Machine Learning Theory

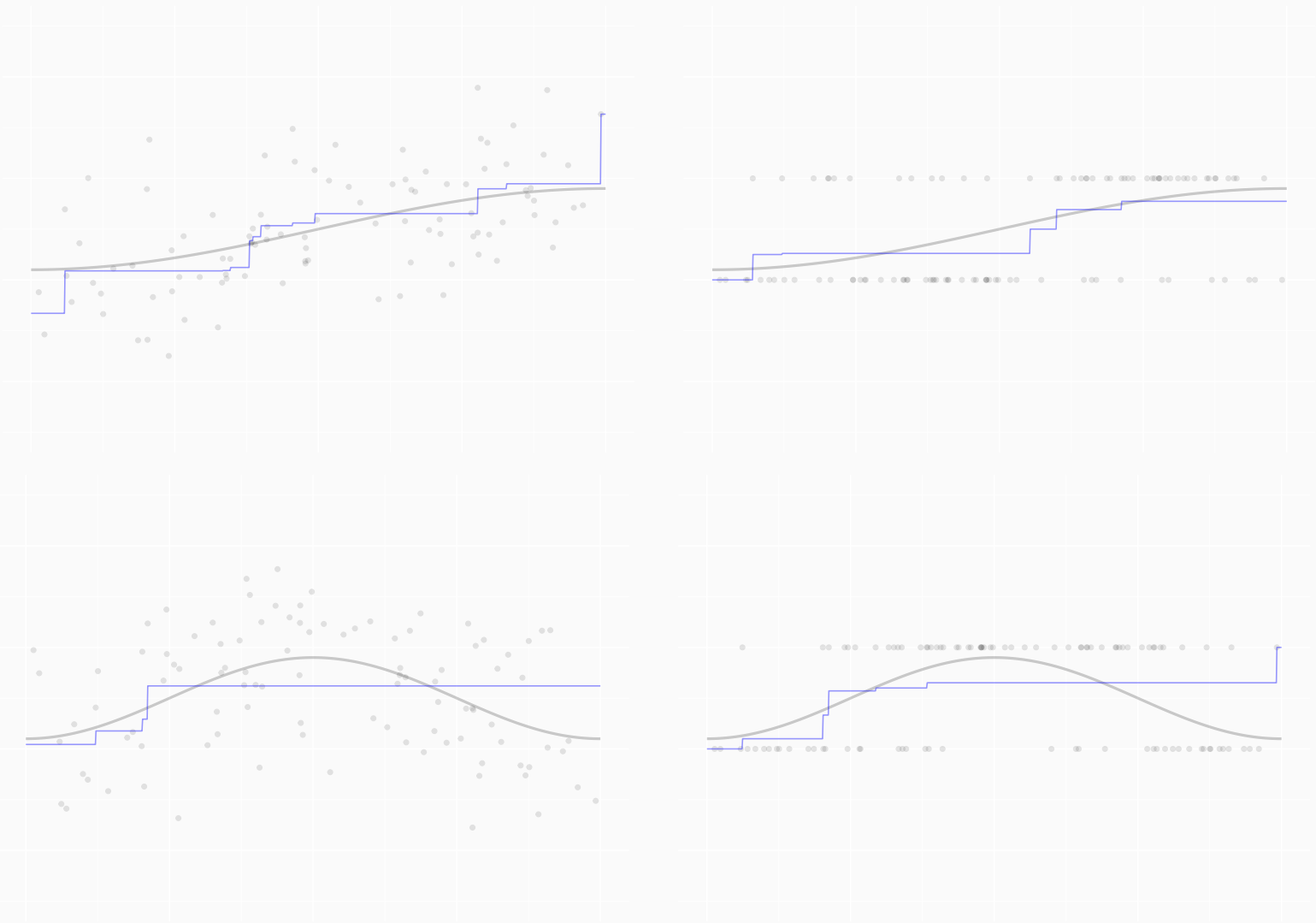
Lecture 5: Least Squares with Misspecification and Non-Gaussian Noise

David A. Hirshberg

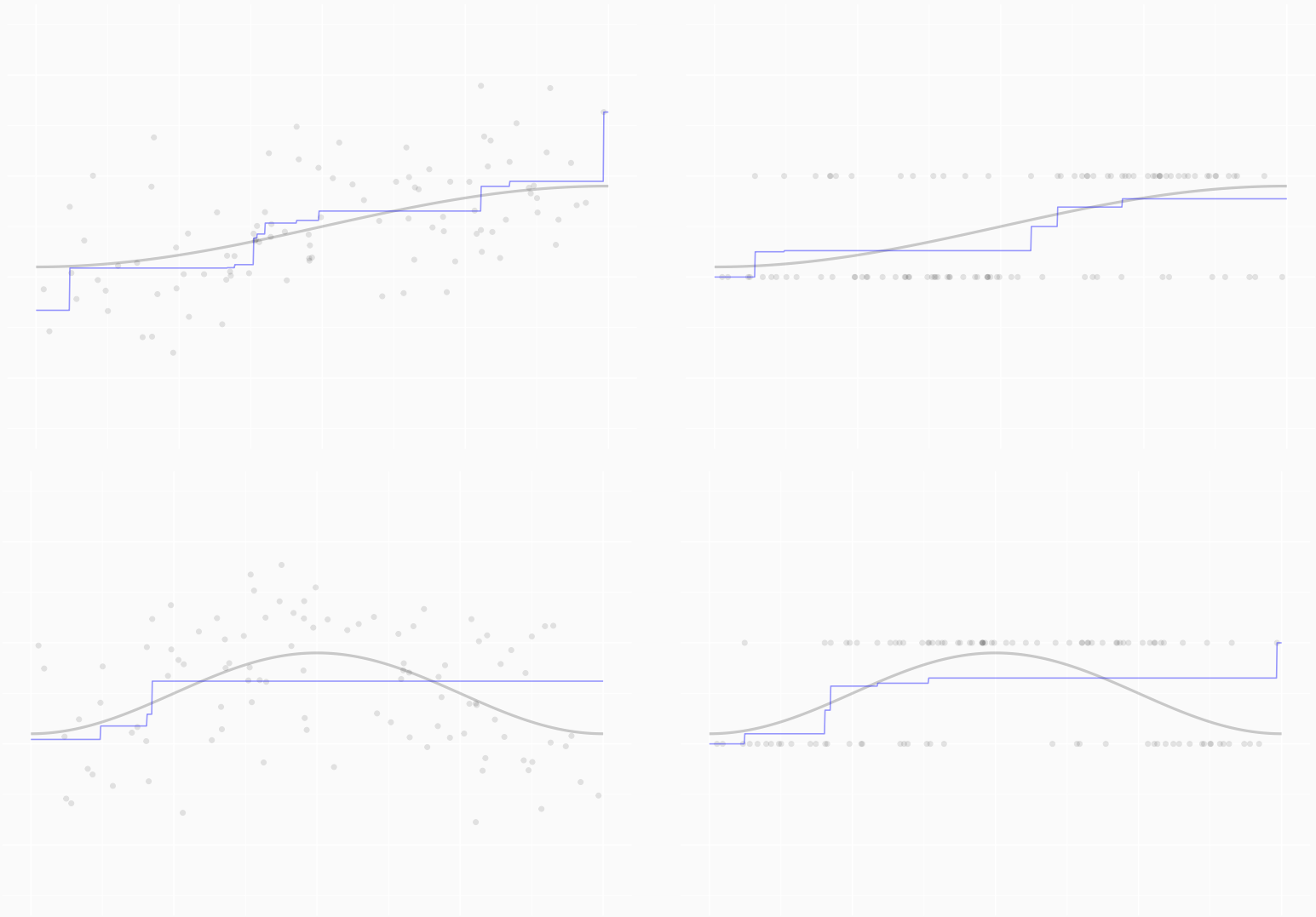
May 24, 2024

Emory University

When Does Our Theory Apply?

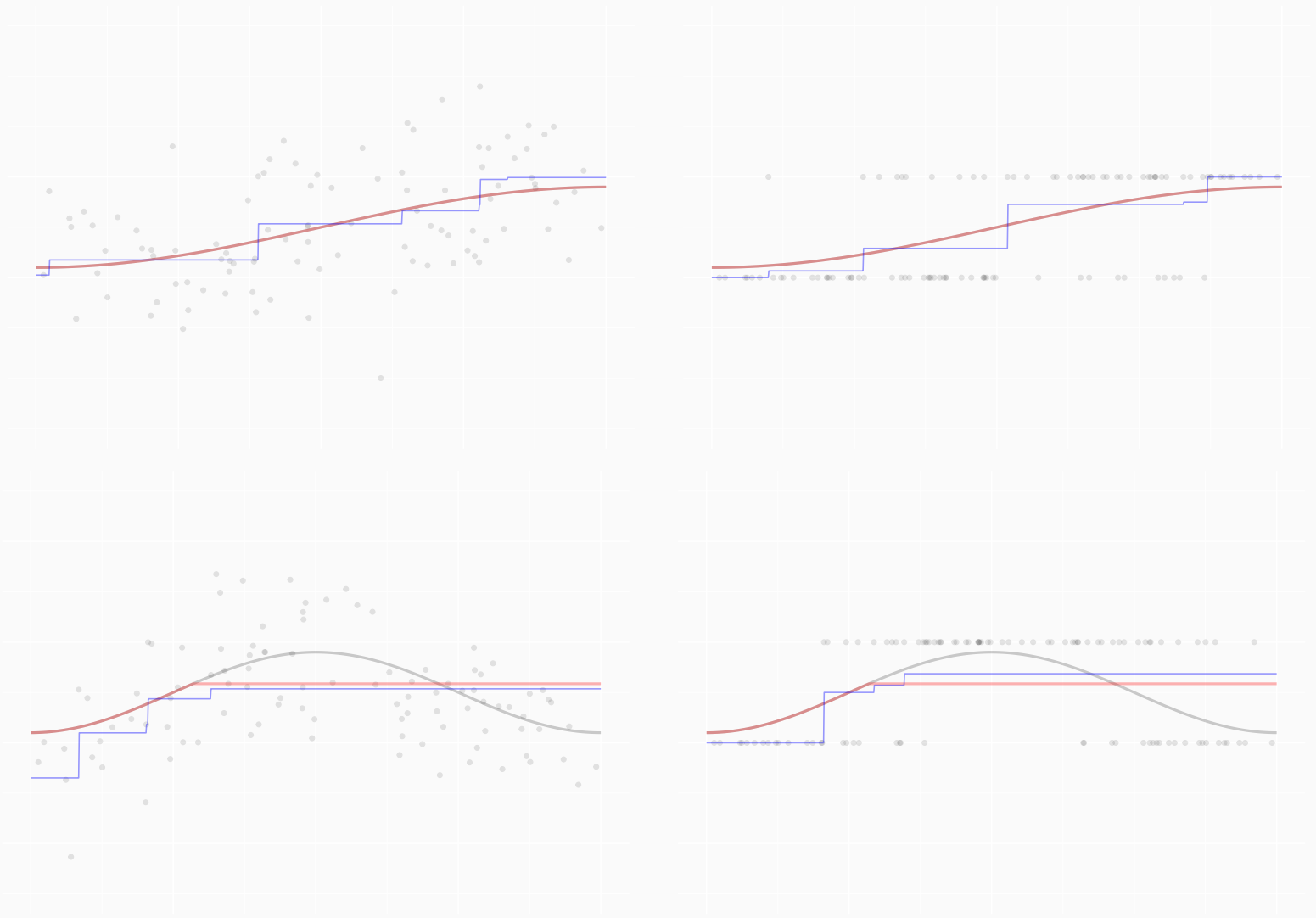


When Does Our Theory Apply?

