MLP

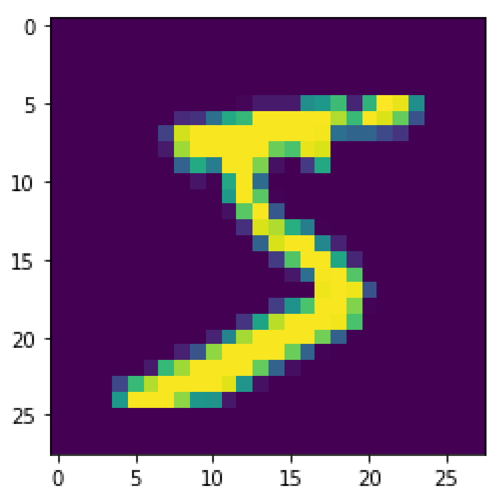
In [ ]:
```
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
from tensorflow.keras.datasets import mnist
from tensorflow.keras.models import Sequential
from tensorflow.keras.utils import to_categorical
```

Load Dataset

- MNIST dataset

In [ ]:
```
(X_train, y_train), (X_test, y_test) = mnist.load_data()
```

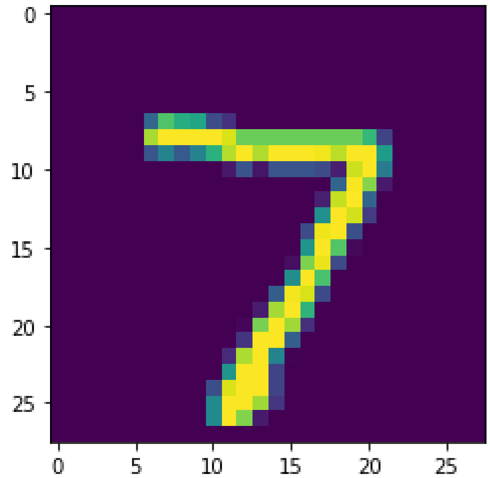
In [ ]:
```
plt.imshow(X_train[0])     # show first number in the dataset
plt.show()
print('Label: ', y_train[0])
```




```
Label:  5
```

In [ ]:

```
plt.imshow(X_test[0])    # show first number in the dataset
plt.show()
print('Label: ', y_test[0])
```



Label: 7

In [ ]:

```
# reshaping X data: (n, 28, 28) => (n, 784)
X_train = X_train.reshape((X_train.shape[0], -1))
X_test = X_test.reshape((X_test.shape[0], -1))
```

In [ ]:

```
# converting y data into categorical (one-hot encoding)
y_train = to_categorical(y_train)
y_test = to_categorical(y_test)
```

In [ ]:

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

(60000, 784) (10000, 784) (60000, 10) (10000, 10)

In [ ]:

MLP model

- Naive MLP model without any alterations

In [ ]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Activation, Dense
from tensorflow.keras import optimizers
```

In [ ]:
```
model = Sequential()
model.add(Dense(50, input_shape = (784, )))
model.add(Activation('sigmoid'))
model.add(Dense(50))
model.add(Activation('sigmoid'))
model.add(Dense(50))
model.add(Activation('sigmoid'))
model.add(Dense(50))
model.add(Activation('sigmoid'))
model.add(Dense(10))
model.add(Activation('softmax'))
```

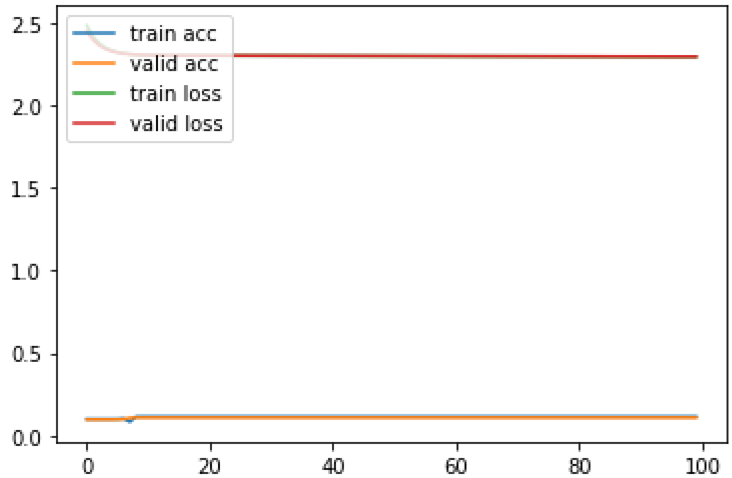
In [ ]:
```
sgd = optimizers.SGD(lr = 0.001) model.compile(optimizer = sgd, loss =
'categorical_crossentropy', metrics = ['accuracy'])
```

In [ ]:
```
history = model.fit(X_train, y_train, batch_size = 256, validation_split = 0.3,
epochs = 100, verbose = 1)
```

