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Кафедра «Автоматизированные системы обработки информации и управления»

"Методы машинного обучения"

Отчет по лабораторной работе №3

"Обработка пропусков в данных, кодирование категориальных признаков, масштабирование данных"

Выполнил:

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# Лабораторная работа №3

Цель: изучение способов предварительной обработки данных для дальнейшего формирования моделей.

#### Задание:

- 1. Выбрать набор данных (датасет), содержащий категориальные признаки и пропуски в данных. Для выполнения следующих пунктов можно использовать несколько различных наборов данных (один для обработки пропусков, другой для категориальных признаков и т.д.)
- 1. Для выбранного датасета (датасетов) на основе материалов лекции решить следующие задачи:
- обработку пропусков в данных;
- кодирование категориальных признаков;
- масштабирование данных.

# Ход выполнения лабораторной работы

#### In [0]:

```
!pip install -U -q PyDrive
import os
from pydrive.auth import GoogleAuth
from pydrive.drive import GoogleDrive
from google.colab import auth
from oauth2client.client import GoogleCredentials
```

### In [0]:

```
# 1. Authenticate and create the PyDrive client.
auth.authenticate_user()
gauth = GoogleAuth()
gauth.credentials = GoogleCredentials.get_application_default()
drive = GoogleDrive(gauth)
```

```
# choose a local (colab) directory to store the data.
local_download_path = os.path.expanduser('~/data')
try:
   os.makedirs(local_download_path)
except: pass
```

```
In [0]:
```

```
for f in file_list:
    # 3. Create & download by id.
print('title: %s, id: %s' % (f['title'], f['id']))
fname = os.path.join(local_download_path, f['title'])
print('downloading to {}'.format(fname))
f_ = drive.CreateFile({'id': f['id']})
f_.GetContentFile(fname)
```

title: dc-wikia-data.csv, id: lmp\_Y-60LZLTtpzYI8UA7-\_EulThJZK-o downloading to /root/data/dc-wikia-data.csv

#### In [0]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
sns.set(style="ticks")
```

# In [0]:

```
data = pd.read_csv(fname, sep=",")
```

### In [0]:

data.head()

#### Out[0]:

	page_id	name	urlslug	ID	ALIGN	EYE	HAIR	SEX	GS
0	1422	Batman (Bruce Wayne)	√wiki√Batman_(Bruce_Wayne)	Secret Identity	Good Characters	Blue Eyes	Black Hair	Male Characters	Na
1	23387	Superman (Clark Kent)	\/wiki\/Superman_(Clark_Kent)	Secret Identity	Good Characters	Blue Eyes	Black Hair	Male Characters	Na
2	1458	Green Lantern (Hal Jordan)	\/wiki\/Green_Lantern_(Hal_Jordan)	Secret Identity	Good Characters	_	Brown Hair	Male Characters	Na
3	1659	James Gordon (New Earth)	\/wiki\/James_Gordon_(New_Earth)	Public Identity	Good Characters	Brown Eyes	White Hair	Male Characters	Na
4	1576	Richard Grayson (New Earth)	\/ \text{Wiki\/Richard_Grayson_(New_Earth)}	Secret Identity	Good Characters	Blue Eyes	Black Hair	Male Characters	Na

### In [0]:

data.shape

Out[0]:

(6896, 13)

```
In [0]:
data.dtypes
Out[0]:
                       int64
page_id
                      object
name
urlslug
                      object
ID
                      object
ALIGN
                      object
EYE
                      object
HAIR
                      object
SEX
                      object
GSM
                      object
ALIVE
                      object
APPEARANCES
                     float64
FIRST APPEARANCE
                     object
YEAR
                     float64
dtype: object
In [0]:
data.isnull().sum()
Out[0]:
page_id
                        0
                        0
name
urlslug
                        0
ID
                     2013
ALIGN
                      601
EYE
                     3628
HAIR
                     2274
SEX
                     125
GSM
                     6832
ALIVE
                        3
APPEARANCES
                      355
FIRST APPEARANCE
                       69
                       69
YEAR
dtype: int64
Удаление
In [0]:
# Удаление колонок
data_new_1 = data.dropna(axis=1, how='any')
(data.shape, data_new_1.shape)
Out[0]:
((6896, 13), (6896, 3))
In [0]:
# Удаление строк
data_new_2 = data.dropna(axis=0, how='any')
(data.shape, data_new_2.shape)
```

Out[0]:

((6896, 13), (38, 13))

# Заполнение нулями

### In [0]:

```
# Заполнение всех пропущенных значений нулями data_new_3 = data.fillna(0) data_new_3.head()
```

Out[0]:

	page_id	name	urlslug	ID	ALIGN	EYE	HAIR	SEX	GS
0	1422	Batman (Bruce Wayne)	Vwiki\/Batman_(Bruce_Wayne)	Secret Identity	Good Characters	Blue Eyes	Black Hair	Male Characters	0
1	23387	Superman (Clark Kent)	\/wiki\/Superman_(Clark_Kent)	Secret Identity	Good Characters	Blue Eyes	Black Hair	Male Characters	0
2	1458	Green Lantern (Hal Jordan)	\/wiki\/Green_Lantern_(Hal_Jordan)	Secret Identity	Good Characters		Brown Hair	Male Characters	0
3	1659	James Gordon (New Earth)	\/wiki\/James_Gordon_(New_Earth)	Public Identity	Good Characters	Brown Eyes	White Hair	Male Characters	0
4	1576	Richard Grayson (New Earth)	VwikiVRichard_Grayson_(New_Earth)	Secret Identity	Good Characters	Blue Eyes	Black Hair	Male Characters	0

# Внедрение значений (числовые данные)

### In [0]:

```
# Выберем числовые колонки с пропущенными значениями
# Цикл по колонкам датасета
total_count = data.shape[0]
num_cols = []
for col in data.columns:
    # Количество пустых значений
    temp_null_count = data[data[col].isnull()].shape[0]
    dt = str(data[col].dtype)
    if temp_null_count>0 and (dt=='float64' or dt=='int64'):
        num_cols.append(col)
        temp_perc = round((temp_null_count / total_count) * 100.0, 2)
        print('Колонка {}. Тип данных {}. Количество пустых значений {}, {}%.'
            .format(col, dt, temp_null_count, temp_perc))
```

Колонка APPEARANCES. Тип данных float64. Количество пустых значений 355, 5.15%. Колонка YEAR. Тип данных float64. Количество пустых значений 69, 1.0%.

data\_num = data[num\_cols]
data\_num

	APPEARANCES	YEAR
0	3093.0	1939.0
1	2496.0	1986.0
2	1565.0	1959.0
3	1316.0	1987.0
4	1237.0	1940.0
5	1231.0	1941.0
6	1121.0	1941.0
7	1095.0	1989.0
8	1075.0	1969.0
9	1028.0	1956.0
10	1028.0	1956.0
11	969.0	1940.0
12	951.0	1967.0
13	951.0	1940.0
14	934.0	1938.0
15	930.0	1943.0
16	803.0	1940.0
17	716.0	1994.0
18	706.0	1961.0
19	677.0	1986.0
20	654.0	1941.0
21	635.0	1976.0
22	605.0	1942.0
23	595.0	1965.0
24	593.0	1968.0
25	584.0	1980.0
26	560.0	1993.0
27	558.0	1960.0
28	557.0	1986.0
29	549.0	1971.0
6866	NaN	1967.0
6867	NaN	1967.0
6868	NaN	1967.0
6869	NaN	1967.0
6870	NaN	1967.0
6871	NaN	1966.0
6872	NaN	1966.0
6873	NaN	1965.0
6874	NaN	1963.0
6875	NaN	1962.0
6876	NaN	1960.0

	1	ı
6877	NaN	1955.0
6878	NaN	1948.0
6879	NaN	1946.0
6880	NaN	1946.0
6881	NaN	1944.0
6882	NaN	1941.0
6883	NaN	1941.0
6884	NaN	1940.0
6885	NaN	1940.0
6886	NaN	1936.0
6887	NaN	NaN
6888	NaN	NaN
6889	NaN	NaN
6890	NaN	NaN
6891	NaN	NaN
6892	NaN	NaN
6893	NaN	NaN
6894	NaN	NaN
6895	NaN	NaN

6896 rows × 2 columns

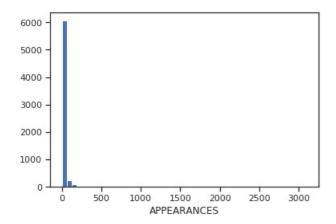
```
# Гистограмма по признакам
for col in data_num:
   plt.hist(data[col], 50)
   plt.xlabel(col)
   plt.show()
```

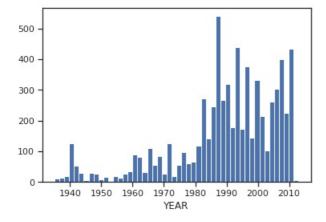
 $/usr/local/lib/python 3.6/dist-packages/numpy/lib/function\_base.py: 780: Runtime Warning: invalid value encountered in greater\_equal$ 

keep = (tmp\_a >= first\_edge)

/usr/local/lib/python3.6/dist-packages/numpy/lib/function\_base.py:781: RuntimeWarning: invalid value encountered in less\_equal

keep &= (tmp\_a <= last\_edge)</pre>





In [0]:

# Фильтр по пустым значениям поля YEAR data[data['YEAR'].isnull()]

	page_id	name	urlslug	ID	ALIGN	EYE	