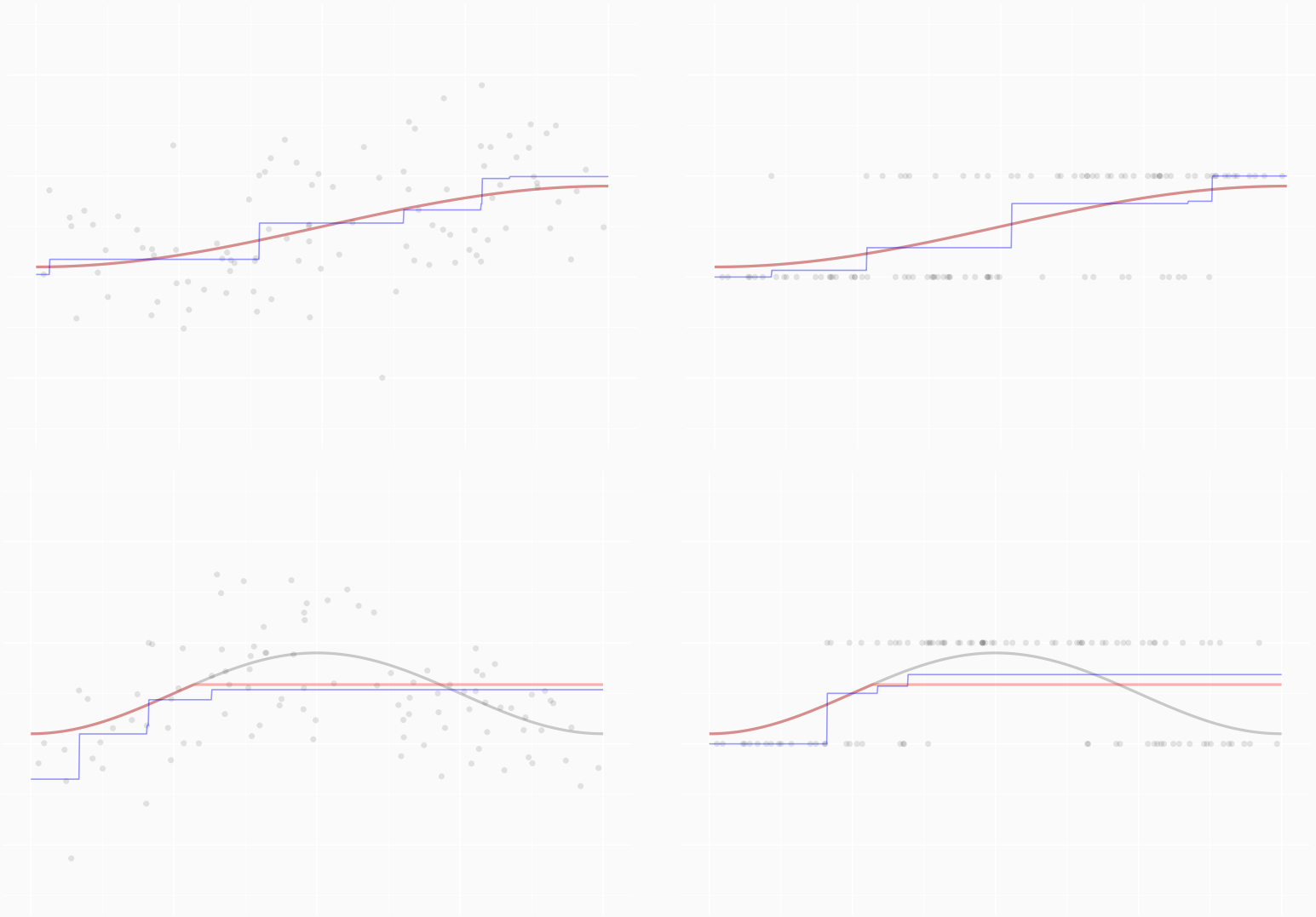


- The second column is out. We've assumed correct specfication.
- The second row is out. We've assumed normality.

Today, We Fix That



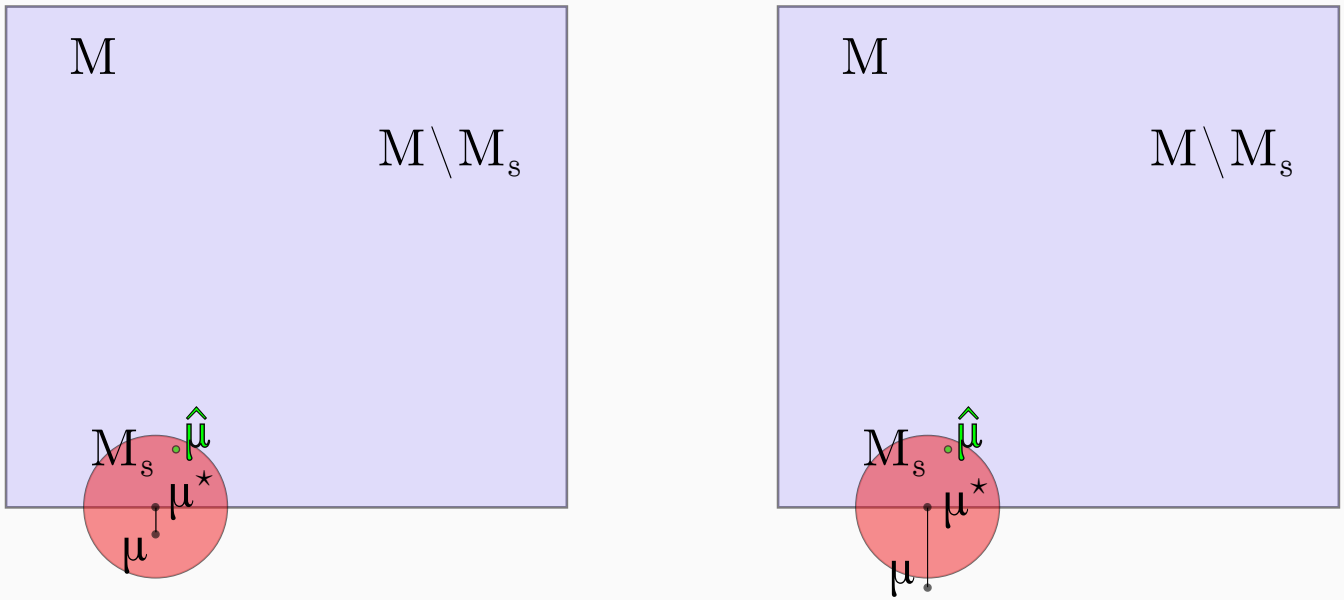
Today, We Fix That



- With misspecification, we estimate the model's best approximation to μ.
- Non-normality doesn't really matter much. We'll look at how it affects our bound.

Misspecification

What happens when μ isn't in the model?



- Our error in estimating μ is bounded by a sum of two terms.
  - The critical radius s, i.e., the one satisfying $s^2 \geq 2\sigma c_\delta \, \mathrm{w}(\mathcal{M}_s)$.
  - The distance from μ to its best approximation in the model. Or really 3 times that.

  We showed this in the model selection lab using the Cauchy-Schwarz inequality.
- In convex models, we can say more.
  Our error in estimating $\mu^\star$ does not depend on its distance to μ.

The Argument

For any $\mu^\star \in \mathcal{M}$, we can expand our mean squared error difference as before.

$$\ell(m) - \ell(\mu^\star) = \|m - \mu^\star\|^2_{L_2(\mathrm{P_n})} - \frac{2}{n}\sum_{i=1}^{n} \varepsilon_i^\star \{m(X_i) - \mu^\star(X_i)\} \quad \text{for} \quad \varepsilon_i^\star = Y_i - \mu^\star(X_i).$$

But our new 'noise' $\varepsilon_i^\star$ doesn't have mean zero. It's our old noise ε_i, minus something.

$$\varepsilon_i^\star = \{Y_i - \mu(X_i)\} - \{\mu^\star(X_i) - \mu(X_i)\}.$$
$$\varepsilon_i \qquad \text{something}$$

So we can think of our mean squared error difference as having three terms:

$$\ell(m) - \ell(\mu^\star) = \|m - \mu^\star\|^2_{L_2(\mathrm{P_n})}$$ squared distance, like before;

$$- \frac{2}{n}\sum_{i=1}^{n} \varepsilon_i \{m(X_i) - \mu^\star(X_i)\}$$ a mean zero term, like before;

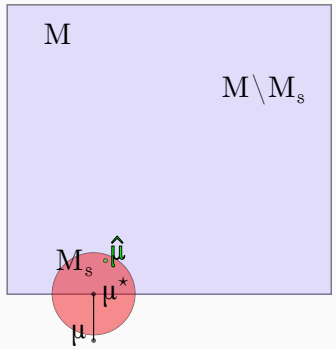
$$+ \frac{2}{n}\sum_{i=1}^{n} \{\mu^\star(X_i) - \mu(X_i)\}\{m(X_i) - \mu^\star(X_i)\}$$ and something else.

We can use our argument, ignoring the new term, if that term is always *non-negative*.

Why?

Why.

$$\ell(m) - \ell(\mu^\star) = \|m - \mu^\star\|^2_{L_2(\mathrm{P_n})} - \frac{2}{n}\sum_{i=1}^{n} \varepsilon_i \{m(X_i) - \mu^\star(X_i)\} + \frac{2}{n}\sum_{i=1}^{n} \{\mu^\star(X_i) - \mu(X_i)\}\{m(X_i) - \mu^\star(X_i)\}$$



We want to show that if distance from m to $\mu^\star$ is big enough, it wins.

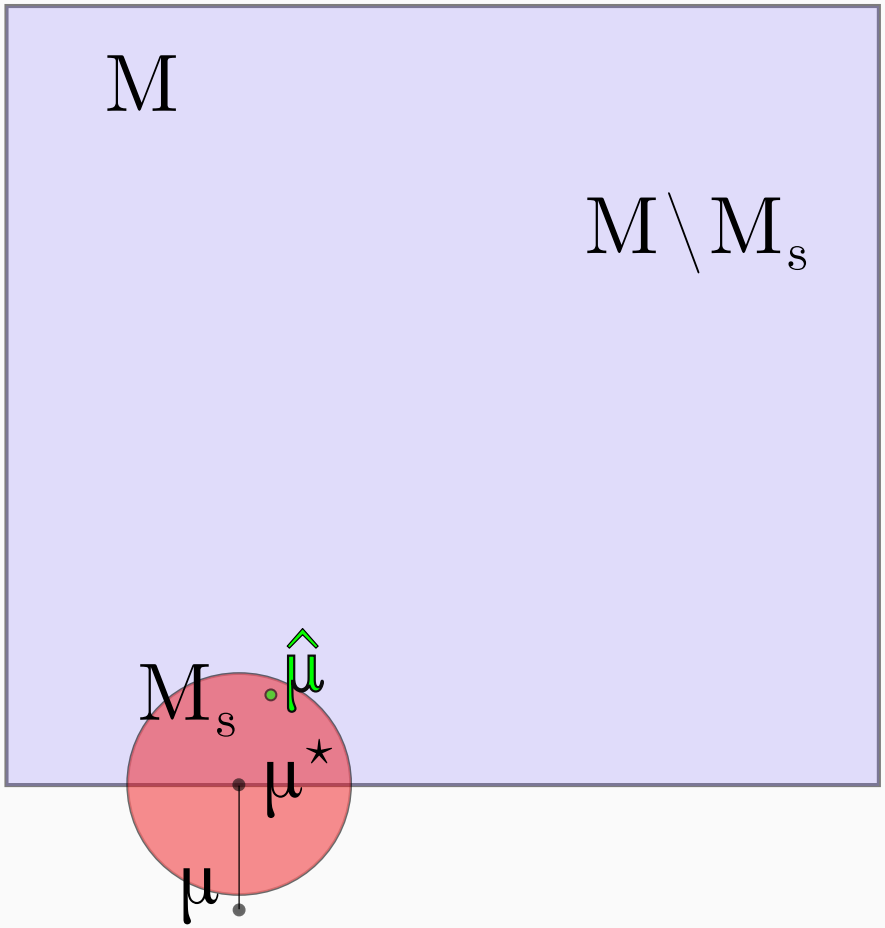
- In particular, it wins in the sense that the loss difference $\ell(m) - \ell(\mu^\star)$ is positive.
- That implies distance from $\hat{\mu}$ to $\mu^\star$ is smaller, as distance doesn't win in that case.

If this new term is non-negative, it helps distance win.

- If the MSE difference is positive when we ignore a non-negative term, then it's positive when we don't.

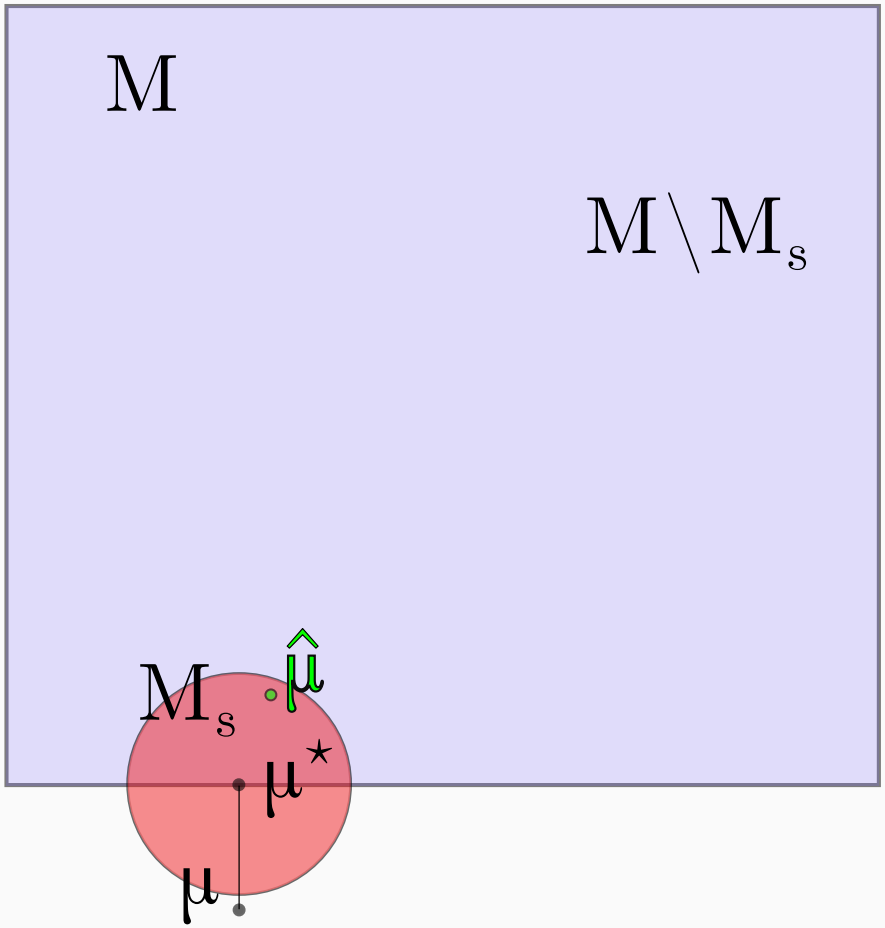
So we want to make sure this new term is non-negative. And we get to choose $\mu^\star$.

