## A Appendix: Remaining Proofs

In this section, we present the proofs of Theorems 3.1 and 3.4.

## A. 1 Proof of Theorem 3.1

In the following, we quote a version of Talagrand's inequality due to Bousquet (2002) from Steinwart and Christmann (2008, Theorem 7.5) and a (slightly simplified) bound on the expected suprema of empirical processes indexed by Vapnik-Cervonenkis (VC) classes of functions, from Giné and Guillou (2001, Proposition 2.1). Both will be used to prove Theorem 3.1.

Theorem A.1. Let $(Z, P)$ be a probability space and $\mathcal{G}$ be a set of measurable functions from $Z$ to $\mathbb{R}$. Furthermore, let $B \geq 0$ and $\sigma \geq 0$ be constants such that $\mathbb{E}_{P} g=0, \mathbb{E}_{P} g^{2} \leq \sigma^{2}$, and $\|g\|_{\infty} \leq B$ for all $g \in \mathcal{G}$. For $n \geq 1$, define $G: Z^{n} \rightarrow \mathbb{R}$ by

$$
G(z):=\sup _{g \in \mathcal{G}}\left|\frac{1}{n} \sum_{j=1}^{n} g\left(z_{j}\right)\right|, \quad z=\left(z_{1}, \ldots, z_{n}\right) \in Z^{n}
$$

Then, for all $\tau>0$, we have
$P^{n}\left(\left\{z \in Z^{n}: G(z) \geq 4 \mathbb{E}_{P^{n}} G+\sqrt{\frac{2 \tau \sigma^{2}}{n}}+\frac{\tau B}{n}\right\}\right) \leq e^{-\tau}$.
Theorem A.2. Let $(Z, P)$ be a probability space and $\mathcal{G}$ be a set of measurable functions from $Z$ to $\mathbb{R}$. Furthermore, let $B \geq 0$ and $0 \leq \sigma \leq B$ be constants such that $\mathbb{E}_{P} g^{2} \leq \sigma^{2}$, and $\|g\|_{\infty} \leq B$ for all $g \in \mathcal{G}$. Suppose $\mathcal{G}$ is a uniformly bounded VC-class, i.e., there exist positive numbers $A$ and $\nu$ such that, for every probability measure $P$ on $Z$ and every $0<\epsilon \leq B$, the covering numbers satisfy

$$
\mathcal{N}\left(\mathcal{G}, L_{2}(P), \epsilon\right) \leq\left(\frac{A B}{\epsilon}\right)^{\nu}
$$

Then there exists a universal constant $C$ such that $G$ defined as in Theorem A. 1 satisfies

$$
\begin{equation*}
\mathbb{E}_{P^{n}} G \leq C\left(\frac{\nu B}{n} \log \frac{A B}{\sigma}+\sqrt{\frac{\nu \sigma^{2}}{n} \log \frac{A B}{\sigma}}\right) \tag{15}
\end{equation*}
$$

Given a measurable $g: \mathbb{R}^{d} \rightarrow \mathbb{R}$ and a $\delta>0$ we define the function $g_{\delta}: \mathbb{R}^{d} \rightarrow \mathbb{R}$ by $g_{\delta}(x):=g(x / \delta), x \in \mathbb{R}^{d}$. The following lemma, which establishes a stability of covering number bounds under this operation, will also be needed in the proof of Theorem 3.1.
Lemma A.3. Let $\mathcal{G}$ be set of measurable functions $g: \mathbb{R}^{d} \rightarrow \mathbb{R}$ such that there exists a constant $B \geq 0$ with $\|g\|_{\infty} \leq B$ for all $g \in \mathcal{G}$. For $\delta>0$, we write
$\mathcal{G}_{\delta}:=\left\{g_{\delta}: g \in \mathcal{G}\right\}$. Then, for all $\epsilon \in(0, B]$ and all $\delta>0$, we have

$$
\sup _{P} \mathcal{N}\left(\mathcal{G}, L_{2}(P), \epsilon\right)=\sup _{P} \mathcal{N}\left(\mathcal{G}_{\delta}, L_{2}(P), \epsilon\right)
$$

where the suprema are taken over all probability measures $P$ on $\mathbb{R}^{d}$.

