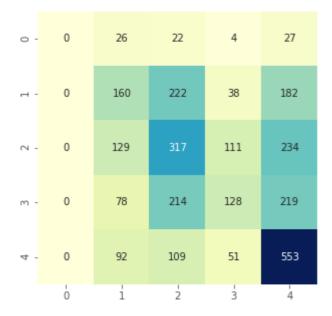
## In [204]:

```
t_start = time.time()
log_reg = LogisticRegression(C=0.3, solver='liblinear')
log_reg.fit(X_train, y_train)
t_end = time.time()

print(f" Score = {cohen_kappa_score(y_test, log_reg.predict(X_test), weights='quadratic')}"
print(f"Time = {t_end - t_start} seconds")

cm = confusion_matrix(y_test, log_reg.predict(X_test))
conf_matrix = pd.DataFrame(data = cm, index=range(0, 5), columns=range(0, 5))
plt.figure(figsize = (5,5))
sns.heatmap(conf_matrix, annot=True,fmt='d',cmap="YlGnBu", cbar=False);
```

Score = 0.28277812414804937 Time = 2.5267982482910156 seconds



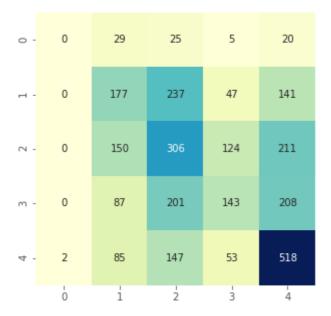
# In [205]:

```
t_start = time.time()
log_reg = LogisticRegression(C=0.3)
log_reg.fit(X_train_ohe, y_train_ohe)
t_end = time.time()

print(f" Score = {cohen_kappa_score(y_test_ohe, log_reg.predict(X_test_ohe), weights='quadr
print(f"Time = {t_end - t_start} seconds")

cm = confusion_matrix(y_test_ohe, log_reg.predict(X_test_ohe))
conf_matrix = pd.DataFrame(data = cm, index=range(0, 5), columns=range(0, 5))
plt.figure(figsize = (5,5))
sns.heatmap(conf_matrix, annot=True,fmt='d',cmap="YlGnBu", cbar=False);
```

Score = 0.3121781593532168 Time = 0.978381872177124 seconds



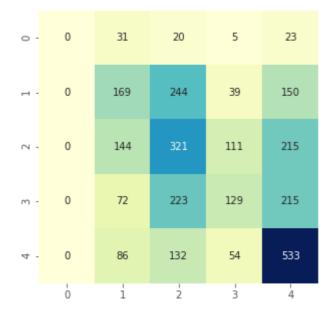
# In [206]:

```
t_start = time.time()
log_reg = LogisticRegression(C=0.1)
log_reg.fit(X_train_tar, y_train_tar)
t_end = time.time()

print(f" Score = {cohen_kappa_score(y_test_tar, log_reg.predict(X_test_tar), weights='quadr
print(f"Time = {t_end - t_start} seconds")

cm = confusion_matrix(y_test_tar, log_reg.predict(X_test_tar))
conf_matrix = pd.DataFrame(data = cm, index=range(0, 5), columns=range(0, 5))
plt.figure(figsize = (5,5))
sns.heatmap(conf_matrix, annot=True,fmt='d',cmap="YlGnBu", cbar=False);
```

Score = 0.31682352217717025 Time = 0.48667168617248535 seconds



# **Ансамбли**

# Модель случайного леса

# In [176]:

```
t_start = time.time()
r_forest = RandomForestClassifier()
r_forest.fit(X_train, y_train)
t_end = time.time()

print(f" Score = {cohen_kappa_score(y_test, r_forest.predict(X_test), weights='quadratic')}
print(f"Time = {t_end - t_start} seconds")
```

Score = 0.42468184626683303 Time = 3.2750773429870605 seconds

```
In [177]:
t start = time.time()
r_forest = RandomForestClassifier()
r_forest.fit(X_train_ohe, y_train_ohe)
t end = time.time()
print(f" Score = {cohen_kappa_score(y_test_ohe, r_forest.predict(X_test_ohe), weights='quad
print(f"Time = {t_end - t_start} seconds")
Score = 0.41310541944009205
Time = 3.155869960784912 seconds
In [178]:
t_start = time.time()
r forest = RandomForestClassifier()
r_forest.fit(X_train_tar, y_train_tar)
t_end = time.time()
print(f" Score = {cohen_kappa_score(y_test_tar, r_forest.predict(X_test_tar), weights='quad
print(f"Time = {t_end - t_start} seconds")
Score = 0.4196636690065916
Time = 2.7579550743103027 seconds
```

