Model Building

May 31, 2022

1 Logistic Regression

[1]:
```
import pandas as pd
from sqlalchemy import create_engine
from sqlalchemy.sql import text
```

[2]:
```
import numpy as np
```

[3]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.pipeline import Pipeline
from sklearn.metrics import roc_curve, roc_auc_score, classification_report,␣
↪accuracy_score, confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt
```

[8]:
```
!pip install psycopg2
```

```
Collecting psycopg2
  Downloading psycopg2-2.9.3-cp39-cp39-win_amd64.whl (1.2 MB)
Installing collected packages: psycopg2
Successfully installed psycopg2-2.9.3
```

[4]:
```
engine = create_engine('XXXXXXX://XXXXXXX:XXXXXXX:XXXXXXX/XXXXXXX')
conn = engine.connect().execution_options(autocommit=True)
```

[5]:
```
df_sig = pd.read_sql_query('select * from significance_table as st join␣
↪submission_vectors as sv on st.submission_id = sv.submission_id where␣
↪t_sample_t_test is not null;', con = conn)
```

[6]:
```
df_inputs = df_sig.drop(columns=['submission_id','topic_champion','date'])
df_inputs
```

[6]:
```
     upvotes  t_sample_t_test         0         1         2         3  \
0          3            False -0.804775  0.315904 -0.045163  0.100483
1       1040            False -0.185703  0.023682  0.207782  0.530416
```

```
2            0            False -0.516388  0.254332  0.183559  0.475579
3            0            False -0.192984 -0.142646  0.125904  0.382128
4            0            False -0.192984 -0.142646  0.125904  0.382128
…         …              …       …         …         …         …
32734      174            False -0.286790 -0.243372  0.259694  0.596197
32735      174            False -0.286790 -0.243372  0.259694  0.596197
32736       20            False -0.221735 -0.005563  0.136709  0.446870
32737     1575            False -0.356414  0.122949  0.040761  0.409273
32738        0            False -0.876947  0.388674  0.577009 -0.533535

              4         5         6         7  …        90        91  \
0      0.480817  0.443167 -0.319338  0.516226  … -0.095464  0.503082
1     -0.544296  0.114059 -0.380009  0.627888  …  0.041726  0.392014
2      0.455851  0.557130 -0.195927  0.583042  … -0.130465  0.116177
3      0.254417  0.257000 -0.637827  0.068707  …  0.124186  0.797552
4      0.254417  0.257000 -0.637827  0.068707  …  0.124186  0.797552
…           …         …         …         …  …         …         …
32734 -0.380780 -0.032148  0.061175  0.234752  … -0.400553  0.664949
32735 -0.380780 -0.032148  0.061175  0.234752  … -0.400553  0.664949
32736 -0.313393  0.185552 -0.421806  0.473120  …  0.197290  0.318249
32737 -0.053394  0.316902  0.157393  0.449702  …  0.306242 -0.034132
32738 -0.360431  0.439926 -0.068141 -0.190432  …  0.497551  1.106310

             92        93        94        95        96        97        98  \
0      0.525933 -0.406394  0.815783  0.151320 -0.144457 -0.481676 -0.180171
1      0.440717  0.400752  0.027663  0.116840 -0.704573  0.659166  0.310418
2      0.354175  0.015838 -0.305019 -0.006427 -0.540465 -0.014772  0.244741
3      0.310523 -0.135499  0.940158  0.501260 -0.530605 -0.101638  0.484378
4      0.310523 -0.135499  0.940158  0.501260 -0.530605 -0.101638  0.484378
…           …         …         …         …         …         …         …
32734  0.484354  0.101292  0.173315  0.235715 -0.620059 -0.012455  0.445785
32735  0.484354  0.101292  0.173315  0.235715 -0.620059 -0.012455  0.445785
32736  0.350785  0.158812  0.144754  0.085425 -0.757788  0.405676  0.390924
32737  0.334505  0.188771  0.046193 -0.066672 -0.695834  0.058594  0.004527
32738 -0.610491  0.593853  1.490107 -0.162837 -1.350688  0.967860 -0.104110

