## STRUCTURED MODEL LEARNING (WS2021/22) SEMINAR 3

Assignment 1. Let $\mathcal{G} \subseteq[0,1]^{\mathcal{Z}}$ be a set of functions $g: \mathcal{Z} \rightarrow[0,1]$. Let $\mathcal{U}^{m}=$ $\left\{z^{1}, \ldots, z^{m}\right\} \in \mathcal{Z}^{m}$ be drawn i.i.d. from $p(z)$. The Rademacher complexity of $\mathcal{G}$ w.r.t. the distribution $p(z)$ is

$$
\hat{\mathcal{R}}_{m}(\mathcal{G})=\mathbb{E}_{\mathcal{U}^{m} \sim p^{m}(z)} \mathbb{E}_{\sigma \sim \mathrm{Unif}\{-1,+1\}}\left[\sup _{g \in \mathcal{G}} \frac{1}{m} \sum_{i=1}^{m} \sigma_{i} g\left(z_{i}\right)\right]
$$

a) What is the minimal value of the Rademacher complexity?
b) What is the value of the Rademacher complexity when $\mathcal{G}$ contains just a single function, i.e. $|\mathcal{G}|=1$ ?
c) What is the maximal value of the Rademacher complexity? What is the minimal number of functions in $\mathcal{G}$ to achieve the maximal value?

Assignment 2. Let $\left\{\left(\boldsymbol{x}^{i}, y^{i}\right) \in \mathbb{R}^{n} \times\{-1,+1\} \mid i=1, \ldots, m\right\}$ be $m$ points in $\mathbb{R}^{n}$ that are assigned into two classes. Assume that there exists an ellipse separating the points in the positive class from the points in negative class, i.e., there exists a positive definite matrix $\mathbf{A} \in \mathbb{R}^{n \times n}$ and scaler $r>0$ such that

$$
\begin{align*}
& \left\langle\boldsymbol{x}^{i}, \mathbf{A} \boldsymbol{x}^{i}\right\rangle \geq r^{2}, \quad \forall i \in\left\{j \in\{1, \ldots, m\} \mid y^{i}=+1\right\}, \\
& \left\langle\boldsymbol{x}^{i}, \mathbf{A} \boldsymbol{x}^{i}\right\rangle<r^{2}, \quad \forall i \in\left\{j \in\{1, \ldots, m\} \mid y^{i}=-1\right\} . \tag{1}
\end{align*}
$$

Show how to use the Perceptron algorithm to find $\mathbf{A}$ and $r$ which satisfy the inequalities (1).

Assignment 3. Let $\mathcal{X}=\mathcal{A}^{n}$ be a set of input sequences and $\mathcal{Y}=\mathcal{B}^{n}$ a set of hidden sequences of length $n$ which are defined over finite alphabets $\mathcal{A}$ and $\mathcal{B}$, respectively. Let $h: \mathcal{X} \rightarrow \mathcal{Y}$ be a prediction rule that for each $x \in \mathcal{X}$ returns a sequence $h(x)=$ $\left(h_{1}(x), \ldots, h_{n}(x)\right)$ obtained solving

$$
\begin{equation*}
h(x)=\underset{\left(y_{1}, \ldots, y_{n}\right) \in \mathcal{B}^{n}}{\arg \max }\left(\sum_{i=1}^{n} q\left(x_{i}, y_{i}\right)+\sum_{i=2}^{n} g\left(y_{i-1}, y_{i}\right)\right) \tag{2}
\end{equation*}
$$

where $q: \mathcal{A} \times \mathcal{B} \rightarrow \mathbb{R}$ and $g: \mathcal{B} \times \mathcal{B} \rightarrow \mathbb{R}$ are quality fucntions describing compatibility between inputs and hidden states.
a) Show that (2) is a linear classifier.
b) Describe a dynamic programming algorithm which computes the output of the classifier (2) in time polynomial in the size of the input instances. How does the algorithm scale with $|\mathcal{A}|,|\mathcal{B}|$ and $n$ ?
c) Describe an instance of Perceptron algorithm which learns the quality functions $q$ and $g$ from linearly separable examples $\left\{\left(x_{1}^{j}, \ldots, x_{n}^{j}, y_{1}^{j}, \ldots, y_{n}^{j}\right) \in \mathcal{A}^{n} \times \mathcal{B}^{n} \mid j=\right.$ $1, \ldots, m\}$.

Assignment 4. Consider a linear ordinal classifier $h: \mathbb{R}^{n} \rightarrow\{1, \ldots, Y\}$ defined by

$$
\begin{equation*}
h(\boldsymbol{x})=1+\sum_{y=1}^{Y-1} \llbracket\langle\boldsymbol{w}, \boldsymbol{x}\rangle \geq b_{y} \rrbracket \tag{3}
\end{equation*}
$$

and parameterized by a vector $\boldsymbol{w} \in \mathbb{R}^{n}$ and an increasing sequence of thresholds $b_{1}<$ $b_{2}<\cdots<b_{Y-1}$. Let $\mathcal{T}^{m}=\left\{\left(\boldsymbol{x}^{j}, y^{j}\right) \in\left(\mathbb{R}^{n} \times \mathcal{Y}\right) \mid j=1, \ldots, m\right\}$ be a training set of examples. Describe a variant of the Perceptron algorithm which finds the parameters $\boldsymbol{w} \in \mathbb{R}^{n}$ and $b_{y} \in \mathbb{R}, y \in\{1, \ldots, Y-1\}$, such that the classifier (3) predicts all examples from $\mathcal{T}^{m}$ correctly provided such parameters exist.