## In [179]:

```
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': range(2,20),
    'min_samples_leaf': [3, 5, 7, 9, 11], # минимальное количество наблюдений в листе
    'class_weight': [None, 'balanced'],
    'criterion': ["gini", "entropy"]
}
forest_model = randomized_cv(RandomForestClassifier(random_state=42), param_grid, X_train,
```

```
Fitting 10 folds for each of 40 candidates, totalling 400 fits
[CV 1/10; 1/40] START class weight=None, criterion=gini, max depth=17, min
_samples_leaf=7, n_estimators=200
[CV 1/10; 1/40] END class weight=None, criterion=gini, max depth=17, min s
amples_leaf=7, n_estimators=200; total time=
[CV 2/10; 1/40] START class_weight=None, criterion=gini, max_depth=17, min
samples leaf=7, n estimators=200
[CV 2/10; 1/40] END class weight=None, criterion=gini, max depth=17, min s
amples leaf=7, n estimators=200; total time=
                                              3.3s
[CV 3/10; 1/40] START class_weight=None, criterion=gini, max_depth=17, min
samples leaf=7, n estimators=200
[CV 3/10; 1/40] END class_weight=None, criterion=gini, max_depth=17, min_s
amples leaf=7, n estimators=200; total time=
[CV 4/10; 1/40] START class weight=None, criterion=gini, max depth=17, min
samples leaf=7, n estimators=200
[CV 4/10; 1/40] END class_weight=None, criterion=gini, max_depth=17, min_s
amples_leaf=7, n_estimators=200; total time=
                                               3.3s
[CV 5/10; 1/40] START class_weight=None, criterion=gini, max_depth=17, min
_samples_leaf=7, n_estimators=200
```

## In [180]:

```
forest_model = randomized_cv(RandomForestClassifier(random_state=42), param_grid, X_train_c
```

```
Fitting 10 folds for each of 40 candidates, totalling 400 fits
[CV 1/10; 1/40] START class weight=balanced, criterion=gini, max depth=10,
min_samples_leaf=5, n_estimators=200
[CV 1/10; 1/40] END class_weight=balanced, criterion=gini, max_depth=10, m
in_samples_leaf=5, n_estimators=200; total time=
[CV 2/10; 1/40] START class_weight=balanced, criterion=gini, max_depth=10,
min_samples_leaf=5, n_estimators=200
[CV 2/10; 1/40] END class weight=balanced, criterion=gini, max depth=10, m
in_samples_leaf=5, n_estimators=200; total time=
                                                   2.6s
[CV 3/10; 1/40] START class_weight=balanced, criterion=gini, max_depth=10,
min_samples_leaf=5, n_estimators=200
[CV 3/10; 1/40] END class_weight=balanced, criterion=gini, max_depth=10, m
in_samples_leaf=5, n_estimators=200; total time=
[CV 4/10; 1/40] START class_weight=balanced, criterion=gini, max_depth=10,
min_samples_leaf=5, n_estimators=200
[CV 4/10; 1/40] END class_weight=balanced, criterion=gini, max_depth=10, m
in_samples_leaf=5, n_estimators=200; total time=
[CV 5/10; 1/40] START class_weight=balanced, criterion=gini, max_depth=10,
min_samples_leaf=5, n_estimators=200
```

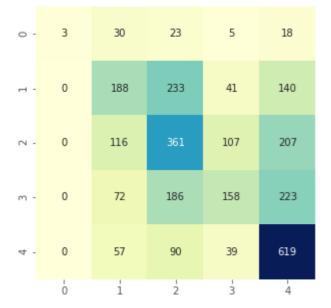
## In [181]:

forest\_model = randomized\_cv(RandomForestClassifier(random\_state=42), param\_grid, X\_train\_t

```
Fitting 10 folds for each of 40 candidates, totalling 400 fits
[CV 1/10; 1/40] START class_weight=balanced, criterion=entropy, max_depth=
8, min_samples_leaf=7, n_estimators=300
[CV 1/10; 1/40] END class_weight=balanced, criterion=entropy, max_depth=8,
min_samples_leaf=7, n_estimators=300; total time=
[CV 2/10; 1/40] START class_weight=balanced, criterion=entropy, max_depth=
8, min_samples_leaf=7, n_estimators=300
[CV 2/10; 1/40] END class_weight=balanced, criterion=entropy, max_depth=8,
min_samples_leaf=7, n_estimators=300; total time=
[CV 3/10; 1/40] START class weight=balanced, criterion=entropy, max depth=
8, min_samples_leaf=7, n_estimators=300
[CV 3/10; 1/40] END class_weight=balanced, criterion=entropy, max_depth=8,
min samples leaf=7, n estimators=300; total time=
[CV 4/10; 1/40] START class weight=balanced, criterion=entropy, max depth=
8, min_samples_leaf=7, n_estimators=300
[CV 4/10; 1/40] END class_weight=balanced, criterion=entropy, max_depth=8,
min_samples_leaf=7, n_estimators=300; total time=
[CV 5/10; 1/40] START class_weight=balanced, criterion=entropy, max_depth=
8, min samples leaf=7, n estimators=300
```

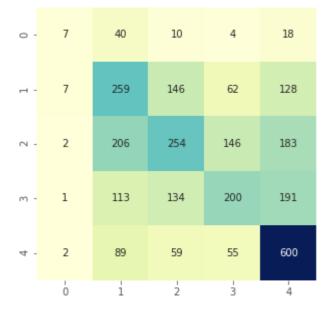
# In [207]:

Score = 0.4098590420354743 Time = 13.883994102478027 seconds



# In [208]:

Score = 0.4168135477070587 Time = 10.02495813369751 seconds



# In [209]:

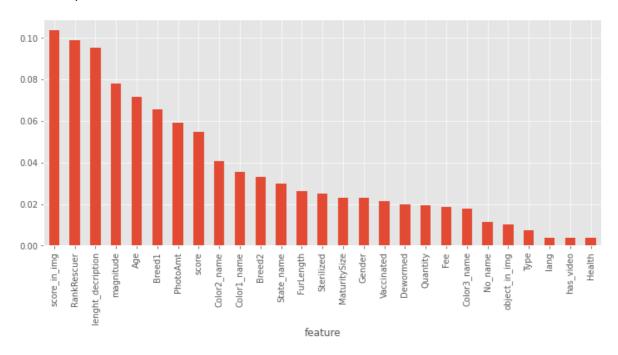
Score = 0.4166656016064654 Time = 8.586639642715454 seconds



#### In [210]:

## Out[210]:

<AxesSubplot:xlabel='feature'>



# Бустинг

# Адаптивный бустинг

```
In [182]:
```

```
ada_clf = AdaBoostClassifier()
ada_clf.fit(X_train, y_train)
print(cohen_kappa_score(y_test, ada_clf.predict(X_test), weights='quadratic'))
```

#### 0.34706331658842127

# In [183]:

```
ada_clf = AdaBoostClassifier()
ada_clf.fit(X_train_ohe, y_train_ohe)
print(cohen_kappa_score(y_test_ohe, ada_clf.predict(X_test_ohe), weights='quadratic'))
```

#### 0.3589410274110435

## In [184]:

```
ada_clf = AdaBoostClassifier()
ada_clf.fit(X_train_tar, y_train_tar)
print(cohen_kappa_score(y_test_tar, ada_clf.predict(X_test_tar), weights='quadratic'))
```

#### 0.3403528515979196

#### In [185]:

```
param_grid = {
    'n_estimators': [50, 100, 200, 300],
    'learning_rate': [1.0, 0.5, 0.25, 0.1],
    'algorithm': ['SAMME', 'SAMME.R']
}
ada_model = randomized_cv(AdaBoostClassifier(DecisionTreeClassifier(max_depth=7)), param_gr
Fitting 10 folds for each of 32 candidates, totalling 320 fits
```

0......
C:\Users\Irina\Anaconda3\lib\site-packages\sklearn\model\_selection\\_searc
h.py:289: UserWarning: The total space of parameters 32 is smaller than n\_
iter=40. Running 32 iterations. For exhaustive searches, use GridSearchCV.

% (grid\_size, self.n\_iter, grid\_size), UserWarning)

[CV 1/10; 1/32] START algorithm=SAMME, learning rate=1.0, n estimators=5

localhost:8888/notebooks/Downloads/adoption\_predict.ipynb

#### In [186]:

ada\_model = randomized\_cv(AdaBoostClassifier(DecisionTreeClassifier(max\_depth=7)), param\_gr

Fitting 10 folds for each of 32 candidates, totalling 320 fits [CV 1/10; 1/32] START algorithm=SAMME, learning\_rate=1.0, n\_estimators=50......

C:\Users\Irina\Anaconda3\lib\site-packages\sklearn\model\_selection\\_searc
h.py:289: UserWarning: The total space of parameters 32 is smaller than n\_
iter=40. Running 32 iterations. For exhaustive searches, use GridSearchCV.
 % (grid\_size, self.n\_iter, grid\_size), UserWarning)

## In [187]:

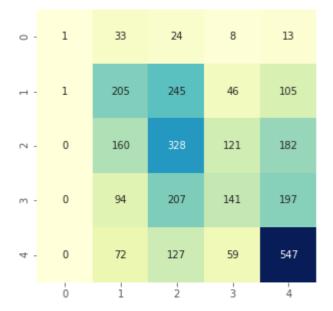
ada\_model = randomized\_cv(AdaBoostClassifier(DecisionTreeClassifier(max\_depth=7)), param\_gr

Fitting 10 folds for each of 32 candidates, totalling 320 fits [CV 1/10; 1/32] START algorithm=SAMME, learning\_rate=1.0, n\_estimators=50......

C:\Users\Irina\Anaconda3\lib\site-packages\sklearn\model\_selection\\_searc
h.py:289: UserWarning: The total space of parameters 32 is smaller than n\_
iter=40. Running 32 iterations. For exhaustive searches, use GridSearchCV.
% (grid size, self.n iter, grid size), UserWarning)

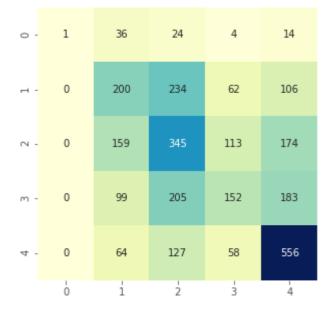
## In [211]:

Score = 0.39884805613239827 Time = 10.266168117523193 seconds



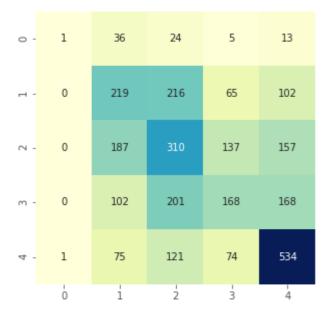
# In [212]:

Score = 0.40414212117212533 Time = 13.761859893798828 seconds



# In [213]:

Score = 0.4006763933568349 Time = 30.173818826675415 seconds



# Градиентный бустинг

```
In [188]:
```

```
est = GradientBoostingClassifier()
est.fit(X_train, y_train)
print(cohen_kappa_score(y_test, est.predict(X_test), weights='quadratic'))
```

#### 0.3834166296276056

#### In [189]:

```
est = GradientBoostingClassifier()
est.fit(X_train_ohe, y_train_ohe)
print(cohen_kappa_score(y_test_ohe, est.predict(X_test_ohe), weights='quadratic'))
```

#### 0.3932465272677671

## In [190]:

```
est = GradientBoostingClassifier()
est.fit(X_train_tar, y_train_tar)
print(cohen_kappa_score(y_test_tar, est.predict(X_test_tar), weights='quadratic'))
```

#### 0.39724209611651895

## In [191]:

```
param_grid = {
    'n_estimators': [50, 100, 200, 300],
    'learning_rate': [1.0, 0.5, 0.25, 0.1],
    'criterion': ['friedman_mse', 'mse'],
    'max_depth': [1, 3, 5, 7]
}
gbc_model = randomized_cv(GradientBoostingClassifier(), param_grid, X_train, y_train, 30)

Fitting 10 folds for each of 30 candidates, totalling 300 fits
[CV 1/10; 1/30] START criterion=mse, learning_rate=1.0, max_depth=5, n_est
imators=200
```

```
imators=200
[CV 1/10; 1/30] END criterion=mse, learning_rate=1.0, max_depth=5, n_estim
ators=200; total time= 42.9s
[CV 2/10; 1/30] START criterion=mse, learning rate=1.0, max depth=5, n est
imators=200
[CV 2/10; 1/30] END criterion=mse, learning rate=1.0, max depth=5, n estim
ators=200; total time= 43.1s
[CV 3/10; 1/30] START criterion=mse, learning_rate=1.0, max_depth=5, n_est
imators=200
[CV 3/10; 1/30] END criterion=mse, learning rate=1.0, max depth=5, n estim
ators=200; total time= 43.8s
[CV 4/10; 1/30] START criterion=mse, learning rate=1.0, max depth=5, n est
imators=200
[CV 4/10; 1/30] END criterion=mse, learning_rate=1.0, max_depth=5, n_estim
ators=200; total time= 43.8s
[CV 5/10; 1/30] START criterion=mse, learning rate=1.0, max depth=5, n est
imators=200
FO. F /40
```

## In [192]:

```
gbc_model = randomized_cv(GradientBoostingClassifier(), param_grid, X_train_ohe, y_train_oh
```

```
Fitting 10 folds for each of 30 candidates, totalling 300 fits
[CV 1/10; 1/30] START criterion=mse, learning rate=1.0, max depth=7, n est
imators=300
[CV 1/10; 1/30] END criterion=mse, learning_rate=1.0, max_depth=7, n_estim
ators=300; total time= 2.3min
[CV 2/10; 1/30] START criterion=mse, learning_rate=1.0, max_depth=7, n_est
imators=300
[CV 2/10; 1/30] END criterion=mse, learning rate=1.0, max depth=7, n estim
ators=300; total time= 2.4min
[CV 3/10; 1/30] START criterion=mse, learning_rate=1.0, max_depth=7, n_est
imators=300
[CV 3/10; 1/30] END criterion=mse, learning_rate=1.0, max_depth=7, n_estim
ators=300; total time= 2.4min
[CV 4/10; 1/30] START criterion=mse, learning_rate=1.0, max_depth=7, n est
imators=300
[CV 4/10; 1/30] END criterion=mse, learning_rate=1.0, max_depth=7, n_estim
ators=300; total time= 2.5min
[CV 5/10; 1/30] START criterion=mse, learning_rate=1.0, max_depth=7, n_est
imators=300
FOY E /40 4 /207 END
```

## In [193]:

# gbc\_model = randomized\_cv(GradientBoostingClassifier(), param\_grid, X\_train\_tar, y\_train\_ta

```
Fitting 10 folds for each of 30 candidates, totalling 300 fits
[CV 1/10; 1/30] START criterion=friedman_mse, learning_rate=0.25, max_dept
h=5, n estimators=50
[CV 1/10; 1/30] END criterion=friedman_mse, learning_rate=0.25, max_depth=
5, n_estimators=50; total time=
[CV 2/10; 1/30] START criterion=friedman_mse, learning_rate=0.25, max_dept
h=5, n_estimators=50
[CV 2/10; 1/30] END criterion=friedman_mse, learning_rate=0.25, max_depth=
5, n_estimators=50; total time=
                                 9.7s
[CV 3/10; 1/30] START criterion=friedman mse, learning rate=0.25, max dept
h=5, n_estimators=50
[CV 3/10; 1/30] END criterion=friedman mse, learning rate=0.25, max depth=
5, n estimators=50; total time=
                                  9.7s
[CV 4/10; 1/30] START criterion=friedman mse, learning rate=0.25, max dept
h=5, n estimators=50
[CV 4/10; 1/30] END criterion=friedman_mse, learning_rate=0.25, max_depth=
5, n_estimators=50; total time=
                                9.8s
[CV 5/10; 1/30] START criterion=friedman_mse, learning_rate=0.25, max_dept
h=5, n_estimators=50
FOVE FIAD. 4/201 FND suitanism Children was largering water 0.25 was doubt
```

