- a) A loss function describes the cost or loss of precision/information when performing a prediction. It give bigger value if the "distance" of the prediction from the real value is greater. Since the prediction depends on the powameters used in the classifier / predictor the low function can be used to estimate good parameter by minimising the low function.
- The law tunction can be minimised by looking for local minimum by variating the parameters.

Practically if you have a low function that directly reliev on the parameter you can follow its gradient to local vininum while adjustry the parameters towards the descending amakent in each slep.

The purpose of activation functions is to add non-linearity to neural network. It allows to use many neurow that perform linear transformations x = Wx +6 with different weights. Without an activation function the layers of nodes would collapse to 1 size transformation because of the linearity.

A neuron is a node in a neural network. Similar to the neurous in the human brain it receives and processes data. A neuron can receive data from other neurons in layer behind it and applies the linear transformation (weights) and passes the weighted data to other neurons depending on the activation function. e)

- 1) Text, image & voice recognition
- 21 Creating images / text

21 Creating images / text

3) Artifical Intelligence in Gares

· Big amounts of data need to be handled in this examples also there is a lot of easy accessible training data

. These tasks are very complex to solve and good

features con't be easily generated.

The neural network can handle big amounts of data and can also solve complex classificator tasks through its many free parameters and noural layers.

Exercise 23

21

din [x:] = M (column vector)

din (C) = 1 (ocalar)

din[W] = Mx M

dim [6] = 1 (column vector)

din [a, ?]

din[of []

din[Ofui]

dim [3thii]

 $\nabla_{\xi_{a}} C(f) = \frac{1}{n} \sum_{i=1}^{n} \left[\frac{\partial}{\partial f_{a}} \left(-\sum_{k=1}^{K} 1 (\gamma_{i} = k) \log \frac{e \times p(f_{k,i})}{\sum_{i} e \times p(f_{i,i})} \right) \right]$ $= 0 \text{ for } k \neq a$

 $\Rightarrow \nabla_{fa} C(f) = -\frac{1}{m} \sum_{i=1}^{m} \frac{\partial}{\partial f_a} 1(y_i = a) \left(o_{\delta} \left(\frac{e \times p(f_{a,i})}{\sum_{i} e \times p(f_{i,i})} \right) \right)$

 $\frac{\partial}{\partial t_{A}} \mathcal{L}(y_{i} = a) \left(o_{0} \frac{\exp(t_{a,i})}{\sum \exp(t_{a,i})} = \mathcal{L}(y_{i} = a) \frac{\sum \exp(t_{a,i})}{\exp(t_{a,i})} \cdot \frac{\partial}{\partial t_{a}} \frac{\exp(t_{a,i})}{\sum \exp(t_{a,i})} \cdot \frac{\partial}{\partial t_{a}} \frac{\partial}{\partial t_{$

= 1(yi=a) [exp(fii) . [exp(fii) exp(fai) - exp(fai)]

$$= 1(\gamma_{i} = a) \sum_{exp(f_{i},i)} \sum_{exp(f_{i},i)} exp(f_{a,i}) - exp(f_{a,i})$$

$$= 1(\gamma_{i} = a) \sum_{i} exp(f_{i},i) - exp(f_{a,i})$$

$$= 1(\gamma_{i} = a) \sum_{i} exp(f_{i},i)$$

$$= 1(\gamma_{i} = a) \cdot (1 - \frac{exp(f_{a,i})}{\sum_{i} exp(f_{i},i)})$$

$$\Rightarrow \nabla_{f_{a}} (f_{a}) = 1 \cdot (1 - \frac{exp(f_{a,i})}{\sum_{i} exp(f_{i},i)})$$