

## Lab 4

Mayank Shouche, ms73656

Daniel Li, ddl933

Sunny Kharel, sk37963

**Problem 1: Logistic Regression and CIFAR-10.** In this problem you will explore the dataset CIFAR-10, and you will use multinomial (multi-label) Logistic Regression to try to classify it. You will also explore visualizing the solution.

Use the `fetch_openml` command from `sklearn.datasets` to import the CIFAR-10-Small data set.

```
In [ ]: from sklearn.datasets import fetch_openml  
dataset = fetch_openml('CIFAR_10_small')
```

Figure out how to display some of the images in this data set, and display a couple. While not high resolution, these should be recognizable if you are doing it correctly. ¶

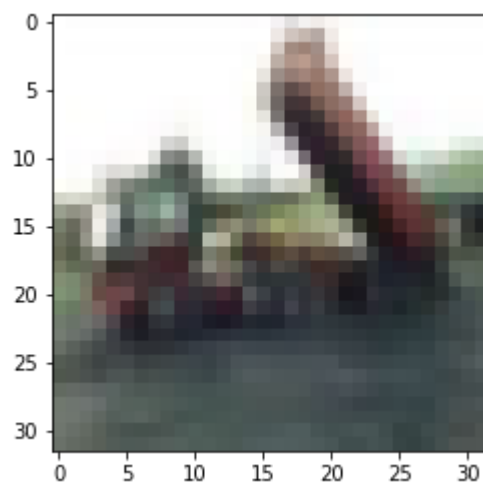
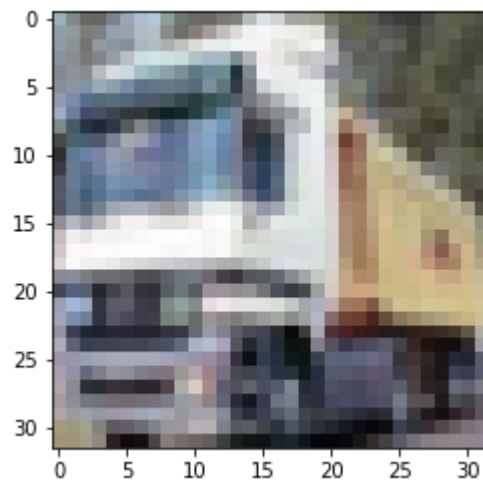
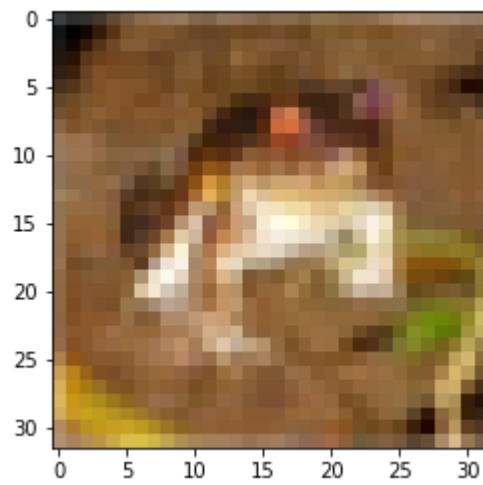
```
In [ ]: import matplotlib.pyplot as plt
import numpy as np
%matplotlib inline

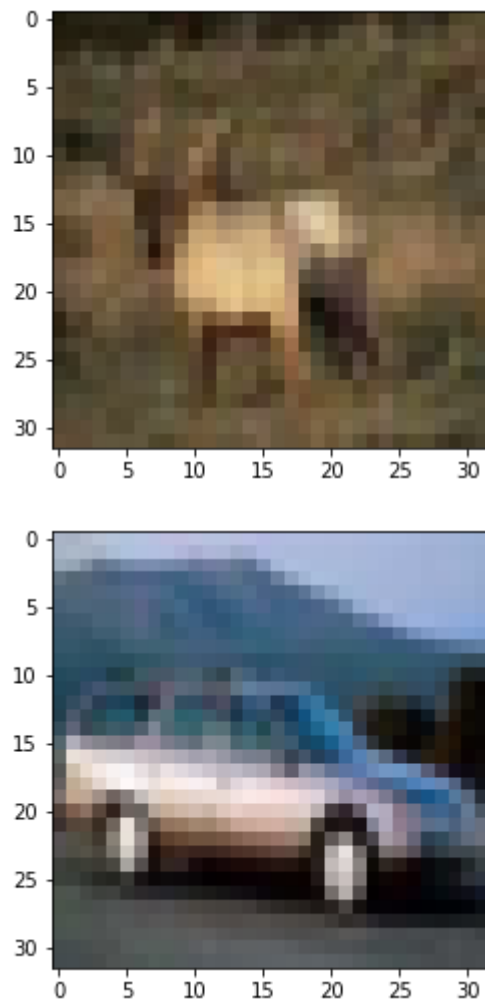
for i in range(5):
    plt.figure(i)

    img_raw = dataset['data'][i]
    r = img_raw[0:1024].reshape(32, 32)/255.0
    g = img_raw[1024:2048].reshape(32, 32)/255.0
    b = img_raw[2048:].reshape(32, 32)/255.0

    img = np.dstack((r, g, b))

    plt.imshow(img)
```





There are 20,000 data points. Do a train-test split on 3/4 - 1/4.

```
In [ ]: from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(dataset['data'],
dataset['target'], test_size=0.25)

print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)

(15000, 3072) (5000, 3072) (15000,) (5000,)
```

You will run multi-class logistic regression on these using the cross entropy loss. You have to specify this specifically (multiclass='multinomial'). Use cross validation to see how good your accuracy can be. In this case, cross validate to find as good regularization coefficients as you can, for l1 and l2 regularization (called penalties), which are naturally supported in `sklearn.linear_model.LogisticRegression`. I recommend you use the solver saga.

```
In [ ]: from sklearn.linear_model import LogisticRegressionCV
from sklearn.metrics import log_loss

model_l1 = LogisticRegressionCV(solver='saga',
                                multi_class='multinomial',
                                n_jobs=-1,
                                tol=0.1,
                                penalty='l1',
                                scoring='neg_log_loss').fit(X_train, y_train)

model_l2 = LogisticRegressionCV(solver='saga',
                                multi_class='multinomial',
                                n_jobs=-1,
                                tol=0.1,
                                penalty='l2',
                                scoring='neg_log_loss').fit(X_train, y_train)
```

```
In [ ]: print('l1 coef:', 1/model_l1.C_[0])
print('l2 coef:', 1/model_l2.C_[0])
```

```
l1 coef: 0.3593813663804626
l2 coef: 166.81005372000593
```

**Report your training and test loss from above.**

```
In [ ]: print("Train w/ l1:", np.abs(model_l1.score(X_train, y_train)))
print("Test w/ l1:", np.abs(model_l1.score(X_test, y_test)))

print("Train w/ l2:", np.abs(model_l2.score(X_train, y_train)))
print("Test w/ l2:", np.abs(model_l2.score(X_test, y_test)))
```

```
Train w/ l1: 1.6296040666090694
Test w/ l1: 1.762818066401256
Train w/ l2: 1.6341026544055688
Test w/ l2: 1.772966737275393
```

**How sparse can you make your solutions without deteriorating your testing error too much? Here, we ask for a sparse solution that has test accuracy that is close to the best solution you found.**

```
In [ ]: from sklearn.linear_model import LogisticRegressionCV
from sklearn.metrics import log_loss

regs = [1e-5, 5e-4, 1e-3, 5e-3, 1e-2, 1e-1, 1]
for reg in regs:
    sparse_model = LogisticRegressionCV(solver='saga',
                                       multi_class='multinomial',
                                       n_jobs=-1,
                                       tol=0.1,
                                       penalty='l1',
                                       Cs=[reg]).fit(X_train, y_train)

    sparse_model.scoring = 'neg_log_loss'
    print(reg, np.abs(sparse_model.score(X_test, y_test)))
```

```
1e-05 2.3025850950869753
0.0005 1.7767636930883317
0.001 1.7676368653290497
0.005 1.761947968320324
0.01 1.768226351513758
0.1 1.763062933403209
1 1.765298939611872
```

```
In [ ]: from sklearn.linear_model import LogisticRegression
most_sparse_model = LogisticRegression(solver='saga',
                                       multi_class='multinomial',
                                       n_jobs=-1,
                                       tol=0.1,
                                       penalty='l1',
                                       C=0.0005).fit(X_train, y_train)

print(most_sparse_model.coef_.shape)
```

```
(10, 3072)
```

```
In [27]: zeros = np.sum([1 for x in most_sparse_model.coef_.flatten() if x ==
0])
print(f'Sparsity: {zeros/3072:.2f}%')
```

```
Sparsity: 1.15%
```

Looks like we can go as high as  $1/0.0005 = 2000$  for  $\ell_1$  regularization coefficient while not really sacrificing anything in terms of log-loss.

## Problem 2: Multi-class Logistic Regression – Visualizing the Solution

```
In [ ]: from sklearn.datasets import fetch_openml
from sklearn.model_selection import train_test_split
import numpy as np
```

```
In [ ]: train_samples = 5000
        test_samples = 10000

X, y = fetch_openml('mnist_784', version=1, return_X_y=True)
```

```
/usr/lib/python3.5/importlib/_bootstrap.py:222: RuntimeWarning: numpy.ufunc size changed, may indicate binary incompatibility. Expected 192 from C header, got 216 from PyObject
    return f(*args, **kwargs)
```

```
In [ ]: X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=
        train_samples, test_size=test_samples)
```

```
In [ ]: from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

```
In [ ]: from sklearn.linear_model import LogisticRegression

'''
Note that 'sag' and 'saga' fast convergence is only guaranteed on fea
tures with approximately the same scale.
You can preprocess the data with a scaler from sklearn.preprocessing.
'''

'''
tol: the min change in update until optimization stops
'''

'''
C = 1/lambda, inverse regularization
'''
```

```
Out[ ]: LogisticRegression(C=0.01, class_weight=None, dual=False, fit_interce
        pt=True,
                                intercept_scaling=1, l1_ratio=None, max_iter=100,
                                multi_class='multinomial', n_jobs=None, penalty='l
2',
                                random_state=None, solver='saga', tol=0.01, verbos
e=0,
                                warm_start=False)
```

```
In [ ]: clf1 = LogisticRegression(C=50. / train_samples, solver='saga', tol=
0.01, multi_class='multinomial')
clf1.fit(X_train,y_train)

sparsity = np.mean(clf1.coef_ == 0) * 100
score = clf1.score(X_test, y_test)

print("Sparsity with Cross-entropy penalty: %.2f%%" % sparsity)
print("Test score with Cross Entropy penalty: %.4f" % score)
```

Sparsity with L1 penalty: 16.45%  
 Test score with L1 penalty: 0.8955

## Cross Entropy Loss without L1 Regularization

```
In [ ]: clf1 = LogisticRegression(solver='saga', tol=0.01, multi_class='multi
nomial')
clf1.fit(X_train,y_train)
```

```
Out[ ]: LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercep
t=True,
                           intercept_scaling=1, l1_ratio=None, max_iter=100,
                           multi_class='multinomial', n_jobs=None, penalty='l
2',
                           random_state=None, solver='saga', tol=0.01, verbos
e=0,
                           warm_start=False)
```

```
In [ ]: sparsity = np.mean(clf1.coef_ == 0) * 100
train_score = clf1.score(X_train, y_train)
test_score = clf1.score(X_test, y_test)

print("Sparsity with Cross-entropy loss: %.2f%%" % sparsity)
print("Train score with Cross Entropy loss: %.4f" % train_score)
print("Test score with Cross Entropy loss: %.4f" % test_score)
```

Sparsity with Cross-entropy loss: 16.45%  
 Train score with Cross Entropy loss: 0.9482  
 Test score with Cross Entropy loss: 0.8984

### Attempting to tune hyperparameters



```
In [ ]: ## tune on solver and tol
from sklearn.model_selection import GridSearchCV
clf_init = LogisticRegression(multi_class='multinomial')

param_test_tol = {
    'tol':[0.1, 0.01, 0.001, 0.0001],
    'solver': ['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga']
}
grid_search = GridSearchCV(estimator = clf_init,
                           param_grid = param_test_tol,
                           scoring='neg_log_loss', #neg_log_loss == c
                           ross-entropy
                           cv=5,
                           verbose=0)
```

```
In [ ]: grid_search.fit(X_train, y_train)
```

```
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

Increase the number of iterations (max\_iter) or scale the data as shown in:

<https://scikit-learn.org/stable/modules/preprocessing.html>

Please also refer to the documentation for alternative solver options:

[https://scikit-learn.org/stable/modules/linear\\_model.html#logistic-regression](https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression)

```
extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

```
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

Increase the number of iterations (max\_iter) or scale the data as shown in:

<https://scikit-learn.org/stable/modules/preprocessing.html>

Please also refer to the documentation for alternative solver options:

[https://scikit-learn.org/stable/modules/linear\\_model.html#logistic-regression](https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression)

```
extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

```
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

Increase the number of iterations (max\_iter) or scale the data as shown in:

<https://scikit-learn.org/stable/modules/preprocessing.html>

Please also refer to the documentation for alternative solver options:

[https://scikit-learn.org/stable/modules/linear\\_model.html#logistic-regression](https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression)

```
extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

```
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

Increase the number of iterations (max\_iter) or scale the data as shown in:

<https://scikit-learn.org/stable/modules/preprocessing.html>

Please also refer to the documentation for alternative solver options:

[https://scikit-learn.org/stable/modules/linear\\_model.html#logistic-regression](https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression)

```
extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