This sounds weird



- It sounds like we choose what our estimator converges to when we analyze it.
- Obviously we don't really get to do that. It's not really a choice—it's a guess.
- If $\hat{\mu}$ converges to some curve $\mu^\star$, then it can't converge to anything else.

The right choice



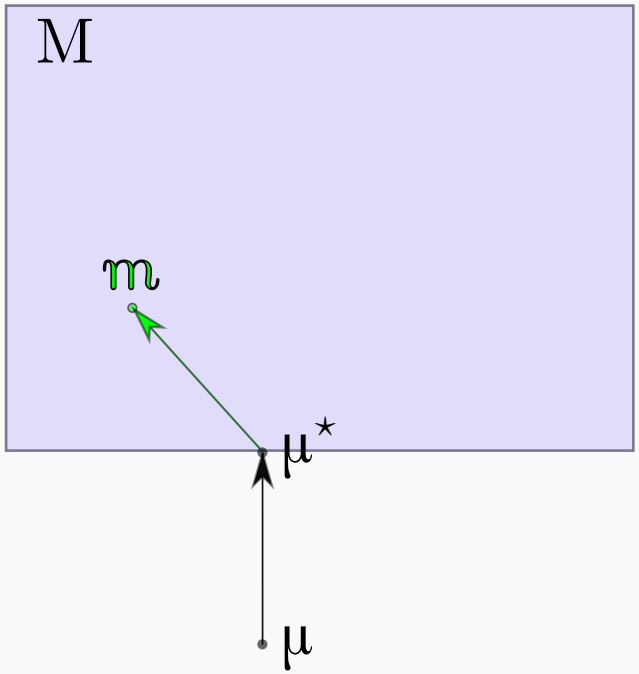
It's the best approximation to μ in the model.

$$\mu^\star = \underset{m \in \mathcal{M}}{\operatorname{argmin}} \|m - \mu\|^2_{L_2(\mathrm{P_n})}.$$

With this choice, the new term is always non-negative

$$\frac{2}{n}\sum_{i=1}^{n}\{\mu^\star(X_i)-\mu(X_i)\}\{m(X_i)-\mu^\star(X_i)\} = 2\langle \mu^\star-\mu, m-\mu^\star\rangle_{L_2(\mathrm{P_n})}$$

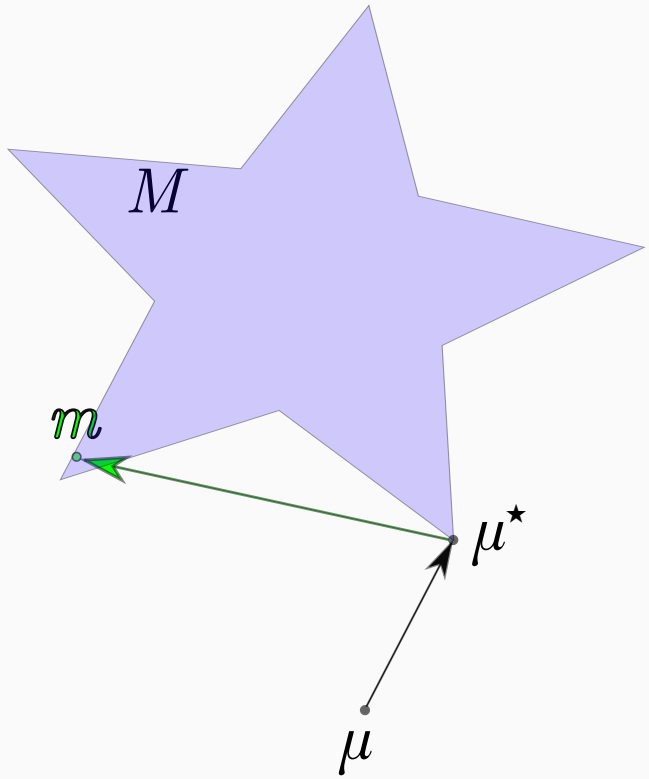
It's proportional to the dot product between two vectors: $\mu \to \mu^\star$ and $\mu^\star \to m$.



When the model $\mathcal{M}$ is convex, these vectors are always in the same direction. That is, this dot product is non-negative for all $m \in \mathcal{M}$. Proof for Homework!

That's not true for other choices

When $\mu^\star \in \mathcal{M}$ isn't the closest point to μ,
these vectors can point in opposite directions.
That is, this dot product can be negative for some $m \in \mathcal{M}$.



The same thing can happen *for the closest point* in a non-convex model.

Summary

When we use a convex model, the least squares estimator $\hat{\mu}$ converges to the model's closest point to μ.

- If μ is in the model, that's μ.
- Otherwise, it's something else.

We can bound our estimator's distance to that closest point $\mu^\star$ just like we've been bounding distance to μ when we assumed it was in the model.

$$\|\hat{\mu} - \mu^\star\|_{L_2(\mathrm{P_n})} < s \;\text{ w.p. }\; 1-\delta \;\text{ if }\; s^2 \geq 2\sigma\, c_\delta\, \mathrm{w}(\mathcal{M}_s)$$

$$\mathcal{M}_s = \left\{m \in \mathcal{M} : \|m - \mu^\star\|_{L_2(\mathrm{P_n})} \leq s\right\}.$$

Let's get a feel for what that means by looking at some examples.

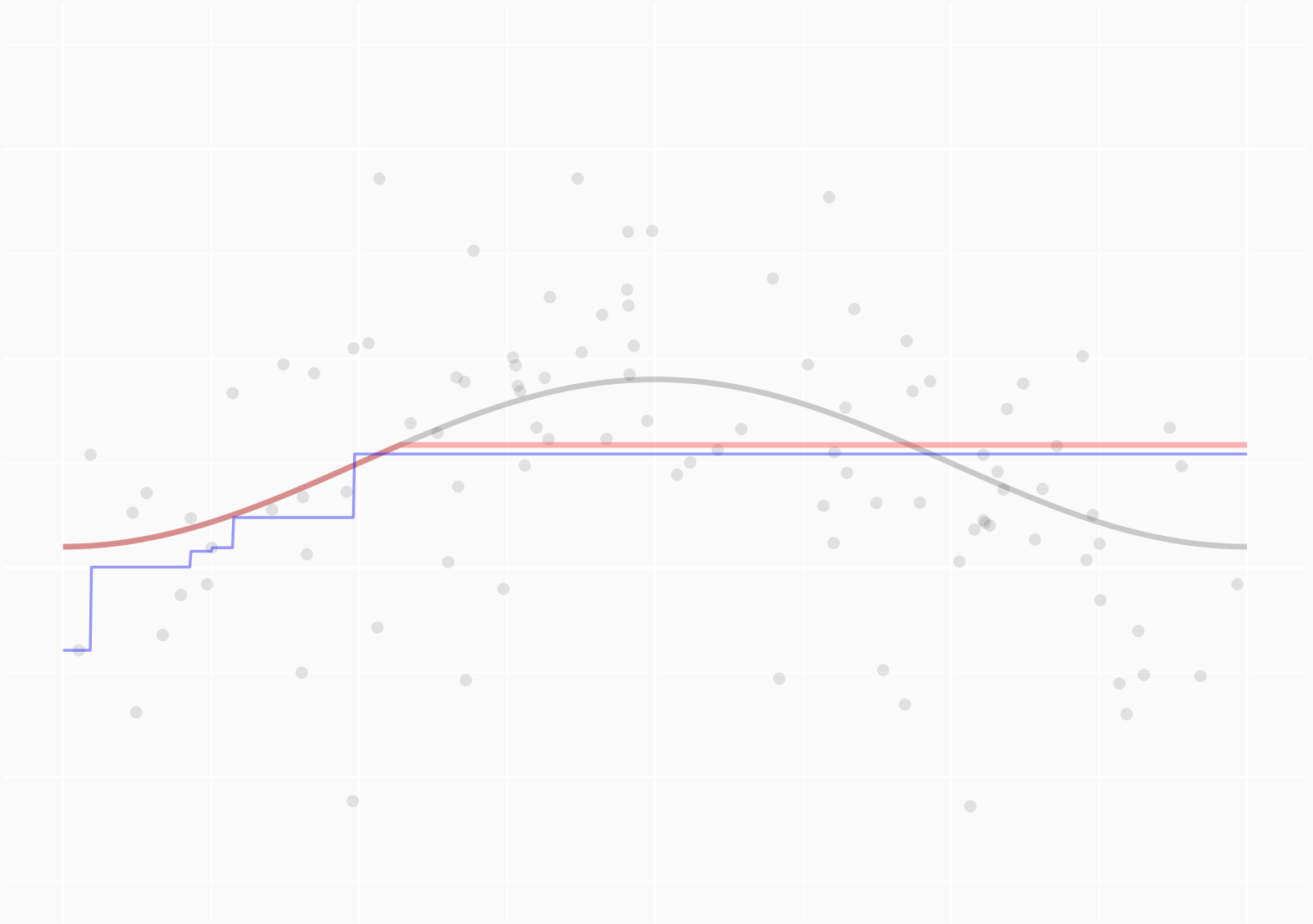


Figure 1: Increasing Curves.

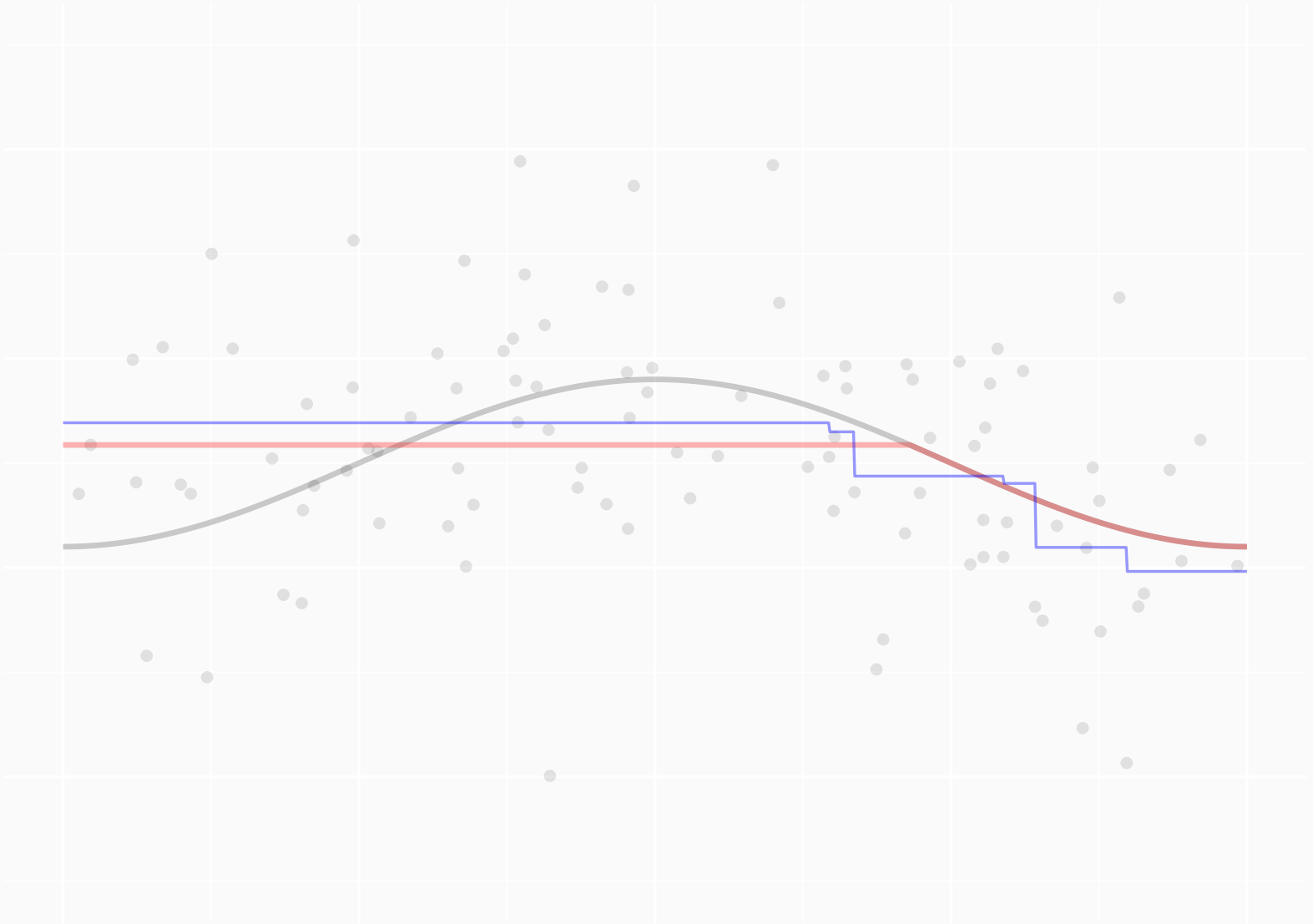


Figure 2: Decreasing Curves.

