

# ML using Matlab, Sheet 1

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## Question 1

We visualize the (dis)advantages of the two options in a tabular

	advantages	disadvantages
scanned image in email	<ul style="list-style-type: none"><li>unchanged / not compressed → real "information"</li></ul>	<ul style="list-style-type: none"><li>possibly really large file size</li></ul>
OCR as txt in email	<ul style="list-style-type: none"><li>way smaller file size</li><li>instant information usage for a machine</li><li>access from every system (one just needs a command line)</li></ul>	<ul style="list-style-type: none"><li>loss and possible corruption of data due to scanning tool</li><li>possible no / bad result because of bad scan quality</li></ul>

- Usage:
- If one wants to process further the data via a machine respectively one only wants the contained data (and not all information) or only a low data transmission is available, one should use OCR
  - If one has only a low scanner quality available or a possible loss of information is no option, then sending the scanned image is the way to go.

## Question 2: We list different options and shortly evaluate them

- Check labels <sup>by hand!</sup> manually: This option provides the safest results but the effort is so high, that this is often impossible or a lot of people are needed.

- Increase scanning quality : Could be cost intensive.
- Define a measure to compare similar data points (e.g. norm of the differences of two vectors containing image pixels). Here we have two options:
  - check labels manually if the data is similar (using a threshold) and the labels differ
  - give probability, using a classifier, that a data point is misclassified (comparing multiple similar data points) with respect to the measure and decrease its weight in the calculation process (e.g. in weighted logistic regression)

Question 3 Due to lack of notation, we assume  $w, b \in \mathbb{R}$ .

Proof:

linear regression:

$$\frac{\partial}{\partial w} L(w, b) = \frac{\partial}{\partial w} \left( \frac{1}{m} \sum_{i=1}^m (w x^{(i)} + b - y^{(i)})^2 \right) = \frac{1}{m} \sum_{i=1}^m (w x^{(i)} + b - y^{(i)}) x^{(i)}$$

$$= \frac{1}{m} \sum_{i=1}^m (h(x^{(i)}) - y^{(i)}) x^{(i)}$$

$$\frac{\partial}{\partial b} L(w, b) = \frac{\partial}{\partial b} \left( \frac{1}{m} \sum_{i=1}^m (w x^{(i)} + b - y^{(i)})^2 \right) = \frac{1}{m} \sum_{i=1}^m (w x^{(i)} + b - y^{(i)}) \cdot 1$$

$$= \frac{1}{m} \sum_{i=1}^m (h(x^{(i)}) - y^{(i)})$$

logistic regression: Write  $\frac{\partial}{\partial w}$  instead of  $\frac{\partial}{\partial w}$

$$\frac{\partial}{\partial w} (y^{(i)} \log h(x^{(i)})) = y^{(i)} \cdot \frac{1}{h(x^{(i)})} \cdot (-1) \cdot h(x^{(i)})^2 \cdot (-x^{(i)}) \exp(-w x^{(i)} + b)$$

$$= y^{(i)} \cdot h(x^{(i)}) \cdot (x^{(i)}) \exp(-w x^{(i)} + b)$$

$$\frac{\partial}{\partial w} (\log(1 - h(x^{(i)}))) = \frac{1}{1 - h(x^{(i)})} \cdot (-1) \cdot (-1) \cdot h(x^{(i)})^2 \cdot (-x^{(i)}) \exp(-(w x^{(i)} + b))$$

$$= \frac{(-1)}{1 - h(x^{(i)})} h(x^{(i)})^2 x^{(i)} \exp(-(w x^{(i)} + b))$$

Therefore we obtain using the derivation rules for sums and the calculations above

$$\begin{aligned}
 \frac{\partial}{\partial w} L(w, b) &= -\frac{1}{m} \sum_{i=1}^m y^{(i)} h(x^{(i)}) x^{(i)} e^{-(w x^{(i)} + b)} - \frac{1 - y^{(i)}}{1 - h(x^{(i)})} h(x^{(i)})^2 x^{(i)} e^{-(w x^{(i)} + b)} \\
 &= -\frac{1}{m} \sum_{i=1}^m h(x^{(i)}) x^{(i)} e^{-(w x^{(i)} + b)} \cdot \left( y^{(i)} - (1 - y^{(i)}) \frac{1}{h(x^{(i)})} - 1 \right) \\
 &= -\frac{1}{m} \sum_{i=1}^m h(x^{(i)}) x^{(i)} e^{-(w x^{(i)} + b)} \cdot \underbrace{\left( y^{(i)} - (1 - y^{(i)}) \cdot e^{w x^{(i)} + b} \right)}_{= (y^{(i)}) \left( 1 + e^{w x^{(i)} + b} \right) - e^{w x^{(i)} + b}} \\
 &= (y^{(i)}) \left( 1 + e^{w x^{(i)} + b} \right) - e^{w x^{(i)} + b}
 \end{aligned}$$

$$\begin{aligned}
 \text{(*)} &= -\frac{1}{m} \sum_{i=1}^m h(x^{(i)}) x^{(i)} \left( y^{(i)} \cdot \underbrace{\left( 1 + e^{-w x^{(i)} - b} \right)}_{= 1/h(x^{(i)})} - 1 \right) \\
 &= \frac{1}{m} \sum_{i=1}^m x^{(i)} \left( h(x^{(i)}) - y^{(i)} \right)
 \end{aligned}$$

} minus into brackets.

In an analogous way, we obtain

$$\begin{aligned}
 \partial_b \log(h(x^{(i)})) &= \frac{1}{h(x^{(i)})} \cdot \partial_b h(x^{(i)}) = \frac{1}{h(x^{(i)})} \cdot (-1) \cdot h(x^{(i)})^2 e^{-(w x^{(i)} + b)} \cdot (-1) \\
 &= h(x^{(i)})^2 e^{-(w x^{(i)} + b)}
 \end{aligned}$$

$$\begin{aligned}
 \partial_b \log(1 - h(x^{(i)})) &= \frac{1}{1 - h(x^{(i)})} \cdot (-1) \cdot \underbrace{\partial_b (1 - h(x^{(i)}))}_{= (-1) \cdot \partial_b h(x^{(i)})} \\
 &= \frac{1}{1 - h(x^{(i)})} \partial_b h(x^{(i)}) \\
 &\stackrel{\text{calc. from above}}{=} \frac{1}{1 - h(x^{(i)})} h(x^{(i)})^2 e^{-(w x^{(i)} + b)}
 \end{aligned}$$

All in all, repeating the reshaping in (\*) without the factor  $x^{(i)}$ , we obtain the following

$$\begin{aligned}
 \partial_b L(w, b) &= -\frac{1}{m} \sum_{i=1}^m y^{(i)} h(x^{(i)}) e^{-(w x^{(i)} + b)} + (1 - y^{(i)}) \left( \frac{1}{1 - h(x^{(i)})} h(x^{(i)})^2 e^{-(w x^{(i)} + b)} \right) \\
 \text{(*)} &\equiv \frac{1}{m} \sum_{i=1}^m h(x^{(i)}) - y^{(i)}
 \end{aligned}$$

This was our initial claim. □