             99
0     -0.400925
1     -0.337699
2     -0.074475
3     -1.014775
4     -1.014775
…           …
32734 -0.026895
32735 -0.026895
32736 -0.353025
32737 -0.310824
```

```
32738 -0.494431

[32739 rows x 102 columns]
```

[7]:
```python
cols = df_inputs.columns.tolist()
```

[13]:
```python
len(cols)
```

[13]:
```
102
```

[8]:
```python
cols = cols[0:1] + cols[2:102] + cols[1:2]
```

[15]:
```python
len(cols)
```

[15]:
```
102
```

[16]:
```python
cols
```

[16]:
```
['upvotes',
 '0',
 '1',
 '2',
 '3',
 '4',
 '5',
 '6',
 '7',
 '8',
 '9',
 '10',
 '11',
 '12',
 '13',
 '14',
 '15',
 '16',
 '17',
 '18',
 '19',
 '20',
 '21',
 '22',
 '23',
 '24',
 '25',
 '26',
 '27',
```

```
'28',
'29',
'30',
'31',
'32',
'33',
'34',
'35',
'36',
'37',
'38',
'39',
'40',
'41',
'42',
'43',
'44',
'45',
'46',
'47',
'48',
'49',
'50',
'51',
'52',
'53',
'54',
'55',
'56',
'57',
'58',
'59',
'60',
'61',
'62',
'63',
'64',
'65',
'66',
'67',
'68',
'69',
'70',
'71',
'72',
'73',
'74',
```

```
 '75',
 '76',
 '77',
 '78',
 '79',
 '80',
 '81',
 '82',
 '83',
 '84',
 '85',
 '86',
 '87',
 '88',
 '89',
 '90',
 '91',
 '92',
 '93',
 '94',
 '95',
 '96',
 '97',
 '98',
 '99',
 't_sample_t_test']
```

[9]:
```
df_inputs = df_inputs[cols]
```

[10]:
```
df_inputs
```

[10]:
```
       upvotes         0         1         2         3         4         5  \
0            3 -0.804775  0.315904 -0.045163  0.100483  0.480817  0.443167
1         1040 -0.185703  0.023682  0.207782  0.530416 -0.544296  0.114059
2            0 -0.516388  0.254332  0.183559  0.475579  0.455851  0.557130
3            0 -0.192984 -0.142646  0.125904  0.382128  0.254417  0.257000
4            0 -0.192984 -0.142646  0.125904  0.382128  0.254417  0.257000
…          …        …        …        …        …        …        …
32734      174 -0.286790 -0.243372  0.259694  0.596197 -0.380780 -0.032148
32735      174 -0.286790 -0.243372  0.259694  0.596197 -0.380780 -0.032148
32736       20 -0.221735 -0.005563  0.136709  0.446870 -0.313393  0.185552
32737     1575 -0.356414  0.122949  0.040761  0.409273 -0.053394  0.316902
32738        0 -0.876947  0.388674  0.577009 -0.533535 -0.360431  0.439926

             6         7         8  …        91        92        93  \
0    -0.319338  0.516226  0.806492  …  0.503082  0.525933 -0.406394
1    -0.380009  0.627888 -0.179360  …  0.392014  0.440717  0.400752
```

```
2     -0.195927  0.583042  0.112773  …  0.116177  0.354175  0.015838
3     -0.637827  0.068707  0.139172  …  0.797552  0.310523 -0.135499
4     -0.637827  0.068707  0.139172  …  0.797552  0.310523 -0.135499
…           …         …         …   …       …         …         …
32734  0.061175  0.234752  0.055850  …  0.664949  0.484354  0.101292
32735  0.061175  0.234752  0.055850  …  0.664949  0.484354  0.101292
32736 -0.421806  0.473120 -0.163098  …  0.318249  0.350785  0.158812
32737  0.157393  0.449702  0.471984  … -0.034132  0.334505  0.188771
32738 -0.068141 -0.190432 -0.403182  …  1.106310 -0.610491  0.593853