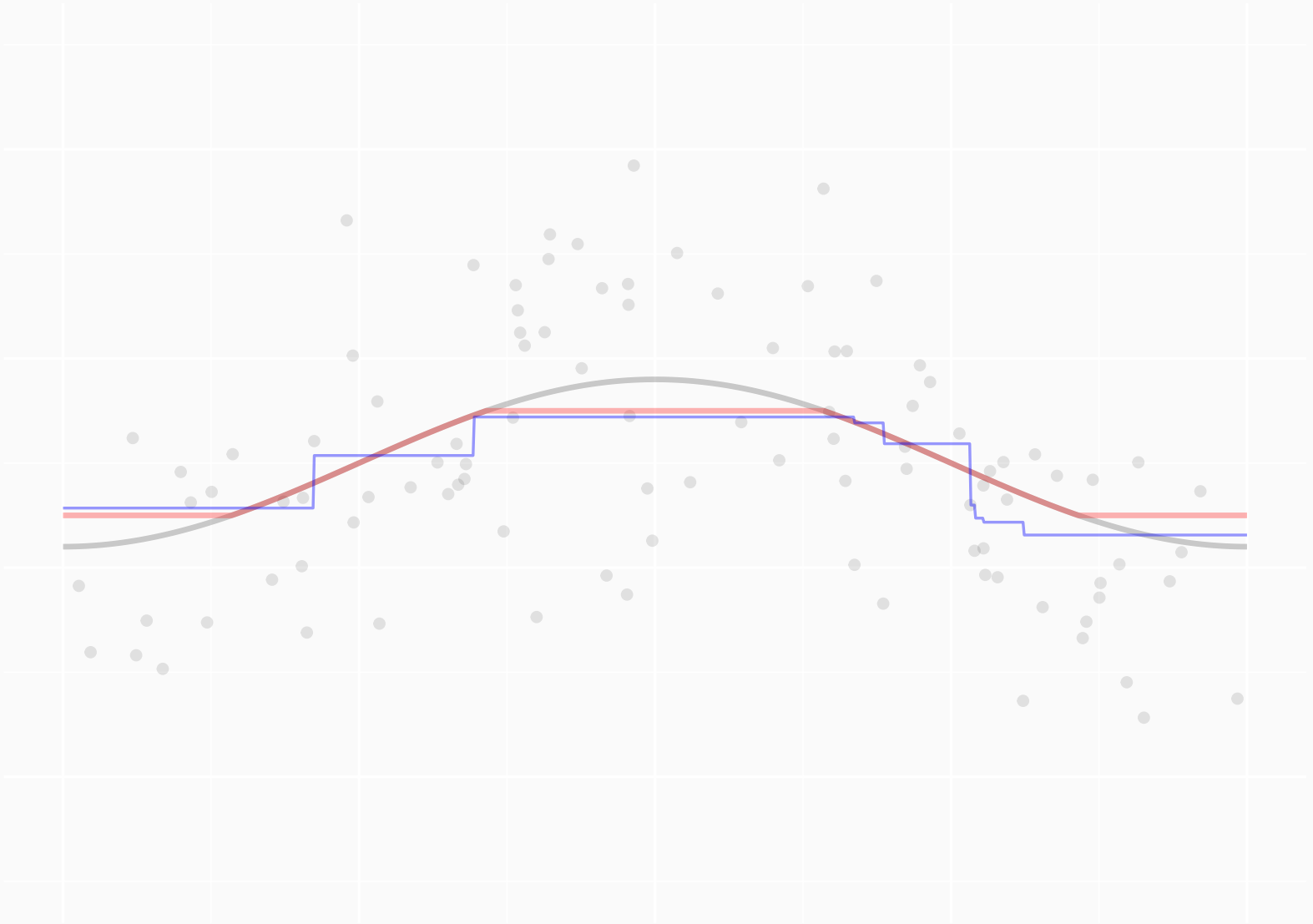


Figure 3: Bounded Variation Curves. $\rho_{\mathrm{TV}} \leq 1$

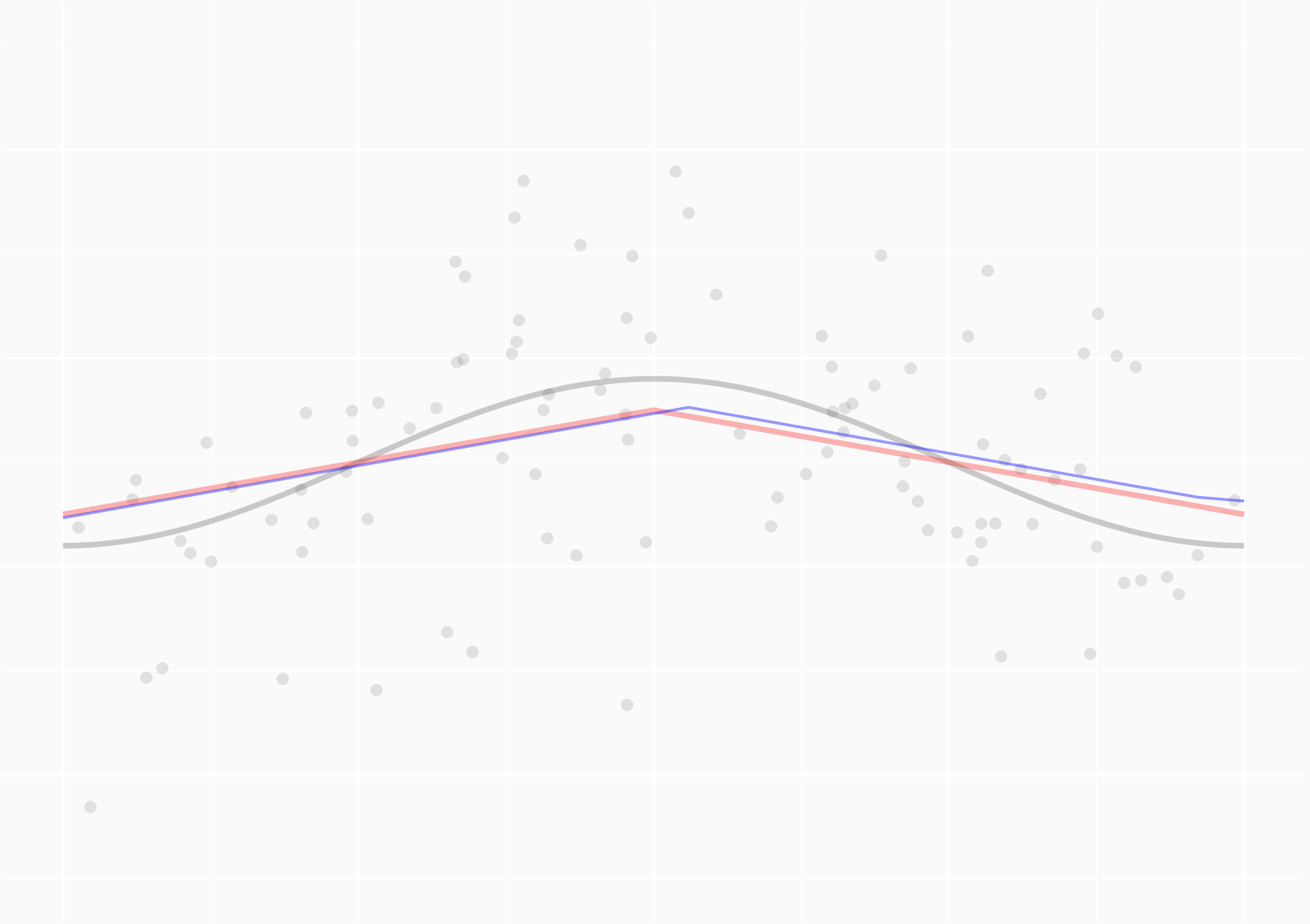


Figure 4: Lipschitz Curves. $\rho_{\text{Lip}} \leq 1$

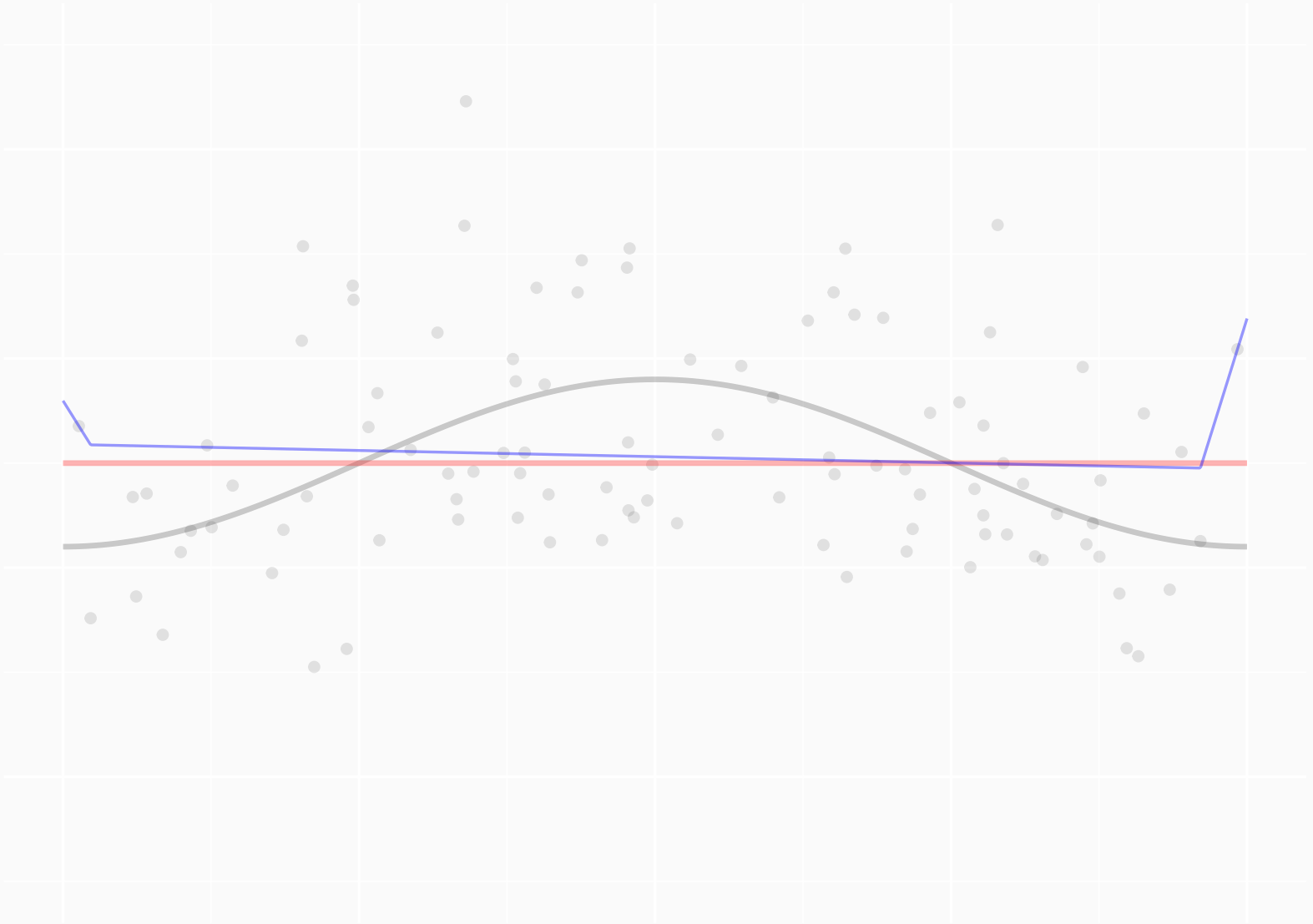


Figure 5: Convex Curves.