Proof. We only prove " $\leq$ ", the converse inequality can be shown analogously. Let us fix $\epsilon, \delta>0$ and a distribution $P$ on $\mathbb{R}^{d}$. We define a new distribution $P^{\prime}$ on $\mathbb{R}^{d}$ by $P^{\prime}(A):=P\left(\frac{1}{\delta} A\right)$ for all measurable $A \subset \mathbb{R}^{d}$. Furthermore, let $\mathcal{C}^{\prime}$ be an $\epsilon$-net of $\mathcal{G}_{\delta}$ with respect to $L_{2}\left(P^{\prime}\right)$. For $\mathcal{C}:=\mathfrak{C}_{1 / \delta}^{\prime}$, we then have $|\mathcal{C}|=\left|\mathfrak{C}^{\prime}\right|$, and hence it suffices to show that $\mathcal{C}$ is an $\epsilon$-net of $\mathcal{G}$ with respect to $L_{2}(P)$. To this end, we fix a $g \in \mathcal{G}$. Then $g_{\delta} \in \mathcal{G}_{\delta}$, and hence there exists an $h^{\prime} \in \mathcal{C}^{\prime}$ with $\left\|g_{\delta}-h^{\prime}\right\|_{L_{2}\left(P^{\prime}\right)} \leq \epsilon$. Moreover, we have $h:=h_{1 / \delta}^{\prime} \in \mathcal{C}$, and since the definition of $P^{\prime}$ ensures $\mathbb{E}_{P^{\prime}} f_{\delta}=\mathbb{E}_{P} f$ for all measurable $f: \mathbb{R}^{d} \rightarrow[0, \infty)$, we obtain
$\|g-h\|_{L_{2}(P)}=\left\|g_{\delta}-h_{\delta}\right\|_{L_{2}\left(P^{\prime}\right)}=\left\|g_{\delta}-h^{\prime}\right\|_{L_{2}\left(P^{\prime}\right)} \leq \epsilon$,
i.e. $\mathcal{C}$ is an $\epsilon$-net of $\mathcal{G}$ with respect to $L_{2}(P)$.

We further need the following result, which is a reformulation of van der Vaart and Wellner (1996, Theorem 2.6.4).

Theorem A.4. Let $\mathcal{A}$ be a set of subsets of $Z$ that has finite $V C$-dimension $V$. Then the corresponding set of indicator functions $\mathcal{G}:=\left\{\mathbf{1}_{A}: A \in \mathcal{A}\right\}$ is a uniformly bounded VC-class and the corresponding VCcharacteristics $A$ and $\nu$ only depend on $V$.

With these preparation we are now able to establish the following generalization of Theorem 3.1. Applying this generalization to $K$ of the form (3) immediately proves Theorem 3.1.
Proposition A.5. Let $P$ be a probability measure on $\mathbb{R}^{d}$ with a bounded Lebesgue density $h$ and $K$ be a realvalued function on $X$ such that $K \in L_{\infty}\left(\mathbb{R}^{d}\right) \cap L_{2}\left(\mathbb{R}^{d}\right)$. Suppose that

$$
\mathcal{F}:=\{K(x-\cdot): x \in X\}
$$

is a uniformly bounded VC-class. Then, there exists a positive constant $C$ only depending on $K, h$ and $V C$ characteristics $A$ and $\nu$ of $\mathcal{F}$ such that, for all $n \geq 1$, $\delta>0$, and $\tau>0$ we have

$$
\begin{aligned}
& P^{n}\left(\left\{D \in X^{n}:\left\|\bar{h}_{D, \delta}-\bar{h}_{P, \delta}\right\|_{\infty}<\frac{C}{n \delta^{d}} \log \frac{C}{\delta}\right.\right. \\
& \left.\left.\quad+\sqrt{\frac{C}{n \delta^{d}} \log \frac{C}{\delta}}+\frac{\tau C}{n \delta^{d}}+\frac{C \sqrt{\tau}}{\sqrt{n \delta^{d}}}\right\}\right) \geq 1-e^{-\tau}
\end{aligned}
$$

Proof. Let us assume without loss of generality that $\|K\|_{\infty} \leq 1$. We define $k_{x, \delta}:=\delta^{-d} K\left(\frac{x-\dot{\delta}}{\delta}\right)$ and $f_{x, \delta}:=k_{x, \delta}-\mathbb{E}_{P} k_{x, \delta}$. Then it is easy to check that $\mathbb{E}_{P} f_{x, \delta}=0$ and $\left\|f_{x, \delta}\right\|_{\infty} \leq 2 \delta^{-d}$ for all $x \in X$ and $\delta>0$. Moreover, we have

$$
\begin{aligned}
\mathbb{E}_{P} f_{x, \delta}^{2} & \leq \mathbb{E}_{P} k_{x, \delta}^{2}=\delta^{-2 d} \int_{\mathbb{R}^{d}} K^{2}\left(\frac{x-y}{\delta}\right) h(y) d y \\
& \leq \delta^{-d}\|h\|_{\infty}\|K\|_{2}^{2}
\end{aligned}
$$