             94        95        96        97        98        99  \
0      0.815783  0.151320 -0.144457 -0.481676 -0.180171 -0.400925
1      0.027663  0.116840 -0.704573  0.659166  0.310418 -0.337699
2     -0.305019 -0.006427 -0.540465 -0.014772  0.244741 -0.074475
3      0.940158  0.501260 -0.530605 -0.101638  0.484378 -1.014775
4      0.940158  0.501260 -0.530605 -0.101638  0.484378 -1.014775
…           …         …         …         …         …         …
32734  0.173315  0.235715 -0.620059 -0.012455  0.445785 -0.026895
32735  0.173315  0.235715 -0.620059 -0.012455  0.445785 -0.026895
32736  0.144754  0.085425 -0.757788  0.405676  0.390924 -0.353025
32737  0.046193 -0.066672 -0.695834  0.058594  0.004527 -0.310824
32738  1.490107 -0.162837 -1.350688  0.967860 -0.104110 -0.494431

       t_sample_t_test
0                False
1                False
2                False
3                False
4                False
…                    …
32734            False
32735            False
32736            False
32737            False
32738            False

[32739 rows x 102 columns]
```

2 Logistic Model Setup

[14]:
```
X = df_inputs.drop(columns=['t_sample_t_test'])
y = df_inputs.t_sample_t_test

np.random.seed(42)
X_train, X_test, y_train, y_test = train_test_split(X, y)
```

[15]:
```
scaler = StandardScaler()
lr = LogisticRegression()
model1 = Pipeline([('standardize', scaler),
                    ('log_reg', lr)])
```

[16]:
```
model1.fit(X_train, y_train)
```

[16]:
```
Pipeline(steps=[('standardize', StandardScaler()),
                ('log_reg', LogisticRegression())])
```

[17]:
```
y_train_hat = model1.predict(X_train)
y_train_hat_probs = model1.predict_proba(X_train)[:,1]

train_accuracy = accuracy_score(y_train, y_train_hat)*100
train_auc_roc = roc_auc_score(y_train, y_train_hat_probs)*100

print('Confusion matrix:\n', confusion_matrix(y_train, y_train_hat))

print('Training AUC: %.4f %%' % train_auc_roc)

print('Training accuracy: %.4f %%' % train_accuracy)
```

```
Confusion matrix:
 [[22589     7]
 [ 1955     3]]
Training AUC: 61.4989 %
Training accuracy: 92.0094 %
```

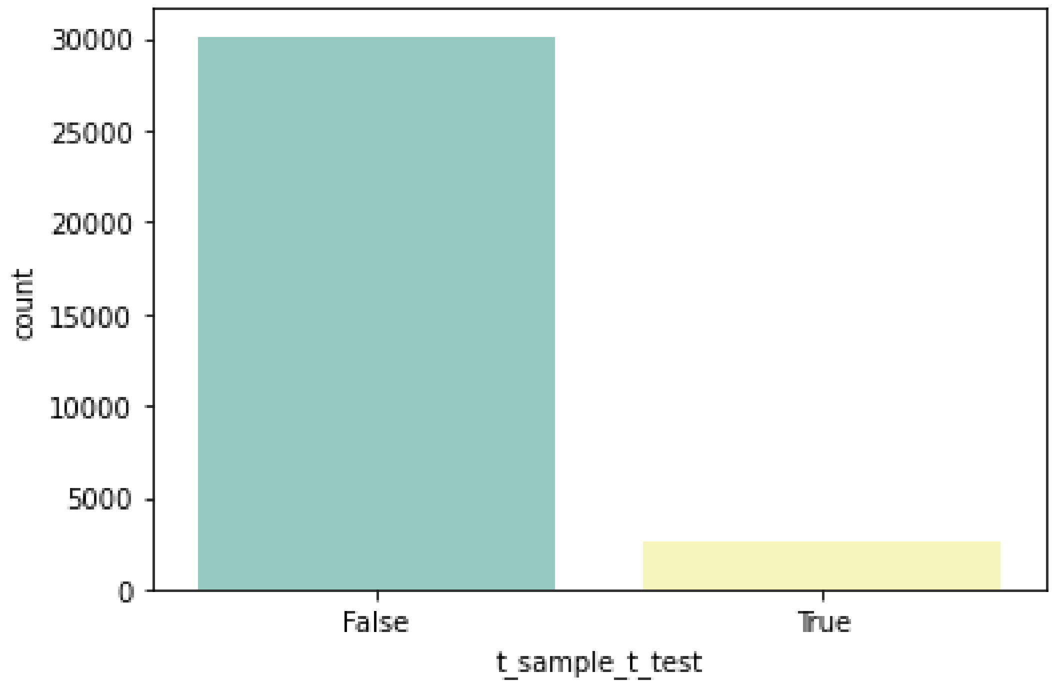
[18]:
```
y_test_hat = model1.predict(X_test)
y_test_hat_probs = model1.predict_proba(X_test)[:,1]

