

# Assignment for Week 5 - Neural Network

## Task 1:

### Neural Networks

Bike Share data: <https://archive.ics.uci.edu/ml/dataset/bike-sharing+dataset>

Train a regression neural net to predict the amount of bike rentals each hour.

Try at least 5 different architectures, pick the best one and defend your choice

The following sites might be good references for you:

- <https://www.springboard.com/blog/beginners-guide-neural-network-in-python-scikit-learn-0-18/>
- <https://data-science.stackexchange.com/questions/36049/how-to-adjust-the-hyperparameters-of-mlp-classifier-to-get-more-perfect-performance>

In [91]:

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np

# sklearn packages
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import StandardScaler
from sklearn.neural_network import MLPClassifier

# plotting
import seaborn as sns

# will show plots without doing plt.show()
%matplotlib inline
```

Task 1

In [92]:

```
# Read dataset to pandas dataframe
bike = pd.read_csv('data_bike/hour.csv')
```

In [93]:

```
bike.head()
```

Out[93]:

	instant	dayed	season	yr	mnth	hr	holiday	weekday	workingday	weathersit	temp	atemp	hum	windspeed	casual	registered	cnt
0	1	2011-01-01	1	0	1	0	0	6	0	1	0.24	0.2727	0.81	0.0	3	13	16
1	2	2011-01-01	1	0	1	1	0	6	0	1	0.22	0.2727	0.80	0.0	8	32	40
2	3	2011-01-01	1	0	1	2	0	6	0	1	0.22	0.2727	0.80	0.0	5	27	32
3	4	2011-01-01	1	0	1	3	0	6	0	1	0.24	0.2879	0.75	0.0	3	10	13
4	5	2011-01-01	1	0	1	4	0	6	0	1	0.24	0.2879	0.75	0.0	0	1	1

In [94]:

```
bike.info()
```

Out[94]:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17379 entries, 0 to 17378
Data columns (total 17 columns):
# Column Non-Null Count Dtype
---  ---
0 instant 17379 non-null int64
1 dayed 17379 non-null object
2 season 17379 non-null int64
3 yr 17379 non-null int64
4 mnth 17379 non-null int64
5 hr 17379 non-null int64
6 holiday 17379 non-null int64
7 weekday 17379 non-null int64
8 workingday 17379 non-null float64
9 weathersit 17379 non-null int64
10 temp 17379 non-null float64
11 atemp 17379 non-null float64
12 hum 17379 non-null float64
13 windspeed 17379 non-null float64
14 casual 17379 non-null int64
15 registered 17379 non-null int64
16 cnt 17379 non-null int64
dtypes: float64(4), int64(12), object(1)
memory usage: 2.3+ MB
```

In [95]:

```
bike.describe(include='all')
```

Out[95]:

	instant	dayed	season	yr	mnth	hr	holiday	weekday	workingday	weathersit
count	17379.00000	17379	17379.0000000	17379.0000000	17379.0000000	17379.0000000	17379.0000000	17379.0000000	17379.0000000	17379.0000000
unique	NaN	731	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
top	NaN	2012-01-01	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
freq	NaN	24	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
mean	8660.00000	NaN	2.501640	0.502561	6.537775	11.546752	0.028770	3.003683	0.682721	1.425283
std	5071.0295	NaN	1.106918	0.500008	3.438776	6.914405	0.167165	2.005771	0.465431	0.639357
min	1.00000	NaN	1.000000	0.000000	1.000000	0.000000	0.000000	0.000000	0.000000	1.000000
25%	4345.5000	NaN	2.000000	0.000000	4.000000	6.000000	0.000000	1.000000	0.000000	1.000000
50%	8660.0000	NaN	3.000000	1.000000	7.000000	12.000000	0.000000	3.000000	1.000000	1.000000
75%	13034.5000	NaN	3.000000	1.000000	10.000000	18.000000	0.000000	5.000000	1.000000	2.000000
max	17379.0000	NaN	4.000000	1.000000	12.000000	23.000000	1.000000	6.000000	1.000000	4.000000

In [96]:

```
bike.shape
```

Out[96]:

```
(17379, 17)
```

Dropping instant, year, month. I am dropping them because instant is the row number, and as for year and month I will extract them from the date for more accurate data

In [97]:

```
bike.drop(['instant'],axis=1, inplace=True)
bike.drop(['yr',axis=1, inplace=True)
bike.drop(['mnth'],axis=1, inplace=True)
```

