## 582631 Introduction to Machine Learning, Fall 2016 Exercise set I

## Model solutions

1. 

(a) Let's solve the value of $\epsilon$ for which the upper bound for the considered probability equals $\alpha$ :

$$
\begin{aligned}
\alpha & =2 e^{-2 n \epsilon^{2}} \\
e^{-2 n \epsilon^{2}} & =\frac{\alpha}{2} \\
-2 n \epsilon^{2} & =\ln \alpha-\ln 2 \\
\epsilon & = \pm \sqrt{\frac{\ln 2-\ln \alpha}{2 n}} .
\end{aligned}
$$

The length of the considered interval is $2 n \epsilon$, and by plugging $\alpha=0.05$ and $n=$ $10,100,1000$ into the formula we get:

| $n$ | 10 | 100 | 1000 |
| :---: | :---: | :---: | :---: |
| $2 n \epsilon$ | 8.6 | 27.2 | 85.9 |

(b) Using the union bound and the previous exercise we get:

$$
P\left(\bigcup_{i=1}^{k} A_{i}\right) \leq \sum_{i=1}^{k} P\left(A_{i}\right) \leq 2 k e^{-2 n \epsilon^{2}}
$$

Let's again solve the value of $\epsilon$ for which this upper bound for equals $\alpha$ :

$$
\begin{aligned}
\alpha & =2 k e^{-2 n \epsilon^{2}} \\
\epsilon & = \pm \sqrt{\frac{\ln (2 k)-\ln \alpha}{2 n}} .
\end{aligned}
$$

By plugging $\alpha=0.05$, and different values of $n$ and $k$ into the formula, we get the following interval lengths:

|  | $n$ | 10 | 100 | 1000 |
| :---: | :---: | :---: | :---: | :---: |
| $k=1$ | $2 n \epsilon$ | 8.6 | 27.2 | 85.9 |
| $k=10$ | $2 n \epsilon$ | 10.9 | 34.6 | 109.5 |
| $k=100$ | $2 n \epsilon$ | 12.9 | 40.7 | 128.8 |

Notice that while the width of the above interval, within which the number of correct predictions $\sum_{i} X_{i}$ is likely to be, grows with $n$ at rate $\sqrt{n}$, the corresponding interval for the proportion of correct predictions $n^{-1} \sum_{i} X_{i}$ shrinks at rate $1 / \sqrt{n}$ :

|  | $n$ | 10 | 100 | 1000 |
| :---: | :---: | :---: | :---: | :---: |
| $k=1$ | $2 \epsilon$ | 0.86 | 0.27 | 0.09 |
| $k=10$ | $2 \epsilon$ | 1.09 | 0.35 | 0.11 |
| $k=100$ | $2 \epsilon$ | 1.29 | 0.41 | 0.13 |

In summary, the observed accuracy (number of correct prediction divided by $n$ ) tends to get closer and closer to the true accuracy $p$ as the sample size $n$ grows. On the other hand, as the number of classifiers, $k$, is increased, the interval grows but as can be deduced from the formula for $\epsilon$, the dependency on $k$ is of the order $\sqrt{( } \ln k)$, which is very slow (as can also be seen in the above tables).