test_accuracy = accuracy_score(y_test, y_test_hat)*100
test_auc_roc = roc_auc_score(y_test, y_test_hat_probs)*100

print('Confusion matrix:\n', confusion_matrix(y_test, y_test_hat))

print('Testing AUC: %.4f %%' % test_auc_roc)

print('Testing accuracy: %.4f %%' % test_accuracy)
```

```
Confusion matrix:
 [[7533    2]
 [ 649    1]]
Testing AUC: 55.4365 %
Testing accuracy: 92.0464 %
```

[19]:
```
print(classification_report(y_test, y_test_hat, digits=6))
```

```
              precision    recall  f1-score   support

       False   0.920680  0.999735  0.958580      7535
        True   0.333333  0.001538  0.003063       650

    accuracy                       0.920464      8185
   macro avg   0.627006  0.500637  0.480821      8185
weighted avg   0.874036  0.920464  0.882699      8185
```

[20]:
```
ax = sns.countplot(x="t_sample_t_test", data=df_inputs, palette="Set3")
```



[21]:
```
sum(y_test_hat== False)
```

[21]: 8182

3 Random Forest Model

[11]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import RandomizedSearchCV
```

[12]:
```
X = df_inputs.drop(columns=['t_sample_t_test'])
y = df_inputs.t_sample_t_test
```

```
np.random.seed(42)
X_train, X_test, y_train, y_test = train_test_split(X, y)
```

3.1 Starting Point (One Set of Hyperparameters)

[24]:
```
# creating a RF classifier
clf = RandomForestClassifier(n_estimators = 100)

# Training the model on the training dataset
# fit function is used to train the model using the training sets as parameters
clf.fit(X_train, y_train)

# performing predictions on the test dataset
y_pred = clf.predict(X_test)

# metrics are used to find accuracy or error
from sklearn import metrics
print()

# using metrics module for accuracy calculation
print("ACCURACY OF THE MODEL: ", metrics.accuracy_score(y_test, y_pred))
```

```
ACCURACY OF THE MODEL:  0.9071472205253512
```

[28]:
```
print('Confusion matrix:\n', confusion_matrix(y_test, y_pred))
```

```
Confusion matrix:
 [[7399  136]
 [ 626   24]]
```

[29]:
```
y_pred_probs = clf.predict_proba(X_test)[:,1]

test_accuracy = accuracy_score(y_test, y_pred)*100
test_auc_roc = roc_auc_score(y_test, y_pred_probs)*100


print('Confusion matrix:\n', confusion_matrix(y_test, y_pred))

print('Testing AUC: %.4f %%' % test_auc_roc)

print('Testing accuracy: %.4f %%' % test_accuracy)
```

```
Confusion matrix:
 [[7399  136]
 [ 626   24]]
Testing AUC: 53.9190 %
```

Testing accuracy: 90.6903 %

The confusion matrix appears to be better, but the testing AUC and testing accuracy are acutally **worse**.