```
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

Increase the number of iterations (max\_iter) or scale the data as shown in:

<https://scikit-learn.org/stable/modules/preprocessing.html>

Please also refer to the documentation for alternative solver options:

[https://scikit-learn.org/stable/modules/linear\\_model.html#logistic-regression](https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression)

```
extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

Increase the number of iterations (max\_iter) or scale the data as shown in:

<https://scikit-learn.org/stable/modules/preprocessing.html>

Please also refer to the documentation for alternative solver options:

[https://scikit-learn.org/stable/modules/linear\\_model.html#logistic-regression](https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression)

```
extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

Increase the number of iterations (max\_iter) or scale the data as shown in:

<https://scikit-learn.org/stable/modules/preprocessing.html>

Please also refer to the documentation for alternative solver options:

[https://scikit-learn.org/stable/modules/linear\\_model.html#logistic-regression](https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression)

```
extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

Increase the number of iterations (max\_iter) or scale the data as shown in:

<https://scikit-learn.org/stable/modules/preprocessing.html>

Please also refer to the documentation for alternative solver options:

[https://scikit-learn.org/stable/modules/linear\\_model.html#logistic-regression](https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression)

```
extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

Increase the number of iterations (max\_iter) or scale the data as shown in:

<https://scikit-learn.org/stable/modules/preprocessing.html>

Please also refer to the documentation for alternative solver options:

```

https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

```

Increase the number of iterations (max\_iter) or scale the data as shown in:

```

https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:

```

```

https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

```

Increase the number of iterations (max\_iter) or scale the data as shown in:

```

https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:

```

```

https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

```

Increase the number of iterations (max\_iter) or scale the data as shown in:

```

https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:

```

```

https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

```

Increase the number of iterations (max\_iter) or scale the data as shown in:

```

https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:

```

```

https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning: lbfgs failed

```

```
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

Increase the number of iterations (max\_iter) or scale the data as shown in:

```
https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
https://scikit-learn.org/stable/modules/linear\_model.html#logistic-regression
extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

Increase the number of iterations (max\_iter) or scale the data as shown in:

```
https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
https://scikit-learn.org/stable/modules/linear\_model.html#logistic-regression
extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

Increase the number of iterations (max\_iter) or scale the data as shown in:

```
https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
https://scikit-learn.org/stable/modules/linear\_model.html#logistic-regression
extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

Increase the number of iterations (max\_iter) or scale the data as shown in:

```
https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
https://scikit-learn.org/stable/modules/linear\_model.html#logistic-regression
extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/linear_model/_logistic.py:940: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

Increase the number of iterations (max\_iter) or scale the data as shown in:

<https://scikit-learn.org/stable/modules/preprocessing.html>  
 Please also refer to the documentation for alternative solver options:  
[https://scikit-learn.org/stable/modules/linear\\_model.html#logistic-regression](https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression)  
 extra\_warning\_msg=\_LOGISTIC\_SOLVER\_CONVERGENCE\_MSG)  
 /home/sunny/fall\_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/linear\_model/\_logistic.py:940: ConvergenceWarning: lbfgs failed to converge (status=1):  
 STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max\_iter) or scale the data as shown in:

<https://scikit-learn.org/stable/modules/preprocessing.html>  
 Please also refer to the documentation for alternative solver options:  
[https://scikit-learn.org/stable/modules/linear\\_model.html#logistic-regression](https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression)  
 extra\_warning\_msg=\_LOGISTIC\_SOLVER\_CONVERGENCE\_MSG)  
 /home/sunny/fall\_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/linear\_model/\_logistic.py:940: ConvergenceWarning: lbfgs failed to converge (status=1):  
 STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max\_iter) or scale the data as shown in:

<https://scikit-learn.org/stable/modules/preprocessing.html>  
 Please also refer to the documentation for alternative solver options:  
[https://scikit-learn.org/stable/modules/linear\\_model.html#logistic-regression](https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression)  
 extra\_warning\_msg=\_LOGISTIC\_SOLVER\_CONVERGENCE\_MSG)  
 /home/sunny/fall\_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/model\_selection/\_validation.py:536: FitFailedWarning: Estimator fit failed. The score on this train-test partition for these parameters will be set to nan. Details:  
 ValueError: Solver liblinear does not support a multinomial backend.

FitFailedWarning)  
 /home/sunny/fall\_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/model\_selection/\_validation.py:536: FitFailedWarning: Estimator fit failed. The score on this train-test partition for these parameters will be set to nan. Details:  
 ValueError: Solver liblinear does not support a multinomial backend.

FitFailedWarning)  
 /home/sunny/fall\_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/model\_selection/\_validation.py:536: FitFailedWarning: Estimator fit failed. The score on this train-test partition for these parameters will be set to nan. Details:  
 ValueError: Solver liblinear does not support a multinomial backend.

FitFailedWarning)  
 /home/sunny/fall\_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/model\_selection/\_validation.py:536: FitFailedWarning: Estimator fit failed. The score on this train-test partition for these parameters will be set to nan. Details:

ValueError: Solver liblinear does not support a multinomial backend.

```
FitFailedWarning)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/model_selection/_validation.py:536: FitFailedWarning: Estimator fit failed. The score on this train-test partition for these parameters will be set to nan. Details:
ValueError: Solver liblinear does not support a multinomial backend.
```

```
FitFailedWarning)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/model_selection/_validation.py:536: FitFailedWarning: Estimator fit failed. The score on this train-test partition for these parameters will be set to nan. Details:
ValueError: Solver liblinear does not support a multinomial backend.
```

```
FitFailedWarning)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/model_selection/_validation.py:536: FitFailedWarning: Estimator fit failed. The score on this train-test partition for these parameters will be set to nan. Details:
ValueError: Solver liblinear does not support a multinomial backend.
```

```
FitFailedWarning)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/model_selection/_validation.py:536: FitFailedWarning: Estimator fit failed. The score on this train-test partition for these parameters will be set to nan. Details:
ValueError: Solver liblinear does not support a multinomial backend.
```

```
FitFailedWarning)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/model_selection/_validation.py:536: FitFailedWarning: Estimator fit failed. The score on this train-test partition for these parameters will be set to nan. Details:
ValueError: Solver liblinear does not support a multinomial backend.
```

```
FitFailedWarning)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/model_selection/_validation.py:536: FitFailedWarning: Estimator fit failed. The score on this train-test partition for these parameters will be set to nan. Details:
ValueError: Solver liblinear does not support a multinomial backend.
```

```
FitFailedWarning)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/model_selection/_validation.py:536: FitFailedWarning: Estimator fit failed. The score on this train-test partition for these parameters will be set to nan. Details:
ValueError: Solver liblinear does not support a multinomial backend.
```

```
FitFailedWarning)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/model_selection/_validation.py:536: FitFailedWarning: Estimator fit failed. The score on this train-test partition for these parameters will be set to nan. Details:
ValueError: Solver liblinear does not support a multinomial backend.
```



```
FitFailedWarning)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/model_selection/_validation.py:536: FitFailedWarning: Estimator fit failed. The score on this train-test partition for these parameters will be set to nan. Details:
ValueError: Solver liblinear does not support a multinomial backend.
```

```
FitFailedWarning)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/model_selection/_validation.py:536: FitFailedWarning: Estimator fit failed. The score on this train-test partition for these parameters will be set to nan. Details:
ValueError: Solver liblinear does not support a multinomial backend.
```

```
FitFailedWarning)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/model_selection/_validation.py:536: FitFailedWarning: Estimator fit failed. The score on this train-test partition for these parameters will be set to nan. Details:
ValueError: Solver liblinear does not support a multinomial backend.
```

```
FitFailedWarning)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/model_selection/_validation.py:536: FitFailedWarning: Estimator fit failed. The score on this train-test partition for these parameters will be set to nan. Details:
ValueError: Solver liblinear does not support a multinomial backend.
```

```
FitFailedWarning)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/model_selection/_validation.py:536: FitFailedWarning: Estimator fit failed. The score on this train-test partition for these parameters will be set to nan. Details:
ValueError: Solver liblinear does not support a multinomial backend.
```

```
FitFailedWarning)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/model_selection/_validation.py:536: FitFailedWarning: Estimator fit failed. The score on this train-test partition for these parameters will be set to nan. Details:
ValueError: Solver liblinear does not support a multinomial backend.
```

```
FitFailedWarning)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/model_selection/_validation.py:536: FitFailedWarning: Estimator fit failed. The score on this train-test partition for these parameters will be set to nan. Details:
ValueError: Solver liblinear does not support a multinomial backend.
```

```
FitFailedWarning)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/model_selection/_validation.py:536: FitFailedWarning: Estimator fit failed. The score on this train-test partition for these parameters will be set to nan. Details:
ValueError: Solver liblinear does not support a multinomial backend.
```

[illegible]

```

/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/linear_model/_sag.py:330: ConvergenceWarning: The max_iter was reached which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/linear_model/_sag.py:330: ConvergenceWarning: The max_iter was reached which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/linear_model/_sag.py:330: ConvergenceWarning: The max_iter was reached which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/linear_model/_sag.py:330: ConvergenceWarning: The max_iter was reached which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/linear_model/_sag.py:330: ConvergenceWarning: The max_iter was reached which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/linear_model/_sag.py:330: ConvergenceWarning: The max_iter was reached which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)
/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/linear_model/_sag.py:330: ConvergenceWarning: The max_iter was reached which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)

```

```

-----
-----
NameError                                Traceback (most recent call last)
<ipython-input-68-b6a47f09c0cb> in <module>
      1 grid_search.fit(X_train, y_train)
----> 2 grid_search.best_params_, gsearch1.best_score_

NameError: name 'gsearch1' is not defined

```

```
In [ ]: grid_search.best_params_, grid_search.best_score_
```

```
Out[ ]: ({'solver': 'saga', 'tol': 0.001}, -0.3475164287665922)
```

```
In [ ]: clf_best_params = LogisticRegression(solver='saga', multi_class='multinomial', tol=0.001)
        clf_best_params.fit(X_train, y_train)
        clf_best_params.score(X_test, y_test)
```

```

/home/sunny/fall_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/linear_model/_sag.py:330: ConvergenceWarning: The max_iter was reached which means the coef_ did not converge
  "the coef_ did not converge", ConvergenceWarning)

```

```
Out[ ]: 0.8991
```

```
In [ ]: grid_search_score = clf_best_params.score(X_test, y_test)

print("Test score before tuning: {}, test score after tuning: {}".format(test_score, grid_search_score))
print("Score increase {}".format(grid_search_score-test_score))
```

Test score before tuning: 0.8984, test score after tuning: 0.8991  
 Score increase 0.00070000000000000339

## Cross Entropy Loss with L1 Regularization

```
In [ ]: param_l1_reg = {
        'C':[10, 50, 100, 200, 400, 1000, 2000, 100000],
    }
clf_l1_reg_estimator = LogisticRegression(solver='saga', multi_class=
'multinomial', tol=0.001, penalty='l1')
grid_search_l1_reg = GridSearchCV(estimator = clf_l1_reg_estimator,
                                param_grid = param_l1_reg,
                                scoring='neg_log_loss', #neg_log_loss == c
                                ross-entropy
                                cv=5,
                                verbose=0)
```

```
In [ ]: grid_search_l1_reg.fit(X_train, y_train)
```

[illegible]

[illegible]





```

Out[ ]: GridSearchCV(cv=5, error_score=nan,
                    estimator=LogisticRegression(C=1.0, class_weight=None, dual=False,
                                                  fit_intercept=True,
                                                  intercept_scaling=1, l1_ratio=None,
                                                  max_iter=100,
                                                  multi_class='multinomial',
                                                  n_jobs=None, penalty='l1',
                                                  random_state=None, solver='saga',
                                                  tol=0.001, verbose=0,
                                                  warm_start=False),
                    iid='deprecated', n_jobs=None,
                    param_grid={'C': [10, 50, 100, 200, 400, 1000, 2000, 10000]},
                    pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
                    scoring='neg_log_loss', verbose=0)

```

```

In [ ]: grid_search_l1_reg.best_params_, grid_search_l1_reg.best_score_

```

```

Out[ ]: ({'C': 10}, -0.34736907065081774)

```

```

In [ ]: clf_params_l1_reg = LogisticRegression(solver='saga', multi_class='multinomial',
tol=0.001, C=10, penalty='l1', max_iter=100)
clf_params_l1_reg.fit(X_train, y_train)
regularization_score = clf_params_l1_reg.score(X_test, y_test)
regularization_score

```

/home/sunny/fall\_2020/ee460j/dslabenv/lib/python3.5/site-packages/sklearn/linear\_model/\_sag.py:330: ConvergenceWarning: The max\_iter was reached which means the coef\_ did not converge  
 "the coef\_ did not converge", ConvergenceWarning)

