Homework 7 - Grant Jackson

November 6, 2024

```
[1]: import os
     import numpy as np
     import pandas as pd
     from sklearn.datasets import fetch_20newsgroups
     from sklearn.feature_extraction.text import TfidfVectorizer
     from sklearn.model selection import GridSearchCV, train test split
     from sklearn.svm import SVC
     from sklearn.naive bayes import MultinomialNB
     from sklearn.metrics import classification_report, make_scorer, u

→precision_score, recall_score

[2]: # Load the 20newsgroups dataset
     categories = [
         'alt.atheism', 'comp.graphics', 'sci.space', 'talk.religion.misc',
         'rec.sport.baseball', 'rec.sport.hockey', 'sci.crypt', 'sci.electronics',
         'comp.os.ms-windows.misc', 'comp.sys.mac.hardware'
     remove = ('headers', 'footers', 'quotes')
     data_train = fetch_20newsgroups(subset='train', categories=categories,_
      oremove=remove, shuffle=True, random_state=42)
     data_test = fetch_20newsgroups(subset='test', categories=categories,__
      ⇒remove=remove, shuffle=True, random_state=42)
     # extract Y and X from the datasets
     y_train = data_train.target
     y_test = data_test.target
     X_train = data_train.data
     X_test = data_test.data
[3]: y_train
[3]: array([3, 4, 2, ..., 7, 7, 4], dtype=int64)
[4]: # Check how each category is indexed
     data_train.target_names
```

```
[4]: ['alt.atheism',
       'comp.graphics',
       'comp.os.ms-windows.misc',
       'comp.sys.mac.hardware',
       'rec.sport.baseball',
       'rec.sport.hockey',
       'sci.crypt',
       'sci.electronics',
       'sci.space',
       'talk.religion.misc']
 [5]: print(X_train[0]) # text
      print(y_train) # integers (0-3)
     Applied Engineering makes a NuBus card called the QuadraLink which is
     a board that contains 4 serial ports, which I believe can be used
     simultaneously. I'm not a user of one of these, but I have installed
     a couple for people at work (I'm a technician). Hope this helps.
     [3 4 2 ... 7 7 4]
 [6]: # Convert texts to numerical vectors using TfidfVectorizer
      vectorizer = TfidfVectorizer(stop_words='english')
      X_train = vectorizer.fit_transform(X_train)
      X_test = vectorizer.transform(X_test)
      # Check the size of X_train
      print(X_train.shape)
      print(X_test.shape)
     (5586, 71611)
     (3717, 71611)
 [7]: # Define parameter grid of SVC
      tuned_parameters_svc = [
          {'kernel': ['rbf'], 'C': [1, 10, 100, 1000]},
          {'kernel': ['linear'], 'C': [1, 10, 100, 1000]},
          {'kernel': ['poly'], 'degree': [5, 5], 'C': [1, 10, 100]},
          {'kernel': ['sigmoid'], 'coef0': [0, 1, 2, 'C': [1, 10, 100]}
      ]
 [8]: # Define scoring metrics
      scores = ['precision_macro', 'recall_macro']
[10]: # GridSearch Optimize SVC
      for score in scores:
          print(f"# Tuning hyper-parameters for {score}\n")
```

```
clf_svc = GridSearchCV(SVC(), tuned_parameters_svc, scoring=score, cv=5)
    clf_svc.fit(X_train, y_train)
    print("Best parameters set found on train set:")
    print(clf_svc.best_params_)
    print("\nGrid scores on train set:")
    means = clf_svc.cv_results_['mean_test_score']
    stds = clf svc.cv results ['std test score']
    for mean, std, params in zip(means, stds, clf_svc.cv_results_['params']):
        print(f''(mean:.3f) (+/-{std * 2:.03f})) for {params}'')
    print("\nDetailed classification report:")
    print("The scores are computed on test set.")
    y_pred = clf_svc.predict(X_test)
    print(classification_report(y_test, y_pred, zero_division=1))
    print()
# Tuning hyper-parameters for precision_macro
```

```
C:\ProgramData\anaconda3\Lib\site-
packages\sklearn\metrics\ classification.py:1344: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
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```

Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

_warn_prf(average, modifier, msg_start, len(result))

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packages\sklearn\metrics_classification.py:1344: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

_warn_prf(average, modifier, msg_start, len(result))

Best parameters set found on train set:
{'C': 1, 'degree': 5, 'kernel': 'poly'}

