Supervised Learning Algorithms Comparison with MNIST-Data

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Testing Scikit-Learn-Classes with preprocessed MNIST-Dataset

Imports

In [23]:

```
# Basics
import pandas as pd
import gzip
import os
import numpy as np

# Visualisation
%matplotlib inline
import matplotlib.pyplot as plt

# Scikit Learn Algos
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression

# Scikit Learn Pipeline
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV
```

Loading MNIST

In [2]:

```
train_data = os.path.join("./", "train-images-idx3-ubyte.gz")
train_labels = os.path.join("./", "train-labels-idx1-ubyte.gz")

test_data = os.path.join("./", "t10k-images-idx3-ubyte.gz")
test_labels = os.path.join("./", "t10k-labels-idx1-ubyte.gz")
```

In [3]:

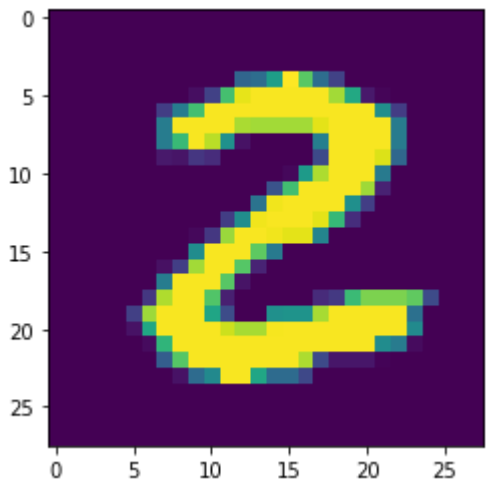
```
# Division by 255 to speed up compute time

def mnist_images(filename):
    with gzip.open(filename, "rb") as file:
        data = np.frombuffer(file.read(), np.uint8, offset = 16)
        return data.reshape(-1, 28, 28) / 255

def mnist_labels(filename):
    with gzip.open(filename, "rb") as file:
        return np.frombuffer(file.read(), np.uint8, offset = 8)

X_train = mnist_images(train_data)
y_train = mnist_labels(train_labels)

X_test = mnist_images(test_data)
y_test = mnist_labels(test_labels)
```

First look

In [4]:

```
print(y_train[25])
plt.imshow(X_train[25])
plt.show()
```

2



Reduces sample for first analysis, to reduce compute time

In [5]:

```
X_train_1000 = X_train[0:1000]
X_test_1000 = X_test[0:1000]
y_train_1000 = y_train[0:1000]
y_test_1000 = y_test[0:1000]
```

Logistic Regression

In [6]:

```
# Saga
model = LogisticRegression(solver = "saga", n_jobs = 4)
model.fit(X_train_1000.reshape(-1, 784), y_train_1000)
```

```
/Users/roeper/anaconda3/lib/python3.7/site-packages/sklearn/linear_m
odel/logistic.py:469: FutureWarning: Default multi_class will be cha
nged to 'auto' in 0.22. Specify the multi_class option to silence th
is warning.
  "this warning.", FutureWarning)
/Users/roeper/anaconda3/lib/python3.7/site-packages/sklearn/linear_m
odel/sag.py:337: ConvergenceWarning: The max_iter was reached which
means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
```

Out[6]:

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_interce
pt=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='warn', n_jobs=4, penalty='l2',
                   random_state=None, solver='saga', tol=0.0001, ver
bose=0,
                   warm_start=False)
```

In [7]:

```
model.score(X_test_1000.reshape(-1, 784), y_test_1000)
```

Out[7]:

```
0.847
```

In [8]:

```
# sag
model = LogisticRegression(solver = "sag", n_jobs = 4)
model.fit(X_train_1000.reshape(-1, 784), y_train_1000)
model.score(X_test_1000.reshape(-1, 784), y_test_1000)
```

```
/Users/roeper/anaconda3/lib/python3.7/site-packages/sklearn/linear_m
odel/logistic.py:469: FutureWarning: Default multi_class will be cha
nged to 'auto' in 0.22. Specify the multi_class option to silence th
is warning.
  "this warning.", FutureWarning)
/Users/roeper/anaconda3/lib/python3.7/site-packages/sklearn/linear_m
odel/sag.py:337: ConvergenceWarning: The max_iter was reached which
means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
```

Out[8]:

```
0.848
```

In [9]:

```
# newton-cg
model = LogisticRegression(solver = "newton-cg", n_jobs = 4)
model.fit(X_train_1000.reshape(-1, 784), y_train_1000)
model.score(X_test_1000.reshape(-1, 784), y_test_1000)
```

```
/Users/roeper/anaconda3/lib/python3.7/site-packages/sklearn/linear_m
odel/logistic.py:469: FutureWarning: Default multi_class will be cha
nged to 'auto' in 0.22. Specify the multi_class option to silence th
is warning.
  "this warning.", FutureWarning)
```

Out[9]:

```
0.843
```

In [10]:

```
%%time
# sag wins, so ...
# use sag with the full dataset
# and measure the time

model = LogisticRegression(solver = "sag", n_jobs = 4)
model.fit(X_train.reshape(-1, 784), y_train)
model.score(X_test.reshape(-1, 784), y_test)
```