```

Out[ ]: 0.8991

```

```

In [ ]: sparsity_l1_reg = np.mean(clf2.coef_ == 0) * 100
regularization_score_train = clf_params_l1_reg.score(X_train, y_train)
regularization_score = clf_params_l1_reg.score(X_test, y_test)

print("Sparsity with Cross-entropy loss: %.2f%%" % sparsity_l1_reg)
print("Train score with Tuned-Cross Entropy loss and L1 Regularization: %.4f" % regularization_score_train)
print("Test score with Tuned-Cross Entropy loss and L1 Regularization: %.4f" % regularization_score)

```

Sparsity with Cross-entropy loss: 91.22%  
 Train score with Tuned-Cross Entropy loss and L1 Regularization: 0.9596  
 Test score with Tuned-Cross Entropy loss and L1 Regularization: 0.8991

Achieved the same score with l1 regularization

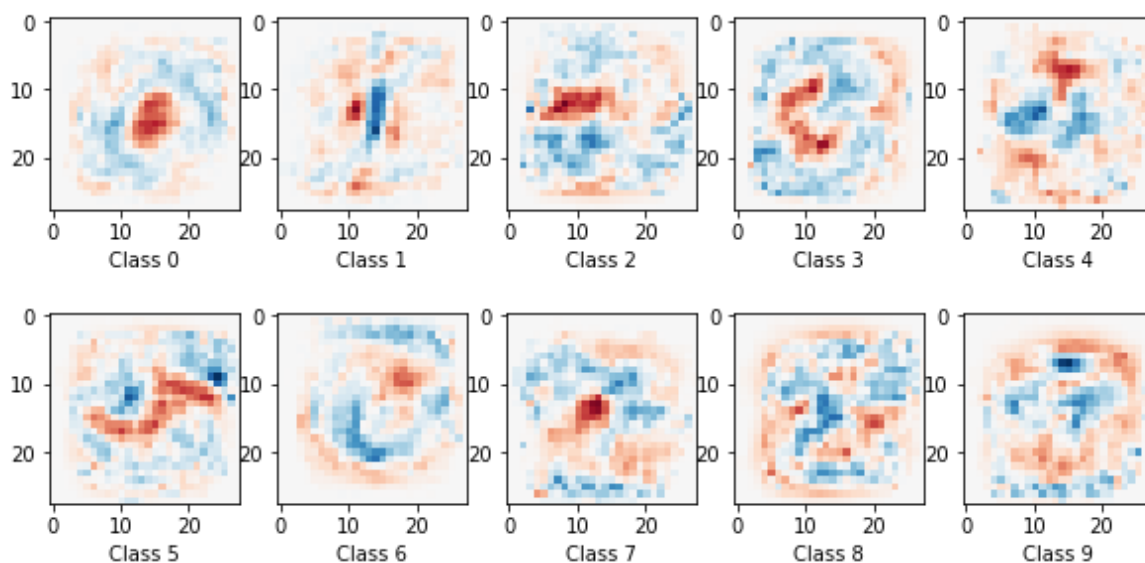
**Pretend that the coefficients of the solution are an image of the same dimension, and plot it.**

```
In [ ]: import matplotlib.pyplot as plt

coef = clf_params_l1_reg.coef_.copy()
plt.figure(figsize=(10, 5))
scale = np.abs(coef).max()
for i in range(10):
    l1_plot = plt.subplot(2, 5, i + 1)
    l1_plot.imshow(coef[i].reshape(28, 28), interpolation='nearest',
                  cmap=plt.cm.RdBu, vmin=-scale, vmax=scale)
    l1_plot.set_xlabel('Class %i' % i)
plt.suptitle('Classification vector for...')

plt.show()
```

Classification vector for...



### Problem 3: Revisiting Logistic Regression and MNIST

```
In [9]: from sklearn.datasets import fetch_openml
        from sklearn.model_selection import train_test_split
        import numpy as np

        train_samples = 5000
        test_samples = 5000

        X, y = fetch_openml('mnist_784', version=1, return_X_y=True)

        X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=
train_samples, test_size=test_samples)
```

### Performance without fine-tuning

```
In [10]: from sklearn.ensemble import RandomForestClassifier

        base_classifier = RandomForestClassifier()
        base_classifier.fit(X_train, y_train)
        base_score = base_classifier.score(X_test, y_test)
```

```
In [11]: print('Base score without fine tuning is: {}'.format(base_score))

Base score without fine tuning is: 0.9408
```

```
In [1]: from sklearn.model_selection import GridSearchCV

        params = {
            'max_depth': [10, 20, 30, 40, 50, 60, 70, 80, 90, 100, None],
            'criterion': ['gini', 'entropy'],
            'n_estimators': [500, 800, 1000, 1200, 1400, 1600, 1800, 2000]
        }

        gsearch = GridSearchCV(estimator = RandomForestClassifier(n_jobs = -1
, max_features='sqrt'), param_grid = params, scoring='accuracy', cv=5
, verbose = 4)
        gsearch.fit(X_train, y_train)

        #Run on colab for 4 hours
```

```
In [ ]: Best scoring group of hyper parameters

        #[CV] criterion=gini, max_depth=60, n_estimators=1000, score=0.959,
total= 12.4s
        #[CV] criterion=entropy, max_depth=30, n_estimators=1000, score=0.95
8, total= 10.8s
```

```
In [18]: # winner_rcf = RandomForestClassifier(n_jobs = -1, max_features='sqrt', criterion='gini', max_depth=60, n_estimators=1000)
# winner_rcf.fit(X_train, y_train)
score = winner_rcf.score(X_test, y_test)

print('Score of {} after tuning hyperparameters'.format(score))
```

Score of 0.9458 after tuning hyperparameters

```
In [22]: winner_rcf1 = RandomForestClassifier(n_jobs = -1, max_features='sqrt', criterion='entropy', max_depth=30, n_estimators=1000)
winner_rcf1.fit(X_train, y_train)
score2 = winner_rcf1.score(X_test, y_test)

print('Score of {} after tuning hyperparameters'.format(score2))
```

Score of 0.9452 after tuning hyperparameters

## Now using Gradient Boosting

```
In [16]: from scipy import stats
from scipy.stats import randint
from sklearn.model_selection import RandomizedSearchCV
from sklearn.metrics import precision_score, recall_score, accuracy_score, f1_score, roc_auc_score
from sklearn.model_selection import KFold

from sklearn.datasets import fetch_openml
from sklearn.model_selection import train_test_split
import numpy as np
```

```
In [15]: train_samples = 5000
test_samples = 10000

X, y = fetch_openml('mnist_784', version=1, return_X_y=True)
```

```
In [17]: X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=train_samples, test_size=test_samples)
```

## Run on colab

```
In [23]: import xgboost as xgb
from sklearn.model_selection import GridSearchCV
import warnings

clf_xgb = xgb.XGBClassifier(debug=2, colsample_bytree=0.8)

dtrain = xgb.DMatrix(X_train, label=y_train)
dtest = xgb.DMatrix(X_test)

param_dist = {'n_estimators': stats.randint(150, 1000),
              'learning_rate': stats.uniform(0.01, 0.6),
              'max_depth': [3, 4, 5, 6, 7, 8, 9],
              }
clf = RandomizedSearchCV(clf_xgb,
                        param_distributions = param_dist,
                        cv = 5,
                        n_iter = 10,
                        scoring = 'accuracy',
                        error_score = 0,
                        verbose = 3,
                        n_jobs = -1)
warnings.filterwarnings("ignore")
clf.fit(X_train, y_train)
```

best parameters after running on colab were the parameters as follows:

n\_estimators=1000, max\_depth=5, learning\_rate=0.3

```
In [12]: best_clf = xgb.XGBClassifier(n_estimators=1000, colsample_bytree=0.8,
learning_rate=0.3)
best_clf.fit(X_train,y_train)
score = best_clf.score(X_test, y_test)
```

```
In [25]: print('Score on gradient boosted model {}'.format(score))
```

Score on gradient boosted model 0.9493

## Problem 4: Revisiting Logistic Regression and CIFAR-10. As before, we'll throw the kitchen sink of classical ML (i.e. pre-deep learning) on CIFAR-10. Keep in mind that CIFAR-10 is a few times larger.

What is the best accuracy you can get on the test data, by tuning Random Forests? What are the hyperparameters of your best model?

```
In [1]: from sklearn.datasets import fetch_openml
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.model_selection import RandomizedSearchCV
        from sklearn.model_selection import train_test_split

        dataset = fetch_openml('CIFAR_10_small')

In [ ]: X_train, X_test, y_train, y_test = train_test_split(dataset['data'],
        dataset['target'], test_size=0.25)

        print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)

(15000, 3072) (5000, 3072) (15000,) (5000,)
```

```
In [ ]: random_grid = {
    'n_estimators': [int(x) for x in np.arange(50, 300, 10)],
    'max_features': ['auto', 'sqrt'],
    'max_depth': [int(x) for x in np.arange(50, 300, 10)] + [None],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'bootstrap': [True, False]
}

r = RandomForestClassifier()

model = RandomizedSearchCV(estimator=r, param_distributions=random_grid,
                           n_iter=100, cv=3, verbose=2, n_jobs=-1)
model.fit(X_train, y_train)
```

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

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
```

```
[Parallel(n_jobs=-1)]: Done 25 tasks      | elapsed: 7.6min
```

```
[Parallel(n_jobs=-1)]: Done 146 tasks    | elapsed: 33.8min
```

```
[Parallel(n_jobs=-1)]: Done 300 out of 300 | elapsed: 66.7min finished
```



```

-----
KeyboardInterrupt                                Traceback (most recent call
last)
<ipython-input-17-aa9b8924f04f> in <module>
    14
    15 model = RandomizedSearchCV(estimator=r, param_distributions=r
andom_grid, n_iter=100, cv=3, verbose=2, n_jobs=-1)
--> 16 model.fit(X_train, y_train)

~/local/lib/python3.8/site-packages/sklearn/utils/validation.py in i
nner_f(*args, **kwargs)
    70                                     FutureWarning)
    71     kwargs.update({k: arg for k, arg in zip(sig.parameter
s, args)})
--> 72     return f(**kwargs)
    73     return inner_f
    74

~/local/lib/python3.8/site-packages/sklearn/model_selection/_search.
py in fit(self, X, y, groups, **fit_params)
    763         refit_start_time = time.time()
    764         if y is not None:
--> 765             self.best_estimator_.fit(X, y, **fit_params)
    766         else:
    767             self.best_estimator_.fit(X, **fit_params)

~/local/lib/python3.8/site-packages/sklearn/ensemble/_forest.py in f
it(self, X, y, sample_weight)
    384         # parallel_backend contexts set at a higher leve
l,
    385         # since correctness does not rely on using thread
s.
--> 386         trees = Parallel(n_jobs=self.n_jobs, verbose=self
.verbose,
    387                         **_joblib_parallel_args(prefer=
'threads'))(
    388             delayed(_parallel_build_trees)(

~/local/lib/python3.8/site-packages/joblib/parallel.py in __call__(s
elf, iterable)
    1030         self._iterating = self._original_iterator is
not None
    1031
-> 1032         while self.dispatch_one_batch(iterator):
    1033             pass
    1034

~/local/lib/python3.8/site-packages/joblib/parallel.py in dispatch_o
ne_batch(self, iterator)
    845         return False
    846     else:
--> 847         self._dispatch(tasks)
    848         return True
    849

~/local/lib/python3.8/site-packages/joblib/parallel.py in _dispatch

```

```

(self, batch)
    763         with self._lock:
    764             job_idx = len(self._jobs)
--> 765             job = self._backend.apply_async(batch, callback=c
b)
    766             # A job can complete so quickly than its callback
is
    767             # called before we get here, causing self._jobs t
o

~/.local/lib/python3.8/site-packages/joblib/_parallel_backends.py in
apply_async(self, func, callback)
    206     def apply_async(self, func, callback=None):
    207         """Schedule a func to be run"""
--> 208         result = ImmediateResult(func)
    209         if callback:
    210             callback(result)

~/.local/lib/python3.8/site-packages/joblib/_parallel_backends.py in
__init__(self, batch)
    570         # Don't delay the application, to avoid keeping the i
nput
    571         # arguments in memory
--> 572         self.results = batch()
    573
    574     def get(self):

~/.local/lib/python3.8/site-packages/joblib/parallel.py in __call__(s
elf)
    250         # change the default number of processes to -1
    251         with parallel_backend(self._backend, n_jobs=self._n_j
obs):
--> 252             return [func(*args, **kwargs)
    253                     for func, args, kwargs in self.items]
    254

~/.local/lib/python3.8/site-packages/joblib/parallel.py in <listcomp>
(.0)
    250         # change the default number of processes to -1
    251         with parallel_backend(self._backend, n_jobs=self._n_j
obs):
--> 252             return [func(*args, **kwargs)
    253                     for func, args, kwargs in self.items]
    254

~/.local/lib/python3.8/site-packages/sklearn/ensemble/_forest.py in _
parallel_build_trees(tree, forest, X, y, sample_weight, tree_idx, n_t
rees, verbose, class_weight, n_samples_bootstrap)
    168         tree.fit(X, y, sample_weight=curr_sample_weight, chec
k_input=False)
    169     else:
--> 170         tree.fit(X, y, sample_weight=sample_weight, check_inp
ut=False)
    171
    172     return tree

~/.local/lib/python3.8/site-packages/sklearn/tree/_classes.py in fit

```

```

(self, X, y, sample_weight, check_input, X_idx_sorted)
    888         """
    889
--> 890         super().fit(
    891             X, y,
    892             sample_weight=sample_weight,

~/local/lib/python3.8/site-packages/sklearn/tree/_classes.py in fit
(self, X, y, sample_weight, check_input, X_idx_sorted)
    373         min_impurity_split)
    374
--> 375         builder.build(self.tree_, X, y, sample_weight, X_idx_
sorted)
    376
    377         if self.n_outputs_ == 1 and is_classifier(self):

```

KeyboardInterrupt:

In [ ]: model.best\_params\_

Out[ ]: {'n\_estimators': 250,  
'min\_samples\_split': 5,  
'min\_samples\_leaf': 2,  
'max\_features': 'auto',  
'max\_depth': 180,  
'bootstrap': False}

```

In [ ]: best_model = RandomForestClassifier(n_estimators= 250,
                                           min_samples_split= 5,
                                           min_samples_leaf= 2,
                                           max_features= 'auto',
                                           max_depth= 180,
                                           bootstrap= False,
                                           random_state= 42).fit(X_train, y_
train)

baseline_model = RandomForestClassifier(random_state=42).fit(X_train,
y_train)

```

```
In [ ]: from sklearn.metrics import confusion_matrix, roc_auc_score, classification_report, log_loss

best_pred = best_model.predict(X_test)
baseline_pred = baseline_model.predict(X_test)
print('Tuned AUC:\n', confusion_matrix(y_test, best_pred), '\n\n',
      'Baseline AUC:\n', confusion_matrix(y_test, baseline_pred))

print('\n\nTuned AUC:\n', classification_report(y_test, best_pred), '\n\n',
      'Baseline AUC:\n', classification_report(y_test, baseline_pred))

best_pred_proba = best_model.predict_proba(X_test)
baseline_pred_proba = baseline_model.predict_proba(X_test)

print('\n\nTuned AUC: (auc, log_loss)', roc_auc_score(y_test, best_pred_proba, multi_class='ovr'),
      ', ', log_loss(y_test, best_pred_proba))
print('Baseline AUC: (auc, log_loss)', roc_auc_score(y_test, baseline_pred_proba, multi_class='ovr'),
      ', ', log_loss(y_test, baseline_pred_proba))
```

Tuned AUC:

```
[[274 28 16 12 21 10 13 14 78 19]
 [ 15 262 3 13 14 16 11 24 24 103]
 [ 70 33 148 52 85 36 67 37 19 13]
 [ 29 15 35 136 40 89 77 25 15 42]
 [ 37 6 52 17 199 25 66 46 11 13]
 [ 17 16 25 66 37 187 44 32 15 22]
 [ 13 20 32 35 69 30 292 13 3 16]
 [ 28 27 16 25 78 47 21 214 11 47]
 [ 56 44 7 7 9 21 10 11 315 40]
 [ 21 59 4 16 7 12 13 16 31 298]]
```

Baseline AUC:

```
[[271 31 19 5 23 10 13 13 76 24]
 [ 17 248 3 20 16 14 17 24 32 94]
 [ 74 31 138 39 91 35 73 37 21 21]
 [ 35 19 39 127 54 81 70 31 9 38]
 [ 37 6 67 29 195 22 56 34 16 10]
 [ 20 23 38 81 39 161 43 18 11 27]
 [ 15 20 43 43 83 33 247 13 5 21]
 [ 29 23 27 28 87 55 26 187 11 41]
 [ 55 43 9 13 10 17 5 14 317 37]
 [ 24 67 3 15 6 17 17 18 40 270]]
```

Tuned AUC:

	precision	recall	f1-score	support
0	0.49	0.56	0.52	485
1	0.51	0.54	0.53	485
2	0.44	0.26	0.33	560
3	0.36	0.27	0.31	503
4	0.36	0.42	0.39	472
5	0.40	0.41	0.40	461
6	0.48	0.56	0.51	523
7	0.50	0.42	0.45	514
8	0.60	0.61	0.60	520
9	0.49	0.62	0.55	477
accuracy			0.47	5000
macro avg	0.46	0.47	0.46	5000
weighted avg	0.46	0.47	0.46	5000

Baseline AUC:

	precision	recall	f1-score	support
0	0.47	0.56	0.51	485
1	0.49	0.51	0.50	485
2	0.36	0.25	0.29	560
3	0.32	0.25	0.28	503
4	0.32	0.41	0.36	472
5	0.36	0.35	0.36	461
6	0.44	0.47	0.45	523
7	0.48	0.36	0.41	514
8	0.59	0.61	0.60	520
9	0.46	0.57	0.51	477

accuracy			0.43	5000
macro avg	0.43	0.43	0.43	5000
weighted avg	0.43	0.43	0.43	5000

Tuned AUC: (auc, log\_loss) 0.8549996866120487 , 1.6511792074987515  
 Baseline AUC: (auc, log\_loss) 0.8344963069087414 , 1.7177172152828577

Looks like, on average, the hyperparameter-tuned model performs slightly better than the baseline, with an accuracy of .47 vs .43, and better precision and recalls.

What is the best accuracy you can get on the test data, by tuning any model including Gradient boosting? What are the hyperparameters of your best model?

```
In [3]: import xgboost as xgb
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import confusion_matrix, roc_auc_score, classification_report, log_loss
from sklearn.datasets import fetch_openml
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import train_test_split

dataset = fetch_openml('CIFAR_10_small')

X_train, X_test, y_train, y_test = train_test_split(dataset['data'],
dataset['target'], test_size=0.25)
print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)

X_train /= 255.
X_test /= 255.

(15000, 3072) (5000, 3072) (15000,) (5000,)
```

```
In [20]: from sklearn.model_selection import RandomizedSearchCV, KFold
from scipy import stats
import numpy as np

param_dist = {'n_estimators': stats.randint(150, 500),
              'learning_rate': stats.uniform(0.01, 0.07),
              'subsample': stats.uniform(0.3, 0.7),
              'max_depth': [3, 4, 5, 6, 7, 8, 9],
              'colsample_bytree': stats.uniform(0.5, 0.45),
              'min_child_weight': [1, 2, 3]
              }

model = xgb.XGBClassifier()
rnd_search = RandomizedSearchCV(model,
                                param_distributions=param_dist,
                                n_iter=3,
                                cv=2,
                                verbose=5,
                                n_jobs = -1)

rnd_search.fit(X_train, y_train, verbose=5)
```

Fitting 2 folds for each of 3 candidates, totalling 6 fits

[Parallel(n\_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.

[Parallel(n\_jobs=-1)]: Done 3 out of 6 | elapsed: 42.5min remaining: 42.5min

[Parallel(n\_jobs=-1)]: Done 6 out of 6 | elapsed: 65.8min finished



```

-----
KeyboardInterrupt                                Traceback (most recent call
last)
<ipython-input-20-2beb50221de9> in <module>
    19                                     n_jobs = -1)
    20
--> 21 rnd_search.fit(X_train, y_train, verbose=5)

~/.local/lib/python3.8/site-packages/sklearn/utils/validation.py in i
nner_f(*args, **kwargs)
    70                                     FutureWarning)
    71                                     kwargs.update({k: arg for k, arg in zip(sig.parameter
s, args)})
--> 72                                     return f(**kwargs)
    73                                     return inner_f
    74

~/.local/lib/python3.8/site-packages/sklearn/model_selection/_search.
py in fit(self, X, y, groups, **fit_params)
    763                                     refit_start_time = time.time()
    764                                     if y is not None:
--> 765                                     self.best_estimator_.fit(X, y, **fit_params)
    766                                     else:
    767                                     self.best_estimator_.fit(X, **fit_params)

~/.local/lib/python3.8/site-packages/xgboost/sklearn.py in fit(self,
X, y, sample_weight, base_margin, eval_set, eval_metric, early_stopp
ing_rounds, verbose, xgb_model, sample_weight_eval_set, callbacks)
    826                                     missing=self.missing, nthread
=self.n_jobs)
    827
--> 828                                     self._Booster = train(xgb_options, train_dmatrix,
    829                                     self.get_num_boosting_rounds(),
    830                                     evals=evals,

~/.local/lib/python3.8/site-packages/xgboost/training.py in train(par
ams, dtrain, num_boost_round, evals, obj, feval, maximize, early_stop
ping_rounds, evals_result, verbose_eval, xgb_model, callbacks)
    206                                     callbacks.append(callback.record_evaluation(evals_res
ult))
    207
--> 208                                     return _train_internal(params, dtrain,
    209                                     num_boost_round=num_boost_round,
    210                                     evals=evals,

~/.local/lib/python3.8/site-packages/xgboost/training.py in _train_in
ternal(params, dtrain, num_boost_round, evals, obj, feval, xgb_model,
callbacks)
    73                                     # Skip the first update if it is a recovery step.
    74                                     if version % 2 == 0:
--> 75                                     bst.update(dtrain, i, obj)
    76                                     bst.save_rabit_checkpoint()
    77                                     version += 1

~/.local/lib/python3.8/site-packages/xgboost/core.py in update(self,
dtrain, iteration, fobj)

```

```

1157
1158         if fobj is None:
-> 1159             _check_call(_LIB.XGBoosterUpdateOneIter(self.handle,
1160                                                         ctypes.c_
int(iteration),
1161                                                         dtrain.handle))

```

KeyboardInterrupt:

In [21]: `rnd_search.best_params_`

```

Out[21]: {'colsample_bytree': 0.5379282694060158,
          'learning_rate': 0.07096741825751023,
          'max_depth': 7,
          'min_child_weight': 2,
          'n_estimators': 491,
          'subsample': 0.8877151910953791}

```

```

In [26]: best_model = xgb.XGBClassifier()
best_model.set_params(**rnd_search.best_params_)
best_model.fit(X_train, y_train)

prediction = best_model.predict(X_test)

print(classification_report(y_test, prediction))
print(confusion_matrix(y_test, prediction))

```

	precision	recall	f1-score	support
0	0.57	0.62	0.60	486
1	0.65	0.58	0.61	495
2	0.46	0.40	0.43	506
3	0.37	0.33	0.35	520
4	0.45	0.46	0.45	482
5	0.44	0.41	0.43	474
6	0.48	0.67	0.56	477
7	0.65	0.58	0.61	546
8	0.63	0.69	0.66	526
9	0.58	0.57	0.57	488
accuracy			0.53	5000
macro avg	0.53	0.53	0.53	5000
weighted avg	0.53	0.53	0.53	5000

```

[[302  8 17 13 10 11  9 12 83 21]
 [ 18 286  8 15  9  3 22 13 40 81]
 [ 51 12 202 46 59 35 53 26 16  6]
 [ 13 13 41 171 45 92 87 21 18 19]
 [ 24  2 77 26 220 16 64 38  7  8]
 [ 14  6 35 93 31 196 46 32 15  6]
 [  5  3 28 40 39 22 321  9  4  6]
 [ 15  7 20 34 60 39 26 315  4 26]
 [ 61 23  5  9  8 10 13  7 363 27]
 [ 26 81  7 15  7 17 22  8 28 277]]

```

We were definitely able to obtain a better score using a tuned xgboost model. Accuracy on the test set got to 0.53, versus the 0.47 we got from tuned random forests.

```
In [1]: %matplotlib inline
```

## Problem 5: Getting Started with Pytorch

### Loading MNIST Dataset

```
In [2]: # Loading Dataset libraries
from pathlib import Path
import requests
import pickle
import gzip
# Computational and Graphical libraries
from matplotlib import pyplot
import numpy as np
import torch
# Debugger Library
from IPython.core.debugger import set_trace

DATA_PATH = Path("data")
PATH = DATA_PATH / "mnist"

PATH.mkdir(parents=True, exist_ok=True)

URL = "http://deeplearning.net/data/mnist/"
FILENAME = "mnist.pkl.gz"

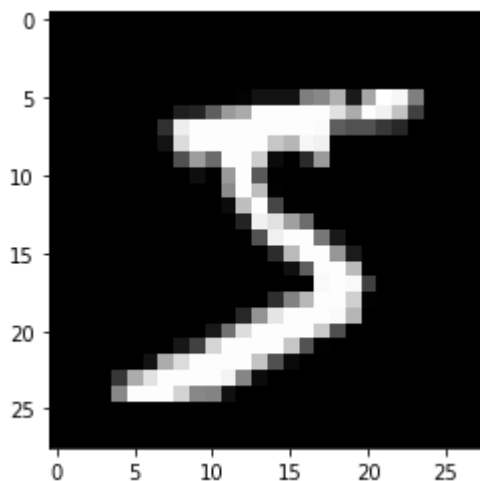
if not (PATH / FILENAME).exists():
    content = requests.get(URL + FILENAME).content
    (PATH / FILENAME).open("wb").write(content)

with gzip.open((PATH / FILENAME).as_posix(), "rb") as f:
    ((x_train, y_train), (x_valid, y_valid), _) = pickle.load(f,
encoding="latin-1")

pyplot.imshow(x_train[0].reshape((28, 28)), cmap="gray")
print(x_train.shape)

x_train, y_train, x_valid, y_valid = map(
    torch.tensor, (x_train, y_train, x_valid, y_valid)
)
```

(50000, 784)



**Is GPU available?**

```
In [3]: print(torch.cuda.is_available())  
dev = torch.device(  
    "cuda") if torch.cuda.is_available() else torch.device("cpu")
```

True

## Classes and Functions

```

In [4]: # Training and Validation Datasets/DataLoaders Libraries
from torch.utils.data import TensorDataset
from torch.utils.data import DataLoader
# Optim and NN libraries
from torch import optim
from torch import nn
import torch.nn.functional as F

def get_data(train_ds, valid_ds, bs):
    return (
        DataLoader(train_ds, batch_size=bs, shuffle=True),
        DataLoader(valid_ds, batch_size=bs * 2),
    )

loss_func = F.cross_entropy

def loss_batch(model, loss_func, xb, yb, opt=None):
    loss = loss_func(model(xb), yb)

    if opt is not None:
        loss.backward()
        opt.step()
        opt.zero_grad()

    return loss.item(), len(xb)

def fit(epochs, model, loss_func, opt, train_dl, valid_dl):
    for epoch in range(epochs):
        model.train()
        for xb, yb in train_dl:
            loss_batch(model, loss_func, xb, yb, opt)

        model.eval()
        with torch.no_grad():
            losses, nums = zip(
                *[loss_batch(model, loss_func, xb, yb) for xb, yb in
valid_dl]
            )
        val_loss = np.sum(np.multiply(losses, nums)) / np.sum(nums)
        val_acc = sum(accuracy(model(xb), yb) for xb, yb in valid_dl)
#valid_loss / len(valid_dl)

        val_acc = val_acc.cpu().detach().numpy()
        print(epoch, val_loss, val_acc / len(valid_dl))

class Lambda(nn.Module):
    def __init__(self, func):
        super().__init__()
        self.func = func

    def forward(self, x):
        return self.func(x)

def preprocess(x, y):
    return x.view(-1, 1, 28, 28).to(dev), y.to(dev)

