## Solutions week 3

## 3.1

In 1-nearest neighbours you will always perfectly fit the training set, so $e_{\text {train }}=$ 0 . The average over all data will be the average of the errors for the individual datasets since they are equally large, and so we get

$$
\begin{equation*}
e=\frac{e_{\text {train }}+e_{\text {test }}}{2}=\frac{e_{\text {test }}}{2}=18 \% \Rightarrow e_{\text {test }}=36 \% \tag{1}
\end{equation*}
$$

Given that the test error for the logistic regression was $30 \%$, which is less that $36 \%$, we choose it over 1-NN since it has better generalization error.

## 3.2

Programming task...

## 3.3

We get the distributions for the test given the persons status (healthy $=1$ or sick $=2$ ) as

$$
\begin{aligned}
& p(x \mid y=1)=\mathcal{N}\left(10,4^{2}\right) \\
& p(x \mid y=2)=\mathcal{N}\left(20,5^{2}\right)
\end{aligned}
$$

and we also get that $p(y=1)=0.99=1-p(y=2)$.

## (a)

We can calculate the expression for the cancer probability given a measurement using the given distributions and bayes theorem.

$$
\begin{aligned}
p(y=2 \mid x) & =\frac{p(x \mid y=2) p(y=2)}{p\left(x \mid y^{\prime}=1\right) p\left(y^{\prime}=1\right)+p\left(x \mid y^{\prime}=2\right) p\left(y^{\prime}=2\right)} \\
& =\frac{\frac{1}{\sqrt{2 \pi 5^{2}}} e^{-\frac{(x-20)^{2}}{2 \cdot 5^{2}}} 0.01}{\frac{1}{\sqrt{2 \pi 4^{2}}} e^{-\frac{(x-10)^{2}}{2 \cdot 4^{2}}} 0.99+\frac{1}{\sqrt{2 \pi 5^{2}}} e^{-\frac{(x-20)^{2}}{2 \cdot 5^{2}}} 0.01}
\end{aligned}
$$

We now just insert the values for our patients and get

$$
\begin{aligned}
& p_{A}(y=2 \mid 15)=0.01059 \\
& p_{B}(y=2 \mid 20)=0.1553 \\
& p_{C}(y=2 \mid 25)=0.8472
\end{aligned}
$$

(b)

Assuming our assumptions about the distributions are correct, we want to use the most probable according to Bayes classifier, so A and B are healthy while $B$ has cancer.
(c)

Test (maybe in some programming language) for which $x$ we get $p(y=2 \mid x)=$ 0.5 , and this turns out to be $x \approx 22.59$

## (d)

Given the impact of misclassification in the different cases (miss someone who has cancer, or do a more accurate test on someone who didn't have) we might want to err on the side of predicting cancer.

## 3.4

(a)

Programming task...

## (b)

Catching $99 \%$ of all true cancer cases requires that the ratio between true positive cases and actual positive cases is larger or equal to $99 \%$. This fraction is called TPR or recall.

It can be found looking at the cumulative distribution function for the measurements given it is a cancer case. So we want to find for what $t$ we get that $p(x>t \mid y=2)=0.99$, and since the cdf is the cumulative sum we get that $p(x<t)=c d f(t)$ and can thus write

$$
\begin{aligned}
p(x>t \mid y=2) & =1-p(x<t \mid y=2) \\
& =1-c d f(t \mid y=2)=0.99 \\
c d f(t \mid y=2) & =0.01
\end{aligned}
$$

In some languages you have functions for the inverse normal cdf, but if you you can just test what $t$ gives a good approximation of 0.01 , I got it to around $t \approx 8.36826$.
(c)

Now we want to look at the ratio of true positive cases and predicted positive cases which is called precision. We predict cancer if $x>t$, so what is the probability we actually have cancer given that $x>t$ ?

$$
\begin{aligned}
p(y=2 \mid x>t) & =\frac{p(x>t \mid y=2) p(y=2)}{p(x>t \mid y=1) p(y=1)+p(x>t \mid y=2) p(y=2)} \\
& =\frac{(1-p(x<t \mid y=2)) 0.01}{(1-p(x<t \mid y=1)) 0.99+(1-p(x<t \mid y=2)) 0.01} \\
& =\frac{(1-c d f(t \mid y=2)) 0.01}{(1-c d f(t \mid y=1)) 0.99+(1-c d f(t \mid y=2)) 0.01} \\
& \approx 0.014962
\end{aligned}
$$

## 3.5

Programming task...