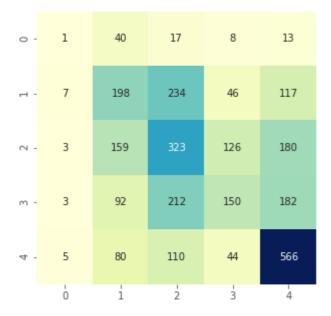
## In [214]:

```
t_start = time.time()
gbc = GradientBoostingClassifier(n_estimators=200)
gbc.fit(X_train, y_train)
t_end = time.time()

print(f" Score = {cohen_kappa_score(y_test, gbc.predict(X_test), weights='quadratic')}")
print(f"Time = {t_end - t_start} seconds")

cm = confusion_matrix(y_test, gbc.predict(X_test))
conf_matrix = pd.DataFrame(data = cm, index=range(0, 5), columns=range(0, 5))
plt.figure(figsize = (5,5))
sns.heatmap(conf_matrix, annot=True,fmt='d',cmap="YlGnBu", cbar=False);
```

Score = 0.38852285898740946 Time = 41.428433895111084 seconds



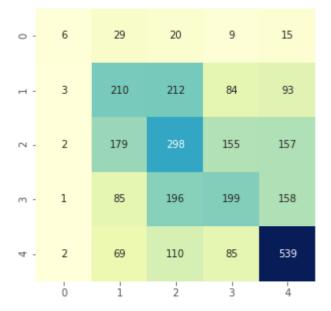
## In [215]:

```
t_start = time.time()
gbc = GradientBoostingClassifier(max_depth=7, n_estimators=300)
gbc.fit(X_train_ohe, y_train_ohe)
t_end = time.time()

print(f" Score = {cohen_kappa_score(y_test_ohe, gbc.predict(X_test_ohe), weights='quadratic
print(f"Time = {t_end - t_start} seconds")

cm = confusion_matrix(y_test_ohe, gbc.predict(X_test_ohe))
conf_matrix = pd.DataFrame(data = cm, index=range(0, 5), columns=range(0, 5))
plt.figure(figsize = (5,5))
sns.heatmap(conf_matrix, annot=True,fmt='d',cmap="YlGnBu", cbar=False);
```

Score = 0.4082036027987961 Time = 179.62291812896729 seconds



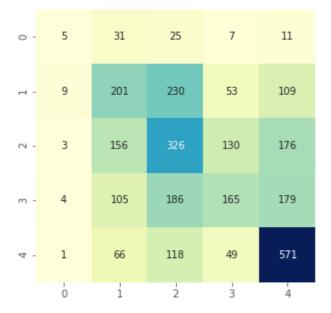
# In [216]:

```
t_start = time.time()
gbc = GradientBoostingClassifier(max_depth=5)
gbc.fit(X_train_tar, y_train_tar)
t_end = time.time()

print(f" Score = {cohen_kappa_score(y_test_tar, gbc.predict(X_test_tar), weights='quadratic
print(f"Time = {t_end - t_start} seconds")

cm = confusion_matrix(y_test_tar, gbc.predict(X_test_tar))
conf_matrix = pd.DataFrame(data = cm, index=range(0, 5), columns=range(0, 5))
plt.figure(figsize = (5,5))
sns.heatmap(conf_matrix, annot=True,fmt='d',cmap="YlGnBu", cbar=False);
```

Score = 0.41129513918161065 Time = 31.47444725036621 seconds



# **XGB**

```
In [217]:
```

```
xgb_model = xgb.XGBClassifier()
xgb_model.fit(X_train, y_train)
print(cohen_kappa_score(y_test, xgb_model.predict(X_test), weights='quadratic'))
```

#### 0.4175859196649011

#### In [218]:

```
xgb_model = xgb.XGBClassifier()
xgb_model.fit(X_train_ohe, y_train_ohe)
print(cohen_kappa_score(y_test_ohe, xgb_model.predict(X_test_ohe), weights='quadratic'))
```

#### 0.41794548529289366

## In [219]:

```
xgb_model = xgb.XGBClassifier()
xgb_model.fit(X_train_tar, y_train_tar)
print(cohen_kappa_score(y_test_tar, xgb_model.predict(X_test_tar), weights='quadratic'))
```

#### 0.4231012369500242

## In [220]:

```
param_grid = {
    'max_depth': [1, 3, 5, 7, 9],
    'n_estimators': [50, 100, 200, 300],
    'learning_rate': [1.0, 0.5, 0.1, 0.05, 0.025, 0.01, 0.005]
}
```