```
Epoch 1/100
165/165 [==============================] - 1s 7ms/step - loss: 2.4838 - accur
acy: 0.0995 - val_loss: 2.4486 - val_accuracy: 0.0966
Epoch 2/100
165/165 [==============================] - 1s 5ms/step - loss: 2.4176 - accur
acy: 0.0995 - val_loss: 2.3965 - val_accuracy: 0.0966
Epoch 3/100
165/165 [==============================] - 1s 5ms/step - loss: 2.3761 - accur
acy: 0.0995 - val_loss: 2.3634 - val_accuracy: 0.0966
Epoch 4/100
165/165 [==============================] - 1s 5ms/step - loss: 2.3496 - accur
acy: 0.0995 - val_loss: 2.3422 - val_accuracy: 0.0966
Epoch 5/100
165/165 [==============================] - 1s 5ms/step - loss: 2.3327 - accur
acy: 0.0995 - val_loss: 2.3283 - val_accuracy: 0.0966
Epoch 6/100
165/165 [==============================] - 1s 5ms/step - loss: 2.3217 - accur
acy: 0.0997 - val_loss: 2.3193 - val_accuracy: 0.0970
Epoch 7/100
165/165 [                              ]   1s 5ms/step    loss: 2 3145 accur
```

In [ ]:

```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.legend(['train acc', 'valid acc', 'train loss', 'valid loss'], loc = 'upper
left')
plt.show()
```



Training and validation accuracy seems to improve after around 60 epochs

In [ ]:

```
results = model.evaluate(X_test, y_test)
```

```
313/313 [==============================] - 0s 1ms/step - loss: 2.2944 - accurac
y: 0.1135
```

In [ ]:

```
print('Test accuracy: ', results[1])
```

```
Test accuracy:  0.11349999904632568
```

1. Weight Initialization

- Changing weight initialization scheme can sometimes improve training of the model by preventing vanishing gradient problem up to some degree
- He normal or Xavier normal initialization schemes are SOTA at the moment

```
# from now on, create a function to generate (return) models
def mlp_model():
    model = Sequential()

    model.add(Dense(50, input_shape = (784, ), kernel_initializer='he_normal'))
    # use he_normal initializer
model.add(Activation('sigmoid'))
    model.add(Dense(50, kernel_initializer='he_normal'))
```

In [ ]:

```
    # use he_normal initializer
model.add(Activation('sigmoid'))
    model.add(Dense(50, kernel_initializer='he_normal'))
    # use he_normal initializer
model.add(Activation('sigmoid'))
    model.add(Dense(50, kernel_initializer='he_normal'))
    # use he_normal initializer
model.add(Activation('sigmoid'))
    model.add(Dense(10, kernel_initializer='he_normal'))
    # use he_normal initializer
model.add(Activation('softmax'))

    sgd = optimizers.SGD(lr = 0.001)
    model.compile(optimizer = sgd, loss = 'categorical_crossentropy', metrics =
['accuracy'])
return model
```

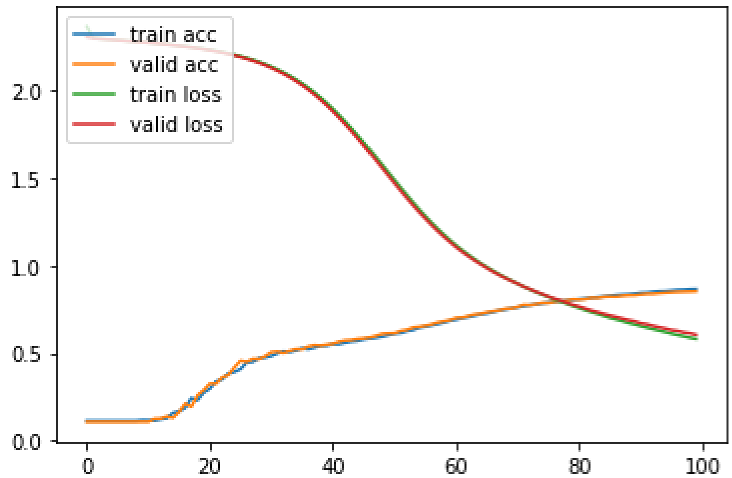
In [ ]:

```
model = mlp_model() history = model.fit(X_train, y_train, validation_split
= 0.3, epochs = 100, verbose = 1)
```

```
Epoch 1/100
1313/1313 [==============================] - 2s 2ms/step - loss: 2.3656 - acc
uracy: 0.1143 - val_loss: 2.3063 - val_accuracy: 0.1079
Epoch 2/100
1313/1313 [==============================] - 2s 2ms/step - loss: 2.3001 - acc
uracy: 0.1143 - val_loss: 2.2984 - val_accuracy: 0.1079
Epoch 3/100
1313/1313 [==============================] - 2s 2ms/step - loss: 2.2958 - acc
uracy: 0.1143 - val_loss: 2.2955 - val_accuracy: 0.1079
Epoch 4/100
1313/1313 [==============================] - 2s 2ms/step - loss: 2.2929 - acc
uracy: 0.1143 - val_loss: 2.2927 - val_accuracy: 0.1079
Epoch 5/100
1313/1313 [==============================] - 2s 2ms/step - loss: 2.2902 - acc
uracy: 0.1143 - val_loss: 2.2900 - val_accuracy: 0.1079
Epoch 6/100
1313/1313 [==============================] - 2s 2ms/step - loss: 2.2876 - acc
uracy: 0.1143 - val_loss: 2.2872 - val_accuracy: 0.1079
Epoch 7/100
1313/1313 [                              ] 2s 2ms/step    loss: 2 2849   acc
```

In [ ]:

```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.legend(['train acc', 'valid acc', 'train loss', 'valid loss'], loc = 'upper
left')
plt.show()
```



Training and validation accuracy seems to improve after around 60 epochs

In [ ]:

```
results = model.evaluate(X_test, y_test)
```

```
313/313 [==============================] - 0s 1ms/step - loss: 0.5939 - accurac
y: 0.8625
```

In [ ]:

```
print('Test accuracy: ', results[1])
```

```
Test accuracy:  0.862500011920929
```

2. Nonlinearity (Activation function)

- Sigmoid functions suffer from gradient vanishing problem, making training slower
- There are many choices apart from sigmoid and tanh; try many of them!
  - **'relu'** (rectified linear unit) is one of the most popular ones
  - **'selu'** (scaled exponential linear unit) is one of the most recent ones

In [ ]:

```
def mlp_model():
    model = Sequential()
    
    model.add(Dense(50, input_shape = (784, )))
    model.add(Activation('relu'))    # use relu
    model.add(Dense(50))
    model.add(Activation('relu'))    # use relu
    model.add(Dense(50))
    model.add(Activation('relu'))    # use relu
    model.add(Dense(50))
    model.add(Activation('relu'))    # use relu
    model.add(Dense(10))
    model.add(Activation('softmax'))
    
    sgd = optimizers.SGD(lr = 0.001)
    model.compile(optimizer = sgd, loss = 'categorical_crossentropy', metrics = 
['accuracy'])
    
    return model
```

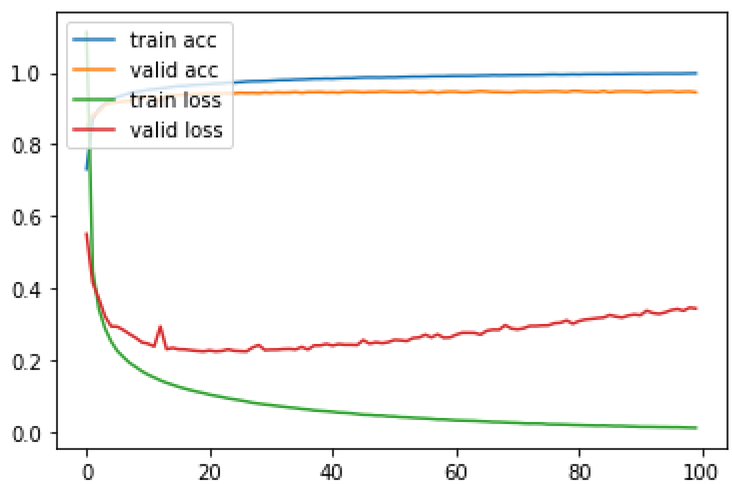
In [ ]:

```
model = mlp_model()
history = model.fit(X_train, y_train, validation_split = 0.3, epochs = 100,
verbose = 1)
```

```
Epoch 1/100
1313/1313 [==============================] - 2s 2ms/step - loss: 1.1128 - acc
uracy: 0.7314 - val_loss: 0.5504 - val_accuracy: 0.8466
Epoch 2/100
1313/1313 [==============================] - 2s 2ms/step - loss: 0.4489 - acc
uracy: 0.8700 - val_loss: 0.4168 - val_accuracy: 0.8827
Epoch 3/100
1313/1313 [==============================] - 2s 2ms/step - loss: 0.3434 - acc
uracy: 0.8988 - val_loss: 0.3719 - val_accuracy: 0.8918
Epoch 4/100
1313/1313 [==============================] - 2s 2ms/step - loss: 0.2895 - acc
uracy: 0.9141 - val_loss: 0.3231 - val_accuracy: 0.9103
Epoch 5/100
1313/1313 [==============================] - 2s 2ms/step - loss: 0.2528 - acc
uracy: 0.9248 - val_loss: 0.2951 - val_accuracy: 0.9153
Epoch 6/100
1313/1313 [==============================] - 2s 2ms/step - loss: 0.2266 - acc
uracy: 0.9321 - val_loss: 0.2940 - val_accuracy: 0.9170
Epoch 7/100
1313/1313 [                              ]   2   2   / t      l      0 2094
```

In [ ]:

```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.legend(['train acc', 'valid acc', 'train loss', 'valid loss'], loc = 'upper
left')
plt.show()
```



Training and validation accuracy improve instantaneously, but reach a plateau after around 30 epochs