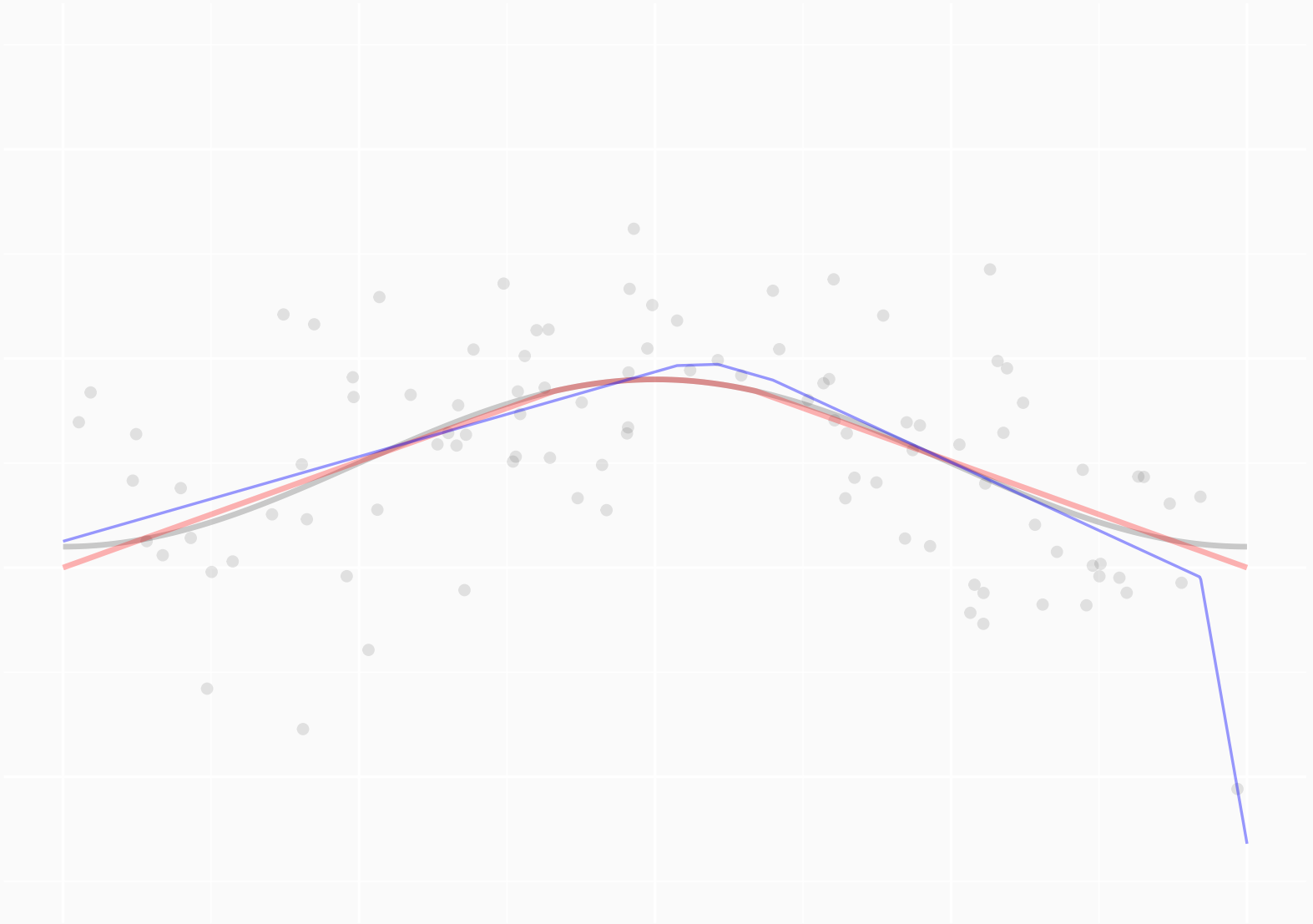


Figure 6: Concave Curves.

Non-Gaussian Noise

Summary

$$\ell(m) - \ell(\mu^\star) = \|m - \mu^\star\|^2_{L_2(\mathrm{P_n})} \qquad \text{squared distance}$$

$$- \frac{2}{n}\sum_{i=1}^n \varepsilon_i \{m(X_i) - \mu^\star(X_i)\} \qquad \text{a mean zero term}$$

$$+ \frac{2}{n}\sum_{i=1}^n \{\mu^\star(X_i) - \mu(X_i)\}\{m(X_i) - \mu^\star(X_i)\} \qquad \text{a non-negative term.}$$

- No matter what noise vector ε we have, we have an error bound determined by the *width* associated with it.

$$\|\hat{\mu} - \mu^\star\|_{L_2(\mathrm{P_n})} < s \quad \text{w.p. } 1-\delta \text{ for } \quad s^2 \geq 2c_\delta \, \mathrm{w}_\epsilon(\mathcal{M}_s^\circ)$$

$$\text{where } \mathrm{w}_\epsilon(\mathcal{V}) = \mathrm{E} \max_{v \in \mathcal{V}} \langle \epsilon, v \rangle_{L_2(\mathrm{P_n})}.$$

- To take advantage of our gaussian width calculations, we'll bound this width in terms of gaussian width.
- At the heart of it are two ideas called *symmetrization* and *contraction*.
- We'll substitute for ϵ_i a variant that's symmetric around zero.

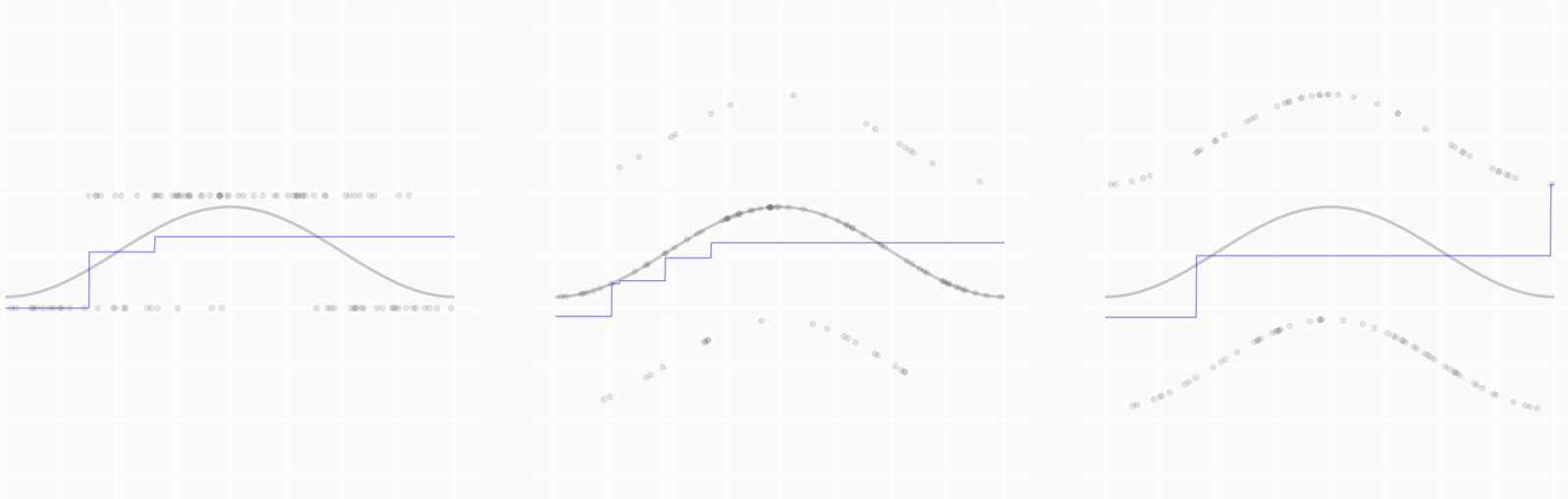
$$\epsilon_i \to \epsilon_i - \epsilon_i' \quad \text{where} \quad \epsilon_i' \text{ is an independent copy of } \epsilon_i$$

- We'll show this substitution doesn't change much. That's symmetrization.
- Substituting a gaussian often doesn't change much either. That's contraction.

Non-Gaussian Noise

Probabilistic Classification

The Setting



Suppose we have independent *binary observations*.

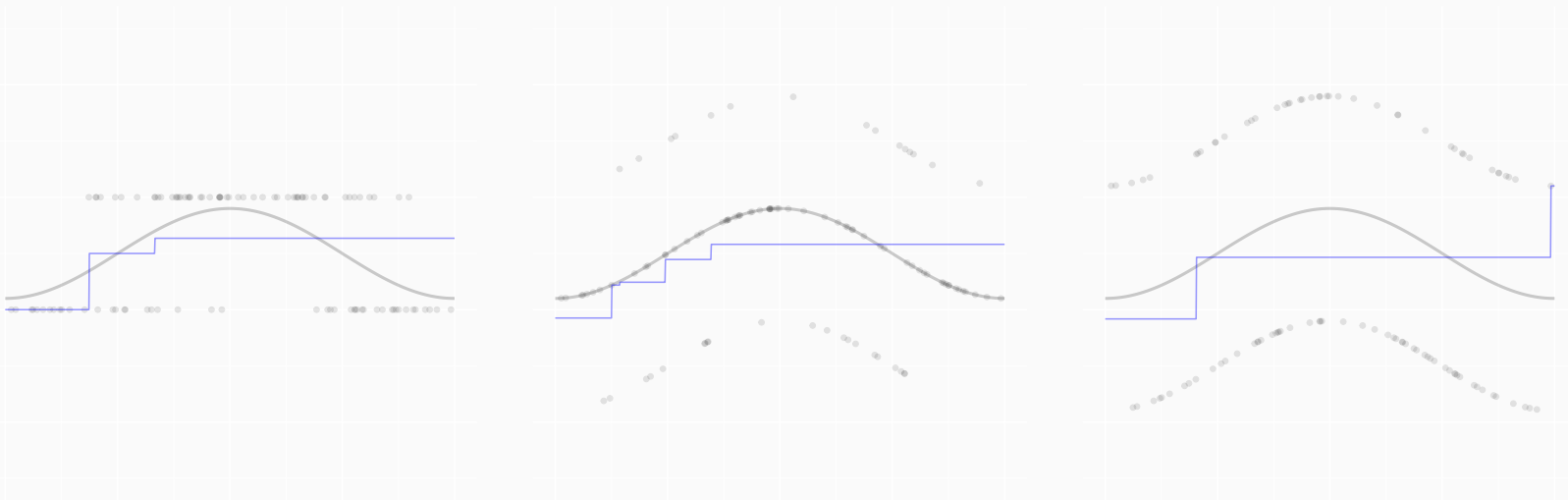
$$Y_i = \begin{cases} 1 & \text{with conditional probability } \mu(X_i) \\ 0 & \text{otherwise} \end{cases}$$

$$= \mu(X_i) + \varepsilon_i \quad \text{for} \quad \varepsilon_i = \begin{cases} 1 - \mu(X_i) & \text{with conditional probability } \mu(X_i) \\ -\mu(X_i) & \text{with conditional probability } 1 - \mu(X_i) \end{cases}.$$

Note that this *classification noise* ε_i has conditional mean zero.

$$\mathrm{E}[\varepsilon_i \mid X_i] = \mu(X_i)\{1 - \mu(X_i)\} + \{1 - \mu(X_i)\}\{-\mu(X_i)\} = 0.$$

The Setting



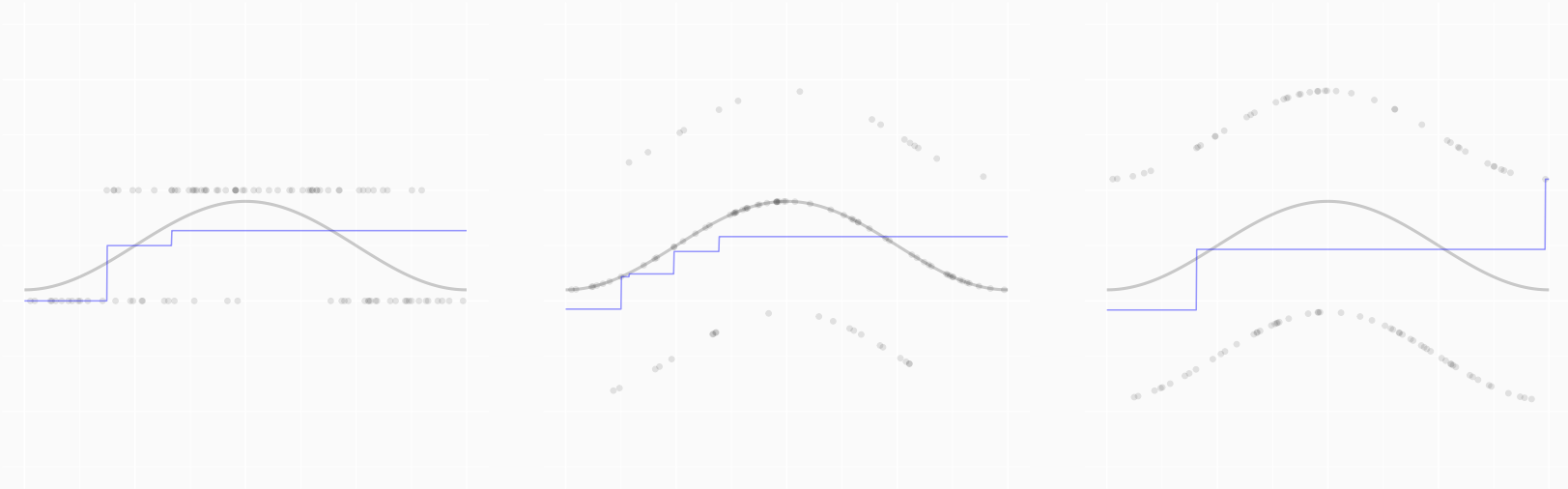
What we need to bound is *classification-noise width*

$$\mathrm{w}_\epsilon(\mathcal{V}) = \frac{1}{n}\,\mathrm{E}\max_{v\in\mathcal{V}}\sum_{i=1}^{n}\varepsilon_i v_i.$$

We'll show it's no bigger than a version with *symmetrized noise*.

$$\varepsilon_i - \varepsilon_i' = \begin{cases} +1 & \text{when } \varepsilon_i = 1-\mu(X_i),\ \varepsilon_i' = \mu(X_i) \\ -1 & \text{when } \varepsilon_i = \mu(X_i),\ \varepsilon_i' = 1-\mu(X_i) \\ 0 & \text{when } \varepsilon_i = \varepsilon_i' \end{cases}$$

The Setting



And we'll show that *this* is no bigger than a version with *random sign noise*

$$\mathrm{w}_\epsilon(\mathcal{V}) \leq \mathrm{w}_{\epsilon-\epsilon'}(\mathcal{V}) \leq \mathrm{w}_s(\mathcal{V}) \quad \text{where} \quad s_i = \pm 1 \text{ w.p. } 1/2.$$

The trick will be multiplying the symmetrized noise by a random sign.
It's already symmetric, so that doesn't change its distribution.

$$\varepsilon_i - \varepsilon_i' \overset{dist}{=} s_i(\varepsilon_i - \varepsilon_i')$$

Then we'll *contract out* the symmetrized noise, leaving the random sign. You'll see.

