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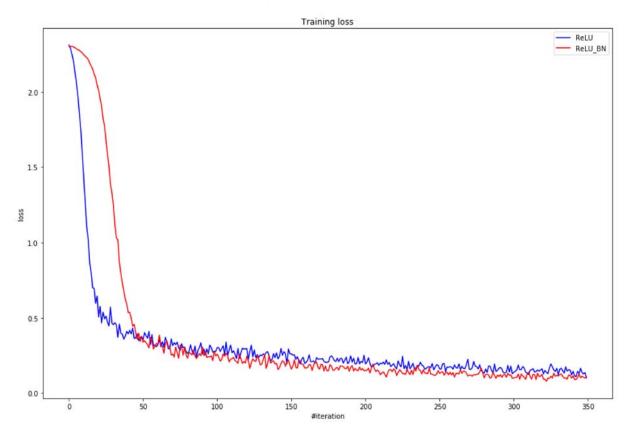
```
print("Number of neurons in the inner layer: ", node_size)
for (a, l, bn_l) in losses:
    # Visualize
    plt.figure(figsize=(15, 10))

    plt.title("Training loss")
    plt.xlabel("#iteration")
    plt.ylabel("loss")
    line = plt.plot(l, 'b', label=a)
    line_bn = plt.plot(bn_l, 'r', label=a + "_BN")

    plt.legend(loc="best")
    plt.show()

    print(a," loss: ", np.min(l))
    print(a," loss BatchNorm : ", np.min(bn_l))
```

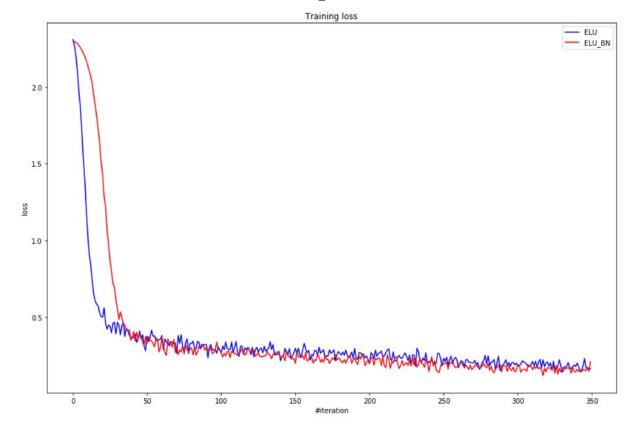
Number of neurons in the inner layer: 200



ReLU loss: 0.10053982531142128

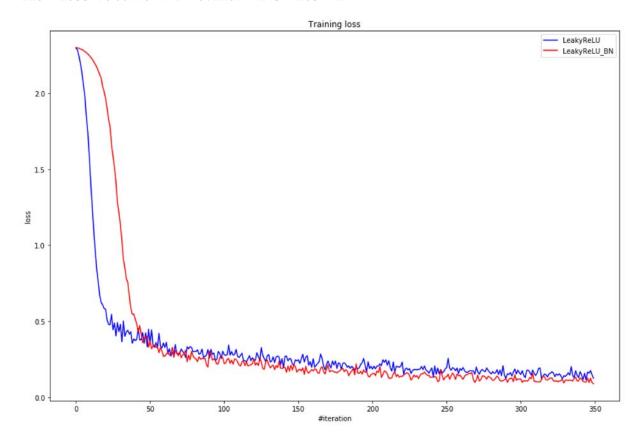
ReLU loss BatchNorm : 0.07718396767398226

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ELU loss: 0.13873209248259433

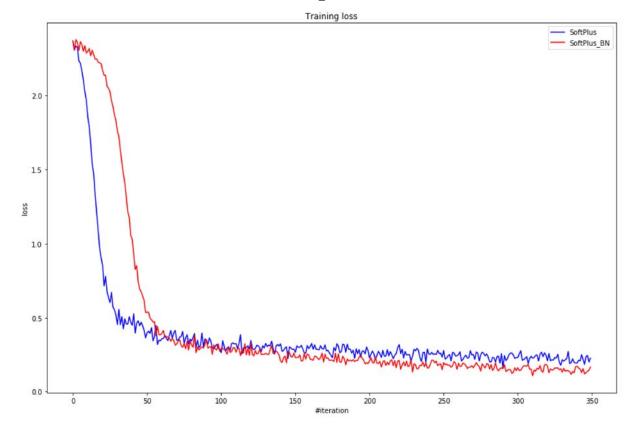
ELU loss BatchNorm : 0.11674414394265792



LeakyReLU loss: 0.11341953401912494

LeakyReLU loss BatchNorm : 0.08772101119969121

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SoftPlus loss: 0.1584598205432189

SoftPlus loss BatchNorm : 0.10737357330850125

Write your personal opinion on the activation functions, think about computation times too. Does BatchNormalization help?

- BatchNorm yields lower loss and leads to a smoother descent (not faster, but more steady descent)
- LeakyReLU and ReLU are the best performing nonlinearities
- More nodes in the inner layer lead to smaller loss
- There exists a "smooth spot" where increasing the number of inner nodes does not give more performance. Therefore we can say that the performance is given by the available data, and not the number of neurons

Finally, use all your knowledge to build a super cool model on this dataset, do not forget to split dataset into train and validation. Use **dropout** to prevent overfitting, play with **learning rate decay**. You can use **data augmentation** such as rotations, translations to boost your score. Use your knowledge and imagination to train a model. Don't forget to call training() and evaluate() methods to set desired behaviour of BatchNormalization and Dropout layers.

Print here your accuracy. It should be around 90%.