```
results = model.evaluate(X_test, y_test)
```

In [ ]:

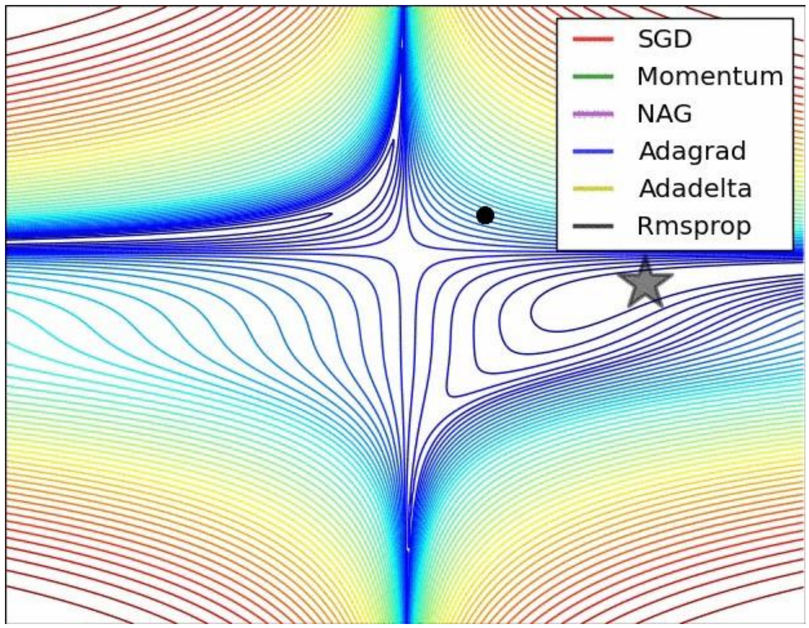
```
313/313 [==============================] - 0s 1ms/step - loss: 0.3152 - accurac
y: 0.9488
```

In [ ]:
```
print('Test accuracy: ', results[1])
```

```
Test accuracy:  0.9488000273704529
```

3. Optimizers

Many variants of SGD are proposed and employed nowadays
One of the most popular ones are Adam (Adaptive Moment Estimation)



Relative convergence speed of different optimizers

In [ ]:

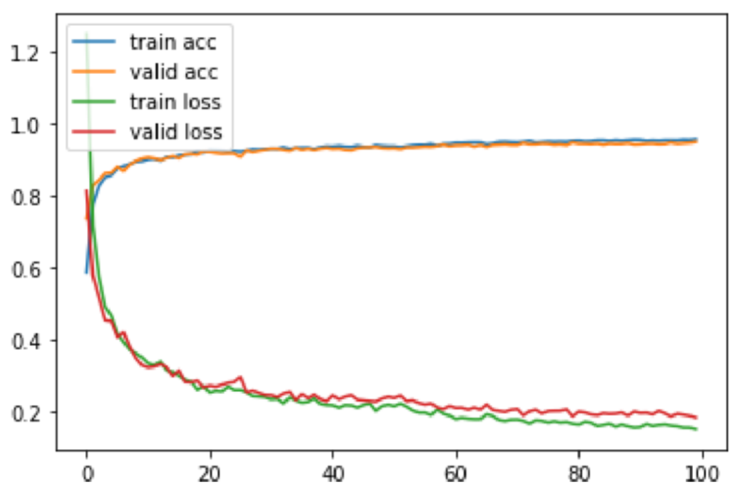
```
def mlp_model():
    model = Sequential()

    model.add(Dense(50, input_shape = (784, )))
    model.add(Activation('sigmoid'))
    model.add(Dense(50))
    model.add(Activation('sigmoid'))
    model.add(Dense(50))
    model.add(Activation('sigmoid'))
    model.add(Dense(50))
    model.add(Activation('sigmoid'))
    model.add(Dense(10))
    model.add(Activation('softmax'))

    adam = optimizers.Adam(lr = 0.001)                    # use Adam optimizer
    model.compile(optimizer = adam, loss = 'categorical_crossentropy', metrics =
['accuracy'])

    return model
```

In [ ]:

```
model = mlp_model()
history = model.fit(X_train, y_train, validation_split = 0.3, epochs = 100,
verbose = 0)
```

In [ ]:

```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.legend(['train acc', 'valid acc', 'train loss', 'valid loss'], loc = 'upper
left')
plt.show()
```



Training and validation accuracy improve instantaneously, but reach plateau after around 50 epochs