for all $x \in X$ and $\delta>0$, where the norm $\|K\|_{2}$ is with respect to the Lebesgue measure on $\mathbb{R}^{d}$. In addition, we have

$$
\frac{1}{n} \sum_{i=1}^{n} f_{x, \delta}\left(x_{i}\right)=\bar{h}_{D, \delta}(x)-\bar{h}_{P, \delta}(x)
$$

where $\bar{h}_{P, \delta}$ and $\bar{h}_{D, \delta}$ are defined in (1) and (2) respectively. Applying Theorem A. 1 to $\mathcal{G}:=\left\{f_{x, \delta}: x \in \mathbb{R}^{d}\right\}$, we hence obtain, for all $\delta>0, \tau>0$, and $n \geq 1$, that

$$
\begin{align*}
\left\|\bar{h}_{D, \delta}-\bar{h}_{P, \delta}\right\|_{\infty}< & 4 \mathbb{E}_{P^{n}}\left\|\bar{h}_{D, \delta}-\bar{h}_{P, \delta}\right\|_{\infty}+\frac{2 \tau}{n \delta^{d}} \\
& +\sqrt{\frac{2 \tau\|h\|_{\infty}\|K\|_{2}^{2}}{n \delta^{d}}} \tag{16}
\end{align*}
$$

holds with probability $P^{n}$ not smaller than $1-e^{-\tau}$. It thus remains to bound the term $\mathbb{E}_{P^{n}}\left\|\bar{h}_{D, \delta}-\bar{h}_{P, \delta}\right\|_{\infty}$. Note that since $\mathcal{F}$ is a uniformly bounded VC-class, so is $\tilde{\mathcal{F}}:=\{f-a: f \in \mathcal{F}, a \in[-1,1]\}$, i.e. there exist positive numbers $A$ and $\nu$ such that

$$
\sup _{P} \mathcal{N}\left(\tilde{\mathcal{F}}, L_{2}(P), \epsilon\right) \leq\left(\frac{2 A}{\epsilon}\right)^{\nu}
$$

for all $0<\epsilon \leq 2$. For $\delta>0$, we further have $\delta^{d} \mathcal{G} \subset \tilde{\mathcal{F}}_{\delta}$, and hence Lemma A. 3 implies

$$
\mathcal{N}\left(\delta^{d} \mathcal{G}, L_{2}(P), \epsilon\right) \leq \mathcal{N}\left(\tilde{\mathcal{F}}_{\delta}, L_{2}(P), \epsilon\right) \leq\left(\frac{2 A}{\epsilon}\right)^{\nu}
$$

for all probability measures $P$ on $\mathbb{R}^{d}$ and all $0<\epsilon \lesssim 2$. Now, our very first estimates show that every $g \in \tilde{\tilde{\mathcal{G}}}:=$ $\delta^{d} \mathcal{G}$ satisfies $\|g\|_{\infty} \leq 2$ and $\mathbb{E}_{P} g^{2} \leq \delta^{d}\|h\|_{\infty}\|K\|_{2}^{2}$, and hence Theorem A. 2 yields

$$
\begin{aligned}
& \mathbb{E}_{P^{n} \sup _{g \in \tilde{\mathcal{G}}}}\left|\frac{1}{n} \sum_{j=1}^{n} g\left(X_{j}\right)\right| \leq C\left(\frac{2 \nu}{n} \log \frac{2 A}{\sqrt{\delta^{d}\|h\|_{\infty}\|K\|_{2}^{2}}}\right. \\
&+\sqrt{\frac{\nu \delta^{d}\|h\|_{\infty}\|K\|_{2}^{2}}{n}} \log \frac{2 A}{\sqrt{\delta^{d}\|h\|_{\infty}\|K\|_{2}^{2}}}
\end{aligned}
$$

Multiplying both sides by $\delta^{-d}$, we obtain

$$
\begin{gathered}
\mathbb{E}_{P^{n}}\left\|\bar{h}_{D, \delta}-\bar{h}_{P, \delta}\right\|_{\infty} \leq C\left(\frac{2 \nu}{n \delta^{d}} \log \frac{2 A}{\sqrt{\delta^{d}\|h\|_{\infty}\|K\|_{2}^{2}}}\right. \\
\left.+\sqrt{\frac{\nu\|h\|_{\infty}\|K\|_{2}^{2}}{n \delta^{d}} \log \frac{2 A}{\sqrt{\delta^{d}\|h\|_{\infty}\|K\|_{2}^{2}}}}\right)
\end{gathered}
$$

which, when used in (16), yields the result.