In [98]:

```
bike.info()
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17379 entries, 0 to 17378
Data columns (total 14 columns):
# Column Non-Null Count Dtype
--- ---
0 dayed 17379 non-null object
1 season 17379 non-null int64
2 hr 17379 non-null int64
3 holiday 17379 non-null int64
4 weekday 17379 non-null int64
5 workingday 17379 non-null float64
6 weathersit 17379 non-null int64
7 temp 17379 non-null float64
8 atemp 17379 non-null float64
9 hum 17379 non-null float64
10 windspeed 17379 non-null float64
11 casual 17379 non-null int64
12 registered 17379 non-null int64
13 cnt 17379 non-null int64
dtypes: float64(4), int64(9), object(1)
memory usage: 1.9+ MB

Because date column is not float or integer, model will not be fitted. So, here I am creating 3 columns for year, month, and day. Then dropping Date column

In [99]:

```
# we need to convert dayed to int
new = bike['dayed'].str.split("-", n = 2, expand = True)
bike['year'] = new[0]
bike['month'] = new[1]
bike['day'] = new[2]
```

In [100]:

```
bike['year'] = bike['year'].astype(str).astype(int)
bike['month'] = bike['month'].astype(str).astype(int)
bike['day'] = bike['day'].astype(str).astype(int)
```

In [101]:

```
bike.drop('dayed',axis=1, inplace=True)
```

In [102]:

```
bike.info()
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 17379 entries, 0 to 17378
Data columns (total 16 columns):
# Column Non-Null Count Dtype
--- ---
0 season 17379 non-null int64
1 hr 17379 non-null int64
2 holiday 17379 non-null int64
3 weekday 17379 non-null int64
4 workingday 17379 non-null float64
5 weathersit 17379 non-null int64
6 temp 17379 non-null float64
7 atemp 17379 non-null float64
8 hum 17379 non-null float64
9 windspeed 17379 non-null float64
10 casual 17379 non-null int64
11 registered 17379 non-null int64
12 cnt 17379 non-null int64
13 year 17379 non-null int32
14 month 17379 non-null int32
15 day 17379 non-null int32
dtypes: float64(4), int32(13), int64(9)
memory usage: 1.9+ MB