```
results = model.evaluate(X_test, y_test)
```

In [ ]:

```
313/313 [==============================] - 0s 1ms/step - loss: 0.1801 - accurac
y: 0.9465
```

In [ ]:

```
print('Test accuracy: ', results[1])
```

```
Test accuracy:  0.9465000033378601
```

4. Batch Normalization

Batch Normalization, one of the methods to prevent the "internal covariance shift" problem, has proven to be highly effective

Normalize each mini-batch before nonlinearity

Batch normalization layer is usually inserted after dense/convolution and before nonlinearity

In [ ]:

```
from keras.layers import BatchNormalization
```

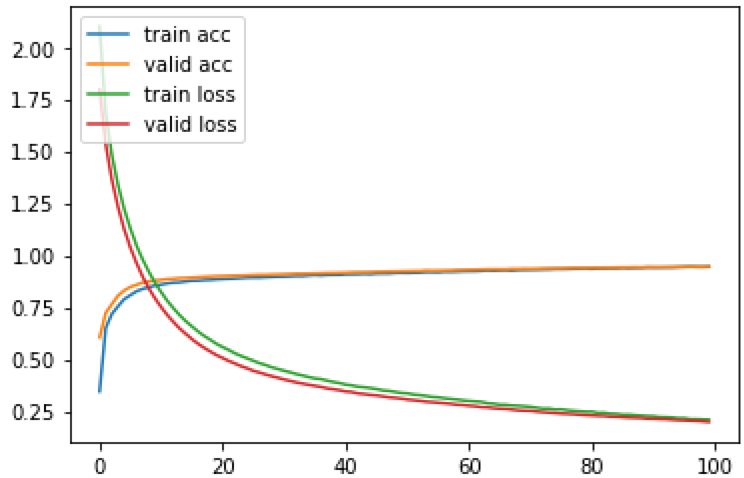
```
def mlp_model():
model = Sequential()

    model.add(Dense(50, input_shape = (784, )))
    model.add(BatchNormalization())                    # Add Batchnorm layer
before Activation
    model.add(Activation('sigmoid'))
model.add(Dense(50))
    model.add(BatchNormalization())                    # Add Batchnorm layer
before Activation
    model.add(Activation('sigmoid'))
model.add(Dense(50))
    model.add(BatchNormalization())                    # Add Batchnorm layer
before Activation
    model.add(Activation('sigmoid'))
model.add(Dense(50))
    model.add(BatchNormalization())                    # Add Batchnorm layer
before Activation
    model.add(Activation('sigmoid'))
model.add(Dense(10))
    model.add(Activation('softmax'))

    sgd = optimizers.SGD(lr = 0.001)
    model.compile(optimizer = sgd, loss = 'categorical_crossentropy', metrics =
['accuracy'])
return model
```

In [ ]:

```
model = mlp_model() history = model.fit(X_train, y_train, validation_split
= 0.3, epochs = 100, verbose = 0)
```

In [ ]:

```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.legend(['train acc', 'valid acc', 'train loss', 'valid loss'], loc = 'upper
left')
plt.show()
```



Training and validation accuracy improve consistently, but reach plateau after around 60 epochs

In [ ]:

```
results = model.evaluate(X_test, y_test)
```

```
313/313 [==============================] - 0s 1ms/step - loss: 0.1866 - accurac
y: 0.9481
```

In [ ]:

```
print('Test accuracy: ', results[1])
```

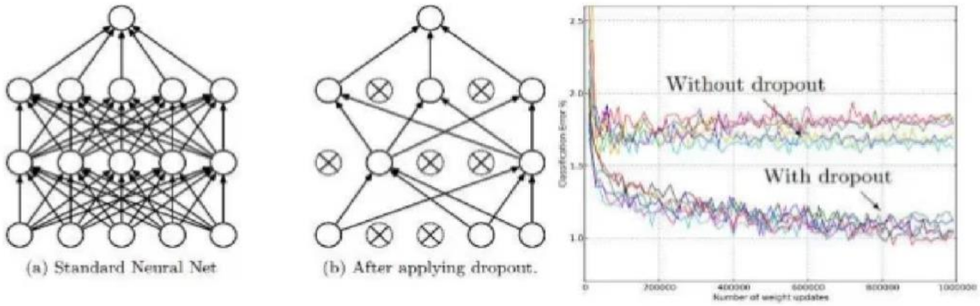
```
Test accuracy:  0.9480999708175659
```

5. Dropout (Regularization)

- Dropout is one of powerful ways to prevent overfitting
- The idea is simple. It is disconnecting some (randomly selected) neurons in each layer
- The probability of each neuron to be disconnected, namely 'Dropout rate', has to be
- designated

In [ ]:

Dropout



Model	Top-1 (val)	Top-5 (val)	Top-5 (test)
SVM on Fisher Vectors of Dense SIFT and Color Statistics	-	-	27.3
Avg of classifiers over FVs of SIFT, LBP, GIST and CSIFT	-	-	26.2
Conv Net + dropout (Krizhevsky et al., 2012)	40.7	18.2	-
Avg of 5 Conv Nets + dropout (Krizhevsky et al., 2012)	38.1	16.4	16.4

Table 6: Results on the ILSVRC-2012 validation/test set.

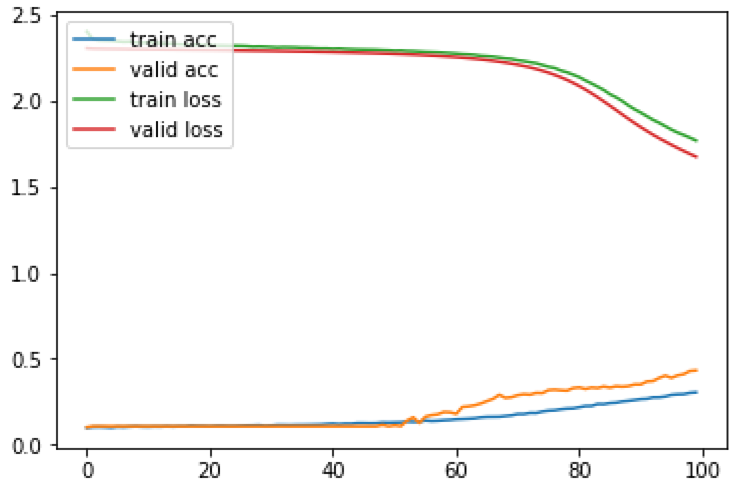
Dropout: A simple way to prevent neural networks from overfitting [Srivastava JMLR 2014]

In [ ]:
```
from keras.layers import Dropout
```

In [ ]:
```
def mlp_model():
    model = Sequential()
    
    model.add(Dense(50, input_shape = (784, )))
    model.add(Activation('sigmoid'))
    model.add(Dropout(0.2))                        # Dropout layer after 
Activation
    model.add(Dense(50))
    model.add(Activation('sigmoid'))
    model.add(Dropout(0.2))                        # Dropout layer after 
Activation
    model.add(Dense(50))
    model.add(Activation('sigmoid'))
    model.add(Dropout(0.2))                        # Dropout layer after 
Activation
    model.add(Dense(50))
    model.add(Activation('sigmoid'))
    model.add(Dropout(0.2))                         # Dropout layer after 
Activation
    model.add(Dense(10))
    model.add(Activation('softmax'))
    
    sgd = optimizers.SGD(lr = 0.001)
    model.compile(optimizer = sgd, loss = 'categorical_crossentropy', metrics = 
['accuracy'])
    
    return model
```

```
model = mlp_model()
history = model.fit(X_train, y_train, validation_split = 0.3, epochs = 100,
verbose = 0)
```

In [ ]:
```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.legend(['train acc', 'valid acc', 'train loss', 'valid loss'], loc = 'upper
left')
plt.show()
```



Validation results does not improve since it did not show signs of overfitting, yet.
Hence, the key takeaway message is that apply dropout when you see a signal of overfitting.

In [ ]:
```
results = model.evaluate(X_test, y_test)
```

```
313/313 [==============================] - 0s 1ms/step - loss: 1.6782 - accurac
y: 0.4227
```

In [ ]:
```
print('Test accuracy: ', results[1])
```

```
Test accuracy:  0.4226999878883362
```

6. Model Ensemble

Model ensemble is a reliable and promising way to boost performance of the model
Usually create 8 to 10 independent networks and merge their results
Here, we resort to scikit-learn API, **VotingClassifier**

In [ ]:

In [ ]:
```python
import numpy as np

from tensorflow.keras.wrappers.scikit_learn import KerasClassifier
from sklearn.ensemble import VotingClassifier
from sklearn.metrics import accuracy_score
```

In [ ]:
```python
y_train = np.argmax(y_train, axis = 1)
y_test = np.argmax(y_test, axis = 1)
```

In [ ]:
```python
def mlp_model():
    model = Sequential()

    model.add(Dense(50, input_shape = (784, )))
    model.add(Activation('sigmoid'))
    model.add(Dense(50))
    model.add(Activation('sigmoid'))
    model.add(Dense(50))
    model.add(Activation('sigmoid'))
    model.add(Dense(50))
    model.add(Activation('sigmoid'))
    model.add(Dense(10))
    model.add(Activation('softmax'))

    sgd = optimizers.SGD(lr = 0.001)
    model.compile(optimizer = sgd, loss = 'categorical_crossentropy', metrics =
['accuracy'])

    return model
```

In [ ]:
```python
model1 = KerasClassifier(build_fn = mlp_model, epochs = 100, verbose = 0)
model2 = KerasClassifier(build_fn = mlp_model, epochs = 100, verbose = 0)
model3 = KerasClassifier(build_fn = mlp_model, epochs = 100, verbose = 0)
model1._estimator_type = "classifier"
model2._estimator_type = "classifier"
model3._estimator_type = "classifier"
```

Out[131]:
```
VotingClassifier(estimators=[('model1',
                              <tensorflow.python.keras.wrappers.scikit_learn.Ke
rasClassifier object at 0x7f3b1c1f9438>),
                             ('model2',
                              <tensorflow.python.keras.wrappers.scikit_learn.Ke
rasClassifier object at 0x7f3b1c1ce7b8>),
                             ('model3',
                              <tensorflow.python.keras.wrappers.scikit_learn.Ke
rasClassifier object at 0x7f3b1c10d978>)],
                 flatten_transform=True, n_jobs=None, voting='soft',
 weights=None)
```

In [ ]:
```python
y_pred = ensemble_clf.predict(X_test)
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow/pytho
n/keras/wrappers/scikit_learn.py:264: Sequential.predict_proba (from tensorflo
```

```
ensemble_clf = VotingClassifier(estimators = [('model1', model1), ('model2', model2), ('model3', model3)]
                                , voting = 'soft')
```

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

```
w.python.keras.engine.sequential) is deprecated and will be removed after 2021-01-01.
Instructions for updating:
Please use `model.predict()` instead.
```

In [ ]:
```
print('Test accuracy:', accuracy_score(y_pred, y_test))
```

```
Test accuracy: 0.9002
```

Summary

Below table is a summary of evaluation results so far. It turns out that all methods improve the test performance over the MNIST dataset. Why don't we try them out altogether?

Model	Baseline	Weight initialization	Activation function	Optimizer	Batchnormalization	Regularization	Ensemble
Test Accuracy	0.1134	0.8625	0.9488	0.9465	0.9480	0.4226	0.9002