```

```

class WrappedDataLoader:
    def __init__(self, dl, func):
        self.dl = dl
        self.func = func

    def __len__(self):
        return len(self.dl)

    def __iter__(self):
        batches = iter(self.dl)
        for b in batches:
            yield (self.func(*b))

# Accuracy check from Validation Test.
def accuracy(out, yb):
    preds = torch.argmax(out, dim=1)
    return (preds == yb).float().mean()

```

## Initial Variables

```

In [5]: bs = 64 # batch size
        lr = 0.1 # learning rate
        epochs = 2 # how many epochs to train for
        a = np.zeros((20, 10), dtype=(float,5))

```

## Training and Validation Datasets/DataLoaders

```

In [6]: train_ds = TensorDataset(x_train, y_train)
        valid_ds = TensorDataset(x_valid, y_valid)
        train_dl, valid_dl = get_data(train_ds, valid_ds, bs)
        train_dl = WrappedDataLoader(train_dl, preprocess)
        valid_dl = WrappedDataLoader(valid_dl, preprocess)

```

## Model and Optim (Use to do Foward Step)

```

In [7]: model = nn.Sequential(
        nn.Conv2d(1, 16, kernel_size=3, stride=2, padding=1),
        nn.ReLU(),
        nn.Conv2d(16, 16, kernel_size=3, stride=2, padding=1),
        nn.ReLU(),
        nn.Conv2d(16, 10, kernel_size=3, stride=2, padding=1),
        nn.ReLU(),
        nn.AdaptiveAvgPool2d(1),
        Lambda(lambda x: x.view(x.size(0), -1)),
    )
    model.to(dev)
    opt = optim.SGD(model.parameters(), lr=lr, momentum=0.9)

```

## Training of Model. Outputs Validation Loss.

```
In [8]: fit(epochs, model, loss_func, opt, train_dl, valid_dl)
0 0.339774385368824 0.8920094936708861
1 0.21009030851125718 0.9386867088607594
```

## Testing different learning rate and momentum values.



```

In [10]: def fit(epochs, model, loss_func, opt, train_dl, valid_dl, mat, lr, momentum):
    for epoch in range(epochs):
        model.train()
        for xb, yb in train_dl:
            loss_batch(model, loss_func, xb, yb, opt)

        model.eval()
        with torch.no_grad():
            losses, nums = zip(
                *[loss_batch(model, loss_func, xb, yb) for xb, yb in
valid_dl]
            )

            val_loss = np.sum(np.multiply(losses, nums)) / np.sum(nums)
            val_acc = sum(accuracy(model(xb), yb) for xb, yb in valid_dl)
#valid_loss / len(valid_dl)
            val_acc = val_acc.cpu().detach().numpy() / len(valid_dl)
            mat_data = (epoch, lr, momentum, val_loss, val_acc)
            mat[int(((lr*20)-2)+epoch)][int(momentum*10)] = mat_data
            print(epoch, val_loss, val_acc)
        return mat

#####
#####
model = nn.Sequential(
    nn.Conv2d(1, 16, kernel_size=3, stride=2, padding=1),
    nn.ReLU(),
    nn.Conv2d(16, 16, kernel_size=3, stride=2, padding=1),
    nn.ReLU(),
    nn.Conv2d(16, 10, kernel_size=3, stride=2, padding=1),
    nn.ReLU(),
    nn.AdaptiveAvgPool2d(1),
    Lambda(lambda x: x.view(x.size(0), -1)),
)
model.to(dev)
for x in range(10):          # Varying for LR from 0.1 to 1.0
    lr = (x+1)/10
    for y in range(10):      # Varying for Momentum 0.0 to 0.9
        momentum = y/10
        opt = optim.SGD(model.parameters(), lr=lr, momentum=momentum)
        print(lr, momentum)
        a = fit(epochs, model, loss_func, opt, train_dl, valid_dl, a, lr,
momentum)

```

```
0.1 0.0
0 1.4863000289916992 0.45905854430379744
1 1.1271489278793334 0.6269778481012658
0.1 0.1
0 0.6791762075424195 0.7776898734177216
1 0.6144604323863984 0.7991495253164557
0.1 0.2
0 0.3710880497455597 0.8862737341772152
1 0.37908401839733125 0.8816257911392406
0.1 0.3
0 0.2817768128156662 0.9165348101265823
1 0.2684560010433197 0.9212816455696202
0.1 0.4
0 0.25333035026788714 0.9282041139240507
1 0.2586450876951218 0.9212816455696202
0.1 0.5
0 0.4873069658279419 0.8554193037974683
1 0.28710642221570015 0.912381329113924
0.1 0.6
0 0.24276638667583467 0.9288963607594937
1 0.18893379352390766 0.9445213607594937
0.1 0.7
0 0.22176867967247962 0.9373022151898734
1 0.19824675492346286 0.9425435126582279
0.1 0.8
0 0.18635324544012546 0.9465981012658228
1 0.1841644081056118 0.9479825949367089
0.1 0.9
0 0.16314728631675243 0.9553006329113924
1 0.18670903607010841 0.9434335443037974
0.2 0.0
0 0.18890684643387795 0.9449169303797469
1 0.13567996456772088 0.9623219936708861
0.2 0.1
0 0.13560908826291562 0.9614319620253164
1 0.13865472483336924 0.9605419303797469
0.2 0.2
0 0.143240681129694 0.9605419303797469
1 0.13303159916996957 0.9636075949367089
0.2 0.3
0 0.1266035877585411 0.9653876582278481
1 0.14329623847603798 0.9594541139240507
0.2 0.4
0 0.1692038366049528 0.9527294303797469
1 0.1319958964318037 0.9638053797468354
0.2 0.5
0 0.1292878429055214 0.9634098101265823
1 0.15155372014343738 0.9547072784810127
0.2 0.6
0 0.19529641719460486 0.9409612341772152
1 0.14397044867277145 0.9579707278481012
0.2 0.7
0 0.12994211793243884 0.9634098101265823
1 0.1205447984278202 0.9657832278481012
0.2 0.8
0 0.16830104094743728 0.9522349683544303
1 0.12831478562355042 0.9618275316455697
```

```
0.2 0.9
0 0.16074707213640213 0.9518393987341772
1 0.14952371793985367 0.9547072784810127
0.3 0.0
0 0.11870482016801834 0.9660799050632911
1 0.10813531310111284 0.9692444620253164
0.3 0.1
0 0.1210621126294136 0.9652887658227848
1 0.12322547079324722 0.9623219936708861
0.3 0.2
0 0.10488862806260586 0.9710245253164557
1 0.11765727536678314 0.9677610759493671
0.3 0.3
0 0.10943166644871236 0.9676621835443038
1 0.1112074060536921 0.9690466772151899
0.3 0.4
0 0.1177787490002811 0.9668710443037974
1 0.1046140064574778 0.9691455696202531
0.3 0.5
0 0.11730511011183262 0.9655854430379747
1 0.10850781296938658 0.9671677215189873
0.3 0.6
0 0.10955738279595971 0.9684533227848101
1 0.13792303424477578 0.9615308544303798
0.3 0.7
0 0.11805085754543543 0.966376582278481
1 0.12346452119648457 0.9660799050632911
0.3 0.8
0 0.12732999440878628 0.964003164556962
1 0.1368689041465521 0.960245253164557
0.3 0.9
0 0.21382727062702178 0.9417523734177216
1 0.1464859338864684 0.9604430379746836
0.4 0.0
0 0.11167256118580698 0.9682555379746836
1 0.11187256010994315 0.9684533227848101
0.4 0.1
0 0.12224916501864791 0.9654865506329114
1 0.10780785501897334 0.9686511075949367
0.4 0.2
0 0.10693383365571499 0.9705300632911392
1 0.11585912493914366 0.968057753164557
0.4 0.3
0 0.11361051338221878 0.9682555379746836
1 0.10292249005138875 0.9716178797468354
0.4 0.4
0 0.10658358543086797 0.9702333860759493
1 0.11027148991525174 0.969442246835443
0.4 0.5
0 0.10987296913899482 0.9679588607594937
1 0.10616927255773917 0.9726068037974683
0.4 0.6
0 0.1370148770544678 0.9642009493670886
1 0.11390638188868761 0.9676621835443038
0.4 0.7
0 0.1279700640693307 0.965684335443038
1 0.12727716157063843 0.9648931962025317
```

```
0.4 0.8
0 0.12709024610742928 0.9645965189873418
1 0.11362509560994805 0.969442246835443
0.4 0.9
0 0.1565808003079146 0.9567840189873418
1 0.16366909954622388 0.9576740506329114
0.5 0.0
0 0.11490244829319418 0.9677610759493671
1 0.10485177903529257 0.969442246835443
0.5 0.1
0 0.10865686457138508 0.9700356012658228
1 0.10605004655136727 0.9703322784810127
0.5 0.2
0 0.10234110887050629 0.9707278481012658
1 0.11160295746605843 0.9706289556962026
0.5 0.3
0 0.10941569313211366 0.9709256329113924
1 0.10463866094239056 0.9707278481012658
0.5 0.4
0 0.11531584353912622 0.9695411392405063
1 0.10886933372747153 0.9703322784810127
0.5 0.5
0 0.12324651898182928 0.9678599683544303
1 0.11962020082129166 0.9691455696202531
0.5 0.6
0 0.10589607935778331 0.9705300632911392
1 0.11080604134802706 0.9705300632911392
0.5 0.7
0 0.12489337472445332 0.9679588607594937
1 0.12234699442279526 0.9686511075949367
0.5 0.8
0 0.12919992827028037 0.9651898734177216
1 0.15545565596881789 0.9581685126582279
0.5 0.9
0 0.2169283072590828 0.9428401898734177
1 0.20986214278787374 0.9420490506329114
0.6 0.0
0 0.12065319787710906 0.9662776898734177
1 0.11690907094143331 0.9685522151898734
0.6 0.1
0 0.10886775563322007 0.9693433544303798
1 0.1109960504842922 0.9692444620253164
0.6 0.2
0 0.10812090906258673 0.971123417721519
1 0.1299099268297665 0.9644976265822784
0.6 0.3
0 0.10774974656235427 0.9732990506329114
1 0.109175579745695 0.9710245253164557
0.6 0.4
0 0.12967835938688368 0.9639042721518988
1 0.12200700463801623 0.96875
0.6 0.5
0 0.1196379111431539 0.9684533227848101
1 0.12681130185239017 0.9662776898734177
0.6 0.6
0 0.11307888658381998 0.9712223101265823
1 0.11486162941623479 0.9721123417721519
```