Step 1

We bound our maximum in terms of one involving symmetric noise.

- We'll work with a conditionally independent copy $\varepsilon'_1 \dots \varepsilon'_n$ of our noise.
- It has the same distribution as $\varepsilon_1 \dots \varepsilon_n$ conditional on $X_1 \dots X_n$.

$$\begin{aligned}
\mathrm{E}_\varepsilon \max_{v \in \mathcal{V}} \sum_{i=1}^n \varepsilon_i v_i &\overset{(a)}{=} \mathrm{E}_\varepsilon \max_{v \in \mathcal{V}} \sum_{i=1}^n (\varepsilon_i - \mathrm{E}_{\varepsilon'} \varepsilon'_i) v_i \\
&\overset{(b)}{=} \mathrm{E}_\varepsilon \max_{v \in \mathcal{V}} \mathrm{E}_{\varepsilon'} \sum_{i=1}^n (\varepsilon_i - \varepsilon'_i) v_i \\
&\overset{(c)}{\leq} \mathrm{E}_\varepsilon \mathrm{E}_{\varepsilon'} \max_{v \in \mathcal{V}} \sum_{i=1}^n (\varepsilon_i - \varepsilon'_i) v_i.
\end{aligned}$$

Why do these steps work?

(a) $\mathrm{E}_{\varepsilon'} \varepsilon'_i = 0$.

Step 1

We bound our maximum in terms of one involving symmetric noise.

- We'll work with a conditionally independent copy $\varepsilon'_1 \dots \varepsilon'_n$ of our noise.
- It has the same distribution as $\varepsilon_1 \dots \varepsilon_n$ conditional on $X_1 \dots X_n$.

$$\begin{aligned}
\mathrm{E}_\varepsilon \max_{v \in \mathcal{V}} \sum_{i=1}^n \varepsilon_i v_i &\overset{(a)}{=} \mathrm{E}_\varepsilon \max_{v \in \mathcal{V}} \sum_{i=1}^n (\varepsilon_i - \mathrm{E}_{\varepsilon'} \varepsilon'_i) v_i \\
&\overset{(b)}{=} \mathrm{E}_\varepsilon \max_{v \in \mathcal{V}} \mathrm{E}_{\varepsilon'} \sum_{i=1}^n (\varepsilon_i - \varepsilon'_i) v_i \\
&\overset{(c)}{\leq} \mathrm{E}_\varepsilon \mathrm{E}_{\varepsilon'} \max_{v \in \mathcal{V}} \sum_{i=1}^n (\varepsilon_i - \varepsilon'_i) v_i.
\end{aligned}$$

Why do these steps work?

(a) $\mathrm{E}_{\varepsilon'} \varepsilon'_i = 0$.
(b) Expectation is linear.

Step 1

We bound our maximum in terms of one involving symmetric noise.

- We'll work with a conditionally independent copy $\varepsilon'_1 \dots \varepsilon'_n$ of our noise.
- It has the same distribution as $\varepsilon_1 \dots \varepsilon_n$ conditional on $X_1 \dots X_n$.

$$\begin{aligned}
\mathrm{E}_\varepsilon \max_{v \in \mathcal{V}} \sum_{i=1}^n \varepsilon_i v_i &\overset{(a)}{=} \mathrm{E}_\varepsilon \max_{v \in \mathcal{V}} \sum_{i=1}^n (\varepsilon_i - \mathrm{E}_{\varepsilon'} \varepsilon'_i) v_i \\
&\overset{(b)}{=} \mathrm{E}_\varepsilon \max_{v \in \mathcal{V}} \mathrm{E}_{\varepsilon'} \sum_{i=1}^n (\varepsilon_i - \varepsilon'_i) v_i \\
&\overset{(c)}{\leq} \mathrm{E}_\varepsilon \mathrm{E}_{\varepsilon'} \max_{v \in \mathcal{V}} \sum_{i=1}^n (\varepsilon_i - \varepsilon'_i) v_i.
\end{aligned}$$

Why do these steps work?

(a) $\mathrm{E}_{\varepsilon'} \varepsilon'_i = 0$.
(b) Expectation is linear.
(c) Maximizing the average gives us something smaller than averaging the maxima.

Step 1

We bound our maximum in terms of one involving symmetric noise.

- We'll work with a conditionally independent copy $\varepsilon'_1 \dots \varepsilon'_n$ of our noise.
- It has the same distribution as $\varepsilon_1 \dots \varepsilon_n$ conditional on $X_1 \dots X_n$.

$$\begin{aligned}
\mathrm{E}_\varepsilon \max_{v \in \mathcal{V}} \sum_{i=1}^n \varepsilon_i v_i &\overset{(a)}{=} \mathrm{E}_\varepsilon \max_{v \in \mathcal{V}} \sum_{i=1}^n (\varepsilon_i - \mathrm{E}_{\varepsilon'} \varepsilon'_i) v_i \\
&\overset{(b)}{=} \mathrm{E}_\varepsilon \max_{v \in \mathcal{V}} \mathrm{E}_{\varepsilon'} \sum_{i=1}^n (\varepsilon_i - \varepsilon'_i) v_i \\
&\overset{(c)}{\leq} \mathrm{E}_\varepsilon \mathrm{E}_{\varepsilon'} \max_{v \in \mathcal{V}} \sum_{i=1}^n (\varepsilon_i - \varepsilon'_i) v_i.
\end{aligned}$$

Why do these steps work?

(a) $\mathrm{E}_{\varepsilon'} \varepsilon'_i = 0$.
(b) Expectation is linear.
(c) Maximizing the average gives us something smaller than averaging the maxima.
    - In the second, we choose the maximizing $v \in \mathcal{V}$ *for each* ε'.

Step 1

We bound our maximum in terms of one involving symmetric noise.

- We'll work with a conditionally independent copy $\varepsilon'_1 \dots \varepsilon'_n$ of our noise.
- It has the same distribution as $\varepsilon_1 \dots \varepsilon_n$ conditional on $X_1 \dots X_n$.

$$\begin{aligned}
\mathrm{E}_\varepsilon \max_{v \in \mathcal{V}} \sum_{i=1}^n \varepsilon_i v_i &\overset{(a)}{=} \mathrm{E}_\varepsilon \max_{v \in \mathcal{V}} \sum_{i=1}^n (\varepsilon_i - \mathrm{E}_{\varepsilon'} \varepsilon'_i) v_i \\
&\overset{(b)}{=} \mathrm{E}_\varepsilon \max_{v \in \mathcal{V}} \mathrm{E}_{\varepsilon'} \sum_{i=1}^n (\varepsilon_i - \varepsilon'_i) v_i \\
&\overset{(c)}{\leq} \mathrm{E}_\varepsilon \mathrm{E}_{\varepsilon'} \max_{v \in \mathcal{V}} \sum_{i=1}^n (\varepsilon_i - \varepsilon'_i) v_i.
\end{aligned}$$

Why do these steps work?

(a) $\mathrm{E}_{\varepsilon'} \varepsilon'_i = 0$.
(b) Expectation is linear.
(c) Maximizing the average gives us something smaller than averaging the maxima.
   - In the second, we choose the maximizing $v \in \mathcal{V}$ *for each* ε'.
   - If we wanted to choose the same one each time, like we do in the first, we could.

Step 2

We introduce independent random signs $s_i = \pm 1$ w.p. $1/2$, changing nothing.

$$\mathrm{E}_{\varepsilon}\,\mathrm{E}_{\varepsilon'}\max_{v\in\mathcal{V}}\sum_{i=1}^{n}(\varepsilon_i-\varepsilon_i')v_i = \mathrm{E}_{s}\,\mathrm{E}_{\varepsilon}\,\mathrm{E}_{\varepsilon'}\max_{v\in\mathcal{V}}\sum_{i=1}^{n}s_i(\varepsilon_i-\varepsilon_i')v_i.$$

Why does this change nothing?

Step 2

We introduce independent random signs $s_i = \pm 1$ w.p. $1/2$, changing nothing.

$$\mathrm{E}_{\varepsilon}\,\mathrm{E}_{\varepsilon'}\max_{v\in\mathcal{V}}\sum_{i=1}^{n}(\varepsilon_i-\varepsilon_i')v_i = \mathrm{E}_{s}\,\mathrm{E}_{\varepsilon}\,\mathrm{E}_{\varepsilon'}\max_{v\in\mathcal{V}}\sum_{i=1}^{n}s_i(\varepsilon_i-\varepsilon_i')v_i.$$

Why does this change nothing?

- Because the inner mean $(\mathrm{E}_{\varepsilon}\,\mathrm{E}_{\varepsilon'})$ doesn't depend on the signs s_i.
- That's because ε_i and ε_i' have the same distribution.
- And this implies $(\varepsilon_i - \varepsilon_i')$ and $-(\varepsilon_i - \varepsilon_i')$ do, too.

Step 3

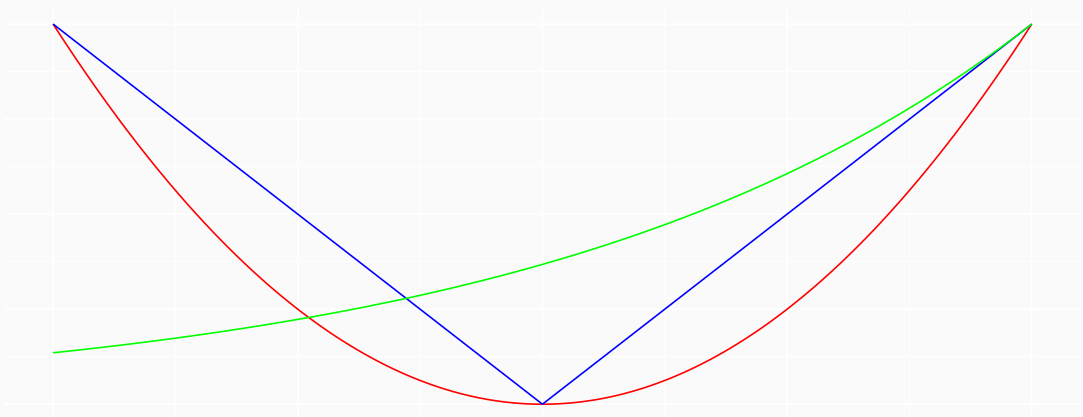
We swap the order of our averages and think about the inner average as a *function* of our vector of symmetric noise.

$$\mathrm{E}_s\,\mathrm{E}_\varepsilon\,\mathrm{E}_{\varepsilon'}\max_{v\in\mathcal{V}}\sum_{i=1}^n s_i(\varepsilon_i-\varepsilon_i')v_i = \mathrm{E}_\varepsilon\,\mathrm{E}_{\varepsilon'}\,\mathrm{E}_s\max_{v\in\mathcal{V}}\sum_{i=1}^n s_i(\varepsilon_i-\varepsilon_i')v_i$$

$$= \mathrm{E}_\varepsilon\,\mathrm{E}_{\varepsilon'}\,f(\varepsilon-\varepsilon') \quad \text{for} \quad f(u) = \mathrm{E}_s\max_{v\in\mathcal{V}}\sum_{i=1}^n s_i u_i v_i.$$

This function f is convex.

What does that mean? These, for example, are all convex.



$f\{(1-\lambda)a+\lambda b\} \le (1-\lambda)f(a)+\lambda f(b)$ for $\lambda\in[0,1]$. That's Convexity

Step 3

We swap the order of our averages and think about the inner average as a *function* of our vector of symmetric noise.

$$\mathrm{E}_s\,\mathrm{E}_\varepsilon\,\mathrm{E}_{\varepsilon'}\max_{v\in\mathcal{V}}\sum_{i=1}^n s_i(\varepsilon_i-\varepsilon_i')v_i = \mathrm{E}_\varepsilon\,\mathrm{E}_{\varepsilon'}\,\mathrm{E}_s\max_{v\in\mathcal{V}}\sum_{i=1}^n s_i(\varepsilon_i-\varepsilon_i')v_i$$

$$= \mathrm{E}_\varepsilon\,\mathrm{E}_{\varepsilon'}\,f(\varepsilon-\varepsilon') \quad \text{for} \quad f(u) = \mathrm{E}_s\max_{v\in\mathcal{V}}\sum_{i=1}^n s_i u_i v_i.$$

This function f is convex.