# In [221]:

```
xgb = randomized_cv(xgb.XGBClassifier(), param_grid, X_train, y_train, 30)
```

```
Fitting 10 folds for each of 30 candidates, totalling 300 fits
[CV 1/10; 1/30] START learning rate=0.025, max depth=9, n estimators=30
0.......
[CV 1/10; 1/30] END learning_rate=0.025, max_depth=9, n_estimators=300; to
tal time= 1.2min
[CV 2/10; 1/30] START learning_rate=0.025, max_depth=9, n_estimators=30
0.....
[CV 2/10; 1/30] END learning rate=0.025, max depth=9, n estimators=300; to
tal time= 1.1min
[CV 3/10; 1/30] START learning_rate=0.025, max_depth=9, n_estimators=30
0......
[CV 3/10; 1/30] END learning_rate=0.025, max_depth=9, n_estimators=300; to
tal time= 1.1min
[CV 4/10; 1/30] START learning rate=0.025, max depth=9, n estimators=30
[CV 4/10; 1/30] END learning_rate=0.025, max_depth=9, n_estimators=300; to
tal time= 1.0min
[CV 5/10; 1/30] START learning_rate=0.025, max_depth=9, n_estimators=30
0......
```

#### In [225]:

```
xgb = randomized_cv(XGBClassifier(), param_grid, X_train_ohe, y_train_ohe, 30)
Fitting 10 folds for each of 30 candidates, totalling 300 fits
[CV 1/10; 1/30] START learning_rate=0.1, max_depth=9, n_estimators=10
[CV 1/10; 1/30] END learning_rate=0.1, max_depth=9, n_estimators=100; tota
1 time= 21.3s
[CV 2/10; 1/30] START learning_rate=0.1, max_depth=9, n_estimators=10
0.........
[CV 2/10; 1/30] END learning rate=0.1, max depth=9, n estimators=100; tota
l time= 19.5s
[CV 3/10; 1/30] START learning_rate=0.1, max_depth=9, n_estimators=10
[CV 3/10; 1/30] END learning_rate=0.1, max_depth=9, n_estimators=100; tota
l time= 18.6s
[CV 4/10; 1/30] START learning rate=0.1, max depth=9, n estimators=10
[CV 4/10; 1/30] END learning_rate=0.1, max_depth=9, n_estimators=100; tota
1 time= 17.9s
[CV 5/10; 1/30] START learning_rate=0.1, max_depth=9, n_estimators=10
FOY E /40 4 /201 END 1
                      . . . . .
                                          1 LL 4 L
                                                               400 ---
```

## In [226]:

```
xgb = randomized_cv(XGBClassifier(), param_grid, X_train_tar, y_train_tar, 30)
```

```
Fitting 10 folds for each of 30 candidates, totalling 300 fits
[CV 1/10; 1/30] START learning_rate=0.005, max_depth=7, n_estimators=5
0.......
[CV 1/10; 1/30] END learning_rate=0.005, max_depth=7, n_estimators=50; tot
al time=
         4.5s
[CV 2/10; 1/30] START learning_rate=0.005, max_depth=7, n_estimators=5
0......
[CV 2/10; 1/30] END learning_rate=0.005, max_depth=7, n_estimators=50; tot
al time= 4.5s
[CV 3/10; 1/30] START learning rate=0.005, max depth=7, n estimators=5
0........
[CV 3/10; 1/30] END learning rate=0.005, max depth=7, n estimators=50; tot
al time= 4.5s
[CV 4/10; 1/30] START learning rate=0.005, max depth=7, n estimators=5
[CV 4/10; 1/30] END learning_rate=0.005, max_depth=7, n_estimators=50; tot
al time=
         4.4s
[CV 5/10; 1/30] START learning rate=0.005, max depth=7, n estimators=5
FOV E/40. 4/201 FMD locuring moto 0 005 move doubt 7 m continuation FO. tot
```

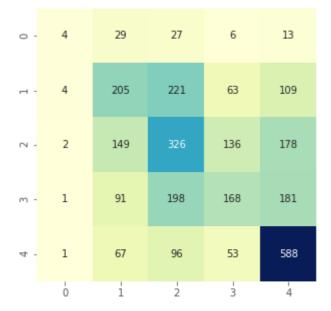
# In [228]:

```
t_start = time.time()
xgb = XGBClassifier(learning_rate=0.025, max_depth=9, n_estimators=300)
xgb.fit(X_train, y_train)
t_end = time.time()

print(f" Score = {cohen_kappa_score(y_test, xgb.predict(X_test), weights='quadratic')}")
print(f"Time = {t_end - t_start} seconds")

cm = confusion_matrix(y_test, xgb.predict(X_test))
conf_matrix = pd.DataFrame(data = cm, index=range(0, 5), columns=range(0, 5))
plt.figure(figsize = (5,5))
sns.heatmap(conf_matrix, annot=True,fmt='d',cmap="YlGnBu", cbar=False);
```

Score = 0.41817708886538607 Time = 46.994672536849976 seconds



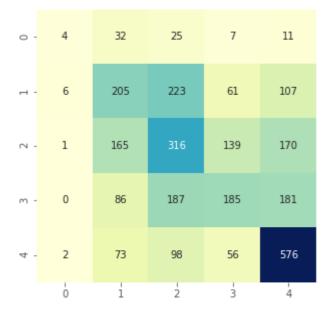
## In [229]:

```
t_start = time.time()
xgb = XGBClassifier(base_score=0.5, booster='gbtree', learning_rate=0.025, max_depth=9, n_e
xgb.fit(X_train_ohe, y_train_ohe)
t_end = time.time()

print(f" Score = {cohen_kappa_score(y_test_ohe, xgb.predict(X_test_ohe), weights='quadratic
print(f"Time = {t_end - t_start} seconds")

cm = confusion_matrix(y_test_ohe, xgb.predict(X_test_ohe))
conf_matrix = pd.DataFrame(data = cm, index=range(0, 5), columns=range(0, 5))
plt.figure(figsize = (5,5))
sns.heatmap(conf_matrix, annot=True,fmt='d',cmap="YlGnBu", cbar=False);
```