0.6 0.7  
0 0.12463826639540493 0.9684533227848101  
1 0.1202967264120467 0.9697389240506329  
0.6 0.8  
0 0.18207455490157007 0.9553006329113924  
1 0.15961586581133305 0.9575751582278481  
0.6 0.9  
0 0.2331263549953699 0.9370055379746836  
1 0.3555778139934642 0.9196004746835443  
0.7 0.0  
0 0.12838277786765248 0.9630142405063291  
1 0.11857154126800597 0.9641020569620253  
0.7 0.1  
0 0.11722004994563759 0.9665743670886076  
1 0.11774743082895875 0.9657832278481012  
0.7 0.2  
0 0.11728704131096601 0.9676621835443038  
1 0.11426017383895815 0.9677610759493671  
0.7 0.3  
0 0.11367953536324203 0.9683544303797469  
1 0.11592016365341842 0.968057753164557  
0.7 0.4  
0 0.11763628113716841 0.9664754746835443  
1 0.11609601347595454 0.9667721518987342  
0.7 0.5  
0 0.11953599300570786 0.9677610759493671  
1 0.12701219744682313 0.9634098101265823  
0.7 0.6  
0 0.12506643275618554 0.966376582278481  
1 0.11592082122713328 0.9662776898734177  
0.7 0.7  
0 0.15440672205814626 0.9603441455696202  
1 0.14081323669441045 0.9597507911392406  
0.7 0.8  
0 0.13948908088728784 0.9593552215189873  
1 0.19045573742687702 0.9464992088607594  
0.7 0.9  
0 0.2720762509636581 0.9302808544303798  
1 0.2640857982933521 0.9305775316455697  
0.8 0.0  
0 0.14614345505908133 0.9598496835443038  
1 0.1311442175731063 0.9623219936708861  
0.8 0.1  
0 0.13875602120757102 0.9598496835443038  
1 0.13322172701619567 0.9627175632911392  
0.8 0.2  
0 0.12103391640931369 0.9671677215189873  
1 0.12757812152914702 0.9651898734177216  
0.8 0.3  
0 0.13006909120976926 0.9637064873417721  
1 0.1291356104362756 0.9636075949367089  
0.8 0.4  
0 0.12094522495009005 0.9653876582278481  
1 0.12024650327637791 0.9658821202531646  
0.8 0.5  
0 0.12572852872870863 0.9648931962025317  
1 0.11854034664519131 0.9665743670886076

```
0.8 0.6
0 0.12452222608029842 0.9661787974683544
1 0.12961134017035364 0.9658821202531646
0.8 0.7
0 0.12943860225658863 0.9641020569620253
1 0.1360952475104481 0.9606408227848101
0.8 0.8
0 0.15003418617844583 0.9608386075949367
1 0.1521322960022837 0.9595530063291139
0.8 0.9
0 0.3283165837407112 0.9094145569620253
1 0.3572272372722626 0.893690664556962
0.9 0.0
0 0.23423945236206054 0.9349287974683544
1 0.21415408178567885 0.9350276898734177
0.9 0.1
0 0.1971885336071253 0.9427412974683544
1 0.2110540614426136 0.9399723101265823
0.9 0.2
0 0.19980920732021332 0.9411590189873418
1 0.20893248408436776 0.9401700949367089
0.9 0.3
0 0.19360853391885757 0.9433346518987342
1 0.17934903336763383 0.9485759493670886
0.9 0.4
0 0.17535237710177898 0.9510482594936709
1 0.262751783297956 0.9265229430379747
0.9 0.5
0 0.18892815390229226 0.9431368670886076
1 0.1643377272516489 0.9517405063291139
0.9 0.6
0 0.1596179372623563 0.9550039556962026
1 0.15983628551363946 0.955498417721519
0.9 0.7
0 0.17997167784571647 0.948378164556962
1 0.16808373177945612 0.9519382911392406
0.9 0.8
0 0.18387740416526793 0.9471914556962026
1 0.198883735665679 0.9449169303797469
0.9 0.9
0 0.4305316368103027 0.8915150316455697
1 0.513553396654129 0.8509691455696202
1.0 0.0
0 0.20188690141141416 0.9430379746835443
1 0.18997681085467338 0.9467958860759493
1.0 0.1
0 0.18076044195890426 0.947685917721519
1 0.17901626200675963 0.9490704113924051
1.0 0.2
0 0.2164471524477005 0.9428401898734177
1 0.17398800148963928 0.9493670886075949
1.0 0.3
0 0.17637476187944412 0.9482792721518988
1 0.17718745999336244 0.9487737341772152
1.0 0.4
0 0.1699304197192192 0.9525316455696202
1 0.16306727154254913 0.9521360759493671
```

```

1.0 0.5
0 0.1781700668990612 0.9470925632911392
1 0.17355914738178252 0.9506526898734177
1.0 0.6
0 0.17900192398428916 0.9473892405063291
1 0.1801849832892418 0.9448180379746836
1.0 0.7
0 0.1967512058854103 0.9419501582278481
1 0.25477542139291764 0.9253362341772152
1.0 0.8
0 0.22830823081731796 0.9333465189873418
1 0.2421811589717865 0.9311708860759493
1.0 0.9
0 3.5250786003112795 0.6431962025316456
1 0.7367884540557861 0.7876780063291139

```

## Graphical Illustration of Accuracy for Varying Values of Learning Rate and Momentum

```

In [11]: def Largest_Moment(mat, index):
          best_Momentum_index = 0;
          for x in range(10):
              if(mat[index][x][4] > mat[index][best_Momentum_index][4]):
                  best_Momentum_index = x
          return best_Momentum_index

          mat_lr = np.zeros(20)
          mat_moment = np.zeros(20)
          mat_acc = np.zeros(20)

          for i in range(20):
              mat_lr[i] = a[i][0][1]
              # Momentum index with greatest Accuracy of a given LR.
              large = Largest_Moment(a, i)
              mat_moment[i] = a[i][large][2]
              mat_acc[i] = a[i][large][4]

```

The arrays of LR, Momentum, and Accuracy should be counted in groups of 2. First Value is epoch 1, second value is epoch 2. Then LR/Momentum will increment. For example, below we see that the 8th value in accuracy array is the largest. This corresponds to a learning rate of 0.5 and momentum 0.4 and epoch 1. Loss of validation sets are also shown as 0.9500714.

```

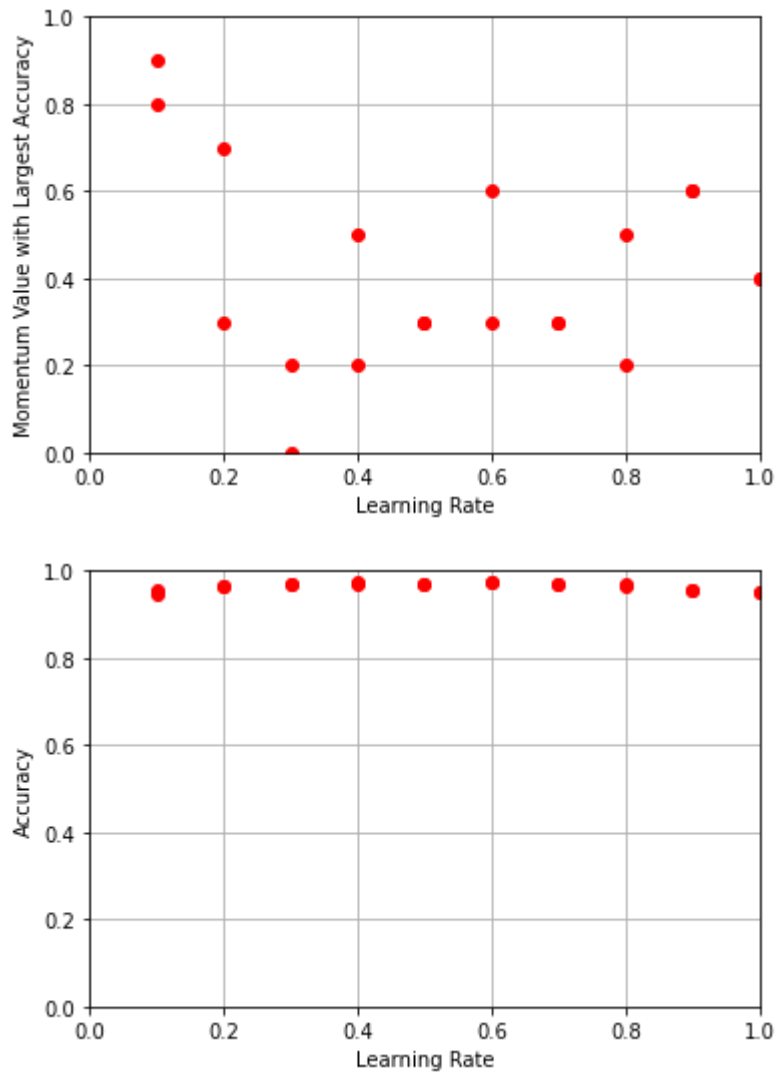
In [15]: print(mat_acc)
          print(mat_moment[10])
          print(a[10][3])

[0.95530063 0.94798259 0.96538766 0.96578323 0.97102453 0.96924446
 0.97053006 0.9726068 0.97092563 0.97072785 0.97329905 0.97211234
 0.96835443 0.96805775 0.96716772 0.96657437 0.95500396 0.95549842
 0.95253165 0.95213608]
0.3
[0.          0.6          0.3          0.10774975 0.97329905]

```

```
In [13]: fig, ax = pyplot.subplots()
ax.plot(mat_lr, mat_moment, 'ro')
ax.axis([0, 1, 0, 1])
ax.set(xlabel='Learning Rate', ylabel='Momentum Value with Largest Ac
curacy')
ax.grid()
pyplot.show()

fig, ax = pyplot.subplots()
ax.plot(mat_lr, mat_acc, 'ro')
ax.axis([0, 1, 0, 1])
ax.set(xlabel='Learning Rate', ylabel='Accuracy')
ax.grid()
pyplot.show()
```



From the plot above. We got our best accuracy, 0.97329905 , with a learning rate of 0.6 and a momentum of 0.3. In the graphs above, every LR has two dots since there is 2 epochs.



## Problem 6: CNNs for CIFAR-10

- Build a CNN and optimize the accuracy for CIFAR-10. Try different number of layers and different architectures (depth and convolutional filter hyperparameters).
- Is momentum and learning rate having a significant effect? Track the train and test loss across training epochs and plot them for different learning rates and momentum values.
- Is the depth of the CNN having a significant effect on performance? Describe the hyperparameters of the best model you could train.

## Loading CIFAR-10 Dataset

```
In [2]: # Loading Dataset libraries
from sklearn.datasets import fetch_openml
from sklearn.model_selection import train_test_split
# Computational and Graphical libraries
from matplotlib import pyplot
import numpy as np
import torch
# Debugger Library
from IPython.core.debugger import set_trace

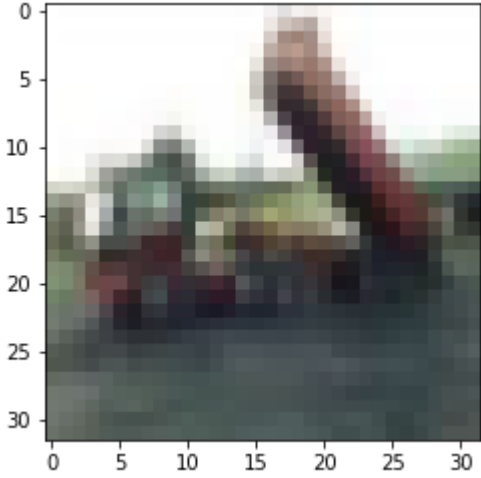
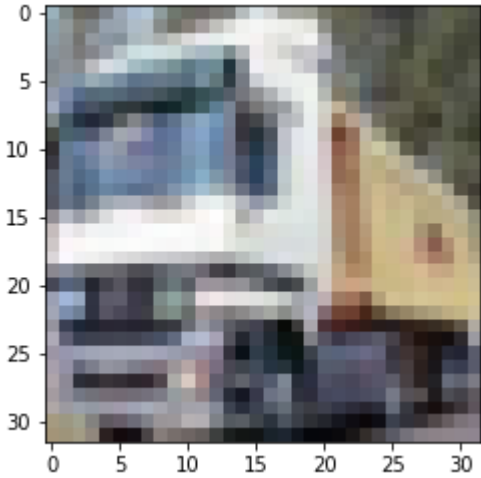
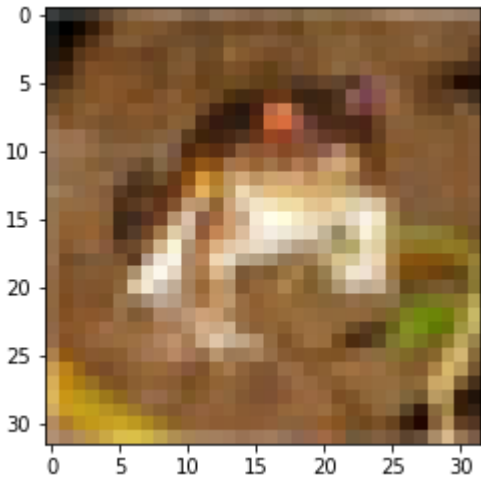
# The CIFAR-10 Dataset loading steps are just from our Q.1
dataset = fetch_openml('CIFAR_10_small')
```

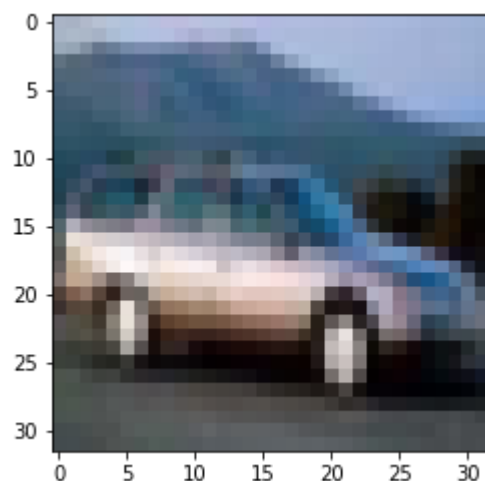
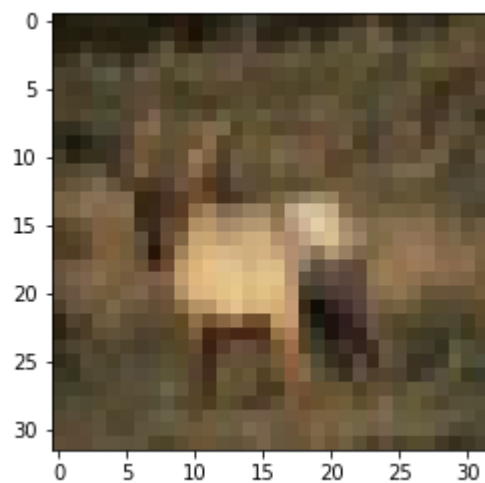
```
In [3]: # Some images to make sure we loaded correctly
for i in range(5):
    pyplot.figure(i)

    img_raw = dataset['data'][i]
    r = img_raw[0:1024].reshape(32, 32)/255.0
    g = img_raw[1024:2048].reshape(32, 32)/255.0
    b = img_raw[2048:].reshape(32, 32)/255.0

    img = np.dstack((r, g, b))

    pyplot.imshow(img)
```





```
In [4]: x_train, x_valid, y_train, y_valid = train_test_split(dataset['data'],
dataset['target'], test_size=0.25)
y_train = y_train.astype(int)
y_valid = y_valid.astype(int)
x_train = x_train/255.0
x_valid = x_valid/255.0
x_train, y_train, x_valid, y_valid = map(torch.tensor, (x_train, y_train,
x_valid, y_valid))
```

