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Задание

Для заданного набора данных проведите обработку пропусков в данных. Какие способы обработки пропусков в данных для категориальных и количественных признаков Вы использовали? Какие признаки Вы будете использовать для дальнейшего построения моделей машинного обучения и почему? Для заданного набора данных произведите масштабирование данных и преобразование категориальных признаков в количественные. Какие методы Вы использовали для решения задачи и почему?

Набор данных: [kaggle.com (Marvel)]

Описание набора данных

In [92]:

```
from google.colab import files
# files.upload()

!ls -lha kaggle.json

!pip install -q kaggle


!mkdir -p ~/.kaggle
!cp kaggle.json ~/.kaggle/

# This permissions change avoids a warning on Kaggle tool startup.
!chmod 600 ~/.kaggle/kaggle.json


!kaggle datasets list

!kaggle datasets download -d fivethirtyeight/fivethirtyeight-comic-characters-dataset
```

```
-rw-r--r-- 1 root root 68 Apr  3 16:26 kaggle.json
Warning: Looks like you're using an outdated API Version, please consider updating (server 1.5.6 / client 1.5.4)
ref                                                          title                                               size  lastUpdated          downloadCount
-----------------------------------------------------------  --------------------------------------------------  -----  -------------------  -------------
allen-institute-for-ai/CORD-19-research-challenge            COVID-19 Open Research Dataset Challenge (CORD-19)  729MB  2020-03-27 23:46:53
41093
ryanxjhan/cbc-news-coronavirus-articles-march-26             CBC News Coronavirus/COVID-19 Articles (NLP)          6MB  2020-03-27 23:23:07
245
vitaliymalcev/russian-passenger-air-service-20072020         Russian passenger air service 2007-2020             239KB  2020-04-02 22:27:03            1
58
danevans/world-bank-wdi-212-health-systems                   World Bank WDI 2.12 - Health Systems                  6KB  2020-03-29 19:00:14          310

sobhanmoosavi/us-accidents                                   US Accidents (3.0 million records)                  199MB  2020-01-17 04:45:09        12153
fireballbyedimyrnmom/us-counties-covid-19-dataset            US counties COVID 19 dataset                        206KB  2020-04-03 11:21:53          514
eswarchandt/amazon-music-reviews                             Amazon Musical Instruments Reviews                    5MB  2020-03-29 02:59:52          125
trtmio/project-coviewed-subreddit-coronavirus-news-corpus    Project COVIEWED Coronavirus News Corpus              8MB  2020-03-31 11:32:45
22
monogenea/birdsongs-from-europe                              Bird songs from Europe (xeno-canto)                   7GB  2020-03-23 15:35:20           28
dheerajmpai/hospitals-and-beds-in-india                      Hospitals and beds in India (Statewise)               5KB  2020-03-27 14:05:50          187
lakritidis/identifying-influential-bloggers-techcrunch       Identifying Influential Bloggers: Techcrunch        112MB  2020-03-30 19:22:09           34
bappekim/air-pollution-in-seoul                              Air Pollution in Seoul                               20MB  2020-03-29 07:42:23          147
roche-data-science-coalition/uncover                         UNCOVER COVID-19 Challenge                          154MB  2020-04-01 15:17:39          599
sudalairajkumar/novel-corona-virus-2019-dataset              Novel Corona Virus 2019 Dataset                     661KB  2020-04-03 05:56:48        10455
3
kimjihoo/coronavirusdataset                                  Data Science for COVID-19 (DS4C)                      3MB  2020-03-30 19:54:12        24580
unanimad/dataisbeautiful                                     Reddit - Data is Beautiful                           11MB  2020-04-01 12:10:09         1456
jessemostipak/hotel-booking-demand                           Hotel booking demand                                  1MB  2020-02-13 01:27:20        12311
rubenssjr/brasilian-houses-to-rent                           brazilian_houses_to_rent                            282KB  2020-03-25 22:51:17         1554
paultimothymooney/covid19-containment-and-mitigation-measures  COVID-19 containment and mitigation measures      216KB  2020-04-03 11:08:
32         1217
clmentbisaillon/fake-and-real-news-dataset                   Fake and real news dataset                           41MB  2020-03-26 18:51:15          605
fivethirtyeight-comic-characters-dataset.zip: Skipping, found more recently modified local copy (use --force to force download)
```

In [93]:

```
# !unzip /content/fivethirtyeight-comic-characters-dataset.zip
!head marvel-wikia-data.csv
```

673702,Yologarch (Earth-616),\/Yologarch_(Earth-616),,Bad Characters,,,,,Living Characters,,,

In [94]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.datasets import load_wine
%matplotlib inline

data = pd.read_csv('marvel-wikia-data.csv', sep=",")
# data = pd.get_dummies(data)
data.head()
```

Out[94]:

	page_id	name	urlslug	ID	ALIGN	EYE	HAIR	SEX	GSM	ALIVE	APPEARANCES	APPE
0	1678	Spider-Man (Peter Parker)	\/Spider-Man_(Peter_Parker)	Secret Identity	Good Characters	Hazel Eyes	Brown Hair	Male Characters	NaN	Living Characters	4043.0	
1	7139	Captain America (Steven Rogers)	\/Captain_America_(Steven_Rogers)	Public Identity	Good Characters	Blue Eyes	White Hair	Male Characters	NaN	Living Characters	3360.0	
2	64786	Wolverine (James \"Logan\" Howlett)	\/Wolverine_(James_%22Logan%22_Howlett)	Public Identity	Neutral Characters	Blue Eyes	Black Hair	Male Characters	NaN	Living Characters	3061.0	
3	1868	Iron Man (Anthony \"Tony\" Stark)	\/Iron_Man_(Anthony_%22Tony%22_Stark)	Public Identity	Good Characters	Blue Eyes	Black Hair	Male Characters	NaN	Living Characters	2961.0	
4	2460	Thor (Thor Odinson)	\/Thor_(Thor_Odinson)	No Dual Identity	Good Characters	Blue Eyes	Blond Hair	Male Characters	NaN	Living Characters	2258.0	

In [95]:

```
data.shape
```

Out[95]:

(16376, 13)

In [96]:

```
# Список колонок с типами данных
data.dtypes
```

Out[96]:

```
page_id              int64
name                object
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 [97]:

```
# Количество пустых значений
data.isnull().sum()
```

Out[97]:

```
page_id             0
```

```
name              0
urlslug           0
ID             3770
ALIGN          2812
EYE            9767
HAIR           4264
SEX             854
GSM           16286
ALIVE             3
APPEARANCES    1096
FIRST APPEARANCE  815
Year            815
dtype: int64
```

In [98]:

```
# Основные статистические характеристки набора данных
data.describe()
```

Out[98]:

	page_id	APPEARANCES	Year
count	16376.000000	15280.000000	15561.000000
mean	300232.082377	17.033377	1984.951803
std	253460.403399	96.372959	19.663571
min	1025.000000	1.000000	1939.000000
25%	28309.500000	1.000000	1974.000000
50%	282578.000000	3.000000	1990.000000
75%	509077.000000	8.000000	2000.000000
max	755278.000000	4043.000000	2013.000000

In [99]:

```
total_count = data.shape[0]
print('Строк в наборе : {}'.format(total_count))
```

Строк в наборе : 16376

Обработка пропусков

Удаление колонок, содержащих пустые значения

In [100]:

```
data_new_1 = data.dropna(axis=1, how='any')
(data.shape, data_new_1.shape)
```

Out[100]:

((16376, 13), (16376, 3))

Удаление строк, содержащих пустые значения

In [101]:

```
data_new_2 = data.dropna(axis=0, how='any')
(data.shape, data_new_2.shape)
```

Out[101]:

((16376, 13), (58, 13))

Заполнение всех пропущенных значений нулями

In [102]:

```
data_new_3 = data.fillna(0)
data_new_3.head()
```

Out[102]:

	page_id	name	urlslug	ID	ALIGN	EYE	HAIR	SEX	GSM	ALIVE	APPEARANCES	APPE
0	1678	Spider-Man (Peter Parker)	\/Spider-Man_(Peter_Parker)	Secret Identity	Good Characters	Hazel Eyes	Brown Hair	Male Characters	0	Living Characters	4043.0	
1	7139	Captain America (Steven Rogers)	\/Captain_America_(Steven_Rogers)	Public Identity	Good Characters	Blue Eyes	White Hair	Male Characters	0	Living Characters	3360.0	
2	64786	Wolverine (James \"Logan\" Howlett)	\/Wolverine_(James_%22Logan%22_Howlett)	Public Identity	Neutral Characters	Blue Eyes	Black Hair	Male Characters	0	Living Characters	3061.0	
3	1868	Iron Man (Anthony \"Tony\" Stark)	\/Iron_Man_(Anthony_%22Tony%22_Stark)	Public Identity	Good Characters	Blue Eyes	Black Hair	Male Characters	0	Living Characters	2961.0	
4	2460	Thor (Thor Odinson)	\/Thor_(Thor_Odinson)	No Dual Identity	Good Characters	Blue Eyes	Blond Hair	Male Characters	0	Living Characters	2258.0	

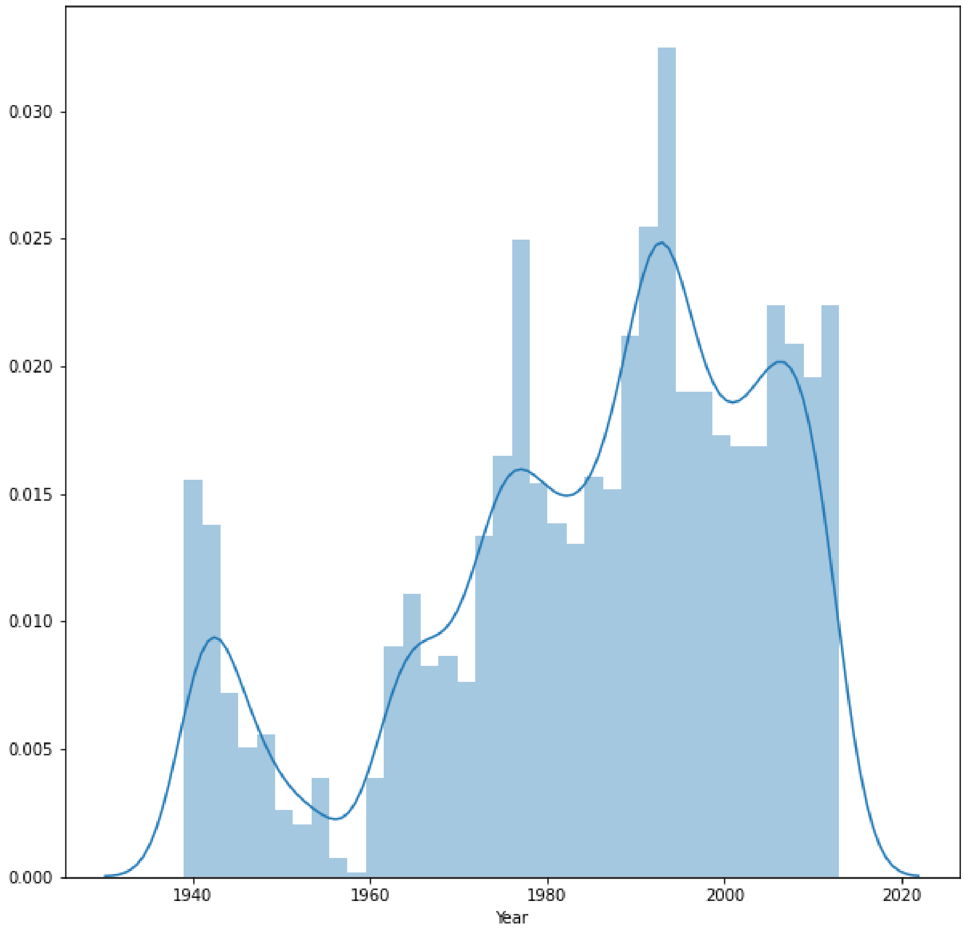
Построение гистограммы

In [103]:

```
# для колонки Year
fig, ax = plt.subplots(figsize=(10,10))
sns.distplot(data['Year'])
```

Out[103]:

<matplotlib.axes._subplots.AxesSubplot at 0x7fdc9d836048>



Импьютация

Импьютация

Числовые данные

Выберем числовые колонки с пропущенными значениями

In [104]:

```
# Выберем числовые колонки с пропущенными значениями
# Цикл по колонкам датасета
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 1096, 6.69%.
Колонка Year. Тип данных float64. Количество пустых значений 815, 4.98%.

In [105]:

```
# Фильтр по колонкам с пропущенными значениями
data_num = data[num_cols]
data_num
```

Out[105]:

	APPEARANCES	Year
0	4043.0	1962.0
1	3360.0	1941.0
2	3061.0	1974.0
3	2961.0	1963.0
4	2258.0	1950.0
...	...	...
16371	NaN	NaN
16372	NaN	NaN
16373	NaN	NaN
16374	NaN	NaN
16375	NaN	NaN

16376 rows × 2 columns

In [106]:

```
# Фильтр по пустым значениям поля APPEARANCES
data[data['ALIVE'].isnull()]
```

Out[106]:

	page_id	name	urlslug	ID	ALIGN	EYE	HAIR	SEX	GSM	ALIVE	APPEARANCES	FIRST APPEARANCE	Year
16293	541449	Mj7711	\/User:Mj7711	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
16329	714409	Sharjeel786	\/User:Sharjeel786	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
16347	462671	TOR\/test	\/User:TOR\/test	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

Запоминаем индексы строк с пустыми значениями

In [107]:

```
flt_index = data[data['APPEARANCES'].isnull()].index
flt_index
```

Out[107]:

```
Int64Index([15280, 15281, 15282, 15283, 15284, 15285, 15286, 15287, 15288,
            15289,
            ...
            16366, 16367, 16368, 16369, 16370, 16371, 16372, 16373, 16374,
            16375],
           dtype='int64', length=1096)
```

In [108]:

```
data_num[data_num.index.isin(flt_index)]['APPEARANCES']
```

Out[108]:

```
15280   NaN
15281   NaN
15282   NaN
15283   NaN
15284   NaN
         ..
16371   NaN
16372   NaN
16373   NaN
16374   NaN
16375   NaN
Name: APPEARANCES, Length: 1096, dtype: float64
```

In [109]:

```
data_num_MasVnrArea = data_num[['APPEARANCES']]
data_num_MasVnrArea.head()
```

Out[109]:

	APPEARANCES
0	4043.0
1	3360.0
2	3061.0
3	2961.0
4	2258.0

In [0]:

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

Фильтр для проверки заполнения пустых значений

In [111]:

```
indicator = MissingIndicator()
mask_missing_values_only = indicator.fit_transform(data_num_MasVnrArea)
mask_missing_values_only
```

Out[111]:

```
array([[False],
       [False],
       [False],
       ...,
       [ True],
       [ True],
       [ True]])
```

In [0]:

```
strategies=['mean', 'median','most_frequent']

def test_num_impute_col(dataset, column, strategy_param):
    temp_data = dataset[[column]]

    indicator = MissingIndicator()
```

```
    indicator = MissingIndicator()
    mask_missing_values_only = indicator.fit_transform(temp_data)

    imp_num = SimpleImputer(strategy=strategy_param)
    data_num_imp = imp_num.fit_transform(temp_data)

    filled_data = data_num_imp[mask_missing_values_only]

    return column, strategy_param, filled_data.size, filled_data[0], filled_data[filled_data.size-1]
```

In [113]:

```
data[['ALIVE']].describe()
```

Out[113]:

	ALIVE
count	16373
unique	2
top	Living Characters
freq	12608

In [114]:

```
test_num_impute_col(data, 'APPEARANCES', strategies[0])
```

Out[114]:

('APPEARANCES', 'mean', 1096, 17.033376963350786, 17.033376963350786)

In [115]:

```
test_num_impute_col(data, 'APPEARANCES', strategies[1])
```

Out[115]:

('APPEARANCES', 'median', 1096, 3.0, 3.0)

In [116]:

```
test_num_impute_col(data, 'APPEARANCES', strategies[2])
```

Out[116]:

('APPEARANCES', 'most_frequent', 1096, 1.0, 1.0)

Выберем категориальные колонки с пропущенными значениями

Цикл по колонкам датасета

In [117]:

```
cat_temp_data = data[['ALIGN']]
cat_temp_data.head()
```

Out[117]:

	ALIGN
0	Good Characters
1	Good Characters
2	Neutral Characters
3	Good Characters
4	Good Characters

In [118]:

```
cat_temp_data['ALIGN'].unique()
```

Out[118]:

```
array(['Good Characters', 'Neutral Characters', 'Bad Characters', nan],
      dtype=object)
```

In [119]:

```
cat_temp_data[cat_temp_data['ALIGN'].isnull()].shape
```

Out[119]:

```
(2812, 1)
```

Импьютация наиболее частыми значениями

In [120]:

```
imp2 = SimpleImputer(missing_values=np.nan, strategy='most_frequent')
data_imp2 = imp2.fit_transform(cat_temp_data)
data_imp2
```

Out[120]:

```
array([['Good Characters'],
       ['Good Characters'],
       ['Neutral Characters'],
       ...,
       ['Bad Characters'],
       ['Neutral Characters'],
       ['Bad Characters']], dtype=object)
```

Пустые значения отсутствуют

In [121]:

```
np.unique(data_imp2)
```

Out[121]:

```
array(['Bad Characters', 'Good Characters', 'Neutral Characters'],
      dtype=object)
```

Импьютация константой

In [122]:

```
imp3 = SimpleImputer(missing_values=np.nan, strategy='constant', fill_value='!!!')
data_imp3 = imp3.fit_transform(cat_temp_data)
data_imp3
```

Out[122]:

```
array([['Good Characters'],
       ['Good Characters'],
       ['Neutral Characters'],
       ...,
       ['Bad Characters'],
       ['Neutral Characters'],
       ['Bad Characters']], dtype=object)
```

In [123]:

```
np.unique(data_imp3)
```

Out[123]:

```
array(['!!!', 'Bad Characters', 'Good Characters', 'Neutral Characters'],
      dtype=object)
```

In [124]:

```
data_imp3[data_imp3=='!!!'].size
```

Out[124]:

2812

Какие способы обработки пропусков в данных для категориальных и количественных признаков Вы использовали? -- удаление строк и колонок с пустыми значениями, заполнение всех пропущенных значений нулями, импьютацию для количественных признаков и для категориальных (импьютация наиболее частыми значениями и константой)

Какие признаки Вы будете использовать для дальнейшего построения моделей машинного обучения и почему? -- для дальнейшего построения моделей будем использовать категориальные признаки со стратегиями "most_frequent" или "constant" для корректной работы класса SimpleImputer

Масштабирование данных

In [0]:

```
from sklearn.preprocessing import MinMaxScaler, StandardScaler, Normalizer
```

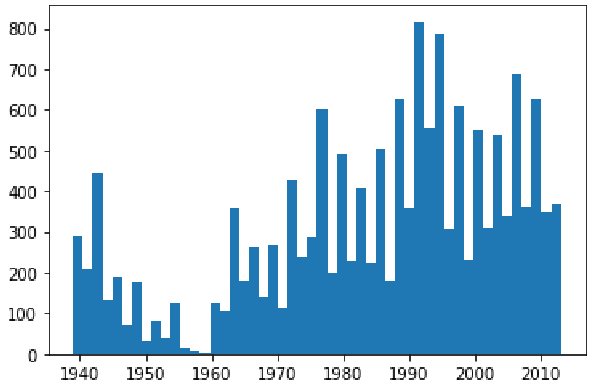
In [0]:

```
sc1 = MinMaxScaler()
sc1_data = sc1.fit_transform(data[['Year']])
```

In [127]:

```
plt.hist(data['Year'], 50)
plt.show()
```

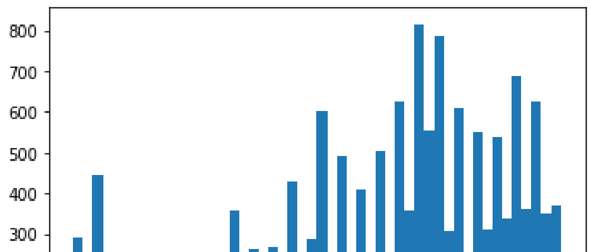
```
/usr/local/lib/python3.6/dist-packages/numpy/lib/histograms.py:839: RuntimeWarning: invalid value encountered in greater_equal
  keep = (tmp_a >= first_edge)
/usr/local/lib/python3.6/dist-packages/numpy/lib/histograms.py:840: RuntimeWarning: invalid value encountered in less_equal
  keep &= (tmp_a <= last_edge)
```

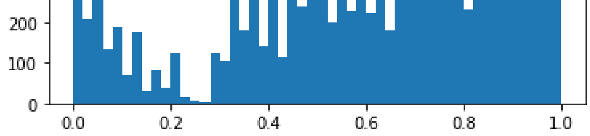


In [128]:

```
plt.hist(sc1_data, 50)
plt.show()
```

```
/usr/local/lib/python3.6/dist-packages/numpy/lib/histograms.py:839: RuntimeWarning: invalid value encountered in greater_equal
  keep = (tmp_a >= first_edge)
/usr/local/lib/python3.6/dist-packages/numpy/lib/histograms.py:840: RuntimeWarning: invalid value encountered in less_equal
  keep &= (tmp_a <= last_edge)
```





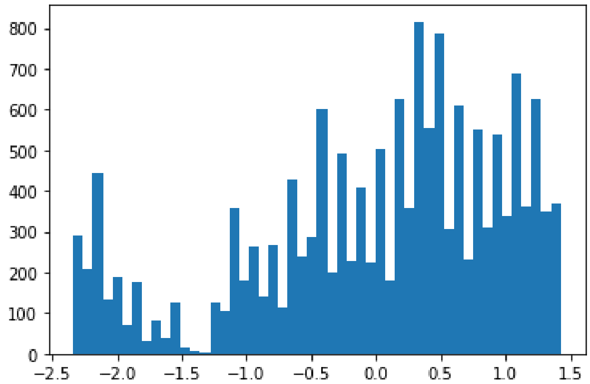
In [0]:

```
sc2 = StandardScaler()
sc2_data = sc2.fit_transform(data[['Year']])
```

In [130]:

```
plt.hist(sc2_data, 50)
plt.show()
```

```
/usr/local/lib/python3.6/dist-packages/numpy/lib/histograms.py:839: RuntimeWarning: invalid value encountered in greater_equal
  keep = (tmp_a >= first_edge)
/usr/local/lib/python3.6/dist-packages/numpy/lib/histograms.py:840: RuntimeWarning: invalid value encountered in less_equal
  keep &= (tmp_a <= last_edge)
```

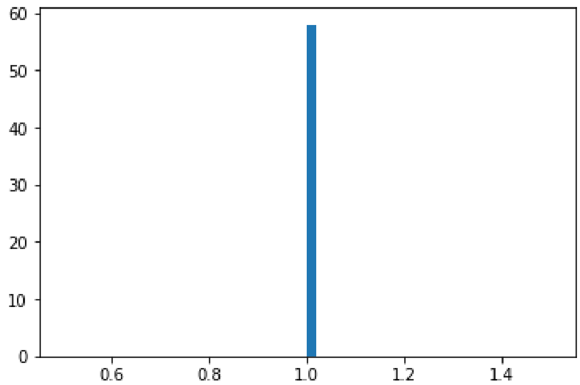


In [0]:

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

In [132]:

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



In [133]:

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

Out[133]:

	c1
0	Good Characters
1	Good Characters
2	Neutral Characters

	c1
3	Good Characters
4	Good Characters
...	...
16371	Bad Characters
16372	Good Characters
16373	Bad Characters
16374	Neutral Characters
16375	Bad Characters

16376 rows × 1 columns

In [0]:

```
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
```

In [0]:

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

In [136]:

```
cat_enc['c1'].unique()
```

Out[136]:

```
array(['Good Characters', 'Neutral Characters', 'Bad Characters'],
      dtype=object)
```

In [137]:

```
np.unique(cat_enc_le)
```

Out[137]:

```
array([0, 1, 2])
```

In [138]:

```
le.inverse_transform([ 0,  1,  2])
```

Out[138]:

```
array(['Bad Characters', 'Good Characters', 'Neutral Characters'],
      dtype=object)
```

In [0]:

```
ohe = OneHotEncoder()
cat_enc_ohe = ohe.fit_transform(cat_enc[['c1']])
```

In [140]:

```
cat_enc.shape
```

Out[140]:

```
(16376, 1)
```

In [141]:

```
cat_enc_ohe.shape
```

Out[141]:

```
(16376, 3)
```

In [142]:

```
cat_enc_ohe
```

Out[142]:

```
<16376x3 sparse matrix of type '<class 'numpy.float64'>'
 with 16376 stored elements in Compressed Sparse Row format>
```

In [143]:

```
cat_enc_ohe.todense()[0:3]
```

Out[143]:

```
matrix([[0., 1., 0.],
        [0., 1., 0.],
        [0., 0., 1.]])
```

In [144]:

```
cat_enc.head(3)
```

Out[144]:

	c1
0	Good Characters
1	Good Characters
2	Neutral Characters

In [145]:

```
pd.get_dummies(cat_enc).head()
```

Out[145]:

	c1_Bad Characters	c1_Good Characters	c1_Neutral Characters
0	0	1	0
1	0	1	0
2	0	0	1
3	0	1	0
4	0	1	0

In [146]:

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

Out[146]:

	ALIGN_Bad Characters	ALIGN_Good Characters	ALIGN_Neutral Characters	ALIGN_nan
0	0	1	0	0
1	0	1	0	0
2	0	0	1	0
3	0	1	0	0
4	0	1	0	0