How do we know? Maximizing two things separately is better than maximizing their sum.

$$f\{(1-\lambda)a+\lambda b\} = \mathrm{E}_s\max_{v\in\mathcal{V}}\left\{(1-\lambda)\sum_{i=1}^n s_i a_i v_i + \lambda\sum_{i=1}^n s_i b_i v_i\right\}$$

$$\le \mathrm{E}_s\left\{\max_{v\in\mathcal{V}}(1-\lambda)\sum_{i=1}^n s_i a_i v_i + \max_{v\in\mathcal{V}}\lambda\sum_{i=1}^n s_i b_i v_i\right\}$$

$$= (1-\lambda)\,\mathrm{E}_s\max_{v\in\mathcal{V}}\sum_{i=1}^n s_i a_i v_i + \lambda\,\mathrm{E}_s\max_{v\in\mathcal{V}}\lambda\sum_{i=1}^n s_i b_i v_i$$

$$= (1-\lambda)f(a)+\lambda f(b).$$

Step 3

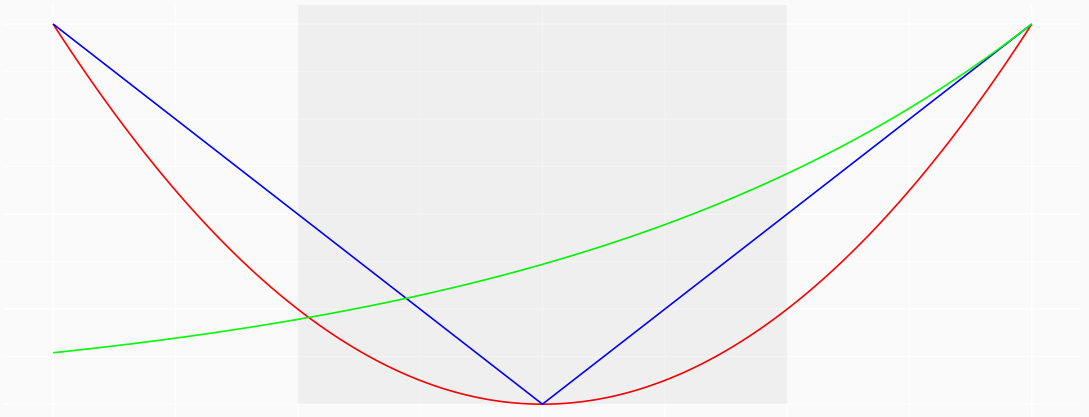
We swap the order of our averages and think about the inner average as a *function* of our vector of symmetric noise.

$$\mathrm{E}_s \mathrm{E}_\varepsilon \mathrm{E}_{\varepsilon'} \max_{v \in \mathcal{V}} \sum_{i=1}^n s_i(\varepsilon_i - \varepsilon_i')v_i = \mathrm{E}_\varepsilon \mathrm{E}_{\varepsilon'} \mathrm{E}_s \max_{v \in \mathcal{V}} \sum_{i=1}^n s_i(\varepsilon_i - \varepsilon_i')v_i$$

$$= \mathrm{E}_\varepsilon \mathrm{E}_{\varepsilon'} f(\varepsilon - \varepsilon') \quad \text{for} \quad f(u) = \mathrm{E}_s \max_{v \in \mathcal{V}} \sum_{i=1}^n s_i u_i v_i.$$

This function f is convex.

Why does this matter? The max of a convex function over a cube occurs at a corner.



What cube?

Step 4

The vector of symmetric noise, $\varepsilon - \varepsilon'$, is in the *unit cube* $[-1, 1]^n$.

$$\varepsilon_i - \varepsilon'_i = \begin{cases} 0 & \text{when } \varepsilon_i = \varepsilon'_i \\ +1 & \text{when } \varepsilon_i = 1 - \mu(X_i),\ \varepsilon'_i = \mu(X_i) \\ -1 & \text{when } \varepsilon_i = \mu(X_i),\ \varepsilon'_i = 1 - \mu(X_i). \end{cases}$$

The average over this random vector is bounded by the maximum over the cube it's in.

$$\begin{aligned} \mathrm{E}_\varepsilon \, \mathrm{E}_{\varepsilon'} \, \mathrm{E}_s \max_{v \in \mathcal{V}} \sum_{i=1}^n s_i(\varepsilon_i - \varepsilon'_i) v_i &\leq \max_{u \in [-1,1]^n} \mathrm{E}_s \max_{v \in \mathcal{V}} \sum_{i=1}^n s_i u_i v_i \\ &= \max_{u \in [-1,1]^n} f(u) \qquad \text{max over the cube} \\ &= \max_{u \in \{-1,1\}^n} f(u) \qquad \text{max over its corners} \end{aligned}$$

Step 5

We characterize this maximum over corners. Remember what f is.

$$\max_{u \in \{-1,1\}^n} f(u) = \max_{u \in \{-1,1\}^n} \mathrm{E}_s \max_{v \in \mathcal{V}} \sum_{i=1}^{n} s_i u_i v_i$$

$$= \mathrm{E}_s \max_{v \in \mathcal{V}} \sum_{i=1}^{n} s_i v_i.$$

Why?

Hint. What's the distribution of s_i? And $s_i u_i$ for $u_i \in \{-1, 1\}$?

Step 5

We characterize this maximum over corners. Remember what f is.

$$\max_{u \in \{-1,1\}^n} f(u) = \max_{u \in \{-1,1\}^n} \mathrm{E}_s \max_{v \in \mathcal{V}} \sum_{i=1}^{n} s_i u_i v_i$$

$$= \mathrm{E}_s \max_{v \in \mathcal{V}} \sum_{i=1}^{n} s_i v_i.$$

Why?

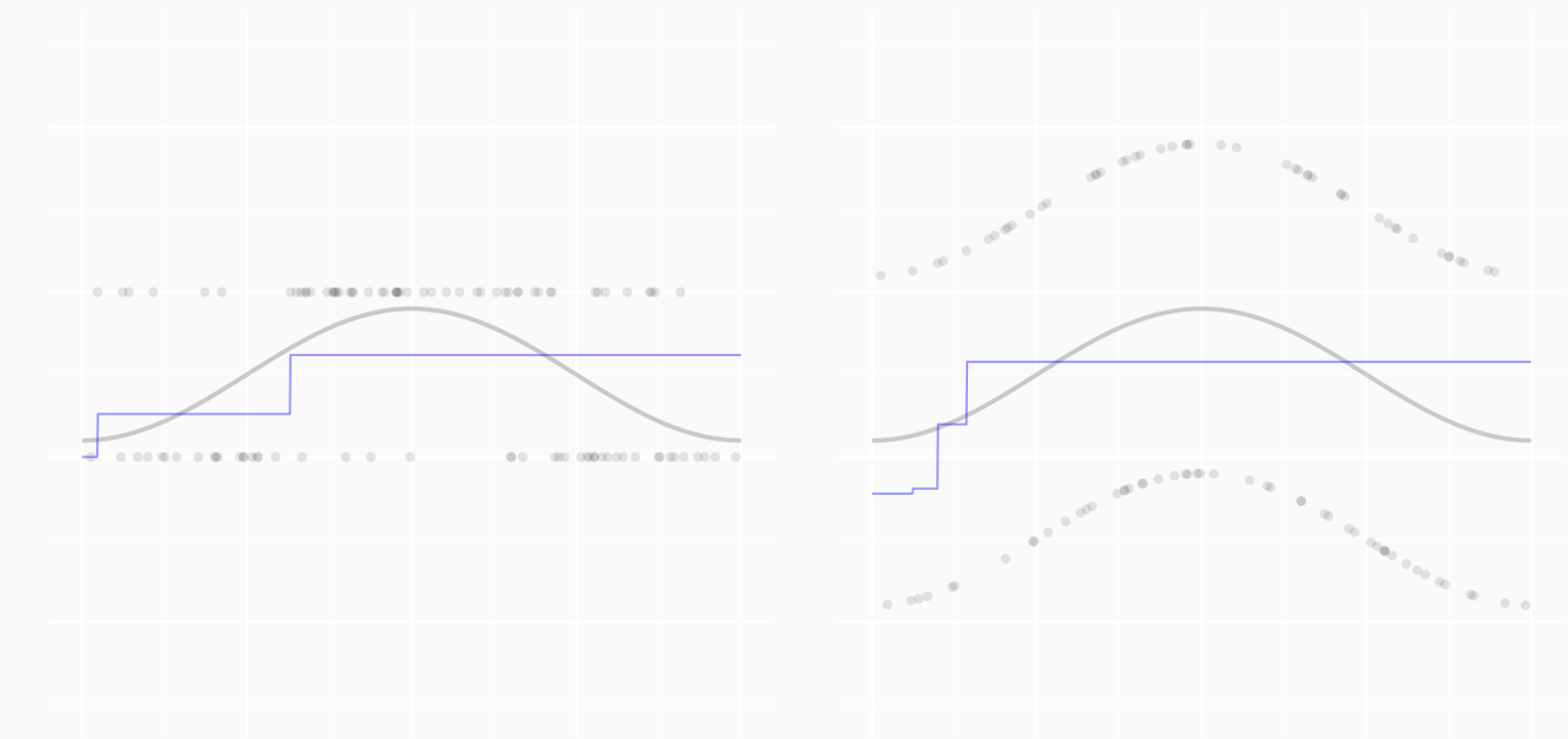
Hint. What's the distribution of s_i? And $s_i u_i$ for $u_i \in \{-1, 1\}$?

They're the same.

So the distribution of the sum—and its maximum—is the same at every corner u.

Including the vector of all ones.

Summary



classification noise width $\leq$ random sign width

This means probabilistic classification is *easier* than regression with random sign noise.
Or, at least, that we get a better bound.

$$s^2 \geq 2c_\delta \, \mathrm{w}_s(\mathcal{M}_s^\circ) \quad \text{and} \quad \mathrm{w}_s(\mathcal{M}_s^\circ) \geq \mathrm{w}_\varepsilon(\mathcal{M}_s^\circ) \quad \Longrightarrow \quad s^2 \geq 2c_\delta \, \mathrm{w}_\varepsilon(\mathcal{M}_s^\circ)$$

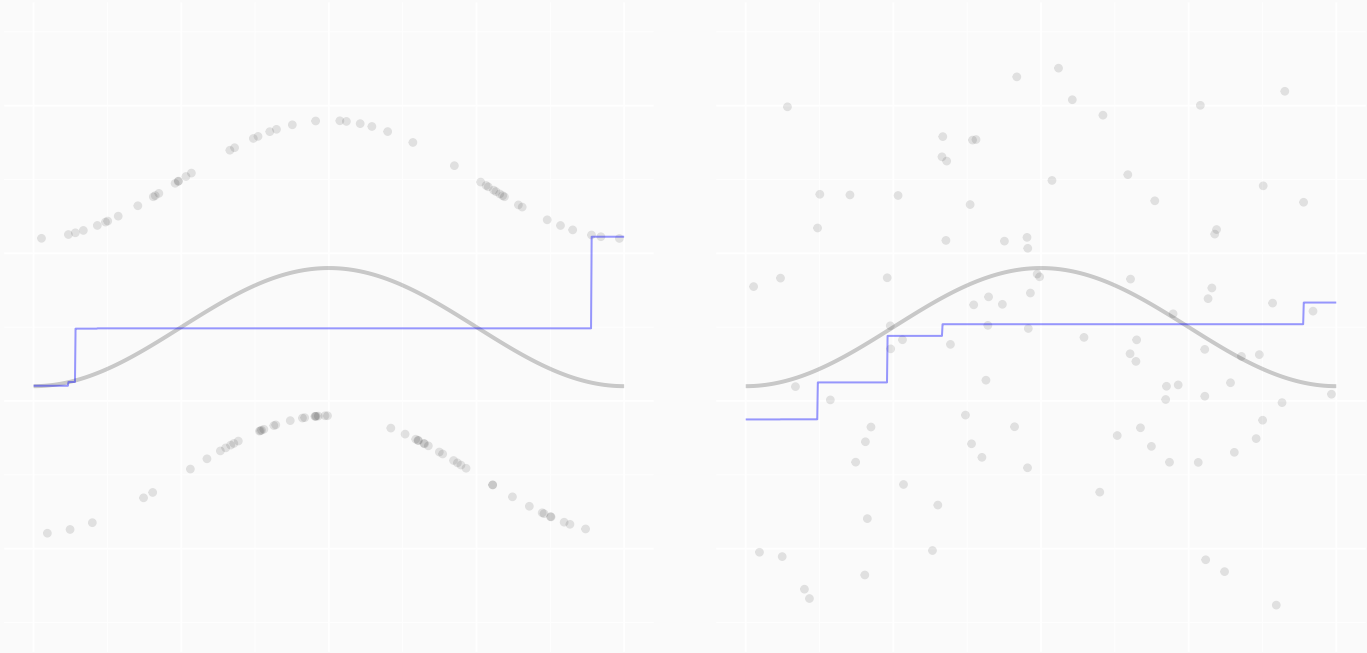
Names

People call this random sign width, or something like it, *Rademacher Complexity*.

$$\text{Rademacher Complexity}(\mathcal{V}) = \mathrm{E} \max_{v \in \mathcal{V}} \langle s, v \rangle_{L_2(\mathrm{P_n})}$$

$$\text{or maybe } = \mathrm{E} \max_{v \in \mathcal{V}} \left| \langle s, v \rangle_{L_2(\mathrm{P_n})} \right| \qquad \text{which is slightly different.}$$

Comparison To Gaussian Width



Regression with random sign noise isn't much harder than with gaussian noise.
Random sign width can't be much bigger than gaussian width.

$$\mathrm{w}_s(\mathcal{V}) \leq \sqrt{\frac{\pi}{2}}\,\mathrm{w}_g(\mathcal{V}) \approx 1.25\,\mathrm{w}_g(\mathcal{V}).$$

$$\mathrm{E} \max_{v\in\mathcal{V}} \sum_{i=1}^{n} g_i v_i = \mathrm{E}_s\,\mathrm{E}_g \max_{v\in\mathcal{V}} \sum_{i=1}^{n} |g_i| s_i v_i$$

$$\geq \mathrm{E}_s \max_{v\in\mathcal{V}} \mathrm{E}_g \sum_{i=1}^{n} |g_i| s_i v_i = \mathrm{E}_s \max_{v\in\mathcal{V}} \sum_{i=1}^{n} \mathrm{E}|g_i| s_i v_i = \mathrm{E}_s \max_{v\in\mathcal{V}} \sum_{i=1}^{n} \sqrt{\frac{2}{\pi}}\, s_i v_i.$$

We've got the tools to show it isn't much smaller, either.

Next Time

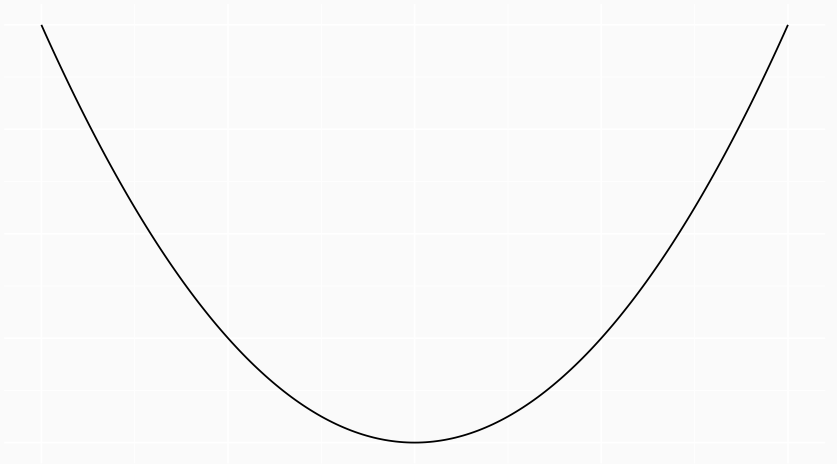
- We'll prove that. It's a factor $\propto \sqrt{\log(n)}$ smaller at most.
- We'll bound widths for arbitrary noise in terms of random sign width.
  - And therefore in terms of gaussian width.
  - It'll be almost exactly the same symmetrization and contraction argument.
- We'll talk about *sampling*, too. We'll bound population mean squared error.
  - We'll see that sampling isn't much more problematic than random sign noise.
  - That's a symmetrization and contraction thing, too.
  - But we'll need a subtler contraction argument.

Background: Convex Functions Are Maximized At Extreme Points

Definition

A function f is convex if *secants* lie above the curve.

$$f\{(1-\lambda)a + \lambda b\} \leq (1-\lambda)f(a) + \lambda f(b) \quad \text{for} \quad \lambda \in [0,1]$$



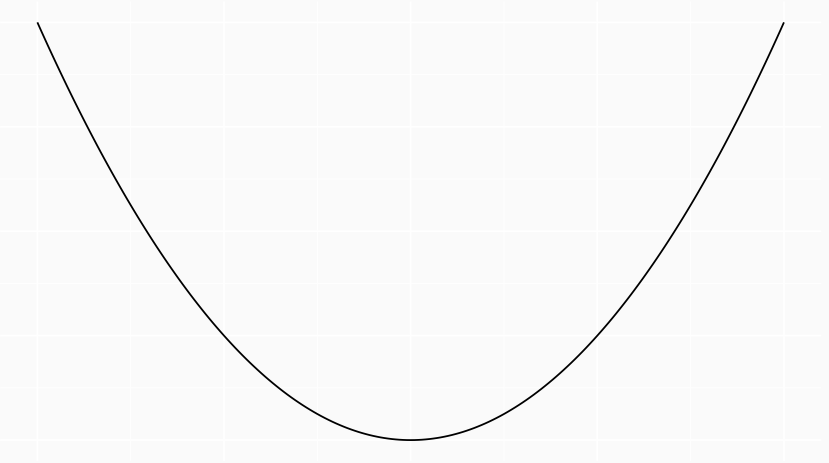
We can give this a *probabilistic interpretation* for a random variable Z_λ.

$$f(\mathrm{E}\, Z_\lambda) \leq \mathrm{E}\, f(Z_\lambda) \quad \text{where} \quad Z_\lambda =$$

Definition

A function f is convex if *secants* lie above the curve.

$$f\{(1-\lambda)a + \lambda b\} \leq (1-\lambda)f(a) + \lambda f(b) \quad \text{for} \quad \lambda \in [0,1]$$



We can give this a *probabilistic interpretation* for a random variable Z_λ.

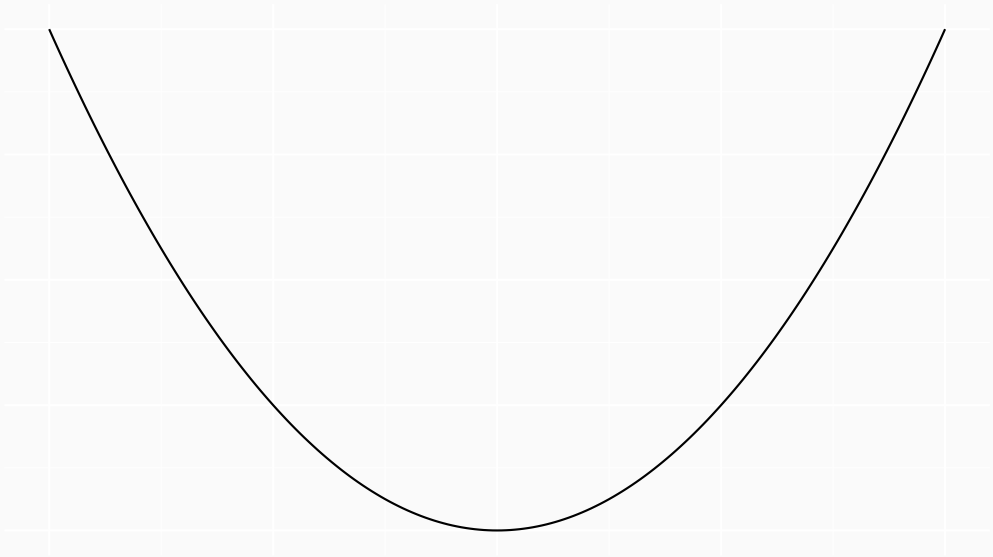
$$f(\mathrm{E}\, Z_\lambda) \leq \mathrm{E}\, f(Z_\lambda) \quad \text{where} \quad Z_\lambda = \begin{cases} a & \text{w.p. } 1-\lambda \\ b & \text{w.p. } \lambda \end{cases}$$

Jensen's Inequality

In fact, this is true all random variables Z.
If f is convex, its mean value exceeds its value at the mean.

$$f(\mathrm{E}\, Z) \leq \mathrm{E}\, f(Z)$$

That's called Jensen's Inequality.



You can prove it for discrete random variables via induction.

Jensen's Inequality Proof

Base case.

It's true for random variables taking on 2 values.

$$f(\lambda_1 z_1 + \lambda_2 z_2) \leq \lambda_1 f(z_1) + \lambda_2 f(z_2) \quad \text{if} \quad \lambda_1, \lambda_2 \geq 0 \quad \text{satisfy} \quad \lambda_1 + \lambda_2 = 1$$

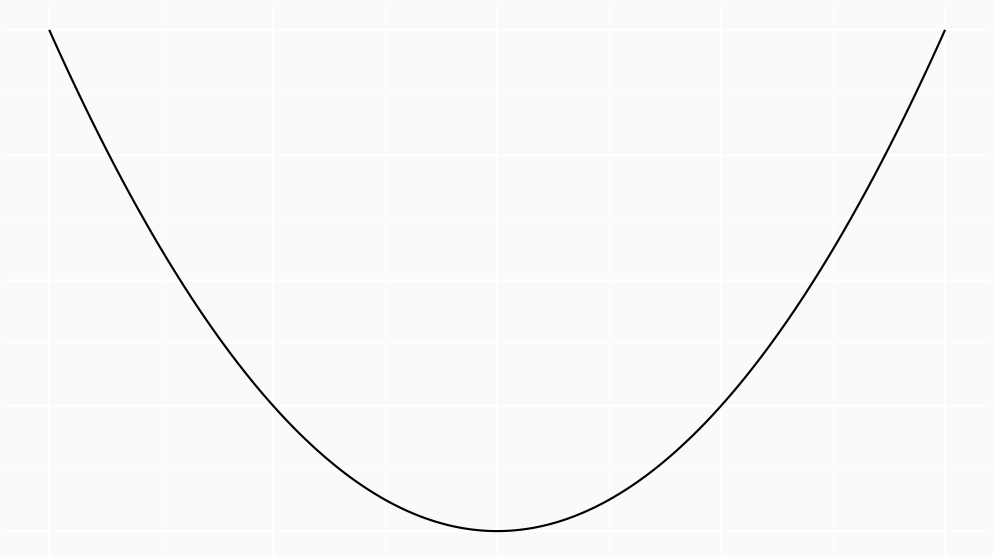
Inductive Step.

We'll show that if it's true for random variables taking on $n-1$ values, then it's also true for ones taking on n values.

$$\begin{aligned}
f\left\{\sum_{i=1}^{n} \lambda_i z_i\right\} &= f\left\{(1-\lambda_n)\left(\sum_{i=1}^{n-1} \frac{\lambda_i}{1-\lambda_n} z_i\right) + \lambda_n z_n\right\} \\
&\leq (1-\lambda_n) f\left(\sum_{i=1}^{n-1} \frac{\lambda_i}{1-\lambda_n} z_i\right) + \lambda_n f(z_n) \\
&\leq (1-\lambda_n) \sum_{i=1}^{n-1} \frac{\lambda_i}{1-\lambda_n} f(z_i) + \lambda_n f(z_n) \\
&= \sum_{i=1}^{n-1} \lambda_i f(z_i) + \lambda_n f(z_n)
\end{aligned}$$

Maxima of Convex Functions

Convex functions have no local maxima.



That means the maximum of a convex function over an interval occurs at an endpoint.

Proof.

$$\max_{x\in[a,b]} f(x) = \max_{\lambda\in[0,1]} f\{(1-\lambda)a+\lambda b\} \leq \max_{\lambda\in[0,1]} (1-\lambda)f(a)+\lambda f(b) = \max\{f(a), f(b)\}$$

This is essentially true in higher dimensions as well.
We just need the right generalizations of *interval* and its *endpoints*.

Convex Polytopes

The natural generalizations a *convex polytope* and its *extreme points*.

Definitions.

A **convex polytope** is the set of all weighted averages of some set of vectors $u_1 \dots u_K$.

$$\mathcal{U} = \left\{ \sum_i \lambda_i u_i \ : \ \lambda \in \Lambda \right\} \quad \text{where} \quad \Lambda = \left\{ \lambda \ : \ \lambda_i \geq 0 \ \text{ for all } i \ \text{ and } \ \sum_i \lambda_i = 1 \right\}$$

Its **extreme points** are the subset of these vectors that are not redundant.
That is, they're the ones we cannot write as weighted averages of the others.

Examples.

- A triangle is the set of weighted averages of its three vertices, its extreme points.
- A square is the set of weighted averages of its four vertices, its extreme points.
- A cube in $\mathbb{R}^n$ is the set of weighted averages of its 2^n vertices, its extreme points.

Maxima of Convex Functions over Polytopes

The maximum of a convex function over a polytope
occurs at an extreme point.

Proof.
It's more-or-less the same as the one-dimensional case. We use Jensen's inequality.

$$\max_{u \in \mathcal{U}} f(u) = \max_{\lambda \in \Lambda} f\left(\sum_i \lambda_i u_i\right) \leq \max_{\lambda \in \Lambda} \sum_i \lambda_i f(u_i) \leq \max_i f(u_i)$$