```
Grid scores on train set:
0.809 (+/-0.031) for {'C': 1, 'kernel': 'rbf'}
0.815 (+/-0.029) for {'C': 10, 'kernel': 'rbf'}
0.815 (+/-0.029) for {'C': 100, 'kernel': 'rbf'}
0.815 (+/-0.029) for {'C': 1000, 'kernel': 'rbf'}
0.811 (+/-0.025) for {'C': 1, 'kernel': 'linear'}
0.801 (+/-0.034) for {'C': 10, 'kernel': 'linear'}
0.801 (+/-0.027) for {'C': 100, 'kernel': 'linear'}
0.802 (+/-0.022) for {'C': 1000, 'kernel': 'linear'}
0.800 (+/-0.022) for {'C': 1, 'degree': 3, 'kernel': 'poly'}
0.883 (+/-0.033) for {'C': 1, 'degree': 5, 'kernel': 'poly'}
0.846 (+/-0.031) for {'C': 10, 'degree': 3, 'kernel': 'poly'}
0.839 (+/-0.079) for {'C': 10, 'degree': 5, 'kernel': 'poly'}
0.878 (+/-0.045) for {'C': 100, 'degree': 3, 'kernel': 'poly'}
0.773 (+/-0.063) for {'C': 100, 'degree': 5, 'kernel': 'poly'}
0.809 (+/-0.029) for {'C': 1, 'coef0': 0, 'kernel': 'sigmoid'}
0.813 (+/-0.032) for {'C': 1, 'coef0': 1, 'kernel': 'sigmoid'}
0.783 (+/-0.025) for {'C': 10, 'coef0': 0, 'kernel': 'sigmoid'}
0.774 (+/-0.038) for {'C': 10, 'coef0': 1, 'kernel': 'sigmoid'}
0.778 (+/-0.020) for {'C': 100, 'coef0': 0, 'kernel': 'sigmoid'}
0.695 (+/-0.031) for {'C': 100, 'coef0': 1, 'kernel': 'sigmoid'}
```

Detailed classification report:

The scores are computed on test set.

	precision	recall	f1-score	support
0	0.93	0.04	0.08	319
1	0.90	0.12	0.21	389
2	0.87	0.10	0.18	394
3	0.88	0.10	0.18	385
4	0.12	1.00	0.21	397
5	0.96	0.20	0.33	399
6	0.85	0.13	0.22	396
7	0.81	0.06	0.10	393
8	0.88	0.15	0.25	394
9	0.00	0.00	0.00	251

accuracy			0.20	3717
macro avg	0.72	0.19	0.18	3717
weighted avg	0.74	0.20	0.19	3717

Tuning hyper-parameters for recall_macro

Best parameters set found on train set:
{'C': 1, 'kernel': 'linear'}

```
Grid scores on train set:
0.769 (+/-0.026) for {'C': 1, 'kernel': 'rbf'}
0.786 (+/-0.030) for {'C': 10, 'kernel': 'rbf'}
0.786 (+/-0.030) for {'C': 100, 'kernel': 'rbf'}
0.786 (+/-0.030) for {'C': 1000, 'kernel': 'rbf'}
0.788 (+/-0.029) for {'C': 1, 'kernel': 'linear'}
0.763 (+/-0.040) for {'C': 10, 'kernel': 'linear'}
0.695 (+/-0.029) for {'C': 100, 'kernel': 'linear'}
0.688 (+/-0.032) for {'C': 1000, 'kernel': 'linear'}
0.601 (+/-0.051) for {'C': 1, 'degree': 3, 'kernel': 'poly'}
0.255 (+/-0.022) for {'C': 1, 'degree': 5, 'kernel': 'poly'}
0.378 (+/-0.065) for {'C': 10, 'degree': 3, 'kernel': 'poly'}
0.172 (+/-0.034) for {'C': 10, 'degree': 5, 'kernel': 'poly'}
0.153 (+/-0.038) for {'C': 100, 'degree': 3, 'kernel': 'poly'}
0.118 (+/-0.011) for {'C': 100, 'degree': 5, 'kernel': 'poly'}
0.782 (+/-0.033) for {'C': 1, 'coef0': 0, 'kernel': 'sigmoid'}
0.723 (+/-0.034) for {'C': 1, 'coef0': 1, 'kernel': 'sigmoid'}
0.758 (+/-0.029) for {'C': 10, 'coef0': 0, 'kernel': 'sigmoid'}
0.763 (+/-0.036) for {'C': 10, 'coef0': 1, 'kernel': 'sigmoid'}
0.701 (+/-0.027) for {'C': 100, 'coef0': 0, 'kernel': 'sigmoid'}
0.658 (+/-0.022) for {'C': 100, 'coef0': 1, 'kernel': 'sigmoid'}
```

Detailed classification report:

The scores are computed on test set.

	precision	recall	f1-score	support
0	0.59	0.59	0.59	319
1	0.71	0.77	0.74	389
2	0.80	0.68	0.74	394
3	0.80	0.72	0.76	385
4	0.83	0.83	0.83	397
5	0.91	0.84	0.87	399
6	0.88	0.72	0.79	396
7	0.63	0.71	0.67	393
8	0.57	0.81	0.67	394
9	0.62	0.53	0.57	251