386	1891	Jakeem Williams (New Earth)	VwikiVJakeem_Williams_(New_Earth)	Secret Identity	NaN	Brown Eyes	NaN
1400	64303	Hadley Jaggar (New Earth)	VwikiVHadley_Jaggar_(New_Earth)	Secret Identity	Good Characters	Blue Eyes	Blor
1401	13097	Nergal (New Earth)	VwikiVNergal_(New_Earth)	NaN	Bad Characters	Yellow Eyes	NaN
1832	65286	Gregory Wolfe (New Earth)	\text{Vwiki\text{VGregory_Wolfe_(New_Earth)}}	Public Identity	Neutral Characters	Brown Eyes	Blac
1937	146333	Clarence Charles Batson V (New Earth)	VwikiVClarence_Charles_Batson_V_(New_Earth)	Public Identity	Good Characters	NaN	Blac
1938	113413	Chad Graham (New Earth)	VwikiVChad_Graham_(New_Earth)	Secret Identity	Bad Characters	NaN	Blor
2065	344513	Jupiter (New Earth)	VwikiVJupiter_(New_Earth)	NaN	Good Characters	NaN	Whi
		Pegasus			Good		

2066	344983	(New Earth)	\/wiki\/Pegasus_(New_Earth)	NaN	Characters	NaN	Blac
2067	286906	Asteroth (New Earth)	VwikiVAsteroth_(New_Earth)	Secret Identity	Bad Characters	Yellow Eyes	Blac
2230	155569	Red Panzer IV (New Earth)	\/\text{Vwiki\/Red_Panzer_IV_(New_Earth)}	Secret Identity	Bad Characters	NaN	NaN
2231	19044	Gernsback (New Earth)	VwikiVGernsback_(New_Earth)	NaN	Good Characters	NaN	NaN
2232	202057	Henry Cosgei (New Earth)	VwikiVHenry_Cosgei_(New_Earth)	Secret Identity	Good Characters	Black Eyes	Blac
2413	216380	Marilyn Batson (New Earth)	\/wiki\/Marilyn_Batson_(New_Earth)	Public Identity	Good Characters	Brown Eyes	Bro
2414	178197	Michael Tree (New Earth)	VwikiVMichael_Tree_(New_Earth)	NaN	NaN	NaN	Blac
2841	383108	Brunhilde (New Earth)	Vwiki\/Brunhilde_(New_Earth)	NaN	Good Characters	NaN	NaN
2842	251517	Kuan Ti (New Earth)	\/wiki\/Kuan_Ti_(New_Earth)	Public Identity	Good Characters	NaN	Blac
3104	383914	Helen of Troy (New Earth)	\/\text{Vwiki\/Helen_of_Troy_(New_Earth)}	NaN	Good Characters	NaN	Blor
3105	256793	Pluto (New Earth)	VwikiVPluto_(New_Earth)	Public Identity	Bad Characters	NaN	NaN
3431	15909	Ammon-Ra (New Earth)	VwikiVAmmon-Ra_(New_Earth)	Secret Identity	Neutral Characters	NaN	NaN
3432	348898	Kreaven (New Earth)	VwikiVKreaven_(New_Earth)	Public Identity	Neutral Characters	NaN	NaN
3433	345589	Vulcan (New Earth)	\/wiki\/Vulcan_(New_Earth)	NaN	Good Characters	NaN	NaN
3434	57839	Donna Cavanagh (New Earth)	VwikiVDonna_Cavanagh_(New_Earth)	Public Identity	Good Characters	Green Eyes	Blor
3435	68612	Amadeus Arkham (New Earth)	VwikiVAmadeus_Arkham_(New_Earth)	Public Identity	Good Characters	NaN	NaN
3819	182833	Scott Spencer (New Earth)	VwikiVScott_Spencer_(New_Earth)	Public Identity	Neutral Characters	NaN	Blac
3820	213354	Maria Montez (New Earth)	VwikiVMaria_Montez_(New_Earth)	NaN	NaN	NaN	NaN
3821	345591	Diana, Goddess of the Hunt (New Earth)	VwikiVDiana,_Goddess_of_the_Hunt_(New_Earth)	NaN	Good Characters	NaN	NaN
3822	47346	Gregory the Gargoyle (New Earth)	\/wiki\/Gregory_the_Gargoyle_(New_Earth)	NaN	Good Characters	NaN	NaN
3823	345586	Minerva (Roman Goddess) (New Earth)	VwikiVMinerva_(Roman_Goddess)_(New_Earth)	NaN	Good Characters	NaN	NaN
3824	66157	Auerbach (New Earth)	VwikiVAuerbach_(New_Earth)	Secret Identity	NaN	NaN	Bro

4320	139807	Virgil Adams (New Earth)	\/wiki\/Virgil_Adams_(New_Earth)	Public Identity	Bad Characters	NaN	Bla
5527	112333	Lisa Morice (New Earth)	\/ \wiki\/ Lisa_Morice_(New_Earth)	Public Identity	Good Characters	Grey Eyes	Str Blo
5528	189975	Carter Nichols (New Earth)	\/wiki\/Carter_Nichols_(New_Earth)	Public Identity	Good Characters	NaN	Bro
5529	139768	Cupid (New Earth)	\/wiki\/Cupid_(New_Earth)	NaN	Good Characters	NaN	Na
5530	345585	Juno (New Earth)	\/wiki\/Juno_(New_Earth)	NaN	Good Characters	NaN	Na
5531	271506	Luki Lo (New Earth)	\/wiki\/Luki_Lo_(New_Earth)	NaN	Good Characters	NaN	Bla
5532	177249	Stanley Wilson (New Earth)	\wiki\stanley_Wilson_(New_Earth)	NaN	Good Characters	NaN	Bla
5533	250224	Elena Leal (New Earth)	\/ \text{Vwiki\/Elena_Leal_(New_Earth)}	Public Identity	Good Characters	NaN	Wh
5534	185720	Druid (New Earth)	\text{Vwiki\text{India}(New_Earth)}	Secret Identity	Bad Characters	NaN	Bla
5535	218828	Crone (New Earth)	VwikiVCrone_(New_Earth)	Secret Identity	Bad Characters	NaN	Gr
5536	95738	Fancy Feet (New Earth)	VwikiVFancy_Feet_(New_Earth)	NaN	Bad Characters	NaN	Na
5537	182478	Rico Strada (New Earth)	VwikiVRico_Strada_(New_Earth)	NaN	Bad Characters	Blue Eyes	Blo
5538	31642	Benjamin Hubbard (New Earth)	\wiki\Benjamin_Hubbard_(New_Earth)	NaN	NaN	NaN	Na
6532	159528	Materna Minnx (New Earth)	\forall \wiki\forall Materna_Minnx_(New_Earth)	Public Identity	NaN	NaN	Bro
6533	19799	Frank Baker, Jr. (New Earth)	\forall \text{WikiVFrank_Baker,_Jr(New_Earth)}	Public Identity	Neutral Characters	Blue Eyes	Gre
6534	242167	Prowley (New Earth)	\/ \text{Vwiki\/Prowley_(New_Earth)}	Public Identity	Neutral Characters	Yellow Eyes	Bla
6535	95767	Smother (New Earth)	\text{Vwiki\symmetry}\text{Smother_(New_Earth)}	NaN	Neutral Characters	NaN	Na
6536	16094	Mark Antaeus (New Earth)	\forall \text{Wiki\forall Mark_Antaeus_(New_Earth)}	Public Identity	Good Characters	Blue Eyes	Bla
6537	128000	Jerome Cox (New Earth)	\/wiki\/Jerome_Cox_(New_Earth)	Public Identity	Bad Characters	NaN	Na
6538	345590	Apollo (Roman God) (New Earth)	\/wiki\/Apollo_(Roman_God)_(New_Earth)	NaN	Good Characters	NaN	Na
6539	15050	Ben Lo (New Earth)	VwikiVBen_Lo_(New_Earth)	Public Identity	Good Characters	Brown Eyes	Bla
6540	205584	Auctioneer II (New Earth)	\wiki\/Auctioneer_II_(New_Earth)	Secret Identity	Bad Characters	NaN	Wł
6887	283661	Herbert Hoover (New Earth)	\/\text{\text{Wiki\/Herbert_Hoover_(New_Earth)}}	Public Identity	Good Characters	NaN	Na

6888	283657	William Howard Taft (New Earth)	\/wiki\/William_Howard_Taft_(New_Earth)	Public Identity	Good Characters	NaN	NaN
6889	21655	Frank Fitzsimmons (New Earth)	VwikiVFrank_Fitzsimmons_(New_Earth)	Public Identity	Good Characters	NaN	Gre
6890	283482	James Garfield (New Earth)	VwikiVJames_Garfield_(New_Earth)	Public Identity	Good Characters	NaN	NaN
6891	66302	Nadine West (New Earth)	VwikiVNadine_West_(New_Earth)	Public Identity	Good Characters	NaN	NaN
6892	283475	Warren Harding (New Earth)	VwikiVWarren_Harding_(New_Earth)	Public Identity	Good Characters	NaN	NaN
6893	283478	William Harrison (New Earth)	VwikiVWilliam_Harrison_(New_Earth)	Public Identity	Good Characters	NaN	NaN
6894	283471	William McKinley (New Earth)	\/ \wiki\/ \William_McKinley_(New_Earth)	Public Identity	Good Characters	NaN	NaN
6895	150660	Mookie (New Earth)	√wiki√Mookie_(New_Earth)	Public Identity	Bad Characters	Blue Eyes	Blor

```
# Запоминаем индексы строк с пустыми значениями flt_index = data[data['YEAR'].isnull()].index flt_index
```

### Out[0]:

### In [0]:

```
# Проверяем что выводятся нужные строки data[data.index.isin(flt_index)]
```

	page_id	name	urlslug	ID	ALIGN	EYE	
386	1891	Jakeem Williams (New Earth)	\/wiki\/Jakeem_Williams_(New_Earth)	Secret Identity	NaN	Brown Eyes	NaN
1400	64303	Hadley Jaggar (New Earth)	Vwiki\/Hadley_Jaggar_(New_Earth)	Secret Identity	Good Characters	Blue Eyes	Blor
1401	13097	Nergal (New Earth)	VwikiVNergal_(New_Earth)	NaN	Bad Characters	Yellow Eyes	NaN
1832	65286	Gregory Wolfe (New Earth)	Vwiki\/Gregory_Wolfe_(New_Earth)	Public Identity	Neutral Characters	Brown Eyes	Blac
1937	146333	Clarence Charles Batson V	Vwiki\/Clarence_Charles_Batson_V_(New_Earth)	Public Identity	Good Characters	NaN	Blac

		(New Earth)					
1938	113413	Chad Graham (New Earth)	VwikiVChad_Graham_(New_Earth)	Secret Identity	Bad Characters	NaN	Blor
2065	344513	Jupiter (New Earth)	\forall wiki\forall Jupiter_(New_Earth)	NaN	Good Characters	NaN	Whi
2066	344983	Pegasus (New Earth)	\/wiki\/Pegasus_(New_Earth)	NaN	Good Characters	NaN	Blac
2067	286906	Asteroth (New Earth)	\/wiki\/Asteroth_(New_Earth)	Secret Identity	Bad Characters	Yellow Eyes	Blac
2230	155569	Red Panzer IV (New Earth)	\forall \wiki\rangle \text{Red_Panzer_IV_(New_Earth)}	Secret Identity	Bad Characters	NaN	NaN
2231	19044	Gernsback (New Earth)	\forall \wiki\rangle Gernsback_(New_Earth)	NaN	Good Characters	NaN	NaN
2232	202057	Henry Cosgei (New Earth)	\/\text{Wiki\/Henry_Cosgei_(New_Earth)}	Secret Identity	Good Characters	Black Eyes	Blac
2413	216380	Marilyn Batson (New Earth)	\/wiki\/Marilyn_Batson_(New_Earth)	Public Identity	Good Characters	Brown Eyes	Bro
2414	178197	Michael Tree (New Earth)	\forall \text{Wiki} \text{Michael_Tree_(New_Earth)}	NaN	NaN	NaN	Blac
2841	383108	Brunhilde (New Earth)	\/wiki\/Brunhilde_(New_Earth)	NaN	Good Characters	NaN	NaN
2842	251517	Kuan Ti (New Earth)	\/wiki\/Kuan_Ti_(New_Earth)	Public Identity	Good Characters	NaN	Blac
3104	383914	Helen of Troy (New Earth)	\/wiki\/Helen_of_Troy_(New_Earth)	NaN	Good Characters	NaN	Blor
3105	256793	Pluto (New Earth)	\/wiki\/Pluto_(New_Earth)	Public Identity	Bad Characters	NaN	NaN
3431	15909	Ammon-Ra (New Earth)	\/wiki\/Ammon-Ra_(New_Earth)	Secret Identity	Neutral Characters	NaN	NaN
3432	348898	Kreaven (New Earth)	\/wiki\/Kreaven_(New_Earth)	Public Identity	Neutral Characters	NaN	NaN
3433	345589	Vulcan (New Earth)	\/wiki\/Vulcan_(New_Earth)	NaN	Good Characters	NaN	NaN
3434	57839	Donna Cavanagh (New Earth)	\/wiki\/Donna_Cavanagh_(New_Earth)	Public Identity	Good Characters	Green Eyes	Blor
3435	68612	Amadeus Arkham (New Earth)	\/wiki\/Amadeus_Arkham_(New_Earth)	Public Identity	Good Characters	NaN	NaN
3819	182833	Scott Spencer (New Earth)	\text{Vwiki\text{Vscott_Spencer_(New_Earth)}}	Public Identity	Neutral Characters	NaN	Blac
3820	213354	Maria Montez (New Earth)	\/wiki\/Maria_Montez_(New_Earth)	NaN	NaN	NaN	NaN
3821	345591	Diana, Goddess of the Hunt (New Earth)	\forall wiki\text{Diana,_Goddess_of_the_Hunt_(New_Earth)}	NaN	Good Characters	NaN	NaN
3822	47346	Gregory the Gargoyle (New Earth)	\/wiki\/Gregory_the_Gargoyle_(New_Earth)	NaN	Good Characters	NaN	NaN

3823	345586	Minerva (Roman Goddess) (New Earth)	VwikiVMinerva_(Roman_Goddess)_(New_Earth)	NaN	Good Characters	NaN	NaN
3824	66157	Auerbach (New Earth)	VwikiVAuerbach_(New_Earth)	Secret Identity	NaN	NaN	Bro
4320	139807	Virgil Adams (New Earth)	Vwiki\Virgil_Adams_(New_Earth)	Public Identity	Bad Characters	NaN	Blac
•••							
5527	112333	Lisa Morice (New Earth)	VwikiVLisa_Morice_(New_Earth)	Public Identity	Good Characters	Grey Eyes	Stra Blor
5528	189975	Carter Nichols (New Earth)	VwikiVCarter_Nichols_(New_Earth)	Public Identity	Good Characters	NaN	Bro
5529	139768	Cupid (New Earth)	VwikiVCupid_(New_Earth)	NaN	Good Characters	NaN	NaN
5530	345585	Juno (New Earth)	Vwiki\/Juno_(New_Earth)	NaN	Good Characters	NaN	NaN
5531	271506	Luki Lo (New Earth)	VwikiVLuki_Lo_(New_Earth)	NaN	Good Characters	NaN	Blac
5532	177249	Stanley Wilson (New Earth)	VwikiVStanley_Wilson_(New_Earth)	NaN	Good Characters	NaN	Blac
5533	250224	Elena Leal (New Earth)	VwikiVElena_Leal_(New_Earth)	Public Identity	Good Characters	NaN	Whi
5534	185720	Druid (New Earth)	VwikiVDruid_(New_Earth)	Secret Identity	Bad Characters	NaN	Blac
5535	218828	Crone (New Earth)	VwikiVCrone_(New_Earth)	Secret Identity	Bad Characters	NaN	Gre
5536	95738	Fancy Feet (New Earth)	VwikiVFancy_Feet_(New_Earth)	NaN	Bad Characters	NaN	NaN
5537	182478	Rico Strada (New Earth)	VwikiVRico_Strada_(New_Earth)	NaN	Bad Characters	Blue Eyes	Blor
5538	31642	Benjamin Hubbard (New Earth)	VwikiVBenjamin_Hubbard_(New_Earth)	NaN	NaN	NaN	NaN
6532	159528	Materna Minnx (New Earth)	VwikiVMaterna_Minnx_(New_Earth)	Public Identity	NaN	NaN	Bro
6533	19799	Frank Baker, Jr. (New Earth)	VwikiVFrank_Baker,_Jr(New_Earth)	Public Identity	Neutral Characters	Blue Eyes	Gre
6534	242167	Prowley (New Earth)	VwikiVProwley_(New_Earth)	Public Identity	Neutral Characters	Yellow Eyes	Blac
6535	95767	Smother (New Earth)	VwikiVSmother_(New_Earth)	NaN	Neutral Characters	NaN	NaN
6536	16094	Mark Antaeus (New Earth)	VwikiVMark_Antaeus_(New_Earth)	Public Identity	Good Characters	Blue Eyes	Blac
6537	128000	Jerome Cox (New Earth)	VwikiVJerome_Cox_(New_Earth)	Public Identity	Bad Characters	NaN	NaN
6538	345590	Apollo (Roman God) (New Earth)	VwikiVApollo_(Roman_God)_(New_Earth)	NaN	Good Characters	NaN	NaN
6539	15050	Ben Lo (New Earth)	Vwiki∀Ben_Lo_(New_Earth)	Public Identity	Good Characters	Brown Eyes	Blac

	1	1					
6540	205584	Auctioneer II (New Earth)	VwikiVAuctioneer_II_(New_Earth)	Secret Identity	Bad Characters	NaN	Whi
6887	283661	Herbert Hoover (New Earth)	\forall \text{WikiVHerbert_Hoover_(New_Earth)}	Public Identity	Good Characters	NaN	NaN
6888	283657	William Howard Taft (New Earth)	\/wiki\/William_Howard_Taft_(New_Earth)	Public Identity	Good Characters	NaN	NaN
6889	21655	Frank Fitzsimmons (New Earth)	VwikiVFrank_Fitzsimmons_(New_Earth)	Public Identity	Good Characters	NaN	Gre
6890	283482	James Garfield (New Earth)	VwikiVJames_Garfield_(New_Earth)	Public Identity	Good Characters	NaN	NaN
6891	66302	Nadine West (New Earth)	\text{Vwiki\text{Nadine_West_(New_Earth)}}	Public Identity	Good Characters	NaN	NaN
6892	283475	Warren Harding (New Earth)	\/wiki\/Warren_Harding_(New_Earth)	Public Identity	Good Characters	NaN	NaN
6893	283478	William Harrison (New Earth)	\forall \text{William_Harrison_(New_Earth)}	Public Identity	Good Characters	NaN	NaN
6894	283471	William McKinley (New Earth)	\/wiki\/William_McKinley_(New_Earth)	Public Identity	Good Characters	NaN	NaN
6895	150660	Mookie (New Earth)	VwikiVMookie_(New_Earth)	Public Identity	Bad Characters	Blue Eyes	Blor

data\_num\_Year = data\_num[['YEAR']]
data\_num\_Year.head()

Out[0]:

	YEAR
0	1939.0
1	1986.0
2	1959.0
3	1987.0
4	1940.0

In [0]:

from sklearn.impute import SimpleImputer
from sklearn.impute import MissingIndicator

```
In [0]:
# Фильтр для проверки заполнения пустых значений
indicator = MissingIndicator()
mask_missing_values_only = indicator.fit_transform(data_num_Year)
mask_missing_values_only
Out[0]:
array([[False],
                                   [False],
                                   [False],
                                   [True],
                                  [True],
                                   [ True]])
In [0]:
strategies=['mean', 'median', 'most frequent']
In [0]:
def test num impute(strategy param):
                   imp num = SimpleImputer(strategy=strategy param)
                   data num imp = imp num.fit transform(data num Year)
                   return data num imp[mask missing values only]
In [0]:
strategies[0], test num impute(strategies[0])
Out[0]:
('mean', array([1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178,
                                       1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178,
                                       1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178,
                                       1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178,
                                     1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.7
                                       1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178,
                                       1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178,
                                       1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178,
                                      1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.7
                                       1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178,
                                       1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178,
                                      1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178, 1989.76666178,
                                       1989.76666178]))
In [0]:
strategies[1], test num impute(strategies[1])
Out[0]:
('median'
    array([1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992.,
                                      1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992., 19
                                       1992., 1992., 1992., 1992., 1992., 1992., 1992., 1992.,
```

1992., 1992.]))

```
In [0]:
```

# Внедрение значений (категориальные данные)

```
Колонка ID. Тип данных object. Количество пустых значений 2013, 29.19%. Колонка ALIGN. Тип данных object. Количество пустых значений 601, 8.72%. Колонка EYE. Тип данных object. Количество пустых значений 3628, 52.61%. Колонка HAIR. Тип данных object. Количество пустых значений 2274, 32.98%. Колонка SEX. Тип данных object. Количество пустых значений 125, 1.81%. Колонка GSM. Тип данных object. Количество пустых значений 6832, 99.07%. Колонка ALIVE. Тип данных object. Количество пустых значений 3, 0.04%. Колонка FIRST APPEARANCE. Тип данных object. Количество пустых значений 69, 1.0%.
```

```
In [0]:
cat_temp_data = data[['HAIR']]
cat_temp_data.tail(10)
Out[0]:
```

```
HAIR
6886 NaN
6887 NaN
6888 NaN
6889 Grey Hair
6890 NaN
6891 NaN
6892 NaN
6893 NaN
6894 NaN
6895 Blond Hair
```

np.unique(data\_imp2)

Out[0]:

```
In [0]:
cat temp data['HAIR'].unique()
Out[0]:
array(['Black Hair', 'Brown Hair', 'White Hair', 'Blond Hair', 'Red Hair',
        nan, 'Green Hair', 'Strawberry Blond Hair', 'Grey Hair', 'Silver Hair', 'Orange Hair', 'Purple Hair', 'Gold Hair', 'Blue Hair', 'Reddish Brown Hair', 'Pink Hair', 'Violet Hair',
        'Platinum Blond Hair'], dtype=object)
In [0]:
cat temp data[cat temp data['HAIR'].isnull()].shape
Out[0]:
(2274, 1)
In [0]:
# Импьютация наиболее частыми значениями
imp2 = SimpleImputer(missing values=np.nan, strategy='most frequent')
data imp2 = imp2.fit transform(cat temp data)
data_imp2
Out[0]:
array([['Black Hair'],
        ['Black Hair'],
        ['Brown Hair'],
        ['Black Hair'],
        ['Black Hair'],
        ['Blond Hair']], dtype=object)
In [0]:
# Пустые значения отсутствуют
```

'Platinum Blond Hair', 'Purple Hair', 'Red Hair', 'Reddish Brown Hair', 'Silver Hair', 'Strawberry Blond Hair',

'Violet Hair', 'White Hair'], dtype=object)

# Преобразование категориальных признаков в числовые

# In [0]:

```
cat_enc = pd.DataFrame({'c1':data_imp2.T[0]})
cat_enc
```

	c1					
0	Black Hair					
1	Black Hair					
2	Brown Hair					
3	White Hair Black Hair Black Hair Blond Hair					
4						
5						
6						
7	Black Hair					
8	Blond Hair					
9	Blond Hair					
10	Blond Hair					
11	Blond Hair					
12	Red Hair					
13	Brown Hair					
14	Black Hair					
15	Black Hair					
16	Brown Hair					
17	Black Hair					
18	Black Hair					
19	Black Hair					
20	Red Hair					
21	Blond Hair					
22	Black Hair					
23	Green Hair					
24	Red Hair					
25	Black Hair					
26	Black Hair					
27	Red Hair					
28	Red Hair					
29	Black Hair					
6866	Black Hair					

6867	Black Hair
6868	Black Hair
6869	Black Hair
6870	Black Hair
6871	Black Hair
6872	Black Hair
6873	Black Hair
6874	Black Hair
6875	Black Hair
6876	Red Hair
6877	Black Hair
6878	Blond Hair
6879	Black Hair
6880	Black Hair
6881	Red Hair
6882	Brown Hair
6883	Black Hair
6884	Black Hair
6885	Black Hair
6886	Black Hair
6887	Black Hair
6888	Black Hair
6889	Grey Hair
6890	Black Hair
6891	Black Hair
6892	Black Hair
6893	Black Hair
6894	Black Hair
6895	Blond Hair

6896 rows × 1 columns

# **Label encoding**