3.2 Multiple Permutations

[45]:
```
# Number of trees in random forest
n_estimators = [int(x) for x in np.linspace(start = 100, stop = 300, num = 3)]

# Number of features to consider at every split
max_features = ['auto', 'sqrt']

# Maximum number of levels in tree
max_depth = [int(x) for x in np.linspace(10, 110, num = 4)]
max_depth.append(None)

# Minimum number of samples required to split a node
min_samples_split = [2, 5, 10]

# Minimum number of samples required at each leaf node
min_samples_leaf = [1, 2, 4]

# Method of selecting samples for training each tree
bootstrap = [True, False]

# Create the random grid
random_grid = {'n_estimators': n_estimators,
               'max_features': max_features,
               'max_depth': max_depth,
               'min_samples_split': min_samples_split,
               'min_samples_leaf': min_samples_leaf,
               'bootstrap': bootstrap,
               'class_weight': [{0:1, 1:12}]}

print(random_grid)
```

```
{'n_estimators': [100, 200, 300], 'max_features': ['auto', 'sqrt'], 'max_depth':
[10, 43, 76, 110, None], 'min_samples_split': [2, 5, 10], 'min_samples_leaf':
[1, 2, 4], 'bootstrap': [True, False], 'class_weight': [{0: 1, 1: 12}]}
```

[46]:
```
# Use the random grid to search for best hyperparameters
# First create the base model to tune
rf = RandomForestClassifier()

# Random search of parameters, using 3 fold cross validation,
# search across 100 different combinations, and use all available cores
```

```
rf_random = RandomizedSearchCV(estimator = rf, param_distributions =␣
↪random_grid, n_iter = 100, cv = 3, verbose=2, random_state=42, n_jobs = -1)

# Fit the random search model
rf_random.fit(X_train, y_train)
```

```
Fitting 3 folds for each of 100 candidates, totalling 300 fits
```

[46]:
```
RandomizedSearchCV(cv=3, estimator=RandomForestClassifier(), n_iter=100,
                   n_jobs=-1,
                   param_distributions={'bootstrap': [True, False],
                                        'class_weight': [{0: 1, 1: 12}],
                                        'max_depth': [10, 43, 76, 110, None],
                                        'max_features': ['auto', 'sqrt'],
                                        'min_samples_leaf': [1, 2, 4],
                                        'min_samples_split': [2, 5, 10],
                                        'n_estimators': [100, 200, 300]},
                   random_state=42, verbose=2)
```

[47]:
```
rf_random.best_params_
```

[47]:
```
{'n_estimators': 100,
 'min_samples_split': 10,
 'min_samples_leaf': 4,
 'max_features': 'auto',
 'max_depth': 76,
 'class_weight': {0: 1, 1: 12},
 'bootstrap': True}
```

3.3 "Best" Model

[13]:
```
# creating a RF classifier
clf = RandomForestClassifier(n_estimators = 100,
                             min_samples_split=10,
                             min_samples_leaf=4,
                             max_features='auto',
                             max_depth=76,
                             bootstrap=True,
                             class_weight={0:1, 1:12})

# Training the model on the training dataset
# fit function is used to train the model using the training sets as parameters
clf.fit(X_train, y_train)

# performing predictions on the test dataset
y_pred = clf.predict(X_test)
```

```python
# metrics are used to find accuracy or error
from sklearn import metrics
print()

# using metrics module for accuracy calculation
print("ACCURACY OF THE MODEL: ", metrics.accuracy_score(y_test, y_pred))
```

```
ACCURACY OF THE MODEL:  0.8984728161270616
```