## Is GPU available?

```
In [5]: print(torch.cuda.is_available())
dev = torch.device(
    "cuda") if torch.cuda.is_available() else torch.device("cpu")
```

True

## Classes and Functions

```

In [6]: # Training and Validation Datasets/DataLoaders Libraries
from torch.utils.data import TensorDataset
from torch.utils.data import DataLoader
# Optim and NN libraries
from torch import optim
from torch import nn
import torch.nn.functional as F

def get_data(train_ds, valid_ds, bs):
    return (
        DataLoader(train_ds, batch_size=bs, shuffle=True),
        DataLoader(valid_ds, batch_size=bs * 2),
    )

loss_func = F.cross_entropy

def loss_batch(model, loss_func, xb, yb, opt=None):
    loss = loss_func(model(xb), yb)

    if opt is not None:
        loss.backward()
        opt.step()
        opt.zero_grad()

    return loss.item(), len(xb)

def fit(epochs, model, loss_func, opt, train_dl, valid_dl):
    for epoch in range(epochs):
        model.train()
        for xb, yb in train_dl:
            loss_batch(model, loss_func, xb, yb, opt)

        model.eval()
        with torch.no_grad():
            losses, nums = zip(
                *[loss_batch(model, loss_func, xb, yb) for xb, yb in
valid_dl]
            )
            val_loss = np.sum(np.multiply(losses, nums)) / np.sum(nums)
            val_acc = sum(accuracy(model(xb), yb) for xb, yb in valid_dl)
#valid_loss / len(valid_dl)

            val_acc = val_acc.cpu().detach().numpy()
            print(epoch, val_loss, val_acc / len(valid_dl))

# Accuracy check from Validation Test.
def accuracy(out, yb):
    preds = torch.argmax(out, dim=1)
    return (preds == yb).float().mean()

class Lambda(nn.Module):
    def __init__(self, func):
        super().__init__()
        self.func = func

    def forward(self, x):

```

```
        return self.func(x)

def preprocess(x, y):
    return x.view(-1, 3, 32, 32).to(dev), y.to(dev)

class WrappedDataLoader:
    def __init__(self, dl, func):
        self.dl = dl
        self.func = func

    def __len__(self):
        return len(self.dl)

    def __iter__(self):
        batches = iter(self.dl)
        for b in batches:
            yield (self.func(*b))
```

## Initial Variables

```
In [7]: bs = 64  # batch size
        lr = 0.1  # learning rate
        epochs = 2  # how many epochs to train for
        a = np.zeros((20, 10), dtype=(float,5))
```

## Training and Validation Datasets/DataLoaders

```
In [8]: train_ds = TensorDataset(x_train, y_train)
        valid_ds = TensorDataset(x_valid, y_valid)
        train_dl, valid_dl = get_data(train_ds, valid_ds, bs)
        train_dl = WrappedDataLoader(train_dl, preprocess)
        valid_dl = WrappedDataLoader(valid_dl, preprocess)
```

## Original Model, Optim (Use to do Forward Step), and Training

```
In [9]: model = nn.Sequential(
    nn.Conv2d(3, 16, kernel_size=3, stride=2, padding=1),
    nn.ReLU(),
    nn.Conv2d(16, 16, kernel_size=3, stride=2, padding=1),
    nn.ReLU(),
    nn.Conv2d(16, 10, kernel_size=3, stride=2, padding=1),
    nn.ReLU(),
    nn.AdaptiveAvgPool2d(1),
    Lambda(lambda x: x.view(x.size(0), -1)),
)
model.to(dev)
opt = optim.SGD(model.parameters(), lr=lr, momentum=0.9)
model = model.double()
fit(epochs, model, loss_func, opt, train_dl, valid_dl)
```

```
0 2.109213362124643 0.2107421875
1 2.0545586561993057 0.2380859375
```

## Training of Model. Outputs Validation Loss.

```
In [10]: # 5 Conv Layers with just more fully connected layers
model1 = nn.Sequential(
    nn.Conv2d(3, 16, kernel_size=3, stride=2, padding=1),
    nn.ReLU(),
    nn.Conv2d(16, 16, kernel_size=3, stride=2, padding=1),
    nn.ReLU(),
    nn.Conv2d(16, 16, kernel_size=3, stride=2, padding=1),
    nn.ReLU(),
    nn.Conv2d(16, 16, kernel_size=3, stride=2, padding=1),
    nn.ReLU(),
    nn.Conv2d(16, 10, kernel_size=3, stride=2, padding=1),
    nn.ReLU(),
    nn.AdaptiveAvgPool2d(1),
    Lambda(lambda x: x.view(x.size(0), -1)),
)
model1.to(dev)
model1 = model1.double()
opt1 = optim.SGD(model1.parameters(), lr=lr, momentum=0.9)
fit(epochs, model1, loss_func, opt1, train_dl, valid_dl)

# Results show this is worse than with only one fully connected layer.
```

```
0 2.3025850929940455 0.1103515625
1 2.3025850929940455 0.1103515625
```

```
In [11]: # 5 Conv Layers with pooling in between
model2 = nn.Sequential(
    nn.Conv2d(3, 16, kernel_size=3, stride=2, padding=1),
    nn.ReLU(),
    nn.Conv2d(16, 16, kernel_size=3, stride=2, padding=1),
    nn.ReLU(),
    nn.Conv2d(16, 16, kernel_size=3, stride=2, padding=1),
    nn.ReLU(),
    nn.AdaptiveAvgPool2d(8),
    nn.Conv2d(16, 16, kernel_size=3, stride=2, padding=1),
    nn.ReLU(),
    nn.Conv2d(16, 10, kernel_size=3, stride=2, padding=1),
    nn.ReLU(),
    nn.AdaptiveAvgPool2d(1),
    Lambda(lambda x: x.view(x.size(0), -1)),
)
model2.to(dev)
model2 = model2.double()
opt2 = optim.SGD(model2.parameters(), lr=lr, momentum=0.9)
fit(epochs, model2, loss_func, opt2, train_dl, valid_dl)

# Results same as pooling on last layer only. That is weird.

0 2.3025850929940455 0.1103515625
1 2.3025850929940455 0.1103515625
```

```
In [12]: # 5 Conv Layers with pooling in between
model3 = nn.Sequential(
    nn.Conv2d(3, 16, kernel_size=3, stride=2, padding=1),
    nn.ReLU(),
    nn.Conv2d(16, 16, kernel_size=3, stride=2, padding=1),
    nn.ReLU(),
    nn.Conv2d(16, 13, kernel_size=3, stride=2, padding=1),
    nn.ReLU(),
    nn.Conv2d(13, 13, kernel_size=3, stride=2, padding=1),
    nn.ReLU(),
    nn.Conv2d(13, 10, kernel_size=3, stride=2, padding=1),
    nn.ReLU(),
    nn.AdaptiveAvgPool2d(1),
    Lambda(lambda x: x.view(x.size(0), -1)),
)
model3.to(dev)
model3 = model3.double()
opt3 = optim.SGD(model3.parameters(), lr=lr, momentum=0.9)
fit(epochs, model3, loss_func, opt3, train_dl, valid_dl)

0 2.3025850929940455 0.1103515625
1 2.3025850929940455 0.1103515625
```



```
In [13]: model4 = nn.Sequential(
    nn.Conv2d(3, 16, kernel_size=4, stride=2, padding=1),
    nn.ReLU(),
    nn.Conv2d(16, 16, kernel_size=4, stride=2, padding=1),
    nn.ReLU(),
    nn.Conv2d(16, 10, kernel_size=4, stride=2, padding=1),
    nn.ReLU(),
    nn.AdaptiveAvgPool2d(1),
    Lambda(lambda x: x.view(x.size(0), -1)),
)
model4.to(dev)
model4 = model4.double()
opt4 = optim.SGD(model4.parameters(), lr=lr, momentum=0.9)
fit(epochs, model4, loss_func, opt4, train_dl, valid_dl)

# Changing Kernel_size to be larger seems to have worse results.

0 2.302584732159884 0.1107421875
1 2.302556248813278 0.103515625
```

```
In [14]: model5 = nn.Sequential(
    nn.Conv2d(3, 16, kernel_size=5, stride=2, padding=1),
    nn.ReLU(),
    nn.Conv2d(16, 16, kernel_size=5, stride=2, padding=1),
    nn.ReLU(),
    nn.Conv2d(16, 10, kernel_size=5, stride=2, padding=1),
    nn.ReLU(),
    nn.AdaptiveAvgPool2d(1),
    Lambda(lambda x: x.view(x.size(0), -1)),
)
model5.to(dev)
model5 = model5.double()
opt5 = optim.SGD(model5.parameters(), lr=lr, momentum=0.9)
fit(epochs, model5, loss_func, opt5, train_dl, valid_dl)

0 2.3025512627227736 0.1169921875
1 2.302378666186078 0.1130859375
```

```
In [15]: model6 = nn.Sequential(
    nn.Conv2d(3, 16, kernel_size=2, stride=2, padding=1),
    nn.ReLU(),
    nn.Conv2d(16, 16, kernel_size=2, stride=2, padding=1),
    nn.ReLU(),
    nn.Conv2d(16, 10, kernel_size=2, stride=2, padding=1),
    nn.ReLU(),
    nn.AdaptiveAvgPool2d(1),
    Lambda(lambda x: x.view(x.size(0), -1)),
)
model6.to(dev)
model6 = model6.double()
opt6 = optim.SGD(model6.parameters(), lr=lr, momentum=0.9)
fit(epochs, model6, loss_func, opt6, train_dl, valid_dl)

0 2.243114498017494 0.1849609375
1 2.0964484900731475 0.2154296875
```

## Testing different learning rate and momentum values.

```

In [16]: def fit(epochs, model, loss_func, opt, train_dl, valid_dl, mat, lr, momentum):
    for epoch in range(epochs):
        model.train()
        for xb, yb in train_dl:
            loss_batch(model, loss_func, xb, yb, opt)

        model.eval()
        with torch.no_grad():
            losses, nums = zip(
                *[loss_batch(model, loss_func, xb, yb) for xb, yb in
valid_dl]
            )

        val_loss = np.sum(np.multiply(losses, nums)) / np.sum(nums)
        val_acc = sum(accuracy(model(xb), yb) for xb, yb in valid_dl)
#valid_loss / len(valid_dl)
        val_acc = val_acc.cpu().detach().numpy() / len(valid_dl)
        mat_data = (epoch, lr, momentum, val_loss, val_acc)
        mat[int(((lr*20)-2)+epoch)][int(momentum*10)] = mat_data
        print(epoch, val_loss, val_acc)
    return mat

#####
#####
model7 = nn.Sequential(
    nn.Conv2d(3, 16, kernel_size=3, stride=2, padding=1),
    nn.ReLU(),
    nn.Conv2d(16, 16, kernel_size=3, stride=2, padding=1),
    nn.ReLU(),
    nn.Conv2d(16, 10, kernel_size=3, stride=2, padding=1),
    nn.ReLU(),
    nn.AdaptiveAvgPool2d(1),
    Lambda(lambda x: x.view(x.size(0), -1)),
)
model7.to(dev)
model7 = model7.double()
for x in range(10):          # Varying for LR from 0.1 to 1.0
    lr = (x+1)/10
    for y in range(10):      # Varying for Momentum 0.0 to 0.9
        momentum = y/10
        opt7 = optim.SGD(model7.parameters(), lr=lr, momentum=momentum)
        print(lr, momentum)
        a = fit(epochs, model7, loss_func, opt7, train_dl, valid_dl, a, l
r, momentum)