```
accuracy 0.73 3717
macro avg 0.74 0.72 0.72 3717
weighted avg 0.74 0.73 0.73 3717
```

```
[]: # I had trouble debugging the code above,
# I tried several different methods in defining the scoring metrics and editing_
the GridSearchCV itself.

[14]: # GridSearch Ontimize NB
```

```
[14]: # GridSearch Optimize NB
      print("\nOptimizing Naive Bayes...")
      nb_parameters = {
          'alpha': [0.1, 0.5, 1.0, 2.0, 5.0]
      }
      for score in scores:
          print(f"\nTuning NB hyper-parameters for {score}")
          nb_clf = GridSearchCV(
              MultinomialNB(),
              nb_parameters,
              scoring=score # Remove the _macro suffix since 'scores' already_
       \hookrightarrow includes it
          nb_clf.fit(X_train, y_train)
          print("\nBest parameters found:")
          print(nb_clf.best_params_)
          print("\nGrid scores on training set:")
          means = nb_clf.cv_results_['mean_test_score']
          stds = nb clf.cv results ['std test score']
          for mean, std, params in zip(means, stds, nb_clf.cv_results_['params']):
              print(f''\{mean:0.3f\} (+/-\{std*2:0.03f\}) \text{ for } \{params\}'')
          print("\nDetailed classification report on test set:")
          y_pred = nb_clf.predict(X_test)
          print(classification_report(y_test, y_pred))
```

Optimizing Naive Bayes...

Tuning NB hyper-parameters for precision_macro

Best parameters found:
{'alpha': 0.1}

Grid scores on training set:

0.832 (+/-0.033) for {'alpha': 0.1} 0.813 (+/-0.032) for {'alpha': 0.5} 0.803 (+/-0.036) for {'alpha': 1.0} 0.790 (+/-0.057) for {'alpha': 2.0} 0.775 (+/-0.050) for {'alpha': 5.0}

Detailed classification report on test set:

	precision	recall	f1-score	support
0	0.66	0.65	0.66	319
1	0.75	0.78	0.76	389
2	0.81	0.70	0.75	394
3	0.80	0.77	0.79	385
4	0.92	0.85	0.88	397
5	0.71	0.94	0.81	399
6	0.66	0.84	0.74	396
7	0.83	0.68	0.75	393
8	0.79	0.83	0.81	394
9	0.75	0.43	0.54	251
accuracy			0.76	3717
macro avg	0.77	0.75	0.75	3717
weighted avg	0.77	0.76	0.76	3717

Tuning NB hyper-parameters for recall_macro

Best parameters found:

{'alpha': 0.1}

Grid scores on training set:

0.810 (+/-0.028) for {'alpha': 0.1} 0.774 (+/-0.018) for {'alpha': 0.5} 0.755 (+/-0.021) for {'alpha': 1.0} 0.733 (+/-0.030) for {'alpha': 2.0} 0.699 (+/-0.025) for {'alpha': 5.0}

Detailed classification report on test set:

	precision	recall	f1-score	support
0	0.66	0.65	0.66	319
1	0.75	0.78	0.76	389
2	0.81	0.70	0.75	394
3	0.80	0.77	0.79	385
4	0.92	0.85	0.88	397
5	0.71	0.94	0.81	399
6	0.66	0.84	0.74	396

7	0.83	0.68	0.75	393
8	0.79	0.83	0.81	394
9	0.75	0.43	0.54	251
accuracy			0.76	3717
macro avg	0.77	0.75	0.75	3717
weighted avg	0.77	0.76	0.76	3717