Merc Database XGBoost Project

September 7, 2021

Mercedes-Benz Greener Manufacturing

DESCRIPTION

Reduce the time a Mercedes-Benz spends on the test bench.

Problem Statement Scenario: Since the first automobile, the Benz Patent Motor Car in 1886, Mercedes-Benz has stood for important automotive innovations. These include the passenger safety cell with a crumple zone, the airbag, and intelligent assistance systems. Mercedes-Benz applies for nearly 2000 patents per year, making the brand the European leader among premium carmakers. Mercedes-Benz is the leader in the premium car industry. With a huge selection of features and options, customers can choose the customized Mercedes-Benz of their dreams.

To ensure the safety and reliability of every unique car configuration before they hit the road, the company's engineers have developed a robust testing system. As one of the world's biggest manufacturers of premium cars, safety and efficiency are paramount on Mercedes-Benz's production lines. However, optimizing the speed of their testing system for many possible feature combinations is complex and time-consuming without a powerful algorithmic approach.

You are required to reduce the time that cars spend on the test bench. Others will work with a dataset representing different permutations of features in a Mercedes-Benz car to predict the time it takes to pass testing. Optimal algorithms will contribute to faster testing, resulting in lower carbon dioxide emissions without reducing Mercedes-Benz's standards.

Following actions should be performed:

If for any column(s), the variance is equal to zero, then you need to remove those variable(s). Check for null and unique values for test and train sets. Apply label encoder. Perform dimensionality reduction. Predict your test_df values using XGBoost.

The data set is already divided into train and test

[2]:
```
import numpy as np
import pandas as pd
from datetime import datetime as dt
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
from matplotlib.pylab import rcParams
rcParams['figure.figsize'] = 15, 6

import warnings
```

```
warnings.filterwarnings('ignore')
```

[3]:
```
# importing csv module
import csv
# csv file name
train_df = pd.read_csv(r'D:\OneDrive\Studies\AI - ML\Python\Examples\ML␣
↪Pracs\train.csv')
```

[4]:
```
# importing csv module
import csv
# csv file name
test_df = pd.read_csv(r'D:\OneDrive\Studies\AI - ML\Python\Examples\ML␣
↪Pracs\test.csv')
```

[5]:
```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4209 entries, 0 to 4208
Columns: 378 entries, ID to X385
dtypes: float64(1), int64(369), object(8)
memory usage: 12.1+ MB
```

[6]:
```
test_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4209 entries, 0 to 4208
Columns: 377 entries, ID to X385
dtypes: int64(369), object(8)
memory usage: 12.1+ MB
```

[7]:
```
train_df.describe()
```

[7]:

	ID	y	X10	X11	X12	\
count	4209.000000	4209.000000	4209.000000	4209.0	4209.000000	
mean	4205.960798	100.669318	0.013305	0.0	0.075077	
std	2437.608688	12.679381	0.114590	0.0	0.263547	
min	0.000000	72.110000	0.000000	0.0	0.000000	
25%	2095.000000	90.820000	0.000000	0.0	0.000000	
50%	4220.000000	99.150000	0.000000	0.0	0.000000	
75%	6314.000000	109.010000	0.000000	0.0	0.000000	
max	8417.000000	265.320000	1.000000	0.0	1.000000	

	X13	X14	X15	X16	X17	…	\
count	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	…	
mean	0.057971	0.428130	0.000475	0.002613	0.007603	…	
std	0.233716	0.494867	0.021796	0.051061	0.086872	…	
min	0.000000	0.000000	0.000000	0.000000	0.000000	…	
25%	0.000000	0.000000	0.000000	0.000000	0.000000	…	

```
50%        0.000000     0.000000     0.000000     0.000000     0.000000  ...
75%        0.000000     1.000000     0.000000     0.000000     0.000000  ...
max        1.000000     1.000000     1.000000     1.000000     1.000000  ...

                  X375         X376         X377         X378         X379  \
count  4209.000000  4209.000000  4209.000000  4209.000000  4209.000000
mean      0.318841     0.057258     0.314802     0.020670     0.009503
std       0.466082     0.232363     0.464492     0.142294     0.097033
min       0.000000     0.000000     0.000000     0.000000     0.000000
25%       0.000000     0.000000     0.000000     0.000000     0.000000
50%       0.000000     0.000000     0.000000     0.000000     0.000000
75%       1.000000     0.000000     1.000000     0.000000     0.000000
max       1.000000     1.000000     1.000000     1.000000     1.000000

                  X380         X382         X383         X384         X385
count  4209.000000  4209.000000  4209.000000  4209.000000  4209.000000
mean      0.008078     0.007603     0.001663     0.000475     0.001426
std       0.089524     0.086872     0.040752     0.021796     0.037734
min       0.000000     0.000000     0.000000     0.000000     0.000000
25%       0.000000     0.000000     0.000000     0.000000     0.000000
50%       0.000000     0.000000     0.000000     0.000000     0.000000
75%       0.000000     0.000000     0.000000     0.000000     0.000000
max       1.000000     1.000000     1.000000     1.000000     1.000000

[8 rows x 370 columns]
```

[8]:
```
test_df.describe()
```

[8]:
```
                    ID          X10          X11          X12          X13  \
count  4209.000000  4209.000000  4209.000000  4209.000000  4209.000000
mean   4211.039202     0.019007     0.000238     0.074364     0.061060
std    2423.078926     0.136565     0.015414     0.262394     0.239468
min       1.000000     0.000000     0.000000     0.000000     0.000000
25%    2115.000000     0.000000     0.000000     0.000000     0.000000
50%    4202.000000     0.000000     0.000000     0.000000     0.000000
75%    6310.000000     0.000000     0.000000     0.000000     0.000000
max    8416.000000     1.000000     1.000000     1.000000     1.000000

                   X14          X15          X16          X17          X18  ...  \
count  4209.000000  4209.000000  4209.000000  4209.000000  4209.000000  ...
mean      0.427893     0.000713     0.002613     0.008791     0.010216  ...
std       0.494832     0.026691     0.051061     0.093357     0.100570  ...
min       0.000000     0.000000     0.000000     0.000000     0.000000  ...
25%       0.000000     0.000000     0.000000     0.000000     0.000000  ...
50%       0.000000     0.000000     0.000000     0.000000     0.000000  ...
75%       1.000000     0.000000     0.000000     0.000000     0.000000  ...
max       1.000000     1.000000     1.000000     1.000000     1.000000  ...
```

```
              X375         X376         X377         X378         X379  \
count  4209.000000  4209.000000  4209.000000  4209.000000  4209.000000
mean      0.325968     0.049656     0.311951     0.019244     0.011879
std       0.468791     0.217258     0.463345     0.137399     0.108356
min       0.000000     0.000000     0.000000     0.000000     0.000000
25%       0.000000     0.000000     0.000000     0.000000     0.000000
50%       0.000000     0.000000     0.000000     0.000000     0.000000
75%       1.000000     0.000000     1.000000     0.000000     0.000000
max       1.000000     1.000000     1.000000     1.000000     1.000000

              X380         X382         X383         X384         X385
count  4209.000000  4209.000000  4209.000000  4209.000000  4209.000000
mean      0.008078     0.008791     0.000475     0.000713     0.001663
std       0.089524     0.093357     0.021796     0.026691     0.040752
min       0.000000     0.000000     0.000000     0.000000     0.000000
25%       0.000000     0.000000     0.000000     0.000000     0.000000
50%       0.000000     0.000000     0.000000     0.000000     0.000000
75%       0.000000     0.000000     0.000000     0.000000     0.000000
max       1.000000     1.000000     1.000000     1.000000     1.000000

[8 rows x 369 columns]
```

[9]:
```python
print("Number of datapoints: ", train_df.shape[0])
print("Number of features: ", train_df.shape[1])
train_df.head()
```

```
Number of datapoints:  4209
Number of features:  378
```

[9]:
```
   ID       y  X0 X1  X2 X3 X4 X5 X6 X8  …  X375  X376  X377  X378  X379  \
0   0  130.81   k  v  at  a  d  u  j  o  …     0     0     1     0     0
1   6   88.53   k  t  av  e  d  y  l  o  …     1     0     0     0     0
2   7   76.26  az  w   n  c  d  x  j  x  …     0     0     0     0     0
3   9   80.62  az  t   n  f  d  x  l  e  …     0     0     0     0     0
4  13   78.02  az  v   n  f  d  h  d  n  …     0     0     0     0     0

   X380  X382  X383  X384  X385
0     0     0     0     0     0
1     0     0     0     0     0
2     0     1     0     0     0
3     0     0     0     0     0
4     0     0     0     0     0

[5 rows x 378 columns]
```

[10]:
```
print("Number of datapoints: ", test_df.shape[0])
print("Number of features: ", test_df.shape[1])
test_df.head()
```

```
Number of datapoints:  4209
Number of features:  377
```

[10]:

```
   ID  X0 X1  X2 X3 X4 X5 X6 X8  X10  …  X375  X376  X377  X378  X379  X380  \
0   1  az  v   n  f  d  t  a  w    0  …     0     0     0     1     0     0
1   2   t  b  ai  a  d  b  g  y    0  …     0     0     1     0     0     0
2   3  az  v  as  f  d  a  j  j    0  …     0     0     0     1     0     0
3   4  az  l   n  f  d  z  l  n    0  …     0     0     0     1     0     0
4   5   w  s  as  c  d  y  i  m    0  …     1     0     0     0     0     0

   X382  X383  X384  X385
0     0     0     0     0
1     0     0     0     0
2     0     0     0     0
3     0     0     0     0
4     0     0     0     0

[5 rows x 377 columns]
```

[11]:
```
dtype_df = train_df.dtypes.reset_index()
dtype_df.columns = ["feature name","dtypes"]
dtype_df.groupby("dtypes").agg("count").reset_index()
```

[11]:

	dtypes	feature name
0	int64	369
1	float64	1
2	object	8

there are 369 binary features, 8 features which have datatype = ‘object’ is most probably categorical features and 1 remaining feature is our target variable i.e. ‘y’.

Performing univariate analysis on categorical features, to get the insight out of it. Any feature that has very low variance as compared to other categorical features, will be removed

[12]:
```
dtype_df = test_df.dtypes.reset_index()
dtype_df.columns = ["feature name","dtypes"]
dtype_df.groupby("dtypes").agg("count").reset_index()
```

[12]:

	dtypes	feature name
0	int64	369
1	object	8

Question 1: If for any column(s), the variance is equal to zero, then you need to remove those variable(s). Starting with train and then with test data

[13]:
```
variance = pow(train_df.drop(columns={'ID','y'}).std(),2).to_dict()

null_cnt = 0
for key, value in variance.items():
    if(value==0):
        print('Name = ',key)
        null_cnt = null_cnt+1
print('No of columns which has zero variance = ',null_cnt)
```

```
Name =  X11
Name =  X93
Name =  X107
Name =  X233
Name =  X235
Name =  X268
Name =  X289
Name =  X290
Name =  X293
Name =  X297
Name =  X330
Name =  X347
No of columns which has zero variance =  12
```

[14]:
```
train_df = train_df.
↪drop(columns={'X11','X93','X107','X233','X235','X268','X289','X290','X293','X297','X330','X
train_df.shape
```

[14]: (4209, 366)

[15]:
```
variance = pow(test_df.drop(columns={'ID'}).std(),2).to_dict()

null_cnt = 0
for key, value in variance.items():
    if(value==0):
        print('Name = ',key)
        null_cnt = null_cnt+1
print('No of columns which has zero variance = ',null_cnt)
```

```
Name =  X257
Name =  X258
Name =  X295
Name =  X296
Name =  X369
No of columns which has zero variance =  5
```

[16]:
```
train_df = train_df.drop(columns={'X257','X258','X295','X296','X369'})
train_df.shape
```

[16]: (4209, 361)

Question 2: Check for null and unique values for test and train sets.

[17]:
```
print(train_df.nunique())
print(test_df.nunique())
```

```
ID      4209
y       2545
X0        47
X1        27
X2        44
        …
X380       2
X382       2
X383       2
X384       2
X385       2
Length: 361, dtype: int64
ID      4209
X0        49
X1        27
X2        45
X3         7
        …
X380       2
X382       2
X383       2
X384       2
X385       2
Length: 377, dtype: int64
```

[18]:
```
#Check for null value
print(train_df.isnull().sum().any())
print(test_df.isnull().sum().any())
```

```
False
False
```

[19]:
```
train_df.describe(include='object')
```

[19]:

	X0	X1	X2	X3	X4	X5	X6	X8
count	4209	4209	4209	4209	4209	4209	4209	4209
unique	47	27	44	7	4	29	12	25
top	z	aa	as	c	d	w	g	j
freq	360	833	1659	1942	4205	231	1042	277

[20]:
```
test_df.describe(include='object')
```

[20]:

	X0	X1	X2	X3	X4	X5	X6	X8
count	4209	4209	4209	4209	4209	4209	4209	4209
unique	49	27	45	7	4	32	12	25
top	ak	aa	as	c	d	v	g	e
freq	432	826	1658	1900	4203	246	1073	274

[21]:
```
dup_ID = train_df['ID'].duplicated().sum()
print(f"Here we have {dup_ID} duplicate IDs")
```

```
Here we have 0 duplicate IDs
```

No null data, all unique values across the file listed. Henceforth working with Train data only as it is the data that we would use for our model.

Question 3: Apply label encoder.

No null variable. All the variables are categorical applying encoder

[22]:
```
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
for i in train_df.columns:
    train_df[i]=le.fit_transform(train_df[i])
```

[23]:
```
train_df.head()
```

[23]:

	ID	y	X0	X1	X2	X3	X4	X5	X6	X8	…	X375	X376	X377	X378	\
0	0	2466	32	23	17	0	3	24	9	14	…	0	0	1	0	
1	1	366	32	21	19	4	3	28	11	14	…	1	0	0	0	
2	2	69	20	24	34	2	3	27	9	23	…	0	0	0	0	
3	3	133	20	21	34	5	3	27	11	4	…	0	0	0	0	
4	4	106	20	23	34	5	3	12	3	13	…	0	0	0	0	

	X379	X380	X382	X383	X384	X385
0	0	0	0	0	0	0
1	0	0	0	0	0	0
2	0	0	1	0	0	0
3	0	0	0	0	0	0
4	0	0	0	0	0	0

[5 rows x 361 columns]

[24]:
```
train_df.corr()
```

[24]:

	ID	y	X0	X1	X2	X3	X4	\
ID	1.000000	-0.053835	-0.012938	0.085511	-0.022195	-0.032942	0.018940	
y	-0.053835	1.000000	-0.235347	0.012417	0.111803	-0.153171	-0.015482	
X0	-0.012938	-0.235347	1.000000	-0.271123	-0.139904	-0.070645	0.017988	
X1	0.085511	0.012417	-0.271123	1.000000	0.088266	0.205657	-0.020724	
X2	-0.022195	0.111803	-0.139904	0.088266	1.000000	-0.093546	0.002289	

```
…         …         …         …         …         …         …         …
X380 -0.013644  0.047247 -0.038618 -0.022360  0.006473  0.004166  0.002611
X382 -0.038092 -0.139801 -0.060401  0.120044  0.024392 -0.046271  0.002533
X383 -0.009363  0.018200 -0.011174 -0.029253 -0.019873 -0.028280  0.001181
X384 -0.015531 -0.003465  0.009110  0.017603 -0.002614  0.007273  0.000631
X385  0.028997 -0.024460  0.011660  0.008356 -0.004529  0.045180  0.001093

            X5        X6        X8  …      X375      X376      X377  \
ID    0.649727 -0.017728  0.006444  …  0.045307 -0.079988 -0.022990
y    -0.035435  0.001477 -0.003473  …  0.021055  0.131811  0.055796
X0    0.012293  0.037549  0.047735  …  0.113272  0.070546  0.045173
X1    0.046417 -0.079119 -0.000306  …  0.056874 -0.102424 -0.248791
X2   -0.017722  0.065778 -0.069932  … -0.174308  0.033697  0.122503
…          …         …         … …         …         …         …
X380  0.010434 -0.014059  0.009511  … -0.061741 -0.022240 -0.061168
X382 -0.031128  0.054548 -0.000996  … -0.059883 -0.021571 -0.059327
X383 -0.007337 -0.021293  0.038712  … -0.015413 -0.010059  0.035107
X384  0.007030  0.023867  0.008950  … -0.014917 -0.005373  0.008694
X385  0.032027 -0.021254  0.045040  …  0.055225 -0.009311 -0.025610

          X378      X379      X380      X382      X383      X384      X385
ID    0.030387  0.023399 -0.013644 -0.038092 -0.009363 -0.015531  0.028997
y    -0.226880  0.073029  0.047247 -0.139801  0.018200 -0.003465 -0.024460
X0   -0.102136  0.083352 -0.038618 -0.060401 -0.011174  0.009110  0.011660
X1    0.145282  0.070753 -0.022360  0.120044 -0.029253  0.017603  0.008356
X2    0.131974  0.033645  0.006473  0.024392 -0.019873 -0.002614 -0.004529
…          …         …         …         …         …         …         …
X380 -0.013110 -0.008839  1.000000 -0.007899 -0.003683 -0.001968 -0.003410
X382 -0.012716 -0.008573 -0.007899  1.000000 -0.003572 -0.001908 -0.003307
X383 -0.005930 -0.003998 -0.003683 -0.003572  1.000000 -0.000890 -0.001542
X384 -0.003168 -0.002136 -0.001968 -0.001908 -0.000890  1.000000 -0.000824
X385 -0.005489 -0.003701 -0.003410 -0.003307 -0.001542 -0.000824  1.000000

[361 rows x 361 columns]
```

Summarize outcome (testing time) in training dataset

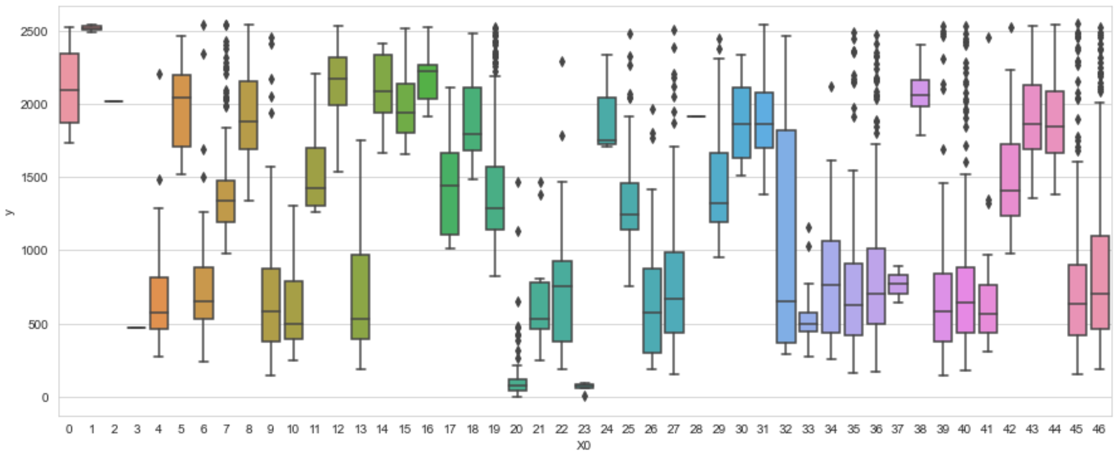
[25]:
```python
# Draw a vertical boxplot grouped
# by a categorical variable: X0
sns.set_style("whitegrid")

object_columns = test_df.describe(include='object').columns
print('\nobject columns:\n',object_columns)
cols = len(object_columns)
```

```
object columns:
 Index(['X0', 'X1', 'X2', 'X3', 'X4', 'X5', 'X6', 'X8'], dtype='object')
```

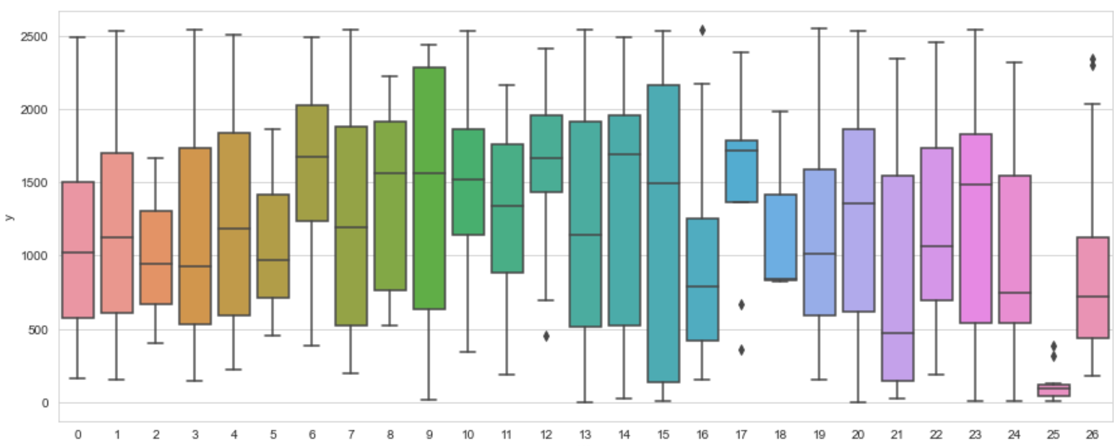
[26]:
```
sns.boxplot(x = 'X0', y = 'y', data = train_df)
```

[26]: <AxesSubplot:xlabel='X0', ylabel='y'>



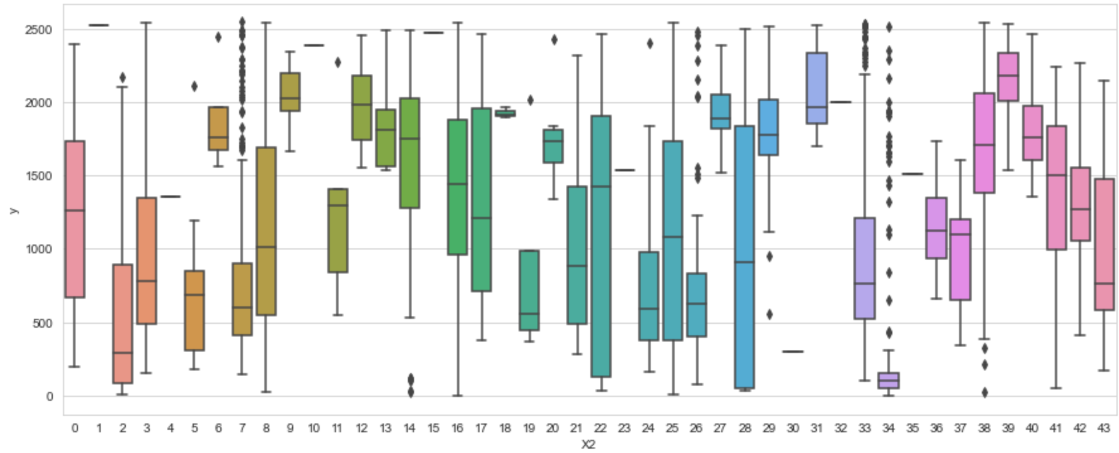
[27]:
```
sns.boxplot(x = 'X1', y = 'y', data = train_df)
```

[27]: <AxesSubplot:xlabel='X1', ylabel='y'>



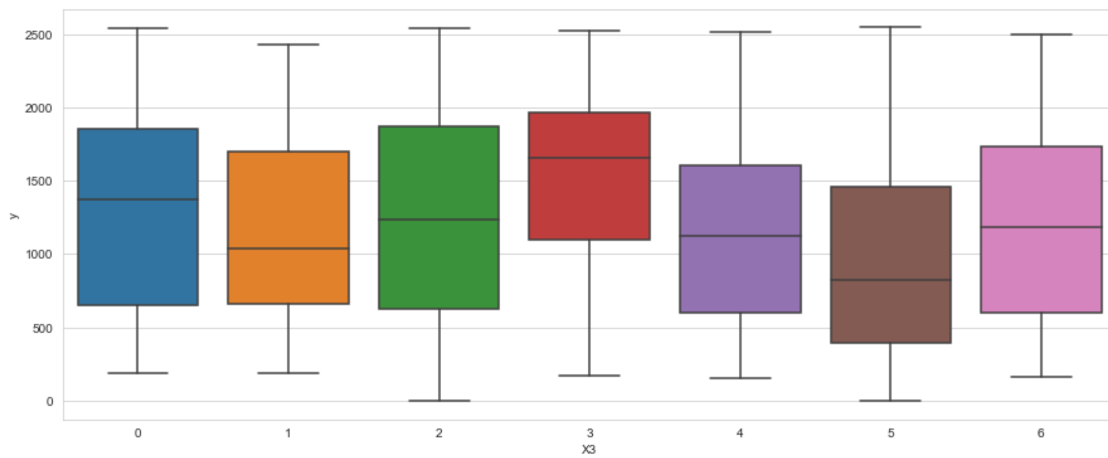
[28]:
```
sns.boxplot(x = 'X2', y = 'y', data = train_df)
```

[28]: <AxesSubplot:xlabel='X2', ylabel='y'>



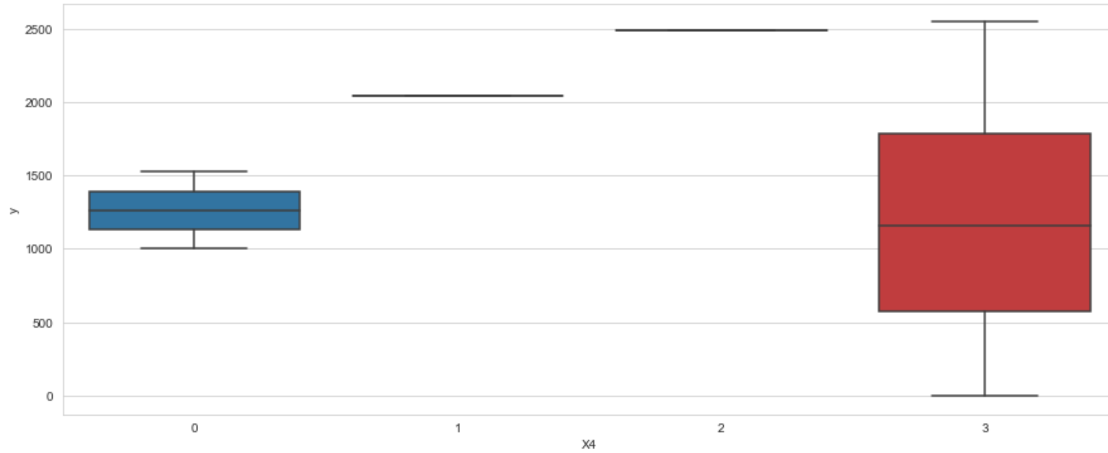
[29]:
```
sns.boxplot(x = 'X3', y = 'y', data = train_df)
```

[29]: <AxesSubplot:xlabel='X3', ylabel='y'>



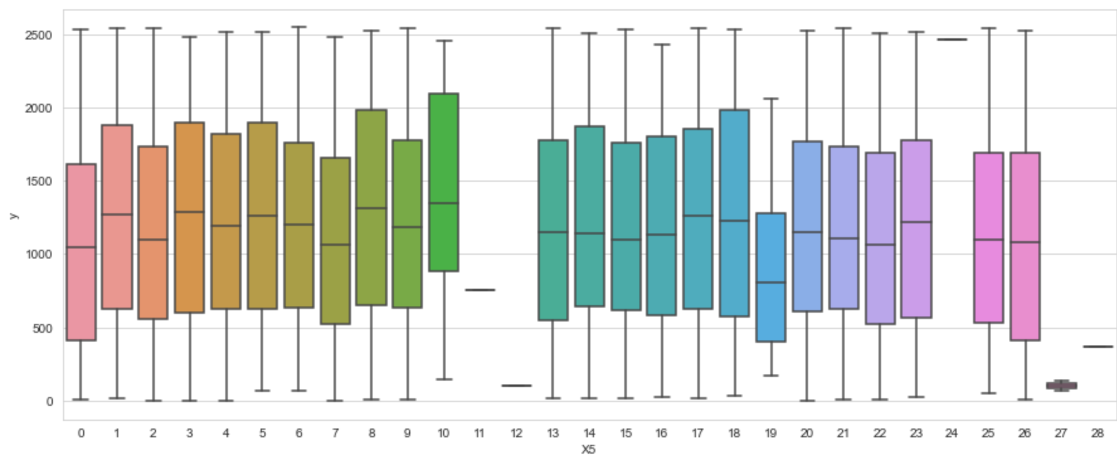
[30]:
```
sns.boxplot(x = 'X4', y = 'y', data = train_df)
```

[30]: <AxesSubplot:xlabel='X4', ylabel='y'>



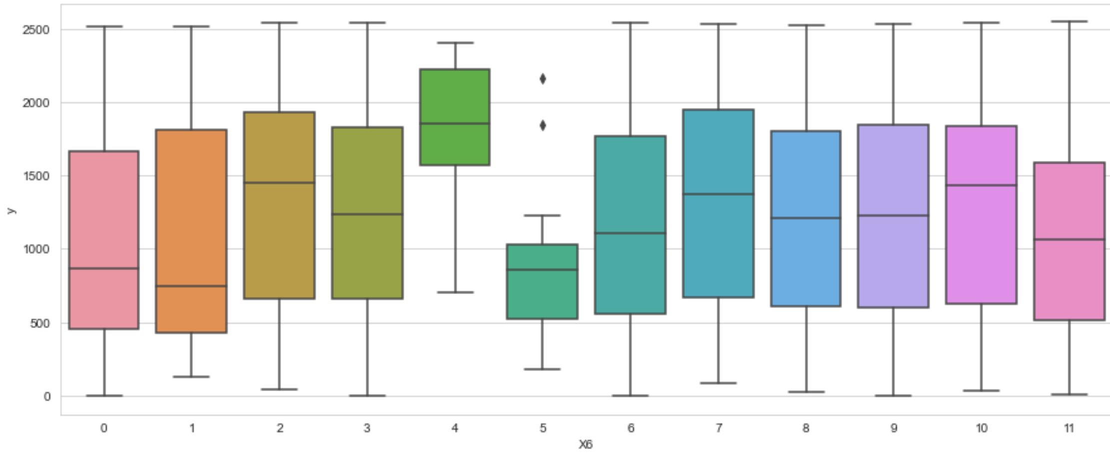

```
[31]: sns.boxplot(x = 'X5', y = 'y', data = train_df)
```

[31]: <AxesSubplot:xlabel='X5', ylabel='y'>



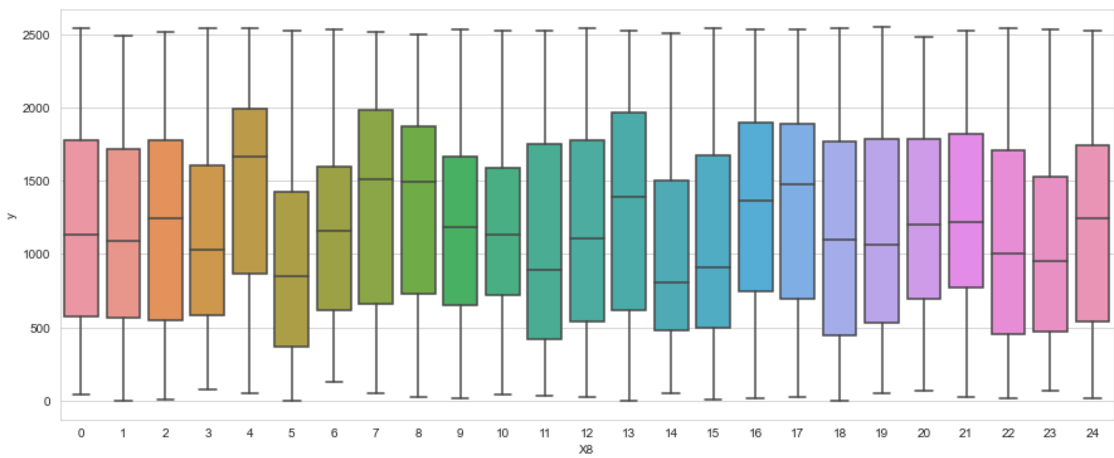

```
[32]: sns.boxplot(x = 'X6', y = 'y', data = train_df)
```

[32]: <AxesSubplot:xlabel='X6', ylabel='y'>



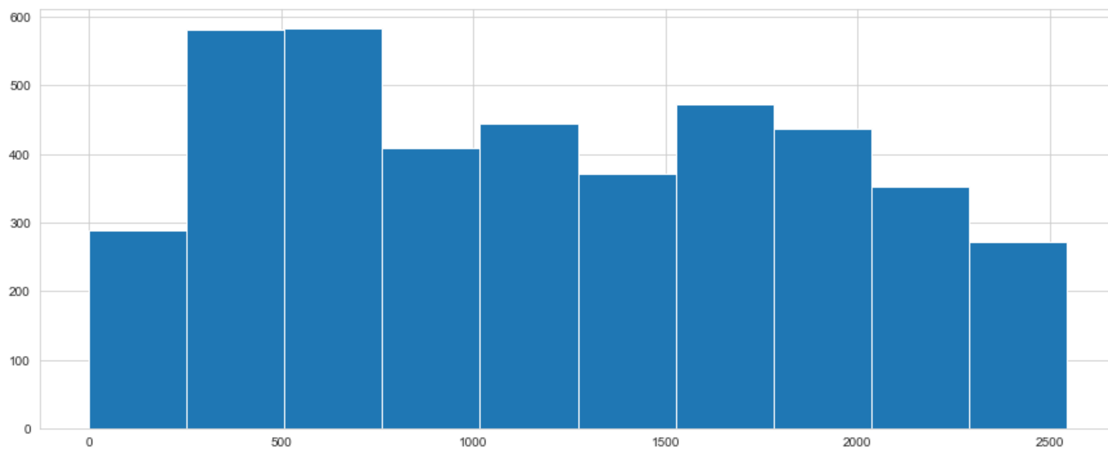

```
[33]: sns.boxplot(x = 'X8', y = 'y', data = train_df)
```

[33]: <AxesSubplot:xlabel='X8', ylabel='y'>



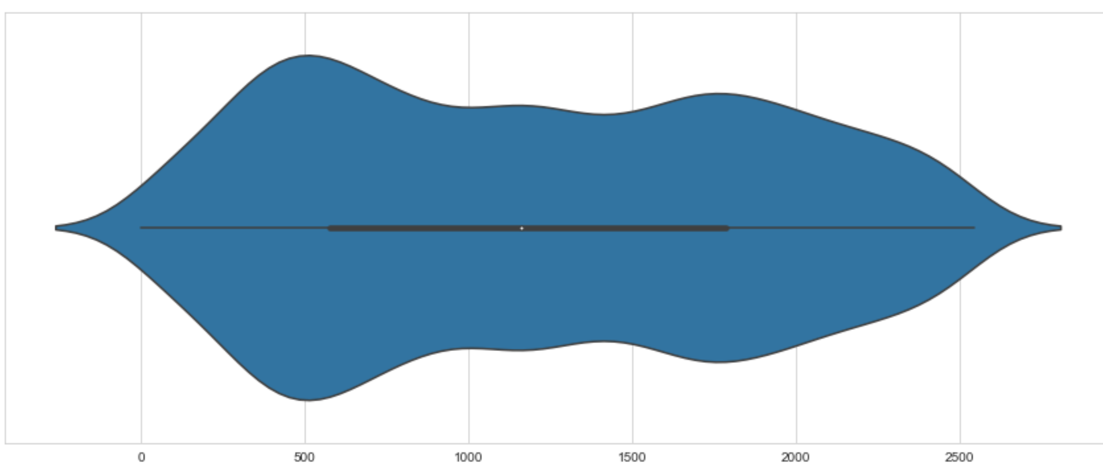

```
[34]: #Now the target y
train_df['y'].hist()
```

[34]: <AxesSubplot:>



[35]:
```
sns.violinplot(train_df['y'].values)
```

[35]: <AxesSubplot:>



The data seems optimized. The removal of few data points which had no variance had optimized the y. No reason to test for any more outliers. Idealy, this test is done first, but if variance 0 is removed, it increases the chances of y being optimized, with no outliers.

Dimensionality reduction refers to techniques for reducing the number of input variables in training data. Fewer input dimensions often means correspondingly fewer parameters or a simpler structure in the machine learning model, referred to as degrees of freedom. A model with too many degrees of freedom is likely to overfit the training dataset and may not perform well on new data.

It is desirable to have simple models that generalize well, and in turn, input data with few input variables. This is particularly true for linear models where the number of inputs and the degrees of freedom of the model are often closely related.

Dimensionality reduction is a data preparation technique performed on data prior to modeling. It might be performed after data cleaning and data scaling and before training a predictive model.

Question 4: Perform dimensionality reduction.

The methods at our disposal using linear algebra are:

Principal Components Analysis Singular Value Decomposition Non-Negative Matrix Factorization

[36]:
```python
# Draw a vertical boxplot grouped
# by a categorical variable: X0
train_df.describe(include='int64')
```

[36]:
```
                ID            y          X10          X12          X13  \
count  4209.000000  4209.000000  4209.000000  4209.000000  4209.000000
mean   2104.000000  1200.809931     0.013305     0.075077     0.057971
std    1215.177971   694.116229     0.114590     0.263547     0.233716
min       0.000000     0.000000     0.000000     0.000000     0.000000
25%    1052.000000   575.000000     0.000000     0.000000     0.000000
50%    2104.000000  1161.000000     0.000000     0.000000     0.000000
75%    3156.000000  1784.000000     0.000000     0.000000     0.000000
max    4208.000000  2544.000000     1.000000     1.000000     1.000000

               X14          X15          X16          X17          X18  …   \
count  4209.000000  4209.000000  4209.000000  4209.000000  4209.000000  …
mean      0.428130     0.000475     0.002613     0.007603     0.007840  …
std       0.494867     0.021796     0.051061     0.086872     0.088208  …
min       0.000000     0.000000     0.000000     0.000000     0.000000  …
25%       0.000000     0.000000     0.000000     0.000000     0.000000  …
50%       0.000000     0.000000     0.000000     0.000000     0.000000  …
75%       1.000000     0.000000     0.000000     0.000000     0.000000  …
max       1.000000     1.000000     1.000000     1.000000     1.000000  …

              X375         X376         X377         X378         X379  \
count  4209.000000  4209.000000  4209.000000  4209.000000  4209.000000
mean      0.318841     0.057258     0.314802     0.020670     0.009503
std       0.466082     0.232363     0.464492     0.142294     0.097033
min       0.000000     0.000000     0.000000     0.000000     0.000000
25%       0.000000     0.000000     0.000000     0.000000     0.000000
50%       0.000000     0.000000     0.000000     0.000000     0.000000
75%       1.000000     0.000000     1.000000     0.000000     0.000000
max       1.000000     1.000000     1.000000     1.000000     1.000000

              X380         X382         X383         X384         X385
count  4209.000000  4209.000000  4209.000000  4209.000000  4209.000000
mean      0.008078     0.007603     0.001663     0.000475     0.001426
std       0.089524     0.086872     0.040752     0.021796     0.037734
min       0.000000     0.000000     0.000000     0.000000     0.000000
25%       0.000000     0.000000     0.000000     0.000000     0.000000
```

```
50%        0.000000     0.000000     0.000000     0.000000     0.000000
75%        0.000000     0.000000     0.000000     0.000000     0.000000
max        1.000000     1.000000     1.000000     1.000000     1.000000

[8 rows x 353 columns]
```

[37]:

```
bin_columns = train_df['ID']
print('\nobject columns:\n',bin_columns)
```

```
object columns:
 0           0
1           1
2           2
3           3
4           4
        …
4204    4204
4205    4205
4206    4206
4207    4207
4208    4208
Name: ID, Length: 4209, dtype: int64
```

[38]:

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(train_df)
sdata = scaler.transform(train_df)
from sklearn.decomposition import PCA
sdata.shape
```

[38]: (4209, 361)

[39]:

```
# lets take top 6 pca components
pca = PCA(n_components=6)
pca.fit(sdata)
x_pca = pca.transform(sdata)
x_pca.shape

# number of components
n_pcs= pca.components_.shape[0]
n_pcs
```

[39]: 6

[40]:

```
 # get the index of the most important feature on EACH component i.e.␣
 ↪largest␣,→absolute value
# using LIST COMPREHENSION HERE
```

```
most_important = [np.abs(pca.components_[i]).argmax() for i in range(n_pcs)]
initial_feature_names = bin_columns
most_important
```

[40]:
```
[325, 27, 180, 161, 309, 85]
```

[41]:
```
# using LIST COMPREHENSION HERE AGAIN
dic = {'PC{}'.format(i): most_important[i] for i in range(n_pcs)}
```

[42]:
```
dic
```

[42]:
```
{'PC0': 325, 'PC1': 27, 'PC2': 180, 'PC3': 161, 'PC4': 309, 'PC5': 85}
```

[43]:
```
pca.components_
```

[43]:
```
array([[ 0.00298087,  0.04008865, -0.05383831, …,  0.00264079,
        -0.0010312 , -0.00385943],
       [ 0.0009552 , -0.07749275, -0.04202541, …, -0.00619854,
        -0.00015713,  0.00249218],
       [ 0.00404084,  0.07298527, -0.07779572, …, -0.00623733,
         0.0032457 ,  0.01468631],
       [ 0.00105837, -0.06918154,  0.07034037, …, -0.01677918,
         0.00068049,  0.00571765],
       [ 0.00282563,  0.05230824, -0.02121129, …,  0.00476864,
        -0.00123327, -0.00107366],
       [-0.00801843, -0.05646235,  0.01216829, …,  0.00684181,
         0.000352  ,  0.00965898]])
```

[44]:
```
explained_variance = pca.explained_variance_ratio_
explained_variance
#it is a measure of the variance of the data when projected onto that axis. The␣
 ↪projection of each data point onto the
#principal axes are the "principal components" of the data. .4 is the var of PCA
#and .179 is the var of PCA2
```

[44]:
```
array([0.06957044, 0.05767919, 0.04598234, 0.03464726, 0.03299007,
       0.03192876])
```

[45]:
```
#Creating training and test data with only these columns

selected_columns = train_df[['ID', 'X325', 'X27', 'X180', 'X161', 'X309',␣
 ↪'X85',  'y']]
X_train = selected_columns.copy()
X_train.shape
X_train
```

[45]:
```
        ID  X325  X27  X180  X161  X309  X85     y
0        0     0    0     0     0     0    1  2466
1        1     0    1     0     0     0    1   366
2        2     0    1     0     0     0    1    69
3        3     0    1     0     0     0    0   133
4        4     0    1     0     0     0    0   106
…     …     …   …    …    …    …   …    …
4204  4204     0    1     0     0     0    1  1657
4205  4205     0    0     0     0     0    0  1766
4206  4206     0    1     0     0     0    1  1801
4207  4207     0    0     0     0     0    0   280
4208  4208     0    0     0     0     0    0  1921

[4209 rows x 8 columns]
```

[46]:
```
#Now creating a df with only these 5 components

selected_columns = test_df[['ID', 'X325', 'X27', 'X180', 'X161', 'X309', 'X85']]
X_test = selected_columns.copy()
X_test.shape
X_test
```

[46]:
```
        ID  X325  X27  X180  X161  X309  X85
0        1     0    1     0     0     0    0
1        2     0    1     0     1     0    0
2        3     0    1     0     0     0    1
3        4     0    1     0     0     0    0
4        5     0    1     0     0     0    1
…     …     …   …    …    …    …   …
4204  8410     0    1     0     0     0    1
4205  8411     0    1     0     0     0    0
4206  8413     0    1     0     0     0    0
4207  8414     0    1     0     0     0    1
4208  8416     0    1     0     0     0    0

[4209 rows x 7 columns]
```

#now will perfrom XGBoost

Predict your test_df values using XGBoost. Model Selection

Logistic Regression KNN SVM Random Forest

[47]:
```
#Now splitting the data into train & test. Before that, identifying all input␣
↪parameters as X, and output parameter as y
y_train=train_df['y']
y_train
```

[47]:
```
0       2466
1        366
2         69
3        133
4        106
        …
4204    1657
4205    1766
4206    1801
4207     280
4208    1921
Name: y, Length: 4209, dtype: int64
```

[48]:
```
y_train.shape
```

[48]:
```
(4209,)
```

[49]:
```
from sklearn.model_selection import learning_curve
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import cross_val_score
from sklearn.metrics import classification_report, confusion_matrix

import xgboost as xgb
from sklearn.metrics import r2_score
from sklearn.model_selection import train_test_split
```

[50]:
```
X_train.shape
```

[50]:
```
(4209, 8)
```

[51]:
```
X_test.shape
```

[51]:
```
(4209, 7)
```

[52]:
```
y_train.shape
```

[52]:
```
(4209,)
```

[53]:
```
#We do not have X & y. Creating X
```

[54]:
```
X = X_train
#X = pd.concat([X_train,X_test])
print(X)
```

```
        ID  X325  X27  X180  X161  X309  X85     y
0        0     0    0     0     0     0    1  2466
1        1     0    1     0     0     0    1   366
2        2     0    1     0     0     0    1    69
```

3	3	0	1	0	0	0	0	133
4	4	0	1	0	0	0	0	106
…	…	…	…	…	…	…	…	…
4204	4204	0	1	0	0	0	1	1657
4205	4205	0	0	0	0	0	0	1766
4206	4206	0	1	0	0	0	1	1801
4207	4207	0	0	0	0	0	0	280
4208	4208	0	0	0	0	0	0	1921

[4209 rows x 8 columns]

[55]:
```
X.shape
```

[55]: (4209, 8)

[56]:
```
#y = pd.concat([y_train,y_train])
y = y_train
y.shape
```

[56]: (4209,)

[57]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
↪random_state=72)
```

[60]:
```
# Logistic Regression
logreg=LogisticRegression(solver='liblinear',multi_class='ovr')
logreg.fit(X_train,y_train)
y_pred=logreg.predict(X_test)
y_pred
#Accuracy Score
#print(metrics.accuracy_score(y_pred,y_train))
accuracy = (logreg.score(X_train,y_train))
print(accuracy)
```

0.017311608961303463

[61]:
```
# Logistic Regression
logreg=LogisticRegression(solver='lbfgs',multi_class='auto')
logreg.fit(X_train,y_train)
y_pred=logreg.predict(X_test)
y_pred
#Accuracy Score
#print(metrics.accuracy_score(y_pred,y_train))
accuracy = (logreg.score(X_train,y_train))
print(accuracy)
```

0.007467752885268160

[62]:
```
#SVM "Support Vector Classifier"
from sklearn.svm import SVC
svm = SVC(kernel='linear')

# fitting x samples and y classes
svm.fit(X_train,y_train)
y_pred = svm.predict(X_test)

from sklearn import metrics
accuracy = metrics.accuracy_score(y_test, y_pred)
print(accuracy)
```

```
0.0958036421219319
```

[67]:
```
#KNN with 5 neighbours
knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
print(metrics.accuracy_score(y_test, y_pred))
```

```
0.0023752969121140144
```

[68]:
```
print(classification_report(y_test,pred))
```

```
              precision    recall  f1-score   support

           0       0.00      0.00      0.00         0
           1       0.00      0.00      0.00         0
           2       0.00      0.00      0.00         1
           3       0.00      0.00      0.00         0
           4       0.00      0.00      0.00         0
           5       0.00      0.00      0.00         0
           6       0.00      0.00      0.00         0
           8       0.00      0.00      0.00         0
          11       0.00      0.00      0.00         1
          12       0.00      0.00      0.00         0
          13       0.00      0.00      0.00         1
          14       0.00      0.00      0.00         0
          15       0.00      0.00      0.00         1
          16       0.00      0.00      0.00         1
          17       0.00      0.00      0.00         0
          19       0.00      0.00      0.00         1
          20       0.00      0.00      0.00         0
          22       0.00      0.00      0.00         1
          23       0.00      0.00      0.00         1
          24       0.00      0.00      0.00         1
          25       0.00      0.00      0.00         0
          27       0.00      0.00      0.00         0
          29       0.00      0.00      0.00         0
```

30	0.00	0.00	0.00	1
31	0.00	0.00	0.00	0
32	0.00	0.00	0.00	0
33	0.00	0.00	0.00	1
34	0.00	0.00	0.00	1
35	0.00	0.00	0.00	0
41	0.00	0.00	0.00	0
42	0.00	0.00	0.00	1
46	0.00	0.00	0.00	0
47	0.00	0.00	0.00	0
48	0.00	0.00	0.00	1
49	0.00	0.00	0.00	0
51	0.00	0.00	0.00	1
52	0.00	0.00	0.00	1
53	0.00	0.00	0.00	1
54	0.00	0.00	0.00	1
60	0.00	0.00	0.00	1
63	0.00	0.00	0.00	1
64	0.00	0.00	0.00	1
66	0.00	0.00	0.00	1
67	0.00	0.00	0.00	0
68	0.00	0.00	0.00	1
69	0.00	0.00	0.00	0
72	0.00	0.00	0.00	0
75	0.00	0.00	0.00	1
76	0.00	0.00	0.00	0
77	0.00	0.00	0.00	1
82	0.00	0.00	0.00	1
84	0.00	0.00	0.00	0
87	0.00	0.00	0.00	0
88	0.00	0.00	0.00	0
89	0.00	0.00	0.00	0
93	0.00	0.00	0.00	1
95	0.00	0.00	0.00	1
96	0.00	0.00	0.00	1
98	0.00	0.00	0.00	1
99	0.00	0.00	0.00	0
100	0.00	0.00	0.00	1
103	0.00	0.00	0.00	0
106	0.00	0.00	0.00	1
109	0.00	0.00	0.00	1
112	0.00	0.00	0.00	1
113	0.00	0.00	0.00	1
114	0.00	0.00	0.00	0
115	0.00	0.00	0.00	1
117	0.00	0.00	0.00	0
120	0.00	0.00	0.00	1
121	0.00	0.00	0.00	0

123	0.00	0.00	0.00	0
124	0.00	0.00	0.00	0
126	0.00	0.00	0.00	1
128	0.00	0.00	0.00	1
129	0.00	0.00	0.00	0
131	0.00	0.00	0.00	1
135	0.00	0.00	0.00	0
136	0.00	0.00	0.00	1
138	0.00	0.00	0.00	1
146	0.00	0.00	0.00	1
147	0.00	0.00	0.00	0
152	0.00	0.00	0.00	0
154	0.00	0.00	0.00	1
157	0.00	0.00	0.00	0
159	0.00	0.00	0.00	1
160	0.00	0.00	0.00	0
161	0.00	0.00	0.00	1
164	0.00	0.00	0.00	1
166	0.00	0.00	0.00	1
167	0.00	0.00	0.00	1
168	0.00	0.00	0.00	1
169	0.00	0.00	0.00	0
170	0.00	0.00	0.00	1
171	0.00	0.00	0.00	0
172	0.00	0.00	0.00	0
173	0.00	0.00	0.00	0
175	0.00	0.00	0.00	1
176	0.00	0.00	0.00	0
177	0.00	0.00	0.00	0
179	0.00	0.00	0.00	0
180	0.00	0.00	0.00	2
181	0.00	0.00	0.00	1
183	0.00	0.00	0.00	1
184	0.00	0.00	0.00	0
185	0.00	0.00	0.00	1
190	0.00	0.00	0.00	1
191	0.00	0.00	0.00	0
192	0.00	0.00	0.00	1
193	0.00	0.00	0.00	1
194	0.00	0.00	0.00	2
196	0.00	0.00	0.00	1
197	0.00	0.00	0.00	1
198	0.00	0.00	0.00	0
199	0.00	0.00	0.00	1
200	0.00	0.00	0.00	0
202	0.00	0.00	0.00	0
204	0.00	0.00	0.00	0
206	0.00	0.00	0.00	1

207	0.00	0.00	0.00	0
208	0.00	0.00	0.00	1
209	0.00	0.00	0.00	0
210	0.00	0.00	0.00	0
217	0.00	0.00	0.00	0
218	0.00	0.00	0.00	1
219	0.00	0.00	0.00	1
220	0.00	0.00	0.00	0
221	0.00	0.00	0.00	1
223	0.00	0.00	0.00	1
224	0.00	0.00	0.00	0
229	0.00	0.00	0.00	1
230	0.00	0.00	0.00	1
232	0.00	0.00	0.00	1
233	0.00	0.00	0.00	0
234	0.00	0.00	0.00	2
235	0.00	0.00	0.00	1
237	0.00	0.00	0.00	1
239	0.00	0.00	0.00	1
240	0.00	0.00	0.00	0
241	0.00	0.00	0.00	0
242	0.00	0.00	0.00	1
243	0.00	0.00	0.00	1
245	0.00	0.00	0.00	1
246	0.00	0.00	0.00	0
247	0.00	0.00	0.00	1
248	0.00	0.00	0.00	1
249	0.00	0.00	0.00	2
250	1.00	1.00	1.00	1
251	0.00	0.00	0.00	1
252	0.00	0.00	0.00	0
254	0.00	0.00	0.00	0
255	0.00	0.00	0.00	1
256	0.00	0.00	0.00	0
257	0.00	0.00	0.00	0
258	0.00	0.00	0.00	1
259	0.00	0.00	0.00	0
260	0.00	0.00	0.00	1
261	0.00	0.00	0.00	3
263	0.00	0.00	0.00	2
264	0.00	0.00	0.00	3
265	0.00	0.00	0.00	0
267	0.00	0.00	0.00	2
268	0.00	0.00	0.00	1
269	0.00	0.00	0.00	0
270	0.00	0.00	0.00	1
272	0.00	0.00	0.00	0
273	0.00	0.00	0.00	1

277	0.00	0.00	0.00	1
279	0.00	0.00	0.00	0
281	0.00	0.00	0.00	0
282	0.00	0.00	0.00	1
284	0.00	0.00	0.00	1
286	0.00	0.00	0.00	0
287	0.00	0.00	0.00	1
288	0.00	0.00	0.00	2
289	0.00	0.00	0.00	0
290	0.00	0.00	0.00	1
291	0.00	0.00	0.00	2
292	0.00	0.00	0.00	1
295	0.00	0.00	0.00	1
296	0.00	0.00	0.00	0
299	0.00	0.00	0.00	2
300	0.00	0.00	0.00	0
302	0.00	0.00	0.00	0
303	0.00	0.00	0.00	1
304	0.00	0.00	0.00	1
305	0.00	0.00	0.00	1
306	0.00	0.00	0.00	0
307	0.00	0.00	0.00	1
308	0.00	0.00	0.00	1
309	0.00	0.00	0.00	1
310	0.00	0.00	0.00	1
311	0.00	0.00	0.00	1
313	0.00	0.00	0.00	1
314	0.00	0.00	0.00	0
315	0.00	0.00	0.00	1
316	0.00	0.00	0.00	1
317	0.00	0.00	0.00	1
318	0.00	0.00	0.00	0
319	0.00	0.00	0.00	0
320	0.00	0.00	0.00	0
321	0.00	0.00	0.00	1
322	0.00	0.00	0.00	1
323	0.00	0.00	0.00	1
324	0.00	0.00	0.00	1
325	0.00	0.00	0.00	1
326	0.00	0.00	0.00	1
328	0.00	0.00	0.00	1
329	0.00	0.00	0.00	0
330	0.00	0.00	0.00	1
331	0.00	0.00	0.00	0
332	0.00	0.00	0.00	0
335	0.00	0.00	0.00	1
336	0.00	0.00	0.00	2
337	0.00	0.00	0.00	1

338	0.00	0.00	0.00	1
339	0.00	0.00	0.00	0
340	0.00	0.00	0.00	2
341	0.00	0.00	0.00	0
342	0.00	0.00	0.00	1
343	0.00	0.00	0.00	1
344	0.00	0.00	0.00	1
346	0.00	0.00	0.00	0
347	0.00	0.00	0.00	0
348	0.00	0.00	0.00	1
349	0.00	0.00	0.00	1
350	0.00	0.00	0.00	1
351	0.00	0.00	0.00	2
352	0.00	0.00	0.00	2
353	0.00	0.00	0.00	3
354	0.00	0.00	0.00	1
356	0.00	0.00	0.00	0
358	0.00	0.00	0.00	0
359	0.00	0.00	0.00	2
361	0.00	0.00	0.00	0
362	0.00	0.00	0.00	0
363	0.00	0.00	0.00	1
364	0.00	0.00	0.00	2
365	0.00	0.00	0.00	1
366	0.00	0.00	0.00	0
367	0.00	0.00	0.00	1
368	0.00	0.00	0.00	1
369	0.00	0.00	0.00	1
370	0.00	0.00	0.00	1
371	0.00	0.00	0.00	1
372	0.00	0.00	0.00	1
373	0.00	0.00	0.00	2
374	0.00	0.00	0.00	1
375	0.00	0.00	0.00	2
376	0.00	0.00	0.00	0
378	0.00	0.00	0.00	2
381	0.00	0.00	0.00	2
382	0.00	0.00	0.00	1
383	0.00	0.00	0.00	2
385	0.00	0.00	0.00	0
386	0.00	0.00	0.00	1
387	0.00	0.00	0.00	0
388	0.00	0.00	0.00	2
389	0.00	0.00	0.00	1
391	0.00	0.00	0.00	0
392	0.00	0.00	0.00	1
393	0.00	0.00	0.00	2
394	0.00	0.00	0.00	1

395	0.00	0.00	0.00	0
396	0.00	0.00	0.00	1
397	0.00	0.00	0.00	0
398	0.00	0.00	0.00	1
399	0.00	0.00	0.00	2
401	0.00	0.00	0.00	0
404	0.00	0.00	0.00	1
405	0.00	0.00	0.00	0
406	0.00	0.00	0.00	1
407	0.00	0.00	0.00	1
408	0.00	0.00	0.00	0
409	0.00	0.00	0.00	2
410	0.00	0.00	0.00	0
411	0.00	0.00	0.00	1
412	0.00	0.00	0.00	2
413	0.00	0.00	0.00	1
415	0.00	0.00	0.00	1
416	0.00	0.00	0.00	3
420	0.00	0.00	0.00	1
421	0.00	0.00	0.00	1
423	0.00	0.00	0.00	1
428	0.00	0.00	0.00	1
429	0.00	0.00	0.00	2
430	0.00	0.00	0.00	1
432	0.00	0.00	0.00	3
433	0.00	0.00	0.00	2
434	0.00	0.00	0.00	1
435	0.00	0.00	0.00	1
436	0.00	0.00	0.00	2
437	0.00	0.00	0.00	1
441	0.00	0.00	0.00	1
442	0.00	0.00	0.00	1
443	0.00	0.00	0.00	1
444	0.00	0.00	0.00	2
445	0.00	0.00	0.00	0
446	0.00	0.00	0.00	1
447	0.00	0.00	0.00	0
448	0.00	0.00	0.00	1
450	0.00	0.00	0.00	1
453	0.00	0.00	0.00	1
454	0.00	0.00	0.00	1
455	0.00	0.00	0.00	1
456	0.00	0.00	0.00	1
457	0.00	0.00	0.00	1
458	0.00	0.00	0.00	0
459	0.00	0.00	0.00	0
462	0.00	0.00	0.00	0
465	0.00	0.00	0.00	1

466	0.00	0.00	0.00	2
467	0.00	0.00	0.00	1
468	0.00	0.00	0.00	0
469	0.00	0.00	0.00	1
470	0.00	0.00	0.00	1
471	0.00	0.00	0.00	2
473	0.00	0.00	0.00	2
474	0.00	0.00	0.00	1
475	0.00	0.00	0.00	1
477	0.00	0.00	0.00	1
478	0.00	0.00	0.00	0
480	0.00	0.00	0.00	1
481	0.00	0.00	0.00	1
482	0.00	0.00	0.00	0
483	0.00	0.00	0.00	2
485	0.00	0.00	0.00	0
486	0.00	0.00	0.00	1
489	0.00	0.00	0.00	0
490	0.00	0.00	0.00	0
491	0.00	0.00	0.00	1
492	0.00	0.00	0.00	1
493	0.00	0.00	0.00	1
494	0.00	0.00	0.00	2
495	0.00	0.00	0.00	0
496	0.00	0.00	0.00	2
497	0.00	0.00	0.00	1
498	0.00	0.00	0.00	0
499	0.00	0.00	0.00	1
501	0.00	0.00	0.00	1
502	0.00	0.00	0.00	0
503	0.00	0.00	0.00	0
505	0.00	0.00	0.00	3
507	0.00	0.00	0.00	0
508	0.00	0.00	0.00	1
509	0.00	0.00	0.00	1
511	0.00	0.00	0.00	1
512	0.00	0.00	0.00	1
513	0.00	0.00	0.00	1
514	0.00	0.00	0.00	1
515	0.00	0.00	0.00	2
516	0.00	0.00	0.00	1
517	0.00	0.00	0.00	0
518	0.00	0.00	0.00	0
521	0.00	0.00	0.00	0
522	0.00	0.00	0.00	1
525	0.00	0.00	0.00	2
526	0.00	0.00	0.00	0
527	0.00	0.00	0.00	1

529	0.00	0.00	0.00	1
532	0.00	0.00	0.00	2
533	0.50	0.50	0.50	2
535	0.00	0.00	0.00	1
536	0.00	0.00	0.00	2
537	0.00	0.00	0.00	1
541	0.00	0.00	0.00	2
542	0.00	0.00	0.00	0
543	0.00	0.00	0.00	0
544	0.00	0.00	0.00	2
545	0.00	0.00	0.00	1
546	0.00	0.00	0.00	0
547	0.00	0.00	0.00	0
548	0.00	0.00	0.00	2
549	0.00	0.00	0.00	1
550	0.00	0.00	0.00	2
553	0.00	0.00	0.00	0
554	0.00	0.00	0.00	0
556	0.00	0.00	0.00	2
557	0.00	0.00	0.00	0
558	0.00	0.00	0.00	1
560	0.00	0.00	0.00	1
561	0.00	0.00	0.00	2
562	0.00	0.00	0.00	2
563	0.00	0.00	0.00	2
564	0.00	0.00	0.00	2
565	0.00	0.00	0.00	1
566	0.00	0.00	0.00	0
567	0.00	0.00	0.00	2
568	0.00	0.00	0.00	0
569	0.00	0.00	0.00	2
571	0.00	0.00	0.00	2
572	0.00	0.00	0.00	0
573	0.00	0.00	0.00	2
575	0.00	0.00	0.00	0
576	0.00	0.00	0.00	0
577	0.00	0.00	0.00	0
579	0.00	0.00	0.00	3
581	0.00	0.00	0.00	0
584	0.00	0.00	0.00	1
587	0.00	0.00	0.00	1
588	0.00	0.00	0.00	1
589	0.00	0.00	0.00	1
591	0.00	0.00	0.00	0
593	0.00	0.00	0.00	0
594	0.00	0.00	0.00	1
595	0.00	0.00	0.00	1
596	0.00	0.00	0.00	1

599	0.00	0.00	0.00	1
600	0.00	0.00	0.00	1
602	0.00	0.00	0.00	1
603	0.00	0.00	0.00	0
604	0.00	0.00	0.00	3
605	0.00	0.00	0.00	0
607	0.00	0.00	0.00	1
609	0.00	0.00	0.00	0
611	0.00	0.00	0.00	0
612	0.00	0.00	0.00	1
614	0.00	0.00	0.00	1
615	0.00	0.00	0.00	1
616	0.00	0.00	0.00	1
617	0.00	0.00	0.00	1
618	0.00	0.00	0.00	0
619	0.00	0.00	0.00	1
620	0.00	0.00	0.00	3
621	0.00	0.00	0.00	1
622	0.00	0.00	0.00	1
623	0.00	0.00	0.00	2
624	0.00	0.00	0.00	1
625	0.00	0.00	0.00	2
626	0.00	0.00	0.00	0
627	0.00	0.00	0.00	2
628	0.00	0.00	0.00	0
629	0.00	0.00	0.00	0
630	0.00	0.00	0.00	1
632	0.00	0.00	0.00	1
633	0.00	0.00	0.00	1
634	0.00	0.00	0.00	1
637	0.00	0.00	0.00	1
638	0.00	0.00	0.00	1
639	0.00	0.00	0.00	1
640	0.00	0.00	0.00	1
641	0.00	0.00	0.00	2
642	0.00	0.00	0.00	2
643	0.00	0.00	0.00	1
644	0.00	0.00	0.00	1
645	0.00	0.00	0.00	2
647	0.00	0.00	0.00	0
648	0.00	0.00	0.00	2
649	0.00	0.00	0.00	1
652	0.00	0.00	0.00	1
654	0.00	0.00	0.00	0
655	0.00	0.00	0.00	1
656	0.00	0.00	0.00	1
658	0.00	0.00	0.00	1
659	0.00	0.00	0.00	1

660	0.00	0.00	0.00	0
661	0.00	0.00	0.00	2
662	0.00	0.00	0.00	1
663	0.00	0.00	0.00	1
664	0.00	0.00	0.00	0
665	0.00	0.00	0.00	0
666	0.00	0.00	0.00	2
671	0.00	0.00	0.00	1
672	0.00	0.00	0.00	2
673	0.00	0.00	0.00	0
674	0.00	0.00	0.00	1
676	0.00	0.00	0.00	2
678	0.00	0.00	0.00	1
679	0.00	0.00	0.00	0
680	0.00	0.00	0.00	1
681	0.00	0.00	0.00	0
682	0.00	0.00	0.00	1
684	0.00	0.00	0.00	0
685	0.00	0.00	0.00	1
688	0.00	0.00	0.00	1
689	0.00	0.00	0.00	0
690	0.00	0.00	0.00	1
691	0.00	0.00	0.00	1
693	0.00	0.00	0.00	1
694	0.00	0.00	0.00	1
695	0.00	0.00	0.00	0
696	0.00	0.00	0.00	1
697	0.00	0.00	0.00	2
699	0.00	0.00	0.00	0
700	0.00	0.00	0.00	0
704	0.00	0.00	0.00	1
705	0.00	0.00	0.00	0
707	0.00	0.00	0.00	0
708	0.00	0.00	0.00	0
709	0.00	0.00	0.00	1
710	0.00	0.00	0.00	3
711	0.00	0.00	0.00	0
712	0.00	0.00	0.00	0
713	0.00	0.00	0.00	2
714	0.00	0.00	0.00	1
715	0.00	0.00	0.00	0
716	0.00	0.00	0.00	1
717	0.00	0.00	0.00	2
718	0.00	0.00	0.00	1
719	0.00	0.00	0.00	0
720	0.00	0.00	0.00	0
721	0.00	0.00	0.00	0
722	0.00	0.00	0.00	1

724	0.00	0.00	0.00	1
725	0.00	0.00	0.00	1
726	0.00	0.00	0.00	1
727	0.00	0.00	0.00	1
728	0.00	0.00	0.00	0
729	0.00	0.00	0.00	1
730	0.00	0.00	0.00	1
731	0.00	0.00	0.00	2
732	0.00	0.00	0.00	2
734	0.00	0.00	0.00	1
735	0.00	0.00	0.00	0
736	0.00	0.00	0.00	0
737	0.00	0.00	0.00	0
738	0.00	0.00	0.00	0
739	0.00	0.00	0.00	1
740	0.00	0.00	0.00	1
742	0.00	0.00	0.00	1
744	0.00	0.00	0.00	1
745	0.00	0.00	0.00	1
746	0.00	0.00	0.00	0
747	0.00	0.00	0.00	0
748	0.00	0.00	0.00	2
749	0.00	0.00	0.00	1
751	0.00	0.00	0.00	0
752	0.00	0.00	0.00	1
757	0.00	0.00	0.00	1
758	0.00	0.00	0.00	1
759	0.00	0.00	0.00	1
760	0.00	0.00	0.00	1
761	0.00	0.00	0.00	1
762	0.00	0.00	0.00	2
763	0.00	0.00	0.00	2
765	0.00	0.00	0.00	0
766	0.00	0.00	0.00	1
768	0.00	0.00	0.00	1
770	0.00	0.00	0.00	2
771	0.00	0.00	0.00	0
772	0.00	0.00	0.00	0
774	1.00	1.00	1.00	1
776	0.00	0.00	0.00	0
777	0.00	0.00	0.00	1
778	0.00	0.00	0.00	1
779	0.00	0.00	0.00	0
780	0.00	0.00	0.00	1
781	0.00	0.00	0.00	1
782	0.00	0.00	0.00	1
784	0.00	0.00	0.00	1
785	0.00	0.00	0.00	1

787	0.00	0.00	0.00	0
788	0.00	0.00	0.00	0
789	0.00	0.00	0.00	0
791	0.00	0.00	0.00	2
792	0.00	0.00	0.00	1
793	0.00	0.00	0.00	0
794	0.00	0.00	0.00	0
795	0.00	0.00	0.00	0
797	0.00	0.00	0.00	1
799	0.00	0.00	0.00	1
800	0.00	0.00	0.00	2
801	0.00	0.00	0.00	0
802	0.00	0.00	0.00	1
804	0.00	0.00	0.00	1
806	0.00	0.00	0.00	2
808	0.00	0.00	0.00	1
809	0.00	0.00	0.00	1
810	0.00	0.00	0.00	1
812	0.00	0.00	0.00	0
813	0.00	0.00	0.00	2
815	0.00	0.00	0.00	2
817	0.00	0.00	0.00	2
818	0.00	0.00	0.00	1
819	0.00	0.00	0.00	1
820	0.00	0.00	0.00	1
822	0.00	0.00	0.00	1
823	0.00	0.00	0.00	0
825	0.00	0.00	0.00	1
826	0.00	0.00	0.00	1
827	0.00	0.00	0.00	1
828	0.00	0.00	0.00	1
829	0.00	0.00	0.00	1
831	0.00	0.00	0.00	1
833	0.00	0.00	0.00	0
834	0.00	0.00	0.00	1
835	0.00	0.00	0.00	0
836	0.00	0.00	0.00	0
837	0.00	0.00	0.00	0
838	0.00	0.00	0.00	1
839	0.00	0.00	0.00	1
841	0.00	0.00	0.00	1
842	0.00	0.00	0.00	1
844	0.00	0.00	0.00	2
846	0.00	0.00	0.00	0
847	0.00	0.00	0.00	2
848	0.00	0.00	0.00	0
850	0.00	0.00	0.00	0
851	0.00	0.00	0.00	1

855	0.00	0.00	0.00	2
857	0.00	0.00	0.00	1
859	0.00	0.00	0.00	1
860	0.00	0.00	0.00	1
863	0.00	0.00	0.00	1
865	0.00	0.00	0.00	1
866	0.00	0.00	0.00	1
870	0.00	0.00	0.00	1
871	0.00	0.00	0.00	1
872	0.00	0.00	0.00	0
876	0.00	0.00	0.00	1
877	0.00	0.00	0.00	1
878	0.00	0.00	0.00	1
880	0.00	0.00	0.00	0
881	0.00	0.00	0.00	1
885	0.00	0.00	0.00	0
886	0.00	0.00	0.00	0
887	0.00	0.00	0.00	1
888	0.00	0.00	0.00	0
889	0.00	0.00	0.00	0
891	0.00	0.00	0.00	1
893	0.00	0.00	0.00	1
894	0.00	0.00	0.00	1
896	0.00	0.00	0.00	2
897	0.00	0.00	0.00	1
898	0.00	0.00	0.00	2
901	0.00	0.00	0.00	1
904	0.00	0.00	0.00	1
905	0.00	0.00	0.00	0
906	0.00	0.00	0.00	0
908	0.00	0.00	0.00	0
909	0.00	0.00	0.00	0
912	0.00	0.00	0.00	1
913	0.00	0.00	0.00	0
914	0.00	0.00	0.00	1
919	0.00	0.00	0.00	0
921	0.00	0.00	0.00	0
923	0.00	0.00	0.00	0
924	0.00	0.00	0.00	0
926	0.00	0.00	0.00	1
928	0.00	0.00	0.00	1
929	0.00	0.00	0.00	1
932	0.00	0.00	0.00	0
933	0.00	0.00	0.00	1
935	0.00	0.00	0.00	0
937	0.00	0.00	0.00	0
938	0.00	0.00	0.00	1
941	0.00	0.00	0.00	1

942	0.00	0.00	0.00	1
944	0.00	0.00	0.00	0
947	0.00	0.00	0.00	1
948	0.00	0.00	0.00	1
952	0.00	0.00	0.00	1
955	0.00	0.00	0.00	0
956	0.00	0.00	0.00	0
958	0.00	0.00	0.00	1
959	0.00	0.00	0.00	1
960	0.00	0.00	0.00	1
961	0.00	0.00	0.00	1
962	0.00	0.00	0.00	1
963	0.00	0.00	0.00	2
966	0.00	0.00	0.00	1
967	0.00	0.00	0.00	1
968	0.00	0.00	0.00	0
970	0.00	0.00	0.00	1
971	0.00	0.00	0.00	0
972	0.00	0.00	0.00	1
974	0.00	0.00	0.00	1
975	0.00	0.00	0.00	1
976	0.00	0.00	0.00	0
977	0.00	0.00	0.00	1
979	0.00	0.00	0.00	0
983	0.00	0.00	0.00	0
984	0.00	0.00	0.00	0
985	0.00	0.00	0.00	3
986	0.00	0.00	0.00	0
987	0.00	0.00	0.00	1
988	0.00	0.00	0.00	0
989	0.00	0.00	0.00	1
990	0.00	0.00	0.00	1
991	0.00	0.00	0.00	1
992	0.00	0.00	0.00	0
993	0.00	0.00	0.00	1
996	0.00	0.00	0.00	1
998	0.00	0.00	0.00	0
999	0.00	0.00	0.00	1
1000	0.00	0.00	0.00	1
1002	0.00	0.00	0.00	1
1005	0.00	0.00	0.00	0
1011	0.00	0.00	0.00	1
1012	0.00	0.00	0.00	1
1013	0.00	0.00	0.00	1
1014	0.00	0.00	0.00	1
1016	0.00	0.00	0.00	1
1019	0.00	0.00	0.00	1
1021	0.00	0.00	0.00	0

1022	0.00	0.00	0.00	2
1024	0.00	0.00	0.00	0
1025	0.00	0.00	0.00	1
1028	0.00	0.00	0.00	1
1030	0.00	0.00	0.00	1
1031	0.00	0.00	0.00	1
1032	0.00	0.00	0.00	1
1034	0.00	0.00	0.00	0
1035	0.00	0.00	0.00	1
1036	0.00	0.00	0.00	1
1037	0.00	0.00	0.00	1
1038	0.00	0.00	0.00	0
1040	0.00	0.00	0.00	0
1041	0.00	0.00	0.00	0
1042	0.00	0.00	0.00	1
1043	0.00	0.00	0.00	1
1044	0.00	0.00	0.00	1
1047	0.00	0.00	0.00	1
1048	0.00	0.00	0.00	0
1050	0.00	0.00	0.00	1
1051	0.00	0.00	0.00	1
1052	0.00	0.00	0.00	2
1054	0.00	0.00	0.00	1
1056	0.00	0.00	0.00	0
1058	0.00	0.00	0.00	1
1059	0.00	0.00	0.00	1
1061	0.00	0.00	0.00	0
1062	0.00	0.00	0.00	0
1063	0.00	0.00	0.00	1
1064	0.00	0.00	0.00	2
1065	0.00	0.00	0.00	1
1066	0.00	0.00	0.00	1
1069	0.00	0.00	0.00	0
1070	0.00	0.00	0.00	1
1071	0.00	0.00	0.00	2
1073	0.00	0.00	0.00	0
1074	0.00	0.00	0.00	0
1075	0.00	0.00	0.00	0
1076	0.00	0.00	0.00	0
1077	0.00	0.00	0.00	0
1078	0.00	0.00	0.00	0
1080	0.00	0.00	0.00	2
1081	0.00	0.00	0.00	1
1082	0.00	0.00	0.00	1
1084	0.00	0.00	0.00	1
1085	0.00	0.00	0.00	1
1086	0.00	0.00	0.00	0
1088	0.00	0.00	0.00	1

1091	0.00	0.00	0.00	0
1092	0.00	0.00	0.00	1
1094	0.00	0.00	0.00	1
1095	0.00	0.00	0.00	2
1096	0.00	0.00	0.00	0
1098	0.00	0.00	0.00	4
1101	0.00	0.00	0.00	0
1102	0.00	0.00	0.00	1
1103	0.00	0.00	0.00	1
1104	0.00	0.00	0.00	1
1105	0.00	0.00	0.00	1
1106	0.00	0.00	0.00	2
1107	0.00	0.00	0.00	1
1108	0.00	0.00	0.00	1
1109	0.00	0.00	0.00	1
1110	0.00	0.00	0.00	0
1113	0.00	0.00	0.00	1
1114	0.00	0.00	0.00	0
1115	0.00	0.00	0.00	2
1117	0.00	0.00	0.00	0
1118	0.00	0.00	0.00	0
1120	0.00	0.00	0.00	2
1121	0.00	0.00	0.00	1
1122	0.00	0.00	0.00	0
1123	0.00	0.00	0.00	2
1124	0.00	0.00	0.00	0
1126	0.00	0.00	0.00	1
1127	0.00	0.00	0.00	1
1129	0.00	0.00	0.00	0
1130	0.00	0.00	0.00	0
1131	0.00	0.00	0.00	0
1132	0.00	0.00	0.00	0
1134	0.00	0.00	0.00	1
1135	0.00	0.00	0.00	1
1136	0.00	0.00	0.00	1
1137	0.00	0.00	0.00	0
1138	0.00	0.00	0.00	0
1140	0.00	0.00	0.00	0
1141	0.00	0.00	0.00	1
1142	0.00	0.00	0.00	0
1143	0.00	0.00	0.00	1
1144	0.00	0.00	0.00	2
1145	0.00	0.00	0.00	1
1146	0.00	0.00	0.00	1
1147	0.00	0.00	0.00	1
1148	0.00	0.00	0.00	1
1149	0.00	0.00	0.00	2
1150	0.00	0.00	0.00	0

1151	0.00	0.00	0.00	1
1152	0.00	0.00	0.00	0
1153	0.00	0.00	0.00	1
1155	0.00	0.00	0.00	1
1156	0.00	0.00	0.00	1
1158	0.00	0.00	0.00	1
1159	0.00	0.00	0.00	0
1160	0.00	0.00	0.00	1
1161	0.00	0.00	0.00	1
1162	0.00	0.00	0.00	1
1164	0.00	0.00	0.00	0
1165	0.00	0.00	0.00	1
1166	0.00	0.00	0.00	1
1167	0.00	0.00	0.00	1
1168	0.00	0.00	0.00	1
1169	0.00	0.00	0.00	1
1175	0.00	0.00	0.00	1
1176	0.00	0.00	0.00	1
1177	0.00	0.00	0.00	1
1180	0.00	0.00	0.00	2
1181	0.00	0.00	0.00	1
1182	0.00	0.00	0.00	1
1183	0.00	0.00	0.00	1
1185	0.00	0.00	0.00	1
1186	0.00	0.00	0.00	0
1187	0.00	0.00	0.00	1
1188	0.00	0.00	0.00	2
1189	0.00	0.00	0.00	1
1194	0.00	0.00	0.00	1
1195	0.00	0.00	0.00	1
1196	0.00	0.00	0.00	0
1198	0.00	0.00	0.00	0
1200	0.00	0.00	0.00	0
1201	0.00	0.00	0.00	1
1202	0.00	0.00	0.00	1
1203	0.00	0.00	0.00	1
1204	0.00	0.00	0.00	0
1205	0.00	0.00	0.00	2
1208	0.00	0.00	0.00	0
1209	0.00	0.00	0.00	2
1210	0.00	0.00	0.00	0
1211	0.00	0.00	0.00	0
1213	0.00	0.00	0.00	0
1215	0.00	0.00	0.00	1
1216	0.00	0.00	0.00	0
1217	0.00	0.00	0.00	1
1219	0.00	0.00	0.00	0
1220	0.00	0.00	0.00	0

1221	0.00	0.00	0.00	0
1222	0.00	0.00	0.00	1
1223	0.00	0.00	0.00	1
1224	0.00	0.00	0.00	2
1226	0.00	0.00	0.00	1
1227	0.00	0.00	0.00	1
1228	0.00	0.00	0.00	1
1229	0.00	0.00	0.00	2
1232	0.00	0.00	0.00	0
1233	0.00	0.00	0.00	1
1234	0.00	0.00	0.00	0
1235	0.00	0.00	0.00	0
1236	0.00	0.00	0.00	1
1238	0.00	0.00	0.00	1
1239	0.00	0.00	0.00	1
1240	0.00	0.00	0.00	0
1241	0.00	0.00	0.00	0
1242	0.00	0.00	0.00	1
1243	0.00	0.00	0.00	1
1244	0.00	0.00	0.00	1
1245	0.00	0.00	0.00	1
1246	0.00	0.00	0.00	0
1247	0.00	0.00	0.00	0
1248	0.00	0.00	0.00	1
1251	0.00	0.00	0.00	1
1252	0.00	0.00	0.00	0
1254	0.00	0.00	0.00	1
1256	0.00	0.00	0.00	1
1257	0.00	0.00	0.00	0
1258	0.00	0.00	0.00	1
1259	0.00	0.00	0.00	1
1262	0.00	0.00	0.00	1
1263	0.00	0.00	0.00	0
1265	0.00	0.00	0.00	2
1266	0.00	0.00	0.00	0
1268	0.00	0.00	0.00	1
1269	0.00	0.00	0.00	1
1271	0.00	0.00	0.00	0
1273	0.00	0.00	0.00	1
1274	0.00	0.00	0.00	1
1275	0.00	0.00	0.00	0
1279	0.00	0.00	0.00	0
1280	0.00	0.00	0.00	1
1281	0.00	0.00	0.00	0
1283	0.00	0.00	0.00	1
1285	0.00	0.00	0.00	1
1286	0.00	0.00	0.00	2
1289	0.00	0.00	0.00	1

1290	0.00	0.00	0.00	1
1291	0.00	0.00	0.00	0
1294	0.00	0.00	0.00	1
1298	0.00	0.00	0.00	1
1300	0.00	0.00	0.00	0
1301	0.00	0.00	0.00	1
1302	0.00	0.00	0.00	0
1303	0.00	0.00	0.00	2
1308	0.00	0.00	0.00	0
1309	0.00	0.00	0.00	1
1310	0.00	0.00	0.00	1
1312	0.00	0.00	0.00	2
1316	0.00	0.00	0.00	1
1319	0.00	0.00	0.00	1
1320	0.00	0.00	0.00	0
1321	0.00	0.00	0.00	0
1324	0.00	0.00	0.00	2
1325	0.00	0.00	0.00	0
1326	0.00	0.00	0.00	1
1327	0.00	0.00	0.00	0
1328	0.00	0.00	0.00	1
1329	0.00	0.00	0.00	1
1330	0.00	0.00	0.00	0
1331	0.00	0.00	0.00	1
1336	0.00	0.00	0.00	0
1337	0.00	0.00	0.00	0
1339	0.00	0.00	0.00	1
1340	0.00	0.00	0.00	1
1344	0.00	0.00	0.00	0
1345	0.00	0.00	0.00	0
1347	0.00	0.00	0.00	0
1348	0.00	0.00	0.00	0
1349	0.00	0.00	0.00	1
1350	0.00	0.00	0.00	0
1351	0.00	0.00	0.00	1
1354	0.00	0.00	0.00	0
1355	0.00	0.00	0.00	1
1356	0.00	0.00	0.00	0
1360	0.00	0.00	0.00	1
1362	0.00	0.00	0.00	1
1363	0.00	0.00	0.00	1
1365	0.00	0.00	0.00	0
1366	0.00	0.00	0.00	0
1368	0.00	0.00	0.00	1
1369	0.00	0.00	0.00	0
1370	0.00	0.00	0.00	0
1373	0.00	0.00	0.00	2
1376	0.00	0.00	0.00	1

1378	0.00	0.00	0.00	1
1379	0.00	0.00	0.00	0
1381	0.00	0.00	0.00	0
1382	0.00	0.00	0.00	0
1383	0.00	0.00	0.00	1
1385	0.00	0.00	0.00	1
1386	0.00	0.00	0.00	0
1387	0.00	0.00	0.00	0
1388	0.00	0.00	0.00	1
1389	0.00	0.00	0.00	2
1390	0.00	0.00	0.00	1
1391	0.00	0.00	0.00	1
1394	0.00	0.00	0.00	0
1395	0.00	0.00	0.00	1
1396	0.00	0.00	0.00	1
1399	0.00	0.00	0.00	1
1400	0.00	0.00	0.00	2
1403	0.00	0.00	0.00	1
1404	0.00	0.00	0.00	0
1405	0.00	0.00	0.00	1
1406	0.00	0.00	0.00	1
1412	0.00	0.00	0.00	0
1415	0.00	0.00	0.00	1
1416	0.00	0.00	0.00	0
1417	0.00	0.00	0.00	1
1418	0.00	0.00	0.00	0
1420	0.00	0.00	0.00	1
1421	0.00	0.00	0.00	0
1422	0.00	0.00	0.00	0
1424	0.00	0.00	0.00	1
1425	0.00	0.00	0.00	1
1426	0.00	0.00	0.00	1
1427	0.00	0.00	0.00	1
1428	0.00	0.00	0.00	1
1433	0.00	0.00	0.00	0
1434	0.00	0.00	0.00	2
1435	0.00	0.00	0.00	1
1437	0.00	0.00	0.00	1
1440	0.00	0.00	0.00	1
1442	0.00	0.00	0.00	1
1443	0.00	0.00	0.00	0
1444	0.00	0.00	0.00	1
1445	0.00	0.00	0.00	1
1446	0.00	0.00	0.00	0
1448	0.00	0.00	0.00	0
1449	0.00	0.00	0.00	1
1451	0.00	0.00	0.00	1
1453	0.00	0.00	0.00	1

1456	0.00	0.00	0.00	1
1457	0.00	0.00	0.00	1
1459	0.00	0.00	0.00	1
1460	0.00	0.00	0.00	1
1461	0.00	0.00	0.00	0
1464	0.00	0.00	0.00	0
1465	0.00	0.00	0.00	2
1466	0.00	0.00	0.00	1
1467	0.00	0.00	0.00	1
1470	0.00	0.00	0.00	1
1471	0.00	0.00	0.00	0
1472	0.00	0.00	0.00	1
1473	0.00	0.00	0.00	0
1474	0.00	0.00	0.00	1
1476	0.00	0.00	0.00	1
1477	0.00	0.00	0.00	0
1479	0.00	0.00	0.00	1
1480	0.00	0.00	0.00	0
1483	0.00	0.00	0.00	1
1487	0.00	0.00	0.00	0
1491	0.00	0.00	0.00	1
1492	0.00	0.00	0.00	1
1493	0.00	0.00	0.00	1
1494	0.00	0.00	0.00	0
1496	0.00	0.00	0.00	1
1498	0.00	0.00	0.00	1
1499	0.00	0.00	0.00	0
1500	0.00	0.00	0.00	1
1501	0.00	0.00	0.00	0
1503	0.00	0.00	0.00	2
1504	0.00	0.00	0.00	1
1506	0.00	0.00	0.00	0
1507	0.00	0.00	0.00	1
1509	0.00	0.00	0.00	1
1510	0.00	0.00	0.00	1
1511	0.00	0.00	0.00	0
1512	0.00	0.00	0.00	0
1513	0.00	0.00	0.00	0
1514	0.00	0.00	0.00	1
1515	0.00	0.00	0.00	2
1516	0.00	0.00	0.00	0
1518	0.00	0.00	0.00	0
1521	0.00	0.00	0.00	1
1523	0.00	0.00	0.00	1
1524	0.00	0.00	0.00	1
1525	0.00	0.00	0.00	0
1526	0.00	0.00	0.00	0
1527	0.00	0.00	0.00	0

1532	0.00	0.00	0.00	0
1534	0.00	0.00	0.00	1
1535	0.00	0.00	0.00	0
1539	0.00	0.00	0.00	1
1541	0.00	0.00	0.00	1
1542	0.00	0.00	0.00	0
1543	0.00	0.00	0.00	1
1545	0.00	0.00	0.00	0
1546	0.00	0.00	0.00	0
1548	0.00	0.00	0.00	1
1551	0.00	0.00	0.00	0
1552	0.00	0.00	0.00	1
1553	0.00	0.00	0.00	2
1554	0.00	0.00	0.00	2
1557	0.00	0.00	0.00	2
1558	0.00	0.00	0.00	0
1559	0.00	0.00	0.00	1
1561	0.00	0.00	0.00	2
1562	0.00	0.00	0.00	0
1563	0.00	0.00	0.00	1
1564	0.00	0.00	0.00	0
1565	0.00	0.00	0.00	1
1566	0.00	0.00	0.00	1
1568	0.00	0.00	0.00	0
1569	0.00	0.00	0.00	0
1571	0.00	0.00	0.00	1
1572	0.00	0.00	0.00	2
1573	0.00	0.00	0.00	0
1577	0.00	0.00	0.00	0
1578	0.00	0.00	0.00	1
1579	0.00	0.00	0.00	0
1580	0.00	0.00	0.00	2
1581	0.00	0.00	0.00	1
1583	0.00	0.00	0.00	1
1585	0.00	0.00	0.00	0
1587	0.00	0.00	0.00	1
1589	0.00	0.00	0.00	1
1590	0.00	0.00	0.00	2
1591	0.00	0.00	0.00	0
1592	0.00	0.00	0.00	1
1594	0.00	0.00	0.00	0
1595	0.00	0.00	0.00	0
1597	0.00	0.00	0.00	0
1606	0.00	0.00	0.00	1
1612	0.00	0.00	0.00	1
1613	0.00	0.00	0.00	1
1614	0.00	0.00	0.00	1
1615	0.00	0.00	0.00	0

1616	0.00	0.00	0.00	0
1617	0.00	0.00	0.00	1
1618	0.00	0.00	0.00	0
1619	0.00	0.00	0.00	1
1620	0.00	0.00	0.00	2
1622	0.00	0.00	0.00	1
1623	0.00	0.00	0.00	1
1624	0.00	0.00	0.00	1
1625	0.00	0.00	0.00	1
1628	0.00	0.00	0.00	2
1630	0.00	0.00	0.00	1
1631	0.00	0.00	0.00	1
1632	0.00	0.00	0.00	1
1635	0.00	0.00	0.00	0
1636	0.00	0.00	0.00	0
1637	0.00	0.00	0.00	0
1640	0.00	0.00	0.00	2
1641	0.00	0.00	0.00	1
1642	0.00	0.00	0.00	2
1643	0.00	0.00	0.00	1
1644	0.00	0.00	0.00	1
1645	0.00	0.00	0.00	1
1646	0.00	0.00	0.00	0
1647	0.00	0.00	0.00	0
1650	0.00	0.00	0.00	2
1651	0.00	0.00	0.00	0
1653	0.00	0.00	0.00	0
1654	0.00	0.00	0.00	1
1655	0.00	0.00	0.00	1
1656	0.00	0.00	0.00	0
1657	0.00	0.00	0.00	0
1658	0.00	0.00	0.00	2
1661	0.00	0.00	0.00	1
1664	0.00	0.00	0.00	1
1665	0.00	0.00	0.00	1
1666	0.00	0.00	0.00	1
1667	0.00	0.00	0.00	1
1668	0.00	0.00	0.00	0
1669	0.00	0.00	0.00	0
1670	0.00	0.00	0.00	1
1671	0.00	0.00	0.00	1
1674	0.00	0.00	0.00	0
1675	0.00	0.00	0.00	1
1677	0.00	0.00	0.00	1
1679	0.00	0.00	0.00	1
1680	0.00	0.00	0.00	1
1681	0.00	0.00	0.00	0
1682	0.00	0.00	0.00	1

1683	0.00	0.00	0.00	1
1684	0.00	0.00	0.00	0
1685	0.00	0.00	0.00	0
1686	0.00	0.00	0.00	0
1687	0.00	0.00	0.00	0
1688	0.00	0.00	0.00	0
1690	0.00	0.00	0.00	1
1693	0.00	0.00	0.00	2
1695	0.00	0.00	0.00	0
1696	0.00	0.00	0.00	1
1697	0.00	0.00	0.00	0
1698	0.00	0.00	0.00	1
1699	0.00	0.00	0.00	2
1700	0.00	0.00	0.00	0
1701	0.00	0.00	0.00	1
1702	0.00	0.00	0.00	1
1703	0.00	0.00	0.00	1
1704	0.00	0.00	0.00	1
1705	0.00	0.00	0.00	0
1706	0.00	0.00	0.00	2
1707	0.00	0.00	0.00	0
1709	0.00	0.00	0.00	0
1710	0.00	0.00	0.00	0
1711	0.00	0.00	0.00	1
1712	0.00	0.00	0.00	1
1713	0.00	0.00	0.00	2
1714	0.00	0.00	0.00	1
1715	0.00	0.00	0.00	1
1716	0.00	0.00	0.00	3
1718	0.00	0.00	0.00	0
1719	0.00	0.00	0.00	1
1720	0.00	0.00	0.00	0
1721	0.00	0.00	0.00	0
1723	0.00	0.00	0.00	1
1724	0.00	0.00	0.00	1
1725	0.00	0.00	0.00	1
1726	0.00	0.00	0.00	1
1727	0.00	0.00	0.00	1
1729	0.00	0.00	0.00	2
1730	0.00	0.00	0.00	2
1731	0.00	0.00	0.00	1
1732	0.00	0.00	0.00	3
1733	0.00	0.00	0.00	1
1737	0.00	0.00	0.00	1
1738	0.00	0.00	0.00	2
1739	0.00	0.00	0.00	0
1742	0.00	0.00	0.00	0
1743	0.00	0.00	0.00	1

1744	0.00	0.00	0.00	1
1745	0.00	0.00	0.00	0
1746	0.00	0.00	0.00	0
1748	0.00	0.00	0.00	1
1749	0.00	0.00	0.00	1
1750	0.00	0.00	0.00	1
1751	0.00	0.00	0.00	2
1752	0.00	0.00	0.00	1
1753	0.00	0.00	0.00	2
1755	0.00	0.00	0.00	1
1757	0.00	0.00	0.00	2
1758	0.00	0.00	0.00	2
1759	0.00	0.00	0.00	0
1760	0.00	0.00	0.00	1
1761	0.00	0.00	0.00	2
1762	0.00	0.00	0.00	0
1763	0.00	0.00	0.00	1
1764	0.00	0.00	0.00	1
1765	0.00	0.00	0.00	2
1767	0.00	0.00	0.00	1
1768	0.00	0.00	0.00	1
1769	0.00	0.00	0.00	0
1770	0.00	0.00	0.00	2
1771	0.00	0.00	0.00	1
1772	0.00	0.00	0.00	1
1773	0.00	0.00	0.00	0
1774	0.00	0.00	0.00	1
1775	0.00	0.00	0.00	1
1776	0.00	0.00	0.00	0
1777	0.00	0.00	0.00	0
1778	0.00	0.00	0.00	2
1779	0.00	0.00	0.00	1
1780	0.00	0.00	0.00	0
1781	0.00	0.00	0.00	1
1782	0.00	0.00	0.00	0
1783	0.00	0.00	0.00	1
1785	0.00	0.00	0.00	1
1790	0.00	0.00	0.00	0
1791	0.00	0.00	0.00	1
1792	0.00	0.00	0.00	1
1794	0.00	0.00	0.00	0
1796	0.00	0.00	0.00	0
1799	0.00	0.00	0.00	1
1800	0.00	0.00	0.00	1
1801	0.00	0.00	0.00	1
1802	0.00	0.00	0.00	1
1803	0.00	0.00	0.00	0
1805	0.00	0.00	0.00	1

1807	0.00	0.00	0.00	1
1808	0.00	0.00	0.00	1
1810	0.00	0.00	0.00	1
1811	0.00	0.00	0.00	0
1812	0.00	0.00	0.00	1
1813	0.00	0.00	0.00	2
1814	0.00	0.00	0.00	0
1817	0.00	0.00	0.00	1
1819	0.00	0.00	0.00	1
1823	0.00	0.00	0.00	1
1824	0.00	0.00	0.00	1
1825	0.00	0.00	0.00	1
1826	0.00	0.00	0.00	0
1827	0.00	0.00	0.00	1
1828	0.00	0.00	0.00	1
1829	0.00	0.00	0.00	1
1830	0.00	0.00	0.00	1
1831	0.00	0.00	0.00	1
1832	0.00	0.00	0.00	0
1833	0.00	0.00	0.00	1
1834	0.00	0.00	0.00	1
1835	0.00	0.00	0.00	1
1836	0.00	0.00	0.00	0
1837	0.00	0.00	0.00	1
1838	0.00	0.00	0.00	1
1840	0.00	0.00	0.00	1
1842	0.00	0.00	0.00	0
1843	0.00	0.00	0.00	1
1844	0.00	0.00	0.00	1
1846	0.00	0.00	0.00	0
1848	0.00	0.00	0.00	0
1850	0.00	0.00	0.00	0
1852	0.00	0.00	0.00	1
1854	0.00	0.00	0.00	0
1855	0.00	0.00	0.00	1
1858	0.00	0.00	0.00	0
1859	0.00	0.00	0.00	0
1861	0.00	0.00	0.00	1
1863	0.00	0.00	0.00	2
1866	0.00	0.00	0.00	1
1867	0.00	0.00	0.00	1
1869	0.00	0.00	0.00	1
1871	0.00	0.00	0.00	1
1872	0.00	0.00	0.00	1
1876	0.00	0.00	0.00	1
1879	0.00	0.00	0.00	0
1880	0.00	0.00	0.00	1
1881	0.00	0.00	0.00	1

1882	0.00	0.00	0.00	1
1883	0.00	0.00	0.00	0
1884	0.00	0.00	0.00	1
1885	0.00	0.00	0.00	2
1889	0.00	0.00	0.00	1
1890	0.00	0.00	0.00	1
1891	0.00	0.00	0.00	1
1892	0.00	0.00	0.00	1
1893	0.00	0.00	0.00	2
1895	0.00	0.00	0.00	1
1900	0.00	0.00	0.00	2
1901	0.00	0.00	0.00	1
1903	0.00	0.00	0.00	1
1905	0.00	0.00	0.00	1
1906	0.00	0.00	0.00	0
1907	0.00	0.00	0.00	1
1908	0.00	0.00	0.00	0
1909	0.00	0.00	0.00	0
1911	0.00	0.00	0.00	0
1913	0.00	0.00	0.00	0
1914	0.00	0.00	0.00	1
1916	0.00	0.00	0.00	0
1920	0.00	0.00	0.00	1
1922	0.00	0.00	0.00	1
1926	0.00	0.00	0.00	0
1929	0.00	0.00	0.00	0
1931	0.00	0.00	0.00	1
1936	0.00	0.00	0.00	1
1938	0.00	0.00	0.00	1
1939	0.00	0.00	0.00	1
1941	0.00	0.00	0.00	1
1942	0.00	0.00	0.00	1
1943	0.00	0.00	0.00	1
1944	0.00	0.00	0.00	0
1947	0.00	0.00	0.00	1
1948	0.00	0.00	0.00	1
1949	0.00	0.00	0.00	0
1950	0.00	0.00	0.00	1
1951	0.00	0.00	0.00	1
1952	0.00	0.00	0.00	0
1953	0.00	0.00	0.00	0
1955	0.00	0.00	0.00	2
1956	0.00	0.00	0.00	1
1957	0.00	0.00	0.00	1
1958	0.00	0.00	0.00	0
1961	0.00	0.00	0.00	0
1963	0.00	0.00	0.00	1
1967	0.00	0.00	0.00	1

1968	0.00	0.00	0.00	2
1970	0.00	0.00	0.00	1
1973	0.00	0.00	0.00	1
1974	0.00	0.00	0.00	0
1977	0.00	0.00	0.00	0
1978	0.00	0.00	0.00	1
1979	0.00	0.00	0.00	1
1981	0.00	0.00	0.00	0
1982	0.00	0.00	0.00	1
1983	0.00	0.00	0.00	0
1984	0.00	0.00	0.00	1
1985	0.00	0.00	0.00	1
1986	0.00	0.00	0.00	1
1991	0.00	0.00	0.00	0
1993	0.00	0.00	0.00	1
1994	0.00	0.00	0.00	1
1996	0.00	0.00	0.00	1
1997	0.00	0.00	0.00	1
1999	0.00	0.00	0.00	1
2000	0.00	0.00	0.00	0
2001	0.00	0.00	0.00	1
2003	0.00	0.00	0.00	2
2005	0.00	0.00	0.00	0
2007	0.00	0.00	0.00	1
2008	0.00	0.00	0.00	1
2010	0.00	0.00	0.00	1
2013	0.00	0.00	0.00	1
2014	0.00	0.00	0.00	1
2018	0.00	0.00	0.00	1
2019	0.00	0.00	0.00	0
2023	0.00	0.00	0.00	1
2026	0.00	0.00	0.00	0
2027	0.00	0.00	0.00	1
2028	0.00	0.00	0.00	0
2029	0.00	0.00	0.00	2
2030	0.00	0.00	0.00	1
2031	0.00	0.00	0.00	1
2032	0.00	0.00	0.00	0
2033	0.00	0.00	0.00	1
2035	0.00	0.00	0.00	0
2036	0.00	0.00	0.00	1
2040	0.00	0.00	0.00	1
2041	0.00	0.00	0.00	1
2042	0.00	0.00	0.00	1
2043	0.00	0.00	0.00	1
2044	0.00	0.00	0.00	1
2046	0.00	0.00	0.00	1
2048	0.00	0.00	0.00	0

2049	0.00	0.00	0.00	0
2051	0.00	0.00	0.00	1
2053	0.00	0.00	0.00	0
2054	0.00	0.00	0.00	1
2056	0.00	0.00	0.00	0
2057	0.00	0.00	0.00	0
2058	0.00	0.00	0.00	0
2059	0.00	0.00	0.00	0
2060	0.00	0.00	0.00	0
2061	0.00	0.00	0.00	0
2062	0.00	0.00	0.00	1
2063	0.00	0.00	0.00	1
2066	0.00	0.00	0.00	1
2068	0.00	0.00	0.00	1
2069	0.00	0.00	0.00	0
2072	0.00	0.00	0.00	1
2073	0.00	0.00	0.00	0
2075	0.00	0.00	0.00	0
2076	0.00	0.00	0.00	0
2077	0.00	0.00	0.00	1
2078	0.00	0.00	0.00	1
2079	0.00	0.00	0.00	2
2080	0.00	0.00	0.00	2
2081	0.00	0.00	0.00	1
2082	0.00	0.00	0.00	0
2083	0.00	0.00	0.00	1
2085	0.00	0.00	0.00	1
2087	0.00	0.00	0.00	1
2088	0.00	0.00	0.00	1
2089	0.00	0.00	0.00	1
2091	0.00	0.00	0.00	0
2092	0.00	0.00	0.00	1
2093	0.00	0.00	0.00	1
2095	0.00	0.00	0.00	1
2102	0.00	0.00	0.00	1
2104	0.00	0.00	0.00	1
2105	0.00	0.00	0.00	1
2106	0.00	0.00	0.00	0
2107	0.00	0.00	0.00	0
2109	0.00	0.00	0.00	1
2111	0.00	0.00	0.00	0
2112	0.00	0.00	0.00	0
2114	0.00	0.00	0.00	0
2117	0.00	0.00	0.00	1
2118	0.00	0.00	0.00	1
2120	0.00	0.00	0.00	2
2121	0.00	0.00	0.00	1
2122	0.00	0.00	0.00	0

2125	0.00	0.00	0.00	0
2127	0.00	0.00	0.00	0
2128	0.00	0.00	0.00	1
2129	0.00	0.00	0.00	0
2130	0.00	0.00	0.00	0
2131	0.00	0.00	0.00	0
2133	0.00	0.00	0.00	1
2138	0.00	0.00	0.00	1
2139	0.00	0.00	0.00	1
2140	0.00	0.00	0.00	1
2141	0.00	0.00	0.00	1
2142	0.00	0.00	0.00	1
2143	0.00	0.00	0.00	1
2144	0.00	0.00	0.00	1
2145	0.00	0.00	0.00	0
2147	0.00	0.00	0.00	0
2148	0.00	0.00	0.00	0
2150	0.00	0.00	0.00	0
2153	0.00	0.00	0.00	0
2155	0.00	0.00	0.00	3
2156	0.00	0.00	0.00	1
2157	0.00	0.00	0.00	1
2159	0.00	0.00	0.00	0
2160	0.00	0.00	0.00	1
2162	0.00	0.00	0.00	1
2163	0.00	0.00	0.00	1
2164	0.00	0.00	0.00	0
2165	0.00	0.00	0.00	0
2166	0.00	0.00	0.00	1
2167	0.00	0.00	0.00	1
2169	0.00	0.00	0.00	0
2171	0.00	0.00	0.00	2
2172	0.00	0.00	0.00	1
2175	0.00	0.00	0.00	1
2176	0.00	0.00	0.00	0
2178	0.00	0.00	0.00	0
2179	0.00	0.00	0.00	0
2183	0.00	0.00	0.00	0
2184	0.00	0.00	0.00	1
2186	0.00	0.00	0.00	1
2189	0.00	0.00	0.00	1
2190	0.00	0.00	0.00	1
2191	0.00	0.00	0.00	1
2192	0.00	0.00	0.00	1
2193	0.00	0.00	0.00	1
2195	0.00	0.00	0.00	0
2197	0.00	0.00	0.00	1
2198	0.00	0.00	0.00	1

2203	0.00	0.00	0.00	1
2205	0.00	0.00	0.00	1
2206	0.00	0.00	0.00	1
2207	0.00	0.00	0.00	3
2208	0.00	0.00	0.00	0
2209	0.00	0.00	0.00	1
2211	0.00	0.00	0.00	0
2212	0.00	0.00	0.00	1
2213	0.00	0.00	0.00	1
2217	0.00	0.00	0.00	1
2218	0.00	0.00	0.00	1
2219	0.00	0.00	0.00	0
2220	0.00	0.00	0.00	1
2221	0.00	0.00	0.00	0
2223	0.00	0.00	0.00	1
2225	0.00	0.00	0.00	0
2230	0.00	0.00	0.00	0
2231	0.00	0.00	0.00	0
2233	0.00	0.00	0.00	1
2234	0.00	0.00	0.00	2
2235	0.00	0.00	0.00	1
2239	0.00	0.00	0.00	1
2240	0.00	0.00	0.00	0
2241	0.00	0.00	0.00	0
2242	0.00	0.00	0.00	0
2246	0.00	0.00	0.00	0
2249	0.00	0.00	0.00	1
2250	0.00	0.00	0.00	0
2251	0.00	0.00	0.00	1
2254	0.00	0.00	0.00	1
2255	0.00	0.00	0.00	1
2257	0.00	0.00	0.00	0
2258	0.00	0.00	0.00	1
2259	0.00	0.00	0.00	0
2262	0.00	0.00	0.00	1
2263	0.00	0.00	0.00	0
2264	0.00	0.00	0.00	1
2265	0.00	0.00	0.00	1
2267	0.00	0.00	0.00	1
2268	0.00	0.00	0.00	0
2269	0.00	0.00	0.00	0
2270	0.00	0.00	0.00	0
2271	0.00	0.00	0.00	1
2275	0.00	0.00	0.00	1
2278	0.00	0.00	0.00	1
2280	0.00	0.00	0.00	1
2281	0.00	0.00	0.00	1
2283	0.00	0.00	0.00	0

2284	0.00	0.00	0.00	0
2285	0.00	0.00	0.00	1
2287	0.00	0.00	0.00	0
2288	0.00	0.00	0.00	2
2290	0.00	0.00	0.00	1
2297	0.00	0.00	0.00	0
2301	0.00	0.00	0.00	0
2303	0.00	0.00	0.00	1
2305	0.00	0.00	0.00	1
2306	0.00	0.00	0.00	0
2309	0.00	0.00	0.00	1
2310	0.00	0.00	0.00	0
2314	0.00	0.00	0.00	0
2315	0.00	0.00	0.00	1
2316	0.00	0.00	0.00	0
2319	0.00	0.00	0.00	1
2321	0.00	0.00	0.00	1
2322	0.00	0.00	0.00	1
2323	0.00	0.00	0.00	0
2325	0.00	0.00	0.00	1
2326	0.00	0.00	0.00	0
2328	0.00	0.00	0.00	1
2329	0.00	0.00	0.00	1
2330	0.00	0.00	0.00	1
2334	0.00	0.00	0.00	1
2335	0.00	0.00	0.00	1
2336	0.00	0.00	0.00	1
2337	0.00	0.00	0.00	0
2338	0.00	0.00	0.00	1
2339	0.00	0.00	0.00	0
2340	0.00	0.00	0.00	1
2341	0.00	0.00	0.00	0
2344	0.00	0.00	0.00	0
2349	0.00	0.00	0.00	1
2350	0.00	0.00	0.00	1
2353	0.00	0.00	0.00	0
2357	0.00	0.00	0.00	1
2358	0.00	0.00	0.00	0
2360	0.00	0.00	0.00	1
2362	0.00	0.00	0.00	0
2363	0.00	0.00	0.00	0
2364	0.00	0.00	0.00	0
2365	0.00	0.00	0.00	1
2366	0.00	0.00	0.00	0
2370	0.00	0.00	0.00	1
2372	0.00	0.00	0.00	0
2374	0.00	0.00	0.00	1
2375	0.00	0.00	0.00	0

2377	0.00	0.00	0.00	0
2378	0.00	0.00	0.00	1
2379	0.00	0.00	0.00	1
2380	0.00	0.00	0.00	0
2381	0.00	0.00	0.00	1
2383	0.00	0.00	0.00	1
2385	0.00	0.00	0.00	0
2387	0.00	0.00	0.00	1
2389	0.00	0.00	0.00	1
2395	0.00	0.00	0.00	0
2396	0.00	0.00	0.00	0
2397	0.00	0.00	0.00	1
2398	0.00	0.00	0.00	1
2401	0.00	0.00	0.00	1
2403	0.00	0.00	0.00	1
2404	0.00	0.00	0.00	0
2407	0.00	0.00	0.00	1
2410	0.00	0.00	0.00	1
2411	0.00	0.00	0.00	1
2412	0.00	0.00	0.00	1
2414	0.00	0.00	0.00	0
2415	0.00	0.00	0.00	0
2419	0.00	0.00	0.00	0
2421	0.00	0.00	0.00	1
2422	0.00	0.00	0.00	1
2425	0.00	0.00	0.00	0
2426	0.00	0.00	0.00	0
2427	0.00	0.00	0.00	2
2429	0.00	0.00	0.00	1
2430	0.00	0.00	0.00	0
2431	0.00	0.00	0.00	1
2432	0.00	0.00	0.00	1
2433	0.00	0.00	0.00	0
2434	0.00	0.00	0.00	1
2435	0.00	0.00	0.00	1
2437	0.00	0.00	0.00	1
2438	0.00	0.00	0.00	1
2439	0.00	0.00	0.00	1
2442	0.00	0.00	0.00	1
2443	0.00	0.00	0.00	1
2444	0.00	0.00	0.00	1
2448	0.00	0.00	0.00	0
2449	0.00	0.00	0.00	1
2450	0.00	0.00	0.00	1
2451	0.00	0.00	0.00	1
2453	0.00	0.00	0.00	0
2455	0.00	0.00	0.00	1
2456	0.00	0.00	0.00	0

```
        2459       0.00      0.00      0.00         0
        2460       0.00      0.00      0.00         1
        2468       0.00      0.00      0.00         1
        2469       0.00      0.00      0.00         1
        2470       0.00      0.00      0.00         1
        2472       0.00      0.00      0.00         1
        2477       0.00      0.00      0.00         1
        2480       0.00      0.00      0.00         1
        2481       0.00      0.00      0.00         0
        2483       0.00      0.00      0.00         1
        2485       0.00      0.00      0.00         1
        2488       0.00      0.00      0.00         1
        2490       0.00      0.00      0.00         0
        2492       0.00      0.00      0.00         1
        2493       0.00      0.00      0.00         1
        2500       0.00      0.00      0.00         1
        2501       0.00      0.00      0.00         1
        2503       0.00      0.00      0.00         1
        2504       0.00      0.00      0.00         1
        2505       0.00      0.00      0.00         1
        2511       0.00      0.00      0.00         1
        2516       0.00      0.00      0.00         1
        2517       0.00      0.00      0.00         1
        2527       0.00      0.00      0.00         1
        2532       0.00      0.00      0.00         1
        2537       0.00      0.00      0.00         1
        2539       0.00      0.00      0.00         1
        2540       0.00      0.00      0.00         1

    accuracy                           0.00      1263
   macro avg       0.00      0.00      0.00      1263
weighted avg       0.00      0.00      0.00      1263
```

[70]:
```
knn = KNeighborsClassifier(n_neighbors=1)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
print(metrics.accuracy_score(y_test, y_pred))
```

```
0.011084718923198733
```

[71]:
```
print(classification_report(y_test,pred))
```

```
              precision    recall  f1-score   support

           0       0.00      0.00      0.00         0
           1       0.00      0.00      0.00         0
           2       0.00      0.00      0.00         1
           3       0.00      0.00      0.00         0
```

4	0.00	0.00	0.00	0
5	0.00	0.00	0.00	0
6	0.00	0.00	0.00	0
8	0.00	0.00	0.00	0
11	0.00	0.00	0.00	1
12	0.00	0.00	0.00	0
13	0.00	0.00	0.00	1
14	0.00	0.00	0.00	0
15	0.00	0.00	0.00	1
16	0.00	0.00	0.00	1
17	0.00	0.00	0.00	0
19	0.00	0.00	0.00	1
20	0.00	0.00	0.00	0
22	0.00	0.00	0.00	1
23	0.00	0.00	0.00	1
24	0.00	0.00	0.00	1
25	0.00	0.00	0.00	0
27	0.00	0.00	0.00	0
29	0.00	0.00	0.00	0
30	0.00	0.00	0.00	1
31	0.00	0.00	0.00	0
32	0.00	0.00	0.00	0
33	0.00	0.00	0.00	1
34	0.00	0.00	0.00	1
35	0.00	0.00	0.00	0
41	0.00	0.00	0.00	0
42	0.00	0.00	0.00	1
46	0.00	0.00	0.00	0
47	0.00	0.00	0.00	0
48	0.00	0.00	0.00	1
49	0.00	0.00	0.00	0
51	0.00	0.00	0.00	1
52	0.00	0.00	0.00	1
53	0.00	0.00	0.00	1
54	0.00	0.00	0.00	1
60	0.00	0.00	0.00	1
63	0.00	0.00	0.00	1
64	0.00	0.00	0.00	1
66	0.00	0.00	0.00	1
67	0.00	0.00	0.00	0
68	0.00	0.00	0.00	1
69	0.00	0.00	0.00	0
72	0.00	0.00	0.00	0
75	0.00	0.00	0.00	1
76	0.00	0.00	0.00	0
77	0.00	0.00	0.00	1
82	0.00	0.00	0.00	1
84	0.00	0.00	0.00	0

87	0.00	0.00	0.00	0
88	0.00	0.00	0.00	0
89	0.00	0.00	0.00	0
93	0.00	0.00	0.00	1
95	0.00	0.00	0.00	1
96	0.00	0.00	0.00	1
98	0.00	0.00	0.00	1
99	0.00	0.00	0.00	0
100	0.00	0.00	0.00	1
103	0.00	0.00	0.00	0
106	0.00	0.00	0.00	1
109	0.00	0.00	0.00	1
112	0.00	0.00	0.00	1
113	0.00	0.00	0.00	1
114	0.00	0.00	0.00	0
115	0.00	0.00	0.00	1
117	0.00	0.00	0.00	0
120	0.00	0.00	0.00	1
121	0.00	0.00	0.00	0
123	0.00	0.00	0.00	0
124	0.00	0.00	0.00	0
126	0.00	0.00	0.00	1
128	0.00	0.00	0.00	1
129	0.00	0.00	0.00	0
131	0.00	0.00	0.00	1
135	0.00	0.00	0.00	0
136	0.00	0.00	0.00	1
138	0.00	0.00	0.00	1
146	0.00	0.00	0.00	1
147	0.00	0.00	0.00	0
152	0.00	0.00	0.00	0
154	0.00	0.00	0.00	1
157	0.00	0.00	0.00	0
159	0.00	0.00	0.00	1
160	0.00	0.00	0.00	0
161	0.00	0.00	0.00	1
164	0.00	0.00	0.00	1
166	0.00	0.00	0.00	1
167	0.00	0.00	0.00	1
168	0.00	0.00	0.00	1
169	0.00	0.00	0.00	0
170	0.00	0.00	0.00	1
171	0.00	0.00	0.00	0
172	0.00	0.00	0.00	0
173	0.00	0.00	0.00	0
175	0.00	0.00	0.00	1
176	0.00	0.00	0.00	0
177	0.00	0.00	0.00	0

179	0.00	0.00	0.00	0
180	0.00	0.00	0.00	2
181	0.00	0.00	0.00	1
183	0.00	0.00	0.00	1
184	0.00	0.00	0.00	0
185	0.00	0.00	0.00	1
190	0.00	0.00	0.00	1
191	0.00	0.00	0.00	0
192	0.00	0.00	0.00	1
193	0.00	0.00	0.00	1
194	0.00	0.00	0.00	2
196	0.00	0.00	0.00	1
197	0.00	0.00	0.00	1
198	0.00	0.00	0.00	0
199	0.00	0.00	0.00	1
200	0.00	0.00	0.00	0
202	0.00	0.00	0.00	0
204	0.00	0.00	0.00	0
206	0.00	0.00	0.00	1
207	0.00	0.00	0.00	0
208	0.00	0.00	0.00	1
209	0.00	0.00	0.00	0
210	0.00	0.00	0.00	0
217	0.00	0.00	0.00	0
218	0.00	0.00	0.00	1
219	0.00	0.00	0.00	1
220	0.00	0.00	0.00	0
221	0.00	0.00	0.00	1
223	0.00	0.00	0.00	1
224	0.00	0.00	0.00	0
229	0.00	0.00	0.00	1
230	0.00	0.00	0.00	1
232	0.00	0.00	0.00	1
233	0.00	0.00	0.00	0
234	0.00	0.00	0.00	2
235	0.00	0.00	0.00	1
237	0.00	0.00	0.00	1
239	0.00	0.00	0.00	1
240	0.00	0.00	0.00	0
241	0.00	0.00	0.00	0
242	0.00	0.00	0.00	1
243	0.00	0.00	0.00	1
245	0.00	0.00	0.00	1
246	0.00	0.00	0.00	0
247	0.00	0.00	0.00	1
248	0.00	0.00	0.00	1
249	0.00	0.00	0.00	2
250	1.00	1.00	1.00	1

251	0.00	0.00	0.00	1
252	0.00	0.00	0.00	0
254	0.00	0.00	0.00	0
255	0.00	0.00	0.00	1
256	0.00	0.00	0.00	0
257	0.00	0.00	0.00	0
258	0.00	0.00	0.00	1
259	0.00	0.00	0.00	0
260	0.00	0.00	0.00	1
261	0.00	0.00	0.00	3
263	0.00	0.00	0.00	2
264	0.00	0.00	0.00	3
265	0.00	0.00	0.00	0
267	0.00	0.00	0.00	2
268	0.00	0.00	0.00	1
269	0.00	0.00	0.00	0
270	0.00	0.00	0.00	1
272	0.00	0.00	0.00	0
273	0.00	0.00	0.00	1
277	0.00	0.00	0.00	1
279	0.00	0.00	0.00	0
281	0.00	0.00	0.00	0
282	0.00	0.00	0.00	1
284	0.00	0.00	0.00	1
286	0.00	0.00	0.00	0
287	0.00	0.00	0.00	1
288	0.00	0.00	0.00	2
289	0.00	0.00	0.00	0
290	0.00	0.00	0.00	1
291	0.00	0.00	0.00	2
292	0.00	0.00	0.00	1
295	0.00	0.00	0.00	1
296	0.00	0.00	0.00	0
299	0.00	0.00	0.00	2
300	0.00	0.00	0.00	0
302	0.00	0.00	0.00	0
303	0.00	0.00	0.00	1
304	0.00	0.00	0.00	1
305	0.00	0.00	0.00	1
306	0.00	0.00	0.00	0
307	0.00	0.00	0.00	1
308	0.00	0.00	0.00	1
309	0.00	0.00	0.00	1
310	0.00	0.00	0.00	1
311	0.00	0.00	0.00	1
313	0.00	0.00	0.00	1
314	0.00	0.00	0.00	0
315	0.00	0.00	0.00	1

316	0.00	0.00	0.00	1
317	0.00	0.00	0.00	1
318	0.00	0.00	0.00	0
319	0.00	0.00	0.00	0
320	0.00	0.00	0.00	0
321	0.00	0.00	0.00	1
322	0.00	0.00	0.00	1
323	0.00	0.00	0.00	1
324	0.00	0.00	0.00	1
325	0.00	0.00	0.00	1
326	0.00	0.00	0.00	1
328	0.00	0.00	0.00	1
329	0.00	0.00	0.00	0
330	0.00	0.00	0.00	1
331	0.00	0.00	0.00	0
332	0.00	0.00	0.00	0
335	0.00	0.00	0.00	1
336	0.00	0.00	0.00	2
337	0.00	0.00	0.00	1
338	0.00	0.00	0.00	1
339	0.00	0.00	0.00	0
340	0.00	0.00	0.00	2
341	0.00	0.00	0.00	0
342	0.00	0.00	0.00	1
343	0.00	0.00	0.00	1
344	0.00	0.00	0.00	1
346	0.00	0.00	0.00	0
347	0.00	0.00	0.00	0
348	0.00	0.00	0.00	1
349	0.00	0.00	0.00	1
350	0.00	0.00	0.00	1
351	0.00	0.00	0.00	2
352	0.00	0.00	0.00	2
353	0.00	0.00	0.00	3
354	0.00	0.00	0.00	1
356	0.00	0.00	0.00	0
358	0.00	0.00	0.00	0
359	0.00	0.00	0.00	2
361	0.00	0.00	0.00	0
362	0.00	0.00	0.00	0
363	0.00	0.00	0.00	1
364	0.00	0.00	0.00	2
365	0.00	0.00	0.00	1
366	0.00	0.00	0.00	0
367	0.00	0.00	0.00	1
368	0.00	0.00	0.00	1
369	0.00	0.00	0.00	1
370	0.00	0.00	0.00	1

371	0.00	0.00	0.00	1
372	0.00	0.00	0.00	1
373	0.00	0.00	0.00	2
374	0.00	0.00	0.00	1
375	0.00	0.00	0.00	2
376	0.00	0.00	0.00	0
378	0.00	0.00	0.00	2
381	0.00	0.00	0.00	2
382	0.00	0.00	0.00	1
383	0.00	0.00	0.00	2
385	0.00	0.00	0.00	0
386	0.00	0.00	0.00	1
387	0.00	0.00	0.00	0
388	0.00	0.00	0.00	2
389	0.00	0.00	0.00	1
391	0.00	0.00	0.00	0
392	0.00	0.00	0.00	1
393	0.00	0.00	0.00	2
394	0.00	0.00	0.00	1
395	0.00	0.00	0.00	0
396	0.00	0.00	0.00	1
397	0.00	0.00	0.00	0
398	0.00	0.00	0.00	1
399	0.00	0.00	0.00	2
401	0.00	0.00	0.00	0
404	0.00	0.00	0.00	1
405	0.00	0.00	0.00	0
406	0.00	0.00	0.00	1
407	0.00	0.00	0.00	1
408	0.00	0.00	0.00	0
409	0.00	0.00	0.00	2
410	0.00	0.00	0.00	0
411	0.00	0.00	0.00	1
412	0.00	0.00	0.00	2
413	0.00	0.00	0.00	1
415	0.00	0.00	0.00	1
416	0.00	0.00	0.00	3
420	0.00	0.00	0.00	1
421	0.00	0.00	0.00	1
423	0.00	0.00	0.00	1
428	0.00	0.00	0.00	1
429	0.00	0.00	0.00	2
430	0.00	0.00	0.00	1
432	0.00	0.00	0.00	3
433	0.00	0.00	0.00	2
434	0.00	0.00	0.00	1
435	0.00	0.00	0.00	1
436	0.00	0.00	0.00	2

437	0.00	0.00	0.00	1
441	0.00	0.00	0.00	1
442	0.00	0.00	0.00	1
443	0.00	0.00	0.00	1
444	0.00	0.00	0.00	2
445	0.00	0.00	0.00	0
446	0.00	0.00	0.00	1
447	0.00	0.00	0.00	0
448	0.00	0.00	0.00	1
450	0.00	0.00	0.00	1
453	0.00	0.00	0.00	1
454	0.00	0.00	0.00	1
455	0.00	0.00	0.00	1
456	0.00	0.00	0.00	1
457	0.00	0.00	0.00	1
458	0.00	0.00	0.00	0
459	0.00	0.00	0.00	0
462	0.00	0.00	0.00	0
465	0.00	0.00	0.00	1
466	0.00	0.00	0.00	2
467	0.00	0.00	0.00	1
468	0.00	0.00	0.00	0
469	0.00	0.00	0.00	1
470	0.00	0.00	0.00	1
471	0.00	0.00	0.00	2
473	0.00	0.00	0.00	2
474	0.00	0.00	0.00	1
475	0.00	0.00	0.00	1
477	0.00	0.00	0.00	1
478	0.00	0.00	0.00	0
480	0.00	0.00	0.00	1
481	0.00	0.00	0.00	1
482	0.00	0.00	0.00	0
483	0.00	0.00	0.00	2
485	0.00	0.00	0.00	0
486	0.00	0.00	0.00	1
489	0.00	0.00	0.00	0
490	0.00	0.00	0.00	0
491	0.00	0.00	0.00	1
492	0.00	0.00	0.00	1
493	0.00	0.00	0.00	1
494	0.00	0.00	0.00	2
495	0.00	0.00	0.00	0
496	0.00	0.00	0.00	2
497	0.00	0.00	0.00	1
498	0.00	0.00	0.00	0
499	0.00	0.00	0.00	1
501	0.00	0.00	0.00	1

502	0.00	0.00	0.00	0
503	0.00	0.00	0.00	0
505	0.00	0.00	0.00	3
507	0.00	0.00	0.00	0
508	0.00	0.00	0.00	1
509	0.00	0.00	0.00	1
511	0.00	0.00	0.00	1
512	0.00	0.00	0.00	1
513	0.00	0.00	0.00	1
514	0.00	0.00	0.00	1
515	0.00	0.00	0.00	2
516	0.00	0.00	0.00	1
517	0.00	0.00	0.00	0
518	0.00	0.00	0.00	0
521	0.00	0.00	0.00	0
522	0.00	0.00	0.00	1
525	0.00	0.00	0.00	2
526	0.00	0.00	0.00	0
527	0.00	0.00	0.00	1
529	0.00	0.00	0.00	1
532	0.00	0.00	0.00	2
533	0.50	0.50	0.50	2
535	0.00	0.00	0.00	1
536	0.00	0.00	0.00	2
537	0.00	0.00	0.00	1
541	0.00	0.00	0.00	2
542	0.00	0.00	0.00	0
543	0.00	0.00	0.00	0
544	0.00	0.00	0.00	2
545	0.00	0.00	0.00	1
546	0.00	0.00	0.00	0
547	0.00	0.00	0.00	0
548	0.00	0.00	0.00	2
549	0.00	0.00	0.00	1
550	0.00	0.00	0.00	2
553	0.00	0.00	0.00	0
554	0.00	0.00	0.00	0
556	0.00	0.00	0.00	2
557	0.00	0.00	0.00	0
558	0.00	0.00	0.00	1
560	0.00	0.00	0.00	1
561	0.00	0.00	0.00	2
562	0.00	0.00	0.00	2
563	0.00	0.00	0.00	2
564	0.00	0.00	0.00	2
565	0.00	0.00	0.00	1
566	0.00	0.00	0.00	0
567	0.00	0.00	0.00	2

568	0.00	0.00	0.00	0
569	0.00	0.00	0.00	2
571	0.00	0.00	0.00	2
572	0.00	0.00	0.00	0
573	0.00	0.00	0.00	2
575	0.00	0.00	0.00	0
576	0.00	0.00	0.00	0
577	0.00	0.00	0.00	0
579	0.00	0.00	0.00	3
581	0.00	0.00	0.00	0
584	0.00	0.00	0.00	1
587	0.00	0.00	0.00	1
588	0.00	0.00	0.00	1
589	0.00	0.00	0.00	1
591	0.00	0.00	0.00	0
593	0.00	0.00	0.00	0
594	0.00	0.00	0.00	1
595	0.00	0.00	0.00	1
596	0.00	0.00	0.00	1
599	0.00	0.00	0.00	1
600	0.00	0.00	0.00	1
602	0.00	0.00	0.00	1
603	0.00	0.00	0.00	0
604	0.00	0.00	0.00	3
605	0.00	0.00	0.00	0
607	0.00	0.00	0.00	1
609	0.00	0.00	0.00	0
611	0.00	0.00	0.00	0
612	0.00	0.00	0.00	1
614	0.00	0.00	0.00	1
615	0.00	0.00	0.00	1
616	0.00	0.00	0.00	1
617	0.00	0.00	0.00	1
618	0.00	0.00	0.00	0
619	0.00	0.00	0.00	1
620	0.00	0.00	0.00	3
621	0.00	0.00	0.00	1
622	0.00	0.00	0.00	1
623	0.00	0.00	0.00	2
624	0.00	0.00	0.00	1
625	0.00	0.00	0.00	2
626	0.00	0.00	0.00	0
627	0.00	0.00	0.00	2
628	0.00	0.00	0.00	0
629	0.00	0.00	0.00	0
630	0.00	0.00	0.00	1
632	0.00	0.00	0.00	1
633	0.00	0.00	0.00	1

634	0.00	0.00	0.00	1
637	0.00	0.00	0.00	1
638	0.00	0.00	0.00	1
639	0.00	0.00	0.00	1
640	0.00	0.00	0.00	1
641	0.00	0.00	0.00	2
642	0.00	0.00	0.00	2
643	0.00	0.00	0.00	1
644	0.00	0.00	0.00	1
645	0.00	0.00	0.00	2
647	0.00	0.00	0.00	0
648	0.00	0.00	0.00	2
649	0.00	0.00	0.00	1
652	0.00	0.00	0.00	1
654	0.00	0.00	0.00	0
655	0.00	0.00	0.00	1
656	0.00	0.00	0.00	1
658	0.00	0.00	0.00	1
659	0.00	0.00	0.00	1
660	0.00	0.00	0.00	0
661	0.00	0.00	0.00	2
662	0.00	0.00	0.00	1
663	0.00	0.00	0.00	1
664	0.00	0.00	0.00	0
665	0.00	0.00	0.00	0
666	0.00	0.00	0.00	2
671	0.00	0.00	0.00	1
672	0.00	0.00	0.00	2
673	0.00	0.00	0.00	0
674	0.00	0.00	0.00	1
676	0.00	0.00	0.00	2
678	0.00	0.00	0.00	1
679	0.00	0.00	0.00	0
680	0.00	0.00	0.00	1
681	0.00	0.00	0.00	0
682	0.00	0.00	0.00	1
684	0.00	0.00	0.00	0
685	0.00	0.00	0.00	1
688	0.00	0.00	0.00	1
689	0.00	0.00	0.00	0
690	0.00	0.00	0.00	1
691	0.00	0.00	0.00	1
693	0.00	0.00	0.00	1
694	0.00	0.00	0.00	1
695	0.00	0.00	0.00	0
696	0.00	0.00	0.00	1
697	0.00	0.00	0.00	2
699	0.00	0.00	0.00	0

700	0.00	0.00	0.00	0
704	0.00	0.00	0.00	1
705	0.00	0.00	0.00	0
707	0.00	0.00	0.00	0
708	0.00	0.00	0.00	0
709	0.00	0.00	0.00	1
710	0.00	0.00	0.00	3
711	0.00	0.00	0.00	0
712	0.00	0.00	0.00	0
713	0.00	0.00	0.00	2
714	0.00	0.00	0.00	1
715	0.00	0.00	0.00	0
716	0.00	0.00	0.00	1
717	0.00	0.00	0.00	2
718	0.00	0.00	0.00	1
719	0.00	0.00	0.00	0
720	0.00	0.00	0.00	0
721	0.00	0.00	0.00	0
722	0.00	0.00	0.00	1
724	0.00	0.00	0.00	1
725	0.00	0.00	0.00	1
726	0.00	0.00	0.00	1
727	0.00	0.00	0.00	1
728	0.00	0.00	0.00	0
729	0.00	0.00	0.00	1
730	0.00	0.00	0.00	1
731	0.00	0.00	0.00	2
732	0.00	0.00	0.00	2
734	0.00	0.00	0.00	1
735	0.00	0.00	0.00	0
736	0.00	0.00	0.00	0
737	0.00	0.00	0.00	0
738	0.00	0.00	0.00	0
739	0.00	0.00	0.00	1
740	0.00	0.00	0.00	1
742	0.00	0.00	0.00	1
744	0.00	0.00	0.00	1
745	0.00	0.00	0.00	1
746	0.00	0.00	0.00	0
747	0.00	0.00	0.00	0
748	0.00	0.00	0.00	2
749	0.00	0.00	0.00	1
751	0.00	0.00	0.00	0
752	0.00	0.00	0.00	1
757	0.00	0.00	0.00	1
758	0.00	0.00	0.00	1
759	0.00	0.00	0.00	1
760	0.00	0.00	0.00	1

761	0.00	0.00	0.00	1
762	0.00	0.00	0.00	2
763	0.00	0.00	0.00	2
765	0.00	0.00	0.00	0
766	0.00	0.00	0.00	1
768	0.00	0.00	0.00	1
770	0.00	0.00	0.00	2
771	0.00	0.00	0.00	0
772	0.00	0.00	0.00	0
774	1.00	1.00	1.00	1
776	0.00	0.00	0.00	0
777	0.00	0.00	0.00	1
778	0.00	0.00	0.00	1
779	0.00	0.00	0.00	0
780	0.00	0.00	0.00	1
781	0.00	0.00	0.00	1
782	0.00	0.00	0.00	1
784	0.00	0.00	0.00	1
785	0.00	0.00	0.00	1
787	0.00	0.00	0.00	0
788	0.00	0.00	0.00	0
789	0.00	0.00	0.00	0
791	0.00	0.00	0.00	2
792	0.00	0.00	0.00	1
793	0.00	0.00	0.00	0
794	0.00	0.00	0.00	0
795	0.00	0.00	0.00	0
797	0.00	0.00	0.00	1
799	0.00	0.00	0.00	1
800	0.00	0.00	0.00	2
801	0.00	0.00	0.00	0
802	0.00	0.00	0.00	1
804	0.00	0.00	0.00	1
806	0.00	0.00	0.00	2
808	0.00	0.00	0.00	1
809	0.00	0.00	0.00	1
810	0.00	0.00	0.00	1
812	0.00	0.00	0.00	0
813	0.00	0.00	0.00	2
815	0.00	0.00	0.00	2
817	0.00	0.00	0.00	2
818	0.00	0.00	0.00	1
819	0.00	0.00	0.00	1
820	0.00	0.00	0.00	1
822	0.00	0.00	0.00	1
823	0.00	0.00	0.00	0
825	0.00	0.00	0.00	1
826	0.00	0.00	0.00	1

827	0.00	0.00	0.00	1
828	0.00	0.00	0.00	1
829	0.00	0.00	0.00	1
831	0.00	0.00	0.00	1
833	0.00	0.00	0.00	0
834	0.00	0.00	0.00	1
835	0.00	0.00	0.00	0
836	0.00	0.00	0.00	0
837	0.00	0.00	0.00	0
838	0.00	0.00	0.00	1
839	0.00	0.00	0.00	1
841	0.00	0.00	0.00	1
842	0.00	0.00	0.00	1
844	0.00	0.00	0.00	2
846	0.00	0.00	0.00	0
847	0.00	0.00	0.00	2
848	0.00	0.00	0.00	0
850	0.00	0.00	0.00	0
851	0.00	0.00	0.00	1
855	0.00	0.00	0.00	2
857	0.00	0.00	0.00	1
859	0.00	0.00	0.00	1
860	0.00	0.00	0.00	1
863	0.00	0.00	0.00	1
865	0.00	0.00	0.00	1
866	0.00	0.00	0.00	1
870	0.00	0.00	0.00	1
871	0.00	0.00	0.00	1
872	0.00	0.00	0.00	0
876	0.00	0.00	0.00	1
877	0.00	0.00	0.00	1
878	0.00	0.00	0.00	1
880	0.00	0.00	0.00	0
881	0.00	0.00	0.00	1
885	0.00	0.00	0.00	0
886	0.00	0.00	0.00	0
887	0.00	0.00	0.00	1
888	0.00	0.00	0.00	0
889	0.00	0.00	0.00	0
891	0.00	0.00	0.00	1
893	0.00	0.00	0.00	1
894	0.00	0.00	0.00	1
896	0.00	0.00	0.00	2
897	0.00	0.00	0.00	1
898	0.00	0.00	0.00	2
901	0.00	0.00	0.00	1
904	0.00	0.00	0.00	1
905	0.00	0.00	0.00	0

906	0.00	0.00	0.00	0
908	0.00	0.00	0.00	0
909	0.00	0.00	0.00	0
912	0.00	0.00	0.00	1
913	0.00	0.00	0.00	0
914	0.00	0.00	0.00	1
919	0.00	0.00	0.00	0
921	0.00	0.00	0.00	0
923	0.00	0.00	0.00	0
924	0.00	0.00	0.00	0
926	0.00	0.00	0.00	1
928	0.00	0.00	0.00	1
929	0.00	0.00	0.00	1
932	0.00	0.00	0.00	0
933	0.00	0.00	0.00	1
935	0.00	0.00	0.00	0
937	0.00	0.00	0.00	0
938	0.00	0.00	0.00	1
941	0.00	0.00	0.00	1
942	0.00	0.00	0.00	1
944	0.00	0.00	0.00	0
947	0.00	0.00	0.00	1
948	0.00	0.00	0.00	1
952	0.00	0.00	0.00	1
955	0.00	0.00	0.00	0
956	0.00	0.00	0.00	0
958	0.00	0.00	0.00	1
959	0.00	0.00	0.00	1
960	0.00	0.00	0.00	1
961	0.00	0.00	0.00	1
962	0.00	0.00	0.00	1
963	0.00	0.00	0.00	2
966	0.00	0.00	0.00	1
967	0.00	0.00	0.00	1
968	0.00	0.00	0.00	0
970	0.00	0.00	0.00	1
971	0.00	0.00	0.00	0
972	0.00	0.00	0.00	1
974	0.00	0.00	0.00	1
975	0.00	0.00	0.00	1
976	0.00	0.00	0.00	0
977	0.00	0.00	0.00	1
979	0.00	0.00	0.00	0
983	0.00	0.00	0.00	0
984	0.00	0.00	0.00	0
985	0.00	0.00	0.00	3
986	0.00	0.00	0.00	0
987	0.00	0.00	0.00	1

988	0.00	0.00	0.00	0
989	0.00	0.00	0.00	1
990	0.00	0.00	0.00	1
991	0.00	0.00	0.00	1
992	0.00	0.00	0.00	0
993	0.00	0.00	0.00	1
996	0.00	0.00	0.00	1
998	0.00	0.00	0.00	0
999	0.00	0.00	0.00	1
1000	0.00	0.00	0.00	1
1002	0.00	0.00	0.00	1
1005	0.00	0.00	0.00	0
1011	0.00	0.00	0.00	1
1012	0.00	0.00	0.00	1
1013	0.00	0.00	0.00	1
1014	0.00	0.00	0.00	1
1016	0.00	0.00	0.00	1
1019	0.00	0.00	0.00	1
1021	0.00	0.00	0.00	0
1022	0.00	0.00	0.00	2
1024	0.00	0.00	0.00	0
1025	0.00	0.00	0.00	1
1028	0.00	0.00	0.00	1
1030	0.00	0.00	0.00	1
1031	0.00	0.00	0.00	1
1032	0.00	0.00	0.00	1
1034	0.00	0.00	0.00	0
1035	0.00	0.00	0.00	1
1036	0.00	0.00	0.00	1
1037	0.00	0.00	0.00	1
1038	0.00	0.00	0.00	0
1040	0.00	0.00	0.00	0
1041	0.00	0.00	0.00	0
1042	0.00	0.00	0.00	1
1043	0.00	0.00	0.00	1
1044	0.00	0.00	0.00	1
1047	0.00	0.00	0.00	1
1048	0.00	0.00	0.00	0
1050	0.00	0.00	0.00	1
1051	0.00	0.00	0.00	1
1052	0.00	0.00	0.00	2
1054	0.00	0.00	0.00	1
1056	0.00	0.00	0.00	0
1058	0.00	0.00	0.00	1
1059	0.00	0.00	0.00	1
1061	0.00	0.00	0.00	0
1062	0.00	0.00	0.00	0
1063	0.00	0.00	0.00	1

1064	0.00	0.00	0.00	2
1065	0.00	0.00	0.00	1
1066	0.00	0.00	0.00	1
1069	0.00	0.00	0.00	0
1070	0.00	0.00	0.00	1
1071	0.00	0.00	0.00	2
1073	0.00	0.00	0.00	0
1074	0.00	0.00	0.00	0
1075	0.00	0.00	0.00	0
1076	0.00	0.00	0.00	0
1077	0.00	0.00	0.00	0
1078	0.00	0.00	0.00	0
1080	0.00	0.00	0.00	2
1081	0.00	0.00	0.00	1
1082	0.00	0.00	0.00	1
1084	0.00	0.00	0.00	1
1085	0.00	0.00	0.00	1
1086	0.00	0.00	0.00	0
1088	0.00	0.00	0.00	1
1091	0.00	0.00	0.00	0
1092	0.00	0.00	0.00	1
1094	0.00	0.00	0.00	1
1095	0.00	0.00	0.00	2
1096	0.00	0.00	0.00	0
1098	0.00	0.00	0.00	4
1101	0.00	0.00	0.00	0
1102	0.00	0.00	0.00	1
1103	0.00	0.00	0.00	1
1104	0.00	0.00	0.00	1
1105	0.00	0.00	0.00	1
1106	0.00	0.00	0.00	2
1107	0.00	0.00	0.00	1
1108	0.00	0.00	0.00	1
1109	0.00	0.00	0.00	1
1110	0.00	0.00	0.00	0
1113	0.00	0.00	0.00	1
1114	0.00	0.00	0.00	0
1115	0.00	0.00	0.00	2
1117	0.00	0.00	0.00	0
1118	0.00	0.00	0.00	0
1120	0.00	0.00	0.00	2
1121	0.00	0.00	0.00	1
1122	0.00	0.00	0.00	0
1123	0.00	0.00	0.00	2
1124	0.00	0.00	0.00	0
1126	0.00	0.00	0.00	1
1127	0.00	0.00	0.00	1
1129	0.00	0.00	0.00	0

1130	0.00	0.00	0.00	0
1131	0.00	0.00	0.00	0
1132	0.00	0.00	0.00	0
1134	0.00	0.00	0.00	1
1135	0.00	0.00	0.00	1
1136	0.00	0.00	0.00	1
1137	0.00	0.00	0.00	0
1138	0.00	0.00	0.00	0
1140	0.00	0.00	0.00	0
1141	0.00	0.00	0.00	1
1142	0.00	0.00	0.00	0
1143	0.00	0.00	0.00	1
1144	0.00	0.00	0.00	2
1145	0.00	0.00	0.00	1
1146	0.00	0.00	0.00	1
1147	0.00	0.00	0.00	1
1148	0.00	0.00	0.00	1
1149	0.00	0.00	0.00	2
1150	0.00	0.00	0.00	0
1151	0.00	0.00	0.00	1
1152	0.00	0.00	0.00	0
1153	0.00	0.00	0.00	1
1155	0.00	0.00	0.00	1
1156	0.00	0.00	0.00	1
1158	0.00	0.00	0.00	1
1159	0.00	0.00	0.00	0
1160	0.00	0.00	0.00	1
1161	0.00	0.00	0.00	1
1162	0.00	0.00	0.00	1
1164	0.00	0.00	0.00	0
1165	0.00	0.00	0.00	1
1166	0.00	0.00	0.00	1
1167	0.00	0.00	0.00	1
1168	0.00	0.00	0.00	1
1169	0.00	0.00	0.00	1
1175	0.00	0.00	0.00	1
1176	0.00	0.00	0.00	1
1177	0.00	0.00	0.00	1
1180	0.00	0.00	0.00	2
1181	0.00	0.00	0.00	1
1182	0.00	0.00	0.00	1
1183	0.00	0.00	0.00	1
1185	0.00	0.00	0.00	1
1186	0.00	0.00	0.00	0
1187	0.00	0.00	0.00	1
1188	0.00	0.00	0.00	2
1189	0.00	0.00	0.00	1
1194	0.00	0.00	0.00	1

1195	0.00	0.00	0.00	1
1196	0.00	0.00	0.00	0
1198	0.00	0.00	0.00	0
1200	0.00	0.00	0.00	0
1201	0.00	0.00	0.00	1
1202	0.00	0.00	0.00	1
1203	0.00	0.00	0.00	1
1204	0.00	0.00	0.00	0
1205	0.00	0.00	0.00	2
1208	0.00	0.00	0.00	0
1209	0.00	0.00	0.00	2
1210	0.00	0.00	0.00	0
1211	0.00	0.00	0.00	0
1213	0.00	0.00	0.00	0
1215	0.00	0.00	0.00	1
1216	0.00	0.00	0.00	0
1217	0.00	0.00	0.00	1
1219	0.00	0.00	0.00	0
1220	0.00	0.00	0.00	0
1221	0.00	0.00	0.00	0
1222	0.00	0.00	0.00	1
1223	0.00	0.00	0.00	1
1224	0.00	0.00	0.00	2
1226	0.00	0.00	0.00	1
1227	0.00	0.00	0.00	1
1228	0.00	0.00	0.00	1
1229	0.00	0.00	0.00	2
1232	0.00	0.00	0.00	0
1233	0.00	0.00	0.00	1
1234	0.00	0.00	0.00	0
1235	0.00	0.00	0.00	0
1236	0.00	0.00	0.00	1
1238	0.00	0.00	0.00	1
1239	0.00	0.00	0.00	1
1240	0.00	0.00	0.00	0
1241	0.00	0.00	0.00	0
1242	0.00	0.00	0.00	1
1243	0.00	0.00	0.00	1
1244	0.00	0.00	0.00	1
1245	0.00	0.00	0.00	1
1246	0.00	0.00	0.00	0
1247	0.00	0.00	0.00	0
1248	0.00	0.00	0.00	1
1251	0.00	0.00	0.00	1
1252	0.00	0.00	0.00	0
1254	0.00	0.00	0.00	1
1256	0.00	0.00	0.00	1
1257	0.00	0.00	0.00	0

1258	0.00	0.00	0.00	1
1259	0.00	0.00	0.00	1
1262	0.00	0.00	0.00	1
1263	0.00	0.00	0.00	0
1265	0.00	0.00	0.00	2
1266	0.00	0.00	0.00	0
1268	0.00	0.00	0.00	1
1269	0.00	0.00	0.00	1
1271	0.00	0.00	0.00	0
1273	0.00	0.00	0.00	1
1274	0.00	0.00	0.00	1
1275	0.00	0.00	0.00	0
1279	0.00	0.00	0.00	0
1280	0.00	0.00	0.00	1
1281	0.00	0.00	0.00	0
1283	0.00	0.00	0.00	1
1285	0.00	0.00	0.00	1
1286	0.00	0.00	0.00	2
1289	0.00	0.00	0.00	1
1290	0.00	0.00	0.00	1
1291	0.00	0.00	0.00	0
1294	0.00	0.00	0.00	1
1298	0.00	0.00	0.00	1
1300	0.00	0.00	0.00	0
1301	0.00	0.00	0.00	1
1302	0.00	0.00	0.00	0
1303	0.00	0.00	0.00	2
1308	0.00	0.00	0.00	0
1309	0.00	0.00	0.00	1
1310	0.00	0.00	0.00	1
1312	0.00	0.00	0.00	2
1316	0.00	0.00	0.00	1
1319	0.00	0.00	0.00	1
1320	0.00	0.00	0.00	0
1321	0.00	0.00	0.00	0
1324	0.00	0.00	0.00	2
1325	0.00	0.00	0.00	0
1326	0.00	0.00	0.00	1
1327	0.00	0.00	0.00	0
1328	0.00	0.00	0.00	1
1329	0.00	0.00	0.00	1
1330	0.00	0.00	0.00	0
1331	0.00	0.00	0.00	1
1336	0.00	0.00	0.00	0
1337	0.00	0.00	0.00	0
1339	0.00	0.00	0.00	1
1340	0.00	0.00	0.00	1
1344	0.00	0.00	0.00	0

1345	0.00	0.00	0.00	0
1347	0.00	0.00	0.00	0
1348	0.00	0.00	0.00	0
1349	0.00	0.00	0.00	1
1350	0.00	0.00	0.00	0
1351	0.00	0.00	0.00	1
1354	0.00	0.00	0.00	0
1355	0.00	0.00	0.00	1
1356	0.00	0.00	0.00	0
1360	0.00	0.00	0.00	1
1362	0.00	0.00	0.00	1
1363	0.00	0.00	0.00	1
1365	0.00	0.00	0.00	0
1366	0.00	0.00	0.00	0
1368	0.00	0.00	0.00	1
1369	0.00	0.00	0.00	0
1370	0.00	0.00	0.00	0
1373	0.00	0.00	0.00	2
1376	0.00	0.00	0.00	1
1378	0.00	0.00	0.00	1
1379	0.00	0.00	0.00	0
1381	0.00	0.00	0.00	0
1382	0.00	0.00	0.00	0
1383	0.00	0.00	0.00	1
1385	0.00	0.00	0.00	1
1386	0.00	0.00	0.00	0
1387	0.00	0.00	0.00	0
1388	0.00	0.00	0.00	1
1389	0.00	0.00	0.00	2
1390	0.00	0.00	0.00	1
1391	0.00	0.00	0.00	1
1394	0.00	0.00	0.00	0
1395	0.00	0.00	0.00	1
1396	0.00	0.00	0.00	1
1399	0.00	0.00	0.00	1
1400	0.00	0.00	0.00	2
1403	0.00	0.00	0.00	1
1404	0.00	0.00	0.00	0
1405	0.00	0.00	0.00	1
1406	0.00	0.00	0.00	1
1412	0.00	0.00	0.00	0
1415	0.00	0.00	0.00	1
1416	0.00	0.00	0.00	0
1417	0.00	0.00	0.00	1
1418	0.00	0.00	0.00	0
1420	0.00	0.00	0.00	1
1421	0.00	0.00	0.00	0
1422	0.00	0.00	0.00	0

1424	0.00	0.00	0.00	1
1425	0.00	0.00	0.00	1
1426	0.00	0.00	0.00	1
1427	0.00	0.00	0.00	1
1428	0.00	0.00	0.00	1
1433	0.00	0.00	0.00	0
1434	0.00	0.00	0.00	2
1435	0.00	0.00	0.00	1
1437	0.00	0.00	0.00	1
1440	0.00	0.00	0.00	1
1442	0.00	0.00	0.00	1
1443	0.00	0.00	0.00	0
1444	0.00	0.00	0.00	1
1445	0.00	0.00	0.00	1
1446	0.00	0.00	0.00	0
1448	0.00	0.00	0.00	0
1449	0.00	0.00	0.00	1
1451	0.00	0.00	0.00	1
1453	0.00	0.00	0.00	1
1456	0.00	0.00	0.00	1
1457	0.00	0.00	0.00	1
1459	0.00	0.00	0.00	1
1460	0.00	0.00	0.00	1
1461	0.00	0.00	0.00	0
1464	0.00	0.00	0.00	0
1465	0.00	0.00	0.00	2
1466	0.00	0.00	0.00	1
1467	0.00	0.00	0.00	1
1470	0.00	0.00	0.00	1
1471	0.00	0.00	0.00	0
1472	0.00	0.00	0.00	1
1473	0.00	0.00	0.00	0
1474	0.00	0.00	0.00	1
1476	0.00	0.00	0.00	1
1477	0.00	0.00	0.00	0
1479	0.00	0.00	0.00	1
1480	0.00	0.00	0.00	0
1483	0.00	0.00	0.00	1
1487	0.00	0.00	0.00	0
1491	0.00	0.00	0.00	1
1492	0.00	0.00	0.00	1
1493	0.00	0.00	0.00	1
1494	0.00	0.00	0.00	0
1496	0.00	0.00	0.00	1
1498	0.00	0.00	0.00	1
1499	0.00	0.00	0.00	0
1500	0.00	0.00	0.00	1
1501	0.00	0.00	0.00	0

1503	0.00	0.00	0.00	2
1504	0.00	0.00	0.00	1
1506	0.00	0.00	0.00	0
1507	0.00	0.00	0.00	1
1509	0.00	0.00	0.00	1
1510	0.00	0.00	0.00	1
1511	0.00	0.00	0.00	0
1512	0.00	0.00	0.00	0
1513	0.00	0.00	0.00	0
1514	0.00	0.00	0.00	1
1515	0.00	0.00	0.00	2
1516	0.00	0.00	0.00	0
1518	0.00	0.00	0.00	0
1521	0.00	0.00	0.00	1
1523	0.00	0.00	0.00	1
1524	0.00	0.00	0.00	1
1525	0.00	0.00	0.00	0
1526	0.00	0.00	0.00	0
1527	0.00	0.00	0.00	0
1532	0.00	0.00	0.00	0
1534	0.00	0.00	0.00	1
1535	0.00	0.00	0.00	0
1539	0.00	0.00	0.00	1
1541	0.00	0.00	0.00	1
1542	0.00	0.00	0.00	0
1543	0.00	0.00	0.00	1
1545	0.00	0.00	0.00	0
1546	0.00	0.00	0.00	0
1548	0.00	0.00	0.00	1
1551	0.00	0.00	0.00	0
1552	0.00	0.00	0.00	1
1553	0.00	0.00	0.00	2
1554	0.00	0.00	0.00	2
1557	0.00	0.00	0.00	2
1558	0.00	0.00	0.00	0
1559	0.00	0.00	0.00	1
1561	0.00	0.00	0.00	2
1562	0.00	0.00	0.00	0
1563	0.00	0.00	0.00	1
1564	0.00	0.00	0.00	0
1565	0.00	0.00	0.00	1
1566	0.00	0.00	0.00	1
1568	0.00	0.00	0.00	0
1569	0.00	0.00	0.00	0
1571	0.00	0.00	0.00	1
1572	0.00	0.00	0.00	2
1573	0.00	0.00	0.00	0
1577	0.00	0.00	0.00	0

1578	0.00	0.00	0.00	1
1579	0.00	0.00	0.00	0
1580	0.00	0.00	0.00	2
1581	0.00	0.00	0.00	1
1583	0.00	0.00	0.00	1
1585	0.00	0.00	0.00	0
1587	0.00	0.00	0.00	1
1589	0.00	0.00	0.00	1
1590	0.00	0.00	0.00	2
1591	0.00	0.00	0.00	0
1592	0.00	0.00	0.00	1
1594	0.00	0.00	0.00	0
1595	0.00	0.00	0.00	0
1597	0.00	0.00	0.00	0
1606	0.00	0.00	0.00	1
1612	0.00	0.00	0.00	1
1613	0.00	0.00	0.00	1
1614	0.00	0.00	0.00	1
1615	0.00	0.00	0.00	0
1616	0.00	0.00	0.00	0
1617	0.00	0.00	0.00	1
1618	0.00	0.00	0.00	0
1619	0.00	0.00	0.00	1
1620	0.00	0.00	0.00	2
1622	0.00	0.00	0.00	1
1623	0.00	0.00	0.00	1
1624	0.00	0.00	0.00	1
1625	0.00	0.00	0.00	1
1628	0.00	0.00	0.00	2
1630	0.00	0.00	0.00	1
1631	0.00	0.00	0.00	1
1632	0.00	0.00	0.00	1
1635	0.00	0.00	0.00	0
1636	0.00	0.00	0.00	0
1637	0.00	0.00	0.00	0
1640	0.00	0.00	0.00	2
1641	0.00	0.00	0.00	1
1642	0.00	0.00	0.00	2
1643	0.00	0.00	0.00	1
1644	0.00	0.00	0.00	1
1645	0.00	0.00	0.00	1
1646	0.00	0.00	0.00	0
1647	0.00	0.00	0.00	0
1650	0.00	0.00	0.00	2
1651	0.00	0.00	0.00	0
1653	0.00	0.00	0.00	0
1654	0.00	0.00	0.00	1
1655	0.00	0.00	0.00	1

1656	0.00	0.00	0.00	0
1657	0.00	0.00	0.00	0
1658	0.00	0.00	0.00	2
1661	0.00	0.00	0.00	1
1664	0.00	0.00	0.00	1
1665	0.00	0.00	0.00	1
1666	0.00	0.00	0.00	1
1667	0.00	0.00	0.00	1
1668	0.00	0.00	0.00	0
1669	0.00	0.00	0.00	0
1670	0.00	0.00	0.00	1
1671	0.00	0.00	0.00	1
1674	0.00	0.00	0.00	0
1675	0.00	0.00	0.00	1
1677	0.00	0.00	0.00	1
1679	0.00	0.00	0.00	1
1680	0.00	0.00	0.00	1
1681	0.00	0.00	0.00	0
1682	0.00	0.00	0.00	1
1683	0.00	0.00	0.00	1
1684	0.00	0.00	0.00	0
1685	0.00	0.00	0.00	0
1686	0.00	0.00	0.00	0
1687	0.00	0.00	0.00	0
1688	0.00	0.00	0.00	0
1690	0.00	0.00	0.00	1
1693	0.00	0.00	0.00	2
1695	0.00	0.00	0.00	0
1696	0.00	0.00	0.00	1
1697	0.00	0.00	0.00	0
1698	0.00	0.00	0.00	1
1699	0.00	0.00	0.00	2
1700	0.00	0.00	0.00	0
1701	0.00	0.00	0.00	1
1702	0.00	0.00	0.00	1
1703	0.00	0.00	0.00	1
1704	0.00	0.00	0.00	1
1705	0.00	0.00	0.00	0
1706	0.00	0.00	0.00	2
1707	0.00	0.00	0.00	0
1709	0.00	0.00	0.00	0
1710	0.00	0.00	0.00	0
1711	0.00	0.00	0.00	1
1712	0.00	0.00	0.00	1
1713	0.00	0.00	0.00	2
1714	0.00	0.00	0.00	1
1715	0.00	0.00	0.00	1
1716	0.00	0.00	0.00	3

1718	0.00	0.00	0.00	0
1719	0.00	0.00	0.00	1
1720	0.00	0.00	0.00	0
1721	0.00	0.00	0.00	0
1723	0.00	0.00	0.00	1
1724	0.00	0.00	0.00	1
1725	0.00	0.00	0.00	1
1726	0.00	0.00	0.00	1
1727	0.00	0.00	0.00	1
1729	0.00	0.00	0.00	2
1730	0.00	0.00	0.00	2
1731	0.00	0.00	0.00	1
1732	0.00	0.00	0.00	3
1733	0.00	0.00	0.00	1
1737	0.00	0.00	0.00	1
1738	0.00	0.00	0.00	2
1739	0.00	0.00	0.00	0
1742	0.00	0.00	0.00	0
1743	0.00	0.00	0.00	1
1744	0.00	0.00	0.00	1
1745	0.00	0.00	0.00	0
1746	0.00	0.00	0.00	0
1748	0.00	0.00	0.00	1
1749	0.00	0.00	0.00	1
1750	0.00	0.00	0.00	1
1751	0.00	0.00	0.00	2
1752	0.00	0.00	0.00	1
1753	0.00	0.00	0.00	2
1755	0.00	0.00	0.00	1
1757	0.00	0.00	0.00	2
1758	0.00	0.00	0.00	2
1759	0.00	0.00	0.00	0
1760	0.00	0.00	0.00	1
1761	0.00	0.00	0.00	2
1762	0.00	0.00	0.00	0
1763	0.00	0.00	0.00	1
1764	0.00	0.00	0.00	1
1765	0.00	0.00	0.00	2
1767	0.00	0.00	0.00	1
1768	0.00	0.00	0.00	1
1769	0.00	0.00	0.00	0
1770	0.00	0.00	0.00	2
1771	0.00	0.00	0.00	1
1772	0.00	0.00	0.00	1
1773	0.00	0.00	0.00	0
1774	0.00	0.00	0.00	1
1775	0.00	0.00	0.00	1
1776	0.00	0.00	0.00	0

1777	0.00	0.00	0.00	0
1778	0.00	0.00	0.00	2
1779	0.00	0.00	0.00	1
1780	0.00	0.00	0.00	0
1781	0.00	0.00	0.00	1
1782	0.00	0.00	0.00	0
1783	0.00	0.00	0.00	1
1785	0.00	0.00	0.00	1
1790	0.00	0.00	0.00	0
1791	0.00	0.00	0.00	1
1792	0.00	0.00	0.00	1
1794	0.00	0.00	0.00	0
1796	0.00	0.00	0.00	0
1799	0.00	0.00	0.00	1
1800	0.00	0.00	0.00	1
1801	0.00	0.00	0.00	1
1802	0.00	0.00	0.00	1
1803	0.00	0.00	0.00	0
1805	0.00	0.00	0.00	1
1807	0.00	0.00	0.00	1
1808	0.00	0.00	0.00	1
1810	0.00	0.00	0.00	1
1811	0.00	0.00	0.00	0
1812	0.00	0.00	0.00	1
1813	0.00	0.00	0.00	2
1814	0.00	0.00	0.00	0
1817	0.00	0.00	0.00	1
1819	0.00	0.00	0.00	1
1823	0.00	0.00	0.00	1
1824	0.00	0.00	0.00	1
1825	0.00	0.00	0.00	1
1826	0.00	0.00	0.00	0
1827	0.00	0.00	0.00	1
1828	0.00	0.00	0.00	1
1829	0.00	0.00	0.00	1
1830	0.00	0.00	0.00	1
1831	0.00	0.00	0.00	1
1832	0.00	0.00	0.00	0
1833	0.00	0.00	0.00	1
1834	0.00	0.00	0.00	1
1835	0.00	0.00	0.00	1
1836	0.00	0.00	0.00	0
1837	0.00	0.00	0.00	1
1838	0.00	0.00	0.00	1
1840	0.00	0.00	0.00	1
1842	0.00	0.00	0.00	0
1843	0.00	0.00	0.00	1
1844	0.00	0.00	0.00	1

1846	0.00	0.00	0.00	0
1848	0.00	0.00	0.00	0
1850	0.00	0.00	0.00	0
1852	0.00	0.00	0.00	1
1854	0.00	0.00	0.00	0
1855	0.00	0.00	0.00	1
1858	0.00	0.00	0.00	0
1859	0.00	0.00	0.00	0
1861	0.00	0.00	0.00	1
1863	0.00	0.00	0.00	2
1866	0.00	0.00	0.00	1
1867	0.00	0.00	0.00	1
1869	0.00	0.00	0.00	1
1871	0.00	0.00	0.00	1
1872	0.00	0.00	0.00	1
1876	0.00	0.00	0.00	1
1879	0.00	0.00	0.00	0
1880	0.00	0.00	0.00	1
1881	0.00	0.00	0.00	1
1882	0.00	0.00	0.00	1
1883	0.00	0.00	0.00	0
1884	0.00	0.00	0.00	1
1885	0.00	0.00	0.00	2
1889	0.00	0.00	0.00	1
1890	0.00	0.00	0.00	1
1891	0.00	0.00	0.00	1
1892	0.00	0.00	0.00	1
1893	0.00	0.00	0.00	2
1895	0.00	0.00	0.00	1
1900	0.00	0.00	0.00	2
1901	0.00	0.00	0.00	1
1903	0.00	0.00	0.00	1
1905	0.00	0.00	0.00	1
1906	0.00	0.00	0.00	0
1907	0.00	0.00	0.00	1
1908	0.00	0.00	0.00	0
1909	0.00	0.00	0.00	0
1911	0.00	0.00	0.00	0
1913	0.00	0.00	0.00	0
1914	0.00	0.00	0.00	1
1916	0.00	0.00	0.00	0
1920	0.00	0.00	0.00	1
1922	0.00	0.00	0.00	1
1926	0.00	0.00	0.00	0
1929	0.00	0.00	0.00	0
1931	0.00	0.00	0.00	1
1936	0.00	0.00	0.00	1
1938	0.00	0.00	0.00	1

1939	0.00	0.00	0.00	1
1941	0.00	0.00	0.00	1
1942	0.00	0.00	0.00	1
1943	0.00	0.00	0.00	1
1944	0.00	0.00	0.00	0
1947	0.00	0.00	0.00	1
1948	0.00	0.00	0.00	1
1949	0.00	0.00	0.00	0
1950	0.00	0.00	0.00	1
1951	0.00	0.00	0.00	1
1952	0.00	0.00	0.00	0
1953	0.00	0.00	0.00	0
1955	0.00	0.00	0.00	2
1956	0.00	0.00	0.00	1
1957	0.00	0.00	0.00	1
1958	0.00	0.00	0.00	0
1961	0.00	0.00	0.00	0
1963	0.00	0.00	0.00	1
1967	0.00	0.00	0.00	1
1968	0.00	0.00	0.00	2
1970	0.00	0.00	0.00	1
1973	0.00	0.00	0.00	1
1974	0.00	0.00	0.00	0
1977	0.00	0.00	0.00	0
1978	0.00	0.00	0.00	1
1979	0.00	0.00	0.00	1
1981	0.00	0.00	0.00	0
1982	0.00	0.00	0.00	1
1983	0.00	0.00	0.00	0
1984	0.00	0.00	0.00	1
1985	0.00	0.00	0.00	1
1986	0.00	0.00	0.00	1
1991	0.00	0.00	0.00	0
1993	0.00	0.00	0.00	1
1994	0.00	0.00	0.00	1
1996	0.00	0.00	0.00	1
1997	0.00	0.00	0.00	1
1999	0.00	0.00	0.00	1
2000	0.00	0.00	0.00	0
2001	0.00	0.00	0.00	1
2003	0.00	0.00	0.00	2
2005	0.00	0.00	0.00	0
2007	0.00	0.00	0.00	1
2008	0.00	0.00	0.00	1
2010	0.00	0.00	0.00	1
2013	0.00	0.00	0.00	1
2014	0.00	0.00	0.00	1
2018	0.00	0.00	0.00	1

2019	0.00	0.00	0.00	0
2023	0.00	0.00	0.00	1
2026	0.00	0.00	0.00	0
2027	0.00	0.00	0.00	1
2028	0.00	0.00	0.00	0
2029	0.00	0.00	0.00	2
2030	0.00	0.00	0.00	1
2031	0.00	0.00	0.00	1
2032	0.00	0.00	0.00	0
2033	0.00	0.00	0.00	1
2035	0.00	0.00	0.00	0
2036	0.00	0.00	0.00	1
2040	0.00	0.00	0.00	1
2041	0.00	0.00	0.00	1
2042	0.00	0.00	0.00	1
2043	0.00	0.00	0.00	1
2044	0.00	0.00	0.00	1
2046	0.00	0.00	0.00	1
2048	0.00	0.00	0.00	0
2049	0.00	0.00	0.00	0
2051	0.00	0.00	0.00	1
2053	0.00	0.00	0.00	0
2054	0.00	0.00	0.00	1
2056	0.00	0.00	0.00	0
2057	0.00	0.00	0.00	0
2058	0.00	0.00	0.00	0
2059	0.00	0.00	0.00	0
2060	0.00	0.00	0.00	0
2061	0.00	0.00	0.00	0
2062	0.00	0.00	0.00	1
2063	0.00	0.00	0.00	1
2066	0.00	0.00	0.00	1
2068	0.00	0.00	0.00	1
2069	0.00	0.00	0.00	0
2072	0.00	0.00	0.00	1
2073	0.00	0.00	0.00	0
2075	0.00	0.00	0.00	0
2076	0.00	0.00	0.00	0
2077	0.00	0.00	0.00	1
2078	0.00	0.00	0.00	1
2079	0.00	0.00	0.00	2
2080	0.00	0.00	0.00	2
2081	0.00	0.00	0.00	1
2082	0.00	0.00	0.00	0
2083	0.00	0.00	0.00	1
2085	0.00	0.00	0.00	1
2087	0.00	0.00	0.00	1
2088	0.00	0.00	0.00	1

2089	0.00	0.00	0.00	1
2091	0.00	0.00	0.00	0
2092	0.00	0.00	0.00	1
2093	0.00	0.00	0.00	1
2095	0.00	0.00	0.00	1
2102	0.00	0.00	0.00	1
2104	0.00	0.00	0.00	1
2105	0.00	0.00	0.00	1
2106	0.00	0.00	0.00	0
2107	0.00	0.00	0.00	0
2109	0.00	0.00	0.00	1
2111	0.00	0.00	0.00	0
2112	0.00	0.00	0.00	0
2114	0.00	0.00	0.00	0
2117	0.00	0.00	0.00	1
2118	0.00	0.00	0.00	1
2120	0.00	0.00	0.00	2
2121	0.00	0.00	0.00	1
2122	0.00	0.00	0.00	0
2125	0.00	0.00	0.00	0
2127	0.00	0.00	0.00	0
2128	0.00	0.00	0.00	1
2129	0.00	0.00	0.00	0
2130	0.00	0.00	0.00	0
2131	0.00	0.00	0.00	0
2133	0.00	0.00	0.00	1
2138	0.00	0.00	0.00	1
2139	0.00	0.00	0.00	1
2140	0.00	0.00	0.00	1
2141	0.00	0.00	0.00	1
2142	0.00	0.00	0.00	1
2143	0.00	0.00	0.00	1
2144	0.00	0.00	0.00	1
2145	0.00	0.00	0.00	0
2147	0.00	0.00	0.00	0
2148	0.00	0.00	0.00	0
2150	0.00	0.00	0.00	0
2153	0.00	0.00	0.00	0
2155	0.00	0.00	0.00	3
2156	0.00	0.00	0.00	1
2157	0.00	0.00	0.00	1
2159	0.00	0.00	0.00	0
2160	0.00	0.00	0.00	1
2162	0.00	0.00	0.00	1
2163	0.00	0.00	0.00	1
2164	0.00	0.00	0.00	0
2165	0.00	0.00	0.00	0
2166	0.00	0.00	0.00	1

2167	0.00	0.00	0.00	1
2169	0.00	0.00	0.00	0
2171	0.00	0.00	0.00	2
2172	0.00	0.00	0.00	1
2175	0.00	0.00	0.00	1
2176	0.00	0.00	0.00	0
2178	0.00	0.00	0.00	0
2179	0.00	0.00	0.00	0
2183	0.00	0.00	0.00	0
2184	0.00	0.00	0.00	1
2186	0.00	0.00	0.00	1
2189	0.00	0.00	0.00	1
2190	0.00	0.00	0.00	1
2191	0.00	0.00	0.00	1
2192	0.00	0.00	0.00	1
2193	0.00	0.00	0.00	1
2195	0.00	0.00	0.00	0
2197	0.00	0.00	0.00	1
2198	0.00	0.00	0.00	1
2203	0.00	0.00	0.00	1
2205	0.00	0.00	0.00	1
2206	0.00	0.00	0.00	1
2207	0.00	0.00	0.00	3
2208	0.00	0.00	0.00	0
2209	0.00	0.00	0.00	1
2211	0.00	0.00	0.00	0
2212	0.00	0.00	0.00	1
2213	0.00	0.00	0.00	1
2217	0.00	0.00	0.00	1
2218	0.00	0.00	0.00	1
2219	0.00	0.00	0.00	0
2220	0.00	0.00	0.00	1
2221	0.00	0.00	0.00	0
2223	0.00	0.00	0.00	1
2225	0.00	0.00	0.00	0
2230	0.00	0.00	0.00	0
2231	0.00	0.00	0.00	0
2233	0.00	0.00	0.00	1
2234	0.00	0.00	0.00	2
2235	0.00	0.00	0.00	1
2239	0.00	0.00	0.00	1
2240	0.00	0.00	0.00	0
2241	0.00	0.00	0.00	0
2242	0.00	0.00	0.00	0
2246	0.00	0.00	0.00	0
2249	0.00	0.00	0.00	1
2250	0.00	0.00	0.00	0
2251	0.00	0.00	0.00	1

2254	0.00	0.00	0.00	1
2255	0.00	0.00	0.00	1
2257	0.00	0.00	0.00	0
2258	0.00	0.00	0.00	1
2259	0.00	0.00	0.00	0
2262	0.00	0.00	0.00	1
2263	0.00	0.00	0.00	0
2264	0.00	0.00	0.00	1
2265	0.00	0.00	0.00	1
2267	0.00	0.00	0.00	1
2268	0.00	0.00	0.00	0
2269	0.00	0.00	0.00	0
2270	0.00	0.00	0.00	0
2271	0.00	0.00	0.00	1
2275	0.00	0.00	0.00	1
2278	0.00	0.00	0.00	1
2280	0.00	0.00	0.00	1
2281	0.00	0.00	0.00	1
2283	0.00	0.00	0.00	0
2284	0.00	0.00	0.00	0
2285	0.00	0.00	0.00	1
2287	0.00	0.00	0.00	0
2288	0.00	0.00	0.00	2
2290	0.00	0.00	0.00	1
2297	0.00	0.00	0.00	0
2301	0.00	0.00	0.00	0
2303	0.00	0.00	0.00	1
2305	0.00	0.00	0.00	1
2306	0.00	0.00	0.00	0
2309	0.00	0.00	0.00	1
2310	0.00	0.00	0.00	0
2314	0.00	0.00	0.00	0
2315	0.00	0.00	0.00	1
2316	0.00	0.00	0.00	0
2319	0.00	0.00	0.00	1
2321	0.00	0.00	0.00	1
2322	0.00	0.00	0.00	1
2323	0.00	0.00	0.00	0
2325	0.00	0.00	0.00	1
2326	0.00	0.00	0.00	0
2328	0.00	0.00	0.00	1
2329	0.00	0.00	0.00	1
2330	0.00	0.00	0.00	1
2334	0.00	0.00	0.00	1
2335	0.00	0.00	0.00	1
2336	0.00	0.00	0.00	1
2337	0.00	0.00	0.00	0
2338	0.00	0.00	0.00	1

2339	0.00	0.00	0.00	0
2340	0.00	0.00	0.00	1
2341	0.00	0.00	0.00	0
2344	0.00	0.00	0.00	0
2349	0.00	0.00	0.00	1
2350	0.00	0.00	0.00	1
2353	0.00	0.00	0.00	0
2357	0.00	0.00	0.00	1
2358	0.00	0.00	0.00	0
2360	0.00	0.00	0.00	1
2362	0.00	0.00	0.00	0
2363	0.00	0.00	0.00	0
2364	0.00	0.00	0.00	0
2365	0.00	0.00	0.00	1
2366	0.00	0.00	0.00	0
2370	0.00	0.00	0.00	1
2372	0.00	0.00	0.00	0
2374	0.00	0.00	0.00	1
2375	0.00	0.00	0.00	0
2377	0.00	0.00	0.00	0
2378	0.00	0.00	0.00	1
2379	0.00	0.00	0.00	1
2380	0.00	0.00	0.00	0
2381	0.00	0.00	0.00	1
2383	0.00	0.00	0.00	1
2385	0.00	0.00	0.00	0
2387	0.00	0.00	0.00	1
2389	0.00	0.00	0.00	1
2395	0.00	0.00	0.00	0
2396	0.00	0.00	0.00	0
2397	0.00	0.00	0.00	1
2398	0.00	0.00	0.00	1
2401	0.00	0.00	0.00	1
2403	0.00	0.00	0.00	1
2404	0.00	0.00	0.00	0
2407	0.00	0.00	0.00	1
2410	0.00	0.00	0.00	1
2411	0.00	0.00	0.00	1
2412	0.00	0.00	0.00	1
2414	0.00	0.00	0.00	0
2415	0.00	0.00	0.00	0
2419	0.00	0.00	0.00	0
2421	0.00	0.00	0.00	1
2422	0.00	0.00	0.00	1
2425	0.00	0.00	0.00	0
2426	0.00	0.00	0.00	0
2427	0.00	0.00	0.00	2
2429	0.00	0.00	0.00	1

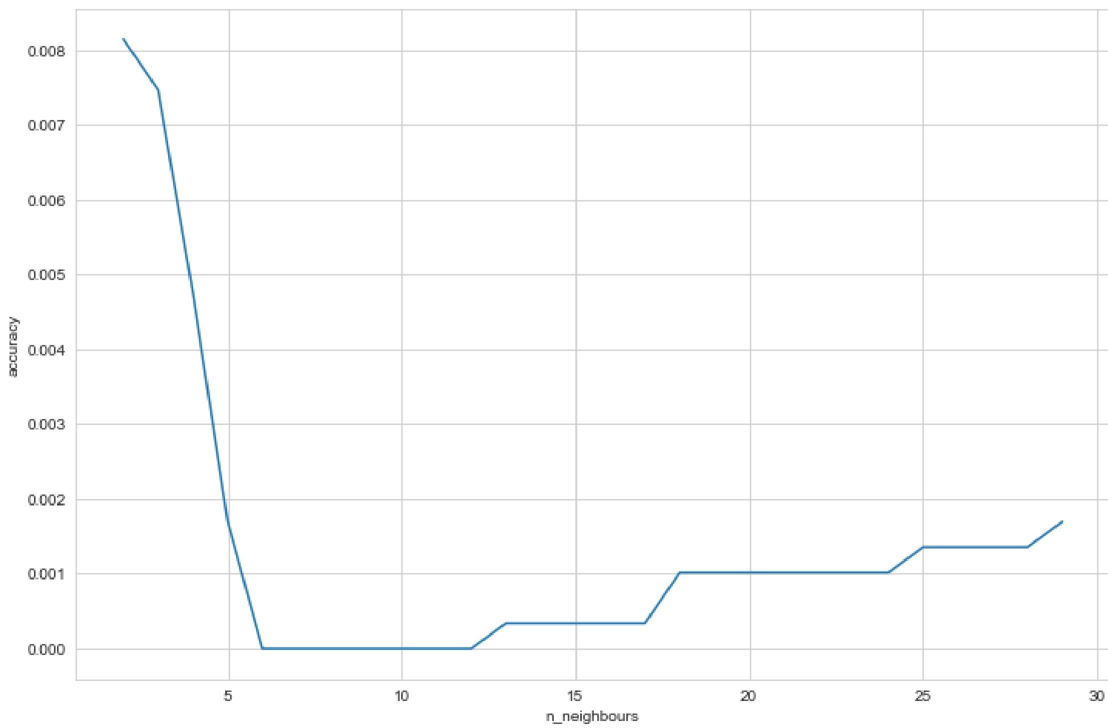
2430	0.00	0.00	0.00	0
2431	0.00	0.00	0.00	1
2432	0.00	0.00	0.00	1
2433	0.00	0.00	0.00	0
2434	0.00	0.00	0.00	1
2435	0.00	0.00	0.00	1
2437	0.00	0.00	0.00	1
2438	0.00	0.00	0.00	1
2439	0.00	0.00	0.00	1
2442	0.00	0.00	0.00	1
2443	0.00	0.00	0.00	1
2444	0.00	0.00	0.00	1
2448	0.00	0.00	0.00	0
2449	0.00	0.00	0.00	1
2450	0.00	0.00	0.00	1
2451	0.00	0.00	0.00	1
2453	0.00	0.00	0.00	0
2455	0.00	0.00	0.00	1
2456	0.00	0.00	0.00	0
2459	0.00	0.00	0.00	0
2460	0.00	0.00	0.00	1
2468	0.00	0.00	0.00	1
2469	0.00	0.00	0.00	1
2470	0.00	0.00	0.00	1
2472	0.00	0.00	0.00	1
2477	0.00	0.00	0.00	1
2480	0.00	0.00	0.00	1
2481	0.00	0.00	0.00	0
2483	0.00	0.00	0.00	1
2485	0.00	0.00	0.00	1
2488	0.00	0.00	0.00	1
2490	0.00	0.00	0.00	0
2492	0.00	0.00	0.00	1
2493	0.00	0.00	0.00	1
2500	0.00	0.00	0.00	1
2501	0.00	0.00	0.00	1
2503	0.00	0.00	0.00	1
2504	0.00	0.00	0.00	1
2505	0.00	0.00	0.00	1
2511	0.00	0.00	0.00	1
2516	0.00	0.00	0.00	1
2517	0.00	0.00	0.00	1
2527	0.00	0.00	0.00	1
2532	0.00	0.00	0.00	1
2537	0.00	0.00	0.00	1
2539	0.00	0.00	0.00	1
2540	0.00	0.00	0.00	1

```
    accuracy                           0.00      1263
   macro avg       0.00      0.00      0.00      1263
weighted avg       0.00      0.00      0.00      1263
```

[83]:
```python
avg_score=[]
for k in range(2,30):
    knn=KNeighborsClassifier(n_jobs=-1,n_neighbors=k)
    score=cross_val_score(knn,X_train,y_train,cv=5,n_jobs=-1,scoring='accuracy')
    avg_score.append(score.mean())

plt.figure(figsize=(12,8))
plt.plot(range(2,30),avg_score)
plt.xlabel("n_neighbours")
plt.ylabel("accuracy")
#plt.xticks(range(2,30,2))
```

[83]: Text(0, 0.5, 'accuracy')



[84]:
```python
#Random Forests Classifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import f1_score

rfc=RandomForestClassifier(n_jobs=-1,random_state=51)
```

```
rfc.fit(X_train,y_train)
print(rfc.score(X_test,y_test))
print(f1_score(y_test,rfc.predict(X_test),average='macro'))
```

```
0.021377672209026127
0.010958631662688942
```

[85]:
```
#Till now SVM followed by Random forest is the leading model

from xgboost import XGBClassifier
from sklearn.metrics import mean_squared_error
from sklearn import svm
from xgboost import XGBClassifier
import xgboost as xgb
```

[86]:
```
#Here, we are using XGBRegressor as a Machine Learning model to fit the data.
model = xgb.XGBRegressor(booster='dart', objective='reg:squarederror',␣
↪num_class = 1,  eval_metric = 'merror', n_estimators = 10, seed = 123)
model.fit(X_train, y_train)
print(); print(model)

# Predict the model
pred = model.predict(X_test)
```

```
XGBRegressor(base_score=0.5, booster='dart', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, eval_metric='merror',
             gamma=0, gpu_id=-1, importance_type='gain',
             interaction_constraints='', learning_rate=0.300000012,
             max_delta_step=0, max_depth=6, min_child_weight=1, missing=nan,
             monotone_constraints='()', n_estimators=10, n_jobs=8, num_class=1,
             num_parallel_tree=1, random_state=123, reg_alpha=0, reg_lambda=1,
             scale_pos_weight=1, seed=123, subsample=1, tree_method='exact',
             validate_parameters=1, verbosity=None)
```

[87]:
```
# RMSE Computation
rmse = np.sqrt(mean_squared_error(y_test, pred))
print("RMSE : % f" %(rmse))
```

```
RMSE :  41.334797
```

[88]:
```
expected_y  = y_test
predicted_y = model.predict(X_test)
print(metrics.r2_score(y_test, predicted_y))
```

```
0.9964555983971704
```

[89]:
```
predicted_y
```

[89]:
```
array([1535.3035 , 2051.473  ,  856.6799 , …,  793.9099 , 1325.2578 ,
        211.49554], dtype=float32)
```

[90]:
```
#Here, we are using XGBRegressor as a Machine Learning model to fit the data.
model = xgb.XGBRegressor(booster='gblinear', objective='reg:squarederror',␣
 ↪num_class = 1,  eval_metric = 'merror', n_estimators = 10, seed = 123)
model.fit(X_train, y_train)
print(); print(model)

# Predict the model
pred = model.predict(X_test)
```

```
XGBRegressor(base_score=0.5, booster='gblinear', colsample_bylevel=None,
             colsample_bynode=None, colsample_bytree=None, eval_metric='merror',
             gamma=None, gpu_id=-1, importance_type='gain',
             interaction_constraints=None, learning_rate=0.5,
             max_delta_step=None, max_depth=None, min_child_weight=None,
             missing=nan, monotone_constraints=None, n_estimators=10, n_jobs=8,
             num_class=1, num_parallel_tree=None, random_state=123, reg_alpha=0,
             reg_lambda=0, scale_pos_weight=1, seed=123, subsample=None,
             tree_method=None, validate_parameters=1, verbosity=None)
```

[91]:
```
# RMSE Computation
rmse = np.sqrt(mean_squared_error(y_test, pred))
print("RMSE : % f" %(rmse))
```

```
RMSE :  196.384819
```

[92]:
```
expected_y  = y_test
predicted_y = model.predict(X_test)
print(metrics.r2_score(y_test, predicted_y))
```

```
0.9199931585102286
```

[93]:
```
#As we see gbliner is not the right model.
#Here, we are using XGBRegressor as a Machine Learning model to fit the data.
model = xgb.XGBRegressor(booster='gbtree', objective='reg:squarederror',␣
 ↪num_class = 1,  eval_metric = 'merror', n_estimators = 10, seed = 123)
model.fit(X_train, y_train)
print(); print(model)

# Predict the model
pred = model.predict(X_test)
```

```
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, eval_metric='merror',
             gamma=0, gpu_id=-1, importance_type='gain',
```

```
             interaction_constraints='', learning_rate=0.300000012,
             max_delta_step=0, max_depth=6, min_child_weight=1, missing=nan,
             monotone_constraints='()', n_estimators=10, n_jobs=8, num_class=1,
             num_parallel_tree=1, random_state=123, reg_alpha=0, reg_lambda=1,
             scale_pos_weight=1, seed=123, subsample=1, tree_method='exact',
             validate_parameters=1, verbosity=None)
```

[94]:
```
# RMSE Computation
rmse = np.sqrt(mean_squared_error(y_test, pred))
print("RMSE : % f" %(rmse))
```

```
RMSE :  41.334797
```

[95]:
```
expected_y  = y_test
predicted_y = model.predict(X_test)
print(metrics.r2_score(y_test, predicted_y))
```

```
0.9964555983971704
```

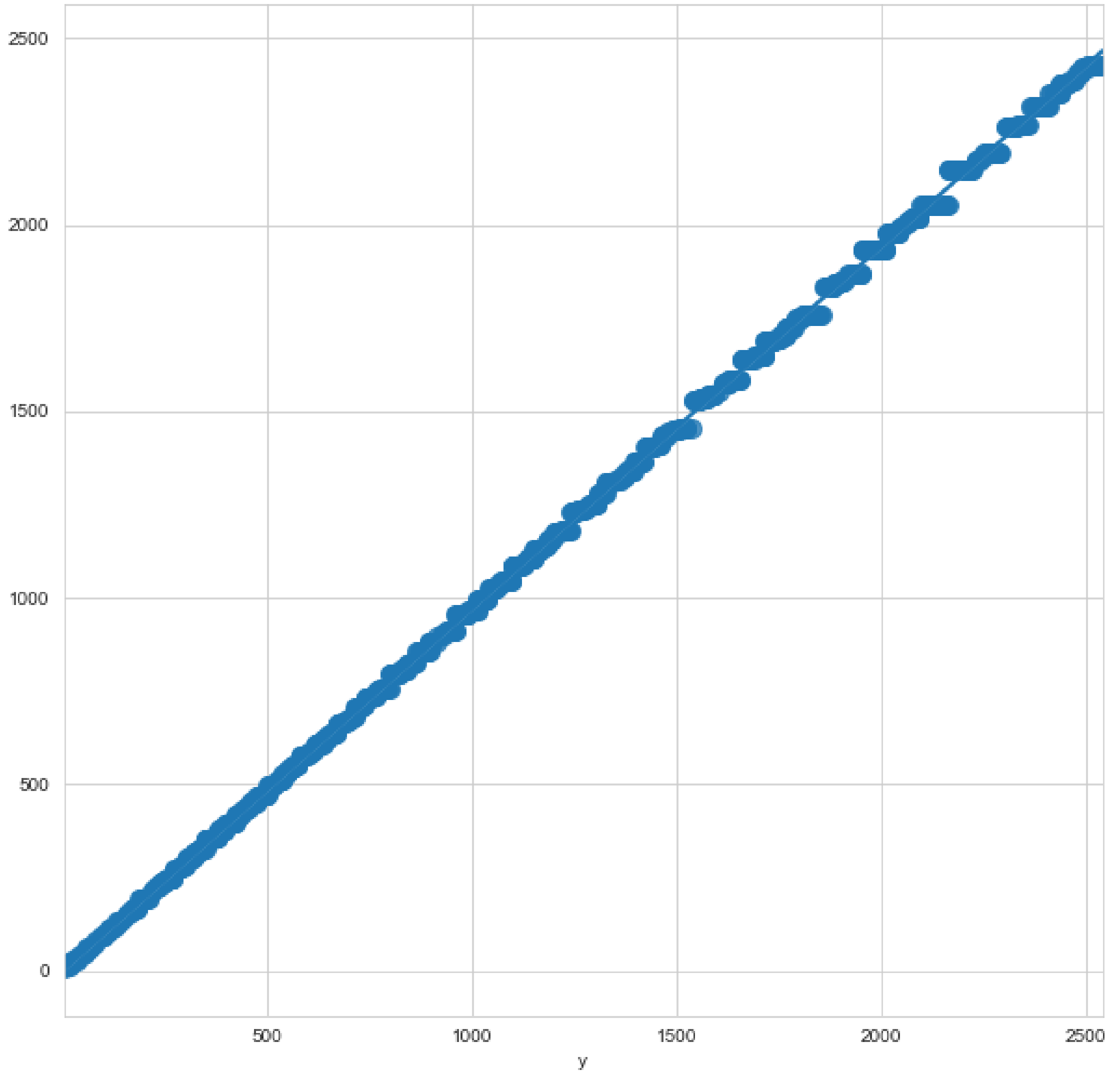
[96]:
```
model = xgb.XGBRegressor()
model.fit(X_train, y_train)
print(); print(model)
```

```

XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
             importance_type='gain', interaction_constraints='',
             learning_rate=0.300000012, max_delta_step=0, max_depth=6,
             min_child_weight=1, missing=nan, monotone_constraints='()',
             n_estimators=100, n_jobs=8, num_parallel_tree=1, random_state=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
             tree_method='exact', validate_parameters=1, verbosity=None)
```

[97]:
```
plt.figure(figsize=(10,10))
sns.regplot(expected_y, predicted_y, fit_reg=True, scatter_kws={"s": 100})
```

[97]:
```
<AxesSubplot:xlabel='y'>
```



[98]:
```
#e'll check the training accuracy with cross-validation and k-fold methods.
# Applying k-Fold Cross Validation
from sklearn.model_selection import cross_val_score, KFold

kfold = KFold(n_splits=10, shuffle=True)
kf_cv_scores = cross_val_score(model, X_train, y_train, cv=kfold )
print("K-fold CV average score: %.2f" % kf_cv_scores.mean())
```

```
K-fold CV average score: 1.00
```

[99]:
```
#Now we have predicted the output by passing X_test and also stored real target␣
↪in expected_y.
expected_y  = y_test
predicted_y = model.predict(X_test)
```

```
print(metrics.r2_score(expected_y, predicted_y))
```

0.9999877471875119

#This is the best model so far #Q 5. Predicting y with XGBoost

[107]:
```
#Displaying predicted values

predicted_y
```

[107]:
```
array([1571.9796 , 2096.447  ,  880.59326, …,  814.5298 , 1368.8103 ,
        217.89659], dtype=float32)
```

[ ]:
```

```