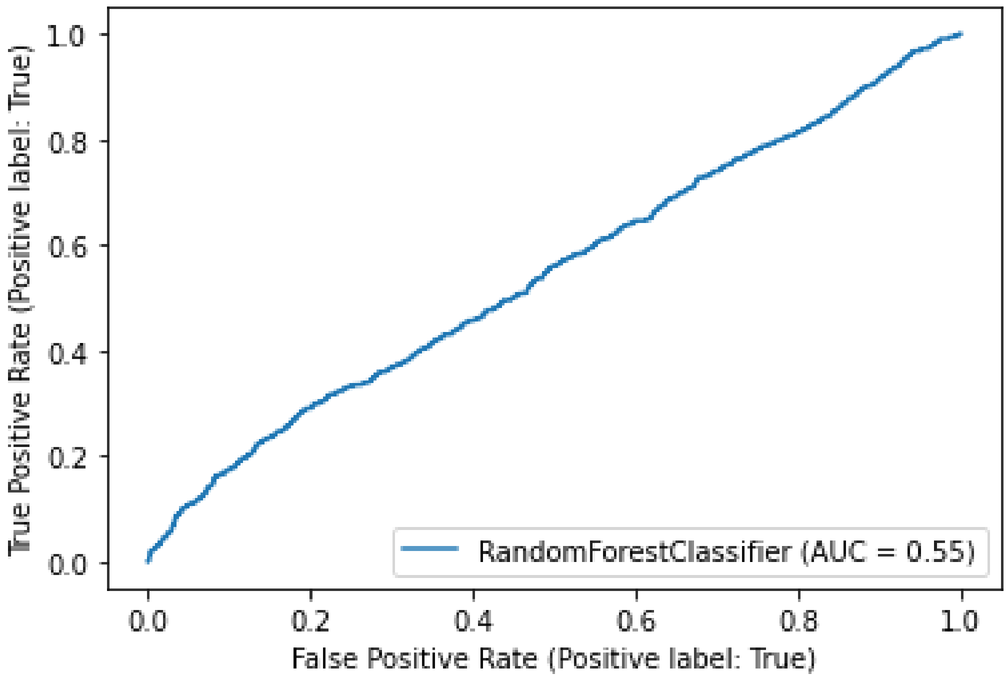
[14]:
```python
y_pred_probs = clf.predict_proba(X_test)[:,1]

test_accuracy = accuracy_score(y_test, y_pred)*100
test_auc_roc = roc_auc_score(y_test, y_pred_probs)*100


print('Confusion matrix:\n', confusion_matrix(y_test, y_pred))

print('Testing AUC: %.4f %%' % test_auc_roc)

print('Testing accuracy: %.4f %%' % test_accuracy)
```

```
Confusion matrix:
 [[7316  219]
 [ 612   38]]
Testing AUC: 54.7914 %
Testing accuracy: 89.8473 %
```

[16]:
```python
metrics.plot_roc_curve(clf, X_test, y_test)
```

```
C:\Users\aKost\anaconda3\lib\site-packages\sklearn\utils\deprecation.py:87:
FutureWarning: Function plot_roc_curve is deprecated; Function
:func:`plot_roc_curve` is deprecated in 1.0 and will be removed in 1.2. Use one
of the class methods: :meth:`sklearn.metric.RocCurveDisplay.from_predictions` or
:meth:`sklearn.metric.RocCurveDisplay.from_estimator`.
  warnings.warn(msg, category=FutureWarning)
```

[16]:
```
<sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x140c75e8b20>
```



4 Neural Network Modeling

[ ]:
```
## IMPORTS
import sys
import math
import numpy as np
import pandas as pd
import os
import torch
import time
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torch.autograd import Variable

import matplotlib.pyplot as plt
```