## A. 2 Proof of Theorem 3.4

Proof of Theorem 3.4. i). Let $D \in X^{n}$ be a dataset such that $\left\|\bar{h}_{D, \delta}-\bar{h}_{P, \delta}\right\|_{\infty}<\varepsilon$. Moreover, let $\rho \geq 0$ be the current level that is considered by Algorithm 1. Then, Theorem 3.3 shows that, for $\rho \in\left[0, \rho^{* *}-3 \varepsilon-3 \eta\right]$, Algorithm 1 identifies exactly the topologically connected components of $\mathcal{M}_{\rho, \delta}$ in its loop that belong to the set $\zeta\left(\mathcal{C}\left(M_{\rho+\varepsilon+\eta}\right)\right)$, where $\zeta: \mathcal{C}\left(M_{\rho+\varepsilon+\eta}\right) \rightarrow$ $\mathcal{C}\left(\mathcal{M}_{\rho, \delta}\right)$ is the top-CCRM. In the following, we thus consider the set $\zeta\left(\mathcal{C}\left(M_{\rho+\varepsilon+\eta}\right)\right)$ for $\rho \in\left[0, \rho^{* *}-3 \varepsilon-3 \eta\right]$.
Let us first consider the case $\rho \in\left[0, \rho^{*}-\varepsilon-\eta\right)$. Then, $\left(c_{1}\right)$ and $\left(c_{3}\right)$ together with the assumed $\rho+\varepsilon+\eta<\rho^{*}$ show $\left|\mathcal{C}\left(M_{\rho+\varepsilon+\eta}\right)\right|=1$. This yields $\left|\zeta\left(\mathcal{C}\left(M_{\rho+\varepsilon+\eta}\right)\right)\right|=$ 1, and hence Algorithm 1 does not stop. Consequently, we have $\rho^{*}(D) \geq \rho^{*}-\varepsilon-\eta$.

Let us now consider the case $\rho \in\left[\rho^{*}+\varepsilon^{*}+\eta^{*}+\varepsilon+\eta, \rho^{*}+\right.$ $\left.\varepsilon^{*}+\eta^{*}+2 \varepsilon+2 \eta\right]$. Then we first note that Algorithm 1 actually inspects such an $\rho$, since it iteratively inspects all $\rho=i \varepsilon+i \eta, i=0,1, \ldots$, and the width of the interval above is $\varepsilon+\eta$. Moreover, our assumptions on $\varepsilon^{*}, \eta^{*}, \varepsilon$ and $\eta$ guarantee $\rho^{*}+\varepsilon^{*}+\eta^{*}+2 \varepsilon+2 \eta \leq \rho^{* *}-$ $3 \varepsilon-3 \eta$ and hence we have $\rho \in\left[\rho^{*}+\varepsilon^{*}+\eta^{*}+\varepsilon+\eta, \rho^{* *}-\right.$ $3 \varepsilon-3 \eta]$. Let us write $\zeta_{+}: \mathcal{C}\left(M_{\rho^{* *}}\right) \rightarrow \mathcal{C}\left(M_{\rho+\varepsilon+\eta}\right)$, $\zeta_{-}: \mathcal{C}\left(M_{\rho^{* *}}\right) \rightarrow \mathcal{C}\left(M_{\rho-\varepsilon-\eta}\right)$, and $\zeta_{+,-}: \mathcal{C}\left(M_{\rho+\varepsilon+\eta}\right) \rightarrow$ $\mathcal{C}\left(M_{\rho-\varepsilon-\eta}\right)$ for the top-CCRMs between the involved sets. Using the composition property of top-CCRMs in $\left(b_{2}\right)$, we then obtain the following diagram:


Moreover, we have $\rho-\varepsilon-\eta \geq \rho^{*}+\varepsilon^{*}+\eta^{*}>\rho^{*}$ and $\rho+\varepsilon+\eta>\rho^{*}$, and hence $\left(c_{1}\right)$ and $\left(c_{2}\right)$ show that $\left|\mathcal{C}\left(M_{\rho-\varepsilon-\eta}\right)\right|=2$ and $\left|\mathcal{C}\left(M_{\rho+\varepsilon+\eta}\right)\right|=2$. Consequently, $\left(c_{3}\right)$ ensures that the maps $\zeta_{+}$and $\zeta_{-}$are bijective. Consequently, $\zeta_{+,-}$is bijective. Let us further consider the top-CCRM $\zeta^{\prime}: \mathcal{C}\left(\mathcal{M}_{\rho, \delta}\right) \rightarrow \mathcal{C}\left(M_{\rho-\varepsilon-\eta}\right)$. Then the composition property of top-CCRMS in $\left(b_{2}\right)$-yields another diagram:


Since $\zeta_{+,-}$is bijective, we then find that $\zeta$ is injective, and since we have already seen that $M_{\rho+\varepsilon+\eta}$ has two top-connected components, we conclude that $\zeta\left(\mathcal{C}\left(M_{\rho+\varepsilon+\eta}\right)\right)$ contains two elements. Consequently,
the stopping criterion of Algorithm 1 is satisfied, that is, $\rho^{*}(D) \leq \rho^{*}+\varepsilon^{*}+\eta^{*}+2 \varepsilon+2 \eta$.
ii). Theorem 3.3 shows that in its last loop Algorithm 1 identifies exactly the topologically connected components of $\mathcal{M}_{\rho^{*}(D), \delta}$ that belong to the set $\zeta_{\varepsilon}\left(\mathcal{C}\left(M_{\rho^{*}(D)+\varepsilon+\eta}\right)\right)$, where $\zeta_{\varepsilon}: \mathcal{C}\left(M_{\rho^{*}(D)+\varepsilon+\eta}\right) \rightarrow$ $\mathcal{C}\left(\mathcal{M}_{\rho^{*}(D), \delta}\right)$ is the top-CCRM. Moreover, since Algorithm 1 stops at $\rho^{*}(D)$, we have $\left|\zeta_{\varepsilon}\left(\mathcal{C}\left(M_{\rho^{*}(D)+\varepsilon+\eta}\right)\right)\right| \neq$ 1 and thus $\left|\mathcal{C}\left(M_{\rho^{*}(D)+\varepsilon+\eta}\right)\right| \neq 1$. From $\rho^{*}(D)+$ $\varepsilon+\eta \leq \rho^{* *}$ and $\left(c_{1}\right)$ we thus conclude that $\left|\mathcal{C}\left(M_{\rho^{*}(D)+\varepsilon+\eta}\right)\right|=2$. For later purposes, note that the latter implies the injectivity of $\zeta_{\varepsilon}$. In addition, since $\left|\mathcal{C}\left(M_{\rho^{*}(D)+\varepsilon+\eta}\right)\right|=2,\left(c_{3}\right)$ yields $\zeta_{-, \rho^{*}(D)+\varepsilon+\eta}$ : $\mathcal{C}\left(M_{\rho^{* *}}\right) \rightarrow \mathcal{C}\left(M_{\rho^{*}(D)+\varepsilon+\eta}\right)$ is bijective. Since $\rho^{*}(D)+$ $3 \varepsilon+3 \eta>\rho^{*}$, it follows from $\left(c_{1}\right)-\left(c_{3}\right)$ that we have $\zeta_{+, \rho^{*}(D)+\varepsilon+\eta}: \mathcal{C}\left(M_{\rho^{* *}}\right) \rightarrow \mathcal{C}\left(M_{\rho^{*}(D)+3 \varepsilon+3 \eta}\right)$ is bijective. Using the composition property of topCCRMS in $\left(b_{2}\right)$, we obtain that $\zeta_{+,-, \rho^{*}(D)+\varepsilon+\eta}$ : $\mathcal{C}\left(M_{\rho^{*}(D)+3 \varepsilon+3 \eta}\right) \rightarrow \mathcal{C}\left(M_{\rho^{*}(D)+\varepsilon+\eta}\right)$ is bijective, and hence $\left|\mathcal{C}\left(M_{\rho^{*}(D)+3 \varepsilon+3 \eta}\right)\right|=2$. Let us now consider the following commutative diagram:

where again, all occurring maps are the top-CCRMs between the respective sets. Now we have already shown that $\zeta_{\varepsilon}$ is injective and that $\zeta_{+,-, \rho^{*}(D)+\varepsilon+\eta}$ is bijective. Consequently, $\zeta_{3 \varepsilon}$ is injective.
iii). Follows from Theorem 3.3 and $\rho^{*}(D)+2 \varepsilon+2 \eta \leq$ $\rho^{* *}-3 \varepsilon-3 \eta$.
iv). Since $\rho^{*}(D)+3 \varepsilon+3 \eta>\rho^{*}(D)+\varepsilon+\eta>\rho^{*}$, by $\left(c_{1}\right)-\left(c_{3}\right)$, we see that the maps $\zeta_{-, \rho^{* *}}$ and $\zeta_{+, \rho^{* *}}$ are bijective. Therefore $\zeta_{+,-, \rho^{*}(D)+\varepsilon+\eta}$ is bijective and the diagram follows.