```

```
0.1 0.0
0 2.28720088555686 0.1498046875
1 2.285584655364973 0.1533203125
0.1 0.1
0 2.286292898719735 0.151171875
1 2.249462868456282 0.171875
0.1 0.2
0 2.121332032971835 0.2103515625
1 2.0975444850309555 0.255859375
0.1 0.3
0 2.0604419508548695 0.2689453125
1 1.9982703734114629 0.2880859375
0.1 0.4
0 1.9737876159231718 0.308203125
1 1.9432801668428197 0.328125
0.1 0.5
0 1.9398057983550272 0.302734375
1 1.8868234068432033 0.3125
0.1 0.6
0 1.7716240237317864 0.3640625
1 1.7499525268071554 0.3708984375
0.1 0.7
0 1.7039730151178722 0.4005859375
1 1.73939459486864 0.3734375
0.1 0.8
0 1.6526357994236591 0.3908203125
1 1.6495322156049 0.398828125
0.1 0.9
0 1.626560652886935 0.4185546875
1 1.5860305003204371 0.4201171875
0.2 0.0
0 1.5390252734280874 0.4369140625
1 1.6015119675439928 0.405078125
0.2 0.1
0 1.576604671296549 0.4162109375
1 1.5524823023864927 0.43046875
0.2 0.2
0 1.495589268229011 0.456640625
1 1.551299569743376 0.4416015625
0.2 0.3
0 1.5360280605341687 0.437890625
1 1.5282796734514854 0.4501953125
0.2 0.4
0 1.5196151832247347 0.45546875
1 1.5831183875744423 0.446484375
0.2 0.5
0 1.5676567962457097 0.4392578125
1 1.5250483893347286 0.4498046875
0.2 0.6
0 1.6173538908108867 0.4279296875
1 1.533771326096457 0.444140625
0.2 0.7
0 1.6472909003192369 0.405859375
1 1.4992865129905 0.454296875
0.2 0.8
0 1.5993406339321963 0.42578125
1 1.5975942763618687 0.4353515625
```

```
0.2 0.9
0 1.7212505153020687 0.3935546875
1 1.671520445913457 0.40078125
0.3 0.0
0 1.5276907760470808 0.4568359375
1 1.5305365694813466 0.455078125
0.3 0.1
0 1.5304316381444514 0.4638671875
1 1.4693325933230699 0.47109375
0.3 0.2
0 1.5356444592106406 0.451953125
1 1.4669740464735748 0.476953125
0.3 0.3
0 1.5236447819911985 0.455859375
1 1.5249653729353796 0.4666015625
0.3 0.4
0 1.519845183379272 0.4630859375
1 1.6185637093543241 0.4306640625
0.3 0.5
0 1.5228387837758721 0.4681640625
1 1.6533597605628394 0.420703125
0.3 0.6
0 1.5174920704100354 0.4546875
1 1.493816808832351 0.4626953125
0.3 0.7
0 1.5849158113882187 0.434375
1 1.6487697025139587 0.4197265625
0.3 0.8
0 1.6283918789014076 0.41484375
1 1.5759258212675549 0.4333984375
0.3 0.9
0 1.7731909991718704 0.373046875
1 1.6998956824080669 0.3822265625
0.4 0.0
0 1.5826860848855537 0.433984375
1 1.5242404886905212 0.4537109375
0.4 0.1
0 1.5441659307874855 0.4525390625
1 1.5902993720010576 0.444140625
0.4 0.2
0 1.6782904295230499 0.41796875
1 1.5058311010816021 0.4640625
0.4 0.3
0 1.681400450284127 0.4283203125
1 1.5942562786254233 0.4279296875
0.4 0.4
0 1.5688856129397648 0.4423828125
1 1.60633693331116 0.4400390625
0.4 0.5
0 1.5753127262244089 0.4328125
1 1.5532679565992613 0.44140625
0.4 0.6
0 1.6752523826862866 0.419140625
1 1.6441675198945043 0.4193359375
0.4 0.7
0 1.6946059016299675 0.3951171875
1 1.6333694015307438 0.407421875
```

```
0.4 0.8
0 1.7311891380424285 0.3923828125
1 1.6308012264661398 0.408984375
0.4 0.9
0 1.8036060428156107 0.337109375
1 1.7874386059891527 0.3607421875
0.5 0.0
0 1.6095361943505408 0.4212890625
1 1.6420810360566274 0.4287109375
0.5 0.1
0 1.5747680180988737 0.436328125
1 1.6910364931299744 0.4013671875
0.5 0.2
0 1.594357403249431 0.4357421875
1 1.5919509283193076 0.4294921875
0.5 0.3
0 1.6026638585160975 0.433984375
1 1.5752141244914026 0.4380859375
0.5 0.4
0 1.6760327973525964 0.425390625
1 1.5567989766132342 0.4412109375
0.5 0.5
0 1.5956291470759956 0.4373046875
1 1.5952080663844932 0.443359375
0.5 0.6
0 1.6434401228952054 0.417578125
1 1.656541228502876 0.4173828125
0.5 0.7
0 1.6730557629393679 0.4197265625
1 1.685194177241192 0.4263671875
0.5 0.8
0 1.635486694622768 0.41953125
1 1.6408942764779832 0.4140625
0.5 0.9
0 1.928301872651426 0.303515625
1 1.8191197960617909 0.344921875
0.6 0.0
0 1.6269912336322117 0.4107421875
1 1.6094420833537522 0.4193359375
0.6 0.1
0 1.5822230264260964 0.4296875
1 1.5749005499369304 0.4328125
0.6 0.2
0 1.6149306408514614 0.425
1 1.6638515340550886 0.4125
0.6 0.3
0 1.5930660838789814 0.4314453125
1 1.712138523928824 0.39453125
0.6 0.4
0 1.8094987525032669 0.3806640625
1 1.7451989920557405 0.3970703125
0.6 0.5
0 1.5814609186976307 0.437109375
1 1.6499347686562131 0.4232421875
0.6 0.6
0 1.6704601870186977 0.412109375
1 1.6113145699984384 0.4263671875
```

```
0.6 0.7
0 1.643665092909888 0.43203125
1 1.6314952246263097 0.4091796875
0.6 0.8
0 1.7057912962596897 0.3849609375
1 1.7506826396136221 0.3923828125
0.6 0.9
0 1.906678294586491 0.303515625
1 1.9508093586218826 0.30859375
0.7 0.0
0 1.6501617053862763 0.3966796875
1 1.645197166137708 0.41015625
0.7 0.1
0 1.6401819345257582 0.406640625
1 1.602534908051069 0.42421875
0.7 0.2
0 1.6449545066185667 0.408984375
1 1.6129166171311329 0.4173828125
0.7 0.3
0 1.5918505521064343 0.430859375
1 1.671708242189893 0.4083984375
0.7 0.4
0 1.729935970411595 0.3849609375
1 1.6255896309380196 0.4361328125
0.7 0.5
0 1.648523996990316 0.4142578125
1 1.687139752416914 0.3982421875
0.7 0.6
0 1.6558893006744293 0.4263671875
1 1.6782260712328008 0.413671875
0.7 0.7
0 1.708451174993562 0.3810546875
1 1.7264227294455776 0.389453125
0.7 0.8
0 1.6788590612816843 0.4044921875
1 1.6626821449174702 0.401953125
0.7 0.9
0 1.9724466224785298 0.3041015625
1 1.8671035238613223 0.323046875
0.8 0.0
0 1.691999712268493 0.3884765625
1 1.6669811354337187 0.398046875
0.8 0.1
0 1.6372535936927528 0.406640625
1 1.642226751652248 0.396875
0.8 0.2
0 1.6357932308764729 0.402734375
1 1.6641251652214786 0.3892578125
0.8 0.3
0 1.6149695878663854 0.410546875
1 1.6707085635109882 0.3955078125
0.8 0.4
0 1.6208908406391955 0.4185546875
1 1.608242287140399 0.426953125
0.8 0.5
0 1.6392845898492836 0.4126953125
1 1.6607074297002218 0.3943359375
```

```
0.8 0.6
0 1.6419101276942758 0.4095703125
1 1.6514093281821318 0.4154296875
0.8 0.7
0 1.6834023789525636 0.4072265625
1 1.6992146238981616 0.4064453125
0.8 0.8
0 1.852616840570115 0.3419921875
1 1.725779598399087 0.374609375
0.8 0.9
0 2.001102750492032 0.26015625
1 2.0738365792933666 0.2642578125
0.9 0.0
0 1.8433126091940961 0.3306640625
1 1.7660400399312959 0.3607421875
0.9 0.1
0 1.7526934757578878 0.357421875
1 1.7595836519315158 0.3650390625
0.9 0.2
0 1.7325436845761997 0.3708984375
1 1.7053166184795694 0.384375
0.9 0.3
0 1.7006994148103156 0.3826171875
1 1.6657086584980858 0.393359375
0.9 0.4
0 1.743137532321977 0.373046875
1 1.6557292572249138 0.4015625
0.9 0.5
0 1.715958871525432 0.3865234375
1 1.6779386825115281 0.4021484375
0.9 0.6
0 1.6913477311885274 0.38359375
1 1.7233712184395547 0.387109375
0.9 0.7
0 1.7634492711444982 0.3736328125
1 1.6947959082099406 0.387109375
0.9 0.8
0 1.802620593499807 0.3609375
1 1.7621542670075374 0.36328125
0.9 0.9
0 2.0187187899809786 0.2748046875
1 2.081445917965387 0.262890625
1.0 0.0
0 1.7907332538677372 0.3396484375
1 1.771271634750884 0.34296875
1.0 0.1
0 1.754205221300893 0.35234375
1 1.7842320590086678 0.3578125
1.0 0.2
0 1.756601530785684 0.373046875
1 1.7215810765359782 0.371875
1.0 0.3
0 1.714033612460794 0.3712890625
1 1.7805534339342746 0.35078125
1.0 0.4
0 1.7452605075947598 0.37109375
1 1.722088663360539 0.373046875
```



```

1.0 0.5
0 1.7070804487822595 0.38125
1 1.709371387830865 0.3708984375
1.0 0.6
0 1.708436043795327 0.38125
1 1.7464949251905593 0.366796875
1.0 0.7
0 1.7624333191944068 0.343359375
1 1.744648733560161 0.372265625
1.0 0.8
0 1.9042793332817491 0.2943359375
1 1.8275813594786137 0.339453125
1.0 0.9
0 2.138698845466445 0.209375
1 2.118299081226765 0.1984375

```

## Graphical Illustration of Accuracy for Varying Values of Learning Rate and Momentum

```

In [17]: def Largest_Moment(mat, index):
          best_Momentum_index = 0;
          for x in range(10):
              if(mat[index][x][4] > mat[index][best_Momentum_index][4]):
                  best_Momentum_index = x
          return best_Momentum_index

          mat_lr = np.zeros(20)
          mat_moment = np.zeros(20)
          mat_acc = np.zeros(20)

          for i in range(20):
              mat_lr[i] = a[i][0][1]
              # Momentum index with greatest Accuracy of a given LR.
              large = Largest_Moment(a, i)
              mat_moment[i] = a[i][large][2]
              mat_acc[i] = a[i][large][4]

```

The arrays of LR, Momentum, and Accuracy should be counted in groups of 2. First Value is epoch 1, second value is epoch 2. Then LR/Momentum will increment. For example, below we see that the 8th value in accuracy array is the largest. This corresponds to a learning rate of 0.5 and momentum 0.4 and epoch 1. Loss of validation sets are also shown as 0.9500714.

```

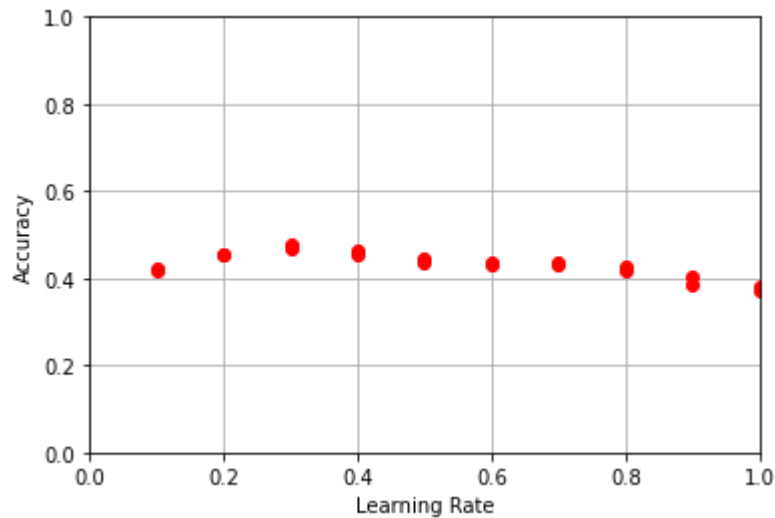
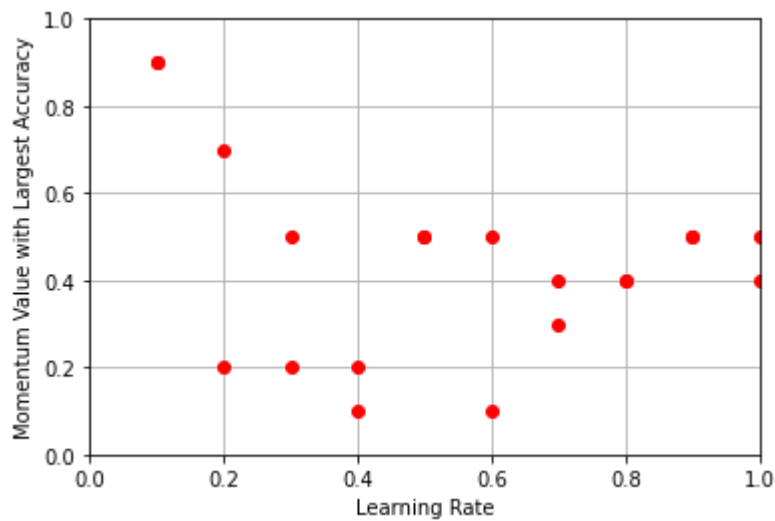
In [23]: print(mat_acc)
          print(mat_moment[5])
          print(a[5][2])

[0.41855469 0.42011719 0.45664063 0.45429687 0.46816406 0.47695312
 0.45253906 0.4640625  0.43730469 0.44335938 0.43710938 0.4328125
 0.43085937 0.43613281 0.41855469 0.42695312 0.38652344 0.40214844
 0.38125    0.37304688]
0.2
[1.          0.3          0.2          1.46697405 0.47695312]

```

```
In [19]: fig, ax = pyplot.subplots()
ax.plot(mat_lr, mat_moment, 'ro')
ax.axis([0, 1, 0, 1])
ax.set(xlabel='Learning Rate', ylabel='Momentum Value with Largest Ac
curacy')
ax.grid()
pyplot.show()

fig, ax = pyplot.subplots()
ax.plot(mat_lr, mat_acc, 'ro')
ax.axis([0, 1, 0, 1])
ax.set(xlabel='Learning Rate', ylabel='Accuracy')
ax.grid()
pyplot.show()
```



Overall Kernel\_sizing seemed to be fine where it was at, at Kernel\_size = 3. Adding extra Conv2D and ReLu() fully connected layers seems to have caused greater loss and a lower accuracy score than when only using 3 conv layers.

From the plot above. We got our best accuracy, 0.47695312, with a learning rate of 0.3 and a momentum of 0.2. In the graphs above, every LR has two dots since there is 2 epochs. Compared to adjusting Kernel\_size and convolution layers, adjusting LR and Momentum seems to have the most significant effects.