Score = 0.4213457502881114 Time = 52.873796463012695 seconds



# In [230]:

```
t_start = time.time()
xgb = XGBClassifier(base_score=0.5, booster='gbtree', learning_rate=0.1, max_depth=9, n_est
xgb.fit(X_train_tar, y_train_tar)
t_end = time.time()

print(f" Score = {cohen_kappa_score(y_test_tar, xgb.predict(X_test_tar), weights='quadratic
print(f"Time = {t_end - t_start} seconds")

cm = confusion_matrix(y_test_tar, xgb.predict(X_test_tar))
conf_matrix = pd.DataFrame(data = cm, index=range(0, 5), columns=range(0, 5))
plt.figure(figsize = (5,5))
sns.heatmap(conf_matrix, annot=True,fmt='d',cmap="YlGnBu", cbar=False);
```

Score = 0.4191713864260447 Time = 8.319628953933716 seconds



# **LightGBM**

# In [233]:

```
lgb_model = lgb.LGBMClassifier()
lgb_model.fit(X_train, y_train)
print(cohen_kappa_score(y_test, lgb_model.predict(X_test), weights='quadratic'))
```

#### 0.42737008915551244

## In [234]:

```
lgb_model = lgb.LGBMClassifier()
lgb_model.fit(X_train_ohe, y_train_ohe)
print(cohen_kappa_score(y_test_ohe, lgb_model.predict(X_test_ohe), weights='quadratic'))
```

#### 0.4192884742700542

#### In [235]:

```
lgb_model = lgb.LGBMClassifier()
lgb_model.fit(X_train_tar, y_train_tar)
print(cohen_kappa_score(y_test_tar, lgb_model.predict(X_test_tar), weights='quadratic'))
```

#### 0.43022984971564404

## In [236]:

```
param_grid = {
    'max_depth': [1, 3, 5, 7, 9],
    'n_estimators': [50, 100, 200, 300],
    'learning_rate': [1.0, 0.5, 0.1, 0.05, 0.025, 0.01, 0.005]
}
```

# In [237]:

```
lgb_model = randomized_cv(lgb.LGBMClassifier(), param_grid, X_train, y_train, 30)

Fitting 10 folds for each of 30 candidates, totalling 300 fits
[CV 1/10; 1/30] START learning_rate=0.5, max_depth=9, n_estimators=5
0......
[LightGBM] [Warning] Accuracy may be bad since you didn't set num_leaves a
nd 2^max_depth > num_leaves
```

[CV 1/10; 1/30] END learning\_rate=0.5, max\_depth=9, n\_estimators=50; total time= 1.3s

[CV 2/10: 1/30] START learning\_rate=0.5 max\_depth=9 n\_estimators=5

[CV 2/10; 1/30] START learning\_rate=0.5, max\_depth=9, n\_estimators=5 0.....

[LightGBM] [Warning] Accuracy may be bad since you didn't set num\_leaves a nd 2^max\_depth > num\_leaves

[CV 2/10; 1/30] END learning\_rate=0.5, max\_depth=9, n\_estimators=50; total time= 1.5s

[CV 3/10; 1/30] START learning\_rate=0.5, max\_depth=9, n\_estimators=5

[LightGBM] [Warning] Accuracy may be bad since you didn't set num\_leaves a
nd 2^max\_depth > num\_leaves

[CV 3/10; 1/30] END learning\_rate=0.5, max\_depth=9, n\_estimators=50; total time= 1.5s

FOV 4/40: 4/201 CTART location mate 0 F. many death 0 in continuous F

#### In [238]:

```
Fitting 10 folds for each of 30 candidates, totalling 300 fits
[CV 1/10; 1/30] START learning rate=0.01, max depth=1, n estimators=30
0......
[CV 1/10; 1/30] END learning_rate=0.01, max_depth=1, n_estimators=300; tot
al time=
         1.7s
[CV 2/10; 1/30] START learning_rate=0.01, max_depth=1, n_estimators=30
0.......
[CV 2/10; 1/30] END learning rate=0.01, max depth=1, n estimators=300; tot
al time=
         1.6s
[CV 3/10; 1/30] START learning rate=0.01, max depth=1, n estimators=30
0.......
[CV 3/10; 1/30] END learning_rate=0.01, max_depth=1, n_estimators=300; tot
al time= 1.6s
[CV 4/10; 1/30] START learning rate=0.01, max depth=1, n estimators=30
[CV 4/10; 1/30] END learning_rate=0.01, max_depth=1, n_estimators=300; tot
al time=
         1.6s
[CV 5/10; 1/30] START learning_rate=0.01, max_depth=1, n_estimators=30
FOU F /40 4 /201 FND 1
                       عدا ما د
```

lgb model = randomized cv(lgb.LGBMClassifier(), param grid, X train ohe, y train ohe, 30)