```
from sklearn.preprocessing import LabelEncoder, OneHotEncoder

In [0]:
le = LabelEncoder()
cat_enc_le = le.fit_transform(cat_enc['c1'])
```

```
In [0]:
cat_enc['c1'].unique()
Out[0]:
array(['Black Hair', 'Brown Hair', 'White Hair', 'Blond Hair', 'Red Hair',
```

```
array(['Black Hair', 'Brown Hair', 'White Hair', 'Blond Hair', 'Red Hair', 'Green Hair', 'Silver Hair', 'Orange Hair', 'Purple Hair', 'Gold Hair', 'Blue Hair', 'Reddish Brown Hair', 'Pink Hair', 'Violet Hair', 'Platinum Blond Hair'], dtype=object)
```

```
In [0]:
np.unique(cat_enc_le)
Out[0]:
array([ 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16])
In [0]:
le.inverse_transform([x for x in range(16)])
Out[0]:
'Platinum Blond Hair', 'Purple Hair', 'Red Hair', 'Reddish Brown Hair', 'Silver Hair', 'Strawberry Blond Hair',
       'Violet Hair'], dtype=object)
In [0]:
cat_enc_le
Out[0]:
array([0, 0, 3, ..., 0, 0, 1])
One-hot encoding
In [0]:
ohe = OneHotEncoder()
cat_enc_ohe = ohe.fit_transform(cat_enc[['c1']])
In [0]:
cat_enc.shape
Out[0]:
(6896, 1)
In [0]:
cat_enc_ohe.shape
Out[0]:
(6896, 17)
In [0]:
cat_enc_ohe
Out[0]:
<6896x17 sparse matrix of type '<class 'numpy.float64'>'
       with 6896 stored elements in Compressed Sparse Row format>
```

```
In [0]:
```

```
cat enc ohe.todense()[0:10]
```

```
Out[0]:
```

```
0.],
0.],
1.],
0.],
0.],
0.],
0.],
0.]])
```

### Или

#### In [0]:

```
pd.get_dummies(cat_enc).tail()
```

### Out[0]:

	c1_Black Hair	_	_	_	_	_		c1_Orange Hair	_	
6891	1	0	0	0	0	0	0	0	0	0
6892	1	0	0	0	0	0	0	0	0	0
6893	1	0	0	0	0	0	0	0	0	0
6894	1	0	0	0	0	0	0	0	0	0
6895	0	1	0	0	0	0	0	0	0	0

### In [0]:

```
pd.get_dummies(cat_temp_data, dummy_na=True).tail()
```

	HAIR_Black Hair	_	_	HAIR_Brown Hair	_	_		HAIR_Ora
6891	0	0	0	0	0	0	0	0
6892	0	0	0	0	0	0	0	0
6893	0	0	0	0	0	0	0	0
6894	0	0	0	0	0	0	0	0
6895	0	1	0	0	0	0	0	0

# Масштабирование данных

```
In [0]:
```

from sklearn.preprocessing import MinMaxScaler, StandardScaler, Normalizer

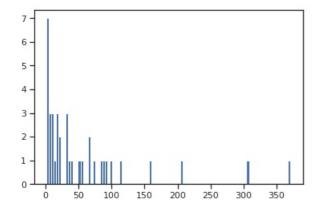
# MinMax масштабирование

```
In [0]:
```

```
sc1 = MinMaxScaler()
sc1_data = sc1.fit_transform(data_new_2[['APPEARANCES']])
```

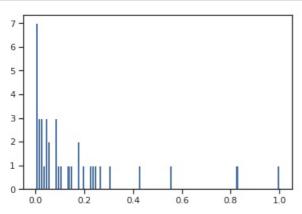
# In [0]:

```
plt.hist(data_new_2['APPEARANCES'], 100)
plt.show()
```



# In [0]:

```
plt.hist(sc1_data, 100)
plt.show()
```

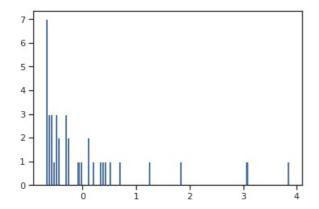


```
sc2 = StandardScaler()
sc2_data = sc2.fit_transform(data_new_2[['APPEARANCES']])
```

# **Z-**оценка

# In [0]:

```
plt.hist(sc2_data, 100)
plt.show()
```



# Нормализация данных

### In [0]:

```
sc3 = Normalizer()
sc3_data = sc3.fit_transform(data_new_2[['APPEARANCES']])
```

```
plt.hist(sc3_data, 50)
plt.show()
```