The target has a huge unique values

In [103]:

```
bike.cnt.unique()
```

Out[103]:

```
array([ 16, 40, 32, 13, 1, 2, 3, 8, 14, 36, 56, 84, 94, 106, 110, 93, 67, 35, 37, 34, 28, 39, 17, 9, 6, 20, 70, 75, 59, 74, 76, 65, 39, 22, 31, 64, 156, 88, 44, 51, 61, 77, 72, 157, 52, 12, 4, 179, 100, 42, 57, 78, 97, 63, 83, 212, 182, 118, 54, 48, 11, 33, 195, 123, 46, 73, 71, 62, 89, 180, 169, 132, 43, 19, 95, 219, 122, 45, 86, 172, 163, 69, 23, 7, 210, 134, 73, 50, 87, 129, 128, 63, 23, 180, 102, 55, 15, 49, 82, 58, 41, 38, 188, 47, 178, 155, 24, 18, 27, 99, 217, 130, 136, 29, 128, 81, 68, 139, 137, 202, 60, 162, 144, 186, 117, 90, 159, 101, 184, 129, 226, 104, 91, 113, 105, 21, 80, 125, 133, 197, 109, 161, 249, 143, 215, 185, 152, 126, 166, 120, 96, 103, 58, 116, 177, 184, 153, 108, 238, 222, 225, 146, 119, 149, 107, 156, 111, 135, 176, 165, 175, 147, 220, 127, 205, 174, 121, 230, 86, 114, 216, 243, 199, 170, 165, 160, 140, 211, 145, 256, 223, 85, 208, 288, 236, 240, 452, 383, 284, 291, 309, 321, 337, 388, 300, 209, 234, 259, 285, 274, 272, 191, 232, 327, 224, 136, 171, 198, 187, 237, 209, 141, 252, 189, 183, 193, 259, 282, 261, 268, 142, 131, 214, 242, 148, 201, 150, 228, 204, 164, 233, 257, 151, 248, 194, 244, 213, 181, 221, 250, 304, 261, 271, 353, 237, 299, 315, 540, 207, 138, 280, 173, 332, 331, 267, 301, 312, 278, 203, 279, 308, 226, 276, 356, 307, 273, 227, 239, 254, 287, 294, 263, 192, 281, 387, 349, 292, 303, 339, 386, 386, 325, 386, 314, 343, 333, 287, 288, 236, 240, 452, 383, 284, 291, 309, 321, 337, 388, 300, 209, 234, 259, 285, 274, 272, 191, 232, 327, 224, 136, 171, 198, 187, 384, 361, 386, 277, 426, 362, 286, 351, 411, 421, 396, 432, 441, 365, 481, 324, 346, 391, 397, 426, 376, 283, 289, 317, 420, 369, 359, 270, 333, 321, 499, 382, 449, 186, 508, 328, 234, 246, 444, 216, 412, 260, 398, 455, 530, 404, 269, 508, 439, 416, 464, 497, 371, 387, 264, 266, 537, 518, 265, 459, 537, 544, 290, 410, 296, 440, 535, 520, 258, 450, 344, 553, 470, 298, 347, 373, 436, 378, 342, 340, 380, 358, 385, 374, 598, 524, 384, 425, 611, 550, 434, 318, 442, 401, 594, 527, 364, 491, 295, 322, 456, 437, 392, 231, 394, 453, 684, 480, 895, 489, 487, 302, 547, 513, 319, 330, 554, 473, 323, 418, 493, 462, 506, 471, 305, 316, 409, 429, 548, 564, 355, 531, 601, 405, 494, 478, 419, 399, 402, 341, 231, 229, 350, 311, 405, 485, 417, 454, 466, 467, 373, 525, 379, 502, 558, 293, 247, 451, 335, 363, 357, 438, 579, 556, 334, 477, 539, 551, 102, 424, 466, 326, 463, 380, 275, 315, 369, 476, 586, 423, 569, 538, 379, 498, 638, 607, 552, 208, 468, 381, 377, 431, 536, 529, 540, 400, 352, 557, 375, 443, 403, 447, 591, 504, 570, 588, 320, 559, 492, 427, 461, 422, 414, 408, 457, 545, 486, 368, 245, 596, 563, 562, 372, 514, 472, 511, 488, 595, 579, 348, 967, 497, 433, 475, 430, 262, 485, 546, 541, 483, 338, 543, 413, 435, 523, 532, 585, 584, 559, 582, 571, 516, 465, 329, 600, 609, 651, 519, 567, 621, 484, 469, 576, 608, 446, 628, 389, 505, 460, 590, 599, 566, 482, 568, 415, 589, 345, 593, 393, 500, 479, 620, 625, 614, 395, 445, 512, 490, 515, 526, 509, 448, 580, 610, 522, 548, 501, 612, 587, 474, 634, 852, 868, 745, 812, 669, 642, 730, 627, 645, 637, 577, 680, 717, 710, 622, 705, 630, 770, 659, 602, 753, 650, 873, 846, 644, 712, 676, 734, 662, 782, 749, 623, 713, 746, 686, 690, 679, 685, 648, 503, 721, 601, 750, 535, 723, 779, 649, 610, 857, 630, 657, 664, 684, 458, 591, 658, 641, 654, 703, 681, 606, 605, 561, 573, 618, 757, 800, 744, 759, 822, 698, 655, 643, 626, 615, 617, 630, 646, 692, 704, 624, 656, 738, 671, 678, 660, 635, 616, 673, 781, 775, 677, 748, 776, 700, 580, 819, 688, 640, 639, 691, 732, 709, 532, 702, 633, 603, 683, 743, 666, 813, 627, 706, 575, 769, 680, 717, 710, 622, 705, 630, 770, 659, 602, 753, 650, 873, 846, 474, 634, 852, 868, 745, 812, 669, 642, 730, 627, 645, 637, 577, 680, 717, 710, 622, 705, 630, 770, 659, 602, 753, 650, 873, 846, 681, 631, 845, 871, 832, 893, 815, 878, 780, 783, 707, 941, 735, 845, 864, 808, 870, 754, 844, 853, 856, 725, 863, 792, 696, 701, 871, 968, 970, 925, 977, 758, 884, 766, 880, 783, 707, 941, 735, 892, 978, 805, 898, 967, 838, 953, 905, 899, 663, 727, 784, 809, 917, 901, 887, 761, 806, 948, 670, 619, 943, 817, 888, 890, 714, 711, 731, 675, 728, 922, 786, 938, 826, 963, 708, 6361, dtype=int64)
```

In [104]:

```
#gather up names of all the columns
cols = bike.columns

#set the prediction col = 'cnt'
prediction_col = 'cnt'
feature_cols = [c for c in cols if c != prediction_col]

x = bike[feature_cols]
y = bike[prediction_col]

#split the dataset into the train and test data
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=41)
```

Scaling the feature on train data.

In [105]:

```
scaler = StandardScaler()
scaler.fit(x_train)

x_train = scaler.transform(x_train)
x_test = scaler.transform(x_test)
```

Fitting the model with 10,10,10 hidden layers parameters.

In [106]:

```
mlp = MLPClassifier(hidden_layer_sizes=(10, 10, 10), max_iter=1000)
mlp.fit(x_train, y_train.values.ravel())
```

Out[106]:

```
MLPClassifier(hidden_layer_sizes=(10, 10, 10), max_iter=1000)
```

In [107]:

```
predictions = mlp.predict(x_test)
```

In [108]:

```
print(predictions)
```

[ 1 24 218 ... 21 210 179]

26% accuracy, the model performed badly. I think it's because we need to put the target to categories because the model is a classifier. For example, putting every 100 bike into one value so we minimize the target levels. Also, number of nodes for hidden layers plays a role in the model performance

In [109]:

```
print(confusion_matrix(y_test,predictions))
print(classification_report(y_test,predictions))
```



```
[[33 0 0... 0 0]
 [ 0 0 0... 0 0]
 [ 0 1 42... 0 0]]
```

```
precision recall f1-score support
```

1	0.94	1.00	0.97	33
2	0.97	0.97	0.97	38
3	1.00	0.98	0.99	43
4	0.96	0.98	0.97	50
5	1.00	0.96	0.98	52
6	0.96	0.98	0.97	53
7	1.00	0.92	0.95	43
8	0.59	1.00	0.75	41
9	0.92	0.99	0.95	29
10	0.92	0.38	0.53	32
11	0.45	0.59	0.51	29
12	0.32	0.35	0.34	22
13	0.67	0.08	0.14	26
14	0.32	0.35	0.34	22
15	0.00	0.00	0.00	18
16	0.00	0.00	0.00	19
17	0.00	0.00	0.00	25
18	0.17	0.05	0.07	21
19	0.00	0.00	0.00	1
20	0.00	0.00	0.00	8
21	0.38	0.93	0.54	14
22	0.00	0.00	0.00	3
23	0.00	0.00	0.00	15
24	0.17	0.92	0.29	13
25	0.00	0.00	0.00	15
26	0.00	0.00	0.00	23
27	0.00	0.00	0.00	15
28	0.50	0.29	0.39	16
29	0.17	0.50	0.26	8
30	0.00	0.00	0.00	1
31	0.19	1.00	0.33	7
32	0.00	0.00	0.00	13
33	0.00	0.00	0.00	14
34	0.25	0.14	0.18	7
35	0.00	0.00	0.00	11
36	0.33	0.18	0.24	11
37	0.00	0.00	0.00	9
38	0.00	0.00	0.00	1
39	0.14	0.83	0.24	12
40	0.00	0.00	0.00	15
41	0.00	0.00	0.00	4
42	0.00	0.00	0.00	15
43	0.00	0.00	0.00	7
44	0.42	0.38	0.40	13
45	0.00	0.00	0.00	7
46	0.00	0.00	0.00	1
47	0.00	0.00	0.00	17
48	0.33	0.17	0.22	6
49	0.00	0.00	0.00	12
50	0.00	0.00	0.00	14
51	0.00	0.00	0.00	11
52	0.11	1.00	0.20	10
53	0.00	0.00	0.00	6
54	0.00	0.00	0.00	1
55	0.09	0.08	0.09	12
56	0.00	0.00	0.00	9
57	0.00	0.00	0.00	8
58	0.00	0.00	0.00	7
59	0.38	0.56	0.45	7
60	0.00	0.00	0.00	10
61	0.00	0.00	0.00	8
62	0.00	0.00	0.00	7
63	0.00	0.00	0.00	1
64	0.17	0.82	0.28	11
65	0.10	0.33	0.15	7
66	0.00	0.00	0.00	10
67	0.00	0.00	0.00	9
68	0.00	0.00	0.00	9
69	0.00	0.00	0.00	9
70	0.00	0.00	0.00	12
71	0.00	0.00	0.00	9
72	0.09	0.75	0.16	8
73	0.00	0.00	0.00	2
74	0.00	0.00	0.00	11
75	0.00	0.00	0.00	10
76	0.00	0.00	0.00	6
77	0.00	0.00	0.00	8
78	0.00	0.00	0.00	1
79	0.00	0.00	0.00	11
80	0.00	0.00	0.00	7
81	0.00	0.00	0.00	4
82	0.00	0.00	0.00	8
83	0.00	0.00	0.00	1
84	0.00	0.00	0.00	12
85	0.18	0.67	0.29	6
86	0.00	0.00	0.00	3
87	0.00	0.00	0.00	10
88	0.00	0.00	0.00	7
89	0.00	0.00	0.00	1
90	0.00	0.00	0.00	9
91	0.00	0.00	0.00	8
92	0.00	0.00	0.00	8
93	0.14	0.18	0.16	11
94	0.00	0.00	0.00	3
95	0.00	0.00	0.00	11
96	0.13	0.80	0.22	5
97	0.00	0.00	0.00	2
98	0.00	0.00	0.00	10
99	0.00	0.00	0.00	10
100	0.00	0.00	0.00	7
101	0.31	0.45	0.37	11
102	0.00	0.00	0.00	6
103	0.17	0.33	0.22	6
104	0.17	0.20	0.18	5
105	0.00	0.00	0.00	1
106	0.37	0.79	0.50	14
107	0.00	0.00	0.00	6
108	0.00	0.00	0.00	10
109	0.00	0.00	0.00	6
110	0.00	0.00	0.00	1
111	0.00	0.00	0.00	13
112	0.00	0.00	0.00	5
113	0.00	0.00	0.00	5
114	0.00	0.00	0.00	7
115	0.43	1.00	0.60	6
116	0.67	0.33	0.44	6
117	0.00	0.00	0.00	5
118	0.00	0.00	0.00	5
119	0.00	0.00	0.00	1
120	0.23	1.00	0.37	7
121	0.00	0.00	0.00	2
122	0.00	0.00	0.00	8
123	0.00	0.00	0.00	1
124	0.30	0.42	0.34	17
125	0.25	0.29	0.27	7
126	0.00	0.00	0.00	9
127	0.75	0.38	0.50	3
128	0.00	0.00	0.00	8
129	0.00	1.00	0.00	4
130	0.00	0.00	0.00	4
131	0.00	0.00	0.00	4
132	0.42	1.00	0.76	8
133	0.29	0.25	0.27	8
134	0.00	0.00	0.00	1
135	0.00	0.00	0.00	4
136	0.67	0.33	0.44	6
137	0.40	1.00	0.65	11
138	0.00	0.00	0.00	9
139	1.00	0.80	0.89	5
140	1.00	0.14	0.25	7
141	0.25	1.00	0.40	7
142	0.00	0.00	0.00	1
143	0.00	0.00	0.00	8
144	0.89	1.00	0.94	8
145	0.00	0.00	0.00	3
146	0.25	0.20	0.22	5
147	0.44	1.00	0.62	12
148	0.00	0.00	0.00	1
149	1.00	0.14	0.25	7
150	0.00	0.00	0.00	1
151	1.00	0.30	0.46	10
152	0.00	0.00	0.00	9
153	0.00	0.00	0.00	1
154	0.13	1.00	0.23	7
155	0.00	0.00	0.00	7
156	0.00	0.00	0.00	11
157	0.00	0.00	0.00	7
158	0.00	0.00	0.00	5
159	0.50	0.43	0.46	7
160	0.71	0.62	0.67	8
161	0.00	0.00	0.00	6
162	0.40	0.67	0.50	3
163	0.00	0.00	0.00	7
164	0.14	0.25	0.18	4
165	0.00	0.00	0.00	6
166	0.00	0.00	0.00	6
167	1.00	0.69	0.17	11
168	0.34	0.85	0.49	13
169	0.00	0.00	0.00	8
170	0.00	0.00	0.00	12
171	0.00	0.00	0.00	10
172	0.21	1.00	0.35	9
173	0.00	0.00	0.00	7
174	0.00	0.00	0.00	1
175	0.80	0.50	0.62	8
176	0.80	0.44	0.57	9
177	0.00	0.00	0.00	1
178	0.00	0.00	0.00	13
179	0.24	0.92	0.39	11
180	0.00	0.00	0.00	4
181	0.00	0.00	0.00	9
182	0.00	0.00	0.00	10
183	0.00	0.00	0.00	4
184	0.00	0.00	0.00	6
185	0.00	0.00	0.00	1
186	0.00	0.00	0.00	5
187	0.00	0.00	0.00	11
188	0.00	0.00	0.00	7
189	0.00	0.00	0.00	3
190	0.00	0.00	0.00	5
191	0.00	0.00	0.00	7
192	0.00	0.00	0.00	5
193	0.00	0.00	0.00	3
194	0.00	0.00	0.00	4
195	0.00	0.00	0.00	5
196	0.17	0.22	0.17	6
197	0.00	0.00	0.00	6
198	0.00	0.00	0.00	14
199	0.00	0.00	0.00	7
200	0.00	0.00	0.00	8
201	0.00	0.00	0.00	2
202	0.00	0.00	0.00	7
203	0.00	0.00	0.00	8
204	0.00	0.00	0.00	5
205	0.00	0.00	0.00	8
206	0.00	0.00	0.00	1
207	0.00	0.00	0.00	5
208	0.50	0.20	0.29	5
209	0.00	0.00	0.00	1
210	0.17	0.17	0.17	6
211	0.27	0.80	0.40	5
212	1.00	0.00	0.00	2
213	1.00	0.23	0.38	13
214	0.00	1.00	0.33	2
215	0.00	0.00	0.00	6
216	0.00	0.00	0.00	3
217	0.00	0.00	0.00	1
218	0.25	0.88	0.39	8
219	0.00	0.00	0.00	10
220	0.10	0.67	0.17	6
221	0.00	0.00	0.00	7
222	0.00	0.00	0.00	2
223	0.00	0.00	0.00	6
224	0.00	0.00	0.00	11
225	0.00	0.00	0.00	9
226	0.00	0.00	0.00	7
227	0.00	0.00	0.00	4
228	0.00	0.00	0.00	7
229	0.17	1.00	0.29	9
230	0.00	0.00	0.00	5
231	0.00	0.00	0.00	3
232	0.00	0.00	0.00	6
233	0.00	0.00	0.00	4
234	0.00	0.00	0.00	3
235	0.00	0.00	0.00	9
236	0.00	0.00	0.00	8
237	0.00	0.00	0.00	9
238	0.00	0.00	0.00	1
239	0.06	0.75	0.11	4
240	0.00	0.00	0.00	4
241	0.00	0.00	0.00	5
242	0.00	0.00	0.00	6
243	0.00	0.00	0.00	5
244	0.00	0.00	0.00	1
245	0.00	0.00	0.00	5
246	0.00	0.00	0.00	1
247	0.00	0.00	0.00	4
248	0.00	0.00	0.00	6
249	0.00	1.00	0.29	5
250	0.00	0.00	0.00	3
251	1.00	0.25	0.40	5
252	0.08	0.33	0.13	3
253	0.00	0.00	0.00	1
254	0.00	0.00	0.00	2
255	0.00	0.00	0.00	7
256	0.57	1.00	0.73	4
257	0.00	0.00	0.00	1
258	0.50	0.30	0.37	10
259	0.32	0.88	0.47	8
260	0.00	0.00	0.00	2
261	0.43	0.38	0.40	8
262	0.00	0.00	0.00	2
263	1.00	0.12	0.22	8
264	0.00	0.00	0.00	7
265	0.00	0.00	0.00	1
266	0.00	0.00	0.00	1
267	0.00	0.00	0.00	6
268	0.19	0.50	0.31	10
269	0.00	0.00	0.00	3
270	0.00	0.00	0.00	4
271	0.00	0.00	0.00	5
272	0.09	0.10	0.10	10
273	0.00	0.00	0.00	3







```
[[30 3 0 ... 0 0]
 [0 37 0 ... 0 0]
 [0 0 0 ... 1 0 0]
 [0 0 0 33 ... 0 0]]
```

	precision	recall	f1-score	support
0	1.00	0.91	0.95	33
1	0.93	0.97	0.95	38
2	0.97	0.77	0.86	43
3	0.97	0.77	0.86	43
4	0.92	0.63	0.75	52
5	0.97	0.77	0.86	43
6	0.97	0.77	0.86	43
7	0.97	0.77	0.86	43
8	0.46	0.98	0.62	41
9	0.50	0.98	0.72	39
10	0.54	0.97	0.73	38
11	0.33	0.07	0.11	29
12	0.30	0.00	0.00	26
13	0.00	0.00	0.00	26
14	0.30	0.00	0.00	26
15	0.90	0.50	0.64	18
16	0.57	0.42	0.48	18
17	0.50	0.00	0.00	25
18	0.00	0.00	0.00	21
19	0.50	0.06	0.11	16
20	0.20	0.00	0.00	13
21	1.00	0.07	0.13	14
22	0.30	0.00	0.00	13
23	0.45	0.33	0.38	15
24	0.10	0.08	0.09	13
25	0.42	0.87	0.56	23
26	0.42	0.87	0.56	23
27	0.00	0.00	0.00	16
28	0.60	0.20	0.30	15
29	0.12	0.25	0.16	18
30	0.16	0.86	0.27	7
31	0.00	0.00	0.00	13
32	0.00	0.00	0.00	13
33	0.00	0.00	0.00	13
34	0.00	0.00	0.00	11
35	0.25	1.00	0.40	7
36	0.00	0.00	0.00	11
37	0.00	0.00	0.00	9
38	0.97	0.77	0.86	43
39	0.97	0.77	0.86	43
40	0.97	0.77	0.86	43
41	0.92	0.63	0.75	52
42	0.97	0.77	0.86	43
43	0.97	0.77	0.86	43
44	0.97	0.77	0.86	43
45	0.97	0.77	0.86	43
46	0.97	0.77	0.86	43
47	0.97	0.77	0.86	43
48	0.97	0.77	0.86	43
49	0.97	0.77	0.86	43
50	0.97	0.77	0.86	43
51	0.97	0.77	0.86	43
52	0.97	0.77	0.86	43
53	0.97	0.77	0.86	43
54	0.97	0.77	0.86	43
55	0.97	0.77	0.86	43
56	0.97	0.77	0.86	43
57	0.97	0.77	0.86	43
58	0.97	0.77	0.86	43
59	0.97	0.77	0.86	43
60	0.97	0.77	0.86	43
61	0.97	0.77	0.86	43
62	0.97	0.77	0.86	43
63	0.97	0.77	0.86	43
64	0.97	0.77	0.86	43
65	0.97	0.77	0.86	43
66	0.97	0.77	0.86	43
67	0.97	0.77	0.86	43
68	0.97	0.77	0.86	43
69	0.97	0.77	0.86	43
70	0.97	0.77	0.86	43
71	0.97	0.77	0.86	43
72	0.97	0.77	0.86	43
73	0.97	0.77	0.86	43
74	0.97	0.77	0.86	43
75	0.97	0.77	0.86	43
76	0.97	0.77	0.86	43
77	0.97	0.77	0.86	43
78	0.97	0.77	0.86	43
79	0.97	0.77	0.86	43
80	0.97	0.77	0.86	43
81	0.97	0.77	0.86	43
82	0.97	0.77	0.86	43
83	0.97	0.77	0.86	43
84	0.97	0.77	0.86	43
85	0.97	0.77	0.86	43
86	0.97	0.77	0.86	43
87	0.97	0.77	0.86	43
88	0.97	0.77	0.86	43
89	0.97	0.77	0.86	43
90	0.97	0.77	0.86	43
91	0.97	0.77	0.86	43
92	0.97	0.77	0.86	43
93	0.97	0.77	0.86	43
94	0.97	0.77	0.86	43
95	0.97	0.77	0.86	43
96	0.97	0.77	0.86	43
97	0.97	0.77	0.86	43
98	0.97	0.77	0.86	43
99	0.97	0.77	0.86	43
100	0.97	0.77	0.86	43
101	0.97	0.77	0.86	43
102	0.97	0.77	0.86	43
103	0.97	0.77	0.86	43
104	0.97	0.77	0.86	43
105	0.97	0.77	0.86	43
106	0.97	0.77	0.86	43
107	0.97	0.77	0.86	43
108	0.97	0.77	0.86	43
109	0.97	0.77	0.86	43
110	0.97	0.77	0.86	43
111	0.97	0.77	0.86	43
112	0.97	0.77	0.86	43
113	0.97	0.77	0.86	43
114	0.97	0.77	0.86	43
115	0.97	0.77	0.86	43
116	0.97	0.77	0.86	43
117	0.97	0.77	0.86	43
118	0.97	0.77	0.86	43
119	0.97	0.77	0.86	43
120	0.97	0.77	0.86	43
121	0.97	0.77	0.86	43
122	0.97	0.77	0.86	43
123	0.97	0.77	0.86	43
124	0.97	0.77	0.86	43
125	0.97	0.77	0.86	43
126	0.97	0.77	0.86	43
127	0.97	0.77	0.86	43
128	0.97	0.77	0.86	43
129	0.97	0.77	0.86	43
130	0.97	0.77	0.86	43
131	0.97	0.77	0.86	43
132	0.97	0.77	0.86	43
133	0.97	0.77	0.86	43
134	0.97	0.77	0.86	43
135	0.97	0.77	0.86	43
136	0.97	0.77	0.86	43
137	0.97	0.77	0.86	43
138	0.97	0.77	0.86	43
139	0.97	0.77	0.86	43
140	0.97	0.77	0.86	43
141	0.97	0.77	0.86	43
142	0.97	0.77	0.86	43
143	0.97	0.77	0.86	43
144	0.97	0.77	0.86	43
145	0.97	0.77	0.86	43
146	0.97	0.77	0.86	43
147	0.97	0.77	0.86	43
148	0.97	0.77	0.86	43
149	0.97	0.77	0.86	43
150	0.97	0.77	0.86	43
151	0.97	0.77	0.86	43
152	0.97	0.77	0.86	43
153	0.97	0.77	0.86	43
154	0.97	0.77	0.86	43
155	0.97	0.77	0.86	43
156	0.97	0.77	0.86	43
157	0.97	0.77	0.86	43
158	0.97	0.77	0.86	43
159	0.97	0.77	0.86	43
160	0.97	0.77	0.86	43
161	0.97	0.77	0.86	43
162	0.97	0.77	0.86	43
163	0.97	0.77	0.86	43
164	0.97	0.77	0.86	43
165	0.97	0.77	0.86	43
166	0.97	0.77	0.86	43
167	0.97	0.77	0.86	43
168	0.97	0.77	0.86	43
169	0.97	0.77	0.86	43
170	0.97	0.77	0.86	43
171	0.97	0.77	0.86	43
172	0.97	0.77	0.86	43
173	0.97	0.77	0.86	43
174	0.97	0.77	0.86	43
175	0.97	0.77	0.86	43
176	0.97	0.77	0.86	43
177	0.97	0.77	0.86	43
178	0.97	0.77	0.86	43
179	0.97	0.77	0.86	43
180	0.97	0.77	0.86	43
181	0.97	0.77	0.86	43
182	0.97	0.77	0.86	43
183	0.97	0.77	0.86	43
184	0.97	0.77	0.86	43
185	0.97	0.77	0.86	43
186	0.97	0.77	0.86	43
187	0.97	0.77	0.86	43
188	0.97	0.77	0.86	43
189	0.97	0.77	0.86	43
190	0.97	0.77	0.86	43
191	0.97	0.77	0.86	43
192	0.97	0.77	0.86	43
193	0.97	0.77	0.86	43
194	0.97	0.77	0.86	43
195	0.97	0.77	0.86	43
196	0.97	0.77	0.86	43
197	0.97	0.77	0.86	43
198	0.97	0.77	0.86	43
199	0.97	0.77	0.86	43
200	0.97	0.77	0.86	43
201	0.97	0.77	0.86	43
202	0.97	0.77	0.86	43
203	0.97	0.77	0.86	43
204	0.97	0.77	0.86	43
205	0.97	0.77	0.86	43
206	0.97	0.77	0.86	43
207	0.97	0.77	0.86	43
208	0.97	0.77	0.86	43
209	0.97	0.77	0.86	43
210	0.97	0.77	0.86	43
211	0.97	0.77	0.86	43
212	0.97	0.77	0.86	43
213	0.97	0.77	0.86	43
214	0.97	0.77	0.86	43
215	0.97	0.77	0.86	43
216	0.97	0.77	0.86	43
217	0.97	0.77	0.86	43
218	0.97	0.77	0.86	43
219	0.97	0.77	0.86	43
220	0.97	0.77	0.86	43
221	0.97	0.77	0.86	43
222	0.97	0.77	0.86	43
223	0.97	0.77	0.86	43
224	0.97	0.77	0.86	43
225	0.97	0.77	0.86	43
226	0.97	0.77	0.86	43
227	0.97	0.77	0.86	43
228	0.97	0.77	0.86	43
229	0.97	0.77	0.86	43
230	0.97	0.77	0.86	43
231	0.97	0.77	0.86	43
232	0.97	0.77	0.86	43
233	0.97	0.77	0.86	43
234	0.97	0.77	0.86	43
235	0.97	0.77	0.86	43
236	0.97	0.77	0.86	43
237	0.97	0.77	0.86	43
238	0.97	0.77	0.86	43
239	0.97	0.77	0.86	43
240	0.97	0.77	0.86	43
241	0.97	0.77	0.86	43
242	0.97	0.77	0.86	43
243	0.97	0.77	0.86	43
244	0.97	0.77	0.86	43
245	0.97	0.77	0.86	43
246	0.97	0.77	0.86	43
247	0.97	0.77	0.86	43
248	0.97	0.77	0.86	43
249	0.97	0.77	0.86	43
250	0.97	0.77	0.86	43
251	0.97	0.77	0.86	43
252	0.97	0.77	0.86	43
253	0.97	0.77	0.86	43
254	0.97	0.77	0.86	43
255	0.97	0.77	0.86	43
256	0.97	0.77	0.86	43
257	0.97	0.77	0.86	43
258	0.97	0.77	0.86	43
259	0.97	0.77	0.86	43
260	0.97	0.77	0.86	43
261	0.97	0.77	0.86	43
262	0.97	0.77	0.86	43
263	0.97	0.77	0.86	43
264	0.97	0.77	0.86	43
265	0.97	0.77	0.86	43
266	0.97	0.77	0.86	43
267	0.97	0.77	0.86	43
268	0.97	0.		