[ ]:
```
# HYPERPARAMETERS
in_f = 101
out_f = 1
hidden_l = [0,1,2,3,4,5]
lr = 1e-3
```

```
## CLASS
class FFN(nn.Module):
    def __init__(self, in_features=101, n_hidden_layers=1, out_features=1):

        ## VALUE CHECKING
        if not isinstance(in_features, int):
            raise TypeError(f"Instance 'in_features' must be of type 'int',␣
 ↪received type '{type(in_features)}'")
        if in_features <= 1:
            raise ValueError(f"Attribute 'in_features' must be >= 1, received␣
 ↪value {in_features}")

        if not isinstance(n_hidden_layers, int):
            raise TypeError(f"Instance 'n_hidden_layers' must be of type 'int',␣
 ↪received type '{type(n_hidden_layers)}'")
        if n_hidden_layers < 0 or n_hidden_layers > 5:
            raise ValueError(f"Attribute 'n_hidden_layers' must be >= 0 or <=␣
 ↪5, received value {n_hidden_layers}")

        if not isinstance(out_features, int):
            raise TypeError(f"Instance 'out_features' must be of type 'int',␣
 ↪received type '{type(out_features)}'")
        if out_features < 1:
            raise ValueError(f"Attribute 'out_features' must be >= 1 , received␣
 ↪value {out_features}")

        super(FFN, self).__init__()

        self.in_features = in_features
        self.n_hidden_layers = n_hidden_layers
        self.out_features = out_features

        self.0l = nn.Sequential(
            F.sigmoid()
        )
        self.1l = nn.Sequential(
            nn.Linear(in_features, out_features),
            nn.Dropout(0.1),
            F.sigmoid()
        )
        self.2l = nn.Sequential(
            nn.Linear(in_features, 200),
            nn.Dropout(0.1),
            nn.Linear(200, out_features),
            F.sigmoid()
        )
```

```
        self.3l = nn.Sequential(
            nn.Linear(in_features, 200),
            nn.Linear(200, 100),
            nn.Dropout(0.2),
            nn.Linear(100, out_features),
            F.sigmoid()
        )
        self.4l = nn.Sequential(
            nn.Linear(in_features, 200),
            nn.Linear(200, 200), nn.Linear(200, 100),
            nn.Dropout(0.3),
            nn.Linear(100, out_features),
            F.sigmoid()
        )
        self.5l = nn.Sequential(
            nn.Linear(in_features, 200),
            nn.Linear(200, 400), nn.Linear(400, 200), nn.Linear(200, 100),
            nn.Dropout(0.3),
            nn.Linear(100, out_features),
            F.sigmoid()
        )

def forward(self, x):
    if self.n_hidden_layers == 0:
        return self.0l(x)
    if self.n_hidden_layers == 1:
        return self.1l(x)
    elif self.n_hidden_layers == 2:
        return self.2l(x)
    elif self.n_hidden_layers == 3:
        return self.3l(x)
    elif self.n_hidden_layers == 4:
        return self.4l(x)
    elif self.n_hidden_layers == 5:
        return self.5l(x)

    return temp4
```

[ ]:
```
## MODEL DEFINITION
model = FFN(input_size, hidden_size, num_classes).to(device)

criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(model.parameters(), lr=lr)

## TRAINING
e_l = [e+1 for e in range(num_epochs)]
l_l = []
```

```
a_l = []

for epoch in range(num_epochs):
    for i, (inputs, classes) in enumerate(training_data):
    inputs = inputs.reshape(-1,101).to(device)

    classes = classes.to(device)
    y_hat = model(inputs)

    loss = criterion(y_hat, classes)
    optimizer.zero_grad()

    loss.backward()
    optimizer.step()

    if (i+1) % 100 == 0:
        print (f'Epoch [{epoch+1}/{num_epochs}], Loss: {loss.item():.4f}')
        l_l.append(loss.item())

with torch.no_grad():
    correct = 0
    total = 0
    for inputs, classes in testing_data:
        inputs = inputs.reshape(-1, 28*28).to(device)
        classes = classes.to(device)
        y_hat = model(inputs)

        _, predicted = torch.max(y_hat.data, 1)

        total += classes.size(0)
        correct += (predicted == classes).sum().item()
    acc = correct / total
    print(f'Accuracy of the network: {(100.0 * acc):.2f} %')
    a_l.append(acc)
```