```
/Users/roeper/anaconda3/lib/python3.7/site-packages/sklearn/linear_m
odel/logistic.py:469: FutureWarning: Default multi_class will be cha
nged to 'auto' in 0.22. Specify the multi_class option to silence th
is warning.
  "this warning.", FutureWarning)
/Users/roeper/anaconda3/lib/python3.7/site-packages/sklearn/linear_m
odel/sag.py:337: ConvergenceWarning: The max_iter was reached which
means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)

CPU times: user 4min 51s, sys: 298 ms, total: 4min 51s
Wall time: 1min 26s
```

Out[10]:

```
0.92
```

In [ ]:

In [ ]:

KNN

In [11]:

```
model = KNeighborsClassifier(n_neighbors=10)
model.fit(X_train_1000.reshape(-1, 784), y_train_1000)
print(model.score(X_test_1000.reshape(-1, 784), y_test_1000))
```

```
0.799
```

In [12]:

```
%%time
model = KNeighborsClassifier(n_neighbors=10)
model.fit(X_train.reshape(-1, 784), y_train)
print(model.score(X_test.reshape(-1, 784), y_test))
```

```
0.9665
CPU times: user 9min 12s, sys: 180 ms, total: 9min 12s
Wall time: 9min 11s
```

... took the double of time compared to LR, but the score is significant better :-)

Naive Bayes

In [13]:

```
model = GaussianNB()
model.fit(X_train_1000.reshape(-1, 784), y_train_1000)
print(model.score(X_test_1000.reshape(-1, 784), y_test_1000))
```

```
0.625
```

In [16]:

```
%%time
model = GaussianNB()
model.fit(X_train.reshape(-1, 784), y_train)
print(model.score(X_test.reshape(-1, 784), y_test))
```

```
0.5558
CPU times: user 5.13 s, sys: 252 ms, total: 5.38 s
Wall time: 1.11 s
```

... really fast, but with a disappointing result.

Decision Tree

In [17]:

```
model = DecisionTreeClassifier(criterion="entropy")
model.fit(X_train_1000.reshape(-1, 784), y_train_1000)
print(model.score(X_test_1000.reshape(-1, 784), y_test_1000))
```

```
0.639
```

In [18]:

```
%%time
model = DecisionTreeClassifier(criterion="entropy")
model.fit(X_train.reshape(-1, 784), y_train)
print(model.score(X_test.reshape(-1, 784), y_test))
```

```
0.8878
CPU times: user 13.6 s, sys: 59.4 ms, total: 13.6 s
Wall time: 13.6 s
```

... fast and the second best result. Interesting!

SVM

In [19]:

```
model = SVC(kernel="linear")
model.fit(X_train_1000.reshape(-1, 784), y_train_1000)
print(model.score(X_test_1000.reshape(-1, 784), y_test_1000))
```

```
0.853
```

In [20]:

```
%%time
model = SVC(kernel="linear")
model.fit(X_train.reshape(-1, 784), y_train)
print(model.score(X_test.reshape(-1, 784), y_test))
```

```
0.9404
CPU times: user 7min 3s, sys: 1.18 s, total: 7min 4s
Wall time: 7min 3s
```

... okay, nice result, worth the time. But KNN was slightly better (and took a two minutes longer)

SVM with Kernel

First test with fixed hyperparameters

In [21]:

```
model = SVC(kernel="rbf", gamma=0.01, C=1)
model.fit(X_train_1000.reshape(-1, 784), y_train_1000)
print(model.score(X_test_1000.reshape(-1, 784), y_test_1000))
```

```
0.869
```

Let's create a pipeline to find the best hyperparameters, before going with the full dataset

In [25]:

```
pipeline = Pipeline([
    ("svm", SVC())
])
clf = GridSearchCV(pipeline, param_grid = {
    "svm__C": [0.001, 0.01, 0.1, 1, 10],
    "svm__gamma": [0.001, 0.01, 0.1, 1, 10]
})
clf.fit(X_train_1000.reshape(-1, 784), y_train_1000)
print(clf.best_params_)
print(clf.score(X_test_1000.reshape(-1, 784), y_test_1000))
```

```
/Users/roeper/anaconda3/lib/python3.7/site-packages/sklearn/model_se
lection/_split.py:1978: FutureWarning: The default value of cv will
change from 3 to 5 in version 0.22. Specify it explicitly to silence
this warning.
  warnings.warn(CV_WARNING, FutureWarning)
/Users/roeper/anaconda3/lib/python3.7/site-packages/sklearn/model_se
lection/_search.py:813: DeprecationWarning: The default of the `iid`
parameter will change from True to False in version 0.22 and will be
removed in 0.24. This will change numeric results when test-set size
s are unequal.
  DeprecationWarning)

{'svm__C': 10, 'svm__gamma': 0.01}
0.885
```

... with these hyperparameters let's do the final test with the full dataset

In [26]:

```
%%time
model = SVC(kernel="rbf", gamma=0.01, C=10)
model.fit(X_train.reshape(-1, 784), y_train)
print(model.score(X_test.reshape(-1, 784), y_test))
```

```
0.9833
CPU times: user 6min, sys: 925 ms, total: 6min 1s
Wall time: 6min 1s
```

... and the winner is: SVM with kernel, with tuned hyperparameters

Score 0.9833, time 6:01 minutes