## In [239]:

```
lgb_model = randomized_cv(lgb.LGBMClassifier(), param_grid, X_train_tar, y_train_tar, 30)
```

```
Fitting 10 folds for each of 30 candidates, totalling 300 fits
[CV 1/10; 1/30] START learning_rate=0.1, max_depth=5, n_estimators=20
0........
[CV 1/10; 1/30] END learning_rate=0.1, max_depth=5, n_estimators=200; tota
1 time= 2.9s
[CV 2/10; 1/30] START learning_rate=0.1, max_depth=5, n_estimators=20
0.....
[LightGBM] [Warning] Accuracy may be bad since you didn't set num_leaves a
nd 2^max_depth > num_leaves
[CV 2/10; 1/30] END learning rate=0.1, max depth=5, n estimators=200; tota
l time=
        2.9s
[CV 3/10; 1/30] START learning_rate=0.1, max_depth=5, n_estimators=20
0........
[LightGBM] [Warning] Accuracy may be bad since you didn't set num leaves a
nd 2^max depth > num leaves
[CV 3/10; 1/30] END learning_rate=0.1, max_depth=5, n_estimators=200; tota
l time=
         3.1s
[CV 4/10; 1/30] START learning_rate=0.1, max_depth=5, n_estimators=20
Flichtonna Floreiga Accounts may be had about your didn't ack now leaves a
```

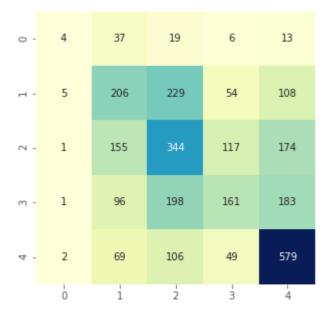
# In [240]:

```
t_start = time.time()
lgb_model = lgb.LGBMClassifier(learning_rate=0.05, max_depth=9, n_estimators=200)
lgb_model.fit(X_train, y_train)
t_end = time.time()

print(f" Score = {cohen_kappa_score(y_test, lgb_model.predict(X_test), weights='quadratic')
print(f"Time = {t_end - t_start} seconds")

cm = confusion_matrix(y_test, lgb_model.predict(X_test))
conf_matrix = pd.DataFrame(data = cm, index=range(0, 5), columns=range(0, 5))
plt.figure(figsize = (5,5))
sns.heatmap(conf_matrix, annot=True,fmt='d',cmap="YlGnBu", cbar=False);
```

Score = 0.42031303461617664 Time = 3.1988062858581543 seconds



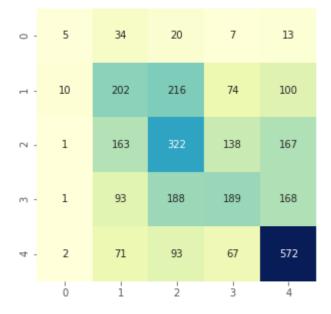
## In [241]:

```
t_start = time.time()
lgb_model = lgb.LGBMClassifier(max_depth=7, n_estimators=200)
lgb_model.fit(X_train_ohe, y_train_ohe)
t_end = time.time()

print(f" Score = {cohen_kappa_score(y_test_ohe, lgb_model.predict(X_test_ohe), weights='qua
print(f"Time = {t_end - t_start} seconds")

cm = confusion_matrix(y_test_ohe, lgb_model.predict(X_test_ohe))
conf_matrix = pd.DataFrame(data = cm, index=range(0, 5), columns=range(0, 5))
plt.figure(figsize = (5,5))
sns.heatmap(conf_matrix, annot=True,fmt='d',cmap="YlGnBu", cbar=False);
```

[LightGBM] [Warning] Accuracy may be bad since you didn't set num\_leaves and
2^max\_depth > num\_leaves
Score = 0.4228013688152027
Time = 3.471630811691284 seconds



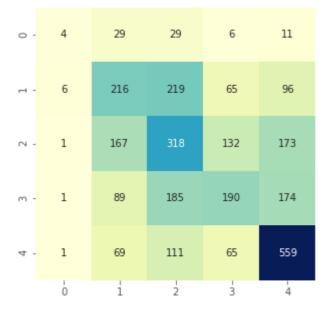
# In [242]:

```
t_start = time.time()
lgb_model = lgb.LGBMClassifier(max_depth=9, n_estimators=200)
lgb_model.fit(X_train_tar, y_train_tar)
t_end = time.time()

print(f" Score = {cohen_kappa_score(y_test_tar, lgb_model.predict(X_test_tar), weights='qua
print(f"Time = {t_end - t_start} seconds")

cm = confusion_matrix(y_test_tar, lgb_model.predict(X_test_tar))
conf_matrix = pd.DataFrame(data = cm, index=range(0, 5), columns=range(0, 5))
plt.figure(figsize = (5,5))
sns.heatmap(conf_matrix, annot=True,fmt='d',cmap="YlGnBu", cbar=False);
```

[LightGBM] [Warning] Accuracy may be bad since you didn't set num\_leaves and
2^max\_depth > num\_leaves
Score = 0.4249991191199106
Time = 3.408841609954834 seconds



## In [ ]: