

photo: New Jersey/New York

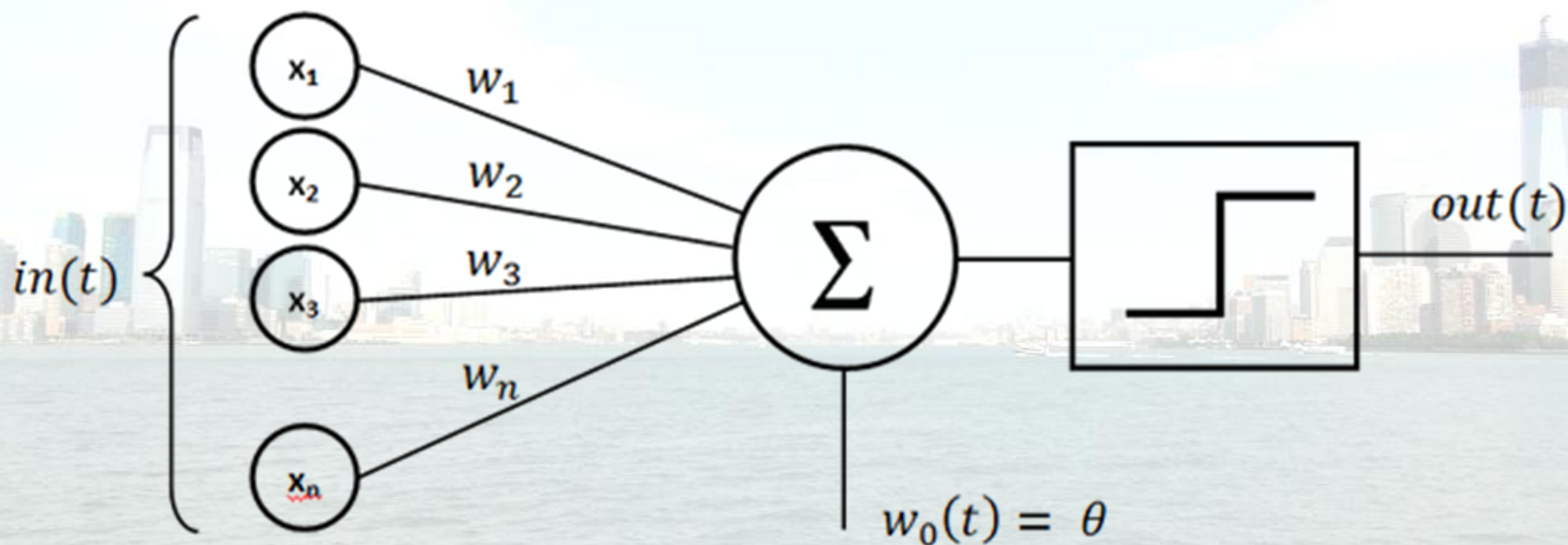
Artificial Intelligence

Neural Networks

Paweł Kasprowski, PhD, DSc.

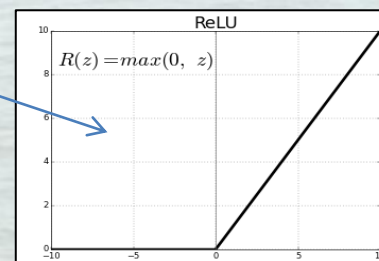
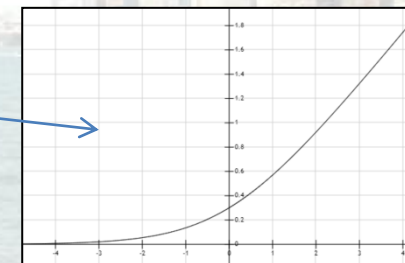
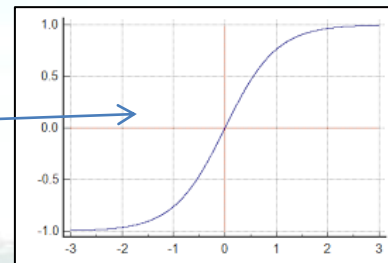
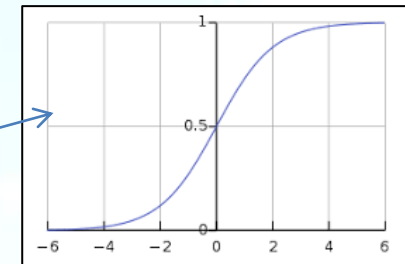


Perceptron (Rosenblatt 1957)



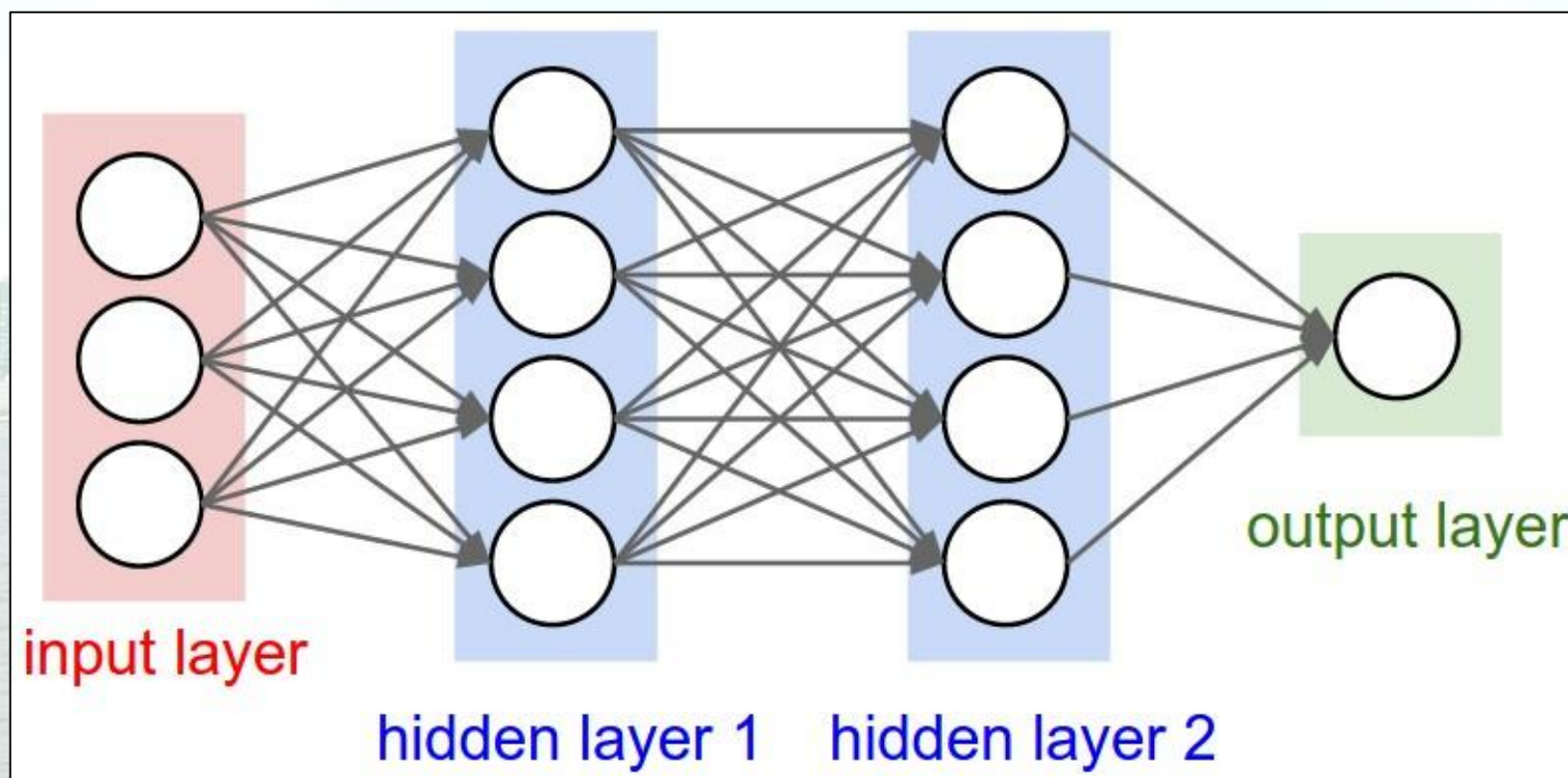
Activation function

- Linear combination of inputs
- Activation functions may be different
 - threshold function
 - sigmoid function
 - tanh function
 - softplus
 - RELU



Artificial Neural Network (ANN)

- input layer > hidden layers > output layer



Training the network

- Back propagation
 - the state-of-the art method to train the network
 - utilizes the already mentioned Gradient Descent algorithm
- The algorithm:
 - initialize weights
 - repeat many times:
 - use network to calculate output (Y_{pred}) for some examples (X)
 - calculate error (loss function) using Y_{pred} and Y (real)
 - update weights to minimize loss (using gradient for direction)

Tuning - hyperparameters

- Network structure
 - Number of layers
 - Number of neurons for layer
 - Connections
 - Activation functions for layers
- Loss function
- Optimization algorithm
 - how to change the weights
 - learning rate (how big changes of weights)

Implementations

- Many classification libraries like scikit-learn or WEKA implement the neural networks
 - but only the simplest models
- For Deep Learning there are many libraries developed by leading companies:
 - Tensorflow, Google
 - PyTorch, Facebook
 - CNTK, Microsoft
 - ...
- We will use the most popular: Keras/Tensorflow

Keras

- General interface to use deep networks
- Works with Tensorflow, Theano, CNTK...
- User-friendly, modular, and extensible
- Created in Google
- Works in Python
- Tensorflow library includes Keras by default
 - that is why we installed Tensorflow and we use Keras
- Tensorflow 2 is integrated with Keras

FRAMEWORKS USAGE

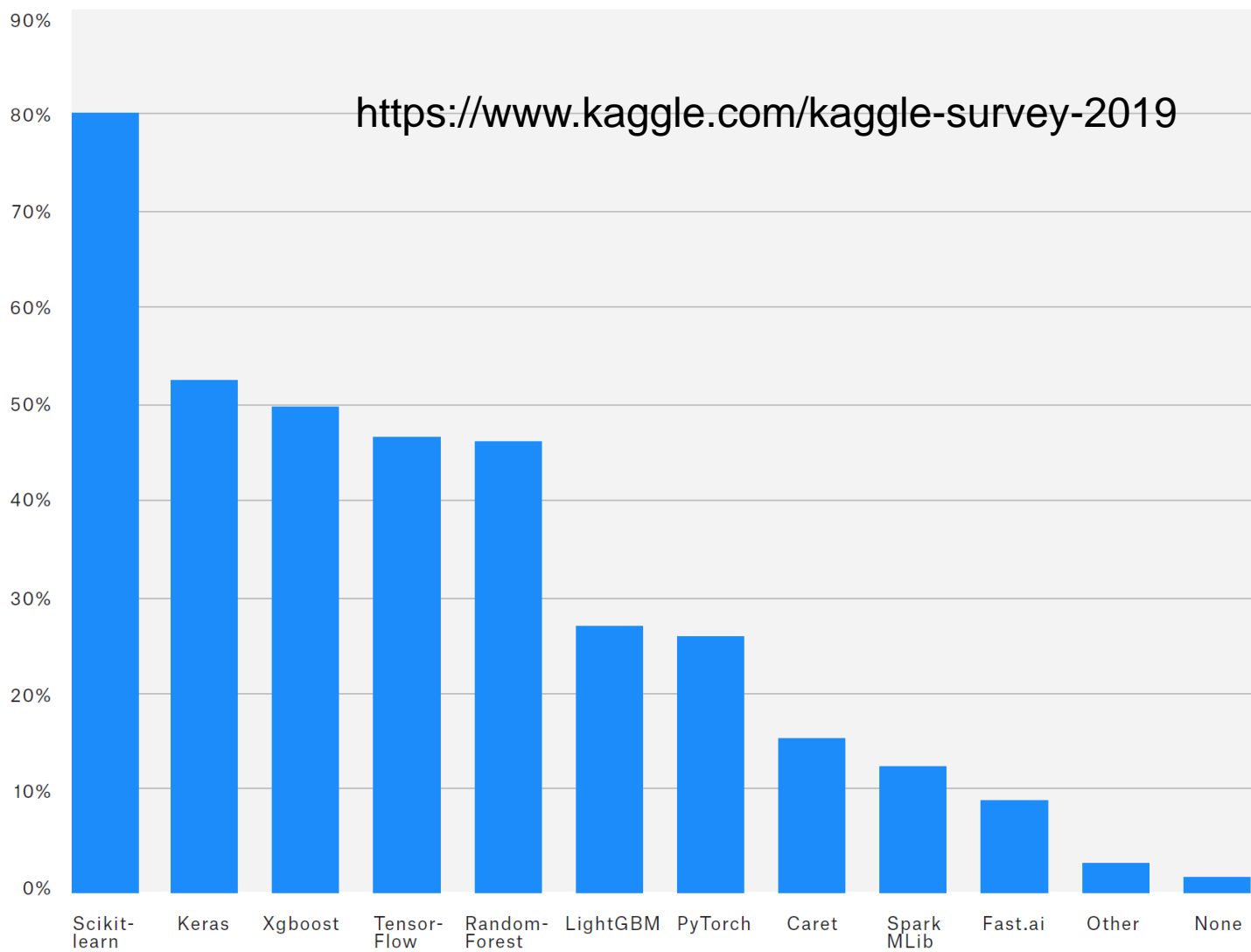


Table 3: Major Deep Learning Platforms

| Platform | 2019 % share | 2018 % share | % change |
|-----------------------------|-----------------|-----------------|----------|
| Tensorflow | 31.7% | 29.9% | 5.8% |
| Keras | 26.6% | 22.2% | 19.7% |
| PyTorch | 11.3% | 6.4% | 75.5% |
| Other Deep Learning Tools | 5.6% | 4.9% | 15.2% |
| DeepLearning4J | 2.5% | 3.4% | -25.6% |
| Apache MXnet | 1.7% | 1.5% | 13.1% |
| Microsoft Cognitive Toolkit | 1.6% | 3.0% | -45.5% |
| Theano | 1.6% | 4.9% | -67.4% |
| Torch | 0.9% | 1.0% | -6.1% |
| TFLearn | 0.7% | 1.1% | -34.7% |
| Caffe | 0.6% | 1.5% | -58.3% |

<https://www.kdnuggets.com/2019/05/poll-top-data-science-machine-learning-platforms.html>

Keras basics

- Build the model (network)
 - contains layers with neurons and connections
- Compile the model (model.compile)
 - define loss function and optimizer
- Train the model (model.fit)
 - provide samples with known labels
- Use the model for predictions (model.predict)
 - predict labels of unknown samples

The simplest example

```
# import keras
```

```
from tensorflow.keras.models import Sequential
```

```
from tensorflow.keras.layers import Dense
```

```
# build model
```

```
model = Sequential()
```

```
model.add(Dense(50, activation='sigmoid'))
```

```
model.add(Dense(1, activation='sigmoid'))
```

```
# compile model
```

```
model.compile(loss='binary_crossentropy',  
              optimizer="adam", metrics=['accuracy'])
```

```
# train model
```

```
model.fit(samples, labels, epochs=100, batch_size=10)
```

```
# use model
```

```
predicted = model.predict(sample)
```


Decoder

decoder1.ipynb

- Decodes a binary list:
 - [1,0,0,1,0,0,0,1]
- to the number:
 - 145
- Input: 8 values (0 or 1)
- Output: one value (the number)

model.compile parameters

- loss – loss function
 - *binary_crossentropy* for 2-class problem
 - *categorical_crossentropy* for many classes (one-hot encoded)
 - *mean_squared_error* for regression
- optimizer – algorithm for back propagation
 - SGD
 - adam
 - RMSprop
- metrics – metrics to measure after each iteration
 - *accuracy* for classification
 - *mean squared error* for regression

model.fit parameters

- samples – array of samples
- labels – array of labels (one for each sample)
- epochs – number of iterations
- batch_size – number of samples per batch (each back propagation pass)
 - stochastic (1 – backprop after every sample)
 - mini-batch (from 2 to N-1)
 - batch (N – backprop after all samples – one per epoch)
- validation_split – percent of validation samples
- validation_data = (samples, labels)

Input parameters

- samples – a list of samples
 - every sample may be multidimensional (e.g. 3D for images)
- labels – a list of correct labels for each sample
 - a list of values [0,1,4,2,1,4,2...] (one output node)
 - one-hot encoded:
 - $0 > [1,0,0,0,0]$
 - $1 > [0,1,0,0,0]$
 - $4 > [0,0,0,0,1]$
 - (five output nodes)

Example

iris-keras.ipynb

- Create model:

```
model = Sequential()
```

```
model.add(Dense(50, input_dim=4, activation='sigmoid'))
```

```
model.add(Dense(50, activation='sigmoid'))
```

```
model.add(Dense(1, activation='sigmoid'))
```

- Use model

```
model.compile(loss='binary_crossentropy',  
              optimizer="adam", metrics=['accuracy'])
```

```
model.fit(trainSamples, trainLabels,  
          epochs=10, batch_size=10)
```

Multinomial classification

- More than two classes
 - E.g. cats, dogs, snakes and elephants
- The model returns a probability for each class
- We choose the class with the highest probability
- Typical output:
 - binary class matrix (one-hot encoding)
 - 1 -> [1,0,0,0,0]
 - 2 -> [0,1,0,0,0]
 - 3 -> [0,0,1,0,0]
 - ...
- The simplest method:
`onehot_labels = tf.keras.utils.to_categorical(labels)`
 - *(it requires integer labels!)*

Dataset with tree classes

iris-keras.ipynb / Multinomial

- Encoding labels

```
data.loc[data['iris']=='Iris-versicolor'] = 0
```

```
data.loc[data['iris']=='Iris-setosa'] = 1
```

```
data.loc[data['iris']=='Iris-virginica'] = 2
```

```
labels = tf.keras.utils.to_categorical(labels)
```

- shape: (150,3)

- Output from the network:

```
model.add(Dense(3, activation='softmax'))
```

Conversion of labels

- LabelEncoder – encodes labels to int numbers
encoder = sklearn.preprocessing.LabelEncoder()
int_labels = encoder.fit_transform(labels)
- It is possible to find the original label for integer
encoder.inverse_transform(int_label))

One-hot encoding

- `oh_labels = tf.keras.utils.to_categorical(labels)`
- Problems:
 - original labels must be integer
 - no inverse transform
- More sophisticated way – `LabelBinarizer`
 - `lb = sklearn.preprocessing.LabelBinarizer()`
 - `oh_labels = lb.fit_transform(labels)`
 - decoding:*
 - `lb.inverse_transform(oh_label))`

Labeling example

binarizer.ipynb

- LabelBinarizer
- Problem with two classes
- Combining LabelEncoder and to_categorical



EMVIC 2012 data

- Identification of people based on their eye movements
- Part of EMVIC 2012^[1] dataset:
 - 155 samples
 - 3 classes (persons)
 - 16384 attributes (position-vel-acc)
- unbalanced distribution
 - {'a25': 104, 'a41': 39, 'a37': 11}

[1] Kasprowski, Komogortsev, Karpov: First eye movement verification and identification competition at BTAS 2012, IEEE Fifth International Conference on Biometrics: Theory, Applications and Systems (BTAS)

Loading and preparing data

emvic.ipynb

- Loading

```
dataframe = pandas.read_csv(file)
```

```
dataset = dataframe.values
```

```
samples = dataset[:,1:]
```

```
labels = dataset[:,0]
```

- Another useful class - Counter

```
from collections import Counter
```

```
print("Class distribution:", Counter(labels))
```


Dataset preparation (1)

- Choose 100 best attributes

```
newSamples = SelectKBest(k=100)  
                .fit_transform(samples, labels)
```

- Add weights to classes (dictionary!)

```
class_weights = class_weight.compute_class_weight(  
    'balanced', np.unique(labels), labels)
```

```
d_class_weights = dict(enumerate(class_weights))
```

- Normalize the dataset

```
normalize(samples)
```

Dataset preparation (2)

- One-hot encoding

```
lb = LabelBinarizer()
```

```
labels = lb.fit_transform(labels)
```

```
classesNum = labels.shape[1]
```

- Division to training and testing

```
(trainSamples, testSamples, trainLabels, testLabels) =  
train_test_split(samples, labels, test_size=0.25)
```

The model

- Simple MLP model:

```
model = Sequential()  
model.add(Dense(250, activation='sigmoid'))  
model.add(Dense(250, activation='sigmoid'))  
model.add(Dense(250, activation='sigmoid'))  
model.add(Dense(classesNum, activation='softmax'))  
  
model.compile(loss= 'categorical_crossentropy',  
              optimizer="adam", metrics=['accuracy'])
```

Training, testing, reporting

- Training:

```
H = model.fit(trainSamples, trainLabels  
              ,class_weight=d_class_weights  
              ,validation_data=(testSamples,testLabels)  
              batch_size=BATCH, epochs=EPOCHS, )
```

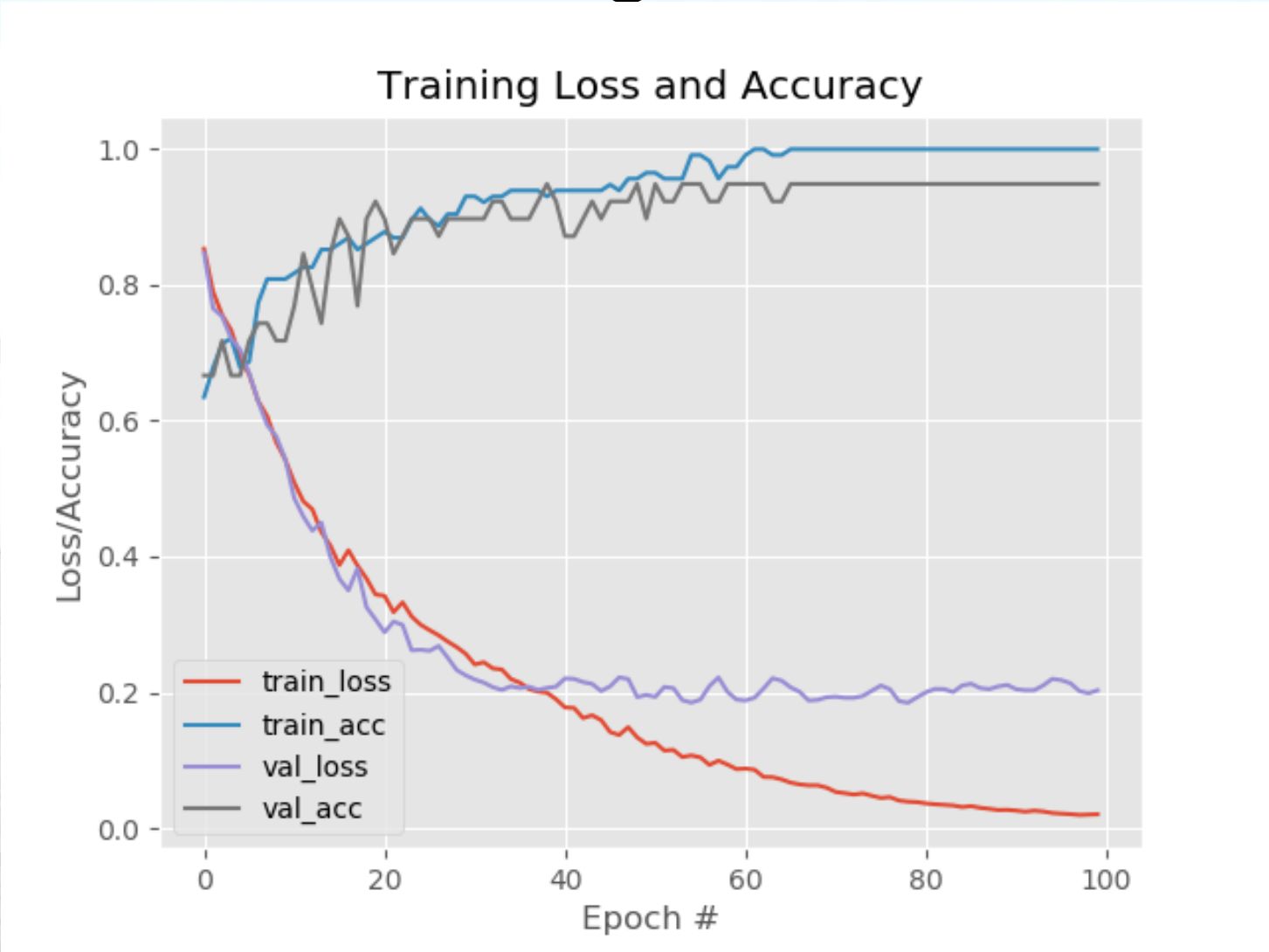
- Testing:

```
mlpResults = model.predict(testSamples)
```

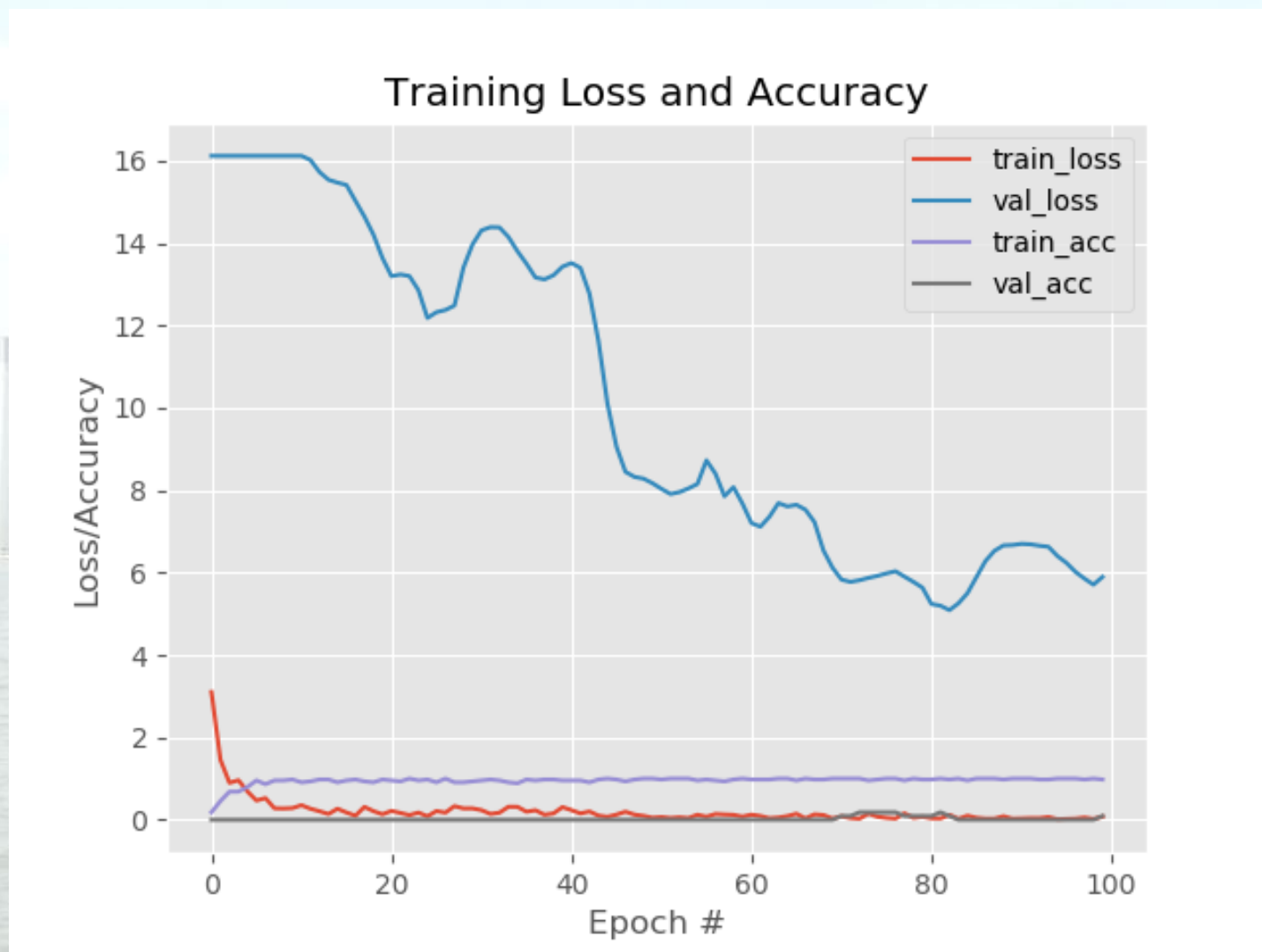
- Reporting (using methods from sklearn):

```
print(confusion_matrix(testLabels.argmax(axis=1),  
                        mlpResults.argmax(axis=1)))  
print(classification_report(testLabels.argmax(axis=1),  
                             mlpResults.argmax(axis=1),target_names=lb.classes_))
```


Training results



It may be worse...



It may be worse...



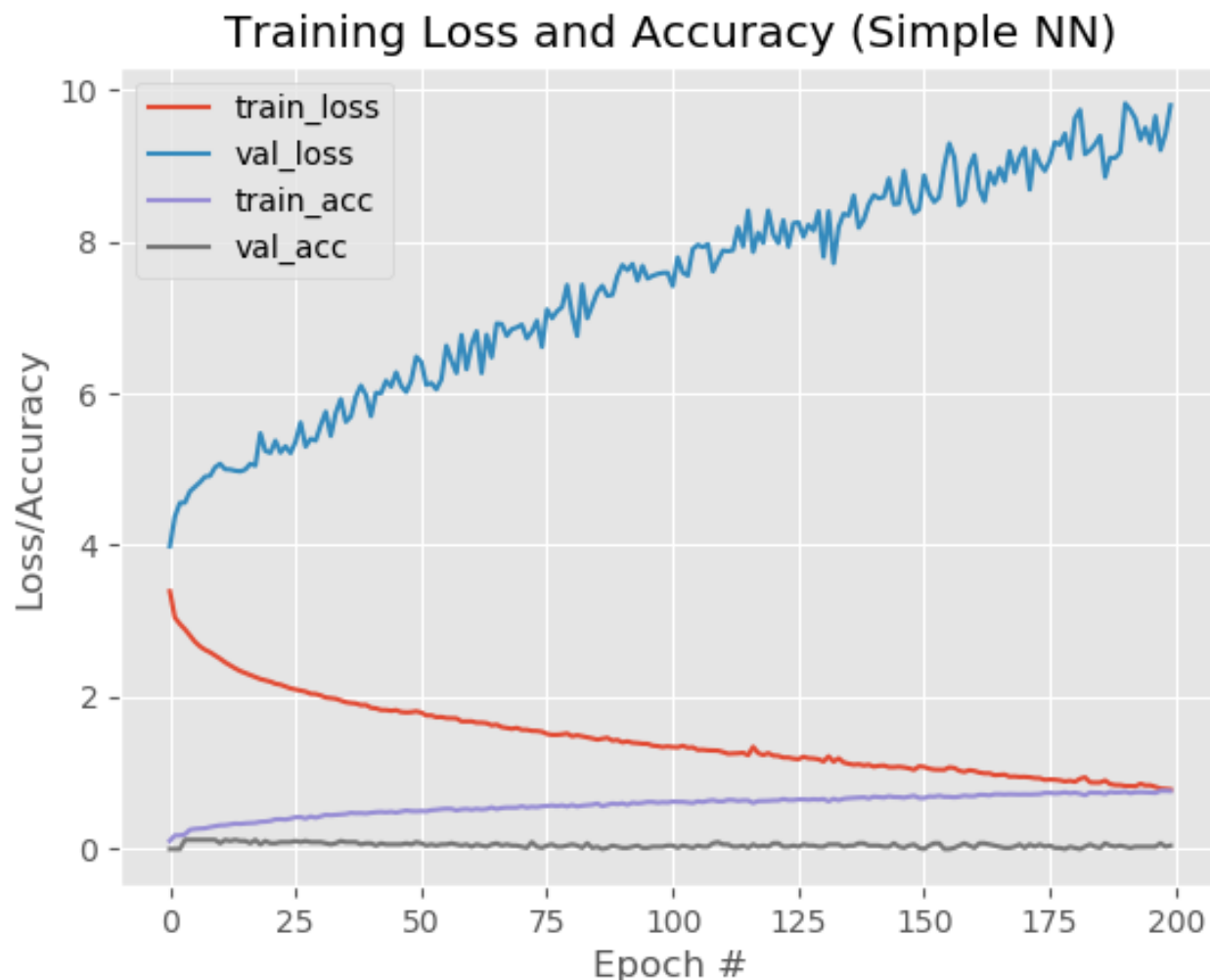
It may be worse...



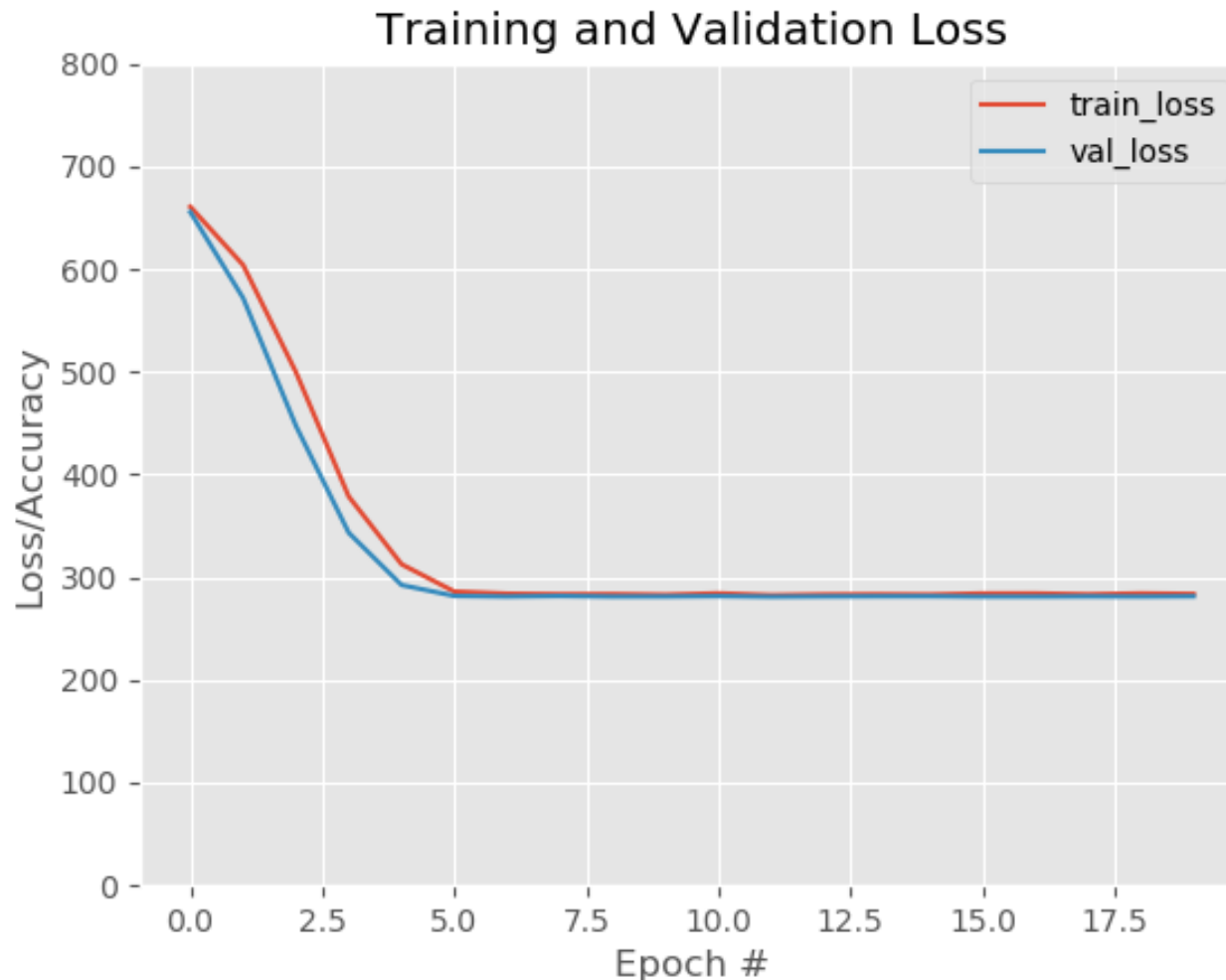
It may be even worse...



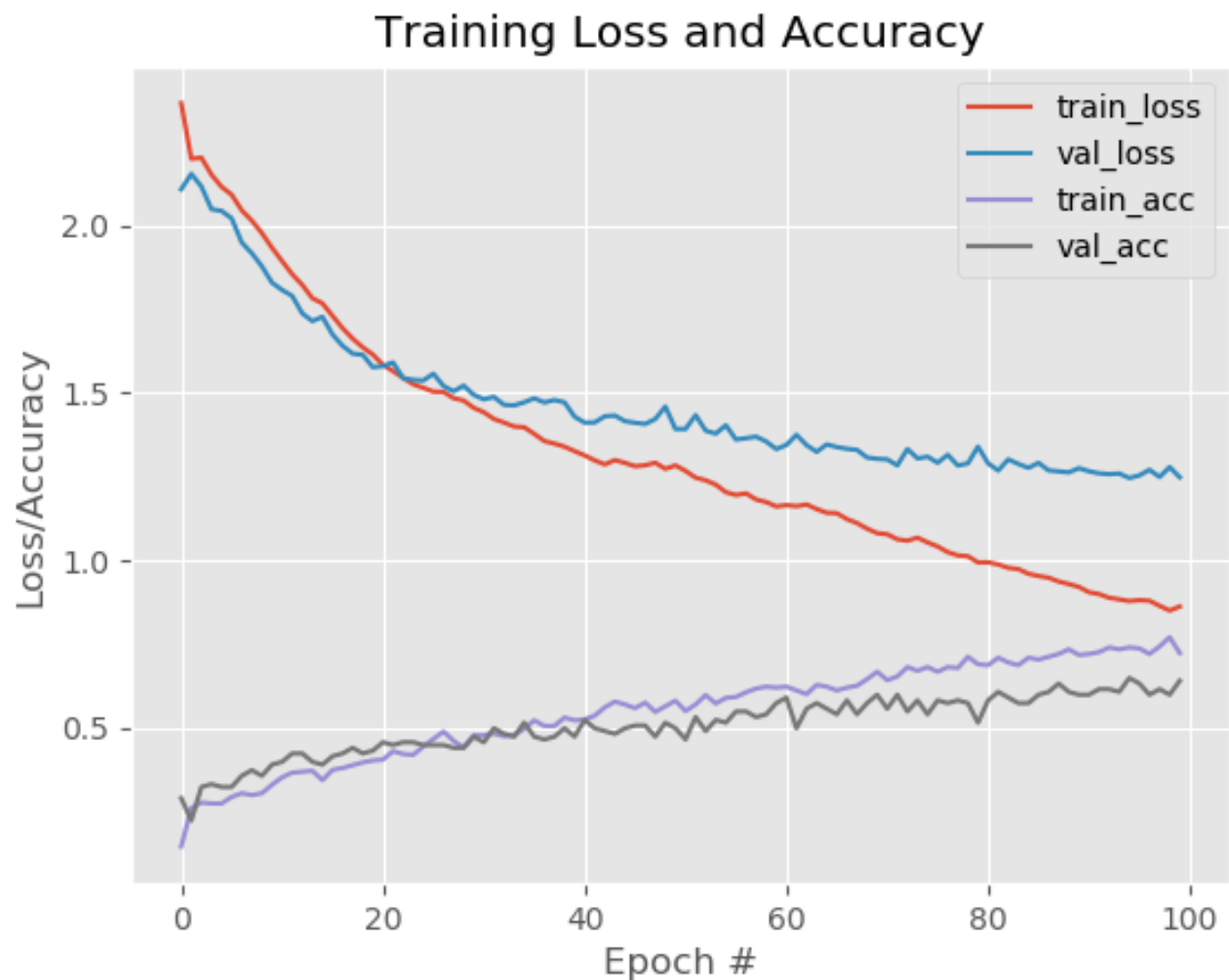
It may be even worse...



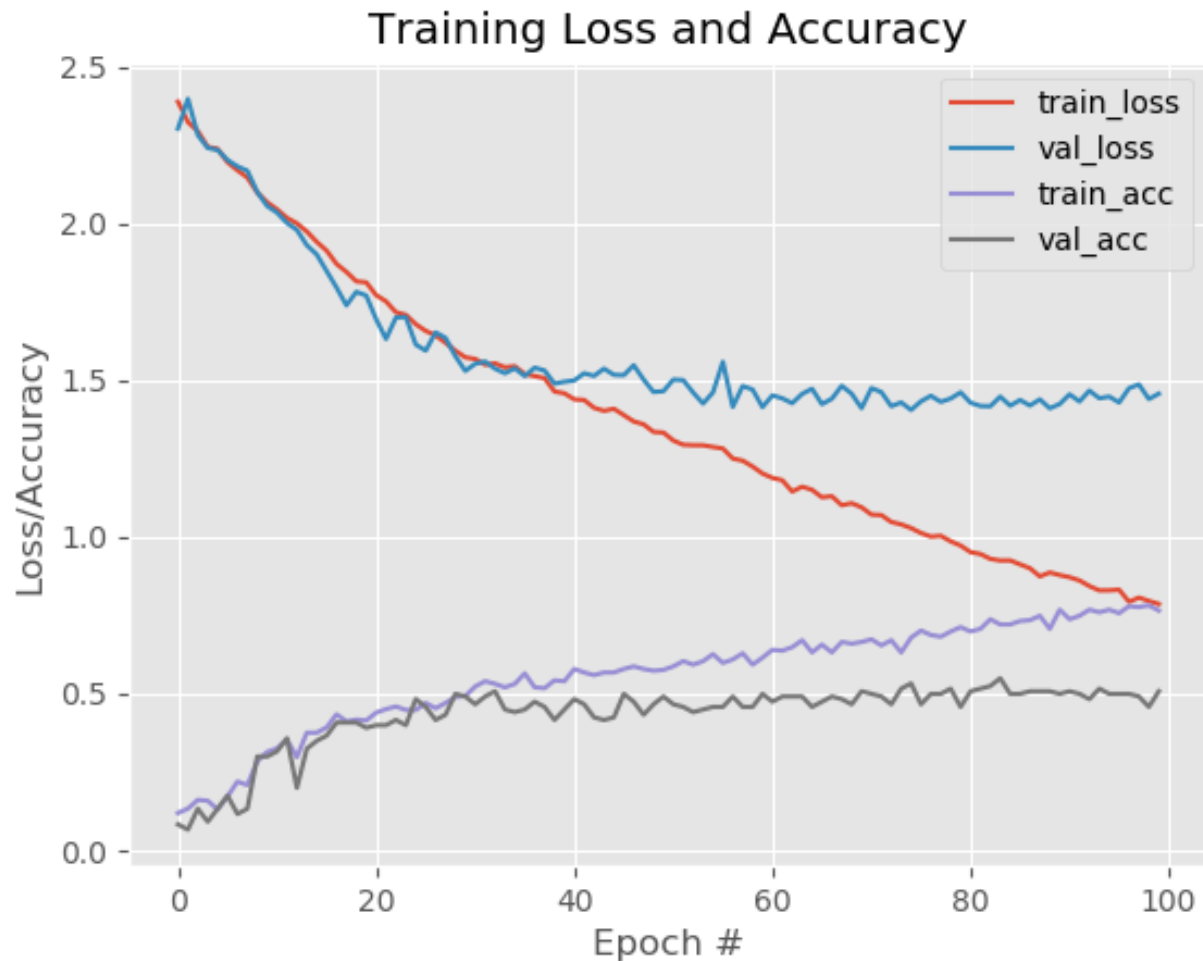
Sometimes even loss is not decreasing...



So ,this is quite OK



This is worse



Comparison with Decision Tree

- Code for Decision Tree:

```
from sklearn.tree import DecisionTreeClassifier  
treemodel = DecisionTreeClassifier()  
treemodel.fit(trainSamples, trainLabels)  
treeResults = treemodel.predict(testSamples)
```
- Results:
 - Comparable...

Problems with neural networks

- Configuration is complicated (many hyperparameters)
 - layers, number of neurons
 - activation functions
 - optimizers
- Training is challenging
 - A lot of computations – a lot of weights
 - A lot of examples needed
- Training of many layers may fail
 - Vanishing gradient problem
 - Exploding gradient problem

Question for today

- So why Deep Learning has become so popular?

- **Next part is about it!**